Voyage Organization for Combination of Fortuitous

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ABSTRACT

As the worlds of commerce, entertainment, travel, and Internet technology become more inextricably linked, new types of business data become available for creative use and formal analysis. Recent years have witnessed an increased interest in recommender systems. Conventional models present their topics to users, user must select the uploaded data only. Indeed, this project provides a study of exploiting online travel information for personalized travel package recommendation. In this project, we first analyse the characteristics of the existing travel packages and develop a tourist-area-season topic (TAST) model.we propose a new approach to generate the lists for personalized travel package recommendation. Furthermore, we extend the TAST model to the tourist-relation-area-season topic (TRAST) model for capturing the latent relationships among the tourists in each travel group. Finally, we evaluate the TAST model, the TRAST model, and the novel recommendation approach on the real-world travel package data.

I.INTORDUCTION

Data mining is the process of extracting patterns from data. Data mining in general is the search for hidden patterns that may exist in large databases. Data Mining scans through a large volume of data to discover patterns and correlations between patterns. Data mining is becoming an increasingly important tool to transform this data into information. Data mining involves the use of sophisticated data analysis tools to discover previously unknown, valid patterns and relationships in large data sets. Consequently, data mining consists of more than collecting and managing data, it also includes analysis and prediction. Data mining can be performed on data represented in quantitative, textual, or multimedia forms. Data mining applications can use a variety of parameters to examine the data. They include association (patterns where one event is connected to another event, such as purchasing a pen and purchasing paper), sequence or path analysis (patterns where one event leads to another event, such as the birth of a child and purchasing diapers), classification (identification of new patterns, such as coincidences between duct tape purchases and plastic sheeting purchases), clustering (finding and visually documenting groups of previously unknown facts, such as geographic location and brand preferences), and forecasting (discovering patterns from which one can make reasonable predictions regarding future activities, such as the prediction that people who join an athletic club may take exercise classes).Data Mining tools predict future trends and behaviors. The Data Mining Tool will contain different tasks. The prime functionality of the task will be analyzing the data and generate the results. Data mining tools need to be versatile, scalable, capable of accurately predicting responses between actions and results, and capable of automatic implementation. Data mining has become increasingly common in both the public and private sectors. Organizations use data mining as a tool to survey customer information, reduce fraud and waste, and assist in medical research. The process of data mining consists of three stages: (1) the initial exploration, (2) model building or pattern identification with validation/verification, and (3) deployment (i.e., the application of the model to newdata in order to generate predictions). Data Mining is commonly used in a wide range of profiling practices, such as marketing, Surveillance, fraud detection and scientific discovery. An important concept is that building a mining model is part of a larger process that includes everything from defining the basic problem that the model will solve, to deploying the model into a working environment.

II. RESEARCH WORK:

Data mining consists of five major elements: Extract, transform, and load transaction data onto the data warehouse system. Store and manage the data in a multidimensional database system. Provide data access to business analysts and information technology professionals. Analyze the data by application software. Present the data in a useful format, such as a graph or table.

There are many technical and domain challenges inherent in designing and implementing an effective recommender system for personalized travel package recommendation. Travel data are much fewer and sparser than traditional items, such as movies for recommendation, because the costs for a travel are much more expensive than for watching a movie. Every travel package consists of many landscapes (places of interest and attractions), and, thus, has intrinsic complex spatio-temporal relationships. For example, a travel package only includes the landscapes which are geographically collocated together. Also, different travel packages are usually developed for different travel seasons. Therefore, the landscapes in a travel package usually have spatial temporal autocorrelations. Traditional recommender systems usually rely on user explicit ratings. However, for travel data, the user ratings are usually not conveniently available. Recommendation has a long period of stable value. To replace the old ones based on the interests of the tourists. A values of travel packages can easily depreciate over time and a package usually only lasts for a certain period of time.

III. Approaches to Recommendation System

Recommender systems have been generally classified, according to the way in which they analyze the information of the user and filter the list of items, into content-based, collaborative and hybrid systems.

