

Enhanced Social Trip Recommendation on U-POI with TAG Compare Model

A.Karthika¹, Dr.S.Prema²

M. Phil Research Scholar, Department of Computer Science (PG), KS Rangasamy Arts and Science College (Autonomous), Erode, Tamilnadu, India

Assistant Professor, Department of Computer Science (PG), K.S.Rangasamy College of Arts and Science (Autonomous), Thiruchengod, Tamilnadu, India

Abstract: This dissertation mainly concentrates on recommending the user who wishes to travel throughout the world. As people will consider many of travelling websites before they travel for the particular place. These website consists of huge number of reviews posted by the person who had been visited that place already. On considering travel recommendations from multiple websites posted by several users, user could not predict the best results and come into conclusion based on their suggestion. So the existing system works on analysing the travel recommendation using location filtering model. The location filtering model employs on suggesting travel packages by considering the factors such as POI, Tag, City, Topic content. But it could not produce the exact results because it does not consider multiple point of interest. In proposed system, travel package is recommended by considering multiple point of interest and route optimization technique. Here the route optimization technique produces the result by computing package ranking similarity, routing ranking similarity and package size similarity. This three similarity value plays a major role in best recommendation system.

Keywords: GTAG, LBSN, POIs, TBHG, Greedy

I. INTRODUCTION

1.1 DATA MINING

Data mining is in relation to decision new information in a set of data. Data mining, the extraction of hidden predictive information from large databases, it is a powerful new technology with great potential to help companies focus on the most important information in their data warehouses. Data mining tools predict future developments and behaviours, allowing businesses to make proactive, knowledge-driven decisions. The automated, prospective analyses offered by data mining move beyond the analyses of past events provided by retrospective tools typical of decision support systems. The data mining functionalities and the variety of knowledge they discover process are temporarily accessible in the following list:

- Characterization
- Discrimination
- Association analysis
- Classification
- Prediction
- Clustering
- Outlier analysis
- Evolution analysis

Data warehousing is defined as a process of federal data executive and retrieval. Data warehousing, like data mining, is a relatively new term although the concept itself has been around for few years. Data warehousing correspond to an ideal vision of maintaining a central depository of all clerical data. Centralization of data is needed to maximize user access and analysis. Impressive technological advances are making this vision a reality for much organization and equally dramatic advances in data analysis software are allowing users to access this data freely. Big data is expressions that refer to blend of data sets whose volume, variability, and velocity make them complex to be captured, managed, processed or analysed by conventional technologies and tools, such as relational databases and desktop statistics or visualization packages, within the time necessary to make them useful. The big data size used to determine whether a particular data set is considered big data is not confidently defined and keep on to change over time, most analysts and practitioners currently refer to data sets from 30-50 terabytes (10¹² or 1000 gigabytes per terabyte) to multiple petabytes (10¹⁵ or 1000 terabytes per petabyte) as big data.

A Big Data analysis system must support input from multiple human experts, and shared exploration of results. These multiple experts may be separated in space and time when it is too expensive to assemble an entire team together in one room. The data system has to accept this distributed expert input, and support their collaboration. Travel Package Recommendation systems are tools providing plan for package item for a user. The recommendation provided is aimed at supporting their users in various decision making processes. Travel Package Recommender systems have proven to be valuable means for online social users to handle with the information overload and have become one of the most popular and powerful tools in electronic commerce field. In various techniques for travel package recommendation system have been proposed like content-based, user-based and item based collaborative filtering and hybrid recommendation system. Many of them have also been deployed successfully in commercial environments. In this big data recommendation are many evolutionary methods that could be incorporated to achieve better results package in terms of handling various challenges of recommendation system like data scarcity, cold start problem, scalability and accuracy issues and accuracy in prediction. Travel package recommendation system is very useful for both customers and providers. For the customers it will help to narrow down the set of choices, explore the set of options, find the things that are more interesting to user and discovers the new things. In case of provider, it will help to increase trust and customer loyalty, increase customer conversation, sales, click through rates. It will provide good opportunity for promotion and obtain more knowledge about the customer. A distinct feature of the clustering with typicality-based CF recommendation is that it selects the “neighbours” of users by calculating typicality degrees in user groups, which differentiates it from previous methods.

