

Social Media and Policing: Computational Approaches to Enhancing Collaborative Action between Residents and Law Enforcement

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Certificate

This is to certify that the thesis titled “**Social Media and Policing: Computational Approaches to Enhancing Collaborative Action between Residents and Law Enforcement**” being submitted by **Niharika Sachdeva** to the Indraprastha Institute of Information Technology Delhi, for the award of the degree of Doctor of Philosophy, is an original research work carried out by her under my supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted in part or full to any other university or institute for the award of any degree/diploma.

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Abstract

Law and order concerns are one of the major disquiets of urban societies in day-to-day life. Various crime prevention theories show the importance of collaboration between residents and police for maintaining law and order and addressing concerns. Collaborative action across public organizations such as police shows different challenges like enabling collective action, problem-solving, accountability, and responsiveness of the organizational actors towards residents. To enable collective action and problem solving with the help of residents, modern police departments explore innovative mechanisms to overcome the barrier of reachability and communication. Using these mechanisms, residents can convey their concerns and enquire/provide information useful for police contributing towards the collaborative process. With growing reach of web 2.0, social media has emerged as an effective platform to enable collaboration between police and resident. Social media use for communication between police and resident introduces various challenges for organizations. Owing to the massive volume of content on social media, the responsiveness of the police to the online content determine the overall success of the collaborative efforts. Additionally, social media raises challenges such as inferring actionable information and quantifying behavior (like emotions and other linguistic attributes) from unconstrained natural language text. Police organizations seek the support of technology and automation to address these challenges. Several researchers have examined the efficacy of collaborating through social media in a diverse set of scenarios like crises (natural and man-made) and socio-political upheavals. Despite its usefulness in crises, social media role to enable police in collective action and responding to day-to-day concerns of residents remains largely unexplored.

Therefore, we believe it is important to understand, analyze and enhance the opportunity for collaboration between police and residents using day-to-day life using social media. In this thesis, we study collaborative efforts by police on social media in the specific context of India. The policing department in India has only 130 personnel per 100,000 residents which is much lower than the UN recommended 270–280 personnel per 100,000 residents [35, 82]. Given the constraint on number of officers, police in India have felt the need to obtain community based collaboration to accomplish its increasingly vast duties [35]. Social media popularity among residents has motivated the police to use it for day-to-day interactions and improved community policing. Based on this understanding, we define the core research question of this thesis as *how can a platform such as social media be utilized to support, analyze, and enhance collaborative action by police organization and residents?* This thesis makes following contributions towards the core research question: a) Investigate the current role of social media in supporting police and residents' collaboration for community policing and collective action, b) Mine and quantify unstructured data on social media for managing

actionable information and understanding societal beliefs affecting day-to-day policing for improved collective action, and c) Develop a framework for extracting “serviceable requests” from social media to enhance engagement among residents and predicting expected police response to such requests.

To answer the first research question of this thesis, we conduct semi-structured interviews and surveys of both the stake-holders (police and residents) to understand social media usage requirements. Through our analysis, we highlight residents and police thoughts about information shared, need for measures to handle offensive comments, and acknowledgment overload for police on social media. Following this, we adopt a mixed method approach (qualitatively and quantitatively analysis) for analyzing the content generated on police profiles on social media. We perform this analysis along multiple dimensions: content attributes, meta-data (likes and comments), image attributes, and police response time. Our results show that residents post information (e.g., location) about various crimes such as neighborhood issues, financial frauds, and thefts. Police response to residents’ post varies from ‘reply’, ‘acknowledge’, ‘follow-up’, and ‘ignore’. We demonstrate that using statistical, unsupervised, and bag-of-words LIWC methods; we can quantify interaction patterns / cues and translate them into features that can be helpful for developing frameworks to corroborate collective intelligence. We also present a real-time image search system using Convolution Neural Networks (CNN) which retrieves modified images that allow first responders such as police to analyze the current spread of images, sentiments floating, and details of users propagating such content. The system aids officials to save the time of manually analyzing the content as it reduces the search space on an average by 67%. Finally, towards our third research goal, this thesis proposes a request–response detection framework for identifying resident’s posts that elicit police response (called serviceable posts), based on the input of police experts. Our observations show a decrease in police response time of the serviceable requests that can be immediately resolved, thus suggesting that successful identification of serviceable posts may ultimately result in systems that facilitate in extending timely police support and improve police responsiveness towards residents. Lastly, we evaluate a series of statistical models to predict serviceable posts and its different types.

Dedicated to my parents and sister

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Chapter 1

Introduction

Information flow on social media is changing the way computer systems affect our daily life. With growing reach of web 2.0, social media has emerged as an effective platform to enable collaborative action between residents and various organizations (such as police, local government bodies (municipal corporation) and first responders) [64, 98]. These organizations often regard the residents who provide information through social media as their alternate “eyes and ears” that may help enhance effectiveness of the organizations to discharge their duties and improve resident’s satisfaction [119]. To sustain and promote these interactions over social media, organizations have realized the need to regularly engage and perform routine interactions with residents on social media. Police departments are one such important organizations that are extensively using social media to address the safety concerns of residents and bring a change in the safety landscape of urban societies [64, 98]. These safety concerns could be a major reason of dissatisfaction and fear of life among residents, thus making it imperative to the cognisance of such safety concerns and issues [67]. Residents (User) generated information through their participation on social media enables police to understand residents’ concerns.

Police are often considered to be the most representative and perpetual government service to address the safety concerns of residents [58]. The kind of interactions that happen between police and residents as a consequence of a safety issue may bear detrimental effects on the psychological well-being of the residents and society at large [124]. Considering the police image of “coercive arm of the state” residents often do not share their experiences/law and order concerns with the police [29]. Thus providing little opportunity for police to change the crime landscape, explain their actions, and collaborate with residents in crime prevention activities. Police often explore effective collaborative strategy to obtain timely information from residents and understand their concerns [16, 29, 49, 68]. However, these collaborative strategies across police organizations exhibit various challenges such as enabling collective action, problem-solving, accountability, and responsiveness between organizational actors and residents [19]. To enable collective action and problem solving with the help

of residents, modern police departments explore innovative mechanisms to overcome the barrier of reachability and communication.

Research in this thesis is uniquely placed at the intersection of the vast literature in the field of Computer Mediated Communication (CMC) [132] for collaboration and user-generated information on social media. We study these collaboration in a unique context of social media and take residents' generated content as a type of user generated content. Social media use for collaboration between police and residents introduces various challenges for the organizations. Due to the enormous volume of residents' generated content on social media, the responsiveness of the police officers to these online content regarding promptness and action they take determines the overall success of the collaborative efforts [29, 112]. Additionally, social media raises challenges such as inferring actionable information and quantifying behavior (like emotions and other linguistic attributes) from unconstrained natural language text [53, 61, 140]. Police organizations seek the support of technology and automation to address these challenges [53, 65]. In this thesis, we use the rich knowledge of various social media parameters such as text attributes, images, and social capital (likes, comments, etc.) from resident's generated content to address these challenges of interaction between police and residents.

Broadly, this thesis makes contributions to the following two paradigms of computer science – *abstraction (modeling)* and *design*.

- Contributions towards the design paradigm: We operationalize measures to enable computational management of social interactions, actionable information, and police responsiveness in terms of promptness and action taken to improve collaborative problem-solving. Towards this end, we use non-parametric statistical tests to identify the difference and quantify these measures such as Mann-Whitney Test. This operationalization of measures helps to articulate the organizational needs for assessing the effect of crime on the residents and residents' expectations from the police. Operationalizing the responsiveness and promptness of police organization, we propose survival analysis method that helps overcome the observation period bias while evaluating time taken by police to respond in social media based studies. This thesis also highlights the design needs of the various stakeholders such as police and residents from socio-technical systems that support collaboration between police-residents.
- Contributions towards modeling paradigm: We use the above-identified measures to model serviceable requests from residents i.e., automatically identifying resident's requests that seek/elicit police response. To this end, we perform exhaustive feature evaluation using Forward Stepwise Logistic Regression and perform a comparative evaluation of different models using different Machine Learning algorithms. In this process, we face challenges such as high coherence among the topics discussed in residents posts that may elicit police response. To address this challenge, we demonstrate the applicability of Non-negative Matrix Factorization

(NMF) approach to identify various topics in residents’ generated posts. Complementing this identification process of serviceable posts, we also model such content (specifically images) that are of interest to police organization to understand safety issues that may cause unrest in the society at large. Handling some of the challenges of the hand-crafted features, we propose a deep neural network to assess similarity among images that are of interest to police for maintaining safety.

In this chapter, the following sections describe the emergence of social media for collaboration and need for assessing the online social interactions for improved collaboration between police and residents. Further, we describe our research statement and our contributions to the domain that can help to enhance collaboration between police and residents for improved safety landscaping.

1.1 Emergence of Social Media for Collaboration and Collective Action

Social media contributes to the improved tradition of participation, responsiveness, and openness to different government organizations [79,150]. It provides a mechanism to develop personal relationships with residents by disseminating information about performance and government agency’s actions followed by inputs from residents on these actions. Developing personal relationships can increase the trust residents place on the government agencies [61]. Research shows that unlike other organizations, police departments represent the most omnipresent and ubiquitous body of society. Competing demands of the residents that police must be “leaner” and “do more with less” result in greater expectations among residents that police performs their duties better in comparison to any other organization [58]. Researchers recommend that successful collaborative actions between residents and government organization would require efforts along three dimensions - people, data, and more accurate analytical / modeling tools (See Figure 1.1) with every passing year on the online platforms [12]. Social media can facilitate increase along all three dimensions as it provides unparalleled opportunity to express and share their beliefs, exchange information from alternate sources, and communicate observations about their experiences from surroundings in comparison to other media. Police in different countries have rigorously used social media as a direct platform to communicate with the public during critical events such as crisis. Many studies have shown how social media played a useful role to provide critical real-time information and reduce the spread of misinformation in developed countries [78,101,122,141]. Researchers also found that residents used social media for general coordination during a crisis, categorized public response, and showed the existence of different communities on social media during crises [44,54].

These studies highlight the residents’ unique and voluminous use of social media to generate information as compared to face-to-face interactions in similar events [44,54]. These social media inter-

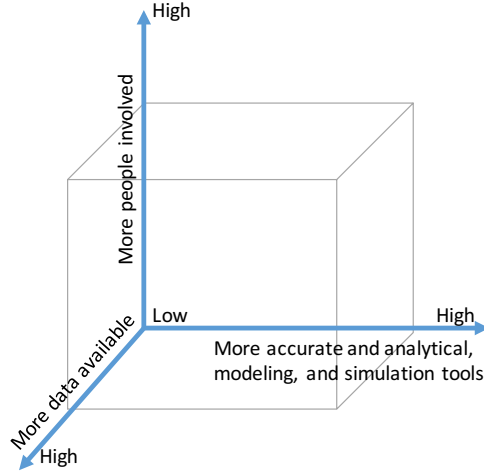


Figure 1.1: Successful collaboration requires efforts along three dimensions - people, data, and more accurate analytical / modeling tools. Figure adapted from [12].

actions result in greater expectations and lead to unique challenges regarding action taken, services provided, engagement intentions, and promptness of organizations such as police departments across social media profiles. Several researchers have examined the efficacy of social media in a diverse set of scenarios like crises (natural and man-made) and socio-political upheavals [78, 101, 122, 141]. In such scenarios, exchanges between residents, emergency responders, and police organizations for collaboration have also been explored. Despite its usefulness in crises, social media role to enable police in collective action and responding to day-to-day concerns of residents remains largely unexplored. Literature also makes little effort to understand if the knowledge of social media usage in event-driven safety campaigns (that last for specific time period) can be helpful for police to strategize day-to-day collaboration for policing. Therefore, we believe there is an important requirement to understand, analyze and enhance the opportunity for collaboration between police and residents using day-to-day interactions between them on social media.

The research in the field of computational social science [66] recognizes and suggests approaches that help operationalize societal behaviors with respect to safety concerns using novel computing methods. In this thesis, we concentrate on designing and modeling socio-technical systems by mining resident-generated content on social media that can aid day-to-day organizational tasks of police departments. Our work in this thesis can help address two fundamental limitations of exiting methods in safety promoting technologies. First, current technological solutions incentivise residents to avoid situations where they can be victimized rather than promoting collective action which is proven to be a stable solution for safety concerns. For instance, most of the current technologies focus on management of law enforcement content and use of video surveillance or providing crime maps to residents to avoid unsafe areas. Second, the current state-of-the-art requires extensively uses manual methods to collect, process, and identify information of interest to the police organizations

for maintaining societal safety in day-to-day life. However, computational approaches that can help to overcome the constraints and labour involved in manual analysis remains largely unexplored in the literature. Complementing these lines of research, we propose mechanisms to operationalize societal behavior through collective knowledge and improve collaboration between police and residents; to this end, we employ statistical and machine learning approaches.

Social media based communication for policing involves multiple stakeholders whose analysis is a need for designing an information system (or media). This thesis helps to understand the generation, flow, and consumption of information among the stakeholders for building better systems for enhanced collaboration. Reuter et. al. show different categories and types of actors, who participate in public safety during a crisis on social media [106]. Broadly, these categories include, a) residents who face the law and order situation on-the-ground, b) the virtual residents and volunteers who utilize OSN to inform about crises or crime and c) the authorities such as police and other first responders. These three stakeholders are connected, and their interactions result in many other stakeholders becoming users of OSN based system. For instance, authorities need to solve and provide safety in the real world and gather eyewitnesses' information that may easily be available on virtual media. In addition to affected residents and authorities, research shows that voluntweeters, resident journalists, repeaters, readers, and retweeters are also present in the virtual media [39, 105, 122].

Social media as used for policing in the current state offers remote and mostly asynchronous interactions between police and residents. Designing a framework that supports collaborative work in such a setting (remote and asynchronous) needs the understanding of various dimensions of collaboration. One such model that helps explain different aspects of a collaborative tool is the time/space groupware matrix developed by scholars of collaborative work [5, 59]. The model defines two dimensions that can characterize work domain in collaborative tasks – *time and space*. Figure 1.2 describes the various quadrants of the time/space groupware matrix. For instance, as social media may not be the only and primary source of interaction with police, police may need to collaborate with residents at a different time. Also, given the police impressions of coercive arm of the state residents may not be willing to have frequent face-to-face interactions with the police. Thus collaborative tools designed for interaction between police and residents need to support a remote and asynchronous form of communication.

Given our scenario of remote and asynchronous communication between police and residents on social media, we concentrate on the bottom two quadrants of the time/space groupware matrix in Figure 1.2. The remote interactions can be achieved using various technological aids such as messaging and social media posts. These may happen at the same time or at different instances depending upon the availability (time function) of the collaborators. In case of asynchronous communication, these may include interacting through blogs or social media pages [5, 59]. In this asynchronous and remote scenario, enhancing day-to-day collaboration would require a framework that could

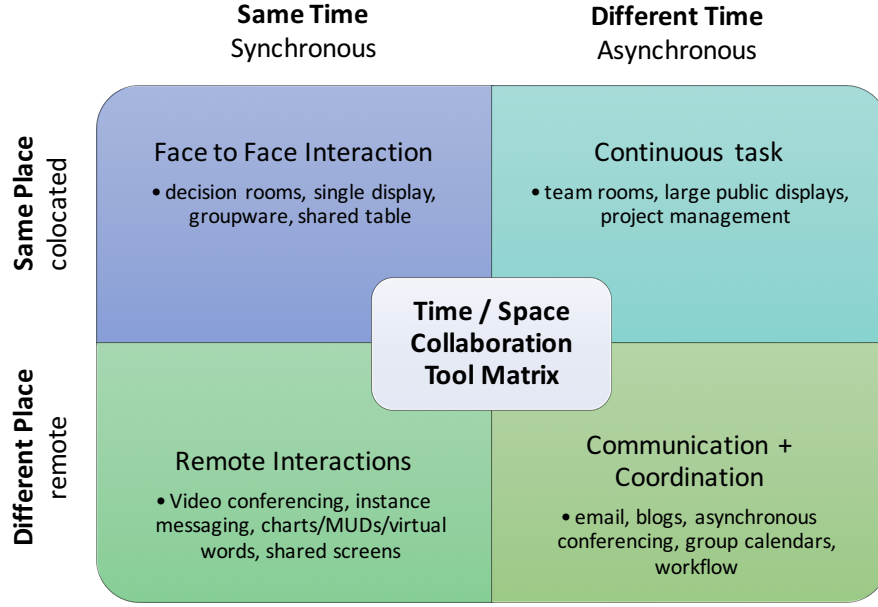


Figure 1.2: Time/space groupware matrix developed by researchers working to improve collaborative work between stakeholders. Figure taken from [5, 59].

use computational and modeling approaches to address challenges of police organizations such as responsiveness, promptness, action taken and engagement in remote online interactions.

1.1.1 Indian policing - context to this thesis

In this work, we take India as a case study to understand the role of social media content in improving collaboration between police and residents. India is second largest populous country employing the second largest police force in the world [30, 127]. For every 100,000 residents in India, 130 police officers are deputed [127]. This number is far less than the number suggested by UN guideline i.e., 270-280 police personnel per 100,000 residents [35]. To alleviate this shortage, police adopts multiple media to stay connected with the community. Residents can individually connect with the police by calling the telephonic helpline (100 similar to 911), writing to official email, or visiting a police station [57]. The provisions so far adopted by police for community policing are mostly non-technology based. Realizing the importance of community involvement, police have introduced provisions for community members to watch their neighborhood, join beat constables to perform beats, and arrange get-togethers to understand neighborhoods [57]. Involving social media for community policing in one such initiative of Indian Police to involve residents for improved safety. This thesis builds upon the unique yet under explored domain of social media for safety in day-to-day life of urban society.

Understanding of Social Media Pages / Profiles use by Police Organizations in India

Owing to the popularity of social media such as Facebook, Indian Police is adopting and encouraging residents to use social media [87]. Many cities have set up their Facebook pages under the supervision of senior officials to answer residents' concerns. Figure 1.3 shows various elements of conversations initiated by police and residents on social media.



Figure 1.3: Various elements of conversations between police and residents on social media.

More than 3 Million people have liked the pages that we study in this thesis. Police have issued guidelines on how residents can use Facebook to report incidences and ask to include information such as time, date and place of the incidence while reporting [72]. Police also issue action taken reports and conducts these social media endeavors under the guidelines of the Govt. of India [31]. In this thesis, we use the knowledge of community policing components and analyze the role of OSN to facilitate the community policing process. We also identify the design challenges that need to be addressed to increase OSN role in community partnership and problem-solving. We found that for almost all the police departments, the number of followers on Twitter is less in comparison to Facebook likes. Given that the *number of likes* is more on Facebook than followers on Twitter (for most of the departments), wherever appropriate, we provide examples from Facebook. The analysis in this thesis includes data published on various Indian police departments, however, the content is dominated by tier 1 and tier 2 cities where social media is extensively used. We believe our observations in this thesis would be applicable for urban and sub-urban areas of Indian cities and similar cities across the globe.

1.2 Core Thesis Question

Based on the understanding developed so far, we define the core research question of this thesis as:

How can social media platforms be utilized to support, analyze, and enhance day-to-day collaborative interaction between police and residents?

In this work, we follow a mixed method approach to address the above research goal. We perform the following analysis: a) we investigate the current role of social media in supporting police and residents' collaboration for community policing and collective action, b) next, we perform a deep dive to understand different data types available on social media; to this end, we mine and quantify unstructured data on social media for managing actionable information and understanding societal beliefs affecting day-to-day policing for improved collective action, and finally, c) we develop a framework for extracting "serviceable requests" from social media to enhance engagement among residents and predicting expected police response to such requests using textual content available on social media.

1.3 Thesis Contribution

This thesis work is placed at the intersection of the literature on social media informatics, textual extraction, and forecasting from interactions through CMC (Computer Mediated Communication) for police organizations. We believe that investigating mechanisms for extracting evidence for collaboration to improve collective action and responsiveness of police towards residents using residents' generated content during day-to-day interactions on social media is a need for various reasons. For instance, residents' information going unnoticed by the police organization may have significant influence on the assistance seeking patterns of residents; multiple such incidents may have implications for future interactions and may influence other residents' opinion about satisfaction with police; and understanding information as part of collective action efforts may help in creating intelligence regarding crime landscape and necessary reforms needed. Thus to learn about attributes that can prompt for and enhance collaborative action this thesis makes the following contributions:

1.3.1 Identification of social media appropriation for collaborative policing and usage intent of the Stakeholders

We adopt multi-stakeholder and mixed method approach to investigate whether social media based technology can be adapted to support communication and collaboration for making safer urban society through community policing efforts. For this, we conduct extensive interviews (20 Indian

Police Service officers and 21 residents) and surveys (445 police personnel and 204 residents). Using grounded theory analysis, we show that social media can offer improved collaboration opportunity enabling police to identify actionable information with the help of residents and enhance coordination among them (police and residents). We also identify opportunities for designing technologies such as semi-automated acknowledgment system for resident request and automated methods to classify the residents' content in various actionable information categories. These technological aids can reduce the overhead on police enabling frequent social media use for collective problem solving and action.

1.3.2 Mining and measuring unstructured data for understanding actionable information and societal beliefs

This thesis presents an in-depth analysis of social media interactions of residents and police on social media for sharing law and order concerns. Using data mining approaches, we investigate if the richness of social media data can be helpful to involve residents in connecting with police for improved collective action.

- Quantitative operationalization and characterization of social interactions between police-residents for improved collaboration: Our work shows that it is possible to operationalise and measure social interactions between police and residents for improved collaboration in a fine-grained manner through three dimensions: engagement, affective expression and intensity, and linguistic attributes of cognitive and social processes. We make an attempt to quantitatively infer intelligent cues and patterns regarding topical, engagement, emotional, and cognitive and social orientation characteristics from residents and police interactions. To this end, we examine and characterize content from 85 Facebook pages of Indian police departments. Our analysis, using Kmeans++ seeding based clustering, validates the topics exchanged on resident initiated discussion and police initiated discussion threads. Residents focused on topics concerning crime tips and complaints, neighborhood problems, missing people information, and appreciation for police work. Compared to police-initiated discussions, resident-initiated discussions show lower engagement. Further, discussions involving both police and residents show higher negative emotions, anger, and arousal than resident only discussions; these interventions involving both (police and residents) reveal a stronger notion of a collective identity. We demonstrate that using statistical tests, unsupervised methods such as clustering and bag-of-words LIWC methods; we can quantify these patterns/cues and translate them into features. We believe this knowledge can be helpful for developing frameworks to corroborate collective intelligence through social media.

- Studying image similarity for collective intelligence and action by police: Prior studies in this thesis (Chapter 4, Chapter 5 and Chapter 6) primarily help in understanding collective action through textual analysis. However, social media offers a significant amount of multimedia content such as images that can be a rich source of information for collective action to address law and order concerns. Therefore, complementing these studies on textual content, we investigate other multimedia content such as images shared on social media that may contain information of interest contributing towards collective intelligence and action. These initiatives motivated us to propose a real-time image search system that can serve the first responders by reducing the search space involved in identifying images of interest security during safety critical scenarios. Towards this, we present a comparison of different hand-crafted features and a Convolutional Neural Network (CNN) model to retrieve images of interest for collective intelligence. Our solution addresses the modifications done on the images like cropping, scaling, stitching image, wrapping around the text, contrast enhancement and changing colors which are one of the biggest challenges faced in image analysis. These challenges often create barriers to access these images directly and utilize information like image spread, etc., which makes image retrieval a complex and daunting process for collective intelligence. The system can aid officials to save the time of manually analyzing the content by reducing the search space on an average by 67%.
- Opportunity for mining actionable information and residents’ opinion about policing activities from social media: We explore the utility of social media for understanding important aspects of collaboration such as collective action and responsiveness of police. We investigate whether residents’ post on social media contain actionable information that police can use for collective action and how residents use social media to hold police accountable. We present a qualitative analysis of textual content (posts and comments) on the Facebook page of Bangalore City Police, India, over a period of one month as an endeavor to achieve collective action through social media. Our results show that residents post information (including location) about various crimes such as neighborhood issues (drunkards, illegal construction), financial frauds, property crime, and thefts. Police response to residents’ post varies from ‘reply’, ‘acknowledge’, ‘follow-up’ and ‘ignore’. In addition to actionable information, we find evidence that residents use social media to express the fear of crime. As part of this thesis, we present a collective knowledge visualization system that allows for easy consumption of above-mentioned analysis from public pages of Police departments on social media.

1.3.3 A method for request–response detection framework and responsiveness of police response to residents

This thesis proposes a request - response detection framework for identifying residents’ posts that elicit police response (called serviceable posts), based on the input of police experts. Research shows

that a) how well police deals with and responds to these service requests defines the overall satisfaction of community with the police and b) these requests account for the major information source contributing towards collective action for improved safety and psychological well-being of residents. In this work, we pursue the use of social media as a source of crowd generated requests and a means to characterize service requests that need a response from the police organization. We provide insights on six content based textual features – emotional, cognitive and interpersonal, linguistic, question asking, entity-based and topical attributes that can be useful to identify serviceable posts. We find such posts are marked by high negative emotions, more factual, and objective content such as location and time of incidences. We perform temporal analysis using non-parametric survival method (Kaplan-Meier) to explore and estimate the police response time to serviceable posts. Our observations show a decrease in police response time of the serviceable requests that can be immediately resolved. These observations thus suggest that successful identification of serviceable posts may ultimately result in systems that facilitate in extending timely police support and improve police responsiveness towards residents. Lastly, we evaluate a series of statistical models to predict serviceable posts and its different types. We believe this understanding can help improve the responsiveness of police to day-to-day requests by residents highlighting the posts that need their action and response. As a proof of concept of the proposed statistical model, we design and develop a web browser (Google Chrome) plugin. The viability of this implementation is demonstrated through a system-level performance evaluation.

1.4 Thesis Organization

This document is organized as follows. Chapter 2 elaborates the background and related work in the domain of social media for policing and community policing. In Chapter 2, we discuss the state-of-the-art approaches and research gaps that this thesis will address. Chapter 3 provides insights on social media appropriation and usage intent of the Stakeholders – police and residents for improved safety. In Chapter 4, we elaborate on operationalization of measures and characterization of social interactions between police-residents for improved collaboration. Emphasizing the role of images in safety critical scenarios, Chapter 5 discusses the opportunity for mining actionable information and residents’ opinion about policing activities from social media. We formulate the building blocks for “serviceable framework” in this Chapter 5. Following this work, Chapter 6 proposes a request - response detection framework for identifying residents’ posts that elicit police response (called serviceable posts), based on the input of police experts. Chapter 7 discusses a framework to detect similarity among images that may result in mass unrest in the society. Lastly, Chapter 8 concludes with the discussion on impact, future extensions and limitations of this work.

1.5 Thesis Publications

Below are the publications that are part of the thesis:

- Chapter 3

1. **Sachdeva, N.** and Kumaraguru, P. Online Social Media - New face of policing? A Survey Exploring Perceptions, Behavior, Challenges for Police Field Officers and Residents. Accepted at 18th International Conference on Human-Computer Interaction (HCII), 2016.
2. **Sachdeva, N.** and Kumaraguru, P. Deriving requirements for social media based community policing: insights from police. Accepted at ACM 16th International Digital Government Research Conference (dg.o 2015), 2015.
3. **Sachdeva, N.** and Kumaraguru, P. Online Social Networks and Police in India - Understanding the Perceptions, Behavior, Challenges. Accepted at the European Conference on Computer-Supported Cooperative Work (ECSCW), 2015.

- Chapter 4

1. **Sachdeva, N.** and Kumaraguru, P. Characterising Behavior and Emotions on Social Media for Safety: Exploring Online Communication between Police and Citizens. Accepted at 30th British Human Computer Interaction Conference (HCI) 2016.

- Chapter 5

1. **Sachdeva, N.**, and Kumaraguru, P. Social Networks for Police and Residents in India: Exploring Online Communication for Crime Prevention. Accepted at the ACM 16th Annual International Conference on Digital Government Research (dg.o), 2015. [Best paper award].

- Chapter 6

1. **Sachdeva, N.**, and Kumaraguru, P. Call for Service: Characterizing and Modeling Police Response to Serviceable Requests on Facebook. Accepted at the ACM Conference on Computer-Supported Cooperative Work and Social Computing (CSCW), 2017.

- Chapter 7

1. Goel, S., **Sachdeva, N.**, Kumaraguru, P., Subramanyam, A., and Gupta, D. PicHunt: Social Media Image Retrieval for Improved Law Enforcement. Accepted at 8th International Conference on Social Informatics. 2016.

Other publications: Below are the publications that were done during the Ph.D. life and are not part of this thesis.

Journal Papers

- Manar Mohamed, Song Gao, **Niharika Sachdeva**, Nitesh Saxena, Chengcui Zhang, Pon-nurangam Kumaraguru and Paul van Oorschot. On the Security and Usability of Dynamic Cognitive Game CAPTCHAs. In Journal of Computer Security (JCS), 2017.

Peer-reviewed Conference Papers

- Lamba, H., Bharadhwaj, V., Vachher, M., Agarwal, D., Arora, M., **Sachdeva, N.**, Kumaraguru, P. From Camera to Deathbed: Understanding Dangerous Selfies on Social Media. 11th International Conference on Web and Social Media (ICWSM), 2017
- Mohamed, M., **Sachdeva, N.**, Georgescu, M., Gao, S., Saxena, N., Zhang, C., Kumaraguru, P., Van Oorschot, P., and Chen, W. A Three-Way Investigation of a Game-CAPTCHA: Automated Attacks, Relay Attacks and Usability. Accepted at 9th ACM Symposium on Information, Computer and Communications Security (ASIACCS), 2014.
- **Sachdeva, N.**, Saxena, N., and Kumaraguru, P. On the Viability of CAPTCHAs for Use in Telephony Systems: A Usability Field Study. 16th Information Security Conference November 2013 in Dallas, Texas (ISC), 2013.
- **Sachdeva, N.**, Saxena, N., and Kumaraguru, P. On the Viability of CAPTCHAs for Use in Telephony Systems: A Usability Field Study [Poster]. (APCHI) 2013
- Ion, I., **Sachdeva, N.**, Kumaraguru, P., and Capkun, S. Home is safer than the cloud! privacy concerns for consumer cloud storage. In Symposium on Usable Privacy and Security (SOUPS) (2011).

Chapter 2

Related Work and Background

Work in this thesis presents a combination of various domains including – computational social science, computer-mediated communication, criminology, and community policing. Using our work in this thesis, we contribute towards two core computer science paradigms – *abstraction (modeling)* and *design*. In this Chapter, we present the prior research work done in the field of designing and modeling social media interactions for improved collaborative activities. We review public organizations’ use of social media for community engagement [17, 116, 126, 142].

This chapter is structured as follows: in Section *Safety Technologies, Collaborative Action, and Police Organization*, we discuss prior work done to develop technologies that enable safety and collaborative action through online means such as community forums and social media during scenarios like a crisis. These contribute to the design and operationalization of computational measurement of social interactions, actionable information, and police responsiveness. Next, we present different studies showing types of online interactions based on who initiates the discussion – organizational actors or residents. These interactions help understand computer-mediated-communication between police and residents. Following this, we focus on the literature regarding social media based technologies for improved interactions and collaboration. Here, we describe various aspects such as the need for collaboration between police and residents for community policing. This review also presents the uniqueness and need for analyzing social media for collaborative policing in India. In conclusion of this chapter, we present the research gaps in the literature on social media based solutions for collaboration between police and residents in day-to-day policing.

2.1 Safety Technologies, Collaborative Action, Police Organization

Residents-police interactions are well-studied in psychology, criminology and other social science literature [29, 49, 68]. A key observation in this body of work is that collaboration between resident

and police such as collective action can successfully help reduce anxiety and fear related to crime [67]. However, getting residents involved and getting them to share their experiences with police is often a difficult task, considering police impressions of “coercive arm of the state” [29]. Lack of resident involvement to provide information about their experiences with police and crime incidents gives little opportunity to police for changing the crime landscape and explaining their actions; this also prohibits involving residents in crime prevention and civic engagement activities.

Collaboration between police and residents requires major cultural changes as in most countries across the globe policing has evolved from semi-military and highly hierarchical systems [84]. Indian policing systems finds its roots in the British ruled India which has led to a divide of ‘you’ vs ‘us’ among police and residents. After independence, police is majorly viewed as the tool of the state rather than a service. Developing a culture of collaboration needs intensive training and sensitization of the police department which could develop confidence in the policing services. This would also require enabling and training residents to involve in meaningful conversation with the police department. However, the already overworked police departments find it difficult to develop a cultural change at the organizational level. Also, residents mostly hold police accountable and look up to them for maintaining law and order rather than involving themselves in improving the law and order [88].

Research work has explored developing technological solutions to improved safety. Such research efforts focus on technologies to satisfy requirements of the police such as - managing content that is of relevance to law enforcement agencies and use of video surveillance [15,139]. These technologies often ignore the residents’ participation and needs for maintenance of law and order. On the other end, there are technologies that focus on residents for personal safety, report unsafe locations, wearable gadgets and mechanisms to take a decision based on community consensus to reduce fear [9]. These research endeavors capitalize on the approach of making information available to residents so that they can avoid crime or can be protected from being victimized.

However, very few studies focus on the technologies that promote collaboration between police and residents to address safety concerns [49,67]. Literature imparts little insights about measuring behavioral attributes of residents-police discussions: such as emotional, social and cognitive processes induced due to encountering a law and order situation. Measuring these behavioral attributes is an important element for successful collaboration between organizations and individuals striving to achieve societal safety [68,151]. Hence, prior research has suggested analyzing residents and the community behavior for societal change and social determination [33]. We believe with the advent of using social media for policing, there is a need to explore social media as a source of useful user generated content and a means to understand the social relations and nuances of day-to-day interaction between residents and police on social media.

2.2 Online Interactivity and Organisations

Various emotional and social processes may unfold through everyday online interactions between government organizations and residents [11]. Studies on computer-mediated communication explore multiple dimensions of these interactions such as the direction of communication, sense of place, time flexibility, timely feedback, and responsiveness [32,75]. Specifically, researchers operationalised interactions between resident and government as a measure of individuals' perceptions, communication process and features such as user control in the context of websites, community forums, and emails [147].

Studies on interactions between the stakeholders (residents and authorities) during critical situations such as crisis like floods and fires present four different types of interaction directions on online systems [107]. Figure 2.1 represents the types of the interaction. Type 1 consists of communication from Organizations to the Public (Police to Residents). This is the classical form of communication adopted by most authorities to inform residents about law and order situation. Research shows the need for appropriate alert systems and tag to help improve the recognition of information posted by the organizations for residents' attention [107]. These studies also highlight that residents prioritize the information that they like to receive from authorities. Therefore, organizations may adopt different approaches to get information conveyed to residents. The approach used to connect with residents have a different influence on survival of the online communication between stakeholders [29]. In this thesis, we propose a mechanism which enables police with automatic methods to analyze resident's request using machine learning approaches. We also look at statistical methods to measure police promptness and response time to residents' request posted on social media.

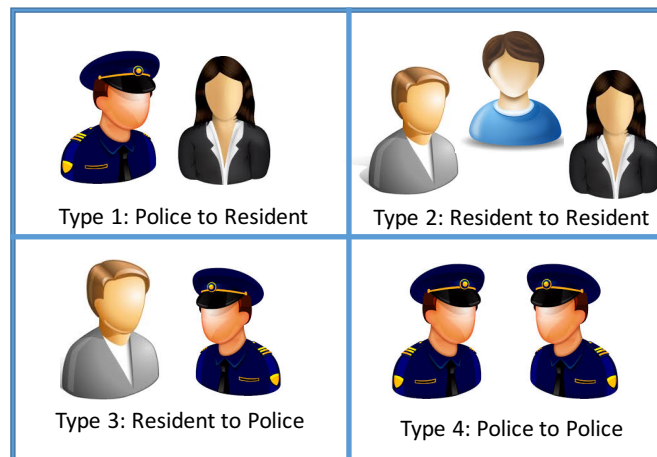


Figure 2.1: Communication matrix for use of social media by authorities and Residents.

Type 2 category of information exchange is from the Public to Public (Residents to Residents) such as self-help communities. Residents may exchange situational details, activities observed on-

the-ground, and seek emotional and material resources to address safety critical situations such as natural crisis [107]. Research shows that social software such as community forums for policing create opportunities for residents to themselves develop self-help groups to take collective action. Lewis et. al. show that participants of the online forum could use online communication to achieve following four goals – strengthen social ties, identify ways to collect information for collective action, sharing information and advice with other group members and implementing social norms for crime prevention through community forums. Their results show that technology for community or collective crime prevention should encourage problem - solving communication among residents [68]. In this thesis, we operationalize behavioral measures that help in computational traceability of communication from residents to residents as a gesture of community support.

Type 3 category involves information flow from the Public to the Organizations (Residents to Police). This type includes technologies that enable police to get information from the residents [107]. The shared information may address two dimensions – a) police passively monitors the content generated by residents and b) police explicitly asking residents to provide some information. In this thesis, we propose a system which enables police to passively monitor images shared by residents on social media that may complement the existing systems that primarily monitor text shared on social media.

Type 4 category involves information exchange from Organizations to Organizations (Police to Police). At present, this category gets less attention in the literature. Few researchers study the social media use by EMS (Energy Management System) professionals to find that information integrity, user identification, privacy, and technology reliability were among the major apprehensions for using OSN ¹ by authorities. Among the most popular use is sharing information, communication, and networking. Anecdotal studies show that authorities may use social for quick internal communication. Similar efforts of inter-organizational exchange were presented following a technological disaster of coal fly ash spill into the valley and tributaries of the Tennessee River [128].

2.3 Social Media for Collaboration

Aiding police and residents through social media has gained a significant interest of researchers working on Computer-Mediated-Communication (CMC) [55]. The focus of CMC researchers in this domain has been on studying varied aspects such as communication needs, social media response strategies, and grassroots coordination and support [29, 55]. With few exceptions, these studies analyze large-scale crisis situation such as earthquake, riot, fire, and floods [17, 29, 92, 101, 113]. In [29, 49], authors discussed effective communication strategies for police organization to provide timely information to residents during crises. Studies also investigate communication patterns

¹In this thesis, we use OSM, OSN, and social media interchangeably

of different police departments and styles of engagement during crises [29]. Further research also explores communication challenges arising due to diversity in groups that seek police assistance through social media especially during crisis situations [29, 55, 68].

Our work also relates to a plethora of studies on police strategies to use social media and challenges in adopting it as a platform for engaging with residents [29, 55, 68]. These studies highlight that organizational support for online interactions is constrained by limited resources, insufficient tools and training to use social media. Also, organizations such as police adhere to formal hierarchical command and control systems that require necessary approvals before engaging in public conversations [55]. Thus making it hard to integrate social media as a real-time response system into existing formal process. These platforms also expose police to continuous check and denunciation of residents making it challenging to sustain communication [29].

To understand the role of social media in collaboration and communication for enhanced safety in day-to-day life, we briefly discuss community interaction strategies of police and community policing approach.

2.3.1 Community policing approach

Community policing aims to achieve following objectives: a) offering decentralized decision-making that empowers field officers to identify crime, b) prioritizing the problem with the help of residents and consult the residents to decide the issues, and c) introducing transparency in the policing decisions. To achieve these objectives, two prime components are recognized – community partnership paradigm and problem-solving approach [19]. We discuss each of this component below.

Community partnership involves maintaining orderliness and safe neighborhoods with the help of residents [19]. For this partnership, Indian police introduced provisions such as neighborhood watch committee i.e. members watching their neighborhood turn by turn, join beat constables to perform night beats, inform police about any child or youth going astray, and arrange social and cultural get-togethers to understand neighborhoods [6]. These activities of community partnership help develop trust between the police and the community. Police need to develop community trust before involving residents in the decision-making process. With increased trust police can get valuable information available to the residents about their neighborhoods. Therefore, community partnership involves developing relationships that contribute towards building a “bond of trust” by maintaining community contact and frequent communication with residents [19].

The problem-solving approach involves four aspects: information exchange, problem identification, problem-solving, and trust. It involves identifying concerns for both residents and the police [19, 95]. The prioritization happens with the help of residents, e.g., a police team might think that burglary is the biggest problem in their locality; however, the community might consider women assault and harassment as a bigger concern. Once the problems are prioritized, police work at providing solutions

to the issues raised by residents. The problem-solving approach suggests proposing solutions that can include community members to improve safety, reduce anxiety, and strengthen the ties between police and residents [117]. Improved satisfaction levels strengthen trust among the residents and increased information exchange among the members of community and residents.

2.3.2 Mining collective action through user-generated content

Emphasizing social media's role in crisis informatics, various studies highlight that residents can become a valuable resource for gathering crisis information [91, 122, 140]. These research works show that residents exchange information on social media for various activities including – a) report relevant information, b) inquire information situation on ground such as affected location and well-being people, c) request for assistance and help, and d) coordinate actions. Research also highlighted social media role in public reactions during critical events such as societal upheavals [54]. These studies also investigate the possibility of developing real-time systems to extract information for first responders such as emergency response teams [25, 45, 78, 122, 141]. An important aspect of this information include situational information related to a crisis event such as earthquake and floods that can help to understand situation on ground. Studies also demonstrate role of social media in extracting situational awareness using natural language processing (NLP) strategies from the textual content of tweets [140].

Studies also investigate mechanisms to extract information regarding useful resources such as tweets related to medical, volunteering, and clothing needs [100, 141]. These studies highlight information that residents share during a crisis and how it is utilized. During law and order situation such as crises, research show only a small number of posts / tweets contain information that is posted by the local members of the affected area. Despite this sparse behavior, researchers found that this information is valuable information source for various stakeholders such as emergency responders, event planners, affected people, journalists, and the digital crowd [121]. A major challenge in such studies has been monitoring a large volume of public information being shared by residents to identify information of interest [53, 61]. Most of these studies characterize textual content shared during crisis events [53, 61, 140]. It remains, however, unclear if this vast understanding of content characteristics available for event-driven situations can be helpful for police to understand characteristics of a resident's request for service in the context of routine day-to-day policing.

2.3.3 Analyzing behaviour through user-generated (resident) content

Researchers show that residents use social media for general coordination during a crisis, categorized public response, and showed the existence of different communities during crises on OSN [44, 54]. Shklovski et al. analyze how community members use various ICT including OSN to organize

community support through resident to resident (Type 2) communication during events such as crises [116]. Shklovski et al showed that ICT provides opportunities for authorities to provide relevant information to residents (Type 1 interactions). Research recognize that people tweeting from affected area (“on-the-ground”) can provide such information which is otherwise either not available or difficult for authorities to collect (Type 3 interactions, See Figure 2.1). They also found that residents on ground may also have information regarding the geographic or cultural aspects which is important for organization trying to control the situation [123]. Despite OSN usefulness in community engagement, Hughes et al. found that relatively few police and fire departments in the USA used OSN for public communication. Also, different departments showed a varied use of different media [55]. They found OSN plays a crucial role in reassuring people in the state of conflict and increased public accountability of organizations. This study also suggested that OSN should be made more “listenable” for both emergency managers and the resident communities they serve. This would involve analysing both Type 3 and Type 2 interactions in the Figure 2.1.

Complementary work on the responsiveness of the police officers to the resident’s request has been extensively studied in criminology and social science research [50, 74]. The key contribution of these criminology studies are: a) how well police deals with and responds to these service requests defines the overall satisfaction of community with the police and b) these requests account for the major information source contributing towards collective action for improved safety and psychological well-being of residents. We note that characterization and identification of how such residents’ posts differ from general conversations between police and residents on social media remain largely unexplored. In this thesis, we pursue the use of social media as a source of crowd generated requests and a means to characterize requests that need a response from the police organization. We believe this understanding can help improve the responsiveness of police to day-to-day requests by residents highlighting the posts that need their action and response.

