EmoTwitter – A Fine-Grained Visualization System for Identifying Enduring Sentiments in Tweets

Myriam Munezero[1], Calkin Suero Montero[1], Maxim Mozgovoy[2], and Erkki Sutinen[1]

[1] School of Computing, University of Eastern Finland, Joensuu, Finland
{mmunez,calkins,erkki.sutinen}@uef.fi
[2] The University of Aizu, Aizu-wakamatsu, Fukushima, Japan
mozgovoy@u-aizu.ac.jp

Abstract. Traditionally, work on sentiment analysis focuses on detecting the positive and negative attributes of sentiments. To broaden the scope, we introduce the concept of *enduring sentiments* based on psychological descriptions of sentiments as enduring emotional dispositions that have formed over time. To aid us identify the enduring sentiments, we present a fine-grained functional visualization system, EmoTwitter, that takes tweets written over a period of time as input for analysis. Adopting a lexicon-based approach, the system identifies the Plutchik's eight emotion categories and shows them over the time period that the tweets were written. The enduring sentiment patterns of *like* and *dislike* are then calculated over the time period using the flow of the emotion categories. The potential impact and usefulness of our system are highlighted during a user-based evaluation. Moreover, the new concept and technique introduced in this paper for extracting enduring sentiments from text shows great potential, for instance, in business decision making.

Keywords: Sentiment Analysis, Emotions, Enduring.

1 Introduction

The ability to accurately identify and reflect the sentiments 'out there' is valuable and challenging. This ability influences real world text analysis applications such as, targeting marketing or political campaigns to users and voters with specific likes and dislikes, or identifying online antisocial behavior e.g., cyberbullying. Thus, understanding and being able to detect the development of sentiments in text is a desirable asset.

The area of natural language processing (NLP) that broadly deals with the computational treatment of opinions, feelings, emotions and subjectivity in texts is sentiment analysis (SA) [20]. Current work in SA focuses on classifying sentiments based on the polarity/valence (positive, negative, neutral) of text [20]. Some research have further explored classifying the sentiment intensity ([31]; [29]); while others have further explored extracting features such as the source and target of a

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sentiment expressed in text [30]. Although sentiments are characterized by valence and intensity, they are in fact more complex.

Sentiments are not just momentous constructs, they are defined as "an acquired and relatively permanent major neuropsychic disposition to react emotionally, cognitively, and conatively toward a certain object (or situation) in a certain stable fashion, with awareness of the object and the manner of reacting" [2] (See section 2.3 for further discussion). Unlike brief emotional episodes, sentiments about an object are formed over time and are enduring [23]. For example, a single tweet may read "I am angry at my sister today", this statement is an emotional response to something that"the sister" has done "today", whereas the enduring sentiment towards the sister might be in fact pleasant and loving majority of the time. It is the dynamics of sentiment formation that lead to "enduring patterns of liking and disliking" of objects [26]. Research in SA has thus far concentrated on the momentous expression of feelings and emotions, and not made strides to identify the enduring sentiments (see [17] for an analysis on the differences between emotions and sentiments).

To rectify this problem, our work in this paper goes into the deeper analysis of "sentiment over time" to explore the concept of *enduring sentiment*. The proliferation of social media allows us to obtain enough user data to go deeper and analyze this concept. Hence, beyond negative and positive attributes, we can investigate changes in emotion dispositions formed over time and how these changes reflect into sentiments.

The main contribution of our work relies on the ability to extract intrinsic emotional knowledge through the social network Twitter and provide a fine-grained visualization of that knowledge. EmoTwitter presents a visual time analysis of the emotional information flow of Twitter users towards certain topics and estimates the enduring sentiment towards those topics. The current work is part of a broader project on detecting antisocial behavior from online sources, whereby identifying enduring sentiments is beneficial in the prediction of future behavior.

