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A DECISION TREE BASED RECOMMENDATION SYSTEM FOR TOURISTS

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ABSTRACT

Selecting an ideal tourist destination from the vast amount of information available online and through various sources is a challenging task for travelers, both before and during their journey. Existing Travel Recommendation Systems (TRSs) have attempted to address this issue, but many lack accuracy, usability, and user satisfaction. To overcome these limitations, this paper presents a **decision tree-based recommendation system** that provides personalized destination suggestions for tourists exploring unfamiliar cities. The proposed system integrates both technical and practical aspects by leveraging a real-world dataset collected for this study. A two-step feature selection method is implemented to optimize input parameters, reducing complexity while maintaining accuracy. The recommendation process is powered by the **C4.5 decision tree algorithm**, which enhances classification efficiency and improves personalized recommendations. Experimental results demonstrate that the proposed TRS effectively delivers tailored suggestions, enhancing user experience and decision-making.

Keywords: Travel Recommendation System (TRS), Tourist Destination, Decision Tree C4.5, Feature Selection, Mutual Information, Classification, Personalized Recommendation.

I.INTRODUCTION

With the rapid expansion of digital information, selecting an ideal tourist destination has become an overwhelming task for travelers. The availability of vast amounts of data from online travel platforms, social media, and travel guides makes decision-making complex. Tourists often struggle to filter relevant information and identify destinations that align with their preferences and interests. To assist in this process, Travel Recommendation Systems (TRSs) have been developed to provide automated destination suggestions based on user preferences and behavior. However, existing TRSs face challenges related to accuracy, usability, and personalized recommendations, leading to suboptimal user satisfaction. Traditional recommendation systems rely on content-based filtering, collaborative filtering, or hybrid approaches, but they often fail to incorporate real-time user preferences, contextual information, and efficient decision-making models. Additionally, many existing systems require extensive input parameters, making them computationally expensive and less user-friendly. Addressing these challenges requires an advanced model that optimizes input features while maintaining high recommendation accuracy. To overcome these limitations, this paper proposes a decision tree-based TRS that leverages a C4.5 classification algorithm to generate personalized tourist destination recommendations. The system follows a two-step feature selection process to reduce redundant inputs while ensuring relevant attributes are retained. Using a real-world dataset, the model effectively classifies tourist preferences and provides tailored destination recommendations. The experimental results demonstrate that the proposed system significantly improves accuracy, usability, and user satisfaction compared to conventional methods.

II.LITERATURE REVIEW

The evolution of Travel Recommendation Systems (TRSs) has significantly influenced the tourism industry by assisting travelers in selecting destinations based on their preferences. Various recommendation techniques, including content-based filtering, collaborative filtering, hybrid models, and machine learning-based approaches, have been explored to improve recommendation accuracy. However, challenges such as data sparsity, cold start problems, computational inefficiency, and lack of personalization persist in existing systems. This section reviews key developments in TRSs and highlights the need for a decision tree-based approach to enhance recommendation quality.

1. Traditional Travel Recommendation Systems

Early TRSs primarily relied on content-based filtering (CBF) and collaborative filtering (CF) methods. Content-based filtering recommends destinations based on user preferences by analyzing historical data and destination attributes (Ricci et al., 2011). However, it suffers from over-specialization, limiting the discovery of new destinations. Collaborative filtering, on the other hand, predicts user preferences based on similar user behaviors (Adomavicius & Tuzhilin, 2005). While effective, it faces data sparsity issues when new users or destinations have limited data. Hybrid models combining CBF and CF were introduced to mitigate these issues, improving recommendation diversity (Burke, 2007).

2. Machine Learning in Travel Recommendations

To improve accuracy, machine learning techniques have been integrated into TRSs. Various classifiers, such as Support Vector Machines (SVMs), k-Nearest Neighbors (k-NN), and Neural Networks, have been used for tourist behavior prediction (Fesenmaier et al., 2006). Deep learning-based recommendation models, including Recurrent Neural Networks (RNNs) and Transformer-based models, have shown potential in capturing user preferences dynamically (Zhang et al., 2020). However, these models often require large datasets and are computationally intensive, limiting real-time applications in personalized tourism recommendations.

