2015

Mining Behavior of Citizen Sensor Communities to Improve Cooperation with Organizational Actors

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Mining Behavior of Citizen Sensor Communities to Improve Cooperation with Organizational Actors

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy

by

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2015
Wright State University

Wright State University
GRADUATE SCHOOL

August 31, 2015

I HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER MY SUPERVISION BY Hemant Purohit ENTITLED Mining Behavior of Citizen Sensor Communities to Improve Cooperation with Organizational Actors BE ACCEPTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF Doctor of Philosophy.

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ABSTRACT

Purohit, Hemant. Ph.D., Department of Computer Science and Engineering, Wright State University, 2015. *Mining Behavior of Citizen Sensor Communities to Improve Cooperation with Organizational Actors.*

Web 2.0 (social media) provides a natural platform for dynamic emergence of citizen (as) sensor communities, where the citizens generate content for sharing information and engaging in discussions. Such a citizen sensor community (CSC) has stated or implied goals that are helpful in the work of formal organizations, such as an emergency management unit, for prioritizing their response needs. This research addresses questions related to design of a cooperative system of organizations and citizens in CSC. Prior research by social scientists in a limited offline and online environment has provided a foundation for research on cooperative behavior challenges, including '*articulation*' and '*awareness*', but Web 2.0 supported CSC offers new challenges as well as opportunities. A CSC presents information overload for the organizational actors, especially in finding reliable information providers (for *awareness*), and finding actionable information from the data generated by citizens (for *articulation*). Also, we note three data level challenges–*ambiguity* in interpreting unconstrained natural language text, *sparsity* of user behaviors, and *diversity* of user demographics. Interdisciplinary research involving social and computer sciences is essential to address these socio-technical issues.

I present a novel web information-processing framework, called the Identify-Match-Engage (IME) framework. IME allows operationalizing computation in design problems of *awareness* and *articulation* of the cooperative system between citizens and organizations, by addressing data problems of group engagement modeling and intent mining. The IME framework includes: a.) *Identification* of cooperation-assistive intent (seeking-offering) from short, unstructured messages using a classification model with declarative, social and contrast pattern knowledge, b.) Facilitation of coordination modeling using bipartite *matching* of complementary intent (seeking-offering), and c.) Identification of user groups to

prioritize for *engagement* by defining a content-driven measure of *group discussion divergence*.

The use of prior knowledge and interplay of features of users, content, and network structures efficiently captures context for computing cooperation-assistive behavior (intent and engagement) from unstructured social data in the online socio-technical systems. Our evaluation of a use-case of the crisis response domain shows improvement in performance for both intent classification and group engagement prioritization. Real world applications of this work include use of the engagement interface tool during various recent crises including the 2014 Jammu and Kashmir floods, and intent classification as a service integrated by the crisis mapping pioneer Ushahidi's CrisisNET project for broader impact.

List of Definitions

- **Formal Organization**. An organization or institution that has a defined structure of communication, roles, and work, e.g., city emergency management unit (EMU).
- **Organizational actor**. A member of the formal organization who understands and acts for the organizational tasks, processes and workflows, e.g., first responders.
- **Citizen sensor**. A user of social media platform, who participates in discussions on topics related to real world events by generating and sharing information. Roles of citizen sensors and organizational actors are assumed mutually exclusive.
- **Citizen sensor community (CSC)**. A group of citizen sensors on social media who participate in discussing various topics. No prior structure is assumed in a CSC.
- **Goal-oriented CSC**. A type of CSC where users have various intents to serve a goal, e.g., a voluntary group during crisis response, a group discussing insights on brand features, etc.
- **Crisis**. An escalated emergency event that may be specific, unexpected, and non-routine event or a series of events. It creates high levels of uncertainty and threat to an organization's high priority goals and its capacity.
- **Behavior**. A response to a stimulus environment, e.g., acts of offering help in a crisis.
- **Intent**. An aim/plan for (future) action, e.g., wish to donate clothes for help in a crisis.
- **Engagement**. A degree of involvement in discussions of a CSC, by participation in generating and sharing information.
- **Coordination**. Managing dependencies between tasks in an organizational workflow by *deliberate* joint actions. e.g., during crisis, a team of organizational actors of EMU collects information for resource needs from many sources, and processes collected information to achieve the goal of prioritizing responses.
- **Cooperation**. A *voluntary* joint action to help other actors achieve their goal—a contrast to coordination, which is deliberate due to managing the interdependent tasks of a defined workflow. Cooperation facilitates organizational coordination, e.g., during crisis, when organizational actors of EMU with defined roles are coordinating (deliberately) to collect information on resource needs, CSC members cooperate (voluntarily) with them to help mine data on urgent needs.
- **Awareness for Cooperation**. A challenge of facilitating shared knowledge among participating actors of cooperation, e.g., what-where-when-who during crisis response.

- **Articulation for Cooperation**. A challenge of managing task divisions and assembling various subtasks and sequences. In order to allow cooperation with citizens, organizational actors identify information needs specific to their task divisions, e.g., during crisis, seeking and offering resources are key information needs for clearly divided tasks of resource scarcity and availability information collection, which helps improve decision making of prioritization of response.

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Acknowledgment

I would like to acknowledge my adviser Prof. Amit Sheth (Semantic Computing), and my interdisciplinary committee members Prof. Valerie Shalin (Cognitive Science), Prof. Srinivasan Parthasarathy (Network Science), Prof. Krishnaprasad Thirunarayan (Algorithm Analysis and Modeling), Prof. Guozhu Dong (Pattern Mining), and Dr. Patrick Meier (Humanitarian Technology) for their eminent guidance. I also want to thank U.S. National Science Foundation for supporting my dissertation work under the award IIS-1111182, Social Computational Systems (SoCS) grant, titled "Social Media Enhanced Organizational Sensemaking in Emergency Response".

Especially, the curiosity of Prof. Sheth has inspired me to think broad and appreciate the value of research from the end users perspective, and I will be grateful for his guidance to investigate social impact related problems. His strong belief in making student success as the first priority and ensuring not only the much needed guidance from him but also if needed, enabling a channel to work with other experts has extensively helped me. His precious lessons on 'learning how to learn' has made a great impact on my work style.

I am thankful to Prof. Shalin to help me inculcate strong interdisciplinary thinking and significance of human factors in computing research that I will cherish forever in my life. Her frequent advice beyond just research on social and interpersonal skills has also helped me improve communication, given my background of coming from a modest family and non-native English language region. I am grateful to Prof. Parthasarathy, who not only guided me to strive for high quality research in the technical field while inspiring with deep curiosity for 'how can we do better with our algorithm', but also 'how to position ideas' in a systematic framework. I am thankful to Prof. Krishnaprasad Thirunarayan for his insightful questions to help me stay on track for a focused problem-centric research, and performing my best in that. His interests and expertise in a variety of problems indeed helped me for guidance to position the work well by systematically investigating how to model a problem give a choice of several possible forms. I am thankful to Dr. Patrick Meier for his guidance on ensuring the outcome significance for real world end users than merely creating technical methods. My work has been greatly inspired by his work and leadership in the domain of humanitarian technology on how to position the research and focus on simplicity of the research outcome. I want to thank Prof. Guozhu Dong for his guidance on modeling data-driven knowledge. Discussions with him on how to merge declarative human-guided and statistical data-driven knowledge have greatly influenced my thinking about positioning this research work.

I also take this opportunity to thank my mentors Dr. Meenakshi Nagarajan (IBM), Dr. Carlos Castillo (QCRI), Dr. Fernando Diaz (Microsoft), Dr. Alex Dow (Facebook), Dr. Omar Alonso (Microsoft), Dr. Shubha Nabar (LinkedIn), Dr. Jitendra Ajmera (IBM), Dr. Ashish Verma (IBM), Sachindra Joshi (IBM), Kevin Haas (Microsoft), and Lei Duan (Yahoo), for their invaluable guidance at various points of time beyond internships, and help me shape a sound thought process for this research. I am thankful for their supervision that has really enabled me to progress in the right direction for leading my goal of understanding human behavior for cooperation and organize this dissertation work.

I am also grateful to my collaborators, colleagues and professors at Kno.e.sis and Data Mining Lab at The Ohio State University for helping me find the exciting synergies in the collaborative work. I am thankful to my friends in the humanitarian sector's professional organizations and volunteer communities from CrisisMappers Network, Standby Task Force, InCrisisRelief.org, ITU Young Innovators program, United Nations Population Fund, DHS Virtual Social Media Working Group and others for supporting me in all the possible ways to work with perseverance on understanding challenges of humanitarian development. It has greatly assisted me in shaping thought process for the dissertation.

I am indebted to my family and friends in this journey. It would not have been possible without support from my family, especially inspiration from my grandfather Mr. P.S. Purohit, and uncle Dr. Y.C. Bhatt. My close friends made this PhD life a fun experience, and without their great support it would have been a difficult journey, especially Dr.

Meenakshi Nagarajan (mentor-cum-friend and Kno.e.sis alumnus), Pramod Anantharam, Ashutosh Jadhav, Raghava Muthuraju, Vinh Nguyen, Andrew Hampton, Shreyansh Bhatt, Dr. Tanvi Banerjee, Alan Smith, Jeremy Brunn, Wenbo Wang, and Lu Chen among the great labmates at Kno.e.sis; Dr. Yiye Ruan (now at Google), and David Fuhry at The Ohio State University, as well as other friends (indeed, a long list to mention!). Their intellectual, and emotional support has greatly helped me enjoy this wonderful journey of learning and creation while enjoying and experiencing all parts of the PhD life. At last, I also want to thank our administrative coordination team at Kno.e.sis, Tonya Davis, Amber McCurdy (former), and Jibril Ikharo for invaluable support throughout the PhD program.

Dedicated to

my grandfather Mr. P. S. Purohit, who taught us several important lessons including, "Life should be a purposeful journey that can give back to the humanity, and not simply a trip to a materialistic destination" …

Chapter 1: Introduction

The emergence of online communication platforms in the Web 2.0 era and the growing adoption of social media have revolutionized how citizens now interact with information. Unlike face-to-face communication, citizens now participate (act as sensors) in generating information instead of merely consuming information [109]. Consequently, online citizen sensor communities (CSCs) have emerged to share and engage in discussion surrounding real world events, for stated or implied goals, generating massive amounts of data in the process. Such citizen sensing, sharing, and participation provide a vehicle for organizations to interact and engage with citizens where there are likely interdependencies for organizational tasks, such as the prioritization of resource needs during crisis response when organizational capacity to respond exhausts [106, 4, 93]. Another scenario is the prioritization of customer concerns in the context of brand relationship management. However, CSCs supported by Web 2.0 social media platforms pose new challenges in the design of cooperative information system between citizens and organizational actors, and demand an interdisciplinary research approach.

This research lies at the intersection of computer and social sciences in the broad areas of computer-supported cooperative work (CSCW) and information science. Specifically, its contribution falls in the last two of the three paradigms of computer science [22] – *theory, abstraction (modeling), and design*. We have addressed the design problems of *'awareness'* and *'articulation'* for a cooperative web information system between citizens and organizational actors facilitated by a CSC on a Web 2.0 social platform. We have ad-

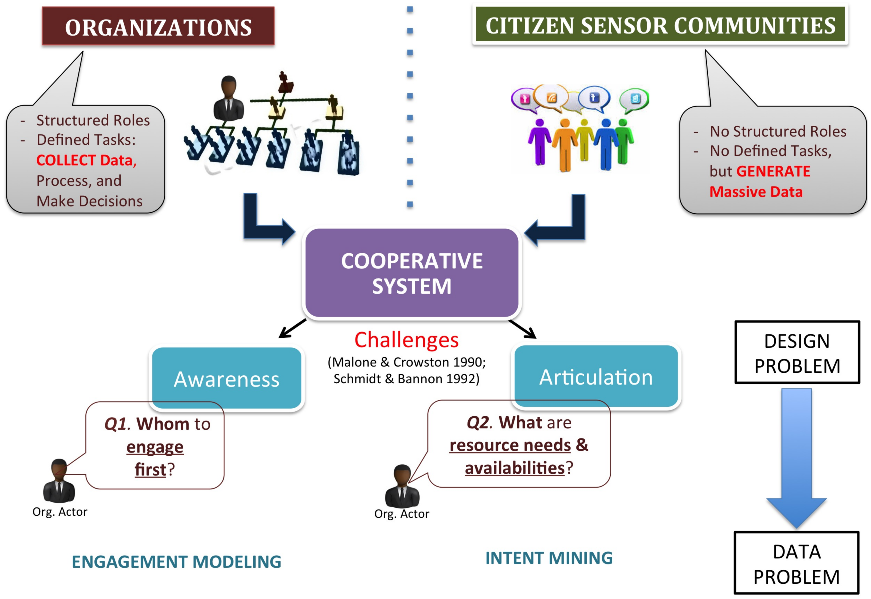


Figure 1.1: Transforming parts of the design level problems of *awareness* and *articulation* for a cooperative information system into computationally tractable data level problems in an online socio-technical environment.

dressed the design problems by operationalizing parts of them into two computationally tractable data problems (see Figure 1.1). First is the intent mining problem that accommodates *articulation* of organizational tasks to address the question *"what types of organizational information needs exist in the citizen-generated data"*. Second is the engagement modeling problem that informs *awareness* for organizational actors to address the question *"whom to prioritize to engage among citizens"*. In modeling intent using a priori knowledge, this work addresses the challenges of *ambiguity* in interpreting unconstrained natural language (e.g., "wanna help" appearing in opposing intentional content of seeking-offering help), and *sparsity* of user behaviors (e.g., lack of expression of specific type of intent such as offering help during crisis). In modeling engagement, this work addresses the challenge of *diversity* of user demographics (e.g., medical or technical professional) in the groups, using group representation guided by social identity and cohesion theories. We summarize the advantage of our fusion approach of top-down and bottom-up processing methods to

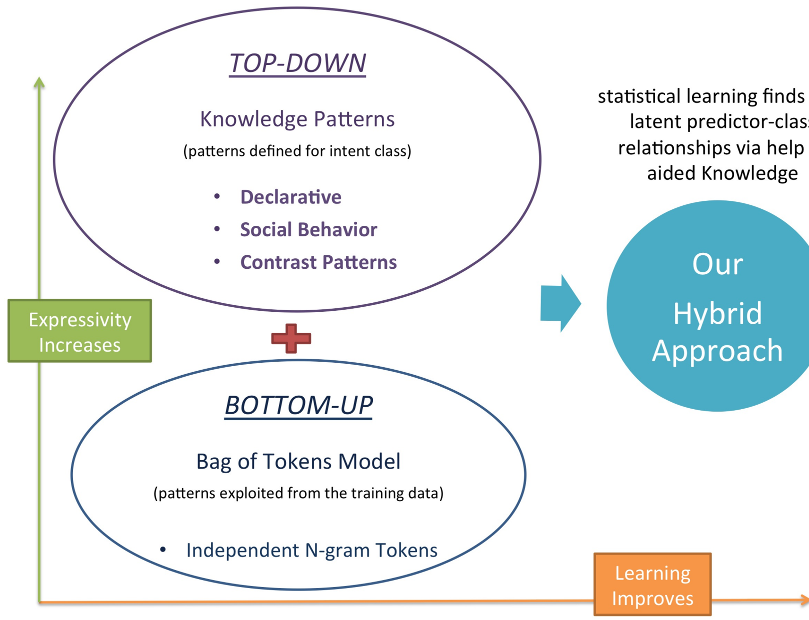


Figure 1.2: Improving representation of context in the data for learning intent, by fusing top-down and bottom-up processing approaches via a variety of knowledge sources (Details in Chapter 3).

address the data problems using various knowledge sources in Figure 1.2.

The following sections describe the emergence of goal-oriented CSCs, and the challenges of understanding cooperative behavior in such communities, followed by a novel approach to addressing those challenges via intent and engagement modeling.

1.1 Online Citizen Sensor Community (CSC) and Goal-orientation

Below we discuss the key component of the online citizen sensor communities–citizen sensors, followed by the existence of goals in CSC. We introduce the role of computational social science that has emerged to investigate new complexities of individual and group behavior.

- **Citizen Sensors**

Online social media has enabled citizens in unprecedented ways, letting them express and share their experiences and opinions, helping them propagate information from other sources, and allowing them to report observations about their surroundings—enabling a form of sensing. Sheth [109] termed this citizen sensing. This differs from the prior technology-mediated communication age, where citizens were merely recipients of information from the authoritative channels of organizations.

- **Goal Orientation of Citizen Sensors and Organizations in CSC**

Modern online platforms for social interaction facilitate the formation of communities of interest surrounding a goal—explicit or implicit—such as volunteering during times of crisis [116]. Growing citizen sensor participation and networked engagement forms online communities around discussions of real world events. For instance, 'Digital Humanitarians' as Meier [73] notes, played a key role in the unprecedented donation and relief coordination efforts after the Haiti earthquake in 2010. This exemplifies Clay Shirky's commentary on the social media technology in the formation of self-organizing groups. In the chapter "It Takes a Village to Find a Phone" from Shirky's book "Here comes everybody: The Power of Organizing Without Organizations" [112], he notes the emergence of groups and implicit goals regardless of any provided incentives or functional structures of traditional grouping characteristics. The existence of goal-oriented community behavior opens the potential to leverage CSC to improve cooperation between citizens and organizational actors. However, the stated or implied goals of a CSC drive a variety of specific individual or group intents. The persisting variety of intent challenges any sensemaking of the data.

- **Emergence of Computational Social Science**

Online citizens generate data on an unprecedented scale relative to face-to-face interactions. The resulting challenges include scale and speed of user-generated data, *diversity* of user demographics beyond geographical constraints, varied intentions of engagement, and *sparsity* of behavior across the corpus. The emergence of the new interdisciplinary research field of computational social science [61] acknowledges this opportunity to study the behavior of individuals and groups in the society with the help of computing. Within the scope of computational social science, we focus on a cooperative web information system design for citizens and organizational actors in CSC that can assist coordination of organizational tasks by mining the social media data during events such as crisis response. A key limitation of the state-of-the-art methods within organizations for this purpose is use of manually intensive efforts in the process of collection, filtering, and management of the information. For example, the registration of requests for needs and offers via platforms such as Recovers.org and AidMatrix.org during crisis response coordination. Computational approaches to overcoming the limitations in manual analysis require advances in understanding cooperative behaviors of citizen sensors in CSC.

1.2 Challenges for Cooperation of Citizens and Organizations: *Articulation* and *Awareness*

The emerging opportunity to study the human interaction data in the CSC promises to improve cooperation between citizens and organizational actors. Citizen sensing alone cannot ensure coordinated actions in the communities efficiently, by time and effort. We discuss the general challenges of coordination and cooperation first, and then place the present work in the context of the CSCW matrix.

- **Coordination and Cooperation**

Social scientists and computer scientists in the area of CSCW have been investigating the challenges of community behavior, self-organization, cooperation (behavior of *voluntary* joint action) and coordination (behavior of *deliberate* joint action) in both offline and online environments for several decades. The CSCW literature clarifies the challenges of cooperative work in general, and allows us to reflect on the potential roles and responsibilities of the formal (institutionalized) organizational actors, and the informal citizen sensor communities in cooperative online socio-technical environment, such as crisis response. However large-scale online social platforms test the validity of existing theories of cooperative behavior in the new medium and inform the need for new theories.

Malone and Crowston [71] defined coordination as managing dependencies between activities. On the other hand, cooperation is defined as a voluntary joint action for shared goals and therefore, assisting in managing dependencies. Cooperation provides a foundation for improving coordination. Participants engage in cooperative work when they are mutually dependent in the completion of their work (e.g., regarding decision making and task sequencing, etc.) [104]. Cooperating workers must *articulate* (divide, allocate, coordinate, schedule, mesh, interrelate) their distributed activities. Dividing the work, often between personnel units with specialized skills, distributes task interdependencies among those units [70]. One unit's effort to ameliorate the situation inevitably changes it, and each unit must track these intentional changes. In established organizations, pre-defined agreement on roles and responsibilities facilitates tracking and provides the shared understanding essential to cooperative work [53, 19]. But the decomposition of a complex problem can never fully avoid unanticipated interaction [113]. As a result, members of a cooperative system must be able to monitor the conduct of the interactive working parts [46]. That is, each unit requires information in order to maintain mutual *awareness* of activity that affects the others [104]. For instance, personnel who are co-located talk out loud to render their activities visible to other members of the cooperative system [46]. But when cooperative work occurs in a dynamic and distributed environment of remote interactions, unanticipated changes place further demand on maintaining *awareness*. Furthermore, these challenges of *articulation* and *awareness* are highly context dependent, as is the complex cooperative

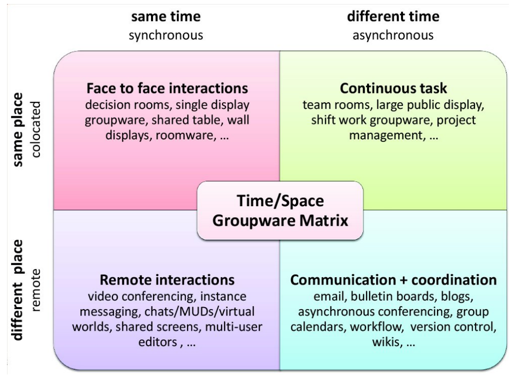


Figure 1.3: Summary of CSCW research matrix [56, 8]. Focus of this dissertation lies in mining citizen-sensed data to address challenges of *articulation* and *awareness* for cooperative behavior in the context of the bottom two quadrants of this matrix. The ultimate objective is to assist coordination of organizational workflow via cooperation between citizen sensors and organizational actors. (Image Credit: Wikipedia)

web information system of citizens and organizational actors.

- **The CSCW Matrix**

The CSCW literature identifies two dimensions to characterize work domains: time and space. This dissertation focuses on addressing issues of CSCW for domains that involves remote and potentially asynchronous interactions between cooperative actors from both CSCs and organizations. Therefore, we focus on the challenges in the bottom two quadrants of the CSCW matrix [56, 8] shown in Figure 1.3. These challenges require a systematic conceptual framework to develop computational methods that can address issues of *awareness* for and *articulation* of remote participation.

1.3 Identify-Match-Engage (IME) Framework for addressing Cooperation Challenges

An effective, goal-oriented CSC, such as with goal-orientation to help prioritize crisis response requires a framework for semantically abstracting the geographically unconstrained citizen sensed data into higher-level knowledge suitable for organizational actors. We propose an Identify-Match-Engage (IME) framework as shown in Figure 1.4 to structure the conceptual solution to the above-mentioned two issues of cooperation—*awareness* and *articulation*.

In the IME framework, the IDENTIFY function (m1 in Figure 1.4) guides data mining for citizen sensed data in CSC for "what is the information behavior (e.g., seeking help intent) and information type (e.g., medical resource during crisis)", aligned with organizational workflow tasks to meet *articulation* with efficient representation of information. The MATCH and ENGAGE functions support other information facets (who-where-when) from the data that guide formal organizational *awareness* regarding "whom to prioritize to communicate/engage in CSC" (m3 in Figure 1.4), and "where and when to prioritize resources based on matching interdependent seeking-offering behavioral actors" (m4 in Figure 1.4).

Dealing with the massive citizen-sensed data creates information overload for recipient organizational actors. The explicit representation of implicit attributes of behavioral data (e.g., seeking intent) in an annotated semi-structured information repository (m2 in Figure 1.4) serves as knowledge base to support cooperation with better access to information generated by CSC for the organizational actors, such as via visual exploration and semantic search of seeking-offering resource information (m5 in Figure 1.4).

1.4 Intent Mining and Engagement Modeling in IME Framework

Modeling the intent under the IDENTIFY function helps understand user expressions of the citizen sensors in the CSC that affect interdependencies in the organizational workflow tasks, and therefore, it is used to address the *articulation* issue of cooperation. For instance,

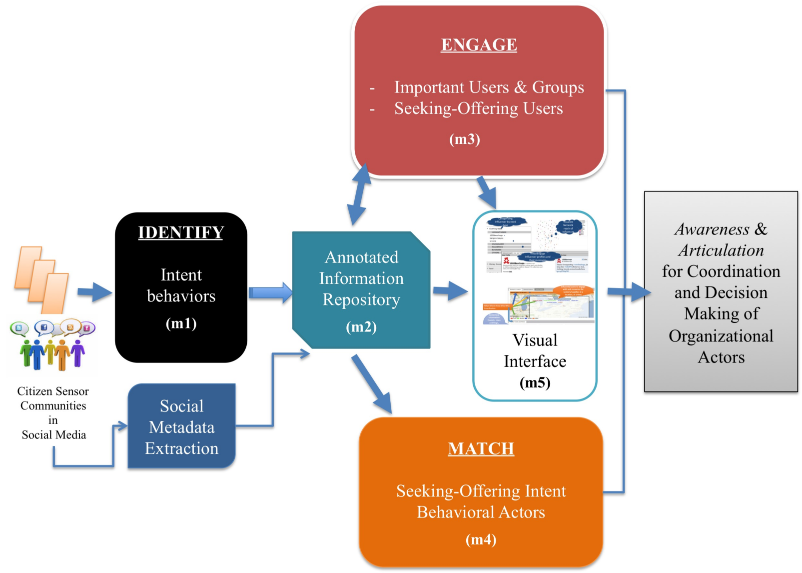


Figure 1.4: Summary of IME (Identify-Match-Engage) framework to design a cooperative web information system for users in CSC as well as organizational actors. Identify function (Intent Mining) is used to address the challenge of mining data for *articulation* of organizational needs, and the Engage function is used for addressing the challenge of *awareness* for organizational actors.

intent of seeking and offering help during a crisis response constitutes critical information for organizational workflow to prioritize resource allocation. On the other hand, modeling user and group engagement under the ENGAGE function addresses the *awareness* issue of information from prioritized set of individuals and groups in the CSC that can improve cooperation.

