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Context-aware recommender system based on ontology for recommending tourist destinations at Bandung

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Context-aware recommender system based on ontology for recommending tourist destinations at Bandung

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Abstract. Recommender System is software that is able to provide personalized recommendation suits users' needs. Recommender System has been widely implemented in various domains, including tourism. One approach that can be done for more personalized recommendations is the use of contextual information. This paper proposes a context aware recommender based ontology system in the tourism domain. The system is capable of recommending tourist destinations by using user preferences of the categories of tourism and contextual information such as user locations, weather around tourist destinations and close time of destination. Based on the evaluation, the system has accuracy of of 0.94 (item recommendation precision evaluated by expert) and 0.58 (implicitly from system-end user interaction). Based on the evaluation of user satisfaction, the system provides a satisfaction level of more than 0.7 (scale 0 to 1) for speed factors for providing liked recommendations (PE), informative description of recommendations (INF) and user trust (TR).

1. Introduction

Improvements in the mobile technology and communications networks field made mobile services available for access anywhere. In order for this mobile service to match the state of the user, the services that are available should be responsive to the context around the user [1]. Context that can be used as an object's characteristic is defined as any information [2].

The majority of studies related to the recommender system still focus on recommending items to users based on user profiles or preferences without taking contextual information such as user locations, weather around tourist destinations and local time into account. Contextual information will become an especially important aspect of decision making for mobile app users [3].

There are several approaches to recommender system algorithms such as content-based, collaborative filtering and knowledge based Recommender systems with content-based approaches recommend items which are similar to what the users liked in the past. Similar to content-based, collaborative filtering recommends items that have been favored by other users with the same tastes. Because of relying on user history, both content-based and collaborative filtering have cold start problem. This problem does not appear on the recommender system that does not rely on user history such as knowledge-based.

Systems with a knowledge-based approach recommend items based on the knowledge of how an item characteristic can meet user needs and preferences [4].

One of the models that can be used to represent the domain of knowledge is ontology. Ontology offers good expressiveness and support reasoning task better than key-pair value, object oriented and logic based on contextual-based case [5].

Context-aware recommender system topic has been widely studied. One study proposed a recommender system model to recommend venues based on what users liked in the past and take advantage of user location and local time. The division of venue categories according to the category used by Foursquare [6]. While other studies propose a model of recommender system that utilizes contextual information to predict information categories that may be interesting to users. Items from category prediction results are evaluated with a model named distance punisher that utilizes the user's location, the weather in the destination, and the user's mode of transport [3]. However, the models mentioned only cover the general category of point of interest. Meanwhile, there are many tourist destination categories that have not been covered by the tourism destinations classification proposed by Inskeep [7].

In this paper we propose a context-aware recommender system method that is able to recommend tourist destinations by utilizing ontology developed in accordance with the principles of development and tourism planning, as well as taking user preferences and contextual information, such as user location, weather in tourist destinations and tourist destination’s open time, into account. The proposed context-aware recommender system method is evaluated based on recommendation accuracy and user perceptions to application.

2. Ontology

The recommender system we developed using ontology as a representation of knowledge on the domain of tourism category. Ontology is built on the results of consultations with experts (academics and officials of cultural and tourism government services) and literature studies with reference to Inskeep's work [7].

On the ontology developed there are tourism destination categories and subcategories that become ontology class. One subcategory can be one or more subclasses of the tourism destination categories. The destination becomes direct individual from the tourist destination subcategories. One tourist destination can be an individual of one or more subcategories. Figure 1 is a visualization of some part of ontology we develop.

