Short-term passenger flow prediction for multi-traffic modes: A residual network and Transformer based multi-task learning method

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Abstract

With the prevailing of mobility as a service (MaaS), it becomes increasingly important to manage multi-traffic modes simultaneously and cooperatively. As an important component of MaaS, short-term passenger flow prediction for multi-traffic modes has thus been brought into focus. It is a challenging problem because the spatiotemporal features of multi-traffic modes are critically complex. To solve the problem, this paper proposes a multi-task learning-based model, called Res-Transformer, for short-term passenger flow prediction of multi-traffic modes (subway, taxi, and bus). Each traffic mode is treated as a single task in the model. The Res-Transformer consists of three parts: (1) several modified transformer layers comprising 2D convolutional neural networks (CNN) and multi-head attention mechanism, which helps to extract the spatial and temporal features of multi-traffic modes, (2) a residual network architecture used to extract the inner pattern of different traffic modes and enhance the passenger flow features of multi-traffic modes. The Res-Transformer model is evaluated on two large-scale real-world datasets from Beijing, China. One is the region of a traffic hub and the other is the region of a residential area. Experiments are conducted to compare the performance of the proposed model with several state-of-the-art models to prove the effectiveness and robustness of the proposed method. This paper can give critical insights into the short-term passenger flow prediction for multi-traffic modes.

Keywords: Multi-traffic modes; short-term passenger flow prediction; multi-task learning; Transformer; deep learning

1 Introduction

With the rapid development of mobility as a service (MaaS), managing multi-traffic modes simultaneously and cooperatively become increasingly important. Under the environment of MaaS, people can reach their destinations by many traffic modes. In some busy regions, such as traffic junctions, subway or bus stations, the pick-up or drop-off areas of the taxi, etc., over-saturated situations often occur due to the complex passenger flow. To improve the service level and eliminate traffic congestions in these hot regions, it is important to capture the spatiotemporal distribution of passengers for different traffic modes. As an important component of intelligent traffic systems, short-term passenger flow prediction for multi-traffic modes has been attracted much attention both practically and academically because it can be applied to obtaining the future passengers’ volume and distribution. Accurate short-term passenger flow prediction can help operators to schedule resources more efficiently to eliminate over-saturated situations and is also helpful for passengers to plan their trips.
In reality, it is significant to conduct short-term passenger flow prediction for multi-traffic modes. In terms of the short-term passenger flows of multi-traffic modes, there seem to exist different travel patterns and regularities. However, it might be predictable in some situations because people may get to or leave the same region with the same purposes by different traffic modes. For example, commuters in resident areas might take the subway, buses, or taxies in the morning of weekdays to go to work. Passengers might transfer using different traffic modes in traffic hubs. In these cases, it is feasible to make the short-term passenger flow prediction for multi-traffic modes. However, the existing short-term passenger flow prediction mostly aims to forecast flows in a particular scene or a single mode, such as subway, bus, taxi, and so forth. Studies seldom simultaneously make predictions for different traffic modes because it is challenging to capture the different travel patterns and regularities of different traffic modes and find the inside correlations of them. To overcome these problems, the main motivation of this study is thus to predict the short-term passenger flow of different traffic modes in certain regions.

With the development of deep learning, it is feasible to make the short-term passenger flow prediction for multi-traffic modes by applying emerging deep learning techniques. Deep learning has been proved to have the ability to conduct time-series predictions. Some deep learning models are quite suitable for time series data and can extract the non-linear features inside data. The short-term passenger flow prediction for multi-traffic modes can be deemed as a time-series problem and different traffic modes show similar patterns on weekdays. However, there exists some challenges for the short-term multi-traffic modes predictions. First, even if there exist some common patterns, e.g., different traffic modes all present double peaks every weekday, it is still challenging to extract the patterns of different traffic modes simultaneously. Second, although the passenger flow of the subway in transportation junctions is quite stable, the passenger flows of taxis and buses fluctuate significantly. Deep-learning-based multitask learning techniques provide some insights for considering both the differences and similarities of multi-traffic modes. Therefore, this study tries to conduct short-term passenger flow prediction for multi-traffic modes leveraging multitask learning model.

To tackle the aforementioned issues, this study proposes a multi-task-learning architecture called Res-Transformer, using modified Transformer layers and the residual network to predict the short-term passenger flows for multi-traffic modes. The modified Transformer is composed of 2D convolutional layers and multi-head attention mechanism called the conv-transformer layer, which helps to extract the spatial and temporal features of different traffic modes. The residual network is proposed to extract the inner pattern of different traffic modes and enhance the passenger flow features of multi-traffic modes. The contributions of this paper are summarized as follows.

- To the best of our knowledge, this is the first time that a novel short-term passenger flow prediction model for multi-traffic modes is proposed.
- We propose a multi-task learning-based architecture called Res-Transformer, in which the subway, taxi, and bus are treated as different tasks. Combining the 2D CNN with the multi-head attention mechanism, we introduce a conv-transformer
layer to better extract the spatial and temporal passenger flow features of different traffic modes. Moreover, the conv-transformer layer is cast into the residual network to further enhance the extracted passenger flow features of multi-traffic modes.

- The Res-Transformer model is tested on two large-scale real-world datasets from Beijing, China and is compared with seven state-of-the-art models. Prediction results show that the proposed model outperforms all baseline models. Five ablation analyses results prove the feasibility and effectiveness of the proposed model.

The remainder of this study is organized as follows. In Section 2, we review the related work. Section 3 demonstrates the problem definition. Section 4 introduces the origin Transformer model and residual network, then presents the framework overview and the proposed model. Section 5 shows the details of the experiment, including data description, experiment’s platform and parameters of the model, the metrics and loss function, and the comparison with other existing models. The conclusion is summarized in Section 6.

