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Travel Route Prediction Using Travel Habits and Real-Time Traffic Condition

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Abstract. The traffic problems of cities at home and abroad, especially major cities, have become focus issues. To solve this problem, traffic guidance is one of the most important solutions. For traffic guidance, precisely prediction of travel route of the users becomes one more and more urgent issue. To find out which factor affects the prediction mostly or to propose one efficient route prediction algorithm is attracting more researchers' attentions. In this paper, we proposed one route prediction model to deal with the problem by considering both travel habits and real-time traffic condition. By embedding LSTM model, the proposed approach has the ability of predict sequence data to predict the travel route. Also the logistical model is introduced to embedding the real-time traffic condition data into the proposed model. Experiment results have evaluated the performance of the proposed approach.

1. Introduction

With the rapid development of social economy and the improvement of people's living standards, the number of urban residents' car and resident trips have been increased constantly. As a result, the traffic problems of cities at home and abroad, especially major cities, have become focus issues. Problems such as poor road network, insufficient facilities, crowded traffic, etc, have been more and more prominent. In many cities, blocked traffic, parking difficulties, disordered traffic, etc have have been increasingly emerging, resulting in great impact and pressure of transportation system management[1].

In addition to paying attention to urban transportation facilities, traffic guidance is also important for solving the problem of heavy traffic. Efficient traffic guidance provides the means to improve road resources utilization, improve traffic speed and ease traffic congestion[2].

The research results of travel route prediction and guidance methods at home and abroad show that travelers' response speed can be accelerated to adjust routes in time and avoid traffic congestion by certain methods applied to accurately predict the travel routes in theory[3].

Therefore, this paper aims to analyze routes selection by effective survey methods and determine to introduce new considered variables in the process of travel routes prediction, so as to make the prediction more practical[4, 5].

The LSTM and Binary Logistical model can be used to predict road segments and overall travel route selection, and to guide car travel, which can help residents avoid traffic congestion, reduce travel time, make travel convenient and improve travel efficiency.

2. Related Work

2.1. ADVANCE System of America

ADVANCE (Advanced Driver and Vehicle Advisory Navigation Concept) is a typical distributed traffic guidance system[6]. Traffic Information Center acquires real-time traffic data by collecting the data of floating cars and fixed detectors on the road, and forms synthetic impedance function of road segments by traffic state discrimination and travel time estimation. Thetn the impedance function will be sent to related vehicle-mounted device, which could provide the driver with optimal driving path and guide the car to the starting point according to driver's individual requirement.

2.2. Ali-Scout System of Europe

Ali-Scout System is a centralized traffic route guidance system in Europe[7]. Its central processing platform is responsible for data maintenance, travel time calculation and optimal route calculation. In addition, it can connect with vehicles in the road network through infrared beacons installed on both sides of the intersection. When a vehicle pass through the beacon, the beacon will send information, such as local map, shortest pate, etc, to the vehicle and the vehicle will transmit data, such as road operation condition, to the data center.

2.3. VICS System of Japan

Japan's Vehicle Information and Communication System, established on July 1, 1995, was set up and managed by Japan Road Traffic Information Center[8]. This system aims to improve road traffic safety, road traffic liquidity and road environment. It is regarded as the most successful system in the world for providing traffic information. The VICS system has been spread throughout Japan. In actual operation, it consists of four parts: information collection, information processing, information publishing and information application. VICS can provide traffic information for travelers through radio beacon, light beacon and FM multicast.

The internal traffic guidance system is currently in the research stage of positioning system, electronic map, both-way communication, etc. Those traffic guidance means that have already put into use are based on radio broadcasting and variable message sign (VMS). With relatively simple functions, for them, there are many issues needed to be improved further. The guidance information generation and management system with perfect functions and architecture has not been formed yet. (1) System-based optimal route prediction

Fu Dongmian proposed a minimum transfer algorithm based on the breadth search for sets of several nodes so as to calculate travel route with minimum transfer times[9].

Zhang Shujian analyzed features of urban traffic network and summarized problems existing in the traffic network to apply GIS-T System with function of spatial analysis into travel route algorithm. He proposed a dynamic route guidance algorithm on the basis of GIS- and genetic algorithm[10].

