WEP Warwick Evans Publishing

Transactions on Computer Science and Intelligent Systems Research
ISSN: 2960-1800, eISSN: 2960-2238 | Volume 5
AIDML 2024

Prediction of Vacant Parking Spaces in the City based on LSTM

Yuhao Zhang*

School of Software Engineering, Xinjiang University, Xinjiang, 830000, China

*Corresponding author: 20212501504@stu.xju.edu.cn

Abstract. With the continuous progress of modern society, more and more families have their own private cars for the convenience of travel and other needs, making it easier and faster to go anywhere. However, with the increase in the number of private cars, parking spaces in parking lots cannot keep up with the growing number of cars. It is increasingly difficult to find parking spaces everywhere when driving, and even if they are found, they are often full. The problems of chaotic management in parking lots have become more serious, greatly affecting people's pace of life. This study aims to predict the vehicle access situation of a parking lot in the future by constructing a prediction model. Based on the collected information of nearly 9,000 vehicles entering and leaving a parking lot, this paper uses the LSTM model to analyze the data by comparing the entry and exit times of different vehicles and whether the vehicles leave the parking lot, and obtain a highly fitted parameter model. The results show that the distribution state of the fitted value of the model is quite close to the real value. The model predicts the data of different time periods in the next 6 days, and obtains relatively accurate prediction results.

Keywords: Parking spaces; LSTM; prediction.

1. Introduction

Intelligent transportation incorporates advanced IT technologies such as the Internet of Things, cloud computing, big data, and mobile internet to provide real-time traffic data and information services based on the foundation of smart transportation systems. This deeply integrated information-based transportation system not only optimizes the allocation of transportation resources but also improves traffic operational efficiency, effectively alleviating urban traffic pressure and injecting new vitality into the sustainable development of modern cities [1].

With the continuous rise of China's population and the increase of per capita disposable income, the number of cars in China is also increasing rapidly. The number of private cars has increased, however, there is a clear shortage of available land. In many cities, there are too many vehicles and parking spaces are scarce. And it is also accompanied by problems such as unreasonable parking lot planning and low utilization rate of land resources [2]. In the face of limited parking space resources, there are often problems for car owners such as not being able to find a parking space and parking spaces being too far away. Also, the government is worried about, such as road congestion due to excessive concentration of vehicles and increased risk of accidents [3].

In response to the current parking challenges in urban transportation, the following measures can be adopted to address the issue. Firstly, optimizing urban transportation planning is crucial. It is necessary to consider constructing additional underground public parking facilities to effectively increase parking space availability, thereby alleviating the parking problem. Secondly, integrating existing route navigation and parking information services is important. By simplifying the process of accessing traffic and parking information, drivers can obtain the necessary parking details more conveniently, enhancing parking efficiency [4]. Lastly, achieving information interoperability between parking facilities and balancing the allocation of parking resources are essential. By enhancing information sharing and collaboration among parking facilities, parking resources can be better distributed within a region, improving their utilization and meeting the parking demands of more drivers [5].

With the gradual popularization and application of big data, smart parking has emerged. Based on the analysis capability of big data, the system can realize the planning of urban parking spaces, update parking space data in real time, and optimize the city's parking services [6]. From the perspective of parking users, smart parking can solve the problems of difficulty finding parking spaces, time-consuming searches, and confusing charging. From the government's point of view, smart parking can make urban land planning more reasonable, save land, and improve management efficiency [7]. Urban static traffic management centers around the integration of a unified platform, database, and model. Through the utilization of big data, parking facilities can evolve into dynamic platforms for real-time data retrieval and operations. This shift harmonizes technical standards, fortifies collaboration between governments and enterprises, and ultimately fosters the development of a distinctive static transportation system.

Some researchers suggest that the RNN model can be used to analyze existing parking lot data [8]. By establishing a model, it is possible to predict future vehicle access situations in parking lots, thus enabling more effective planning and management of parking lots. One such method, which combines particle swarm optimization with LSTM models, allows for precise forecasting of fluctuating parking demands across weekdays and weekends [9]. Furthermore, by scrutinizing vehicle entry and exit patterns in parking lots throughout different timeframes, it becomes feasible to discern whether long-term or short-term parking is more prevalent during those periods [10]. This type of analysis offers invaluable insights that can inform and guide parking lot design and planning efforts.

