Do You Feel What I Feel?
Social Aspects of Emotions in Twitter Conversations

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Abstract

We propose a computational framework for analyzing the social aspects of sentiments and emotions in Twitter conversations. We explore the question of sentiment and emotion transitions, asking the question *do you feel what I feel?* in a conversation. We also inquire whether conversational partners can influence each other, altering their sentiments and emotions, and if so, how they can do so. Further, we examine overall sentiment patterns for interesting cases of two conversational partners with opposing sentiments. We use a probabilistic topic model, based on the latent Dirichlet allocation, for automatically discovering the sentiments and emotions from an unannotated corpus of Twitter conversations.

1 Introduction

Popular social network services (SNS), such as Twitter, have become good resources for researchers interested in studying social behaviors. The public nature of Twitter makes it appropriate for various behavioral studies, and it has become especially useful for studying sentiments and emotions [2, 5]. However, these studies do not take into account that emotions and sentiments are inherently social [10]. They often arise in social situations, and when expressed in a communicative setting such as Twitter, the sentiments and emotions expressed affect the interactions among the communicative participants. The goal of this paper is to study how Twitter conversations can be used for understanding the social aspects of sentiments and emotions.

In much of existing literature (see [9] for a review), sentiment analysis is usually a simple classification of positive and negative (and sometimes neutral), and in this paper, we follow this convention for our sentiment analysis. Emotion analysis has not been explored as much, but in [8], Kamvar and Harris show that emotions are much more diverse, including for example, *anger*, *surprise*, and *joy*. Both the simple classification of sentiments and the diverse set of emotions are important aspects of conversations, so we present analyses of both sentiments and emotions.

Twitter is widely used for conversations [13], and prior work has studied different aspects of human conversations by using Twitter as a source [3, 4, 6, 14]. Ours is the first paper to look at emotions in Twitter conversations, and we present the computational methods and results for analyses of

- how different sentiments and emotions in a tweet lead to the sentiments and emotions in a tweet responding to it,
- how certain words by one interlocutor triggers sentiment and emotion changes in the conversational partner, and
- how the disagreement in overall sentiment of the conversational partners can reveal interesting conversational topics.

2 Data Collection and Analysis

In this section, we describe how we collected and analyzed Twitter conversation data. We call a Twitter conversation a *chain* and define it as follows:

> ***chain***: a sequence of replies between two users. A conversation is a *chain* of tweets where two users are consecutively replying to each other's tweets using the Twitter *reply* button.

We start with the Twitter Gardenhose API which returns a random sample of all public tweets. Then, we identified users who *replied* to other people's tweets, and we considered those users as *candidates*. We expanded candidates by looking at the target users of the *replies* within those tweets. We then only used dyads of users within the candidate set who replied to each other. To protect users' privacy, we anonymized the data to remove all identifying information.

In this way, we identified 136,730 users, 222,024 dyads, and 1,668,308 chains. For running the experiments, we filtered the data by keeping only the chains of four tweets or more. This resulted in 153,054 chains containing 871,544 tweets, 5.69 tweets per chain on average. Our analysis shows that the chain length follows the Power Law, which is found in many SNS data characteristics.

Our analysis of the social aspects of emotions is based on a computational model for automatic discovery of topics and sentiments. Topics and sentiments are two pivotal aspects of tweets that form influence patterns in a conversation. We use the aspect and sentiment unification model (ASUM) [7], an extension of the latent Dirichlet allocation [1] to analyze unannotated Twitter corpus. ASUM discovers topics that are closely coupled with sentiment in an unsupervised way. Given a set of positive and negative seed words, ASUM forms topics with words that have strong co-occurrence patterns with the seed words. We used positive and negative emoticons from Wikipedia.org[1] as the seed words. Using emoticons as a sentiment label of text is proved effective in [12]. ASUM outputs a set of topics obtained from given data and a sentiment-topic classification result for each tweet. For each topic, we show the words with high probabilities as representing the topic.