2 Literature review

In the studies, the passenger flow prediction for multi-traffic modes receives little attention, few researchers consider this topic. And as the passenger flow prediction for multi-traffic modes task can be deemed as a time-series prediction task, we extend the range to a more general question, such as traffic flow prediction, passenger flow prediction, and so forth. From classic models to machine learning models, and lately the deep learning models, the accuracy of prediction has been improved gradually. Furthermore, as the ideal of multi-task learning is proposed, the factors that affect the prediction task of time series tasks can be considered in the models.

The autoregressive Integrated Average model, also called ARIMA, which is one of the most popular parametric models, has been widely applied to predict traffic flow. Ahmed and Cook(1979) were the first who applied the ARIMA model in traffic flow prediction. Zhang(2003) put forward a hybrid methodology combining both ARIMA and artificial neural network (ANN) for the time series forecasting task and used the real-world data, viz. Wolf’s sunspot data, the Canadian lynx data, and British pound/US dollar exchange rate data to prove the effectiveness of the model. Cai et al.(2014) proposed a multiply ARIMA model to predict the urban railway station’s entrance and exit passenger flow. Williams(2001) applied ARIMAX to predict traffic flow.

Nevertheless, as the prediction tasks of traffic flow or passenger flow can be regarded as a kind of time-series task, the key is to capture the nonlinear features of the data, the classic models like ARIMA, show their weakness in their performance. With the fast development of machine learning and deep learning, models based on machine learning and deep learning outperform the classic models.

Many machine-learning models show their ability to extract the features of traffic flow data. Castillo et al.(2008) built a Bayesian network to predict traffic flow, which considers the variability of OD pair flows, and other random characters. Sun et al.(2006) used a
Bayesian network to predict traffic flow. The model has two sparkles, (1) the model considers the adjacent road links and utilizes them to analyze the trends of the current link, and (2) the model solved the problem when the data is incomplete. Antoniou et al.(2013) proposed a probabilistic graphical model for the local traffic state estimation and prediction. Castro-Neto et al.(2009) introduced an SVR model for short-term traffic flow prediction. Cai et al.(2016) introduced an SVR model for short-term traffic flow prediction. Cai et al.(2016) proposed an improved k-Nearest Neighbors (k-NN) model for short-term traffic multistep forecasting. The model, compared to the original k-NN model, uses a spatiotemporal state matrix to describe the traffic state of a road segment instead of only a time series. And a machine learning-based model, which consists of three models, is regression models, example-based models using Support Vector Machine (SVM), kernel-based models using k-NN, is proposed by Boukerche and Wang(2020). Smith and Demetsky(1994) compared the mapping model, i.e., the Backpropagation Neural Network (BPNN) with clustering model, i.e., k-NN, and the result is that the k-NN outperformed the BPNN in short-term traffic flow prediction task, and is easier to be understood. Rzeszótko and Nguyen(2012) applied a resilient propagation neural network to approximate the average velocity on any edge of a street graph. Allström et al.(2016) developed a model called CTM-v (cell transmission model using velocity as a state), using a neural network.

Note that, although machine learning has reached a high prediction accuracy in comparison to the classic models, there is still room for improvement when the available data are massive. Thus, with the development of deep learning, it is much more meaningful to conduct short-term passenger flow prediction with massive data. Deep learning, as a branch of machine learning, has received attention both industrial and academic up to now (Bengio 2009). For instance, Liu and Chen (2017)constructed a hybrid model called SAE-DNN, which combines stacked auto-coders with a deep neural network, to predict the passenger flow of four stations of bus rapid transit (BRT) in Xiamen. In 2015, LeCun et al.(2015) wrote a review of deep learning, mentioned that Recurrent Neural Network (RNN), one of the many models in deep learning, is quite suitable for tasks, who have sequential inputs, such as speech(Wang et al. 2002), text(Ilya Sutskever, 2011), and the abnormal detection(Qian and Lu 2021). Ma, et al.(2015) utilized the Restricted Boltzmann Machine and Recurrent Neural Network to construct a deep learning model for network congestion evolution prediction. Liu et al.(2019) proposed a deep learning-based architecture, called DeepPF, which uses both metro passenger flow data and other relevant information like environmental factors and fuses them for the prediction, because LSTM can deal with the variable-length sequences. The DeepPF model is developed with the Long Short-Term Memory (LSTM) method, which is one of the RNN models. Many researchers employ this method for the prediction task. For example, Zhang et al(2019) proposed a novel indicator called OD attraction degree for the origin-destination prediction and used the LSTM to prove the efficiency of the indicator. Yang et al.(2021) applied wavelet analysis to decompose the inbound passenger flow of the chosen subway station into several parts, and these parts are inputted into the LSTM model. The outputs of the model are reconstructed to form the predicted flow data. Lu et al.(2021) put forward
a hybrid model, i.e., ARIMA-LSTM, to predict the traffic flow. Theoretically, LSTM is much suitable for capturing temporal characters. However, when we aim to capture spatial characters, i.e., network-wide passenger flow prediction, the Convolutional Neural Network (CNN) shows its ability to obtain the spatial character in data. Zhang et al. (2021) put forward a CNN-based model called CAS-CNN, which consists of many parts, i.e., the channel-wise attention mechanism and split CNN. The CAS-CNN shows its efficiency in short-term origin-destination flow prediction. Liu et al. (2020) proposed the Spatio-temporal ensemble net, which was based on CNN, to predict large-scale traffic state. The proposed method can combine multiple base models to improve the accuracy of the prediction task. Shi et al. (2015) first proposed a hyper model called Conv-LSTM, utilizing CNN and LSTM, for the precipitation nowcasting. The Conv-LSTM model shows its advantage in capturing both spatial and temporal features. Besides, Narmadha and Vijayakumar (2021) introduced a mixed model through utilizing CNN and LSTM, for spatiotemporal vehicle traffic flow prediction. As the residual network first proposed by He et al. (2016), it has been widely used in time series data prediction. Zhang et al. (2016) proposed a residual-network-based model called ST-ResNet for citywide crowd flows prediction. Zhang et al. (2021) proposed the ResLSTM, which consists of residual network, graph convolutional network, and LSTM. Li et al. (2022) put forward a novel model, called Graph-GAN, which is quite simple and have significant advantage in predicting short-term passenger flows of subway.

