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Editorial

Special Issue on Transportation Big Data and Its Applications

Xiaolei Ma [1,2,*], Xinqiang Chen [3] and Zhuang Dai [4]

1 School of Transportation Science and Engineering, Beihang University, Beijing 100191, China
2 Key Laboratory of Intelligent Transportation Technology and System, Ministry of Education, Beijing 100191, China
3 Institute of Institute of Logistics Science and Engineering, Shanghai Maritime University, Shanghai 201306, China; chenxinqiang@stu.shmtu.edu.cn
4 School of Transportation and Logistics, National Engineering Laboratory of Integrated Transportation Big Data Application Technology, Southwest Jiaotong University, Chengdu 611756, China; dz@swjtu.edu.cn
* Correspondence: xiaolei@buaa.edu.cn

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1. Introduction

Large-scale traffic sensors are strategically deployed across various infrastructures and modes of transportation (e.g., vehicles, ships, airplanes, bridges, and traffic signals) [1–3]. These sensors offer a vast and readily accessible trove of traffic data, pivotal for the advancement of intelligent transportation systems (ITS) [4–7]. Additionally, diverse data sources from crowdsourcing, social media, and mapping platforms present clear opportunities for both efficient and sophisticated traffic management [8–11]. To date, various big data relevant architectures and applications (e.g., transfer learning, online learning, and edge computing) have been tailored to utilize multiple traffic source data to enhance and optimize real-time traffic operations and safety [12–15]. A notable focus has been on discerning spatial–temporal traffic patterns and predicting traffic flows across various temporal and spatial scales, aided by a range of deep learning models [16–19]. Furthermore, numerous studies aim to achieve seamless cooperation between vehicles, ships, and airplanes in a connected and intelligent traffic environment, leveraging edge computing, 5G, and lightweight machine learning models [20–24]. In essence, data from diverse sensors, including video, radar, and inductive loop detectors, across transportation modes (e.g., vehicles, trains, subways, ships, and airplanes) are harnessed to understand spatial–temporal mobility and commuter behavior [25–28]. Consequently, there is a pressing demand for more efficient models to discern transportation trends in the smart city era.

This Special Issue is dedicated to the exploration of knowledge and the application of big data in transportation, including big data systems and architectures (e.g., Spark and Hadoop-related traffic systems and geo-and-temporal data visualization systems), big data processing (e.g., machine learning, deep learning, edge computing, cloud computing, parallel computing, and 5G), and big data utilization (e.g., for traffic pattern discovery, collision identification, dynamic route planning, traffic demand prediction, operational efficiency optimization, urban planning, and customer service improvement). Historical data analytics, real-time traffic management, and visual data-supported analytics are all included.

