How to Balance Privacy and Money through Pricing Mechanism in Personal Data Market

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ABSTRACT
In the big data era, most countries have shifted their interest and investment to the new priceless asset known as personal data. With this trend, personal data is, recently, perceived as a new oil or currency in the digital world. Both public and private sectors want to utilize it for their studies and businesses. However, there is a restricted access to those personal data mainly because of the privacy issues. If the privacy issues are compromised, it is obvious that the benefits of making personal data available for various usages outweigh the drawbacks. Therefore, the notion of personal data market is introduced to serve as a sound platform for data trading. A personal data market is a platform including three participants: data owners (individuals), data buyers and market maker. Data owners who provide personal data are compensated according to their privacy loss. Data buyers can submit a query and pay for the result according to their desired accuracy. Market maker coordinates between data owner and buyer. This framework has been previously studied based on differential privacy. However, the previous study assumes data owners can accept any level of privacy loss and data buyers can conduct the transaction without regard to the financial budget.

In this paper, we propose a practical personal data trading framework that is able to strike a balance between money and privacy. In order to gain insights on user preferences, we first conducted an online survey on human attitude toward privacy and interest in personal data trading. Second, we identify the 5 key principles of personal data market, which is important for designing a reasonable trading framework and pricing mechanism. Third, we propose a reasonable trading framework for personal data which provides an overview of how the data is traded. Fourth, we propose a balanced pricing mechanism which computes the query price for data buyers and compensation for data owners (whose data are utilized) as a function of their privacy loss. The main goal is to ensure a fair trading for both parties. Finally, we will conduct an experiment to evaluate the output of our proposed pricing mechanism in comparison with other previously proposed mechanism.

1. INTRODUCTION

Personal data is, recently, perceived as a new oil or currency in the digital world. Massive amount of personal data have been constantly produced and collected in every second (i.e., via smart devices, search engines, sensors, social network services,...). Those personal data are extraordinarily valuable for public and private sector to improve their products or services. However, personal data reflects the unique value and identity of each individual; therefore, the access to an abundance of personal data is very restricted. For this reason, some big Internet companies and social network services have provided free services in exchange for their users' personal data. A study by [3] revealed that a unique user's data is worth $4 to Facebook and $24 to Google. Obviously, although many big Internet companies have collected a massive amount of personal data, they are not willing to sell or share it not only because of privacy issue but also because personal data are their core competence in the current business model. On the other hand, the demand of personal data for research and business purposes excessively increases while there is practically no safe and efficient supply of personal data. Consequently, it becomes a major cause of illegal trading of personal data as well as frequent data breaching cases. As a result, users lost their privacy without any fair compensations. To solve this issue, the notion of personal data market is introduced. This notion has transformed a perception on personal data as an undisclosed type to a commodity, as mentioned in [5] and [11]. To perceive personal data as a commodity, many lines of research such as [2], [10], [13], and [14] asserted that there should be a monetary compensation to real data producers/owners for their privacy loss whenever their data is accessed. However, personal data is a type of information good which is very difficult to assign a price tag to it, so it is quite challenging to define how much money the data seekers have to pay and how much money data owners should receive as a compensation for their privacy loss in a fair trade.

1.1 Personal Data Market

Personal data market is a sound platform where personal data trading happens. What is traded is a noisy version of statistical data. It is basically an aggregated query answer, derived from users' personal data, with some random noise injection to guarantee the privacy protection for data
owners. The process of injecting random noise is coined as perturbation. The magnitude of perturbation directly impacts the query price and amount of data owners’ privacy loss. A higher query price yields a lower perturbation (less noise injection).

As described in Figure 1, there are three main participants: data owners, data buyers, and market maker. Data owners contribute their personal data and receive appropriate monetary benefits. Data buyers pay an amount of money to obtain their desirable noisy aggregated data. Market maker is a trusted mediator between the two key players, and he will compute a query answer, calculate query price for buyers and compensation for owners, and most importantly design a variety of payment schemes for owners to choose.

![Figure 1: How much is personal data worth?](image)

The existence of personal data market will make abundance of personal data available for various usages, giving birth to many sophisticated developments and innovations. For this reason, several startup companies have been developing online personal data trading sites as well as mobile applications following this market notion. These sites are www.personal.com, and www.datacoup.com, which aim at creating personal data vaults. They buy the actual personal data from each data owner and compensate them accordingly. The main problem is that some data owners are not convinced to sell their raw data (without perturbation). In www.datacoup.com, their payment is fixed, approximately $8 for SNS data and financial data like credit/debit card transactions. It is questionable whether $8 is a reasonable compensation, and how this price is computed. Another inefficiency is the absence of data buyers. There could be a problem if buyers are not interested in those collected data. In addition, CitizenMe and digi.me recently launched their personal data collection mobile applications. They assist data owners to collect and store all their personal data in their devices. Although the framework connects the buyers and data owners, it might be inefficient and impractical for buyers to buy individual raw data one at a time. Moreover, there is no pricing mechanism provided; as a result, the data owner and buyer need to negotiate the price on their own, which might not be efficient because not all data owners know or truthfully report the price of their data.

To make this market operational, there are many challenges from all disciplines, but we narrow the fundamental technical challenges to two factors:

- **Trading framework for personal data**: How should personal data be fairly traded? In other words, how to design a reasonable trading framework?
- **Balanced Pricing mechanism**: How much should personal data be worth? How to compute a price that balances data owners’ privacy loss and buyers’ payment? This balance is crucial to convince both data owners and data buyers to participate in the personal data market.