All the models in the aforementioned studies are called single-task learning, i.e., they are formulated for a specific task. Nevertheless, when the task is changed, the model might not be suitable for the new task, and a new one should be further developed. In the real world, we usually need to process multiple tasks that may have something in common, leading to the concept of multi-task learning.

Multi-task learning has been applied for prediction tasks in many fields and can be conducted based on many kinds of models, such as machine learning-based models or deep learning-based models. Liu et al. (2021) put forward a multi-task learning-based model to predict the multiple deterioration forms of the tool. Montieri et al. (2021) proposed a multitask deep learning model, using time series data, for a packet-level prediction task of mobile-app traffic. Besides, in the medical field, Warrier et al. (2022) investigate a novel multitask method based on RNN to predict bladder pressure. As for the traffic field, there are many prediction tasks of traffic based on multi-task learning. In terms of ground transportation, most studies use spatial and temporal features of roads to form two graphs, namely, the direct graph and the indirect graph, and many models are based on these graphs. Chen et al. (2020) proposed a GCN-based model to predict taxi demand for a traffic road network. Song et al. (2021) introduced a Multi-task Spatial-Temporal Graph Convolutional Network (MSTGCN). The model is slightly different from the aforementioned GCN-based model, in which the temporal and spatial features of the network were formed into a single graph, called a spatial-temporal graph, and using main task and secondary task are used to predict the idle time of taxi in a specific area.

Apart from two-graphs-based models, Zhang et al. (2020) proposed a novel GCN-
based model called Conv-GCN for the short-term passenger flow prediction task. Zhang et al. (2020) used the nonlinear Granger causality analysis and Bayesian optimization to process data. And an MTL model, which employed Gated Recurrent Unit (GRU), is developed to predict network-wide traffic speed. Huang et al. (2014) proposed a Deep Belief Networks (DBN) with multitask learning for traffic flow prediction. Besides these studies, forecasting the travel time of a trip is also a hot topic in the literature. In the real world when the origin and destination are fixed, the routes of the trip can be affected by many factors, and even if they are different, they take up a similar time to reach the destination. Li et al. (2018) proposed a multi-task representation learning model for arrival time estimation (MURAT), which first embeds the raw link information and spatiotemporal information and learns the features. Then with the learned features, other numerical features, namely the travel distance, the number of traffic lights, and turns, are joined together and inputted into the residual network to predict the travel time. Mena-Yedra et al. (2018) proposed a multitask learning approach for the short-term traffic prediction, which views the task from a perspective of data streams. Zhong et al. (2017) propose a multitask-learning-based model to predict the passenger flow for a city, which considers three traffic modes, namely, subway, taxi, and bus. In this paper, they regarded the summation of these three traffic modes as the total passenger flow of a region, and predict the total passenger flow of the region, which means they didn’t consider different traffic modes respectively.

The tasks of these aforementioned multitask-learning models are all about predicting a target area or the whole network, which also of processing massive information by multitasking learning.

Here, we need to mention that, although many researchers have applied multitask-learning models to the prediction of traffic flow or passenger flow, most of them still merely focus on a single-traffic model. As the multi-mode transit system is becoming a hot research topic in recent decades, it is worthy to consider different traffic modes together and fully extract the inner correlations of them, and then obtain a better prediction accuracy for each traffic mode.

### 3 Problem definition

In this section, the definition of the inbound passenger flow prediction task of multi-traffic modes is demonstrated.

Consider a region of a city, such as a residential area or a transportation junction, with three traffic modes, namely subway, bus, and taxi. The objective of this paper is to utilize the historical passenger flow of subway, taxi, and bus to learn the inner features of these three modes and accurately predict the inbound passenger flow of them in the following time slot in this region.

Let $S^\text{in}$, $B^\text{in}$, $T^\text{in}$ represent the time series of inbound passenger flow. Assume that the length of a time slot is $t$ minutes, e.g., 30 min. Then, a day can be divided into a total of $24 \times 60 / t$ time slots, and we only use the time slots in the prediction, which are within the service time of subway and bus. We use $s^\text{in}_t$, $b^\text{in}_t$, $t^\text{in}_t$ to denote the inbound passenger
flow of subway, bus, and taxi in the $t$-th time slot. Assume that the total length of previous time slots is $L$, and the short-term inbound passenger flow forecasting task aims to obtain a function $F(\cdot)$ that maps $L$ previous inbound passenger flows of the subway, bus and taxi to the inbound passenger flow of these three traffic means at time $t+1$, i.e.,

$$
\left[ s_{t-L+1}^{\text{in}}, s_{t-L}^{\text{in}}, \ldots, s_t^{\text{in}} ; b_{t-L+1}^{\text{in}}, b_{t-L}^{\text{in}}, \ldots, b_t^{\text{in}} ; t_{t-L+1}^{\text{in}}, t_{t-L}^{\text{in}}, \ldots, t_t^{\text{in}} \right] \xrightarrow{F(\cdot)} \left[ s_{t+1}^{\text{in}} ; b_{t+1}^{\text{in}} ; t_{t+1}^{\text{in}} \right]
$$

Clearly, the input of the function can be denoted as $X \in R^{3 \times L}$, and the output can be denoted as $Y \in R^{1 \times 1}$.

4 Methodology

In this section, we firstly introduce the architecture of the canonical transformer and explore the details of the multi-head attention mechanism. Then, the benefits of the residual network will be demonstrated. Finally, we elaborate on the details of the proposed model and introduce the framework overview.

4.1 Introduce of Transformer

Vaswani, A., et al. (2017) first proposed the transformer model and used two machine-translation tasks to prove its efficiency. The highlight of the original model is that this model is solely based on the multi-head attention mechanism which consists of several self-attention mechanisms.

