ISSN: 0974-5823 Vol. 6 No. 3 December, 2021

International Journal of Mechanical Engineering

Applying Probabilistic Adversarial Neural Network to Assess the Tourism Sentiment Analysis in Big data analytics

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Abstract

Sentiment analysis is a technology that accompanies with the field of natural language processing. The field of sentiment analysis has recently seen a lot of interest from the scientific community. This involves automatically determining the polarity of the text data based on the sentences as whether they are positive, negative or neutral. The previous method has provided a better result but it has inconsistent result-based limited reviews which are based on hotel and tourism. It has less accuracy for sentimental analysis review. Hence, Probabilistic Adversarial Neural Network (PANN) algorithm is proposed to give better accuracy and reviews compared to the previous system. In this, PANN is to investigate the adequacy of word cloud for general text analysis errands and also analyze the sentence to find out the sentiment of text. The proposed tourist review based sentiment analysis system is used for classifying the selected features as positive or negative.To achieve this goal, it is necessary to focus on three main steps presented in this work. The first step is that Gabor Filter is used to preprocessing and cleaning of review data. The second step is word cloud, term frequency based Multi-Objective Harmony Search Method is used to identify the sentiment word. The final step is PANN based classification updated for classifying the sentiment words in which a large amount of data is used for the classification process.

Keywords: Gabor Filter, Multi-Objective Harmony Search Method, Probabilistic Adversarial Neural Network (PANN), Word Cloud, Sentimental Review

1. Introduction

Tourism is the key to dynamically developing industries and the country's economic growth. Its meaning and importance cannot be overemphasized. Every year, thousands of tourists visit different parts of the world and share their feelings in the form of online comments on the visitor's website, including logged-in and open forms. These emotions represent the visitor's feelings about various aspects of a particular location. For emotional diversity, it is a difficult task to post about tourist destinations, extract and divide emotions into positive or negative ones. Several emotional text big data techniques have been proposed in the past for emotional classificationlike Naive Bayes, SVM (Support Vector Machine). But these methods didn’t provide proper classification results.

Sentiment analysis is used to plan collections from different types of data (text, video or audio). These are the various areas most often used for marketing, customer needs and customer services such as travel and text analysis. The emotions and relationships of customers and users who check items, are analyzed mainly through the analysis of texts such as donations, ratings and reviews. Social media explosion has produced a large amount of unstructured comments in the form of user generated data. Online reviews are important decisions made by individuals and organizations.

Sources of information in the social media have been so useful for travelers. And user-generated content online travel refers to all travel-related review, including a review of attractions, hotels, restaurants and so on. In these comments, people do a lot (for example, sharing personal experiences and evaluating services). Therefore, it is clear that the target image, called a new form of expression (e.g., assessment of local culture, transportation, food, or infrastructure) expresses collective beliefs, knowledge, thoughts, and the emotions of the target traveler. It is especially necessary and important to analyze and understand better user browsing data. But it's tricky without the help of a computer that manipulates large amounts of data.

2. Related Work

Content analysis results show that tourists' perceptions of air quality are primarily positive during Weibo's adaptation phase, with a bad sense of air pollution crisis. Taking into account the objective emotional words in an objective and subjective emotions, then it is the subjective emotions that help to fully understand the comments [1] of emotional content.

The deep penetration of mobile-cited cities is looking for opportunities to better plan, monitor in-depth analysis of citizen mobility and usage data, and manage service functions. Instead of relying on the analysis, reporting, optimization and portfolio planning, a variety of different tools, it is a stand-alone tool in the implementation. The interactive user interface [2] allows carriers to intuitively explore the spatial and temporal mobility which need to be associated with the transportation network, and the transmission network evaluates the quality of service it provides to the public in detail.

Works data analysis method is the use of mobile phones frequent pattern, anonymous location data and merges them to generate the candidate's route design. Utility and other routines to select the best route and frequency setting are used to select the service by the network routing configuration to maximize system [3] wide travelers. Automatic Vehicle Identification (AVI) data, Integrated Circuit (IC) card data and Global Positioning System (GPS) data which provide the emergence and promising source of information for traffic problem analysis. Research insights and analysis of information from AVI data traffic has made some progress, especially in the development of specific applications. Emergence of multi-source data provides a new approach for a multi-modal transport [4].

