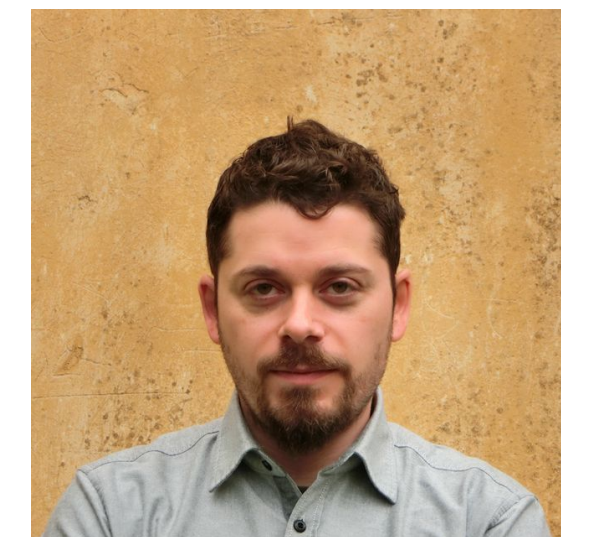
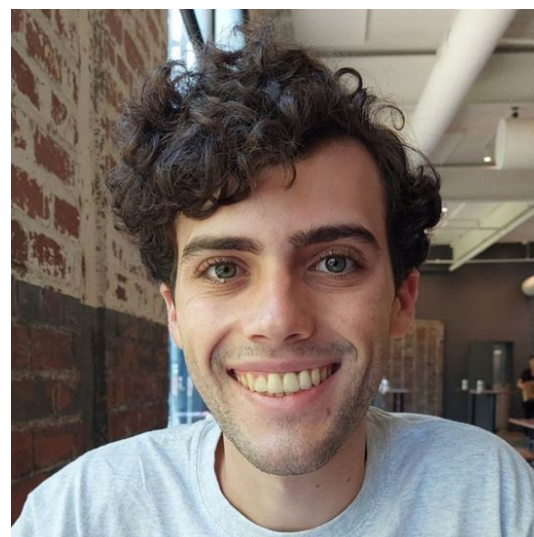


ORQ: Complex Analytics on Private Data with Strong Security Guarantees

Eli Baum



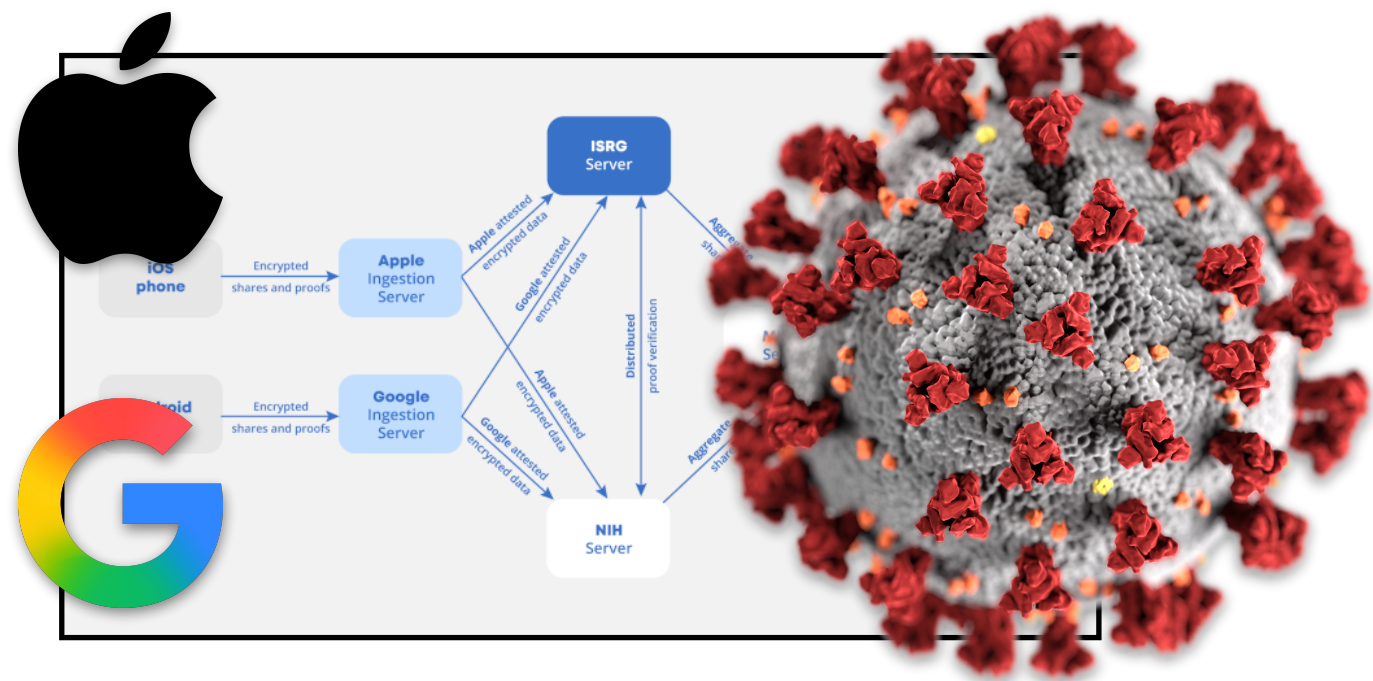
joint work with Sam Buxbaum, Nitin Mathai, Muhammad Faisal, Vasia Kalavri, Mayank Varia, and John Liagouris
SOSP 2025 — 16 October 2025