2 Background

2.1 Twitter Microblogging Platform

Twitter is a social microblog platform that allows people to post their views and sentiments on any subject; from new products launched, to favorite movies or music to political decisions [14]. As a microblog platform, users can only share short messages called tweets (max 140 characters) which are usually written by one person who updates it personally [14]. The content of tweets can be personal or things that a person considers of interest.

The popularity of Twitter and the vast amount of information posted through it has made it attractive for natural language analysts. The tweets are also public and hence accessible to researchers unlike most social network sites [28]. Furthermore, tweets are reliably time stamped so that they can be analyzed from a temporal perspective.

2.2 Sentiment Analysis for Twitter

SA has usually been treated as a simple classification task, classifying texts into positive and negative (and sometimes neutral) categories (see [20] for a review). Martínez-Cámara et al., [14] note that SA on tweets is no different from the analysis on long texts even though the short length of the tweets or their linguistic style that tends to be informal, with abbreviations, short hand, idioms, misspellings and incorrect use of grammar, make it difficult for NLP analysis.

Over the past two years a large number of SA programs have been developed to predict the sentiment content of texts in tweets. Normally, analyzing sentiment in tweets takes one of two approaches: lexicon-based or machine learning (ML). Lexicon-based approaches rely upon different features such as the presence of emoticons or certain words and phrases in order to determine the polarity of a sentence or document [28]. For example, Hogenboom et al., [10] made use of emoticons as features. Emoticons are a reoccurrence in tweets, and were found to be a good classification feature. Other lexicons used for sentiment classification include SentiWordNet [4] and WordNet-affect [27], both which contain words that have been labeled with their polarity orientation.

On the other hand, ML techniques involve the building of classifiers (e.g. Näive Bayes, maximum entropy and support vector machines) from instances of labeled tweets [7]. ML techniques can be employed to use several features including ones from lexicons for classification.

Our work falls within the lexicon-based approach. Advantageously, using the lexicon-based approach allows our system to handle slang words, misspellings and also keyword sets for different sets of languages like Spanish or French.

2.3 Enduring Sentiment

Murray and Morgan [18] define sentiment as "a more or less enduring disposition (predilection or readiness) in a personality to respond with a positive or negative affect to a specified entity". The word enduring is defined by Oxford as "lasting over a period of time" [19]. In Gordon [8], a similar definition of sentiment is found; sentiments are "socially constructed patterns of sensations, expressive gestures, and cultural meanings organized around a relationship to a social object, usually another person (...) or group such as a family". Broad [1] explains that a sentiment is formed when a certain object is constantly perceived or thought of by a person and, over time, the person creates a dispositional idea towards the object. This dispositional idea has corresponding emotional tendencies that are evoked whenever the person perceives, thinks about the object or any symbols related to the object. In Pang and Lee [20], a sentiment "suggests a settled opinion reflective of one's feelings", where the word 'settled' indicates something that reoccurs over time.

The definition of sentiment in SA has often been simplified to, for instance, as an explicit or implicit expression in text of the writer's positive, negative or neutral regard toward a subject [12]. However, beyond this, sentiments are enduring and that is the focus of our investigation.

Identifying the enduring sentiment could prove beneficial, for instance, in sorting reviewers by relevancy. For example, a bad review of the movie 'Sky Fall' from a person who likes action movies would have more merit for a recommendation system, than a bad review from someone who dislikes action movies. The enduring sentiment attribute can additionally be used in market analysis to identify the loyal customers; those who have liked a brand or product for a long period of time even if they have been instances of dislike.

2.4 Temporal Sentiment Visualization

Havre et al., [9] proposed an information visualization system called ThemeRiver that visualizes thematic variations over time within a large collection of documents. The "river" flows from left to right through time, changing width to depict changes in thematic strength of temporally associated documents. Colored "currents" flowing within the river narrow or widen to indicate decreases or increases in the strength of an individual topic or a group of topics in the associated documents.

