Abstract

The rapid expansion of urban areas globally necessitates innovative approaches for understanding and managing complex urban dynamics. However, traditional urban monitoring methods relying on sparsely distributed static stations are inadequate to capture the intricate dynamics and fine-grained spatio-temporal variability inherent in complex urban environments. Participatory sensing, leveraging the ubiquitous presence of smartphones equipped with various sensors, presents a compelling alternative for acquiring large-scale, high-resolution data on diverse urban phenomena.

Despite its potential, existing participatory sensing solutions are hampered by several limitations. Notably, the absence of a unified framework hinders seamless integration and data exchange between diverse applications. Additionally, inadequate attention is paid to privacy-aware solutions, potentially compromising user anonymity and trust. Also, lack of fair task allocation techniques exist for participatory / crowd sensing systems which is leading to efficient incentive mechanism. Furthermore, limited analysis of the inherent spatio-temporal variability in urban dynamics restricts the accuracy and generalizability of insights derived from the collected data. Finally, insufficient exploration of the geographically varying relationships between urban dynamics and various risk factors hinders the development of targeted interventions and resource allocation strategies.

This thesis bridges these critical research gaps by introducing novel techniques for studying urban dynamics using participatory sensing data. We propose JUSense, a unified framework that integrates diverse urban sensing applications, fostering seamless data exchange and collaboration. We propose a privacy-preserving user identification module based on deep learning for robust user authentication while safeguarding anonymity. To address data quality concerns, we explore context-aware data cleaning and device-specific calibration mechanisms to ensure data accuracy. Additionally, we propose TATA, a truthful double auction-based incentive mechanism that promotes fair task allocation and motivates user participation in data collection.

To leverage the rich spatio-temporal data collected through participatory sensing, we explore advanced analytical methods. We present a system that enables dynamic noise pollution mapping as a service, employing novel spatial interpolation techniques to address sparse data scenarios and ensure high accuracy. Furthermore, we investigate the spatio-temporal variability of deep learning models for predicting health outcomes, such as COVID-19 cases and mortalities. This analysis allows for the identification of regions where specific models perform exceptionally well, enabling targeted and efficient resource allocation for healthcare interventions. Finally, we delve into the issue of geographical heterogeneity by employing geographically weighted regression models to explore the spatially varying relationships between COVID-19 health outcomes and diverse socio-economic, demographic, and environmental risk factors. This analysis provides valuable insights into the localized factors influencing the pandemic's course and informs targeted interventions tailored to specific geographical regions.

By addressing the critical research gaps, the contributions in this thesis pave the way for the development of robust and efficient urban dynamics analysis systems. These advancements hold significant potential to empower urban planners and policymakers with the necessary insights to make informed decisions, ultimately leading to improved resource management, enhanced urban planning strategies, and a better quality of life for citizens.