Cawangan Melaka

PCMJ

Progress in Computing and Mathematics Journal

volume 1

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Progress in Computing and Mathematics Journal
College of Computing, Informatics, and Mathematics
Universiti Teknologi MARA Cawangan Melaka, Kampus Jasin
77300, Merlimau, Melaka Bandaraya Bersejarah

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EDITORS

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PREFACE

Welcome to the inaugural volume of the **Progress in Computing and Mathematics Journal (PCMJ)**, a publication proudly presented by the College of Computing, Informatics, and Mathematics at UiTM Cawangan Melaka.

This journal represents a significant step in our commitment to fostering a vibrant research culture, initially providing a crucial platform for our undergraduate students to showcase their intellectual curiosity, dedication to scholarly pursuit, and potential to contribute to the broader academic discourse in the fields of computing and mathematics. However, we envision PCMJ evolving into a beacon for researchers both nationally and internationally. We aspire to cultivate a space where groundbreaking research and innovative ideas converge, fostering collaboration and intellectual exchange among established scholars and emerging talents alike.

The manuscripts featured in this first volume, predominantly authored by our undergraduate students, are a testament to the hard work and dedication of these budding researchers, as well as the guidance and support provided by their faculty mentors. They cover a diverse range of topics, reflecting the breadth and depth of research interests within our college, and set the stage for the high-quality scholarship we aim to attract in future volumes.

As editors, we are honored to have played a role in bringing this journal to fruition. We extend our sincere gratitude to all the authors, reviewers, and members of the editorial board for their invaluable contributions. We also acknowledge the unwavering support of the college administration in making this initiative possible.

We hope that PCMJ will inspire future generations of students and researchers to embrace research and innovation, to push the boundaries of knowledge, and to make their mark on the world of computing and mathematics.

Editors
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UiTM Cawangan Melaka

TABLE OF CONTENTS

PCMJ

Progress in Computer and Mathematics Journal (PCMJ)
volume 1 [October, 2024]
e-ISSN: 3030-6728
Website: fskmjebat.uitm.edu.my/pcmj

TRAVEL TIME CONTEXT-BASED RECOMMENDATION SYSTEM USING CONTENT-BASED FILTERING

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Article Info

Abstract

Tourism, defined as travelling to various locations for pleasure, has long been crucial to a country's economic development. However, the rapid expansion of the tourism industry, particularly in Europe, has brought about challenges linked to information overload for travellers seeking suitable destinations and optimal travel times. These challenges manifest in two significant technological aspects. Firstly, the vast amount of tourism-related information available on the internet poses a daunting task for individuals to identify suitable travel destinations. Information from various sources, such as websites, blogs, and newspapers, needs more organization, making it overwhelming for visitors. This often leads travellers to make misguided choices, causing dissatisfaction if their selected destination aligns differently from their preferences. Secondly, tourist itinerary planning faces challenges in obtaining precise information about the optimal time context to visit diverse destinations. Travellers frequently rely on guidebooks, online platforms, or recommendation systems, which require optimization for factors like time feasibility. This complexity increases the likelihood of travellers missing experiences best enjoyed at particular times. In response to these challenges, this research introduces a personalized travel recommendation system for Malaysian tourists exploring select European countries—namely, the United Kingdom, Germany, France, Switzerland, and Italy. Employing content-based filtering techniques, the system considers user profiles and preferred travel times to provide tailored recommendations, enhancing the overall travel experience. The prototype, implemented as a user-friendly web application, aims to offer comprehensive guidance on optimal travel times and destinations. Functionality testing indicates a successful implementation, albeit with minor interface and data handling issues. For future recommendations, the prototype will incorporate advanced machine learning techniques, such as exploring hybrid models that integrate collaborative filtering, to enhance recommendation accuracy and overall performance.

Received: February 2024
Accepted: August 2024
Available Online: October 2024

Keywords: Recommendation System; Travelling Time; Content-based Filtering

INTRODUCTION

The tourism industry has experienced significant growth recently, with people engaging in travel for various reasons, such as vacationing, visiting friends and relatives, or pursuing personal interests (Bai et al., 2019; Wayan Priscila Yuni Praditya et al., 2021). As a global leader in tourism, Europe is a popular destination (Ordóñez et al., 2020). However, the abundance of online tourism-related information makes it challenging for travellers to find suitable destinations. This abundance of information comes from various sources, including websites, blogs, and newspapers, making it disorganized and overwhelming for visitors (Garipelly et al., 2021). As a result, travellers may experience dissatisfaction if their selected destination aligns differently from their preferences.

