Available online at www.sciencedirect.com

ScienceDirect

Transportation Research Procedia 00 (2018) 000–000

Transportation Research Procedia

www.elsevier.com/locate/procedia

International Symposium of Transport Simulation (ISTS'18) and the International Workshop on Traffic Data Collection and its Standardization (IWTDCS'18)

A Hybrid Method for Predicting a Potential Next Rest Stop of Commercial Vehicles

Rathachai Chawuthai[a,*], Nattaphon Chankaew[a,b], Thanunchai Threepak[a]

[a]*Faculty of Engineering, King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand*
[b]*Transcode Co Ltd., Thailand*

Abstract

Long-distance trips such as freight and passenger transports over cities can create driver fatigue, so drivers prefer to get a rest for a while during their long-time driving. In Thailand, there are rest stops along main roads between cities, such as petrol stations, travel plazas, wayside parks, and scenic areas. In order to provide a better service to customers, the rest stops must have a good management, so the prediction of the number of potential vehicles in a period of time is primarily needed. One important task is to predict the next rest stop of every car at a period of time. Due to this requirement, this paper aims to introduce a prediction model for predicting the next rest stop of a vehicle by analyzing the global positioning system (GPS) tracking data of all commercial vehicles in Thailand. The proposed prediction model is a hybrid model that comprises of three scoring functions depended on the frequent pattern of connected rest stops, the direction of connected rest stops in a route, and the popularity of the rest stops. The experimental result shows that the proposed prediction model gives high accurate result in terms of the area under the receiver-operating-characteristic curve (AUC). This predicted result is also useful for a government department and rest stops' owner to improve transportation, road safety, and other service.

Keywords: Rest Stop Prediction; GPS Tracking System; Prediction; Data Analysis; Transportation; Freight Movement;

* Corresponding author. Tel.: +66 95 465 0692; fax: +66 2 329 8343.
E-mail address: rathachai.ch@kmitl.ac.th

2352-1465 © 2018 The Authors. Published by Elsevier Ltd.
This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0/)
"Peer-review under responsibility of the scientific committee of the International Symposium of Transport Simulation (ISTS'18) and the International Workshop on Traffic Data Collection and its Standardization (IWTDCS'18)"

1. Introduction

It is known that long-distance trips of commercial vehicles in Thailand such as freight and passenger transports over cities are common situation in many areas. Driving for long time makes drivers be fatigued which is one cause of roadway accident. Thus, during long-time trip, drivers prefer to park for a while at any rest stops. Most preferable rest stops on routes between cites in Thailand are petrol stations, travel plazas, wayside parks, and scenic areas. Thus, in order to provide better services to drivers at there, every rest stop should manage resources for supporting every driver well. It is better if the rest stop's owner can predict the number of vehicles parking there every period of time. The government department also get benefit from this information for improving transport safety. However, predicting the temporal frequency of vehicles at rest stops has to deal with many aspects such as time, weather, season, etc., and one important task is to predict the next rest stop of an individual vehicle. In this case, this work is originated to address this task.

To predict the potential next rest stop of a vehicle is a challenging mission, because it needs to deal with spatio-temporal data. Thanks to the Department of Land Transport of Thailand, we can access global positioning system (GPS) tracking data of every commercial vehicles for conducting this research. Based on the GPS data and concepts from existing works, predicting the future location using trajectory data always employ a hybrid model including the frequent pattern of the route of vehicles together with other aspects such as time and distance. Thus, to address the issue about predicting the next rest stops, we steer this research on the following objectives.

1) To introduce a hybrid prediction model for predicting the next stop of a commercial vehicles using data from a GPS tracking system.
2) To report the accuracy of the model for each type of vehicles and time.

Our paper is organized into 5 sections. The introduction is informed in this section, the literature review and data preparation are described in Section 2, the proposed approach is introduced in Section 3, the experimental steps and results are discussed in Section 4, and the conclusion and future work are drawn in Section 5.

