

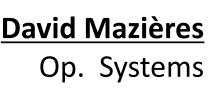
Cryptography for IoT

Dan Boneh
Stanford University

... but first: Computer Security at Stanford



<u>Alex Aiken</u> software analysis





<u>Dan Boneh</u> applied Crypto, crypto currencies

Phil LevisIoT Security



Matei Zaharia security and big data

John Mitchell protocol design, online ed.



<u>Dawson Engler</u> automated bug finding

Mendel Rosenblum VM's in security



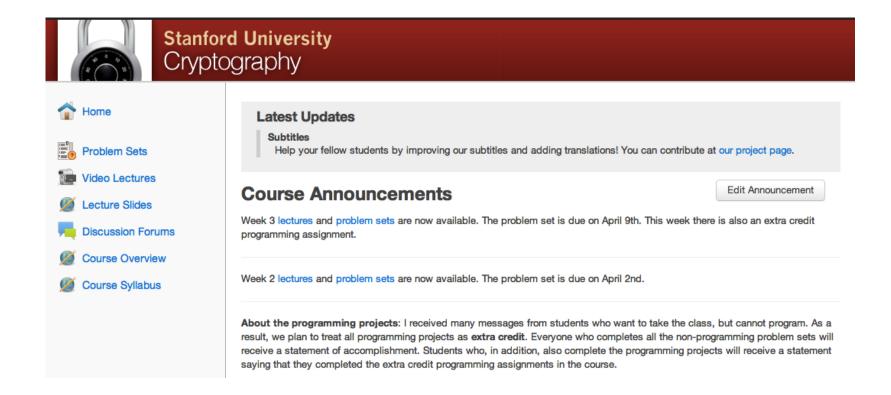
Courses

- Courses:
 - CS55N (freshmen seminar): ten ideas in computer security
 - CS155: Computer Security
 - CS251: Crypto currencies and blockchain technologies
 - CS255: Intro to Crypto
 - CS259: Security analysis of network protocols
 - CS355: Graduate course in cryptography

Stanford Advanced Computer Security Certificate http://scpd.stanford.edu/computerSecurity/

Online Courses

//www.coursera.org/learn/crypto



Course open to the public

Free Book Draft

A Graduate Course in Applied Cryptography

Dan Boneh and Victor Shoup

Free at: //cryptobook.us

Please send us comments

Multiparty computation (MPC) and SGX

MPC for genomic data analysis

[Jagadeesh, Wu, Birgmeier, Boneh, Bejerano, Science 2017]

What genes causes a specific disorder?

$$V_1$$
:

 $\begin{bmatrix}
 0 & 1 & 0 & 2 & 0 & 1 \\
 1 & 0 & 1 & 2 & 0 & 1 \\
 2 & 0 & 0 & 2 & 1 & 1 \\
 0 & 0 & 1 & 2 & 0 & 1
 \end{bmatrix}$



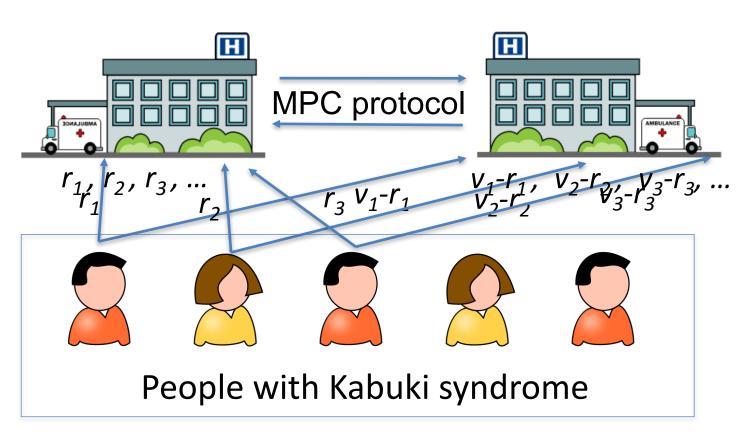
People with Kabuki syndrome

Each has 211 to 374 rare genes out of ≈20,000 genes

Patient i: vector v_i of dim 20,000 that is 0 for normal genes

MPC for genomic data analysis

[Jagadeesh, Wu, Birgmeier, Boneh, Bejerano, 2017]

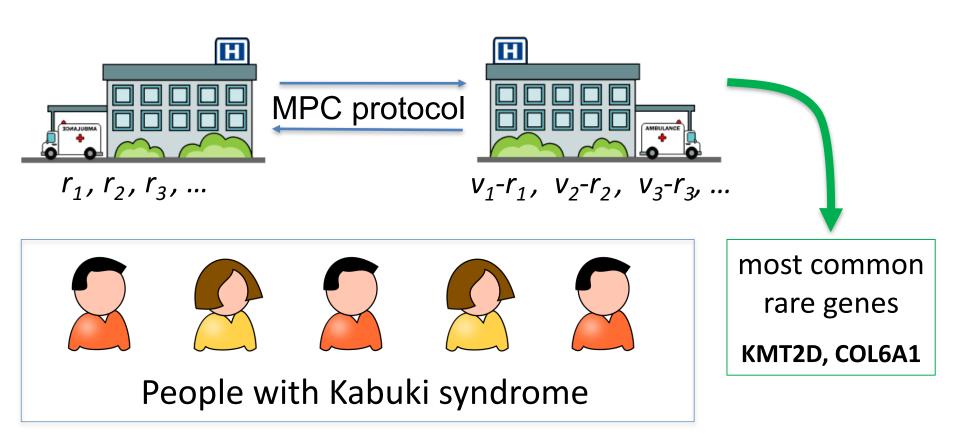


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MPC for genomic data analysis

[Jagadeesh, Wu, Birgmeier, Boneh, Bejerano, 2017]

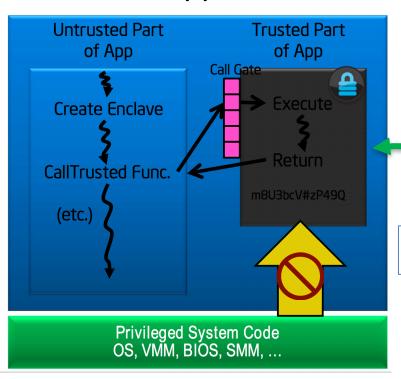


Nothing else is revealed about the individual genomes!!

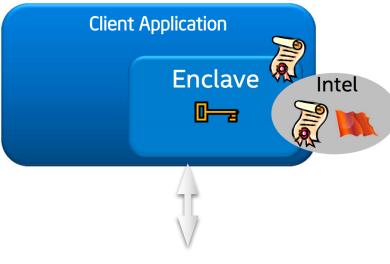
Can we do this with Intel's SGX?

