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TEXT ANALYTICS TO SUPPORT SENSE-MAKING IN SOCIAL MEDIA: A LANGUAGE-ACTION PERSPECTIVE[1]

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Social media and online communities provide organizations with new opportunities to support their business-related functions. Despite their various benefits, social media technologies present two important challenges for sense-making. First, online discourse is plagued by incoherent, intertwined conversations that are often difficult to comprehend. Moreover, organizations are increasingly interested in understanding social media participants' actions and intentions; however, existing text analytics tools mostly focus on the semantic dimension of language. The language-action perspective (LAP) emphasizes pragmatics; not what people say but, rather, what they do with language. Adopting the design science paradigm, we propose a LAP-based text analytics framework to support sense-making in online discourse. The proposed framework is specifically intended to address the two aforementioned challenges associated with sense-making in online discourse: the need for greater coherence and better understanding of actions. We rigorously evaluate a system that is developed based on the framework in a series of experiments using a test bed encompassing social media data from multiple channels and industries. The results demonstrate the utility of each individual component of the system, and its underlying framework, in comparison with existing benchmark methods. Furthermore, the results of a user experiment involving hundreds of practitioners, and a four-month field experiment in a large organization, underscore the enhanced sense-making capabilities afforded by text analytics grounded in LAP principles. The results have important implications for online sense-making and social media analytics.

Keywords: Design science, text analytics, social media, natural language processing, language-action perspective, conversation disentanglement, coherence analysis

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The appendices for this paper are located in the "Online Supplements" section of the *MIS Quarterly*'s website (http://www.misq.org).

Introduction

The rapid growth of social media and online communities has dramatically changed the manner in which communication takes place. Organizations are increasingly utilizing general-purpose social media technologies to support their business-related functions (Mann 2011). According to a *McKinsey Quarterly* report, 50% of the more than 1,700 organizations surveyed are using social networking, 41% are using blogs, 25% are using wikis and 23% are using microblogs (Bughin and Chui 2010). Moreover, these numbers have more than doubled over a four-year period (Bughin and Chui 2010). Web 2.0 technologies are being leveraged for internal purposes, customer-related purposes, and to work with external suppliers and partners. Organizations are deriving considerable benefits from their use, including increased speed of access to knowledge, enhanced identification of experts, increased number of successful innovations, and reduced communication and operational costs (Bughin and Chui 2010; Chau and Xu 2012).

Sense-making is an information-processing task that serves as a critical prerequisite for decision-making (Russell et al. 1993; Weick et al. 1995). Despite their various benefits, existing social media technologies suffer from two important limitations which inhibit sense-making:

- Communication modes such as chat rooms, newsgroups, forums, blogs, social networking discussions, and microblogs are highly susceptible to intertwined conversations and incoherence (Honeycutt and Herring 2009). In group discussion, these issues make it difficult for analysts and supporting technologies to determine the correct message-conversation affiliations and reply-to relations among messages (Aumayr et al. 2011; Fu et al. 2008; Herring 1999).

- Existing text and social media analytics tools tend to focus on the semantic dimension of language: what people are saying. However, while using such technologies, organizations have difficulty understanding discussants' actions, interactions, and intentions (Mann 2011).

These limitations have significant implications. Ineffective sense-making can impact quality of decisions and actions (Klein et al. 2006; Russell et al. 1993). Furthermore, information sources and/or technologies deemed by users to not adequately support sense-making see diminished usage in future decision-making processes (Pirolli and Card 2005; Russell et al. 1993). In the context of social media analytics tools, based on industry surveys of key value-driving use cases, and multiple independent assessments of existing social media technologies that support these use cases, Table 1 summarizes challenges stemming from the two aforementioned limitations (Mann 2013; Zabin et al. 2011). According to industry surveys, three of the most important use cases for social media analytics are (1) identifying issues described in user-generated content; (2) identifying ideas and opportunities; and (3) identifying important discussion participants (Zabin et al. 2011). Multiple independent assessments of the functionalities of nearly 40 major existing social media analysis technologies highlight their exclusive reliance on keyword, topic, and sentiment analysis, underscoring their limitations for key use cases (Mann 2013; Zabin et al. 2011). Consequently, the inability of state-of-the-art text and social media analytics tools to provide sufficient sense-making has diminished their perceived return on investment (Zeng et al. 2010). Supplementing the pervasive semantic view with a pragmatic perspective is critical for comprehending communicative context and intentions surrounding issues and ideas (Te'eni 2006), and for understanding participant roles and importance (Fu et al. 2008). Over 80% of organizational data is represented in the form of unstructured data (Kuechler 2007), with email and social media accounting for a growing proportion (Chau and Xu 2012; Halper et al. 2013; Kuechler 2007). There is thus a need for advanced text analytics tools capable of supporting sense-making in online discourse.

In addressing the aforementioned challenges, there are two major research gaps. First, existing text analytics research has adopted a semantic view (Abbasi and Chen 2008; Lau et al. 2012), with thousands of studies looking at topic and sentiment analysis. The body of literature on the pragmatic view emphasizing communication context, actions, and interactions, has received less attention. Second, text analytics studies that have adopted the pragmatic perspective are fragmented. No overarching framework exists to guide the design and development of these artifacts. In order to address these gaps, in this study, we adopt the design science paradigm to guide the development of the proposed IT artifacts (Hevner et al. 2004): a language aspect perspective (LAP) based text analytics framework and system. By emphasizing the pragmatic aspect of language, LAP provides insights for the design of information systems that consider communicative context and actions (Schoop 2001; Winograd and Flores 1986). In particular, LAP emphasizes the interplay between conversations, communication interactions between users and messages, and the speech act composition of messages. Guided by LAP, the proposed framework encompasses three components designed to collectively alleviate the current challenges and facilitate enhanced sense-making from online discourse.

We rigorously evaluated a system that was developed based on the framework in a series of experiments that demonstrate the utility of each individual component of the system in com-

Table 1. Summary of Key Social Media Analysis Use Cases and Challenges

<table>
<tr><th>Use Case</th><th>Challenges</th></tr>
<tr><td>Identifying Issues</td><td rowspan="2">Most state-of-the-art social media analysis tools only include keyword, topic, or sentiment analysis for messages or threads. These tools make it very difficult to identify questions, suggestions, desires, assertions, declarations, etc. Furthermore, by focusing at the message or discussion thread level, these tools fail to consider communication within its conversation context. Collectively, these challenges can impact capabilities for identifying issues or opportunities such as customer churn, brand devaluation issues, popular suggestions, etc.</td></tr>
<tr><td>Identifying Ideas and Opportunities</td></tr>
<tr><td>Identifying Important Participants</td><td>Key participants, including brand advocates, influencers, experts, connectors, and leaders, are typically identified using interaction metrics based on social network centrality measures. Existing tools' reliance on system-based interaction cues dramatically diminishes the accuracy and quality of insights pertaining to participant roles and rankings in social media.</td></tr>
</table>

parison with existing methods. Furthermore, the results of a user experiment involving practitioners from multiple industries illustrate the enhanced sense-making capabilities afforded by LAP-based text analytics systems. Additionally, a four-month field experiment revealed that social media team members at a telecommunications company perceived the additional LAP-based (pragmatic) information to improve system usefulness and ease-of-use for monitoring tasks, relative to those members relying on (solely semantic) information from an existing social media analytics system.

The study makes two sets of research contributions. Our primary contributions are from a design science perspective. We present a robust *framework* and *system instantiation* grounded in LAP principles, which emphasizes the interplay between conversations, coherence relations, and message speech acts. We also propose *novel text analytics methods* for conversation disentanglement, coherence analysis, and speech act classification, thereby enhancing the state-of-the-art for IT artifacts that analyze social media. We also present several *empirical insights*, such as the impact of incoherent reply-to relations on error rates for social network centrality metrics across various social media channels. By demonstrating the efficacy of the proposed system in user and field studies, the results have important implications for researchers analyzing social media, as well as various organizational functions that leverage internal and/or external sources of social media to support communication and decision-making, including customer relationship management, workforce analytics, risk management, and market research.

The remainder of the paper is organized as follows. The next section presents a motivating industry example highlighting the need for sense-making. The subsequent section describes our LAP-based framework, reviews work related to key components of the framework, and presents research questions. Based on this framework, we then describe a text analytics system for online sense-making that incorporates important concepts from prior LAP studies. This is followed by the presentation of robust evaluation of various facets of the proposed system, including experiments that evaluate each component, user experiments, and a field study that provides an in-depth assessment of the system's overall sense-making capabilities. The final section offers our conclusions.

The Need for Sense-Making: The TelCorp Example

In this section, we present a motivating industry example highlighting the need for enhanced sense-making from social media. It is important to note that the example presented is not nuanced or niche, but rather, represents the type of situation encountered by organizations in various industry verticals on a routine basis. We mention a few other high-profile examples at the end of this section, and later incorporate data from organizations in different industries as part of the test bed.

In the fall of 2012, TelCorp (fictious name), one of the ten largest telecommunications and data service providers in the United States, increased the maximum upload speed for customers subscribed to their highly profitable premium Internet plan. A press release was placed on the company's website and messages describing the move were posted on several social media channels, including TelCorp's Facebook fan page, Twitter, and various web forums. Like most large telecommunications service providers, TelCorp's customer relationship management (CRM) division included a team that monitored their social media presence through dashboards that provided real-time data on key topics, sentiments, and users. During the first 24 hours, the team monitored sentiments and key users in over 2,000 threads related to the increase, across various channels, noting that discussions were positive. However, during the same time frame, TelCorp's call centers observed a marked increase in customer complaints. Over the next 24 hours, various CRM teams carefully combed through all customer communications across channels and surmised that the problem was as follows. The majority of TelCorp's customers were subscribed to non-premium plans and either thought this offer applied to them and didn't notice improved performance, and/or were upset that it didn't apply to their plans. In hindsight, publicizing something that only applied to 20% of the customer base, and then poorly describing it in some of the social media channels, created a feeling of exclusion and/or confusion, leading to anger (i.e., a perfect storm of customer discontent). Exactly 54 hours after the initial announcement, the company made amends by introducing similar maximum upload speed increases for customers on non-premium plans, providing promotional offers on additional services and upgrades, and apologizing for the confusion. Nevertheless, over that 54-hour period, their customer churn rate was 5 times higher than usual, resulting in an estimated $110 million in lost revenue during the next 12-month period alone, not to mention long-term losses based on customer lifetime value.

In the era of viral media, it should not have taken TelCorp 48 hours to understand the gravity of the situation. Clearly, there was a need for enhanced sense-making capabilities. The TelCorp situation is not unique. There are many well-documented cases of organizations failing to appropriately make sense of employee and/or customer communications in internal and external-facing social media, resulting in significant financial consequences. Examples include employee relations at Wal-Mart (Berfield 2013), Gap's failure to understand customers' preferences during logo redesign (Halladay 2010), and Maker's Marks' production-related misstep (Lee 2013). In each of these incidents, sense-making from social media could have been used proactively to inform decision making, and/or reactively as part of a real-time monitoring strategy to mitigate damage. However, enhanced sense-making requires IT artifacts capable of effective text analytics. In the next section, we present an overview of LAP and describe how it can help improve the state-of-the-art for sense-making from social media. We also illustrate how the proposed LAP-based framework could facilitate enhanced sense-making in the context of TelCorp.

The Language-Action Perspective and Sense-Making in Online Discourse

Three important aspects of language are semantics, syntax, and pragmatics (Winograd and Flores 1986). Numerous prior technologies that support analysis of computer-mediated communication content have emphasized the semantics of language with particular focus on topics and sentiments of discussion; that is, what people are saying (Abbasi and Chen 2008). As new internet-enabled Web 2.0 based technologies gain widespread adoption in organizations, they are increasingly being used to facilitate communicative and discursive action involving employees, customers, partners, suppliers, etc. (Bughin and Chui 2010). While these technologies have great potential for supporting such activities, comprehensibility and clarity remain critical concerns: computer-mediated communication is highly incoherent (Herring 1999; Honeycutt and Herring 2009). Furthermore, the conventional Information System's perspective stresses the content of messages rather than the participants' interactive behavior (Aakhus 2007). There is a need for IT artifacts capable of accurately presenting pragmatic information such as communicative context and actions for enhanced sense-making (Schoop et al. 2006).

Design science provides concrete prescriptions for the development of IT artifacts, including constructs, models, methods, and instantiations (Hevner et al. 2004). Several prior studies have utilized a design science approach to develop business intelligence and analytics-related IT artifacts, including methods and instantiations (Abbasi and Chen 2008; Chau and Xu 2012; Lau et al. 2012). When creating IT artifacts in the absence of sufficient guidelines, design theories may help govern the development process (Storey et al. 2008; Walls et al. 1992). We use language-action perspective as a kernel theory to guide the development of the proposed framework and system (Winograd and Flores 1986).

The language-action perspective (LAP) emphasizes pragmatics; not what people say, but rather, what people do with language (Winograd and Flores 1986). LAP highlights "what people do by communicating, how language is used to create a common basis for communication partners, and how their activities are coordinated through language" (de Moor and Aakhus 2006, pp. 93-94). LAP's principles are based on several important theories, including speech act theory (Searle 1969), discourse analysis, and argumentation. Speech act theory (SAT) emphasizes the ordinary speaking view of language, where language is a social fact and its primary function is to promote sense-making in social interactions (Kuo and Yin 2011; Lyytinen 1985). Specifically, two LAP principles may provide important insights for the design and development of text analytics tools capable of improving sense-making from online discourse (Winograd and Flores 1986):

1. Conversation structures: LAP advocates considering messages in the context of the conversations in which they occur. Conversations encompass interactions between users and their messages. There are different types

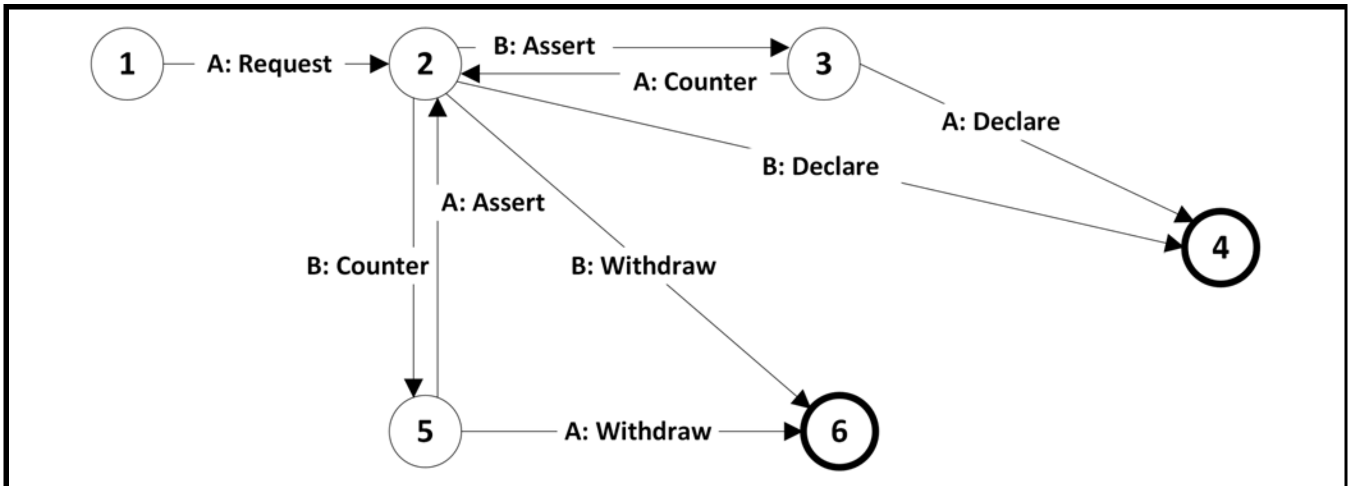

Figure 1. A Conversation for Clarification (adapted from Winograd and Flores 1986)

of conversations: conversations for action, conversations for clarification, conversations for possibilities, conversations for orientation, etc.

2. Actions and context: LAP advocates the pragmatic view, which can complement the semantic perspective by emphasizing actions, intentions, and communication context through consideration of speech acts.

Figure 1 presents a "conversation for clarification" example to illustrate the LAP principles, adapted from Winograd and Flores (1986). The example depicts two parties, A and B, and potential conversation sequences. For instance, A submits a request for information followed by B making an assertion, putting forth a counter request for additional information, declaring the issue resolved or inappropriate, or electing to withdraw from the conversation (and so on). The example shows a conversation template encompassing a collection of messages labeled with action information, multiple users, and their interactions (arrows). From an organizational social media analytics vantage point, the ability to analyze various types of conversations involving customers, employees, and other stakeholders can provide valuable sense-making capabilities which can complement the existing pervasive semantic view.

Despite the potential sense-making opportunities afforded by social media analytics guided by LAP, existing social media analytics tools used in organizational settings almost exclusively rely on semantics: analysis of topics and sentiments (Zabin et al. 2011). Accordingly, we propose a LAP-based framework for analyzing online discourse which emphasizes conversation structures, actions, and communication context (see Figure 2). The framework is predicated on the notion that methods which employ LAP principles can complement topic-sentiment-centric systems to facilitate enhanced sense-making through

1. Conversation disentanglement: the ability to accurately affiliate messages in discussion threads with their respective conversations. From a LAP perspective, conversations are an important unit of analysis that is presently not represented in text/social media analytics systems: messages are too atomic and threads encompass multiple intertwined conversations (Elsner and Charniak 2010).

2. Coherence analysis: the ability to infer reply-to relations among series of messages within a discussion thread (Nash 2005). Social media technologies make it difficult to accurately infer interrelations between messages (Honeycutt and Herring 2009), impacting quality of participant interaction and social network information (Aumayr et al. 2011; Khan et al. 2002).

3. Message speech act classification: the ability to infer the speech act composition of messages within discussion threads – for instance, assertions, questions, suggestions, etc. (Kim, Li, and Kim 2010).