Another significant challenge in tourist itinerary planning is the need for precise information about the optimal time to visit destinations. This optimal time context refers to periods when a location offers optimal weather conditions, cultural events, or unique experiences. Travellers often rely on guidebooks, online platforms, or recommendation systems to plan their trips. However, these sources often need more optimization for factors like time feasibility, specific localities, and individual user preferences (Ho & Lim, 2021). This challenge is compounded by the need for time context-based recommendations, making itinerary planning complex and increasing the likelihood of travellers missing out on unforgettable experiences best enjoyed at specific times.

A travel recommendation system is being developed to address these challenges and enhance user satisfaction. This system will suggest places of interest based on user profiles and preferred travel times, considering factors such as seasons, months, times of the day (e.g., morning), and the week (e.g., weekend or weekday). By providing detailed information about recommended locations, this system aims to empower users to make informed decisions aligned with their preferences, ultimately improving the overall user experience in the tourism industry.

LITERATURE REVIEW

The current section delves into a literature review of the existing literature on the tourism industry, travel recommendation systems, and information filtering techniques that could be integrated into the travel recommendation system.

Tourism Industry

Tourism is the process by which people spend their time travelling from one location to another for enjoyment (Khan et al., 2020). Factors such as multiple destination spots, accommodation choices, and attractions contribute to tourist interest in visiting a country (Bai et al., 2019). Europe, in particular, has emerged as a premier tourist destination, with 3.3 billion visitors in 2018, representing substantial market potential (Robaina et al., 2020). Europe led the recovery of international tourism in 2022, hosting 585 million tourists, nearly 80% of pre-pandemic levels, with Western Europe excelling at 87%, which is attributed to effective travel measures (World Tourism Organization, 2023). Intelligent tourism, incorporating travel recommendation systems, has become a key strategy in responding to the industry's growth (Pai et al., 2021).

Smart tourism, an information system that utilizes data from various tourism environments, offers intelligent decision-making options for organizing tourism activities (Pai et al., 2021). The rapid development of intelligent tourism technology presents growth opportunities as destinations adopt innovative technology to attract visitors (Pai et al., 2020). Using algorithms and artificial intelligence, travel recommendation systems analyze user data to provide personalized travel recommendations, including destination suggestions based on user preferences such as travel time.

Travel Time Based Recommendation System

Developing a travel time-based-context recommendation system requires two essential requirements, which are user profile and time context. User profiles capture individual preferences and characteristics, while time context includes considerations such as the temporal factors and constraints that influence travel choices.

User Profile

User profiles, consisting of information like geographical location, interests, preferences, and opinions, are crucial for recommender systems in the tourism industry (Anjali et al., 2021; Diao et al., 2020). These profiles are used to understand individual users' characteristics and provide personalized travel suggestions, enhancing their planning and overall experience. By analyzing user profiles and comparing item features, the system can generate tailored recommendations matching user interests with suitable travel destinations, increasing user satisfaction and engagement.

Time Context

Time context, referring to the specific timeframe when a recommendation is made, significantly influences user choices as preferences evolve over time (Xu et al., 2019). Dynamic user preferences, such as changing fashion styles or travel interests, highlight the importance of considering time context in recommendation systems (T. R. et al., 2023). In travel recommendations, time context is crucial for aligning suggestions with users' evolving preferences, considering seasonal variations, and ensuring relevance throughout the year. For example, users may prefer beach destinations in the summer but shift towards winter experiences as the seasons change. By considering the time of year and day, the system can provide personalized recommendations for morning, afternoon, evening, or nighttime activities, enhancing the user experience and relevance. This time-contextual approach ensures that the travel recommendations remain pertinent and aligned with users' ever-changing tastes, providing a personalized and relevant experience throughout the year.

Information Filtering

Generally, recommendation systems are a type of information filtering system. Troussas et al. (2020) define information filtering systems as computer-based systems that remove unnecessary or irrelevant information before presenting it to users. Several algorithms exist within information filtering, such as content-based, collaborative, and hybrid filtering.

