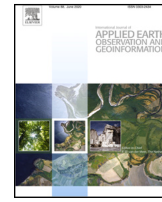
International Journal of Applied Earth Observation and Geoinformation 118 (2023) 103290

Contents lists available at ScienceDirect

International Journal of Applied Earth Observation and Geoinformation

journal homepage: www.elsevier.com/locate/jag



Spatio-temporal parking occupancy forecasting integrating parking sensing records and street-level images

Shuhui Gong [a], Jiaxin Qin [a], Haibo Xu [a], Rui Cao [b], Yu Liu [c], Changfeng Jing [a,*], Yuxiu Hao [a], Yuchen Yang [a]

[a] *School of Information Engineering, China University of Geosciences, Beijing 100083, China*
[b] *Department of Land Surveying and Geo-Informatics & Otto Poon Charitable Foundation Smart Cities Research Institute, The Hong Kong Polytechnic University, Hong Kong Special Administrative Region of China*
[c] *Institute of Remote Sensing and Geographical Information Systems, School of Earth and Space Sciences, Peking University, Beijing, China*

ARTICLE INFO

Keywords:
Parking occupancy prediction
Parking behaviours analysis
Spatial correlations
Graph convolutional network (GCN)
Gated recurrent unit (GRU)

ABSTRACT

The prediction of parking occupancy is of great importance to urban planning. As the number of cars increases and parking resources become limited, the lack of parking supply has become a challenge for urban design. Previous works ignore the correlation between car parks when predicting parking occupancy, which limits the accuracy of the prediction. To address this issue, this study proposes a Temporal-GCN-based correlated parking prediction model (CPPM) to forecast the temporal occupancy of car parks. In particular, the model utilises Convolutional Neural Networks (CNN) and Bayesian probabilities to extract street view similarities in car parks, as well as their spatial correlations, cosine similarity is used to calculate the activity type similarity, and Graph Convolutional Networks (GCN) and Gate Recurrent Units (GRU) are integrated to predict spatio-temporal car park occupancy, taking into account both temporal parking records, similarities in car parks, and their spatial correlations. We conducted two case studies in Ningbo and Beijing, China, integrating over 10 million parking sensing records and corresponding street view images of parking lots to predict parking occupancy. The results show that our model has outstanding performance over the baselines and can be extended for various types of car parks in cities of different sizes and different levels of development. The results also reveal the parking preferences of the citizens of Ningbo and Beijing, which is valuable for a quantitative understanding of commuters' parking patterns and behaviour and can be used as a guide for urban planning and management.

1. Introduction

With the development of the economy and the improvement of people's living standards, more and more families own their private cars for facilitating travel (Mohamad and Kiggundu, 2007; Qureshi and Lu, 2007). The global production of automobiles has also increased in recent years (3% increase in production in 2021, 2.36% in 2017 and 4.5% in 2016), and total production of automobiles has increased more significantly in several countries (69% in Argentina, 12% in Brazil and 69% in Indonesia in 2021).[1] The number of private cars is increasing rapidly, while the parking space is limited. This puts enormous pressure on citizens' daily commutes (Qureshi and Lu, 2007). The difficulty in parking can also lead to road congestion and disorder, increasing the burden of traffic management (Yang et al., 2019). Therefore, how to accurately predict and properly analyse parking behaviours remains a challenge for governments to optimise parking services, reduce the burden of passengers' daily commute, and ultimately, ease the burden of traffic management (Gong et al., 2021).

A few studies have utilised temporal parking records to predict and analyse citizens' daily movements. For instance, Feng et al. (2019) explored the influence of weather and time on parking behaviour, and used the parking lot data of a shopping mall in Ningbo for prediction; Paidi (2022) considered the effect of time, using data from a free parking lot next to a shopping centre to make real-time predictions of space availability in the parking lot; Tamrazian et al. (2015) utilised historical characteristic data (such as time) of parking lot occupancy as well as real-time data to predict future parking lot occupancy. However, although previous studies considered the temporal correlations of passengers' parking behaviours for parking occupancy forecasting, the

* Corresponding author.
E-mail address: jingcf@cugb.edu.cn (C. Jing).

[1] The data is collected from 2021 production statistics. The website is: https://www.oica.net/category/production-statistics/2021-statistics/.

https://doi.org/10.1016/j.jag.2023.103290
Received 15 January 2023; Received in revised form 23 March 2023; Accepted 31 March 2023
Available online 8 April 2023

correlations of parking lots are ignored. Moreover, few studies have investigated the relationship between the parking lots' correlation and passengers' parking behaviours.

To explore this relationship, the big challenge is measuring the correlations between the parking lots. Practically, there are several ways to measure such correlations. The first one is the Manhattan distance (Gong et al., 2021). In particular, when people parking, they may face a shortage of the currently chosen parking lot, and need to select a neighbouring parking lot. Therefore, the Manhattan distances between parking lots are very likely to be negatively correlated to the parking lots attractiveness, namely, their occupancy. In particular, during the same period, the more closely located parking lots could have more similar car volumes.

Another way to measure the correlation is the category similarities of the parking lots. Parking lots with the same category may also attract similar visitors (Paidi, 2022). In general, there are three main categories of parking lots: (i) on-street parking lots, in which passengers park their private cars on the roadside, and they are generally located between the driveway and the sidewalk, as a number of cars end to end parked under the sidewalk steps. In many countries, there are such parking lots that all the parking places in one street link. These parking spaces are usually grouped into several on-street parking lots that are organised by several companies; (ii) open-air parking lots, which usually have a large parking square, and are often located near a point-of-interest (POI); (iii) underground parking lots, which are usually located on the basement level of some special building facilities, such as shopping malls, office buildings, residential estate, etc. For different types of parking lots, passengers may have different parking behaviours. For example, some passengers may prefer underground parking lots to avoid strong sunlight; some other passengers may prefer the roadside parking lot for a short stay. Moreover, the similarities of the environment around a parking lot could also be a good way to measure the parking lot correlations. More specifically, people have different preferences for parking lots under different parking purposes and scenarios, and the nearby POIs may also influence passengers' parking choices, such as shopping centres, amusement parks, etc (Wang and Liu, 2022; Chao et al., 2022).

The function and features of one POI could be described using street-view image (Zhang et al., 2022). Similarly, the parking lots with similar environments and categories reflect similarities in the street view. More specifically, the interior and entrance of the underground parking lot are darkly lit; The large above-ground car park is well-lit and many vehicles are parked neatly; On-street parking is usually on the side of the road with vehicles parked neatly in a row. With the development of technology, we could automatically collect street view images of parking lots from street view maps.

Focusing on the shortcomings of previous work, we proposed a Correlated Parking lot Prediction Model (CPPM) to predict the spatio-temporal parking occupancy, using graph convolutional network (GCN), gated recurrent unit (GRU) network, Convolutional Neural Network (CNN) and Bayesian probabilities.

Historical time-series occupancy from the parking lots and the correlations of the parking facilities are utilised in CPPM to predict the occupancy. More specifically, we utilised two ways to estimate their correlations: (i) travel distance. We collect the travel distance between every two parking lots as their spatial correlations; (ii) parking lots' images similarities, which are calculated from the image similarities of the parking lots. Since the parking images have multi-features of the parking lots, especially parking lot types, parking spaces, plants, and even the related infrastructures. Each factor may influence passengers' parking choices, and parking lots with very similar factors could attract similar visitors to park their cars. Previous research also proved that passengers have different parking behaviours for different parking lots' types (Lee et al., 2017; Shoup, 2006); (iii) POI's similarities around the parking lots. Since people may choose a parking lot for purposes such as returning to their residence, work, shopping or entertainment, it is therefore assumed that car parks with similar proportions of different activity types in their vicinity may have a similar ability to attract passengers. Therefore, we utilised similarities of the parking lots and travel distance as their correlations to predict parking occupancy.

To predict the future occupancy, we employed Bayesian probabilities to estimate the spatial correlations of the parking lots using Manhattan distance among the parking lots; we also utilised CNN to quantitatively discover the environmental similarities of the parking lots using street-view images; Cosine similarity is used to obtain the similarity of activity types between parking lots. GCN was employed to extract the spatial patterns from the parking lots, and GRU was used to estimate the temporal parking patterns from historical parking occupancy. The prediction results are compared with other two methods with high accuracy in prediction tasks: GRU and Temporal-GCN (Zhao et al., 2020). In this paper, we conducted two case studies in Ningbo and Beijing, China to evaluate the generalisation of the CPPM. Moreover, the results of CPPM also demonstrated passengers' parking preferences in different time and cities.

The remainder of our paper is composed as follows. Section 2 focuses on the existing related work on parking behaviour prediction. Section 3 focuses on our model and methodology. In Sections 4 and 5, we conducted two case studies in two cities in China (Ningbo and Beijing), for parking occupancy forecasting. Finally, Section 6 concludes the paper.

