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TRAVEL PACKAGE RECOMMENDATION USING COCKTAIL APPROACH

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***Abstract*— Recommender systems are very popular now a day. Despite significant progress in this field, there still remain numerous avenues to explore. Indeed, 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 that end, in this paper, we first analyze the characteristics of the existing travel packages and develop a tourist-area-season topic (TAST) model. This TAST model can represent travel packages and tourists by different topic distributions, where the topic extraction is conditioned on both the tourists and the intrinsic features (i.e., locations, travel seasons) of the landscapes. Then, based on this topic model representation, we propose a cocktail 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.**

***Index Terms*— Travel package, recommender systems, cocktail, collaborative filtering, Nearest Neighbor.**

I. INTRODUCTION

As an emerging trend most travel companies provide online services. The rapid growth of online travel information increases the challenges for tourists also increases. The tourist who has to choose from a large number of available travel packages for satisfying their needs. The travel companies have to understand tourist preferences to increase their profit. So what travel companies do, they use intelligent travel services. The intelligent travel services are nothing but a recommender system, who recommends different packages for tourist. The recommender systems applied to increase the quality of service in number of fields [1], so provide a travel package recommendation.

II. NECESSITY

Increasing interest in this field features to distinguish personalized travel package [2] recommendation from traditional recommender systems remains pretty open. The travel data are much sparser as compare to traditional items like movies; it is normal for a customer to watch more than one movie each month, while they may only travel one or two times per year. Here the packages contain many landscapes. The packages are design as per the season behavior, therefore landscapes having spacio-temporal relationship between them. The packages contain only those landscapes which are geographically collocated together.

III. OBJECTIVE

The TAST (tourist-area-season-topic) Model can represent the tourist and travel packages. In this model we can distinguish topics as per the tourist interest and intrinsic features of landscapes. We get the tourist interest and the travel packages. Using all this information the cocktail approach is developed. Cocktail approach includes additional features like behavior of tourist as per season, price and new problem. Here new model is developed i.e. TRAST (tourist-relationship-area-season-topic) with the help of this model we can find the relationship between tourist.

IV. THEME

Using the data about tourist and landscapes we can develop the packages. The Travel Package is nothing but a general service package provided by Travel Company for one or group of tourist. Package is consists of landscapes which are co-located together, price, transportation and travelling period. The Travel Topic is the theme designed for this package and the Landscapes are the travelling places of interest and attraction. The TAST model can extract tourist interested topics and tourists, this output is giving to cocktail approach as input produces the package list, removes inactive packages, to do this cocktail model use collaborative filtering [3],[4]. Finally we predict the relationship between tourist by using their interest and packages.

V. LETERATURE REVIEW

We know that every person is interested to travel but they don't get the package as per there personalized need. To provide such packages to the user we develop this cocktail approach. The TAST model can give the tourist and travel topic by using nearest neighbor method.

The collaborative filtering can rank the packages. New packages are added by comparing with existing packages, and remove the packages which are no longer use. The collaborative pricing are used to predict the possible price distribution of all tourist and reorder the package list.

