Research Statement

1 Research Overview

Vision: My research interests are broadly in the areas of **Data Science** and **Cyber-Physical Systems** (CPS). My research is driven by **rich data** collected from urban physical systems and focus on the integration of **human behavior learning** and **decision making** in urban CPS. In particular, my research vision is:

With the data collected from urban physical systems, learning human behavior can successfully bridge humans and systems in the Human-in-the-Loop Urban CPS and support decision making to improve CPS.

Motivation: Since the Coke machine was first connected on the Internet in Pittsburgh, an idea began to spread: a vision of an interconnected world where information on most everyday objects was accessible. Following this vision, scientists and engineers have developed this idea into a concept called *Cyber-Physical Systems (CPS)* or *Internet of Things (IoT)*, which interconnects a large number of heterogeneous devices, from traditional desktop PCs to smartphones, from household appliances to wearable devices. However, a key element, e.g., human being, is less studied compared to the physical and cyber components, which is of great importance considering the intrinsic purpose of CPS is to serve humans. Nowadays, with the various data collected from urban physical systems, we have an unprecedented opportunity to incorporate humans into CPS, which motivates my research.

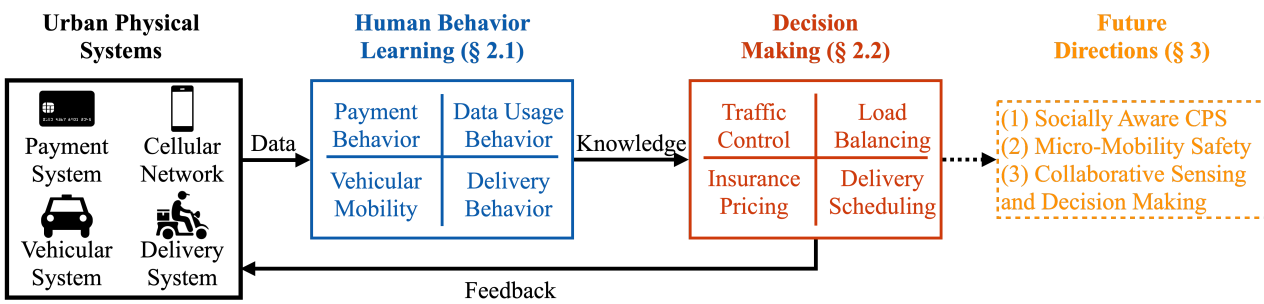

Figure 1: Research Framework

Thesis Work Summary: The framework of my research is shown in Figure 1. My work explores a wide range of large-scale urban physical systems including a citywide cellular network system, a citywide on-demand delivery system, a statewide payment system, and a nationwide vehicular system. Based on the data collected from these systems, my work focuses on two fundamental challenges that are unique in the human-in-the-loop urban CPS:

(1) **Human Behavior Learning:** learning human behavior such as vehicular mobility behavior, data usage behavior, payment behavior, and delivery behavior;

(2) **Decision Making:** making decisions based on the knowledge from human behavior learning such as traffic control, load balancing, insurance pricing, and delivery scheduling.

To learn human behavior, I integrate the fundamental characteristics of human behavior with domain-specific insights into the urban physical systems, and design new machine learning techniques. The unifying knowledge underlying human behavior learning is the uniqueness and conformity that different humans have their unique behavior while also conform to the crowds. Based on the learned knowledge, I design a human behavior aware decision making process to improve the effectiveness and efficiency of the urban physical systems, which is sent as feedback to adapt the systems. The future directions are described in § 3.

Thesis Work Impact: The impact of my thesis work is substantiated in both industry and academia.

