On the Fairness of Quality-based Data Markets

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Abstract
For data pricing, data quality is a factor that must be considered. To keep the fairness of data market from the aspect of data quality, we proposed a fair data market that considers data quality while pricing. To ensure fairness, we first design a quality-driven data pricing strategy. Then based on the strategy, a fairness assurance mechanism for quality-driven data marketplace is proposed. In this mechanism, we ensure that savvy consumers cannot cheat the system and users can verify each consumption with Trusted Third Party (TTP) that they are charged properly. Based on this mechanism, we develop a fair quality-driven data market system. Extensive experiments are performed to verify the effectiveness of proposed techniques. Experimental results show that our quality-driven data pricing strategy could assign a reasonable price to the data according to data quality and the fairness assurance mechanism could effectively protect quality-driven data pricing from potential cheating.

Keywords: Data Marketing, Data Pricing, Data Quality, Fairness

1 Introduction
Trading of data is an effective way to show the value of big data. Online data markets provide platform for data trading \cite{17}. In data markets, data pricing is an essential step and data quality is a factor to be considered during data pricing.

Data quality is the fitness or suitability of data to meet business requirements \cite{7}. Low-quality data tend to require additional “cleaning” which usually costs much money and time. We use an example to illustrate the impact of data quality on data price.

For example, the relation shown in Table \ref{tab:1} contains information about universities, like those sold at USNEWS\footnote{http://www.usnews.com/education}. Data shown in the table is apparently
Table 1: University information

| Uname | Location | Country | Country_Code | Apply_Deadline     | Min_Score |
|-------|----------|---------|--------------|--------------------|-----------|
| $t_1$ | Uni_A    | New York| US           | 001                | 2013-Dec-25| 90        |
| $t_2$ | Uni_B    | London  | UK           | 0044               | 12/12/2013 | 85        |
| $t_3$ | Uni_C    | New York| US           | 002                |            | 3.5       |

of poor quality. $t_1$ and $t_2$ have different formats of time which need further processing to uniform, while $t_3$ lacks the value in the attribute which would possibly make the data unusable. Meanwhile, although $t_1$ and $t_3$ share the same “Country” value, they differ in the “Country_Code” attribute. This violates the functional dependency between these two attributes. The user has to purchase extra data to correct the mistake. Also, the value of attribute “Min_Score” of $t_3$ deviates obviously from that of other tuples. There is a great chance that the deviation may be noise. As we can conclude, data quality greatly affects the usability of data and extra expenditure of consumers.

Data cleaning is not a cheap step. It is estimated that data cleaning accounts for 30%-80% of the development time in a data warehouse project [4]. Therefore, low quality decreases the value of data since further efforts are required to clean them. To show the impact of data quality on their value, data pricing should take data quality into consideration.

Integrating quality factors in data pricing requires the re-consideration of many properties of data market, among which fairness is significant one. In data market, the fair value of a product is a rational and unbiased estimate of the potential market price of a good, service, or asset. First of all, to assure the fairness in quality-based data market, a proper pricing strategy with the consideration of data quality should be considered. Besides, with the consideration of data quality in data pricing, some behaviors may affect the fairness. We use an example to illustrate this point. For example, a buyer can try all the possible combinations of parameters to find the “cheapest” tuple in a badly-designed system. He will then use such set of parameters to obtain unfair advantage over other users.

The requirement of a fair quality-based data market brings two main technical challenges. One is how to integrate quality factors into pricing process of data. The other is how to provide a cheat-free fair quality-based data market.

This paper studies the fairness of quality-based data market. As far as we know, this is the first work that considers overall quality factor in pricing of data markets and the fairness of quality-based data market. This is the first contribution of this paper.

We assure the fairness in two aspects. The first is the data pricing strategy with the consideration of data quality. In our strategy, data of better quality can be sold at a higher price and buyers pay less for poor-quality data. A purposed quality-based pricing system takes as input the respective need of consumers and derives the price for the particular user. The underlying idea is that different

2http://en.wikipedia.org/wiki/Fair_value
consumers and applications may have their own emphasis on important quality factors. A proper quality-based data pricing strategy is the second contribution of this paper.

The other aspect is a mechanism that prevents savvy buyer from using former query knowledge to trick the system. With such trading mechanism, savvy buyers cannot get lower price of the same content by a maliciously designed query. The trading mechanism that prevents the cheating is the third contribution of this paper.

1.1 Organization

In section 2 we define the problems of this paper and discuss the related assumptions. Our quality-based data pricing framework consists of two parts: quantization and quality-based floating. The framework of quality-related data pricing strategy is described in Section 3. In Section 4 we depict the mechanisms used in our marketplace to prevent savvy user from cheating the market management system in the context of our definition of “cheat-free”. In Section 5 we evaluate the effectiveness and efficiency of our system by experiments. The related work is summarized in Section 6. Section 7 conclusions the paper.

2 Background and Problem Definitions

In this section, we introduce the background of data market and define the problems studied in this paper.

Several pricing models have been proposed for data markets. Among them, the query-based pricing framework [? 10] is an effective and flexible one. Query-based pricing framework can derive the price of a query automatically once given explicit price points. In such framework, a seller is not required to define a fixed set of views that the buyer may be interested in and assign specific price to each of them. Meanwhile, the data buyer can avoid scanning through the catalog or being forced to accept the superset of interested data. He can get exactly what he wants by issuing queries according to his need. The charge of the results of the query is automatically calculated with the system. Thus we choose the query-based framework in our system.