2. Literature review

In this section, we reviewed and discussed previous works on parking prediction. Previously, compared with traditional statistical models, machine learning methods are more effective, and have been widely used to predict parking lot occupancy (Avşar et al., 2022; Gong et al., 2021). For example, Avşar et al. (2022) applied the Long Short-Term Memory (LSTM) and Autoregressive Integrated Moving Average model (ARIMA) to predict the future value of the parking lot occupancy, and compared the prediction results of the two methods, and found that the LSTM model is more suitable for a larger prediction range and has a smaller error than the ARIMA model. It shows the superiority of the machine learning method (LSTM) over the statistics method (ARIMA). Therefore, compared with traditional statistical models, machine learning methods are more effective, and have been widely used to predict parking lot occupancy.

One of the most commonly used machine learning methods for parking behavioural prediction is regression-related methods (Kumar and Garg, 2018; Ostrom, 1990; Shi and Conrad, 2009). For example, a decision tree is a predictive approach to mapping relationships between object attributes and object values (Ketkar and Santana, 2017). Another popular regression method is random forest. It employs multiple decision trees for model training, classifying and predicting (Ketkar and Santana, 2017). Feng et al. (2019) used linear regression, decision tree, and random tree to predict parking behaviours. They primarily considered the impact of weather on parking behaviours, as well as parking fees, parking service levels, and average turnover. However, since they only used the parking lot data in one shopping mall, which may made the model not representative. In addition, the work did not consider the temporal variation of passengers' parking behaviours for parking prediction.

While traditional machine learning methods have good results in prediction on small data sets, they are not effective enough on large data sets. Deep learning is a branch of machine learning that draws on the neural network framework formed by the interconnected nature of many neurons in the human brain and has good results in training on large data sets (Liu and Lang, 2019).

Artificial neural networks (ANN) are biologically-inspired programs that mimic the way the human brain operates, constantly adjusting parameters by learning patterns and relationships in data, often as a predictive method (Agatonovic-Kustrin and Beresford, 2000). Slavova

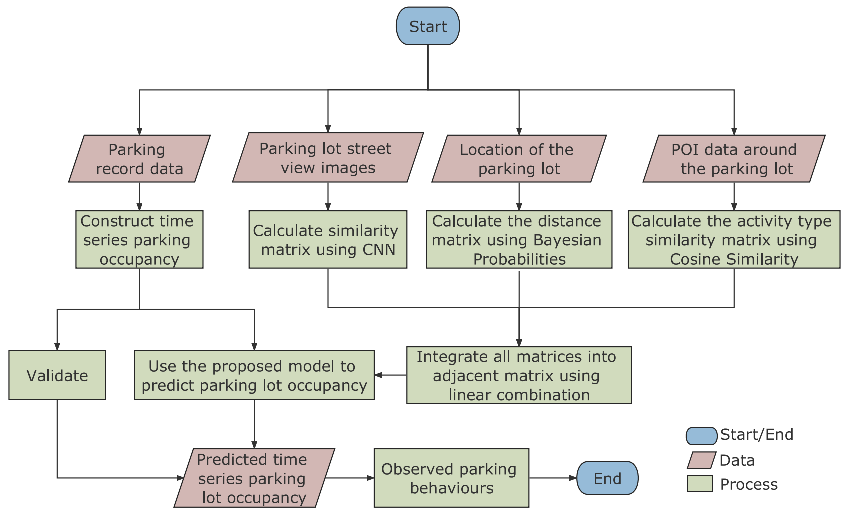


Fig. 1. The overview of the CPPM.

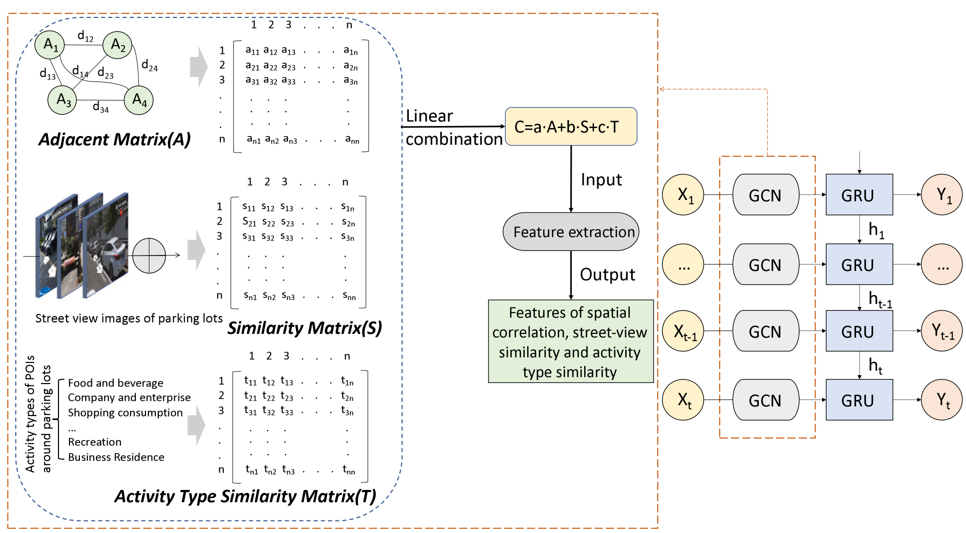


Fig. 2. The process of prediction model.

et al. (2022) used several machine learning methods to predict parking lot occupancy using temporal features and historical occupancy to improve truck parking utilisation. By comparing the prediction results (RMSE, Standard deviation, running time) of generalised linear regression models, ANN, decision trees, random forests, gradient boosted trees and support vector machines (SVM), the decision tree model worked best. However, the study only considered the temporal variations of parking lots' occupancy but ignored other factors that could influence passengers' parking behaviours.

Long Short Term Memory (LSTM) is a variant of the Recurrent Neural Network (RNN), which is a neural network with the ability to memorise long and short-term information and has good performance in processing temporal data (Yu et al., 2019). It introduces a gate mechanism for controlling the circulation and loss of features to solve the long-term dependence problem of RNNs. Avşar et al. (2022) applied LSTM and the statistical method Autoregressive Integrated Mean Shift (ARIMA) to predict the future values of parking occupancy. The results show that LSTM is suitable for a larger temporal prediction range, demonstrating the feasibility of deep learning algorithms in predicting parking lot occupancy in a long period.

A graph convolutional network (GCN) (Kipf and Welling, 2016) is a machine learning method that performs convolutional operations on spatial correlations. It consists of spectral domain methods to perform signal processing transformations on the graph, such as Fourier transform or Laplace transform, to convolve the graph with topology and extract features of the graph. RNN is a neural network used to process sequential data, where the current output of a sequence is related to the previous output (Sherstinsky, 2020). Yang et al. (2019) performed on-street parking occupancy prediction using GCNN and RNN. More specifically, it utilised traffic flow between two nearby roads to estimate the correlations between the nearby parking lots. However, it did not perform a novel way to estimate spatial correlations of every parking lots. Moreover, the traffic flow between nearby on-street parking lots could hardly represent the correlations, since traffic flow volume did not equal to the parking volume on the road. Also, they only considered on-street parking, which only takes relatively a small percentage of all parking lots. Open-air parking lots and underground parking lots are not considered in this work. As a result, the passengers' parking behaviours in different types of parking lots could be buried.

T-GCN is a deep learning framework that combines GRU and GCN for short or long-term spatio-temporal prediction tasks. GCN learns

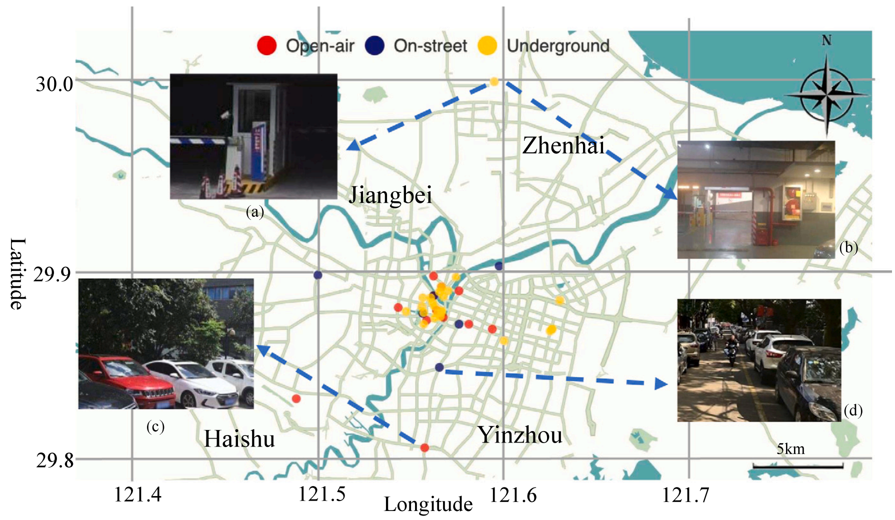


Fig. 3. The distribution of the selected parking lots in Ningbo.

the complex topology to obtain spatial correlation, and GRU learns the dynamic changes of data to obtain temporal dependence. Zhao et al. combined these two to build a T-GCN deep learning framework for traffic spatio-temporal prediction (Zhao et al., 2020). Gong et al. (2021) employed T-GCN to predict the parking lots occupancy before and during the COVID-19 outbreak. In addition, they also considered the impact of weekdays and weekends on residents' parking behaviours. Still, they did not take the potential impact of parking type and the types of activities around the parking lots on people's parking behaviours into account.