Enclave

Enclave Application



Remote Attestation



Remote Platform



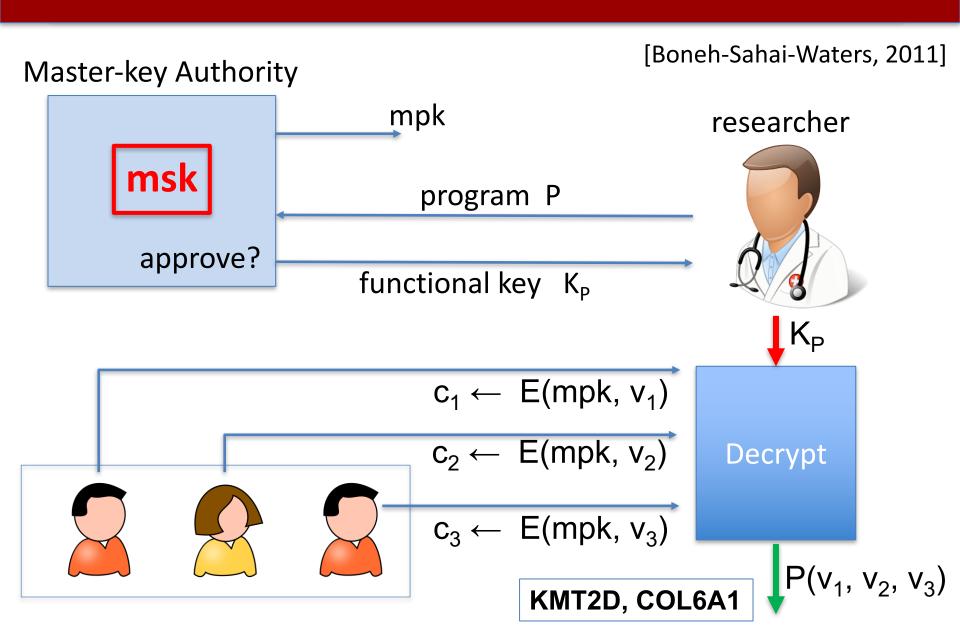
Source: ISCA 2015 tutorial slides for Intel SGX

Iron: Functional encryption and obfuscation using Intel SGX

Ben Fisch, Dhinakaran Vinayagamurthy,
Dan Boneh, Sergey Gorbunov

In proc. ACM CCS 2017

Functional Encryption



Functional Encryption

[Boneh-Sahai-Waters, 2011]

Why is functional encryption hard? no interaction during decryption can't use MPC techniques

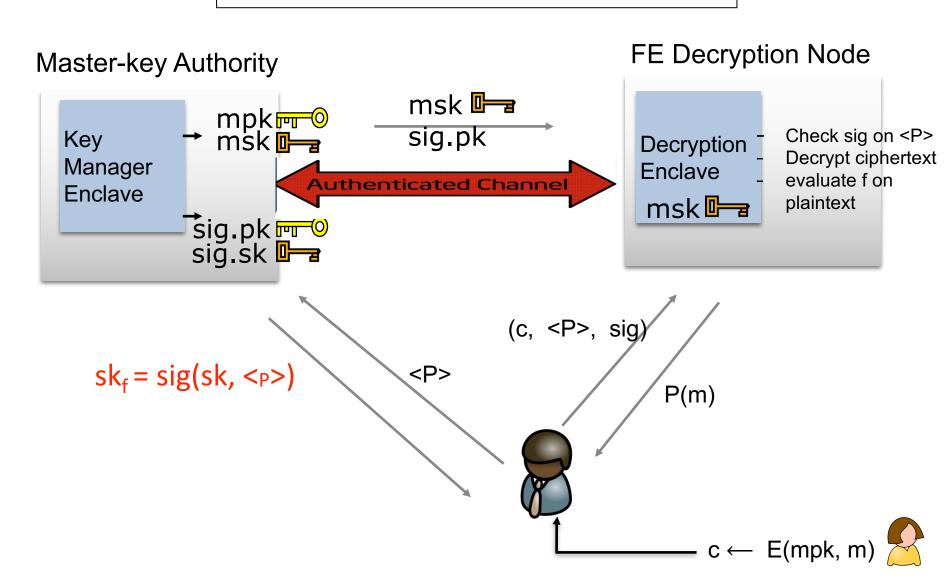
researcher $c_1 \leftarrow E(mpk, v_1)$ $c_2 \leftarrow E(mpk, v_2)$ Decrypt

Satisfy regulators?

$$c_3 \leftarrow E(mpk, v_3)$$

SGX Functional Encryption: approach

mpk: multi-input func. enc. public key



But not so simple ...

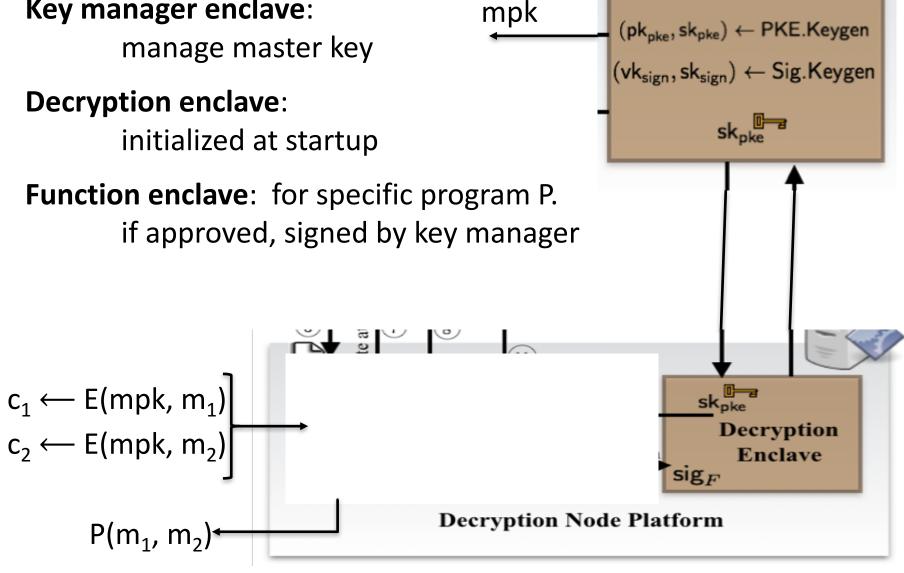
 Enclave memory access pattern leaks and can break FE security

- How to represent the program P:
 - Cannot move code into enclave after EINIT
 - Difficult to safely implement interpreter in enclave: performance and memory access pattern leak

Side channel attacks (timing, power)

Iron architecture

Key manager enclave:



Key Manager Enclave

Security

Formally model the SGX HW interface:

Setup, Load, Run, Run&Report, Run&Quote, ReportVerify, QuoteVerify

Builds on HW security models of:

Pass et. al. [PST'17], Bahmani et. al. [BBB+'16]

 MIFE simulation-based security, assuming: adversary cannot distinguish black-box HW interface and real SGX

Side-channel atacks

Security proof does not capture side channel attacks on SGX

- Cache-timing attacks [CD16] leak memory access patterns at cache-line granularity
- Page-fault attacks [XCP15] leak memory access patterns at 4KB page granularity
- Branch shadowing attacks [LSG+16] can directly view branch history (saved for pipeline branch prediction)

