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ANALYSIS OF DIFFERENT CHARGING STATION ON MULTIPLE REVIEWS USING MACHINE LEARNING

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Abstract

The growing demand for an efficient and user-friendly station booking system has necessitated the development of an integrated platform that streamlines the booking process while incorporating user feedback mechanisms. This paper presents a structured station booking and review system that enables two types of users station administrators and customers to interact seamlessly. The system ensures that new users undergo a registration process before gaining access through a secure login mechanism. Administrators can manage station details, update information, and oversee user feedback, thereby improving service quality. Customers, on the other hand, can search for stations based on area or category, select a station, and book a slot for their requirements. To enhance user experience, the system also incorporates a review management module, allowing customers to view existing reviews and submit their own feedback after utilizing the station's services.

Keywords:-

Station Booking System, Online Slot Reservation, User Authentication, Feedback Management, Review System, Customer Experience, Service Optimization, Station Administration, Area-Based Search, Real-Time Availability, Data Management, User Engagement, Automated Booking, Digital Reservation System, Web-Based Application, Smart Booking Platform,

Cloud-Based Reservation, User-Friendly Interface, Secure Login System, Data Privacy, Review Analysis, Station Management System, AI-Based Recommendation, Predictive Analytics, Automated Scheduling, Service Enhancement, Reservation Tracking, Intelligent Booking System, Digital Transformation, Self-Service Booking.

I. Introduction

Sentiment analysis, also called opinion mining, is the field of study that analyzes people opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics and their attributes. There are also many names and slightly different tasks, e.g., sentiment analysis, opinion mining, opinion extraction, sentiment mining, subjectivity analysis, affect analysis, emotion analysis, review mining, etc. Sentiment analysis and opinion mining mainly focuses on opinions which express or imply positive or negative sentiments. In recent years, with the growing volume of online reviews available on the Internet, sentiment analysis and opinion mining, as a special text mining task for determining the subjective attitude (i.e., sentiment) expressed by the text, is becoming a hotspot in the field of data mining and natural language processing. Sentiment classification is a basic task in sentiment analysis, with its aim to classify the sentiment (e.g., positive, negative or neutral) of a review given by the user.

Sentiment analysis is the task of finding sentiment words in a given piece of text. It Comprises three functions i) dividing sentences into words, ii) identification of sentiment in sentence using a sentiment analysis tool, iii) finding positive and negative polarities of the sentiment words and rating the reviews as positive or negative based on their polarities or score. Sentiment classification looks, for words or emotional states such as sweet, happy, angry, and sad. Let us consider an example for each type of reviews, such as “the product was simply awesome”, and “it was a horrible product” is positive review and negative review respectively for the product.

II. Literature Survey

[Rui Xia, Feng Xu, and Chengqing Zong 2015] propose a simple yet efficient model called dual sentiment analysis (DSA), to address the polarity shift problem in sentiment classification. By using the property that sentiment classification has two opposite class labels (i.e., positive and negative), first propose a data expansion technique by creating sentiment reversed reviews. The original and reversed reviews are constructed in a one-to-one correspondence. Thereafter, propose a dual training (DT) algorithm and a dual prediction

(DP) algorithm respectively, to make use of the original and reversed samples in pairs for training a statistical classifier and make predictions. In DT, the classifier is learnt by maximizing a combination of likelihoods of the original and reversed training data set. In DP, predictions are made by considering two sides of one review. That is, measure not only how positive/ negative the original review is, but also how negative/ positive the reversed review is. Further extend our DSA framework from polarity (positive vs. negative) classification to 3-class (positive vs. negative vs. neutral) sentiment classification, by taking the neutral reviews into consideration in both dual training and dual prediction. To reduce DSA's dependency on an external antonym dictionary, finally develop a corpus-based method for constructing a pseudo-antonym dictionary. The pseudo antonym dictionary is language-independent and domain- adaptive. It makes the DSA model possible to be applied into a wide range of applications [1].

[Zhen Hai, Kuiyu Chang and Christopher C. Yang 2014] proposed a novel inter-corpus statistics approach to opinion feature extraction based on the IEDR feature-filtering criterion, which utilizes the disparities in distributional characteristics of features across two corpora, one domain-specific and one domain-independent. IEDR identifies candidate features that are specific to the given review domain and yet not overly generic (domain independent). Experimental results demonstrate that the proposed IEDR not only leads to noticeable improvement over either IDR or EDR, but also outperforms four mainstream methods, namely, LDA(latent dirichlet allocation), ARM (association rule mining), MRC (mutual reinforcement clustering), and DP, in terms of feature extraction performance as well as feature based opinion mining results. In addition, since a good quality domain-independent corpus is quite important for the proposed approach, evaluated the influence of corpus size and topic selection on feature extraction performance. Found that using a domain independent corpus of a similar size as but topically different from the given review domain will yield good opinion feature extraction results [2].

