A Lotting Method for Electronic Reverse Auctions

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A Lotting Method for Electronic Reverse Auctions

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Abstract

An increasing number of commercial companies are using online reverse auctions for their sourcing activities. In reverse auctions, multiple suppliers bid for a contract from a buyer for selling goods and/or services. Usually, the buyer has to procure multiple items, which are typically divided into lots for auctioning purposes. By steering the composition of the lots, a buyer can increase the attractiveness of its lots for the suppliers, which can then make more competitive offers, leading to larger savings for the procuring party. In this paper, a clustering-based heuristic lotting method is proposed for reverse auctions. Agglomerative clustering is used for determining the items that will be put in the same lot. A suitable metric is defined, which allows the procurer to incorporate various approaches to lotting. The proposed lotting method has been tested for the procurement activities of a consumer packaged goods company. The results indicate that the proposed strategy leads to 2–3% savings, while the procurement experts confirm that the lots determined by the proposed method are acceptable given the procurement goals.

Keywords

Reverse auctions, e–commerce, e–procurement, lotting, hierarchical clustering.

1 Introduction

Electronic auctions is one of the more promising applications of e-business. In addition to the selling of many items through online auction sites (e.g. www.ebay.com), many industries also consider the use of reverse auctions for industrial sourcing and procurement. Nowadays, virtually every major industry has begun to use electronic sourcing (e–sourcing) and adopt online reverse auctions [3]. More than 40 specialized solutions providers such as the FreeMarkets Inc. offer e–sourcing platforms, services and the technology for online reverse auctions [7]. It has been estimated that the annual throughput in online reverse auctions is over $40 billion [3].

Price negotiation is one of the most time–intensive activities in the purchasing process [2]. Online reverse auctions can significantly speed up the pricing process. Apart from the gains in the time spent on purchasing, the popularity of the online reverse auctions stems from the fact that they can help reduce the purchasing costs. It has been reported in the literature that online reverse auctions can produce cost savings from 5% to 40% [9]. Furthermore, online auctions have the potential to restructure the procurer's relation to its suppliers, for example, by allowing contact with more suppliers and improving the ability to evaluate the suppliers.

Multiple issues must be considered for a successful online reverse auction, such as the auditing of the suppliers, training of the users, implementation of the technology and the specification of the auction items. One of the important considerations for maximizing the cost savings is the so–called lotting, the grouping of items that will be auctioned as a single entity. One one hand, the lots must be as attractive as possible for the suppliers, so that they will have the incentive to make good offers that will save money for the buyer. On the other hand, the buyer wants to ensure that all the items are bid for, even if some of them are of less interest for the suppliers. Therefore, the optimal lotting should balance the interests of the suppliers and of the buyer. This suggests that the lotting problem should be handled through negotiations between the suppliers and the buyer. There are indeed auctioning systems in development, which allow negotiation between different parties during the auctions [8]. However, many existing online reverse auction systems do not allow negotiations. Furthermore, one of the main advantages of sourcing through reverse auctions is that it saves time through the elimination of negotiations, and hence negotiations should never become a substantial aspect of online auctions. In other words, attention must be paid to the lotting strategy that will lead to the maximal benefits.

Interestingly, the lotting problem for online reverse auctions has not been considered extensively in the literature. It seems that the lotting of items is usually handled in an *ad hoc* manner, through the beliefs and expertise of the procurement agent. In this paper, we investigate automated approaches to lotting that can support the lottig decisions of the procurement experts. We propose a clustering-based approach for lotting in online reverse auctions. Agglomerative clustering is used for determining the items that are put in the same lot. A suitable metric is defined, which allows the procurer to incorporate various approaches to lotting. We have applied the proposed lotting algorithm to a procurement campaign of a consumer packaged goods company. The results are encouraging, indicating that the proposed algorithm leads to 2–3% savings, while the procurement experts confirm that the lots determined by the proposed strategy are acceptable, given the procurement goals.

