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Spatiotemporal Data Analysis of Urban Traffic Systems: Understanding Operational Patterns and Inferring Future States

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Abstract. Urban traffic flow data constitutes a complex dynamic system, exhibiting both temporal evolution and spatial dependence. In the context of high-density metropolitan areas such as the Greater Bay Area in China and the construction of emerging smart cities, extracting operational patterns from historical traffic observation data and inferring future traffic conditions has become a core issue in urban computing and intelligent transportation. This paper conducts a logic-oriented analysis of urban traffic spatiotemporal data. First, it examines three temporal evolution characteristics: periodicity, trend, and abrupt change. Then, it analyzes how road network topology affects the spatial dependence between road segments. Based on this, the paper explores the coupling mechanism between the temporal and spatial dimensions from the perspective of congestion propagation dynamics and extracts a logical framework for traffic condition prediction. This paper also discusses key challenges such as cross-regional multi-modal analysis, the integration of domain knowledge and data-driven methods, and the shift from open-loop prediction to closed-loop decision support, aiming to provide a structured analytical framework that contributes to understanding the intrinsic mechanisms of urban traffic system operation.

Keywords: urban traffic, spatiotemporal data analysis, traffic flow prediction, congestion propagation, smart city

1. Introduction

The first part of a new-era city is a good urban transport system. As the pace of urbanisation increases and more cars have been added to the cities, traffic congestion has gradually worsened to this extent. Traffic congestion around the world is now a serious problem that affects the lives of many people, and accurate forecasts of future traffic conditions are required [1]. In some highly integrated metropolitan areas and urban clusters, such as the Guangdong-Hong Kong-Macao Greater Bay Area in China, the demand for cross-city commuting and regional coordinated governance is even higher, and traffic management is thus more complicated. Given the above, Intelligent Transportation Systems (ITS) are now highly desired. At the base of intelligent transportation systems (ITS) is data-driven perception and analysis of traffic situations to forecast future traffic changes.

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Traffic flow data are not fixed cross-sectional observations, but continuous, dynamic streams of information that change over time in daily life. Urban road systems are affected by commuting patterns at different times of the day, holiday activities, emergencies, etc., and are therefore continuously varying in traffic flow. At the same time, some roads are close to each other in space. Thus, traffic flow data are spatiotemporal data. Spatio-temporal data contain both time-varying and space-correlated information, and are generally high-dimensional, nonlinear and complex dynamic systems [2].

Therefore, in light of the above, neither time-series nor spatial statistics can be used alone to analyse traffic data. Therefore, an all-encompassing analysis system is required to observe changes in time and space at the same time. As [3] pointed out in their review, urban spatiotemporal traffic flow prediction is influenced by many complex dynamic factors, such as changes in human activity patterns, weather, special events and holidays, etc.; therefore, all-encompassing studies from various angles have been carried out.

This paper will introduce the structure and reasons for change in this dynamic system, and then address the following problems:

RQ1: What identifiable and modelable patterns do the traffic flows show in time?

RQ2: How does the Spatial Structure affect the Correlation of Traffic States in Different Road Sections? How are temporal regularities and spatial dependencies combined in the phenomenon of congestion propagation?

RQ3: Based on the above regularities, what is the logical path of inference for future traffic states?

Systematically examine the problems mentioned above to provide a rational theoretical basis for analysing urban traffic spatiotemporal data in this paper.

2. Temporal evolution characteristics of urban traffic flow

The three characteristics of the temporary changes in urban traffic flow are introduced in this paper, and they are shown in Figure 1. The above will be presented in the following sections.