2. Literature Review and Data Preparation

In this section, we report some studies that are related to our work and demonstrate how to prepare data for our prediction model.

2.1. Literature Review

As we learned from existing works, there are several studies that attempt to solve the issue about the prediction of future location of an object based on trajectory data. Morzy (2006 and 2007) applied the Appriori and PrefixSpan, which are based on support and confidence used in the field of data mining, to find the frequent pattern of vehicles' movements. However, both techniques do not rely on the aspects of location and time in the routes of objects. Yavas et al. (2005) retrieved location from a mobile device in a car for analyzing the pattern of an individual vehicle based on the confident and support of the distance to a future location using a data mining technique. Jeung et al. (2008) used a hybrid method including features that were mined from the Apriori technique for predicting the future movement of an object. Monreale et al. (2009) introduced a model named *WhereNext* for predicting the next location of a moving object. It used the hybrid methods including the order of location, travel time, and frequent user visits. Scellato et al. (2011) proposed a prediction model named *NextPlace* for a single user to visit the next place based on the most important places, but it does not focus on the transition between different location.

As we reviewed, most studies employed the frequent pattern of the movement of an object for making a prediction. In addition, some works used a hybrid prediction model for improving the accuracy of the prediction model. However, the commercial vehicles are both regular route service and non-regular route service. Thus, only the aspect of frequent pattern is not enough. It needs other aspects, such as the frequent user visits and the time domain, to build a hybrid prediction method as other studies uses.

2.2. Data Preparation

Having GPS tracking data of commercial vehicles in Thailand is a challenging task. Due to the ack of the Department of Land Transport of Thailand, all commercial vehicles such as buses, vans, trucks, etc. have had to install a GPS tracking system and sent data to the department. GPS tracking data from each vehicle are collected in very minute. They include a unit-id (a unique identifier of a GPS device in a vehicle), timestamp, latitude, longitude, and speed in kilometer per hour (km/h). There are about 20,000 vehicles that are categorized into 10 types: Air-conditioned Buses, Buses, Coaches, Container trucks, Hazardous Trucks, Limousine Buses, Liquid trucks, Pickup trucks, Pick-Up Trucks with Labor-Saving Devices, and Special-Purpose Trucks. In this paper, we used data in October 2017, and there are almost 1,000 million records for our experiment.

For predicting the next rest stop of commercial vehicles in Thailand, the frequency of rest stops has to be constructed together with some related data such as the type of a vehicle and time at the current rest stop. There are several steps to construct the data as follows:

1) The definition of the rest stop in our work is the place where a vehicle stops more than 30 minutes. Thus, the dataset is queried to select a unit-id, latitude, longitude, arrived-timestamp, and leaved-timestamp, where the difference between the arrived-timestamp and leaved-timestamp is more than 30 minutes.
2) All locations are simply grouped by two decimal places of latitudes and longitudes in order to gather all locations within 1 kilometer (km) into a single point of a rest stop.
3) Locations including latitudes and longitudes are selected only the places where vehicles stop more than 100 times in a day in order to remove some outlier places.
4) After that, sequences of rest stops of each vehicle are built. If a vehicle stops at a rest stop more than 10 hours, this rest stop will be used to be a point to slice that sequence into two sequences.
5) Lastly, the three connected rest stops are collected into one records together with the unit-id of a device, the type of a vehicle, and a timestamp. In this work, we initially introduce a notation for describing our approach. The GPS tracking data are transformed into the relation of used elements as follows:

$$(s0 \ \rightarrow s1 \ \rightarrow s2, unit\_id, vtype, time1) \tag{1}$$

where *s1* is the current rest stop of a vehicle, *s0* is the previous rest stop of a vehicle, and *s2* is the next rest stop of a vehicle, *vtype* is the type of a vehicle, and *time1* is the timestamp of the vehicle at the rest stop *s1*.

