Privacy-Preserving Multi-Party Clustering: An Empirical Study

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Privacy in Multi-Party Data Analytics

Computation involving multiple parties
- Business processes across companies
- Research collaboration

E.g. Multi-Party Healthcare Analytics
Privacy in Multi-Party Data Analytics

Computation involving multiple parties
- Business processes across companies
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E.g. Multi-Party Healthcare Analytics

How to maintain the privacy/security of the data?
- Organizations are hesitant to share data with third parties
- Massive data breaches (e.g., Target and Boston Medical)
This Work

Comprehensive empirical study of several existing approaches for privacy-preserving multi-party analytics

Case study: clustering task
- Popular task in many applications
- E.g. cohort analysis and information retrieval

Obfuscation techniques
1. Additive data perturbation;
2. Random subspace projection;
3. Secure multi-party computation

Centralized vs. distributed settings

Trade-off between quality, privacy, and performance
- Multiple evaluation metrics and datasets
- Under same framework and settings
Multi-Party Clustering and K-Means Algorithm

Task: Partition data points into groups based on similarity

Multi-party setting: Data points belong to different parties
  ▶ E.g. Each hospital has data from a set of patients
  ▶ Horizontal partitioning

K-means Algorithm:
  ▶ Most popular approach;
  ▶ Iterative;
  ▶ Centroid-based.

K-means Algorithm
Multi-Party Clustering and K-Means Algorithm

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- Most popular approach;
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- Centroid-based.
Privacy-Preserving Clustering Approaches

The Mediator is a third-party that facilitates computation

1. Trusted: Operates on *raw data*
2. Untrusted: Operates on *obfuscated data*

<table>
<thead>
<tr>
<th>Computation</th>
<th>Mediator</th>
<th>Privacy</th>
<th>What is shared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Centralized</td>
<td>Trusted</td>
<td>–</td>
<td>Local data</td>
</tr>
<tr>
<td>Centralized</td>
<td>Untrusted</td>
<td>ADP</td>
<td>Perturbed data</td>
</tr>
<tr>
<td>Centralized</td>
<td>Untrusted</td>
<td>RSP</td>
<td>Projected data</td>
</tr>
<tr>
<td>Distributed</td>
<td>Trusted</td>
<td>–</td>
<td>Partial results</td>
</tr>
<tr>
<td>Distributed</td>
<td>Untrusted</td>
<td>ADP</td>
<td>Perturbed results</td>
</tr>
<tr>
<td>Distributed</td>
<td>Untrusted</td>
<td>RSP</td>
<td>Projected results</td>
</tr>
<tr>
<td>Distributed</td>
<td>Untrusted</td>
<td>SMC</td>
<td>Encrypted results</td>
</tr>
</tbody>
</table>

Overview of approaches studied in this paper.
Additive Data Perturbation (ADP)

\[ x_{i,j}' = x_{i,j} + \epsilon, \epsilon \sim N(0, \sigma) \]

Original data

Noisy data, \( \sigma = .01 \)

Noisy data, \( \sigma = .1 \)

Perturbs data while preserving underlying clusters
Random Subspace Projection (RSP)

\[ x' = \frac{1}{\sqrt{q\sigma}} x R, r_{i,j} \sim N(0, \sigma) \]

- \( q \) is the number of projected dimensions
- \( R \) is a random projection matrix

Projects data into a low-dimensional space while preserving underlying clusters
Secure-Multiparty Computation (SMC)

Applied only for the distributed solution

Random sharing and partially homomorphic encryption

Encryption using the Paillier cryptosystem

Secure random sharing

Homomorphic addition

Homomorphic multiplication

Secure aggregation

Main sub-routines of SMC approach
Privacy-Preserving Multi-Party Clustering

Centralized:
1. Parties agree on obfuscation parameters;
2. Each party obfuscates its local data and shares it with mediator;
3. Mediator computes clusters and returns the results.

Distributed:
1. Parties agree on obfuscation parameters;
2. Parties cluster local data and share obfuscated results with mediator;
3. Mediator aggregates local results and returns to the parties;
4. Parties update centroids;
5. Repeat 2-4 until convergence.
Attacks on Privacy-Preserving Clustering

Goal: reconstruct original data given its obfuscated version

We study attacks on the mediator

For ADP and RSP we consider attacks from the literature

We assume that the SMC approach is secure under the honest-but-curious model with no collusion

Original data

Reconstruction, $\sigma = .01$

Reconstruction, $\sigma = .1$

Example of attack on ADP

(See details in the paper)
Evaluation Metrics

Privacy:
- Conditional privacy loss;
- Root mean squared error.

Clustering quality:
- Intra-cluster distance;
- Adjusted rand-score.

Computational performance:
- Running time;
- Communication.
Testbed and Data

10-16 node Amazon AWS EC2 cluster

All solutions implemented in Python

<table>
<thead>
<tr>
<th>name</th>
<th># objects</th>
<th># dimensions</th>
<th># clusters</th>
</tr>
</thead>
<tbody>
<tr>
<td>SYNTHETIC</td>
<td>50K</td>
<td>10</td>
<td>10</td>
</tr>
<tr>
<td>HEART</td>
<td>920</td>
<td>13</td>
<td>4</td>
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<tr>
<td>CANCER</td>
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<td>20</td>
<td>15</td>
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<tr>
<td>DIABETES</td>
<td>100K</td>
<td>12</td>
<td>12</td>
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<tr>
<td>GAS</td>
<td>320K</td>
<td>16</td>
<td>10</td>
</tr>
</tbody>
</table>

Table: Dataset statistics.
Privacy vs. Quality

Local+Centralized

Distributed

RSP outperforms ADP in most of the settings; ADP covers a broader privacy versus quality spectrum; Distributed approaches are more private than their centralized counterparts.
Privacy vs. Quality

Local+Centralized

Distributed

RSP often outperforms ADP (up to 1/2 privacy loss);

ADP is more flexible (centralized optimal for .6 privacy loss);

Distributed approaches are more private than their centralized counterparts.
Privacy vs. Quality vs. Performance

Local+Centralized

Distributed

Distributed trusted, ADP and RSP are very efficient. SMC requires 2 order of magnitude more time and communication.
Privacy vs. Quality vs. Performance

Local + Centralized

Distributed trusted, ADP and RSP are very efficient

SMC requires 2 orders of magnitude more time and communication
Scalability

Scalability results for SYNTHETIC dataset

Local, dist. trusted, ADP and RSP are highly scalable.

For centralized approaches, the mediator is a bottleneck.

For large databases, SMC outperforms the centralized methods.
Scalability

Scalability results for SYNTHETIC dataset

Local, dist. trusted, ADP and RSP scale linearly

For centralized approaches, the mediator is a bottleneck

For large data, SMC outperforms the centralized methods
Conclusions

We evaluated several privacy-preserving multi-party clustering strategies that differ in terms of:
- The computation model used (local, centralized, distributed);
- The type of mediator assumed (trusted and untrusted).

We studied three privacy-preserving techniques:
- Additive data perturbation;
- Random subspace projection;
- Secure multi-party computation.

Main findings:
- RSP outperforms ADP in most of the settings;
- ADP covers a broader privacy versus quality spectrum;
- Distributed approaches are scalable and more private than their centralized counterparts;
- SMC achieves high quality and privacy, but poor performance.
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