Improved Reconstruction Attacks on Encrypted Data Using Range Query Leakage

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Outsourcing Data with Search Capabilities

Client

Server
Outsourcing Data with Search Capabilities

Client → Data upload → Server
Outsourcing Data with Search Capabilities

Data upload
Search query
Matching records
For an **encrypted database management system**:

- **Data** = collection of records in a database.  
  *e.g. health records.*

- **Search query examples:**
  - find records with given value.  
    *e.g. patients aged 57.*
  - find records within a given range.  
    *e.g. patients aged 55-65.*
Adversaries:
- **Snapshot**: breaks into server, gets snapshot of memory.
- **Persistent**: corrupts server, sees all communication transcripts. Can be server itself.

Security goal = **privacy**.
→ Adversary learns as little as possible about the client’s data and queries.
• Structure-preserving encryption. Vulnerable to snapshot attackers.
Solutions

• **Structure-preserving encryption.**
  Vulnerable to *snapshot* attackers.

• **Second-generation schemes:**
  Aim to protect against *snapshot* and *persistent* attackers.
Solutions

• **Structure-preserving encryption.**
  Vulnerable to snapshot attackers.

• **Second-generation schemes:**
  Aim to protect against snapshot and persistent attackers.

• **Very active research topic.**
  
  [AKSX04], [BCLO09], [PKV+14], [BLR+15], [NKW15], [KKNO16], [LW16],
  [FVY+17], [SDY+17], [DP17], [HLK18], [PVC18], [MPC+18]…
Schemes Supporting Range Queries

Range = [40, 100]
Schemes Supporting Range Queries

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Schemes Supporting Range Queries

Range = [40, 100]

Client

Server

1 3
45 83

1 2 3 4
45 6 83 28
Most schemes leak set of matching records = access pattern leakage.
OPE, ORE schemes, POPE, [HK16], BlindSeer, [Lu12], [FJ+15], …
• Most schemes leak set of matching records = **access pattern** leakage.
  OPE, ORE schemes, POPE, [HK16], BlindSeer, [Lu12], [FJ+15], …

• Some schemes also leak #records below queried endpoints = **rank** leakage.
  FH-OPE, Lewi-Wu, Arx, Cipherbase, EncKV, …
Exploiting Leakage

- Most schemes prove that nothing more leaks than their leakage model allows. For example, leakage = access pattern + rank.

What can we really learn from this leakage?
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What can we really learn from this leakage?

Our goal: full reconstruction = recovering the exact value of every record.
Exploiting Leakage

• Most schemes prove that nothing more leaks than their leakage model allows. For example, leakage = access pattern + rank.

What can we really learn from this leakage?

• Our goal: **full reconstruction** = recovering the exact value of every record.

• [KKNO16]: $O(N^2 \log N)$ queries suffice for full reconstruction using only access pattern leakage!
  - where $N$ is the number of possible values (e.g. 125 for age in years).
Assumptions for our Analysis

- Data is **dense**: all values appear in at least one record.

- Queries are **uniformly distributed**.
  
  Our algorithms don’t actually care though – the assumption is for computing data upper bounds.
Our Main Results

- **Full reconstruction** with $O(N \cdot \log N)$ queries from access pattern leakage
  - in fact, $N \cdot (3 + \log N)$. 
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- **Approximate reconstruction** using an *auxiliary distribution* and access pattern + rank leakage.
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- **Approximate reconstruction** with relative accuracy $\epsilon$ with $O(N \cdot (\log \frac{1}{\epsilon}))$ queries.

- **Approximate reconstruction** using an auxiliary distribution and access pattern + rank leakage.
Full reconstruction
Assume $N = 7$ values, and 5 queries.

$M_i = \text{set of records matched by } i\text{-th query.}$
Step 1: Partitioning

\[ M_1 \]

\[ M_2 \]

\[ M_3 \]

\[ M_4 \]

\[ M_5 \]
Step 1: Partitioning

\[ M_1 \setminus (M_2 \cup M_3 \cup M_4) \quad \ldots \quad M_1 \cap M_3 \setminus (M_2 \cup M_4) \quad \ldots \]
Step 1: Partitioning

If there are $N$ minimal subsets → each of them correspond to a single value.
Step 2a: Finding an Endpoint

\[ M_1 \cup M_3 \text{ cover all but 1 minimal set} \]
Step 2a: Finding an Endpoint

\[ M_1 \cup M_3 \text{ cover all but 1 minimal set} \]

Endpoint!
Step 2a: Finding an Endpoint

\[ M_1 \cup M_3 \text{ cover all but 1 minimal set} \]

Endpoint!
Step 2b: Propagating

- Intersect
Step 2b: Propagating

- Intersect
- Trim
Step 2b: Propagating

- Intersect
- Trim
Step 2b: Propagating

- Intersect
- Trim

Next point!
Step 2b: Propagating

- Intersect
- Trim

Next point!
Step 2b: Propagating

- Intersect
- Trim
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- Intersect
- Trim
- Intersect
- Trim
• **Generic setting**: only access pattern leakage.
• **Partitioning**, then **sorting** steps.

