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TOURIST'S GROUP RECOMMENDATION APPROACH

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Abstract— Real time information such as safety issues, budget, mode of transportation, altitude of the destination place, likelihood of sports activities etc. has direct impact on the Group recommendation in case of Tourism domain. Tourist spot recommendation based upon a group overall preference requires several analyses in order to avoid both the least misery and most pleasure approach. In a heterogeneous group which may comprises of children's, older age people, spouse, colleagues may lead to different preferences by each individual. This paper deals with hill station recommendation considering the practical issues and requirement of tourist group in order to maximize the satisfaction level of overall group.

Keywords—Group recommendation; ontology; tourism; preference aggregation.

I. INTRODUCTION

With the help of online tourism recommendation services, it is easier to recommend a ranked list of destination to an individual. However, this traditional approach fails if there are group of people who are planning for a common place to visit. The bottleneck may be the heterogeneous nature of the group [1] as it may comprise of children, old age group, spouse, colleagues, etc. As many individuals might refrain to express socially their likes or dislikes and budget issues and it's difficult to manage the preferences manually as the group size increases. With help of recommendation approach these issues could be addressed as registering with preference does not reveals one's preferences.

Knowledge based recommender systems are suited to complex domains such as cars, homes [2][3]. Further examples are financial services, digital products and tourist destinations. Rating based systems often do not perform well in these domains due to less number of available ratings.

The goal is to have an application that uses the current context every time it generates a recommendation and learns from every case of recommendation.

Moreover, the traditional approached requires additional time to search for different webpages for particular information. At present the available systems do not recommend tourists their preferred hill stations based on age factors, natural disasters, weather conditions and calamities.

This research work aims for optimizing the overall satisfaction of travel groups considering preferences like budget, mode of transport, companions, time of visit. Concept of semantic web has been utilized to retain some of the inherent knowledge of the group members. For instance, older people generally do not prefer for higher altitude regions and children prefers

for the amusement park, sports activities. These information's has been stored as RDF to increase machine understandability which improves the recommendation results.

The dataset comprises of hill station and the relevant information about these hill station like altitude, best time to visit etc has been extracted from goibob.com [4] and Wikipedia [5]. On the basis of these data, scores have been calculated for each hill station with the help of a matching algorithm. Protégé tool has been used to design the place ontology, and SPARQL query has been framed to retrieve the relevant results.

II. RELATED WORK

J. Anthony[1] has raised several challenges for group of two or more user's recommendation for scenario where the explicit preferences are taken from members. The bottleneck is explaining the overall recommendation based on nonmanipulable aggregation of suitable preferences. The author has addressed the advantages and drawback of explicit user's inputs preferences, probable nonmanipulative specification for the preference and recommendation process where members cannot engage in discussion among themselves.

C. Isabel et.al [6] has discussed the effect of tourist place updated information maintenance and its impact on the user's preferences. Personalized social networks information's where human recommended destinations has been suggested. The maintenance of updated information and its modelling for travelling groups is the underlying problem.

R. Colomo-palacios et.al [7] states about the tourist relevance with loyalty. As per author survey the places with improved safety standard and leisure services/events (entertainment, sports, creative workshops) are likely to be more preferred by tourists.

Knowledge repository about the places is ever increasing with historical and static data. The authors [8] has given ontological approach where semantic web technology helps to minimize the access time for acquiring information effectively.

C. Ingrid et.al. [9] proposed a social based approach for group of tourists. In this research work the group profile is created by considering the individual preferences as well as the social relationship between the members. This group profiling incorporates the effect of compromise/influence of the group members.

C. Jansen et.al [10] has proposed the preference aggregation for fixed group of people. The preference profile of individual is approximated based on either imprecise probabilities or maximum entropy.

Z. Bahramian et.al [11] states about the information overload problem about the point of interest and related information's. The author has proposed the personalized recommendation to user based on the preferences. The concept of confidence score has been introduced along with the preference score to recommend the final point of interest.

Availability of numerous unfamiliar tourist's attraction poses a challenge for individual as well as group of persons for deciding about the destination. The authors [12] has proposed scheduling of various activities like sightseeing activities and lunch breaks session, waiting time at transit shops etc. The context aware services extract and schedule personalized multimodal tours via selected urban attractions.

B. Yoram et.al.[13] states about tourist recommender user crowdsourcing. In the proposed work, new places and their rating predictions has been estimated using machine learning approach.

Joan Borras et.al. [14] has surveyed different recommendation system for different domains particularly tourism. The problem could be categorized into travel planner, point of interest recommendation, classification of tourist types and their inclination towards context of places, proactive tourist recommendation based on individual behavior.

III. PROPOSED MODEL

In this research work we proposed a recommendation model which recommends the point of interest more precisely as per the user preferences. Figure 1 depicts the proposed model.

