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HYBRID RECOMMENDER SYSTEM FOR HOSPITALITY

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Abstract

Recommendation systems have experienced a surge in popularity, with their adoption on the rise in various fields, including e-commerce, films, tourism, news, advertising, stock markets and social networks. This review paper focuses on machine learning approach utilized in hybrid recommendation systems aims to enhance the precision and variety of recommendations by integrating multiple recommendation methods. In addition, the paper introduces the methodology of the TF-IDF, which incorporates n-grams to capture the weight of the term more accurately by taking into account the frequency of the n-word sequence with taking into consideration on evaluating the appropriate weights of different features based on customer preferences and industry standards. Moreover, it incorporates sentiment polarity analysis using deep learning techniques, encryption techniques and matrix factorization for analysis of hotel data. Overall, the research papers cover a wide range of techniques and methods for analyzing and extracting valuable insights from hotel data extracted from TripAdvisor.com on Hospitality Sector.

Keywords—Hybrid Recommender System, Machine Learning Algorithms, Deep Learning Techniques, Multi-criteria analysis.

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Introduction

Recommendation Systems (RS) [1] are required for filtering the massive flow of information circulating on the web and seemingly usable by the user as a direct result of the exponential growth of digital data. These systems are capable of making suggestions that are suitable for user preferences and needs. [1]Recommendation systems have garnered considerable interest in diverse domains such as including e-commerce, movie and music, tourism, news, advertisement, stock markets, and social networks, has gained significant attention. These systems rely on model user preferences, there are two primary approaches: content-based filtering and collaborative filtering. The present survey paper provides an overview of machine learning techniques utilized in recommendation systems, particularly focusing on hybrid recommender systems. The inclusion of contextual information in recommendation systems, which has emerged as a critical strategy to improve recommendation accuracy. It categorizes the various types of contexts utilized in existing literature and examines their influence on the challenges encountered by recommendation systems, and explores effective strategies for leveraging these contexts. Additionally, the paper highlights future research directions, challenges, and opportunities across all surveyed techniques. The results indicate that hybrid recommender systems show considerable potential for enhancing recommendation accuracy. Furthermore, the integration of contextual information in recommendation systems can significantly improve their performance. The paper emphasizes the importance of categorizing contextual information and understanding its impact on recommendation performance. Future research should aim to develop more effective techniques for utilizing contextual information and improving recommendation accuracy.

This survey paper highlights the growing popularity of recommendation systems in various domains and their reliance on diverse techniques to model user preferences. It also underscores the importance of contextual information in improving recommendation accuracy and recommends avenues for future research to advance the state-of-the-art in this field. Recommender systems are typically categorized into the following groups, depending on the methodology employed to generate recommendations:

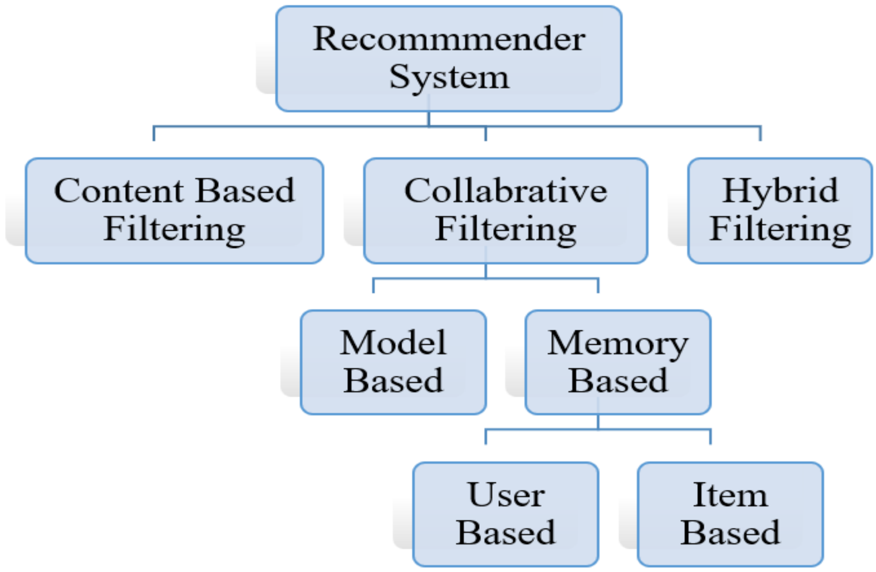

Fig. 1. Types of Recommender System

1.1 Content Based Recommendation System

Content-based recommendation systems have emerged as a popular technique that utilizes attributes of items to provide personalized recommendations to users. By analysing the content of items such as movies, music, or products, these systems can generate recommendations that match the user's interests. Items comparable to those previously selected by the customer will be recommended to them.