By measuring or vehicle damage resulting availability of traffic data, data integrity attacks prediction error generated by operating conditions and inappropriate route guidance determination to guide the vehicle increases traffic congestion, which can reduce efficiency and traffic safety. Plan and lead the way affect the validity of our formal models and analysis of attack. To discover [5] display, data integrity attacks can be effectively used for congestion, destruction of route guidance program, increased travel time and transportation resources imbalance. Learning algorithms for achieving the predicted travel time are based on data from the DSRC (Dedicated Short Range Communication) and the RTMS (Remote Traffic Microwave Sensor).First, the travel time is based on DSRC and RTMS data extraction respectively. Both the travel time propagation time value is then input to a Gated Repeating Unit (GRU) model based on multiple data [6], thus the prediction results are obtained.

Congestion prediction accuracy assessment of the absolute level of passenger is discrete. Idle, real-time load data forecasts exceed historical average levels, with improved accuracy at target stations and railcars that change significantly as load changes. The results show that real-time congestion information can reduce car congestion [7] and can provide early and influential travel route, train, and vehicle selection.

To explain the observed deviation from the stroke simulator trip, a small event is processed to introduce passenger travel concept. he technology develops them into integrations into the generated itineraries and learns such integrations from the two sources available namely travel records and travel planning recommendations. For the entered travel demand, we use the Monte Carlo Markov Chain Algorithm (MCMCA) to establish a Markov chain within the [8] itinerary collection and combine small activities so that the driving characteristics converge to the target distribution.

However, it is extended with new patterns as a basic data model that describes the spatiotemporal path trajectories of moving objects and the complex areas of interest. In addition, the proposed system does not allow conventional data models [9] for this purpose, to provide a framework for processing the trajectories of moving objects in an interoperable manner of dissimilar sensors. They are distinguished by use. Also, most existing works do not consider user preferences or historical root datum as important ancillary information as an attribute of such a Point of Interest (POI).In this paper, we propose a flexible Multi-task Deep Travel Route Planning (MDTRP) framework and rich auxiliary information into more effective planning. Specifically, the heterogeneous network will be established by the relationship between the user and the first POI, embedding method using heterogeneous network to learn POI and [10] the function of the user.

Pass a signalized intersection or pursue the shortest time or distance to avoid left / right chips. Test results show that driver selection for this route is not always the best described in any of these rules. On the contrary, we believe that taxi drivers have limited rationality and are usually selecting one of several ways to consume the shortest time [11] and choose a satisfying route. Daily routes and departure times are usually processed separately and they together comply with the Rational Behavior Adjustment Criterion (RBAC) in existing models and rarely pay attention to additional behavioral preferences. In that proposed model, an integrated model of daily departure times and route selection is developed. Also, in addition to RBAC, micro behavioral preferences (i.e., simple, prone, and marginal cost preferences) are recommended for modeling. The problem is Departure Time and Route Adjustment Process (DTRAP) [12] called daily departure time and discrete-time dynamics.

The effect of sentiment analysis is to be enhanced. However, online travel review is largely uneven distribution of short text emotional feature, which makes it difficult to obtain accurate sentiment analysis results. Therefore, in order to improve the online travel review text sentiment classification accuracy, this research into sentiment analysis of multi-classification method is based on machine learning, and further designs [13] Key words semantic extension based on knowledge map.

Travel content shared via social media has become a highly influential source of information that impacts the reputation and performance of the travel industry. However, the amount of data on the Internet has reached a level such that manual processing is almost impossible, and requires a new analysis method [14]. Sentiment analysis is fast becoming a source of study for Semantic relationships and an automated review process. In this article, sentiment analysis method to travel for different purposes should be reviewed and evaluated in terms of the use of [15] Main datasets and performance indicators.

