

Deep-learning architecture to forecast destinations of bus passengers from entry-only smart-card data

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Abstract: Although smart-card data secures collective travel information on public transportation users, the reality is that only a few cities are equipped with an automatic fare collection (AFC) system that can provide user information for both boarding and alighting locations. Many researchers have delved into forecasting the destinations of smart-card users. Such effort, however, have never been validated with actual data on a large scale. In the present study, a deep-learning model was developed to estimate the destinations of bus passengers based on both entry-only smart-card data and land-use characteristics. A supervised machine-learning model was trained using exact information on both boarding and alighting. That information was provided by the AFC system in Seoul, Korea. The model performance was superior to that of the most prevalent schemes developed thus far.

1 Introduction

Many researchers have attempted to infer missing destination information for entry-only smart-card data. However, they commonly faced an obstacle while validating their model, because obtaining a sufficient amount of data for revealed destinations is difficult. Although several studies have validated their destination estimation models against true origin–destination information obtained from direct household surveys, the sample size was not large enough to generalise the validation results. Only a few cities in the world are equipped with an automatic fare collection system (AFC) that can provide both boarding and alighting locations of smart-card holders. The Seoul metropolitan area has such a system. This means that the destination inference methods developed thus far can be validated against a large amount of true origin–destination trips on an individual basis, and a more robust estimation model with higher accuracy can be developed.

Prior to emphasising the contribution of the present paper, there is a need to introduce past effort to infer the destination locations of entry-only smart-card data. Many researchers have dealt with inferring missing destination information for smart-card data [1–18]. Many methods have been tried, but the basic logic was the same for all of them. That is, several rules were set up to infer the destination of a smart-card transaction, and if a transaction met these predefined rules, the destination could be determined. A prevalent rule was that a smart-card holder's destination for a certain transaction should be closest to the next boarding location [1]. Another rule employed frequently was that a transaction's destination could be inferred by the regularity of similar transactions, which required multi-day smart-card data with the encoded card identification (ID) unchanged.

All existing methods had the limitation that data for the true destinations was unavailable for validation. Instead of direct validation, most researchers have evaluated an inference rate that corresponds to the proportion of entry-only transactions that matched several rules they had established to estimate destinations. That is, they designated several matching conditions, and if the conditions were met for a candidate bus stop, the stop was regarded as a potential destination. Other researchers validated their results at the aggregate level [2–4]. That is, the origin–destination flow matrix derived from the destination inference model was compared with that estimated from a sampled household survey [3, 4]. On the other hand, only a few studies have validated their results against revealed data on an individual trip basis [1, 4, 5]. These studies

obtained a sample including origin–destination pairs of transit passengers, applied their model to the sample, and then compared both the estimated and observed destinations. However, their sample size was so small that their results could not be generalised. The reality is that there has been no practical validation based on large-scale revealed data on an individual trip basis. Basically, the present approach was totally different from previous studies that depended on naive inferences or on insufficient validation. The accuracy presented in the present paper was computed based on the true destinations of smart-card holders. A comparison of the estimation methodologies is summarised in Table 1.

The contribution of the present paper is three-fold. First, the accuracy of destination inference for entry-only smart-card data was enhanced by adopting a novel deep-learning model. In addition, the deep-learning model mobilised the land-use data around transit stops as additional input features. Second, our investigation focused on trip-chains that were composed of bus travels only, for which inferring the destination was more difficult than other trip-chains that contained metro travels. The most troublesome situations with regard to estimating destinations occurred where passengers used only buses in a row, because bus networks were denser. Third, the present paper represents the first utilisation of large-scale data from the true destinations of smart-card holders when validating a destination inference model. The developed model was also fully validated against real origin–destination information on an individual trip basis. As a reference for comparison, the present study used the model structure suggested by Munizaga and Palma [6], which is the most prevalent from among the methods developed thus far. Parameters of the reference model were chosen from [7] in order to reflect the local conditions of transit use in Seoul.

Section 2 describes how data were collected, and also addresses the concept of training, cross-validating, and the testing datasets. This data division is inevitable when setting up a machine-learning model. Section 3 introduces deep-learning architecture to estimate the destination locations of smart-card holders. Test results from the present model are presented and compared with those from the existing model in the Section 4. Section 5 draws conclusions and suggests several extensions for further development of the present model.

