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Sentiment Analysis in Geo Social Streams by using Machine Learning Techniques

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SENTIMENT ANALYSIS IN GEO SOCIAL STREAMS BY USING MACHINE LEARNING TECHNIQUES

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SENTIMENT ANALYSIS OF GEO SOCIAL STREAMS USING MACHINE LEARNING TECHNIQUES

ABSTRACT

Massive amounts of sentiment rich data are generated on social media in the form of Tweets, status updates, blog post, reviews, etc. Different people and organizations are using these user generated content for decision making. Symbolic techniques or Knowledge base approaches and Machine learning techniques are two main techniques used for analysis sentiments from text.

The rapid increase in the volume of sentiment rich data on the web has resulted in an increased interaction among researchers regarding sentiment analysis and opinion (Kaushik & Mishra, 2014). However, limited research has been conducted considering location as another dimension along with the sentiment rich data. In this work, we analyze the sentiments of Geotweets, tweets containing latitude and longitude coordinates, and visualize the results in the form of a map in real time.

We collect tweets from Twitter using its Streaming API, filtered by English language and location (bounding box). For those tweets which don’t have geographic coordinates, we geocode them using geocoder from GeoPy. Textblob, an open source library in python was used to calculate the sentiments of Geotweets. Map visualization was implemented using Leaflet. Plugins for clusters, heat maps and real-time have been used in this visualization. The visualization gives an insight of location sentiments.

KEYWORDS

Geovisualization

Machine Learning

Opinion Mining

Sentiment Analysis

ACRONYMS

API – Application Programming Interface

GPS – Global Positioning System

IDF – Inverse Document Frequency

IR – Information Retrieval

LVQ – Learning Vector Quantization

PCA – Principal Component Analysis

PMI – Pointwise Mutual Information

REST – Representational State Transfer

SA – Sentiment Analysis

SO – Sentiment Orientation

SVM – Support Vector Machine

Table of Contents

INDEX OF FIGURES

1. INTRODUCTION

1.1 Background

The internet has brought massive change in the way people express their views. Social media is generating a vast amount of sentiment rich data in the form of tweets, status updates, blog posts, product reviews, etc. (Neethu & Rajasree, 2013). “Rapid increase in the volume of sentiment rich social media on the web has resulted in an increased interact among researchers regarding sentiment analysis and opinion mining” (Kaushik & Mishra, 2014). The presence of a huge volume of opinionated data on the web has motivated many researchers to carry out research on such data. Individuals and different organization are increasingly using such data for decision-making. Although the main source of such sentiment rich data are from product review, it is not only limited to that. Product reviews can play a vital role in decision-making to the business holders as they can have an insight of the user’s opinion about the product and can make necessary improvements.

Besides that, sentiment analysis in Twitter data has been used for prediction or measurement in several domains, such as the stock market, political debates, news articles, sports debates and social movements (Bollen, Mao, & Zeng, 2011; Choy, Cheong, Laik, & Shung, 2011; Tumasjan, Sprenger, Sandner, & Welpe, 2010; Zeitzoff, 2011). With this vast amount of sentiment rich data in different domains came the need by companies, politicians, analysts and researchers to analyse the data for different users. For mining and analyzing these data, an automated technique is required as manual mining and analyzing are difficult and time consuming.

Twitter has become one of the most popular microblogging platforms for all ordinary people including celebrities, politicians, companies, etc. Identifying the sentiments of news articles about stock market can facilitate an investor’s decision-making as stock trends can be predicted with this technique (Yu, Wu, Chang, & Chu, 2013). The investors may be encouraged to buy more shares with the positive news thus forcing the price hike while negative news may have opposite effects. However, finding such information from news articles on daily basis is tedious task. Thus, sentiment analysis technique can play an important role in classification and identification of the positive and negative sentiments from stock market news for prediction of stock trend.

Most companies, if not all, are active in social media, and use microblogging site like Twitter to promote their brands and services. But, we should not take social media just as a platform to post and promote goods and services. From the managerial perspective, social media should also be considered as source of information about what the target user thinks about the services.

1.2 Problem Statements

This thesis aims to analyze the location based sentiment analysis for streams of geo-tweets in real-time to analyze geography of happiness. The first step is to identify a big data source, which can deliver data in real-time. This research is using Twitter Streaming API as a feeding data source. Secondly, it is important to have geographical coordinates from where the tweet was sent. The GPS capability in smartphones allow users to create social media data with geotags containing latitude and longitude coordinates. However most people don't turn on the GPS service on their devices to save battery life. This narrows down our data source. To overcome this problem to a certain limit, we use geocoding services to get the geographical coordinates along with tweets. Once the tweet is captured with location information, the project will undertake detail data analysis.

People use very informal languages in most of social media. They create their own shortcuts and punctuation, use slangs and misspellings. Generally, tweets contains hash-tags (marked with the character #), white spaces, URLs, genre specific terminology and abbreviations, and special characters. Before analyzing the text, the text HTML, URLs, white spaces, punctuations, emoticons and special characters needed to be removed. After the pre-processing, it will generate more concise tweet strings, which will make the sentiment analysis process easier and more precise.

1.3 Objectives

The objectives of this research are as follows:

- To connect with the Twitter API for collecting data using location and keyword as filters.
- To apply an algorithm for automatic classification of tweets into positive, negative or neutral.
- Visualization in the form of maps and analysis of the sentiments based on location.

2. CONCEPT AND DEFINITIONS

2.1 Background on Sentiment Analysis

2.1.1 Sentiment Analysis: An Introduction

Sentiment analysis (also referred to as: opinion mining, sentiment mining, sentiment classification, subjectivity analysis, review mining and in some cases polarity classification) refers to the use of natural language processing, statistics, text analysis and machine learning methods to extract and identify sentiments from the source materials. Although, sentiment analysis and opinion mining are referred to as synonyms, (Tsytsarau & Palpanas, 2012) stated that sentiment analysis and opinion mining have slightly different notions. The authors stated that, opinion mining extracts and analyses people's opinion about an entity while sentiment analysis identifies the sentiment expressed in a text then analyses it. Therefore, sentiment analysis deals with extracting opinions, identifying sentiments expressed in the text and classifying them according to their polarity.

2.1.2 Why Sentiment Analysis is Important?

There are millions of online users around the world, who use the internet to write and read things. The internet has made life easier for those who wants to express their opinions. The sentiments expressed online have become one of the most significant factors in decision-making. Dimensional Research conducted a survey, which discusses the percentage of trust people have in online reviews (Freund & Cellary, 2014). The study suggests 74% of customer's confidence is based on reading online recommendations or reviews in 2011, 60% in 2012, and 57% in 2013. However, this figure increases massively in 2014 with 94% customers having trust in online sentiments.

2.1.3 Classification of Sentiment Analysis

The classification process of sentiment analysis of product reviews can be illustrated as in Figure 1. The existing work done on sentiment analysis can be classified according to the level of detail of text, techniques used, etc.

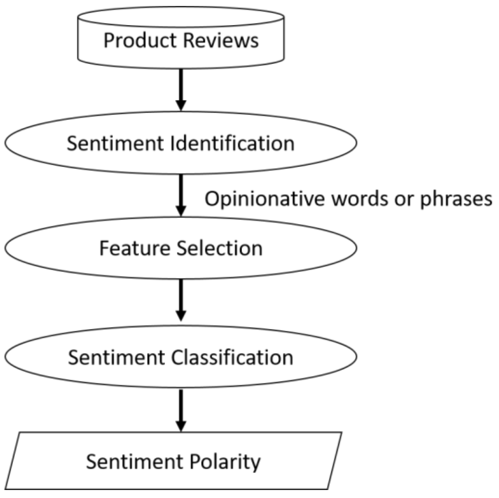


Figure 1: Sentiment Analysis Process on Product Reviews (Medhat, Hassan, & Korashy, 2014)

2.1.3.1 Techniques

The following approaches are used for the sentiment classification.

A. Machine learning approach
B. Lexicon-based approach

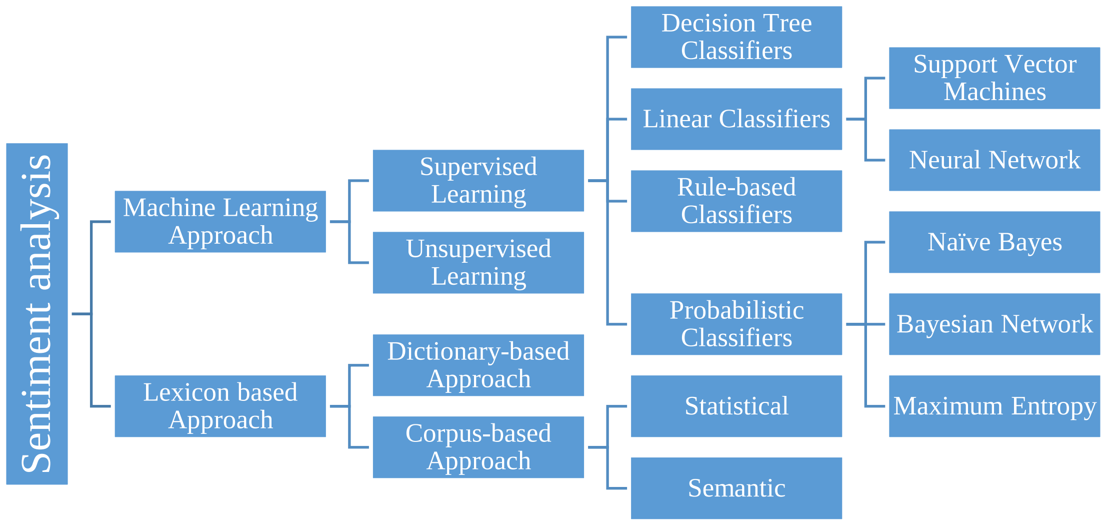


Figure 2: Sentiment Analysis Classification (Medhat et al., 2014)

A. Machine Learning Approach

The machine learning technique uses linguistic features, and is one of the most useful techniques to classify sentiments and categorized the text into positive, negative or neutral categories. The text classification methods using ML approach is classified into two basic approaches as follows:

1. Supervised Machine Learning Approach

   Supervised technique is used for classifying the document or sentence into positive, negative and neutral, and this approach depends on the existence of labelled training documents. In this approach, the system classifies the document based on the training dataset using one of the common classification algorithm or combination of different algorithm. The algorithms or the families of algorithms used in this approach are as follows:

   a) Decision tree Classifier
   b) Linear Classifier
      i. Support Vector Machine
      ii. Neural Network (Perceptron)
   c) Rule Based Classifier
   d) Probabilistic Classifier
      i. Naïve Bayes
      ii. Bayesian Network
      iii. Maximum Entropy

2. Unsupervised Machine Learning Approach

   In supervised learning approach, large number of labelled training documents are used for text classification. However, sometimes it is difficult to create these labelled documents. Unsupervised learning approach overcome these difficulties. In this method, it breakdown documents to sentences, and then categorized the sentences using keywords or opinion words. Sentiment Orientation (SO) of these keywords are determined and based on whether the SO is positive, negative or neutral, the documents are classified.

B. Lexicon Based Approach

Lexicon based technique work on an assumption that the collective polarity of a document or sentence depends on the polarity of the micro phrases or words that compose it. In other words, the collective polarity is the sum of polarities of the individual words or phrases. A microphrase is built whenever a splitting cue is found in the text. Conjunctions, adverbs and punctuations are used as splitting cues. For example, in this sentence “*I don’t like this weather, it’s hot*”, the comma “,” acts as a splitting cue. The lexicon based technique can be also divided as follows:

1. Dictionary Based Approach

   In a dictionary-based approach, first it finds the opinionated words from the document and then searches the dictionary for their synonyms and antonyms. It counts the number of positive and negative words from predefined lexicon in a big corpus, and gives the sentiments of the document. (Goyal & Daumé III, 2011) suggested that dictionaries can also be created manually for lexicon-based approaches using seed words to expand the list of words. This approach is unsupervised in nature and it assumes that positive adjectives appear more frequently with positive opinionated words and negative adjectives appear more frequently with negative opinionated words (Harb, Planti, Roche, & Cedex, 2008).

2. Corpus Based Approach

   Corpus based approach is a data driven approach in which, sentiments of opinionated words are found from a large corpus along with their context. This approach requires large dataset to calculate polarity and consequently sentiment of the document. This approach relies on the polarity of the terms that appear in the training dataset. If the terms don’t appear in the training corpus, it doesn’t calculate its polarity, which is one of the major drawbacks of this approach.

2.1.3.2 Text View

Based on the nature of the text view, sentiment analysis is further categorized into three levels: document level, sentence level and aspect level also known as feature level sentiment analysis.

