Problems in Computational Mechanism Design

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ABSTRACT

My research area is interdisciplinary to Mechanism Design and Algorithm Design. The problems I find interesting in Computational Mechanism Design are about Voting preferences, Environment protection by reducing the emission of harmful gases from automobiles, Shareable good allocation on a network and Peer grading. In this paper, I explain two of such problems and roadmaps for them. First is the domain of preferences in the voting. It is often observed that preferences are never completely arbitrary; instead, they possess correlated structures. After learning the preferences, the next main task is to aggregate them and have an outcome out of it. My interest is to explore the different domains of preferences so that we can have specific desirable properties in the social choice function. Another problem I am interested in is, to devise a mechanism which incentivises the riders to prefer to share the ride than to ride solo, where the objective of the mechanism is to reduce the emission of harmful gases and control the pollution in the environment by reducing the total travelled distance by the vehicles. A significant challenge when addressing the problem of ridesharing is that it needs to explore a vast decision space while computing solutions fast enough to provide users with the experience of real-time booking and service.

KEYWORDS

Computational social choice; preferential domains; sampling; algorithms; Ridesharing

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1 TESTING PREFERENTIAL DOMAINS

In a typical voting scenario, there are a set of agents or voters; each of them has preference over a set of alternatives; and a voting rule (respectively an aggregation function) which selects an alternative (respectively an aggregated preference) as the winner. The tuple of the preferences of all the agents is called a profile. Despite having plenty of applications, a series of cornerstone results in social choice theory [10] establish that it is impossible to devise voting rules or aggregation functions which respect some of the desirable properties. A popular approach to escape these impossibility results is to assume that the profile under consideration is not entirely arbitrary but belongs to some restricted preferential domain.

There are some polynomial time algorithms (known as recognition algorithms) to decide whether a preference profile, P belongs to the domain, D, e.g., single-peaked, single crossing. The two main limitations of these recognition algorithms are 1.) They require the whole preference profile which is not always possible to get. In many situations, e.g., pre-election polls, surveys, etc., we only have access to samples of the whole preference profile. 2.) The real world profiles are almost never perfect, and thus they can only be at most close to some domain, or the removal of some alternatives/participants makes the preference profile to be able to belong to some specific domains. One may ideally like to decide whether a profile of n Preferences over m alternatives can belong to the domain $\mathcal{D}$ after deleting, say at most k preferences (or alternatives) or not, by drawing a small number of samples. However, any algorithm for this problem would provably need to observe $\Omega(n)$ samples which defeat the main purpose of testing (except when $\mathcal{D}$ is empty, or $\mathcal{D}$ contains all possible profiles). Erdélyi et.al.[6] study complexity of the computational problem of deciding whether a given profile can be made single peaked by deleting few preferences or alternatives; Bredereck et al. [3] study complexity of this problem for many other domains, e.g., single-caved, single-crossing, etc.

One of my work [4], which is accepted in AAMAS'19, uncovers the problem of testing, whether a given preference profile results from a pure or mixed preferential domain structure, through sampling a small number of preferences or alternatives. In [4] some sampling-based algorithms are developed for testing whether a profile is close to some specific domain or far from it. It is shown that the testing problem can be solved with high probability by observing a small number of samples for most of the cases. In particular, the required number of samples is often independent of the number of preferences. The algorithms require some *comparison queries* such as two alternatives x and y are presented to the participant v. And v replies whether it prefers x over y or y over x, where the participant v is picked uniformly randomly with replacement from the set of all participants. The *sample complexity* of the algorithm is the number of comparisons queries it needs.

In all the testing problems, a profile of n Preferences over m alternatives as input are given which is guaranteed to be one of two possible types. The problems in these settings are to distinguish between two different profiles with error probability δ. The first profile (first possibility) is such that, it can be made to belong to the domain $\mathcal{D}$ after simultaneously deleting at most $\epsilon_a m$ alternatives and $\epsilon_v n$ preferences. And, for another profile (second possibility) we need to simultaneously delete at least $\epsilon'_a m$ alternatives and $\epsilon'_v n$ preferences to make it belong to $\mathcal{D}$ for any $0 \le \epsilon_a m \le \epsilon'_a m \le 1$ and $0 \le \epsilon_v n \le \epsilon'_v n \le 1$. [4] states some other problems by varying the assumptions regarding the type of generator from which the profiles are generating, e.g. whether the profile is uniformly randomly generated or is some arbitrary profile, whether by only removing some of the alternatives the profile can belong to some specific domain or some preferences are also need to be deleted. The testing problem can be quite accurately solved by observing a

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small number of samples for most of the cases, and the numbers are often independent of the number of preferences or alternatives. In other cases, there are impossibility result. Although the results in [4] are for an arbitrary domain, for ease of exposition, I summarise our results, specialised for the single peaked domain, in Table 1.

