ABSTRACT

Urban traffic networks encompass the collection and interlinking of urban entities, including but not limited to road networks, congested segments, mobile populations, and emergency occurrences. These entities facilitate daily human activities, support economic endeavors, and influence the trajectory of societal advancement. Comprehending the characteristics and anticipating the evolution of dynamic urban traffic networks have been fundamental building blocks in urban science. Typical examples include the primal and dual representations of road networks, the macroscopic fundamental diagram applied to congested roads, and models on the spread of diseases. Current seminal studies either devise physics metrics and models to elucidate universal traits of urban traffic networks, or exploit data-driven approaches to depict the urban landscape using vast amounts of urban data. However, these physics and data-driven methods primarily function separately, resulting in a lack of a comprehensive framework to accurately and interpretably 1) characterize the topology and dynamics of urban traffic networks; and 2) forecast the evolution of dynamics within urban traffic networks.

In this dissertation, we develop physics-informed graph learning methods to learn and forecast urban traffic networks in manners that are accurate, interpretable, adaptable, and applicable, aiming to advance urban science theories and support urban decision-making processes.

In Chapters 3 and 4, we explore novel physics knowledge of urban traffic networks in terms of new **metrics** and **equations**. In Chapter 3, we define new morphological **metrics** for urban road networks [1]. Specifically, we present a network metric called spatial homogeneity (SH), which gauges the topological similarities among urban road networks using graph neural networks. Employing this metric, we analyze 11,790 urban road networks across 30 cities worldwide. Our findings reveal the inherent correlations between innercity SH, gross domestic product, and population growth. Furthermore, we quantify learning trajectories between cities from intercity SH and connect them with existing qualitative urban studies. In Chapter 4, we establish new differential **equations** governing dynamic urban traffic [2]. Through a symbolic regression-based learning approach, we come up with

network-level dynamic traffic equations (NDTEs), which capture time-of-day traffic flow and traffic occupancy dynamics. The advantages of NDTEs are twofold: (1) all input variables are easily obtainable; (2) they incorporate vehicle count-related variables. Our experiments on road networks in Zurich and Toronto demonstrate that the generated NDTEs offer enhanced fitting accuracy compared to the baseline model while maintaining a moderate level of equation complexity.

In Chapters 5, 6, and 7, we harness physics knowledge to devise graph learning approaches for urban **prediction** and **imputation**. In Chapter 5, we present NMFD-GNN, a physics-informed machine learning method that integrates the network macroscopic fundamental diagram and the graph neural network for traffic state **imputation** [3]. Our approach is the first physics-informed machine learning model specifically designed for real-world traffic networks with multiple roads, while existing studies have primarily focused on individual road corridors. In Chapter 6, we develop the spatio-temporal physics ordinary differential equation (ST-PODE), which connects PODEs with spatio-temporal neural networks. ST-PODE is composed of the spatio-temporal neural network module, the PODE module, and the state transition module. We downscale our focus to the **prediction** of morning traffic patterns and evaluate our models using datasets from the Bay Area and Los Angeles. In Chapter 7, we address the multiwave COVID-19 **prediction** challenge on urban mobility networks [4]. The proposed social awareness-based graph neural network (SAB-GNN) models the evolution of public awareness across multiple pandemic waves as an exponential function with learnable parameters. We employ the mobility, web search, and infection data in Tokyo from April 2020 to May 2021 to validate its performance.

The intended audiences of this dissertation comprise colleagues in the fields of artificial intelligence, urban science, transportation engineering, and network science. Our goal is to offer instructive insights to the community to (1) explore universal properties, (2) foresee future evolution, and (3) interpret models and results using massive graph-structured data in urban traffic networks.