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Optimizing Intelligent Parking Decisions using Q-Learning

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Abstract. With urbanization progressing rapidly, the availability of transportation resources in large cities has become increasingly strained. Among these resources, parking spaces are crucial for maintaining the smooth functioning of cities and ensuring the efficient operation of vehicles. However, due to spatial limitations, it is not always feasible to continuously increase the number of parking spaces. Hence, accurate prediction of future parking space demand has become imperative. The purpose of this paper is to predict the future parking space demand by using a mathematical model, to provide scientific decision support for the transportation department. Specifically, the author chose a Q-learning model in reinforcement learning, using a dataset from the year beginning 2016 combined with an algorithm to make predictions about future data. The accuracy of the model is 81.31% and the mean square error is 2200.30. In addition, the author also combined the weather and holiday conditions to analyze the data box line. Through the analysis and modeling of urban parking data, the author will discuss the feasibility and effectiveness of the Q-learning model in future parking demand prediction. Through this study, it is concluded that the Q-learning model performs well in the prediction of future available parking Spaces.

Keywords: Transportation; parking spaces; Q-learning; future prediction; decision support.

1. Introduction

With the acceleration of urbanization, the problem of parking congestion has become increasingly prominent, and obstacles have become apparent. Accurately predicting future parking availability is critical to alleviating traffic congestion and improving parking efficiency. While traditional methods such as time series forecasting show some degree of predictive power, they often fail to effectively exploit multi-source data and environmental cues. In recent years, deep learning algorithms have become powerful tools in various fields, providing new insights and methods for parking lot prediction.

Time series forecasting has always been the basis for parking lot forecasting. Smith uses the Autoregressive Integrated Moving Average (ARIMA) model to predict the availability of parking spaces, which has higher prediction accuracy than traditional methods [1]. In addition, Jones also proposed a forecasting method based on the long short-term memory (LSTM) model, which is good at capturing long-term dependencies in time series data, thereby improving forecasting results [2].

In addition to time series data, integrating multiple data sources such as weather and traffic is expected to enhance parking lot forecasting. Razak proposed a parking lot prediction method based on multi-layer perceptron, using machine learning algorithms to achieve higher prediction accuracy [3]. In addition, Wang developed a multi-task learning method that can simultaneously predict the availability and duration of parking spaces, thereby improving the overall prediction efficiency [4].

Deep reinforcement learning provides an alternative approach to parking lot prediction, leveraging environmental dynamics to make optimal decisions. Johnson proposed a prediction method based on deep reinforcement learning, which can effectively predict the availability of future parking spaces based on historical data and current environmental factors, thereby providing decision support for parking lot management [5].

Further research explored other methods, such as spectral clustering, aiming to improve prediction accuracy [6]. Prediction based on an attention mechanism has also been proposed [7]. In addition, a prediction method based on CNN-LSTM was also introduced to combine time series with weather data to further improve the prediction accuracy [8, 9]. It is worth noting that the proposed recurrent neural network model considers multiple data sources, thereby improving the prediction accuracy of parking lot occupancy.

Parking lot prediction based on deep learning algorithms is still in its infancy, providing avenues for future research. First of all, it is necessary to further explore the value of multi-source data and improve prediction accuracy. Second, researchers should work on developing more efficient deep-learning models to improve prediction efficiency. Finally, combining deep learning algorithms with other methods can enhance the robustness of predictions. Previous research has explored this aspect and made significant progress, such as a parking lot occupancy prediction method based on LSTM and multi-source attention mechanism, which combines deep learning and statistical methods to improve the robustness of prediction [10].

The future of parking prediction lies in continuous exploration and innovation. Opportunities for further research include leveraging the value of multi-source data to improve prediction accuracy, exploring more efficient deep learning models to improve prediction efficiency, and combining deep learning algorithms with other methods to enhance prediction robustness.

2. Methods

2.1. Data Source and Description

The data used in this study were collected from sensors in the KLCC parking lot in Kuala Lumpur City Centre. KLCC has a total of 5,500 parking Spaces. The dataset includes information on the date, time, and number of parking spaces available at KLCC. Each entry corresponds to a specific timestamp and indicates the availability of parking spaces at that particular time.

