International Journal of Scientific Research in Computer Science, Engineering and Information Technology
© 2020 IJSRCSEIT | Volume 6 | Issue 2 | ISSN : 2456-3307
DOI : https://doi.org/10.32628/CSEIT2062149

Effective Methodology for Co-Referential Aspect Based Sentiment Analysis of Tourist Reviews

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ABSTRACT

Tourist reviews are the source of data that is going to be used for the travelers around the world to find the hotels for their stay according to their comfort. In this the hotels are ranked over the parameters or aspects considered keeping travelers in mind. This computation of data sets is done with the help of the machine learning algorithms and the neural network. The knowledge processing done over the reviews generates the sentiment score for each hotel with respect to the aspects defined. Here, the explicit , implicit and co-referential aspects are identified by suppressing the noise. This paper proposes the method that can be best used for the detection of the sentiments with the high accuracy.

Keywords : Sentiment Analysis, Machine Learning, Neural Network.

I. INTRODUCTION

Tourism is a most expanding industry in today's world. It has brought up various trends in market. In today's generation people are connected because of the limitless connectivity with the people over the social media platforms. Because of these trends people are invited constantly to share their opinions, suggestions and preferences which are used for future references. The data from such platforms helps us to collect the data for multiple application designing and data processing for generating information[1]. After tourist visits places they review the hotels and restaurants and they mostly rank in the order of the service they receive and this helps to collect the data and give a complete rating to that place. This knowledge processing helps in getting and delivering the information to the tourist or people for selecting the place to stay. These opinions are helpful to multiple application domains as they add value to the research as well as helps in analyzing the place for stay. The opinions they share are their sentiments about the service they received with respect to the payment made. These sentiments are with respect to their level of satisfaction which might be excellent in some cases and in some can be very poor. So here we analyze the various perspectives from the customer point of view[2]. These can be rated on the food, price, ambience, Service and miscellaneous. Here we have defined service related to the hospitality or any other medical needs also with the other services like ironing, washing machine, etc. Ambience is defined for the atmosphere, hygiene and the cleanliness in the hotel[1]. Food is made in relation with the taste, various cuisine served and the other. In the miscellaneous the other factors that affect the rating is taken into consideration. The sentiment classification is done into positive and negative depending upon the aspect talked about. The aspect based sentiment classification is about identifying the aspects considered for the ranking and the sentiments associated to that aspect. The aspects are classified into three categories : explicit, implicit and co-referential aspects. The implicit refers to the implied , explicit is referred to as told specifically and co- referential is using a synonym for the referred word. [1]

This paper illustrates about the methods used for the aspect based sentiment classification on the tourist reviews using the machine learning algorithm and the neural network. In this we are using the n-gram and part-of-speech tag for classifying the opinions about the aspect into negative and positive. Here we have used naïve bayes multinomial(NBM), Support vector Machine(SVM), Recurrent neural network (RNN) and Long short term memory(LSTM).

II. LITERATURE REVIEW

Pang and Lee [3] set forth sentiment analysis with a quick summary of the definations for aspect-level. The term subjectivity analysis is mostly termed as encompassing opinion mining and sentiment analysis [4]. The field of opinion mining, sentiment analysis, or subjectivity analysis, studies the phenomena of opinion, sentiment, evaluation, appraisal, attitude, and emotion [5]. An opinion is defined as judgment or belief based on certainty or proof[6]. In general, three processing steps can be distinguished when performing aspect-level sentiment analysis: identification, classification, and aggregation [4].

Tang et al. [7] it mainly focuses on document-level machine learning approaches as well, it the domain of consumer reviews is also specifically addressed. Tsytsarau and Palpanas [4] was focused on document-level sentiment analysis, distinguishing between four different approaches in order to identify the sentiment value of words: machine learning, dictionary-based, statistical, and semantic, which mainly described how the sentiment value of a single word is determined.