Mishne and Rijke [15] also developed a system called MoodViews, which is a collection of tools for analyzing, tracking and visualizing moods and mood changes in blogs posted by LiveJournal users.

Fukuhara et al., [6] similarly to ThemeRiver, focus on the visualization of both topical and sentiment flow along within a timeline. The method accepts texts with timestamps such as Weblogs and news articles, and produces two kinds of graphs, i.e., (1) topic graph that shows temporal change of topics associated with a sentiment, and (2) sentiment graph that shows temporal change of sentiments associated with a topic.

TwitInfo, a prototype system for monitoring events on Twitter, uses a timeline graph showing the major peaks of publication of tweets about a particular topic, the most relevant tweets, and the polarity of the opinions they express [13].

Duan et al., [3] further developed three interactive widgets that are arranged together to create coordinated multiple views: the sentiment trend view showing the temporal sentiment dynamics and sentiment comparisons among different categories/topics, the chart visualization view illustrating the associated structured facets, and the snippet/document panel providing details of documents and context of sentiment. Mash-up capabilities among the three views allow the user to navigate the data set using optimal interactions.

A more recent visualization system is that from Kempter et al., [11] called EmotionWatch. It automatically recognizes emotions using the Geneva Emotion Wheel, version 2.0 [25]. They score tweets into 20 discrete emotion categories. In their research, they found out that 20 emotions are too many for users.

However in all the visualization systems above, they aggregate the sentiments and summarize the results topic-wise or polarity-wise. None of them have yet to create a visual representation illustrating the flow of emotions a single user has towards a topic over a period of time. This is necessary when analyzing the emotional dispositions that form the enduring sentiment.

Ours is the first visualization system to combine multiple views while allowing for extraction of emotions, as well as polarity and the analysis the emotions over time in order to identify the enduring sentiments.

3 EmoTwitter

For the purposes of emotional analysis of tweets we have designed and implemented an automated system that performs several actions. First, EmoTwitter accepts a Twitter user name and downloads Twitter posts written by the user (Fig. 1). The system then extracts the emotions present in the tweets, their negative and or positive attributes, and the topics in the tweets. It then produces a fine-grained visualization of the emotional information in the collection and produces a visualization of the enduring sentiment.

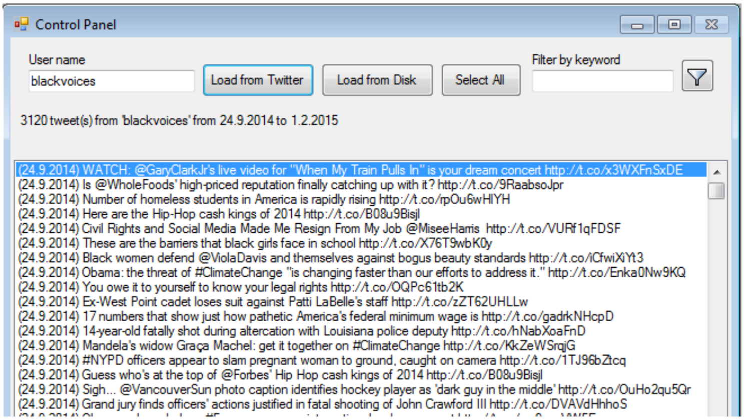

Fig. 1. View of downloaded tweets from Twitter user 'blackvoices'. The window shows the total count and time period of the downloaded tweets. It also includes a place to enter keyword and filter tweets by that particular keyword.

3.1 Downloading Tweets

It is fairly easy to obtain a collection of tweets as the posts are inherently public and a percentage of them are available for download [28]. Using the Twitter API, our software system can download a collection of past tweets of any specified user. For the subsequent analysis, we remove retweets as they might reflect emotions of Twitter users other than the user in consideration. Note, however, that the Twitter API can only return up to 3,200 of a user's most recent tweets, including retweets. A possible way to overcome this limitation would be to constantly follow certain users and store their tweets as they appear.

