Survey on Travel Packages with Clustering

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Abstract- **Last few years ago a business requires travel, and sometimes that is a lot of the time for created good packages and suitable to customers. This paper provides a study of exploiting online travel information for personalized travel package recommendation. A critical challenge along this line is to address the unique characteristics of travel data, which differentiate travel packages from traditional items for recommendation. Prediction of travel time has related in the research domain of ITS. Clustering Strategy can be used as a prevailing tool of discovering hidden knowledge that can be applied on historical traffic data to predict accurate travel time. A critical challenge along this line is to address the unique characteristics of travel data, which distinguish travel packages from traditional items for suggestion. This TAST model can represent travel packages and tourists by different topic distributions. In MKC approach, a set of historical data is portioned into a group of meaningful sub-classes (also known as clusters) based on travel time, frequency of travel of travel time and velocity for specific road segment and time group. we extend the TAST model to the TRAST model for capturing the latent relationships among the tourists in each travel group. The TAST model, the TRAST model, and the cocktail recommendation approach on the real-world travel package data. TAST model can effectively capture the unique characteristics of the travel data and the cocktail approach is, thus, much more effective than traditional recommendation techniques for travel package recommendation.**

Keywords: **Tourist Relation Area Season topic (TRAST), Intelligence Transport System (ITS), Modified K-Means Clustering (MKC).**

I. INTRODUCTION

Recommender systems are commonly defined as applications that e-commerce sites exploit to suggest products and provide consumers with information to facilitate their decision-making processes. They implicitly assume that we can map user needs and constraints.

Through appropriate recommendation algorithms, like MKC, KNN, and convert them into product selections using knowledge compiled into the intelligent recommender [1]. Knowledge is extracted from either domain experts or extensive logs of previous purchases. Furthermore, the interaction process, which turns needs into products, is presented to the user with a rationale that depends on the underlying recommendation technology and algorithms [2]. For example, if the system funnels the behavior of other users in the recommendation, it explicitly shows reviews of the selected products or quotes from a similar user. Recommender systems are now a popular research area and are increasingly used by e-commerce sites. Travel recommender systems are aimed at supporting the critical travel planning decisions that the traveler will face before travel or while on-the-move. This paper provides a study of exploiting online travel information for personalized travel package recommendation. A critical challenge along this line is to address the unique characteristics of travel data, which distinguish travel packages from traditional items for recommendation. To this end, we first analyze the characteristics of the travel packages and develop a TAST model and TRAST model, which can extract the topics conditioned on both the tourists and the intrinsic features (i.e. locations, travel seasons) of the landscapes. The main objective of a travel recommender system is to ease the information search process of the traveler and to convince her of the appropriateness of the proposed services. In recent years, a number of travel recommender systems have been designed and some of them are now operational in major tourism portals.

The TAST model and the cocktail approach on real-world travel package data. The TAST model can effectively capture the unique characteristics of the travel data and the cocktail approach is thus much more effective than traditional recommendation methods for travel package recommendation. This goes beyond personalized package recommendations and is helpful for capturing the latent relationships among the tourists in each travel group. In addition, 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 [5]. In summary, the contributions of the TAST model, the cocktail approaches, and the TRAST model for travel package recommendations.

II. 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 be used as powerful tool by discover hidden knowledge. The hidden knowledge of clustering that can easily applied on historical traffic data to calculate accurate travel time in our modified K-means clustering 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 segment and 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 based on vehicle speed, 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 uncertain 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 of weekend may differ from that of weekday. So, time-varying 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 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 able to address the arbitrary route on road networks that is given by user. Furthermore proposed method flushes a functional 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. In a 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”. In social approach algorithms have a semantic attraction to both the concept of collaborating individuals and the process of find persons with similar interest of travel packages for particular 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 packages for the travelling peoples. Therefore, the demand for intelligent travel services is expected to increase significantly. Since 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 by 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 technical and domain challenges inherent in designing and implementing an effective recommender system for personalized travel package recommendation [9]. First, 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. Second, every travel package consists of many places of interest and attractions, and, thus, has 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 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 [6],[7]. 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 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 different seasons and areas.