Table 1 Results of previous studies

Literature	Target transit mode	Validation data	Number of validation examples	True accuracy (inference rate) ^a
[1] Barry <i>et al.</i>	metro	travel diary survey	two subway trips more than two subway trips	100 passengers (200 trips) 150 passengers (595 trips)
[15] Zhao <i>et al.</i>	metro–metro metro–bus	no validation	—	(71.2%)
[16] Trépanier <i>et al.</i>	bus	no validation	—	(66%)(80% at peak hours)
[14] Zhang <i>et al.</i>	bus	no validation	—	—
[2] Farzin	bus	no validation	—	(100%)
[12] Barry <i>et al.</i>	bus, metro, tram, and ferry	ride check data (two weeks study period)/ entrance and exit counts	N/A	N/A
[11] Nassir <i>et al.</i>	bus	no validation	—	(60.74%)
		AFC–APC–VL data	10,886 transactions	95.4%
[3] Wang <i>et al.</i>	bus	no validation	—	(66%, Northbound)(65%, Southbound)
[6] Munizaga and Palma	bus and metro	no validation	—	(80.77%, March 2009) (83.01%, June 2010)
[4] Munizaga <i>et al.</i>	bus–metro metro–bus	53 volunteers (primarily students)	715 transactions	84.2%(602/715)
[5] Zhang <i>et al.</i>	bus	102 participants (manually labelled using given free smart-card)	102 IDs for 4 months(December 2012– March 2013)	75%
[10] Alsger <i>et al.</i>	bus, metro, and ferry	no validation	—	—
[8] Nunes <i>et al.</i>	bus	no validation	—	(62.4%)

^a The values in brackets are inference rate which is not validated based on observed data.

APC - Automated passenger counter

VL - vehicle location

2 Data preparation

2.1 Data sources

Data for the present paper were obtained from two different sources. First, smart-card data contains both temporal and locational information for fare transactions. As mentioned earlier, the Seoul metropolitan area is equipped with an AFC system that records IDs for both boarding and alighting bus stops. Time stamps are also recorded whenever smart-card holders tag their card into a fare collection unit within a bus. The reason passengers tag their cards when alighting is to obtain a free transfer. The Seoul metropolitan government allows transit passengers to freely transfer up to three times a day. The time between alighting and the next boarding for the free transfer is limited to 30 min. If a smart-card holder does not tag his/her card when alighting, he/she must pay for the maximum distance that can be travelled from his/her origin by the bus he/she chooses. Thus, almost every smart-card holder tag their card when alighting.

In addition to the temporal and locational information elicited from smart-card data, the present paper also mobilised land-use data. Previous studies depended only on temporal and locational information of boarding transactions to infer the destination. To match destinations, the basic rule adopted by previous studies was dependent on the distance between a candidate destination location and the next boarding location. The present study was focused on the fact that no other crucial criterion, besides this determinant rule, has been adopted to reinforce the inferences that are drawn. We assumed that a candidate destination location with a greater intensity of socio-economic activities would have a higher probability to be chosen as the true destination. More concretely, if a smart-card holder spends a relatively long amount of time in an area, the card holder is likely to finish his/her walking itinerary at a bus stop located in a busy area. Such behaviour would be observed where inter-boarding times are longer. To accommodate this behaviour, land-use characteristics around candidate bus stops were adopted as additional input features to forecast the destinations of smart-card users. On the basis of 28 typical uses, the floor areas of

individual buildings were examined and catalogued by the Korean government for taxation purposes. The present paper utilised this floor area data to infer the destinations of smart-card holders, after reducing the original 28 uses into residential, commercial, cultural, and office.

