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Machine-aided analysis of emotions in Twitter conversation

by

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The thesis titled

Machine-aided analysis of emotions in Twitter conversation

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Abstract

With the availability of social media, its abilities and influence on people continues to increase. It is being used for many purposes, such as communication with friends and business partners, advertisement, news delivery, information spread, and so on. To support the analysis of social media content, we developed EmoTwitter, a tool for emotional analysis of twitter messages. Our experiments show that EmoTwitter is able to get tweets in arbitrary location and extract tweets including specific emotions.

The purpose of this paper is to present EmoTwitter, a system for visualizing discussions and emotions of Twitter users. First EmoTwitter can get tweets in real time over a specific geographical location. The system, given location information as input, streams users' tweets posted in real time using the Twitter API. In addition, using content analysis, it extracts and visualizes the most frequent words and emotional content of the streamed tweets. Next EmoTwitter can extract only tweets containing specific emotions from the acquired tweets. The system use NRC word-emotion association lexicon and lexicon is annotated into eight categories according to Pluthick's eight basic emotions [1]. EmoTwitter can describe emotions contained in tweets by digitizing and graphing and extract tweets according to the annotation. Digitizing the emotions makes it easy to know what kind of thoughts and feelings the user is tweeting, which is useful for marketing and crime prevention.

Chapter 1

Introduction

1.1 Background and importance of emotional analysis on Twitter

Recently, many communication tools are used on the Internet, such as Facebook, Instagram, Twitter, WhatsApp etc. Facebook and WhatsApp specialize in communication among acquaintances and specific communities. Instagram and Twitter are good at sharing information with an unspecified group; the former uses pictures, the latter uses tweets. Both of these popular services have hundreds of millions people users and huge amounts of information.

The reason why we chose Twitter is that Twitter has an environment in which it is easy to create a strong emotional tweet and share information. Twitter originally developed as a tool for information dissemination, and real-time property, openness, conversation are emphasized. We think that tweets contain strong emotions and they have different meanings and values from simple sentences. So accurate recognition of emotions is very valuable on Twitter. Twitter is one of the most famous microblogs, having more than 30 million active users [2]. Twitter has also become an important tool for marketing. According to research, many users follow some companies' accounts and take action that are useful for companies [3]. Onnit uses Twitter for communication with users of its own products and for interaction with brand supporters. With this, Onnit has succeeded in keeping the cost for acquiring customers to 40% of the target amount [4]. This trend is expected to continue in the future. So tools for twitter analysis can be of interest to sociologists and business analysts. Bollen et al. investigated whether measurements of collective mood states, derived from a large Twitter feed, correlate with the value of the Dow Jones Industrial Average (DJIA) over time [5]. Kireyev et al. said that they can obtain valuable information for disaster response from disaster microblogging and also explain new clustering methods [6]. Lermen et al. extracted the active user's SNS and examined how the information is diffused on SNS [7]. The ability to identify emotions and output text accurately is important. Still now, it is difficult to read true emotions from sentences without information such as facial expression or voice color of the companion. And many NLP dictionaries have been developed and used according to that purpose [8]. Specifically, they are designed to grasp the customer's review in marketing, predict the outcome in the political campaigns and identify online antisocial behavior (e.g. cyberbullying). Ajao et al. surveyed a range of techniques applied to infer the location of Twitter users from inception to state-of-the-art. It explains that new algorithm processing speed is fast and good for handling proper names and keywords such as place names. [9].

1.2 EmoTwitter

EmoTwitter is a tool for emotional analysis of Twitter messages, created at the University of Aizu [10]. It is written in C# with the support of several third-party libraries and supports several types of text analysis. The most recent version of EmoTwitter is powered by Tweetinvi library [11]. Tweetinvi is a .NET C# library that allows developers to easily and reliably interact with Twitter. When a user inputs a Twitter account name into a textbox, EmoTwitter displays the retrieved tweets of the given user. We implemented some functionality with API support and authentication by substituting a modern Twitter library and making an OAuth authentication module [12]. As described below, EmoTwitter realized various emotional analyses by acquiring a large amount of data by streaming API and filtering by position information and emotional value.

1.3 Objective

The goal of the research is to provide a tool that is easy to use and enables accurate emotional analysis on Twitter. EmoTwitter can decide parameters 8 emotions “joy”, “trust”, “fear”, “surprise”, “sadness”, “disgust”, “anger”, “anticipation” and judgement of “positive” and “negative”. Together with word searches, it helps to know the feelings and thoughts of a person related to a specific person or product. In this thesis, to show the ability of EmoTwitter to detect emotions we analyzed a collection of tweets related to President Trump, who raised a lot of emotional comments in the microblogosphere in recent months.

Chapter 2

Related Works

There are two methods for emotion analysis: lexicon-based and machine learning (ML). Dictionary-based approach is used to determine the polarity of sentences. SentiWordNet [13] and WordNet-affect contain words with polarity labels. Emotwitter uses NRC-Word-Emotion Associations lexicon to deal with not only sensitive but also emotion. This lexicon was developed by S. Mohammad et al. [14], for example, "absolution" includes emotions joy and trust, and sentiment is positive. "Abandon" includes the emotions of fear and sadness, and sentiment is negative. ML technique can be used to use some features, including those from lexicons for classification. Pennacchiotti et al automatically infered the values of user attributes such as political orientation or ethnicity [15] by leveraging observable information such as user behavior, network structure and the linguistic content of the users Twitter feed.

Research on twitter tweets and emotion analysis has been actively conducted. Stefan et al investigated how emotional elements included in political remarks affect retweet number [16]. Jansen et al analyzed micro-blog postings containing branding comments, sentiments, and opinions [17]. Although both are excellent evaluation methods, they do not have a GUI and lack ease of use. As a study combining location information and emotion analysis by dictionary data in Twitter, Marcus et al made application aggregating and visualizing microblogs for event exploration [18]. This research acquires location information obtained from the Google Map API and makes positive and negative decision of surrounding tweet using Stanford CoreNLP. Our research focuses on the development of a tool that can more easily and accurately analyze emotion. Emotwitter has GUI to get tweets various places and feelings, deal with using NRC-lexicon, and corresponds to more detailed analysis.