3. Method: A Hybrid Recommender Model

As we review techniques about future location prediction and take a look at the data and the association between rest stops and route paths in Thailand, we found that there are three aspects for making prediction. These aspects are formalized into scoring functions that are based on (1) the frequent pattern between rest stops, (2) the directions of connected rest stops, and (3) the popularity of the rest stop. These concepts are described in the following steps. It is noted that dataset is based on the schema in Eq. 1. The prediction will be done by predicting *s2* based on the given *s1* and *s0*, while *vtype* and *time1* are used for demonstrating the accuracy of our approach based on the type of vehicles and the periods of time. In addition, the candidates of the next rest stop or *s2* are selected from any rest stops that are in the range from the current rest stop *s1*. The proper range can be configured such as 300 km from *s1*.

3.1. Scoring Function based on the Frequent Pattern between Rest Stops (SF)

This function predicts the next rest stop (*s2*) on the basis of the association between *s2* and the current rest stop (*s1*) together with the previous rest stop (*s0*). This technique is grounded by the prediction based on association method from Morzy (2006 and 2007), Yavas et al. (2005), Jeung et al. (2008), and Monreale et al. (2009). In this paper, we find the possibility of a vehicle that parks at the given *s0* and *s1*, and then that vehicle also parks at the *s2*. Based on this proposition, we use the following equation to find the probability of the relation between *s0*→*s1* and *s1*→*s2*.

$$SF(s2|s0 \rightarrow s1) = \frac{NV(s0 \rightarrow s1 \rightarrow s2)}{NV(s0 \rightarrow s1)} \tag{2}$$

where $SF(s2 \mid s0 \rightarrow s1)$ is the possibility of the next rest stop $s2$ of a vehicle that parked at $s0$ and $s1$ before, NV is the function that returns the number of vehicles passing through the given rest stops. In this case, the $NV(s0 \rightarrow s1 \rightarrow s2)$ and $NV(s0 \rightarrow s1)$ returns the numbers of vehicles parking at the $s0 \rightarrow s1 \rightarrow s2$ and $s0 \rightarrow s1$ respectively. If there are 100 vehicles parked at $s0$ and $s1$ before, and *80* of them also parked at $s2$; $SF(s2 \mid s0 \rightarrow s1)$ would be 80/100 = 0.8.

3.2. Scoring Function based on the Directions of Connected Rest Stops (SD)

Next, as we observed the main routes in Thailand, the routes from Bangkok to the north, north-east, east, and south are generally linear. In other words, the connected rest stops $s0$, $s1$, and $s2$ are commonly arranged in straight direction. It means that the vector between the points s0 and s1 has the same direction as the vector between the points $s1$ and $s2$. In this case, the cosine similarity is employed in this scoring function. The cosine similarity method is commonly used in the recommendation systems as described in the work of Pazzani and Bilsus (2007). The equation of this scoring function is expressed as follows:

$$SD(s2|s0 \rightarrow s1) = \frac{\overrightarrow{s0\,s1} \cdot \overrightarrow{s1\,s2}}{\|\overrightarrow{s0\,s1}\| \cdot \|\overrightarrow{s1\,s2}\|} \tag{3}$$

where $SD(s2 \mid s0 \rightarrow s1)$ is the possibility of the next rest stop $s2$ of a vehicle that parked at $s0$ and $s1$ using the direction between stops, $\overrightarrow{s0\,s1}$ is a vector between points $s0$ and $s1$, and $\|\overrightarrow{s0\,s1}\|$ is the size of that vector.

3.3. Scoring Function based on the Popularity of Rest Stops (SP)

The last scoring function is to give priority to the popularity of rest stops, which were included in the hybrid methods from Jeung et al. (2008) and Scellato et al. (2011). For the pattern of a vehicle in Thailand, a vehicle has a high possibility to park at rest stops where other vehicles always visit such as petrol stations. The scoring function is defined as follows:

$$SP(s2|s0 \rightarrow s1) = \frac{NVD(s2)}{NVD_R(s1)} \tag{4}$$

where $SP(s2 \mid s0 \rightarrow s1)$ is a scoring function that demonstrates the popularity of the rest stop $s2$; NVD is a function that returns the number of vehicles at the given rest stop per day; and NVD_R returns the number of vehicles parked from the given point within a radius of a configured distance per day such as the number per day of vehicles stopped within 300 km from the location $s1$.

