Web-Centric Human Mobility Analytics: Methods, Applications, and Future Directions in the LLM Era

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Abstract

Human mobility analytics is essential to enabling a broad range of web-related applications, such as navigation, urban planning, and point-of-interest (POI) recommendation. The proliferation of mobility data, including geo-social media check-ins and geo-location data, offers unprecedented opportunities for analyzing human mobility. This *lecture-style tutorial* offers an in-depth look at web-centric human mobility analytics, organized according to three levels: location-level, individual-level, and macro-level. Location-level analytics focus on spatial activities within specific geographical locations, using points of interest and other data to forecast future visits and identify urban mobility patterns. Individual-level analytics delve into the movements of individuals, *e.g.,* considering sequences of visited locations over time, elucidating individual movement behaviors. Macro-level analytics broaden the scope of analyses to include large-scale spatial patterns and population flows across regions, offering a macro perspective on mobility. The tutorial encompasses cutting-edge learning frameworks such as federated learning as well as continual learning and innovative applications of Large Language Models (LLMs), which enhance predictive analytics and expand the capabilities of mobility analysis. The tutorial aims to afford the participants a comprehensive overview of the current state and future directions of web-centric human mobility analytics, making it an invaluable resource for using web-sourced human mobility data to facilitate a more informed and interconnected world. The video teaser is available at https://shorturl.at/HShNc.

CCS Concepts

• **Information systems** → **Traffic analysis**; **Spatial-temporal systems**; **Mobile information processing systems**.

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Human Mobility Analytics, Web-Centric Modeling, LLM

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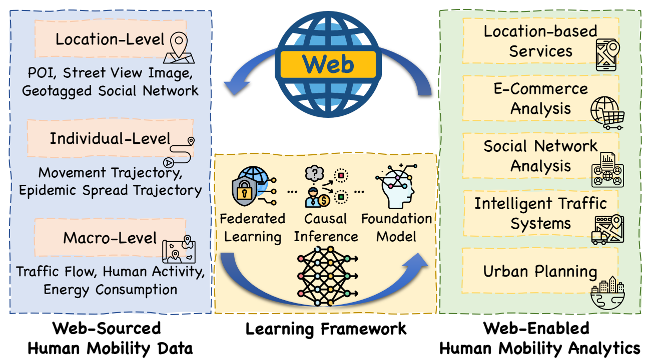

Figure 1: The pipeline of web-centric human mobility analytics, enables diverse human mobility analytics and supports decision-making in many fields.

1 Background and Topic

Human mobility analysis finds use in a myriad of modern life scenarios, from shaping urban landscapes and enhancing transportation systems to managing public health crises and environmental impact assessments [19]. Over the past few decades, the rapid advance in Internet technologies has led to a remarkable increase in the online digital footprint of human activity, including mobility. Based on diverse web services, *e.g.,* geo-social media check-ins [46], mobile application usage [1, 32], and transportation records [44], we are afforded unprecedented opportunities to observe and analyze human mobility behavior. Human mobility analytics provide critical insight into how people move within and across geographic spaces, enabling policymakers to make informed decisions that can optimize city infrastructure [37], facilitate emergency response [47], and foster sustainable development [19].

Web-sourced human mobility data, which includes point-of-interest (POI) data, trajectory data, and regional crowd flow data, offers a multifaceted view of human mobility from fine-grained to aggregate levels. These datasets capture human mobility patterns with granularity ranging from discrete geographic coordinates to broader individual movement and large-scale, regional population shifts. The past decades have seen notable progress in human mobility analytics, particularly with the advent of deep learning techniques, which have been crucial for enabling the extraction of valuable insight into complex mobility patterns. Recently, the emergence of Large Language Models (LLMs) has marked a new frontier, offering technical innovations and performance enhancements.