Addressing the challenge of cooperative web information system design for citizens and organizational actors via a unique approach of intent mining and engagement modeling in CSC faces the following challenges:

- ***Ambiguity*, *Sparsity* and *Diversity* Challenges**

The citizen sensor generated content in the CSC presents a variety of challenges to intent mining, specifically the highly varied *ambiguity* in user expressions. Furthermore, the specific intent behaviors are often sparse despite the importance of such behaviors for cooperation. For instance, the intent behavior related to offering to help during crisis response was observed extremely low compared to seeking help during our analysis of hurricane Sandy in 2012 (class imbalance ratio of nearly 1:8, refer Chapter 3). The *diversity* in user demographics, exacerbated by the global nature of the CSC, also influences the modeling of engagement behavior. For example, the engagement of someone with a humanitarian background may differ from another type of user. Also, analytical models must deal with massive amounts of user-generated data in the CSC. Hence, the modeling also demands computational scalability.

We address these specific data challenges in the intent and engagement modeling by infusing knowledge from the Web resources (e.g., Wikipedia) and theories of behavior (e.g., social identity) into statistical methods of text mining and machine learning. Unlike traditional behavioral computing restricted to one of the three fundamental dimensions of social networks—*user*, *content*, and *network*—the techniques presented here combine all three dimensions in addition to prior knowledge for improving the data representation of subjective context, and compensate for the lack of features to model learning of latent (hidden) predictor relationships from the data.

1.5 Thesis Questions and Contributions

The Identify-Match-Engage (IME) framework focuses on actors and actions of cooperation. It fuses top-down (prior knowledge-driven) and bottom-up (data-driven) processing approaches in modeling intent and engagement for addressing cooperation challenges between citizens and organizational actors in a cooperative web information system. Correspondingly, the specific thesis statement is:

The use of prior knowledge, and interplay of features of users, content, and network structures efficiently capture context for computing cooperation-assistive behavior (intent and engagement) from unstructured social data in the online socio-technical systems.

Modeling intent and engagement prioritization in the citizen sensor community helps address macro level design challenges of *articulation* and *awareness* for cooperation between citizens and organizations.

From the social science viewpoint, the research questions we address focus on organizational sensemaking and cooperation between actors of the cooperative web information system, comprising of institutionalized formal organizations, and the citizens of informal CSC. Specifically-

R1. Can general theories of offline conversation be applied in the online context [Chapter 2]?

R2. Can we model abstract behaviors (such as intentions) among interdependent actors to inform organizational workflows using goal-oriented semantic cues [Chapter 3]?

R3. Can we incorporate the social theories that shape group dynamics (e.g., Identity and Cohesion) in the modeling and analysis of online user-group behavior to address cooperation between CSC and formal organizational actors [Chapter 4]?

From the computer science viewpoint, our research questions focus on design and modeling of a cooperative web information system that is built on user intent and engagement modeling. It focuses on mining of content with intent behavior from citizen sensor generated data that meets *articulation* of workflow tasks of the formal organizational community, and model the prioritized user groups to engage for enhancing *awareness*. The proposed Identify-Match-Engage framework to improve cooperation between the formal organizational actors and the citizens in the CSC raises the following specific research questions–the first related to *actions*, the next related to *actors* of cooperation-

R4. How to identify relevant intentions from ambiguous, unconstrained natural language text of social media (e.g., ‘seeking help’ intention) [Chapter 3]?

R5. Can we better understand dynamics of group engagement to prioritize groups by complementing existing methods of structural measures with a content-driven measure of *group discussion divergence* over time [Chapter 4]?

Prior works in intent mining have not explored the fusion of modeling declarative, and social behavioral knowledge with statistically mined contrast pattern knowledge to address imbalance and class dependence relationships in the document-level intent classification. On the other hand, the earlier work on user engagement modeling was limited to structural connections that are sparse in certain domains such as crisis response.

The key contributions driven by the thesis statement while addressing the aforementioned research questions are the following:

1. Transforming the design challenges of *awareness* and *articulation* into data level problems, by addressing parts of them into two computationally tractable problems, and building a computational IME framework to accommodate the cooperative system design that can scale.

2. Classification of cooperation-assistive intentions from short, unstructured text documents using fusion of top-down and bottom-up approaches to improve context for learning in the binary and multiclass classification framework.

3. Modeling engagement of actors (individuals and groups) to prioritize via a novel measure of *group discussion divergence*, and predicting its trend using features of users, their generated content, and their dynamic network connections in the user interaction networks.

1.6 Use-case of Crisis Response Domain and Applications

In the context of crisis domain, reliance on both the formal (professional) and informal (citizen-based/initiated/coordinated) response communities is a well-recognized require-ment for effective crisis management [93, 81]. Citizen sensed data flow via social media potentially amplifies the influence of the informal community, both by expanding the geographic region that participates in emergency response from onsite to remote, and by extensively distributing information and requests. Yet despite a seemingly viable role for citizens in emergency response, and recent initiatives by the formal response community, such as the U.S. Federal Emergency Management Agency (FEMA), command and control models from the formal response organizations do not easily accommodate the social media data that the informal community has so readily adopted [82, 117, 127].

Applications of cooperation among various actors in the CSC and organizations can be invaluable; for example, collecting data from social media communities to change priorities of specific resource needs during crisis response by the organizational actors, who are tasked to collect and filter relevant information (e.g., seeking-offering resources). This was evident from our participation during an exercise of local emergency management organizations [44]. One of the key lessons from the post-exercise review with formal organizational responders to effectively assist them was the need for better alignment of information filtering and data mining with the organizational actor needs. Therefore, our approach to mine intent for addressing specific *articulation* problems in the IME framework (module m2 in Figure 1.4) attempts to address this issue. Similarly, exemplary applications in other problem spaces include prioritizing the concerns about the brand to manage an organizational reputation by engaging with brand communities, and executing team tasks such as the red balloon search by DARPA in 2009[1] by identifying potentially high engaging sources in the discussion community. Figure 1.5 shows an example of demand-supply matching application to assist organizational task coordination for donation resource management and volunteering services during an Oklahoma (USA) tornado in May of 2013, based on intent mining of seeking and offering help (modules m2 and m4 in the IME Framework, Figure 1.4). This work has been published in [87]. If proper cooperation and engagement

[1] http://www.engadget.com/2009/12/06/mit-based-team-wins-darpas-red-balloon-challenge-demonstrates/

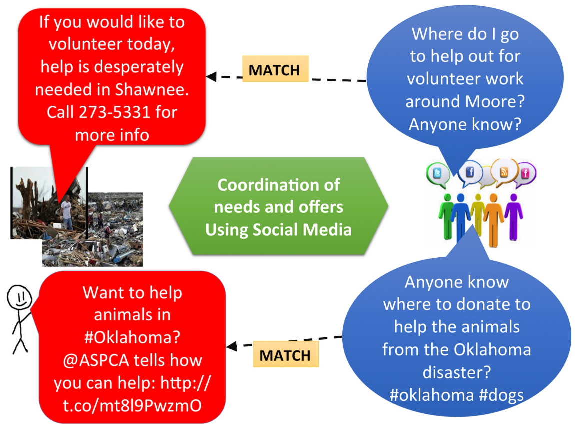


Figure 1.5: Application of assisting task coordination of emergency response organizations via identifying and matching seeking (demand) offering (supply) intent related information on social media, during a tornado in Oklahoma (USA), May 2013. [87]

with the social media community is lacking, responders may face a second disaster, such as reported by NPR about managing all the unnecessary and unused clothes donated after hurricane Sandy in 2012[2].

1.7 Dissertation Organization

The following chapters describe our inter-disciplinary approach to address research questions discussed above to provide a solution via the IME framework using intent and engagement modeling in CSC. A summary of the organization of chapters discussed is as follows.

Chapter 2 describes insights about verification of offline human behavior of language usage in the online conversations with the help of offline theory guided features in conversational classification tasks, and presents a case to leverage knowledge of social behavioral theories in analyzing online social data.

Chapter 3 discusses techniques for identifying intent (classes are guided by the *articu-*

[2]http://www.npr.org/2013/01/09/168946170/thanks-but-no-thanks-when-post-disaster-donations-overwhelm

lation of organizational tasks) from citizen sensor generated data for binary and multiclass problems by fusing bottom-up and top-down processing. Mining Intent would eventually transform raw unstructured social media messages into a structured form that can enrich the annotated information repository with seeking and offering behavior metadata.

Chapter 4 discusses a technique based on improving context via modeling social theories for characterizing user engagement dynamics by *group discussion divergence* based on content generated in the groups, in contrast to prior work on network structure-based measures.

Chapter 5 provides an overview of real-world engagements, and lessons learned that influenced our research, while also applying this research in the use-case of various crisis responses.

Chapter 6 discusses the improvements, limitations, and future work directions. Finally, we conclude with a summary of this dissertation.

Chapter 2: Verifying Existence of Offline Human Behavior in Online Conversations

One of the *a priori* knowledge sources to support modeling intent and engagement behavior from the user-generated content concerns offline conversational behavior. Our motivation is to assess if offline conversation theories can provide knowledge to enrich feature design in the online social data analysis. As we detail below, conversation itself entails linguistic coordination, and is fundamental to cooperative behavior. Therefore, the detection of conversation identifies the intent to cooperate within a CSC. The specific aim of this chapter is to understand the role of offline conversational behavior, in particular the theory-based indicators of conversation, to guide the analysis of the conversational behavior on online social platforms.

Conversation, defined as an exchange of sentiments, observations, opinions, or ideas (cf. Merriam Webster Dictionary), is a well-studied phenomenon in social sciences and linguistics. Language is a medium of expression for participants of the conversational exchange in a context. Various theories identify the specific linguistic constructs employed during (generally face-to-face) conversational coordination. We hypothesize the presence of these linguistic constructs in online conversations in CSC. Using simple linguistic indicators drawn from offline conversation analysis in social science, we create classification models for the on-line (mediated) conversations. We show that domain-independent, offline theory-guided linguistic cues distinguish likely conversation from non-conversation in mediated online communication. This work was published in [91]. In the following, we first discuss insights from the related offline theories for conversational coordination, followed by a presentation of conversational forms in CSC on social media, and the design of theory-guided features to create conversation classifiers.

2.1 Insights from Offline Theories of Linguistic Coordination

The present research aims to exploit domain-independent linguistic features of coordination in off-line conversation [20, 39, 72]. These studies claim that general processes of social interaction lead to the coordination of human conduct. The characterization of human conduct will guide the analysis of online conversational behavior in CSC.

Goodwin and Heritage [39] observed that conversations reveal an underlying social organization, which reflects an institutionalized communication of interactional rules, procedures, and conventions. Clark and Wilkes-Gibbs [20] showed that users follow certain linguistic patterns for coordinated behavior in conversations. Properties of an exchange, including opening and closing phrases, anaphora, and deixis, reveal the existence of coordination between conversational actors. For example, Chafe [17] noted that the use of determiners, (“a” versus “the”) distinguishes between previously established and new topics in a conversation reflecting the presence of shared context for coordination. Clarke [21] observed behavior of backchanneling in verbal exchange, where the listener confirms continued attention and comprehension with action that supports conversational coordination. Similarly, Mark [72] illustrated communication conventions in the collaborative environment.

These insights provide a principled foundation for the verification of conversational cues in the online environment. However, the online socio-technical environment presents a variety of conversational types, with different characteristics and involving different degree of participating actors.

2.2 Types of Online Conversations Facilitated by Social Platforms

Here we employ the Twitter social media platform as our experimental data source. Our analysis promotes the view that Twitter supports conversational exchange in CSC with inherent coordination properties.

2.2.1 About Twitter Social Medium

Twitter is a microblogging service (or platform) started in 2007 that provides an online social network structure and a medium for information flow, where citizen sensors post updates and subscribe to (referred to as 'following') other citizen sensors to receive updates (microblogs). A subscribed user is called 'follower' of the subscription user, 'followee'. Key definitions and functions include:

- ***Tweet***: A short message/post/status/microblog from a user on Twitter, spanning a maximum of 140 characters. Tweets include updates about user activities, share useful information, forward other users' statuses, converse with others, etc. The 140 character limit influences expression.

- ***Hashtag***: Denoted by a word with preceding '#' symbol (e.g., #JapanEarthquake), the hashtag is a platform convention for user-defined topics, invented to identify a topic of communication using minimal characters. It is also an important tool for grouping conversations by topic.

- ***Short URLs***: Tweets may contain links to web-pages, blogs, etc. To avoid lengthy URLs, Twitter users employ condensed versions of those URLs, shortened by external services (e.g., http://bit.ly/IyBgIO).

- ***Reply***: Reply is a platform-provided function to communicate with a tweet author by clicking on Twitter's 'Reply' button in response to a tweet. For example, user *hemant_pt* tweets *"today's discussion on linguistic coordination was just brilliant!"*, while user *U* uses the built-in Reply button to indicate *"@hemant_pt I was excited too about today's discussion"*. The Reply syntax automatically inserts the originator's user name.

- ***Retweet***: Retweet forwards a tweet from users to their followers, similar to e-mail forwarding. In so doing, the writer credits the source using the built-in 'Retweet' function resulting in *'RT @USER_NAME'*. For example, *"RT @hemant_pt: it is not enough to depend on platform provided indicators for conversations #coordination #psycholinguistic"*. Here a new user retweeted a tweet from *hemant_pt*.

- ***Mention***: Mention acknowledges a user with the symbolic '@' sign, but without using the 'Reply' platform function. For example, *"Thanks @hemant_pt, we hope to see you in next year's conference too for further discussion on #coordination"*.

2.2.2 Twitter Conversations

Danescu-Niculescu-Mizil, Gamon, and Dumais [24] showed that Twitter exchanges reflect the psycholinguistic concept of communication accommodation, where participants in conversations tend to converge to one another's communicative behavior. They coordinate using a variety of dimensions including choice of words, syntax, utterance length, pitch and gestures. Gouws, Metzler, Cai, and Hovy [40] analyzed the effects of user demographics, context and modes of information sources (web vs. mobile clients) on lexical usage in the Twitter medium. Their study showed a convergence in the adoption of unusual vocabulary terms, another indicator of coordination. Further, the authors found that contextual indicators, including geographic location, account for lexical variants relative to the standard English language. This phenomenon of lexical accommodation supports our conceptualization of some Twitter exchanges as a kind of conversation.

To identify the diagnostic features for a classification model of online conversation, we require positive instances of messages that likely reflect conversation. Most of the relevant work on Twitter focused on a data corpus based on the 'Reply' platform function. However, this is unnecessarily restrictive, and potentially misleading . Therefore, we examine 'Reply', 'Retweet', and 'Mention' platform functions of Twitter in this study for establishing the existence of offline conversation cues in a variety of online conversations, potentially reflecting a range of conversation-like behavior. Figure 2.1, Figure 2.2 and Figure 2.3 below provide examples for each function, illustrating both positive and negative examples of conversation. The negative examples support our claim that platform functions alone do not assure conversation (see Figure 2.4).

Focusing exclusively on postings with Reply function, Ritter, Cherry, and Dolan [99] analyzed content dependent and language dependent vocabulary in a computationally intensive model of structuring conversation element sequences and disentangling dialogues on Twitter. While their distinction between content and language dependent vocabulary is similar to our distinction between domain dependent and independent analyses, we advocate reliance on the domain independent cues as a computationally inexpensive way of screening the Twitter corpus prior to domain dependent analysis.

While Twitter's Retweet function usage seems like a means simply to disseminate information, it also potentially functions as a type of conversation where multiple recipients

A positive Example:
user1: *We have performed analysis on Twitter #conversation. Specifically, we are using platform provided REPLY feature to call something as conversation*
user2: *@user1 it's not enough 2 depend on Twitter indicators for conversations leading to #coordination #psycholinguistic* ***(REPLY TO user1)***

A negative example:
user1*: We intend to demonstrate the shortcomings of platform indicators*
user2*: @user1 new James Bond movie is out! #OMG* ***(technically a REPLY TO user1)***

Figure 2.1: 'Reply' feature based conversation

A positive Example:
user1*: it's not enough 2 depend on Twitter indicators for conversations leading to #coordination #psycholinguistic*
user2*: I agree! RT @user1: it's not enough 2 depend on Twitter indicators for conversations leading to #coordination #psycholinguistic*
(Conversational RETWEET TO user1)

A negative example:
user2*: RT @user1: what does a fish say after running into a wall? dam!*
(RETWEET of a generic joke)

Figure 2.2: 'RT' feature based conversation

A positive Example:
user1*: We have performed analysis on Twitter #conversation. Specifically, we are using platform provided REPLY feature to call something as conversation*
user2*: I kind of agree with @user1 that it's not enough 2 depend on Twitter indicators for conversations #coordination #psycholinguistic*
(MENTION OF user1, but not using REPLY feature)

A negative example:
user*: felt like @MichaelJordan at last basketball game!*

Figure 2.3: 'Mention' feature based conversation

comprise listeners for the original author. Three observations support our claim for conceptualizing Retweet function based exchange as conversation. In their extensive study of the Retweet function, Boyd, Golder, and Lotan [11] noted distribution across a non-cohesive network in which the recipients of each message change depending on the sender. While such exchanges need not include conversational properties. Figure 2.2 demonstrates that users in the Retweet diffusion chain sometimes prefix their opinion to the forwarded message. This represents a localized conversation between the followee and her immediate followers based on the action of the follower. Finally, the action of retweeting bears some

User@user1:
@**user2** *goodnight I am about out of here also :)*

User@user2:
@**user1** *I adore charlie sheen everyday He is Kewl I pray he puts on a Telethon for Japan & HELPS them out!charlie sheen follows me*

Figure 2.4: Online social platform functions do not ensure coherent conversation.

similarity to backchanneling in verbal exchange, in which the listener confirms continued attention and comprehension with action [21].

Similarly, Mention-based tweeting can form a conversation, where one user addresses another user rather than simply referring to him (e.g., *"@user1 it's not enough 2 depend on Twitter indicators for conversations leading to #coordination #psycholinguistics"*) without using the Reply function of Twitter. Honeycutt and Herring [50] focused on the coherence of exchanges involving the '@' sign. They observed a surprising degree of conversationality using lexical patterns particularly when using '@' as a marker of addressivity. It reflects potential for facilitating conversations within an event context by utilizing the Mention platform function.

- **Assumptions for conversation classification**

We identify two implications of our focus on platform function-driven (e.g., Retweet messages) subsets of data as linked to conversation. First, each subset is more likely to exhibit coordination indicative features relative to the remainder tweets. Everything else is less likely to be a conversation. Therefore we should see relatively more coordination indicators in the platform function-driven subsets than the remainder. Second, the prevalence of coordination language may decline with the type of platform function. Reply should have the most coordination indicative linguistic features, as it is the most explicit indicator of conversational intent.

We specifically deny the stronger claim that platform functions alone determine coordination. For example, using the Reply function may simply reflect a convenient way to distribute a message. Blind retweeting to a broader network need not reflect concurrence or endorsement consistent with a kind of conversation. And including the name of another Twitter user in a message need not invoke a response.

Just as platform functions do not guarantee conversation, the absence of platform functions does not guarantee the absence of conversation. We are particularly concerned with messages that contain hidden conversation, without platform functions, e.g., *"what's going on with that city? How many people escaped? Please tell me!"* by a user *@JT800*.

We do claim that platform functions, relative to the remaining subset of tweets, are more likely to reflect the properties of conversational coordination. By identifying a reliable set of theoretically based indicators of conversational coordination for selecting features, we obtain a bootstrapped model for classifying any message as reflecting linguistic coordination and we can potentially identify the features that reflect coordinated effort in any individual posting, independent of platform functions. A final justification of the search for conversational coordination indicators independent of platform functions is that compliance with artificial convention often fails under stressful circumstances of disaster. We suspect that recommendations for coordination that hinge on imposing low-level communication templates on informal social media communities will fail under stressful and non-standard circumstances [25]. Therefore, the ability to mine conversation provides a robust alternative to brittle user compliance.

We provide the conversation classification problem statement as the following:

- **Problem Statement p2.a**: Given a community of citizen sensors u_v as $CSC = \{u_v \, | v \,\epsilon\, \mathbb{N}\}$ formed around discussion of a real world event E, with tweet messages m_i generated by u_v as a corpus $A = \{m_i \, |i \,\epsilon\, \mathbb{N}\}$. Classify a set of messages $\{m_i\}$ for a platform function based conversation class c versus the non-conversation class NC, where $c \,\epsilon\, \{Reply, Retweet, Mention\}$, and $NC = A \backslash \{Retweet, Reply, Mention\}$.

2.3 Offline Theory-guided Features as Social Knowledge for Classifying Conversations

Table 2.1 presents the linguistic-based coordination features that represent social knowledge to examine tweet text for conversation. The examination of articles (h1 and h2) follows [17], who asserted that "the" assumes a previously established topic. A set of dialogue management items (h9) captures the typical conversational openings and closings and requests for clarification. The preponderance of hypotheses related to pronouns captures anaphora (reference to a previous exchange) and deixis (grounding in a physical setting). We anticipate more of these words when participants share common ground established outside the observed exchange. We identified separate hypotheses by grammatical part of speech and person. First and second person pronouns should appear in a coordinated exchange. However, first person pronouns also appear in the personal status reports that pervade Twitter, and may therefore not diagnose conversation. Other pronoun forms (possessives, relatives, reflexives) could obtain grounding within the message itself, rather than a previous message. We now identify our hypotheses related questions to refine research question R1 of this dissertation as discussed in Chapter 1. Our specific hypotheses are:

H2.1. Linguistic coordination features (heuristics in Table 2.1) distinguish Reply, Retweet and Mention from other tweets.

H2.2. Linguistic coordination features correlate with information density.

These hypotheses leads to questions of assessing consistency between the degree of success in separating Reply (RP), Retweet (RT) and Mention-based (M) conversations from non-conversations (NC) and the degree to which these platform functions behave as conversation. Furthermore, we explore dependence between the degree of success in separating these platform function based conversations from non-conversations and the extent to which the surrounding event context promotes coordination. Finally, we investigate if the diagnostic linguistic coordination features of conversation transcend the platform functions of conversation.

We discuss our approach to the classification of online conversations in the next section, using datasets from a variety of real world events.

Heuristic	Heuristic Description
h1	Determiners (the)
h2	Determiners (a, an)
h3	Subject Pronouns (she, he, we, they)
h4	Mixed Subject/ Object pronouns but centered on individual (my, I, me)
h5	Relative Pronouns (that, this, these, those)
h6	Possessive Pronouns (mine, yours, his, hers, ours, theirs)
h7	Relative Pronouns (who, what, which, whom, whose)
h8	Intensive/ Reflexive Pronouns (myself, yourself, himself, herself, itself, ourselves, themselves, yourselves)
h9	Dialogue management indicators (thanks, yes, ok, sorry, hi, hello, bye, anyway, how about, so, what do you mean, please, {could, would, should, can, will} followed by pronoun)
h10	Word Counts
h11	Hedge Words (kinda,sorta)
h12	Ambiguous Pronoun (you)
h13	Ambiguous Pronoun (it)
h14	Object Pronouns (us,them,him,her)

Table 2.1: Linguistic coordination features as social knowledge for identifying conversation

2.4 Classification of Conversations in CSC: Experiments and Results

We first describe the data collection method for this study, followed by our approach for testing the hypotheses mentioned above via conversational corpus categorization, extraction of linguistic coordination features, and modeling conversation classification.

- **Data collection**

The Twitter Streaming API provides real-time tweet collection. Alternatively, the Twitter Search API provides keyword based search query, returning the 1500 most recent tweets in one response and excluding tweets from users who opt for privacy. The query provides tweet text and metadata, such as timestamp, location, and author information (such as profile description, profile location, number of followers and followees, etc.).

EVENTS	DURATION	DAYS	TWEETS	AUTHORS	RP	RT	M	NC
Japan Earthquake 2011	2011-03-11 – 2011-03-30	20	609853	26916	60223	240090	41234	268306
Haiti Earthquake 2010	2010-01-13 – 2010-03-10	57	583747	26460	56896	200955	54171	271725
Hurricane Irene Storm 2011	2011-08-26 – 2011-09-10	16	181871	8335	14345	72441	12146	82939
Debt Ceiling Debate 2011	2011-07-25 – 2011-07-30	6	75788	4068	8294	29761	6490	31243
Skype Microsoft Deal 2011	2011-05-10 – 2011-05-15	6	19331	959	1158	5709	3640	8824
Glenn Beck Rally 2010	2010-08-30 – 2011-09-05	7	3848	386	594	1173	372	1709
TOTAL			1474438	67124	141510	550129	118053	664746

Table 2.2: Statistics about the event-centric data sets and for various conversational corpuses Reply (RP), Retweet (RT), Mention (M) and Non-conversation (NC)

To study tweets generated by citizen sensors in CSC related to conversations of real world events, we created a crawler using the Twitris v1 system [77] that queried the Twitter Search API every 30 seconds for event-related keywords (e.g., “hurricane irene” for the event “Hurricane Irene storm 2011”) for the duration of the event period. We initiated the keyword set with seed keywords and hashtags. We then expanded the initial set by extracting its top key phrases and adding them to the crawler while maintaining human oversight for keyword selection to maintain relevance to the event context. We collected tweets for six different events. To reflect language behavior in response to a crisis type of events, we examined the Haitian 2010 and Japanese 2011 earthquakes and hurricane Irene 2011. For the purposes of comparison with non-crisis type of events, we examined the debt ceiling debate of 2011, the Skype Microsoft deal in 2011, and the Glenn Beck rally in 2010 (described in the Table 2.2).

- **Algorithm to construct data corpuses for conversation types**

As described above in Section 2.2, Twitter provides three functions Reply, Retweet and Mention that potentially enable conversation. We constructed our separate corpuses using

Algorithm 1 Platform Conversational Corpus Construction Algorithm

1. Crawl a corpus A of messages m_i related to an event E for a given time duration slice ts
2. $RP = \varnothing$, # *A Reply conversation set*
3. $RT = \varnothing$, # *A Retweet conversation set*
4. $M = \varnothing$, # *A Mention conversation set*
5. $NC = \varnothing$ # *A Non-conversation set*
6. For each $m_i \in A$
   - 6a. if $is\_Reply(m_i) = True$
     $RP = RP \sqcup m_i$
     Crawl each m_j in the *Reply-based Conversation thread* of m_i
     $A = A \sqcup m_j$
   - 6b. else if $is\_Retweet(m_i) = True$
     $RT = RT \sqcup m_i$
   - 6c. else if $is\_Mention(m_i) = True$
     $M = M \sqcup m_i$
   - 6d. else
     $NC = NC \sqcup m_i$

Note: $is\_c(x)$ tests if a platform conversation function c (*Reply*, *Retweet*, *Mention*) is observed in the tweet x

Algorithm 1.