In a data market, users always expect real-time interaction. This requires the pricing in data market to be either very efficient or performed offline. Since in the query-based framework, the price of data depends on the submitted query and should be computed online, we choose an instance-based manner to compute the quality offline to save the total computation time. By stating instance-based pricing, we imply that the results of the quality-based pricing system are determined by the quality of the whole database instance, and perform similarly to every query on the instance.

In a data market, the fair value of a data set is the amount at which it could be bought or sold in a current transaction among willing parties, or transferred
to an equivalent party, other than in a liquidation sale. Following this concept, for a quality-based data market, fairness means that users and applications with different requirements pay a price for the data according to their needs on data quality. For example, a buyer who needs the most updated data would like to pay a higher price for the query results on the latest data set with good “timeliness” quality aspect since this one possibly satisfies his requirement. On the contrary, he would be charged less if the data are of poor “timeliness” because the data set may be out-of-date and could not provide the much useful information for him.

Since data quality has different aspects, a user may emphasize on some special aspect. Consider the example shown in table 1. If one just want to count the number of universities in a certain country, clearly, the format of “Apply Deadline” or the accuracy value of “Min Score” would not affect the result. However if the data are not complete in the attribute “Country”, the counting result is inaccurate. Therefore, the factors such as consistency and accuracy are not as important as completeness in this case.

As a result, embedding data quality in data pricing requires a quality-based pricing strategy investigating various quality factors such as accuracy and completeness and then combine them. Assigning different weights for different quality factors according to the requirements of users is the first problem which is to be solved in Section 3.

Such framework will lead to an unfair problem. Consider the following example scenario. A savvy user can maliciously issue queries claiming different needs, then he can cheat the system by inferring the distributions of quality factors of the underlying database with some designed queries. For instance, a user can compare prices of the same query content with different distribution of quality aspects. He may discover that the database has a highest “consistency” score if the price of the query results on the data emphasizing “consistency” is the highest.

With the distributions of quality factors, the user can pay relative lower price for required data. In the example above, he could issue his query claiming that he care about the completeness of data most which may belies his true need to obtain the data in lower price. Therefore, beside a quality-based pricing strategy, mechanism assuring that the quality-based data market to be “cheat-free” is the second problem that is studied in Section 4.

3 Quality-Based Pricing

In this section, we propose a quality-based pricing strategy for fair data market. To integrate data quality factors in the pricing, data quality should be described separately in aspects at first, which is discussed in Section 3.1. Section 3.2 discusses the way to integrate and calculate the overall quality value of a dataset for a particular user. Final data price could be computed according to both of the quantitative data quality and original query price. The final price computation method will be presented in Section 3.3.
We first design the quantitative description for each data quality aspect respectively and consider them all together.

3.1 Quality Aspects

We have two considerations on quantization. One is efficiency. In a data market, the data quality information will be computed quantitatively with new submission of data and the size of data may be large, the data quality evaluation algorithm should be cheap to assure the efficiency of the data market. The other is the diversity issue due to the various aspects of data quality. The quantitative description of the data quality should be the combination of various data quality aspects with different weights. It requires that values of these aspects to fall in similar ranges and follow similar formats.

We investigate the quality of data in the following four aspects: accuracy, completeness, timeliness, consistency. We choose these factors for two reasons. One is that these attributes are among the most often investigated data quality factors [6,15]. The other is that these factors are closely related to the value of the data and influence the price. Violating them may cause direct financial loss or even worse consequences.

Other quality factors either are not directly related to data pricing or overlap with our choice. For examples, “Accessibility” [15] is the quality aspect that does not directly affect the price, and “Appropriate Amount of Data” [15] is overlapping with “completeness”.

When we are investigating the four quality aspects in the following paragraphs, we will be focusing on the violation value $K_s$. They represent the overall extent to which the restrictions are violated. In other words, it shows how bad the quality is in certain aspects and is reflects the efforts one will need to clean them.

Assume that the schema of the database has $m$ attributes $R = (R_1, \ldots, R_m)$. Database instance $D = (R^D_1, R^D_2, \ldots, R^D_m)$ is a instance of $R$. Assume $D$ has $n$ tuples.

3.1.1 Accuracy

Accuracy [5,15,19] of data refers to the extent to which data are free of error. To measure the accuracy of data, we need to spot and count the appearance of inaccuracy in the set. We judge the validation of data according to type, formats and pre-defined patterns. To locate inaccurate data, we need to first analyze the data with pattern analysis, domain analysis and data type analysis. Here pattern analysis discovers patterns of records by analyzing the data stored in the attributes, domain analysis identifies a domain or set of commonly used values within the attribute by capturing the most frequently occurring values, and data type analysis enables the system to discover information about the data types found in the attribute [20]. Then after the pattern, domain and type of every attribute is obtained, we check the value of each attribute in all
tuples in a data set and if one of the following metrics are satisfied, this value is considered as inaccurate.