2.2. Indicator Selection and Description

In this study, the number of KLCC parking Spaces available per timestamp was used as the primary indicator to measure parking lot availability. This indicator reflects the demand for parking Spaces in the area over some time, making it possible to analyze changes in the availability of parking spaces over time. By analyzing fluctuations in the supply of parking Spaces, it is possible to understand the time patterns and trends of parking demand in central Kuala Lumpur. The data centralizes time, location, and usage. The time granularity is 15 minutes, which ensures a suitable time interval and better reflects the special time (Table 1).

Table 1. Name and explanation of variables

Full Name	Data type	Explanations
Availability	INT	Real-time available parking spaces
Date	DATE	Date of observation
Time	TIME	Specific time in 15-minute intervals
Weather	String	Recorded descriptions of various weather phenomena
Weekend_Weekday	String	Records whether the date of observation data was a business day

2.3. Method Introduction

This study will use the Q-learning method in reinforcement learning to predict the number of available parking Spaces. Q-learning is a reinforcement learning algorithm based on value function, which is used to learn the optimal strategy to take different actions in different states. In this study, the author defines the state of a parking lot as a combination of temporal and spatial information, i.e. the parking space situation under each timestamp, while an action is a management decision on parking resources, such as adjusting parking rates or offering promotions. Through continuous interaction with the environment, the Q-learning algorithm will learn the optimal parking resource management strategy to maximize the utilization and satisfaction of Parking Spaces.

Specifically, the author will implement Q-learning algorithms using the Python programming language and train them using historical data from KLCC parking lots. First, the author will preprocess the data, including dealing with missing values and normalized features, to facilitate the learning of the algorithm. Next, the author will design the state space, action space, and reward mechanism of the Q-learning algorithm, so that it can accurately reflect the reality of the parking lot and management strategy. Then, the author will use the historical data to train the Q-learning algorithm, so that it gradually learns the best strategy of parking lot resource management. Finally, the trained model will be used to predict the number of parking spaces available in the future and provide decision support and optimization recommendations for parking lot management.

By adopting the Q-learning algorithm, the author can make use of the time and space information in the historical data of the parking lot to learn the optimal parking resource management strategy, to effectively predict the available number of parking Spaces in the future, and improve the utilization rate of the parking lot and user satisfaction (Figure 1).

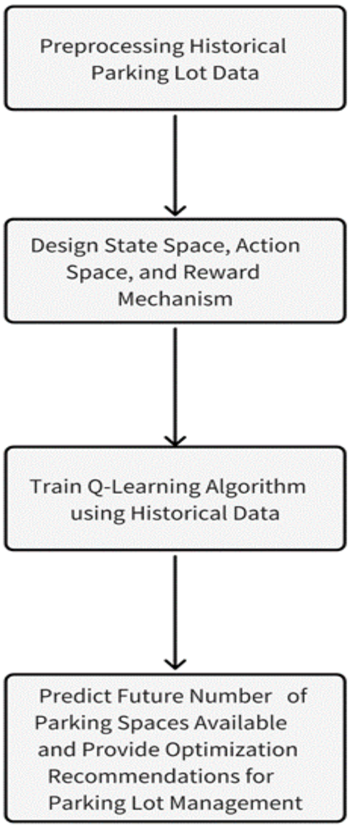

Fig. 1 Reinforcement learning predicts parking flow

2.3.1. Data processing

A parking space probe (PSP) is a sensor installed on the parking lot or the ceiling to detect the real-time occupancy of parking Spaces. Researchers use specific scientific and technological means to obtain the available parking space data of the parking lot covering time and space data, which also allows the author to study the relationship between parking and time and space, so it can generate research in many directions.