1.2 Collaborative-Based Recommendation System

Collaborative-based recommendation systems are one of the popular techniques used for personalized recommendations. These systems rely on user-item interaction data to build a model of user preferences and then recommend items that are similar to those previously rated positively by similar users. Collaborative-based recommendation systems have gained popularity because they do not require explicit domain knowledge and can be applied in a wide range of domains.

1.3 Hybrid-Based Recommendation System

Hybrid recommendation systems have become increasingly popular in recent years, combining the advantages of both content-based and collaborative filtering techniques. These systems utilize multiple sources of data, including user-item interactions and item attributes, to provide personalized recommendations to users. [2].

This survey research attempts to investigate and categorize the many Hybrid Recommendation Methods, together with problems, future directions, and algorithms utilized in them. We will discuss the numerous end-milling hybrid recommender system methods employed in various fields of research in the first section. Also, we focus on the algorithms that were employed, their limitations, and potential future possibilities for creating the best recommender system

I. RELATED WORK

The purpose of this work is to develop a personalized hotel recommendation system that suggests hotel names to travellers based on their preferences. The system leverages reviews and ratings provided by other travellers to enhance the accuracy of its recommendations. In order to tackle the challenge of the cold start problem, a context-aware hybrid approach is adopted in this study. This approach combines collaborative filtering techniques with sentiment analysis to enhance the recommendation process. Specifically, sentiment analysis is conducted using an aspect-based approach, wherein the weights of each aspect are calculated to determine their orientation scores. Moreover, a semi-supervised clustering algorithm is employed to group aspects with similar meanings, and a lexicon-based approach is utilized to identify the sentiment towards hotel aspects within the defined context. By integrating contextual information into the recommendation system, the proposed approach aims to enhance the accuracy of hotel recommendations and provide a more personalized experience for travellers. [1]

This paper utilized the Trip Advisor data-set and extracted various features to create an item x feature matrix. To ensure accuracy, message language correction was employed using an NLP library to correctly identify polarity. The online algorithm was used to generate recommendations based on user preferences for various input criteria, taking into consideration the user profile. The algorithm provided two different recommendations to ensure that the final recommendations were appropriate and satisfactory. [2]

This research paper presents a new approach to collaborative filtering (CF) recommendations, which incorporates sentiment analysis based on opinions to construct a hotel feature matrix using polarity identification. The proposed approach leverages lexical analysis, syntax analysis, and semantic analysis to understand sentiments associated with various hotel features, taking into account guest profiling factors such as solo travellers, families, and couples. This enables the generation of personalized recommendations. To handle heterogeneous data, the system is implemented using the big data Hadoop platform, and fuzzy rules are employed to recommend hotel classes based on guest types. The evaluation metrics, including precision, recall, and F-measure, are calculated and extensively discussed. The results indicate that the proposed approach is both effective and efficient in generating personalized recommendations tailored to potential customers. [3]

This research paper introduces a novel hotel recommender system designed to address the cold start problem. The system utilizes text data extracted from reviews obtained from popular platforms such as TripAdvisor.com and Venere.com. To capture the various contexts within the reviews, the system defines context groups. A weighted algorithm for text mining is proposed to analyse the reviews effectively. The algorithm takes into account factors such as trip intent, background (nationality), and preferences for hotel aspects to emulate a user's preference. The method utilizes unsupervised clustering to generate a hotel-specific vocabulary, semantic analysis to comprehend sentiment towards various hotel attributes, and the characterization of intention and nationality groups. By considering these contextual factors, the system aims to provide more personalized and accurate hotel recommendations, particularly in situations where limited user data is available. [4]

This paper proposes a new method for hotel recommendation that combines dimensionality reduction and prediction techniques with multi-criteria collaborative filtering (CF) recommender system using Gaussian mixture models with Expectation Maximization (EM) algorithm and Adaptive Neuro Fuzzy Inference System (ANFIS). The Principal Component Analysis (PCA) is used to reduce dimensionality and address multi-collinearity in the multi-criteria CF dataset. [5]

