ICCEPM 2024 https://dx.doi.org/10.6106/ICCEPM.2024.0242
The 10th International Conference on Construction Engineering and Project Management
Jul. 29-Aug.1, 2024, Sapporo

Artificial Intelligence and Stochastic Optimization Framework for Trip Purpose Based Route Planning

Wen YI[1]*, Huiwen WANG[2]*, Shuaian WANG[3]*, Xiaobo QU[4]

[1] *Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong 999077, China,* E-mail address: wen.yi@polyu.edu.hk
[2] *Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong 999077, China,* E-mail address: huiwen.wang@connect.polyu.hk
[3] *Faculty of Business, The Hong Kong Polytechnic University, Hong Kong, China 999077,* E-mail address: hans.wang@polyu.edu.hk
[4] *School of Vehicle and Mobility, Tsinghua University, Beijing 100084, China,* E-mail address: xiaobo@tsinghua.edu.cn

Abstract: Automated route planning is an important tool in the field of built environment. For example, a high-quality route planning method can improve the logistics planning of projects, thereby enhancing the performance of projects and the effectiveness of management. However, the traditional automated route planning is performed based on the predicted mean value travel time of candidate routes. Such a point estimate neglects the purpose of the trip and can further lead to a suboptimal decision. Motivated by this challenge, this study proposes an innovative framework for trip purpose based route planning. The proposed artificial intelligence and stochastic optimization framework recommends the most appropriate travel route for decision makers by fully considering their trip requirements beyond just the shortest mean value travel time. In addition to its theoretical contributions, our proposed route planning method will also contribute to the current logistics planning practice. Future research may be devoted to the real-life implementation of the proposed methodology in a broader context to provide empirical insights for practitioners in various industries.

Key words: automated routing planning, artificial intelligence, stochastic optimization, sustainable built environment

1. INTRODUCTION

Automated route planning has become an essential tool for driving trips, especially for truck drivers, taxi drivers, and private car drivers. A number of companies provide free automated route planning services, such as Google, Gaode, and Baidu. When one inputs the origin—which is often set to the current location of the vehicle based on the Global Positioning System (GPS)—and destination, the routing services will provide a few recommended routes, listed in the increasing order of travel time. An example is shown in Figure 1: once the origin “The Hong Kong Polytechnic University” and the destination “The University of Hong Kong” are input, Google Map provides two recommended routes: route 1 has a travel time of 20 min and route 2 has a travel time of 23 min.

In general, the routing services can recommend routes to users based on a two-step approach, as shown in Figure 2. In the first step, taking advantage of historical travel data and auxiliary information (e.g., weather), machine learning models are used to predict the travel time for each road segment. In the second step, based on the predicted travel time for each road segment in the transport network, the shortest-time path is identified using mathematical optimization (e.g., the Dijkstra’s algorithm); several paths with short travel times can be identified using advanced mathematical optimization techniques.

Since the identification of paths with short travel times is less challenging, most efforts have been focused on developing machine learning models to improve the accuracy of predicting the travel time for each road segment. For example, Chien and Kuchipudi [1] used both real-time and historical data to predict the travel time; Zhang and Rice [2] proposed a linear model to predict freeway travel time; Wu et al. [3] designed a support vector regression model to predict the travel time; Zhang and Haghani [4] presented a gradient boosting method for predicting the travel time of two freeway sections in Maryland; Duan et al. [5] formulated a neural network model to predict travel time; Zhou et al. [6] provided a naïve Bayes network approach to predict the travel time.

All the above-mentioned studies provide a point estimate of the travel time, in particular, they try to estimate the mean value time of a road segment. This is also the case for the route planning service providers. Evidently, the travel times shown in Figure 1 are estimated mean travel times, and the estimated mean travel times will be different from the true travel times almost surely due to (i) prediction errors and (ii) randomness in travel time. As a result, the existing two-step approaches for recommend routes to users are problematic, as shown in the example below.

