Travel Destination Recommendation Based on Probabilistic Spatio-temporal Inference

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Abstract. Recently, a lot of users are increasing for searching travel information through smart devices such as, tourist attractions, accommodation, entertainment, local gourmet food and so on. A general method for recommendation system has a data sparseness and the first rate problem. This problem can be solved by ontology and inference rules. In this paper, we propose the travel destination recommendation using Markov Logic Networks based on probabilistic spatio-temporal inference. The most inference engines determine simply if there is a result from inference or not. However, probabilistic inference methods have emerged and classified problems that cannot be defined easily in the probabilistic way, which provides better results.

Keywords: Recommendation system · Ontology · Markov Logic Networks

1 Introduction

The information retrieval for travel destination has become commonplace through smart devices due to the development of IT technology. A travel destination is the most important factor and travel information is consists of tourist attractions, accommodation, entertainment, local gourmet food. Many researches have been studied about travel destination recommendation using personalized information based on user preference. Also, there have been studied the recommendation method using social data [1]. A lot of recommendation systems are built to use the historical data and the profile file. Generally, the collaboration filtering algorithm is used in recommendation system but this approach will suffer from the problem of data sparseness and the first rate problem. Another method is the content based recommendation method. This method provides recommendation for users by comparing the representation content in list. However, content based recommendation method is needed more effort on extraction of content list [2]. This problem can be solved by ontology and inference rules.

In this paper, we propose the travel destination recommendation using Markov Logic Networks based on probabilistic spatio-temporal inference. The travel ontology

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building used our previous work between object movement information and vocabulary based on spatio-temporal relation. In this case, spatio-temporal relation consist of temporal relation depending on the passage of time, directional relation depending on changes of object movement direction, changes of object size relation, topological relation depending on changes of object movement position, and velocity relation using concept relations between topology models. To this end, ontology building part defines the inference rules using proposed spatio-temporal relation and the use of Markov Logic Networks (MLNs) for probabilistic reasoning [3]. Travel Destination information is consists of accommodation, restaurant, activities and so on in Jeju (located in the Southern Korea, is famous for a volcanic Island) [9].

2 Previous Work

2.1 Travel Destination Recommendation

This proposal has been extended from the previous intelligent recommendation system architecture based on travel ontology [2] in order to give efficient recommendations to the tourists throughout their trip without getting any help from travel agency. The system's ontology used the tourist attraction places, available hotels and sight-seeing spots in Jeju Island in Korea. According to those properties and relationships of the ontology, the system provides the most relevant information and destinations upon what the user needs [10, 11]. The previous travel recommendation system architecture consists of three parts. Firstly, the metadata which holds the user information such as user's preference profile and transaction must be collected since most of the recommendation systems are depending on the stored records of what the users have been gone or what the users have visited, and the record of their feedbacks for the places they visited. Secondly, the information repository of ontology for the recommendation system takes place which was built based on the information in Jeju. Finally, the recommendation agent preserves the visualization of recommendation service to the user on AIMap.

2.2 Probabilistic Spatio-temporal Inference

The proposed probabilistic spatio-temporal inference using spatio-temporal relation and MLN for probabilistic reasoning [3], which is used to detect the motion of moving object in previous work, will be applied to build travel ontology. The method indicates the object movement in a vocabulary form as high-level information according to the specific relations such as temporal relation which relies on the passage of time, directional relation which depends on the object movement direction, object size relation, velocity relation depending on the changes in speed of moving object, and topological relation relies object movement position. The proposed spatio-temporal relation used Markov Logic Networks for inference rules to obtain the probabilistic reasoning.