The outline of the paper is as follows. Reverse auctions and the significance of lotting for reverse auctions are discussed in Section 2. An overview of clustering methods is given in Section 3. A lotting algorithm based on clustering is proposed in Section 4. The algorithm uses hierarchical clustering and a distance metric that allows the procurer to incorporate various approaches to lotting. The application of the proposed method in a procurement campaign of a consumer packaged goods company is discussed in Section 5. Finally, conclusions are given in Section 6.

2 Reverse auctions and lotting

An *auction* is a mechanism to re-allocate goods or services to a set of market participants on the basis of bids and asks [6]. In general, there are two types of participants in an auction: the *auctioneer* and the *bidders*. In the classical form of an auction, the auctioneer is the seller of a product. He wants to find a buyer for a single, indivisible item among a group of interested bidders. Typically, the bidders will start from a small amount and increase their bid during an auction. An integral part of every auction are the *auction rules*, which consist of two parts: the *bidding rules* and the *market clearing rule*. The bidding rules define what the bidders may bid for and when they may place their bids. The market clearing rule defines when and how the allocation of items to bidders is decided, and what the bidders have to pay. For example, the classical English auction has the simple bidding rule that every bidder can make a bid at every time, and the market clearing rule that the highest bidder wins the auction, paying his bid.

In reverse auctions, the auctioneer is the buyer of a good or service, while the bidders are the suppliers of the good or service. Thus, a reverse auction provides a mechanism to procure a good or service from market participants on the basis of bids and asks. The reversal of the roles of the auctioneer and the bidders explains the term "reverse" in reverse auctions. The bids in a reverse auction evolve from large amounts to smaller amounts, hence making the bids more and more attractive for the auctioneer (i.e. the buyer). It is possible to design different reverse auction mechanisms, such as *descending* reverse auctions or *sealed-bid* reverse auctions. In all these auctions, the suppliers bid for entities called lots.

A *lot* is an item or a combination of items that the suppliers can bid for in its entirety. *Lotting* is the process of dividing the items into lots. Lotting is needed, because it is not efficient to auction all the items separately. A company may need to procure hundreds of different items. It is then simply not time and cost efficient to auction the items separately. Furthermore, if the quantity of an item to be procured is very large, it may be desirable to divide the total amount into multiple lots. It is important to realize that lotting gives the procurer the possibility to influence the attractiveness of the auctioned items for the suppliers, balancing two (possibly conflicting) goals. One one hand, the lots must be as attractive as possible for the suppliers, so that they will have the incentive to make good offers that will save costs for the buyer. On the other hand, the buyer wants to ensure that all the items are bid for, even if some of them are of less interest for the suppliers.

Let the items to be procured be represented by K–dimensional vectors $\vec{x}_n$, $n = 1, \ldots, N$. Hence, each item is described by a vector of K features. The goal of lotting is to divide the vectors $\vec{x}_n$ into I lots, so that the total procurement costs are minimized, while the constraints imposed by the auctioneer are satisfied. Mathematically,

$$
\begin{array}{ll}
\text{minimize} & \displaystyle\sum_{i=1}^{I} f_i(w_{i1}, \ldots, w_{iN}, \vec{x}_1, \ldots, \vec{x}_N) \\
\text{such that} & g_p(w_{i1}, \ldots, w_{iN}, \vec{x}_1, \ldots, \vec{x}_N) \leq 0, \qquad p = 1, \ldots P, \\
& \displaystyle\sum_{i=1}^{I} w_{in} = 1, \qquad n = 1, \ldots, N.
\end{array}
$$

In the above formulation, f_i denotes the price for lot i, and g_p are the constraints that may be imposed by the auctioneer. These constraints can be a result of the procurement approach (e.g. items procured for the same country should be grouped together), or it can be the result of boundary conditions (e.g. certain items cannot be procured from the same supplier). The decision variables are the allocation weights $w_{in} \in \{0, 1\}$, which indicate whether the item n is included in lot i.

