ISSN : 2455-135X

TripSmart: An ML-Powered Group Travel Decision Support and Recommendation System

Sheela Verma[1], Aman Dhruwanshi[2], Ketan Miree[3], Omprakash Bhagat[4], Arshmit Singh Bhatia[5]

[1]Department of Computer Science, Bhilai Institute of Technology, Raipur, Chhattisgarh, India
[2]Department of Computer Science, Bhilai Institute of Technology, Raipur, Chhattisgarh, India
[3]Department of Computer Science, Bhilai Institute of Technology, Raipur, Chhattisgarh, India
[4]Department of Computer Science, Bhilai Institute of Technology, Raipur, Chhattisgarh, India
[5]Department of Computer Science, Bhilai Institute of Technology, Raipur, Chhattisgarh, India

[1]sheelav1912@gmail.com
[2]amandhruwanshi013@gmail.com
3ketanmiree@gmail.com
[4]ombhagat89@gmail.com
[5]arshmitbhatia@gmail.com

Received: Revised: Accepted: Published:

Abstract *- This paper proposes TripSmart, a hybrid group travel recommendation system that integrates Content-Based Filtering (CBF) and Neural Collaborative Filtering (NCF) to enhance recommendation accuracy and personalization. The CBF component utilizes TF-IDF vectorization and cosine similarity to model semantic relationships between user preferences and destination attributes, while the NCF component leverages deep neural architectures to capture latent user-item interaction patterns. The proposed hybrid framework combines both approaches using a weighted scoring mechanism to generate optimized recommendations. The system incorporates contextual parameters such as budget constraints, geographical location, and group preferences to improve decision relevance. Experimental evaluation demonstrates superior performance of the hybrid model, achieving a precision of 0.886, recall of 0.863, F1-score of 0.874, and accuracy of 0.819. The results indicate significant improvements in recommendation diversity, cold-start handling, and overall system robustness compared to standalone models.*

Keywords *- machine learning, neural collaborative filtering, recommendation systems, travel recommendation systems, hybrid models*

1. Introduction

The exponential growth of online travel platforms and digital tourism ecosystems has resulted in an overwhelming volume of destination-related data, leading to increased complexity in user decision-making processes. Traditional recommender systems predominantly focus on individual user preferences and fail to address the complexities associated with group-based decision scenarios.

To overcome these limitations, this research introduces a hybrid recommendation framework that integrates Content-Based Filtering with Neural Collaborative Filtering. The proposed system aims to model both explicit user preferences and implicit behavioral patterns, thereby improving recommendation accuracy, scalability, and adaptability in group travel scenarios.

2. Literature Review

Recent advancements in recommendation systems have demonstrated the effectiveness of various approaches such as collaborative filtering, content-based filtering, and hybrid models. Neural Collaborative Filtering has shown significant improvements in capturing complex user-item interactions through deep learning techniques. Additionally, context-aware recommendation systems incorporate factors such as location and weather to enhance relevance, while explainable AI approaches improve transparency and user trust. Modern systems using large language models and retrieval-augmented generation further enhance personalization capabilities. Despite these advancements, several limitations remain, including poor scalability, lack of real-time data integration, insufficient evaluation metrics, and weak handling of user constraints. These challenges highlight the need for a hybrid approach that combines multiple techniques to achieve better accuracy, diversity, and personalization, which

ISSN : 2455-135X

forms the foundation of the TripSmart system.

3. Dataset

The TripSmart system utilizes multiple data sources to ensure accurate and relevant recommendations. The primary dataset is collected from Kaggle and is enhanced with additional features such as category tags, user preferences, and processed attributes to support model training. User input data, including preferences such as interests, budget, location, and group type, is incorporated to personalize recommendations. Additionally, user-item interaction data consisting of user IDs, destination IDs, and ratings is used to train the Neural Collaborative Filtering model. External data sources such as weather APIs are also integrated to provide real-time contextual information. The dataset undergoes preprocessing steps including data cleaning, text normalization, TF-IDF transformation, and proper structuring to ensure efficient processing and improved model performance.

