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A brief review on missing traffic data imputation in intelligent transportation systems

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Highlights:

- Propose a systematic classification framework for imputation methods.
- Summarize commonly used datasets, missing patterns, and evaluation metrics.
- Compare performance of representative methods under a unified experimental setting.

Abstract: The development of Intelligent Transportation Systems (ITS) has been accompanied by rapid advancements in sensors, wireless communications, cloud computing, and data science, making a significant contribution to reducing traffic congestion, optimizing traffic flow, and promoting the construction of smart cities. However, in practical applications, due to reasons such as sensor malfunctions, software issues, or network connection interruptions, the collected traffic data often has missing values, which negatively impact subsequent traffic management and decision-making processes. Therefore, effective recovery of missing traffic data becomes critical. This paper reviews some methods for missing traffic data imputation that have emerged in recent years and provides a systematic classification and in-depth analysis of these approaches. The methods are primarily categorized into two types: structure-based methods and learning-based methods. Each approach has its unique advantages and limitations and is suitable for different patterns of missing data. Moreover, the paper discusses common patterns of missing data, public datasets, and performance evaluation metrics, providing researchers with references for choosing appropriate experimental resources. Finally, this paper points out the challenges currently faced and suggests future research directions to promote the development of traffic data imputation techniques.

Keywords: intelligent transportation systems; missing data imputation; tensor decomposition; low-rank tensor; deep learning

1. Introduction

Owing to the quick evolution of wireless communication, Internet of Vehicles (IoV), cloud computing, and artificial intelligence, significant progress has been made in the field of Intelligent Transportation Systems (ITS) [1]. With the help of technologies such as loop sensors, in-vehicle cameras, and smartphones, massive traffic information is collected, processed, and stored in distributed traffic information systems. This data is crucial for improving traffic efficiency, enhancing safety, optimizing services, and supporting the development of ITS [2,3].

However, in real-world scenarios, traffic data is often corrupted or incomplete due to issues such as sensor malfunctions, software failures, or network disconnections. For instance, fixed sensors exposed to outdoor environments for extended periods are susceptible to interference from weather conditions [4], which can reduce the accuracy of the collected data or cause data missing. Handheld GPS devices and in-vehicle sensors transmit data during vehicle movement. However, when the vehicle enters complex environments, transmission performance degradation and signal attenuation could bring about interruptions in data transfer, which can subsequently lead to data loss [5].

Incomplete traffic data can have an adverse impact on subsequent traffic management and decision-making processes [6]. To address the challenges posed by missing data, a variety of data imputation methods have been proposed. This paper systematically reviews recent studies in traffic data imputation, aiming to present the latest achievements and development trends, while also providing references and support for future studies.

We note that in the field of missing traffic data imputation, there have been several review studies [7–9], but their focuses differ significantly from this paper. For example, reference [7] systematically summarizes various missing data imputation methods proposed between 2006 and 2017, but does not cover the rapidly developing deep learning techniques in recent years. Reference [8] provides a detailed introduction of commonly applied missing data imputation methods in ITS, including prediction models, interpolation methods, and statistical learning approaches, yet it also lacks an in-depth discussion of deep learning-related techniques. Reference [9] reviews several common data completion techniques, such as low-rank representation and deep neural networks, summarizing the research advancements, advantages, disadvantages, and challenges, but does not systematically organize different missingness patterns in data, publicly available datasets, or commonly used performance evaluation metrics.

In order to address the aforementioned limitations, this paper constructs a conceptual classification framework that goes beyond specific technical terminology, providing a systematic review and categorization of missing traffic data imputation methods. Figure 1 presents a structural diagram of data imputation methods based on different technological classifications. The advantages, limitations, and future development trends of each category of methods are thoroughly analyzed in the paper. Additionally, this paper comprehensively discusses representative datasets and commonly used evaluation metrics. The main contributions are as follows:

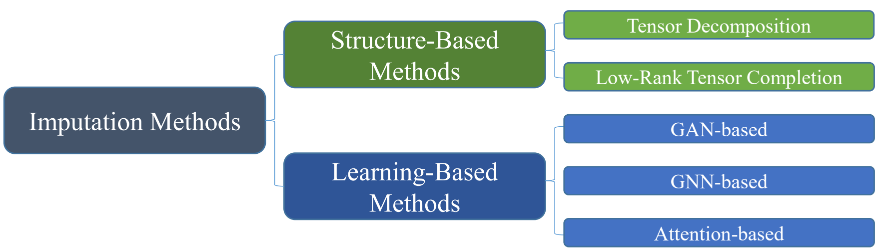

Figure 1. The classification diagram of imputation methods.

(1) We construct a conceptual classification framework that systematically categorizes existing methods for missing traffic data imputation.

(2) We summarize the data missing patterns, datasets, and evaluation metrics, providing references and benchmarks for future research.

(3) We analyze the imputation performance of several representative methods on a unified dataset, comprehensively demonstrating their differences under various missing rates.

(4) We discuss the major challenges and propose potential future research directions and development trends.

The rest of this paper is organized as follows: Section 2 summarizes missing data patterns, datasets, and model performance evaluation metrics. Section 3 summarizes structure-based traffic data imputation methods. Section 4 provides a classification of learning-based traffic data imputation methods. Section 5 evaluates the performance of some imputation methods and proposes a decision-making process to guide users in selecting appropriate methods. Section 6 discusses the challenges faced by current research and suggests future research directions.