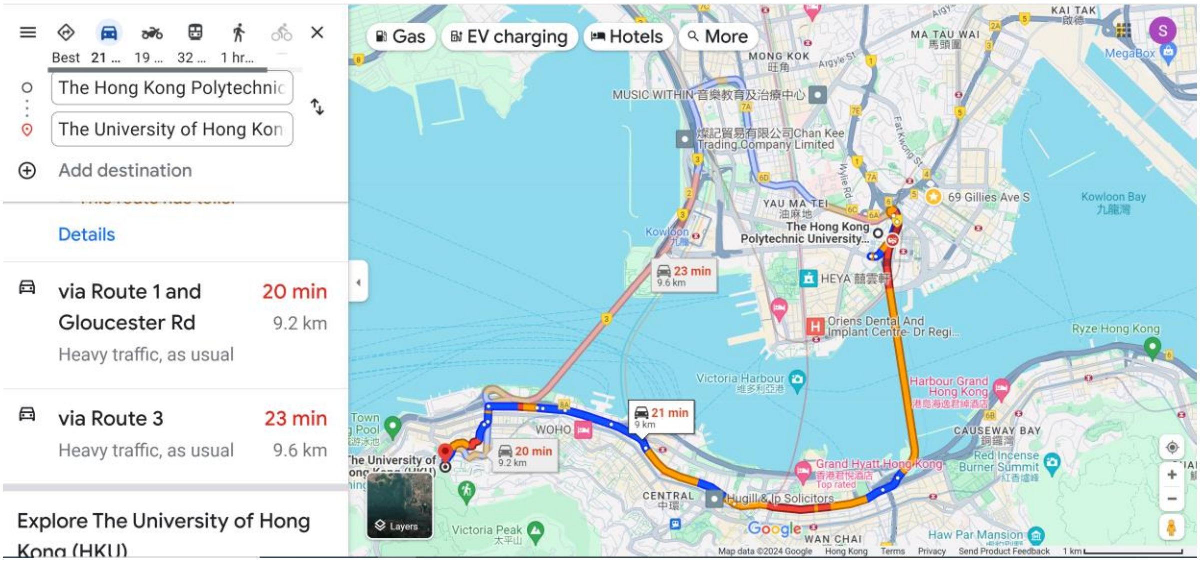

Figure 1. An example of automated route planning (Source: Google)

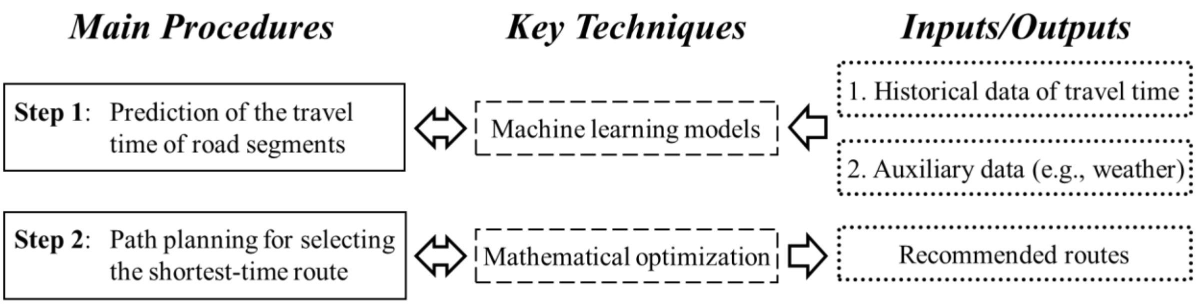

Figure 2. A two-step approach used by automated route planning service providers

1.1. An illustrative example

Suppose that a traveller is about to depart from A to B to take a flight whose check-in counter will be closed in 60 min. There are two routes from A to B: route 1 and route 2. The travel time on route 1 can be 50 min with 50% chance or 64 min with 50% chance, and the travel time on route 2 is 58 min with 100% chance. Suppose that a route planning service provider has access to a large volume of historical data and has developed an advanced machine learning model. The route planning service provider has correctly predicted that the mean travel time on route 1 is 57 min and on route 2 is 58 min. Therefore, it recommends the two routes to users, showing that route 1 has a travel time of 57 min and route 2 has a travel time of 58 min. Evidently, most users will select route 1, and, as a result, they will be late for the flight with a high 50% chance. The deficiency for the route planning service provider is that it does not take into account the purpose of the trip. Here, the traveller is interested in finding a route with the largest chance that the travel time does not exceed 60 min, instead of finding a route with the shortest mean travel time.

