CS 410: Final Project Documentation

Brand Sentiment on Twitter using Sentiment Analysis

Team Stanley (Fall 2021)

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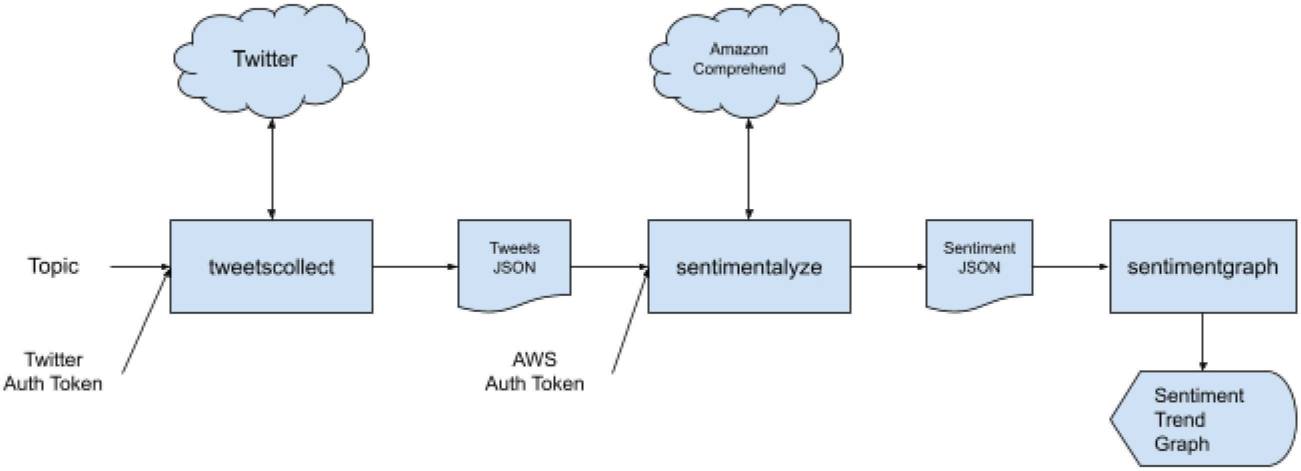
1. Introduction

Sentiment analysis can capture the market or customer sentiment towards a brand. Companies can use this information to better understand their audiences' reactions to the brand's news or marketing campaigns, and to further enhance the brand. Investors or traders can also leverage this information to determine whether they should long or short their positions in the stock behind the brand.

This project is to perform *sentiment analysis* on the *Twitter* tweets related to a given brand over a period of time, and create a sentiment trend graph to visualize the sentiment towards the brand.

There are several tools developed for this project:

1. ***tweetscollect*** for collecting the tweets for a topic from *Twitter* for the past 7 days into a dataset.
2. ***sentimentalyze*** for performing *sentiment analysis* on the dataset.
3. ***sentimentgraph*** for plotting the *Sentiment Trend Graph* based on the result from the *sentiment analysis.*



First, ***tweetscollect*** is used to collect the tweets for a given topic from *Twitter* and write the tweets into a file (i.e. tweets.json). Next, ***sentimentalyze*** takes the tweets returned from ***tweetscollect,*** and performs *sentiment analysis* on these tweets using *Amazon Comprehend* and output the result into another file (i.e. sentiment.json). Afterwards, ***sentimentgraph*** takes the results from ***sentimentalyze*** to create a *Sentiment Trend Graph* for visualization.

2. tweetscollect

2.1. Overview

tweetscollect is a tool for collecting the tweets for a topic from *Twitter* for the past 7 days into a dataset. The topic could be one or more words in English. If the word contains special characters, e.g. "`$`", the character must be escaped accordingly, i.e. "`\$`".

