Privacy Preserving Measurement

Eric Rescorla
ekr@rtfm.com

November 6, 2021

Overview

- Measurement scenarios
- Anonymous measurement
- MPC-based privacy-preserving measurement techniques
- Technical architecture

Many situations where we want to learn about people

- Public research (e.g., the census)
  - Demographics
  - Income
  - Medical issues
- Product development
  - Which features do they use/don't use?
  - How much do they use them?
  - Where/why are products failing?
- Behavioral measurements
  - Discovering new Web sites
  - Which information are people most interested in?

This information is very useful

- But can be very sensitive
  - Medical issues, income, sexual orientation, etc.
- Even “less” sensitive data can be very revealing
  - Especially when you put a lot of “less” sensitive data together


Feb 16, 2012, 11:02am EST

How Target Figured Out A Teen Girl Was Pregnant Before Her Father Did

Kashmir Hill Former Staff
Tech
Welcome to The Not-So Private Parts where technology & privacy collide

Follow

What do we really want to measure?

- Mostly we want *aggregates*
  - What is the distribution of people's income?
  - What is relationship between income and height?
  - What are the most popular Web sites?
- Need to slice the data multiple ways
  - Just look at a given region
  - Compare two variables
- Individual values are neither necessary nor useful
  - As long as we can compute the aggregates

Motivating Use Case: Broken Certificates

- Firefox was seeing mysterious certificate failures in the field
- Very hard to diagnose
    - We just see counts of failures
    - Didn't have copies of certificates or CRLs so hard to reproduce
- Much easier with a reproduction case

Motivating Use Case: Web Site Breakage

- Web compatibility is a big problem
  - Some sites will not render properly in some browsers
  - Big problem for smaller browsers like Safari and Firefox
  - Only a small fraction gets reported
- Often we can detect breakage on the client
  - People hit reload or disable tracking protection
  - API errors
  - Call setup failures in WebRTC
- No way to learn about it
  - We need the URL so we can fix it
  - But browsing history is sensitive
- Problem statement: collect the URLs with the most breakage

Preview of Other Use Cases

- Measuring failing certificates
- Advertising
  - Conversion measurement
  - Ad display measurement
- COVID Exposure notification

Measurement Types

- Simple aggregates (mean, median, sum, histograms...)
- Relationships between multiple values (correlation, OLS, ...)
- Common strings ("heavy hitters")

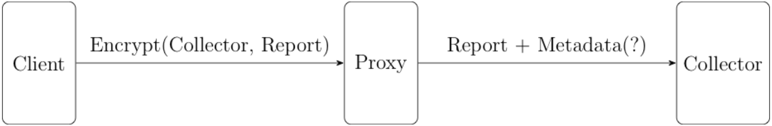
Privacy Threats

- Tying sensitive data directly to identifying information
  - Directly via user identifiers (E-mail, cookies, etc.)
  - Indirectly via metadata (IP address, E.164 number, etc.)
- Collecting sensitive data along with non-sensitive identifying information
  - Example: (birthday, zip code, initials) $\rightarrow$ income

It was found that 87% (216 million of 248 million) of the population in the United States had reported characteristics that likely made them unique based only on 5-digit ZIP, gender, date of birth.
— Sweeney, 2014 [Swe00]

Anonymized Data Collection

- Basic idea: collect user information without identifiers
- Practically speaking
  - Strip direct identifiers on the client side
  - Strip metadata using a proxy



- Example technologies:
  - Connection-level proxies (IPsec, RFC 2817 CONNECT, MASQUE)
  - Application-level proxies (OHAI)

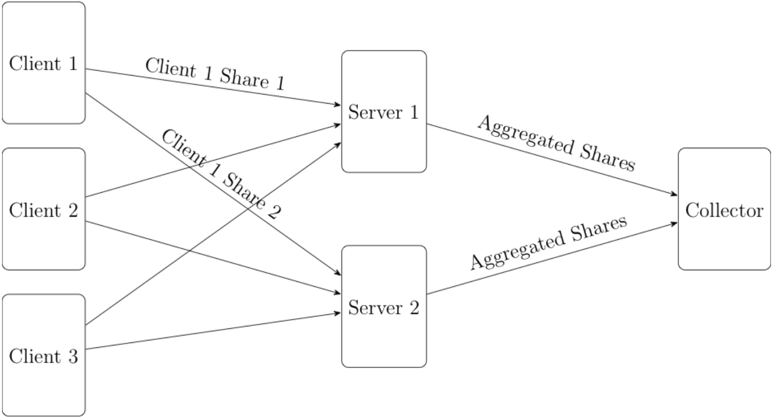
Good Use Cases for Anonymization

- Boosting the privacy of semi-sensitive data
  - Example: existing browser Telemetry is done with no privacy
- Individual values where you don't need to "dig into" the data
- Freeform data
  - E.g., JSON blobs
- Anything that needs an answer
  - DNS requests
  - Safe Browsing queries

Bad Use Cases for Anonymization

- High dimensionality data
  - Multiple variables that need to be reported together
  - When you want to look at subgroups
  - Any time you want to do correlation/regression
  - *Anonymized data needs to be disaggregated to prevent de-anonymization*
- Collecting common values
  - The "top N" values
  - Only values common to $> N$ users
  - *Anonymized data collects every value and depends on reporting only common values*