2.4 Research Gaps

We highlight the research work in the space of computing solutions for data-driven policing to improve collaborative efforts for public safety. We examine how computational techniques, machine learning approaches, information retrieval, and natural language processing methods can be utilized to understand social media data. Our observations of the research studies show that social media is used largely to explore concerns, characterizing or analyzing the nature of issues during law and order situations such as wars, floods, earthquakes which are mostly event driven. However, using OSN data for social impact on the community and day-to-day policing is largely unexplored. Some of the specific open research problems in this domain which we will address in this thesis are:

- Identification of social media appropriation and usage intent of the Stakeholders.**

There has been in-depth and focused research on what contributes to collaboration on other online entities like websites and web forums. Lewis et al. analyze community web forums and websites, and understand opportunities of improved public safety [68]. Henman et al. provide the knowledge about the role of government such as police websites, the online communities, and the dynamics of the information exchange through these platforms [48]. Such focused and targeted research also needs to be done on OSN platform to understand users perceptions of collaborative policing and appropriating social media more useful for collaborative public safety. These studies showcase that collaboration among residents and police can help develop trust, improve public safety, introduce transparency, and mutual information generation. Some preliminary work describing residents informing police is analyzed by Metaxas et al. [80]. However, these studies focus little on understanding the reasons resulting in successful vs not so successful social media collaborations.
- Mine and assess information from user resident-generated content on social media for improving public safety.**

Social media, due to its massive and pervasive reach, has emerged as a prominent medium to support online interaction between resident and government organizations such as police [29, 55]. Prior work has investigated the effectiveness of social media in a variety of scenarios - e.g., crisis (hurricanes and fires) and socio-political upheavals [17, 92, 113]. Interactions between residents, first responders, and organizations for effective collaboration have also been explored [116, 142]. These studies demonstrate the role of social media in collective action and in providing social support during crises [25, 29, 55, 69]. However, there is little knowledge about operationalizing measures that can help quantify the rich social media data to improve and understand resident perceptions/needs for day-to-day policing. This knowledge about online interactions between police and residents can help to change resident perceptions about community safety, police efforts, and improve the relationship between them (police and residents) [147]. In this thesis, we mine and quantify unstructured data that residents share on social media that can help police to assess residents safety concerns and needs.
- Develop automated techniques to filter out information of interest to improve engagement and responsiveness for improved collaborative policing from the large volume of data generated.**

The research investigates the differences between behavioral attributes of residents and police during day-to-day communication [40]. These studies highlight how communication and types of information are exchanged in discussions between police and residents. Criminology and social science research also show that the importance of responsiveness of the police officers towards the resident's request [50, 74]. These criminology studies show that overall satisfaction of community with the police is related to how well police deals with and responds to these service requests. Also, criminology studies show that these requests

account for the major information source contributing towards collective action for improved safety and psychological well-being of residents. However, it remains largely unexplored that in the diverse context of day-to-day policing, what characteristics differentiate a general conversation from a conversation containing relevant information for policing activities. Given the importance of police response to resident posts, we believe there is a dire need to pursue the use of social media as a source to characterize relevant policing requests that require a response from the police organization and improve the responsiveness of police to day-to-day requests by residents that need their action and response.

Chapter 3

Studying Social Media Appropriation for Collaboration

Police departments across the globe are increasingly using Online Social Networks (OSNs) to connect with residents, share law and order ¹ related information, and receive information from residents. For instance, in 2011 riots, UK Police used Twitter to provide localized information, dispel rumors, reassure residents and to find looters. After the riots, looking at the impact of OSN (Twitter) on policing, the UK government emphasized the need for each police force to develop an OSN communications plan [29]. Even though OSNs have demonstrated potential to reform policing; it introduces various challenges [22]. Firm legal restrictions on public disclosures and police impressions of state-driven tool makes it difficult for police organization to communicate with residents [29]. Further, past events show that the misunderstanding residents' expectation resulted in reputation loss of the police department [70]. OSN attributes like openness, volume, and velocity at which information spreads also introduce unique challenges for the police. For example, during Vancouver riots (2010), police had no procedure in place to collect residents' tweets mentioning clues about possible suspects (mentioning @VancouverPD) [130]. Similarly, before the shooting attack in Garland, Texas, a user informed police of a possible conversation on Twitter hinting of a possible attack conspiracy, however, it was missed by the police [18].

Research shows benefits, effectiveness, and challenges of using OSN by police in developed world [17, 92, 113]. However, need for OSN mediated communication, collaboration, and connectedness between residents and police in developing nations is largely unexplored. With the increased penetration of OSN in developing countries like India, police are exploring the effectiveness of OSN as a communication channel to maintain law and order [89]. Police organizations in India lack adequate police personnel which results in many under-policed areas. Police have felt the need to

¹In this thesis, we use 'law and order' synonymous with social issues like theft, crime, traffic violations, etc.

obtain community collaboration to accomplish its increasingly vast duties and is exploring use of technology like OSN to reach community [35]. However, police personnels have limited exposure to technology [134]. These limitations (inadequate number of police personnel and technology exposure) make it difficult to adopt findings of OSN use by police in developed world to facilitate policing needs in developing countries like India.

In this Chapter, we study needs, challenges, and preparedness of police and residents for using OSN in a developing nation like India. We adopt multi-stakeholder approach to examine the OSN use for community policing in India. Our approach includes interviews of 21 residents and 20 IPS (Indian Police Services) officers who lead and command various police and intelligence organizations in India. This study provides an insight about how OSN can help Indian police to build a community and communicate with residents to achieve community policing goals.

3.1 Research Objective

As part of this thesis, we analyze *whether OSN based technology can be adopted to support communication and collaboration for making safer society in developing countries like India*. To analyze our research objective, we study the following sub-aspects: Why police and residents can use OSN for improving policing and preventing crime? Which are the different kinds of OSN platforms police is exploring to use? What is the target audience that the police want to reach through OSN? We also analyze the challenges police and residents think they might face while using OSN for communication and collaboration. Our work particularly aims to analyze the role of OSN in supporting collaboration between police and residents to fight crime, recover from ongoing threats, and maintain law and order.

3.2 Methodology

In this research, we conducted a multi-stakeholder mixed method study consisting of 41 semi-structured, in-depth interviews and 649 surveys. We were not required to go through an Institutional Review Board (IRB) approval process before conducting the study. However, the authors of this work have previously been involved in studies with the US IRB approvals and have applied similar practices in this study. Participants were shown consent information, when they agreed to participate in our study.

3.2.1 Interviews

We recruited all police officers through word-of-mouth and mailing lists dedicated for IPS officers; IPS is one among the *All India Services* [82]. We completed 20 individual interviews with IPS officers, each of about an hour. They provided services in different states and three officers served special branches. They were of the rank ADG (Additional Director General) and DGP (Director General of Police). Interview questions (See Appendix-A) comprised of topics such as the need for police to use OSN, how OSN has been helpful so far to police, understand OSN usage policies followed by departments, and challenges in adoption of OSN. Among eight officers who used OSN for official purposes, only two officers had used OSN for more than two years. Rest were planning to use OSN for official purposes. Demographics of the police Officers who participated in the interviews is discussed in Table 3.3

Next, we interviewed 21 residents to understand their perspective on the presence of police on OSN. The participation was voluntary and we ran the study for almost 3 months. The participants were recruited through email on various mailing lists / social media posts. All the resident participants (17) were from Delhi and National Capital Region. Interview sessions involved one participant at a time and were administered by one of the authors. All interviews were recorded, and transcribed for analysis. We used randomly generated numbers to identify the subjects in our notes so as to maintain subjects' privacy. We took participants consent before taking part in the interviews and we compensated all participants for their time and efforts. Resident participants' demography was diverse (e.g. age group, education, and occupation). Interview questionnaire for residents comprised of different topics such as, ways in which residents will like police to help through OSN, and the preferred OSN for communication with police (See Appendix-B). Most resident participants reported using OSN like Facebook for the last three to five years, whereas police officers reported recent use (almost an year) for policing activities. Ten residents were aware of Facebook police pages; among these, six had heard or visited these police pages on OSN. Another three mentioned that they had used these pages to communicate issues to the police. Demographics of the residents who participated in the interviews is discussed in Table 3.3

These interviews (both residents and police) were conducted by one of the authors and she met the interviewee one-on-one. Few interviews were conducted through telephone. We chose to conduct interviews in English language as it is the common business language used in the country. All interviews were recorded and transcribed for analysis. We used randomly generated numbers to identify the subjects in our notes so as to maintain subjects' privacy. Participants were shown consent information, after they agreed to participate in our study. Recruitment approach followed in this work has also been used in other CSCW studies [113].

Qualitative Analysis: We applied limited grounded theory analysis on interview responses. A single analyst iteratively assigned open codes, axial codes and dimensional codes (See Table 3.2). Limited

	Resident Interview N=21	IPS Officers Inter- view N=20
Gender		
Female	42.86	5.00
Male	57.14	95.00
Age		
18 – 24	23.81	–
25 – 34	42.86	20.00
35 – 44	14.29	10.00
45 – 54	9.52	55.00
55- 65+	9.52	15.00
Education		
Computer IT	29.41	
Teaching / Re- search	25.53	
Fashion Designing	11.76	
MBA	5.88	
Others	29.42	

Table 3.1: Demographics of the participants in the interviews. Values in the table are in percentage.

grounded theory method allows coding by a single analyst because of the intense labor involved in the coding process without need for developing a theory [13]. Initially, 25 codes were developed, which were condensed to four categories – *why OSN*, *preferred OSN*, *target audience*, and *limitation of OSN for policing*. Over successive iterations of coding, 3 categories – *why OSN*, *preferred OSN* and *limitation of OSN* categories became independent dimensions with their own subcategories. For *target audience*, participants indicated mixed and nuanced responses, therefore we combined tentative subcategories as one category.

During the process, we developed various memos based on the incidences and cases shared by the participants and relationships observed between the categories. We used conceptual memos to record our thinking about the meaning of codes and recorded when events happened, and what were their consequences. In the memos, we find similarities and differences by comparing the cases and codes using residents and police data and recorded questions raised which could be answered in subsequent interviews. Authors are aware that the core aspect of grounded theory method is an emerging theory from comparisons of codes and successive iterations. However, in this chapter, we do not report a full theory analysis and use these categories in combination with quantitative results to understand the policing scenario on OSN. This limited use of grounded theory method, for interpreting qualitative data is an established approach in CSCW and HCI [13, 85, 86].

3.2.2 Survey

The survey questionnaire was created to understand general activities on OSN for policing, concerns, scope of use, hindrances, and need for policies. To understand why OSN is needed, we asked police

Why OSN: What are the ways police can use OSN to maintain law and order? How can residents help police using OSN ? <i>Increase resident volunteers to report crime.</i> <i>Reduce communication gap / engage better.</i> <i>Improve Coordination.</i>
Preferred OSN platform: Which OSN will police and residents like to use for maintaining law and order? Which OSN is most useful and helpful for law and order purposes? <i>Among officers only.</i> <i>With residents.</i>
Target audience: Who is the target audience for police on OSN for building intelligence, staying connected, broadcasting information? (no subcategories)
Challenges and limitations: Are there any hindrances which stop the use of OSN as an effective tool for maintaining law and order? What according to you are the major hindrances? What do you think can go wrong? Any example? <i>Meaningful information.</i> <i>Verify the information.</i> <i>Acknowledge resident's messages.</i> <i>Need technical teams and guidelines</i>

Table 3.2: Categories and subcategories from the grounded theory derived by the analyst.

personnel questions such as “*for which of the policing activities can you use OSN e.g. Facebook?*” and options given included choices such as *crime investigations, listening / monitoring, notifying the public of crime*, and *do not use social media tools* (See Appendix C). We also included *Others* as an option for police personnel to write their own choice. This list was constructed based on interviews and similar surveys conducted in the developed nations [28].

Next, we surveyed residents on the use of OSN for policing, concerns regarding police presence on OSN, and activities that police can perform using OSN (See Appendix D). For instance, we asked residents *for which of the following activities should police use OSN e.g. Facebook?* and showed them same options as shown to police personnel . To understand the challenges and expectation on how residents will like to communicate with police on OSN, we asked *how would you like to communicate information (e.g. complaints and feedbacks) to police using Online Social Media?* Participants could choose to *post anonymous information, post on police page with minimal personal information e.g. email id, send direct messages, create a fake account to inform police, would use police pages to get information only or other reasons.*

In total, we collected responses from 445 police personnel and 204 residents. Table 3.3 shows the demographics of the survey participants. Our questionnaire included demographics questions such as age, gender and profession of the participants. We administered surveys via services such as

Google forms and Survey Monkey. The number of male police personnel in our survey is dominant, however male and female ratio in our survey, is representative ratio of the genders in Indian police services [60]. Almost equal number of male and female residents participated in the survey. To compare resident and police perception, we used the same questions in the two surveys with minimal modification to suit the concerned group. In some questions, we used a 5-point Likert scale ranging from *Strongly agree* to *Strongly disagree* to capture participant’s response. Further, we applied statistical tests such as Mann-Whitney U Test to analyze the difference in opinion for survey questions using likert scales.

	Resident Survey N=204	Police Survey N=445
Gender		
Female	40.66	8.98
Male	56.59	85.85
Not shared	2.75	5.17
Age		
18 – 24	80.22	3.05
25 – 34	16.48	37.79
35 – 44	0.55	21.36
45 – 55	0.55	27.93
55- 65+	–	9.87
Not shared	2.20	–
Education		
Computer IT	54.40	Field Officers
Teaching/Research	10.99	
Fashion Designing	10.99	
MBA	3.30	
CA	0.55	
Others	19.77	

Table 3.3: Demographics of the participants in the interviews and surveys. Values in the table are in percentage. Almost equal number of male and female residents participated in the survey.

3.3 Results

In this section, we report participants’ perception, evaluate the current status of OSN for policing and the associated challenges.

3.3.1 Which OSNs police prefer to reach the residents?

We asked officers, *which OSN do you use for your day-to-day activity to maintain law and order?* We find that police organizations are using or planning to use a variety of OSN platforms. Among these, Facebook and WhatsApp are the most preferred networks. Some platforms are used to communicate with residents (Facebook and Twitter) and some are used only within the organization (WhatsApp and Youtube). Sixteen officers prefer Facebook over other OSN for activities involving resident participation; among these sixteen, 6 officers use only Facebook. P4 said: *“Facebook is more interesting. Personal viewpoint can be expressed and it is more interactive. People [residents] prefer to give their inputs through Facebook.”* Few officers advocate the need of dedicated Facebook pages for policing tasks. P19 says, *“Depending upon the need of the department they can have it [a Facebook page] for specific purposes like woman’s extortion cell, child abuse cell, and extortion cell.”* Few officers mention using Twitter; these officers believe that Twitter requires less time as it is used by few people. P15 says, *“Actually it is the matter of how much time you can devote. Facebook gets too big and involves many more people [whereas on] Twitter you make a small comment and it is done.”*

For personal and within organization use, officers use mobile-based applications like WhatsApp and BlackBerry Messenger. Many officers feel that WhatsApp is better than Facebook to get instant information about the current situation on the ground. P13 says: *“During a gathering or law and order situation, the usual question is how many people [are there]. Then they [officers in control rooms] start guessing, if officers on duty have a phone they can click the picture and upload it, so that in the control room, we have an idea.”* Officers further add that WhatsApp showed when the person was last seen online and therefore cannot deny receiving the message. P12 mentions, *“Nobody can deny that he or she have received a message.”* While comparing Facebook with WhatsApp, P18 says, *“With WhatsApp, we can send an audio file as well. We can transfer photos, images instantly with WhatsApp. I feel Facebook is terrible in this case. Suppose you want to upload an image to Facebook, it will take a lot of time.”* Officers feel that policing requires instant response, as time plays a crucial role and can make or break things.

Following the interviews, in the survey, we asked police officers which OSN they will use for day to day activities? Similar to interviews, our survey results showed that Facebook and WhatsApp were the preferred networks; 72.17% officers preferred Facebook and almost 60% preferred WhatsApp. We asked residents which OSN they will like to use to communicate with police. Almost 80% residents preferred to use Facebook, followed by WhatsApp (44.54%) whereas 42.02% residents prefer Twitter in comparison to 15.80% police personnel, (see Figure 3.1). We found statistically significant difference between police personnel and residents choice of OSN (χ^2 test, p-value < 0.001). However, preferred platform for both was the same.

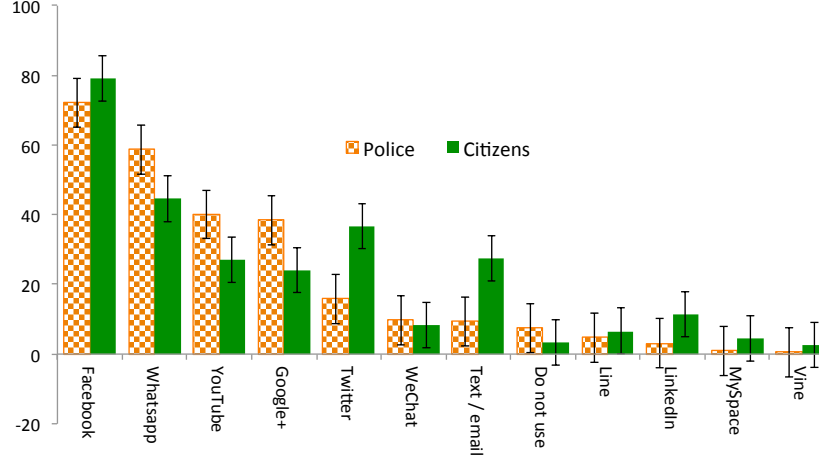


Figure 3.1: Comparison of residents (N=204) and police (N=445) choice for OSN as policing tool.

3.3.2 Who is the target audience?

We asked officers, *who are the target audience you want to reach through OSN*. We find that there was no clear understanding of target audience on OSN among the officers. P6 says, *“every resident is our target audience, but audience is limited to account holders [on OSN].”* Similarly P4 remarks, *“persons who are using it [OSN], affluent classes, students younger generation who can afford to use the Internet.”* Few officers who feel that younger population and students are common audience on OSN believe that OSN can help reach and connect with youth better. P3 says, *“Youth is sometimes available only on OSN; what they have to say is sometimes not available on traditional media / sources of information. They have very strong ideas which are otherwise missed out.”*

Few officers say that currently OSN was restricted to urban areas and did not have good reach in rural areas. P9 says, *“Urban sector, yes we can find some information. Rural areas, it is not of priority [to reach through OSN].”* We find similar views among few officers regarding the use of mobile phone applications like WhatsApp; P13 believes that there are few WhatsApp users in India. The limited reach restricts efforts to use OSN for policing by few agencies in urban areas only; but in the past, we find that OSN effect percolated to rural areas in crises situations like riots in Muzzafarnagar and Assam [51,99]. This shows that officers have limited understanding of OSN reach and audience it impacts. Officers do not mention any distinction in the population on different platforms and believe that OSN can be used to connect with anybody.

3.3.3 Why are OSNs needed?

Three themes emerge from our analysis of the interviews: 1) OSN can support policing by increasing resident participation to identify crime, 2) OSN can reduce the communication gap, and 3) OSN can improve co-ordination between the police and residents. We now discuss these themes and support

these inferences through evidences from content analysis of Facebook pages. We refer interviewed IPS officers as P1 . . . , P20, and residents as C1 . . . , C21. To analyze the situation on actual position on OSN, we provide anecdotal evidences from Facebook pages which substantiate the perceptions of IPS officers and residents on use of OSN for policing.

Increase resident participation to identify crime

Officers express that OSN can help increase the personnel (resident volunteers) available for police to identify offenders. According to officers, using OSN, residents can easily report defaulters and law breakers. P7 says, *“OSN can be used to create a community of people who will be using it (OSN) [to identify crime].”* Another officer states that before the introduction of OSN, only traffic police on roads were responsible for catching traffic violators, but now anybody can use OSN pages to post pictures of traffic violators. P17 says, *“Delhi Traffic Police page involves public [residents] in finding traffic violators, on the basis of which challans [fine] are issued. So our limited resources are increased, and we can catch many more people by seeking help of public [than before].”* Officers believe that using OSN, residents can provide real time content to inform about crime. For example, P9 states, *“Young people are using OSN on the mobile devices. They can upload real time content [from the crime location].”*

Consistent with police officers, residents also agree that OSN pages can help report issues related to traffic and crime. These issues include traffic congestion, accidents, beggars, corruption, and other issues with public transport. Most residents remark that they will like to use OSN pages to report traffic issues like unruly behavior of taxi or autorickshaw drivers. For example, C1 says, *“I use public transport like autorickshaw; they [auto drivers] either overcharge or harass passengers by refusing to go. I will like to report these cases.”* According to residents, OSN can also provide opportunities to engage with police to report crime such as theft, neighborhood issues, and crime against women. C13 states, *“if I see a girl in a vulnerable situation I might give this information [on the Facebook page of police], and they [Police] can take instant action.”* C12 says that she can instantly *geo-tag* the crime location in the Facebook post to help officers receive quick information about exact location of the crime.

Facebook content analysis shows that residents use these pages to report activities such as the use of tinted dark glasses in cars (keeping tinted glasses in cars is not allowed as per the traffic rules), crimes against women, and neighborhood issues like drunk men on streets. For example, A resident complains about drunk men and posts a video as an evidence, *“I am posting a video as well of people drinking openly at XXX wines, sec 1X-1Z road. I had posted pics from the same location on 13th Aug as well”* (see Figure 3.2). These observations show that resident participation on OSN can increase the personnel available for identifying crime and law offenders.²

²reporting activities such as drunk men on streets may expose the resident reporters to retaliation if identified by the reported people when they find the report against them on Facebook.



Figure 3.2: An image posted on Facebook by a resident to report illegal use of streets for alcohol consumption.

Survey participants believed that OSN can improve *transparency in problem solving process* by offering an open platform to discuss crime and safety related issues / activities. We found that residents were interested in reporting different issues to police through OSN, such as eve-teasing (public sexual assault) (73%), child labour (71.4%), traffic issues (59.9%), domestic violence (57.7%), neighborhood issues (56.6%). This shows OSN can increase the number of community volunteers to identify crime. Residents agreed that they will like to give feedback (67%) to police through OSN.

Through surveys, we found different expectation between police and resident with respect to policing activities that can be performed using OSN. Top three activities for which residents thought police can use OSN were – notifying the public about crime, emergency situation or disaster related issues, and crime prevention activities. In contrast to this, top three activities which police personnel preferred were crime investigation, intelligence, and public relation / reputation management (see Figure 3.4). We found statistical difference between the residents and police for preferred policing activities (χ^2 test, p-value < 0.001).

Survey analysis confirms that OSN offers opportunities for residents and police to identify and improve law and order situation in the society. Police develop better understanding about residents' need using the feedback and information available on OSN. For improved resident satisfaction, police can consider using OSN for notifying the public about crime, emergency situation or disaster related issues, and crime prevention in addition to the activities they will like to perform.

Reduce the communication gap

We find that OSN can reduce the communication gap between police and residents in three ways: 1) OSN can help understand the public opinion about various law and order issues, 2) OSN can help get feedback from residents, and 3) OSN allows residents to overcome social pressures to approach the police.

Understand resident opinion: Officers mention that OSN can provide effective understanding of public sentiments and opinion. P3 states, “*Whenever we think of OSN, we think it in terms of what*

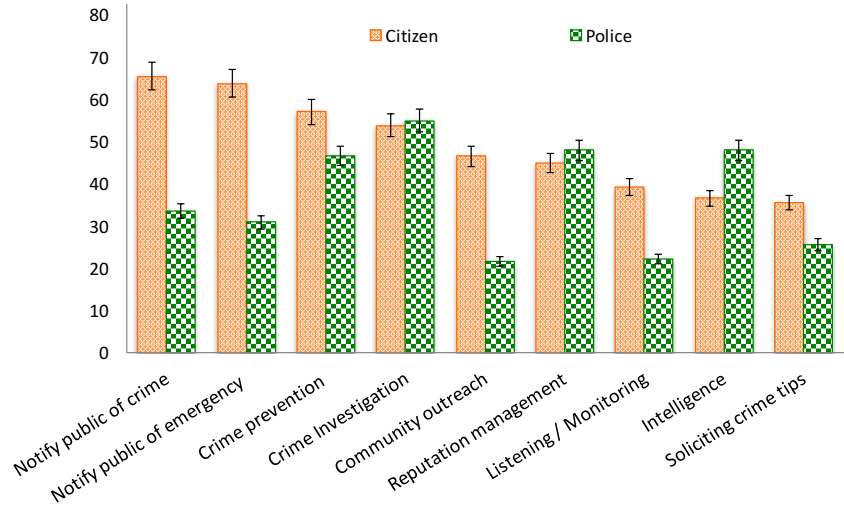


Figure 3.3: Choices of Indian residents (N=204) and police personnel (N=445) for policing activities on OSN.

are the aspirations of the public [residents], what they want from us, what are their grievances and how we can address them.” Officers report OSN to be better than existing media (such as television) to gauge public opinions. P3 states, “OSN is more representative; police delivery [of services] can be more up to mark. On TV we are not sure of how many people are interviewed, they show only 2 - 3 people. This number cannot be used to show mass opinion.” According to officers, understanding the opinion of residents is important for early crime detection, crime prevention, and for reducing communication gap between police and residents. Similar to police officers, few residents also agree that police can know about public opinion using OSN. C6 states, “Your status speaks everything. They [Police] can know what is going in mind of residents and take action accordingly.”

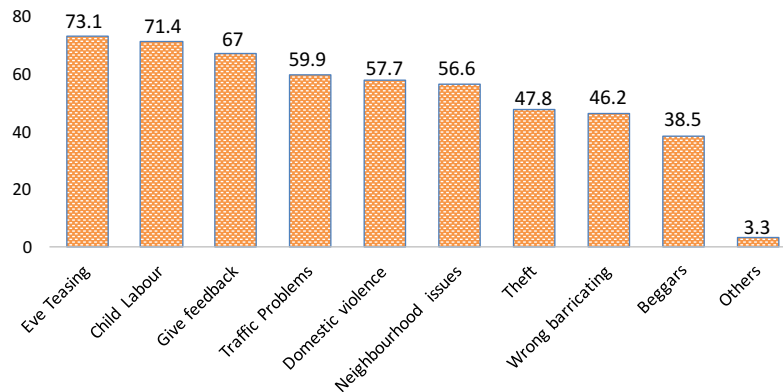


Figure 3.4: Resident (N=204) issues which they will like to report using OSN.

Feedback from residents: Officers believe that OSN based feedback (both positive and negative) from residents can bridge the gap between police and public. We asked officers, *what will be their reaction to the message* such as Scenario A, in which a resident posts *I will like to thank the police to*

improve law and order. P9 says, “make it reach as many people as possible and post it. Helps to show a positive image of your organization. Good feeling among the community and for people.” P12 says, “further propagate such message; these tweets are hardly to be seen. Definitely they will boost up the moral.” Officers considered it important to reply to feedback posts to keep the connection with residents and show that residents’ views are respected. P8 says, “convey thanks for posting; it should be taken cognizance of. The other person should feel that somebody is taking note of his thoughts.” Officers said that they will also appreciate negative feedback and take appropriate actions. We showed officers a post, Scenario B, in which a resident had complained about unavailability of police on a highway where a girl was being beaten. P1 says, “we will check if actually it is happening and take action; subsequently will post about the action.” Officers believed that OSN can help explain the reasons for such lapse so that people can understand the situation better. Adding, further officers mentioned that in the absence of OSN, police depend upon existing media such as television and newspaper to explain their decisions. On these existing media, the police views are presented as understood by the journalists. However, with OSN police officers can directly communicate with residents and express their views (without influence of journalists). P4 says, *I would like to use OSN to give official version of any information. Because they [residents] always hear the story from what media [television or newspaper] has to say which always might not be correct. [Using OSN] They [residents] can hear what we have to say directly from us. Police version is the correct version and people should start trusting it [police version] instead of media [television or newspaper].*

We showed the above discussed scenarios – A and B to residents. Few residents said that they will like to spread / reply to positive messages. C1 says, “There are certain situations when police really give their best. [I will share this post to] Encourage police and let others know that police is doing something.” More residents mention that they will share or like a post in Scenario B than Scenario A, so that police are more informed about the issue. residents believe that *like* or *share* utility might let police understand the gravity of the situation. A resident mentions that if many people complain about the same issue police might take some action.

In Facebook posts, we find that residents appreciate police for the good work and share what troubles them. For example, a resident complains about an indisciplined drunk police constable (see Figure 3.5). Such posts can help police understand residents’ concern which play a significant role in reducing communication gap. Understanding the residents’ need for anonymity, police say in a post that residents need not reveal their identity if they want to help solve violent crimes. Thus, content analysis of Facebook pages shows that OSN can reduce the communication gap between residents and police by encouraging frequent exchange of information and feedback.

In surveys, we asked residents what will they like to do with a tweet / post with a positive feedback about police organization of your area / state, e.g. *We thank the police for reducing crime in our city.* Residents could choose to share / retweet, like / favorite, comment / reply, delete, report–abuse/spam or Ignore the message. Almost 65% residents said that they will like or favorite the post with



Figure 3.5: Post showing police acknowledging residents' concern regarding indisciplined police constable. This post received 102 likes.

positive feedback and 30.77% said that they will repost / share. Thus showing the effectiveness of OSN generated feedback in building police - resident community. We also found that 52.20% residents said that they will share / retweet the post with negative comments about police and 39.01% said they will comment or reply to such posts. This shows potential of OSN to understand the disagreement expressed by the resident's community to strategize better and communicate police opinion.

Provides anonymity: The third method which helps reduce the communication gap is OSN's ability to facilitate anonymous communication between police and residents. Many residents mention that they will prefer an anonymous platform to communicate with police. C7 says that he will like to make an anonymous complaint on OSN against local Member of Legislative Assembly (MLA, politician), and illegal activities of a local shopkeeper, which otherwise is not possible as these influential people can harm him. residents report that they are fearful and concerned about their security, therefore, use fake-profiles to share information with police. For example, C16 states, *"I created a fake profile to post pictures of traffic offenders, so that law offenders are punished, but they do not get to know that I complain about them."* Few officers also acknowledge that residents may not feel comfortable revealing their identity on Facebook, and may use pseudonyms similar to undercover informers. These observations show that OSN helps overcome social fears and pressures while communicating with police.

In survey also residents responded that they will like to leverage the anonymity offered by OSN to communicate with police. We asked residents, *–"How will you like to communicate information (e.g. complaints and feedbacks) to police using Online Social Media?"* We found that 36.26% of residents will like to post anonymous information on police page, whereas, 29.67% will like to reveal minimal personal information e.g. email id. Only 2.75% might create a fake account. This shows that anonymity offered by OSN can help in providing more information to police from residents. We contemplate that anonymity offered increased the chances of residents interacting with police as they would now share their thoughts without being fearful that police could harass them or people against whom they are complaining can identify and attack them [111].

Improve coordination

This section shows that OSN can improve coordination between police and residents by keeping residents informed and helping police deliver targeted messages.

Keep residents informed: Officers mention that the police can use OSN to keep residents informed about various arrangements. For example, P15 states, “*OSN help in disseminating information and forewarn [residents] about areas that might see a conflict.*” Further, P2 states, “*OSN can help inform residents about jewellery snatching cases, time it can happen, and precautions to be taken.*” Officers show interest in posting wide variety of advisories (an official announcement or warning) through OSN such as crime alerts, safety tips for women, children and senior residents, places to avoid during major events and natural calamities like cyclone or floods. An officer states, “*A cricket match and a popular festival happened on the same day; we were expecting a large gathering for both the events. These crowds were required to cross each other’s route to reach their destinations. To avoid traffic, we issued instructions through public post on OSN; this proved helpful to manage the crowds and avoid traffic on roads.*” Residents also view OSN as a means to obtain timely alerts from police. C7 says, “*Suppose there is a threat in Delhi, and they [Police] give me alerts on it [OSN] then I would have liked to follow it [police Facebook page].*” Such alerts can keep residents informed and improve coordination.

Targeted communication: Officers acknowledge the need to communicate appropriate advisories to appropriate audiences for improving coordination with them. These advisories are communication-intensive, highly social, cultural, and influence social networks in the real world. Officers in different regions have different needs and priorities for issuing these advisories. For instance, P1 states that OSN can be used to spread awareness regarding social evil practices of witch-hunting in northeast India.³ Officers from Haryana (a state in North India) mention that they will like to create awareness about women, children and senior resident safety as one agenda. Few residents also mention that they will like or share an advisory only when it is relevant to their network. This suggests that OSN can help in spreading targeted messages to improve coordination.

Consistent with the interview analysis, we find that the police use Facebook pages to keep residents informed about policing arrangements. A police post informs residents which *roads will be closed for general traffic from 5.00 AM to 9.00 AM* (see Figure 3.6). Another post informs residents about criminals and states “*Nataraja@Mallu, a notorious rowdy involved in assault, extortion, kidnapping and attempt to murder booked under Goonda Act today.*” To target specific audiences, we find that Delhi police maintains a dedicated page for North Eastern Indian residents who were recently victimized in the city.

³Superstitious practice of declaring women as witches.

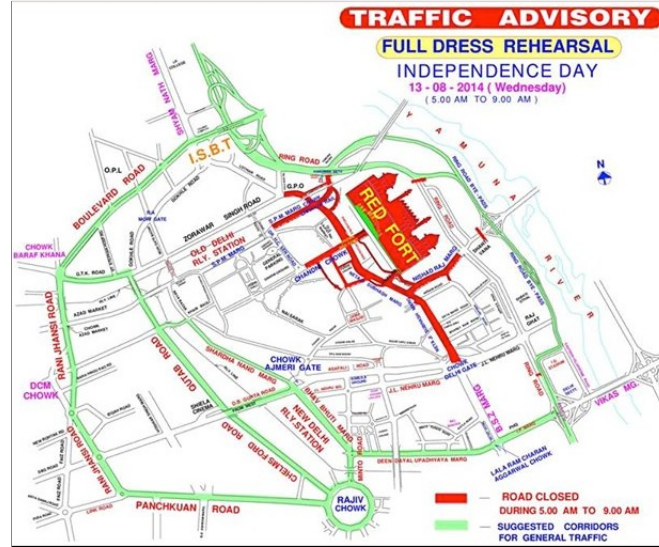


Figure 3.6: Image posted by Delhi Traffic Police on Facebook informing residents about traffic diversion for Independence day celebrations.

3.3.4 OSN challenges and overheads

Despite various opportunities that OSN offers, officers believe that police need to be conscious while using OSN. We identify the following four challenges that can hinder community policing efforts using OSN: maintain meaningful communication, verification overhead, acknowledgment overhead, and lack of technical capabilities. We now discuss these in detail.

Maintain meaningful communication

Participants acknowledge the need for maintaining information exchange through OSN that is meaningful to improve policing decisions and arrangements (here after referred as meaningful information). We identify two factors that can inhibit this meaningful information exchange on OSN: 1) unclear and generic information from police and 2) violent and abusive content from residents. Residents remark that advisories during riots help take appropriate decisions but think that certain police posts are too ambiguous and may not help take appropriate decisions. For instance, residents find that police advisory released on Facebook asking residents not to trust any rumors posted on OSN during Muzzafarnagar riots (See Figure 3.7) was too generic to be understood. For example, C4 states, *“This information is useless. If my friend is tweeting or sharing [Figure 3.7] how will I know that it is not fake. The post says not to trust any tweet, why should I trust this post.”* However, most police officers feel that it is useful to share such information.

Officers fear that on OSN, residents may use inappropriate expressions and informal language to communicate their thoughts. P10 states, *“Expectation of people how police should use OSN is not based on the clear understanding of law enforcement agencies. They think that the way they use*



Figure 3.7: Advisory shown to participants posted by UP police on Facebook “Please, do not trust any rumor, video clipping shown on Facebook, Twitter, You Tube, WhatsApp. Nuisance creators are being controlled sternly.” Post received 26 likes.

informal style language on Facebook accounts, law enforcement will also do the same. That is not possible.” An officer mentions that Twitter profile and Facebook wall have the potential to create havoc. Officers also express inability to remove or control the spread of abusive content from the official pages. They believe that removing inappropriate comments may give the impression that the police are censoring the page and may obstruct community policing initiatives. Similar to interview analysis, online posts on Facebook pages show that residents post abusive content. For example, in reply to a police post informing residents about arrest of a criminal, a resident posts comments like “*Shoot all bloody rapists,*” “*bastard,*” and “*That bastard private parts shud be cut so it sets an example for others too.*”

Verification Overhead

Officers believe that information obtained from OSN is a starting point, and it is essential to verify the information. P17 states, “*Any information is just information as long as it is there. After that it has to be verified, correlated with other information, for this piece of information to go to the category of intelligence.*” Officers also mention about various techniques they may use to verify the information available on OSN. One approach is to look at the number of responses (multiple posts) posted related to an issue. P3 states, “*More are the number of responses that we check, more we are close to the truth.*” Another approach that officers mention for virtual verification is to check the source of the information.

Residents also agree that information obtained from OSN is not completely trustworthy and requires verification. However, most residents say that if information comes from police pages, it will be trustworthy and will need no verification. Residents (similar to police) rely upon the source of the information to judge its reliability. C12 states, “*I do not trust the information, I verify the source of it.*”

Analysis of behavioral data shows that police may ask residents for additional information for verification. For example, one of the police pages posted, “*Thanks, Kindly re-post the pictures with clearly visible R/C [Vehicle Registration] No., time and place also so that proper action can be taken against the police personnel.*” In few cases, police request residents to contact an officer who can verify the details and take action. For example, “*Dear [name], Please visit at [XXX] Police Station*

and lodge a complaint with the details, and they will take necessary action in this regard. Thank you;” shows police need to verify information shared on OSN.

In survey, we find that only few participants trusted the information that was available on OSN. In the survey, we asked both residents and police to mark on a 5-point likert scale, *how much will they agree with the statement that the information obtained via OSN is trustworthy*. In comparison to 49.63% police personnel (M=2.4, SD=0.84, N=391), only 17.03% (M=3.15, SD=0.9, N=204) resident agreed with statement (Wilcoxon rank-sum test, $z=-1.19$, $p>0.05$).

Acknowledgement overload

OSN users often expect a quick response when they post a complaint or a request on OSN [62]. We analyze residents’ view on how long police can take to respond to a resident’s request. residents’ expectation varied from few minutes to a week. C5 states, *“if police has to use OSN, then there should be a team who should be checking it every second.”* For few residents, type of complaint and volume of complaints received on OSN influence frequency of acknowledgement. C14 states, *“That depends upon the issue, traffic problems can be answered in 1 or 2 days. Children / people who need immediate help like accident cases should get an immediate response.”* Very few residents state that the police should send an immediate acknowledgement that they have received the complaint. According to police officers, responses cannot be provided immediately. Few officers say that they can respond once in a day and for other officers it depends on the need. This expectation difference between police and residents can inhibit the active use of OSN for policing. Analysis of Facebook pages shows that the police do acknowledge residents’ post, for example in a post police states, *“Dear [name], Your post has been conveyed to High Ground Police Station (080-229XX587/XX83), They will assist you in this regard. Thank You.”*

Survey also shows that absence of acknowledgement from the police officers to the residents’ posts can be a challenge for successful use of OSN. We found that 31.87% residents said that police should take less than an hour to acknowledge that they had seen the post /message (See Figure 3.8). With crunch of police personnel, this can slightly overload the police but police departments will need to setup a concrete acknowledgement process for community sustain over a long period.

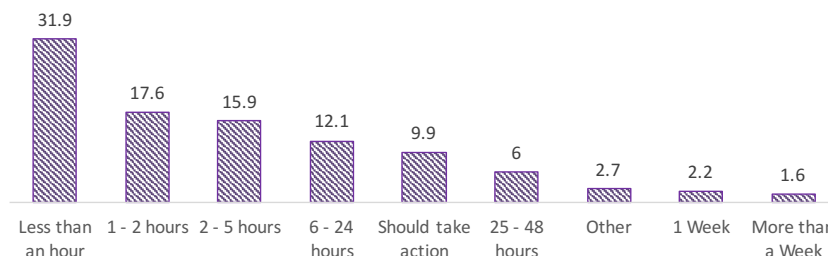


Figure 3.8: Residents’ responses (N=204) for the time that police can take to acknowledge the residents’ post.

Lack of technical teams and policies

Officers think that lack of manpower who are capable of handling OSN pages of police inhibits social media adoption for community policing. They also mention about the need for guidelines and policies which can lead to uniformity and clarity in decisions while using OSN.

Most officers believe that police departments require trained people who can help leverage the benefits of OSN. P9 states, *“Team of better people as of now, it is a resource constraint for us who can help us use it better.”* Officers think that the OSN team should be acquainted with police decisions and be very specific about content they post on OSN. P3, while discussing characteristics of the person handling OSN page states, *“Person, who can be very specific about what he speaks; for now, he will share very limited type of information.”*

Officers mention the need for policies that can help understand the pros and cons of using OSN. For example, P4 states, *“It [OSN for policing] is still in an experimental phase but to leverage its benefits, policy has to be built, keeping in mind – OSN usage, pros, and cons. Like Facebook’s servers are outside India, so how information [confidential] can be saved [stored] on them.”* Officers mention a need for guidelines on content to be posted. They believe guidelines on content are important to generate information that can keep resident communities interested during lean periods (time when there is no crisis to deal with). Few officers think that policy can help define boundaries and extent to which OSN should be used by police. P5 states, *“Centralized guidelines should be there on how to use Facebook, Twitter and YouTube otherwise everybody will start using it in his or her ways.”*

Lack of policies is a concern for both police and residents in surveys also. We asked both residents and police that *how much would they agree that Police should make an Online social media usage policy (rules and regulation) for using and benefitting from Online Social Media effectively?* Almost 94% police strongly agreed or agreed with this statement and 75% residents strongly agreed or agreed that policy is needed. Police seemed to be significantly more concerned than residents. We found this difference to be statistical significant (Wilcoxon rank-sum test, $z=-7.54$, $p<0.001$) between residents ($M=2.03$, $SD=0.84$, $N=204$) and police ($M=1.79$, $SD=0.58$, $N=399$).

3.4 Discussion

In this chapter, we explore how OSN can facilitate community policing in India. Consistent with the previous research in the developed world, we find that OSN can help involve residents in policing through various ways: increasing resident participation in neighborhood watch, reducing communication gap and improving coordination between “grassroots” members of community and police department [49]. Researchers in the CSCW field are uniquely positioned to develop tools necessary to support police-resident relationship on OSN. Current CSCW research investigates OSN use by

first responders and residents primarily during crisis situations, which are event-driven and have specific goals to be achieved in a short term [29]. It is unclear how this knowledge can be used for day-to-day communication in policing activities that are diverse and are not time bound. We find that effective policing through OSN requires identifying the needs, planning activities, creating useful content to be shared, and constantly communicating with residents. We now discuss OSN role to facilitate frequent contact and ease information exchange as required in different components of community policing in day-to-day policing.

OSN Role in Community Partnership Paradigm: An important element of community partnership is to maintain frequent contact and communication with police [19]. Lack of communication is frequently cited as a major problem resulting in lack of trust in services offered by police [67]. In Section 3.3.1 of this chapter, we discuss that OSN provides opportunities for police to keep residents informed about policing arrangements and decisions. However, officers in our study think that they need to understand the content and characteristics of interaction that can happen on OSN during “lean periods” (when no major event is happening of law and order interest). This understanding can help keep the community involved and get persistent visibility to police. We think that persistent presence on OSN can also help police to get quick visibility during high impact events like blasts where communication need has been felt the most. Similar observation on utility of lean period for collaboration is observed in [143].

In Section 3.3.1 we discuss role of OSN for obtaining *Feedback from residents*. Our observations show that police believe OSN can help reach the desired set of population and can provide opportunity to have a constructive dialogue and exchange feedback among police and residents. However, police officers say that constant communication needs to be regularly guided through specialized 24X7 OSN teams, policies, and guidelines. We find that though OSN facilitates quick *information exchange* between police and residents, designing appropriate nudges that educate about the legal and social implications of abusive content can reduce the misuse of OSN. This can help improve effective communication between the two stakeholders. Defamatory content can be a major block for successful adoption on OSN by police. Most residents during interviews mention that abusive content (Section 3.3.4) should not be used on OSN while expressing disagreement on police actions. We find that, in recent events, defamatory content posted against a politician on Facebook and WhatsApp led to violent protests in Mumbai, India. Police filed a complaint against the accused, but lacked concrete mechanisms to educate residents about implications (legal and social) of such content.

Community partnership paradigm requires police to act as “facilitator” for community partnership. However, residents often fear police and feel that revealing facts about crime may expose them to criminals; these apprehensions hinder police – community association [19]. Prior work in developed world suggests that residents may not trust community-policing technology that does not keep their submission anonymous [68]. Similarly, in this chapter, Section 3.3.1 (Provides Anonymity) and 3.4.2

show that residents prefer to use OSN as it provides anonymity that can help residents reach police without social pressures and fear; thus, OSN *facilitates* community contact and partnership. OSN provides a platform where residents can hold police accountable for taking action against crime but not expose themselves to criminals or other social pressures. However, anonymous posts involve legitimacy issues that make it difficult for police to take actions. We believe that technological solutions require amalgamation of security and CSCW domain such that the proposed technology can provide anonymity to residents, but also keep minimal checks to authenticate information if needed.