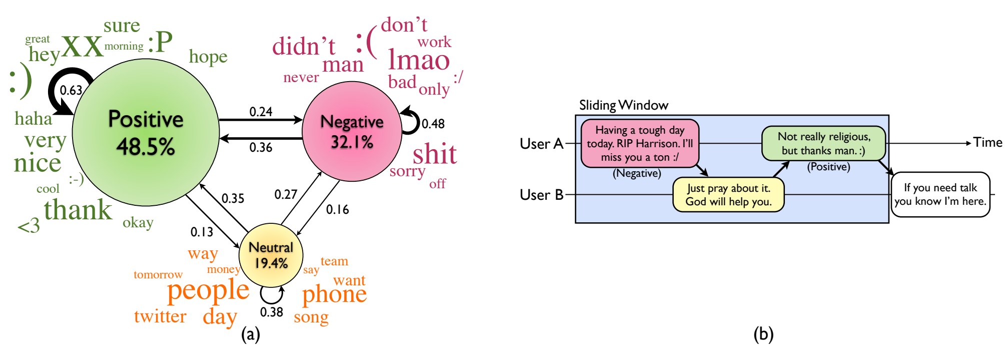

Figure 1: (a) Sentiment transitions and (b) sentiment influence example. In (a), each edge represents a sentiment transition from a tweet to its reply. The number next to the edge indicates the transition probability, and the width of the edge indicates the relative number of tweet pairs for that transition. Size of the word represents the relative probability P(word|sentiment). In (b), second tweet in the window (yellow) *influences* User A's sentiment from negative (red) to positive (green). Sentiment *transition* from negative sentiment (red) to neutral sentiment (yellow) also occurs.

3 Social Aspects of Sentiments

We first investigate how sentiments in a tweet lead to the sentiments in the reply tweets (*transition*), and how certain topics in a tweet changes the conversational partner's sentiment (*influence*). We analyzed our corpus of tweets with three sentiments (positive, neutral, and negative), setting the number of topics to 30 for each sentiment for a total of 90 topics.

Figure 1 (a) shows the sentiment distribution of all tweets and the top words of the tweets categorized in each sentiment. 48.5% of the tweets show positive sentiment. The figure also shows the sentiment

[1] http://en.wikipedia.org/wiki/List_of_emoticons

transitions from each of the tweets to the tweet that replies to it. For example, of all tweets that show positive sentiment, 24% will show negative sentiment. As the figure shows, for all three sentiments, self-transitions make up the largest proportions, implying both conversational partner's sentiment are likely to be same. Note that the transitions to the positive sentiment are also quite large.

To analyze the topics of tweets that influence the sentiment of the conversation partner, we used a sliding window containing three consecutive tweets in a chain. In that window, shown in Figure 1 (b), the first and the third tweets are from user A, and the second tweet is from user B. In this sliding window, we can assume that the second tweet influences A's sentiment from the first to the third.

Figure 2 shows some interesting topics from the sentiment influence. Topics that change the partner's sentiment from negative to positive include *sympathy* (topic 44), and topics that change the partner's sentiment from positive to negative include *teasing* (topic 17) and *complaint* (topic 38).

Positive → Positive		Positive → Negative		Negative → Positive		Negative → Negative	
Topic 16	Topic 19	Topic 17	Topic 38	Topic 44	Topic 47	Topic 72	Topic 42
follow	heart	lmao	:(	hope	today	shit	off
thank	xD	ur	school	better	week	bro	still
please	big	ass	exam	sorry	still	da	bad
followed	kisses	lol	tomorrow	feel	feel	chillin	feel
welcome	much	shit	year	soon	work	nigga	down
Topic 8	Topic 21	Topic 48	Topic 54	Topic 59	Topic 37	Topic 49	Topic 32
thank	morning	weather	sleep	home	money	game	ur
:D	day	rain	work	want	buy	lmao	loool
much	hope	:(	still	house	want	shit	lool
very	hello	hot	awake	sleep	had	team	looool
welcome	happy	cold	tired	bed	pay	win	man

Figure 2: Topics that influence the conversational partner's sentiment. Green and red colors indicate positive and negative topics, respectively.

4 Social Aspects of Emotions

We now analyze the corpus for transitions and influences of emotions. To automatically classify the emotions, we use the tree-structured list of emotions defined by Parrott in [10]. Parrott divided the human emotion into six categories: love, joy, surprise, anger, sadness, and fear, and each emotion contains secondary and tertiary levels of emotions. We ran ASUM as *topic finder* with seed words as positive and negative emoticons, setting the number of topics to 50 for each sentiment.