1.2. Objective and contributions

The objective of this study is to propose an artificial intelligence and stochastic optimization framework for trip purpose based route planning. Specifically, the recommended route will be based on the purpose of the trip, as shown by the above taking-a-flight example, thus better meeting the users' needs. The contributions of the research are two-fold. First, to the best of our knowledge, this is the first study that proposes the concept of trip purpose based route planning, which has fundamental theoretical and practical implications. Second, we apply prescriptive analytics techniques to demonstrate how to integrate machine learning and stochastic optimization to address the problem of trip purpose based route planning.

2. MODELING FRAMEWORK

Consider a user traveling from A to B. There are a total of R routes, denoted as route 1, …, route R. The route planning service provider needs to recommend one route to the user (the problem of recommending more than one route is similar).

Suppose that the route planning service provider has access to the auxiliary data for route $r = 1, \dots, R$, denoted by x_r, for instance, x_r can contain the information on weather and the travel times on route r in the past 168 hours (168 hours = 1 week). The route planning service provider has a large number of historical travel data. For simplicity, we assume that it has N records for each route r, denoted by $\{(x_r^1, y_r^1), \dots, (x_r^N, y_r^N)\}$, in which x_r^i is the auxiliary data of record $i = 1, \dots, N$ for route r, and y_r^i is the corresponding travel time.

For simplicity, we use the k-nearest-neighbour (kNN) machine learning model in this framework. Of course, more advanced machine learning models can be used.

2.1. Traditional route planning approach

The traditional route planning approach works as follows. First, for each route r, it identifies the k historical records that have the most similar auxiliary data to x_r, where k is a hyperparameter (e.g., $k = 10$). Suppose that these k historical records are $\left(x_r^{(1)}, y_r^{(1)}\right), \dots, \left(x_r^{(k)}, y_r^{(k)}\right)$. Then, the predicted travel time for route r, denoted by $\hat{y}_r$, is

$$\hat{y}_r = \frac{1}{k}\sum_{j=1}^{k} y_r^{(j)}, r = 1, \dots, R. \tag{1}$$

Then, the route with the shortest predicted mean travel time, denoted by r^*, is recommended:

$$r^* \in \mathrm{argmin}_{r=1,\dots,R}\, \hat{y}_r. \tag{2}$$

For example, suppose that there are two routes from A to B. Route 1 has a set of two historical records $\{(8,50), (8,64)\}$ (note that for simplicity, we assume both records have the same auxiliary data 8, which can mean e.g., 8:00 am). Route 2 has a set of two historical records $\{(8,58), (8,58)\}$. $x_1 = x_2 = 8$ and $k = 2$. The predicted travel times for route 1 and route 2 are 57 and 58, respectively. That is, $\hat{y}_1 = \frac{50+64}{2} = 57$ and $\hat{y}_2 = \frac{58+58}{2} = 58$. As route 1 yields a shorter predicted mean travel time than route 2, we have $r^* = 1$, indicating that route 1 is recommended by the route planning service provider.

2.2. Trip purpose based route planning approach

In the trip purpose based route planning approach, one has to specify the purpose of the trip. For instance, the purpose is to arrive at B within $T = 60$ min to take a flight. Then, we should not predict the mean travel time, but the distribution of the travel time.

