# Enhanced Personalized Recommendation for Prediction of Travel Sequence

**M. Mohanasundari[1], D. Kaviya [2], S. Karthik[3], T. Indhu[4]**

[1]Assistant Professor (Senior Grade), Department of Computer Science & Engineering, VCET, TN, India.
[2, 3, 4]IV Year B. E., CSE, Department of Computer Science & Engineering, VCET, TN, India.

**Abstract** - To recommend personalized travel routes based on the users Point of Interest (POI). The famous routes are ranked according to the similarity between user package and route package. Then Social similar users' travel records further optimize top-ranked routes. Also, the huge volume of information makes it a challenge for every tourist to pay attention to a potential set of POIs to make a visit in any unknown city. To sort out these problems, suggest an Author Topic Matrix Modeling Algorithm (ATMA) for personalized tours. This method implies that optimizing the POIs to the users' interest preferences and POI popularity.

**Keywords**-Travel recommendation, POI-Point Of Interests, social media, multimedia information retrieval.

## I. Introduction

Introduce the Recommendation system and the adaptive system in travel applications to support the travelers in their decision-making process. Travel based recommendation and journey planning are demanding efforts because of various concern for each people and trip restrictions such as limitation of time, source and destination points for each tourist. Collect a large amount of information from the Internet and travel guides, but they normally recommend only the individual Point of Interest (POI) that is acknowledged to be familiar, but they do not provide ample information based on interest preference of the users or hold to their trip constraints. Also, the huge volume of information makes it is a challenge for every tourist to pay attention to a potential set of POIs to make a visit to the unknown city. After the tourist uncovers an agreeable set of POIs to go to, it'll take ample time and energy for him/her to make a brief outline of the suitable duration to visit the places based on POI and the order in which to visit the POIs. To sort out these problems, suggest an Author Topic Matrix modeling Approach (ATMA) for personalized tours. This method offers that the POIs are better to the users' interest choice and POI fame. Hence, this method is elaborate for tour recommendation problem based on similar user and similar city prediction, which considers user tags.

The rapidly growing Social Network provides an outsized quantity of knowledge about the services based on the point of interest. In this approach, a study of latest POI proposal was adopted to predict the users' current cities. The challenge is it is not easy to learn the user's ordered information and provide personalized recommendation model. So the implementation of Author Topic Matrix Modeling approach provides personalized travel recommendation system that is an extended version of topical package model (TPM). This system collects the knowledge of the author and the cities.

## II. System Models

A. Existing System

Mainly introduce three aspects of related works

(1) Travel recommendation on various big social media.
(2) Personalized travel recommendation.
(3) Travel sequence and travel package recommendation.

POI Recommendation Using Author Topic Collaborative Filtering (ATCF)

The rapidly growing of Social Networks provides an outsized measure of knowledge that allows the services based on the point of interest. In this approach, a study of latest POI recommendation drawback to suggest predicts the users' current cities. The challenge is that it is not easy to learn the user's ordered information and provide personalized recommendation model. So the implementation of Author Topic Modeling approach provides personalized travel recommendation system that is the extended version of LDA technique. This system collects the knowledge of the author and therefore the cities. Through ATM, the category and mine the user's travel preferences just by modifying the latent model simultaneously. The ATM chiefly consists of two steps such as probabilistic generative model and Bayesian estimation model. Through ATM the probabilities of every word to different topics can be determined and also obtain the author topic matrix for all the users. Then, represent each POI as one point in a latent space. Assume that the Euclidean distance between the points of interests in the latent space reflects the transition probability. Larger the gap and lower the strength of transitions. With all POIs embedded in a latent space, this model estimates the sensible transition probabilities of POIs.

Drawbacks of the Existing Methods

- The existing studies related to travel sequence recommendation did not well consider the popularity and personalization of travel routes at the same time.

- It is far more difficult and time consuming for users to plan travel sequence than individual POIs.
- However, general travel route planning cannot well meet users' requirements.
- Existing studies focused more on famous Route mining but without automatically mining user travel interest.

