Project Report

on

Twitter Sentiment Analysis

(A dissertation submitted in partial fulfillment of the requirements of Bachelor of Technology in Computer Science and Engineering of the Maulana Abul Kalam Azad University of Technology, West Bengal)

Submitted by

SUBHASISH MANDAL
RUPESH GHOSH
TAUSEEF EQBAL
SUMON MUNDA
SUKUMAR KARMAKAR

Under the guidance of

Mr. Debyan Ganguly

Asst. Prof.
Dept. of Computer Science and Engineering

Government College of Engineering and Leather Technology

(Affiliated to MAKAUT, West Bengal)

Kolakta - 700106, WB

2018-2019

Certificate of Approval

This is to certify that the project report on Twitter Sentiment Analysis is a record of bonafide work, carried out by Shri Subhasish Mandal, Shri Rupesh Ghosh, Shri Tauseef Eqbal, Shri Sumon Munda and Shri Sukumar Karmakar under my guidance and supervision

In my opinion, the report in its present form is in conformity as specified by Government College of Engineering and Leather Technology and as per regulations of the Maulana Abul Kalam Azad University of Technology, West Bengal. To the best of my knowledge the results presented here are original in nature and worthy of incorporation in project report for the B.Tech. Program in Computer Science and Engineering.

Signature of
Supervisor/ Guide

Signature of
Head, Dept. of CSE

ACKNOWLEDGEMENT

With great pleasure, I would like to express my profound gratitude and indebtedness to Mr Debyan Ganguly, Department of Computer Science and Engineering, Government College of Engineering and Leather Technology, W.B. for his continuous guidance, valuable advice and constant encouragement throughout the project work. His valuable and constructive suggestions at many difficult situations are immensely acknowledged. I am in short of words to express his contribution to this thesis through criticism, suggestions and discussions.

I would like to take this opportunity to thank Dr. Santanu Halder, Project Coordinator and Prof. Kalyan Mahata, HOD, Department of Computer Science & Engineering, Government College of Engineering and Leather Technology.

I would like to express my gratitude to Mr. Debyan Ganguly for their valuable suggestions and help.

1. Subhasish Mandal - 11200116022 -
2. Rupesh Ghosh - 11200116035 -
3. Tauseef Eqbal - 11200116018 -
4. Sumon Munda - 11200116021 -
5. Sukumar Karmakaran - 11200117003 -

Dedicated to

To my Parents and Faculty

ABSTRACT

Twitter is a micro-blogging site used by people to express their opinions on various topics. Sentiment Analysis is the process of extracting meaningful customer insight from the text in terms of sentiment score. Twitter Sentiment analysis is an application of sentiment analysis, on the twitter data (tweets). But today it has become difficult to analyze tweets because of the changed and challenging formats of the tweets. The increase in the use of various slangs, emoticons, abbreviations, and puns in tweets, has made it difficult to analyze tweets in the same ways as before. In this paper, we aim to review some papers regarding research in sentiment analysis on Twitter, describing the methodologies adopted and models applied; along with describing Vader Sentiment Analysis which is a Python-based approach.

CONTENTS

1. INTRODUCTION

The growth of user-generated content in web sites and social networks, such as Twitter, Facebook, and Instagram, has led to an increasing power of social networks for expressing opinions about services, products or events, among others. This tendency, combined with the fast spreading nature of content online, has turned online opinions into a very valuable asset. In this context, many Natural Language Processing (NLP) tasks are being used in order to analyze this massive information.

Sentiment Analysis (SA) is an increasingly growing task, whose goal is the classification of opinions and sentiments expressed in text, generated by a human party. It is intended to serve as an application to understand the attitudes, opinions and emotions expressed within an online mention. The intention is to gain an overview of the wider public opinion behind certain topics. Precisely, it is a paradigm of categorizing conversations into positive, negative or neutral labels. Many people use social media sites for networking with other people and to stay up-to-date with news and current events. These sites (Twitter, Facebook, Instagram) offer a platform to people to voice their opinions. For example, people quickly post their reviews online as soon as they watch a movie and then start a series of comments to discuss about the acting skills depicted in the movie. This kind of information forms a basis for people to evaluate, rate about the performance of not only any movie but about other products and to know about whether it will be a success or not. This type of vast information on these sites can used for marketing and social studies. Therefore, sentiment analysis has wide applications and include emotion mining, polarity, classification and influence analysis.