- It violates the pattern of the attribute. Patterns can be expressed as regular expressions. For example, a valid date can be expresses by "\d{4}−\d{2}−\d{2}". If such patterns are set, a date "98-01-01" is considered a violation.
- It exceeds the valid data domain. For example, a negative number is an inaccurate age attribute, since it is out of the valid domain of rational age value.
- The data are of wrong types. An example is that a string type in a column that is required to be integer.

We denote the number of all the inaccurate values by \( n_{ac} \). Then we use the ratio of the inaccurate values to evaluate the inaccuracy of the whole data set. To avoid extreme values in each data quality aspect, we choose negative logarithm of the original ratios as the uniform form. The accuracy violation rate is computed as

\[
K_1 = K_{acc} = -\log\left(\frac{n_{ac}}{mn}\right).
\]

With such form, the quality values fall in a reasonable range and more accurate data sets get higher \( K_1 \) values.

### 3.1.2 Completeness

Completeness \([8, 15, 21]\) of a data set is the extent to which the data are not missing, and are of sufficient breadth and depth for the task. To measure the degree of completeness, we need to examine if the data set is satisfactory in three aspects, (1) appropriate amount, (2) adequate attributes, and (3) few missing values. All these three aspects influence the usability of data set.

First, the volume of a database should reach a minimal number to be meaningful. For example, statistical data of teenager health condition in a city cannot just contain 10 tuples. We measure the degree that a data set violates the appropriate amount requirement with the degree that the volume violating the minimal required number of a data set. Thus such degree is computed as \( \lfloor \frac{n_{min}}{n} \rfloor \), where \( n_{min} \) is the minimum record number of a certain genre of data. In the case discussed above, \( n_{min} \) may be a number of the same order of magnitude as the number of teenagers of a typical city. With such formula, if the volume of the data set is sufficient, the result is 0 and it has no impact on the value of completeness. With \( n_{min} \) as a constant, the smaller \( n \) is, the larger \( \frac{n_{min}}{n} \) is. Thus when \( \frac{n_{min}}{n} > 1 \), this formula shows the degree of violation.

Second, data tables should contain adequate attributes to assure that it delivers effective information. In this example, table of health condition should at least contain the attributes “age” and “gender”. The degree of the violation of this property is measured as the ratio of uncovered attributes to necessary attributes. With \( R_{nee} = \{ R_1, R_2, ..., R_p \} \) as the necessary set of attributes of
a certain data genre, the number of attributes that lies in the necessary set is denoted by \( p' \). Then the violation degree of this property is \( \frac{p - p'}{p} \). In the example above, if the data set to evaluate only has the “age” attribute but lacks “gender”, then we have \( p = 2, p' = 1 \). The violation degree is 0.5.

Third, the existence of missing values may lead to incapability to answer certain query or lead to incomplete query results. The numbers of three aspects are counted quantitatively according to following rules, respectively. We use the ratio of missing values \( \frac{n_{\text{mis}}}{mn} \) to describe the violation degree of this property, where \( n_{\text{mis}} \) is the number of missing values.

Summing of these factors, we compute the incompleteness of a data set in the following way.

The relative importance of the three aspects of data completeness are described as weights \( w_{\text{com}1}, w_{\text{com}2}, w_{\text{com}3} \). The distribution is also determined by the specific need of data consumers or derived automatically from feedback of users by machine learning algorithms. Following the same format with accuracy value, the completeness violation rate is computed as

\[
K_2 = K_{\text{com}} = -\log\left( w_{\text{com}1} \cdot \frac{n_{\text{min}}}{n} + w_{\text{com}2} \cdot \frac{p - p'}{p} + w_{\text{com}3} \cdot \frac{n_{\text{mis}}}{mn} \right). \tag{2}
\]

3.1.3 Timeliness

Timeliness \([15,18]\) refers to the degree of data to be up-to-date for a particular task. Including the evaluation of timeliness in the quality assessment makes the results with expire data get lower price.

To evaluate the aspect of timeliness, we count the number of expired values \( n_{\text{exp}} \) according to the effective time of the particular data genre. The timeliness violation rate value is calculate as

\[
K_3 = K_{\text{tim}} = -\log\left( \frac{n_{\text{exp}}}{n_{\text{exp}}} \right), \tag{3}
\]

where \( n_{\text{exp}} \) refers to the number of tuples with effective timestamps. \( n_{\text{exp}} \) can be computed by checking whether the result of current time minus the timestamp on the data is larger than the expiration time. This equation still follows the form above and gives higher degree for data set with fewer expired data.

3.1.4 Consistency

Consistency of data refers to the extent to which the data conform to the functional dependency and conditional function dependency of database.

First we investigate the data set using methods from \([2]\) and discover the tuples violating the functional dependencies and conditional function dependencies. Then we calculate the number of tuples that violate the function dependency and conditional function dependency as \( n_{\text{vio}} \). Following the common form we have
\[ K_4 = K_{con} = -\log\left(\frac{\pi_{vio}}{n}\right). \]  

3.2 Integrating

In defining the quality of data, we use the cost of cleaning to as a measurement. Since the data quality affects data value such way: data of low quality tend to require more cleaning by the consumer which may cost a lot of money and time. So it is reasonable for consumers to pay more for data they can use right after purchase or need only slight cleaning.