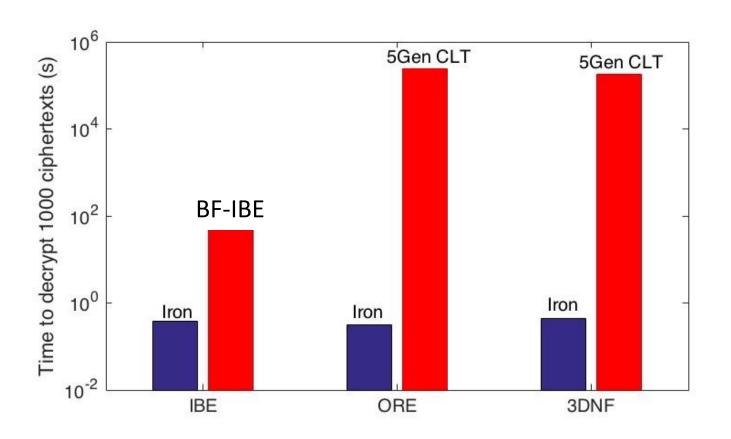
DEFENSE: only sign function enclaves whose memory access pattern is independent of sensitive data (e.g. ORAM based)

Implementation and Evaluation

C++ using the Intel(R) SGX SDK 1.6 for Windows
 Intel Skylake i7-6700, 3.40 GHz, 8 GiB RAM,
 Windows Server 2012 R2 Standard

• Function enclave implementation is data-oblivious to resist side-channels

Comparing Iron to cryptographic constructions



Private data aggregation

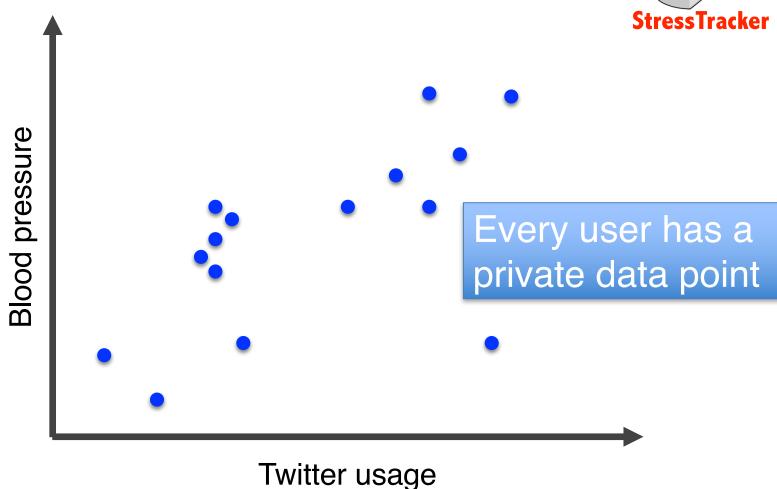
Prio: Private, Robust, and Efficient Computation of Aggregate Statistics