II. RELATED WORKS

Bernd Ludwig [1] describe ROSE a mobile application which combines these features. The main motivation is to free the passenger from many tedious tasks, e.g. finding an interesting event and navigating to it. ROSE determines the best possible transport link and then accompanies the passenger throughout his entire journey. It reacts in real time to delays in the public recommendation system and calculates alternative routes when necessary. The combining pedestrian navigation with event Recommendation and Live Public Transport Routing process to separated the system in three parts

- **Recommendation Part:** To get a recommendation, the user enters a query, like 'travel route', into his mobile phone. The recommender then generates a list of suggestions based on the user input and the user preferences
- **Route Generation Part:** After the user chose one of the presented options, the system calculates a route from the current location to the selected goal.
- **Navigation Part:** how the route is displayed on a map on the mobile phone.

Hsun-Ping Hsieh [2] describes a time-sensitive route recommender system, Time Router, using location check-in data. Author argues that a good route should consider four factors such that, (a) the popularity of a place: popular landmarks will likely attract more visitors, (b) the proper time to visit a place: the pleasure of visiting a place can be significantly diminished if arriving at the wrong time, (c) the amount of time transiting from one place to another and (d) the visiting order of places: for example, going to the gym first then going to restaurant for dinner might be a better plan than the other way around since it is not healthy to exercise right after a meal. In this framework, a statistical-based approach is proposed to model the time-sensitivity of location, and a novel search algorithm to recommend time-sensitive routes with respect to the queries. In general, our work consists of two important issues. First, we aim to design a goodness function, which integrates the abovementioned four requirements about a good trip route to measure the quality of a route. Second, given a query, we devise an effective and efficient search method, Guidance Search, to identify the places to be visited by optimizing the route goodness function.

Jie Li et al [3] describe the user a travel route covering a set of POIs by giving consideration to both popularity and distance. Three approaches are proposed: Distance-based recommendation (DR), Popularity-based recommendation (PR) and Distance-Popularity-based recommendation (DPR). The methods are designed to be deployed in an application scenario that is suitable for everyone, without limitation to the tourists who already have travel history in the given dataset or have been the registered members of some specific website and the user's personalized demands, such as selecting the travel city/date and setting the start point for the route. In proposed system best of knowledge, this is the first work that local activities information is included to construct the travel route.

- **Popularity:** in order to define the level of a POI being interested by users quantitatively, we adopt the concept of popularity and apply a new definition of it, which considers not merely the number of unique visits made to those POIs but also the number of views/comments/favorites produced on the website.
- **Activity/event:** the travel route incorporates both scenic spots and temporal activities. The common travel recommendation only takes attractions into account, which could be visited almost at any time. In our opinions, attending some popular online activities is a good way to understand local history and culture.

Yan-Ying Chen et al [4] describe a focus on the personalized recommendation framework to provide a context-aware recommendation system (i.e., mobile travel recommendation). The personalization is achieved by adopting specific user profiles with the automatically detected people attributes (e.g., gender, age and race) and travel group types along with the trips. That the people attributes are very informative and helpful for mobile travel recommendation. To summarize, the contributions of this paper are:

- To best knowledge, this is the first research work that uses the additional contexts in the photo and travel group types, to support the personalized recommendation framework.
- To predict the travel group type of a photo stream by using the people attributes and social contexts shown in these photos
- To probabilistic personalized travel recommendation model considering users' attributes as well as their group types and the knowledge mined from travel logs.
- To improve the personalized travel recommendation, especially in the location where people have diverse choices of the next stops.
- To examine the association of people attributes and more contexts (e.g., time, popular landmarks) and show the benefits for profiling human activities

Yukiko Kawai et al [5] describe an advanced tour recommendation system, which includes the extraction of famous spots from the Web and route search based on the visibility of scenery along a route. The Web is a useful resource in which famous spots are usually introduced. We propose a method for automatically extracting spots from the Web. The visibility of scenery along a route is an important factor for deciding an actual driving route. The proposed system has two features: first a personalized tourist spot recommendation technique using the Web information dependent on users' preferences, and second, a route search technique based on the visibility of scenic sights from a path. Especially, for the latter author construct a 3D virtual space by using GIS and calculate the visibility of scenic sights by using a method called Z-Buffer. The routes with attractive scenic sights between spots are highly ranked by system.

