Consumer Data Marketplaces

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1 Introduction and Related Work

As machine learning models increasingly contribute to the bottom line of modern enterprise, scandals involving the misuse of personal and sensitive data have also grown more common. Indeed, the means by which corporations acquire data often lack transparency, and it is clear that in many cases, users are not compensated despite the potentially large economic benefit derived from the data that they provide.

To make it easier for corporations to acquire data necessary for the operation of key services in a way that allows data owners to be fairly compensated, we propose a two-sided *consumer* data marketplace. In our model, a large collection of users each possess an i.i.d sample of the same signal. One example would be the user's location data. Each user then sets a price to exchange their data with a potential seller. This price corresponds to the privacy cost they incur by revealing their data. We are then interested in market mechanisms that satisfy five properties: individual rationality, incentive compatibility, surplus efficiency, privacy, and representativeness. A mechanism satisfies the privacy constraint if it does not access user data while computing an allocation. The representativeness constraint is satisfied if the market is further able to guarantee that the sample it returns is representative of the whole population. Such a guarantee may be hard to make naively if the prices that the sellers post are correlated with the data samples themselves.

There is some literature on data marketplaces [8, 3, 6, 7, 1, 2], and there have been some Blockchain-based implementations of these marketplaces [4, 9, 5]. None of these marketplaces allow sellers to set their own price. Instead, sellers must choose to fully opt in or out, and are given Shapley fairness guarantees. Only in [8] is there a competitive equilitbrium set by all market participants, as in their setting, all participants are concurrently buyers and sellers. On the flip side, multiple of these marketplaces aim to maximize revenue, and thus do not aim to maximize surplus or welfare. Furthermore, these marketplaces do not satisfy the privacy property. Indeed, [1] and [8] consider mechanisms that involve "data rationing", or the controlled perturbation of data in order to guarantee certain economic outcomes. If user data is stored in a decentralized manner, the form of the data is difficult to work with, or if the reaction of a buyer to such a perturbation is difficult to know apriori, then such methods can be inefficient or impractical. We seek to address these concerns in our paper.

In Section 2, we formally define our model, including the five aforementioned properties. In Section 3, we show that a unique deterministic mechanism exists that satisfies all five properties. This mechanism is an extension of the well-known VCG mechanism. In Section 4, we show that the deterministic mechanism has a fundamental limit in its ability to satisfy representativeness constraints. Indeed, we show that as the number of sellers becomes large, it becomes impossible to satisfy any reasonable request for representativeness deterministically. We then provide a random mechanism, and prove that it is able to satisfy *any* representativeness constraint, while also meeting a baseline surplus guarantee. Section 5 concludes.

2 Model

We consider a model where there are n sellers, each possessing an i.i.d sample X_i of a random element $X : \Omega \to \mathcal{D}$ with law μ, and a single buyer[1] that aims to collect s samples of X. In our setting, we imagine $n \gg s$. Each seller $i \in [n]$ values their sample at $c_i \in \mathbb{R}_{>0}$, and posts a price $p_i \in \mathbb{R}_{>0}$ to the market. The cost c_i denotes the privacy cost that seller i incurs by giving their data to the buyer. The buyer obtains value V from obtaining any sample of size s, and posts a bid B to the market. The market then selects a subset of samples $S \subset [n]$ where $|S| = s$, in addition to a collection of payments $\{t_i\}_{i\in S}$. The buyer then pays $\sum_{i\in S} t_i$ and obtains the collection of samples $\{X_i\}_{i\in S}$. Seller i receives t_i in payment, and incurs a cost of c_i for releasing their data to the buyer. Formally, the buyer and sellers have quasi-linear utilities, given by

$$U(V, B) = V - \sum_{i\in S} t_i \qquad\qquad u_i(c_i, p_i) = \mathbb{1}_{i\in S}\,(t_i - c_i)$$

We are then interested in designing a market mechanism that satisfies

- Individual Rationality: $U(V, B), u_i(c_i, p_i) \geq 0$ for all choices of V, B, c_i, p_i
- Incentive Compatibility:

$$U(V, V) = \sup_{B\in\mathbb{R}} U(V, B) \qquad\qquad u_i(c_i, p_i) = \sup_{p_i\in\mathbb{R}} u_i(c_i, p_i)$$

- Surplus-Maximizing:

$$S, (t_i)_{i\in S} = \text{argmax}_{S,(t_i)_{i\in S}}\, U(V, B) + \sum_{i=1}^{n} u_i(c_i, p_i)$$

- Private: The values of $S, (t_i)_{i\in S}$ do not depend on the samples X_i themselves.

