Deep Learning Based Auction Design for Selling Agricultural Produce through Farmer Collectives to Maximize Nash Social Welfare

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Abstract

This paper is motivated by the need to design a robust market mechanism to benefit farmers (producers of agricultural produce) as well as buyers of agricultural produce (consumers). We design a volume discount auction with a farmer collective as the selling agent and consumers (high volume or retail consumers) as buying agents. A farmer collective is a group of farmers coming together to gain from the power of aggregation. Our auction mechanism seeks to satisfy key properties such as incentive compatibility, individual rationality, and Nash social welfare maximization, subject to realistic business constraints. Since an auction satisfying all of these properties is a theoretic impossibility, we propose designing deep learning networks that learn such an auction with minimal violation of the desired properties. The proposed auction, which we call PROSPER (PROtocol for Selling agricultural Produce for Enhanced Revenue), is superior in many ways to the classical VCG (Vickrey-Clarke-Groves) mechanism in terms of richness of properties satisfied and further outperforms other baseline auctions as well. We demonstrate our results for a realistic thought experiment on selling perishable vegetables. [1]

1. Introduction

Small and marginal farmers generally own 2 to 5 acres of land and grow 1 or 2 crops at a time. In terms of selling the produce that they grow, they may not always be able to reach consumers and even if they do, they may not be able to negotiate a competitive price. Consumers can be classified into three categories based on the volumes they purchase. The first category of consumers is made up of large chains of retail and grocery stores who buy large volumes of the produce and redistribute it through several outlets or online platforms. The second category of consumers comprises those who own standalone retail stores and generally sell to individual consumers in a certain locality. The third category consists of the individual consumers themselves who generally purchase a smaller quantity that suffices to satisfy their household needs. In reality, it is not practical for an individual farmer to be matched directly with consumers as several logistical issues arise. Some examples of these are a farmer not being able to reliably satisfy all the needs of the matched consumers, large companies looking to purchase produce of a particular grade, etc. For individual farmers to reach individual consumers, several other issues may arise such as transportation logistics and the preference to sell all of the harvested crop. It is important to find a way of selling the produce that maximizes the social welfare (sum of utilities of farmers and consumers).

For these reasons, it is essential for an organisation or official intermediary to step in and solve the problem of selling produce to all potential consumers in a way that is competitive for the farmers as well as the consumers. This is one of the primary objectives of Farmer Collectives (FCs) or Farmer Producer Organisations (FPOs), which have been set up in different parts of the world. An FPO or FC can be thought of as an entity that represents a large group of small and marginal farmers (generally between 100 to a few thousand farmers) of a certain geographical region. Grouping of small farmers into FPOs or FCs can greatly support small farmers in modern agricultural markets, through functions that small farmers cannot perform individually, such as supplying high-quality inputs closer to villages, aggregation and marketing of produce, facilitating access to infrastructure and technology, and providing training [12].

There exist more than 1500 FCs in Brazil, more than 7500 FCs in Germany, more than 63000 FCs in India, and more than 1700 FCs in USA. A recent report [18] mentions a staggering 1.2 million farmer collectives across the globe today. Harnessing the potential of FCs through collective action to make agricultural marketing more attractive for farmers as well as consumers has high potential for huge impact.

Since scientifically designed auction mechanisms can promote honest behavior and healthy competition among buyers and sellers [11], we propose to develop a suitable auction for selling agricultural produce through intermediation by FCs. In this paper, we propose an auction mechanism that can help small and marginal farmers sell their produce while obtaining the best price that also remains competitive to the consumers. Currently, auction mechanisms are not very popular for selling agricultural produce and we show in this paper that an intermediary such as an FC will make auctions a viable option to use. Although platforms like the National Agricultural Market (eNAM) (https://www.enam.gov.in/web/) exist, their effective usage requires the farmers to be highly technologically proficient.

The mechanism proposed is a volume discount auction where bids are invited from consumers, possibly seeking discounts

based on volumes. We call our mechanism PROSPER auction (Protocol for Optimal Selling of Produce for Enhanced Revenue). The PROSPER auction satisfies the following properties: incentive compatibility, individual rationality, Nash social welfare (NSW) maximization, fairness, and business constraints. Such an auction, according to mechanism design theory [9, 13] is a theoretical impossibility, hence, we propose a deep learning based approach that minimizes a loss function that captures the violation from the desired properties. We show that our mechanism almost achieves the performance of a standard VCG (Vickrey-Clarke-Groves) mechanism even while satisfying several additional properties.

2. Review of Relevant Work

Selling the agricultural output produced by the farmers (producers) to various consumers is an age old problem that has been attempted in a variety of ways. There have been several efforts to match farmers to consumers to maximize the utilities for the farmers and the consumers.

Several countries have experimented with online platforms for selling agricultural produce so as to benefit farmers and consumers. Examples include exchange platforms in Ethiopia, Kenya, Nairobi, and Uganda, the eNational Agriculture Market (eNAM) in India, and the Unified Market Platform (UMP) in the state of Karnataka, India [10]. The mechanisms used in these platforms are from a wide spectrum: warehouse-based negotiation, ascending auctions, first-price sealed-bid auctions, etc. [10]. It is not clear which mechanism is most beneficial for farmers [17]. Empirical evidence shows that the mechanisms may or may not be beneficial. As a case in point, the Ethiopia Commodity Exchange is very popular for coffee and sesame seeds and not popular for any other crops [5]. In India, for example, only 14% of all farmers have registered on eNAM, and over half of these registered farmers are reported to not have benefited from the platform [8].