3. Methodology

In this study, we proposed CPPM to predict parking occupancy on weekdays and weekends, using GRU, GCN, CNN, and Bayesian Probabilities. We compared our results with previous studies: (i) parking occupancy prediction without considering the spatial correlation of parking lots, which we employed GRU to predict the results, and (ii) parking occupancy prediction considering a single factor separately. That is, the travel distance, the similarities of street view images of parking lots, and the similarity of the activity types around parking lots. We utilised GRU and GCN to predict the results.

3.1. Overview of the proposed parking behaviour prediction model

The overall process is shown in Fig. 1. Firstly, we pre-processed the parking record data, to construct time series as features in the time dimension. We divided the time series into training data (to train the proposed model) and testing data (to verify the feasibility of the model). To build features in the spatial dimension, we used three types of data: street view images of the parking lots, the parking lots' locations (longitude and latitude), and POIs data around the parking lots.

For each type of data, we generated a matrix to describe the correlation of the parking lots. Specifically, (i) we used the cosine similarity of CNN on the similarities of the street view images of the parking lots, to calculate the street view similarity among the parking lots. Afterwards, the calculated similarity values (from 0–1) of the parking lots were generated into the parking lots' similarity matrix, which reflects the similarities of parking lots' environment; (ii) we collected POI data with activity labels, and statistically calculated the numbers of the POIs for each activity, and considered them as the activity features of the parking lots. We utilised cosine similarities to discover the activity types similarities of the parking lots, and generated an activity type similarity matrix. We also generated a distance adjacent matrix by calculating the Manhattan distances among the parking lots.

Since in our both study areas, Beijing and Ningbo, most of the routes are vertical (see Figs. 3 and 5). Therefore, the Manhattan distance in our study areas is very similar to the route distance, and we selected the Manhattan distance to represent passengers' driving distance. In this study, the distance adjacent matrix represents the spatial correlations of the parking lots. We utilised linear combinations to integrate distance matrix and similarity matrix into adjacent matrix. The training data of spatial series and adjacency matrix are for model training on parking occupancy prediction, and the testing data set are used to validate CPPM. We could also observe passengers' parking patterns from the prediction results.

3.1.1. Spatial correlation modelling

We proposed CPPM for spatio-temporal prediction of parking lots' occupancies. Fig. 2 shows the general structure of CPPM. CPPM consists of two main components: GRU and GCN. First, we generated the time series parking occupancy as the temporal features for model training. We also integrated the distance matrix and the adjacent matrix as adjacent matrix for GCN, to predict the correlations among the parking lots.

3.2. Correlated Parking lots Prediction Model (CPPM)

GCN is a feature extractor for topological data (Kipf and Welling, 2016). The spatial correlation between parking lots can be represented in the form of a graph. We assumed that the weighted graph $G = (V, E)$ was a graph structure relationship of N parking lots, where $V = \{v_i\}_{i=1}^{N}$, v_i represented parking lot i; $E = \{e_{i,j}\}_{i,j=1}^{N}$ was the set of edges of G, and the edge $e_{i,j}$ represented the connection between parking lot i and parking lot j. Supposed a distance matrix Dis, whose elements $d_{i,j}$ represented the distance between parking lot i and parking lot j. We utilised the distance matrix Dis to construct the adjacency matrix $A \in R^{N\times N}$ with weights. Here we use Bayesian probabilities to calculate it (Gong et al., 2020b, 2022). The Bayesian formula is expressed as follows:

$$P(A_i|B) = \frac{P(A_i)P(B|A_i)}{\sum_{i=1}^{n} P(A_i)P(B|A_i)} \tag{1}$$

where A_i represents the ith event of a set of events A_1, $A_2 ... A_n$ and B represents an arbitrary event. Based on our experiment, we transformed

Eq. (1) into:

$$P(v_i|v) = \frac{P(v_i)P(v|v_i)}{\sum_{i=1}^{n} P(v_i)P(v|v_i)} \tag{2}$$

where v_i represents the ith parking lot, v represents a certain location. $P(v_i|v)$ represents the probability of people choosing the ith parking lot as a parking spot. Applying Eq. (2), we can express our adjacency matrix as follows.

$$A_{i,j} = \begin{cases} d_{i,j}^{\beta}, & d_{i,j} \le d_0 \\ 0, & otherwise \end{cases} \tag{3}$$

where d_0 is defined in this study, which means the Maximum Searching Radius (MSR) of the citizens to search for a parking lot. In real situations, people may search for another parking lot if the closest parking lot is full of cars. d_0 means the farthest distance people could accept to find another parking lot when the lot is full, and β denotes the distance decay factor.

We also constructed the street view similarity matrix $S \in R^{N\times N}$ of parking lots, where $S_{i,j}$ represented the street view similarity between parking lot i and parking lot j. Its value is between 0 and 1. In particular, the higher the similarity is, the closer the value is to 1. Considering the CNN's applications on image recognition in previous works (Chen and Tsou, 2022), we used CNN's cosine similarity to calculate the similarity between the street view images in the parking lot. The formula is as follows:

$$\cos(\theta) = \frac{\sum_{i=1}^{n} (x_i \times y_i)}{\sqrt{\sum_{i=1}^{n} (x_i)^2} \times \sqrt{\sum_{i=1}^{n} (y_i)^2}} \tag{4}$$

where x_i, y_i represent the coordinate values of the ith dimension of the x, y vector in the n-dimensional space. In particular, x and y represent the feature vectors of the street view images of the parking lot, which is extracted from resnet50.

Inspired by the Huff model, passengers' spatial choice for the destination is determined by two attributes: (i) the attractiveness of the destination, and (ii) the travel cost, therefore, in this study, we also determined two factors when passengers' selecting a parking lot. In particular, we assumed the environment of the parking lots (street images) as the attractiveness, and the route distance for one parking lot to another as the travel cost.

In addition, we considered the type of activity that may be involved around the parking lot (as in Table 1[2]) as one of the influencing factors and characterised the percentage of POIs of different activity types within a 500 m radius of each parking lot. The normal range at which a destination usually attracts people to go past it, i.e. the normal range at which they are willing to walk, is 500 m (Yue et al., 2012), so we have used 500 m as the radial range we look for POIs around parking lots.

Inspired by this, we constructed an adjacent matrix for CPPM by combining two matrices: distance adjacent matrix A, similarity adjacent matrix S and activity type similarity matrix T (which is calculated by Eq. (4)). The formula is:

$$C = a \cdot A + b \cdot S + c \cdot T \tag{5}$$

where a represents the coefficient of the adjacency matrix A; b means the coefficient of the street view similarity matrix S; c is the coefficient of the activity type matrix T. a, b and c represent passengers' sensitivity to the influential factors. In particular, the value a means the citizens' consideration on parking environment, while the value b means passengers' attention on travel cost for finding a parking lot, and c represents the degree of influence of activities around the parking lot on passengers' choice of parking lot. We fed the matrix C into the GCN to represent the spatial correlation of parking lots for model training.

[2] The classification of activity types in the table is based on POI data obtained from the OpenStreetMap: http://www.openstreetmap.org/.

Table 1
The types of activities that may be involved in the parking lot perimeters.

