Optimal Auction Based Automated Negotiation in Realistic Decentralised Market Environments

Pankaj Mishra,[1] Ahmed Maustafa,[2] Takayuki Ito,[3] Minjie Zhang[4]
[1,2,3]Department of Computer Science,Nagoya Institute of Technology, Japan
[4]Department of Computer Science,University of Wollongong, Australia
{pankaj.mishra, ahmed, ito}@itolab.nitech.ac.jp[1,2,3] and minjie@uow.edu.au[4]

Abstract

Automated negotiations based on learning models have been widely applied in different domains of negotiation. Specifically, for resource allocation in decentralised open market environments with multiple vendors and multiple buyers. In such open market environments, there exists dynamically changing supply and demand of resources, with dynamic arrival of buyers in the market. Besides, each buyer has their own set of constraints, such as budget constraints, time constraints, etc. In this context, efficient negotiation policies should be capable of maintaining the equilibrium between the utilities of both the vendors and the buyers. In this research, we aim to design a mechanism for an optimal auction paradigm, considering the existence of interdependent undisclosed preferences of both, buyers and vendors. Therefore, learning-based negotiation models are immensely appropriate for such open market environments; wherein, self-interested autonomous vendors and buyers cooperate/compete to maximize their utilities based on their undisclosed preferences. Toward this end, we present our current proposal, the two-stage learning-based resource allocation mechanism, wherein utilities of vendors and buyers are optimised at each stage. We are aiming to compare our proposed learning-based resource allocation mechanism with two state-of-the-art bidding-based resource allocation mechanism, which are based on, fixed bidding policy (Samimi, Teimouri, and Mukhtar 2016) and demand-based bidding policy (Kong, Zhang, and Ye 2015). The comparison is to be done based on the overall performance of the open market environment and also based on the individual performances of vendors and buyers.

Introduction

The focus of my doctoral research is to investigate an efficient mechanism to design an optimal auction for open market environments. In such open market environments, multiple vendors aim to maximise their utility by selling their limited resources, such that they earn higher profits. On the other hand, buyers aim to maximise their utility by buying their requested resources at the lowest possible price, which is within their budget, quality requirement and completion deadline. In this regard, both vendors and buyers have their respective set of objectives/preferences, which should be optimised while resource allocation in the open market environments. Therefore, in such environments, optimal negotiation policies play an important role to reach an agreement between vendors and buyers, which maximises the utility of both, vendors and buyers. Therefore, in this context, there are two key guiding questions of my research, which are: (1)ˆ*"what are the aspects of an optimal auction paradigm in practical applications?"* and (2) "*truthfulness / incentive-compatible is only way for bidders to maximize their utilities?*". My interest in these questions are based on the two contradicting assumptions about environment setting, which are, independent private values and interdependent private values. In addition to that, latest mechanism design for optimal auction paradigm (Dütting et al. 2017) are designed based on unrealistic assumptions in open market environments, such as unlimited resources, prior bidders common knowledge, unbounded time, unlimited budget, etc. However, these assumptions do not fit into the real-word open market environments, with dynamically changing resource demands, limited resources with the vendors, limited budget of the buyers, etc. In order to realise this goal of designing an optimal auction mechanism for real-world open market environments, I have divided my research investigation into three major stages, which are: (1) investigating the impact of bid optimisation in interdependent bid valuation, (2) investigating the correlation between different aspects of optimal auction, such as revenue, incentive-capability, etc., and (3) investigating the equilibrium between truthful and untruthful auction paradigm. Presently, I am working on the first stage of my investigation, i.e investigating impact of interdependent private valuation on auction paradigm discussed in the next section.