Inclusion of these three components can be used to collectively improve sense-making capabilities by providing an enhanced representation of coherence relations and communication actions through the use of speech act trees (SATrees): the transformation of linear discussion threads into a series of conversations with reply-to relations and message speech act information. SATrees, and the information generated using

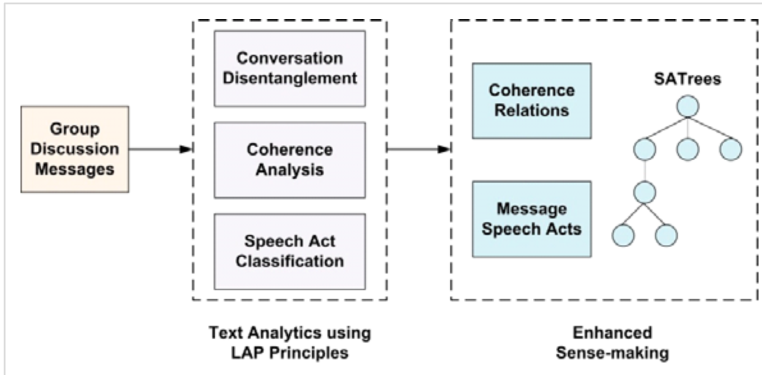

Figure 2. A LAP-Based Framework to Support Sense-Making in Online Discourse

LAP-based systems, can enable augmented support for key social media analytics use cases. The framework incorporates LAP concepts in two important ways. First, the composition and sequence of stages in the framework is closely aligned with LAP studies which emphasize conversations as the unit of analysis, interactions within these conversations, and the speech act composition of utterances (Winograd and Flores 1986). Second, within each component of the framework, principles from the LAP body of knowledge are used to prescribe design guidelines which are later operationalized through a LAP-based text analytics system. The proposed framework and related research questions are presented in the remainder of the section, along with discussion pertaining to the TelCorp example.

Conversation Disentanglement

A critical problem that arises in discourse are parallel, intertwined conversations (Elsner and Charniak 2010). Entangled conversations, which are highly prevalent in various forms of computer-mediated communication, occur as a result of multiple simultaneous conversations between two or more users appearing within a single discussion thread (Auramaki et al. 1992; McDaniel et al. 1996). In order to avoid thread confusion, disentanglement is widely regarded as an essential precursor for more advanced forms of discourse analysis (Adams and Martell 2008). It is especially important "when there are several streams of conversation and each stream must be associated with its particular feedback" (Te'eni 2001, p. 297). Consequently, in the proposed framework, disentanglement information/variables are key input for coherence analysis and speech act classification.

In order to illustrate the importance of conversation disentanglement, we revisit the TelCorp example. TelCorp examined sentiments in 2,000 discussion threads pertaining to its initiative. However, due to intertwined conversations, discussions threads are not the ideal unit of analysis (Honeycutt and Herring 2009). Figure 3 shows three initiative-related discussion threads taken from a web forum, Facebook, and Twitter, respectively. The threads were sampled from, and are representative of, the types of user-generated content found in the 2,000 threads pertaining to the initiative. In each thread, circles denote individual messages (e.g., a forum posting, a Facebook comment/reply, or a tweet). The vertical axes indicate thread turns, and the horizontal axes indicate conversations within the thread (with each column of circles signifying the messages in the same conversation). The arrows and boxes indicate the general topic of that particular conversation. As depicted in the figure, the web forum thread example encompassed six different conversations over a span of only 53 messages; the Facebook and Twitter threads, although shorter, also had 5 and 3 conversations, respectively. The initial conversations, which accounted for the majority of messages, were mostly positive expressions about the initiative—hence the positive thread-level sentiments observed by the monitoring team. However, some of the subsequent conversations drifted from positive, to questions, to criticisms, and even declarations of switching to other providers. Decomposing the threads to more meaningful semantic units by performing conversation-level analysis (Elsner and Charniak 2010) would have provided TelCorp's social media monitoring team with a better understanding of the situation.

This example underscores the importance of conversation disentanglement. Prior methods for disentanglement have mostly relied on single-pass clustering methods that compare newer messages against existing conversation clusters (e.g., Adams and Martell 2008; Shen et al. 2006; Wang and Oard 2009). While these methods utilize information regarding content similarity and spatial/temporal proximity between mes-

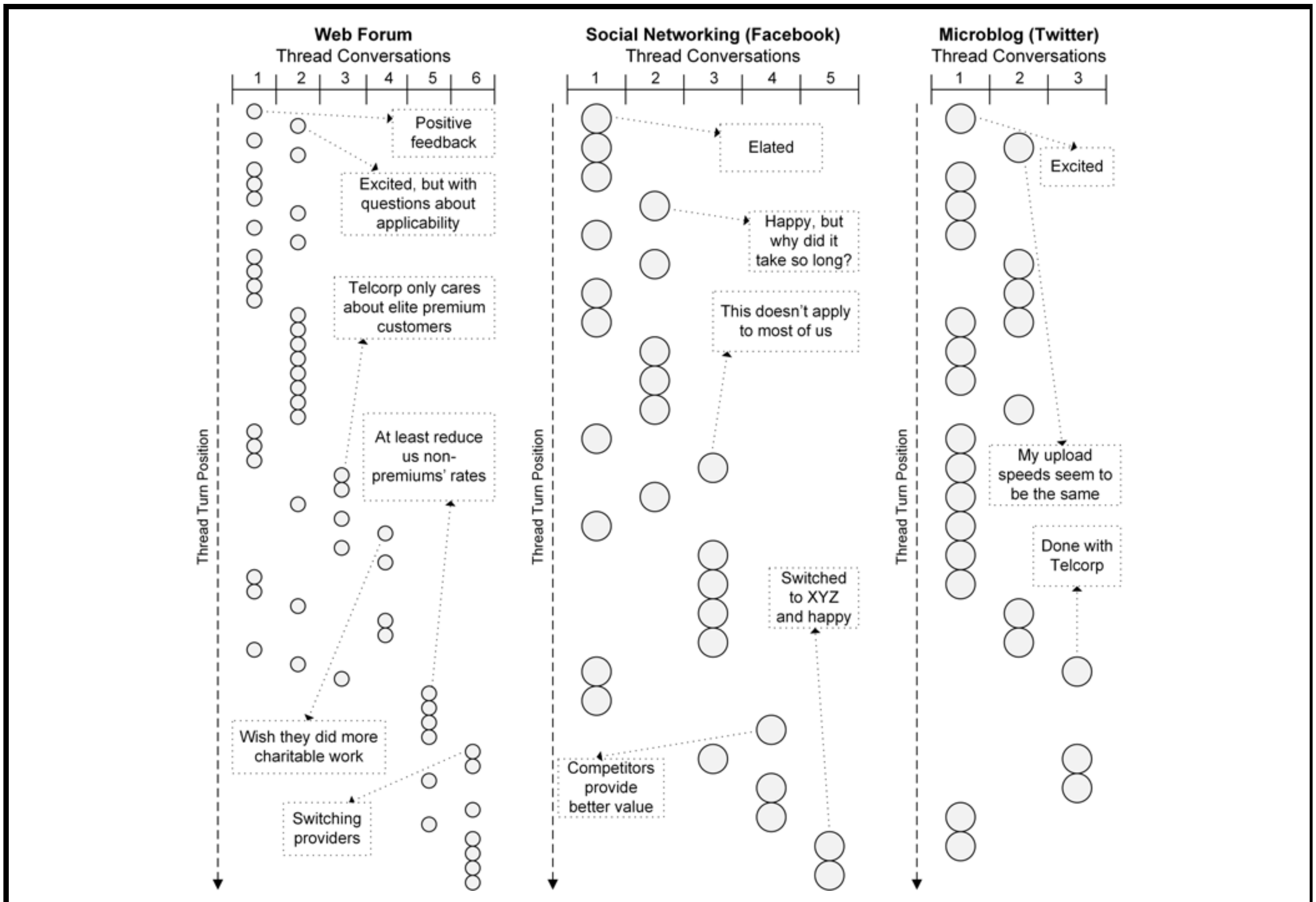

Figure 3. Illustration of Three Discussion Threads on Different Social Media Channels, Each with Multiple Conversations Related to TelCorp's Initiative

sages, they do not incorporate information pertaining to conversation structure. According to LAP, conversations are initiated by a specific illocutionary act, such as an assertion or a directive, subsequently followed by a finite sequence of acts (Kuo and Yin 2011; Winograd 1986). Hence, using LAP principles, a conversation can be decomposed into a beginning act succeeded by a series of "reacting" or "continuing moves" (Auramaki et al. 1992). A primitive message is a stand-alone assertion, and a derivative message is defined as a strictly logical or defeasible consequence of others (Raghu et al. 2001). Hence, primitive message identification is of great importance for disentanglement (Khan et al. 2002), as subsequent response messages are highly dependent upon it in terms of their illocutionary acts and propositional content (Kuo and Yin 2011; Winograd and Flores 1986). However, existing disentanglement methods do not attempt to explicitly identify primitive messages. Elsner and Charniak (2010, p. 405) used an empirical example to observe that a "detector for utterances which begin conversations could improve disentanglement scores." Given the importance of primitive messages, we pose the following question:

RQ1: Will methods that emphasize conversation structure elements such as primitive message identification during the disentanglement process outperform existing techniques devoid of such information?

Coherence Analysis

Text comprehension involves the construction of a coherent mental representation of situations described by texts. In online discourse, coherence is represented in terms of reply-to relationships between messages (Fu et al. 2008). However, communication technologies are susceptible to the sociotechnical gap—a gap between social requirements and technical feasibility (de Moor and Aakhus 2006). Jackson (1998) observed that there is a dichotomy between discourse practices

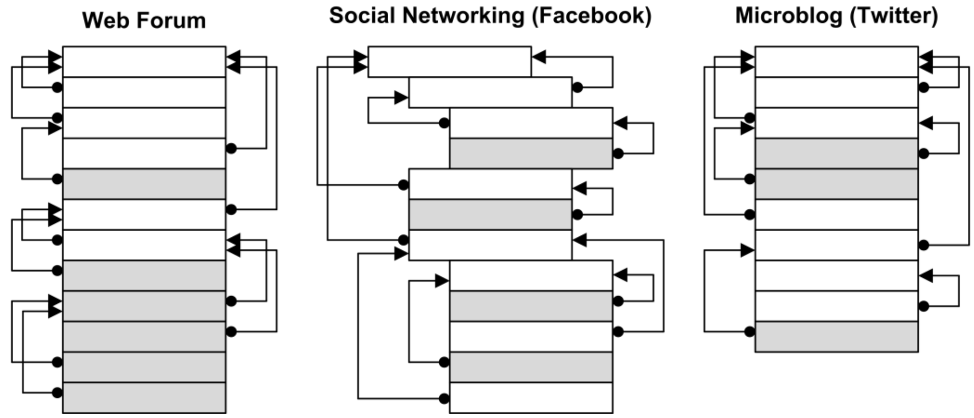

Figure 4. Reply-To Relations Between Messages in Web Forum, Facebook, and Twitter Discussions Pertaining to the TelCorp Initiative

and the tools intended to support online discussion. One such problem is "the imposition of a simple sequential ordering" (Jackson 1998, p. 192), which limits the effectiveness of temporal and spatial proximity-based system features. Consequently, social media discussions are highly susceptible to disrupted turn adjacency: a situation where adjacent messages in threads are often not related to one another, making threads highly incoherent (Herring 1999; Honeycutt and Herring 2009). For instance, 50% of messages in discussion threads do not respond to the previous or first post in the thread (Fu et al. 2008). Even in social networking sites such as Facebook, where users can comment on the original post or reply directly to prior comments, more than 30% of messages are incoherent (i.e., ambiguous with respect to reply-to relations). Similarly, microblogs such as Twitter, which were not originally designed to support conversations, are highly incoherent with respect to reply-to relations (Honeycutt and Herring 2009). Figure 4 shows examples of web forum, Facebook, and Twitter discussions pertaining to the TelCorp initiative. Each rectangle denotes a message; messages are ordered sequentially as they are generated (from top to bottom), while arrows indicate correct reply-to relations. Shaded messages are those deemed to be incoherent based on that particular social media channel's system-supported reply-to features. The illustrations only include the first 10 to 12 messages in the threads, and still 30% to 50% of the messages are out of place.

Coherence analysis attempts to offset the incoherent nature of online discourse by correctly reconstructing coherence relations among messages. Accurately attributing reply-to relations is critical to ensuring that participants' in-degree values are correct in social media-based social networks (Abbasi and Chen 2008; Anwar and Abulaish 2012). In the case of TelCorp, as later demonstrated, coherence analysis is critical to ensure proper sense-making of participant roles and centrality measures in online communities. Two important facets of coherence analysis are the features and techniques utilized. We review both and present a related research question in the remainder of the section.

Coherence Analysis Features

Three important categories of features used to identify coherence relations are system, linguistic, and conversation structure attributes. *System* features provide insights regarding the message context, including header (e.g., date/ime, message id, and subject/title) and quotation information (Abbasi and Chen 2008). For instance, Netscan extracted the "contents of Subject, Date, Organization, Lines, MessageID and Reference lines" to generate relationships in Usenet newsgroups, including conversation trees (Smith 2002). However, not all forms of group discussion contain a full range of system features, and the aforementioned sociotechnical gap hinders the utility of system features (Jackson 1998).

Linguistic features derived from message content can also provide important cues for coherence analysis. Common categories include direct address, co-reference, lexical relation, and semantic information (Donath 2002; Fu et al. 2008; Herring 1999; Nash 2005). Direct address occurs when a reply message includes the screen name of the author of a previous message (Donath 2002). Lexical relation is defined as a "cohesive relation where one lexical item refers back to another, to which it is related by having common referents" (Nash 2005). Co-reference also occurs when a lexical item refers to a previously posted lexical item; however, in this case the relation is implicit in that it can only be identified by the context (Soon et al. 2001). Nash (2005) divided co-reference into three subcategories: personal (e.g., use of pronouns), demonstratives, and comparatives (e.g., words such as "same" and "similar"). Examples of semantic information include opinions, emotions, synonymy information, parts-of-speech, etc. Such advanced NLP-based features have not been widely adopted (Abbasi and Chen 2008).

Group discussion is a repetitive process of subtopic/solution generation and evaluation. As previously alluded to, this process often results in simultaneous parallel conversations within a single discussion thread (Elsner and Charniak 2010). *Conversation structure features* are attributes that can shed light on the relations between messages and conversations within a discussion. Despite their importance for sense-making (McDaniel et al. 1996), conversation structure features have not been used much in previous coherence analysis research.

Coherence Analysis Techniques

Prior automated methods for coherence analysis include linkage, heuristic, and classification. *Linkage* methods construct interaction patterns using predefined rules that are primarily based on system features and assumptions regarding message sequences (Sack 2000). Most linkage methods employ two types of rules: direct linkage and naïve linkage (Fu et al. 2008). Direct linkage rules assume that users follow system features to post messages and clearly quote messages to which they respond. Naïve linkage rules are then applied to residual messages unidentified by direct linkage; these rules assume that all residual messages are responding to either the first message in the thread or the previous message (Comer and Peterson 1986). Linkage methods work fairly well with email-based discussion lists; however, as previously alluded to, social media is far less coherent. Nash (2005) manually analyzed 1,099 turns from Yahoo! Chat and found the lag between a message and its response to be as many as 100 turns. Herring and Nix (1997) concluded that nearly half of all turns were "off-topic." Consequently, linkage methods have performed poorly on web forums and chat (Abbasi and Chen 2008; Fu et al. 2008).

Heuristic methods rely on metrics derived from observations of online discourse (Fu et al. 2008). These metrics are based on a small, fixed, assumed set of communication patterns pertaining to system and/or linguistic features (Anwar and Abulaish 2012). For instance, the hybrid interactional coherence method uses an ordered list of heuristics, where messages unidentified by one heuristic are then evaluated by the next heuristic on the list (Fu et al. 2008). Khan et al. (2002) used finite state automata using linguistic features to identify interaction patterns in multi-person chat rooms. In many of these methods, the choice of heuristics (and their order) was based on prior observations of occurrence (Fu et al. 2008; Nash 2005). However, previous work has identified a plethora of different, context-specific discussion patterns and themes. In a group support system discussion involving 40 employees, Kuo and Yin (2011) noted that while 11 speech act patterns accounted for approximately 50% of the conversations, these patterns were very specific to, and dependent upon, the nature of the discussion topic. Similarly, Khan et al. (2002, p. 4) acknowledged the complexity caused by "factors such as number of participants, the topic(s) of chat, the familiarity of users with each other, etc." Consequently, the effectiveness of heuristic methods is predicated on the validity and generalizability of the set of heuristics incorporated.

Classification methods formulate coherence analysis as a binary classification problem (Aumayr et al. 2011). These techniques couple system and/or linguistic features with supervised machine-learning methods: predictive analytics algorithms that build models from a set of labeled training data (Wang et al. 2011). For example, in order to handle highly incoherent text from student online forums, Kim, Li, and Kim (2010) used supervised learning to classify discussion threads. Soon et al. (2001) adopted a machine learning approach to identify co-reference of noun phrases both within and across sentences which had been used for discourse analysis and language understanding.

The key gaps with respect to coherence analysis pertain to limited representational richness of feature sets and the need for classification methods capable of learning interaction patterns used in communication. Whereas few prior studies have used system, linguistic, and structure features in unison, as noted by prior studies based on LAP, linguistic and conversation structure features may help overcome the limitations of system features. Linguistic features allow users to assess relevance. Relevance is a critical component of a conversation; it requires "speakers to pick up elements from the preceding contributions appropriately and employ them in their own utterances" (Auramaki et al. 1992, p. 346). This process, which is analogous to leaving a trail of bread crumbs for fellow discussion participants, is essential for proper contextualization (Te'eni 2006). Similarly, conversation structure features that can help illuminate relations between messages and conversations are critical for identifying coher-

Table 2. Overview of Searle's Speech Acts

Speech Act	Description	Examples
Assertive	The speaker represents facts of the world.	statements that can be assessed as true or false
Commissive	The speaker commits to some future action.	agreement, support, disagreement, opposition, promises
Expressive	The speaker says something about his/her feelings or psychological attitudes.	apologies, congratulations, gratitude
Declarative	The speaker brings about changes in the world.	pronouncements, declarations, verdicts
Directive	The speaker gets the hearer to do something.	suggestions, questions, requests, commands, desires

ence relations (Auramaki et al. 1992; Winograd and Flores 1986). In summary, accurate identification of coherence relations necessitates the consideration of system, linguistic, and conversation information in conjunction with robust classifiers that can offer enhanced pattern recognition capabilities over linkage and heuristic methods (Wang et al. 2011).