2. An Overview of the Published Articles

A total of sixteen papers (fifteen research papers and one review paper) in various fields of transportation big data analytics including maritime traffic evaluation, urban traffic intersection extraction, bus–metro-transfer and ride-hailing ridership analysis, assessment of bridge passage, traffic state prediction, crowd prediction, risk measurement and forecasting, electric taxi battery swapping strategy, anomaly detection, ship classification, and tourism activity modeling are presented in this Special Issue. Hou et al. (contribution 1) presented a forecasting model based on the trip chain and entropy-maximizing theory to predict the trip distributions of tourists on suburban tourist railways. The model was able to accurately reflect the real trip distribution characteristics of tourists and can be used for the planning and construction of suburban tourist railways. Gnap et al. (contribution 2) reported a global assessment approach for bridge passage in relation to oversized and excessive road transport. They analyzed vehicle/vehicle combination parameters and assessed routes for heavy and oversized transportation in Slovakia. The authors proposed a new procedure for obtaining special permission for road use and introduced the concept of the cumulative axle load for assessing bridge passage. Kim et al. (contribution 3) developed a new method for the density analysis of Automatic Identification System (AIS) data in the coastal waters of Korea. They used spatial–temporal density analysis and standard deviation-based stretch symbolization to calculate and visualize the density distribution of different ship types. The method allowed for the identification of major maritime traffic patterns and will be valuable for confirming maritime traffic patterns and density in the coastal areas of Korea. Wang et al. (contribution 4) developed a ship classification method that integrated multiple base classifiers and effectively integrated the static and dynamic information of ships. The method outperformed individual base classifiers and achieved near real-time online classification. Gao et al. (contribution 5) proposed a method for the automatic extraction of urban road intersections using trajectory line segment intersection points. The method achieved better recognition accuracy compared to the benchmark method and effectively identified intersections in low-traffic or low-sampling areas. They used a maximum reconstruction error method to extract straight-line segments and merged them to enhance the road network structure pattern. However, the method had limitations in terms of identifying different types of intersections and when the distances between adjacent intersections were less than 60 m. Wang et al. (contribution 6) developed a short-term traffic state prediction model based on the data acquisition strategy of a mobile edge computing-assisted vehicle-to-everything (V2X) network. The model combined the advantages of a Graph Convolutional Network (GCN) and a Gated Recurrent Units (GRU) soft-attention mechanism to analyze the spatial–temporal characteristics of traffic data. The proposed model showed improved accuracy in predicting traffic flow compared to other models. Working on a similar issue, Mai et al. (contribution 7) presented a traffic prediction model called Time-Evolving Graph Convolutional Recurrent Network (TEGCRN). The model utilized time-evolving adjacency graphs to capture dynamic internode dependency and achieved superior performance compared to the baseline models, especially in short-term prediction. Zou et al. (contribution 8) proposed a hybrid model for vehicle acceleration prediction using Hidden Markov Models (HMM), Long Short-Term Memory (LSTM), and GRU. They used MHMM to divide the driving behavior semantics, evaluate the similarity, and group drivers accordingly. The results showed that the MHMM-based approach improved the prediction accuracy, and the GRU outperformed the LSTM in predicting vehicle acceleration. Tišljarić et al. (contribution 9) presented a tensor-based approach for road traffic anomaly detection. They used Speed Transition Matrices (STMs) to model the spatial–temporal traffic patterns and applied anomaly detection based on the center of mass computation. The proposed method achieved a precision score of 92.88% in detecting anomalies on urban road networks. Liu et al. (contribution 10) analyzed the impact of urban built-environment variables on bus–metro-transfer ridership using the XGBoost model. They found that the XGBoost model had a better fitting degree compared to traditional linear and nonlinear models. The model identified the relative importance of different variables and revealed the nonlinear and threshold effects of built-environment variables on ridership. The study also explored the moderating impact of station location on the relationship between the built environment and ridership. Liu et al. (contribution 11) proposed a modular battery swapping mode for electric taxis and developed a data-driven approach to configure and operate modular battery swapping stations (BSSs). Their study showed that a BSS with modular battery swapping can save on investment costs and better respond to time-of-use pricing compared to traditional battery swapping modes. Utilizing the ride-hailing order data from Chengdu, Wang et al. (contribution 12) employed the

Nugget–Sill Ratio (NSR) method and the Optimal Parameter-Based Geographical Detector (OPGD) model to determine the optimal grid scale. Furthermore, they integrated the "5D" built-environment determinants to construct a model assessing the impact factors influencing ride-hailing during morning and evening peak hours. Hu et al. (contribution 13) reported the development of a dynamic graph convolutional network model (Res-DGCN) for crowd flow prediction in urban areas. The model incorporates a spatial–temporal attention module and a conditional convolution module to capture spatial and temporal dependencies in the crowd flow data. The model was trained using the Huber loss function, which improved its robustness to outliers. The experimental results showed that the Res-DGCN model outperformed the baseline models in terms of the mean absolute error and the root mean square error, demonstrating its effectiveness in crowd flow prediction tasks. Chen et al. (contribution 14) developed a driving behavior risk measurement model that calculates the risk of different driving behaviors based on four indicators: lateral stability, longitudinal stability, car-following risk, and lane-changing risk. The model used weights to combine these indicators and provided a comprehensive risk evaluation of a driver's behavior. The study found that most drivers' behavior fell within a normal distribution, with the majority exhibiting a risk measurement between 0.1 and 0.3. Ye et al. (contribution 15) presented a traffic accident risk prediction model based on an LSTM algorithm. The model was able to accurately forecast the accident risk by analyzing the regional risk index and capturing long-term dependencies in the data. Zhou et al. (contribution 16) reviewed the intersection between ITS sensing and edge computing applications. They discussed the recent advances in ITS sensing and identified key challenges in this field. The authors also highlighted the potential benefits of integrating edge computing with ITS sensing and proposed future research directions.

