Trading Data in Good Faith: Integrating Truthfulness and Privacy Preservation in Data Markets

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Introduction

Figure 1. Emerging Data Tradings.

Data Market Model

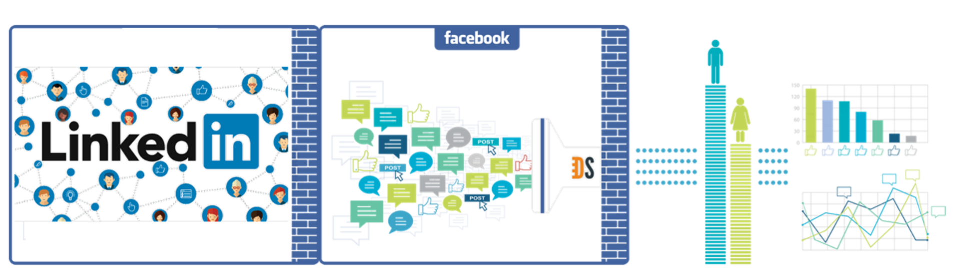
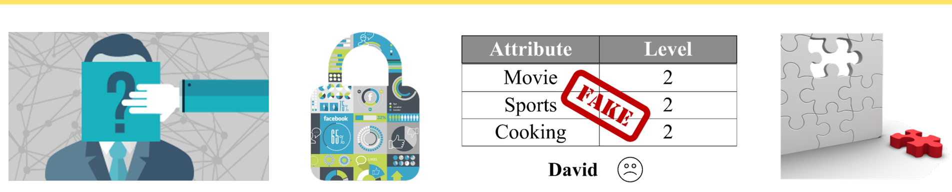


Figure 2. System Architecture of DataSift [5].

Why trade **data services** rather than raw data?

- For data contributors: privacy concerns [1]
- For service provider: value-added data services [2]
- For data consumers: data copyright infringement [12]

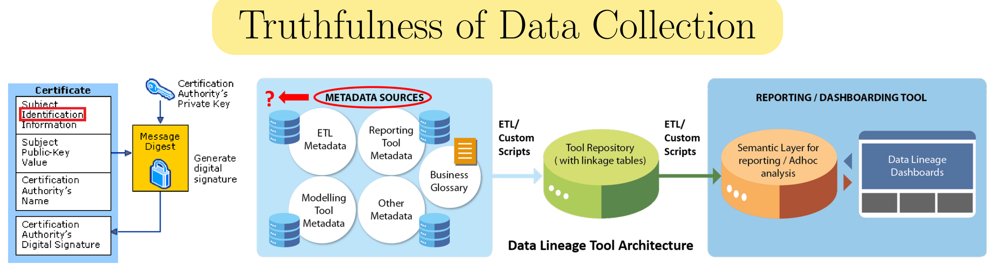
Two Security Issues



- Privacy Preservation
  - Identity Preservation: real identity, *e.g.*, SSN
  - Data Confidentiality: mainly against data consumers
- Data Truthfulness
  - *Partial Data Collection Attack*
  - *No/Partial Data Processing Attack*

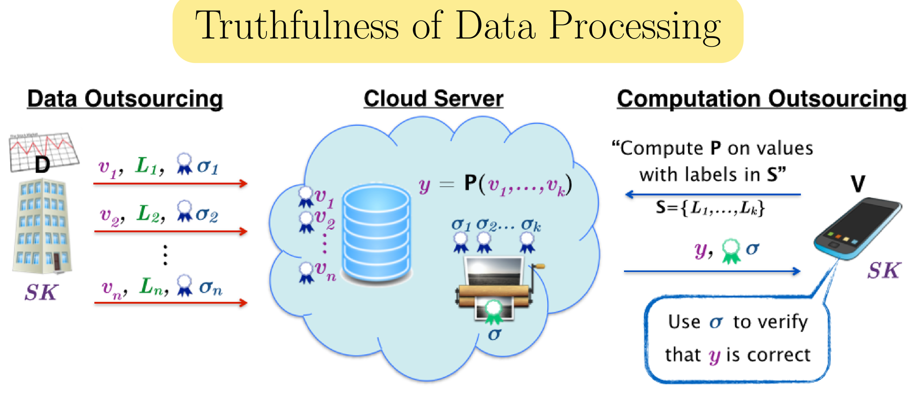
Design Challenges

Truthfulness of Data Collection



- Privacy preservation
  - Digital signature (**non-repudiation**)
  - Message authentication code? secret key sharing
- Data processing
  - Semantic inconsistency [8]
  - Data provenance/lineage [10]