RQ2: How extensively can classification methods that leverage conversation structure, linguistic, and system features outperform existing methods for coherence analysis?

Speech Act Classification

According to SAT, the minimal unit of an utterance is a speech act (Searle 1969). There are two distinct components of a speech act: the propositional content and the illocutionary force (Searle 1969). The propositional content is the topic of the utterance, while the illocutionary force describes the way in which it is uttered (Schoop 2001). Both elements must be considered in order to understand the speech act. Based on the illocutionary point, Searle (1969) defined five types of speech acts: assertive, directive, commissive, expressive, and declarative. Table 2 provides details regarding the five speech act categories.

Analysis of speech acts is useful for improving understanding of participant intentions (Te'eni 2006), an important problem for online discourse analysis (Mann 2011). While topic and sentiment analysis are essential components of any social media content analysis, they fail to capture underlying actions and intentions. Looking back at the TelCorp discussion threads depicted in Figure 2, the threads encompassed positive expressives in earlier conversations, followed by conversations comprised of questions, suggestions, assertions of indifference/negligence, negative expressives, and declarations of having switched to other providers. In other words, the threads encompassed many conversations for clarification (confusion) and conversations for action (churn) (Winograd and Flores 1986). Beyond what was being said, how and why were also important, especially with respect to customer confusion and churn.

Consequently, recent studies have explored automated methods for classifying speech acts in online discourse (Cohen et al. 2004; Kim, Wang, and Baldwin 2010; Moldovan et al. 2011). These methods have typically incorporated linguistic features such as bag-of-words and parts-of-speech tags in conjunction with machine-learning classification methods (e.g., Moldovan et al. 2011). However, speech acts are not individual unrelated events, but participate in larger conversational structures (Winograd and Flores 1986). While some prior methods leveraged basic information regarding speech act sequences (e.g., Carvalho and Cohen 2005), these studies failed to include a holistic representation of conversation structure such as that offered by conversation trees. Conversation trees have been used in prior social media analytics tools for visualizing conversation structures (Herring 1999; Smith 2002). They represent conversations as a tree comprised of coherence relations between parent, child, and sibling messages. Conversation trees can effectively represent the structure and flow of various conversations occurring within a discussion thread, thereby enabling enhanced representation of the relations dependencies among message speech acts.

RQ3: Will methods that utilize conversation trees attain enhanced speech act classification performance over existing methods that do not include such information?

Sense-Making

When performing sense-making tasks, users evaluate relevant costs and benefits associated with support technologies, including time, effort, and information quality (Russell et al. 1993). Hence, evaluation of sense-making artifacts requires assessment of information quality, the impact on users' sense-

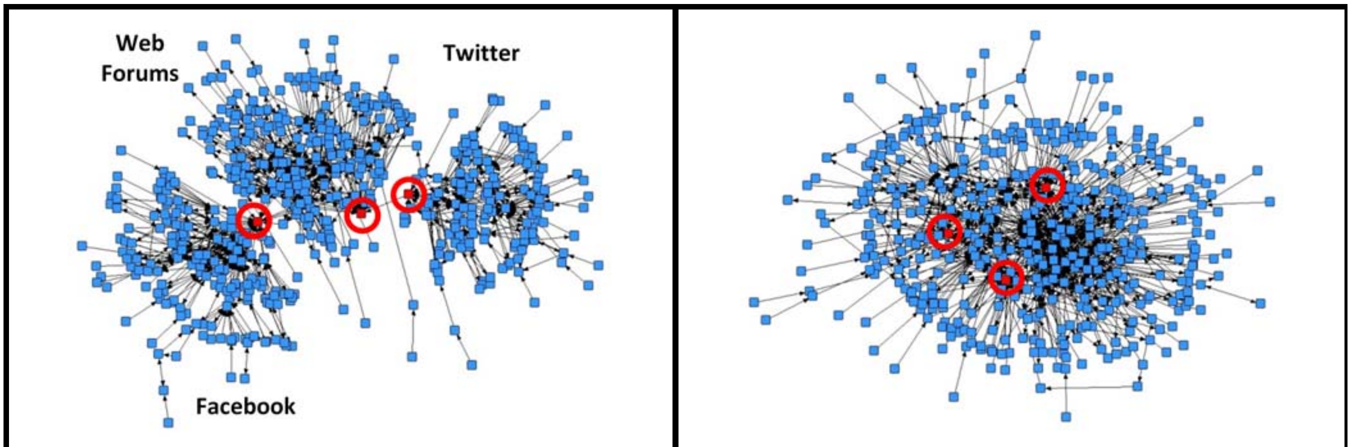

Figure 5. Social Media Social Networks for 50 TelCorp Initiative-Related Threads: Actual Network (left) and Constructed Network Using Existing Coherence Analysis Method (right)

making capabilities, and users' perceptions regarding costs and benefits (Pirolli and Card 2005).

Organizational use of social network analysis is on the rise (Mann 2013). From an organizational discourse perspective, important applications of social network analysis include identifying experts and influencers (de Moor and Aakhus 2006; Heracleous and Marshak 2004; Mann 2013). Given the prevalence of social network analysis in academia and industry, assessing the accuracy of social networks represents an important information quality evaluation for sense-making. For instance, the chart on the left in Figure 5 shows the *actual* social media interaction network for participants in 50 TelCorp initiative-related discussion threads encompassing web forums, Facebook, and Twitter. The interactions are generally intra-channel, with the exception of cross-channel links/mentions facilitated by three critical participants (circled). Interestingly, these three posted negative comments about the TelCorp initiative and garnered significant replies. Not surprisingly, these three discussants have the highest betweenness centrality values, as they serve as important bridges for the discussions occurring across the web forums, Facebook, and Twitter. However, in the interaction network *constructed* for the same threads (chart on the right Figure 5) using an existing state-of-the-art coherence analysis method, due to 30% misclassified reply-to relations, the network structure looks very different. In fact, the degree centrality measures in this constructed network for the *actual* top 20 discussants have mean absolute percentage error rates of over 40%, with over 50% of them not even being included in the top 20 of this network. Furthermore, the importance of the high-betweenness discussants (circled) is also significantly underestimated, with all three ranked outside the top 10 in terms of betweenness centrality in the network on the right. In this case, inadequate text analytic capabilities influenced TelCorp analysts' ability to identify key network members; a critical social media use case (Zabin et al. 2011).

As illustrated in this example, social networks derived from conversations can illuminate participant roles using measures such as degree centrality, betweenness, closeness, etc. (Fu et al. 2008). However, accurately computing these measures requires precise values for in-degree: the number of messages responding to a participant (Anwar and Abulaish 2012; Aumayr et al. 2011). Otherwise participant roles can be distorted; either exaggerated for some or understated for others (Fu et al. 2008).

RQ4: How extensively will enhanced coherence analysis attributable to LAP-based methods improve representation of social network centrality measures for discussion participants?

Ultimately, enhanced sense-making entails user involvement to reap the benefits of better text analytics (Russell et al. 1993; Weick et al. 2005). Visualization of discussion thread structure can coherently show the dynamics of communicative interaction and collaboration, and depict disentangled conversations (Donath 2002; Smith 2002). Similarly, depicting the speech act composition of messages can alleviate discourse ambiguity, a situation where participants are unclear as to the propositional content and/or illocutionary force of a message (Auramaki et al. 1988). However, demonstrating efficacy entails presenting the conversation, coherence, and speech act results to users. Accordingly, we employ SATrees: visualization of conversation trees where message nodes are labeled with their respective speech act information. As input, SATrees use methods for identifying conversations, coherence relations, and speech acts inspired by LAP principles.

It is important to note that our focus is not to develop a new visualization technique, but rather, to illustrate the utility of the underlying conversation disentanglement, coherence analysis, and speech act classification text analytics, which provides invaluable *input* for the SATree. Effective visualization is in itself a large research area (Donath 2002; Sack 2000; Smith 2002), beyond the scope of this paper. SATrees are merely labeled conversation trees (Honeycutt and Herring 2009) intended to provide a visual representation of coherence relations and illocutionary acts attributed to messages, allowing better understanding of conversation structure and flow, as well as participant intentions and group dynamics. Given the significance of information quality and coherence for sense-making (Weick et al. 2005), we present the following question:

RQ5: Can SATrees facilitate enhanced user sense-making of online discourse compared to conversation trees generated using existing methods or the sequential message ordering approach commonly used by communication technologies?

Further examining the sense-making value of an artifact within organizational settings, beyond short-term sense-making potential, entails field experimentation over an extended period of time. When performing sense-making tasks using supporting technologies longitudinally, users evaluate the utility of available methods in terms of their time/effort and information quality tradeoffs (Pirolli and Card 2005). "Collectively, these factors and tradeoffs form a cost structure guiding choices made during sense-making, including future usage of decision aids" (Russell et al. 1993, p. 269).

RQ6: Will systems incorporating LAP-based text analytics garner greater perceived usefulness, actual usage, and productivity improvements over time than systems devoid of such information?

A LAP-Based Text Analytics System for Sense-Making in Online Discourse

In the design science paradigm, kernel theories can be used to guide requirements for the design artifact, and both the theory and requirements can be used to inform design (Walls et al. 1992). Using LAP principles, in the previous section we presented the requirements: a framework for enhanced sense-making based on effective conversation disentanglement, coherence relations, and speech act classification. In this section we propose a design instantiation of the framework: a LAP-based text analytics system (LTAS) for sense-making in online discourse (Figure 6). LTAS has three major components: conversation disentanglement, coherence analysis, and speech act classification. For each discussion thread, the key outputs of the conversation disentanglement component are predictions of conversation beginnings and inter-message conversation affiliations, which serve as important conversation structure variables for the coherence analysis and speech act classification components. Within each discussion thread, the coherence analysis component leverages conversation structure information provided by the disentanglement component and basic speech act information, along with system and linguistic features, to output conversation trees encompassing finalized conversation affiliations and message reply-to relations. The output of the first two components is also leveraged by the speech act classification component, which uses conversation tree information to assign speech act labels to each message. The collective output of the system is an SATree, showing disentangled conversations within a discussion thread, with reply-to relations among messages that are labeled with their respective speech acts. As previously noted, SATrees signify the rich *types* of information offered by LTAS; this information can enable enhanced support for various social media analytics use cases as later demonstrated through user studies and a field experiment.

Prior LAP studies have emphasized close interrelatedness among conversations, coherence, and speech act compositions (Winograd and Flores 1986). In LAP, conversations form the building block for deeper analysis of interactions and speech act exchanges (Kuo and Yin 2011). Accordingly, LTAS considers the interplay of conversations, coherence, and speech acts. The output of the conversation disentanglement component is part of the input for coherence relations, since interactions are highly dependent on conversation context (Auramaki et al. 1992). Similarly, reply-to relations inform speech act classification since speech act composition for future messages within a conversation is dependent on those messages which precede them (Schoop 2001; Winograd and Flores 1986). Furthermore, each of the three components of LTAS leverages several important concepts from the discourse analysis and argumentation literature that have been incorporated into prior LAP-based studies, as summarized in Table 3. These concepts include context, relevance, conversation-beginning identification, thematization, discourse ambiguity, conversation structure elements, and message and conversation-level speech act composition. The three components of the system are discussed in the remainder of this section.

Conversation Disentanglement

The conversation disentanglement component of LTAS uses a two-stage approach. First, candidate primitive messages

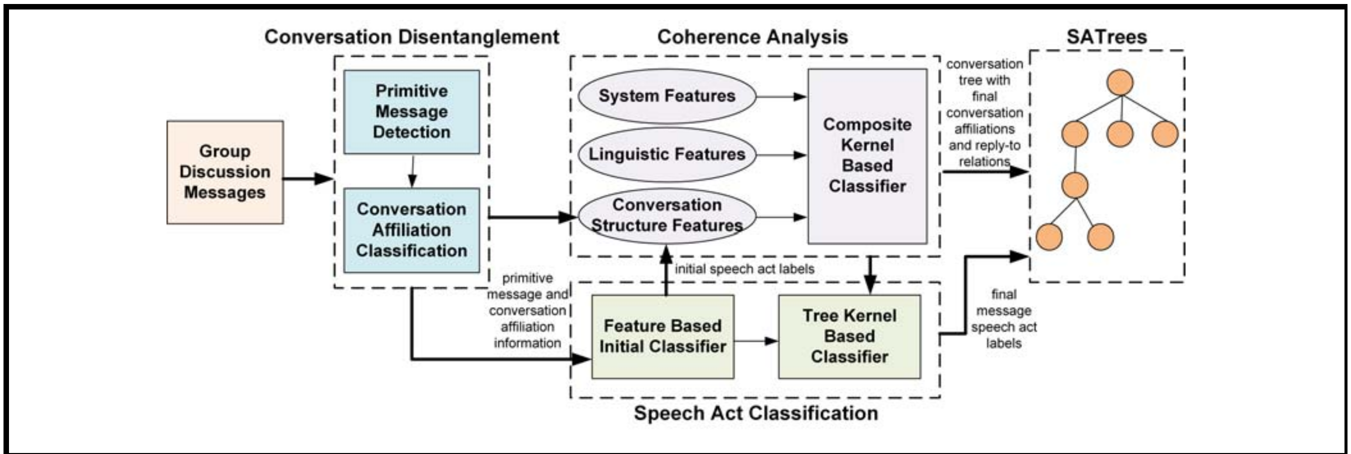

Figure 6. A LAP-Based Text Analytics System (LTAS) to Support Sense-Making in Online Discourse

Table 3. Select LAP-Based Principles Guiding Design of LTAS

LAP-Based Principle	Design Implications for LTAS
Interplay between conversations, interactions, and message acts (Winograd and Flores 1986)	Inclusion of three key system components, sharing of information between components for enhanced performance.
Importance of conversation beginnings as drivers of conversation structure, coherence relations, and conversation speech act composition (Auramaki et al. 1992; Winograd and Flores 1986)	Inclusion of the primitive message detection stage which provides key features to disentanglement, coherence analysis, and speech act classification components.
Contextualization and lexical chaining (Te'eni 2006)	Use of rich similarity measures between messages for conversation disentanglement and coherence analysis.
Thematization for uncovering conversation elements (Auramaki et al. 1992)	Inclusion of similarity bins from different regions to perform thread-level thematization for conversation affiliation classification.
Interdependency among speech acts (Auramaki et al. 1988; Kuo and Yin 2011; Winograd and Flores 1986)	Utilization of conversation tree-based message sequence patterns for speech act classification.

(i.e., conversation beginnings) are identified by using linguistic features to compute inter-message similarity. The features and output of the primitive message detection stage are then used as input for the second disentanglement stage. As previously discussed, prior conversation disentanglement studies have mostly used unsupervised clustering methods (e.g., Adams and Martell 2008; Wang and Oard 2009) and, to a lesser extent, supervised classification techniques with clustering overlaid (e.g., Elsner and Charniak 2010). We used supervised classification to garner enhanced precision and recall, and since conversation affiliations are not finalized until the coherence analysis component. The key outputs of our conversation disentanglement component are primitive message classifications and a pairwise message-to-message conversation affiliation classification (i.e., whether two messages belong to the same conversation), which serve as key conversation variables in the subsequent coherence analysis and speech act classification components. Details regarding the two-stage approach follow.

Primitive Message Detection

Participants in the same discussion thread often use contextualization to allow others to more easily understand conversation and coherence relations associated with their message (Te'eni 2006). One common approach for contextualization is lexical chains: the use of terms that are semantically related to terms appearing in prior messages within the same conversation (Auramaki et al. 1988). Therefore, an important cue regarding the conversation affiliation of a particular message is the degree of relevance between the message and topical themes of the existing conversations (Auramaki et al. 1992). Within a discussion thread, conversation beginnings (i.e., primitives) are messages that significantly deviate from existing conversations with respect to their topical themes (Aumayr et al. 2011; Khan et al. 2002). They are characterized by low topical similarity with messages that precede them, and high similarity with some of the messages that follow (Elsner and Charniak 2010). Conversely, non-primitive messages are likely to have higher similarity with at least some prior messages. Furthermore, while research has shown that as many as 20% of successive conversation messages can be separated by more than 10 turns within a forum thread (Nash 2005), or 5 tweets in a Twitter conversation (Honeycutt and Herring 2009), similarity between messages that are closer, both preceding and following, is typically of greater importance. For instance, many conversations exhibit topic drift: a gradual deviation from the starting point of a topic (Herring and Nix 1997). One implication of topic drift is that non-primitive messages may have higher max similarity with prior messages that are closer in proximity. Hence, message proximity and sequential trends are also important considerations for both primitive message detection in particular and conversation disentanglement in general.

The primitive message detection stage, depicted in Figure 7, leverages these important insights. It treats primitive message detection as a binary classification problem: predicting whether or not a given message within the discussion thread is a primitive. Let X represent a message in turn position p within a discussion thread of length l. All messages preceding X are placed into n roughly equal-sized bins, with each bin containing $(p\text{-}1)/n$ messages on average. Similarly, all messages following X within the thread are placed into n bins, each of size $(l\text{-}p)/n$ messages on average. Binning is used since discussion thread lengths vary and due to the fact that messages occur at different turns within a thread. Bins provide a consistent mechanism for representing message feature vectors in the statistical learning theory-based kernel function employed, while facilitating the inclusion of thematic trend information and proximity-sensitive similarity measurement. While the use of fixed-sized bins does present some limitations, as later discussed in the results section and Appendix C, binning also facilitates enhanced primitive message detection performance. Next, in order to capture information about lexical chains, we compute the average and max similarity scores between message X and messages within its surrounding $2n$ bins. For a given bin B_i, if $i \leq n$, the average similarity $\text{Ave}\{\text{Sim}(X,B_i)\} = \sum_{Y \in B_i} \frac{\text{Sim}(X,Y)}{(p-1)/n}$, where Y is one of the $(p-1)/n$ messages in B_i. It is worth noting that for threads where $l < 2n$, $\text{Sim}(X, B_i) = 0$ if Bi is empty.

