OSOUM Framework for Trading Data Research

Gregory Goren, Roee Shraga, Alexander Tuisov∗
{gregory.goren,shraga89,alexandt}@campus.technion.ac.il
Technion – Israel Institute of Technology
Haifa, Israel

ABSTRACT

In the last decades, data have become a cornerstone component in many business decisions, and copious resources are being poured into production and acquisition of the high-quality data. This emerging market possesses unique features, and thus came under the spotlight for the stakeholders and researchers alike. In this work, we aspire to provide the community with a set of tools for making business decisions, as well as analysis of markets behaving according to certain rules. We supply, to the best of our knowledge, the first open source simulation platform, termed Open SOUrc Market Simulator (OSOUM) to analyze trading markets and specifically data markets. We also describe and implement a specific data market model, consisting of two types of agents: sellers who own various datasets available for acquisition, and buyers searching for relevant and beneficial datasets for purchase. The current simulation treats data as an infinite supply product. Yet, other market settings may be easily implemented using OSOUM. Although commercial frameworks, intended for handling data markets, already exist, we provide a free and extensive end-to-end research tool for simulating possible behavior for both buyers and sellers participating in (data) markets.

1 INTRODUCTION

In the last decades, data have become a cornerstone component in many business decisions, and copious resources are being poured into production and acquisition of the high-quality data. This emerging market possesses unique features, and thus came under the spotlight for the stakeholders and researchers alike. Consider the following case:

Example 1. A new content provider is stepping into the entertainment industry, providing streaming media and video on demand. To understand its target customers, the provider chooses to use the power of data. Typical relevant data sources may include competing content providers and complementary industries that may hold valuable information regarding potential customers. In terms of a data market, the new provider has to decide which of the relevant datasets should it purchase, when, and at what cost. Buying all the relevant datasets is usually impossible as the initial budget usually is not sufficient, and even if so, postponing the purchase may result in a drop in buying prices. However, having a consistent benefit from the retained datasets may encourage the buyer to buy the datasets early, even if the supply is infinite, making timing an important ingredient.

In this work, we aspire to provide the community with a set of tools for making business decisions, as well as analysis of markets behaving according to certain rules. We supply, to the best of our knowledge, the first open source simulation platform, termed Open SOUrc Market Simulator (OSOUM) to analyze trading markets and specifically data markets. We also describe and implement a specific data market model, consisting of two types of agents: sellers who own various datasets available for acquisition, and buyers searching for relevant and beneficial datasets for purchase. The current simulation treats data as an infinite supply product. Yet, other market settings may be easily implemented using OSOUM.

Although commercial frameworks, intended for handling data markets, already exist (e.g., [1–5]), we provide a free and extensive end-to-end research tool for simulating possible behavior for both buyers and sellers participating in (data) markets. Our main contribution can be summarized as follows:

• We provide a publicly available novel market simulation, including a convenient method of adding custom behaviors for both the sellers and buyers, as well as a wide variety of possible contracts between the parties.

• We implement several baseline approaches to the following tasks:
  (1) Estimating market prices for data products,
  (2) Choosing subset of these products to be procured, based on price prediction and personal valuations
  (3) Maximizing profit by purchase timing w.r.t. market prices

We begin by describing OSOUM (Section 2) and discussing related work on data markets (Section 3). Then, we provide an OSOUM proof-of-concept handling data trading (Section 4).

2 THE OSOUM FRAMEWORK

We now describe our market simulation framework, OSOUM, which is publicly available at https://github.com/shraga89/RGA. Using OSOUM, researchers can flexibly implement different market scenarios in various settings, run simulations, analyze markets behaviour and more. OSOUM is composed of players, products, and simulator.

