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Destination Decision Model for Cruising Taxis Based on Embedding Model

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***Abstract*—**In Japan, taxi is one of the popular transportations and taxi industry is one of the big businesses. However, in recent years, there has been a difficult problem of reducing the number of taxi drivers. In the taxi business, mainly three passenger catching methods are applied. One style is "cruising" that drivers catches passengers while driving on a road. Second is "waiting" that waits passengers near by the places with many requirements for taxies such as entrances of hospitals, train stations. The third one is "dispatching" that is allocated based on the contact from the taxi company. Above all, the cruising taxi drivers need the experience and intuition for finding passengers, and it is difficult to decide "the destination for cruising". The strong recommendation system for the cruising taxies supports the new drivers to find passengers, and it can be the solution for the decreasing the number of drivers in the taxi industry. In this research, we propose a method of recommending a destination for cruising taxi drivers. On the other hand, as a machine learning technique, the embedding models that embed the high dimensional data to a low dimensional space is widely used for the data analysis, in order to represent the relationship of the meaning between the data clearly. Taxi drivers have their favorite courses based on their experiences, and the courses are different for each driver. We assume that the course of cruising taxies has meaning such as the course for finding business man passengers (go around the business area of the city of go to main stations) and course for finding traveler passengers (go around the sightseeing places or big hotels), and extract the meaning of their destinations. We analyze the cruising history data of taxis based on the embedding model and propose the recommendation system for passengers. Finally, we demonstrate the recommendation of destinations for cruising taxi drivers based on the real-world data analysis using proposing method.

***Keywords*—**Taxi industry, decision making, recommendation system, embedding model.

I. Introduction

IN, Japan, taxies have long been an important transportation for people in Japan, as well as trains and buses. In addition, the demand for taxis is expected to increase after the settlement of the COVID-19 virus and during the Tokyo Olympics in 2020 (held in 2021) and as the number of foreign tourists increases. However, in recent years, there has been a difficult problem of a decrease in the number of taxi drivers because taxi drivers are considered to have a difficulty in terms of the physical and the experiential problems especially for the new drivers. Here, we focus on the method for catching passengers. There are three types of methods for catching passengers: "Nagashi," a taxi driver catches passengers while driving, "Tsutsume-waiting," a taxi driver waits for passengers near the entrance to a station or tourist spot, and "Radio Dispatch," driver is assigned to a passengers based on a phone call from the company. In the three, "Nagashi" requires drivers' experience and intuition, and it is difficult to determine "where to go during Nagashi" especially in unfamiliar places [1] or the driver does not have enough experience. In order to solve this problem, we propose a method to recommend a destination to a driver who cannot decide where to go. Here, it is considered that each taxi driver has its own preference for target passengers such as tourists or elderly people. In addition to the attributes of the passengers, drivers have preference for the destinations such as sightseeing spots, stations, and hospitals are also considered. Therefore, if the driver who is not familiar with the place could know the destination of experienced drivers, recommendation of the destination from the place should be helpful. On the other hand, Doc2Vec [2] is widely used in the field of natural language processing as a method of representing sentences and words as vectors in a semantic space using documents and words, considering the tendency for the occurrence of words. This framework should be applicable for the recommendation of the destination of the taxi. In this study, we propose a method for recommending "target experienced drivers" and "taxi destinations" based on the vectorization of documents as drivers and words as destinations in the semantic space. Furthermore, we apply the proposed model to actual taxi driving history data including the latitude and longitude information for every 30 seconds provided in the in the data analysis competition 2019 conducted by Joint Association Study Group of Management Science [6].

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This paper is composed of six sections. In Section II, we present a basic analysis of the provided taxi travel history data. Section III describes Doc2Vec, the method used for the analysis in this study. In Section IV, we explain the destination decision model for cruising taxies. Section V describes the results of applying the model described in Section IV to real taxi data. Finally, in the last section, we summarize our research and present our future work.

II. Data Description

A. Variables of the Data

This paper analyzes the travel history data of taxis in Tokyo, which was provided in the data analysis competition 2019 conducted by Joint Association Study Group of Management Science [6]. In the data, information of latitude and longitude of the approximately 10,000 taxis is recorded every 30 seconds for a period of two years, from April 2016 to March 2018. The recorded information is shown in Table I.

The data contained many missing values, and in particular, the number of the missing data varied greatly depending on the taxi company. Therefore, in this study, we focused on a certain taxi company with few missing values, and analyzed using the data of 181 taxis belonging to that company.