One challenge in analyzing the emotion transitions and influences is categorizing the tweets into the six emotions. Most previous works related to this problem were mainly of naïve word-counting. To do this better, we re-run ASUM with the emotion words from whole Parrott's emotion tree and expand the word list from 139 to 702 words, average 117 words for each emotion. With the expanded lexicons, we calculate the probability of generating the set of expanded seed words of each emotion for each topic, and identify the topic that has a high probability of generating seed words of one emotion compared to all others. We define a metric *Corr* for correlation of emotion and topic, the probability of generating the set of seed words $\mathbf{w}$ of emotion c from topic t as $Corr(c,t) = \frac{\gamma_c}{n_c}\sum_{i=1}^{n_c} P(w_i|\phi_t)$, where γ_c is the normalization constant for each emotion and n_c is the number of seed words for each emotion. We also define a metric *Spec* for specialization of a certain emotion for topic t as $Spec(t) = \frac{\max_c Corr(c,t)}{\sum_c Corr(c,t) - \max_c Corr(c,t)}$. We select the topics with high *Spec* values for each emotion, and Figure 3 shows those topics.

Joy		Sadness		Love		Fear		Anger		Surprise	
Topic 31	Topic 40	Topic 99	Topic 86	Topic 1	Topic 3	Topic 60	Topic 87	Topic 95	Topic 59	Topic 18	Topic 30
day	happy	hope	:'(	her	twitter	:/	dont	eat	she	song	where
hope	birthday	sorry	miss	smiles	justin	school	lmao	want	:(	album	live
morning	th	better	him	laughs	follow	tomorrow	tell	food	car	music	here
great	hahaha	feel	sorry	eyes	selena	exam	want	chicken	were	new	same
weekend	year	soon	want	want	fan	year	him	hungry	off	her	awesome
Topic 23	Topic 46	aww	sad	Topic 47	Topic 9	doing	her	Topic 73	home	she	Topic 68
party	thank	okay	wish	school	pic	much	please	she	her	amazing	she
home	much	hugs	wanna	luck	hair	day	face	hate	phone	listening	old
fun	very	feeling	much	exam	look	next	who	being	house	awesome	than
tomorrow	hope	happened	cry	tomorrow	nice	maths	omg	never	night	great	look

Figure 3: Set of topics categorized as the primary six emotions of Parrott's tree-structured list of emotions.

To observe the effect of emotions in a conversation chain, we analyze the transitions of emotions in the same ways as the sentiment transitions. Figure 4 (a) shows the emotion transitions. In this figure, we show only the edges with transition probability of 0.1 and higher. Note that the transitions to positive emotions, such as *joy* and *love* are quite high, regardless of the emotion of the original tweet. Also, transitions across the opposing emotion pairs of Plutchik's wheel of emotions [11], such as *joy-sadness* and *anger-fear*, are quite low, compared to the other pair of emotions.

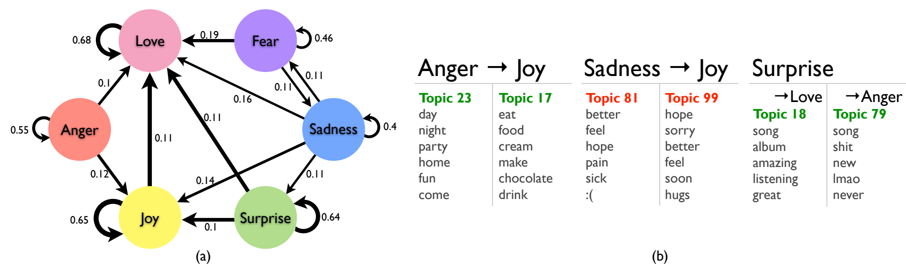

Figure 4: (a) Emotion transitions and (b) emotion influences. In (a), edges represent the probability of emotion transitioning from a tweet to its reply tweet. The weight of an edge represents the number of tweet-reply pairs for that transition.

We run an experiment to capture the influential aspect of emotions in the conversation chain. With the similar procedure to previous section, we run a sliding window method to observe what topics of tweets change the partner's emotions. Figure 4 (b) shows interesting examples of emotion influences. Similar to the sentiment influences, *sympathy* tends to change partner's sentiment from a negative emotion to a positive emotion. It is notable that topics with similar subject but in different sentiment changes partner's emotions in different way (e.g., Topic 18 and Topic 79).

