Outline

Security requirements
Key concepts and tools
Differential privacy
Other security tools
Outline

Security requirements

Key concepts and tools

Differential privacy

Other security tools
Why Security & Privacy?
Why Security & Privacy?

Data is valuable & can cause harm if released
» Example: medical records, purchase history, internal company documents, etc

Data releases can’t usually be “undone”

Security policies can be complex
» Each user can only see data from their friends
» Analyst can only query aggregate data
» Users can ask to delete their derived data
Why Security & Privacy?

It’s the law! New regulations about user data:

- Mandatory encryption, access control, training

**EU GDPR, CA CCPA**: (2018)
- Users can ask to see & delete their data

**PCI DSS**: Payment Card Industry standard (2004)
- Required in contracts with MasterCard, etc
Consequence

Security and privacy must be baked into the design of data-intensive systems
» Often a key differentiator for products!
The Good News

**Declarative** interface to many data-intensive systems can enable powerful security features

» One of the “big ideas” in our class!

Example: System R’s access control on views

```
Tables                      SQL View
<p>| |</p>
<table>
<thead>
<tr>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>arbitrary SQL query</td>
</tr>
<tr>
<td>read</td>
</tr>
<tr>
<td>write</td>
</tr>
</tbody>
</table>

Users
```
Outline

Security requirements

Key concepts and tools

Differential privacy

Other security tools
Some Security Goals

Access Control: only the “right” users can perform various operations; typically relies on:
  » Authentication: a way to verify user identity (e.g. password)
  » Authorization: a way to specify what users may take what actions (e.g. file permissions)

Auditing: system records an incorruptible audit trail of who did each action
Some Security Goals

Confidentiality: data is inaccessible to external parties (often via cryptography)

Integrity: data can’t be modified by external parties

Privacy: only a limited amount of information about “individual” users can be learned
Clarifying These Goals

Say our goal was access control: only Matei can set CS 245 student grades on Axess.

What scenarios should Axess protect against?
Clarifying These Goals

Say our goal was **access control**: only Matei can set CS 245 student grades on Axess

What scenarios should Axess protect against?

1. Bobby T. (an evil student) logging into Axess as himself and being able to change grades
Clarifying These Goals

Say our goal was access control: only Matei can set CS 245 student grades on Axess

What scenarios should Axess protect against?

1. Bobby T. (an evil student) logging into Axess as himself and being able to change grades
2. Bobby sending hand-crafted network packets to Axess to change his grades
Clarifying These Goals

Say our goal was **access control**: only Matei can set CS 245 student grades on Axess

What scenarios should Axess protect against?

1. Bobby T. (an evil student) logging into Axess as himself and being able to change grades
2. Bobby sending hand-crafted network packets to Axess to change his grades
3. Bobby getting a job as a DB admin at Axess
Clarifying These Goals

Say our goal was access control: only Matei can set CS 245 student grades on Axess

What scenarios should Axess protect against?

1. Bobby T. (an evil student) logging into Axess as himself and being able to change grades
2. Bobby sending hand-crafted network packets to Axess to change his grades
3. Bobby getting a job as a DB admin at Axess
4. Bobby guessing Matei’s password
Clarifying These Goals

Say our goal was **access control**: only Matei can set CS 245 student grades on Axess

What scenarios should Axess protect against?

1. Bobby T. (an evil student) logging into Axess as himself and being able to change grades
2. Bobby sending hand-crafted network packets to Axess to change his grades
3. Bobby getting a job as a DB admin at Axess
4. Bobby guessing Matei’s password
5. Bobby blackmailing Matei to change his grade
Clarifying These Goals

Say our goal was **access control**: only Matei can set CS 245 student grades on Axess

What scenarios should Axess protect against?