The author did some basic processing on the data set (Figures 2 and 3). Outliers, when the sensor is not available, are eliminated, and the daily average available parking space is visualized. The author found that there are fewer parking Spaces available in Kuala Lumpur Center in May and June every year. Through the analysis of economic and humanistic direction, the author found that May every year is a holiday for students in Kuala Lumpur, and parents may drive their children to KLCC to play. On the other hand, there are many major events in May, such as the Kuala Lumpur International Film Festival at this time of the year, and during Ramadan, Muslims will conduct Iftar after sunset, resulting in increased demand for night parking. This is presented in the results section of the following article.

Fig. 2 KLCC area map from QGIS [11]

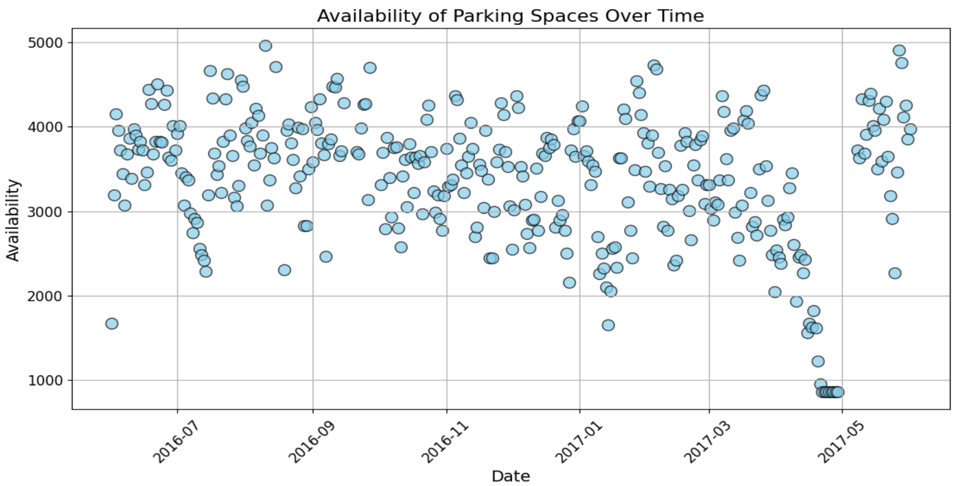

Fig. 3 KLCC annual available parking space distribution

2.3.2. Q-learning model

Q-learning is a reinforcement learning algorithm based on value iteration, which is used to solve Markov decision process (MDP) problems with finite state space and finite action space. It is widely used in the fields of machine learning and artificial intelligence, especially in the fields of automatic control, game intelligence, and robotics. The main advantage of using historical data to predict future parking space demand in this article is the ability to automatically learn and adjust the predictive model without prior knowledge and models. By learning the complex relationships between states and actions, Q-learning can capture complex patterns of parking space demand and provide accurate predictions. In addition, Q-learning has the characteristics of adaptability, flexibility, and real-time decision-making, which can make personalized forecasts according to different periods, weather conditions, and other relevant factors, and support real-time adjustment of parking space supply to achieve the best use of parking spaces and service quality.

$$Q(s(t), a(t)) \leftarrow (1 - \alpha) \times Q(s(t), a(t)) + \alpha \times \{R(t) + \gamma \times maxQ(s(t+1), a(t+1))\} \quad (1)$$

This formula is an update rule in the Q-learning algorithm, which is used to update Q-value functions. At each time step, the Q value under the current state and action is partially retained based on a learning rate and updated based on the immediate reward and the action selected for the highest Q value in the next state. In this way, the Q-value function is gradually updated based on the agent's interaction with the environment to better estimate the value of each state-action pair and thus find the optimal strategy.

In this equation, $Q(t, a)$ denotes the expected return after taking action a at time t. α represents the learning rate, controlling the influence of new information, and lies between 0 and 1. It balances the weight between the new reward and the existing Q value. $R(t)$ signifies the immediate reward, whigamma isthe discount factor, determining the significance of future rewards. It also ranges between 0 and 1, balancing the weight between the current and future rewards.

