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by Jefree Fahana 60160979

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Possible System Architecture for Travel Recommender

Supriyanto[1], Jefree Fahana[2]
[1,2]Informatics Department, Universitas Ahmad Dahlan, Yogyakarta, Indonesia

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ABSTRACT

Travel recommender systems have been developed to meet the needs of users in the field of tourism. This system has several versions depending on the characteristics of the country, users and filtering techniques used. The development of recommendation filtering system techniques is very rapid so that the recommendation system has high enough complexity, but it also must have high usability. This paper discusses how the travel recommender system architecture is built by examining data structures, processing procedures and interaction design. The goal is to obtain the best usability in implementing a travel recommendation system. The system is built using the example case of finding the right tourist spot in Yogyakarta, Indonesia. This system applies several filtering techniques such as knowledge-based filtering, content-based filtering, and collaborative filtering. The evaluation results show that the system architecture optimized gets a usability level acceptable.

Corresponding Author:

Supriyanto,
Informatics Department,
Universitas Ahmad Dahlan,
Jl. Ringroad Selatan, Yogyakarta, Indonesia
Email: supriyanto@tif.uad.ac.id

1. INTRODUCTION

The needs of the tourism sector for information technology are increasingly high. The implementation of information technology services in smart tourism can increase tourist visits, and facilitate tourists in various ways [1]. Information technology in tourism can also support tourism managers and the government in improving services for tourists. The application of information technology can also improve the quality of data that will later be processed into recommendations and considerations for decision making [2].

For tourists, choosing a location and type of tour that suits what they want is quite complex [3]. Tourists must conduct a search while comparing one another's tours. Tourists must consider the cost, duration, and type of tour in accordance with the pleasure in question. Tourists need recommendations on which attractions to visit when going on vacation to an area. Applying recommendations on web-based information systems can help tourists find the tourist attractions they want [4]. Tourists can search for travel recommendations according to the desired travel reference, cost plan, or based on tourism popularity.

Many recommendation system techniques that can be used such as Content-based Filtering that provide recommendations by looking for items in common based on certain characteristics. Examine the application of a content-based search for articles based on the title, theme, and preferences of the reader [5]. Collaborative Filtering combines preferences of other users for existing items. Examples of its application to the music or movie recommendation system are based on ratings from user preferences [6].

Hybrid Filtering Technique is a technique that combines several techniques to improve its accuracy. This technique utilizes the advantages of content-based and collaborative techniques. The system will initially build user groups, then mining will be done to create content-based rules using fuzzy algorithms. This rule will be used to process the user's last transaction in the system. The hybrid technique works very well when applied to tourism to recommend tourist attractions based on the ranking of the number of recommendations from the tour itself [7].

This paper discusses how the optimal system architecture for implementing a recommendation system on the travel information system. case is used as a sample of tourism problems that must be resolved. This

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paper takes an example of implementing a travel destination recommendation system in the Yogyakarta City of Indonesia. This is based on the increasing number of tourist attractions references triggered by social media. New places have sprung up so it is increasingly difficult for tourists to determine where they should go on vacation. Based on data from the government, the average increase in the number of new tourist location data is 15%. This city is an ideal example of the study of implementing a recommendation system. The information system currently available is a web-based information system that mostly contains a tourism profile. This system contains news about tourist destinations, tourism event agenda, accommodation and promotion of new tourism.

This paper discusses a new system that can be used as a complement to the system currently available. The aim is to provide recommendations to tourists about tourism destinations so as to improve the usability system and user involvement. The variables considered in this application are the cost, duration, and type of tours that are adjusted to the preferences of potential tourists. This paper will not discuss the performance of each technique. Another factor considered is user interaction and the initial data available. The system optimizes the data on this journey architecture in accordance with the case. Furthermore, the process of determining appropriate recommendations by structuring filtering techniques in accordance with the characteristics of available data. Finally, consider the design of user interactions to improve system usability.

Technical studies on the Travel Recommender System [8] examined at least eleven recommendation techniques. As a result, the most widely used system in the field of travel and tourism is collaborative filtering. While the Hybrid technique ranks second with a total implementation of 21%. At least collaborative filtering will always be used when item rating data becomes a consideration in computing. This item rating comparison matrix is the main basis for computing collaborative filtering techniques.

In other studies, the recommendation system in the tourism sector states that content-based and collaborative are classic techniques [3]. This study adds a non-classical approach that is personalized and context-aware. This means that the recommender system must consider more complex data items and user data. The solution offered is to adopt a new approach by adding semantic knowledge of items and users. The aim is to improve the recommendations, because making travel plans requires complex considerations.