Sentiment-aware Multi-modal Topic Model (SMTM) has many potentials to solve the problem of personalized travel recommendations using data available from real-world social media, the so-called emotional perception probability graph model. It is proposed to meaningful online travel sites. To distinguish from the traditional method, the attempt of our proposed method [16] is to disclose the tourist theme and attraction theme of meaning from the tourist attraction and domain theme of each mine.

With the development of the tourism market, people's living standards and transportation have made tourism a basic way of people's lives in their leisure time. From the tourist's point of view, tourists are facing the problem of choosing tourist attractions. From a tourist attraction point of view, it should be properly understood and developed as how to attract tourists to the current fiercely competitive environment [17].

Comments from a single language such as those written in English are ideal as there are no artifacts or distortions that can come out of the translation process. However, tourist attractions such as beaches attract tourists from non-English speaking countries around the world [18], even for essential business purposes. Embedding words and phrases mapped to real number vector letters help learning algorithms to broadly group similar words to achieve better performance in natural language processing tasks by capturing meaningful grammar and semantic regularity. It is used to obtain the first acceptable accuracy [19] as a feature vector, Bag-Of-Words (BOW) and skip-gram representation are used for text treated as fixed length.

The tourism industry needs to consider multiple sources and measure customer satisfaction when using different hotel services in order to increase the service to tourists. There are a lot of comments out there, and problems arise when it's difficult for an administrator to identify what's reflected in a customer's sentiment review. In this study, some applications in language programming like Python [20] is produced to assign good and evil standards by the method of text.

This section describes the problems of tourist review based sentiment analysis. These methods do not support the development of sentiment word identification and classification .To overcome this problem, the PANN is proposed to utilize the sentiment analysis accurately.

3. Implementation of the proposed system

Online customer reviews of hotels and restaurants at travel destinations while choosing a hotel destination or restaurant play an important role in the decision-making process. Travel blogs and travel site comments play an important role in selecting destination, hotel selection, location, weather. Visitors then use the same information to meet their tastes. Similarly, authorities such as hotels use the same information to improve customer service. All reviews can be used for better and easier reasoning if they are analyzed for a given location while reading the sample reviews.

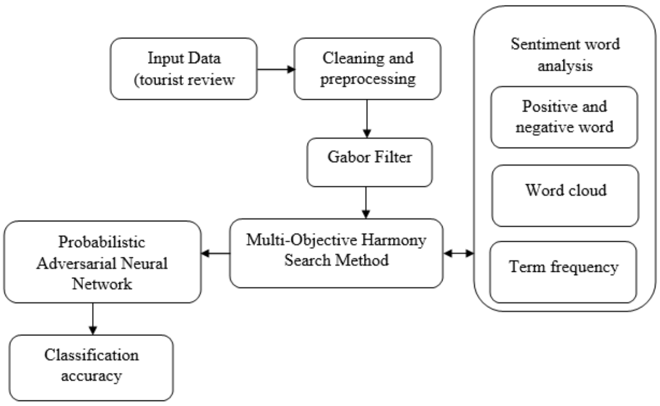

Figure 1 Proposed Block Diagram

The above figure 1describes tourist review based sentiment classification analysis. The sentiment analysis is based upon the Gabor Filter to remove the noise from the given data set. Term frequency is used to split the common words from the preprocessing sentence word cloud to extract the visualizing qualitative data and then Multi-Objective Harmony Search Method is used to remove the repeated words from the sentence. Finally, the Probabilistic Adversarial Neural Network (PANN) algorithm based classification is used to identify the misclassification data and to correctly classify the sentiment word.

3.1 Gabor Filter based Cleaning and Preprocessing of Review Data

Preprocessing data is the process of preparing text for cleaning and classification. Online text usually contains a lot of noise and does not provide any information such as HTML tags, scripts or advertisements. Also, at the word level, many words in the text do not affect their general orientation and this stage, the reliability of the data is improved.

Step1: Given the tourist review dataset r_d

Step2: Split the r_d data set

Train data← T_d

Test data← S_d

Step3: The train data T_d and it's contain the user_ id U_d, label $L_b$is the binary target variable.