3.2 Extraction of Emotional Indicators

In order for a richer exploration of emotions that goes beyond the mere polarity of tweets, we extract emotions from the tweets by comparing each sentence in a tweet against the NRC word-emotion association lexicon [16]. The lexicon has been manually annotated into eight categories according to Plutchik's [21] eight basic emotions: joy, sadness, fear, anger, anticipation, surprise, disgust, and trust. The annotations also include scores for whether a word is positive or negative. Each score in the lexicon is simply a boolean marker, denoting whether the given word belongs to a given emotion category. In our calculations, when a word in a tweet matches a word in the lexicon, we mark that word with a score of 1 within the matched emotion category, and when the word does not match any word in the lexicon, we mark it with a score of 0. Currently the lexicon includes emotional annotations for 6,468 unique words. Further descriptions of the lexicon can be found in an article by Mohammad and Turney [16].

In our work, an emotion score (*eScore*) is calculated for each one of Plutchik's eight categories represented in each tweet as follows:

$$eScore_{category} = \frac{eWords_{category}}{eWords_{all}} \tag{1}$$

Where:

- $\mathrm{eWords}_{\mathrm{category}}$ is the number of words in the uploaded tweets that have nonzero emotional score for the category according to the NRC lexicon.

- $\mathrm{eWords}_{\mathrm{all}}$ is the number of words in the uploaded tweets that have nonzero emotional score for any category according to the NRC lexicon.

3.3 Data Visualization

Our system visualizes obtained scores with a variety of graphical forms. The visualization shows the following:

3.3.1 Emotion Distribution

Emotional scores, calculated over a sequence of tweets, are visualized on a radar chart that directly resembles Plutchik's wheel of emotions.

The radar chart (Fig. 2) has eight independent axes, corresponding to the individual primary emotions. For each axis, we calculate a point of average emotional score over the uploaded tweets (i.e., for each tweet, we calculated the *eScore* and then summed up all the *eScores*, and divided the resulting value by number of entries). Then these points become vertices of a filled polygon, thus providing a convenient visualization for the eight primary emotional scores.

3.3.2 Emotion Polarity

In addition, polarity attribute scores are visualized on a bar graph (see Fig. 3). Since "positive" and "negative" annotations are directly present in the NRC lexicon, in Fig. 3, we make use of this information. The visualization shows the positive and negative average values for the given range of uploaded tweets.

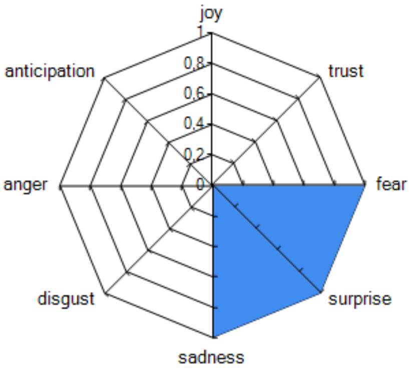

Fig. 2. Distribution of emotions within the downloaded tweets of Twitter user 'blackvoices'

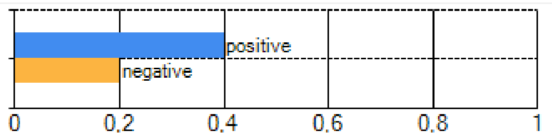

Fig. 3. Downloaded tweets' positive and negative score averages of Twitter user 'blackvoices'

3.3.3 Topics

Most topics found frequently in the uploaded tweets are displayed as a word cloud, which is convenient for identifying frequent topics conveyed by one particular Twitter user (see Fig. 4). Before building a word cloud, we apply a stopword removal procedure and Porter's stemming algorithm [22]. These steps help to focus on the linguistically significant components of text by removing common words that are not topics such as "without", "soon", "sometime", etc.