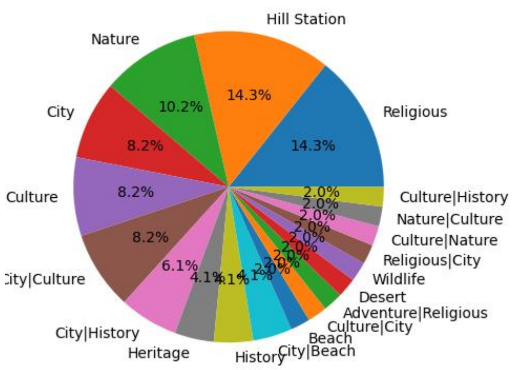

Fig 1 Data Distribution

4. Materials and Methods

4.1 System Architecture

The proposed TripSmart framework adopts a hybrid recommendation architecture that integrates feature-based and interaction-based learning mechanisms. The system processes heterogeneous data sources, including user preferences, destination metadata, and historical interaction records, to generate personalized recommendations.

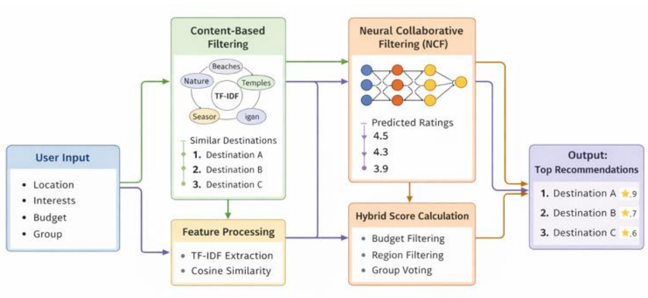

Fig 2 Methodology of TripSmart

4.2 Content-Based Filtering Module

The CBF module employs TF-IDF (Term Frequency–Inverse Document Frequency) to transform textual destination features into high-dimensional vector representations. Cosine similarity is then computed between user preference vectors and destination vectors to quantify semantic similarity.

Mathematically:

$$Similarity(\boldsymbol{A}, \boldsymbol{B}) = \frac{\boldsymbol{A} \cdot \boldsymbol{B}}{\| \boldsymbol{A} \| \| \boldsymbol{B} \|}$$

This approach enables the system to recommend destinations that closely match user-defined interests.

4.3 Neural Collaborative Filtering Module

The NCF component models user-item interactions using deep neural networks. User IDs and item IDs are mapped into dense embedding vectors, which are concatenated and passed through a Multi-Layer Perceptron (MLP). The network learns non-linear interaction patterns and predicts preference scores.

The architecture consists of:

- *Embedding layer*
- *Hidden dense layers*
- *Output layer (sigmoid activation)*

4.4 Hybrid Recommendation Strategy

The final recommendation score is computed using a weighted aggregation of CBF and NCF outputs:

$$\boldsymbol{Score} = \boldsymbol{\alpha} \cdot \boldsymbol{Score_{CBF}} + (\mathbf{1} - \boldsymbol{\alpha}) \cdot \boldsymbol{Score_{NCF}}$$

where $\boldsymbol{\alpha}$ controls the contribution of each component

4.5 *Data Processing and Feature Engineering*

The dataset is preprocessed using:

- Text normalization
- Stopword removal
- TF-IDF vectorization
- Feature scaling

User-item interaction matrices are constructed to train the NCF model, while additional contextual features such as budget constraints and geographical filters are incorporated during post-processing.

4.6. Implementation Steps

The implementation of the proposed TripSmart system follows a structured pipeline to ensure efficient processing and accurate recommendation generation.

In the next stage, the Content-Based Filtering module is applied, where destination features are transformed using TF-IDF vectorization and cosine similarity is computed to identify relevant destinations based on user interests. Subsequently, the Neural Collaborative Filtering model processes historical user-item interaction data by learning latent representations through embedding layers and a Multi-Layer Perceptron to predict preference scores.

The outputs of both modules are then combined using a weighted hybrid scoring mechanism. Additional filtering criteria such as budget constraints, geographical preferences, and group-specific requirements are applied to refine the results. Finally, the system ranks the candidate destinations and presents the top-N personalized recommendations to the user.

Results and Discussion

ISSN : 2455-135X

The performance of the proposed hybrid model is evaluated using Precision, Recall, F1-score, and Accuracy. The model achieves a precision of 0.886, recall of 0.863, F1-score of 0.874, and accuracy of 0.819, showing improved recommendation quality compared to individual models.