This represents the first use of a large-scale dataset with information on both origin and destination as well as on building use around bus stops in developing and validating a destination inference model. Whereas smart-card data from the Seoul metropolitan area include transactions of both bus and metro, the present paper dealt with only transaction data for buses, since most metro systems provide tag-in and tag-out information. Furthermore, regarding transfers between bus and metro, a bus stop at which a passenger has alighted or boarded can be easily inferred by the bus stop closest to the metro station that the passenger uses next. More concretely, inferring the destination of a bus trip would be a trivial undertaking if the next boarding location to the trip were a metro station, because most bus lines are likely to allocate their stops as close to a metro station as possible. Similarly, inferring the destination of a metro trip would be also easy if the next boarding location were a bus trip.

It is more difficult to infer the destination of bus trips, particularly when only smart-card data for a single day are available. There are privacy issues when using multi-day smart-card data, since it is a great burden to keep the same ID for a smart-card holder during the period, even though the ID is encoded. For the present paper, only smart-card data during a specific date was available (2015/11/02). Another factor that makes it difficult to infer the destination of bus trips is that previous studies have shown that the Seoul metropolitan area has a very dense bus network compared with other cities, which increases the difficulty in inferring destinations in a trip-chain of only bus trips. The public transport networks adopted in previous studies are compared with that of the present paper in Table 2.

Table 2 Comparison of the size of transportation networks adopted in previous studies

Studies	Testbed	Testbed area	Population	Transit network size
present paper	Seoul, Korea	605.2 km ²	10,204,057	7482 buses (415 routes)311 subway stations (9 lines)
[1] Barry <i>et al.</i>	New York City, New York, USA	789 km ²	8,491,079	4525 buses (230 routes)6344 subway cars (25 lines)
[15] Zhao <i>et al.</i>	Chicago, IL, USA	606.1 km ²	2,720,546	1879 buses (140 routes)1190 rail cars (8 lines)
[16] Trepanier <i>et al.</i>	Gatineau, Quebec, Canada	589 km ²	240,000	302 buses (66 routes)
[2] Farzin	São Paulo, Brazil	1521 km ²	12,038,175	1400 buses (equipped global positioning system)64 stations (5 lines)
[12] Barry <i>et al.</i>	New York City, New York, USA	789 km ²	8,491,079	4525 buses (230 routes)6344 subway cars (25 lines)
[11] Nassir <i>et al.</i>	Minneapolis-Saint Paul, MN, USA	2646 km ²	3,112,117	1010 buses (186 routes)
[3] Wang <i>et al.</i>	London, Britain	1572 km ²	8,538,689	8000 buses (700 routes)
[6] Munizaga and Palma	Santiago, Chile	641 km ²	6,158,080	6591 buses (391 routes)108 subway stations (5 lines)
[4] Munizaga <i>et al.</i>	Santiago, Chile	641 km ²	6,158,080	6591 buses (391 routes)108 subway stations (5 lines)
[5] Zhang <i>et al.</i>	—	—	—	—
[10] Alsger <i>et al.</i>	South East Queensland, Queensland, Australia	22,420 km ²	3,400,000	—
[8] Nunes <i>et al.</i>	Porto, Portugal	41.42 km ²	240,000	472 buses (83 routes)

Table 3 Input features adopted in the present paper

Number of transactions within a trip-chain	2	3	4	5	6	Total
population trip-chains	507,651 (61.29%)	148,405 (17.92%)	119,637 (14.44%)	35,711 (4.31%)	16,935 (2.04%)	828,339 (100%)
sample trip-chains	66,320 (61.18%)	17,212 (15.88%)	17,316 (15.98%)	5058 (4.67%)	2486 (2.29%)	108,392 (100%)

2.2 Preparing data for training and testing

The model proposed in the present paper falls into the category of supervised machine learning. That is, it requires separate datasets for training and testing. Sample data composed of only bus transactions were selected from a single day of smart-card data, and then a proportion of the data examples was separately targeted for testing. The remaining data were used for training.

The following procedure accounts for how the bus transaction data were selected for training and testing the present deep-learning model. First, smart-card data for a single day were prepared, and it consisted of more than 10 million transactions. Second, trip-chains associated with, at least, a single metro transaction were excluded for the reasons mentioned above. At the next stage, transactions processed outside the boundary of Seoul city were excluded. Also, the present paper left only transactions for which land-use data around candidate destinations were available. The reason we adopted the first criterion is self-evident. The second criterion was employed since we attempted to concentrate on the most difficult situation for the destination inference. The third criterion was inevitable in order to secure a robust estimation given the availability of complete data. After screening with the above criteria, the final dataset that was obtained for the present paper, and trip-chains in the dataset (=dataset 3) were defined as 'population trip-chains' in Table 3.