In this tutorial, we will provide a timely and comprehensive overview of web-centric human mobility analytics in the LLM era, as shown in Figure 1. We consider the human mobility analytics at three levels, from micro to macro: (i) the ***location-level*** focuses on analyzing human mobility patterns by examining activities within specific geographic points or regions; (ii) the ***individual-level*** aims to understand human movement over time, *e.g.,* by tracking the sequences of locations visited by individuals; and (iii) the ***macro-level*** captures a broader picture of human mobility by analyzing large-scale spatial patterns and flows across regions and cities. In addition, we discuss diverse advanced learning frameworks to provide comprehensive and timely insight into web-enabled human mobility analytics.

Location-level human mobility analytics focuses on the analysis of human mobility at specific locations, and location representation modeling is a prerequisite for mobility analytics. It involves analyzing data from geo-social media check-ins, street view imagery, and POI databases that can enable insights into human mobility. NeuNext [46] improves POI recommendation accuracy by jointly modeling spatio-temporal patterns and POI context. UrbanCLIP [37] is an LLM-based method that integrates textual descriptions with satellite imagery to enhance urban region profiling, achieving superior performance in urban indicator prediction.

Individual-level human mobility analytics analyzes sequences of coordinates that track individual movements over time. This enables analyses of the dynamics of human movement across space and time, which facilitates applications such as urban planning, traffic management, and location-based services. In individual-level human mobility analytics, trajectory compression and recovery play essential roles in optimizing data storage and quality. REST [48], a reference-based trajectory compression framework, compresses trajectories by representing them according to reference trajectories, reducing storage needs while retaining key spatial and temporal patterns. Trajectory recovery methods, *e.g.,* LightTR [18], focus on reconstructing high-resolution data from sparse samples, enabling accurate missing trajectory points recovery.

Macro-level human mobility analytics involves regional analyses, exploring data on crowd flows and energy consumption, and supporting tasks such as traffic flow prediction and urban planning. We will cover universal knowledge modeling within regional human flow data, encompassing multi-region modeling [21], multi-task learning [44], and the common knowledge captured by the foundation models [43], which can provide insight into large-scale mobility patterns and their societal implications. Specifically, HIEST [21] models sensor dependencies from both regional and global perspectives and proposes a hierarchical method that enables effective crowd flow prediction. PromptST [43] leverages a spatio-temporal transformer and prompt tuning strategy to efficiently capture specific attributes while maintaining common knowledge across multiple human activities, achieving good performance with strong transferability among urban computing applications.

Advanced learning framework covers cutting-edge technical and theoretical directions in human mobility analytics. We will discuss federated human mobility learning [14, 24] for collaborative modeling while preserving data locality and privacy. Additionally, we will present spatio-temporal continuous learning to handle streaming spatio-temporal data and prevent performance degradation due to catastrophic forgetting [23]. Moreover, Foundation models [16, 36], like LLMs, will be highlighted for their essential role in enhancing human mobility prediction tasks and identifying research gaps, challenges, and directions.

2 Relevance to the Web Conference

The Web Conference (WWW) consistently attracts a large number of attendees and top-tier papers that focus on human mobility and web analytics, reflecting the conference's commitment to exploring the latest advances in these areas. For more than two decades, human mobility analytics has been a prominent and recurrent theme in the conference series. In the most recent proceedings, this is reflected in the *Systems and Infrastructure for Web, Mobile, and WoT* research track, which accounts for approximately 10% (39/406) of the accepted papers. The tutorial is expected to contribute to WWW's mission of showcasing impactful research that has the potential to influence web technologies and their use for understanding and optimizing human mobility.

3 Overlap Statement

Previous Related Tutorials from Our Organizers:

- **Foundation Models for Time Series Analysis (KDD'24 Tutorial [13])**: This tutorial was held at KDD'24 in Barcelona, Spain, Aug. 29, 2024. It attracted around 120 onsite participants and over 1,000 tutorial website pageviews. The tutorial focused on recent advances in time series foundation models, covering both model design (*e.g.,* pre-training data, model architecture, and training tricks) and the application of pre-trained time series models aimed at achieving universal analytical intelligence for understanding data from real-world dynamic systems.
- **Foundation Models for Time Series Analysis (AAAI'25 Tutorial)**: This tutorial will be held at AAAI'25 in Philadelphia, PA, in February or March. It extends the KDD'24 tutorial by considering more recent advances in model-centric and data-centric approaches.