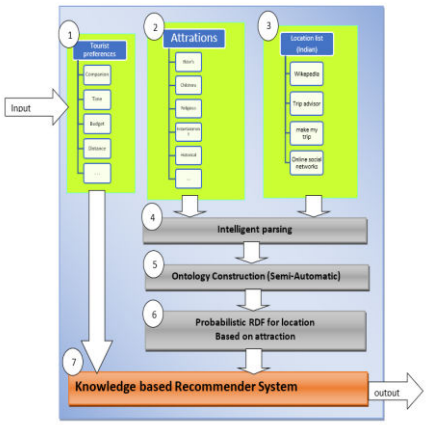

Figure 1: Proposed Recommendation model

The proposed model comprises of seven different modules. Module 1 consists of capturing the user preferences in term of attributes like companion type, season for travel, budget, distances and transportation means.

All the preferences are gathered by web server and passed on to recommendation module to generate a rank list of hill stations.

Module 2 is for gathering information mostly from the linked open data sources like Wikipedia. Selected information is fetched about the hill station from different tourism sites, for example from Goibibo.com [1], the best time to visit, temperature and local languages. From Google places API [2], the latitude and longitude of every hill station. From Trip Advisor, the points of interest and types of attractions are retrieved.

Moreover, some live information is also considered from these sites like weather, any present natural calamity, criminal activities, and celebrity visit etc. from local news agencies. All these attributes are structured into an XML file of every hill station.

Module 3 comprise of ontology structure for person and places. This is semiautomatic ontology creation as the ontology structure is static however the instances are created and keep on updating with automated query. Constructed, i.e. classes and subclasses and data properties for all data using protégé ontology editor. Inference rules and properties are defined for the ontology based on relations between the classes and subclasses of subjects and objects and constants.

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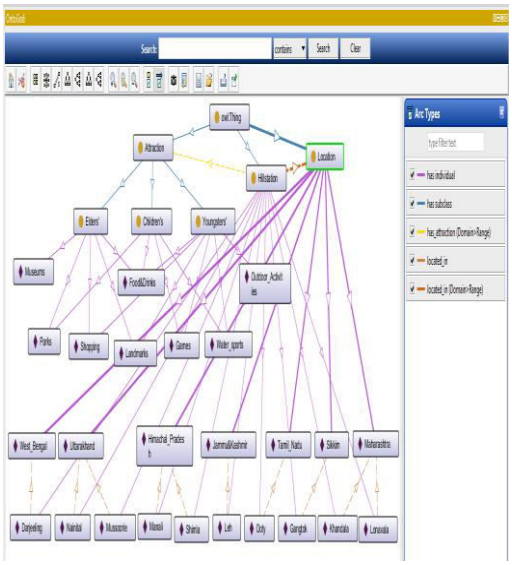

Figure 2 : Ontology for Point of Interest (Hill stations))

It is then stored in an ontology to facilitate better access, expansion and better understanding of the data by the machine.

Then the data is converted from XML format to RDF/OWL format.

```
▼<hill_station>
   <altitude>2050</altitude>
   <best-season>jan feb mar apr may jun jul aug sep oct</best-season>
  ▼<weather>
     <low>-1</low>
     <high>23</high>
   </weather>
   <languages>pahari hindi english</languages>
   <current-month>SEP</current-month>
  ▼<live-weather>
     <high>22</high>
     <low>11</low>
   </live-weather>
   <lat>32.2396325</lat>
   <lng>77.1887145</lng>
  ▼<attraction>
     <attraction-type>Nature & Parks</attraction-type>
     <value>17</value>
   </attraction>
  ▼<attraction>
     <attraction-type>Sights & Landmarks</attraction-type>
     <value>13</value>
   </attraction>
  ▼<attraction>
     <attraction-type>Outdoor Activities</attraction-type>
     <value>26</value>
   </attraction>
  ▼<attraction>
     <attraction-type>Tours</attraction-type>
     <value>22</value>
   </attraction>
  ▼<attraction>
     <attraction-type>Fun & Games</attraction-type>
     <value>3</value>
   </attraction>
  ▼<attraction>
     <attraction-type>Museums</attraction-type>
     <value>1</value>
   </attraction>
```

Module 4 comprise of probabilistic RDF for locations formulation on the basis of which locations could be assigned different scores and further these could be used in relevant recommendation,

Module 5 consists of recommendation based on the real-time knowledge about the place.

This module is instantiated by the web server and gets all user preferences from web server. Now, the recommender queries the Data Store and generates rank list by applying the recommendation algorithm. This rank list is again sent back to web server.