C. Tourist-Area-Season Topic model (TAST)

TAST model which 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 basic 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 behaviors of 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 season factors. The second one is the Tourist Area Topic (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.

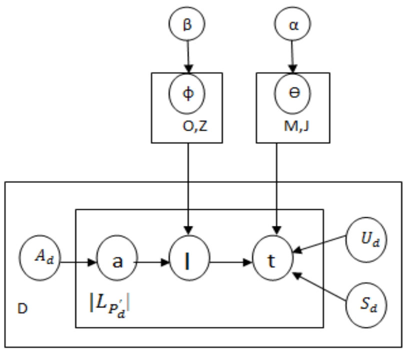

Figure 1: TAST model

Finally, some additional information like price, transportation, and accommodations should be included. Mathematically, the generative process corresponds to the hierarchical Bayesian model for TAST is shown in Fig. 2.3, where shaded and un-shaded variables indicate observed and latent variables, respectively. In TAST model, the notation P_d is different from P_d, where P_d is the ID for a package in the package set while P_d stands for the package ID of one travel log, and each travel log can be distinguished by a vector of three attributes (P_d ; U_d; timestamp), where the timestamp can be further projected to a season S_d and $P_d^{'}$. Specifically, in Fig. 1, each package P_d is represented as a vector of landscapes where landscape l is chosen from one area a and a $\in A_d$(A_d includes the located area(s) for P_d) and (U_d, S_d) is the specific tourist-season pair, t is a topic which is chosen from the set T with Z topics. Ø and θ correspond to the topic distribution and landscape distribution specific to each tourist-season pair and area-topic pair, respectively, where α *and* β are the corresponding hyper parameters. The distributions, such as Ø and θ, can be extracted after inferring this TAST model.

While the generation processes in TAST are similar to those in the text modeling problems for both documents, articles and emails , the TAST model is quite different from these traditional ones (e.g., LDA, AT, and ART models). The benefit is that the TAST model can describe the travel package and the tourist interests more precisely, because the nearby landscapes or the landscapes preferred by the same tourists tend to have the same topic. In addition, the text modeling has the assumption that the words in an email/article are generated by multiple authors, while we assume that the landscapes in the package are generated for the specific tourist of this travel log. However, each package may appear many times in the TAST model according to their records in the travel logs.

D. Cocktail recommendation approach

In cocktail approach travel package based on the TAST model, a cocktail approach a hybrid recommendation strategy and has the ability to combine many possible constraints that exist in the real-world scenarios. Specifically, firstly use the output topic distributions of TAST to find the seasonal nearest neighbors for each tourist, and collaborative filtering will be used for ranking the candidate packages [11]. Next, new packages are added into the candidate list by computing similarity with the candidate packages generated previously. Finally, it uses collaborative pricing to predict the possible price distribution of each tourist and reorder the packages. After removing the packages in TAST model are no longer active, final stage of cocktail approach recommendation list. The major computation cost for this approach is the inference of the TAST model.

In cocktail approach diagram is provide offline as well as on line service to customer and also recommended the good session for the travelling for particular area and tourist packages as shown in fig 2. As the increase of travel records, the computation cost will increase. However, since the topics of each landscape evolves very slowly, in cocktail approach.