Chapter 3

EmoTwitter Development

3.1 Streaming API

Twitter supports two kinds of APIs REST API and Streaming API. Figure 3.1 and 3.2 are comparisons of REST API and Streaming API. REST API is the most basic API to put on replacement and reference of tweets, tweet, follow, searching past tweets etc. EmoTwitter was using this API to get tweets before. Streaming API gives developers low latency access to twitter's global stream of tweet data. It is a big advantage of being able to acquire tweets for EmoTwitter in real time, but what you can do compared with the REST API is limited. For example, Streaming API can't get past tweets. Either APIs use HTTP connection, but Streaming API requires keeping a persistent HTTP connection open [19]. When application deal with big data, if application uses REST API, it takes time to download data, then displays and user may get annoyed. But Streaming API downloads data and displays tweets at the same time. So we think Streaming API is suitable than REST API to deal with big data and we decide to use Streaming API. From these features, we use the REST API for the past tweets of certain people and use the Streaming API to get real-time tweets.

3.2 Google Maps API

Google Maps API for .NET is a C# google Maps API interface for interacting with the backend web service for Google Maps. EmoTwitter uses this API to display Google Maps by web browser, search arbitrary location and get latitude and longitude.

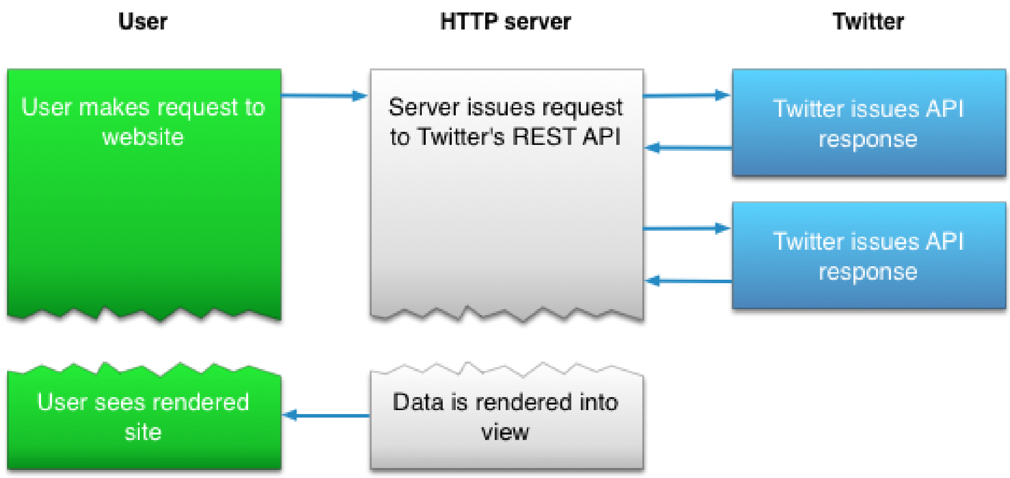


Figure 3.1: REST API process

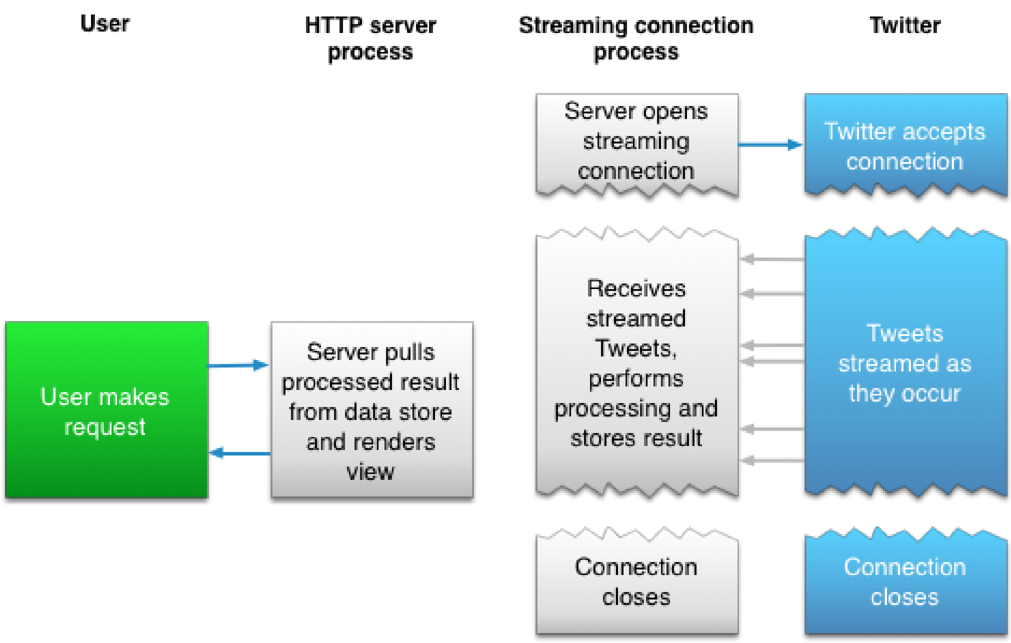


Figure 3.2: Streaming API process

3.3 Get arbitrary location real-time tweets by Streaming API and Google Maps API

EmoTwitter became to be able to search tweets in arbitrary area. This module uses Streaming API and Google Maps API. EmoTwitter uses these API to be able to display arbitrary location and get latitude and longitude of the location. First, user inputs location name that want to search. Then click "Get SearchLocation" button, Google Maps starts display and gets latitude and longitude of location to search. Search range is square area consists of 4 coordinates (latitude+0.5mile, longitude+0.5 mile), (latitude+0.5 mile, longitude-0.5 mile), (latitude-0.5 mile, longitude+0.5 mile) and (latitude-0.5 mile, longitude-0.5 mile). Next click "Start stream" and "Show" button, EmoTwitter displays tweets of the people in this location in listbox. At the same time tweets obtained are displayed in Word cloud. Figure 3.3 visualize tweets in and around New York.

As an example that can effectively use this function, suppose you are trying to study some local event (a football match, a concert, an earthquake, local elections). Then it makes sense to gather local tweets only. Also there are many languages that share the same countries. You might be interested in something UK-related and ignore Canada/US/Australia/etc.