Many prior conversation disentanglement studies have used the vector space model (VSM) to represent the similarity between messages (Adams and Martell 2008; Wang and Oard 2009). In VSM, documents are typically represented with vectors of *tfidf*: term frequency multiplied by inverse document frequency (Adams and Martell 2008; Shen et al. 2006). *tfidf* downgrades the weight attributed to common terms. Similarities between *tfidf* document vectors are computed using the cosine similarity measure, with values ranging from 0 to 1, and higher values indicating greater similarity. Sim (X, Y) uses a document similarity measure with two important refinements: the use of parts-of-speech (POS) tag and synonymy information. Research has shown that noun phrases and verb phrases carry most of the important topical meaning in a sentence (i.e., the "bread crumbs" in the lexical chain), while conjunctions, adverbs, and adjectives are less important (Soon et al. 2001). Thus, we define meaningful terms to be nouns, noun compounds, named entities, verbs, and verb phrases. Instead of taking into consideration every term within a document, we only focus on ones with these POS tags, thereby narrowing the feature space to those terms most relevant to the lexical chain. Additionally, in group discussion text, users tend to use different words to express the same thing (Nash 2005). In other words, the "bread crumbs" in the lexical chain are not simply keyword repetition. A traditional VSM will treat synonyms or hypernyms as unrelated entries (Adams and Martell 2008). We take such information into consideration by computing a similarity value s_{tr} between two terms, which is incorporated into the *tfidf* calculation, thereby allowing better representation of semantic relations between messages. Accordingly, the similarity score between a pair of messages X and Y is as follows:

$$\text{Sim}(X,Y) = \frac{\sum_{t=1}^{k} w_{xt} \max_{r}\left(w_{yr} s_{tr}\right) + \sum_{r=1}^{j} w_{yr} \max_{t}\left(w_{xr} s_{tr}\right)}{2\sqrt{\sum_{t=1}^{k} w_{xt}^2}\sqrt{\sum_{r=1}^{j} w_{yr}^2}}$$

Where $w_{xt} = tf_{xt}idf_t$, t is one of the k unique terms in X, r is one of the j unique terms in Y, t and r are nouns, verbs, noun/verb phrases, or named entities, and s_{tr} is the similarity between t and r based on the shortest path that connects them in the is-a (hypernym/hypnoym) taxonomy in WordNet (Miller 1995). The set of nouns and verbs in WordNet includes many noun compounds, such as "prescription drug," and verb phrases, such as "give in" and "throw up." However, some noun compounds may not be present. In such cases, we compare the individual components of the noun compounds, and calculate s_{tr} as the average of the component-level similarities (Kim and

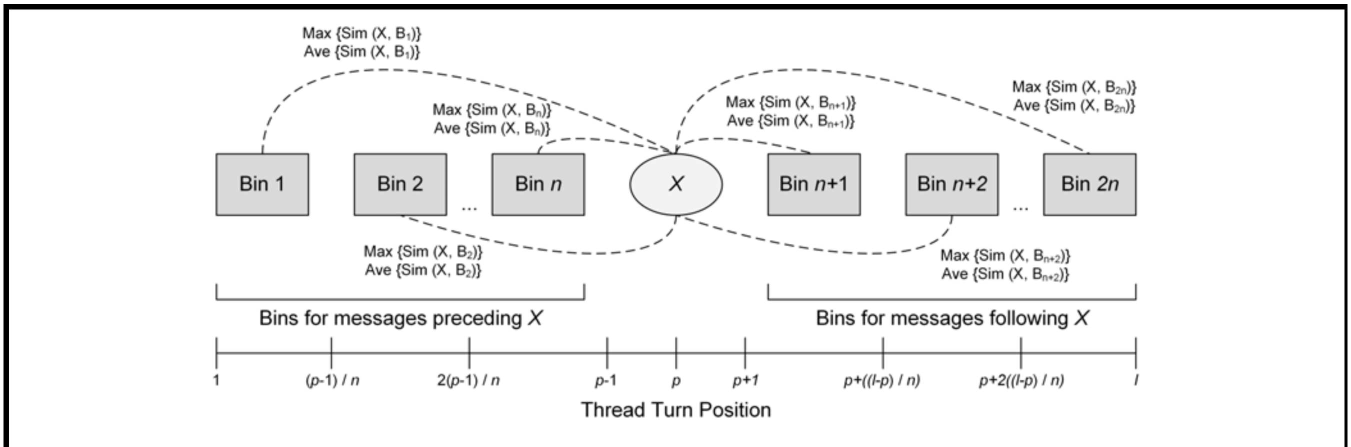

Figure 7. Illustration of Bins and Similarity Scores Used in Primitive Message Detection Stage

Baldwin 2005). For example, let's assume t = "customer service" and r = "client support." Assuming neither compound is present in WordNet, we compare the two head nouns "service" and "support" to one another, and two modifiers "customer" and "client." If the noun compound contains more than one modifier, the product of the similarities among various modifier combinations in tr is used (Kim and Baldwin 2005). A similar approach is taken for the verb phrases "intend switch" and "am leaving" from the statements "I intend to switch" and "I am leaving TelCorp." Appendix L empirically demonstrates the viability of our WordNet-based approach versus alternative state-of-the-art methods.

In the training data set, for each message X, the max and average Sim(X, B_i) are computed, resulting in a feature vector of length 4n. These feature vectors constitute rows in the training data matrix, appended with class labels indicating primitive or non-primitive. Due to the class-imbalance, with non-primitives significantly outnumbering primitives, a moving threshold was adopted (Fang 2013). Such an approach has been shown to outperform traditional minority class over-sampling and majority class under-sampling methods in prior research (Fang 2013). See Appendix A for details. In this case, given classes i (X is not a primitive message) and j (X is a primitive message), let $p(X)$ represent the true classification probability of an unclassified instance X belonging to class i. Given training data set T, with each instance's class label $\in \{i, j\}$, and let c(i) denote the number of elements of T with class label equal to i, the classification Z = i if $p(X) \geq \frac{c(j)}{c(i)+c(j)}$, and Z = j otherwise (Fang 2013).

On each data set, we trained a support vector machine (SVM) classifier with a linear kernel on T, and applied it to each test instance X to generate p(X).

Conversation Affiliation Classification

Guided by prior LAP-based studies, stage two of the conversation disentanglement approach performs conversation affiliation classification. Traditionally, thematization has been proposed as a mechanism for linearizing a conversation to sequentially uncover important themes within a single conversation (Auramaki et al. 1992). The conversation affiliation classification stage performs what can be considered discussion thread-level thematization by utilizing conversation segments to infer whether two given messages are part of the same conversation (illustrated in Figure 8). Two critical components of this thematization strategy are inclusion of similarities from messages in surrounding regions to the two messages of interest and inclusion of primitive message information. The intuition for the proposed method is as follows. Conversations are collections of messages. Consequently, many prior methods have employed clustering methods for grouping messages based on inter-message similarity (e.g., Adams and Martell 2008). In addition to the similarity between two messages themselves, similarity to other messages within the thread "can provide further evidence to the semantics" (Wang and Oard 2008, p. 204). Given that message lengths in social media may introduce sparsity in linguistic feature vectors, which can impact similarity assessments, evaluating similarity with other messages can improve robustness, acting as a message similarity evidence "expansion" strategy (Wang and Oard 2008). Primitive message information is included since similarity relative to conversation beginnings is a key conversation affiliation cue, providing insights into discussion schisms, topic drift, and floor tracking (Elsner and Charniak 2010). Consequently, the successful inclusion of such information is believed to be capable of boosting affiliation classifications by at least 5% to 10%

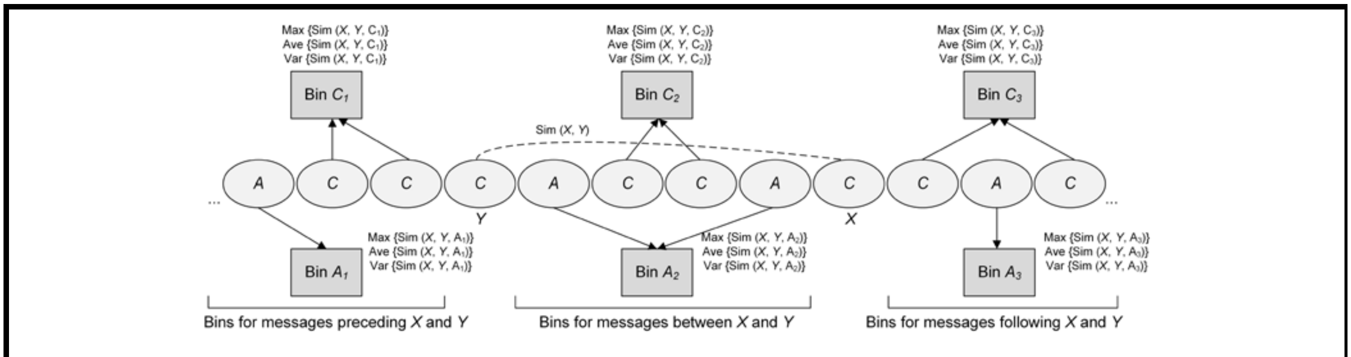

Figure 8. Illustration of Region, Bins, and Similarity Scores Used in the Affiliation Classification Stage

(Elsner and Charniak 2010). Our own experiment results presented later support the importance of primitive messages.

This intuition is operationalized as follows. Based on the output from the primitive message detection stage, all messages within the thread are labeled primitive or non-primitive (denoted by *A* and *C* in Figure 8, respectively). All message pairs within the thread are compared and classified as either belonging to the same conversation or not, as follows. For a given message pair *X* and *Y*, three conversation regions are derived: region 1 for messages preceding *X* and *Y*, region 2 for messages between *X* and *Y*, and region 3 for messages that follow *X* and *Y*. In addition to the similarity between X and *Y* (i.e., Sim (*X*,*Y*)), within these three regions, the difference in similarity between *X* and *Y* with respect to primitive (A_1, A_2, A_3) and non-primitive (C_1, C_2, C_3) message bins are leveraged using average, max, and variance measures. For a given bin C_i, the average similarity $\text{Ave}\{\text{Sim}(X,Y,C_i)\} = \sum_{Z \in C_i} \frac{|\text{Sim}(X,Z) - \text{Sim}(Y,Z)|}{d}$, where *Z* is one of the *d* messages in the non-primitive bin C_i. The maximum and variance measures are computed in a similar manner. For instance, $\text{Max}\{\text{Sim}(X,Y,C_i)\} = \max_z(|\text{Sim}(X,Y) - \text{Sim}(Y,Z)|)$. It is important to note that if *X* and *Y* are adjacent messages, Ave/Max/Var{Sim(X, Y, C_2)} and Ave/Max/Var{Sim(X, Y,A_2)} are all 0 since C_2 and A_2 are empty. The intuition for incorporating average and max similarity is based on the use of similar cluster centroid and nearest-neighbor style measures in past studies (Adams and Martell 2008; Shen et al. 2006; Wang and Oard 2009). Variance was included since the preceding, between, and following message region sizes can vary considerably as thread length increases, impacting average and max similarity values, and as a gauge for intertwined conversations within the region.

In the training data set, for each message pair *X* and *Y*, the max, average, and variance attributes from the three regions as well as Sim (*X*,*Y*) are derived, resulting in a feature vector encompassing 19 independent variables and the yes/no class label indicating whether *X* and *Y* belong to the same conversation. As with the primitive message detection stage, threshold moving was utilized for conversation affiliation classification to alleviate class imbalance for the linear SVM classifiers when applied to threads in the test set (Fang 2013). The output of the conversation disentanglement module of LTAS are two-fold: (1) classification of primitive messages within a thread and (2) classification of each message pairs' conversation affiliations (i.e., whether they belong to the same/different conversations). This information is leveraged extensively as input variables in the coherence analysis and speech act classification components of LTAS, as discussed in subsequent sections.

Coherence Analysis

Consistent with prior work (Kim, Li, and Kim 2010), the identification of coherence relations is modeled as a binary classification problem, where each message pair in the discussion thread either constitutes a reply-to relation or does not. The attributes used are three feature vectors for each message pair: system, linguistic, and conversation structure features. These feature vectors are inputted into a composite kernel function for an SVM classifier. Details are as follow.

Coherence Analysis Features

Table 4 shows the various system, linguistic, and conversation structure features derived for each message pair *X* and *Y*, where *X* precedes *Y* within the discussion thread. System features include those commonly used in prior studies, including the message proximity in turns (Nash 2005), temporal distance in minutes (Aumayr et al. 2011), and whether *Y* includes system-generated quoted content from *X* (Abbasi and Chen 2008; Smith 2002). Messages closer in turn or temporal prox-

Table 4. Features of Candidate Message Pairs

Category	Feature	Description
System Features	Turn Proximity	Turn index of message *Y* – turn index of message *X*
	Temporal Distance	Timestamp of message *Y* – timestamp of message *X* (in minutes)
	Quoted Content	Whether *Y* contains system-generated quoted content from *X*
	Reply-To	Whether *Y* contains system-generated reply to *X* in header, subject, or title
Linguistic Features	Lexical Relation	Sim (*X*,*Y*) based on formulation presented in Section 4.1
	Direct Address	Whether *Y* references screen name of author of *X*
	Co-reference	Whether *X* and *Y* have personal pronouns and comparatives (4 features)
	Sentiment Polarity	Whether *X* and *Y* are objective or subjective (2 features)
	Length Difference	Length of *X* (in words) – length of *Y*
Conversation Structure Features	Message Status	Whether messages *X* and *Y* are primitive messages (2 features)
	Conversation Status	Whether messages *X* and *Y* are part of the same conversation
	Between Status	Number of primitive messages between *X* and *Y*
	Prior Status	Number of primitive messages prior to *X* and *Y*
	Speech Act	Speech act classifications for messages *X* and *Y* (2 features)
	First Message	Whether *X* or *Y* are the first message in the discussion thread

imity are more likely to have a reply-to relation between one another (Aumayr et al. 2011; Honeycutt and Herring 2009; Nash 2005). While turn proximity has been shown to provide utility in prior coherence analysis studies (Fu et al. 2008), its effectiveness is diminished by the sociotechnical gap; in this case through the imposition of a simple, sequential ordering (Jackson 1998).

As previously alluded to, linguistic features are important for understanding contextual elements and lexical relations between messages (Auramaki et al. 1992; Te'eni 2006), and therefore have important implications not only for conversation disentanglement, but also for coherence analysis. We use several important linguistic features. The lexical relation between messages (Nash 2005) is derived using the Sim(X, Y) formulation described in the "Conversation Disentanglement" section. Direct address indicates whether message Y explicitly references the screen name of the author of message X (Fu et al. 2008). The four co-reference features indicate whether X and Y each include the following two implicit lexical chain elements: personal pronouns (e.g., your) and comparatives (e.g., worse) (Soon et al. 2001). The two sentiment polarity features indicate whether X and Y contain subjective or objective content, respectively. Subjective messages are those that have greater sentiment polarity (Abbasi and Chen 2008; Lau et al. 2012). Sentiment information is useful since users often express their opinion towards a prior message with positive polarity (e.g., "I like your idea") or negative polarity ("I think that's a terrible suggestion"). Sentiment lexicons such as SentiWordNet provide an effective mechanism for inferring sentiment polarity (Esuli and Sebastiani 2006). We adopt a straightforward approach to determine whether a message is subjective or objective, where each term in a message is compared against items in the sentiment lexicon to compute a subjectivity score on a 0–1 scale (with higher values indicating greater subjectivity). SentiWordNet contains a positive, negative, and neutral polarity score ranging from 0 to 1 for each term. Our sentiment feature is the average, across all terms in the message, of each term's (positive + negative score)/2. Message length information can be a useful coherence relation cue, especially when combined with speech act features. For instance, shorter agreement messages are less likely to be responded to by lengthier messages (Kim, Wang, and Baldwin 2010).

As noted in prior LAP and discourse analysis studies, coherence relations and salient underlying interaction cues are highly dependent upon conversation context (Fu et al. 2008; Khan et al. 2002). Conversation disentanglement information is essential in order to reduce the likelihood of creating coherence relations between messages from different conversations (Elsner and Charniak 2010). Since interactions are highly dependent on the context surrounding the conversations in which they occur (Winograd and Flores 1986), six types of conversation structure features are utilized based on the conversation disentanglement component described earlier. The two message status attributes are the primitive/non-primitive message classifications from the primitive message detector. Obviously, if message Y is deemed primitive, it is less likely to be responding to X. However, if X is a primitive and Y is not, the likelihood of a reply-to relation increases since conversation beginnings typically attain more responses than non-primitive messages (Elsner and Charniak 2010; Fu et al. 2008). Similarly, the conversation status feature is the conversation affiliation classification for X and Y. The primitive message detector is also the basis for the between status and prior status attributes. Since primitive messages attain more replies, greater between and prior status may reduce the likelihood of a reply-to relation. As previously alluded to, conversations, interactions, and speech acts are closely interrelated (Winograd and Flores 1986). Hence, the speech acts for X and Y are included as attributes, predicted using the "initial classifier" described later in the section "Initial Classifier."

Coherence Analysis Technique

Consistent with prior work (Kim, Li, and Kim 2010), the training corpus is comprised of all positive and negative (i.e., non-reply-to cases) reply-to cases encompassed in a collection of conversations. For a given message, negative cases are all previous messages with which it does not have a reply-to relation. The number of negative cases considerably exceeds the number of positive cases, warranting the use of threshold moving as done in the conversation disentanglement experiments (Fang 2013).

