International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 10, October-2020

Trip Purpose and Prediction

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Abstract:- This survey gives a basic idea about the different ways by which we can predict the trip and its purpose and explains the importance of prediction trips in our day to day life. It gives a brief idea about 6 methods for the prediction of trip and its purpose with a brief detail of the techniques that are applied in each paper. The architecture of the problem signifies the flow of the steps which are followed for the prediction of the trip and trip purpose accurately.

This survey also differentiates between all the six papers that have been surveyed in all aspects of the method followed, the data set used, the advantages of each paper, the disadvantages of each paper and the different models that are used in the approach.

INTRODUCTION

Trip purpose and trip prediction or knowing the reason of the trip is crucial to travel behavior modeling and travel demand estimation for transportation planning and investment decisions. Determining the trip purpose these days helps in a lot of things. It helps in saving time by helping us find alternate routes to reach the same destination in less time as compared to the other routes. To make it easier to understand we categorize the trips into different factors depending upon the frequency of the route followed, the frequency of the destination, days of visit to a place. Arranging them into categories makes it easier to understand and predict the destination. There are many methods by which we can retrieve data which helps us to get information about the trip and its purpose. This data which is collected by the various methods is analyzed with various techniques. By the help of this analyzed data we can filter and get relevant information that can help in prediction of trip and its purpose.

Amongst many possible ways to predict the trip purpose and its destination few of the methods have been discussed in these papers. They are:

- Trip destination prediction based on multiday GPS data.
- An automated approach from GPS traces to complete trip information.
- Assessment of trip validation interfaces for smartphone-based travel surveys.
- Understanding traveler's preference for different types of trip destination based on mobile internet usage data.
- Public transport trip purpose inference using smart card fare data.
- Forecasting current and next trip purpose with social media data and Google Places.

DEFINITIONS

- A **Bayesian neural network (BNN)** refers to the extension of the standard networks with posterior inference. Standard NN training via optimization is (from a probabilistic perspective) equivalent to maximum likelihood estimation[1].

- The **General Transit Feed Specification** (**GTFS**) is defined as an open standard format for the exchange of public transportation schedule, geographic and fare information. GTFS "feeds" let public transit agencies publish data in a format that can be consumed and utilized in applications in an interoperable way[2].

- The **Elevations** API he Elevation API provides a simple interface to query locations on the earth for elevation data. Additionally, you may request sampled elevation data along paths, allowing you to calculate elevation changes along routes. With the Elevation API, you can develop hiking and biking applications, positioning applications, or low resolution surveying applications[3].

- **Point of interest**, or **POI**, is a specific point location that someone may find useful or interesting. An example is a point on the Earth representing the location of the Space Needle, or a point on Mars representing the location of the mountain, Olympus Mons. Most consumers use the term when referring to hotels, campsites, fuel stations or any other categories used in modern (automotive) navigation systems[4].