Joint work with Henry Corrigan-Gibbs

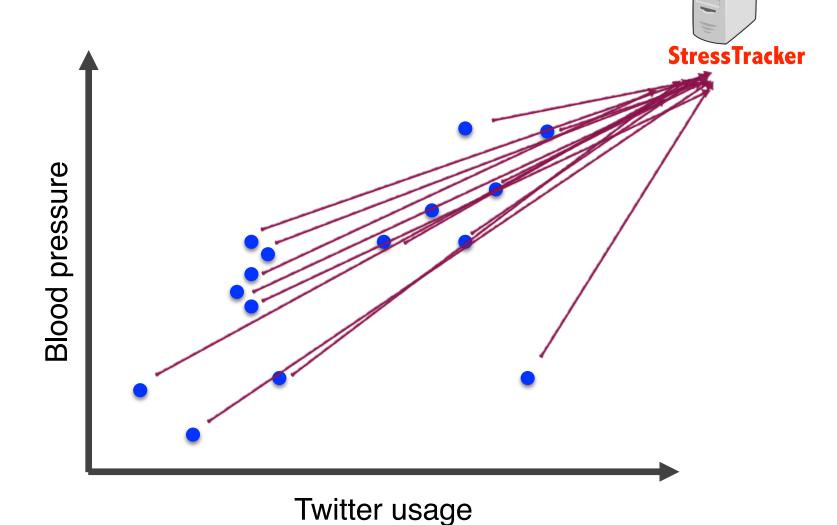
NSDI 2017

Today: Non-private aggregation

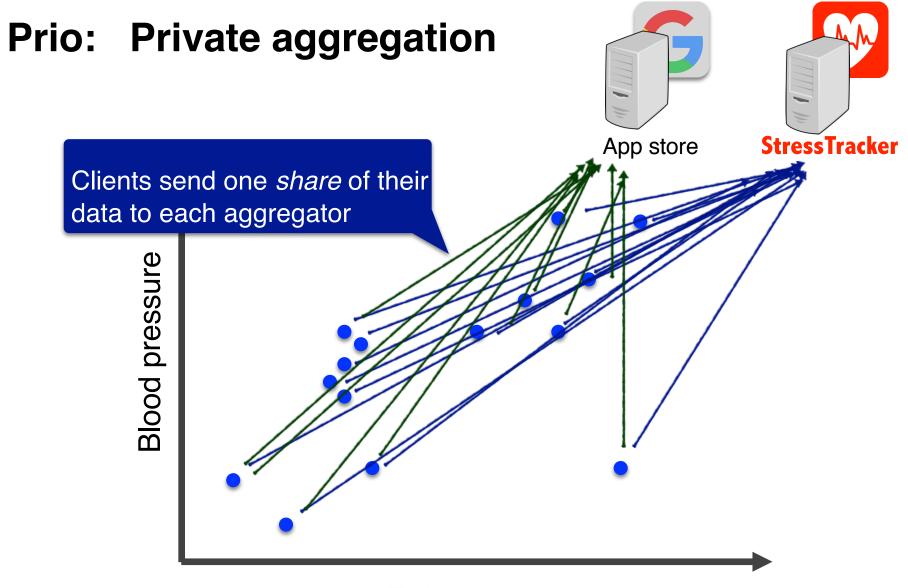




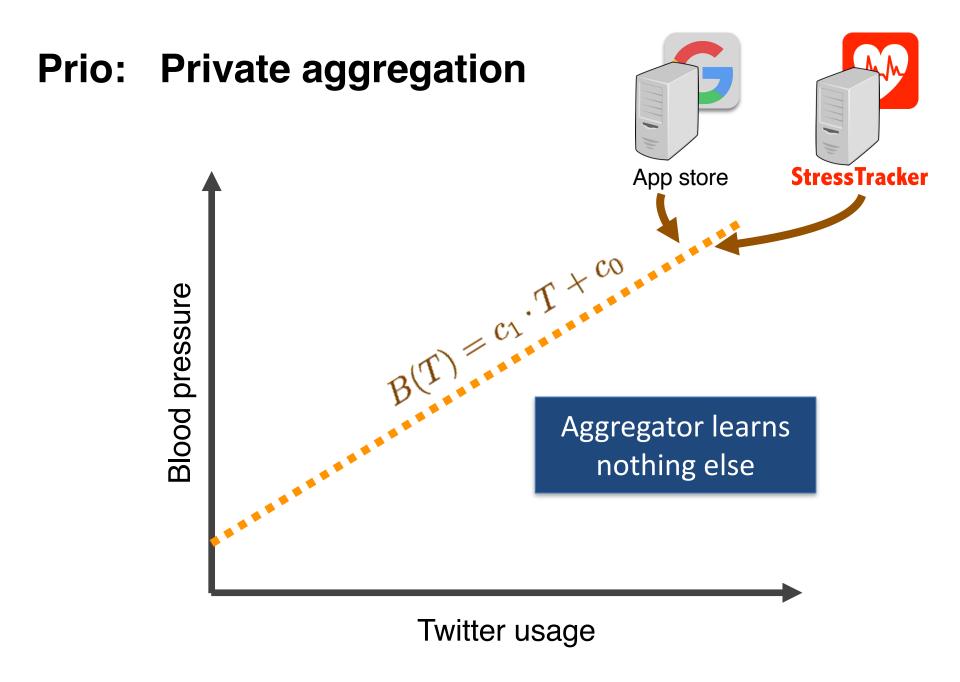
Today: Non-private aggregation

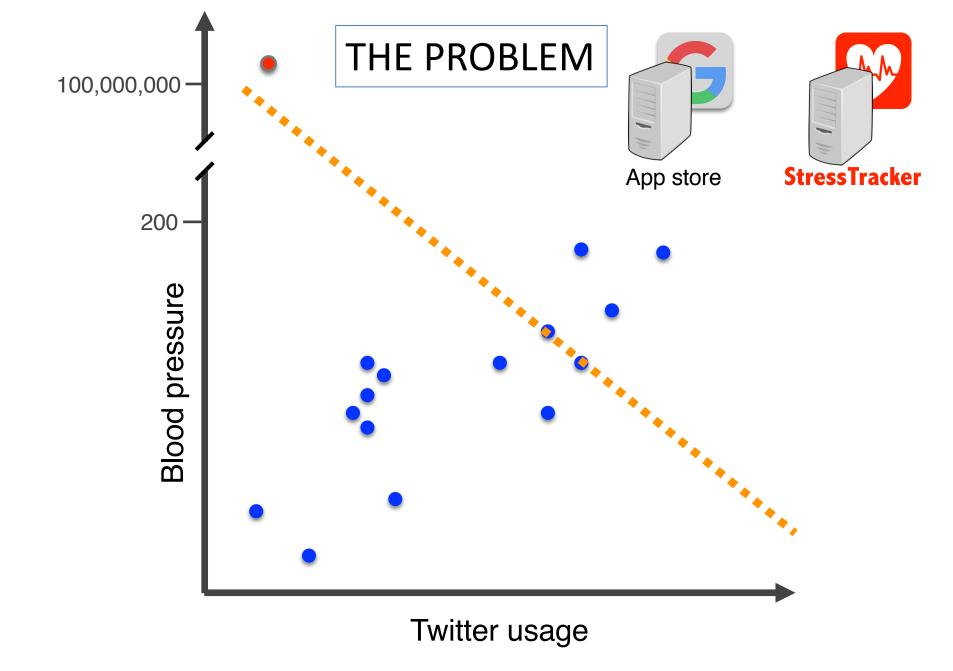


Today: Non-private aggregation StressTracker Blood pressure The app provider learns more than it needs Twitter usage



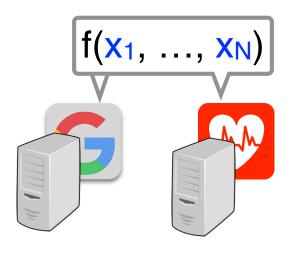
Twitter usage





Private aggregation





Exact correctness: if all servers are honest they learn $f(x_1,...,x_n)$

Privacy: if one server is honest they learn <u>only</u> $f(x_1,...,x_n)$

Robustness: malicious clients have bounded influence

Scalable: no public-key crypto (other than TLS)

Prio contributions

Achieves all four goals

- Robustness using secret-shared non-interactive proofs (SNIPs)
 - Every client efficiently proves to servers that its submission is well formed
 - Takes advantage of non-colluding servers (verifiers)

2. Aggregatable encodings

Compute sums privately \implies compute $f(\cdot)$ privately for many f's of interest

Existing approaches

Additively homomorphic encryption

P4P (2010), Private stream aggregation (2011), Grid aggregation (2011), PDDP (2012), SplitX (2013), PrivEx (2014), PrivCount (2016), Succinct sketches (2016), ...

- Multi-party computation [GMW87], [BGW88]
 FairPlay (2004), Brickell-Shmatikov (2006), FairplayMP (2008), SEPIA (2010),
 Private matrix factorization (2013), JustGarble (2013), ...
- Anonymous credentials/tokens VPriv (2009), PrivStats (2011), ANONIZE (2014), ...
- Randomized response [W65], [DMNS06], [D06], RAPPOR (2014, 2016)

Private aggregation needed in many settings

Private client value (xi)	Aggregate f(x ₁ ,, x _N)
Location data (phones/cars)	 Number of devices in location L Ten most popular locations Locations with weakest signal strength
Web browsing history	 Most common bug-triggering websites Websites with TLS certificate errors
Health information	Min, max, avg, stddev heart rateML model relating BP to Twitter usage
Text messages	Min, max, average number per dayML model relating time of day to emotion

Warm-up: Computing private sums

Every device i holds a value $x_i \in \mathbb{F}$

Think: integers modulo a prime p

Cloud wants to compute

$$f(x_1, ..., x_N) = x_1 + ... + x_N$$

without learning any users' private value $x_i \in \mathbb{F}$

Example: Privately measuring traffic congestion

$$x_i = \begin{cases} 1 & \text{if user i is on Golden Gate Bridge} \\ 0 & \text{otherwise} \end{cases}$$



 $x_1 + ... + x_N$ gives number of users on bridge

[Chaum88], [BGW88], ... [KDK11] [DFKZ13] [PrivEx14] ...

Server A



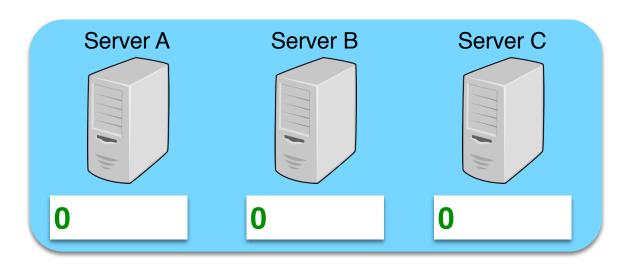
Server B



Server C



Assume that at least one server is honest.