We distinguish between two main types of players: buyers and sellers. Generally, both share most functionalities, including price setting, strategy, budget, etc. In addition, each player stores a history of transactions to make flexible use of past interactions for future decisions. OSOUM allows players to employ different strategies with regard to any decision made, may it be market price prediction, choosing which goods to sell/purchase, price setting or something else. Strategies can be either picked from an existing pool or implemented using OSOUM.
The simulation supports both consumable and non-consumable products, as well as items with finite and infinite supplies, e.g., physical and digital goods respectively.

OSOUM also allows different market rules and various types of contracts between players. For example, a simple supply and demand market simulation (finite supply) without auctions is implemented as a simple interaction between seller and buyers (randomly assigned pairs at each timestamp). In this setting a transaction occurs if the buying price exceeds the selling price; accordingly, the budgets of the buyers and sellers are updated as well as the inventory. OSOUM also supports selling via various types of auctions and provides the tools for easy addition of other forms of contracts and financial instruments.

3 RELATED WORK

Before we dive into our proof-of-concept dealing with data markets, we now describe related work in the area. A variety of approaches and frameworks have addressed data markets. From a commercial perspective, an abundant of frameworks exists, e.g., Dawex [1], Onaudience [2], Qlik [3], Tase [5] and snowflake’s data exchange [4]). These frameworks act as mediators and enable transactions between competing sellers and buyers. Using our suggested data market simulation, buyers and sellers willing to use these frameworks will have the opportunity to test and analyze their strategies before committing to a real-world environment.

Originated in economics, where trading data has been ongoing for more than 30 years now [13], research into data markets has been a focus for other disciplines as well, such as data management [9, 10, 12]. In game theory, the focus is on the theory of creating algorithmic solutions specifically tailored for data-like products, and taking their unique traits (infinite replicability, combinatorial value etc.) into account [6, 7]. In this work we focus on a market setup simulation for be used for other researchers. In addition, while other works use the characteristics of data (size, features, use in ML framework, cleanness, etc.), we provide a proof-of-concept for an infinite supply market, not limited to data products.

4 SIMULATING A DATA MARKET USING OSOUM

In this section we give a concrete example of a market model that can be faithfully simulated and investigated using OSOUM.

4.1 A Data Market Model

A data market $M$ is a composition of three sets of entities, namely buyers $B$, sellers $S$, and a mediator. We shall refer to the first two entities also as the players $G = B \cup S$ in the market. Players may be individuals or groups (e.g., companies or organizations) interested in trading datasets. We use $D$ to denote the set of authorized datasets in $M$. Usually, a dataset $d \in D$ is associated with a domain and several of other properties that represent it including e.g., the features it contains. Each buyer $b \in B$ is interested in a set of datasets $D_b \subseteq D$ whereas each seller offers a set of products $D_s \subseteq D$. In addition, each player has a budget $L_b$, which is updated according to the transactions of a player. The mediator is in charge of the transactions between the different players in the market.

Each player $g \in G$ has a different utility from a dataset and a different perceived value, according to which it can set prices. A market is a temporal ecosystem. We assume that the market has a finite horizon $T$ and each interaction between the different entities takes place in a discrete timestamp $t < T$. Each timestamp $t$ includes a set of transactions supervised by the mediator.

Being a part of a data market, players must decide what is the value of a dataset, i.e., how profitable is a dataset for them. Establishing a value for a dataset (and information goods in general) is not easy [8, 13]. The core challenge in a competing market is that the value of data is different for sellers and buyers. Sellers may price a dataset reflecting e.g., the effort in gathering the data, while buyers may choose the price they are willing to pay according to their profit expectation. We separate the price of a product from its valuation which are denoted as $p_g(d)$ and $v_g(d)$, respectively.

A transaction is when a buyer $b$ acquires a dataset $d$ from a seller $s$. The buyer pays $p(d)$, $L_b$ and $L_s$ are updated, and the buyer is no longer interested in buying $d$. The seller is still willing to sell $d$, as the inventory of a dataset is assumed to be unlimited. At the end of each timestamp, buyers and sellers update their datasets pricing.