[R. Xia, T. Wang, X. Hu, S. Li, and C. Zong 2013] In this work, propose a method, called dual training and dual prediction (DT DP), to address the polarity shift problem in sentiment classification. The basic idea of DTDP is to generate artificial samples that are polarity-opposite to the original samples, and to make use of both the original and opposite samples for dual training and dual prediction. For example, given the original sample "I don't like this book. It is boring," its polarity-opposite version, "I like this book. It is interesting", is artificially

generated. Second, the original and opposite training samples are used together for training a sentiment classifier (called dual training), and the original and opposite test samples are used together for prediction (called dual prediction). Experimental studies show that our DTDP algorithm is very effective for sentiment classification and it beats other alternative methods of considering polarity shift. One limitation of current work is that the tuning of parameters in DTDP (such as a and t) is not well discussed [3].

[C. Lin, et al 2012] proposes a joint sentiment-topic model and a re-parameterized version of JST (Joint sentiment topic) called Reverse-JST. While most of the existing approaches to sentiment classification favor supervised learning, both JST and Reverse-JST models target sentiment and topic detection simultaneously in a weakly supervised fashion. Without a hierarchical prior, JST and Reverse-JST are essentially equivalent. However, extensive experiments conducted on data sets across different domains reveal that these two models behave very differently when sentiment prior knowledge is incorporated, in which case JST consistently outperformed Reverse-JST. For general domain sentiment classification, by incorporating a small amount of domain independent prior knowledge, the JST model achieved either better or comparable performance compared to existing semi-supervised approaches despite using no labeled documents, which demonstrates the flexibility of JST in the sentiment classification task. Moreover, the topics and topic sentiments detected by JST are indeed coherent and informative [4].

[X. Yu, Y. Liu, X. Huang 2012] The wide spread use of online reviews as a way of conveying views and comments has provided an unique opportunity to understand the common public's sentiments and derive business intelligence. In this paper, explored the predictive power of reviews using the movie domain as a case study, and studied the problem of predicting sales performance using sentiment information mined from reviews. They approached this problem as a domain-driven task, and managed to synthesize human intelligence (e.g., identifying important characteristics of movie reviews), domain intelligence (e.g., the knowledge of the "seasonality" of box office revenues), and network intelligence (e.g., online reviews posted by moviegoers). The outcome of the proposed models leads to actionable knowledge that can be readily employed by decision makers [5].

[T. Wilson, J. Wiebe, and P. Hoffmann 2009] Proposes a work automatically distinguish between the prior and contextual polarity, with a focus on understanding which features are important for this task. Because

an important aspect of the problem is identifying when polar terms are being used in neutral contexts, features for distinguishing between neutral and polar instances are evaluated, as well as features for distinguishing between positive and negative contextual polarity. These experiments show that presence of neutral instances greatly degrades the performance of these features and that perhaps the best way to improve the performance across all polarity classes is to improve the polarity classes is to improve the system's ability to identify when an instance is neutral [7].

[Xiaowen Ding and Bing Liu 2007] Proposed to use some linguistic rules to deal with the problem together with a new opinion aggregation function. Extensive experiments show that these rules and the function are highly effective. A system, called Opinion Observer, has also been built. In this paper, study the latter problem, i.e., determining whether an opinion is positive or negative. Assume that product features are given or have been discovered by another system. And studies the problem of determining the semantic orientations (positive or negative) of opinions expressed on product features in reviews. Most existing approaches use a set of opinion words for the purpose. However, the semantic orientations of many words are context dependent. Existing techniques use opinion words such as "great", "amazing", "poor", "bad", etc. to decide the orientation of an opinion on a product feature. Although the orientations of these words are obvious, the orientations of many other words depend on context. For example, the word "small" can indicate a positive or a negative opinion on a product feature depending on the feature. Propose several linguistic rules to deal with the problem. The approach tries to infer the orientations of opinions on a product feature using context. A new function for aggregating multiple opinions in a sentence is also presented. Experiment results show that the rules and the aggregation function are very useful [8].

