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Short-Term Passenger Flow Prediction for Urban Rail Transit Based on Machine Learning

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Abstract: Short-term demand forecasting, often defined as less than an hour into the future, is critical to implementing dynamic control strategies and providing useful customer information in transportation applications. By understanding expected demand, bus operators can deploy real-time control strategies before demand surges and minimize the impact of anomalies on service quality and passenger experience. One of the most useful applications of traffic demand forecasting models is to predict congestion and vehicle congestion at station platforms.This paper explores the integration of machine learning into urban rail transit systems to enhance efficiency, reliability, and sustainability. By leveraging machine learning paradigms, the paper examines how advanced data analytics can revolutionize passenger flow prediction, train operations, maintenance strategies, and system optimization. Ultimately, the goal is to propel urban rail transit into a new era of intelligent and resilient transportation, contributing to sustainable and livable cities.

Keywords: Urban Rail Transit, Machine Learning, Passenger Flow Prediction, CNN, LSTM.

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1 Introduction

Urban rail transit systems have risen as vital arteries of contemporary urban life, embodying unparalleled convenience, efficiency, and environmental sustainability. Despite their pivotal role in modern transportation networks, many of these systems operate with outdated methods and suboptimal intelligence. However, the wealth of data they generate presents a ripe opportunity for enhancement. [1-2] Enter machine learning, a powerful tool for extracting insights from vast datasets, poised to transform urban rail transit.As cities burgeon and transportation demands escalate, urban rail systems face a pressing need to evolve. In contrast to private vehicles, urban rail transit offers significant advantages, including reduced energy consumption, congestion mitigation, and environmental benefits.

Therefore, this paper comprehensively explores the integration of machine learning into urban rail transit systems [3]. By leveraging the power of machine learning, we aim to address the challenges faced by urban rail systems and unlock new opportunities for enhancing their efficiency, reliability, and sustainability. Through a detailed examination of machine learning paradigms and their application in various aspects of urban rail transit, we seek to provide insights into how advanced data analytics can revolutionize passenger flow prediction, train operations, maintenance strategies, and overall system optimization. Ultimately, our goal is to harness the potential of machine learning to propel urban rail transit into a new era of intelligent and resilient transportation, contributing to the realization of sustainable and livable cities for future generations.

2 Related Word

2.1 Artificial intelligence and Traffic management

Traditional traffic light controls are often fixed time intervals that cannot be adjusted according to real-time traffic conditions. After the introduction of artificial intelligence technology, the duration and phase of the signal light can be dynamically adjusted by analyzing traffic flow data and forecasting models, minimizing traffic congestion and queuing time. [4] The intelligent dispatching system can be established by establishing train running model and forecasting model, combining with real-time train location and passenger demand information. The system can adjust the train speed and departure interval according to the actual situation, improve the transportation efficiency and reduce the delay.

Urban rail transit system generates a lot of data, including train operation data, passenger flow data, station congestion data and so on [5]. These data provide a sufficient basis for the application of artificial intelligence. Through the analysis and mining of these data, the potential rules and trends can be revealed to provide scientific basis for traffic management decision-making.

Artificial intelligence technology has made great progress in recent years, especially in fields such as machine learning and deep learning. These technologies have been widely used in image recognition, natural language processing, prediction model and so on to provide a powerful tool for urban rail transit management. For example, traffic violations can be monitored through image recognition technology, and passenger flow and congestion can be predicted through predictive models [6].

Artificial intelligence applications require large amounts of computing resources and storage space to process and analyze massive amounts of data. With the development of cloud computing and big data technology, urban rail transit systems can utilize cloud platforms and distributed storage systems to support the deployment and operation of AI applications. In addition, with the popularization of Internet of Things technology, urban rail transit systems can obtain more real-time data by connecting various sensor devices, providing more accurate input for artificial intelligence applications.

2.2 Application of artificial intelligence in urban rail transit

2.2.1 Develop urban rail Internet of Things

The operation and management of urban rail is based on timeliness, sustainability and service social benefits. Urban rail accelerates integration in time through signal and communication to avoid the occurrence of information islands and build an integrated information management platform. A variety of key information, including communication, video surveillance, network monitoring, etc. can be integrated, analyzed, and output to realize the interconnection of everything and information guidance of urban rail facilities and equipment. Urban rail Internet of Things to achieve integrated applications, its internal formation of a relatively complete information path, can build external information contact points, in a modular form into the entire urban network.