Motivation: Collaborative Analytics on Sensitive Data



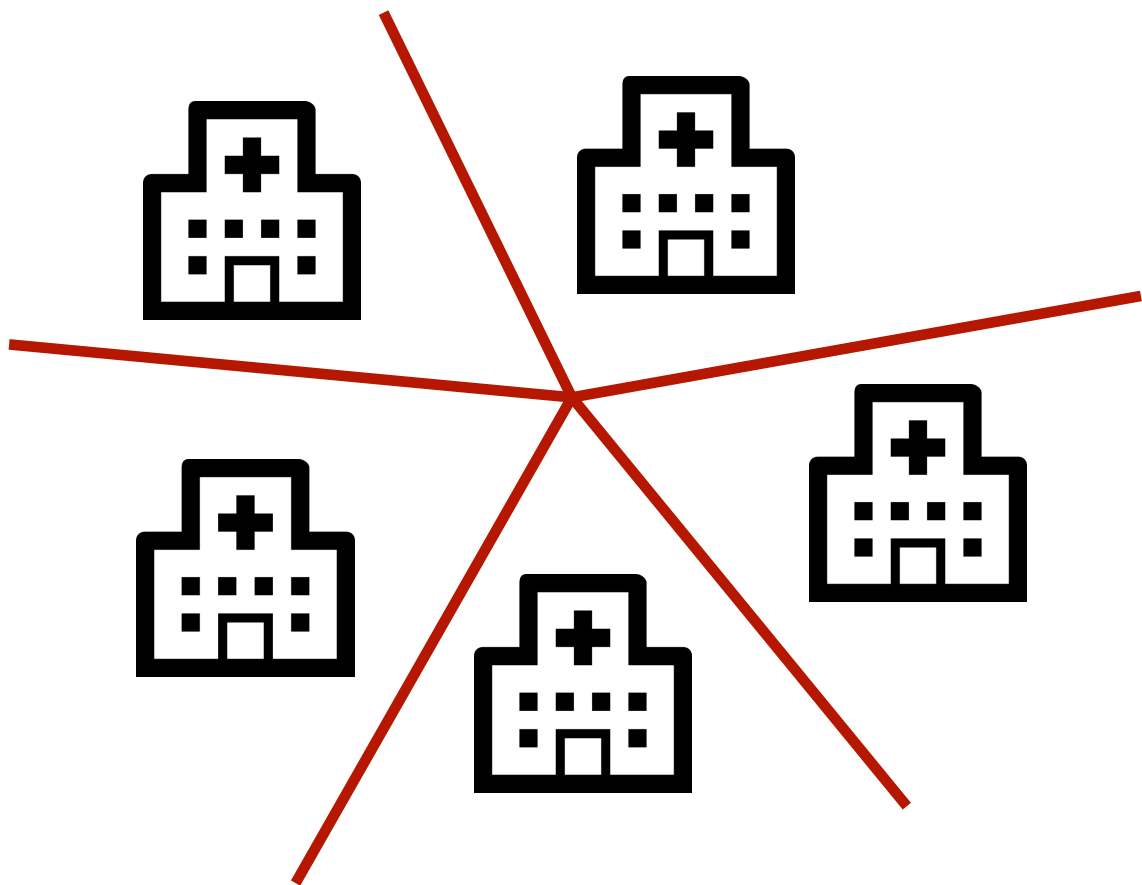
Motivation: Collaborative Analytics on Sensitive Data