III. System Diagram

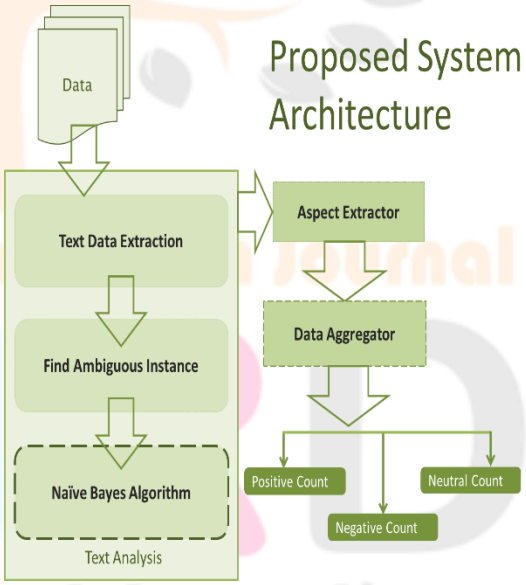


Fig: Proposed System Diagram

IV. Working Methodology

The system breaks user review to see for sentiment keywords. Once the keywords are found it associates the review with a sentiment rank. The system now gathers all

review for a particular product and then calculates the positive-negative-neutral count. This provides an automatic product rating system supported on sentiment analysis.

- **Aspect Extractor**

In aspect extractor, users predict the reviews like positive and negative based on the relevant data extracted. This collection of reviews used for various opinion analysis tasks. Users give the reviews on product online. The admin then checks reviews, and displays an online rating for every product.

- **Data Aggregator**

Data aggregator, gathered and presented the relevant data in a summarized format based on the user reviews like positive, negative and neutral.

- **Naive Bayes Algorithm**

Naive Bayes is a simple but effective algorithm for classification tasks. It is based on Bayes' theorem, which is a fundamental theorem in probability theory. The algorithm is "naive" because it assumes that all features are independent of each other, which is often not the case in real-world scenarios. Despite this simplification, Naive Bayes is widely used in text classification, spam filtering, sentiment analysis, and many other applications.

The basic idea of Naive Bayes is to calculate the probability of each class given the input features, and then choose the class with the highest probability. The probability of each class is calculated using Bayes' theorem:

$$P(C | X) = P(X | C) * P(C) / P(X)$$

where C is the class, X is the input features, P(C | X) is the probability of class C given input X, P(X | C) is the probability of observing input X given class C, P(C) is the prior probability of class C, and P(X) is the probability of observing input X.

The Naive Bayes algorithm assumes that all features are independent of each other given the class, so we can write:

$$P(X | C) = P(x1 | C) * P(x2 | C) * ... * P(xn | C)$$

where xi is the ith feature of input X.

To classify a new input, we calculate the probability of each class given the input features using Bayes' theorem, and then choose the class with the highest probability:

$$P(Ci | X) = P(X | Ci) * P(Ci) / P(X)$$

where Ci is the ith class, X is the input features, P(Ci | X) is the probability of class Ci given input X, P(X | Ci) is the probability of observing input X given class Ci, P(Ci) is

the prior probability of class Ci, and P(X) is the probability of observing input X.

The Naive Bayes algorithm is computationally efficient and works well with high-dimensional data. However, it may suffer from the "zero probability problem" when a feature has not been observed in the training set, resulting in a probability of zero. This problem can be addressed by using smoothing techniques such as Laplace smoothing.

Algorithm for Social Sentiment Analysis

This algorithm takes an English sentence as an input and assigns sentiment ratings of "positive", "negative" and "neutral". Also identify and extract sentiment in given English string. Sentiment analysis or opinion mining refers to the use of natural language processing, text analysis and computational linguistics to identify and extract subjective information in source material. Four sentiment types are returned- Positive, negative, neutral & compound. The first three sentiments scale from 0 to 1. Compound sentiment is the overall sentiment, where it scales between -1 to 1, negative to positive respectively.

Input:

- **(Required):** String sentence***** or A list of strings******

Output:

- Sentiment* of given sentence(s).