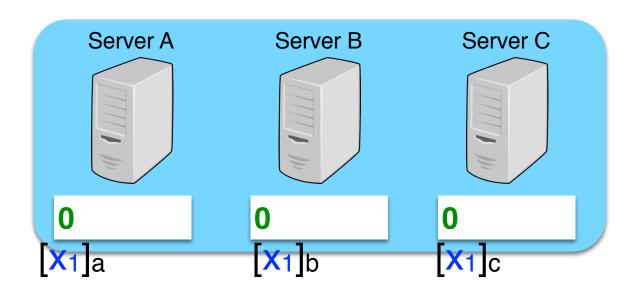




Split into shares s.t.

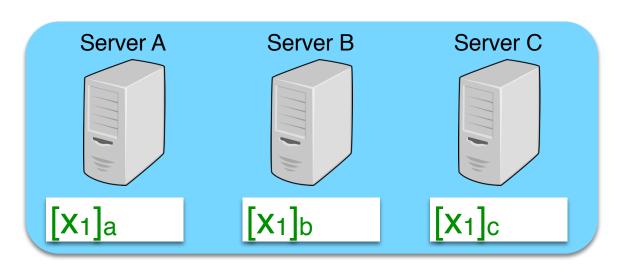
$$\mathbf{X}_1 = [\mathbf{X}_1]_a + [\mathbf{X}_1]_b + [\mathbf{X}_1]_c \in \mathbb{F}$$

[x] means "additive share of x"

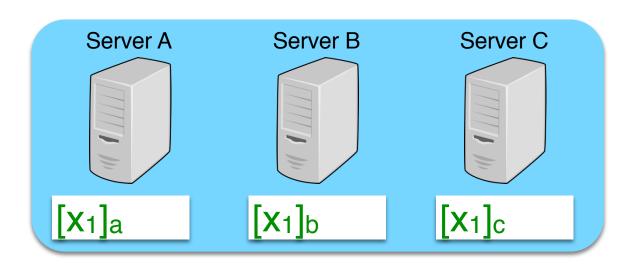




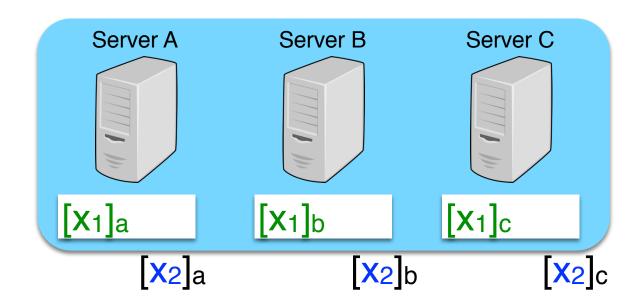






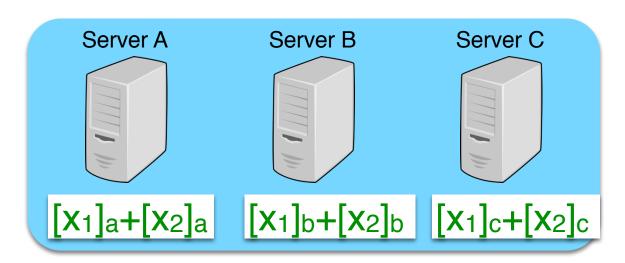






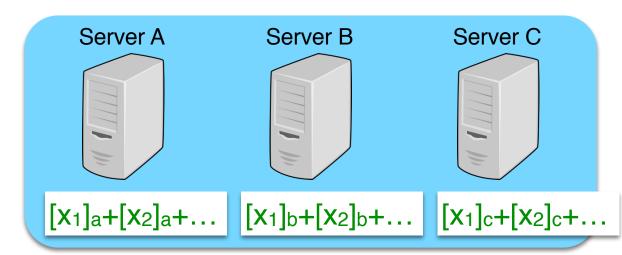










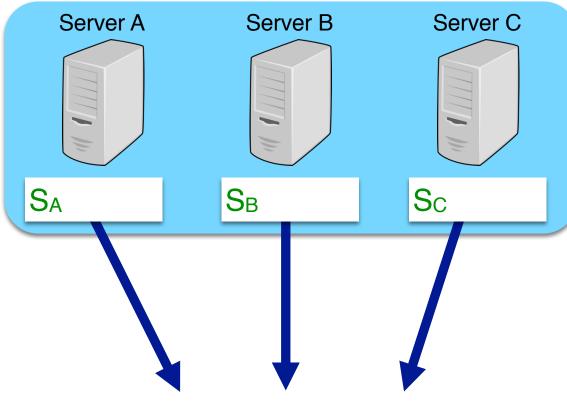














$$S_A + S_B + S_C = [x_1]_a + [x_1]_b + [x_1]_c + ... \in \mathbb{F}$$

= $x_1 + x_2 + ... + x_N$

Learn that three phones are on the Bridge—but not which three

Strawman computing private sums

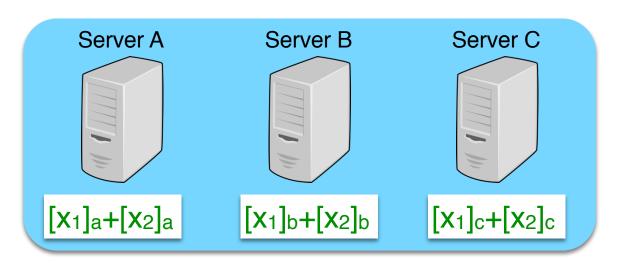
Correctness: if everyone follows the protocol, servers compute the sum of all x_is.

Privacy: any proper subset of the servers can simulate everything given

- (a) the public parameters, and
- (b) the sum of the xis.

Scalability: by inspection.

Robustness: ???



x₃ is supposed to be a 0/1 value

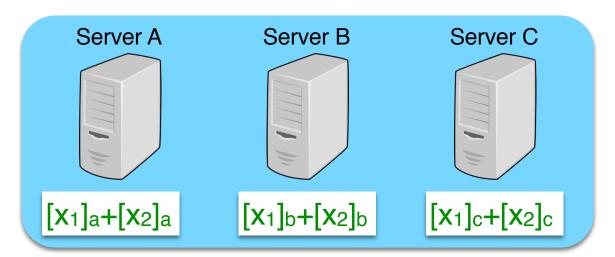






 $x_3 \in \mathbb{F}$





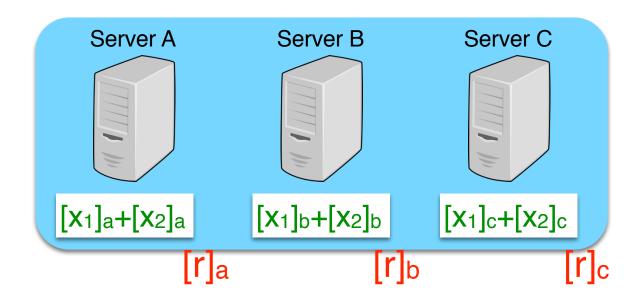
An evil client needn't follow the rules!