Liu updated overview of the entire field of aspect-level sentiment analysis enlisted sub-problems that one come across when finding an actual solution: from illustrations to aspect extraction, including different challenges that can be emphasized as part of aspect-level sentiment analysis, like dealing with implicit and explicit sentiment and entities, to how to identfy and link aspects and sentiment values to one another.

The GERBIL framework [9] also had the aim of directly distinguishing approaches from one another with the help of same, controlled, evaluation methodology. In other cases, the main focus of an assessment may not be aspect-level sentiment analysis, like in [10] where the task of selecting comprehensive reviews is evaluated, soliciting the use of a huge variety of assessment metrics.

Ranking Loss [7], used in [11], calculates the average difference between the true rank and the estimated rank. The normalized Discounted Cumulative Gain [13], also used in [14], is specifically needful for the evaluation of relevance for lists of returned aspects.

In [15], aspect detection casted as a labeling problem solved by using a linear chain Conditional Random Field (CRF), common in natural language processing, to work on a complete sequence of words. Probabilistic Latent Semantic Analysis [19]is used, but it utilizes a Dirichlet prior instead of a uniform topic distribution for the topic distribution. In [12] distinction is made between global and local topics. While searching both global and local topics is useful to get coherent local topics that basically illustrates aspects, whereas in [17], LDA is used with a Hidden Markov Model (HMM) to differentiate between aspect-words and background words. In [13], the issue of covering is illustrated by predicting the emphasis placed on each aspect by the reviewer. [13] evaluates the emphasis on a specific aspect in a review by its influence on the overall rating. Continuing the work on aspect-level sentiment analysis and LDA models, a method to deal with cold start problem is proposed in [18]. In [16], a supervised joint aspect and sentiment model is found to determine the usefulness of reviews on aspect level.

III. PROPOSED METHODOLOGY\

The four algorithms that are used for the sentiment analysis and deriving the results are:

1. Naïve Bayes Multinomial Algorithm:

It is based upon the conditional probability of an event. The occurrence of event A only when event B has already happened i.e. the probability of occurrence of A only after the B has occurred.The occurrence of features f1, f2,…fn for the class c can be calculated simply by:

$$p(f1, f2, \dots, fn|c) = \prod_{i=1}^{n} p(fi|c)$$

In addition, Naive Bayes classifiers are scalable as they require a number of parameters linear in the number of features. A logical extension of the Naïve Bayes model is Multinomial Naive Bayes, which allows each feature distribution[1].

2. Support vector Machine:

It defines the points of separation in a plane for classification. It is basically a binary classification method where the data points near to the hyperplane are classified into the categories, making it the decision boundary. It differentiates the two classes into the frame. [1]

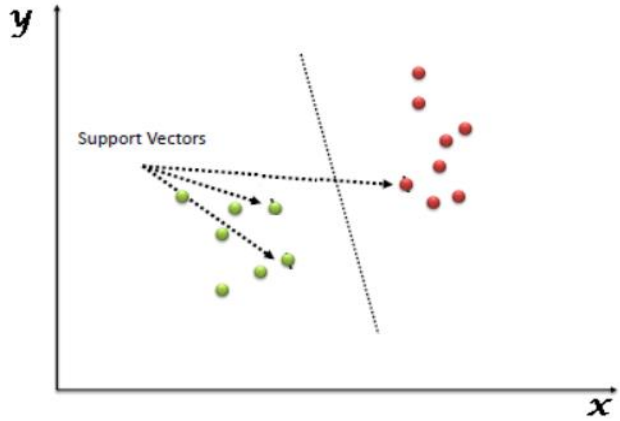

Fig. 1. Support Vector Diagram

3. Recurrent Neural Network:

In RNN the most important layer is hidden layer, this helps you to generate the memry for remembering the information previously processed. It can predict the next word probably to appear. It processes each input from the starting and also processes at the hidden layer and then generates the output.