Kudu is an agricultural marketplace in Uganda [14] in which farmers and traders use their mobile devices to place bids (requests to buy) and asks (requests to sell) using a centralized nationwide database. Kudu identifies profitable trades, which are proposed to the participants. The platform also gathers price data and broadcasts it back to farmers and traders using SMS, drawing from a large set of national, regional, and local markets and providing a uniquely tailored information set to each user. An automatic matching algorithm takes as input a set of bids and asks, and algorithmically proposes trades. Manual matching is also provided as an option. The matching algorithm runs three times a day. At run time, the algorithm simultaneously considers all bids and asks in the system and proposes a feasible set of trades that maximizes the total gains from trade, according to the scoring function. The matching algorithm uses a maximum weight matching algorithm in a bipartite graph. The method tries to find a fair price by setting the recommended price of a transaction to the minimum competitive (i.e., Walrasian) prices for the matching market. This makes truthful bidding a dominant strategy for buyers. The mechanism is not

incentive compatible for sellers (farmers). The Kudu marketplace has been fairly successful but its widespread deployment has been hampered by many logistical issues.

Viswanadham, Chidananda, Narahari, and Dayama [19] provide a good overview of the working of the Indian Agricultural markets, which are called mandis. They propose that mandis should be transformed into electronic exchanges and present a mixed integer programming model that the electronic exchange needs to solve in an iterative way to optimally match buyers with sellers. They also present a stylized case study to illustrate the functioning of such an electronic exchange.

Prasanna Devi, Narahari, Viswanadham, Kiran, and Manivannan [3] propose a matching algorithm that innovatively uses the GAle Shapley algorithm [7]. The results obtained using this approach outperform the results obtained using an English auction based method. It is found that the proposed method produces stable matching, which is preference-strategy proof and it also reduces the need for number of rounds of allocation.

Levi, Rajan, Singhvi, and Zheng [10] introduce a behavior-centric, field-based, data-driven methodology to propose and design auction mechanisms to enhance the revenue of agricultural farmers in online agricultural platforms. They propose and implement a new two-stage auction for the agri platform for the Karnataka State in India for a major lentils market. Their implementation saw the participation of more than 10,000 small and marginal farmers in the market in three months time. The Karnataka state Government is set to select suitable commodities and markets to implement the two-stage auction on a larger scale.

In this paper, our idea is to propose a convenient intermediary, namely a farmer collective (FC), to match farmers and consumers. Farmer collectives (FCs) which are quite popular in many countries serve this purpose in a natural way. Our idea is simple: A farmer collective will aggregate all the output from its farmers members and sell the aggregated commodities to potential consumers using a suitable mechanism such as auctions. In particular, the mechanism we propose is a volume discount forward auction that we call PROSPER (Protocol for Selling Produce for Enhanced Revenue) auction.

In an earlier paper [1], Bhardwaj, Diwakar, Ahmad, Ghalme, and Narahari have proposed the use of farmer collectives in the context of agricultural input procurement. The situation considered in [1] is, in a manner, the reverse of the situation considered in this work. In [1], the input requirements of farmers (for example, seeds, fertilizers, or pesticides) are aggregated by the farmer collective and the aggregated requirements are bulk procured in a cost-effective way from suppliers through a volume discount auction which is a reverse auction. The volume discount reverse auction proposed there seeks to satisfy incentive compatibility, individual rationality, cost minimization, fairness, and business constraints, with a slight compromise in social welfare maximization. The auction is designed using a deep learning based approach. In the current work we seek to design a volume discount (forward) auction using a deep learning approach where, instead of cost minimization, we seek Nash social welfare maximization. Nash social welfare maximization is chosen specifically in order to ensure that the

allocation balances the requirements of the farmers as well as the consumers; see [2] for the nice properties that Nash social welfare maximization achieves. This ensures that the market mechanism in this work, PROSPER, favours farmers as well as consumers and is sustainable. Our work is, to the best of our knowledge, the first application of a deep learning approach for auction design considering Nash social welfare maximization as an objective. Additionally, PROSPER ensures incentive compatibility, individual rationality, fairness, and meeting business constraints.

3. PROSPER AUCTION

During our initial interactions with a few farmer collectives we realized that PROSPER auctions would work best for perishables such as vegetables. Hence, to explain the PROSPER auction we consider the example of an FC whose farmers largely grow vegetables that are sold by the FC. For each vegetable that is grown by the farmers of the collective, a separate auction is conducted. Let us, for the sake of this example, consider the sale of tomato. While the description of the auction is given only for tomatoes, it can be replicated for any vegetable of a perishable nature. The consumers in the auction belong to the first two categories of consumers mentioned in Section 1, i.e., large chains of retail stores and standalone retail stores. We do not include small individual consumers in the auction marketplace since an auction is not required for the small individual consumers. Instead, a simple e-commerce platform would be most convenient there.

The setup of the auction is as follows. Individual farmers approach the FC with the produce that they have grown. The FC notes the quantities brought by the individual farmers and accumulates all the produce. Following this accumulation the FC announces, to all potential consumers, the total volume available for sale. Each consumer is asked to place a bid, which includes the price per unit that the consumer is willing to pay along with the quantity required. Large scale consumers may usually obtain the daily market values based on current supply and demand in the market and submit their bids based on these values. Volume discounts may also be sought as part of the bids. Figure 1 captures the workflow in the PROSPER auction.

