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Dynamic Prediction of Shared Micromobility Usage with Multi-Task Learning

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POLICY BRIEF

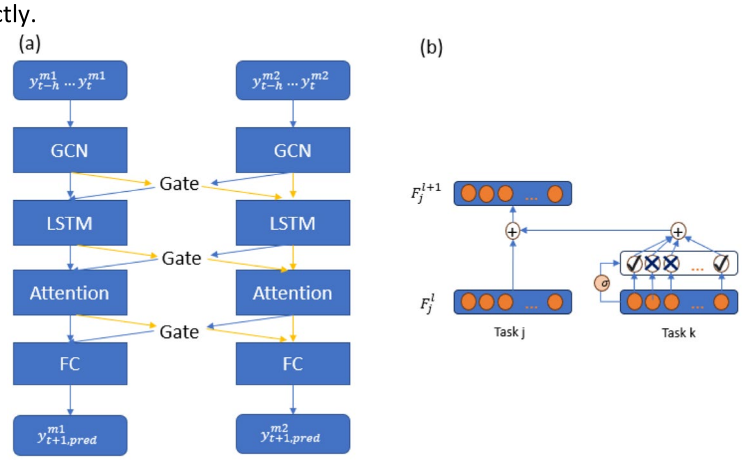
BACKGROUND AND OBJECTIVES

Taxi and Transportation Network Company (TNC) services play essential roles in the urban transportation system. Taxis offer traditional ride-hailing services, while TNCs such as Uber and Lyft connect drivers and riders using internet-based mobile technology. The ridership of TNCs has grown rapidly and the capacity utilization rate of TNCs (the fraction of the time/mile in which a driver takes fare-paying passengers) is much higher than that of taxis. Improving short-term demand forecasting for both TNCs and taxis has positive impacts on sustainability. With accurate prediction, operators can assign the right number of vehicles at the right time to reduce the idle time of drivers and waiting time for passengers, leading to an improved capacity utilization ratio. Improving the utilization ratio could potentially help address traffic congestion problems, improve traffic speeds, and reduce traffic emissions. In New York City, Yellow Cabs can be hailed on the Uber app, a partnership that provides an opportunity for data sharing and modeling, which could potentially improve the demand forecasting accuracy for both the taxi and TNC modes. The objective of this study is to develop a more advanced multi-task learning (MTL) model for better predicting the demand of Taxi and TNC simultaneously by taking a higher order of spatial dependency of demand into consideration. The model adopts a gating mechanism that selectively shares information between the two modes to avoid the negative transfer that commonly occurs in MTL models. In addition, the model also captures the second-order spatial dependency of the demand by applying a graph convolutional network. The contribution of this study is threefold:

- The evolving shared mobility sector longs for better demand prediction for different formats of sharing services. This study proposes a multi-task learning model to predict the demand for the TNC and taxi modes simultaneously to meet these needs.
- This study explores methodological improvements to increase the prediction accuracy. The techniques considered include a gating mechanism to mitigate the negative transfer between the two modes and spatial embedding, capturing the interaction of spatial dependency.
- Extensive experiments are conducted using actual taxi and TNC trip data from Manhattan, NYC. The experimental results show that the proposed modeling approach outperforms the single task learning model and other benchmark learning models from the literature.

METHODOLOGY

The multi-task learning model structure is shown on the left of the figure below, which adopts a "gating" mechanism called a Gated Sharing Unit (GSU) that is detailed on the right of the figure. A GSU allows the model to filter features from other tasks and select those that are useful to the task; it avoids harmful feature inference if two feature maps are concatenated directly.



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There are two steps involving a GSU. Assume that there are two modes, *j* and *k*. The first step computes how much information will be merged from mode *k* to mode *j*. The second step computes the merge of features between mode *j* and mode *k*. The formulas for computing the variables in the two steps can be found from the final report of this research, as well as from the journal publication in *Sustainability* (https://doi.org/10.3390/su16052065).