2.2. Implementation

tweetscollect uses Twitter's standard search API v1 to query against a mixture of the recent and popular tweets for the past 7 days for a given topic. Each API call returns a limited number of tweets, and multiple paginations are involved in order to collect all the tweets across 7 days. After all the tweets are collected, the tweets are sorted and each tweet is further reduced to include only the date, text, language, favorite count, and retweeted count. At the end, the resulting tweets are written out to a file in json format based on a schema as described in tweets-schema.json.

There were several considerations for the implementation:

1. *Twitter API v1.1 vs v2.* When we developed *tweetscollect, Twitter's API v2* was in early access, and it lacked some of the functionalities we needed, hence we decided to use the *Twitter API v1.1* instead.

2. *Query abilities and rate limiting.* Using the *Twitter's* standard developer account to collect tweets has several restrictions:
    a. For the standard developer account, *Twitter* focuses only on relevance and not completeness in search results. This means that some tweets could be missing from search results.
    b. There is also a limit which only allows querying the tweets in the past 7 days.
    c. Each query request could return up to 100 tweets, but there is a rate limit allowing only 180 requests (with user authentication) in a 15-min window.
    d. There is also a monthly tweet cap usage which allows only 500,000 tweets to be pulled.

As a result, *tweetscollect* focuses on collecting a mixture of recent and popular tweets over the past 7 days for a given topic, and its focus is on relevance and not completeness of the tweets.

3. *Standard mode vs extended mode. Twitter* originally supported only 140 characters in tweets, and later extended the support to 280 characters for certain languages. However, the *Twitter* API returns the tweet by default in compatibility mode which truncates the text. Hence, our implementation explicitly requests the text to be returned from *Twitter* in extended mode in order to overcome this issue.

4. *Tweets in different languages. Twitter* is a global service available in over 200 countries, and the tweets are written by the users all over the world in various languages. To analyze the tweets for a given topic, this presents a challenge as the entire tweet might not be written in a language which sentiment analysis would understand. For simplicity, our implementation only collects the tweets written in English.

5. *Tweets ordering. Twitter* returns most tweets in reverse chronological order, but there are often a few outliers in the result which don't follow the ordering. Hence, our implementation needs to sort all the collected tweets afterwards to ensure proper ordering.

6. Cost of sentiment analysis. It turns out that it is cost prohibitive to perform sentiment analysis on large volumes of text with public cloud's NLP service, and please see Section 3.2 below for more details. There are 500 millions tweets put up on average every day on *Twitter*. Even if 0.01% of the tweets are relevant to our topic for sentiment analysis, that's 50,000 tweets per day, and the cost could add up quickly. The total number of recent + popular relevant tweets is several orders of magnitude less than the total number of complete relevant tweets, and this is another motivation for our implementation to collect tweets focusing on relevance instead of completeness to make this project affordable.

2.3. Usage

To run *tweetscollect*, here are the prerequisites:

1. You must have Go 1.17 installed.
2. You must have a *Twitter developer accoun*t in order to create a *Bearer Token* to be used by *tweetscollect* for authentication. **If you are a reviewer who wants to test out the tool, please contact the author smho2@illinois.edu directly to get the *Bearer Token*.**

Notice that running *tweetscollect* to collect tweets for the past 7-days involves retrieving tens of thousands of tweets from *Twitter*, and it will take a few minutes for the tool to run to completion. Please be patient!

Also notice that the *Twitter developer account* has a rate limit on the maximum number of requests allowed in a 15-minutes time window, and collecting the tweets for one topic alone might get very close to the limit. Hence, in order to use the tool successfully, please run the tool at most once in a 15-minutes time window.

```
# Build tweetscollect into an executable.
#
$ go build ./cmd/tweetscollect/...

# Show tweetscollect usage.
#
$ ./tweetscollect
Usage:
  tweetscollect -b <bearer-token> -t <topic> [-o <output-file>] [flags]

Flags:
  -b, --bearer-token string   Bearer token
  -h, --help                  help for tweetscollect
  -o, --output-file string    Output file (default "tweets.json")
  -t, --topic string          Topic, e.g. Facebook
  -v, --verbose count         Increase verbosity. May be given multiple times.

# Run tweetscollect to collect tweets for a topic, by using the bearer token
# from your Twitter developer account, and write the collected tweets to file.
#
$ ./tweetscollect -b "<bearer-token>" -t "<topic>"
Collecting tweets from Twitter on topic "<topic>" ...

{ "date": "2021-11-16T00:46:05Z", "text": "JUST IN: Ohio Attorney General sues
Facebook (Meta) for securities fraud.", "lang": "en", "favorite": 1077, "retweet":
328 }
...

Writing collected tweets to tweets.json ...
Done.
```