2. Missing patterns, datasets, and performance metrics

In this section, we reviewed the missing data patterns in the transportation domain and provided a summary of public datasets, as well as the metrics for evaluating model performance.

2.1. Missing patterns

Through a study of current literature, we categorize the patterns of missing data into three types: Missing Completely at Random (MCAR), Missing at Random (MAR), and Missing Not at Random (MNAR).

MCAR. In this mode, the missing data occurs completely at random. In other words, whether a data point is missing does not depend on the values of any variables, including its own value or those of related or unrelated variables. MCAR is typically caused by external factors such as measurement device failure, errors in the data entry process, or oversights in data management procedures that are non-systematic in nature.

MAR. The missing of data is dependent on the observed data, meaning that the absence of data points is dictated by the other variables in the dataset that can be observed, rather than by those variables that are missing and unrecorded. For instance, in a dataset of traffic speeds, the occurrence of missing data could be influenced by factors such as time and location, yet it would not be contingent upon the actual speed values that are missing. This may result in missing data points that appear consecutively according to a certain pattern.

MNAR. The absence of data is linked to the values of the missing data points themselves or to unobserved variables. In other words, whether data is missing depends on the value of the missing data point itself, or it depends on the values of variables that are not included in the dataset. Due to this dependency, handling MNAR types of missing data is more complex and difficult.

2.2. Public datasets

For traffic data imputation, conducting comparative experiments on benchmark datasets can effectively evaluate model performance and enhance the persuasiveness of research findings. This paper compiles widely used datasets to provide a reference for future researchers so they can select appropriate data resources for the experiments. Further, we categorize these datasets into three major types: large-scale datasets, datasets with repetitiveness and volatility, and datasets with complex spatiotemporal characteristics. The specific information for each dataset is listed in Table 1, mainly including region, sampling time range, time resolution, and data type.

Table 1. Summary of public datasets.

	Dataset	Region	Duration	Time Resolution	Data Type
Large-scale Datasets	PeMS [10]	California	2011/6/1–2011/8/31	5 min	Speed/Volume/Occupancy
	PeMS-4W [11]	California	2018/1/1–2018/1/28	5 min	Speed
	PeMS-8W [11]	California	2018/1/1–2018/2/25	5 min	Speed
	Portland [12]	Portland	2021/1/1–2021/3/31	15 min	Speed/Volume/Occupancy
	Guangzhou [13]	Guangzhou	2016/8/1–2016/9/30	10 min	Speed
Repetitiveness and Volatility Datasets	METR-LA [14]	Los Angeles	2012/3/1–2013/6/30	5 min	Speed
	PeMS04 [15]	California	2018/1/1–2018/2/28	5 min	Speed/Volume/Occupancy
	PeMS08 [15]	California	2016/7/1–2016/8/31	5 min	Speed/Volume/Occupancy
	PeMS-BAY [16]	California	2017/1/1–2017/5/31	5 min	Speed/Volume/Occupancy
	Seattle [17]	Seattle	2015/1/1–2015/12/31	5 min	Speed
Complex Spatiotemporal Datasets	TaxiNYC [18]	New York	2009–now	60 min	Pick-up and drop-off times
	TaxiBJ [19]	Beijing	2013–2016	30 min	Inflow and outflow
	FHWA [20]	Los Angeles	2004–now	60 min	Location/speed/acceleration
	T-drive [21]	Beijing	2008/2/2–2008/2/8	177 s	Trajectory

Large-scale Datasets. They include PeMS [10], PeMS-4W [11], PeMS-8W [11], as well as Portland [12] and Guangzhou datasets [13]. These datasets aggregate millions of observation records collected by numerous sensors deployed across extensive road networks.

Repetitiveness and Volatility Datasets. They include METR-LA [14], PeMS04 [15], PeMS08 [15], PeMS-BAY [16], and Seattle datasets [17]. These datasets not only exhibit clear cyclical patterns, such as daily and weekly regularities, but also encompass significant intra-day traffic fluctuations and the impact of random events. This makes them highly suitable for testing how models perform in complex and dynamic data environments.

Complex Spatiotemporal Datasets. They include TaxiNYC [18], TaxiBJ [19], FHWA [20], and T-drive [21]. These are collected through sensors installed on moving vehicles, providing detailed records of the complex traffic flow in urban areas. Given that urban transportation systems are often subject to various unforeseen factors, such datasets are highly suitable for testing models' ability to handle complex spatiotemporal patterns, ensuring that the models remain efficient and accurate when faced with uncertainties and variations in the real world.

2.3. Evaluation metrics

For traffic data imputation, selecting appropriate performance evaluation metrics is crucial. Different evaluation metrics can reveal the strengths and limitations of a model from various perspectives. We have summarized several commonly used performance evaluation metrics, including Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Squared Error (RMSE). The definitions are as follows:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{1}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{2}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{3}$$

where y_i represents the observed value, $\hat{y}_i$ represents the predicted value, and n is the total number of observations.

3. Structure-based methods

Structural-based methods primarily rely on modeling the inherent structural characteristics of data to achieve effective imputation of missing values. In traffic data analysis, such methods often consider factors like the spatial adjacency relationships of road networks and the temporal evolution characteristics of traffic flow. These methods generally assume that high-dimensional traffic data possesses an underlying low-rank structure. Despite the high dimensionality and possible missing entries in the observed data, its core information can still be characterized by a set of low-dimensional, low-rank latent factors. Based on this assumption, structural-based approaches aim to recover these latent factors from the observed parts of the data by exploiting spatiotemporal correlations or network topological structures, and further use them to infer the missing values.