Truthfulness of Data Processing



- Information asymmetry due to data confidentiality
- Differs from verifiable/outsourced computing [7]

Efficiency Requirements

- Large-scale data acquisition (*e.g.*, on DataSift [5] and Gnip [9])
- Data authentication and data integrity? sequential verification, PKI maintenance (computation and communication overheads)

Profile Matching Data Service

Attribute	Level
Movie	3
Sports	0
Cooking	5

Alice

Attribute	Level
Movie	2
Sports	5
Cooking	1

Bob

Attribute	Level
Movie	3
Sports	4
Cooking	2

Charlie $\delta = 2$

Figure 3. Motivating Example: An Illustration of Fine-grained Profile Matching [14].

1. The service provider defines a public attribute set $\mathbb{A} = \{A_1, A_2, \cdots, A_\beta\}$.
2. A data contributor o_i, *e.g.*, a Twitter or OkCupid user, selects an integer u_{ij} to indicate her level of interest in A_j, and thus forms her profile vector $\vec{U}_i = (u_{i1}, u_{i2}, \cdots, u_{i\beta})$.
3. To generate a customized friending strategy, the data consumer also needs to provide her profile vector $\vec{V} = (v_1, v_2, \cdots, v_\beta)$ and an acceptable similarity threshold δ.
4. Without loss of generality, we assume that the service provider employs *Euclidean distance* $f(\cdot)$ to measure the similarity difference, where $f(\vec{U}_i, \vec{V}) = \sqrt{\sum_{j=1}^{\beta}(u_{ij} - v_j)^2}$.

Our Approach: TPDM

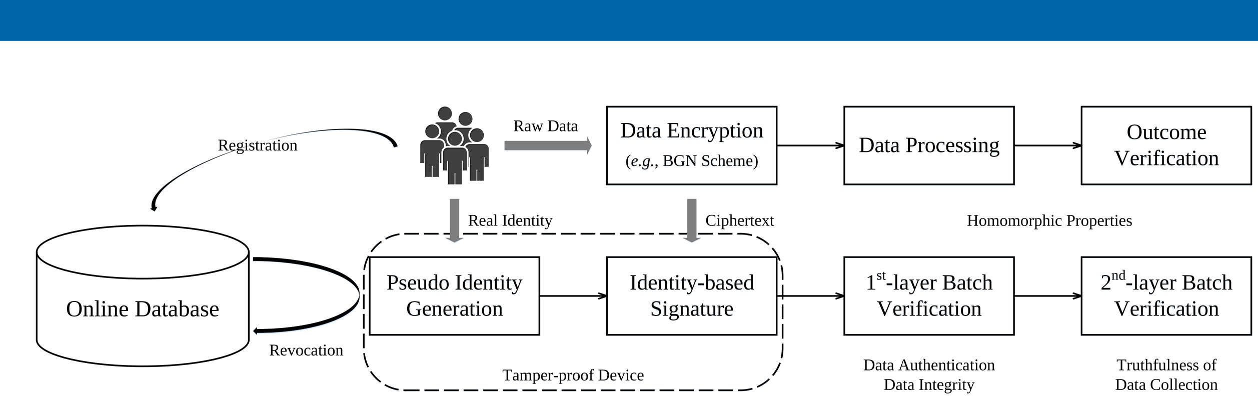


Figure 4. Design Overview of TPDM.

Phase I: Initialization

- The registration center sets up the system parameters at the beginning of data trading:
  - Three multiplicative cyclic groups $\mathbb{G}_1, \mathbb{G}_2, \mathbb{G}_T$ with the same prime order q; g_1, g_2 are generators of $\mathbb{G}_1, \mathbb{G}_2$, respectively; an admissible pairing $\hat{e}: \mathbb{G}_1 \times \mathbb{G}_2 \to \mathbb{G}_T$ [3].
  - Master keys: $s_1, s_2 \in \mathbb{Z}_q^*$; public keys: $P_0 = g_1^{s_1}, P_1 = g_2^{s_1}, \ P_2 = g_2^{s_2}$.
  - BGN cryptosystem [4]: an encryption scheme $E(\cdot)$, a decryption scheme $D(\cdot)$.
  - Registration for a "real" identity $RID_i \in \mathbb{G}_1$ and a password PW_i.

