An Effective Hotel Recommendation System Based on Ensemble stacking Methods

Rakesh Verma[1], Abhishek[2], Amarpreet Singh[3]

[1, 2, 3]Department of Computer Science, CT Group of Institution, Jalandhar, Punjab, India

[1]Corresponding Author Email: *r.verma0211[at]gmail.com*

Abstract: ***The choice of an appropriate hotel location or lodging reservations have recently become crucial concerns for travelers. Because of the abundance of online information, searching for hotels online has become quite time - consuming & has grown rapidly. Due to its relevance in helping people make decisions and offering thorough information on the product or service they are looking for, recommender systems (RSs) are becoming more and more popular. Gathering quantitative rankings, votes, ratings, and video view counts has posed a challenge in effectively managing textual hotel evaluations. . Different machine learning techniques for hotel suggestions were created in the conventional way. The previous approach fared well, but there is still room for improvement in the hotel recommendations system, according to the report. Use ensemble stacking techniques to create a hotel recommendations system in this study. utilize ensemble stacking techniques for hotel recommendations. The suggestion for a model was developed and tested using benchmark recommendation methods. MAE and RMSE, two commonly used measurements, are utilized to evaluate the predicted effectiveness of the techniques suggested. The reliability of predictions was evaluated using MAE and RMSE, and coverage was utilized to evaluate prediction area.***

Keywords: Hotel recommendation system, Sentimental analysis, Ensemble stacking methods, PCA

1. Introduction

Nowadays, the majority of online service systems, including e - commerce or new media websites, make use of personalized recommendations to their customers' advantage by making suggestions for content that may be of interest to them according to what they like or prior knowledge for e - commerce [1], music/video/movie online businesses, and travel, recommendation systems have been incorporated into platforms to serve the online market. Travellers frequently take the time to explore hotels on online travel websites in accordance with their particular needs; for instance, a business traveller may place the greatest emphasis on the hotel's location and cost, while a tourist may place the greatest emphasis on the hotel's comfort and cleanliness. A traveller able to choose one hotel at a time,, so it is very difficult to take back an incorrect choice. fairly good hotel RS is therefore really beneficial for lowering passengers 'and time saving hotel owners' money on promotion.

In general, RS strives to recommend products to consumers that they may be interested in. RS techniques essentially fall into three categories: Items are recommended using collaborative filtering methods that utilize past interactions between the user and the item, such as a comments or ratings; While the approaches content - based eliminate the information between the customer and the elements to convey the recommendation, hybrid RS methods allow for several ways to express the suggestion. These techniques work with audio, video, or text data. . The majority of RSs rely on user ratings, which help them learn about user preferences, item qualities, as well as more details about how users and/or items are correlated [3]. This information may be utilized later to foresee an unknown user rating for an item. This method, also known as user - and based on item collaborative filtering techniques, predicts an unknown rating using the average rating from the user's or the item's k - nearest neighbour [4].

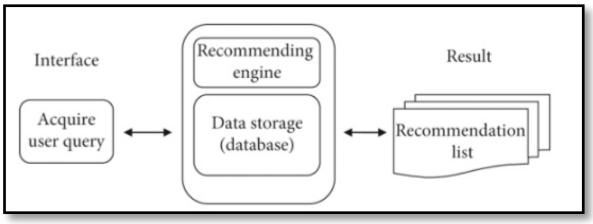

Figure 1: Generic architecture of a recommender system [2]

The rest of the document is structured as follows: Ensemble methodologies are discussed in Section II, a literature review is provided in Section III, and the proposed work is contained in Section IV. The findings are presented in Section V, and the paper's conclusion is provided in Section VI.

2. Ensemble Techniques

When creating an ideal prediction model, ensemble methods combine several learning models. When compared to the base learners alone, the model developed performs better. The selection of key features, data fusion, and other uses of ensemble learning are also possible. The three main categories of ensemble approaches are bagging, boosting, and stacking [5].