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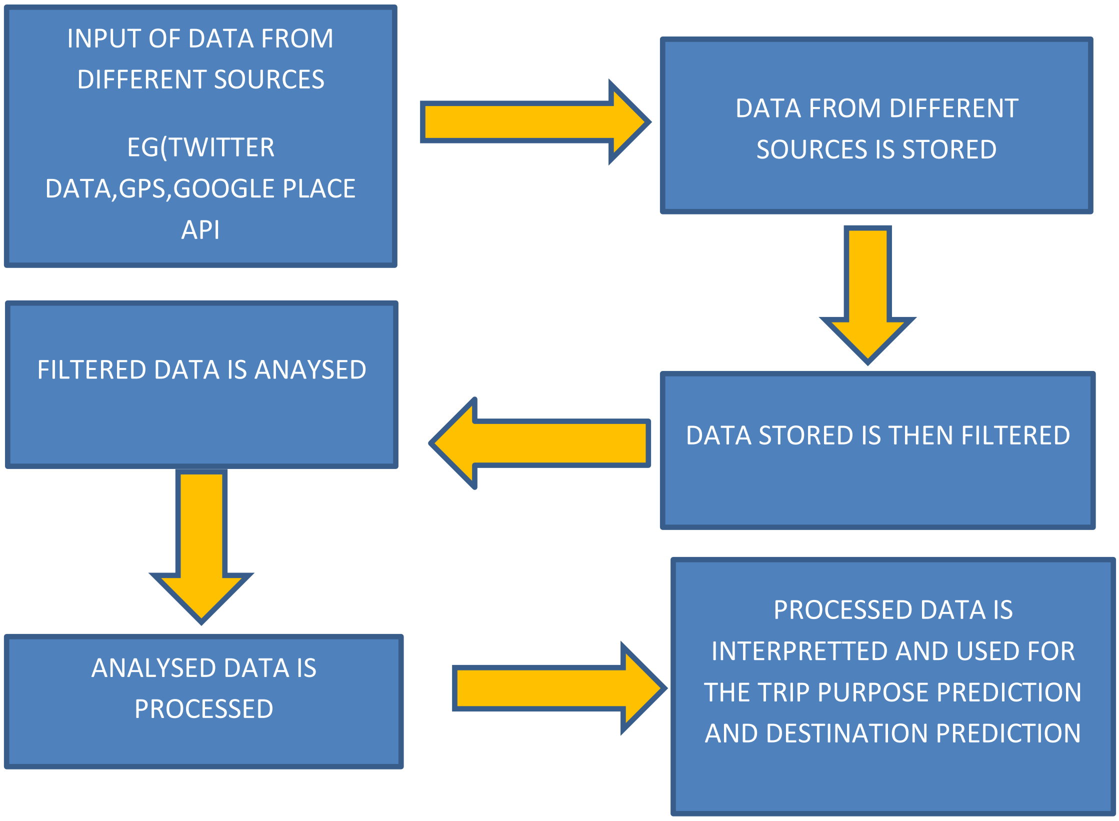
ARCHITECTURE OF THE PROBLEM



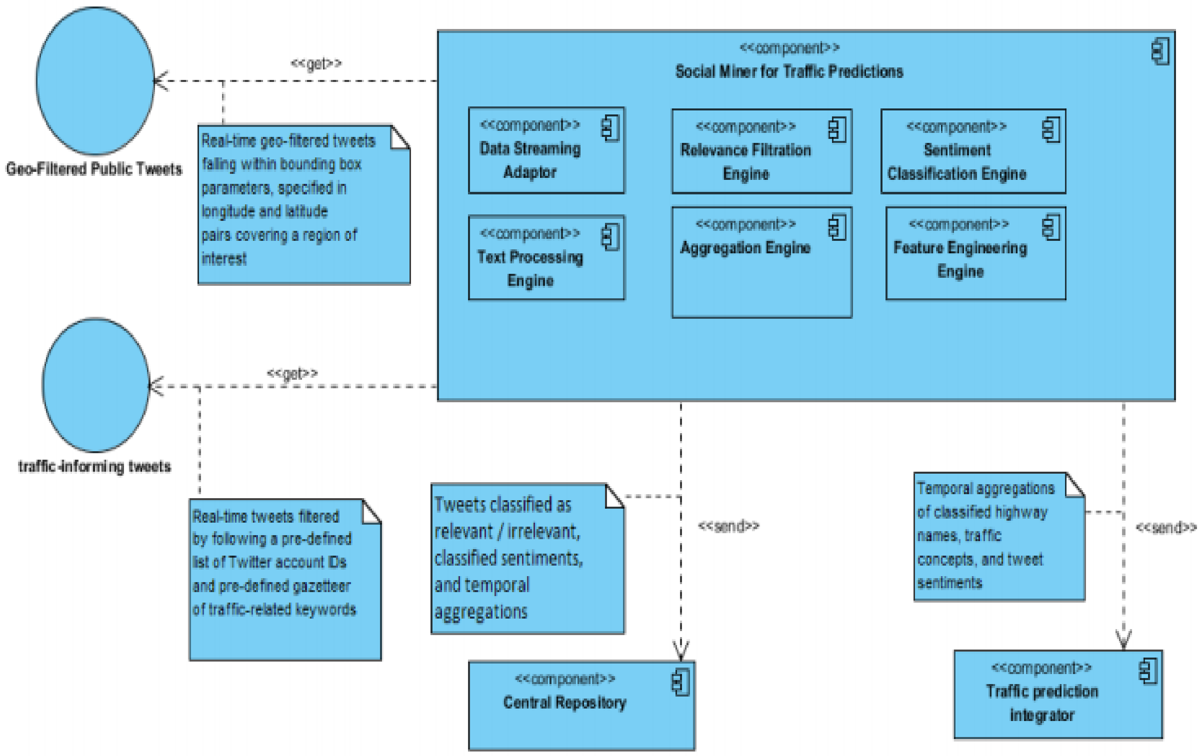


Figure 2[9]

