# Guest Editorial Introduction to the Special Issue on Graph-Based Machine Learning for Intelligent Transportation Systems

WITH the advance of artificial intelligence (AI), the Internet of Things (IoT), and 5G communication technologies, various kinds of traffic data from diverse devices can be acquired nowadays, and they can help us look into intelligent transportation systems (ITSs) with a new eye. Graph-based machine learning holds out the potential as a powerful tool for modeling complex structural data relationships and also mining both useful information and temporal patterns which could be used for building powerful analytics for ITS construction. Considering the benefit of graph-based machine learning for ITS, some graph-based machine learning methods/architectures have been proposed. Even though these methods have achieved certain success, there exist various scientific and engineering challenges.

The objective of this Special Issue is to solicit high-quality original papers, which address open issues in graph-based machine learning-driven discovery of ITS from both academia and industry. Based on the reviewers' feedback, as well as the evaluations of editors, 40 papers are selected in this Special Issue from more than 130 submissions. The 40 papers which cover broad topics are introduced briefly as follows.

In [A1], Lakhan et al. devise the cost-efficient and secure serverless blockchain enable task scheduling (SBETS) ITS system and algorithm framework. The main goal is to reduce processing and security blockchain costs for ITS applications in the system. The processing cost minimizes based on the new proposed function-based price model and secures the data by the suggested graph neural network (GNN) scheme in the network. The results show that SBETS outperforms all existing ITS systems regarding processing cost and fraud detection problems.

In [A2], Pan et al. propose a location recommendation model to generate location preferences through mobility graphs constructed from users' check-in data. In this article, a spatio-temporal interaction-enhanced GNN encodes the graph nodes with comprehensive information exchanges. The recommendation result combines individual and group mobility behaviors and simulates dynamic preferences using a weighted stacked scoring method. The performance against baselines demonstrates the model's effectiveness.

In [A3], Manogaran et al. propose a graph-transient security method (GTSM) for improving the cybersecurity features of ITS. The proposed method uses a trusted graph model for identifying reliable infrastructure and neighboring units in communication. The experimental results prove that the proposed method improves sharing rate by 11.4% and detection ratio by 7.84% and reduces the downtime and latency by 11.53% and 10.7%, respectively, in different sharing intervals.

In [A4], Liang et al. propose a spatial–temporal aware data recovery network (STAR) to handle data recovery tasks in a unified model, enabling a real-time and inductive inference. A residual gated temporal convolution network is designed to capture the temporal pattern from long sequences with masks and an adaptive memory-based attention model for utilizing implicit spatial correlation. To further exploit the generalization power of GNN, a sampling-based method is adopted to train the proposed model to be robust and inductive for online servicing. Extensive experiments on two real-world spatial–temporal traffic datasets are performed, and results demonstrate that the proposed STAR model consistently outperforms other baselines. The experimental results also prove that this proposed STAR model provides adequate performance and rich features for multiple data recovery tasks under the C-ITS scenario.

In [A5], He et al. propose a novel vehicle trip destination prediction method named Hybrid Trip Destination Prediction Model of Vehicle Based on Autoencoder and High-Order Interaction Features (HAHIF). The HAHIF model extracts robust hidden features using the autoencoder model and considers the second-order association between them using a factorization machine to improve its superiority and effectiveness. Compared with some popular benchmarks, the HAHIF model has a better prediction ability.

In [A6], Lu et al. propose a heterogeneous context-aware graph convolutional network (GCN) model for vehicle trajectory prediction in connected environments. The proposed model is able to incorporate vehicles' individual contexts, interactional patterns, and road conditions simultaneously. The experimental results show that the proposed model outperforms state-of-the-art models in terms of trajectory prediction accuracy. Also, the proposed model realizes the online prediction in the order of centiseconds and thus is suitable for real applications.