The self-attention mechanism, also called scaled dot-product attention in the origin paper, can be regarded as a function, which maps three parameters, i.e., $Q$, $K$, and $V$ representing query, key, and value, to the output. In this paper, the input is not a sentence, but time-series data. Assume the length of historical time slots is $L$, and the time series data are from the aforementioned traffic modes, then the input can be denoted as $X \in R^{3 \times L}$. There are three weight matrices $W_Q \in R^{L \times d_Q}$, $W_V \in R^{L \times d_V}$, $W_K \in R^{L \times d_K}$, which are used to produce parameters $Q$, $K$, and $V$. For clarity, Figure 1 is given to show how to calculate $Q$, $K$, and $V$. 
Then, the self-attention function is defined as follows.

\[
\text{Attention}(Q,K,V) = \text{Softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V
\]

(1)

It is worth mentioning that, \(\text{Softmax}(QK^T/\sqrt{d_k}) \in R^{3 \times 3}\) represents the score matrix, where \(\sqrt{d_k}\) is used to scale the dot products, and \(\text{Softmax}(\cdot)\) is the activation function, which makes the sum up of all the rows of the matrix is 1. The score matrix, also a weight matrix, shows how the passenger flow data of each traffic mode affect the target passenger flow data. As shown in Figure 2, assume the output is \(P \in R^{3 \times 3}\), and the first row is \(P_1\) which represents the output of subway. In the score matrix, the lighter the color is, the less it affects the result. As we can see in the figure, the subway dominates the result \(P_1\), and compared to the bus, the taxi has a more significant impact on the subway passenger flow.

However, we need to say that, only one self-attention cannot fully mine the inner links among different traffic modes. If we gather many self-attention mechanisms to form a group, we can call it multi-head attention, in which different heads will pay attention to different features. For illustration, Figure 3 is given to show how the multi-head attention works. Assume the input’s shape is \(3 \times L\). The idea is to perform self-attention \(m\) times in...
parallel, where $m$ represents the number of self-attention layers we use, or we can call it the number of heads, which is a hyper-parameter. Then, we concatenate the results of different self-attention layers and feed them into a linear layer to transform the output shape into $3 \times L$.

![Diagram of multi-head attention](image)

Figure 3 Diagram of multi-head attention

To show the benefits of the multi-head attention mechanism, we use the XZM dataset to train the canonical transformer model and obtain the score matrices of different heads. Here, we set 8 heads. It is worth mentioning that every input corresponds to a group of score matrices, and we only select one group of score matrices for visualization (Figure 4). Accordingly, there are 8 matrices in total. Each matrix consists of 9 blocks, and each block indicates how the previous inbound passenger flow of one traffic mode impacts the future inbound passenger flow of the other. For example, the block of the first row and second column, subway-taxi block, means how the historical inbound passenger flow of taxi affect the future inbound passenger flow of the subway. Different heads take different attention. In the second and third heads, they seem like a crossing, which means the passenger flow of taxi has a majority impact on other traffic modes in the second and third heads. However, the sixth head, which also seems like a crossing, is in contrast to the second and third heads. The color of the taxi is lighter and has less impact compared to the subway and bus. A single head can only learn several features and cannot perfectly represent the whole picture. So, it is worth using multi-head mechanisms to learn the features inside the data.
Figure 4 Score matrixes of different heads

The aforementioned example shows the situation of one layer, however, just like a single head, a single multi-head attention layer can only get a small part of data, and we can set different layers to learn different features. As shown in Figure 5, we set 4 layers, and each layer has 2 heads. We check the score matrixes of different layers. The first head of different layers learns different information. Both layer 0 and layer 1 learn that the taxi has a great impact on the future passenger flow data of the subway on the first head. But, in layer 2 and layer 3, the situations are opposite, i.e., the subway and bus have more influence on the future inbound passenger flow of the subway. All heads of the four layers find that the previous passenger flow of taxis affects the bus data since the block of bus-taxi is at the middle level.

Figure 5 Score matrixes of different layers

4.2 Residual Network

Since the residual network was proposed (He et al. 2016), it has been widely used in many fields, like computer vision and time series prediction. As for the passenger flow prediction, an advanced model called ST-ResNet, fuse the passenger flow data and other factors like weather conditions, to predict the future passenger flow(Zhang et al. 2016). The architecture of the residual network is shown in Figure 6. The novelty of this architecture is that there is a shortcut, which prevents the degradation of the network. Besides, the short-cut value is summed up with the value of 2D convolution, then input into several fully connected layers.

As for the passenger flow prediction task of multi-traffic modes, the short-cut value is fused with the output of 2D convolution layers that contain the information and features of different traffic modes at different time slots. This process aims to enhance the information of each block of the input data, which helps the model to better obtain the inner correlations between different traffic modes. From this point of view, the short-cut will certainly improve the prediction accuracy.
4.3 Res-Transformer and framework overview

The Res-Transformer consists of two parts, modified transformer layers, and a shortcut. Transformer plays a vital role in the Res-Transformer model, because of its ability to extract the features of time series data. Li, S., et al. (2019) firstly changed the architecture of the transformer and used the modified transformer in the time series prediction. One of their contributions is that they proposed convolution self-attention, using convolution operation to produce the query, key instead of using linear layer. Enlightened by their work, in the Res-Transformer, we proposed the modified transformer layer, as shown in Figure 7. The input is divided into three parts to produce query, key, and value. The first part is fed into a conv-transformer layer, which uses convolutions to produce query, key, and value, namely Q, K and V. The convolution operation can do better in obtaining the information inside data, and sharing the parameters among different modes. As the input consists of three different traffic modes, the CNN-2D can learn the information of different traffic modes, and share the parameters. As the kernel slides the information matrix, it can learn the passenger flow at a certain time slot but come from different modes, and learn the correlation of them. Then, the output is taken as the query. The remaining parts are separately fed into different linear layers to produce the key and value, which is the same as the origin transformer model. After producing Q, K and V, they are inputted into multi-head attention layers, which consists of several self-attention layers.