- **Classification Model**

We created a classification model to establish the degree of conversationality for a message set $\{m_i\}$ sample, each one characterized as a feature vector of linguistic coordination indicative features (heuristics) shown in Table 2.1, including variants of the heuristic words in the social media space to compensate for informalism (e.g., 'you' as 'u'). The variants were inspired from a popular slang words knowledge base–Urban Dictionary, and screened through manual inspection. We used the Supervised Machine Learning techniques of Decision Tree classifiers [101] for our analysis. This provides an interpretable classification tree with a series of nodes consisting of linguistic indicator features, ending with a leaf node comprising a decision for the class.

We created training sets (to learn from the data) and separate testing sets (to test on the new data and make a more robust classifier) of the data samples. We created balanced (equal number of positive and negative class samples) training sets and test sets using data samples corresponding to each of the conversation type classes (RP, RT or M) and non-conversation class (NC). We used the established Weka Data Mining tool [43] to perform modeling and experimentation.

- **Assessing Performance of Offline-theory Guided Features**

Using a chi-squared test we ranked the linguistic coordination features that reflected significant alignment with the conversation class suggested by any of RP, RT or M corpuses as compared to NC without these platform function properties. In a separate analysis that examined only correctly classified tweet segments (hits and correct rejections) we confirmed the direction of the relationship between linguistic features and a class.

- **Evaluation Method**

We use a 10-fold cross validation [43] to assess the unbiased accuracy of conversation classifiers. This allows computation of robust statistics for classification ability across the ten repetitions such as the area under the Receiver Operating Characteristic (ROC) curve, True Positive (TP) Rate, False Positive (FP) Rate, Accuracy, Precision, Recall, and also a measure d' in the perspective of signal detection theory [131].

- **Experiments and results**

We collected a set of six diverse events for analyzing conversation characteristics spanning different time periods of different length and covering varied social significance. We defined the end of the event period when the volume of information flow dropped steeply. Table 2.2 shows a summary of the corpus. The first three events in Table 2.2 draw on the disaster situation, which is likely to correlate with higher coordination due to potential goal-orientation of citizen sensor conversations in CSC. The remaining three events are more generic. The choice of events allows us to demonstrate generalized usage of linguistic cues for conversation conducted via social media.

Table 2.3 summarizes the results for learned models of conversation classifiers. The table includes accuracy for the classifier (ability to distinguish between the platform function based conversation-RP/RT/M and NC) for each of the platform functions as well as

	REPLY based				
DATASET	**TP Rate**	**FP Rate**	**d'**	**Accuracy%**	**ROC value**
Japan Earthquake 2011	0.781	0.219	**1.551**	**78.06**	**0.84**
Haiti Earthquake 2010	0.705	0.295	1.078	70.54	0.75
Hurricane Irene Storm 2011	0.752	0.248	1.362	75.2	0.8
Debt Ceiling Debate 2011	0.689	0.311	0.986	68.9	0.73
Skype Microsoft Deal 2011	0.655	0.345	0.798	65.54	0.67
Glenn Beck Rally 2010	0.624	0.376	0.632	62.37	0.63
Common/Mixed dataset	0.743	0.257	1.305	***74.27***	***0.8***
Common/Mixed dataset for Disasters	0.746	0.254	1.324	***74.61***	***0.8***
Common/Mixed dataset for Non-Disasters	0.69	0.31	0.992	***68.96***	***0.73***
	RT based				
DATASET	**TP Rate**	**FP Rate**	**d'**	**Accuracy%**	**ROC value**
Japan Earthquake 2011	0.713	0.287	1.124	71.33	**0.78**
Haiti Earthquake 2010	0.711	0.289	1.113	71.07	0.77
Hurricane Irene Storm 2011	0.715	0.285	**1.136**	**71.46**	0.77
Debt Ceiling Debate 2011	0.688	0.312	0.98	68.77	0.74
Skype Microsoft Deal 2011	0.678	0.322	0.924	67.76	0.72
Glenn Beck Rally 2010	0.643	0.357	0.733	64.32	0.67
Common/Mixed dataset	0.709	0.291	1.101	***70.9***	***0.77***
Common/Mixed dataset for Disasters	0.712	0.288	1.119	***71.24***	***0.78***
Common/Mixed dataset for Non-Disasters	0.681	0.319	0.941	***68.15***	***0.73***
	MENTION based				
DATASET	**TP Rate**	**FP Rate**	**d'**	**Accuracy%**	**ROC value**
Japan Earthquake 2011	0.665	0.335	**0.852**	**66.49**	**0.71**
Haiti Earthquake 2010	0.649	0.351	0.765	64.9	0.69
Hurricane Irene Storm 2011	0.594	0.406	0.476	59.45	0.61
Debt Ceiling Debate 2011	0.625	0.375	0.637	62.51	0.66
Skype Microsoft Deal 2011	0.564	0.436	0.322	56.38	0.57
Glenn Beck Rally 2010	0.649	0.351	0.765	64.92	0.65
Common/Mixed dataset	0.643	0.357	0.733	***64.35***	***0.69***
Common/Mixed dataset for Disasters	0.647	0.353	0.755	***64.72***	***0.69***
Common/Mixed dataset for Non-Disasters	0.615	0.385	0.585	***61.53***	***0.65***

Table 2.3: Classification performance for various types of online platform function based conversations, using the offline-theory guided linguistic coordination features

other statistics, including dand ROC area values in the subsequent columns. Higher accuracy, dand ROC area values indicate a better classifier.

Each row in the Table 2.3 shows the classification ability for a dataset of an event (or a mixture of events, denoted as common or mixed), with accuracy and ROC measures in addition to the True Positive (TP) Rate, False Positive (FP) Rate and d' value for each of the three platform function based classes (Reply, Retweet and Mention). Accuracy measures range from 62% to 78%. ROC measures range from 0.63 to 0.84. These measures suggest fair to good accuracy in general, with relatively superior scores for the case of disaster events relative to the non-disasters events, Reply relative to Retweet and Retweet relative to Mention. Across all events, the ROC area values are 0.8, 0.77 and 0.69 for distinguishing RP, RT, and M from NC using a common dataset based model. Moreover, the conversation classifier suggests the elimination of 23 percent of the Reply, 30 percent of the Retweet and 33 percent of the Mention-based conversational tweets, despite the presence of platform functions. However, the conversation classifier also promotes an average of 31 percent of the tweets that are not marked with these platform functions as exemplifying the characteristics of conversation.

- **Discriminability of Offline-theory Guided Features for Online Conversation**

The features we use to classify conversation are not equally useful. Table 2.4 shows the features in the models ranked from left (best) to right column (worst) for classification, for each of the event datasets and for each of the conversation type corpuses RP (Reply), RT (Retweet), M (Mention). As in Table 2.3, the last rows in Table 2.4 provide results for the comprehensive (mixture of all events) dataset, and specific to all disaster and non-disaster events dataset. Figure 2.5, Figure 2.6 and Figure 2.7 provide graphical summaries for the top four heuristics features from our Table 2.1, omitting the highly influential heuristic "you" [h12] to preserve a readable effectiveness scale on the remaining heuristics. In general, pronouns (h3, h4 and h12) and dialogue management (h9) appear in the top 5 features across the platform function based conversation classes and types of events. Retweet-based and Mention-based exchanges are identified by word count (h10) and determiners (h1) features as well.

- **Correlation study for linguistic features in the correctly classified samples**

Table 2.5 shows the correlation coefficients for correctly classified data samples only. While the magnitude is meaningless because of the restricted sample space, the direction of the relationship is always positive for the most highly ranked features. Thus, the presence of the offline-theory guided linguistic coordination features under assessment discriminate between positive and negative instances of online conversation samples. It supports our hypothesis H2.1.

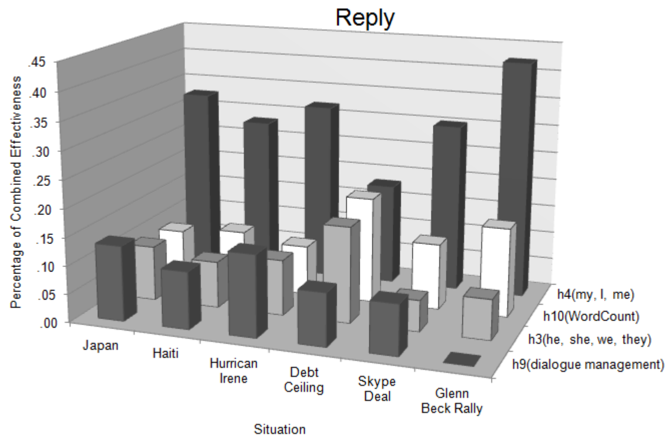


Figure 2.5: Top linguistic coordination features within the Reply-based conversations

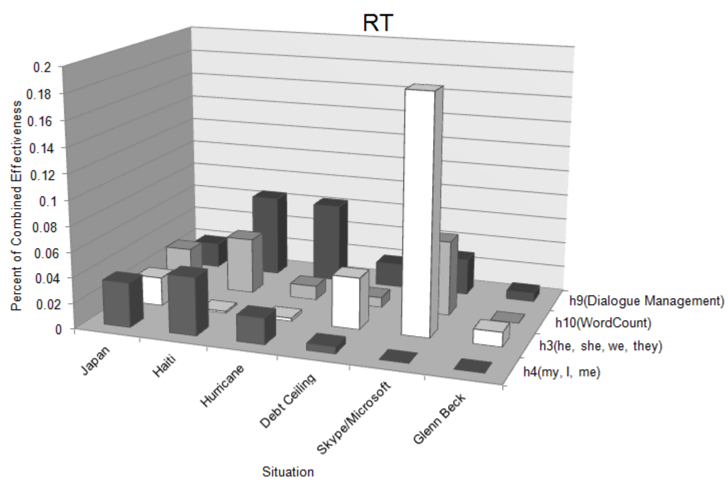


Figure 2.6: Top linguistic coordination features within the RT-based conversations

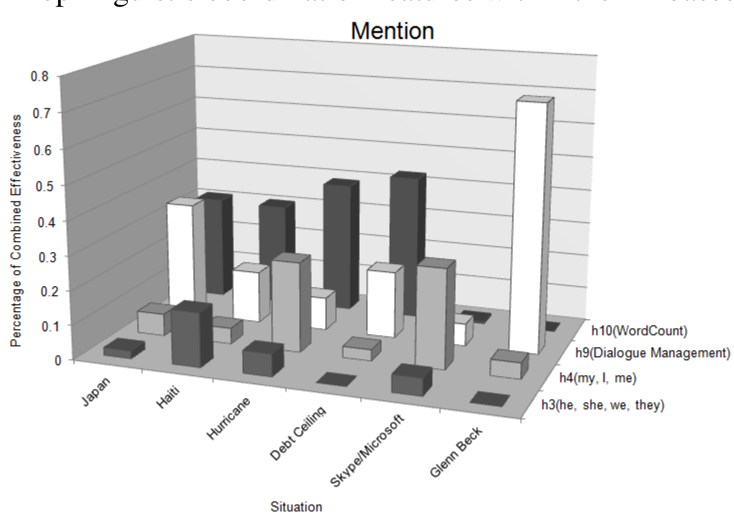


Figure 2.7: Top linguistic coordination features within the Mention-based conversations

REPLY-based	**Feature Rank**							
EVENTS	**Top-1**	**Top-2**	**Top-3**	**Top-4**	**Top-5**	**Top-6**	**Top-7**	**Top-8**
Japan Earthquake 2011	h4	h12	h9	h13	h3	h10	h5	h2
Haiti Earthquake 2010	h12	h4	h13	h10	h9	h3	h5	h2
Hurricane Irene Storm 2011	h4	h12	h9	h3	h13	h10	h5	h2
Debt Ceiling Debate 2011	h12	h10	h4	h3	h13	h5	h9	h2
Skype Microsoft Deal 2011	h4	h12	h10	h13	h5	h9	h3	h2
Glenn Beck Rally 2010	h4	h12	h13	h3	h10	h5	h1	h2
Common/Mixed dataset	**h4**	**h12**	**h9**	**h13**	**h3**	**h5**	**h10**	**h2**
Common/Mixed dataset for Disasters	**h4**	**h12**	**h9**	**h13**	**h3**	**h5**	**h10**	**h2**
Common/Mixed dataset for Non-Disasters	**h4**	**h12**	**h9**	**h13**	**h3**	**h5**	**h10**	**h2**
RT-based	**Feature Rank**							
EVENTS	**Top-1**	**Top-2**	**Top-3**	**Top-4**	**Top-5**	**Top-6**	**Top-7**	**Top-8**
Japan Earthquake 2011	h10	h9	h12	h6	h3	h7	h1	h4
Haiti Earthquake 2010	h10	h4	h9	h12	h1	h2	h13	h14
Hurricane Irene Storm 2011	h10	h4	h14	h9	h6	h12	h7	h13
Debt Ceiling Debate 2011	h10	h3	h4	h5	h14	h2	h8	h12
Skype Microsoft Deal 2011	h10	h3	h13	h14	h12	h6	h5	h7
Glenn Beck Rally 2010	h10	h1	h5	h4	h7	h2	h3	h14
Common/Mixed dataset	**h10**	**h9**	**h12**	**h4**	**h1**	**h3**	**h14**	**h6**
Common/Mixed dataset for Disasters	**h10**	**h9**	**h12**	**h4**	**h1**	**h3**	**h14**	**h6**
Common/Mixed dataset for Non-Disasters	**h10**	**h9**	**h4**	**h12**	**h1**	**h6**	**h3**	**h14**
MENTION-based	**Feature Rank**							
EVENTS	**Top-1**	**Top-2**	**Top-3**	**Top-4**	**Top-5**	**Top-6**	**Top-7**	**Top-8**
Japan Earthquake 2011	h9	h10	h12	h4	h14	h3	h6	h5
Haiti Earthquake 2010	h12	h10	h3	h9	h2	h4	h13	h1
Hurricane Irene Storm 2011	h10	h4	h12	h9	h3	h6	h1	h2
Debt Ceiling Debate 2011	h10	h12	h9	h1	h4	h5	h2	h3
Skype Microsoft Deal 2011	h5	h6	h3	h7	h1	h2	h4	h12
Glenn Beck Rally 2010	h1	h9	h5	h6	h2	h4	h12	h3
Common/Mixed dataset	**h12**	**h10**	**h9**	**h3**	**h4**	**h2**	**h6**	**h14**
Common/Mixed dataset for Disasters	**h12**	**h10**	**h9**	**h3**	**h4**	**h2**	**h6**	**h14**
Common/Mixed dataset for Non-Disasters	**h10**	**h12**	**h9**	**h3**	**h4**	**h2**	**h6**	**h13**

Table 2.4: Ranking of linguistic coordination features (heuristics in Table 2.1) for performance in the classification for online conversation types for real world events

- **Information density**

According to our hypotheses, conversation indicates coordination. Coordination in turn implies a higher degree of substantive information, or information density. A domain-dependent analysis of tweet information content is beyond the scope of the present chapter. However, we provide a generic indication of tweet information density using the well-known Pennebaker's Linguistic Inquiry Word Count (LIWC) software [85] (`http://www.liwc.net/`). LIWC provides percentages for the presence of various pre-defined categories of words. Here we report analyses using predefined LIWC measures of communication, sensed experience, and social interaction. Measures of communication include 130 words such as "call", "speak", and "listen". Measures of sensed experience include 112 words, such as "drink", "eat", and "look". Measures of social interaction include 325 words such as "rumor", "secret", and "aunt". Although LIWC provides separate values for these measures, we note some degree of content overlap. For example, the word "ask"

REPLY-based		RT-based		MENTION-based	
CORR(C,h4)	0.5379435089	CORR(C,h10)	0.6890163385	CORR(C,h12)	0.4951287188
CORR(C,h12)	0.4933621573	CORR(C,h9)	0.1427287627	CORR(C,h9)	0.4317517945
CORR(C,h13)	0.3608575332	CORR(C,h12)	0.1373937122	CORR(C,h10)	0.418519636
CORR(C,h9)	0.3603677094	CORR(C,h3)	0.0990999819	CORR(C,h4)	0.2772313278
CORR(C,h3)	0.3298950158	CORR(C,h6)	0.0635809668	CORR(C,h3)	0.2370879435
CORR(C,h5)	0.2904841023	CORR(C,h7)	0.0511771093	CORR(C,h2)	0.1006701597
CORR(C,h10)	0.1302279126	CORR(C,h5)	0.0506748247	CORR(C,h13)	0.1000650892
CORR(C,h2)	0.1295144148	CORR(C,h14)	0.023213349	CORR(C,h5)	0.0941631627
CORR(C,h7)	0.0615535592	CORR(C,h8)	0.001804053	CORR(C,h6)	0.0596707947
CORR(C,h8)	0.0468423027	CORR(C,h13)	-0.0074445414	CORR(C,h14)	0.0381844937
CORR(C,h6)	0.0467575461	CORR(C,h11)	-0.0152468614	CORR(C,h8)	0.0084248154
CORR(C,h11)	0.0425604815	CORR(C,h2)	-0.029237837	CORR(C,h7)	0.0049817937
CORR(C,h14)	0.0313333062	CORR(C,h1)	-0.0708892543	CORR(C,h11)	0.0044300814
CORR(C,h1)	0.0298269769	CORR(C,h4)	-0.1322003669	CORR(C,h1)	-0.0446478387

Table 2.5: Correlation of linguistic features with predicted conversation class c in the positively classified samples, for different conversation types and for the case of common/mixed dataset for disaster events

appears in the LIWC dictionaries for all three measures. However we edited the social interaction measure to exclude the words we used to build our conversation classifiers.

Table 2.6 presents analyzed data for over 850,000 tweets. The left third (horizontal segment 1) contains analysis data for Reply-based tweets. The middle third (segment 2) contains data for Retweet-based tweets. The right third (segment 3) contains analysis data for Mention-based tweets. In the vertical organization, the top quarter (e.g., 1a) of the table presents data for the number of tweets analyzed. The second quarter (b) of the table presents data for the social measure. The third quarter (c) presents data for the senses measure. The bottom quarter (d) presents data for the communication measure. The combination of conversation models (Reply, Retweet and Mention-based) with three different LIWC analysis measures defines nine different analyses (sub-tables under 1b-1d, 2b-2d, and 3b-3d). In each case we have a separate two by two sub-table (e.g., 2b), with existence of platform-based functions of conversation serving as a ground truth defining the rows with respect to noise, and our conversation classifier defining the columns. Values inside the cells of a two by two analysis sub-table correspond to the LIWC rating per 1000 words for the measure in question. We also provide row and column LIWC ratings.

1. Reply			
1a.			
# of Tweets	Conv	~Conv	
Replies	94240	32500	
Noise	30000	100000	
1b.			
Social	Conv	~Conv	
Replies	3.59	3.47	3.56
Noise	3.8	3.06	3.25
	3.64	3.17	
1c.			
Senses	Conv	~Conv	
Replies	2.08	1.6	1.96
Noise	1.71	1.37	1.46
	1.99	1.42	
1d.			
Communication	Conv	~Conv	
Replies	1.55	1.29	1.49
Noise	1.3	1.12	1.17
	1.49	1.16	

2. RT			
2a.			
# of Tweets	Conv	~Conv	
Retweets	100000	100000	
Noise	100000	100000	
2b.			
Social	Conv	~Conv	
Retweets	3.7	3.31	3.52
Noise	3.48	3.04	3.29
	3.58	3.17	
2c.			
Senses	Conv	~Conv	
Retweets	1.62	1.54	1.58
Noise	1.43	1.31	1.38
	1.52	1.42	
2d.			
Communication	Conv	~Conv	
Retweets	1.48	1.31	1.41
Noise	1.23	1.13	1.19
	1.35	1.22	

3. Mention			
3a.			
# of Tweets	Conv	~Conv	
Mentions	57400	45800	
Noise	30400	76200	
3b.			
Social	Conv	~Conv	
Mentions	4.17	3.53	3.91
Noise	3.71	3.21	3.37
	4.01	3.33	
3c.			
Senses	Conv	~Conv	
Mentions	1.6	1.57	1.59
Noise	1.54	1.42	1.46
	1.58	1.48	
3d.			
Communication	Conv	~Conv	
Mentions	1.44	1.33	1.39
Noise	1.29	1.14	1.19
	1.39	1.21	

Table 2.6: Three LIWC analysis measures social interaction, senses, and communication, for three tweet conversation classification models (Reply, Retweet, Mention). [Light gray for non-significant effects - refer details under subsection 'Information Density'])

The number of tweets in each small cell of Table 2.6 is large, but not equal (see sub-tables marked with a in the top quarter, e.g., 1a). To conduct a statistical analysis, we divided the contents of each cell into 20 equal subsets, and submitted each subset to LIWC analysis. Thus, while the total number of tweets differed among cells, the number of scores (subsets) in the statistical analysis did not. We conducted a two-by-two analysis of variance on the four combinations of ground truth and conversational classification, and followed up with t-tests as needed. We assumed a fixed effects model, as the two levels of each (ground-truth row, and conversation-classifier column) variable exhaust the possible range of values. The general pattern of findings is significant main effects demonstrating increased information density for tweets classified as conversation. The rare significant interaction contrast in the factorial design is not theoretically interesting. Non-significant effects appear in Table 2.6 with light gray labels.

The ground-truth (row) main effect is significant for two measures of the Reply tweets (Social, F (1, 76) = 1.05, $p > .10$; Senses, F (1, 76) = 42.43, $p < .01$; Communication, F

(1, 76) = 76.35, $p < .01$). The ground-truth main effect is significant for all three measures of the Retweet-based conversation tweets (Social, F (1, 76) = 4.40, $p < .05$; Senses, F (1, 76) = 13.12, $p < .01$; Communication, F(1, 76) = 14.31, $p < .01$). The ground-truth main effect is significant for two measures of the Mention-based tweets (Social, F (1, 76) = 9.20, $p < .01$; Senses, F (1, 76) = 3.37, $p > .05$; Communication, F (1, 76) = 12.25, $p < .01$).

The conversation-classifier (column) main effect is significant for all three measures of the Reply tweets (Social, F(1, 76) = 19.51, $p < .01$; Senses, F (1, 76) = 77.88, $p < .01$; Communication, F (1, 76) = 82.72, $p < .01$). The conversation-classifier main effect is significant for two measures of the Retweet-based conversation tweets (Social, F (1, 76) = 12.97, $p < .01$; Senses, F (1, 76) = 2.83, $p > .10$; Communication, F (1, 76) = 4.99, $p < .05$). The conversation-classifier main effect is significant for two measures of the Mention-based tweets (Social, F (1, 76) = 18.97, $p < .01$; Senses, F(1, 76) = 1.61, $p > .10$; Communication, F (1, 76) = 7.67, $p < .01$). For the two cases of missing conversation effects we examined contrasts between the (Noise, Non-Classified-Conversation) cell and the remaining three cells combined in an analysis sub-table. These contrasts were significant with a one-tailed test at $p < .025$, t (76) = 3.25 and t (76) = 2.23 for Retweet and Mention respectively. Thus, we demonstrate that our conversation-based classification for tweets correlates with higher densities of information content to support the hypothesis H2.2.

2.5 Discussion and Hypotheses: Reviewing the Usability of Offline Social Knowledge for Understanding Online Social Data

Our goal was to separate the online conversations on Twitter data stream into subsets more and less likely to contain citizen coordination revealed in conversation by analyzing offline-theory guided linguistic properties of the content. We modeled linguistic coordination features in conversation classifiers for Twitter datasets, including three types of platform function-based messages (Reply, Retweet, Mention) assumed to contain a high proportion of conversation. Using simple heuristic features of linguistic coordination, based on pronouns, dialogue management, and word count, we demonstrated the ability to classify tweet messages sets that are instances of Reply, Retweet, and Mention based conversation versus none of these with accuracy up to 78% and ROC area values up to 0.84. These generally good performance values support H2.1, and address our research question R1 of this dissertation as mentioned in the Chapter 1. The linguistic coordination indicative features guided by offline theories distinguish online messages (tweets) containing platform functions of conversation from other non-conversation tweets. Thus, our contribution adds insights to existing knowledge of conversational behavior online on Twitter [24, 40] for additional dimensions of conversational indicators in citizen sensor communities.

Consistent with our question assumption for hypothesis H2.1, our ability to classify conversation declines with the type of Twitter exchange, but in an interpretable fashion. We do best at classifying Reply-based conversations, which should rely most heavily on coordination indicators because the intended purpose of Reply is conversation. The accuracy pattern is also consistent with Honeycutt and Herring [50] who noted a high degree of conversationality using lexical patterns while using '@' sign of addressivity. However, in contrast to Ritter et al. [99], we also classify a large percentage of Reply, as well as Retweet and Mention as non-conversation. Consistent with our assumption on effect of event content, we do better with the disaster event corpus than the non-disaster corpus as shown in Table 2.3. This supports a potential association between linguistic features of coordination and the potential of actual coordination that the disaster invokes, and the corresponding conversations around it. Despite relative success in distinguishing different types of tweets from non-conversation, our discrimination statistics are not perfect. This is in part due to the expected contamination of Reply, Retweet, and Mention function usage with non-conversation. As Boyd, Golder, and Lotan [11] explained, various motivations apart from conversation drive retweeting behavior. Alternatively, we assert the presence of otherwise undetected conversation in the non-conversation subset.

- **Psycholinguistic Theory**

We know of no other studies that attempt to test an account of conversation against a control corpus, in part because of the challenge of defining such a corpus. The bulk of linguistic theory hinges on the analysis of positive instances of conversation. Thus, we had not previously been able to test the diagnosticity of conversation indicators.

Consistent with H2.1, the models generally depend on a common set of effective heuristic features, across individual events, types of events, and types of conversation. The superior features overall included subject pronouns and dialogue management indicators. The utility of pronouns reflects the prior common grounding of important entities (agents and objects) in previous exchange. Less effective features include the relative, possessive and reflexive pronouns. Those pronouns may readily obtain grounding within the message posting itself (i.e., anaphora) and are therefore potentially less dependent upon the collaborative establishment of common ground, consistent with [20]. However, the classification of Retweet and Mention-based conversations also relies upon the determiner "the" and word count. Crediting the original source and adding opinion prefixes necessarily extend the length of tweets, unless already at the 140 character limit. Thus the length heuristic feature is likely an artifact of the Twitter medium. Nevertheless, space-driven unconventional English and new writing conventions such as hashtags did not eliminate the tacit concern for coordination in ordinary conversation. Even the Retweet reflects some conversational coordination.

