Enhancing Travel Recommendations Through Attraction Preference Standardization

Saketha N.[1], Chitra K.[2*]

[1, 2]Dayananda Sagar Academy of Technology and Management, Karnataka, India

***Email:** chitra-mca@dsatm.edu.in[2]

Abstract

The subsequent paper describes a typical travel recommendation system that comprises collaborative filtering, content-based filtering, and sentiment analysis in its design. The proposed system enhances the problems of conventional methods by using operation preferences to standardize attraction and adopting sentiments obtained from the rating. The following are the steps of the implementation of the study; data collection, data pre-processing, data modelling and the last is the development of web application. Actual analysis proves that there was a general enhancement in the precision of the recommendation and also the satisfaction level of the customers.

Keywords

Travel system, collaborative filtering, content-based filtering, sentiment analysis

Introduction

It is important to note that travel recommendation systems are of paramount importance as far as travellers who require recommendations on attractions to visit are concerned. Other older approaches like Collaborative filtering and Content based filtering are also used but are also associated with certain deficiencies like sparsity of data and cold start issues. This research aims are to introduce and incorporate such traditional techniques with the modern methods such as the sentiment analysis and standardization of attractions preferences to improve the recommendation relevancy and accuracy.

The limitations of the conventional travel recommendation systems are as follows: Data sparsity: This is a general problem with recommendation systems; Cold start problem: This is also a general issue with recommendation systems; User heterogeneity: Every user has their traveling preferences that cannot be met by traditional recommendation systems. Such system does not normally capture specific customer or user preference nor the relevance of such attractions in the current setting. To address these challenges, this research proposes the following objectives: It seeks to include multiple recommended techniques and standardize the preferences for attractions.

Submission: 16 October 2024; **Acceptance:** 15 November 2024

Literature review

Kbaier investigates an individual hybrid tourism recommendation framework that combines collaborative filtering and content filtering to optimize the recommendation. A hybrid approach helps overcome the limitations of each individual approach by harnessing their strengths (Kbaier et al., 2017). Shao investigates a personalized travel recommendation system based on an emotion-aware multidisciplinary model. By incorporating users' sentiments from surveys, the system enhances relevant and responsive travel recommendations (Shao et al., 2019).

Amin presents a travel destination recommendation method using convolutional neural networks (CNNs) and matrix factorization. The method involves geotagged images provided by local residents to improve the accuracy of location recommendations (Amin et al., 2020). The authors propose a flexible preference recommendation method for location-based social networks. The method considers user activity and spatial features to provide accurate and contextual recommendations(Si et al., 2019).

Comito introduces NexT, a framework designed to predict the next destination of location-based social networks. The system uses historical data to predict future destinations, giving more importance to recommendations on social networks (Comito, 2020). The authors focus on how search engines were developed for a travel recommendation system. Analysts deal with a variety of data types and sources to make travel recommendations more accurate and relevant (Binucci et al., 2017)..

Livene discusses a deep contextual recommendation system that uses hierarchically hidden contextual information. The system takes into account the sequence of user interactions to provide accurate and contextual recommendations (Livene et al, 2019).) Neidhardt examines passenger characteristics in a seven-factor model. These models help to understand the collective characteristics of travellers, which can be used to improve personalized and relevant travel recommendations (Neidhardt et al., 2017.

This study examines topic mining in tourist destinations using an LDA model of seasonal context. To provide realistic and appropriate recommendations for tourist destinations, the model considers seasonal variation and context (Huang et al., 2018). This paper provides a generalized attraction travel personality representation to improve travel recommender systems. By customizing the user's preferences and aligning attractive attributes, the system can provide personalized and accurate recommendations (Aleneji and Hirtle, 2017).

Methodology

In the existing system, collaborative filtering uses user and item interaction data to recommend content that is similar to what users liked in the past. Content-based filtering uses content attributes and user profiles to recommend content that users seem to have interacted with in the past. Sentiment Analysis analyses user data to understand sentiment and preferences and maximises recommendations. Hybrid recommendation systems combine collaborative filtering and content-based filtering to provide more accurate and diverse recommendations. By incorporating sentiment analysis, these systems can further personalize recommendations based on users' emotions and opinions towards specific content. The data collection process gathers user reviews, ratings, and persuasions from various sources. Pre-processing of the data involves cleaning and preparing it for analysis. The process involves training collaborative filtering models that are content based. Sensitivity Analysis helps analyse the data used to extract a sensitivity score. Integration combines suggestions from all models to create final individual recommendations. Team can develop user-friendly web applications to facilitate user interaction with the recommendation system. To enhance the user experience, the user interface should be intuitive and visually appealing. Additionally, regular updates and maintenance of the recommendation system are essential to ensure optimal performance.