Phase II: Signing Key Generation

- Generate a pair of pseudo identity PID_i and secret key SK_i for registered o_i:

$$PID_i = \langle PID_i^1, PID_i^2 \rangle = \langle {g_1}^r, RID_i \odot {P_0}^r \rangle, \quad (1)$$
$$SK_i = \langle SK_i^1, SK_i^2 \rangle = \langle {PID_i^1}^{s_1}, H(PID_i^2)^{s_2} \rangle, \quad (2)$$

where r is a per-session random nonce, $\odot$ represents the Exclusive-OR (XOR) operation, and $H(\cdot)$ is a MapToPoint hash function [3], *i.e.*, $H(\cdot): \{0,1\}^* \to \mathbb{G}_1$.

Phase III: Data Submission

- Data Encryption: $\vec{D}_i = \left(E(u_{ij}), E({u_{ij}}^2)\right)|_{j \in [1,\beta]}$.
- Encrypted Data Signing:

$$\sigma_i = SK_i^1 \cdot {SK_i^2}^{h(D_i)}, \quad (3)$$

where "$\cdot$" denotes the group operation in $\mathbb{G}_1$, $h(\cdot)$ is a one-way hash function such as SHA-1 [6], and D_i is derived by concatenating all the elements of $\vec{D}_i$ together.

Phase IV: Data Processing and Verifications

- First-layer Batch Verification:

$$\hat{e}\left(\prod_{i=1}^{n} \sigma_i, g_2\right) = \hat{e}\left(\prod_{i=1}^{n} PID_i^1, P_1\right) \hat{e}\left(\prod_{i=1}^{n} H(PID_i^2)^{h(D_i)}, P_2\right). \quad (4)$$

- Data Submission by Data Consumer: $\vec{D}_0 = \left(E({v_j}^2), E(v_j)^{-2} = E(-2v_j)\right)|_{j \in [1,\beta]}$.
- Similarity Evaluation via Homomorphic Multiplication and Homomorphic Addition:

$$R_{ij} = E(1) \otimes E({v_j}^2) \oplus E(u_{ij}) \otimes E(-2v_j) \oplus E({u_{ij}}^2) \otimes E(1) = E\left((u_{ij} - v_j)^2\right),$$
$$R_i = R_{i1} \oplus R_{i2} \oplus \cdots \oplus R_{i\beta} = E\left(\sum_{j=1}^{\beta} (u_{ij} - v_j)^2\right) = E\left(f(\vec{U}_i, \vec{V})^2\right). \quad (5)$$

- Signatures Aggregation: $\sigma = \prod_{i=1}^{m} \sigma_{c_i}$, where $\{o_{c_1}, o_{c_2}, \cdots, o_{c_m}\}$ are matched ones.
- Second-layer Batch Verification:

$$\hat{e}(\sigma, g_2) = \hat{e}\left(\prod_{i=1}^{m} PID_{c_i}^1, P_1\right) \hat{e}\left(\prod_{i=1}^{m} H(PID_{c_i}^2)^{h(D_{c_i})}, P_2\right). \quad (6)$$

- Outcome Verification:
  - Real identity recovery: $PID_{c_i}^2 \odot {PID_{c_i}^1}^{s_1} = RID_{c_i} \odot {P_0}^r \odot {g_1}^{s_1 \cdot r} = RID_{c_i}$.
  - No need of homomorphic multiplications: $R_{ij} = E({u_{ij}}^2) \oplus E(u_{ij})^{-2v_j} \oplus E({v_j}^2)$.
  - Sampling, *e.g.*, p(not evaluating each profile)$= 20\%$, 26 checks, success rate $= 99.70\%$.

