Deep Learning-Powered Iterative Combinatorial Auctions with Active Learning

Extended Abstract

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ABSTRACT
Deep learning-powered iterative combinatorial auctions (DL-ICA) are auctions that utilize machine learning techniques. Unlike traditional auctions, bidders in DL-ICA do not need to report the valuations for all bundles upfront. Instead, they report their value for certain bundles iteratively, and the allocation of the items is determined by solving a winner determination problem. During this process, the bidder profiles are modeled with neural networks. However, DL-ICA may not always achieve the optimal winner allocation due to the relatively low number of reported bundles, resulting in reduced economic efficiency. This paper proposes an algorithm that uses active learning for initial sampling strategies to improve the resulting economic efficiency (social welfare). The proposed algorithm outperforms previous studies in real-world combinatorial auction models across various domains while using fewer samples on average.

KEYWORDS
Active Learning for Regression; Deep Learning; Combinatorial Auctions

ACM Reference Format:

1 INTRODUCTION
Traditional auctions only allow bidders to bid on individual items, which can result in the exposure problem. For example, consider an auction for advertisement slots on a TV channel where a bidder needs three consecutive slots to broadcast a 30-second commercial. If the first two slots have unexpectedly high prices due to intense competition, the bidder may not have enough funds to acquire the third slot, rendering the first two slots useless and decreasing the social welfare of the auction. Combinatorial auctions (CA) allow bidders to bid on bundles of items to avoid the exposure problem [1, 3, 6], but the bundle space grows exponentially with the number of items, making it impossible for bidders to report their full value function. To address this issue, iterative algorithms have been developed [5, 8], which interact with bidders and ask for a limited number of bundles in each round. However, these algorithms may not always lead to the optimal allocation, resulting in reduced economic efficiency.

Our work builds on previous research in deep learning-powered iterative combinatorial auctions (DL-ICA) [12] and proposes a modification of the machine learning-based elicitation algorithm by selecting a set of initial bundles more efficiently in order to improve the efficiency of the final allocation. Previous studies have used uniform random sampling for the initial request [2, 4, 12]. Uniform sampling is a simple and straightforward method for selecting initial bundles in combinatorial auctions, but it has a fundamental limitation: it does not take into account the complexity of the bidder's valuation of different bundles. Since the bundle space can be exponentially large, a random sample of bundles is unlikely to explore the entire space and may not include bundles that are highly valued by bidders. This can lead to a poor quality of elicited valuations and, consequently, a suboptimal allocation.

Active learning is a solution that can significantly reduce the amount of labeled data needed to train a model [10, 13]. In active learning, the machine learning algorithm selects the most informative data points from a pool of unlabeled data points, and asks an annotator to label them [11]. In DL-ICA, active learning allows the algorithm to select the most informative bundles to ask the bidders about. By doing so, the algorithm can gain a better understanding of the bidder’s valuation function with fewer queries compared to uniform sampling. This can lead to a more accurate and complete estimation of the bidder’s valuation function, resulting in a higher probability of finding an optimal allocation. Therefore, active learning is a promising approach to improve the efficiency of the elicitation process in combinatorial auctions.

Specifically, we propose a new algorithm, Greedy Active Learning on Input Values (GALI), which uses a greedy approach [14] to select the most informative initial bundles in DL-ICA. Our contribution is significant because it addresses an important challenge in combinatorial auctions: improving economic efficiency while reducing the number of bundles required from bidders. By using
machine learning combined with active learning techniques, our proposed algorithm achieves better results than previous studies.

2 GREEDY ACTIVE LEARNING ON INPUT VALUES (GALI)

The goal of GALI is to ensure maximum diversity among the bundles initially queried. To determine which bundle to query, the active learning algorithm proposed by [13] iterates over all unlabeled bundles in the pool and computes their distance to the closest labeled bundle. The next bundle to be queried is then the bundle with the greatest distance to the closest labeled bundle. Since the total number of bundles is not used to decide the next sample, so the bidders could submit all of their bids at the end instead of being queried in each iteration.

3 EXPERIMENTAL EVALUATION

We evaluate our approach on two well-known auction models, Global Synergy Value Model (GSVM) [7] and Local Synergy Value Model (LSVM) [9], both of which include bidder profiles with regional and national bidders. GSVM models an auction with 18 items and 7 bidders, 6 regional and one national bidder. The items are arranged in two circles, a national circle with 12 items and a regional circle with 6 items. The national bidder is interested in all of the items in the national circle, while the regional bidders are interested in 2 items in the national circle and 4 items in the regional circle. LSVM consists of 18 items and 6 bidders. As in GSVM, one of them is of national type, while the others are regional bidders. For each model, we run 51 different instances. All hyperparameters were kept consistent across both sampling strategies and were set according to the optimal values found by [12]. The results are summarized in Table 1. GALI is able to consistently outperform the UF baseline in both auction models in terms of efficiency achieved. It even does so while using on average fewer samples and fewer iterations.

4 CONCLUSION

This paper presents a novel approach to the initial sampling strategy of the machine learning-based elicitation algorithm of Brero et al. [5], with the aim of improving economic efficiency. The approach involves the use of active learning to acquire initial bundle-value pairs, specifically through the method of Greedy Active Learning on Input Values (GALI). The experiments show that the use of GALI can lead to higher efficiency in the allocation of goods for the GSVM and LSVM auction models while requiring fewer bundles to be queried from the bidders. In future work, it may be useful to explore other active learning methods and evaluate their potential for improving the efficiency of DL-ICA. In addition, further research could be conducted to determine the optimal number of initial bundle-value pairs required to achieve the desired level of efficiency. It may also be worthwhile to consider how the proposed modification to the iterative phase of the elicitation algorithm could be further refined or combined with other techniques to improve performance.

ACKNOWLEDGMENTS

We thank the AAMAS 2023 reviewers for their feedback. This work was supported in part by University of Macau grants SRG2022-00032-FST and MYRG-CRG2022-00013-IOTSC.

Table 1: Comparison of Uniform Sampling (UF) and Greedy Active Learning on Input Values (GALI) in the LSVM and GSVM models. The results “Average #Queries” and “Max #Queries” are measured per bidder. The value in parantheses in the Efficiency column is the standard deviation of the efficiency.

<table>
<thead>
<tr>
<th>Model</th>
<th>Sampling Technique</th>
<th>Average #Queries</th>
<th>Max. #Queries</th>
<th>Average #Iterations</th>
<th>Max. #Iterations</th>
<th>Efficiency in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>GSVM</td>
<td>UF</td>
<td>39.7</td>
<td>49.6</td>
<td>4.6</td>
<td>10.0</td>
<td>97.95 (0.32)</td>
</tr>
<tr>
<td></td>
<td>GALI</td>
<td>37.2</td>
<td>45.5</td>
<td>3.9</td>
<td>8.4</td>
<td>99.18 (0.20)</td>
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<tr>
<td>LSVM</td>
<td>UF</td>
<td>50.9</td>
<td>57.2</td>
<td>5.0</td>
<td>10.3</td>
<td>96.80 (0.41)</td>
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<tr>
<td></td>
<td>GALI</td>
<td>47.5</td>
<td>52.3</td>
<td>4.0</td>
<td>8.8</td>
<td>97.55 (0.32)</td>
</tr>
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REFERENCES