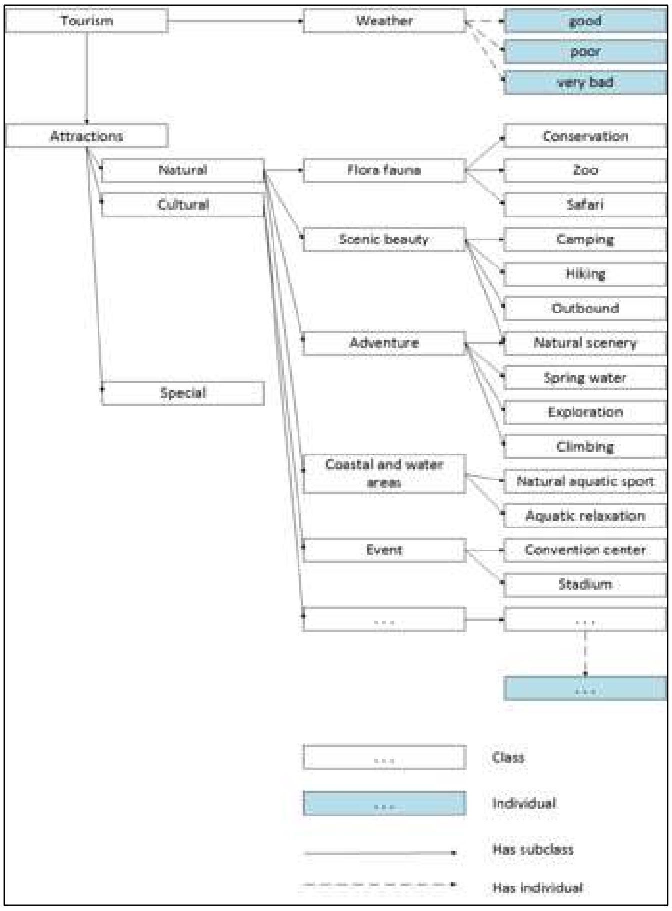

Figure 1. Part of ontology visualization.

All tourist destination individuals have attributes related to the processing of contextual information such as latitude, longitude and open-close time. In addition there are also supporting attributes such as description of tourist destinations. The latitude and longitude attribute serves to indicate the position of the destination on the map. This is required for calculating the distance from the user to the destination.

Tourist destination's open time becomes fourteen different attributes because every day there are two times when a tourist destination changes it's status, those changes are from close to open and from open to close. Open and close time values are not stored in the standard format (hh: mm: ss), but are stored in real number. Converting to a real number is required to make searching for a destination with queries easier. To convert the time of the standard format to the real value, the following equation 1 is used:

$$tn = \frac{60h + m}{1440} \tag{1}$$

while h is the hour and m is the minute. The value of tn will be in the range of zero to one. 1440 is the constant number of minutes per day. Table 1 is an example of a tourist destination specification with the mentioned attributes.

Table 1. Individual Specification Example

Specification	Description
Name	Alam wisata cimahi
Latitude	-6.841073f
Longitude	107.54805f
Monday open	0.3334f
Monday closed	0.875f
--	--
Sunday closed	0.875f
Class	Kuliner umum, outbound, taman bermain
Description	Tourist destination that unites several concepts of tourism such as, resorts, culinary, outbound and natural scenery

In addition to categories and subcategories of tourist destinations, the weather is also a class of its own. The weather class has an individual that represents the weather level. There are three levels of weather that is good, poor weather and very bad weather.

Each individual of the weather class has two attributes namely the weather value and the weather code. The weather value is the weather weight. The worse the weather, the greater the weight. While the weather code is a code of representation of weather conditions according to OpenWeatherMap standards. One individual can have multiple attributes of weather code. Table 2 is individual specification of good weather individual from weather class.

Table 2. Good Weather Individual Specification

Specification	Description
Name	Good weather
Weather code	801, 802, 803, 804, 952, 953
Weather value	1

3. Recommendation Model

We propose a recommendation model of destination based on user preferences on the category of tourist and user contextual information. Contextual information such as location, weather around the tourist destination and the open time of the tourist destination, is taken into account.