[1] As data is freely replicable, one buyer's demands do not impose any constraints on the ability of the sellers to satisfy another buyer's demands. Thus, each buyer can be considered separately.

Privacy is an especially important feature to respect. In addition to the security risk the comes with working with user data directly, if seller data is stored in a decentralized way, querying user data can be very expensive. Furthermore, the set $\mathcal{D}$ in which the user data lies may not be well-structured. Finally, if the market queries seller i's data to select a sample S, but does not actually include X_i in the sample S, seller i may arguably incur a privacy cost without receiving compensation.

2.1 The Naive VCG Approach

As stated, noting that the above model is a depiction of a reverse auction, it is quite straightforward to see that the VCG mechanism satisfies all of these properties. That is, by expanding

$$\begin{aligned}
\text{argmax}_{S,(t_i)_{i\in S}} U(V,B) + \sum_{i=1}^{n} u_i(c_i,p_i) &= \text{argmax}_{S,(t_i)_{i\in S}} V - \sum_{i\in S} t_i + \sum_{i=1}^{n} \mathbb{1}_{i\in S}\,(t_i - c_i) \\
&= \text{argmax}_{S,(t_i)_{i\in S}} V - \sum_{i\in S} t_i + \sum_{i\in S} t_i - \sum_{i\in S} c_i \\
&= \text{argmin}_{S,(t_i)_{i\in S}} \sum_{i\in S} c_i
\end{aligned}$$

we find that to maximize surplus, it suffices to minimize the aggregate cost over the sellers selected in the sample. Defining $S' := \text{argmin}_{S\subset[n]} \sum_{i\in S} p_i$, and

$$t_i' := \min_{S\subset[n]\setminus\{i\}} \sum_{i\in S} p_i - \min_{S\subset[n]} \sum_{i\in S} p_i$$

Finally, the market then allocates

$$S,(t_i)_{i\in S} := \begin{cases} S',(t_i')_{i\in S} & \text{if } \sum_{i\in S} t_i' \leq B \\ \emptyset, 0 & \text{else} \end{cases}$$

As the sample S and payments t_i are determined only by the prices p_i and the bid B, the VCG mechanism satisfies privacy in addition to the other three properties.

2.2 Enforcing Representativeness

Unfortunately, although the VCG mechanism as described above satisfies all four properties, it is unable to make any guarantee on how *representative* the sample S that the buyer obtains is relative to the true law of μ, since the posted prices p_i may be correlated with the underlying sample X_i. As an extreme example, suppose that X_i was exactly equal to p_i. The VCG mechanism then returns the sample $\{X_i\}_{i\in S} = \left\{X_{(i)}\right\}_{i\in[s]}$, where $X_{(i)}$ denotes the ith order statistic. This sample can look extremely different from the true distribution, especially when $n \gg s$ as in our setting. We modify our model to take this into account.

We now assume that the sellr's prices $p_i : \Omega \to \mathbb{R}_{>0}$ are drawn i.i.d from some unknown distribution with cumulative density function F that is absolutely continuous with respect to the Lebesgue measure. We let ν be a measure over $\mathcal{D} \times \mathbb{R}$ that gives the joint distribution of the price and data sample. In addition to specifying their bid and the number of samples s, we further ask the buyer to set an information-theoretic threshold τ, which denotes a tolerance on the amount of information (in nats) that they are willing to forego. In order to satisfy the representativeness property, the market must also ensure that

$$D_{KL}\left(\mu \mid\mid \frac{1}{s}\sum_{i\in S}\mu_i\right) = \int_{\mathcal{D}} \log\left(\frac{d\mu}{d\left(\frac{1}{s}\sum_{i\in S}\mu_i\right)}\right) d\mu \leq \tau$$

That is, the market must guarantee that by approximating the sampling process for μ with the sampling process given by procuring s samples, and selecting one uniformly at random, the buyer loses at most τ nats of information.