3.1. An Example of a PROSPER Auction

An example of a volume discount bid is shared here. Let us assume that 100 kg of tomato has been brought by the farmers to be sold by the FC. A particular consumer may bid ₹5.5/kg for the first 50 kg and ₹5/kg for any further tomatoes bought up to 100 kg. This means that for purchasing 75 kg of tomatoes, this consumer is ready to pay ₹5.5 × 50 + ₹5 × 25 = ₹400.

It is worth noting that different consumers may use different bidding languages. All the bids can be converted to the same bidding language before running the auction. For example, a consumer planning to purchase 100 kg of tomato may bid ₹5.25/kg for up to 50 kg and ₹5/kg if the quantity is more than 50 kg. This means that if 75 kg of A is purchased by the consumer, we consider the bid price as (₹5/kg * 75). This is an example of a flat discount.
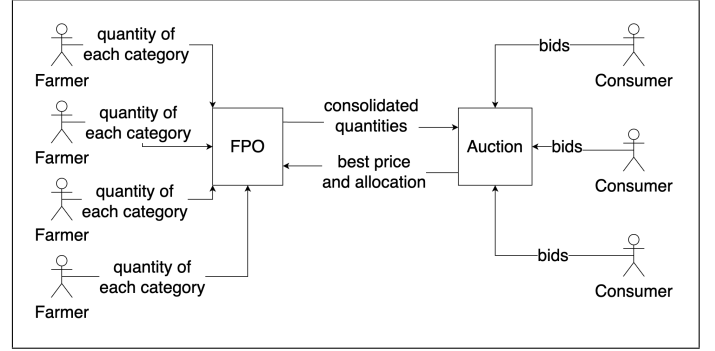

Figure 1: PROSPER auction for maximizing social welfare

There are several factors to be considered while determining who is allocated how much of the produce, and at what price. These will be elaborated in the rest of the paper.

3.2. A Desiderata of Properties for PROSPER Auction

We mention below the most desirable properties that a crop auction should possess. Our analysis is based on our familiarity with and study of FCs and the dynamics of selling agricultural produce.

Incentive Compatibility (IC)

Incentive compatibility ensures truthful bidding by the consumers and is a fundamental requirement of any auction mechanism. The most powerful version of IC is dominant strategy incentive compatibility (DSIC). DSIC ensures that, irrespective of the bids of the other consumers, it is in the best interest of each consumer to bid their true value.

Individual Rationality (IR)

Individual rationality ensures that the FC and consumers obtain non-negative utility by participating in the auction. The most powerful version of IR is ex-post IR, which implies that the utility to each participating player (all the consumers as well as the FPO) will be non-negative irrespective of the actions of the other players.

Social Welfare Maximization (SWM)

It is desirable to increase the net social welfare or the sum of utilities of the participants in the auction. In the PROSPER auction, the participants involved are the FC and the consumers. The utility of the FC captures the joint utility of all the farmers whose produce is aggregated by the FC. The utility of the FC or the consumer is defined as the amount of money they gain through the auction mechanism. Assume a consumer submits a truthful bid of ₹6 for a kg of tomato. Through the auction mechanism, let us assume, the consumer is asked to pay the FC ₹5/kg. Then the consumer's utility is ₹1/kg. If the average cost to produce 1 kg of tomato is ₹3.5 and the FC is paid ₹5/kg, then the utility of the FC is ₹1.5/kg. SWM aims to maximize

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the sum of utilities of the FC and all the consumers. The profit made by the FC is distributed to the farmers either based on the quantities of tomato brought by the individual farmers or based on the amount of stake the farmer holds in the FC.

Nash Social Welfare Maximization

Although social welfare maximization satisfies the utilitarian rule, it allows a particular player's utility to take a hit if another player is receiving a commensurate or greater utility boost. A more egalitarian approach would be to maximize the product of utilities of all the participants in the auction. In this paper, we focus on NSW maximization rather than SWM since NSW maximization is known to benefit both the seller (farmer collective on behalf of farmers) and the consumers [2].

Revenue Maximization for Farmers (FOPT)

It is desirable that the expected total revenue generated for the farmers is maximized. FOPT makes the auction farmer-friendly.

Cost Minimization for Consumers (COPT)

For running multiple successful iterations of the mechanism it is imperative that the expected total cost incurred by the consumers is minimized. COPT implies a consumer-friendly auction.

Fairness (FAIR)

Fairness implies that the winning consumers are chosen in a fair way. An index of fairness would be envy-freeness – no consumer can increase their utility by adopting another consumer's outcome. If envy-freeness is not achievable, the next best option is envy minimization (which is what we pursue in this paper).

Business Constraints (BUS)

It would help the FPO run the auctions effectively over a longer time duration if certain business rules were implemented. Satisfaction of business constraints refers to constraints such as having a minimum number of winning consumers (to avoid monopoly by a single or small number of consumers), a maximum number of winning consumers (to minimize logistics costs), a maximum fraction of business to be awarded to any consumer, etc.

Which set of Properties to Satisfy?

Ideally, we would like the PROSPER auction to satisfy IC, IR, NWM, FAIR, and BUS. The properties FOPT and COPT make the auction farmer friendly or consumer friendly, respectively. They have been included for the sake of completeness and for comparison purposes. Satisfying the set of properties (IC, IR, NWM, FAIR, BUS) is clearly a tall order. The classical Vickrey-Clarke-Groves (VCG) mechanisms [13] satisfy IC, IR, and SWM but may not always satisfy FAIR and BUS. Mechanism design theory [9, 13] is replete with impossibility theorems which make it clear that all these properties cannot be satisfied simultaneously. The ambitious goal of this paper is to devise innovative auctions that achieve these properties with as little compromise as possible, using a deep learning approach.