1. Bobby T. (an evil student) logging into Axess as himself and being able to change grades
2. Bobby sending hand-crafted network packets to Axess to change his grades
3. Bobby getting a job as a DB admin at Axess
4. Bobby guessing Matei’s password
5. Bobby blackmailing Matei to change his grade
6. Bobby discovering a flaw in AES to do #2
Threat Models

To meaningfully reason about security, need a threat model: what adversaries may do
  » Same idea as failure models!

For example, in our Axess scenario, assume:
  » Adversaries only interact with Axess through its public API
  » No crypto algorithm or software bugs
  » No password theft

Implementing complex security policies can be hard even with these assumptions!
Threat Models

No useful threat model can cover everything

» Goal is to cover the most feasible scenarios for adversaries to increase the **cost** of attacks

Threat models also let us divide security tasks across different components

» E.g. auth system handles passwords, 2FA
Threat Models

A CRYPTO NERD'S IMAGINATION:

His laptop's encrypted. Let's build a million-dollar cluster to crack it.

Blast! Our evil plan is foiled!

WHAT WOULD ACTUALLY HAPPEN:

His laptop's encrypted. Drug him and hit him with this $5 wrench until he tells us the password.

GOT IT.
Useful Building Blocks

Encryption: encode data so that only parties with a key can efficiently decrypt

Cryptographic hash functions: hard to find items with a given hash (or collisions)

Secure channels (e.g. TLS): confidential, authenticated communication for 2 parties
Security Tools from DBMSs

First-class concept of users + *access control*

» Views as in System R, tables, etc

Secure channels for network *communication*

*Audit logs* for analysis

*Encrypt* data on-disk (perhaps at OS level)
Modern Tools for Security

Privacy metrics and enforcement thereof (e.g. differential privacy)

Computing on encrypted data (e.g. CryptDB)

Hardware-assisted security (e.g. enclaves)

Multi-party computation (e.g. secret sharing)
Threat Model

- Database software is working correctly
- Adversaries only access it through public API
- Adversaries have limited # of user accounts
Private statistics

SELECT AVG(income) FROM professors WHERE state="California"
Private statistics

Are aggregate statistics *more private* than individual data?

SELECT AVG(income) FROM professors WHERE state="California"

SELECT AVG(income) FROM professors WHERE name="Matei Zaharia"
Private statistics

Are aggregate statistics more private than individual data? No!

SELECT AVG(income) FROM professors WHERE state="California"

SELECT AVG(income) FROM professors WHERE name="Matei Zaharia"
Private statistics

Robust De-anonymization of Large Datasets
(How to Break Anonymity of the Netflix Prize Dataset)

Arvind Narayanan and Vitaly Shmatikov
The University of Texas at Austin
February 5, 2008

Abstract

We present a new class of statistical de-anonymization attacks against high-dimensional micro-data, such as individual preferences, recommendations, transaction records and so on. Our techniques are robust to perturbation in the data and tolerate some mistakes in the adversary’s background knowledge.

We apply our de-anonymization methodology to the Netflix Prize dataset, which contains anonymous movie ratings of 500,000 subscribers of Netflix, the world’s largest online movie rental service. We demonstrate that an adversary who knows only a little bit about an individual subscriber can easily identify this subscriber’s record in the dataset. Using the Internet Movie Database as the source of background knowledge, we successfully identified the Netflix records of known users, uncovering their apparent political preferences and other potentially sensitive information.

1 Introduction
Private statistics

Robust De-anonymization of Large Datasets

(How to

Resolving Individuals Contributing Trace Amounts of DNA to Highly Complex Mixtures Using High-Density SNP Genotyping Microarrays

Nils Homer1,2, Szabolcs Szelinger1, Margot Redman1, David Duggan1, Waibhav Tembe1, Jill Muehling1, John V. Pearson1, Dietrich A. Stephan1, Stanley F. Nelson2, David W. Craig1*

1 Translational Genomics Research Institute (TGen), Phoenix, Arizona, United States of America, 2 University of California Los Angeles, Los Angeles, California, United States of America

