Spatio-Temporal Hybrid Neural Network

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The prediction of crowd flow in key urban areas is an important basis for city informatization development and management. Timely understanding of crowd flow trends can provide cities with data support in epidemic prevention, public security management, and other aspects. The model uses the Node2Vec graph embedding algorithm combined with LSTM (NDV-LSTM) to predict crowd flow.

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1. Introduction

Urban big data constitute an important information resource for urban economic development. With the continuous development and progress of cities, urban data such as crowd flow, street grid, crowd trajectory, regional information, and weather features are quietly emerging. Urban data collection is an integral activity [1]. By mining and analyzing various types of data, urban computing describes the internal model of urban development and provides decision support for subsequent management and development of the city. The movement track of people produced by activities within the city shows different features in different types of areas, and there are different crowd flow rules [1]. At the same time, urban population distribution and population activities display a regular spatio-temporal dynamic evolution [2]. Population prediction in key urban areas has gradually become a research hotspot for scholars [3][4][5][6][7], which is of great significance and utility for urban epidemic and public security prevention and other emergency needs. Researchers believe that, in the future, applications based on trajectory data will become closely related to people's daily lives [8].

For the problem of predicting crowd flow, the performance of mathematical formulas is not as good as that of neural network models. This is because the size of crowd flow is influenced by various factors, such as weather features and holiday features, which can cause significant fluctuations. The neural network model can capture these features well. In the early stage, most researchers in the field of crowd flow prediction used statistical learning algorithms or neural network models to solve the problem of crowd flow prediction with complex features [9][10]. Subsequently, many researchers attempted to explore the law of population flow from various aspects to understand the features of crowd activity in different time ranges, such as trend, cycle law, spatial flow law, and other features that can be adopted and modeled by existing models [11]. With the regular division of urban grid regions, a large number of grid-based population flow data are generated correspondingly, providing a new analytical idea for the study of population flow prediction in key urban areas. Some researchers also use the historical dynamic movement trajectory of a population to learn the law of population flow and predict the future movement trajectory of the population [12]. Population flow data often have complex nonlinear correlation features

[13]. The generation and change of urban crowd flow data are directly related to human activities [14] and are also affected by complex factors such as weather, geographical location, and environment. However, the common time series model prediction method can only predict the time series of crowd flow, which lacks an exploration of regional spatial correlation, and the single model does not combine well with the spatial attributes of crowd flow. Conventional convolutional neural networks input regular grid partition when extracting spatial features, which does not take into account the flow relationship between grids well.

2. Spatio-Temporal Hybrid Neural Network

Recently it was proved that computational techniques, specifically machine learning, have numerous applications in all engineering fields. Azimirad et al. [15] proposed a consecutive hybrid spiking-convolutional (CHSC) neural controller by integrating convolutional neural networks (CNNs) and spiking neural networks (SNNs). Roshani et al. [16] proposed a system to measure both density and velocity of fluids simultaneously. Mozaffari et al. [17] proposed an equal and equitable federated learning (E2FL) to produce fair federated learning models by preserving two main fairness properties, equity and equality, concurrently.

The existing crowd flow prediction methods mainly include: a method based on historical crowd flow statistics, a prediction method based on spatial clustering, a prediction method based on a time series model, and a prediction method based on the neural network combination model.

The method based on historical crowd flow statistics can predict the result of crowd flow in the future by collecting historical data. The autoregressive comprehensive moving average (ARIMA) model [18] is a classic model based on statistical analysis. This model needs to present the time series information as linear correlation features and is not suitable for trend prediction with complex changes, such as the prediction of regional crowd flow. Aiming at the problem that the ARIMA model is affected by the residual and the results are unstable, Shen [19] proposed an improved residual model for short-term crowd flow prediction. Gui [20] proposed a density-based spatial clustering (DBSCAN) method with noise to identify hot spots in different time periods.

In recent years, the neural network-based crowd flow prediction method has made effective progress [21]. Ma et al. [22] mapped the crowd flow data into images for learning through convolutional neural networks and predicted the crowd flow speed within the scope of large-scale networks with high-precision spatio-temporal correlation. Zhang et al. [23] proposed a Deep-ST model, which uses convolutional neural networks (CNN) to rasterize the spatio-temporal data and models the distance dependence, time proximity, cycle, and trend of space. It also adds features such as weather and holidays to predict the urban crowd flow. Xie et al. [24] adopted the multi-scale sequential convolutional network to realize the re-calibration of short dependence and multi-scale temporal pattern features in the temporal data of human crowd flow. On the basis of the previous model, Zhang et al. [25] added a residual module and proposed a spatio-temporal residual network (ST-ResNet), replacing CNN module in the Deep-ST model with ResNet, so that the model can carry out convolutional mining of distant spatial correlation features.

Recently, many scholars have begun to shift their research perspective from multi-level spatial distribution of population [26] to population mobility. Most of the existing studies use national census data, and there is a lack of research on the population flow of urban areas, the relationship between regions, and the discovery of popular areas from the trajectory database [27]. Guo [28] proposed a spatio-temporal cyclic convolutional network (ASTRCNs) model based on the attention mechanism, taking into account various factors affecting regional population flow and conducting unified modeling. Xiong [29] proposed a DCGRu-RF (diffusion convolutional recurrent unit-random forest) model for short-term crowd flow prediction. Xiong firstly used the DCGRU network to learn the spatial correlation features of crowd flow data. Then, the RF model was selected as the predictor, and the nonlinear prediction model was formed and combined with the flow data to learn the timing features. Qiao et al. [30] proposed an adaptive trajectory prediction of moving objects in the case of big data. The model processed position density through massive moving object data, automatically selected parameters according to moving objects, and then output trajectory prediction results. The most existing studies use a single model to predict urban population data, which has achieved good prediction effect. However, due to the poor combination effect with the spatial attributes of crowd flow, there is a lack of comprehensive exploration of the regular features of crowd activities [31]. When extracting spatial features, the traditional convolutional neural network ignores the flow relationship between grids and poorly captures the information features in regional crowd flow data, with some shortcomings in efficiency. The region association digraph is built dynamically based on the crowd flow, and the flow relationship between the grids is considered. The spatial features of the graph and the time features of the crowd flow are extracted, and the Node2Vec algorithm is used to integrate various crowd flow data features such as urban area type, area area, weather, and holidays. The embedding of the region association digraph is more expressive, resulting in a higher quality sequence of graph nodes, so as to improve the accuracy of model prediction.

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