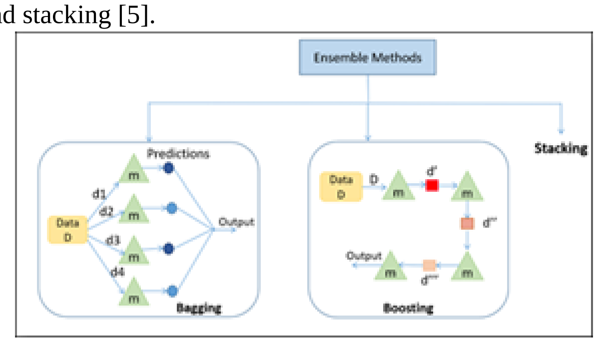

Figure 2: Displaying the various ensemble method kinds. Here, m stands for a weak learner, and the random samples

d1, d2, d3, and d4 are taken from Data D. The updated training data d', d'', and d''' are based on the findings of the previous weak learner [2]

The principal applications of bagging are in supervised learning issues. The process consists of the two processes of bootstrapping & aggregation. The replacement approach is used to create samples using the bootstrapping random sampling technique. Bootstrapping, shown in Fig.2, is the first stage of bagging, in which random samples of data are provided to each base learner. The process is finished by applying the base learning approach to the samples. Similar to a Random Forest, the results from the base learners are combined during aggregation in order to significantly lower variance while raising accuracy.

1. Boosting: It is a team approach where every predictor learns from the errors of earlier predictors to improve future predictions. The method includes a number of weak base learner that are stacked sequentially (Fig.3) so that weak learners can learn from the mistakes of the preceding weak learner to produce a more accurate predictive model. Consequently, by considerably increasing the predictability of designs, one strong learner is created. Like XGBoost and AdaBoost.

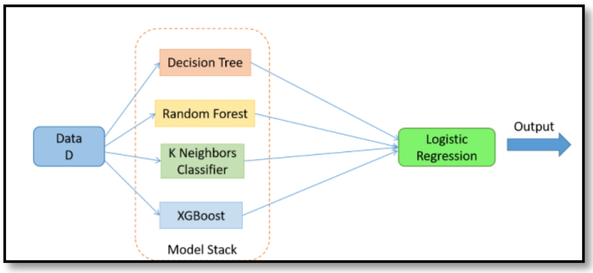

Figure 3: Weak learners such as Decision Tree, Random Forest, K Neighbours Classifier, and XGBoost are examples of weak learners in the stacked model with a meta learner, which is Logistic Regression [4].

2. Stacking: Contrary to bagging and boosting, where homogeneous weak learners were employed for ensemble, stacking usually involves heterogeneous weak learners. These weak learners are learned in parallel, and their predictions are combined by training a meta - learner to generate a prediction based on the multiple weak learners' predictions. By using the predictions as input features along with the ground truth values in the data D, the meta learner attempts to determine the optimal approach for combining the input predictions and producing a more accurate output prediction (Fig.4).

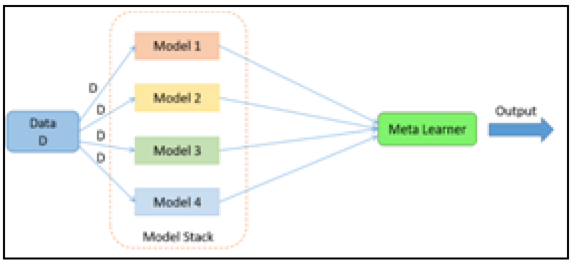

Figure 4: Stacking formula. The proportion of weak learners in the stack varies [5].

3. Literature Survey

This section discusses earlier work on the hotel recommender structure, which aids in understanding and realizing the necessity of recommenders in the current era of online technologies.

Quang et al., (2022) Broad tests on real - world information illustrate the convenience and viability of the recommended approach in comparison to past multi - criteria collaborative sifting strategies. The essential objective of this approach is to analyze client inclinations for lodging proposals from different points of view utilizing multi - criteria evaluations. The method consolidates lattice factorization into a profound learning show to foresee the multi - criteria appraisals. The instability related with these evaluations, spoken to as mass capacities within the Dempster - Shafer hypothesis of verification, is at that point modeled utilizing the evidential thinking strategy. At last, the in general review for suggestion is calculated by averaging the scores over different categories utilizing Dempster's run the show of combining.

Alper et al., (2022) A well - strategized DNN model is used to predict user interaction using the polarity created by dimension - based thinking in aggregate and score and user analysis. The model has three parts. In the first stage, the analysis goes through reflective analysis (ABSA) to establish the polarity and results in the final data. The second part integrates user and object placements and includes a color layer. The resulting features are then put into polarity and put into the sub - rating deep neural network (DNN) to predict sub - ratings and polarity. Finally, the third estimates the total score by feeding the resulting canonical sequence into the Total Score DNN. The theory uses aspect - based consumer theory based on polarity. According to the findings, the proposed method performs better in TripAdvisor dataset.

Bekir et al., (2019) Bekir et al. (2019) developed a novel hybrid hotel suggestion system that combines content - based and collaborative filtering approaches. This system recommends hotels to consumers based on their specific needs, effectively saving them time in the decision - making process.