Step4: Most of the smaller words are remove from the list

$$T_d \leftarrow S_w$$

Step5: Remove numbers, punctuation, special characters and symbol

$$T_d \leftarrow U_w$$

Step6: Tokenize the T_d data's. The tokenization data is splitting a number of text into tokens

$$T_W \leftarrow T_d$$

Step7: Stemming the word T_W

$$T_W \rightarrow St_w$$

Gabor Filter removes punctuation, numbers, and special characters because these characters aren't very useful. It involves data exchange such as handling such missing or inconsistent values and removing noise and outliers. This is to eliminate duplicate records, unnecessary data fields and standardized data formats.

3.2 Multi-Objective Harmony Search Method

A proposed method utilizes a knowledge-based method of word-sense disambiguation using the Multi-Objective Harmony Search Algorithm (MHAS).

It works well in simple TF (Term Frequency) model and paying attention to unusual words with all the words in the same situation in the word model. However, in this model, it is not executed exactly in the event of any penalty, including negation. This negation affects word / sentence polarity and is a very common language structure. Therefore, the model should be framed for better results when given the negative presence.

Step1: Understanding the common words from the St_w

Common words $C_w \leftarrow St_w$

Step2: Word cloud is to be imported from theC_w. The word cloud is to identify the width, height and maximum font size.

Step3: Analyze the common words as how many timesT_f appear in the sentence (review) and identify the entire sentence using Term frequency. The repeated words are removed from the review (sentence) to assign the corrected review

$$TF(t,s) = \text{number of times term } (t) \text{ appears in the sentence } (s) \Big/ \text{total number of terms in the sentence}$$

C_w=$TF(t, s)$

Step4: The word cloud to identify the sentiment words from theC_w.

$$S_w \leftarrow C_w$$

Word Cloud visualization is a great way to communicate results. In a Common word analysis, a Word Cloud is used to visualize data into a basic package of datasets. The importance of each word can be interpreted as a cloud diagram using different sized Word Cloud. Use at least the most commonly used maximum and small sizes. Customers using these different sizes will convey more discussions about travel locations. From the given list of comments, the overall emotional attitude of each word is used to draw the Word Cloud which can identify trends and patterns that are difficult to determine because reading them will help to identify frequency of word-based analysis of emotions from the review opinion.

3.3 Probabilistic Adversarial Neural Network based Classification

The next process is a different oriented label, and comments about it are given positive or negative labels. This classifies whether the specified text is positive, negative or neutral, and sometimes according to the classification level of a given sentence. This task is accomplished by identifying the emotions and opinions of subjective factors in the text. The method used to classify parts of the text is sentiment-based in that it is positive and negative.

Each layer of the multilayer proposed emotions are organized into words. PANN, the feedforward network has four layers namely the input layer, a pattern layer, the summarization layer and output layer functions. Input layer is an input node of a set of measurements. Pattern layer is completely connected to the input layer, each neuron is using a pattern in the training set. The output of the patterned layer is connected to the summarization unit selectively according to the type of pattern present in figure 2. The following are the steps included in the PANN algorithm.

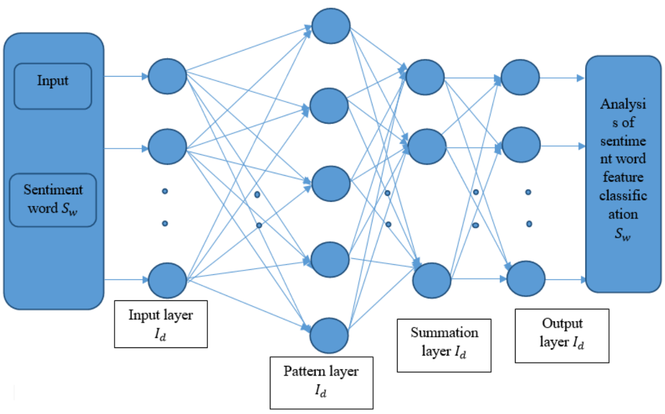

Figure 2 Probabilistic Adversarial Neural Network based Classification Diagram

Step 1. The neuron S_w in the input layer distributes the input measurements to all neurons in the pattern layer.