LITERATURE REVIEW

1. TRIP DESTINATION PREDICTION BASED ON MULTIDAY GPS DATA

Transportation planning and management is the need of the hour. To attain this ,the knowledge of free trip destination is required, which analyzes the crowded locations and play a major role in trip destination prediction. The travelers need the information regarding traffic condition, commercial facilities around the destination for making decisions about the routes to be followed and the right time to travel to the destination to avoid traffic jams. In this survey it was observed that weekdays and weekends have different destinations and so the calculations for them was done separately.

The solution for the problem basically follows a habit-based destination prediction. The destination prediction is basically divided into two parts that are pre -trip prediction and during trip prediction which provides travelers and planners with information before and during the trip. GPS technology is used to record the travelers multiday movements. Over here a sequence of time stamped locations through GPS and the movement pattern in the trip destination model was developed. The data is studied after performing a few filtration methods which removes all the unwanted data. This filtered data is analyzed and is characterized which helps in giving an idea about the future predictions of the trip and its purpose. This method helps in identifying frequently visited destinations by analyzing the frequency of visit and the time of frequency during the whole week. The pre-trip destination prediction is calculated by using Markov’s chain rule which showed high average accuracy for average weekdays and weekend trip destinations. A multinomial logic model was employed to develop a habit-based destination model. In trip destination prediction it is needed to update and present real time travel information which is mainly applied for travel navigation for which HMM model is applied. The HMM leads to increase in the accuracy in destination prediction during the weekends. This model only needs the traveler’s previous destination choice records which is directly obtained from the GPS device. This study showed that the destination choice behavior is more regular on weekdays than on weekends. Pre-trip forecasting results can be used by ATIS to reveal pre-trip information and space distribution of crowded location in road network before peak hours. It has a major part in the transportation planning.

2. AN AUTOMATED APPROACH FROM GPS TRACES TO COMPLETE TRIP INFORMATION

The recent modernization and development in the communication technologies have enabled the researchers to obtain the travel based data from the smartphones. These advances guarantee the automatic detection of the critical aspects like the mode of transportation , purpose of the trip ,the frequency of the trip in that location[7].Till now major efforts were made to obtain these aspects of the trip (like the mode) one at a time. Usually this type of information that is gathered is developed on a small data set.

Here in this research a Machine Learning based framework has been designed which helps in obtaining the complete trip information from the smartphone and the data available online from the General Transit Feed Specification(GTFS).This framework has the capability to be used with the smartphone travel survey system which will produce the trip characteristics through the travel surveys .The data that is collected from the smartphone is used with the GTFS data to obtain models that will help in predicting he mode of transportation, the transit literary and the trip purpose[7].In reference to the cross validation data the models used for the prediction show 87%,81%,71% accuracy respectively [7].Furthermore the cross validation on data also suggests that the Machine Learning based framework is an effective and automated tool to extract information for large scale smartphone based travel survey’s . This is also capable to be an efficient and a reliable data extraction technique.