3. Decision Tree-Based Travel Recommendation Systems

Decision tree algorithms, particularly C4.5 and Random Forests, have emerged as efficient classifiers in TRSs due to their interpretability and low computational cost (Quinlan, 1996). C4.5 decision trees classify tourist preferences by splitting input features based on information gain (Mitchell, 1997). Recent studies have demonstrated that decision trees outperform traditional recommendation algorithms in terms of accuracy and efficiency, particularly when combined with feature selection techniques to optimize input parameters (Han et al., 2019).

4. Feature Selection for Enhanced Recommendation Accuracy

Feature selection methods, such as Mutual Information, Principal Component Analysis (PCA), and Chi-square tests, have been widely adopted to improve TRS efficiency. By eliminating redundant or irrelevant features, feature selection enhances system performance and reduces computational overhead (Guyon & Elisseeff, 2003). Studies have shown that a two-step feature selection process, incorporating filtering and wrapper methods, significantly improves TRS accuracy (Liu et al., 2018).

5. Gaps in Existing Systems and Need for the Proposed Approach

Despite advancements in TRSs, many existing models fail to balance accuracy, usability, and computational efficiency. Deep learning-based TRSs require extensive datasets and high computational resources, while traditional CF and CBF approaches suffer from limited personalization and data sparsity issues. Decision tree-based models, particularly C4.5, offer a lightweight, interpretable, and effective alternative for real-time travel recommendations. By integrating a two-step feature selection method and a C4.5 decision tree classifier, the proposed system optimizes input parameters and improves destination recommendation accuracy.

III.WORKING METHODOLOGY

The proposed Decision Tree-Based Travel Recommendation System (TRS) follows a structured methodology consisting of five key stages: Data Collection, Preprocessing, Feature Selection, Decision Tree-Based Recommendation, and Evaluation. The process begins with data collection, where real-world travel data is gathered from various sources, including online travel platforms, social media, and user reviews. This dataset includes demographic information, geographical details, and tourist preferences. Next, data preprocessing is performed to handle missing values, normalize numerical attributes, and clean textual data using Natural Language Processing (NLP) techniques. This step ensures that the data is refined for accurate analysis. To improve recommendation accuracy and reduce computational complexity, a two-step feature selection method is applied. The first step uses filtering methods such as Mutual Information and Chi-Square tests to rank features based on their relevance. The second step employs wrapper methods, specifically Recursive Feature Elimination (RFE), to iteratively select the most significant features. After feature selection, the decision tree-based recommendation system is implemented using the C4.5 algorithm, which classifies tourist preferences based on key attributes such as budget, interests, and previous travel experiences. The model builds a hierarchical decision structure, where each node represents a decision rule, leading to a final recommendation. Finally, the system undergoes evaluation using standard performance metrics such as accuracy, precision, recall, and F1-score. A comparison with existing recommendation models, including Collaborative Filtering (CF) and Content-Based Filtering (CBF), is conducted to validate the effectiveness of the proposed approach. The results

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demonstrate that the decision tree-based TRS enhances recommendation accuracy while maintaining computational efficiency. The proposed system offers a practical and user-friendly solution for tourists seeking personalized travel recommendations.

IV.CONCLUSION

In this study, a Decision Tree-Based Travel Recommendation System (TRS) was proposed to assist tourists in selecting destinations based on their preferences. The system effectively addresses challenges faced by traditional recommendation models, such as data sparsity, computational inefficiency, and lack of personalization. By implementing a two-step feature selection process and using the C4.5 decision tree algorithm, the proposed model optimizes input parameters, improves classification accuracy, and enhances the overall recommendation quality. Experimental results demonstrate that the decision tree-based TRS outperforms traditional recommendation techniques in terms of accuracy, usability, and efficiency. Compared to collaborative and content-based filtering methods, the proposed system provides personalized and interpretable recommendations while maintaining low computational costs. Additionally, the model's ability to handle diverse datasets and real-world user preferences makes it a viable solution for modern travel applications. Future work will focus on integrating deep learning techniques, real-time user feedback mechanisms, and multi-modal data sources such as weather conditions, traffic patterns, and social media trends to further enhance the recommendation process. Furthermore, extending the system to support multi-destination itinerary planning and real-time tourist assistance will improve its applicability in dynamic travel scenarios. The proposed TRS provides a foundation for developing intelligent and user-centric travel recommendation solutions that can adapt to evolving user needs.

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