A. Document Level Sentiment Analysis

In document level sentiment analysis, the whole document is considered as a single unit. It classifies the document and expresses the overall sentiments as positive, negative or neutral. Subjectivity or objectivity classification is very important in this type of classification. The document level sentiment analysis has its own benefits and drawbacks. The main advantage of document level sentiment analysis is getting an overall polarity of whole opinion text, which may be also considered as a drawback as a document may consist of different emotions about different features, which cannot be extracted separately. As a result, the emotions with minority are overshadowed by the majority emotions. Generally, this type of classification is not desirable in forums and blogs. Both supervised and unsupervised techniques can be used in document level classification. Supervised techniques like Naïve Bayesian and Support vector machine can be used to train a system while unsupervised technique can be applied by extracting opinions from the document and finding semantics of the extracted words or phrase.

B. Sentence Level Sentiment Analysis

Sentence level sentiment analysis has similar approach to that of the document level sentiment analysis, but in this method, the polarity of each sentence is calculated instead of the whole document. Sentences are just like short documents. Likewise, to document level sentiment analysis, the first step is to identify whether the sentence is subjective or objective. The opinionated words in a subjective sentence helps to determine the sentiments, which are later classified into positive, negative and neutral classes. (Wilson, Wiebe, & Hoffman, 2005) have pointed out that sentiment expressions are not necessarily subjective in nature. For example, "*I love this story"* is a subjective sentence with positive sentiment; whereas "*This is a love story"* is an objective sentence with neutral sentiment. The benefit of sentiment level sentiment analysis deceives the subjectivity/objectivity classification.

C. Aspect/Feature Level Sentiment Analysis

Many applications require detailed opinions for text classification which, both document level sentiment analysis and sentence level sentiment analysis cannot provide. To achieve the detailed opinions from the text, we need to go to the aspect level sentiment analysis, which is also referred to as feature level sentiment analysis. This approach classifies the sentiments in text with respect to specific aspects of entities. Aspect level sentiment analysis also has its own advantages and disadvantages, with an advantage being accurate extraction of opinions. However, in some cases, where the negating words are far apart from the opinion words, the result may not be fully accurate. Phrase level analysis is not desirable in such cases. For example, the sentence "*The picture quality of this phone is good, but the battery life is short*" has different opinions for different aspects of the same entity.

2.2 Geovisualization

Geovisualization stands for Geographic Visualization. Wikipedia defines Geovisualizatoin as a set of tools and techniques for analysis of geospatial data through the use of interactive visualization (Wikipedia). MacEachren and Kraak (2011) refers to "geovisualization as set of cartographic technologies and practices that take advantage of the ability of modern microprocessors to render changes to a map in real time, allowing users to adjust the mapped data on the fly". It emphasizes the construction of knowledge over knowledge storage or information transmission (MacEachren & Kraak, 2011). Geovisualization when combined with human understanding, allows for data exploration and decision making processes (Jiang & Li, 2005; MacEachren & Kraak, 2011; Pultar et. al., 2009; Rhyne et al., 2004).

Visualization is an important part of data analysis process for efficient exploration and description of complex dataset. It helps to summarize the main characteristics of the datasets with a visual graph. The datasets can be visualize in the form of histogram, line chart, bar chart, pie chart and so on. There are significant amount of researches done on sentiment analysis. However, verylittle research has visualized the results. It's not enough to just classify the sentiments without proper visualization. In this research, we are analyzing stream of tweets with location, filtered by keywords, language or some geographical extent (bounding box). Therefore, to have actionable insights, we need to visualize the differences in sentiment by location. For example, let’s consider the weather report in TV channels. They show the weather information like fog, rain or snow, displayed over a map as a background. That visualization gives us a detailed look on the weather and most importantly, where, the location information. In a similar way, sentiments can also be visualized based on location.

3. LITERATURE REVIEW

3.1 Limitation of Prior Art

A decent amount of research has been done on sentiment analysis in different domains. These research differs from Twitter mainly because of the character limit allowed from the Twitter. The character limit allowed by Twitter was 140 characters per tweet earlier. Twitter has now changed that to 280 characters per tweet. With the popularity of microblogging sites and social networking sites like Twitter and Facebook, they are considered a good source of sentiment rich data. (Tumasjan et al., 2010) analyze over 100000 political tweets published between August 13th and September 19th 2009, prior to the German national election to predict the election. The authors used LIWC2007, Linguistic Inquiry and Word count, (Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007) to automatically extract the sentiments from these tweets. The authors examine the attention the political parties received on Twitter and analyzed the ideology between the parties and potential political coalitions after the election in order to understand whether tweets can help to predict the election outcome. A system was developed for the real-time Twitter sentiment analysis of 2012 U.S. Presidential Election Cycle (H. Wang, Can, Kazemzadeh, Bar, & Narayanan, 2012) which offers new and timely perspective on the dynamics of the electoral process and public opinion to the media, politicians, scholars and public. Although lots of research has been done in this field, there is still a need of proper visualization of the analysis for comparisons between results achieved from different techniques. Most available visualizations are limited to pie charts, bar diagram, line graphs, scatter plot, etc. and to some extent heat maps.

3.2 Related Work

(Medhat et al., 2014) stated that sentiment analysis can be classified in two main categories: Machine Learning Approach and Lexicon-based Approach (Figure 2). The machine learning approach is further divided into Supervised learning and unsupervised learning, the former being divided into different classifying techniques. Lexicon-based approach is divided into Dictionary-based approach and Corpus-based approach. Much research on sentiment analysis has be carried out using these techniques. The research so far has mainly focused on two things: identifying whether a given text is subjective or objective, and identifying polarity of subjective texts (Pang & Lee, 2006).

3.2.1 Machine Learning Approach

Naïve Bayes and Support Vector Machines are the two most used techniques for sentiment analysis. These supervised learning techniques provides best results and are very expensive as manual labelling is required. Some work has been done using unsupervised (e.g., (Brody & Diakopoulos, 2011; Turney, 2002)) and semi-supervised (e.g., (Barbosa & Feng, 2010; Pak & Paroubek, 2010)) approaches leaving lots of room for further improvements.

3.2.1.1 Unsupervised Learning Approach

(Turney, 2002) presents a simple unsupervised learning algorithm for classifying reviews predicted by the average semantic orientation (SO) of the phrases in the review containing adjectives or adverbs. The reviews were classified as recommended (thumbs up) or not recommended (thumbs down). The algorithm classifies the written review in three steps.

First, to identify the phrase in the input text/review containing adjectives or adverbs, the author used part-of-speech tagger. It is a simple process of identification of words as nouns, verbs, adjectives, adverbs, etc. Some words may have dual orientation depending upon the context. Therefore, two consecutive words are extracted, one adjective or adverb and the second providing context.

Second, the semantic orientation of the extracted phrase is estimated using PMI-IR algorithm. The algorithm uses Pointwise Mutual Information (PMI) and Information Retrieval (IR) to measure the similarity of pairs of words or phrases. The phrase is compared to a positive reference word and negative reference word to calculate the semantic orientation. The word “excellent” was used as positive reference word while for negative reference, the word “poor” was used.

In the third step, the author assign the calculated semantic orientation to a class, recommended or not recommended, based on the average semantic orientation of the phrase extracted from the review. The review is assigned as recommended if the average semantic orientation is positive. The author evaluated 410 reviews from Epinions, sampled from four different domains (reviews of automobiles, banks, movies, and travel destinations). Average accuracy of 74% was achieved with automobile reviews getting the highest accuracy of 84% and movie reviews getting the lowest of 66%.

(Brody & Diakopoulos, 2011) present an unsupervised method for sentiment detection in microblogs using word lengthening. The method used word lengthening phenomenon to expand an existing sentiment lexicon and tailor it to the domain. The authors detect the sentiment in three steps. First, the authors demonstrate the widespread use and importance of word lengthening in microblogs and social messaging. Normally people use the lengthening phenomenon to emphasize important words conveying sentiments and emotions. The authors showed the association of lengthening with subjectivity and sentiments in the second part. Finally, an unsupervised method was used to demonstrate the implications of that association for detecting sentiments using an existing sentiment lexicon. For evaluation, the authors compared the methods to human judgement through volunteers and categorized into five class: strongly negative, weakly negative, neutral, weakly positive, and strongly positive.

3.2.1.2 Supervised Learning Approach

(Suresh & Bharathi, 2016) classified sentiments from the RatingSystem.com database using decision tree based feature selection. The customer review information is collected in the database in the form of web forms and emails. In this algorithm, Inverse document frequency (IDF) are used to extract features from the database. The use of the Principal Component Analysis (PCA) decreases the features. The authors used a local classification algorithm, Learning Vector Quantization (LVQ) for effective classification obtaining 75% of accuracy.

Most of the techniques in sentiment analysis use information from diverse sources. The Support Vector Machines (SVMs) approach provides ideal tool in bringing these sources together and is one of the most commonly used approach by the researchers in sentiment analysis field. Support Vector Machines is a well-known and powerful tool for classifying vectors of real-valued features as positive or negative. (Mullen & Collier, 2004) use support vector machines to analyze sentiments from diverse information sources. The authors used the approach adopted by (Turney, 2002) to predict the semantic orientation expressed by a word or phrase using part-of-speech tagger to identify the adjectives or adverbs in the phrase. Further, the authors used WordNet relationships, method of Kamps and Marx (2002) to derive three values appropriate to the emotive meaning of adjectives. The three values introduced in Charles Osgood's Theory of Semantic Differentiation are potency (strong or weak), activity (active or passive) and evaluative (good or bad). The authors believes that sentiment expressed with respect to particular subjects can be best identified with reference to the subject itself. The feature space created from employing semantic orientation values from different sources were separated using an SVM. The SVM technique uses a kernel function to map a space of data points. The authors analyze sentiment analysis on two different datasets: first datasets consisting of total 1380 Epinions.com movie reviews and a second dataset consisting of 100 record reviews from the Pitchfork Media online record review publication.

(Santos & Gatti, 2014) proposed a deep convolutional neural network that exploits from character-to-sentence level information to perform sentiment analysis of short texts. The authors applied the approach for two short texts of two different domains: the Stanford Sentiment Tree-bank (STTb) containing movie reviews; and the Stanford Twitter Sentiment Corpus (STS), containing twitter messages. The proposed network, named Character to Sentence Convolutional Neural Network (CharSCNN), uses two convolutional layers to extract relevant features from words and sentences to explore the richness of word embeddings produced by unsupervised pre-training. With this approach, the authors achieves 85.7 % accuracy in positive/negative classification for SSTb corpus while for the STS corpus, the achieved accuracy is 86.4%.

(Troussas, Virvou, Espinosa, Llaguno, & Caro, 2013) stated few challenges for opinion mining in sentiment analysis from the system developer's viewpoint. One of the challenges includes the insignificance of all the words in a sentence and the possibility of insignificant words being classified as noise. The authors mentioned that, some words like "not" might provide negative meaning to the existing opinion even if they are used with a positive words. The authors see another big challenge in how data are collected for corpus. They developed a system able to classify an opinion using sentence-level classification. Their methods use Facebook application as a main user interface to collect data for the corpus. While collecting the data, they focus on the user's Facebook status post excluding photo stories and application stories. The authors use Naïve Bayes Classifier, Rocchio Classifier and Perception Classifier to compare their performance in terms of precision, recall and F-score in predicting whether a Facebook status update is positive or negative. Around 7000 status updates from 90 users were collected for the classification and the same training and testing set were used for each classifier.

(Berger, Pietra, & Pietra, 1996) in their research prove that Maximum Entropy technique can be effective in number of natural language processing applications. Since Maximum Entropy allows the unrestricted use of contextual features, it is the convenient for natural language processing among several machine learning algorithms. (Y.-Y. Wang & Acero, 2007) also mentioned that the Maximum Entropy algorithm supports convex objective function converging to a global optimum with respect to a training set. (Lee & Bhd, 2011) used Maximum Entropy classification for the comments in Chinese language given for electronic product to examine the effectiveness of the techniques in a language different than English.

First, to retrieve the meaning of the sentences, the authors did segmentation, which then followed by application of conjunction rules, elimination of stop words and punctuation, dealing with negation, and comparison with keywords. The authors classified the results into positive and negative class. Furthermore, the authors also analyze the feature selection and pre-processing of the messages for training and testing purpose, apart from presenting the results obtained from Maximum Entropy technique.

The authors found the increment in overall accuracy of sentiment analysis stage by stage from 81.65% to 87.05% thus proving higher accuracy can be achieved using Maximum Entropy classification. Other researchers (Nigam, John, & McCallum, 1999) also found that Maximum Entropy works better than Naïve Bayes for their experiment.

3.2.2 Lexicon-based Approach

In a Lexicon-based approach, the semantic orientation of words or phrases in a document are used to calculate the semantic orientation of the document (Turney, 2002). In most of the research based on lexicon-based approach, the semantic orientation of the text is calculated using adjectives as indicators. Previous studies also show that adjectives are good indicators of semantic orientation (Hatzivassiloglou & McKeown, 1997).