In [A7], Xu et al. propose a one-shot neural architecture search (NAS) to realize derivative models with different scales. In order to study the relation between adversarial robustness and model scales, a graph-based method is designed to select the best sub-models generated from one-shot NAS. Besides, an evaluation method is proposed to assess the robustness of deep learning models under various scales of models. The experimental results show an interesting phenomenon about

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the correlations between network sizes and model robustness, reducing model parameters will increase model robustness under maximum adversarial attacks, while increasing model parameters will increase model robustness under minimum adversarial attacks. The phenomenon is analyzed, which is able to help understand the adversarial robustness of models with different scales for edge AI transportation systems.

In [A8], Djenouri et al. describe the development of a new system known as the secure and intelligent system for the Internet of Vehicles (SISIV). An attention mechanism and deep learning architecture based on GCN are developed. Blockchain technology is also used to secure data transfer between Internet-of-Vehicles (IoV) system nodes. Using a branch-and-bound approach, the hyperparameters of the generated deep learning model are intelligently selected. To verify SISIV, experiments are conducted on four networked vehicle datasets dealing with prediction problems. The results clearly show that SISIV outperforms the state-of-the-art traffic prediction technologies, and provide efficient and reliable traffic flow prediction in an IoV environment.

In [A9], Gupta et al. aim to provide a technique for resolving authentication and security issues in ITS using lightweight cryptography and graph-based machine learning. This proposed solution uses the concepts of identity-based authentication techniques and graph-based machine learning in order to provide authentication and security to the smart vehicle in ITS. By authenticating smart vehicles in ITS and identifying various cyber threats, this proposed method substantially contributes to the development of an intelligent transportation communication environment.

In [A10], Shu and Li propose an improved ant colony optimization and clustering algorithm for the demand-responsive customized bus. Finally, the proposed planning scheme based on the improved ant colony optimization and clustering algorithm is verified by some experimental results. The results show that the station line planning scheme proposed in this article can better realize the line planning of a demand-responsive customized bus as well as meet diverse passenger travel needs.

In [A11], Xu et al. propose a new deep learning architecture, named spatio-temporal multi-graph transformer (STMGT), to forecast the dockless scooter-sharing demand in real-time. Based on the transportation domain knowledge, the STMGT model integrates GCN and transformer to capture spatial and temporal dependencies. The case studies have shown that this proposed STMGT model significantly outperforms all the state-of-the-art benchmark models, and the most important model component is weather information. This proposed model can help micro-mobility operators to develop optimal vehicle rebalancing schemes and guide cities to better manage dockless scooter-sharing services in real-time operations.

In [A12], Sun and Liu propose an end-to-end two-stage text spotting model named Center TextSpotter for autonomous driving, which is a convolution model that can be effectively deployed on autonomous unmanned vehicles. In order to improve the performance of the model in real scenes, this article proposes a weakly supervised training method and a feature fusion module. Moreover, this article presents an extension scheme based on GNN. This method improves the performance of text recognition. The feature fusion module enhances the overall performance. By adding the GNN before the fully connected layer, the model learns better features. Some experiments verify the effectiveness of the method in this article.

In [A13], Wang et al. propose a graph-based deep learning model for predicting origin–destination demand. The proposed model treats the dynamic traffic networks as multiple weighted directed network snapshots and encodes the direction and weight information of links via a directed attention-based neighborhood aggregation mechanism. Then, the pair of vector representations for each node is fed into a long short-term memory (LSTM) network to learn the temporal dependencies and evolution patterns. Next, two asymmetric inner product decoders are used to predict both the existence and weight of links independently. Finally, the prediction result of link existence is used to refine the result of weight prediction. The experimental results demonstrate this approach's effectiveness for the travel forecasting task, which can help traffic management, resource pre-allocation, and services optimization.

In [A14], Zhang et al. propose a multimodal graph attention network (MCGAT) for joint traffic event detection and sentiment classification. It provides a multimodal, multitasking, interactive graphical structure with nodes representing words and pixels and edges representing contextual and cross-modal connections. Using two benchmarking datasets, MGTES and Twitter, demonstrates the model's effectiveness.

In [A15], Lin et al. combine the fuzzy control theory with the adaptive sequencing mutation multi-objective differential evolution algorithm for traffic signal optimization. This optimization method for traffic signal control at urban intersections is considered as a solution for traffic flow optimization to solve the problem of traffic signal coordination and control of urban trunk lines. The results demonstrate the effectiveness of the optimization algorithm proposed in this article.