2. Methods

2.1. Data Source and Description

In this research, the data is collected from the Shenzhen Government Data Open Platform. The data collected concerns the establishment of parking lots in various districts of Shenzhen, as well as the vehicle entry and exit situation of port parking lots in 2023. This data presents a detailed distribution of parking lots in various regions of Shenzhen, along with the total number of vehicle entries and exits for each parking lot. To obtain the temporal characteristics of data, researchers screened and classified a large and unstructured dataset, which allowed meaningful subsets to be further analyzed after division (Table 1).

Table 1. Attribute information for raw data

timein	timeout	price	state	rps
2018-01-01 00:03:13	2018-01-01 00:23:52	3	1	99
2018-01-01 00:09:37	2018-01-01 00:44:54	3	1	99
2018-01-01 00:38:08	2018-01-01 00:45:29	3	1	100
2018-01-01 00:52:53	2018-01-01 00:59:04	3	1	100
2018-01-01 01:20:37	2018-01-01 01:24:10	3	1	100
2018-01-01 01:29:35	2018-01-01 01:44:23	3	1	100
2018-01-01 02:01:33	2018-01-01 02:25:47	3	1	97
2018-01-01 02:06:34	2018-01-01 07:28:33	15	1	94
2018-01-01 02:19:09	2018-01-01 02:33:56	3	1	98
2018-01-01 02:25:11	2018-01-01 06:10:50	12	1	89

In this study, the researchers utilized the number of parking occurrences per parking space within a year as an indicator to measure the demand for parking spaces in a given area. The parking frequency in different parking lots per parking space reflects the demand for parking spaces among the local populace, thus corresponding to the spatial distribution of parking demand. This information can provide guidance for optimizing the specific distribution of parking lots within urban areas

2.2. Method Introduction

In this study, the author used Python to write programs to uniformly process the data and filter out the data on changes in parking volume in various regions. Subsequently, the author utilized the LSTM algorithm to decompose and reconstruct the time series of parking data, determining the prediction intervals and intervals for parking trends in different time periods, thus achieving analysis of parking demand.

In traditional RNN (recurrent neural networks), all w's are the same w, and when passing through the same cell, they retain the memory of the input, plus another input to be predicted. Therefore, the prediction includes all previous memories plus the current input. All RNNs have a chain-like form of repeating neural network modules. In standard RNNs, this repeating module has a very simple structure, such as a tanh layer. When the weight is greater than 1, the error will be amplified during backpropagation, resulting in gradient explosion; when the weight is less than 1, the error will be reduced, resulting in vanishing gradient, which leads to slow weight updates in the network and cannot reflect the long-term memory effect of RNNs, making RNNs too forgetful.

The long-short term memory model is a special RNN model that is designed to address the problems of vanishing and exploding gradients during backpropagation. By introducing a gate mechanism, it solves the long-term memory problem that RNN models do not possess.

The Markov birth-death process stipulates that the parking status at any given moment can only transition to an adjacent state, meaning there are only three possible changes in parking status: an increase of one parking space, a decrease of one parking space, or no change. Assuming a parking arrival rate of λ and a parking departure rate of p per unit time, the transition probabilities for the parking status happen-end process are given by the following equation.

When the number of parked cars increases by 1.

$$P(N_t + h = N_t + 1) = \lambda \mathrm{h} + \mathrm{o(h)} \tag{1}$$

When the number of parked cars decreases by 1.

$$P(N_t + h = N_t - 1) = pN_t h + o(h) \tag{2}$$

When the number of parked cars remains the same.

$$P(N_t + h = N_t) = 1 - \lambda \mathrm{h} - \mathrm{p}N_t h + o(h) \tag{3}$$

When the arrival process of vehicles in a parking lot follows a Poisson distribution and the departure process follows a binomial distribution, based on the Markov process and through algebraic transformations, the parking status over time can be obtained given a fixed parking arrival rate and departure rate.

$$E_t = (1-p)_t \left(E_0 - \frac{\lambda}{p}\right) + \frac{\lambda}{p} \tag{4}$$

After combining these formulas, LSTM model can be fitted and the subsequent can be predicted. When comparing the predictions of the model with the test data, one can evaluate the accuracy of the prediction model, specifically the mean squared error.