3.2.2.1 Dictionary-based approach

(Cruz, Ochoa, Roche, & Poncelet, 2016) experiments dictionary based sentiment analysis over two domains: Agricultural domain and a Movie domain. For the agricultural domain, the authors extracted the opinions from Twitter while for the Movie domain, they used the dataset introduced in (Pang, Lee, & Vaithyanathan, 2002). First, the authors acquired the data containing positive and negative opinion, for specific domain from the web followed by preprocessing to remove HTML tags and scripts from the text. The opinion adjectives and nouns extracted using POS-Tagging and the Window Size algorithm are used to compute correlation score, which is classified into positive and negative lexicons. (Chopra & Bhatia, 2016) also followed similar algorithm, but for the text in Punjabi language. In their experiment, the authors found that positive words are used less in reviews in comparison with the negative words.

3.2.2.1 Corpus-based approach

Moreno-Ortiz & Fernández-Cruz (2015) applied corpus-based, machine learning sentiment analysis approach for financial text. The authors used a simple 3-step model based on weirdness ratio to extract candidate term from the corpora, which are then matched against existing general language polarity database. This approach allows to obtain sentiment-bearing words whose polarity is domain specific. (Abdulla, Ahmed, Shehab, & Al-ayyoub, 2013) also performed corpus based sentiment analysis for an Arabic dataset composed of 2000 Tweets; 1000 positive and 1000 negative. The authors observed that the accuracy of corpus-based tool using SVM for classification yields higher accuracy.

4. Methodology

This section will explain the architecture of our system along with the main components. The process begins with data collection from Twitter API, Data Filtering, Geocoding, Pre-Processing, Sentiment analysis, Data storage and finally map visualization. Figure 3 represents the system architecture.

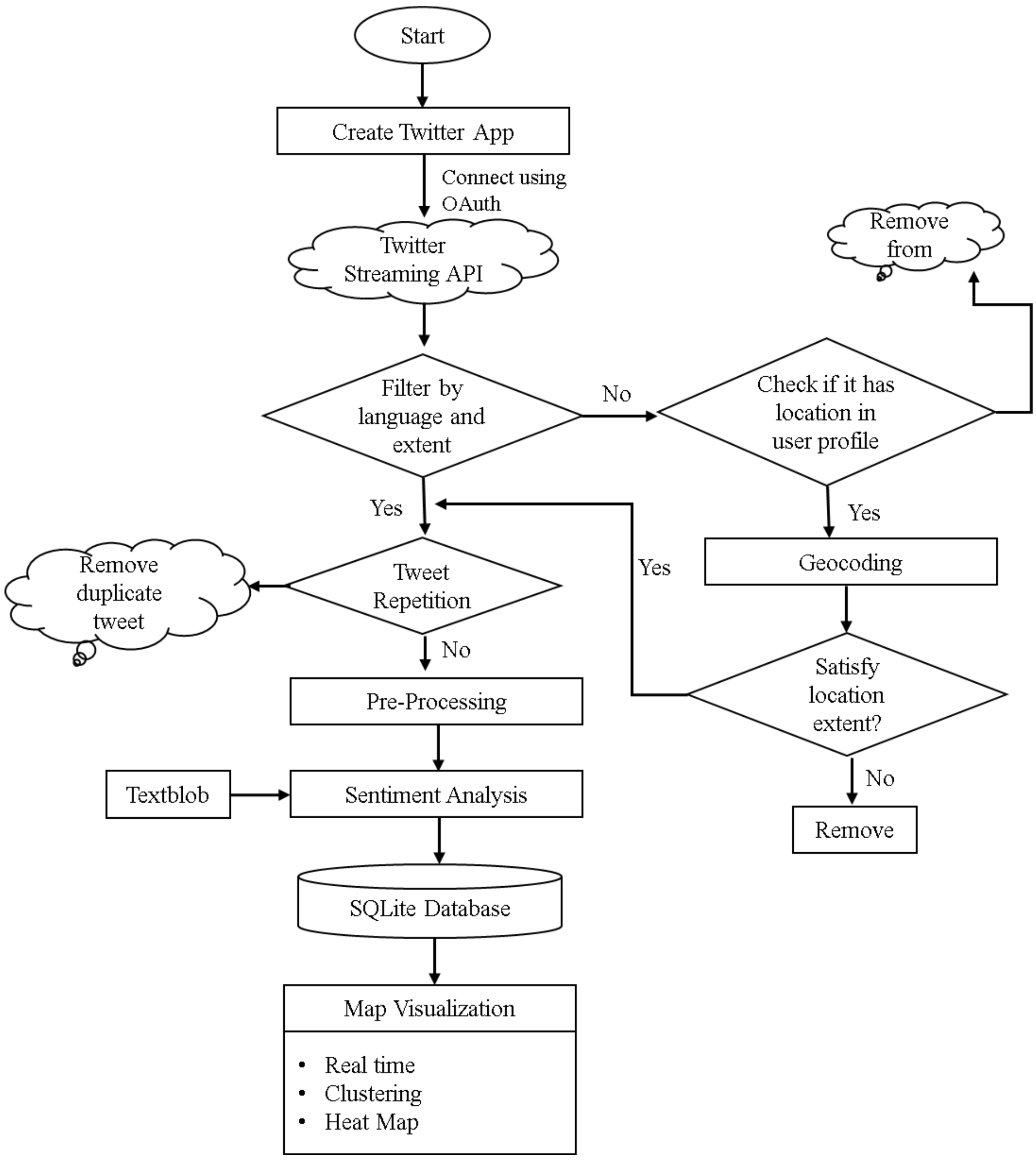


Figure 3: Approach Methodology Flowchart

4.1 Data Collection

4.1.1 Twitter API

An API, or Application Programming Interface, is the instruction set that allows two software programs to communicate with each another. It allows for a smooth access and interaction with Twitter data and its features. The access to an open API allows developers to develop technology and clients to use that technology. Twitter provides two APIs: REST API and Streaming API. Both APIs requires OAuth authentication: either application-only authentication or application-user authentication to request data.

REST APIs work in a request and response way. It is the most common way to access Twitter data. Clients send Requests to servers and server Respond to a client's Request. REST API provides two main functionalities of GET data from Twitter and POST data to Twitter. The connection to the server is terminated once the requested data is received. REST API allows access to twitter data such as status updates (tweets) and user info regardless of time. Twitter does not make available the data, which are older than a week, so, the REST access is limited to the tweets less than one week old. In addition, Twitter has limited the number of tweets a user can extract using REST API to 3200 tweets, regardless of the query criteria.. Moreover, the number of request a user can make is limited to 180 request in a period of 15 minutes. Nevertheless, REST API meets the needs of most Twitter application programmers.

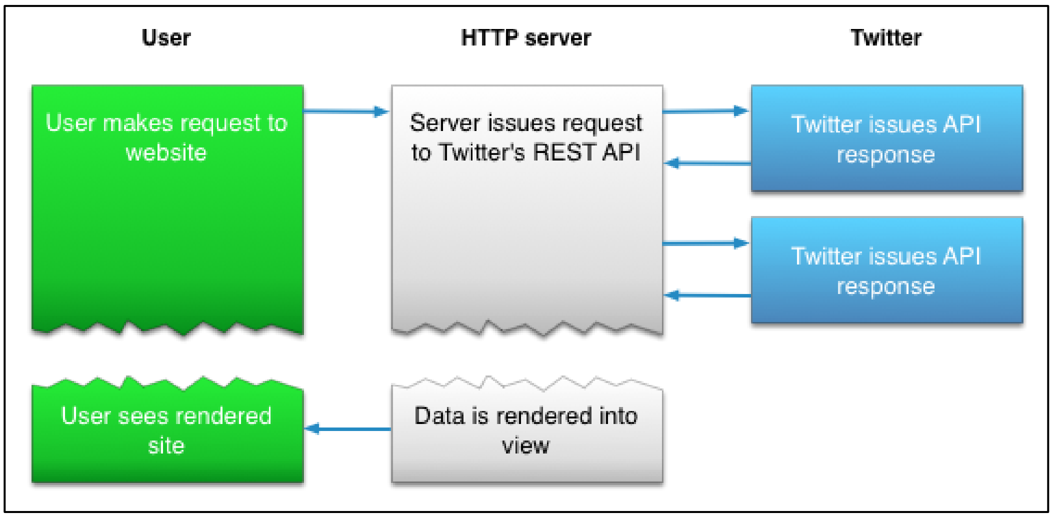

User
HTTP server
Twitter
User makes request to website
Server issues request to Twitter's REST API
Twitter issues API response
Twitter issues API response
User sees rendered site
Data is rendered into view

Figure 4: REST API

(Source: Twitter Developer Archive **https://archive.li/t6jp4)**

The streaming API delivers data based on users requested criteria like by keyword, location, etc. along with the info about the author, in real-time. In a Streaming API, whenever a client sends a Request to the server, the server continuously send streams of Response whenever an update is available. However, the Streaming API requires continuous connection between the client server and the Twitter. One advantage of Streaming API is that, there is no such rate limits as in REST API, and the connection is open for as long as possible. The Streaming API is different from REST API in a sense that REST API is only used to pull data from Twitter whereas Streaming API also pushes data thus allowing more data to be downloaded in real time than using the REST API. The Twitter Streaming API has three variations:

a) The Public Stream: This allows us to monitor public data on Twitter, such as tweets, hashtags, etc. via our application.
b) The User Stream: This allows us to track tweet streams of a specific user in real time.
c) Site Streams: The Site Streams require prior approval from Twitter. It allows us to monitor real-time Twitter feeds for a hefty number of user through our application.

Studies have estimated that the clients receive data anywhere from 1% to over 40% in near real-time using Twitter's Streaming API. Twitter Firehose overcome this problem with guaranteed delivery of 100% of the data that match user's criteria. However, it is only available commercially.

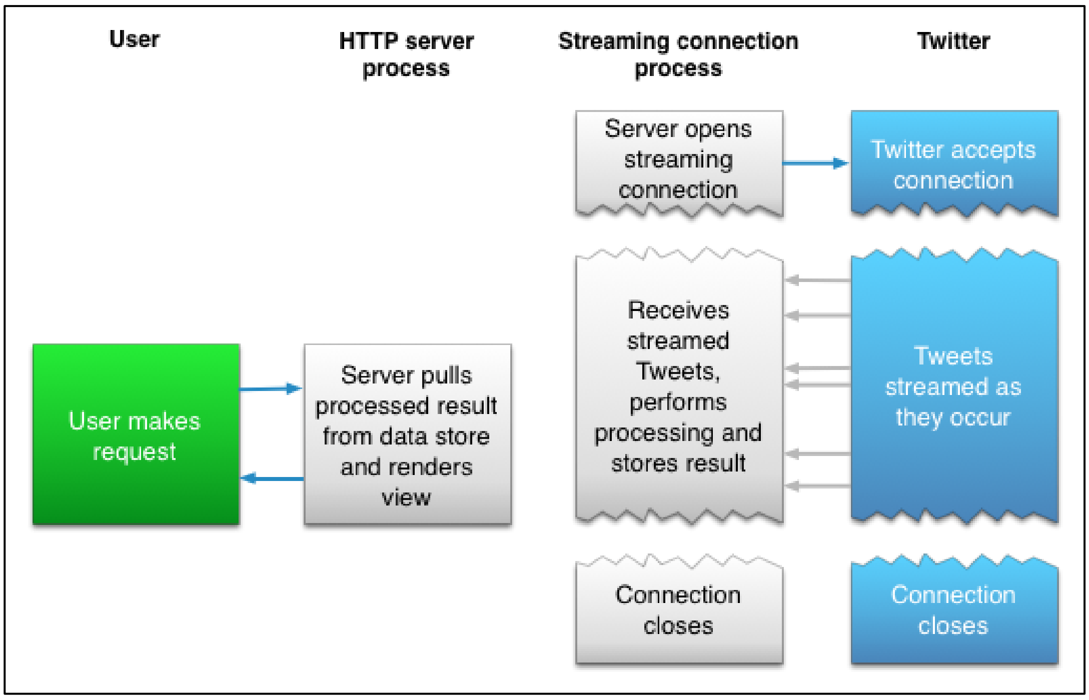

User
HTTP server process
Streaming connection process
Twitter
Server opens streaming connection
Twitter accepts connection
Receives streamed Tweets, performs processing and stores result
Tweets streamed as they occur
User makes request
Server pulls processed result from data store and renders view
Connection closes
Connection closes

Figure 5: Streaming API

(Source: Twitter Developer Archive https://archive.li/t6jp4)

Data Collection

The tweets for this research are collected using Twitter's Streaming API. We used Tweepy, an easy-to-use python library for accessing the Twitter API. First, to obtain the OAuth application keys, the user should sign in to the Twitter developer site, https://apps.twitter.com with their credentials. A new application should be registered by clicking on "Create New App". The authorization is called 3-legged authorization and it allows the application to obtain an access token. The 3-legged sign in interaction is illustrated in the flowchart in Figure no 5.

