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Dynamic Pricing Using Sentimental Analysis

Thumati Manju Priyanka, Srujana Inturi
M.Tech, CSE, CBIT, Hyderabad
Asst Professor,CSE, CBIT, Hyderabad

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ABSTRACT— Currently, we may observe floods of emotions on social media on every issue you can think of Companies in the hospitality, advertising, and retail industries, among others. To categorise, combine, and apply these feelings in order to anticipate emotional analyses that can be used utilised to increase income By keeping track of changes in attitudes about a firms using dynamic pricing methods that take use of a certain products This project is founded and centred on Big Data socioeconomic aspects, which achieves the planned Dynamic Pricing Mechanism Model using sentiment analysis by LSTM as the primary element and how we can implement it through the mobile is taken into consideration. The outcomes demonstrate the suggested dynamic pricing generates a significant increase in revenue .

keywords: Dynamic pricing, LSTM, Sentiment analysis

I. INTRODUCTION

Presently, social media is an essential component of people's digital lives. A person has several social media profiles on various platforms that define his digital presence. A person utilises these many forms of accounts (for example, Instagram, Facebook, Twitter, Reddit) to take use of the various services they offer. In between all of the deliberate usage Social media is being used in unconventional ways for reasons other than those intended.

Twitter and community forums have technology such as social media and content production, but they are also increasingly being used to spread hate speech and organise absolutely despise events [1, 3].

Sentiment analysis (SA) is a popular method that is increasingly being used to examine the emotions of people on social media against a certain topic. Extending the innovative research in sentiment analysis done in [2], we examine primary sources and apply natural language processing techniques such as LSTM to determine the writer's opinion toward a certain issue. In general, sentiment analysis is a method of categorising text materials into several groupings. Most of the time, we merely need to categorise the papers as good or bad.

With the rising popularity of social media, massive databases (Big Data) of feedback and social network updates are constantly being created. Big Data approaches are employed. We gather and manage the data of different applications. A large volume of data in Higher information volume and intensity is required When technology backup and recovery resources expand Science of Big Data The key idea in Big Data analytics is identifying a meaningful pattern in a large volume of data Special approaches for extracting Big Data are required.

The reason behind the evolution of this method is the confidentiality and accessibility given by such media, the cultivation and spread of hate speech – eventually leading to hate crime – has become easy in a virtual terrain beyond the reach of traditional enforcement agencies. Hate speech was explicitly defined as "any communication that disparages a person or a group on the basis of any characteristics" such as race, colour, ethnicity, gender, sexual orientation, nationality, religion, or other characteristics[3]. Following recent events such as Brexit, the Manchester and London attacks, there has been a considerable spike in hate speech directed towards migrant and Muslim populations in the United Kingdom.As a variety of worldwide activities have been initiated to qualify the concerns and devise counter-measures, the importance of this topic has become more acknowledge. Some important concepts here are defined as:

(1) Sentimental Analysis

It is the extraction and identification of subjective information from sources using text analysis, natural language processing, and computational linguistics. It is also referred to as Opinion Mining.

(2) Dynamic Pricing

Pricing strategy in which a firm sets a dynamic price for its products or operations based on market demand and other external factors such as demand supply and competition prices, among others.

Businesses who focus more on e-commerce can effectively watch consumer habits using technology by analysing their buying patterns over time, demographics, etc., and making decisions about setting prices for particular products. Retailers can change the prices for their products after examining and taking note of these criteria. Although setting prices for products is simple, changing those prices can be difficult. The users can utilise devices to detect the behaviour of their customers, and once the results are known, they can adjust their product prices.

Review of container datasets when flow detection is very useful to know anonymous and less congestion, most analysis techniques deal with false-positive rate. Unrelated information about a less number of different containers selected from a given stream is useful to identify the flow as dangerous . Payload detection has already been successfully deployed for classifying flows by Karagianis et al. who used this method to verify a flow-based classification method .

II. METHODOLOGY

In this section, we define the algorithmic approach used for the pricing and aggregating the data. Here we use the LSTM approach.which is most effective[4]. This architecture utilises model parameters more effectively than the others, converges quickly, and outperforms a deep feed-forward neural network with an approximate amount of parameters. the main modules here we used are data extraction, data cleaning, sentiment analysis, lstm, dynamic pricing

Data extraction:

The activity of gathering or extracting various forms of data from many sources, many of which may be erratically organised or entirely unstructured, is known as data extraction. Data extraction enables the consolidation, processing, and refinement of data so that it can be kept in a single location and later altered. These areas could be on-site, in the cloud, or a combination of the two.

It mainly undergoes ETL processes which are nothing but to extract, to transform, to load.

Extraction: The process of obtaining data from one or more sources or systems. Relevant data is located and identified during the extraction process, and then it is prepared for processing or transformation. Extraction makes it possible to mix a variety of data types and eventually mine them for business knowledge.

After data has been effectively extracted, it is ready for transformation.