Mean Squared Error (MSE) is a common metric used to evaluate the performance of predictive models, especially in regression problems. It measures the average squared difference between the model's predicted values and the true values. A lower MSE value indicates a better fit between the model's prediction and the true value. However, MSE is very sensitive to outliers, as it amplifies large differences when calculating the squared difference.

3. Results and Discussion

3.1. LSTM Model Results

The collected raw data are screened, classified, and processed to obtain several data required for prediction. The further processed data are shown in the following table 2.

Table 2. Part of the processed data

date	time	rps
2018-01-01	0	99.5
2018-01-01	1	100
2018-01-01	2	97.5
2018-01-01	3	96
2018-01-01	4	90
2018-01-01	5	90
2018-01-01	6	91.28571
2018-01-01	7	93.5
2018-01-01	8	96.05882
2018-01-01	9	93
2018-01-01	10	90.33333
2018-01-01	11	91.66667

According to the data in Table 2, this paper establishes an LSTM model, which shows the rps for the next six days, that is, the current number of available parking spaces. The x-axis is the time of day, and the y-axis represents the normalized rps value. The prediction model is shown in figure 1.

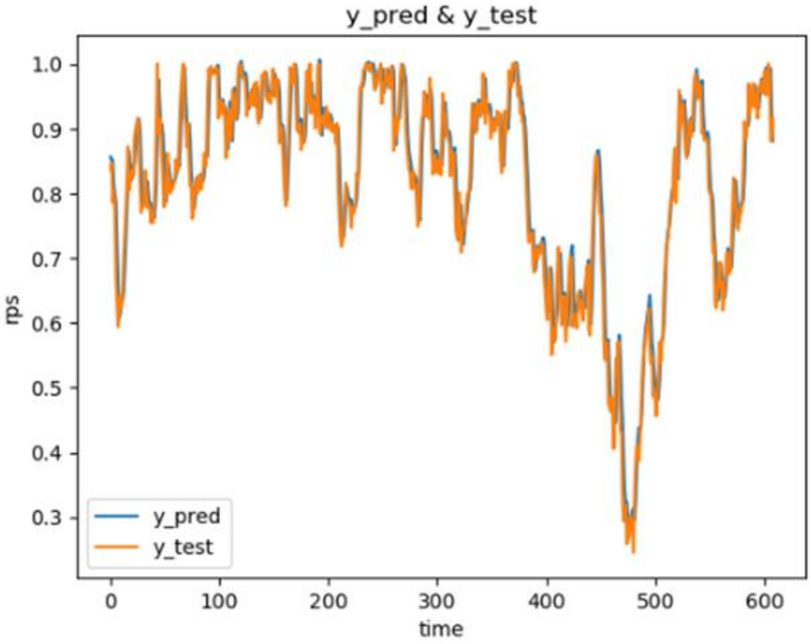

Fig. 1 LSTM model prediction results

The visualization shows the mean squared error of the model, which is approximately 0.03, indicating the difference between the predicted value and the true value, reflecting the high degree of fitting of the model. The RMSE is 0.0399. According to this model, it is possible to accurately predict the number of vacant parking spaces in various time periods of the parking lot for the next six days.

3.2. ARIMA Model Results

To confirm the reliability of the predicted values obtained by the LSTM model, this article also used the ARIMA model to predict the data. For RPS, combined with the AIC information criterion, the lower the value, the better. The researchers modeled and compared multiple potential candidate models, and ultimately identified the optimal model as ARMA(1,1,0). The model statistics are shown in Table 3 below.

