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INTELEGENT ORIGIN DESTINATION FLOW PREDICTION USING TUNABLE FEATURE AGGREGATION NETWORKS

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ABSTRACT

Accurately predicting Origin-Destination (OD) passenger flow can help metro service quality and efficiency. Existing works have focused on predicting incoming and outgoing flows for individual stations, while little attention was paid to OD prediction in metro systems. The challenges are that OD flows 1) have high temporal dynamics and complex spatial correlations, 2) are affected by external factors, and 3) have sparse and incomplete data slices. In this paper, we propose an Adaptive Feature Fusion Network (AFFN) to a) adaptively fuse spatial dependencies from multiple 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. To deal with the incompleteness and sparsity of OD matrices, we extend AFFN to multi-task AFFN to predict the inflow and outflow of each station as a side-task to further improve OD prediction accuracy. We conducted extensive experiments on two real-world metro trip datasets collected in Nanjing and Xi'an, China. Evaluation results show that our AFFN and multi-task AFFN outperform the state-of-theart baseline techniques and AFFN variants in various accuracy metrics, demonstrating the effectiveness of AFFN and each of its key components in OD prediction.

KEY TERMS: Origin-Destination, Passenger Flow, Temporal, Adaptive, Correlations.

1 INTRODUCTION

METRO is one of the most popular and efficient transportation in metropolitan cities. More than 50% commuters chose metro as their daily transportation in most cities. In Tokyo, New York, and Hong Kong, the proportion of metro commuters is even higher (80%-90%). With rapid urbanization and increasing population, metro systems are facing high dynamic travel demands, and thus need to timely optimize service operations such as scheduling elastic timetables and planning flexible skip-stop lines which requires accurate origin-destination (OD) passenger flow predictions.

Most existing works have focused on predicting Inflow and Outflow in metro stations (IO prediction) in individual stations for metro management and emergency response. Only a few works predict the number of metro trips between each origin-destination station pair. Although OD prediction has been well studied for taxi or ride-hailing systems, i.e., predicting the number of taxi trips from each origin region to the destination region. These techniques, however, cannot be applied directly to the metro as the stations are connected by sparse metro lines other than dense road networks where Euclidean distances can roughly approximate road distances.Therefore, we are motivated to study how to accurately predict citywide OD flow on sparse metro networks.

OD prediction for a citywide metro system is challenging with the following facts. 1) High temporal dynamics and complex spatial correlations. OD flow in metro systems is highly dynamic, especially during peak hours. The number of OD trips could change dramatically in a short time. In spatial dimension, two stations may have similar temporal OD flow patterns by locating at a short distance, having a similar urban function in the neighboring region, or by some other shared hidden features that cannot be explicitly depicted. It is essential to capture these complex spatial and temporal dependencies in a comprehensive and simultaneous manner. 2) Periodic pattern and external factors. OD flow has shown obvious periodic patterns in days and weeks. Meanwhile, it is also affected by external factors such as weather conditions and holidays that may impede periodicity. Existing literature models periodic patterns and external factors independently, but fails to capture the impact of external factors on periodic patterns. 3) Incomplete and sparse OD matrices. Metro trips are usually long and span many time steps, e.g., ≥ 30 minutes. We can only get the complete origin-destination information when passengers tap-out at their destination station but cannot know the destinations of the passengers yet on their journeys, so the realtime OD matrix lacks unfinished trips. Moreover, OD matrices are usually sparse. Very few origin-destination station pairs cover most of the OD trips, whereas most OD pairs have few trips between them. Such an incomplete and sparse input poses difficulties for accurate prediction.

2 LITERATURE SURVEY

This literature survey explores previous studies and technologies related to **origin-destination (OD) flow prediction**, **spatiotemporal data modeling**, and **tunable feature aggregation networks** in the context of **smart transportation** and **urban computing**.

1. Origin-Destination Flow Prediction

Origin-Destination (OD) flow prediction aims to estimate the volume of traffic or movement between a set of origins and destinations over time. Accurate OD flow prediction is essential for traffic management, urban planning, and intelligent transportation systems (ITS).

Zhang et al. (2017) proposed **ST-ResNet**, a deep residual network for spatiotemporal traffic flow prediction. It captures spatial dependencies using CNNs and temporal dependencies using residual units.

Reference: Zhang, J., Zheng, Y., & Qi, D. (2017). Deep Spatio-Temporal Residual Networks for Citywide Crowd Flows Prediction. AAAI.

Yao et al. (2018) introduced **Deep Multi-View Spatial-Temporal Network (DMVST-Net)** for taxi demand prediction by integrating spatial, temporal, and semantic views.