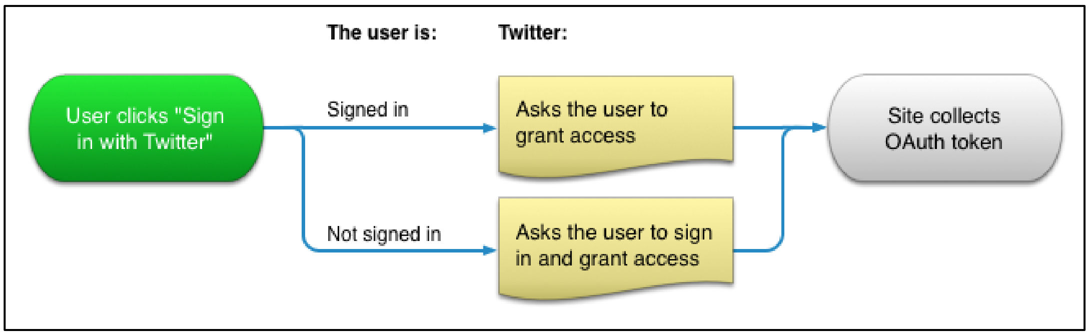

The user is:
Twitter:
User clicks "Sign in with Twitter"
Signed in
Asks the user to grant access
Site collects OAuth token
Not signed in
Asks the user to sign in and grant access

Figure 6: Possible states for the 3-legged sign in interaction

(Source: https://developer.twitter.com/en/docs/basics/authentication/overview/3-legged-oauth)

Tweepy is an open source library that handles the authentication, connection, creating and destroying the session, reading incoming messages, and partially routing messages, thus making it easier to use the Twitter Streaming API for Python. There are three steps using the Streaming API with Tweepy:

1. Creating StreamListener

   First, a class for StreamListener should be created. Stream listener are used to print text. The on_data method on Tweepy's StreamListener conveniently passes data from status to the on_status method. The python script for creating StreamListener is as follows:

   ```
   >>> import tweepy
   >>> class MyStreamListener(tweepy.StreamListener)
   >>>     def on_status(self, status):
   >>>         print(status.text)
   ```

2. Creating Stream

   A Stream establishes a streaming session and routes messages to StreamListener. An API authentication is needed. Once both StreamListener and API is ready, stream object can be created.

   ```
   >>> myStreamListener = MyStreamListener( )
   >>> twitterStream = tweepy.Stream(auth = api.auth, listener = myStreamListener())
   ```

3. Starting Stream

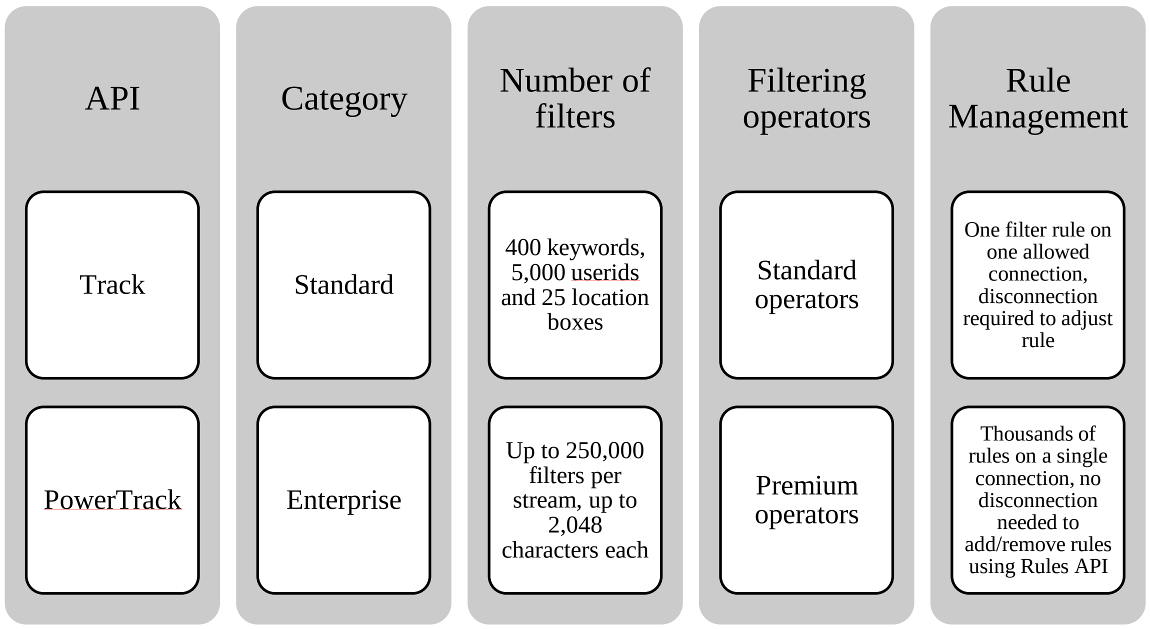
   Most of the twitter streams available through Tweepy uses filters, the user_stream or the sitestream. In this research, we use filter by language and location (bounding box). The script is written in such a way that, it can be further filtered with keywords or hashtags. An example of stream filter with language and bounding box is as follows:

   ```
   >>> twitterStream.filter (languages = ["en"], locations = [-9.50, 38.68, -8.78, 39.32])
   ```

Apart from these above-mentioned three steps, errors should also be handled, as streams does not terminate unless the connection is closed. There is a possibility of crossing the rate limit defined by Twitter. In such cases, we can use on_error to catch such failed attempts and disconnect our stream.

4.2 Data Filtering

The Twitter API platform offers two options for streaming real-time Tweets, each offering a varying number of filters and filtering capabilities (Figure:7).



API	Category	Number of filters	Filtering operators	Rule Management
Track	Standard	400 keywords, 5,000 userids and 25 location boxes	Standard operators	One filter rule on one allowed connection, disconnection required to adjust rule
PowerTrack	Enterprise	Up to 250,000 filters per stream, up to 2,048 characters each	Premium operators	Thousands of rules on a single connection, no disconnection needed to add/remove rules using Rules API

Figure 7: Filters for Twitter Streaming and their capabilities

(Source: Twitter Developer https://developer.twitter.com/en/docs/tweets/filter-realtime/overview)

For this research, we use Standard Track filter for filtering Tweets by language, location and keywords in real-time. As we can see in thefigure above, the standard filters are only allowed to use one filter at one connection, first we filtered the tweets by language in English followed by location using a bounding box. We can turn on and off the location filter from the code. In addition to that, the script is written in such a way that we can also filter the Tweets stream with keywords.

4.3 Geocoding

Google geocoder, Yahoo geocoder, geocoder.us (only for US address), Microsoft MapPoint, GeoNames and MediaWiki are some of the available geocoding web services. Geocoders allows us to get geographic coordinates from textual location, the process is called forward geocoding. Google geocoder and GeoNames also offer capabilities of reverse geocoding (finding textual location from geographic coordinates). It is not necessary that all the tweets are geo-tagged. If the tweets are geo-tagged, then it will proceed to the next step. Else, the program will check, whether there is place name available or not in location description of the user profile. If the place name is unavailable, the tweets will be ignored as we are only analysing the tweets with geographical coordinates. If the place name is available in user profile, the place name will be geocoded, and checked if it lies within our initial boundary extent. Only the tweets satisfying the condition will proceed to next step. In this research, we use geocoders from GeoPy to locate the coordinates of Tweets without coordinate information. GeoPy is a Python package which relies on a web API to do the conversion. As we are using Google Maps API's standard usage, there is a limit of 2500 free request per day, calculated as the sum of client-side and server-side queries. Also, the limit of requests per second is 50, which is also the calculated sum of client-side and server-side queries.

4.4 Pre-Processing

Pre-processing is the process of cleaning and preparing the text for classification. Online texts contains lots of unnecessary and uninformative parts such as HTML tags, scripts and advertisements. The case is even worse in case of social media as the language used by the users is very informal. In addition to that, the users even create their own words and spellings shortcuts and punctuation, misspellings, slang, URLs, etc. These data needs to be cleaned before analysing the sentiments of the text. In this research, the pre-processing includes the removal of URLs, @user and hashtags. For example:

"@xyz I really love that shoes at #sprinter. https://www.sprinter.es/tienda-sprinter-castellon "

The above text will be like following after pre-processing:

"I really love that shoes at sprinter"

4.5 Sentiment Analysis

Initially we planned to use a machine learning sentiment analysis algorithm from MonkeyLearn using an application called Zapier, a web based service that allows end users to integrate the web applications. However, the application is free only if we classify each tweet manually. They charge a certain amount of money if we build a model for automation of our workflow. The idea was then dropped in the middle of this research and we opt for Textblob.

TextBlob is an open source text processing library written in Python with capabilities to perform various natural language processing tasks such as part-of-speech tagging, noun-phrase extraction, sentiment analysis, text translation and many more. TextBlob is more easily-accessible and is built on top of Natural Language Toolkit (NLTK). TextBlob is popular for its fast prototyping that doesn’t require highly optimized performance.

4.6 Data Storing

After Sentiment Analysis, the Tweets along with geographical coordinates, polarity, subjectivity and other user information were stored in SQLite database. SQLite is a software library that provides relational database management system with noticeable features like server-less, self-contained, zero configuration, and transactional. The lite in SQLite refers to light weight in terms of setup, database administration, and required resources.

Unlike other Relational Database Management System (RDBMS) such as MySQL, PostgreSQL, etc., SQLite doesn’t require a separate server process to operate. SQLite database is integrated with an application that interact with the database read and write directly from the database files stored on disk. The SQLite server-less architecture is illustrated in following diagram.

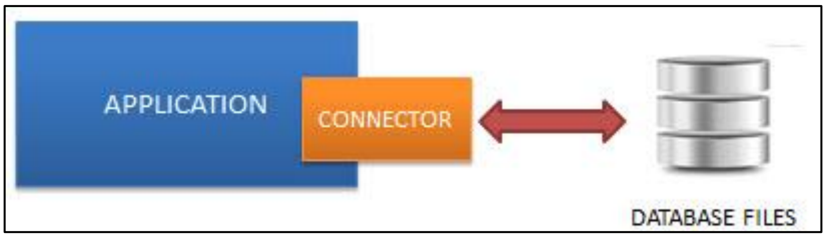
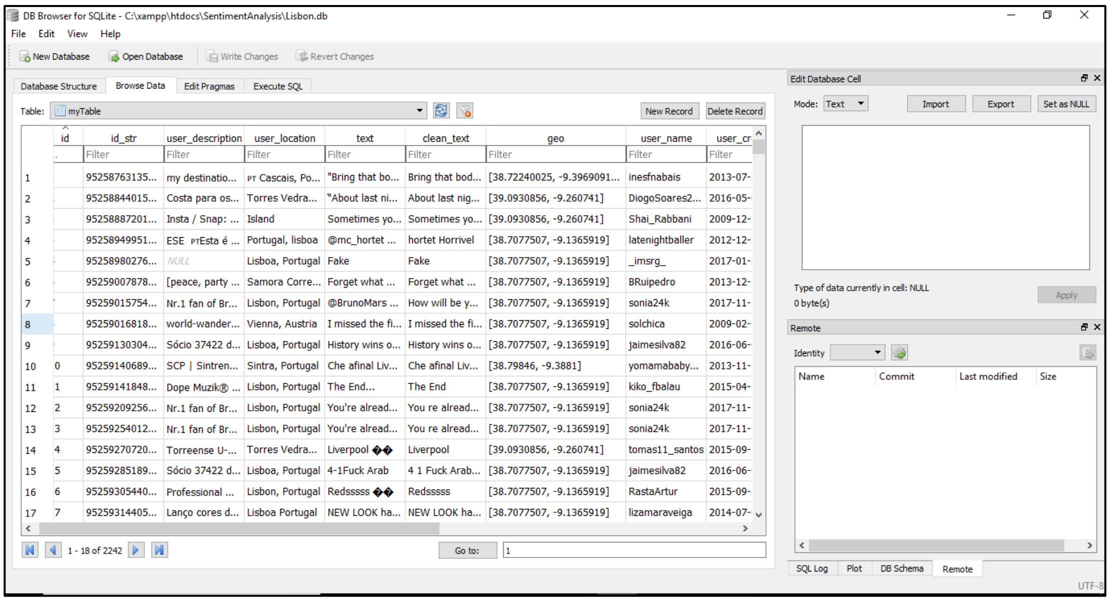


Figure 8: SQLite server-less architecture

(Source: https://sqlite.org/docs.html)

In addition to that, we don't need to install SQLite before using it because of the server-less architecture. It also requires minimal support from the operating system or external library making it usable in any environment.