In [A16], Wang et al. propose a tracking system for multiple pedestrians. In this system, several candidates surrounding each detected pedestrian are selected sparsely, and the associating relationship between the target and these candidates is determined based on a graph attention map, which contains positional correlations of the matching pairs and is applicable to pedestrians' posture variations. Weighted correlating values are estimated with the positional weighted matrix and merged attention map. The correlating relationship is confirmed with weighted correlating value and distance matching loss. Convolutional features are extracted from one specific middle layer of the backbone network with high efficiency and are used to represent each target/candidate. The proposed tracker achieves better performance than other state-of-the-art trackers.

In [A17], Lin et al. present how to utilize the multi-AUVs system to track underwater diffusion pollution, especially the equipotential line of particular concentration. Different from most of the current research, this work utilizes the software-defined networking (SDN) technique to optimize the network architecture, constructing an SDN-enabled AUV network ITS. After showcasing the proposed system initialization steps, this work utilizes Soft Actor-Critic (SAC) algorithm to optimize the system control and management and embeds the self-attention mechanism into the critic network construction. This leads to a self-attention-based SAC algorithm to schedule the AUV-based ITS to track the equipotential line of underwater diffusion pollution. The evaluation results demonstrate that the proposed tracking framework is able to exactly track the equipotential lines of a particular concentration in many categories of underwater diffusion fields.

In [A18], Yao et al. propose a transfer learning with a spatial–temporal GCN model to predict traffic indicators for data-scarce road networks. The proposed model first develops a spatial–temporal GCN that combines the GCN and GRU to extract spatial–temporal dependencies from source and target road networks. Then, the spatial–temporal GCN is integrated with a transfer learning model to learn discriminative and domain-invariant features to facilitate knowledge transfer. The effectiveness of this proposed method is demonstrated by extensive simulations using three real-world traffic datasets.

In [A19], Guo et al. propose a fast spatiotemporal learning (FSTL) framework containing the fast spatiotemporal GCN module, which reduces the computational complexity of the spatiotemporal GCN. To mine globally and fast the correlations of road node pairs, a correlation analysis based on the normal distribution is proposed to construct the global correlation matrix. Besides, multi-scale temporal learning is integrated into the FSTL to overcome the receptive field constraints of the spatiotemporal GCN. The experimental results on four real-world datasets demonstrate that the FSTL achieves 48.88% and 5.26% reductions in the training time and mean absolute error, respectively, compared with the state-of-the-art model.

In [A20], Yu et al. propose a new lane detection model, Bi-Lanenet, to solve the problems that still exist in the current methods, aiming to overcome the disadvantages in these methods and improve the practicality of the lane detection algorithm. For the task of lane detection, this article improves the segmentation accuracy and improves the traditional Lanenet model while ensuring that the network model is lightweight and more robust. Then, a new bilateral lane recognition network based on semantic segmentation and details is proposed, and the random sample consensus method is used to optimize the post-processing process. Some experiments on the TuSimple and CULane datasets are conducted, and the results prove that the method can detect lanes in the image efficiently with 110 frame-per-second (FPS) and accurately at 97.08%.

In [A21], Li et al. propose a short-range navigation algorithm based on deep reinforcement learning. The proposed algorithm utilizes deep reinforcement learning and takes the cost of time and the reward function into consideration. In order to fit the hardware condition of the robot, a three-channel fusion mechanism is proposed to fuse the input observation and action and the total number of parameters in the model is 90% less than the baseline. Moreover, this proposed algorithm achieves 62.9% less in time cost, and 12.0% less in distance cost. The experimental results show this proposed algorithm achieves better efficiency and convergence performance.

In [A22], Aung et al. propose a social-aware vehicular edge computing architecture that solves the content delivery problem using some vehicles in the network as edge servers that can store and stream popular content to close-by end-users. The proposed architecture includes three main components: 1) the proposed social-aware graph pruning search algorithm computes and assigns the vehicles to the shortest path with the most relevant vehicular content providers. 2) The proposed traffic-aware content recommendation scheme recommends relevant content according to its social context. This scheme uses graph embeddings in which the vehicles are represented by a set of low-dimension vectors (vehicle2vec) to store information about previously consumed content. 3) Finally, a deep reinforcement learning method is proposed to optimize the content provider vehicle distribution across the network. The results obtained from a real-world traffic simulation show the effectiveness and robustness of the proposed system when compared to the state-of-the-art baselines.