There are N modified transformer layers, which is a hyperparameter. The output of the modified transformer layers is a matrix, in which each block stands for the information at a certain time of a certain traffic mode, and we can call it the information matrix. Then the information matrix is fed into several convolution layers. Since each block of the information has its meaning, the location of the block is critical for the result. Thus, it is suitable for the convolution layer to further learn the features between the blocks. There is a shortcut in Res-Transformer, just like a residual network. The short-cut sums up the origin input and processed information matrix, and we call it the information enhancing process. Then, we input the result into linear layers. The input consists of the passenger flows of three traffic modes, via parameters sharing and the fusing of origin data and information matrix, and the model can perfectly learn the historical information and predict the future inbound passenger flow of different traffic modes.
The framework overview of this paper is shown in Figure 8. The framework consists of three parts. The first is data preprocessing, which includes extracting the target data and fusing data to generate the input of the model. The origin passenger flow data of subway, taxi and bus at the selected region cannot be used directly. Since there are some missing data, we then sum up the ridership data which comes from the same day but different weeks, and get the average to fill these missing data. Besides, the original data have both weekdays and weekends, and the target data is the passenger flow on weekdays. So, we need to extract them from the data. Then, use a sliding window to form the dataset whose length is the previous time slots $L$. Also, to get the inner features of different traffic modes, the passenger flow data of these three modes need to be formed into a matrix to generate the input $P \in \mathbb{R}^{\text{batch} \times 3 \times L}$. Second, the training part. The processed data is put into the Res-Transformer network, which is a modified transformer network. The input of the network is a matrix $X \in \mathbb{R}^{3 \times L}$. It is firstly fed into a transformer network and then through some convolution network and summed up with the value, which comes from the shortcut and finally inputs in to fully connect layer to form the output $Y \in \mathbb{R}^{3 \times 1}$. After training the model, we use the test dataset to predict the inbound passenger flow data of the three
traffic modes and compare the performance of Res-Transformer with baseline models.

Figure 8 Framework overview

5 Evaluation

In this section, we firstly describe the datasets used in this paper. Then, the model configurations and evaluation metrics are represented. We conduct a series of experiments for hyperparameter tuning, to find the best performance of the proposed model. Also, the proposed model is compared with many benchmark models, namely, LSTM, CNN-1d, CNN-2d, ConvLSTM, Res-Net, Transformer. It is worth mentioning that the inputs of all these benchmark models are the same as the proposed model. Moreover, we analyze the results of the experiment, and then use the ablation analysis to validate the benefits of each part of the proposed model.

5.1 Datasets description

This set of experiments is conducted based on two regions of Beijing, namely Xizhimen (XZM) and Wangjing (WJ). In each region, the dataset consists of three parts, i.e., subway, taxi, and bus, and is collected from February 29 to April 1, 2016 (about a month). We only use the weekday data of the dataset and take into account the inbound passenger flow data. Since the service time of subway, taxi and bus are different, this study only selects passenger flow data ranging from 5:00 a.m. to 11:00 p.m., and time granularity is 30 min, i.e., there are 36 time slots a day.

**Subway passenger flow dataset.** It contains inbound and outbound ridership data of the selected region with different time granularity, such as 30min, which is obtained after processing the Automatic Fare Collection System (AFC) of the station. In this paper, we set time granularity as 30min and only consider the inbound passenger flow data of weekdays.

**Taxi passenger flow dataset.** We use the TaxiBJ dataset(Zhang et al. 2016) and extract the inbound flow data of the two selected regions, XZM and WJ. The period of the extracted data is ranging from February 29 to April 1, 2016, and only the weekday. More
details of the dataset are shown in Table 1.

| DataSet       | TaxiBJ          |
|---------------|-----------------|
| Location      | Beijing         |
| Time Span     | 7/1/2013 – 10/30/2013 |
|               | 3/1/2014 – 6/30/2014 |
|               | 3/1/2015 – 6/30/2015 |
|               | 11/1/2015 – 4/10/2016 |
| Time Granularity | 30min          |

To be more specific, we set the subway station as the center of the selected region, and then select a 3*3 area to be the drop-off area of the taxi. We use QGIS to obtain the target area. The obtained taxi areas of these selected regions, i.e., Xizhimen and Wangjing, are shown in Figure 9.

**Bus passenger flow dataset.** When the passengers take the bus as their way to travel,
they will swipe their IC cards when they get on and get off the bus. First, we collect the IC card data. Then we select the bus stations, which are within about 1,000 meters from the subway station in the selected region. Besides, we select the uptime and deal time, which is between 5:00 a.m. and 11:00 p.m. Lastly, we need to sum up the total passenger flow data of each chosen bus station to form the bus time series data.

Here, we briefly analyze these three types of time-series data. As shown in Figure 10 and Figure 11, in Beijing, the subway is the primary traffic mode that most passengers will select, and it has distinct peak and off-peak periods. Apparently, the inbound passenger flows of buses and subways have similar trends during workdays, as the peak of passenger flow occurs at almost the same time. However, if we check the peaks of the inbound passenger flow of taxis, there are slight delays compared to the peaks of bus and subway. Still, all of these three passenger flow patterns are similar, namely, they all have double peaks. Although the passenger flow pattern of the two regions is quite similar, it is apparent that in XZM, the passenger flow of all the traffic modes is much greater than that in WJ. To specify the features and gain the best results, we use max-min normalization to process the data of the two regions and map the data into the interval [0, 1].