The survey of the recommendation system for tourism discusses the use of artificial intelligent [9]. The system built is quite complex with the use of various platforms such as the web and mobile. In addition, the case discussion is also more complex because it adds a travel route as a recommendation system variable. The technique used to produce travel recommendations is content-based filtering. Complex similarity techniques are also used to compare user profiles, objects and user preferences for objects.

The recommendation system also has its own obstacles and challenges in the implementation process [10]. They stated that the challenges of the recommendation system are: cold start problem, sparsity problem, scalability, overspecialization problem [11], diversity, novelty, serendipity, privacy, shilling attacks, and gray sheep. The challenge according to the case in this paper is the cold start problem, sparsity problem, and overspecialization problem.

Cold start problem is a condition where content-based cannot process recommendations because the system does not have sufficient transactions. Usually this happens when the system is first used or released. Sparsity problems occur when users only provide an assessment of certain items, so items that can be processed in the recommendation system are limited. This will result in users being able to find new items or other available options. This condition is usually called overspecialization.

2. METHOD

This paper discusses the recommendation system that will be implemented in the city of Yogyakarta, Indonesia. Yogyakarta is a cultural city that has 185 attractions and has 26 million visitors each year. It becomes Yogyakarta is ideal to be used as an example the case of a travel application recommender system. The system considers the aspect of cost, duration, reference visitors and tourist popularity. The filtering technique used is hybrid by considering the cold start problem. The system applies three basic techniques of recommendations namely knowledge-based, content-based, and collaborative filtering. This filtering technique is arranged in order to get a recommendation for a tour itinerary that best suits visitors.

Knowledge-based filtering is placed as the first filtering technique to be used when there is little or no data collected. This technique is very suitable for use in situations where users have clear requirements [12], such as certain costs, tours with certain categories, and other specifications. This technique has been used in the Recommender Personal Shopper (RPS) which can be applied to other recommendation systems by adding product data and knowledge similarity data in other cases. [13]. The main purpose of the system is applying knowledge-based to handle new users of the application [14]. Users must enter the specification of the recommendation requirements to provide knowledge to the system [15]. The approach at this stage uses constraint-based recommendations, namely by mapping the needs of users with a touristic profile [16]. In addition to the application of constraint-based approach, this system also implements rule-based approach [17]. This approach is used to determine the rules of the conditions of knowledge and information obtained from users through the mechanism of conversation.

Preliminary data that can be obtained from the users of this travel recommendation system are travel plan data that includes time (duration of travel), cost, and type of desired tour. The data will then be processed with the tourism profile [18] as shown in Figure 1. Broadly speaking the system will compare the data entered by users with tourist profiles. User budget data compared with profile and location attributes of tourist attractions. Data on the duration of the tour is compared with the categories and locations of the tourist attractions Whereas user preference data is compared with the attributes of the tourist attractions category. For the record, the category attribute stores more than one value. The results of the recommendation are a list of tourist attractions that can be included in the user's travel itinerary.

