ParkiTech: A Parking Lot Recommendation System

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1 BACKGROUND

In San Francisco, finding a parking spot is a relatively hard problem for most people who live in or travel to this city. Based on the Department of Parking and Traffic, for per square mile, San Francisco contains more cars than other cities in the United States [11]. Therefore, it is important to build a parking lot recommendation system to facilitate parking in urban areas.

2 TASK

We will build a website to recommend available parking spots nearby to drivers. Users can customize the recommendations based on their preferences (e.g., shortest walk distance, lowest cost, most guaranteed availability, etc.).

3 RELATED WORK SURVEY

Our project involves three main issues, time series analysis, geographic data aggregation, and risk-distance-cost trade-off problem.

3.1 Time series analysis

Consider the prediction of parking spot number as a time-based issue. Sun *et al.*[12] used a local linear regression model to predict short-term traffic based on the traffic speed data of Houston's freeway. Deshpande and Bajaj [3] discussed the implementation of the traffic flow prediction model using SVM based on the traffic data obtained near the Perungudi toll plaza in the corridor in Chennai, India. Chen *et al.*[1] and Hong *et al.*[5] both combined GA and support vector regression to predict the tourism flow.

These papers provide us with a large number of machine learning models in traffic timing series prediction. At the same time, deep learning also proves helpful in time series prediction. Pflugler *et al.*[9] used a neural network to predict parking space availability in urban areas of Munich based on various factors. Chen [2] predicted parking occupancy in San Francisco using neural networks, ARIMA, linear regression, and support vector regression. It is found that theneural network provides the best prediction results among the models above. Haviluddin *et al.*[4], Purnawansyah *et al.*[10] and Wang [15] all used BPNN to forecast daily traffic and achieved excellent predicted results. However, Tavafoghi *et al.*[13] compared LSTM recursive neural network with the SARIMA model they proposed. They argued that the model-free model, like the LSTM, although results in a better prediction performance for short forecast horizons, may deteriorate much faster than that does the model-based method. Similarly, in Zhao *et al.*'s article [16], SVM outperformed the neural networks in predicting the hourly occupancy of a single parking lot. Hence, the use of deep learning also requires caution and comprehensive comparison.

We may also need to take significant incidental events' effect into consideration. Nelson *et al.*[7] focused on the prediction of future trends of stock price based on multiple long-term market factors and incidental events. P. Oncharoen *et al.*[8] addressed a similar stock market prediction problem by training a CNN-LSTM model with both technical indicators from historical price data and events embedded vectors from news headlines. They all show that considering special events is necessary and effective in real-life time series prediction problems.

3.2 Geographic data aggregation

The functional division of cities is often regional. Parking demand in different urban functional areas has different patterns. Hence, it is possible to classify parking lots by area, to exploit geographical aggregation effects to obtain clearer data patterns and improve prediction accuracy. Chen [2] revealed the effect of aggregation on prediction for parking occupancy and used the k-means method to divide up the San Francisco city into seven regions. The clustering not only improved the accuracy of a single parking lot occupancy prediction but also had better interpretability. Similarly, Lin *et al.*[14] also segmented the on-street parking sensors data of Santander, Spain, into four different regions and developed neural network models for each region separately.

3.3 Risk-distance-cost trade-off

Several important factors should be taken into consideration when making a recommendation for parking. The tradeoff between walk distance from the parking spot to the destination, cost of parking, and the risk of parking spots actually being fully occupied should be scientifically quantized. Landry *et al.*[6] used the expectation of searching time to measure the cost of finding an empty spot. Similarly, we could use the expectation of the time required to find a new spot over the risk of the spot being occupied to measure the risk. Walk distance and cost could also be measured in the same way, and be assigned different weights.

4 INNOVATION

Our design has some unique edges over the other products available today. **ParkMobile** and **Parkopedia** show the cost and location of parking spots, but has no indication of availability. **Google maps** has a vague indicator of busy hours around the day, but still, could not bring sufficient confidence to users. In addition, **Google maps** shows only off-street parking while on-street parking tends to be more convenient for drivers in urgent need of parking spots.

The innovation of our design lies mainly in two parts - parking spot prediction and recommendation. Our prediction of available parking spot numbers for designated time slots is based on historical records. We will adjust the time slots according to the ETA provided by Google Map, which is based on the current location and destination of the user. Finally, we will make a proper balance between the risk of parking spots actually being fully occupied, walk distance and parking cost, and provide our recommendation. Users can also customize the recommendation mechanism by changing their preferences.

5 EVALUATION

5.1 Prediction evaluation

As we will use the dataset of parking spot occupancy within 6 weeks, we will evaluate our prediction according to cross-validation. The measurements will include the l2-distance between the real number of available spots and predicted available spots, street-wise and region-wise.

5.2 Website test

We will simultaneously generate virtual users in different locations in the San Francisco City area, provide virtual navigation service and compare the result with actual situation.

6 POSSIBLE IMPACTS AND RISKS

Our design will be a great help to the drivers who are eager to find available parking spots. Also, city planners can adjust the infrastructure layout according to the popularity of different parking spots reviewed by our design. However, incidental events, which could cause unusually a large parking demand during relatively short time slots, will severely influence the accuracy of our prediction. In addition, incorrect recommendations will impair the trust of users, which could further lead to a reduction in the number of feedback and delay of recommendation adjustment.

7 TIMELINE AND COSTS

Our main costs are rentals for web server and poster printing fee. All development and test work will be accomplished with in 2 months (before 4/20/2020).
Shown below are Work to do, effort distribution and time line. We will stick to the plan and try our best to finish assigned work in given time.

Task	Week	People (abbr.)
Data acquisition and clean	1, 2	JZ, YC
Construction of website prototype	1, 2	TW
Data visualization over city map	2, 3	TW, YZ
Prediction model design	3, 4, 5	YW, JZ, YC
Tradeoff quantization	3, 4, 5	YZ, JZ, YC
Assembly of models and website	6	YW, TW, JZ
Website overall test	6, 7	All

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