	id	id_str	user_description	user_location	text	clean_text	geo	user_name	user_cr
		Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter
1		95258763135...	my destinatio...	PT Cascais, Po...	"Bring that bo...	Bring that bod...	[38.72240025, -9.3969091...	inesfnabais	2013-07-
2		95258844015...	Costa para os...	Torres Vedra...	"About last ni...	About last nig...	[39.0930856, -9.260741]	DiogoSoares2...	2016-05-
3		95258887201...	Insta / Snap: ...	Island	Sometimes yo...	Sometimes yo...	[39.0930856, -9.260741]	Shai_Rabbani	2009-12-
4		95258949951...	ESE PTEsta é ...	Portugal, lisboa	@mc_hortet ...	hortet Horrivel	[38.7077507, -9.1365919]	latenightballer	2012-12-
5		95258980276...	NULL	Lisboa, Portugal	Fake	Fake	[38.7077507, -9.1365919]	_imsrg_	2017-01-
6		95259007878...	[peace, party ...	Samora Corre...	Forget what ...	Forget what ...	[38.7077507, -9.1365919]	BRuipedro	2013-12-
7		95259015754...	Nr.1 fan of Br...	Lisbon, Portugal	@BrunoMars ...	How will be y...	[38.7077507, -9.1365919]	sonia24k	2017-11-
8		95259016818...	world-wander...	Vienna, Austria	I missed the fi...	I missed the fi...	[38.7077507, -9.1365919]	solchica	2009-02-
9		95259130304...	Sócio 37422 d...	Lisboa, Portugal	History wins o...	History wins o...	[38.7077507, -9.1365919]	jaimesilva82	2016-06-
10	0	95259140689...	SCP | Sintren...	Sintra, Portugal	Che afinal Liv...	Che afinal Liv...	[38.79846, -9.3881]	yomamababy...	2013-11-
11	1	95259141848...	Dope Muzik® ...	Lisbon, Portugal	The End...	The End	[38.7077507, -9.1365919]	kiko_fbalau	2015-04-
12	2	95259209256...	Nr.1 fan of Br...	Lisbon, Portugal	You're alread...	You re alread...	[38.7077507, -9.1365919]	sonia24k	2017-11-
13	3	95259254012...	Nr.1 fan of Br...	Lisbon, Portugal	You're alread...	You re alread...	[38.7077507, -9.1365919]	sonia24k	2017-11-
14	4	95259270720...	Torreense U-...	Torres Vedra...	Liverpool ��	Liverpool	[39.0930856, -9.260741]	tomas11_santos	2015-09-
15	5	95259285189...	Sócio 37422 d...	Lisboa, Portugal	4-1Fuck Arab	4 1 Fuck Arab...	[38.7077507, -9.1365919]	jaimesilva82	2016-06-
16	6	95259305440...	Professional ...	Lisbon, Portugal	Redsssss ��	Redsssss	[38.7077507, -9.1365919]	RastaArtur	2015-09-
17	7	95259314405...	Lanço cores d...	Lisboa Portugal	NEW LOOK ha...	NEW LOOK ha...	[38.7077507, -9.1365919]	lizamaraveiga	2014-07-

Figure 9: Screenshot of data stored in SQLite database

4.7 Visualization

After getting the data to the server, we require visualization of data. Since we opt for a web based visualization, a webserver based visualization was implementation based on web technologies of client server for publishing, HTML/CSS/JavaScript for presentation and PHP for communication and control is suitable for our case.

Our visualization is based on internet browsers technologies which are supported by all the major internet browsers (Firefox, Chrome, and Opera). It should work on any standard browsers, but have not been tested as it is out of scope. The browsers being the client, an apache server serves up the pages to the clients. Apache is implemented through the XAMPP infrastructure as it is best for development with many debugging facilities, but it may not be the best for production stage.

XAMPP is an easy to install Apache distribution containing MySQL, PHP, and Perl. XAMPP is a very easy to install Apache Distribution for Linux, Solaris, Windows, and Mac OS X. The package includes the Apache web server, MySQL, PHP, Perl, a FTP server and phpMyAdmin. Here we require only apache and PHP.

Map visualization is implemented through Leaflet. Leaflet is a widely used open source JavaScript library used to build web mapping applications. It supports most mobile and desktop platforms, supporting HTML5 and CSS3. Along with OpenLayers, and the Google Maps API, it is one of the most popular JavaScript mapping libraries and is used by major web sites such as FourSquare, Pinterest and Flickr. We choose it for its easy use and small size which improves performance and its rich plugins. Plugins for clusters, heatmaps and realtime have been used in this visualization. Realtime fetches data every 3 seconds from an API and provides data to clusters and heatmaps. Clusters and heatmaps form a major part of visualization. Realtime uses Asynchronous JavaScript and XML (AJAX) so that the page load times are reduced and the data integration is efficient. So far we have not felt any lag in the visualization, except during initialization. During initialization, traffic load is heavy so some lag is expected.

An API is implemented to connect the SQLite data and convert it to GeoJSON format. GeoJSON formats can be easily consumed by leaflet as well as other visualization mediums. The API is implemented through PHP. The process of updating the database by python and visualization by PHP can run in parallel.

5. RESULTS

For our experiment about location-based sentiment analysis of tweets for Lisbon, we collected 2245 tweets over a period of 9 days. No any specific topics were covered for this purpose. We didn't use any keywords to filter these tweets. We tried to analyze the trends and patterns about people's sentiments from general text. 1240 (55.31%) were classified as having neutral sentiments. 31.31% of tweets were positive while 13.38% have negative sentiments. Furthermore, from the heat map in Figure 10, we can clearly observe that, the tweets are mostly concentrated in and around Lisboa Municipality. One of the reasons behind this is geocoding. As tweets without geographical coordinates and having their location as Lisbon in their Twitter Profile are geocoded to same geographical coordinates in Lisbon.

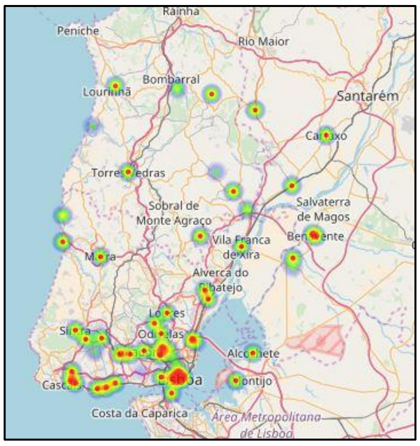
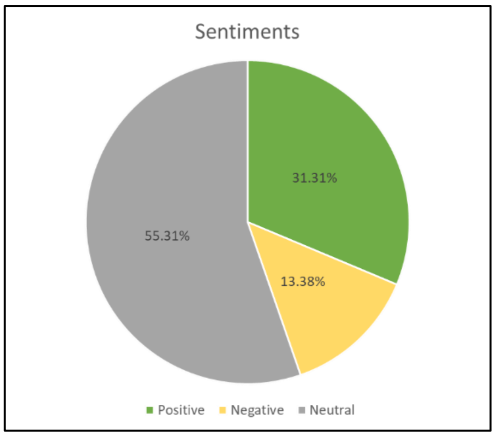



Figure 10: Heat maps and Pie-chart of sentiments for Lisbon

Figure 11 and 12 shows the heat maps of Lisboa for positive and negative sentiments respectively. It is quite clear from the heat maps that the number of tweets with negative sentiments are comparatively lesser than the tweets with positive sentiments. From the heat maps, we can have an overview of sentiments of people on the basis of location. We can say that, people in an around Lisboa are more positive in general.