2.2.2 Structure of intelligent security system of rail transit

According to the requirements of the [7]"Code", the intelligent security system of rail transit is independently set, and the video surveillance, intrusion alarm, access control, electronic patrol and security check system are deeply integrated. At the same time, the intelligent security system of rail transit can be deeply integrated with the comprehensive monitoring system, and can seamlessly share the data and information of the public broadcasting, environment and equipment management, fire alarm, platform door, passenger information, ticket sales and other systems in the comprehensive monitoring system, so that all relevant professional and equipment of urban rail transit can be integrated into a whole, according to different operation scenarios. [8] Different safety strategy prevention mechanisms should be applied to achieve efficient safety prevention decision support and linkage, improve the operation and management level of urban rail transit, increase the efficiency of rail transit safety prevention management, improve the service quality and service level of rail transit, and provide a comfortable riding environment for passengers. [9] The intelligent security system of rail transit and the comprehensive monitoring system can use two modes to achieve deep integration, and the two sides cooperate closely to jointly build the intelligent security operation scenario of urban rail transit.

2.2.3 Big data analysis of urban rail transit

Through the Internet application of passengers in rail travel and the development of the Internet of Things in urban rail itself, the collection of application data is realized, and then the traffic big data analysis is carried out. After the collection of traffic data, through precipitation, filtering and model processing analysis, the effective analysis conclusions of production and management are extracted [10-12]. For example, through the analysis of passenger portraits, passenger age, travel frequency, average travel time, ticket purchase method, etc., so as to further analyze the passenger flow characteristics of railway stations. The Internet of Things of rail transit makes the monitoring of facilities and equipment broad and fine, which can realize the full life cycle of rail transit facilities and equipment, reduce the frequency of maintenance and repair, and analyze and screen high-quality products and suppliers. Basic production data to provide analysis materials, big data analysis after production, management, timely detection of problems and hidden dangers, improve management efficiency, the formation of a benign, sustainable development of "Internet +" big data intelligent application.

2.2.4 The structure of the integrated monitoring system

While realizing the integration of some subsystems' center-level functions, the integrated monitoring system can also receive data from the station's comprehensive monitoring system to perform secondary processing operations on it, and then provide users with more abundant monitoring functions, including but not limited to statistical reports, center-level linkage, and program control. In the context of the increasingly urgent need for data and resource sharing, the central-level integrated monitoring system can also provide a highly stable and highly convenient data sharing transmission channel, docking with the network command center and the local dispatch center of the power supply bureau to provide data support [13-14]. Through multi-party cooperation, it can effectively ensure that urban rail transit has a high level of operation. In the field of urban rail transit engineering construction, the integrated monitoring system generally adopts a layered and distributed structure, but the operation needs of rail transit systems are different, so other architectures will be used in some cases.