1. Content based Recommendation System (CB)

Content-based (CB) systems calculate a degree of similarity between the users and the items to be recommended. The inspiration of this kind of recommendation methods comes from the fact that people have their subjective evaluations on some items in the past and will have the similar evaluations on other similar items in the future. This process is carried out by comparing the features of the item with respect to the user's preferences. So, it is assumed that both users and alternatives share a common representation (e.g., they are composed of the same set of attributes or keywords). The output of the comparison process is usually an overall performance score, which indicates the degree of matching between the user's profile and each alternative. The higher the score is, the higher the performance of the alternative for a given user. Sometimes these methods also take into account the rating history of the user. In this approach, the recommendation system relies on having an accurate knowledge of the user's preferences to be able to select the appropriate items. This kind of approaches may suffer from the ''cold start'' problem when a new user enters in the system, because we can elicit poor knowledge about the user in an initial stage. For CB recommender systems, it is important to learn user's profiles. Various learning approaches have been applied to construct profiles of users. For example – a statistic-based approach is used to build user's profile to recommending Web pages; a reinforcement learning method was employed for Book recommendations.

2. Collaborative Filtering Recommendation System (CL)

Collaborative filtering systems make recommendations based on groups of users with similar preferences. The similarity between users is normally computed by comparing the ratings that they give to some of the items. When the system identifies who are the people that share similar interests with the current user, then the items that those people liked are recommended to this user. In this approach, some feedback about the provided recommendations is necessary, so as to know which items the user has liked or disliked (e.g. which places she has enjoyed visiting).For the reason that CF methods do not require well-structured item descriptions, they are often implemented than CB methods and many collaborative systems are developed in academia and industry. There are two types of CF approach namely – user-based and item-based. The basic idea of user-based CF approach is to provide recommendation of an item for a user based on the opinions of other like-minded users on that item. The user-based CF approach initially finds out a set of nearest "neighbors"(similar users) for each user, who share similar interests or favorites. Finally, based on the ratings given by the user's "neighbors" on the item, the rating of a user on an unrated item is predicted. The basic idea of item-based CF approach is to provide a user with the recommendation of an item based on the other items with high correlations. The item based CF approach first finds out a set of nearest "neighbors"(similar items) for each item. The item based CF try to predict a user's rating on an item based on the ratings given by the user on the neighbors of the target item. For both user-based CF and item-based CF, to find similarity of measurement between users or items is a significant step. Pearson correlation coefficients, cosine-based similarity, vector space similarity, distance based similarity and so on are widely used as similarity measurement in CF methods.

3. Typicality based Collaborative Filtering approach for recommendation system

This is new approach for recommendation system in which the problems like data sparsely, accuracy in prediction are addressed. System adopts this idea from cognitive psychology in which find "neighbors" of users based on user typicality degrees in user groups (instead of the curated items of users, or common users of items, as done in traditional CF) and predict the ratings. It gives better performance, more accurate results and takes lower time cost [1]. The mechanism of typicality-based CF recommendation is as follows: First, cluster all items into several item groups. Second, form a user group corresponding to each item group (i.e., a set of users who like items of a particular item group), with all users having different degree of typicality in each of the user groups. Third, build a user-typicality matrix and measure user's similarities based on user's typicality degrees in all user groups so as to select a set of "neighbors" of each user. Then, predict the unknown rating of a user on an item based on the ratings of the "neighbors" of at user on the item.

4. Hybrid Recommendation System

Several recommender systems use a hybrid approach by combining collaborative and content based methods, to avoid some limitations of content-based and collaborative systems. A hybrid approach initially implement collaborative and CB methods separately and then combines their predictions by a linear combination of ratings or a voting scheme or other metrics.

Hybrid systems can integrate these techniques in different ways. Three approaches can be distinguished:

1. Selection of the method: The system incorporates DM, CB and CL methods, but only one of them is applied depending on the particular situation of each user.

2. Sequential use: Each recommendation technique is used in different stages of the process. Once the model has been trained, CB techniques generate the list of recommendations by computing ratings for each item based on the current and predicted values.

3. Integrated use: Both CB and CL techniques are combined during the execution. For hybrid recommender systems it is also possible to combine item-based CF and user-based CF.

IV.PROPOSED SYSTEM

A. TAST MODEL

Here develop a tourist-area-season topic (TAST) model, which can represent travel packages and tourists by different topic distributions. In the TAST model, the extraction of topics is conditioned on both the tourists and the intrinsic features (i.e., locations, travel seasons) of the landscapes. As a result, the TAST model can well represent the content of the travel packages and the interests of the Travel package recommendation tourists. Based on this TAST model, a cocktail approach is developed for personalized travel package recommendation by considering some additional factors including the seasonal behaviors of tourists, the prices of travel packages, and the cold start problem of new packages. In this work study some related topic models of the TAST model, and explain the corresponding travel package recommendation strategies based on them.

