

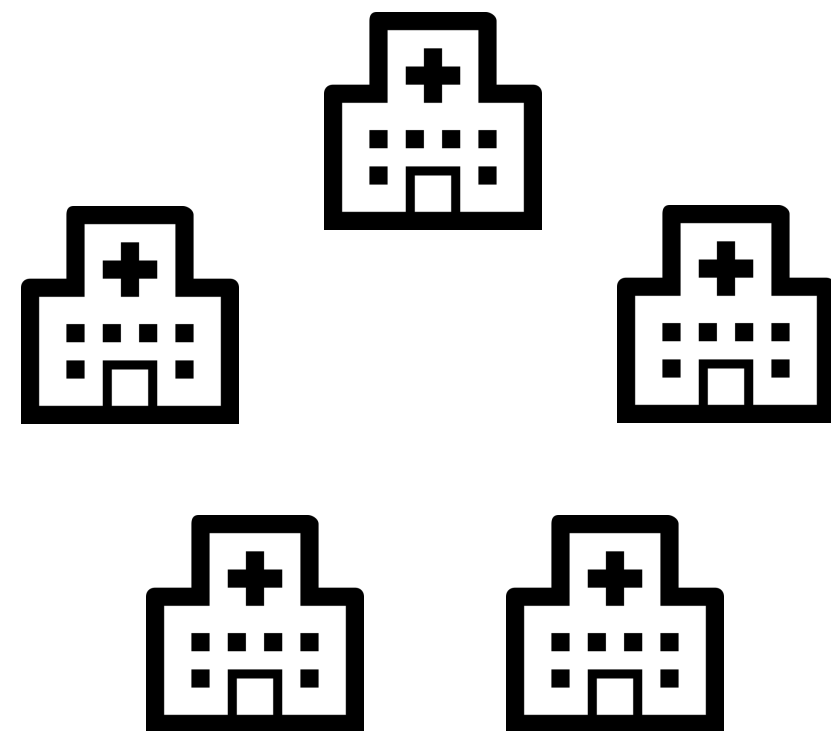
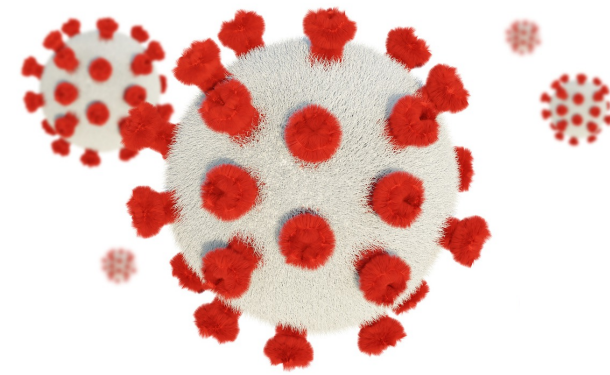


SECRECY: SECURE COLLABORATIVE ANALYTICS IN UNTRUSTED CLOUDS

John Liagouris, Vasiliki Kalavri, Muhammad Faisal, Mayank Varia
Boston University

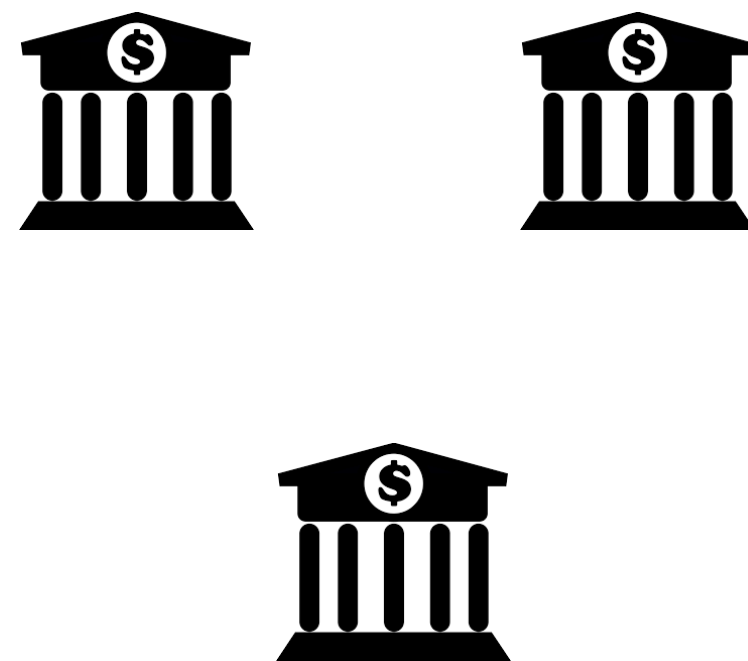
MOTIVATION: SECURE COLLABORATIVE ANALYTICS

Medical Studies



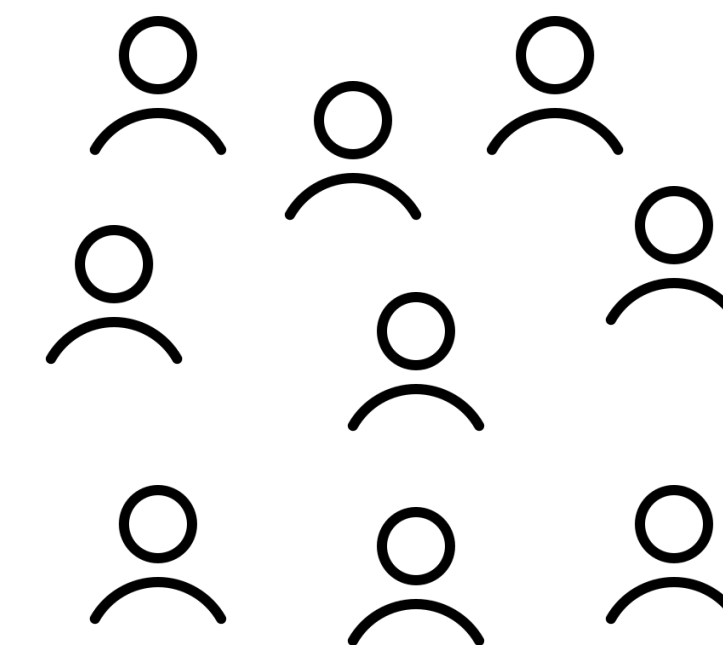
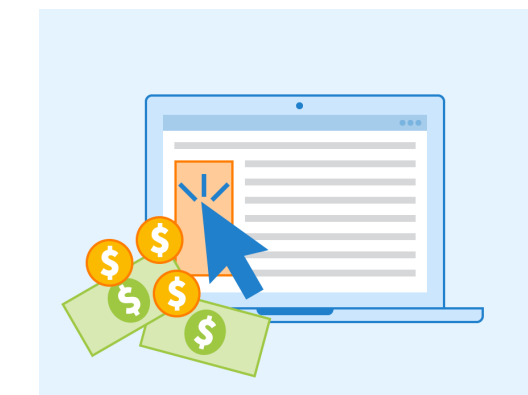
Healthcare providers

Market Analyses



Credit score agencies

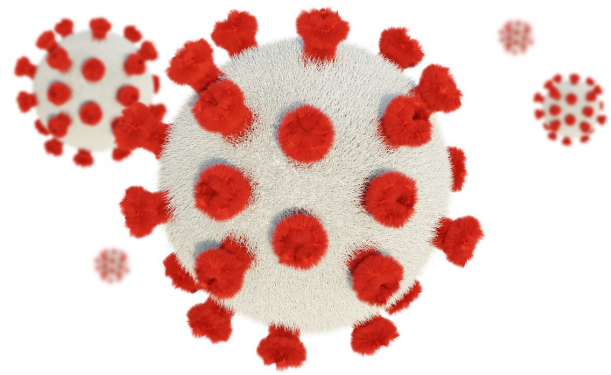
Privacy-preserving advertising



Web users

MOTIVATION: SECURE COLLABORATIVE ANALYTICS

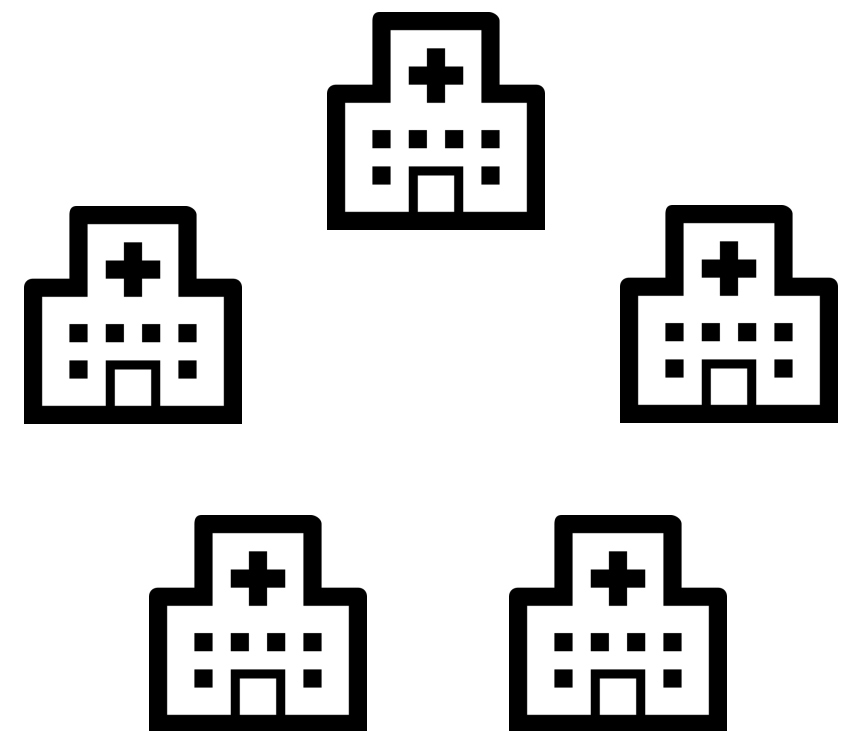
Medical Studies



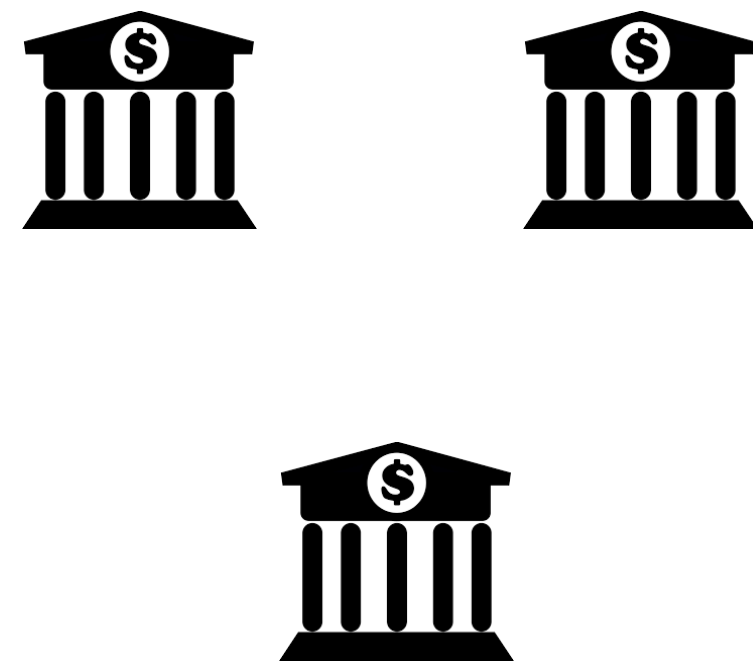
Market Analyses



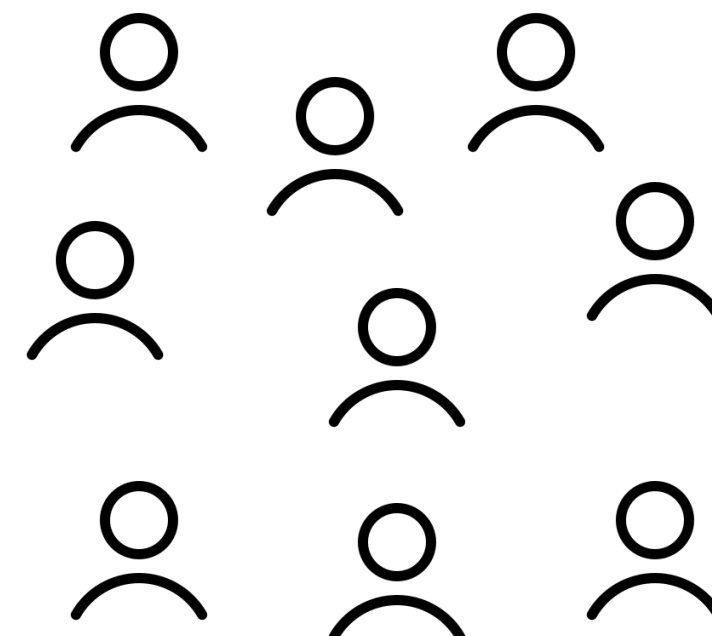
Privacy-preserving advertising



Healthcare providers



Credit score agencies



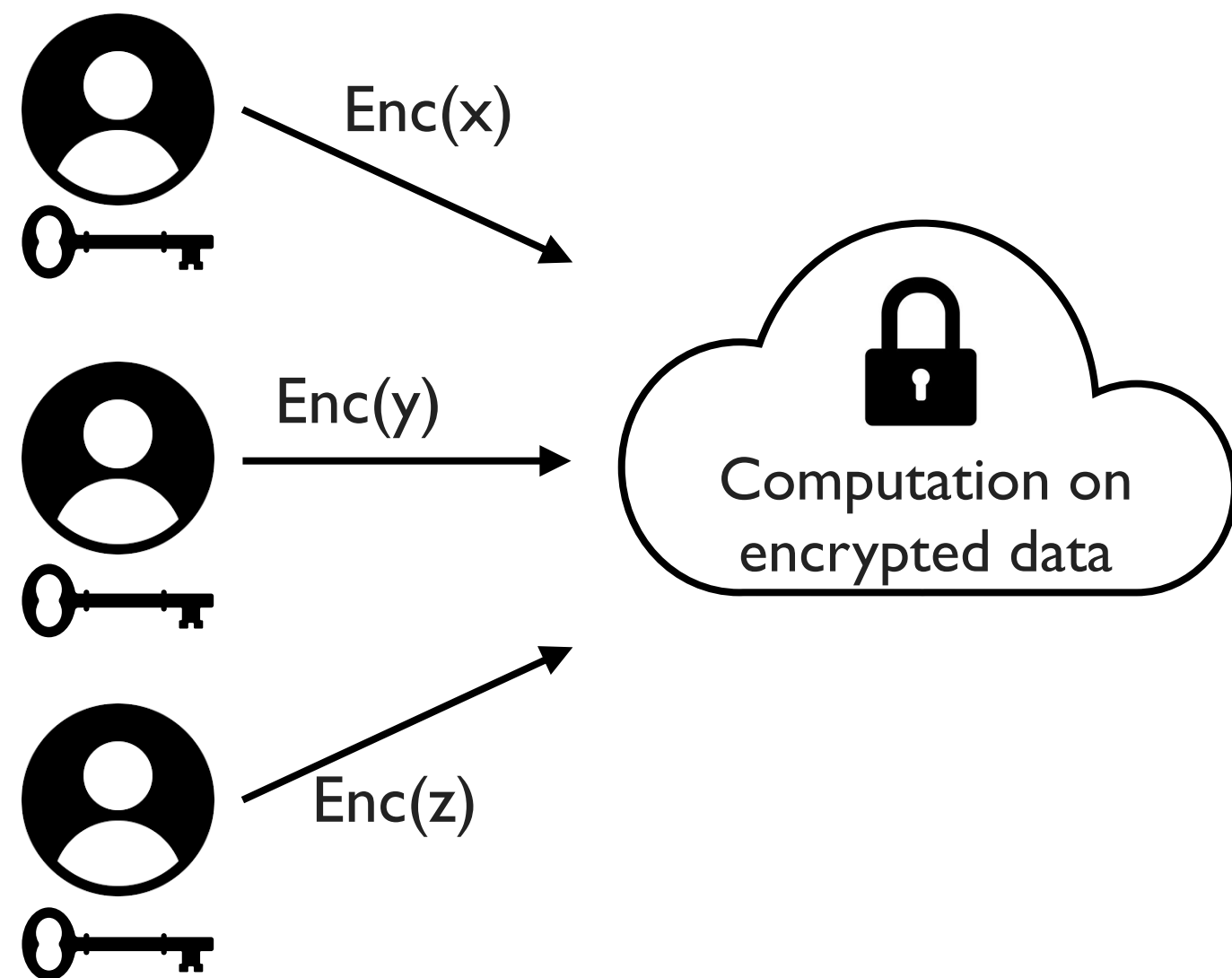
Web users

Requirements:

- **No information leakage to untrusted entities**
- **No reliance on trusted resources**
- **Relational analytics**
- **Practical performance**

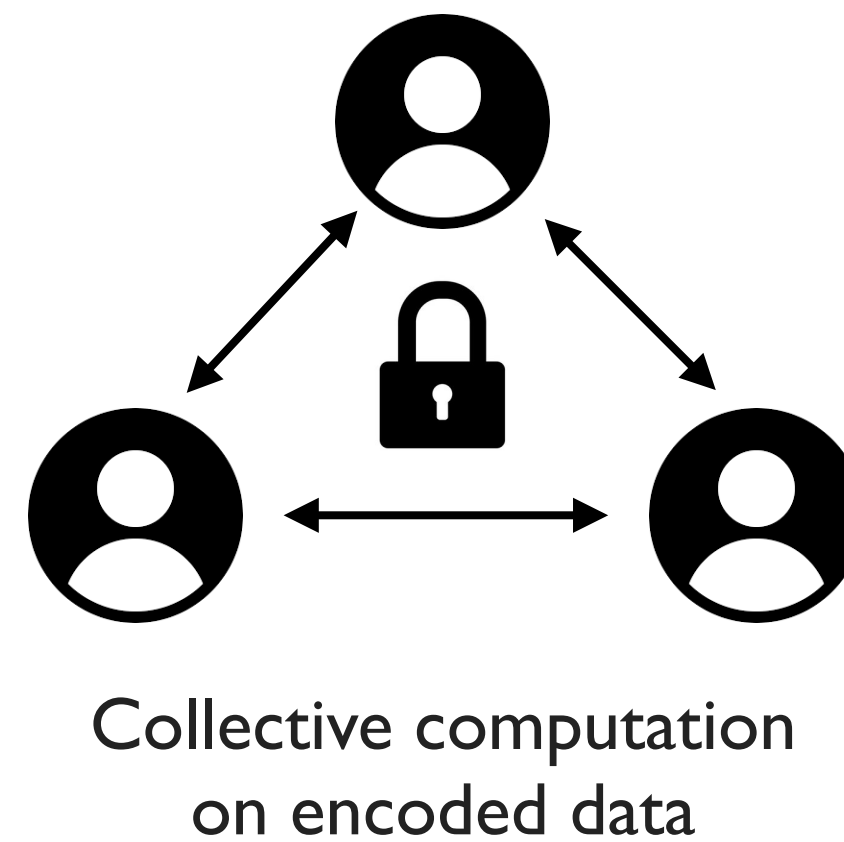
APPROACHES TO SECURE COLLABORATIVE ANALYTICS

Fully Homomorphic Encryption (FHE)



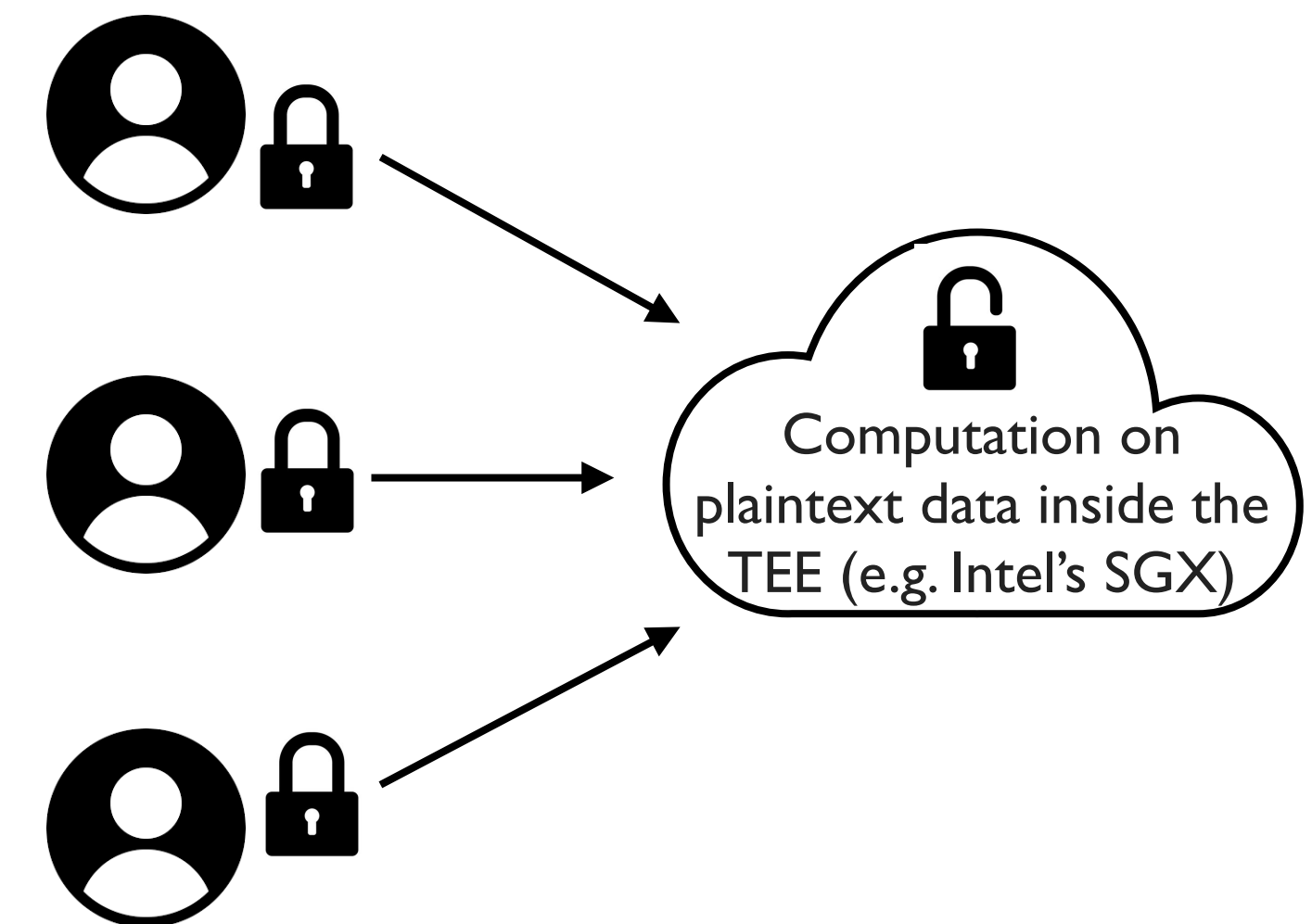
Security via homomorphic encryption
(very high computational cost)

Secure Multi-Party Computation (MPC)



Security via decentralized trust
(high communication cost)

Trusted Execution Environments (TEEs)



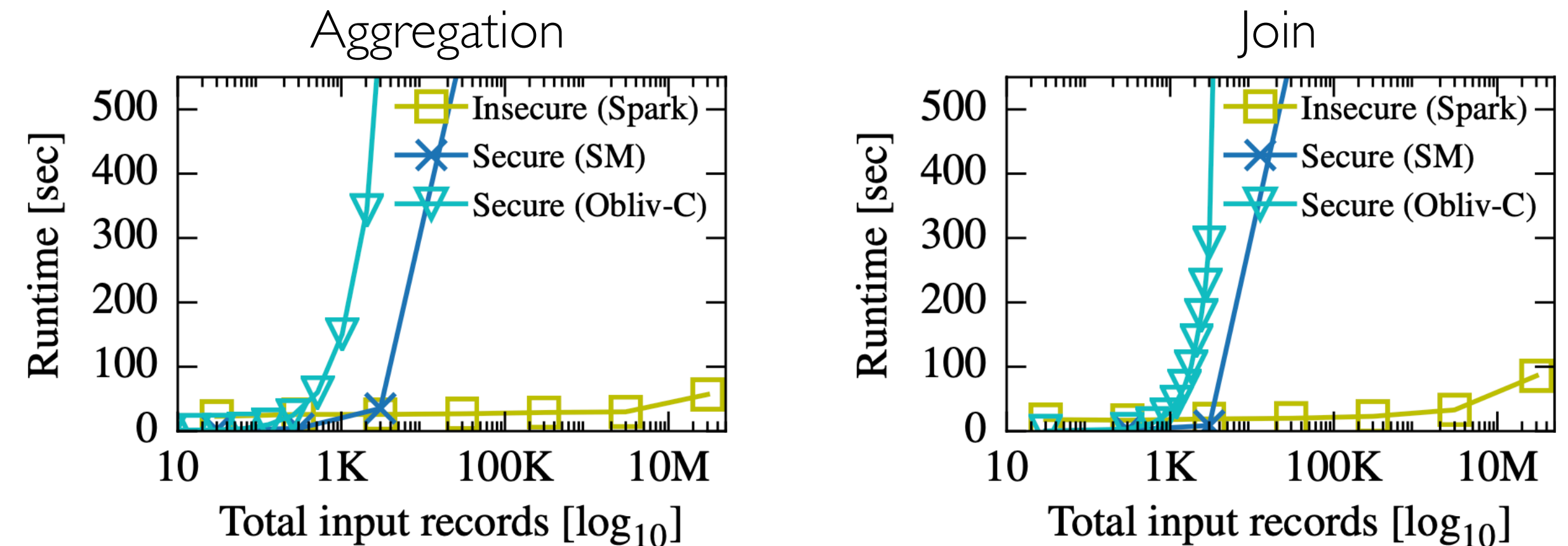
Security via physically protected HW
(prone to side-channel attacks)

CHALLENGE: HOW TO REDUCE THE MPC COST?

“Running the query entirely under MPC [...] **fails to scale beyond 3,000 total records...**”

“Computing a function f on millions of client inputs [...] could potentially take an **astronomical amount of time** in a full MPC.”

“The primary source of the slowdown arises from their join operators that have **hundreds of input tuples...**”



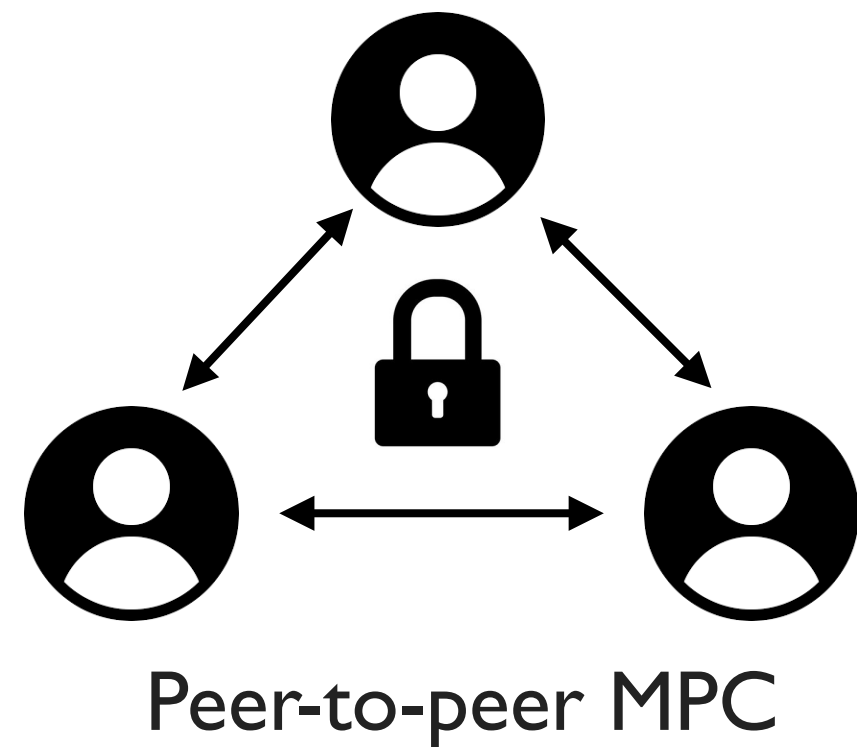
Plaintext	Secure	Slowdown
158	253,894	1,609X
165	159,145	967X
193	8,195,317	43,337X

¹ N. Volgushev, M. Schwarzkopf, B. Getchell, M. Varia, A. Lapets, and A. Bestavros. *Conclave: secure multi-party computation on big data*. EuroSys, 2019.

² J. Bater, G. Elliott, C. Eggen, S. Goel, A. N. Kho, and J. Rogers. *SMCQL: secure querying for federated databases*. PVLDB, 10(6):673-684, 2017.

³ H. Corrigan-Gibbs and D. Boneh. *Prio: Private, Robust, and Scalable Computation of Aggregate Statistics*, NSDI, 2017.