Example 2. Recall Example 1. Our content provider is denoted by $b_1$. Let its relevant datasets be $D_{b_1} = \{d_1, d_2\}$, and its initial budget by $L_{b_1} = 10$. $b_1$ price estimations are $p_{b_1}(d_1) = 8$ and $p_{b_1}(d_2) = 4$ and its valuations are $v_{b_1}(d_1) = 3$ and $v_{b_1}(d_2) = 2$. In this case, $b_1$ cannot aim to buy both $d_1$ and $d_2$, and has to choose just one of them. This decision may depend on the horizon and can be expressed as $2T - 4 > 3T - 8$. Then, for example, if $T < 4$ then buying $d_3$ is more beneficial, yielding e.g., a profit of $3$ compared to $2$ for $T = 3$. However, for $T > 4$ its more beneficial to buy $d_1$, yielding e.g., a profit of $7$ compared to $6$ for $T = 5$. If $T = 4$, both will yield $4$.

In practice, it is not always possible to purchase all the profitable products because of either funds available being insufficient, or because of pricing mismatch between a buyer and a seller. So a choice must be made at each time point what are the datasets to be bought immediately. We call this choice datasets allocation problem.

4.2 Datasets Allocation Optimization Strategy

The datasets allocation problem is defined with respect to a single player $g$ before timestamp $t$ in the market horizon $T$. Recall that a player $g$ is associated with $D = \{d_1, d_2, \ldots, d_n\}$ (set of relevant datasets) and $L$ (budget). In addition, a dataset $d_i$ has an overall valuation value $v_i = (T - t) \cdot v_g(i)$. At timestamp 0, the set of datasets $D$, its corresponding valuations $V$ and an initial $L$ are set. While the valuation values of datasets stays constant throughout the horizon, the $D$ and $L$ change with respect to the interaction in the market. The available datasets at time $t$, $D^t$, changes when a player purchases a dataset and thus, $D^t \subseteq D^{t'}$, $t' < t$ and $D^0 = D$. The budget $L^t$ changes with respect to the revenue of purchased products and costs.

At time $t$ the player has to select a subset of datasets $D^t \subseteq D^{t-1}$ that maximizes her future revenues. To simplify the notation, we denote that number of datasets available at time $t$ as $m \leq n$. Let $C = (c_1, c_2, \ldots, c_m)$, $c_i \in \mathbb{R}$ and $W = (w_1, w_2, \ldots, w_m)$, $w_m \in \{0, 1\}$.

\footnote{note that the values are acquired each timestamp, e.g., having $d_1$ for 5 timestamps yields a value of 15}
represent a realization of costs and win indicators of the relevant datasets after timestamp \( t \) has completed, respectively. In practice, a player has to allocate a subset of products at the beginning of time \( t \). Thus, the player does not know the actual cost of datasets when the dataset allocation takes place. Accordingly, the player has to estimate the costs \( \hat{C} = (\hat{c}_1, \hat{c}_2, \ldots, \hat{c}_m) \) and winning indicators \( \hat{W} = (\hat{w}_1, \hat{w}_2, \ldots, \hat{w}_m) \). Using these estimations, the datasets allocation problem can be formalized as follows:

\[
\begin{align*}
\text{maximize} & \quad \sum_{i=1}^{m} (v_i - \hat{c}_i) \cdot \hat{w}_i \cdot X_i \\
\text{subject to} & \quad \sum_{i=1}^{m} \hat{c}_i \cdot \hat{w}_i \cdot X_i \leq L \\
& \quad X_i \in \{0, 1\} \quad i = 1, \ldots, m.
\end{align*}
\]

Since \( \hat{w}_i \in \{0, 1\} \), the size of \( D^f \) can only decrease to the set of product she estimates she would win, i.e., \( \text{win}(D^f) = \{p_j \in D^{f-1} | \hat{w}_j = 1\} \). Denoting the size of \( \text{win}(D^f) \) as \( m_{\text{win}} \), we can modify the objective to be \( \sum_{i=1}^{m_{\text{win}}} (v_i - \hat{c}_i) \cdot X_i \) and the constraints to be \( \sum_{i=1}^{m_{\text{win}}} \hat{c}_i \cdot \hat{w}_i \cdot X_i \leq L \) and \( X_i \in \{0, 1\} \quad i = 1, \ldots, m_{\text{win}}, \) respectively.