B. TRAST MODEL

We propose the tourist-relation-area-season topic (TRAST) model, which helps understand the reasons why tourists form a travel group. This goes beyond personalized package recommendations and is helpful for capturing the latent relationships among the tourists in each travel group. In addition, we conduct systematic experiments on the real world data. These experiments not only demonstrate that the TRAST model can be used as an assessment for travel group automatic formation but also provide more insights into the TAST model and the cocktail recommendation approach. Case-based recommenders implement a particular style of content-based recommendation that is very well suited to many travel recommendation scenarios. They rely on items or products being represented in a structured way using a well-defined set of features and feature values; for instance, in a travel recommender a particular vacation might be presented in terms of its price, duration, accommodation, location, mode of transport, etc. In turn the availability of similarity knowledge makes it possible for case-based recommenders to make fine grained judgments about the similarities between items and queries for informing high-quality suggestions to the user. Case-based recommenders borrow heavily from the core concepts of retrieval and similarity in case-based reasoning. Items or products are represented as cases and recommendations are generated by retrieving those cases that are most similar to a user's query or profile. For instance, when the user submits a target query—in this instance providing a relatively vague description of their requirements in relation to camera price and pixel resolution—they are presented with a ranked list of k recommendations which represent the top k most similar cases that match the target query. As a form of content-based recommendation case-based recommenders generate their recommendations by looking to the item descriptions, with items suggested because they have similar descriptions to the user's query. To evaluate the similarity of non-numeric features in a meaningful way requires additional domain knowledge. For example, in a vacation recommender it might be important to be able to judge the similarities of cases of different vacation types. Is a skiing holiday more similar to a walking holiday than it is to a city break or a beach holiday? One way to make such judgments is by referring to suitable domain knowledge such as ontology of vacation types. In this way, the similarity between two arbitrary nodes can be evaluated as an inverse function of the distance between them or the distance to their nearest common ancestor. Accordingly, a skiing holiday is more similar to a walking holiday (they share a direct ancestor, activity holidays) than it is to a beach holiday, where the closest common ancestor is the ontology root node.

V. BASIC TECHNIQUES OF TRAVEL PACKAGES

A. Modified K-Means Clustering (MKC)

In recent years the major concern in to research domain of ITS. In MKC approach the clustering methods are used [4]. In Clustering strategy to discover hidden knowledge. The hidden knowledge of clustering that can easily applied on histocalculate accurate travel time in our modified Kclustering approach. A set of historical data is portion group of meaningful subclasses or clusters based on travel time, frequency of travel time and velocity for specific road sand time group [5]. With use of same set of historical travel time estimates, compression is also made to the forecasting results of other three methods successive moving average (SMA), Chain Average (CA), and NBC method. Travel time prediction is traffic flow and occupancy which are extremely sensitive to external event like weather condition and traffic incident [3]. Addressing the uncertainty on the road network is also a crucial issue in the re-search domain. Prediction on situation is very complex, so it is important to reach optimal accuracy. Yet, the structure of the traffic flow of a specific road net-work fluctuates based on daily, weekly and occasional events. For example, the traffic condition ofweekend may differ from that of weekday. So, time feature of traffic flow is one of the major issues to estimate accurate travel time [12].

In this study, we focus a new method that is able to predict travel time reliably and accurately. Generally this effort is the extension of our previous works. In this rewe have tried to combine the advantages of our previous methods namely NBC [12], SMA and CA [13] by eliminating the shortcomings of those methods. Proposed MKC method is able to address the arbitrary route on road networks that is given by user. Furthermore proposed method flushfunctional relationship between traffic data as input variables and predicted travel time as the output variables. According to the experimental result, our method exhibits satisfactory performance in terms of prediction accuracy. At the same time, the result is considered to be superior rather than other prediction methods like NBC, SMA and CA. Travel time prediction forms an integral part of any ATIS. The grouping style of whole day is efficiently and effectively done by NBC. But a significant problem will arise when we calculate velocity level for a particular route. Moreover, this method emphasize on those data whose probabilities are higher.