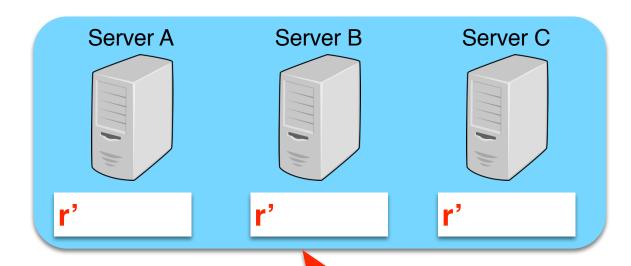












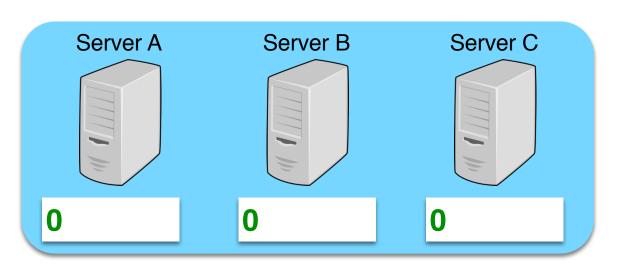


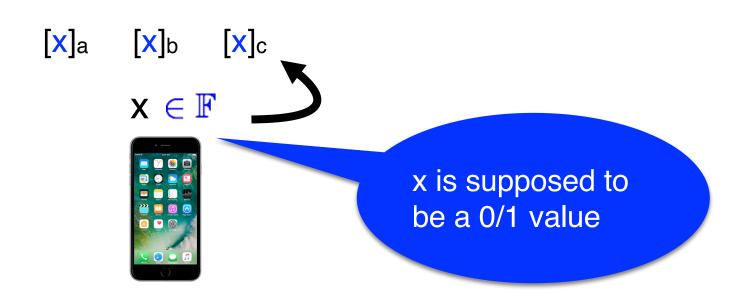


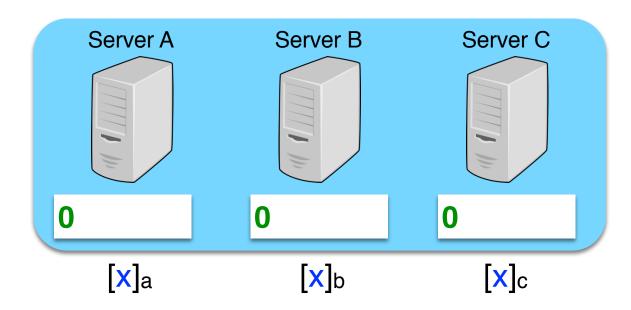
A single bad client can undetectably corrupt the sum

Users have incentives to cheat

Typical defenses (NIZKs) are costly







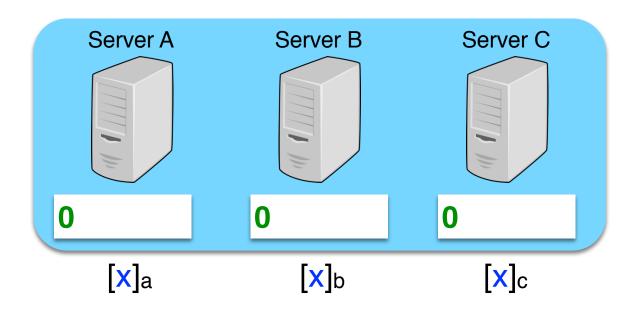




Without learning x, the servers want to ensure that:

$$[x]_a + [x]_b + [x]_c \subseteq \{0,1\}$$

Remember: these are big integers mod *p*

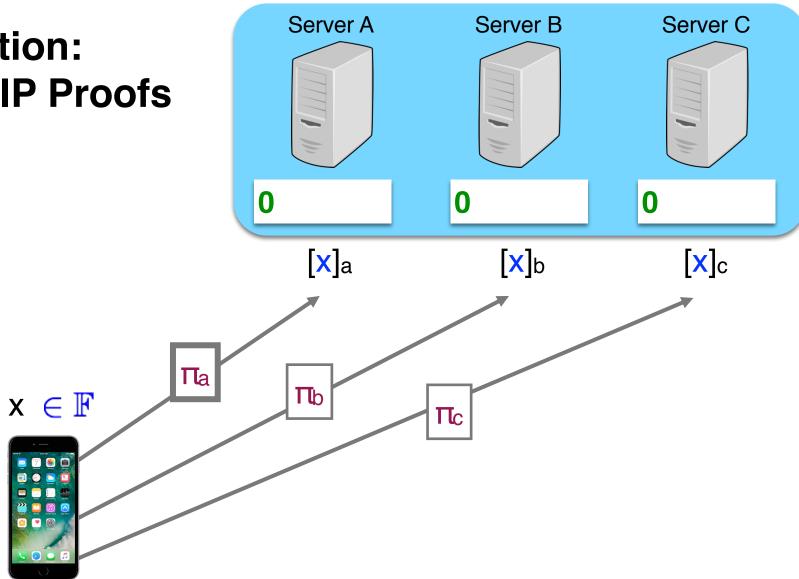


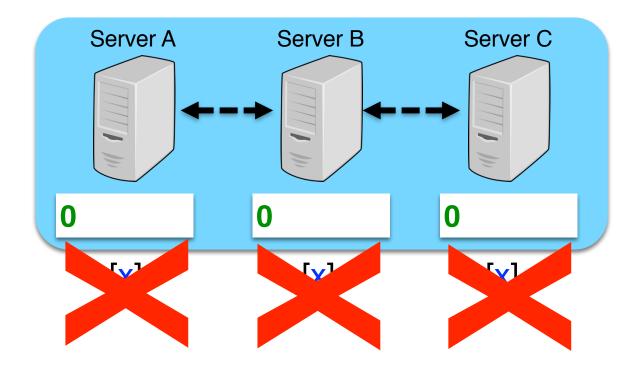




- Servers hold shares of x and a public predicate Valid(·)
- Servers want to test if "Valid(x) = 0" without leaking anything else about x
- The Valid predicate can be an arbitrary circuit:

Valid(
$$x_1, x_2$$
) = "3 < x_1 < 19 and $x_2 \in \{0, 1, 2\}$ "



