Towards Modeling Social and Content Dynamics in Discussion Forums

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Extended Abstract

Recent years have witnessed the transformation of the World Wide Web from an information-gathering and processing tool into an interactive communication medium in the form of online discussion forums, chat–rooms, blogs, and so on. There is strong evidence suggesting that social networks facilitate new ways to interact with information in such media. Understanding the mechanisms and the patterns of such interactions can be important for many applications. Currently, there is not much work that adequately models interaction between social networks and information content. From the perspective of social network analysis, most existing work is concerned with understanding static topological properties of social networks represented by such forums. For instance, Park and Maurer (2009) applied node clustering to identify consensus and consensus facilitators, while Kang et al. (2009) uses discussion thread co-participation relations to identify (static) groups in discussions. On discussion content analysis research side, there have been approaches for classifying messages with respect to dialogue roles (Carvalho and Cohen, 2005; Ravi and Kim, 2007), but they often ignore the role and the impact of underlying social interactions.

Thus, the current static network and content analysis approaches provide limited support for

- Capturing dynamics of social interactions: the sequence of communication or who is responding to whom is important in understanding the nature of interactions.

- Relating social interactions to content analysis: the content can give hint on the nature of the interaction and vice versa (e.g., users with more social interactions are more likely to have common interests).

To address the above issues, one needs to go beyond the static analysis approach, and develop dynamical models that will explicitly account for the interplay between the *content* of communication (topics) and the *structure* of communications (social networks). Such framework and corresponding algorithmic base will allow us to infer "polarizing" topics discussed in forums, identify evolving communities of interests, and examine the link between social and content dynamics.

To illustrate the advantages and the need for more fine–grained analysis, we now turn to a concrete example. Figure 1(a) provides a sample of discussion co-participation network from an online discussion forum. Each oval node represents a user and each square shows a discussion thread, while each arrow represents users participating in the thread. The numbers on the arrow represent the number of messages contributed to the thread. Ten discussion threads with 127 messages from 43 users are captured. Based on this network, we can identify users that have similar interests, cluster topics and/or users according to similarities, and so on. However, this network is too coarse–grained to get additional information about the social interactions. For instance, it does not say anything whether co–participating users have similar or conflicting views.

We now contrast the above network with a more fine–grained representation of forum dynamics. We performed a thorough manual analysis of threads, by taking into account the sequence of messages to construct response–to graph, and then manually annotating the *attitudes* of each message towards the one it was responding to. Figure 1(b) provides a signed attitude network from the same dataset as the one used for Figure 1(a). Each node represents a user and an arrow shows how one replies to the other.
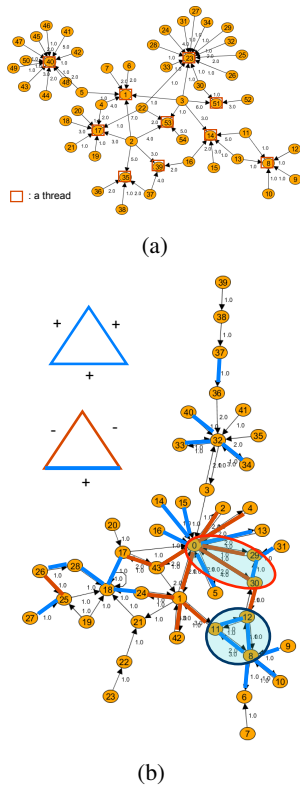
(a)

(b)

Figure 1: (a) Thread participation network; (b) Signed attitude network. In (b), the circles show two triangle relationships suggested by structural balance theory.

The numbers on the arrow represent the number of the reply–to occurrences, while the color of the link represents the attitude. Here we use a very loose definition of "attitude". Namely, positive (blue) attitude means that the posting user agrees with the previous comment or message, or expresses friendly sentiments. And negative attitude means disagreeing with the previous message or using outright offensive language. The resulting signed network differentiates links between the users (friends or foes).

Clearly, the resulting network is much more informative about the social interactions among the users. Remarkably, even for the small manually collected data-set, the resulting network reproduces some of the known features of signed networks from social sciences (Lescovec et. al., 2010; Wassermanc and Faust, 1994). For instance, the highlighted ovals show balanced triads: two friends with a common enemy and three mutual friends. This with structural balance theory, which suggests that in signed network particular triads with odd number of positive links (three mutual friends or two friends with a

common enemy) are more plausible than other cases (e.g. three mutual foes). As we add more data, we expect more occurrences of such triads.

Our current research focuses on automating the above process of network construction and analysis. To this end, we have been developing approaches based on Dynamic Bayesian Networks where the nodes correspond to participating users and messages, and the edges encode probabilistic dependence between message content and user attitudes. In this framework, the content of a message depends on the previous message as well as on the attitude of the posting user towards both the content and the other user. The observables in this model are the messages (and in some cases, some user–attributes such as age, location etc). And the *unobservables* such as users' attitudes and social preferences are modeled through latent variables that need to be inferred. To be more specific, let u_1 and u_2 denote the variables describing the users, and $m_1, m_2, ...$ denote the message sequence. Within the proposed generative framework, the goal is to calculate the posterior probability $P(u_1, u_2|m_1, m_2, ...) \propto \pi(u_1)\pi(u_2)\pi(m_1|u_1) \prod_{t=2}^{K} P(m_t|m_{t-1}, u_{i=1,2})$. Here $\pi(.)$ are the priors, and $P(m_t|m_{t-1}, u_i)$ is a probability of seeing a particular response by the user u_i to a message m_{t-1}, which will be estimated using annotated data and further refined through EM–type approach.

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