In the last stage, transactions for 140,000 ID's were randomly sampled from dataset 3 to reduce computational burdens, and 146,551 transactions survived after screening by the rule established in a previous study [11] where the distance between the origin of the next transaction and potential destinations should be <750 m. The last transaction within all trip-chains, which had no next boarding information, was also eliminated. Consequently, 124,513 transactions survived (see Fig. 1). This is the first attempt to develop and validate a destination inference model based on such a vast amount of transactions, though many transactions were eliminated from the raw smart-card data.

Each card ID represents a trip-chain on a daily basis that consists of multiple transactions. Table 3 shows the compatibility in the length of trip-chains between the final dataset and the population (=dataset 3). The final transaction data were divided into training and testing sets. We randomly chose 20% of the total transactions to be reserved for testing, and the remaining 80% was used for training. Among the training examples, 5% was used for

cross-validation that determined the convergence of training. According to the conventional training method in machine learning, the convergence was judged by the loss function value for the cross-validation dataset rather than the training dataset. That is, the estimation routine ended when the gap in the loss function value for the cross-validation dataset between consecutive iterations was less than a predefined threshold.

2.3 Variable selection for modelling

Since all transactions in the final dataset had their exact origin–destination pair information, the labels for each transaction example were easily tagged. This is a distinction of the present paper from other studies. Input features to feed the present deep-learning model can be categorised into two groups. Variables in the first group represented the characteristics of the transactions. These variables were chosen from both the temporal and spatial information of the transactions, and these have also been used by previous studies to infer the destination of entry-only smart-card data.

Land-use data characterising the area around candidate bus stops were utilised in this paper to support finding the missing destinations of smart-card holders. Table 4 shows a full list of variables that were used in the present paper, and a short description of each. We then adopted 27 input features to train and test the proposed model. The maximum number of candidate destinations was limited to five, which stemmed from an observation about smart-card data. Thus, the total number of features that fed the proposed model was tantamount to 135 (=27×5).

3 Deep-learning model

The proposed deep-learning architecture was found after testing as many different model structures as possible. Such a trial-and-error manner has been criticised as a drawback of deep learning. However, when considering computation time, this is the best way to choose the final model architecture. Fig. 2 shows the final model architecture for inferring the destination of smart-card transactions.

The proposed model architecture consisted of four layers. Besides input and output layers, two hidden layers were included. The number of nodes in the input layer was identical to the number

