COMMENTARY

AI-enhanced spatial-temporal data-mining technology: New chance for next-generation urban computing

Fei Wang,[1,2,4,*] **Di Yao,**[1,2,4,*] **Yong Li,**[3,4,*] **Tao Sun,**[1] **and Zhao Zhang**[1]

[1]Institute of Computing Technology, Chinese Academy of Sciences, Beijing 100190, China
[2]University of Chinese Academy of Sciences, Beijing 100049, China
[3]Department of Electronic Engineering, Tsinghua University, Beijing 100084, China
[4]These authors contributed equally
*Correspondence: wangfei@ict.ac.cn (F.W.); yaodi@ict.ac.cn (D.Y.); liyong07@tsinghua.edu.cn (Y.L.)

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In the previous few decades, urbanization has accelerated. In 2020, the average worldwide urbanization rate was 56.2%,[1] suggesting that most nations are urbanized. Despite enormous gains, contemporary cities' common resources and infrastructures cannot meet the needs of all people, resulting in undesirable consequences such as traffic congestion, food waste, water contamination, and high crime rates. To remove these impacts, urban computing, which bridges the gap between urban science and computer science, is proposed. It attempts to make wise judgments and improve the city's resource distribution using extensively gathered spatial-temporal data. Continuously gathering and analyzing urban data yields significant benefits in many applications (see Figure 1). The recent growth of artificial intelligence (AI) technology[2] presents both new potential and obstacles for urban computing. Traditional analytical methodologies, such as physical modeling, heavily rely on empirical information or make strict assumptions that are unsuitable for complicated urban computing problems. In contrast, data-driven AI models automatically learn from data, complementing traditional methodologies (Figure 1, box 1).

DILEMMAS IN URBAN COMPUTING DEVELOPMENT

In this section, we highlight the challenges of applying AI techniques (see Figure 1, box 2).

Extracting valuable knowledge from explosive urban data is still challenging. People can only extract sparse and noisy knowledge, such as simple patterns in trajectories of vehicles and time series of electrical load, from raw urban data. This makes it difficult to make comprehensive and accurate decisions. However, what people really need is deeply refined knowledge, such as population growth laws and economic development laws.[3] This often requires researchers to design complicated models and include expert inference, which is

Figure 1. AI-enhanced spatial-temporal data mining in urban computing

dramatically hard. Moreover, applying knowledge in real-world urban applications is also an edging issue.

Modeling the giant spatial-temporal system is challenging. Urban prediction tasks require consideration of many factors, and determining how to fully consider these related factors is a tough problem. Data-driven intelligent learning has recently received increased attention in academy. However, large-scale variables in the real world severely limit the performance and efficiency of data-driven intelligent learning, posing challenges for urban computing.

Although current AI techniques directly learn models from data, most of them rely on the expression power of deep neural networks (DNNs), which is known as a vulnerable "black box" lacking transparency of how inputs are transformed into model outputs. Users are unclear on how DNNs work, and even the designers cannot explain why the models made a decision. For urban computing, reliability is critical for decision-making. Thus, directly using DNN-based AI techniques for urban computing is risky.

The ultimate goal of urban computing is to assist people in intelligent decision-making at the macro-level of urban governance and the micro-level of personal life. For example, we suppose it is the foundation of construction planning, traffic control, logistics optimization, emergency response, epidemic prevention and control, etc. However, at present, the applications of urban computing lie more in data display or status evaluation, creating a dilemma in which the current development of urban computing does not match its long-term goal.

POTENTIAL CHANGE OF AI-ENHANCED SPATIAL-TEMPORAL DATA-MINING TECHNOLOGY

Despite the challenges of urban computing, recent advances in AI-enhanced spatial-temporal data-mining technology provide new chances. We rethink current AI technologies, particularly in knowledge discovery, system-scale spatial-temporal prediction, causality analysis, and intelligent decision-making, to improve the development of urban computing (Figure 1, box 3).

Rethinking knowledge discovery and application: knowledge discovery and utilization are critical steps in urban computing. In recent years, knowledge reasoning has developed rapidly, allowing us to represent and discover knowledge in real-world scenarios. Transfer learning allows for the sharing of information with different tasks, which aids the model in discovering knowledge with limited data. The reinforcement learning decision-making process allows us to remove false and noisy data while retaining true data, ensuring the effect and quality of knowledge reasoning. Finally, the knowledge obtained through collection or inference can provide a wealth of external information for various applications. And we are hopeful that this knowledge would improve the effectiveness of existing applications.

Rethinking system-scale spatial-temporal prediction: a city is a giant spatial-temporal system with multiple interrelated variables. In urban computing, a single result often comes from the interaction of multiple factors. Multivariate time series forecasting can construct a forecasting model for multiple correlated variables and effectively improve the forecasting effect of every single variable.[4] It can be applied to a number of real-world applications such as weather forecasting and traffic forecasting. Besides, recent years have witnessed the development of Transformer and its variants, with which we can make long-term predictions, broadening people's perception of the future. In addition, graph neural networks have attracted much attention in recent years and effectively utilize the graph structure to model the dependencies between various variables. Using graph neural networks to model the spatial relationships between variables may improve the performance of urban computing applications. Finally, building large-scale, pre-trained models based on historical data of various variables is also the future direction of urban computing in order to further improve the utilization of data.

Rethinking causal-inspired machine-learning techniques: causality is a critical tool for human beings to understand how the physical world works. It can be used to formalize the data-generation process, which is naturally explainable. Recently, involving causality in the DNN models has become one of the most promising research directions for improving the reliability of AI algorithms.[5] Recent causal AI techniques have been adopted for enhancing the reliability of prediction, classification, and decision-making. In urban computing, many applications can also be defined as causal problems. For example, scheduling traffic lights requires knowing the causality of traffic jams. Optimizing scheduling policy based on the causal mechanism would boost stability and reliability. Unfortunately, causality-based works in urban computing research are very rare. We believe that integrating the causal mechanism of urban operations into AI models will be of benefit to many urban computing tasks.

Rethinking intelligent decision making: the essence of urban decision-making is decision-making on complex systems. Traditional algorithms suffer from the dilemma of high model complexity and heavy calculations. Thus, on one hand, we need to model large amounts of high-dimension variables with various distributions, which are intractable without simplifications. On the other hand, the decision action space is extremely large. Traditional methods fail to give feasible solutions within an acceptable time. On the contrary, due to the representation ability, the recently developed data-driven decision-making models show advantages in solving complex problems. It is naturally suitable for dealing with high-dimensional variables and is easy to parallel.

CONCLUSION

Urban computing makes our cities more intelligent and efficient. It has effectively served public service, social governance, public security, and other applications. At present, urban data analysis still heavily relies on expert knowledge and mainly focuses on specific scenarios. AI techniques have many limitations, leading to a significant gap to practice. Nevertheless, AI-enhanced spatial-temporal data-mining technologies such as knowledge discovery, system-scale spatial-temporal prediction, data-driven causality analysis, and intelligent decision-making are promising to solve the dilemmas in urban computing and achieve new development.

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DECLARATION OF INTERESTS

The authors declare no competing interests.