In [A23], Zhao et al. describe that capturing correlations between road network nodes is crucial to improving traffic flow forecasting accuracy. In general, there are spatial, temporal, and joint spatial–temporal correlations between two nodes, whose strength is related to spatial and temporal position factors. Although spatial–temporal GCN has become a popular paradigm for modeling those correlations, there are still some issues with existing models. To cope with these issues, this article proposes a novel Spatial–Temporal Position-aware Graph Convolution Network (STPGCN) for traffic flow forecasting. Extensive experiments on six real-world datasets demonstrate the superiority of this proposed STPGCN model in terms of prediction performance and computational efficiency.

In [A24], Wang et al. propose a multi-objective optimization model, including the distribution cost and carbon emissions to improve the distribution efficiency under the increasingly stringent traffic restrictions. Given the limits of battery capacity and cargo capacity, a green vehicle routing problem with a soft time windows model with heterogenous fleets is built. In this study, three different factors, that is restricted area, travel time of vehicles, and carbon tax prices, are discussed in detail. The experimental results show the impacts of traffic restriction policies on the formulation of a distribution scheme and offer reference opinions for both the government and the logistics enterprises.

In [A25], Qu et al. present a temporal–spatial quantum GCN algorithm that can capture temporal and spatial features of traffic data simultaneously for traffic congestion prediction. The algorithm consists of the following steps. First, a closed-form solution in the Schrodinger approach is theoretically presented to analyze this traffic congestion prediction problem in a time dimension. Then the temporal features from the solution are obtained. At last, a quantum GCN is constructed and temporal features are applied in it. The experimental results show the average error rate is 0.21 and can resist perturbation effectively.

In [A26], Qi et al. propose a deep learning approach based on a spatiotemporal GCN for long-term traffic flow prediction with multiple-factor fusion. In this proposed method, the GCN is used to capture the spatial correlation, and the GRU is used to capture the temporal correlation. The innovative idea is to introduce an attribute feature unit (AF-unit) to fuse external factors into a spatiotemporal GCN. Moreover, the proposed method is applied to a real-world traffic prediction scenario. The experimental results indicate that the proposed method can achieve high accuracy and stability in long-term traffic flow prediction, and the fusion of meteorological factors can reduce the inaccuracy of traffic prediction.

In [A27], Manibardo et al. describe that artificial traffic flow datasets can be obtained from a data generative approach fed with data distributions of analogous roads. The key point is how to detect roads with similar traffic profiles without collecting traffic flow metrics. A method for discovering such locations by inspecting topological and contextual features is presented. These features are built from domain-specific knowledge as numerical representations, then compared between the target and candidate locations. After finding a similar source of data, a generative method is used to synthesize traffic profiles. Depending on the resemblance of the traffic behavior at the sensed road, the generation method can be fed with data from one road only. Several generation approaches are analyzed in terms of the precision of the synthesized samples.

In [A28], Cheng et al. propose a highway traffic image enhancement algorithm based on improved generative adversarial networks (GANs) in complex weather conditions. The attention mechanism and the multiscale feature fusion are combined to improve the generator network, which could effectively reduce noise while improving the attention of high-frequency region information. The improved PatchGAN in the discriminator used a local discrimination strategy to distinguish the generated image from the real image, and then the Nash equilibrium is achieved through the continuous interaction between the generator and the discriminator, to ensure the integrity and authenticity of the restored image. Compared with other image enhancement algorithms, using PSNR and SSIM as measurement indicators, the experimental results showed that the proposed algorithm's results are, respectively, 21.97% and 12.89% higher in nighttime enhancement, 26.16% and 12.75% higher in rain removal, and 26.56% and 12.1% higher in fog removal. The proposed algorithm can not only retain the image details and feature information but also produce effective denoising, which increases the reliability of image-based traffic information processing and analysis.