Once the features between all message pairs in the training set discussion threads have been extracted, a composite kernel is used to leverage the system, linguistic, and conversation structure feature categories in an ensemble-like manner (Szafranski et al. 2010). In part, the beauty of kernel-based methods such as SVM lies in their ability to define a custom kernel function K tailored to a given problem, or to use the standard predefined kernels (e.g., linear, polynomial, radial basis function, sigmoid, etc.). When dealing with classification tasks involving diverse patterns, composite kernels are well-suited to incorporate broad relevant features while reducing the risk of over-fitting (Collins and Duffy 2002; Szafranski et al. 2010). In our case, diversity stems from differences in the occurrence of system, linguistic, and conversation structure features across users, social media channels, and/or industries. In Appendix K we present further background on kernel methods and empirically demonstrate the proposed composite kernel's effectiveness versus a single SVM classifier.

Let s_i, l_i, and c_i represent the system, linguistic, and conversation structure feature vectors for a given message pair X and Y. We define a combinatorial ensemble of kernels $K = \{K_1, \ldots, K_Q\}$ encompassing all combinations of linear composite kernels involving s, l, and c (here Q = 7 due to $2^3 - 1$ total combinations). Given two instance rows in the training data matrix, their similarity is defined based on the inner product between all combinations of their three vectors s_1, l_1, c_1, and s_2, l_2, and c_2. For instance,

$$K_1(s_1,s_2)=\frac{\langle s_1,s_2\rangle}{\sqrt{\langle s_1,s_1\rangle\langle s_2,s_2\rangle}},\quad K_2(l_1,l_2)=\frac{\langle l_1,l_2\rangle}{\sqrt{\langle l_1,l_1\rangle\langle l_2,l_2\rangle}},$$

$$K_4(s_1+l_1,s_2+l_2)=\frac{\langle s_1,s_2\rangle}{\sqrt{\langle s_1,s_1\rangle\langle s_2,s_2\rangle}}+\frac{\langle l_1,l_2\rangle}{\sqrt{\langle l_1,l_1\rangle\langle l_2,l_2\rangle}},$$

$$K_5(s_1+c_1,s_2+c_2)=\frac{\langle s_1,s_2\rangle}{\sqrt{\langle s_1,s_1\rangle\langle s_2,s_2\rangle}}+\frac{\langle c_1,c_2\rangle}{\sqrt{\langle c_1,c_1\rangle\langle c_2,c_2\rangle}}.$$

The composite kernel K_σ is the combination of these Q kernels: $K_\sigma = \sum_{q=1}^{Q} \frac{K_q}{Q}$. The SVM classifier trained using this kernel outputs a prediction confidence score for each instance (scores are real numbers), where negative numbers indicate a non-reply-to classification and values greater than or equal to zero indicate positive reply-to relation classifications. Hence, for a message Y in a discussion thread, we attain predictions for each message X that precedes it. Since a given message in a conversation may reply to multiple prior messages, in theory, if Y is preceded by 10 messages in the discussion thread, the classifier outputs may predict 0 to 10 reply-to relations originating from Y. However it is worth noting that in our data sets as well as in prior research, multi-replies happen very infrequently (in less than 1% or 2% of instances). Though not done in this study, some prior research has used a fixed "single reply-to relation from a message" rule to reduce false positives. Irrespective, to evaluate coherence analysis relations, metrics such as precision and recall of positive reply-to relation classifications are typically adopted.

The output of the coherence analysis component is a conversation tree encompassing the finalized disentangled conversations and message reply-to relations within the discussion threads. Most studies represent conversations as trees with a single parent for each child node (Herring 1999; Smith 2002). In order to leverage a tree structure here as well, we create a duplicate node for each message (and its subtree) with multiple reply-to relations, under each of its respective parent nodes (as illustrated in Appendix F).

Speech Act Classification

Within a conversation, speech act occurrences are closely related to one another, with subsequent speech acts highly dependent upon those speech acts which precede them

(Stolcke et al. 2000; Winograd and Flores 1986). In order to represent these interdependencies, prior methods incorporated information regarding the transition probabilities between speech act pairs (Carvalho and Cohen 2005). While such information is highly useful, speech acts are part of the larger overall conversation structure (Winograd and Flores 1986). To represent such information more holistically, the speech act classification component of LTAS uses a two-stage approach comprised of an initial classifier and a tree kernel-based classifier. The initial classifier employs attributes derived using system, linguistic, and conversation structure information to provide an initial speech act label for each message in the conversation tree. The kernel method then uses this labeled tree as input to improve performance by leveraging important facets of conversation structure.

Initial Classifier

The feature set used by the initial classifier consists of content attributes and contextual attributes. The content attributes include (1) binary/presence vector for all nouns and verbs appearing at least three times in the training corpus, lemmatized with their part-of-speech information; (2) whether or not the message has sentiment; and (3) whether or not the message is deemed a primitive message by the classifier described earlier. Emphasis is placed on nouns and verbs since prior research has shown that these two parts-of-speech are strong indicators of message speech act composition (Carvalho and Cohen 2005 Cohen et al. 2004; Stolcke et al. 2000). Sentiment information is often present in commissive and expressive speech acts (Kuo and Yin 2011).

The contextual attributes extracted for each message pertain to primitive message and thread length and proximity information: (4) the distance from the closest preceding primitive message in the thread, in message turns, as a percentage of total messages in the thread; (5) the total number of preceding primitive messages in the thread; (6) the total number of messages in the thread; and (7) the position of the message in the thread, as a percentile. These attributes are intended to capture basic conversation context information from the discussion thread. For instance, depending on the context, certain speech acts such as assertives and directives are more likely to begin a new conversation, whereas expressives often appear later in conversations (Kuo and Yin 2011). Other studies have also noted the varying occurrence probabilities of certain speech acts at different stages of a conversation (Carvalho and Cohen 2005; Winograd and Flores 1986). Similarly, lengthier threads are more likely to have commissive and directive speech acts that extend the discussion through agreement, disagreement, follow-up questions, etc. (Rowe et al. 2011). The position of a message in the thread, as a percentile, has been shown to be a useful contextual attribute for speech act classification (Wang et al. 2011).

The features are input into a series of linear SVM classifiers. Since SVMs are binary-class classifiers, for each pair of speech act combinations (e.g., assertives and expressives, assertives and commissives, etc.), a separate SVM classifier is constructed. Test messages are evaluated by each of the binary classifiers and assigned to the classes receiving the highest aggregate prediction scores across classifiers (Szafranski et al. 2010). The output of the initial classifier is a speech act category prediction for each test message.

Labeled Tree Kernel-Based Classifier

Conversation structures vary considerably depending upon their speech act compositions. For example, conversations for action often begin with a declarative, followed by a series of commissives, declaratives, and assertives (Winograd and Flores 1986). Similarly, conversations for clarification, possibilities, and orientation each have distinct structural and composition-related elements. Coherency is important for understanding the stage structure of a discourse, and consequently, the relations between speech acts (Auramaki et al. 1988). In order to leverage coherence relations, we propose a novel labeled tree kernel classifier (Figure 9). Kernel-based methods are useful since custom kernels can incorporate rich structural information into the learning process (Abbasi et al. 2010; Collins and Duffy 2002). As input, the classifier uses a labeled conversation tree constructed using coherence relations and message speech act labels. The coherence relations are based on the coherence analysis component of LTAS, while message speech act labels are generated using the initial classifier. For illustrative purposes, let's assume our speech act label set L = {A, C, D, E} for assertive, commissive, declarative, and expressive.

For each message y_i in the test set Y, we extract a sub-tree Sy_i comprised of parent, child, and sibling nodes. Figure 9 illustrates how the sub-tree for the test message originally labeled "D" by the initial classifier is extracted. Parent message is the one that D replies to, child messages are ones replying to D, and sibling messages are ones that share the same parent message as D. In the extracted sub-tree, the label for the message of interest is always changed to "?".

For each message x_i in the training set X, we extract sub-tree Sx_i. Training sub-trees are also derived by applying the initial classifier and coherence analysis classifier using 10-fold cross-validation on the training data. While we could simply incorporate the gold-standard coherence relations and message speech act labels for the training sub-trees, we found that

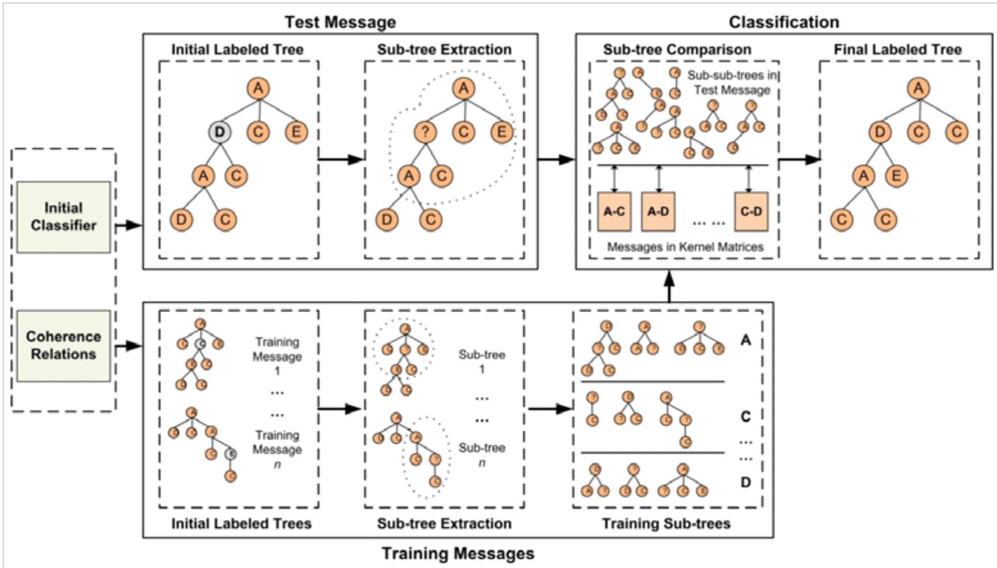

Figure 9. Labeled Tree Kernel for Speech Act Classification

using the same classifiers on the training/testing data improved performance by allowing input classifier biases to be incorporated into the kernel classifier's learning process. This process results in a collection of training message sub-trees for each speech act class, as depicted in the "Training Sub-trees" component of Figure 9.

Classifier training is performed as follows. For each pair of speech act classes in L, a separate kernel matrix K is constructed on the training data. For instance, K_{AC} is comprised of similarity scores $K_{AC}(x_i, x_j)$ between each pair of training messages in X_{ac}, the subset of X with class label assertive or commissive, intended to learn patterns to differentiate assertives from commissives. $K_{AC}(x_i, x_j)$ is a similarity measure between Sx_i and Sx_j computed by comparing all tree fragments in Sx_i and Sx_j, where a fragment is defined as any sub-graph containing more than one node (Collins and Duffy 2002). $K_{AC}(x_i, x_j)$ is simply equal to two times the number of common fragments in Sx_i and Sx_j, divided by the total number of fragments in Sx_i and Sx_j. Formally, let $h_k(x_i)$ denote the presence of the k^{th} tree fragment in Sx_i (where $h_k(x_i) = 1$ if the kth tree fragment exists in x_i) such that Sx_i is now represented as a binary vector $h(x_i) = (h_1(x_i),\ldots,h_n(x_i))$:

$$K_{AC}\left(x_i, x_j\right) = \frac{2\sum_{k=1}^{n} h_k\left(x_i\right)h_k\left(x_j\right)}{\sum_{k=1}^{n} h_k\left(x_i\right) + \sum_{k=1}^{n} h_k\left(x_j\right)}$$

Similar to the process described in the "Coherence Analysis Technique" section with respect to the coherence analysis classifier, each K is used to build a separate binary classifier for each speech act label pair using SVM Light (Joachims 1999). In Figure 9, the trained models are depicted by boxes in the classification section (e.g., A-C, A-D).

Test message y_i is classified by all of the trained binary SVM models, each of which takes a vector of sub-tree comparison-based similarity scores as input. For instance, the A-C classifier would take $(K_{AC}(x_i, y_i), \ldots, K_{AC}(x_z, y_i))$ as input, where $|X_{ac}| = z$, and output a prediction score. Voting across the binary classifiers is used where the final speech act label for each y_i is the class receiving the highest aggregate prediction score. The eventual outcome is a final labeled tree for each conversation in the test set.

Speech Act Tree (SATree)

The conversation disentanglement, coherence relation, and speech act classification components of LTAS are combined to create an SATree for each group discussion. Figure 10 presents an example of an SATree. In the tree, each branch represents a conversation; nodes under those branches represent messages in the conversations. Symbols to the left of each message are used to indicate speech act composition; for example, assertions ↑, directive-suggestions ☆, directive-questions **?**, commissives ✓, and expressives ⌁. Even from this small example, it is apparent that this particular discus-

Figure 10. Illustration of SATree Showing Conversations, Coherence Relations, and Speech Acts

sion encompasses multiple conversations, some of which have elaborate interaction patterns and diverse message speech act compositions. Appendix O presents an extended illustration of how the conversation structure, reply-to relation, and message speech act composition information encompassed in SATrees can support key social media use cases such as identifying issues, suggestions, and key participants. It is also important to reiterate that our focus is not to develop a new visualization technique, but rather, to illustrate the utility of the underlying conversation disentanglement, coherence analysis, and speech act classification text analytics encompassed in LTAS, which provides invaluable *input* for the SATree based on LAP. Effective visualization is in itself a large research area (Donath 2002; Sack 2000). The visualization style employed for SATree was inspired by visual dynamic topic analysis diagrams (Honeycutt and Herring 2009).

Evaluation

Consistent with Hevner et al. (2004), a series of experiments were conducted to evaluate the effectiveness of various components of our LTAS text analytics system and underlying LAP-based framework. The six experiments, which were closely aligned with the questions presented earlier, were set up in three parts. Part 1 was intended to demonstrate the superiority of the proposed LAP-based system (LTAS) relative to state-of-the-art methods for text-based sense-making through a series of data mining experiments which follow. Experiment 1 assessed the effectiveness of the conversation disentanglement component (RQ1). Experiment 2 evaluated the usefulness of using linguistic and conversation structure features in conjunction with system features and a robust classification method (RQ2). Experiment 3 assessed the speech act component of the system (RQ3).

Part 2 showed the efficacy of LTAS for sense-making, through data and user experiments involving sense-making tasks, conducted in four different organizational settings. Specifically, experiment 4 empirically demonstrated enhancements in information quality for social network centrality measures (RQ4), while experiment 5 illustrated how SATrees could allow practitioners to improve sense-making from online discourse as compared to existing methods (RQ5).

In part 3 of the evaluation, we used a field experiment (experiment 6) to demonstrate the business value of LTAS over a 4-month period, where the social media monitoring team members using LTAS garnered enhanced issue identification capabilities estimated by TelCorp to be worth millions of dollars. Collectively, these three forms of evaluation demonstrate the art of the possible, practical, and valuable for text analytics grounded in the pragmatic view.

Working closely with our industry collaborators, the experiments related to parts 1 and 2 were performed on 10 group discussion data sets spanning four industries: telecommunications, health, security, and manufacturing. The 10 data sets encompassed several important social media channels used routinely for both intra-organizational and customer-facing communication, collaboration, and engagement, including web

Table 5. Overview of Test Bed

Domain or Industry	Channel	Description	No. of Threads	Messages		Particip. Per Thread	Convo. Per thread
				Total	Per Thread		
Telecom	Web Forum	Telus forum postings on DSLReports	69	2608	37.8 (20.0)	18.7 (9.9)	4.3 (2.7)
	Social Network	Telus Facebook fan page comments	208	3209	15.4 (4.1)	4.5 (1.1)	2.6 (0.9)
	Microblog	Telus-related tweets	228	2403	10.5 (2.3)	4.0 (1.0)	1.8 (0.6)
Health	Web Forum	Prescription drug posts on Drugs.Com	66	2764	41.9 (28.4)	13.2 (10.4)	6.2 (4.8)
	Social Network	Drug comments on PatientsLikeMe	128	2026	15.8 (5.4)	9.5 (3.3)	1.7 (1.3)
	Microblog	Prescription drug-related tweets	383	2905	7.6 (2.1)	3.1 (0.9)	1.3 (0.5)
Security	Web Forum	McAfee posts on Bleeping Computer and Malwarebytes	65	3491	53.7 (23.3)	25.2 (13.9)	6.1 (3.3)
	Social Network	McAfee Facebook fan page comments	180	2471	13.7 (3.5)	5.3 (2.0)	2.1 (0.7)
	Microblog	McAfee-related tweets	268	2445	9.1 (2.4)	3.5 (0.9)	1.6 (0.6)
Manufac-turing	Chat	Comments on tea bag over-production	20	835	41.8 (14.0)	4.0 (0.0)	6.8 (3.1)
Total			**1,615**	**25,157**			

*A separate training set encompassing a similar quantity of data per domain/channel was used by LTAS/comparison methods (Appendix H).

forums, social networking sites, micro-blogs, and group chat (Bughin and Chui 2010; Mann 2013). Table 5 provides an overview of the data sets, including the number of discussion threads, total number of messages, and messages/participants/conversations per thread (mean and standard deviation). The total test bed included over 25,000 messages associated with 1,615 discussion threads. Looking at Table 5, we make a few observations about the test bed. Web forum discussion threads tend to be lengthier (and involve more participants) than those appearing in social networking sites such as Facebook and Patients Like Me, or on microblogs like Twitter (Fu et al. 2008; Honeycutt and Herring 2009). As later observed, these channels also varied considerably in conversation structure, dynamics, interaction patterns and cues, and speech act composition. These differences made inclusion of a variety of industries and channels important to ensure a robust evaluation test bed.

The telecommunications data sets pertained to Telus, one of the three largest telecommunications service providers in Canada. In the telecommunications industry, customer churn is a big problem (ACSI 2014). Consequently, industry leaders such as Telus rely heavily on social media monitoring and analytics for brand reputation management, better understanding pain points, and to derive customer-related insights (Kobielus 2011). Since Telus' social media presence and their online mentions span several channels, three different data sets were included. The Telus forum on DSLReports.com allows current, past, and prospective customers to discuss services and issues pertaining to Telus' cable and high-speed internet offerings. Visitors of Telus' Facebook fan page post comments regarding the company's community outreach initiatives, on-going promotions, and their personal experiences with Telus' mobile, home phone, and cable/Internet services. The third telecommunications data set was comprised of Twitter discussion threads mentioning Telus and/or the company's products and services.