OSN for facilitating problem-solving: OSN can help police act as a “catalyst” to community policing by providing a platform where residents can easily reach police [19]. We find that both residents and police believe that using OSN, residents can inform the police about vulnerable streets in the city, report geo-tagged posts that can give instant information about the location of the crime to the police. Residents can also post images and videos of unsafe neighborhoods. This information exchange can facilitate two important aspects of community policing: a) the problem-identification and b) prioritization based on resident’s input. Problem-solving approach suggests that best solutions are those that satisfy the community. Police after examining OSN generated content can identify priorities of different communities and use this information to make appropriate judgement to satisfy the safety needs of residents. This can help make community feel safer and can generate trust in police. Police Officers in our study (Section 3.3.1, Feedback from residents) mention that OSN can help explain reasons for lapse in policing arrangements directly to residents without involving journalists (as needed in other mediums like television and newspapers). This can help residents understand the situation at hand and also encourage useful information exchange to address the lapse.

We find that for success of OSN, police will need to acknowledge the information exchanged through OSN; our work shows this can be an overhead for the police (Section 3.3.4, Acknowledgement overload). Therefore, the police departments need a technology that can imbibe an effective acknowledgment system on OSN platforms. We find that residents’ preference for response time on the post varied depending upon the case. An analysis of communication patterns can reveal expectation of residents regarding response time to complain. This knowledge can be used to design a semi-automated acknowledgement system. Social tools can also help classify the content posted by residents on OSN in various categories, and police departments can set flags to send an acknowledgement based on the category. This can help reduce the overhead and enable frequent OSN use.

We also find that legitimacy of information exchanged through OSN can impede the information exchange during problem-solving process. The police department that creates the OSN profiles and pages, can get a large number of residents’ posts to address through these pages. Legitimacy of this information is also a concern for police and they feel it is challenging to verify all the information

posted on OSN. However, police feel that multiple responses on the topic can be a good indicator that the information is legitimate and verified. Tools and applications can be built to ease this verification and validation. These tools can provide cross-platform verification and get responses from different OSN, resulting in increased pace at which police obtains responses from different platforms on the issue. Alerts can be generated to inform police about the verification being done on the content; this can expedite the police decision.

Design Implication and Conclusion: In this work, we provide insights for HCI researchers and technologists building social media technologies for policing (See Figure 3.9). Our research is necessary to formulate appropriate communication strategies and collaboration methods.

We found that legitimacy of information is concern for residents, and they feel it is challenging to verify information posted on OSN. The implication of this on technology suggests that verification and validation applications should be an essential part of technology design.

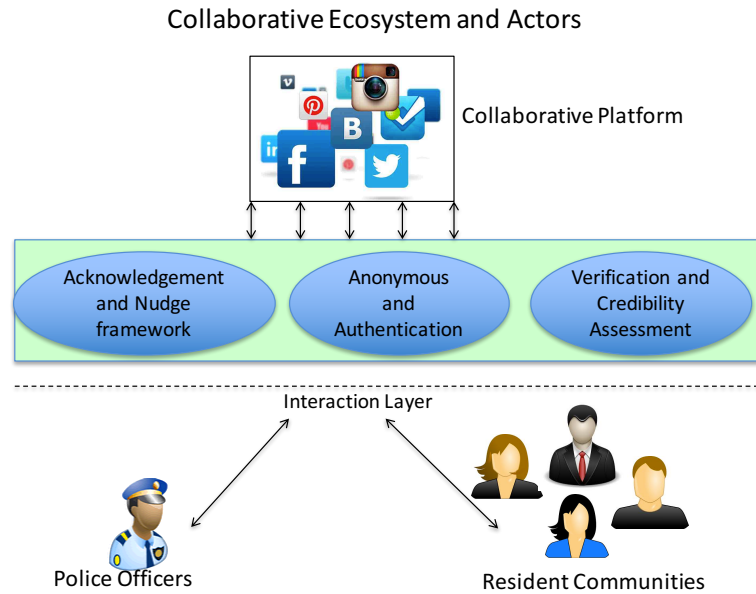


Figure 3.9: Design and technological opportunities for collaborative innovation in policing on OSN.

We find that residents may not trust community-policing technology that does not keep their submission anonymous. However, anonymous posts involve legitimacy issues that make it difficult for police to take actions. We believe that security and the HCI community should design mechanisms that provide anonymity and also keep minimal checks to authenticate information, if needed. Our results show that residents post defamatory content inhibiting meaningful information exchange. To develop accountability among residents, HCI researchers can design appropriate nudges [144] that educate residents about the legal and social implications of abusive content on OSN.

As we conclude this chapter, we believe that this work outlines the requirements (as extracted

from our interviews) for a socio-technical solution that can facilitate two important component of community policing – community partnership and problem-solving process. This study creates an understanding about policing requirements from OSN (latest communication technology). This can enable to setup OSN based systems that residents can use to report crime and remove some of the barriers to community policing participation which currently exist on OSN. Our work in this chapter of the thesis also provides designers and researchers with insights for designing technology that empowers and encourages police - resident communities to address social issues. Community policing so far has been addressed using non-technology tools but community oriented platforms like OSN can act as a facilitator and catalyst to policing.

Among the various opportunities and challenges identified in this Chapter, we focus on the aspect of extracting actionable and meaningful information from social media. In the following chapters, we will discuss the aspects to support, analyze, and enhance extraction of meaning information for collective action and developing systems to improve police responsiveness to residents' need. We focus on these aspects, as they are fundamental to improved collaboration and improving police accountability / residents' trust in the police.

Chapter 4

Quantitative Operationalization of Collaborative Efforts between Police and Residents

Positive interactions (e.g. addressing residents' complaints) with police can help increase trust and generate a feeling of safety among the residents; whereas negative interaction (e.g., misconduct by police) may increase insecurity among residents [67, 124]. Increased interactions between police and residents in day-to-day life may also lead to improved resident awareness, collective action, and social change [124]. Police-resident communication in day-to-day policing can make residents feel that the police is available to help and hold itself accountable to residents; feelings of accountability are known to help reduce negative affect [27]. Therefore, studying day-to-day communication between police and resident community accounts for both social determination and social change through collective efforts in multiple ways [33]. Despite the importance of day-to-day policing, it remains underexplored whether the richness of such social media data can be helpful to improve and understand resident perceptions in day-to-day policing. Such online interactions between police and residents can help change resident perceptions about community safety, police efforts, and the relationship between them [147].

This chapter examines the communication between police and residents in the emergent yet non-conventional setting: social media. To the best of our knowledge, this thesis makes the first attempt to empirically explore the role of social media interactions to: 1) characterize behaviour of and engagement between police and residents to address crime and safety concerns in day-to-day life, and in 2) investigate if social media platforms can be a way for law enforcement agencies to assess, record and sense public safety in a macro or community-sense. Our specific study goals include:

- Exploring the feasibility of social media in quantifying attributes of police and resident inter-

action around issues of day-to-day policing, such as crime and safety;

- Identifying behavioral attributes like the affective expression, engagement and social and cognitive response processes of police and residents as they interact on social media.

This thesis shows that it is possible to operationalise and measure social interactions between police-residents in a fine-grained manner through three dimensions: engagement, affective expression and intensity, and linguistic attributes of cognitive and social processes. We find that discussions involving residents and police significantly reduce negative sentiment such as anxiety among residents experiencing safety concerns exhibiting opportunity for improved emotional support through social media. Finally, we also observe that police department adopt a focused approach to use social media for discussing limited topics rather than multiple topics.

4.1 Research Questions

In view of the above literature and our objective to explore the feasibility of a framework to characterize interaction between police and residents, we address the following research questions:

- *RQ 1: Topical Characteristics* - What is the nature of content and topics that characterize social media discussion threads from residents and police on safety issues?
- *RQ 2: Engagement Characteristics* - How do residents and police engage in social media discussion threads?
- *RQ 3: Emotional Exchanges* - What is the nature of emotions and affective expression that manifest on social media during resident-police interactions?
- *RQ 4: Cognitive and Social Orientation* - What are the linguistic attributes that characterize cognitive and social response processes during resident and police interactions on social media?

4.2 Data and Methods

4.2.1 Collection methodology

We utilized data from 85 public and official Facebook pages of police departments in India to study social media interactions. We employed a variety of mechanisms to identify these pages and then to filter posts and comments for analysis. We referred to a government website¹ that provides a list of all police departments to identify various Indian police organization on Facebook. Using our initial list, we were able to recognize 100 police departments on Facebook. Next, we verified these

¹<http://arunpol.nic.in/>

department Facebook pages for their authenticity and credibility. We manually checked if these pages were linked to the official government website of the police department, or had stated on their web page that these were the official government organization representative. After this cleaning, we were left with 85 police departments' pages on Facebook, most of these pages had an average age of 3 years.

We then collected data using the Facebook Graph API² from the day these pages were created through April 20, 2015. We obtained all wall posts (content posted by residents); and status updates (content posted by police) from these pages. This gave us 47,474 wall posts and 85,408 status updates. Further, to understand discussions on these pages, we collected all 'comments' and 'likes' associated with the posts, including their time of creation. Since we wanted to study interaction characteristics between police & residents and among residents, we considered posts that had at least one comment (reply). Our dataset had 46,845 police posts and 24,984 resident posts where there was at least one comment. Note that our data did not include private messages that people might have sent to police using Facebook, or other forms of "spill-over" activity that may be present in residents' profile such as private discussions with friends.

4.2.2 Terminology and data categorisation

We now explain the terminology and notations used to categorize different types of *discussion threads* (posts and associated comments) prevalent in our dataset. To understand the role of police interaction with residents through social media, we look at two kinds of discussions: one where both police and resident participate and, the other where only the residents participate in the discussion. We consider discussion threads initiated by both police and residents. We categorize these threads into four classes based on the CMC literature including initiator and responders:

- (a) Police initiated discussion threads where both police (P) and residents (C) had left comments and were part of discussion ($P_{P\&C}$);
- (b) Police initiated discussion threads where only residents left comments (P_C);
- (c) resident initiated discussion threads where police and residents both left comments ($C_{P\&C}$); and
- (d) resident initiated discussion threads where only residents left a comment and were part of the discussion (C_C).

Table 4.1 shows a number of discussion threads in each category where there was at least one comment.

²<https://developers.facebook.com/docs/graph-api>

Table 4.1: Number of discussion threads (DT), threads with at least one comment, DTs where police and residents comment (P&C) and those where only residents comment (C).

	Total DT	DT w/ ≥ 1 Comment	P&C	C
Police	85,408	46,845	5,519 ($P_{P\&C}$)	41,326 (P_C)
residents	47,474	24,984	17,196 ($C_{P\&C}$)	7,788 (C_C)

4.2.3 Measures

We now identify and propose three broad measures to landscape and quantify the interactions between police and residents in social media and also to address our various research questions. These measures are discussed below:

Engagement: In the context of policing, engaging with residents is an important aspect of the problem-solving process [95]. We measure the engagement of police and residents regarding their activity patterns in the different discussion threads: $P_{P\&C}$, P_C , $C_{P\&C}$, C_C .

We first consider the following measures of *content generation*:

- Number of police and residents who comment on police and resident initiated discussion threads.
- Number of unique residents who comment on police and resident discussion threads.
- Entropy (Shannon’s Wiener Diversity index) or the diversity in the number of unique residents involved in initiating different discussion threads. This helps us quantify the randomness in the amount of content generated by every resident [115].

$$H = - \sum_{i=1}^R p_i \ln p_i \quad (4.1)$$

H represents the Shannon’s Wiener Diversity index, p_i is the relative abundance of posts made by each resident on a police page, and R is the total number of individual residents participating on a police page.

We also consider two measures of *content interaction*:

- Average number of ‘comments’ on resident and police initiated discussion threads.
- Average number of ‘likes’ on resident and police initiated discussion threads.

Emotional Expression: Individual safety and threat are associated with a high emotional activity. Research shows that interaction between police and residents can reduce anxiety and apprehension [27]. Moreover, criminological points of inquiry such as understanding ‘fear’ of crime, victimization and its effects, or the fervent pressure of residents are also vital in the maintenance of law and order [26].

To measure emotional expression in our discussion thread categories, we consider two measures: a) emotional valence and b) emotional intensity. This measure has been employed in prior social media analytics work and is also validated on social media data [23, 25, 151].

- Emotional valence is measured in terms of Positive Affect (PA), Negative Affect (NA), “anger”, “anxiety”, and “sadness” — we make use of the popular and well-validated psycholinguistic approach LIWC (<http://liwc.wpengine.com/>). We find the percentage of each category in the text using LIWC approach that consists of pre-defined words in various linguistic categories. For emotional valence, LIWC provides 915 words that measure affective processes accounting for Positive Affect (406 words) and Negative Affect (499 words). Further, NA consists of three category anxiety, anger, and sadness. To measure “anxiety”, LIWC includes 91 words such as worried, fearful, nervous, etc. Similarly “anger” is measured using words such as hate, kill, annoyed and category sadness includes 101 words such as crying, grief, and sad.
- Emotional intensity is measured based on the psychological arousal measures of words given in the ANEW dictionary (Affective Norms for English Words: <https://www.csc2.ncsu.edu/faculty/healey/msa-17/text/index.html>).

Cognitive and Social Orientation: Mutual awareness and collective psychosocial processes in the context of policing can increase social cohesion and reduce safety concerns among residents [68]. Hence we study linguistic attributes relating to the cognitive and social orientation as manifested in the different discussion thread categories. We again utilize LIWC and focus on the following word categories that have been examined in prior literature [23, 24]:

- Measures of *interpersonal focus* given by pronoun use, such as 1st person singular, 1st person plural, 2nd person, 3rd person singular, 3rd person plural, and impersonal pronouns. The percentage of these categories in a post are calculated using LIWC dictionaries. LIWC includes 116 pronoun words among these 70 are personal pronouns such as I, them, itself and 46 impersonal pronouns.
- Measures of *cognition* given by the categories “cognitive mech”, “tentativeness” and “discrepancy”. LIWC measures cognition using 730 words such as cause, know, and ought. It further

provides a dictionary of 155 words such as maybe, perhaps, guess and 76 words such as should, would, could to measure the percentage of “tentativeness” and “discrepancy” in the given text.

- Measures of *social orientation* obtained based on the categories “friends”, “family”, and “humans”. These dictionaries for these measures consists of 455 words that explain social processes. Among these “Family” category consists of 64 words such as daughter, husband, aunt; “Friend” includes 37 words such as buddy, friend, neighbor and Humans consists of 61 words such as Adult, baby, boy, etc.

4.3 RQ 1: Topic Characteristics

Per RQ 1: *What is the nature of content and topics that characterize social media discussion threads from residents and police on safety issues?*, we begin by characterizing the topics expressed in police and resident discussion threads. Our first analysis employs n -gram (unigrams) analysis on the content of the discussion threads. Thereafter, we adopt a clustering approach in an unsupervised manner based on the k -means algorithm to examine the nature of topics discussed.

4.3.1 Unigram analysis

Police Initiated Discussion Threads. First, we analyze the nature of content shared in discussion threads initiated by the police: we discuss both the posts and the associated comments in these threads. Through unigram analysis, we observe that the top words in the police posts are *safety*, *residents*, *people*, *notice*, *issued* (Table 4.2). In essence, these posts include advisories, the status of different cases being investigated, *notice* or “*challans*” (local word for fine) issued by the police in public interest on subjects such as safety drives conducted and people prosecuted.

In $P_{P\&C}$ discussions, we find that posts broadly span general safety of the public. E.g., in a post, police remarked:

“Snatching is a big menace in the cities especially in the colonies and during early hours, afternoons and nights. Although this menace can’t be eradicated totally, the vulnerability can be minimized, If you take the following precautions...”

Next, in Table 4.2, the posts of $P_{P\&C}$ discussion threads are observed to be 57.14% higher in use of the word *please*, 16.68% more in *safety*, and 149.99% in *rules*, than posts in P_C discussions; indicating that $P_{P\&C}$ posts comprise advisories requesting residents for specific actions or respecting rules. On comparing posts, we find statistically significant difference in the most frequent unigrams ($N = 50$) of $P_{P\&C}$ and P_C discussion threads ($U = 700, p < .05, z = -3.57$) based on Mann-Whitney U tests. We find the most frequent unigrams in comments of $P_{P\&C}$ discussion threads to

include: *good, people, sir, please, job, great, thanks, and work*, indicating resident appreciation of police work; For instance, a resident commented “Great job.”

In posts of P_C discussion threads (Table 4.2), we find that the posts are largely about actions taken or developments made by police, such as individuals prosecuted, notices issued, action taken reports. For example, in a post, police informed the residents that:

“29584 persons were prosecuted by Delhi Traffic Police for drunken driving during the year 2014. These drivers are requested not to drink & drive again....”

Resident Initiated Discussion Threads. Secondly, in the posts initiated by residents, most posts tend to request police to take action on their complaints. The unigram analysis shows a high occurrence of words such as *please, take, action, sir* (Table 4.2). On comparing the posts and associated comments in the $C_{P\&C}$ and C_C threads, we find that the C_C category involves a higher reference to people (15% higher), and eyewitness experience of residents (14.94% higher) than the $C_{P\&C}$ category. For instance, a resident said:

“they [sic] are so many foreigners whose visa is expired, other countries take serious action, why not in India, these people are mostly found in Yelahanka and around, some of them may be smugglers, terrorists, some of them spy working for enemy countries / terrorist org”

We also find statistically significant difference in frequent unigrams ($N = 50$) of $C_{P\&C}$ and C_C posts ($U = 961, p < .05, z = -1.99$), as well as among the frequent unigrams ($N = 50$) in the comments of these two discussion threads ($U = 957, p < .05, z = -2.02$). Top unigrams in $C_{P\&C}$ comments include *action, thanks, please, dear, and complaint*.

4.3.2 Analyzing themes in discussion threads

Next, to identify broad themes, we calculate the *tf-idf* vectors for all the posts in each of the four discussion thread categories (ref. Table 4.1). Then we perform *k*-means clustering on this data. *k*-means is a popular algorithm used for clustering. In this algorithm, from a set of n sample points $X \subset \mathbb{R}^d$ and k integers, k centers C need to be selected such that:

$$\phi_c(X) = \sum_{x \in X} \min_{c \in C} ||x - c||^2 \quad (4.2)$$

One cluster is defined as a set of data points that are closer a specific center than the others. However, solving the exact solution for the *k*-means is a NP-hard problem. Therefore, research suggests to find optimal clustering for an instance of the *k*-means. Therefore, for a given Clustering

$P_{P\&C}$		P_C		$C_{P\&C}$		C_C	
Unigram	Freq.	Unigram	Freq.	Unigram	Freq.	Unigram	Freq.
rules	0.015	safety	0.012	please	0.026	people	0.022
safety	0.014	following	0.011	take	0.021	please	0.02
violations	0.014	notice	0.010	action	0.019	one	0.019
challans	0.011	prosecuted	0.009	people	0.019	take	0.016
please	0.011	shall	0.009	one	0.019	action	0.015
residents	0.010	bus	0.009	time	0.017	time	0.015
one	0.010	movement	0.008	near	0.017	number	0.013
people	0.010	complaint	0.008	car	0.017	driving	0.012
public	0.010	near	0.008	sir	0.016	sir	0.011
special	0.010	advisory	0.008	also	0.016	public	0.011
due	0.009	commissioner	0.008	number	0.015	even	0.011
side	0.009	avoid	0.008	vehicles	0.015	rules	0.010
various	0.009	public	0.007	parking	0.015	parking	0.010
drunken	0.008	heavy	0.007	taxi	0.014	see	0.010
marg	0.008	side	0.007	vehicle	0.014	near	0.009
number	0.008	taken	0.007	bus	0.012	side	0.009
parking	0.008	take	0.007	station	0.011	know	0.009
places	0.008	right	0.007	driver	0.011	driver	0.009
requested	0.008	please	0.007	today	0.011	signal	0.009
shall	0.008	action	0.007	even	0.010	get	0.009

Table 4.2: Unigram Analysis: strength of normalised most frequent words across our four discussion thread categories.

C with potential ϕ , let $\phi(A)$ represent the contribution of $A \subset X$ to the potential where potential is defined as:

$$\phi_c(A) = \sum_{x \in A} \min_{c \in C} ||x - c||^2 \quad (4.3)$$

To find the optimal solution, k-means starts with a random set of k integers and then a cluster is obtained from the already chosen set of centers iteratively. The process continues till the clusters become stable. In comparison to the k-means algorithm, which selects an arbitrary set of cluster centers, k-means++ suggests a specific algorithm to select the centers. Specifically, we use *k-means++* seeding method that has been proved to perform better than random seeding [3]. For calculating the centers, we define $D(x, C)$ as the shortest distance between a sample point x and the already chosen closest center (C). The specific k-means++ algorithm comprise of the steps discussed in Algorithm K-means++ (See K seeding Algorithm).

This method has been used in previous studies to clustering tasks on social media [2]. We iteratively apply this methodology with different values of k , chosen in an empirical data-driven manner and

Algorithm 1 K-means++ (K seeding Algorithm)

$C \leftarrow$ choose a point as initial centre uniformly at random from X
while $|C| < k$ **do**
 Choose $x \in X$ with probability $\frac{D^2(x, C)}{\phi_C(X)}$
 $C \leftarrow C \cup \{x\}$
end while
Continue as with the regular k-means algorithm.

using elbow method, and then obtain silhouette score ($[0, 1]$) for each iteration. We obtain optimal value of k via maximizing silhouette score, which is found to be 3 and 6 for police and resident initiated threads respectively. The silhouette score is defined as:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \quad (4.4)$$

Here, for every data point i , $a(i)$ represents the average intra-cluster distance and $b(i)$ represents the average nearest cluster distance. The mean $s(i)$ thus calculated over all data points represents the measure showing appropriateness of different data points in clusters.

Next, adopting a qualitative approach, two researchers independently engaged to annotate the clusters, using a semi-open codebook. The annotators referred to existing literature in criminology to develop the codebook [104, 112]. We summarize these clusters in Table 4.3 and present a qualitative analysis on them below.

Police Discussion Threads contain three prime clusters:

- (1) *Awareness drive / safety campaigns*: Top tokens in this cluster include words such as *drive, rules, safety, vehicles, city, follow, aware*. We find that criminology and community policing literature [7] identifies creating awareness about rules and safety issues as prime objective of police departments to prevent crime and address safety issues.
- (2) *Prosecuted / action taken reports*: This cluster is characterized by tokens such as — *notice, issuing, served, prosecuted, facebook basis complaint, photographs, following, action, dated*. Precisely, this cluster includes posts that inform residents that police has sent *challans* to violators or has prosecuted the violators appropriately.
- (3) *Advisories on situations*: Here we find the manifestation of specific words such as *traffic, slow, heavy, movement, safety flyover, bus, road*. Thus, this cluster is characterized by posts where police informed residents of areas where they could expect heavy or slow traffic.

Resident Discussion Threads consist of six prime clusters:

- (1) *Appreciation*: This cluster shows manifestation of appreciation for police departments: *great job, doing, police, good, nice, work, initiative, gr8, congratulations*.
- (2) *Newspaper articles*: We find this cluster to show a practice of posting newspaper articles: *indiatimes, timesofindia, bangaloremirror*. On qualitative analysis, we find that these articles include news about crime reported in different parts of the cities, that the residents wanted to bring within the notice of police.
- (3) *resident tips and complaints*: We identify following top tokens in this cluster: *people, driving, rules, wrong, vehicles, stop*. They indicate that residents complain to police about others not following rules, or breaking a law.
- (4) *Traffic problems*: This cluster includes tokens such as *jam, traffic, bridge, heavy, huge, evening hours, route*. It shows residents to have reported about traffic problems, heavy congestion areas, and blocked places.
- (5) *Neighborhood problems*: This cluster shows discussions on neighborhood problems such as inappropriate parking areas, cars with dark tinted glasses (prohibited by law). This is indicated by words such as: *parked, road, near, parking, black, tinted*.
- (6) *Missing people*: We find evidence of residents asking for help to identify missing people. This cluster is marked by tokens such as *help, missing, son, contact, plz, kindly*.

4.4 RQ 2: Engagement

Moving on to RQ 2 i.e., *How do residents and police engage in social media discussion threads?*, we now present observations on the measures of engagement.

Content Generation. First, based on Table 4.4, in the police initiated discussion threads, we find that number of individuals who participate in the P_C (i.e. residents participants only) discussions are higher than those in $P_{P\&C}$ (both police and residents participants). Qualitative analysis shows that the posts corresponding to the former are mainly action taken reports and people prosecuted by police departments:

[withheld] this is to inform you that both the vehicles were prosecuted under the provision of law and removed to concerned P.S. for further action. Now the said area is free from illegal parking. And we are keeping sharp look on the area.

Further, we find that number of individuals who participate in resident initiated discussion threads where only residents comment (C_C) is almost 26% lower than the $C_{P\&C}$ category where both police

Topics	Top Words / Tokens
<i>Police Initiated Discussion Threads</i>	
Awareness drive	drive, rules, safety, vehicles, follow, aware
Prosecuted / action taken	notice, issuing, served, prosecuted facebook basis complaint, photographs, action following, dated
Advisories	traffic, slow, heavy, movement, safety, flyover bus, road, avoid, near, delhi
<i>Resident Initiated Discussion Threads</i>	
Appreciation	great, job, doing, police, good, nice, work initiative, gr8, congratulations, commendable
News articles	articleshow, indiatimes, timesofindia bangaloremirror
resident tips and complaints	people, driving, rules, traffic wrong, bus, way, lane, right, drivers, vehicles, stop
Traffic problems	jam, traffic, bridge, heavy, problem, area, huge evening hours, route
Neighbourhood	parked, road, traffic, near parking, black, tinted
Missing people	help, missing, son, contact, plz, kindly, identify

Table 4.3: Extracted topics for police and resident initiated discussion threads.

	$P_{P\&C}$	P_C	$C_{P\&C}$	C_C
Police + residents	55,028	1,79,176	17,124	12,630
residents Only	54,982	1,79,176	17,081	12,630
Entropy	4.39	4.96	3.23	3.60

Table 4.4: Number of individuals involved in commentary in different discussion thread categories, and entropy of comments shared by each user.

and residents participate in the discussion (Table 4.4). As we discussed in the previous section, these are mostly residents’ posts that include individual complaints; they may not relate to a larger audience on police pages. It could, therefore, explain the lower number of residents participating in this category of resident posts. Prior work shows that more people contributing to content generation increase the social capital of an organization [37]. We conjecture that $C_{P\&C}$ discussion threads might be contributing more towards social capital building (due to engaging both police and residents) than those involving resident commentary only (Table 4.4).

Next, to understand the contribution of individual residents towards content generation process, we focus on discussion threads initiated by the police. For the purpose, in Table 4.4, we report the entropy (variation) in the number of comments per resident. We find that entropy is 12.98% higher in P_C discussion threads, as compared to $P_{P\&C}$. Lower entropy in the latter discussions shows that there is less volatility among those who engage in content generation, and police and resident participation is likely more balanced in them. Similarly, in the discussion threads initiated by the

	Comments			'Likes'		
	Avg	Std dev.	Med	Avg	Std dev.	Med
$P_{P\&C}$	19.68	86.17	7	114.71	805.55	22
P_C	9.88	74.92	3	88.05	1025.53	22
z -score	-48.25**			-1.19		
$C_{P\&C}$	3.34	19.19	2	9.4	253.85	2
C_C	3.69	13.79	2	13.38	201.57	3
z -score	-2.275*			-19.54**		

Table 4.5: Mean, median and standard dev. of comments and ‘likes’ on posts of different discussion threads. ** $p < .01$ and * $p < .05$, per Mann Whitney U tests.

residents, entropy or variation in the number of comments by each resident is found to be 10.28% lower in $C_{P\&C}$ discussion threads as compared to C_C discussions. Here lower entropy value signifies that a large number of comments are posted by a small number of residents and police in the $C_{P\&C}$ threads. Thus, we conjecture that these threads may contribute less towards police endeavors to obtain mass public participation in community policing.

Content Interaction. Next, we analyze the number of comments and ‘likes’ on posts to understand which category of discussion threads gets maximum interest and support.

In resident initiated threads, we find that $C_{P\&C}$ gets fewer ‘likes’ (9.49% lower) and ‘comments’ (29.75% lower) per post compared to C_C (Table 4.5). We observe that these posts are regarding specific issues such as lost vehicle or mobile phone, some problem regarding FIR (First Information Report) ³ filed, complaints, and so on. In most of such posts, police suggest an appropriate action and the discussion tends to close early, resulting in lower interaction in the form of comments and ‘likes’ by others:

resident post: My family and I are getting the unwanted calls from the given number [withheld].

Especially he is misbehaving with a female member. My Number is - [withheld]

Police reply: Dear [withheld], Please visit at your nearest Police Station and lodge a complaint with details and they will assist you in this regard... Thank you

In contrast, in police initiated discussion threads, the ($P_{P\&C}$) category gets more ‘likes’ (30.28% higher) and comments (99.19% higher) per post than ones where only residents comment (P_C). As posts in $P_{P\&C}$ discussions are mainly advisories where police request residents for some action or shares information with them, these may generate more engagement in the form of ‘likes’ and

³It is a report that a victim files for action with the police department against the accused. It is called so as this is the first information about an offense. Once a FIR is registered, police department can begin the investigation of the crime.

	$C_{P\&C}$			C_C			
	Avg	Std	Median	Avg	Std	Median	z
PA**	0.08	0.11	0.05	0.06	0.12	0.02	-37.46
NA**	0.021	0.03	0.01	0.018	0.04	0.00	-14.41
Anx**	0.001	0.01	0.00	0.003	0.02	0.00	-10.29
Anger**	0.006	0.02	0.00	0.005	0.02	0.00	-3.52
Sad**	0.001	0.01	0.00	0.002	0.01	0.00	-8.03

Table 4.6: Emotional valence averaged across resident initiated discussion threads. We use Mann Whitney U Test for statistical testing. ** $p = .01$. PA = Positive Affect, NA = Negative Affect, Anx= Anxiety.

commentary among police and residents. However, in P_C discussions, posts largely include topics like notice issued or people prosecuted, which may result in a lesser commentary in individual posts.

4.5 RQ 3: Emotional Expression

In addressing RQ 3 (*What is the nature of emotions and affective expression that manifest on social media during resident-police interactions?*), we now discuss our observation on the two measures of emotional expression — *emotional valence and emotional intensity* expressed by residents and police on the different discussion thread categories.

Emotional Valence. Emotional valence analysis shows residents to generally express negative emotions both in $C_{P\&C}$ and C_C threads (Table 4.6). However, Negative Affect (NA) is 16.67% higher in $C_{P\&C}$ than C_C discussions. We further analyze the distribution of “anger”, “anxiety”, and “sadness” expressed in comments on resident posts. We find that in both $C_{P\&C}$ and C_C discussion threads, dominant emotion is “anger” followed by “sadness” and “anxiety”. However, we find that “anxiety” is significantly higher (200%) in the C_C threads than $C_{P\&C}$. This may indicate that discussions where only residents comment, manifest higher levels nervousness and worry (expressions of anxiety) than the residents’ discussions where police also participate in the commentary. Previous work shows that feelings of accountability help reduce anxiety and feelings of victimization [27,68]: presumably, a police comment would make residents feel that the police is available to help and holds itself accountable to residents:

I am just **worried** if Hyderabad Traffic Police [HTP] makes things worse like always and create more chaos. Frankly speaking... it’s the lower income group or the people who are not aware using high beams. Try to educate people on road by campaigns at traffic signals

We find a similar trend of expression of “anxiety” in the police initiated discussion threads (Table 4.7). Anxiety is lower (9.52%) in the discussions where police also participate ($P_{P\&C}$) than P_C discussion.

$P_{P\&C}$				P_C			
	Avg	Std	Median	Avg	Std	Median	z
PA**	0.0668	0.07	0.04	0.0702	0.12	0.018	-12.99
NA**	0.0157	0.02	0.01	0.0157	0.03	0.019	-9.43
Anx**	0.0019	0.005	0.00	0.0021	0.008	0.015	-6.64
Anger**	0.0050	0.009	0.00	0.0049	.018	0.012	-11.40
Sad**	0.0016	0.005	0.00	0.0021	0.014	0.009	-4.71

Table 4.7: Emotional valence averaged across discussion threads initiated by the police. ** $p < .01$.

$C_{P\&C}$				C_C			
	Avg	Std	Median	Avg	Std	Median	z
Arousal**	4.40	1.74	5.01	3.90	2.16	4.66	-11.74
$P_{P\&C}$				P_C			
Arousal**	4.19	1.23	4.35	3.75	2.00	4.15	-8.43

Table 4.8: Emotional intensity averaged across the four different categories of discussion threads. ** $p < .01$.

On analyzing positive affect (PA), we find that $C_{P\&C}$ threads are observed to share 33.34% higher positivity than in the threads where only residents participate in the commentary (C_C) – refer Table 4.6. Otherwise considered as a “coercive arm of the state” [68], this finding indicates that community discussions where police also participate can be used to transfuse positive feelings and perceptions among the residents.

Emotional Intensity. Next, analyzing the emotional intensity expressed in resident initiated discussion threads, we find that $C_{P\&C}$ threads show 12.82% higher arousal than C_C (Table 4.8). We find similar trends in the police initiated discussion threads: $P_{P\&C}$ threads show higher arousal (11.74%) than those with only resident commentary, i.e., P_C (Table 4.8). We also find that for $P_{P\&C}$ threads, there exists a stronger correlation between arousal and negative affect ($r = 0.07$, $p < .05$) than arousal and positive affect ($r = -0.05$, $p < .05$).

This shows that residents on these Facebook pages are more anxious to communicate their negative emotions with greater intensity. This is aligned with the theory of mutual sympathy of negative emotions [68] and shows that residents try to educate other residents more about negative incidences they encounter. Previous work also recognizes higher arousal and negative affect to be markers of sensitization [25]; presumably, in police-resident discourse, residents are highly sensitized due to disclosure of personal and community challenges, or experience of erosion of law and order.

	$C_{P\&C}$			C_C			
	avg	std	median	avg	std	median	z
Interpersonal Focus							
<i>ppron</i> **	0.062	0.059	0.053	0.045	0.056	0.033	-24.49
<i>i</i> **	0.008	0.017	0.000	0.014	0.033	0.000	-16.02
<i>we</i> **	0.014	0.031	0.000	0.007	0.021	0.000	-16.01
<i>you</i> **	0.033	0.047	0.018	0.012	0.032	0.000	-45.85
<i>shehe</i> **	0.002	0.010	0.000	0.003	0.016	0.000	-4.44
<i>they</i> **	0.005	0.013	0.000	0.008	0.022	0.000	-14.20
<i>ipron</i> **	0.030	0.036	0.023	0.037	0.051	0.025	-6.03
Social Orientation							
<i>family</i> **	0.001	0.005	0.00	0.002	0.015	0.00	-9.49
<i>friend</i> **	0.0003	0.003	0.00	0.001	0.010	0.00	-8.17
<i>humans</i> **	0.008	0.026	0.00	0.012	0.033	0.00	-12.91
Cognition							
<i>CogMech</i> ***	0.121	0.077	0.124	0.114	0.100	0.113	-8.52
<i>tentativeness</i> **	0.015	0.024	0.000	0.017	0.029	0.000	-3.98
<i>Discrepancy</i> **	0.009	.018	0.000	0.013	0.032	0.000	-2.69

Table 4.9: Social and cognitive orientation measures in $C_{P\&C}$ and C_C discussion threads. ** $p < .01$. *ppron* = personal pronouns, *i* = 1st person singular pronouns, *we* = 1st person plural pronouns, *you* = 2nd person, *shehe* = 3rd person singular pronouns, *they* = 3rd person plural pronoun, *ipron* = impersonal pronouns.

4.6 RQ 4: Cognitive and Social Orientation

Finally, in RQ 4 i.e., *What are the linguistic attributes that characterize cognitive and social response processes during resident and police interactions on social media?*, we analyze linguistic constructs of cognitive and social orientation in different discussion threads.

From Table 4.9, we find that in resident initiated threads, use of impersonal pronouns is higher (23.34%) in the C_C category than $C_{P\&C}$, whereas personal pronouns use is 37.78% higher in $C_{P\&C}$ than C_C . Further C_C threads show a higher (75% more) use of 1st person personal singular pronouns, 3rd person personal singular pronouns, and 3rd person plural pronouns than those in which both police and residents comment ($C_{P\&C}$). Together, this indicates that discussion threads involving just the residents are highly self-attention focused; likely residents mostly express their own concerns that they face with others:

I have lived in the UK and all the time **I have never heard** anyone honking. Honking is not required if you know how to drive [...] Can anyone advise me where to complain if **I see anyone** who don't comply?

We also find that C_C threads have more mentions of “family”, “friends”, and “social” words, than $C_{P\&C}$ (Table 4.9). However, collective identity words such as 1st person personal plural pronouns are

	$P_{P\&C}$			P_C			
	avg	std	median	avg	std	median	z
Interpersonal Focus							
ppron**	0.051	0.036	0.047	0.040	0.043	0.037	-20.96
i**	0.013	0.016	0.009	0.014	0.025	0.006	-5.51
we**	0.008	0.013	0.004	0.007	0.016	0.000	-15.35
you**	0.021	0.032	0.012	0.011	0.025	0.000	-32.86
shehe**	0.002	0.007	0.000	0.002	0.013	0.000	-8.91
they**	0.007	0.011	0.000	0.007	0.013	0.000	-9.96
ipron	0.036	0.026	0.036	0.039	0.043	0.036	-1.33
Social Orientation							
family**	0.11	0.48	0.00	0.09	0.62	0.00	-8.77
friend**	0.08	0.42	0.00	0.06	0.50	0.00	-10.03
humans**	1.42	1.98	1.00	1.62	4.19	0.60	-10.42
Cognition							
CogMech**	0.128	0.057	0.133	0.118	0.081	12.50	-8.54
discrep**	0.014	0.015	0.012	0.013	0.019	0.72	-10.13
tentat**	0.018	0.017	0.017	0.017	0.024	1.30	-9.94

Table 4.10: Social and cognitive orientation measures in $P_{P\&C}$ and P_C discussion threads. ** $p < .01$.

very few in these conversations. Next, the occurrence of 2nd person pronoun words is 63.64% lower in C_C threads than $C_{P\&C}$. Literature shows that 2nd person pronoun use is higher when people show increased focus on others [96]. This could be to advise others or to hold others accountable. When police and residents both participate in the commentary, they tend to indulge in direct references to each other in the conversation. This could also be attributed to police participation in answering resident queries, and the latter’s use of gratification words toward the former.

Cognitive process words in C_C discussion threads show higher “tentativeness” (*should, would, could* and higher “discrepancy” (*guess, maybe, perhaps* – refer Table 4.9; these are known to indicate increased awareness of one’s social environment [96].

I **guess** law needs to change. This needs to be restricted to law enforcement vehicles during emergency-only. In the above case, there was only the driver in the car.

We find similar trends of pronoun use in police initiated discussion threads (Table 4.10). P_C threads have 92.31% higher mention of 1st person singular pronouns and less mention of 1st person plural pronouns, showing high self-focus. However, contrary to resident initiated threads, we find that mention of “family” and “friends” is less in these posts.

4.7 Implication and Discussion

Behavioral patterns reflected on social media may act as markers of the psychological state of residents and may also help understand civic needs and general well-being of the society. We explore the viability of using content generated on Facebook police pages as an instrument to quantify and characterize attributes of police and resident's interactions around day-to-day safety needs. Towards improving safety and law enforcement, we find that residents are appropriating a public platform like Facebook to discuss collective solutions with police and members of civic society at large.

Understanding resident reactions is a challenge for police departments as they mostly depend upon administrative and crime reports to gauge resident reactions. This thesis highlights that Facebook can be used to record and sense behavioral attributes such as engagement, emotions, and social support expressed between police and residents. We show the four distinctive measures i.e. topics discussed, emotions, engagement characteristic and cognitive processes can be used to extract and measure these attributes from large-scale data available on social media. This understanding can help police improve policing and community sensing.

Further, social media seems to enable police and resident community to enhance emotional support to residents experiencing safety issues. We observed that discussion threads with police and resident commentary showed reduced levels of anxiety, showing police interactions can be calming to residents. Measuring emotional needs of residents using social media may help police and other law enforcement agencies to interact with residents promptly. We also found that discussion threads where residents and police both comments were marked by high negative affect and arousal. In fact, arousal was more strongly correlated with negative affect than positive effect; thus exhibiting the fact that residents may increasingly try to educate others about negative incidents they counter and gain the mutual sympathy of other members in the community [118].

Our finding also indicates social exchange between police and residents on an informal public platform like Facebook, wherein both parties might be motivated to address lawlessness and safety concerns together. The discussion threads with both police and resident commentary indicated a stronger notion of a collective identity via the use of 1st person plural pronouns. Thus, highlighting social media role in supporting discussions on collective action among police and resident community.

We further observed that Facebook discussion threads where only the residents commented manifested higher self-focus (greater use of the first person pronoun singular), and cognitive processing ("cognitive mech", "tentativeness", "discrepancy") than those with both police and resident commentary. These discussion threads likely point to how residents are purposing a public social media platform to voice their opinion around their personal everyday challenges. In a way, these platforms are enabling them to engage with others and to address accountability concerns on the part of the

police, as have been observed in other community platforms (crime discussion web forums) [68].

Summarily, we envisage technologies that can help communities to make consensus-based decisions on support and actions they seek from police using social media content. Technologies may also be built for authorities and police that help gauge changing emotions and behavior among residents, including timely and early predictive analytical systems. These technologies could help police to sense and record the reactions of residents and share these records with decision makers to help take timely measures and gain better insights about residents' concerns.

4.8 Summary

In this chapter, we examined discussions between police and residents on Facebook pages of 85 Indian police departments. We showed that how fine-grained manner analysis of dimensions like topics discussed, engagement, affective expression and intensity, and linguistic attributes of cognitive and social processes can be used to operationalise and measure social interactions between police–residents in a fine-grained manner. We found that compared to resident initiated discussions, police initiated discussions contribute more towards engaging masses on safety related topics. Discussions where both police and residents participated were marked by higher negative emotions (such as anger) and psychological arousal. resident only discussions showed higher self-focus and contributed less towards collective action than discussions involving both police and residents. Our findings bear implications in the design of social media technologies to provide timely help and support for police to gauge safety and well-being of residents.

Chapter 5

Exploring Actionable Information and Residents' Opinion from Collaborative Interactions

In this chapter, we present a case study of Bangalore police department to provide a focussed view on the strategy to use social media for improved collaboration. Police officers interact with residents in multiple ways to address the day-to-day safety and crime issues. These interactions include responding to residents' calls, creating awareness and resolving residents' queries. Police are often considered to be the most representative and perpetual government service. Positive experiences (e.g. addressing the complaints) can help generate feeling of safety among the people; whereas a negative experience (e.g., misconduct by police) leads to sense of insecurity among residents [124]. Negative encounters isolate residents and result in crime going unidentified and unreported. However, resident's experiences are often not shared with police, considering their harsh and state-driven image [29]. In lack of the information about resident's experience with police and crime incidents, there is a little opportunity for police to change the crime landscape, explain their actions, and involve residents in crime prevention activities. For police, understanding the community perceptions are helpful to know the effectiveness of safety measures and improve the organization's plan to address crime [67]. Police needs effective communication strategy to obtain timely information from residents and understand their concerns [16, 29, 49, 68].

Our study focuses on understanding a) what actionable information (i.e. necessary information to deal with the situation at hand) is available on OSN for police and b) how residents use OSN to express fear of being victimized, policing needs, and police performance in developing countries such as India. We study Facebook page of Bangalore City Police one among popular pages of police departments to provide a deep dive into strategies used for enhanced policing. In this part of the

thesis, we analyze 255 posts and 1,600 comments from residents on Facebook page of Bangalore City Police (BCP) in India.

Bangalore City Police (BCP) was stabilized in 1963 and is responsible for the overall policing in the Bangalore city. Bangalore police department supports 107 Police Stations [6]. BCP established its Facebook Page in 2011 to encourage community participation in crime prevention, maintenance of law and order, and traffic management (See Figure 5.1). BCP Facebook page has more than 505,000 likes and is actively used to engage with residents. A trained team of six people manages the page on OSN [109]. This team is responsible for collaborating with the residents and responding to the resident's posts for resolving issues. Bangalore city is an ideal place to study community crime response as the city has developed the most prominent policing program on OSN in last few years [6].