In [A29], Chen et al. propose a graph attention network with spatial–temporal clustering (GAT-STC), which considers the so-called recent-aware features and periodic-aware features, to improve the GNN-based traffic flow forecasting in ITS. Specifically, for the recent-aware feature extraction, a distance-based graph attention network (GAT) is improved and constructed to better utilize the hidden features of neighbor nodes within a reliable distance during the recent time interval, thus can effectively capture the dynamic changes in spatial feature representation. For the periodic-aware feature extraction, a spatial–temporal clustering algorithm, in which both features in terms of nodes' current traffic states and similar trends in terms of their dynamic changes are taken into account, is developed and applied to achieve better learning efficiency. Experiments using three public traffic datasets demonstrate the higher accuracy and better efficiency of this proposed model for traffic flow forecasting, compared with five baseline methods in ITS.

In [A30], Yuan et al. propose a federated deep learning based on spatial–temporal long and short-term network (FedSTN) algorithm to improve the distributed learning ability of traffic flow data and enhance data security. They deploy traffic flow prediction models on edge servers to facilitate federated learning and use the homomorphic encryption method to improve the security of parameter sharing. The results show that this proposed algorithm has higher prediction accuracy than other distributed learning models.

In [A31], Cui et al. propose a data-driven cloud-fog-edge collaborative driver–vehicle–road (CFEC-DVR) framework. As DVR collaboration, privacy quality, and analytic accuracy are three key issues in the framework, a relation graph privacy-preserving scheme with high accuracy is proposed in this framework, which is named as RGPP-HA. Based on machine learning, this proposed method nearly maximizes the difficulty for attackers to know exactly how many other roles are connected to the attacked role, which enhances the privacy quality. Meanwhile, as much valuable information as possible from roles' encrypted relations for more accurate analytic performance is found. Based on the experiments, this proposed scheme RGPP-HA is compared with existing classic and relevant schemes. The experimental results show that this proposed scheme has the best privacy quality and analytic accuracy. This further verifies the feasibility of the CFEC-DVR framework.

In [A32], Zou et al. propose a real-time traffic flow detection system framework based on video image collection and analysis. According to the vehicle detection and tracking results, a traffic flow parameter estimation model and an improved LSTM network are proposed for spatiotemporal counting feature recognition. The results conclude that the developed framework can estimate the traffic flow density and count vehicles, as well as estimate the traffic flow velocity and traffic volume to estimate and optimize traffic flow, respectively. In addition, the simulation results show that the proposed method can not only counts the two-way traffic vehicles quickly and accurately, but also avoids the use of the complex multi-target tracking method for spatiotemporal correlation of a single target, increases the speed and accuracy of the spatiotemporal information processing procedure, and has stronger scene adaptability.

In [A33], Liu et al. describe the autonomous navigation of mobile robots in large-scale environments with crowded static and dynamic objects (such as humans) is considered in this paper. Particularly, local interactions among dynamic objects are learned for better understanding their moving tendency and relational graph learning is introduced for aggregating both the object-object interactions and object-robot interactions. In addition, robot local observations are transformed into graphical inputs to achieve scalability to various surrounding dynamic objects and various static obstacle patterns, and the globally guided reinforcement learning strategy is introduced to achieve the fixed-sized learning model even in large-scale complex environments. Physical robotic experiments demonstrate the effectiveness and practical applicability in real scenarios.

In [A34], Li et al. propose a new approach for few-shot learning on point clouds, which are critical for applications such as autonomous driving and robotics. The proposed Cascade Graph Neural Networks (CGNN), uses two cascade GNNs to extract intra-object topological information and inter-object relations. To increase the discriminability of point cloud features, a novel discriminative edge label and few-shot circle loss are introduced. This work addresses the challenging issue of obtaining discriminative representations of unseen classes with high intra-class similarity and inter-class difference, which is essential for 3-D few-shot learning. Experiments on benchmark CAD and real LiDAR point cloud datasets show that CGNN outperforms state-of-the-art GNN-based few-shot classification methods.