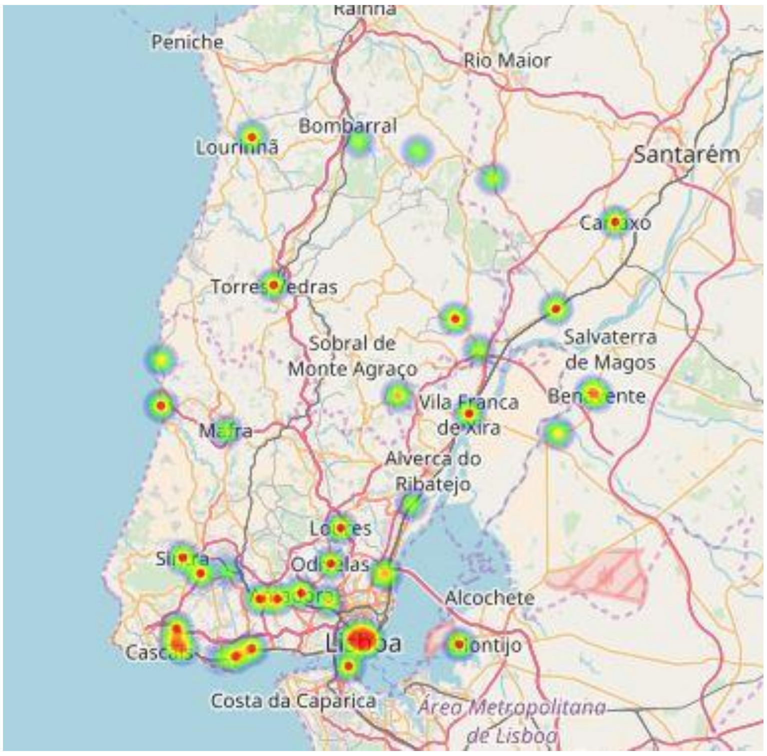


Figure 11: Heat map of Lisbon for Positive Sentiments

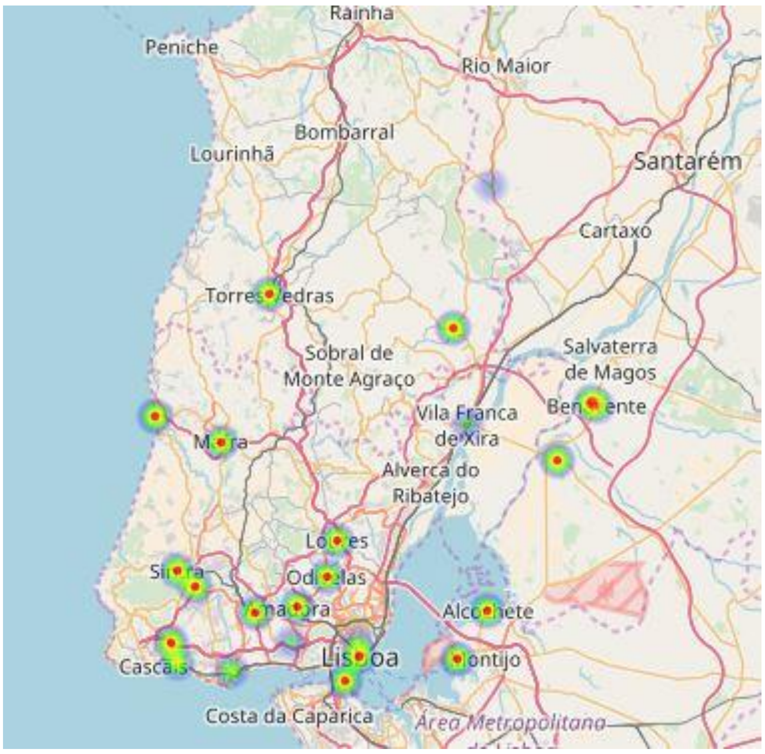


Figure 12: Heat map of Lisbon for Negative Sentiments

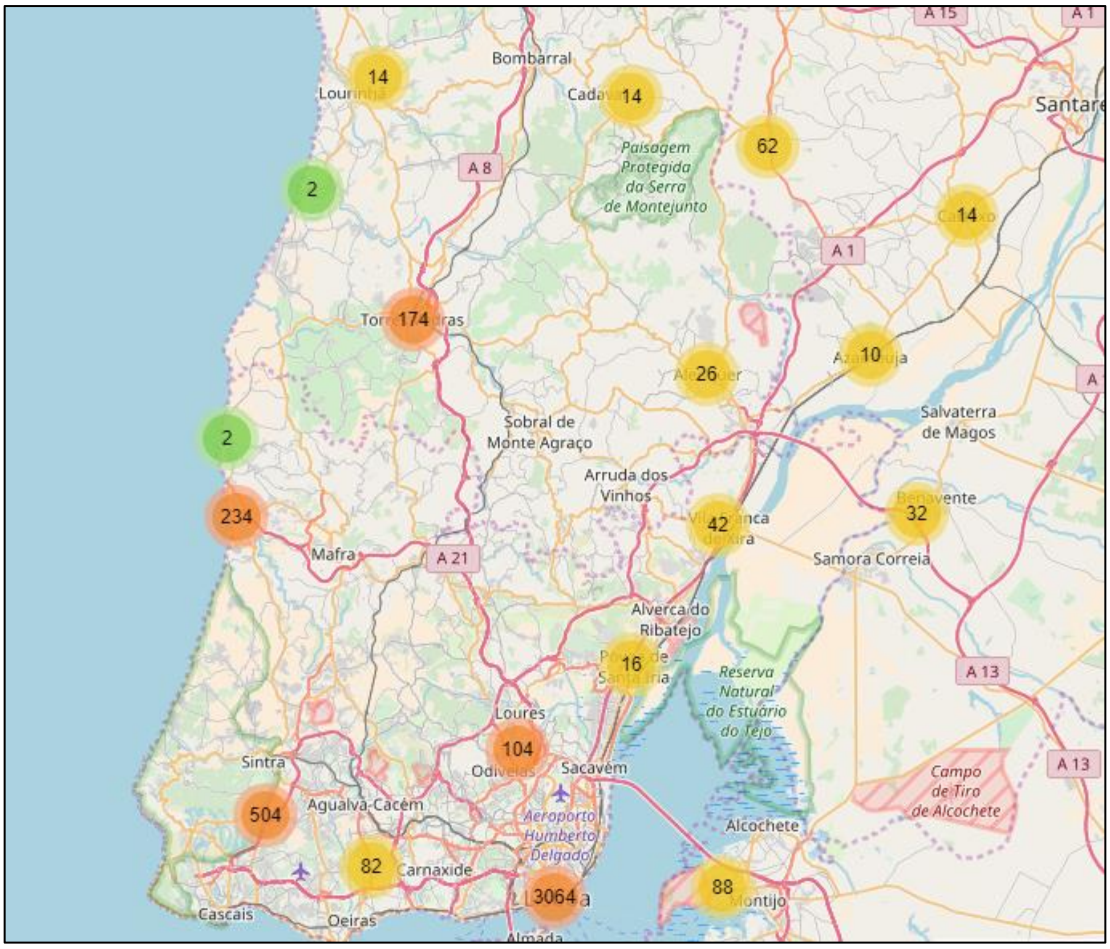
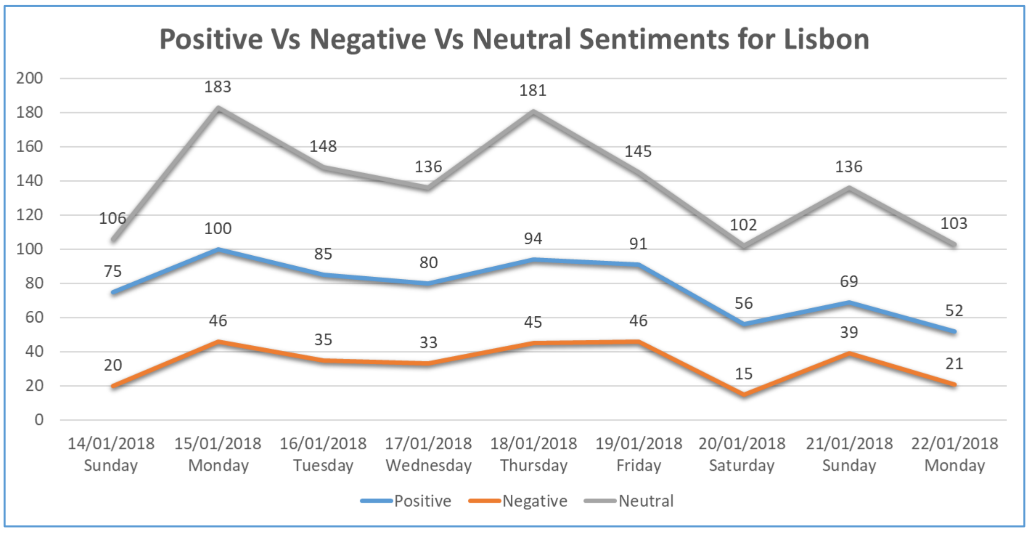


Figure 13: Tweets Cluster in Lisbon

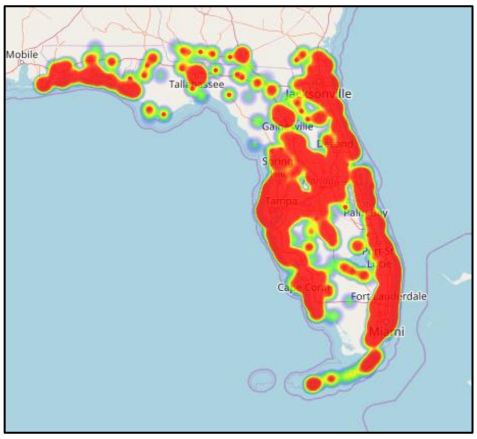


	14/01/2018 Sunday	15/01/2018 Monday	16/01/2018 Tuesday	17/01/2018 Wednesday	18/01/2018 Thursday	19/01/2018 Friday	20/01/2018 Saturday	21/01/2018 Sunday	22/01/2018 Monday
Positive	75	100	85	80	94	91	56	69	52
Negative	20	46	35	33	45	46	15	39	21
Neutral	106	183	148	136	181	145	102	136	103

Figure 14: Line graphs for Positive Vs Negative Vs Neutral Sentiments

The line graph in Figure 14 shows a comparison of the positive vs negative vs neutral sentiments of twitter users in Lisbon. It can be seen that, the trend of the increasing and decreasing of positive sentiments is similarto negative sentiments. Both positive and negative sentiments record highest number of tweets on Monday, 2018/01/15 and lowest on Saturday, 2018/01/20. Whereas, the graph of neutral sentiments has sharp changes. Monday, 2018/01/15 and Thursday 2018/01/18 recorded the highest with 183 and 183 tweets respectively. It reached the bottom low on Saturday 2018/01/20 with 102 tweets.

For our next experiment of Florida, a total of 16169 tweets were collected in three days. Likewise for the experiment in Lisbon, here also we didn't filter the tweets with keywords. The positive class got the highest percentage of tweets with 46.46% while 46.11% tweets were classified as neutral. Only 7.43% of tweets were classified as having negative sentiments.



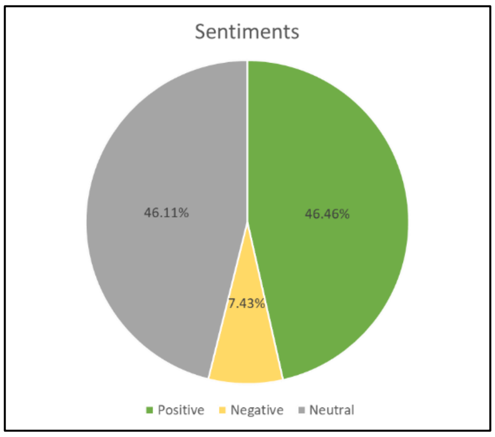


Figure 15: Heat maps and Pie-chart of sentiments for Florida

The heat map of the sentiments for Florida is shown in Figure 14. It also illustrates that the tweets are well distributed along Florida. Figure 16-18 represents the heat maps for Florida with positive, negative and neutral sentiments respectively. From the figures, we can say that tweets with positive and neutral sentiments dominates the tweets with negative sentiments. In general Twitter users in Florida are more positive or neutral.