3.4. A Hybrid Method for Predicting a Potential Next Rest Stop of Commercial Vehicles (PNRS)

The prediction on a next rest stop has several factors. As we demonstrated, there are based on the pattern of frequent pattern of continuous rest stops (*SF*), the direction of connected rest stops (*SD*), and the popularity of the target rest stops (*SP*). A vehicle having similar route daily may have a clear pattern, however, in terms of the commercial vehicles in Thailand, their routes are depended on the jobs given. Thus, the prediction model has to consider several viewpoints as we informed.

The combination of scoring functions is commonly found in the problems about prediction and recommendation as demonstrated by Ricci et al. (2011), Chawuthai et al. (2014), Jeung et al. (2008). Burke (2002) reviewed that there are several ways to combine scoring functions. (1) A weighted hybrid model uses a linear combination of all scoring functions with different coefficients to produce a single score. It is simple and straightforward, so it is flexible for plugging with other new prediction methods. (2) A mixed hybrid model uses different prediction models to produce separated results and lets users to choose a desirable one. (3) A switching hybrid model switches among prediction methods based on criteria of the dataset such as the use of only maximum value in each predicting process. However, the mixed and switching hybrid models do not produce a single prediction score, so it is not proper for our research goal.

Thus, this paper chooses the weighted hybrid model in order to predict the next rest stop based on the highest prediction score. The hybrid model is expressed in the following equation.

$$P^{Next}(s2|s0 \rightarrow s1) = \alpha \cdot SF(s2|s0 \rightarrow s1) + \beta \cdot SD(s2|s0 \rightarrow s1) + \gamma \cdot SP(s2|s0 \rightarrow s1) \tag{5}$$

where P^{Next} is the hybrid prediction model of all scoring functions; α, β, and γ are constant variables indicating weights of scoring functions *SF*, *SD*, and *SP* respectively.

In order to create a precise prediction model, the proper α, β, and γ have to be adjusted. The next section demonstrates the experiment and result of our approach.

4. Experimental Result and Discussion

This section aims to demonstrate the experimental result including experimental steps, evaluation methods, and result; and discuss about the result.

4.1. Experiment

Since, the prediction method P^{Next} has been introduced, the next step is to measure the accuracy of the proposed method. Our experiment is done by the following steps:

1) From the dataset of the relation ($s0 \rightarrow s1 \rightarrow s2$, *vtype*, *time1*), the actual next stop *s2* will be replaced by any possible next rest stops that are located within a configured distance from a given *s1*. In this case, we used 300 km as a configured distance. Thus, it can be s_a, s_b, s_c, s_d, and s_e.
2) Find ranking scores for all possible rest stops using Eq. 5., for example, $P^{Next}(s_a \mid s0 \rightarrow s1)$, $P^{Next}(s_b \mid s0 \rightarrow s1)$, $P^{Next}(s_c \mid s0 \rightarrow s1)$, $P^{Next}(s_d \mid s0 \rightarrow s1)$, and $P^{Next}(s_e \mid s0 \rightarrow s1)$.
3) Compare the ranking scores of all possible next rest stops with the score of actual next rest stop using the evaluation method named AUC, which is described hereafter.
4) From the Eq. 5., use different α, β, and γ for finding proper coefficients of the equation. The different coefficients (α, β, γ) that we use in this experiment are (1,0,0), (0,1,0), (0,0,1), (1,1,0), (1,0,1), (0,1,1), and (1,1,1) in order to find an appropriate combination of scoring functions based on the AUC result.
5) Adjust the α, β, and γ for creating an accurate model for this dataset that gives the highest AUC value. This experiment evaluates each coefficient one by one. If a coefficient is focused, its value is changed while the others are constant. For example, if α is evaluated, the value of α is slightly increased from 0 to 1, while β and γ remain 0.5.
6) After the experiment is executed, the result becomes in form of ($s0 \rightarrow s1 \rightarrow s2$, *vtype*, *time1*, *AUC*). In this step, the report is generated by grouping the *vtype* and *time1* in terms of daytime and nighttime with the average of AUC in these groups in order to demonstrate the accuracy of our approach.