3. Results and Discussion

3.1. Holiday and Weather Impact

The author uses group box plots to reflect the working day and the impact of bad weather on parking Spaces. As Kuala Lumpur is located in a tropical area, often with heavy rainfall and thunderstorms brought by monsoons, the author will take torrential thunderstorms, haze, and air pollution as Hazardous weather according to regional characteristics, and the rest as Normal weather. Parking space is a dynamic resource related to strong social characteristics, and the analysis of these two characteristics has many functions such as humanity, society, and urban planning (Figures 4 and 5).

Through reading the two box-type drawings, the author found that the box in May is very large, which also proves the previous speculation. At the same time, the author found that there was a significant increase in the availability of parking spaces in bad weather conditions every month, and the author speculated that people avoid traveling in extreme weather. At the same time, the author saw an increase in available parking Spaces during weekends, reflecting KLCC's office function as a commercial office cluster, and an increase in available parking Spaces during weekends and holidays.

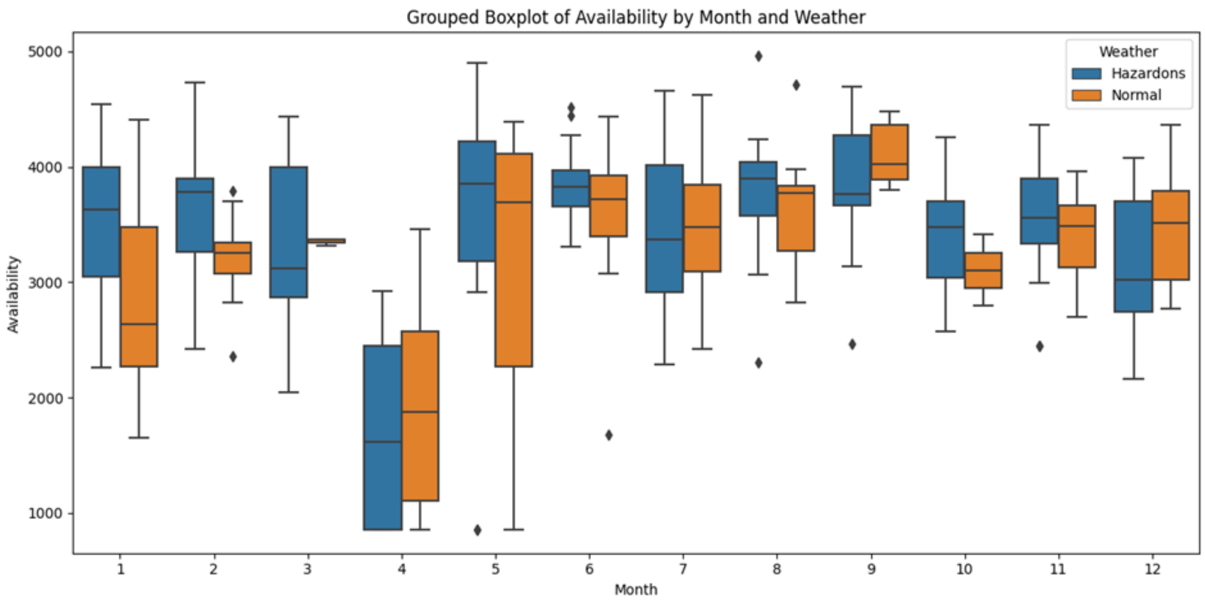

Fig. 4 Holiday and weather impact on parking

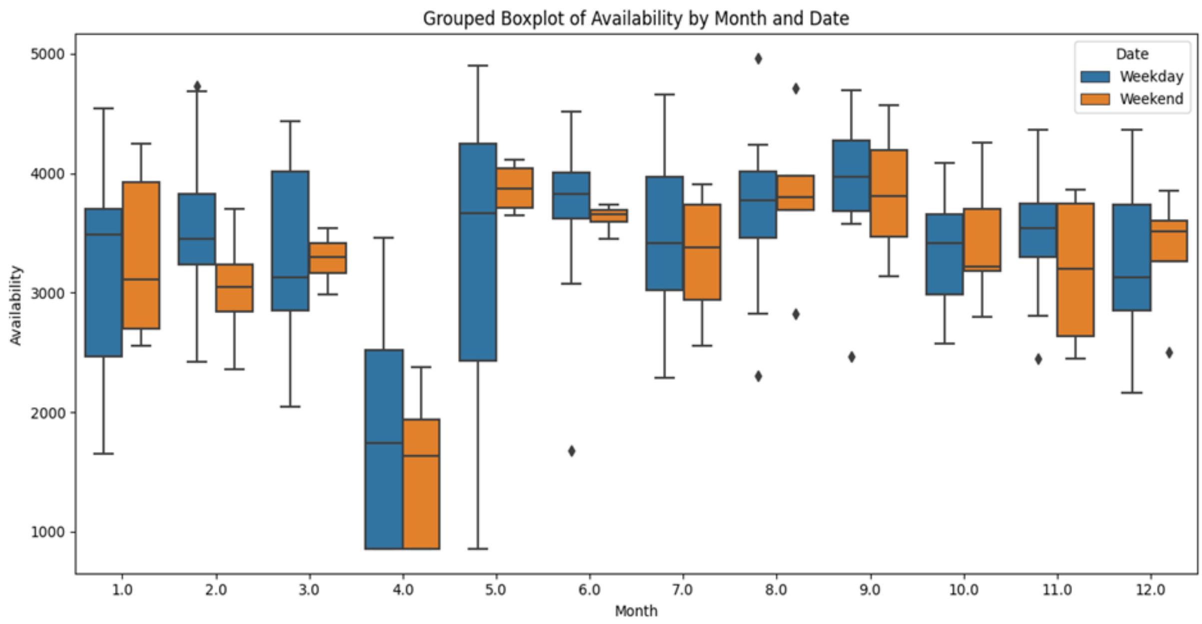

Fig. 5 Working and rest days' parking impact

3.2. Q-Learning for Predicting Parking Availability

3.2.1. Model results

The author plotted the predicted data and the actual values and selected the data included in the test set as of June 1, 2017. The author can see that in the first half of the day, Q-learning accurately predicted the specific value. In the middle of the day, because this period is a period with a large margin of entry and exit, the author can see that the predicted value fluctuates up and down in the actual value, and returns to a high level in the evening (Figure 6).