Ray et al., (2020) The hotel recommendation system you developed incorporates user requests, aspect - based review categorization, and sentiment analysis of hotel reviews. Additionally, you gathered an extensive dataset of online hotel reviews from Tripadvisor. com. The methodical approach you followed involved using the Bidirectional Encoder Representations from Transformers (BERT) model, which incorporates different steps for positive - negative, neutral - negative, and neutral - positive attitudes. By combining these phases using a weighting process and utilizing the RF classifier with pre - trained word embeddings, you were able to split the reviews into different categories based on fuzzy logic and cosine similarity. Your efforts resulted in the development of an effective recommender system

Gomathi et al., (2019) described how to utilize a machine learning algorithm for NLP by looking at user behavior, using text data, and using user ratings. In order to assess user attitudes regarding hotel characteristics and further aid in assessing user opinion, authors has developed a recommendation system with the hotel sector as its target market. The results show that the recommender system produces with great precision.

Yu Mon Aye et. al, (2017) suggested creating a sentiment lexicon for Myanmar that is relevant to the restaurant & food industries, as well as using sentiment analysis for lexicon - related suggestion studies for customer text input in Myanmar. The suggested method has effectively read data for Myanmar's Language supply, providing a total precision of 96% based on feedback from 500 consumers in the restaurant or food industries. The analysis of 500 customers' reviews has produced results that are very accurate.

Khushbu Jalan et. al, (2017) The aim of this research project is to provide travelers with hotel brand recommendations based on their preferences and preferences, using feedback and reviews from other travelers to improve forecast accuracy. A context - sensitive relationship is used to provide personalized hotel recommendations by combining the CF approach with sentiment analysis. Therefore, the recommendations are expanded using a content - based approach.

4. Proposed Work

Problem Formulation

When there is a lot of information about a customer's preferences, machine learning is frequently utilised to provide product recommendations.37 million Expedia users were given the task of choosing hotel clusters by Kaggle using a dataset that had detailed information about these customers. Utilizing non - linear user data to suggest hotel clusters is difficult. Another challenge is the large quantity of useful prediction classes. The goal of this project is to accurately categorise the dataset by first using well - known machine learning techniques on it, then modifying and combining existing techniques. In the traditional manner, various machine learning algorithms for hotel recommendations were proposed. The investigation found that the conventional approach worked well, but that the hotel recommendations system still needed to be enhanced. .

Objectives

1) To use ensemble stacking techniques to aggregate predictions from algorithms that use trees as their basis.
2) To create and implement an ensemble stacking - based hotel recommendation system. .
3) To compare the suggested system with the current methodology.

5. Research Methodology

Data collection during the first stage requires using an online database. The dataset is subsequently put through a preparation process. After that, Principal Component Analysis is used to compress the dataset. The model is trained using this compressed dataset and ensemble stacking techniques. Finally, the model's performance is assessed using a variety of performance indicators.

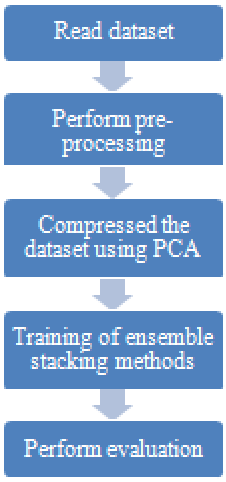

Figure 5: Flowchart of Proposed work

Steps:
1) Acquiring and reading the Expedia users dataset from kaggle.
2) Pre - processing Phase: In this phase some filtration work will going to be done in order to clean the dataset from unwanted/unreadable data eg: NaN values, Empty values etc.
3) After the reprocessing, the dataset is then compressed using Principal Component Analysis (PCA) algorithm.
4) Designing and preparing the model using ensemble stacking methods.
5) Designed models will be trained using the compressed dataset from PCA.
6) Once training is completed, trained model is then tested using the dataset.
7) Calculating variables such as precision, recall, F1 score, MAP5 score, etc.
8) Comparative analysis of result parameters of proposed work with base paper.

6. Results

A few evaluation metrics are employed to gauge how accurate the suggested system. These evaluation metrics show that the targeted users are satisfied with the outcomes produced by the suggested system. Performance analysis mostly reveals areas that need to be addressed before the product is released. Without performance analysis, software applications are more prone to experience problems like slow performance when numerous users are using it at once or slow system response. Therefore, we conducted a performance analysis to show that the suggested system generates useful recommendations. Although there are many measures, we choose to use two that are relevant to this study.