Previous Related Surveys by the presenters:

- Survey on location-level mobility analytics: VLDBJ'21 [4], Information Fusion'24 [51].
- Survey on individual-level mobility analytics: ICDE'23 [2], TKDE'24 [32].
- Survey on macro-level mobility analytics: TKDE'23 [9] (selected as a popular TKDE paper).

- Survey on spatio-temporal data mining: TPAMI'24 [41] (selected as a popular TPAMI paper), PVLDB'24 [27] (received a PVLDB'24 Best Paper Runner-up Award).

Previous Related Papers by the presenters:

- Location-level human mobility analytics: ICDE'22 [12], NeurIPS'24 [8], WWW'24 [37], MM'24 [49].
- Individual-level human mobility analytics: KDD'25 [35], KDD'18 [48], TKDE'22 [3], KDD'23 [39], WWW'24 [31], IJCAI'24 [20], KDD'24 [50], PVLDB'24 [6], ICDE'24 [5], IJCAI'21 [38].
- Macro-level human mobility analytics: AAAI'23 [44], ICDE'23 [25], KDD'21 [15], ICLR'24 [30], IJCAI'24 [40], WSDM'24 [29], TKDE'24 [26], NeurIPS'24 [34].
- Advanced learning frameworks: KDD'25 [28], KDD'24 [36], ICDE-'24 [18, 23], KDD'23 [7], IJCAI'24 [42], PVLDB'24 [45], WWW'24 [11], TKDE-'24 [24], PVLDB'25 [22].
- LLM/Foundation models for spatio-temporal data mining: NeurIPS'24 [14], ICLR'24 [10], WWW'24 [16].
- Mobility dataset & benchmark papers: NeurIPS'23 [17], IJCAI'24 [20], KDD'24 [33].

4 Tutors, Short Bio, and Expertise

In-person Presenter #1: Christian S. Jensen is a professor at Aalborg University. His research focuses on analytics and management in relation to time series and spatio-temporal data. He is a fellow of the ACM and IEEE. He is a member of the Academia Europaea, the Royal Danish Academy of Sciences and Letters, and the Danish Academy of Technical Sciences. Recent awards include the 2022 ACM SIGMOD Contributions Award and the IEEE TCDE Impact Award.

In-person Presenter #2: Yuxuan Liang is a tenure-track Assistant Professor at Hong Kong University of Science and Technology (Guangzhou), working on the research, development, and innovation of spatio-temporal data mining and urban computing. He has published 90+ papers in prestigious venues (*e.g.,* TPAMI, AI, TKDE, KDD, NeurIPS, and WWW). His publications have gathered 6,300 citations on Google Scholar, with h-index of 41. He has received ACM SIGSPATIAL China Rising Star Nomination, Singapore Data Science Consortium Research Fellowship, and The 23rd China Patent Excellence Award. He has been recognized as Stanford/Elsevier Top 2% Scientists.

In-person Presenter #3: Yan Zhao is a Professor at the University of Electronic Science and Technology of China, specializing in spatio-temporal databases, trajectory computing, spatial crowdsourcing, and other data-driven applications. She has published over 80 peer-reviewed papers in top-tier conferences and journals in big data management, receiving over 2,400 citations with an h-index of 26 (according to Google Scholar). She received the ACM SIGSPATIAL China Chapter Doctoral Dissertation Award in 2021.

In-person Presenter #4: Zijian Zhang is a tenure-track Assistant Professor at Jilin University, working on spatio-temporal data mining, traffic prediction, and other machine learning applications. He has published over 20 papers in top-tier venues.