B. Proposed System

Introduce the Recommendation system and adaptive system in travel applications to support the travelers in their decision-making processes. Travel based recommendation and journey arrangements are challenging tasks because of various interests for each people and trip restriction such as limitation of time, source, and destination points for each tourist. Collect a large amount of information from the Internet and travel guides, but they normally recommend only the individual Point of Interest (POI), but they do not provide enough information based on interest preference of the users or hold to their trip constraints. Unlike most existing travel recommendation approaches, this approach is not only personalized to user's travel interest but also be able to recommend a travel sequence rather than personalized Points of Interest (POIs). Topical package space including the representative tags, distribution of cost, visiting time and visiting season of each affair, is mined to a platform the vocabulary gap between user travel preference and travel routes. It takes the advantage of complementary of two kinds of social media: travelogue and community-contributed photos, and map both user's and routes' textual description to the topical package space to obtain user topical bag model and route topical package miniature (i.e., topical-interest, cost, time and season). By recommend personalized POI sequence, rank first, the famous routes according to the similarity between users' package and route package. Then Social similar users' travel records optimize most-ranked routes. Also, the huge volume of information provided on the internet makes it a challenge for every tourist to pay attention to a potential set of POIs to make a visit to the unknown city. To sort out these problems, suggest an ATMA for personalized tours. It suggests that augmenting the POIs the users' interest preferences and POI popularity. Hence, this method detailed for tour recommendation problem based on similar user and similar city prediction, which considers user tags.

## III. Results and Discussion

A. System Overview

This is a personalized travel recommendation rather than a general recommendation. It automatically mines the users' travel interest from the user-contributed photo collections which include the consumption capability, preferred time and season which is important to route planning and difficult to get directly. It recommends personalized POI sequence rather than individual travel POIs. The Famous routes are ranked according to the similarity between users' package and route package. Finally, the top-ranked famous routes are further optimized according to Social similar users' travel records. Use the Topical Package Model (TPM) method and ATMA to learning users and route's travel characteristics. It overpasses the gap of user interest and routes attributes. It takes the advantage of complementary of two big social media to construct topical package space with local cities.

B. System Environment

Figure 1 gives an example for recommendation results. Compared with general routes recommendation, the recommended personalized travel sequential POIs are more accordant to user's interest and more helpful for travel planning. To recommend personalized POI sequence, rank first, famous routes about the resemblance between user package and route package. Then Social similar users' travel records further enhance top-ranked routes. Also, the enormous volume of details makes it a challenge for every tourist considers to a possible set of POIs to make a visit in any unknown city. To sort out these problems, provide an author topic matrix modeling algorithm (ATMA) for personalized tours. This method put that optimizing the POIs to the users' interest preferences and POI popularity.

C. Modules

1) Modules Description

- Dataset Preprocessing.
- User Topical Package Space Model.
- Route Topical Package Model.
- Personalized Travel Route Recommendation.

Dataset Preprocessing

Data pre-processing describes that can perform any processing on raw data to prepare it for another processing procedure. Commonly used as a preliminary data mining practice, data pre-processing will transform the collected data into a format for the purpose of the user. Our dataset consists of travelogues and community-contributed photos.

User Topical Package Space Model (Mined user travel preference)

User Topical Interest Mining Method ($\alpha^{(U)}$)

This module illustrates user topical interest mining method. It maps the textual description (tags) of user's community photos to the topical package space to present the user's travel preference of different topics, which is defined as user topical interest distribution. It makes an assumption that if a user's tags frequently appear in one topic and less in others, the user has a higher interest towards this topic.

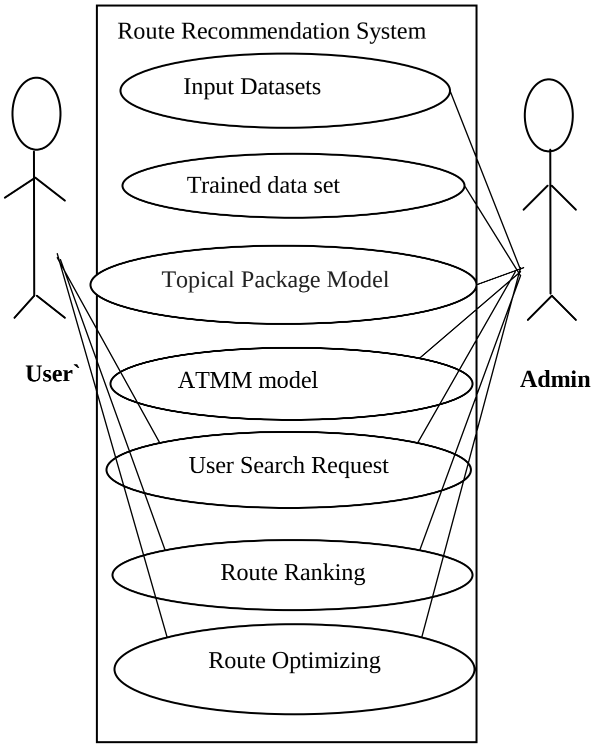


**Fig.1 Use Case Diagram**

The summation of all the tags distribution represents the topic distribution,
$\Sigma_k^{(U)} = \Sigma_k^{(U)'} / _i^{(U)'}$ , where i=0 to N, where, $\Sigma_k^{(U)'}$ denotes the user's topical interests towards $_{CK.}$

Cost, Time, and Season Distribution Mining ($\beta^{(U)}$, $\gamma^{(U)}$, $\zeta^{(U)}$)
Although the user’s photo set contains lots of information about the user, it does not provide any information about the consumption capability and the time preference of the user. The easiest way to obtain the time preference seems to analyze the “date taken” of the photo. However, the time difference of the country between where the user lives and where he or she visits may cause errors.