Common interest



Disease Surveillance

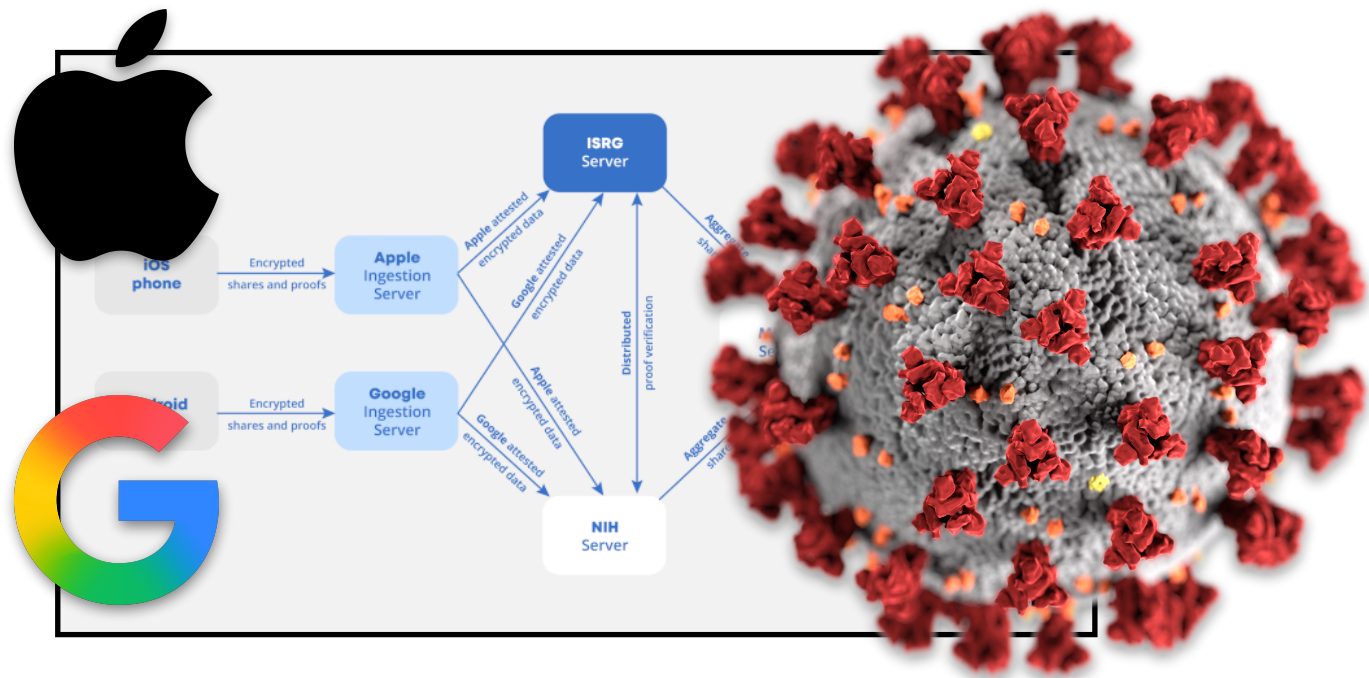
Private data



Hospitals

Motivation: Collaborative Analytics on Sensitive Data

Common interest