In addition to demonstrating the diagnosticity of conversational indicators relative to a control condition of non-conversation, we also have demonstrated a greater density of information content in tweets that reflect conversation, consistent with H2.2. The Twitter data stream that does not get classified as conversation appears to have less content. This theoretically relevant association between linguistic coordination features of conversations and content has practical merit. We cannot assume that all platform-marked conversation (via function of Reply, Retweet, Mention), is actually information rich conversation, providing a basis for trimming an otherwise unwieldy volume of message traffic in online social platforms.

- **Limitations and Future Direction**

Alternative machine learning approaches such as boosting and bagging could improve the performance of the conversation classifier. However, our goal here is to present an existence proof for a domain-independent conversation classifier as the foundation for the use of existing social knowledge of offline conversation behavior in detection of coordination in online conversations. Although linguistic theory assumes a universal need for cooperation in conversation, our heuristic features are limited to English and could require revision as we extend them to other languages.

We relied on generic semantic metrics (for communication, sensed experience, and social interaction) simply to demonstrate the potential information gain in the conversational subsets detected using help of offline-theory guided features. Although encouraging, this is no substitute for the semantic analysis that identifies actionable nuggets.

There is a need to focus on the semantic abstraction model, both domain independent and domain specific, to further mine, sort, and aggregate actionable content from CSC for addressing cooperation challenges of *awareness* and *articulation* for organizational actors. We, therefore, discuss our approach of intent mining to meet the *articulation* of organization's actionable information needs in the next chapter.

Chapter 3: Identify function: Intent Classification to Meet *Articulation* of Organizational Needs

Intent is defined as an aim or plan for action. We observe this behavior every day, for instance, when a user queries on a search engine in order to buy a laptop, or when a user participates in a conversation to inform. We assess the intent of user expressions in the context of cooperation in goal-oriented CSC. Specifically, organizational tasks have information needs, and require mining of information related to those tasks from user-generated messages in CSC. We focus on mining information specific to relevant intent classes that meet the need of an *articulated* organization and enable cooperation between citizens and organizational actors. Much prior work in intent mining addresses the challenge of understanding queries on search engines by modeling search logs (e.g., query terms, click graphs, action sequences) in the problem space of Information Retrieval. Intent during search is a specific behavior of finding navigational, informational and transactional information instead of social communication. However, the objective of our study is to model intent in user-generated content of CSC for understanding human expressions in online social platforms for cooperation, and not search queries. We contrast our objective with different types of intent mining research in the related work section. We denote citizen sensor generated messages as short-text documents to better situate the mining problem in the related context of text mining. Our research question is "How to identify relevant intent from an ambiguous, unconstrained natural language text document?" We first discuss the issues in interpreting the intent of a short-text document, then formalize our problem as a classification problem, noting gaps in the related work, and then presenting our knowledge-guided approach to fuse top-down and bottom-up processing paradigms for efficiently mining intent.

3.1 Addressing the Challenge of Multiple Intent as a Classification Problem

Citizen sensors often express a variety of intents within single short-text document as they try to capture the specifics of information concisely in the small space constrained by the online social platform. For instance, in the use-case of crisis, recent studies showed citizens on- and off-site using Twitter to share information on situational updates, asking for help as well as offering help [127, 125]. Table 3.1 shows examples of some of these short-text documents and associated potential intent from a crisis event dataset of hurricane Sandy in US in the year 2012. Note the informal language (e.g., wanna, thx, etc.) characteristic of short-text documents (see Section 2.2).

Multiple potential intent classes complicate natural language interpretation. A variety of factors affect an individual's expression of intentionality [3, 69, 114]. In fact, natural language understanding is an AI-Complete problem [108]. Therefore, to make the intent identification problem computationally tractable, we exploit top-down processing, and define a classification form of this problem for mining specific intent classes.

We define a general form of intent classification as a multi-label classification problem [96], with the special case of one label per document as a multi-class classification prob-

	Short-text Document	Potential Intent
M1	Text redcross to 90999 to donate $10 to help those people that were effected by hurricane sandy please donate #SandyHelp	Seeking help
M2	Anyone know where the nearest #RedCross is? I wanna give blood today to help the victims of hurricane Sandy	Offering help
M3	@Zuora wants to help @Network4Good with Hurricane Relief. Text SANDY to 80888 & donate $10 to @redcross @AmeriCares & @SalvationArmyUS #help	Offering help Seeking help
M4	Would like to urge all citizens to make the proper preparations for Hurricane #Sandy - prep is key - http://t.co/LyCSprbk has valuable info!	Advising Reporting
M5	Thx to all in Kettering who brought supplies for those affected by Hurricane Sandy. Visit http://t.co/IWSCVity to help. ...	Acknowledging Seeking help

Table 3.1: Examples of short-text documents and associated potential intent

lem [36]. The scope of this chapter is focused on multi-class classification. Our specific problem statement is:

- **Problem Statement p3.a**: Given a community of citizen sensors (users) u_i as CSC = $\{u_v \mid v \in \mathbb{N}\}$ formed around discussion of a real world event E, with short-text documents m_i generated by u_v creating a document corpus A = $\{m_i \mid i \in \mathbb{N}\}$, and a set of K intent classes, $c \in \{C1, C2,..,CK\}$; predict an intent class c for each $m_i \in A$.

3.2 Related Work and the Challenges of *Ambiguity* in Interpretation, and *Sparsity* of Intent

Work related to problem p3.a crosses multiple issues. We describe each of them in the following:

- **Data and Domain Variant Characteristics of Intent Mining**

For search engine data, researchers designed approaches to mining intent in user queries using data from user search logs, including clicks, click sequence graphs and query terms, with broadly identified content categories such as navigational, informational and transactional types [13, 28, 5, 16, 118]. A major limitation of this approach for our problem context is the dependence on (an unavailable) large data set of user behavior. Furthermore, the variety of intent classes prohibits bottom up search.

For well-formed text data, prior intent mining work spans varying problem areas including analysis of presidential speeches [59], and product reviews [94, 133, 18]. In contrast with the short-text document content of social platforms (e.g., Twitter), such reviews and large text documents provide more explicit information about the applicable context, and typically comply with formal language usage and syntactic structure that enables established methods of Natural Language Processing.

Within social platforms data, earlier research has mainly focused on mining transaction related intent due to practical commercial merits [49, 15, 18]. The limited action motives pertain to the transactional intent of buying and selling, and therefore, the nature and interplay of other kinds of complex intent requires more investigation, such as helping (a broad intent class). Researchers have also modeled cultural differences in the expression of user intent via signals of goals, perceptions of control, and rewards using a hashtags based approach [121], however, hashtags have limited ability to capture the variety of intent expressions. Past work has also dealt with the identification of problems or aid report recognition during a crisis event [125], which closely relates to intent identification of seeking and offering help in our context. However, a report may not capture the expression of future actions, such as the intent of donation offering.

- **Problem Variant Characteristics of Text Classification**

Problem p3.a is a form of text classification [45]. However, there are subtle differences in the type of text classification problem under investigation here. In the literature, researchers have studied topic classification [129], opinion or sentiment or emotion classification [129, 83], as well as intent classification [49, 18]. Consistent with the observation of Kröll and Strohmaier [59], topic classification is focused on the subject matter of the document while opinion classification is focused on the current state of affairs. In contrast, intent classification is focused on the future state of affairs. For example, "I wanna watch awesome Fast & Furious 7. Yh, Vin Disel is COOLESt!!!". In this example, topic classification of the message focuses on the noun, the movie 'fast & furious 7'; sentiment and emotion classification is focused on the positive feeling of the author's message expressed with the adjective awesome. In contrast, intent classification concerns the author's future action of going to watch the movie, the action expressed via the verb phrase wanna watch. Furthermore, topic classification would typically ignore stopwords such as 'the' (Determiner) or a verb, which as shown in Chapter 2 on conversation classification, can be quite important features for indicating a context. Therefore, the data representation in feature vector space, algorithms for modeling, and their performance measures in these various forms of the text classification problem have a different focus than ours [129].

- **Classification Approach Variant Characteristics**

Prior research work on intent classification has mainly focused on binary classification methods due to the complexity of intent prediction from the natural language, and given that the multiclass classification is a hard-to-predict problem. Also, for multiclass classification, increasing the number of classes further increases complexity. It is still an open problem for the best method to employ depending on the data and problem domain. Researchers have studied, therefore, different learning schemes under mainly two areas of the learning methods, a.) A standalone multiclass learner, and b.) Binarization by dividing the problem into multiple binary (base) learners, followed by combining them [36, 107]. In the multiclass learner, the higher complexity of learning the decision boundaries for the classification due to number of classes is a major challenge. The binarization method has the benefit of simplified learning due to only two-class problems for the base learners. Binarization also takes advantage of and leverages well-studied binary classification algorithms for the base learners, and can be parallelized for addressing scalability. The most popular schemes for the binarization framework are decomposition based one-vs-one (OVO), and one-vs-all (OVA). Furthermore, binarization techniques include the fusion of results of the binary classifiers. Therefore, aggregation based approaches such as error-correcting-codes

(ECOC) have been studied. Although these approaches have been mainly investigated on the UCI gold standard datasets [36, 37], within the context of a more challenging intent classification problem these schemes are yet to be tested. There is an additional challenge of imbalance and class dependence relationships in expressing intent in our problem context, such as the higher likelihood of complementary existence of both intent classes of seeking-offering in a message.

- **Challenges of *Ambiguity* and *Sparsity***

Informal language usage creates *ambiguity* in interpreting a document. *Ambiguity* here refers to the existence of overlapping characteristics corresponding to multiple intent classes within a single document, causing the weak learning of predictor-class relationships for that document. *Sparsity* of behaviors of specific intent classes in the corpus creates imbalance issues.

In the current objective of this chapter, the mining of intent classes is focused in the social setting (in contrast to the more narrow *search* intent such as transactional), where a user expresses intent in the short-text document to be socially communicative with other users, specifically to promote cooperation. This focus opens an opportunity to explore social behavior as a context for improving intent mining performance. We focus on three intent classes in this work, relevant to the *articulation* of organizational tasks for our cooperative system design: {*Seeking*, *Offering*, *None* (Neither Seeking nor Offering)}.

We now identify the following hypotheses related to the broader research questions R2 and R4 in Chapter 1, on the potential of exploiting psycholinguistic research for mining the relevant intent from unstructured, ambiguous short-text documents:

H2.1. Psycholinguistic research can inform semantic and syntactic feature design to improve expressivity of data representation for the intent classification of user-generated content in CSC.

H2.2. Intent classification can be improved by fusing top-down knowledge-guided and bottom-up statistical learning approaches to address the imbalance and label dependence of intent classes in user-generated content.

H2.3. Performance for intent classification by fusing top-down knowledge-guided and bottom-up approaches improves both popular frameworks of multiclass classification using binarization – one-vs-one (OVO) and one-vs-all (OVA).

We discuss our intent classification approaches to address the *ambiguity* and *sparsity* challenges in three forms: bottom-up processing (v1), top-down processing (v2), and a fusion approach of top-down and bottom-up paradigms (v3).

We summarize the key lessons of our approach, and the organization of this chapter's logic in Figure 3.1. Approach v1 of bottom-up processing exploits the implicit semantics of the local content achievable by statistical processing of the training data alone. On the other hand, approach v2 of top-down processing exploits the semantics of the content using features guided by declarative knowledge and social behavioral patterns, acquired outside the context of the given training data. Finally, approach v3 reflects a powerful form of exploiting semantics with richer representation of data by combining top-down and bottom-up approaches, and learning intent with the knowledge-enhanced representation of the training data. The knowledge-guided features inform the expressivity in the data representation for efficient machine learning to solve a hard-to-predict intent classification problem.

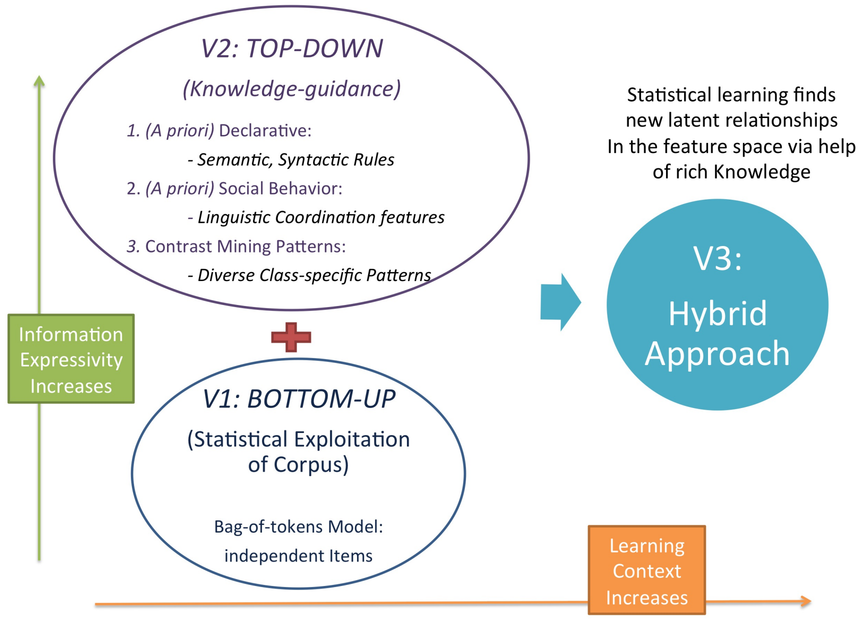


Figure 3.1: A knowledge-guided approach can improve representation of context in the feature space for training an intent classifier, by employing guidance from a variety of knowledge sources in designing features.

3.3 Approach v1: Learning with a Bottom-Up Approach of Local Content-driven Features

The prior literature for both binary and multiclass classification has employed a basic approach to text classification problems by learning local text features contained within the document [49, 125, 129]. Therefore, we first perform such content-based feature extraction.

The bag of tokens model is a well-known content exploitation approach in text mining. Each short-text document mi can be represented as,

m_i = { $(w_i, f(w_i))$ $|w_i \in W$, $f(w_i) \in$ [0,1]}, where w_i is a n-gram token, and $f(w_i)$ is a function for choice of the feature design, such as n-gram token frequency.

We create features using a dictionary W of n-gram tokens w_i that is acquired using a tokenization process (e.g., single-space delimiter for uni-gram tokens) on the documents of corpus A, and employ term frequency (*tf*) function as $f(w_i)$ for each n-gram token feature.

The learning process derives patterns in this token-based feature space. We hypothesize this simple but effective approach to text classification as applicable in our problem context. We further explore role of knowledge about human behavior in the next section as our approach v2 to address the challenge of exploring further improvements in expressivity of data in representation.

3.4 Approach v2: Learning with a Top-Down Approach of Global Knowledge-driven Features: Declarative, Social, and Contrast Patterns

We note the challenge of semantics in understanding of implicit relationships between features in a bag-of-tokens model, as in approach v1 to interpret intent. A learning algorithm can identify several relationships between features, and derive patterns of such relationships that correlate with the learning objective classes. However, mining of such relationships is limited to the provided training data *locally*. Also, it can be highly complex and time consuming, given that textual data can generate a large dictionary of n-gram features.

Human beings often find relationships between two objects by connecting them via a reference lookup, or compare and contrast with their prior experience. Similarly, our goal is to acquire such a knowledge source that can assist finding relationships between items in the feature space of the intent learning task. We present three kinds of knowledge sources for informing intent classification in the settings of an online socio-technical system as follows: *Declarative*, *Social*, and *Contrast Patterns*.

- **(DK) Declarative Knowledge: Interplay of Semantics and Syntax**

Declarative knowledge includes facts, and in this context, knowledge about the expression of different intent classes. We rely on domain experts, who can provide rules for specific lexical patterns based on experience. Another approach is to rely on studies of human expression from linguistics, natural language understanding in Artificial Intelligence, and psychology, which inform the design of ontological rules of domain independent intent expression.

Conceptual Dependency Theory. Taking inspiration from conceptual dependency theory by Schank [103], we rationalize our design of a psycholinguistic rule base. Conceptual dependency theory supports the concept abstraction for establishing meaning independent of specific word occurrences in the document so as to represent two documents with similar meaning by a conceptual class representation.

Semantics for Intent. Linguistic syntactic classes such as verbs or adjectives also convey semantic content when they associate with a context-specific meaning. Concept classes specific to a domain (such as ‘shelter’ in a crisis response) are higher-level abstractions [74] for domain specific information needs. Including the semantics of the textual constituents establishes relationships at an abstract level, and therefore, captures multiple data instances containing different textual constituents within a specific sense of intent. We rely on a lexicon for the psycholinguistic class of verbs, to design a foundational rule base for distinguishing between intent classes, given that verbs imply a plan for action. While it is possible to express a human need without a verb to express an intent class, for example by stating the noun in question, such formulations are potentially ambiguous and our objective is to create meaningful intent representations. Levin’s analysis of verbs [62] is well grounded in the scholarly literature, and provides a resource for selecting the verbs of specific intent expressions.

Syntax for Intent. Apart from syntactic classes such as verbs corresponding to semantic content, specific syntactic constructions have implications for intent. For example, a subject with the main verb “have” and any noun suggests an Offering intent expression. However, the same text preceded by the auxiliary verb “do” and the pronoun “you” suggests a Seeking intent expression because the combination of syntax and pronoun reverses the illocutionary force through an interrogative structure. However, the abbreviated and unconstrained Twitter medium prevents reliance on punctuation for the identification of interrogatives. Pronouns and word order assist in the complementary intent class expressions associated with interrogatives, e.g., "Can you send water?" (Seeking) and "I can send water" (Offering). Similarly, word order (e.g. verb-subject positions) also plays a crucial role in the intent expression, and provides stark contrast to the unordered bag-of-tokens model for data representation.

Semantic Classes for Relevant Intent Categories in the Context of Cooperation. Given our focus on the relevant intent classes for meeting *articulation* of organizational needs as *Seeking* and *Offering*, we focus primarily on verbs corresponding to Schank's P-Trans primitive [103], reflecting the transfer of property. Our lexicon of Seeking-Offering verbs includes the Levin categories of: give, future having, send, slide, carry, sending/carrying, put, removing, exerting force, change of possession, hold/keep, contact, combining/attaching, creation/transformation, perception, communication. We exploit the semantic classes of auxiliary verbs ('be', 'do', 'have'), the modals ('can', 'could', 'may', 'might', 'would', etc.), consistent with exploration by [94], question words ('wh'-words and 'how') and the conditional ('if').

Supporting Study. We performed a preliminary study of the psycholinguistic knowledge based approach on the hurricane Sandy event that occurred in the US in 2012, as discussed in Section 2.4. We processed a dataset of 4.9 million tweets collected using the Twitter Streaming API from October 27 to November 7, through a domain independent conversation classifier created using a mixed event dataset, as discussed in the Chapter 2. We applied the rules in Table 3.2 to classify the tweets suggesting conversation, and selected a sample of 2,000 tweets for validating with two native English-speaking annotators, for *Seeking help* versus *Offering help* intent classes. On the subsample with strict agreement of both the annotators for a class with Cohen's Kappa being "moderate", we observed

Behavior	Linguistic Rules
Seeking	(Pronouns except you = yes) ∧ (need/want = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Seeking (need = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Seeking (please = yes) ∧ (Levin Verb = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Seeking (who = yes) ∧ (has/had = yes) ∧ (Determiner = yes/no) ∧ (Adjective = yes/no) ∧ (Things = yes) → Seeking (what = yes) ∧ (can/could = yes) ∧ (Pronoun/Proper Noun = yes) ∧ (do = yes) → Seeking *(Weak Offering)* (shall/will = yes) ∧ (Pronoun/Proper Noun = yes) ∧ (Levin Verb = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Seeking (do/does/did) ∧ (Pronoun/Proper Noun = yes) ∧ (have/has/had = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Seeking
Offering	(Pronoun/Proper Noun = yes) ∧ (have/has/had = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Offering (if you = yes) ∧ (need/want = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Offering (Pronoun except 'you'/Proper Noun = yes) ∧ (can/could/would/should = yes) ∧ (Levin Verb = yes) ∧ (Determiner = yes/no) ∧ (Adjective= yes/no) ∧ (Things = yes) → Offering (Pronoun/Proper Noun = yes) ∧ (may/might/must/can/could = yes) ∧ (help/assist/aid/lend a hand = yes) → Offering (do = yes) ∧ (you = yes) ∧ (need = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Offering (Pronoun/Proper Noun = yes) ∧ (shall/will = yes) ∧ (Levin Verb = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Offering (shall/will = yes) ∧ (Pronoun/Proper Noun = yes) ∧ (Levin Verb = yes) ∧ (Adjective = yes/no) ∧ (Things = yes) → Offering

Table 3.2: Psycholinguistics based semantic and syntactic rules to identify Seeking and Offering intent classes. (x = yes) is a binary function to check presence of the feature x in the document. The lowercase word x implies literal usage, e.g., 'need/want' implies presence of either of 'need' or 'want' word. A capitalized word implies presence of any of the class of word types, e.g., 'Adjective' for adjectives and 'Things' for resources from domain ontology (our design of crisis domain ontology is discussed in the Appendix)

F-1 score of 0.78 and AUC as 0.79. This supports the investigation of psycholinguistic research for further improving intent classification. Detailed analysis of this study appears in [90].

We noted that an exhaustive list of such limited rules is still subject to error, largely due to the phenomenon of indirect speech acts, which rely on shared background knowledge to reinterpret apparently factual information [105]. Accordingly, asserting a problem is a classic approach to expressing a need, e.g., "it is hot in here" means "I need air" and/or "open the window". Similarly, "The Red Cross can provide housing" provides a supplier fact. However, "I bet the darn governor can provide housing" could imply a disgruntled seeker employing an indirect speech act, because unlike the Red Cross, the governor does not directly offer housing. Moreover, we cannot yet identify the implicit interrogative in "Sam thought that Beth had water", which calls into question whether Beth in fact had water [47]. The factual statement could also imply that Beth is seeking water, Sam is seeking water, or the speaker is seeking water, none of which is actually asserted. In this regard, we hypothesize two further types of knowledge that can help enrich context.

- **(SK) Social Knowledge: Offline-theory Guidance**

Intent classification in the online socio-technical environment for cooperative behavior can leverage the contextual features of conversations, as the conversations are foundation for cooperation. In online socio-technical systems, citizen sensors will generate intentional content in the expectation of a cooperative listening audience. This differs from user actions that may or may not have a motive for social interaction (e.g., search intent). Exploiting such a social aspect of conversational behavior as a knowledge source can improve the context of intent classification. We considered linguistic coordination indicators discussed in Chapter 2 as a potential source for this type of knowledge (e.g., Dialogue Management, Determiner, etc.).

- **(CPK, CTK) Contrast Pattern Knowledge: Exploiting Power of Data Mining**

In the declarative knowledge provided by domain experts and social knowledge, there is likely a possibility of missing relationships due to the challenge of creating an exhaustive rule set for that knowledge. Therefore, our goal is to incorporate the power of data mining to discover contrasting patterns for each of the intent classes as a priori knowledge for the learning process. Such patterns can boost data representation for learning predictor-response relationships [27]. The patterns should be sequential due to the importance of token (word) order in intent expressions as noted earlier. There has been work in the literature to observe the importance of sequential pattern-aided text classification for topic as well as sentiment and opinion mining [98, 54, 51, 55].

The typical sequential pattern mining [31] is unsupervised and oriented to discovering patterns in a temporal transactional database to glean knowledge of interesting patterns with no supervision in the core process, unlike declarative knowledge. However, this approach generates a huge number of patterns based on the chosen parameter for minimum frequency, and requires pruning in a post-processing step.

Our objective is, first, to mine sequential patterns within a labeled dataset of an intent class to observe any interesting class-wise frequent patterns [55]; this is followed by contrasting such class-wise pattern sets against each other to derive interesting, and novel emerging patterns [26, 66] for classes as described in the following. Incorporating this technique in our knowledge guidance framework can therefore help address challenges of efficiently capturing context for some of the imbalanced intent classes, as well as provide the contrasting features as a means to boost the discriminative power of the representation of data in the feature space for learning.

Formally, adopting basic definitions from [66] in our problem context, we define a measure to select contrasting patterns, *Sparse-Contrast-Strength*(P,C_j) for a pattern P and intent class C_j:

1. A dataset, a corpus A in problem definition $p3.a$, is defined upon a set of k features (also referred as dimensions) $\{F_1, F_2, ..., F_k\}$ for mining patterns. For every feature F_i, the domain of its values (or items) is denoted by $dom(F_i)$. Let I be the aggregate of the domains across all the features, i.e. $I = \cup_{i=1,..,k}\, dom(F_i)$.

2. An itemset is a subset of I. Let P and Q be two itemsets. We say P contains Q if $Q \subset P$. A dataset is a collection of transactions corresponding to each short-text documents $m_i \epsilon A$. Each transaction T is a set of feature values, i.e. $T \subset I$. The number of transactions in A is denoted by $|A|$.

3. The support of an itemset P in dataset A, denoted by $support(P, A)$:

$$support(P, A) = |T_p|/|A|, \quad \text{where } T_p = \{T|P \subset T\}, \text{ and } 0 \leq support(P, A) \leq 1 \tag{3.1}$$

4. Assume two candidate classes in dataset A, namely $C1$ and $C2$. The support ratio of

an itemset P between two classes, termed as *growth rate (gr)*:

$$gr(P, C1, C2) \; = \; support(P, C1)/support(P, C2) \tag{3.2}$$

5. Each itemset is associated with a discriminating power (or contrasting *strength*):

$$strength(P, C1, C2) = support(P, A) * gr(P, C1, C2)/(1 + gr(P, C1, C2)) \tag{3.3}$$

6. An Emerging Pattern (EP) is a simple contrast pattern, defined as an itemset P, s.t. $support(P, C2) \leq \beta$ (i.e. infrequent in $C2$), and $support(P, C1) \geq \alpha$ (i.e. frequent in $C1$). Moreover, P is a minimal emerging pattern if it does not contain other emerging patterns. A Jumping Emerging Pattern (JEP) is an EP that has an infinite *growth rate*.

