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PREDICTING OCCUPANCY OF PARKING SPACES IN TRANSPORTATION NETWORKS: A DEEP LEARNING APPROACH WITH MULTI-SOURCE SPATIO-TEMPORAL DATA

Shuguan Yang
Department of Civil and Environmental Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
Email: shuguany@cmu.edu

Wei Ma
Department of Civil and Environmental Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
Email: weima@cmu.edu

Xidong Pi
Department of Civil and Environmental Engineering
Carnegie Mellon University
Pittsburgh, PA 15213
Email: xpi@andrew.cmu.edu

Zhen (Sean) Qian (corresponding author)
Department of Civil and Environmental Engineering and Heinz College
Carnegie Mellon University
Pittsburgh, PA 15213
Email: seanqian@cmu.edu

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INTRODUCTION

Growing parking demand and limited spaces has become one of the major issues of urban transportation systems. During peak hours, "cruising for parking" is a common phenomenon in areas with dense population. In coping with this issue, numerous parking intervention and guidance systems have been developed during the last few decades, among most of them, a reliable source of predicted future parking occupancies is one of the key factors to their effectiveness. By obtaining a reliable prediction of on-street parking occupancies, proper parking location recommendations and cruising strategies can be generated in advance, by sharing these information to en-route drivers vis mobile devices or Advanced Driving Assistance Systems (ADAS), drivers will cruise and park in a more efficient way.

As for predicting short-term parking occupancy, most approaches in literature follow one of the following two paths: (1) Model individual driver's stochastic arrival and departure behaviors in a microscopic way(*1–4*). The distributions of the arriving/departure process are commonly assumed Poisson or Negative Exponential(*5, 6*), and usually evaluated via simulations. (2) Data-driven approaches, which utilize statistical models on historical and real-time observations to predict aggregated parking occupancies in a msesoscopic manner, such as on street or block levels. In this study, we adopt the data-driven approach by incorporating multiple traffic-related sources with real-time and historical data, including historical parking occupancy, traffic status, road characteristics, weather and network topology, and predict short-term parking occupancy via a deep neural network method.

In our method, we utilize parking meter transactions data instead of sensor data as the parking occupancy, which offers the following advantages: Since 95% of the on-street paid parking are managed by meters, a prediction model based on transactions is more adaptive and cost efficient than one based on parking sensors data. In our previous study, we have shown that the estimation of parking occupancy based on transactions can be calibrated to a satisfying level given a small amount of ground truth data(*4*), which can be collected manually or picked from sensor records in their best conditions. To model the complicated correlation as well as causality relationship between on-street parking occupancy, information from various traffic-related sources and network topology, we proposed a method of combining the graph based theories with a convolutional neural network. The temporal relationships of parking occupancies along with other traffic-related data are simulated via Long-Short Term Memory(LSTM), while their spatial correlations are model through graph-based CNN.

METHODOLOGY

Apart from parking occupancies, external traffic-related data sources can serve as indicators for future parking demand, such as speed, traffic counts, transit information, incidents and weather. Under certain scenarios, like abnormal congestions, nearby incidents or incoming snowstorms, information acquired from these sources are critical to the success of short-term occupancy predictions. Multiple data sources are incorporate simultaneously in the network framework of our method, specifically, individual data source are first embedded separately in our framework, then, the embedded values are merged by a multi-layer decoder, which outputs the predicted occupancies. As a result, our network framework provides the flexibility that individual data sources can be attached or detached from the network without compromising the overall structure of the prediction model. This improves the generosity of model since not all the aforementioned data sources are available for a given location. Also, by evaluating the performance of different combinations of input features, we can infer the effectiveness of each data source in occupancy prediction and find the most proper models.