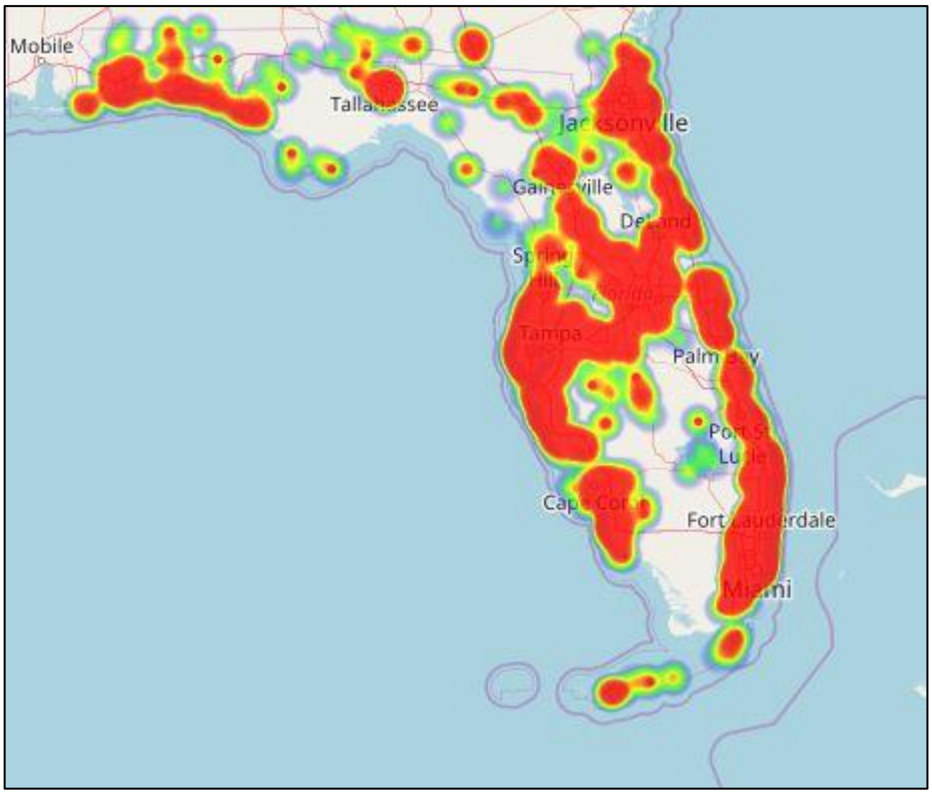


Figure 16: Heat map of Florida for Positive Sentiment

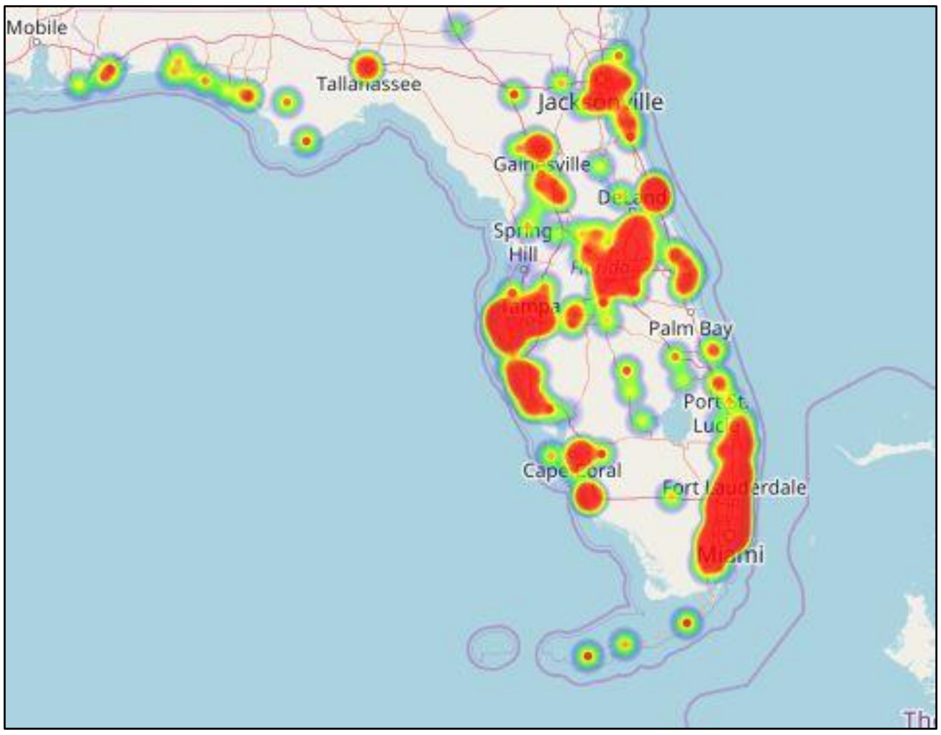


Figure 17: Heat map of Florida for Negative Sentiment

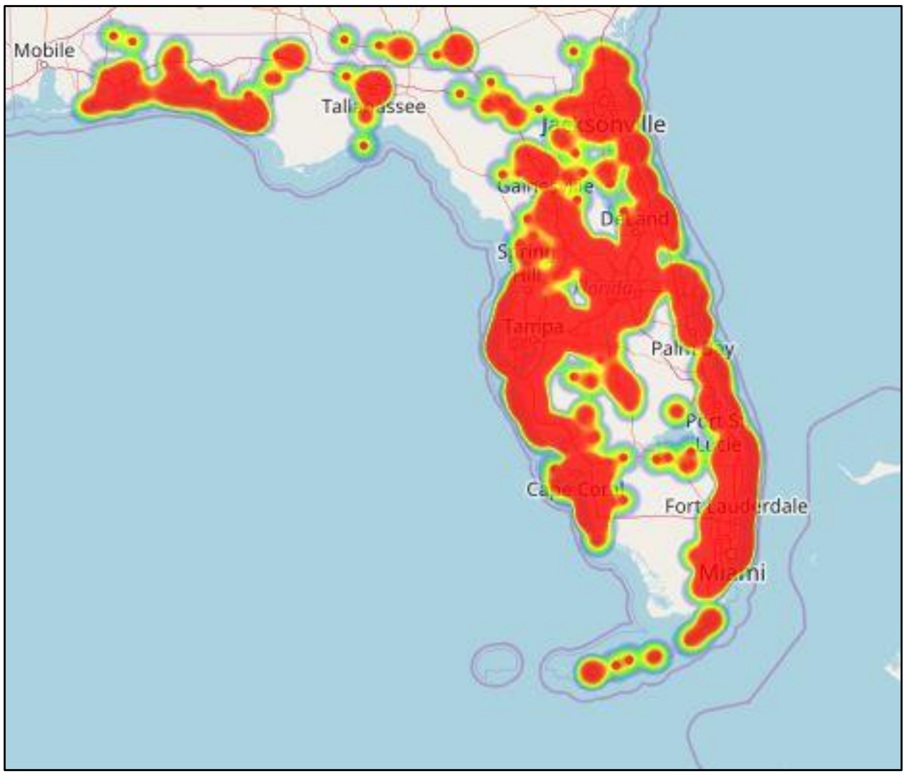


Figure 18: Heat map of Florida for Neutral Sentiments

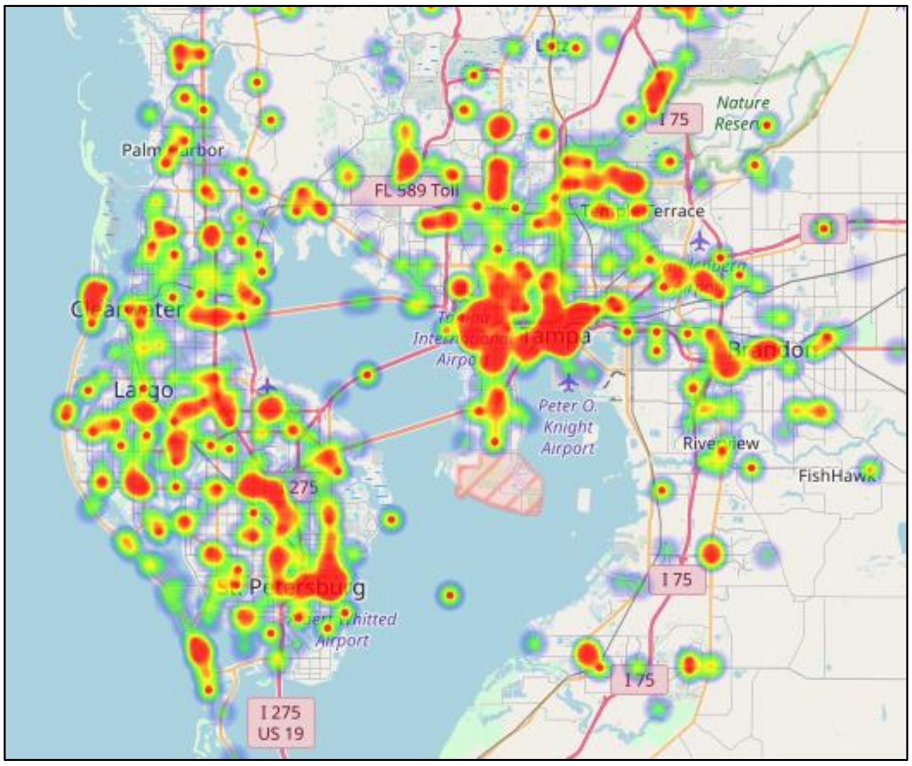


Figure 19: Screenshot of Heat maps of sentiments for Florida

6. CONCLUSIONS

In this thesis, we analyze the sentiments of geotweets and visualize the result in the form of heat maps and clusters in real time. Sentiment analysis has become the most important source in decision-making. Most people depends on it to achieve the efficient product. The tremendous amount of sentiment rich data in microblogging sites makes them an attractive source of data for opinion mining and sentiment analysis.

In this work, we performed location based sentiment analysis on tweets from Lisbon and Florida. We collected geotweets using Twitter Streaming API. We filtered the tweets by geographical extent and only considered the tweets which were in English language. We use geocoder from Geopy to geocode tweets without geographic coordinates. Textblob, an open source text processing library written in python was used to calculate polarity of the tweets, which later were classified into positive, negative and neutral sentiments. We visualize the result in the form of heat maps and clusters in leaflet. In both cases, we saw how positive, negative and neutral sentiments differs for different location. Also, we studied how the change of sentiments over a period of week in Lisbon. We collected comparatively lower number of tweets for Lisbon than for Florida and that too within longer time period than the later. The main reason behind this is English not being a local language in Portugal.

Location based sentiment analysis can be applied to control the decision making in any domain. And the visualization helps us to perceive information even more quickly. If a company is targeting a specific geographic location as potential clients or users, then location based sentiment analysis can help them understand the opinions of people of that region towards the company and their products or project.

For the future work, we can improve our approach to work on multi-languages so that language should not be a barrier for the analysis. In this work, we convert the non-Unicode characters like emoji and smileys into question mark sign "?", as the non-unicode characters cannot be processed and was throwing errors. We should find a way to consider these emoji and smileys as they can change tone of a statement. Furthermore, our approach fall short to detect irony, humor or any sarcasm. We should pair our approach with human analysts to examine the contextual references. To improve the effectiveness of our sentiment analysis, we should go beyond the polarity of “positive”, “negative”, and “neutral” to classify sentiments. We should use more fine-grained categories like “angry”, “happy”, “frustrated”, “sad”, “neutral”, etc.

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ANNEX

A. Python script for connecting with Twitter API and sentiment analysis

```
from __future__ import absolute_import, print_function

import tweepy

import dataset

from textblob import TextBlob

from tweepy import OAuthHandler

from tweepy import Stream

from tweepy.streaming import StreamListener

import json

import re

import sys

from sqlalchemy.exc import ProgrammingError

from geopy.geocoders import Nominatim

from geopy.exc import GeocoderTimedOut


#Twitter OAuth key

consumer_key ="4pWHutE2ZjsxKzQ3mkBNLV4xY"

consumer_secret =
"1iqXjJOR9hzmP0ppPcdUC10ygNtRFFdIYq8d3CY6mSsQMnbDbw"

access_token ="262541721-pnsraIrVxNi4LXqysD9UDBEy6cjTE1UjXwcwTZCQ"

access_secret ="GGKsYkYiRu06UHSxP3VCHJgHJJ2GVOFVYo2BwGh5hKv7P"

#Convert emoji and smiley (non unicode character) into "?". Otherwise non unicode
character cannot be processed.

non_bmp_map = dict.fromkeys(range(0x10000, sys.maxunicode + 1), 0xfffd)


Location_Filter = True # If true boundary extent filter is considered. If false all
tweets from around the world is considered.

#filter tweets by keywords
```

```
#keyword = ["england", "castellon", "Nokia", "London", "Nepal", "happy", "sad",
"good", "bad"]

keyword = [""]

geolocator = Nominatim() #OSM geocoding service handler. To use other services
consult geopy.geocoders

extent = [-87.63, 24.52, -79.72, 31.00]

location = None #Initialize global variable location as none. If not initialized, gives
error.


class MyListener(StreamListener):

    def on_status(self, status):

        #print (status)

        if status.retweeted: #Ignores retweets

            return


        #Checks for keywords in tweets

        for word in keyword:

            if word in status.text.lower():

                #print(status.text.translate(non_bmp_map))

                id_str = status.id_str

                description = status.user.description

                loc = status.user.location

                text = status.text.translate(non_bmp_map)

                #print ("No Error in Text")

                clean_text = ' '.join(re.sub("(@[A-Za-z0-9]+)|([^0-9A-Za-z
\t])|(\w+:\/\/\S+)"," ",text).split()) #Remove urls, mentions, etc.

                coords = status.coordinates

                geo = status.geo

                name = status.user.screen_name

                user_created = status.user.created_at

                followers = status.user.followers_count
        created = status.created_at

        retweets = status.retweet_count

        blob = TextBlob(clean_text)

        sent = blob.sentiment


                        #If tweet has geographical coordinates, check whether
it is within the extent

                        #If tweet doesn't have coordinates, geocode the place
name given in user's profile and check extent.

        if geo is not None:

            print (geo["coordinates"])

            if (Location_Filter == True)& ((geo["coordinates"][0] > extent[1]) &
(geo["coordinates"][0] < extent[3]) & (geo["coordinates"][1] > extent[0]) &
(geo["coordinates"][1] < extent[2])):

                geo = json.dumps(geo["coordinates"])

                print (geo)

            else:

                geo = None

        elif loc is not None:

            try:

                global location

                #location = geolocator.geocode(loc)

            except GeocoderTimedOut as err:

                geo = None

                location = None

        if location is not None:

            if (Location_Filter == True & ((location.latitude < extent[1]) |
(location.latitude > extent[3]) | (location.longitude < extent[0]) | (location.longitude >
extent[2]))):

                continue

            else:
                print (location)

                geo = "["+str(location.latitude)+", "+str(location.longitude)+"]"



                              #If the tweet has keyword and within the extent, write
in the database

          if geo is not None:


              table = db['myTable']


              try:

                sentiment = "positive" if sent.polarity > 0 else "negative" if
sent.polarity<0 else "neutral"

                table.insert(dict(

                  id_str = id_str,

                  user_description = description,

                  user_location = loc,

                  #coordinates = coords,

                  text = text,

                  clean_text = clean_text,

                  geo = geo,

                  user_name = name,

                  user_created = user_created,

                  user_followers = followers,

                  created = created,

                  retweet_count = retweets,

                  polarity = sent.polarity,

                  subjectivity = sent.subjectivity,

                  sentiment = sentiment,
                ))
            except ProgrammingError as err:
                print(err)




    def on_error(self, status_code):
        if status_code == 420:
            return False


if __name__ == '__main__':
    db = dataset.connect('sqlite:///florida.db') #connect with sqlite database. If database
doesn't exist, creat a new one.
    result = db['myTable'].all()
    auth = tweepy.OAuthHandler(consumer_key, consumer_secret)
    auth.set_access_token(access_token, access_secret)
    api = tweepy.API(auth)
    twitterStream = Stream(auth, MyListener()) #
    #twitterStream.filter(languages=["en"],track=['england'], locations=[-6.38, 49.87,
1.77, 55.81])
    if Location_Filter == True:
        twitterStream.filter(languages=["en"], locations=[-87.63, 24.52, -79.72, 31.00])
    else:
        twitterStream.filter(languages=["en"], locations= [-180, -90, 180, 90])
```

B. SQLite database to GeoJSON

```
<?php

$sentiment = $_GET['sentiment']; #sentiment can be positive, negative or
neutral.
# echo $sentiment;
# Connect to SQLite database
$conn = new PDO('sqlite:Lisbon.db');
# Build SQL SELECT statement and return the geometry as a GeoJSON element
$sql = 'SELECT *, geo FROM myTable WHERE sentiment = "'.$sentiment.'"';

# Try query or error
$rs = $conn->query($sql);
if (!$rs) {
     echo "\nPDO::errorInfo():\n";
     print_r($conn->errorInfo());
    echo 'An SQL error occured.\n';
    exit;
}
# Build GeoJSON feature collection array
$geojson = array(
   'type'      => 'FeatureCollection',
   'features'  => array()
);
# Loop through rows to build feature arrays
while ($row = $rs->fetch(PDO::FETCH_ASSOC)) {
    $properties = $row;
     $latlong = json_decode($row['geo']);
    $feature = array(
         'type' => 'Feature',
         'geometry' => array('type' => 'Point', 'coordinates' => array($latlong[1],
$latlong[0])), #In database coordinate is in latlong format, but geojson requires
coordinate in longlat format.
         'properties' => $properties
    );
    # Add feature arrays to feature collection array
    array_push($geojson['features'], $feature);
}

header('Content-type: application/json'); #declare content type(mime type) as
json
echo json_encode($geojson, JSON_NUMERIC_CHECK);
$conn = NULL;
?>
```