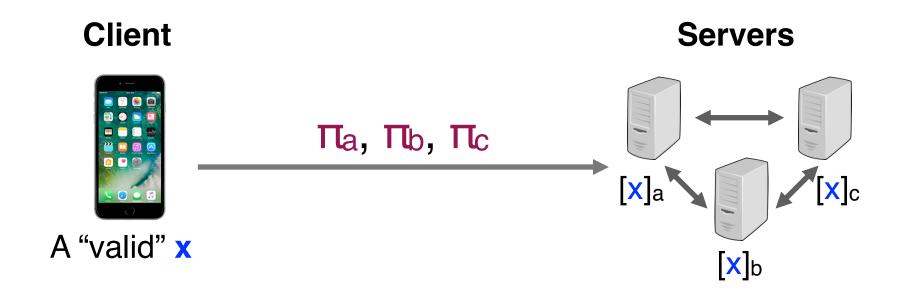






Prio servers detect and reject malformed client submissions

 \Rightarrow a client can influence aggregates by at most ± 1



Security goals for SNIPs

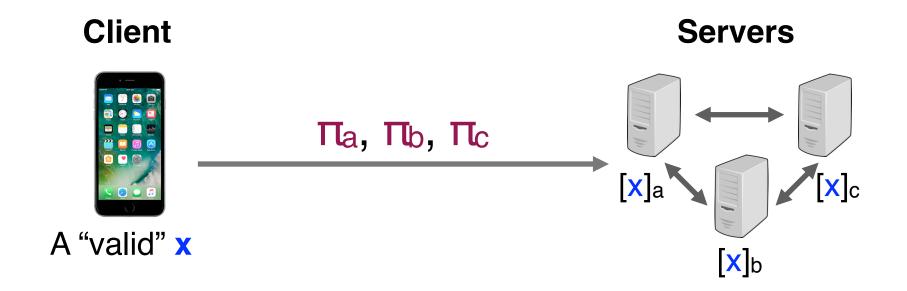
Completeness: Honest client convinces honest servers

Soundness: Dishonest client almost never convinces

honest servers

Zero-knowledge: Any proper subset of malicious servers learns

nothing about x, except that x is valid



Existing techniques

Full blown MPC

Commitments + NIZKs

Commitments + SNARKs

Limitations

Heavy setup and comm.

High corver work

Info. theoretic techniques

 \Rightarrow little comp. overhead

Func. secret sharing [BGI O(1) server-to-server comm.

 $|\pi_a|$ is linear in circuit size

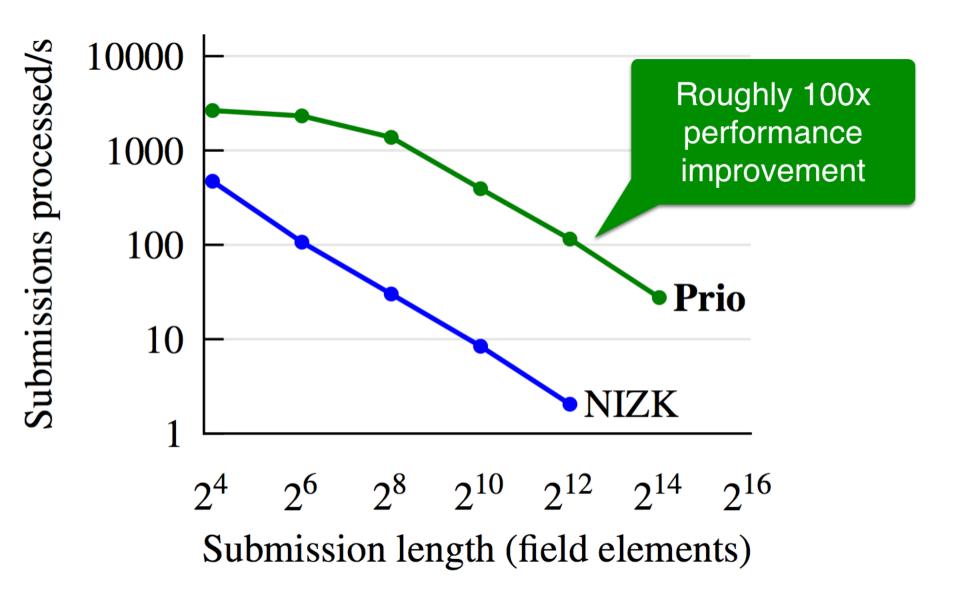
SNIP

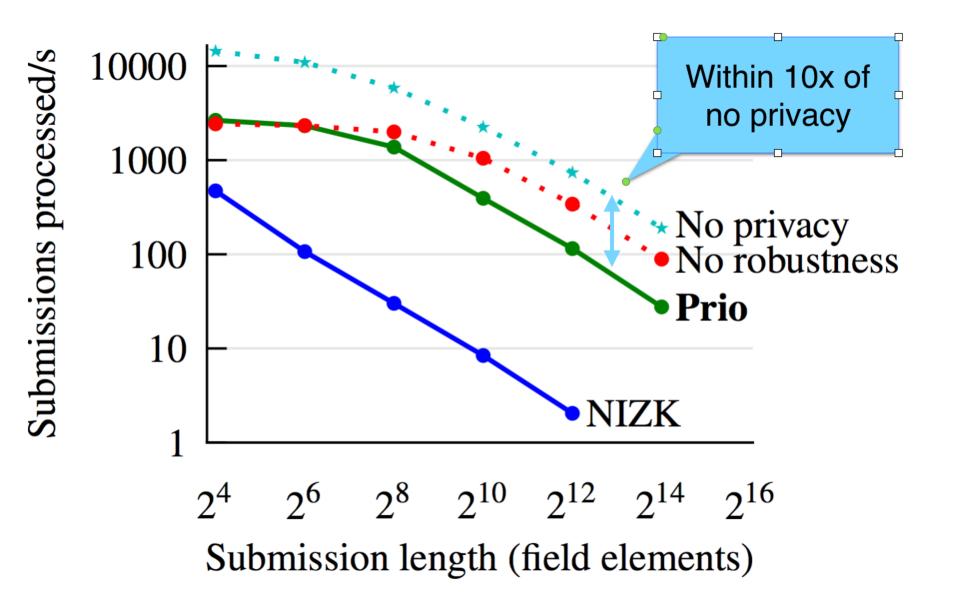
SNIPs: How?

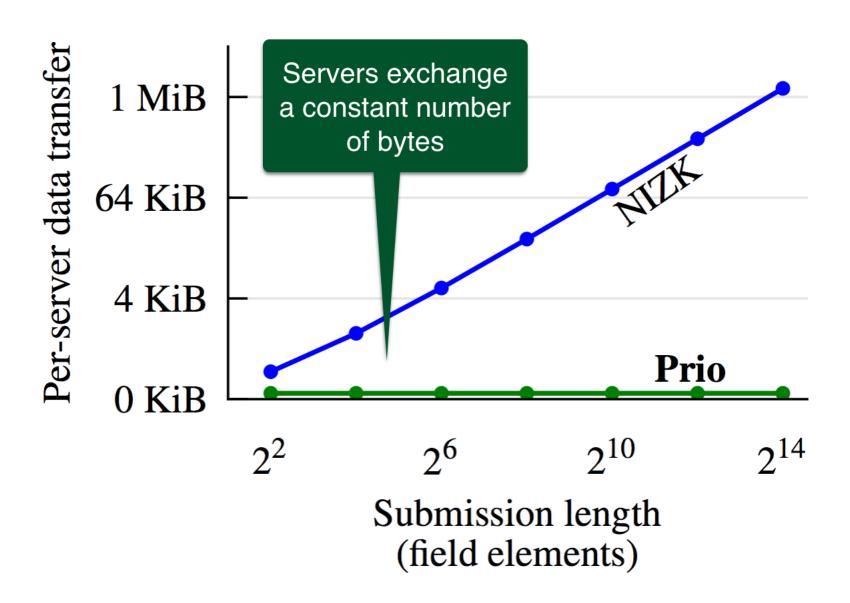
Step 1: reduce verifying circuit to verifying a single multiplication

Step 2: Use "Beaver triple" <u>supplied by client</u> to verify the multiplication

Step 3: Inject additional entropy to defend against malicious servers (similar to AMD codes)







Complex statistics

Computing private sums \Rightarrow can compute many other interesting aggregates

[PrivStats11], [KDK11], [DFKZ13], [PrivEx14], [MDD16], ...