In the context of large scale road network with multiple data sources, the dimension of model input space is too high to be modeled by simple statistical methods. In our method, we propose a deep neural network by connecting graph CNN, LSTM and multi-layer feed-forward decoder. Such a structure can handle the high dimensional input space by modeling the non-linear correlations among spatial-temporal data sources and filtering out redundant information. Specifically, the spatial information is modeled through layers of convolutional neural network on graph (GCNN) (*7, 8*). The GCNN uses graph spectral theory (*9*) to filter the signal on localized sub-graphs, then uses the filtered signal as the features for the neural networks. The temporal information could then be captured through a recurrent neural network (RNN), in our case, Long Short Term Memory (LSTM) (*10*). Multiple data sources can be handled separately first by feature embedding and feature extractions for each data source, the extracted features are then combined as the input for a multi-layer decoder which yields the prediction of occupancies for each road link in the network. Specifications of the above modules in our model is discussed in the following subsections.

Graph CNN

In our method, the road network is modeled as a directed graph, with nodes being road link or parking locations, and edges transfer the traffic flow or parking demand among nodes. To model the spatial correlations among road links or parking block of the road network, graph convolution operations are used to conduct message passing on the graph. Since nodes in a graph are not homogeneous to pixels in an Euclidean structure(such as an image), it is critical to define the local reception field in order to perform the convolution operations. Thus, we utilize spectral filters on signals(*7*) to conduct convolutions on an directed graph. As explained below.

Given a graph $G = (V, E, W)$, where V is the set of nodes, $|V| = n$, E is the set of edges and $W \in \mathbb{R}^{n\times n}$ is the weight matrix for all pairs of nodes. We define a signal $x \in \mathbb{R}^n$ on the graph, where x_i is the signal for node i. Define the normalized Lagrangian of the graph $L = I - D^{-\frac{1}{2}} W D^{-\frac{1}{2}}$, where D is the diagonal degree matrix with $D_{ii} = \sum_j W_{ij}$. The eigenvalues of L are known as the frequencies of the graph, and the corresponding eigenvalues are known as graph Fourier modes. Thus by signal value decomposition, we have $L = U\lambda U^T$, where $\lambda = \mathtt{diag}([\lambda_0, \cdots, \lambda_{n-1}])$, U is the unitary eigenvector matrix.

We can then define a convolution operator on graph G on the Fourier domain, the definition is presented in Equation 1.

$$y = g_\theta(L)x = U g_\theta(\lambda) U^T x \tag{1}$$

We use localized filter so that the convolution operation on one signal only focuses on it neighborhoods. The localized filter shares the same ideas with tradition CNN on parameter sharing and connectivity localization. The localized polynomial filter is presented in Equation 2.

$$g_\theta(\Lambda) = \sum_{k=0}^{K-1} \theta_k \Lambda^k \tag{2}$$

To enhance the computational efficiency, we apply Chebyshev expansion to the polynomial filters(*11*). By defining $T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x)$ and $\tilde{\Lambda} = 2\Lambda/\lambda_{max} - I$, the polynomial filter can be formulated as in Equation 3.

$$g_\theta(\Lambda) = \sum_{k=0}^{K-1} \theta_k T_k(\tilde{\Lambda}) \tag{3}$$

CASE STUDY OF PITTSBURGH DOWNTOWN

To evaluate the performance of the proposed prediction model, we conducted a case study in Pittsburgh downtown area, which contains 97 on-street parking meters scattered over the road network. Due to the availability of data sources, three types of data alone with the topology of the road network are used in this case study, including parking meter transactions, traffic speed and weather conditions. To evaluate the effectiveness of the proposed method as well as the contributions of each dataset, numerous experiments are conducted, results of the experiments are presented in this subsection. The proposed framework is implemented on PyTorch, all the experiments are conducted on a Linux workstation with two 1080Ti GPUs. All networks are trained by ADAM for 1000 epochs or early stop if no improvement in 5 epochs. The performance of all networks are evaluated by the Mean-squared-error(MSE) of predicting parking occupancies of all street blocks 30 minutes in advance.

The training progress of the final model is presented in Fig. 1, the y-axle is the loss in log scale, notice the loss is measured in Mean Square Error of the block-wise occupancies after preprocessing, i.e. occupancies values in the range of [-1, 1]. As we can see, the proposed model converges quickly in the first 15 epochs, after that, the training loss continues to drop slowly while the testing loss starts to go up a little bit as the sign of over-fitting. Finally, the training progress is terminated at the 37th epoch triggered by early stopping.