EmoTwitter further allows for the interaction with the word cloud. By clicking on any word in the word cloud, the system filters the tweets to only display those tweets talking about the clicked topic. Fig. 5 displays a screenshot of the word cloud where for instance the topic "Ferguson" has been selected.

3.3.4 Temporal Flow of Emotions

Our system also allows for the visualization of the temporal flow of emotions in the uploaded tweets. For the temporal flow-chart, a user has the choice of visualizing all the emotions or selecting a combination of emotions. Fig. 6 shows the visualization when four of the emotions are selected.

For the temporal flow-chart, we build average emotional scores for each time entry and thus obtain a calendar-like view of emotional changes in the writings. In the given samples, the entries are given for the three different dates; hence,

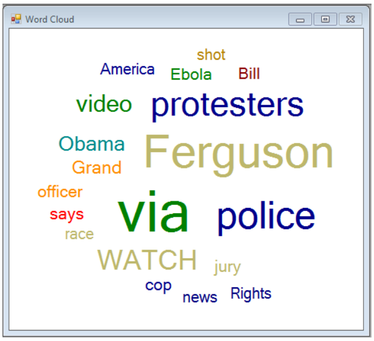

Fig. 4. Word cloud illustrating frequent topics for the Twitter user 'blackvoices'

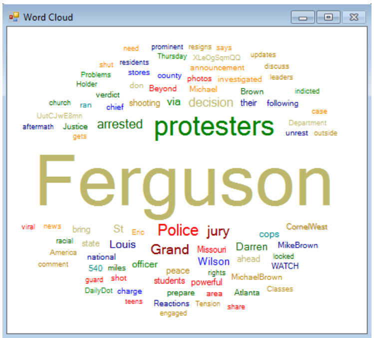

Fig. 5. Word cloud illustrating a selected topic 'Ferguson' from the topics of Twitter user 'blackvoices'

the graphs are built for all time points. The Y-axis values for the flow chart are calculated in the same manner as for the *eScore*, (i.e., number of emotional words for the given category divided by the number of emotional words).

As sentiments can be classified according to the nature of their emotional disposition or according to their objects [5], we classify the enduring sentiments according to the former as it fits our purpose of investigating the sentiments formed towards an object.

Thus, we mapped the observed emotions given in the tweets onto two broad categories of enduring sentiments, *Like* and *Dislike* with the following formula:

$$Like = Average(eScore_{joy,trust,anticipation}) \tag{2}$$

$$Dislike = Average(eScore_{anger,fear,disgust,sadness}) \tag{3}$$

Whereby, *like* includes the emotions that have a positive evaluation of the object, i.e, joy, trust and anticipation. *dislike* includes the emotions that have a negative evaluation of the object, i.e, anger, fear, disgust, and sadness.

That is to say that like and dislike are enduring tendencies to experience certain emotions whenever an object comes to mind and or in contact.

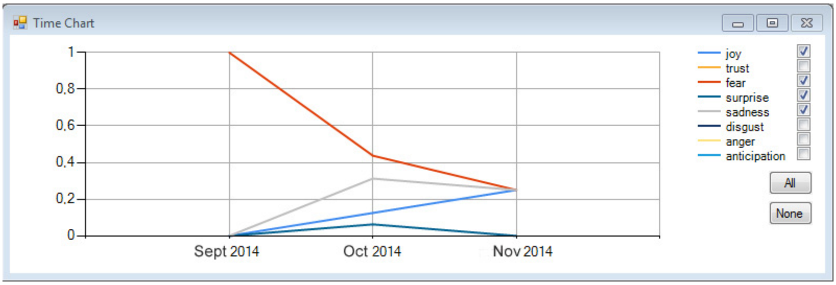

Fig. 6. Emotion distribution for the Twitter user 'blackvoices' with four emotions selected: joy, fear, surprise, and sadness