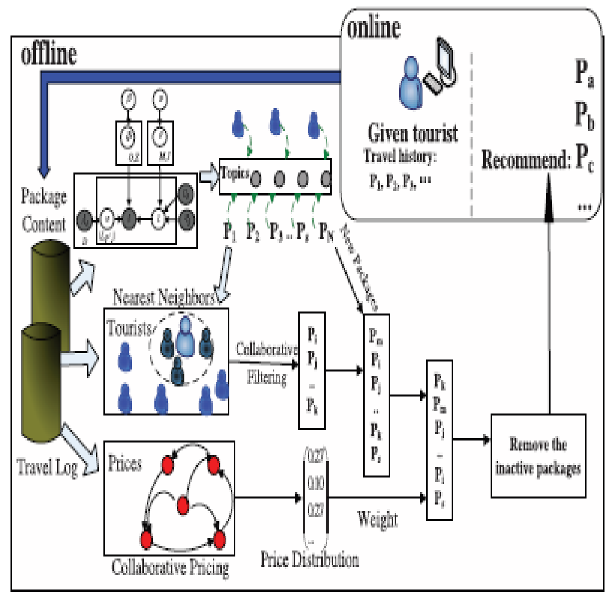

Figure 2: Cocktail approach model

III. PROPOSED SYSTEM

A Tourist-Area-Season-Topic (TAST) model can represent travel packages and tourists by different topic distribution as per customer requirement and suitable to customer. The TAST model can well represent the content of the travel packages and the interests of the tourists and search best option to the customer as per suitable to customer requirements. Based on the TAST model we propose a cocktail approach which follows recommendation strategy. The TAST model generates travel packages for different topic to the suitable to customer. We also extend the TAST model to the Tourist-Relation-Area-Season Topic (TRAST) model for developing the travel group among the tourist. TRAST model is use for searching the suitable season to the customer and recommend the best package to the customer.

Apriori algorithm is show the frequent item set mining for customer transaction and association rule learning over transactional databases is shows the best packages for suitable season. Apriori algorithm identifying the frequent individual items in the database and extending them to larger and larger item sets as long as those item sets appear sufficiently often in the database. The frequent item sets determined by Apriori can be used to determine association rules which highlight best package using the database. Apriori is designed to operate on databases containing transactions for the customer packages. The number of packages available to the customer and customer are search best packages, using apriori algorithm customer can easily search the best option and best package. In apriori algorithm is applied in o the database of the recent transaction and show he best option to the customer for travel also showing suitable season option to the customer.

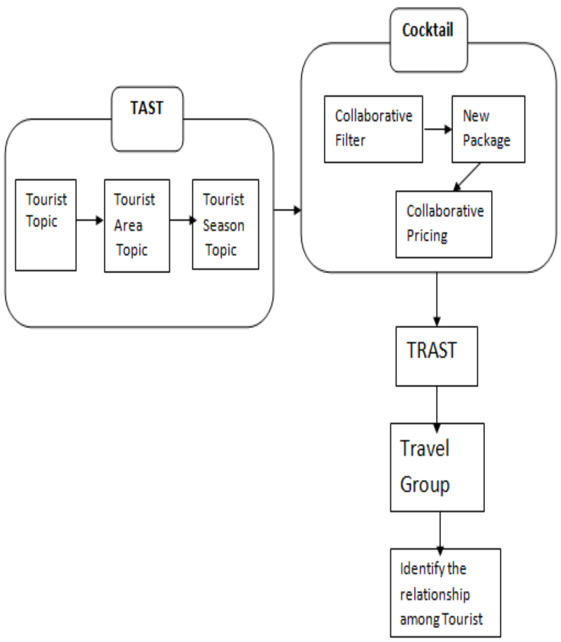

Figure 3: Proposed System Architecture

Advantages of Proposed System

1. We can develop the personalized candidate package set for each tourist by the collaborative method.

2. Provides Spatial-Temporal relationship for tourist using cocktail approach.

3. TAST model can effectively capture the unique characteristics of travel data.

4. The TAST model can well represent the content of the travel packages and based on the interests of the tourists.

5. TRAST model is used to identify the relationship among the tourist in each travel group.

IV. CONCLUSION AND FUTURE SCOPE

In travel system approach is depending on the different packages of the recommendation system. A TAST model can capture the unique characteristics of the travel packages, the cocktail approach can lead to better performances of travel package recommendation, tourists need system support throughout stages of travel, beginning from pre travel planning through to the final stages of travel the cocktail approach can lead to better performances of travel package recommendation, and the TRAST model can be used as an effective assessment for travel group automatic formation.

By using apriori algorithm we can give better influence to the packages. Apriori algorithm is generating travelling packages of tourist with suitable tourist session. Because TRAST suggest the different packages to tourist according there interest. By giving some kind of schemes and gifts to old customers will increase the interest of them in our company.

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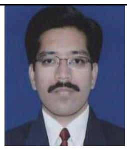

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