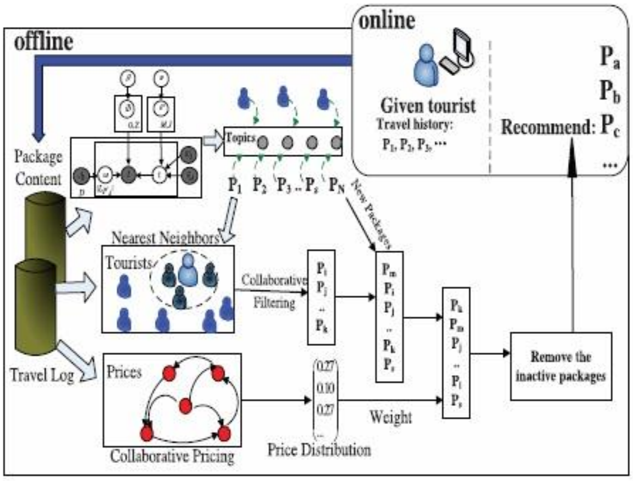

Fig.1 Cocktail Model

A. Collaborative Filtering

The collaborative filtering [5] helps to exact the interest of tourist from the record. Here one tourist website is considered, and using real time data we can develop this model. The tourist profiles contain all data related to each tourist; we can compute similarity between each tourist by their topic distribution similarity. Recommender systems provide users with personalized suggestions for products or services. These systems often rely on Collaborating Filtering (CF) [6], where past transactions are analyzed in order to establish connections between users and products. The two more successful approaches to CF are latent factor models, which directly profile both users and products, and neighborhood models, which analyze similarities between products or users. In this work we introduce some innovations to both approaches. The factor and neighborhood models can now be smoothly merged, thereby building a more accurate combined model. Further accuracy improvements are achieved by extending the models to exploit both explicit and implicit feedback by the users.

B. Nearest Neighbor

This method is used to find the similarity in the topic of all users [7]. Hence create group of similar users and find nearest neighbor. After finding similarity between packages we can predict the relationship among them using the TRAST Model. Clustering validation is a long standing challenge in the clustering literature. While many validation measures have been developed for evaluating the performance of clustering algorithms, these measures often provide inconsistent information about the clustering performance and the best suitable measures to use in practice remain unknown. This paper thus fills this crucial void by giving an organized study of 16 external validation measures for K-means clustering [8]. Specifically, we first introduce the importance of measure normalization in the evaluation of the clustering performance on data with imbalanced class distributions. We also provide normalization solutions for several measures.

C. Collaborative Pricing

The price is also one important attribute because some person can choose high price packages but some people can't afford packages, so here we can use collaborative filtering method for price distribution [9]. The prices for packages are available in five ranges like Low, Medium, High, Very High, Very Low etc.

D. Data Flow Analysis

Figure 2 can show the exact flow of this paper. The TAST Model can extract the tourist interest and using output of TAST model the cocktail model can decide the price and create the candidate Packages. The packages which are of no use can be removed. If user is not satisfied with our packages then user can create their own package.

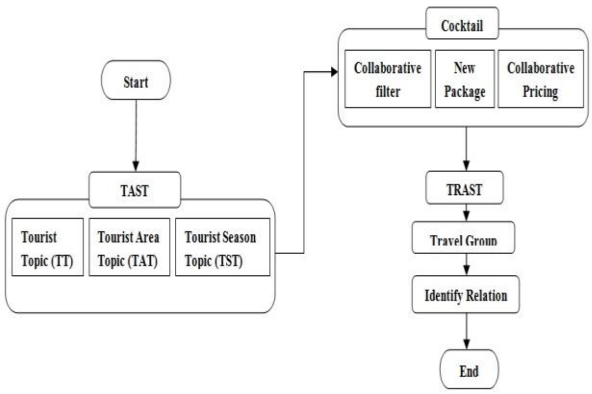

Fig.2 Flow Analysis

Here the packages recommended to each tourist is ranked using Graph based Algorithm. In [10] the packages are ranked by using LItemRank algorithm. In this paper we study and compare different algorithms.

E. Benchmark Method

To demonstrate the effectiveness of Cocktail, we compare it with many other methods for both the fitness of the TAST model and the recommendation accuracies. For the fitness purpose, we compare TAST with three related models TAT (Tourist-Area Topic model), TST (Tourist-Season Topic model) and TT (Tourist Topic model), which do not take the season, area, and both season and area factors into consideration, respectively.

For the recommendation accuracies, we compare Cocktail with two other topic model based approaches TTER (a similar cocktail method but based on the TT model) and the TASTcontent (the content based cocktail method where the content similarity between packages and tourists are used instead of using collaborative filtering). For the memory based collaborative filtering, we implemented the user based collaborative filtering method (UCF) [11].

