Enthusiasm and Support: Alternative Sentiment Classification for Social Movements on Social Media

Shubhanshu Mishra
University of Illinois
Urbana-Champaign
The iSchool
smishra8@illinois.edu

Sneha Agarwal
University of Illinois
Urbana-Champaign
The iSchool
sagarwa8@illinois.edu

Jinlong Guo
University of Illinois
Urbana-Champaign
The iSchool
jguo24@illinois.edu

Kirstin Phelps
University of Illinois
Urbana-Champaign
The iSchool
kphelps@illinois.edu

Johna Picco
University of Illinois
Urbana-Champaign
The iSchool
picco2@illinois.edu

Jana Diesner
University of Illinois
Urbana-Champaign
The iSchool
jdiesner@illinois.edu

ABSTRACT
We present a novel sentiment classifier particularly designed for modeling and analyzing social movements; capturing levels of *support* (supportive versus non-supportive) and degrees of *enthusiasm* (enthusiastic versus passive). The resulting computational solution can help organizations involved with social causes to disseminate messages in a more informed and effective fashion; potentially leading to greater impact. Our findings suggest that enthusiastic and supportive tweets are more prevalent in tweets about social causes than other types of tweets on Twitter.

ACM Classification Keywords: I.2.7; H.3.3

Author Keywords
Social Network Analysis; Data Classification; Data Corpus; Social Causes; Human Factors

1. INTRODUCTION
Common sentiment classifiers typically label statements as positive, negative or neutral. While helpful for consumer products or marketing initiatives, this simplistic scale of sentiments is of limited applicability to other real-world problems, e.g. social causes. We present a novel sentiment classifier unique to social causes which captures more nuances of sentiment along the level of *support* (supportive versus non-supportive) and degree of *enthusiasm* (enthusiastic versus passive). With this classifier, relevant types of stakeholders for social causes can be identified, and this information be further used for collective action and advocacy.

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2. BACKGROUND
Twitter has redefined the way in which social activities are discussed, coordinated and executed. Of particular interest for social media studies is the detection of influencers on Twitter, with a focus on the understanding of influence based on the number of followers, retweets and/or mentions [1]. Identifying influencers on Twitter has a number of important real-world applications, including marketing/advertising costs [2] and consumer feedback [3]. While relying only an account's indegree (number of followers) reveals little about a user's influence[1], categorizing users by specific roles based on their dynamic communication behavior (e.g. URLs and hashtags) can improve retweetability [4].

Sentiment extracted from Twitter is found to be predictive of real-world outcomes. Yet, the majority of sentiment analysis of Twitter involves labeling tweets according to polarity, or a scale of positive-neutral-negative [6]. However, especially from a social science point of view, solutions to reliably capturing more nuanced dimensions of emotions (on social media) are lacking. Thus, we address the following research questions:

1. *How can we construct a better classification system for sentiment analysis on Twitter fine-tuned for better understanding social movements?*
2. *How can we improve the identification of influential users on Twitter via such a novel sentiment analysis approach?*

3. METHODS
3.1 Classification Schema
Digging deeper into the needs for identifying users/tweets for social causes, we identified the classification of two orthogonal classes shown in Figure 1. This schema allows us to move beyond the classic positive/ negative/ neutral categorization.

3.2 Corpus Collection
We collected over 1,500 tweets related to three social causes: "Cyberbullying", "Concussions in NFL", and "LGBT" during the 1st week of November 2013.

3.3 Codebook Generation

We created a codebook to label tweets for generating a training corpus for each of the four classes considered herein. The codebook was used to hand code the 1500 tweet corpus. We avoided using context based knowledge for the coding to limit personal opinions from the coding process. Inter-coder reliability scores were high for both classes [Table 1.]

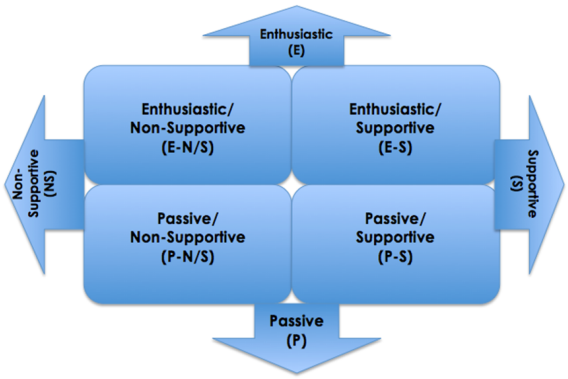

Figure 1 Orthogonal Classification Schema

For the Non-Supportive class, we considered the case where the tweets could be categorized as being either directly against the cause, or just spreading negative information about the cause. We merged these two cases to build the Non-Supportive class. The corpus contained only a very few tweets that spoke directly against a cause.

Table 1. Inter-Coder reliability for annotation

Classification Schema	Inter- coder Reliability
Enthusiastic v/s Passive	93%
Supportive v/s Non - Supportive	85%

3.4 Classifier Training

We used a Linear Support Vector Machine (SVM) based classifier, which we trained using the following features: # of Emoticons, # of URLS, # of Mentions, # of Hashtags, Word Features, # of Double Quotes Length of Tweets. Our 10 fold cross validation achieved a 77% to 79% prediction accuracy in terms of the F-measure [Table 2].

Table 2. Prediction accuracy

Classification Schema	Accuracy
Enthusiastic v/s Passive	79%
Supportive v/s Non - Supportive	77%

3.5 User Classification

The classifiers were made actionable by using them to identify particular types of influencers on Twitter, as follows: We leverage the classifier confidence scores for each tweet to calculate a sum total of sentiment shared by the users for that specific class. Then, we rank the users and construct a social network of users to identify influencers per sentiment based on a) sentiment scores and b) centrality measures like degree and betweeness. The technology (*SentiNets)* and results are made publicly available through a web-based tool (http://people.lis.illinois.edu/~smishra8/sentinets.php). This tool allows users to search for tweets on a social topic and then share all the metrics for all the users involved.

We envision *SentiNets,* the user dashboard, to benefit organizations and individuals working with social causes by providing a way to classify tweets according to the level of support and degree of enthusiasm on Twitter.

4. DISCUSSION AND CONCLUSION

Our work contributes to ongoing research that aims to expand and leverage our understanding of language use, specifically sentiment, on social media. While still limited by sarcasm and other jargon, our work moves the conversation forward, beyond simple positive-negative scales.

Social media has the potential to build relationships, raise awareness, and support advocacy of important issues facing our communities. However, social causes are nuanced, at times controversial, and infused with opinions that are often lost when evaluated along a scale of simple positive/negative polarity. Our work provides a possible solution for this problem by creating a way to classify tweets according to the level of support and degree of enthusiasm. Even with unstructured data, our classifier was able to successfully predict sentiments on social causes with decent performance. Our classifier is limited by the use of language on social media, however, and may not be able to classify context based tweets or sarcastic tweets.

A public interface is provided with our solution. Through *SentiNets*, we are able to combine our sentiment classifier with aspects of user influence in social networks to help those working toward important social causes to make sense of social media data for desirable social outcomes.

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