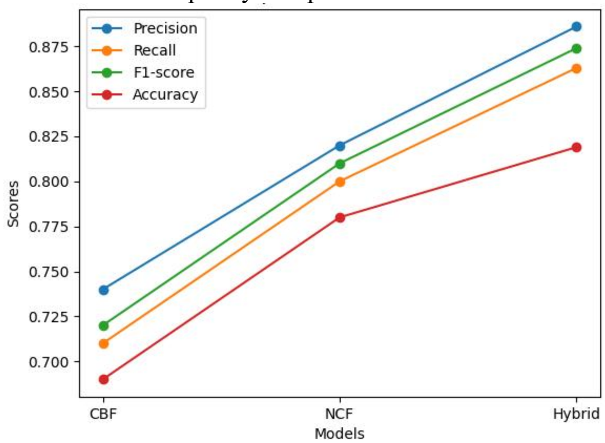

Fig 3 Performance Comparison of Recommendation Models

The improved performance is due to the combination of content-based and collaborative filtering techniques, which enhances personalization, handles cold-start issues, and increases recommendation diversity.

5. Conclusion

This paper presents TripSmart, a hybrid travel recommendation system that integrates Content-Based Filtering and Neural Collaborative Filtering to generate personalized group travel recommendations. The proposed approach effectively improves recommendation accuracy, relevance, and diversity by combining semantic analysis with deep learning-based user-item interaction modeling. The experimental results demonstrate that the hybrid model outperforms individual approaches, achieving higher precision, recall, F1-score, and accuracy. The system also addresses key challenges such as cold-start problems and limited personalization, making it suitable for real-world travel planning applications.

Future work can focus on integrating advanced techniques such as Graph Neural Networks and real-time data processing to further enhance recommendation quality. Additionally, incorporating user feedback mechanisms, explainable AI, and integration with booking platforms can improve system scalability, transparency, and practical usability.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

Funding Statement

This research received no external funding.

Acknowledgments

The authors would like to express their sincere gratitude to Bhilai Institute of Technology, Raipur, for providing the necessary infrastructure, resources, and academic support to carry out this research work.

References

[1] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T. S. Chua, "Neural Collaborative Filtering," in Proc. World Wide Web Conf. (WWW), pp. 173–182, 2025.
[2] L. Wu, X. He, X. Wang, K. Zhang, and M. Wang, "A Survey on Neural Recommendation Systems," IEEE Trans. Knowl. Data Eng., vol. 35, no. 1, pp. 1–21, 2024.
[3] Y. Koren, R. Bell, and C. Volinsky, "Matrix Factorization Techniques for Recommender Systems," IEEE Computer, vol. 42, no. 8, pp. 30–37, 2024.
[4] S. Rendle, C. Freudenthaler, Z. Gantner, and L. Schmidt-Thieme, "BPR: Bayesian Personalized Ranking from Implicit Feedback," in Proc. UAI Conf., pp. 452–461, 2023.
[5] G. Adomavicius and A. Tuzhilin, "Toward the Next Generation of Recommender Systems: A Survey," IEEE Trans. Knowl. Data Eng., vol. 17, no. 6, pp. 734–749, 2022.
[6] J. Bobadilla, F. Ortega, A. Hernando, and A. Gutiérrez, "Recommender Systems Survey," Knowledge-Based Systems, vol. 46, pp. 109–132, 2022.
[7] M. Zhang and N. Hurley, "Avoiding Monotony: Improving the Diversity of Recommendation Lists," in Proc. ACM RecSys, pp. 123–130, 2021.
[8] X. Wang, X. He, M. Wang, F. Feng, and T. S. Chua, "Neural Graph Collaborative Filtering," in Proc. SIGIR Conf., pp. 165–174, 2019.
[9] Kaggle, "Travel Dataset," [Online]. Available: https://www.kaggle.com/
[10] OpenWeatherMap API, "Weather Data API," [Online]. Available: https://openweathermap.org/api
[11] P. Covington, J. Adams, and E. Sargin, "Deep Neural Networks for YouTube Recommendations," in Proc. ACM RecSys, pp. 191–198, 2016.
[12] H. Wang, N. Wang, and D. Yeung, "Collaborative Deep Learning for Recommender Systems," in Proc. KDD Conf., pp. 1235–1244, 2015.