3. ASSESSMENT OF TRIP VALIDATION INTERFACES FOR SMARTPHONE-BASED TRAVEL SURVEYS

In this survey the smartphone based travel survey solutions obtain the trip-data of the respondent .These travel survey solutions are capable of gathering the data in detail when compared to the traditional methods[8].Some advanced systems use server based solutions where the data is collected manually in several phases. The first phase is the registration phase in which the respondent has to register in the program which will enroll him/her in the survey. After the registration phase is over the respondent has to install the application that will gather the data from all the sensors of the smartphone. Along with the sensor data the application also monitors the location data from the GPS of the smartphone. During the travel phase the application transfers the data that has been collected to the server. A special software to analyze the data is used in the server to divide the data into different segments known as the trip segments. These segments are further classified into number of classes depending on the locality, frequency ,mode, time of trip etc. Next is the validation phase in which the data that has been collected from the sensors is validated by the user whenever necessary[8].The validation process requires the respondent to interact with the graphical representation of data in order to give accurate information about the trip. This validation process provides a better accuracy in knowing the exact trip purpose ,the mode of transportation, trip starting time and the trip ending time[8].The data that is obtained after the validation process is an indicator about the user acceptance for the smartphone based travel survey[8].The validated responses of the user helps us to get high accuracy in comparison with the traditional household survey’s which helps in a better and accurate trip prediction process.

International Journal of Engineering Research & Technology (IJERT)
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4. UNDERSTANDING TRAVELER'S PREFERENCE FOR DIFFERENT TYPES OF TRIP DESTINATION BASED ON MOBILE INTERNET USAGE DATA

New mobility of the data sources like mobile phone has revealed individuals movements in space and time. However the socioeconomic attributes of travelers are missing in those data. It is very difficult to partition the population and have an in-depth understanding of the socio-demographic factors influencing travel behavior[5]. Aiming at filling this gap, over here we used the mobile internet usage behavior, including one's preferred type of website and application (app) visited through mobile internet as well as the amount of frequency the user has visited or used the website. As a distinguishing factor between the different population segments, we compare the travel behavior of each segment in terms of the preference for types of trip destinations. The point of interest (POI) data is used to cluster the grid cells of a city according to the main function of a grid cell which serves as a reference to determine the type of trip and its destination. The method was tested for the city of Shanghai by using a special mobile phone dataset that included not only the spatial-temporal traces but also the mobile internet usage behavior of the same users[6]. We identify statistically significant relationships between a traveler's favorite category of mobile internet content and more frequent types of trip destinations that he/she visits. For example, compared to others, people whose favorite type of app/website is in the "tourism" category he/she will significantly prefer to visit tourist areas. Moreover, users with different levels of internet usage intensity show difference in preferences for types of destinations as well. It was found that people who use mobile internet more intensively were more likely to visit more commercial areas, and people who used it less preferred to have activities in predominantly residential areas. Trip approval additionally gives reference information to uninvolved studies preparing PDA flag information[6], e.g. At the point when study respondents have issues with altering their trip information by means of the excursion approval UI, almost certainly, the approved datasets will at present contain misleading information, which will at last lead to one-sided execution assessments[6][5].

5. PUBLIC TRANSPORT TRIP PURPOSE INFERENCE USING SMART CARD FARE DATA

The smart card fare data information has turned out to be prevalent as a rich, exhaustive and consistent wellspring of data. In all the related researches there are still some missing attributes which restrains its ability in the examination field. One key missing piece of attribute is the traveler's trip purpose. This paper examines the capability of the smart card information to deduce travelers trip purpose, consequently diminishing the utilization of the costly and tedious Household Travel Surveys(HTS)[10]. In this paper, an improved model has been proposed, aligned and approved for trip purpose by coordinating diverse information sources.

A smart card data does not record travelers trip data, instead relevant adjustment and approval methods are performed on HTS information. In view of the approval results, the proposed procedure demonstrates a solid capacity to foresee trip purpose at a high state of precision. The results show an overall 67% accuracy after applying spatial attributes, but the accuracy increases to 78% after applying temporal attributes[10]. Distinctive trip purposes show diverse sensitivities to the connected spatial and temporal properties. Work and home outings have the most accurate results with 92% and 96% accuracy separately[10]. Besides, the accuracy of right deduction in the case of shopping and training trips improved significantly when the temporal attributes were applied[10].

6. FORECASTING CURRENT AND NEXT TRIP PURPOSE WITH SOCIAL MEDIA

Forecasting current and next trip purpose with social media data involves gathering of data from GPS and Twitter .Most of the times the information that is gathered from tweets are in short structures or slangs which are required to be de-coded and assembled to comprehend the information present in the tweets. In the conventional models, it was discovered that Google Places and Twitter data can incredibly improve the general precision of forecast for specific exercises, including "Eat Out", "Individual", "Diversion" and "Shopping", however not for "Training" and "Transportation" .Moreover, the term trip is observed to be an essential factor in constructing movement/trip purposes. Further, to address the computational test in the BNN (Bayesian Neural Network), a versatile net is executed for highlight determination before the order undertaking. Our examination can prompt three sorts of conceivable applications that are: action-based travel request demonstrating, overview naming help, and online suggestions.