III. METHODOLOGY

Tourism can be considered as most favourite pass time when user gets free time. Several travel organizations are available on the web. The user or the tourist selects their own User Travel Package according to their personal interest. The travel companies concentrate on the interest associated with tourist making sure to increase their particular market value and supply enormous Travel Package deals. Now-a-days Recommender system is becoming very famous and people are getting attracted to it, as it is helping them to choose the best user travel package in a short time. The problem of unique features to distinguish personalized travel package recommendations from traditional recommender systems remains pretty open. There are many technical and domain problems designing and implementing the effective recommender system for personalized travel recommendation system. This thesis will help tourist to suggest the best User Travel Package among all the package deals on the web. In this, a customer will select a User Travel Package for a particular place based on the recommendations provided by the previous customers who had experience with the package.

A) *Tourism and travel package information:*

Tourism is commonly associated with domestic or international travels. Many travel companies are offering online services to people who want to travel and also this business domain is expanding. As there are large numbers of travel package information available, it is important to satisfy a tourist's personal needs and preferences to serve with more attractive packages.

B) *Tourist-Area-Season-Topic model*

Travel time and travelling areas are divided into distinct seasons and locations. Based on these factors, we develop a Tourist-Area-Season Topic Model which represents distinct distributions of a topic model in a travel package. The content of the travel packages and the interests of the tourists represent the intrinsic features such as locations, travel seasons etc., where the tourist's topic is mined. A personalized travel package recommendation is developed which is based on TAST Model, while considering some additional factors such as seasonal behaviors of tourists and the cost of travel package.

C) *Mixed Recommendation approach*

In this approach, we use the list of topic distribution which was generated in TAST model. For personalized travel package recommendation, the data is displayed for location and price. As the tourist selects the package based on location or price, the data is updated in the database and the admin or the users can view the count of people who has selected a package based on a particular location or a particular price. It is important for the user, as it helps the users in deciding the location based on the popularity of the location and also it helps when pricing plays a major role in deciding a package. It will give admin a perspective about the Travel packages which was added as it will be useful for the admin to add future packages based on the popularity of the location and the price the users have selected.

D) ENHANCED PERSONALIZED TRAVEL RECOMMENDATION

The architecture behind our approach is depicted in Fig.1. It is configured into various modular tasks. An overview of these operations here and details are presented in the following point.

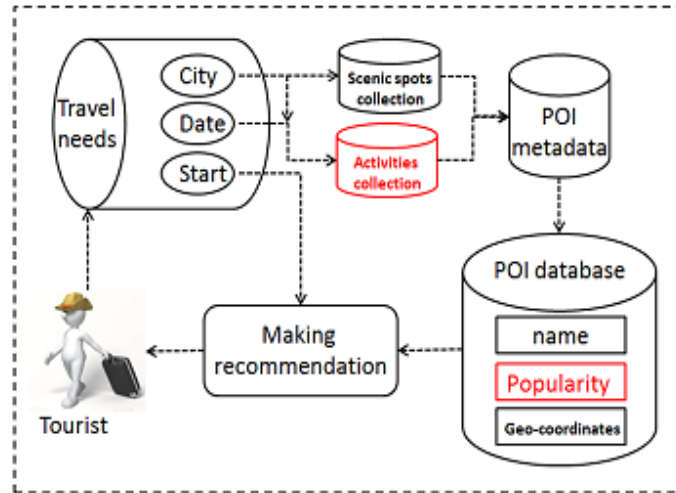


Figure 1: Enhanced Travel Recommendation System

- Tourist input the travel requirements, including the visiting city, visiting date and the start point;
- Collect scenic spots metadata based on the city and activities metadata based on the city and date;
- Calculate popularity of U-POI and extract name & geo-coordinates from the U-POI metadata;
- Recommend travel route based on popularity and distance