Notice that in order to make this guarantee in addition to the privacy guarantee, we must be able to make claims on the representativeness of a sample *without being able to see the sample itself*. In the next two sections, we show how it is indeed possible to make such guarantees within a certain capacity.

3 Deterministic Mechanisms

In this section, we describe the unique surplus-maximizing mechanism that satisfies individual rationality, incentive compatibility, privacy, representativeness, and is also deterministic in the order of the prices. That is, for each ordering σ of the sellers by price, the mechanism will query data from the same sample of seller indices $S \subset [n]$. To construct this mechanism, we make a modification of the VCG algorithm described in Section 2.1 to constrain the mechanism to only those collections of samples S such that the Kullback-Leibler divergence is below the given threshold τ. The existence of this mechanism follows from the observation that the KL-divergence of any sample S can be tightly upper-bounded *even without access to the data itself*. To see this, we first apply the disintegration theorem to find a family of probability measures $\{\mu^r\}_{r\in\mathbb{R}}$ such that for any measurable event $E \subset \mathcal{D} \times \mathbb{R}$,

$$\nu(E) = \int_{\mathbb{R}} \int_{\mathcal{D}} f(r)\mu^r\left(E \cap (\{r\} \times \mathcal{D})\right) dr$$

Here, $f := F'$ denotes the probability density function of the seller price distribution. Next, let γ be a measure over $\mathcal{D}$ such that $\mu^r \ll \gamma$ for all $r \in \mathbb{R}$. Observe then that we have that $\nu \ll \gamma \otimes \lambda$, where $\gamma \otimes \lambda$ denotes the product measure of γ and the Lebesgue measure over the space $\mathcal{D} \times \mathbb{R}$. We may subsequently write, for any $(x, r) \in \mathcal{D} \times \mathbb{R}$,

$$\frac{d\nu}{d\left(\gamma \otimes \lambda\right)}(x, r) = \frac{d\mu^r}{d\gamma}(x) f(r)$$

Now, consider the joint law $\nu_{(i)}$ of the data and price of the seller with the ith smallest price. By the usual combinatorial identity, we can compute

$$\begin{aligned}\frac{d\nu_{(i)}}{d(\gamma\otimes\lambda)}(x,r) &= \frac{n!}{(i-1)!(n-i)!}F(r)^{i-1}(1-F(r))^{n-i}\,\frac{d\nu}{d(\gamma\otimes\lambda)}(x,r)\\ &= \frac{n!}{(i-1)!(n-i)!}F(r)^{i-1}(1-F(r))^{n-i}\,\frac{d\mu^r}{d\gamma}(x)f(r)\end{aligned}$$

As the mechanism is deterministic in the ordering of the prices, the set of orderings

$$O(S) := \{|\{j\in[n]\mid p_j\le p_i\}|\}_{i\in S}$$

is fixed, no matter the values of the prices posted by the sellers. Thus, we may write