The health data sets were social media discussions of prescription drug offerings from Merck KGaA's major competitors. The three data sets included threads from the Drugs.com web forum, Twitter, and the social networking site Patients Like Me. In these social media channels, users talk about their experiences, potential side-effects, other adverse reactions, ask questions, and seek advice. As post-marketing drug surveillance using social media gains popularity, organizations also seek to leverage such information for competitive intelligence and demand forecasting (Adjeroh et al. 2014; Zabin et al. 2011).

The security data sets were comprised of web forum postings, Facebook fan page comments, and tweets related to McAfee, Inc. and its security software, respectively. In the discussion threads, customers talk about observed strengths and weaknesses, problems encountered, and their overall experiences with McAfee's B2C offerings, as well as those of competitors. Insights derived from analysis of such social media content have important implications for operations and product strategy (Mann 2011; Zabin et al. 2011).

The manufacturing discussion test bed was derived from a series of group support system (GSS) chat-based discussions. The data was comprised of 20 discussion threads involving 4 participants each; 80 total participants that were all experienced with the GSS software employed. Each of the 20 threads focused on the discussion topic of how to best address the overproduction problem for a tea bag manufacturer. Subjects were told to discuss solutions. Whereas the other nine data sets were derived from external-facing web forums, social networking sites, or micro-blogs, this data set differed one important way: it was comprised of chat sessions with a more internal-facing perspective.

It is important to note that due to the need for manually annotating a gold standard for each thread/message, most *labeled* social media and/or text document test beds used in prior studies appearing in top IS journals have typically used 5,000 documents/messages or fewer (e.g., Abbasi and Chen 2008; Lau et al. 2012). From that perspective, the test bed incorporated in this study is fairly extensive and robust with respect to the total volume of data as well as the variety of industries, domains, and social media channels incorporated. Consistent with prior studies (Fu et al. 2008; Lau et al. 2012; Kuo and Yin 2011), all data sets in the test bed were rigorously labeled by two independent human annotators with backgrounds in linguistics and experience in discourse analysis (Honeycutt and Herring 2009; Nash 2005). Additionally, these annotations were further validated by practitioner social media analysts. See Appendix H for details.

Experiment 1: Conversation Disentanglement

In the first experiment, we evaluated the effectiveness of the conversation disentanglement component of LTAS, which utilizes primitive message detection as a precursor to conversation affiliation classification. LTAS was compared against several existing disentanglement methods, most of which utilized VSM-based features to compute similarity between messages, which were then used as input for clustering methods. Choi (2000) performed segmentation using VSM applied to bag-of-words and clustering based on the Euclidean distance between messages. Wang and Oard (2009) also used VSM on bag-of-words and single-pass clustering. However, they incorporated information regarding the author and temporal and conversational context (e.g., posting author information, time between messages, and direct address). Shen et al. (2006) used VSM applied to bag-of-words coupled with additional linguistic features and messages weighted by time as input for a single-pass clustering algorithm. Adams and Martell (2008) used VSM with bag-of-words, hypernym information, a message distance penalty, as well as direct address information. Elsner and Charniak (2010) performed disentanglement using word repetition and discourse-based features, time windows, and direct address as input for a maximum entropy algorithm. For all comparison methods, parameters were tuned retrospectively in order to yield the best possible results. See Appendix H for details. Consistent with prior work, micro-level precision, recall, and f-measure were used as our performance measures (Shen et al. 2006).

Table 6 shows these f-measures. Precision and recall values can be found in Appendix N. LTAS outperformed all five comparison methods by a wide margin on all ten data sets. The performance lift was consistent for precision, recall, and f-measure. In most cases, LTAS was 15% to 20% better than the best competing methods. Paired t-tests were conducted to evaluate LTAS against the comparison methods. The tests were performed on the f-measures for the 1,615 discussion threads (i.e., n = 1,615). LTAS significantly outperformed all five comparison methods (all p-values < 0.001). The results presented here (RQ1), as well as further analysis presented in Appendices B, C, and E, underscore the efficacy of the primitive message detection-oriented LTAS method as a viable method for conversation disentanglement.

LTAS performed better across all 10 data sets spanning different industries and social media channels. Figure 11 shows the f-measures for LTAS and comparison methods across each of the 1615 discussion threads. The chart on the left shows mean f-measures for threads encompassing 1 to 10+ conversations. The chart on the right shows mean f-measures by thread length percentile rankings (with lower percentile values on the horizontal axis indicating shorter thread lengths). Not surprisingly, the f-measures of all techniques declined as the number of conversations and messages per thread increased. Interestingly, although LTAS performed better across the board, the performance margins were greater on threads with a higher number of conversations and/or messages (i.e., the right half of each of the two charts in Figure 11). Whereas the average f-measures of the two best comparison methods dipped by 22% to 35% or more, LTAS's performance dropped by only about 15% to 18%. The enhanced performance was largely attributable to LTAS's emphasis on identifying primitive messages (i.e., conversation beginnings). Analysis revealed that LTAS correctly identified approximately 85% of the primitive messages whereas com-

Table 6. F-Measures for Conversation Disentanglement Experiment on Various Channels

	Telco			Health			Security			Manu.
Method	**Forum**	**Social**	**Twitter**	**Forum**	**Social**	**Twitter**	**Forum**	**Social**	**Twitter**	**Chat**
LTAS*	**70.6**	**84.2**	**88.5**	**69.0**	**72.6**	**87.0**	**72.5**	**78.6**	**90.3**	**68.0**
Elsner and Charniak (2010)	45.9	62.6	73.6	48.8	59.9	78.6	46.0	59.2	72.7	37.7
Adams and Martell (2008)	48.4	61.6	64.2	44.3	51.9	68.1	48.3	56.7	63.7	44.6
Shen et al. (2006)	37.3	58.7	61.8	40.6	58.9	65.2	37.1	55.0	65.2	28.9
Choi (2000)	26.8	51.9	53.7	24.4	56.6	52.5	26.3	51.1	52.5	24.3
Wang and Oard (2009)	30.9	40.3	45.8	28.9	59.8	43.1	30.4	42.6	43.1	33.0

*Significantly outperformed comparison methods, with all p-values < 0.001

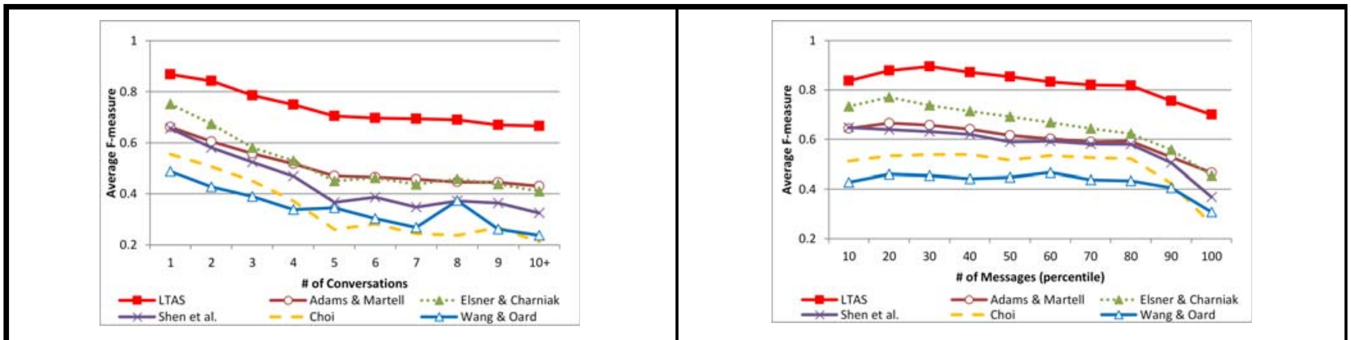

Figure 11. Average F-Measures for LTAS and Comparison Methods across Discussion Threads Grouped by Number of Conversations (left) and Number of Messages (right)

parison methods typically only detected 60% of primitives. LTAS was also more accurate at identifying marginal messages. Another factor was that LTAS only included terms with noun or verb parts-of-speech to compute similarity between messages, whereas the comparison methods did not incorporate parts-of-speech information. These factors resulted in better conversation disentanglement, with margins being more pronounced as the number of conversations and messages per discussion thread increased.

Experiment 2: Coherence Analysis

In the second experiment, we evaluated the effectiveness of the coherence analysis component of LTAS against existing classification, heuristic, and linkage techniques. LTAS uses system, linguistic, and conversation structure features for coherence analysis, as described earlier. While few studies have leveraged system, linguistic, and conversation structure features in concert, we examined the use of all three feature categories in conjunction with a robust classification method embodying LAP principles. Consistent with prior work, we treated this as a binary classification problem: whether the latter message in a pair replied to the earlier one or not. However, in this classification problem, we were only interested in those message pairs that were classified as having a reply-to relation. While the number of pairs that were classified as having no reply-to relationships was much larger, including these instances in the performance evaluation would have artificially inflated precision and recall rates for all experiment settings. Thus, our precision and recall metrics were based only on correctly classified reply-to relationships.

We compared LTAS against existing heuristic, linkage, and classification methods for coherence analysis. The heuristic-based method (Fu et al. 2008) relied on three linguistic features derived from the message body: direct address, lexical similarity, and residual match. The direct address match identified coherence relations based on references to user/screen names. Lexical similarity between messages was derived using VSM. A naïve linkage-based residual match rule was applied to the remaining messages (Comer and Peterson 1986; Fu et al. 2008).

The classification-based method used linguistic and system features (Kim, Li, and Kim 2010). We extracted four types of features from the message pairs: "time_gap" and "dist" were the interval of time and distance between message pairs, respec-

Table 7. F-Measures for Coherence Analysis Technique Comparison Experiment										
	Telco			Health			Security			Manu.
Method	Forum	Social	Twitter	Forum	Social	Twitter	Forum	Social	Twitter	Chat
LTAS*	**81.1**	**87.2**	**91.0**	**78.7**	**80.1**	**86.4**	**81.0**	**83.7**	**92.5**	**84.8**
Heuristic	59.0	51.5	71.6	52.2	53.4	73.8	54.4	59.7	74.5	56.1
Classification	58.0	57.4	78.8	50.9	56.8	81.6	50.7	65.4	78.4	43.5
Linkage-Previous	38.9	44.6	71.1	33.1	38.2	70.3	29.9	53.9	69.0	21.7
Linkage-First	35.9	32.6	52.2	26.2	32.0	61.9	27.2	42.1	51.3	13.7

*Significantly outperformed comparison methods, with all p-values < 0.001

tively. "repeatNoun" was the number of repeated nouns between message pairs, and "viewer_timeGap" examined the time interval for messages pairs from the same author. The linkage methods used available system features and assumed all residual messages (i.e., ones not containing any system-based interaction cues) were replying to either the previous message (Linkage-Previous) or the first message (Linkage-First).

Table 7 shows the f-measures. Precision and recall values can be found in Appendix N. LTAS outperformed the comparison heuristic, linkage, and classification methods by a wide margin in terms of thread-level f-measures (all paired t-test p-values < 0.001, n = 1,615). With respect to comparison methods, the poor performance of the linkage methods was attributable to disrupted turn adjacency and lack of system-based interaction cues. Particularly in the case of the web forums and chat data sets, over 70% of the time adjacent messages in the discussion thread did not have a reply-to relationship with one another. Furthermore, many messages in these data sets were not replying to the first message. Consequently, Linkage-Previous and Linkage-First yielded poor results on web forums and chat. The comparison classification method also attained lower precision and recall. This was attributable to limitations in the coverage provided by the classifier's rules, which were mostly based on system features related to message proximity and time gaps. The limited use of linguistic features and lack of conversation structure attributes contributed to the classification method's low recall. While the heuristic method performed better than the classification method on web forums and chat, its performance was adversely affected by the utilization of discourse pattern-related assumptions that did not hold as well, particularly in the context of social networking sites and Twitter.

Figure 12 shows the f-measures for LTAS and comparison methods across each of the 1,615 discussion threads. The chart on the left shows mean f-measures for threads encompassing 1 to 10+ conversations. The chart on the right shows mean f-measures by thread length percentile rankings (with lower percentile values on the horizontal axis indicating shorter thread lengths). As with the conversation disentanglement results presented in the previous section, all coherence analysis techniques' f-measures declined as the number of conversations and messages per thread increased. However, once again, although LTAS performed better across the board, the performance margins were greater on threads with a higher number of conversations and/or messages. Whereas the average f-measures of the two best comparison methods dipped by 15% to 30% or more, LTAS's performance dropped by 10% or less. The was partly attributable to the inclusion of conversation structure features which allowed lengthier threads to be "decomposed" into smaller conversations, making accurate coherence analysis classifications more feasible (see Appendices D and F for further details). The results demonstrate the efficacy of the proposed coherence analysis method, which combines system, linguistic, and conversation structure features with a robust classification method.

Experiment 3: Speech Act Classification

Speech acts are important for understanding communicative actions and intentions (Janson and Woo 1996; Te'eni 2006). Consistent with prior work, the annotators labeled six categories of speech acts using the approach previously described (Moldovan et al. 2011; Stolcke et al. 2000): assertives, suggestions and questions (directives), expressives, commissives, and declaratives. The final annotation results are presented in Figure 13. Across the various data sets in the test bed, messages were concentrated along the assertive, directive, commissive, and expressive speech acts. In other words, messages were primarily statements, suggestions, questions, agreement/disagreement, and sentiments/affects. Interestingly, due to the problem-solving nature of discussion in the web forums, suggestions were more prevalent and expressives occurred less frequently relative to prior studies (e.g., Kuo and Yin 2011; Twitchell et al. 2013). Conversely, in Facebook and Twitter discussions, expressives such as opinions,

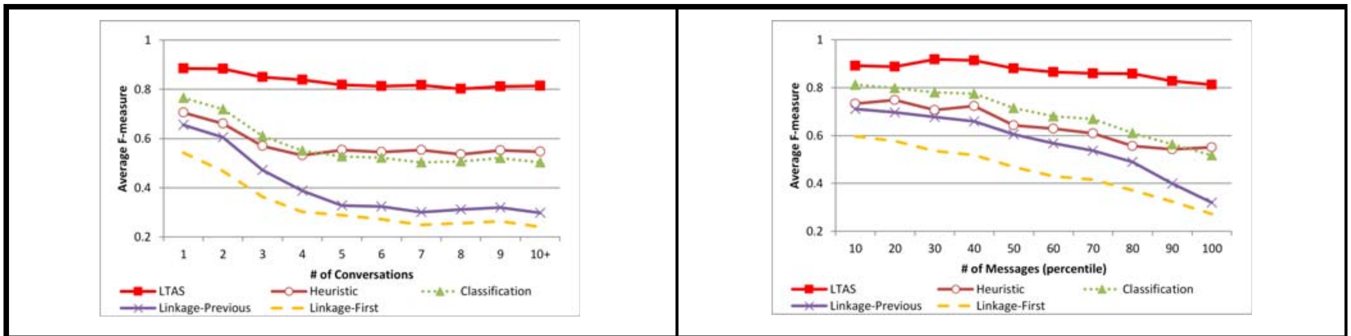

Figure 12. Average F-Measures for LTAS and Comparison Methods across Discussion Threads Grouped by Number of Conversations (left) and Number of Messages (right)

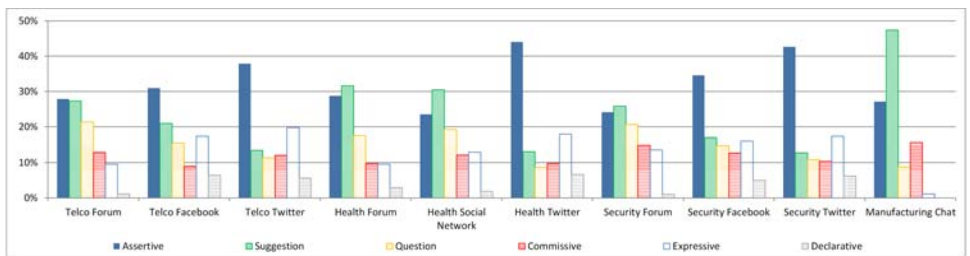

Figure 13. Speech Act Composition across Data Sets in Test Bed

sentiments, and emotional content were more prevalent. The tea manufacturing group chat discussions involved an ideation task; such discussions are generally rich in questions and suggestions (Kuo and Yin 2011). Declaratives accounted for less than 5% of messages in most data sets. Their limited occurrence is consistent with previous work (Kuo and Yin 2011). Speech act annotation details appear in Appendix H.

We compared the speech act classification component of LTAS against several existing methods. For all methods, the settings yielding the best results were reported. The *n*-Word method extracts the first *n* tokens and their associated POS tags for each message, where *n* ranges between 2 and 6 (Moldovan et al. 2011). These attributes are then used as input for a decision tree classifier. In our experiments, we set *n* to 2 since it yielded the best results. The n-gramSVM method proposed by Cohen et al. (2004) attained the best results on our test bed when using unigrams (i.e., single words) and bigrams (i.e., word pairs) with a linear SVM classifier. Kim, Wang, and Baldwin (2010) used lexical and conversation context features that included the frequency of lemmatized token and POS tag combinations, message position relative to thread length, and whether the posting author was the thread initiator. These features were input into a conditional random fields (CRF) classifier. Collective classification iteratively improves speech act predictions using a series of underlying local classifiers that rely on bag-of-words and relational features such as the speech act labels of parent/child nodes (Carvalho and Cohen 2005). Joint classification utilizes a conditional random field meta-learner with an embedded dependency parsing classifier as well as conversation context, semantic, and message relation attributes (Wang et al. 2011).

