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Passenger Flow Prediction in Metro Systems Using LSTM

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ABSTRACT:

Metro service quality and efficiency may be improved by accurately anticipating Origin-Destination (OD) passenger flow. While OD prediction in subway systems has received less attention, previous research has concentrated on forecasting incoming as well as outgoing flows at specific stations. Three aspects provide obstacles for OD flows: 1) sparse and partial data slices; 2) high temporal variability and complicated geographical correlations; and 3) external influences. In order to: a) automatically fuse spatial relationships derived from various based on knowledge graphs and even undetected relationships between stations; and b) precisely represent the periodic trends in passenger traffic based on the auto-learned affect from external factors, we propose in this paper a Flexible Feature Fusion Network (AFFN). In order to address the sparsity and incompleteness of OD matrices that we multi-task AFFN by predicting each station's intake and outflow as a side work to increase the accuracy of OD predictions. Two practical metro trip datasets that were gathered in Nanjing and Xi'an, China, served as the subject of our comprehensive experimentation. The evaluation findings show our AFFN and multitasking AFFN perform better in a number of accuracy measures than the most advanced baseline approaches and AFFN variations, proving the usefulness of AFFN and all of its essential elements in OD prediction.

INTRODUCTION

In urban areas, the METRO has become one of the most well-liked and effective modes of transportation. In most cities, metro is the mode of transportation of choice for over 50% of commuters. The percentage in Hong Kong, New York, and Tokyo Revised manuscript received on March 21, 2022; approved on January 12, 2023. 28 January 2023 is the publishing date; the current

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networks. Our goal is to learn how to effectively forecast the OD flow of an entire city using sparse metro networks. Considering the following considerations, OD forecast for a citywide subway system is difficult. 1) Complex spatial correlations and high temporal dynamics. Particularly at peak hours, OD flow of metro systems is quite dynamic. In a little amount of time, the quantity of OD excursions might fluctuate significantly. By being close together, performing comparable urban functions in the surrounding area, or sharing other unobservable but shared characteristics, two stations might display comparable temporal OD patterns of flow in the spatial dimension. Accurately and simultaneously capturing these intricate spatial and temporal connections is needed. 2) External influences and periodic patterns. Evident weekly and daily trends have been seen in the OD flux. Additionally, outside variables that may interfere with periodicity, including the weather and holidays, have an impact on it. While regularities and external influences are modelled separately in the literature currently in publication, the influence of external factors and periodic patterns is not accurately captured. (3) Sparse and incomplete OD matrices. Trips to the metro often take a long time, several hours, for example. The real-time origin-destination matrix is incomplete since we are only able to get the whole origin-destination information when riders tap-out at their destination station. OD matrices are often sparse as well. Most OD pairings have a small number of trips between them, but very few pairs of origin-destination stations span the majority of OD excursions. Reliability of prediction is hampered by such sparse and partial information. We suggested an Adapted Feature Fusion Net (AFFN) to overcome these difficulties. It can fuse adaptively two types of data: 1) spatial dependencies across stations with various knowledge facets and even hidden correlations, and 1) periodic patterns with the influence of external elements that have auto-learned. In particular, we suggest using several knowledge-based networks and an attention-based graphing for hidden correlations to create an enhanced multi-graph convolution graphRU (EMGC-GRU) that encodes spatial connections between stations. To capture temporal dynamics, graph convolutions are embedded into each GRU layer. Next, EMGC-GRU uses a gating unit to fuse periodic OD flow into real-time prediction, weighted by attention

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weights learnt from external inputs. We build multi-task AFFN to anticipate each station's influx and outflow as a sub-task, addressing the sparsity and incompleteness of OD matrices. With more comprehensive, dense, and highly connected IO matrices than OD matrices, IO forecasting is a significantly simpler operation. Shared IO prediction network thereby contributes to increased accuracy in OD prediction. Our contributions are as follows, in summary:

• The Enhanced Multi-Graph The term convolution Recurrent Unit with Gated Recurrent (EMGC-GRU) is intended to discover hidden attention-based connections between stations inside GRUs and to capture spatial correlations that are specified in various knowledge-based graphs in an exhaustive manner. To enhance the accuracy of predictions, a suggested external factor-based concentration module aims to jointly include regular data flow with weights for attention acquired from outside sources. Using a task-shared Iop encoder or a task-shared outside factor-based attention, an asymmetric multitasking Adaptive Feature Integration Network (AFFN) may jointly forecast both IO and OD flow. This enhances the accuracy of OD prediction even more.

• In terms of prediction errors, assessments on three real-world datasets reveal that our AFFN with multitasking AFFN perform better than the most advanced baseline methods and AFFN variations, proving the efficacy of AFFN and all of its essential elements in OD flow prediction. This is the format for the remainder of the paper: A formal definition of prediction issues is provided in Section III, while Section II examines related work. The adaptive fused feature network we propose in Section IV is extended to multi-task AFFN.

RELATED WORK

China's urban rail transit condition now and its prospects for growth in the future: An overview according to national policies & strategic plans for 2016–2020

The rapid and extensive development of urban rail transport in China over the last several years has captured global interest. The research and progress report would serve as useful resources for future financial investments, service enhancements, and regional urban transportation planning and policy. This article provides an overview of infrastructure statistics at a high level. This

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paper examined the operational efficiency, passenger service performance, and spatial service coverage of urban mass transit systems in Mainland China. It also examined the development characteristics, including developing scales as well as multi-type urban rail transit modes, based on the China Urban Mass Transit work Annual Report from 2008 to 2015. There are trends and recommendations for how China's urban rail system should continue to expand.

Time-dependent passenger volume as the basis for a bi-objective schedule optimisation framework for urban rail transportation

The increasing prevalence of environmental and social challenges makes energy saving in urban rail transportation systems a difficult subject. Temporal variations in passenger demand at individual stations are often overlooked in the research currently available on this subject. This work presents a bi-objective schedule optimisation model to minimise both the pure energy consumption and the overall passenger waiting time, based on real-world period-dependent smart-card automated fare collecting data. According to the model's formulation, the disparity in the traction use of energy and the regeneration energy within a certain period represents the pure energy consumption, and the total customer waiting time is subject to the train capacities in the oversaturated state. Based on actual information of Beijing Yichuan metro line, numerical demonstrations are carried out. Comparing the created model to the present schedule, the findings show that it can effectively minimise energy usage and enhance passenger service.

metro train schedule rescheduling model that saves energy while taking ATO profiles and variable passenger traffic into account

Because of the frequent nature and density of metro traffic, trains operating in busy metro systems may experience unexpected disruptions. Due to train capacity restrictions and service interruptions, a significant number of people may get stuck on platforms. In this work, we create a mixed integer programme (MIP) model for the metro train schedule rescheduling challenge in order to jointly optimise the total train postponement, the number of stranded passengers, as well as the energy use for

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trains. This is achieved by introducing binary values as choosing signs for ATO profiles that were preset in on-board ATO platforms by metro signal suppliers. Taking into account the mass of passengers inside the vehicle, we construct the overall consumption of energy as the difference in tractive energy use and the regenerated energy. Next, we solve the suggested model using the commercial optimisation programme CPLEX, which can quickly find trade-off solutions. In order to confirm the efficacy of the suggested approach, three numerical trials based on actual operational data are conducted.