4. Long short term memory:

The sentences are divided into cell states and then processed. In the LSTM we use the feed forward neural network and works better then RNN at times. LSTM can selectively forget or remember the words. It has a long term memory hence the predictions are made also on the not most recent input.

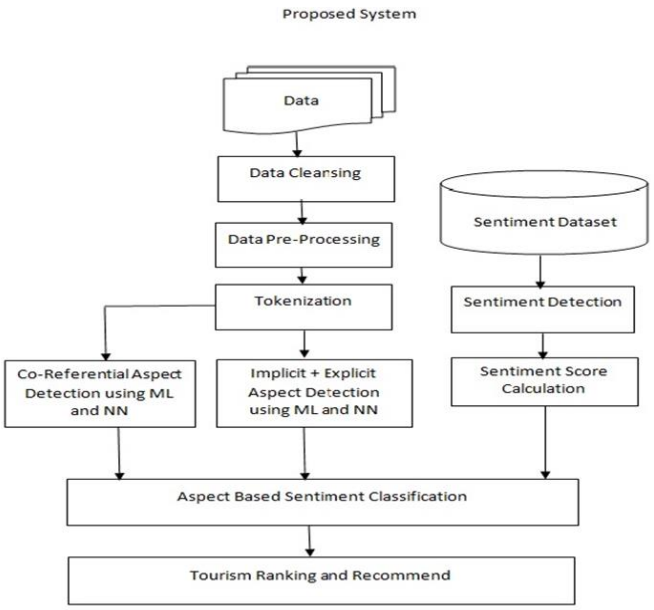

Fig. 2. Proposed methodology

1.1 Data:

Data sets is the tourist reviews collected from the social media platforms

1.2 Data Cleaning:

Removal of irrelevant sentences which has no value for the computation of knowledge

1.3 Data preprocessing and Tokenization: Data preprocessing handles the removal of punctuation marks, exclamations, grammatical errors and other short forms used in the sentences. Tokenization is dividing the sentences into tokens and picking up the key words such as adjectives, adverbs and verbs which add values to the sentences.

1.4 Sentiment Dataset and Sentiment Detection:

Sentiment Dataset is picked up from the online platform. Sentiment detection is done by using the n gram algorithm. Here we are finding the sentiments which are found in the dataset.

1.5 Sentiment Score Calculation

In this we are calculating the sentiment score on the different parameters and the complete score is made for the hotel by aggregating the scores from the different parameters.

1.6 Co-Referential Aspect Detection using NN and ML

Here, the co-referential aspects are detected using the NN and ML algorithms.

1.7 Implicit and Explicit Aspect Detection using NN and ML:

Here, the Implicit & Explicit aspects are detected using the NN and ML algorithms.

1.8 Aspect Based Sentiment Classification:

In this we are classifying the sentiments into positive and negative. The aspects are already classified and then sentiment classification is done.

1.9 Tourism Ranking and Recommendation:

In this the final ranking is done depending upon the aggregated result of the sentiment score related to the various parameters of the hotel facilities. Hence the ranking is done and recommendation is done by checking the customer requirements.

IV. EVALUATION

1.10 Aspects Identification:

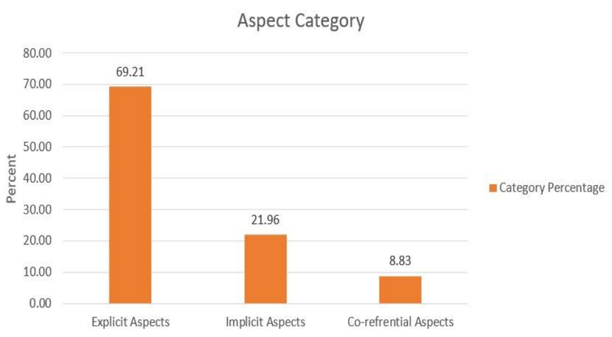

Fig. 3. Aspect Category Detected

In this Figure 3, they have shown us how the aspect category is detected, the highly detected is explicit i.e.