3.4 Extraction of tweets including specific emotions

EmoTwitter uses NRC word-emotion association lexicon. This lexicon is annotated into eight categories according to Plutchik's eight basic emotions (joy, sadness, fear, anger, anticipation, surprise, disgust, and trust) and two sentiments (positive and negative) [20]. Each score in the lexicon is a Boolean marker, denoting whether the given word belongs to a given emotion category. When a word in a tweet matches in the lexicon, EmoTwitter marks that word with a score of 1 within the matched emotion category, and when the word does not match any word in the lexicon, EmoTwitter mark it with a score of 0 [10]. $Emo_{Category}$, the score of the specific emotions that the tweet contains can be expressed by the following formula.

$$Emo_{Category} = \frac{Emo_{WordsCategory}}{Emo_{WordsAll}} \tag{3.1}$$

$Emo_{WordsCategory}$ is the number of words including emotion of category. $Emo_{WordsAll}$ is the number of words including either emotion.

Bottom left of Figure 3.3 is the module of emotional filter. Each numbers in boxes correspond to the filter of emotion. These maximum values are 1.0 and the minimum values are 0. EmoTwitter main module has two listboxes to store tweets. The left side stores all of the tweets getting streaming API. The right side stores tweets extracted by emotional filter. Example in the Figure 3.3, emotional filter allows only tweets that "positive" of $Emo_{Category}$ value is 0.5 or more. Click listbox item, Radar chart displays value of emotion in tweet. Figure 3.4 is Radar-chart of tweet "Radical, Democratic, liberal, terrorists! Trump shuts down ginned-up liberal 'uprising' in three words". This graph indicates that this tweet is from negative and includes emotion of "anger" and a little "fear" and "surprise". Click "Write" button, EmoTwitter outputs tweets in right side listbox in text file. Figure 3.5 is the dataset. Each tweets has 10 numbers behind, in order "joy", "trust", "fear", "surprise", "sadness", "disgust", "anger", "anticipation", "positive" and "negative" score.

