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IMPROVED METRO PASSENGER FLOW FORECASTING USING ADAPTIVE FEATURE FUSION NETWORKS

[1]Mandapati Teja, MCA Student, Department of MCA
[2] Emmanuel Raju A, M.Tech, Assistant Professor, Department of MCA
[12]Dr KV Subba Reddy Institute of Technology, Dupadu, Kurnool

ABSTRACT

Predicting Origin-Destination (OD) passenger flow accurately helps improve the effectiveness and quality of metro services. Predicting incoming and outgoing flows for individual stations has been the main focus of previous efforts; OD prediction in metro networks has received less attention. The difficulties arise from the fact that OD flows 1) have complicated geographical correlations and high temporal dynamics, 2) are influenced by outside variables, and 3) contain sparse and partial data slices. In order to a) adaptively fuse spatial dependencies from various knowledge-based graphs and even hidden correlations between stations, and b) accurately capture the periodic patterns of passenger flows based on the auto-learned impact from external factors, we propose an Adaptive Feature Fusion Network (AFFN) in this paper. To address the sparsity and incompleteness of OD matrices, we further enhance the accuracy of OD prediction by extending AFFN to multi-task AFFN, which predicts each station's intake and outflow as a side-task. Two real-world metro trip datasets gathered in Nanjing and Xi'an, China, were the subjects of our intensive research. The evaluation findings demonstrate the efficacy of AFFN and all of its essential components in OD prediction, as our AFFN and multi-task AFFN exceed the state-of-the-art baseline approaches and AFFN variations in a variety of accuracy measures.

I. INTRODUCTION

One of the most well-liked and effective modes of travel in big cities is METRO. In the majority of cities, over half of commuters picked metro as their regular mode of transportation. The percentage of people who travel by metro is much greater (80%–90%) in Tokyo, New York, and Hong Kong [1]. Metro systems must promptly optimise service operations, such as scheduling elastic timetables [2], [3], and planning flexible skip-stop lines [4], [5], which necessitate precise origin-destination (OD) passenger flow predictions, in light of the rapidly growing urbanisation and population.

For metro management [11], [12], and emergency response [13], [14], the majority of previous efforts have been on forecasting inflow and outflow at metro stations (IO prediction) [6, 7], [8], [9], [10] in individual stations. The number of metro journeys between each pair of origin and destination stations is only predicted by a small number of studies [15], [16]. Even yet, OD prediction—that is, estimating the number of taxi journeys from each origin zone to the destination region—has been well researched for ride-hailing or taxi systems [17], [18], and [19]. However, since the stations are linked by sparse metro lines rather than extensive road networks, where Euclidean distances may approximately match road lengths, these methodologies cannot be directly applied to the metro. We are thus driven to investigate the methods for precisely forecasting the OD movement over the whole city on sparse metro networks.

The following facts make OD prediction difficult for a citywide metro system. 1)

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Complex spatial correlations and high temporal dynamics. Metro systems have very changeable OD flow, particularly during peak hours. In a short period of time, the number of OD excursions might alter significantly. Due to their close proximity, similar urban functions in the surrounding area, or other unspoken but shared characteristics, two stations may exhibit comparable temporal OD flow patterns in the spatial dimension. It is crucial to simultaneously and thoroughly capture these intricate temporal and spatial connections. 2) External influences and periodic patterns. In days and weeks, the OD flow has clearly shown periodic patterns. In the meanwhile, it is also impacted by outside variables that might interfere with periodicity, such the weather and holidays. The influence of external variables on periodic patterns is not captured by the literature currently in publication, which models periodic patterns and external factors separately [17], [20], and [21]. 3) Sparse and incomplete OD matrices. Metro journeys are often lengthy, spanning many time steps, such as more than half an hour. The real-time OD matrix does not include incomplete trips since we can only get the full origin-destination information when passengers tap out at their destination station and do not yet know the passengers' destinations. Additionally, most OD matrices are sparse. While the majority of OD pairings have few trips between them, very few pairs of origin-destination stations span the majority of OD excursions. It is challenging to make an accurate forecast with such a sparse and partial data.

1.1. Purpose Of The Project

Improving service quality, operational efficiency, and strategic planning are crucial for metro systems, and one way to do this is by developing an advanced deep learning framework for reliably forecasting Origin-Destination (OD) passenger flows.