3. sentimentalyze

3.1. Overview

sentimentalyze is a tool for performing *sentiment analysis* over the dataset with tweets which *tweetscollect* has collected.

3.2. Implementation

sentimentalyze first normalizes all the tweets from the dataset, as there are many retweets and dedupling the tweets could significantly reduce the unique number of tweets for sentiment analysis. Afterwards, *sentimentalyze* sends the unique tweets to *Amazon Comprehend* in batches to determine the sentiment. After all the unique tweets have been analyzed, *sentimentalyze* would reprocess each of the original tweets from the dataset, identify its associated unique tweet and sentiment, and eventually write out the tweets along with their sentiment to a file in json format.

There were several considerations for the implementation:

1. *Retweet.* Many *Twitter* users don't write their own tweets, and they often favorited or retweeted what others had written instead. This means many tweets returned from Twitter had almost identical text, as the duplication is not ideal. Hence, our implementation normalizes the tweets by deduplication, and only performs sentiment analysis on the unique tweets. After the analysis, our implementation would reprocess all the tweets again and associate the sentiment result with each tweet accordingly.

2. Cost of *Amazon Comprehend* for sentiment analysis. It turns out that it is cost prohibitive to perform sentiment analysis on large volumes of text with *Amazon Comprend*. For example, Amazon charges $0.0001 per unit (up to 10M units) which each unit is 100 characters. Simply analyzing 10,000 tweets each with 200 characters alone would cost $2. This is another motivation for our implementation to normalize the tweets to reduce duplication before performing sentiment analysis.

3.3. Usage

To run *sentimentalyze*, here are the prerequisites:

1. You must have Go 1.17 installed.
2. You must have an AWS account in order to create an access key to be used by *sentimentalyze* for authentication. **If you are a reviewer who wants to test out the tool, please contact the author smho2@illinois.edu directly to get a temporary *AWS access key*.**

Notice that running *sentimentalyze* to perform sentiment analysis involves sending all the tweets to *Amazon Comprehend* in multiple batches to process, and it will take a few minutes for the tool to run to completion. Please be patient!

Please be aware that since *sentimentalyze* will use *Amazon Comprehend* from the *AWS account*, the *AWS account* will be charged for usage. On average, each run involves between 40,000 to 60,000 tweets, and that's approximately 15,000 to 25,000 unique tweets which costs $1.5 to $2.5 to perform a single run of *sentiment analysis*.

```
# Build sentimentalyze into an executable.
#
$ go build ./cmd/sentimentalyze/...

# Show sentimentalyze usage.
#
$ ./sentimentalyze
Usage:
  sentimentalyze -i <input-file> -o <output-file> -a <access-key-id> -s
<secret-access-key> [-r <region>] [-l <lang>] [flags]

Flags:
  -a, --access-key-id string       Access key ID
  -h, --help                       help for sentimentalyze
  -i, --input-file string          Input file (default "tweets.json")
  -o, --output-file string         Output file (default "tweets-sentiment.json")
  -r, --region string              Region (default "us-east-1")
  -s, --secret-access-key string   Secret access key
  -v, --verbose count              Increase verbosity. May be given multiple times.

# Run sentimentalyze to perform sentiment analysis on the tweets in the
# input file, using the access key ID and secret access key from the
# AWS account.
#
$ ./sentimentalyze -i <input-file> -o <output-file> -a <access-key-id> -s
<secret-access-key> [-r <region>]
Reading 40655 tweets from tweets.json ...
Normalizing 40655 tweets into 13089 unique tweets ...
Performing sentiment analysis on the unique tweets ...
{ "text": "Insight into the big rebrand.. 😎\nvia \n#Facebook #AR #VR #meta
#Metaverse #virtualworlds\n\nhttps://t.co/bMQ4hhKlTW", "sentiment": "NEUTRAL" }
{ "text": "Facebook owner Meta has opened up more about the amount of bullying and
harassment on its platforms amid pressure to increase transparency\n\n✍️:",
"sentiment": "NEUTRAL" }
...
Writing tweets with analyzed sentiment to sentiment.json ...
Done.
```

