A Deep learning Approach to Sentiment Analysis with CNN based Hotel Recommendation System Using Hotel Reviews

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***Abstract*—The tourism sector has seen signs of growth, and the emergence of a deep learning-based hotel recommendation system has had a revolutionary impact in this sector. Huge numbers of online reviews are flooding multiple websites, and it is nearly impossible to find a preferred accommodation from those reviews without any machine learning interpretation. Thus, we perform multiple deep learning algorithms (LSTM, TF-IDF, sequential model from Keras, bidirectional model) to efficiently achieve accurate sentiment analysis of those reviews and build a custom made hotel recommendation system using a convolutional neural network. The sequential bidirectional model outperformed all other deep learning models with an accuracy of 91% in sentiment analysis, and our custom-built convolutional neural network gives 89% accuracy for successfully predicting the positively reviewed hotel recommendation.**

***Index Terms*—component, formatting, style, styling, insert**

I. Introduction

In the new age of modern technology, online reviews have become one of the most popular approaches to determining whether a service is good or bad. But there is a huge amount of review data presented on the internet, and it is very challenging to read those whole reviews and formulate the sentiment behind those reviews. Data from online reviews can be used to estimate the hotel's desirability and level of service among people all around the world. Customer comments on TripAdvisor websites can be recognized as important information in the hotel industry for improving service quality and identifying vulnerabilities in order to succeed in a highly competitive environment. But it is very time-consuming and challenging for clients to read all the text reviews and get an idea of the best accommodations. People are now using internet reservation services to arrange their holidays, and choosing the best accommodation is more difficult because people may overlook better possibilities due to the abundance of information available on these platforms. That is why a deep learning based framework has been proposed to recommend the positively reviewed hotel based on the hotel review data. Multiple deep learning approaches (TF-IDF, Bidirectional Model, Sequential Model from Tensorflow, LSTM) have been used to efficiently implement sentiment analysis, and a custom made CNN model has been designed to recommend the best accommodation. Refining the data set was a huge challenge for us, multiple natural Language techniques have been used to remove the null values, stop word, deleting unnecessary values and formatting the reviews. Another biggest challenge was to build the sequential model from keras to overcome over fitted or under fitted, for doing that we fine tuned the parameters, with custom made dense layers. Custom made Convolutional Neural Network (CNN) has been built with appropriate hidden layers, the model accurately recommended the best accommodation based on the sentiment analysis.

II. Literature Review

The revolutionary evolution of the online reviews has made a magnificent impact on people's preferences in the field of hotel management and services. But analysing text reviews, auto labeling text data has always been a challenging task for the text mining researchers. For extracting impartial opinions of hotel services from reviews, a model has been proposed that employs Naive Bayes multinomial, sequential minimal optimization, Compliment Naïve Bayes (CNB) and Composite hypercubes on iterated random projections to terms sentiment polarity to dynamically generate a sentiment dataset for training and testing purposes. By applying this model in the OpinRank dataset, 80.9% accuracy was achieved by the naive bayes algorithm [1]. Using Python's textblob library, Stanford Dependency Parser, and word2vec approaches, an automated model was developed to retrieve aspect words from reviews and execute aspect oriented sentiment analysis. This model generates ratings based on the prominence of aspect terms by summarizing the reviews [2]. Big data and multivariate regression analysis on user reviews can be used to understand consumer satisfaction. The study discovered that online reviewers from cultures with higher individualism tend to give lower online ratings and all of the essential accommodation service attributes are strongly crucial for organizational satisfaction online rating with a p ¡ 0.001 value [3]. Using three components of GloVe, BERT, and Google Flight information to feed the CNN model, a prediction approach delivers better accuracy to predict the most cost-effective airline ticket to clients. Because Textblob or TF-IDF are operationally inefficient for a large social media data stream in terms of both limited memory capacity and time, the BERT model was employed in this study to classify Twitter sentiment. Because Glove has better scalability and efficiency for transforming large quantities of reviews than the word2vec model, this work employs it instead of the word2vec model for word embedding [4]. Using the wording on the title of a client testimonial on the Booking.com portal, Probabilistic Latent Semantic Analysis can predict consumers positive and negative sentiment [5]. A framework for aspect-based sentiment classification that can effectively identify aspects, executes classification tasks with high efficiency by suppressing the noise with 85% identification and 90% classification accuracy [6]. To decompose a lengthy review into its constitutive phrases and detecting the primary objective within each sentence, a new method is proposed by implementing most occurring first, most general first, most specific first, first occurring first, and last occurring first with an extensive sentiment lexicon to quantify the polarisation of the sentences [7]. When compared to the Recursive Neural Tensor Network approach, SVM as a classification model performing a review classification method with positive and negative sentiment can generate a greater accuracy of 94% in online consumer reviews [8]. A prior study conducted Sentiment analysis-based hotel recommendation using TF-IDF approach but their accuracy was lower than other methods [9]. Deep learning approaches are providing higher accuracy in the field of sentiment analysis. Using the LSTM network's distinctive short-term memory features, it was likely to obtain a positive impact on sentiment classification of hotel reviews, with an accuracy rate of over 95To produce the classification model, word2vec and word segmentation techniques are applied to integrate the short comment text into the LSTM network, and a dropout technique is incorporated to avoid overfitting [10]. By merging content-based and collaborative filtering approaches, a proposed hybrid hotel recommendation framework was built that provides the best hotel, and hybrid strategies can overcome the drawbacks of single techniques [11]. In a system where hotel reviews were evaluated and derived the general impression of the reviews as opinions elements with their connected features to propose the best hotels by applying data gathering, data pre-processing, aspect extraction, and sentiment analysis [12]. On the Guizhou Province Country Hotel Reservation System dataset, a Hybrid Recommendation approach based on Graph Embedding (HRGE) is developed, which improves the F1 score by 20% [13]. When employing the ARIMA and LSTM algorithms on Manali tourism data, the LSTM model outperformed the classic ARIMA model for hotel recommendation when utilizing the Normalised Root Mean Squared Error (NRMSE) as an evaluation criterion [14]. To assist tourists in their decision-making and resolve confusion, recommendation methodologies have been introduced, and a new conceptual hybrid approach can enhance the customer experiences by recommending the most relevant content and assisting them in personalizing their trip through the use of advanced machine learning techniques [15].