Figure 5.1: Bangalore City Police's Facebook page with 505,391 likes as on 19th March 2017. <https://www.facebook.com/blrcitypolice>.

5.1 Research Objective

In this thesis, we now explore *whether OSN can support police to get actionable information about crime and residents' opinion about policing activities in urban cities of India*. We identify following supporting aspects to examine our research goal – a) analysing if residents use the police Facebook page to report a crime and express concerns, b) identifying the different kind of crimes reported through Facebook Page, and c) analysing if residents' post contain enough information for the police to take action. We also analyze whether the complaints made through Facebook page are answered by the police and to what extent. This information helps to assess if OSN like Facebook is becoming a passive repository of complaints.

To answer the above-mentioned questions, first we provide an overview of Victimization theory and modern organization's communication need. These theories provide a relevant theoretical back-

ground to illustrate the characteristics that affect the adoption and use of OSN. Next, we provide our analysis showing use of OSN by residents to express policing needs and fear of crime.

5.1.1 Our contributions

This research builds upon prior knowledge of OSN use by government organizations (for active collaboration), community crime prevention theory (Victimization Theory) and organizational communication theory [67, 79, 131]. Our results show that:

- Residents’ use OSN to post information about various crimes such as neighborhood issues, financial frauds, property crime, and thefts. Also, these posts contain residents’ reported spatial (location) and temporal (time) details of the crime. In addition to this, Facebook page provides information about resident’s satisfaction with policing arrangements. Residents used police Facebook page to appreciate the good work of police. This was the second most common category of posts on the Facebook page.
- Police respond to posts that contain particular complaint and suggestion from residents. Police response to resident’s post vary from reply, ignore, acknowledge to follow-up. Neighborhood safety issues get most follow-up posts.
- OSN page helps police to connect victims with the concerned authorities who can address victim’s issues and improves accountability among residents and police for keeping city safe.

Our work makes following contributions: it develops an understanding of how OSN can be used in urban cities of developing countries like India to build community policing and accountability for policing. Our work focuses on understanding technology like OSN for community policing. Our contributions illustrate OSN can support policing by encouraging community crime prevention between police and residents. Using the findings of our thesis, police can evaluate the actionable information and sense of safety among residents in urban cities.

5.2 Theoretical Background

We now discuss the theories that provide a background explaining the characteristics that affect the adoption and use of OSN for policing and crime prevention.

5.2.1 Victimization theory

According to Victimization theory, a crime is an event that can happen when an offender finds a victim in an exploitable environment [67]. Removing any one of the three – victim, offender or

exploitable environment can deter crime from being executed. Therefore, a victim may analyse risk involved in the environment he / she is part of and accordingly decide. For example, residents often avoid secluded areas as they think it might be unsafe to visit them. In case of a crime, victims may choose to react individually or collectively. The individual reaction can disable residents trust in others, isolate them, and contribute to the disintegration of community. In extreme cases, such individuals might take the law into their hands. However, if residents choose to take collective action to fight crime, this may help to reduce victimizations and increase *social cohesion*. For example, people might trust individual or authority that promises to restore law and order. Residents and police may conduct community meetings to plan an action on crime and address resident's concern. The police organizations develop strategies to increase the probability of resident participation in collective efforts as such intervention strategies can help to prevent victimizations and increase community cohesion [67].

In India, most crime prevention approaches provide potential victim with the information in order to protect them from falling in danger or prevent crime (e.g., police websites to keep residents informed about crime affected places) rather than increasing community crime prevention. In this thesis, we examine BCP Facebook Page designed to involve residents to participate in crime prevention. We found that though this page provides residents with information, residents use the Facebook page to facilitate collective action and keep police informed. According to victimization theory, fear of crime is a consequence of experiencing direct (self-victimization) or indirect victimization (getting to know about crime from different sources). We also examine how the knowledge of victimization theory can help police understand the fear of crime among residents and policing needs.

5.2.2 Modern organization's communication

Literature suggests that communication is a complex task for the modern organizations such as police and municipal co-operation. All organizations take different approaches to involve residents for accomplishing the tasks [131]. Similarly, modern police organization need well-equipped communication system to promote the flow of information [58]. This information flow is vital for operational effectiveness so that police have clear and comprehensive picture of what is happening. Communication style (such as being polite and patient) and engagement with the users (being expressive about the situation) influence the success of the organization [131]. We analyze the elements of communication such as communication style and engagement type to understand how police and residents use OSN to communicate, engage, and share information among themselves and how helpful would the interaction through OSN be to improve policing.

5.3 Background

In this section, we discuss general Bangalore police strategy to interact with community.

5.3.1 City policing in Bangalore

Bangalore is an Information Technology (IT) hub of India and supports people with diverse backgrounds such as different ethnic communities. Recent reports show that the city experienced maximum number of robbery and dacoity cases.¹ in the country. According to a report by National Crime Research Bureau, Bangalore was the second highest city where cases of rape, kidnap, and murder were reported [41]. Thus, crime remains a major concern for residents of the city. It also among the top metropolitan cities in India and supports a population of almost ten million [56], police departments need increased support to counter crime. Bangalore city police provide various ways for residents to reach the police individually. These approaches include a telephone helpline to police control rooms, Women’s helpline, Children’s helpline, Elder’s helpline. Formal procedures to file a complaint include residents visiting the police station, mailbox to drop the complaint at all police stations, letter to the concerned ACP / DCP, or Police Control Room or by E-mail. Residents unsatisfied with the police can visit the nearest police station to file a complaint. The City Police jurisdiction consists of seven zones – North, South, East, West, Central, South East and North East. An officer of the rank – Deputy Commissioner of Police heads each zone. Each zone is further divided into subdivision and each subdivision is headed by an Assistant Commissioner of Police [6].

For community policing and crime prevention, police introduced provision of neighborhood watch committee i.e. members watching their neighborhood turn-by-turn, join beat constables to perform night beats, inform police about any child or youth going astray, and arrange social and cultural get-togethers to understand neighborhoods [6]. These provisions are mostly non-technology based. Realizing the potential of OSN, Bangalore police started its Facebook page in the year 2011, for community engagement at the city level. The page has more than 505,000 likes and police allow residents to post on this page, providing them [police] a two-way information-sharing mechanism as on March 2017. Residents use OSN to inform residents about various crimes and opinion on policing activities. Police time and again have emphasized that OSN should not be treated as grievance redressing systems. Similar to Facebook page, Bangalore Police also has a verified twitter account (@BlrCityPolice) which has almost 66.2K followers as on 19th March 2017. Since the number of followers is less (almost ten times) in comparison to Facebook, in this study we look at Facebook use. We plan to do the comparison with Twitter in follow-up future work.

¹When five or more persons conjointly commit attempt to commit a robbery.

5.4 Methodology

We now discuss about the data collection, and analysis methodology for our study.

5.4.1 Data collection

We selected the Bangalore community and studied their online interaction with police on Facebook Page to investigate OSN significance in community accountability and satisfaction to fight crime. We collected data from online Facebook page of Bangalore City Police and used different mechanisms to filter the required posts for analysis. To start with, we collected all the public posts posted from 21st July - 21st Aug, 2014 on BCP Facebook page. Since we are interested in studying resident's satisfaction, we filtered all posts and comments from residents to police. We used the filtered posts to understand, what did the residents use this page for? Next, we collected all the posts that were replied by police. In total, we collected 255 posts and 1,600 comments from residents. The collected posts and comments (from the police and residents) included only public posts and did not include private messages that people might have sent using Facebook to police. We collected all the metadata like time, date, story, and usernames through the Facebook API using a Python script. We also collected likes and shares on these posts.

5.4.2 Data analysis

We analyzed the collected data to understand communication content, style and engagement type. This was followed by analyzing the fear of crime and safety concerns that residents expressed in their posts and comments on the Facebook page. As used in previous research, we use inductive thematic approach (a qualitative method [68]) to analyze the posts. We coded the content and description of each post to study the emerging themes.

Communication content and style: Our analysis of the posts, resulted in a detailed categorization of the filtered posts. We read each post and the codes were iteratively examined and condensed. Finally, we had 40 codes that were grouped further into 24 themes (see Table 5.1) to show various crime and complaints that emerged from the Facebook page. We also analyzed whether the residents report direct incidents of victimization (reporting a personal experience) or if the page received indirect victimization (report crime that happened with somebody else) posts. Next, we developed a coding scheme to understand communication style used by police and residents on OSN, i.e., whether they used formal or informal language to communicate with residents. We also performed lexical analysis using word trees to understand the fear of crime and safety concerns among residents.

Table 5.1: Themes showing various crime / complaints that emerged from the content posted on Facebook page by residents (categories may overlap).

Theme	Explanation
Missing	Missing people
Promotional	Promoting products for policing
Query	How to get police assistance, where to complain
Traffic	Traffic menace on roads
General resource information	Information regarding police stations etc.
Phone theft	Stolen phones
Hit and run	Road rage
Case inquiry	Seeking progress on pending cases
Online fraud	Nigerian Scam, Credit card frauds etc.
resident dissatisfaction	Dissatisfaction with policing working
FIR issue	Cases FIR was refused
Greetings	Good wishes to community and police
Fraud	Real world frauds e.g. Property Fraud, financial fraud
Police misconduct	Behavior issues with police
Theft	Burglary and stolen vehicles
Suggestion	Suggestion to improve policing
Construction issue	Illegal construction and construction hours
Community action	residents requested by fellow residents to come together and fight crime
Auto-driver	Problems with drivers of public transport e.g., Autoriskshaw, Taxi, Buses etc.
Neighborhood	People making menace in local society, e.g. hawkers, drunkards etc.
Women harassment	Women sexual assault
Success story	Posting about solved cases
Appreciation Post	Appreciating police for good work
Satisfaction	resident satisfaction on solved cases

Engagement type: Engagement type includes four categories: *acknowledge*, *reply*, *follow-up* and *ignore* posts (See Table 5.2).

- Acknowledged posts category consisted of the post that police liked or wrote “thanks for sharing the information.”
- Reply category included the posts to which police suggest a solution.
- Follow-up posts consisted of posts in which the complainant resident asks for further information or police asks for more details.
- Ignored posts were those posts that received no reply from the police.

Table 5.2: Engagement types that police used to interact with residents.

Type	Explanation
Acknowledge	Like or say thanks for information
Reply	Suggest a solution
Follow-up	Ask for further details
Ignore	No reply

5.5 Findings

In this section, we first discuss the different communication elements i.e. content, style and engagement. Next, we show how OSN data help understand fear, direct and indirect victimization, and needs of residents.

5.5.1 Communication content

To understand whether actionable information was available on this page, we analyzed the type of content residents posted on BCP Facebook page. Figure 5.2 shows the percentage of resident's posts (N=255) related to categories shown in Table 1. Maximum complaints that residents posted were related to neighborhood safety (36 posts), e.g., *"Today I saw some drunk boys fighting with the staff of Temptation lounge bar in Koramangala behind Legend of Rocks. They had hockey, knife and daggers. After fighting one of them who was drunk too much started fighting with a boy and two girls going on the road in front of Balaji temple Please look into this matter and put curb on such incidents in the future. Thanks."* Neighborhood issues were followed by posts appreciating police work (31 posts), for instance, a resident posted, *"Congratulations MN Reddi for your swift action within days of taking a new post!"* Suggestion to police was the third largest category of posts, e.g., *"Hi, Sir today everybody uses smartphone or high end costly mobile phones and there are lot of lost phone cases unsolved in this regard the police can setup [make] a separate team to solve the cases. Hope you will think about it."*

Next, we analyzed the categories of posts that most residents liked and commented on (See Figure 5.3). The posts that were most liked included appreciation of police work and success story shared by residents. The next category of posts that were most liked by residents were women harassment posts and posts including cases of women sexual assault. For example, *"Dear Bangalore City Police, eve teasers [common term for people harassing women] are increasing day by day. Bus stops, auto stands, college gates, etc. are becoming nightmares to women. In and around majestic bus stand, the problem is even worse. Today's eve-teaser may turn into a rapist tomorrow, so please take action."* The 5th most liked category was neighborhood issues such as street violence, issues with street hawkers, car parking issues, and unidentified vehicles. Resident's post regarding dissatisfaction with police working and police misconduct got least likes and comments.

From 255 resident's posts, police responded to 172 posts. Maximum cases that received police response were about neighborhood safety issues (11.48%) followed by suggestion for using new technologies and improving security in particular areas (9.02%). Police did not reply to posts that encouraged or appreciated their work; however, police liked such posts to acknowledge observing them. To most residents' suggestion, police replied that the police department was planning to implement them.

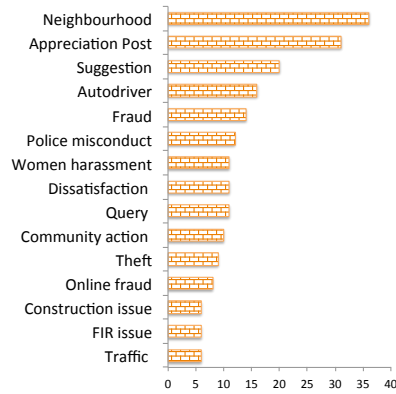


Figure 5.2: Shows distribution of types of cases reported on Facebook. X - axis shows the number of posts (categories may overlap).

We found that people posted queries, gave information, made complaints, appreciated police efforts and provided feedback on different policing activities using BCP Facebook Page. Apart from the type of concern, these posts could be used to assemble actionable information as spatial data (See Figure 5.4) and temporal data about the crime. For example, a resident posted *“Saturday evening. Time – between 5.30 pm and 6pm. Location: The circle between Freedom Park and the route that goes into Cubbon Park, towards Century Club. Not a single police posted here. I was waiting for an auto at the circle and these two guys rode by asking if they could drop me. ...Please ensure there are police put here for safety.”* The posts on Facebook Page helped police to know direct, persistent, and most apparent concerns of the residents.

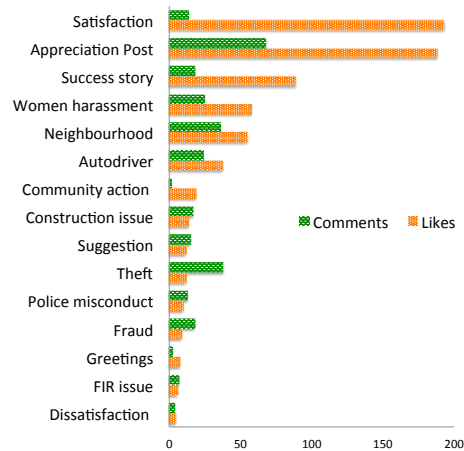


Figure 5.3: Shows likes and comments posted on different types of cases reported on Facebook. X - axis shows the number of posts

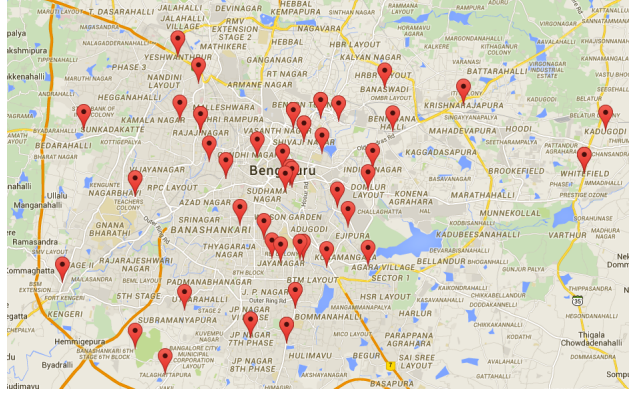


Figure 5.4: Shows spatial information (places where residents experienced crime) was available in the posts of the residents.

5.5.2 Communication style

On comparing communication style, we found that residents used a mixed style of communication including both informal (187 posts) and formal interaction (68 posts). Few residents while expressing their concerns, disagreement and dissatisfaction used formal words like “Dear” or “Respected Sir”. For example, *“Dear Sir, Request to take action on Railway Station parking contractors they are not issuing parking slips . . . today @Yashwantpur Railway Station Tumkur Roadside Entrance Parking.”* While using an informal style of writing, residents used words like “hi BCP” and slangs like “Kudos”, “pls”, etc. For instance, *“Kudos to the Banasawadi Traffic Police Team. My Salute and sincere thanks to the Banasawadi Traffic Inspector XXX. . . An ANGEL in disguise.”* Residents also used violent words like “kill”, “hang”, or abusive words while expressing need for punishment to criminals. A resident posted, *“Kill him [criminal]. Feed him to dogs or wolves or rats. Zero tolerance.”*

In comparison to residents, police always used a formal communication style of writing. While replying to resident’s posts police politely addressed resident with their name and used words like “Dear XXX”, before replying with a solution to the issue. However, if residents continued to complain about the issue, police chose to repeat the same answer as given before or not reply. Police used words like “please” and “kindly” while asking residents to provide information about the crime. Police expressed their gratitude through words like “thanks” while acknowledging resident’s posts. *“Dear XXX, Please provide the exact landmark..Thank you.”* This strategy to engage in online conversation with residents through OSN such as Facebook can become an efficient instrument that help police always stay visible and connected with residents.

5.5.3 Engagement type

To analyze, whether police Facebook page was becoming just repository of complaints and suggestions, we assigned each resident post with a type of engagement (acknowledge, reply, follow-up, and

ignore). We found that the police chose to react to 172 posts from residents, ignoring 82 posts. Among the 172 posts to which police replied to 43.44% complaints and said that the posts were forwarded to the concerned police station, officer-in-charge, or higher authorities like commissioner of police. For instance, a police comment stated, *Dear XXX, This post has been forwarded to appropriate Police Station for taking necessary action on this. Thank you.* Almost 22% posts were suggested to contact the police station with the necessary details, e.g. *Dear XXX, Please lodge a complaint at your nearest police station with the details and contact police inspector in this regard. They will assist you further in this. Thank you.* For 21.31%, police acknowledged the residents with a thanks or a reply that they will look into the matter, for example, *“Dear XXX, We will take all possible legal measures in this regard. Thank you.”*

Almost 10% posts required follow-up as these posts needed to contain more details for the police to help residents. Police commented on such posts asking residents to post more details. For instance, *“Dear XXX, Please provide the police station details. Thank you.”* Among these posts that needed follow-up from residents, we found that 29 posts were such in which residents replied back to the police. If the post had enough information, it was forwarded to the appropriate authority for action. In reply to the comments on follow-up reply of police, few residents answered that they [residents] disagreed with the solution or suggestion provided by police; however, police did not reply further to such posts. In such cases, one particular resident replied saying that the solution provided by the police is the correct suggestion. Police liked some 50 posts that were mainly appreciation or greetings posted by residents. On an average police took almost a day to give response for residents post. The statistics for the temporal analysis of when the residents posted and when police responded to are as follows: average time (30.53 hours), maximum time taken (211.16 hours), minimum time taken (4 minutes), and standard deviation (41.26 hours). Police ignored posts that were newspaper articles forwarded by a resident with no specific request, e.g., *Wishing to share something good about a task undertaken by Police in Kerala...<http://www.youtube.com/watch?v=09csXiarD7U>*

5.5.4 Understanding fear

Research shows that *“crime weakens the fabric of social life by increasing fear, suspicion, and distrust. It also reduces public support for the law, in terms of unwillingness to report crime and criticism of the police.”* [67] We analyzed, how people used Facebook page to express their concern and fear. We found multiple occurrence of words like *fear* (occurred 7 times), *concern* (occurred 8 times), *worried* (occurred 6 times), *trouble* (occurred 4 times), *notice of* (occurred 13 times) and *issue* (occurred 22 times). Mostly, residents were fearful of self-causality; residents who were victims of some crime mentioned being *worried* (See Figure 5.5) about more harm being caused to them and used OSN to call for police help. Residents feared that somebody might misuse stolen vehicles and documents. Few mentioned threat of being attacked or being traced by offenders. Residents

used word *notice* to get police attention on their fear or concern.

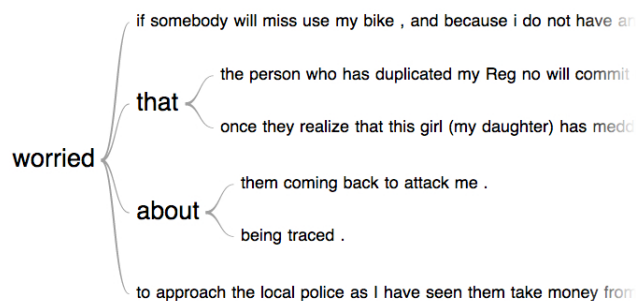


Figure 5.5: Shows popular discussions on BCP page where residents mentioned being worried about crime and safety. Word Tree visualizations of popular discussions on BCP page where residents mentioned “worried”. The visualization shows phrases that branch off from “worried” across all the text in the posts.

Apart from direct mention of the word fear and worried, we found multiple occurrences of various words such as concerned, troubled, and issue, showing the fear and dissatisfaction in the policing activities. Lexical analysis shows, participants mentioned being *concerned* about police station, control room or officer not taking necessary action, when needed. For instance, a resident posted, “*This photo [of a criminal incident] is taken just less than 30 meters of Surana College, South End Circle - in this road Asst. Commissioner of Police office is also situated - This Sidvin Condiments person sells Cigarette, Pan etc., to college students and there is one software company also there next to this shop - many people smoke in front of this shop also on the Footpath - there are many police personnel who pass on this road but are silent spectators!! This is our Kanoon [Law] and is this the way of maintaining law and order in Bangalore.*” Residents said that as *concerned* residents, they would like to know what actions police took. In some posts, residents said that they hope, the *concerned* police officer would contact residents to solve the problem. Some people expressed fear of going to the police station to report issues.

Report victimization: Direct or indirect

Victimization theory shows fear is a consequence of either direct or indirect experience with the crime event. We found that Facebook page was used both to report direct and indirect victimization cases. We found that out of 255 posts, 91 posts (35.68%) reported direct cases of victimization, 61 posts (23.92%) reported indirect experience of a crime. In indirect experience, residents witnessed a crime but were not victims of it. Rest of the posts were of a different nature such as appreciations, greetings, or the general query that did not represent direct or indirect victimization.

While reporting direct victimization cases, residents posted how they were victimized and requested police to take action. For example a resident said, “*My Vehicle KA-02-HW-3183 white color Honda Dio was stolen from Kadamba Hotel(Near Modi Hospital), RajajiNagar on Friday(25th July) evening between 6:30-7:45PM. Please help in tracing my vehicle.*” In few direct victimization posts, one

individual, on behalf of a group, complained of being victimized and used words like “We faced.” For example, a resident posted, “ *Hi Bangalore City Police, We are facing many hassles with Auto Rickshaws operating from a stand near Vydehi Hospital, Whitefield. ... We would appreciate if you could take immediate action against this and help us out. I am sure residents of Whitefield and near around areas will be thankful!*” This showed a form of collective action against crime (self-experienced) that informed police that it was a problem for many people.

While reporting indirect experience of a crime, residents posted the details of a crime they witnessed and expected police to help the victims. Indirect victimization posts indicated collective action in which residents supported other residents from being victimized. “*Dear BCP, though I stay at JP Nagar, but being part of KSFC Layout RWA (Banaswadi Police station), I got to know that there are frequent problem at KSFC Layout near BBMP Hall ... 8-10 youths were creating a public nuisance > (shouting, boozing, manhandling, etc.) yesterday i.e. on 27/7/14, Sunday night 9 pm. We need your support to help avoid a molestation scenario at KSFC Layout. Thank you*” This showed a form of collective action against crime (not faced by complainant him / herself) but informing police that it was a problem for many people.

5.5.5 Online public communication: Increased accountability

Facebook provides opportunities for police organisation to obtain information about what frustrates public and hold its officers accountable. Using Facebook, residents asked questions which held police accountable for their action and functioning. For instance, a resident posted “*Where is our police? Seems like these criminals are not scared of anyone... SHAME!!!*” Also, Bangalore police also actively participated on this platform supporting organisational policy of public accountability. Police maintained their communication style even while answering to frustrated residents. Figure 5.6 shows one such conversation between police and a resident. A resident said, “*Dear Commissioner of Police, After all these rapes, molestations and kidnappings occurring in cars and vehicles with tinted cars, how is it that we can see so many cars and buses, and especially school buses plying around with their vehicles tinted? or curtains inside that block the windows? Doesn't it encourage and embolden the criminals? Why aren't all the constables empowered to punish the drivers of tinted or curtained vehicles like cars and buses, on the spot?*” Police responses followed the protocols and policy of official responses. This strategy shows that OSN based communication can change dissatisfaction among residents to accountability on an online public platform.

We found that OSN also helped residents to express discontent about some of the official protocols. For example, a resident posted about police solving women sexual assault case, “*Skating instructor held for 6-yr-old's rape. A 30-year-old skating instructor was arrested on Sunday on the charge of raping a six-year-old girl student at Vibgyor High, Marathahalli.*” This post was followed by a flurry of comments from public expressing concerns such as delay in justice for such victims and demanding

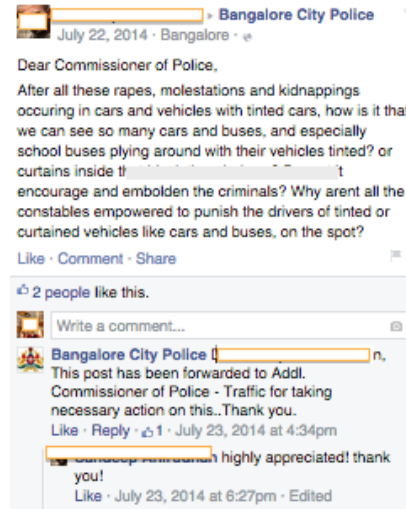


Figure 5.6: Police maintained their communication style while answering to frustrated residents.

that such culprit should be killed. For instance, a resident said, “*Why can’t you shoot at his head.*” These conversations continued for quite a while, and the post was among the top commented posts (532 likes, 184 comments). Responses were sent to and fro by the community members. Police, however, chose not be part of these conversations and did not reply to these comments. This kind of OSN usage leaves an open question that how exposure to crime news influences the community opinion about police.

We performed lexical analysis with word trees using words such as *why*, *where*, *which*, *how can*. Figure 5.7 provides a deeper view into the structure around the accountability posts using word tree visualizing use of *why*. This analysis helped us to understand different ways residents held police accountable. Residents questioned *why* police functioned in specific ways. We also found instances, where residents reported need for mutual accountability. There were multiple posts in which residents accepted that they had equal responsibility (as the police) to keep the city safe (See Figure 5.8).

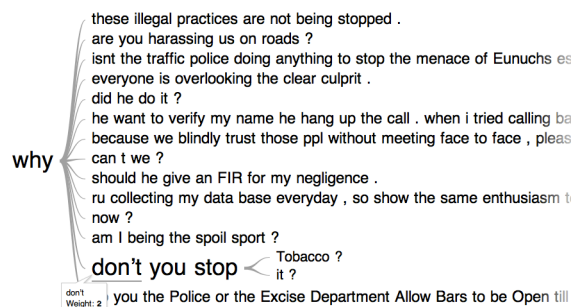


Figure 5.7: Word Tree visualizations of posts in which residents questioned police using the word *why*.

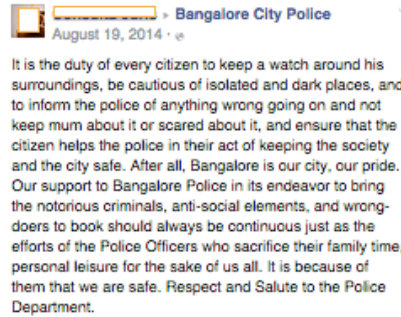


Figure 5.8: A post showing that residents accepted that they had the equal responsibility (as the police) to keep the city safe.

5.5.6 Understanding residents' needs and wants

Research shows that increased fear and anxiety can be encountered, if the police know what residents expect and want from the police. The expectations of residents, if met, can increase feeling of safety in community [67]. We performed lexical analysis to understand what are residents *need* and *want* from the police. The word tree in Figure 5.9 summarizes the needs and wants of the residents. The word *need* occurred in 48 time and *want* occurred 17 times in posts and comments. The analysis shows major needs of the residents could be clubbed into two categories, a) need for more resources and b) need to punish, strict legal system, need to take issues with senior officers.

One of the prominent need that residents posted was asking for more resources to improve policing. These requests included needs such as increased patrolling, more CCTV cameras, the need of police on OSN and developing mechanism using which people can take an instant picture and send to the police for immediate action. For example, a resident posted, *“Congrats Mr. M N Reddi. The safety of womanhood is with you and your team. A small suggestion: Make mandatory to install CCTV at all public and private institution; . . . with better CCTV at the entrance for their venue. This will bring additional check and help.*

While mentioning the need to strengthen legal procedure and police resources, residents discussed developing a strict law system and giving strict punishments. For example, a resident posted, *“He [criminal charged with a girl’s sexual assault] should be hanged till death! I am scared to send my little ones to the school!”* The residents felt that they were dependent on police to make the city safe; e.g., a resident posted, *“Sir, will this punishment stop him attacking women ever in his life... honestly this is not enough. We want a safe city and we are dependent on you.”* The posts show the residents’ concern and expectation that police need to be ‘on top of things’. These posts also demonstrate the extent residents’ think police should react to offenders if needed. This post also shows that residents believed giving harsh punishments could be a way to reduce crime in the city.

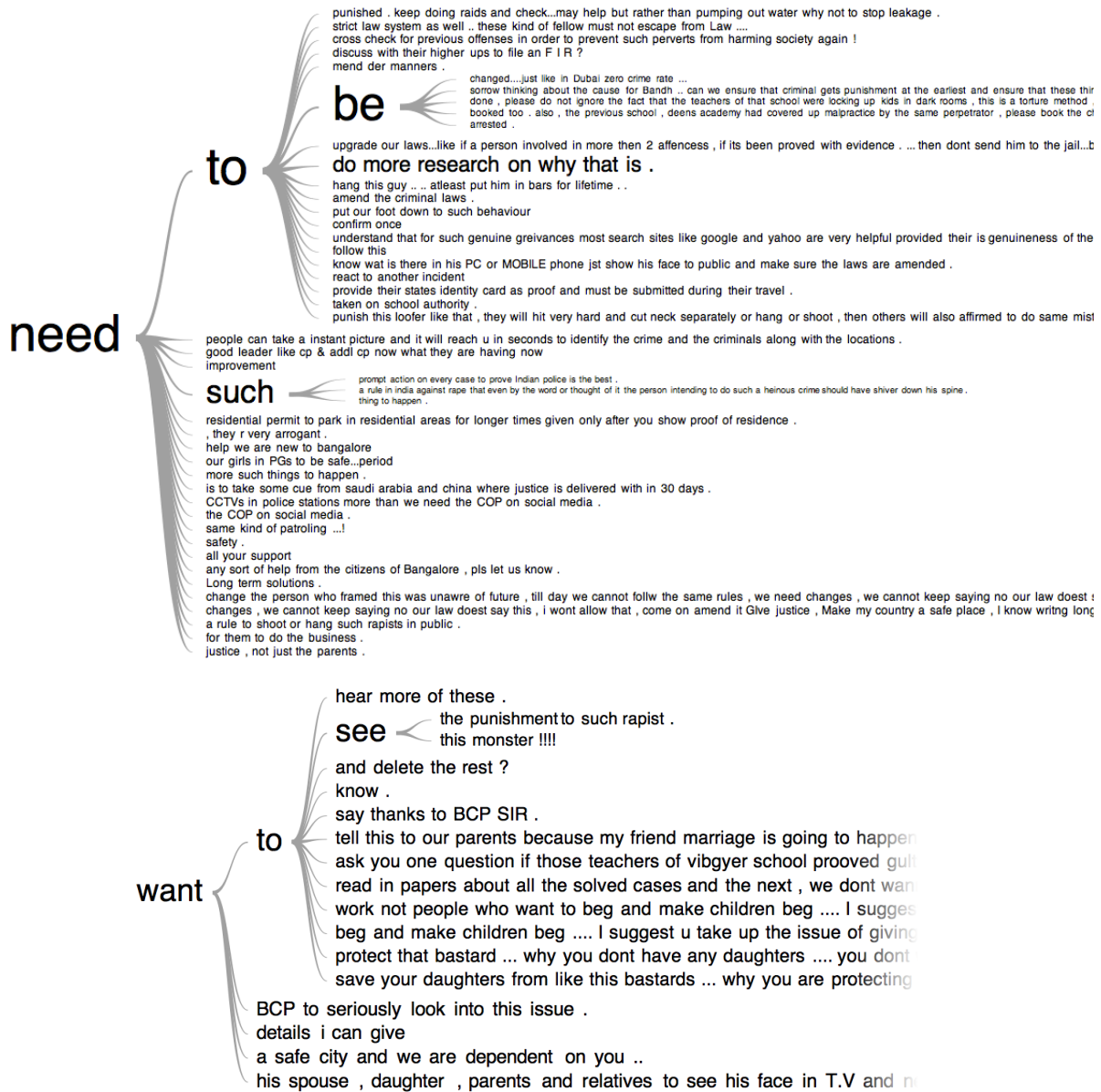


Figure 5.9: Word Tree visualizations of posts in which residents expressed want to or need to tell their needs to police. This tree shows phrases branching from phrases “need to” and “want to” in the text from our dataset. The word that occurs more frequently is larger in size.

5.6 System Implementation for Easy Information Consumption

We develop a system that allows for easy consumption of above mentioned measures from public pages of Police departments on online social media. The system can be used to make social media channels more observable to residents’ reactions. The system consists of three components – data retrieval, analyzer, and user interface. Figure 5.10 shows the various components of the system

through an architectural framework.

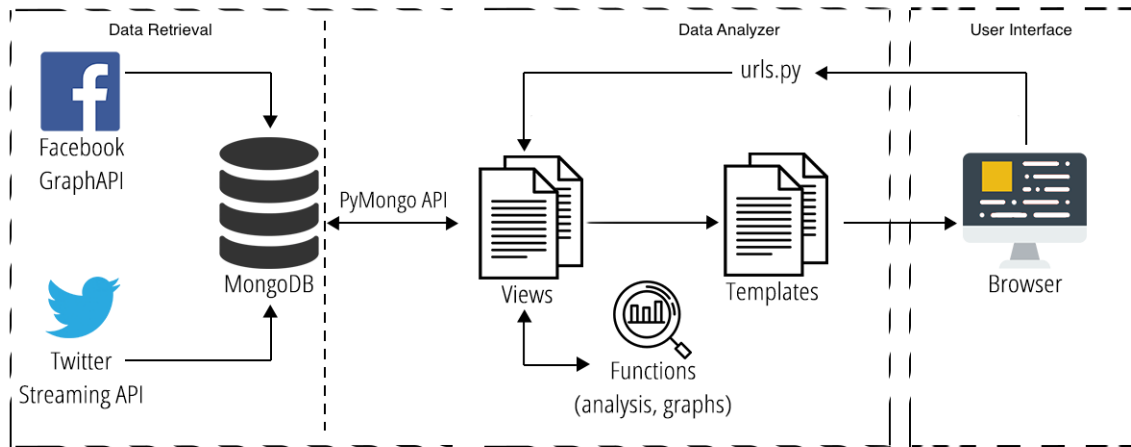


Figure 5.10: The architectural framework of the system presenting the three components – data retrieval, analyser, and user interface.

Data retrieval: This component makes calls to Twitter and Facebook API to retrieve data. A collection is formed in a MongoDB database to collect the posts for processing. We use a Python API called Facebook-sdk for collecting different information such as likes, comments, picture, message, and created time for every post. Similarly for Twitter, we make use of Rest API and the Streaming API to collect all the content. We use the Tweepy, Python API to collect all the details available from the API.

Data analyzer: Data Analyzer component filters and processes the data to evaluate engagement, accountability, and sentiment measures for different social media pages. This component triggers a script that takes the data from the MongoDB using a PyMongo API call. This data is passed onto various Python scripts for following analysis - Engagement, Lexical Analysis, and Sentiment and topics associated with different posts.

To analyze engagement the data analyzer calculates the number of posts made by police department and engagement these posts receive in terms of likes and comments. This is followed by visualization of the calculated engagement received on the Facebook pages by police. Further, we complement Facebook data analysis with Twitter data analysis. Twitter returns the tweets created by the user, tweets which are retweeted by the user, replies to any tweet created by the user, retweets of any tweet created by the user, and manual replies.² We filter these measures to analyse and account for the number of tweets / posts in a day, likes, comments, retweets on Twitter by police and residents.

The data analyzer module also provides a “Compare To” feature, which allows to compare a given Police Department’s engagement with another department. The “Compare To” feature can be used

²<https://dev.twitter.com/streaming/overview/request-parameters#follow>

to plot the activity of both departments together or in isolation to each other. This feature can help authorities to evaluate which department gets significantly more engagement than others or which ones are not able to engage with residents. This knowledge about residents' engagement can help police to plan their strategies accordingly for improved engagement. Figure 5.11 shows the “Compare To” feature of the tool.

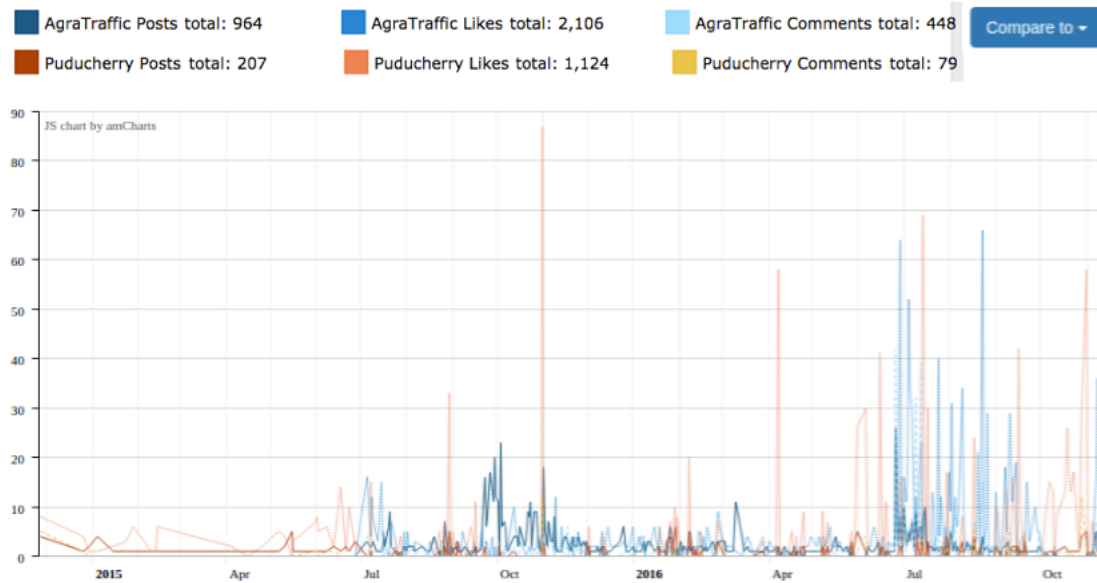


Figure 5.11: Comparison of Engagement between Agra Traffic and Puducherry Police Facebook pages.

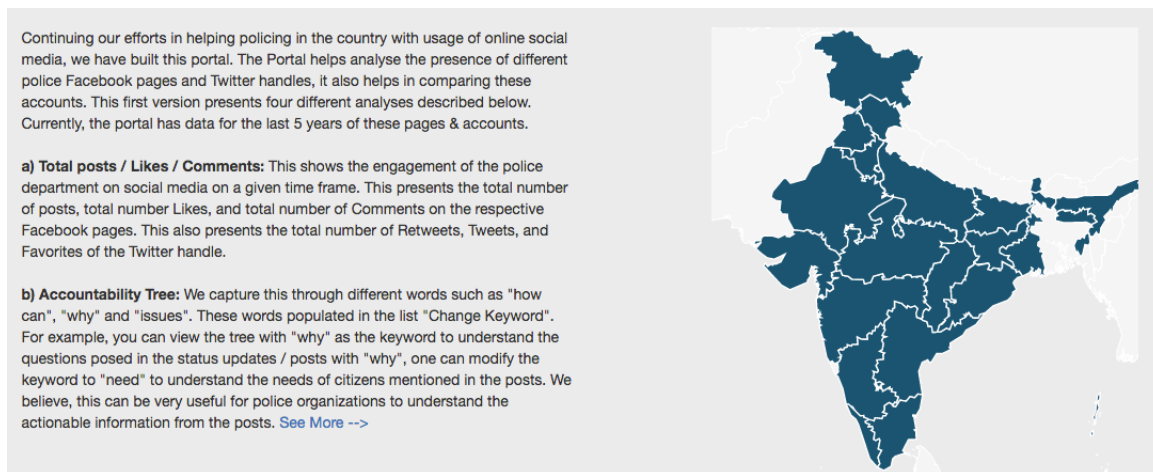
The data analyzer module also provides a Lexical Analysis by visualizing the text through word trees. A word tree represents the occurrence of various phrases with respect to a word in the content. These word trees are implemented using Google Charts. Currently the system supports 10 key words for lexical analysis including “why”, “want”, “need”, “worried”, “how can”, and “where” among others. The keywords can be changed and after filtering the data for the new keyword, the word-tree is generated again including the phrases that occur with it. The system also allows to visit the posts where these words occur.

The data analyser also provides sentiment analysis functionality to the tool. We use TextBlob API ³ that processes the textual content to find the sentiment using the “sentiment.polarity attribute.” Once the sentiment is calculated for every post, we count the posts with positive, negative, and neutral sentiment. These are then represented through a pie-chart visualization. Finally the analyzer also presents the most frequent words that exist in the content. These are calculated based on bag-of-words principle and induces knowledge on most frequent words being discussed on police pages.

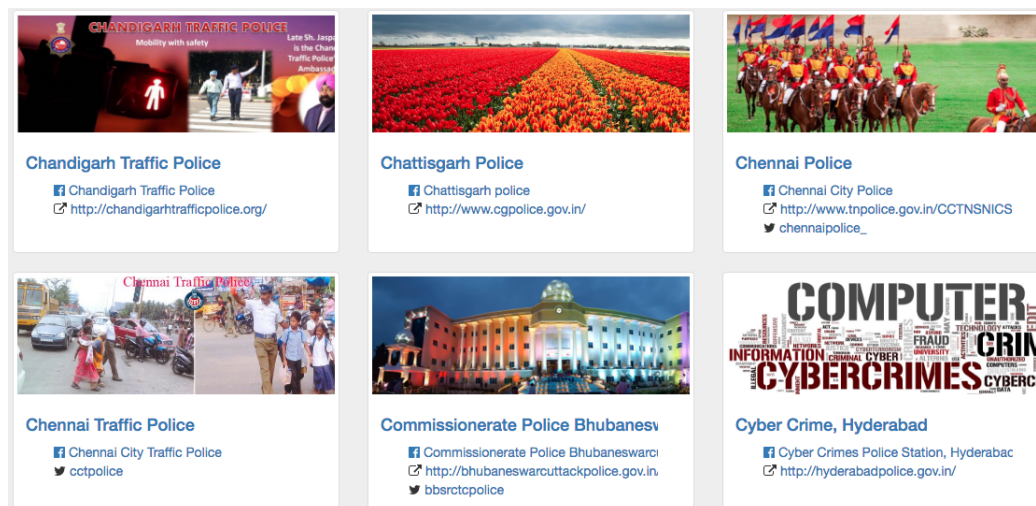
User interface: The last component of the system presents the above mentioned analysis on a

³ <https://textblob.readthedocs.io/en/dev/>

web-based user interface using Django2 (a Python-based web framework). When a browser tries to access a valid url corresponding to a Police Department, a python script is called upon which gets the data from the database collection using PyMongo API call and presents the analysis through different visualization. Figure 5.12 represents the landing page of the system that helps navigate through various analysis.



(a)



(b)

Figure 5.12: The web browser module to visualize and present the analysis. The user can click on any of the police department to analyze the data.