Transformation: Sorted, organised, and cleaned data are performed on it during the transformation process. To provide data that is dependable, coherent, and usable, for instance, identical entries will be eliminated, missing values removed or supplemented, and audits will be carried out.

Loading: The high-quality data that has been changed is subsequently provided to a solitary, integrated target place for storage and analysis.

Data cleaning

Remove duplicate or pointless observations as well as undesirable observations from your dataset. The majority of duplicate observations will occur during data gathering. Duplicate data can be produced when you merge data sets from several sources, scrape data, or get data from clients or other departments. One of the most important factors to take into account in this procedure is deduplication. When you observe observations that do not pertain to the particular issue you are attempting to study, those observations are deemed irrelevant. You might eliminate those useless observations, for instance, if you wish to examine data about millennial clients but your dataset also includes observations from earlier generations. This can increase the effectiveness of analysis, reduce divergence from your main objective, and produce a dataset that is easier to handle and performs better.

LSTM

Compared to traditional RNNs, Long Short-Term Memory is an enhanced recurrent neural network (RNN) architecture that was created to better accurately simulate chronological sequences and their long-range dependencies. The interior of a fundamental LSTM cell, the modifications made to the LSTM architecture, and a select number of highly sought-after LSTM applications are the main highlights. Additionally, it contrasts LSTMs with GRUs. The article ends with a list of the LSTM network's drawbacks and a brief overview of the future attention-based models, which are quickly displacing LSTMs in the real world.

Before being used in real-world applications, LSTM models must be trained using a

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training dataset. The following is a discussion of some of the most demanding applications:

When a word sequence is provided as input for language modelling or text production, words are computed. Language models can be used at several levels, including characters, n-grams, sentences, and even paragraphs. To be taught and prepared for use in the real world, they need a lot of resources and time. Technically speaking, they require a high memory bandwidth because each cell contains linear layers, which the system typically is unable to provide. Thus, LSTMs become relatively inefficient in terms of hardware. Because of how different random weight initializations affect them, LSTMs exhibit behaviour that is very similar to that of a feed-forward neural network. Instead, they choose minimal weight initialization. Technically speaking, they require a high memory bandwidth because each cell contains linear layers, which the system typically is unable to provide. Thus, LSTMs become relatively inefficient in terms of hardware.

III. DATASET DESCRIPTION

The data is provided in the form of a comma-separated values file including tweets and their associated feelings[5]. The training dataset is a CSV file of the following types: tweet id, sentiment, tweet, where tweet id is a unique number identifying the tweet, sentiment is either 1 (positive) or 0 (negative), and tweet is the tweet contained in "". The test dataset is also a CSV file of the form tweet id, tweet.

To get the data directly from twitter we use some API keys to get it. Here firstly we create a twitter developer account to get the API keys and take the keys and we select some hashtag keyword to get the analysis of that data and we insert

In fig (2) we can see the positive, negative and neutral analysis of the sentiment analysis with minimal accuracy.

fig (2) Analysis of tweets

The sentimental analysis we get it by the storing of temp.py, test.py after testing the data and we have to preprocess it to remove all the noisy data from the database and we can achieve the graphs by the running of sentimental analysis on linking it with the LSTM model which is long short term model in neural network area

Here we have considered an example of the ipl series matches from a twitter account and taken the number of tweets as 50 so out of that we get positive 42%, negative 26% and the neutral analysis of the tweets 32%. So for that we get the graphs on tides of analysis as either by different types as bar, plot, pie etc.

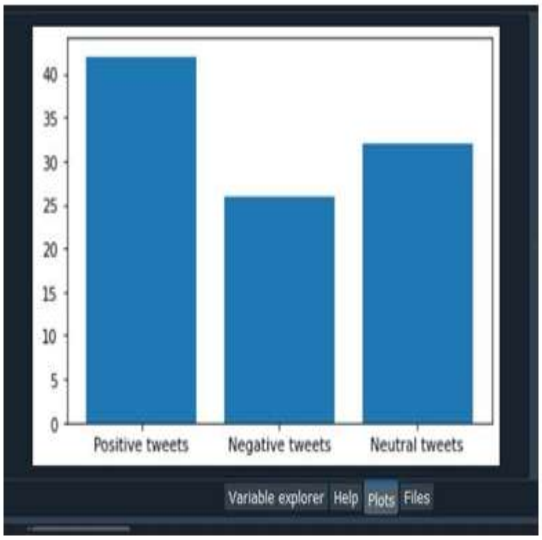

fig (3) sentimental analysis using LSTM

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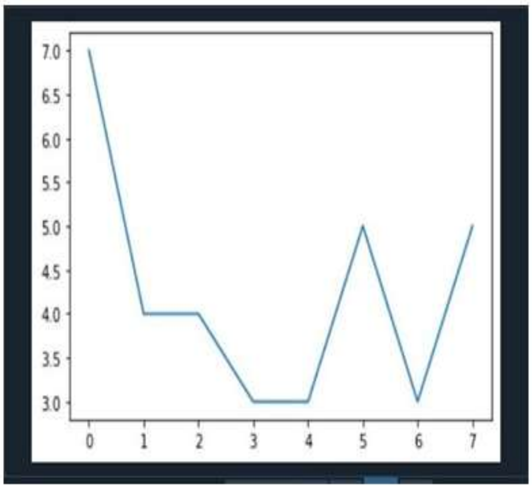