To combine various factors, we choose the linear sum of the evaluated data qualities as the skeleton according to the Occam’s razor principle. That is, when there is no golden rule to judge different methods, we choose a simple way. Relative importance of data quality aspects is determined by the buyers according to their requirement. To represent it, we require the buyer of data to state a weight vector \([w_1, w_2, w_3, w_4]\) that indicates the weights of the four aspects mentioned above and satisfies \(w_1 + w_2 + w_3 + w_4 = 1\). The distribution of weight shows the relative concern of the buyer.

As discussed, consumers may emphasize on different quality aspects according to different application background. The difference is denoted by weight vector \(W\). We could not expect that every consumer got the ability to precisely quantify their need based on particular application and give a relative weight to each quality aspect on their own. So the system assists their users by giving advices.

Consider an example in which a consumer is particularly concerned about the completeness of data, he would certainly spend more time on making data more complete after his purchase. Now there are three general types of cleaning approaches regarding completeness: 1) ignore all the records with missing values; 2) fill missing ones with a special value; 3) capture the missing values. The third approach gives the most accurate cleaning results while at the same time costs the most. So if a user needs the data to be very complete, he may perform the third approach; if he just need the active parts of data and doesn’t care about completeness, he may simply discard the incomplete tuples. In other words, the consumer knows which level of cleaning he would like to pay for each quality aspect.

The system evaluates the potential cost of typical cleaning methods and archive them in different levels. Then the system gives weight ranges of corresponding levels. The user finds the level according to such guide and still have the freedom to change slightly with in the range. We continue with the example with completeness, the system could give four types of methods and their corresponding weight range: 1) ignore all the records with missing values, \([0, 0.1]\); 2) fill missing ones with special value, \([0.1, 0.2]\); 3) capture missing values through statistic methods, \([0.2, 0.3]\); 4) capture missing values through machine learning methods, \([0.3, 0.4]\). If a consumer need the dataset to be very complete, and he would use the most expensive type of cleaning method, he could set the weight of completeness to 0.35, for example. Then if the data set he purchased
happened to be low quality especially on completeness, he gets the results at a lower price. The price in some way “compensate” the potential loss due to the heavy cleaning need.

For the $j$-th level in the $i$-th quality aspect, the system got an offline-generated cleaning cost function $f_{ij}(K, D, V)$. These are the estimated time consumption functions of different cleaning methods. With the relative weight of the $i$-th quality aspect $w_i$, the system choose the suitable $f_{ij}$ according to the range $r$ that $w_i$ falls into: $F_i((K_i, D_i, V_i), w_i) = f_{ix}(K_i, D_i, V_i)$, where $w_i \in r_s$. And the final quality value is $FQ = \sum_i F_i((K_i, D_i, V_i), w_i)w_i$.

### 3.3 Floating

This section combines the quality factors evaluated with the methods in Section 3.2 into the data price. The data price change caused by data quality is called floating. The computation of quantitative floating requires the combination of multiple data quality factors and distinguishes the importance of different aspects of data quality according to the requirement.

In order to achieve fairness in a particular data market, we also need a set of standard quality values $S = (S_1, S_2, S_3, S_4)$ which shows the average level of quality in the market to make the floating of prices according to the same baseline. This baseline could be computed as the average quality of all current databases in the market.

With the set of quality assessment result $K$ of a database instance and the vector $W = [w_1, w_2, w_3, w_4]$ as the weights of a particular buyer, the system then calculates the price floating and performs it on the original query price. The price floating is computed in two steps. In the first step, the quality factor of a database instance $FQ$ is computed as shown in Section 3.2 and the standard quality of all databases $FQS$ are computed in similar ways, using $S$ instead of $W$. User can choose $w_i$ according to their own need or rely on automatic algorithms that give suggestions based on former records. In the second step, the price is computed with the original price $p$ of query results and the floating computed with $FQ$ and $FQS$.

For the second step, there are two natural ways to perform the floating.

- **additive floating**

  we calculate the price as

  $$p_{ad} = p + (FQ - FQS) \cdot E,$$

  where $E$ is a coefficient of the data market to indicate how much the quality may affect the final price. $E$ is the part of the initial settings of the whole data market. However, the drawback of such floating manners is that it influences cheaper data more than expensive data. For instance, with $FQ = 1.5, FQS = 1$, an adding floating $E \cdot (FQ - FQS) = 0.5$ would change a query worth $2$ to $2.5$, while changes a query worth $2000$ only to $2000.5$. 


• multiplicative floating

we calculate the price as

\[ p_{mul} = \frac{FQ}{FQS} \times p. \]  

(6)

Similarly, such manners may also cause problems. It tend to influence price of expensive data too dramatically. For the example above, a multiplicative floating \( \frac{FQ}{FQS} = 1.5 \) changes price $2 to $3, while a price $2000 would end up to be $3000.

To overcome the drawbacks, we the combined manners of additive and multiplicative. The final price is computed as

\[ p_{final} = p + \left( FQ - FQS \right) \frac{p}{FQS} \times C, \]  

(7)

where \( C \) is a coefficient of the data market to indicate the quality may affect the final price. For the stated example, if we choose \( C = 0.1 \), $2 is changed to $2.1 and $2000 to $2100. \( C \) can be adjusted according to the level of quality requirement.