Abstract

We use high-density single nucleotide polymorphism (SNP) genotyping microarrays to demonstrate the ability to accurately and robustly determine whether individuals are in a complex genomic DNA mixture. We first develop a theoretical framework for detecting an individual’s presence within a mixture, then show, through simulations, the limits associated with our method, and finally demonstrate experimentally the identification of the presence of genomic DNA of specific individuals within a series of highly complex genomic mixtures, including mixtures where an individual contributes less than 0.1% of the total genomic DNA. These findings shift the perceived utility of SNPs for identifying individual trace contributors within a forensics mixture, and suggest future research efforts into assessing the viability of previously sub-optimal DNA sources due to sample contamination. These findings also suggest that composite statistics across cohorts, such as allele frequency or genotype counts, do not mask identity within genome-wide association studies. The implications of these findings are discussed.

1 Introduction


Editor: Peter M. Visscher, Queensland Institute of Medical Research, Australia

Received December 3, 2007; Accepted July 15, 2008; Published August 20, 2008
Idea: differential privacy

A *contract* for algorithms that output statistics
Idea: differential privacy

A *contract* for algorithms that output statistics

Intuition: the function is differentially private if removing or changing a data point does not change the output "too much"
Idea: differential privacy

A *contract* for algorithms that output statistics

Intuition: the function is differentially private if removing or changing a data point does not change the output "too much"

Intuition: plausible deniability
Idea: differential privacy

A contract for algorithms that output statistics

For $A$ and $B$ that differ in one element,

$$\Pr[M(A) \in S] \leq e^\varepsilon \Pr[M(B) \in S]$$
Idea: differential privacy

A *contract* for algorithms that output statistics

For $A$ and $B$ that differ in one element,

$$\Pr[M(A) \in S] \leq e^{\varepsilon} \Pr[M(B) \in S]$$

Randomized algorithm that computes statistic
Idea: differential privacy

A *contract* for algorithms that output statistics

For $A$ and $B$ that differ in *one element*,

$$\Pr[M(A) \in S] \leq e^\varepsilon \Pr[M(B) \in S]$$

Any subset of possible outcomes
Idea: differential privacy

A *contract* for algorithms that output statistics

For \( A \) and \( B \) that differ in **one element**,

\[
\Pr[M(A) \in S] \leq e^\varepsilon \Pr[M(B) \in S]
\]

Privacy parameter

Smaller \( \varepsilon \) \( \sim \) more privacy, less accuracy
What Does It Mean?

Say an adversary runs some query and observes a result \( X \).

Adversary had some set of results, \( S \), that lets them infer something about Matei if \( X \in S \).

Then:

\[
\Pr[X \in S | \text{Matei } \in \text{DB}] \leq e^{\varepsilon} \Pr[X \in S | \text{Matei } \notin \text{DB}]
\]
\[
\Pr[X \notin S | \text{Matei } \in \text{DB}] \leq e^{\varepsilon} \Pr[X \notin S | \text{Matei } \notin \text{DB}]
\]

Similar outcomes whether or not Matei in DB.
What Does It Mean?

Private information is noisy. Can we determine anything useful?
What Does It Mean?

Private information is noisy. Can we determine anything useful?

Query:

```
SELECT COUNT(*) FROM patients WHERE causeOfDeath = ...
```

Assume $\varepsilon=0.1$
What Does It Mean?
What Does It Mean?

![Bar chart showing the number of deaths caused by different causes: accident, aliens, and heart attack. The chart compares the ground truth and private data.](chart.png)
What Does It Mean?  