This paper proposes a hybrid recommendation model which consists of an embedding generation model and a deep prediction and ranking model based on deep recurrent neural networks. The results of the study show significant improvements in performance compared to existing collaborative filtering models, across different geographies and hotel supply densities. The success of the model at OYO highlights the potential of deep learning-based recommender systems in various industries, such as travel and hospitality. [6]

The emergence of social media has transformed online visual content, such as photos and videos, into a popular medium for hotel managers and travellers to share information. conveyed through online photos posted by travellers. To achieve this, the research paper introduces an innovative approach to analysing online photo content utilizing deep learning theory Given this, the goal of this study is to develop a thorough understanding of the perceptions and a computer vision framework. This methodology enables a thorough analysis of large-scale photo datasets. The effectiveness of this approach is demonstrated and evaluated through a case study involving the examination of over 53,000 photos sourced from the prominent hotel review platform, TripAdvisor. The analysis reveals intriguing disparities in the content of photos posted by hotel managers and travellers, including variations in photo content between hotels with low and high ratings. These findings carry valuable implications for hotel marketing strategies that rely on visual assets. [7]

In this study, the existing research on Collaborative Filtering (CF) and Context-Aware Recommendation Systems (CARS) with time constraints is reviewed. Based on this literature review, the study introduces the CAPH system, which utilizes User-based Collaborative Filtering (UCF) and Item-based Collaborative Filtering (ICF) techniques for rating prediction. The proposed method incorporates review text as a representation of rating data preferences, resulting in recommendations derived from a denser matrix compared to the original sparse matrix. A comparative analysis of the results indicates that leveraging users' reviews can effectively address the sparsity issues commonly encountered in contextual recommendation systems. [8]

The present research paper introduces a framework aimed at ranking hotels by analyzing customer reviews and nearby amenities. The framework incorporates both user review scores and the presence of surrounding facilities to establish an overall ranking for each hotel. To evaluate the framework's efficacy and applicability, datasets from well-known online hotel booking platforms, including TripAdvisor and Booking, are utilized. The approach involves the extraction and storage of keywords from reviews, assigning weights to each keyword, and calculating a numerical score for each keyword. The proposed system aggregates scores from reviews and the surrounding environment, considering various categories of facilities. Experimental results verify the effectiveness of the recommendation framework in producing reliable rankings for hotels. [17]

This research paper introduces a hotel recommender system that addresses the challenge of recommending items that are frequently purchased, where users may switch to new items, and where obtaining rating information is difficult. The proposed system utilizes preference transition to identify user preferences and generate personalized recommendations based on these transitions. The preference transition is determined through a three-step process: establishing hotel relations using sales records, filtering these relations using the Simpson coefficient, and identifying preference transitions using the Mann-Whitney U test. The recommendation process involves selecting potential recommendations and ranking them based on their in-degree and out-degree within the preference transition network. The prototype system validates the effectiveness of the preference transition network and the recommendation process, providing novel insights. Although the system's recommendations may be subjective and open to interpretation, it offers users a clear understanding of the recommendation process and visual representation of preference transitions between hotels. [18]

This research paper introduces an innovative fusion-based multi-criteria collaborative filtering model designed specifically for hotel recommendations. The primary objective of this model is to offer more efficient and personalized recommendations by improving prediction accuracy and overcoming the limitations of rating information in the hotel domain. The proposed model utilizes multi-criteria ratings to capture the intricate preferences of travelers and incorporates implicit similarity between users and items, propagation of users' similarity, as well as user/item reputation concepts. Through extensive experiments, the results demonstrate that the proposed model surpasses other benchmark recommendation algorithms in terms of recommendation accuracy and coverage. [19]

II. Our Proposed Model

Hotel recommendation systems play a significant role in assisting users in finding suitable accommodations. Various approaches, such as collaborative filtering, content-based filtering, and association rule methods, have been proposed for hotel recommendation. These methods leverage hotel features, user ratings, online reviews, and social network comments associated with hotels as data sources. Despite their effectiveness, these methods often suffer from slow processing speeds due to the complexity of the utilized data. Hotel recommendation systems are essential for catering to the diverse preferences and needs of users who travel for various purposes such as leisure or work. Existing recommendation systems often overlook the importance of recommending hotels that align with the specific requirements and travel occasions of individual users.