### 1.2 Contribution

In order to address the above challenges, we first conducted a survey on human attitude toward privacy and interest in personal data trading. Detailed of survey analysis can be found in Section 2. Second, from the survey analysis, we propose a reasonable trading framework for personal data, which provides an overview of how data is traded and what the three key participants do. Third, we propose a balanced pricing mechanism which computes the price of a noisy aggregated query answer and calculates the compensation for each data owner (whose data are utilized) as a function of his or her actual privacy loss. The main goal is to ensure a fair trading, which means data buyers have to exactly pay for what they want without circumventing the query price and data owner could not benefit from intentionally reporting an unreasonably high privacy requirement with a large amount of payment, known as untruthfulness. Our mechanism will ensure unbiased result with as minimal noise/error as possible while guaranteeing each data owner’s required privacy level. Most importantly, our mechanism is designed to balance the benefits and expenses of both data owners and buyers. Remarkably, this issue has not been addressed in previous researches. For instance, a theoretical pricing mechanism [10] is designed in favor of only data owner. 10 empowered buyer to determine the privacy loss of data owners while assuming data owners can accept an infinite privacy loss.

## 2. SURVEY RESULT

To gain a deeper insight about personal data trading and to collect data for our experiment, we conducted idea crowdsourcing via an online survey. There are 486 participants who are from 46 different states throughout USA. The participants’ age ranges from 14 to above 54 years old. Our data is quite diversified, which consists of participants from different levels of education, occupation, and income. In our survey, they are required to answer 11 questions (see Appendix A.1). We will discuss the analysis results from some significant questions.

Given 4 types of their personal data:

- **Type 1**: Commute type to school/work
- **Type 2**: Yearly income
- **Type 3**: Yearly expense on medical care
- **Type 4**: Bank service you’re using

More than 50% of participants said they cannot sell the data (see Figure 2a), and more than 50% of those who can sell said they do not know how much to sell (see Figure 2b).

**Analysis 1:** Most participants do not know how much their data is worth, which is one of the previously mentioned challenges of personal data market. Similarly, 1 addressed that it is very difficult for data owners to articulate the valuation of their data.

If asked to sell their anonymized personal data, 49% of participants said it depends on type of personal data and amount of money, 35% Not interested, and 16% Interested (see Figure 3). However, if providing more privacy protection by both anonymizing and altering (perturbing) the real data, more than 50% of respondents became interested in
solving. It means that more people are now convinced to sell their data (see Figure 3b).

Analysis 2: Anonymization is not sufficient to convince people to sell their personal data. Providing extra protection via data alteration or perturbation on the anonymized data make them feel safer to sell their data.

In order to know the preferred privacy level of each participants, we asked them to select the how much they want to alter/perturb their real data. Very low alteration (low noise injection) means low privacy protection, but more likely to get many buyers. As a result (see Figure 4a), the alteration level varied throughout the 4 types of data. Similarly, the preferred payment schemes (see Figure 4b) varied throughout all the data types.

Analysis 3: Privacy protection level and desired payment schemes varied based on data types and people. Thus, in reality, people have different privacy and money attitude. Thus, it is crucial to allow a personalized privacy level and payment scheme.

Figure 4: Preferences in privacy and money
Among the 4 given criteria to decide when selling personal data,

- **Usage:** Who and how buyers will use your data
- **Sensitivity:** Sensitivity of data (salary, disease,...)
- **Risks:** Future risks/impacts
- **Money:** To get as much money as possible

Participants exhibited more importance toward who and how the data will be used, followed by sensitivity, future risks/impacts, and lastly money (see Figure 5).

Analysis 4: Money is the least important criterion while who and how data will be used is the most important criterion when deciding to sell personal data. Thus, in reality, money cannot buy everything if the seller does not want to sell.

Figure 5: Importance of criteria when selling personal data

3. TRADING FRAMEWORK
Prior to a detailed explanation about the framework, we summarize the notations used within research as shown in table 1.

3.1 Key Principles of Personal Data Market
In order to design a reasonable trading framework and a balanced pricing mechanism, it is important to know the chief principles of personal data market. These key principles are derived from previous researches as well as the analysis of our survey. These principles are categorized into 5 different groups: query price, differential privacy as a privacy protection, arbitrage-free pricing model, truthful privacy valuation, and unbiased result. Regarding query type, only linear aggregated queries are allowed in our framework because of the implementation of differential privacy theory, so data owner’s privacy should be guaranteed. To protect data owner’s privacy, differential privacy plays a major role in privacy preservation and as a metric to quantify privacy loss. The pricing model should be arbitrage-free and must not allow any circumvention from the buyers on the query price and obtained result. Similarly, framework should not be designed to deal with untruthful privacy valuation from data owners by ensuring that untruthful valuation will not provide them more benefits. Lastly, the query result should be unbiased because without a careful selection or with a purposed selection of the sample, it will lead to biased result (large $MSE$).

A. Query Type
In our framework, we restrict the query type to only linear aggregated queries which attracted a significant attention in the differential privacy line of work. Similarly, [10] also adopted this query type in their proposed theoretical
As defined in [10], linear query is a vector $q = (q_1, q_2, ..., q_n)$ with real value computing over a finite data vector $x$ with positive integral counts. $x_i$ represents an individual data owner whose record matches a possible element of attribute domains cross product. However, in [10], $x_{i,j}$ represents the number of individuals whose attributes values match the $i^{th}$ entry in crossproduct of attribute domains, so an individual is placed into one possible element of attribute domains cross product. We adapt their structure because in our framework, each individual selects their $\hat{\varepsilon_i}$, and $\hat{w_i}$, so it is good to treat each record individually. Ultimately, the answer $q(x)$ to a linear query on $x$ is computed as a vector product $q.x = q_1.x_1 + ... + q_n.x_n$.