4. A DEEP LEARNING APPROACH FOR VOLUME DISCOUNT AUCTIONS

We propose a data-driven approach to auction design that is an extension of [6, 4, 20, 1]. It is to be noted that all these mechanisms guarantee Individual Rationality. [4] maximizes the revenue of the seller in the auction while minimizing the violation of IC. The architecture we use for the PROSPER auction is similar to the architectures used by [4] and [1]. However, it is to be noted that these architectures cannot be used as is, because of the following reasons.

In the PROSPER auction, we are dealing with the selling of homogeneous units with volume discounts whereas the work of [4] considers auctions with additive (or unit-demand) valuations. Our volume discount auction setting is not additive and is not unit-demand either. To see this, observe that the value of $2x$ units with volume discounts is not the same as twice the value of x units. Additionally, the consumers in our setting wish to buy any number of units, unlike the unit-demand buyers considered by [4]. Auctions with additive valuations and unit-demand valuations make it possible to use allocation networks whose outputs are simply (stochastic) allocation matrices. We simply cannot do this in our case, so instead, we produce an allocation tuple as output - with each element in the tuple being the allocation for the corresponding consumer. This complicates the computation of the payments and makes theoretical analysis non-trivial.

[1] consider the case of procurement auctions with the primary aim of minimizing the procurement cost. Ours is a forward auction whose primary aim is to maximize the NSW subject to IR, while minimizing the violations of IC, envy, and business constraints. Further, our work, in addition to minimizing IC violation, also explores the case where the revenue of the FC is maximized as well as the case where the revenue of the consumers is maximized.

4.1. The Volume Discount Auction Setting

In this section, we formally describe the volume discount auction setting. The notations used here are similar to the ones used by [6, 4, 20, 1]. The FC is a single seller intending to sell m homogeneous units of a certain item to n consumers using a forward auction.

The volume discount bidding is implemented as follows. The mechanism solicits volume discount bids from each consumer. These bids represent each consumer's valuation for a single unit from each 'lot' of units. All the items from a given lot are valued equally. Thus, if the FC sells more lots, their valuation per item decreases. In the agricultural domain, this corresponds to savings from the use of bulk transport, warehouse clearance, mass production, etc.

There are k lots of (almost) equal size. The consumer i's bid $b_1^{(i)}$ is applied to all the items if the seller sells at most one lot; i.e. ℓ items. For the items from the second lot, the bid $b_2^{(i)}$ is used, i.e., a price of $b_1^{(i)}$ per unit for the first ℓ items and a price of $b_2^{(i)}$ for the remaining items (up to ℓ). And so on. That is, consumer i submits a volume discount bid in the form of a vector $b^{(i)} = (b_1^{(i)}, b_2^{(i)}, \cdots, b_k^{(i)})$ of k lots. All the lots are

assumed to be of the same size, $\ell := \lfloor \frac{m}{k} \rfloor$ and the extra $m - (k \times l)$ items are assumed to be added to the last lot. The value of k depends on certain endogenous factors like the packaging method, carton size, nature and price of the items, etc.

When k is a design parameter, it presents an interesting challenge in auction design. A larger value of k introduces more granularity, which is better for the buyer. But it also increases the complexity of bidding as well as winner determination procedures, possibly leading to a less effective implementation. We leave the study of this aspect as an interesting future work.

Note that this simple model can be used to encapsulate a wide variety of situations. Consider the case where $m = 2500$. Say a consumer would like to bid: ((1-500: 20), (501-1500: 18), (1501-2500: 16)) where the first value of the tuple represents the size of that lot and the second value of the tuple represents the bid for that lot. Assume that another consumer would like to procure only 1500 units, and would like to bid 18 for the first 500 units and a discount of 1 thereafter. Inspite of the difference in their requirements and bidding language, we can incorporate the bids of both these consumers in the following manner. We will have $\ell = 500$. The lots would be $[1, 500]$, $[501, 1000]$, $[1001, 1500]$, $[1501, 2000]$, $[2001, 2500]$. The first consumer's bid vector would be $b^{(1)} = (20, 18, 18, 16, 16)$ while that of the second consumer would be $b^{(2)} = (18, 17, 17, -\infty, -\infty)$. If 1800 items are allocated to the first consumer, then the corresponding willingness to buy would be $500 \times 20 + 500 \times 18 + 500 \times 18 + 300 \times 16 = 32800$. Similarly, if the allocation for the second consumer is 700 units, then the corresponding willingness to buy would be $500 \times 18 + 200 \times 17 = 12400$.

Given the vector of bids $b = (b^{(1)}, \cdots, b^{(n)})$ as input, the mechanism outputs allocation and payment vectors denoted by the tuple $\langle a(b), p(b) \rangle$. Here, $a(b) = (a_1(b), \cdots, a_n(b))$ denotes the allocation vector and $p(b) = (p_1(b), \cdots, p_n(b))$ denotes the payment vector with each $a_i(b)$ being the number of units sold to consumer i and $p_i(b)$ being the total payment made by consumer i for the $a_i(b)$ units.