Activity types	Related POIs
Food and beverage	Restaurants; cafés; snack and fast food, etc.
Company and enterprise	Agriculture, forestry and fisheries; factories; companies, etc.
Shopping consumption	Shopping malls; supermarkets; convenience stores; flowers, birds, fish and insects; markets; shopping streets; home building materials; sports and cultural good; home appliances and digital, etc.
Transportation facilities	Airports; bus stations; railway stations; coach stations; port terminals; service areas; toll stations, etc.
Financial institution	Banks; security firms; insurance companies; investment banking; ATMs, etc.
Hotel accommodation	Hotels; hostels;guesthouses, etc.
Science and education culture	Exhibitions and Conferences; culture houses; libraries; museums; schools; educational institutions; scientific research units, etc.
Tourist Attractions	Scenic spots; parks; memorials; squares; resort areas; religious attractions, etc.
Car-related	Charging stations; petrol stations; car repairs; car maintenance; car accessories; car rental, etc.
Business Residence	Community centres; villa areas; residential areas; office buildings; industrial parks; dormitories, etc.
Life Service	Public toilets; Hairdressing; Post office; information; rain massage; telecommunications; public utilities,etc.
Recreation	Cinemas; farmhouses; holiday homes; amusement parks; chess and card rooms, etc.
Healthcare	General hospitals; specialist hospitals; clinics; pharmaceutical sales; animal medical care; emergency centres; disease prevention, etc.
Sports & Fitness	Sports complexes; specialised sports; outdoor fitness; campsites; fitness centres, etc.

Afterwards, we utilised the historical time series data of each parking lot as the feature matrix $X \in R^{N\times P}$, where P represented the length of the historical time series data. $X_t \in R^{N\times i}$ represented the average occupancy rate of parking lots in the ith time period of each parking lot. It is worth mentioning that the feature matrix X can be any kind of parking record data, such as the number of vehicles. GCN is constructed in the Fourier domain with a filter acting on each node of the graph to obtain the spatial features of the graph through its weighted adjacency matrix (Zhao et al., 2020).

We employed a two-layer GCN model (Yu et al., 2017) for spatial correlation extraction, which can be represented by Eq. (6). First, the feature matrix X_t and the matrix C containing spatial features and street view similarity features are input to the GCN model, and the GCN learns its features X_t^s. The model can be expressed below:

$$X_t^s = f(X_t, C) = \sigma(\hat{C}\, ReLU(\hat{C} X_t W_0) W_1) \tag{6}$$

where $\hat{C} = \widetilde{D}^{-\frac{1}{2}} \widetilde{C} \widetilde{D}^{-\frac{1}{2}}$, $\widetilde{C} = C + I_N$, I_N is the identity matrix, $\widetilde{D} = \sum_j C_{i,j}$, W_0 and W_1 are the weighted matrices of the first and second layer. σ is the sigmoid function while ReLU is the activation function.

3.2.1. Temporal dependence modelling

Recurrent neural networks (RNNs) are commonly used to process serial data, and it is widely used to learn time-series data to obtain time-dependence on parking behaviour prediction. However, since traditional RNN methods suffer from gradient disappearance and explosion (Bengio et al., 1994), we need to find improved RNN algorithms to solve the gradient problem that we may face. GRU (Cho et al., 2014) model and LSTM (Hochreiter and Schmidhuber, 1997) model are variants of RNN, which can better solve the above problems. They are similar in that they both use a gate mechanism to remember long-term information to achieve the effect of processing sequential data (Chung et al., 2014). However, GRU has a simpler structure, fewer parameters, and shorter training time than LSTM, so we chose GRU as our time series training model. The training process can be expressed as follows.

$$u_t = \sigma(W_u[X_t^s, h_{t-1}] + b_u) \tag{7}$$

$$r_t = \sigma(W_r[X_t^s, h_{t-1}] + b_r) \tag{8}$$

$$c_t = tanh(W_u[X_t^s, (r_t * h_{t-1})] + b_c) \tag{9}$$

$$h_t = u_t * h_{t-1} + (1 - u_t) * c_t \tag{10}$$

where u_t and r_t are the update gate and reset gate at time t, c_t is the state recorded at time t, and h_t is the output state at time t. W and b represent the weights and biases, respectively.

In summary, CPPM processed the parking data and extract the features of parking behaviours spatially and temporally, and predict future parking occupancy. In the training process of CPPM, we minimise the real parking occupancy records as much as possible using the following loss function.

$$loss = \|y_t - \hat{y}_t\| + \lambda L_{reg} \tag{11}$$

where y_t represents the true value of the parking record, $\hat{y}_t$ represents the predicted value of the parking behaviour, λ is the hyperparameter set to 0.0015, and L_{reg} is the $L2$ regularisation term.

3.3. Evaluation metrics for model validation

We used GRU, T-GCN, and CPPM to predict parking occupancy and evaluated the performance of these models by comparing the prediction results of these two methods and analysing our hypotheses through the results. Here, we used five metrics to evaluate these models (Zhao et al., 2020).

(1) Root Mean Squared Error:

$$RMSE = \sqrt{\frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{n}(y_i^j - \hat{y}_i^j)^2} \tag{12}$$

(2) Mean Absolute Error:

$$MAE = \frac{1}{MN}\sum_{j=1}^{M}\sum_{i=1}^{n}\left|y_i^j - \hat{y}_i^j\right| \tag{13}$$

(3) Prediction precision:

$$P = 1 - \frac{\|Y - \hat{Y}\|_F}{\|\hat{Y}\|_F} \tag{14}$$

(4) Explained Variance Score:

$$var = 1 - \frac{Var\{Y - \hat{Y}\}}{Var\{Y\}} \tag{15}$$

(5) Coefficient of Determination:

$$R^2 = 1 - \frac{\sum_{j=1}^{M}\sum_{i=1}^{n}(y_i^j - \hat{y}_i^j)^2}{\sum_{j=1}^{M}\sum_{i=1}^{n}(y_i^j - \bar{Y})^2} \tag{16}$$

where y_i^j, $\widehat{y_i^j}$ represented the true and predicted values of the ith parking lot occupancy at time j. M, N represent the number of time samples and the number of parking lots. y and $\hat{Y}$ represent the set of y_i^j, $\widehat{y_i^j}$, respectively, and $\bar{Y}$ represents the mean value of Y. RMSE and MAE are used to measure the prediction error, and their smaller values represent better predictions. Prediction precision is used to measure the prediction accuracy of the model. R^2, var are used to evaluate the ability of the prediction results to represent the true results, and their larger values represent better ability.

4. Case study in Ningbo, China

4.1. Study area and data

In this study, We selected Ningbo, China as our study area. Ningbo is an important port city located in the east of China. It is a famous industrial city with a population of 9.54 million. We uniformly selected 44 parking lots in Ningbo for parking occupancy prediction. We numbered these parking lots from NB.0 to NB.43. The locations distribution of the parking lots are shown in Fig. 3. In the figure, most of the selected parking lots are located at the junction of Jiangbei District, Yinzhou District and Haishu District. The parking lots are sorted into three categories: (i) Open-air parking lots, where the parking space is usually in front of some Point of Interests (POIs). In this case study, NB.0 to NB.12 parking lots are open-air parking lots; (ii) On-street parking lots (from NB.13 to NB.18 parking lots), where passengers parking cars on the roadside, and (iii) Underground parking lots, where the parking spaces are served within a large infrastructure, such as shopping mall, office building, or residential apartment. In this study, NB.19 to NB.43 are underground parking lots.

We collected parking lot name, record time, location (latitude and longitude), and parking occupancy rate (%) for two weeks (5 weekdays and 2 weekend days per week) in mid-2019. The format of the parking lots' occupancy data is shown in Table 2. We generated the parking occupancy time series data as follows: (i) We calculated the hourly average occupancy by dividing the number of parking cars in the current hour by the total number of spaces (which we utilised it using Algorithm 1), and we kept the hourly occupancy data for each parking lot; (ii) for each parking lot for each day, we kept only the hourly average occupancy data from 8:00 am to 8:00 pm. These gave us our time series data. In this study, we split the first 85% of the time series as the training data and the other 15% of the data as the testing data set. The testing data was used to compare the gap between the occupancy predicted by the model and the true value, and for model evaluation.

Algorithm 1: Ningbo time series generation

```
/* The input data is car park occupancy for n
   car parks at t time points and t time
   points, and output is hourly occupancy of n
   car parks (m hours in total)                */
Input: raw_occupancy[t][n], time[t]
Output: nb_time_series[m][n]
for i ← 1 to n do
    for j ← 1 to t do
        count ← 0
        for l ← 1 to m do
            if l time point in hour j then
                nb_time_series[j][i] ← raw_occupancy[l][i]
                count ← count + 1
            end
        end
        nb_time_series[j][i] ← nb_time_series[j][i]/count
    end
end
```

Except travel cost, the environment of parking lots may also influence residents' parking decisions, such as the parking lot categories, nearby infrastructure, the parking lot size, the locations of the parking lots, etc. In this study, we utilised street view images of the parking lots to represent the environment, and Manhattan distance among the parking lots as the travel cost, to estimate two factors that influence passengers' parking behaviours.

Table 2
The format of parking lots' occupancy data.