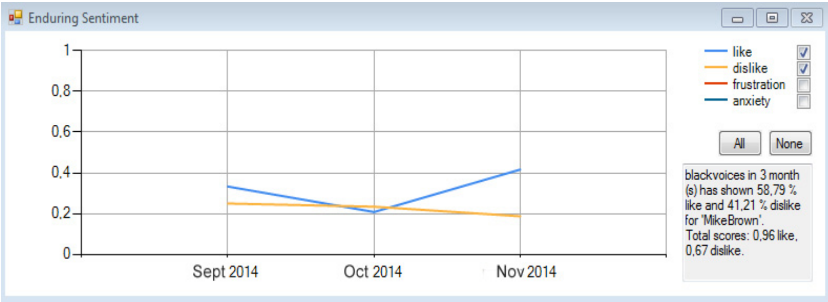

Fig. 7. Like and dislike distribution for the topic 'MikeBrown' from Twitter user 'blackvoices'

A similar graph as Fig. 6 is used to visualize the *like* and *dislike* patterns, with the option of viewing both or one at a time.

Fig. 7, illustrates that a person may experience various emotions towards a particular topic over a period of time. But the enduring pattern of like or dislike towards a topic will become visible over time. In our system, as we are at the moment only able to retrieve and analyze tweets over a couple of months, we made a summary in the enduring sentiment window to indicate percentage and total scores of like and dislike that could be indicative of the enduring sentiment targeted at a particular object. The scores are defined as follows:

$$Like(\%) = \frac{eScore(Like)}{eScore(Like) + eScore(Dislike)} \tag{4}$$

$$Dislike(\%) = \frac{eScore(Dislike)}{eScore(Like) + eScore(Dislike)} \tag{5}$$

$$TotalLike = \sum eScore(Like) \tag{6}$$

$$TotalDislike = \sum eScore(Dislike) \tag{7}$$

Hence, in Fig. 7 we see that for instance, Twitter user 'blackvoices' has shown 58.79% like, 41.21% dislike, 0.96 total like, and 0.67 total dislike towards the topic 'MikeBrown' in the period of three months.

4 Preliminary Evaluation

EmoTwitter is a visualization tool that is designed to explore the emotional and enduring sentiment content in tweets. As an exploratory visualization system, it is difficult to define appropriate evaluation metrics. Since the goal of EmoTwitter is not to classify a whole tweet into an emotion category or polarity category but to identify the emotions in the tweet, traditional metrics such as precision and recall are not applicable. However, to get a sense of the coverage of the lexicon, we compared our measurements to a hand-annotated tweet dataset that aims to serve as the gold standard for model evaluation, the STS-Gold dataset [24]. In addition, as EmoTwitter is an exploratory system, in order for us to get feedback on the usefulness of its capability in accomplishing a variety of analytical tasks, we carried out a user-based evaluation. We evaluate the possible use of the visualization: viewing tweets, and polarity distribution, topics, emotion flow, and like and dislike patterns.

4.1 Lexicon Evaluation

As currently no lexicon exists that has been annotated with Plutchik's eight emotions, we evaluated the coverage of the lexicon based on polarity since there exist publicly available tweet datasets that have been annotated for polarity. For this we compared our system measurements to the hand annotated STS-Gold dataset. The dataset was developed to allow for the evaluation of sentiment classification models at tweet level.

From the STS-Gold dataset, we randomly selected a sample of 50 positive and negative tweets in order to compare the polarity output categorizations by EmoTwiter. In EmoTwitter, if a tweet had a higher proportion of positive words than negative, we counted it as a positive tweet and negative if it had a higher proportion of negative words. Using a chi-square test, we found that the categorizations from EmoTwitter were related with the hand annotations for the whole sample set ($p=0.146$, $df=2$), with an actual agreement of 74% between the hand-annotated and the EmoTwitter results. The agreement number is not itself impressive; however, the lexicon was built independently from the data to which it was applied. These scores however provide an indication that the lexicon we used correlates with the hand annotations from the STS-Gold dataset.