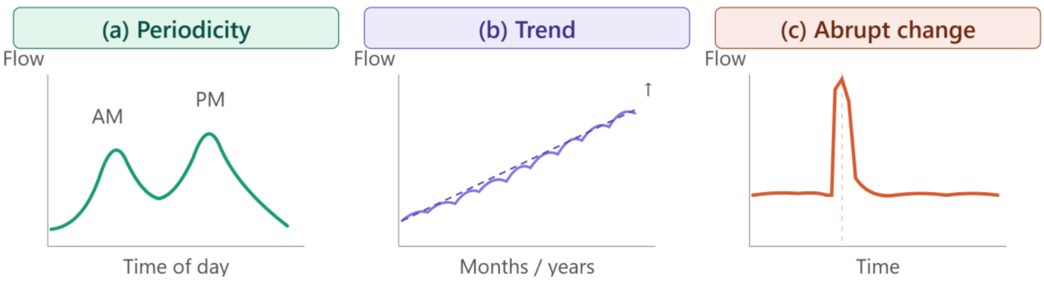

Figure 1. Temporal evolution characteristics: periodicity, trends, abrupt changes

2.1. Periodicity: structured periodic patterns

The traffic flow in the city exhibits a general regularity in time. There is a regularity in the organised periodic patterns of urban life and social rhythms. Traffic flow is a typical "bi-peak" in the peak hours of the day; that is to say, there are morning and evening peaks around 7:00-9:00 and 17:00-19:00 due to people's commuting needs. The above-mentioned intra-day periodicity is the result of the combined effects of urban functional zoning (spatial separation of residential and commercial areas) and fixed working hours. Behaviourally different sets of traits exist on weekdays and

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weekends at the same time each week. Weekday commuting flow is concentrated and directed; weekend travel is more dispersed, and peaks are generally delayed and reduced.

Li and others have found that at various time scales, the periodicity of traffic flow can be observed, and periodic changes in urban traffic conditions are often associated with daily life and work habits [4]. Additionally, it should be pointed out that a period is not fixed. Particular events or holidays will significantly change traffic patterns; for instance, a change in the number of people travelling for school or vacation, peak-hour travel during holidays, and localised reorganisation of traffic caused by large-scale sporting or cultural activities will all lead to a deviation from the normal cycle of traffic flow.

Cyclicity offers a basis for traffic forecasting in a logical way; that is, if the characteristic flow pattern of traffic at different time scales can be accurately described, a reasonable lower bound of traffic conditions at any future time can be obtained by fitting historical patterns. The above are the reasons that provide the foundation for many time-series forecasting methods.

2.2. Trends: systemic evolution at long-term scales

Traffic flow will be altered or distributed differently after a relatively long time. The above changes are due to the construction of a new urban transport system. Urbanisation has extended the commuting radius, a new subway line has been constructed to shift the mode of travel, and changes in travel demand due to alterations in population structure have all resulted in structural changes at the macro level. Based on the above analysis, the presence of a trend indicates that the transportation system is not stable, and consequently, the statistical regularity of historical data may gradually be lost over time. Therefore, forecasting methods that rely on the stability of past patterns may not be suitable here, and more adaptive models need to be developed due to the slow changes in the system.

2.3. Abrupt changes: the impact of non-periodic events

Other Disruptions in the urban transport system include traffic accidents, road construction, bad weather and other public security emergencies. The above events share the feature of being unpredictable in terms of both when and where they will occur, and they can lead to a sudden drop or rise in traffic at any time.

Emergencies are also a type of traffic forecast problem. These events are not regular and cannot be predicted by repeating patterns in the historical data; therefore, they are considered exogenous shocks to the time series and require the rapid incorporation of real-time data and anomaly detection for effective response. There are also sudden changes in the data, so time-series forecasting models are not suitable. Therefore, although there are detailed descriptions of the historical situation, the forecasting system still needs to account for changes in reality due to new circumstances in time.

3. Spatial dependence structure of urban traffic flow

3.1. Road network topology and traffic state transmission

The Road network in a city is divided into sections and is directed. Road segments in these networks are connected by intersections, ramps and other links at various levels. This network structure shows that traffic states also propagate along the network links; upstream congestion can cause overflow queuing in downstream road sections, and congestion on main roads may lead to diversion of traffic

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onto alternative routes [5]. Pointed out in their review that with the development of sensing technology, smart cities are generating a large amount of spatio-temporal data, and predicting the evolution pattern of this data requires considering the characteristics of the graph structure of the road network comprehensively. Theoretically, a graph model of a traffic network can be used to express the adjacency relationship, distance and functional connection among road sections formally, and thus provide a mathematical system for the analysis of spatial dependence.