TABLE I
ATTRIBUTES OF THE DATA

Attributes	Comment
DIRECTION	Direction of the moving taxies (i.e., parameters of west or east, and north or south)
COMPANY ID	ID assigned to the taxi company
DRIVERNMBER	ID assigned to each drive
LATITUDE	Parameter of latitude
LONGITUDE	Parameter of longitude
RADIONUMBER	ID assigned to each vehicle body
STATUSTIME	Data acquisition time
VEHICLESTATUS	Status of the taxi (i.e., hired or vacant)

B. Definition of the "Trip"

In this study, we propose a model for recommending the destination of cruising taxies. Therefore, the location where a taxi picks up a passenger are converted into data and embedded into semantic space. For converting the information to data, we specified timing and location where the taxi picks up a passenger from given data as follows. First, we set the time when the taxi picked up the passenger, that is, the timing of taxi's status changed to a "hired" from "vacant". Then we specified the picking location as the intersection closest to the latitude and longitude of taxi at the relevant time.

In the data, the 181 taxis were focused and a total of 626,025 boarding places over a one-year period is accumulated. Using this data, we recommended "target experienced drivers" and "taxi destinations" using the proposal method.

III. DOCUMENT TO VECTORS (DOC2VEC) [2]

Doc2Vec embeds words in a document into a semantic space consisting of their occurrence data, and first learns the weights of the words. First, T words $\{w_1, w_2, w_3, \dots, w_T\}$ are given. We predict the probability that the word located at the center is w_t from the k words before and after each word. Fig. 1 shows the probabilities of the three words "the", "cat", and "sat" in the document "Paragaraph id". "the", "cat", and "sat" in the document "Paragaraph id".

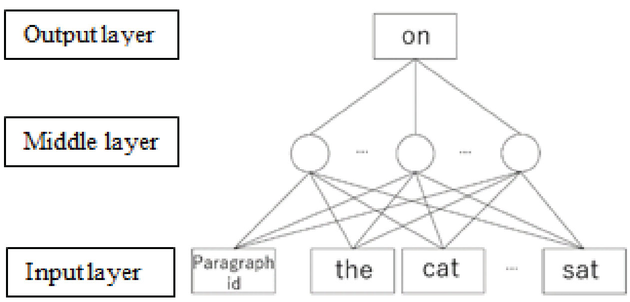

Fig. 1 Structure of Doc2vec

The weights are adjusted so that the output probability and (1) are close to each other. To adjust the parameters, we use the error back propagation method. First, we set the weights matrix W to appropriate initial values. Then, there is an error between the output and the correct answer. Therefore, the weights are updated to reduce the error.

$$\frac{1}{T}\sum_{t=k}^{T-k} \log p(w_t | w_{t-k}, \dots, w_{t+k}, d_j) \quad (1)$$

Then probability that the output word will appear in the document is predicted by neural network with learning the weight of each edge. The learned weights from the input layer to the middle layer are denoted by $W = \{w_{ij}\}$(i : index of a word, j : index of semantic space). The one-hot vector representing a word or a document vector $\boldsymbol{v}$ ($\boldsymbol{v} = \{v_1, \dots, v_i\}$, $\sum_i v_i = 1$, $v_i = \{0,1\}$), embedding $\boldsymbol{v}$ onto the semantic space as $W\boldsymbol{v}$.

$$\mathbf{W}\boldsymbol{v} = \begin{pmatrix} w_{1,1} & w_{2,1} & \cdots & w_{i,1} \\ w_{1,2} & w_{2,2} & \cdots & w_{i,2} \\ \vdots & \vdots & \cdots & \vdots \\ w_{1,j} & w_{2,j} & \cdots & w_{i,j} \end{pmatrix} \begin{pmatrix} 0 \\ \vdots \\ 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \begin{pmatrix} w_{v,1} \\ w_{v,2} \\ \vdots \\ w_{v,j} \end{pmatrix}$$

Doc2vec was originally proposed as a method for analyzing document data [2], it has since been used for constructing recommendation systems using personal behavior log data [3], anomaly detection [4], and article retrieval [5], and its application is expanding.

In this study, we propose a model to identify drivers who should be a reference for new drivers, and to recommend the destination of cruising taxis by extracting taxi drivers' preferences for destinations and the relationship between intersections and drivers from data of the location of each taxi.