While most studies have concentrated on predicting inflows and outflows at the station level, this study tackles the trickier problem of OD prediction, which is fraught with difficulties:
• The impact of extraneous environmental elements like weather and events; • Complex geographical connections between stations; and
• High temporal dynamics.
• The OD data is sparse and incomplete.

In order to address these concerns, the project introduces the Adaptive Feature Fusion Network (AFFN). This network: • Learns periodic patterns of passenger flow affected by external factors through data-driven modeling. • Adaptively fuses spatial dependencies from various knowledge-based graphs, revealing hidden inter-station correlations.

The research aims to improve forecast performance by extending AFFN into a multi-task learning framework. This framework will include auxiliary tasks that reinforce the core OD prediction job, such as station-level inflow and outflow prediction.

1.2. EXISTING SYSTEM

1) Methods Based on Direct Estimation: These methods use surveys tailored to particular locations to get the overall passenger numbers [26], [27]. In order to gather data on their journey, a certain percentage of passengers are chosen at random. These methods work for estimating demand in the present, but they can't be used in real time because of the enormous quantity of data that has to be gathered.

2) Disaggregated Estimation Methods: These methods are based on models and consist of three primary steps: 1) defining the functional form of the model, 2) calibrating the model by tuning its parameters, and 3) validating the model by checking its statistical quality. [28], [29], [30], [31], [32], [33] are all examples of such methods. An effective demand estimating model can faithfully replicate the initial data and is therefore the product of an iterative process.

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Approaches to disaggregated estimation may be further classified as either Reveal Preference (RP)-based or Stated Preference (SP)-based, depending on the method used to gather the training data [28], [29], [30], [31], [32], [33]. Current demand estimate and future demand simulation may both benefit from disaggregated estimation methodologies.

3) Methods for Aggregated Estimation: Methods for aggregated estimation have been suggested to enhance the arrival-departure passenger flow estimates [22]. These methods calibrate the demand model's initial estimate using aggregate travel demand data found in traffic counts. In order to find an origin-destination matrix that minimises the difference between the predicted and observed passenger flows on network connections (traffic counts), several strategies are used. The assignment matrix, which specifies the O/D flow percentages using each network connection, must often be estimated, either implicitly or explicitly, via these approaches [34]. On the other hand, several researchers have suggested other congestion network methods[34,37,38,39,40], arguing that the assignment matrix and traffic flow are interdependent. With the use of aggregated estimating methods, we can get good estimates of demand using traffic counts.

Nevertheless, there is an inherently difficult task of finding the exact assignment matrix, which causes an error that is never insignificant in the resultant estimate.

Disadvantages

- It is not possible to use an Adaptive Feature Fusion Network (AFFN) with an existing system.
- The more accurate and efficient Integrating Multiple Graphs with RGCN was never employed by an existing system.

1.3. PROPOSED SYSTEM

To adaptively combine the 1) geographical dependencies between stations with various elements of information and even hidden correlations and 2) periodic patterns with the auto-learned influence from external sources, the system suggested an Adaptive Feature Fusion Network (AFFN). Our proposed method, Enhanced Multi-Graph Convolution GRU (EMGC-GRU), uses one attention-based graph to encode hidden correlations and several knowledge-based graphs to encode spatial relationships across stations. In order to record changes over time, graph convolutions are included into every GRU layer. In order to include periodic OD flow into real-time prediction, EMGC-GRU and a gating unit acquire attention weights from external sources and then apply them.

We augment AFFN to multi-task AFFN in order to anticipate the incoming and outgoing data from each station as a separate sub-task, therefore addressing the sparsity and incompleteness of OD matrices. The increased density and completeness of IO matrices, together with their significant correlation with OD prediction, makes IO prediction a much simpler operation. Therefore, enhancing the accuracy of OD predictions is possible via sharing the IO prediction network.

Advantages

The EMGC-GRU is a kind of Enhanced Multi-Graph Convolution Gated Recurrent Unit that can learn hidden attention-based correlations between stations in GRUs as well as capture spatial correlations that are preset in various knowledge-based graphs.

For better prediction accuracy, it is suggested to use an attention module that is based on external variables. This module would combine periodic data flow with attention weights learnt from external factors in a collaborative manner.

Using a shared IO encoder and a task-sharing external factor-based attention, an asymmetric

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multi-task Adaptive Feature Fusion Network (AFFN) may jointly forecast IO and OD flows, which further improves the accuracy of OD predictions.

