

Sentimental Analysis Based on Social Media using Multi Modal Algorithm

Sahil Nagare, Rushikesh Kale, Hrutik Gitekar, Rushikesh Pathania, Prof. A. A. Pund

Department of Information Technology Engineering

Dr. Vithalrao Vikhe Patil College of Engineering, Ahmednagar, Maharashtra, India

Savitribai Phule Pune University, Pune, Maharashtra, India

Abstract: *Propose system tend to concentrate on analysis sentiment of text from social media, aim of system is to find whether piece of text is positive or negative. The goal of Sentiment Analysis is to harness this data in order to obtain important information regarding public opinion that would help make smarter business decisions, political campaigns and better product consumption. Sentiment Analysis focuses on identifying whether a given piece of text is subjective or objective and if it is subjective, then whether it is negative or positive. Sentiment analysis deals with the computational treatment of opinion, sentiment, and subjectivity of texts. Moreover, we tend to conjointly develop economical illation methodology for parameter estimation of sup-ported folded Gibbs sampling. We tend to judge SJASM extensively on real-world review knowledge, and experimental results demonstrate that the planned model outperforms seven well-established base- line strategies for sentiment analysis tasks.*

Keywords: Sentiment analysis.

I. INTRODUCTION

Sentiment Analysis (SA) is one of the most widely studied applications of Natural Language Processing (NLP) and Machine Learning (ML). This field has grown tremendously with the advent of the Web 2.0. The Internet has provided a platform for people to express their views, emotions and sentiments towards products, people and life in general. Thus, the Internet is now a vast resource of opinion rich textual data. The goal of Sentiment Analysis is to harness this data in order to obtain important information regarding public opinion, that would help make smarter business decisions, political campaigns and better product consumption. Sentiment Analysis focuses on identifying whether a given piece of text is subjective or objective and if it is subjective, then whether it is negative or positive. Sentiment analysis deals with the computational treatment of opinion, sentiment, and subjectivity of texts. Sentiment analysis starts with a small question: "What other people think?", and finally convert into billions of dollars of commercial deal. After the great success of Web-2.0, sentiment analysis became a demanding and commercially supported research field. Recently, certain events, which affected Government, have been triggered using the Internet. The social networks are being used to bring together people so as to organize mass gatherings and oppose oppression. On the darker side, the social networks are being used to insinuate people against an ethnic group or class of people, which has resulted in a serious loss of life. Thus, there is a need for Sentiment Analysis systems that can identify such phenomena and curtail them if needed. This purpose of this project is to develop an automated way of gauging the mood of any topic based on social media, specifically Twitter, using a portable Android device. The software should determine the sentiment of the Twitter community with respect to a given topic, without looking at traditional news sources. Sentiment analysis has been an important tool for brands looking to learn more about how their customers are thinking and feeling. It is a relatively simplistic form of analytics that helps brands find key areas of weakness (negative sentiments) and strengths (positive sentiments). The insights gained from these tools are becoming much deeper, as a result of emerging social media platforms and features.

II. LITERATURE SURVEY

Title of Paper: Evaluation of deep learning techniques, Sentimental analysis on twitter.

Author: Sani Kamus, Dionysis Goularas

Description: In this paper author presented a comparison of different deep learning methods used for sentiment analysis in Twitter. Particularly, two categories of neural networks are utilized, convolution-al neural networks (CNN), which are especially per formant in the area of image processing and recurrent neural networks (RNN) which are applied with success in natural language processing task.

Title of paper: Character based convolutional neural network from language agnostic twitter sentiment analysis.

Author: Jonatas Wehrmann, William Becker

Description: In this paper author proposed a language-agnostic translationfree method for Twitter sentiment analysis, which makes use of deep convolutional neural networks with character-level embedding for pointing to the proper polarity of tweets that may be written in distinct (or multiple) languages.

Title of Paper: Social Media Sentimental Analysis on twitter on datasets.

Author: Shikha Tiwari, Anshika Verma

Description: In this paper author proposed only sentence level analysis in which analysis of emotion is done by each sentence that is how each sentence expresses any types of emotion that are mentioned.

Title of paper: Sentimental analysis with NPL on twitter data.