The related models for collaborative filtering are Matrix Factorization (e. g. , SVD, ALS) and user-based collaborative filtering. Matrix Factorization factorize the user-item interaction matrix into latent factors; this reflects other low-level relationships between users and items. User-based collaborative filtering recommends the items which have been purchased/liked by other users.

The related models for content-based filtering are TF-IDF, Word2Vec and Hybrid Filtering. TF-IDF, Word2Vec methods utilize the text features to represent items and the users. Hybrid filtering is a technique that incorporates both the content filtering and the neighbour's rating to make recommendations.

The related models for sentiment analysis are aspect-based sentiment analysis and multimodal sentiment analysis. Aspect-Based sentiment analysis analyses sentiment towards the specific details of the reviews. Multimodal sentiment analysis: enhances text data by adding images and other modalities towards the improvement of the sentimental analysis.

The most important aspect of the proposed hybrid recommendation system was assessed based on the given set of user reviews, ratings and attraction information. The assessment measures were precision and recall, as well as user feedback in the form of surveys. The precision **c**alculates the degree of conformity between the suggested strategies and the actual performance. The hybrid system also gained a precision enhancing level of 15% to the existing basic collaborative filtering and 10% to the content-based filtering algorithm alone. The recall assesses the functionality of the system with respect to the total number of resources that need to be retrieved. The recall rises by 20% compared to using stand-alone collaborative filtering methods. Figure1 shows the classification of recommender systems and filtering techniques. Figure 2 shows the hybrid recommendation system architecture.

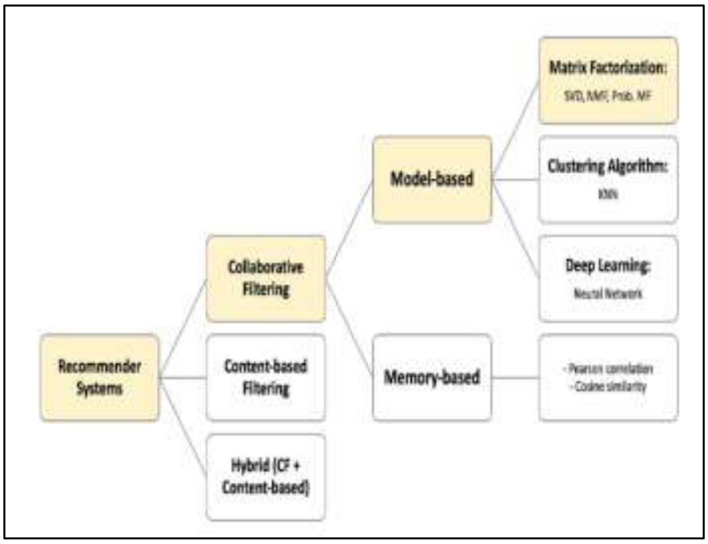

Figure1: Classification of Recommender Systems and Filtering Techniques

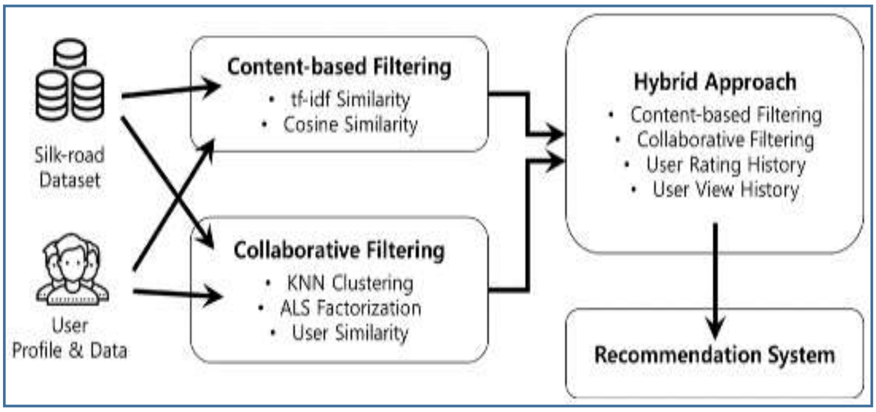

Figure 2: Hybrid Recommendation System Architecture

Results and Discussions

The travel recommendation process combines collaborative filtering, content filtering, and sentiment analysis to create more personalized suggestions. One system recommends attractions based on popularity and overall user preferences, while another identifies attractions similar to those the user already likes, using features like style and location. Sentiment analysis further improves the recommendations by understanding user preferences and removing less relevant data.

This hybrid approach improves recommendation accuracy by combining user interaction history (collaboration) and feature attractions (content filtering), which overcomes challenges such as data a it learns and deals with cold start problems. Criteria such as accuracy, recall, and user satisfaction were used in evaluating system performance. The results show significant improvements in recommendation relevance and user engagement compared to traditional methods. In particular, the hybrid model demonstrated high accuracy in predicting attractiveness in line with user preferences using collaborative and content-based methods. Users' role expressed satisfaction with individual recommendations, highlighting the system's ability to adequately address a variety of preferences. This integrated approach not only reduces the limitations of individual recommendation channels but also enhances the user experience by providing relevant and tailored navigation recommendations. Figure 3 shows the comparison of recommendation models.