Kong Huixin studied a route recommendation method based on real-time passenger flow distribution. She proposed the calculation method of its passenger carrying probability and measurement standard - PVC (Potential Vacant Cost) equation - of route recommendation through K-means clustering algorithm to divide, so as to design the minimum cost recommendation algorithm for taxi travel routes[11].

3. Route Prediction Based on Travel Habits and Real-time Traffic

A traveler's route selection depends to a great extent on the traveler's habits. The traveler's route selection can be regarded as the accumulation process of habitual routes, that is, acquiring habitual routes from historical routes selection and choosing the next route according to habitual routes. Each route selection has a certain probability, as a result, it can be described and predicted by LSTM. According to the investigation and modeling analysis of the travel routes selection mentioned above, it can be seen that a traveler's selective behaviour of route not only depends on his/her traveling habits, but also affected by the actual road conditions.

The information input the model includes three aspects. The first is traveler's basic information, including traveler's social, economic and travel attribute. The second is historical route selection data, that is, the actual routes selection data of all kinds of travel in several days, including travel routes data and actual routes selection for several days. The third is real-time traffic conditions. After obtaining the relevant data, the model is applied to predict the rout selection[12].

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3.1. LSTM

LSTM is one of the most common approaches for sequence data prediction[13]. As shown in Figure 1, the repeat cell of LSTM can be embedded into a neural net model to predict the sequence information. As described in equation (1), the sigmoid layer called the "input gate layer" decides updated values is introduced.

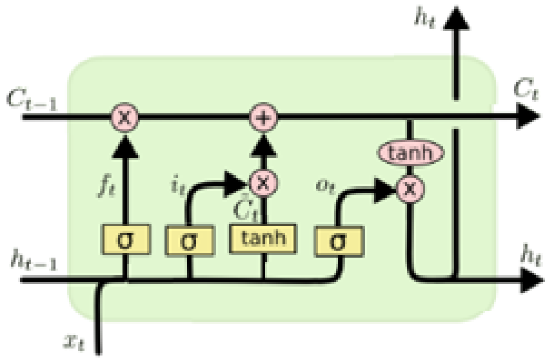

Figure 1. The structure of LSTM

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{1}$$

To calculate the input of time t, equation (2) is introduced:

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{2}$$

Then a tanh layer creates a vector of new candidate values is added into the state as show in equation (3).

$$\tilde{C}_t = \tanh\left(W_C[h_{t-1}, x_t] + b_C\right) \tag{3}$$

Using equation (4), the old cell state C_{t-1} is added into the new cell state C_t.

$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t \tag{4}$$

Then a sigmoid layer which decides what parts of the cell state we're going to output as shown in equation(5).

$$o_t = \sigma\left(W_o[h_{t-1}, x_t] + b_o\right) \tag{5}$$

Finally LSTM puts the cell state through tanh (to push the values to be between −1 and 1) and multiply it by the output of the sigmoid gate, so that we only output the parts we decided to.

$$h_t = o_t * \tanh\left(C_t\right) \tag{6}$$

3.2. Logistical Prediction Model

Logistical prediction model is one of the most famous prediction models in route prediction[14]. It assumes utility maximization hypothesis on the observed data. The corresponding utility function of it is defined as follows:

$$U_{ip} = o_{ip} + e_{ip} \tag{7}$$

As shown in equation (7), i is signal of choice. p is choice of user. o_{ip} means the observed influence factor and e_{ip} is the influence factor of unobserved. When i equals 1, it means that user chooses the customary section.

$$o_{ip} = \sum_{k=1}^{K} \alpha_k x_{ik} \tag{8}$$

x_{ik} means that the user choose the k-th influenced factor of route i.

To calculate model, optimization technique should be used. Model parameters optimality is usually defined with a loss function and the objective task is to minimize the sum of losses on the observed data.