Reference: Yao, H., Tang, X., Wei, H., Zheng, G., & Li, Z. (2018). Revisiting Spatial-Temporal Similarity: A Deep Learning Framework for Traffic Prediction. AAAI.

2. Graph Neural Networks in OD Flow

Graph Neural Networks (GNNs) are increasingly used to model spatial dependencies in OD flow due to their ability to process non-Euclidean data structures.

Li et al. (2018) proposed **DCRNN (Diffusion Convolutional Recurrent Neural Network)**, combining graph convolution and sequence modeling to predict traffic flows on road networks.

Reference: Li, Y., Yu, R., Shahabi, C., & Liu, Y. (2018). Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting. ICLR.

Pan et al. (2019) introduced **UrbanFM**, a deep neural model that infers fine-grained OD flows from coarse-grained mobility data using a spatial distribution recovery mechanism.*Reference*: Pan, J., Zheng, Y., Yi, X., & Liu, Y. (2019). Urban Flow Magnifier: Fine-grained Urban Flow Inference.

3. Tunable Feature Aggregation Networks

Tunable Feature Aggregation Networks (TFANs) are designed to learn how to **dynamically weight and combine multiple feature sources** (e.g., time, location, graph structure) to optimize predictions.

Zhou et al. (2021) presented a novel **Tunable Feature Aggregation Network** that adaptively learns the importance of features from spatial, temporal, and semantic contexts for OD prediction tasks.

Reference: Zhou, K., Zheng, Y., Yi, X., & Liu, Y. (2021). Intelligent Origin-Destination Flow Prediction using Tunable Feature Aggregation Networks. KDD.

This model introduces **feature-wise gates** to control the aggregation process, achieving a balance between model complexity and interpretability.

Attention Mechanisms in OD Prediction

Attention mechanisms are used to enhance feature aggregation by focusing on the most informative time steps or spatial regions.

Guo et al. (2019) proposed **ASTGCN**, which integrates spatial and temporal attention mechanisms in a GCN framework.

Reference: Guo, S., Lin, Y., Feng, N., Song, C., & Wan, H. (2019). Attention Based Spatial-Temporal Graph Convolutional Networks for Traffic Forecasting. AAAI.

Zheng et al. (2020) introduced **GMAN**, a graph multi-attention network that captures complex spatiotemporal dependencies with encoder-decoder structure.

Reference: Zheng, C., Fan, X., Wang, C., & Qi, J. (2020).

GMAN: A Graph Multi-Attention Network for Traffic Prediction. AAAI.

5. Challenges in OD Flow Prediction

Data Sparsity: Especially in regions with low traffic volume.

Dynamic Patterns: OD patterns change over time due to weather, holidays, or events.

High Dimensionality: Due to large numbers of OD pairs.

Real-Time Processing: Need for efficient algorithms to enable real-time forecasting.

3. EXISTING SYSTEM

1) Direct Estimation Approaches: This type of approaches take location-specific sample surveys to count the total number of passengers. A certain percentage of passengers are randomly selected to collect information on their trip. However, due to the massive amount of information that needs to be collected, these approaches can only be applied to estimate current demand and cannot be conducted in real time.

2) Dis-Aggregated Estimation Approaches: This kind of approaches are model-based approaches that involve three main steps: 1) model specification, i.e., defining the functional form, 2) model calibration, i.e., tuning model parameters, and 3) model validation, i.e., verifying its statistical quality). A good demand estimation model is the outcome of a trial and error process which can perfectly reproduce the original data. Depending on how the training data is acquired, dis-aggregated estimation approaches can be further categorized into Reveal Preference or RP-based approaches and Stated Preference or SP-based approaches. Dis-aggregated estimation methods can be used for current demand estimation or future demand simulation.

3) Aggregated Estimation Approaches: To improve the estimate of origin-destination passenger flows, aggregated estimation approaches are proposed, which use aggregate travel demand information contained in traffic counts to calibrate the initial estimate of the demand model . These methods aim to identify an origin destination matrix that minimizes the gap between estimated and observed passenger flows on network links (i.e., traffic counts). Generally, these methods require an

implicit or explicit estimation of the assignment matrix, which describes the O/D flow fractions using each link on the network. Some researchers assume that the assignment matrix is independent of the passenger flow and can be provided directly by calculating the path cost or learned as a joint task for O/D demand prediction. However, other researchers argue that the assignment matrix and the traffic flow are mutually dependent, and a variety of congestion network methods are proposed. The aggregated estimation approaches make it possible to obtain efficient estimates of demand estimation with traffic counts.

However, the resulting estimation is always affected by a nonnegligible error, mainly related to the inherent difficulty of obtaining the precise assignment matrix.