In this research paper, we propose a novel hotel recommendation system, specifically designed to address the limitations of existing approaches. The proposed system combines the advantages of Hybrid Filtering to recommend hotels we propose an enhanced hotel recommendation system that takes into account the unique preferences of each user and recommends hotels accordingly. By considering factors such as the purpose of travel, the system aims to ensure that users are recommended hotels that best suit their specific needs and travel occasions. Furthermore, we incorporate textual analysis of user reviews to capture nuanced preferences and mitigate the sparsity issue commonly encountered in contextual recommendation systems.

The proposed system utilizes a combination of collaborative filtering, content-based filtering, and contextual information to personalize recommendations. User profiles are enriched with data related to travel purpose, past preferences, and contextual factors such as location, amenities, and hotel facilities. This comprehensive approach enables the system to understand the varying preferences and requirements of different users. The aforementioned steps have been comprehensively elaborated upon in this section:-

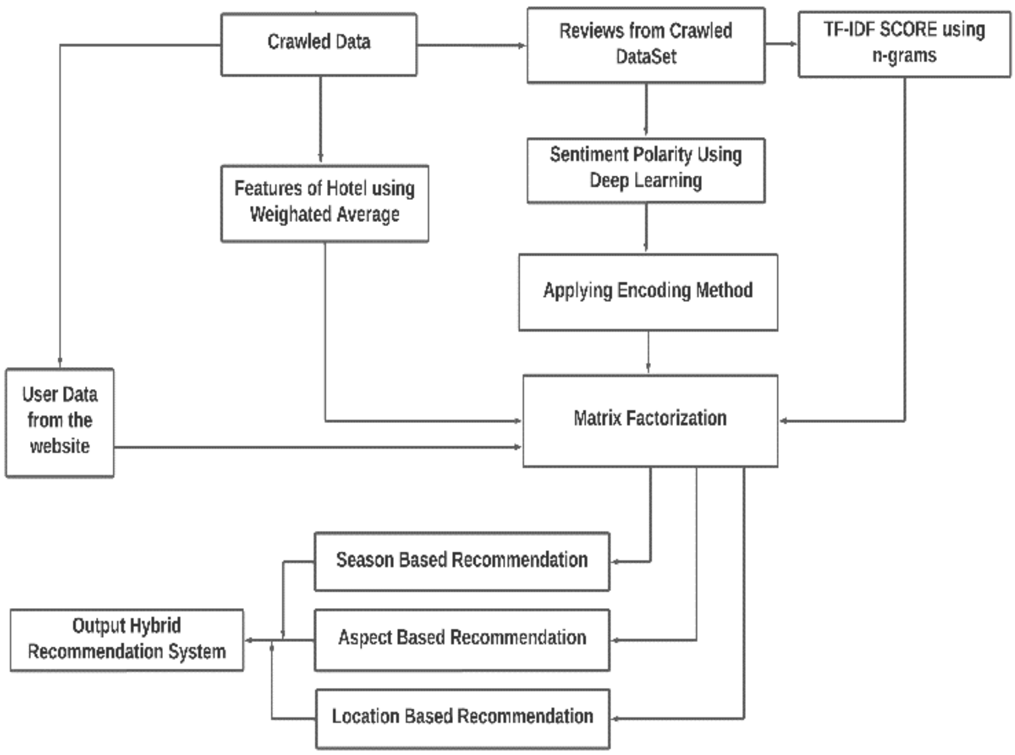

Fig. 2. Proposed Method of Hotel Recommendation

3.1 Crawling Data from TripAdvisor.com

The data extraction of the web, TripAdvisor.com, isa process that automatically extracts information from the web for various purposes. However, it is important to approach the scrapping of websites responsibly and ethically while respecting the terms of service and legal restrictions imposed by website owners.