In-person Presenter #5: Hao Miao is a postdoctoral researcher at Aalborg University with research interests in spatio-temporal data analytics, trajectory computing, and spatial crowdsourcing. He has published over 20 research papers in top-tier computer science conferences and journals (*e.g.,* PVLDB, KDD, ICDE, and TKDE). He has received a SIGIR CIKM 2020 Travel Award and Otto Moensted Foundation Study Abroad Award.

In-person Presenter #6: Xiao Han is a PhD student at City University of Hong Kong. His research interests include spatiotemporal data analytics and intelligent transportation systems.

In-person Presenter #7: Pengyue Jia is a PhD candidate at City University of Hong Kong, working on LLMs and geographic information systems.

In-person Presenter #8: Bin Yang is a Chair Professor at East China Normal University, working on data-driven decision intelligence, with a focus on time series and spatio-temporal data. He has published over 100 research papers on top-tier conferences and journals (*e.g.,* SIGMOD, PVLDB, ICDE, NeurIPS, and TKDE).

5 Tutorial Outline

S1. Welcome and Introduction (10 mins)
Presenter: Christian S. Jensen
1.1 Overview of Human Mobility Analytics
S2. Location-Level Human Mobility Analytics: (40 mins)
Presenter: Yuxuan Liang
2.1 Predictive Modeling for Next Location Visits
2.2 Applications of Location-Level Analytics
S3. Individual-Level Human Mobility Analytics: (40 mins)
Presenter: Yan Zhao
3.1 Trajectory Compression
3.2 Trajectory Recovery
S4. Macro-Level Human Mobility Analytics: (40 mins)
Presenter: Zijian Zhang and Xiao Han
4.1 Regional Crowd Flows Modeling
4.2 Universal Knowledge Modeling
S5. Advanced Learning Framework: (30 mins)
Presenter: Hao Miao
5.1 Federated Human Mobility Learning
5.2 Spatio-Temporal Continuous Learning
5.3 Foundation Models (*e.g.,* LLMs) for Mobility: Challenges, Applications, and Directions
S6. Conclusion and Open Discussion: (20 mins)
Presenters: Bin Yang and Pengyue Jia
6.1 Conclusions
6.2 Questions and Discussions

6 Intended Audience

This tutorial is designed for a diverse audience of professionals, researchers, and practitioners who are interested in the field of human mobility analytics. We assume participants have a basic understanding of artificial intelligence and data analysis, making the content suitable for professionals and students alike.

Attendees will gain a thorough understanding of the methodologies and applications of human mobility analytics across location-level, individual-level, and macro-level data. They will also become familiar with advanced learning frameworks such as federated learning and causal inference, and they will learn how to apply these concepts to real-world scenarios.

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References

[1] Xin Cao, Gao Cong, and Christian S Jensen. 2010. Mining significant semantic locations from GPS data. *PVLDB* 3, 1-2 (2010), 1009–1020.

[2] Yanchuan Chang, Jianzhong Qi, Yuxuan Liang, and Egemen Tanin. 2023. Contrastive trajectory similarity learning with dual-feature attention. In *ICDE*. 2933–2945.

[3] Meng Chen, Yan Zhao, Yang Liu, Xiaohui Yu, and Kai Zheng. 2022. Modeling spatial trajectories with attribute representation learning. *TKDE* 34, 4 (2022), 1902–1914.

[4] Zhida Chen, Lisi Chen, Gao Cong, and Christian S Jensen. 2021. Location-and keyword-based querying of geo-textual data: a survey. *VLDBJ* 30, 4 (2021), 603–640.

[5] Liwei Deng, Yan Zhao, Jin Chen, Shuncheng Liu, Yuyang Xia, and Kai Zheng. 2024. Learning to Hash for Trajectory Similarity Computation and Search. In *ICDE*. 4491–4503.

[6] Chenjuan Guo, Ronghui Xu, Bin Yang, Ye Yuan, Tung Kieu, Yan Zhao, and Christian S Jensen. 2024. Efficient stochastic routing in path-centric uncertain road networks. *PVLDB* 17, 11 (2024), 2893–2905.