Completed Research

At present, I have implemented a learning-based two-stage resource allocation in an auction paradigm, the two stages are, (1) real-time bid optimisation stage: vendors optimise theirs selling price and (2) vendor selection stage: potential buyers select most appropriate vendors based on their multiple preferences. Figure 1 represents the architecture of the proposed learning-based two-stage resource allocation

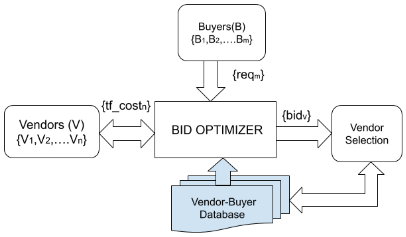

Figure 1: Proposed Architecture: Real-Time Bidding Platform for Resource Allocation

approach. This architecture has two main modules, which are: (1) the *Bid Optimiser* module and (2) the *Vendor Selection* module. In an open market environment, as soon as, the buyers broadcast their requirements to all available vendors in the open market. Then, all the available vendors, offer their optimised selling price (bid values) to potential buyers. Whereas, the vendor-buyer database of all the past auction information, is utilised by the *Bid Optimiser* module to analyse the existing preferences of similar buyers and vendors. Finally, the potential buyer selects a vendor based on the proposed multiple preferences decision-making approach. In the next two subsections, we would briefly discuss each stage of the proposed approach.

Real-Time Bid-Optimisation

At this stage, the selling prices of all the vendors for the requested resources by the potential buyers are optimised in a reverse auction paradigm. Such that, we model the resource allocation in decentralised open market environments into a Markov decision process (MDP), similar to work proposed by Cai et al.(Cai et al. 2017). Specifically, in such environments, multiple vendors offer their resources at an optimal selling price to each resource requesting buyer. Besides, it should be noted that every vendors earn a profit only when a potential buyer selects them; otherwise, penalties are incurred on the losing vendor. Therefore, in this proposed approach, each vendor examines the preferences (Myerson 1981) of the vendors and buyers and supply-demand in the environment, to optimising their selling prices. In order to do that, we train neural networks based on the reinforcement learning technique, using the supply and demand of each vendors and buyers along with historical database for preference analysis. Then finally, these optimised selling prices of each vendor is submitted to the potential buyer for selecting one vendor.

Vendor Selection

At this second stage, buyers select a single vendor from the list of bidding vendors, based on the submitted bids from all the vendors. As soon as, vendors submit their selling price for each buyer's request, then the potential buyer selects a vendor based on the proposed multi-criteria selection approach. In this proposed approach, we consider multiple conflicting issues while selecting a vendor from the list of bidding vendors. In this regard, we have considered, three conflicting criteria for experimentation, which are: the resource availability of vendors, the success rate with the vendors and the selling price of the vendors. Towards this end, the final preference vector is computed for each vendor, and vendor with the highest preference score is selected by the buyer.

Current Work

Currently, we are working on analysing the impact of bid valuation in an interdependent environment setting. Because, submitted bid values are optimised based on interdependent parameters, and the truthful bids. Although, at this moment, we have considered different attributes, which denotes the performances of both vendors and buyers, such as, availability, revenue, wait time, etc. However, more experiments are being performed with different settings, to analyse the proposed auction paradigm based on the other aspects such as incentive compatibility, social-welfare, etc. Thus, I am gradually moving towards the next stage of our investigation, through performing experiments with different settings.

Future Work

From the beginning of my research, I am hoping to investigate to answer two basic questions in designing an optimal auction mechanism, which are: (1) designing an optimal auction mechanism, which is appropriate for the real world open market environments and (2) designing an resource allocation mechanism, which should maximise the utilities of both, vendors and buyers. In this context, as mentioned before, these two problems are investigated in three stages. Therefore, after the completion of stage one of the investigation, I would gradually investigate the other two subinvestigation stages. Specifically, during my doctoral course, I should be able to solve a classical problem of optimal auction design (Myerson 1981), but for the realistic open market environments.

References

Cai, H.; Ren, K.; Zhang, W.; Malialis, K.; Wang, J.; Yu, Y.; and Guo, D. 2017. Real-time bidding by reinforcement learning in display advertising. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, 661–670. ACM.

Dütting, P.; Feng, Z.; Narasimhan, H.; Parkes, D. C.; and Ravindranath, S. S. 2017. Optimal auctions through deep learning. *arXiv preprint arXiv:1706.03459*.

Kong, Y.; Zhang, M.; and Ye, D. 2015. An auction-based approach for group task allocation in an open network environment. *The Computer Journal* 59(3):403–422.

Myerson, R. B. 1981. Optimal auction design. *Mathematics of operations research* 6(1):58–73.

Samimi, P.; Teimouri, Y.; and Mukhtar, M. 2016. A combinatorial double auction resource allocation model in cloud computing. *Information Sciences* 357:201–216.