5.7 Implications of the Study

In this thesis, we study OSN role in improving Online Public Communication between police and residents for: a) obtaining actionable information related to crime; and b) evaluating resident's satisfaction with safety that police provides in urban cities. The results show that OSN use by residents to reach the police needs to address a combination of technical and social science challenges:

Observable OSN for actionable information and collective action: We find that people posted relevant queries, shared information, made complaints and provided feedback on different policing activities using BCP Facebook Page. Police can use residents' posts and comments posted on the Facebook page to collate actionable information on the type of the crime, location, and time of the crime. Residents' posts that receive the maximum reply from the police is about neighborhood safety (11.48%) followed by resident's suggestion for using new technologies and improving security in particular areas (9.02%). Analysis of BCP Facebook page shows that active participation of police to answer resident's queries is also needed to make OSN useful as a crime prevention tool. In our study, police responses are grouped into four categories – acknowledge, reply, ignore, and follow-up the post. Police efforts to answer residents' post show that when OSN is used as a Crime prevention technology; it should offer social engagement that includes facilitating problem-solving discussions and allowing residents to participate in collective action. Residents use OSN to express safety concerns and needs and police can use this information to prioritize policing activities based on residents' input. This prioritization can be used to address the crime early and can help improve residents' trust in law and order.

In order to maximize OSN advantage in providing actionable information, technologists should consider making OSN tools more “*observable*” for both police and residents. Police on OSN may receive a large volume of posts at a high velocity. For this, new tools with better functionality can be developed that help police to observe, respond, and follow-up with residents. We find that currently there are no means to mark posts that need a reply or follow up, differentiate posts that just need an acknowledgment of thanks and should not be mixed with crime critical messages. Similarly for residents, *observable* interfaces can help identify posts of interest. We find that most of the suggestions by the police to residents were repetitive, e.g., meeting the concerned authority and asking for more details. If OSN is made more observable, then residents can easily get this information from existing posts. Making OSN “observable” can make addressing crime easy and efficient.

OSN as instrumental communication platform: We find that so far police choose to adopt a very formal communication style while interacting with residents on Facebook. This style is governed by organizational goals to forward complaints to appropriate officers. Police try to maintain distinct police - public relationship by, not getting into descriptive assistance for residents. Thus, police followed an instrumental approach on OSN [131]. Literature shows police often fear situation going

out of control while publicly interacting with residents that lead to wrong impressions about police organization [70]. Literature also shows police's decision to use an instrumental approach could be to avoid high maintenance, overstepping of organizational boundaries; easy polarization of public opinions (as required by the expressive approach) [55].

The literature on communication for the modern organization shows that organizations that follow expressive approach while providing service tend to enjoy a longer and satisfactory association with users [131]. Residents, however, use an informal approach to reach the police and other residents for improving policing. These posts contained detail explanations, slangs, and personal experiences. Such interaction in literature is considered as expressive approach and is expected to increase the longevity of an organization. However, being extremely expressive on OSN can invite problems. In few cases, residents were arrested because of mentioning comments on OSN that hurt community feelings [10]. There is a need to design technology that can assist users to identify information that is not law abiding with curtailing the freedom of speech.

OSN to contact concerned authorities: We find that by using Facebook, police informs that the resident's post is forwarded to the concerned authority and in some cases, police request residents to reach the specified police station with details of the crime. However, police do not give immediate solutions through OSN. A reason to ask residents approach the police station or authority rather than giving immediate solution can be that the police need to verify the information posted on Facebook. In some cases, evidence such as Facebook image are secondary evidence and, therefore, need verification [114]. This strategy of asking residents contact police station can also help reduce false reporting. It would be interesting to analyze how many residents who are asked to contact authorities do so and how much is the assistance offered by these authorities useful for residents.

OSN for mutual accountability: Our results show that OSN offers various opportunities to improve accountability and introduce transparency in the community policing process. We find that using OSN police help residents reach the concerned authorities. Police also accept resident's complaint publicly on police misconduct and replied to residents about actions being taken. This can help reduce the anxiety and dissatisfaction among the residents. These results are aligned with the literature that shows for success of community policing platform accountability is essential [55]. OSN is used considerably by residents to spread positive work of police and success stories. Thus, as suggested by victimization theory, the posts containing good work, success story and appreciation of police can help to generate feeling of being protected among residents. Residents publicly discussed and informed police about threats and concerns which were to a large extent acknowledged by police and other residents. These exchanges could have helped address residents' accountability concerns.

OSN for understanding fear and victimization effects: Developing countries have been using technological solutions such as helplines to assist victimized residents whereas community policing has been largely non-technology based. Victimisation theory and OSN use of police give

a larger perspective that technologies that encourage collective action can be designed for effective community policing. OSN use when combined with Victimization theory's concept can help predict factors that induce fear or increase feeling of safety through collective measures. We see that residents posted various experiences where they mentioned fear, trouble, worry, and concern after being victimized. Facebook page offered opportunity for police to understand residents' fear using this data.

Victimization theory suggests that individual complaints and attempts to fight crime result in community disintegration and isolation of individuals. We find that OSN offers an opportunity to reduce the number of residents who try to fight crime individually and seek police help. A large number of residents post direct victimization cases where they experienced crime. The individual who is a victim of a crime gets support from other residents in the form of comments, likes, and probable solutions. Some of the posts also echo safety concern and help others to lodge complaints on behalf of individuals whom themselves cannot express crime. Thus, converting the individual action to a collective response.

5.8 The Way Forward

Our results show that police can use OSN to obtain actionable information like location, place, and evidence of a crime using OSN. Police adopt formal and polite communication style on OSN to address resident concerns. We find that the police uses different types of engagement with residents. Police helped victimized residents reach the concerned authority and forwarded complaints to appropriate departments. Also, police used OSN to acknowledge residents for their suggestions and appreciation for police. Our results show that OSN offers an opportunity for public accountability of police and residents for policing. This transparency can be used to increase accountability and to foster trust in the police. The posts can help to generate feeling of being protected.

In the next Chapter, we plan to use this information to design systems that can assess: a) actionable information available through Facebook page and forward it to the concerned authority and b) track the engagement type in each post for instance, was the post acknowledges, does it need a follow-up or a reminder, mark the posts which don't require further action so that actionable information is not lost in the flurry of posts. This can help to improve residents' satisfaction by maximizing the number of posts that police answers. The system will be able to highlight the reply of police to the residents for future reference.

Chapter 6

A Method for Request–Response Detection Framework and Measuring Police Response to Residents

Research shows that how well police deals with and responds to resident’s service request defines the overall satisfaction of community with the police. Also, these requests account for the major information source contributing towards collective action for improved safety and psychological well-being of residents. This thesis proposes a *Request - Response Detection Framework* for identifying residents’ posts that elicit police response (called serviceable posts), based on the input of police experts. We examine resident requests concerning day-to-day issues that elicit police response on social media. Requests to which police should respond, evaluate or take action are considered as *serviceable requests* [138]. Owing to the massive volume of content on social media, identifying serviceable requests from general conversation and spam messages results in additional load on already resource constrained police organizations [53, 65]. To the best of our knowledge, this is the first work that determines the possibility of identifying *what type of posts should get a response from police (serviceable requests)* and estimates how long police would take to respond a particular type of service request. To this end, we formulate our specific research goals as:

- Investigating attributes that can characterize and identify residents’ service requests and expected police response to such posts;
- Identifying patterns and estimating the response time by the police to residents.

For the above-stated goals, we study resident generated content from 85 official (and public) Facebook pages of police organizations in India. To understand what should elicit police response on these pages, we contacted the state police organizations to understand what posts police officers

consider serviceable on social media. We make following contributions: a) based on the response elicited by police for the residents posts, we develop a hybrid methodology that integrates text characteristics and annotations from expert police officers to identify different serviceable posts; b) create a new police experts annotated dataset to help identify attributes of serviceable requests; c) propose six text-based measures – emotions, cognitive and interpersonal expression, low-level linguistic attributes, question-centric approach, topic-based, and entity based attributes to characterize posts that qualify to be serviceable. Using this approach, we are able to predict with 85% F1 measure if a post is serviceable and further predict its different types with F1-measure of 61%; and d) show that police response time varies significantly with different serviceable requests. Using robust survival analysis, we estimate the expected time when residents could get a reply from police. Our observations show a decrease in response time associated with the serviceable requests that can be immediately resolved, thus suggesting that successful identification of serviceable posts may ultimately result in systems that facilitate in extending timely police support to residents and improve police responsiveness towards residents. As a proof of concept of our approach, we develop a web-browser based plugin that identifies serviceable posts and further identifies various sub-categories of serviceability among these posts.

6.1 Research Questions

In this work, to characterize and identify attributes of serviceable requests from residents to police, we address the following research questions:

- *RQ 1:* What are the attributes that differentiate– a) serviceable and non-serviceable requests and b) sub-types of serviceable requests on social media w.r.t content characteristics such as linguistic and emotional attributes of a post?
- *RQ 2:* How does police response time vary between serviceable and non-serviceable posts made on social media?
- *RQ 3:* Can we using machine learning approaches to automatically identify serviceable requests? If yes, can we further classify them into different sub-types of the serviceable requests using post characteristics (content and metadata)?

6.2 Data and Methods

Given our interest in studying serviceable posts to identify the resident’s law and order related posts that should elicit police response, we adopt a mixed method approach analyzing the posts both qualitatively and quantitatively. We perform this analysis on two dimensions: content attributes

and police response time. Our analysis (qualitative and quantitative) helps us understand the nature of the resident’s concern and response time from police. Finally, based on the understanding of the dimensions mentioned above, we develop prediction and statistical models to achieve our goal i.e. identify serviceable posts. Finally, we develop a Chrome plugin as a concept of proof to show real-time applicability of our model.

6.2.1 Collection methodology

Our study utilized data from a number of public and official Facebook pages of police departments in India. We employed a variety of mechanisms to identify these pages and then to filter posts and comments for analysis. We started by identifying all the police departments in India on Facebook; for this purpose, we referred to a government website ¹ that provides a list of all police departments. Using our initial list, we were able to recognize 100 police departments on Facebook. Next, we verified these department Facebook pages for their authenticity and credibility. We manually checked if the pages were linked to the official police department’s webpage (e.g. <http://www.bcp.gov.in/>). After this cleaning, we were left with 85 police departments’ pages on Facebook. In the 1,000 annotated posts, we find that only four posts were in regional languages. English is the common business language used in India which can be a reason for the majority of the posts being in English in our dataset.

We then collected data using the Facebook Graph API ² for four months (Aug - November 2015). We obtained all posts (wall posts, or content posted by residents on police page; and status updates, or content posted by police on its page) from these pages. To study serviceable requests sent by residents to police on social media, we filtered the posts that residents posted in the four months, giving us 22,213 wall posts. Further, to evaluate how many posts received a response on these pages, we collected all comments and ‘likes’ associated with the posts, including their time of creation. Our data did not include private messages that people might have sent to police using Facebook, or other forms of “spill-over” activity that may be present in users’ personal Facebook profiles.

6.2.2 Data sampling and police officers (human expert) coding

After collecting the dataset, we randomly selected 1,000 posts for expert annotators. As we were interested in identifying serviceable posts relevant to police, we approached a state police department’s social media team to annotate the posts. Six police officers of the group performed the annotation tasks. Police officers were provided a link to an annotation portal which we developed, where they could provide their responses. Officers were shown the text, photograph, video and description or

¹<http://arunpol.nic.in/>

²<https://developers.facebook.com/docs/graph-api>

story (if any) associated with the post. Each officer labeled the wall post as serviceable or non-serviceable using the coding scheme suggested in the literature, which defines serviceable request as *a message that solicits a response in a form of an action or information from the police* [138].

If a police officer marked a post as serviceable, they further labeled it with the action needed on that post i.e. forwarding the post to the concerned police station, need more information from the resident, give a solution to the query asked, reply thanks to the post of the residents. This coding scheme was developed in our previous work discussed in Chapter 5 [112]. Two police officers annotated each post; we determined the final label for posts based on the mutual vote (where both the annotators agreed). We also found that many of these posts did not have any text (message, story or description) associated with them; these posts were mostly videos and photographs displaying some incident. For the purpose of this study, we were interested in using the content of the post to identify serviceable posts; we excluded such posts (with no text) leaving us with 663 expert annotated posts. Among these, 300 posts received a reply from the police. Next, we calculated Fleiss Kappa to assess the reliability of the labels generated after the annotation tasks. We found that inter-annotator reliability was 0.77 showing substantial agreement among the police officers and was comparable to similar tasks performed on social media data in the literature.

6.2.3 Terminology and data categorization

We now explain the terminology used in the chapter to categorize types of posts prevalent in our dataset. We categorize the post that should get a response from police as serviceable requests and based on expected police action suggested in literature [112], these are categorized into four sub-types:

- (a) **Forward:** This sub-type category included posts which had enough information and could be forwarded to appropriate authorities for action. For instance, a resident posted, *Date : 4/11/2015 (Wednesday), Time : 10:17 pm, Number : [withheld], Location : [withheld], Violations : Crossing line by way too much obstructing the vehicles which were coming from [withheld] entrance later he jumped the signal*
- (b) **Give solution:** These posts mostly included queries by residents to police that could be answered without any detail; resident asks, *Admin !! Can U Explain to Me How Two Challans On Same Date Same Time in Just 5 Minutes Gap !! How Its Possible ?? Any Thing Wrong ??*
- (c) **Acknowledge with thanks:** Acknowledged posts sub-type consisted of the posts to which the police wrote “thanks for sharing the information” or “thanks for the appreciation.” For instance, resident remarks, *Chennai City Traffic Police a humble salute from a fellow Chennaiite for the commendable job in such rains!!*
- (d) **Need more details:** In these resident’s posts, police inquired more details so that action could

be taken, e.g., a resident asks, *Cops driving wrong side [of road] near XXX hotel .. what action will be taken against them?* This post lacks information such as time and date when the incident happened.

Table 6.1 shows the number of posts, likes, and comments on residents’ post in our annotated dataset for each category.

Post Type	Posts	Likes	Comments
Serviceable			
Forward	286	1383	661
Give solution	88	183	121
Thanks	72	1288	63
Need more information	104	1245	258
Total	550	4099	1103
Non-Serviceable			
Total	113	316	32

Table 6.1: Number of posts in the annotated dataset that residents made on Facebook for police action and reply.

6.3 Measures and Feature set

Residents often use different language styles in posts while expressing their concerns and asking queries to police. We begin by discussing various handcrafted features used to characterize different language styles in serviceable posts. Next, we complement the handcrafted features with LDA and NMF based features that create an understanding of the latent dimensions and induce semantic features in our data as handcrafted features may not account for all patterns in the data. In this section, we explain different content-based features to detect serviceable posts.

Emotional attributes: Individual safety and threat are associated with a high emotional activity of individuals [27]. Emotions, being a strong tool for expression of thoughts and opinions, influence expression of attitude and behavior of individuals. To estimate emotional expression in the residents’ requests, we consider three measures: a) emotional state, b) emotional intensity, and c) emotional Valence. Emotional states are measured in terms of “anger”, “disgust”, “fear”, “joy”, and “sadness” expressed in the residents’ posts using IBM Watson’s Alchemy API.³ Research validates use of Alchemy API and finds high correlation between emotional states and sentiment extracted using Alchemy API [8, 155]. The results obtained from this API are reported to be better than state-of-the-art models on social media data [71].

We measure emotional intensity based on the psychological arousal measures of words given in

³<http://www.alchemyapi.com/api/emotion-analysis>

the ANEW dictionary (Affective Norms for English Words).⁴ Emotional valence is measured in terms of Positive Affect, Negative Affect, Anxiety – we make use of the popular and well-validated psycholinguistic tool LIWC.⁵ Prior social media analytics work uses and validates applicability of these measures on social media data [23, 25, 102].

Cognitive and Interpersonal attributes: Individuals encountering law and order situations may either be directly or indirectly affected. When directly affected, residents talk about their own experiences whereas if indirectly affected, they focus on others; such experiences are marked with high cognitive uncertainty [67]. Hence, we study some forms of cognitive uncertainty, interpersonal focus, and cognitive orientation mentioned in the posts by residents using LIWC; prior literature has examined these in social media content [23, 24]: 1) measures of *interpersonal focus* given by pronoun use, such as 1st person singular, 1st person plural, 2nd person, 3rd person singular, 3rd person plural, and impersonal pronouns; 2) measures of *cognition* given by the categories “cognitive mech”, “tentativeness” and “discrepancy”.

Linguistic attributes: Subject to the social and psychological ecosystem, linguistic styles can assess the resident’s use of language and identify evidence about their behavioral characteristics [21]. To measure the variation in linguistic attributes, we consider four measures: 1) Objectivity, 2) Tenses, 3) Lexical Density and 4) Parts-Of-Speech. Posts containing situational information about law and order contain more objective than subjective words [140]. We use OpinionFinder subjectivity lexicon to count the number of subjective and objective tags in a post.⁶ We capture various other Linguistic Attributes using LIWC: 1) measure of “past”, “present”, and “future” tenses. This can help quantify residents’ complaints about events in the past and concerns that may cause law and order problems in future; 2) measure of *Lexical Density* given by use of “article”, “verb”, “auxverb”, “adverb”, “preposition”, “negation”, “quantifier”, and “number”.

Research shows that Parts-Of-Speech are associated with emotional states and information given in the posts [145]. For instance, information is associated with Proper nouns such as “MG Road” Police Station and emotion is associated with adjective such as “disgusted” resident. We used Stanford’s Part-of-speech (POS) tagger to label words in each post.⁷

Question asking attributes: We measured information seeking behavior to identify serviceable posts and its sub-types. For this purpose, we captured various posts containing words “who”, “how”, “why”, “what”, “where”, “whom” and containing a “?” as well. Since all questions could not be captured using this method, we made heuristic rules e.g. “Can you...” and “Do you want” to capture all questions that were part of the posts.

⁴<http://www.csc.ncsu.edu/faculty/healey/maa-16/text/>

⁵<http://liwc.wpengine.com/>

⁶<http://mpqa.cs.pitt.edu/opinionfinder/>

⁷<http://nlp.stanford.edu/software/tagger.shtml>

Entity-Based attributes: While reporting a violation, police recommends a format for residents, including, location, date and time, and the name of the affected individual / organization in their posts. Thus indicating a correlation between the presence of these entities and serviceable posts. We tagged each post with various entities such as “people”, “companies”, “organizations”, “cities”, “geographic features”, “facility” using Alchemy API to identify entities.⁸ Next, we also used heuristic based rules and a regular expression to capture if a post contains date and time.

Topical attributes: Generating intelligence from the content shared on social media requires capacity to cluster and link related concepts [38]. We employ n-gram (unigrams, bigrams, and trigram) analysis on the content posted. We adopt LDA topic modeling to examine the nature of topics discussed. **Latent Dirichlet Allocation (LDA)** provide probabilistic assignments of different topics to every post. Given a corpus of documents (D) (in our case posts), LDA identifies a specified number of topics |T| in the corpus; this specified number |T| defines the granularity of the topics in the results. LDA relies on concepts of generative statistical modeling, e.g. in a document containing words, LDA positions every document as a mixture of a specified numbers of topics and every word in the document is attributable to one of the specified topic in the document. Formally, explaining, LDA determines the mixture of topics t for each document d in the corpus of documents as $P(t|d)$; in this statement, each topic t is defined by the terms w such that $P(w|t)$.

The equation below summarises this explanation:

$$P(w_i|d) = \sum_{j=1}^{|T|} P(w_i|t_j)P(t_j|d) \quad (6.1)$$

where $P(w_i|d)$ represents the probability that the i th n-gram in a document d , $P(w_i|t_j)$ shows the probability of w_i being within the topic t_j ; lastly $P(t_j|d)$ represents what is the probability of that a term will be selected from a topic t_j in the document from the corpus. Finally, for the classification purpose, we need to know topics associated with each document i.e. a post. We determine the probability that each document belongs to a particular topics using the probability $P(t_j|d_i)$.

For our purpose, we first train LDA model on annotated posts from our dataset. Next, we derive an optimal number of top topics (K) in these posts, then, we iteratively apply this method with different values of k , chosen in an empirical data-driven manner. We obtain optimal value of k via minimizing K-L divergence and maximizing log-likelihood, which is found to be 7; following this, we got two annotators label these seven topics. Topics derived for these models include: fines issued for violations, traffic light violations, traffic congestion in different areas, etc. We summarize these topics in the Table 6.2.

⁸<http://www.alchemyapi.com/products/alchemylanguage>

Non-negative Matrix Factorization (NMF) has been found to learn and perform well in detecting incoherent topics [125]. As serviceable sub-types contain mostly posts on similar topics, it makes the topics more incoherent i.e. discuss diverse topical words associated with each topic. Next, we use Non-negative Matrix Factorization to identify optimal top topics (k) in serviceable posts and iteratively evaluate k to minimize Frobenius norm. The resultant optimal value of k is found to be 5 for serviceable sub-types (See Table 6.2). We now explain NMF in the context of topic modeling:

NMF is a matrix approximation approach which gives a lower-rank approximation matrix given a non-negative matrix $X \in \mathbb{R}_+^{m \times n}$ and an integer k such that $k \ll \min(m, n)$. The lower rank matrix appropriation thus found is define as:

$$X \approx WH \quad (6.2)$$

where $W \in \mathbb{R}_+^{m \times k}$ and $H \in \mathbb{R}_+^{k \times n}$ such that all three matrices have no negative elements. Commonly, to realise the non-negative factorization Frobenius norm is used which is defined as:

$$\min_{W, H} ||X - WH||_F^2 \quad (6.3)$$

such that $W \geq 0$ and $H \geq 0$

NMF possesses an inherent clustering property that captures the topic modeling contexts. It clusters the columns of the data $X = (x_1, x_2, \dots, x_n)$ such that given $x_i \in \mathbb{R}_+^{m+1}$ where i^{th} column of X presents the bag-of-word representation created from the document i using tf-idf or count-vectoriser w.r.t to m keywords. The number of topics are represented by k and every topic l is represented by the l^{th} column of non-negative vector W as a combination of m -keywords. To identify topics corresponding to a document, we consider the H vector where in $h_i \in \mathbb{R}_+^{k+1}$, every document i is the i^{th} column of H vector and is a weighted combination of topics that are k in number. We use these values to identify topics associated with each document.

6.4 Serviceable Versus Non-Serviceable Requests

6.4.1 RQ1: Characterizing posts that get a police response

Per RQ 1(a) and 1(b), we begin by characterizing the differences in Serviceable and Non-Serviceable requests in terms of six content-based measures defined above. We further characterize the difference in posts based on the type of expected response by police (Serviceable sub-types).

Emotional attributes: Table 6.3 presents the average value of residents' emotional states, intensity, and valence expressed in their posts. We find that serviceable requests show significantly higher value of negative emotional states i.e. "anger" (+15.38%), "disgust" (+47.8%), "fear" (+60%), and

LDA topic	Vocabulary
Traffic congestion	Traffic, road, signal, bus, people, turn, vehicles, junction, stop, time, jam
Shared photos websites	com, www, facebook, https, videos, traffic, http, type, old, photos, job
Appreciation	signal, great, good, taking, act, ask facebook ,post ,news ,action
Question posed	asked, rules, Police, traffic, vehicle, number sir, said, car, know, time
Places	PS, telangana, state, hyderabad, city, nagar, afzalgunj, narayanguda, chaderghat, ousity
Fines issued	Challan [fine charged], violation, sir, bike, vehicle helmet, riding, traffic, like, documents
Cyber crime	Police, city, cyber, crime nampally, complaint, better, safe
NMF Topic	Vocabulary
Police incorrect decision	Police, asked, said, constable, taken, public wrong, driving, pay, vehicle, come, way
Awareness	documents, bike, know, mobile, rules need, people, let, share, helmet, circle, year
Dangerous driving complains	wrong, dangerous, action, driving, turn, going junction, coming, time, main, help, green
Fines issued	Vehicle, challan [fine charged], number, violation fine, documents, driving, guys, stopped, pay
Parking issues	Parking, people, bus, stop, parked, time, action notice, request, police, check, got, pollution, jams

Table 6.2: Extracted topics from annotated posts. LDA vocabulary includes content from serviceable and non-serviceable posts; NMF includes topics from serviceable sub-types.

“sadness” (+10%) in comparison to non-serviceable requests. These posts show significantly higher arousal and valence than non-serviceable requests (See Table 6.3). Anxiety is also measured to be (+100%) higher in serviceable posts in comparison to non-serviceable posts. Presumably, these emotional states are experienced due to distress caused because of encounters with law and order situation.

On comparing different sub-types of serviceable requests (See Table 6.4), we find that “anger” is highest *Forward* (0.17) subtype posts followed by *Give Solution* (0.16) sub-type. Posts where police could reply with a “Thanks”, express maximum “Joy” (0.16) and “Fear”(0.28) in comparison to other sub-types. We find statistically significant difference between “Thanks” and all other three sub-types of serviceability for “anger” (Dunn Test with correction, $p < 0.05$). On analyzing posts in this subtype, we find that residents mention their encounters with law and order situations (experiencing

Emotional States							
	Serviceable			Non-Serviceable			
	Mn	Std	Md	Mn	Std	Md	Man
Anger	0.15	0.13	0.12	0.13	0.17	0.09	-3.43**
Disgust	0.34	0.25	0.27	0.23	0.27	0.13	-3.88**
Fear	0.24	0.21	0.18	0.15	0.18	0.07	-6.09**
Sad	0.11	0.10	0.08	0.10	0.14	0.05	-5.45**
Joy	0.06	0.11	0.02	0.11	0.20	0.01	-1.34
Valence							
Pos	3.78	5.88	2.08	2.71	5.67	0.00	-3.92**
Neg	2.3	4.34	0.63	2.03	6.35	0.00	-3.32**
Anxiety	0.18	0.77	0.00	0.09	0.52	0.00	-1.58
Intensity							
Arousal	4.90	1.73	5.42	2.64	2.77	0.00	-6.53**

*p<0.01 *p<0.05

Pos=Positive affect, Neg=Negative affect

Table 6.3: Mn (Mean), standard deviation (Std.), and Median (Md) of Emotional attributes across serviceable posts. Statistical significance tested using Mann-Whitney U (Man).

fear) where police came to their rescue, marked by increased joy. For instance, in a post, resident shared that

I salute [withheld], [withheld] of Police (East), who did a great job of searching for the bodies of 3 missing children ([withheld]) by getting into sewage water at midnight 1:30AM at [withheld]

“Negative valence” (4.62), “anxiety” (0.2) are maximum whereas positive valence is significantly less for *Needs more information* sub-type compared to others (Dunn Test with correction, $p<0.05$). Seemingly, these characteristics may indicate that residents when experiencing extreme emotions often do not mention complete information that is required for the police to help them. For example, complaining about a police officer, a resident shared feeling unsafe but did not mention the place or any identity of cops required to take action.

Two policemen tried to harass me today both of them were over speeding, and one of them abused me for taking a U-turn They were telling me that they will take a picture of my vehicle number plate and then show what the power of police.... #htp#imreallyfeelingunsafe

Cognitive and Interpersonal attributes: We observe that most of the *cognitive and Interpersonal attributes* can distinguish between serviceable and non-serviceable requests.

On comparing *interpersonal focus* attributes (see Table 6.5), we find that serviceable requests show significantly higher use of 1st person singular pronouns (+9.1%) possibly indicating that service-

Emotional State						
		Frwd	Give	Thnk	Need	Krs
Anger	Mn	0.17	0.16	0.10	0.14	13.66**
	Std	0.14	0.14	0.10	0.12	
Joy	Mn	0.04	0.06	0.16	0.08	44.42**
	Std	0.08	0.08	0.19	0.11	
Fear	Mn	0.26	0.20	0.28	0.21	3.97
	Std	0.22	0.17	0.24	0.18	
Valence						
Pos	Mn	3.19	5.00	6.92	2.21	24.90**
	Std	4.41	8.22	8.55	3.40	
Neg	Mn	2.34	0.94	0.45	4.62	71.86**
	Std	2.64	2.06	1.32	8.19	
Anxiety	Mn	0.20	0.13	0.13	0.20	2.37
	Std	0.80	0.59	0.85	0.76	

*p<0.01 *p<0.05

Pos=Positive affect, Neg=Negative affect

Frwd = Forward; Give = Give Solution, Thnk = Thanks, Need = Need more Information

Table 6.4: Mean (Mn) and standard deviation (Std) for Emotional attributes across serviceable posts subtypes. Statistical significance tested using Kruskal Wallis (Krs). Values of other features discussed in Appendix E Table 1.

able requests are highly self-attention focused; also 3rd person pronouns (they (+18.2%)) are used significantly higher. First person singular pronoun shows a positive correlation with psychological distress [21]. In such posts, presumably, residents mostly express their own concerns.

Analysing serviceable subtypes, we observe that 1st person singular pronoun (2.56) is maximum in *Give Solution* subtype and minimum in *Thanks* (0.7) subtype (See Table 6.5). On analyzing posts, we find that *Give Solution* has maximum references to residents who need the police assistance to solve their own concerns. Contrastingly, *Thanks* includes post appreciating the police work which need not have references to one’s own self but society as a whole. For instance,

Its really good by Hyderabad Traffic Police making traffic Awareness and teaching traffic rules to children.

In Table 6.5, we observe that *cognitive process* measures can be used to decide between serviceable requests to non-serviceable requests. We find that “insight” (+46.2%), “cause” (+21.4%) and “certainty” (+64%) related words were significantly higher in serviceable posts than non-serviceable posts (See Table 6.5). Research shows that causal words are used while explaining reasons behind distressed experiences [129]. We conjecture that higher use of causal words explains the distress caused because of encountering a law and order situation.

Interpersonal Focus									
		Serv	Non	Man	Frwd	Give	Thnk	Need	Krs
i	Mn	1.68	1.54		1.61	2.56	0.70	1.80	
	Std	2.96	9.50	-3.80**	2.45	3.54	2.36	3.77	24.80**
she	Mn	0.37	0.32		0.30	0.25	0.37	0.62	
	Std	1.53	1.50	-1.06	0.97	1.04	1.44	2.74	2.63
they	Mn	0.52	0.44		0.63	0.32	0.26	0.53	
	Std	1.37	1.71	-2.19*	1.37	1.08	0.77	1.84	16.92**
Cognitive Mechanisms									
Cogn	Mn	11.68	8.63		11.68	14.4	11.24	9.70	
	Std	8.36	10.66	-4.37**	6.61	9.42	11.48	8.70	16.26**
Insght	Mn	1.14	0.78		1.01	1.9	0.75	1.13	
	Std	2.30	2.31	-3.54**	1.75	3.42	2.48	2.21	16.96**
Cause	Mn	1.53	1.26		1.55	1.63	1.42	1.50	
	Std	2.59	2.66	-2.44**	2.14	3.05	3.56	2.57	9.93*
Crtain	Mn	1.46	0.89		1.17	2.9	1.64	0.93	
	Std	4.19	3.55	-2.76**	1.97	7.28	3.92	5.03	19.32**

*p<0.01 *p<0.05

i = 1st person singular pronouns, she = 3rd person singular pronouns, they = 3rd person plural pronoun, Cong = Cognitive mechanisms;

Table 6.5: Interpersonal Focus and Cognitive orientation in serviceable posts and sub-types. These are statistically different using Mann-whitney U (Man) and Kruskal Wallis (Krs) test. Other features shown in Appendix E, Table 2.

Our observations on serviceable sub-types show statistically significant difference in all measures of *cognitive processes* (Kruskal-Wallis $p<0.05$, Dunn test with correction $p<0.05$). Thus suggesting, it can be informative to study these processes not only to differentiate between serviceable and non-serviceable posts but also to identify serviceable sub-type.

Linguistic attributes: We find that serviceable posts showed higher (+40.2%) objective content than non-serviceable requests (See Table 6.6). Comparison of serviceable sub-types shows that objective statements are highest (3.47) in *Forward* posts and is least (1.9) in *Need more information* posts. Literature shows objectivity is strongly correlated with factual information [140]. We conjecture that requests high on objectivity contain more factual information on which the police can act upon.

Following this, we find that most dominant tense among serviceable posts is present tense (See Table 6.6). Presumably, our observation indicates that residents primarily request solutions for their ongoing concerns and issues. Analysis of serviceable sub-types shows that “present” tense is most frequently used in *Give solution* subtype. Further, past tense is most commonly used in *Need*

more information followed by *Forward* subtype. We find that most of these posts, from *Need more information* and *Forward*, inquire about requests on which reply is awaited:

Cops driving the wrong side near [withheld] hotel .. what action will be taken against them?

Objectivity									
		Serv	Non	Man	Frwd	Give	Thnk	Need	Krs
Object -ive	Mn	2.86	2.04	-4.57**	3.47	2.64	2.07	1.9	37.70**
	Std	2.84	2.63		3.16	2.8	2.6	1.29	
Tense									
Past	Mn	1.75	0.81	-5.32**	1.88	1.68	0.78	2.14	18.49**
	Std	2.99	2.87		2.86	3.55	2.13	3.23	
Pres -ent	Mn	7.34	4.96	-4.76**	6.93	11.05	6.72	5.76	36.78**
	Std	6.29	7.14		4.47	8.03	9.02	5.48	
Lexical Density									
Article	Mn	4.99	2.47	-6.20**	5.49	4.1	4.18	4.91	3.45
	Std	4.64	4.53		4.25	4.27	5.31	5.31	
Verb	Mn	10.46	6.38	-5.85**	10.26	14.56	8.48	8.91	5.90
	Std	7.26	8.42		5.41	8.92	9.67	6.97	
Aux -verb	Mn	6.55	3.45	-6.69**	6.56	10.64	3.51	5.14	6.23
	Std	5.58	6		4.14	8.23	4.93	4.68	

*p<0.01 *p<0.05

Auxverb=auxiliary verb; Mn=Mean, Std=Standard Deviation

Frwd = Forward; Give = Give Solution, Thnk = Thanks, Need = Need more Information, Serv = serviceable, Non = Non-serviceable;

Table 6.6: Linguistic attributes in serviceable posts and its sub-types with statistical significance using Mann-whitney (Man) and Kruskal Wallis (Krs) test. Median and other features reported in Appendix E, Table 3.

Further, we find that lexical density is significantly higher in serviceable posts than non-serviceable posts (see Table 6.6). The frequent occurrence of articles may indicate that residents make high attribution to things around them in their requests to police. Our observations show statistically significant difference between serviceable and non-serviceable posts for other measures of lexical density as well. However, analyzing the serviceable sub-types, we do not find any statistically significant differences between different sub-types for the use of lexical density terms. Thus indicating these to be useful measures for differentiating serviceable from non-serviceable posts.

Question asking attributes: On analyzing question asking attribute as a binary feature, we find that 38.18% serviceable posts contain question-centric words in comparison to 33.62% non-serviceable posts (See Table 6.7). The difference in use of question-centric words is not statistically significant between serviceable and non-serviceable posts. While comparing sub-types, we find sta-

tistically significant difference between 4 sub-types regarding the use of question-centric words (χ^2 , Phi = 0.384, $p < 0.05$). For instance, almost 80% of posts in *Give Solution* use question-centric words followed by *Need more information* subtype with only 39.42% question-centric words. Qualitative analysis shows that *Give Solution* sub-type mostly consists of general queries regarding rules such as maximum fine that can be levied for any violation, which police can answer immediately on reading the post, e.g.,

Dear Admin, ...I had sold the 2-wheeler when I went to echallans.org site and queried my vehicle there were a number of pending challans [fine charged in case of violation] which were clearly violated by the new owner..... How can I force the person to transfer the vehicle in his name?

Entity-Based Attributes: Comparing number of *entities* mentioned in a post, we find that non-serviceable posts contain almost 23.17% higher the number of entities in serviceable posts (See Table 6.7). On qualitative analysis of non-serviceable posts, we find that residents mark their post to all possible police departments of a state thus increasing the number of entity count. We conjecture that residents show such behaviour as they want to propagate their content through these popular channels to get a response from some police organization. For example, below is a post where resident has tagged many police organizations to get attention:

WWW.HITECHNEWS.BIZ Konaraopet PS PS Habeeb Nagar, Hyderabad City, Telangana State Kothapet PS PS Shahinayathgunj.....

Table 6.7 shows that, among serviceable sub-types, *Give Solution* sub-type contain least number (0.86) of entities on an average per post followed by *Need more information* sub-type (1.14). As entity represent a person, place, or organization contained in a post, low entity count in *Need more information* sub-type may indicate that resident is not sharing complete details. For instance, in the post below the resident did not provide information about place and time making it difficult for police to act on it.

Dear Hyderabad Traffic Police, Vehicle parked at NO PARKING place... take necessary action.

However, this may not hold true for *Give Solution* sub-type as most of the post in this sub-type are queries regarding rules or other facts containing limited references to different entities.

Topical attributes: Our observations show statistically significant difference between serviceable and non-serviceable requests for topic labels associated with each post. Figure 6.1 (a) shows the most frequent topic in serviceable requests is “question posed to police” with frequent occurrence of words

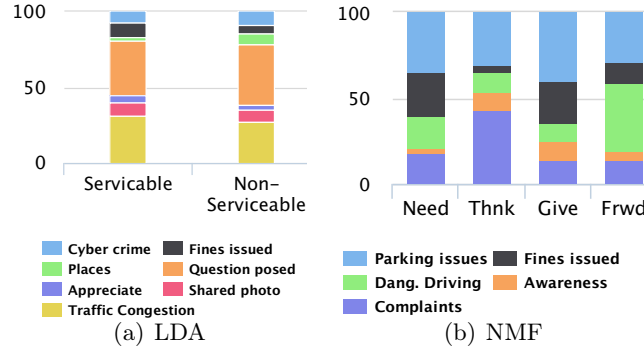


Figure 6.1: Number of topics using LDA and NMF for serviceable and its sub-types. Most frequent topic is question posed to police (Complaints represents complaints against cops incorrect decisions).

such as “asked”, “rules”, “said”, and “know” (See Table 6.2). This topic is followed by information regarding “traffic congestion” caused due to nonfunctional signals, buses stopping anywhere on roads and complaints with autos drivers; contrastingly, the least frequent topic in non-serviceable posts refers to “appreciation” posts.

Further, on comparing serviceable sub-types, we find that “complaints regarding cops and decision with which residents don’t agree” are most frequently mentioned in *Thanks* followed by *Forward* subtype. *Give solution* subtype shows the maximum occurrence of “parking issues” such as parking in no no-parking zones followed by “fines issued” sub-type (See Figure 6.1 (b)). We find statistically significant difference in the occurrence of four topics among all serviceable sub-types. Figure 6.1 demonstrates the distribution of different topics in serviceable (with its sub-types) and non-serviceable requests indicating it to be an effective measure for categorisation in our kind of task.

Question Asking Attributes								
	Frwd	Give	Thnk	Need	χ^2	Serv	Non	χ^2
%	28.32	79.55	25.00	39.42	80.93**	38.18	33.63	0.83
N	286	88	72	104		550	113	
Entity Count								
	Frwd	Give	Thnk	Need	Krs	Serv	Non	Man
Mn	1.89	0.86	1.72	1.14	37.22**	1.56	2.04	-3.20**
Std	1.86	1.20	2.00	1.34		1.75	4.51	

Table 6.7: Percentage of posts containing Question attributes and number of entities in serviceable posts and its sub-types with statistical significance **p<0.05. Mn=Mean and Std = Standard deviation

	Total N	N of Events	Not Responded (Censored) N	% Censored
Forward	286	182	104	36.40%
Give Solution	88	53	35	39.80%
Thanks	72	5	67	93.10%
Need More Info.	104	60	44	42.30%
Serviceable	550	300	250	45.50%

Table 6.8: Number of posts that received responses (N of Events) and Not Responded (censored) event showing posts that did not get response from the police.

6.4.2 RQ2: How long does police take to respond?

In our annotated dataset, we find that among all the serviceable requests almost 55% (i.e. 300) got a response from police whereas none of the non-serviceable posts got any response. Comparing serviceable sub-types, we observe that 93.10% posts in *Thanks* sub-type did not receive a response from police. Posts in *Forward* sub-type received the maximum number of responses from police (63.6%, 182 posts). Table 6.8 summarizes the number of posts that did not receive police responses.

Next, we apply survival analysis to explore and estimate the police response time to serviceable posts and its subtypes. Survival analysis is a statistical method which examines the influence of time-related events such as estimating the probability that an event of interest occurs as a function of time [4, 81]. For this thesis, we define an event of interest as receiving a response from police. Survival analysis, in comparison to other statistical methods, offers an advantage that it considers truncated nature of events i.e. events which may not occur during the observation period of study but may occur after that. This technique is equipped to deal with such scenarios where the event of interest occurs at varying times. Thus taking into account such posts which do not receive a response from police during observation period i.e. data collection phase. We use Kaplan-Meier estimator for survival analysis, a nonparametric method, used to estimate the probability of survival past given time points.

For survival analysis techniques use in this thesis, we define the following terms:

- *Survival Time*: This is the time until the event of interest occurs i.e. time until a post receives a reply from the police. We define time intervals in minutes. Time when the police reply to a post is the *observed event*.
- *Censoring Event*: This consists of those posts which did not receive a reply during our observation period. However, these posts may receive a reply from police in future. For such posts, the exact survival time is not known and are called censored events. For a post that is not replied by police, survival time is the entire data collection phase from the time the post was created.

- *Survival Probability*: This gives the probability that a post remains unanswered by police longer than some specific time (t) given by survival function S(t). Survival function defines the relationship between probability of an event (i.e. receiving a reply from police) and the time estimated from time based events (posts made and reply received). Mathematically, a Survival Function S(t) is defined as:

$$S(t) = Pr(T > t) \quad (6.4)$$

where the time of event occurrence is denoted by random variable ‘T’ and ‘t’ denotes some specified time. Probability $Pr(T > t)$ represents that the event occurs later than the specified time ‘t’. We use Kaplan-Meier estimator, a form of non-parametric maximum likelihood estimator to estimate the survival function.

Further, to quantify the size of effect, we use *mean and median survival time* from our analysis. These values represent how long it takes for police to reply a post on an average. The Kaplan-Meier estimator (See Table 6.9) shows that the median time to answer serviceable posts is 2,000 minutes (33 hours 20 min.). On comparing survival median for different sub-types of serviceable posts, we find after 1,226 minutes (20 hours 26 min.), 50% of the posts have received a reply in *Give Solution* sub-type where as it took 1,696 minutes (28 hours 16 min.) to achieve the same in *Needs more information* subtype (See Table 6.9).

	Mean Est.	Std. Err.	Median Est.	Std. Err.
Forward	1062.52	82.22	21.33	2.05
Give Solution	1064.37	138.08	20.43	8.45
Thanks	2693.14	86.42	.	.
Need More Info.	1136.31	127.48	28.26	10.45
Serviceable	1326.94	61.23	33.33	.

Table 6.9: Means and Medians for Survival Time of different serviceable posts and sub-types. Survival median cannot not be calculated if not responded (censored) data points are more than 50%.

To plot the survival function we estimate the survival probability using the following procedure:

- The data points of time-based data are arranged in an ascending order and the the time value are denoted as as $t_0, t_1, \dots, t_n$.
- Then, for every event, we calculate the probability using a recurrence relation which is defined below:

$$S(t_i) = \frac{r_i - n_i}{r_i} S(t_{i-1}) \quad (6.5)$$

where r_i shows the total number of events (including censored events) having time value $\geq t_i$, and n_i is the number of events (non-censored) $> t_{i-1}$ but smaller than t_i .

Figure 6.2 shows survival curve as estimated (non-parametric) by Kaplan-Meier using above defined procedure. Curve with lower probabilities represents shorter response time from the police which in our case is *Give Solution*. Our observations show statistically significant difference between all four sub-types of serviceable posts using Log Rank (Mantel-Cox) test ($\chi^2=57.03$, $df=3$, $p<0.005$).

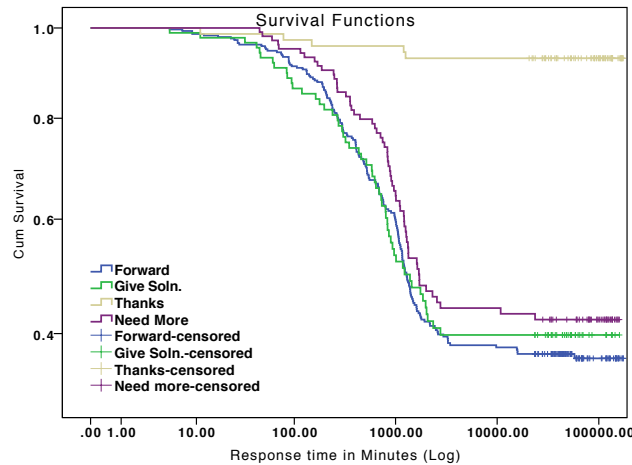


Figure 6.2: Survival curve as estimated (non-parametric) by Kaplan Meier for serviceable sub-types. Y-axis shows Cumulative Survival (Cum Survival).

