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

Doctoral Consortium

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ABSTRACT

This work proposes the use of game-theoretic solutions and multi-agent reinforcement learning in the mechanism design of smart and sustainable mobility services. In particular, we focus on applications to ridesharing as an example of a cooperative cost game. As such, we firstly solve the coalition formation problem and propose algorithms to allocate riders into cars in a socially optimal way. Secondly we propose a mechanism to share the cost in an equitable way so that ridesharing is incentivized. For the proposed methods, we study properties of individual rationality and stability. Lastly, we discuss future work, where we plan to compare centralized solutions with decentralized algorithms based on multi-agent reinforcement learning.

KEYWORDS

Mobility services; Ridesharing; Multi agent reinforcement learning; Game theory.

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1 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 [3], while sustainable mobility involves the reduction of negative impacts on the environment and the promotion of positive impacts on society [9]. 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 [14].

The combination of game theory and multi-agent reinforcement learning has been applied to various problems in transportation and mobility, including ridesharing [10]. 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 [8] or the interaction between the agents involved [1, 7]. 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 people who want to travel from the same origin **O** to the same destination **D** and decide to share a car splitting the costs equally. This type of game is known as a *superadditive game* with *subadditive costs* [12], 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 mutually beneficial. Now, consider the same situation but now each additional rider included in 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 ask for some walking from riders, like in Figure 1. Usually, ridesharing services optimize the car's route to minimise the travelling distance and thus, 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.

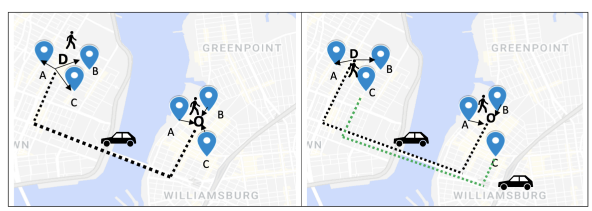

Figure 1: Example of a ridesharing formation for three individuals. The arrows show their walking distance to the common O-D points and the dotted line the distance travelled by the car. On the left panel, the three riders share a car, while on the right panel A,B share a car.

1.1 Ridesharing as a Cooperative Cost Game

A ridesharing game is a tuple (A, C, M), where $A = \{a_1, .., a_n\}$ is the set of riders, $C : 2^A \to \mathbb{R}$ is the characteristic function, and $M : A \to \mathbb{R}^2 \times \mathbb{R}^2$ is the coordinate function that yields the origin and

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destination coordinates for each rider, i.e., $M(a_i) = (o_i, d_i)$, where $o_i \in \mathbb{R}^2$ and $d_i \in \mathbb{R}^2$ are the origin and destination coordinates of a rider, respectively. The objective in a ridesharing game is to find the socially optimal coalition structure with the minimum travel cost. After obtaining the socially optimal coalition structure, the second objective is to calculate a payoff vector representing the share of the car cost allocated to each rider. This aspect is important, as it determines whether individuals would prefer ridesharing over traveling alone and ultimately, whether a coalition can be formed.

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:

1.2 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.

2 GENERATION OF THE OPTIMAL COALITION STRUCTURE

In our previous work [4], we tackled the first two questions from our research list in Section 1.2. In that work, we introduced a novel coalition formation algorithm 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 need to determine the optimal location of the rider's meeting points (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 [6] to account for the increasing marginal cost of the walking requirements. This allows us to effectively account for a user's value of time when walking. Lastly, we presented an algorithm for the calculation of the optimal coalition structure based on dimensionality reduction. The main idea to reduce the dimensionality of the problem is to form clusters of feasible coalitions (i.e., no more than four individuals) within an *epsilon* distance of each other such that the number of individuals within a cluster is computationally tractable.

3 CENTRALIZED APPROACH TO THE COALITION FORMATION PROBLEM

In [5] , we tackled the third questions from our research list in Section 1.2. In that work, 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.

4 DECENTRALIZED APPROACH TO THE COALITION FORMATION PROBLEM

As a future work, we investigate the fourth research question on Section 1.2. we are currently working towards the proposal of a decentralized mechanism to achieve a socially optimal coalition structure for ridesharing. Following [13], 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 [2] 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 [11]. 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.

5 FUTURE WORK AND OPEN PROBLEMS

There are multiple open research opportunities in the intersection of ridesharing and game theory. One interesting feature of ridesharing games is the large number of users in the system. This poses a challenge for coalition generation games as it is an NP-hard problem (since the number of possible coalitions increases exponentially with the number of agents). For this, it is necessary to resort on approximation algorithms for coalition formation. Decentralized coalition formation algorithms are an active area of research.

6 CITATIONS AND REFERENCES

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