IV. DESTINATION DECISION MODEL FOR CRUISING TAXIS BASED ON EMBEDDING MODEL

In this study, we propose a model to assist a taxi driver who cannot decide where to go. We represent the driver and the destination intersection as vectors in the semantic space, which allows for understanding relationships. The model determines the target driver to be a reference and determines the destination that the target driver should prefer.

A. Vector Representation of Drivers and Intersections

Let $\mathrm{X} = \{\mathrm{x}_1, \dots, \mathrm{x}_\mathrm{i}, \dots, \mathrm{x}_\mathrm{I}\}$, set of destinations $\mathrm{Y} = \{\mathrm{y}_1, \dots, \mathrm{y}_\mathrm{j}, \dots, \mathrm{y}_\mathrm{J}\}$, and the drive history of the driver i be $\mathrm{R}_\mathrm{i} = \{\mathrm{r}_{\mathrm{i}1}, \dots, \mathrm{r}_{\mathrm{it}}, \dots, \mathrm{r}_{\mathrm{iT}}\}$ ($\mathrm{r}_{\mathrm{it}} \in \mathrm{Y}$). Then, by positioning the document index as the driver and the word as the destination and applying to Doc2Vec, we estimate the semantic vector h_i of the driver and v_i of the destination. The proposed model is illustrated as Fig. 2.

B. Decision Model for the Target Drivers

In order to recommend a destination for efficient cruising of taxi in the area, a target driver is determined as a reference is preferable. We assume the target driver picks up passenger in the region well where the driver not familiar with the region.

The target driver $i^*$is optimized by (2) where $Z \subseteq Y$, and the function $I(\cdot)$ is an indicator function that takes 1 when the logical expression of $\cdot$ is true.

$$i^* = argmax_i \sum_{t=1}^{T} \sum_Z I(r_{it} = y_j) \tag{1}$$

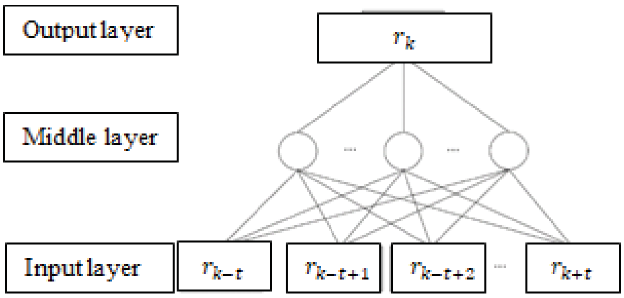

Fig. 2 Structure of network of proposal

C. Decision Model for the Destination for Cruising Taxi

Now, each taxi driver is assumed to have a destination he/she prefers, and is able to meet many passengers there. Therefore, we extract the destination j^* where the target driver i^* picks up the most passengers and this is his/her favorite destination. The following formula is used to extract destination j^*:

$$j^* = argmax_{j \in Z} \sum_{t=1}^{T} \sum_Z I(r_{it} = y_j) \tag{3}$$

Then we determine the destination g_i that has the same tendency to be the destination j^* of target taxi drivers i^*. This means that the equation "target driver i^* "+ "destination j^*"="driver i" + "destination g_i" is valid. From this equation, we transform it to the following equation to determine the destination g_i.

$$g_i = argmin_j \left| \boldsymbol{h}_{i^*} + \boldsymbol{v}_{j^*} - \boldsymbol{h}_i - \boldsymbol{v}_j \right| \tag{4}$$

V. Real Data Analysis

A. Analyzed Data and Settings

In this section, we analyze the driving history data of taxis in Tokyo, which was provided in the data analysis competition 2019 conducted by Joint Association Study Group of Management Science [6]. We use 181 taxis from April 2017 to March 2018. For the destination, only the data of the intersection of taxi where the passenger is likely to be got on can be identified, based on the change of the taxi's status from "Vacant" to "hired".

Using the obtained data, drivers and destinations are vectorized using Doc2vec, and examples of target driver determination and destination recommendation examples are shown. The number of dimensions of the vector is 200, and the number of words used for prediction is three, respectively.

B. Interpretation of the Estimation Model

Analysis at Locations with High Number of Boarding

In order to discuss the validity of the obtained model, we consider the similarity between several intersections. First, we look at the intersections that have a high degree of similarity to "Kabukicho," which is a famous downtown intersection in Shinjuku area and a frequently used intersection (the number of rides is 1841). Fig. 3 is the detailed map of the "Shinjuku area" and the three intersections with high similarity to "Kabukicho" is plotted on a map.