3.3. The Proposed Model

In the following, we present our algorithm which is generalized from LSTM and logistical. If the collected ratings are entering sequentially, we could adjust the model by considering the coming data only. Dual-average method for the two model which absorbs previous information in an approximate average gradient of the loss is one of the most widely used methods to solve optimization problems[15]. The proposed algorithm is detailed as follows:

ALGORITHM1: *Proposed Model*

Step 1: Prediction of habits-based routes selection. Markov Prediction Model is used for habits-based route selection. Based on historical data of route selection, the model can predict selective probability of traveler's alternative routes under the condition of considering habits only and set the route with maximum probability as the habitual route. The road segments consisted all the alternative routes can be regarded as the habitual segments in the route.

Step 2: If there are more than one optional road segment in the road segment selection, the selective probability of habitual routes and non-habitual routes should be calculated repeatedly under different road conditions and ratiometric conversion should be carried out to determine the selective probability of each segment in one route selection. If there are multiple segment selections, above steps should be repeated until the end of the route.

Step 3: Utility calculation of route selection based on habits and road conditions. On the basis of the selective probability of each route based on habits in the first step and selective probability of each road segment in the third step, the selection utility can be obtained by amending the selection probability of each route according to the segment composition of each route.

Step 4: The selection probability calculation of the travel route. The selection probability of route selected by the model can be calculated according to the selection utility of each route calculated in the third step.

return *prediction result*

4. Experiments

To evaluate the performance of our algorithm, several experiments are conducted on a dataset that is described in section III. The questions we want to deal with include:

1) How is the performance of the proposed algorithm?
2) In which way do parameters affect the method's performance?
3) What is the time overhead of the proposed method?

4.1. Evaluation Metrics

We carried out several experiments to evaluate the performance of the proposed algorithm. The experiments are conducted on a dataset.

For the purpose of measuring the prediction quality of our method in comparison with other approaches, hit-ratio metrics which is one of the widely used methods in the field of prediction system is embodied, and it is defined as:

$$hit - ratio = \frac{hit}{testlists} \tag{9}$$

where hit is the actual hits of selected results assigned by user, testLists is estimated value. The higher the hit-ratio, the better the performance[16].

4.2. Performance Evaluation

Table 1 presents the results of prediction accuracy performance of the approaches mentioned above. According to these experiments, we have several important observations. The total prediction hit-ratio is 82.5. When the observation sample is the customary routine, the prediction performance is high and the hit-ratio is 91.6%. When the observation sample is the uncustomary routine, the prediction performance is low and the hit-ratio is 68.9%. At this point, the model overestimates the probability of choosing the habits without considering the road conditions. In fact, road conditions have a certain influence on the choice of road sections, and some of the samples will choose unfamiliar road sections because of the road conditions.

Table 1. Prediction results

observations		*prediction results*		
		route choice		*hit-ratio*
		customary	*uncustomary*	
routine choice	***customary***	522	82	91.6%
	uncustomary	220	321	68.9%
hit-ratio		--	--	82.4%