4.2. Evaluation Method

The evaluation method for measuring the accuracy of our approach is the Area Under the receiver operating characteristic Curve (AUC). As the review of Hanley and McNeil (1982), this method is always used to evaluate any prediction algorithms because it compares the ranking of the actual results to any predicted results. The AUC is

$$AUC = \frac{n' + 0.5n''}{n} \tag{6}$$

where there are n comparisons, n' is times of the P^{Next} score of the actual next rest stop has higher than the other predicted stops, and n'' is the times of the P^{Next} score of the actual next rest stop is same as the other predicted stops. It means that the algorithm is more accurate when the AUC value closes to 1.

Table 1. AUC result of the combination of scoring functions in the hybrid model

Hybrid Model	**AUC**
SF	0.623
SD	0.511
SP	0.337
SF + *SD*	0.782
SF + *SP*	0.681
SD + *SP*	0.662
SF + *SD* + *SP*	0.786
$1.0{\cdot}SF + 0.8{\cdot}SD + 0.2{\cdot}SP$	**0.848**

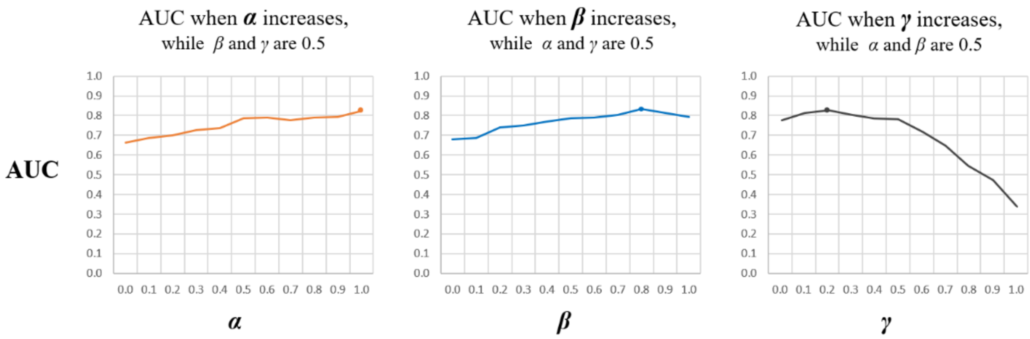


Fig. 1. The evaluation of each coefficients: α, β, and γ

Table 2. AUC results of the dataset grouped by types of vehicles and time

Type of Vehicles	**AUC**		
	Daytime	**Nighttime**	**Whole Day**
Limousine Bus	0.834	0.837	0.836
Air-conditioned Bus	0.835	0.832	0.833
Bus	0.889	0.872	0.880
Coach	0.861	0.825	0.843
Pickup truck	0.841	0.846	0.844
Container truck	0.872	0.897	0.884
Liquid truck	0.938	0.772	0.855
Hazardous Truck	0.871	0.840	0.856
special-purpose truck	0.833	0.835	0.834
Pick-Up Truck with Labor-Saving Device	0.818	0.812	0.815
Average	**0.859**	**0.837**	**0.848**

4.3. Result

The result of our experiment is demonstrated in this part. First, the importance of each scoring function is evaluated using the combination of scoring functions as mentioned in the fourth step of the experiment. The result is shown in Table 1. It shows that the combination of three scoring functions including *SF*, *SD*, and *SP* provides higher AUC. It means that the function P^{Next} has to contain there three scoring functions.

