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Enhancing Taxi Service Efficiency through Real-Time Prediction of Demand with LSTM-based Neural Networks

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ABSTRACT:The use of intelligent transport support systems has greatly impacted urban mobility and optimizing vehicle supply in high-demand areas is still necessary. Improving the distribution of on-demand taxi services can improve traffic, accessibility, safety, and fares. However, much real-time information from vehicle-mounted sensors remains unused. This paper proposes a Taxi Demand Forecasting methodology using stream machine learning algorithms that detect concept drift on the taxi data stream. Real data from the New York open platform feeds a learning model constructed using the Massive Online Analysis (MOA) tool. Results show promising accuracy in forecasting taxi demand at 78%. Although specific to New York, this methodology can be applied to other cities for proactive demand management.

KEYWORDS:Urban mobility, Predictive algorithm, On-demand taxi services, Stream machine learning algorithms.

I. INTRODUCTION

The prediction of taxi demand in a city can enhance the organization of the taxi fleet and minimize wait times for both drivers and passengers. This paper presents a sequence learning model that can anticipate taxi requests in each area of a city by considering recent demand and other relevant data. Since future requests are correlated with past actions, the model uses a long short-term memory sequence learning method with a gating mechanism to store pertinent information for future use. The model is evaluated using a New York City taxi request dataset that is segmented into small areas to predict demand. The results indicate that this approach is superior to other prediction methods, such as feed-forward neural networks. The study also analyzes how including other factors such as weather, time, and drop-offs affects prediction results. Effective taxi dispatching can benefit both drivers and passengers by reducing wait times. However, drivers lack sufficient information to make informed decisions about passengers' and taxi's whereabouts. Therefore, a taxi center that efficiently organizes the taxi fleet and distributes them according to the demand from the entire city is crucial. Such a center would be especially beneficial in the future when self-driving taxis need to determine where to wait and pick up passengers. To achieve this goal, an intelligent system that predicts future demand throughout the city is necessary.

II. RELATED WORK

In the field of taxi demand prediction, several research works have been conducted. For instance, Zhang et al. [5] proposed a passenger hotspot recommendation system for taxi drivers based on historical taxi data to extract hot spots and assign a hotness score to them. Zhao et al. [6] defined maximum predictability for taxi demand at the street block level and implemented three prediction algorithms to validate their theory. Moreira-Matias et al. [13] proposed a framework consisting of three different prediction models to make short-term demand predictions for the 63 taxi stands in the city of Porto, Portugal. Davis et al. [14] used time-series modeling to forecast taxi travel demand in Bengaluru, India.

Regarding the dispatching center, Zhang et al. [7] proposed a real-time taxi dispatching application based on two kinds of passengers: previously left-behind passengers and future arriving passengers. Miao et al. [8] proposed a dispatching framework for balancing taxi supply and demand in a city.

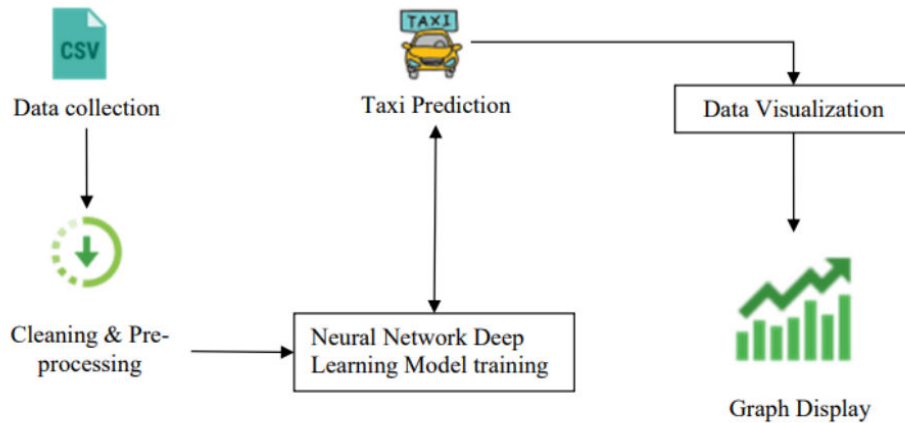
Moreover, historical taxi information has also been used in other prediction applications such as taxi sharing and destination prediction. Yuan et al. [15] presented a recommender system for taxi drivers and passengers based on taxi GPS traces and the mobility pattern of passengers. Ma et al. [16] proposed a taxi ride-sharing system that efficiently serves real-time requests sent by taxi users. Rong et al. [17] modeled passenger-seeking taxis as a Markov Decision Process (MDP) and proposed a method to increase the revenue efficiency of taxi drivers. Azevedo et al. [18] investigated the problem of improving the mobility intelligence of self-driving vehicles through large-scale data analysis.