Representative methods include Tensor Decomposition and Low-Rank Tensor Completion (LRTC). Tensor decomposition aims to decompose the original high-dimensional tensor into several low-rank factor matrices or sub-tensors, thereby revealing the underlying structure and multi-dimensional interaction relationships across different dimensions of the data. On the other hand, LRTC does not depend on an explicit decomposition process but instead directly estimates the missing entries through optimization strategies while maintaining a low-rank approximation of the overall data. Both types of methods can achieve efficient and interpretable reconstruction of missing data while preserving key structural information. We present detailed information on several structure-based models in Table 2, including performance metrics and missing rates.

Table 2. Summary of structure-based methods for traffic data imputation.

		Methods	Performance Metrics	Missing Rate
Tensor Decomposition	CP Decomposition	BATF [22]	MAPE, RMSE	10%–50%
		BRCP [23]	MAPE, RMSE	10%–50%
		DFCP [24]	MAPE, RMSE	10%–50%
		BGCP [25]	MAPE, RMSE	10%–40%
	Tucker Decomposition	ITDI [26]	MAE, MAPE	5%–50%
		STRTD [27]	MAE, MAPE	30%–95%
		LATD [28]	MAE, MAPE	30%–97%
		LR-SETD [29]	MAE	1%–15%
		RTTC [30]	MAE, SMAPE	34%–77%
	TR Decomposition	LTRR-NLS [31]	MAE, MAPE, RMSE	10%–90%
		BTRD [32]	MAPE, RMSE	20%–60%
		TR-VBI [33]	MAPE, RMSE	20%–60%
		CoATR [34]	MAPE, RMSE	30%–95%
	Other Decompositions	BGCP [35]	MAPE, RMSE	10%–50%
		DMD-LRT [36]	MAPE, RMSE	10%–60%
		MTNTF [37]	MAE, MAPE, RMSE	10%–90%
		NT- DPTC [38]	MAE, RMSE	10%–95%
		FNNTEL [39]	MAPE, RMSE	10%–90%
Low-Rank Tensor Completion	Nonconvex Approximation Models	LRTC-TNN [42]	MAPE, RMSE	10%–70%
		LRTC-TSpN [43]	MAE, RMSE	10%–90%
		TC-PFNC [44]	MAPE, RMSE	20%–80%
		NWLRTC [45]	MAE, MAPE, RMSE	20%–80%
		LRTC-TMCP [46]	MAPE, RMSE	10%–90%
		SCPN [47]	MAPE, RMSE	20%–80%
	Temporal Correlation Models	LATC [12]	MAPE, RMSE	30%–90%
		TNN-HTV [48]	MAPE, RMSE	50%–90%
		LSTC-Tubal [11]	MAPE, RMSE	30%–70%
	Spatial Correlation Models	LRSSRTC [49]	RMSE	10%–50%
		LETC [50]	MAE, RMSE	30%–70%
	Spatiotemporal Coupling Models	CNLRTC [51]	MAE, MAPE, RMSE	10%–50%
		ST-LRTC [52]	MAPE, RMSE	10%–90%
		CJSR [53]	MAPE, RMSE	10%–50%

3.1. Tensor decomposition

(1) CANDECOMP/PARAFAC Decomposition

Tensor completion based on CANDECOMP/PARAFAC (CP) decomposition factorizes a high-dimensional tensor into a sum of rank-1 tensors, filling missing values through low-rank approximation to uncover latent data structures. Figure 2 illustrates the schematic diagram of CP decomposition.

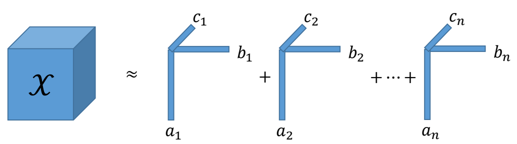

Figure 2. The architecture of tensor CP decomposition.

Chen *et al.* [22] proposed Bayesian Augmented Tensor Factorization (BATF) model, which adopts a fully Bayesian framework and uses variational Bayesian methods to automatically learn parameters. Zhu *et al.* [23] proposed Bayesian Robust CP Decomposition (BRCP) model, which captures both global and local information by combining low-rank tensors with sparse tensors. Xing *et al.* [24] proposed Data Fusion CANDECOMP/PARAFAC (DFCP) model, which integrates vehicle license plate recognition (LPR) and cell phone location (CL) data. The model uses four-dimensional low-rank tensor decomposition to combine information from different road segments, times, days, and data types, achieving more accurate data reconstruction. To address various interferences existing in different data dimensions, the model introduces regularization penalty coefficients. Qi *et al.* [25] proposed the Bayesian Gaussian CANDECOMP/PARAFAC model (BGCP), which leverages spatiotemporal correlations and road functional attributes to impute missing speed data through iterative random variables and CP decomposition.

(2) Tucker decomposition

Tucker decomposition can factorize a tensor into a core tensor and corresponding factor matrices. This approach is effective in restoring data integrity and is particularly suitable for multi-dimensional data recovery.