At first, the tourist tells proposed system which city he wants to visit, the time he wants to come and the place he wants to set as the beginning point. The start point can be determined by the user's manual input or delivered by Travel Package module embedded. After receiving these initial requirements, the system collects the U-POI information. Since the number of cities is limited and the scenic spots information would not change frequently, so the scenic spots metadata of cities have been collected offline. However, activities changed every day, which means there are different activities in a separate day. So the system extracts activities information from online recommendation. The proposed system similarity calculates the popularity of each U-POI, which makes up U-POI database with other two attributes (name and geo-coordinates). With these preparations, the system could provide travel routes for the user.

E) PROBABILISTIC SOCIAL SEQUENTIAL MODEL

Tour recommendation has become a new trend in the field of intelligent urban navigation. The dramatic increase in the amount of publicly available check-in data has generated substantial interest among different research communities to work on this problem. Different from conventional way of recommending independent venues, the objective of tour recommendation is to suggest a sequence of points of interest (U-POIs) that will serve as travel itineraries to users. Tour recommendation is more challenging than the conventional one due to two main reasons. First, since most users are not native to their tour destination (i.e. users are tourists Package), the check-in information of these users is extremely sparse.

F) Quality of Ranked POIs

Quality of Rank is a classic performance measure that is used widely in evaluating information retrieval systems. In our setting, we use this measure to penalize incorrectly ranked POIs based on their positions. Unlike information retrieval, where documents are assigned different relevance levels, our data is binary consequently, set a constant relevance score of 3 for all U-POIs. Therefore, the topic count for this model corresponds to the number of unique U-POI categories. The cosine similarity scores of Travel Package Model reaches a saturation point at about 50 cities and contrary to this, proposed Model performs better with more topics since this essentially translates into more supervised information.

G) User Travel Route Recommendation

Travel route recommendation is an emerging area, where most published papers are relatively new. In the thesis adopt a collaborative retrieval model that incorporates pair-wise weighted approximate rank function, while proposes a pair wise tensor factorization-based framework that models user-POI, POI-time, and POI-POI interactions for successive POI recommendation. The proposed model is interests of travellers using the popular similarity algorithm. By utilizing websites logs from mobile devices various travel sequences are suggested for the users. A time aware tour recommendation framework that optimizes travel routes based on the best visiting times of U-POIs and proposed algorithms that incorporate various constraints, such as variety of venues, budget constraints of users and the

satisfaction provided by the POIs or recommendation and incorporate the semantics of query from user queries in a skyline travel route framework for creating sequential U-POIs

IV. MOTIVATION OF THE PROBLEM

A) SYSTEM MODEL PARAMETER

The necessary input parameters are given in Configure in file. The simulation procedure should be specific about certain parameter as mentioned below to enable table simulation and implementations.

| PARAMETER | VALUE |
|---------------------|---|
| Implementation tool | ASP.Net Framework |
| Simulation Time | 1000 sec |
| Number of Dataset | 1000 |
| Algorithm | Cosine Similarity and ranking |
| Performance Metrics | Average similarity of Package Ranking, Package Size and Routing Ranking |

Table 1: Simulation Parameter

The Table 1 shows the parameters of the proposed network environment. These parameters were adhered to whole process of implementation with the ASP.NET framework. The Performance metrics such as

- Package Ranking Similarity
- Routing Ranking Similarity
- Package Size Similarity

B) PACKAGE RANKING SIMILARITY

The following Table 2 describes experimental result for package ranking similarity for TPM and E-TPM over all experimental result analysis. The table contains package, Average Ranking of package similarity for TPM and E-TPM details are shown.

| NO. OF PACKAGE | TPM-Ranking (AVG %) | ETPM-Ranking (AVG %) |
|----------------|---------------------|----------------------|
| 100 | 72.5 | 73.68 |
| 200 | 74.62 | 76.02 |
| 400 | 72.25 | 78.22 |
| 600 | 79.62 | 80.66 |
| 800 | 82.37 | 83.25 |
| 1000 | 85.12 | 86.72 |

Table 2 Average Package Ranking Analysis – TPM and E-TPM Model

The following Fig 2 describes experimental result for package ranking similarity for TPM and E-TPM over all experimental result analysis.