Step 2. The pattern layer is formed using a given set of data points. The neurons in the pattern layer have the same number of $S_w$input samples, and the total layer has the same number of neurons in the target class.

Step 3. The fourth layer is the functionS_w label to select the confirmation classification.

Use weighted links to interconnect all these layers, including a large number of neurons. The attributes of emotional function are proportional to the number of neurons in the input layer, and emotional words are proportional to the number of neurons in the output layer. With the exception of the input node, the nonlinear activation function is implemented by the node of each neuron.

4. Result and Discussion

The implementation of the tourist review based sentiment analysis is done using the simulation tool anaconda with the programming language python. Python is a dynamic, interpreted and general purpose programming language and it provides lots of high level data structures.

Table1 Details of Simulation Parameters

Parameter	Value
Tool	Anaconda
Programming Language	Python
Data Set Name	Trip advisor
Total Number of Data	1300
Number of Trained Data	1000
Number of Test Data	300

The above Table 1 describes the details of proposed system needed to the resources. The proposed Probabilistic Adversarial Neural Network (PANN) is compared with previous Dedicated Short Range Communications (DSRC), Monte Carlo Markov Chain Algorithm (MCMCA), and Superior Expectation-Maximization Vector Neural Network (SEMVNN).

The misclassification rate is defined by the forecast model as the ratio of the number of false classification evaluations to the total number of classification evaluations. The error classification can be divided into two categories. Negative reviews are classified as positive (N_p) and positive reviews are classified as negative (P_n).

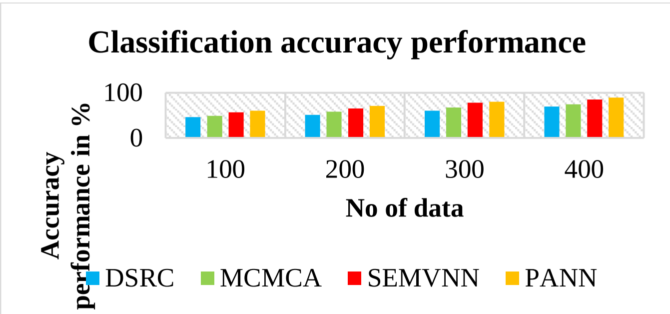

Figure 3 Analysis of Classification Accuracy Performance

The above figure 3 describes the analysis of classification accuracy level. The previous DSRC provides 69%, MCMCA provides 74%, SEMVNN provides 85% and the proposed PANN provides 89%. Hence, the proposed system gives better accuracy result compared to the previous system.

Table 2 Performance Analysis of Precision, Recall and F-Measure

Algorithm	Precision in %	Recall in %
DSRC	68	72
MCMCA	71	74
SEMVNN	74	76
PANN	84	85

The above table 2 shows the performance analysis of precision, and recall. The precision, recall and f-measure equations are given below:

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$F - measure = 2 * \frac{Precision*Recall}{Precision+Recall} \quad (3)$$

Hence, the proposed PANN gives better Precision, Recall and F-Measure value compared to the previous system.

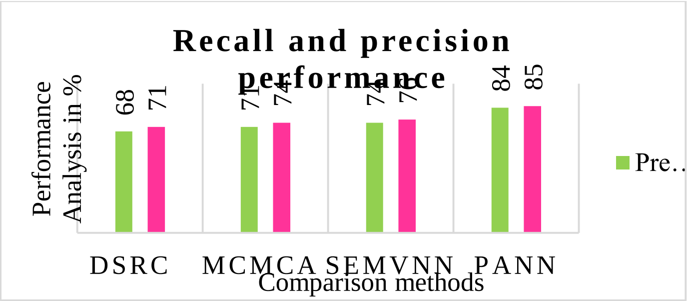

Figure 4:Analysis of Precision and Recall Performance

Figure 4 describes the performance analysis of precision, recall and F-measure. The previous DSRC based precision is 68%, recall is 73% and F-measure is 70%, MCMCA based precision is 71%, and recall is 74%, SEMVNN based precision is 74%, and recall is 76%.The proposed PANN based precision is 84%, and recall is 85%.