4. sentimentgraph

4.1. Overview

sentimentgraph is a tool for creating *Sentiment Trend Graph* based on the result from the *sentiment analysis* which *sentimentalyze* has performed.

4.2. Implementation

sentimentgraph simply reads the result of the *sentiment analysis* from a file, and uses `matplotlib.pyplot` library to create a *Sentiment Trend Graph.* The sentiment returned from the *sentiment analysis* for each tweet is either POSITIVE, NEGATIVE, NEUTRAL, or MIXED. To plot the graph, *sentimentgraph* creates a *stacked area graph* to show how the percentage of positive, negative, neutral, and mixed sentiment have changed over time.

4.3. Usage

To run *sentimentgraph*, here are the prerequisites:

1. You must have [Python 3.10]() installed.
2. You must also have [matplatlib library]() installed.

Notice that running *sentimentgraph* involves plotting a *Sentiment Trend Graph* with tens of thousands of data points, and it will take a few minutes to display the visualization. Please be patient!

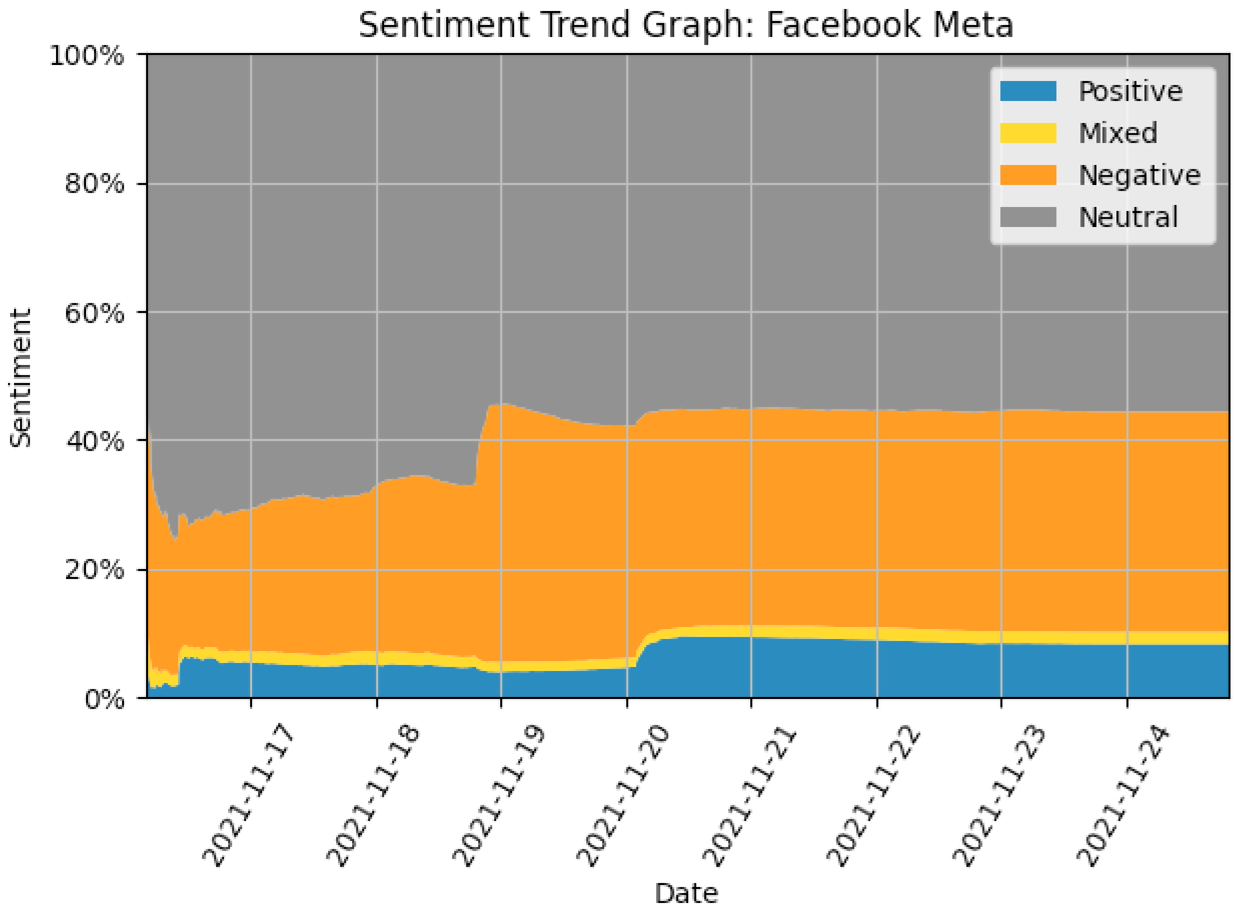
```
# Go to sentimentgraph directory.
#
$ cd ./cmd/sentimentgraph/

# Show sentimentgraph.py usage.
#
$ ./sentimentgraph.py
Usage:
  sentimentalyze.py <sentiment-file>

# Run sentimentgraph.py to create the Sentiment Trend Graph.
#
$ ./sentimentgraph.py sentiment.json
Loading sentiment data from sentiment.json, it will take a minute or two ...
Loaded 2000 sentiment data ...
Loaded 4000 sentiment data ...
Loaded 6000 sentiment data ...
Loaded 8000 sentiment data ...
Loaded 10000 sentiment data ...
Loaded 12000 sentiment data ...
Loaded 14000 sentiment data ...
Loaded 16000 sentiment data ...
Loaded 18000 sentiment data ...
Loaded 20000 sentiment data ...
Loaded 22000 sentiment data ...
Loaded 24000 sentiment data ...
Loaded 26000 sentiment data ...
Loaded 28000 sentiment data ...
Loaded 30000 sentiment data ...
Loaded 32000 sentiment data ...
Loaded 34000 sentiment data ...
Loaded 36000 sentiment data ...
Finished loading 37742 sentiment data!
Plotting sentiment trend graph ...
```