**Definition 1 (Linear Query [10]).** Linear Query is a vector with real value $q = (q_1, q_2, ..., q_n)$. The computation of this query $q$ on a fixed-size data vector $x$ is the result of a vector product $q.x = q_1.x_1 + ... + q_n.x_n$.

Despite the limitation to linear aggregated query, the aggregated query answer without any inclusion of personal identifiable information (i.e., name, date of birth...) could still leak some privacy of data owners taking into account the adversary has some background knowledge about a targeted individual. A well-explained example of this case can be found in [10]. For this reason, differential privacy is incorporated into a personal data trading to ensure the privacy preservation for all the participating data owners and another interesting direction is the use of privacy guarantee parameter $\varepsilon$ as a metric of privacy loss which is later used to compute the compensation to data owners.

Similar to any types of queries, if the buyer issues many cheap queries to compute the average query answers, he or she could derive more information than he or she actually paid for. The cause of this information inference is correlated with the degradation of privacy via composition theorems addressed in [4]. This kind of circumvention is called arbitrage; therefore, it is crucial that our pricing mechanism to also address this problem by designing arbitrage-free pricing model.

### B. Differential Privacy as a Privacy Protection

As addressed earlier, the pricing mechanism should be capable of preserving data owner’s privacy from any undesirable privacy leakages. Otherwise, the data owners will be reluctant in participating in the personal data market knowing that their privacy is not guaranteed. Thus, differential privacy plays an essential and requisite role in assuring that the adversary could not infer any specific information about an individual in the query result despite the combination of some background knowledge about that individual. The differential privacy is defined in [4] as a privacy guarantee by introducing some randomness into the query answer to ensure the same conclusion is derived despite the inclusion or exclusion of an individual user in the dataset. Given a value of privacy parameter $\varepsilon$, it ensures that any responses to queries is likely to occur, regardless of the presence or absence of any individual in the dataset, so that the privacy is guaranteed with $\varepsilon$-differential privacy. A smaller $\varepsilon$ provides better privacy protection, which is a tradeoff with accuracy of a query answer.

In our framework, we define $\varepsilon$ as a quantification of privacy loss of data owner.

**Definition 2 ($\varepsilon$-Differential Privacy [4]).** A random algorithm $M : D \rightarrow R$ satisfies $\varepsilon$-Differential Privacy if the neighboring dataset $x, y \in D$ where $D$ is a whole dataset and dataset $x$ and $y$ differs by only one record, and any set of $S \subseteq \text{Range}(M)$,

$$\text{Pr}(M(x) \in S) \leq \exp(\varepsilon) \cdot \text{Pr}(M(y) \in S)$$

In the traditional differential privacy, the privacy protection is for the tuple level. That means the traditional privacy regards $\varepsilon$ as a public parameter used to retain privacy for all tuples (one for all). However, [8] proposed another theory known as “Personalized Differential Privacy” or Personalized DP derived from differential privacy theory. This study suggested that the privacy protection should be scaled down to the user-level, which means that each user in the dataset can specify their privacy specification $\varepsilon_i$ by claiming that some users may prefer higher privacy preference on some particular data than other users, which is also proved in our survey analysis 3. Therefore, data analyst can take an advantage of this property to maximize the utility of a query answer because not all users require the same strong privacy protection. With similar objective, we adopt this personalized differential privacy to apply in our pricing framework to provide data owner with a personalization of their privacy level as well as providing a solution for better utility for data buyer. Personalized differential privacy defined in [8]:

### Table 1: Summary of notations

| Notation | Description |
|----------|-------------|
| $u_i$    | Data owner $i$ |
| $i, j$   | Index variable of data owner and data buyer |
| $n, m$   | Total number of all data owners and data buyers |
| $h$      | Number of representative samples |
| $h$      | Number of computational run time |
| $x_i$    | Data element of $u_i$ |
| $x$      | Entire dataset consisting of all data elements of all $u_i$ |
| $RS$     | A representative sample of dataset $x$ |
| $w_i$    | Payment contract function of $u_i$ |
| $c_i$    | Coefficient of $w_i$ |
| $\varepsilon_i$ | Maximum tolerable privacy loss of $u_i$ |
| $\varepsilon_i$ | Actual privacy loss of $u_i$ in query computation |
| $b_j$    | Data buyer $j$ |
| $Q$      | Linear aggregated query requested by data buyer |
| $\chi$  | Market maker’s profit |
| $W_{max}$ | Maximum budget of data buyer |
| $W_{ab}$ | Available budget for a query computation $(W_{max} - \chi)$ |
| $W_p$   | Query price |
| $W_r$   | Remaining budget of data buyer |
| $Q(x)$  | True query answer |
| $P(Q(x))$ | Perturbed query answer (with noise) |
| $MSE$   | Mean squared error |
DEFINITION 3 (Personalized DP [8]). Regarding the maximum privacy tolerance $\hat{\epsilon}$ of each user and a universe of users $U$, a randomized mechanism $M : D \rightarrow R$ satisfies $\hat{\epsilon}$-Personalized Differential Privacy (or epsilon-PDP), if for every pair of neighboring datasets $x, y \in D$ where $x$ and $y$ differs in data of user $i$ and for any set of $S \subseteq \text{Range}(M)$,
\[
\Pr(M(x) \in S) \leq \exp(\epsilon_i) \cdot \Pr(M(y) \in S)
\] (2)

Since personalized differential privacy derived from differential privacy is also a theory (not an algorithm), we need to implement some differentially private mechanisms (i.e. Laplace mechanism, Exponential mechanism,...) to achieve personalized differential privacy. Because each data owner in our framework has their own $\hat{\epsilon}_i$, we decide to implement exponential-like mechanism of [8]. This mechanism determines the probability of each possible output based on its score. The score [8] is inversely related to the number of changes in a dataset $x$ that would be required for a possible value become the true answer. The score function is generalized as below.