3.2 TF-IDF SCORE using n-grams

TF-IDF (Term Frequency-Inverse Document Frequency) is a widely used technique in natural language processing and information retrieval for assessing the importance of terms in a document collection. Traditionally, TF-IDF calculates term weights based on single words. However, incorporating n-grams, which are contiguous sequences of n words, can enhance the representation of multi-word expressions and capture additional context.TF-IDF is a weight metric which determines the importance of word for that document. [16]

$$TF = \frac{\text{Number of times term t appears in a document d}}{\text{Total number terms in a document d}}$$

$$\text{IDF} = \log_e \frac{\text{Total number of documents}}{\text{Total number of documents with term t}}$$

The final weight for a term t in a document d is calculated as:

$$\text{TF - IDF (t,d)} = \text{T F(t,d)} \times \text{IDF(t)}$$

This research paper presents an extension of the TF-IDF scoring approach using n-grams. By considering n-gram frequencies within documents and across the entire corpus, the proposed method assigns more accurate and informative weights to terms. The utilization of n-grams provides a richer representation of language patterns, capturing both local and global context, thereby enhancing the overall quality of the TF-IDF scores. The TF-IDF explores different approaches to incorporating n-grams into the scoring process. It also provides insights into the impact of varying n-gram sizes on the performance of the TF-IDF approach. This paper presents a content-based filtering approach for hotel recommendation systems. The dataset used in this study comprises client evaluations from the Kaggle platform. To extract relevant features from the textual data, advanced natural language processing techniques such as word embedding, word2vec, and TF-IDF are employed. These methods enable effective feature extraction from client evaluations. The resulting feature vectors are utilized to compute similarities between hotels and provide personalized recommendations based on user preferences, particularly focusing on the user's past knowledge of hotel locations.

The paper [9] presents a content-based filtering approach for hotel recommendation systems. The dataset used inthis study comprises client evaluations from the Kaggle platform. To extract relevant features from the textual data, advanced natural language processing techniques such as word embedding, word2vec, and TF-IDF are employed. The resulting feature vectors are utilized to compute similarities between hotels and provide personalized recommendations based on user preferences, particularly focusing on the user's past knowledge of hotel locations.

3.3 Features of Hotel using Weighted Average

This paper introduce a novel approach for evaluating hotel features using a weighted average methodology. By assigning appropriate weights to different features, a comprehensive and reliable assessment of hotels can be obtained, aiding travelers in making informed decisions and assisting hotel management in identifying areas for improvement.

In the paper [4] assigns different weights to features based on their relevance to specific context groups. The selection of feature weights is based on user-declared context and preferences, such as intent and nationality. For instance, Similar weight assignments are made for features related to important aspects. This approach allows for customized weighting of features, such as "air conditioning," based on their importance to different user contexts, nationalities, and preferences for specific aspects. The final weight assigned to each feature is determined by combining these context-specific weights, resulting in a comprehensive feature score.

This paper discusses the importance of considering varying degrees of significance for different features the concept of feature weighting based on customer preferences like Solo, Business, Travel , Leisure and industry standards such as amenities, cleanliness, customer service, location, pricing, and more. The results demonstrate the ability of the weighted average methodology to provide a comprehensive and accurate assessment of hotel features. Comparative analyses with existing approaches further highlight the advantages and insights offered by the proposed methodology.

3.4 Sentiment Polarity Using Deep Learning

Sentiment analysis, also known as opinion mining, plays a pivotal role in understanding people's sentiments and attitudes expressed in text. This paper presents an innovative approach for sentiment polarity analysis using deep learning techniques. By leveraging the power of deep neural networks, the proposed method aims to accurately classify text documents into positive, negative, or neutral sentiment categories, enabling businesses to gain valuable insights from customer feedback, social media posts, and online reviews. Deep learning architectures can be widely divided into three basic groups: generative, discriminatory and hybrid architectures [13]. These classifications are determined by how the architecture is implemented.