Exploiting the resemblance to the Knapsack problem [11], one can show that our problem is NP-hard (via a reduction) and use an out-of-the-box solver, e.g., Gurobi,\(^2\) to (optimally) solve the problem.

### 4.3 Simulating the Data Market
We present an example of data market simulation based on the model defined in Section 4.1. The data market was implemented as a part of OSOU/M, and can effortlessly be extended to incorporate far more sophisticated techniques.

#### 4.3.1 Goods
In this context, the only type of product is a dataset. As such, it stores the domain of the dataset, its size (in terms of examples and features) as well as other information.

#### 4.3.2 Buyers
Recall that buyers have different valuations for each dataset in the market. Let \( \mathcal{B} \) be the buyers and \( \mathcal{S} \) be the sellers, respectively. Each player in the market behaves independently. For each dataset \( d \) available in the market, each \( b \) (such that \( d \in D_b^f \)) is randomly assigned to a seller \( s \) (such that \( d \in D_s \)). Then, we split into two cases:

- If \( p_b(d) \geq p_s(d) \): the buyer obtains the dataset \( (D_b^f = D_b^f \setminus d) \) and pays its selling price \( (L_b = L_b \setminus p_b(d)) \).
- If \( p_b(d) < p_s(d) \): the buyer does not obtain the dataset and get allocated to a different seller.

Note that in both cases the dataset remains available for sale. The process continues until no buyer is interested in acquiring this dataset. During a timestamp the set prices remain constant. Once it terminates, each player has the opportunity to change its prices. For example, if a seller did not sell any instance of a dataset it may lower the price.

#### 4.3.3 Sellers
In our setting, we focus on competing buyers as they aim to maximize their utility. A buyer’s strategy, however, may be strongly affected by sellers behavior; thus we cannot completely ignore this issue. To demonstrate the verity of sellers in such setting, we created a set of reasonable ad-hoc rules that dictate sellers’ behavior, without any guarantee of optimality. The implemented sellers are as follows:

- **Adaptive seller**: increases price if she sold the product successfully; and lowers the price otherwise.
- **Linear seller**: price is a linear function of time.
- Noisy variants of the sellers above, using Gaussian noise.

#### 4.3.4 Methodology
We created a proof-of-concept experiment based on an auction-free market. Let \( \mathcal{B} \) and \( \mathcal{S} \) be the buyers and sellers, respectively. Each player in the market behaves independently. For each dataset \( d \) available in the market, each \( b \) (such that \( d \in D_b^f \)) is randomly assigned to a seller \( s \) (such that \( d \in D_s \)). Then, we split into two cases:

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#### 4.3.5 Example Results
Figure 1 presents a possible plot based on a simulation outcome, referring to five types of buyers (see Section 4.3.2). The y-axis represents the funds (or budget) available to each buyer at timestamp \( t \). We do not provide a prior price estimation at \( t = 0 \) and thus, the initial values of cost estimations are drawn randomly. In what follows, we average the values over 10 different simulation runs to minimize the randomization effect. We observe inferiority in the estimation performance of regression based buyer. This may be explained due to the non-linear behavior of some of the sellers as well as the fact that a considerable amount of data is needed for a reasonable regression model. Last price

\[\text{https://www.gurobi.com/}\]
buyer is able to obtain a judicious cost estimations right from the start and the costs do not change vastly between timestamps in our configuration.

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