Despite the mathematical formulation of the lotting problem, it can not be approached as a mathematical optimization problem, because the functions f_i are in general unknown. [1] Therefore, expertise and heuristic–based approaches are often used for determining the lots. The auctioneer can use different strategies for lotting. For example, one can group all items with similar characteristics together. In this case, the suppliers may be able to exploit economies of scale, which could be reflected in their bids. However, there may be lots, which consist of rather unattractive items, for which the bids are very high. In that case, the overall procurement costs are not minimized. Alternatively, one may consider putting different types of items in the same lot. However, this may increase the complexity of production for the supplier, which may be reflected in their bids as increased costs. In the following sections, we investigate the use of clustering algorithms as a method for supporting the lotting decisions of procurers.

3 Data clustering

When the allocation weights w_{in} are determined, the items to be procured are distributed over multiple lots. In this sense, the lotting problem could be interpreted as a segmentation problem. One of the methods that can be used for segmentation is clustering [10]. In clustering, a set of vectors is partitioned into several groups based upon similarity within the group and dissimilarity amongst the groups. There are two general types of clustering algorithms, the hierarchical clustering algorithms, and the objective function based (non-hierarchical) clustering algorithms. Objective function based clustering algorithms (such as the k–means clustering or the fuzzy c–means clustering [1]) solve an optimization problem to partition the data set into a pre-determined number of groups (see e.g. [5]. In contrast, the hierarchical clustering techniques proceed by a series of successive divisions or mergers of data to determine the partitions. Hence, the number of clusters is not pre-determined. This gives the user the possibility to analyze the clustering results at different resolutions, without additional computational burden of re-clustering.

Within the group of hierarchical clustering techniques, the most popular are the linkage algorithms. In linkage algorithms, the distance between all clusters is computed, and at each step the most similar clusters are merged. The linkage algorithms can be summarized as follows

[1] Usually, minimizing the procurement costs is not the only criterion. There are often other criteria to consider, such as the relations with the suppliers or the possibility to audit a supplier. However, multiple objectives are not considered in this paper.

[4].

Algorithm 3.1

Given N items, place each item in a separate cluster.

do

Compute the distance between all possible cluster pairs.

Merge the most similar (minimum distance) clusters.

until all clusters are merged

One obtains different linkage algorithms by modifying the way the distance between the clusters is measured. In the *single linkage* algorithm, the distance between two clusters is defined as the distance between their nearest members. In the *average linkage* algorithm, the distance between two clusters is defined as the average distance between pairs of the members in the two clusters. In the *complete linkage* algorithm, the distance between two clusters is defined as the distance between their farthest members.

The result of hierarchical clustering can be represented graphically in a *dendogram*, (also called a tree diagram). A dendrogram is a special kind of tree structure that visualizes clusters as the branches in a tree. It is usual in a dendogram to convert the distance into similarity, which is normalized between 0 and 1. In that case, one can obtain different clusters by thresholding with different values of $\lambda \in [0, 1]$, as shown in Fig. 1.

4 Clustering-based lotting

In this section, we propose a clustering-based lotting algorithm that can be incorporated in a procedure for reverse auctions. The lotting algorithm is based on hierarchical clustering in order to analyze the clustering results at different resolutions. We have chosen to use a complete linkage algorithm. Complete linkage algorithm has the attractive property that for merging two clusters, all the items in those clusters must be within a certain level of similarity to one another. Consequently, the complete linkage algorithm has a tendency to find relatively compact clusters composed of highly similar items. Furthermore, long chains of clusters are avoided, a disadvantage associated with single linkage and average linkage algorithms.

After having selected a clustering algorithm, the distance metric to be used in the algorithm must be determined. A suitable metric is defined in consultation with procurement experts