The usefulness of AFFN and its essential components in forecasting OD flow is shown by evaluations on two real-world datasets, where our AFFN and multi-task AFFN beat state-of-the-art baseline approaches and AFFN variations in terms of prediction errors.

II. REQUIREMENT AND ANALYSIS

2.1. LITERATURE SURVEY

2.1.1. Overview

Published in March 2018, X. Bao's article "Urban Rail Transit present situation and future development trends in China: Overall analysis based on national policies and strategic plans in 2016-2020" provides a comprehensive overview of the subject.

Taking a macro view, this research examines how China's urban rail transportation business has grown over the last several decades. A number of variables were taken into account, including the extent to which cities have been urbanised, the number of private vehicles on the road, the capacity of roads, the proportion of people using public transportation, and the development of urban rail transit systems in China's major and extra-large cities. This study provides a thorough, methodical, and in-depth analysis and explanation of the environmental backdrop and domestic societal needs for the development of urban rail transportation in China, based on extensive investigations and research. Within the framework of China's 13th Five-Year Plan, this study examines the prospects and threats that the country's urban rail transit development might encounter between 2016 and 2020. It does so by drawing on data on present-day cutting-edge technology, data on the adaptability of different urban rail transit modes, data on industrial technologies, data on local finances, and models of investment and financing. Predicting and discussing the ten most significant trends of the era is the goal of this study. Scale expansion, development differentiation, structural networking, multimodal transportation systems, industrial standardisation, intelligent systems, self-developed technology, various finance sources, foreign markets, and strategic planning are all things that are expected to happen in the near future. This article offers a thorough evaluation of the existing state, future potential, and trends of China's urban rail transport system, as well as recommendations for improvement. For nations like China, the results may be a priceless resource for planning the expansion of urban rail transportation.

This is an article from the February 2018 issue of the IEEE Transactions on Intelligent Transportation Systems titled "A bi-objective timetable optimisation model for urban rail transit based on the time-dependent passenger volume." The authors are H. Sun, J. Wu, H. Ma, X. Yang, and Z. Gao.

Concerns about the environment and society are on the rise, making energy conservation a difficult issue for urban rail transportation systems. The time-varying features of passenger demand at each station are often disregarded in the current research on this subject. A bi-objective schedule optimisation model is developed to minimise total passenger waiting time and pure energy consumption based on real-world time-dependent smart-card automated fare collection data. The model says that in an oversaturated state, the entire waiting time for passengers is equal to the train's capacity, and that the pure energy consumption equals the sum of the traction energy consumption minus the regeneration energy during a certain time period. Using actual data from the Beijing Yizhuang metro line, numerical demonstrations are carried out. According to the findings, the proposed model outperforms the present schedule in terms

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of passenger service and energy consumption reduction efficiency.

The article "Energy-saving metro train timetable rescheduling model considering ATO profiles and dynamic passenger flow" was published in July 2019 in the IEEE Transactions on Intelligent Transportation Systems and authored by Z. Hou, H. Dong, S. Gao, G. Nicholson, L. Chen, and C. Roberts.

Because of the high density and frequency of metro traffic, when an unanticipated disruption happens under overcrowded circumstances, the operation of trains could be disrupted. Because of delays in service and trains' limited capacity, many people may end themselves waiting on platforms. This paper presents a mixed integer programming (MIP) model for rescheduling metro train schedules. The goal is to optimise all three metrics simultaneously: total train delay, number of stranded passengers, and energy consumption. To achieve this, we use binary variables as selection indicators for ATO profiles that were pre-set in on-board ATO systems by metro signal suppliers. Taking the mass of the passengers into account, we derive the total energy consumption as the disparity between the tractive energy consumption and the regenerated energy. Then, to solve the suggested model quickly and provide tradeoff answers, we use the commercial optimisation program CPLEX. In the end, the usefulness of the suggested strategy is confirmed by conducting three numerical experiments using real-world operational data.

"Optimised skip-stop metro line operation using smart card data," published in the January 2017 issue of the Journal of Advanced Transportation, by P. Zhang, Z. Sun, and X. Liu.