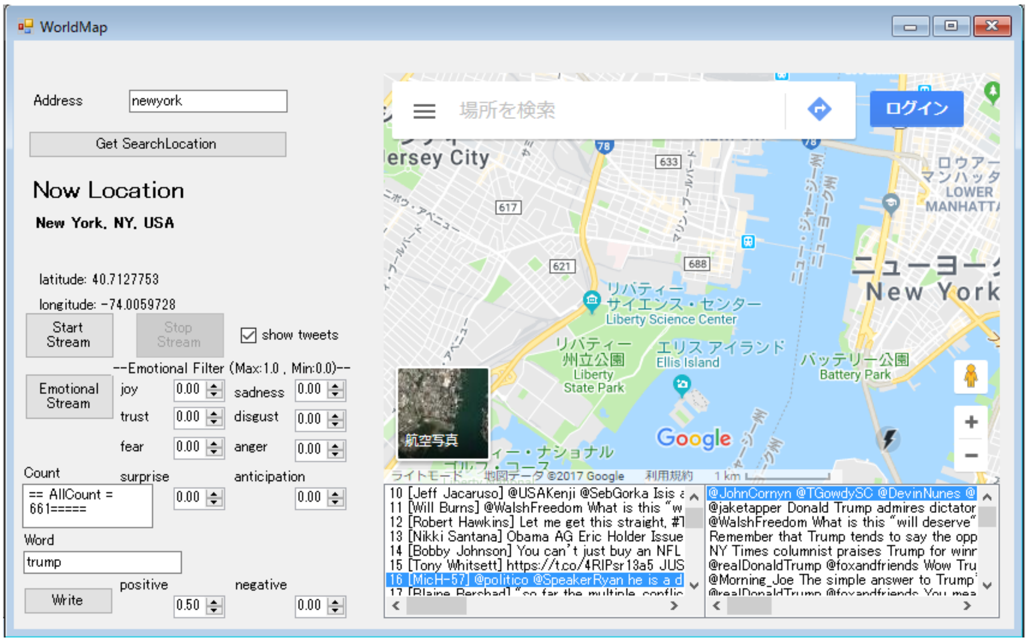


Figure 3.3: EmoTwitter main module

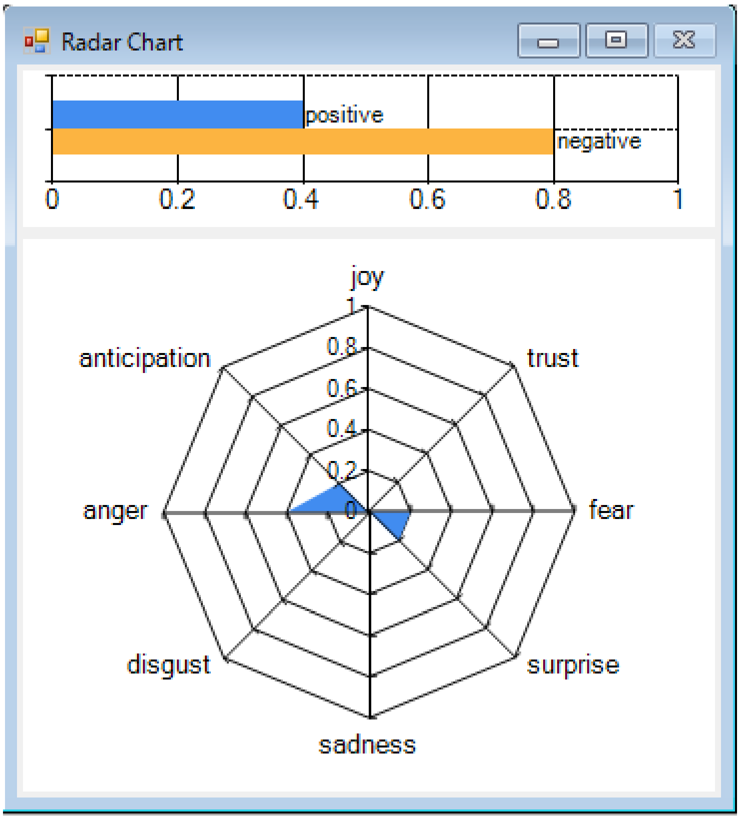
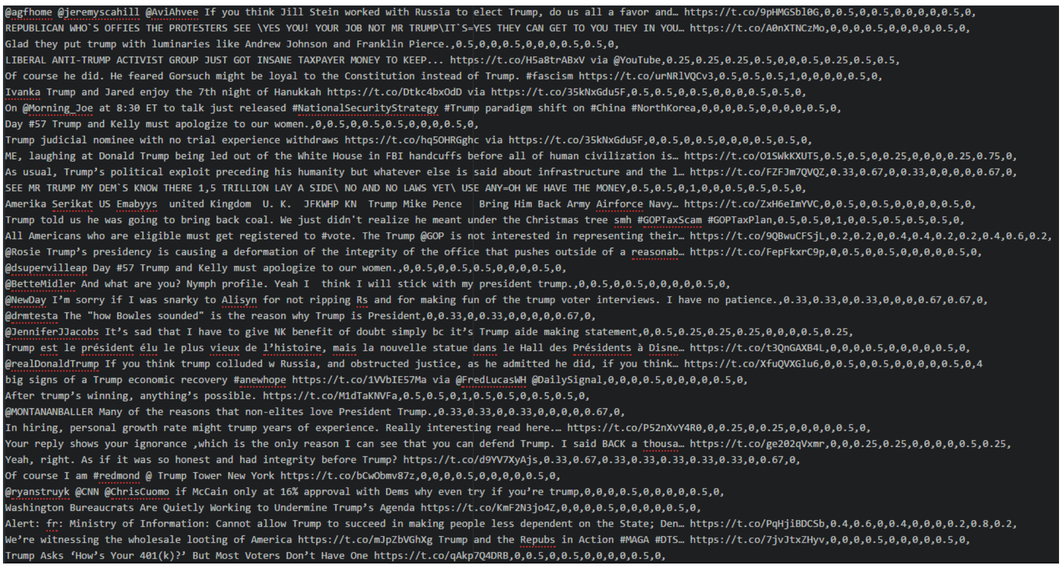


Figure 3.4: Snapshot of Radarchart of tweet "Radical, Democratic, liberal, terrorists! Trump shuts down ginned-up liberal 'uprising' in three words"