$\beta(U) = \alpha(U).\beta(M)$, where, β (U) is a one-dimensional vector.

$$\gamma(U) = \alpha(U).\gamma(M)$$
$$\zeta(U) = \alpha(U).\zeta(M)$$

Thus we get the user topical package model, which is defined as [α (U), β (U), γ (U), ζ (U)]

**Route Topical Package Model (Mined user route package)**
Route Mining: To save the online computing time, travel routes and the attribute of the routes are mined offline. After mining POIs, to construct travel routes, analyze the spatiotemporal structure of the POIs among travelers' records.
Route Package Mining: This section describes the routes' topical package model mining. First, it mines the POIs' package including POI topical interest distribution, POI cost distribution, time distribution and season distribution. Then to each route, all the POIs on the route are average to get route topical package model.

$\Sigma_k^{(P)'} = X_{i,k}$, where i=1 to ήP

**Personalized Travel Routes Recommendation Module (As per user input and search, Routes Ranking)**
After mining user package and route package, introduce the travel routes recommendation module. It contains two main steps: (1) routes ranking according to the similarity between user package and routes packages, and (2) route optimizing according to similar social users’ records.
Routes Ranking: Assume R = {r1; r2; ::: rn} is a set of n travel routes mined offline. these routes are ranked according to the similarity between user package and routes packages. For users $u_i$= and route $_{RI,}$ we measure the similarity of each attribute among topical package interest, cost, time and season, denoted as $\phi_{i,j}^{(\alpha)}$, $\phi_{i,j}^{(\beta)}$,$\phi_{i,j}^{(\gamma)}$,$\phi_{i,j}^{(\zeta)}$ respectively.
To calculate cosine distance is applied to measure the similarity of $\alpha_j^{(U)}$ and $\alpha_i^{(R)}$ as:

$$\Phi_{i,j}^{(\alpha)} = (\alpha_i^{(R)}.\alpha_j^{(U)}) / \|\alpha_i^{(R)}\|.\|\alpha_j^{(U)}\|$$

The overall similarity between $u_j$ and $r_i$ as:

$$\Phi_{i,j=} \Phi_{i,j}^{(\alpha)} + \Phi_{i,j}^{(\beta)} + \Phi_{i,j}^{(\gamma)} + \Phi_{i,j}^{(\zeta)}.$$

Route Optimizing: After POI and route ranking module, obtain set of ranked routes ^R. Here, it further describes the optimization of top-ranked routes according to Social similar users' travel records. First, it introduces how to mine similar social users and their travel records. Then it introduces how to optimize the roads by social users’ travel records.

Let the user to be recommended as $u_{,j.[}$ $\alpha^{(U)}$, $\beta^{(U)}$, $\gamma^{(U)}$, $\zeta^{(U)}$

$$\delta_{i,j}=\omega^{(\alpha)} * \delta_{i,j}^{(\alpha)} + \omega^{(\beta)} * \delta_{i,j}^{(\beta)} + \omega^{(\gamma)} * \delta_{i,j}^{(\gamma)} + \omega^{(\zeta)} * \delta_{i,j}^{(\zeta)}.$$

where, $\omega^{(\alpha)}$, $\omega^{(\beta)}$, $\omega^{(\gamma)}$, $\omega^{(\zeta)}$ respectively represent the weight of topical interest, cost, time and season.

$$\Phi_{i,j}^{(\alpha)} = (\alpha_i^{(U)} . \alpha_j^{(U)}) / \|\alpha_i^{(U)}\| . \|\alpha_j^{(U)}\|$$

## IV. CONCLUSION

To sort out the problem of having a huge volume of information which is a challenge for every tourist to pay attention to a potential set of POIs to make a visit on the unknown city, the ATMA is used. This method recommends that optimizing the POIs to the users' interest preferences and POI popularity. Compared with general routes recommendation, this approach provides more relevant information based on user's interest, and it is also more convenient for travel planning. To recommend personalized POI sequence, rank the first, the famous routes according to the similarity between users' package and route package.

## V. FUTURE WORK

This system provides only the personalized travel route based on the users POI and not able to provide any information regarding the visiting time of POI especially the opening and closing time through travelogues, and it was hard to get more precise distributions of visiting time only through travelogues.

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