Guest Editorial Special Issue on Graph-Powered Machine Learning for Internet of Things

INTERNET of Things (IoT) refers to an ecosystem where applications and services are driven by data collected from devices interacting with each other and the physical world. Although IoT has already brought spectacular benefits to human society, the progress is actually not as fast as expected. From network structures to control flow graphs, IoT naturally generates an unprecedented volume of graph data continuously, which stimulates fertilization and making use of advanced graph-powered methods on the diverse, dynamic, and large-scale graph IoT data.

A variety of graph-powered learning techniques, such as graph embedding, graph neural network (GNN), and graph convolutional network, improve the performance of data management, knowledge discovery, information fusion, etc. Making graph-powered learning to promote IoT services is a nontrivial task, imposing unique challenges from the cyber world and physical world that are yet to be addressed well. Although an enormous amount of effort has been made in both academia and industry, the investigation of how to fully utilize IoT and graph-powered learning to renovate business models and people's everyday life, on the aspects of scalability, reliability, adaptability, security and privacy, and usability, is still at a very early stage. The diverse, dynamic, and large-scale graph IoT data require different sophisticated graph-powered learning methods, data mining techniques, advanced machine learning algorithms, etc., to be involved. How to utilize graph-powered learning methods to meet the demands of IoT design and management in a highly reliable, efficient, low-latency, and secure way is extremely urgent and requires extensive investigations.

The goal of the special issue is to solicit high-quality original papers aimed at demonstrating effective and efficient graph-powered learning methods on data analysis, resource allocation, privacy preservation, architecture design, etc., for IoT. This special issue consists of 27 papers selected from 82 full submissions in response to the call for papers. All submissions were strictly and thoroughly peer reviewed by experts. These submissions cover many current research topics. In the following, we will summarize these articles and highlight their major contributions.

Chen *et al.* [A1] investigated the emergency landing problem of drones and proposed a transferable decision network with the aid of graph convolution to reduce the amount of training data required from the real world. The investigation shows excellent results compared with the state-of-the-art counterparts in predictive accuracy and success landing rate.

Muhati and Rawat [A2] presented a hidden Markov model to predict intrusion detection by combining cyber-attack projection and cyber-defense agility estimation. The proposed algorithm is demonstrated to provide high prediction accuracy on open-source network intrusion detection systems. In addition, a cyber visualization is provided to enhance the output comparison and depiction of security events.

Yang *et al.* [A3] investigated the knowledge graph technology and proposed a tensor graph attention network (TGAT) to improve local information aggregation of intelligent IoT applications and services. Experimental results show that TGAT, combined with parameter compression technique, namely, the Tucker model, outperforms the competitors in terms of hit@1 accuracy.

Liang *et al.* [A4] investigated resource allocation problems in the context of graph-based Industrial IoT (IIoT) systems and proposed a deep Q-network (DQN)-based solution. The smart warehouse simulation results demonstrate that the DQN model combines the advantages of both bandwidth utilization and energy efficiency improvement.

Mao *et al.* [A5] developed a semantic fuzzing tool for voice assistants with symbol-based Asian languages, namely, Harmony-Fuzzer. In this semantic fuzzing tool, the fuzzing process is established based on the Chinese corpus. It also shows that Chinese voice assistants are vulnerable to squatting attacks when attackers delicately leverage linguistic phenomena.

Hu *et al.* [A6] focused on representation learning for multilabel images with the aid of a graph attention network (RRL-GAT), which is composed of a class attention graph convolution module (C-GAT) for exploring the strong association structure and an adaptive attention convolution module (AGT) to reveal subtle dynamic dependencies in images. Experimental results show that the proposed method performs better on authoritative datasets.

Chen *et al.* [A7] studied the framework of multivariate time-series anomaly detection in IoT systems. A transformer-based graph learning architecture is proposed to learn bidirected links among sensors, characterize the anomaly information flow, and address the quadratic complexity barrier.