There are two steps in this model:
- Search for tourist destination that is not closed now. This is performed by utilizing the open and close time attributes on each individual destination.
- Evaluate each selected destination from the first step by assigning a utility value. Utility values are calculated based on user distance to destination, weight of weather value around destination and user preferences.

The first stage in this method relies on SPARQL queries. Results from SPARQL queries are URIs of currently open tourist destinations. The example of SPARQL queries to search for destinations that open on Monday at 12 noon, is as follows,

```
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>
PREFIX owl: <http://www.w3.org/2002/07/owl#>
PREFIX rdfs: <http://www.w3.org/2000/01/rdf-schema#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX ns:
<http://www.semanticweb.org/dell/ontologies/2017/4/tourism#>
SELECT ?destination
WHERE {?destination ns:senin_buka ?open; ns:senin_tutup
?closed

FILTER( (?open < 0.5 && 0.5 < ?closed)
|| ((?closed > 0.5 || ?open < 0.5) && (?closed < ?open)) )}
```

The second stage begins by calculating the distance from the user's location to each destination. To calculate the distance, euclidean equation can be used [8]:

$$d_i(u,i) = \sqrt{(x_u - x_i)^2 + (y_u - y_i)^2} \tag{2}$$

while x is latitude and y is longitude. Where u is the origin location and i is the destination location. After calculating the distance, next task is calculate similarity value between user preferences to the *i-th* tourism destination category by using equation (3) which is a modification of Multi Attribute Utility Theory [9]:

$$p_i = \sum_{j \in m} m_j f(i,j) \tag{3}$$

while m is the vector of interest level of the user to the category of tourist destinations and $f(i,j)$ is the relationship between the destinations to the i to category j. The value of $f(i,j)$ will always be more than equal to zero.

Each tourist destination does not become a direct individual of the category, but becomes an individual of the subcategories that are grouped by a category, so to calculate $f(i,j)$ equations (4) is used.

$$f(i,j) = \sum_{k \in S_j} r_{ik} \tag{4}$$

while r_{ik} is the value of the relationship between the *i-th* tourist destination with the *k-th* subcategory that becomes the subclass of the *j-th* category. The value of the relationship becomes one if the individual tourist destination is indeed an individual of the subclass of that category and zero if it is not.

Next step is to assess how reasonably visiting tourist destinations are based on the weather. To do so, there are two ways that can be done. First, the system must know the actual weather conditions in the destination by requesting direct weather data through the *OpenWeatherMap* API one by one for each destination. Second, by using a weather reference location.

The weather reference location is the location to which the *OpenWeatherMap* weather data is retrieved. Each tourist destination will be associated to a weather reference location using equation (2). Table 3 is a list of weather reference locations used for weather data retrieval in Bandung.

Table 3. Good Weather Individual Specification

No	Location Code	Latitude	Longitude	Geocoded
1	1650357	-6.9039	107.6186	Kota Bandung
2	8059762	-7.2026	108.586	Kota Cimahi

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From the weather condition code obtained in the weather reference location data, the weather conditions code will be used to determine the level of weather conditions, whether good, poor or very bad. This is achieved by searching in all individuals from weather class, which individuals have the rated weather conditions coded. If there are individuals who have the weather condition code, then the weather weight score will be taken from the attribute of the individual weather value as w_i. The weight value for each weather level can be seen at table 4.

Table 4. Good Weather Individual Specification

Weather Level	Weight Value
Good	1
Poor	5
Very Bad	9

The last step is to calculate the utility value of a tourist destination. The calculation of utility values is performed using equation (5), modification of the proposed distance punisher model is as follows,

$$util_i = e^{-(d_i w_i)} p_i \tag{5}$$

Weather values can be determined freely as long as weather weight values follow constraint $w_{good} < w_{poor} < w_{very\_bad}$.

The difference between original distance punisher model with equation (5) is the multiplication with p_i as addition to the original equation. Calculation by equation (5) is performed on all open destinations. After that the system will take ten tourist destinations with the highest utility value.