2.3 Short-term passenger flow prediction by machine learning

At present, there are three commonly used models for short-term passenger flow prediction: (1) Traditional time series models, such as Moving Average (MA) Auto Regressive Integrated Moving Average, ARIMA, Kalman x Filter (KF), etc.; [15]Machine learning models, such as Suppont Vector Machine [16](SVM), Recurent NeuraNetwork (RNN),[17] Long Short-Temm Memory (Long short-temmmemory) LSTM[18], Convolutional Neural Networks (CNN), etc.; (3) Combined prediction model, that is, the combination of the above models. The traditional time series model uses mathematical statistics method to analyze the law of passenger flow with time, so as to establish a mathematical model for predicting the short-term passenger flow of railway stations. Bai Lijia uses ARIMA model to predict normal and abnormal urban rail passenger flow with high accuracy, especially when considering special factors such as holidays, which improves the model's adaptability and prediction accuracy. Chen Jianchung proposed an improved Kalman filter model based on BP neural network correction, which effectively solved the prediction error and divergence problems of the traditional algorithm, and improved the accuracy of short-term bus passenger flow prediction. The traditional model has the advantages of simple calculation and fast speed, but its accuracy will decline when predicting nonlinear passenger flow, and it cannot adapt to the needs of processing massive data. [19-21]Therefore, the prediction model based on machine learning method has become the mainstream. Based on LSTM model, Li Ruoyitian constructs a short-term OD prediction model under multi-factor conditions, which can effectively capture the OD characteristics and the overall characteristics of each period in the OD passenger flow distribution time series. Guan Enchenghe first analyzes the characteristics of various stations through two-step fuzzy clustering, and then predicts the passenger flow OD of Suzhou Metro by using Temporal ConvolutionaNetwork (TCN)[22]. Yang Jing et al., aiming at the passenger flow during the end of large-scale activities, proposed a passenger flow prediction model based on CNN. A single model usually has a good prediction performance only in the special period or for a certain type of feature data, while the combined prediction model can often get better prediction results by using multiple models and integrating features, and has gradually become an important research direction in time series prediction! Wang Qiuwen et al. proposed a Convolutional Long Short.Iemm Memory Network (ConvLSTM), a deep learning method that can take into account both multi-level temporal and spatial features. Zhang et al. proposed a combined model combining Residual Network (ResNet), Graph Convolutiona Network (GCN)[23] and short-duration memory network for prediction, taking into account the topological relationships among subway stations, weather conditions and air quality. Zhang Taocai proposed a short-term passenger flow prediction method of urban rail transit based on the TCN-LSTM model. The method uses TCN to extract passenger flow time series features and external multidimensional features as the input of LSTM, learns the time-short dependence of passenger flow and external influencing factors, and realizes the prediction of multiple scenarios such as regular days, holidays and different weather.

To sum up, the combined model combines the advantages of each basic model, and realizes functions more in line with its characteristics by designing the position of the basic model in the combined structure, which has high accuracy and applicability in all kinds of passenger flow prediction. [24] A combination model of CNN-LSTM is proposed to extract the characteristics of date type, exhibition activity and time series respectively through different modules of parallel structure, so as to predict the inbound passenger flow in short time.

3 Methodology

3.1 Prediction model CNN

CNN is mainly used to process data with grid structure such as images, but in passenger flow prediction, its convolution operation can capture local features in spatiotemporal data and further improve the prediction accuracy. The basic structure of CNN includes convolution layer, activation function, pooling layer and fully connected layer.

Convolution layer is the core part of CNN. For a given two-dimensional input convolution layer, the local features of the input data in the sliding window can be extracted by sliding convolution kernel on the input data. The convolution operation can be expressed as S = ∑ I.K(1) :

$$S_{i,j}=\sum_{u}\sum_{v}I_{i+u,j+v}K_{u,v} \quad (1)$$

Si Output of the convolution operation at position (i, j); lm for input data in location(i+u, j+v)The value at; K is the weight of the convolution kernel at position (u, v); w and v are positional parameters of the convolution kernel. The role of the activation function is to introduce nonlinearity so that the model can learn more complex patterns. ReLU(Rectified Linear Unit) is a common activation function with the following rectified linear unit for input x:

$$f(x)=\max(0,x) \quad (2)$$

The pooling layer reduces the data dimension by downsampling, reduces computation and prevents overfitting by retaining key information. The most common pooling operation is maximum pooling, which selects the maximum value from the output of the convolutional layer, which selects the maximum value for each local region, helping the model capture more prominent features. In the end, [25]CNNS usually have one or more fully connected layers, whose main function is to integrate the local features extracted by the previous convolution layer and pooling layer to form global features and convert them into the final output.

3.2 Prediction model LSTM

As a variant of RNN, LSTM is widely used to model time series data. The core of LSTM is the introduction of a gating mechanism composed of ForgetGate, Input Gate and Output Gate, which can selectively forget and save information, and then update the cell state C to the next unit (see Figure 1).

When the time step is t, the input of LSTM [26]cell unit is new data x, T-1 moment hidden state h, and cell state C. First, the forgetting gate generates activation values based on x and h to control which information needs to be forgotten from C; After that, the activation value is generated by the input gate. And candidate cell states, controlling what information can be saved to C.