Lu *et al.* [26] proposed Improved Tucker Decomposition-based Imputation (ITDI) model by introducing an adaptive rank calculation algorithm and enhancing the objective function. Gong *et al.* [27] proposed the Spatiotemporal Regularized Tucker Decomposition (STRTD) model that combines Tucker decomposition with manifold regularization and temporal constraints. Unlike many traditional matrix- or tensor-based methods, STRTD does not require a predefined tensor rank, but instead optimizes the objective function using an alternating proximal gradient method. Lu *et al.* [28] proposed the Low-Rank Autoregressive Tucker Decomposition (LATD) model that integrates Tucker decomposition with an autoregressive model to better capture both long-term trends and short-term patterns in traffic data. In addition, the model introduces difference operations to enhance the interpretability of spatiotemporal correlations. Pan *et al.* [29] proposed the Low-Rank and Sparse Enhanced Tucker Decomposition (LR-SETD) model that leverages the low-rank property of factor matrices and the sparsity of the core tensor to preserve the intrinsic characteristics of the original dataset, such as periodicity and correlation. Lyu *et al.* [30] proposed the Robust Tucker Decomposition Tensor Completion (RTTC) model that integrates tensor decomposition with rank minimization techniques. RTTC also incorporates a time series decomposition method to account for trends, spatio-temporal correlations, and outliers.

(3) Tensor ring decomposition

Tensor ring (TR) decomposition can factorize a high-order tensor into a sequence of low-rank third-order factor tensors, connected in a ring-like structure. This approach efficiently captures and represents the global structure of the data.

Wu *et al.* [31] proposed a spatiotemporal traffic data imputation method named LTRR-NLS, which utilizes tensor ring decomposition and incorporates a Nonlocal Self-Similarity (NSS) prior. Liu *et al.* [32] proposed Bayesian Tensor Ring Decomposition (BTRD) that leverages TR decomposition to capture global information in the data and can automatically determine the TR rank. Liu *et al.* [33] proposed Tensor Ring Variational Bayesian Inference (TR-VBI) that automatically determines the TR rank by imposing sparsity-inducing hierarchical priors on the core factors. Liao *et al.* [34] proposed Convolutional Autoregressive Tensor-Ring (CoATR) that can capture the global low-rank structure of the data through TR decomposition and employ multi-layer convolutional networks to model complex nonlinear features.

(4) Other decompositions

Chen *et al.* [35] proposed Bayesian Gaussian CANDECOMP/PARAFAC (BGCP) that derives posterior distributions by setting conjugate priors and develops an efficient Markov Chain Monte Carlo (MCMC) algorithm for parameter estimation. Zhang *et al.* [36] proposed Decomposition-based

Low-Rank Tensor (DMD-LRT), which utilizes Dynamic Mode Decomposition (DMD) to extract dynamic features from traffic data tensors, and incorporates low-rank constraints and a temporal regularization term. Zhu *et al.* [37] proposed Multi-Task Neural Tensor Factorization (MTNTF) to reveal nonlinear correlation patterns between speed and flow. Chen *et al.* [38] proposed the Non-negative Temporal Dynamic Programming Tensor Completion (NT-DPTC) model, which introduces a temporal regularization module to constrain local imputation values. Zhang *et al.* [39] proposed a Fuzzy Neural Network (FNN)-based tensor heterogeneous ensemble learning method, named FNNTEL. FNNTEL constructs multiple base learners using different tensor decomposition algorithms and dynamically weights and fuses them through an optimization algorithm to form the final imputation model.

Overall, tensor decomposition methods have demonstrated strong modeling capabilities and good imputation performance in addressing missing data problems in traffic analysis. They are effective at uncovering hidden spatiotemporal correlations within traffic data. By constructing high-order tensors that integrate multi-dimensional information such as time, space, and traffic conditions, and leveraging low-rank approximation to reconstruct the missing parts, these methods can effectively restore data integrity. They are applicable to a variety of missing data scenarios and exhibit robustness and interpretability.

However, these methods also have certain limitations. For instance, tensor decomposition methods typically require predefined parameters, and the stability and convergence of the algorithm can be significantly affected by these initialization parameters. Moreover, when dealing with large-scale datasets, the computational efficiency and performance of tensor decomposition methods may decline considerably as the data volume increases [40]. In cases where the missing rate is extremely high or the missing patterns are complex, relying solely on the low-rank assumption may not yield satisfactory imputation accuracy. Therefore, in practical applications, it is important to optimize model design based on specific scenarios and explore effective integration with deep learning or other data fusion techniques to enhance overall data processing performance.

3.2. Low-Rank Tensor Completion

LRTC methods do not require a predefined rank, which makes them highly flexible. By minimizing the tensor rank, these methods can effectively recover missing data. Figure 3 illustrates the schematic framework of LRTC. Most existing studies adopt the tensor nuclear norm to approximate the tensor rank in order to achieve rank minimization. For example, Ran *et al.* [41] applied a High-Accuracy LRTC (HaLRTC) algorithm for traffic data imputation. However, the over-relaxation issue associated with the nuclear norm leads to suboptimal performance in practical applications.