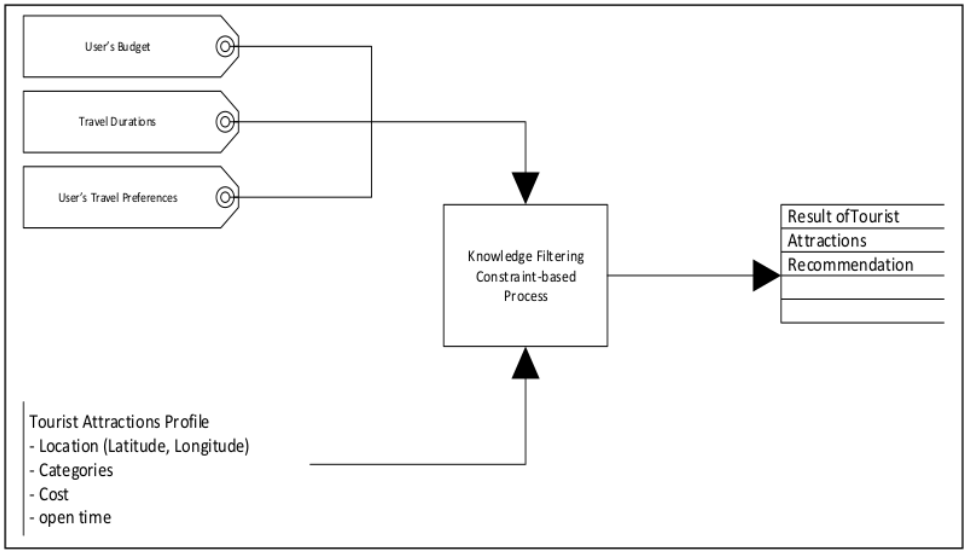

Figure 1. Knowledge-based Filtering System Architecture

Content-based filtering is used to find similarities of products that are similar to certain product criteria [19]. This system utilizes content-based for users who have used the application. The system will compare travel tours that have been chosen by users to produce new travel recommendations. The filtering process using content-based is assumed to be able to run if the system has stored user history. The history that is stored is the data of travel recommendations obtained by the user. In this content-based filtering data, it will be a reference for the next travel recommendation according to the user's profile. This series of processes no longer uses a tourist attraction profile, but only compares the results of previous recommendations to form a user profile as shown in Figure 2.

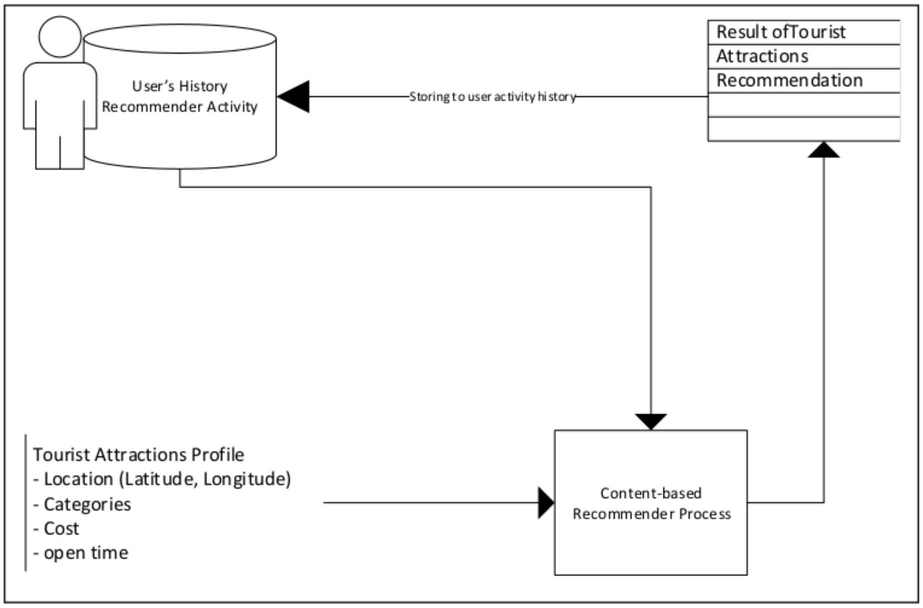

Figure 2. Content-based Filtering System Architecture

When users already have a history of system usage activities, they will immediately get recommendations without having to enter new data again. The system will provide recommendations for new tourist sites whose profiles are the same as those previously recommended. A history of system usage activities will be saved if the user agrees with the recommendations given by including them in the itinerary feature.

The filtering process will be continued with the implementation of collaborative filtering-based that compares the assessment of other users of the items they have [20]. Collaborative filtering is applied to deal with increasingly complex information needs. Users will add new criteria in the future. Data knowledge references must be added and require increasingly complex filtering processes [21].

3. RESULTS AND DISCUSSION

The system to be built is a system that can provide recommendations for Yogyakarta city tourism trips to prospective visitors. Currently the new system considering one city, but eventually the system will be used for all cities and countries. The functional requirements of the system are obtained from research on prospective users consisting of 100 respondents. More than 70% said they would consider the cost, duration, and type / character of the tour to be visited. There are at least 105 tourist attractions with various types / characters that they must choose in one city. Data on the number of tours may be more if information from social media is also included. Users need information on which tourist attractions can be visited according to the cost, duration and character of the tour they like.

Figure 3 shows the priority of the variables used based on 100 respondents. 51% choose cost as priority, 34%-character preference as priority and the last duration is only 15%. The duration has the smallest presentation because the duration of the trip can change at any time. While the cost was chosen as the priority for any onward travel has cost plan that must be obeyed.

The use of three variables cost, duration and user preferences for tourist character are also considered to improve user experience when filling in the form of a system [22]. Users will not be asked to enter variables with a regular form, but use a conversation mechanism. The system is built like a customer service (CS) which will help to determine the destination of a tour based on the cost, duration and character preferences of attractions.