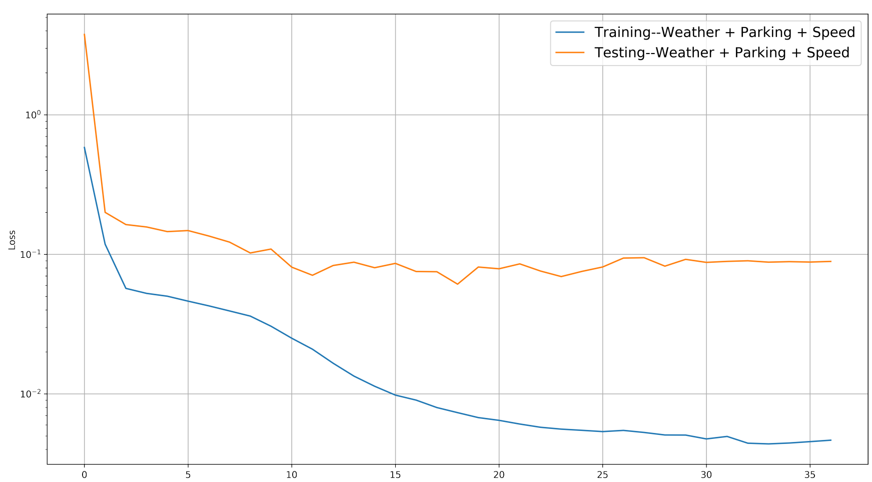

FIGURE 1: Model converge results

Comparison with baseline models

Results of model comparison are shown in Table 1. For the 2-layered LSTM, the best result is reached on a configuration of using 1024 and 256 as the dimensions for the first and second layers, along with a dropout rate of 0.25; For the model of 3-layer LSTM, the best result is reached on

TABLE 1: Comparisons between models

Model	Train RMSE	Test RMSE
GCNN+LSTM+FNN (proposed model)	3.17	4.02
2-layer LSTM	4.25	5.15
3-layer LSTM	5.61	6.34
LASSO	4.27	4.63
Historical Average	11.48	11.51
Last Observation	8.99	9.29

a 2048-512-128 network configuration with a dropout rate of 0.25. As for LASSO, the objective function of optimization is shown in Eq. 4, Where X, y, β being input features, occupancy ground truth and model parameters, respectively. In LASSO, all spatial information are dropped as the input being flattened into a one-dimensional vector. the optimization object of LASSO. In Historical Average, historical occupancy observations of the same time and week-of-day are averaged as the predicted value for individual blocks. In Last Observation, the current occupancy is used as the predicted value for 30 minutes later.

$$\min_{\beta \in \mathbb{R}} \{ \frac{1}{N} ||y - X\beta||_2^2 + \lambda ||\beta||_1 \} \tag{4}$$

As we can see, the proposed network outperforms all baseline models with a significant margin, the closest one to our method is LASSO. Interestingly, the two multi-layer LSTM models are beaten by LASSO, as the linear regression model with L1 constrains, indicating that some complex deep neural network models are prone to failure when applied high-dimensional but small-sized dataset from real world. The GCNN, on the other hands, applies spectral filtering on the graph representation of road network to capture the core spatial correlations while bounding the model complexity by parameter sharing. Thus is more suitable for scenario with strong spatial correlations among features than other deep learning models like vanilla RNN.

CONCLUSIONS

In this paper, a deep learning model is proposed for predicting block-level parking occupancy in real time. The model leverages Graph-Convolutional Neural Networks (GCNN) to extract the spatial relations of traffic flow in large-scale networks, and utilizes Recurrent neural network (RNN) and Long-short term memory (LSTM) to capture the temporal features. In addition, the model is capable of taking multiple heterogeneously structured traffic data sources as input, such as parking meter transactions, speed, transit, weather, etc. The model performance is evaluated on a case study conducted in Pittsburgh downtown area. Parking meter transactions, traffic speed, and weather data along with road networks are used in the case study. The proposed model outperforms other baseline methods including multi-layer LSTM and Lasso with a testing Mean Square Error (MSE) of 4.02 spaces when predicting block-level parking occupancies 30 minutes in advance. The case study also shows that features of traffic speed and weather are effective in predicting parking occupancies.

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