Ex:

Input:

```
{
 "SentenceList":
 [ "I like double cheese pizza",
  "I love black coffee and donuts",
  "I don't want to have diabetes"]
}
```

Output:

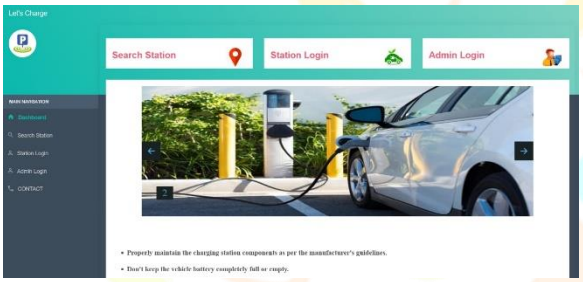
```
[
  {
   "positive": 0.455,
   "negative": 0,
   "sentence": "I like double cheese pizza",
   "neutral": 0.545,
   "compound": 0.3612
  },

  {
   "positive": 0.512,
   "negative": 0,
   "sentence": "I love black coffee and donuts",
   "neutral": 0.488,
   "compound": 0.6369
  },
```

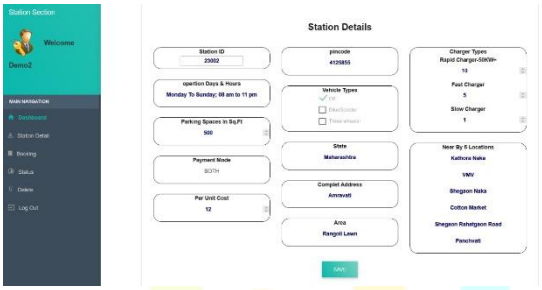
```
 {
   "positive": 0,
   "negative": 0.234,
   "sentence": "I don't want to have diabetes",
   "neutral": 0.766,
   "compound": -0.0572
 }
]
```


Screen Shoots

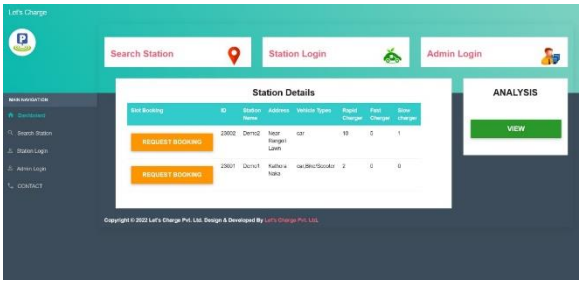
Home Page



Station Registration



View Search Station List:



V. Conclusion

Sentiment Analysis is very important research because Sentiment Analysis helps us in summarizing opinion and reviews of users. They consider as research filed. However, Sentiment Analysis still needs to improve and progress. Moreover, there are many challenges in Sentiment Analysis, like the polarity in a complex sentence.

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VII. References

[1]. R. Xia, F. Xu, C. Zong, Q. Li, Y. Qi and T. Li, "Dual sentiment analysis: Considering two sides of one review", in IEEE Trans. Know l. Data Eng., vol. 27, no. 8, pp. 2120-2133, Aug. 2015.

[2]. Z. Hai, K. Chang, J. Kim, and C. C. Yang, "Identifying Features in Opinion Mining via Intrinsic and Extrinsic Domain Relevance," IEEE Transactions on Knowledge and Data

Engineering (TKDE), vol. 26, no. 3, pp. 447-462, 2014.

[3]. R. Xia, T. Wang, X. Hu, S. Li, and C. Zong, “Dual Training and Dual Prediction for Polarity Classification,” Proceedings of the Annual Meeting of the Association for Computational Linguistics (ACL), pp. 521-525, 2013.

[4]. C. Lin, Y. He, R. Everson, and S. Ruger, “Weakly supervised joint sentiment-topic detection from text,” IEEE Transactions on Knowledge and Data Engineering (TKDE), vol. 24, no. 6, pp. 1134-1145, 2012.

[5]. X. Yu, Y. Liu, X. Huang, and A. An, “Mining online reviews for predicting sales performance: A case study in the movie domain,” IEEE Transactions on Knowledge and Data Engineering (TKDE), vol. 24, no. 4, pp. 720-734, 2012.

[6]. A. Abbasi, S. France, Z. Zhang, and H. Chen, “Selecting attributes for sentiment classification using feature relation networks,” IEEE Transactions on Knowledge and Data Engineering (TKDE), vol. 23, no. 3, pp. 447-462, 2011

[7]. T. Wilson, J. Wiebe, and P. Hoffmann, "Recognizing contextual polarity: An exploration of features for phrase-level sentiment analysis," Computational Linguistics, vol. 35, no. 3, pp. 399-433, 2009.

[8]. X. Ding and B. Liu, "The utility of linguistic rules in opinion mining," Proceedings of the 30th ACM SIGIR conference on research and development in information retrieval (SIGIR), 2007.