Ye *et al.* [A8] proposed a novel graph self-attention network (GSAN). The GSAN can learn the spatial–temporal interaction representation among vehicles in the model and fine-tune

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the entire model quickly. Experiments on interaction-related tasks validate the effectiveness and generality of the proposed spatial–temporal interaction model. A final impact visualization depicts how the proposed model captures interactions and makes predictions.

Chen *et al.* [A9] proposed a zero-shot learning approach for handling large amounts of social text data when there is a shortage of labeled cyber–physical–social–systems (CPSSs) data. By fully utilizing the existing knowledge graph, the proposed approach can effectively address the social media analysis tasks related to COVID-19. Experimental results show that the proposed model outperforms baseline deep learning models for natural language processing.

Wu *et al.* [A10] investigated the GNN-based anomaly detection for complex IIoT infrastructure, which is capable of understanding points, contextual, and collective anomalies. The proposed anomaly detection solutions are explicitly applicable to IIoT applications, such as smart transportation, smart energy, and smart factories, enabling and encouraging the further advancement of anomaly detection in IIoT.

Jiang *et al.* [A11] proposed a spatial–temporal GNNs model to perform the air traffic prediction. In order to predict the mobility level at airports over time, the authors use temporal graph features of departure and arrival flights from airline on-time performance (AOTP) data. This model enables the prediction of spatial–temporal air mobility by combining graph convolution and time-dimensional convolution, revealing both spatial and temporal correlation simultaneously.

Luo *et al.* [A12] investigated the economic approach to IoT network generation by deep graph generative models. By implementing a variable graph autoencoder, named Core-GAE, incorporating the properties of k-core in network generation, local proximity similarity and global structural features can be maintained when learning the structural features of graphs. Core-GAE offers better performance on tasks related to link prediction, graph generation, and node classification compared with traditional graph generative models.

Ming *et al.* [A13] investigated the video surveillance technique in smart construction site with the aid of edge computing and GNNs. The authors develop a DQN-based reinforcement learning (RL) algorithm to adapt the configuration and optimize the task scheduling, where feature extraction is achieved by incorporating the graph convolution. This framework's superiority is demonstrated by experiments of video surveillance carried out on curtain wall projects in commercial residential buildings.

Yan *et al.* [A14] focused on the accurate and real-time traffic flow prediction problem in intelligent transportation systems (ITSs). A novel spatial–temporal Chebyshev GNN model (ST-ChebNet) is developed to solve the problem. Two real-world datasets demonstrate the effectiveness of ST-ChebNet in making accurate flow predictions, as well as the adaptability of the model.

Wang *et al.* [A15] investigated the social relationship discovery problem in the context of Social IoT (SIoT). It is possible to explore potentially relevant users or data objects with respect to social, spatial, and textual preferences by using a novel search method, namely, top-k social-spatial keyword search (top-k SSKS). Finally, the effectiveness and efficiency of two algorithms are demonstrated for the case of top-k SSKS, which are forward search-based algorithm and index-based search algorithm, respectively.

Wang and Li [A16] proposed a general product design framework for IoT platforms with the aid of digital twin, namely, digital twin-aided IoT platform design (DTIPD). By setting distributed digital twin servers, IoT devices' real-time statuses of machine learning models are stored in the servers to improve the product quality while reducing the development lifecycle of the platform. Finally, experimental results support the applicability of digital twin technology for large-scale network management and need reduction of labeled data.

Zheng *et al.* [A17] studied the graph data acquisition in IoT systems. In light of graph data's partially overlapping and sensitive nature, the authors propose a novel framework for a distributed graph data collection that enables partially overlapped graphs to be kept and universal views to be derived by combining data. According to the differences in knowledge and purposes of data brokers, three algorithms are proposed to reduce the total bandwidth consumption for graph collection.

Zhou *et al.* [A18] focused on designing an intelligent network intrusion detection system (NIDS) with limited and imbalanced attack data for detection model training. The level-aware black-box adversarial attack strategy is realized by using a novel hierarchical adversarial attack (HAA) generation method. Next, a hierarchical algorithm for selecting nodes vulnerable to attacks is implemented based on a random walk with restart (RWR).