The consumers have their own private willingness to buy (WTB), which determines the maximum per unit price that the consumer is ready to spend. For consumer i, we denote the WTB by $v^{(i)} = (v_1^{(i)}, ..., v_k^{(i)})$. Here each $v_j^{(i)}$ represents the valuation or the maximum amount that consumer i is ready to pay for one unit, of the homogeneous items being sold, from lot j. Since this is a volume discount auction, the subsequent values of v_j will decrease monotonically, i.e., $v_j \geq v_{j+1} \forall j \in [1, k-1]$. These valuations are assumed to be drawn from some prior distribution $\mathcal{F}$. In our setting, $\mathcal{F}$ is common knowledge among all the consumers and the FC, whereas the realized vector of valuations $v^{(i)}$ is known privately only to the individual consumer i. The mechanism is incentive compatible if we have $b^{(i)} = v^{(i)}$.

The utility for a consumer is defined as a function of their private valuations $v^{(i)}$, allocation $a_i(b)$, and payment $p_i(b)$, and is given by

$$u_i(v^{(i)}; b) = \sum_{j=1}^{a_i(b)} v_{\lceil j/\ell \rceil}^{(i)} - p_i(b) \qquad (1)$$

Having defined the utility, we will now have a better perception of incentive compatibility, individual rationality, and social welfare. A mechanism is DSIC if no agent can gain utility by misrepresenting their valuations, regardless of the strategies adopted by the other agents. That is,

$$u_i(v^{(i)}; (v^{(i)}, b^{(-i)})) \geq u_i(v^{(i)}; b) \qquad \forall v, b, i \qquad (2)$$

An auction mechanism is called ex-post IR if every agent earns non-negative utility by participating in the auction. We assume that there is no participation cost or auction entry cost. Our proposed neural network architecture is designed to ensure the ex-post IR condition by satisfying

$$u_i(v^{(i)}; v) \geq 0 \qquad \forall v, i \qquad (3)$$

It is notable that ex-post IR is the strongest form of individual rationality in mechanism design literature [9].

Our goal is to design a mechanism that maximizes the Nash social welfare, i.e., the product of utilities of all the players are maximized, while ensuring ex-post individual rationality and minimum violation of DSIC. For calculation of the Nash social welfare, we consider the cumulation of all consumers to be a single player and the FC to be the other player. Hence, the Nash social welfare is the product of the utility of the FC and the sum of utilities of all the consumers.

$$nsw = u_{FC} \cdot u_C \qquad (4)$$

where u_{FC} and u_C are the utility of the FC and the sum of utilities of all the consumers respectively. This ensures that the mechanism does not unfairly favour either the collective of farmers or the group of consumers.

The utility of a consumer, i is given in Equation 1. Hence, the sum of the utilities of all consumers is

$$u_C = \sum_{i=1}^{n} u_i(v^{(i)}; b) \qquad (5)$$

For a particular crop, the reserve price, p_{res}, is the lowest unit price at which the FC is willing to sell the crop. It may be considered as the FC's per unit valuation for that particular crop. The reserve price may be, for example, the total costing of one unit of the crop with a minimal profit added to it. Hence, assuming that all unsold crop goes waste, the utility of the FC can be calculated as

$$u_{FC} = \sum_{i=1}^{n} p_i(b) - m \cdot p_{res} \qquad (6)$$

Note that the revenue of the FC is different from the utility of the FC. The revenue of the FC is defined as

$$revenue_{FC} = \sum_{i=1}^{n} p_i(b) \qquad (7)$$

Following section 2.2.2 of [4], one can guarantee DSIC property by ensuring that the expected ex-post regret for every consumer, r_i, is 0. The expected ex-post regret of the PROSPER mechanism is defined as

$$r_i = \mathbb{E}_{v \sim \mathcal{F}}[\max_b [u_i(v^{(i)}; b) - u_i(v^{(i)}; (v^{(i)}, b^{(-i)}))]] \qquad (8)$$

The regret is computed empirically, which adequately approximates the real regret [4].

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4.2. Deep Learning Based Formulation

We propose a neural network based formulation to satisfy individual rationality while minimizing the violation of DSIC, along with some other desirable and practical constraints.

The goal is to minimize a composite loss function that consists of the following parts; the negative of the Nash social welfare, the negative of the FC's revenue, the regret penalty, the envy penalty, the business penalty, and the Lagrangian term (as we use the method of differential multipliers [15]) for regret and envy. We also provide models that respectively maximize the revenue of the FC and maximize the revenue of the consumers as the primary goal while minimizing IC violations.

Based on the requirement, different combinations of the various components of the loss function, which are mentioned below, are used. When a particular component is to be maximized, we take its negative value as a part of the loss function that we minimize. One need not restrict oneself to the usage of the components mentioned in this section. Other nice to have properties such as egalitarian social welfare can also be included in our methodology by adding similar components to the loss function. The individual components are each described in further detail through this section.

$$\texttt{revenue}_{\texttt{FC}} = \sum_{i=1}^{n} p_i(b)$$

$$\texttt{nsw} = u_{FC} \cdot \sum_{i=1}^{n} u_i(v^{(i)}; b)$$

$$\texttt{penalty}_{\texttt{regret}} = \rho_{\texttt{regret}} \sum_{i=1}^{n} \tilde{r}_i^2$$

$$\texttt{penalty}_{\texttt{envy}} = \rho_{\texttt{envy}} \sum_{i=1}^{n} e_i^2$$

where $penalty_{regret}$ and $penalty_{envy}$ are the regret terms corresponding to regret and envy respectively. When trying to minimize envy, the Lagrangian loss used is

$$\texttt{LagrangianLoss} = \sum_{i=1}^{n} \lambda_{\texttt{regret}}^{(i)} \tilde{r}_i + \lambda_{\texttt{envy}}^{(i)} e_i \qquad (9)$$

and when we are not trying to minimize envy, the Lagrangian loss used is

$$\texttt{LagrangianLoss} = \sum_{i=1}^{n} \lambda_{\texttt{regret}}^{(i)} \tilde{r}_i \qquad (10)$$

Here, $\tilde{r}_i$ is the empirical regret. We compute $\tilde{r}_i$ by using another optimizer over the bids, coming from the same distribution as $\mathcal{F}$, which maximizes the utility for agent i. To approximate the expectation over the distribution $\mathcal{F}$, we maximize the sample mean of regret over the batch.