Shinjuku is one of the largest shopping areas in Japan, and people often travel by taxi in the Shinjuku area. In the Shinjuku area, Kabukicho is the most famous and popular place. Many restaurants, shopping centers, and bars are located there; so many people are gathering from elsewhere in Japan and also from other countries. When we focused on the intersections that were extracted, we found that the locations were close to the actual feeling of the intersections, such as the locations where large commercial facilities exist and the locations near the stations.

The similar results were obtained for other intersections where the number of passengers was great. Then we confirmed the usability of our model when the number of meeting passengers of the destination is large.

Fig. 3 Representation of the 3 places of high similarity with Kabukicho intersection

Analysis at a Point with a Small Number of Boarding

In order to see whether the small number of times a passenger boarding on taxies is related to the accuracy for the recommendation, we use the place a passenger rides the train only once. Here, we will use "Odaiba Central," where is a famous sightseeing spot in Tokyo, however, there is not a large demand for taxis due to the well-developed public transportation system. When we calculated similarity of each driver and intersection, the following results were obtained, and difficult to conclude that an appropriate relationship has been observed.

Fig. 3 Representation of the 3 places of high similarity with Odaiba Central intersection

C. Destination Decision Model for Cruising Taxis

The model learned by the "Destination Decision Support Model" will be interpreted by analyzing real data. The data used are for one month in February 2018.

The Case of a Target Driver with a Large Number of Rides

The model learned by the "Destination Decision Support Model" is interpreted by analyzing real data. The data used are for one month in February 2018. Moreover, we focus on a target driver with a large number of passenger boarding exists.

First, we consider the recommendation for a driver who has sufficient experience of the "Nagashi". We assume that there is "Driver A", who does not usually drive in Minato-ku area and preferable to find passenger in Minato-ku area. In this analysis, we extract "Driver B," who has the greatest number of passengers in the Minato-ku in February 2018, as the "target" driver. Driver B's favorite intersection "Intersection a" is set to "Takeshiba Pier". Driver B has picked up passengers 144 times there, making it the intersection where he has picked up the most passengers.

Fig. 4 shows the 5 intersections that are similar to the results of the vector calculation of "Driver B" + "Intersection a" - "Driver A". Intersections in Minato Ward were selected. Intersections where the number of times the driver rides is five or less are listed, but they are not considered in this study. The intersections with a relatively high number of rides are listed. The extracted points are plotted on Fig. 4. The blue circles are, from left to right, "Shinko-nanbashi (near by the Shinagawa station)," "Minamihama-bashi (near by the pier of long cruising)," "Tokyo Gas-mae (near by the luxury hotel Intercontinental hotel)," "Takeshiba Pier entrance (near by the pier of short cruising)," and "Tokyo Big Sight-mae (near by the big event hall Tokyo Bigsight)". The size of each circle is indicated by the number of passengers. Each of these locations has a famous tourist attraction and is considered to be an appropriate recommendation.