The integration of temporal flow with factors of spatial characteristics; temporal relation of object, directional relation, size relation of the object and velocity relation, is the ideal of the spatio-temporal relation model. The model can be expressed based on the movement of the object which coordinates are defined as top, bottom, left and right. The rules of topology between the objects can be drawn in inference rules and the movement of object has 13 rules for each Y-coordinate and X-coordinate respectively. Thus, the spatio-temporal relations are classified to the total of 241 models. All those movements can be classified as “equal”, “inside”, “cover”, “overlap”, “meet”, “disjoint”, “covered-by”, and “contains”, according to M.J. Egenhofer’s proposal. The ontology was built to seek the object relation patterns for sharing and distributing as training set. Eventually, the verified probabilistic inference of the object relation was executed to verify spatio-temporal relation.

3 The Method of Travel Destination Recommendation

3.1 Extended Jeju Travel Ontology

In this paper, Jeju travel ontology is extended from previous Jeju travel ontology [2]. Domain and related classes of extended ontology can be seen in Table 1.

Table 1. Extended Jeju travel ontology

Domain	Classes
Travel Type	Experience activity, Leisure Sports, Healing/Natural Recreation Forest
Accommodation	Hotel, Resort/Condominium, Pension, Motel, Tourist home, Guest house
Restaurant	Korean food, Japanese food, Chinese food, Western food, Local food, Vegetarian
Location Information	Jeju City, Western Jeju City, Eastern Jeju City, Seogwipo, Western Seogwipo, Eastern Seogwipo, Hallasan National Park
Travel Member	Family, Couple, Single, Friend, Team
Shopping	Local specialty market, Traditional Market, Duty-free shop

According to Table 1, the information for Travel Type Domain is collected from the previous Jeju travel ontology, while the other domains and classes are newly extended into the system. More importantly, the location information domain plays as an essential role in travel destination recommendation and it consists of 6 regions such as, Jeju City, Western Jeju City, Eastern Jeju City, Seogwipo, Western Seogwipo and Eastern Seogwipo. Figure 1 indicates seven regions of Location Information.

The proposed travel destination recommendation system provides a different weight according to the regions based on user’s current location. But the Travel member domain contains five categories such as Family, Couple, Single, Friend, and Team. By discriminating the type of traveler group, the recommendation system should offer more accurate suggestions to the travelers. For instance, the museum of Sex & Health is an inappropriate place to visit in Jeju for a group of family members. The Shopping domain consists of three different types such as Local specialty market, Traditional Market, Duty-free shop.

Fig. 1. Classification of location information

3.2 Probabilistic Spatio-temporal Inference

MLN is a language for probabilistic inference that is based on first-order logic and probability model for artificial intelligence. This is expressed in the form of first-order logic [4]. In addition, MLN is used to express semantic method using Markov network and provide logic and probability-based inference [5]. MC-SAT [6], which is used in the MLN, is algorithm that performs learning based on Markov Chain Monte Carlo Algorithms. The algorithm enables extracting sample at a specific stage before clarifying difference in weight value within margin of error where such extracted sample can be accepted, which facilitates classification [7]. Actually, it is necessary to transform description logic rules, which are defined in ontology, to the form of first-order logic for applying of the MLN [3]. Table 2 shows transformation of Description Logic Rules to First-order Logic.

Table 2. Transformation of description logic rules to first-order logic

Description logic	First-order logic
SubClassOf (equal, equal)	∀x: equal(x) => equal(x)
ClassAssertion (spatio-temporal relation, topological relation)	Spatio-temporal relation (topological relation)

Table 3 shows the rules for inference based on Probabilistic Spatio-temporal Inference. According to the table, X, Y and Z are sets of our instances and properties for inference in the extended Jeju travel ontology. Set X is the list of locations of Location Information domain which consists of 7 different regions from Jeju. And Set Y is Travel Member domain consisting of 5 different types as we mentioned in Sect. 3.1. Finally, Set Z is the most common travel destinations in Jeju and it consists of 115 places.