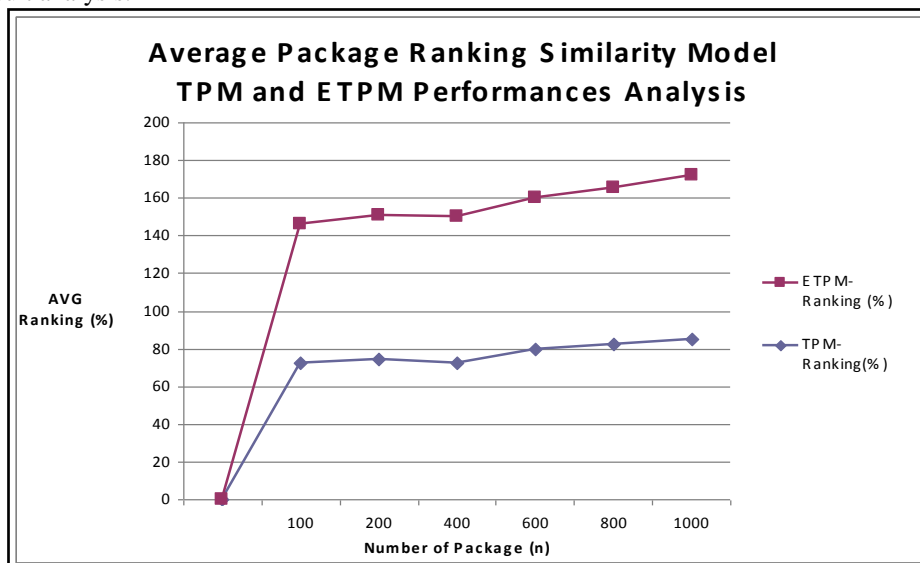


Figure 2: Average Package Ranking Analysis – TPM and E-TPM Model

C) PACKAGE SIZE SIMILARITY

The following Table describes experimental result for package size similarity analysis for TPM and E-TPM over all experimental result analysis. The table contains Total Iteration, number of package size Similarity with TPM and E-TPM Model details are shown.

| Number of Iteration | TPM (Package size Similarity) | E-TPM (Package Size Similarity) |
|---------------------|----------------------------------|------------------------------------|
| A (100) | 53 | 45 |
| B (200) | 132 | 118 |
| C (400) | 205 | 184 |
| D (600) | 316 | 268 |
| E (800) | 432 | 395 |
| F (1000) | 505 | 459 |

Table 3: Package Size Similarity Analysis TPM and E-TPM Model

The following Fig 4.3 describes experimental result for package size similarity analysis for TPM and E-TPM over all experimental result analysis. The figure contains Total number of Iteration, number of package size Similarity with TPM and E-TPM Model details are shown