1.1 Motivation

We have chosen to work with twitter since we feel it is a better approximation of public sentiment as opposed to conventional internet articles and web blogs. The reason is that the amount of relevant data is much larger for twitter, as compared to traditional blogging sites. Moreover, the response on twitter is prompter and also more general (since the number of users who tweet is substantially more than those who write web blogs on a daily basis). Sentiment analysis of public is highly critical in macro-scale socioeconomic phenomena like predicting the stock market rate of a particular firm. This could be done by analyzing overall public sentiment towards that firm with respect to time and using economics tools for finding the correlation between public sentiment and the firm’s stock market value. Firms can also estimate how well their product is responding in the market, which areas of the market is it having a favourable response and in which a negative response (since twitter allows us to download stream of geo-tagged tweets for particular locations. If firms can get this information, they can analyze the reasons behind geographically differentiated response, and so they can market their product in a more optimized manner by looking for appropriate solutions like creating suitable market segments. Predicting the results of popular political elections and polls is also an emerging application to sentiment analysis. One such study was conducted by Tumasjan et al. in Germany for predicting the outcome of federal elections in which concluded that twitter is a good reflection of offline sentiment [3].

1.2 Background

With the rapid development of internet, an increasing number of people are expressing their opinions on-line. E-commerce websites typical examples. Amazon encourages customers to create reviews and provide feedback about the products and services they purchase. By rating the products on a 5-star scale and writing several paragraphs of review, the Amazon shoppers are able to share information on "what people like or do not like".

Social network website is another example where user-generated opinionated data abounds. Social network websites usually contain a great scope of topics, especially those related to big news events. Twitter, for example, is one of the most popular social network websites to which people turn when big events occur. In 2010, after a catastrophic 7.0 magnitude earthquake hit Haiti, Twitter served as a major hub of information. Twitter was proven to be an important tool for fund-raising and relief efforts [4]. Twitter has even changed the outcome of many historical events, especially in political elections where millions of voters' tweet frequently to openly express their political approval or contempt. Sentiment analysis research goes hand in hand with the Internet boom. On the one hand, applications of sentiment analysis provide significant commercial value. On the other, sentiment analysis systems provide basis for academic research in computer science, linguistics, social science, management science etc.

1.3 Summary of Present Work

This project of analyzing sentiments of tweets comes under the domain of "Pattern Classification" and "Data Mining". Both of these terms are very closely related and intertwined, and they can be formally defined as the process of discovering "useful" patterns in large set of data, either automatically (unsupervised) or semi automatically (supervised). The project would heavily rely on techniques of "Natural Language Processing" in extracting significant patterns and features from the large data set of tweets and on "Machine Learning" techniques for accurately classifying individual unlabeled data samples (tweets) according to whichever pattern model best describes them.

The features that can be used for modeling patterns and classification can be divided into two main groups: formal language based and informal blogging based. Language based features are those that deal with formal linguistics and include prior sentiment polarity of individual words and phrases, and parts of speech tagging of the sentence. Prior sentiment polarity means that some words and phrases have a natural innate tendency for expressing particular and specific sentiments in general. For example, the word "excellent" has a strong positive connotation while the word "evil" possesses a strong negative connotation. So, whenever a word with positive connotation is used in a sentence, chances are that the entire sentence would be expressing a positive sentiment. Parts of Speech tagging, on the other hand, is a syntactical approach to the problem. It means to automatically identify which part of speech each individual word of a sentence belongs to: noun, pronoun, adverb, adjective, verb, interjection, etc. Patterns can be extracted from analyzing the frequency distribution of these

parts of speech (ether individually or collectively with some other part of speech) in a particular class of labeled tweets. Twitter based features are more informal and relate with how people express themselves on online social platforms and compress their sentiments in the limited space of 280 characters offered by twitter. They include twitter hashtags, retweets, word capitalization, word lengthening, question marks, presence of url in tweets, exclamation marks, internet emoticons and internet shorthand/slangs.