3.2. Multiple sources of spatial associations

Road segment spatial associations occur via multiple mechanisms of spatial association.

First, there is the association of physical proximity: because the flow of vehicles is physically transmitted, directly connected road segments have the most direct state correlation. Second, there is the functional similarity association: road segments with the same function but not close in space, such as several parallel east-west arterial roads in a city, may have similar traffic patterns because they meet the same travel demands. Thirdly, there is an origin-destination (OD) association: at the city level, traffic flow can be viewed as a demand-satisfaction process for origin-destination pairs, and road segments with the same origin, destination or destination have implicit OD-based associations. Wang et al. studied the multimodal transport system in Shenzhen to find that the problems of urban traffic are caused by the spatiotemporal interaction of all kinds of transport, and this cross-modal interdependence exists at all levels, from micro-local areas to the whole city [6]. Fourth, there is a competitive substitution association: when a road is congested, drivers choose alternative routes and thus increase the traffic volume of the other routes, forming a negatively correlated dynamic association among functionally substitutable road segments.

The multiple sources of these spatial associations indicate that we need to learn the underlying functions and dynamic relationships from the data to better understand the spatially dependent structural associations of traffic states. As Huo et al. pointed out, the first spatiotemporal models based on graph neural networks required well-defined graph structures for information propagation and could not be directly applied to multivariate time series with unknown correlations.

4. Dynamic mechanisms from a spatiotemporal coupling perspective

The spread of urban traffic congestion is a typical case of spatiotemporal coupling mechanisms. Congestion at a particular location of a local road generally does not stay there; instead, it spreads along the road network and exhibits a full-cycle life cycle of emergence, expansion, peak and dissipation. Thus, congestion propagation is both a spatial feature (such as propagation paths and the range of impact) and a temporal process (such as duration and speed of change). Duan etal. provided some typical cases for this idea [7]. Based on all-weather urban traffic speed data, we have recorded the changes in traffic congestion across the entire network of bottlenecks and other problems. The results showed that the length of traffic congestion dissipation is roughly in a power-law distribution, and the rate of dissipation is generally about twice the growth rate. Research shows that even within the first 15 minutes of a traffic jam, the rate of expansion is related to the size of the maximum-length congestion; therefore, predictive information about the future development of traffic jams may be contained in the changes that occur early on.

Based on the above analysis, if one can obtain the actual speed and pattern of congestion at present, an estimated scope of the problem may be known in advance to plan timely countermeasures.

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Saberi and others presented a study in Nature Communications in 2020 that explored the inherent mechanism of traffic congestion spread via contagion dynamics [8]. Based on the epidemiological Susceptible-Infection-Recovery (SIR) model, a system has been established in this study to explore the spread and decline of traffic congestion in an urban network. Addressed the problem of congestion propagation and dissipation, introduced a model, and verified it with real data from six large cities around the world. The research indicates that the spread of congestion in networks has a certain system: when a road section is congested, it will "infect" neighbouring road sections at a certain rate and cause them to become congested; at the same time, already congested road sections will "recover" to a free-flowing state at a certain rate. The proportion of contagion and recovery mechanisms will affect the total congestion of the network. Ambühl et al. have extended the seepage theory and added a macroscopic fundamental graph to explain the phase transition behaviour of congestion propagation: when the congestion density in the network reaches a critical value, local congestion will suddenly become interconnected and eventually lead to the paralysis of the entire network [9].

The above research also reveals another problem: an asymmetry in the process of spatio-temporal coupling. Duan et al. found that the rate of congestion dissipation is generally about twice the rate of congestion growth; thus, the traffic system is not asymmetrical in terms of congestion formation and dissipation [7]. Asymmetry can be viewed from the perspective of physics as a lag effect in the traffic system; that is, even after the root cause of congestion has been addressed, the congested state may persist for some time due to vehicle queuing, driver inertia, and other factors.