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@agfhome @jeremyscahill @AviAhvee If you think Jill Stein worked with Russia to elect Trump, do us all a favor and… https://t.co/9pHMGSbl0G,0,0.5,0,0.5,0,0,0,0,0.5,0,
REPUBLICAN WHO`S OFFIES THE PROTESTERS SEE \YES YOU! YOUR JOB NOT MR TRUMP\IT`S=YES THEY CAN GET TO YOU THEY IN YOU… https://t.co/A0nXTNCzMo,0,0,0,0.5,0,0,0,0,0.5,0,
Glad they put trump with luminaries like Andrew Johnson and Franklin Pierce.,0.5,0,0,0.5,0,0,0,0.5,0.5,0,
LIBERAL ANTI-TRUMP ACTIVIST GROUP JUST GOT INSANE TAXPAYER MONEY TO KEEP... https://t.co/H5a8trABxV via @YouTube,0.25,0.25,0.25,0.5,0,0,0.5,0.25,0.5,0.5,
Of course he did. He feared Gorsuch might be loyal to the Constitution instead of Trump. #fascism https://t.co/urNRlVQCv3,0.5,0.5,0.5,1,0,0,0,0,0.5,0,
Ivanka Trump and Jared enjoy the 7th night of Hanukkah https://t.co/Dtkc4bxOdD via https://t.co/35kNxGdu5F,0.5,0.5,0,0.5,0,0,0,0.5,0.5,0,
On @Morning_Joe at 8:30 ET to talk just released #NationalSecurityStrategy #Trump paradigm shift on #China #NorthKorea,0,0,0,0.5,0,0,0,0,0.5,0,
Day #57 Trump and Kelly must apologize to our women.,0,0.5,0,0.5,0.5,0,0,0,0.5,0,
Trump judicial nominee with no trial experience withdraws https://t.co/hq5OHRGghc via https://t.co/35kNxGdu5F,0,0.5,0,0.5,0,0,0,0.5,0.5,0,
ME, laughing at Donald Trump being led out of the White House in FBI handcuffs before all of human civilization is… https://t.co/O1SWkKXUT5,0.5,0.5,0,0.25,0,0,0,0.25,0.75,0,
As usual, Trump's political exploit preceding his humanity but whatever else is said about infrastructure and the l… https://t.co/FZFJm7QVQZ,0.33,0.67,0,0.33,0,0,0,0,0.67,0,
SEE MR TRUMP MY DEM`S KNOW THERE 1,5 TRILLION LAY A SIDE\ NO AND NO LAWS YET\ USE ANY=OH WE HAVE THE MONEY,0.5,0.5,0,1,0,0,0.5,0.5,0.5,0,
Amerika Serikat US Emabyys  united Kingdom  U. K.  JFKWHP KN  Trump Mike Pence   Bring Him Back Army Airforce Navy… https://t.co/ZxH6eImYVC,0,0.5,0,0.5,0,0,0,0,0.5,0,
Trump told us he was going to bring back coal. We just didn't realize he meant under the Christmas tree smh #GOPTaxScam #GOPTaxPlan,0.5,0.5,0,1,0,0.5,0.5,0.5,0.5,0,
All Americans who are eligible must get registered to #vote. The Trump @GOP is not interested in representing their… https://t.co/9QBwuCFSjL,0.2,0.2,0,0.4,0.4,0.2,0.2,0.4,0.6,0.2,
@Rosie Trump's presidency is causing a deformation of the integrity of the office that pushes outside of a reasonab… https://t.co/FepFkxrC9p,0,0.5,0,0.5,0,0,0,0,0.5,0,
@dsupervilleap Day #57 Trump and Kelly must apologize to our women.,0,0.5,0,0.5,0.5,0,0,0,0.5,0,
@BetteMidler And what are you? Nymph profile. Yeah I  think I will stick with my president trump.,0,0.5,0,0.5,0,0,0,0,0.5,0,
@NewDay I'm sorry if I was snarky to Alisyn for not ripping Rs and for making fun of the trump voter interviews. I have no patience.,0.33,0.33,0,0.33,0,0,0,0.67,0.67,0,
@drmtesta The "how Bowles sounded" is the reason why Trump is President,0,0.33,0,0.33,0,0,0,0,0.67,0,
@JenniferJJacobs It's sad that I have to give NK benefit of doubt simply bc it's Trump aide making statement,0,0.5,0.25,0.25,0.25,0,0,0,0.5,0.25,
Trump est le président élu le plus vieux de l'histoire, mais la nouvelle statue dans le Hall des Présidents à Disne… https://t.co/t3QnGAXB4L,0,0,0,0.5,0,0,0,0,0.5,0,
@realDonaldTrump If you think trump colluded w Russia, and obstructed justice, as he admitted he did, if you think… https://t.co/XfuQVXGlu6,0,0.5,0,0.5,0,0,0,0,0.5,0,4
big signs of a Trump economic recovery #anewhope https://t.co/1VVbIE57Ma via @FredLucasWH @DailySignal,0,0,0,0.5,0,0,0,0,0.5,0,
After trump's winning, anything's possible. https://t.co/M1dTaKNVFa,0.5,0.5,0,1,0.5,0.5,0,0.5,0.5,0,
@MONTANANBALLER Many of the reasons that non-elites love President Trump.,0.33,0.33,0,0.33,0,0,0,0,0.67,0,
In hiring, personal growth rate might trump years of experience. Really interesting read here.… https://t.co/P52nXvY4R0,0,0.25,0,0.25,0,0,0,0,0.5,0,
Your reply shows your ignorance ,which is the only reason I can see that you can defend Trump. I said BACK a thousa… https://t.co/ge202qVxmr,0,0,0.25,0.25,0,0,0,0,0.5,0.25,
Yeah, right. As if it was so honest and had integrity before Trump? https://t.co/d9YV7XyAjs,0.33,0.67,0.33,0.33,0.33,0.33,0.33,0,0.67,0,