It is important to remember that equation (5) will cause utility score drops with high w_i (worsening weather) and high d_i (distance between user current location and tourist destination take further). Equation (5) also cause utility score rises when similarity between interest level of the user to the category of tourist destination also higher.

To summarize the recommendation model step, Figure 2 shows aforementioned steps is applied

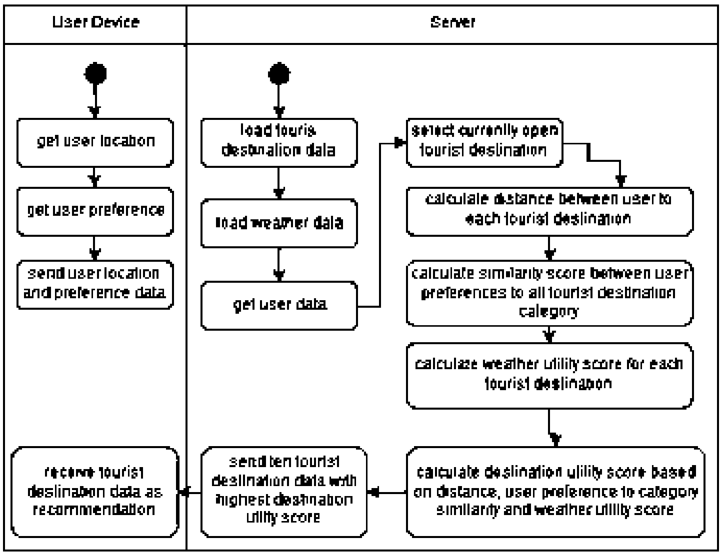

Figure 2. Recommendation model visualization

4. Eliciting User Preference

In order to obtain a user preference for a category of travel destinations, the user explicitly states an interest in a category of travel destination. There are four levels of user interest, those are not interested, less interested, interested enough and not interested. Each preference level has their own weighted value. Table 5 shows the weighted value of each level of interest in the tourism category. Meanwhile, Figure 3 shows the graphical user interface to explicitly insert the reference.

Table 5. Preference Level Weighted Value

Level	Value
Not interested	0
Less interested	0.33
Interested	0.67
Very interested	1

Figure 3. User Preference Input Menu

Users choose the appropriate level of interest through all tourist destination categories which are a direct subset of the natural, cultural and special classes. Users can view the description of categories of tourist destinations by tapping text tap categories. The front-end application will send location data and the level of user interest through the HTTP protocol.

5. Performance and User Satisfaction Evaluation

Evaluation were conducted on tourism experts and end users, so the parameters evaluated in both evaluation were different. The purpose of evaluating to experts and users is to evaluate the level of accuracy of the system from the expert and users' point of view and the level of user satisfaction.

5.1. Recommendation Accuration Evaluation

Evaluations to get the accuracy of recommendations provided involve tourism experts and regular users. Scenarios used in accuracy evaluating involving experts with regular users. System accuracy evaluation with experts was performed using precision parameters to measure the relevance of recommendations [10] [11]. Equation (6) is used to measure recommendation precision.

$$precision = \frac{TP}{TP + FP} \tag{6}$$

while TP (true positive) is the right tourist destination with full category travel preference and FP (false positive) is a less suitable tourist destination. Evaluation scenario is shown on Table 6.

Table 6. Evaluation Scenario With Expert

No	User location	Local time	Weather	Preference Evalution No.
1	Alun-alun cimahi	09:00	Good	1
2	Alun-alun cimahi	09:00	Poor	1
3	Alun-alun cimahi	09:00	Very Bad	1
...	...	...	...	...
13	Jl. Setiabudhi Bandung	13:00	Good	2
...	...	...	...	...
27	Jl. Buah Batu Bandung	18:00	Very Bad	3

There are 27 cases of system accuracy evaluating with experts. 27 cases that use three different locations as the location of the user when using the application. In each location there are three times of application usage evaluating, which is 9 am, 1 pm and 6 pm and at each evaluation time there are three times the weather changes.