7. We compute contrast emerging patterns within a dataset of an intent class from an imbalanced class set, where *sparsity* creates a challenge to identify any meaningful patterns from a minority class using frequent pattern mining, favoring majority class. Therefore, we bias to compute per class frequent patterns with varying support thresholds ST_j for an intent class C_j. After computing frequent patterns, we prune for minimal patterns in each C_j, and then find contrast measure. We define contrast measure of a pattern P for class C_j as,

$$\begin{aligned} Sparse - Contrast - Strength(P, C_j) = \\ support(P, C_j) * Contrast - Growth(P, C_j, C_k) \end{aligned} \tag{3.4}$$

where,

$$
\begin{aligned}
&Contrast - Growth(P, C_j, C_k) = \\
1/(|C_j| - 1) \sum_{C_k, k =/= j} &gr(P, C_j, C_k)/(1 + gr(P, C_j, C_k))
\end{aligned}
\tag{3.5}
$$

and, $Contrast - Growth(P, C_j, C_k) = 1$ if $gr(P, C_j, C_k)$ is infinite (a case of jumping emerging pattern).

8. We use a ranking method for pattern selection per class using a parameter $X\%$ for top-k, based on the measure of $Sparse - Contrast - Strength(P, C_j)$.

We hypothesize that the selected contrast patterns further leverage knowledge to improve context in the data representation, and improve the learning performance. We denote the feature set *CTK* when items are the text tokens, and *CPK* for the case when items are part of speech (POS) tags of the text documents.

3.5 Approach v3: Learning with an Integrated Approach of Global Knowledge- and Local Content-driven Features

Our knowledge-guided classification framework merges the bottom-up processing of approach v1, and top-down processing of approach v2 to address these challenges by improving expressivity of data representation. By merging the top-down approach v2 in our hybrid approach, we exploit *a priori* knowledge external to the training data available for learning, saving on the amount of time to statistically learn expressive and diverse predictor-class relationships by complex processing in the feature space.

Algorithmic level	Improving the learning, e.g., via higher dimensional space discrimination, cost sensitive learning, ensemble via boosting
Data level	Improving resampling of skewed class set such as via oversampling, undersampling, synthetic generation SMOTE
Expressivity level	Improving representation of data via *a priori* knowledge of semantic, syntactic, social behavior and frequent pattern knowledge

Table 3.3: Levels of improving learning performance for intent classification

The specific challenge of *ambiguity* in interpreting an intent class for a short-text document containing unconstrained natural language also presents a problem of class dependence relationships during the learning process (e.g., *Seeking* may be positively associated with *Acknowledging*, while negatively associated with *Offering* in majority of the documents, although using similar strong features such as ‘wanna help’). On the other hand, the challenge of the *sparsity* of specific intent classes in the data leads to an imbalance problem in machine learning. These challenges weaken the learning of strong predictor-class relations by exploiting the feature space, especially when approached by only frequency-based techniques of bottom-up processing, likewise approach v1.

There are three levels in our view to address imbalance and class dependence problems for intent classification described in Table 3.3. We focus on improving the expressivity by generating a rich feature space using algorithm 2 based on both bottom-up and top-down approaches. We address the challenge of class dependence relationships via psycholinguistic knowledge of various intent expressions, as well as imbalance via the infusion of contrast pattern knowledge. For the algorithmic choice for learning, we use the ensemble approach for base learners of a binarization framework to address the challenge of better learning with imbalance distributions for a multiclass classification problem.

We aim to first investigate the role of improving data representation for a binary classification task, followed by multiclass classification. For our experimental design to assess performance of the three approaches, we experiment within the two popular multiclass classification approaches, one-vs-one (OVO), and one-vs-all (OVA), as discussed in the

Algorithm 2 Representation Improvement Algorithm

INPUT:

A = Corpus of labeled short-text documents m_i with intent class $Cj \in C$, $\{Cj, j \in [1,K]\}$

STj = Support threshold for frequent patterns of text items for Cj (STj_pos, in case of POS tag items)
Xj = Contrasting pattern selection threshold for text items (Xj_pos in case of POS tag items)
n = N-gram size to represent an item in the bag-of-tokens model representation

OUTPUT: Feature Vectors for Classification

1. *T* = ∅ # *Bag-of-words (n-grams) Feature Set*
2. *DK* = ∅ # *Declarative Knowledge Pattern Feature Set*
3. *SK* = ∅ # *Social Knowledge Pattern Feature Set*
4. *CTK* = ∅ # *Contrast Emerging Pattern Feature Set for text document corpus A*
5. *CPK* = ∅ # *Contrast Emerging Pattern Feature Set for POS tagged document corpus A*

PROCEDURE:

Compute Document-specific Features

1. *Wn* = ∅ # *Dictionary of cleaned tokens (n-grams of size n)*
2. *Cln_A* = ∅ # *Corpus A with cleaned text documents*
3. *A_pos* = ∅ # *Corpus A with Part of Speech tagged documents*
4. **for** $m_i \in A$ **do**
   a. m_i*_cln* = TEXT-CLEANER (m_i) # *Preprocessing for cleaning informal text*
   b. *Wn* = *Wn* ⊔ N-GRAM-TOKENIZER(m_i*_cln, n*)
   c. *Cln_A* = *Cln_A* ⊔ m_i*_cln*
   d. *A_pos* = *A_pos* ⊔ POS-TAGGER(m_i)
   e. *DK* = *DK* ⊔ DECLARATIVE-KNOWLEDGE-PATTERN-MINER(m_i, m_i*_pos*)
   f. *SK* = *SK* ⊔ SOCIAL-KNOWLEDGE-PATTERN-MINER(m_i)
5. **end for**

Compute Corpus-specific Features

Extract feature on Bag-of-words (n-grams)

6. *F* = VECTORIZE(*Wn*) # *create feature vector of token dictionary*
7. **for** $m_i \in A$ **do**
   a. *T* = *T* ⊔ FREQUENCY-VECTORIZER(*F*, m_i) # *frequency based vectors*
8. **end for**

Mine Contrast Patterns from itemsets in Text and POS tagged document corpuses

 # Frequent Pattern Mining

9. *FP(Cj)* = ∅ # *Frequent sequential patterns for text documents of A, for Cj*
10. *FP_pos(Cj)* = ∅ # *for POS tagged documents of A, for Cj*
11. for *Cj* ∈ *C* **do**
    a. FP(*Cj*) = SEQUENTIAL-PATTERN-MINER(*Cln_A*, *STj*) # *Find Support*
    b. FP_pos(*Cj*) = SEQUENTIAL-PATTERN-MINER(*A_pos, STj_pos*)
12. **end for**

 # Contrast Computation for Sparse-Contrast-Strength(P,Cj)

13. *CP* = ∅ # *Set of (patterns, contrast measure values)*
14. *CP_pos* = ∅
15. for *P* ∈ ($\sqcup_{Cj \in C}$ *FP(Cj)*) **do**
    a. *CP* = *CP* ⊔ (*P*,CONTRAST(*P*,*Cj*))
16. **end for**
17. **for** *P_pos* ∈ ($\sqcup_{Cj \in C}$ *FP_pos(Cj)*) **do**
    a. *CP_pos* =*CP_pos* ⊔ (*P*,CONTRAST(*P*,*Cj*))
18. **end for**

 # Pattern Selection

19. **for** *Cj* ∈ *C* **do**
    a. *CTK* = SELECT-X(*CP*, *Xj*) # *Top X% by contrast strength & support for Cj*
    b. *CSK* = SELECT-X(*CP_pos*, *Xj_pos*)
20. **end for**

 # MINE THE FEATURE SPACE FOR CLASSIFICATION

introduction and related work of this chapter.

3.6 Experimental Design and Implementation

We experimented with the three approaches discussed above; using the Representation Improvement Algorithm 2 by assessing the performance contribution for the alternative approaches. We experiment on two real world datasets created from Twitter social media platform, to observe the value of employing knowledge in the computation of intent in documents generated by users of CSC on Twitter. Our datasets represent a different socio-cultural environment for the participating demographics, due to the nature of real world events. This allows us to assess the role of linguistic and social knowledge from offline theories in understanding human expressions online.

- **Data Collection**

Using the data collection method of keyword-based crawling approach described in the Section 2.4 of the Chapter 2, we collected a set of short-text documents as tweets from Twitter Streaming API. The keyword-based crawling approach is the most popular approach in the prior studies on Twitter platform. We collected two crisis event datasets:

1. Dataset-1: 4.9 million tweets for hurricane Sandy in the US in 2012 for a period of 10 days (October 27 to November 7), and

2. Dataset-2: nearly 2 million tweets for typhoon Yolanda in the Philippines in 2013 for a period of 10 days (November 7 to 17).

- **Sampling for Labeling Cooperation-assistive Intent Classes: Setting Prior Context for Goal-orientation**

Before we label the datasets for acquiring annotations for intent classes in these datasets, we begin with the context of cooperation-assistive intent expressions in the data, for a broader goal of relief donation coordination for the crisis domain datasets. Also, there is a *sparsity* of some of the intent classes in social networks and the context itself. For example, Imran et al. [52] observed only 16% of the data related to donation of goods and services on a dataset of the Joplin tornado event. The *sparsity* of behavior in the data also challenges crowdsourcing for labeling at scale, given the limited budget for the crowdsourcing tasks. Therefore, we first created a classifier of donation-related messages to provide context for labeling specific intent classes. We rationalize the choice of restricting context to donation related messages in goal-oriented CSC based on the real-world goal of achieving relief donation coordination—one of the major challenges of crisis response domain. We sampled dataset-1 for labeling the donation class.

Donation Labeling: A multiple-choice question was asked to crowdsourcing workers (assessors) on Crowdflower platform (`http://www.crowdflower.com/`). "Choose one of the following options to determine the type of a tweet":

a. *Donation* - a person/group/organization is asking or offering help with a resource such as money, blood/medical supplies, volunteer work, or other goods or services.

b. *No donation* - there is no offering or asking for any type of donations, goods or services.

c. *Cannot judge* - the tweet is not in English or cannot be judged.

The options were worded to encourage assessors to understand "donation" in a broad sense, otherwise (as we observed in an initial test) they tend to understand "donations" to mean exclusively donations of money. Given our limited budget for the crowdsourcing task and the relatively small prevalence of donation-related tweets in the data, we introduced some bias in the sample of tweets to be labeled. We selected 1,500 unique tweets by uniform random sampling, and 1,500 unique tweets from the output of a conditional random field (CRF) based donation-related information extractor borrowed from the work of [52]. The two sets of tweets were merged and randomly shuffled before they were given to the assessors.

We asked for three labels per tweet and obtained 2,673 instances labeled with a confidence value of 0.6 or more (the range is 0 to 1). This confidence value was provided by the crowdsourcing platform and it is based on inter-assessor agreement and the assessor agreement with a subset of 100 tweets for which we provided labels. Our labeled dataset contained 29% of tweets of the 'donation-related' class.

Donation Classifier Learning: We experimented with a number of standard machine learning schemes. For this task, we obtained good performance by using attribute (feature) selection using a chi-squared test, considering the top 600 features, and applying a nave Bayes classifier [132]. To reduce the number of false positives, we used asymmetric misclassification costs. That is, we considered a non-donation classified tweet as donation as 15 times more costly than the case of a donation classified as non-donation.

After 10-fold cross-validation, for the donation class we achieved a precision of 92.5% and 47.4% of recall. The area under the ROC curve (AUC) is 0.85, which implies good classification ability. We used this donation classifier to get contextually related tweets to acquire more labeled data for intent classes via crowdsourcing task. We extracted donation-related tweets from dataset-1 using the donation classifier, and randomly sampled 4,000 unique tweets classified as donation-related for labeling intent classes.

- **Labeling Intent Classes**

We asked for three labels per tweet. The supervision of tweets for classes is obtained by crowdsourcing on the Crowdflower platform. A multiple-choice question was asked to crowdsourcing workers, asking to classify a tweet into one of the following categories for expressing intent:

a. *Request to get* - when a person/group/organization needs to get some resource or service such as money

b. *Offer to give* - when a person/group/organization offers/wants to give/donate some resource goods or provide a service

c. *Both request and offer*

d. *Report of past donations of certain resources*, not offering explicitly to give something that can be utilized by someone

e. *None of the above*

f. *Cannot judge*

Having three labels per tweet, we obtained tweets labeled with a confidence value of 0.6 or more (the range is 0 to 1) which is based on minimum two judges and confidence value based on inter-assessor agreement.

We merged the labels to design the class set {*Seeking*, *Offering*, *None* (Neither Seeking nor Offering)} for exclusive intent classes to align with the multiclass problem format and also to account for a lack of enough labeled data for multiple intent labels for a tweet. Hence, we exclude 'Both request and offer', and 'Cannot judge' labeled tweets in this design, such that 'Request to get' presents *Seeking* intent class, 'Offer to give' presents *Offering* intent class, and 'Report of past donations, None of the above' presents *None* class.

Dataset-1: This labeling task on the sample of 4,000 tweets resulted in total 3,135 unique labeled tweets with the confidence (explained above) greater than or equal to 0.6. It comprised of 52% exclusively request to get (Seeking intent), 6% as exclusively offer to give (Offering intent), and the remaining 42% in the other categories (None).

Dataset-2: Given *sparsity* in the data for both donation and intent classes, we created a bias sample for labeling intent classes in dataset-2. We selected 2,000 unique tweets with four diverse random samples of 500 tweets from corpuses of: all the tweets in dataset-2, donation classified tweets, Seeking classified and Offering classified tweets, where we

CLASS	Dataset-1	Dataset-2
Seeking	1,626 (52%)	197 (26%)
Offering	183 (6%)	91 (12%)
None	1,326 (42%)	475 (62%)

Table 3.4: Labeled datasets from Twitter for two different types of real world events

created binary classifiers of Seeking and Offering on the labeled data of dataset-1 discussed in the following under preliminary study with binary classifiers (Our prior study contains extensive details of those classifiers [87]). We used the classified tweets to bias sampling of data for getting more human judged labels on intent classes, and therefore, we used the strict criterion of 'all agree' for the three human judges. The resulting labeled data included 26% Seeking, 12% Offering, and 62% None. The label distribution shows a similar pattern (Seeking intent more prevalent than Offering intent) across the datasets, reported in Table 3.4.

- **Feature Generation**

We used our Representation Improvement Algorithm 2 for this purpose. We process datasets with the following choices of parameters and techniques to create our diverse features sets.

1. T - Text Tokens: We generalize the bag-of-words model to consider N-gram as tokens owing to known superior performance [129]. Tweets are represented as vectors of features, each feature being a word N-gram after pre-processing. We apply text pre-processing operations to clean up informal language usage, and for the purpose of abstracting tokens to a higher-level concept. We use the interactional properties of the platform (*RT* and *Mention*/*Reply*) to represent such abstraction given their importance discussed in the Chapter 2, as well as numeric and external links that represent specific details while sharing information [78]. We used bi-, and tri-grams to capture potential intent representative tokens, and employed normalized term frequency function to create numerical features. Preprocessing includes the following steps:

- Removing non-ASCII characters.
- Separating text into tokens (words), removing stop-words and stemming (to reduce to root words, such as 'helping' to 'help') using Porter's stemmer and string to word vectorization filter in WEKA [43].
- Generalizing some tokens by replacing numbers by the token _NUM_, hyperlinks by the token _URL_, retweets ("RT @user_name") by the token _RT_ and lastly, user mentions in the tweets (@user_name) by the token _MENTION_.

2. DK - Declarative Knowledge Patterns: We create antecedents of a priori knowledge rules using approach v2, and add 29 regular-expression patterns as features expressing knowledge guidance from outside the corpus of training documents. We choose to use regular expressions to represent a feature to enable uniform presentation for declarative knowledge of both domain expert guided rules and psycholinguistic class based rules. A feature function value is determined by binary values, the tweet matching the regular expression, implying 1; or not matching, 0.

   These rules were informed via manual data mining of messages by experts at the American Red Cross, in addition to the linguistic rules mentioned in the Table 3.2. We created an exhaustive representation of linguistic classes whenever possible (e.g., modals, verbs), by initiating with a seed token (e.g., I), and employing the Levin Verbs knowledge base [62], and WordNet knowledge base [32] to gather similar words. An example of a pattern of seed tokens provided for exhaustive representation looks like the following (we provide the list of seed patterns for the 29 features in the appendix): $\backslash b(I|we|they|he|she)\backslash b. * \backslash b(like|want|likes|wants)\backslash b. * \backslash b(to)\backslash b. * \backslash b(LEVIN-VERBSET-FOR-give-CLASS)\backslash b$

3. CTK, CPK - Contrast Emerging Patterns: We employed a sequential pattern mining algorithm SPADE [134] on the corpus of cleaned text corpus A following the text preprocessing steps described above with assumption of each uni-gram token as an

item. We also employed sequential pattern mining on the part-of-speech (POS) tags per document of the corpus A. POS tags for each tweet document were extracted using the ARK-NLP tool provided by CMU [38], which has been trained especially for processing Twitter text.

We used minimum support thresholds for each class *Seeking*, *Offering*, and *None* as 10% equally to derive frequent itemset patterns per class. Often, the support threshold parameter is chosen around 50% in the transactional databases of a large corpus to derive associations that are interesting (frequent enough); however, in processing text of a highly noisy nature and of informal English language, to increase coverage we had to reduce down to the 10% level (total 783 patterns for the three classes). We came up with this parameter choice by testing on dataset-1 for various thresholds, ranging from 50% (on average, 10 patterns for a class) to 2% (on average, 6,000 patterns for a class). In the case of POS tags as transactions, we used minimum support thresholds of 50% for each class; again, based on observations of different choices of thresholds from 50% to 2%. Here, the higher support threshold 50% works because the POS tags represent an abstraction level of the syntactic classes (e.g., Adjective) and are highly frequent across multiple itemsets.

We compute the measure of *Sparse-Contrast-Strength* from equation 3.4, for each minimal frequent pattern per class, and rank them. We select the top-k patterns for final feature set creation based on the percentage parameter X. We used X=100% for the three classes after observing the majority of jumping emerging patterns per class. We transform each of the final selected contrast patterns into regex expression for creating binary features. The features from text-based corpus are CTK, and POS tag-based corpus are CPK.

4. SK - Social Knowledge Patterns: We used the features from Table 2.1 defined in the previous Chapter 2, for incorporating the offline theory-guided knowledge of social

interactions.

- **Learning the classification**

We performed two experimental studies for an intent classification task. First, we used binary classification to observe the challenges, and also create a baseline with a closely related work on the crisis dataset [125]. Second, we used multiclass classification to analyze influence of knowledge-guided features in a more rigorous setting; however, we do not have any baseline to compare against in the crisis domain, and therefore, we consider the feature representation T corresponding to the bottom-up approach v1 as baseline.

Preliminary study on Binary Classifiers: We performed a preliminary study using a sequential binary classifier approach, where we created two classifiers in a sequence: a.) *Seeking* vs. *Not Seeking* (i.e. {*Offering*, *None*}), and b.) *Offering* vs. *None*. We created a chain approach to first train classifier for *Seeking* as a target class, and then used the prediction probabilities from this classifier as an additional feature in the following subsequent classifier design targeted for the *Offering* class. In this experimental setting, we wanted to observe if the additional knowledge of the class probability (*Seeking*) helps in the learning of another class (*Offering*) better, due to complementary dependency of intent classes. This study was performed much earlier than the following experiments on multiclass classification, and therefore, it was limited to the types of knowledge sources exploited. Extensive details related to this preliminary study is part of the prior publication, [87].

We used two types of feature sets, local content-based, T, and the declarative knowledge-based, DK, which was acquired by 18 regular expression patterns using expert searches of the American Red Cross collaborators. We used all the labeled tweet set of the dataset-1 source. We used feature selection using Chi-squared test for 500 features (parameters chosen after a number of repetitions), and ensemble approach using Random Forest with 10 trees and 100 features with cost-sensitive learning, to improve the learning performance at the algorithmic level. We consider the baseline as [125], which created classifiers for

Classifier	Learning Scheme	Precision (%)	F-1 score (%)	Training Distribution
Seeking	RF (CR=50:1)	98 (*79)	46 (*56)	56% Seeking
Offering	RF (CR=9:2)	90 (*65)	44 (*58)	13% Offering

Table 3.5: 10-fold CV results for binary classification with Precision-oriented design. Learning scheme abbreviation RF refers to Random Forest, and CR indicates asymmetric false-alarm Cost Ratios. All classifiers used top 500 features. Precision and F-1 measures are for the positive class. * indicates performance in a closely related baseline work.

identifying problems (closely related to 'Seeking help' intent), and aid (closely related to 'Offering help' intent) messages on the 2011 Japan earthquake crisis dataset. We report the results in Table 3.5. We noted better performance by our fusion approach of T and DK knowledge-guided features for high precision design. During crisis, a precise identification of the intent is essential as compared to higher recall but with poor precision, due to time-critical nature of the high consequence domain. Organizational actors would not have time to go over larger volume of messages with low confidence in contrast to the inverse situation. Therefore, despite our F-1 score was lower than the baseline prior work due to lower recall, the knowledge-guided approach is able to achieve higher precision for both cases of *Seeking*, and *Offering* intent classifiers.

Study on Multiclass Classifiers: We experimented with the combination of all the above-mentioned feature sets (T, DK, SK, CTK, CPK) to design OVO and OVA based multiclass classifiers in the binarization framework. We used Random Forest algorithm [132] for base learners, and address the challenge of imbalance classes by ensemble learning at the algorithmic level to improve performance. We evaluated the performance using 10-fold cross-validation, and used the performance measures of accuracy and F-1 measures, in consistence with other prior work on multiclass classification. These measures are suitable for our experimental settings given the imbalance and potential label dependence issues in intent classification problem. Accuracy and F-1 scores help reflect improvement across the classes including minority classes. In total, there were 1405 features created for 3135 instances for the dataset-1, and 2843 features for 763 instances for the dataset-2. We report the results in Table 3.6.

3.7 Results and Discussion

Observing Table 3.6 for results of 10-fold cross validation, we noted a performance gain in both the accuracy and F-1 scores for every addition of a knowledge-guided feature set with the bottom-up approach's feature set (T). Therefore, we performed statistical significance test using t-test with two tails (for stricter condition than one tail), between scores of the bottom-up approach v1 (T), and the combined v3 approach encompassing knowledge-guided feature sets (T, DK, CTK, CPK, SK). The p value to reject null hypothesis of no significant gain was rejected with p value < 0.02.

	Gain between Approaches v1 & v3	**{T,DK,CTK,CPK,SK} (Approach v3)**	**T (Approach v1)**	**{T,DK}**	**{T,CTK,CPK}**	**{T,SK}**
Dataset-1						
F-1 SCORE						
1-vs-all (OVA)	**7%**	67%	60%	68%	67%	66%
1-vs-1 (OVO)	**7%**	68%	60%	64%	67%	66%
ACCURACY						
1-vs-all (OVA)	**5%**	69%	65%	68%	68%	67%
1-vs-1 (OVO)	**4%**	69%	65%	68%	68%	67%
Dataset-2						
F-1 SCORE						
1-vs-all	**5%**	83%	79%	80%	82%	80%
1-vs-1	**6%**	84%	78%	80%	84%	80%
ACCURACY						
1-vs-all	**5%**	84%	80%	82%	83%	81%
1-vs-1	**5%**	85%	80%	82%	81%	81%

Table 3.6: 10-fold CV results for two measures (F1, Accuracy) for different multiclass learning frameworks on two datasets represented by varying level of rich feature sets (T, DK, CTK, CPK and SK). Algorithm: Random Forest Tree with 10 trees, 100 features and depth level 5 nodes per tree. Gain from the baseline bottom-up approach (v1) to the integrated approach (v3) is statistically significant ($p < 0.02$).

The results show the utility of a generalized Representation Improvement Algorithm

2 in providing a framework for fusing top-down and bottom-up approaches for the intent classification problem. Results support our hypotheses H3.1, H3.2 and H3.3, and we discuss fine-grained rationale in the following:

- **Discriminative Power of Combined Feature Sets and Role of Social Context**

We ranked features in both the datasets using a Chi-squared test. The top 1% features included more than 50% of the knowledge-guided features. It shows the value of fusing the knowledge guidance in the learning feature space, which can help learning algorithms focus on learning newer and better statistical predictor-class relationships between features and an intent class. Combined with the results of accuracy and F-1 score improvements, it supports our hypothesis H3.2 and H3.1. Among the top discriminative features observed by the Chi-squared test, Dialog Management and Subject Pronouns based features are present. It shows the significance of taking offline-theory guidance from linguistic coordination indicators to help improve context for intent classification in the social setting. It is important to acknowledge that a social conversational context of intent expression does not exist in other problem domains, such as user intent in search.

- **Performance in the Popular Multiclass Classification Frameworks**

We observed significant improvement in both F-1 and accuracy scores in both classification frameworks, one-vs-all and one-vs-one. Interestingly the gain observed in both the cases in significant, where it is a known problem that OVA suffers from imbalance created by the framework design itself, and OVO suffers from the label dependence issue owing to the design of pairwise classification. It supports our hypothesis H3.2 that intent classification performance improves in both the popular multiclass classification frameworks using approach v3.

- **Limitations**

We note various limitations of our work, and would address them in the near future:

We have shown the importance of contrast patterns for equal values of class-wise thresholds ST_j, however, we shall explore effects of class-wise selection of thresholds in the future work. Given the subjective task of selecting the thresholds, we would explore approaches to influence selection of thresholds guided by knowledge-driven features not constrained to a corpus, such as those derived from the *a priori* knowledge sources.

Although we performed feature selection test using Chi-squared test, we do not show results for attribute selection-based learning, given it can be subjective and we want to first answer questions of data representation improvement in a generalized setting for a learning space. We shall explore various algorithmic tuning settings, such as cost-sensitive learning combined with the ensemble framework in future work.

We did not capture the interplay of various types of subjectivity in the offline-theory guided social knowledge, and declarative knowledge features, such as emotion expression with intent. We suspect a relationship in/between the subjective behaviors, and would address them in the near future for efficient learning of intent.

