Enhancing Smart, Sustainable Mobility with Game Theory and Multi-Agent Reinforcement Learning

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Abstract

We propose the use of game-theoretic solutions and multi-agent Reinforcement Learning in the mechanism design of smart, sustainable mobility services. In particular, we present applications to ridesharing as an example of cost game.

Introduction

Smart, sustainable mobility refers to the efficient, convenient and environmentally friendly modes of transport. Smart mobility involves the use of technology and data analytics to optimize the performance of the transportation system (Butler, Yigitcanlar, and Paz 2020), while sustainable mobility involves the reduction of negative impacts on the environment and the promotion of positive impacts on society . Ridesharing is a form of smart and sustainable mobility that involves the shared use of private vehicles for commuting or leisure. The literature recognizes its potential to reduce the number of vehicles on the road, decrease travel costs, and lower emissions (**?**).

The combination of game theory and multi-agent reinforcement learning has been applied to various problems in transportation and mobility, including ridesharing (Li et al. 2019). However, the literature recognizes that there is still a need for more research on the subject that can incorporate the reality of these services, such as the cost structure (Fageda 2021) or the interaction between the agents involved (Dhanorkar and Burtch 2022; Babar and Burtch 2020). Our work approaches ridesharing services as a coalitional game where self-motivated agents try to fulfill their travel demands at the lowest cost possible. For this, agents form travel *coalitions* and share the trip cost.

Ridesharing poses several interesting challenges for traditional cooperative game theory. As an example, consider a group of agents who want to travel from the same origin **O** to the same destination **D**. This type of game is known as a *superadditive game* with *subadditive costs* (Osborne and Rubinstein 1994), since the addition of an extra rider in the coalition yields lower costs for the coalition members. In this situation, the *grand coalition* is guaranteed to form as cooperation is beneficial. Now, consider the same situation but each new rider added to the coalition can change the car's origin and destination according to their own travel demands, like in a multi-stop service. Here, the cost structure for the car coalition changes and thus, cooperation among agents is not straightforward. A more realistic situation in ridesharing is to request some walking from the riders. Usually, services optimize the car's route to minimise the travelling distance and riders are requested to walk from their own origin to the car, and then, from the car's destination to their own destination. When adding a high walking time to the overall trip cost, the riding coalition can face a superadditive *cost* function, since the trip cost increases as a new member is added in. In games like this, cooperation among agents is not guaranteed and in the extreme, the *core* of the game is empty. Meaning that no allocation of cost guarantees stable coalition structures.

The example of ridesharing games can be generalized to any cost-sharing game with coalition-formation costs (i.e. there are cost associated in forming a coalition). In this context, our research questions are as follows:

Main Research Questions

1. What is the socially-optimal coalition structure?
2. How to deal with the exponential complexity in the calculation of coalition structures?
3. Is it possible to obtain a cost-sharing mechanism that is individually rational and stable?
4. Is a central-planner needed to achieve the above or can decentralized solutions be implemented? If so, what is the difference in the solution achieved by both?

The foundations of game theory provides us with theoretical guarantees for the above questions while multi-agent Reinforcement Learning provides us with analytical tools for decentralized coalition formation.

Generation of the Optimal Coalition Structure

In (Cipolina-Kun et al. 2022) we introduced a novel coalition formation mechanism for ridesharing services. Specifically, we extended the current literature to account for the walking requirements and its implications. As a first implication, when users are required to walk, we first need to determine the optimal location of the rider's meeting points

*Part of the work was done in collaboration with the CCAIS group at the University of Southampton.

(i.e. car pick-up) and the drop-off points. Existing work on ride sharing assumes that the meeting points for pick-up and drop-off are fixed. To address this, we proposed a method to determine the pick-up and drop-off points based on the geometric median of coordinates, which minimizes the walking distance of riders. Secondly, we modelled the walking cost using a Cobb-Douglass function for the value of time. This allows us to account for the increasing marginal cost of the walking requirements (Cobb and Douglas 1928). This allows us to effectively account for a user's value of time when walking, which is not negligible. Lastly, we presented an algorithm for the calculation of the optimal coalition structure based on dimensionality reduction. The main idea is to form clusters of feasible coalitions within an $epsilon$ distance such that the number of individuals within a cluster is computationally tractable.

Centralized Approach to the Coalition Formation Problem

In (Cipolina-Kun et al. 2023) we built upon our coalition formation algorithm to dive deeper into the cost-allocation mechanism. The aim is to find an equitable distribution of the coalition's trip costs whereby riders are incentivised to participate in ridesharing. Our methodology is equitable in the sense that those who walk more should pay less of the trip's cost. For the calculation of the coalition structure as well as the cost allocation we implemented a centralized approach such as the current ridesharing apps. After users enter their trip's demands, the app allocates riders into cars of up to four members and distributes the cost in an equitable manner. In this work, we presented a formal evaluation of our cost allocation method and we performed an empirical evaluation against the Shapley value using real-world and simulated data. Our results showed that our proposed approach is computationally more tractable than the Shapley value, as it is linear in time while also guaranteeing individual rationality under certain cost conditions. In particular, we showed formally that individual rationality holds for trips where the length of the car ride more than compensates the walking cost incurred.

Decentralized Approach to the Coalition Formation Problem

As a future work, we propose a decentralized mechanism to achieve a socially optimal coalition structure for ridesharing. Following (Rothe 2015), some of the advantages of a decentralized method are: (a) it alleviates the communication burden with a central planner and (b) it avoids (partially or totally) to ask agents to reveal their preferences (at least in a direct, explicit way). Instead of a central planner, each agent negotiates its desired coalition and payments through bargaining, under the assumption that agents have full observability of the other agent's trip demand and they use the same communication protocol. Coalitional bargaining can be seen as a (non-cooperative) extensive-form stochastic game (Chalkiadakis, Elkind, and Wooldridge 2011) and thus the solution to a bargaining problem can be learned using multi-agent reinforcement learning (MARL). The use of MARL in coalition bargaining games has several advantages (Munoz de Cote, Lazaric, and Restelli 2007). First it allows us to learn a decentralized solution and second, it provides an *adaptive* mechanism that is performant under changes in the environment (such as the location of agents). Lastly, MARL allow us to obtain the optimal coalition structure and cost allocation without explicitly knowing the game's characteristic function. Instead, throughout the learning process, agents can implicitly model the characteristic function of the game through exploration.

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