In the pricing strategy, consumers can choose to use default values for the whole set of parameters or modify part of them. The modification can be done with the help of algorithms that give suggestion based on former records.

4 Cheat-free data marketplace

As discussed in Section 2, a savvy buyer may cheat the data market on the weights of data quality factors when the pricing strategy in Section 3 is applied directly. In order to keep the fairness of the data markets, in this section, we propose the cheat-avoiding mechanism.

4.1 Fairness Criterion

At first, we discuss how to evaluate the fairness in presence of the impact of data quality on data pricing.

In Section 2 we show that the unfairness of quality-based pricing is caused by the fact that users can get lower price by cheating the system. From this perspective, we evaluate fairness of data market by the ability of users to cheat.

Formally, if a data market satisfies that a buyer cannot get a set \( W' \) with the knowledge of real weight vector \( W \) and assure that

\[ \sum_{i=1}^{4} F_i((K_i, D_i, V_i), w'_i)w'_i < \sum_{i=1}^{4} F_i((K_i, D_i, V_i), w_i)w_i, \]  

(8)

then such data market is considered as cheat-free in terms of quality-based data market.
Such criterion describes the desired fair feature for data market that a savvy buyer cannot consciously construct a fake input to get lower price than what he really deserves. Violating the criterion shows the user’s the ability to cheat the system. Note that consciousness is important in the criterion. Since in our system which will be discussed in Section 4.2, the user is unconscious about the mapping of weight vector of a query and the price of it. In fact the mapping would give a savvy user advantage over other user.

Also, we may want to guarantee that individual user cannot be cheated by the data market. A user can archive and verify the consumption record to ensure the fairness of the data market.

4.2 Data Market Working Flow

4.2.1 Main Idea

To achieve the goal described in Section 4.1, we propose a fair data market. Generally, a data market contains three parties: the data vendors who provide data and decides the individual point of price of his database, the data buyers who issue queries on the specific database and get charged, the market managing system (MMS) as a platform which performs all the query procedure and quality-related calculations. Also, to provide protection for all sides, we introduce a trusted third party (TTP) into our system. TTP is a trusted, unbiased and authenticated third party who can communicate with other parties and provide arbitration.

Most of the services that ensure fairness is provided by MMS and TTP. Thus the mechanism is included in MMS and TTP as components.

The major mechanism for fairness is the hiding the mapping from price to weight vector, which prevents the buyer from detecting any useful information about the quality distribution of the database he queries. This goal is achieved in our mechanism by avoid revealing the precise final query price to the buyer, and is implemented by encrypting the query price. While at the same time, a buyer may want to make sure that MMS cannot cheat by providing fake price. This requires the user to verify the correctness of the consumption without decrypting the price.

We design the work flow in this section. First, we sketch the behaviors of the users and the data market with such mechanism as shown in Figure 4.2.2.

In the work flow, each user gets an account at the data market and get tokens certificated by the market to replace money in data consumptions. We assume that the communication takes place in a secure and authenticated channel. Every time a query is issued, the buyer gets a range instead of an explicit price. If he accepts the price range, the price will be deducted from the account. A user can usually check the range of his balance instead of a precise number. Thus the user will not be able to detect the mapping between the weight vector he submits and the outcoming price.

After a successful consumption, the buyer may want to check if MMS took the right amount of money from his account. He can perform the verifica-
tion himself through simple and efficient calculation. When he needs to verify
whether the encrypted balance is correct or the encrypted price is really within
the range MMS claims, the buyer communicates with TTP. TTP performs the
verification through communication with MMS and returns a result to the buyer.

4.2.2 Functions

The work flow of Data Market.

Before the whole work flow is proposed, we introduce the functions used
in the flow. In these functions, $\mathbb{G}_n$ denotes a multiplicative group of integers
modulo $n$.

$(i, g_i, s_k, pub_i) \leftarrow \text{Reg}(1^s)$: An algorithm performed by MMS that takes as
input the security parameter and generates a unique identify number for a par-
ticular consumer. For the security parameter $s$, $p$ has $s$ bits and is the order
of the group $\mathbb{G}_n$, ie. $p = |\mathbb{G}|$. User ID $i \in \mathbb{Z}_p$. It also outputs $g_i \in \mathbb{G}$ together with
the secret key and public key of the buyer.

$(E_{\text{value}}) \leftarrow \text{Enc}(i, \text{value})$: A deterministic algorithm that encrypts the price
value or balance value of the particular user with user ID $i$. It returns $E_{\text{value}} =
g_{\text{value}}^i$.

$(\text{range}) \leftarrow \text{Range}(i, p)$: A probabilistic algorithm performed by MMS that
output a range where $p \in \text{range}$.

$(\text{res}, p) \leftarrow \text{Query}(q, W)$: A deterministic algorithm performed by MMS that
takes as input the query $q$ to a certain database and the vector $W = [w_1, w_2, w_3, w_4]$, and
computes the result set res of the query together with the final result of the
quality-based pricing system of the query $p$. It returns res and $p$.