Due to this asymmetry, a longer forecast window is needed for short-term traffic prediction to observe the dissipation of congestion accurately than the time when congestion occurs. Therefore, for traffic managers, the goal should be to prevent congestion rather than to handle it after it occurs; the time and cost of correcting traffic jams at that point will be far higher than the time and cost saved by preventing them beforehand.

5. Logical framework for urban traffic flow prediction

In short, the three components of this logic are: First, temporal pattern extraction: Identify the overlaid structure of periodic components, trend changes and short-term fluctuations in the historical time series, and provide a temporal basis for future state inference. Second, spatial correlation model: Using road network topology and data-driven correlation learning to explore the relationships among road segments, and thus predict a single road segment by integrating information from other connected road segments in the network. Third, Spatiotemporal Coupling Capture: Explore the joint occurrence of time-evolution and space-dependency in the analysis system to assist the model in tackling dynamic processes with simultaneous spatiotemporal fluctuations.

Based on the development history of research on traffic prediction, it can be observed that these studies have gradually become more elaborate and more extensive in scope. The first ways to predict traffic were based on the old time-series models of Autoregressive Moving Average (ARMA) and Kalman filtering. In short, the general idea of the above methods is to consider the traffic flow at a single road section as univariate time-series data and apply linear assumptions for forecasting future values. Although the above methods can identify periodicity and some short-term autocorrelation, they are limited by the assumption of linearity, unable to address the non-linear dynamics in traffic data, and ignore spatial dependencies among road segments [10]. Researchers then added the concept of space and jointly modelled traffic data from multiple road segments as multivariate time series. Therefore, a network-level prediction has been used instead of single-point prediction.

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Deep Learning Technology has provided a new method for traffic prediction in recent years. Wang et al. conducted a systematic review of the application of deep learning in spatiotemporal data mining in their IEEE TKDE paper, and pointed out that with the rapid increase in the quantity, volume and resolution of spatiotemporal data, traditional data mining methods have become inadequate, so deep learning models, with their strong ability to model nonlinear relationships and high-dimensional feature characteristics, have provided entirely new avenues for spatiotemporal data analysis [2].

6. Challenges and prospects

With the development of metropolitan areas such as the Greater Bay Area, the problems of traffic flow analysis in time and space are now complex and cross-administrative divisions and modes of transport. Intercity commuting includes many modes of transportation for different kinds of trips, such as highways, trains, water transport, etc., and their space-time distribution is more complicated than that in a single city. At present, the leading data-driven prediction methods are good at extracting statistical patterns from historical data but lack interpretability and generalisation ability. All the knowledge that has been accumulated in the field of traffic engineering so far, such as traffic flow theory, queuing theory and travel behaviour models, provide robust support and physical consistency guarantees for data-driven methods.

Given the final goal of urban traffic management, prediction may not be the end goal; instead, it can be used to inform the decision-making process for traffic regulation. A complete intelligent traffic analysis framework should itself contain a closed-loop structure of "perception- prediction - decision-execution-feedback". However, most of the current research on traffic forecasting still uses an open-loop model of "predicting future conditions based on historical data" and rarely considers how to translate the forecast results into control measures, or how these measures themselves can alter future traffic conditions. Therefore, the development of some generative artificial intelligence models or tools for traffic condition explanation and improvement-strategy-finding may be one of the main directions to be explored in the future [11].

7. Conclusion

Urban Transport Systems are large-scale dynamic systems that have both a time component and a space component. Systematically explore the periodicity, trend and sudden changes of traffic flow over time in this paper, as well as multi-source correlation structure and time-varying dependence in the spatial dimension. Based on the above analysis, this paper extracts the logical structure of traffic prediction tasks and identifies the current research challenges; thus, a reliable knowledge foundation and decision support for intelligent urban traffic governance are provided. With the rapid development of the metropolitan area in the Greater Bay Area, this study will directly and indirectly affect the actual results of the intelligent transportation system and the travel experience of urban residents.

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