Also, we note the limitation and scope of further work in the document intent classification problem. There can be multiple intent expressions within a message—a setting of multi (intent) label classification problem. We also note another form coming from the behavioral perspective in defining the problem such that instead of answering the question of 'what is the intent of a document,' via classification problem, we need to explore the answer to the questions of actor—'who has intent, and of what type.' That is an actor-specific intent association problem. We plan to address these problems in the near future.

Chapter 4: Engage function: User and Group Engagement Modeling for Addressing *Awareness*

The challenge of *awareness* for cooperation between citizens and organizational actors requires a means for the organizational actors to engage and interact with the citizens in the goal-oriented CSC. The major question is 'who to engage first in the dynamic CSC, and how to address such an engagement prioritization'. Our approach addresses this challenge via identifying prioritized or reliable groups of citizens. Engagement with a prioritized group of citizens would allow organizational actors better coordinate tasks, for example, when emergency coordinators want to collect and verify more specific information for enhanced *awareness*. However, given the scale of the CSC and the *diversity* of participating citizen demographics, it is difficult to model a prioritized group based on the dynamics of its engagement.

Engagement is defined as the degree of involvement, and in the case of CSC, it is the degree of involvement in discussions for both individual users and groups. Prior studies on user group engagement have focused on structural properties in the networks to model dynamics of engagement via group formation, and evolution, which limits the explanation to the perspective of network structure. We focus on content and user properties additionally to model the dynamics of group engagement. We define collective behavior of a group via a measure of divergence in content of discussions generated by members of the group. This provides additional context for explaining the dynamics of group engagement and helps identify high priority groups. We define a reliable, high priority group as the one that shows a smaller change in the collective behavior across time phases, i.e. consistently lesser divergence in the topic of discussions of the group members.

Such techniques can be highly valuable in scenarios like natural disasters, given the surge of 'digital humanitarians' [73] as volunteer and technical communities that support humanitarian response. A small number of less diverging, focused groups (sharing resource or information requests and offerings) must be identified efficiently, so in order to effectively leverage their input to improve *awareness* of organizational actors. This phenomenon of self-organizing small groups is not limited to disasters but also includes CSC for other real-world events that also have goal-orientation, as discussed in the Chapter 1. We discuss social theories of group engagement and specific research questions in the first section, followed by modeling collective behavior in content generation. Work discussed in this chapter has been published in [92].

4.1 Finding Prioritized Groups to Engage by Modeling Discussion Divergence

The prevalence of online social networks in the last decade has enabled computational social scientists to answer various questions of group dynamics that reveal user group engagement, such as group formation, participation and evolution [7, 97, 111, 30, 57, 41]. Most studies, however, investigate implications of the network structure alone in characterizing group dynamics, and they lack the insights regarding the dynamics of user-generated content.

Some social scientists have defined groups based on various common user characteristics and interactions [123]. We define a group as the set of users interacting in discussions about a real-world event. We refer to *group discussion divergence* as collectively behavior of divergence in user-generated discussion topics in CSC. In this study, we focus on Twitter users' discussions related with two types of real-world events: natural disasters and social activism. Particularly, we ask the following specific research questions to validate the role of prior knowledge of social behavior theories, and the interplay of user, content and network features to model group engagement:

- Related to question R3 of the dissertation, outlined in Chapter 1:

R4.1. Do two existing theories of social group behavior, namely, social cohesion and social identity, have implications on the evolution of group's diverging behavior?

R4.2. How can we model offline theories of social identity and cohesion in the online platforms?

- Related to question R5 of the dissertation, outlined in Chapter 1:

R4.3. Can we model the divergence of user discussion in a group that change over time, within and across different phases of events?

Answers to the above questions can aid in understanding which factors contribute more in facilitating cohesion (lower divergence) in the group discussions in CSC. They also enable us to predict the change of *group discussion divergence*, which in turn allows the rapid identification of groups whose voices are showing fewer divergence shifts. However, there is a challenge of modeling *diversity* of users in the groups, quantitatively defining *group discussion divergence*, and learning to predict the divergence shift (increase or decrease) over time. We present the study for the shift between a real world event's three phases: pre-, during-, and post-event (however, our analysis approach is applicable in general beyond the three phases of interests here). Specifically:

- **Problem Statement p4.a.** Given a real-world event E, a collection of N Twitter users in a CSC formed around discussion of E, an assignment of them into K non-overlapping user groups $g_i (1 \geq i \leq K)$ based on interactions, and a measure of *group discussion divergence* $JS(g_i)$; predict the change of each group's *discussion divergence* $JS(g_i)$ between two consecutive event phases (that is, from pre-event to during-event or from during-event to post-event).

We first describe discuss the related work, and then formally describe the *group discussion divergence* measure, and other preliminaries of our approach including data collection for event-based discussions, group identification, and specification of the prediction task. Feature design, experiments, results and analyses are presented in subsequent sections.

4.2 Related work: Challenge of *Diversity* in Groups of CSC

First, we briefly introduce two theories proposed by social psychologists to explain the dynamics of traditional face-to-face social groups and their behaviors, and their rationale of emphasizing on *diversity* of group members, such as few common social identities. We envision that their roles in shaping user engagement in groups [29] will contribute to our understanding of *group discussion divergence*. Then we describe related work on online social group bonding and dynamics.

- **Social Psychological Theories**

Conventional/legacy social group theory includes two closely related parts: social identity [120] and self-categorization [124]. Tajfel et al. [120] defines the concept of social identity as "the individual's knowledge that he belongs to certain social groups together with some emotional and value significance to him of this group membership". Therefore, group membership is the result of "shared self-identification" rather than "cohesive interpersonal relationship", and such shared identity leads to cohesiveness and uniformity, among other features [123]. One commonly cited piece of evidence for social identity theory is team sports [12], where teammates are representing the same organization (a school, a club, or a country) and they are well aware of the desire to sustain the reputation of their associated identity. In contrast, social cohesion theory views social groups from a different perspective. The necessary and sufficient condition for individuals to work as a group is a cohesive social relationships between individuals. We adopt the definition by [67] that interprets cohesiveness as mutual attraction between individuals, which is slightly different from that used in [34]. In accordance with this definition, the positive correlation between group cohesion and performance has been reported in various types of groups [76, 9]. A social cohesion example will attribute the inter-personal friendship between teammates of a sports club as the foundation for group performance and its evolution.

- **User-Group Bonding**

One study relevant to our work is by Grabowicz et al. [41], where the authors translate common identity and common bond theories for group attachment into general metrics applicable to large social graphs. They also devised a method to predict whether a group is social (formation dependent on interpersonal bonds) or topical (formation based on perception of role). Prior to that, Ren, Kraut, and Kiesler [97] presented a similar study, focusing on the implications of the two theories of group attachment and link these theories with design decisions for online communities. Our differing objective here is rather to analyze the role of identity and cohesion features in characterizing a group's *discussion divergence* behavior, instead of predicting group type or evaluating community design decisions. In a similar spirit, Farzan et al. [30] studied group commitment on Facebook within a controlled environment and observed that designs that encourage relationships among members or emphasize the community as an entity, increase both the commitment and retention of players. Budak and Agrawal [14] utilized data analytics and user surveys to study factors that drive group chats on Twitter, and found that social inclusion contributes most to user retention. Our objective here is slightly different, in that it focuses on the effects of group commitment in *discussion divergence* in the communities emerging around real-world events.

- **Group Dynamics**

Most prior work on group dynamics has focused on structural dynamics. Notably, Backstrom et al. [7] proposed a structure-centric model for network membership, growth and evolution by analyzing DBLP and LiveJournal social networks. Their findings show how individuals join communities and how communities grow depending on the underlying network structure, which supports cohesion-based structural features of our study, discussed in the following section. Taking more a user-centric approach, Shi et al. [111] studied the user behavior of joining communities on online forums. Among other features, the authors studied the similarity between users and the similarity's relation with community overlap. They found that user similarity defined by the frequency of communication or number of common friends was inadequate to predict grouping behavior, but adding node/user-level features could improve the model fitting. Kairam, Wang, and Leskovec [57] analyzed the long-term dynamics of communities and modeled future community growth rate. They found that growth rate is correlated with the current size and age of a group and the size of the largest clique is the best feature for indicating community sustainability. Relevant efforts on understanding and modeling individual user-level characteristics include a study by Rao et al. [95], where authors presented an approach for automatic creation of ethnic profiling of users, focusing on names as the key factor. Pennacchiotti and Popescu [84] also proposed a machine learning approach for user classification on Twitter by analyzing a user's friends, user posts and profile information.

These studies of group and individual characteristics provide a base for modeling user and structural features for incorporating prior social behavior in the characterization of *group discussion divergence*, which we discuss in the following.

4.3 Quantification of *Group Discussion Divergence*

We use Jensen-Shannon divergence (JS-divergence) to quantify the divergence of group discussions. Compared with other information-theoretic measures such as Kullback-Leibler divergence, JS-divergence is always bounded, symmetric, and can be generalized to more than two distributions [65]. JS-divergence has long been employed in computational linguistics [64, 68], though its usage in analytics of online social platforms has been limited.

In order to calculate JS-divergence, we first construct a dynamic topic model [10], and infer the topics of discussion. Input into the topic model is a collection of vocabulary vectors, each of which represents one event-related tweet and is indexed by discrete timestamps. The vocabulary includes words and phrases pertaining to the event, as well as hashtags with the leading '#' symbol stripped. The dynamic topic model has the advantage of modeling a systematic topic shift (due to the event's progress) automatically, which allows us to investigate the true difference of an individual member's topic distribution to the corresponding group's topic distribution at any given time.

The inference process of the topic model returns a latent topic distribution for each tweet t, denoted as β_t. A group g's mean topic distribution at phase s over all its users' tweets (T_g^s) can then be calculated as:

$$\beta_g^s(i) = \frac{\sum_{t \in T_g^s} \beta_t(i)}{|T_g^s|}, \forall i = 1, \cdots, \text{number of topics} \tag{4.1}$$

and g's JS-divergence at phase s is defined as

$$JS(g^s) = H(\beta_g^s) - \frac{\sum_{t \in T_g^s} H(\beta_t)}{|T_g^s|} \tag{4.2}$$

where $H(\bullet)$ is the Shannon entropy function (with log base 2) [65]. Intuitively, JS-divergence here gauges the divergence among topic distributions of a group's tweets. **The greater the JS value, the larger the difference and the stronger indication of a group lacking**

conformity in discussion.

4.4 Group Identification via Community Detection in Interaction Network

Social groups can be defined in many ways. Our focus here lies on those groups of people who interact (and potentially emerge) in times of evolving real-world events. For example, the users who emerge as volunteer groups in times of crisis response may not have prior follower-followee connections on Twitter. However, they start interacting for the cause of assistance.

Therefore, it is necessary to identify appropriate social groups on which quantitative analyses will be performed to understand the dynamics of *group discussion divergence*. Resultant social groups should reflect online interaction among users that is beyond simply using the same word in their tweets. Moreover, the grouping criterion needs to be independent of any feature of social structure and user characteristics due to some of our features being based on social cohesion and identity theories (defined in the following sections), so that the results are not biased.

To that end, we propose an approach of clustering users based on their interactions, which can be either retweet, reply or mention. An interaction graph is created to represent those relationships during each phase of the event, where vertices stand for users and edges indicate at least one interaction between two users through the phase. We apply Markov clustering [102], a commonly used community detection algorithm to identify social groups.

4.5 Group Representation Features: Quantification of Social Identity and Cohesion Theories

In this section, we describe the feature design driven by social psychology theories for the problem of predicting a shift in the *group discussion divergence* over event phases.

4.5.1 User Features: Regional, Expertise and Online Identities

To quantify the social identity-based features, we employ a user's profile information as well as activity, as we note that social behavior tends to associate the user with established identities (regional, organizational, etc.) via self-representation and with incentive-based identity via user actions in the cyber-world. For example, 'New Yorker' in a user's profile is a signal of his location-based identity, and a profile containing 'professional NBA player' or 'Emergency Management' is highly suggestive of the user's occupational expertise. A user's action of adding such indicative terms into the profile suggests his identity perception. Moreover, recently emerged social analytics services indicate the online identities of users such as 'celebrity' on Klout, 'Mayor of a place' on Foursquare, etc., and users tend to identify with them [23]. In today's world, therefore, we possess social identities in both our physical as well as cyber world. In the case of Twitter platform, user profiles contain location and description metadata in addition to action metadata (status updates, retweets, etc.), to assist the extraction of social identities. Each identity type is modeled as a discrete feature, and for each social group under this study, we compute the class distribution entropy for each identity and provide them as user features for the analysis. The range of identity features is from 0 to $ln(C)$, where C is the number of unique classes in an identity type.

- **Regional Identity feature**

  Using the location information in user profiles, we map users to regional classes that are sometimes used to represent self-identification in our daily lives – state-based (e.g., ‘Ohio’ for Ohioans) and nation-based (e.g., ‘Brazil’ for Brazilians). For creating feature values, we choose a user’s state identity if it belongs to the host nation of an event (e.g., user from Buffalo will have ‘NY’ as the identity value in the OWS event), otherwise, we choose the user’s national identity (e.g., user from London will have ‘UK’ as the identity value in the OWS event). We use the Google Maps API to convert user profile locations into latitude-longitude, and then state and nation identity. We note that this simple model of two regional levels (state and nation) for self-identity can be expanded further.

- **Expertise Identity feature**

  Users generally write their interests, expertise and affiliations in the description on Twitter user profiles. This is an example of self-representation of social identity (e.g., artist, researcher, etc.). Therefore, we derive expertise classes in 2 steps: a) collect occupation categories and titles from trusted knowledge sources — Wikipedia and the US department of Labor Statistics reports, and b) classify the resulting occupation lexicon into ten broad classes, inspired by news websites and the higher level of analysis on the class tree:

  {*ACADEMICS, BUSINESS, POLITICS, TECHNOLOGY, BLOGGING, JOURNALISM, ART, SPORTS, MEDICAL, OTHERS*}

  For user expertise identity, we first create N-grams from the description metadata in the profile by tokenizing on punctuations, and filter out those missing the occupation lexicon terms. From the remaining N-gram set, each N-gram is associated with one of the ten classes, and its weight is determined by its position in the description text. This is because self-identity perception guides users to place terms that are more socially identifying and important to them at the beginning.

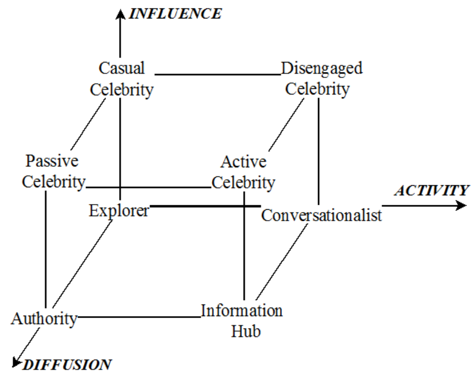


Figure 4.1: Online Identity based on three action measures (Activity, Influence, Diffusion)

- **Online Identity feature**

  Based on user behavior with the platform (Twitter here), we use three measures consistent with expertise presentation work in our prior study [89], modeling influence and passivity (as in [100], which contribute to building a user's incentive-based identity (e.g., 'Celebrity' on Twitter) in the cyber-world—an online identity in contrast to real-world identities by capturing user activity, influence and diffusion strength. We model the activity measure by number of posts of the user, influence metric by number of mentions of the user, and diffusion strength by number of retweets of the user's posts in the data for an event. We compute scores on each of the three measures for all users and then consider the basic 50th percentile threshold to create two levels on each of the dimensions, yielding 8 user classes as shown in Figure 4.1. The computation on number of mentions, number of retweets, and number of posts here is different from the step of identifying social groups in the interaction network, because here user node-centric features (a local viewpoint) are taken for identity measure, and not the connection-centric feature set, (a global viewpoint), which is the basis of clustering.

In contrast with regional and expertise identities, which are meaningful in the physical world, online identities exclusively define behavior in the cyber realm. To our knowledge, few attempts have been made to study the impact of both online and offline identities in the study of user group engagement in online social platforms.

4.5.2 Structural Features: Reciprocity Types in Friendship Network for Reflecting Cohesion

To study the structural features driven by the cohesion of social groups in a quantitative manner, we extract information from the social platforms' friendship network. In case of Twitter, the users' follower-followee network is used. For each social group, we construct its corresponding node-induced sub-graph from the follower network. Because the follower relation is directional, there are three groups of features in this category:

- *Reciprocal*:

  An undirected edge will be created between two users only when both of them are following each other. This choice directly reflects the assumption of mutual interpersonal attraction in the social cohesion theory. Features here include density, transitivity[1], average clustering coefficient[2], and maximum average length of pairwise shortest paths over all connected components (short-named "average shortest path length").

- *Undirected*:

  An undirected edge will be created between two users if either of them is following the other. The underlying assumption is that one-way interpersonal attraction is sufficient to keep the social group sustained. The same group of features as in the reciprocal sub-graph are computed.

- *Directed*:

[1] transitivity = $\frac{3 \times \text{number of triangles}}{\text{number of connected triples of vertices}}$

[2] clustering coefficient of node i = $\frac{2 \times \text{number of triangles in } i\text{'s neighborhood}}{degree(i) \times (degree(i)-1)}$

We also compute density and transitivity on the directed sub-graph for each social group, without converting it to an undirected graph.

The range for all cohesion features is $[0, 1]$, except for the average shortest path length. Note that in existing sociology literature [75, 130] the term "structural cohesion" is a specific measure, defined as the minimum number of nodes one needs to remove from a graph to disconnect it. We do not include this feature as we find that almost all (more than 97% of total) social groups contain at least one fringe node (whose degree is one) or singleton, meaning that the value of this feature for most social groups will be at most one.

From the assumptions of social cohesion and social identity theories, we hypothesize the following:

H4.1. A more structurally cohesive social group has less diverse discussion. Therefore, groups with features values of higher density, transitivity, clustering coefficient, or lower shortest path length are expected to have lower *group discussion divergence*.

H4.2. Groups whose members are similar in identities (i.e., groups having lower entropy for identity features) are speculated to have low *group discussion divergence*, as motivated by the social identity theory.

4.6 Experimental Design and Implementation

In this section, we present the data collection approach and datasets statistics, characteristics of structural and user features described in the previous section on our dataset and their correlation with *group discussion divergence*. It rationalizes the choice of features for the prediction task discussed in the next section.

- **Data Collection for Event-oriented CSC**

Event Name	Type	Duration	#Tweets	#Users	Type
Irene	Disaster (D)	08/24-09/19, 2011	183K	77K	Transient
Sandy	Disaster (D)	10/27-11/07, 2012	4.9M	1.8M	Transient
IAC	Civil Protest (P)	11/05-12/02, 2011	100K	21K	Lasting
OWS	Civil Protest (P)	11/05-12/02, 2011	2.1M	331K	Lasting

Table 4.1: Twitter data statistics centered on diverse set of evolving events

We focus on user-generated content on Twitter and discussions based on particular real-world events. Thus, proper filtering of the generic content stream is required.

We implemented a Twitter Streaming API-based method to collect event-related data using the keyword-based approach as discussed in the Section 2.4 of Chapter 2, and create an event-oriented CSC of users who posted relevant keywords about the event. In addition to tweet content, and its metadata, we also stored metadata associated with tweet authors for their profile information–the author's location, followers/friends, and profile description. We crawled a follower network of each of the users in the interaction network after the event time period at the time of our study, albeit that the dataset size creates a challenge to collect data of follower network for all users under a very low API limit for crawling requests.

In this study, we choose four events for data collection (two for social activism driven civil protests (P) and two for natural disasters (D))—India Anti-Corruption protests 2011 (IAC), Occupy Wall Street protests 2011 (OWS), hurricane Irene 2011 (Irene), and hurricane Sandy 2012 (Sandy). Table 4.1 summarizes basic information about each dataset. We note that events possess varying characteristics on the dimensions of activity, social significance, participant types, etc. In Table 4.1, we specifically show temporal feature values as 'Lasting' and 'Transient' that denotes how enduring an event is. For example, the Occupy Wall Street movement was highlighted in social media discussion for a long time frame, while Twitter users' attention to hurricane Sandy quickly decreased significantly in the volume after it dissipated.

Event	Timeline
IAC	*During-phase* Beginning (11/24): Minister Sharad Pawar got slapped due to alleged corruption *During-phase* End (11/29): No further substantial tweet w.r.t. the incident of slapping Source: `http://en.wikipedia.org/wiki/2011_Indian_anti-corruption_movement`
OWS	*During-phase* Beginning (11/15): Raid of Zuccotti Park *During-phase* End (11/23): President speech interrupted by protesters Source: `https://99.occupymediawiki.org/wiki/Timeline_of_Occupy_movement#November_2011`
Irene	*During-phase* Beginning (08/27): Landfall in North Carolina *During-phase* End (08/30): hurricane dissipated Source: `http://www.theguardian.com/world/blog/2011/aug/27/hurricane-irene-new-york-live`
Sandy	*During-phase* Beginning (10/29): Landfall in New Jersey *During-phase* End (10/31): hurricane dissipated Source: `http://en.wikipedia.org/wiki/Effects_of_hurricane_Sandy_in_New_York`

Table 4.2: Timeline and dates signifying the beginning and end of *during-event* phase of each event

To enable temporal analysis and reasoning, tweets are grouped into three phases (*pre-*, *during-*, and *post-event*). Our categorization of phases for each event is aligned with its real-world timeline, and Table 4.2 shows the occurrences leading to division of phases.

Event	**# Groups**	**# Users**	**Average Group Size**
Irene	137	22,068	161
Sandy	4,947	284,062	57
IAC	76	7,907	104
OWS	6,202	296,279	48

Table 4.3: Characteristics of identified groups

- **Group Identification and Characteristics**

We applied the community detection approach on the user interaction network for different phases of an event as described in Section 4.4 above. Our experimental design used only groups that have at least 10 members and are active (that is, at least one member posts a relevant tweet by mentioning event-related keyword(s)) for at least two days are retained. Again, while there exist other choices of identifying latent online user groups without ground truth labels, we believe our simple approach can effectively capture online interactions and yield meaningful groupings of users. Table 4.3 summarizes the information of each dataset's social groups.

For *group discussion divergence* computation, we use the `dtm` package (available at `https://code.google.com/p/princeton-statistical-learning/`) with default parameters for topic inference in the groups. We evaluated results from 2 to 5 latent topics, and found that topics become similar and redundant after 3. For expository simplicity we use 3 as the default number of topics and report the top vocabulary in the different event phases for two events (hurricane Sandy and Occupy Wall Street) in Table 4.4.

hurricane Sandy			
	Pre-event	**During-event**	**Post-event**
Topic 1	tropical storm	red cross	red cross
	east coast	jersey shore	staten island
	canada	caused	mexico
	path	staten island	caused
Topic 2	new york	new york	new york
	state	new jersey	new jersey
	google	hurricane katrina	states
	android	media	hurricane katrina
Topic 3	frankenstorm	frankenstorm	frankenstorm
	halloween	fema	knicks
	east coast	halloween	fema
	atlantic	mitt romney	nyc
Occupy Wall Street			
	Pre-event	**During-event**	**Post-event**
Topic 1	occupy	occupy	occupy
	protest	n17	oo
	movement	nypd	occupyla
	occupytogether	brooklyn bridge	movement
Topic 2	movement	nypd	nypd
	us	movement	movement
	bahrain	protest	anonymous
	occupy movement	time	protest
Topic 3	occupy	occupy	p2
	oo	p2	tcot
	p2	tcot	republican
	tcot	oo	teaparty

Table 4.4: Top vocabulary representing the latent topics of discussions at each event phase

	Irene	Sandy	IAC	OWS
Structural Features guided by Social Cohesion				
Directed Structural Features				
Density	0.04 ± 0.07	0.06 ± 0.08	0.02 ± 0.03	0.05 ± 0.04
Transitivity	0.23 ± 0.20	0.21 ± 0.23	0.10 ± 0.18	0.19 ± 0.23
Reciprocal Structural Features				
Density	0.03 ± 0.07	0.04 ± 0.07	0.01 ± 0.02	0.03 ± 0.04
Transitivity	0.16 ± 0.19	0.18 ± 0.24	0.07 ± 0.20	0.14 ± 0.24
Average Clustering Coefficient	0.06 ± 0.10	0.08 ± 0.12	0.02 ± 0.05	0.05 ± 0.09
Average Shortest Path Length	2.25 ± 1.19	1.83 ± 1.10	1.06 ± 0.99	1.56 ± 0.76
Undirected Structural Features				
Density	0.05 ± 0.09	0.07 ± 0.09	0.04 ± 0.04	0.06 ± 0.05
Transitivity	0.16 ± 0.16	0.19 ± 0.22	0.08 ± 0.15	0.16 ± 0.21
Average Clustering Coefficient	0.14 ± 0.13	0.13 ± 0.15	0.05 ± 0.09	0.10 ± 0.12
Average Shortest Path Length	2.72 ± 0.90	2.36 ± 1.06	2.01 ± 0.82	2.07 ± 0.64
User Features guided by Social Identity				
Regional Entropy	$2.71 \pm 0.78(5.28)$	$2.24 \pm 0.73(5.74)$	$2.06 \pm 0.45(4.94)$	$2.12 \pm 0.62(5.65)$
Expertise Entropy	$1.79 \pm 0.26(2.30)$	$1.08 \pm 0.46(2.30)$	$1.56 \pm 0.31(2.30)$	$1.50 \pm 0.27(2.30)$
Online Entropy	$0.97 \pm 0.21(2.08)$	$1.03 \pm 0.21(2.08)$	$1.24 \pm 0.24(2.08)$	$1.18 \pm 0.23(2.08)$

Table 4.5: Mean and standard deviation of structural and user features. Identity entropy upper bounds are listed in brackets.

4.6.1 User and Structural Feature Characteristics

In Table 4.5 we summarize the basic statistical information for each of the features related to social cohesion and identity. The upper bounds of entropy values for user features are included in brackets. We identify several interesting trends in the results reported in the table.

In general the entropy values are higher for the Occupy Wall Street (OWS) and India Anti-Corruption (IAC) events, the two on-the-ground social activism events. It is possible that online social identity features do not capture the offline interactions heavily involved in those events. Such distinction is most pronounced when comparing online identity entropy values of those two events with respect to the other two events. The social groups in these two events tend to revolve around opinion leaders who often help direct and orchestrate the movement (such individuals likely will have high online identity values). Therefore social groups formed in those events generally have more diverse online identity composition, reflecting the presence of opinion leaders as well as followers in groups. Another finding from Table 4.5 is that groups have great divergence in terms of their memberships from different regions reflected by the regional entropy. This may simply be a reflection of the times and the fact that online social networks are bringing people closer together and almost all events have had significant media attention.