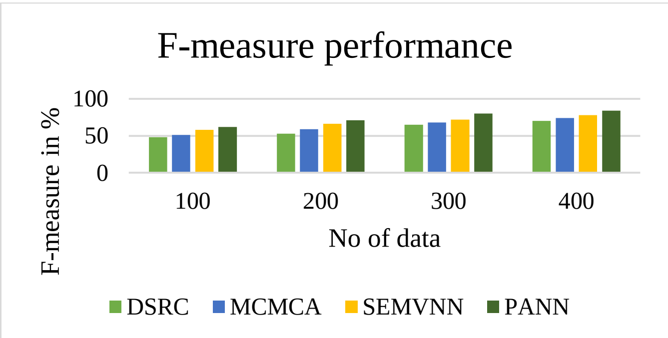

Figure 5: Analysis of F-measure performance

Figure 5 depicts analysis of F-measure performance comparison. The proposed PANN algorithm provides F-measure performance of 84% for 400data; similarly the existing algorithm DSRC method provides F-measure performance of 70%, MCMCA method provides performance of 74%, and SEMVNN method provides F-measure performance of 78% for 400 data.

$$\text{Misclassification rate} = \frac{(N_p+P_n)}{Total\ number\ of\ reviews} \quad (4)$$

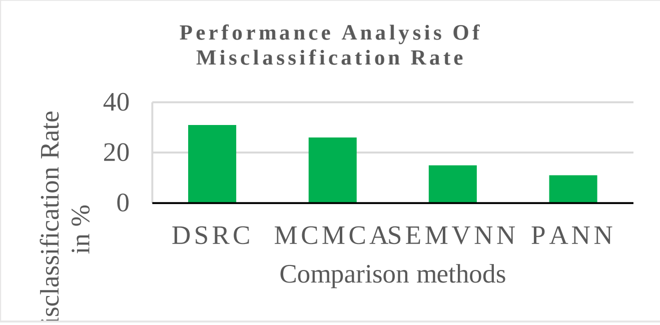

Figure 6: Performance Analysis of Misclassification Rate

The above figure 6 shows the analysis of misclassification rate. The existing DSRC provides 31%, MVMCA provides 26%, SEMVNN provides 15% and the proposed PANN produces only 11%.

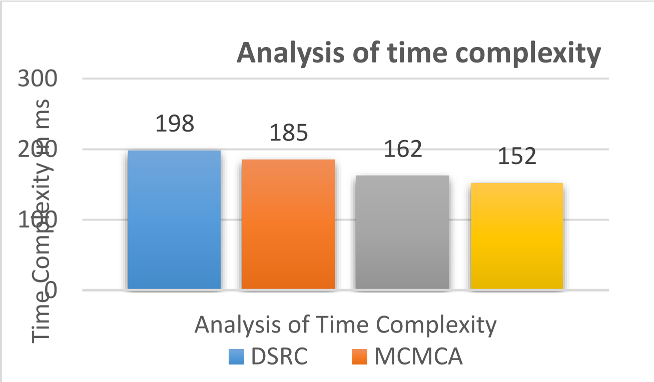

Figure 7: Analysis of Time Complexity

Figure 7 shows the comparison of time complexity level analysis. The proposed PANN produces time complexity in 152 with ms and the existing DSRC produces time complexity in 198 with ms, MCMCA in 185 with ms, SEMVNN in 162 with ms.

5. Conclusion

In tourist review, finding an increase in sentimental thinking about posting travel locations through reviews has become a challenging task. Review-based sentiment analysis covers a number of applications for large alternative information systems, as well as real-time applications that differ from classification, rating, and summary reviews. The proposed PANN algorithm extracted data focuses on the selection of emotional classifications by means of a Multi-Objective Harmony Search Method, mainly after suggesting and classifying. Classification is to identify misleading emotional words and if it is correct, the accuracy will improve after the PANN is updated.The proposed PANNbased performance analysis of misclassification rate is 11%, performance analysis of classification accuracy is 89%, analysis of time complexity is 152 with ms, precision is 84%, recall is 85% and f-measure is 84%.

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