![Figure 10 Inbound passenger flow data of subway, taxi, bus in XZM.](image-url)
5.2 Model configurations and evaluation metrics

Model configuration: In the experiments, we use PyTorch, a framework of deep learning based on Python, to implement our model, in which we use four modified transformer layers. In addition, two fully connected layers are taken into consideration after the modified transformer layers. The first layer has 128 neurons, and the neuron number of the second layer is the length of previous time slots, which is treated as a hyperparameter. Two convolution layers are involved, and the kernel size is 3 for both of them. In the first convolution layer, the input channel is 1 and the output channel is 8, and in the second layer, the input channel and output channel are both set as 8. We set 4 fully connected layers, and the neurons of them are 128, 64, 32 and 3, respectively. Some other hyperparameters also need to be considered, including $d_q$, $d_k$ and $d_v$ (e.g., length of previous time slots, number of heads in the modified transformer layers, and batch size). The tuning of hyperparameters is demonstrated in 5.3.

Evaluation Metrics: We use the root mean square error (RMSE), weighted mean absolute percentage error (WMAPE), and mean absolute error (MAE) to evaluate the performance of different models. The definitions of them are listed below.

\[ RMSE = \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - \hat{y}_i)^2} \]  
(2)

\[ WMAPE = \frac{1}{m} \sum_{i=1}^{m} \left\{ \frac{\hat{y}_i}{\sum_{j=1}^{m} y_j} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right\} \]  
(3)

\[ MAE = \frac{1}{m} \sum_{i=1}^{m} |y_i - \hat{y}_i| \]  
(4)
where $y_i$ is the predicted value, $\hat{y}_i$ is the ground truth, and $m$ is the total length of the input sequence.

In addition, the mean square error (MSE) is used as the loss function of each traffic mode. The loss function of the model is the sum-up of three traffic modes. The definition is given below.

$$loss = \sum_{j=1}^{3} \frac{1}{m} \sum_{i=1}^{m} (y_{ij} - \hat{y}_{ij})^2$$

where $y_{ij}$ and $\hat{y}_{ij}$ represent the predicted value and the ground truth of $j^{th}$ traffic model, and $m$ is the total length of the input sequence.

5.3 Hyperparameter tuning

There are some hyperparameters, namely the value of $d_q$, $d_k$, $d_v$, length of previous time slots, number of heads in the modified transformer layers, and batch size. For best performance, we set a section for the previous time slots, ranging from 5 to 15. The batch size is set as (2, 4, 8, 16, 32, 64, 128). As it is a time series prediction, which is quite different from the translation task, we thus set the parameters $d_q$, $d_k$, and $d_v$ as the same value, and the section is (4, 8, 12, 16, 20, 24, 28, 32). The heads of the two multi-head attention mechanisms in the modified transformer layer are also the same value, and we set the heads as indicated in [2, 10]. In the parameters tuning process, we use the rule of control variates, which means that only one parameter will be tuned and the remaining parameters are maintained unchanged in this process until we find the best result. For instance, firstly, we set a group of aforementioned parameters randomly, and then change the value of batch size, while other parameters stay the same. Once the optimal value of batch size is found, it will not be changed anymore. Afterwards, we tune the next parameter, until the four parameters are optimized and the performance of the model is the best. Next, we choose the dataset in XZM for tuning, and the tuning result is shown in Figure 12. We use the RMSE and MAE to evaluate the performance of different parameters, and according to the results, the value of $d_q$, $d_k$, and $d_v$, the length of previous time slots, the head number in the modified transformer layers and the batch size are set as 12, 12, 4, 4, respectively.
5.4 Baselines and proposed model

It is worth mentioning that, all the inputs of these models, including the Res-Transformer, are the same. Next, we shall introduce the state-of-art models and the proposed model.

**BPNN:** backpropagation neural network, which is a classic machine learning model consisting of several fully connected layers. We use three fully connected layers, and the neurons of them are 128, 32 and 3, respectively. The input is three dimensions, namely the batch size, the traffic mode, and the length of previous time slots.

**CNN-1D:** 1D convolution neural network. We apply a 1D convolution layer with 16 filters, 3×3 kernel size and two fully connected layers, and the numbers of neurons are 64 and 3, respectively. The three traffic modes are taken as 3 channels, and input into the CNN-1D network. The output is the inbound passenger flow of the three traffic modes at the next time slot.

**CNN-2D:** 2D convolution neural network. In the experiment, a general 2D convolution neural network with three fully connected layers is employed. It has only one layer inside the 2D convolution neural network, and inside the layer, the filter number is 8, and the kernel size is 3×3. The neurons of fully connected layers are 64, 32 and 3, respectively. In the 2D convolution neural network, three traffic modes are taken as a graph with only one channel, unlike CNN-1D.

**LSTM:** Long Short-Term Memory network, which is a kind of RNN and quite suitable for time series prediction, used by many researchers. We apply an LSTM model with three hidden layers, and there are 32 neurons in each layer. In the network, we consider four fully connected layers, whose neurons are 128, 64, 32, 3, respectively.

**ConvLSTM:** A hybrid model of CNN-2D and LSTM, was proposed by Shi et al.(2015) and perform well. In the experiment, a ConvLSTM model is applied, which consists of...
ConvLSTM and three fully connected layers. Inside the ConvLSTM, there are 3 ConvLSTM layers, and in each layer, the CNN-2D has 64 flitters and the kernel size is 3×3.

**ST-ResNet:** This model was proposed by Zhang, J., Y. Zheng, and D. Qi (Zhang et al. 2016). There are three branches in the original model, and we only use one branch of them in this experiment. There is only one residual unit and the output is fed into three fully connected layers. In the residual unit, two convolution layers are involved, and each has 8 flitters. The kernel size is 3×3 for both layers, and the number of neurons in fully connected layers are respectively 128, 64, 32 and 3. The input is the same as CNN-2D.

**Transformer:** We apply the canonical transformer in the experiment with only the encoder layer. In the transformer, a total of 6 layers are involved, and in each layer, we have 8 heads, and the values of $d_q$, $d_k$ and $d_v$ are all set as 32. The output of the transformer is inputted into 4 fully connected layers, and the numbers of neurons are 128, 64, 32 and 3, respectively. The input is the same as BPNN.