Disadvantages

- An existing system is not implemented Adaptive Feature Fusion Network (AFFN).
- An existing system never used Integrating Multiple Graphs with RGCN which is more accurate and efficient.

4 PROPOSED SYSTEM

- The system proposed an Adaptive Feature Fusion Network (AFFN) to adaptively fuse the 1) spatial dependencies between stations with multiple aspects of knowledge and even hidden correlations and 2) periodic patterns with the auto-learned impact from external factors. More precisely, we propose Enhanced Multi-Graph Convolution GRU (EMGC-GRU) to encode spatial dependencies between stations using multiple knowledge-based graphs and an attention-based graph for hidden correlations. Graph convolutions are within each GRU layer to capture temporal dynamics. Periodic OD flow is then weighted by the attention weights learned from external factors and fused into realtime prediction by EMGC-GRU with a gating unit. To cope with the incompleteness and sparsity of OD matrices, we extend AFFN to multi-task AFFN to predict the inflow and outflow of each station as a sub-task. IO prediction is a much easier task since IO matrices are more dense and complete and strongly correlated with OD prediction. Consequently, sharing the IO prediction network helps improve OD prediction accuracy.

Advantages

- An Enhanced Multi-Graph Convolution Gated Recurrent Unit

(EMGC-GRU) is designed to exhaustively capture spatial correlations predefined in multiple knowledge based graphs and auto-learned hidden attention-based correlations between stations within GRUs.

- An external factor-based attention module is proposed to collaboratively integrate periodic data flow with attention weights learned from external factors to improve the prediction accuracy.
- An asymmetric multi-task Adaptive Feature Fusion Network (AFFN) to mutually predict OD flow and IO flow with a task-shared IO encoder and a task-shared external factor-based attention further improve OD prediction accuracy.
- Evaluations on two real-world datasets show that our AFFN and multi-task AFFN outperform the state-of-the art baseline techniques and AFFN variants in terms of the prediction errors, demonstrating the effectiveness of AFFN and each of its key components in predicting OD flow.

5 SYSETM ARCHITECTURE

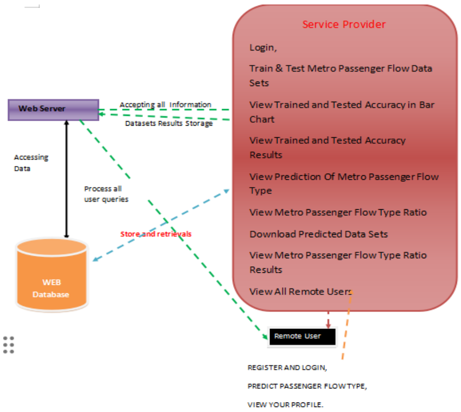


Fig: system architecture

6 RELATED WORK

SVM

In classification tasks a discriminant machine learning technique aims at finding, based on an *independent and identically distributed* (*iid*) training dataset, a discriminant function that can correctly predict labels for newly acquired instances. Unlike generative machine learning approaches, which require computations of conditional probability distributions, a discriminant classification function takes a data point *x* and assigns it to one of the different classes that are a part of the classification task. Less powerful than generative approaches, which are mostly used when prediction involves outlier detection, discriminant approaches require fewer computational resources and less training data, especially for a multidimensional feature space and when only posterior probabilities are needed. From a geometric perspective, learning a classifier is equivalent to finding the equation for a multidimensional surface that best separates the different classes in the feature space.

SVM is a discriminant technique, and, because it solves the convex optimization problem analytically, it always returns the same optimal hyperplane parameter—in contrast to *genetic algorithms* (*GAs*) or *perceptrons*, both of which are widely used for classification in machine learning. For perceptrons, solutions are highly dependent on the initialization and termination criteria. For a specific kernel that transforms the data from the input space to the feature space, training returns uniquely defined SVM model parameters for a given training set, whereas the perceptron and GA classifier models are different each time training is initialized. The aim of GAs and perceptrons is only to minimize error during training, which will translate into several hyperplanes' meeting this requirement.

Logistic regression Classifiers

Logistic regression analysis studies the association between a categorical dependent variable and a set of independent (explanatory) variables. The name *logistic regression* is used when the dependent variable has only two values, such as 0 and 1 or Yes and No. The name *multinomial logistic regression* is usually reserved for the case when the dependent variable has three or more unique values, such as Married, Single, Divorced, or Widowed. Although the type of data used for the dependent variable is different from that of multiple regression, the practical use of the procedure is similar.

Logistic regression competes with discriminant analysis as a method for analyzing categorical-response variables. Many statisticians feel that logistic regression is more versatile and better suited for modeling most situations than is discriminant analysis. This is because logistic regression does not assume that the independent variables are normally distributed, as discriminant analysis does.