(1) Nonconvex Approximation Models

Recently, researchers have begun exploring new non-convex rank functions to replace the nuclear norm in LRTC methods. Chen *et al.* [42] proposed the LRTC with Truncated Nuclear Norm (LRTC-TNN). This model introduces the truncated nuclear norm (TNN) into the traditional LRTC to effectively capture the global low-rank characteristics of spatiotemporal traffic data. Nie *et al.* [43] proposed the truncated tensor Schatten p-norm (LRTC-TSpN) that combines the advantages of the Schatten p-norm and the truncated nuclear norm. He *et al.* [44] presented Parameter-Free Non-Convex Tensor Completion (TC-PFNC) model, which approximates the tensor algebraic rank by designing a logarithmic-based non-convex regularization term. Zhao *et al.* [45] proposed Nonnegative Weighted LRTC (NWLRTC), adopting the truncated nuclear norm and introduces directional weighting factors to reduce dependence on the input data direction. Chen *et al.* [46] proposed LRTC-TMCP that employs a non-convex Truncated Minimax Concave Penalty (TMCP) approach to approximate the tensor rank. Hu *et al.* [47] proposed a tensor completion method named SCPN for traffic data recovery. By introducing the tensor Schatten p-norm with a truncation mechanism, this method balances the relationship between low-rank constraints and sparsity constraints.

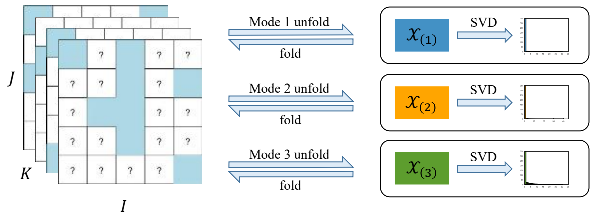

Figure 3. The architecture of LRTC.

(2) Temporal Correlation Models

Relying solely on global low-rankness is insufficient to fully characterize the dynamic complexity of real-world traffic systems. Therefore, local features also need to be considered. For instance, traffic data at the same location typically exhibits smooth changes across adjacent time intervals. To address this, some studies have explored temporal correlations within the framework of LRTC. Chen *et al.* [12] proposed Low-Rank Autoregressive Tensor Completion (LATC), which not only takes into account the global consistency of traffic data, but also captures temporal dynamics through an autoregressive (AR) regularization term with learnable parameters for each time series. Zeng *et al.* [48] proposed a traffic data imputation method based on the low-rank Tensor Nuclear Norm (TNN) and Hybrid Total Variation (HTV) regularization. The model leverages TNN to capture the global low-rank characteristics of the data and enhances local smoothness through first-order and second-order HTV regularization. Chen *et al.* [11] proposed Low-Tubal-Rank Smoothing Tensor Completion (LSTC-Tubal), which enables efficient processing of high-dimensional data by incorporating linear unitary transformation techniques.

(3) Spatial Correlation Models

Traffic conditions on adjacent road segments often exhibit spatial correlations. To leverage this property, Chen *et al.* [49] proposed Low-Rank and Sparse Self-Representation Tensor Completion (LRSSRTC) that can simultaneously capture the global low-rank characteristics of traffic data and the self-similarity among traffic samples. To improve the accuracy of data imputation, the model also incorporates a sparse regularization term to enforce sparsity in the similarity weight matrix. Nie *et al.* [50] proposed Laplacian Enhanced Low-Rank Tensor Completion (LETC), which utilizes various forms of graph Laplacian transformations to capture multi-dimensional correlations. The model employs efficient numerical techniques to design algorithms suitable for network-wide speed kriging interpolation.

(4) Spatiotemporal Coupling Models

By integrating temporal and spatial correlations, subtle variations in traffic data can be more accurately captured. Chen *et al.* [51] proposed a Collaborative Nonconvex LRTC (CNLRTC) algorithm, which employs the Schatten p-norm as a nonconvex approximation to capture global multi-dimensional correlations within data tensors. The model also incorporates an elastic net self-representation method to reveal underlying self-similar structures in traffic data and uses an autoregressive model to capture temporal dependencies. Zhao *et al.* [52] proposed Spatio-Temporal constrained LRTC (ST-LRTC) model that captures global spatiotemporal features and adopts the truncated nuclear norm as a non-convex surrogate function. It also introduces K-order proximity graph embedding to construct spatial constraints and incorporates Laplacian regularization to model local correlations. Furthermore, the method integrates manifold learning to provide prior knowledge. Chen *et al.* [53] proposed a Composite Non-convex LRTC model with Joint Structural Regression (CJSR). This model introduces the logarithm power composite norm as a non-convex proxy and incorporates Joint Structural Regression (JSR) to deeply explore the intrinsic spatiotemporal relationships within the data.

In summary, structural-based methods have the advantage of fully exploiting the inherent correlation structure within data, making them particularly suitable for traffic data with significant spatiotemporal dependencies. However, these methods also have certain limitations. When the underlying data structure exhibits high nonlinearity, drastic dynamic changes, or is heavily affected by noise, these methods may fail to accurately characterize the true data structure. This can hinder the model's ability to capture key structural information and reduce imputation accuracy. In addition, determining appropriate parameters remains a key challenge. Improper selection may lead to underfitting or overfitting, negatively affecting overall model performance. Therefore, in practical applications, it is essential to tailor the model design to specific scenarios, explore adaptive parameter selection strategies, and consider effective integration with nonlinear modeling approaches.

4. Learning-based methods

Learning-based methods leverage machine learning and deep learning techniques to automatically capture the dynamic changes and complex dependencies from data and use them for missing value imputation [73]. The core advantage of these methods lies in their ability to automatically extract features and effectively model complex nonlinear relationships within the data. Common learning-based approaches include: Generative Adversarial Network (GAN), Graph Neural Network (GNN), and Attention. These methods demonstrate strong adaptability and expressive power in handling traffic data. In Table 3, we provide a detailed overview of several learning-based imputation methods, including important information such as performance metrics and missing rates.