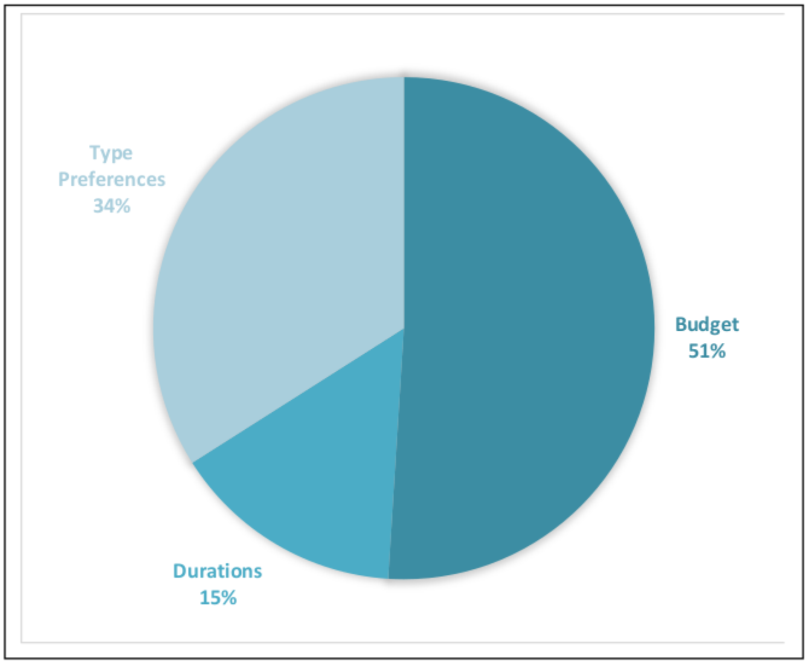

Figure 3. Variable priority based on user opinion

Front end architecture is built using a conversation interface. The conversation interface created provides text input interactions through the keyboard or button options on the conversation layer. User is not given a choice of input types but the text or button input will depend on the user response expected by the system. This mechanism will facilitate the system to determine the flow of conversation. The conversation flow that has been determined will minimize the possibility of users entering text input that has no connection at all to the conversation topic.

The conversation design shown in Table 1 adjusts to the data requirements needed for knowledge-based filtering calculations. Conversations are still structured, meaning that the system has not yet implemented a natural language processing mechanism to respond to words and sentences from users. The system structured directs the user to answer and choose actions according to the desired system.

Table 1. Conversation Steps

No	*Question*	*Available Option*	*Expected Response*
1	Introduction and ask what is user want?	Need travel recommendation Show all tourism attractions	Need travel recommendation
2	if the user has already used the system, new travel recommendations will be given. Else go to 3rd	list of recommended attractions. And option to begin new other recommendation.	Agree with recommendation or begin new other recommendation
3	How long is the duration of a trip planned?	Choice of answers 1, 2, 3, 4, 5 days and 1 week.	Choose an answer option.
4	What is the budget provided for travel?	Choice of funds ranging from 100 thousand to 7 million rupiah.	Choose an answer option.
5	What types of tours do you want to visit?	Given the choice of type and category of tourist attractions	Select one or more types and categories of tourist attractions

Tourist attractions are stored with attributes that are tailored to the needs of users. Tourist attraction data storage attributes are id, name, images, location, cost, and characteristic. Not only used to compare with user data, this attribute is also adjusted to the resulting recommendation plan. The system architecture outline is shown in Figure 4, with the type of user being a non-permanent user or not bound by the system. Users converse with the system while entering user data and preference characteristics of attractions. Furthermore, computing is done using knowledge-based and content-based techniques. The results of the recommendations will be displayed in the form of a list of tourist attractions equipped with photos, locations, costs and types of attractions. The order of tourist attraction list is arranged by location and navigation. The goal is to make it easier for users to understand and accept the list of attractions produced.