IV. PROPOSED RECOMMENDATION APPROACH

Recommendation module is responsible for recommending user best available Hill Station according to his/her choices. For each choice filled in by the user, the algorithm assigns score to each Hill Station based upon factors stated in table-1. For instance, suppose user selects his travelling budget as Rs. 3000/- per person. For Hill Station 'A' suppose fare comes out to be Rs. 5000/- and for Hill Station 'B' fare is Rs. 2000/-. This accounts for higher score to Hill Station 'B' as user is benefited from Hill Station 'B' in this case. Similarly, for each factor, "score" is calculated using the real-time data available over the internet and user's requirements.

Table 1: Different scores calculation factor

Type of factor	Reason for score consideration
Age	Point of Interests, a particular place has for an age group
Altitude	A factor of (Medical) safety: higher altitudes had less oxygen, not recommended for older people
Purpose	POIs of a place and Purpose of the trip are taken into consideration
Travelling Budget	Approximate Traveling fare is calculated and priority is given to lower than user's budget
Temperature	Priority is given to places having user's temperature range
Best Season	Location having best season as user's month of travel would be given good score
Language	Locations speaking native language of user would be given preferences
Accidental	Locations having high recent accidents are given low preferences

Score calculation Methodology

(1)Age score of a Hill Station is calculated by summing up the Points of Interest of a location for an age group * Number of age group companions.

age_i = child * (hs_i.childPOI) + young * (hs_i.youngPOI) + elder* (hs_i.elderPOI)

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(2)Many Point of Interests types are mapped to some purposes. So Purpose score is calculated by summing up these purposes score which user has asked for.

case "Historical Sites": purpose_i += hs_i.historicalPOI

case"Educational Sites": purpose_i += hs_i.educationalPOI

case "Religious Sites": purpose_i += hs_i.religiousPOI

case"AdventurousSites":purpose_i += hs_i.adventerousPOI

case "Amusements": purpose_i += hs_i.amusementPOI

case "Shopping": purpose_i += hs_i.shoppingPOI

case "Bussiness Purpose": purpose_i += hs_i.buisinessPOI

(3)Altitude score is calculated by formula altitude of a location * young members – elder members * altitude of the location.

alt_i = young * (hs_i.altitude) – elder * (hs_i.altitude)

(4)Charge or Budget score is calculated by computing Travelling fare using the

formula charge = budget – fare, where fare is provided by APIs.

charge_i = budget-travelling_charge_i

(5)Temperature Score is computed by using average / live temperature of the location and then assigning a value for specific temperature.

temp_score_i = 100 if max and min in range

temp_score_i = 60 if below range

temp_score_i = 60 if above range

(6)Season Score is given if the location is best suited in the month in which user is planning the trip.

season_score_i = 100 if hs_i.bestSeason=visiting_season

season_score_i = 0 if hs_i.bestSeason!=visiting_season

(7)Language scores are given when hill stations natives speaks same languages as user does.

for lang1 in visitor_language_list:

for lang2 in hs_i.lang_list:

if lang1=lang2:

language_i += 100

(8)Accidents scores are subtracted if accidents had took place in the area.

acc_i=hs_i.accidents

Normalization

For each metric a particular score is given to a hill station before adding that score in the final score these metric score goes through a normalization process. Normalization normalizes the metric score in a particular range so that each metric has the same impact on the total score.Normalization is done between value 0 and 100.

Querying into OWL file

SPARQL queries are used to fetch hill station data to the recommender. SPARQL queries are done dynamically with the help of Jena SPARQL library.

Computing overall Hill Station Score

Each Score is summed up to get net Hill Station Score.

hs_i.score = age_i + purpose_i + altitude_i + charge_i +

temp_score_i + season_i + language_i + acc_iNormalization

For each metric a particular score is given to a hill station before adding that score in the final score, these metric score goes through a normalization process. Normalization normalizes the metric score in a particular range so that each metric has the same impact on the total score.

Steps for dynamic score computation based on real time data

1. Querying into the owl file.
2. Maintaining scores.
3. Preparing and presenting results as output

Normalization is done between value 0 and 100. Currently application does not recommend on basis of reviews and rating

V. CONCLUSION AND FUTURE WORK

The recommendation system gives the recommendation for hill stations based on the preferences of the user like companions' age group, purpose of the trip, budget per person, vacation time, location, mode of transport, preferred weather, languages spoken and the implicit as well as explicit information of the hill station like attitude, best visiting season, location, local languages etc. A major strength of knowledge-based recommender system is the non-existing of slow start problems. A corresponding drawback is a knowledge acquisition which is triggered by the need to define recommendation knowledge in an explicit fashion.

Improvements can be made in disaster computation. There is scope for improvement in approximation of fare calculation. The accuracy of the recommendation system and analysis of data can be improved to be more accurate.

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