Table 3. Summary of learning-based methods for traffic data imputation.

	Methods	Performance metrics	Missing rate
GAN	GAIN [54]	RMSE	20%
	CA-GAN [55]	MRE	20%–80%
	IGANI [56]	MAE	10%–90%
	GAE-GAN-LSTM [57]	MAE, MAPE, RMSE	10%–90%
	SA-GAIN [58]	MAE, RMSE	10%–80%
	MLGAN [59]	MAE, RMSE	5%–95%
	MST-GAN [60]	MAE, RMSE	30%–80%
	STGAN [61]	MAE, RMSE	20%–80%
GNN	SI-GCN [62]	MAPE, RMSE	40%
	MDGCN [63]	MAE, MAPE, RMSE	20%–80%
	MACRO [64]	MAE, RMSE	10%–50%
	GT-TDI [68]	MAPE, RMSE	10%–90%
	GRIN [65]	MAE, MRE	25%
	DGCRIN [67]	MAE, MAPE, RMSE	10%–70%
Attention	MATCN [69]	MAPE, RMSE	30%–70%
	SAITS [70]	MAE, MRE, RMSE	80%
	ST-LBAGAN [71]	MAE, RMSE	10%–60%
	STAR [72]	MAE, MAPE, RMSE	20%

4.1. GAN-based models

GAN consists of a generator and a discriminator. The generator performs data recovery by utilizing synthesized information from missing data, while the discriminator ensures that the generated data aligns with the real data distribution. Figure 4 presents the structural framework of GAN. Yoon *et al.* [54] proposed Generative Adversarial Imputation Networks (GAIN), which extends the traditional GAN framework for missing data imputation. In GAIN, the generator is responsible for filling in missing values, and the discriminator determines whether the data comes from the true distribution. Unlike standard GAN, GAIN introduces a "hint" mechanism into the discriminator to guide the generator in more accurately fitting the real data distribution. Han *et al.* [55] proposed the Content-Aware GAN (CA-GAN), which leverages a generative model to learn high-dimensional data distributions, enabling the recovery of missing data across arbitrary dimensions and regions, thereby enhancing the semantic consistency of the imputation results. Kazemi *et al.* [56] proposed the Iterative GAN Imputation (IGANI) model, which combines the generative capability of GAN with an iterative optimization strategy to progressively refine the estimation of missing data. The loss function integrates spatiotemporal correlations, ensuring consistency of the imputed results in both temporal and spatial dimensions.

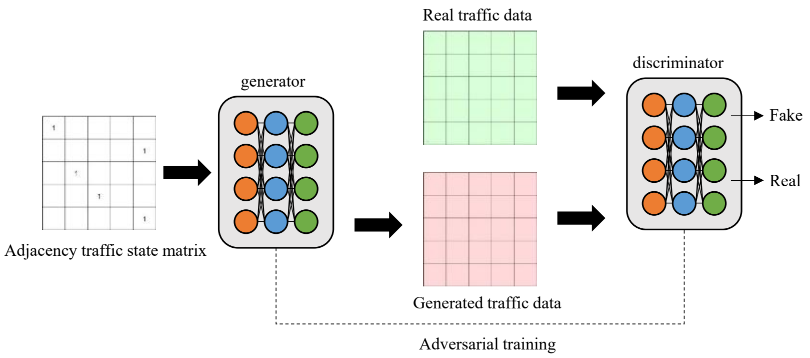

Figure. 4. The architecture of GANs.

Xu *et al.* [57] proposed a hybrid model named GAE-GAN, which combines a Graph Auto Encoder (GAE) with a GAN. The method improves the GAE loss function and leverages the strong data generation capability of GAN to produce complete data features. The generator adopts an LSTM, while the discriminator uses a fully connected neural network to evaluate the authenticity of the generated features. Zhang *et al.* [58] proposed the Self-Attention Generative Adversarial Imputation Network (SA-GAIN), which introduces a self-attention mechanism into the GAN framework. The generator employs Self-Attention Gated Recurrent Units (SA-GRU) to dynamically adjust attention weights across different time periods. The discriminator contains two submodules, which assess the consistency of local and global data distributions, respectively. Zhang *et al.* [59] proposed MLGAN that integrates Bidirectional Gated Recurrent Units (BGRU) to extract temporal features and utilizes GCN to capture spatial dependencies. In addition, the model introduces a dynamic sampling structure to adapt to varying missing data rates, enabling adaptive feature reconstruction and missing value imputation. Shen *et al.* [60] proposed the Multi-View Spatio-Temporal Generative Adversarial Network (MST-GAN), which integrates multi-view information, including spatial correlations, temporal continuity, and periodic patterns. It uses GCN to capture spatial structures, RNN to model temporal dependencies, and introduces an attention mechanism to enhance the learning of key features. Yuan *et al.* [61] proposed the Spatio-Temporal Generative Adversarial Network (STGAN), which combines GCN and RNN to model spatial and temporal dependencies, respectively. The model also incorporates a self-attention mechanism to dynamically focus on important time steps and features.

Despite its enormous potential, GAN faces challenges such as training instability, mode collapse, and vanishing gradients, which limit its application and performance. Some strategies have been investigated to overcome the above drawbacks, such as introducing regularization techniques, improving loss function design, and optimizing network architecture.