4.2 User-Based Evaluation

To further assess the potential use of EmoTwitter, we performed a formative user-based evaluation with seven participants, one PhD holder, four PhD candidates and two master degree students, all in the computer science field. Three participants had previously interacted with other SA tools while for four participants it was their first time. We first briefed the participants on the purpose of the session and then explained how the system works. We then asked them to freely experiment with the system and fill in a questionnaire after using the system. The average time spent with the experiment was 22 minutes. One participant took about 50 minutes as they were very interested in reading the tweets and seeing how the visualization changes with each tweet. The questionnaire covered questions on display, understanding of all the visual components (on a scale of five from very easy to understand, to not so easy), whether the users found the like and dislike patterns informative, suggestions for improvements, and possible applications for EmoTwitter.

The most liked aspect in interacting with EmoTwitter was that it allowed the participant to follow a person's emotions over time. Many participants became very interested in the emotion flow that they started searching online for information of what could have happened in the Twitter user's life to create spikes and dips in the emotions.

As we are interested in the emotion and sentiment representation, the users' answers to these questions were of interest. The emotion distribution representation was found easy or rather easy to understand by all the participants. The emotion flow was found very easy or easy to understand by all but one participant who found it not easy to understand. This particular participant felt that a user manual was needed in order to interact with EmoTwitter. For the like and dislike patterns, all participants found it either very easy or easy to understand.

When asked whether the like and dislike information in the text area was informative, four out of the seven participants asserted that it was informative. One of the participants stated that the representation would be useful as a way for further analysis.

Improvements suggested by the participants included a better organization of each of the visual display components, and more guiding information for new users. In addition, one participant mentioned that it would be nice to have the ability to analyze more than one Twitter user's emotions at a time. One participant also suggested that EmoTwitter would work better as a web application, which is of the things we plan to implement in the future.

When asked in which situations the participants found EmoTwitter useful; one participant mentioned that it would be nice to analyze a friend's, husband's, competitors', boss's or famous people's tweets. With famous people, one participant mentioned that for example they would like to see what their favorite NBA player says on Twitter and whether the player deserves to be respected.

Another participant pointed out that EmoTwitter can be helpful to law enforcement agencies whereby the agencies can monitor a person's messages and see if anything unpleasant is taking place, like cyberbullying, or if a Twitter user is too negative as stated by another participant. Other participants pointed out that EmoTwitter would be useful for news, marketing and advertising agencies.

Content filtering was another practical usage mentioned for EmoTwitter. Additionally, EmoTwitter was said to be useful as an augmented tool to other systems.

5 Conclusion and Future Work

We have presented EmoTwitter, a multifaceted visualization system. In this paper we have explored the automatic analysis and tracking of emotions within tweets. The developed system presented here aimed to function as an improvement into the way sentiments are currently analyzed and reported. In order to move beyond just the analysis of sentiment polarity we have made an attempt to identify regular occurring patterns of like and dislike over a period of time.

The preliminary evaluation showed that the system successfully presented information in an easy-to-understand manner and that the emotional flow of tweets can be meaningfully extracted.

Future work involves analyzing the like and dislike patterns for a longer period of time so as to observe the enduring sentiments a Twitter user has formed towards topics. This will involve constantly following certain Twitter users and storing their tweets as they appear.

In addition, we plan to conduct a deeper linguistic analysis to better understand the expressed emotions. As the current version of the system makes use of a lexicon-based approach for detecting emotions, we intend to extend the capabilities of the system by incorporating approaches such as aspect-level emotion analysis and common-sense analysis for broader emotion detection.

From the user-based evaluation, we learned that users want to know more about the events causing spikes in the emotion flow, thus we also aim to include event analysis in the emotion flow chart.

We conclude that EmoTwitter is potentially valuable for marketing, advertisement, security, and we plan to develop it further into a full system available online.

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