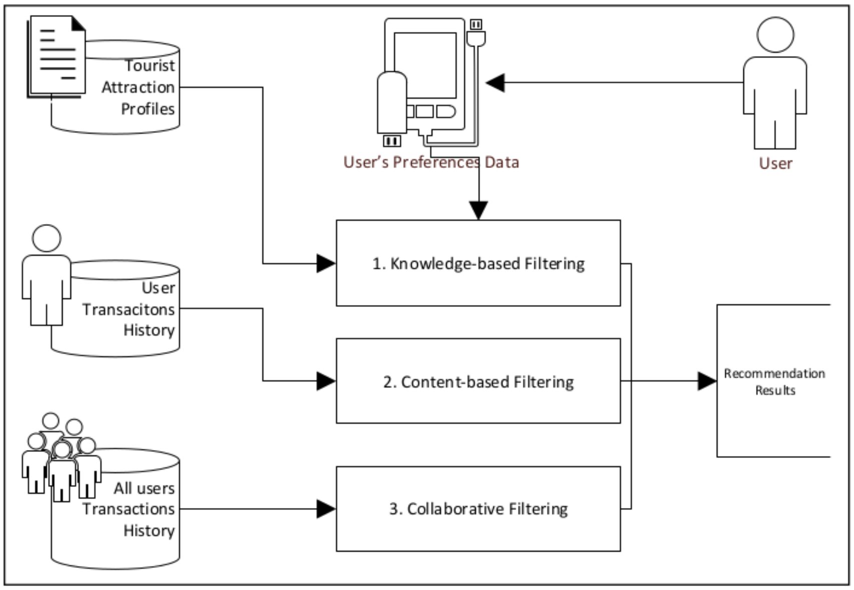

Figure 4. System architecture outline

The initial part of this paper explains that collaborative filtering is the most widely used technique for recommendation systems. But if you consider the three main challenges of the recommendation then it needs to be re-analyzed whether the use of collaborative techniques is the right choice. While collaborative techniques require rating data and preferences of all users and attractions to be grouped according to new requests.

The first feature of the recommendation is the cold start problem, which is a problem that arises when there are new users and new tourist data entering the system. The next challenge sparsity problem is the problem that not all users may honestly give a rating. The third challenge is scalability, namely the scale of data and information used.

4. CONCLUSION

1 After optimizing the recommendation system architecture by developing filtering techniques ranging from knowledge-based, content-based and collaborative filtering, an evaluation is carried out to test the recommendation system that is built. The focus of the evaluation is to measure system usability and user satisfaction. The system usability was tested using a standardized Single Ease Question (SEQ) questionnaire that could describe several scenarios in detail [23] [24]. SEQ can measure system usability in more detail because what is measured is the scenario of each task that must be done by the user. System usability testing involved 20 respondents with characteristics of ages between 18-50 years old, urban and urban-rural, often traveling and working or self-employed. Scenarios are divided into 5 scenarios according to the conversation stages in Table 1. Users will be asked about the ease of working on these stages by choosing from a scale of 1 to 4. One for Disagree, Two for Not Agree, Three for Agree, and Four for Strongly Agree. The results of evaluating the level of user satisfaction with the results of the recommendations are shown in Figure 5. More than 80% feel that the recommendations are in line with what is expected. But the rest are still not satisfied with the results of the recommendations.

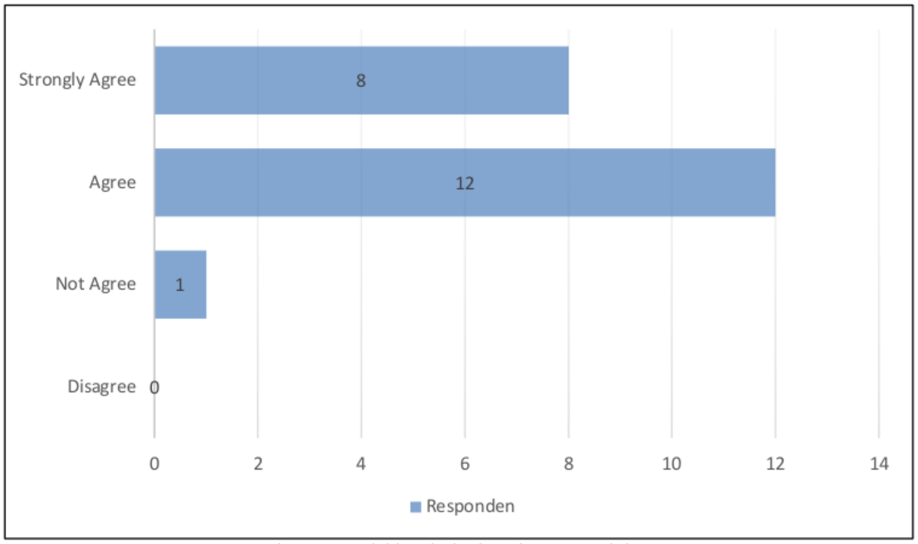

Figure 5. Variable priority based on user opinion

The recommendation system for travel destinations requires high flexibility. Data considerations for items and users must be the basis for implementing content-based filtering. When there is a lot of data recorded, it is necessary to consider the application of collaborative filtering. The system must also adapt when more and more data is collected. But for the initial use of the system with the user's condition is a type of non-permanent user, then knowledge-based is the most appropriate technique.

Optimization in terms of system interactions is also very important and is proven to be able to improve system usability. However, it is necessary to increase interaction by adding natural language processing techniques to provide better responses to users. It should also be considered with the use of the technology stack used during development and deployment.

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