The trip purpose based route planning approach works as follows. First, for each route r, it identifies the k historical records that have the most similar auxiliary data to x_r, where k is a hyperparameter (e.g., $k = 10$). Suppose that these k historical records are $\left(x_r^{(1)}, y_r^{(1)}\right), \dots, \left(x_r^{(k)}, y_r^{(k)}\right)$. Then, the predicted travel time for route r, denoted by $\tilde{y}_r$, is a random variable that has the following distribution:

$$\Pr(\tilde{y}_r = y_r^{(j)}) = \frac{1}{k}, r = 1, \dots, R, j = 1, \dots k. \tag{3}$$

Then, the route with the largest chance of being able to arrive at B within T min, denoted by r^*, is recommended:

$$r^* \in \operatorname{argmax}_{r=1,\ldots,R} \Pr(\tilde{y}_r \leq T). \tag{4}$$

For example, suppose that there are two routes from A to B. Route 1 has a set of two historical records $\{(8{,}50), (8{,}64)\}$ (note that for simplicity, we assume both records have the same auxiliary data 8, which can mean e.g., 8:00 am). Route 2 has a set of two historical records $\{(8{,}58), (8{,}58)\}$. $x_1 = x_2 = 8$ and $k = 2$. The predicted travel time for route 1 is a random variable that can take the value of either 50 or 64 min, each with an equal possibility of 50%. That is, $\Pr(\tilde{y}_1 = 50) = \Pr(\tilde{y}_1 = 64) = 0.5$. Similarly, the predicted travel time for route 2 is also a random variable, but in this case, it always takes the value of 58 minutes with a 100% probability. That is, $\Pr(\tilde{y}_2 = 58) = 1$. Then, the chances for the traveller being able to arrive within 60 min are 50% for route 1 and 100% for route 2, respectively. When the purpose of the trip is considered, we have $r^* = 2$.

3. EXTENSIONS

Typically, the purposes of route planning are of three types, as summarized in Table 1. The *first* type of trip purpose is to arrive at a destination as quickly as possible, such as travelling to a park for a walk. In terms of this type, the traditional approach of determining the route with the shortest mean travel time (described in Section 2.1) is applicable. The *second* type of trip purpose is to arrive at a destination by a specific deadline, such as travelling to an airport to catch a flight. In terms of this type, the newly proposed route planning approach of determining the route with the largest chance of being able to arrive at a destination within a given time period (described in Section 2.2) is applicable. In addition to the above two purposes, the *third* type of purpose is to arrive at a destination as close to a specified time as possible. A representative example is going to the theater to watch a movie. In such a case, there are penalty costs involved regardless of whether arriving early or late. Normally, the penalty costs for late arrivals are higher than those for early arrivals. Arriving early at the theater may result in waiting time, while arriving late may lead to missing part of the movie.

Table 1. Summary of cases in trip purpose based route planning

No.	Description	Example
1	Minimizes mean travel time	Travel to a park to walk
2	Maximize the chance that the travel time is less than or equal to a threshold	Go to the airport to take a flight
3	Maximize the penalty for late and early arrival (usually the penalty for late arrival is larger)	Go to the theater to watch a movie: arriving early means waiting and arriving late means missing some part of the movie

This section presents an extension to the proposed route planning method in a scenario where the trip purpose is to arrive at B on time, as close to T minutes as possible, e.g., go to the theater to watch a movie that is planned to start T min later. The early and late arrivals at the theater incur a unit penalty cost of c_1 and c_2, respectively. Usually, $c_1 \leq c_2$. We define the following function $f(\dot{y})$ to calculate the penalty costs when the travel time is $\dot{y}$ min:

$$f(\dot{y}) = \begin{cases} c_1(T - \dot{y}), \text{if } \dot{y} \leq T \\ c_2(\dot{y} - T), \text{otherwise} \end{cases}. \tag{5}$$

In such a case, the distribution of the travel time, rather than the mean travel time, is to be predicted. To this end, we first identify the k historical records that have the most similar auxiliary data to x_r, where k is a hyperparameter (e.g., $k = 10$). Suppose that these k historical records are $\left(x_r^{(1)}, y_r^{(1)}\right), \ldots, \left(x_r^{(k)}, y_r^{(k)}\right)$. Similarly, the predicted travel time for route r, denoted by $\tilde{y}_r$, is a random variable whose distribution is described in Eq. (3). Then, the route with the minimum expected penalty costs to arrive at B in T min, denoted by r^*, is recommended:

$$r^* \in \text{argmin}_{r=1,\ldots,R} \frac{1}{k} \sum_{j=1}^{k} f\left(y_r^{(j)}\right). \quad (6)$$