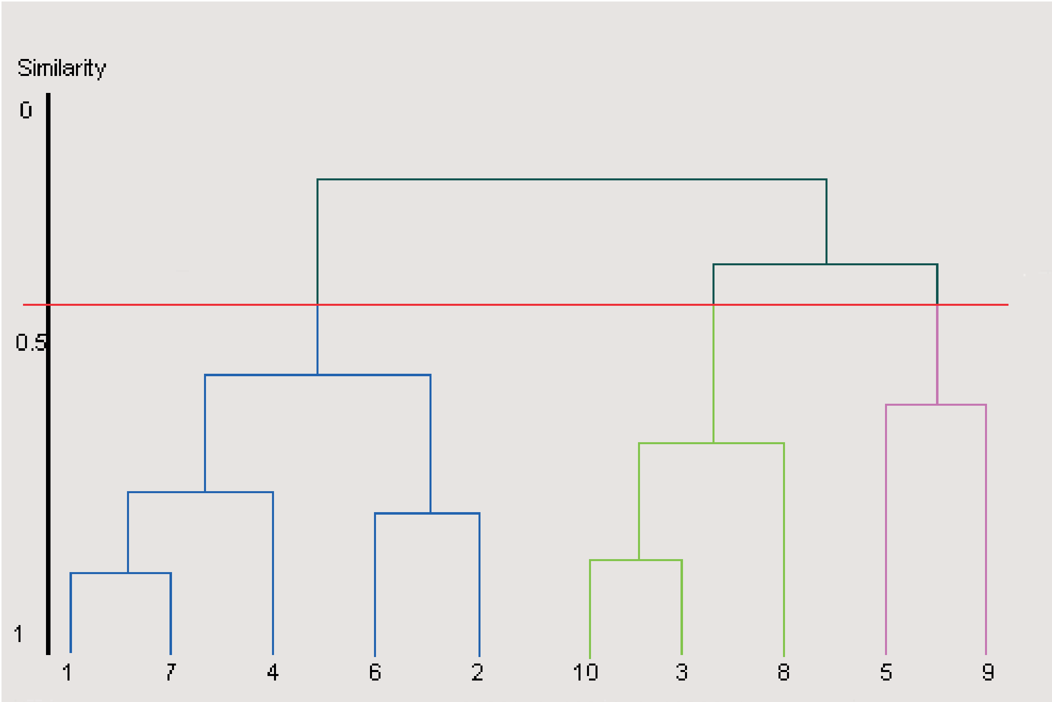
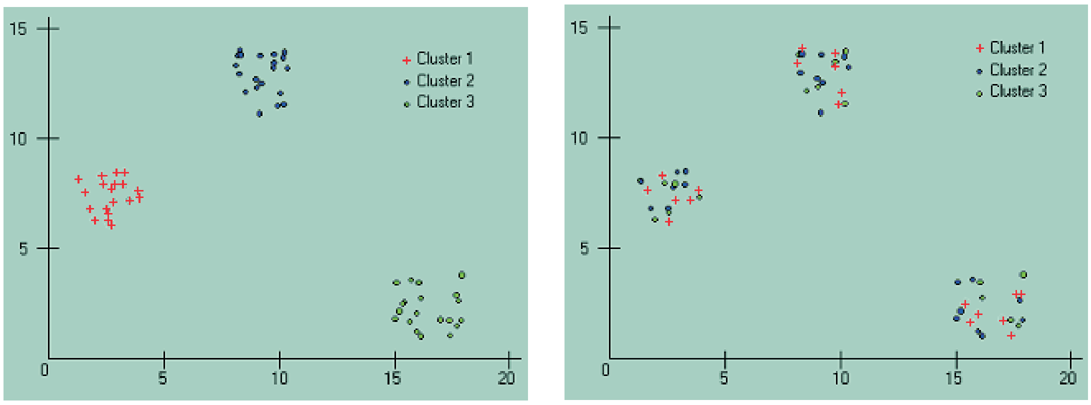


Figure 1: Example of a dendogram.

of a consumer packaged goods company. Procurement experts find it important to have an algorithm that can be tailored in various ways according to the knowledge and the expertise they have developed in many years. The experts have confirmed that, in many cases, they try to put items that look alike in the same lots. This is thought to provide economies of scale for the suppliers, who are then expected to reflect it in their bids. However, in some other cases, the experts want the items that are not similar in the same lots, for example because of policy reasons. This decision is taken on a feature-by-feature basis. Similarity of items in the same lot is required for some features, but it is not required for other features. Furthermore, some features take nominal or categorical values, while some other features take real values. Keeping these considerations in mind, the following distance metric is proposed for lotting.