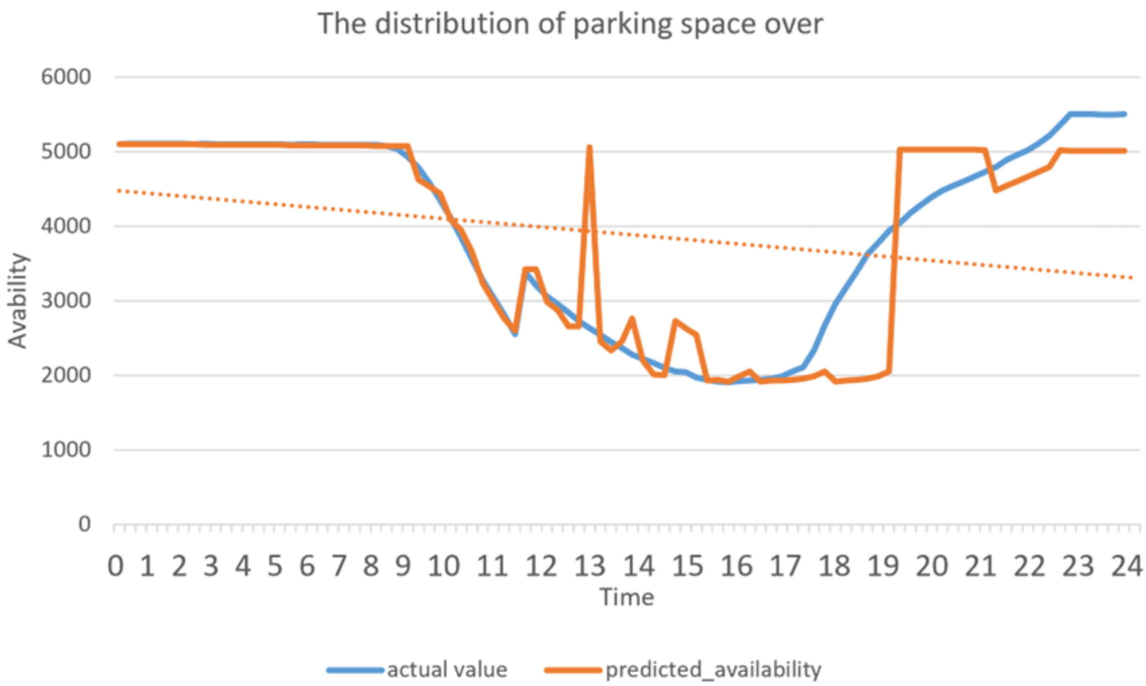

Fig. 6 Predicted values and actual parking Spaces

3.2.2. Accuracy analysis

To show the accuracy and accuracy of the predicted value, the residual test is used.

$$\mathrm{SST} = \sum_{i=1}^{n} (Y_i - \bar{Y})^2 \tag{2}$$

$$\mathrm{SSE} = \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{3}$$

$$\mathrm{SSR} = \mathrm{SST} - \mathrm{SSE} \tag{4}$$

$$R^2 = \frac{\mathrm{SSR}}{\mathrm{SST}} \tag{5}$$

These formulas outline the calculation of R-square values: SST for a total sum of squares, SSE for the residual sum of squares, and SSR for the interpretive sum of squares. The resulting R-square value reflects the model's effectiveness in explaining observed data, calculated as 0.813106864. Given various factors and scenarios, the author regards this accuracy as high.

The author also uses MSE to measure the accuracy of model predictions. MSE represents the mean of the square of the difference between the predicted value and the actual value. It is a commonly used regression model evaluation index to measure the accuracy of model predictions. The smaller the MSE, the smaller the difference between the model predictions and the actual observed values, and the better the model performance. The formula is as follows:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n} (Y_i - \hat{Y}_\iota)^2 \tag{6}$$

Where n is the number of samples, Y_i is the i th observation (the actual value), and $\hat{Y}_i$ is the i th prediction (the model prediction). The mean square error calculated by the authors is 2200.3023.

Since the data set the author is using has a time granularity of 15 minutes, it is a very small and precise period. The number of changes in parking Spaces is 5,500, which is a considerable range. The data set used by the authors is over 35,000 rows, so the author believes that this mean square error is reasonable and valid.

4. Conclusion

The main objective of this study is to address the pressing issue of parking congestion in urban areas, with a particular focus on KLCC car parks in Kuala Lumpur. By employing advanced predictive modeling techniques, the author aims to provide insights into the future availability of parking spaces to ease traffic congestion and improve overall city management efficiency.

As a reinforcement learning algorithm, Q-learning has significant advantages in predicting available parking Spaces in parking lots. Its adaptability enables the model to effectively learn from the changing parking environment and make decisions in real-time. At the same time, Q-learning can cope with complex environmental factors in parking lots, such as time and weather, etc. In this paper, the author presents the multi-dimensional influences intuitively by combining box diagrams, establishes multi-level analysis, and verifies the advantages and usability of Q-learning in parking prediction and scheduling through inspection.

Although Q-learning has adaptive and real-time decision-making capabilities in predicting available parking Spaces in parking lots, there are some challenges. Among them, the complexity of the parking lot environment leads to the state space being very large, increasing the complexity of the model and the computational cost. In addition, the dynamic nature of the parking lot environment will also bring challenges, and Q-learning may be difficult to effectively deal with the rapid changes in the environment, thus affecting the accuracy of the prediction. Therefore, it is necessary to flexibly adjust and decide the learning rate and other parameters to make better use of this reinforcement learning algorithm.

To sum up, Q-learning has many advantages in the prediction of available parking Spaces. Future research can focus on the integration of multidimensional data and optimization of deep learning algorithms to help relevant organizations establish decision-making systems so that this technology can be implemented to assist relevant organizations in decision-making.

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