RESEARCH FINDINGS

This study selected Manhattan, New York, as the case study area, as both Yellow Cabs and TNCs service that area, and trip data are publicly accessible from the NYC Taxi & Limousine Commission. One-year trip data for 2018 are retrieved for the study, including Yellow Cab and For-Hire Vehicle (FHV) trip data. The FHV data includes Uber, Lyft, and other platforms that allow passengers to use apps to request trip services. For both transportation modes, information such as trip pick-up zone, drop-off zone, pick-up time, and drop-off time is selected from the dataset.

To demonstrate the performance of the proposed MTL model, besides the single-task learning model, several popular time-series models are also selected for comparison. To test the effectiveness of MTL and the interaction of spatial dependency, we also compare models that do not consider spatial dependency, considering first-order spatial dependency, and considering the interaction of spatial dependency. Each variation of single task learning and MTL is built. To compare the performance of these models, this study adopted two metrics which are popularly used for regression tasks—the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

To visualize the model's performance, a random sample of the predicted and actual demand for one day (24 timestamps) from the test data was taken (see the figure below). Both curves reveal a close match between the forecasted and observed demand, indicating the good performance of the model. Besides, the comparison of performance metrics of different models is shown in the table below, demonstrating the superior of multi-task learning (GCN-Interaction) model.

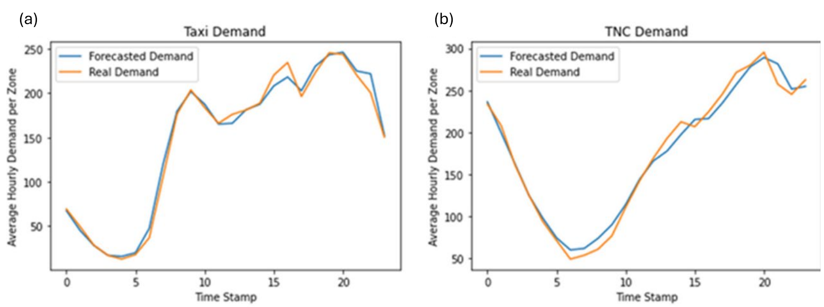

Table 1. Model performance comparison among different methods.

	Taxi		TNC	
	RMSE	MAE	RMSE	MAE
ARIMA	54.1	32.6	56.3	37.1
MLP	47.9	30.0	49.5	34.4
XGBoost	36.9	21.8	41.0	26.1
Single-task learning (without a GCN)	37.7	22.6	41.0	27.2
Multi-task learning (without a GCN)	36.1	21.8	39.5	26.1
Single-task learning (GCN-Distance)	36.7	21.8	40.2	26.2
Multi-task learning (GCN-Distance)	35.8	21.5	40.5	25.9
Single-task learning (GCN-Neighbor)	37.4	22.2	39.8	26.1
Multi-task learning (GCN-Neighbor)	36.5	21.9	39.4	25.5
Single-task learning (GCN-Interaction)	35.8	21.1	38.2	25.0
Multi-task learning (GCN-Interaction)	**34.7**	**20.9**	**37.2**	**24.2**

POLICY AND PRACTICE RECOMMENDATIONS

Accurately predicting spikes in demand within specific areas, TNC companies can strategically deploy TNC or taxi drivers to minimize the wait time for passengers. Additionally, short-term demand forecasting also facilitates the anticipation of traffic congestion in particular areas, enabling TNCs to optimize their routes. From a traffic management standpoint, integrating predictions of demand for taxi and TNC services into existing intelligence transportation systems can effectively contribute to reducing traffic congestion and enhancing the reliability of transportation options.

Several potential research directions could be extended from this study. First, while this study applies effective MTL techniques, it would be worthwhile to explore other advanced MTL techniques, such as gradient surgery to test whether the prediction errors can be further reduced. Second, some transportation modes may exhibit weaker correlations but still have significant implications, such as shared e-scooters and TNCs, which have a competing relationship for short distance trips. Investigating whether MTL can effectively model these modes would be an interesting avenue of research. Third, the GSU technique could be tested with data from different cities or for different tasks (e.g., traffic flow, TNC/taxi forecasting) to demonstrate its generalizability. Fourth, while improved demand forecasting can benefit route planning, the impact of this forecasting on traffic congestion remains a question worth exploring.

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