TRAVEL PACKAGE RECOMMENDATIONS BY USING INTEGRATED APPROACH

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Abstract - *In this paper, 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 integrated 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. Finally, we combine the TAST model, the TRAST model, and the integrated recommendation approach on the real-world travel package data. Experimental results show that the TAST model can effectively capture the unique characteristics of the travel data and the integrated approach which is much more effective than traditional recommendation techniques for travel package recommendation. Also, by considering tourist relationships, the TRAST model can be used as an effective assessment for travel group formation.*

Key Words: **Travel package, recommender systems, integrated, topic modeling, and collaborative filtering.**

1. INTRODUCTION

As an emerging trend, more and more travel companies provide online services. 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. Moreover, to increase the profit, the travel companies have to understand the preferences from different tourists and serve more attractive packages. Therefore, the demand for intelligent travel services is expected to increase dramatically.

Indeed, there are many technical and domain challenges inherent in designing and implementing an effective recommender system for personalized travel package recommendation. 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 [14], . Second, 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 colocated together. Also, different travel packages are usually developed for different travel seasons. Therefore, the landscapes 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 new tour packages to replace the old ones based on the interests of the tourists.

To address these challenges, in our preliminary work, we proposed a cocktail approach on personalized travel package recommendation. Specifically, we first analyze the key characteristics of the existing travel packages. Along this line, travel time and travel destinations are divided into different seasons and areas.

Then 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. 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 integrated 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. Finally, the experimental results on real world travel data show that the TAST model can effectively capture the unique characteristics of travel data and the integrated recommendation approach performs much better than traditional techniques.

In this paper, we further study some related topic models of the TAST model, and explain the corresponding travel package recommendation strategies based on them. Also, 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 integrated recommendation approach

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2. LITERATURE SURVEY

Toward the Next Generation of Recommender Systems[2] said that the current generation of recommendation method usually classified into the following three main categories: content-based, collaborative, and hybrid recommendation approaches also describes various limitations of current recommendation methods and discusses possible extensions that can improve recommendation capabilities and make recommender systems applicable to an even broader range of applications.

Recommender systems have become an important research area since the appearance of the first papers on collaborative filtering in the mid-1990s there has been much work done both in the industry and academia on developing new approaches to recommender systems over the last decade. The interest in this area still remains high because it constitutes a problem-rich research area and because of the abundance of practical applications that help users to deal with information overloads and provide personalized recommendations, content, and services to them. Examples of such applications include recommending books, CDs, and other products at Amazon.com, movies by Movie Lens, and news at VERSIFI Technologies (formerly AdaptiveInfo.com) . Moreover, some of the vendors have incorporated recommendation capabilities into their commerce servers. However, despite all of these advances, the current generation of recommender systems still requires further improvements to make recommendation methods more effective and applicable to an even broader range of real-life applications, including recommending vacations, certain types of financial services to investors, and products to purchase in a store made by a “smart” shopping cart. These improvements include better methods for representing user behavior and the information about the items to be recommended, more advanced recommendation modeling methods, incorporation of various contextual information into the recommendation process, utilization of multcriteria ratings, development of less intrusive and more flexible recommendation methods that also rely on the measures that more effectively determine performance of recommender systems.

Personalized travel package has many challenges while designing and implementing an effective recommender system for personalized travel package recommendation. First, the travel data are less and scattered than traditional items, for an example recommendation for movie may cost more to travel than its price. Second, usually travel package are location based so they are said to be spatial or temporal for example the package contains locations which are geographically near. And these packages vary season vise. 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 landscapes in a travel package usually have spatial temporal autocorrelations. Third, the old recommendation system depends on user explicit rating and the travel data may not contain such rating. 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.

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 involves the use of sophisticated data analysis tools to discover previously unknown, valid patterns and relationships in large data sets. These tools can include statistical models, mathematical algorithms, and machine learning methods (algorithms that improve their performance automatically through experience, such as neural networks or decision trees). 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.

1. They include association (patterns where one event is connected to another event, such as purchasing a pen and purchasing paper).
2. Sequence or path analysis (patterns where one event leads to another event, such as the birth of a child and purchasing diapers).
3. Classification (identification of new patterns, such as coincidences between duct tape purchases and plastic sheeting purchases).
4. Clustering (finding and visually documenting groups of previously unknown facts, such as geographic location and brand preferences).
5. 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).
6. Collaborative filtering (is the process of filtering for information or patterns using techniques involving collaboration among multiple agents, viewpoints, data sources)

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) Initial exploration.
(2) Model building or pattern identification with validation/verification.
(3) Deployment (i.e., the application of the model to new data 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.