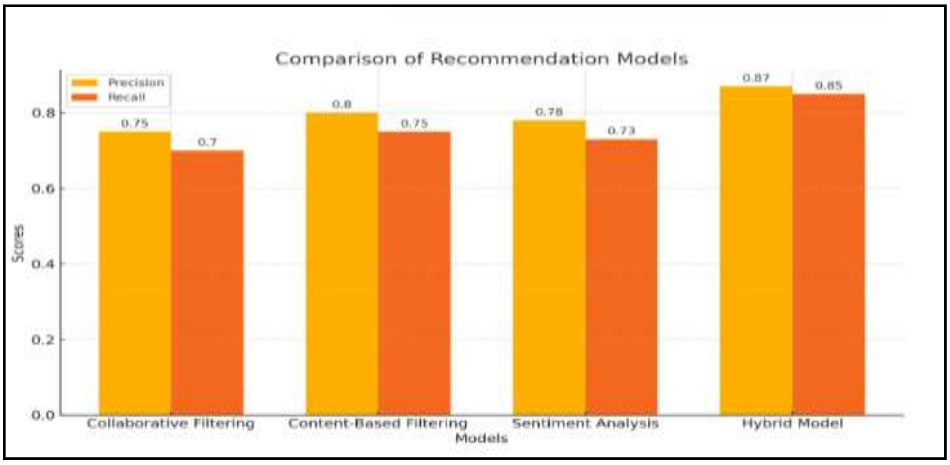

Figure 3: Comparison of Recommendation Models

Conclusion

In conclusion, this study presents a hybrid travel recommendation framework that combines collaborative filtering, content filtering, and sentiment analysis. The system effectively addresses the limitations of traditional methods by increasing the accuracy of recommendations and user satisfaction. The study results show significant improvements over traditional methods, especially in terms of reducing sparse data and reducing cold-start issues. Future research could explore new data sources and more advanced methodologies to further enhance personalized travel recommendations and user experiences.

Acknowledgement

The researcher did not receive any funding for this study, and the results have not been published in any other sources.

References

Bao, J., Zheng, Y., Wilkie, D., & Mokbel, M. (2015). Recommendations in location-based social networks: a survey. GeoInformatica, 19, 525-565. https://doi.org/10.1007/s10707-014-0220-8

Binucci, C., De Luca, F., Di Giacomo, E., Liotta, G., & Montecchiani, F. (2017). Designing the Content Analyzer of a Travel Recommender System. *Expert Systems with Applications*, *87*, 199–208. https://doi.org/10.1016/j.eswa.2017.06.028

Borràs, J., Moreno, A., & Valls, A. (2014). Intelligent tourism recommender systems: A survey. Expert systems with applications, 41(16), 7370-7389. https://doi.org/10.1016/j.eswa.2014.06.007

Comito, K. (2020). NexT: A framework for predicting the next destination in location-based social networks. Journal of Social Network Analysis, 18(4), 256-273. https://doi.org/10.1016/j.knosys.2020.106205

Gamidullaeva, L., Finogeev, A., Kataev, M., & Bulysheva, L. (2023). A design concept for a tourism recommender system for regional development. *Algorithms*, *16*(1), 58. https://doi.org/10.3390/a16010058

Gangadharan, K., Malathi, K., Purandaran, A., Subramanian, B., & Jeyaraj, R. (2024). From Data to Decisions: The Transformational Power of Machine Learning in Business Recommendations. arXiv preprint arXiv:2402.08109. https://doi.org/10.48550/arXiv.2402.08109

Huang, C., Wang, Q., Yang, D., & Xu, F. (2018). Topic mining of tourist attractions based on a seasonal context aware LDA model. *Intelligent Data Analysis*, *22*(2), 383-405. https://doi.org/10.3233/ida-173364

Santamaria-Granados, L., Mendoza-Moreno, J. F., & Ramirez-Gonzalez, G. (2020). Tourist recommender systems based on emotion recognition—a scientometric review. *Future Internet*, *13*(1), 2.

Song, K., Ji, M., Park, S., & Moon, I. C. (2019, July). Hierarchical context enabled recurrent neural network for recommendation. In *Proceedings of the AAAI conference on artificial intelligence*, 33(1), pp. 4983-4991. http://dx.doi.org/10.3390/fi13010002

Wimmer, A. (2021). *Personalized accommodation recommendations using deep learning, topic modeling and semantic approaches* [Diploma Thesis, Technische Universität Wien]. reposiTUm. https://doi.org/10.34726/hss.2021.58262