Table 3. Q Statistics For ARIMA(1,1,0) Model

Term	Statistic	P-value
Q6	0.000	0.994
Q12	0.066	0.968
Q18	1.023	0.796
Q24	1.386	0.847
Q30	2.024	0.846
Q36	2.493	0.869
Q42	2.527	0.925
Q48	3.158	0.924
Q54	3.703	0.930
Q60	5.105	0.884
Q66	5.802	0.886
Q72	5.873	0.922

Term	Statistic	P-value
Q78	6.009	0.946
Q84	6.884	0.939
Q90	7.117	0.954
Q96	8.653	0.927
Q102	8.746	0.948
Q108	10.361	0.919
Q114	10.436	0.941

From the Q statistic result, the p-value of Q6 is greater than 0.1, so the null hypothesis cannot be rejected at the significance level of 0.1, and the residuals of the model are white noise, which basically meets the requirements of the model. The prediction model is shown in the following figure 2.

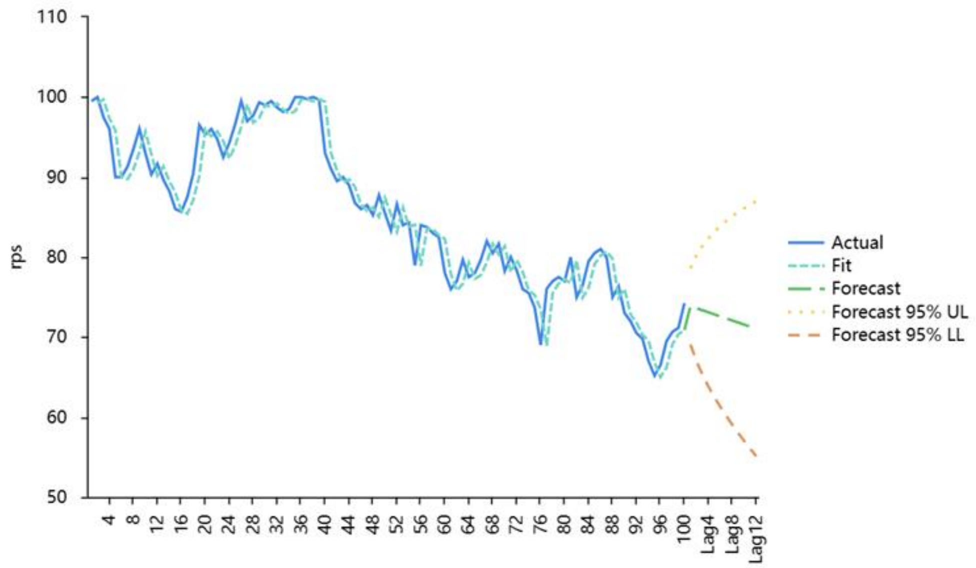

Fig. 2 ARIMA model prediction results

The LM test for residual term is shown in Table 4.

Table 4. LM test for residual term

F-statistic	0.420	p-value	0.933
T * R2 statistic	4.549	p-value	0.919

According to the prediction results of the ARIMA model, it can be concluded that the prediction values obtained by the LSTM model have high credibility.

4. Conclusion

Based on existing data, this study constructed an LSTM model to predict the number of available parking spaces in a specific parking lot, and obtained relatively accurate results, which proves that establishing a predictive analysis model for the number of available parking spaces is feasible in the future. The larger the amount of data available, the higher the fit between the model and real data, and the more accurate the results. Simultaneously, a comparative analysis with the ARIMA model underscores the predictive accuracy of the LSTM model, thereby bolstering the methodological rigor and empirical validity of this study. This affirms the feasibility and reliability of the approach in providing accurate forecasts. To a certain extent, this can also assist in making judgments during urban parking lot planning and construction, improve the rationality of parking lot distribution, and reduce the difficulty of residents parking. In the future, this study aims to enhance the model's accuracy and provide more robust reference data for urban parking lot planning by incorporating a broader range of parking lot types, as well as integrating additional influencing factors such as weather conditions and holiday patterns into the analytical framework. Through this comprehensive approach, the study strives to achieve a more refined and academically rigorous model that offers valuable insights for parking infrastructure planning and development.

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