- Average
- Variance
- Standard deviation
- Most popular value (approx) small universe
- "Heavy hitters" (approx)

... and even more statistics

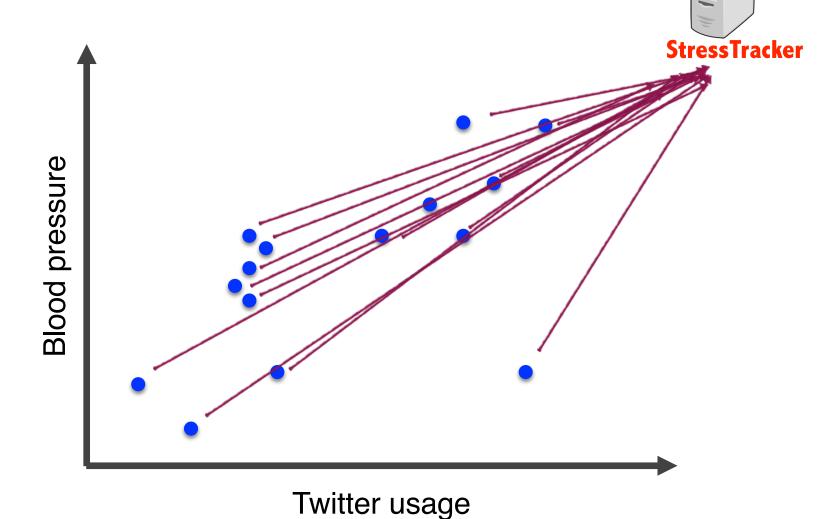
Prio can aggregate a richer class of statistics:

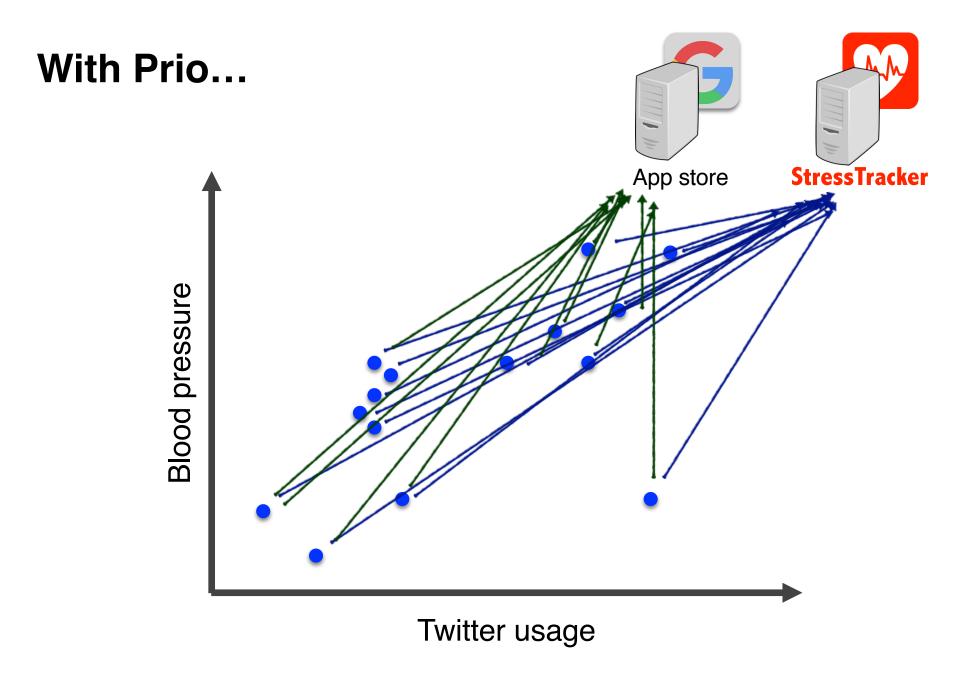
- Approximate min and max
- Most popular value in a large universe
- Quality of arbitrary machine learning model (R²)
- Least-squares regression

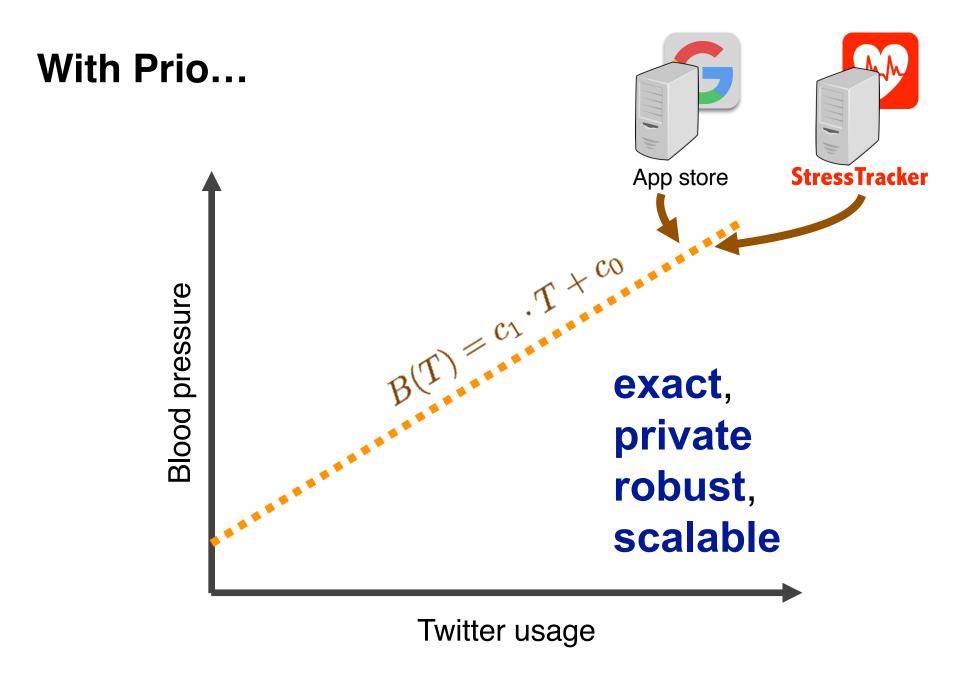
Prio supports a rich set of aggregation functions

Some limitations: cannot compute exact max

Putting it all together: Today







THE END