Label	Time	Longitude	Latitude	Occupancy	Parking spaces
NB.4	9 am	121.5647006	29.87217298	0.674033904	292
NB.23	12 pm	121.4372695	29.32565976	0.97204963	135

Algorithm 2: Distance matrix calculating

```
/* The input are longitude and latitude of n
   parking lots.                                  */
Input: longitudes[n],latitudes[n]
Output: Distance[n][n]
for i ← 1 to n do
    for j ← 1 to n do
        Distance[i][j] ← GetDis-
         tance(latitude[i],latitude[j],longitude[i],longitude[j])
    end
end
```

Algorithm 3: Adjacency matrix calculating

```
/* The input data is a distance matrix and the
   maximum distance a passenger can accept
   another car park.                              */
Input: Distance[n][n],max_dis
Output: Adjacency[n][n]
for i ← 1 to n do
    for j ← 1 to n do
        /* The distance between the ith and jth
           car park is greater than the maximum
           distance acceptable to passengers,
           assuming a correlation of 0.            */
        if distance[i][j] >max_dis then
            Adjacency[i][j] ← 0
        end
    end
end
for i ← 1 to n do
    for j ← 1 to n do
        if i == j then  Adjacency[i][j] ← 1 ;
        else  Adjacency[i][j] ← Adjacency[i][j]^β ;
    end
end
```

4.2. Spatial correlations of parking lots

We calculated the Manhattan distance between two parking lots and constructed a distance matrix (see Algorithm 2). To design the distance matrix, we assumed that the occupancy rate of one parking lot is similar to that of other parking lots located nearby. Therefore, we utilised the distance decay function (see Eq. (3)) to estimate parking lots' spatial correlation (see Algorithm 3). In particular, to discover the value of MSR (d_0 in Eq. (3)), we test the performance of CPPM in different MSR from 200 m to 1000 m. We also calculate the result of CPPM when d_0 is infinity, which means the adjacent distance matrix is fully-connected. The results comparisons are presented in Section 4.5.

Fig. 4(a) presented the distance matrix when d_0 is infinity. The distance matrix is processed using the Bayesian probability method (Eq. (3)), normalised and fed into the model as an input matrix. The normalised matrix values are from 0 to 1; 0 means there are no spatial correlations among the parking lots, and 1 means very strong spatial correlations among the parking lots. In the matrix, we saw that: (1) the parking lots in Ningbo are densely distributed. In particular, most parking lots are located within 3 km away from each other. We also discovered that NB.3 and NB. 24 are relatively isolated parking lots, which are located nearly 10 km from other parking lots; (ii) Ignoring two isolated parking lots (NB.3 and NB.24), we discovered that the average Manhattan distance between every two on-street parking lots (from NB.13 to NB.18, 3359 m) is much shorter than average Manhattan distance of every open-air parking lots (from NB.0 to NB.12, 10,911 m), and average Manhattan distance of every underground parking lots (from NB.19 to NB.43, 9600 m). Since the parking lot distribution in the case study is very similar to the real situations, we therefore indicate that the on-street parking lots are much more densely distributed than other types of parking lots. One interpretation is the underground and open-air parking spaces are usually much larger than on-street parking lots and could meet most of the nearby passengers' parking requirements. Therefore, there is no need to locate underground and open-air parking lots densely.

4.3. Similarity of street view in Ningbo parking lots

Moreover, we also obtained street view images of these parking lots from Street View Maps to generate the adjacent matrix of parking lots' similarities.[3] To construct the similarity matrix of the parking lots, we utilised the street view images of the parking lots. The street view images we obtained mainly include visible features such as the arrangement of vehicles in the parking lot and the surrounding environment of the parking lot. For example, how cars are arranged in different types of parking lots, and environmental factors such as the vegetation cover, area and lighting around the parking lot can be reflected in street view images. Except that the street view images of underground parking lots may be the entrance of parking lots, due to the limitation of obtaining parking lot landscape from Street View maps, the radius around parking lots in the images we can capture is mostly around 50–100 m. We used CNN for feature extraction and cosine similarity for similarity calculation to derive the similarity between the parking lots to form the matrix. As in Fig. 4(b), we visualised the parking lot similarity matrix with a colour block diagram, and the two parking lots with higher similarity have darker corresponding colour blocks.

From Fig. 4(b), we saw that: (i) the colour blocks on the diagonal of the colour block diagram, that is, the similarity between each parking lot and its own street view, are close to 1. The colour block colour distribution of the two parts separated by the diagonal can also be found to be symmetric because the parking lot similarity matrix itself is a symmetric matrix along the diagonal. Focusing on the colour block colours along the diagonal, most of the parking lots have a similarity of about 0.6 and above between the two; (ii) the similarity among open-air parking lots was higher compared to other types. This may be because open-air parking lots were usually well-lit, spacious, and sometimes had more distinct characteristics with a large number of vehicles neatly disposed of (Fig. 3). On-street parking lots, on the other hand, were less similar to each other than open-air parking lots. On-street parking was usually on the side of the road and was likely to be surrounded by sidewalks, street-level stores and vegetation, but these were not essential factors for on-street parking. Underground parking was less similar to each other than other types, probably because we selected underground parking lots with two different street views: the entrance to the underground parking lot and the interior of the underground parking lot (Fig. 3). These two street views had different characteristics: the entrance of the underground parking lot was generally darker,

[3] The street view images of the parking lots are collected from Panoramic map.

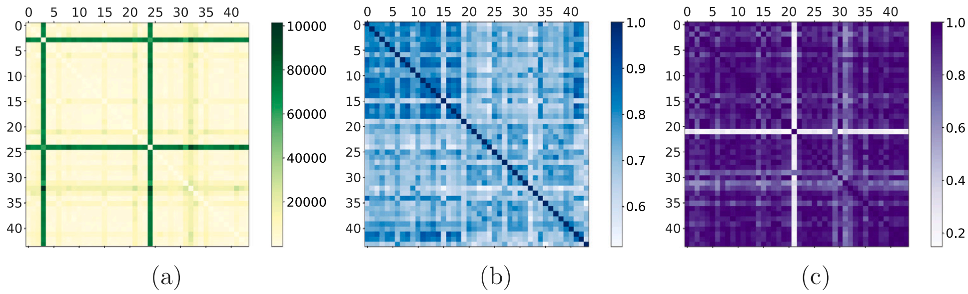


Fig. 4. The distance matrix (a), similarity matrix (b), activity type similarity matrix (c) of Ningbo parking lots, where $d_0 = infinity$ in distance matrix. In particular, NB.0 to NB.12 are open-air parking lots, NB.13 to NB.18 are on-street parking lots, and NB.19 to NB.43 are underground parking lots.

Table 3
The results of CPPM with different settings of parameters.

Time	MSR	a	b	c	β	Prediction precision	var	MAE	R^2	RMSE
Weekdays	200	1	0.625	0	−1	0.919	0.956	0.048	0.955	0.070
	400	1	0.05	0	−1	0.918	0.954	0.048	0.954	0.071
	600	1	0.05	0	−1	0.919	0.956	**0.045**	0.956	0.070
	800	1	0.05	0	−1	0.918	0.955	0.046	0.954	0.073
	1000	1	0.05	0	−1	0.916	0.953	0.048	0.952	0.073
	infinity	1	0.625	0	−1	**0.920**	**0.957**	0.048	**0.957**	**0.069**
Weekends	200	1	0.625	0	−1	0.846	0.886	0.081	0.884	0.121
	400	1	0.01	0	−1	0.854	0.901	0.080	0.897	0.115
	600	1	0.01	0	−1	0.855	0.901	0.079	0.897	0.114
	800	1	0.625	0	−1	**0.858**	**0.902**	**0.075**	**0.901**	**0.112**
	1000	1	0.01	0	−1	0.855	0.900	0.078	0.897	0.114
	infinity	1	0.01	0	−1	0.847	0.887	0.082	0.886	0.120

with speed bumps and other facilities; the interior of the underground parking lot was usually a darker indoor lighting environment and has several vehicles parked neatly.

4.4. Similarity of activity types in Ningbo parking lots

In addition to the similarity of the street view of the parking lots, we also explored the similarity of the types of activities involved in the POIs around the parking lots. We used the latitude and longitude of the car park to obtain POIs within 500 m of its perimeter in OpenStreetMap, and classified the POIs according to Table 1. We calculated the proportion of different activity types around each parking lot and used cosine similarity (Eq. (4)) to calculate the similarity of the proportion of activity types around these parking lots.

From Fig. 4(c) we can see that: (i) the similarity of activity types between the colour blocks on the diagonal, i.e. the parking lots, and themselves is closest to 1; (ii) the similarity of activity types between NB.21 and all other parking lots is low, below 0.3, which indicates that the distribution of POI activity types around NB.21 is different from other parking lots; (iii) except for NB.29, NB.31, NB.32 and most of the car parks with POI activity type similarity between 0.5 and 0.7, the activity type similarity between most of the car parks is high, above 0.7, and even close to 1 between some parking lots. This may be because most of the parking lots we selected are concentrated in several going intersections, and the POIs within 500 m of some parking lots may have overlapped.