COMPARISION

S. No	PAPER TITLE	PROBLEM SOLVED	DATA SET	ADVANTAGES	DISADVANTAGES	MODELS USED
1.	Trip destination prediction based on multiday GPS data	Presents a model system for trip destination prediction using GPS data.	➢ Travel data of 10 respondent from different residential area with discrepant socio-economic characteristics from Changchun city in 2017. First 6 weeks survey data – modelling Last 2 weeks - testing the model. ➢ Survey travel record of the respondence were taken in paper form for testing. ➢ They received 1,341,510 GPS records and the related travel information.	➢ This paper showed accuracy of the pre-trip destination prediction on weekdays and weekends is 90.19% and 74.42% respectively, and that of the during-trip destination prediction on weekdays and weekends is 91.04% and 84.88%. ➢ As it has less number of support points the computation time is greatly reduced and there is improvement in prediction efficiency. ➢ Habit based model has higher hit ratio for weekdays destination prediction.	➢ It doesn't take into account to the possible factors that could affect trip destination choice - traffic condition, some managing strategies like regional congestion charges. Real-time traffic condition and traffic management policy are the points of consideration's habit-related factors should also be considered for predicting travel route.	➢ Multiday GPS Data ➢ Hidden Markov chain ➢ MNL model HMM
2.	An automated approach from GPS traces to complete trip Information.	To predict the current and next trip.	➢ The MTL Transit survey. ➢ A Transit Itinerary survey. ➢ Land-use Data. ➢ Foursquare data ➢ General Transit Feed Specification (GTFS) data. Bing Elevation data.	➢ It shows APIs, like Foursquare, or GTFS data alongside GPS traces to develop more accurate predicting models. Accuracy in detection of data increased.	➢ Large-scale smartphone travel surveys may not produce the same quality of validated data as small or researcher-collected smartphone travel surveys. ➢ Prompted recall surveys can improve the quality of gathered data by reducing the self-report errors, but, this comes at the expense of rising the surveying cost. More burden on the respondent detecting multimodal trips is usually harder than detecting uni-mode trips from GPS traces.	➢ Data preparation. ➢ Random forest model basic terminologies. ➢ Mode detection. ➢ Transit itinerary inference. Activity detection.
3.	Assessment of trip validation	Trip data of survey respondents and	➢ Uses a server based arrangement	➢ The normal time required to check and address consequently	➢ The normal time required to check and address	➢ Task completion time ➢ Errors

	interfaces for smartphone-based travel surveys.	the potential for obtaining data with much more detail compared to traditional travel surveys.	where information is gathered over few stages. ➢ Acquires data from the respondent's cell phones. ➢ Analyses the feedback from the user to increase the accuracy.	recorded outing information of multi day was seven minutes for the modelizer approval interface. AIT brilliant review required eight minutes, and FM Sensing 15 minutes. Half of the members could finish the assignments in under around five minutes for modelizer.	consequently recorded outing information of multi day was seven minutes for the modelizer approval interface. AIT brilliant review required eight minutes, and FM Sensing 15 minutes. Half of the members could finish the assignments in under around five minutes for modelizer. The middle for AIT keen study was roughly seven.	Success rate
4.	Understanding traveller's preference for different types of trip destination based on mobile internet usage data.	Issues with altering the trip information.	➢ Mobile phone data. Point of Interest data.	They found for their situation thinks about that ethnicity affected the spatial inclinations of individuals for out-of-home non-work activities, and the ethnic isolation in action spaces was higher in more youthful age gatherings. Likewise, it is arguably less demanding to re-distinguish clients by utilizing cell phone traces associated to clients' demographics, which isn't attractive from a security viewpoint	An issue of utilizing social media information for such examination is that the clients of a social media item may not be an unbiased example of the general population of travellers, both demographically and geographically when contrasted with the general cell phone clients	➢ Mobile phone data ➢ Travel behaviour ➢ Mobility analysis Data fusion
5.	Public transport trip purpose inference using smart card fare data.	Smart card fare data has recently become more prevalent as rich and there few information missing in research field one of them is missing piece of information is the passengers' trip purpose.	➢ Chained O-D trips and regularity database. ➢ HTS data base. Go card data base.	➢ Strong capability to predict trip purpose at a high level of accuracy. The frequency of the trips shows as a potential attribute to validate the inferred results, especially for work and home trips.	Although smart card fare data has recently become more prevalent as a rich and comprehensive source of information, there is missing information about passengers' trip purpose.	➢ Applying spatial and temporal attributes Applying frequency attributes. Extract the O-D trips from the HTS database that have at least one public transport trip-leg. ➢ Match the HTS stop and station coordinates with the transit stop and station coordinates in the GTFS files. Extract the available destination land use activities from