To improve the efficiency of metro operations and the travel experience for passengers, skip-stop operation is a low-cost option. To optimise the skip-stop strategy for bidirectional metro lines and minimise average passenger travel time, this research suggests a unique approach. In contrast to the traditional "A/B" design, the suggested Flexible Skip-Stop design (FSSS) is more adaptable to passengers' needs that vary across time and space. The next step is to create a method that uses genetic algorithms (GAs) to find the best answer as quickly as possible. Using smart card data that shows time-dependent passenger demand, a case study is carried out on a real-life bidirectional metro line in Shenzhen, China. Transit agencies may reap the benefits of this program, including reduced energy and operating costs, and shorter average passenger journey times, thanks to optimised skip-stop operation. The consequences of a certain number of passengers missing their connecting train (because of a skip operation) are examined in these analyses. Even when the majority of riders from the skipped OD pairs are bewildered and unable to board the correct train, the results reveal that FSSS consistently surpasses the all-stop system.

Planning skip-stop transit service under heterogeneous needs was published in August 2021 in Transp. Res. B, Methodol. and authored by Y. Mei, W. Gu, M. Cassidy, and W. Fan.

Under skip-stop service, transit vehicles only stop at a portion of the stations along a route. Increasing vehicle speeds and decreasing patron travel times are major goals of this method. A continuous approximation model is created in this study to best design a certain sort of skip-stop service, called AB-type service. Slowly changing demand patterns across space are accounted for in the model. Finding answers becomes easier with the help of an effective heuristic. For certain number instances, they are shown to be almost ideal. The results also show that optimised all-stop service isn't always the best option, and that optimum AB-type designs are often the best. When there is a strong demand for travel, a scattering of origins along a corridor, and customers place a high value on

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their time, the AB-type service stands out as the most competitive option. System expenses may be cut by up to 8 percent when AB-type service is used.

2.1.2 ARCHITECTURE

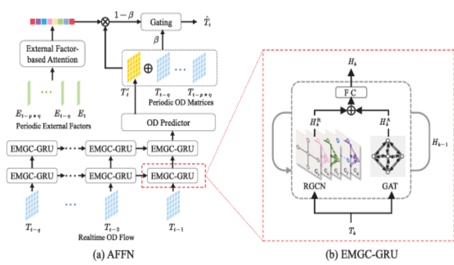

FIG.No.2.1

2.2. MODULES DESCRIPTION

2.2.1. Service Provider

The Service Provider must provide their username and password in order to access this module. Upon successful login, he will be able to do certain actions, including accessing the Train & Test Metro Passenger Flow Data Sets, Get a glimpse of the trained and tested accuracy in a bar chart, check out the results of the trained and tested accuracy, see the predicted data sets, see the results of the predicted flow type ratio, see all the remote users, and see the predicted flow type ratio.

2.2.2. View and Authorize Users

The admin can get a complete rundown of all registered users in this section. Admins can see user info like name, email, and address, and they may also grant users permissions.

2.2.3. Remote User

At least n people are active in this module. Do not proceed with any activities until the user has registered. The user's information will be entered into the database after they register. Once his registration is complete, he will need to log in using the credentials that have been authorised. After logging in, users will be able to do things like see their profile, make flow type predictions, and register and log in.

2.2.4. ALGORITHIMS

Decision tree classifiers

A wide variety of domains make effective use of decision tree classifiers. First and foremost, they may extract descriptive decision-making information from the given data. Training sets may be used to construct decision trees. Here is the process for generating such a set using the objects (S) from the classes C1, C2,..., Ck:
First, there's a leaf in the decision tree for S that is labelled with the class if all the objects in S are of the same class, like Ci.
Second Step. In any case, we may think of T as a test having results O1, O2,..., On. Since every item in S can only have one possible result for T, the test divides S into subsets S1, S2,..., Sn, where every item in Si may have an Oi result for T. Using the same approach recursively on the set Si, we construct a subsidiary decision tree for each result Oi, with T serving as the root of the decision tree.

Gradient boosting

Machine learning techniques like gradient boosting find utility in many different areas, including classification and regression. An ensemble of weak prediction models, usually decision trees, is what it uses to generate a prediction model. the first two The ensuing technique, known as gradient-boosted trees, often surpasses random forest when a decision tree serves as the weak learner. While other boosting approaches use a stage-wise construction, gradient-boosted trees take it a step further by enabling optimisation of any differentiable loss function.