1.4 Hardware and Software Used

Hardware Used:

- Intel Core i-5-8265u
- 8GB RAM
- Intel UHD Graphics 640

Software Used:

- Python 3.8.2
- Visual Studio Code 1.46.1

Python Packages Used:

- tweepy 3.8.0
- matplolib 3.2.1
- vaderSentiment 3.3.2
- regex 2020.4.4
- nltk 3.5

2. LITERATURE REVIEW AND RELATED WORK

Sentiment analysis, or opinion mining, is an active area of study in the field of natural language processing that analyzes people's opinions, sentiments, evaluations, attitudes, and emotions via the computational treatment of subjectivity in text. It is not our intention to review the entire body of literature concerning sentiment analysis. Indeed, such an endeavor would not be possible within the limited space available. We do provide a brief overview of canonical works and techniques relevant to our study

2.1 Lexicon-Based Methods

A substantial number of sentiment analysis approaches rely greatly on an underlying sentiment (or opinion) lexicon. A sentiment lexicon is a list of lexical features (e.g., words) which are generally labeled according to their semantic orientation as either positive or negative [5]. Manually creating and validating such lists of opinion-bearing features, while being among the most robust methods for generating reliable sentiment lexicons, is also one of the most time-consuming. For this reason, much of the applied research leveraging sentiment analysis relies heavily on preexisting manually constructed lexicons. Because lexicons are so useful for sentiment analysis, we briefly provide an overview of several benchmarks.

2.1.1 Sentiment Lexicon

Sentiment lexicon refers to a list of words or phrases that conveys positive or negative polarity information. Lexicon is very important resource in sentiment analysis. It provides sentiment information about the smallest linguistic unit. Even machine-learning based methods can rely on sentiment lexicon in feature engineering. Proper use of well-designed lexicon will improve the performance of sentiment analysis system. In this part, we will introduce most popular lexicons used both in the industry and academia. An overview of methods to compile customized sentiment lexicon is also provided.

MPQA subjective lexicon [6] is part of MPQA Opinion Corpus. The lexicon is made available under the terms of GNU License. Each entry represents a word and its length, strength, Part-of-Speech and polarity. It provides a very comprehensive amount of information which has implications for various fields of study.

SentiWordNet [7] adds real-value sentiment scores to each synset of WordNet to denote its sentiment polarity (positive, negative and objective). Besides, Part-ofSpeech, context information is also incorporated. One advantage of SentiWordNet is that it uses semantic resource to enhance the structure of the lexicon. Another advantage is that it assigns both positive and negative scores to a single word.

VADER Sentiment Lexicon [8] is a comprehensive list of “gold-standard” sentiment words especially applicable to micro-blog and other social network text data. Providing both polarity and intensity, VADER is validated by human experts. Besides common dictionary

words, it also gives information on emoticons, slang (“nah”, “meh” etc.) and acronyms (“LOL”, “LMAO” etc.)

Aside from those lexicons mentioned in previous part, researchers tend to build customized lexicons and tailor them according to their need. Two type of approaches are known: dictionary-based and corpus-based. Dictionary-based approaches make use of lexical databases like WordNet to expand a manually created seed set. The automatic expansion will explore pairwise word relations and generate a lexicon of proper size.

2.1.2 Lexicon-Based Classification Algorithms

The motivation behind lexicon-based classification algorithms is that the sentiment of a document is determined by the dominant components (words or phrases). The basic schemes include majority voting, document scoring with thresholding and simple word counting.

Lexicon based methods usually provide a baseline for further study. Recently there has been a trend of using ensemble learning with multiple weak lexicon-based classifiers. Augustyniak et. al. [9] use a variety of lexicon-based weak classifiers and a C3.4 decision tree as strong classifier. The lexicon extraction method is called Frequentiment and it is proved 3 to 5 times faster than supervised learning. While this is very informative and promising, no similar known work has been conducted to test its effectiveness in English language text.