The maximum time for police to reply to a post is for *Thanks* sub-type where survival mean was maximum 161,588.39 minutes (2693 hours) (See Table 6.9). We find that censored posts (posts which were not responded by police) percentage is 93.10% for *Thanks* sub-type showing that most of these posts did not get a reply during the observation period. These observations may indicate that the police considers it essential to reply to posts that can be *given solution* immediately followed by *Forward* sub-type and thus takes the least time to reply to such posts. On the other hand, *Thanks* consists of appreciation posts which can take some time to be replied to.

We find that survival median for posts from *Need more info.* sub-type is 38.33% greater than survival means of *Give Solution* and 32.50% greater than *Forward* sub-type. We conjecture that such delay may be caused because of police procedural steps involved in addressing the requests.

Next, we show that survival analysis can be used to update the expected response time in case a post does not receive a response from police in the estimated time. For instance, in *Forward* sub-type, if a post does not receive a reply in first 90 minutes, then the probability that the post will receive a reply in next 98 minutes would be $(1-(.084 / .126))*100 = 33.34\%$ (See Table 6.10). These values can be calculated for other sub-types to keep residents updated about when they are expected to receive a response.

Minutes	Survival Prob.	Cumulative Prob.	SE
090	0.916	0.084	0.016
121	0.906	0.094	0.017
133	0.895	0.105	0.018
188	0.874	0.126	0.020

Table 6.10: The cumulative probability that the post (Forward Sub-type) will be waiting for a police response.

6.4.3 RQ3: Modeling and predicting Serviceable posts

As per RQ3(a) and RQ3(b), we now focus on building models which when given to a classifier can identify if a post is serviceable or not. Further, this model is fine-tuned to understand differences between serviceable sub-types. The model makes use of the content based measures – emotions, cognitive attributes, linguistic, question posed, entity and topical attributes discussed in RQ1. For RQ3(a), we formulate the identification task as a binary classification problem predicting whether a post is serviceable or not.

To identify the best model for our task, we explore five different classification algorithms – Random Forest (RF), Logistic Regression (LR), Decision Trees (DT), Adaptive Boosted Decision Trees (ADT), and Gradient Boosting Classifier (GBC). Since, our classification task involves imbalanced dataset for different sub-types, we use balanced class weights. Research shows that balanced class weights perform better for classifying imbalanced classes as these automatically adjust weights inversely proportional to class frequencies in the input data [14]. Further, we use ten-fold cross-validation approach to evaluate our classification models. This method iteratively uses 90% data to train the classifier and rest 10% for testing the data. After ten iterations, the result shows the average accuracy and other performance measures. We also select five most important features using Chi-squared stats of non-negative features for classification tasks.

Table 6.11 shows the accuracy, precision, recall and F1 measure for our model in different algorithms. We find that Random Forest gives the best performance with F1 measure = 0.85 and accuracy of 87% while Logistic regression shows least F1 measure (value = 0.77) and accuracy of 76%. The model that includes all our suggested content based attributes performs best-showing increase of 0.06 (6%) in F-Measure than the baseline bag-of-words model. We report pseudo-R-squared values from logistic regression for our different measures (content based attributes) as a goodness-of-fit statistic. These values are supported with F1, precision, and recall from Random Forest that performs best for our model. As seen from pseudo R-squared, content attributes such as emotions and linguistic attributes are highly predictive of serviceable posts in addition to bag-of-words model (See Table 6.12).

Algorithm	Precision	Recall	F1	Accuracy
RF	0.89	0.97	0.85	0.87
LG	0.90	0.82	0.77	0.76
ADT	0.88	0.96	0.80	0.86
DT	0.90	0.84	0.78	0.77
GBC	0.88	0.94	0.83	0.84

Table 6.11: Performance of different algorithms to correctly identify serviceable posts.

Final Values	R^2	Deviance	Precision	Recall	F1
Emotion	0.23	437.88	0.87	0.96	0.80
Linguistic	0.19	401.83	0.87	0.96	0.76
Cognitive	0.08	417.56	0.87	0.83	0.70
LDA,question,entity	0.03	129.21	0.87	0.70	0.70
Bag-of-words	0.53	260.07	0.91	0.84	0.79

Table 6.12: Goodness-of-fit for different algorithms to correctly identify serviceable posts.

Classifying serviceable sub-types

All serviceable sub-types consist of some information which police may need to act upon, however, there are subtle differences among the four sub-types. The content characteristics based model that separates serviceable posts from non-serviceable ones (described above) when used to classify the serviceable sub-types gives an accuracy of approximately 58% only. Therefore, per RQ3(b), we focus on improved classification of serviceable sub-types and present in-depth analysis of different models that we fit using Step-Entry logistic regression to understand the relative importance of these features. This analysis is based on stepwise multinomial logistic regression; specifically we use *forward entry* method. Independent variables in this regression model are the six content-based measures and dependent variable are the four sub-types – *Forward*, *Give solution*, *Thanks* and *Need more information*. We begin our analysis with a null model and add new measures step-by-step. We further rely upon different performance criteria such as deviance / log likelihood to evaluate these models.⁹ This process helps to determine the importance of each measure in predicting the sub-types.

Table 6.13 shows the increase in performance of different measures. We fit a bag-of-words model as the null model to start with the evaluation process. This model uses frequency of words as a feature for predicting sub-type labels and shows a deviance of value 1,305.72. The corresponding R-square value indicates that this model explains about 2.3% variance in the data (See R-squared value in Table 6.13). Next, we evaluate the influence of emotional attributes in identifying different serviceable sub-types. Our observations show that adding emotional attributes to the null model

⁹We use deviance as the goodness of fit for a model as this measure does not have any direct predictor parameters such as R-squared in OLS regression. We suggest that these values should, therefore, be interpreted with caution.

Effect(s)		Give soln.			Thanks			Need more			Dev	Psuedo R^2	Likelihood	AIC
		B	SE	Sig.	B	SE	Sig.	B	SE	Sig.				
+Model 1	Intercept	0.158	0.402	0.695	-0.542	0.457	0.236	-0.883	0.411	0.032	1127.59	0.156	208.21	1181.59
	Fear	-1.761	0.586	0.003	0.364	0.566	0.521	-1.114	0.545	0.041				
	Joy	1.553	1.362	0.254	7.386	1.245	0.000	4.979	1.220	0.000				
	Sad	2.134	0.987	0.031	-6.049	1.819	0.001	2.475	0.958	0.010				
	Negative	-0.257	0.059	0.000	-0.403	0.101	0.000	0.084	0.027	0.002				
+Model 2	Intercept	-0.842	0.388	0.030	-0.408	0.401	0.308	-1.314	0.384	0.001	1068.82	0.200	266.98	1134.82
	Pronoun	0.091	0.017	0.000	-0.007	0.021	0.753	0.053	0.017	0.002				
	Tentative	0.157	0.037	0.000	-0.242	0.081	0.003	0.018	0.043	0.682				
	Inclusion	-0.085	0.038	0.024	0.062	0.035	0.076	-0.112	0.036	0.002				
+Model 3	Intercept	-1.324	0.416	0.001	-0.108	0.403	0.788	-0.430	0.361	0.233	984.92	0.263	350.88	1080.92
	Negate	-0.265	0.065	0.000	-0.120	0.081	0.138	-0.019	0.046	0.680				
	Auxvrb	0.093	0.02	0.000	-0.121	0.031	0.000	-0.051	0.024	0.031				
	P-O-S	1.752	0.753	0.020	0.612	0.810	0.450	-1.583	0.664	0.017				
	subjective	-0.797	0.181	0.000	-0.314	0.165	0.057	-0.410	0.138	0.003				
+Model 4	Intercept	-0.668	0.535	0.211	-0.258	0.547	0.638	-1.236	0.506	0.015	902.79	0.324	433.01	1004.79
	Question	-2.880	0.284	0.000	-0.861	0.293	0.003	-1.540	0.24	0.000				
	entity	-0.419	0.099	0.000	0.088	0.073	0.228	-0.102	0.074	0.167				
	Datetime	1.452	0.449	0.001	1.099	0.421	0.009	2.256	0.403	0.000				
	Jobtitle	5.237	1.439	0.000	4.496	1.626	0.006	3.411	1.511	0.024				

Table 6.13: Performances of forward-entry logistic regression on different models. The effects (variables) are added incrementally and performance is reported for each model. The reference category is *Forward*.

slightly improves the performance by decreasing deviance. As shown in Table 6.13, this Model 1 explains about 15.6% of the variance in data in comparison to 2.3% that is described by the null model. Further, Model 1 accounts for reducing deviance significantly to 1,127.58 (178.14 less). Some of the distinguishing emotional attributes that act as better predictors of the serviceability sub-types are emotional states including sadness, fear, and joy. This is in agreement with our observations discussed in RQ1 showing that there exist significant differences in emotional state and emotional valence when comparing serviceable sub-types.

We included cognitive and interpersonal attributes to Model 1 to derive Model 2 and evaluated the performance of same. This model further reduces the deviance to 1,068.82 improving the performance. As seen from R-square values, these features explain about 20% variance in the data (See Table 6.13). Despite this improvement, we see that only a few linguistic features such as tentativeness and pronouns act as the major contributors among various cognitive attributes. Logistic Regression analysis shows that 1st person singular pronouns have statistically significant intercept values for both *give solution* and *need more information* category, whereas these values are not significant for *thanks* sub-type. Thus showing the importance of 1st person singular pronouns in classifying the different sub-types.

	Accuracy	F1	Precision	Recall
RF	0.61	0.57	0.58	0.61
LR	0.65	0.61	0.63	0.65
ADT	0.61	0.57	0.63	0.59
GBC	0.61	0.57	0.60	0.61

Table 6.14: Performance of classification for sub-types of serviceable posts as measured by mean values of Accuracy, F1, Precision, and Recall over 10-fold Cross Validation.

Through Model 3, we explore the performance of linguistic features – subjectivity, lexical density, tense use (past, future and present), and Part-Of-Speech tags in predicting the sub-types labels when included to existing model. We find that amount of subjectivity, auxiliary verbs, negations and different Part-Of-Speech used in a post are among the prominent features to distinguish among subtypes of serviceable posts. This model reduces the deviance to a value of 984.92 and explains about 26.3% of the variance in the data (See Table 6.13). However, we find that many attributes such as tenses (present and future) and lexical terms (verbs and adverbs) did not help much in differentiating the four sub-types of serviceability.

The last model (Model 4) examines and incrementally adds four attributes – presence of questions, date and time, entities and topic associated (using Non-negative Matrix Factorization) to the existing model. This model shows significant improvement in the performance of the classifier by reducing the deviance to 902.79 i.e. 82.13 points less than the previous model (See Table 6.13). We find that attributes such as the presence of a question, date, time, and entity count (number of entities in a post) are reliable predictors of serviceable sub-types. This model explains 32.4% of the variance in the model. However, we find that topic associated with a post does not appear in the top deterministic features. This could be because some of these topics appear consistently in multiple subtypes. Thus reducing the significance of ‘topic’ as a feature in comparison to other features.

Finally, based on the feature exploration using multinomial logistic regression discussed above, we gain fair insights about how different attributes contribute to deciding labels of sub-types. Next, we use this knowledge to understand how well classifiers can predict the sub-types of serviceable posts (Table 6.14). Similar to the methodology used in RQ3(a), we use four algorithms for our experiments including – Random Forest (RF), Logistic Regression (LR), Adaptive Boosted Decision Trees (ADT), and Gradient Boosting Classifier (GBC). Table 6.14 summarises the performance (obtained using 10 fold cross-validation) of these different algorithms on our models (See Table 6.14). We find that Logistic Regression gives the best performance with F1 measure = 0.61 and accuracy of 65%. Using our observations, we are able to improve the accuracy by 7% from the initial 58% that is achieved using the same features as for serviceable versus non-serviceable posts.

6.5 Implementation and Evaluation of Serviceability Plugin

Figure 6.3 presents the methodology used to build the plugin. We use the knowledge developed so far to implement the web-browser based application available as plugin to identify serviceability and its subtypes. In this section, we discuss how we built the application and performed its evaluation. The web-browser based application uses the random-forest algorithm on the features identified in previous sections. The sub-module of the architecture that shows the working of the plugin can be logically explained in two parts: the Chrome plugin and the Flask server. The former is responsible for collecting and dispatching Facebook posts to the server, while the latter is responsible for analysing posts received and sending the analysis back to the plugin. These two parts are discussed below:

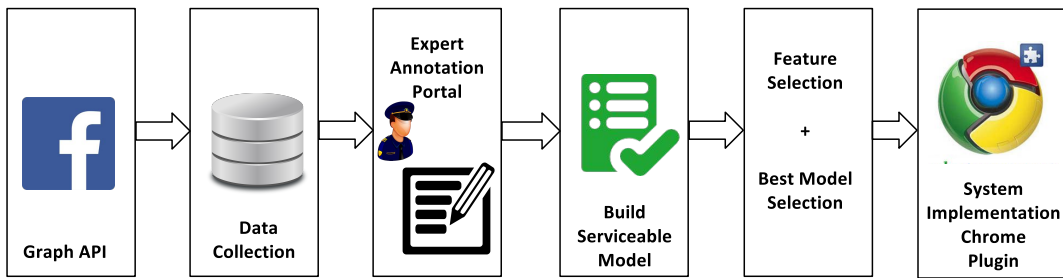


Figure 6.3: Architecture diagram depicting the methodology followed to build the plugin.

6.5.1 The Chrome plugin

We use a manifest file to define settings for a Chrome plugin. The manifest file specifies that the plugin should activate when the user navigates to a page that lies in the <https://www.facebook.com/> domain. Once the plugin is triggered, it searches for the *Visitor Posts* button and analysis starts once the *Visitor Posts* button is clicked. The plugin collects all posts that appear in the *Visitor Posts* window. We extract the text of the post from the page. Once the text is collected, the plugin makes a call to two separate endpoints. The first is the ‘classify’ endpoint which tells what class the post belongs to. The second is the ‘explain’ endpoint, which tells why the classifier predicted a certain class for the post.

1. The Classification Step: This step is executed when a hitherto unseen post is encountered by the mutation observer. It sends a request to the API endpoint ‘classify’, which is used to determine what action the post should trigger (one of ‘Give Solution’, ‘Forward’, ‘Say Thanks’ or ‘Need more information’, if serviceable; simply ‘Not Serviceable’ otherwise). Posts are marked serviceable in green, and non-serviceable in yellow (See Figure 6.4). In both cases, a small label next to the post identifies what category/subcategory the post belongs to.



Figure 6.4: Posts are marked serviceable in green and non-serviceable in yellow. In this figure, green label shows particular example is of a post that needs to be forwarded for appropriate action where as post with yellow label shows a non-serviceable post.

2. The Explanation Step: In order to give the user some intuition as to why the post is being marked with a particular action, all posts which pass through the first step are dispatched to the server again for further analysis. This endpoint (called 'explain'), gives the user a list of features which participated heavily in the decision-making process. This step tends to take longer than the classification step; it is desirable to break the analysis so the quicker step was not not dragged down by the slower step; thus ensuring that the plugin was responsive and quick. The list of features is displayed as a tooltip when the user hovers over the label which marks the post. Figure 6.5 shows the explanation step's output.

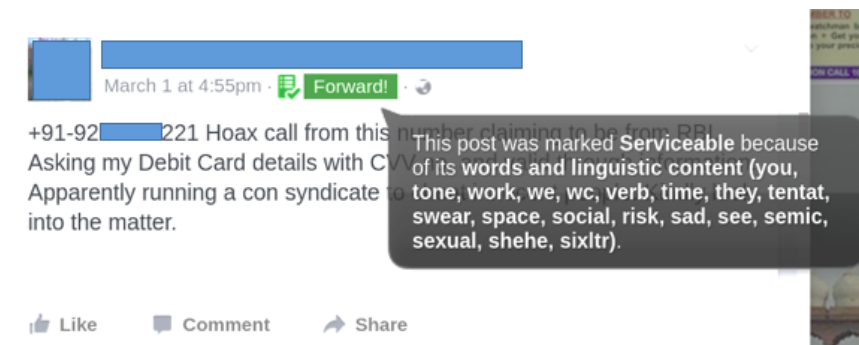


Figure 6.5: Posts are marked serviceable in green. The figure shows the probable reason to mark this post as serviceable.

The plugin uses the popular Javascript library jQuery for DOM manipulation, and the tooltip framework 'opentip' for displaying explanatory tooltips.

6.5.2 The Flask server

The Flask server uses the popular Python libraries Numpy, Pandas and Scikit-Learn for data manipulation and analysis. We deploy our service using gunicorn, which is a popular Python WSGI HTTP Server for UNIX. We spawn dedicated workers for each endpoint in our service. We do this because classification is much faster than generating explanations. With a common pool of workers it is entirely possible that all workers get caught up servicing the slower explanation requests with faster classification requests in the queue falling prey to the convoy effect. We spawn ten workers for the classification task and fifty workers for the explanation task. The hardware for the server is a 8-core Intel(R) Xeon(R) CPU E5-2650 v3 @ 2.30GHz with 64 gigabytes of RAM.

Flask is a popular Python web micro-framework. It is possible to quickly develop and deploy web applications with Flask. Our Flask server exposes two endpoints - the ‘classify’ endpoint, and the ‘explain’ endpoint as with the Chrome Plugin module. The ‘Classify’ endpoint uses two Random Forest Classifiers to partition posts into consequent classes. The first is a binary classifier, which uses outputs ‘serviceable / non-serviceable’ as an answer to the question ‘Is this post serviceable?’. If the answer is ‘yes’, it passes the post through the second, multi-class, classifier, which determines what serviceable subcategory the post falls into.

The ‘Explain’ endpoint describes the reason why a post falls on either side of the serviceable/non-serviceable category. To do so it uses the following algorithm: for each post, each feature in the feature vector is ‘neutralised’, i.e. replaced by its mean in the training set. In each case, the change in the resulting probability reported by the classifier is recorded - if neutralising a feature dramatically changes the probability that a particular post is serviceable, that feature is determined to exert a proportionately high influence on the classification of the post.

6.5.3 Performance evaluation

The extension was evaluated by artificially generating requests using Selenium. Selenium is a popular open-source testing tool. With Selenium, we initialize a Chrome browser equipped with the unpacked extension. We then load 23 pages (Roughly 30%) randomly selected from the officially hosted by the police departments of various Indian cities (identified earlier in the study). For each page, selenium is used to reach the *Visitor Posts* section. When the *Visitor Posts* container appears, it continues to click on the ‘See More Stories’ button until there are no posts left. Using this method, we generated 20,004 requests and analyze 7,292 unique posts. We use response time of the browser extension as an evaluation parameter. Producing a label for the post involves following steps: a) Binary Feature Generation, b) Binary Label Generation, c) Multiclass Feature Generation, d) Multiclass Label Generation, and e) Server Response Time. The overall plugin response time of the browser extension is measured as the time elapsed from the moment at which the request

to process the post is sent to our server to the moment the serviceability label is generated to be displayed on Facebook. Figure 6.6 shows the overall CDF of response times for 7,292 unique posts. We find that almost 90% of the posts are analysed in almost 6 seconds by the Chrome plugin. Thus showing the users of the plugin may experience slight delay while the label appears for each post. However, this delay may help police to identify serviceable posts and possible response elicited for every post. This identification can reduce overall response time of the police department.

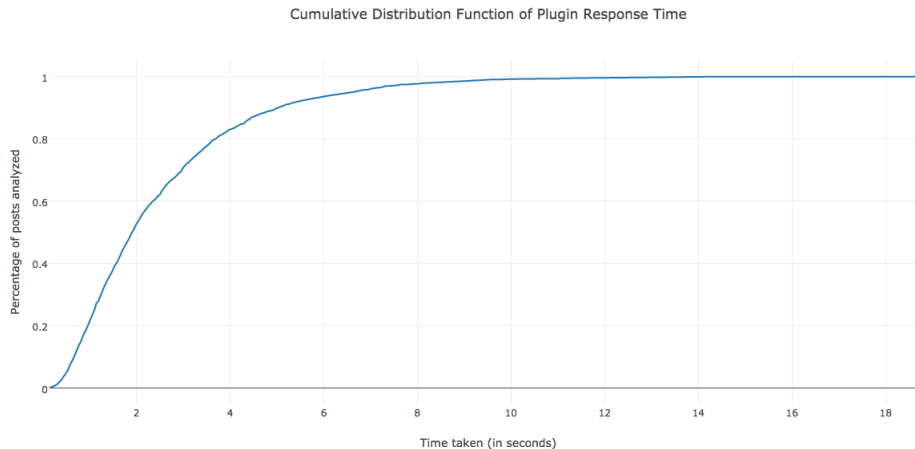


Figure 6.6: CDF of response time for 23 police pages for Serviceability Label. For 90% of the posts, response time was less than 6 seconds.

In our analysis on 23 Facebook pages, we find that once a post is received by the server, the average time taken to generate features for binary classification is 0.23s (Median=0.13s, std. dev. = 0.31s). Following this step, label generation (serviceable / non-serviceable) takes on an average 0.12s (Median=0.11s, std. dev. =0.024273812). In contrast to binary classification process, feature generation for multi-class classification takes 0.27s on an average (Median=0.16, Std. dev=0.32). The most time costly step in plugin information flow is the plugin response time that includes sending the information to the plugin and rendering the labels on the timeline (See Figure 6.7).

We performed various optimizations so the process of serviceability labelling on timeline seem instantaneous. To make labels appear in near-real-time as posts appear on the screen, we parallelise requests to the server running in the backend. Because Chrome uses a single thread to run all plugin code, it is important to handle high latency operations (like network calls) asynchronously to optimise user experience. Posts that appear as the user scrolls down the page are immediately sent to the server, regardless of whether they are currently visible in the viewport. Callbacks are handled asynchronously, i.e., the script does not wait for a request-response cycle to complete before firing the next request. We also separate the classify and explain API calls so the high-latency explain calls do not hamper the performance of the low-latency classify calls. We run separate pools of workers to service the two endpoints so that the faster classify requests are not forced to wait in line because the pool is too busy servicing the slower explain requests. Our binary and multi-class

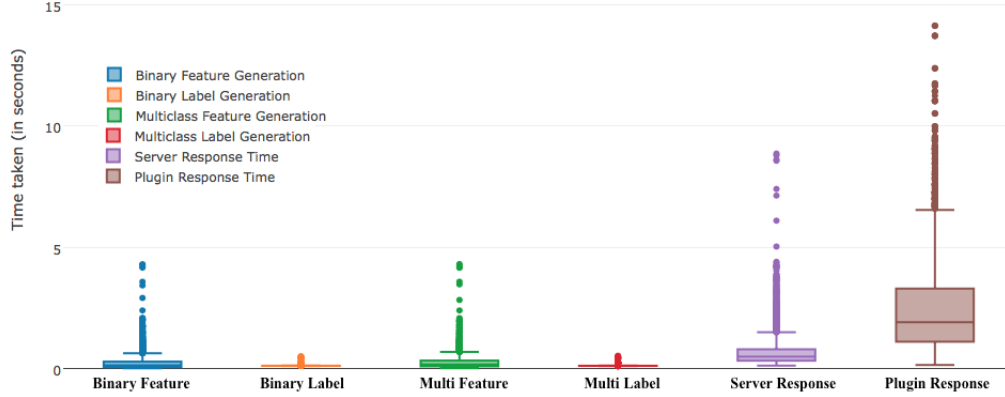


Figure 6.7: The time cost involved at in each step of processing information to generate serviceability labels.

classifiers use separate models to generate features, but preprocessing steps, such as removing non-ascii characters and POS tagging, which are common to the two classifiers, are performed only once to hasten classification.

6.6 Implications

Our work demonstrates the viability of using content generated on Facebook police pages as an instrument to quantify and characterize resident’s requests that should elicit police response (called *serviceable requests* in our context). We describe the subtleties of serviceable requests and response provisions available in the context of policing through social media. This section reflects on our results and discusses contributions of our work towards prior knowledge on police use of social media during crises, data-driven policing, and policing practices in urban communities.

This work contrasts with prior work exploring the use of social media by police in that we study social media use for day-to-day policing needs in comparison to the well-explored scenario of crisis. Highlighting social media’s role, research shows that residents can become a valuable resource for gathering crisis information [122,141]. Prior work also suggests that a non-responsive social media presence can damage the residents’ willingness to engage with and trust in the police [111,112]. Also, most of the existing studies explore how police push information to or extract relevant information from residents to address safety critical situations [77]; whereas our work in this thesis looks at what residents tend to share with police in day-to-day life. This thesis shows that police respond more to serviceable posts than they do to general communication. We believe, social platforms facilitating serviceable requests should allow for design choices that help police monitor serviceable requests and manage a timely response.

Social media use for policing results in a) large volume of content sharing by residents and b) greater

expectations among residents for how police may respond and manage the shared content [55,112]. To address the resident’s expectations, research suggests aiding traditional policing methods with automated / data-driven interventions and making social media streams ‘listenable’ to residents’ concerns [55,112]. In this chapter, we develop an automated approach for detecting posts that should elicit police response that may help make social media streams more listenable for resident’s concerns. As a significant contribution, we present an expert (police officers) annotated dataset useful in assessing serviceable post. The six broad measures proposed in our work help identify the textual constructs that can characterize serviceable requests and act as predictors to recognize incidents of interest for police. Through our work, we hope to help the police departments to use social media effectively for reducing the time taken to address residents’ concern. In countries such as India, for every 100,000 residents there are only 130 police officers deputed. In lack of adequate human resource, it becomes imperative to resort to automated data-driven policing approaches that can aid police departments to provide timely response to the residents.

Community policing theory suggests to involve community members in the problem-solving process to prevent crime and create safer societies [68,111]. Using data-driven techniques, our work makes an attempt to characterize and quantify different residents’ concerns expressed on social media that can complement police documentation of the various incidences reported in the communities. We show that residents top concerns include complaints regarding police incorrect decision, fine charged, traffic violations, and dangerous driving practices. Posts include factual information such as date, time, and location of event helping police identify areas of concerns. Taking cognizance of prominent constituents’ concern and unsafe regions can help police plan their resources better to provide improved safety. Future research may explore ways to highlight important topics emphasized by the community to ensure that they receive proper attention during police organization’s resource planning.

In addition to mentioning factual information, we measure residents’ reactions in a fine-grained manner. Prior work shows that police should account for resident reactions experiencing a law and order situation [33]. We find requests that police respond to are marked by high negative emotions and are highly self-focused. Using our proposed measures, these reactions can be observed on a large scale, through textual posts from Facebook; our work can be extended to other social media too, keeping in mind the basic differences in the different social media services. We believe that various aspects of shared data (e.g., emotions and interpersonal attributes) improve the understanding from mere factual information (incidences reported on conventional helplines) to a more nuanced understanding of psychological aspects such as emotions and social changes. This understanding may have implication on designing early warning systems that indicate targets where improvement in emotional efficacy and social cohesion can be encouraged to enhance emotional support to residents experiencing safety issues.

Previous research shows that by posting concerns to a public forum like Facebook, residents hold

the police publicly accountable [55,68,112]. We explored different types of response that police may give to residents. In our observations, we find that the maximum number of posts from ‘forward’ (63%) received police response followed by ‘need more information’. Police are fastest in replying to ‘Give Solution’ followed by ‘forward’. ‘Need more information’ that did not have all information took longest of the three to receive a reply (Forward, give solution and need more information). These responses may indicate that police makes an attempt to address resident’s accountability concerns on the part of the police and makes efforts to foster trust by addressing their queries.

Online environments lack other signals of communication (for instance, physical proximity and eye gaze) that may ascertain police presence thus comments or reply are an important feedback to increase feelings of connectedness in online communities [42]. Criminology theory suggests that police presence and visibility in the community can have an impact on resident’s behavior and fear of crime [1]. Our work shows that textual characteristics can help gauge if a resident’s post should receive a police reply and probable duration in which response would come. We believe a feedback system could be integrated into the design of social media platforms that informs a resident about the likely time duration that police would take to respond to service requests, thus augmenting the current feedback system. This feedback may also encourage residents to use social media frequently for transmitting information about the neighborhood and give residents a sense of personal contribution in the community.

6.7 Summary

In this chapter, we explored what posts should elicit police response on Facebook pages of Indian police departments. We study six different textual attributes that can help identify such serviceable posts. Our observations show that serviceable posts were marked by high negative emotions, factual content and references to objective content. Further, police response varies based on different type of serviceable posts and almost 50% of serviceable posts receive response within 33.34 hours. We find that textual features identified in our work can help predict if a post should elicit police response. To this end, we explore different statistical and prediction models. Our findings bear implications in the design of data-driven technologies to provide timely help and support to residents for improved safety and well being.

Chapter 7

Image Similarity for Collective Intelligence and Action by Police

So far we have explored the utility of social media content to identify textual features that help analyze and maintain safety and law & order situations in society. Complementing text shared on social media, we find that images shared on social media sites also often yield information of interest to police [146]. However, identifying images of interest for police that can be used to generate collective intelligence and enable action by police, remains largely unexplored.

Often images shared on social media have the potential to hurt religious, political, communal, caste and other sentiments of a certain section of society. Such images intimidate people, instigate anger among them which further leads to law and order situations and security critical scenarios in the society. For example, in April 2016, a journalist tweeted a morphed image of an Indian politician touching feet of a foreign country's king, the image invited anger and backlash on all social media networks, and the political party filed a complaint against the journalist for misleading public [120]. Another example, in June 2014, obscene pictures of Indian warrior-king Chhatrapati Shivaji and a late political party chief were posted on Facebook leading to riots in Maharashtra, India. People went on a rampage damaging public and private vehicles, pelting stones leading to severe injuries and even beating a person death [133].

This has arisen an acute need for police to understand the spread of such images for maintaining law and order in the society. Given the limited exposure of police personnel to technology, it becomes difficult to manually analyze the images posted on social media [111]. Researchers have focussed more on textual content to aid the police but analyzing multimedia content like images and videos on OSN is still largely unexplored [63]. Therefore, a need has been felt to design technological solutions necessary to retrieve, filter, integrate and intelligently present relevant images for police [20, 52]. These initiatives motivated us to propose a real-time image-search system which can serve the

police by bridging the gap between research in technologies and solving real-world problems to improve security during such critical scenarios. But the modifications done on images like cropping, scaling, stitching image, wrapping around the text, contrast enhancement, and changing colors are some of the challenges faced in image analysis. These challenges often create barriers to directly access these images and utilize information like image spread, etc., which makes image retrieval a complex and daunting process. This work in the thesis lies at the intersection of research on crime informatics and utility of images spread on social media which is a understudied & novel context. The main contributions of this chapter are:

1. We analyze different techniques for retrieving similar images and experimentally show that Oriented Fast and Rotated Brief (ORB) in combination with Random sample consensus (RANSAC) performs the best to retrieve similar images using hand-crafted methods.
2. We propose a supervised deep CNN model that outperforms state-of-art hand-crafted technique (ORB+RANSAC) to retrieve similar images.
3. We create a novel human-annotated dataset of images from incidents that caused law and order situations in the society.¹
4. We develop a real-time image search system based on our proposed CNN architecture, which is robust to detecting similar images which are cropped, scaled, blurred, stitched with other images, wrapped around with text, brightened, or modified using other similar image processing techniques.

7.1 Problem Statement

We now formally define the problem definition and notations. Given an image I_A and set of keywords K by a user, find a set of similar images $I_B = \{I_{b1}, I_{b2}, \dots I_{bn}\}$ using a comparison function C , from a search set of images $I_C = \{I_{c1}, I_{c2}, \dots I_{cm}\}$ formed using a search function S on a social network S_N , where $n \leq m$:

$$I_C = S(S_N, K) \text{ and } I_B = C(I_A, I_C)$$

The search function S takes a set of keywords, and a search space S_N as input and returns a search set of images I_C as output. The comparison function takes the given image I_A and I_C as input and returns the required similar images set I_B as the final output of the system.

We model the image similarity as a classification problem with four phases - database formation, feature extraction of images, feature comparison and finally similarity classification (see Fig. 7.1).

¹<http://precog.iitd.edu.in/resources.html>

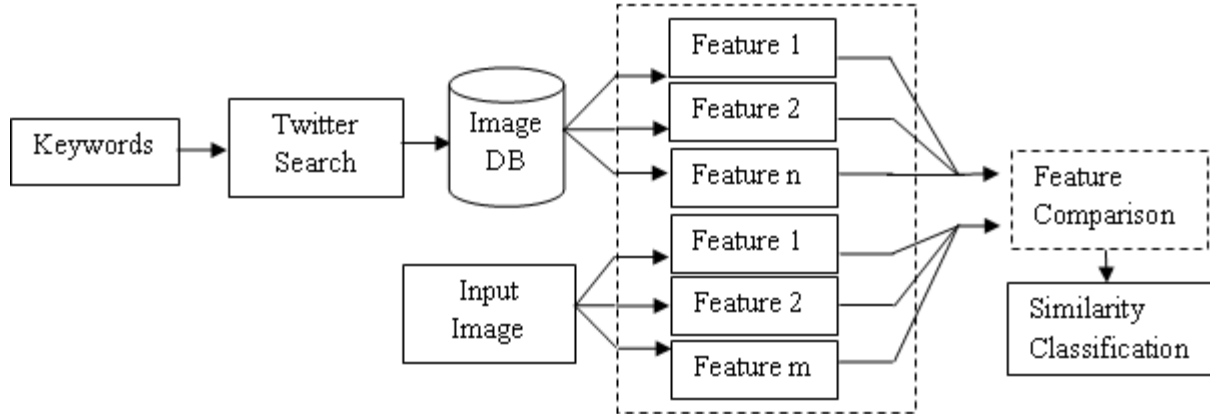


Figure 7.1: Proposed methodology to find image similarity. The system takes keywords and an image from the user, using the search API of Twitter, creates a database of related images. For comparing two images, their features are extracted and fed to a comparison function. Comparison score classifies image similarity.

[Proposed methodology to find image similarity.]

7.2 Background: Images on Social Media

Research shows that the textual attributes available on social media have received attention, but the role of social media images remains largely unstudied [63]. However, reports show that if there is an image attached to a tweet, it increases user engagement by 35% [108]. There are also few studies and tools on social media image analysis in general context; like the analysis of 581 Twitter images of the 2011 Egyptian revolution revealed that more efficacy-eliciting (crowds, protest activities, national and religious symbols) content is posted by Egyptian users than emotionally arousing (violent) content [63]. Most of the research work involving social media image search use text-based queries for building the corpus; for instance, a study describes how to use Wikipedia and Flickr content to improve the match of query text with database vocabulary [97]. They used a combination of Flickr and Wikipedia query model for query expansion to improve the accuracy of image retrieval systems [97]. Images are also used to visually summarize events. In [76], authors propose a technique to find most popular unique images shared on Twitter related to events like sports, law & politics, art, culture, etc. In another study, a tool was developed to show trending images of an event by extracting images from Twitter’s streaming API using text as query and then detecting near duplicates using locality sensitive hashing [46].

Another hybrid approach for image retrieval combines social relevance by understanding the user’s interest using social site Flickr and visual relevance by ranking the images in Google search result according to the interests of the user [20]. A study shows that image search tools such as TinEye and Google Reverse Image Search can be used by journalists to find duplicates, such as other posts of the same image, and near duplicates, such as posts before or after potential Photoshop manipulations, to help find fake posts [149]. Though some of these studies discuss image retrieval aspects but most

of them take the text as the query to retrieve related images, and systems like TinEye and Google Reverse Image Search give better results for searches on the entire web than specifically for social media sites like Twitter in specific [152]. Further, these tools do not provide knowledge management to police, like users propagating the visual content and sentiments floating with them [152]. Also, most of the image-retrieval tools discussed in these studies use basic hand-crafted features for finding image similarity thus, resulting in comparatively lower accuracy.

Our work in this thesis focuses on assisting the need of the police department to analyze image spread on social media. To this end, we provide a comprehensive analysis of different techniques that can be used for image retrieval with the query as an image. Further, we develop a system to aid police in finding & analyzing similar images on social media that may cause a law and order situation.

7.3 Data Collection and Annotation

From October 2015 to February 2016, we collected data related to 5 events that created law and order issues in society. To create this dataset, we collected data from Twitter using Twitter’s search API ², filtering tweets that contain images, counting to a total of 3,725 images. Fig. 7.2 shows images which were viral from these events and are taken as input images for evaluating different image similarity models to be studied. The details of the events are discussed below:

1. Kulkarni Ink: Black ink was sprayed on an Indian technocrat-turned-columnist Sudheendra Kulkarni by the members of a political party, ahead of the launch of former Pakistan’s Foreign Minister book, ‘Neither a Hawk nor a Dove: An Insider’s Account of Pakistan’s Foreign Policy.’ FIR was lodged against the political party workers and six workers got arrested [90]. This incident was slammed on social media arousing political issues and the images of the man with black ink on face went viral. We collected 1,905 tweets with images using the keyword “#Kulkarni”.
2. Baba Ram Rahim: An Indian self-proclaimed Godman Baba Ram Rahim posted pictures posing as Hindu God Vishnu on social media. He was accused by All India Hindu Student Federation for insulting Lord Vishnu and hurting religious sentiments of Hindus by dressing up as Lord Vishnu and lodged a complaint against him [135]. We collected 408 tweets with images using the keyword “#RamRahim”.
3. Lord Hanuman Cartoon: A cartoon tweeted by an Indian politician drew much flak from other political parties of India and its affiliates for allegedly hurting religious sentiments. The cartoon purportedly showed Hindu Lord Hanuman clad in saffron robes and leader of another

²<https://dev.twitter.com/rest/public/search>

political party. The political party lodged a complaint alleging that the cartoon image was posted with the intent to hurt religious sentiments of Hindus [148]. We collected 664 tweets with images using keywords such as “Insults Hanuman”.

4. Charlie Hebdo cartoon: A cartoon in the French satirical magazine Charlie Hebdo sparked outrage by publishing a cartoon attempting to satirize the Syrian refugee crisis. The cartoon imagines Alan Kurdi, the three-year-old Syrian who died in the sea in September 2015, on the way to Europe, has grown up to be a sexual abuser [43]. Many called the cartoon was racist and said it was incredibly bad. We collected 568 tweets with images using the keyword “#CharlieHebdo”.
5. Shani Shingnapur protest: As many as 1,500 women, mostly homemakers and college students, planned to storm the Shani Shingnapur temple in India on Republic Day in 2016. The protesters wanted to end the age-old humiliating practice of not allowing women to enter the core shrine area [34]. The image of one of the activist, giving an interview about the protest on Republic Day to media went viral. We collected 180 tweets with images related to the keyword ‘#ShaniShingnapur’.



Figure 7.2: Input images set. These images represents image which could be of interest to police and were viral from the event (a) Kulkarni Ink (b) Baba Ram Rahim (c) Lord Hanuman cartoon (d) Charlie Hebdo cartoon (e) Shani Shingnapur, respectively.

Keyword	Total Images	Similar Images	Dissimilar Images
#Kulkarni	1,905	354	1,551
#RamRahim	408	97	311
#Insults Hanuman	664	277	387
#CharlieHebdo	568	118	450
#ShaniShingnapur	180	70	110

Table 7.1: Data after annotation shows the number of similar and dissimilar images for each event.

Data Annotation

To create the ground truth for testing the models, we obtained labels for all the 3,725 images. The annotators were given an image from each event (see Fig. 7.2) and from the respective event’s image database they had to mark images that were similar and dissimilar to the given image. The broad definition of image similarity given to them was: images that are cropped, scaled, blurred, wrapped with text, stitched with other images, having color changes, brightness changes or contrast enhancements are considered similar. The images which had agreement from at least two annotators were marked in the final results. Table 7.1 shows the dataset after annotation was completed.

7.4 Similarity Modelling

The retrieval performance of CBIR (Content Based Image Retrieval) system crucially depends on the features that represent images and their similarity measurement. In this section, we will discuss some of the techniques we studied to compare the similarity of two images. We implemented these features using OpenCV library in Python.¹

7.4.1 Hand-Crafted features

1. Color-based feature similarity : Color histograms are frequently used to compare images [93]. It is often done by comparing color histograms of images, which eliminates information on the spatial distribution of colors. For instance, Fig. 7.3(a) and 7.3(c) show similar images according to our description. However, their corresponding histograms Fig. 7.3(b) and 7.3(d) appear distinct from each other and may not be a good similarity function. In our experiments, the image descriptor is a 3D RGB color histogram with 8 bins per channel and we compare the descriptor using a similarity metric.

After extracting image descriptors, we calculated Bhattacharyya distance for comparing the two image’s histogram descriptors (H_1, H_2). The lesser is the distance between two color histograms, more similar the two images are. For our purpose, we employ the Histogram

¹http://opencv-python-tutroals.readthedocs.io/en/latest/py_tutorials/py_setup/py_intro/py_intro.html

Comparison function provided by OpenCV. This function normalises the histograms such that the resulting distance varies between 0 (identical histograms) to 1 (for non-overlapping histograms) and returns the Bhattacharyya distance calculated based on the Bhattacharyya coefficient as:

$$d(H_1, H_2) = \sqrt{1 - \sum_I \sqrt{H_1(I) \cdot H_2(I)}} \quad (7.1)$$

where H_1, H_2 are the histogram descriptors of the two images evaluated over I bins.

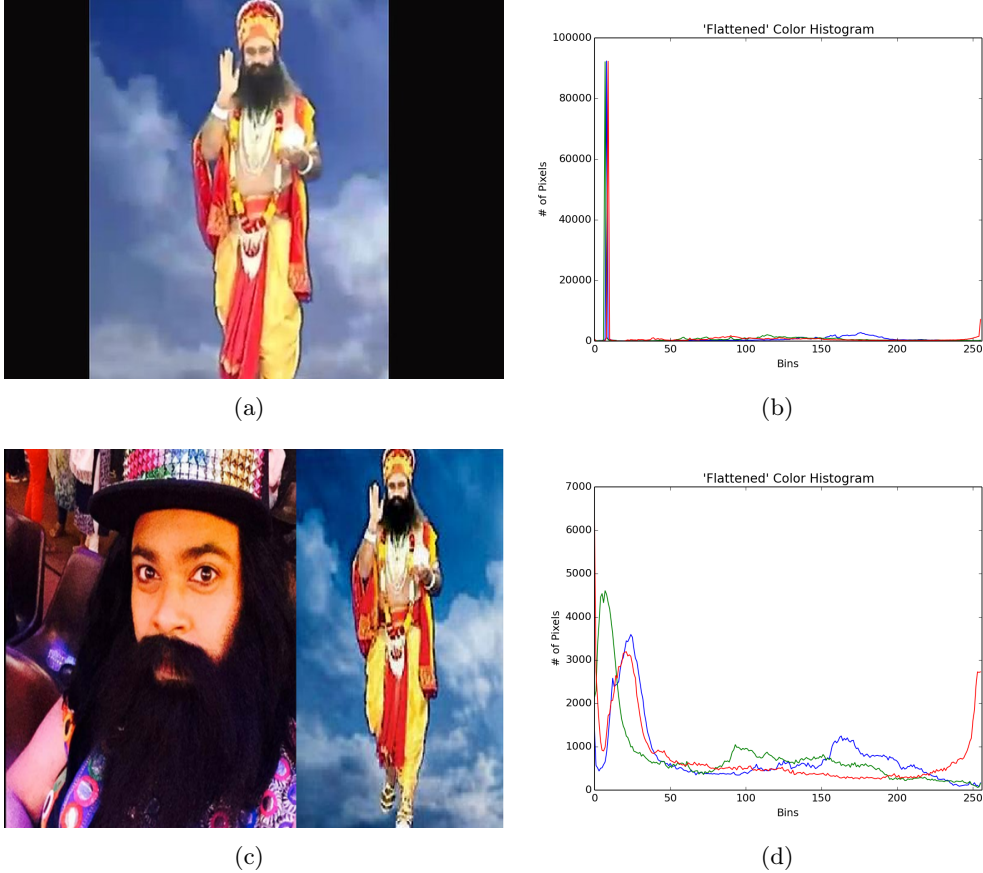


Figure 7.3: Example from Baba Ram Rahim dataset to show distinctions in histogram of two similar images in our context.