B. Collaborative Filtering

These techniques are used in the earliest and most researched recommender systems for travel packages collaborative a social filtering, these algorithms focus on the behavior of users on items, which are to be recommended, rather than on the internal nature of the items themselves. The social approach means, “real-life recommendations”. Approach algorithms have a semantic attraction concept of collaborating individuals and the process of find persons with similar interest of travel packages seasons [8].

In modern trend, more and more travel companies provide online services using social networks. However, the rapid growth of online travel information imposes an increasing challenge for tourists who have to choose from a large number of available travel packages for satisfying their personalized needs and adjustment. Moreover, to increase the profit, the travel companies have to understand the preferences from different tourists and serve more attractive pack the travelling peoples. Therefore, the demand for intelligent travel services is expected to increase significantly recommender systems have been successfully applied to enhance the quality of service in a number of fields, it is natural choice to provide travel package recommendations peoples. In the face of the increasing interests in this field, the problem of leveraging unique features to distinguish personalized travel package recommendations from traditional recommender systems remains pretty open. Indeed, there are many technicalanddomain challenges inherent in designing and implementing an effective recommender system for personalized travel package recommendation [9] data are much fewer and sparser than traditional items, such as y differ from that of weekday. So, time-varying feature of traffic flow is one of the major issues to estimate In this study, we focus a new method that is able to predict travel time reliably and accurately. Generally this t is the extension of our previous works. In this re-search, we have tried to combine the advantages of our previous methods namely NBC [12], SMA and CA [13] by eliminating the shortcomings of those methods. Proposed MKC method is raryroute on road networks that is given by user. Furthermore proposed method flushes a tween traffic data as input variables and predicted travel time as the output variables. According to exhibits satisfactory performance in terms of prediction accuracy. At the same time, the result is considered to be superior rather than other Travel time prediction forms an integral part of any style of whole day is efficiently and effectively done by NBC. But a significant problem will arise when we calculate velocity level for a particular route. Moreover, this method emphasize on those data whose he earliest and most for travel packages. In a social filtering, these algorithms focus on the behavior of users on items, which are to be recommended, generals. The life recommendations”. In social attraction to both and the process of find travel packages for particular trend, more and more travel companies

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Moreover, to increase the profit, the travel companies have to understand the preferences from different tourists and serve more attractive packages for. Therefore, the demand for intelligent significantly. Since recommender systems have been successfully applied to enhance the quality of service in a number of fields, it is voice to provide travel package recommendations by the increasing interests in this field, the problem of leveraging unique features to distinguish personalized travel package recommendations from traditional aims pretty open. Indeed, there are many technical and domain challenges inherent in designing and implementing an effective recommender system for [9]. First, travel all items, such as movies for recommendation, because the costs for a travel are much more expensive than for watching a movie. Second, every travel package consists of many attractions, and, thus, has inherent relationships. For example, a travel package only includes the landscapes which are geographically, different travel packages are usually developed for different travel seasons. Therefore, the attractions in a travel package usually have spatial temporal autocorrelations. Third, traditional recommender systems usually rely on user explicit ratings. However, for travel data, the user ratings are usually not conveniently available.Finally, the traditional items for recommendation usually have a long period of stable value, while the values of travel packages can easily depreciate over time and a package usually only lasts for a certain period of time. The travel companies need to actively create replace the old ones based on the interests of the tourists. Along this line, travel time and travel destinations are divided into different seasons and areas.