The evaluation measures employed were overall accuracy (i.e., percentage of total messages' speech acts correctly classified) and speech act class-level recall: percentage of total messages associated with a particular speech act that were correctly classified. Table 8 shows the experiment results for accuracy. LTAS's Labeled Tree kernel-based speech act classification component attained the best overall accuracy across all 10 data sets in the test bed, outperforming all comparison methods by at least 15% to 20%. Paired t-test results for accuracy were significant (all p-values < 0.001, n = 1,615). Appendix N includes the class-level recall values for the two best comparison methods (joint classification and collective classification) on four of the highly prominent speech acts: assertive, suggestion, question, and commissive. LTAS's Labeled Tree kernel outperformed both comparison methods for all speech acts across the 10 data sets. Moreover,

Table 8. Accuracies for Speech Act Classification Experiment

	Telco			Health			Security			Manu.
Method	**Forum**	**Social**	**Twitter**	**Forum**	**Social**	**Twitter**	**Forum**	**Social**	**Twitter**	**Chat**
LTAS – Labeled Tree*	**92.1**	**92.5**	**93.3**	**93.6**	**93.0**	**95.5**	**91.9**	**90.4**	**93.7**	**90.7**
Collective Classification	76.1	74.6	76.1	74.9	74.5	77.8	74.5	70.7	76.0	72.3
Joint Classification	72.4	69.7	75.3	72.0	72.4	75.5	71.9	70.5	74.2	68.4
CRF	61.1	66.7	67.9	64.0	70.2	73.8	61.8	66.3	69.0	64.2
n-gramSVM	64.1	67.9	68.3	64.4	66.1	66.8	65.6	68.4	67.6	64.8
n-Word Method	61.9	64.0	64.5	59.5	62.1	62.4	61.3	63.4	63.7	57.9

*Significantly outperformed comparison methods, with all p-values < 0.001

it performed fairly consistently across speech acts, with recall rates ranging from 86.5% to 98.8%. Labeled Tree's enhanced performance was attributable to the amalgamation of coherence tree structure and system, linguistic, and conversation attributes in a kernel-based method (see Appendix G). Interestingly, the joint classification and collective classification comparison methods, which also utilized coherence information, also performed markedly better than methods that relied primarily on message-level attributes (e.g., Cohen et al. 2004; Moldovan et al. 2011).

Experiment 4: Information Quality for Sense-Making

An experiment was conducted to evaluate the quality of information generated using LTAS as compared to existing methods (RQ4). Inaccurate coherence relations can distort representations of participants' roles in online group discussions. This has implications for social media use cases such as identification of key discussion participants (Zabin et al. 2011), as well as broader social network analysis using social media. Differences between actual and projected social network centrality measures can shed light on the level of distortion (Aumayr et al. 2011; Fu et al. 2008). Three commonly used measures are degree centrality, closeness centrality, and betweenness centrality. Degree centrality is the total number of out links (sent messages) and in links (received/reply-to messages) associated with a discussant; it is a measure of a discussant's level of participation and interaction within a discussion thread (Aumayr et al. 2011). Closeness centrality is a measure of the level of interaction between participants within a group, with greater interaction between discussants indicating greater closeness. Betweenness centrality is an important measure of how critical an individual is for the flow of communication among other discussants in a conversation (Fu et al. 2008). For a given discussant, it is computed as the proportion of shortest paths between discussants in the network that include the given discussant. We examined the mean absolute percentage error on degree, closeness, and betweenness centrality for the LTAS coherence analysis module and the comparison heuristic, linkage, and classification methods. The values were computed for each of the 10 data sets in our test bed. The results for closeness and betweenness appear in Appendix N.

Table 9 shows the experiment results for degree centrality. LTAS had the smallest mean absolute percentage errors across all data sets in the test bed, with error percentages of less than 7%. Error rates for LTAS were typically two to four times better than for those of comparison methods. Regarding RQ4, the differences were statistically significant (with all p-values < 0.001). With respect to the comparison methods, heuristic and classification each had error rates ranging from 10% to 25% for degree on most data sets. The linkage methods typically had mean absolute percentage errors in excess of 20%. Consistent with, and proportional to, the coherence analysis experiment results, centrality measure error rates were lowest on Twitter and social networking websites relative to web forums and group chat.

Figure 14 depicts the gold standard social network (top left chart), along with results generated by LTAS, heuristic, and linkage methods, for one of the discussions in the Telus (telecom) forum data set. In order to allow easier comparison, the node placements in all four charts are identical, node sizes are proportional to degree centrality, and reply-to links/ties obviously vary for the different ICA methods. Looking at the four charts, it is apparent that LTAS most closely resembles the gold standard in terms of links between nodes and node sizes. Conversely, the linkage method (bottom right) tends to exaggerate the degree centrality of many nodes (e.g., Wonton Noodle, beachside, BadMagpie, zod5000, etc.). This is consistent with prior studies, which have also observed that linkage methods inflate degree centrality (by over-attributing in-degree) for discussants with greater posting frequency (Fu

Table 9. Mean Absolute Percentage Error for Degree Centrality Measure

	Telco			Health			Security			Manu.
Method	**Forum**	**Social**	**Twitter**	**Forum**	**Social**	**Twitter**	**Forum**	**Social**	**Twitter**	**Chat**
LTAS*	**4.9**	**4.3**	**2.6**	**6.1**	**6.2**	**3.3**	**4.7**	**4.3**	**2.1**	**7.9**
Heuristic	15.2	14.0	13.7	17.2	17.1	10.3	15.2	13.7	8.9	16.9
Classification	18.3	15.9	14.9	18.0	16.5	8.7	15.9	12.5	8.0	17.1
Linkage-Previous	25.2	29.9	23.9	27.8	26.2	16.9	26.6	19.6	14.7	41.3
Linkage-First	37.0	34.8	35.8	37.9	35.6	23.7	42.2	30.2	26.1	55.7

*Significantly outperformed comparison methods, with all p-values < 0.001

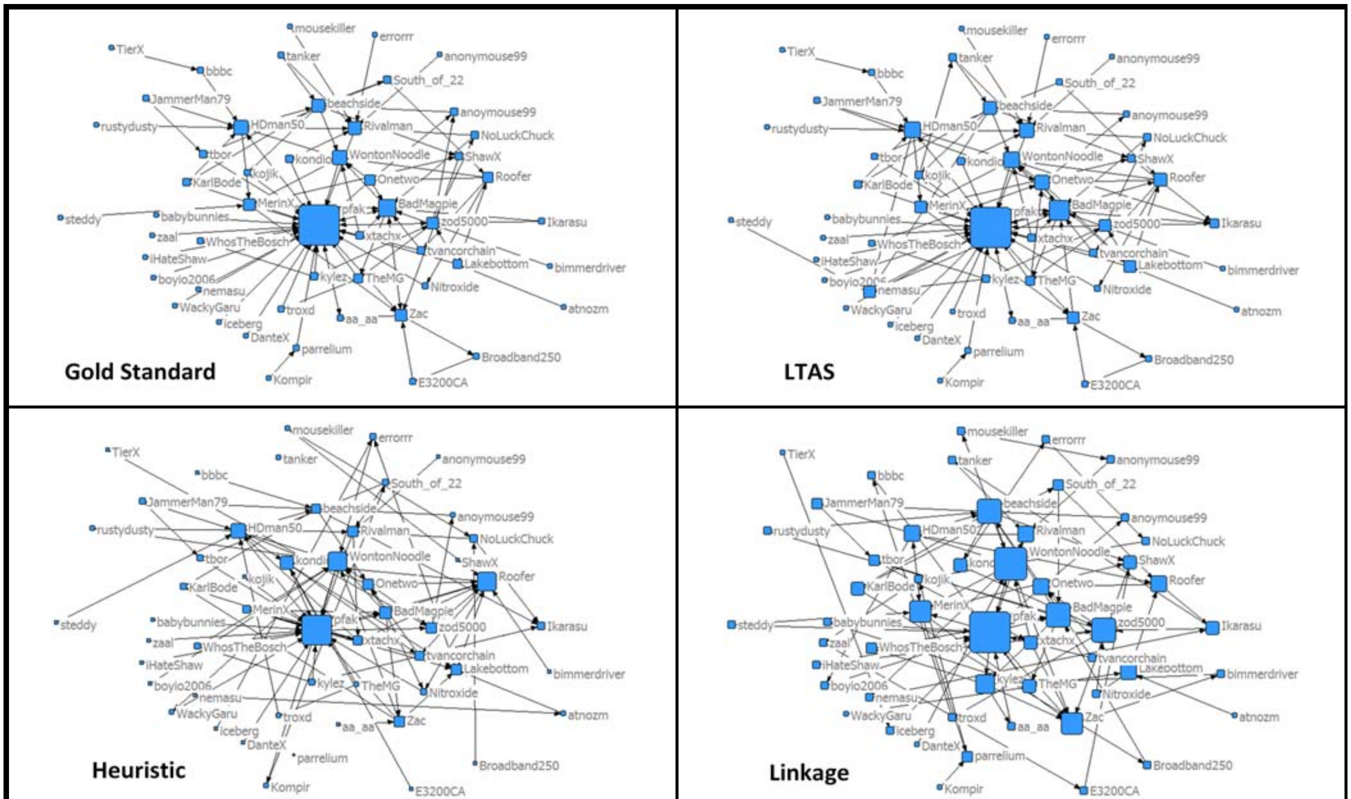

Figure 14. Social Network for Example Discussion Thread from Telus Forum

et al. 2008). Similarly, the heuristic method exaggerated degree centrality for some nodes while understating it for others (bottom left of Figure 14). The figure visibly illustrates how lower coherence analysis performance can significantly hurt the quality of a social media thread discussion's network. When applied across entire forums and social media channels, these effects become even more pronounced (as shown earlier in Figure 5). Overall, the results from the experiment suggest that LTAS is less likely to inflate or underestimate the perceived importance of discussion participants (in terms of centrality). Given that over 75% of organizations surveyed consider identification of influential participants as one of the most important use cases for social media analytics (Zabin et al. 2011), the results further demonstrate the usefulness of the LTAS system.

Experiment 5: User Sense-Making

The prior experiments demonstrated information quality enhancements, an important prerequisite for user sense-making (Weick et al. 2005). Ultimately, for these enhancements to be

Table 10. Overview of Participants in User-Sense-Making Experiment

Dimension	Telecom	Health	Security	Manufacturing
Number of Participants	120	103	85	132
Organization	TelcoInc	HealthInc	SecurityInc	Three companies and university
% Female	37%	31%	35%	43%
Bachelor's Degree	96%	97%	98%	99%
Master's Degree	41%	64%	59%	67%

meaningful, users must be able to derive knowledge and insights. Accordingly, we evaluated the effectiveness of SATrees generated by LTAS in assisting users with sense-making (RQ5) in comparison with three additional experiment settings: (1) A conversation tree comprised of **gold standard** coherence relations and human expert tagged speech acts; (2) a conversation tree comprised of **best benchmark** methods for coherence analysis (classification) and speech act classification (joint classification); and (3) **sequential order**, chronologically ordered discussion messages without coherence relation information or speech act tags. The methodology used was a controlled experiment; participants were assigned to one of the four experiment settings and asked to answer sense-making questions.

The experiments were performed in the four industry contexts previously described in the evaluation section: telecommunications, health, security, and manufacturing. Table 10 summarizes the experiment participants. For the telecom, health, and security contexts, the participants were practitioners in three large North American telecommunications, health, and security companies, respectively. These practitioners included members of social media monitoring teams, customer relationship management team members, marketing analysts, marketing managers, product design team members, etc. For the manufacturing data set, participants were recruited by email invitations to employees at three companies, graduate students, and faculty members from the school of management at a major university.

User Experiment Design

We selected two representative discussion threads from our test bed for each of the four industry contexts depicted in Table 10. The threads were presented to the participants using the aforementioned presentation formats to which they were assigned, through a web-based interface. Four sense-making questions were used in the experiment. The questions were closely aligned with some of the major social media use cases alluded to in the introduction, namely identifying issues and ideas. The questions were tailored to each industry context, but entailed similar sense-making tasks and cognitive effort (Klein et al. 2006). Appendix I provides details about the questions and thread topics used for each industry context.

Here we describe the four questions for the tea manufacturing context. The first was a *general* sense-making question: users were asked to list all the solutions proposed in the discussion. Following Heracleous and Marshak's (2004) work pertaining to analyzing discourse, we employed three additional sense-making questions associated with *action*, *situated action*, and *symbolic action* as they involve differing levels of data fusion (Klein et al. 2006). In the first of these three questions (*action*), we asked which solutions a particular discussant supported. The second (*situated action*) question asked the participants to identify the solution that resulted in the greatest amount of conflict among discussants in the entire discussion thread (i.e., one creating the largest dichotomy between support and opposition). The third (*symbolic action*) question asked participants to sense certain discussants' characteristics based on their utterances and interactions in the discussion (e.g., level of enthusiasm toward others' ideas).

Participants were required to structure their answers as bulleted lists. Responses were evaluated using theme identification, an approach that has been used to evaluate user performance in complex information retrieval tasks when a correct answer contains multiple themes (Zhou et al. 2006). A theme was considered correct if it matched any of the themes identified by experts; evaluators were used to determine what constituted a match. By examining the themes that participants derived using different representation tools, we were able to evaluate how effectively each experimental setting aided subjects with sense-making.

The experiment protocol was pretested with 2 doctoral students and a pilot study was conducted with a total of 12 doctoral and master's students. Based on their feedback, we clarified the wording in questions and refined the experiment process and instructions. Each participant was randomly assigned to one of the four experimental settings. All partici-

Table 11. Results Across All Eight Sense-Making Questions for User Experiment

	Telecom			Health		
Technique	**Precision**	**Recall**	**F-Measure**	**Precision**	**Recall**	**F-Measure**
Gold Standard	80.4	74.1+	77.1+	79.0	74.1	76.4
SATree	**77.8***	**72.6***	**75.1***	**75.5***	**71.0***	**73.2***
Best Benchmark	63.3	59.9	61.5	61.5	56.4	63.9
Sequential Order	58.7	53.4	55.9	54.0	47.4	50.2
	Security			**Manufacturing**		
Technique	**Precision**	**Recall**	**F-Measure**	**Precision**	**Recall**	**F-Measure**
Gold Standard	84.8+	80.0+	82.3+	67.8+	57.5+	60.9+
SATree	**84.7***	**80.5***	**82.5***	**66.5***	**55.7***	**58.4***
Best Benchmark	70.0	72.0	71.0	45.8	36.2	38.8
Sequential Order	61.1	64.7	62.7	48.0	35.6	39.2

*Significantly outperformed Best Benchmark and Sequential Order methods, with all p-values < 0.001
+Did not significantly outperform SATree

pants answered all four questions for both discussion threads, resulting in eight total questions and answers per participant. The order in which the two threads were presented was randomized to avoid biases. For each thread, participants had 5 minutes to familiarize themselves with the discussion's messages before they started answering the questions. During the experiment, the tasks performed by participants were timed. All answers were cross-judged by two domain experts. In order to measure participant's sense-making capabilities, theme precision, recall, and f-measure were calculated (Pirolli and Card 2005). Participants who failed to answer one or more of the eight total questions or those that failed to follow instructions were removed from the data. In each of the four contexts, the number removed was less than 4% (i.e., two from telecom, four from health, three from security, and five from manufacturing).

User Experiment Results

Table 11 depicts the average theme precision, recall and f-measure across all questions for the four experiment settings, on the four industry contexts. As expected, subjects using the Gold Standard conversation tree attained the best overall results. Interestingly, however, this gain was not significantly better than the performance for subjects that used SATree on three of the four data sets: telecom, security, and manufacturing. This result suggests that in many cases SATree may provide somewhat comparable support for sense-making as compared to gold standard coherence relations and speech act composition information. Furthermore, SATree yielded significantly better performance than the best benchmark and sequential ordering for all four contexts (all pair-wise t-test p-values < 0.001). Participants leveraging SATree attained precision and recall that were 20 percentage points higher than status quo sequential ordering, and more than 10 percentage points better than the best benchmark. These results demonstrate the transference of the proposed LAP-based systems' improved information quality representations into augmented user sense-making performance. Two critical criteria for analytical technologies that support sense-making are information quality and time (Pirolli and Card 2005). Although not reported here, the three conversation tree-based representations (gold standard, SATree, and best benchmark) also had significantly lower participant response times than the sequential ordering method on the telecom, health, and security settings. In other words, those using SATrees were not only markedly more accurate, they were also faster than participants using the sequential ordering method.

Table 12 shows the f-measure results for the four questions across the two discussion threads for all four industry contexts. Consistent with the overall results, SATree significantly outperformed best benchmark and sequential order for all questions, suggesting that it is better suited to support sense-making for the issue/idea identification and participant analysis use cases. Participants using the gold standard did not perform significantly better than those using SATree on 7 of the 16 questions, further underscoring the relative lack of information degradation when using the LAP-based system. Overall, the results presented in Tables 11 and 12 lend credence to the notion that text analytics systems guided by LAP-based principles may facilitate enhanced sense-making in online discourse.

Table 12. Results by Question Type in User Experiment

Technique	Telecom				Health			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Gold Standard	75.3	82.4+	77.7	72.8	76.2	80.3	77.5	71.7
SATree	**73.0***	**81.5***	**75.3***	**70.6***	**71.9***	**77.3***	**73.7***	**69.8***
Best Benchmark	59.6	65.7	61.1	59.8	62.6	65.7	65.4	62.0
Sequential Order	54.8	60.6	56.4	51.9	50.7	51.6	46.4	52.3
Technique	Security				Manufacturing			
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4
Gold Standard	83.4+	85.0+	82.1+	78.7+	69.0	46.6+	82.8	55.3+
SATree	**84.5***	**84.8***	**82.0***	**78.7***	**60.8**	**48.4***	**77.1***	**55.8***
Best Benchmark	72.0	74.1	71.5	66.2	48.5	30.9	50.4	34.7
Sequential Order	63.2	63.6	64.4	59.8	51.9	33.6	53.3	32.0

*Significantly outperformed Best Benchmark and Sequential Order methods, with all p-values < 0.001
+Did not significantly outperform SATree

Field Experiment

For novel IT artifacts, field experiments are useful for demonstrating value in organizational settings. Accordingly, for RQ6 we conducted a 4-month field experiment at TelCorp to show the utility of the information provided by the proposed LAP-based system (LTAS). The experiment was performed using members of TelCorp's large social media monitoring team, encompassing 23 analysts. This team previously used a customized version of a popular social media analysis tool provided by a major vendor in the space. The tool presented tables and charts, searching, and browsing features at different levels of granularity: social media channels, discussants, messages, and threads. The browsing capability presented threads using existing channel-system features (i.e., they appeared as they would in the actual forum, social networking chat, and/or microblog). Analytics features included topic (keyword) and sentiment analysis, which could be used as filters/dimensions in the existing search, browsing, and visualization capabilities. TelCorp's engineering team had developed custom dashboards on top of the tool to support their internal reporting needs pertaining to various use cases, including issues, ideas, and key participants.