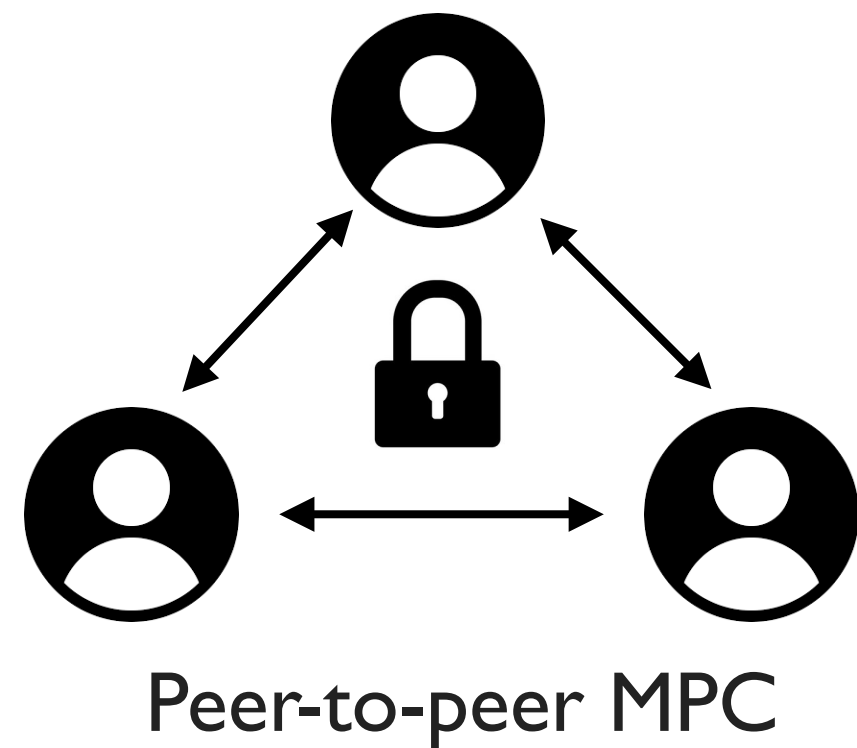
PRIOR WORK ON RELATIONAL MPC



Data owners act as computing parties using **trusted resources**

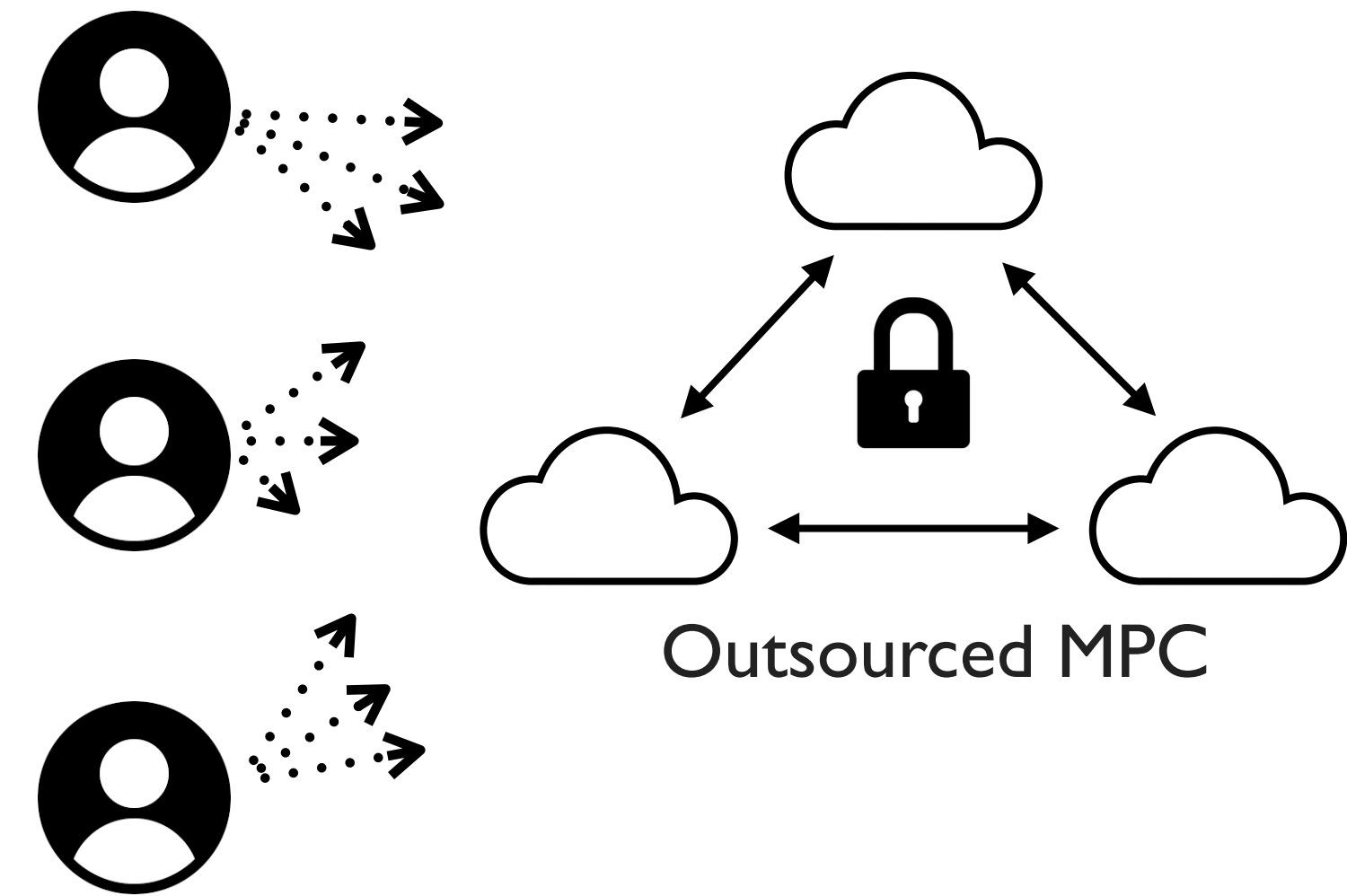
- ⊖ Data owners may not have domain expertise or private infrastructure
- ⊖ MPC does not scale well with the number of data owners

OUR FOCUS: OPTIMIZE MPC IN THE CLOUD



Data owners act as computing parties using **trusted resources**

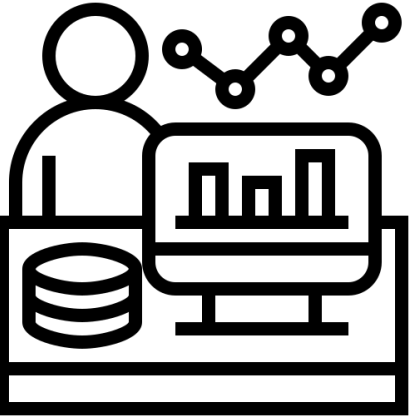
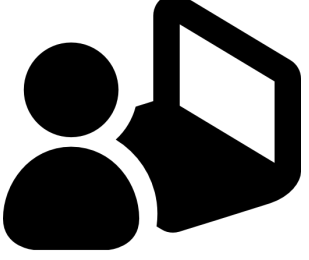
- Data owners may not have domain expertise or private infrastructure
- MPC does not scale well with the number of data owners



Data owners outsource secret shares of their data to **untrusted third parties**



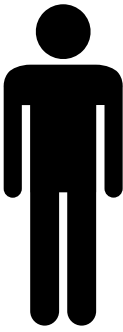
- + Data owners can use untrusted cloud resources on demand
- + A small number of third parties can support a large number of data owners

SECRECY AS A SERVICE



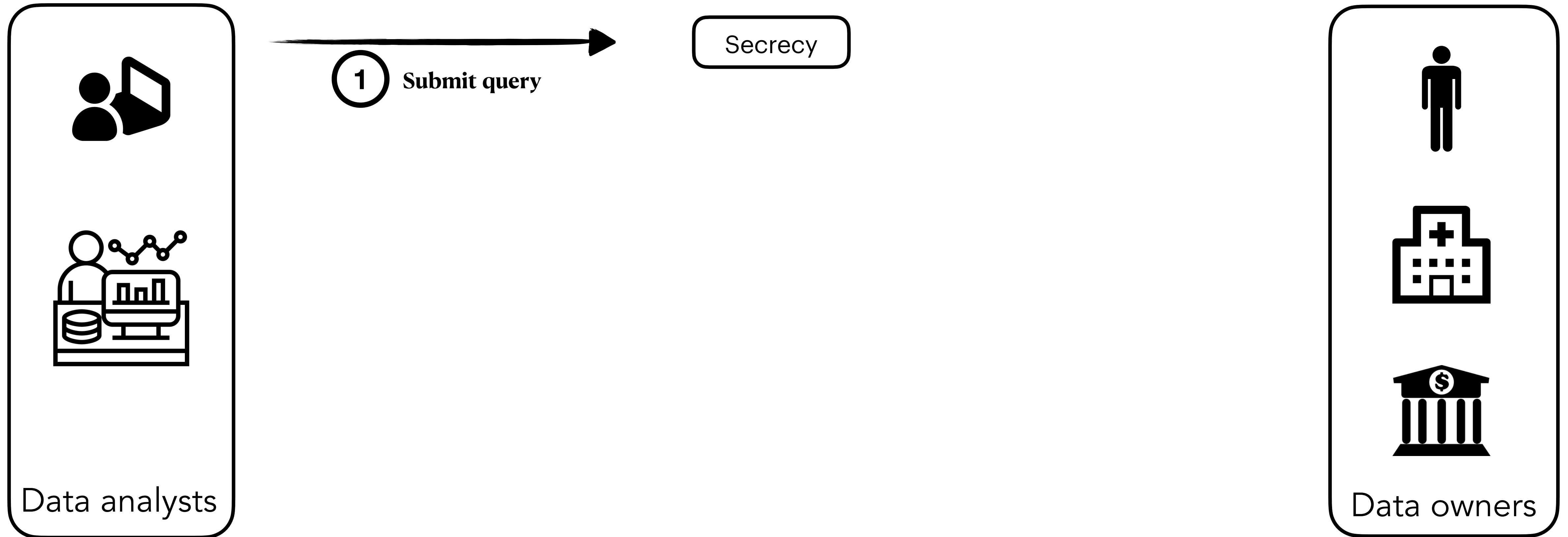
Data analysts

Secrecy

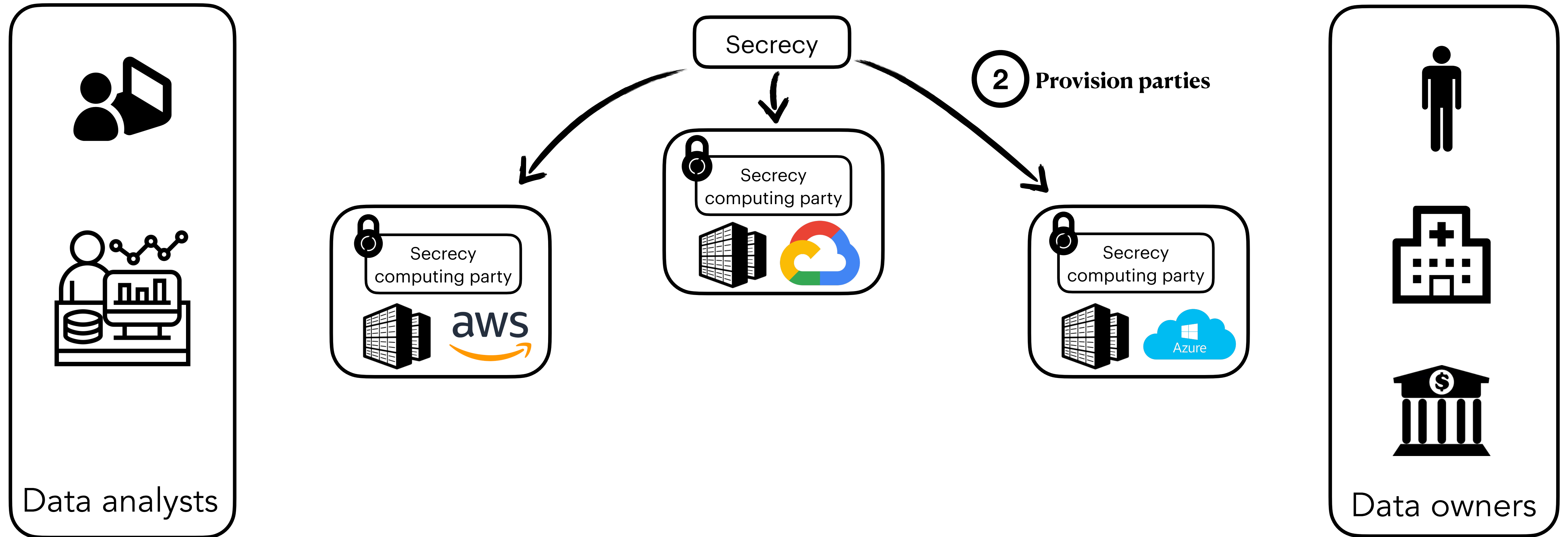


Data owners

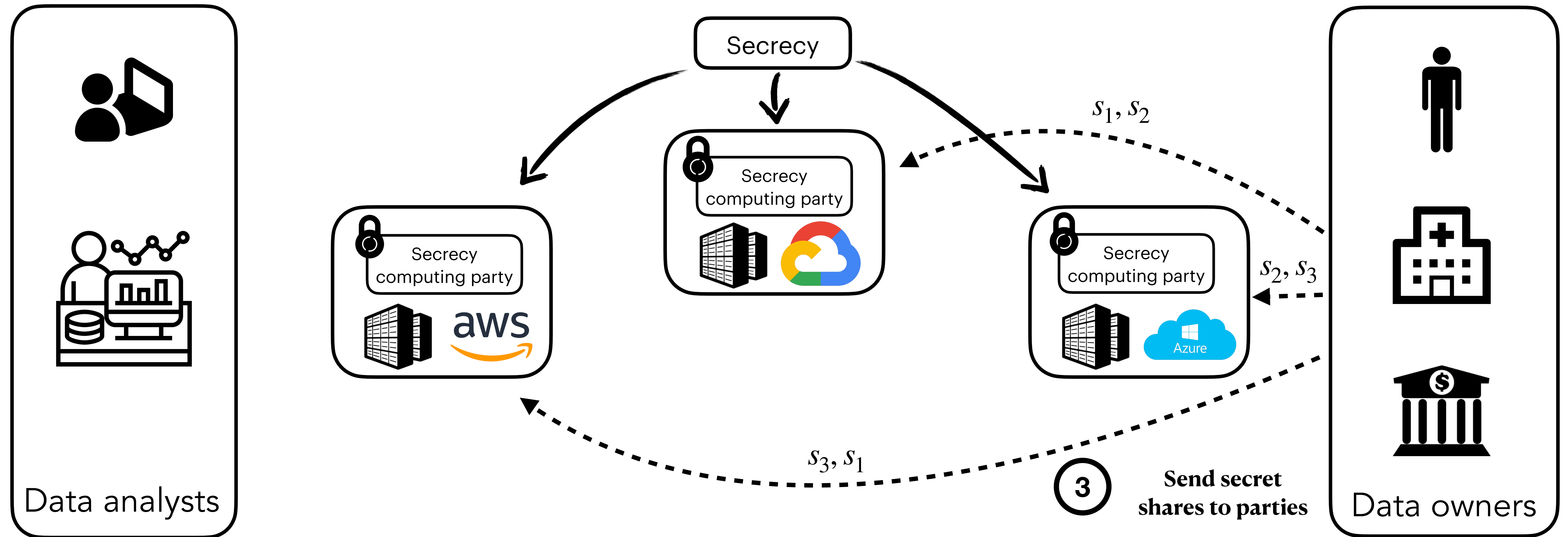
SECRECY AS A SERVICE



SECRECY AS A SERVICE



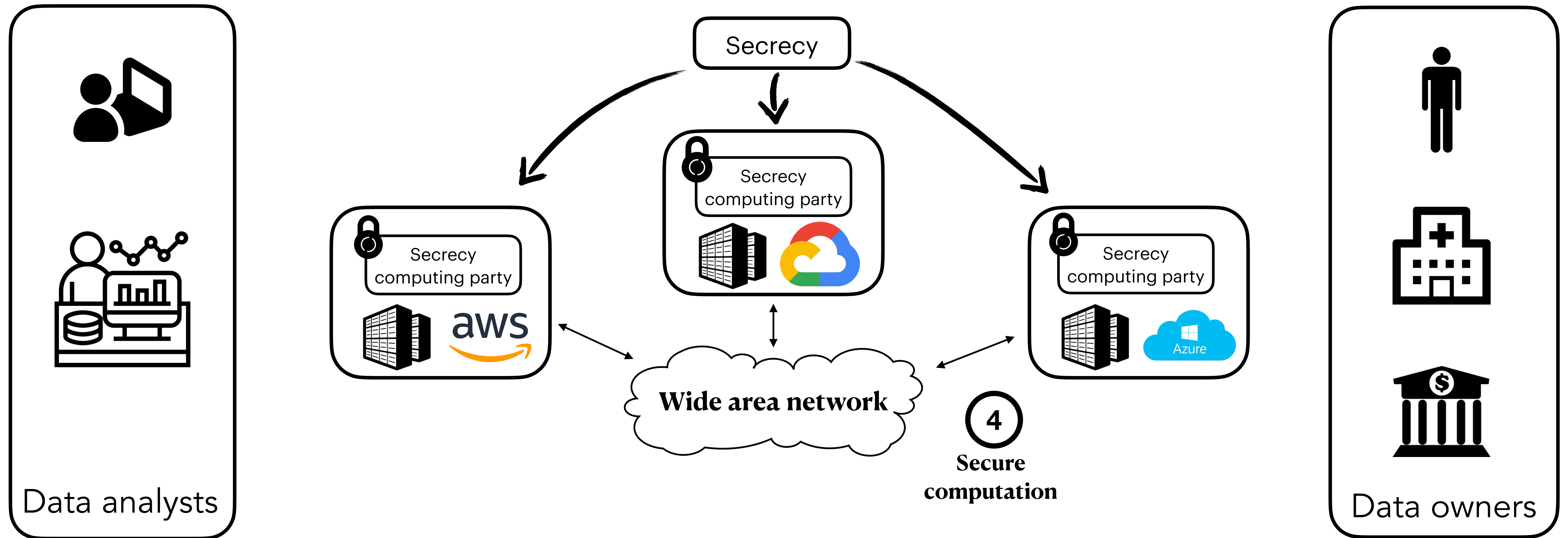
SECRECY AS A SERVICE



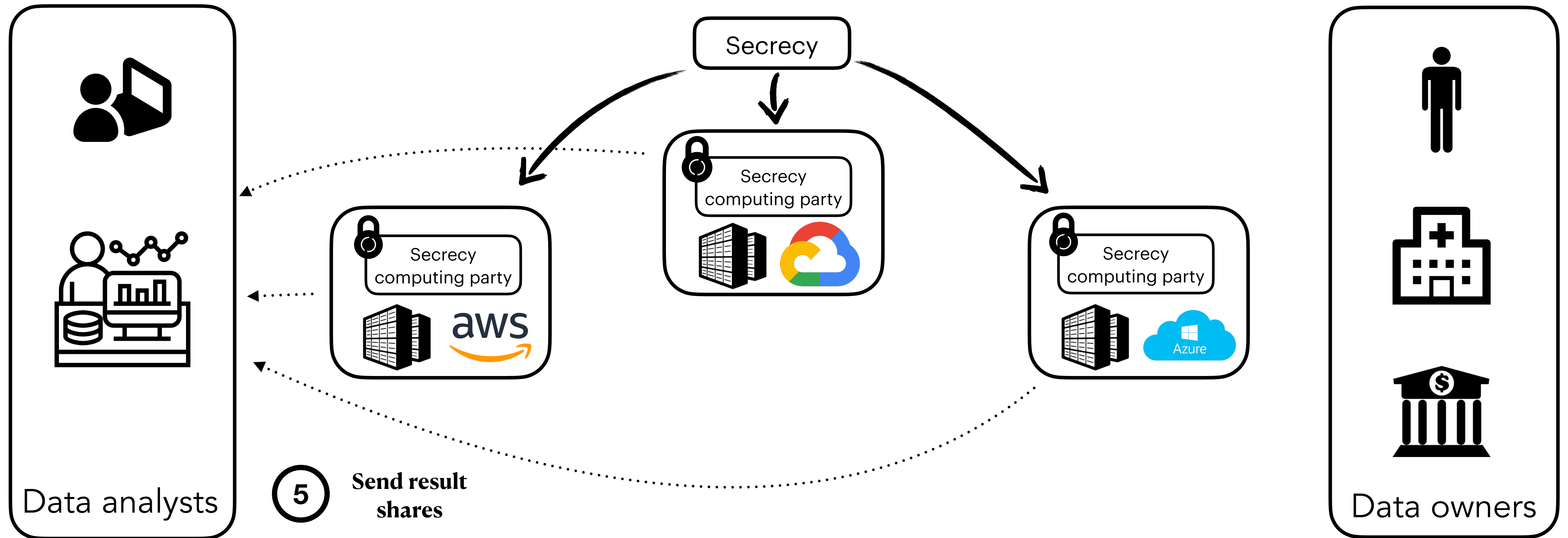
Arithmetic sharing: $s = s_1 + s_2 + s_3 \pmod{2^k}$
(for k-bit integers)

