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Hourly Demand Prediction for Taxi Services Using Deep Learning

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ABSTRACT: Predicting taxi demand throughout a city can help to organize the taxi fleet and minimize the wait-time for passengers and drivers. In this paper, we propose a sequence learning model that can predict future taxi requests in each area of a city based on the recent demand and other relevant information. Remembering information from the past is critical here, since taxi requests in the future are correlated with information about actions that happened in the past. For example, someone who requests a taxi to a shopping center, may also request a taxi to return home after few hours. We use one of the best sequence learning methods, long short term memory that has a gating mechanism to store the relevant information for future use. We evaluate our method on a data set of taxi requests in New York City by dividing the city into small areas and predicting the demand in each area. We show that this approach outperforms other prediction methods, such as feed-forward neural networks. In addition, we show how adding other relevant information, such as weather, time, and drop-offs affects the results.

I. INTRODUCTION

Taxi drivers need to decide where to wait for passengers in order to pick up someone as soon as possible. Passengers also prefer to quickly find a taxi whenever they are ready for pickup. Effective taxi dispatching can help both drivers and passengers to minimize the wait-time to find each other. Drivers do not have enough information about where passengers and other taxis are and intend to go. Therefore, a taxi center can organize the taxi fleet and efficiently distribute them according to the demand from the entire city. This taxi center is especially needed in the future where self-driving taxis need to decide where to wait and pick up passengers. To build such a taxi center, an intelligent system that can predict the future demand throughout the city is required. Predicting taxi demand is challenging because it is correlated with many pieces of underlying information. One of the most relevant sources of information is historical taxi trips.Taxi trip information can be collected from GPS enabled taxis. Analyzing this data shows that there are repetitive patterns in the data that can help to predict the demand in a particular area at a specific time. Several previous studies have shown that it is possible to learn from past taxi data.

II. LITERATURE SURVEY

Modeling the distribution of natural images is a landmark problem in unsupervised learning. This task requires an image model that is at once expressive, tractable and scalable. We present a deep neural network that sequentially predicts the pixels in an image along the two spatial dimensions. Our method models the discrete probability of the raw pixel values and encodes
the complete set of dependencies in the image. Architectural novelties include fast two dimensional recurrent layers and an effective use of residual connections in deep recurrent networks. We achieve log-likelihood scores on natural images that are considerably better than the previous state of the art. Our main results also provide benchmarks on the diverse ImageNet dataset. Samples generated from the model appear crisp, varied and globally coherent.
In big cities, taxi service is imbalanced. In some areas, passengers wait too long for a taxi, while in others, many taxis roam without passengers. Knowledge of where a taxi will become available can help us solve the taxi demand imbalance problem. In this paper, we employ a holistic approach to predict taxi demand at high spatial resolution. We showcase our techniques using two real-world data sets, yellow cabs and Uber trips in New York City, and perform an

evaluation over 9,940 building blocks in Manhattan. Our approach consists of two key steps. First, we use entropy and the temporal correlation of human mobility to measure the demand uncertainty at the building block level. Second, to identify which predictive algorithm can approach the theoretical maximum predictability, we implement and compare three predictors: the Markov predictor (a probability-based predictive algorithm), the Lempel-Ziv-Welch predictor (a sequence-based predictive algorithm), and the Neural Network predictor (a predictive algorithm that uses machine learning). The results show that predictability varies by building block and, on average, the theoretical maximum predictability can be as high as 83%. The performance of the predictors also vary: the Neural Network predictor provides better accuracy for blocks with low predictability, and the Markov predictor provides better accuracy for blocks with high predictability. In blocks with high maximum predictability, the Markov predictor is able to predict the taxi demand with an 89% accuracy, 11% better than the Neural Network predictor, while requiring only 0.03% computation time. These findings indicate that the maximum predictability can be a good metric for selecting prediction algorithms.
Traditional transportation systems in metropolitan areas often suffer from inefficiencies due to uncoordinated actions as system capacity and traffic demand change. With the pervasive deployment of networked sensors in modern vehicles, large amounts of information regarding traffic demand and system status can be collected in real-time. This information provides opportunities to perform various types of control and coordination for large scale intelligent transportation systems. In this paper, we present a novel receding horizon control (RHC) framework to dispatch taxis, which combines highly spatiotemporally correlated demand/supply models and real-time GPS location and occupancy information. The objectives include reducing taxi idle driving distance and matching spatiotemporal ratio between demand and supply for service quality. Moreover, our RHC framework is compatible with different predictive models and optimization problem formulations. Extensive trace driven analysis with a real taxi data set from San Francisco shows that our solution reduces the average total idle distance by 52%, and reduces the total supply demand ratio error across the city by up to 45%.