Author: Md.Rakibul Hasan, Maisha Malisha

Description: In this paper author developed a natural language processing (NLP) based pre-processed data framework to filter tweets. Secondly, we incorporate Bag of Words (Bow) and Term Frequency-Inverse Document Frequency (TF-IDF) model concept to analyse sentiment. They used different machine learning algorithms, such as Naive Bayes, Maximum Entropy and Vector Machine support, to sentiment analysis

2.1 Summary of Literature Survey

Sentiment analysis has been an important tool for brands looking to learn more about how their customers are thinking and feeling. It is a relatively simplistic form of analytics that helps brands find key areas of weakness (negative sentiments) and strengths (positive sentiments). The insights gained from these tools are becoming much deeper, as a result of emerging social media platforms and features.

III. PROPOSED SYSTEM

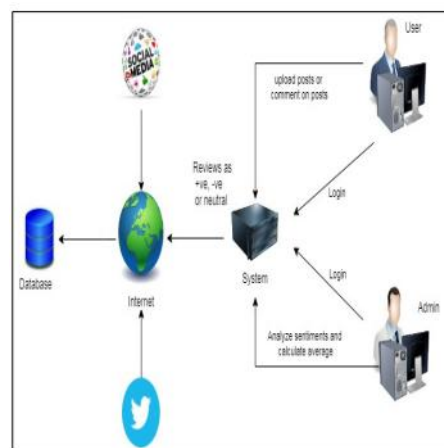


Fig: Proposed System

3.1 Algorithm

A. Latent Dirichlet Allocation

In natural language processing, the latent Dirichlet allocation (LDA) is a generative statistical model that allows sets of observations to be explained by unobserved groups that explain why some parts of the data are similar. For example, if observations are words collected into documents, it posits that each document is a mixture of a small number of topics and that each word's presence is attributable to one of the document's topics. LDA is an example of a topic model. The basic idea behind LDA is that documents exhibit multiple topics. The topics, using the bag-of-words assumption, are formally defined as a distribution over a fixed vocabulary. To summarise how the topics are inferred and to achieve an LDA model from the documents generated, the generative process is described as:

1. For each topic: Decide what words are likely.
2. For each document:
 - a. Decide the proportions of topics that should be in the document,
 - b. For each word:
 - i. Choose a topic
 - ii. Given this topic, choose a likely word (Generated in step)

B. Sentimental Analysis

Opinions influence human behaviours such that our thoughts or choices can depend on the evaluation by other people. The study of sentiment analysis contains the subjects, includes opinions on these subjects, and the related conceptions of these subjects. Sentiment analysis has grown into one of the most active areas in natural-language processing (NLP) and data mining. Sentiment analysis is broken into five steps. A typical model is shown in Fig. 1. Data Collection is collecting user-generated data, which can involve data from social media networks and blogs, etc. This data is generally unstructured, expressed in various ways by word choices, idiomatic phrases, and so on. Text Preparation is the preparation step before data extraction. Irrelevant contents and non-textual data are eliminated. Sentiment Detection examines the opinions in the extracted text. The contents with opinions are retained, and the contents with factual information are discarded. Sentiment Classification is to apply some approaches to classify the sentiments. Typical approaches include the machine learning approach, the sentiment orientation approach, and a lexicon-based approach. Presentation of Output is to display the results in a direct way such as in graphs (pie charts, line graphs, and so on).

Algorithm Steps:

1. Data Retrieving In general, a tweet by any user is public and readable by anyone by default. Registering an account on the Twitter developer platform provides access to all the tweeted data. Filter Stream is used to retrieve tweet data in the experiment. This function is provided stream, which connects to the Twitter Streaming API and opens a stream to capture the results based on specific conditions, such as keywords and locations.

2. Data Processing

- Most of the Twitter data are highly unstructured. There could be typos, slang usage, and grammar mistakes. Then cleansing steps are applied to the documents to generate structured data.
- Convert to lower case letters: Conversion into lower case letters is necessary because text analysis is case sensitive. In the probabilistic model, the frequency of each letter is counted so that "Text" and "text" are treated as different words if the case conversion is not applied. All the letters are converted into lower cases.
- Remove @user and links:

Twitter has special rules regarding reserved symbols and links that could cause confusion in later analysis. The @ symbol is used when the user mentions some other user to read this tweet. item Remove punctuations and digits: This is a general step used in many text mining techniques. Punctuation in sentences makes the text more readable for humans, but a machine does not distinguish punctuation and digits from other characters. Punctuation is removed because text analysis is not concerned with the digits. Numeric digits usually do not influence the meaning of the text.