<table>
<tr><th colspan="2">Input profile</th><th rowspan="2">Sample complexity</th></tr>
<tr><th>Possibility 1</th><th>Possibility 2</th></tr>
<tr><td>$\epsilon_v n$ random preferences away</td><td rowspan="3">random</td><td>$O(\frac{1}{(1-\epsilon_v)^2} \log \frac{1}{\delta})$</td></tr>
<tr><td>$\epsilon_v n$ arbitrary preferences away</td><td>$O(\frac{1}{(1-3\epsilon_v)^2} \ln \frac{1}{\delta})$ for $\epsilon_v < 1/3$</td></tr>
<tr><td>$\epsilon_a m$ alternatives away</td><td>$O(\log \frac{\log_{1/\epsilon_a} 1/\delta}{\delta} * \log_{1/\epsilon_a} \frac{1}{\delta} \log \log_{1/\epsilon_a} 1/\delta)$</td></tr>
<tr><td>$\epsilon_v n$ arbitrary preferences away</td><td>$\epsilon'_v n$ arbitrary preferences away</td><td>$O(\frac{1}{(\epsilon'_v - \epsilon_v)^2}(2^m m^2 \log^2 m + \log 1/\delta))$</td></tr>
<tr><td>$\epsilon_a m$ alternatives away</td><td>$\epsilon'_a m$ alternatives away</td><td>$\Omega(n \log 1/\delta)$ even for $\epsilon_a = 0$ and for every $0 < \epsilon'_a \leq 1$ and $0 < \delta < 12$</td></tr>
</table>

In [4] only two proximity measures are considered. Erdélyi et al. [6] introduce several distance measurements in the aspect of single-peaked preferences such as $k-$ Local Candidate Deletion. Personal friendships or hatreds between voters and candidates may affect a voter's preference order and may result in an up or down in the preference order. And, this personal relationship cannot be represented on the axis. To eliminate the influence, the notion of $k-$ Local Candidate Deletion is applicable. Another suggestion by Escoffier et al. [7] was the $k-$Voter Partition, which uses the minimum number of axis to partition the voters in such a way that each group of voters is single-peaked concerning at least one of the axes. A similar measurement is $k-$Candidate Partition, which is to partition the set of candidates in place of voters. Elkind et al. [5] studied clone sets in elections, and the distance to single-peakedness is here the minimal number of clones that need to be removed from the ballot via de-cloning to make it single-peaked. A clone set is a set of candidates that are ranked consecutively in every vote, but not necessarily in the same order and de-cloning, replace the clone sets by a single candidate contained in the clone set. I am exploring the different distance measures in this literature and how to test a profile whether it is close to some specific domain or not, and what is the distance between the profile and any other profile in the specified domain.

2 RIDESHARING

The goal of Ridesharing is to reduce traffic congestion, the number of trips a vehicle makes, the emissions that come from vehicles, travel time, conserving fuel, etc. The concept is very widely accepted worldwide, and it offers a service that is both convenient and cost-effective for the drivers and the riders. The challenges of ride-sharing includes dynamic matching of passengers with drivers depending on their location and timings and capacity of the vehicle, pricing and payments, re-balancing or repositioning the fleet to service demand and with minimum waiting time and travel delay. The literature for ride-sharing requires to complete two different tasks: Planning and Payments. Planning includes the assignment of vehicles and their routes. And, payment includes the monetary transfers between riders, drivers or the organisation. The optimal plan or route helps to accomplish the objectives to reduce the total distance covered and hence to minimise the ratio of the length of the shortest possible route in the solo ride to that of the shared ride which is the *Environmental Improvement Factor (EIF)*. The payment part may help to increase the incentive to the drivers or riders to have a shared ride as we also need to ensure that the suggested assignment and route is individually rational for the passenger, i.e., this gives her at least the same utility as a solo ride. The mechanism should be *welfare optimal*, *envy free*, *individually rational*, *budget balance* and minimize the *EIF*.