A/B testing is a commonly used method to concurrently examine the performance of alternative artifacts or design settings. The key outputs of LTAS are conversation affiliations, coherence relations, and message speech acts. Treating the existing system used by TelCorp as setting A, we worked with the TelCorp's IT staff to develop setting B. In order to test our premise that the pragmatic view can enrich analytical capabilities over the pervasive semantic perspective, this setting entailed inclusion of coherence relation, conversation, and speech act information on top of the existing system already supporting topics and sentiments. For the B system setting, LTAS was embedded into TelCorp's real-time analysis pipeline adding conversation affiliation, reply-to relation, and speech act labels to all messages. Furthermore, participant importance rankings were computed using these revised social network analysis metrics. In the custom dashboards, sequential ordering was complemented with an SATree option. Conversation and speech acts were added as additional filters/dimensions for search, browsing, and visualization.

Members of TelCorp's monitoring team were randomly assigned to one of the two settings. One team member left the company during the 4-month experiment, resulting in 12 employees being assigned to A and 10 being assigned to B. Each team member had access only to their respective system setting for the duration of the experiment; they were asked to perform all daily monitoring tasks using this system. Using prior research as guidelines, a longitudinal data collection schedule was used (Venkatesh et al. 2003). Surveys were utilized to capture all users' perceptions about system A, one week of training on B for those assigned, followed by the use of surveys to capture user reactions for A and B at periodic intervals. After the one week period, user reactions were gathered again at the two month and four month marks, along with system usage data (Venkatesh et al. 2003). The user reaction constructs, which were adapted from Venkatesh et al. (2003), included perceived usefulness of the system, perceived usefulness of the information provided by the system, perceived ease of use of the system, perceived usefulness of the thread browsing capability, and perceived usefulness of the participant ranking capability. These were measured on a

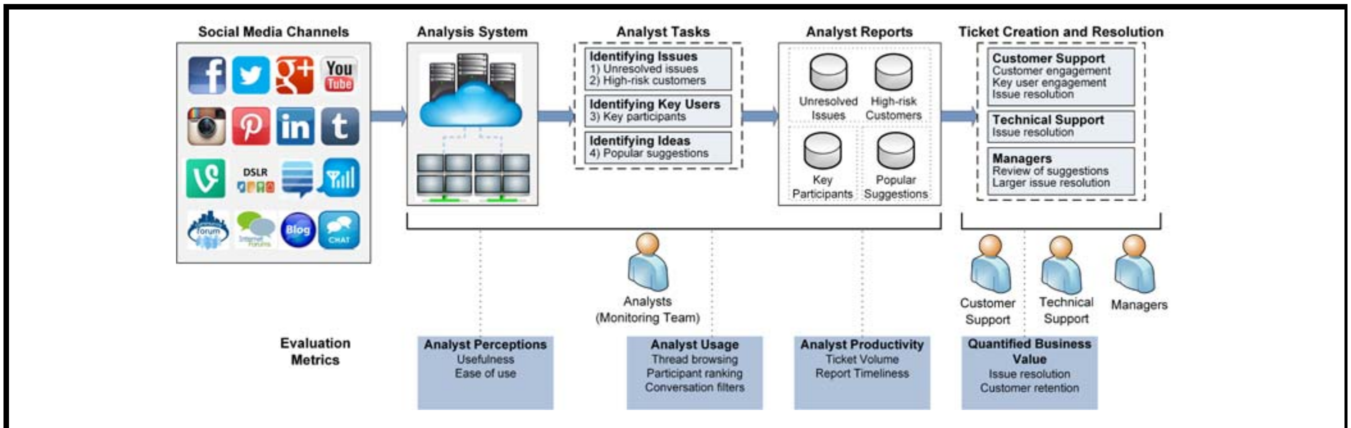

Figure 15. High-Level Overview of TelCorp's Business Process for Social Media Monitoring

1–10 continuous scale (see Appendix J for further details). The system usage measurements were captured through system logs and transformed to a 1–10 scale using a simple range transformation. The system automatically logged off inactive users after 10 minutes to reduce idle time in usage logs.

Figure 15 provides an overview of TelCorp's social media monitoring team workflow. Further details appear in Appendix M. TelCorp's monitoring team focuses on three key social media monitoring tasks: identifying issues, identifying key users, and identifying suggestions. Identifying issues encompasses (1) unresolved issues and (2) high-risk customers. TelCorp defines unresolved issues as events that adversely impact a set of customers. A good, extreme example is the one presented the second section of this article on the need for sense-making. Two other examples that arose during the 4-month field experiment include an error in the billing system which caused customers in three U.S. states to receive excess charges on their monthly statements, and a technical issue with the installation software of a new, integrated router-plus-modem which caused tens of thousands of customers to experience random Internet outages. High-risk customers are customers that may possibly churn due to what TelCorp considers "standard operational issues." Examples include an individual upset about call center wait times, or a customer considering switching to another carrier due to price differences. While issue identification is the primary use case for TelCorp's monitoring team, they also look to identify key discussion participants based on social network centrality—these include key positive/negative influencers, brand advocates, etc. Additionally, analysts in the monitoring team seek to identify popular suggestions. Examples include ideas about fund-raising events, charities valued by existing and prospective customers, requests for new product and/or service offerings, and suggestions on how to enhance the customer web portal and mobile app.

For the field experiment, four types of evaluation metrics were incorporated. The first two were analyst perceptions and actual system usage (measured through the process described in the prior paragraph). The other two were analyst productivity and quantified business value. The first two sections in Table 13 shows mean values for survey responses and actual usage, at the four-month mark. Users of system B responded much higher for perceived usefulness of the system, its information for identifying issues, thread browsing capability, as well as actual usage of thread browsing, participant ranking, and thread/conversation-level analysis. The increased perceived usefulness and actual usage of the thread browsing capability is attributable to the SATree-based browsing feature in system B. The participant ranking capability based on LTAS coherence relations also garnered higher perceived usefulness and actual usage. Various characteristics, including speech act composition, contributed to higher perceived usefulness of information for identifying issues. Furthermore, the use of conversations in B was higher than the use of threads in A (even though thread capability was also available in B).

Ultimately tangible value results from observed increases in productivity leading to quantifiable business value. Using the system, analysts submit reports, with each report including a description, severity level, and associated social media discussants, conversations, and/or threads. These reports are routed to customer support representatives, technical support, and/or managers. For a subset of reports, tickets are created indicating cases requiring action. Customer support reps attempt to engage with high-risk customers with the goal of reducing attrition. They also reach out to key users in order to preemptively garner brand advocacy or mitigate negative influence. Tech support reps work to resolve technical issues. Managers review suggestions and may also be involved in resolution of larger issues. Since Systems A and B were run

Table 13. Results of Field Experiment at TelCorp

Dimension		System A Status Quo N = 12	System B with LTAS N = 10
Analyst Perceptions	Usefulness of system (1–10)	7.9	**8.7**
	Ease of system use (1–10)	**8.1**	7.8
	Usefulness of information for identifying issues (1–10)	7.6	**8.5**
	Usefulness of thread browsing capability (1–10)	6.0	**7.2**
	Usefulness of participant ranking capability (1–10)	7.9	**8.2**
System Usage	Usage of thread browsing capability (1–10)+	7.1	**8.0**
	Usage of participant ranking capability (1–10)	8.2	**8.6**
	Usage of thread/conversation filters and charts (1–10)*	7.9	**8.8**
Analyst Productivity	Mean timeliness of reports (in minutes)	84.3	**30.7**
	Ticket volume—unresolved issues: total Ticket volume—unresolved issues: non-overlapping	19,040 1,548	**28,263** **10,771**
	Ticket volume—high-risk customers: total Ticket volume—high-risk customers: non-overlapping	9,520 1,415	**15,073** **6,968**
	Ticket volume—suggestions: total unique Ticket volume—suggestions: unique non-overlapping	452 54	**1,153** **755**
	Ticket volume—key participants: total Ticket volume—key participants: non-overlapping	492 134	**640** **302**
Quantified Business Value	Issue resolution	$9,139,200	**$13,566,000**
	Customer retention	$4,569,600	**$7,235,200**

*Measured thread-level usage for A versus conversation-level for B
+System B users also significantly higher for web forums, social networking sites, and microblogs

in parallel using non-overlapping teams, reports generated by users of each system were tracked, resulting in two sets of reports. The first of the two productivity measures incorporated by TelCorp was *timeliness* of overlapping reports created by users of both systems: in other words, the timeliness delta between report submission timestamps. The second productivity measure was *ticket volume*. Only those reports deemed to be the most important are converted to tickets by the customer/technical support reps or managers. For TelCorp, the total number of generated tickets, as well as non-overlapping tickets attributable to reports submitted by users of System A versus System B signified important productivity measures. Business value stems from *better* identifying issues, key participants, and ideas in a *timelier* manner. Appendix M offers further details. For the field experiment, TelCorp chose to quantify business value primarily in terms of identified issues, including the value of resolving issues on customer churn reduction (i.e., for those impacted by the issue), and successfully engaging and retaining high-risk customers. Hence we report business value metrics related to these use cases.

Looking at the productivity metric rows in Table 13, it is apparent that analysts using System B were able to generate reports resulting in a much larger number of total tickets for unresolved issues and high-risk customers. Furthermore, looking at the unique ticket volumes, users of System A produced fairly few tickets that were not covered in the set generated by users of System B. Based on customer/technical support rep and manager follow-up, the quantified value of these tickets to TelCorp in terms of post-issue customer retention or standard churn avoidance was over $7 million during the 4-month field experiment. Similarly, System B garnered higher ticket volumes for suggestions—more than double those attributable to users of System A (with few unique tickets in System A). Additionally, System B also resulted in greater tickets for key participants. The findings highlight the potential utility of information generated by the proposed LAP-based system in an organizational setting. In fact, TelCorp was so pleased with the field experiment results that, moving forward, they have adopted System B as their full-time analysis tool for the entire monitoring team. Overall, the analyst perceptions, system usage, productivity results, and quantified business value over an extended period of time further bolster external validity (Russell et al. 1993).

Results Discussion

Following Walls et al. (1992), we used a kernel theory to govern requirements and design, each of which was carefully tested. Each phase of the LAP-based framework is intended

Table 14. Summary of Results for Research Questions

Eval. Part	RQ	Result
(1) LAP-Based Methods	1	Conversation disentanglement methods explicitly incorporating detection of conversation beginnings (primitives) able to significantly outperform state-of-the art techniques.
	2	Coherence analysis methods incorporating conversation structure information in conjunction with system and linguistic cues able to markedly outperform existing methods, which are devoid of conversation structure information.
	3	Speech act classification methods leveraging conversation trees and kernel-based methods able to markedly boost classification capabilities.
(2) Sense-making	4	Improved coherence analysis can significantly enhance social network analysis centrality measures over existing methods that primarily rely on system-generated features.
	5	Sense-making user experiments in multiple organizations, with several hundred practitioners, revealed significantly higher precision and recall for sense-making tasks, relative to benchmark methods.
(3) Business Value	6	Four-month field experiment at TelCorp revealed that social media team members' perceptions, usage, and productivity were higher when using a system with LAP-based information relative members relying on existing social media analytics systems, resulting in significant quantified business value.

to improve sense-making while simultaneously serving as an input refinement mechanism for other phases of the framework. The conversation disentanglement component produces the conversation structure attributes used as part of the input feature set for the coherence analysis component. Results from the conversation disentanglement and coherence analysis components are used to enhance speech act classification. The coherence relations and message-speech act information is used to create SATrees. Consistent with design science principles (Hevner et al. 2004), we used a series of experiments to rigorously test each component of the proposed IT artifacts. The experiment results, summarized in Table 14, demonstrate the efficacy of LTAS and its underlying LAP-based framework.

Regarding the first part of our evaluation, experiments 1 through 3 demonstrated the effectiveness of the conversation disentanglement, coherence analysis, and speech act classification components of LTAS relative to benchmark methods (RQs 1–3). In the second part of the evaluation, experiment 4 showed how the LTAS components collectively resulted in augmented information quality in the context of social networks (RQ4). Based on experiment 5 (RQ5), LTAS facilitated demonstratively better sense-making than comparison methods, allowing users to better understand discussion elements pertaining to social media use cases. Experiment 6 (RQ6) presented results from a 4-month field experiment at TelCorp where the use of LTAS-based information enhanced social media monitoring team members' perceptions, system usage, and productivity, resulting in considerable quantified business value.

The findings have important design implications for text/social analytics artifacts, which is a growing body of literature in IS (e.g., Abbasi and Chen 2008; Chau and Xu 2012; Lau et al. 2012). The results also provide insights for the broader social media analysis researcher and practitioner communities. Key takeaways include:

- *Consider making conversations more of a focal point*—the interplay between conversations, coherence relations, and speech act composition of messages in social media is valuable for enhanced sense-making. For instance, conversation structure, including conversation beginnings, message conversation affiliation information, and conversation trees received limited attention in prior work despite their ability to dramatically enhance coherence analysis and speech act identification. Conversations may serve as a more meaningful unit of analysis than system-generated aggregate discussion threads, or stand-alone messages devoid of communication context.

- *Proceed with caution when performing social network analysis using system-generated reply-to relations*—social networks constructed purely based on system features and naïve linkage methods in web forums, social networking sites, and microblogs can distort important centrality measures such as degree and betweenness for key network members by 15% to 50%. Enhanced coherence analysis methods are essential for ensuring information quality in social media-based networks.

- *Incorporating the pragmatic view in monitoring systems can enhance sense-making*—the semantic view of language is pervasive in text/social media analytics, and for good reason. Topic, sentiment, and affect analysis are incredibly important and valuable analysis dimensions (Abbasi and Chen 2008). However, also incorporating the pragmatic view in text/social analytics systems (e.g., conversation structure, coherence relations, and speech act information) can significantly improve users' social media sense-making capabilities. We observed increases of 20 to 40 percentage points for various tasks in four organizations, with hundreds of practitioners. Based on field experiment results, these findings also translated into enhanced analyst perceptions, usage, and productivity, resulting in meaningful quantified business value.

- *Developing and/or utilizing advanced machine learning and data science-based IS design artifacts can further the state-of-the-art for text/social media analytics*—our proposed LTAS artifact demonstrated the utility of advanced kernel-based methods, including tree and ensemble kernel-based approaches. As data science continues to play a bigger role in IS research geared toward deriving economic and societal value from unstructured Big Data (Abbasi et al. 2016; Saar-Tsechansky 2015), exploration of advanced machine learning-based constructs, methods, and instantiations seems advantageous.

Conclusions

Our contributions are three-fold. First, we presented several key findings relevant to the design of text analytics artifacts and to the social media analysis research and practitioner communities (summarized in the previous section). Additionally, our two design science contributions are as follows. Second, we described how a framework based on LAP principles can be used to inform the design of text analytics systems for enhanced sense-making. Third, we developed LTAS, which adopted these principles in its feature sets and techniques for conversation disentanglement, coherence analysis, and speech act classification. LTAS employed several important concepts that have been incorporated into prior LAP-based studies, including context, relevance, thematization, discourse ambiguity, conversation structure elements, and message and conversation-level speech act composition. In order to effectively incorporate structural, linguistic, and interaction information, novel kernel-based classifiers were developed. A series of experiments were used to illustrate the efficacy of various components of LTAS. User studies and a field experiment demonstrated the external validity of the proposed design artifacts. With respect to recent design science guidelines, our research contribution represents an "improvement": a novel and holistic solution to an established, important problem (Goes 2014; Gregor and Hevner 2013).

Analytical technologies that support enhanced sense-making from online discourse constitute an increasingly critical endeavor as comprehension lays the foundation for reasoning and decision-making (Weick et al. 1995). The results of our work have important implications for social media analytics. As intra-organizational and external-facing communication via social media becomes increasingly pervasive (Bughin and Chui 2010), sense-making remains a paramount concern (Honeycutt and Herring 2009). The results can shed light on interaction dynamics in intra-organizational communication, corporate blogs and wikis, and group support systems. Furthermore, organizations are increasingly interested in understanding customer actions and intentions expressed via social media; that is, going beyond the *what* to uncover contextual elements such as the *why* and *how* (Mann 2013). Some specific, important use-cases for social media analytics are identifying issues and important participants (Zabin et al. 2011). While topic and sentiment analysis remain essential semantic forms of analyses, as shown in the TelCorp and other examples, the pragmatic view emphasized by LAP provides considerable complementary value to allow better understanding of issues through examination of interactions and speech acts within conversations. Furthermore, enhanced coherence analysis enables meaningful representation of social media social networks, making identification of key discussion participants more feasible.

Future work can extend this study in various ways. LAP-based text analytics systems for sense-making could be evaluated in other contexts, on other discussion topics, languages, and communication modes. LTAS could be improved via adaptive learning where components iteratively improve one another, or via automated detection of conversation types. Additionally, the SATrees in LTAS signify the key outputs of systems using the LAP-based framework. As done in our field experiment, these outputs can be leveraged with alternative visual formats, or for other social media use cases as an information/feature space refinement, such as social media for predicting adverse events, financial metrics, health-related outcomes, etc. Nevertheless, the system and underlying framework presented demonstrate the viability of applying LAP concepts, which advocate the pragmatic perspective centered around conversations and actions as complementary to the pervasive semantic view, enabling enhanced text analytics for sense-making. Given the ubiquitous nature of online discourse, the results of our work constitute an important and timely endeavor; one which future research can build upon.

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