3. Conclusions

In this Special Issue, it is evident that the intersection of knowledge discovery and big data in transportation heralds a transformative era for the sector. The diverse topics explored, from advanced architectures to innovative applications, underscore the vast potential and multifaceted challenges in harnessing data for transportation's evolution [29]. As we navigate the complexities of urbanization and the demands of modern mobility [30], the insights presented herein serve as both a compass and catalyst. We extend our gratitude to all the contributors for shedding light on these pivotal areas and anticipate that the discussions sparked will drive further research and real-world applications in the ever-evolving landscape of transportation.

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List of Contributions

1. Hou, Z.-W.; Yu, S.; Ji, T. Modeling the Trip Distributions of Tourists Based on Trip Chain and Entropy-Maximizing Theory. *Appl. Sci.* **2021**, *11*, 10058.
2. Gnap, J.; Jagelčák, J.; Marienka, P.; Frančák, M.; Vojteková, M. Global Assessment of Bridge Passage in Relation to Oversized and Excessive Transport: Case Study Intended for Slovakia. *Appl. Sci.* **2022**, *12*, 1931.
3. Kim, Y.-J.; Lee, J.-S.; Pititto, A.; Falco, L.; Lee, M.-S.; Yoon, K.-K.; Cho, I.-S. Maritime Traffic Evaluation Using Spatial-Temporal Density Analysis Based on Big AIS Data. *Appl. Sci.* **2022**, *12*, 11246.

4. Wang, Y.; Yang, L.; Song, X.; Chen, Q.; Yan, Z. A Multi-Feature Ensemble Learning Classification Method for Ship Classification with Space-Based AIS Data. *Appl. Sci.* **2021**, *11*, 10336.
5. Gao, L.; Wei, L.; Yang, J.; Li, J. Automatic Intersection Extraction Method for Urban Road Networks Based on Trajectory Intersection Points. *Appl. Sci.* **2022**, *12*, 5873.
6. Wang, P.; Liu, X.; Wang, Y.; Wang, T.; Zhang, J. Short-Term Traffic State Prediction Based on Mobile Edge Computing in V2X Communication. *Appl. Sci.* **2021**, *11*, 11530.
7. Mai, W.; Chen, J.; Chen, X. Time-Evolving Graph Convolutional Recurrent Network for Traffic Prediction. *Appl. Sci.* **2022**, *12*, 2842.
8. Zou, Y.; Ding, L.; Zhang, H.; Zhu, T.; Wu, L. Vehicle Acceleration Prediction Based on Machine Learning Models and Driving Behavior Analysis. *Appl. Sci.* **2022**, *12*, 5259.
9. Tišljarić, L.; Fernandes, S.; Carić, T.; Gama, J. Spatiotemporal Road Traffic Anomaly Detection: A Tensor-Based Approach. *Appl. Sci.* **2021**, *11*, 12017.
10. Liu, D.; Rong, W.; Zhang, J.; Ge, Y.-E. Exploring the Nonlinear Effects of Built Environment on Bus-Transfer Ridership: Take Shanghai as an Example. *Appl. Sci.* **2022**, *12*, 5755.
11. Liu, Z.; Ma, X.; Liu, X.; Correia, G.H.d.A.; Shi, R.; Shang, W. Optimizing Electric Taxi Battery Swapping Stations Featuring Modular Battery Swapping: A Data-Driven Approach. *Appl. Sci.* **2023**, *13*, 1984.
12. Wang, Z.; Liu, S.; Zhang, Y.; Gong, X.; Li, S.; Liu, D.; Chen, N. Exploring the Relative Importance and Interactive Impacts of Explanatory Variables of the Built Environment on Ride-Hailing Ridership by Using the Optimal Parameter-Based Geographical Detector (OPGD) Model. *Appl. Sci.* **2023**, *13*, 2180.
13. Hu, C.; Liu, X.; Wu, S.; Yu, F.; Song, Y.; Zhang, J. Dynamic Graph Convolutional Crowd Flow Prediction Model Based on Residual Network Structure. *Appl. Sci.* **2023**, *13*, 7271.
14. Chen, S.; Cheng, K.; Yang, J.; Zang, X.; Luo, Q.; Li, J. Driving Behavior Risk Measurement and Cluster Analysis Driven by Vehicle Trajectory Data. *Appl. Sci.* **2023**, *13*, 5675.
15. Ye, Q.; Li, Y.; Niu, B. Risk Propagation Mechanism and Prediction Model for the Highway Merging Area. *Appl. Sci.* **2023**, *13*, 8014.
16. Zhou, X.; Ke, R.; Yang, H.; Liu, C. When Intelligent Transportation Systems Sensing Meets Edge Computing: Vision and Challenges. *Appl. Sci.* **2021**, *11*, 9680.