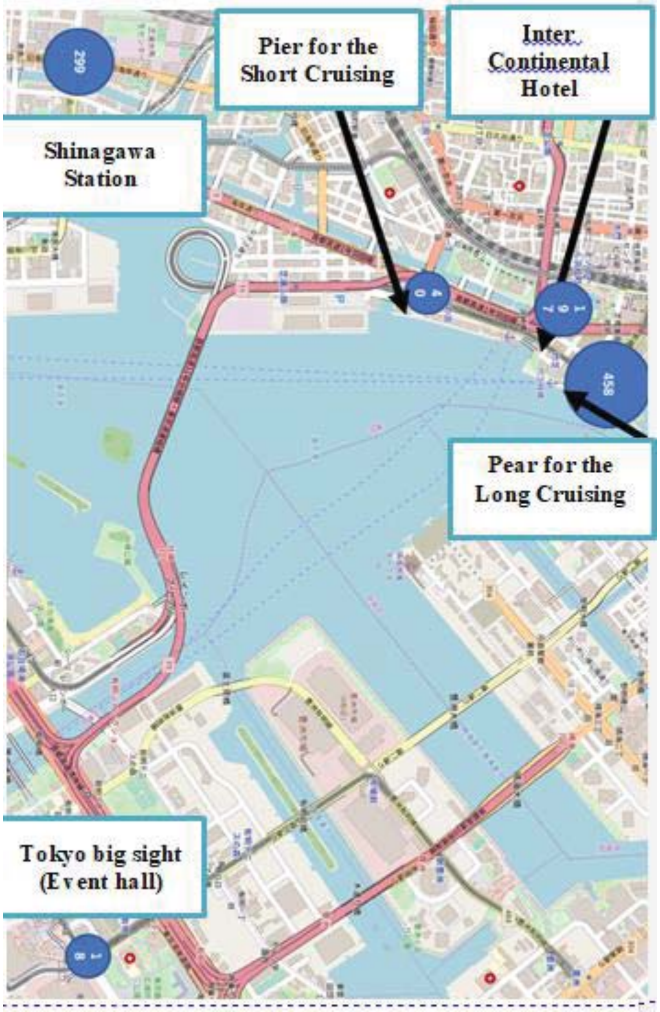

Fig. 4 Representation of the 3 places of high similarity with Odaiba Central intersection

The Case of Target Driver with a Small Number of Rides

Next, we consider that there is Driver D, who usually operates in Koto-ku, operates in Chuo-ku. Also, there are not many drivers who operate well in Chuo Ward, but Driver C, who has a large number of passengers, is selected as the target driver. Intersection c, which is a good intersection for "Driver C", is set as "Yaesu Chuo-guchi-mae". Driver C picked up passengers seven times at the intersection "near the Yaesu central exit". This "Driver C" picked up passengers seven times at this "Yaesu-chuo-guchi-mae" station, and the demand for taxis is considered to be high because of the Shinkansen exit at Tokyo Station. Here, we tried to find similar locations to the results of the vector operation of "Driver C" + "Intersection c" - "Driver D", and found that the intersections with few passengers were extracted, which is not appropriate for learning.

From the results, we conclude that the proposal is appropriate when the preferable data exist; however, otherwise, we cannot judge whether analysis results can represent the real situation well or not. Therefore, it is our future work.

VI. Consideration

When the actual data were applied to the cruising taxi destination support, the results showed that both good and bad results were obtained. The reason for the good results for Drivers A and B is that we extracted the drivers and their favorite destinations according to the model. We selected the driver who picked up the most passengers in Minato-ku and the intersection where that driver picked up the most passengers, and performed vector operations on them. In contrast, the poor results for Drivers C and D were due to insufficient reasons for the selection of drivers and intersections. Because the meanings of drivers and intersections were not well structured, drivers were selected when intersections should have been selected as destinations, and intersections with a small number of rides were selected because of insufficient learning.

When the model learned from the rich number of data by accumulating the data for long span, we can obtain the results more useful for taxi drivers to operate their businesses. As a concrete idea, when the taxi meter is not working, the car navigation can be used to recommend a destination for the taxi driver. If the recommended destination can be updated in real time by taking into account the direction and distance of the taxi, it will help drivers who are having trouble deciding on a destination.

VII. Conclusion

In this study, we used Doc2Vec to assist taxi drivers in deciding where to go. First, we found that Doc2Vec was not able to learn enough for all intersections. Specifically, Doc2Vec was able to learn sufficiently for intersections with a large number of rides, but not for intersections with a small number of rides. One of the reasons for the lack of learning was that the data used for learning were for 181 taxis over a one-year period and did not cover all of the 23 wards of Tokyo. In addition, it is possible to adjust the hyperparameters without affecting the learning even if there are intersections with a small number of rides.

In this study, we used the similarity between the intersection vectors and the meaning of the driver vectors and intersections to recommend destinations for sink sales. Since we could not consider doing something using only the driver vectors, one of the future issues is how to utilize the learned taxi driver vectors. In addition, each driver has his or her own unevenness. For example, there are times when the driver is able to pick up a lot of passengers and make good sales, and other times when the driver is not able to pick up any passengers and make poor sales. This kind of unevenness makes it difficult to expect stable income, so we should use driver vectors to represent the ambiguity of good and bad performance. In addition, if the differences between experienced drivers and new drivers can be expressed using vector representation, it is expected to be used in new driver training. In this research, we thought of breaking down the barrier to taxi business, which requires experience and intuition, by recommending destinations, but it will be possible to solve the problem of the decreasing number of taxi drivers by stabilizing income and providing appropriate training for new drivers using the driver vector. The construction of Doc2Vec, which can utilize driver vectors as described above, will be a challenge in the future.

Acknowledgment

In this study we analyzed the data provided in the data analysis competition 2019 conducted by Joint Association Study Group of Management Science [6].

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