For example, suppose that there are two routes from A to B. Route 1 has a set of two historical records $\{(8,50),(8,64)\}$ (note that for simplicity, we assume both records have the same auxiliary data 8, which can mean e.g., 8:00 am). Route 2 has a set of two historical records $\{(8,58),(8,58)\}$. $x_1 = x_2 = 8$ and $k = 2$. The unit penalty costs for early and late arrivals are 5 and 10, respectively, i.e., $c_1 = 5$ and $c_2 = 10$. The predicted travel time for route 1 is a random variable that can take the value of either 50 or 64 min, each with an equal possibility of 50%. That is, $\Pr(\tilde{y}_1 = 50) = \Pr(\tilde{y}_1 = 64) = 0.5$. Similarly, the predicted travel time for route 2 is also a random variable, but in this case, it always takes the value of 58 minutes with a 100% probability. That is, $\Pr(\tilde{y}_2 = 58) = 1$. The expected penalty costs to travel to the theatre via route 1 is 45, that is, $50\% \times [5 \times (60 - 50)] + 50\% \times [10 \times (64 - 60)]$. The expected penalty costs to travel to the theatre via route 1 is 10, that is, $100\% \times [5 \times (60 - 58)]$. Therefore, we have $r^* = 2$.

4. CONCLUSIONS

This study investigates the automated route planning problem considering trip purpose. An innovative artificial intelligence and stochastic optimization framework is proposed, which can effectively address the existing challenge posed by the traditional point estimate method. First, an easy-to-understand example of taking a flight is presented to justify the significance of considering the trip purpose. Then, we propose the modelling framework for the traditional route planning and the trip purpose based route planning, which is further extended to a watching-a-movie case.

The artificial intelligence and stochastic optimization framework designed in this research makes significant contributions both in theory and practice. From the theoretical perspective, it represents the first attempt at the concept of trip purpose based route planning. From the practical perspective, the proposed method can be applied to various real-life route planning scenarios. For follow-up research, it is suggested that more efforts should be devoted to real-world implementation of the method in a broader context. This would involve conducting empirical studies to provide practical insights for practitioners across different industries.

ACKNOWLEGEMENTS

This work was supported by the National Natural Science Foundation of China [Grant Nos. 72201229, 72361137006].

REFERENCES

[1] S. I.-J. Chien, C. M. Kuchipudi, “Dynamic travel time prediction with real-time and historic data”, Journal of Transportation Engineering, vol. 129, no. 6, pp. 608–616, 2003.

[2] X. Zhang, J. A. Rice, “Short-term travel time prediction”, Transportation Research Part C: Emerging Technologies, vol. 11, no. 3, pp. 187–210, 2003.

[3] C.-H. Wu, J.-M. Ho, D. T. Lee, “Travel-time prediction with support vector regression”, IEEE Transactions on Intelligent Transportation Systems, vol. 5, no. 4, pp. 276–281, 2004.

[4] Y. Zhang, A. Haghani, “A gradient boosting method to improve travel time prediction”, Transportation Research Part C: Emerging Technologies, vol. 58, pp. 308–324, 2015.

[5] Y. Duan, L. V. Yisheng, F. Y. Wang, “Travel time prediction with LSTM neural network”, in 2016 IEEE 19th International Conference on Intelligent Transportation Systems (ITSC), IEEE, pp. 1053–1058, 2016.

[6] X. Zhou, M. Su, Z. Liu, Y. Hu, B. Sun, G. Feng, “Smart tour route planning algorithm based on naïve Bayes interest data mining machine learning”, ISPRS International Journal of Geo-Information, vol. 9, no. 2, p. 112, 2020.