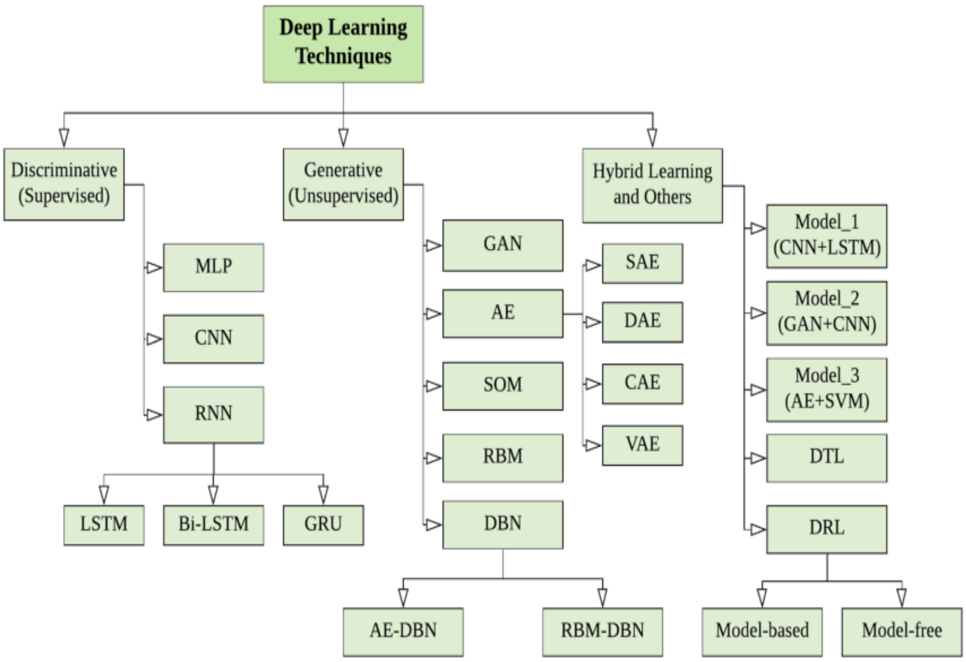

Fig. 2. A taxonomy of DL techniques, broadly divided into three major categories (i) discriminative learning,(ii) generative learning, and (ii) hybrid learning and relevant others
Proposed Method of Hotel Recommendation

The deep neural networks, specifically recurrent neural networks (RNNs) and convolutional neural networks (CNNs), for sentiment polarity analysis. The paper delves into the architectural design of these models, emphasizing the use of sequential information capture by RNNs and the ability of CNNs to capture local features intext. It also explores different variants of deep learning models, such as long short-term memory (LSTM) and attention mechanisms, to improve the performance of sentiment analysis.

In paper [10] approach extends the conventional latent factor model by integrating the neural network. They have described how neural networks can effectively capture latent factors by mapping text information to factors. In addition, we use RNN to convert text data into auxiliary factor characteristics and promote a more comprehensive representation of elements which can be further used in our methodology to enhance the recommendation. Also paper Deep learning algorithms such as Auto Encoders, Boltzmann Machines and Generative Adversarial Networks have been studied, followed by discriminatory approaches such as RNN, CNN, and MLP. Some hybrid methods have also been studied and it has been found that some of them partially address the problems of the Hybrid model.

In paper [11], the authors employed two parallel CNN architectures to capture latent features of users and items based on textual content. This approach effectively addresses the cold start problem and enhances model interpretability by utilizing user reviews to understand the semantic meaning of words. Once the features are extracted, they are fed into the convolutional layer, which convolves them with multiple kernels. Subsequently, the pooled layer and the fully connected layer further process these features. The output of the two parallel networks is concatenated and used as input for the prediction layer. In this layer, user ratings on items are estimated using factorization machine.

These hybrid methods utilize the strengths of different deep learning techniques to enhance the performance of recommender systems in various aspects such as semantics, sequential information, feature representation, and addressing data sparsity or cold start challenges.

In recent years, deep learning has emerged as a powerful technique, finding successful applications across a wide range of fields. These fields encompass natural language processing, sentiment analysis, cybersecurity, business, virtual assistants, visual recognition, healthcare, robotics, and many others.

3.5 Applying Encoding Method

This paper explores the application of encoding methods for effectively processing and analysing hotel data. Specifically, it investigates the use of encoding techniques to transform categorical variables into numerical representations, enabling the utilization of machine learning algorithms for data analysis and prediction tasks. Several encoding techniques, including label encoding, ordinal encoding, frequency encoding, and target encoding, are presented and compared in terms of their advantages, limitations, and applicability to hotel data.

3.6 Matrix Factorization

Matrix factorization is a powerful technique widely used in recommendation systems and data analysis to uncover latent factors and patterns within high-dimensional data. This paper the application of matrix factorization for hotel data analysis, focusing on collaborative filtering approaches to provide personalized recommendations and uncover hidden relationships within hotel-related datasets.

The paper uses handling sparse and high-dimensional hotel datasets. The proposed approach utilizes collaborative filtering, a popular matrix factorization technique, to decompose the hotel data matrix into latent feature matrices.