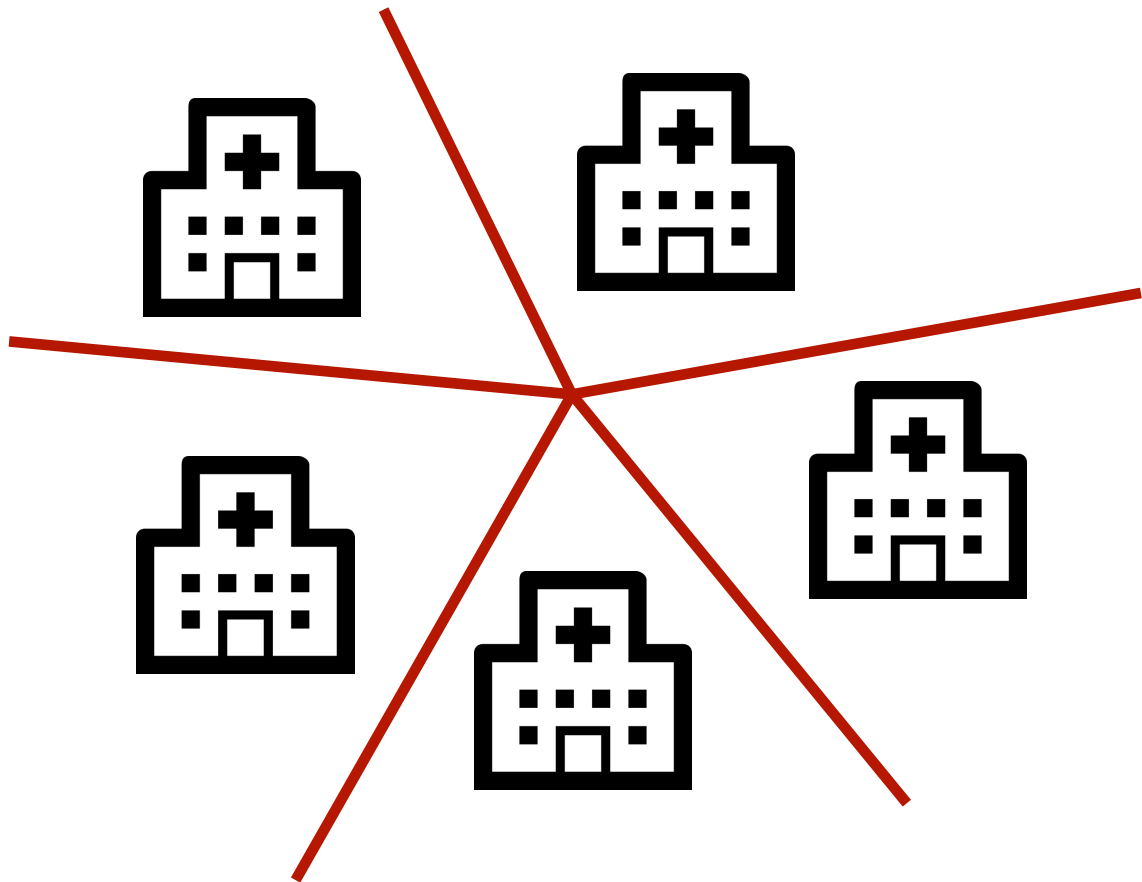


Disease Surveillance

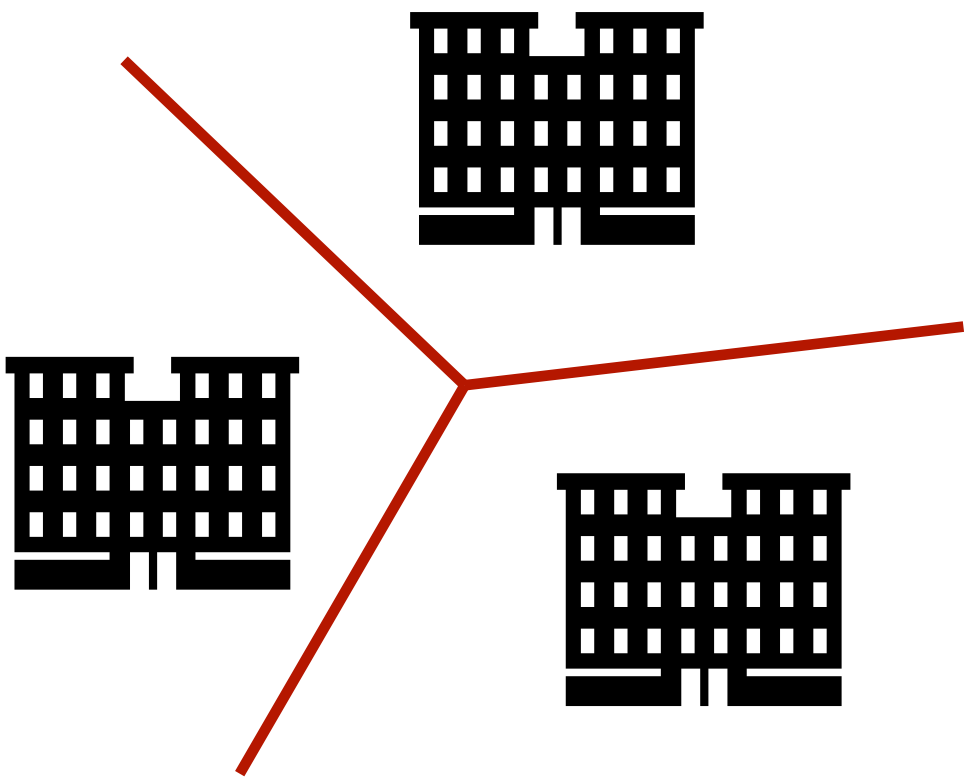


Gender Wage Gap

Private data



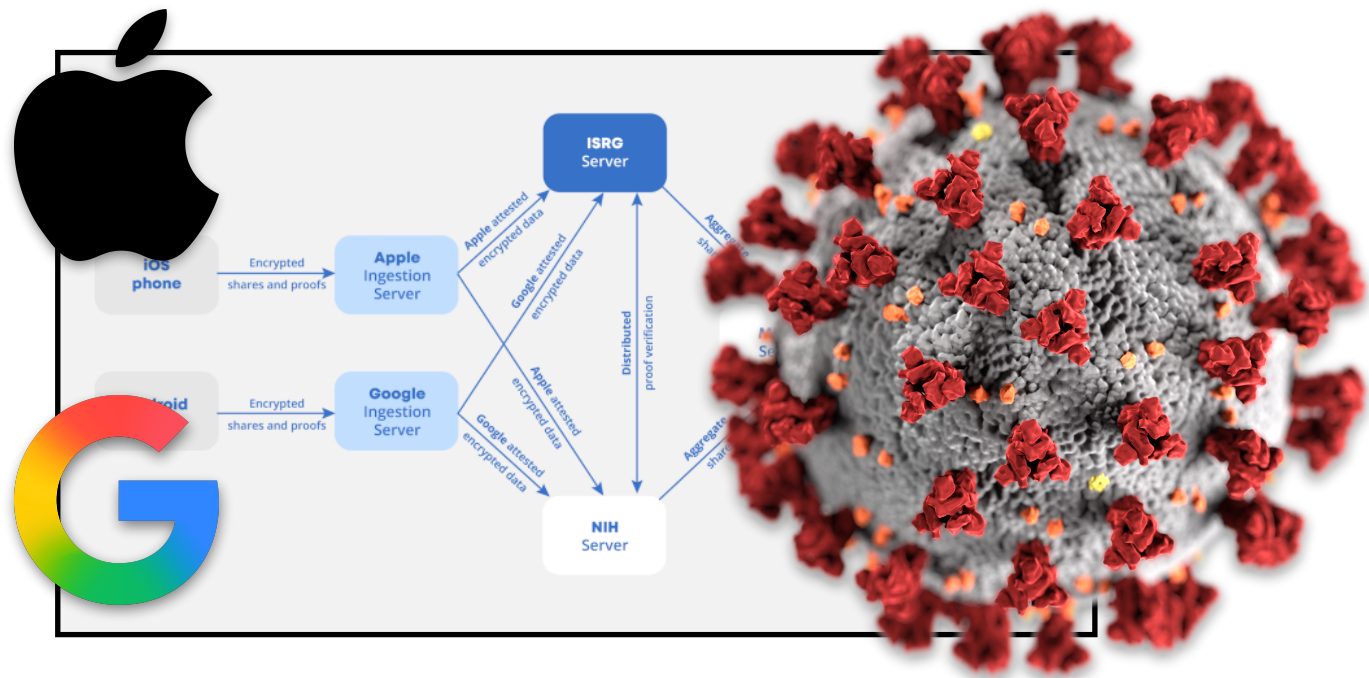
Hospitals



Employers