A. *Proposed framework*

Data collection and Data preprocessing: We collected trip advisors dataset for our proposed model. The set contains a huge amount of data but for computations time and space we choose to feed our model into a total of 50000 hotel reviews around the world. The dataset has ten distinct columns (review, title, service, rating, cleanliness, location, comfortable, username and date stayed) but for building our framework we only needed two columns such as review text and ratings. Where the review text section contains a short review text from the users and the rating column represents their overall rating of the services in a scale of 1 to 5. Then we filtered out the top five most used words such as hotel (9550), room (8281), rooms (4983), hotels (3560), stay (3014) using word count features for correctly predicting the sentiment of those reviews. We used sentiment intensity analyzer to tag the sentiment into positive, negative and neutral and achieve the polarity sentiment score where from our dataset we have 39020 positive reviews, 6209 neutral reviews and 5067 negative reviews. The vocabulary size was 87169 and max length of the sentences was 1516 in our dataset. Among the ratings 5 points

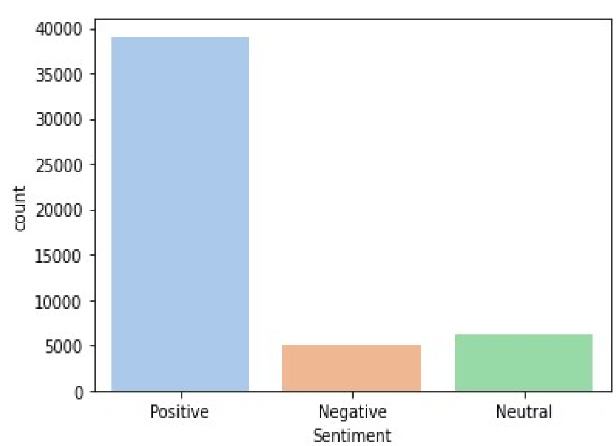

Fig. 1. Fig. 1

occurred 17814 times, 4 points occurred 16407 times, 3 points occurred 7709 times, 2.0 points occurred 3833 times and 1.0 point occurred 4531 times. Then we combined sentiment analysis with ratings and pursued that 5 point rating contains most of the positive sentiment and 1 point rating contains most of the negative sentiment.

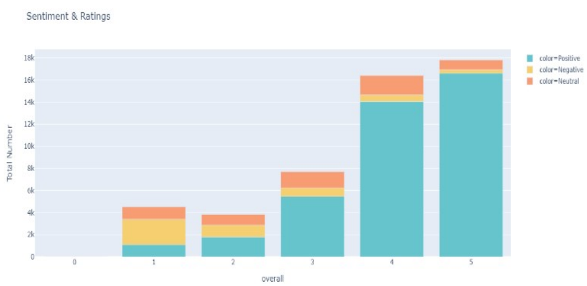

Fig. 2. Fig. 2

After that we applied multiple natural language processing techniques (Tokenization, steaming, normalization, stop word removal, lemmatization) to processing our review text data. Then we filtered out the dataset to feed our customized sentiment analysing model.