2. Keypoint-Descriptor-based similarity: Certain parts of an image have more information than others, particularly at edges and corners. Keypoints can be generated using this information. After finding the keypoints of an image, next step is to find their descriptors. Descriptors are fixed length vectors that describe some characteristics about the keypoints. Next, we compare each keypoint descriptors of one image to each keypoint descriptors of the other

image. Since, the descriptors are vectors of numbers, we can compare them using different distance metrics. We studied techniques like DAISY [136], ORB (Oriented Fast and Rotated Brief) [110] and Improved ORB (Oriented Fast and Rotated Brief+Random sample consensus) [154] for computing keypoint descriptors and then comparing them.

- The *DAISY* dense image descriptor is based on gradient orientation histograms similar to the SIFT (Scale Invariant Feature Transform) descriptor. It is formulated in a way that allows for fast dense extraction which is useful for bag-of-features image representations [137]. After extracting DAISY descriptors we calculate the distance between the descriptor vectors of two images using Brute Force matcher with KNN (K-Nearest Neighbors) as the distance metric. We use this distance as the score to measure the similarity of two images.
- *Oriented Fast and Rotated Brief (ORB)* uses improved Features from accelerated segment test (FAST) for feature detection, and these features are described using an improved Rotated Binary Robust Independent Elementary Features feature descriptor (BRIEF) [154]. Since the speed of FAST and BRIEF are very fast this can be the choice for real-time systems. ORB is rotational invariant, noise invariant and uses image pyramids for scale invariance [110]. It returns binary strings to describe feature points, which is used for feature point matching using Hamming distance. We use this hamming distance as the score to evaluate the similarity of two images. Figure shows performance of ORB in detecting similar images from Baba Ram Rahim event in our dataset.



Figure 7.4: ORB to detect similar images from Baba Ram Rahim event in our dataset.

In order to improve the matches given by ORB we add one extra step. After comparing the keypoint descriptors given by ORB, we find homography of two images using Random SAmple Consensus (RANSAC) [154]. We extract top 30 matches having the least distance and pass these matches to RANSAC to weed out wrong matching points. This technique is called as *Improved ORB*. RANSAC returns a binary array equal to size of input matches array, where 0 represents a false match and 1 represents a true match.

We define true ratio as the ratio of true matches returned by RANSAC to total matches given to it. We use this true ratio to evaluate the similarity of two images. In the given equation, t_r denotes true ratio, n is the size of matches set passed to RANSAC, A is the array returned by RANSAC and A_i represents the value of array returned by RANSAC at i^{th} index.

$$t_r = \frac{\sum_{i=0}^{n-1} A_i}{n} \quad (7.2)$$

7.4.2 Trained features

In this section we discuss one important technique “deep learning” which is organised in a deep architecture and processes information through multiple stages. To that end, inspired by recent advances in neural architectures and deep learning, we choose to address CBIR using deep convolutional neural network.

For implementation of *Convolutional Neural Network (CNN)*, we took inspiration from the architecture discussed in [103]. To create the dataset for training, we used an unsupervised approach. We extracted around 25K images from popular news websites and then on each of 25K image, we applied various image processing operations like cropping, distorting, blurring, scaling, adding text, stitching image, adding noise, and changing color, to generate the corresponding similar image. These image processing operations were made on images using OpenCv library in Python. Through this process, we created a dataset of 50K images. To train the model we had 25K pairs of similar and dissimilar images. Similar approach of transforming images to create dataset is used by Fischer et al., 2014 [36]. As a pre-processing step, we first align the images. We extract SIFT descriptors to map the matching features of both the images and align the images by applying a perspective transformation using the homography. We then club the two aligned images to form a 6 channel image which is passed to the CNN model. The CNN model was implemented in Python using Keras neural networks API. ²

The model contains 15 layers out of which 6 are trainable (Figure 7.5). First 5 of trainable layers are convolutional and one is fully connected. The output of the last fully connected layer is a 1D vector and is fed to a sigmoid activation which produces the final output between 0 and 1. Our network minimizes binary cross entropy loss objective and uses adam optimizer as the optimizer. The convolutional layers contain 64 filters 122×122 pixels, 32 filters 61×61 pixels, 16 filters 31×31 pixels, 6 filters 16×16 pixels, 1 filter 16×16 pixels. All the convolution layers are applied with a stride of 4 pixels. The fully connected layer contains 1 neuron. All the convolution layers use LeakyRelu and batch normalization except the first layer which doesn’t use batch normalization and the last convolution layer directly feeds output to the fully connected layer. Batch Normalization method helps to normalize the input of each unit such that its mean is zero and has unit variance.

²<https://keras.io/>

This helps to stabilize learning and allow gradient flow deep in the model by dealing with the poor initialization problem. All the layers use a subsampling of 2×2 except the last layer, which uses a subsampling of 1×1 . The initial convolution layers extract the low level features like edges and gradients. The other convolution layers learn to compare the extracted features of the two images. The similar areas of the images get propagated till top and fully connected layers calculate a similarity score using the high level features. The design decisions of the architecture are taken to achieve best performance using accuracy as evaluation metric and minimize response time to perform classification.

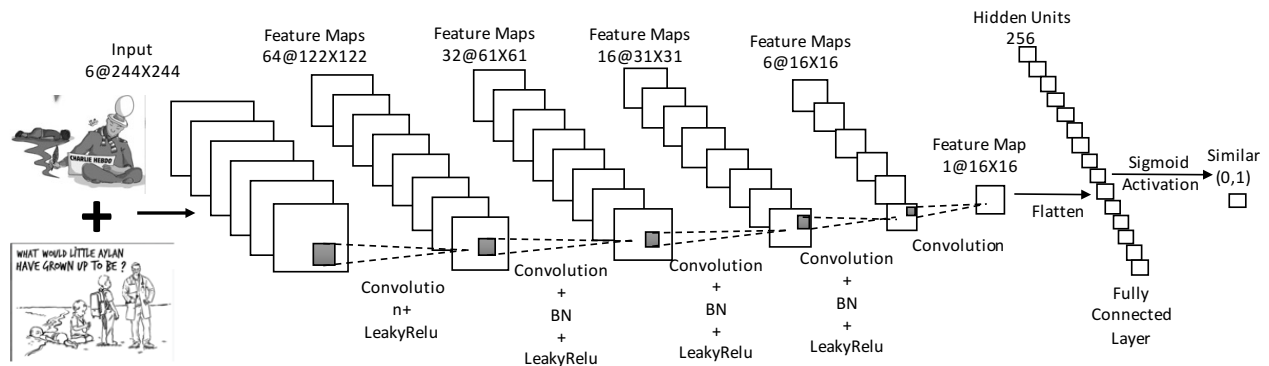


Figure 7.5: CNN-Model containing 15 layers out of which 5 are trainable convolutional layers and one is fully connected. The output of the last fully connected layer is a 1D vector and is fed to a sigmoid activation.

7.5 Hand-crafted vs. Trainable Features

In this section, we evaluate different techniques discussed in the above section on the annotated test data. To evaluate the performance of the above-discussed image similarity models we calculate accuracy of their classification results, which is the ratio of true classification to the total population.

7.5.1 Histogram

For each of the five events, we plotted the accuracy for Bhattacharyya distance between color histogram of two images, ranging from 0.1 to 0.9. Figure 7.6(a) shows accuracy for different events at different histogram distance. The graph shows a lot of variation in the accuracy corresponding to the histogram distance values. We calculated average variance in accuracy at 3 distance points on the x-axis (0.2, 0.4, 0.5) as 104.24, which is high making it tough to choose a distance value as the threshold. For example, If we choose threshold distance as 0.4, the accuracy for ShaniShignapur and Lord Hanuman cartoon is close to 60% whereas for Charlie Hebdo it is 90%. Another drawback

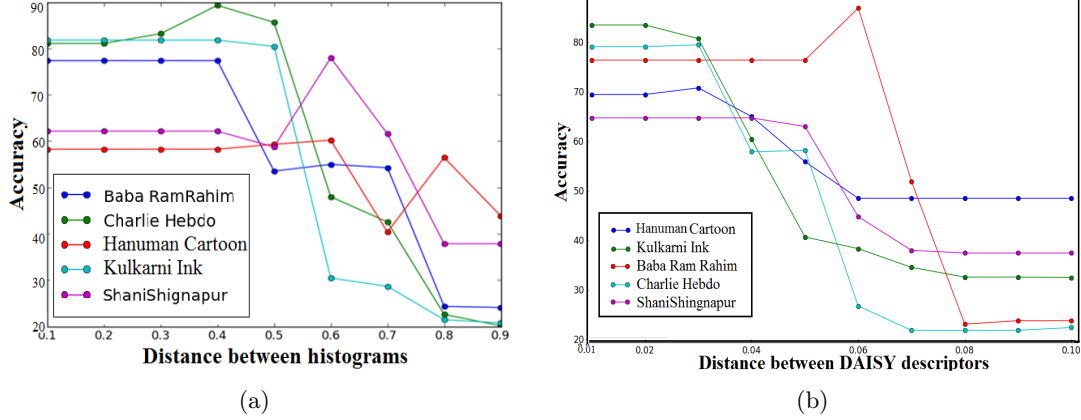


Figure 7.6: (a) Accuracy for different events at different distance between histograms of two images. (b) Accuracy for different events for different distance between DAISY descriptors of two images. Both graphs shows high variance in accuracy.

of this method is, it lacks spatial information, so images with very different appearances can also have similar histogram [93].

7.5.2 DAISY

The mean distance between DAISY descriptors of both similar and dissimilar images was in the range of 0.0 to 0.10. To choose the threshold distance values between this range, we plotted the accuracy graph for each event at different threshold value. Figure 7.6(b) shows the accuracy vs. threshold plot, where the threshold is the mean distance between DAISY descriptors of two images. Since the range of distance returned by DAISY descriptors is very small there was a very high overlap between distance values of similar and dissimilar images leading to high error. Due to this high error, the maximum accuracy achieved overall is less than 88%, at a distance of 0.06 but, at this point accuracy for remaining events 4 events is less than 50%. We also calculated the average variance in accuracy at 3 distance points on the x-axis (0.02, 0.05, 0.06) to be 196.58, which is even higher than the Histogram technique. Thus, making it hard to choose an optimal threshold value.

7.5.3 ORB

For all the 5 events, we plotted the accuracy for different values of mean distance between ORB descriptors. We use this plot to choose an optimal threshold distance value. Figure 7.7(a) represents the accuracy plot for different events at different distance between ORB descriptors. The variation in accuracy is less as compared to the Histogram and DAISY technique. Average variance in accuracy at 3 distance points on the x-axis (29, 32, 35) is 17.6. Also, the accuracy for all the events at threshold distance 29 is above 88%. This shows that ORB is certainly a better choice than Histogram and DAISY for our data.

7.5.4 Improved ORB

In Improved ORB, after getting the match set of the descriptors from ORB, we pass the top thirty matches having least distance to RANSAC, which filters matches which are true. The threshold value here is the ratio of true matches returned by RANSAC to the total matches passed (thirty in our case), defined as true match ratio. Figure 7.7(b) shows the accuracy of Improved ORB for different true match ratio taken as the threshold. Average variance in accuracy at 3 true match ratio values on the x-axis (0.33, 0.35, 0.37) is 6.2, which is least among all the techniques discussed till now. Also, after true match ratio of 0.3, the accuracy for each event is almost constant and is above 90% for all events. If compared with above methods Improved ORB is giving best results. Hence, Improved ORB can be termed the state-of-art technique in hand-crafted features discussed.

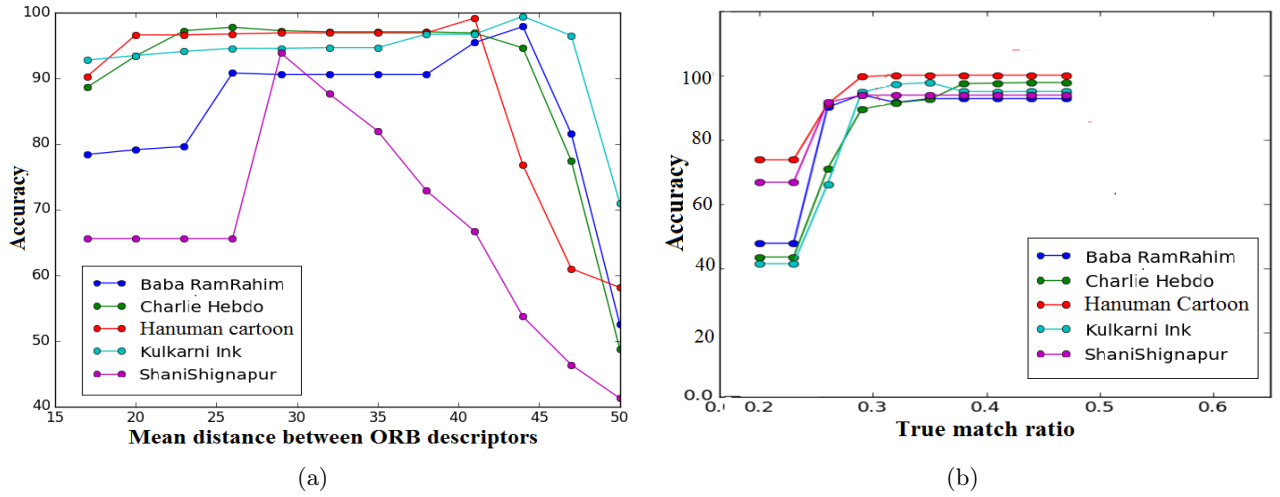


Figure 7.7: (a) Accuracy for various events at different distance values between ORB descriptors, at distance value 29 on x-axis all the events have accuracy more than 88% and (b) Accuracy for different events at different true match ratio returned by Improved ORB, at true ratio of 0.35 all events have accuracy above 90%.

7.5.5 Trainable features

We trained a deep CNN model for 25K pairs of similar and dissimilar images, and to test the model we gave input image and images from annotated set to the model for different epoch values. To choose optimal epoch for the model, we plot the accuracy for different events, for models trained on different epoch values. Figure 7.8 shows the accuracy for each event at different epoch value. The model trained for epoch value 35 is showing an accuracy above 97% for all events. Also, average variance at three epoch values on the x-axis (30, 35, 40) is 0.71, which is even lower than what we achieved in Improved ORB. Since the overall accuracy for CNN model is higher and the variance is

lesser than Improved ORB, we can conclude that our proposed CNN model outperforms state-of-art Improved ORB. In the next section, we'll see how these two techniques perform when the input image is modified.

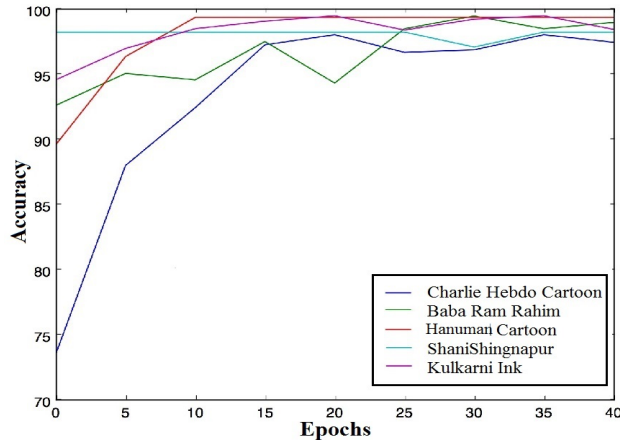


Figure 7.8: CNN models trained for different epochs and their accuracy for five test events. For model trained for 35 epochs, accuracy for all events is above 97%.

7.6 Comparison: Improved ORB and CNN

In this section, we analyze the performance of Improved ORB (state-of-art technique in hand-crafted features) and CNN when the input image is modified. For all the 5 events, we take different cases of modified images usually seen on social media sites like Twitter and compare the accuracy of both the image retrieval techniques. Figure 7.9 shows modified images taken from all the events and Table 7.2 shows the accuracy of the image retrieval models for these images. For each event, we picked three kinds of modified images: one with single modification like cropped or scaled or color changes, second with dual modification together like cropping & scaling or adding text & scaling, etc., and third with multiple modifications together like scaling, cropping, adding text and stitching image, represented as All in Table 7.2.

Among different modifications seen, the most common modification technique was scaling the image. Hence, we calculated the scaling factors of the modified images and found that as the scaling factor increases, the accuracy dip for Improved ORB also increases. For example, in Table 7.2 image ‘a’ is modified by a scaling factor of 7.42×5.23 and the accuracy of Improved ORB is 84.1% while, for the same image CNN is showing an accuracy of 99.4%. Likewise, for image ‘c’, ‘m’, ‘n’, ‘o’ also the scaling factor is high leading to low accuracy in Improved ORB but, the accuracy of CNN in all these cases outperforms Improved ORB. Another common modification affecting accuracy is cropping of an image, for instance; image ‘f’ has only the cropped face from the complete body of

Baba Ram Rahim (original picture see in Fig. 7.2), and again the accuracy dip in Improved ORB is much higher than CNN. Likewise, is the case for image ‘d’, cropping reduced the accuracy of Improved ORB while CNN still outperforms it. Hence, we can conclude that the proposed CNN model is more robust to modifications like high scaling and high cropping than state-of-art Improved ORB.

7.7 Benefits: Improved Understanding of Law & Order Scenario

To showcase the real-time applicability our proposed technique, we build a system with the aim to: a) aid police to find the spread of images that can create law and order situations by retrieving similar images and b) find & analyze the users propagating the content, sentiments floating, etc. We believe this may be helpful in reducing their human efforts in identifying the visual content of the interest. In the previous sections, we saw comparison between different hand-crafted methods and CNN to compare image similarity. The experimental results show that CNN outperforms Improved ORB and hence, CNN is a more suitable technique to find image spread for the system. We now explain various other measures used to evaluate image similarity as used in our system that help in achieving goals for better law enforcement using similar image retrieval process discussed above.

Search Space Reduction: The system takes a set of keywords from the user to create a database of images and an image using which it retrieves a set similar images from the database created. Thus, reducing the search space for police and saving their time and efforts to analyse the overall dump. We were able to reduce the search space on an average by 67% and by 65%, using CNN and Improved ORB as image retrieval technique respectively. Our results show maximum reduction in search space was seen for Baba Ram Rahim event followed by Charlie Hebdo cartoon. Table 7.3 shows the details of search space reduction for all the events using the two techniques.

Users Analysis: Users play a vital role in spreading the content on social media. Thus, it is important for security analysts to identify people who are spreading the images. Our system tries to deliver this need by producing a list of users who spread the visual content and their details like, their Twitter usernames, profile pictures, description, location, and links to their Twitter profiles. In our dataset, we found maximum users for Lord Hanuman cartoon event propagating the content, for images retrieved using both CNN and Improved ORB. Table 7.3 shows the number of users listed when we used Improved ORB and CNN as image retrieval techniques.

Sentiment Analysis & Tweets vs. Retweets Analysis: Sentiments of the tweets play an important role in spreading the content and eliciting the reaction of people. Thus, making it an important analysis to find the percentage of content having positive, negative and neutral sentiments. Our system currently analyzes the sentiment of the textual content having images using

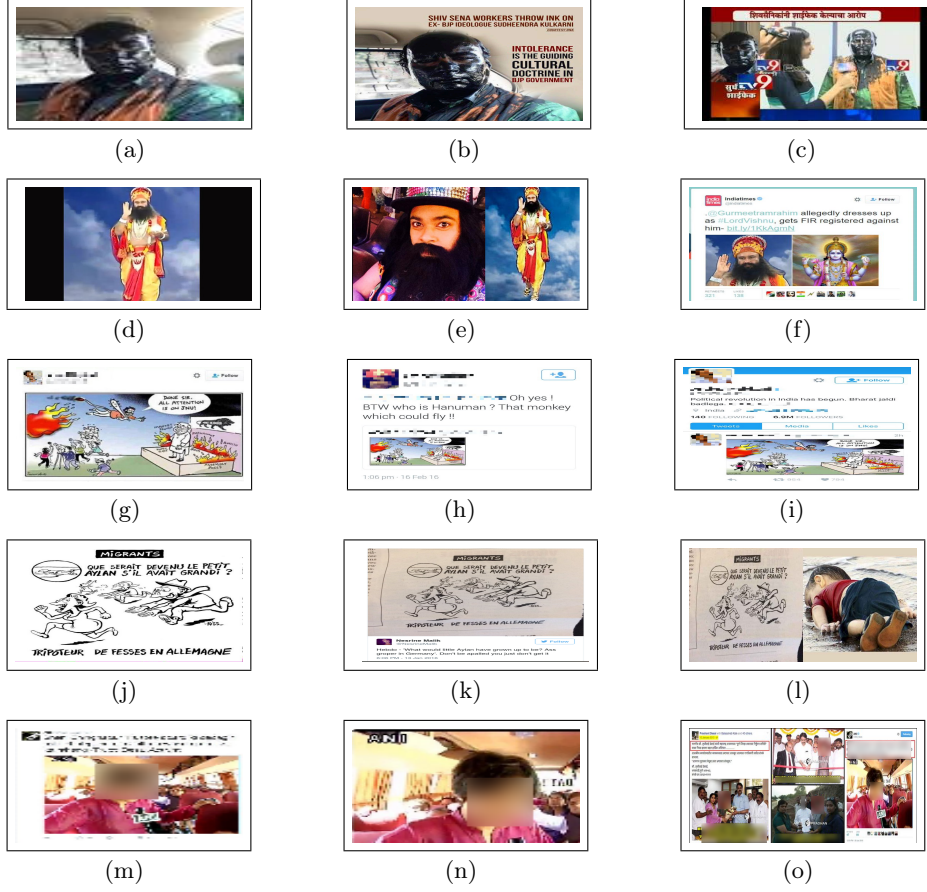


Figure 7.9: Event-wise modified images. By Row: (1) Kulkarni Ink Event (2) Baba Ram Rahim (3) Lord Hanuman Cartoon (4) Charlie Hebdo Cartoon (5) Shani Shingnapur.

Image-Id	Improved ORB	CNN	Modification	Scaling Factor	Event
(a)	84.1	99.4	Scaled	7.42×5.23	Kulkarni Ink
(b)	95.6	99.5	Text added & scaled	1.23×1.08	Kulkarni Ink
(c)	80.7	87.3	All	9.61×3.87	Kulkarni Ink
(d)	91.2	99.5	Cropped	—	Baba Ram Rahim
(e)	88.2	92.6	Stitched & scaled	2.31×0.92	Baba Ram Rahim
(f)	77.4	93.8	All	2.65×1.56	Baba Ram Rahim
(g)	96.9	99.3	Scaled	1.04×1.09	Lord Hanuman Cartoon
(h)	90.3	99.5	Text added & scaled	2.32×2.47	Lord Hanuman Cartoon
(i)	92.2	92.7	All	1.27×1.25	Lord Hanuman Cartoon
(j)	96.8	97.2	Background color	—	Charlie Hebdo Cartoon
(k)	97.2	97.6	Text added & scaled	1.04×1.28	Charlie Hebdo Cartoon
(l)	94.5	95.3	All	2.02×1.54	Charlie Hebdo Cartoon
(m)	90.4	95.3	Scaled	4.98×6.09	Shani Shingnapur
(n)	62.1	98.2	Cropped & scaled	5.88×5.91	Shani Shingnapur
(o)	93.7	98.3	All	3.24×2.35	Shani Shingnapur

Table 7.2: Table showing the accuracy comparison of different modified images for test events. In all the test cases, CNN has out-performed state-of-art Improved ORB.

Event	Search Space Reduction (%)		Number of Users	
	Improved ORB	CNN	Improved ORB	CNN
Kulkarni ink	51.1	54.3	770	1,144
Baba Ram Rahim	83.1	90.7	75	96
Lord Hanuman cartoon	60.1	61.6	2,210	2,657
Charlie Hebdo cartoon	74.1	75.2	2,132	2,037
Shani Shingnapur	57.9	57.9	186	186

Table 7.3: Event-wise reduction in search space and analysis on number of users after retrieving similar images using Improved ORB and CNN.

Sentiment140 API ³, widely used in the literature to study social media data. In our dataset, we found 7% of tweets have negative sentiments and 5% have positive sentiments and remaining have neutral sentiments which might be due to broken language, non-english, hinglish language or absence of text. Tweets vs. Retweets analysis shows the percent of retweets and original tweets. Our analysis shows, most of the images in the result were spread by retweeting, average retweeted posts were 89.4%.

7.8 Implementation and Response Time

7.8.1 Implementation

Our system takes an image and keywords as input. These keywords are then given to Twitter’s Search API (Application Program Interface), part of Twitter’s REST API. The API returns a set of tweets related to the keywords it takes as the query, and the system then filters and saves the tweets containing images in a database. As the images get stored in the database, the image comparison model computes the similarity score between the input image and the images in the database. We then set a threshold t , if the similarity score is above t , images are marked similar else dissimilar. After getting similar images, the system does analysis on the retrieved set of images and finds the users propagating them, the sentiment analysis and retweets analysis. Fig 7.10 shows input and different output and analysis screens of the proposed system.

7.8.2 Response time

Since our aim is to build a real-time image search system, apart from the accuracy of the model we also need to select the technique that is time efficient. We compare the approximate time consumed by Improved ORB and CNN to compare one pair of image and we found that Improved ORB took 0.2 seconds and CNN model took 0.55 seconds. We believe, even though CNN exhibits

³<http://help.sentiment140.com/home>

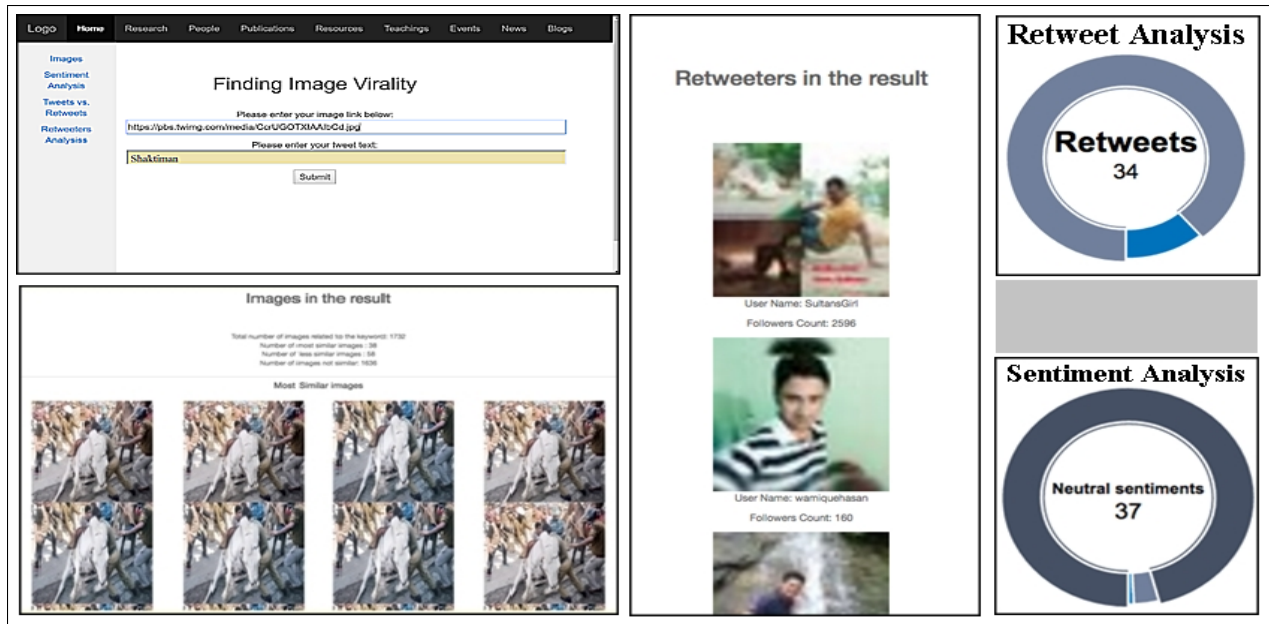


Figure 7.10: Moving in anti-clockwise from top-left image the images represent (a) Input to the system is a image url and a keyword. (b) Output screen: Our system retrieves similar images (c) Analysis screen: Users propagating (d) Analysis screen: Sentiment analysis on text of the resultant images (e) Analysis Screen: Retweets analysis on text of the resultant images.

higher response time, it may still be better for detecting safety issues through images as precision is identifying correct set of images happens to be more crucial to identify individuals involved in such tasks.

7.9 Summary

In this chapter, we focused on using images on social media and maintaining safety in the society. We look at various state-of-the art techniques to identify similar images that can aid police departments to analyze and further find the spread of images creating law & order situations in society. To find similar images we conducted an in-depth experimental analysis of different CBIR techniques. We performed an experimental study on the data collected for the 5 events which created law and order situations in society and whose images were viral during the duration of the study. We compared different hand-crafted techniques and found that Improved ORB (ORB + RANSAC) is the state-of-art technique for the hand-crafted approach. We also proposed a CNN model which outperforms the accuracy of state-of-art hand-crafted technique. Further, we proposed a OSINT real-time image search system robust to find modified images, that aids police to analyze and find the current spread of images creating law & order situations in society, analyze users propagating such images and sentiments floating with them. Using the system first responders can identify the users affected

and interested in discussing the image under question. We believe first responders can analyze these images and related users to identify people of interest to them / quantify the spread of images. The system performs a hybrid search by taking a keyword to create an image database and an image as input and returns similar images. The system also aims to reduce search space for police on average by 67%. We suggest future research to work and focus on reducing the response time of our proposed CNN-architecture, improve results of textual sentiment analysis that takes broken or non-english language into consideration, and include more image analytics features like, sentiments of images in result to aid maintaining safety in society during security critical scenarios.

Chapter 8

Conclusion and Future Work

In this thesis, we evaluated the importance of knowledge of textual, psycholinguistic, image and social networking websites' meta-data in operationalizing and modeling behaviour of residents impacted by safety issues and police response to residents' request for assistance in day-to-day life. We believe this knowledge contributes and helps in designing collaborative interactive systems for police and residents. In this chapter, we discuss the implications of our work on collaboration between police and residents. This discussion is followed with limitations of the work in this thesis and recommendations for future work.

8.1 Contributions and Takeways from Our Findings

Community policing theory suggests to involve community members in the problem-solving process to prevent crime and create safer societies [68, 111]. Using data-driven techniques, our work in thesis makes an attempt to characterize and quantify residents' concerns expressed on social media that can complement police documentation of the various incidences reported in the communities. Research also shows that behavioral attributes reflected on social media may be helpful in studying the psychological state of residents and may also help to understand civic needs and general well-being of the society [27, 33, 147]. This thesis explores the viability of using content generated on social media such as Facebook police pages as an instrument to quantify and characterize attributes of police and residents' interactions. Towards improving safety and law enforcement, we find that residents appropriate a public platform like Facebook to discuss collective solutions with police and members of civic society at large.

8.1.1 Identify different stakeholders need to use Social Media for community policing and collective action

Current CSCW research investigates social media use by first responders and residents primarily during crisis situations, which are event-driven and have specific goals to be achieved in a short term [53,65]. It is unclear how this knowledge can be used for day-to-day communication in policing activities that are diverse and are not time bound. Drawing inspiration from the existing literature on social media by police during crisis situations, we find that effective policing through social media requires identifying the needs, planning activities, creating useful content to be shared, and constantly communicating with residents (as discussed in Chapter 3). To explore how different stakeholders (police and residents) will like to appropriate social media platforms, we interview and survey IPS officers and residents to understand their perceptions, and explore challenges experienced while using social media for policing. Interview analysis, highlights how residents and police think about information shared on social media, handling offensive comments, and acknowledgment overload, as they pursue social and safety goals. We find that success of social media for policing demands effective communication between the stakeholders (residents and police). This thesis shows that social media offers community-policing opportunities, enabling police to identify crime with the help of residents. It can reduce the communication gap and improve coordination between police and residents. We also discuss design opportunities for tools to support social interactions between stakeholders.

8.1.2 Mine and operationalize residents' concerns and behaviors

In this thesis, we contribute to the design paradigm of computer science by proposing necessary measurements that can help operationalize the collective action efforts and psycholinguistic parameters that define behavioral aspects of residents facing safety issues (Chapter 4). We also demonstrate that our approach to use statistical and unsupervised methods to quantify four distinctive measures i.e. topics discussed, emotions, engagement characteristic and cognitive processes can be used to extract and measure these attributes from large-scale data available on social media. This understanding can help police improve policing and community sensing. Figure 1.1 in Chapter 1 shows the relationship of improved data analytics and community sensing. We believe our defined measures in context of day-to-day policing can complement the existing efforts to improve informational access through improved, more accurate and analytical tools for police organizations.

We also operationalize measures to quantify promptness and responsiveness of the police departments towards the safety concerns of the residents during daily course of life. We demonstrate that the statistical tool known as Survival Analysis can be effectively used to measure promptness and responsiveness to different posts made by police (Chapter 7). Previous studies signify the need for police responsiveness on social media to better engage with and develop trust in the residents for

police [111, 112]. We show that police responds more to serviceable posts than they do to general communication. Thus operationalizing measures to identify such serviceable requests could be helpful to improve informational access through improved, more accurate and analytical tools for police organizations.

8.1.3 Detect image similarity for collective knowledge and action

In this thesis, we also explore and identify images shared on social media such as Twitter that may result in a law and order situation. In Chapter 7, we show a unique need of police departments to identify and aggregate images related to an event that may cause mass-unrest in the society. Our approach to use Deep Convolutional Neural Network (Deep CNN) for mining similar images of interest to police may help to address informational access needs from image like content and develop knowledge from these. Using CNN based approach, helps to improve the learning space and boosts the accuracy of the results to mine relationships between matched-similar images. This helps to improve the way image similarity has been addressed using hand-crafted features in the prior work. It also better addresses the ambiguities arising as a results of stitching one image to another, cropping or changing resolutions of the images in the resident generated content on social networks where such changes in the images are expected but are largely unexplored in case of policing. Our approach helps to reduce the manual search effort to identify specific images from plethora of images generated on social media when residents share and discuss law and order related issues. This approach complements the prior research that focusses more on textual content to aid the police but analyzing multimedia content like images and videos on social media is still largely unexplored [63]. Also, we demonstrate a web-based tool that can allow to retrieve, filter, integrate and intelligently present relevant images complementing the existing studies on information needs or better safety during security critical scenarios [20, 52].

8.1.4 Identify evidences of existence of real-world behavioral experiences in online conversational threads

We mine social media to identify presence of actionable information and residents' opinion such as fear on social media. This knowledge can contribute to collective actionable information that police can use for collective action and gain knowledge on residents' use social media to hold police accountable. We show that residents post information (including location) about various crimes such as neighborhood issues (drunkards, illegal construction), financial frauds, property crime, and thefts. We believe these messages are posted with a hope that police will respond and act upon these. Towards, this end we identify four distinct category of responses that police might give to residents such as *reply*, *acknowledge*, *follow-up* and *ignore*. Residents also post content expressing the fear resulting from being either indirectly or directly victimized. For easy consumption of this

information, we present a web-based tool that can help police to aggregate this information. This assists police in understanding the communication discussed in asynchronous and remote fashion with them (Chapter 1, Figure 1.2) on social media platforms thus making these platforms more *Observable* to residents' requests. We believe, in order to maximize social medias' advantage in providing actionable information, technologists should consider designing tools that make social media communication containing actionable information more *observable* for both police and residents.

Based on extensive analysis discussed in Chapter 5 of this thesis, we address the research question of identifying existence of real-world behavioral experiences related to sensitive safety issues in online conversational threads on social media. This understanding can help to improve the measures used to compute and operationalize behavioral measures towards safety concerns. We also use this knowledge as the stepping stone to compute and identify serviceable posts from textual content on social media (discussed in Chapter 6).

8.1.5 Model serviceable posts and their multiple classes through knowledge of various behavioral measures

In this thesis, we demonstrate a method to model challenging problem of serviceable posts and their multiple classes through knowledge of various behavioral measures and representation of textual content. We demonstrate how our technique discussed in this thesis can be applicable to design of socio-technical systems that can help to predict and log the responses and various context that residents' post consists of on social media. Our technique makes use of various unsupervised knowledge creation methods such as emotional analysis, psycho linguistic analysis and topic modeling techniques specifically to the resident generated content on social media. Using in-depth analysis through forward step-wise regression, our research efficiently captures what are the distinguishing factors being computed, complementing the goal of identifying serviceable posts.

8.2 Limitations

8.2.1 Causality

Although we see potential use of social media to develop technologies for improved landscaping of safety in urban cities, we understand that these technologies may not work as standalone solutions. Rather these solutions may complement existing methods and become part of broader detection systems about residents' psychological and social responses. We also suggest caution in interpreting findings of our work. Our work on operationalizing measures leverages a variety of computational methods and measures to make sense of the interactions between police and residents, but requires further proof through surveys and interviews. Similarly, while modeling service requests that get

police response, we do not make any claims about whether these responses meet the expectation and actual need of the residents. We recommend this as an important step for future studies which could use interview and survey methods to evaluate the usefulness of these responses. Therefore, we do not intent to make any causal inferences of our studies and leave that as a dimension to study in future.

8.2.2 Data Limitations and Restricted multimodality

In this thesis, specifically while classifying serviceable posts we primarily perform textual analysis. Therefore current approach has restricted modality issue (considering mostly textual features). Similarly, our work on images in Chapter 7, considers only images as a source of information for identifying similarity. However, we acknowledge that social media streams consist of other data modalities like videos that when combined with textual and images could be useful to characterize serviceable posts. We identify this restricted multimodality of data types and lack of usability insights as one of the limitations of our proposed work. Further, in this thesis, the focus is to enhance collaboration however, one important aspect is veracity of the information. This thesis makes no claims about the veracity of the information provided by the residents to the police. Author strongly recommends future work to validate the applicability of existing literature on veracity of general social media information to policing context.

In this thesis, author could analyze only public information available on social media platform such as Facebook and Twitter. The analysis in this thesis shows that residents may not feel comfortable reporting or discussing crime in public. Analysis of the interviews shows that police departments feel the need of a well-defined policy for social media which protects privacy of both police and residents. However, our data did not include private messages that people might have sent to police using Facebook, or other forms of “spill-over” activity that may be present in users’ personal Facebook profiles or residents following up their complains through physical walk-in to the police stations. It would be relevant to study that how do complains reported on social media get addressed on ground. Future work could analyse these aspects through interviews of police officials managing these social media profiles.

8.2.3 Cultural limitations

We believe that our suggested measures can help account for concerns of residents who willingly express their views on social media. However, we understand that the willingness to share data may differ among communities based on their broader cultures. For instance, communities that may have a tradition and culture of community policing may be more willing to engage in collective action through these methods. However, communities where historically trust has been a challenge between

police and residents may need to be persuaded more to participate. Also, we study users from urban and sub-urban areas where social media penetration is high. It is worthwhile to examine if factors such as demography, education, the cultural background could influence resident participation in social media. Different cultural setting may result in different expectations of residents from police, however, we believe that even then police would need general understanding of what residents feel and what issues concern them. Future work could explore the influence of culture variations in this context. Our methodology can help police departments from varied cultures to use social media for understanding their resident communities. Further, to complement our work in this thesis, we recommend future work to compare our findings for rural communities where Facebook is showing fast penetration. Rural communities may show varied concerns than discussed in urban areas.

While developing the model for serviceability, we find that out of 1000 posts only four posts were in regional languages. Moreover, English is the common business language used in India that can be a reason for the majority of the posts being in English in our dataset. We conjecture, it could be that writing in English gives more confidence to complainant that their complain will be taken seriously. We excluded the posts in regional language from our analysis. Future research could invest on gathering more posts in regional languages and analyzing them using similar metrics as discussed in our study.

Traditionally police and other government organization have used media like Television and Radio to keep connected with residents in these rural areas. Specially in the areas where there is limited connectivity to the internet, researchers have showed importance of phone based IVRs for collaboration between residents and government organizations. These technologies help to maintain accountability of local bodies to residents. For instance, Jharkhand Mobile Radio (JMR), a phone based platform is used to raise issues with the development authorities and resolve problems in rural areas of Jharkhand state in India [83]. Also interactive voice application based social media such as Avaaj Otalo have helped residents in rural areas to have open discussions on issues of interest with other residents [94]. Similarly, through projects such as Mobile Vani and CGNET Swara, citizen journalism is being promoted in rural areas in India [73]. Using this platform residents report or listen to the concerns raised by others in the community. Thus more exploration is required to understand how our suggested measures calibrate in such contexts. It may also be worthwhile to examine if factors such as demography, regional languages, and education influence police responses.

8.3 Future Work

8.3.1 Improve awareness and articulation towards Safety Issues

CSCW research makes continuous efforts to assists organisational actors such as police and other first responders with technologies that help to create awareness related to safety critical issues.

In this thesis, we looked at improving the way police understands residents' concerns. However, an important aspect of community policing involves creating awareness among residents regarding security issues. In this thesis, we found that a large number of posts by police on social media are to create awareness among residents. We suggest creating measures that can help evaluate the impact such awareness drives on social media. Advanced survival analysis techniques could be used to model and compute features that effect long term impact of police awareness campaigns on residents. Future work in HCI domain should also explore mechanisms which can suggest innovative techniques to create awareness campaigns that can help police articulate their messages better and improve interactions between police and residents.

8.3.2 Multimodal feature extraction for Improved Classification

Currently, our technique proposed in this thesis, concentrates on textual content shared on social media to operationalize and model behavioral aspects of safety issues shared on social media. Further, the usability evaluation and perspective of the police officers towards the plugin and current unimodal model has not been performed. We strongly recommend future studies to evaluate the applicability of the model in supporting day-to-day activity of police. Also, the way content is consumed on social media is changing at a fast pace. Visual content such as images and videos contribute to large share of content generated on social media. Our work in thesis makes a limited use of this content such as image similarity or taking image presence as binary feature with other meta data while modeling serviceability. Future work can explore visual content as binary feature and use computer vision techniques such as objects detection and text recognition in the visual content to identify serviceability. Multimodal systems combining different modalities such as images, videos, and text could also be explored to understand the impact of social media in policing.

8.3.3 Identifying information overload on residents in day-to-day Interactions

CSCW research is placed in a unique position to identify and design technologies that enable successful collaboration efforts between police and residents. In this thesis, we propose mechanisms that can reduce information on police department as they provide service to residents. Community policing efforts involve creating awareness among residents, however, the frequency and extent to which police shares information on social media may create information overload on residents. This may result in some important information going through the cracks and being unnoticed by the residents. We recommend future work to identify and suggest methodologies to reduce information overload on residents. Research could consider proposing mechanism that helps create custom timeline and recommending information of their interest to residents. These efforts may help sustain long term interactions and content consumption between police and residents. Further this could be complemented with detailed characterization of users willing to interact with police and how

frequently they like to interact with police.

Appendix-A

Project IPS – Innovate Policing through Social_Networking_Sites

INTRODUCTION

This study is focused on understanding how to build technologies, evolve policies that will empower police to use Online Social Media (OSM) more effectively for their day-to-day activity to maintain law and order. We will explore how OSM can be used to build intelligence as well as to stay connected with citizens. We believe outcomes of this study can help create awareness among the Law Enforcement Agencies about using OSM for their benefit.

All views presented during the study will be treated as your own views and not of your organization. Please do not mention the name of your organization or any other person during the interview. Even if it appears, we will anonymize it in our analysis. We will refer to your organization as “Organization” or “group” and your colleagues as “team”. Please keep in mind that you are an expert in this domain; there is nothing right or wrong as response for the questions that we will be asking.

Aggregated statistics and anonymized quotes from the audio recordings will be published in an academic article. If you would not like us to record some part of this discussion, we will stop recording for those parts of the discussion. Please share your thoughts, which can be used on public forums. We plan to write a report from the analysis we do from this study. We will be making the report public and will be happy to share with you.

- 1) Which OSM do you use for your day-to-day activity to maintain law and order / official purposes?
 - a. Facebook, Twitter, Google+, YouTube, Instagram, Pinterest, Any other.....
 - b. Which OSM is most useful and helpful for law and order purposes?
 - c. For how long have you been using OSM for law and order purposes?
- 2) Do you think some information can only be found on OSM and is difficult to find on any other platform? [If participant just stops with a yes/no probe more say examples of what is it?]
 - a. What information is it? (Friends network, public opinion about a topic etc.)
 - b. How helpful is this information?
- 3) Does your organization support the use of OSN when at work?
 - a. If yes, is the infrastructure good?
 - i. If yes, do you use it at work?
 - ii. What do you use it for?
 - b. If No, do you think if allowed to use OSM in office, it will help you in your work?
- 4) Does your organization have an official Facebook / Twitter page.
 - a. If yes, will it be possible for you to share the handle with us.
 - b. If no, do you think your organization should have one Facebook /

Twitter page.