Motivation: Collaborative Analytics on Sensitive Data

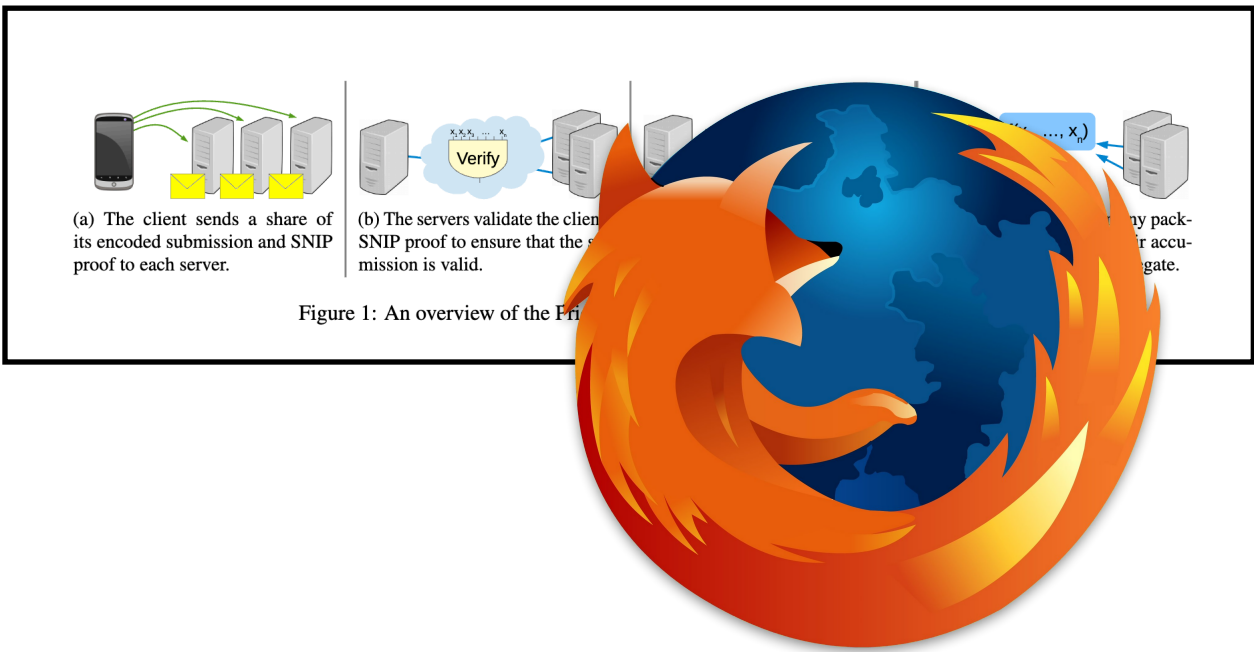
Common interest



Disease Surveillance

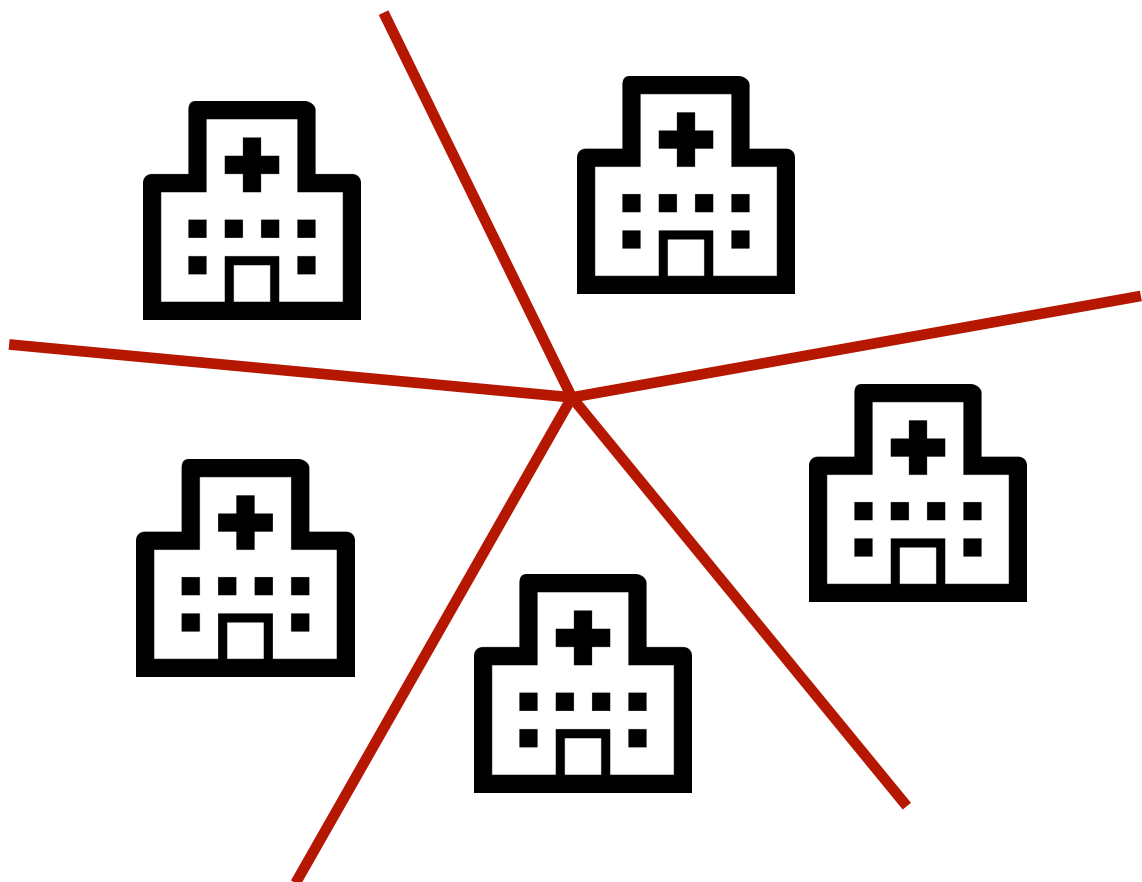


Gender Wage Gap