III. SCREEN SHOTS

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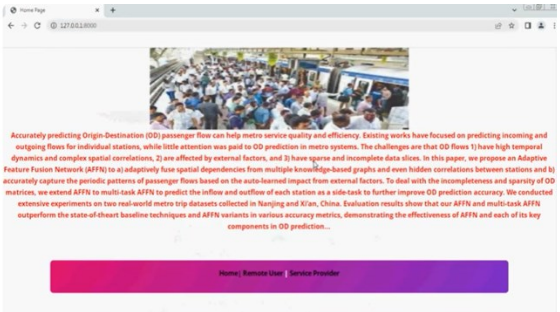

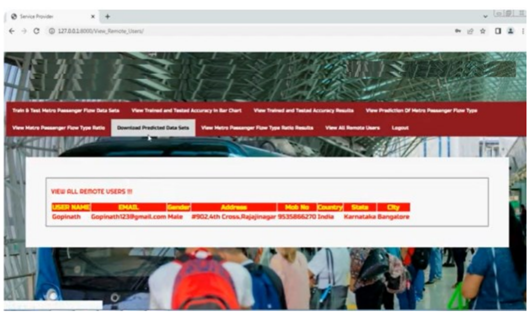

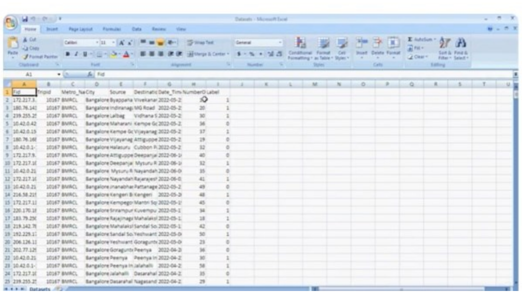

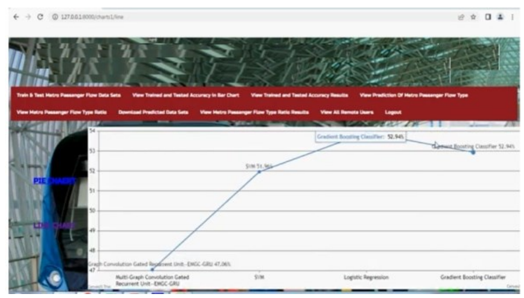

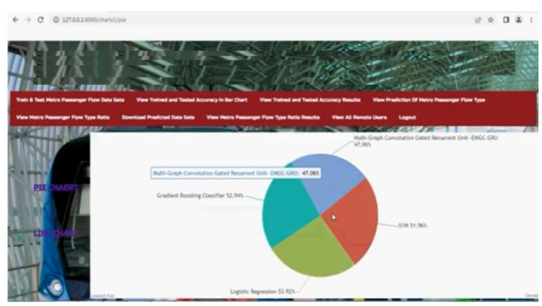

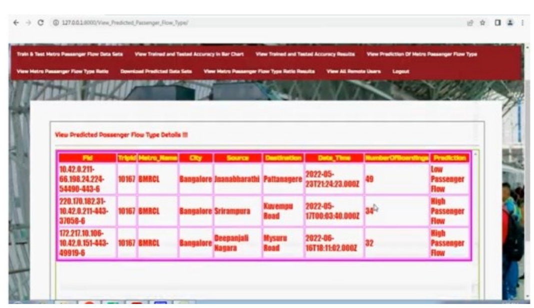

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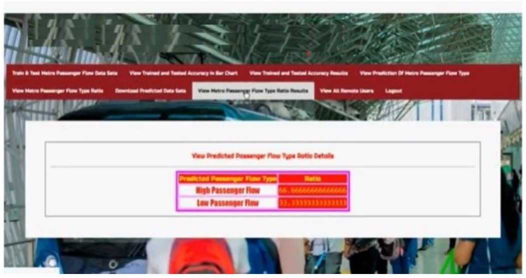