Lastly, we point out that the average directed transitivity (global clustering coefficient) is at least 82% higher than that of the whole follower network (not shown in the table), and results based on the reciprocal and undirected definitions are similar, indicating that there is likely a community structure embedded in the social groups we have identified.

- **Correlation Between Features and *group discussion divergence***

To investigate the relation between structural/user features and *group discussion divergence*, we first compute their statistical correlation. Particularly, we use a bootstrap method (sampling with replacement) to construct the 95% confidence interval of correlation coefficients. In Table 4.6, we report a subgroup of features whose correlation with *group discussion divergence* is considered significant.

User features statistics: We note in Table 4.6 that user features (especially regional identity entropy and online identity entropy) have a moderate to high positive correlation with *group discussion divergence*, for the first three events. This finding agrees with our hypothesis H4.2 that *group discussion divergence* increases when group members' identities become less distinctive, reflected by higher identity entropy values. On the other hand, correlation values for Occupy Wall Street are less significant.

For social groups with a stronger regional concentration, in-group discussions tend to be more location-specific and consistent, leading to a smaller degree of member-wise discussion divergence, compared with groups whose members' locations are more dispersed. Similarly, the presence of users with similar expertise or interest domain in a social group tends to keep the scope of discussions more focused.

For the online identity feature, we note that it is reflective of user actions. Therefore, we speculate that for the sake of maintaining their incentive-based action identity via reduced change in their actions, users are likely to maintain a pattern of focused topical discussions in the groups.

Structural features statistics: For structural features, we find that patterns of correlation with *group discussion divergence* can be categorized into following types:

Density features have a moderate negative correlation with *group discussion divergence* for hurricane Irene and hurricane Sandy, indicating that a better-connected social group tends to have a more cohesive discussion. We can ask an event-type specific question: Why is the correlation weaker for Occupy Wall Street and the India anti-corruption movements? As mentioned earlier, both of them are long-lasting events accompanied by an arguably more engaged offline component, whose information is not captured in cohesion features. Therefore, the density of online social groups is low (see Table 4.5), indicative of high divergence for those two events.

	Irene	Sandy	IAC	OWS
Directed Structural Features				
Density	$[-0.37, -0.06]$	$[-0.22, -0.16]$	$[-0.38, 0.07]$	$[-0.03, 0.05]$
Reciprocal Structural Features				
Density	$[-0.36, -0.06]$	$[-0.20, -0.15]$	$[-0.29, 0.06]$	$[-0.01, 0.07]$
Shortest Path	$[0.27, 0.52]$	$[0.10, 0.15]$	$[-0.14, 0.21]$	$[0.10, 0.16]$
Undirected Structural Features				
Density	$[-0.36, -0.05]$	$[-0.22, -0.17]$	$[-0.43, 0.10]$	$[-0.05, 0.04]$
Shortest Path	$[0.31, 0.56]$	$[0.16, 0.21]$	$[0.02, 0.37]$	$[0.09, 0.13]$
User Features				
Regional Entropy	$[0.23, 0.50]$	$[0.25, 0.30]$	$[0.07, 0.52]$	$[0.09, 0.14]$
Expertise Entropy	$[0.11, 0.51]$	$[0.45, 0.50]$	$[0.37, 0.66]$	$[0.01, 0.06]$
Online Entropy	$[0.45, 0.69]$	$[0.20, 0.25]$	$[0.11, 0.57]$	$[0.26, 0.31]$

Table 4.6: 95% confidence intervals of correlation coefficients between structure/user-based features and *group discussion divergence*

Average shortest path length (especially the undirected version) shows consistency in its positive correlation with *group discussion divergence*, which also agrees with our hypothesis H4.1. Compared with other structural features that reflect the tightness of a social group, average shortest path length shows clearer dispersion in values, making the result from its correlation analysis more meaningful.

When comparing correlation strengths for reciprocal features and undirected features, we find that they are often comparable. In fact, a one-sided binomial test rejects the alternative hypothesis that "reciprocal features have stronger correlation with *group discussion divergence* than undirected features" with a p-value of 0.89. This finding is particularly interesting as the key premise of reciprocal structural features is mutual interpersonal attractions (social cohesion theory), an assumption that undirected structural features do not make. This leads to the question of whether mutual attraction is still a necessary condition for online communities to form and last. We believe this requires more research attention in the future.

Contrasting High and Low Divergent Groups: We performed a case study of the 10 highest and lowest divergent groups in each event, to check for a contrast between the content practices. Specifically, we compared the frequency of using hashtags, retweets (RT), mentions, URL links, and emoticons in the content of candidate group members. In fact, some of the least divergent groups use the RT heavily, while the most divergent groups use hashtags heavily, indicating diverging nature of user-classified topics. Therefore, we suspect content practices also play a role in predicting trend of divergence.

Effects of Event Characteristics: From Table 4.6 we note that transient events (hurricane Irene and hurricane Sandy) have stronger correlations for user features than for structural features. We conjecture this is due to the fact that groups in such volatile events form in an ad-hoc setting, where groups are less likely to have existing cohesively connected users, undermining the effects of structural features. Therefore, discussions can be highly dependent on the idiosyncratic characteristics of participants of the group, their personal

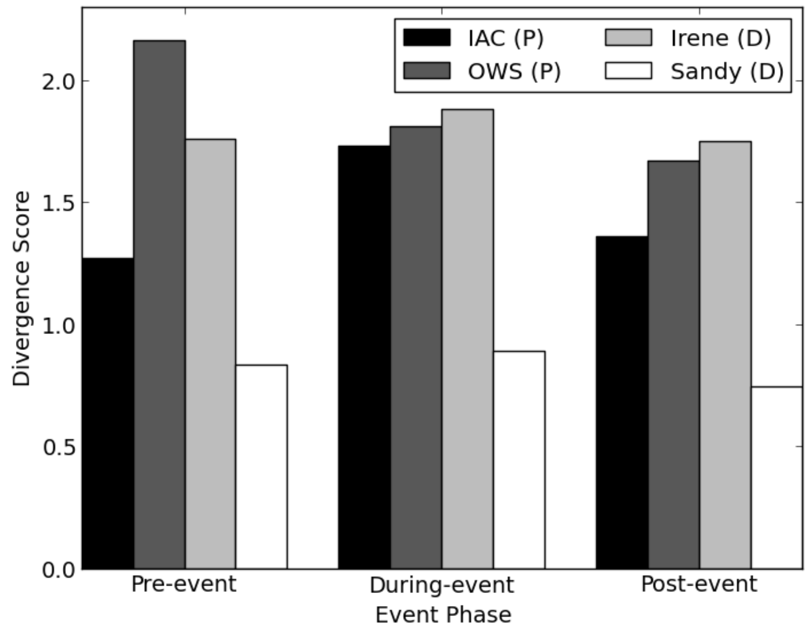


Figure 4.2: Average discussion divergence of groups in each of the phases for various events.

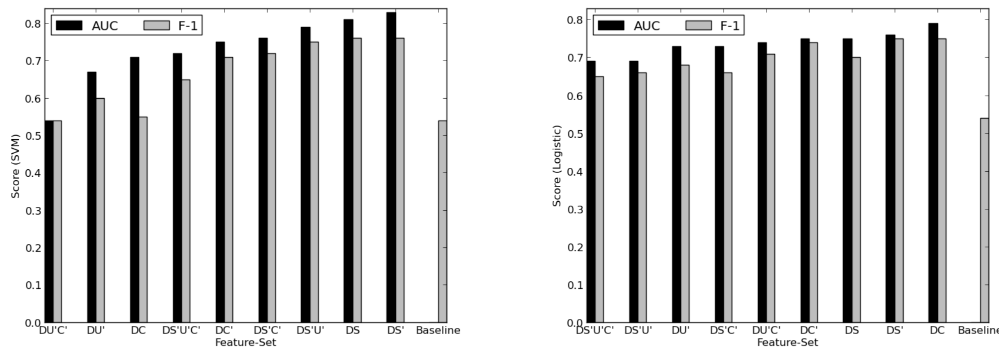
behavior and identities.

Furthermore, Figure 4.2 shows the general pattern of lower topical divergence in the pre-event phase, while increasing in the during-event phase and then again decreasing to lower value in the post-event phase. OWS is an outlier here likely due to high number of incidents even prior to the pre-event phase of the event in our dataset.

4.6.2 Prediction of Trend for *group discussion divergence*

In this section, we present the methods and results for our main task in problem p4.a, i.e., to predict the trend of *group discussion divergence*. We will leverage observations from previous sections, including 1) statistical correlations between features and *group discussion divergence*, and 2) disparities of a subgroup of feature values between groups of high versus low *group discussion divergence*.

More precisely, our goal is to solve a learning problem where the label is whether



(a) SVM

(b) Logistic Regression

Figure 4.3: AUC and F-1 score of prediction for SVM and logistic regression, organized by feature set and sorted by AUC. D=$Divergence$, U'=$User_{all}$, S=$Structure_{sub}$, S'=$Structure_{all}$, C=$Content_{sub}$, C'=$Content_{all}$.

the discussion divergence of a group of users will increase or decrease over time. Since each event is divided into three phases, there are two transitions: pre-event to during-event, during-event to post-event. Feature selection is guided by the statistical analyses and case studies in previous sections.

Feature Sets and Learning Instances: We consider three main categories of features to use in the prediction problem. First, structural features focus on the cohesion and connectivity of each group's follower network. Second, user features emphasize the conformity of group users' offline and online identities. We have defined a family of those features in previous sections, and we noted that their significance varies in terms of correlation with the *group discussion divergence*. Lastly, content features capture the content practices of user-generated content. Based on the analyses in previous sections, we select different subsets of features from all of them, in order to reduce redundancy and improve prediction performance. The subsets are as follows:

- $Divergence$: Discussion divergence of the group at the current phase.
- $Structure_{sub}$: Directed density, reciprocal density, undirected density, reciprocal average shortest path length, undirected average shortest path length.

- $Structure_{all}$: All structural features described in the Feature Design section.
- $User_{all}$: Location entropy, occupation entropy, and online entropy.
- $Content_{sub}$: Average numbers of retweets and hashtags.
- $Content_{all}$: $Content_{sub}$ and average numbers of mentions, URLs and emoticons.

For each event, we identify pairs of social groups that are overlapping (Jaccard similarity[3] is above 0.5) before and after transition between two phases. There are 69 instances of group pairs meeting this criterion, and for 35 pairs their *group discussion divergence* values increase. We assign a label of 'increase' or 'decrease' to each group pair, depending on the change of its *group discussion divergence* value.

Experiment Setup: For each pair of social groups of consideration, we use its features *before* the transition for the prediction task. Both SVM[4] (*SVM*) and logistic regression (*logistic*) are used.

We also create another baseline method (referred to as *baseline*), which relies its classification on the current phase. In the preliminary analysis of content divergence above, it is observed that groups' content divergence in general increases from *pre-event* to *during-event*, and decreases from *during-event* to *post-event*. Therefore, *baseline* always predicts a group's discussion divergence to 'increase' if it is currently in the *pre-event* phase, and 'decrease' if it belongs to the *during-event* phase.

Learning performance: To evaluate the performance of *group discussion divergence* prediction, we perform a five-fold cross validation on *SVM* and *logistic*. For *baseline*, we directly compute its F-1 score (0.54). Figure 4.3 shows the performance of various feature sets and learning models, measured by area under the curve (AUC) and F-1 score.

[3]The Jaccard similarity between two sets A and B is $\frac{|A \cap B|}{|A \cup B|}$.
[4]RBF kernel with γ value set to 0.5.

4.7 Results and Discussion

We noted the following observations to help us answer our research questions R4.1 to R4.3.

- **Performance**

It is demonstrated from Figure 4.3 that classification based on features described in previous sections are significantly more accurate than the baseline method (F-1 of SVM using structural and user features is 0.75, a 39% improvement), addressing R4.1 and R4.3. Furthermore, the performance of classifiers varies according to the selection of features to use. While user features have shown high correlation with static *group discussion divergence*, our results suggest that structural features contribute most to accurately predicting the dynamic change of *group discussion divergence*. Using structural features only, SVM achieves the best AUC (0.83) and F-1 score (0.76).

- **Content Characteristics and Social context**

We performed qualitative study on the content of the overlapping groups by transition of phase (e.g., mid to post), and the divergence shift (e.g., decrease) using the Linguistic Inquiry Word Count (LIWC) software (`http://www.liwc.net`). We observe that groups who tend to diverge in their discussions write more of general reporting type content based on past incidents. While the groups with decreasing diverging behavior write more social and future action related content, likely due to users being organized to inform the fellow group members about updates on the any goal-oriented situation for cooperation, such as volunteering during crisis response. For example, we found in the overlapping candidate groups of hurricane Sandy event that a group with decreasing diverging behavior was highly focused on the updates of flight statuses of different airlines, first delays and cancellation, and later on the resuming parts. Such focused and active topic-specific groups will be valuable to engage with by the response coordinators.

- **Limitations**

Summarizing limitations about our study, we note that other group formation methods can be used and evaluated. We also limit ourselves to three phases in the prediction model experiment, namely pre-, during- and post-event, based on the real-world incidents on the event timeline. However, more phases may be considered for longer events, as they could also possess long-term impact. We acknowledge the need for study across more events of diverse types in the future to validate the work's generalizability in a variety of context. We also did not consider other types of group behaviors for this first effort in analyzing event-oriented group discussion for collective behavior.

For our future work, we plan to extend our features of social identity and cohesion, including ethnic and religious social relationships, and structural properties from Twitter List subscriptions. We shall also validate models into other social networks, such as Facebook, Google+, LinkedIn, and the DBLP co-authorship network, to see if they show a similar social phenomenon of group dynamics. Finally, we are also interested in detecting transition point of *group discussion divergence* over time, which may corresponds to a phase change from storming to norming in the group developmental sequence theory.

To summarize, we can identify groups of audience that are active and concerned about specific issues, and prioritize such reliable groups to engage for the organizational actors for enhancing their *awareness*. In the massive social media community after crisis, identifying reliable sources for engagement to cooperate about specific needs is a daunting task. Another application of the proposed approach is for deciphering the self-organizing behavior of groups by learning the collective diverging trends.

Revisiting our main contribution, we present an approach to understand factors (driven by offline social theories) that improve context for predicting and explaining, the shift of collective behavior to diverge in the group discussion, and help model prioritized (reliable) groups to engage. We illustrate by a prediction model to show that these factors can help track the behavior of *group discussion divergence*, addressing our research question R4.3 and dissertation question R5 outlined in Chapter 1.

Chapter 5: Real World Engagements, Outcomes, and Impact

We often observe challenges with coordination when it is lacking in an environment [71], rather than when the activities of a cooperative system functions smoothly. Therefore, we discuss here challenges and lessons experienced during volunteering participation in the real world crisis responses, to help position the role of technology and need for intent and engagement modeling in CSC. We discuss application areas first, and then describe real world experiences, that helped inform our research about coordination challenges and designing applications for addressing them.

5.1 Applications of Intent and Engagement Modeling for a Cooperative System

The challenge of coordination appears in all aspects of real world cooperative group. Therefore, intent mining research to address issues for cooperation–*articulation* and *awareness* in CSC has applicability across the domains. We discuss two applications of this research below.

- **Crisis Response**

Formal (professional) crisis response communities face the challenge of better coordination within teams, and citizens [35, 82, 73]. However, they also experience information overload from the massive online data generated by citizens on the new online social platforms [81, 48]. One approach is labor-intensive manual filtering. Another is crowdsourcing-based information filtering such as rephrasing the message using a syntax template such as tweak-the-tweet [117], and micro-tasking via *MicroMappers* platform (`http://micromappers.org`). The application of automatically mining intent for user-generated CSC content can help quickly filter data that requires human oversight using platforms like *MicroMappers*, and *Verily* (`http://veri.ly`), such as for requests to help. Mining the requests and offers of help can aid task workflow coordinators and help update priorities for resource allocation decision making.

Furthermore, Figure 1.5 in Chapter 1 shows an example of a seeking-offering matching application to assist coordination for donation of resources and volunteering services in the community. It could serve future emergency coordinators both formal and local community leaders to help manage need priorities via social media matchmaking, as well as improve the existing community based matchmaking systems like Recovers.org. Complete automation of coordination is challenging due to multiple socio-cultural factors. For example clothing of only a specific kind might be acceptable by an affected community women in the context of a crisis response (From the experience in volunteering for the North India flood response in Meghalaya and Assam, 2014). Therefore, this research attempts to assist coordinators by mining the critical information to enable engagement with prioritized actors in CSC. As Asmolov [6] (who experienced operations of the Ushahidi platform based *Help Map* during 2010 Russian wildfires, and *Ryanda.org*) notes *"even if the algorithm is good, it might not be good enough. In some cases, people need help but do not know what resources they need and who potentially can help them–they only know that they are generally in need."*

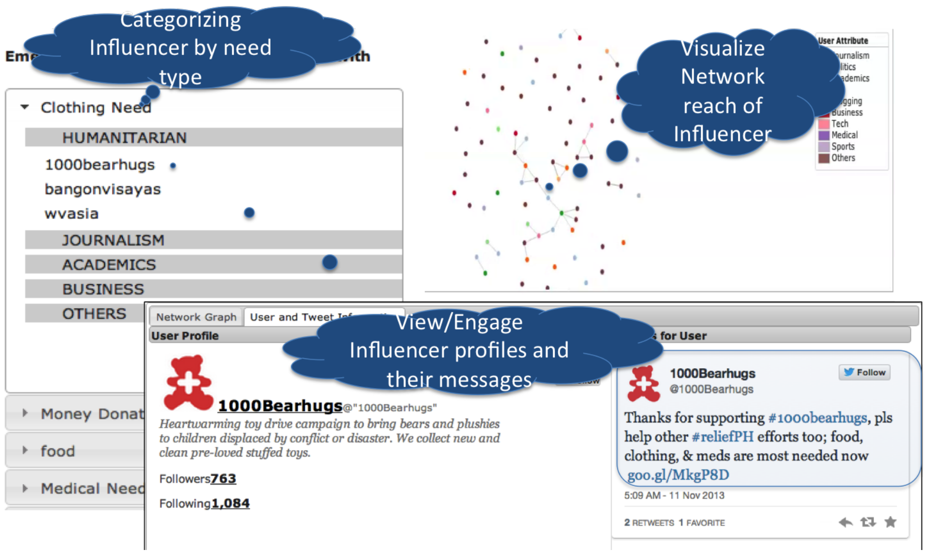


Figure 5.1: Engagement interface components to assist organizational task coordination. Its prototype has been integrated into *Twitris* tool (http://twitris.knoesis.org). This engagement interface application (*SoMeC*), was winner of UN ICT agency ITU's 2014 Young Innovators Challenge on Open Source Technology for Disaster Management.

If proper coordination and engagement with the citizens is not facilitated, responders can face a second disaster, leading to additional overhead to an already stressed coordination environment.

- **Brand page community**

Brands want to manage and maintain reputation online. Brand-oriented CSC requires the identification and prioritization of users with whom to engage. The earlier identification of help seeking customers, and addressing their concerns helps manage customer retention for the brand. Furthermore, identifying groups with specific potential collective behavior can detect emerging groups of customers with concerns, and experts unknown to coordinators earlier.

5.2 Real world Crises, and Role of Technology: Lessons Learned

We have participated in various volunteering efforts in citizen-led crisis responses for crisis mapping to aid *awareness* about the situation. These experiences to participate for volunteering, and sharing the technology with the volunteering community have taught us important design applications lessons. We list two of them here.

- **JKFloodRelief.org – Proactive citizen engagement prevents relief-donation mismanagement**

During the Jammu & Kashmir floods in India in September 2014, along with few citizens, we helped launch a website JKFloodRelief.org (now InCrisisRelief.org) to inform the general public about prioritized resource needs, based on a cooperation with the local on-ground organization working for relief. This real world cooperative information system was supported by on- and off-line coordination between this team, response organizations and citizens [88]. The team quickly bridged a gap to express information needs of local organizational actors to remote citizens for ensuring donation needs are not mismatched, and avoid the second disaster. The group facilitated the largest international citizen-led response drive for relief coordination in the early days of the floods, involving 25 organizations and setup of 28 collection centers across India. The key lesson from this experience was the need for the design of systems that efficiently help in mining information that can meet *articulation* of task-coordination needs, and ensuring *awareness* by distributing information to citizens. The volunteer group coordinated with citizens by using the engagement interface platform in Figure 5.1 to identify important users in the community to engage for spreading critical information about prioritized needs (e.g., medical needs) proactively, as well as verify information by engaging with right set of prioritized citizen actors. In this socio-technical environment, coordination can be assisted by technology, but not replaced.

Volunteers used this engagement interface platform for engagement with citizens during North India floods in 2014, as well as Nepal Earthquake in 2015.

- **Phailin and Uttarakhand Crisis Mapping – Organizational response requires *articulation***

Our digital volunteering initiative in collaboration with Google Crisis Response team led to creation of crisis maps for the two major crisis events in India in the year 2013. The volunteering team was monitoring, collecting, filtering, and enriching the information in collaborative Google spreadsheets. The spreadsheets were fed to a crisis-mapping tool for a visual interface. In this process, the end users of the crisis map, the response organizational actors, were not clear on how to use the mapping tool, but more important, what types of information they could gain from such maps or how could it help their task priorities. The Digital Humanitarian Network [73] provides a better interface for collaboration between formal response organizations and volunteer communities. A key lesson from this experience was the need for the identification of organizational needs, and goal-driven data mining for those specific information needs from citizen generated data.

5.3 Interface for Organizational Actors to Cooperate with Citizens

We discuss a user engagement interface for assisting coordination of organizational tasks by facilitating efficient cooperation between organizational actors and citizens. This interface is integrated as a prototype into *Twitris* social analytics tool (http://twitris.knoesis.org) [110]. It was a global winner of the UN ICT agency ITU's Young Innovators challenge on Open Source Technology for Disaster Management[1].

[1] ITU YIC Blog: https://ideas.itu.int/blog/post/60076

We employ crisis response as a use case to illustrate an application of this interface. We note three approaches to identify citizens to engage for an organizational actor: first, using the prioritized group members as modeled in the Chapter 4; second, by identifying key on-site informants [115]; and third, a more generalized way for on- or off-site coverage in the absence of on-site informants. We describe the third approach in the following discussion (this work has been published in [86]. Our interface extracts important resource-related content via influential users. These influential users can act as both sources and disseminators of important information and hence, contribute as emerging virtual responders to assist organizational task coordination. Given the sparse follower network among users in the CSC for crisis event oriented discussions, as noted in the Chapter 4, our method exploits the network of user interactions (who talks to whom) to identify emerging influencers based on the content of social media exchanges.

Engaging with filtered layers of users serves two purposes. First, it acknowledges the information content that makes users influential, and that may be useful for situational updates. Second, important users serve as nodes in the network to direct crucial time-sensitive information effectively. For example, rumors can be controlled by channeling correct information via these influential nodes. Resource donations could better reflect the priorities of responders, to avoid the second disaster of managing unsolicited resources. For instance, while clothing donations actually impeded the response to hurricane Sandy [33], more power batteries would have helped greatly.

- **Whom to Engage: Influential User Identification**

Alternative methods for identifying the influential user can rely on on-ground twitter users [115], centrality measures based community representatives [42], and whom-to-follow set based on a user's topical affinity [60], etc. However, because we acknowledge the evolving nature of the CSC on social media formed around a disaster event, we exploit user interactions to capture the dynamics of influence, specific to need types (e.g., clothing, food, etc.) This is similar in spirit to previous research for identifying influential users in brand-page communities [89]. Our method analyzes user interactions about specific needs (e.g., food, clothing, medical, etc.) for a given time window. We create a network of users as nodes and directed edges based on the interactions, such that the edge is created from USER-A to USER-B if 'USER-A interacts with (retweets/mentions/replies to) USER-B'. The weight of the edge is equal to the number of interactions. We then apply the popular algorithm, PageRank [80] on the resulting network to identify key influential user nodes. The algorithm iteratively assigns a weight of importance to a user USER-B by aggregating the importance of all such users USER-A who have incoming edge to the USER-B. This way, a user accrues importance based on various factors; such as if other influential nodes interact with (e.g., retweet) her, a greater number of users interact with her, etc.

To identify the set of user interactions pertaining to specific needs, we created a bag-of-words model based lexicon sets for describing needs and used it to filter the corresponding tweet set; however, more sophisticated approaches beyond bag-of-words are possible such as a topic model [128]. For example, a clothing need can be represented by a bag of 'cloth, blanket, jacket'. Certainly better methods can be utilized to find the subset of data relevant to specific needs. In any case, the required method must be independent of pre-established need types to allow response coordination to prioritize based on emerging requirements. We also note that the subsets of tweets related to needs are not mutually exclusive, for example, *"Thanks for supporting #1000bearhugs, pls help other #reliefPH efforts too; food, clothing, & meds are most needed now http://goo.gl/MkgP8D"* will be present in both clothing and food type subsets.