For Rules for inference, there are basically four rules in to distinguish and to predict the definition of destination recommendation system [12]. If the domain of Location Information (X) intersects with Travel Member (Y), the suggestion definition will be

Table 3. Rules for probabilistic spatio-temporal inference

Rules for Inference
Definition
X = { Jeju City, Western Jeju City, Eastern Jeju City, Seogwipo, Western Seogwipo, Eastern Seogwipo, Hallasan National Park }
Y = { Family, Couple, Single, Friend, Team }
Z = { Banglimwon, Drama World, Aqua Planet Jeju, World Seashell Museum, Bonte Museum, Nexon Computer Museum, The Museum of Sex & Health in Jeju, …} 115 cases
Rules
$\forall$X,Y : Location(X) ∧ Travel_Member(Y) → Preference_1(X,Y)
$\forall$X,Z : Location(X) ∧ Travel_Destination(Z) → Preference_2(X,Z)
$\forall$Y,Z : Travel_Member(Y) ∧ Travel_Destination(Z) → Preference_3(Y,Z)
$\forall$X,Y,Z : Preference_1(X,Y) ∧ Preference_2(X,Z) ∧ Preference_3(Y,Z) → Recommendation(X,Y,Z)

Preference_1, while the Location Information domain (X) intersects with Travel Destination (Z), the system will produce a suggestion as Preference_2. Moreover, if Travel Member domain (Y) intersects with Travel Destination (Z), the system will produces Preference_3 for the definition. On the other hand, preference 1, 2 and 3 intersect with each other together, the prediction definition will be Recommendation (X,Y,Z).

4 Experiment and Evaluation

In general, inference for ontology is performed by using ontology inference engine. There are a variety of inference engines such as Jena, FOWL, Pellet, and Fact++. These inference engines simply determine whether there is a result from inference or not. Recently, probabilistic inference methods such as the MLNs have emerged and classified problems that cannot be defined easily in the probabilistic way, which provides better results. Against this background, this paper intends to use probabilistic inference method with use of the MLNs, rather than the existing ontology inference engine, for conduction of experiment [2].

This proposal evaluates the inference results of travel destination recommendation which is slightly similar to Disaster Information Sharing system [8]. In experiment, Scenario is as follows: (1) User's current location information assumes staying in Eastern Seogwipo. (2) Also, user is alone and he wants to search travel destination. Totally, travel destination consists of 115 cases and some of the experimental results are shown in Table 4.

Table 4 shows the probabilistic results depending on weight values and probabilistic results is values between 1.0 and 0.5. When inference result exists in Table 4, result value is higher than around 0.5 because the sampling value p = 0.500000. It means that the first probability value is 0.5. In order to obtain result from learning, the test was performed 1000 times.

In Table 4, the place is Eastern Seogwipo between case number 1 and case number 7. And the place is neighborhood Eastern Seogwipo between case number 7 and case number 11. According to the results, the performance is satisfactory.

Table 4. Experiment results for travel destination recommendation

No.	Probabilistic result	Place
1	0.629	Seongsang Ilchulbong
2	0.627	Seopjikoji
3	0.626	Micheon Cave
4	0.623	Seongeup Folk Village
5	0.621	Jeju Horse Park
6	0.619	Jeju Land ATV
7	0.619	Jeju Folk Village
8	0.570	Jeju National Museum
9	0.567	Jeju April 3rd Peace Park
10	0.563	Seokbujak Museum
11	0.562	Jeongbang Waterfalls
…	…	…

5 Conclusion

This proposed method for travel destination recommendation system has been extended from the previous proposal in order to provide the travelers with more accurate suggestions to the closet and relevant destination from user's current location and to improve the travelling experience at ease. In this paper, the travel destination recommendation system is extended by using Markov Logic Networks based on probabilistic spatio-temporal inference. The extended travel ontology is built from our previous work. In building ontology section, we define the inference rules using proposed spatio-temporal relation and the use of Markov Logic Networks (MLNs) for probabilistic reasoning. Our future study will be focusing on extending of travel information domain and improving the suggestion accuracy with weight values.

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