References

1. Guerrero-Ibáñez, J.; Zeadally, S.; Contreras-Castillo, J. Sensor technologies for intelligent transportation systems. *Sensors* **2018**, *18*, 1212. [CrossRef] [PubMed]
2. Pascale, A.; Nicoli, M.; Deflorio, F.; Dalla Chiara, B.; Spagnolini, U. Wireless sensor networks for traffic management and road safety. *IET Intell. Transp. Syst.* **2012**, *6*, 67–77. [CrossRef]
3. Zhang, J.; Wang, Y.; Li, S.; Shi, S. An architecture for IoT-enabled smart transportation security system: A geospatial approach. *IEEE Internet Things J.* **2020**, *8*, 6205–6213. [CrossRef]
4. Boukerche, A.; Wang, J. Machine learning-based traffic prediction models for intelligent transportation systems. *Comput. Netw.* **2020**, *181*, 107530. [CrossRef]
5. Lian, Y.; Zhang, G.; Lee, J.; Huang, H. Review on big data applications in safety research of intelligent transportation systems and connected/automated vehicles. *Accid. Anal. Prev.* **2020**, *146*, 105711. [CrossRef] [PubMed]
6. Won, M. Intelligent traffic monitoring systems for vehicle classification: A survey. *IEEE Access* **2020**, *8*, 73340–73358. [CrossRef]
7. Chan, R.K.C.; Lim, J.M.Y.; Parthiban, R. A neural network approach for traffic prediction and routing with missing data imputation for intelligent transportation system. *Expert Syst. Appl.* **2021**, *171*, 114573. [CrossRef]
8. Niu, H.; Silva, E.A. Crowdsourced data mining for urban activity: Review of data sources, applications, and methods. *J. Urban Plan. Dev.* **2020**, *146*, 04020007. [CrossRef]
9. Nelson, T.; Ferster, C.; Laberee, K.; Fuller, D.; Winters, M. Crowdsourced data for bicycling research and practice. *Transp. Rev.* **2021**, *41*, 97–114. [CrossRef]
10. Anik, M.A.H.; Sadeek, S.N.; Hossain, M.; Kabir, S. A framework for involving the young generation in transportation planning using social media and crowd sourcing. *Transp. Policy* **2020**, *97*, 1–18. [CrossRef]
11. Aljoufie, M.; Tiwari, A. Citizen sensors for smart city planning and traffic management: Crowdsourcing geospatial data through smartphones in Jeddah, Saudi Arabia. *GeoJournal* **2022**, *87*, 3149–3168. [CrossRef]
12. Liu, G.; Shi, H.; Kiani, A.; Khreishah, A.; Lee, J.; Ansari, N.; Liu, C.; Yousef, M.M. Smart traffic monitoring system using computer vision and edge computing. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 12027–12038. [CrossRef]
13. Song, X.; Guo, Y.; Li, N.; Zhang, L. Online traffic flow prediction for edge computing-enhanced autonomous and connected vehicles. *IEEE Trans. Veh. Technol.* **2021**, *70*, 2101–2111. [CrossRef]
14. Zhang, P.; Sun, H.; Situ, J.; Jiang, C.; Xie, D. Federated transfer learning for IIoT devices with low computing power based on blockchain and edge computing. *IEEE Access* **2021**, *9*, 98630–98638. [CrossRef]