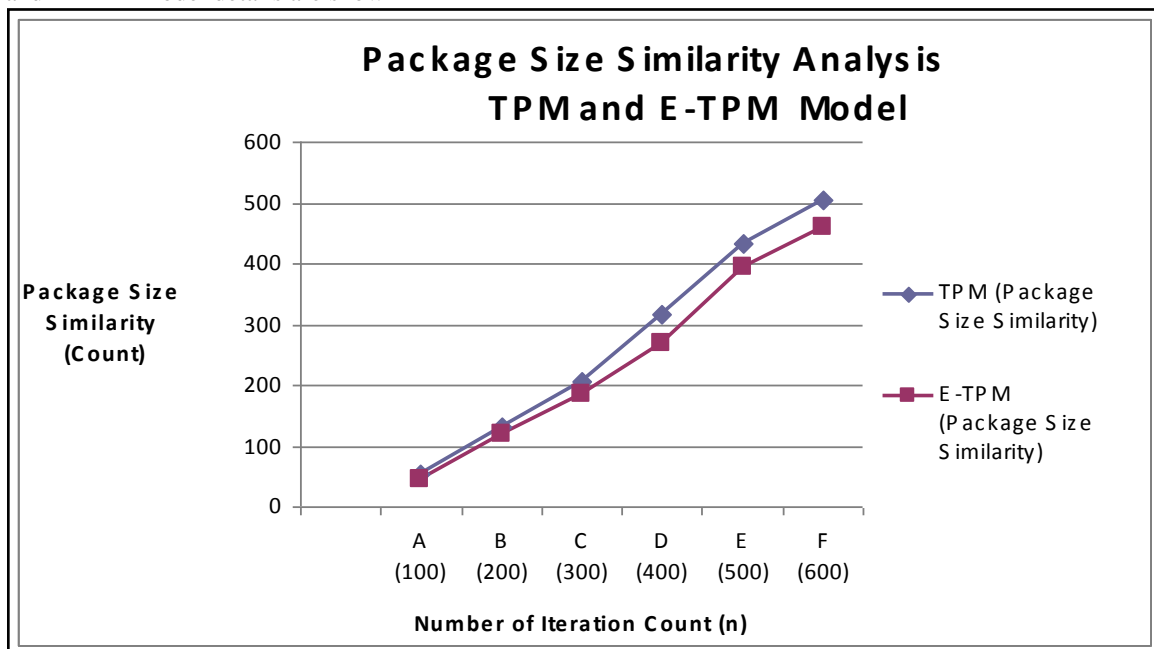


Figure 3: Package Size Similarity Analysis TPM and E-TPM Model

4.4 ROUTING PACKAGE SIMILARITY

The following Table 4.4 describes experimental result for routing package similarity for TPM and ETPM over all experimental result analysis. The table contains Number of package, average package rank similarity for TPM and E-TPM Model details are shown.

| Package | TPM (Routing Similarity) | E-TPM (Routing Similarity) |
|----------|-----------------------------|-------------------------------|
| A (100) | 33 | 42 |
| B (200) | 47 | 55 |
| C (400) | 53 | 67 |
| D (600) | 69 | 78 |
| E (800) | 74 | 83 |
| F (1000) | 79 | 87 |

Table 4: Routing Package Similarity -Analysis TPM and ETPM Model

The following Fig 4.3 describes experimental result for routing package similarity for TPM and ETPM over all experimental result analysis. The figure contains Number of package, average package rank similarity for TPM and E-TPM Model details are shown.