69.21% and much lower to this are the other two aspect category. The implicit is much lower detected which is only 21.96%.The co-referential is too lesser detected as compared to the above two categories i.e. 8.83% only. The difference between the implicit and explicit is too higher than the difference between the co-referential and implicit aspect.

The percentage of aspect identification is higher for explicit aspect and hence too low for the co-referential aspect.

1.11 Aspect-Based Sentiment Classification

In this we are analyzing the classifier algorithms performance by seeing the percentage of accuracy, precision, recall and F-Measure. In the table the classifier RNN+LSTM is seen the best in performance in any record. It has the efficiency to nullify the effect of false positive rates. The other algorithms such as the NBM & SVM machine learning algorithms are used and is seen to have a minor difference between the accuracy ranked on their performance. They almost work the same depending upon the datasets and environment. The accuracy for neural network algorithm is 94.82% and the F-measure is 84.98%.

Table 4.2: Classifiers performance

Classifier	Accuracy	Precision	Recall	F-Measure
NBM	91.49	80.43	82.45	81.43
SVM	92.89	83.04	84.43	83.88
RNN+LSTM	94.82	86.94	89.05	84.98

Figure 4, the accuracy of identifying the feature types by using different algorithms. The Accuracy percentage of RNN+LSTM is the highest in every feature. The difference between the two machine learning is very less in predicting the different features.

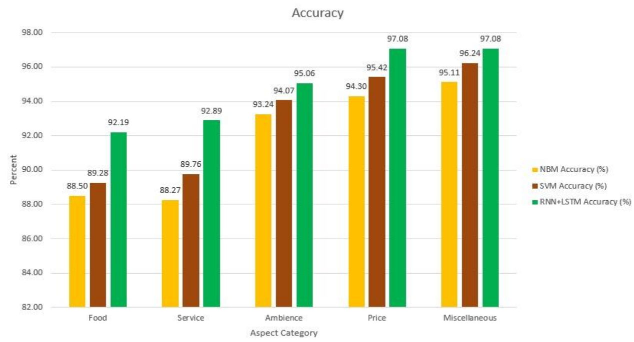

Fig. 4. Accuracy in predicting feature types

Figure 5, the F-measure is the aggregated result of the precision and recall. This gives the accurate percentage of real positive reviews by detecting the false positives in the reviews. The RNN +LSTM is with the highest accuracy frequency to find the false positives.

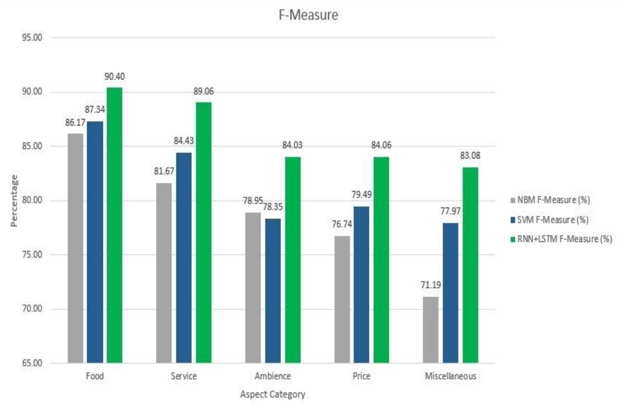

Fig. 5. F-Measure(%)

Figure 6, illustrates the recall percentage which effectively senses and measures the fraction of total relevant reviews to those which are actually retrieved. The recall percentage is quite better for the neural network algorithm. The RNN+LSTM ranks at the highest in prediction for every other feature type. The NBM ranks good to SVM only in predicting the ambience whereas in all the other aspect category SVM is working more better than NBM.