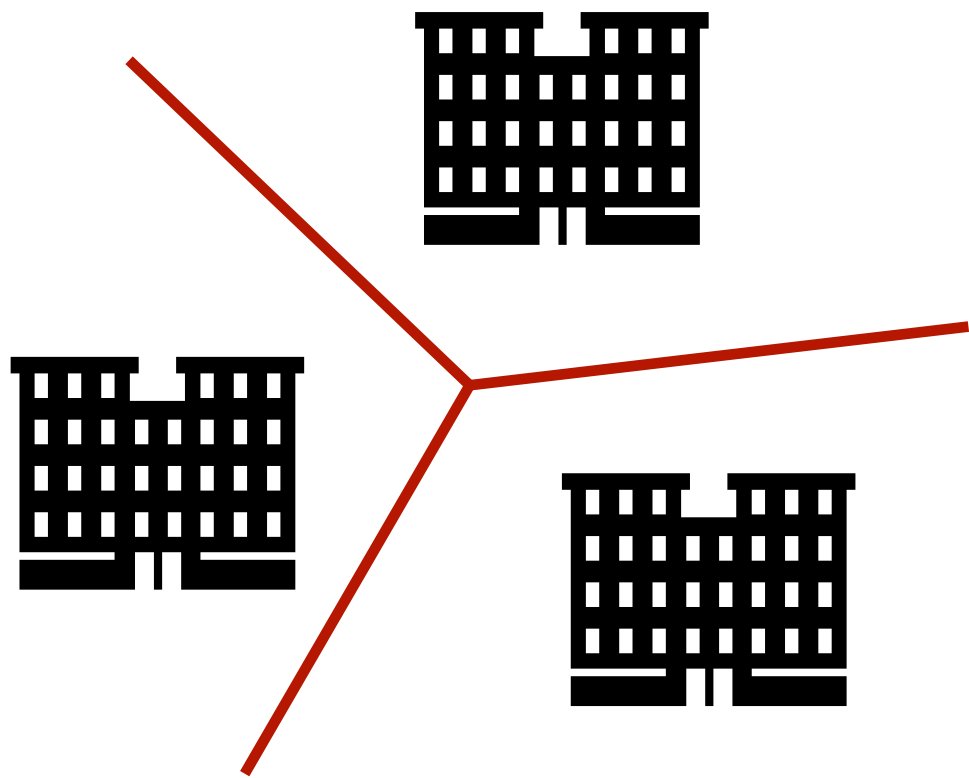


Browser Telemetry

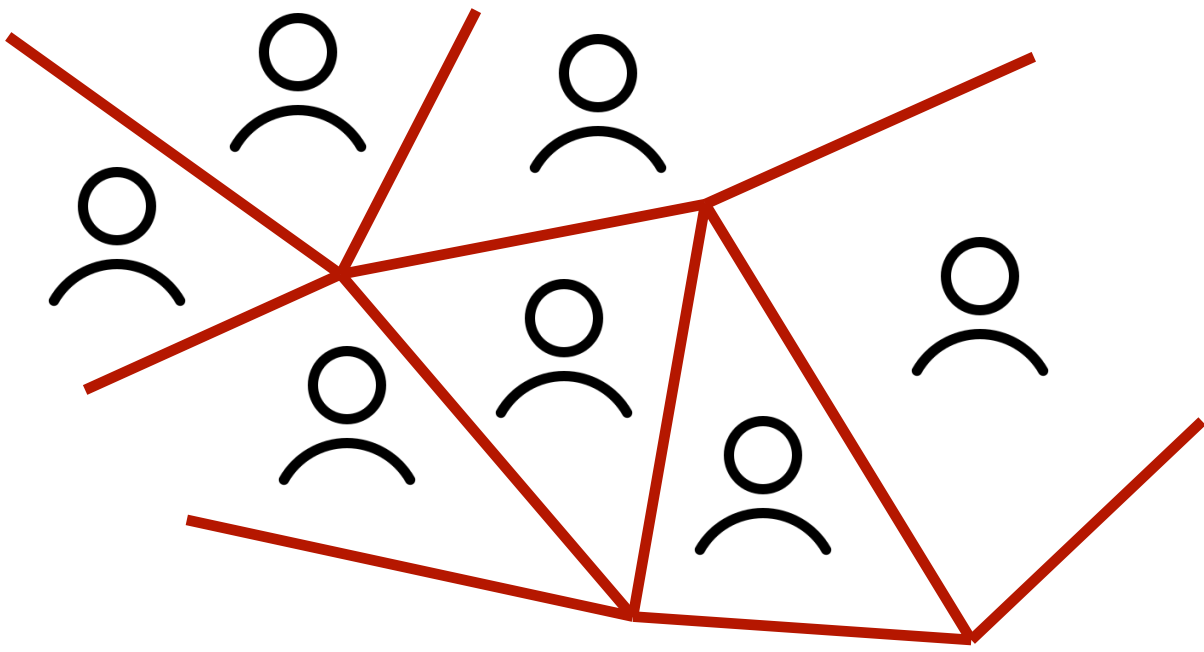
Private data



Hospitals



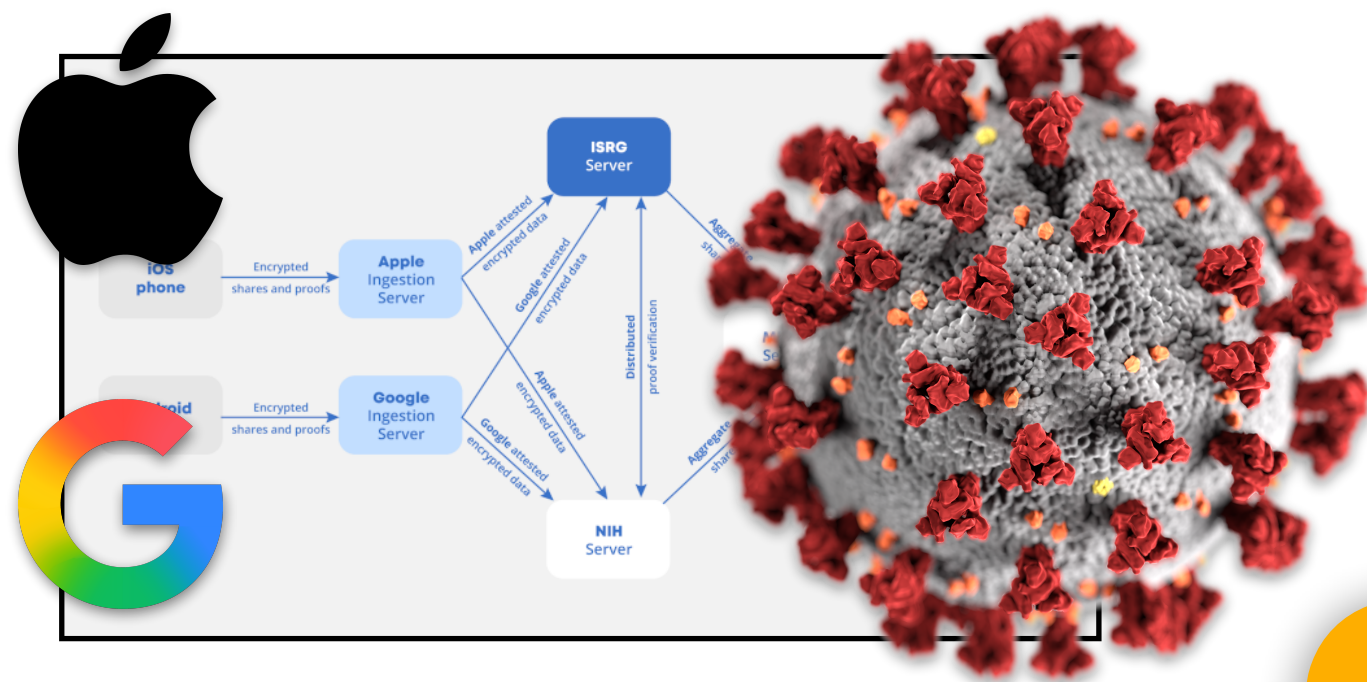
Employers