With enough base signal, DP can still give useful information!
Side Information

Consider the following query:

```
SELECT AVG(income) FROM professors WHERE state="CA"
```
Consider the following query:

SELECT AVG(income) FROM professors WHERE state="CA"

What if adversary knows: 
"Matei makes $100k more than the average professor in CA"
Side Information

Consider the following query:

SELECT AVG(income) FROM professors WHERE state="CA"

What if adversary knows: 
"Matei makes $100k more than the average professor in CA"

Equally bad for Matei whether or not he personally participates in DB!
Some Nice Properties of Differential Privacy

**Composition:** can reason about the privacy effect of multiple (even dependent) queries

Let queries $M_i$ each provide $\varepsilon_i$-differential privacy; then the set of queries $\{M_i\}$ provides $\sum_i \varepsilon_i$-differential privacy

Proof:

$$\Pr[\forall i M_i(A) = r_i] \leq e^{(\varepsilon_1 + \ldots + \varepsilon_n) |A \oplus B|} \Pr[\forall i M_i(B) = r_i]$$

Adversary’s ability to distinguish DBs A & B grows in a bounded way with each query
Some Nice Properties of Differential Privacy

Parallel composition: even better bounds if queries are on disjoint subsets (e.g., histograms)

Let $M_i$ each provide $\varepsilon$-differential privacy and read disjoint subsets of the data $D_i$; then the set of queries $\{M_i\}$ provides $\varepsilon$-differential privacy

Example: query both average patient age in CA and average patient age in NY
Some Nice Properties of Differential Privacy

Easy to compute: can use known results for various operators, then compose for a query
» Enables systems to automatically compute privacy bounds given declarative queries!
Disadvantages of Differential Privacy
Disadvantages of Differential Privacy

Each user can only make a limited number of queries (more precisely, limited total $\varepsilon$)
  » Their $\varepsilon$ grows with each query and can’t shrink
  » Have to specify how much $\varepsilon$ to use

How to set $\varepsilon$ in practice?
  » Apple system: 2? 4? 16?
  » NBER paper: 8?
  » Hard to tell what various values mean, though there is a nice Bayesian interpretation
Disadvantages of Differential Privacy

Each user can only make a limited number of queries (more precisely, limited total $\varepsilon$)

- Apple system: 2? 4? 16?
- NBER paper: 8?
- Hard to tell what various values mean, though there is a nice Bayesian interpretation

---

Changes to the Census Could Make Small Towns Disappear

By Gus Wezerek and David Van Riper
FEB. 6, 2020
Computing Differential Privacy Bounds

Let’s start with COUNT aggregates:

```
SELECT COUNT(*) FROM A
```

The randomized algorithm $M(A)$ that returns $|A| + \text{Laplace}(1/\epsilon)$ is $\epsilon$-differentially private.

Laplace($b$) distribution:

$$p(x) = \frac{1}{2b} e^{-|x|/b}$$

Mean: 0
Variance: $2b^2$
Computing Differential Privacy Bounds

Let’s start with COUNT aggregates:

```
SELECT COUNT(*) FROM A
```

The randomized algorithm $M(A)$ that returns $|A| + \text{Laplace}(1/\epsilon)$ is $\epsilon$-differentially private.
Computing Differential Privacy Bounds

What about AVERAGE aggregates:
SELECT AVERAGE(x) FROM A
Computing Differential Privacy Bounds

What about AVERAGE aggregates:
SELECT AVERAGE(x) FROM A

How much can one element of A affect result?
  » In general case, unboundedly much! No privacy
    • SELECT AVG(wealth) WHERE city=“Omaha, NE”
  » If x ∈ [0,m] for all x in A, then by at most m
    • Adding Laplace(m/ε) noise is ε-differentially private

Paper bounds AVG, SUM for values x ∈ [-1,1]
Computing Differential Privacy Bounds

General notion to capture the impact of one element: sensitivity

Sensitivity of a function $f: U \rightarrow \mathbb{R}$ on sets is

$$\Delta f = \max_{A,B \in U \text{ differ in 1 element}} |f(A) - f(B)|$$
Sensitivity Examples

f(A) = |A|  

f(A) = sum(A), x ∈ [0,m] ∀ x ∈ A  

f(A) = avg(A), x ∈ [0,m] ∀ x ∈ A  

f(A) = |{x ∈ A | x is male}|  

f(A) = |A⨝B|  

f(A) = |A⨝B|, each key has ≤ k matches
Multi-dimensional Sensitivity

Can also define sensitivity for functions that return multiple numerical results:

Sensitivity of a function $f: U \rightarrow \mathbb{R}^d$ on sets is

$$\Delta f = \max_{A, B \in U \text{ differ in 1 element}} \|f(A) - f(B)\|_1$$

Example: $f$ fits a linear model to the data...
Computing Differential Privacy Bounds

How do we reason about functions involving cardinality (e.g. GROUP BY . . . )?
Computing Differential Privacy Bounds

How do we reason about functions involving cardinality (e.g. GROUP BY...)?