- **How to engage: User Profession Categorization**

Domain familiarity influences both the crafting and sharing of a message. Thus slicing and dicing access paths to information potentially helps coordination. In this step, we categorize the influential users based on profession, such as those related to humanitarian, journalism, or medical. We first created ten popular user profession domains and then cre-

KEYWORD-BASED FILTERING
K1. [Clothing] Donated clothes for the victims of Yolanda. I hope it helps. #ReliefPH
K2. [Clothing] I won't believe it's a true disaster until Anderson Cooper heads to the Philippines wearing his typhoon flak jacket and poncho. Oh, wait! ??
K3. [Medical] Typhoon #Haiyan: Doctors of the World sends medical teams to worst-affected areas — DOTW http://t.co/2X4c0Csjva via @USERK1
K4. [Volunteer] RT @USERK2: @USERK3 RT please Not in the Philippines but want to help for relief efforts? Details: #PrayForThePhilippines
INFLUENTIAL USER-BASED FILTERING
I1. [Clothing → Humanitarian → @USERI1] Thanks for supporting #1000bearhugs, pls help other #reliefPH efforts too; food, clothing, & meds are most needed now http://goo.gl/MkgP8D
I2. [Clothing → Journalism → @USERI2] #Ormoc urgently needs food, water, medicines, blankets. Barge is headed from Cebu to Ormoc tomorrow , please spread @USERI3 #ReliefPH
I3. [Medical → Humanitarian → @USERI4] #ReliefPH @USERI5 sent team of 15 to #Tacloban with medical kits supplied by @USERI6 http://bit.ly/19Swygc #hmrd
I4. [Volunteer → Humanitarian → @USERI7] Interested in volunteering with our #SuperTyhpoon #Haiyan response? Let us know here: http://bit.ly/19W3k4X #volunteer #YolandaPH

Table 5.1: Examples of tweets randomly selected from the keyword-based content filtering on top, and the influential user generated content filtering on the bottom. Example K2 shows the limitation of keyword-based approach due to lack of semantics of relevance. Dataset: Philippines typhoon event, Twitter data of 24 hrs. on Nov 11, 2013. User handles are anonymized.

ated a lexicon using identifiers from Wikipedia and the U.S. Department of Labor statistics, borrowing from the occupation-based method of our previous research on user interest presentation [89]. We noted this as occupational user identity in Chapter 4. The set was then expanded manually to capture general terms. For example, the lexicon for the humanitarian profession domain contains words such as 'humanitarian', 'emergency', 'disaster', etc. The final step is to perform entity spotting of the lexicon terms in the user's description metadata of his or her Twitter profile. We acknowledge that alternative methods can be employed. Our objective is to support the key functionality at the interface to enable faceted engagement for coordination.

Tables 5.1 show how filtering based on influential users reduces the information overload by identifying tweets with unique and useful information of greater relevance to aid *awareness* about the situation, for example, I1 and I2 in Table 4.1 indicates prioritized needs [86]. Keyword based filtering, on the other hand, does not address the issue of information overload due to the mere syntactic approach of filtering without context. Influential users become so via attribution from community members and therefore, are likely to be sources of important information. We anticipate that coordinators will be able to locate useful sources more easily with this indication of information reliability. Figure 5.1 shows our interface.

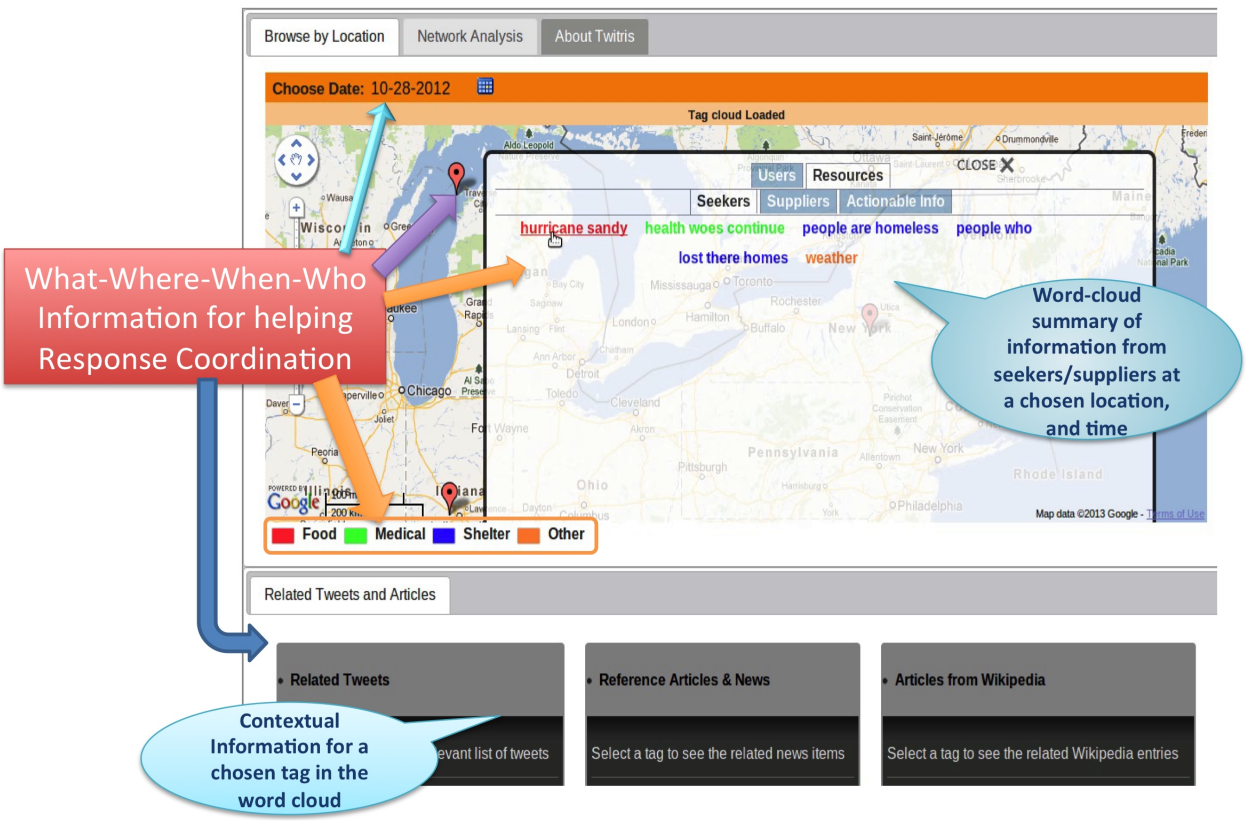


Figure 5.2: Prototype for visual interface to explore the intent classified information at a varying level of abstraction by thematic, spatial and temporal dimensions for helping task coordination.

5.4 Intent Classification-as-a-Service: Ushahidi CrisisNET Integration

We provide intent classification as a web service with POST request mechanism for classifying text messages (test page is available at: http://knoesis-twit.cs.wright.edu/CrisisComputingAPI/. The service currently provides intent classes relevant for the cooperative system design in a use-case of crisis response, but is generic to adopt any other application domain.

- **CrisisNET**

It is a project by Ushahidi, the crisis mapping pioneer. CrisisNET is considered as a firehose of global crisis data (http://crisis.net), providing rich metadata of crisis datasets. The intent classifiers from our research for Seeking and Offering intent classes (details in Chapter 3) for a crisis response use-case have been integrated by the CrisisNET project for broader impact. A study using this service on UK Floods is available at: http://blog.crisis.net/who-helps-when-crisis-hits/

- **Visualization Interface**

We explored the visualization (refer Figure 5.2) of classified information for various intent categories (seeker, offering/supplying) using an initial prototype built on Twitris tool [110] to learn the challenges in interfacing with the actionable information. In this interface, an organizational actor can see information at a varying level of abstraction by thematic (anchored tags in the word cloud), spatial (geographical map) and temporal dimensions (date widget).

Chapter 6: Discussion, Limitations, and Future Work

Based on the previous five chapters, we have validated the role of prior knowledge, and interplay of user, content and network features in efficiently modeling intent classification, and evolution of engagement of user groups to prioritize in CSC, and therefore, helping the design of a cooperation system between citizens and organizations. We discuss the improvements to the state-of-the-art and refer back our research questions outlined in the Chapter 1, followed by limitations and scope of our current and future direction of research.

6.1 Lessons on Improvements

We note several observations on how to address the problem of analyzing data in CSC that serves the design of cooperative web information system for citizens and organizational actors. We organize these points in the following topics:

6.1.1 Operationalizing Computation in the Cooperative System Design

We demonstrated how to operationalize the design problems of a cooperative system between citizens and organizations into data problems by accommodating *articulation* in intent mining, and enriching *awareness* by engagement modeling. We showed a modeling approach to mine intents expressed in the user-generated content of CSC *articulated* by the organizational workflow tasks (Information collection on resource scarcity-availability) and addressed our research question R2. Our efficient mining approach renders the implicit information in the user-generated content explicit. This improves knowledge representation of the noisy data for providing better information access to organizational actors as shown in the Figure 1.b. We also showed an approach to better understanding the user engagement of groups, and their divergence over time to efficiently detect groups with focus–the reliable/prioritized groups. Modeling group engagement helped address the research questions R3 and R5. Providing access to such identified reliable groups in CSC helps organizational actors address the *awareness* challenge by engaging with such group members for sourcing more information timely.

In the context of crisis response, during a post-exercise review of our local emergency management organizations, one of the key lessons for researchers to effectively assist organizational actors was the need for better alignment of data mining outputs for improving cooperation between citizens and formal response organizational actors. Our approach to mining a cooperation-assistive intent addresses the concerns of emergency managers for such goal-driven data mining of content. It complements the earlier work on leveraging the power of crowdsourcing [73] to mining information needs for the collaborating organizations during crisis response, when there is a massive amounts of data being generated.

6.1.2 Data Representation Improvement for Intent and Engagement Models

We demonstrated a performance improvement for the hard-to-predict problem of intent multiclass classification via data representation. In Chapter 3, we contrasted the work on intent mining highly focused on Search logs with limited applicability to socio-technical system due to lack of user action logs, as well as the context of social conversation. We distinguished intent classification from topic classification in text mining, specifically because of the social conversational context. A key lesson from our research is that an efficient representation of what is being computed (capturing context) is as important as how to compute a given dataset for intent classification. In Chapter 4, we showed the interpretability of factors that affect group engagement and its divergence over time could be efficiently modeled using offline social theories. The measure of content-driven *group discussion divergence* complements the existing work on network structured based modeling for the evolution of group engagement.

6.1.3 Fusing Top-down and Bottom-Up Approaches to Address *Ambiguity*, *Sparsity*, and *Diversity*

We showed in Chapter 3 that modeling the fusion of top-down and bottom-up approaches helps in efficient data representation to learn intent from the natural language text documents, especially for the short, user-generated text on social media. We addressed the dissertation research question R4 in this work. Top-down, knowledge-based features assist in improving learning space by boosting statistical processing to mine predictor-class relationships. This better addresses the issues of interpreting ambiguous natural language text, and sparsely available intent classes in user-generated content on online social platforms, consisting of a diverse set of user demographics.

6.1.4 Importance of Social Behavioral Knowledge in Analyzing Online Social Data

We note the influence of knowledge-guided features based on social behavior from the offline world in online communication platforms. Human behavior from the offline world is apparent in the conversations of online mediated communication. Based on extensive analysis in the Chapter 2, we address the dissertation research question R1 for the existence of offline behavior in online conversations. This can be used to improve context in computing data on the online social platforms. We used this knowledge in computing intent from the natural language text. We also used prior knowledge in modeling *diversity* of group members using social cohesion and identity theories, which provided a better explanation for the dynamics of group engagement, and the prediction of *group discussion divergence*. It addressed our dissertation research question R3.

6.2 Assumptions and Limitations

Likewise any computing research investigations, this research also has certain limitations, and we list them under the following categories:

6.2.1 Domain Dependence: Context in CSCW Applications

The CSCW literature shows that coordination and cooperation are highly dependent on the domain of application. Coordination and cooperation requires capturing various nuances of the domain characteristics. We have addressed the use-case for crisis response coordination; however, investigation in other domains would be helpful to observe if different intent expressions are of significance for mining user-generated data.

6.2.2 Knowledge Sources

We used the declarative knowledge from domain experts and linguistic theory. We acknowledge further potential to leverage dedicated knowledge bases designed for the domain, such as Humanitarian Exchange Language (HXL) [58] for crisis response domain. We have also developed a preliminary ontology (accessible at http://knoesis.org/projects/socs) for the domain of crisis response coordination to further enrich declarative knowledge modeling in the computational process (discussed in Appendix).

6.2.3 Intent Classes

We experimented with a limited set of intent class to provide a first step towards modeling cooperation-assistive intent. However, there exists other type of intent in user-generated content during emerging events on online social platforms that need further investigation, such as relationships between acknowledging and seeking help during crisis events. Our Representation Improvement Algorithm although provides a framework for facilitating this exploration, using a variety of knowledge sources for differing intent.

6.2.4 Consideration of Temporal Drift in the Intent

We assumed that ways of expressing intent do not change over time, and considered a static distribution of the intent related data while learning the intent classification. However, there is a possibility of intent expressions being changed over time as a real world event evolves, such as during a crisis where seeking intent for resources can be dynamic in nature based on resource need types (e.g., medical, shelter).

6.2.5 Group Behaviors in Engagement Modeling

We only modeled social cohesion and identity theories for group behavior. However, other theories of group formation and evolution suggest alternative, systematic explanations for social groups, e.g., modeling the roles of leadership consistent with [122] forming-storming-norming-performing. Although more complex to model, such approaches would inform the explanation of group engagement over time.

6.2.6 Non-Twitter Social Data

Our dataset is based on one social network, Twitter microblogging service due to its importance during events of crises in the recent years. However, investigation is needed to apply the developed models on different datasets to identify model transfer challenges across datasets of different social networking platforms, such as Facebook, and Google+.

6.2.7 Interplay of Offline and Online Environments

We acknowledge that interaction effects of offline and online actions of users and groups are not captured in the analysis presented. It is challenging to validate the actual effects on potential offline actions expressed via the intentional expressions in the online social data, due to variety of reasons such as the scale of user communities, and the ground truth. We consider it as a key limitation to online social data analysis, and also a good opportunity to address in the future work.

6.2.8 Correlation but not Causality for Action

The group engagement modeling based on social theories is dependent on the correlation between specific features guided by identity and cohesion theories and the collective behavior of divergence in topical discussions. As correlation does not imply causation, and therefore, we acknowledge that the identified prioritized groups would not always be actionable.

6.3 Future Work

Besides addressing the limitations noted above, the future work should also consider the following directions extending this work:

6.3.1 Multilabel Classification

Intent interpretation is a challenging hard-to-predict problem. Modeling multiple intents within a document would improve understanding of natural language text when *ambiguity* of interpretation challenges a human reader. We have often observed the expression of intent with another intent class; for example, intent of asking for help in a message during crisis response exists with the acknowledgement also. We shall explore the classifier chain approach for address the problem in an ensemble-learning framework. We shall also investigate multitask learning to explore the idea of jointly learning the multiple objectives together, such as for the presence of intent for asking for help occurring with specific resource class (e.g., shelter, food) during crises.

6.3.2 Parameter-free Algorithm for Top-down and Bottom-Up Fusion

We also note a possible extension of the Representation Improvement Algorithm for creating a parameter-free approach to fuse the top-down and bottom-up processing. We shall address the problem of modeling the parameters of contrast pattern mining for discovering knowledge by using the declarative knowledge, which is guided by specialized domain expert knowledge sources, such as extensions of Humanitarian Exchange Language ontology.

6.3.3 Actor-specific Intent Mining

We note another form of intent mining problem in the user-generated content of CSC, from a pragmatic perspective. Instead of answering simple question 'what is the intent of a document' as a classification problem, we should consider the actor-specific intent association problem, i.e., who has the intent, and of what type'. Understanding such fine-grained details of the intent behavior would allow precise and efficient organization of user-generated content. Also, the fine-grained intent would allow the efficient matching models for coordination as explained next.

6.3.4 Matching Algorithms for Coordination Modeling

We identify a bipartite matching problem for a graph containing two sets of complementary intentions, such as demand or seeking intent versus supply or offering intent, which could help the coordination of resources and information. In this, we have multiple problems involving uncertainty of nodes, and edges in the bipartite graph, which specifically contains the sub-problems of intent classification for document nodes, user resolution for nodes, and faster graph matching. Our on-going work is exploring the challenge of graph-matching problem using partitioning based method to reduce time and space complexity in the weighted bipartite matching.

6.3.5 Visualization for Assisting Coordination

We also note an important challenge of computer human interaction to make the technologies accessible and usable for end users. We must test the existing interface as discussed in the Chapter 5 and examine better information visualization and search interfaces to facilitate human decision-making.

CONCLUSION

We have presented a novel approach to transform the design level cooperative system challenges of *articulation* and *awareness* into computationally tractable problems, for cooperation between citizens and organizational actors in the online citizen sensor communities (CSC). We model specific intent types expressed in the user-generated content in CSC that align data mining with the *articulation* of organizational workflow tasks (e.g., seeking-offering resources to assist response prioritization during a crisis). We model user engagement in groups of CSC to address *awareness* challenge of cooperation to determine whom to prioritize in CSC for engagement with organizational actors for coordination.

We have demonstrated a hybrid approach of fusing top-down and bottom-up processing to efficiently model user intent and engagement in CSC. In the hybrid approach, the interplay of prior knowledge from a variety of sources (declarative, offline social behavior and contrast patterns) in combination with user, content and network features improve data representation and address the challenges of *ambiguity* in interpretation, *sparsity* of specific behaviors, and *diversity* of user demographics. Better-represented data improves modeling efficiency for user intent mining via multiclass classification and group engagement evolution using a novel content-driven measure of *group discussion divergence*. Our approach provides an interpretation of the structure of highly noisy data generated in CSC.

Throughout this dissertation research, we had opportunities to collect and work with real-world crisis data as well as participate in rescue or relief coordination efforts. This informed our research by providing real world requirements, as well as provided interim opportunities to apply our research. We have described applications of addressing cooperation issues in the online socio-technical system, and provided intent classification as a service in the crisis response domain, which has been integrated by Ushahidi CrisisNET project for broader impact of the research outcome. Resulting techniques from this research has potential impact on the conduct of emergency response coordination, by enhancing *awareness* in the formal response community to focus on patterns of need and assisting *ar-*

ticulation by clarifying available resources. Future work will expand the domain analysis, assess the contributions of existing organizational processes, and increase and evaluate social data analysis capability to support the decision making of formal organizations. Also, we plan to explore deeper intent mining approaches using multilabel and multitask learning to better understand human expressions in the online social medium.

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Appendix A

Crisis Coordination Ontology

We extend the concepts of domain knowledge-driven models for the crisis response use-case, MOAC–Management Of A Crisis ontology [63], and UNOCHA's HXL–Humanitarian Exchange Language [58] ontology. Using these models, we created an extended ontology, named as 'SOCS Ontology for Crisis Coordination' with required but missing concepts for organizing data during crisis response for seeker (seeking intent) and supplier (offering intent) behavior, and indicators of resource needs using a lexicon. For example, the 'shelter' class contains words 'emergency center,' 'tent,' and 'shelter,' along with lexical alternatives. For the initial demonstration, we focus on three resource categories: food, shelter and medical needs. Thus, we endeavor to exploit a minimum, but always expandable subset that provides the maximum coverage while controlling false alarms. For creating lexicons of indicator words for concepts, we relied on various documents collected via interactions with domain experts [35], our Community Emergency Response Team (CERT) training, Rural Domestic Preparedness Consortium training, and publically available references [1, 2, 126]. Using a first aid handbook [119], we created an extensive 'medical' subset of emergency indicators, where we identified words which pertained specifically to first aid or injuries and included those words along with variations in tense (i.e., breath, breathing, breathes) and common abbreviations (i.e. mouth to mouth, mouth 2 mouth, CPR). A local expert with FEMA experience augmented the model with additional indicators and provided anecdotal context. The current model with food, medical, and shelter resource indicators contain 43 concepts and 45 relationships. We created this domain model in the OWL language using the Protégé ontology editor [79]. Each type of disaster is listed as an entity type with indicators for that disaster listed as individuals under a corresponding indicator entity. Therefore a relationship is declared stating that a particular disaster concept, say Flood, relates by property 'has_a_positive_indicator', with 'Flood_i' indicator entity, that includes all relevant words. Each disaster has a declared negative relationship with the negative indicator list (e.g., 'erotic' under sexual words indicators) under the entity name Negative_Indicator_i. Finally resources are declared as individuals under the appropriate entity in the same way, but relationships are not explicitly stated with any disaster in order to provide flexibility. The description of how to leverage this ontology for computation is available in [90], and it is accessible from our project website: http://www.knoesis.org/projects/socs

Appendix B

Declarative Knowledge Patterns

In reference to section 3.6, for experiments to classify intent, we crafted the following seed patterns for declarative knowledge with the help of expert guidance, which were further expanded using WordNet and Levin Verbs knowledge bases, as discussed earlier. The prefix ('OFFERING=' or 'SEEKING=') denotes the potential class association of the pattern, and the '_REQ_ ' and '_OFR_' in the pattern string are just indicators for explaining a potential intender for *Seeking* and *Offering* intent classes. For example, consider the first pattern, a message 'I am donating to Red Cross' would fit in this case, and the intent of message author is *Offering*, who is donating to 'Red Cross', a *Seeking* intender. These patterns were used to generate binary features.

```
OFFERING=\b(I|we)\b.*\b(m|am|are|r|will be|shall be)\b.*\b(bringing|giving|helping|raising|donating|auctioning)\b _REQ_

OFFERING=\b(I'm|we're|they're|we'r|they'r)\b.*\b(bringing|giving|helping|raising|donating|auctioning)\b _REQ_

OFFERING=\b(I|we|they|it)\b.*\b(ll|will|shall|would|wud|would like to|wud like to|wd like to)\b.*\b(bring|give|help|raise|donate|auction|work|volunteer|assist)\b _REQ_

OFFERING=\b(I'll|we'll|they'll|he'll|she'll|it'll|I'd|we'd|they'd|he'd|she'd|it'd)\b.*\b(bring|give|help|raise|donate|auction)\b _REQ_

OFFERING=\b(I|we)\b.*\b(ready|prepared)\b.*\b(bring|give|help|raise|donate|auction)\b _REQ_

OFFERING=\b(where|how)\b.*\b(can|could|cud|cd|may|might|would|wud|wd)\b.*\b(I|we|he|she|it|they)\b.*\b(bring|give|help|raise|donate|work|volunteer|assist)\b _REQ_

OFFERING=\b(I|we)\b.*\b(like|want)\b.*\bto\b.*\b(bring|give|help|raise|donate|work|volunteer|assist)\b _REQ_

OFFERING=\b(can|could|cud|cd|may)\b.*\b(I|we|he|she|it|they)\b.*\b(bring|give|help|raise|donate|work|volunteer|assist)\b _REQ_

OFFERING=_OFR_ \b(is|are|will be|shall be)\b.*\b(bringing|giving|helping|raising|donating|volunteering|assisting|working)\b _REQ_

OFFERING=\b(I|we|he|she|they|it)\b.*\b(can|cn|could|cud|would|wud|should|may|might)\b.*\b(feed|give|lease|lend|loan|pass|pay|refund|render|rent|serve|trade|assign|award|extend|grant|issue|leave|offer|send|ship|slip|sneak)\b.*\b(a|an|the)\b _REQ_

OFFERING=\b(I|we|he|she|they|it)\b.*\b(may|might|must|can|cn|could|cud|would|wd|wud)\b.*\b(help|assist|aid|lend a hand|volunteer)\b _REQ_

OFFERING=\b(I|we|he|she|they|it)\b.*\b(shall|will)\b.*\b(feed|give|lease|lend|loan|pass|pay|refund|render|rent|serve|trade|assign|award|extend|grant|issue|leave|offer|send|ship|slip|sneak)\b _REQ_

OFFERING=\b(I'll|we'll|he'll|she'll|they'll|it'll)\b.*\b(feed|give|lease|lend|loan|pass|pay|refund|render|rent|serve|trade|assign|award|extend|grant|issue|leave|offer|send|ship|slip|sneak)\b _REQ_

OFFERING=\b(shall|will|should|would|can|could|cud|wud|shud|may)\b.*\b(I|we|he|she|they|it)\b.*\b(feed|give|lease|lend|loan|pass|pay|refund|render|rent|serve|trade|assign|award|extend|grant|issue|leave|offer|send|ship|slip|sneak)\b _REQ_

OFFERING=_OFR_ \b(like|want|likes|wants)\b[^?]*\b(to)\b[^?]*\b(bring|give|help|raise|donate|work|volunteer|assist|support)\b(?!.*\?)\b _REQ_

SEEKING=\b(like|want)\b.*\b(to)\b.*\b(give|help|raise|donate|work|volunteer|assist|support)\b _REQ_

SEEKING=\b(you|u)\b.*\b(can|could|should|want to)\b.*\b(bring|give|help|raise|donate|text)\b _REQ_

SEEKING=\b(can|could|cud|would|wud|should)\b.*\b(you|u)\b.*\b(bring|give|help|raise|donate)\b _REQ_

SEEKING=\b(I|we|he|she|they|it|I'll|we'll|he'll|she'll|they'll|it'll)\b.*\b(need|needs|needing)\b

SEEKING=\b(please|plz|pls)\b.*\b(bring|give|help|raise|donate|work|volunteer|assist|feed|give|lease|lend|loan|pass|pay|refund|render|rent|serve|trade|assign|award|extend|grant|issue|leave|offer|send|ship|slip|sneak)\b _REQ_

SEEKING=\b(who)\b.*\b(has|had|have|hv)\b.*\b(a|an|the)\b _REQ_

SEEKING=\b(what)\b.*\b(can|could|cn|cld)\b.*\b(you|u)\b.*\b(do)\b _REQ_

SEEKING=\b(shall|will)\b.*\b(you|u)\b.*\b(bring|give|help|raise|donate|work|volunteer|assist|feed|give|lease|lend|loan|pass|pay|refund|render|rent|serve|trade|assign|award|extend|grant|issue|leave|offer|send|ship|slip|sneak)\b _REQ_

SEEKING=\b(do|does|did)\b.*\b(you|u|he|she|they|it)\b.*\b(have|hv|has|had)\b _REQ_

SEEKING=\b(donate|bring|give|raise|text|work|volunteer)\b.*\b(to)\b.*\b(help|support|assist)\b _REQ_

SEEKING=\b(like|want|likes|wants)\b.*\b(to)\b.*\b(bring|give|help|raise|donate|work|volunteer|assist|support)\b.*(\?).*\b _REQ_

SEEKING=\b(like|want|likes|wants)\b.*\b(to)\b.*\b(bring|give|help|raise|donate|work|volunteer|assist|support)\b.*(check|chk|go to).*\b _REQ_

SEEKING=_REQ_ \b(who|you|u)\b.*\b(like|want|likes|wants)\b.*\b(to)\b.*\b(bring|give|help|raise|donate|work|volunteer|assist|support)\b _REQ_

SEEKING=_REQ_ \b(need|needing)\b.*\b(help|support)\b _REQ_
```

Figure B.1: Pattern set for declarative knowledge.