DEFINITION 4 (Score Function [8]). Given a function $f : D \Rightarrow R$ and outputs $r \in \text{Range}(f)$ with a probability proportional to that of exponential mechanism differential privacy [4], the $s(D, r)$ is a real-valued score function. The higher score, the better $r$ is relative to $f(D)$. Assuming that $D$ and $D'$ differ only in the value of a tuple, denoted as $D \oplus D'$.

\[
s(D, r) = \max_{f(D') = r} - |D \oplus D'| \quad (3)
\]

In Personalized Differential Privacy, each record or data owner has their own privacy setting $\hat{\epsilon}_i$, so it is important to make a distinction among the different $D'$ that make a specific value become the output. To formalize this mechanism, [8] defined it as below.

DEFINITION 5 (\textit{PE} Mechanism [8]). Given a function $f : D \rightarrow R$, an arbitrary input dataset $D \subseteq D$, a privacy specification $\phi$, the mechanism \textit{PE}$_{\phi}(D)$ outputs $r \in R$ with probability
\[
\Pr[\textit{PE}^i_{\phi}(D) = r] = \frac{\exp\left(\frac{1}{2} d_f(D, r, \phi)\right)}{\sum_{q \in R} \exp\left(\frac{1}{2} d_f(D, q, \phi)\right)}
\] (4)

where $d_f(D, r, \phi) = \max_{f(D') = r} \sum_{i \in D \oplus D'} -\phi^i$

In our framework, $\phi$ refers to the sets of maximum tolerable privacy loss $\hat{\epsilon}_i$ of all data owners in the dataset $x$. We implement this mechanism to guarantee that each data owner’s privacy is protected even though they have different privacy requirements. The proof of this mechanism can be found in [8].

C. Arbitrage-free Pricing Model

Arbitrage-free is a requisite property integrated to combat the circumstance of a savvy data buyer on the query price. For instance, a perturbed query answer with $\epsilon_1 = 1$ costs $10$ and that with $\epsilon_2 = 0.1$ costs $0.1$. If a savvy buyer wants a perturbed query answer with $\epsilon = 1$, he or she will buy the query answer with $\epsilon_2 = 0.1$ 10 times to compute the average of them for the same result of query answer with $\epsilon_2 = 1$. Thus, the buyer will never have to pay $10$ for the same result of the average of many cheap queries costing him/her only $1$. In [10], arbitrage-free property is defined as:

DEFINITION 6 (Arbitrage-Free [10]). A pricing function $\pi(Q)$ is arbitrage-free if, for every multiset $S = Q_1, ..., Q_m$, if $Q$ can be determined from $S$ denoted as $S \rightarrow Q$ then:
\[
\pi(Q) \leq \sum_{i=1}^{m} \pi(Q_i)
\] (5)

where $\pi$ is drawn i.i.d from $\text{Lap}(S_i/\epsilon)$ satisfied.

An explanation and discussion of query determinacy $(S \rightarrow Q)$ can be found in [10].

Arbitrage-free pricing function: [10] proved that a pricing function $\pi(Q)$ can be made equal to the sum of all payment to data owners if the framework is balanced. A framework is balanced if:

- The pricing function $\pi$ and payment function to data owners are arbitrage-free.
- The query price is cost-recovering. That is, the price of query should not be less than that required to compensate all data owners.

In our framework, we simply adopt their arbitrage-free property by ensuring that the query price $W_q$ is always greater than the compensation to all the data owners whose data is accessed.

In addition, we, for simplicity, limit that the buyer cannot request the same query for more than once because each data owner has their $\hat{\epsilon}_i$, so we need to guarantee that their privacy loss is no larger than their specified $\hat{\epsilon}_i$. Alternatively, the market maker can predefine the sets of queries that buyer can ask so that they can study the relation between all queries in advance to avoid arbitrage problem. However, this also poses a limitation on the choice of query buyer can request, so we decide to allow buyer to ask any linear aggregated query but limited to only one time per query. Implementing this arbitrage-free property, we can prevent the data buyer’s circumvent on the query price.

D. Truthful Privacy Valuation

In our framework, data owners are given a list of payment contract functions to select to determine their payment corresponding to their privacy loss. Each user may select different payment contract function due to their privacy attitude and profit or risk orientation. This assumption is illustrated in the experiment result of [2]. Without any constraints on the choice of data owner’s payment contract function, there is a problem of untruthful privacy valuation in [10]. The data owners will try to maximize their profit by untruthfully reporting a very high non-decreasing payment contract function $w : \epsilon \rightarrow R^+$ because in any query computations, all data owners will be included and compensated to the function of their privacy loss.

To deal with this issue, we designed two different types of payment contract functions as illustrated in Figure 6. These two payment contract functions provide different payment according to their selected privacy level and risk orientation. In our framework will put some constraints on the data owners’ choice of payment contract function. Whatever choice
they made, their privacy is still guaranteed up to their specified level \( \epsilon \). However, we impose some constraints on their selection by giving the possibility of having their data used in query computation and thus monetarily compensated corresponding to their privacy loss. If they select an unacceptably high payment contract function, they will have less possibility to sell their data compared to those with appropriate contract function. For the simplicity of our study, we first limit the choice to within linear payment contract function, which means data owners will be compensated linearly to the function of their privacy loss.