Methodologies: A single method can not appropriately predict the accuracy of sentiment analysis that is why we decided to perform multiple machine learning approaches to predict higher accuracy sentiment analysis. We used the Python TextBlob module to categorize the texts into three groups: positive, negative, and neutral, with a score of 1 for positive sentiment, 1 for negative sentiment, and 0 for neutral sentiment. Then multiple deep learning models will be implemented for train and test purposes.

LSTM: Deep learning algorithms for sentiment analysis have inspired a lot of attention and achievement in current publications. Because of its optimizing and tree structure to conserve sequence data and information, LSTM has obtained better consequences between all these inputs [16]. The LSTM model has been developed, with four hyperparameters whose values are somewhat intuitive, and which can and must be tweaked to produce decent results. The softmax function serves as an activation function in this case. The explanation for this is that our System employs categorical cross entropy, for which softmax is the ideal activation strategy. Then, with 80% test data and 20% test data, we declared the train and test datasets and performed 10 epochs. After that, we retrieved a validation set and assessed its score and accuracy. Our dropout value was 02 and we used Adam optimizer in our designed model.

TF-IDF: Term Frequency — Inverse Document Frequency" used to turn text documents into a TF-IDF feature matrix. We used n-gram range 1-3 as parameters for the model in TF-IDF vectorizer. After labeling the sentiment data has been transformed and splitted into 70% train and 30% test set. Then we build a logistic regression model for TF-IDF features with a max iteration 500 and random state value of 42. Then we analysis the logistics regression performance and predicted the model for TF-IDF features. Then we pursue the accuracy of the model. But we did not get improved accuracy nby performing this model.

Sequential and Bidirectional model: After pre-processing the dataset with multiple NLP techniques, we splitted our dataset into train and test sets with 80% train and 20% test sets. The values have been seated as 1 is positive, 0 is neutral and -1 is negative sentiment. Then we padded the sequences as a max length of 400. After that we splitted the dataset into a test and train set where the size of the test set was 0.1 and the random state was 42. Then we implemented the tensorflow keras sequential model with the activation function of relu and softmax. Then we ran 10 epochs with a batch size of 125. Finally using sparse categorical cross-entropy we validated the accuracy.

Hotel recommendation CNN model: GloVe [17] is used to word embed all online user reviews. The word embedding phase's outputs serve as an input space for the Convolutional neural network model in the next phase. Hotels were labeled as "recommended" or "not recommended," with "recommended" indicating positive evaluations and "not recommended" indicating negative ones. The data set was split into two parts: 80% for training and 20% for testing. Sequential model sentiment analysis, which gives sentiment scores to each online customer's hotel reviews, and GloVe word embedding of all user reviews and hotel names from our dataset are included in the input space for the convolutional neural network model in this study. Our Convolutional Neural Network model is a sequential model with three-dimensional convolution, flattening, and four dense layers. Based on the Microsoft CNN design [18] [19] for semantic data extraction for sentences, we define the hyperparameters and pooling size for the CNN model. In this study, we employ the CLSM model for CNN. It's one of the most effective methods for extracting text semantics. The first dense layer's activation function was softmax, while the final layer was Sigmoid. The accuracy of our custom-made model was then calculated.

III. Accuracy

We choose to use various machine learning algorithms to forecast sentiment analysis with improved accuracy since a single method cannot effectively predict the accuracy of sentiment analysis. First Python TextBlob module is used and after that many multiple deep learning model is implimented. The sequential bidirectional model outperformed all other deep learning models with an accuracy of 91% in sentiment analysis, and our custom-built convolutional neural network gives 89% accuracy for successfully predicting the positively reviewed hotel recommendation.

IV. Conclusion and future work

Hotel recommendation system plays a significant role for modern tourist loving peoples life. It makes these tourist loving peoples life much easier by cutting of the hassle to go on a unknown hotel and have bad experience. Hence, deep learning based hotel recommendation system add a noteworthy value to choose best types of hotel. We mainly focus on give a best experience of the customers by filtering the hotels using various kinds of neural network based model such as LSTM, TF-IDF, sequential model from Keras, bidirectional model and by using convolutional neural network make a custom made hotel recommandation system.

For the future work, we want to make this custom made hotel recommandation system more accurate to give tourist loving people the best experience they have ever had and low down their burden to find a best hotel from the flood of hotel reviews.

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