4.2. GNN-based models

Graph Neural Networks (GNN) excel in handling traffic data imputation because they can transform the road network into a graph structure, where sensors act as nodes and associations between nodes are represented through edges. This approach helps model the spatial relationships among multiple sensors within complex road networks.

Yao *et al.* [62] proposed the Spatial Interaction Graph Convolutional Network (SI-GCN), which combines graph convolution with a mapping function. By embedding geographical units into local spatial networks and introducing a negative sampling mechanism, the model improves prediction accuracy. Liang *et al.* [63] proposed the Memory-Augmented Dynamic Graph Convolutional Network (MDGCN), which integrates GCN with a memory network. It models spatiotemporal dependencies using multi-spatiotemporal blocks (ST-blocks) and enhances traffic data imputation through an external memory network and a dynamic graph learning. Ming *et al.* [64] proposed the MACRO, which employs a multi-graph convolutional network to model complex spatial correlations, combined with an improved bidirectional recurrent network and a temporal decay mechanism. The model also includes a spatiotemporal knowledge fusion module. Reference [65] proposed to model complex spatiotemporal dependencies by GNN, thereby recovering and predicting data from unsampled sensors. Reference [66] proposed Inductive Graph Neural Network Kriging (IGNNK), which generates random subgraphs as samples and constructs corresponding adjacency matrices for each sample to generalize the effects of distance and reachability. Kong *et al.* [67] proposed the Dynamic Graph Convolutional Recurrent Imputation Network (DGCRIN), which models spatial correlations and spatiotemporal dependencies through a graph generator and DGCGRU. The model introduces an auxiliary GRU and a fusion layer to effectively integrate information about missing patterns. Zhang *et al.* [68] proposed the Graph Transformer-based Traffic Data Imputation (GT-TDI) that integrates GNN with the Transformer architecture. This model leverages sensor connectivity, semantic descriptions, and incomplete observations to infer missing values, and incorporates semantic understanding and prompt engineering techniques to enhance the model's interaction capabilities.

Although GNN are powerful in processing complex structured data, they face several challenges. First, as the size of the graph increases, computational costs and scalability issues become more prominent. Second, GNN are highly dependent on the quality of the input graph. Inaccurate or noisy relationships can significantly degrade their performance.

4.3. Attention-based models

Attention-based models are a class of deep learning architectures that utilize attention mechanisms to enable the model to identify key information in the input data. The core idea of attention mechanisms is to assign different weights to different positions or features when processing an input sequence, thereby focusing more on the parts most relevant to the current task.

Reference [69] proposed Multi-Attention Tensor Completion Network (MATCN). MATCN that integrates historical features with spatiotemporal variables and uses gated diffusion convolution to generate an initial imputation scheme. Reference [70] proposed Self-Attention-based Imputation for Time Series (SAITS) that leverages the self-attention mechanism and learns missing values through a joint optimization strategy. The model consists of a weighted combination of two diagonal-masked self-attention blocks to explicitly capture temporal dependencies between time steps and correlations among features. Yang *et al.* [71] proposed ST-LBAGAN that combines GAN with BiLSTM and introduces a bidirectional attention mechanism for traffic data imputation. The model generates realistic data through adversarial training and utilizes a multi-scale loss function to ensure consistency of the generated results at both local and global levels. Liang *et al.* [72] proposed the Spatiotemporal-Aware Data Recovery Network (STAR) by combining GNN with the attention mechanism to capture long-range spatiotemporal correlations.

While attention mechanisms emphasize modeling global dependencies, they may neglect the capture of local structural information, which can affect model performance in tasks that are sensitive to local patterns. In addition, although the flexibility of attention weights enhances the model's expressive capacity, it also increases the risk of overfitting, especially when the training data is limited or the task involves significant noise.

In summary, the main advantage of learning-based methods lies in their strong expressive power and good adaptability, making them suitable for handling high-dimensional and complex traffic data. However, these methods also have certain limitations. First, the performance heavily relies on the availability of large amounts of high-quality training data. Second, deep learning models are often regarded as "black boxes", making their decision-making processes hard to interpret. Third, improper model design or unreasonable hyperparameter settings can lead to overfitting or poor generalization. Furthermore, training these models typically requires substantial computational resources and time, resulting in significant computational overhead.

5. Performance analysis and discussion

In this section, we conduct a systematic and comprehensive performance comparison of various missing value imputation methods on a unified dataset. We select the Guangzhou dataset, and the considered methods include structure-based approaches (e.g., BGCP [25], BRCP [23], BATF [22], LTRR-NLS [31], FNNTEL [39], HaLRTC [41], LRTC-TSpN [43], LRTC-TNN [42], LSTC-Tubal [11], and LATC [12]) as well as learning-based approaches (e.g., CoSTCo [73], IGNNK [66], GRIN [65], CoATR [34], CSDI [74], SAITS [70], MATCN [69], and SCMDI [75]). The experiments adopt a MCAR mechanism, with multiple missing rate levels (e.g., 10%, 30%, 50%, 70% and 90%) to simulate data missingness scenarios of varying severity. Additionally, the RMSE is selected as the primary evaluation metric to quantify the accuracy of the imputation results. The performance of different models is presented in Table 4. Note that these results are collected from their original papers while '-' indicates the absence of corresponding results.