**Proposition 1** (Payment Contract Function). A payment contract function is a non-decreasing function \( w : \epsilon \rightarrow R^+ \) representing a promise between market maker and data owner on how much data owner should be compensated corresponding to their actual privacy loss \( \epsilon \). Any non-decreasing functions can be a contract function. For instance,

- **Type A**: This Logarithm function is designed to favor the conservative (low-risk, low-return) data owners whose \( \epsilon \) is small.
  \[ w = \frac{\log(30) \times \ln(9000\epsilon + 1)}{130} \]  

- **Type B**: This Sublinear function is designed to favor liberal data owners (high-risk, high-return) data owners whose \( \epsilon \) is large.
  \[ w = \frac{8\epsilon}{\sqrt{1100 + 500\epsilon^2}} \]

With these two proposed payment contract functions, it is obvious that data owners will select the one that provides them more benefit corresponding to their privacy attitude (\( \epsilon \) value) and their risk attitude. Therefore, there is no reason that the data owners have to untruthfully report their privacy valuation because doing so will not give them any benefits. For a more profit, the data owners will exhibit their true privacy level because any privacy level provides them the best benefits they could receive.

The design of payment contract function is deemed an essential part in dealing with untruthful privacy valuation, but in our current study, we only include two different types of functions to give different options for conservative and liberal data owners. We will leave a more sophisticated function design as our future work.

**E. Unbiased Result**

Besides the privacy protection and price optimization, unbiased result has been a crucial factor in trading. The buyer will not want to obtain a result that is biased or far different from the true result, so it is important to ensure an unbiased result.

In our setting, we will guarantee a more unbiased result through randomly selecting the data owners, which both liberal and conservative data owners have equal probability to be selected. This random selection will eliminate the biased content because it is believed that true value of data has a connection with the selected \( \epsilon \) of each data owner. For example, a data owner with HIV positive may set very high privacy for that data which means very small \( \epsilon \), while the data owner with HIV negative can set very large \( \epsilon \). Thus, the random selection will provide each data owner with the same chance of selection, resulting in less biased sample.

Moreover, to optimize the query price, it is necessary to select a representative sample for the whole dataset because paying each individual data owner in the dataset (as in [10]) is not an ideal way as it leads to very high query price for the same utility of data. Thus, selecting a good number of sample size is deemed crucial, and we will apply sampling method from statistics to compute the number of representative sample given a dataset. This method is also implemented in [2].

According to all these 5 key principles, a pricing mechanism should adopt them to avoid some certain issues and get a more optimal result. However, previous researches as such [10] did not include all these key principles in their trading framework and pricing mechanism. One of which is that data owners are not allowed to specify their own privacy level and they are assumed to be able to accept an infinite loss if more money paid. In addition, their mechanism did not properly tackle the untruthfulness because everyone will be compensated without any constraints and the contract functions are assumed to be linear function, so each data owner will try to untruthfully report a high privacy valuation to get more benefits.

**3.2 Personal Data Trading Framework**

To balance data owner’s privacy loss and data buyer’s payment to guarantee a fair trading, we propose a personal data trading framework (see Figure 3) that consists of 3 main participants: market maker, data owner, and data buyer.

- **Market maker** is a mediator between the data buyer and data owner. Market maker has some coordinating roles. First, market maker is a trusted server that answers data buyer’s query by accessing to data elements of data owners. Second, market maker computes and distributes the payment to data owners whose data has been accessed while keeping a small cut of the price as his/her own profit. Third, market maker devises some payment contract functions (payment schemes) for data owners to select. Our pricing mechanism is designed to assist the market maker’s tasks and prevent circumvention on query pricing from data buyer.
and untruthful privacy valuation from data owner.

- **Data owner** sells his/her data element $x_i$ by selecting the maximum tolerable privacy loss $\hat{\varepsilon}_i$ and preferred payment contract function $w_i$. Although the privacy budget parameter $\varepsilon$, in Differential Privacy theory (see Definition 2), is a real non-negative value given, how to determine $\varepsilon$ value remains an open question. However, [6] conducted a study on an economic way of setting $\varepsilon$. Thus, with a good user interface, we assume that data owner can understand and determine their $\hat{\varepsilon}_i$. The payment contract function is a non-decreasing function that computes the payment for each data owner as a function of their actual privacy loss $\varepsilon_i$, i.e. \( w_i : \varepsilon_i \rightarrow R^+ \) where $\varepsilon_i \in [0, \hat{\varepsilon}_i]$. This function is a promise between market maker and data owner to guarantee that their privacy loss will be appropriately compensated according to the selected contract function. Detailed computation will be discussed in Section 4.

- **Data buyer** purchases an aggregated query answer from the market maker by specifying a query $Q$ and a maximum budget $W_{max}$. Instead of asking the buyer to specify the variance in the query answer as in [10], we design our mechanism to be able to obtain the most optimal result with smallest noise/error within the given budget $W_{max}$, because data buyers are highly unlikely to know which value of variance to specify to get their desired utility within their limited budget. Thus, designing the mechanism to tackle this issue is an ease for the buyers and market maker.

How our framework works can be described as the following. Data owner $u_i(x_i, \varepsilon_i, w_i)$, $i \in [1, n]$ sells his/her data element $x_i$ by demanding that their actual privacy loss $\varepsilon_i$ must not be greater than their specified $\hat{\varepsilon}_i$ and their payment should be corresponding to their selected payment contract function $w_i$. Those data elements are stored by a trusted market maker. The trading happens when data buyer makes a purchase request by specifying his $Q$ and $W_{max}$. Having received the purchase request, the market maker selects a number of representative samples $RS$ from the dataset $x$ then conducts a query computation by perturbing the answer to ensure privacy guarantee for all data owners whose data was accessed. Next, the market maker distributes the payment to the data owners in the selected sample $RS$ and returns the perturbed query answer $P(Q(x))$, the remaining budget $W_r$ from the computation, the number of data owners in $RS$, and the mean squared error $MSE$ in the query answer. Note that the transaction aborts in case where the market maker cannot meet both of these requirements simultaneously. For simplicity of our framework, we consider that each data owner can sell only one data element at a time, and each data buyer can request any linear aggregated queries, but the same query is allowed only once.