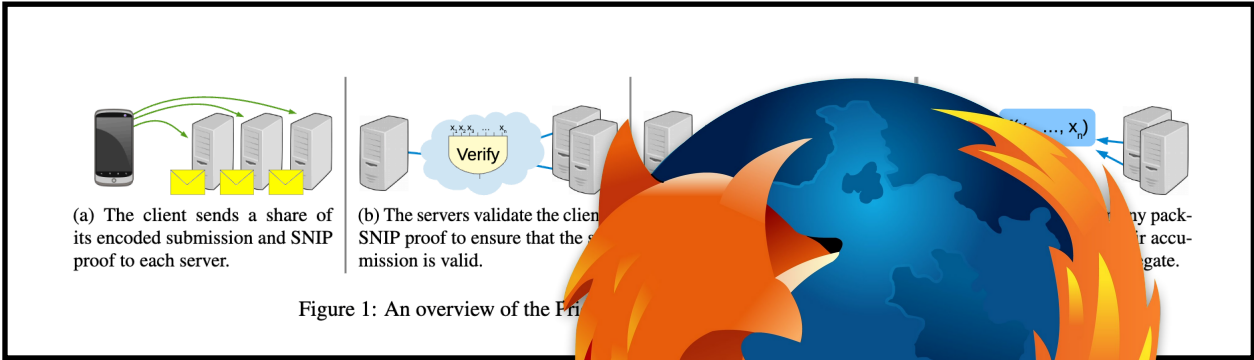
End Users

Motivation: Collaborative Analytics on Sensitive Data

Common interest



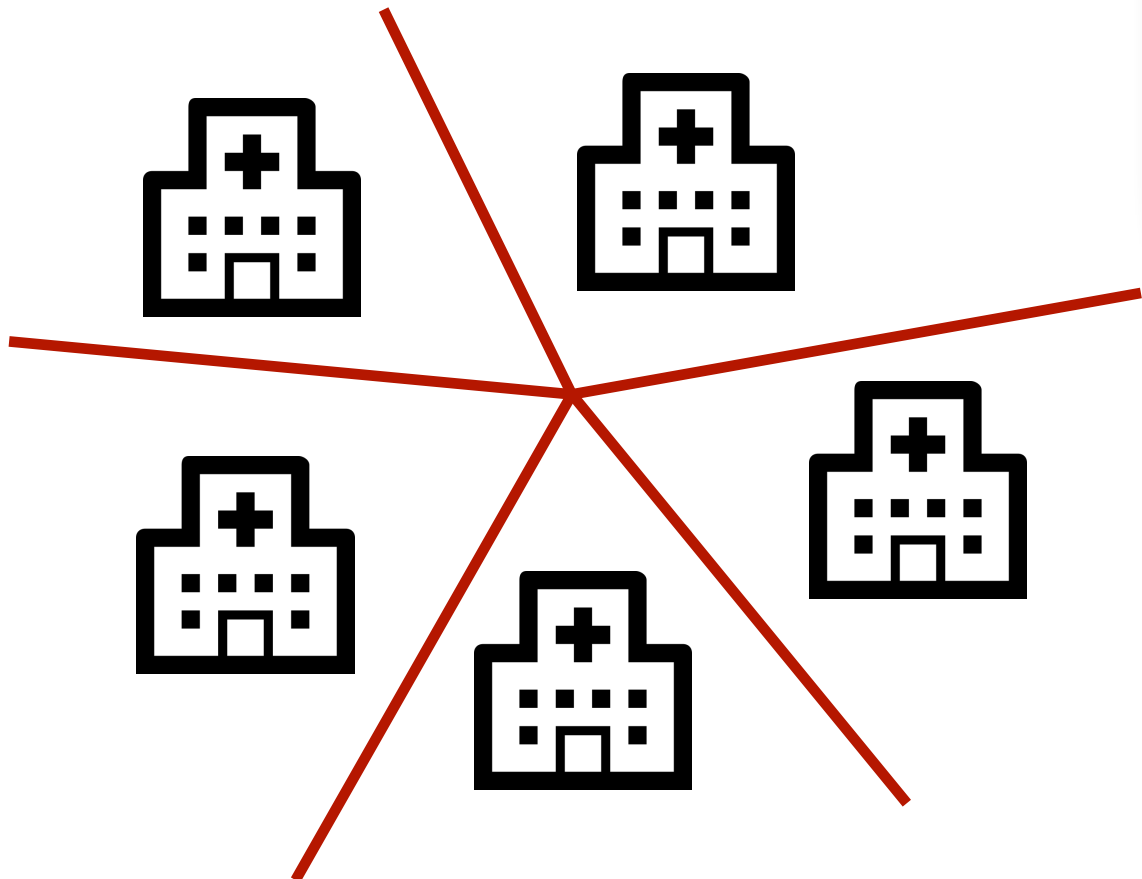
Disease Surveillance



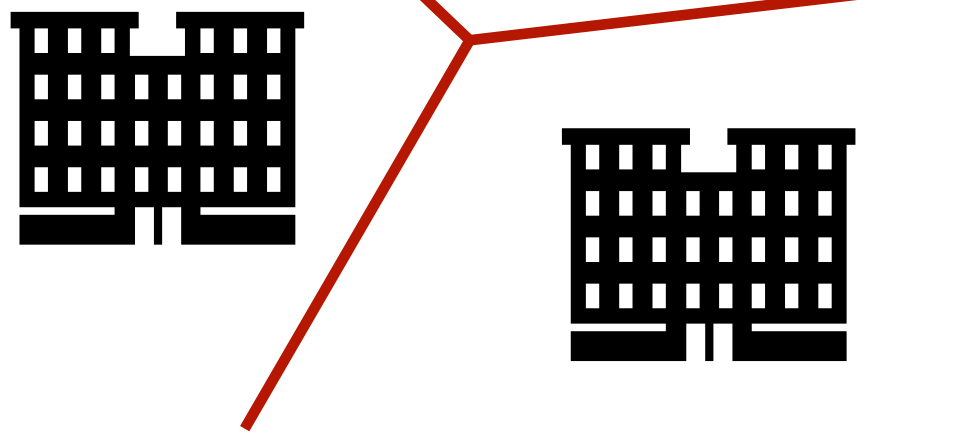
