

Artificial Intelligence for Smart Transportation

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1 INTRODUCTION

There are more than 7,000 public transit agencies in the U.S. (and many more private agencies), and together, they are responsible for serving 60 billion passenger miles each year. Additionally, new on-demand modalities including ride-share, bike-share, and e-scooters have been introduced in recent years and transformed the transportation landscape in urban environments. A well-functioning transit system fosters the growth and expansion of businesses, distributes social and economic benefits, and links the capabilities of community members, thereby enhancing what they can accomplish as a society [6, 11, 15]. However, the explosion in transportation options and the complicated relationship between public and private offerings present myriad new challenges in the design and operation of these systems. There are also complex, and often competing, operational objectives that complicate the implementation of efficient services. Since affordable public transit services are the backbones of many communities, solving these problems and understanding state-of-the-art methods for AI-driven smart transportation has the potential to strengthen urban communities, address the climate challenge, and foster equitable growth.

Fundamentally, the design of a well-functioning transit system requires solving complex combinatorial optimization problems related to planning and real-time operations. These problems span many well studied fields, from classical line planning to offline and online vehicle routing problems (VRPs). While there are many ways to assess the performance of smart transportation systems, we largely focus on evaluating these systems in the context of optimizing *utilization* (i.e. ridership) and *efficiency* (i.e. reducing operational costs). Increasing utilization requires learning mobility patterns over wide geographical areas and adapting systems to better meet the demand for mobility. It also requires flexible mobility options such as on-demand and multi-modal transportation to adapt to demand in real-time and thus better serve potential passengers. Additionally, more efficient systems alleviate the impact on the environment by reducing emissions and can free resources by reducing costs. Lastly, *coverage* is an important consideration that often competes with utilization and efficiency. Therefore it is important to discuss optimization in the context of *ridership* versus *coverage*, the latter of which is an important consideration in the design of equitable and fair transportation. While the problem of ridership versus coverage is open-ended, there are ways in which these dimensions can be modelled such that transit agencies can better optimize over the objectives that matter most to them.

Efficient transportation systems require making decisions in real-time over large geographical areas and computationally intractable state-action spaces. Due to the intractability of these problems, traditional analytical methods fall short. Therefore, transit agencies have turned to computational approaches that enable large-scale data-driven optimization. AI-driven transportation can address this problem by learning complex abstractions of vast volumes of data to make decisions in a

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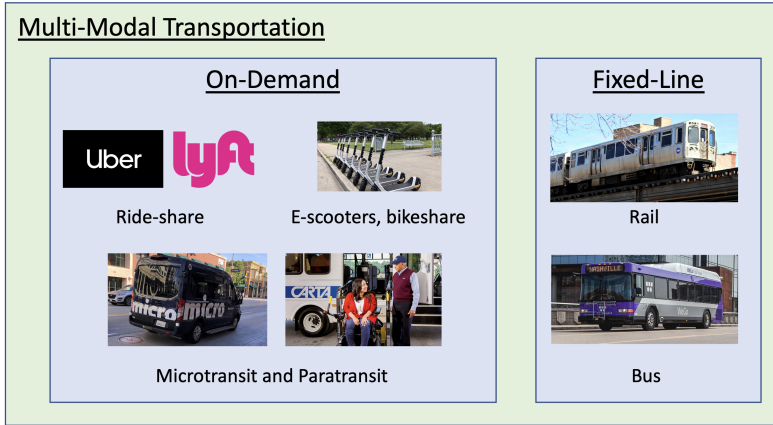


Fig. 1. Transportation modalities: there is a variety of mobility options in today’s urban environments, provided by both public transit agencies and private mobility providers, which can be classified as *on-demand* or *fixed-line*. On-demand transportation provides direct service and is often accessed through a smart-phone application. Fixed-line transportation utilizes mass transit vehicles that service fixed routes and schedules. Multi-modal transportation is a broad categorization that includes any service that combines multiple modes of transit to serve passengers.

computationally efficient manner at scale and in real-time. However, it requires solving complex challenges in model representation, decision-making under uncertainty, as well as data ingestion and processing.

Since smart transportation is a broad field, we primarily focus on two high-impact modalities: fixed-line and on-demand transportation systems. Fixed-line transportation utilizes vehicles (bus or rail) that traverse pre-defined routes over the course of a day following fixed schedules. On-demand transportation is a flexible service in which users request rides either in real-time or ahead-of-time, and transportation is provided from origin to destination through ride-share, e-scooters, or bike-share. Additionally, many transit agencies have recently investigated the potential of multi-modal transportation, which provides a more flexible and adaptive transportation model that combines fixed-line and on-demand transportation.

This chapter discusses the primary requirements, objectives, and challenges related to the design of AI-driven smart transportation systems. The major content involves the following:

- (1) Data sources and data management for AI-driven transportation.
- (2) An overview of how AI can aid decision-making with a focus on transportation.
- (3) Computational problems in the transportation domain and AI approaches.

2 CONTEXT

Large-scale adoption of smart phones and sensing technologies have revolutionized urban mobility in recent years. Led by companies such as Uber, Lyft and Via, new on-demand transportation options such as ride-share, e-scooters, and bike-share have been introduced to complement existing transportation services provided by public transit agencies. As the mobility landscape evolves, public transit agencies are tasked with managing ever more complex systems. To understand the relationship between transportation modalities, we can classify these systems as *on-demand*, *fixed-line*, and *multi-modal* as shown in Figure 1.

Autonomy in general has great potential to improve mobility options in urban environments. We already discussed autonomy at the system level, e.g. in the context of designing real-time ride-share and ride-pooling algorithms or optimizing trip-vehicle assignment for fixed-line. Moving forward, there is great potential for improving control systems for autonomous vehicles. At a system level, autonomous vehicles have the potential to reduce accidents as well as traffic, thereby increasing safety and efficiency [19, 33]. As these systems become more capable it will be important for transit agencies to adapt to solve increasingly complicated control and optimization problems that arise from operating mixed fleets that include conventional as well electric and autonomous vehicles.

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