Boolean sharing: $s = s_1 \oplus s_2 \oplus s_3$
(for k-bit strings)

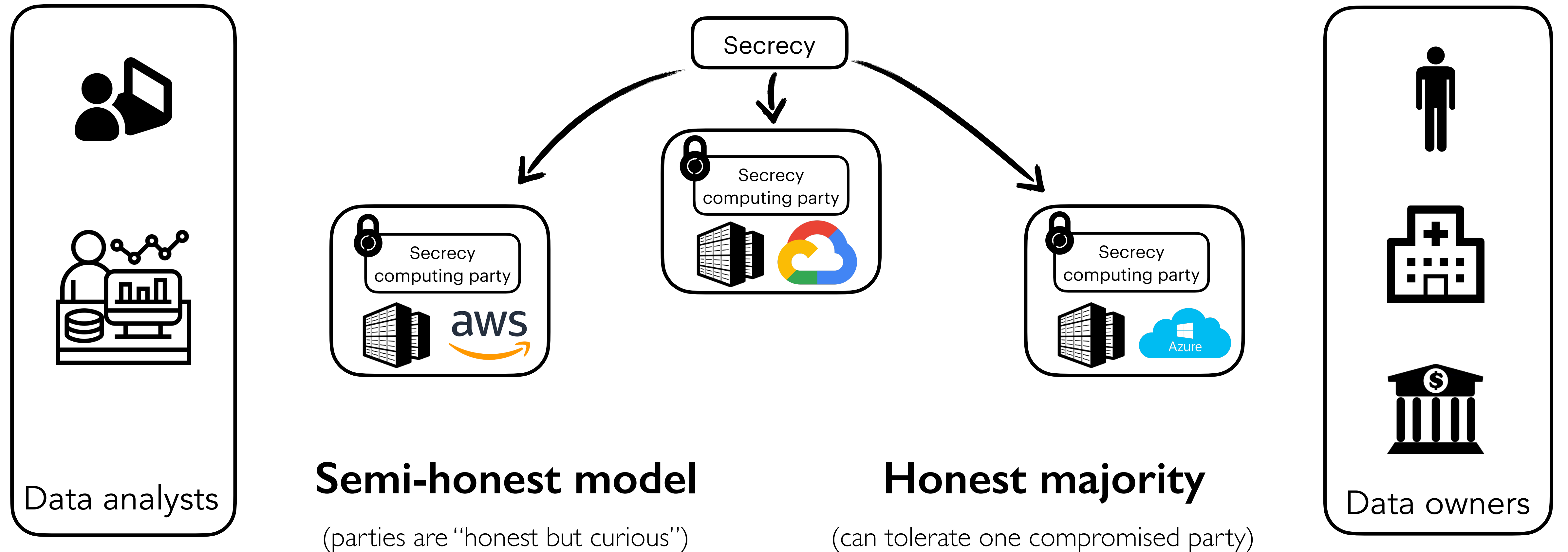
SECRECY AS A SERVICE



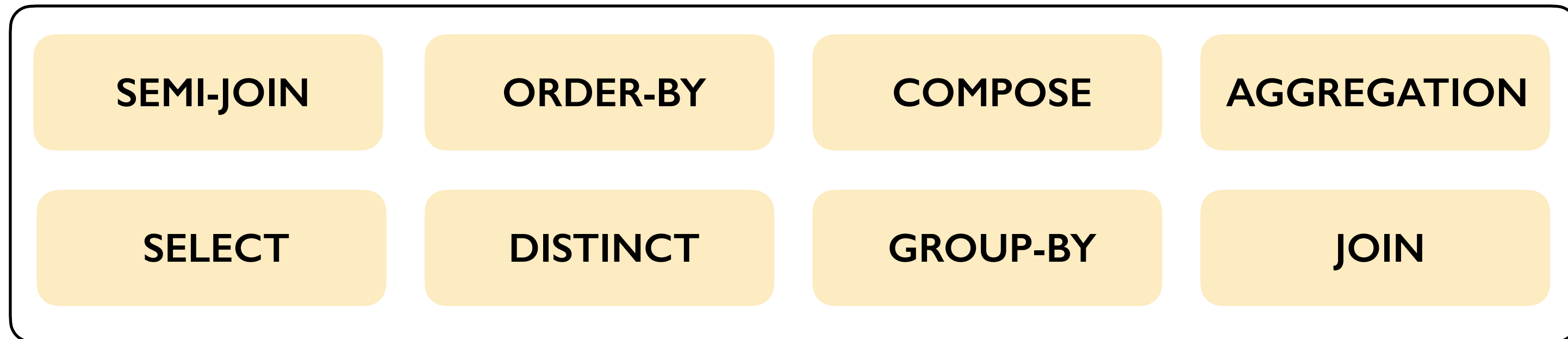
SECRECY AS A SERVICE



SECRECY AS A SERVICE



FROM SECURE MPC PRIMITIVES TO RELATIONAL ANALYTICS



Secure SQL operators



Complex operations



MPC primitives

Arithmetic sharing: $s = s_1 + s_2 + s_3 \pmod{2^k}$

Boolean sharing: $s = s_1 \oplus s_2 \oplus s_3$

SECRECY's CORE CONTRIBUTIONS

I. Relational MPC primitives

- Amortize network I/O
- Make secret-sharing competitive in WAN

EXAMPLE: MESSAGE BATCHING IN **SECRECY**

k bits

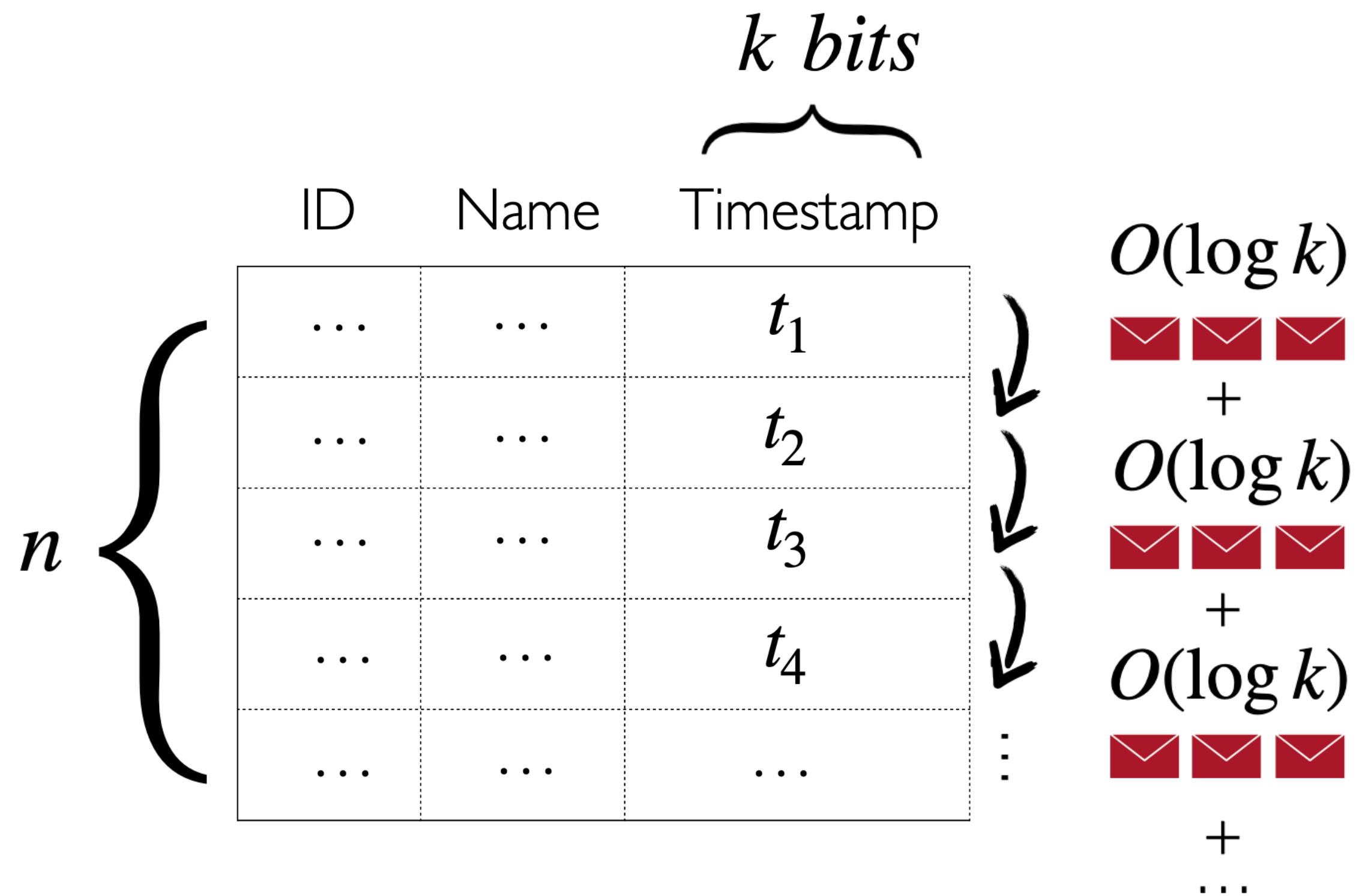
⏟

ID	Name	Timestamp
...	...	t_1
...	...	t_2
...	...	t_3
...	...	t_4
...

n {

“Select all records with timestamp $t > T$ ”

EXAMPLE: MESSAGE BATCHING IN **SECRECY**



Secret-sharing protocols exchange **many small messages** between parties

“Select all records with timestamp $t > T$ ”

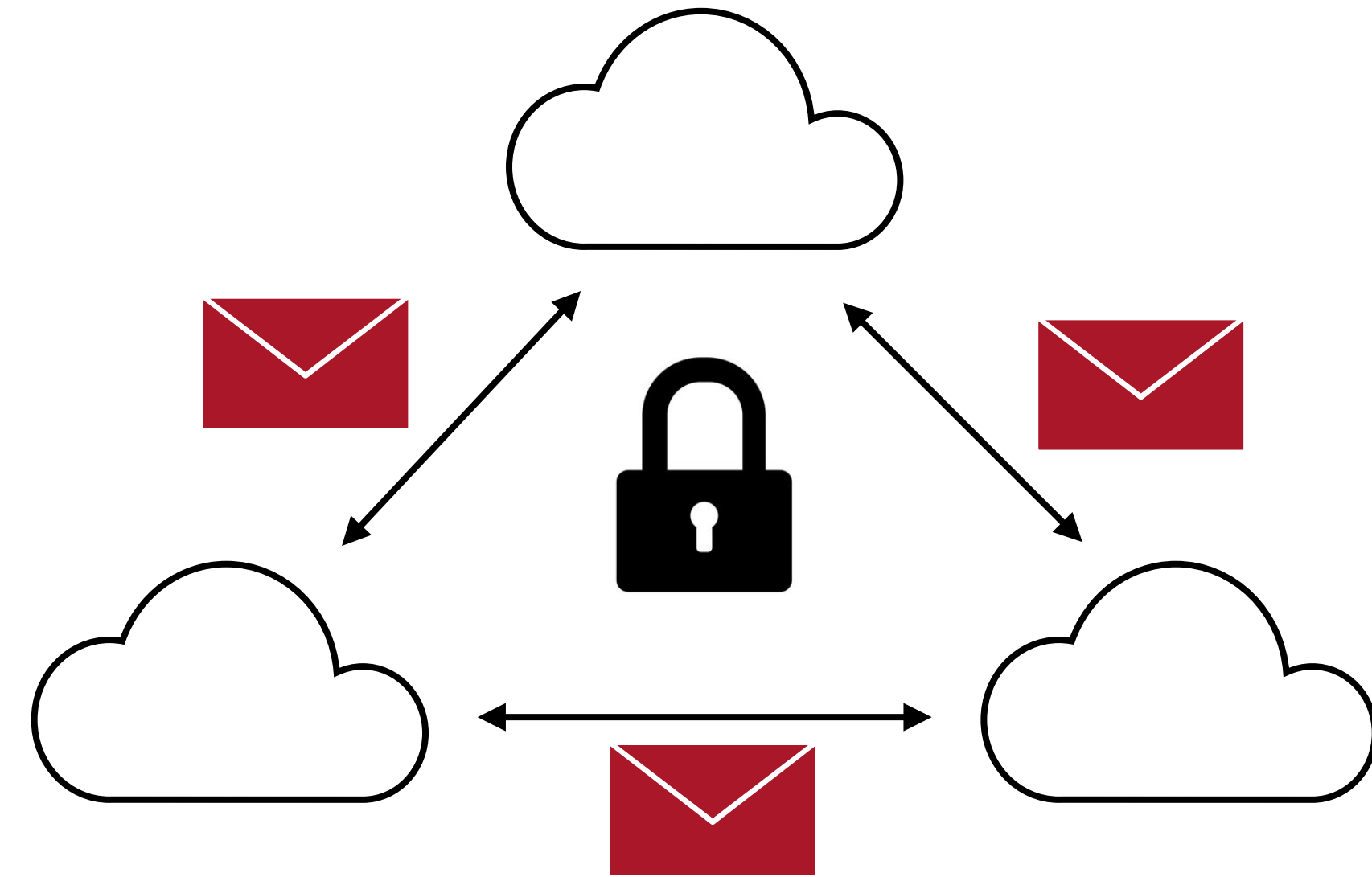
Each inequality requires $O(\log k)$ **communication rounds** under MPC

EXAMPLE: MESSAGE BATCHING IN **SECRECY**

n {

ID	Name	Timestamp
...	...	t_1
...	...	t_2
...	...	t_3
...	...	t_4
...