The preference evaluation number is the number in the preference case table that is the input of the system. Preference evaluation number corresponds to application time usage, e.g evaluation number 1 for clock 9, evaluation number 2 for clock 13 and so on. Preference evaluation number refers to table 7. Table 7 is a table of user preference cases used as input.

Table 7. Preference Evaluation Cases

Preference Evaluation No.	Tourist destination category	Preference level
1	Adventure	Very interested
	Flora fauna	Interested
	Scenic beauty	Interested
	Coastal and water areas	Interested
	Economic activity	Less interested
2	Entertainment	Interested
	Event	Interested
	Sport	Interested
	Shopping center	Interested
	Culinary	Very interested
	Theme parks	Very interested
	Cultural facilities	Very interested
	Arts	Very interested
	Cultural sites	Very interested
3	Entertainment	Very interested
	Sport	Interested
	Shopping center	Very interested
	Culinary	Interested
	Art	Interested
	Urban tourism	Very interested

The steps taken for evaluating recommender system with experts are as follows,
- We ran the system according to scenario at Table 6 and get system output data.
- We submitted the system output data to the expert.
- Expert evaluated system output data.
- Evaluation result was processed with equation (6).

The precision mean from evaluating 27 system output results is 0.94. Precision based on weather system is shown in Figure 4.

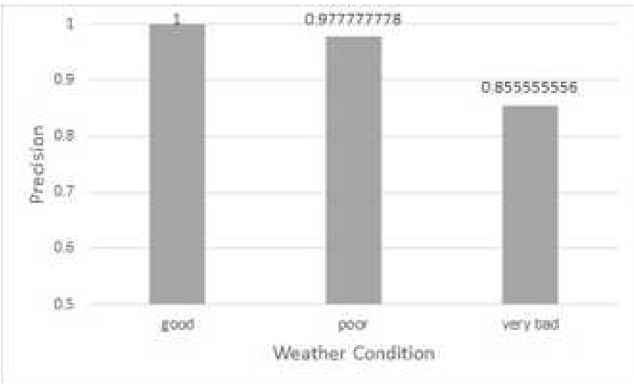

Figure 4 Precision Mean Group by Weather Condition

Precision of tourist destination recommendation is declining along with worsening weather. This is happened because the result of equation (5) is decreased if the wi value increases. However, the precision recommendations of tourist destinations during very bad weather can still be said to be quite high. Logically, the precision of the very bad weather should be lower, as searching for a destination that fits the user's preferences and the weather at the destination is still good is difficult when the actual weather is categorized as very bad. While the mean system precision based on application usage time is shown in Figure 5.

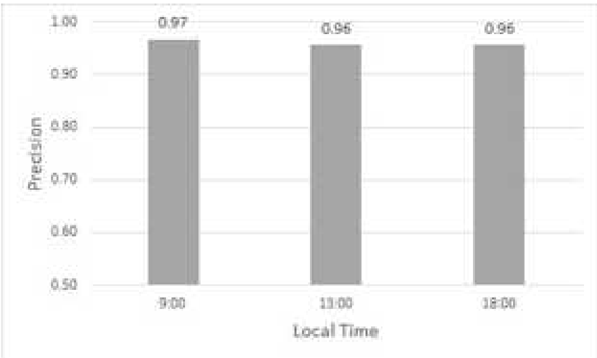

Figure 5. Precision Mean Group by Local Time

Recommendation precision declined with the passing of the day, although not significant. The cause of insignificant precision decline is due to the adjustment of the preference evaluation number to the local time. For example, preference evaluation number one and two are preference case for tourist destination category that have the majority of tourist destinations open in the morning until late afternoon. While the preference evaluation number three is preference case skewed towards tourist destination categories that have majority of tourist destination open until the evening.