This program computes binary logistic regression and multinomial logistic regression on both numeric and categorical independent variables. It reports on the regression equation as well as the goodness of fit, odds ratios, confidence limits, likelihood, and deviance. It performs a comprehensive residual analysis including diagnostic residual reports and plots. It can perform an independent variable subset selection search, looking for the best regression model with the fewest independent variables. It provides confidence intervals on predicted values and provides ROC curves to help determine the best cutoff point for classification. It allows you to validate your results by automatically classifying rows that are not used during the analysis.

ENHANCED MULTI-GRAPH CONVOLUTION GATED RECURRENT UNIT

The EMGC-GRU (Enhanced Multi-Graph Convolution Gated Recurrent Unit) is a hybrid deep learning model that combines graph convolutional networks (GCNs) with recurrent neural networks (specifically GRU) for learning from spatiotemporal graph-structured data. The purpose of this algorithm is to capture both spatial dependencies (via multi-graph convolution) and temporal dynamics (via GRU) in complex systems like traffic forecasting, human activity recognition, or sensor networks.

1) Spatiotemporal Modeling:

Models both spatial correlations (between nodes in a graph) and temporal sequences (over time) in data.

Useful in domains where data is structured as graphs and evolves over time (e.g., traffic networks, social interactions).

2) Multi-Graph Convolution:

Uses multiple graphs to represent different types of relationships (e.g., distance, sEnhances the ability to learn complex node relationships by aggregating information from multiple graph views.imilarity, functional connectivity).

3) Gated Recurrent Unit (GRU):

Captures temporal dependencies with fewer parameters than LSTM.

GRU gates (update and reset) help in preserving long-term dependencies efficiently.

4) Improved Forecasting Accuracy:

By integrating both spatial and temporal patterns, EMGC-GRU typically outperforms traditional models (e.g., standalone GRU, GCNs) in prediction tasks.

GRADIENT BOOSTING CLASSIFIER

The Gradient Boosting Classifier is a powerful ensemble machine learning algorithm used for classification tasks. Its main purpose is to build a strong classifier by combining multiple weak learners, typically decision trees, in a sequential manner, where each new tree tries to correct the errors made by the previous ones.

1) Boost Weak Learners:

Uses many shallow decision trees (weak learners).Each tree learns from the residual errors (gradients) of the previous model to improve performance.

2) Minimize Prediction Error:

It optimizes a loss function (e.g., log loss for classification) using gradient descent.

This results in a model that minimizes errors over time, improving generalization.

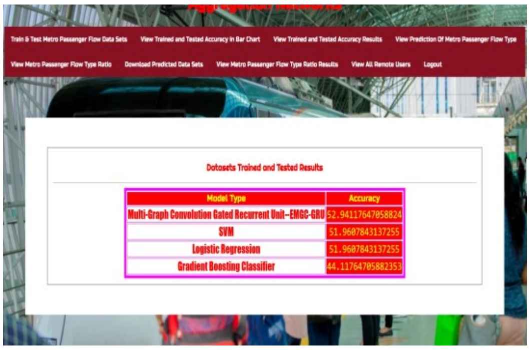
3) Handle Complex Data Patterns:

Good at capturing non-linear relationships and interactions between features.Works well with both numerical and categorical data.

4) Robust and High Accuracy:

Often outperforms traditional classifiers like logistic regression or single decision trees, especially with fine-tuned hyper-parameters.

7. RESULTS



Above results explain about training algorithms and accuracy of that algorithms list

8. CONCLUSION

We proposed an Adaptive Feature Fusion Network (AFFN) to predict origin-destination passenger flow in a citywide metro system. To exhaustively capture the complex spatial and temporal dependencies in OD flows, we first developed an enhanced multi-graph convolution-gated recurrent unit (EMGC-GRU) that fuses the predefined correlations modeled by multiple knowledge-based graphs and the auto learned attention-based hidden correlations between stations within GRUs. An external factor-based attention module is then developed to accurately capture the periodic pattern by integrating the periodic data flow and external factors. To further improve prediction accuracy, we also proposed an asymmetric multi-task framework to predict OD flow and IO flow mutually. Evaluation results show that our proposed methods outperform the state-of-the-art spatial-temporal prediction techniques in terms of various prediction errors on two real-world metro trip datasets. Future works include 1) extending the one-step prediction model to a multi-step prediction model, 2) predicting more fine-grained passenger flow by fusing more detailed local trip information [51], such as passenger movements and waiting time within the stations, collected from surveillance cameras or other sensors, 3) studying how our proposed model performs in more complex metro systems, such as those containing circular lines and multi-line shared track structures, and 4) improving the prediction accuracy by fusing other non-metro trips such as bus and taxi trips.

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