$$\begin{aligned}D_{KL}\left(\mu\;||\;\frac{1}{s}\sum_{i\in S}\mu_i\right) &\le D_{KL}\left(\nu\;||\;\frac{1}{s}\sum_{i\in O(S)}\nu_{(i)}\right)\\ &= \int_{\mathcal{D}\times\mathbb{R}}\log\left(\frac{d\nu}{d\left(\frac{1}{s}\sum_{i\in O(S)}\nu_{(i)}\right)}\right)d\nu\\ &= -\int_{\mathcal{D}\times\mathbb{R}}\log\left(\frac{d\left(\frac{1}{s}\sum_{i\in O(S)}\nu_{(i)}\right)}{d\nu}\right)d\nu\\ &= -\int_{\mathcal{D}\times\mathbb{R}}\log\left(\frac{1}{s}\sum_{i\in O(S)}\frac{d\nu_{(i)}}{d\nu}\right)d\nu\\ &= -\int_{\mathcal{D}\times\mathbb{R}}\log\left(\frac{1}{s}\sum_{i\in O(S)}\frac{\frac{d\nu_{(i)}}{d\lambda\otimes\gamma}}{\frac{d\nu}{d\lambda\otimes\gamma}}\right)d\nu\\ &= -\int_{\mathcal{D}\times\mathbb{R}}\log\left(\frac{1}{s}\sum_{i\in O(S)}\frac{n!}{(i-1)!(n-i)!}F(r)^{i-1}(1-F(r))^{n-i}\right)d\nu\\ &= -\int_{\mathbb{R}}\int_{\mathcal{D}}\log\left(\frac{1}{s}\sum_{i\in O(S)}\frac{n!}{(i-1)!(n-i)!}F(r)^{i-1}(1-F(r))^{n-i}\right)f(r)\frac{d\mu^r}{d\gamma}(x)dr\gamma(dx)\\ &= -\int_{\mathbb{R}}\log\left(\frac{1}{s}\sum_{i\in O(S)}\frac{n!}{(i-1)!(n-i)!}F(r)^{i-1}(1-F(r))^{n-i}\right)f(r)dr\\ &= -\int_0^1\log\left(\frac{1}{s}\sum_{i\in O(S)}\frac{n!}{(i-1)!(n-i)!}u^{i-1}(1-u)^{n-i}\right)du\end{aligned}$$

where in the final step, we use the substitution $u = F(r)$. Observe that this final integral can be computed without knowledge of the distributions ν, μ, or the CDF F. Thus, we may consider a mechanism that first builds the set

$$\mathcal{A} := \left\{ S \subset [n] \mid |S| = s, \ -\int_0^1 \log\left(\frac{1}{s}\sum_{i\in O(S)} \frac{n!}{(i-1)!(n-i)!} u^{i-1}(1-u)^{n-i}\right) du \leq \tau \right\}$$

and subsequently runs the Naive VCG approach described in Section 2.1, but instead computes $\operatorname{argmin}_{S|O(S)\in\mathcal{A}} \sum_{i\in S} p_i$, and makes a similar modification to the Clark pivot rule. The uniqueness of this mechanism follows in part from the uniqueness of the VCG mechanism as a surplus-maximizing mechanism satisfying individual rationality and incentive compatibility. The mechanism described above does not always maximize surplus. However, it does maximize surplus when the inequality $D_{KL}\left(\mu \mid\mid \frac{1}{s}\sum_{i\in S}\mu_i\right) \leq D_{KL}\left(\nu \mid\mid \frac{1}{s}\sum_{i\in O(S)}\nu_{(i)}\right)$ is tight, which occurs e.g. when the data sample is equal to the seller price. As the mechanism must satisfy privacy, it can do no better than constraining to the class $\mathcal{A}$ of orderings.

4 Random Mechanisms

Unfortunately, even the optimal deterministic mechanism as described above fails to provide great guarantees. Notice, for instance, that the minimum KL-divergence of any order statistic is at least the KL divergence of the $\frac{n}{2}$th order statistic. This is given by

$$\begin{aligned} D_{KL}\left(\nu \mid\mid \nu_{\left(\frac{n}{2}\right)}\right) &= -\int_0^1 \log\left(\frac{n!}{(n/2-1)!(n/2)!}u^{n/2-1}(1-u)^{n/2}\right) du \\ &= -(n/2-1)\int_0^1 \log(u)du - (n/2)\int_0^1 \log(1-u)du - \log\left(\frac{n!}{(n/2-1)!(n/2)!}\right) \\ &= n-1-\log\binom{n}{n/2} + \log(n/2) \to \infty \end{aligned}$$

Thus, in the regime $n \gg s$, the deterministic mechanism will be unable to make any guarantees for most reasonable values of τ. In this section, we construct a random mechanism capable of satisfying *any* request for τ, and also satisfies individual rationality, incentive compatibility, and privacy.

The mechanism is described as follows. First, we compile a sorted list of all subsets $S \subset [n]$ of size s by the aggregate price $\sum_{i\in S} p_i$. Next, we select a subset S of s samples uniformly at random. Then, we locate S on our sorted list, shift it back k places, and set S' to be the result. If at any step, S is already the cheapest sample, then we do not continue shifting. For each $i \in S$, we set $t'_i = p_j$ where j is the index of the seller whose price p_j is the next largest after p_i. Finally, we return the sample if the aggregate price is at most B, and do not make any allocation otherwise.