- **Industry**: My work is adopted in the real world industry scenarios. *Eleme*, one of the largest on-demand delivery service companies in the world, has used my result (MobiCom'20 [7]) in a pilot platform to infer the status of delivery couriers; the preliminary result has shown the effectiveness of reducing the late-delivery rate. Also based on my result (NSDI'21 [1]), *Eleme* has deployed and operated one of the largest Bluetooth beacon systems *aBeacon* with more than **12 thousand devices** to support the delivery workflow of **100 thousand** couriers and **64 million** orders. *Shenzhen Institutes of Advanced Technology* has been working with Shenzhen Government to use my result (MobiCom'19 [9]) for a pilot program to monitor the status of a **citywide** highway system.
- **Academia**: My research results have led to more than 10 publications in the premier conferences and journals such as MobiCom, NSDI, UbiComp, and TMC along with two funded grants from the NSF Smart and Autonomous Systems (S&AS) and the NSF CPS. Several papers have been adopted as graduate-level course materials such as *Data Science for Smart Cities* in Rutgers University and were selected to be discussed in the seminar of several universities such as University of Virginia, Tsinghua University, and Shanghai Jiao Tong University. I was also invited to serve on program committees for The Tenth International Conference on Mobile Services, Resources, and Users; I actively served as (external) reviewers for several top journals and conferences such as IEEE Journals/Transactions and IMWUT.

2 Thesis Work

My thesis shows that (i) human behavior can be learned based on the data from the urban physical systems and (ii) the learned knowledge can support decision making. This section presents these two themes in detail.

2.1 Human Behavior Learning in CPS

In this part, I show how human behavior is learned both in a single system and across multiple systems.

2.1.1 Learning in A Single System

One project I did was to learn vehicular mobility such as routes, speed, and real-time locations on highways (MobiCom'19 [9]). The previous work is generally based on the GPS information that vehicular mobility is well observed from the historical data; but it is limited by the low penetration of vehicles with accessible GPS information, which cannot cover even a large proportion of vehicles on highways. I addressed this limitation based on a highway payment system. The advantage of the payment system is that everyone needs to pay before entering highways. which assures a full penetration. However, the challenge is that the highway payment system only collects extremely sparse information only including the entering/exiting time and locations (i.e., toll booths), which makes vehicular mobility between them difficult to learn.

To address this challenge, I identified two insights: (i) humans have the personal driving pattern in the route and driving speed (e.g., used to drive on the same route with a similar speed); (ii) the personal driving pattern is also constrained by the crowd driving pattern (e.g., the more people on the same route, the lower speed they are). Based on these two insights, I designed a system *VeMo* and formulated vehicular mobility learning as an iterative optimization problem using Expectation Maximization (EM), which considers both the personal driving pattern and the crowd driving pattern. Based on the real-world data evaluation, my method achieved an accuracy of 82% when inferring the vehicular mobility on the highways.

The insights turn out to be more general. I applied the same insights to another work (UbiComp'18a [10]): the estimation of the fine-grained travel time on the highways, which leads to an average error of 1.2 minutes.

2.1.2 Learning across Multiple Systems

The aforementioned project can be categorized as a method to learn vehicular mobility based on stationary sensors (i.e., tollbooths in the highway payment systems). A limitation is that stationary sensors generally have limited space coverage in a closed system (e.g., only tollbooths on highways) that we cannot learn vehicular mobility after vehicles leave highways. Previous work addressed this limitation based on mobile sensors (i.e., smartphones or GPS devices on vehicles) because the sensors move with vehicles with broader space coverage; but it is limited by the low penetration rate (e.g., only vehicles installed GPS devices or humans using a particular smartphone app).

To overcome the limitation of a single system, my another project (UbiComp'20a [8]) is to predict vehicles' final destinations after leaving highways with two systems, i.e., a highway payment system and a vehicle GPS collection system. The opportunity is we utilize a small number of vehicles with GPS information as mobile sensors to infer the destinations of those vehicles without GPS information. The insight is that if two vehicles have similar mobility on highways sensed by the highway payment system, they also have a similar destination after leaving highways. However, the challenge is that the "similarity" measurement is not trivial that simple measures do not lead to our goal of finding similar mobility. To address this challenge, I designed a model *Mohen* based on a mobility encoding method. I first learn an encoder to encode vehicular highway mobility into a low dimensional space that mobility would be closer in the space if they have the same destinations. Based on the similar mobility, I designed a spatial-temporal sequential prediction model to predict the vehicular destinations. The experiments show our model outperformed baselines by at least 35%.

In addition, my other work also demonstrated the benefits of learning across multiple systems such as vehicular localization (UbiComp'18b [6]), traffic anomaly (UbiComp'19 [2]), and behavior-aided cellular data usage prediction (UbiComp'20b [5]).