• Expectation of #queries **sufficient** for reconstruction:
  \[ N \cdot (3 + \log N) \quad \text{for } N \geq 26 \]

• Expectation of #queries **necessary** for reconstruction:
  \[ \frac{1}{2} \cdot N \cdot \log N – O(N) \]
  
  for *any* algorithm.

• Our algorithm is **data-optimal**.
Reconstruction with Auxiliary Data + Rank Leakage
Auxiliary Data Attack with Rank Leakage

• Assume access pattern + rank leakage.
• Also assume an approximation to the distribution on values is known.
  “Auxiliary distribution”.
  From aggregate data, or from another reference source.
• We show experimentally that, under these assumptions, far fewer queries are needed.
Assume $N = 125$ values, and 2 queries.

$M_i$ = set of records matched by $i$-th query.
Partitioning and Matching

\[ M_1 \]

\[ M_2 \]
Partitioning and Matching
% records below 10%
Partitioning and Matching

% records below

10% 32%

$M_1$ $M_2$
Partitioning and Matching

% records below 10% 32% 77%

$M_1$ $M_2$
Partitioning and Matching

% records below

10%  32%  77%  85%

$M_1$  $M_2$
Partitioning and Matching

Matching with aux. distribution

Age 12

% records below

10% 32% 77% 85%

$M_1$ $M_2$
Partitioning and Matching

Matching with aux. distribution

<table>
<thead>
<tr>
<th>Age</th>
<th>% records below 10%</th>
<th>% records below 32%</th>
<th>% records below 77%</th>
<th>% records below 85%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>12</td>
<td>43</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Diagram showing two partitions $M_1$ and $M_2$.
Partitioning and Matching

Matching with aux. distribution

Age | % records below 10% | 32% | 77% | 85%
---|---------------------|-----|-----|-----
12 | 43                  | 60  |     |     

$M_1$ and $M_2$
Partitioning and Matching

% records below 10% 32% 77% 85%
Matching with aux. distribution
Age 12 43 60 72

$M_1$ $M_2$
Partitioning and Matching

Matching with aux. distribution

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<td></td>
</tr>
<tr>
<td>72</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Expectation: 19
Partitioning and Matching

Matching with aux. distribution

% records below
10%  32%  77%  85%

Matching with aux. distribution

Age
12  43  60  72

Expectation
19  50

Expectation
Partitioning and Matching

% records below 10% 32% 77% 85%

Matching with aux. distribution

Age 12 43 60 72

Expectation 19 50 65

\[ M_1 \]

\[ M_2 \]
Auxiliary Data Attack: Experimental Evaluation

• Ages, $N = 125$.
• Health records from US hospitals (NIS HCUP 2009).
• **Target**: age of individual hospitals' records.
• **Auxiliary data**: aggregate of 200 hospitals' records.
• **Measure of success**: proportion of records with value guessed within $\varepsilon$. 
Results with Imperfect Auxiliary Data
Conclusions
Reconstruction Attacks: Conclusions

<table>
<thead>
<tr>
<th>Attack</th>
<th>Leakage</th>
<th>Other req'ts</th>
<th>Suff. # queries</th>
</tr>
</thead>
<tbody>
<tr>
<td>KKNO16</td>
<td>AP</td>
<td>Density</td>
<td>(O(N^2 \log N))</td>
</tr>
<tr>
<td>Full</td>
<td>AP + rank</td>
<td>Density</td>
<td>(N \cdot (\log N + 2))</td>
</tr>
<tr>
<td></td>
<td>AP</td>
<td>Density</td>
<td>(N \cdot (\log N + 3))</td>
</tr>
<tr>
<td>(\varepsilon)-approx.</td>
<td>AP</td>
<td>Density</td>
<td>(5/4 N \cdot (\log 1/\varepsilon) + O(N))</td>
</tr>
<tr>
<td>Auxiliary</td>
<td>AP + rank</td>
<td>Auxiliary dist.</td>
<td>Experimental</td>
</tr>
</tbody>
</table>

- **Full reconstruction** \(\approx N \log N\) queries with only access pattern! Efficient, data-optimal algorithms + matching lower bound.

- For \(N = 125\):

  - 800 queries \(\rightarrow\) full reconstruction.
  - 25 queries \(\rightarrow\) majority of records within 5%, using auxiliary distribution + rank.
Reconstruction Attacks: Conclusions

• Many clever schemes have been designed, enabling range queries on encrypted data.
  OPE, ORE schemes, POPE, [HK16], BlindSeer, [Lu12], [FJKNRS15], FH-OPE, Lewi-Wu, Arx, Cipherbase, EncKV,…

• Second-generation schemes defeat the snapshot adversary (with caveats).

• But as our attacks show, no known scheme offers meaningful privacy vs. a persistent adversary (including server itself).

• More research needed!