15. Guo, Z.; Zhang, Y.; Lv, J.; Liu, Y.; Liu, Y. An online learning collaborative method for traffic forecasting and routing optimization. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 6634–6645. [CrossRef]
16. Lu, H.; Huang, D.; Song, Y.; Jiang, D.; Zhou, T.; Qin, J. St-trafficnet: A spatial-temporal deep learning network for traffic forecasting. *Electronics* **2020**, *9*, 1474. [CrossRef]
17. Liu, L.; Zhen, J.; Li, G.; Zhan, G.; He, Z.; Du, B.; Lin, L. Dynamic spatial-temporal representation learning for traffic flow prediction. *IEEE Trans. Intell. Transp. Syst.* **2020**, *22*, 7169–7183. [CrossRef]
18. Zheng, G.; Chai, W.K.; Katos, V. A dynamic spatial–temporal deep learning framework for traffic speed prediction on large-scale road networks. *Expert Syst. Appl.* **2022**, *195*, 116585. [CrossRef]
19. Guo, S.; Lin, Y.; Wan, H.; Li, X.; Cong, G. Learning dynamics and heterogeneity of spatial-temporal graph data for traffic forecasting. *IEEE Trans. Knowl. Data Eng.* **2021**, *34*, 5415–5428. [CrossRef]
20. Wu, Q.; Xu, J.; Zeng, Y.; Ng, D.W.K.; Al-Dhahir, N.; Schober, R.; Swindlehurst, A.L. A comprehensive overview on 5G-and-beyond networks with UAVs: From communications to sensing and intelligence. *IEEE J. Sel. Areas Commun.* **2021**, *39*, 2912–2945. [CrossRef]
21. Wei, P.; Guo, K.; Li, Y.; Wang, J.; Feng, W.; Jin, S.; Ge, N.; Liang, Y.C. Reinforcement learning-empowered mobile edge computing for 6G edge intelligence. *IEEE Access* **2022**, *10*, 65156–65192. [CrossRef]
22. Wei, W.; Chen, K.C.; Rayes, A.; Scherer, R. Guest Editorial Introduction to the Special Issue on Graph-Based Machine Learning for Intelligent Transportation Systems. *IEEE Trans. Intell. Transp. Syst.* **2023**, *24*, 8393–8398. [CrossRef]
23. Ma, X.; Zhong, H.; Li, Y.; Ma, J.; Cui, Z.; Wang, Y. Forecasting Transportation Network Speed Using Deep Capsule Networks with Nested LSTM Models. *IEEE Trans. Intell. Transp. Syst.* **2022**, *22*, 4813–4824. [CrossRef]
24. Yan, H.; Ma, X.; Pu, Z. Learning Dynamic and Hierarchical Traffic Spatiotemporal Features with Transformer. *IEEE Trans. Intell. Transp. Syst.* **2022**, *23*, 2236–22399. [CrossRef]
25. Fu, X.; Yu, G.; Liu, Z. Spatial–temporal convolutional model for urban crowd density prediction based on mobile-phone signaling data. *IEEE Trans. Intell. Transp. Syst.* **2021**, *23*, 14661–14673. [CrossRef]
26. Li, C.; Bai, L.; Liu, W.; Yao, L.; Waller, S.T. Urban mobility analytics: A deep spatial–temporal product neural network for traveler attributes inference. *Transp. Res. Part C Emerg. Technol.* **2021**, *124*, 102921. [CrossRef]
27. Li, W.; Wang, S.; Zhang, X.; Jia, Q.; Tian, Y. Understanding intra-urban human mobility through an exploratory spatiotemporal analysis of bike-sharing trajectories. *Int. J. Geogr. Inf. Sci.* **2020**, *34*, 2451–2474. [CrossRef]
28. Lin, P.; Weng, J.; Alivanistos, D.; Ma, S.; Yin, B. Identifying and segmenting commuting behavior patterns based on smart card data and travel survey data. *Sustainability* **2020**, *12*, 5010. [CrossRef]
29. Liu, X.; Qu, X.; Ma, X. Optimizing electric bus charging infrastructure considering power matching and seasonality. *Transp. Res. Part D Transp. Environ.* **2021**, *100*, 103057. [CrossRef]
30. Liu, X.; Liu, X.; Liu, Z.; Shi, R.; Ma, X. A solar-powered bus charging infrastructure location problem under charging service degradation. *Transp. Res. Part D Transp. Environ.* **2023**, *119*, 103770. [CrossRef]