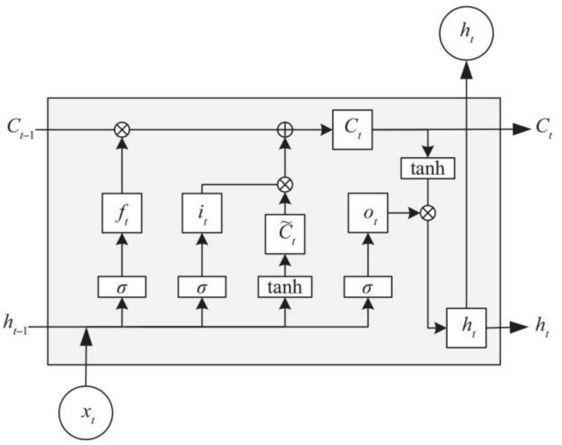

Figure 1 LSTM model structure

f_t, i_t, $\tilde{C}$ Update C_{t-1} to get the cell state of the current moment[27] C_t。Finally, the output gate generates activation value O_t, control C_t, which information can be output, and then get the output result h_t at time t. The calculation process is as follows:

$$
\begin{aligned}
&f_t=\sigma(W_f[h_{t-1}, x_t]+b_f)=\sigma(W_{fx}x_t+W_{fh}h_{t-1}+b_f)\\
&i_t=\sigma(W_i[h_{t-1}, x_t]+b_i=\sigma(W_{ix}x_t+W_{ih}h_{t-1}+b_i)\\
&\tilde{C}_t=\tanh(W_c[h_{t-1}, x_t]+b_c=\tanh(W_{cx}x_t+W_{ch}h_{t-1}+b_c)\\
&o_t=\sigma(W_o[h_{t-1}, x_t]+b_o=\sigma(W_{ox}x_t+W_{oh}h_{t-1}+b_o)\\
&C_t=f_t\odot C_{t-1}+i_t\odot\tilde{C}_t\\
&h_t=o_t\odot\tanh(C_t)
\end{aligned}
\tag{3}
$$

In the short-time prediction model of urban rail passenger flow based on CNNLSTM, CNN module extracts external features through convolution operation and LSTM module is responsible for identifying long-term dependencies in time series.

3.3 Data sets and processing

The experimental data in this paper are the track data of 2,330 taxis in [28-30]Wuhan City in 24 hours within 30 days from June 2014. The text fields include taxi ID, sampling time, latitude and longitude, instantaneous speed, driving direction, etc. The sampling frequency is about 40 s, and a total of 91 million track records are recorded. Firstly, the track data were pre-processed, such as anomaly cleaning, segmentation and road network matching, and then the road sections with relatively large track points were selected to form the road network sub-region as the research area. There were 34 road sections in this region, as shown in Figure 3 (blue and red sections).

Figure 2 The road network structure of study area

The 10 sections numbered 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10 (red sections) were selected as the predicted sections, and 34 sections in the study area were selected as the input sections, and the associated sequence information of the predicted sections were input into the model together with the predicted sections for prediction.

The traffic speed of the section is the average traveling speed of the road traffic flow, so we need to deal with the instantaneous speed. According to the sampling frequency and actual distribution of track data, 20 min is adopted as the time interval, and the length of the speed series of each road section is 3×24×30=2 160. After dividing all track points according to the section and time period, the average instantaneous speed of all track points in each period of each section is calculated as the observation value of the section speed.

3.4 Experimental results and discussion

Three indexes were used to evaluate the prediction accuracy of the model on the test set, namely, mean absolute error MAE, mean percentage error MAPE and root mean square error RMSE.