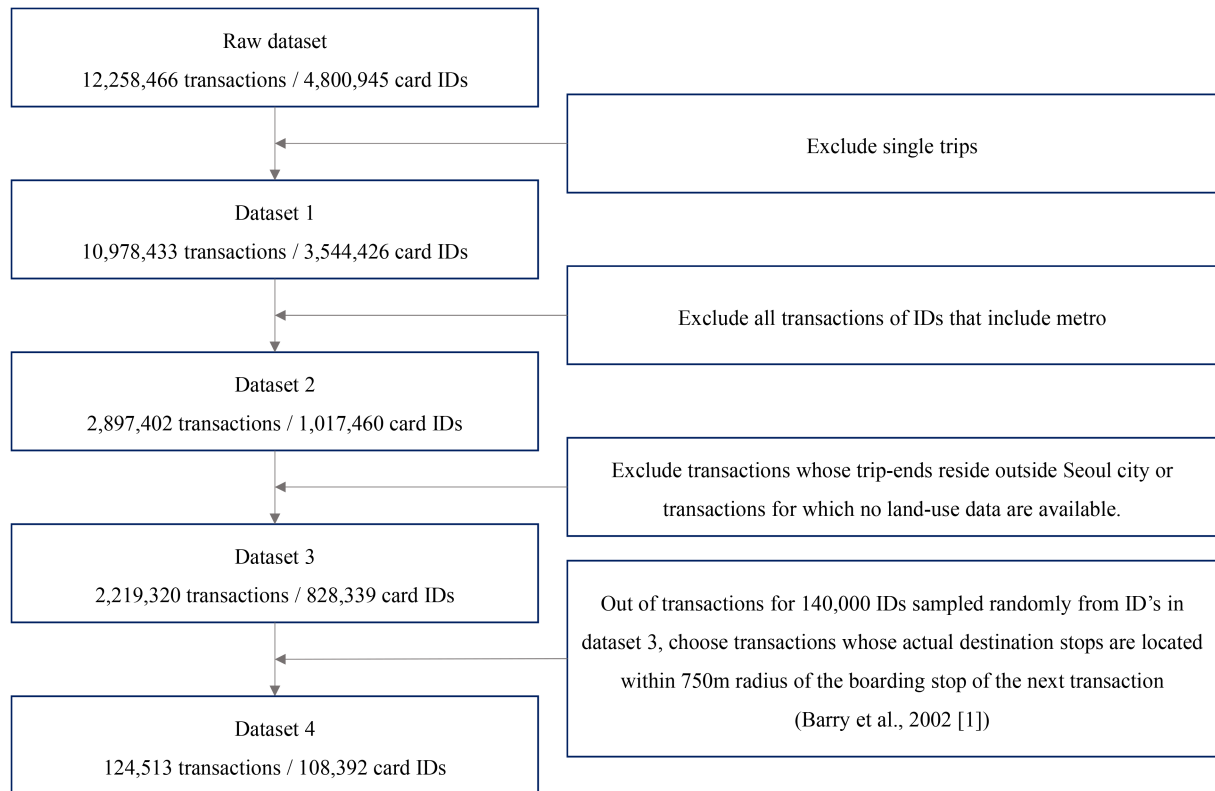


Fig. 1 Process of acquiring data for training and testing the proposed model

of features, as mobilised ($=135$). The number of nodes in the output layer matched the maximum number of destination candidates ($=5$). The input and output nodes were aligned in an increasing order of the distance between a candidate destination and the origin of the next transaction to a target transaction. Consequently, there were 5,529,600 ($=135 \times 64 \times 128 \times 5$) weight parameters to be estimated.

A rectified linear unit (ReLU) was adopted for the two hidden layers to activate the node values computed from the previous layer. A dropout rate (30%) was applied to the hidden layers. A combination of ReLU and dropout rates is known to have led to a big breakthrough in deep learning. For classification, a SoftMax function was chosen for the activation function of each node in the output layer. A conventional back-propagation method was adopted to train the model. The training and testing process was conducted via an open-source library – Keras 3.0 with Python programming language.

4 Results and comparison

In conventional machine learning, the matching accuracy is computed based on testing data that has been prepared in advance separately from training data. Training results usually are superior to testing results, since weighted parameters are susceptible to over-fitting to the training examples. Nonetheless, the results in Table 5 show only a slight discrepancy between the accuracy of the training and testing data, which means the model accuracy would not be enhanced by increasing the training data, according to learning curve theory [19]. Consequently, a sufficient amount of data was utilised for the modelling.

For the present model, the accuracy could not be improved unless a more robust model structure is found. Although the model structure was chosen after testing a sufficiently large number of candidate models, it should be noted that there is a distinct possibility that a more accurate model could be found, which would mean that the results in Table 5 represent a minimum enhancement in accuracy.

The destination inference method that uses the generalised travel time proposed by Munizaga and Palma [6] was selected as a reference to be compared with the proposed model, since that method is the most prevalent. The accuracy of the reference model

was not promising, which refutes the original argument that the accuracy was very high. The reason for this discrepancy could be due to the sample size. The present paper utilised large-scale data, whereas the model validation of previous studies depended on small samples.

The test accuracy of the present model was improved by more than 5% compared with that of the reference model. This enhancement must have been due to the use of additional feature variables. As shown in Table 4, the feature list of the proposed deep-learning model also included all the features that were used by the reference model. It was apparent that the additional feature variables contributed to an enhancement of the accuracy. This enhancement cannot be regarded as trivial, since such a small amount of improvement can be a significant breakthrough in the field of machine learning. For example, it is quite difficult to achieve a 5% increase in the matching rate for the recognition of images or sounds [20].