$$d_{ij} = \frac{\sum_{k \in F_S} \alpha_k \delta_{ijk} + \sum_{k \notin F_S} \alpha_k (1 - \delta_{ijk})}{\sum_{k=1}^{K} \alpha_k}, \tag{1}$$

where d_{ij} is the distance between item $\vec{x}_i$ and $\vec{x}_j$, F_S is the set of features where items are judged on their similarity (the items are judged on their dissimilarity in the complementary set), $\alpha_k \in \{0, 1\}$ indicates whether feature k is of importance for the lotting problem considered and δ_{ijk} indicates the distance between item $\vec{x}_i$ and $\vec{x}_j$ measured along feature k. The way δ_{ijk} are computed depends on the type of the feature. For nominal or categorical features, δ_{ijk} is given



(a) (b)

Figure 2: A clustering example based on (a) similarity, and (b) dissimilarity.

by

$$\delta_{ijk} = \begin{cases} 0 & \text{if } x_{ik} = x_{jk} \\ 1 & \text{otherwise} \end{cases} , \tag{2}$$

while for continuous valued features it is given by

$$\delta_{ijk} = \frac{|x_{ik} - x_{jk}|}{R_k} \tag{3}$$

with R_k representing the range of feature k.

Note that all distances are normalized in $[0, 1]$, so that its complement indicates the similarity between the items $\vec{x}_i$ and $\vec{x}_j$. Complete linkage algorithm is now applied with distance metric (1) after the analyst decides which features should be clustered on similarity and which features on dissimilarity. Once the clustering results are obtained, one need to select a threshold $\lambda \in [0, 1]$, from which the final lot compositions are obtained.

Figure 2 shows the difference between clustering on similarity and clustering on dissimilarity for a data set consisting of three groups described by two features. Note that similarity based clustering finds the three natural groups in the data, while dissimilarity based clustering results ensures that all clusters have members from the three natural groups present in the data. This is the type of behavior expected by procurement experts when the items in a lot should be dissimilar. Intermediate forms between these two extremes are obtained when one clusters based on similarity for some of the features and based on dissimilarity for the other features.

5 Application

We have tested the performance of the clustering-based lotting by using the distance metric (1) by using data from the online procurement campaigns of a consumer packaged good company. The data set consists of 913 different items that the company had to procure for packaging purposes. Each item is described by 45 variables regarding the brand characteristics, the geographical region, the quality of the material, the size of the packaging material, type of print, etc. All variables except for the required volume are nominal or categorized. The data set contains missing values, which we have treated as separate categories for each of the features.

Twelve suppliers have taken part in an online reverse auction that was set up by the company. The lots had been defined by the procurement experts of the company, based upon their expertise and expectations from the auction. After the auction, the suppliers have been asked to provide a cost breakdown for the lots that they have bidden for. Hence, the suppliers provided an estimate of their bids for each of the items that they have bidden for. For purposes of testing the proposed clustering-based lotting algorithm, two subsets of data have been selected. The first subset (case 1) consists of the items for which five suppliers made a bid. There are 90 items in this data set, divided into four lots by the experts. The second subset (case 2) consists of five lots for which four suppliers made a bid. There are 142 items in this data set.

For the clustering-based lotting, the experts have indicated which features they consider to be relevant for the study, which ones should be clustered based on similarity and which ones should be clustered based on dissimilarity. Then the algorithm is applied on the data sets. Figure 3 shows the dendogram obtained for case 2. In order to compare the cluster-based lotting to the lotting of experts, the threshold for determining the lots is selected in such a way that the number of lots obtained equals the number of lots that the experts had used in their lotting. It may be the case, as in Fig. 3, that no threshold gives the same number of lots as the experts. In that case, the threshold has been selected so as to obtain a larger number of lots and then some of the obtained lots are combined manually such that the final number of lots equals the number of lots used by the experts. Then, the performance of the final lot composition has been determined and compared to the performance of the lots determined by the experts. Additionally, the lot composition obtained from clustering is presented to the experts who have judged the solution qualitatively for its acceptability.