Optimised skip-stop metro line operating using smart card data: Skip-stop

operations are a low-cost way to enhance the effectiveness of metro operations and the quality of the passenger experience. In order to reduce the average passenger journey time, this research suggests a unique way to optimise the skip-stop system for bidirectional metro lines. The suggested Flexible Skip-Stop plan (FSSS), in contrast to the traditional "A/B" plan, is better able to handle variations in passenger demand both temporally and geographically. Then, to effectively find the best answer, a GA (genetic algorithm) based method is created. Through the extraction of time-dependent passenger demand from smart card data, a case study is carried out based on a real-world bidirectional metro system in Shenzhen, China. It has been shown that the optimal skip-stop operation may shorten the average passenger journey time. Moreover, the plan may help transit agencies save money on energy and operating expenses. Studies are conducted to determine the impact of the fact that certain passengers (due to skipping operation) fail to board the correct train. Findings indicate that FSSS consistently works better than the all-stop plan, even in situations when the majority of the missed OD pair's passengers are disoriented and unable to board the correct train.

METHODOLOGY

To implement this project, we have designed following modules

1) User login: user can login to system using username and password as admin

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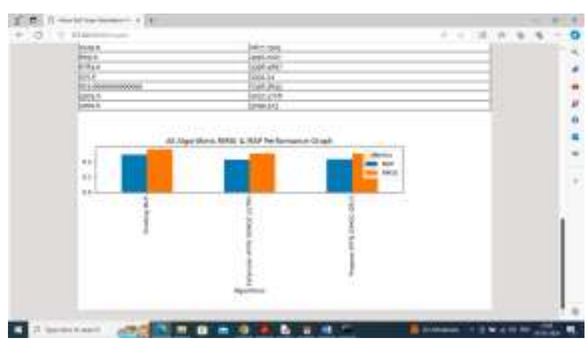
2) Load & Process Dataset: using this module user can upload dataset to application and then normalise and split dataset into train and test part
3) Existing MLP: using this module we can run existing algorithm to predict passenger flow and then calculate RMSE and MAP using true and predicted values
4) Propose AFFN (EMGC-GRU): using this module we can run propose convolution graph based GRU algorithm to predict passenger flow and then calculate RMSE and MAP using true and predicted values
5) Extension AFFN (EMGC-LSTM: using this module we can run propose convolution graph-based LSTM algorithm to predict passenger flow and then calculate RMSE and MAP using true and predicted values
6) Graphs: will plot RMSE and MAP comparison graph between all algorithms and then display true and predicted passenger flow values

RESULT AND DISCUSSION

In above screen click on ‘User Login’ link to get below page

In above screen in all 3 algorithms can see extension AFNN with LSTM got less MAP and RMSE values and can see little less gap in green and red lines and now click on ‘Comparison Graph’ link to get below graph



In above graph x-axis represents algorithm names and y-axis represents MAP and

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RMSE value in different colour bars and in all algorithms, extension got less MAP and RMSE values so extension is better than all algorithms

CONCLUSION

To forecast the movement of passengers from origin to destination in a metropolitan metro system, we suggested using an Adaptive Frequency Fusion Network (AFFN). In order to fully represent the intricate spatial and temporal relationships found in OD flows, we first created an improved multi-graph convolution-gated frequent unit (EMGC-GRU) that combines the auto-learned attention-based concealed relationships between stations inside GRUs with the established correlations modelled using various knowledge-based graphs. Next, by combining the periodic data flow with external variables, a factor-based focus module is created to precisely capture the periodic pattern. We have suggested an asymmetric multitasking framework to anticipate both IO and OD flow mutually, in an effort to further increase prediction accuracy. The outcomes of our evaluation demonstrate that, on two practical metro trip datasets, our suggested approaches perform better than the most advanced spatial-temporal prediction algorithms in terms of different prediction errors. In the future, the one-step prediction model will be expanded to a multi-step prediction model;2) more precise passenger flow predictions will be made by combining more specific local trip data, such as passenger movements and station waiting times, obtained from security cameras or other sensors;3) an analysis of the performance of our suggested model in more intricate metro systems, like those with circular lines as well as multi-line shared track structures; and4) an enhancement of prediction accuracy will be achieved by combining other non-metro trips, like bus and taxi trips.

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