The accuracy improvement by the present model was due to finding true destinations that were not closest to the origin bus stop of the next target transaction. Additional information on land-use made it possible to infer the destination correctly, particularly when considering the activity intensity. In particular, the matched examples showed that the true destinations were farther from the next origin, because the activity duration was longer. The existing method used only the distance or time from the next origin, and it rarely estimated the true destination in this case.

Another promising point was obtained from the tight criterion, which showed that the accuracy was computed only if the estimated destination was exactly the same as the observed destination at an individual bus stop level. When relaxing the criterion to match the second-best candidate destination with the observed destination, the accuracy was increased to 87.5%, which exceeded the reference model by almost 6%. The rationale for relaxing the criterion was that the Seoul metropolitan area is a very dense bus network such that the average distance between consecutive bus stops averaged 250 m. Even though the second-best destination from the present model was chosen as another solution, the estimation error, on average, could not exceed the distance level. The second reason for the relaxation was to accommodate a biased behaviour of bus users in the area. As pointed out in [21], more than 40% of bus passengers had an

experience of tagging their smart-card into an on-board unit prior to reaching the final destination. Most of the pre-tagging passengers tag their cards a single bus stop ahead. As a result, about one in ten transactions determined the destination within a reasonable tolerance.

5 Conclusions

The present paper proposed a novel deep-learning model to infer the destinations of transactions obtained from entry-only smart-card data. A large amount of transaction data (124,513 transaction examples) that had true information on destinations was utilised to

Table 4 Input features adopted in the present paper

	Variables	Explanation
transaction variable	1. target boarding time	the boarding time of a target transaction, the destination of which will be inferred
	2. number of transfers	the number of transfers indicates how many transfers have been experienced until making the trip of concern. When computing this variable, a trip-chain should be cut into multiple segments by activities, and the variable is then computed separately for each segment. (if an inter-trip time between two consecutive trips does not exceed 30 min, the period is regarded as representing a transfer. Otherwise, the period is regarded as an activity)
	3. network distances	network distances from the origin bus stop of a target transaction to each candidate destination bus stop along the same bus line
	4. network travel times	network travel times from the origin bus stop of a target transaction to each candidate destination bus stop along the same bus line
	5. average travel speeds	average travel speeds while travelling from the origin bus stop of a target transaction to each candidate destination bus stop along the same bus line
	6. aerial distances from a target origin	aerial distances from the origin bus stop of a target transaction to each candidate destination bus stop along the same bus line
	7. generalised travel times	generalised travel times from the origin bus stop of a target transaction to each candidate destination bus stop along the same bus line (Munizaga and Palma [6]) ^a
	8. activity durations	the activity duration estimated by subtracting the travel time to each candidate destination from the time difference between the consecutive boarding times of a target transaction and its next transaction
	9. dummy variable for excessive duration	the variable is set at 1 if the activity duration exceeds a half hour, which is the maximum time allowed for free transfer; 0 otherwise
	10. ridership	the ridership of each candidate destination bus stop
	11. bus stop density 1	a proxy variable to indicate bus stop density, which is computed by the network distance from a candidate destination bus stop to its closest bus stop upstream along the same bus line
	12. bus stop density 2	a proxy variable to indicate bus stop density, which is computed by the network distance from a candidate destination bus stop to its closest bus stop downstream along the same bus line
	13. next boarding time	the boarding time of the next transaction
land-use variable	14. aerial distances from the next origin	aerial distances from the origin bus stop of the next transaction to each candidate destination
	15. time gap between consecutive transactions	the time difference between the consecutive boarding times of a target transaction and its next transaction
	16. residential floor area for a target transaction	the residential floor area of buildings within a radius of 500 m from the origin bus stop of a target transaction
	17. commercial floor area for a target transaction	the commercial floor area of buildings within a radius of 500 m from the origin bus stop of a target transaction
	18. cultural floor area for a target transaction	the cultural floor area of buildings within a radius of 500 m from the origin bus stop of a target transaction
	19. office floor area for a target transaction	the office floor area of buildings within a radius of 500 m from the origin bus stop of a target transaction
	20. residential floor area for the next transaction	the residential floor area of buildings within a radius of 500 m from the origin bus stop of the next transaction
	21. commercial floor area for the next transaction	the commercial floor area of buildings within a radius of 500 m from the origin bus stop of the next transaction
	22. cultural floor area for the next transaction	the cultural floor area of buildings within a radius of 500 m from the origin bus stop of the next transaction
	23. office floor area for the next transaction	the office floor area of buildings within a radius of 500 m from the origin bus stop of the next transaction
	24. residential floor area for each candidate destination	the residential floor area of buildings within a radius of 500 m from each candidate destination bus stop
	25. commercial floor area for each candidate destination	the commercial floor area of buildings within a radius of 500 m from each candidate destination bus stop
	26. cultural floor area for each candidate destination	the cultural floor area of buildings within a radius of 500 m from each candidate destination bus stop
	27. office floor area for each candidate destination	the office floor area of buildings within a radius of 500 m from each candidate destination bus stop