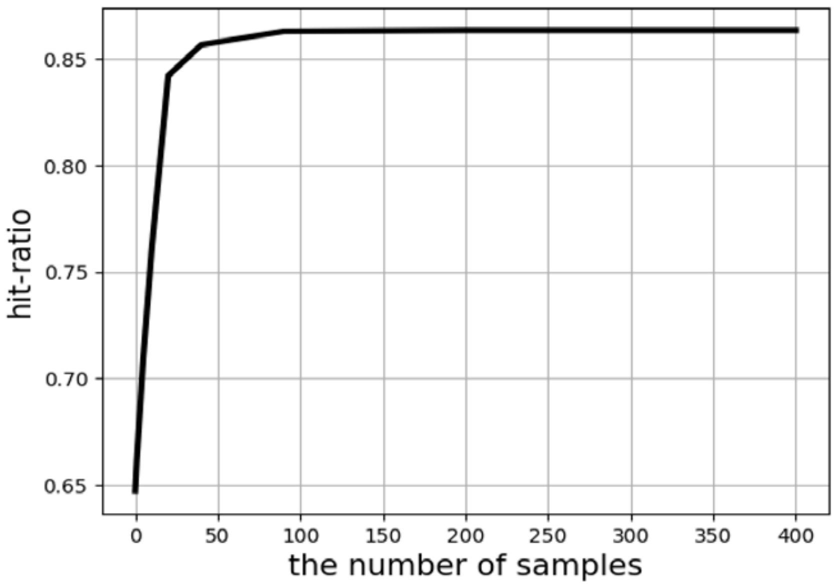

Figure 2. The hit-ratio under different number of samples

A respondent whose number is 18 was performed a one-sample analysis. The respondent #18 belongs to age group 18-30 years old, with a driving age of less than one year, the occupation is a student, the monthly income is below 4000, and the education is bachelor. The purpose of the trip is to go to school, and the departure time is the evening peak. Bringing these independent variable information into the model, predicting the probability that the respondent #18 will select the custom road segment and the uncustomary road segment (adjust the road segment according to the road condition) under different road conditions. The prediction result is shown in Table 2.

Table 2. Prediction Results

C	***Probability of choice***	
	customary route(%)	***uncustomary route(%)***
C1	77.3	22.7
C2	27.4	72.6
C3	36.5	63.6
C4	92.3	7.7
C5	76.8	23.2
C6	53.2	46.8
C7	92.1	7.9
C8	63.7	36.3
C9	72.1	28.9

The results show that, in general, the habit of influence is greater than the road conditions. Specifically, (1) when the road conditions of the two road sections are the same, the respondent tends to follow the habit; (2) when the customary road section is better than the unfamiliar road section, the weight of the habit is considered to be greater than the weight of the road condition. (3) When the road condition of the unfamiliar road section is better than the custom road section, the traveler will prefer to consider the road condition. When the customary road section is normal and the unfamiliar road section is unblocked, although the uncomfortable road section is better than the custom road section, because the customary road sections can pass normally, the weight of the habit is still greater than the weight of the road conditions[17].

5. Time Overhead

The proposed approach takes more than 40 seconds to finish 500 iterations using an implementation in a Win8 PC with Core 2.8 GHz processor and 8GB memory. The time overhead becomes much more significant along with the growth of the data.

As shown in Figure 3, the different algorithm has different time overhead.

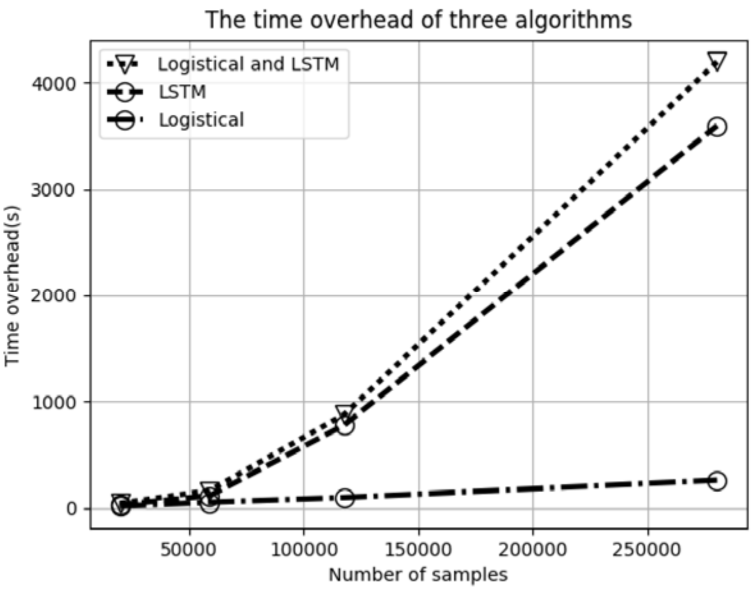

Figure 3. The time overhead under different number of samples

6. Conclusions and Future Work

In this paper, we proposed an routine prediction algorithm based on travel habits and real-time traffic condition. We first give account of LSTM for series data prediction. For the purpose of dealing with

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real-time traffic condition data route prediction, we then embody “logistical model” and propose a combined model of LSTM and logistical model. Experiments show the propose model can get better performance and has less time overhead.

Our future work includes conducting more experiments to improve the performance of our proposed method. We also plan to explore how to solve more complex traffic condition problems.

7. References

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