According to composition theorems 4 of differential privacy, there is a limitation on the number of queries buyer can ask to avoid the degradation of the privacy guarantee $\varepsilon$, which may result in an unacceptable disclosure of the data. For instance, if we compute $\varepsilon_1$-differentially private mechanism and $\varepsilon_2$-differentially private mechanism on the same statistic, the privacy guarantee will be degraded to $(\varepsilon_1 + \varepsilon_2)$-differentially private mechanism once the total privacy $\varepsilon = \varepsilon_1 + \varepsilon_2$ increases. Therefore, to guarantee the privacy requirements for all data owners, it is necessary to set a limitation to only one request per query.

### 4. BALANCED PRICING MECHANISM

Pricing Mechanism is in charge of price computation for data buyer who requests for any information derived from personal data and payment computation for data owners as compensation. Although personal data market becomes a trading platform like other types of market, personal data or information derived from personal data does not have any tangible properties like traditional goods, so it is difficult to set a price or calculate the value of data or information as asserted in [16]. Similarly, [15] and [1] discussed why some conventional pricing models such as cost-based pricing and competition-based pricing are not viable to price digitalized goods like data and information. As mentioned in [17], the only feasible pricing model is value-based pricing which the price is set based on the value the buyer perceived. The study of [12] followed this value-based concept by making information price influenced by information quality and demand. However, soliciting people to score the information demand is quite invalid as the decision might be associated with purposes and future benefits. Thus, the pricing mechanism should be more carefully designed. Regarding the pricing mechanism design, there are two crucial lines of research work: auction-based pricing and query-based pricing. Auction-based pricing has attracted attention of [7], [13], [14], and [6]. Auction-based pricing allows the data owners to report their data valuation and data buyers to place the bid. From practical aspect, it is very difficult for the individuals to articulate their data valuation as reported in [8]. Moreover, the price in [13] is eventually determined by the data buyer without considering data owner’s privacy valuation or actual privacy loss. Meanwhile, there are some researchers extending their work from query-based pricing. This query-based pricing, defined in [9], is a capacity to automatically derive the prices of queries from the given valuation of data. The author in [9] proposed a flexible arbitrage-free query-based pricing model that assigns the price to arbitrary query based on the pre-defined prices.
of view. Despite the flexibility, the price is non-negotiable. The buyer can get the query answer only if he/she is willing to pay full price. Unfortunately, this model is not viable for personal data trading as the mechanism takes no account of privacy preservation. As an extension to this work, researchers in [10] adapted the model to include private data trading setting by implementing differential privacy principle as privacy preservation and quantification of data owners’ privacy loss. As an improvement, they allow a price negotiation in an expense of query accuracy.

Procedure 1. Select data owners

- Compute the size of a representative sample

\[ SS = \frac{DT \times CLS^2}{MER^2} \]  

(8)

where \( SS \) is a sample size, \( DT \) is a distribution of 50%, \( CLS \) is a confident score level, and \( MER \) is a margin of error.

\[ |RS| = \frac{SS \times |x|}{SS + |x| - 1} \]  

(9)

where \( |RS| \) is a representative sample size, and \( |x| \) is a population size (all records in entire dataset \( x \)).

- Randomly select data owners for a representative sample \( RS \)

\[ RS \leftarrow \{ u_i | Unduplicated \_ Randomize(1, |x|) \} \]  

(10)

In our framework, each data owner is subjected to undergo different privacy loss \( \varepsilon_i \) but no larger than their \( \hat{\varepsilon}_i \). He/she receives different amount of payment due to his/her selected payment contract function \( w_i \). Our mechanism will minimize the error or noise in the query answer within the given budget \( W_{max} \) of data buyer.

In our baseline pricing mechanism, we divide the computation into 3 procedures: Select data owners, compute the query price and compensation and perturb query answer, and select the best sample.

In procedure 1 (see Procedure 1), the mechanism first compute the size of a \( RS \) representative sample for the whole population or dataset \( x \). This is basically computed using statistical formula. Then the mechanism randomly selects data owners within that \( |RS| \). After this procedure, the output is a \( RS \).

In procedure 2 (see Procedure 2), the mechanism computes the available budget \( W_{ab} \) after subtracting the data owner’s profit. Then, within that \( W_{ab} \), compute how much privacy loss \( \varepsilon_i \) each data owner \( u_i \) in \( RS \) should undergo. After that the mechanism can compute how much money each \( u_i \) should receive. Also, the mechanism will compute the query price \( W_p \) and remaining budget \( W_r \) if any. Next the mechanism perturb the query answer by running a differentially private exponential-like mechanism \( PE \) and finally compute the mean squared error \( MSE \).

In procedure 3 (see Procedure 3), the mechanism selects the best \( RS \) with smallest \( MSE \) among all the representative samples.