k bits

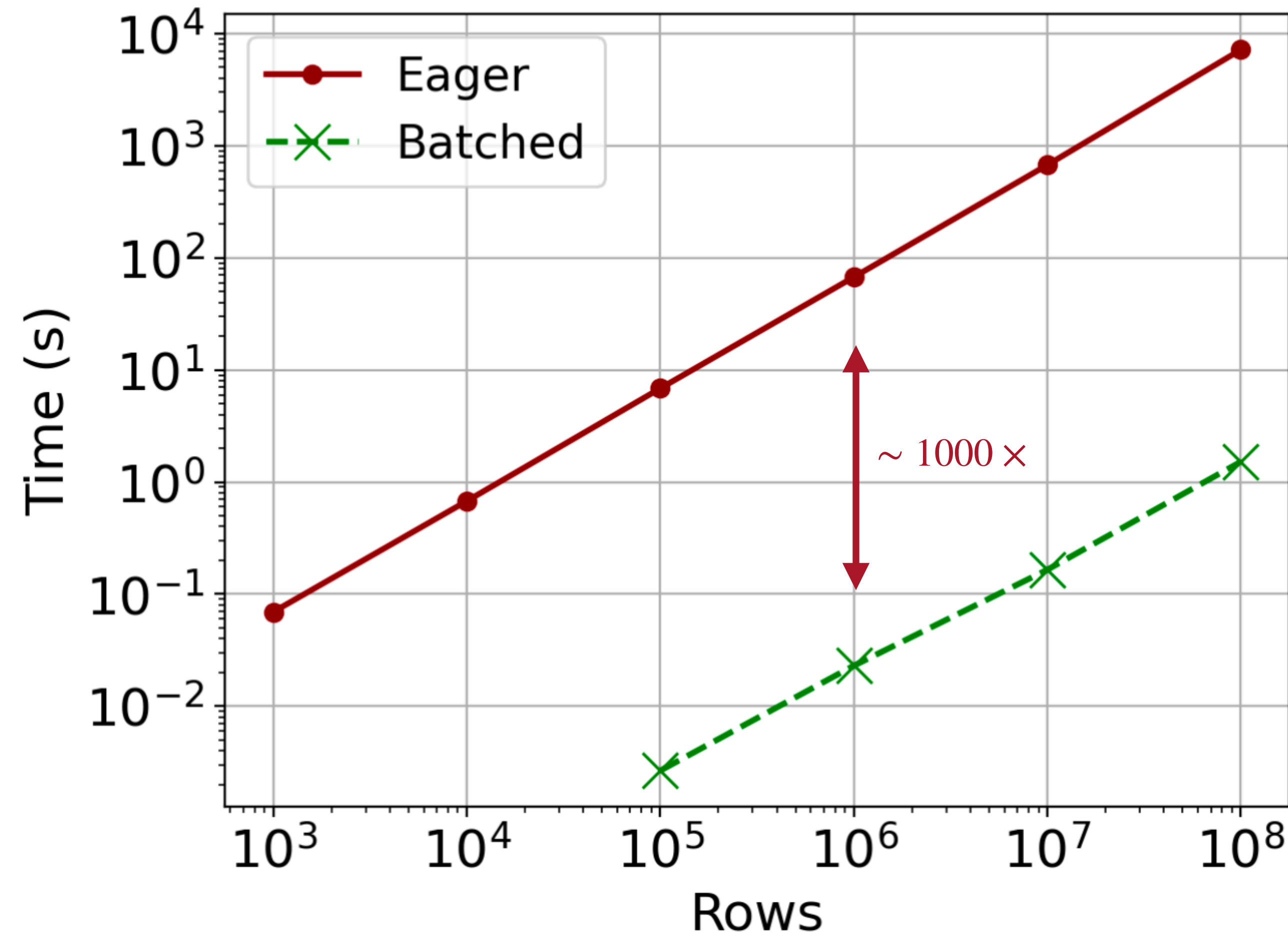


Secrecy requires $\log k + 1$ communication rounds for the **entire data table**

(independent of the number of records)

“Select all records with timestamp $t > T$ ”

EFFECT OF MESSAGE BATCHING (LAN)



- **Eager**: Message batching disabled (one network I/O per row)
- **Batched**: Message batching enabled

Lower is better

* Secrecy servers deployed on AWS EC2 r5.xlarge instances (us-east-2)

SECRECY's CORE CONTRIBUTIONS

1. Relational MPC primitives

- Amortize network I/O
- Make secret-sharing competitive in WAN

2. Analytical cost model for MPC

SECRECY's CORE CONTRIBUTIONS

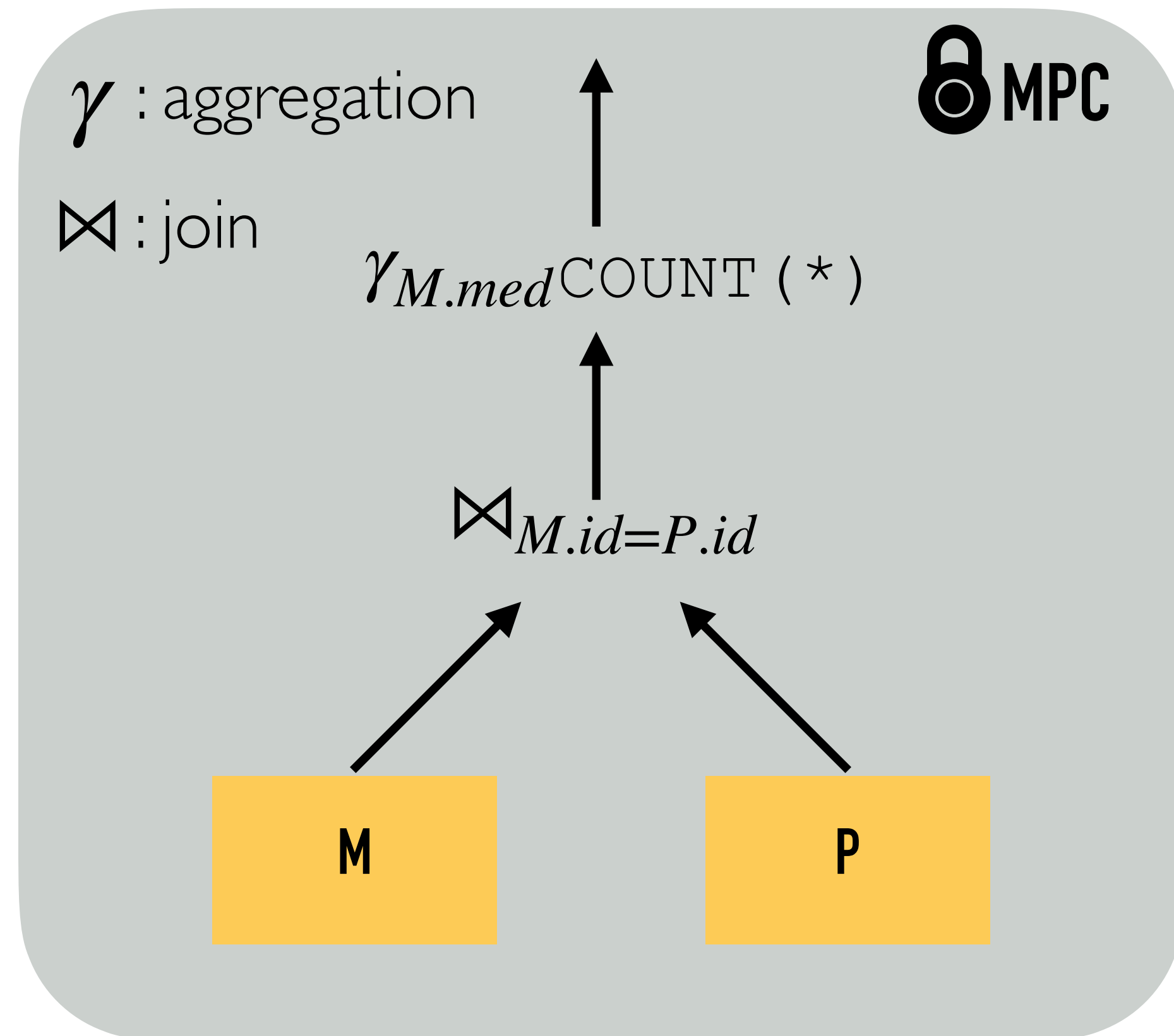
1. Relational MPC primitives

- Amortize network I/O
- Make secret-sharing competitive in WAN

2. Analytical cost model for MPC

- Operation cost
- Synchronization cost
- Composition cost

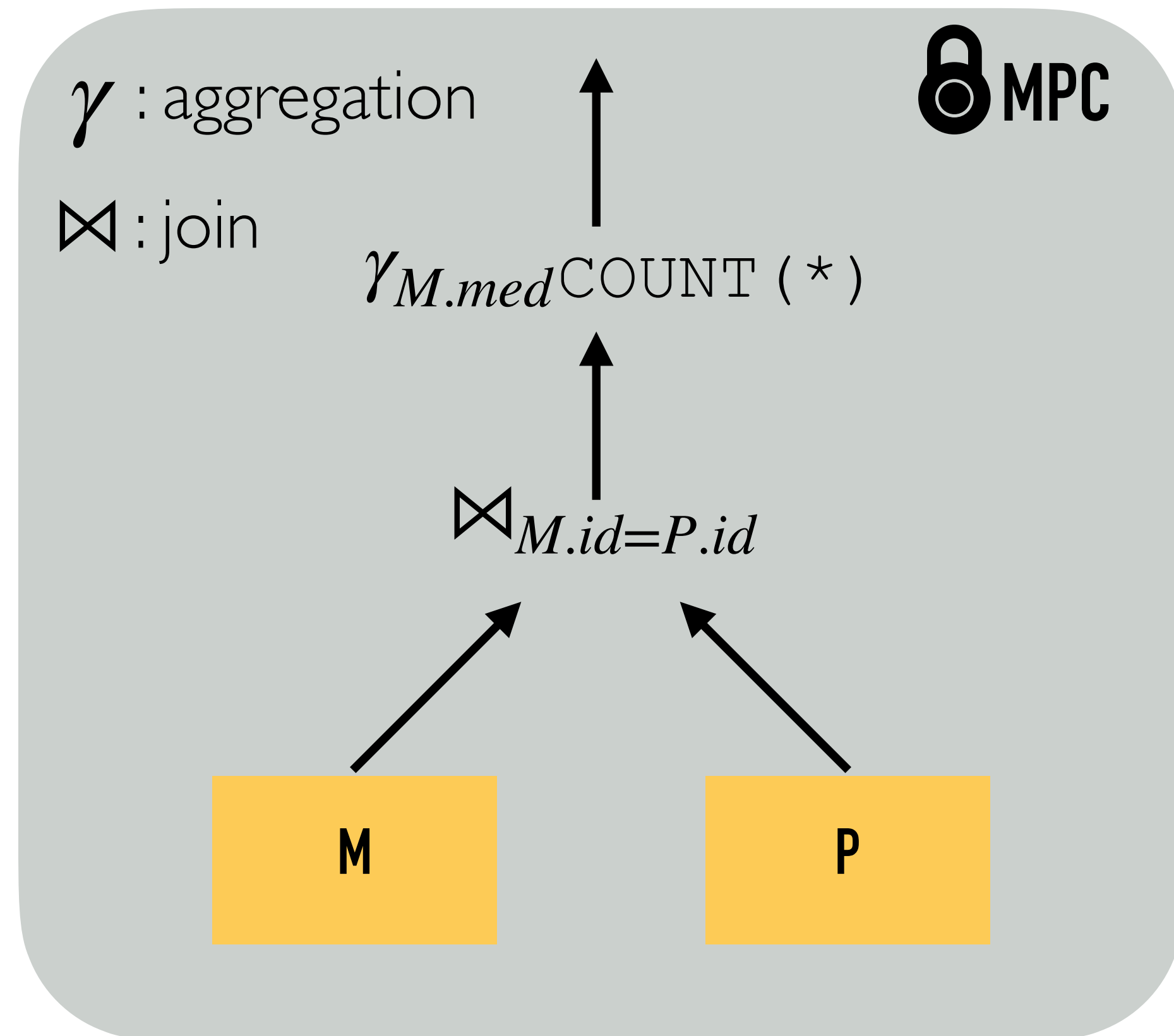
EXAMPLE: OPERATOR DECOMPOSITION IN **SECURITY**



```
SELECT M.med, COUNT(*)  
FROM Medication as M, Patients as P  
WHERE M.id = P.id  
GROUP-BY M.med
```

“Count the number of patients per prescribed medication”

EXAMPLE: OPERATOR DECOMPOSITION IN **SECURITY**



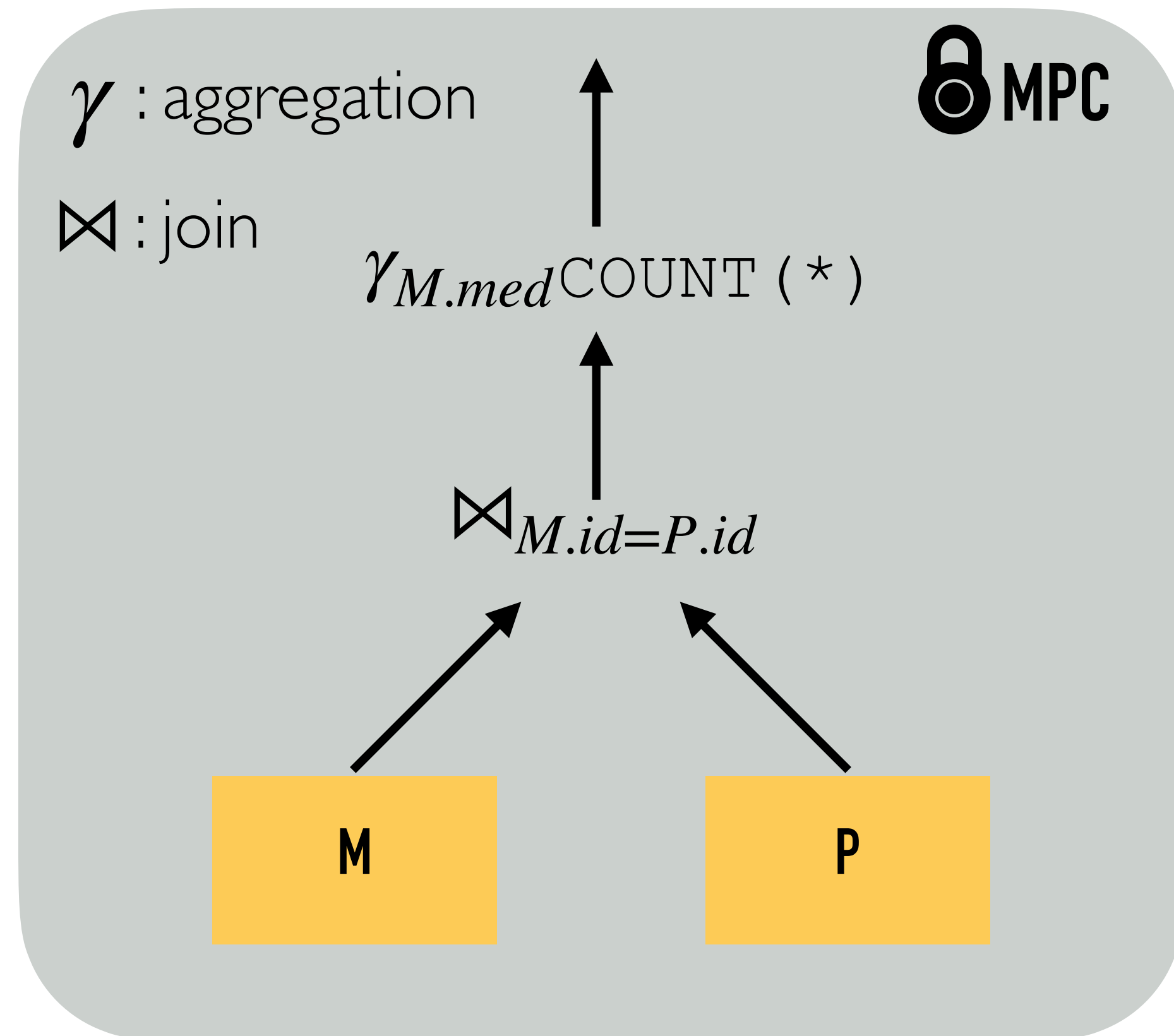
```
SELECT M.med, COUNT(*)  
FROM Medication as M, Patients as P  
WHERE M.id = P.id  
GROUP-BY M.med
```