The cost breakdown estimates by the suppliers have been used to compare the performance

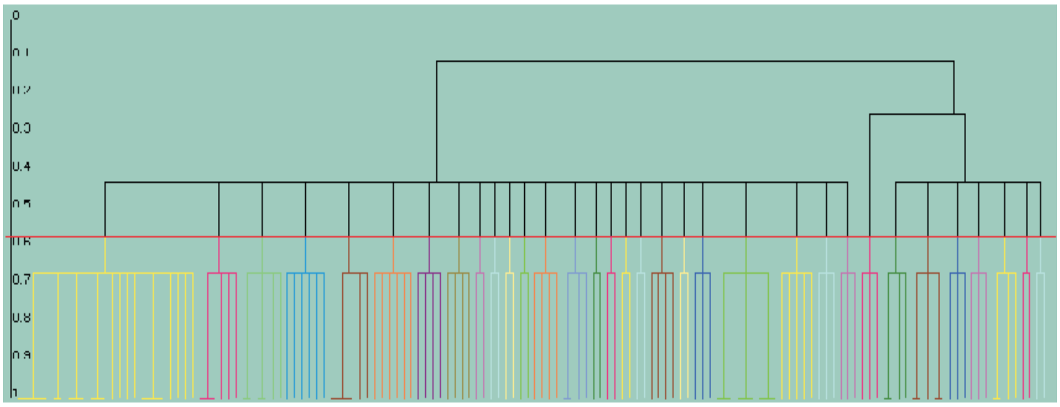


Figure 3: A dendogram obtained as a result of cluster-based lotting.

Table 1: Performance (in M€) of different lotting solutions

	Expert solution	Clustering solution	Optimal solution
Case 1	1.06	1.04	0.85
Case 2	9.73	9.49	9.00

of the clustering-based lotting to the lotting determined by the experts. It is thus assumed that the cost breakdown estimates correspond to the true valuation of an item by the supplier. In reality, the valuation for an item depends on the lot composition, and hence the "true" valuation is unobserved for different lot compositions. However, a better estimate of an item's valuation is not available, and so we have assumed that the cost breakdown from the suppliers is independent of the lot composition.

The performance of different lotting solutions is depicted in Table 1. In case 1, the clustering-based lotting achieves a cost saving of 1.9%, while it achieves a saving of 2.5% in case 2. The column titled "optimal solution" indicates the optimal solution when one assumes that the cost breakdown estimates provide the true valuations independent of the lot composition. We conclude from these results that the clustering-based lotting leads to about 2–3% savings in costs. The solution provided by the clustering-based lotting have also been presented to the procurement experts, who have confirmed that the solutions are acceptable, given the procurement goals.

6 Conclusions

Lotting is an important component of electronic reverse auctions. Large savings can be achieved and significant value can be added to the procurement by carefully considering the lotting strategy employed in a reverse auction. In this paper, we have considered a clustering-based heuristic lotting method. The method uses complete linkage hierarchical clustering algorithm. A special distance metric is defined for this problem, which allows the procurement experts to specify which features are relevant for the problem, for which features the items in a lot should resemble one another and for which feature they should not resemble one another. This metric corresponds to the way the procurement experts reason about the lotting problem.

The proposed algorithm has been applied to the procurement activities of a consumer packaged goods company by using online reverse auctions. It has been found that compared to the expert-based lotting, the proposed lotting algorithm leads to 2–3% savings in the procurement costs, while the procurement experts have confirmed that the resulting lotting solution is acceptable, given the procurement goals.

This study is one of the first regarding lotting in electronic reverse auctions. Our results demonstrate that computer based support of lotting decisions is a promising problem to study in the context of electronic commerce, which can lead to significant cost savings. Our future work will concentrate on further testing of the method in other cases and a more controlled comparison of the performance of the algorithm in relation to existing expert-based approaches.

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