$(\text{consumptionID}, E_p, \text{res}) \leftarrow \text{Consume}(i, \text{confirm}_i, q, W)$: A deterministic
algorithm performed by MMS that takes as input the confirm information of user
$i$ and query information $(q, W)$ on which the consumer agreed on. It generates
a unique ID for the consumption, encrypts $E_p = \text{Enc}(p, i)$, and performs the query by running Query. It finally returns the consumption ID, the encrypted price and the query results. At the same time saves the record and sends it to TTP for archiving.

YES—NO ← Verify($E_{B1}, E_p, E_{B2}$) : A deterministic algorithm performed by the buyer that takes as input the encrypted form of original balance, the price of the query and new balance after the query succeeded. It returns “YES” if $E_{B1} \cdot (E_{B2})^{-1} = E_p$. The inverse of $E_{B2}$ can be computed using the Extended Euclid algorithm.

YES—NO ← checkBalance($i, E_B$): A deterministic algorithm performed by TTP to check whether the provided value is the encrypted form of user ID $i$. It returns “YES” if $E_B = \text{Enc}(B, i)$, where $B_i$ is the current balance of user $i$. Since TTP is tracing every consumption record, it always gets the most updated user balance.

YES—NO ← VerifyRange($\text{consumptionID}, i, \text{range}, E_p$): A deterministic algorithm performed by TTP that takes as input the encrypted form of a price and the claimed range with its consumption ID and user ID. It outputs “YES” if the price is in the range. To void the case that the user maliciously utilizes TTP to narrow the range of $E_p$ or even reveals the value of $p$, TTP searches the consumption records by the provided consumption ID to verify if the input is legal. According the result record of such search, when any of the range and user ID in the record does not match corresponding item provided by the buyer input, “No” is returned. If both of them match, the checking continues. It returns “YES” if $p \in \text{range}$ and $E_p = \text{Enc}(p, i)$ and range matches.

4.2.3 Working Stages

The system runs in the following stages.

• **Setup:** We assume that all roles including data vendors, MMS and TTP have already got their key pairs of public key and private key. Also they are acknowledged of the public key information of others through offline procedures or with the help of public key infrastructure, for example the X.509 Public Key Infrastructure [14,16]. To start the trading, the data vendor provides his database with explicit price points to MMS. MMS stores and investigates the quality information of the database instance. A user who wants to buy data from the market will need to register first. MMS runs Reg on the security parameter $s$ and saves the register information to his database. MMS also sends the information to TTP for future reference.

• **Query:** The buyer forms a query $q$ and also determines the vector of weight distribution $W$. He sends $(q, W)$ to MMS and waits at the range
of the query price. MMS then performs the query, calculates query price, computes final price according to quality with the weight given by the buyer, i.e. run \texttt{Query} on \((q, W)\). MMS sends back the price range and encrypted price \((\text{Range}(p), \text{Enc}(p, i))\). If the buyer agrees on the price in this range, he sends back an agreement message. Then MMS updates the user’s current balance, and sends back the result, unique consumption ID together with price and current balance both in encrypted form. The user saves the encrypted consumption record for possible future verification. MMS sends consumption information to TTP after every successful consumption.

- **Verification:** Since the buyer possesses access to consumption only in encrypted form, he may want to verify if his balance is properly processed. The buyer can require his current balance in encrypted form \(E_B\) at any stage. So for every consumption he made, the buyer has got tuple \((E_{B1}, E_P, E_{B2})\), and he may run \texttt{Verify} on the tuple. If \texttt{Verify} returns “YES”, the buyer is convinced that the price of the consumption he made is properly subtracted from his balance.

- **Record Checking with TTP:** TTP as a trusted party can provide additional checking based on user information from MMS and consumption record provided by the buyer.
  
  - A buyer needs to check the reliability of the original encrypted balance so that the following verification is convincing. The same checking is needed when the user made a recharge to his account. He could run \texttt{checkBalance}.
  
  - A buyer may want to know whether the price of a certain query is really in the range claimed by MMS, then he can send the consumption ID, encrypted price, the claimed range of MMS and his own ID to TTP. TTP runs \texttt{VerifyRange} and returns the answer.

Since each of the function runs in polynomial time complexity in the security parameter \(s\), as mentioned in the interaction stages above, each of above stage can be accomplished in polynomial time.

We use an example to illustrate the above flow. Alice is a buyer who has registered at a data market with the proposed fairness assurance mechanism and gets a user ID \(i = 1\). Assume that the data market is running on a group \(\mathbb{G}_n\) with \(n = 5\). Assume that Alice get \(g_1 = 3\), which is only known by MMS and TTP. Now the balance in her account is $4, she queries MMS for the encrypted balance. MMS computes \(E_{B1} = g_1^4 \mod 5 = 1\) and send it back to Alice. Then Alice issues a query with quality weight vector \((q, W)\) to buy data on the market for query \(q\) with quality preference \(W\). MMS performs the query and calculates the price \(p = 3\), it runs \texttt{range} and get \(\text{range} = [1, 4]\) and compute \(E_p = g_3^3 \mod 5 = 2\). Then MMS sends back the range and encrypted price to Alice, and waits for her agreement. Alice agrees on the price range and sends back the agreement message. MMS subtracts the price from her balance and
sends the query result, encrypted price $E_p$ and new balance $E_{B2}$ to her together with a unique consumptionID to identify the consumption, where $E_{B2} = g_1^{4-3} \mod 5 = 3$.