“Count the number of patients per prescribed medication”

Applying GROUP-BY after the join will require materializing the cartesian product $M \times P$

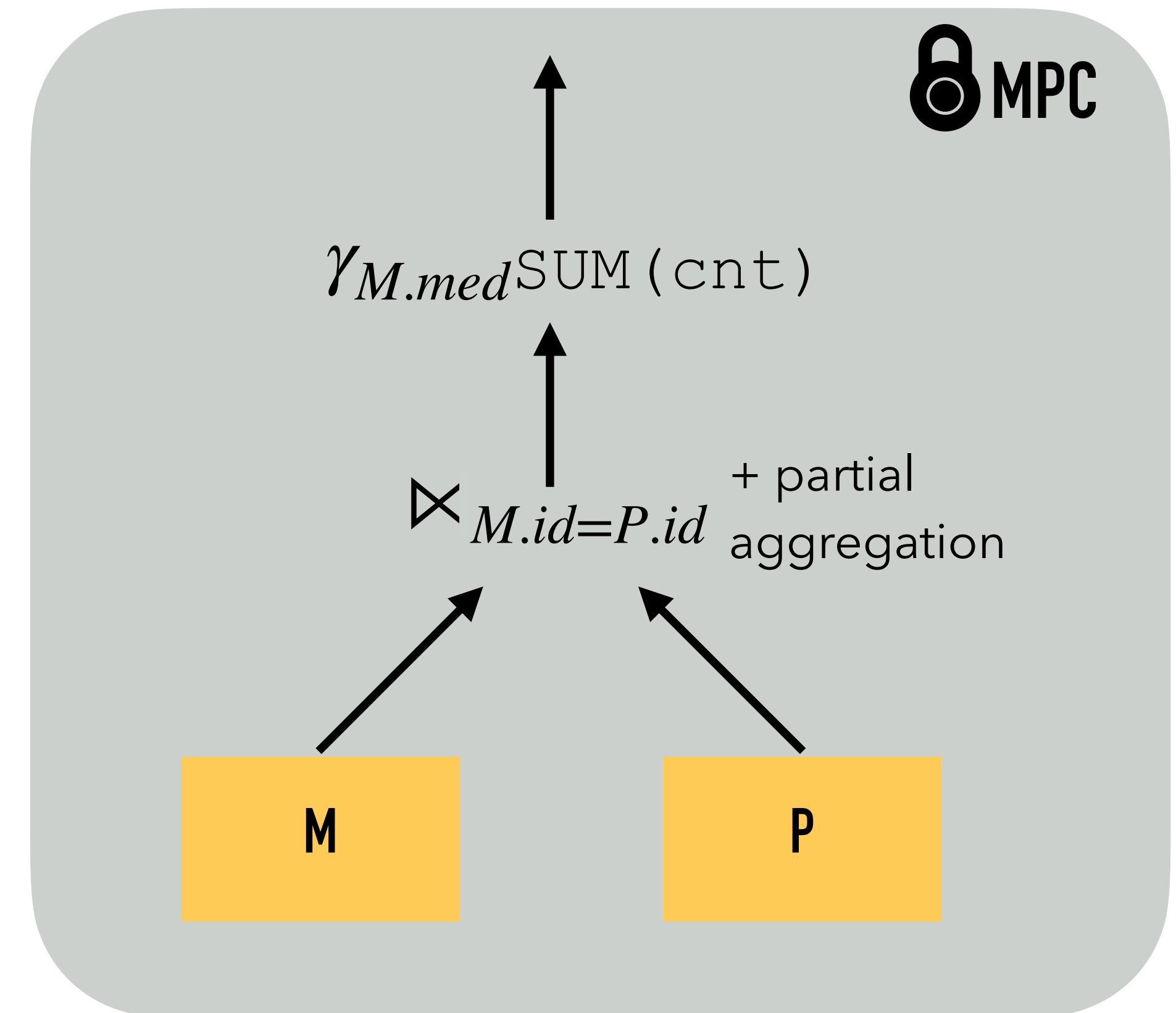
EXAMPLE: OPERATOR DECOMPOSITION IN **SECURITY**

* Assuming the group-by operator is based on an odd-even circuit



$O(n^2 \log^2 n)$ operations / messages

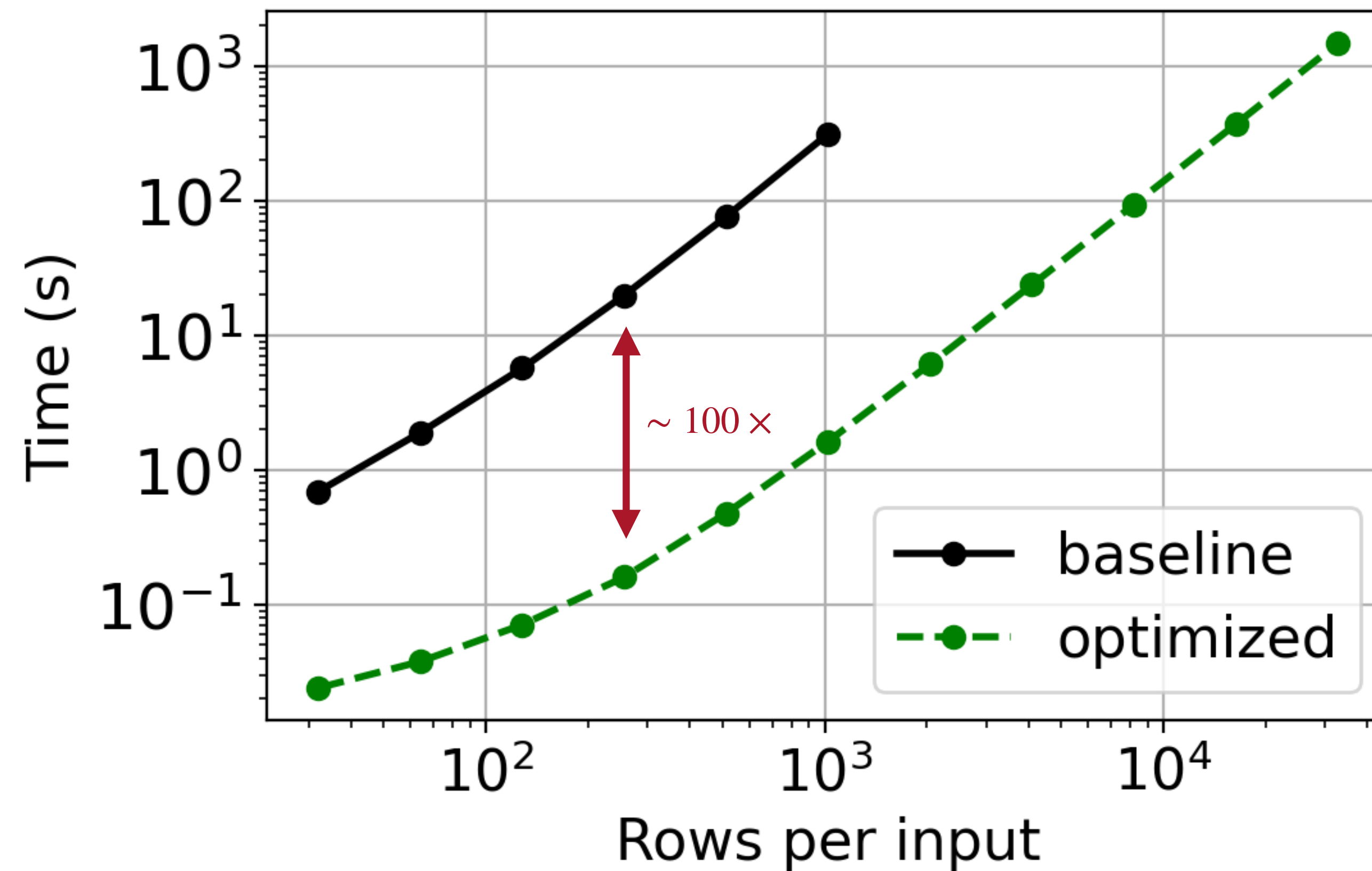
$O(\log^2 n)$ rounds $O(n^2)$ space



$O(n^2)$ operations / messages

$\sim 4 \times$ fewer rounds $O(n)$ space

EFFECT OF JOIN-AGGREGATION DECOMPOSITION (LAN)



Lower is better

* Secrecy servers deployed on AWS EC2 r5.xlarge instances (us-east-2)

SECRECY's CORE CONTRIBUTIONS

1. Relational MPC primitives

- Amortize network I/O
- Make secret-sharing competitive in WAN

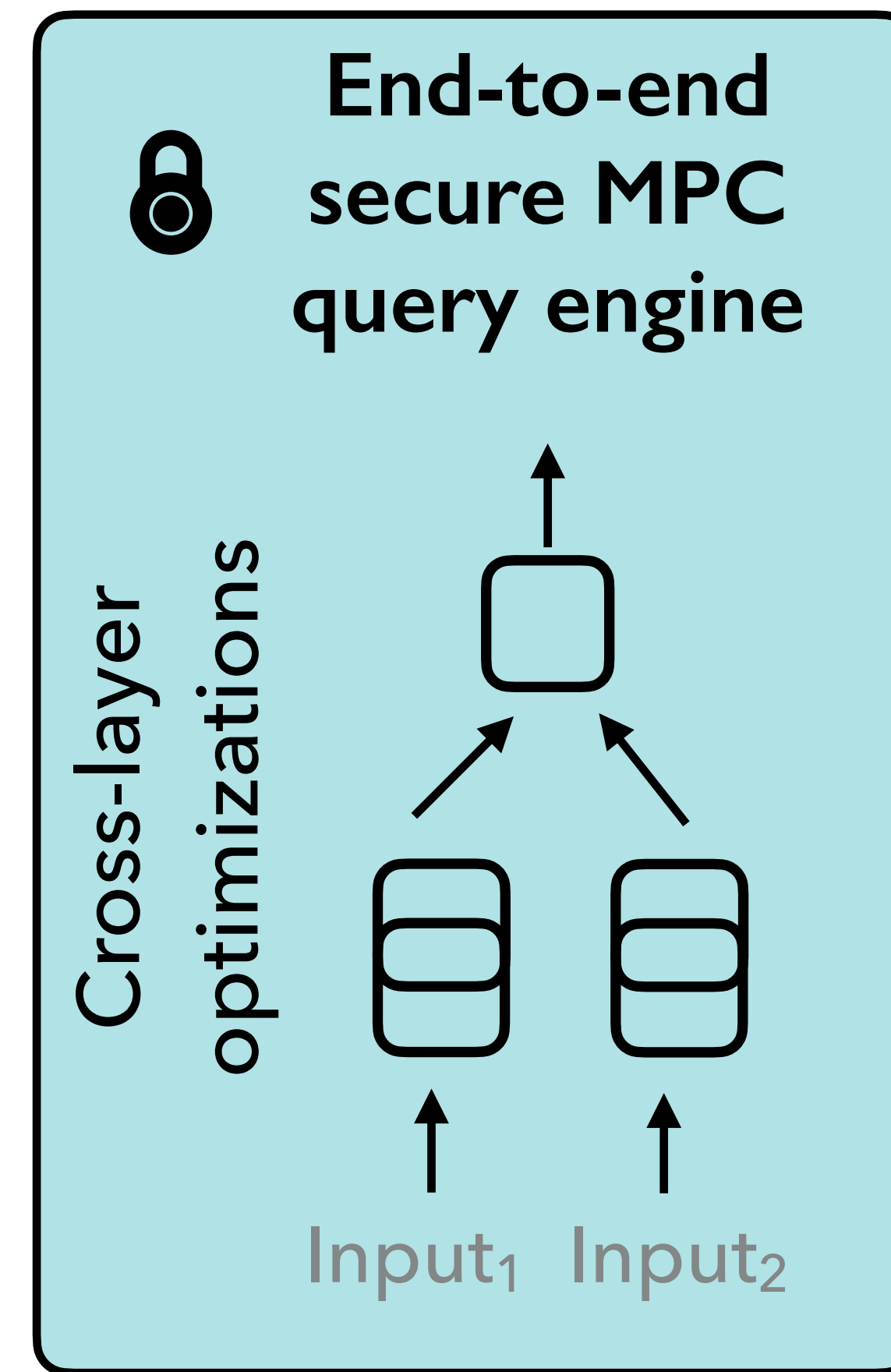
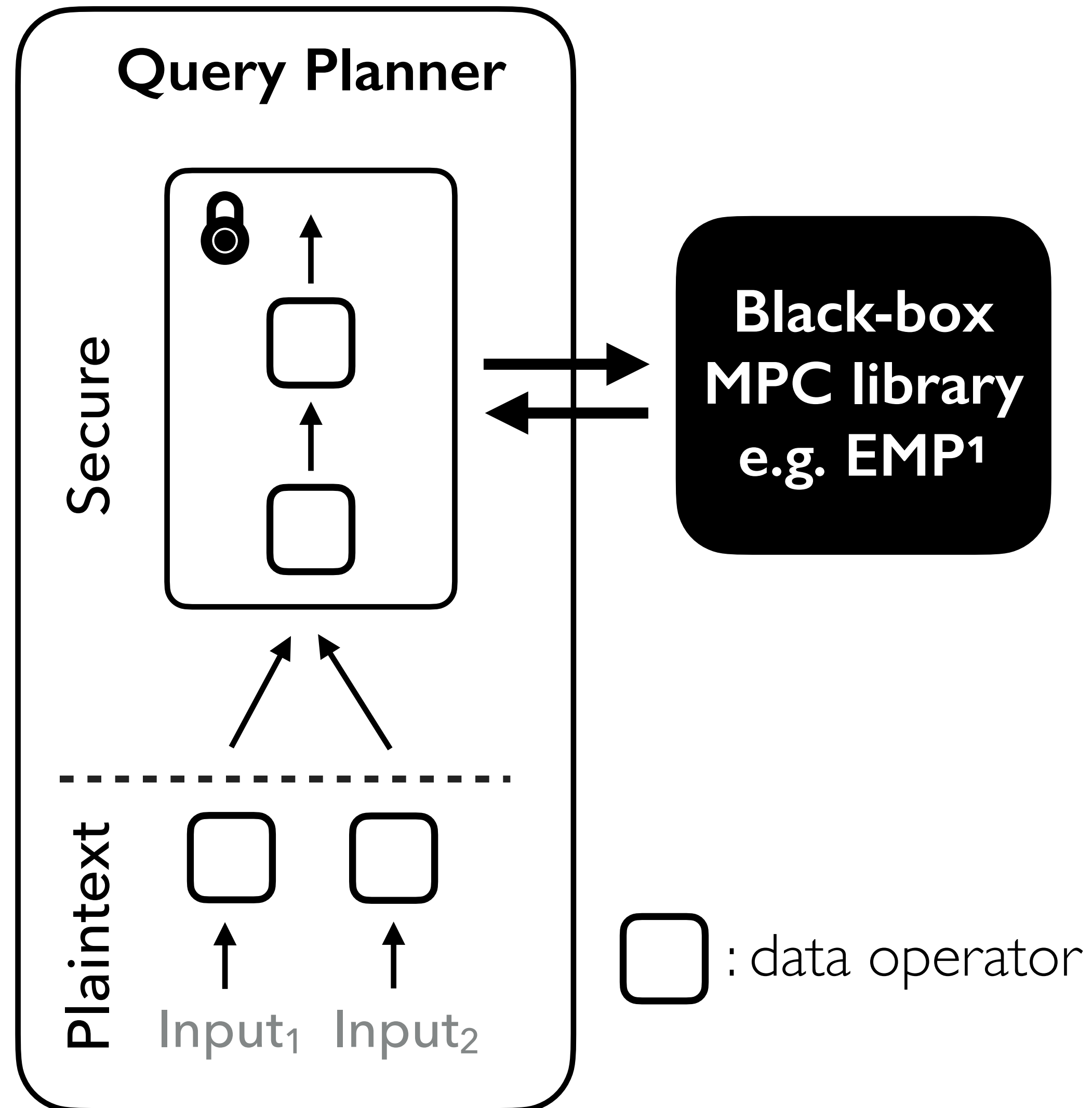
2. Analytical cost model for MPC