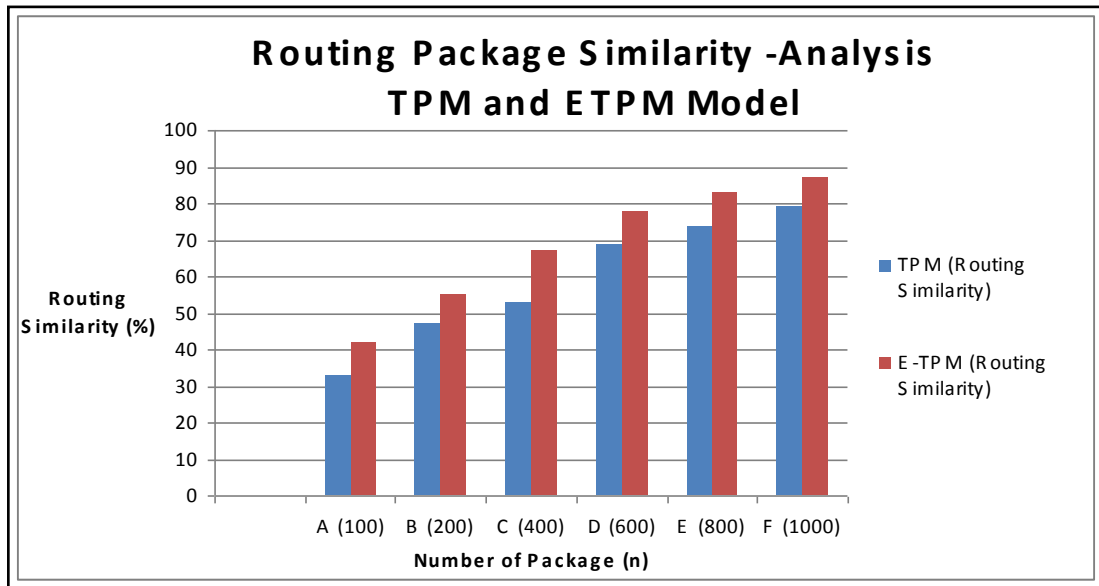


Figure 4: Routing Package Similarity -Analysis TPM and ETPM Model

V. RESULTS AND DISCUSSIONS

C) PACKAGE SIZE SIMILARITY

The following Table describes experimental result for package size similarity analysis for TPM and E-TPM over all experimental result analysis. The table contains Total Iteration, number of package size Similarity with TPM and E-TPM Model details are shown.

| Number of Iteration | TPM (Package size Similarity) | E-TPM (Package Size Similarity) |
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| A (100) | 53 | 45 |
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| C (400) | 205 | 184 |
| D (600) | 316 | 268 |
| E (800) | 432 | 395 |
| F (1000) | 505 | 459 |

Table 5:Package Size Similarity Analysis TPM and E-TPM Model

The following Fig 4.3 describes experimental result for package size similarity analysis for TPM and E-TPM over all experimental result analysis. The figure contains Total number of Iteration, number of package size Similarity with TPM and E-TPM Model details are shown

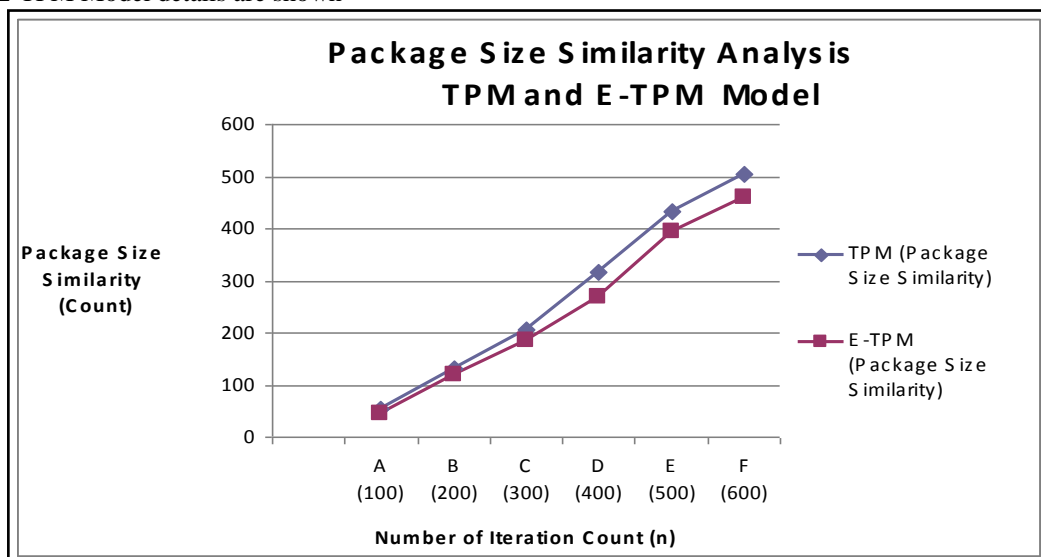


Figure 5: Package Size Similarity Analysis TPM and E-TPM Model

ROUTING PACKAGE SIMILARITY

The following Table 6 describes experimental result for routing package similarity for TPM and ETPM over all experimental result analysis. The table contains Number of package, average package rank similarity for TPM and E-TPM Model details are shown.

| Package | TPM (Routing Similarity) | E-TPM (Routing Similarity) |
|----------|-----------------------------|-------------------------------|
| A (100) | 33 | 42 |
| B (200) | 47 | 55 |
| C (400) | 53 | 67 |
| D (600) | 69 | 78 |
| E (800) | 74 | 83 |
| F (1000) | 79 | 87 |

Table 6: Routing Package Similarity -Analysis TPM and ETPM Model

The following figure 6 describes experimental result for routing package similarity for TPM and ETPM over all experimental result analysis. The figure contains Number of package, average package rank similarity for TPM and E-TPM Model details are shown.