To verify that the new balance is correct, Alice first computes the inverse of $E_p$ using the Extended Euclid algorithm and gets $(E_p)^{-1} = 2$. Then she can verify whether $E_{B1} + E_p^{-1} = E_{B2}$, which is $1\times2 = 2$ in our case. Now Alice knows that she is charged properly. Also, she can check her balance with TTP before any consumption every time she recharges the account. After consumption, she can check the range of the price by querying TTP with consumptionID, range, and encrypted price of the consumption.

In real-world implementations, the group will be much bigger according to the security parameter to ensure the difficulty of discrete logarithm.

On the data market, a cheater Bob wants to issue query with a fake weight vector to get a cheaper price. To achieve this goal, he has to know which quality aspects of the underlying database instance are higher and put relatively low weight on these aspects. However, since Bob cannot solve the discrete logarithm problem, he does not know the real prices of the results of his queries. Thus he cannot detect the quality distributions of underlying data sets. We will prove in Section 4.3 that under such circumstance, Bob has no effective advantage over a random guesser.

Bob may want to construct fake range checking messages to query TTP. For example, if there is a consumption record for Bob with consumptionID = 2, p = 3, range = [1, 4]. He could query TTP first with consumptionID = 2, $E_p$, [2.5, 4], badly designed TTP will return Yes. Bob finds out that $p > 2.5$, then he queries with consumptionID = 2, $E_p$, [2.5, 3.25]. After narrowing the range step by step, he could guess the real price. However, in the mechanism of our system, TTP is required to verify the range before verifying it, only ranges appearing in real consumption records are accepted. In this case, TTP searches the consumption records for the one with consumptionID = 2, TTP only sends back the result to those with $E_p$, [1, 4], but it refuses to answer any other range query for such consumptionID. Thus Bob cannot get additional information about the price range by playing with the system.

Note that in real-world implementations, the group should be much larger according to the security parameter to ensure the difficulty of discrete logarithm for its security.

### 4.3 Reliability of the Mechanism

In this subsection, we show the reliability of the proposed mechanism.

As shown in Section 4.1 the reliability of the mechanism is describd by the criterion.

A discrete logarithm is an integer $k$ solving the equation $b^k = g$, where $b$ and $g$ are elements of a group. Discrete logarithms are thus the group-theoretic analogue of ordinary logarithms, which solve the same equation for real numbers $b$ and $g$, where $b$ is the base of the logarithm and $g$ is the value whose logarithm is being taken. Computing discrete logarithms is believed to be difficult.
No efficient general method for computing discrete logarithms on conventional computers is known.

Based on the difficulty of solving discrete logarithm problem, a polynomial time attacker cannot get the value of certain balance or price with a possibility that is a non-negligible function of security parameter $s$. So with only encrypted price and balance, the user can no longer detect the quality distribution of the underlying database.

Furthermore, we have the following theorem. For the interest of space, we omit the proof.

**Theorem 1.** Without knowledge of relationship between different factors of a particular database instance, the possibility that an attacker can cheat the system is equal to random guessing $W$.

One may argue that without knowledge of the quality distribution, the buyer may issue $n$ queries with different $W$ values and may hope to get a lower sum of price than these $n$ queries. The problem can be reduced to what stated above, to determine $(\sum_{j=1}^{n} w_{ij} - nw_{i})$ for all $i \in \{1, 2, 3, 4\}$. And the possibility is still equal to random selection.

## 5 Evaluation

We experimentally evaluate the system in this section. Our system is implemented on a database management system (DBMS) and interacts with users in roles of data vendors and data consumers.

### 5.1 Experimental Setup

The system is implemented in python and runs on top of the MySQL DBMS. We evaluate our system using data that are sold on real-world data markets of AggData\(^4\) and the Windows Azure Marketplace\(^5\). Five data sets are chosen, including Location of UK Universities, Historical Weather Data, Country Codes, GDP All Industries Per States of US 1997-2011, Complete List of Philanthropy 400 Organizations 2004-2010.

Our system runs on a laptop with 2.5GHZ Core i3 CPU and 8GB of RAM. In our system, all the parameters are stored in a configuration file together with information about the database. These parameters include the valid patterns of a particular attributes or functional dependencies between attributes. In our experiments, we set these parameters manually based on the schema of the data. Take the data set of philanthropy records for example. The schema of the data set is (Year, Rank, OrganizationID, OrganizationName, OrganizationLocation, PrivateIncome, TotalAssets, ServiceExpense, Fundraising). We manually set the parameter $C = 0.05, S = [2.5, 2, 1.5, 2]$, and set the expire

\(^3\)http://en.wikipedia.org/wiki/Discrete_logarithm
\(^4\)http://www.aggdata.com/
\(^5\)https://datamarket.azure.com/
time to 6 years, minimum record number \(n_{\text{min}} = 200\), necessary attribute set \(R_{\text{nec}} = \{\text{OrganizationName}, \text{Fundraising}\}\). Parameter sets in real world implementation can be generated in the same way or in manners with more human involvement.

5.2 Efficiency

We first evaluate the performance of the system with different database instance sizes and attribute numbers. In the experiments, we commit different databases to the system and issue various selection queries. We measure the time to finish the preprocessing of databases, in other words, the time to evaluate the quality of the database instance. Then we measure the query time. The results are shown in Table 2.