Zhou *et al.* [A19] investigated the transient stability assessment (TSA) technique for predicting the type of event that causes a power system to collapse. To achieve this, a conditional generative adversarial network (CGAN) is used to generate unstable samples that balance the training data. A gated GNN (GGNN)-based TSA model is then trained with real-time data input to assess the transient stability of power systems.

Zhou *et al.* [A20] examined a probability graph learning-based coverless information hiding scheme to secure communication in IoT environments. The security of communication between nodes is enabled by concealing secret information in generated data sequence with transition probability graph (TPG) learning methods and highly correlated data element selection.

Fu *et al.* [A21] investigated the person reidentification (re-ID) problem in the application of IoT. In contrast to traditional feature learning methods such as 1-D attention blocks, the authors' proposed self-focusing network (SFNet) exploits both channel- and spatial-dimension attention to extract discriminative features. The performance of SFNet is demonstrated by visualizing the heatmaps of different layers.

Huo *et al.* [A22] investigated the intermittent jamming strategy (IJS) technique along with the feasibility of IJS for a nonslotted transmission IoT system. The jamming duration proportion is studied by exploiting the backpropagation-neural-network model, and the optimal proportion of the binary phase-shift keying modulation is derived. Simulation results from the matching precision optimization algorithm show a preferable secure performance of IJS compared with continuous jamming strategy (CJS) under limited energy.

Chen *et al.* [A23] focused on the dependent task offloading in multiuser edge computing environments. A Markov decision process (MDP) is developed to model the dependent task offloading problem. Then, a two-layer actor–critic mechanism (ACED) is proposed for offloading multiple dependent tasks based on directed acyclic graphs (DAGs). By examining both the topology of the application and the impact of interfering channels, ACED is found to be superior according to the simulation results.

Malawade *et al.* [A24] exploited GNN and long-short-term memory (LSTM) to predict future collisions for autonomous vehicles. With the spatiotemporal scene-graph embedding methodology, namely, SG2VEC, collision prediction is 8.11% more accurate, 39.07% easier on synthesized datasets, and 29.47% more accurate on real-world collision datasets. Furthermore, the method exhibits advanced characteristics, such as faster inferences and lower power consumption when implemented on an industry-standard platform.

Zhang *et al.* [A25] investigated the RL- and graph convolutional neural network (GCNN)-based virtual network embedding (VNE) problem. The algorithm's objective function is defined by setting up a fitness matrix and fitness value, which reduces resource fragmentation effectively. The simulation results show that the RL- and GCNN-based VNE algorithm produces good basic VNE characteristics and flexibility by modifying the physical and virtual network attributes.

Zhang *et al.* [A26] studied a novel two-layer heterogeneous knowledge graph network to extract detailed knowledge and overcome noisy edges during graph construction. The proposed model consists of a hierarchical correlation graph embedding (HCGE) module and a globally guided local attention (GLA) module. Finally, the model utilizes knowledge-fused features to calculate the similarity between the input image and text, thus ending the semantic matching process.

Sun *et al.* [A27] focused on the online movie recommendation problem in the context of the SIoT. A principal component analysis and denoising autoencoder integrated graph convolution network (PCA-DAEGCN) is proposed to obtain effective hidden features and process slight changes in the feedback information. Compared with comparative methods, the proposed method can achieve the best performance on three real SIoT datasets.

First of all, we would like to thank the Editor-in-Chief, Dr. Honggang Wang, for providing us the opportunity to organize the special issue in the IEEE INTERNET OF THINGS. Next, we would like to thank the external reviewers for volunteering their time to review and discuss the submissions. Most importantly, we want to thank all the authors for their contributions. We hope that this special issue will provide a useful insight for researchers, scientists, engineers, practitioners, policy makers, and academics in the field of Graph-powered Machine Learning for IoT.

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APPENDIX: RELATED ARTICLES

[A1] J. Chen *et al.*, "Integrated air-ground vehicles for UAV emergency landing based on graph convolution network," *IEEE Internet Things J.*, vol. 9, no. 12, pp. 9106–9116, Jun. 15, 2022, doi: 10.1109/JIOT.2021.3058192.

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