Procedure 2. Compute query price and compensation; Perturb query answer

**Compute query price and compensation**

- Market maker keeps a fraction of budget \( \chi \) as his/her profit, so the available budget \( W_{ab} \) is

\[ W_{ab} = W_{max} - \chi \]  

(11)

- Within the available budget \( W_{ab} \), compute compensation \( w_i \) for \( u_i \) in \( RS \)

- With \( w_i \), compute the privacy loss \( \varepsilon_i \) for \( u_i \) in \( RS \)

If \( w_i \) is type \( A \)

\[ \varepsilon_i = \frac{130 \times w_i}{e^{log(30)} - 1} \]  

(12)

Else

\[ \varepsilon_i = \sqrt{\frac{1100 \times w_i^2}{64 - (500 \times w_i^2)}} \]  

(13)

- Calculate query price

\[ W_p = \sum_{i=1}^{\frac{|RS|}{SS}} w_i \]  

(14)

- Calculate remaining budget \( W_r \)

\[ W_r = W_{ab} - W_p \]  

(15)

**Perturb query answer**

- Perturb the true query answer \( Q(x) \) by running exponential-like mechanism \( PE(.) \) (See equation [11])

\[ P(Q(x)) = PE(Q(x)) \]  

(16)

- Calculate Mean Squared Error \( MSE \)

\[ MSE = \frac{1}{k} \sum_{i=1}^{k} (P(Q(x)) - Q(x)) \]  

(17)

where \( k \) is the number of run times to obtain more consistent value of MSE.

Procedure 3. Select the best representative sample

- Among all the \( h \) number of \( RS \), select one \( RS \) that has smallest \( MSE \)

\[ Selected \ RS \leftarrow \{ RS_i | Min(MSE), i \in [1, h] \} \]  

(18)

At the end, data buyers will receive the perturbed query answer \( P(Q(x)) \) along with remaining budget \( W_r \) if any, number of data owners in \( RS \), and mean squared error \( MSE \) in the query answer. Data owners will be compensated according to their actual privacy loss \( \varepsilon_i \).

**For example**, in the trading transaction, the buyer may issue a query \( Q = \{ \text{How many people in U.S commute to} \} \)
work by personal car?} by specifying his \( W_{max} = 30 \). Assuming that there are 486 data owners in the dataset \( x \) and the real answer of query \( Q(x) \) is 370. The market maker will run the pricing mechanism. The output is there are 215 data owners in the best selected \( RS \), and the perturbed query answer \( P(Q(x)) = 365 \), \( MSE = 470 \), and the total query price \( W_p = 30 \), so there is no remaining budget \( W_r = 0 \). Each data owner in the selected \( RS \) will be compensated according to their privacy loss \( \varepsilon_i \) and their payment contract function \( w_i \), but in average the payment for one data owner is about \$0.14 per query.

5. EVALUATION

To prove the efficiency of our proposed pricing mechanism, we will conduct an evaluation by comparing the output of our mechanism and that of \[10\]. Since the trading framework of both mechanisms are different, we will slightly modify the setting of \[10\] so that it is possible to compare the two mechanisms. The chief modification is to allow each data owner to determine their maximum tolerable privacy loss \( \varepsilon_i \), which is opposite to the original setting of \[10\] that empower only the buyers to determine the privacy loss. That is, data owners are empowered to decide how much privacy loss they can tolerate despite a large amount of money. This claim is derived from our survey result analysis and the practicality in real world.

In comparing the two mechanisms, we will examine a few output variables such as query price \( W_p \), mean squared error \( MSE \), average privacy loss \( \varepsilon \) of each data owner \( u_i \), and the average compensation \( w \) each data owner receives from the two mechanisms. By comparing the \( W_p \) and \( MSE \), we can conclude which mechanism provides query answer with smallest \( MSE \) within the same amount of budget for data buyer, whereas comparing average \( \varepsilon \) and average \( w \) allows us to report which mechanism provides better privacy protection within the same compensation.

5.1 Experimental Setup

We will divide the experiment into two stages. In the preliminary experiment, we will utilize the real dataset obtained from our survey result, and we first run the experiment with only count query. Next experiment will be extended to include both real dataset and synthetic dataset about US Census, and we will examine count, medium, and min/max query.

Real dataset preparation: From the survey result, we obtained 486 records of personal data from 486 data owners, so our dataset \( |x| \) is 486. In order to utilize this survey result in our experiment, there are two steps we need to process. First, we determine 4 different types of maximum tolerable privacy loss \( \varepsilon_i \) and match with data alteration level each data owner selected in the survey. We did not directly ask the data owner to determine their \( \varepsilon_i \) because it is asserted that data owner, without much knowledge about privacy, normally finds it difficult to articulate a specific value of \( \varepsilon_i \) to choose.

- \( \varepsilon_i = 0.1 \) if data owner’s selected data alteration level is very high. These data owners are very conservative.
- \( \varepsilon_i = 0.3 \) if data owner’s selected data alteration level is high. These data owners are conservative.
- \( \varepsilon_i = 0.7 \) if data owner’s selected data alteration level is low. These data owners are liberal.
- \( \varepsilon_i = 0.9 \) if data owner’s selected data alteration level is very low. These data owners are very liberal.

Second, we will randomly pick the most appropriate contract function for them based on their \( \varepsilon_i \) and risk attitude. Referring back to our two designed payment contract functions (See Figure 4), the type A functions provide more payment to data owners whose \( \varepsilon_i < 0.4 \), while the type B function is good for data owners whose \( \varepsilon_i > 0.4 \). Therefore,

- Payment contract function type A (equation 6) for both very conservative \( (\varepsilon_i = 0.1) \) and conservative \( (\varepsilon_i = 0.3) \) data owners.
- Payment contract function type B (equation 7) for both liberal \( (\varepsilon_i = 0.7) \) and very liberal \( (\varepsilon_i = 0.9) \) data owners.

With these two steps, we obtain a usable dataset for our experiment.

5.2 Experiment Result and Discussion

The experiment result and discussion will be presented in detailed in the next version of the paper.