- 5) What are the different ways you see online social media being used for your day to activity to maintain law and order?
Prompts:
 - a. Monitoring (Which OSM has been / will be most helpful)
 - i. Investigation
 - ii. Gauging public sentiment
 - b. Engaging public participation and using OSM as PR
 - c. Pushing your content on OSM
- 6) How much trustworthy do you think is the information obtained from OSM?
 - a. Can you please give us an example
 - b. Would you like to use OSM as tool to know public opinion about your policies and actions?
- 7) Can you list the kind of crimes OSM is being exploited for?
 - a. Cyber – crimes in general
 - b. Crimes using OSM, like organizing rave parties etc.?
 - c. Do you think you can take help from OSM to combat these crimes?
 - i. If yes how?
 - ii. If No, why?
- 8) Do you think OSM can be / should be used as an investigation tool?
 - a. What all can it be used for?
 - b. How it can be used in investigations e.g.?
 - c. What all techniques / ways you think are being used for investigation on OSM?
 - d. If No, why?
- 9) Do you think OSM can be used for monitoring events and criminal activities?
 - a. If yes how?
 - b. If no why?
- 10) To investigate cases / to monitor OSM, do you feel a need to create fake profiles / accounts?
 - a. Is it allowed legally?
 - b. Do u think you can do this by taking permission from certain higher authority?
- 11) What is the effect of using OSM on pace of investigation for some cases / on activities to maintain law and order?
 - a. What are the benefits / disadvantages?
 - b. And how?
- 12) Do you think OSM can help you to obtain information from public, which can be used to identify criminals / obtain information about crime?
-- If yes; what is it?
- 13) Do you think OSM can be used to push / share information like recent crimes,

- criminals, success stories etc. to citizens?
- a. If Yes, for what kind of information?
 - i. How will it be helpful to the Govt.?
 - ii. Are you aware of any such steps taken by your organization in this respect?
 1. If yes, what are they?
 2. What more should be done?
 - b. If No, why?
- 14) Who do you think would be the appropriate people in your organization to push / share such information on OSM, if at all required for PR / for engaging public?
- 15) According to you, who are the target audience you want to reach through OSM for
- a. Building intelligence
 - b. Staying connected with people
 - c. Broadcasting information
- 16) How often do you use / think OSM should be used for pushing information?
- a. In what context should the information be used?
- 17) Have you ever tried to push some information on OSM?
- a. If yes, was it helpful for you?
 - b. If yes, did it ever result in negative response / lead to a bad experience?
 - c. If no, Why?
- 18) Do you think, OSM can help improve the coordination between Law enforcement agencies and the public?
- a. Is OSM the right platform to engage the public to help maintain law and order
 - i. If yes, How?
 - ii. What information will you like to take / respond to through OSM?
 - iii. How often do you use / think OSM should be used for Public Relations?
 - iv. If no, why?
- 19) Do you think information obtained from OSM during a crisis event is helpful?
- a. If yes, how? Can you please elaborate
- 20) When do you think the impact of online social media is highest during a crisis / critical situation e.g. riots, protests etc.?
- Prompts:
- a. [Rumor generally spreads in first few hours]
 - b. [Real world crime is highest]
- 21) Can you think of some ways to curb negative use of OSM during crisis events?

- a. Do you think Social media can be used during the crisis events to send credible and trust worthy information for people?
 - i. If Yes, How?
 - ii. Who should do this task?
 - b. Do you know of any countries where it is being used for such information dissemination?
 - i. Yes – Can you share some of these examples with us?
 - c. If no, Why not?
- 22) Do you think OSM can be used to give warnings and alerts to general public during crisis?
 - a. If yes, what kind of warnings?
 - b. If No, why not?
- 23) Do you think OSM can be used to anticipate crime?
 - a. If yes, How?
 - b. If no, why not?
 - i. Do you think it is possible to use OSM for crime anticipation in future?
- 24) Do you think OSM is being used satisfactorily by law agencies to maintain law and order?
 - a. If yes? How
 - b. If No, Why? What changes can be done?
- 25) Do you think there are some hindrances which stop the use of OSM as an effective tool for maintaining law and order (in general)
 - a. If Yes, What according to you are the major hindrances?
 - b. What do you think can go wrong? Give example?
- 26) Do you think organizations like yours should be encouraging the use OSM to maintain law and order?
- 27) Do you have any internal guidelines / training material / policies for using OSN for information gathering in your organization?
 - a. What are they?
 - b. If we were to develop a set of guidelines, what would you like us to include in it? E.g. do not share the name.
- 28) What according to you is a trustworthy and useful medium to disseminate information OSM or TV, newspapers etc.?
 - a. How is it a better than other media?
 - b. If no, why? Can it be made a better-broadcast channel?
- 29) What according to you is a trustworthy and useful medium to collect information OSM or TV, newspapers etc.?
- 30) Do you think OSM can be helpful in crime prevention?
 - If yes how?

If no, do you think it can be used in future? How?

Developing Response strategy

Suppose, you are managing the Facebook / Twitter page of your organization. What will be your response (post, retweet, delete, reply or report) in following scenarios or if you see following tweets / posts:

31)

- a. A tweet / Post with a positive feedback about your organization, which others (general public) in OSM should know.
 - i. Eg: We thank police for reducing the crime in our city.
 1. Why?
- b. Tweet from your organization asking information from general public:
 - i. Eg: Police announced a Prize of 10 Lac on providing names of wanted criminals by the Anti Terrorism Squad in Mumbai.
 1. Why?



Bangalore City Police

ಈ ಕೆಳಕಂಡ ವಾಂಟ್ಡ್ ಅಪರಾಧಿಗಳ ಬಗ್ಗೆ ಮಾಹಿತಿ ನೀಡಿದರೆ 10 ಲಕ್ಷ ನಗದು ಹಣ ನೀಡಲಾಗುವುದು. ಯಾಸಿನ್ ಭಟ್ಟರ್, ತಹಸೀನ್, ಅಸದುಲ್ಲಾ ಅಖ್ತರ್ ಮತ್ತು ವಾಕ್ವಾಸ್ ಈ ಎಲ್ಲಾ "ವಾಂಟ್ಡ್ ಅಪರಾಧಿಗಳು" ಮುಂಬೈ ವಿರೋಧಿ ಭಯೋತ್ಪಾದನೆ ಸ್ಕ್ವಾಡ್ (ATS) 2011 ಮತ್ತು 2012 ರಲ್ಲಿ ಮುಂಬೈ ಮತ್ತು ಪುಣೆ ಬಾಂಬ್ ಸ್ಫೋಟಕ್ಕೆ ಸಂಬಂಧಿಸಿದ್ದಾರೆ. ಈ ಅಪರಾಧಿಗಳ ಬಗ್ಗೆ ಯಾವುದೇ ಮಾಹಿತಿ ನಿಮಗಿದ್ದರೆ, ಕೂಡಲೇ ಈ ಸಂಖ್ಯೆಗೆ ಕರೆ ಮಾಡಿ ತಿಳಿಸಿ. ದೂರವಾಣಿ ಸಂಖ್ಯೆ : Tel: 022.23791619, Mob: +91.9619122222 / +91.8652012345
ಈ ಮೇಲ್ : atswantedaccused@gmail.com
ನಿಮ್ಮ ಹೆಸರು ಮತ್ತು ವಿವರಗಳನ್ನು ಸಂಪೂರ್ಣವಾಗಿ ಗೌಪ್ಯವಾಗಿ ಇಡಲಾಗುತ್ತದೆ.

Cash reward of Rs. 10 Lac on providing information of these Wanted Criminals

Yasin Bhatkal, Tahaseen, Asadullah Akhtar and Waqas are all 'WANTED CRIMINALS' by the Anti Terrorism Squad (ATS) Mumbai in connection with the Mumbai and Pune Bomb blasts in 2011 and 2012.

If you have any information about these criminals, please report to the authorities immediately.

Tel: 022. 23791619, Mob: +91. 9619122222 / +91. 8652012345
Email: atswantedaccused@gmail.com

Your name and details will be kept completely confidential.

Like · Comment · Share · February 28

- c. Tweet / post from other organization giving any information:
 - i. Eg: UP police requested people in a tweet not to trust any rumors / messages on Facebook, Twitter, You Tube and Whatsapp



UP Police PR shared Pro TO Dgp UP's status.

September 8

कृपया FACEBOOK, TWITTER, YOU TUBE, WHATSAPP पर प्रचारित किसी भी प्रकार की अफवाह, वीडियो क्लिपिंग पर विश्वास न करें। उपद्रवियों पर सख्ती से काबू पाया जा रहा है।

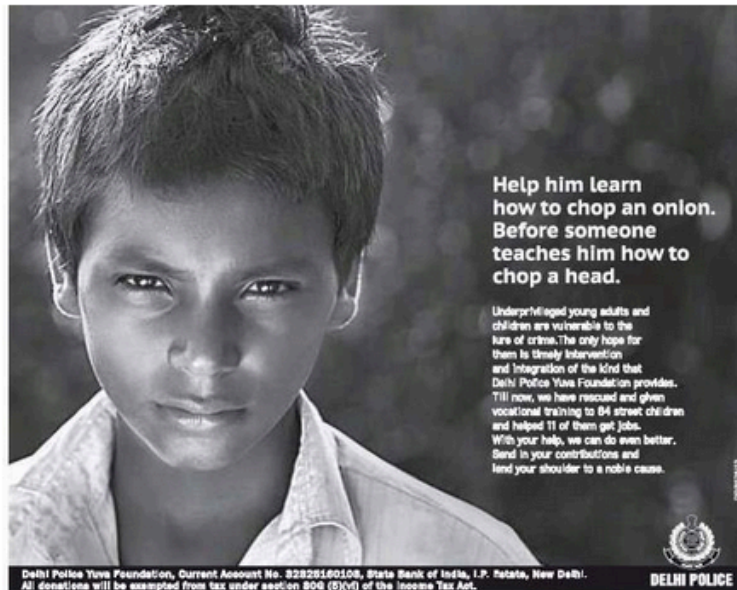
- d. Tweet from higher authority.
 - i. E.g.: Your senior officer posting a tweet enlightening people

- about some current actions, which your department took.
- ii. E.g. A personal post / tweet for your boss

- 32) A tweet with disagreement expressed in it from common people:
- a. For e.g. People complaining about a girl being beaten in a WagonR car on the Greater Noida Expressway. But a single policeman / PCR van was there to help.

Royden D'Souza @roydendsouza 25 Aug
 @uppolicer Man ruthlessly beating girl in a WagonR car on the Greater Noida Expressway. Not a single policeman in sight. No PCR van either
 Expand

 **Aditya Bhandari**  30 Jul
 Are you out of your minds, Delhi Police? That is a CHILD.
pic.twitter.com/yEe0aj3c5F via @BhopalHouse @delhipolice2
 Hide photo  Reply  Retweet  Favorite ... More



- 33) A tweet that is posted on your timeline and has a question for you in it? E.g. In case of riots, people seeking information from you about the current happenings.

- a. If you know the answer for it.
- b. If you can find an answer for it.
- c. If you don't know anything about it.

- 34) A tweet, which is humorous but is negative in nature i.e. Sarcastic?

a. Eg

- 35) A tweet with sensitive information mentioning you in the tweet? Eg: During the Muzaffarnagar riots, a resident tweeted that : *"Plan to attack Krishnapuri*

Muhalla. Assembly in khalapur mosque of Muzaffarnagar. Please do needful @upplicepr and @adgpi”



36) What will be your reaction if you see a tweet misleading / with incorrect information on Facebook / Twitter.

Eg: Toi posting wrong information and apologizing later

What will you do if:

- If you have the correct information or links to resources?
- Can you find the correct information or links to resources?
- Otherwise

37) If you see a post / tweet which is negative and can be flaming? What will you do in the following scenarios:

Eg: In the Muzzafarnagar riots, messaging showing morphed news articles and news items showing dead bodies were posted on facebook and twitter.

#UPriots #Muzaffarnagar
 Fake news: facebook.com/photo.php?fbid...●
 Original link: allbanaadir.net/news.php?readm...●
[@uppolicer pic.twitter.com/XnoYldpUrv](https://twitter.com/XnoYldpUrv)●

◀ Reply ↻ Retweet ★ Favorite ●●● More



- 38) Tweets / posts which are abusive?
 - a. We hate police for not taking action in time.
- 39) Criminals bragging about their crimes.
 - a. E.g. In Muzaffarnagar riots a criminal bragged that he has killed 10 Muslims.
- 40) What actions can be taken against the citizens in scenarios (35 – 39)?
- 41) Will you act on the information presented in the tweets mentioned in above scenarios?
 - a. How long do they think it will take to act on the information?
- 1) Which all-messaging apps do you use for your day-to-day activity to maintain law and order / official purposes ?
 - a. Whatsapp, truecaller, Line, Wechat etc.
 - i. If more than one, which among them is most effective?
- 2) What are different purposes for which law and order agencies use these apps?

On Prompts:

 - a. Investigate cases,
 - b. Faster communication with peers like Transfer important crime reports and statistics, Transmit photographs of crime spots, suspects, accused and victims.
 - c. Better record keeping
 - d. Faster communication with victims
- 3) Have you / somebody you know used messaging apps for such purposes?
 - a. If yes, can you share some of your experiences with us on use of such apps?
 - b. If no, next question.

- 4) Who all do you think your messages sent through whatsapp etc. are available to?
- 5) What is the effect of using messaging services on pace of investigation for some cases / on activities to maintain law and order?
 - a. What are the benefits?
 - b. Do you see some disadvantages?
 - c. And how?
- 6) What all can be done to improve the law and order through these apps?
- 7) Which department do you work for?
- 8) What is your age
 - a. 18 – 24
 - b. 25 - 34
 - c. 35- 44
 - d. 45 -55
 - e. 55 – 65
 - f. 65+
- 9) What is your gender?
- 10) Which state do you work for?

We are done! Any final thoughts on OSN and policing.
Thanks for your time.

Appendix-B

Introduction

This study is focused on understanding the current status of police initiatives to use Online Social Media (OSM). We believe outcomes of this study will help bridge the understandings of citizens to Law and Order services.

All the views presented during this study will be treated as your own views. Please keep in mind that there is nothing right or wrong response for the questions that we will be asking.

For transcribing purposes, we will be recording this conversation. If you would not like us to record some part of this discussion, we will stop recording for those parts of the discussion. We plan to write a report from the analysis we do from this study. We will make the report public and will be happy to share it with you.

- 1) Which OSN do you use for to keep yourself updated on latest activity among your friends and world events?
 - a. Facebook, Twitter, Google +, Youtube, Instagram, Pinterest, Whatsapp, Truecaller Any other.....
- 2) Are you aware of police organization presence on social networks?
 - a. If yes, please tell us something about it.
 - b. If no, would you like police presence on OSM.
- 3) Do you / will you like to follow Police / or law and order agencies on Twitter / Facebook?
 - a. If yes, how will it helpful?
 - b. If no, why?
- 4) Will you / do you like to report issues to police on Facebook / Twitter pages?
 - a. If yes, what kind of issues?
 - i. How frequently?
 - b. If no, have you seen others reporting issues on Facebook / Twitter pages?
 - i. If yes, what kind of issues?
 1. How frequently?
 - ii. If no, why will you not report issues to police on Facebook?
- 5) Will you post your personal information on these police organization pages if required?

Prompts

 - a. Phone numbers
 - b. Evidences of the crime
 - c. Your current location / address

d. Sensitive information e.g. somebody threatened you

--Whom do you think these posts are visible?

-- If No, why?

- 6) How frequently do you expect the police to respond back to you, on the complaint that you have lodged?
 - a. What ways will you want the police to respond to you – public reply to your post / personal post?
 - b. Have you or anybody you know interacted with police on OSM.
 - i. If yes, Please share your experience with us.
- 7) How much trustworthy do you think is the information obtained from OSM?
 - a. How trustworthy is the information on policing pages? E.g. there is a blast in the city.
 - b. Can you please give us an example of some information that you found on these
 - i. Was this information useful?
- 8) How do you think, you can help police using the facebook / twitter pages to improve law and order situation in your city?
 - a. Know more about police initiatives
 - b. Help give timely advice
 - c. On prompt:
 - i. Will you retweet (like /share) or spread the tweets?
 - ii. Will you respond to the posts / police requests.
- 9) What are the different ways you see OSM being used for day-to-day activity of police to maintain law and order?

Prompts:

 - a. Monitoring (Which OSM has been / will be most helpful)
 - i. Investigation
 - ii. Gauging public sentiment
 - b. Engaging public participation and using OSM as PR
 - c. Pushing your content on OSM
- 10) Do you feel a need of alerts from policing services / organization on OSM?
- 11) Which medium (OSM, TV, newspaper) do you think is trustworthy to obtain information from law and order agencies?
 - a. Why do you think so?
 - b. If not OSM, can OSM be improved to be used for law and order purposes.

Suppose, you see following tweets / posts on police page, what will be your response (post, retweet, delete, reply or report, do not do anything) in following scenarios or if you see following tweets / posts:

12)

- a. A tweet / post with a positive feedback about police organization of your area / state, which others (general public) in OSM should know.
 - i. Eg: We thank police for reducing the crime in our city.
 1. Why?
- b. Tweet from your state police organization asking information from general public:
 - i. Eg: Police announced a Prize of 10 Lac on providing names of wanted criminals by the Anti Terrorism Squad in Mumbai.



Bangalore City Police

ಈ ಲೇಔಂಡ ವಾಂಟೆಡ್ ಅಪರಾಧಿಗಳ ಬಗ್ಗೆ ಮಾಹಿತಿ ನೀಡಿದರೆ 10 ಲಕ್ಷ ನಗದು ಹಣ ನೀಡಲಾಗುವುದು. ಯಾಸಿನ್ ಭಟ್ಟರ್, ತಹಸೀನ್, ಅಸದುಲ್ಲಾ ಅಖ್ತರ್ ಮತ್ತು ವಾಕ್ವಾಸ್ ಈ ಎಲ್ಲಾ "ವಾಂಟೆಡ್ ಅಪರಾಧಿಗಳು" ಮುಂಬೈ ವಿರೋಧಿ ಭಯೋತ್ಪಾದನೆ ಸ್ಕ್ವಾಡ್ (ATS) 2011 ಮತ್ತು 2012 ರಲ್ಲಿ ಮುಂಬೈ ಮತ್ತು ಪುಣೆ ಬಾಂಬ್ ಸ್ಫೋಟಕ್ಕೆ ಸಂಬಂಧಿಸಿದ್ದಾರೆ. ಈ ಅಪರಾಧಿಗಳ ಬಗ್ಗೆ ಯಾವುದೇ ಮಾಹಿತಿ ನಿಮಗಿದ್ದರೆ, ಕೂಡಲೇ ಈ ನಂಬರ್ ಗೆ ಕರೆ ಮಾಡಿ ತಿಳಿಸಿ. ದೂರವಾಣಿ ಸಂಖ್ಯೆ : Tel: 022.23791619, Mob: +91.9619122222 / +91.8652012345 ಈ ಮೇಲ್ : atswantedaccused@gmail.com ನಿಮ್ಮ ಹೆಸರು ಮತ್ತು ವಿವರಗಳನ್ನು ಸಂಪೂರ್ಣವಾಗಿ ಗೌಪ್ಯವಾಗಿ ಇಡಲಾಗುತ್ತದೆ.

Cash reward of Rs. 10 Lac on providing information of these Wanted Criminals

Yasin Bhatkal, Tahaseen, Asadullah Akhtar and Waqas are all 'WANTED CRIMINALS' by the Anti Terrorism Squad (ATS) Mumbai in connection with the Mumbai and Pune Bomb blasts in 2011 and 2012.

If you have any information about these criminals, please report to the authorities immediately.

Tel: 022. 23791619, Mob: +91. 9619122222 / +91. 8652012345
Email: atswantedaccused@gmail.com

Your name and details will be kept completely confidential.

[Like](#) · [Comment](#) · [Share](#) · February 28

- c. Tweet / post from other state's organization giving any information:
 - i. Eg: UP police requested people in a tweet not to trust any rumors / messages on Facebook, Twitter, You Tube and Whatsapp



UP Police PR shared Pro TO Dgp UP's status.
September 8

कृपया FACEBOOK, TWITTER, YOU TUBE, WHATSAPP पर प्रचारित किसी भी प्रकार की अफवाह, वीडियो ह्छीपिंग पर विश्वास न करें। उपद्रवियों पर सख्ती से काबू पाया जा रहा है।

- d. Tweet from higher police authority.
 - i. E.g.: Senior officer posting a tweet enlightening people about some current actions, which your department took.
 - ii. E.g. A personal post / tweet of a police inspector

13) A tweet with disagreement expressed in it from other common people:

- a. For e.g. People complaining about a girl being beaten in a WagonR car on the Greater Noida Expressway. But a single policeman / PCR van was there to help.

Royden D'Souza @roydendsouza

25 Aug

@uppolicer Man ruthlessly beating girl in a WagonR car on the Greater Noida Expressway. Not a single policeman in sight. No PCR van either

Expand



Aditya Bhandari

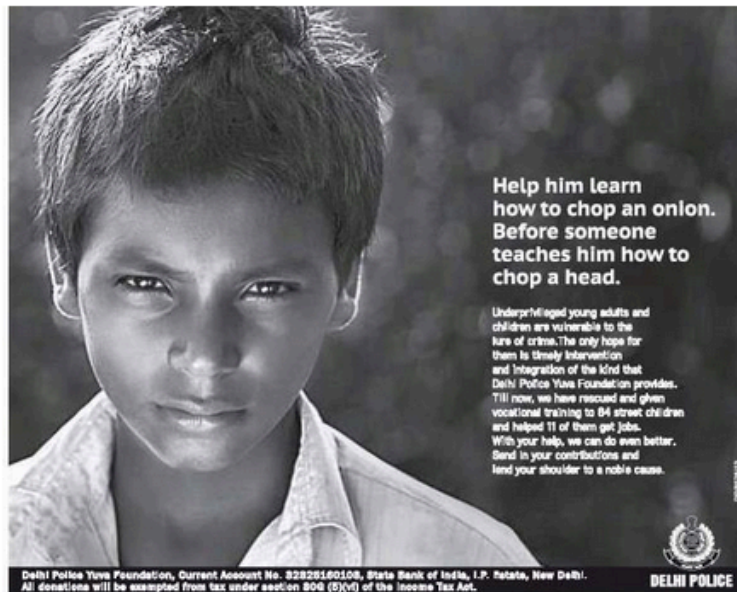
30 Jul

Are you out of your minds, Delhi Police? That is a CHILD.

pic.twitter.com/yEe0aj3c5F via @BhopalHouse @delhipolice2

Hide photo

Reply Retweet Favorite More



14) A tweet that is posted on your timeline and has a question for police in it? E.g. In case of riots, people seeking information from police about the current happenings.

- a. If you know the answer for it.
- b. If you can find an answer for it.
- c. If you don't know anything about it.

15) A tweet, which is humorous but is negative in nature i.e. Sarcastic?

a. Eg

16) A tweet with sensitive information mentioning police department of your state in the tweet? Eg: During the Muzaffarnagar riots, a resident tweeted that :
"Plan to attack Krishnapuri Muhalla. Assembly in khalapur mosque of Muzaffarnagar. Please do needful @uppolicer and @adgpi"

Definitely forward to page / repost it



- 17) What will be your reaction if you see a tweet misleading / with incorrect information on Facebook / Twitter.
- Eg: Toi posting wrong information and apologizing later
 - What will you do if:
 - If you have the correct information or links to resources?
 - Can you find the correct information or links to resources?
 - Otherwise
- 18) If you see a post / tweet which is negative and can be flaming? What will you do in the following scenarios:
- Eg: In the Muzaffarnagar riots, messages showing morphed news articles and news items showing dead bodies were posted on Facebook and Twitter.

#UPriots #Muzaffarnagar

Fake news: facebook.com/photo.php?fbid...

Original link: allbanaadir.net/news.php?readm...

@upplicepr pic.twitter.com/XnoYldpUrv

Reply Retweet Favorite More



- 19) Tweets / posts which are abusive?
 - a. We hate police for not taking action in time.
- 20) Tweets / posts which are spam?
 - a. E.g. Tweets are not relevant.
- 21) Criminals bragging about their crimes.
 - a. E.g. In Muzaffarnagar riots a criminal bragged that he has killed 10 Muslims.
- 22) Which all-messaging apps such as whatsapp do you use for your day-to-day activity to maintain law and order / official purposes ?
 - a. Whatsapp, BBM, hike, truecaller, Line, Wechat etc.
 - b. If more than one, which among them is most effective?
- 23) Do you think police should use it.
- 24) What are different purposes do you think that law and order agencies use these apps?

On Prompts:

 - a. Investigate cases,
 - b. Faster communication with peers like Transfer important crime reports and statistics, Transmit photographs of crime spots, suspects, accused and victims.
 - c. Better record keeping
 - d. Faster communication with victims
- 25) Have you / somebody you know used messaging apps for interacting with police?
 - a. If yes, can you share some of your experiences with us on use of such apps?
 - b. If no, next question.

- 26) What according to you is the effect of using messaging services on the help provided by law and order agencies?
- What are the benefits?
 - Do you see some disadvantages?
 - And how?
- 27) Would you like to have an exclusive app from police departments for interaction with public?
- If yes, what all can be done to improve the law and order through these apps?
- 28) What is your age
- 18 – 24
 - 25- 34
 - 35-44
 - 45 -55
 - 55 – 65
 - 65+
- 29) Which platform, Twitter or Facebook will be better for police to use to keep in touch with you?
- Why
- 30) What is your gender?
- 31) For how long you have been using OSM such as Twitter , Facebook etc.
- 32) Which state do you belong to?

Appendix-C

Survey OSM

**1. Which of the following activities can you use online social media e.g. Facebook for?
[Please check all that apply]**

- ☐ Crime Investigation
- ☐ Listening / Monitoring
- ☐ Intelligence
- ☐ Soliciting tips about crime
- ☐ Notifying the public of crime problems
- ☐ Notifying the public of emergency situation or disaster related issues
- ☐ Crime prevention activities
- ☐ Community outreach / citizen engagement
- ☐ Public relation / reputation management
- ☐ In-service training
- ☐ Recruitment
- ☐ Vetting / background investigation of job candidates
- ☐ Don't use social media tools

Other (please specify)

Survey OSM

2. Which online social media platforms do you currently use? [Please check all that apply]

- ☐ Facebook
- ☐ Google+
- ☐ LinkedIn
- ☐ MySpace
- ☐ Twitter
- ☐ Vine
- ☐ YouTube
- ☐ Other text / email bases communication
- ☐ Whatsapp
- ☐ WeChat
- ☐ Line
- ☐ Do not use any

Other (please specify)

3. What are the barriers to using online social media for your day to day activity? (Select all that apply)

- ☐ Security concerns
- ☐ Privacy concerns
- ☐ Liability concerns
- ☐ Resource constraints like machines, Internet
- ☐ Resource constraints like personnel
- ☐ Not appropriate for my community

Other (please specify)

4. Does your organization have a written online social media policy?

- ☐ Yes
- ☐ No
- ☐ I don't know

Other (please specify)

Survey OSM

5. What are the types of investigation that you think can be done through online social media?

- ☐ Identify persons of interest
- ☐ Identify criminal activity
- ☐ Identify associates and acquaintances affiliated with persons of interest
- ☐ Identify location of criminal activity
- ☐ Gather photos or statements to corroborate evidence
- ☐ Identify/monitor persons of interest's whereabouts
- ☐ Understanding criminal networks
- ☐ Soliciting tips on crimes
- ☐ Use information from social media as probable cause for search warrants

Other (please specify)

6. How much do you agree / disagree with the following statement?

	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Online social media in crime fighting/investigating activities will be critically important in the future.	☐	☐	☐	☐	☐
Online social media policy is necessary for using and benefitting from OSM effectively.	☐	☐	☐	☐	☐
Information obtained via online social media can help me solve my investigations more quickly.	☐	☐	☐	☐	☐
Online Social media is a valuable tool in anticipating crimes.	☐	☐	☐	☐	☐
Information obtained via online social media is trustworthy.	☐	☐	☐	☐	☐

Survey OSM

7. Please specify what is your age?

- ☐ 18 – 24
- ☐ 25 - 34
- ☐ 35- 44
- ☐ 45 -55
- ☐ 55 – 65
- ☐ 65+

8. What is your gender?

- ☐ Male
- ☐ Female

9. Serial number

Appendix-D

Helping Police use Online Social Media

This study, an initiative by PreCog @ IIIT-Delhi is focused on understanding citizens' perceptions and concerns about Online Social Media (e.g. Facebook, Twitter) use by different Police Departments. This survey will help understand citizen's expectation from police Facebook pages / Twitter account and offer better services.

Thank you for your time in filling the survey. It will not take more than 10 - 15 minutes to fill this survey.

***1. According to you, for which of the following activities should police use online social media e.g. Facebook ? [Please check all that apply]**

- ☐ Crime Investigation
- ☐ Listening / Monitoring
- ☐ Intelligence
- ☐ Soliciting tips about crime
- ☐ Notifying the public of crime problems
- ☐ Notifying the public of emergency situation or disaster related issues
- ☐ Crime prevention activities
- ☐ Community outreach / citizen engagement
- ☐ Public relation / reputation management
- ☐ In-service training
- ☐ Recruitment
- ☐ Vetting / background investigation of job candidates
- ☐ Should not use social media tools
- ☐ None of the above
- ☐ All of the above
- ☐ Other (please specify)

***2. According to you, do Police pages / accounts (e.g. Delhi Police Page, Mumbai Police page, or any other state police page) exist on Online Social Media e.g. Facebook, Twitter etc.? Choose one which is applicable.**

- ☐ Yes, I have seen police page / profile on Online Social Media
- ☐ Yes, I have heard about police pages but not seen them
- ☐ No, I am not aware of such pages / profiles on Online Social Media
- ☐ Other (please specify)

***3. Which online social media platforms would do you like to use to communicate with police ? [Please check all that apply]**

- ☐ Facebook
- ☐ Google+
- ☐ LinkedIn
- ☐ MySpace
- ☐ Twitter
- ☐ Vine
- ☐ YouTube
- ☐ Other text / email bases communication
- ☐ Whatsapp
- ☐ WeChat
- ☐ Line
- ☐ Do not use any
- ☐ Other (please specify)

***4. Which of these according to you are potential barriers for using online social media by police departments ? (Select all that apply)**

- ☐ Security concerns
- ☐ Privacy concerns
- ☐ Liability concerns
- ☐ Resource constraints like machines, Internet
- ☐ Resource constraints like personnel
- ☐ Not appropriate for their community
- ☐ Other (please specify)

***5. How would you like to communicate information (e.g. complaints and feedbacks) to police using Online Social Media? Choose one which is applicable.**

- ☐ Post anonymous information on police page.
- ☐ Post on police page with minimal personal results e.g. email id.
- ☐ Send direct messages to police pages.
- ☐ Create a fake account to inform police.
- ☐ Would use police pages to get information only.
- ☐ Other (please specify)

***6. What issues will you like to report to police using OSM? [Choose all the apply]**

- ☐ Eve Teasing cases
- ☐ Neighbor hood problems like drunk people on streets, loud music of streets
- ☐ Traffic Problems
- ☐ Domestic violence
- ☐ Beggars
- ☐ Child Labour
- ☐ Barricading in wrong areas
- ☐ Give feedback about their actions
- ☐ Theft
- ☐ Other (please specify)

***7. How much do you agree / disagree with the following statement?**

	Strongly agree	Agree	Neutral	Disagree	Strongly disagree
Online social media in crime fighting / investigating activities will be critically important in the future.	☐	☐	☐	☐	☐
Police should make an Online social media usage policy (rules and regulation) for using and benefitting from Online Social Media effectively.	☐	☐	☐	☐	☐
Information obtained via online social media can help police solve investigations more quickly.	☐	☐	☐	☐	☐
Online Social media is a valuable tool in anticipating crimes.	☐	☐	☐	☐	☐
Information obtained via online social media is trustworthy.	☐	☐	☐	☐	☐

***8. How much time should Police take to acknowledge that they have seen the posts / messages posted on Online Social Media by citizens? Choose one which is applicable.**

- ☐ Less than an hour
- ☐ 1 - 2 hours
- ☐ 2 - 5 hours
- ☐ 6 - 24 hours
- ☐ 25 - 48 hours
- ☐ 1 week
- ☐ More than a Week
- ☐ Should take action on my problem, need not reply / acknowledge my complaint.
- ☐ Other (please specify)

***9. Suppose, you see following tweets / posts on police page, what will be your response (post, retweet, delete, reply or report, do not do anything) in following scenarios or if you see following tweets / posts: (Choose all that apply in each row.)**

[illegible]

bodies were posted on
Facebook and Twitter.

Tweets / posts which are
abusive. For E.g. We hate
police for not taking action
in time.

☐☐☐☐☐☐

Other (please specify)

***10. Please specify what is your age?**

- ☐ 18 – 24
- ☐ 25 - 34
- ☐ 35- 44
- ☐ 45 -55
- ☐ 55 – 65
- ☐ 65+
- ☐ Do not wish to disclose

***11. What is your gender?**

- ☐ Male
- ☐ Female
- ☐ Do not wish to disclose

***12. What is your profession? (Choose one which is applicable)**

- ☐ CA
- ☐ MBA
- ☐ Computer / IT related
- ☐ Housewife
- ☐ Manufacturing / Business
- ☐ Doctor
- ☐ Teaching / Research
- ☐ Fashion Designing
- ☐ Journalism
- ☐ Other (please specify)

Appendix E

		Emotional State					Valence		Intensity	
		Anger	Joy	Fear	Sadness	Disgust	Pos	Neg	Anxiety	Arousal
Forward	Mean	0.17	0.04	0.26	0.10	0.34	3.19	2.34	0.20	5.15
	Std	0.14	0.08	0.22	0.10	0.25	4.41	2.64	0.80	1.23
	Med	0.12	0.08	0.22	0.10	0.25	2.17	1.90	0.00	5.40
Give Solution	Mean	0.16	0.06	0.20	0.14	0.37	5.00	0.94	0.13	4.62
	Std	0.14	0.08	0.17	0.11	0.23	8.22	2.06	0.59	2.02
	Med	0.14	0.03	0.15	0.11	0.32	1.54	0.00	0.00	5.42
Thanks	Mean	0.1	0.16	0.28	0.09	0.27	6.92	0.45	0.13	4.57
	Std	0.10	0.19	0.24	0.07	0.24	8.55	1.32	0.85	2.46
	Med	0.08	0.09	0.18	0.07	0.18	4.33	0.00	0.00	5.65
Need more Info.	Mean	0.14	0.08	0.21	0.14	0.36	2.21	4.62	0.20	4.70
	Std	0.12	0.11	0.18	0.12	0.26	3.40	8.19	0.76	1.94
	Med	0.12	0.03	0.17	0.10	0.31	0.00	1.58	0.00	5.34
Kruskal Wallis		13.66**	44.42**	3.97	23.58*	10.42	24.90**	71.86**	2.37	3.92
Serviceable	Mean	0.15	0.06	0.24	0.11	0.34	3.78	2.3	0.18	4.90
	Std	0.13	0.11	0.21	0.10	0.25	5.88	4.34	0.77	1.73
	Med	0.12	0.02	0.18	0.08	0.27	2.08	0.63	0.00	5.42
Non-Serviceable	Mean	0.13	0.11	0.15	0.10	0.23	2.71	2.03	0.09	2.64
	Std	0.17	0.20	0.18	0.14	0.27	5.67	6.35	0.52	2.77
	Med	0.09	0.01	0.07	0.05	0.13	0.00	0.00	0.00	0.00
Mann Whitney U		-3.43**	-1.34	-6.09**	-5.45**	-3.88**	-3.92**	-3.32**	-1.58	-6.53**

*p<0.01 *p<0.05

Pos=Positive affect, Neg=Negative affect

Table 1: Mean, standard deviation (Std.), and Median(Med) of Emotional attributes across serviceable posts and its sub-types. Results of differences and statistical significance tests using Mann-Whitney U and Kruskal Wallis Test.

		Cognitive				Interpersonal					
		Cgmch	Insight	Cause	Certain	i	we	you	she	they	ipron
Forward	Mean	11.68	1.01	1.55	1.17	1.61	0.45	0.79	0.30	0.63	3.77
	Std	6.61	1.75	2.14	1.97	2.45	1.11	1.55	0.97	1.37	3.04
	Med	11.81	0.00	0.72	0.00	0.00	0.00	0.00	0.00	0.00	3.46
Give Solution	Mean	14.4	1.90	1.63	2.9 0	2.56	0.82	1.11	0.25	0.32	6.86
	Std	9.42	3.42	3.05	7.28	3.54	1.87	2.98	1.04	1.08	8.77
	Med	12.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.55
Thanks	Mean	11.24	0.75	1.42	1.64	0.70	1.21	1.19	0.37	0.26	3.14
	Std	11.48	2.48	3.56	3.92	2.36	3.53	3.13	1.44	0.77	4.88
	Med	10.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Need More Info.	Mean	9.7	1.13	1.5	0.93	1.80	0.58	0.88	0.62	0.53	3.44
	Std	8.70	2.21	2.57	5.03	3.77	2.08	1.98	2.74	1.84	4.22
	Med	10.44	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.47
Kruskal Wallis		16.26**	16.96**	9.93*	19.32**	24.80**	2.87	3.61	2.63	16.92**	17.64**
Serviceable	Mean	11.68	1.14	1.53	1.46	1.68	0.63	0.91	0.37	0.52	4.12
	Std	8.36	2.30	2.59	4.19	2.96	1.92	2.17	1.53	1.37	4.99
	Med	11.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.14
Non-Serviceable	Mean	8.63	0.78	1.26	0.89	1.54	0.73	1.29	0.32	0.44	2.39
	Std	10.66	2.31	2.66	3.55	9.50	2.85	3.81	1.50	1.71	4.29
	Med	4.55	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mann Whitney		-4.37**	-3.54**	-2.44**	-2.76**	-3.80**	-0.50	-1.68	-1.06	-2.19*	-5.20**

**p<0.01 *p<0.05

Cgmch = Cognitive mechanisms, i = 1st person singular pronouns, we = 1st person plural pronouns, you = 2nd person she = 3rd person singular pronouns, they = 3rd person plural pronoun, ipron = impersonal pronouns

Table 2: Cognitive orientation measures in serviceable posts and sub-types. Cognitive and Interpersonal focus are statistically different in serviceable posts and non-serviceable posts using Mann-whitney U Test.

		Objectivity		Tense			Grammer				
		subj	obj	past	prsnt	futr	artcl	vrb	axvrb	quant	numb.
Forward	Mean	0.77	3.47	1.88	6.93	0.68	5.49	10.26	6.56	2.13	0.54
	Std	1.23	3.16	2.86	4.47	1.40	4.25	5.41	4.14	2.71	1.13
	Med	0.00	3.00	0.26	6.79	0.00	5.21	10.34	6.63	1.41	0.00
Give Solution	Mean	0.24	2.64	1.68	11.05	0.75	4.10	14.56	10.64	2.47	0.33
	Std	0.53	2.8	3.55	8.03	1.64	4.27	8.92	8.23	4.08	1.19
	Med	0.00	2.00	0.00	9.6	0.00	4.09	14.29	9.15	0.00	0.00
Thanks	Mean	0.31	2.07	0.78	6.72	0.62	4.18	8.48	3.51	2.09	0.57
	Std	0.78	2.60	2.13	9.02	1.86	5.31	9.67	4.93	4.16	1.73
	Med	0.00	1.00	0.00	4.55	0.00	2.49	6.31	0.00	0.00	0.00
Need More Info.	Mean	0.38	1.90	2.14	5.76	0.61	4.91	8.91	5.14	1.37	0.53
	Std	1.00	1.29	3.23	5.48	1.82	5.31	6.97	4.68	2.45	1.91
	Med	0.00	1.00	0.00	5.41	0.00	4.17	9.38	5.26	0.00	0.00
Kruskal Wallis		37.18**	37.70**	18.49**	36.78**	10.53*	3.45	5.90	6.23	2.92	6.86
Serviceable	Mean	0.55	2.86	1.75	7.34	0.67	4.99	10.46	6.55	2.03	0.51
	Std	1.07	2.84	2.99	6.29	1.59	4.64	7.26	5.58	3.15	1.40
	Med	0.00	2.00	0.00	6.82	0.00	4.76	10.53	6.40	0.00	0.00
Non-Serviceable	Mean	0.19	2.04	0.81	4.96	0.25	2.47	6.38	3.45	1.93	0.37
	Std	0.59	2.63	2.87	7.14	0.74	4.53	8.42	6.00	4.87	1.43
	Med	0.00	1.00	0.00	0.00	0.00	0.00	0.4 0	0.00	0.00	0.00
Mann Whitney		-4.16**	-4.57**	-5.32**	-4.76**	-3.15**	-6.20**	-5.85**	-6.69**	-3.34**	-2.62**

**p<0.01 *p<0.05

Subj = Subjective; Obj = Objective; prsnt = present; futr = future; artcl=article; vrb=verb; axvrb=auxiliary verb, numb. = number

Table 3: Linguistic attributes of serviceable posts and its sub-types with statistical significance using Mann-whitney and Kruskal Wallis test.

Appendix F

Department	Likes	Followers
Ahmedabad City Police	68,933	68,459
Ahmedabad Traffic Police	25,810	25,627
Andhra Pradesh Police	950	940
Assam Police	9,686	9,679
BENGALURU CITY POLICE	5,98,149	5,94,932
Bengaluru Traffic Police	4,64,395	4,56,968
Bhopal Police	2,122	2,121
Central Police District - Guwahati	1,288	1,284
Chandigarh Police	3,443	3,440
Chattisgarh police	507	506
Chennai City Police	99,244	99,122
Chhattisgarh Police	4,350	4,358
Cyber Crimes Police Station	40,353	40,136
Cyberabad Police	22,954	22,953
Cyberabad traffic police	36,775	36,717
Dadra Nagar Haveli Police	1,917	1,916
Delhi Police	13,948	13,828
Delhi Police For North East Folks	62,380	62,361
Delhi Traffic Police	2,50,181	2,37,390
Durg Police	55,470	55,613
Faridabad Traffic Police	4,780	4,733
Gandhinagar Police	5,125	5,094
Gujarat Police	18,353	18,308
Gujarat Police,Gandhinaga Traffic	1,661	1,661
Gurgaon Traffic Police	57,024	56,335
Gurugram Police	96,054	95,230
HP Police	8,696	8,704
Hyderabad City Police	1,48,223	1,48,808
Hyderabad Traffic Police	2,67,008	2,62,771
IG Police Lucknow Range	194	192
Indore-Police	18,949	18,778
Jaipur Traffic Police	1,755	1,757
Jharkhand Police	3,942	3,943
Jharkhand Police	7,492	7,493
Kabirdham Police	3,478	3,461
Karnal Police	14,500	14,412
Karnataka State Police	24,248	24,268
Kerala Traffic Police	62,268	62,205

Kolkata Traffic Police	1,13,959	1,13,020
Kurnool Police	2,722	2,716
Lucknow Police	36,827	36,932
Mizoram Police	919	920
Orissa police	Na	Na
Patna Police	6,643	6,625
Police Commissionerate Faridabad	7,840	7,892
PS Abids, Hyderabad City, Telangana State	5,180	5,155
PS Begum Bazar, Hyderabad City, Telangana State	6,865	6,833
PS Gandhinagar, Hyderabad City, Telangana State	4,568	4,566
PS Narayanguda, Hyderabad City, Telangana State	5,210	5,221
PS Saifabad, Hyderabad City, Telangana State	3,292	3,284
Puducherry Police	3,557	3,558
Pune Traffic Police	97,124	96,126
Raipur Traffic Police	3,536	3,553
Rajasthan Police	Na	Na
Rohtak Range Police	5,104	5,048
Shillong Traffic Police	5,183	5,122
Shimla Police	9,130	9,079
Sikkim Police	15,075	15,067
Thiruvananthapuram Rural Police	3,070	3,070
Traffic Police Agartala	2,635	2,636
Traffic Police Jaipur	37,170	36,995
Traffic Police Ludhiana	27,587	27,479
Traffic Police Puducherry	2,531	2,528
Traffic Police Ranchi	1,743	1,727
Traffic Police, Udaipur	1,481	1,474
UP Police	34,921	35,103
Uttarakhand Police	8,295	8,307
Visakhapatnam Traffic Police	5,117	5,091
West Bengal Police	Na	Na

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