**Res-Transformer:** The proposed model in this paper. We use modified transformer layers and take advantage of the idea of the residual network. The model consists of 4 modified transformer layers, two 2D convolution layers, and several fully connected layers. The setting of the parameters are shown in 5.3. The input is the same as BPNN and Transformer. The output is the inbound passenger flow of three traffic modes at the next time slot.

### 5.5 Experiment results and analyses

We use the dataset of two selected regions XZM and WJ, and the results are shown in Table 2 and Table 3. According to Table 2 and Table 3, the Res-Transformer outperforms the baseline models in both datasets.

BPNN is the worst among the models in the two datasets. That is because when it comes to multi-modes prediction, every traffic mode has its features. The BPNN cannot efficiently identify them but regard them as the same. Thus, this method can only capture limited temporal features, and the inner correlation between different traffic modes is missing, which shows that it is not appropriate to use only fully connected layers. In comparison, the CNN-1D outperforms the BPNN. Also, although it can identify the different traffic modes, the temporal features learned by this model are limited. As the LSTM has the ability to capture the temporal features, the performance of LSTM is slighter better than that of CNN-1D. However, the result is yet not so good, which means it is not sufficient to capture the temporal features only. It can be observed, the ConvLSTM, which is a complex model and takes the advantage of both LSTM and CNN-2D, shows its ability in predicting the passenger flow of different modes more precisely than the former models. In addition, another complex model, i.e., the ST-Resnet, achieves better results than the ConvLSTM, which means that the LSTM is not suitable for this task, and the CNN-2D is the major factor that improves the performance of the model. In fact, the three traffic modes are regarded as one graph, the parameters are shared among different modes, which can fully learn the inner features of different modes. The learned features help the model to fully understand how the passenger flow change whichever the mode is. There is a real
pattern hidden in the three modes, and the CNN-2D can learn and find the hidden pattern. As shown in the table, if only CNN-2D is used, this simple model outperforms the ST-Resnet, which further proves that CNN-2D is the key for the multi-mode passenger flow prediction. In addition, the Transformer outperforms the CNN-2D, thanks to its multi-head attention mechanism.

As shown in the tables, the vital factor to predict the passenger flow of multi-traffic modes is sharing the parameters among three traffic modes, in which the CNN-2D and Transformer are qualified. So, the Res-Transformer model takes advantage of the CNN-2D and transformer, and the idea of the residual network, which has the best performance in comparison to the state-of-art model. Since the Res-Transformer can obtain the real pattern within the three modes, it has strong robustness in the existing models and shows promising results in both datasets.

The prediction results of Res-Transformer are shown in Figure 13 and Figure 14.

![Figure 13 Prediction results in XZM dataset](image)
As for RMSE for all traffic modes, our proposed model has significant improvements compared to the transformer, which is the best in the existing models. Specifically, the improvements are 14.33% in the dataset of XZM and 8.81% in the dataset of WJ. In terms of MAE, the improvements are 15.92% in the dataset of XZM and 22.22% in the dataset of WJ. As for WMAPE, the improvements are 16.12% in the dataset of XZM and 23.35% in the dataset of WJ, respectively.
### Table 2 Model performance comparison of subway, bus, taxi in XZM

| XZM     | Subway  | Taxi     | Bus     | ALL      |
|---------|---------|----------|---------|----------|
|         | RMSE    | MAE      | WMAPE   | RMSE     | MAE      | WMAPE   | RMSE     | MAE      | WMAPE   |
| BPNN    | 409.51  | 302.02   | 16.39%  | 249.93   | 202.28   | 8.79%   | 167.40   | 129.59   | 12.70%  |
| CNN-1D  | 404.32  | 279.94   | 15.19%  | 245.16   | 197.88   | 8.60%   | 181.55   | 137.29   | 13.45%  |
| LSTM    | 328.56  | 228.89   | 12.52%  | 291.32   | 232.62   | 10.10%  | 187.25   | 143.76   | 14.09%  |
| ConvLSTM | 347.28  | 282.49   | 15.44%  | 276.98   | 238.57   | 10.37%  | 148.90   | 115.66   | 11.33%  |
| ST-ResNet | 350.23  | 244.56   | 13.39%  | 221.54   | 181.80   | 7.90%   | 136.39   | 96.19    | 9.43%   |
| CNN-2D  | 321.01  | 250.04   | 13.58%  | 257.84   | 210.67   | 9.15%   | 138.28   | 104.02   | 10.19%  |
| Transformer | 286.89  | 215.36   | 11.78%  | 222.92   | 171.51   | 7.45%   | 143.81   | 111.62   | 10.94%  |
| Res-Trans | 251.57  | 183.69   | 10.00%  | 173.70   | 136.30   | 5.92%   | 136.30   | 99.13    | 9.71%   |

### Table 3 Model performance comparison of subway, bus, taxi in WJ

| WJ      | Subway  | Taxi     | Bus     | ALL      |
|---------|---------|----------|---------|----------|
|         | RMSE    | MAE      | WMAPE   | RMSE     | MAE      | WMAPE   | RMSE     | MAE      | WMAPE   |
| BPNN    | 337.58  | 213.99   | 24.18%  | 121.52   | 93.50    | 9.91%   | 29.90    | 24.10    | 18.35%  |
| CNN-1D  | 324.23  | 210.14   | 23.48%  | 112.72   | 87.62    | 9.28%   | 31.25    | 24.00    | 18.38%  |
| LSTM    | 303.77  | 213.60   | 24.31%  | 155.01   | 114.77   | 12.16%  | 31.84    | 25.59    | 19.63%  |
| ConvLSTM | 297.02  | 204.34   | 24.13%  | 122.42   | 97.09    | 10.29%  | 32.58    | 25.65    | 19.56%  |
| ST-ResNet | 271.73  | 189.02   | 21.33%  | 146.90   | 116.20   | 12.31%  | 29.26    | 23.89    | 18.25%  |
| CNN-2D  | 214.34  | 161.13   | 18.41%  | 141.89   | 115.31   | 12.22%  | 32.83    | 25.74    | 19.64%  |
| Transformer | 207.45  | 158.00   | 18.67%  | 131.21   | 103.70   | 10.99%  | 29.14    | 22.96    | 17.60%  |
| Res-Trans | 196.50  | 113.42   | 13.01%  | 106.75   | 85.54    | 9.06%   | 28.29    | 22.48    | 17.25%  |
5.6 Ablation Analysis

In this section, in order to further verify the effectiveness of Res-Transformer, we use the dataset of XZM in the experiments. We change the architecture of the Res-Transformer by using the rule of control variates and form 5 different models given below. We use RMSE, MAE, WMAPE as the evaluation metrics, and the result is shown in Table 4.