The equation for the loss function, when only Nash social welfare is considered as an additional objective along with the

regret minimization, is

$$\texttt{loss} = -(\texttt{nsw}) + \texttt{penalty}_{\texttt{regret}} + \texttt{LagrangianLoss}$$

where the Lagrangian loss is calculated using Equation 10. Other loss terms may be added or removed from this equation as per the requirements.

4.2.1. Business Constraints

The seller may wish to impose various business constraints in the PROSPER auction - for example, the seller may require that at least 3 consumers buy at least 20% of the items each. Such a constraint can be introduced by adding a penalty term, while training the network, as shown below. For having a minimum of s consumers, each with an allocation of at least a_{min}, the penalty would be

$$\texttt{penalty}_{\texttt{business}} = \rho_{\texttt{business}} \sum_{t=1}^{s} \max(0, a_{min} - a^{(t)}) \qquad (11)$$

where $a^{(o)}$ is the oth-highest allocation $\forall o \in \{1, 2, ...s\}$. Other business constraints are also possible. For instance, no consumer may be allocated more than 50% of the units. To incorporate various business constraints we add the corresponding penalty for violating those business constraints to the loss function.

4.2.2. Envy Minimization

Envy minimization is one of the most popular fairness constraints in auction design. Envy (or dissatisfaction) for an agent is defined as the maximum utility they could gain if they were given the allocation and payment of some other agent. So the envy for consumer i, given the valuation tuple $v = (v^{(1)}, ..., v^{(n)})$ is

$$e_i(v) = \max_{h \in \{1, 2, ...n\}} [(p_h(b) - \sum_{j=1}^{a_h(b)} v_{\lceil j/\ell \rceil}^{(i)})] - u_i(v^{(i)}; v) \qquad (12)$$

We minimize envy by adding a term for envy in our Lagrangian loss, along with an envy penalty.

4.3. Allocation Network and Payment Network

The model consists of two feed-forward networks - an allocation network and a payment network (See Figure 2 and Figure 3 for details). The input for both networks is the $n \times k$ matrix where the ith row is the bid $b^{(i)}$ for consumer i.

The output of the allocation network is the allocation tuple described in Section 4.1. The allocation network uses the softmax function to ensure that the allocation tuple is a probability vector. This is multiplied by m to ensure that the allocations across the agents sum up to exactly m. If the combined requirements of all the consumers, CR is less than m, then the probability vector is multiplied by CR instead of m to ensure that the net allocation is equal to CR and all the consumers are allotted items in accordance with their respective requirements.

The output of the payment network is a payment multiplier tuple, $\hat{p} = (\hat{p}_1, ..., \hat{p}_n)$. The amount by which a bid exceeds the
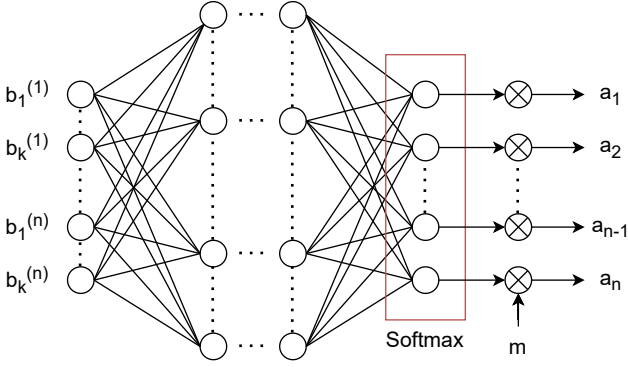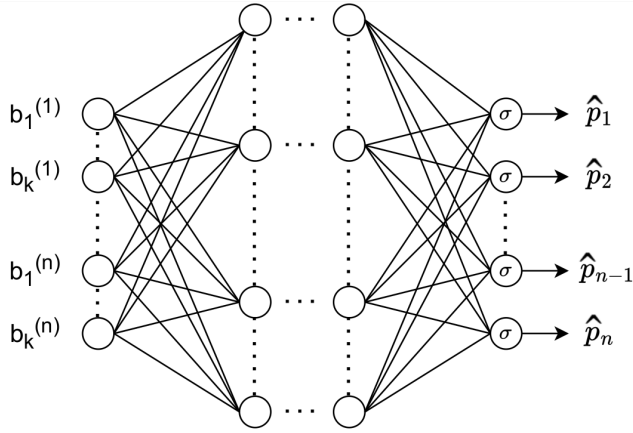
Figure 2: Allocation Network

Figure 3: Payment Network

reserve price is multiplied by the value in the payment multiplier tuple corresponding to that bid. This value is then added to the reserve price to get the corresponding payment. Hence, the total payment made by consumer i would be

$$p_i(b) = p_{res} + \hat{p}_i(b) \sum_{j=1}^{a_i(b)} (b^{(i)}_{\lceil j/\ell \rceil} - p_{res}) \qquad (13)$$

Each $\hat{p}_i$ is guaranteed to be within the range $[0, 1]$ in order to ensure IR for the consumers. This is ensured by adding a sigmoid layer at the end of the payment network. IR for the farmers is ensured by keeping the payments higher than the reserve price in Equation 13.