- Operation cost
- Synchronization cost
- Composition cost

3. Vectorized MPC query processor

- Logical optimizations
- System optimizations
- Protocol-specific optimizations

OPENING THE MPC BLACK BOXES



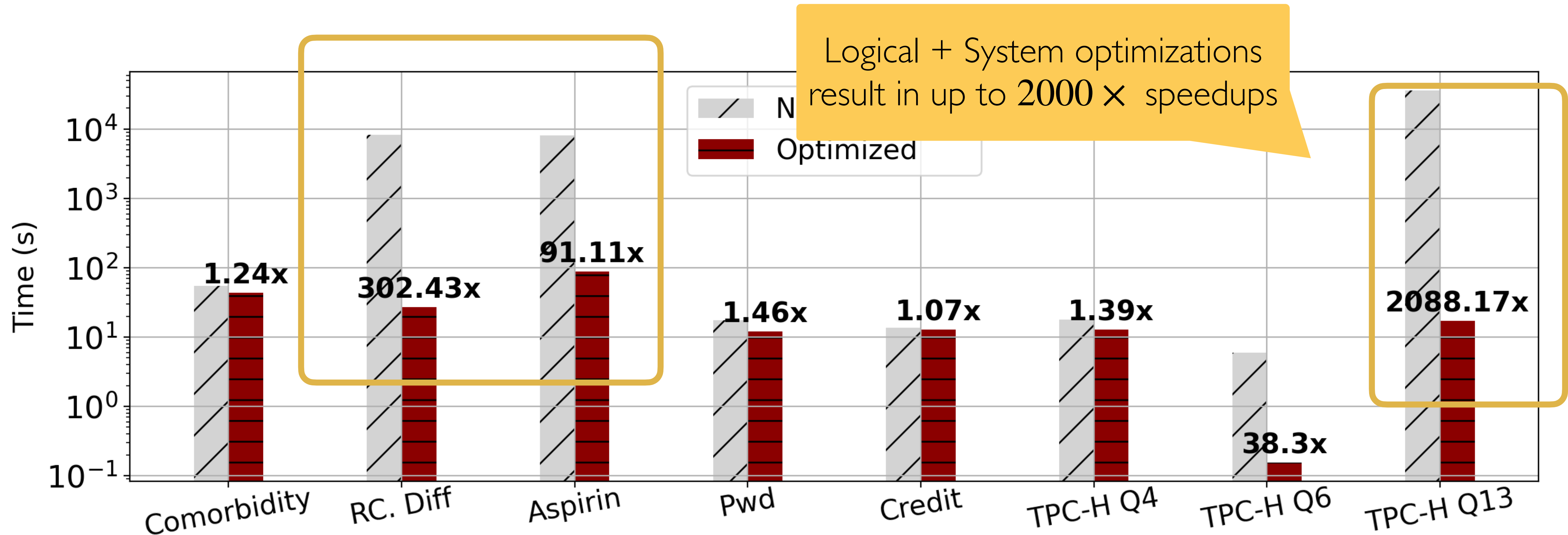
The Secrecy Framework

Supported optimizations:

- Logical (e.g. operator decomposition)
- Physical (e.g. message batching, operator fusion)
- Protocol-specific (e.g. dual sharing)

¹ X. Wang, A. J. Malozemoff, and J. Katz. *EMP-toolkit: Efficient MultiParty computation toolkit*, 2016. <https://github.com/emp-toolkit>

EFFECT OF **SECRECY** OPTIMIZATIONS ON REAL QUERIES (MULTI-CLOUD)

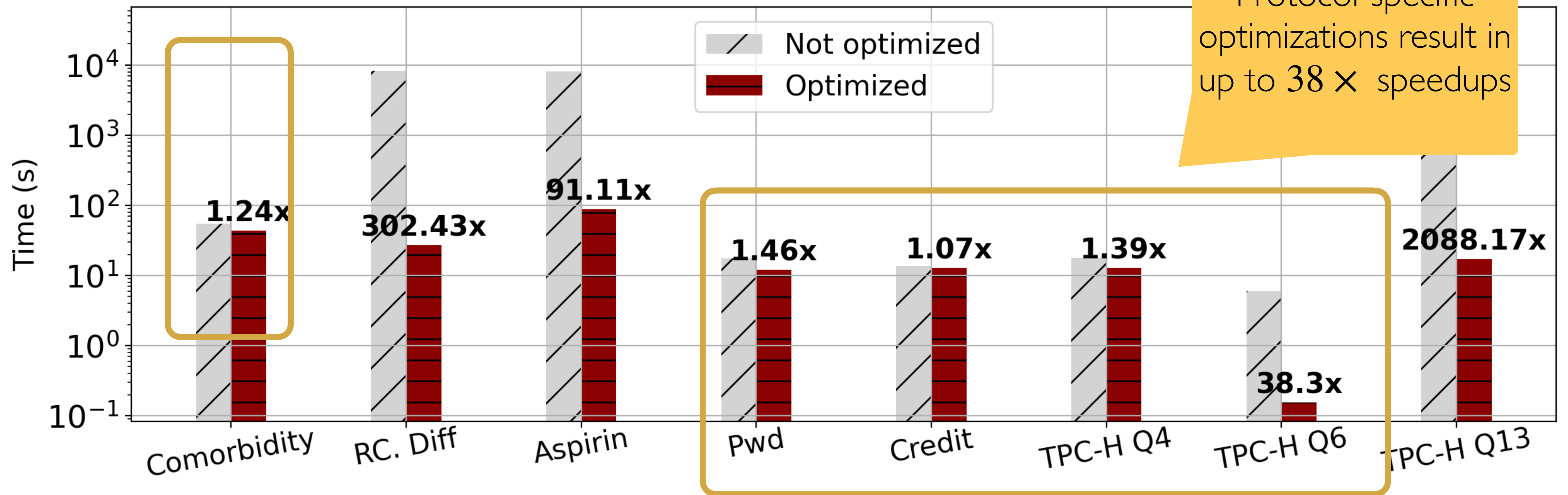


* Secrecy servers deployed in three clouds: AWS (Ohio), GCP (South Carolina), and Azure (Virginia)

* Reported times are for 1000 rows per input table

* Not optimized plans use message batching too (otherwise the cost of MPC is prohibitive)

EFFECT OF **SECRECY** OPTIMIZATIONS ON REAL QUERIES (MULTI-CLOUD)

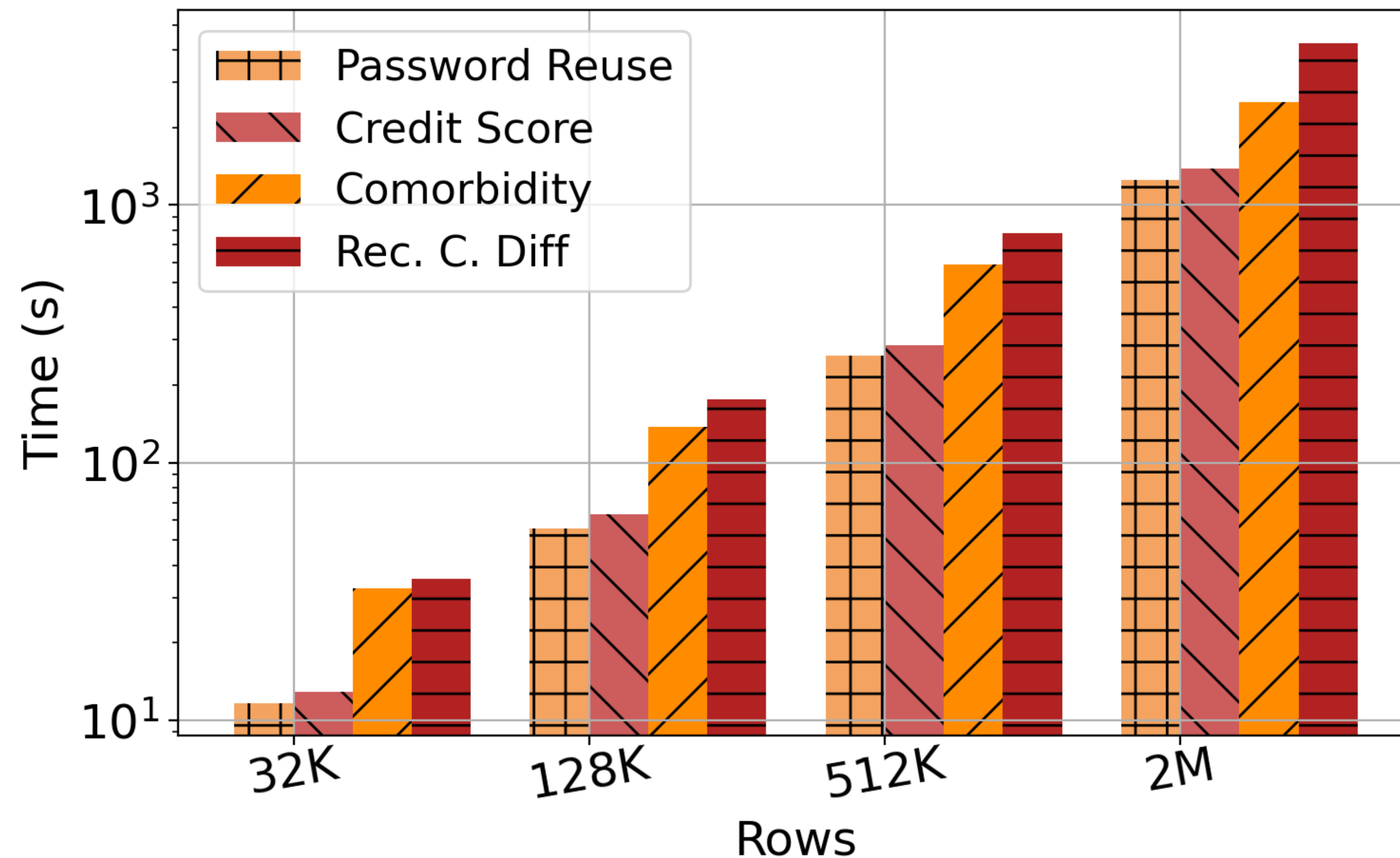


* Secrecy servers deployed in three clouds: AWS (Ohio), GCP (South Carolina), and Azure (Virginia)

* Reported times are for 1000 rows per input table

* Not optimized plans use message batching too (otherwise the cost of MPC is prohibitive)

SECRECY's SCALING BEHAVIOR (LAN)



Rec. C. Diff scales to 2 million rows in ~1.2h

```
WITH rcd AS (  
  SELECT pid, time, row_no() OVER  
    (PARTITION BY pid ORDER BY time)  
  FROM diagnosis  
  WHERE diag=cdiff)  
SELECT DISTINCT pid  
FROM rcd r1 JOIN rcd r2 ON r1.pid = r2.pid  
WHERE r2.time - r1.time >= 15 DAYS  
AND r2.time - r1.time <= 56 DAYS  
AND r2.row_no = r1.row_no + 1
```

“Find the distinct ids of patients who have been diagnosed with cdiff and have two consecutive infections between 15 and 56 days apart”

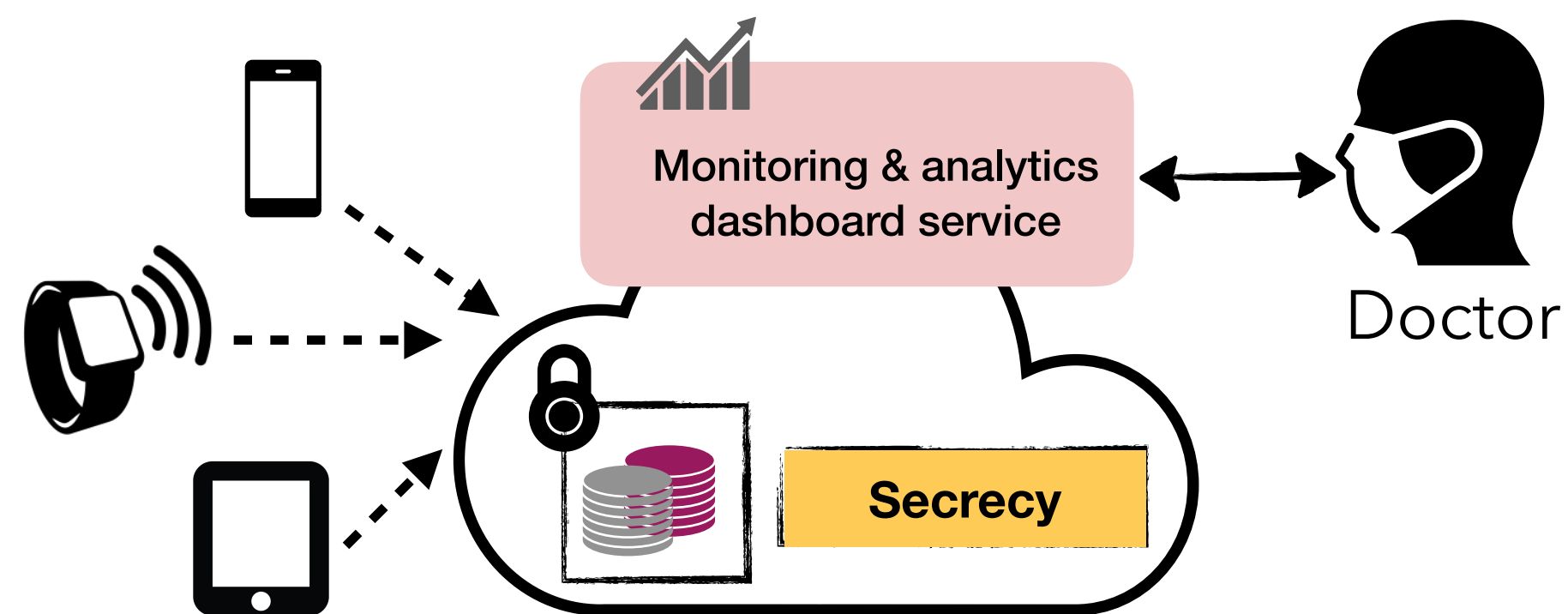
* Secrecy servers deployed on AWS EC2 r5.xlarge instances (us-east-2)