Table 1. Results of prediction model

		1	2	3	4	5	6	7	8	9	10
MAPE(%)	ARIMA	0.174 415	0.186 018	0.186 267	0.101 873	0.105 919	0.333 019	0.179 262	0.215 629	0.226 462	0.294 115
	SVR	0.122 94	0.186 21	0.174 588	0.095 04	0.083 649	0.291 231	0.153 884	0.177 793	0.146 078	0.199 428
	LSTM	0.123 341	0.185 205	0.178 587	0.091 339	0.083 14	0.309 701	0.164 754	0.178 555	0.155 299	0.213 448
	STC-LSTM	0.118 248	0.184 302	0.174 131	0.089 637	0.079 557	0.288 197	0.148 304	0.177 623	0.127 608	0.187 953
MAE(km/h)	ARIMA	1.703 871	1.475 822	1.610 481	1.190 976	1.189 787	1.568 572	1.181 699	1.385 517	1.845 964	2.112 547
	SVR	1.189 264	1.444 843	1.527 184	1.127 825	0.935 758	1.391 558	1.045 496	1.125 883	1.271 981	1.505 928
	LSTM	1.204 975	1.456 357	1.536 84	1.048 684	0.932 88	1.450 256	1.053 565	1.146 286	1.301 957	1.552 282
	STC-LSTM	1.165 199	1.441 613	1.503 392	1.030 819	0.895 358	1.394 284	1.029 284	1.141 031	1.108 162	1.426 691
RMSE	ARIMA	2.162 303	2.005 352	2.185 435	1.779 847	1.502 938	2.056 687	1.637 079	1.805 058	2.307 905	2.733 162
	SVR	1.584 039	1.981 086	2.043 665	1.664 957	1.211 74	1.844 249	1.413 053	1.499 043	1.587 335	1.952 814
	LSTM	1.607 577	1.987 435	2.072 115	1.642 533	1.216 565	1.913 39	1.433 284	1.519 68	1.653 663	2.040 773
	STC-LSTM	1.559 961	1.976 684	2.028 729	1.610 115	1.176 697	1.849 978	1.397 574	1.512 717	1.443 949	1.889 322

As can be seen from the results of speed prediction in Table 1, the prediction accuracy of the model of different road sections varies greatly, and the average percentage error can be as low as 8% or as high as 29%. This is because the traffic change mode of each road section is different, and there may be certain spatial heterogeneity, which makes the prediction effect of the model for different road sections different.

However, the MAPE of CNN-LSTM model is better than that of other models for all roads. The average MAPE and MAE of CNN-LSTM model predicted results was 15.76% and 1.2136 km/h respectively, which decreased by 1.07% and 0.054 km/h respectively compared with LSTM model. This shows that the weighted method of spatio-temporal correlation degree plays a role in speed prediction, and can reflect the spatio-temporal characteristics of traffic speed changes between sections to a certain extent.

However, the root-mean-square error of the [31]LSTM-based model fluctuates between 1.17 and 2.02, which indicates that the prediction speed has a certain deviation. Taking section 1, 2 and 3 as an example, combined with Figure 4, 5 and 6, it can be seen that the predicted speed value can reflect the general trend of speed change, but the real speed fluctuates greatly and frequently, which is difficult for the model proposed in this paper to simulate. On the one hand, there may be errors or anomalies in the true value record itself, which can not reflect the actual situation of the vehicle. On the other hand, this is also a common problem of most prediction models, because the randomness of high-frequency fluctuations is strong, and it is difficult to simulate by learning.

4 Conclusion

In conclusion, traffic speed fluctuates greatly with different time and road sections. Aiming at the traffic speed prediction problem, this paper constructs a LSTM model weighted by spatial-temporal correlation degree. This model excavates the variation characteristics of traffic speed in time and space, quantifies the correlation characteristics of traffic speed change in time and space through the correlation degree of space and time, and makes full use of the ability of LSTM model to learn long-term dependence law, and realizes the prediction of traffic speed. Compared with the common long short term memory network model, the LSTM model based on spatiotemporal correlation degree has achieved obvious accuracy improvement, which proves the effectiveness of the model.

The study demonstrates the potential of machine learning in transforming urban rail transit systems. By implementing models such as CNN and LSTM, significant improvements in short-term passenger flow prediction accuracy have been achieved. The CNN-LSTM model, in particular, weighted by spatial-temporal correlation degree, exhibits notable accuracy enhancements compared to traditional methods. These findings underscore the effectiveness of integrating machine learning into urban rail transit systems, paving the way for more efficient, reliable, and sustainable transportation networks in cities.

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Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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