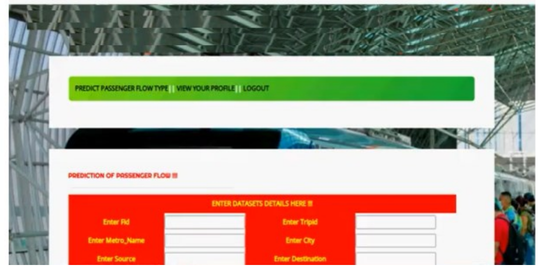

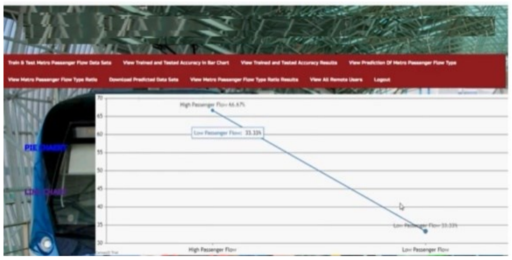

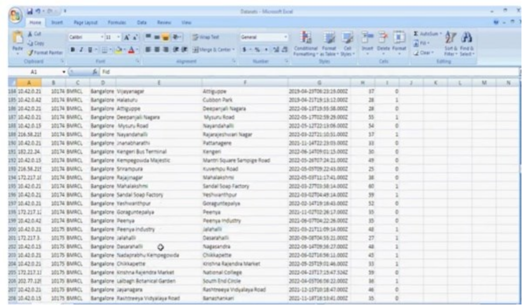

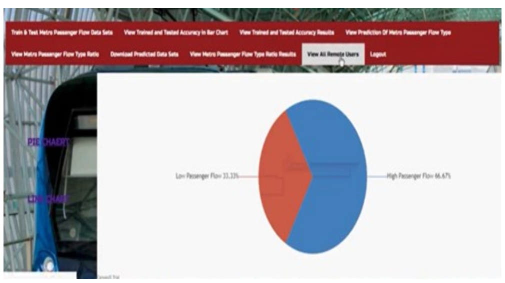

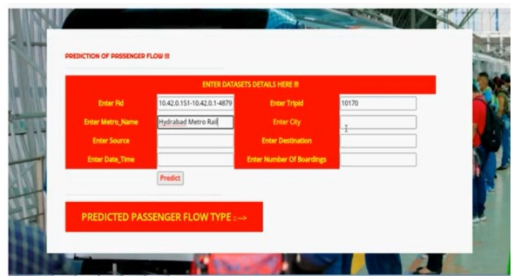

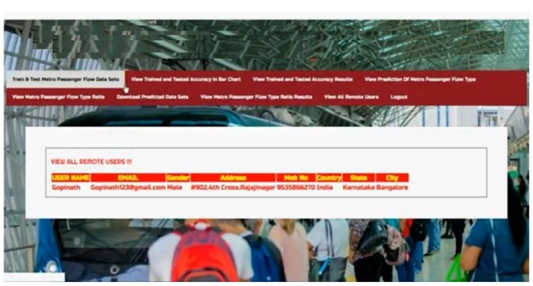

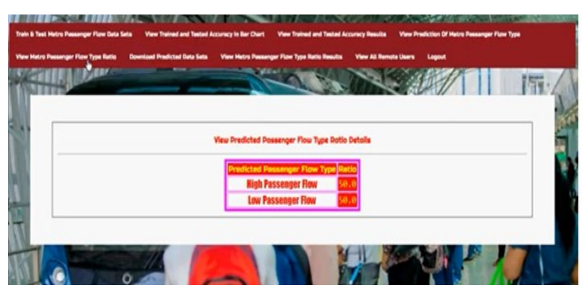

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IV. CONCLUSION

To forecast the movement of passengers from their starting points to their final destinations in a citywide metro system, we put forth an Adaptive Feature Fusion Network (AFFN). We started by creating an improved multi-graph convolution-gated recurrent unit (EMGC-GRU) that combines the predefined correlations modelled by various knowledge-based graphs with the auto-learned attention-based hidden correlations between stations in GRUs. This allowed us to fully capture the complex spatial and temporal dependencies in OD flows. Next, we incorporate the periodic data flow with external variables to create an attention module that is based on external factors. This module will correctly capture the periodic pattern. Additionally, we suggested an asymmetric multi-task framework for predicting IO and OD flows simultaneously in order to increase the accuracy of our predictions. Using two real-world metro trip datasets, we evaluated our suggested approaches and found that they outperformed the state-of-the-art spatial-temporal prediction algorithms in terms of different prediction errors. Here are some things we can work on for future projects: 1) creating a multi-step prediction model from the one-step one, 2) using data from surveillance cameras and other sensors to predict more fine-grained passenger flow (such as station waiting times and passenger movements), 3) testing our model in more complicated metro systems (like those with circular lines and multi-line shared track structures), and 4) enhancing the prediction accuracy by incorporating non-metro trips (like bus and taxi rides).

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