4.4. Training Procedure

In all our experiments 5 layers, with 80 to 100 neurons in each layer, were used for both the payment and allocation networks. The Adam optimizer was used for training the network weights and stochastic gradient descent was used to learn the Lagrangian parameters.

During the training phase, we performed nested optimizations. For one step of optimization over the network weights, we executed R steps of optimization over the bids to compute

the empirical regret. Here, we used gradient ascent to maximize the value of empirical regret that a misreporting consumer would experience. This empirical regret computation and the use of Lagrangian parameters is the same as what is proposed in [4].

4.5. Need for the DL approach

Nash social welfare maximization is widely known for its fairness properties [2] but finding an outcome that maximizes NSW is NP-hard [16]. The methodology we follow essentially transforms a mechanism design problem into an optimization problem. But even an approximate solution to this optimization problem cannot be found as the constraints that we deal with, such as business constraints and envy minimization, are non-linear and, unfortunately, linear approximations do not work well with such constraints. Moreover, the linear approximation will have an exponential number of variables. The deep learning technique has the advantage that a single substantial effort of training will amortize the computational complexity over a large number of experiments.

5. Experimental Results

In this section, we describe our experimentation with an FPO-mediated market for a perishable vegetable such as tomato, brinjal, chili pepper or some seasonal fruit. As described in Section 3, the FPO gathers the produce to be sold from a number of registered farmers and invites volume discount bids from potential consumers. For our experimentation we consider 1000 units of the produce (for example, 1000 kg of Chili pepper) and take all prices in US $ (we will not mention these units henceforth). We consider five consumers – they could be major consumers like retail chains or medium level stores like community grocery stores. It is important to satisfy the requirements of the consumers as far as possible. Further, it is important to benefit the consumers as well as the farmers to ensure sustainability of the market mechanism. We determine the valuation of a single unit of the produce for each consumer to be drawn from the uniform distribution U[350,450]. The values 350 and 450 are in cents, however, the rest of the paper including Table 1 refers to the prices in US $. The consumers place volume discount bids in the following manner. These bids have been formed to cover all representative scenarios.

- Consumer 1 specifies a flat per unit price for the entire range of $[1, 1000]$ units and does not bid with any discount.

- Consumer 2 bids with a discount of 5% if the purchase volume is in the range of $[501, 1000]$ units. This discount is over the base price that applies for the purchase volume range $[1, 500]$.

- Consumer 3 bids with a discount of 3% for any volume in the range of $[301, 600]$ units and 6% for a volume in the range of $[601, 1000]$. The discount is over the base price that applies for the volume range $[1, 300]$.

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- Consumer 4 bids with a discount of 2%, 4% and 6% for the volume ranges $[251, 500], [501, 750]$, and $[751, 1000]$ units, respectively. This discount is over the base price that applies for the purchase volume range $[1, 250]$.

- Consumer 5 bids with a discount of 2%, 4%, 6% and 8% for the volume ranges $[201, 400], [401, 600], [601, 800]$, and $[801, 1000]$ units, respectively. This discount is over the base price that applies for the purchase volume range $[1, 200]$.

An important parameter to be selected is the reserve price. A lower reserve price hurts the farmer while a higher reserve price hurts the consumers. We have logically chosen 300 cents per unit after observing the results for different values of reserve prices. Our model can be used to pick a suitable value for reserve price that serves the farmers and consumers the best. Refer to Table 1 for numerical results. The following performance metrics are computed:

- FPO utility, which is the amount that the total revenue of the FPO exceeds the reserve price.

- Total consumer utility, which is the sum of the utilities of all consumers. A consumer's utility is the amount by which the valuation of all the items allotted to them exceeds the payment made for those items.

- Social welfare, which is the sum of utilities of the FPO and all the consumers.

- Nash social welfare, which is the square root of the product of the FPO's utility and the sum of utilities of all the consumers.

- FPO revenue, which is the total revenue to the FPO and is also the total payments made by all the consumers.

- Envy, which is the maximum possible fractional (per unit) increase in utility of any consumer if they were to be allotted another consumer's allocation and payment.

Each column in Table 1 holds the values for one of the six metrics mentioned above. These values were calculated after averaging the values obtained for over 6000 runs where, in each run, the valuations of the FPO and the consumers were drawn from the uniform distribution U[350,450]. The five rows of the table correspond to five different auctions that are relevant in this scenario: VCG Auction; FPO Optimal Auction; Consumer Optimal Auction; NSW Maximizing Auction; and NSW Maximizing & Envy Minimizing Auction. The first three auctions were included to serve as baseline auctions for making performance comparisons. While the VCG auction can be implemented analytically, the rest of the auctions were implemented using the deep learning approach described in Section 4.

5.1. Baseline Auctions

VCG Auction

Our first baseline auction is the standard VCG mechanism, which maximizes social welfare (sum of utilities of FPO and the consumers) while satisfying dominant strategy incentive compatibility and individual rationality. The results show that the utility of the FPO is much higher than the combined utility of the consumers, thus the mechanism appears to be more FPO friendly (that is farmer friendly) and the consumers may not be excited by this auction mechanism.