C. Html code for visualization

```
<!DOCTYPE html>

<html>

<head>

	<title>Leaflet SQLite GeoJSON Example</title>

	<meta charset="utf-8" />


	<meta name="viewport" content="width=device-width, initial-scale=1.0">


	<!--link rel="stylesheet" href="http://cdn.leafletjs.com/leaflet-
0.7.3/leaflet.css" /-->

	<link rel="stylesheet" href="https://unpkg.com/leaflet@1.3.1/dist/leaflet.css"
/>

	<link rel="stylesheet"
href="https://unpkg.com/leaflet.markercluster@1.3.0/dist/MarkerCluster.css" />

	<!--link rel="stylesheet"
href="https://api.tiles.mapbox.com/mapbox.js/plugins/leaflet-
markercluster/v0.4.0/MarkerCluster.css" /-->

	<link rel="stylesheet"
href="https://unpkg.com/leaflet.markercluster@1.3.0/dist/MarkerCluster.Default.css"
/>

  <!--link rel="stylesheet"
href="https://api.tiles.mapbox.com/mapbox.js/plugins/leaflet-
markercluster/v0.4.0/MarkerCluster.Default.css" /-->

	<style> .leaflet-zoom-hide { position: absolute!important; } </style>

</head>

<body>

	<a href="https://github.com/bmcbride/PHP-Database-GeoJSON"><img
style="position: absolute; top: 0; right: 0; border: 0;"
src="https://s3.amazonaws.com/github/ribbons/forkme_right_gray_6d6d6d.png"
alt="Fork me on GitHub"></a>

	<div style="position: relative; height: 600px; width:100%;" class="heatmap"
id="map"></div>
```

```
            <p>This example demonstrates the ability to view layers from an SQLite
database file as GeoJSON layers.</p>
    <p>
      <ul>
        <li>CDTA data downloaded from the NYS GIS Clearinghouse: <a
href="http://gis.ny.gov/gisdata/inventories/member.cfm?OrganizationID=98"
target="_blank">http://gis.ny.gov/gisdata/inventories/member.cfm?OrganizationID=
98</a>.</li>
        <li>The downloaded shapefiles were exported to SQLite using <a
href="http://www.qgis.org/" target="_blank">Quantum GIS (QGIS)</a>.</li>
      </ul>
    </p>
            <!--script src="http://cdn.leafletjs.com/leaflet-0.7.3/leaflet.js"></script-->
            <script src="https://unpkg.com/leaflet@1.3.1/dist/leaflet.js"></script>
            <script src="http://code.jquery.com/jquery-2.1.4.min.js"></script>
            <script
src="https://unpkg.com/leaflet.markercluster@1.3.0/dist/leaflet.markercluster.js"></s
cript>
            <!--script src="https://api.tiles.mapbox.com/mapbox.js/plugins/leaflet-
markercluster/v0.4.0/leaflet.markercluster.js"></script-->
            <!--script src="leaflet-realtime.js"></script-->
            <script src="https://unpkg.com/heatmap.js@2.0.5"></script>
            <script src="https://unpkg.com/leaflet-heatmap@1.0.0"></script>
            <script type="text/javascript" src="http://www.liedman.net/leaflet-
realtime/dist/leaflet-realtime.js"></script>
            <script src="leaflet-heat.js"></script>
            <script>
            //Polarity ranges from -1 to 1 while intensity ranges from 0 to 1. This function
converts polarity to intensity.
            function polarityToIntensity(polarity){
    return (polarity + 1)/2}
            </script>
            <script>
```

```
		var map;


		var OSM = new
L.TileLayer("http://{s}.tile.osm.org/{z}/{x}/{y}.png", {
			maxZoom: 17,
			//subdomains: ["otile1", "otile2", "otile3", "otile4"],
			attribution: 'Tiles courtesy of <a
href="http://www.mapquest.com/" target="_blank">MapQuest</a>. Map data (c) <a
href="http://www.openstreetmap.org/" target="_blank">OpenStreetMap</a>
contributors, CC-BY-SA.'
		});


		// Positive, negative and neutral icons in openlayers format
		var tweetsIconPositive = L.icon({
			iconUrl: 'Image/Positive.png',
			iconSize: [24, 28],
			iconAnchor: [12, 28],
			popupAnchor: [0, -25]
		});


		var tweetsIconNegative = L.icon({
			iconUrl: 'Image/Negative.png',
			iconSize: [24, 28],
			iconAnchor: [12, 28],
			popupAnchor: [0, -25]
		});


		var tweetsIconNeutral = L.icon({
			iconUrl: 'Image/Neutral.png',
			iconSize: [24, 28],
			iconAnchor: [12, 28],
            popupAnchor: [0, -25]
        });
        //Initialize empty layer
        tweets = new L.geoJson(null, {
            pointToLayer: function (feature, latlng) {
              if(feature.properties.sentiment == "positive"){
                    return L.marker(latlng, {
                icon: tweetsIconPositive,
                //title: feature.properties.address
              });}
              else if (feature.properties.sentiment == "negative"){
                    return L.marker(latlng, {
                    icon: tweetsIconNegative,
              });}
              else {
                    return L.marker(latlng,{
                    icon: tweetsIconNeutral,
              });}

            },
            //Attach pop-up to each tweet
            onEachFeature: function (feature, layer) {


              if (feature.properties) {
                var content = '<table border="1" style="border-
collapse:collapse;" cellpadding="2">' +
                '<tr>' + '<th>User_Name</th>' + '<td>' +
feature.properties.user_name + '</td>' + '</tr>' +
                '<tr>' + '<th>Tweets</th>' + '<td>' + feature.properties.clean_text
+ '</td>' + '</tr>' +
                                        '<tr>' + '<th>Polarity</th>' + '<td>' +
feature.properties.polarity + '</td>' + '</tr>' +
                                '<tr>' + '<th>Sentiment</th>' + '<td>' +
feature.properties.sentiment + '</td>' + '</tr>' +
                                '<table>';
                                    layer.bindPopup(content);
                                   }
                                  }
                        });

                        //Initialize cluster for tweets
                        tweetsClusters = new L.MarkerClusterGroup({
                          spiderfyOnMaxZoom: true,
                          showCoverageOnHover: false,
                          zoomToBoundsOnClick: true,
                          disableClusteringAtZoom: 16
                        });

                        coords = []; //initialize empty array to store location of tweets for
heatlayers
                        map = new L.Map("map",{
                                    layers: [OSM, tweets]
                        });
                        //heat layer of all tweets
                        var heat_all = L.heatLayer([],{"gradient":{0: 'blue', 0.5: 'brown', 1:
'black'}});

                        //heat layer of positive tweets
                        var heat_pos = L.heatLayer(coords,{"gradient":{0.33: 'yellow', 1:
'green'}});
```

```
                //fetch realtime data from database
                realtime_positive = L.realtime({
                        url: 'tweets_geojson.php', //API to access database and
generate geoJson. Take sentiment as parameter
                        crossOrigin: true,
                        type: 'json',
                        data:{'sentiment':'positive'} //sentiment can be positive,
negative or neutral
                }, {
                        interval: 3 * 1000, //fetch data every 3 seconds
                        pointToLayer: function (feature, latlng) {

                          if(feature.properties.sentiment == "positive"){
                                return L.marker(latlng, {
                            icon: tweetsIconPositive,
                            //title: feature.properties.address
                          });}
                          else if (feature.properties.sentiment == "negative"){
                                return L.marker(latlng, {
                                icon: tweetsIconNegative,
                          });}
                          else {
                                return L.marker(latlng,{
                                icon: tweetsIconNeutral,
                          });}

                        },
                        onEachFeature: function (feature, layer) {
                                coords.push([feature.geometry.coordinates[1],
feature.geometry.coordinates[0], polarityToIntensity(feature.properties.polarity)]);
```

```
                }
        });



        var heat_pos = L.heatLayer(coords,{"gradient":{0.33: 'yellow', 1:
'green'}});
        //heatmap combined configuration
        var cfg_pos = {
        "radius": 10,
        "maxOpacity": .8,
        "scaleRadius": false,
        "useLocalExtrema": true,
          latField: 'lat',
          lngField: 'lng',
          valueField: 'polarity'
        };
        //heat layer of positive tweets
        var heatmapLayer_pos = new HeatmapOverlay(cfg_pos);
        realtime_positive.on('update', function(e) {
                //debugger;
                //for each new tweet added, add corresponding feature in
heatmaplayer
                Object.keys(e.enter).forEach(function(key) {

    heat_pos.addLatLng(e.enter[key].geometry.coordinates);

    heatmapLayer_pos.addData({'lat':e.enter[key].geometry.coordinates[1],
'lng':e.enter[key].geometry.coordinates[0],
'polarity':polarityToIntensity(e.enter[key].properties.polarity)});


                });
```

```
                    //map.fitBounds(realtime_positive.getBounds(), {maxZoom:
3});
                    //for each new tweet added, add corresponding feature in tweet
cluster
                    tweetsClusters.addLayer(realtime_positive);
            });

            realtime_negative = L.realtime({
                    url: 'tweets_geojson.php',
                    crossOrigin: true,
                    type: 'json',
                    data:{'sentiment':'negative'}
            }, {
                    interval: 3 * 1000,
                    pointToLayer: function (feature, latlng) {

                      if(feature.properties.sentiment == "positive"){
                              return L.marker(latlng, {
                        icon: tweetsIconPositive,
                        //title: feature.properties.address
                      });}
                      else if (feature.properties.sentiment == "negative"){
                              return L.marker(latlng, {
                              icon: tweetsIconNegative,
                      });}
                      else {
                              return L.marker(latlng,{
                              icon: tweetsIconNeutral,
                      });}
                    },
                    onEachFeature: function (feature, layer) {
                              coords.push([feature.geometry.coordinates[1],
feature.geometry.coordinates[0], polarityToIntensity(feature.properties.polarity)]);
                    }
          });

          var cfg_neg = {
          "radius": 10,
          "maxOpacity": .8,
          "scaleRadius": false,
          "useLocalExtrema": true,
            latField: 'lat',
            lngField: 'lng',
            valueField: 'polarity'
          };

          var heatmapLayer_neg = new HeatmapOverlay(cfg_neg);

          var heat_neg = L.heatLayer(coords,{"gradient":{0.33: 'orange', 1:
'red'}});
          realtime_negative.on('update', function(e) {
                    //debugger;
                    Object.keys(e.enter).forEach(function(key) {

          heat_pos.addLatLng(e.enter[key].geometry.coordinates);

          heatmapLayer_neg.addData({'lat':e.enter[key].geometry.coordinates[1],
'lng':e.enter[key].geometry.coordinates[0],
'polarity':polarityToIntensity(e.enter[key].properties.polarity)});
```

```
                });

                //map.fitBounds(realtime_negative.getBounds(), {maxZoom:
3});
                tweetsClusters.addLayer(realtime_negative);
        });

        realtime_neutral = L.realtime({
                url: 'tweets_geojson.php',
                crossOrigin: true,
                type: 'json',
                data:{'sentiment':'neutral'}
        }, {
                interval: 3 * 1000,
                pointToLayer: function (feature, latlng) {

                  if(feature.properties.sentiment == "positive"){
                        return L.marker(latlng, {
                    icon: tweetsIconPositive,
                    //title: feature.properties.address
                  });}
                  else if (feature.properties.sentiment == "negative"){
                        return L.marker(latlng, {
                        icon: tweetsIconNegative,
                  });}
                  else {
                        return L.marker(latlng,{
                        icon: tweetsIconNeutral,
                  });}
```

```
                        },
                        onEachFeature: function (feature, layer) {
                                coords.push([feature.geometry.coordinates[1],
feature.geometry.coordinates[0], polarityToIntensity(feature.properties.polarity)]);
                        }
                });

                var cfg_neu = {
                "radius": 10,
                "maxOpacity": .8,
                "scaleRadius": false,
                "useLocalExtrema": true,
                  latField: 'lat',
                  lngField: 'lng',
                  valueField: 'polarity'
                };

                var heatmapLayer_neu = new HeatmapOverlay(cfg_neu);

                realtime_neutral.on('update', function(e) {
                        //debugger;
                        Object.keys(e.enter).forEach(function(key) {

        heat_pos.addLatLng(e.enter[key].geometry.coordinates);

        heatmapLayer_neu.addData({'lat':e.enter[key].geometry.coordinates[1],
'lng':e.enter[key].geometry.coordinates[0],
'polarity':polarityToIntensity(e.enter[key].properties.polarity)});


                        });
```

```
                    //map.fitBounds(realtime_negative.getBounds(), {maxZoom:
3});
                    tweetsClusters.addLayer(realtime_neutral);
            });

            var cfg_all = {
            "radius": 10,
            "maxOpacity": .8,
            "scaleRadius": false,
            "useLocalExtrema": true,
              latField: 'lat',
              lngField: 'lng',
              valueField: 'polarity'
            };

            var heatmapLayer_all = new HeatmapOverlay(cfg_all);

            $.getJSON("tweets_geojson_all.php", function (data) {
                    tweets.addData(data);
                    tweetsClusters.addLayer(tweets);
            }).complete(function () {
                    map.fitBounds(tweets.getBounds());

        tweets.eachLayer(function(layer){heatmapLayer_all.addData({'lat':layer.getL
atLng().lat, 'lng':layer.getLatLng().lng,
'polarity':polarityToIntensity(layer.feature.properties.polarity)});});
            });

            var baseLayers = {
                    "OpenStreetMap": OSM
            };
            var overlays = {
                    "tweets": tweets,
                    "Tweets (clustered)": tweetsClusters,
                    "realtime_positive": realtime_positive,
                    "realtime_negative": realtime_negative,
                    "realtime_neutral": realtime_neutral,
                    "heatmapLayer_pos": heatmapLayer_pos,
                    "heatmapLayer_neg": heatmapLayer_neg,
                    "heatmapLayer_neu": heatmapLayer_neu,
                    "heatmapLayer_all": heatmapLayer_all
            };

            layersControl = new L.Control.Layers(baseLayers, overlays, {
                    collapsed: false
            });

            map.addControl(layersControl);
        </script>
</body>
</html>
```