2.1.3 Advantages of Lexicon-Based Classification

The use of lexicon-based techniques has a number of advantages. First, the linguistic content can be taken into account through mechanisms such as sentiment valence shifting considering both intensifiers (e.g. very bad) and negations (e.g. not happy). In addition, sentiment orientation of lexical entities can be differentiated based on their characteristics.

2.1.4 Disadvantages of Lexicon-Based Classification

lexicon-based approaches have several drawbacks: the need of a lexicon that is consistent and reliable, as well as the variability of opinion words across domains, contexts and languages. These dependencies make it hard to maintain domain independent lexicons

2.2 Machine Learning Based Method

Sentiment classification, by its nature, is a type of two-way text categorization task. Text categorization usually classifies data into several pre-defined categories. The majority of research in both text categorization and sentiment analysis fall into machine learning based methodology. Because manually creating and validating a comprehensive sentiment lexicon is labor and time intensive, much work has explored automated means of identifying sentiment relevant features in text. Typical state of the art practices incorporates machine learning approaches to “learn” the sentiment-relevant features of text.

The Naive Bayes (NB) classifier is a simple classifier that relies on Bayesian probability and the naive assumption that feature probabilities are independent of one another. Maximum Entropy (ME) is a general-purpose machine learning technique belonging to the class of exponential models using multinomial logistic regression. Unlike NB, ME makes no conditional independence assumption between features, and thereby accounts for information entropy (feature weightings). Support Vector Machines (SVMs) differ from both NB and ME models in that SVMs are non-probability classifiers which operate by separating data points in space using one or more hyperplanes (centerlines of the gaps separating different classes).

Machine learning approaches are not without drawbacks. First, they require (often extensive) training data which are, as with validated sentiment lexicons, sometimes troublesome to acquire. Second, they depend on the training set to represent as many features as possible (which often, they do not – especially in the case of the short, sparse text of social media). Third, they are often more computationally expensive in terms of CPU processing, memory requirements, and training/classification time (which restricts the ability to assess sentiment on streaming data). Fourth, they often derive features "behind the scenes" inside of a black box that is not (easily) human interpretable and are therefore more difficult to either generalize, modify, or extend (e.g., to other domains).

2.3 Rule-Based Method

The first automatic text categorization systems relied heavily on knowledge engineering techniques, where a set of human-created logical rules would be applied. Building such an expert system is usually labor-intensive, time-consuming and expensive. The study of sentiment analysis emerges after text categorization became a nearly "solved-problem". Therefore, most research pursues a machine learning-based methodology. There are very few pure rule-based methods or systems that we know of. Most rules are incorporated in lexicon-based systems to improve performance. VADER [8] is a rule-based model with rich lexical features. It aims at sentiment analysis in micro-blog data and achieves effective and generalizable results compared to other state-of-the-art methods It is a convention for sentiment analysis researchers to categorize methods as "lexicon-based" and "machine learning-based". Conceptually most of the lexicon-based methods can be regarded as "unsupervised" or "semi-supervised" learning methods. Taboada [10] is the most comprehensive work which uses sentiment lexicon and incorporates intensification and negation to achieve consistent across-domain performance.

3. METHODOLOGY

3.1 Introduction to Problem

Every day massive amount of data is generated by social media users which can be used to analyze their opinion about any event, movie, product or politics. Conventional tools like Apache Storm analyze stream in micro-batch whereas novel tools like Apache Spark process data in real time making analyzing and processing of real time data possible.

3.2 Platform and Technologies Used

Python: Python is an interpreted, high-level, general-purpose programming language. Created by Guido van Rossum and first released in 1991, Python's design philosophy emphasizes code readability with its notable use of significant whitespace. Its language constructs and object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects. Python is dynamically typed and garbage-collected. It supports multiple programming paradigms, including structured (particularly, procedural), object-oriented, and functional programming. Python is often described as a "batteries included" language due to its comprehensive standard library.

There are vast number of modules and packages available in Python language for Sentiment Analysis. Thus, we proceeded with implementation in Python as compared to C++ or Java.

Valence Aware Dictionary and sEntiment Reasoner (VADER): VADER is a lexicon and rule-based sentiment analysis tool that is *specifically attuned to sentiments expressed in social media*. It is fully open-sourced under the MIT License. VADER also takes into consideration word order and degree modifiers [11].