[7] Xiao Han, Xiangyu Zhao, Liang Zhang, and Wanyu Wang. 2023. Mitigating action hysteresis in traffic signal control with traffic predictive reinforcement learning. In *KDD*. 673–684.

[8] Pengyue Jia, Yiding Liu, Xiaopeng Li, et al. 2024. G3: An Effective and Adaptive Framework for Worldwide Geolocalization Using Large Multi-Modality Models. *NeurIPS* (2024).

[9] Guangyin Jin, Yuxuan Liang, Yuchen Fang, Zezhi Shao, Jincai Huang, Junbo Zhang, and Yu Zheng. 2023. Spatio-temporal graph neural networks for predictive learning in urban computing: A survey. *TKDE* (2023).

[10] Ming Jin, Shiyu Wang, et al. 2024. Time-LLM: Time series forecasting by reprogramming large language models. In *ICLR*.

[11] Zhichen Lai, Huan Li, Dalin Zhang, Yan Zhao, Weizhu Qian, and Christian S Jensen. 2024. E2Usd: Efficient-yet-effective Unsupervised State Detection for Multivariate Time Series. In *WWW*. 3010–3021.

[12] Tianyi Li, Lu Chen, Christian S Jensen, Torben Bach Pedersen, Yunjun Gao, and Jilin Hu. 2022. Evolutionary clustering of moving objects. In *ICDE*. 2399–2411.

[13] Yuxuan Liang, Haomin Wen, Yuqi Nie, Yushan Jiang, Ming Jin, Dongjin Song, Shirui Pan, and Qingsong Wen. 2024. Foundation models for time series analysis: A tutorial and survey. In *KDD*. 6555–6565.

[14] Qingxiang Liu, Xu Liu, Chenghao Liu, Qingsong Wen, and Yuxuan Liang. 2024. Time-FFM: Towards LM-Empowered Federated Foundation Model for Time Series Forecasting. *NeurIPS* (2024).

[15] Shuncheng Liu, Han Su, Yan Zhao, Kai Zeng, and Kai Zheng. 2021. Lane change scheduling for autonomous vehicle: A prediction-and-search framework. In *KDD*. 3343–3353.

[16] Xu Liu, Junfeng Hu, Yuan Li, Shizhe Diao, Yuxuan Liang, Bryan Hooi, and Roger Zimmermann. 2024. UniTime: A Language-Empowered Unified Model for Cross-Domain Time Series Forecasting. In *WWW*. 4095–4106.

[17] Xu Liu, Yutong Xia, Yuxuan Liang, Junfeng Hu, Yiwei Wang, Lei Bai, Chao Huang, Zhenguang Liu, Bryan Hooi, and Roger Zimmermann. 2023. LargeST: A benchmark dataset for large-scale traffic forecasting. *NeurIPS* (2023).

[18] Ziqiao Liu, Hao Miao, Yan Zhao, Chenxi Liu, Kai Zheng, and Huan Li. 2024. LightTR: A Lightweight Framework for Federated Trajectory Recovery. In *ICDE*. 4422–4434.

[19] Massimiliano Luca, Gianni Barlacchi, Bruno Lepri, and Luca Pappalardo. 2021. A survey on deep learning for human mobility. *CSUR* 55, 1 (2021), 1–44.

[20] Kang Luo, Yuanshao Zhu, Wei Chen, Kun Wang, Zhengyang Zhou, Sijie Ruan, and Yuxuan Liang. 2024. Towards Robust Trajectory Representations: Isolating Environmental Confounders with Causal Learning. *IJCAI* (2024).

[21] Qian Ma, Zijian Zhang, Xiangyu Zhao, Haoliang Li, Hongwei Zhao, Yiqi Wang, Zitao Liu, and Wanyu Wang. 2023. Rethinking sensors modeling: Hierarchical information enhanced traffic forecasting. In *CIKM*. 1756–1765.