^a $Tg_i = t_i + f_w \times d_{i-post} / s_w$ where, Tg_i = generalised travel time, t_i = in-vehicle travel time to a candidate destination bus stop i , d_{i-post} = distance from the next boarding bus stop to a candidate destination bus stop i , s_w = average walking speed, and f_w = penalisation factor.

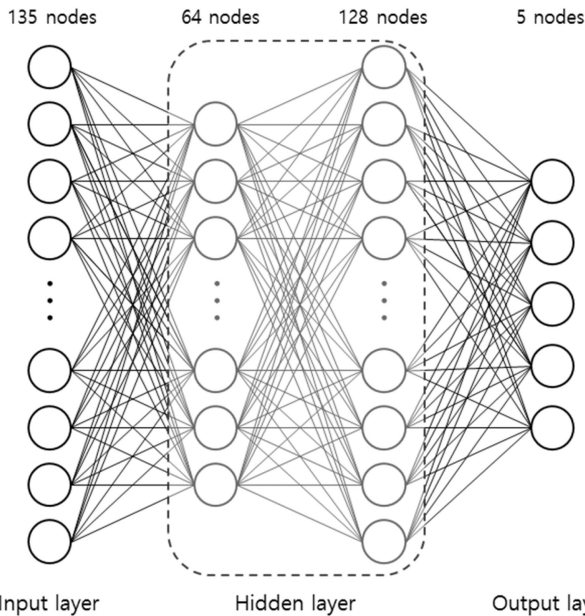


Fig. 2 Final model structure

Table 5 Accuracy of destination inference

Matching rate	Train (with 80% of sample transactions)	Test (with 20% of sample transactions)	Relaxation to the second-best candidate	
			Train	Test
reference model	55.274%	54.835%	81.516%	81.522%
deep-learning model	61.708% (+6.434)	60.104% (+5.269)	88.850% (+7.334)	87.491% (+5.969)

validate the developed model. This was possible owing to the AFC system used by the Seoul metropolitan area that provides both tag-in and tag-out information.

Another contribution of the present paper is that additional features were mobilised to account only for what previous studies had missed with respect to adopting distance or time variables. In particular, land-use characteristics around a candidate destination proved to contribute to enhancing the accuracy when inferring moving destinations.

When validating the most prevalent model based on the same data used by the present paper, that model failed in matching the true destinations at the level reported in the original paper [6]. Similarly, even the proposed deep-learning model did not obtain a satisfactory matching accuracy. As a testing result, the matching rate with true destinations was increased only to 60% when adopting the proposed deep-learning model.

The most promising result was achieved when the matching criterion was somewhat relaxed. The accuracy rate was increased to more than 87% if the destination with the second-best probability was matched with the true destination. This was acceptable in an urban area with dense bus networks, because candidate bus stops are located in close proximity.

In the near future, if a more elaborated model is set up and other more accountable socio-economic data are available, the accuracy in destination inference should grow considerably. Some researchers may believe there is minimal improvement in accuracy in consideration of the large amount of effort needed to prepare

additional data and computation. It is clear, however, that this improvement is a starting point in providing entry-only smart-card data with true destination information by using both Big-data and deep learning.

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