4.5. Parking occupancy prediction results

We used CPPM to predict the share of Ningbo parking lot. The environment in which we run the program is an NVIDIA 3080-10G GPU with 10G of video memory and an 8-core AMD EPYC 7601 CPU with 32G of RAM. Table 3 shows the results of CPPM, setting the MSR as 200, 400, 600, 800, 1000, and fully connected (infinity). We saw that in the case of weekdays, the model prediction result error was small compared to other parameter groups and the prediction precision is the highest when the distance matrix is fully connected, the distance matrix-related parameter $a = 1$, the similarity matrix-related parameter $b = 0.625$, the activity type matrix-related parameter $c = 0$, and the distance decay parameter $\beta = -1.1$; in the case of weekends, the maximum acceptable distance is 800 m, $a = 1$, $b = 0.625$, $c = 0$, and $\beta = -1$, the model has the smallest prediction error and the highest prediction precision. In the case of weekdays and weekends, the model has the best results when the parameter c = 0, i.e. when the type of activity around the parking lot is not considered. We indicate that there is no direct relationship between the movement of private cars between parking lots and the similarity of the related activities.

We also saw that during weekdays, CPPM has the best performance when MSR=infinity (distance matrix is full-connected), while at weekends, CPPM has the highest accuracy when MSR=800 m. This suggests that on weekdays, it could be harder for parking. Passengers usually need to drive further for an available parking space (over 1 km) than at weekends (800 m). One interpretation is that most residents have work-schedule on weekdays (usually from 9 am to 5 pm), and the resulting morning and evening peaks require a large number of parking spaces for passengers to park their private cars.

In addition to this, we also used baseline methods GRU and T-GCN method (using Manhattan distance matrix, the street view similarity matrix and the activity similarity matrix as single matrix for the GCN, respectively) to predict the parking occupancy situation. Table 4 compares these methods with CPPM with the best MSR (see Table 3). We can find that the predictive power of our model has a relatively significant advantage over the other approaches, indicating that the similarity of the surrounding environment of the parking lot has a certain influence on people's parking choices when private cars travel. Moreover, we also discovered that the results on weekdays have higher accuracy than at weekends. This indicates that passengers' parking behaviours on weekdays are easier to be predicted than behaviours st weekends. We interpret it as residents' regular working time on weekdays.

From the results, we could compare the prediction results using one single matrix. In particular, T-GCN with distance matrix has the best performance compared with others (image similarity matrix and activity matrix), while T-GCN with single POI matrix has relatively

Table 4
The result of GRU, $T-GCN_{dis}$, $T-GCN_{image}$, $T-GCN_{poi}$ and CPPM.

Model	Time	a	b	c	β	Precision	var	R^2	RMSE	MAE
GRU	Weekdays	\	\	\	\	0.865	0.877	0.883	0.117	0.073
	Weekends	\	\	\	\	0.822	0.846	0.846	0.140	0.085
$T-GCN_{dis}$	Weekdays	\	\	\	−1.1	0.865	0.928	0.925	0.091	0.059
	Weekends	\	\	\	−1	0.857	0.901	0.900	0.113	0.077
$T-GCN_{image}$	Weekdays	\	0.85	\	\	0.865	0.876	0.875	0.117	0.085
	Weekends	\	0.85	\	\	0.816	0.842	0.835	0.145	0.104
$T-GCN_{poi}$	Weekdays	\	\	0.7	\	0.845	0.837	0.837	0.134	0.103
	Weekends	\	\	0.5	\	0.818	0.847	0.841	0.143	0.098
CPPM	Weekdays	1	0.625	0	−1	0.920	0.957	0.957	0.069	0.046
	Weekends	1	0.625	0	−1	0.858	0.902	0.901	0.112	0.076

Table 5
The format of Beijing parking lots' occupancy data.

Label	Time	Longitude	Latitude	Entering number	Leaving number
BJ.0	8 am	116.321786	39.970133	0	6
BJ.91	20 pm	116.319263	39.90038	6	1

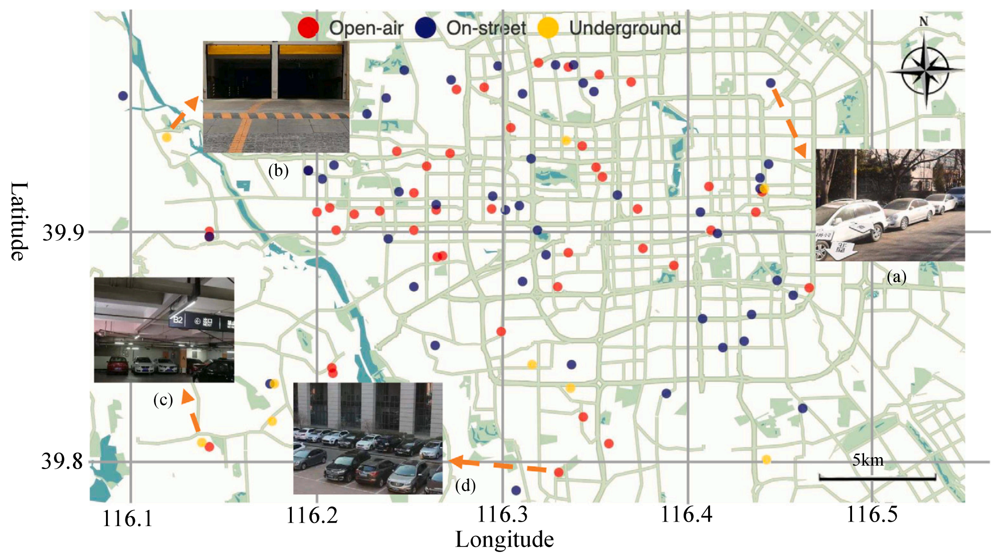


Fig. 5. The distribution of the selected parking lots in Beijing.

lowest accuracy compared with others. We also infer that this is a way to quantify the importance of different factors (trip distance, parking lot types & environments, and activity similarities) in describing parking lots' spatial correlations. In particular, trip distance has the highest influence on cars' movements between two parking lots, while activity similarities could not precisely describe the spatial correlations of the parking lots. One interpretation is that passengers have a very small probability to transfer to the area with the same activity. Since it has been proved in previous work, we believe these results are within our expectations (Gong et al., 2020b,a).

5. Case study in Beijing, China

5.1. Study area and data

We collected parking data from Beijing, China to further validate the accuracy and generalisability of our model. Beijing is the capital of China, a mega-city, political centre and cultural centre with a resident population of 21.88 million.

Fig. 5 shows the distribution of our selected parking lots, and we can see that they are more evenly distributed in downtown Beijing. We collected the historical records of 101 parking lots in Beijing, China from August 10 to August 12, 2018. The data format is presented in Table 5. The parking data includes the parking lot name, location (latitude and longitude), time, and the number of vehicles entering and exiting the parking lot. We sorted and labelled the parking lots by their categories: from BJ.0 to BJ.44 are the open-air parking lots; from BJ.45 to BJ.90 are the on-street parking lots, and the underground parking lots are from BJ.91-BJ.100.

We statistically generated the parking lots' occupancy series data by the following steps: (i) first, we processed the incoming and outgoing vehicle information into the net number of vehicles entering each parking lot every 15 min ($E_0, E_1, E_2, \ldots, E_t$); (ii) second, we consider the initial net entering numbers E_0 (at 0 am in the first day) as the initial parking occupancy O_0, and the parking occupancy at time t are calculated as:

$$O_t = O_{t-1} + E_t \tag{17}$$

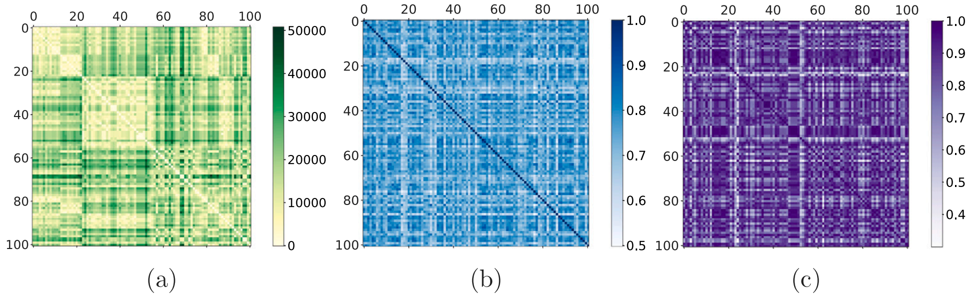


Fig. 6. The distance matrix (a), similarity matrix (b) and activity type similarity matrix (c) of Beijing parking lots. In particular, BJ.0 to BJ.44 are the open-air parking lots, BJ.45 to BJ.90 are the on-street parking lots, and BJ.91-BJ.100 are underground parking lots.