Evaluation Result

- Dataset:
  - R1-Yahoo! Music User Ratings of Musical Artists Version 1.0 [13]
  - 11,557,943 ratings of 98,211 artists given by 1,948,882 users
  - Choose β **common artists** as the evaluating attributes
  - Append each user's ratings ranging from 0 to 10
- Evaluation Settings:
  - Pairing-Based Cryptography (PBC) library [11]
  - Identity-based signature scheme
    - SS512: a supersingular curve with a base field size of 512 bits and an embedding degree of 2
    - MNT159: a MNT curve with a base field size of 159 bits and an embedding degree of 6
    - q is 160-bit long; all hashings are implemented in SHA1, considering its digest size closely matches q.
  - BGN cryptosystem: Type A1 pairing, in which the group order is a product of two 512-bit primes.
  - OS: 64-bit Ubuntu 14.04, Intel(R) Core(TM) i5 3.10GHz

Table I. Computation overhead of identity-based signature scheme per data contributor.

Setting	Preparation		Operation
	Pseudo Identity Generation	Secret Key Generation	Signing
SS512	4.698ms (39.40%)	6.023ms (50.53%)	1.201ms (10.07%)
MNT159	1.958ms (57.33%)	1.028ms (30.10%)	0.429ms (12.57%)

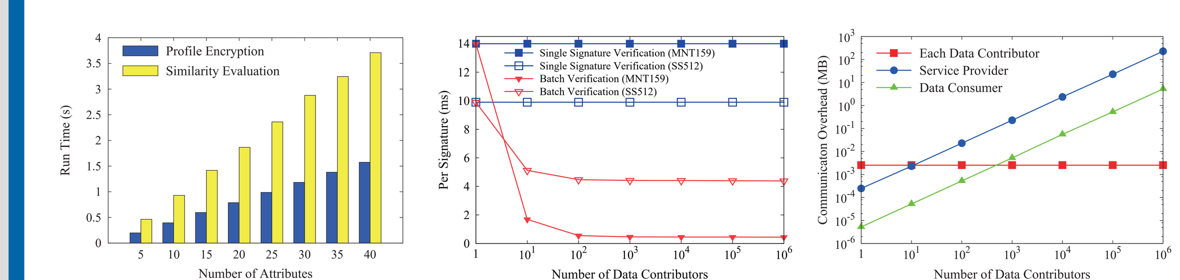


Figure 5. Performance of TPDM on Yahoo! Music Ratings Dataset.

Table I and Figure 5 reveal that TPDM incurs affordable computation and communication overheads, even when supporting as many as 1 million data contributors.

Conclusions

- Consider both data truthfulness and privacy preservation in data markets, and propose TPDM.
- Instantiate TPDM with a profile-matching service, and evaluate its performance on a real-world dataset.
- Evaluation results have demonstrated its scalability, especially from computation and communication overheads.

References

[1] "2016 TRUSTe/NCSA Consumer Privacy Infographic - US Edition," https://www.truste.com/resources/privacy-research/ncsa-consumer-privacy-index-us/.
[2] M. Balazinska, B. Howe, and D. Suciu, "Data markets in the cloud: An opportunity for the database community," in *VLDB*, 2011.
[3] D. Boneh and M. Franklin, "Identity-based encryption from the weil pairing," in *CRYPTO*, 2001.
[4] D. Boneh, E. Goh, and K. Nissim, "Evaluating 2-dnf formulas on ciphertexts," in *TCC*, 2005.
[5] "DataSift," http://datasift.com/.
[6] D. Eastlake and P. Jones, "US Secure Hash Algorithm 1 (SHA1)," *IETF RFC 3174*, 2001.
[7] D. Fiore, R. Gennaro, and V. Pastro, "Efficiently verifiable computation on encrypted data," in *CCS*, 2014.
[8] B. C. M. Fung, K. Wang, R. Chen, and P. S. Yu, "Privacy-preserving data publishing: A survey of recent developments," *ACM Computing Surveys*, vol. 42, no. 4, pp. 1–53, Jun. 2010.
[9] "Gnip," https://gnip.com/.
[10] R. Ikeda, A. D. Sarma, and J. Widom, "Logical provenance in data-oriented workflows?" in *ICDE*, 2013.
[11] "PBC Library," https://crypto.stanford.edu/pbc/.
[12] P. Upadhyaya, M. Balazinska, and D. Suciu, "Automatic enforcement of data use policies with datalawyer," in *SIGMOD*, 2015.
[13] "Yahoo! Webscope datasets," http://webscope.sandbox.yahoo.com/.
[14] R. Zhang, Y. Zhang, J. Sun, and G. Yan, "Fine-grained private matching for proximity-based mobile social networking," in *INFOCOM*, 2012.

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