There are a couple of ways to install and use VADER sentiment. The simplest is to use the command line to do an installation from PyPI using pip

```
$ pip install vaderSentiment
```

Natural Language Toolkit (NLTK): NLTK is a free open-source Python package that provides several tools for building programs and classifying data. NLTK is suitable for linguists, engineers, students, educators, researchers, and developers who work with textual data in natural language processing and text analytics. NLTK provides an easy way to use the interfaces of over 50 corpora and lexical resources. It includes a group of text processing libraries for classification, tokenization, stemming, tagging, parsing, and semantic reasoning [12].

Twitter: It is an online social media platform which is suitable for our use case due to number of factors. Firstly, the amount of relevant data is much larger for twitter as compared to blogs or review websites. Secondly, response on twitter is general and prompt. Other social media giants like Facebook does not provide much data so using their public API was not considered. Finally, most twitter users voice their opinion about other people like actors,

products: in case they bought a new phone or unsatisfied with customer service behaviour as opposed to other social media where users post most status and pictures of themselves. These factors make twitter a logical choice for real time data analysis.

Visual Studio Code (VSCode): Visual Studio Code is a free source-code editor made by Microsoft for Windows, Linux and macOS. Features include support for debugging, syntax highlighting, intelligent code completion, snippets, code refactoring, and embedded Git. Users can change the theme, keyboard shortcuts, preferences, and install extensions that add additional functionality.

Visual Studio Code's source code comes from Microsoft's free and open-source software VSCode project released under the permissive MIT License, but the compiled binaries are freeware for any use.

3.3 Proposed Method

The current study consists of three phases. Phase one concerns the acquisition of Twitter data. Phase two focuses on the initial preprocessing work carried out to clean and remove irrelevant information from the tweets. Phase three deals with the use of the NLTK's VADER analyzer as well as the scoring method applied to the VADER results to assess its ability to classify tweets on compound score.

3.3.1 Data Collection

As aforementioned that, the purpose of the data acquisition phase was to obtain Twitter data. The methods used to extract Twitter data allowed real-time access to publicly available raw tweets. To gather data we use, "tweepy" library of python.

Data in the form of raw tweets is retrieved by using the Python library "tweepy" which provides a package for real time twitter streaming API. Tweepy is a Python library for accessing the Twitter API. It is great for simple automation and creating twitter bots. The API requires us to register a developer account with Twitter and fill in parameters such as consumerKey, consumerSecret, accessTokenaccess, and TokenSecret. This API allows to get all random tweets or filter data by using keywords. Filters supports to retrieve tweets which match a specific criterion defined by the developer. We used this to retrieve tweets related to specific keywords which are taken as input from users.

We can also specify number of tweets to be retrieved. We can also apply filter to not retrieve retweets. We can also apply language filters to retrieve tweets from a specific language only.

Tweepy can be installed in command line from PyPI usin pip,

```
$ pip install tweepy
```

3.3.2 Cleaning and Preprocessing of Tweets

A tweet is a microblog message posted on Twitter. It is limited to 280 characters. Most tweets contain text and embed URLs, pictures, usernames, and emoticons. They also contain misspellings. Hence, a series of preprocessing steps were carried out to remove irrelevant information from the tweets. The reason is that the cleaner the data, the more suitable they are for mining and feature extraction, which leads to the improved accuracy of the results. Each tweet was processed to extract its main message. To preprocess these data, we use a regular expression (Regex) in Python was run to detect and discard tweets special characters, such as URLs (“http://url”), retweet (RT), user mention (@), and unwanted punctuation. Because hashtags (#) often explain the subject of the tweet and contain useful information related to the topic of the tweet, they are added as a part of the tweet, but the “#” symbol was removed.

Python has a rich set of features to do the same effortlessly we use a python based regular expression which does the same work on the go.

For each task of pre-processing, the related regular expression is given below:

 Converting all upper-case letters to lower case.

 Removing URLs: Filtering of URLs can be done with the help of regular expression (http|https)://[a-zA-Z0-9\\./]+.