Algorithm 4: Beijing time series generation

```
Input: Carin[m][n], Carout[m][n]
// The matrices are hourly data.
Output: Timeseries[m][n]
for i ← 1 to m do
    for j ← 1 to n do
        /* Initialise Timeseries[m][n]                      */
        Timeseries[i][j] ← 0;
    end
end
for i ← 1 to m do
    for j ← 1 to n do
        /* Obtain net incoming hourly vehicle
           volume by subtracting outgoing
           hourly vehicle volume                            */
        Timeseries[i][j] ← Carin[i][j] - Carout[i][j]
    end
end
```

where O_{t-1} is the parking occupancy at 15 min earlier than t, and E_t is the net entering number of vehicles at t. We normalised the time series data before predicting parking occupancy. The process of generating the occupancy series data is described in Algorithm 4.

5.2. Spatial correlations of parking lots

Similar to case study in Ningbo (see Section 4), we constructed the distance and similarity matrix of the parking lots in Beijing, and the results are shown in Fig. 6(a). Different to Ningbo, we discovered that in Beijing, the average Manhattan distance between two open-air parking lots (13,997 m) is much shorter than the distance between two underground parking lots (19,192 m), and distance between two on-street parking lots (17,785 m). This suggests the open-air parking lots are more densely distributed. Comparing this phenomenon with the results in Ningbo, we infer that the parking lot distributions are different in different cities. It also indicated that the parking lot distributions in Ningbo are much denser than in Beijing. We interpreted it as the uniform distribution of parking lots and the huge urban area of Beijing. Therefore, the distances between most parking lots are relatively longer than the distances in Ningbo.

5.3. Similarity analysis of street view of the parking lots

We constructed the street view similarity matrix for parking lots in Beijing using the same method for Ningbo parking lots (see Section 4.3). The colour block diagram of street view similarities is shown in Fig. 6(b). Different to the parking lots in Ningbo (see Fig. 4(b), the average similarity of the parking lots is 0.69), the parking lots in Beijing show much higher similarities (0.74). Also, we found that the street view similarity difference between parking lots in Beijing is smaller than that in Ningbo. One interpretation is that the greening of Ningbo City is better. There are more green plants in or near some of the parking lots in Ningbo, which lead to the variance of street views. Moreover, in both Beijing and Ningbo (see Figs. 4(b) and 6(b)), we saw that the similarity between most parking lots is above 0.5. We interpreted that the street view of parking lots basically showed vehicles, an essential object of every parking lot.

5.4. Similarity of activity types in Beijing parking lots

We used the same method to obtain the similarity of POI activity types for Beijing parking lots. From Fig. 6(c) we can see that: (i) similar to the car parks in Ningbo, the colour block on the diagonal is the darkest, i.e. the similarity between the parking lots and themselves is close to or at 1.0; (ii) the similarity between most of the parking lots is between 0.6 and 1.0, with a small number between 0.3 and 0.6, indicating that the proportion of activity types of POIs around most of the parking lots is relatively similar. This may be due to the high degree of urbanisation in downtown Beijing, where most places are more well-equipped, so the types of POI activities around parking lots may also tend to be similar.

5.5. CPPM prediction results

Similar to the study in Ningbo, we also used CPPM, T-GCN (the Manhattan distance matrix, street view similarity matrix and POI activity type similarity matrix are used separately as input data for the GCN), and GRU to forecast the parking lots' occupancy. Since we only collected three days' parking data in Beijing, we temporarily disregarded the impact brought by weekdays and weekends on parking behaviours. Table 6 showed the results of our predictions. The prediction results of CPPM are better than other methods. We saw that passengers prefer to drive at most 600 m (MSR) to search for a parking lot, which is short than that in Ningbo (infinity on weekdays, and 800 m at weekends). We could infer that Beijing has more parking resources than Ningbo. Moreover, the best-fitted parameters are a=1.6 and b=0.08. Compared with the parameters in Ningbo, This is a new and quite interesting finding. One interpretation is that since Beijing is one of the most prosperous cities in China, residents who lived in Beijing have much faster daily routines than in most other cities. Passengers in Beijing would prefer to park their cars in a closer parking lot than a better but further parking lot. Also, we noticed that in Beijing, the activity type does not show a clear correlation with private cars' movements between two parking lots.

By comparing the prediction results of Beijing and Ningbo (Table 4 and Table 6), the b-value for the Beijing experiment (0.08) is lower than the b-value for Ningbo (0.625), which suggests that the street view environment of the Ningbo car park has a greater influence on parking choice than in Beijing. Meanwhile, we also noticed that the best-fitted value of a is quite different in the two cities. In particular,

Table 6
The result of GRU, $T-GCN_{dis}$, $T-GCN_{image}$, $T-GCN_{poi}$, and CPPM in Beijing.

Model	MSR	a	b	c	β	Precision	var	R^2	RMSE	MAE
GRU	\	\	\	\	\	0.757	0.783	0.783	0.146	0.053
$T-GCN_{dis}$	600 m	\	\	\	−1	0.770	0.811	0.807	0.138	0.042
$T-GCN_{image}$	\	\	0.01	\	\	0.737	0.922	0.922	0.122	0.008
$T-GCN_{poi}$	\	\	\	0.1	\	0.672	0.890	0.890	0.136	0.023
CPPM	600 m	1.6	0.08	0	−1	0.780	0.821	0.821	0.133	0.038

Table 7
The travel cost of Beijing and Ningbo.

Area	Time	Average travel distance	Parking charges
Beijing	Weekdays Weekends Holidays	31.4 km/day 39.1 km/day 48.1 km/day	up to 10 yuan/hour
Ningbo	/	10.3 km/day	4-8 yuan/hour

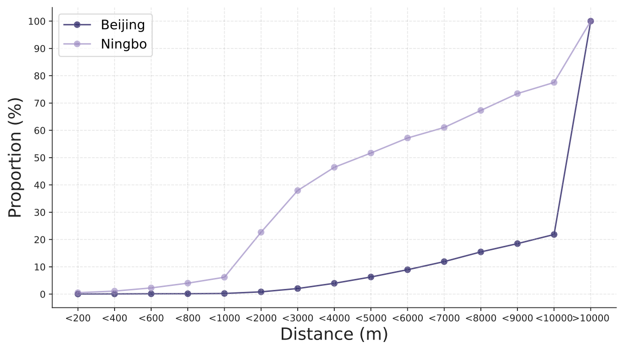


Fig. 7. Comparison of distance distribution between Beijing and Ningbo.

the best value $a = 1$ in Ningbo, and the best value $a = 1.6$ in Beijing. This indicates that the Manhattan distance has a higher influence on passengers' choices in Beijing than in Ningbo. To further investigate this phenomenon, we statistically counted the Manhattan distance between every parking lots, which is presented in Fig. 7. Considering the distribution of parking lots in both cities, it is within our expectations. More specifically, The Manhattan distance in Beijing of two parking lots is usually longer than that in Ningbo. Table 7 lists the travel costs of Beijing and Ningbo.[4] The average daily driving distance of Beijing on weekdays, weekends and holidays (Wang et al., 2015) is much higher than that of Ningbo (Qin et al., 2015), which may be because Beijing has a much larger geographical area than Ningbo and people travel a long distance. Car owners in Beijing would be paying up to 10 yuan per hour to park their cars while the parking charge in Ningbo was about 4–8 yuan per hour (Ye et al., 2020). In summary, the travel cost in Beijing is higher than that in Ningbo.

6. Conclusion

This study proposed a Correlated Parking lot Prediction Model (CPPM) to predict spatio-temporal parking occupancy. We conducted two case studies in Ningbo and Beijing in China, using 145 parking lots with over 13 million parking occupancy records. The results show that our proposed model has a better performance compared with T-GCN and GRU. Therefore, we suggest CPPM is a superior method and could be widely used in analysing parking behaviours.

The results also demonstrated that both parking lot environment and travel distance could influence passengers' parking lot selections. In particular, passengers in Ningbo pay more attention to parking lot environment (parking lot type, street view, price, etc.) when they select a parking location, while people who live in Beijing often consider much more travel costs when they prepare to park their cars. This indicates that parking in Beijing could be more difficult than in Ningbo. Surprisingly, citizens in Beijing travel often drive a shorter search for a parking lot than people in Ningbo. In particular, people drive 800 m at weekends at most for an available parking space in Ningbo, while they only drive 600 m at most in Beijing. This indicates that Beijing has more parking resources than Ningbo. As a result, we suggest the city's planning scheme for parking lots in Beijing could be improved.