2.2 Decision Making in CPS

In this part, I illustrate how human behavior knowledge can support decision making including (i) *soft decision making* (e.g., notifications and recommendations) and (ii) *hard decision making* (e.g., mandatory decisions such as commands and schedules).

2.2.1 Soft Decision Making

One work (NSDI'21 [1]) of soft decision making is based on *Eleme*, one of the largest on-demand delivery companies in the world. In the order delivery process, to obtain the real-time status of orders, couriers are required to report the arriving time when picking up at merchants. However, in practice, the reported arriving time is not accurate with an average error of 3 minutes, which reduces the efficiency of delivery scheduling. In this work, we aimed to send notifications on couriers' smartphones when the reported arriving time is not accurate. The existing applications such as news and alarms can easily achieve notification because the notification time is generally manually predefined. Instead, the key challenge in our work is how to determine the notification time for couriers, i.e., how to know if the couriers actually arrive at merchants or not when reporting. To address this challenge, our team deployed an arrival detection system *aBeacon* with more than 12 thousand Bluetooth beacon devices in a city. If couriers reported arrival while their smartphones did not detect the Bluetooth signal, a notification message would pop up on couriers' smartphone to notify couriers they may not have arrived. Based on this notification system, we reduced the wrongly reported time by 14.2%.

2.2.2 Hard Decision Making

Soft decision making cannot ensure all the participators perform as expected where hard decision making is needed. Another work in my thesis was to improve the couriers' delivery scheduling (MobiCom'20 [7]) based on couriers' reporting behavior learning. The previous work generally schedules delivery tasks based on the status of couriers, especially the locations of couriers. However, different from outdoor locations easily obtained from smartphone GPS, the indoor locations are much more expensive to obtain on a large scale such as a nationwide operational company, using either densely deployed indoor infrastructures such as beacon devices or densely collected indoor fingerprinting such as Wi-Fi signals.

The intuition of this work was that instead of physical indoor locations, delivery scheduling can also be achieved if the couriers' indoor walking time is modeled. The opportunity is that couriers' reported arriving time provides references for indoor walking time to merchants, whereas the challenge is that the reported time is not accurate. Our previous work based on Bluetooth devices provides accurate arriving time detection but cannot be scaled to a large scale because of the expensive deployment and maintenance. To address this challenge, I first correct the reported time based on reporting behavior modeling. Specifically, I unified the indoor and outdoor reporting behavior in a neural-network model and utilize transfer learning to adapt the model to correct the indoor reported time. With the inferred indoor walking time, I integrated it into the delivery scheduling with extra optimization goal of minimizing couriers' indoor walking time to improve the delivery scheduling efficiency. The results showed that the delivery time was reduced by 24% and the late-delivery rate was reduced by 2.5%.

3 Future Directions

Socially Aware CPS: The main goal of the existing work is to incorporate human behavior to improve the effectiveness and efficiency of the systems. So far, very few researches, if any, work on the social properties of human-in-the-loop urban CPS such as diversity, inclusion, and equity. Without considering these social properties, the practical performance of CPS would be constrained when deploying such a system to serve humans. As the leading student in a newly funded project [3], my future work will continue exploring the integration of Social Science (e.g., Intervention, Deliberation, Focus Group Study) and human-in-the-loop urban CPS. With the recently developed computational social science, I envision a *socially aware human-in-the-loop urban CPS*, which jointly optimizes the system effectiveness/efficiency and the social properties.

Micro-mobility Safety: Recently, urban transportation is experiencing rapid changes with the spreading of new micro-mobility options including shared e-scooters, e-bikes, and other options. However, these options have a potential risk due to a variety of factors such as human behavior, road design, and environmental conditions. As a student who participated in a newly funded project [4], I will further extend the breadth and envision *an integration of vision sensors and inertial sensors* to improve the safety of riders.

Collaborative Sensing and Decision Making: Based on my preliminary results on cross-CPS sensing [8] [6], I will further explore collaborative sensing and decision making across CPS. In practice, different CPS generally belong to different parties or departments that work independently from each other. The key gap is there is no trustful protocol for cross-CPS collaboration. Recently developed *Federated Learning* framework brings us a new opportunity that it is promising to achieve collaboration between parties without exchanging sensitive information. I envision a *federated learning based protocol for collaborative sensing and decision making* could synergistically improve the efficiency across multiple CPS.

References

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