It is easy to see that this mechanism satisfies individual rationality, incentive compatibility, and privacy. We now show that it satisfies representativeness when $k = O\left(\frac{\tau}{sn}\right)$. Observe that each sample-price pair within the random returned collection of samples S'

has a mixture distribution

$$\nu_{S'} = \frac{k+1}{\binom{n}{s}} \sum_{i=1}^{s} \frac{1}{s}\nu_{(i)} + \left(1 - \frac{k+1}{\binom{n}{s}}\right) \sum_{S\subset[n] \mid S \notin \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s} - k - 1} \sum_{i \in S} \frac{1}{s}\nu_{(i)}$$

Here, $S_{(i)}$ denotes the ith cheapest subset. The first sum term arises if the subset we chose uniformly at random happened to be among the $k+1$ cheapest subsets. In this case, after shifting k places, we arrive at the cheapest subset. If this case does not occur, then our subset is chosen uniformly at random from the second cheapest to the $n-k$th cheapest subset. As the KL-divergence is convex, we may bound it by

$$\begin{aligned}
D_{KL}\left(\nu \mid\mid \nu_{S'}\right) &\leq \frac{k+1}{\binom{n}{s}} \sum_{i=1}^{s} \frac{1}{s} D_{KL}\left(\nu \mid\mid \nu_{(i)}\right) \\
&\qquad + \left(1 - \frac{k+1}{\binom{n}{s}}\right) D_{KL}\left(\nu \mid\mid \sum_{S\subset[n] \mid S \notin \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s} - k - 1} \sum_{i \in S} \frac{1}{s}\nu_{(i)}\right) \\
&\leq \frac{k+1}{\binom{n}{s}} D_{KL}\left(\nu \mid\mid \nu_{(1)}\right) \\
&\qquad + \left(1 - \frac{k+1}{\binom{n}{s}}\right) D_{KL}\left(\nu \mid\mid \sum_{S\subset[n] \mid S \notin \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s} - k - 1} \sum_{i \in S} \frac{1}{s}\nu_{(i)}\right) \\
&\leq \frac{(k+1)n}{\binom{n}{s}} \\
&\qquad - \left(1 - \frac{k+1}{\binom{n}{s}}\right) \int_{D\times\mathbb{R}} \log\left(\sum_{S\subset[n] \mid S \notin \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s} - k - 1} \sum_{i \in S} \frac{1}{s} \frac{d\nu_{(i)}}{d\nu}\right) d\nu \\
&\leq \frac{(k+1)n}{\binom{n}{s}} - \left(1 - \frac{k+1}{\binom{n}{s}}\right) \log\left(\frac{\binom{n}{s}}{\binom{n}{s} - k - 1}\right) \\
&\qquad - \left(1 - \frac{k+1}{\binom{n}{s}}\right) \int_{D\times\mathbb{R}} \log\left(\sum_{S\subset[n] \mid S \notin \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s}} \sum_{i \in S} \frac{1}{s} \frac{d\nu_{(i)}}{d\nu}\right) d\nu \\
&\leq \frac{(k+1)n}{\binom{n}{s}} - \left(1 - \frac{k+1}{\binom{n}{s}}\right) \log\left(\frac{\binom{n}{s}}{\binom{n}{s} - k - 1}\right) \\
&\qquad + \left(1 - \frac{k+1}{\binom{n}{s}}\right) \int_{D\times\mathbb{R}} \frac{1 - \sum_{S\subset[n] \mid S \notin \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s}} \sum_{i \in S} \frac{1}{s} \frac{d\nu_{(i)}}{d\nu}}{\sum_{S\subset[n] \mid S \notin \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s}} \sum_{i \in S} \frac{1}{s} \frac{d\nu_{(i)}}{d\nu}} d\nu \\
&= \frac{(k+1)n}{\binom{n}{s}} - \left(1 - \frac{k+1}{\binom{n}{s}}\right) \log\left(\frac{\binom{n}{s}}{\binom{n}{s} - k - 1}\right) \\
&\qquad + \left(1 - \frac{k+1}{\binom{n}{s}}\right) \left(\int_{D\times\mathbb{R}} \frac{1}{1 - \sum_{S \in \left\{S_{(1)}, S_{(n)}, \ldots, S_{(n-k+1)}\right\}} \frac{1}{\binom{n}{s}} \sum_{i \in S} \frac{1}{s} \frac{d\nu_{(i)}}{d\nu}} d\nu - 1\right)
\end{aligned}$$