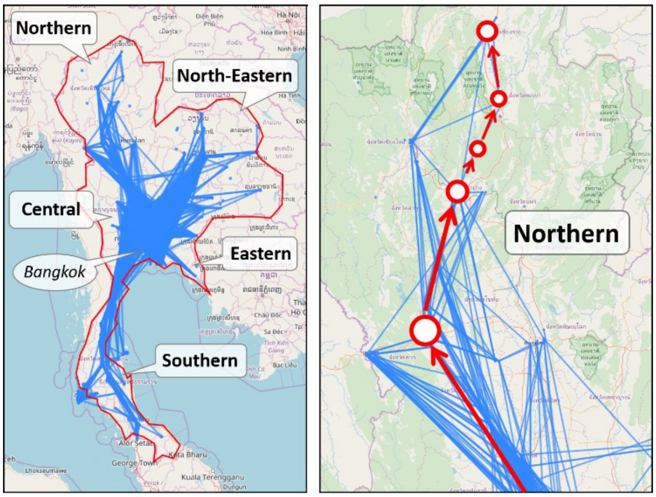
Next, in order to improve the accuracy of the prediction model, the coefficients (α, β, and γ) of three scoring functions are adjusted as described in fifth step of the experiment. It is found that the increasing of the α and β, which are the weights of the scoring function *SF* and *SD*, results in the increasing of the AUC as shown in Fig. 1. In addition, the increasing of the γ provides the inverse result of the AUC. However, according to the result in Fig. 1, the small weight of the scoring function *SP* can help to improve the accuracy. After executing this experiment with the current dataset, it found that the proper value of α, β, and γ are 1.0, 0.8, and 0.2 respectively, and these weights are normalized into 0.5, 0.4, and 0.1, as expressed in the following equation of P^{Next} for our dataset.

$$P^{Next}(s2|s0 \rightarrow s1) = 0.5 \cdot SF(s2|s0 \rightarrow s1) + 0.4 \cdot SD(s2|s0 \rightarrow s1) + 0.1 \cdot SP(s2|s0 \rightarrow s1) \quad (7)$$

Lastly, according to the last step of the experiment, experimental result based on the adjusted equation P^{Next} as defined in Eq. 7 is reported in Table 2. It has found that all types of vehicles provide good accuracy especially in the liquid trucks at the daytime. In addition, the prediction at the daytime is more accuracy than the nighttime a little bit.

4.4. Discussion

The result in Table 1. demonstrates that the prediction model having the combination of these three scoring functions gives more accurate result. The scoring function *SF* based on the frequent pattern of rest stop is the technique that most works in the literature review employed such as Morzy (2006 and 2007), Yavas et al. (2005), Jeung et al. (2008), and Monreale et al. (2009). For the scoring function *SP* which is based on the popularity of the rest stop, the hybrid method between *SF* and *SP* was mentioned in the works of Jeung et al. (2008) and Scellato et al. (2011). However, as we reviewed from existing works in this domain, there is no existing method concerning about the direction among rest stops. The scoring function *SD* represents this concept using the cosine similarity index. Thus, our proposed prediction model that includes the cosine similarity between rest stops' paths for analyzing the trajectory data is firstly introduced in this paper, and the coefficient of this scoring function presented in Eq. 7. supports that the arrangement of the connected rest stops is one key player in the prediction model.



(a) (b)

Fig. 2. The visualization of rest stop routes
(a) All routes in Thailand. (b) Routes in the northern of Thailand.

According to the Eq. 7, it is found that the scoring functions *SF* and *SD* have high importance than the *SP*. It can be inferred that most vehicles have similar pattern of rest stop routes, and there are some popular rest stops in several routes where the vehicles always stop there. This pattern can be seen in the visualization in Fig. 2 (a). The end points of most vehicles are dense in the central of Thailand especially in Bangkok, the capital of Thailand, and they are distributed to four main regions of Thailand: North, North-East, East, and South. In addition, the scoring function *SD* shows that the pattern of three connected rest stops are commonly arranged in the same direction. It is because there are four main directions of four regions as we mentioned, and most routes in each region almost locates in the straight line as can be seen in Fig. 2 (b). In this case, the cosine similarity between $s0 \rightarrow s1$ and $s1 \rightarrow s2$ closes to 1. Moreover, the *SP* is still a player in the equation although its weight is quite small. It helps the prediction model give priority to some nearby popular rest stops. This viewpoint is consistent with the decision of drivers for finding the next rest stops also, because they usually park at some rest stops where other ones often chose.