[22] Hao Miao, Ziqiao Liu, Yan Zhao, Chenjuan Guo, Bin Yang, Kai Zheng, and Christian S. Jensen. 2025. Less is More: Efficient Time Series Dataset Condensation via Two-fold Modal Matching. *PVLDB* (2025).

[23] Hao Miao, Yan Zhao, Chenjuan Guo, Bin Yang, Kai Zheng, Feiteng Huang, Jiandong Xie, and Christian S. Jensen. 2024. A Unified Replay-Based Continuous Learning Framework for Spatio-Temporal Prediction on Streaming Data. In *ICDE*. 1050–1062.

[24] Hao Miao, Xiaolong Zhong, Jiaxin Liu, Yan Zhao, Xiangyu Zhao, Weizhu Qian, Kai Zheng, and Christian S Jensen. 2024. Task Assignment With Efficient Federated Preference Learning in Spatial Crowdsourcing. *TKDE* 36, 4 (2024), 1800–1814.

[25] Weizhu Qian, Dalin Zhang, Yan Zhao, Kai Zheng, and JQ James. 2023. Uncertainty quantification for traffic forecasting: A unified approach. In *ICDE*. 992–1004.

[26] Weizhu Qian, Yan Zhao, Dalin Zhang, Bowei Chen, Kai Zheng, and Xiaofang Zhou. 2024. Towards a Unified Understanding of Uncertainty Quantification in Traffic Flow Forecasting. *TKDE* 36, 5 (2024), 2239–2256.

[27] Xiangfei Qiu, Jilin Hu, Lekui Zhou, Xingjian Wu, Junyang Du, Buang Zhang, Chenjuan Guo, Aoying Zhou, Christian S Jensen, Zhenli Sheng, and Bin Yang. 2024. TFB: Towards Comprehensive and Fair Benchmarking of Time Series Forecasting Methods. *PVLDB* 17 (2024), 2363 – 2377.

[28] Jindong Tian, Yuxuan Liang, Ronghui Xu, Peng Chen, Chenjuan Guo, Aoying Zhou, Lujia Pan, Zhongwen Rao, and Bin Yang. 2025. Air quality prediction with physics-informed dual neural odes in open systems. In *ICLR*.

[29] Chengxin Wang, Yuxuan Liang, and Gary Tan. 2024. CityCAN: Causal Attention Network for Citywide Spatio-Temporal Forecasting. In *WSDM*. 702–711.

[30] Kun Wang, Hao Wu, Yifan Duan, Guibin Zhang, Kai Wang, Xiaojiang Peng, Yu Zheng, Yuxuan Liang, and Yang Wang. 2024. NuwaDynamics: Discovering and Updating in Causal Spatio-Temporal Modeling. In *ICLR*.

[31] Yu Wang, Tongya Zheng, Yuxuan Liang, Shunyu Liu, and Mingli Song. 2024. Cola: Cross-city mobility transformer for human trajectory simulation. In *WWW*. 3509–3520.

[32] Haomin Wen, Youfang Lin, Lixia Wu, et al. 2024. A survey on service route and time prediction in instant delivery: Taxonomy, progress, and prospects. *TKDE* (2024).

[33] Lixia Wu, Haomin Wen, Haoyuan Hu, et al. 2024. LaDe: The first comprehensive last-mile delivery dataset from industry. *KDD* (2024), 5991–6002.

[34] Yutong Xia, Yuxuan Liang, Haomin Wen, Xu Liu, Kun Wang, Zhengyang Zhou, and Roger Zimmermann. 2024. Deciphering spatio-temporal graph forecasting: A causal lens and treatment. *NeurIPS* (2024).

[35] Ronghui Xu, Hanyin Cheng, Chenjuan Guo, Hongfan Gao, Jilin Hu, Sean Bin Yang, and Bin Yang. 2025. MM-Path: Multi-modal, Multi-granularity Path Representation Learning. In *SIGKDD*.

[36] Ronghui Xu, Hao Miao, Senzhang Wang, Philip S Yu, and Jianxin Wang. 2024. PeFAD: A Parameter-Efficient Federated Framework for Time Series Anomaly Detection. In *KDD*. 3621–3632.