Concept introduced in PINQ: stability
Computing Differential Privacy Bounds

Concept introduced in PINQ: stability

A function $T$ on sets is $c$-stable if for any two input sets $A$ and $B$,

$$|T(A) \oplus T(B)| \leq c |A \oplus B|$$

PINQ’s approach: let user do any # of set ops; compute their stability; then let them do one aggregate op and compute its sensitivity
Stability Examples

\[ T(A) = \sigma_{\text{predicate}}(A) \]  \(\text{("Where")}\)  

\[ T(A) = \pi_{\text{exprs}}(A) \]  \(\text{("Select")}\)  

\[ T(A, B) = A \cup B \]  

\[ T(A) = \text{GroupBy}(A, \text{expr}) \]  \(\text{(returns 1 record/group)}\)  

\[ T(A) = A \bowtie B \text{ limited to at most 1 match per key} \]
Partition Operator

Partition(dataset, key_list) returns a set of IQueryables: one for each key in your list

» User provides the desired keys in advance (e.g. “CA” or “NY”); can’t use to discover keys
» Lets PINQ use parallel composition rule since the sets returned are all disjoint

Stability = 1
Analyzing Queries in PINQ

User calls multiple set transformation ops and finally one aggregation/result op

» Transformations are lazy; can’t see result

PINQ computes stability of set ops and multiplies by sensitivity of each aggregate to get total sensitivity

User provides an $\epsilon$ to aggregate; PINQ adds noise proportional to sensitivity/$\epsilon$
Putting It All Together

**Example 5** Measuring query frequencies in PINQ.

```csharp
// prepare data with privacy budget
var agent = new PINQAgentBudget(1.0);
var data = new PINQueryable<string>(rawdata, agent);

// break out fields, filter by query, group by IP
var users = data.Select(line => line.Split(',', ',')).
    Where(fields => fields[20] == args[0])
    .GroupBy(fields => fields[0]);

// output the count to the screen, or anywhere else
Console.WriteLine(args[0] + ": " + users.NoisyCount(0.1));
```

**cricket: 127123.313**
Putting It All Together

Example 7 Transforming IP addresses to coordinates.

```csharp
// ... within the per-query loop, from before ...

// use the searches for query, group by IP address
var users = parts[query].GroupBy(fields => fields[0]);

// extract IP address from each group, and match
var coords = users.Join(iplatlon,
    group => group.Key,
    entry => entry[0],
    (glist, elist) => elist.First());
```
Uses of Differential Privacy

Statistics collection about iOS features

“Randomized response”: clients add noise to data they send instead of relying on provider

Research systems that use DP to measure security (e.g. Vuvuzela messaging)
Outline

Security requirements

Key concepts and tools

Differential privacy

Other security tools
Computing on Encrypted Data

**Threat model:** adversary has access to the database server we run on (e.g. in cloud)

**Idea:** some encryption schemes allow computing on data without decrypting it:

\[ f_{\text{enc}}(\text{Enc}(X)) = \text{Enc}(f(X)) \]

Usually very expensive, but can be done efficiently for some functions f!
Example Systems

CryptDB, Mylar (MIT research projects)

Encrypted BigQuery (CryptDB on BigQuery)

Leverage properties of SQL to come up with efficient encryption schemes & query plans
Example Schemes

Equality checks with deterministic encryption

SELECT * FROM table WHERE state=“CA”