C. Tourist-Area-Season Topic model

TAST model which represent travel tourists by different topic distributions. In the TAST model, the extraction of topics is conditioned on both the tourists and the basic features (i.e., locations, travel seasons) of the landscapes. As a result, the TAST model can well represent content of the travel packages and the interests of the tourists. Based on this TAST model, a cocktail approach is developed for personalized travel package recommendation by considering some additional factors including the seasonal behaviors of tourists, the prices of travel packages, and the cold start problem of new packages. The TAST model divided into here parts, first Topic (TT) model, not consider the travel area and travel season factors. The second one is the (TAT) model, which only considers the travel area. The third one is the Tourist-Season Topic (TST) model, which only considers the travel season. When designing a travel package, to assume that the people in travel companies often consider the following issues. First, it is necessary to determine the set of target tourists, the travel seasons, and the travel places. Second, one or multiple travel topics will be chosen based on the category of target tourists and the scheduled travel seasons. Each package and landscape can be viewed as a mixture of a number of travel topics. Then, the landscapes will be determined according to the travel topics and the geographic locations. Movies for recommendation, because the costs for a travel are much more expensive than for watching a movie. Second, consists of many places of interest and inherent complex spatio-temporal relationships. For example, a travel package only includes the landscapes which are geographically co-located together. Also, different travel packages are usually developed for different travel seasons. Therefore, the places of interest and a travel package usually have spatial temporal autocorrelations. Third, traditional recommender systems usually rely on user explicit ratings. However, for travel data, the user ratings are usually not conveniently available [6],[7]. Traditional items for recommendation usually have a long period of stable value, while the values of travel packages can easily depreciate over time and a package usually only lasts for a certain period of time. The travel companies need to actively create new tour packages to replace the old ones based on the interests of the tourists. Along this line, travel time and travel destinations are divided into model (TAST) represent travel packages and tourists by different topic distributions. In the TAST model, the extraction of topics is conditioned on both the tourists and features (i.e., locations, travel seasons) of the landscapes. As a result, the TAST model can well represent the content of the travel packages and the interests of the tourists. Based on this TAST model, a cocktail approach is developed for personalized travel package recommendation by considering some additional factors including the seasonal tourists, the prices of travel packages, and the cold start problem of new packages. The TAST model divided into here parts, first Tourist Topic (TT) model, not consider the travel area and travel factors. The second one is the Tourist Area Topic (TAT) model, which only considers the travel area. The third Season Topic (TST) model, which only When designing a travel package, to assume that the people in travel companies often consider the following issues. First, it is necessary to determine the set of target tourists, the travel seasons, and the travel places. Second, one or multiple travel topics will be chosen based on the category of target tourists and the scheduled travels. Each package and landscape can be viewed as a mixture of a number of travel topics. Then, the landscapes will be determined according.

VI. PROBLEM DEFINITION:

There are many technical and domain challenges inherent in designing and implementing an effective recommender system for personalized travel package recommendation. Travel data are much fewer and sparser than traditional items, such as movies for recommendation, because the costs for a travel are much more expensive than for watching a movie. Every travel package consists of many landscapes (places of interest and attractions), and, thus, has intrinsic complex patio-temporalrelationships. For example, a travel package only includes the landscapes which are geographically collocated together. Also, different travel packages are usually developed for different travel seasons. Therefore, the landscapes in a travel package usually have spatial temporal autocorrelations. Traditional recommender systems usually rely on user explicit ratings. However, for travel data, the user ratings are usually not conveniently available. Recommendation has a long period of stable value. To replace the old ones based on the interests of the tourists. Values of travel packages can easily depreciate over time and a package usually only lasts for a certain period of time we aim to make personalized travel package recommendations for the tourists. Thus, the users are the tourists and the items are the existing packages, and we exploit a real-world travel data set provided by a travels for building recommender systems. We develop a tourist-area-season topic (TAST) model, which can represent travel packages and tourists by different topic distributions. In the TAST model, the extraction of topics is conditioned on both the tourists and the intrinsic features (i.e., locations, travel seasons) of the landscapes. Based on this TAST model, a cocktail approach is developed for personalized travel package recommendation by considering some additional factors including the seasonal behaviors of tourists, the prices of travel packages, and the cold start problem of new packages. Represent the content of the travel packages and the interests of the tourists. TAST model can effectively capture the unique characteristics of travel data. The cocktail recommendation approach performs much better than traditional techniques.

VII. CONCLUSION AND FUTURE WORK

In the existing system, first develop a tourist-area season topic (TAST) model. This TAST model can represent travel packages and tourists by different topic distributions. However, in this system several issues are there to address. They are, cocktail approach disregards the specific preferences of the tourist while he/she is planning a trip, and quality of the recommendation result is decreased in this system. Thus the reliability of this recommender system is lower. In order to overcome these problems, we are proposing the combination of case based recommendation. Case-based recommendation is a form of content-based recommendation that emphasizes the use of structured representations and similarity-based retrieval during recommendation. In summary then, case-based recommendation provides for a powerful and effective form of recommendation that is well suited to many product recommendation scenarios. As a style of recommendation, its use of case knowledge and product similarity makes particular sense in the context of interactive recommendation scenarios where recommender system and user must collaborative in a flexible and transparent manner. Moreover, the case-based approach enjoys a level of transparency andflexibility that is not always possible with other forms of recommendation.

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