6. RELATED WORK

Regarding the pricing mechanism design, there are two crucial lines of research work: auction-based pricing and query-based pricing. Auction-based pricing has attracted attention of \[9, 13, 14, \] and \[6\]. Auction-based pricing allows the data owners to report their data valuation and data buyers to place the bid. From practical aspect, it is very difficult for the individuals to articulate their data valuation as reported in \[1\]. Moreover, the price in \[13\] is eventually determined by the data buyer without considering data owner’s privacy valuation or actual privacy loss. Meanwhile, there are some researchers extending their work from query-based pricing. This query-based pricing, defined in \[2\], is a capacity to automatically derive the prices of queries from the given valuation of data. The author in \[9\] proposed a flexible arbitrage-free query-based pricing model that assigns the price to arbitrary query based on the pre-defined prices of view. Despite the flexibility, the price is non-negotiable. The buyer can get the query answer only if he or she is willing to pay full price. Unfortunately, this model is not viable for personal data trading as the mechanism takes no account of privacy preservation. As an extension to this work, researchers in \[10\] adapted the model to include private data trading setting by implementing differential privacy principle as privacy preservation and quantification of data owners’ privacy loss. As an improvement, they allow a price negotiation on an expense of query accuracy. On the other hand, there is a research by \[2\] whose pricing mechanism is not belong to the two aforementioned branches. \[2\] computed the query price from the selected sample and created a pricing menu for that buyer to select from. However, this research did not take into account the privacy aspect because they only consider the trade of ordinary data, but not personal data.

7. CONCLUSION AND FUTURE WORK

Apart of the contribution to personal data market, we proposed a reasonable personal data trading framework following the 5 key principles of personal data market: (1)
tackling statistical/linear aggregated queries, (2) guaranteeing arbitrage-free pricing model, (3) allowing personalized privacy protection level, (4) ensuring the truthful privacy valuation, and (5) providing an unbiased result. In addition, we proposed a balanced pricing mechanism that provides better utility to both data owners and data buyers. Although more experiments are required to prove the efficiency, our research has identified and tackled some radical challenges of the market, and this is apart of the contribution to enable the existence of personal data market.

Having investigated the nature and challenges of this market, we have found a few interesting avenues for our future work. With regard to obtaining an optimal query price and query answer, it is important to carefully design the payment contract functions by incorporating the concept of game theory into the design. In our current research, we only designed two contract functions to at least provide different options for conservative and liberal data owners. However, it might be more interesting to take into account the design of payment contract functions in a more thorough manner. Moreover, in our framework, market maker is assumed to be a trust server that stores and accesses data owners’ data on their behalf, yet in some extent, trust has become a difficult question to address from both technical and social aspects. Thus, for our future work, we can consider the trading framework and pricing mechanisms in which market maker is assumed as untrusted.

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APPENDIX

A. SURVEY

A.1 Questions

Our research topic is Privacy and Price of Data. Your provided information will be ANONYMIZED. We really appreciate your sincere response. Estimated time needed to answer is about 5 minutes.

1. How do you commute to school/work?
   - Personal car
   - Bus
   - Train
   - Bike
   - Walking
   - None of the above

2. How much do you earn per year? (approximately in $)
   - $

3. How much do you spend on medical care (i.e. medicine,...) per year (approximately in $)?
   - $

4. Which bank service are you using? (Please choose one if you use many services)
   - JP Morgan Chase
   - Bank of America
   - CitiBank
   - Wells Fargo
   - HSBC
   - Other: ______________________

5. Please choose which type of ANONYMIZED Personal Data you CAN SELL or CANNOT SELL:

| Personal data | Sell for $10 | Sell but not sure how much | Cannot sell |
|---------------|--------------|---------------------------|-------------|
| 1. Commute type to school/work | o | o | o |
| 2. Yearly income | o | o | o |
| 3. Yearly expense on medical care | o | o | o |
| 4. Bank service you are using | o | o | o |

6. In traditional market, if you sell your ANONYMIZED personal data, you will receive MONEY and your privacy is PROTECTED. Will you be interested in selling?
   - Interested
   - It depends on TYPE of personal data and amount of money
   - Not interested

In our new market, we provide MORE privacy protection, both ANONYMIZATION and ALTERATION. Your data will be anonymized and altered based on the LEVEL you prefer. Example:

![Figure 8: Level of alteration](image)

7. Which level of ALTERATION on data do you prefer if selling them? (Very low level → likely get many buyers but the selling data is very similar to your real data)

| Personal data | Very low | Low | High | Very high |
|---------------|----------|-----|------|-----------|
| 1. Commute type to school/work | o | o | o | o |
| 2. Yearly income | o | o | o | o |
| 3. Yearly expense on medical care | o | o | o | o |
| 4. Bank service you are using | o | o | o | o |

8. With your selected ALTERATION level in Q7, how much MONEY do you want if selling these personal data? If sold, you will get MONEY from each buyer. (Cheaper → many buyers)

| Personal data | $10 | $5 | $1 | $0.5 |
|---------------|-----|----|----|------|
| 1. Commute type to school/work | o | o | o | o |
| 2. Yearly income | o | o | o | o |
| 3. Yearly expense on medical care | o | o | o | o |
| 4. Bank service you are using | o | o | o | o |

9. In our market, you can CONTROL how much to ALTER your data and receive appropriate amount of MONEY. Are you more INTERESTED in selling your personal data?
   - Very interested
   - Somewhat interested
   - Somewhat not interested
   - Not interested

10. Which condition is more important when you decide to SELL your personal data? Please rank it (1 = Very important; 4 = Not important)

| Condition | 1 | 2 | 3 | 4 |
|-----------|---|---|---|---|
| 1. Who and how buyers will use your data | o | o | o | o |
| 2. Sensitivity of data (salary, disease,...) | o | o | o | o |
| 3. To get as much money as possible | o | o | o | o |
| 4. Future risks/impacts | o | o | o | o |

11. Based on your understanding in the survey, how do you think your data is sold in our market?
   - Real data
   - Altered version of real data
☐ Other: ______________________