System accuracy evaluation involving the ordinary user is done implicitly, it means the accuracy obtained through analysis of user activity [12]. The calculation of the recommendation accuracy to the user is calculated by the equation (7) [12].

$$accuracy = \frac{number\ of\ successful\ recommendations}{number\ of\ recommendations} \tag{7}$$

Each user requests travel attraction recommendations through the app at least once. The application will count the number of times the user requested a recommendation and how many times the user chose the tourist destination in the recommendation list. The number of recommendation requests will be incremented each time the user requests a recommendation and the number of successes will increase by one if the user selects one of the destinations from the list of recommended travel destination recommendations

5.2. User Satisfaction Evaluation

To measure the level of user satisfaction, there are several evaluation parameter was used. The evaluation parameters used are perceived recommendation quality (PRQ), usability (USA), informative (INF), perceived efficiency (PE) and trust (TR). The five user satisfaction parameters have been used in previous studies that examined the recommender system for recommending smartphones [12].

In user satisfaction evaluating, users will be asked to fill out a questionnaire after requesting a destination recommendation through an app at least once. Table 8 contains a list of statements in the questionnaire given to the user after using the application.

Table 8. Questionnaire Statement List [12]

No	Factor	Statement
1	PRQ	I love the tourist destination I chose from the recommendation list.
2	PRQ	I like the application interaction.
3	INF	I think the tourist destination description on recommendation list is quite informative.
4	USA	I have difficulty while using the application
5	PE	I can find a tourist destination i like quickly.
6	TR	I will use this app if I want to travel in Bandung.

There were 63 respondents using front-end application we developed. Respondents come from various backgrounds ranging from students, lecturers to ordinary citizens. Sampling of respondents was done randomly. User satisfaction evaluation results can be seen in Figure 6.

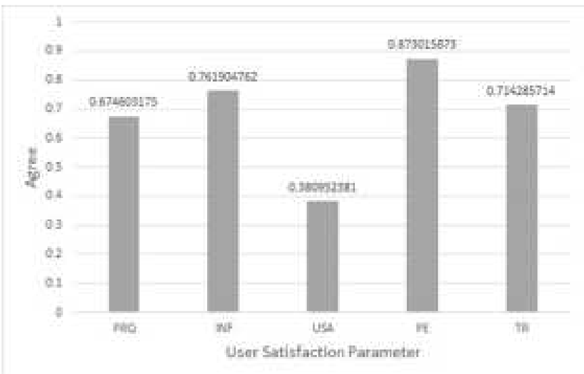

Figure 6. User Experience Questionnaire Result

On the perceived recommendation quality (PRQ) measurements, 67% of users agree that they like the tourist destinations on the recommendation list. PRQ score is still low because there are most users are not quite familiar with the delivery of tourist destination description. It is seen in the evaluation results of INF parameters. Not much different from the PRQ parameter evaluation results, 76% of users agreed that the description of the destination is informative enough (INF). This result is close to the result of PRQ parameter evaluation. Front-end application is still not easy to use. It is proved that 38% of users still encounter difficulties when using the application, the results of usability (USA) parameter evaluation.

Users can find the preferred tourist destination quickly. It is proven that 87% of users stated that they can find their preferred travel destination quickly (perceived efficiency / PE). This parameter gets the highest result because this application only takes three steps to get recommendation of destination. The three steps are clicking the user preference button, select the level of preference for a particular tourist destination category and choose a recommended travel destination. The result of the user trust (TR) parameter evaluation is 71% of users stated that they want to use this app if they want to travel in Bandung.

6. Conclusion

The general classification system in the tourism domain is discussed in the main reference [7] can be converted into a functional ontology model to represent knowledge in the tourism domain. The accuracy of the system is based on evaluating with high experts (overall reaching 0.94) so that the built system has been able to provide appropriate recommendations according to user preferences, but the accuracy of the system based on evaluating with the user is much lower (only 0.58) because it is influenced by high user dissatisfaction with the application (38% of users said the app is hard to use).

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