[37] Yibo Yan, Haomin Wen, Siru Zhong, Wei Chen, Haodong Chen, Qingsong Wen, Roger Zimmermann, and Yuxuan Liang. 2024. Urbanclip: Learning text-enhanced urban region profiling with contrastive language-image pretraining from the web. In *WWW*. 4006–4017.

[38] Sean Bin Yang, Chenjuan Guo, Jilin Hu, Jian Tang, and Bin Yang. 2021. Unsupervised Path Representation Learning with Curriculum Negative Sampling. In *IJCAI*. 3286–3292.

[39] Sean Bin Yang, Jilin Hu, Chenjuan Guo, Bin Yang, and Christian S Jensen. 2023. Lightpath: Lightweight and scalable path representation learning. In *KDD*. 2999–3010.

[40] Huaiwu Zhang, Yutong Xia, Siru Zhong, et al. 2024. Predicting Parking Availability in Singapore with Cross-Domain Data: A New Dataset and A Data-Driven Approach. *IJCAI* (2024).

[41] Kexin Zhang, Qingsong Wen, Chaoli Zhang, et al. 2024. Self-supervised learning for time series analysis: Taxonomy, progress, and prospects. *TPAMI* (2024).

[42] S Zhang, S Wang, H Miao, H Chen, C Fan, and J Zhang. 2024. Score-CDM: Score-Weighted Convolutional Diffusion Model for Multivariate Time Series Imputation. *IJCAI* (2024).

[43] Zijian Zhang, Xiangyu Zhao, Qidong Liu, Chunxu Zhang, Qian Ma, Wanyu Wang, Hongwei Zhao, Yiqi Wang, and Zitao Liu. 2023. Promptst: Prompt-enhanced spatio-temporal multi-attribute prediction. In *CIKM*. 3195–3205.

[44] Zijian Zhang, Xiangyu Zhao, Hao Miao, Chunxu Zhang, Hongwei Zhao, and Junbo Zhang. 2023. Autostl: Automated spatio-temporal multi-task learning. In *AAAI*, Vol. 37. 4902–4910.

[45] Kai Zhao, Chenjuan Guo, Yunyao Cheng, Peng Han, Miao Zhang, and Bin Yang. 2023. Multiple Time Series Forecasting with Dynamic Graph Modeling. *PVLDB* 17, 4 (2023), 753–765.

[46] Pengpeng Zhao, Anjing Luo, Yanchi Liu, Jiajie Xu, Zhixu Li, Fuzhen Zhuang, Victor S. Sheng, and Xiaofang Zhou. 2022. Where to Go Next: A Spatio-Temporal Gated Network for Next POI Recommendation. *TKDE* 34, 5 (2022), 2512–2524.

[47] Xiangyu Zhao, Wenqi Fan, Hui Liu, and Jiliang Tang. 2022. Multi-type urban crime prediction. In *AAAI*, Vol. 36. 4388–4396.

[48] Yan Zhao, Shuo Shang, Yu Wang, Bolong Zheng, Quoc Viet Hung Nguyen, and Kai Zheng. 2018. Rest: A reference-based framework for spatio-temporal trajectory compression. In *KDD*. 2797–2806.

[49] Siru Zhong, Xixuan Hao, Yibo Yan, Ying Zhang, Yangqiu Song, and Yuxuan Liang. 2024. UrbanCross: Enhancing Satellite Image-Text Retrieval with Cross-Domain Adaptation. In *MM*. 6307–6315.

[50] Yuanshao Zhu, James Jianqiao Yu, Xiangyu Zhao, et al. 2024. Controltraj: Controllable trajectory generation with topology-constrained diffusion model. In *KDD*. 4676–4687.

[51] Xingchen Zou, Yibo Yan, Xixuan Hao, et al. 2024. Deep learning for cross-domain data fusion in urban computing: Taxonomy, advances, and outlook. *Information Fusion* 113 (2024), 102606.