Content-Based Filtering

According to Devi et al. (2022), content-based filtering (CBF) is recommended for making recommendations. It relies on item descriptions and user preference profiles. CBF is suitable for utilizing complete item data such as names, locations, and descriptions, but it does not focus on profiling users. A significant advantage of this method is that it provides users with relevant information about items, as the content of each item can be known through its representations. The recommender system uses feature weighting to filter out objects that align with user preferences and their previous profile history (Muneer et al., 2022). In CBF, two commonly used algorithms are vectorization and similarity method.

Collaborative Filtering

Collaborative filtering is a recommender system that relies on user-item interactions, particularly user ratings of items, to make recommendations (Riyahi & Sohrabi, 2020). It involves creating user profiles based on their ratings and identifying similar users or items based on these profiles. Collaborative filtering can be divided into two main approaches: user-based and item-based. In user-based filtering, the system recommends items to a user based on the preferences and behaviours of similar users (Lixia & Junyi, 2021). On the other hand, item-based filtering suggests items to a user based on the similarities between the items themselves (Schelter et al., 2019). This approach is intuitive, reflecting how people make recommendations in everyday life. Both approaches aim to understand user preferences and provide personalized recommendations, enhancing the overall user experience (Xue et al., 2019).

Hybrid Filtering

Hybrid filtering is a method that combines content-based filtering and collaborative filtering recommendation techniques. Its objective is to enhance the prediction accuracy in memory-based and model-based collaborative filtering techniques. The hybrid recommender system method includes different ways of merging, such as Linear Combination, Sequential Combination, and Item-based Clustering Hybrid Method (ICHM) (Devi et al., 2022). Table 1 shows several hybridization methods from Zagranovskaia & Mitura (2021).

Table 1: Hybridization Methods

Hybridization Methods	Description
Weight	Rating made by several recommendation methods are combined to provide recommendations.
Switching	The system switches between recommendation algorithm depending on the situation.
Mixed	Recommendations from several models are presented together.
Feature Combination	Features derived using different data processing algorithms are combined as input to a single algorithm.
Cascade	One recommender system improves recommendations of another recommender system.
Feature Augmentation	Output of one system is used as input for another system.
Meta-level	Parameters of a model trained by one system are used as input for another system.

(*Source*: Zagranovskaia & Mitura, 2021)

METHODOLOGY

This research applies two stages: data preparation and recommendation method implementation. Data preparation serves to prepare a dataset that will be used for the recommendation process in the system. The data is collected using web scraping and manual searching. The first method uses Octoparse software to scrape data from the Trip.com website for five countries: the United Kingdom, Italy, France, Germany, and Switzerland. The second method is used because the data that has been scrapped is not complete, and the time context for each destination is not provided, so it needs to be searched one by one from Trip.com and Tripadvisor. Then, the combination of all the data is saved in one CSV file named POI.csv to create a complete dataset.

After preparing the dataset, the system implements the recommendation method. The recommendation method uses content-based filtering that consists of two algorithms: TF-IDF and cosine similarity. Figure 1 shows the flowchart of the recommendation system in this study to understand it visually.

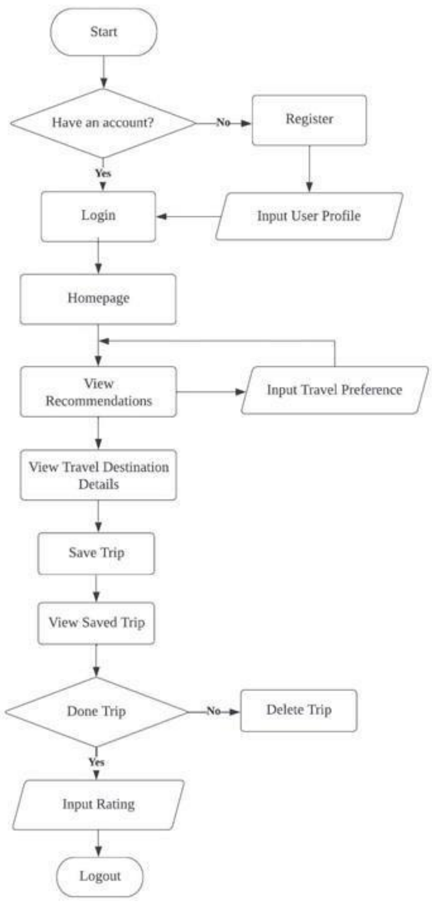

Figure 1: The Flowchart of the Recommendation System

Figure 2 visually represents the process and components involved in the system's recommendation feature. These features help to understand how content-based filtering algorithms work in the recommendation system.