As depicted in the table, for 3 of the 5 data sets, the system can finish the preprocessing within 1 second. The slower two are still less than 5 seconds. This makes the system suitable for large data sets. Also since the processing time is short, the system can deal with updates efficiently simply by repeat the evaluation process. As for query times, all the queries that we tested can be done within 0.1 second. Hence queries can be online processed.

5.3 Effectiveness

Then we evaluate the effectiveness of the system. Since the price of the same query result set on the same database can be different based on the need of consumers, there is no deterministic way to check the correctness. However, we will evaluate the pricing system in two ways.

| Table 2: Time cost | University | Weather | Country | GDP | Philanthropy |
|--------------------|------------|---------|---------|-----|-------------|
| Rows               | 590        | 20750   | 206     | 72900 | 2798        |
| Cols               | 12         | 17      | 27      | 8   | 9           |
| Average Proc Time  | 0.075      | 1.248   | 0.100   | 4.230 | 0.268       |
| Average Query Time | 0.037      | 0.024   | 0.010   | 0.054 | 0.015       |
Distributions of Query Price with Randomly chose $W$: (a) philanthropy, (b) university, (c) weather, (d) GDP, (e) country code.

The first is the intuition that prices of a particular query with different parameter should follow the normal distribution \[3\]. Since most of the price should fall near the original query price (without quality float), the requirement of the price with quality floating is that only a few data with extreme quality conditions or for users of special need should fall far against the expectation. We experimented on each database with 200 randomly chosen weight distribution $W$. The results are depicted in Figure 5.3. As we can see, most of the five cases follow the normal pattern. From this observation, the prices provided by our system coincide to the requirement and are in reasonable distribution.

The second is to test the relationship of data prices and data quality. To avoid the influence of original query price, we test on same query on the same database instance. By randomly adding mistakes in the data set, we manually decrease the quality.

From the results shown in Figure 5.3 it is observed that the query prices decrease with the amount of the adding of mistakes for all data sets. This shows that our pricing strategy can effectively show the quality factors.
5.4 Reliability

Then we evaluate the reliability of our data market experimentally where users try to cheat the system. We compare the results with the parameters chosen by a human and generated randomly. When a certain user issues a query, a \( W \) according to the requirement is generated, but this use still wants to have a try to play with the system. \( W \) can be modified to \( W' \) and the user tries to cheat the system to get a cheaper price. We exam the capability of the user to cheat by comparing the results with randomly chosen \( W' \), as shown in Figure 5.4.
derived from $W'$ and the real price derived from $W$. It is shown that even
with the knowledge of the real $W$, the user has no significant advantages over
randomly chosen $W$ to get lower price.

6 Related work

Data pricing and data quality are research topics related to this paper. We
summarize related results of these issues.

[?] explored the common models of data pricing in earth observation. Then
research about data marketplaces emerge as data is more commonly accepted
as good for trading. [17] identified several categories of data marketplaces and
pricing models and provided a snapshot of the situation as of Summer 2012. [10]
introduced the “Query-Based” pricing model which made the pricing process of
data more flexible. They also developed practical pricing system based on the
theory [11]. There have been other investigations related to the pricing of aggregate
queries [13] and private data [12]. However, none of these research works
related to data pricing or data market has taken data quality into consideration.

Data quality itself is a research area. Using an analogy between product
manufacturing and data manufacturing, [21] developed a framework for analy-
zing data quality research. [15] described principles that can develop usable
data quality metrics [5, 8]. [9] deeply investigated individual aspects of data
quality such as completeness, accuracy and consistency. These work presented
accurate ways to determine data quality of respective aspects. However, these
mechanisms are not suitable for our system for two reasons. First, most of
these algorithms are rather complicated which are too much time-consuming
for real-world data markets. Second, the studies are based on individual as-
pects of quality and are often with results of different formats and scales. While
in quality-based data markets, a combined quality value is needed.

7 Conclusion

Data quality and fairness are neglected in current data market. To make data
markets more effective, we presented a fair data market that considers data
quality during pricing in this paper. To ensure fairness, we first design a quality-
driven data pricing strategy. Then we propose a fairness assurance mechanism
for quality-driven data marketplace based on the strategy. In this mechanism,
we introduced Trusted Third Party (TTP) to ensure that savvy consumers cannot
cheat the system, while at the same time users can verify each consumption
with TTP that they are charged properly. Based on this mechanism, we de-
velop a fair quality-driven data market system. Experimental results show that
our system could generate a fair price with the consideration of data quality
efficiently and the fairness assurance mechanism is effective.

Interesting future work includes the the following topics. The first topic is
the consideration of data quality rules other than FDs and CFDs. We may
investigate data consistency in a wider range including matching dependencies, editing rules, denial constraints and so on. The second topic is query-based quality evaluation. This requires evaluation of data quality every time a query is issued which may lead to large respondent time, integrating the quality information of particular query with its underlying database instance, and the reduction strategy of MMS server and TTP server workload by batch query processing and verification. The third topic is machine learning algorithms that analyze purchasing records of consumers and derive parameters automatically for them. So that the consumers need not to set parameters such as $W$ manually. Another future work is to design more effective quality evaluation algorithms for data markets.

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