5 Sentiment Patterns in Conversations

We propose a way of finding interesting conversations by looking at the overall sentiment patterns of the interlocutors. In most conversations, the interlocutors will share a common sentiment, which we call *sentiment accommodation*, either both positive, both negative, or at least one of them neutral. For each conversation in the corpus, we find the overall sentiment of the interlocutors. Using the sentiment classification of the tweets as positive, negative, and neutral, we define the overall sentiment of an interlocutor u in conversation v as $Senti(u, v) = \frac{p_{u,v} - n_{u,v}}{p_{u,v} + n_{u,v}}$, where $p_{u,v}$ is the number of positive tweets of u in v, and $n_{u,v}$ is the number of negative tweets. For each conversation chain v, we calculate the overall sentiments of users u_1 and u_2 in the chain.

We looked at conversation chains in which both $|Senti(u_1, v)|$ and $|Senti(u_2, v)|$ are greater than 0.5. The overall sentiment patterns that we considered to be interesting are pos-pos, neg-neg, and pos-neg. The most interesting pattern is the pos-neg, where the two conversational partners have opposing overall sentiments, since this pattern violates our finding over patterns of conversations. In our data, about 4%, 6,778 chains, show that pattern, and the topics in that pattern including *complaining*, *sympathy*, and *apology*. That is, one interlocutor is feeling upset about something, and the partner shows sympathy, or one is complaining to the partner, and that partner is making an apology. In future work, we can use this analysis as a starting point for making inferences about the relationship between two Twitter users.

6 Conclusion

We have presented a novel computational framework for analyzing the social aspects of sentiments and emotions in Twitter conversations. First, in sentiment and emotion transitions, we found that the answer to *do you feel what I feel?* is a *yes*, in that self-transitions account for the largest proportions. However, there are significant transitions to other positive sentiments and emotions, implying Twitter users tend feel good even when the conversational partners do not. We also found that *sympathy*, *apology*, and *complaining* play significant roles in sentiment and emotion influences. Finally, we showed that examining sentiment patterns in conversations leads us to discover interesting conversations. There are many future directions stemming from this work including temporal patterns and comparisons with other communication platforms.

References

[1] Blei, D., Ng, A., and Jordan, M. Latent dirichlet allocation. *The Journal of Machine Learning Research 3* (2003), 993–1022.

[2] Bollen, J., Pepe, A., and Mao, H. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. In *Proceedings of ICWSM* (2011).

[3] Boyd, D., Golder, S., and Lotan, G. Tweet, tweet, retweet: Conversational aspects of retweeting on twitter. In *Proceedings of the 43rd Hawaii International Conference on System Sciences* (2010).

[4] Danescu-Niculescu-Mizil, C., Gamon, M., and Dumais, S. Mark my words!: linguistic style accommodation in social media. In *Proceedings of WWW* (2011).

[5] Diakopoulos, N. A., and Shamma, D. A. Characterizing debate performance via aggregated twitter sentiment. In *Proceedings of CHI* (2010).

[6] Honey, C., and Herring, S. Beyond microblogging: Conversation and collaboration via twitter. In *Proceedings of 42nd Hawaii International Conference on System Sciences* (2009).

[7] Jo, Y., and Oh, A. Aspect and sentiment unification model for online review analysis. In *Proceedings of WSDM* (2011).

[8] Kamvar, S., and Harris, J. We feel fine and searching the emotional web. In *Proceedings of WSDM*, ACM (2011), 117–126.

[9] Pang, B., and Lee, L. Opinion mining and sentiment analysis. *Foundations and Trends in Information Retrieval 2*, 1-2 (2008), 1–135.

[10] Parrott, W. *Emotions in social psychology: essential readings*. Psychology Pr, 2001.

[11] Plutchik, R. *Emotion: A psychoevolutionary synthesis*. Harper & Row New York, 1980.

[12] Read, J. Using emoticons to reduce dependency in machine learning techniques for sentiment classification. In *Proceedings of the ACL Student Research Workshop*, Association for Computational Linguistics (2005), 43–48.

[13] Ritter, A., Cherry, C., and Dolan, B. Unsupervised modeling of twitter conversations. In *Proceedings of HLT-NAACL* (2010).

[14] Ritter, A., Cherry, C., and Dolan, W. Data-driven response generation in social media. In *Proceedings of EMNLP* (2011).