Cryptography to the Rescue



- Split data between two servers
- Each server computes aggregated shares
- Aggregate shares combined to produce final value

Example: Prio [CGB17]

- Useful for computing numeric aggregates (sum, mean, etc.)
- Each client i holds a value x_i
  - Generates random $R_i \leftarrow \mathbb{F}_p$
  - Sends $x_i - R_i (mod p)$ to server 1
  - Sends R_i to server 2
- Each server adds up their shares
  - Server 1: $\sum_i x_i - R_i$
  - Server 2: $\sum_i R_i$
- Now add these up:
  $\sum_i x_i - R_i + \sum_i R_i = \sum_i x_i + \sum_i R_i - \sum_i R_i = \sum_i x_i$

What else can Prio compute?

Arithmetic mean	$\sum_i x_i/i$
Product	$exp(\sum_i log(x_i))$
Geometric mean	From product
Variance and stddeviation	From $\sum_i x_i$ and $\sum_i (x_i)^2$
Boolean OR, AND	...
MIN, MAX	...
Ordinarily least squares (OLS)	...

The trick is finding the right encoding

What about bogus data?

- Plausible but false
  - "I am 180cm tall" when I am actually 175cm
  - A problem with any surveying technique
  - We just live with them
- Completely ridiculous
  - "I am 1km tall" (or worse, "I am -1km tall")
  - Easy to remove with standard systems by filtering
    - ... but with Prio the data is encrypted
- Solution: each submission comes with a zero-knowledge proof of validity
  - "This height report is between 100 and 200cm"
  - Servers work together to validate the proof
  - Only aggregate submissions with valid proofs

Heavy Hitters [BBCG+21]

- Each client submits a string (e.g., a URL)
  - Report the N most frequent strings
- Servers jointly can compute the number of strings with prefix p
  - Can use binary search to compute the most common strings
  - "How many strings have prefix $p||0$ versus $p||1$

Subset Queries

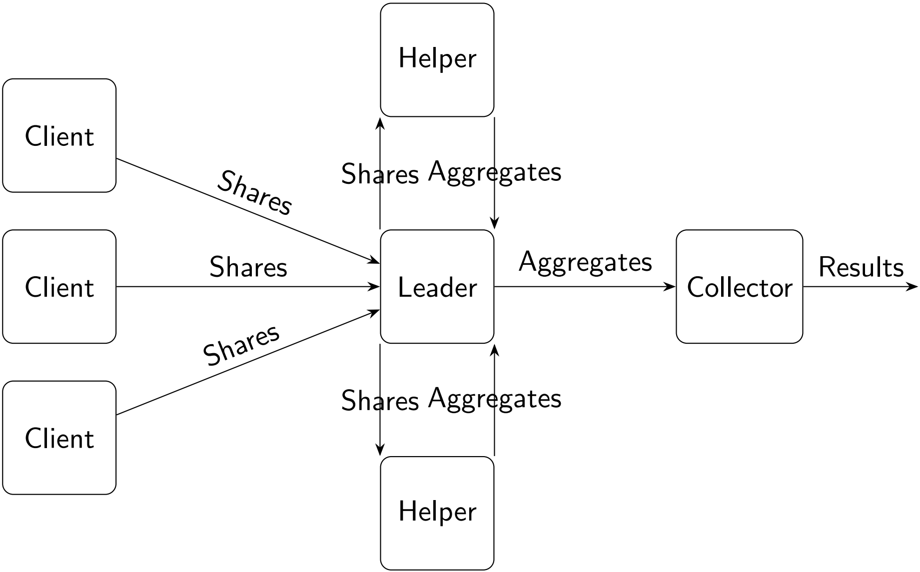
- Submissions can be tagged with demographic data
  - Example: (birthday, zip code, initials) $\rightarrow$ Encrypted(income)
  - This is safe because the sensitive information is encrypted
  - Servers can then compute aggregates over subsets
- Repeated queries can be used to determine individual values
  - Querying for S and $S \setminus I$ reveals I's value
  - Defenses
    - Minimum batch size
    - Anti-replay
    - Differential privacy randomization

Privacy Preserving Measurement Protocol

draft-gpew-priv-ppm-00

- A generic protocol for privacy-preserving measurement
  - Compatible with multiple cryptographic algorithms ("verifiable distributed aggregation functions")
- Build on top of HTTPS
  - Easy to implement with existing services infrastructure

PPM System Architecture



Questions?

Dan Boneh, Elette Boyle, Henry Corrigan-Gibbs, Niv Gilboa, and Yuval Ishai.
Lightweight techniques for private heavy hitters.
Cryptology ePrint Archive, Report 2021/017, 2021.
https://eprint.iacr.org/2021/017.

Henry Corrigan-Gibbs and Dan Boneh.
Prio: Private, robust, and scalable computation of aggregate statistics.
In *14th USENIX Symposium on Networked Systems Design and Implementation (NSDI 17)*, pages 259–282, Boston, MA, March 2017. USENIX Association.

Latanya Sweeney.
Simple demographics often identify people uniquely.
Health (San Francisco), 671(2000):1–34, 2000.