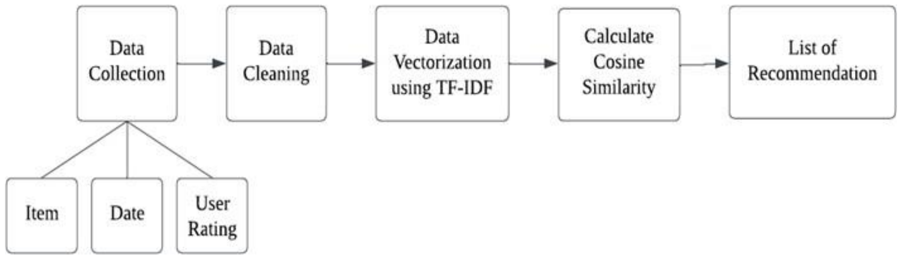

Figure 2: Recommendation System Modelling

TF-IDF (Term Frequency-Inverse Document Frequency) is a technique used in natural language processing and information retrieval to determine the importance of a word or phrase in a document relative to a collection of documents. It considers the frequency of a term in a document (TF) and how often it appears across all documents (IDF). This helps to reduce the importance of common words and gives more weight to unique terms. This project uses TF-IDF to analyze data from the "POI.csv" file, where information such as destination, location, address, description, activities, and opening hours are combined into a single text for analysis. This allows the system to find similarities and make recommendations based on the combined text.

Cosine similarity is a measure used to determine the similarity between two documents based on the frequency of terms, considering their occurrence in a high-dimensional space. It evaluates the alignment of word usage patterns between documents and is often used in text analysis. Combined with TF-IDF, it weighs the importance of terms in a document relative to their occurrence, reducing the impact of frequently appearing words and prioritizing unique terms. This approach enhances the accuracy of assessing document similarity.

This project provides recommendations on the tours page through three main types: initial recommendations for first-time users, search-based recommendations, and rating-based recommendations. For first-time users, recommendations are based on travel preferences provided during system registration. Search-based recommendations are generated from words the user searches, with destinations chosen based on similarity to these keywords. Rating-based recommendations consider destinations already rated by the user, using this as user history to suggest similar destinations upon login.

RESULT AND DISCUSSION

This section provides an explanation of the recommendation outcomes. The system underwent a comprehensive evaluation, and the findings, including the output of each recommendation types – first-time user, search-based recommendations, and rating-based recommendations.

The results of the recommendations are occurring on the tours page. Firstly, this page will recommend destinations for first-time users based on the preferences provided during registration. Figure 3 illustrates the tours page, which suggests destinations for a first-time user with preferences such as enjoying the activity of 'hiking' during the 'winter' season and choosing 'afternoon' as the preferred time of the day for the activity.

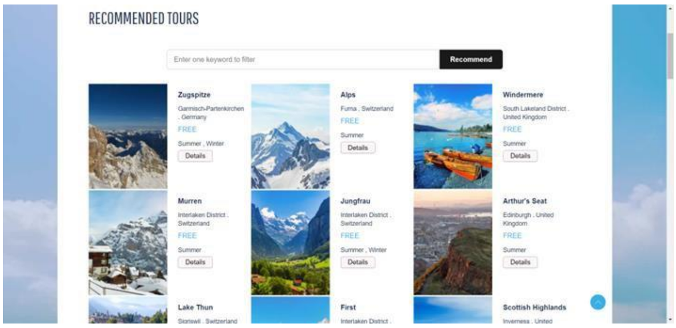

Figure 3: Tours Page for First-time User

User preferences, including those provided during system registration and subsequent search keywords, are stored in the user in a database table. Users can filter recommendations by entering a reference keyword in the search field, which also gets added to the database table. The system then recommends destinations based on all keywords associated with the user in the database. Figure 4 illustrates the user inputting 'February' in the search field, and Figure 5 displays the recommendations after entering the keyword 'February'.