 Removing Handles (User Reference): Handles can be removed using the regular expression - @(\w+).

 Removing hashtags: Hashtags can be removed using the regular expression - #(\w+).

 Removing emoticons: We can use emoticon dictionary to filter out the emoticons or to save the occurrence of them in a different file. (But in our analysis, we use emoticons file for their weight calculation)

 Removing repeated characters.

3.3.3 Feature Extraction

A feature is a piece of information that can be used as a characteristic which can assist in solving a problem (like prediction). The quality and quantity of features are very important as they are important for the results generated by the selected model. Given below are the most common types of features extracted:

Unigram Features: One word is considered at a time and decided whether it is capable of being a feature.

N-gram Features: More than one word is considered at a time.

External Lexicon: Use of a list of words with predefined positive or negative sentiment.

Frequency analysis is a method to collect features with highest frequencies used in. This is the most commonly used method for collecting different types of features from the data. The feature result calculated is divided into two categories: Common Features and Tweet Specific Features.

3.3.4 VADER Sentiment Analysis

In phase three, the sentiments expressed in the tweets were classified. VADER Sentiment Analyzer was applied to the dataset. VADER is a rule-based sentiment analysis tool and a lexicon that is used to express sentiments in social media. First, we created a sentiment intensity analyzer to categorize our dataset. Then the polarity scores method was used to determine the sentiment. The VADER Sentiment Analyzer was used to classify the preprocessed tweets as positive, negative or neutral. The compound value is a useful metric for measuring the sentiment in a given tweet. In the proposed method, the threshold values used to categorize tweets as either positive, negative, or neutral.

About Scoring: [13] The compound score is computed by summing the valence scores of each word in the lexicon, adjusted according to the rules, and then normalized to be between -1 (most extreme negative) and +1 (most extreme positive). This is the most useful metric if you want a single unidimensional measure of sentiment for a given sentence. Calling it a 'normalized, weighted composite score' is accurate. It is also useful for researchers who would like to set standardized thresholds for classifying sentences as either positive, neutral, or negative. Typical threshold values (used in the literature cited on this page) are:

1. **positive sentiment**: compound score >= 0.05
2. **neutral sentiment**: compound score > -0.05 and compound score < 0.05
3. **negative sentiment**: compound score <= -0.05

The pos, neu, and neg scores are ratios for proportions of text that fall in each category (so these should all add up to be 1). These are the most useful metrics if you want multidimensional measures of sentiment for a given sentence.

After Scoring all tweets we can classify them into positive, negative or neutral tweets bases on their compound scores.

4. APPLICATION

Commerce: Companies can make use of this research for gathering public opinion related to their brand and products. From the company's perspective, the survey of a target audience is imperative for making out the ratings of their products. As Twitter has distributed audience with rich data under the desired limit, it serves as a good platform for data collection and analysis to determine customer satisfaction.

Politics: Majority of tweets on Twitter are related to politics. Due to Twitter's widespread use, many politicians are also aiming to connect to people through it. People post their support or disagreement towards government policies, actions, elections, debates etc. Hence analysing data from it can help is in determining public view.

Sports Events: Sports involve many events, championships, gatherings and some controversies too. Many people are enthusiastic sports followers and follow their favourite players present on Twitter. These people frequently tweet about different sports-related events. We can use the data to gather the public view of a player's action, team's performance, official decisions etc.

CONCLUSION

Twitter sentiment analysis comes under the category of text and opinion mining. It focuses on analysing the sentiments of the tweets and presenting the result under different sentiment classes. These results can be used to train a machine learning model which can be used in future to predict customer behaviour for particular product, service or expectation of people in regard to particular political party. The complete process of sentiment analysing comprises of steps like data collection, text pre-processing, sentiment detection, sentiment classification. This topic has evolved as an important research topic during the last decade with the development of models reaching the efficiency of almost 85%-90%. But still, we have to focus on building models that have the capabilities to read between the lines, have the capabilities to understand human slangs and most importantly sarcasm. With the development in the field leaping folds by fold, it's not far when models will have extreme accuracies and would we able to understand slightest of the slightest change in the meaning of the context.

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