III. EXISTING SYSTEM

Taxi drivers need to decide where to wait for passengers in order to pick up someone as soon as possible. Passengers also prefer to quickly find a taxi whenever they are ready for pickup. The control center of the taxi service decides the busy area to be concentrated. Sometimes the taxi were scattered across the larger area missing the time based busy area like Airport, Business area, school area, Train stations etc,.

DISADVANTAGES:

- Managing fleet of taxi to crowded area.
- Effective utilization of resources to reduce waiting time for passengers.
- Serve more customers in short time by organizing the availability of taxi.

IV. PROPOSED SYSTEM

Effective taxi dispatching can help both drivers and passengers to minimize the wait-time to find each other. Drivers do not have enough information about where passengers and other taxis are and intend to go. Therefore, a taxi center can organize the taxi fleet and efficiently distribute them according to the demand from the entire city. To build such a taxi center, an intelligent system that can predict the future demand throughout the city is required. A convolutional neural network based model is trained with given history data. This model is used to predict the demand in different areas of the city.

ADVANTAGES:

- In this proposed system we are using the MD5 algorithm to train the model for accurate prediction.
- In preprocessing, it will find out which data is in null values and then clean the data with non-null values.
- Our algorithm trained model observe the dataset.
- Proceed the user's input gives the prediction results.

MODULES:

- ✓ Dataset pre-processing
- ✓ Create & Train dataset
- ✓ Prediction, result presentation

Dataset pre-processing:

The dataset might contain empty values, negative values or error. Dataset is cleaned in the pre-processing. The preprocessing methods involve of removing records which is not complete. Once the clean dataset is available we have to prepare it to feed to the algorithm.

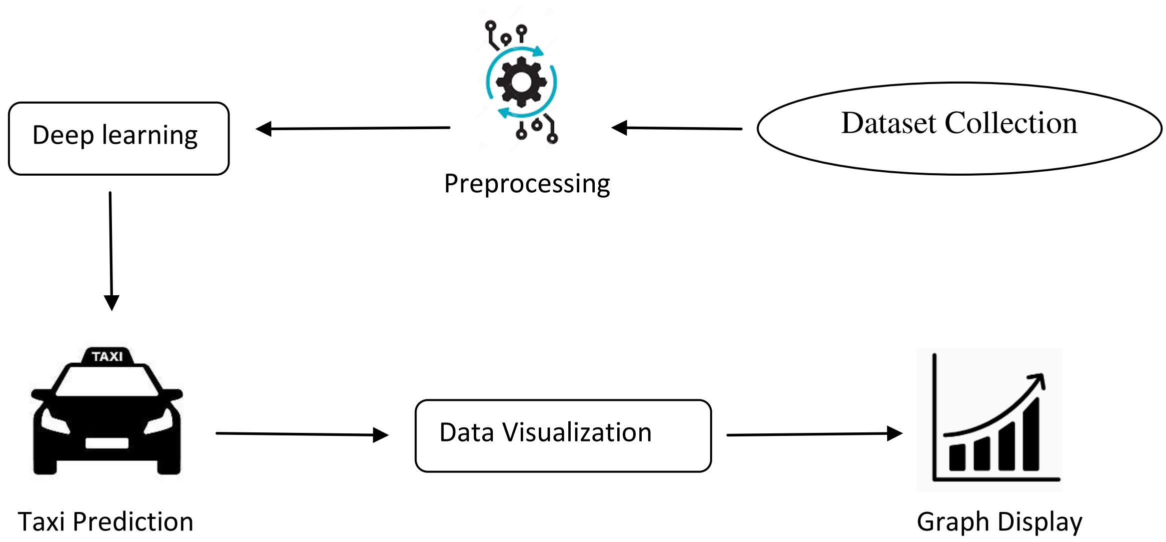
Create & Train dataset:

The network input is the current taxi demand and other relevant information while the output is the demand in the next time-step. The reason we use a convolutional neural network is that it can be trained to store all the relevant information in a sequence to predict particular outcomes in the future. In addition, taxi demand prediction is a time series forecasting problem in which an intelligent sequence analysis model is required. We divide the entire city into small areas. It is desired to predict taxi demand in small areas so that the drivers know exactly where to go. We train our system with dataset and create the model for future prediction.

Prediction, result presentation:

A graph is plotted for the future prediction for the next time slot and the area to be crowded. This machine learning model predicts the future demand area in a city based on NN and the drivers were taken to wait in the area where the system identified as demand area.

ARCHITECTURE DIAGRAM:



We are used kaggle.com to collect dataset and then preprocess the dataset. After that train the model to predict the pickups in particular place. Then proceed the user's data as input in website finally the model predict the particular date pickups and shown as output and also show the graph for next 6 hours wave of pickups.

V. CONCLUSION

The study concludes that the proposed model can improve prediction accuracy. The most important influencing factor of the taxi demand prediction model is the time factor. Some limitations in the research on taxi demand prediction still need to be addressed. Thus we propose a method to predict environmental features for predicting taxi demand more precisely in future.

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