Sentiment Analysis An Intelligent User Interface

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Abstract

In this era of technology sentiment classification is an interesting and major topic in the field of Natural Language Processing (NLP). Data-driven methods, including machine learning and deep learning techniques provide effective solutions for the sentiment classification problem. While there has been a lot of research on various machine learning models to improve the accuracy of the task, there has been no comparison, based on statistical measures, between the best of models, particularly for longer texts. Therefore, we reconstruct the classification task for long reviews as a comparison problem and compare two models known to work well, Long Short-Term Memory (LSTM) and Naive Bayes. The study is constructed as a Human-Computer-Interaction (HCI) experiment for movie reviews and uses user feedback to measure the performance of both models. Analyzing the data collected, we show that there is no notable difference in performance of the LSTM and Naïve Bayes models for shorter reviews. However, for longer reviews LSTMs give significantly better results.

Keywords: sentiment analysis, LSTM, Naive Bayes

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1 Introduction

In the new time period, Internet innovation has incredibly impacted human lives . There are audit remarks accessible for each service or item that exists in our every day life on the Internet. The opinions remembered for the audit remarks become progressively significant for vendors to break down and extend their business . On one hand, client audits mirror the quality and issues of items, which is significant for the vendors. One the other hand, the number review reports can be enormous and from alternate points of view, it is hard to finish up the survey reports physically. As a traditional research subject in the field of natural language processing (NLP), sentiments analysis targets mining clients' mentalities and observations (for example, positive, negative or neutral) from text descriptions created by client awareness . In this manner, sentiment analysis is additionally called opinion mining and perspective investigation, which has been generally concentrated in web based business sites, social networks and different fields [1].

Sentiment analysis is an examination field to analyse people's subjective sentiments. for example, feelings, assessments, conclusions and mentalities towards items, administrations, associations, occasions, subjects and their characteristics. Text sentiment analysis task is one of the most significant assignments in the field of natural language processing. It is discovered that the neural system model which depends on Long Short-Term Memory (LSTM) can effectively extract the context relations of sentences [2]. The classification exactness of the model can be improved by presenting Attention Mechanism with filter irrelevant data.

we know from the previous work that Since opinion analysis are a piece of the data mining that can watch public educe about different services and items[3]. It is likewise the stem of natural language processing, text analysis, computational linguistics, bio -measurements, AI strategies. Twitter has a basic length of the tweets as 140 characters. Tweets have positive, negative, neutral (neither positive nor negative) which helps customers to choose better service airlines .The Airline industry is critical in customer reviews. Traditional methods provide inconsistent information about data to the airline industry[4].

The solution could be the simple in the term of perfect result. For example we can easily got to know that what we want to choose either positive , negative or neutral service or item. Solution will be perfect to helping us to take decision about service or item. LSTM is a special type of recurrent

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neural network , has achieved great success in solving many problems. LSTM network introduces a self- cycling mechanism that makes it easier to learn long-term dependent information than a simple cycling structure[2].

A basic task in sentiment analysis is classifying the polarity of a given text whether the expressed opinion is positive, negative, or neutral. More Advanced, “beyond polarity” sentiment classification looks, for instance, at emotional states such as “angry”, “sad”, and “happy”. We always like when YouTube recommends our favourite videos automatically, or when the Restaurant works on our reviews and facilitates with better results next time we visit. Until and Unless your customers are happy and interestingly interacting, your business is up and running. The User Comments/Reviews contain crucial information which cannot be ignored. By analysing the User Sentiments, We can Improve the User Experience by providing better Results. This makes users happy and there is more human machine interaction.

Firstly we want to Build a generic Machine Learning model for text classification of English language user sentiments. We can also give one name to that model for example “emotion model” The Model accurately extracts people’s opinions from a large number of unstructured review texts and classifies them into sentiment classes, positive, neutral or negative! (Model Training).We would like to use top Classification techniques such as Deep Neural Network using CNN, LSTM etc. and compare the results. LSTM is better in analysing emotion of long sentences and can produce better accuracy rate and recall rate. It can get complete sequence and information effectively.so, we could like to use LSTM and Bayes for our classification problem. This Model can then be further used in multiple specific applications like Recommender Systems, Hotel/Restaurant Review Analysis etc.

2 Related work

In era of new technology, we should have data or information about offices and administrations gave by the supplier. we attempt to gather different sorts of reviews, feedback in type of text, for example, remarks, emotions, expression or any article and afterward need to give a summarization genuine result in short substance.

2.1 Multi task classification

As a significant subject in the NLP field, sentiment classification consistently is an interesting and vital exploration point. With the expanding popularity of deep learning, an expanding number of NLP assignments depend on word embeddings. In 2013, Google opened word2vec, a tool for computing word vectors. It can map words to low-dimensional vector space, reduce the expense of figuring, and make words to be identified with one another as opposed to free. It is a decent distributed representation strategy [1], which defeats the defect of one-hot encoding discrete representation.

The motivation behind the sentiment analysis task is to acquire the sentiment polarity contained in the sentence, while the sentence data contained in the word is not finished, so the sentence encoder is expected to remove the highlights of the sentence in order to create the vector presentation of the sentence. Convolutional Neural Networks (CNN) was initially applied in the field of picture, yet it has additionally been broadly applied in the field of NLP as of late and has accomplished great outcomes [1].

The system structure of deficient association and weight sharing reduces the multifaceted nature of the model. The presence of a convolutional layer makes CNN great at catching spatial nearby relationship and the pooling layer in the system can extraordinarily decrease the calculation [1]. The presence of word2vec makes it workable for CNN to apply to the content, empowering CNN to acquire nearby data in the content and direct feeling arrangement. Comparative works use CNN extensions to characterize sentiment and has finished multi-class classification tasks with great outcomes.