* Each server uses a single vCPU

REAL-WORLD **SECRECY** USE CASES

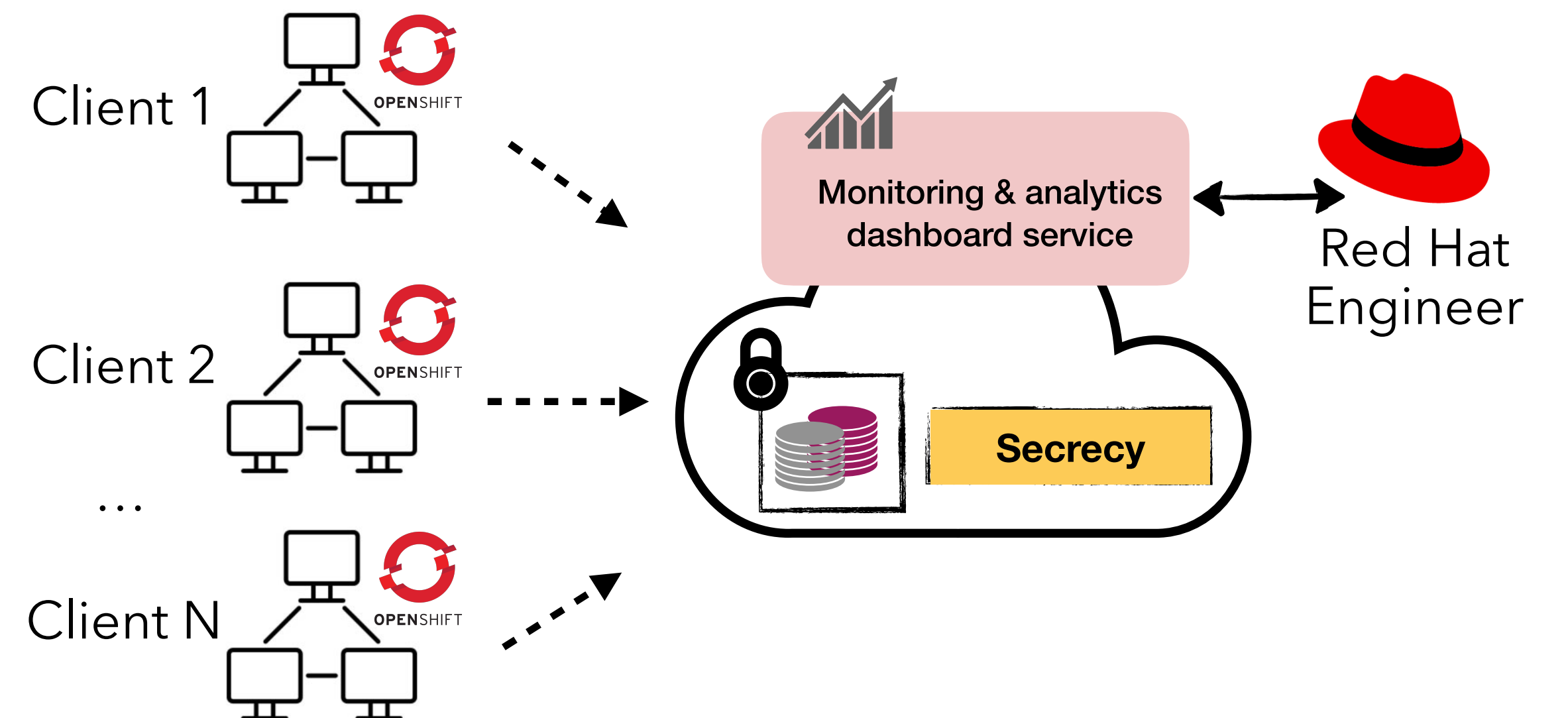
Secure digital health analytics¹

(BU Medical & Hariri Institute for Computing)



Secure cross-site analytics on OpenShift logs²

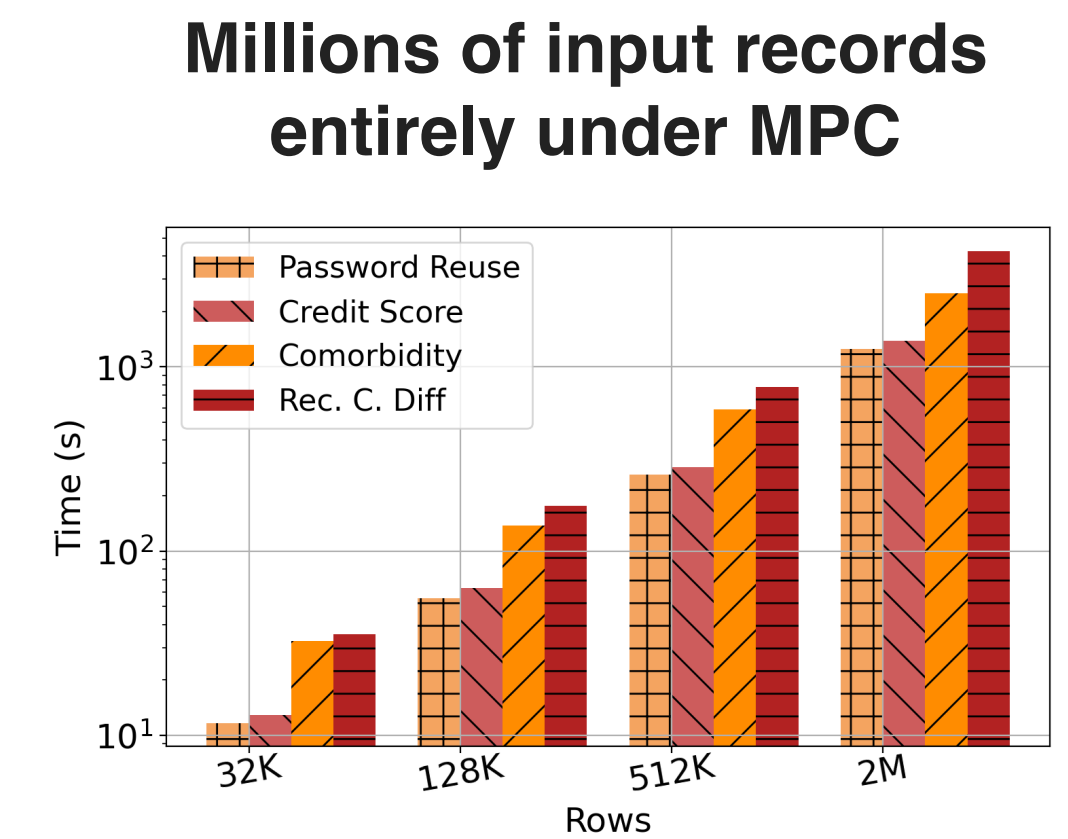
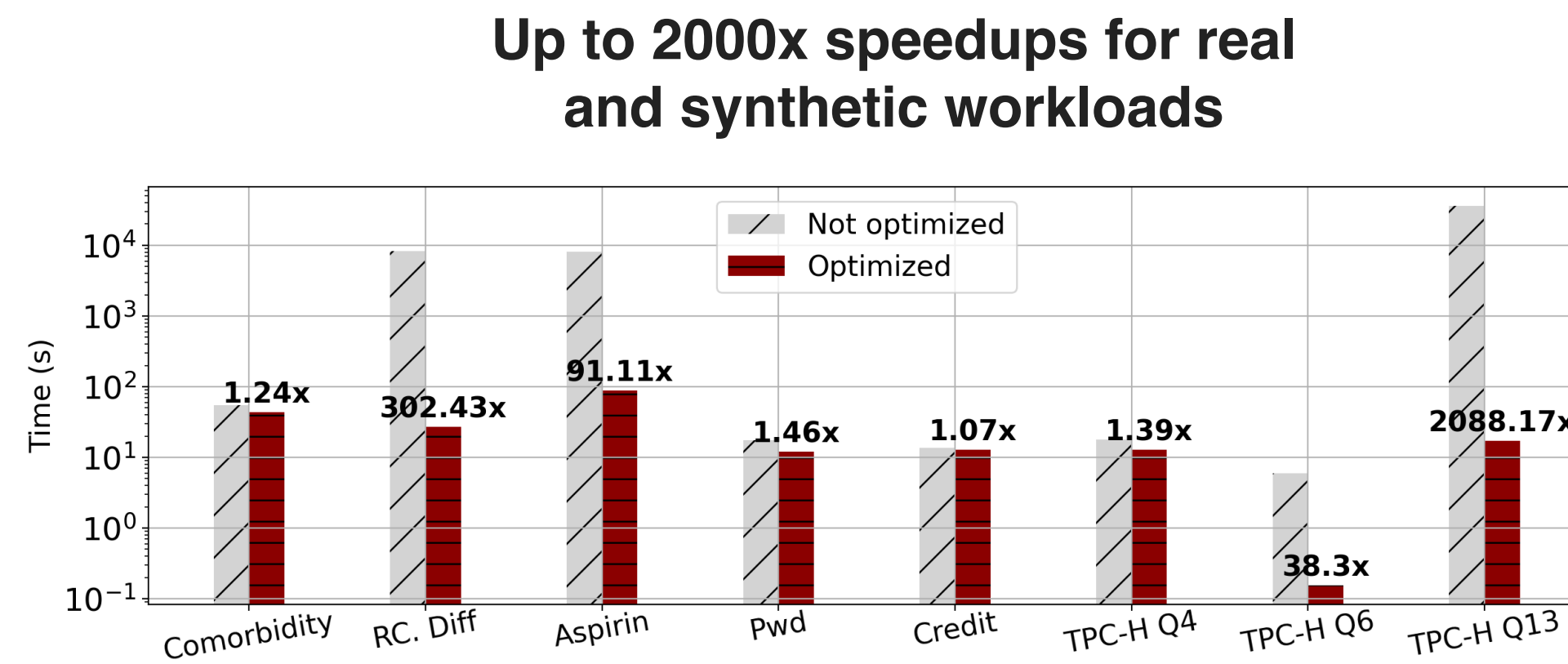
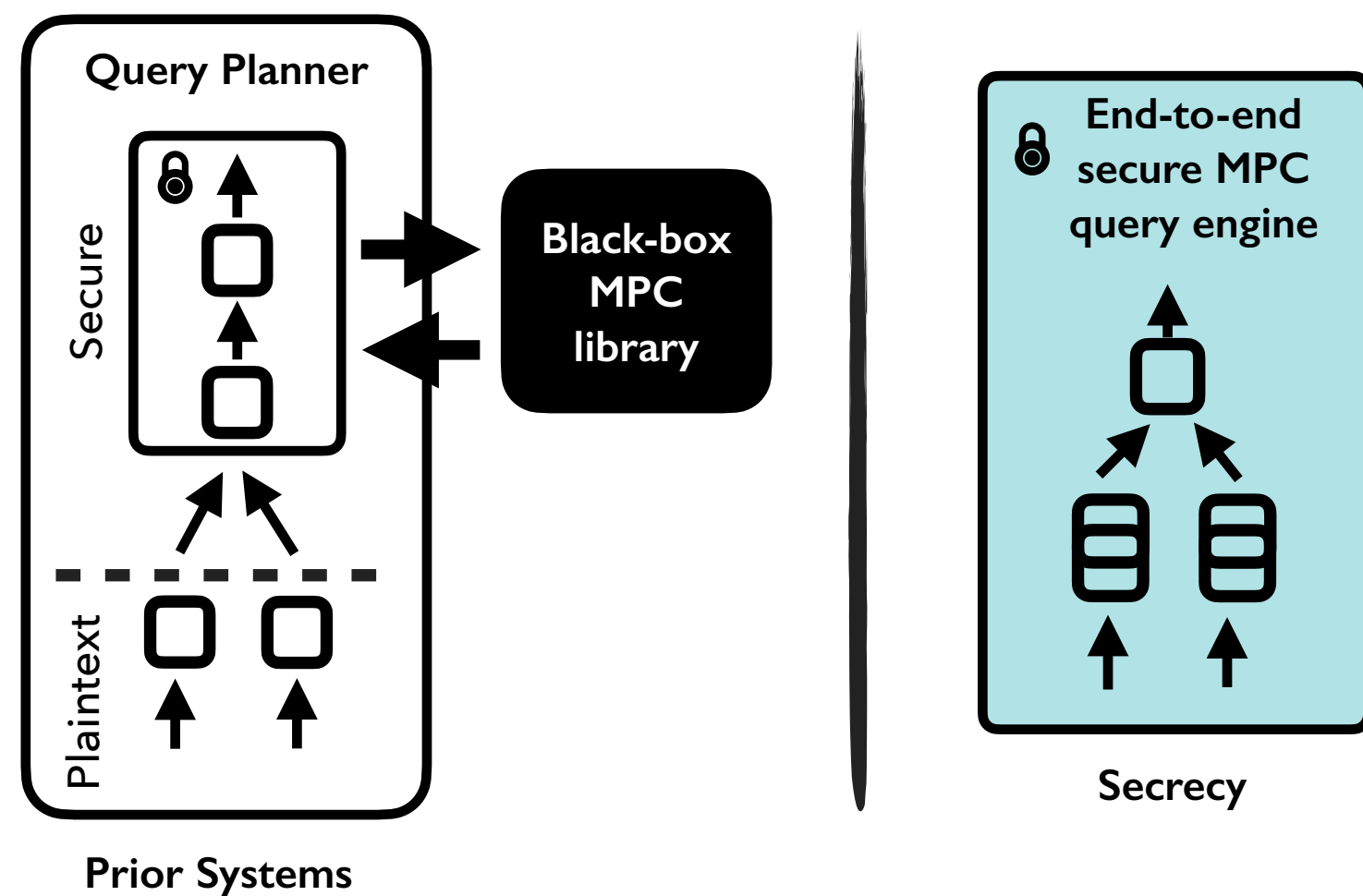
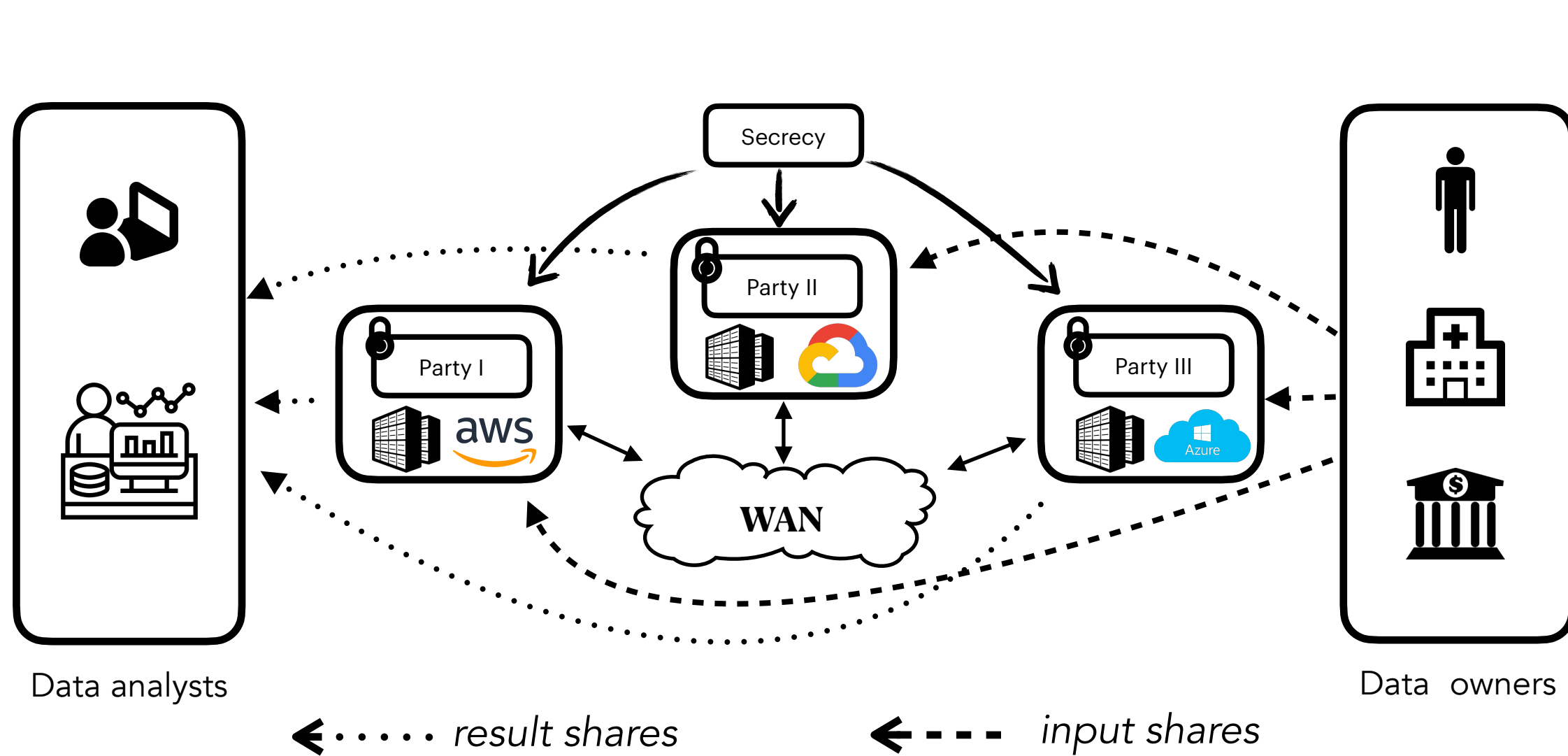
(BU Red Hat Collaboratory)



¹ <https://www.bu.edu/hic/research/focused-research-programs/continuous-analysis-of-mobile-health-data-among-medically-vulnerable-populations/>

² <https://www.bu.edu/rhcollab/projects/security-privacy/secure-cross-site-analytics-on-openshift-logs/>

SECRECY SUMMARY



Source code: <https://github.com/CASP-Systems-BU/Secrecy>