**Res-Transformer (A):** We use a fully connected layer to obtain $Q$ instead of the 2D convolution operation in a modified transformer layer.

**Res-Transformer (B):** We only use the modified transformer layer and fully connected layers, remove the other parts.

**Res-Transformer (C):** We remove the 2D convolution layers.

**Res-Transformer (D):** We remove the short-cut.

**Res-Transformer (E):** We use the origin transformer layers instead of the modified transformer layers.

**Res-Transformer:** The proposed model.

In Table 4, Res-Transformer (A) and Res-Transformer (C) are the models without the 2D convolution. In the results, the RMSEs of these two cases is much higher than the Res-Transformer, i.e., up to 67.11% and 40.63%, respectively, which shows the importance of the 2D convolution. It is obvious that the 2D convolution inside the modified transformer layers which is used to produce the query is the most important among all the components. The convolution operation can fully mine the passenger flow data of different traffic modes and learn their features.

As it can be observed in the table, Res-Transformer (B) with modified transformer layers cannot work alone, and the RMSE, MAE and WMAPE increase respectively about 62.86%, 66.72% and 66.75%, which means that the output of the modified transformer layers, namely the information matrix that contains the features of the three traffic modes, cannot be fed into the fully connected layers directly. Thus, the features need to be further extracted by the 2D convolution layers and fused with the data of the shortcut. If we drop the shortcut, the Res-Transformer (D) performed slightly worse than the proposed model. Compared to the aforementioned three models, the RMSE, MAE and WMAPE increase about 22.08%, 28.36% and 28.69%, respectively.

The Res-Transformer (E), which uses the origin transformer layer instead of the modified transformer layer, shows the best performance among the aforementioned models. Compared to the transformer performance in Table 2, if we use the architecture of the Res-Transformer with transformer layers instead of modified transformer layers, the prediction accuracy is better in all traffic mode, which proves the effectiveness of the proposed architecture. However, the Res-Transformer still outperforms Res-Transformer (E), and the RMSE, MAE, and WMAPE decrease about 8.97%, 10.38% and 9.61% compared to our proposed model.
Table 4 Ablation analysis results of subway, taxi, bus in XZM

| XZM       | Subway | Taxi          | Bus         | ALL          |
|-----------|--------|---------------|-------------|--------------|
|           | RMSE   | MAE           | WMAPE       | RMSE         | MAE           | WMAPE       | RMSE         | MAE           | WMAPE       |
| Res-Trans(A) | 498.00 | 408.86        | 22.08%      | 213.10       | 175.38        | 7.62%        | 139.58       | 113.36        | 11.11%      |
| Res-Trans(B) | 406.81 | 306.23        | 16.68%      | 318.63       | 259.69        | 11.28%       | 173.59       | 132.86        | 13.02%      |
| Res-Trans(C) | 364.49 | 286.48        | 15.69%      | 225.04       | 176.20        | 7.66%        | 195.15       | 149.87        | 14.69%      |
| Res-Trans(D) | 280.11 | 215.34        | 11.80%      | 251.72       | 217.83        | 9.46%        | 141.44       | 104.81        | 10.27%      |
| Res-Trans(E) | 280.42 | 202.43        | 11.09%      | 185.93       | 149.65        | 6.50%        | 140.80       | 110.46        | 10.82%      |
| Res-Trans   | 251.57 | 183.69        | 10.00%      | 173.70       | 136.30        | 5.92%        | 136.30       | 99.13         | 9.71%       |
6 Conclusion and future work

This study proposed a novel multitask-learning architecture called Res-Transformer, which can accurately predict the future inbound passenger flow of multi-traffic modes. The Res-Transformer is composed of modified transformer layers and a residual network. The main conclusions can be summarized as follows.

- The Res-Transformer has significant advantages to obtain the inner correlations and the temporal features of the passenger flow of the selected traffic modes (subway, taxi, and bus). The proposed conv-transofrmer layer is effective enough to integrate the features of multi-traffic modes.

- According to the performance of the Res-Transformer and state-of-the-art models, the LSTM shows weakness in the situation of multi-traffic modes, and the transformer and 2D CNN are much more suitable for the multi-traffic modes passenger flow prediction.

- The results tested on two large-scale real-world datasets shows that the Res-Transformer has strong robustness and significant improvements compared to the best existing models, the RMSE, MAE and WMAPE improves 14.34%, 15.92% and 16.11% in the XZM dataset and 8.81%, 22.22% and 23.35% in the WJ dataset.

However, there are some limitations in this study. First, we only consider subway, taxi, and bus in this paper, but there are many other traffic modes to choose from apart from these three modes. Second, this study only considers two typical regions but does not consider the whole traffic network, for example, the whole city. Besides, it is well known that the weather conditions will affect the passenger’s choices of travel to a certain degree, but we do not consider this in our study. Also, the inbound passenger flow we select is from weekday, but do not take the weekend’s data into account, since there are significant randomness and the travel purposes are uncertain, and there are not clear passenger flow patterns, which have a significant influence on the learning process of the model and affect the prediction accuracy. Therefore, for further studies, researchers can overcome these deficiencies.

Conflicts of Interest

The authors declare no conflict of interest.

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