The mean absolute error (MAE) and root mean square error (RMSE) are commonly used metrics to evaluate the prediction effectiveness of recommendation methods. They measure the agreement between the projected ratings and the actual ratings. Higher accuracy is achieved when the MAE and RMSE values decrease. Furthermore, the expectation scope is considered utilizing the Scope metric, which calculates the proportion of anticipated appraisals to all the appraisals within the test dataset.

The proposed model has been tested on TripAdvisor database, which contains 28, 829 comments of various parameters from 1039 customers of 693 hotels. Consumers rate hotels on a scale of 1 to 5 based on seven criteria, including cleanliness, value for money, location, room quality, quality of service, hospitality, and private economy. The sparseness of Trip Advisor information is 96%. The data consists of two sets: 80% training and 20% testing.

The proposed framework has been assessed utilizing our around the world dataset. This information is utilized to compare the estimate precision of the request show with that of our coordinates sifting framework. Different tests were planned and conducted to assess the viability of the proposed framework relative to the pattern framework. The desired precision and scope of the proposed show and three distinctive CF - based strategies were moreover compared and the comes about appeared.

MSE: Cruel squared mistake (MSE) or cruel squared deviation (MSD) are measurements utilized to degree the exactness of an estimator or demonstrate. Calculates the cruel of the squares of the contrasts between the evaluated and real esteem. The MSE gives a degree of how near the gauge is to the genuine esteem, and lower values show more noteworthy exactness.

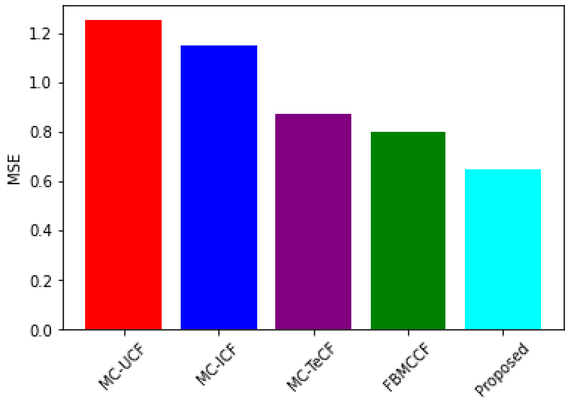

Figure 6: Comparison results of MSE on TripAdvisor dataset

RMSE: Root mean square error (RMSE) is a metric used in many fields such as climatology, forecasting and regression analysis. It helps to evaluate the distribution of residuals representing the distance between the data points and the regression line. By measuring how close the data are around the line of best fit, the RMSE provides important information about the accuracy of the experiment.

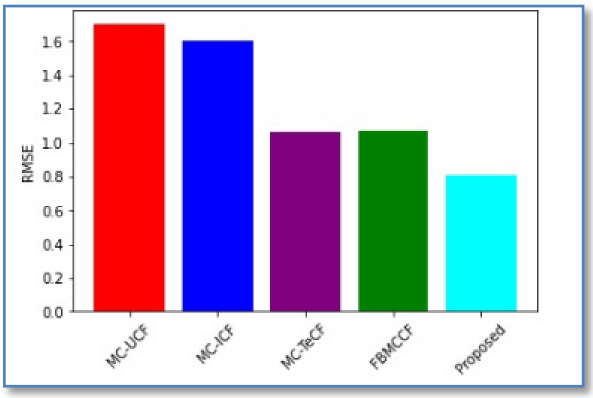

Figure 7: Comparison results of RMSE on TripAdvisor dataset

The recommended demonstrate, created and tried utilizing the TripAdvisor dataset, a real - world lodging multi - criteria dataset. Cruel outright mistake (MAE) and root cruel square blunder (RMSE) were utilized to assess the forecast precision of the demonstrate. Additionally, coverage was employed to assess the prediction coverage of the model.

7. Conclusion

The reservation of a quality hotel should be one of your first priorities when organizing a trip. With dozens of hotels to select from in every location, making an internet hotel reservation may appear a daunting endeavour. We made the decision to work on the assignment of recommending hotels to users as a result of the significance of these circumstances. The model is trained using this compressed datasets and ensemble stacking techniques. The proposed model demonstrated superior performance compared to earlier benchmark algorithms on the TripAdvisor dataset, particularly in terms of expected accuracy. On average, the model achieved higher accuracy levels, showcasing its effectiveness in predicting ratings and providing recommendations.

The system performs better in sparse samples than past benchmark techniques by combining improvements in prediction coverage and predictive accuracy.

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