The present research paper conducts a comparative analysis of various matrix factorization techniques discussed in previous studies [15]. The table provided in the paper highlights the initial parameters considered by each technique for prediction purposes. These parameters encompass explicit ratings, implicit ratings, temporal information, as well as implicit and explicit social trust information. To overcome the challenge of data sparsity in recommendation systems, one common approach is to incorporate additional auxiliary information. Among these techniques, SVD-based methods have gained prominence due to their effective utilization of auxiliary information. Another strategy to address data sparsity issues is through missing data imputations.

Notably, the table in the paper [15] reveals that only the SVD technique incorporates data imputations, while the other techniques rely solely on observed rating information. These techniques acknowledge that data imputation can introduce distortions, potentially compromising the accuracy of the model. Additionally, the paper [15] provides a comparison of the prediction parameters used by these techniques, including explicit ratings, implicit ratings, temporal information, and implicit/explicit social trust information.

3.7 Output Hybrid Recommendation System

The proposed system aims to provide accurate and diverse recommendations by leveraging the strengths of different recommendation algorithms and incorporating various aspects, such as content-based, collaborative filtering, and contextual information. It emphasizes the importance of considering multiple aspects, such as item content, user preferences, and contextual factors, to provide more accurate and comprehensive recommendations. The proposed hybrid recommendation system utilizes a combination of collaborative filtering, content-based filtering, and contextual information to generate recommendations. The paper describes the architectural design of the system, including the integration of different recommendation algorithms, feature extraction techniques, and contextual data processing.

3.1.1 Season Based Recommendation

By incorporating the temporal aspect of travel, the system assists users in selecting accommodations that align with their preferences for specific seasons. The findings can benefit both travellers, who can make informed decisions based on personalized recommendations, and hotel providers, who can enhance customer satisfaction and optimize hotel occupancy rates based on seasonal demand.

3.1.2 Aspect Based Recommendation

The aspect-based recommendation covers the process of aspect extraction from user reviews, aspect-based representation of hotels, with relevant recommendations by considering specific aspects that influence user preferences and the recommendation algorithm that matches user preferences with hotel aspects.

3.1.3 Location Based Recommendation

The methodology covers the integration of location data, user preferences, and geographical information to generate personalized recommendations. The algorithm incorporates proximity calculations and relevance scoring to ensure accurate and context-aware recommendations.

III. CONCLUSION & FUTURE WORK

In conclusion, this research paper explores the field of recommendation systems, focusing on the growing popularity and significance of hybrid recommender systems. The paper emphasizes the importance of incorporating contextual information to improve recommendation accuracy and addresses the challenges faced by recommendation systems in various domains. It categorizes different types of recommender systems, including content-based, collaborative-based, and hybrid-based approaches, and discusses their strengths and limitations. The proposed model in this paper is a novel hotel recommendation system that aims to overcome the limitations of existing approaches. It combines collaborative filtering, content-based filtering, and contextual information to provide personalized recommendations to users based on their specific preferences and travel occasions. The system leverages data from sources such as user reviews, ratings, and hotel features, and employs techniques like sentiment analysis, TF-IDF scoring, feature weighting, deep learning for sentiment polarity analysis, encoding methods, and matrix factorization. By considering factors such as the purpose of travel, user profiles, and contextual information like location and amenities, the proposed system strives to ensure that users receive recommendations that align with their unique needs and preferences. The inclusion of contextual information and the hybrid approach significantly enhance recommendation accuracy and address the sparsity issue commonly encountered in contextual recommendation systems.

The paper also discusses the methodologies employed in the proposed model, including data crawling from TripAdvisor.com, TF-IDF scoring using n-grams, weighted average feature evaluation, sentiment polarity analysis using deep learning, encoding methods, and matrix factorization. These techniques contribute to the comprehensive and accurate analysis of hotel data and the generation of personalized recommendations. Overall, this research paper contributes to the advancement of recommendation systems by proposing a novel hybrid model specifically tailored for hotel recommendations. It sheds light on the importance of incorporating contextual information and employing a combination of techniques to enhance recommendation accuracy. The proposed model holds promise for providing users with more relevant and personalized recommendations in the domain of hotel accommodations. Future research directions, challenges, and opportunities in this field are also highlighted, encouraging further exploration and development of effective techniques for utilizing contextual information and improving recommendation accuracy.

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