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.

3. PROBLEM DEFINITION

In this paper, many of us make an effort to create individualized vacation package deal ideas for your visitors. So, your people would be the visitors and the goods would be the current packages, and many of us make use of a real-world vacation facts arranged offered by a vacation corporation in Tiongkok with regard to making recommender techniques. You will discover almost 220, 000 expenditure files (purchases connected within personal tourists) beginning with the month of January 2000 for you to Oct 2010. From this facts arranged, many of us extracted 3, 351 beneficial files connected with 7, 749 vacation groupings with regard to 5, 211 visitors via 908 domestic and global packages in a manner that every single visitor features moved at the least a couple of distinct packages. This extracted facts contain 1, 065 distinct landscapes in 139 cities via 10 nations around the world. An average of, every single package deal features 11 distinct landscapes, and every single visitor features moved 5. 5 occasions. As illustrated in our primary operate [5], you will discover many special attributes on the vacation facts. First, it really is very sparse, and every single visitor features not many vacation files. This intense sparseness on the facts brings about complications with regard to using traditional suggestion techniques, such as collaborative filtering. One example is, it really is hard to find you're trustworthy nearest friends with the visitors simply because you will discover hardly any contravening packages.

4. PROPOSED SOLUTION

4.1 TAST Model

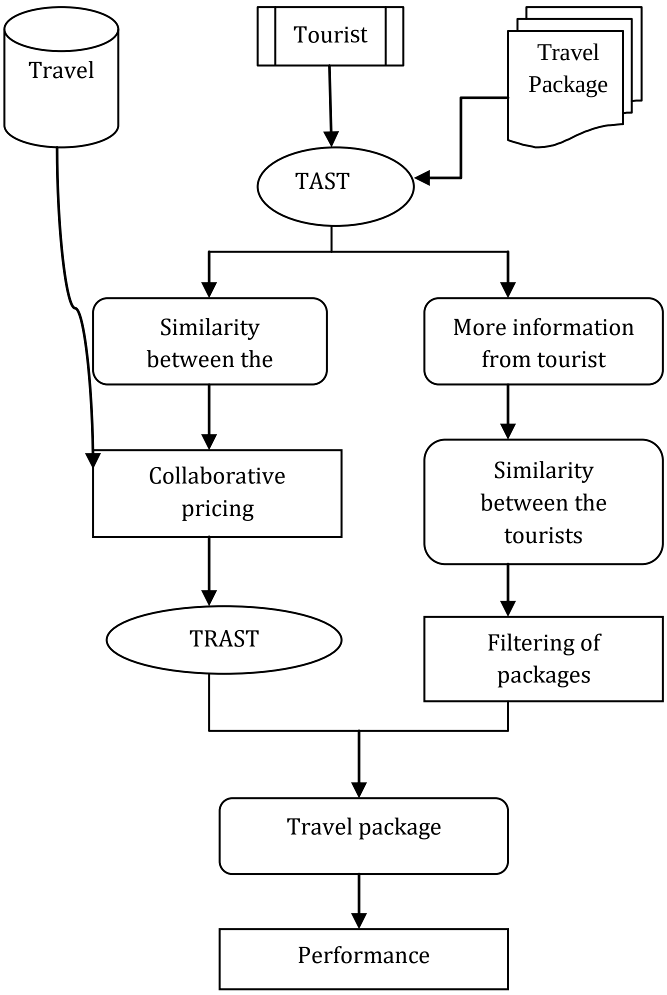
Here develop a tourist-area-season topic (TAST) model, which can represent travel packages and tourists by different topic distributions. In the TAST model, the extraction of topics is conditioned on both the tourists and the intrinsic features (i.e., locations, travel seasons) of the landscapes. As 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.

4.2TRAST 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 integrated 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.

4.3 System Architecture



5. CONCLUSIONS

In this paper, we present study on personalized travel package recommendation. Specifically, we first analyzed the unique characteristics of travel packages and developed the TAST model, a Bayesian network for travel package and tourist representation. The TAST model can discover the interests of the tourists and extract the spatial temporal correlations among landscapes. Then, we exploited the TAST model for developing a cocktail approach on personalized travel package recommendation. This integrated approach follows a hybrid recommendation strategy and has the ability to combine several constraints existing in the real world scenario. Furthermore, we extended the TAST model to the TRAST model, which can capture the relationships among tourists in each travel group. Finally, an empirical study was conducted on real-world travel data. Experimental results demonstrate that the TAST model can capture the unique characteristics of the travel packages, 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. We hope these encouraging results could lead to many future works.

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