In [A35], Pan et al. propose a traffic speed prediction method based on time classification in combination with spatial GCN. This method can simultaneously consider the spatial structure characteristics of the road network and the temporal feature of traffic flow. In other words, the GCN is used to extract the non-Euclidean features of the road network structure. In addition, this method employs a gated recurrent unit (GRU) to extract the temporal correlation. Thus, the fusion of spatial and temporal features is realized. Relevant experiments are carried out in the actual data set, and the results show that the effect of this model is better than other baseline models.

In [A36], Qin et al. describe the trajectory tracking problem of underactuated surface vessels (USVs) that is subject to input saturation, unmodeled dynamics, and marine environmental disturbances is investigated. USV under-actuation problem is handled by constructing a coordinate transformation. An auxiliary dynamic system is adopted to deal with input saturation. The adaptive law is presented to online update the upper bounds of the composite disturbances. The event-triggering condition is introduced to reduce drastically control execution frequency and the transmission load. By combining the auxiliary dynamic system, an adaptive technique, a first-order command filtered technique, and an event-triggered condition, a novel adaptive finite time event-triggered control scheme is proposed. The designed robust adaptive control has proven to enable USVs to track the desired trajectory while guaranteeing closed-loop stability in a finite time and avoiding Zeno behavior. The results demonstrate the effectiveness and superiority of the proposed control strategy.

In [A37], Jin et al. propose a stochastic optimal control method to resolve the conflicts between aircraft and moving convective weather regions. The proposed method is able to incorporate uncertainties in both aircraft and wind dynamics. The simulation results show that the proposed algorithm provides robustness against uncertainties in the system and is suitable for real applications.

In [A38], Gao et al. propose a joint channel attention and multidimensional regression loss method for 3-D object detection in automated vehicles to improve the average precision of 3-D object detection by focusing on the model's ability to infer the locations and sizes of objects. First, channel attention is introduced to effectively learn the yaw angles from the road images captured by vehicle cameras. Second, a multidimensional regression loss algorithm is designed to further optimize the size and position parameters during the training process. Third, the intrinsic parameters of the camera and the depth estimate of the model are combined to reduce the object depth computation error, allowing us to calculate the distance between an object and the camera after the object's size is confirmed. As a result, objects are detected, and their depth estimations are validated. Then, the vehicle can determine when and how to stop if an object is nearby. Finally, experiments conducted on the KITTI dataset demonstrate that this proposed method is effective and performs better than other baseline methods, especially in terms of 3-D object detection and bird's-eye view evaluation.

In [A39], Rahmani et al. provide an overview of the studies utilizing and developing GNN for ITS applications. In this regard, the evolution of GNN frameworks in different domains has been explored, which include traffic forecasting, demand prediction, autonomous vehicles, intersection management, parking management, urban planning, and transportation safety. The studies are micro-categorized based on their application to identify domain-specific research directions, opportunities, and challenges. Moreover, some unique and undiscussed research opportunities and directions are discussed, which have been missed in previous surveys. The neglected role of edge and graph learning in ITS applications, developing multi-modal GNN models, and exploiting the power of unsupervised and reinforcement learning methods for developing GNN frameworks are some examples. Finally, popular baseline models and datasets are identified per transportation domain.

In [A40], Wang et al. propose the uncertainty quantification theory to study the electromagnetic exposure of the human body. A sparse polynomial chaos expansion method is used to establish the surrogate model of the mean value of some human organs' SAR, and the probability distribution function of SAR is calculated. The Sobol is used to quantify the impact of relevant variables on SAR. Combined with the final calculation results, this paper can provide reasonable suggestions for the safety protection of electromagnetic exposure of the human body in the WPT of EVs.

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## APPENDIX: RELATED ARTICLES

[A1] A. Lakhan, M. A. Mohammed, D. A. Ibrahim, S. Kadry, and K. H. Abdulkareem, "ITS based on deep graph convolutional fraud detection network blockchain-enabled fog-cloud," *IEEE Trans. Intell. Transp. Syst.*, early access, Feb. 16, 2022, doi: 10.1109/TITS.2022.3147852.

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