$$\leq \frac{(k+1)n}{\binom{n}{s}} + \left(1 - \frac{k+1}{\binom{n}{s}}\right)\left(\frac{1}{1-\frac{n(k+1)}{\binom{n}{s}}} - 1 - \log\left(\frac{\binom{n}{s}}{\binom{n}{s}-k-1}\right)\right)$$
$$\leq \frac{(k+1)n}{\binom{n}{s}} + \left(1 - \frac{k+1}{\binom{n}{s}}\right)\left(\frac{1}{1-\frac{n(k+1)}{\binom{n}{s}}} - 1 - \frac{(k+1)}{\binom{n}{s}}\right)$$

whence it follows that if we choose $k = \Theta\left(\frac{\tau}{n}\right)\binom{n}{s}$, the mechanism satisfies representativeness. On average, the buyer will have to pay for a subset priced at the $\frac{1}{2}\left(1-\Theta\left(\frac{\tau}{n}\right)\right)^2$ quantile. While it is unclear how close this mechanism is to optimal, the mechanism *is* able to find an allocation for any τ.

5 Conclusions

We designed two mechanisms that seek to satisfy five desirable properties: individual rationality, incentive compatibility, surplus efficiency, privacy, and representativeness. Crucially, the challenge in designing such mechanism lies in trying to meet both the representativeness, privacy, and surplus efficiency constraints concurrently. We first showed that there exists a unique (up to a pivot rule) deterministic mechanism, and further showed that this mechanism is unable to clear most representativeness constraints. We then showed how randomness can be utilized to clear any representativeness constraint, while still guaranteeing that on average, buyers pay at most at the $\frac{1}{2}\left(1-\Theta\left(\frac{\tau}{n}\right)\right)^2$ quantile. A key future research direction is to understand what the optimal tradeoff between representativeness and surplus is, when constrained to a private mechanism. One may also consider mechanisms that aren't private, but aim to minimize the number of queries for additional data.

References

[1] A. Agarwal, M. Dahleh, and T. Sarkar. A marketplace for data: An algorithmic solution. In *Proceedings of the 2019 ACM Conference on Economics and Computation*, pages 701–726, 2019.

[2] D. Bergemann and A. Bonatti. Markets for information: An introduction. *Annual Review of Economics*, 11:85–107, 2019.

[3] L. Chen, P. Koutris, and A. Kumar. Towards model-based pricing for machine learning in a data marketplace. In *Proceedings of the 2019 International Conference on Management of Data*, pages 1535–1552, 2019.

[4] N. Hynes, D. Dao, D. Yan, R. Cheng, and D. Song. A demonstration of sterling: a privacy-preserving data marketplace. *Proceedings of the VLDB Endowment*, 11(12):2086–2089, 2018.

[5] V. Koutsos, D. Papadopoulos, D. Chatzopoulos, S. Tarkoma, and P. Hui. Agora: A privacy-aware data marketplace. In *2020 IEEE 40th International Conference on Distributed Computing Systems (ICDCS)*, pages 1211–1212. IEEE, 2020.

[6] C. Li and G. Miklau. Pricing aggregate queries in a data marketplace. In *WebDB*, pages 19–24, 2012.

[7] J. Liu. Dealer: End-to-end data marketplace with model-based pricing, 2020.

[8] M. Rasouli and M. I. Jordan. Data sharing markets, 2021.

[9] M. Travizano, C. Sarraute, G. Ajzenman, and M. Minnoni. Wibson: A decentralized data marketplace. *arXiv preprint arXiv:1812.09966*, 2018.