5. Walkthrough

Here is a simple walkthrough on how to use all these tools together. The walkthrough involves collecting the tweets related to the brand “Facebook” from *Twitter*, performing *sentiment analysis* over the tweets, and finally creating a *Sentiment Trend Graph*. Because *Facebook* has recently rebranded itself as *Meta*, we use “Facebook Meta” as the topic for this walkthrough.

```
# Run tweetscollect to collect tweets for topic "Facebook Meta"
#
$ ./cmd/tweetscollect/tweetscollect -b "..." -t "Facebook Meta" -o /tmp/tweets.json
Collecting tweets from Twitter on topic "Facebook Meta" ...

{ "date": "2021-11-23T20:36:44Z", "text": "A user on Instagram commented on my post
that "Kyle should have shot many other ethnicities". \n\nI reported it. But IG told
me today it did not violate any of its community guidelines. \n\nWow. @Facebook
@Meta @InstagramComms https://t.co/VTzXfgpSPp", "lang": "en", "favorite": 73,
"retweet": 23 }
...
{ "date": "2021-11-20T21:55:20Z", "text": "I have decided that My number #1 enemy
for life is Mark Zuckerberg.\n\nI will not explain why. @Meta \n#facebook
#Metaverse #meta", "lang": "en", "favorite": 0, "retweet": 0 }

Writing collected tweets to /tmp/tweets.json ...
Done.

# Run sentimentalyze to perform sentiment analysis on the tweets.
#
$ ./cmd/sentimentalyze/sentimentalyze -i /tmp/tweets.json -o /tmp/sentiment.json -a
"..." -s "..."
Reading 34298 tweets from /tmp/tweets.json  ...
Normalizing 34298 tweets into 11273 unique tweets ...
Performing sentiment analysis on the unique tweets ...
{ "text": "Facebook Rebrands To 'Meta' To Focus On Metaverse - #content",
"sentiment": "NEUTRAL" }
...
{ "text": "In July Facebook told that EU users can turn off ad targeting based on
their political or religious beliefs.", "sentiment": "NEUTRAL" }
Writing tweets with analyzed sentiment to /tmp/sentiment.json ...
Done.

# Run sentimentgraph to create Sentiment Trend Graph.
#
$ ./sentimentgraph.py /tmp/sentiment.json
Loading sentiment data from /tmp/sentiment.json, it will take a minute or two ...
Loaded 2000 sentiment data ...
Loaded 4000 sentiment data ...
Loaded 6000 sentiment data ...
Loaded 8000 sentiment data ...
Loaded 10000 sentiment data ...
Loaded 12000 sentiment data ...
Loaded 14000 sentiment data ...
Loaded 16000 sentiment data ...
Loaded 18000 sentiment data ...
Loaded 20000 sentiment data ...
Loaded 22000 sentiment data ...
Loaded 24000 sentiment data ...
Loaded 26000 sentiment data ...
Loaded 28000 sentiment data ...
Loaded 30000 sentiment data ...
Loaded 32000 sentiment data ...
Loaded 34000 sentiment data ...
Finished loading 34298 sentiment data!
Plotting sentiment trend graph ...
```

Afterwards, *sentimentgraph* will plot a *Sentiment Trend Graph* which is technically a *stacked area graph,* and the positive, negative, mixed, and neutral sentiment are represented in different colors as follows:



As you could see from the graph, > 50% of the tweets have neutral sentiment on the topic. However, among the tweets which have positive, negative, or mixed sentiment, the negative sentiment clearly dominates over the positive or mixed sentiment.

6. Future Extensions

This project provides a basic foundation for performing simple *sentiment analysis* on the tweets over a topic. If we have more time, there are improvements we could further consider:

1. *Tweets relevance*. The *Twitter API* is supposed to return only the relevant tweets based on our query, but we often found that not all the tweets returned from*Twitter* are relevant as expected. To address this, we could consider filtering out the non-relevant tweets before we perform *sentiment analysis* using information retrieval techniques, by ranking the tweets based on relevancy and only collect the tweets that exceed a certain ranking threshold.

2. *Brand sentiment via aggregation on multiple topics.* There are many things associated with a brand, e.g. its products, its stores, its services, etc. Some *Twitter* users might only tweet about a product, but not mention the brand name in their tweets. Hence, to have a

more complete picture on the brand sentiment on *Twitter*, we could consider querying the tweets over a variety of brand’s related topics in addition to the brand itself, and performing *sentiment analysis* over the aggregated result.

3. *Advanced sentiment analysis.* We used *Amazon Comprehend* in this project for simplicity, but the service is only capable of analyzing the overall sentiment of the entire text data in a tweet. If the tweet is long or has a very complex structure, the *sentiment analysis* from *Amazon Comprehend* might not be as accurate as we would like. To address this, we could consider using *sentiment analysis* services from Microsoft Azure or Google Cloud that supports entity-level *sentiment analysis*, and this could improve the accuracy of our result.