In theory, the RNN language model could cover the time request structure of the entire content, and manage long-term dependence issues. In the practice, however, RNN could not get familiar with the information effectively [5]. At the point where the interval between the overall data of writings and the current location to be anticipated turns out to be huge, few issues will come out. As there are too many unfold layers in the Back Propagation Through time (BPTT)optimization algorithm which prompts history data misfortune and angle weakening while at the same time preparing [5]. To defeat this trouble, few researchers set forward a procedure named Long Short Term Memory (LSTM), which prompts better exploratory outcomes in some application situations [5].

2.2 Word embeddings

Great word installing is the basis of the characteristic language handling task. As far as improving the quality of word vectors, Mikolov et al. [6] and Pennington [7] first found that the word vectors learned through a RNN have intresting direct substructures conducted an exhaustive preparing of the worldwide word-word co-occurrence of measurable information from the corpus and the subsequent worldwide vector (GloVe) shows interesting straight base with regards to word vector space like [8]. Maas et al. [9] took in the word embeddings with conclusion dependent on the old style neuro-probabilistic language model [9]. Tang et al. [10] proposed three models, considering the passionate propensity of text, and learning the word embeddings with feeling. In their analyses, they likewise utilize the GloVe to get introductory word embeddings. they first use assumption vocabulary as the additional data to pretrain a word sentiment classifier and afterward get the sentiment embedding of each word including the words not in sentiment dictionary. Concatenating the word inserting and its sentiment embedding can improve the nature of word embeddings.

2.3 semantic Compositions

However, the word embeddings can just speak to a singular word. For an expression or an article, it is important to consider how to combine singular word embeddings into a representation of an expression or an article. This requires consideration of the issue of semantic creation. Socher et al. [11,15] utilize Recursive Auto-encoders (RAE) to get a sequence representation of the whole content through a constant recursive combination [11,15]. In any case, so as to get a successive representation, firstly, we have to parse the sentence structure, or utilize a greedy strategy, combining and refactoring the words with the least mistake each recursive. Kim [14] propose a CNN design for text categorization, which has numerous channels of various sizes and two distinct channels. Cho et al. [12] use RNN to process text into an arrangement of words, considering the request for the words in the content.

Since the word embeddings can just represent a single word, sentence and record representations need to think about the semantic mix issue. Semantic com-bination models incorporate RAE [11], CNN [14] and RNN [12]. Among every one of these models, RNN with LSTM unit [13] is generally utilized in text grouping preparing, on account of the capacity in displaying long successive data sources or outputs. It is unequivocally intended for maintaining a strategic distance from the gradient vanishing issue.

2.4 Summery

past work in LSTM give data with the information that NLP field grow the popularity of deep learning, and NLP assignments relies upon word embedding[1].we can likewise apply CNN to the field of picture, yet it has furthermore been comprehensively applied in the field of NLP starting late and has achieved incredible outcomes. As hypothetically RNN language model handle the time the executives of the whole content. Concatenating the word inserting and it's sentiment implanting can improve the idea of word embeddings[16]. word embeddings works just for single word while semantic arrangements work for expression or for an article, and furthermore work to make sentences from the word it is very helpful in representation of the semantic issue[12].

In the following, we need to make simple content classification with the assistance of various sort of algorithms and mechanisms. we likewise need to work away at the content of words, sentences , feelings and can take a try at emojis what they investigate and how they can describe on the feedback or on survey. If we compare past work and our work then we can easily say that previous work is additionally founded on words arrangement and furthermore it derived from sentence , long content audit, long articles, and so forth we attempt to improve that logical characterization and need to improve better results.

3 The Method

Commonly, the significant remarks/surveys of Users/ Customers are overlooked which contain critical data. we Cannot process each audit/remark physically on the grounds that it takes a lot of efforts and sometimes it waste our valuable time. we need to face various Challenges, for example, Irony, Sarcasm, Emojis, Comparisons and so on while text summarization.

3.1 Study Design

Our hypothesis is that LSTM outperforms Bayes model for sentiment classification, particularly for longer reviews. We used an interactive web application to test this hypothesis. A single factor within-subject experiment was carried out with discrete independent variable MODEL TYPE and continuous dependent variable ACCURACY. Many models could be used for sentiment classification. For the purpose of this study, we chose two of the models already known to perform well. So, the independent variable has two levels namely LSTM and Bayes.

3.2 Implementation

Streamlit library of python was used to design the user interface. The participants saw multiple text areas where they could enter their reviews. There was a button to submit the reviews. The submitted reviews were fed to both the LSTM and BAYES models and a sentiment classification was obtained. All this data was stored in a SQLite database. A sentiment to be displayed was returned to the user-interface for each user-review. Finally, the participant was displayed a slider wherein he/she could give a value for his/her sentiments. This actual sentiment value was also stored in the database. Predicted values and actual value from participants were used to calculate the performance metric. This metric, in turn, was used for statistical testing.

3.3 Model

Two machine learning models were created for same operation (Sentiment Analysis). 1. LSTM Model 2. Bayes Model.For implementing these models, we used imdb movie review dataset, python libraries like keras, sklearn, tensorflow, nltk, models etc. The data was pre-processed (stop words, special characters etc. removed) and transformed to one-hot representation. Models were created, trained and evaluated for both LSTM and Bayes. The LSTM model consisted of 3: layers Embedding, LSTM and Dense. The models predicted the review and gave real valued outputs which indicate classified value of sentiments.

3.4 Survey Procedure

After giving informed consent, participants were asked to submit multiple long movie reviews through the user-interface of the web application. After clicking on the submit button, the users were able to see the sentiment classification for all the reviews as predicted according to the already trained models. After that the participants were prompted to themselves classify the reviews. The participant inputs were used for statistical testing to compare the performance of both our models.

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