						the land use database.
6.	Forecasting current and next trip purpose with social media data and Google Places.	Determining current and next trip purpose using social media.	➢ GPS Data- Bay Area California household travel survey Feb 2012 to Jan 2013 It included 108,778 individuals which belong to 412,431 household for 1-day survey for GPS data 10474 traveller's from 5460 household carry GPS devices and report 7 Days of GPS Data. ➢ Twitter data - Bay area with bounding box Jan 31 2013 to Feb 16 2017	➢ Elastic net method implemented because of which running time of BNN is reduced by 75% in trash of current trip prediction. ➢ BNN model outperform another prevailing algorithm. The experiment showed a very high probability of correct prediction within the top 2-3 results. ➢ Google places & Tweets increased accuracy compared with another model. It also predicts the next trip purpose when the next activity location is unknown and the model achieves high accuracy.	➢ Data collection derivation is relatively long because of interval rate limits in both Twitter and Google places API. ➢ "Personal" activities need contemplation due to complexity. ➢ Population of social media users is different from real world population so it may contain sampling bias. 4) Rumours or falsified information at activity places results in trustworthiness of social media data.	➢ Feature selection method with elastic net (hybrid method combining LASSO and ridge regression). BNN- (Bayesian Neural Network to model trip purpose).

YOUR FINDINGS

Trip purpose is crucial to travel behavior modeling and travel demand estimation for transportation planning and investment decisions. The trip purpose and the destination prediction is a very essential part of our life as it helps us save our time through our busy schedule. With the help of trip prediction and destination prediction, we can select a single path amongst many paths to the same destination.. This is done by the use of Twitter Data And Google Place API, Smart Phone-Based Travel Data, Public Transport Trip Purpose Inference Using Smart Card Fare Data, Preference For Different Types Of Trip Destination Based On Mobile Internet Usage Data, An Automated Approach From GPS Traces To Complete Trip Information.

To make it easier to understand the trips we categorize into different factors depending upon the frequency of the route followed, the frequency of the destination, days of visit to a place. Arranging them into categories makes it easier to understand the trip, predict destination, and analyze the trips. In addition to this trip duration is found to be an important factor in inferring the activity/trip purposes. Further, to address this the computational challenges in the BNN, an elastic net is implemented for feature selection before the classification task. The research can lead to three types of possible applications that are: activity-based travel demand modeling, survey labeling assistance, and online recommendations. Also the basic assumption is that weekdays and weekends have different destinations and so the calculations for them was done separately.

The solution for the problem basically follows habit-based destination prediction. The destination prediction is basically divided into pre -trip prediction and during trip prediction which provides travelers and planners with destination prediction information before and during the trip. GPS technology is used to record the travelers multi day movements as the sequence of time stamped location through GPS movement pattern the trip destination model is developed. The data was studied after certain filtration which helped in identifying trip and determining trip destination which also helped in identifying frequently visited destinations and analyzing their frequency that is was it at different time of a day or frequency during a week. Further refinements were made by comparing the data sets of the GPS data with the mobile internet usage data collected from the users smartphone and by collecting feedbacks from the user through the smart phone based travel surveys . As this information is directly obtained from the users responses it gives a mor detailed idea about the trip which is used for the future prediction of trip and the trip destination.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 9 Issue 10, October-2020

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