- Remove stop words: Stop words refer to the words which usually have no analytic value, words such as 'a', 'and', 'the' etc. These words make the sentences more readable to humans, but confound the analysis. Words

can be added to the list of stop words depending on the specific requirements.

- Remove extra white spaces: The earlier pre-processing steps can generate extra white spaces. Removing the extra spaces is necessary in text cleansing.
- Stem Documents: Some words in the text have the same meaning but in different forms. Stemming is the process of eliminating affixes from words to convert the words into their base form; for example, stemming “run”, “runs” and “running” into “run”.

IV. RESULTS

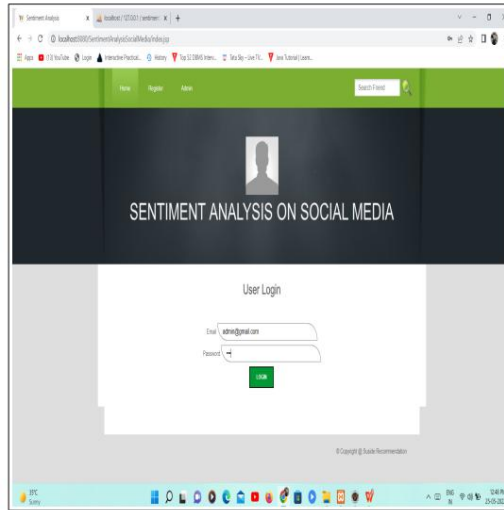


Fig: User Login

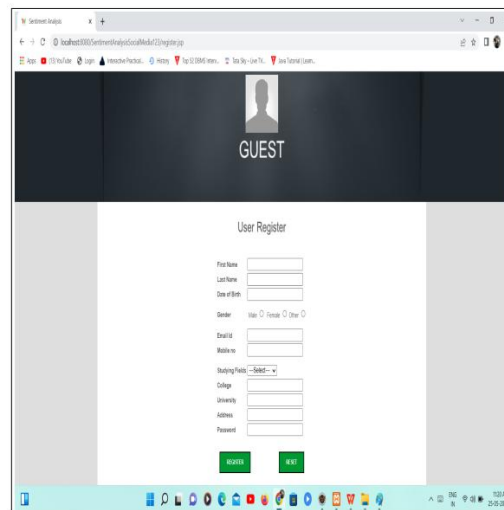


Fig: User Registration

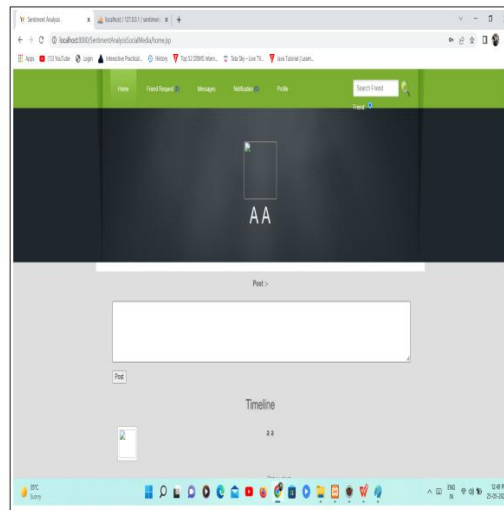


Fig: Add Review

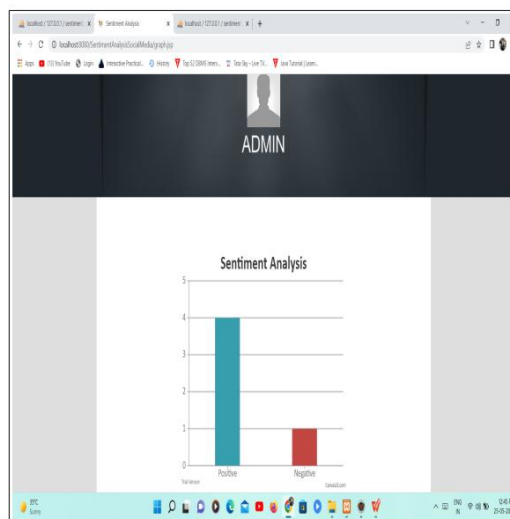


Fig: Graph Display

V. CONCLUSION

The rise of social media has fuelled interest in sentiment classification. Promptly and correctly classifying sentiment from the text has become an important task for individuals and companies. In the development of prediction models to classify the reviews, more reliable approaches are expected to reduce the misclassification. In this study, the results of various hybrid methods are empirically evaluated on datasets of different size for use in sentiment mining. Among the methods used, hybrid ensemble method (HEM1) is highly robust in nature for balanced data models I, II and III, which is studied through various quality parameters. The analysis also shows that the compound combination of unit gram, bigram and trig ram performs better for almost all the prediction methods. To handle imbalance data distribution in real time applications, it is observed from the results that using LDAs for class prediction can be influenced by the data imbalance, although LDAs can adjust itself well to some degree of data imbalance. To cope with the problem, rebalancing the data is chosen as a promising direction, but both under sampling and over sampling have limitations. Through extensive experiments with benchmark and real application datasets, the proposed modified bagging method is shown to be effective and superior to several other methods with different data sampling methods. The results also proved that the

PCA is a suitable dimension reduction method for hybrid methods for both balanced and imbalanced datasets. In future, the effect of various other feature reduction techniques like latent dirichlet allocation can be investigated. Further experiments should be conducted in the future to evaluate the impact of various domain and region specific parameters. Extending sentiment mining to other domains may lead to interesting new results. In future, the use of more combination of n-grams and feature weighting that gives a better accuracy level than this can be considered. The work done in this research is