The mechanism by Kamar et al. [8], provide fair and efficient solutions to the rideshare collaboration challenge. For this mechanism, the riders have to provide the exact time or date of the rides before determination of the assignment and pricing. Apart from the dynamic settings, the mechanism is solving the problem efficiently. Agatz et al. [1] develop optimisation-based approaches that aim at minimising the total system-wide vehicle miles incurred by system users, and their travel costs but is not applicable to manage pricing and payments. Another mechanism is by Ma et al. [9], which study the problem of optimal dispatching and pricing in two-sided ridesharing platforms in a way that drivers would choose to accept the platform's dispatches instead of driving to another area or waiting for a higher price. The mechanism by Ma et al. [9] is welfare-optimal, envy-free, individually rational and the budget balanced from any history onward, but limitations are that the objective it succeeds does not include the minimisation of the total distance travelled by finding an optimal or approximately optimal path for the vehicle with some assigned passengers. Alonso-Mora et al. [2], present a more general mathematical model for real-time high-capacity ride-sharing that (i) scales to large numbers of passengers and trips and (ii) dynamically generates optimal routes concerning online demand and vehicle locations. The algorithm starts from a greedy assignment and improves it through a constrained optimisation, quickly returning solutions of good quality and converging to the optimal assignment over time. This mechanism does not deal with the pricing and payment part. In my thesis, I am trying to devise a mechanism which solves both the problem of planning and payments in ridesharing.

3 SUMMARY AND FUTURE WORK

The paper [4], uncovers the problem of testing, whether a given preference profile results from a pure or mixed preferential domain structure, through sampling a small number of preferences or alternatives. In [4], only two distance measures are considered. The future work is to explore the other distance measures with the same problem. For Ridesharing, I am working on to devise a mechanism which is *welfare optimal*, *envy free*, *individually rational*, *budget balance* minimize the *EIF* and solves the problems of planning and payments in ridesharing and reduce traffic congestion, the number of trips a vehicle makes, the emissions that come from vehicles, travel time, conserving fuel, etc.

REFERENCES

[1] N.A.H. Agatz, A.L. Erera, M.W.P. Savelsbergh, and X. Wang. 2011. Dynamic ride-sharing: a simulation study in Metro Atlanta. In *Transportation Research Part B*, Vol. 45(9). 1450–1464.

[2] Javier Alonso-Mora, Samitha Samaranayake, Alex Wallar, Emilio Frazzoli, and Daniela Rus. 2017. On-demand high-capacity ride-sharing via dynamic trip-vehicle assignment. In *National Academy of Sciences of United States of America (PNAS)*, Vol. 114.

[3] Robert Bredereck, Jiehua Chen, Piotr Faliszewski, Jiong Guo, Rolf Niedermeier, and Gerhard J. Woeginger. 2014. Parameterized Algorithmics for Computational Social Choice: Nine Research Challenges. In *Tsinghua Science and Technology*, Vol. 19. IEEE, 358–373.

[4] Palash Dey, Swaprava Nath, and Garima Shakya. 2019. Testing Preferential Domains using Sampling. In *Proc. 18th International Conference on n Autonomous Agents and Multiagent Systems (AAMAS).*

[5] Edith Elkind, Piotr Faliszewski, and Arkadii M. Slinko. 2012. Clone structures in voters' preferences. In *Proc. 13th ACM Conference on Electronic Commerce (EC)*. 496–513. https://doi.org/10.1145/2229012.2229050

[6] Gábor Erdélyi, Martin Lackner, and Andreas Pfandler. 2017. Computational Aspects of Nearly Single-Peaked Electorates. *J. Artif. Intell. Res.* 58 (2017), 297–337. https://doi.org/10.1613/jair.5210

[7] Bruno Escoffier, Jérôme Lang, and Meltem Öztürk. 2008. Single-peaked consistency and its complexity. In *Proc. 18th European Conference on Artificial Intelligence (ECAI)*. 366–370. https://doi.org/10.3233/978-1-58603-891-5-366

[8] Ece Kamar and Eric Horvitz. 2009. Collaboration and Shared Plans in the Open World: Studies of Ridesharing. In *IJCAI'09 Proceedings of the 21st international joint conference on Artifical intelligence*. 187–194.

[9] Hongyao Ma, Fei Fang, and David C. Parkes. February 2018. Spatio-Temporal Pricing for Ridesharing Platforms. In *TSMO'18, Los Angeles, California USA.*

[10] Andreu Mas-Collel, Michael D Whinston, and Jerry Green. 1995. Microeconomic theory. (1995).