FPO Optimal Auction

Our second baseline auction maximizes the expected revenue of the FC subject to satisfying incentive compatibility and individual rationality via loss function minimization. The following loss function is used

$$\texttt{loss} = -(\texttt{revenue}_{\texttt{FC}}) + \texttt{penalty}_{\texttt{regret}} + \texttt{LagrangianLoss}$$

This auction produces the highest possible revenue of the FPO and the farmers will be delighted with such an auction (see Table 1). At the same time, such an auction may turn away consumers from participating in the auction.

Consumer Optimal Auction

Our third baseline auction maximizes the revenue of the consumers (by minimizing the revenue of the FC) subject to satisfying incentive compatibility and individual rationality via loss function minimization. The following loss function is used

$$\texttt{loss} = \texttt{revenue}_{\texttt{FC}} + \texttt{penalty}_{\texttt{regret}} + \texttt{LagrangianLoss}$$

This auction produces the highest possible revenue for the consumers (see Table 1). However, such an auction will prove to be unattractive to the farmers since the FPO's revenue takes a beating.

5.2. NSW Maximizing Auction

Nash social welfare has the attractive property of satisfying fairness of allocation as well as guaranteeing a high level of social welfare. We now consider an auction that maximizes NSW, ensures incentive compatibility as well as individual rationality, and satisfies certain business constraints. The loss function to be minimized for such an auction would be

$$\texttt{loss} = -(\texttt{nsw}) + \texttt{penalty}_{\texttt{regret}} + \texttt{penalty}_{\texttt{business}} + \texttt{LagrangianLoss}$$

The business constraints used in our experiments try to ensure that the number of consumers who are allotted the produce remains between a minimum number and a maximum number. It should be noted that other business constraints can also be used equally effectively by modifying the *penalty_business* term in accordance with the required business constraints. The motivation for having a constraint on minimum number of consumers is to spread the business among competing consumers to avoid monopolies, duopolies, etc. The constraint on maximum

Table 1: Comparison of all utilities for different Auction Mechanisms

	FPO Utility	Total Consumer Utility	Social Welfare	Nash Social Welfare	FPO Revenue	Envy
VCG	763	264	1027	193016	3763	0.1817
FPO Optimal	859	96	955	79292	3859	0.2274
Consumer Optimal	0.26	875	875.26	243	3000.26	0.1985
NSW Maximizing	397	603	1000	243444	3397	0.1378
NSW Maximizing & Envy Minimizing	251	748	999	190990	3251	0.0129

number of consumers is to optimize logistics costs. Section 4 has brought out the learning process for a deep neural network that satisfies individual rationality, incentive compatibility, and NSW maximization, subject to business constraints. Let us call this auction NSW maximizing auction. We find from Table 1 that the social welfare of the VCG auction is 1027 while that of the NSW maximizing auction is 1000; however, there is a perceptible difference in the utilities of the FPO and consumers between these two auctions. Recall that in the case of the VCG auction, the utilities were loaded in favour of the FPO. In the case of the NSW maximizing auction, the utilities are 397 for the FPO and 603 for the consumers which is more balanced than the values of 763 and 264, respectively, in the case of the VCG auction. The NSW for the NSW maximizing auction is 243,444 which is clearly superior to 193,016 of the VCG auction. The FPO revenue is 3763 in the case of the VCG auction while it is 3397 in the case of the NSW maximizing auction. The decreased revenue of the FPO is compensated by increased revenue of consumers. The envy of the NSW maximizing auction is 0.1378 compared to 0.1817 of the VCG auction. To summarise, the NSW maximizing auction achieves a better balance in the utilities for the FPO and consumers, achieves better NSW, results in more revenue for the consumers, and leads to less envy, at the cost of some decrease in the revenue of the FPO. It is clear that the NSW maximizing auction will be more acceptable to both farmers and consumers than the VCG auction as the VCG auction empirically shows more bias towards the farmers in our experiments.

NSW Maximizing & Envy Minimizing Auction

Though NSW balances social welfare maximization with fairness of allocation, in many situations, fairness may have to be accorded a high priority. In agricultural market situations, there is a critical need to ensure that nobody goes out of business due to aggressive bidding by powerful players. Envyfreeness is a way of ensuring this. An auction that tries to maximize NSW as well as minimize envy would be most desirable. The loss function to be minimized for such an auction would be

$$\texttt{loss} = -(\texttt{nsw}) + \texttt{penalty}_{\texttt{regret}} + \texttt{penalty}_{\texttt{envy}} + \texttt{penalty}_{\texttt{business}} + \texttt{LagrangianLoss}$$

The last row in Table 1 shows the results for this new auction. As expected, this auction achieves a significantly small value of envy, however, at the cost of reduced utility, reduced revenue for

the FPO, and reduced value of NSW. The utility and revenue are higher than that of the NSW maximizing auction, which again tilts this auction in favour of the consumers more than the FPO. Overall, this auction has less desirable properties than the NSW maximizing auction.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we have designed a versatile mechanism for selling harvested produce of farmers to potential consumers through intermediation by farmer collectives using volume discount auctions. The designed auctions maximize Nash social welfare subject to IR, IC, fairness, and business constraints. Detailed experimentation on these auctions show the efficacy of the mechanisms designed. Our work provides clear evidence that the proposed mechanisms will be more attractive than existing traditional methods, in addition to many other benefits they bring in, such as ensuring farmer welfare, consumer delight, inducing honesty in bidding, utilizing scale economies, selecting deserving consumers, and the possibility to ensure fairness of allocation.

Acknowledgments

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