only related to classification sentiment into two of the classes (binary classification) that is a positive class and negative class. In the future development, a multi class of sentiment classification such as positive, negative, neutral and so on might be taken into consideration. In this work, the focus is on finding features that appear explicitly as nouns or noun phrases in the reviews. The finding of implicit features is left to future work. As ensemble learning methods need a lot of computing time, parallel computing techniques should be explored to tackle this problem. A major limitation of ensemble learning methods is the lack of interpret ability of the results and the knowledge learned by ensembles is difficult for humans to understand. Therefore, improving the interpret ability of ensembles is another important research direction. Future opinion-mining systems need broader and deeper common and common sense knowledge bases. This will lead to a better understanding of natural language opinions and will more efficiently bridge the gap between multi-modal information and machine process able data. Blending scientific theories of emotion with the practical engineering goals of analysing sentiments in natural language text will lead to more bio-inspired approaches to the design of intelligent opinion-mining systems capable of handling semantic knowledge, making analogies, learning new affective knowledge, and detecting, perceiving, and feeling emotions.

REFERENCES

- [1]. Md. Rakibul Hasan¹, Maisha Maliha², M. Arifuzzaman³, "Sentiment Analysis with NLP on Twitter Data" 11-12 July, 2019.
- [2]. Jonatas Wehrmann, Willian Becker, Henry E. L. Cagnini, and Rodrigo C. Barros "A Character-based Convolutional Neural Network" 2017.
- [3]. Shikha Tiwari, Anshika Verma "Social Media Sentimental Analysis on twitter on datasets" 2020.
- [4]. Sani Kamus, Dionysis Goularas "Evaluation of Deep Learning Techniques in Sentiment Analysis from Twitter Data" 2019 .
- [5]. I. Ahmad, "how much data is generated every minute info," Social Media Today, Jun 2018. O. Alonso, K. Shiells, H. J. Lee, and C. Carson, "System and method for generating social summaries," Jan 2019.
- [6]. K. C. Yang and Y. Kang, "Microblogs, jasmine revolution, and civil unrest: Reassessing the emergence of public sphere and civil society in people's republic of china," in Censorship, Surveillance, and Privacy: Concepts, Methodologies, Tools, and Applications. IGI Global, 2019, pp. 1153–1178.
- [7]. Z. Lv, H. Song, J. Lloret, D. Kim, and J.-N. De Souza, "Ieee access special section editorial: Big data analytics in the internet-of-things and cyber-physical systems," IEEE Access, vol. 7, pp. 18 070–18 075, 2019.
- [8]. N. Book, "Natural language toolkit," NLTK 3.4 documentation. [Online]. Available: www.nltk.org/
- [9]. V. Sahayak, V. Shete, and A. Pathan, "Sentiment analysis on twitter data," International Journal of Innovative Research in Advanced Engineering(IJIRAE), vol. 2, no. 1, pp. 178–183, 2015.