Of course I am #redmond @ Trump Tower New York https://t.co/bCwObmv87z,0,0,0,0.5,0,0,0,0,0.5,0,
@ryanstruyk @CNN @ChrisCuomo if McCain only at 16% approval with Dems why even try if you're trump,0,0,0,0.5,0,0,0,0,0.5,0,
Washington Bureaucrats Are Quietly Working to Undermine Trump's Agenda https://t.co/KmF2N3jo4Z,0,0,0,0.5,0,0,0,0,0.5,0,
Alert: fr: Ministry of Information: Cannot allow Trump to succeed in making people less dependent on the State; Den… https://t.co/PqHjiBDCSb,0.4,0.6,0,0.4,0,0,0,0.2,0.8,0.2,
We're witnessing the wholesale looting of America https://t.co/mJpZbVGhXg Trump and the Repubs in Action #MAGA #DTS… https://t.co/7jvJtxZHyv,0,0,0,0.5,0,0,0,0,0.5,0,
Trump Asks 'How's Your 401(k)?' But Most Voters Don't Have One https://t.co/qAkp7Q4DRB,0,0.5,0,0.5,0,0,0,0,0.5,0,
```

Figure 3.5: Data set

Chapter 4

EmoTwitter evaluation and demonstration

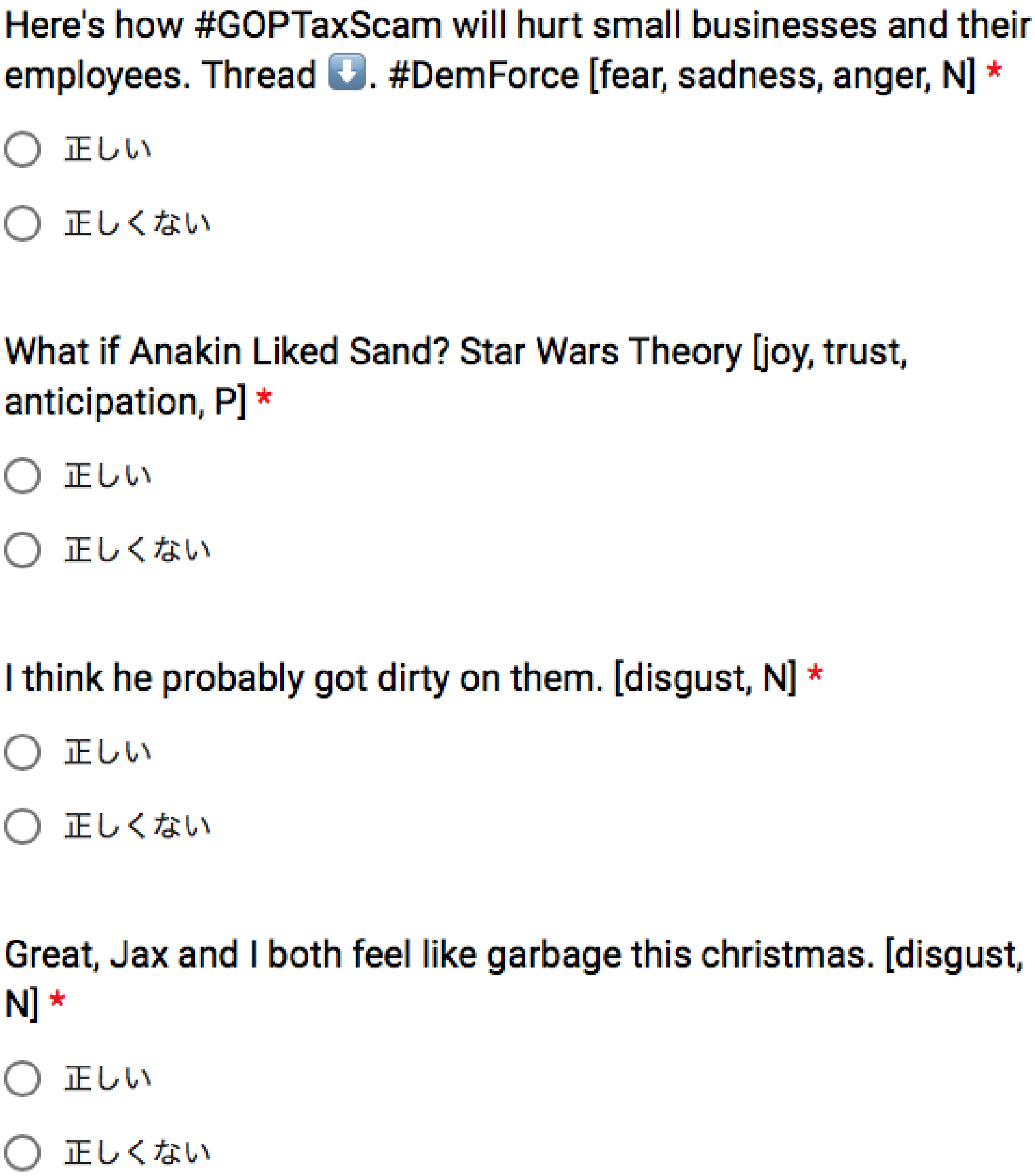
4.1 Case 1: Accuracy survey by questionnaire

We asked 10 collaborators to answer the questionnaire and confirmed the reliability of EmoTwitter. Figure 4.1 is the questionnaire to confirm the accuracy of EmoTwitter. This questionnaire has 50 positive tweets and 50 negative tweets chosen at random judged by EmoTwitter. Each questions has tweets, emotions judged that EmoTwitter is included in the tweet and judgment of positive (P), negative (N). The judges were asked to choose answer, "Correct" or "Incorrect". Then we measured the reliability of the system by comparing it with the answer result. In most tweets, we got a rating of over 72% correct, so EmoTwitter's emotional analysis has reliability.

Table 4.1 is the result of questionnaire about 4 tweets. Each column represents "Tweet", "Positive or Negative", "Emotion included in that tweet judged by EmoTwitter", "Correct vote" and "Incorrect vote". (1) and (2) are questions with the largest number of "Correct" votes. Short tweets and tweets with pronounced emotional bias were found. Over 80% of the questions were such a result. (3) and (4) are questions that "Incorrect" was more. Conspicuous tweets were complicated with positive and negative words with the largest number of "Incorrect" votes. Also tweets that interpretation is easy to change by individuals, and tweets that are difficult to grasp accurate meanings only in the main text were conspicuous.

[Tweets text]

(1) Jumanji was abnormally VERY entertaining... went to see it with very low expectations


Here's how #GOPTaxScam will hurt small businesses and their employees. Thread ⬇️. #DemForce [fear, sadness, anger, N] *

○ 正しい

○ 正しくない

What if Anakin Liked Sand? Star Wars Theory [joy, trust, anticipation, P] *

○ 正しい

○ 正しくない

I think he probably got dirty on them. [disgust, N] *

○ 正しい

○ 正しくない

Great, Jax and I both feel like garbage this christmas. [disgust, N] *

○ 正しい

○ 正しくない

Figure 4.1: Sample fragment of a questionnaire

Table 4.1: The result of questionnaire about 4 tweets

Tweet	Sentiment	Emotion(s)	Correct	Incorrect
(1)	Positive	joy, anticipation	9	1
(2)	Negative	-	10	0
(3)	Positive	trust	1	9
(4)	Positive	trust, surprise	1	9

and was impressed.

(2) Not sure if it's the jet lag or this cold but i cant freaking sleep !!

(3) Sometimes I feel like I have so much to say, but don't always know how to say it.

(4) Can't even imagine what George Carlin would have to say about Trump being president.

4.2 Case 2: Emotional analysis of tweet on specific words

We make use of an interesting use case to demonstrate and test EmoTwitter. The use case is a feeling of tweets about a specific person and their tendency. We gathered positive and negative tweets about Donald J. Trump and decided to explore the trend in and around New York. As the reason for choosing him, he is the president of the United States of America and many people have various opinion to him. Figure 4.2 is an example of Trump's tweet. This tweet is retweeted 10,486 times and there are 14,697 replies. Also we thought, he actively sends his opinion by himself on Twitter and there are many people who moved emotions by him. In this case, positive tweets were targeted for "positive" value were 0.5 or more. Similarly negative tweets were targeted for "negative" value were 0.5 or more.

Figure 4.2: Donald J. Trump's tweet

[The following trend was seen in positive tweets.]