To help practitioners select the most appropriate imputation method based on data characteristics, we have designed a decision-making workflow.

First, it is essential to determine the missingness mechanism: whether the data are MCAR, MAR, or MNAR. In the case of MCAR, relatively simple imputation methods often yield satisfactory results. For MAR, continuous missing patterns may exist, such as extended segments of missing values in data. Traditional methods may struggle to accurately capture temporal trends or spatial correlations, leading to significant bias and increased uncertainty in the imputed values. Therefore, for MAR, it is recommended to use learning-based imputation methods, which are better able to model complex dependencies and thus improve both the accuracy and robustness. For MNAR scenarios, there currently lacks a universally effective and efficient solution. The missingness mechanism in MNAR is related to the unobserved data itself, resulting in complex and difficult-to-model missing patterns. When dealing with MNAR data, it is advisable to investigate potential mechanisms that may have caused the missingness, and assess the impact of missing data on the analysis results.

Table 4. Imputation performance (RMSE) of different models on GuangZhou datasets under MCAR missing pattern.

Category	Methods	Missing rate 10%	30%	50%	70%	90%
structure-based approaches	BGCP	3.57	3.58	3.62	3.70	4.10
	BRCP	3.59	3.62	3.64	-	-
	BATF	3.59	3.60	3.65	3.73	4.17
	LTRR-NLS	-	-	2.80	3.16	3.83
	FNNTEL	3.80	3.89	3.92	3.93	4.16
	HaLRTC	3.19	3.50	3.78	4.19	5.07
	LRTC-TSpN	2.60	2.83	3.09	3.45	4.00
	LRTC-TNN	2.79	3.00	3.27	3.60	4.03
	LSTC-Tubal	2.86	3.11	3.37	3.69	4.27
	LATC	2.41	2.57	2.82	3.19	3.90
learning-based approaches	CoSTCo	-	4.48	-	6.13	7.19
	IGNNK	-	3.31	3.75	4.47	6.06
	GRIN	-	4.67	-	5.12	8.54
	CoATR	-	4.47	-	4.58	5.07
	CSDI	-	3.50	4.02	5.13	6.39
	SAITS	-	3.24	3.89	4.79	5.93
	MATCN	-	2.53	2.67	3.14	4.35
	SCMDI	-	3.18	3.58	4.44	5.41

Secondly, the proportion of missing values should be analyzed to evaluate how the missing rate influences method selection, as different levels of missingness may require specific imputation strategies. For example, under low missing rates (e.g., 10%–30%), many structure-based methods (such as HaLRTC and LSTC-Tubal) can effectively utilize the remaining complete information in the data to achieve efficient and accurate imputation. However, under high missing rates (e.g., over 70%), the amount of observable information is greatly reduced, making it difficult for these methods to accurately capture the underlying structural features of the data. This can lead to decreased stability and increased error in the imputed results.

Finally, considering the available computational resources, such as time and hardware, the most suitable imputation approach should be selected based on the actual conditions of the task. Through this structured workflow, we aim to simplify the process of choosing an imputation method, enabling practitioners to more precisely select strategies that are well-suited to the characteristics of their data

6. Conclusion and future work

This paper reviews the latest research advances in addressing missing traffic data within Intelligent Transportation Systems (ITS), classifying existing methods into two categories: structure-based methods and learning-based methods. Each approach has its own strengths and limitations, making them suitable for data recovery tasks in different scenarios. Additionally, this paper discusses common missing data patterns, public datasets, and the application of evaluation metrics.

Despite significant progress in current traffic data imputation methods, future research must address a series of challenges. First, the patterns of missing data are diverse and complex. Different missing patterns significantly impact model performance, and accurately identifying and modeling these patterns remains a key challenge. Second, in urban traffic environments, traffic signal control has a notable influence on traffic states. However, most existing imputation models fail to incorporate this factor, limiting their applicability in real-world scenarios. Third, with the rapid growth of sensing devices, the volume of traffic data is increasing exponentially, imposing higher demands on the real-time and online processing capabilities of imputation methods. Unfortunately, many high-performance algorithms suffer from high computational complexity, making it challenging to meet the low-latency and high-efficiency requirements of practical applications. Fourth, determining the uncertainty of imputation results remains a challenging issue that has not been fully resolved. In recent years, some methods that include uncertainty estimation in imputation have emerged. However, most models do not provide confidence estimates, which may lead to overconfident results.

Looking ahead, research on traffic data imputation can explore multiple promising directions. First, develop more advanced algorithms to accurately identify and model various missing data patterns, especially by leveraging deep learning techniques to automatically detect and adapt to different missing patterns. Second, enhance the fusion of data from multiple sources (such as sensor data, mobile device information, and social media) to enrich traffic datasets and provide more references for the imputation process. Third, develop lightweight and efficient imputation algorithms that ensure low latency while maintaining high efficiency, using strategies such as distributed computing, edge computing, and parameter sharing, and optimizing algorithm design to reduce computational complexity. Fourth, to address the lack of uncertainty estimation in neural network imputation, the methods such as Monte Carlo Dropout can be adopted, thereby estimating model confidence and avoiding overconfidence.

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Authors' contribution

Kaiyuan Wang: writing—original draft, experiment design. Xiaobo Chen: funding acquisition, resources, supervision, writing-review & editing. Nan Xu: writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Conflicts of interests

The authors declare no conflict of interest.

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