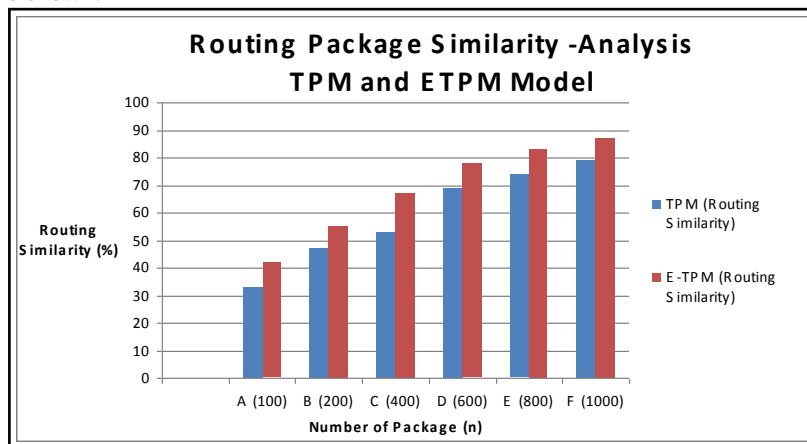


Figure 6: Routing Package Similarity -Analysis TPM and ETPM Model

VI. CONCLUSION

In this proposed system conclude the package recommendation system by learning topical package model from enormous multi source social media: travellers. The benefits of proposed system are the system naturally mined user 's and routes' travel topical inclinations counting the topical interest, cost, time and season, and described U-POIs as well as travel sequence, considering both the prominence and user 's travel inclinations in the mean time. Also, the present system just engaged on POI sequence recommendation more exclude transportation and inn data, which may additionally give comfort to travel arranging. This thesis helps the user with best route optimization technique which shows the best route to travel. The proposed approach used in this system improves the user search by recommending the travel route package. Instead of considering the individual U-POIs, this system considers the many users with much U-POI. This thesis will help to suggest the best Travel Routing package among all the package deals on the web. In this, a user will select a travel package for a particular place based on the recommendations provided by the previous user who had experience with the package. This makes easy for the user to choose the best package deal. The user can select the best package in short amount of time (instead of navigating to other websites). Finally, the goal of the thesis is to make an efficient system which is effective in terms of cost and money.

VII. FUTURE ENHANCEMENT

- It can be made as a mobile app for platforms Android and IOS.
- It can be used to solve other similar problems such as flight deals, best university and so on.
- Festival as an input can be added.
- Best Hotels in the recommended area can also be included.
- As soon as the user logs in, the home page of the user must be displayed with the recommended list of packages based on Hobbies. This helps elderly user to directly purchase the package from the homepage itself.

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BIOGRAPHIES



Dr. S. Prema, currently working as Associate Professor in Department of Computer Science, K.S.R. College of Arts & Science has received Ph.D., from the Bharathiar University in 2015. She is a member of ACM CSTA, IACSIT, TIFR-CORE, WSEAS and WASET. She has published more than 50 research papers in reputed international journals including Thomson Reuters (SCI & Web of Science) and conferences including IEEE, Springer, Elsevier and it's also available online. Her research paper entitled "An NLP based Approach for Facilitating Efficient Web Search Results using BSDS" received the **best paper award**. She has h-index value: 5, i-10 index: 3, Citations: 85 and her profile is listed in Marquis Who is Who in World, International Biography Center, London, UK, 2011. Her main research work focuses on Web Mining, Web personalization, Information Retrieval and Visualization. She has 13 years of teaching experience and 8 years of Research Experience. She is guiding 4 M.Phil and 1 Ph.D Scholars for doing their research. She has been involved in generating funds for R&D

Ms.A.Karthika is pursuing M.Phil (Computer Science) in K.S.R. College of Arts & Science (Autonomous), Tamilnadu, India. She has attended 2 workshops and 1 seminar related to Data mining tools and presented one research paper in National Conference. Her areas of interest are data/web mining, Big data Analytics and Social Media.