- Thanks to Trump

(ex) @realDonaldTrump Yes!!! President Trump!!! Yes!!!!.

[trust = 0.5, surprise = 0.5, positive = 0.5]

(ex) The liberals have become unhinged. President Trump is showing real leadership and MAGA!

[trust = 0.67, surprise = 0.33, positive = 0.67]

- Include word ”president”

(ex) Our President is repulsive, and if you support the #taxbill but not necessarily Trump because you stand to gain, then you too are repulsive.

[joy = 0.33, trust = 0.33, surprise = 0.33, anticipation = 0.33, positive = 0.67]

(ex) 90% of Trump’s success as President has derived from his doing the exact opposite of what Obama did in every area.

[joy = 0.33, trust = 0.33, surprise = 0.33, anticipation = 0.33, positive = 0.67]

- Criticisms about Trump.

(ex) Yes trump has no ability to manage disasters; only to create them.

[joy = 0.25, trust = 0.25, surprise = 0.25, positive = 0.75]

(ex) @realDonaldTrump AMERICA WILL ALWAYS BE STRONG WITHOUT YOU TRUMP! We don’t NEED YOU.

[trust = 0.5, surprise = 0.5, positive = 0.5]

[The following trend was seen in negative tweets.]

- A direct bad mouth to Trump.

(ex) Trump is —(dirty words) guy. His behavior analyzed for itself is just plane bizarre. Like his habits.

[surprise = 0.5, sadness = 0.5, anger = 0.5, negative = 0.5]

(ex) Well Trump, Merry Christmas! You destroyed the GOP & are too stupid to acknowledge it!

[joy = 0.25, fear = 0.25, surprise = 0.25, sadness = 0.25, anger = 0.5, positive = 0.25, negative = 0.5]

- Dissatisfaction with him

(ex) TRUMP nominated him. He *said* he would bring in “the best people” but all he does is complain about the people HE hired.

[fear = 0.5, surprise = 0.5, disgust = 0.5, negative = 0.5]

(ex) Trump tries to bully the world now, hell bring back the “Ugly American” image against US and hurt the country as a whole.

[fear = 0.5, surprise = 0.25, sadness = 0.25, disgust = 0.25, anger = 0.5, negative = 0.5]

- About tax

(ex) There’s nothing more revolting than watching Trump & the republicans celebrate this grotesque tax cut.

[fear = 0.25, surprise = 0.25, sadness = 0.25, disgust = 0.5, anger = 0.25, negative = 0.75]

(ex) I feel GOP will discard Trump once this thieving tax scam bill is signed.

[surprise = 0.5, sadness = 0.5, negative = 0.5]

About positive tweet, praise Trump tweets standed out. But there are many criticisms about him. Including the word ”president” was seen in both and that number greatly exceeded negative tweet. Emotions of “trust” were seen many in praise tweets. About negative tweet, dissatisfaction with Trump tweets standed out and aggressive were seen. Including the word ”tax” were seen voice of dissatisfaction with his tax reform. There were also many other words related to the policies of cards (gop, vote etc). Overall, there were a lot of critical tweets about Trump without regard to positive and negative. Some of the criticisms were sarcastic tweets, and we felt that many of them were judged positive. Also the emotion of “surprise” were seen.

4.3 Tweet trend derived from Wordcloud about Trump

We examined words in word cloud about Trump tweets in a few days. Figure 4.3 and Figure 4.4 is snapshot of wordcloud made by tweets of Trump. What can be said commonly on all days is displaying the word ”realDonaldTrump”. It shows that many users tweets about Trump reply Trump’s official twitter account and use hashtag about his comments. Overall criticism against him was outstanding regardless of positive or negative.

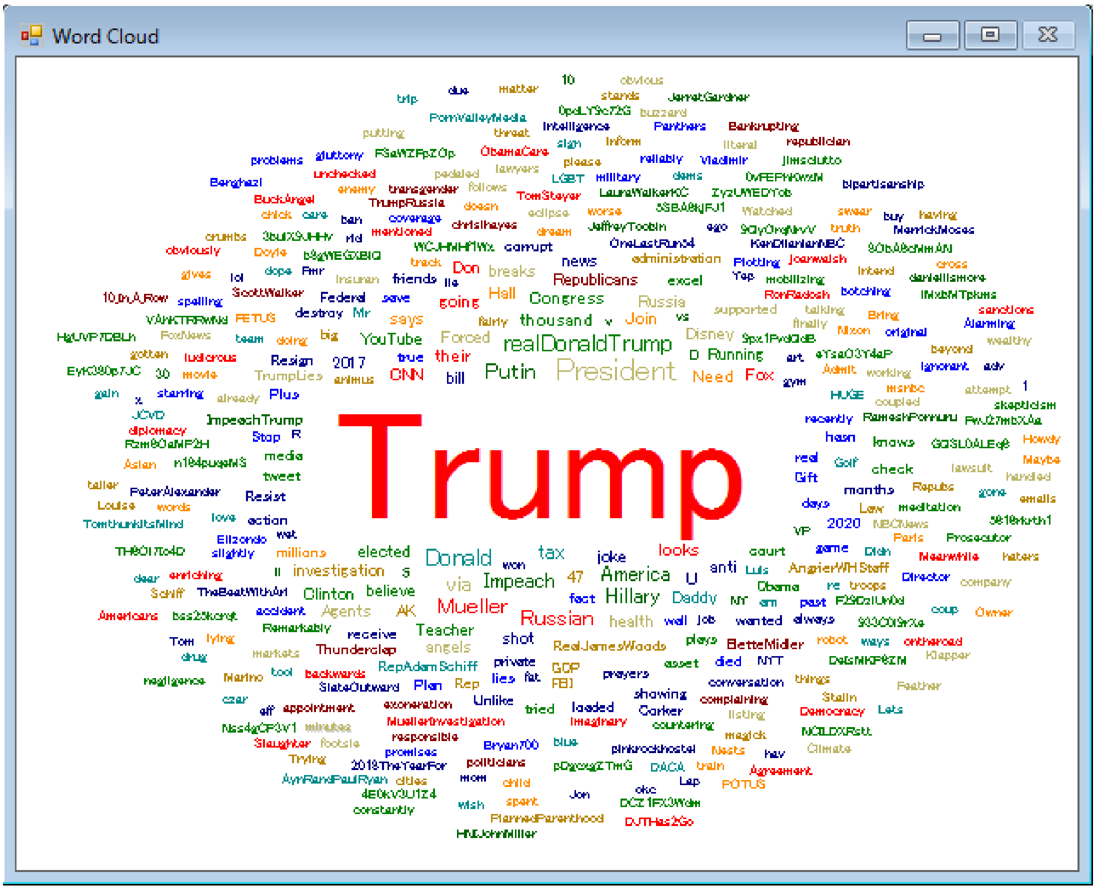


Figure 4.3: Snapshot of wordcloud made by tweets of Trump in Dec.18

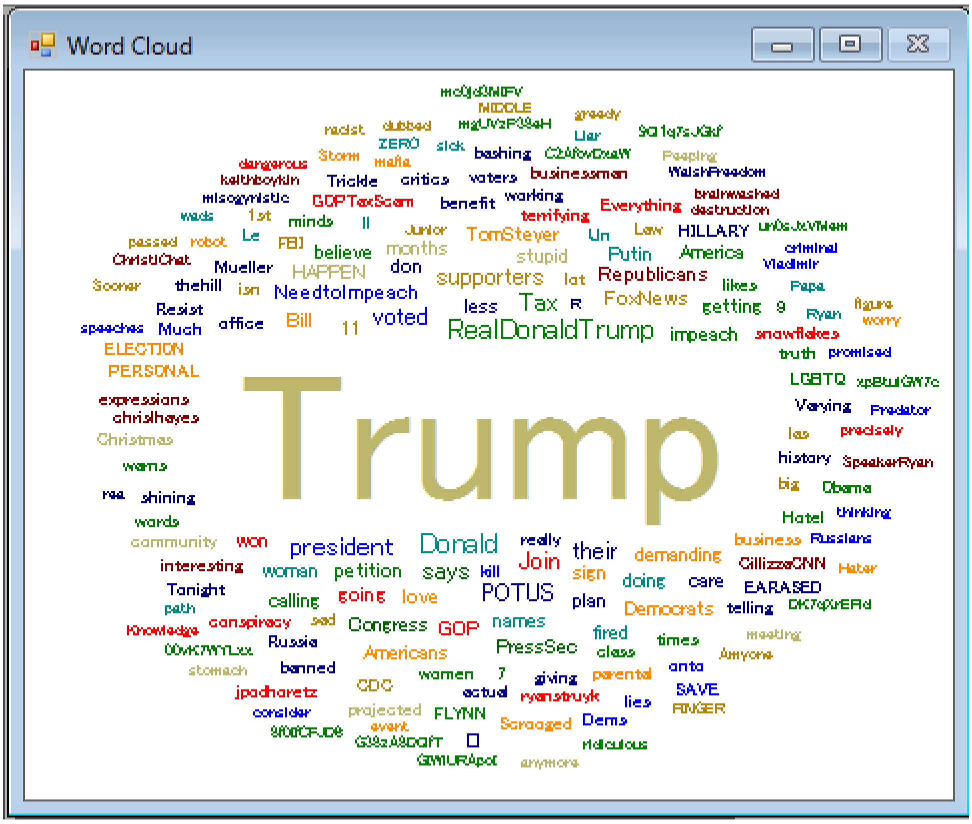


Figure 4.4: Snapshot of wordcloud made by tweets of Trump in Dec.19

Chapter 5

Conclusion

EmoTwitter became to be able to get tweets in arbitrary location and extract tweets including specific emotions. We demonstrated two cases about emotional analysis and got interesting results. EmoTwitter has a module that gathers past user's tweets using the REST API and checks the change of the tendency of emotions included in the tweets [**?**], and it became possible to use it according to the situation. Extraction by emotional filter and Streaming API is useful people's trends for specific keywords like public opinion, trend, election etc. Check the change of the emotion of tweet is useful for marketing, prevention of crime through the Internet. EmoTwitter was able to find tendency from tweets containing specific emotions and prove performance.