Furthermore, the street views of parking lots are much more similar in Beijing than in Ningbo. We discovered that Ningbo has better city greening, which causes the variance of the parking lot environments in Ningbo. It could also highly improve the attractiveness of the parking lots. Similarly, we found no direct correlation between the types of POI around the parking lots and their spatial correlations. Since passengers are less likely to travel to different areas for the same activity, we infer that this finding is reasonable and within our expectation.

Our research has far-reaching implications for optimising parking requirements at different times such as morning and evening peaks on weekdays. By accurately predicting the parking lot conditions at different times, passengers could conveniently choose the best way to travel and reduce the number of private cars. Moreover, with further investigations, this work could provide guidance for governors to improve the design of parking lots, which could largely improve the well-being of the residents.

In the future, this work could be extended in the following aspects: (i) collecting long-term parking lots data to estimate parking preference in different situations (such as before and during COVID-19) (ii) utilising CPPM to explore passengers' preference for parking other travel modes, such as sharing-bikes, scooters, etc.

CRediT authorship contribution statement

Shuhui Gong: Conceptualization, Writing – original draft, Methodology, Data curation. **Jiaxin Qin:** Methodology, Visualization. **Haibo Xu:** Data curation. **Rui Cao:** Writing – review & editing. **Yu Liu:** Supervision, Writing – review & editing. **Changfeng Jing:** Supervision, Writing – review & editing. **Yuxiu Hao:** Data curation. **Yuchen Yang:** Visualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work is supported by the Fundamental Research Funds for the Central Universities, China [Grant No. 2-9-2020-028], National Natural Science Foundation of China [Grant No. 62172373, 61872325, 42101472], GHFUND B [Grant ghfund 202107021958], the Beijing Natural Science Foundation, China [Grant No. 8222009], the Hong Kong Polytechnic University Start-Up [Grant BD41].

[4] The data is China Daily. The website is: http://www.china.org.cn/english/DO-e/34118.htm.

References

Agatonovic-Kustrin, S., Beresford, R., 2000. Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. J. Pharm. Biomed. Anal. 22 (5), 717–727.

Avşar, E., Anar, Y.C., Polat, A.Ö., 2022. Parking lot occupancy prediction using long short-term memory and statistical methods. MANAS J. Eng. 10 (1), 35–41.

Bengio, Y., Simard, P., Frasconi, P., 1994. Learning long-term dependencies with gradient descent is difficult. IEEE Trans. Neural Netw. 5 (2), 157–166.

Chao, Z., Zihao, C., Hao, Q., 2022. Time-domain characteristics of residential parking and SEM-BL integration model of parking method choice behaviour. Math. Probl. Eng. 2022.

Chen, F., Tsou, J.Y., 2022. Assessing the effects of convolutional neural network architectural factors on model performance for remote sensing image classification: An in-depth investigation. Int. J. Appl. Earth Obs. Geoinf. 112, 102865.

Cho, K., Van Merriënboer, B., Bahdanau, D., Bengio, Y., 2014. On the properties of neural machine translation: Encoder-decoder approaches. arXiv preprint arXiv:1409.1259.

Chung, J., Gulcehre, C., Cho, K., Bengio, Y., 2014. Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Feng, N., Zhang, F., Lin, J., Zhai, J., Du, X., 2019. Statistical analysis and prediction of parking behavior. In: IFIP International Conference on Network and Parallel Computing. Springer, pp. 93–104.

Gong, S., Cartlidge, J., Bai, R., Yue, Y., Li, Q., Qiu, G., 2020a. Data-driven agent-based model of intra-urban activities. In: 2020 5th IEEE International Conference on Big Data Analytics. ICBDA, IEEE, pp. 160–166.

Gong, S., Cartlidge, J., Bai, R., Yue, Y., Li, Q., Qiu, G., 2020b. Extracting activity patterns from taxi trajectory data: A two-layer framework using spatio-temporal clustering, Bayesian probability and Monte Carlo simulation. Int. J. Geogr. Inf. Sci. 34 (6), 1210–1234.

Gong, S., Mo, X., Cao, R., Liu, Y., Tu, W., Bai, R., 2021. Spatio-temporal parking behaviour forecasting and analysis before and during COVID-19. arXiv preprint arXiv:2108.07731.

Gong, S., Sun, Z., Zuo, Y., Bian, T., 2022. Spatio-temporal travel volume prediction and spatial dependencies discovery using GRU, GCN and Bayesian probabilities. In: 2022 7th International Conference on Big Data Analytics. ICBDA, IEEE, pp. 130–136.

Hochreiter, S., Schmidhuber, J., 1997. Long short-term memory. Neural Comput. 9 (8), 1735–1780.

Ketkar, N., Santana, E., 2017. Deep Learning with Python. Vol. 1, Springer.

Kipf, T.N., Welling, M., 2016. Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907.

Kumar, V., Garg, M., 2018. Predictive analytics: a review of trends and techniques. Int. J. Comput. Appl. 182 (1), 31–37.

Lee, J., Agdas, D., Baker, D., 2017. Cruising for parking: New empirical evidence and influential factors on cruising time. J. Transp. Land Use 10 (1), 931–943.

Liu, H., Lang, B., 2019. Machine learning and deep learning methods for intrusion detection systems: A survey. Appl. Sci. 9 (20), 4396.

Mohamad, J., Kiggundu, A.T., 2007. The rise of the private car in Kuala Lumpur, Malaysia. IATSS Res. 31 (1), 69.

Ostrom, C.W., 1990. Time Series Analysis: Regression Techniques. (9), Sage.

Paidi, V., 2022. Short-term prediction of parking availability in an open parking lot. J. Intell. Syst. 31 (1), 541–554.

Qin, H.-r., Yang, M., Mi, X.-y., 2015. Urban rail transit pricing strategies for mitigating traffic congestion: a case study of ningbo. In: CICTP 2015. pp. 1952–1961.

Qureshi, I.A., Lu, H., 2007. Urban transport and sustainable transport strategies: A case study of karachi, Pakistan. Tsinghua Sci. Technol. 12 (3), 309–317.

Sherstinsky, A., 2020. Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network. Physica D 404, 132306.

Shi, R., Conrad, S.A., 2009. Correlation and regression analysis. Ann. Allergy Asthma Immunol. 103 (4), S35–S41.

Shoup, D.C., 2006. Cruising for parking. Transp. Policy 13 (6), 479–486. http://dx.doi.org/10.1016/j.tranpol.2006.05.005, Parking.

Slavova, S., Piest, J.P.S., van Heeswijk, W., 2022. Predicting truck parking occupancy using machine learning. Procedia Comput. Sci. 201, 40–47.

Tamrazian, A., Qian, Z., Rajagopal, R., 2015. Where is my parking spot? Online and offline prediction of time-varying parking occupancy. Transp. Res. Rec. 2489 (1), 77–85.

Wang, S., Liu, Y., 2022. Parking in inner versus outer city spaces: Spatiotemporal patterns of parking problems and their associations with built environment features in Brisbane, Australia. J. Transp. Geogr. 98, 103261.

Wang, H., Zhang, X., Wu, L., Hou, C., Gong, H., Zhang, Q., Ouyang, M., 2015. Beijing passenger car travel survey: implications for alternative fuel vehicle deployment. Mitig. Adaptation Strategies Glob. Change 20, 817–835.

Yang, S., Ma, W., Pi, X., Qian, S., 2019. A deep learning approach to real-time parking occupancy prediction in transportation networks incorporating multiple spatio-temporal data sources. Transp. Res. C 107, 248–265.

Ye, X., Sui, X., Xie, J., Wang, T., Yan, X., Chen, J., 2020. Assessment of the economic and social impact of shared parking in residential areas. Information 11 (9), 411.

Yu, Y., Si, X., Hu, C., Zhang, J., 2019. A review of recurrent neural networks: LSTM cells and network architectures. Neural Comput. 31 (7), 1235–1270.

Yu, H., Wu, Z., Wang, S., Wang, Y., Ma, X., 2017. Spatiotemporal recurrent convolutional networks for traffic prediction in transportation networks. Sensors 17 (7), 1501.

Yue, Y., Wang, H.-d., Hu, B., Li, Q.-q., Li, Y.-g., Yeh, A.G., 2012. Exploratory calibration of a spatial interaction model using taxi GPS trajectories. Comput. Environ. Urban Syst. 36 (2), 140–153.

Zhang, Y., Zhang, F., Chen, N., 2022. Migratable urban street scene sensing method based on vision language pre-trained model. Int. J. Appl. Earth Obs. Geoinf. 113, 102989.

Zhao, L., Song, Y., Zhang, C., Liu, Y., Wang, P., Lin, T., Deng, M., Li, H., 2020. T-gcn: A temporal graph convolutional network for traffic prediction. IEEE Trans. Intell. Transp. Syst. 21 (9), 3848–3858.