For the model based collaborative filtering, we chose SVD [12]. Since these two methods (i.e., UCF, SVD) only use package level information, to make a more fair comparison, we implemented two similar methods based on landscapes (i.e. LUCF, LSVD). Also, we compared with one graph-based algorithm, ItemRank [15], where a landscape correlation graph is constructed, and for each tourist, the packages are ranked by the expected average steady-state probabilities on their landscapes. Thus, we name this method LItemRank.

All the above seven methods (i.e., UCF, SVD, LUCF, LSVD, LItemRank, TTER, TASTcontent) are the benchmarks.

VI. CONCLUSION

For all evaluation metrics Cocktail Model performs better and the other models like Cocktail-/TTER have the second best preferences.

The Cocktail- performs same as Cocktail and as compare to TTER both models are performing better. The characteristics of travel data is unique because of that we cannot use collaborative filtering

Cocktail Model is the combination of all Models. As compare to all other model the cocktail model can give best result.

The cocktail model can work on the user profiles and travel logs. The TAST Model is used for detecting tourist interest and topics the output of this model can give input to the Cocktail Model. The Collaborative filtering can be performing on those packages and remove unwanted packages.

VII. FUTURE SCOPE

After implementing review paper we will get the exact results. Accommodation parameter can be part of cocktail approach.

REFERENCES

[1] A Cocktail Approach for Travel Package Recommendation Qi Liu, Enhong Chen, Hui Xiong, Yong Ge, Zhongmou Li, and Xiang Wu IEEE Transactions On Knowledge And Data Engineering, Vol. 26, No. 2, February 2014.

[2] Qi Liu, Yong Ge, Zhongmou Li, Enhong Chen, Hui Xiong | "Personalized Travel Package Recommendation" 2011.

[3] Y. Koren and R. Bell, "Advances in Collaborative Filtering," Recommender Systems Handbook, chapter 5, pp. 145-186, 2011.

[4] W. Chen, J.C. Chu, J. Luan, H. Bai, Y. Wang, and E.Y. Chang, "Collaborative Filtering for Orkut Communities: Discovery of User Latent Behavior," Proc. ACM 18th Int'l Conf. World Wide Web (WWW '09), pp. 681-690, 2009.

[5] R. Pan et al., "One-Class Collaborative Filtering," Proc. IEEE Eighth Int'l Conf. Data Mining (ICDM '08), pp. 502-511, 2008.

[6] Q. Liu, E. Chen, H. Xiong, C. Ding, and J. Chen, "Enhancing Collaborative Filtering by User Interests Expansion via Personalized Ranking," IEEE Trans. Systems, Man, and Cybernetics, Part B: Cybernetics, vol. 42, no. 1, pp. 218-233, Feb. 2012.

[7] B. D. Carolis, N. Novielli, V.L. Plantamura, and E. Gentile, "Generating Comparative Descriptions of Places of Interest in the Tourism Domain," Proc. Third ACM Conf. Recommender Systems (RecSys '09), pp. 277-280, 2009.

[8] J. Wu, H. Xiong and J. Chen, &ldquo,Adapting the Right Measures for K-Means Clustering,&rdquo,*Proc. 15th ACM SIGKDD Int',l Conf. Knowledge Discovery and Data Mining*, pp. 877-886, 2009.

[9] J. Herlocker, J. Konstan, L. Terveen, and J. Riedl, "Evaluating Collaborative Filtering Recommender Systems," ACM Trans. Information Systems, vol. 22, no. 1, pp. 5-53, 2004.

[10] M. Gori and A. Pucci, "ItemRank: A Random-Walk Based Scoring Algorithm for Recommender Engines," Proc. 20th Int'l Joint Conf. Artificial Intelligence (IJCAI '07), pp. 2766-2771, 2007.

[11] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom and J. Riedl. GroupLens: an open architecture for collaborative filtering of netnews. In *ACM CSCW'94*, pp. 175–186, 1994

[12] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl. Application of dimensionality reduction in recommender systems-a case study. In *ACM WebKDD Workshop*, pp. 82–90, 2000.