Furthermore, de Brébisson et al. [20] used recurrent neural networks to predict taxi destinations given the beginning of taxi trip GPS traces, while our work focuses on predicting when and where a new taxi trip will start by learning the past taxi demand pattern. Additionally, LSTMs have been successfully applied to various sequential learning applications such as online handwriting sequence generation [10], robot arm trajectory learning [21], language modeling [22], speech recognition [23], and visual recognition [24].

Compared to previous works on taxi demand prediction, our model can capture long-term dependencies in a sequence that happens very far away from each other, and we train our network on sequences that are as long as a week, which can be extended to a month or a year with sufficient computational power. Moreover, our model predicts the entire probability distribution of taxi demands in all areas of a city at once using a single model, which enables the patterns learned by the LSTM in one area to be used in other areas. Additionally, our approach predicts the probability distribution of taxi demands, which provides a more realistic prediction by considering the uncertainty.

III. METHODOLOGY

We present an innovative method for predicting taxi demand in various regions of a city in real-time. Our approach involves partitioning the city into smaller areas and consolidating the number of taxi requests in each area over a brief period, such as 20 minutes. The resulting data forms a sequence of past taxi activity by region. We then utilize a Long Short-Term Memory (LSTM) recurrent neural network (RNN) to train on this sequential data. The network inputs consist of relevant information, such as the current taxi demand, while the output is the demand in the next time-step. We selected an LSTM RNN due to its ability to retain all the essential information in a sequence, thereby allowing for accurate prediction of future outcomes. Additionally, as taxi demand forecasting is a time-series problem, a sequence analysis model is required, and LSTMs are state-of-the-art models used widely in various applications, such as natural language processing [11] and unsegmented handwriting generation [10]. LSTMs use gating mechanisms to store information and can learn long-term dependencies. As a result, our proposed method can remember the number of people who requested taxis for a concert and subsequently predict that a similar number of people will request taxis from the concert location to different regions after a few hours. [9]



IV. EXPERIMENTAL RESULTS

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 CNN and the drivers were taken to wait in the area that the system identified as the demand area.

The below screenshot represents the output for predicting taxi demand. A few more parameters also exist to predict the accurate demand such as precipitation, weather, and temperature at dates and times. The output is in the graph format which predicts the next six hours of data.

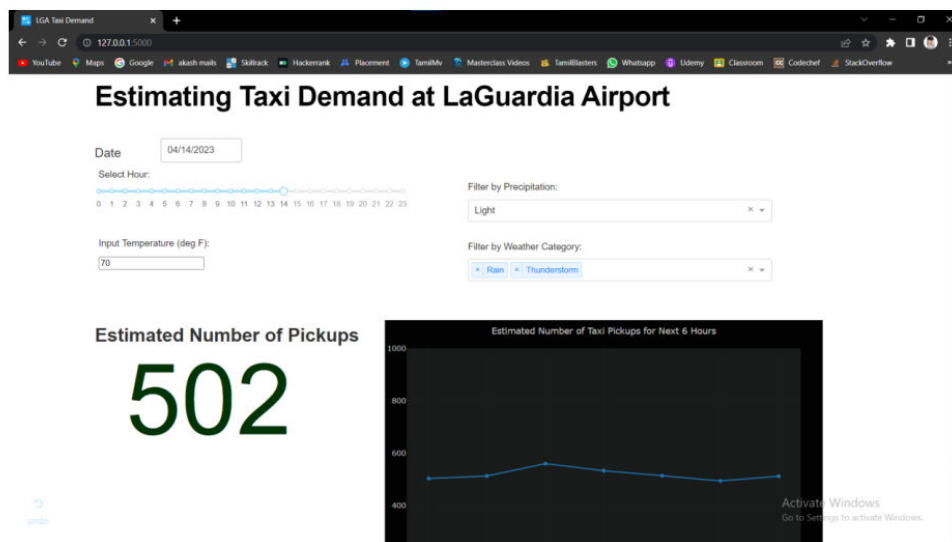


Fig 7.2 Taxi Demand Prediction

V. CONCLUSION

Our research proposes a novel approach to predicting taxi demand in different regions of a city using a sequence learning model based on recurrent neural networks and mixture density networks. By training on historical taxi demand patterns, our LSTM-MDN model can accurately predict taxi demand across the entire city. We utilized over three years of taxi trip data from New York City to train our model and achieved an impressive accuracy of approximately 83% at the city level. Moreover, we extended the LSTM-MDN model to a conditional model that considers current demands in

other areas, resulting in improved prediction performance compared to other models based on fully connected feed-forward neural networks and naive statistic averages.

There are several avenues for future research in this field. One potential approach is to augment the input of the network with additional information, such as the locations of businesses, shops, and restaurants. Additionally, our model could inform a central taxi dispatch system, enabling efficient distribution of taxis in real-time to respond to predicted demand. This would be especially beneficial in scenarios where drivers are competing for passengers in one area while demand is high in another. In the future, such a system could also facilitate the organization of self-driving cars in response to taxi requests, ultimately saving time and reducing fuel consumption.

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