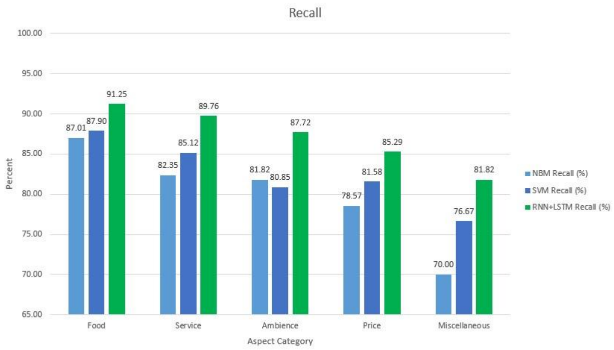

Fig.6.Recall percentage for features

Figure 7, illustrates the precision percentage which is also called as positive predictive value, is the ratio of relevant reviews to the retrieved instances. The RNN+LSTM is working to their highest potential as compared to other two algorithms. The other two algorithms NBM and SVM ranks near to each other and lesser than RNN+LSTM.

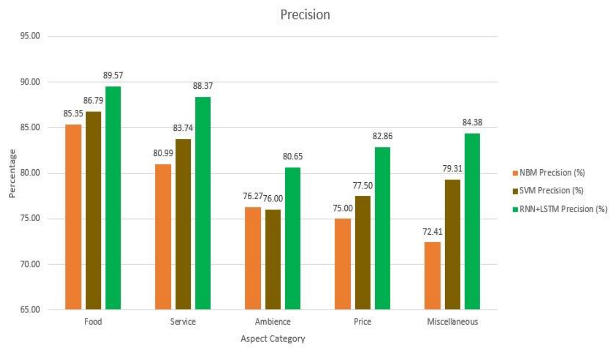

Fig. 7. Precision for different categories

The overall comparison of the different algorithms, in figure 8, for the accuracy measurement over the recall , precision and F-measure helps us to derive that the RNN+ LSTM is more better than the NBM and SVM. The order sequence for the better accuracy is: RNN+ LSTM is better over SVM and SVM is better than NBM.

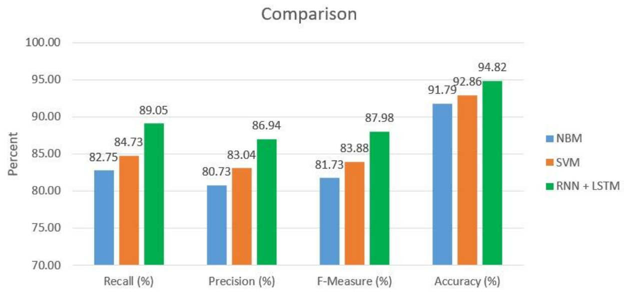

Fig. 8. Comparison between algorithms

V. RESULT AND DISCUSSION

The result shows that the Recurrent neural network and long short term memory works with the highest accuracy in identifying the aspects and classifying the sentiments. As the recurrent neural network is good in identifying the negatively polarized sentiments and the LSTM is good in identtifying the positive sentiments. The precision rate gives us the exact idea of the number of positives. This gives the effectivenesss of the algorithm seen in classifying the sentiments. The precision rates are higher for the RNN+LSTM. That is the frequency of identifying the true positive sentiments is higher. The recall rate deals with the completeness or sensitivity of the classifier. The F measure is again the measure of accuracy by aggregating both the precision and the recall. It measures the effectiveness and completeness of the algorithms in identifying the sentiments. The highest F-measure is for the RNN + LSTM.

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Cite this article as :

Dr. Kamlesh A. Waghmare, Sheetal K. Bhala, "Effective Methodology for Co-Referential Aspect Based Sentiment Analysis of Tourist Reviews", International Journal of Scientific Research in Computer Science, Engineering and Information Technology (IJSRCSEIT), ISSN : 2456-3307, Volume 6 Issue 2, pp. 523-529, March-April 2020. Available at doi : https://doi.org/10.32628/CSEIT2062149

Journal URL : http://ijsrcseit.com/CSEIT2062149