Encrypt “state” column

SELECT * FROM table WHERE state=“XAYDS9”
Example Schemes

Equality checks with deterministic encryption

SELECT * FROM table WHERE state="CA"

SELECT * FROM table WHERE state="XAYDS9"

Potential challenges with this scheme:
  » Adversary can see relative frequency of keys
  » Adversary sees which keys are accessed on each query (e.g. Matei logs in → CA key read)
Other Encryption Schemes

Additive homomorphic encryption:

\[ \text{Enc}(A + B) = \text{Enc}(A) \oplus \text{Enc}(B) \]

Fully homomorphic encryption:

\[ \text{Enc}(f(A)) = f_{\text{enc}}(\text{Enc}(A)) \]

Order-preserving encryption:

if \( A < B \) then \( \text{Enc}(A) < \text{Enc}(B) \)

Possible but very expensive (10^8 or more overhead)
Hardware Enclaves

**Threat model:** adversary has access to the database server we run on (e.g. in cloud) but can’t tamper with hardware

**Idea:** CPU provides an “enclave” that can provably run some code isolated from the OS

» Enclaves returns a certificate signed by CPU maker that it ran code C on argument A
Hardware Enclaves in Practice

Already present in all Intel CPUs (Intel SGX), and many Apple custom chips (T2, etc)

Initial applications were digital rights mgmt., secure boot, secure login
  » Protect even against a compromised OS

Some research systems explored using these for data analytics: Opaque, ObliDB, others
Databases + Enclaves

1. Store data encrypted with an encryption scheme that leaks nothing (randomized)

2. With each query, user includes a public key $k_q$ to encrypt the result with

3. Database runs a function $f$ in the enclave that does query and encrypts result with $k_q$

4. User can verify $f$ ran, DB can’t see result!

Performance is fast too (normal CPU speed)!
Are Enclaves Enough to Secure Against Non-HW Adversaries?
Are Enclaves Enough to Secure Against Non-HW Adversaries?

Not quite! adversary can still learn info by observing **access patterns** to RAM or **timing**

» Similar to some attacks on encrypted DBs

**Oblivious algorithms** can help prevent this but add more computational cost

» Oblivious = same access pattern regardless of underlying data, query result, etc
Multi-Party Computation (MPC)

**Threat model:** participants $p_1, \ldots, p_n$ want to compute some joint function $f$ of their data but don’t trust each other

» E.g. patient stats across 2 hospitals

**Idea:** protocols that compute $f$ without revealing anything else to participants

» Like with encryption, general computations are possible but expensive
Example: Secret Sharing

Users want to store a secret value $x$ among $n$ servers, but doesn’t fully trust them
  » E.g. the servers are public clouds… what if one gets hacked?

Idea: split $x$ into “shares” $x_i$ so that all shares are needed to recover $x$

Additive secret sharing: $x = \text{integer mod } P$, $x_i$ are random integers so $\sum x_i = x$
Secret Sharing Example

$x_1 = 3 \pmod{10}$

$x_2 = 8 \pmod{10}$

$x_2 = 4 \pmod{10}$

Servers

3 + 8 + 4 = 5 \pmod{10}

Note: performance is quite fast (just additions)
Function Secret Sharing

Recent result that allows sharing some functions too (keeping queries private)

Splinter (optional paper): uses FSS to run private SQL queries on public data like Google Maps

Parametrized query:
```
SELECT TOP 10 restaurant
WHERE city = ? AND cuisine = ?
ORDER BY rating
```
Lineage Tracking and Retraction

Goal: keep track of which data records were derived from an individual input record
  » Facilitate removing a user’s data in GDPR, verifying compliance, etc

Some real systems provide this already at low granularity, but could be baked into DB
Summary

Security and data privacy are essential concerns for data-intensive systems

Threat models are a systematic way to measure security and reason about designs

Many nice theoretical tools exist to reason about security needs of relational & math ops
  » Build on declarative and relational APIs!