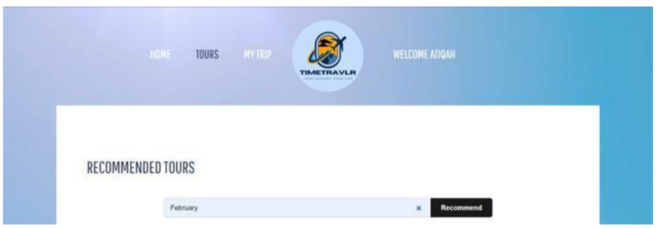

Figure 4: User Input Keyword 'February'

PCMJ
Progress in Computer and Mathematics Journal (PCMJ)
volume 1 [October, 2024]
e-ISSN: 3030-6728
Website: fskmjebat.uitm.edu.my/pcmj

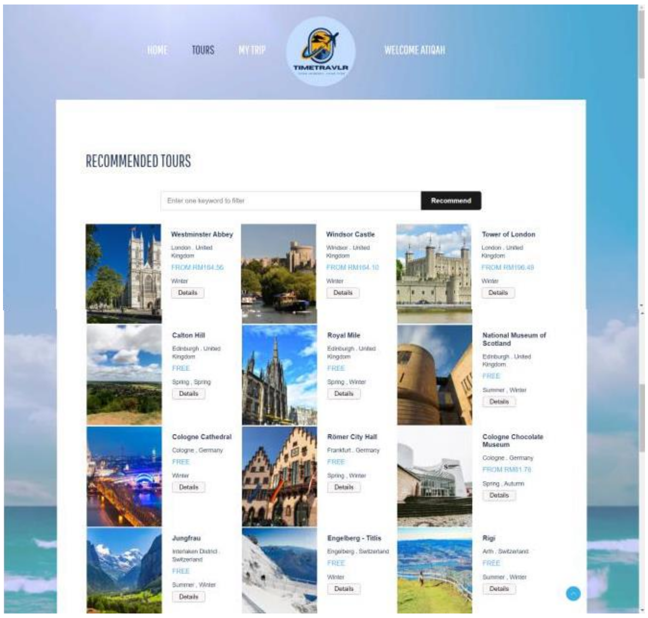

Figure 5: Tours Page After the Keyword 'February' is Inputted

Finally, recommendations will occur after the user provides ratings. These ratings are included in the user's history. The user will be provided with new recommendations based on this user history. If the user logs out and then logs into the system again, the user will be given recommendations based on those ratings. Figure 6 below illustrates the user's tour page after they have rated the destinations named Zugspitze and Bridge of Sighs and logged into the system again.

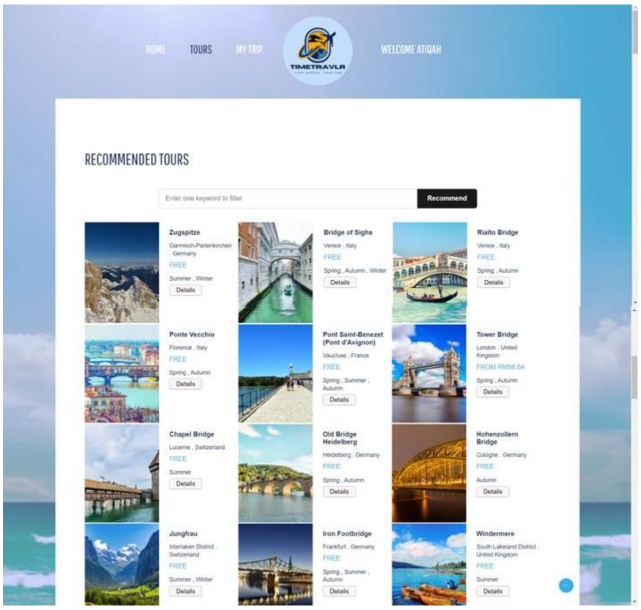

Figure 6: Tours Page After the User Rates

The tour page's destination recommendations have produced highly successful results for all user types. To confirm the similarity of these recommendations, users are encouraged to view the details page, which exhibits comprehensive information about the selected destination. Notably, the top recommended destination is determined to be the most similar based on user types, affirming the system's effective functionality. A commitment to delivering seamless and personalized experiences to users remains paramount. As such, the system will continue to undergo enhancements to meet their evolving needs.

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Progress in Computing and Mathematics Journal

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eISSN 3030-6728