fig (4) dynamic pricing mechanism for sentimental analysis using LSTM

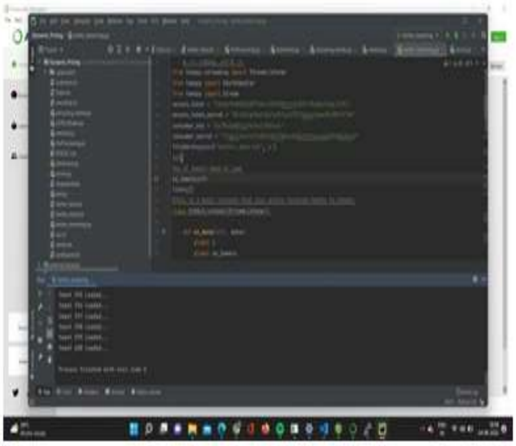


fig (5) dynamic pricing mechanism for sentimental analysis using large data

The hashtag 'ipl' and the language tag 'eng' were used to filter the tweets. The volume of the tweets and the average feelings of the matching tweets were then calculated using the scoring mechanism outlined in the preceding sections. sbase was set to equal the average sentiment score recorded in the time series in the studies[6]. Similarly, to examine the impact of tweet volume on the arrival rate, vbase was set to average daily tweet volume over the time series. Fig 3 and 4 illustrate the resulting time series. it also shows how it can be done through a mobile application using the cloud data which is taken from twitter.

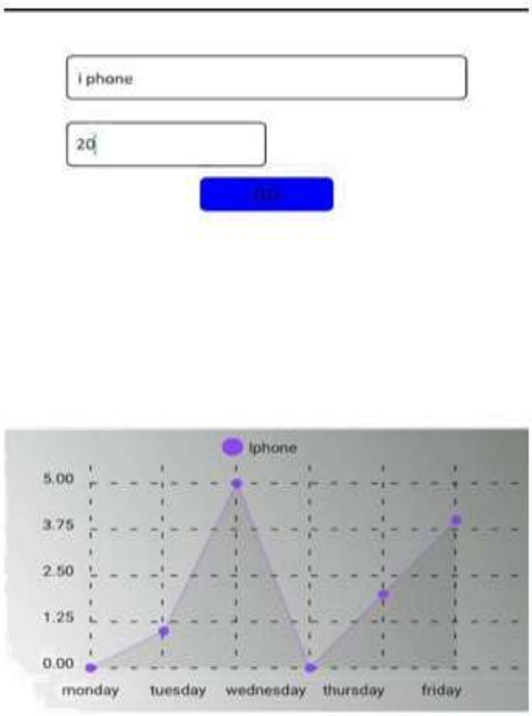
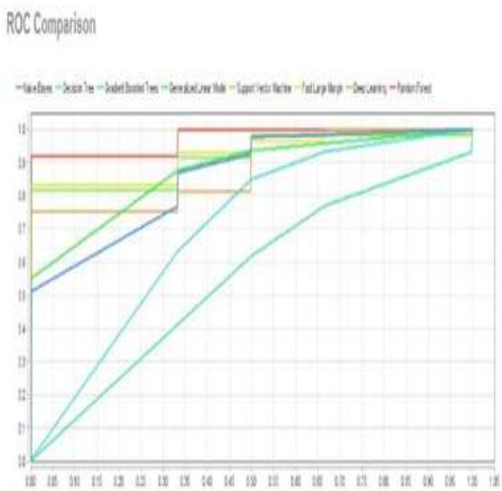


fig (6) Analysis through a mobile application

The fig(7) shows the analysis of different algorithm with different metrics



fig(7) ROC comparison of different algorithms

IV. CONCLUSION

Sentiment analysis is a field of study in and of itself. Several algorithms are available, however because we are dealing with analysing human sentiments from phrases, it is sometimes difficult to

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determine the underlying nature of the sentiment. sentiment. for example. The word nature will be interpreted positively. In today's world, feelings are frequently communicated in addition to words. Using emotions and emojis confuses matters even further. the field of study Considering the intricacy of emotional investigation and comprehension of the primary reason. The project's goal is to comprehend a dynamic pricing strategy.

The algorithm for sentiment analysis was preserved easy –

Whenever a favourable word appears, increase the score and If there is a negative term, it should be decremented.

The data acquired from Twitter includes information on the person's account as well as the location where the tweet happened. This demonstrates how much personal information is present and accessible to anybody who wishes to utilise it. It is critical to comprehend how this information might be safeguarded.

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