The prediction of the next rest stop of a vehicle can help the owner of a rest stop can estimate the capacity for providing a better service, and it is also benefit to the drivers at nighttime. This information is not only directly beneficial to the rest stops, but it also benefits a government department. Knowing the incoming number of cars at each rest stop precisely, it helps the government department improve transportation management and road safety as well.

5. Conclusion

This paper aims to predict next rest stops of vehicles based on the current and the previous rest stops. The dataset is from the GPS tracking system installed in commercial vehicles in Thailand. Based on every position on the Earth of every vehicle collected in every minute, all rest stops are selected by estimating any points where a vehicle stops more than 30 minutes. After that, the prediction of the next rest stops has been done by the function P^{Next} that is a weighted hybrid prediction model containing three scoring functions. First, *SF* is the scoring function based on the frequent pattern between rest stops. Second, *SD* is the scoring function based on the cosine similarity between directions of previous, current, and possible rest stops. Last, *SP* is the scoring function based on the popularity of the focused rest stops in the area round the current stop. The analysis measured by AUC demonstrates that all scoring functions are needed in the hybrid method, in addition, with the weights adjusted, the prediction model P^{Next} can provide the higher accuracy.

However, besides predicting a next rest stop from known locations, giving a suggestion to have new rest stops becomes an opportunity to improve road safety for drivers and passengers who take long-distance trips. Thus, the future work of this research will emphasis on giving a recommendation for finding appropriate locations to build new rest stops using the big data analytics of GPS data together with the behavior of drivers.

References

Burke, R., 2002. Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 12.4, pp.331-370.

Chawuthai, R., Takeda, H., Hosoya, T., 2014, November. Link prediction in linked data of interspecies interactions using hybrid recommendation approach. In Joint International Semantic Technology Conference, Springer, Berlin, Heidelberg, pp. 113-128.

Yavaş, G., Katsaros, D., Ulusoy, Ö., Manolopoulos, Y., 2005. A data mining approach for location prediction in mobile environments. Data & Knowledge Engineering, 54(2), pp.121-146.

Hanley, J.A., McNeil, B.J., 1982. The meaning and use of the area under a receiver operating characteristic (ROC) curve. Radiology, 143.1, pp.29-36.

Jeung, H., Liu, Q., Shen, H.T.,Zhou, X., 2008, April. A hybrid prediction model for moving objects. In Data Engineering, 2008. IEEE 24th International Conference on ICDE 2008, IEEE., pp. 70-79.

Morzy, M., 2007, July. Mining frequent trajectories of moving objects for location prediction. In International Workshop on Machine Learning and Data Mining in Pattern Recognition, Springer, Berlin, Heidelberg, pp. 667-680.

Morzy, M., 2006, November. Prediction of moving object location based on frequent trajectories. In International Symposium on Computer and Information Sciences, Springer, Berlin, Heidelberg, pp. 583-592.

Monreale, A., Pinelli, F., Trasarti, R. and Giannotti, F., 2009, June. Wherenext: a location predictor on trajectory pattern mining. In Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, pp. 637-646.

Pazzani, M.J. and Billsus, D., 2007. Content-based recommendation systems. In The adaptive web, Springer, Berlin, Heidelberg, pp. 325-341.

Ricci, F., Rokach, L. and Shapira, B., 2011. Introduction to recommender systems handbook. In Recommender systems handbook, Springer, US.

Scellato, S., Musolesi, M., Mascolo, C., Latora, V. and Campbell, A.T., 2011, June. Nextplace: a spatio-temporal prediction framework for pervasive systems. In International Conference on Pervasive Computing, Springer, Berlin, Heidelberg, pp. 152-169.