But it is also fact that EmoTwitter has some tasks. EmoTwitter can be improved in a number of ways. First, EmoTwitter can't get a long tweet completely. The part behind the long tweet is omitted because of library specification. Also we got an opinion that some tweets were not easy to judge that there are no tweets around it in questionnaire. If we can identify stories from tweets around the user, or from interesting categories, you may be able to do a good feeling analysis of abstract tweets. I would like to introduce other evaluation methods so as to be able to evaluate correctly, even for questions that were not satisfactory in the questionnaire. We think EmoTwitter may be able to solve this problem and analyze wider.

References

[1] R. Plutchik, "Emotions: A general psychoevolutionary theory," *Approaches to emotion*, vol. 1984, pp. 197–219, 1984.

[2] "https://www.statista.com/statistics/282087/number-of-monthly-active-twitter-users."

[3] "Twitter, https://about.twitter.com/ja/company."

[4] "https://business.twitter.com/ja/success-stories/onnit.html."

[5] J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market," *Journal of computational science*, vol. 2, no. 1, pp. 1–8, 2011.

[6] K. Kireyev, L. Palen, and K. Anderson, "Applications of topics models to analysis of disaster-related twitter data," in *NIPS Workshop on Applications for Topic Models: Text and Beyond*, vol. 1. Canada: Whistler, 2009.

[7] K. Lerman and R. Ghosh, "Information contagion: An empirical study of the spread of news on digg and twitter social networks." *ICWSM*, vol. 10, pp. 90–97, 2010.

[8] "http://www.cse.unsw.edu.au/˜billw/nlpdict.html."

[9] O. Ajao, J. Hong, and W. Liu, "A survey of location inference techniques on twitter," *Journal of Information Science*, vol. 41, no. 6, pp. 855–864, 2015.

[10] M. Munezero, C. S. Montero, M. Mozgovoy, and E. Sutinen, "Emotwitter-a fine-grained visualization system for identifying enduring sentiments in tweets." *CICLing (2)*, vol. 9042, pp. 78–91, 2015.

[11] "Tweetinvi homepage: https://github.com/linvi/tweetinvi."

[12] "Y. kobayashi, m. mozgovoy, "emotwitter – a tool for emotional analysis of twitter stream" figure ."

[13] S. Baccianella, A. Esuli, and F. Sebastiani, "Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining." in *LREC*, vol. 10, 2010, pp. 2200–2204.

[14] S. M. Mohammad and P. D. Turney, "Emotions evoked by common words and phrases: Using mechanical turk to create an emotion lexicon," in *Proceedings of the NAACL HLT 2010 workshop on computational approaches to analysis and generation of emotion in text*. Association for Computational Linguistics, 2010, pp. 26–34.

[15] M. Pennacchiotti and A.-M. Popescu, "A machine learning approach to twitter user classification." *Icwsm*, vol. 11, no. 1, pp. 281–288, 2011.

[16] S. Stieglitz and L. Dang-Xuan, "Political communication and influence through microblogging–an empirical analysis of sentiment in twitter messages and retweet behavior," in *System Science (HICSS), 2012 45th Hawaii International Conference on*. IEEE, 2012, pp. 3500–3509.

[17] B. J. Jansen, M. Zhang, K. Sobel, and A. Chowdury, "Micro-blogging as online word of mouth branding," in *CHI'09 extended abstracts on human factors in computing systems*. ACM, 2009, pp. 3859–3864.

[18] A. Marcus, M. S. Bernstein, O. Badar, D. R. Karger, S. Madden, and R. C. Miller, "Twitinfo: aggregating and visualizing microblogs for event exploration," in *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM, 2011, pp. 227–236.

[19] "The streaming api overview, https://developer.twitter.com/en/docs."

[20] S. Mohammad, "#emotional tweets," in **SEM 2012: The First Joint Conference on Lexical and Computational Semantics – Volume 1: Proceedings of the main conference and the shared task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation (SemEval 2012)*. Montréal, Canada: Association for Computational Linguistics, 7-8 June 2012, pp. 246–255. [Online]. Available: http://www.aclweb.org/anthology/S12-1033