Browser Telemetry

Collaborative analytics requires securely joining data from multiple sources!

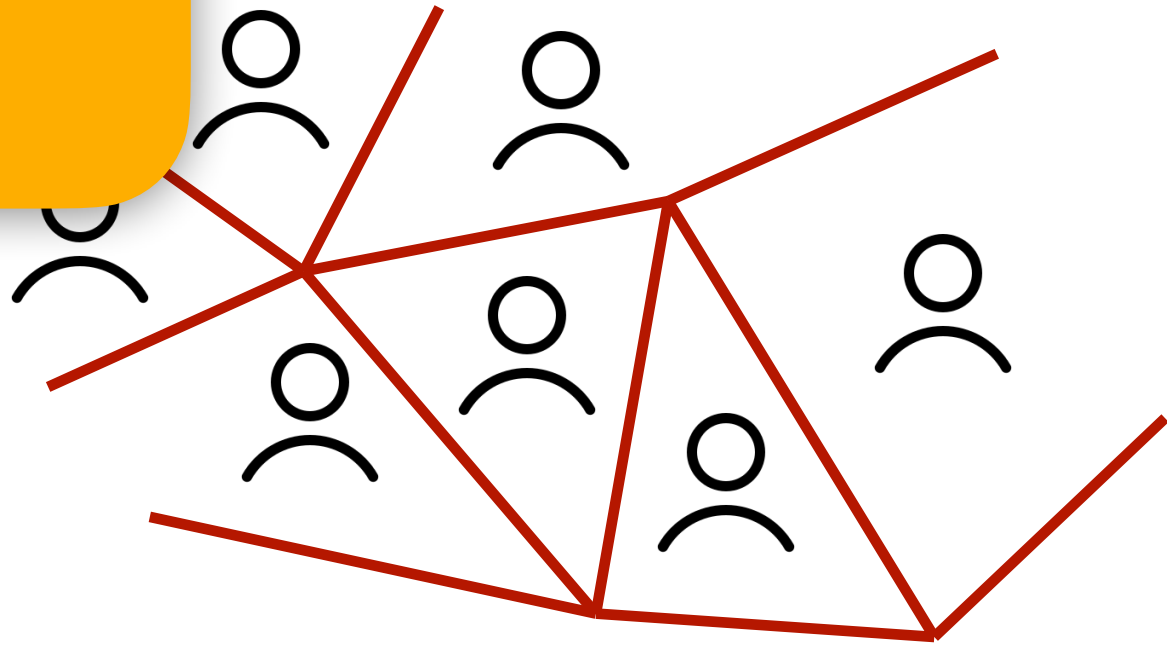
Private data



Hospitals



Employers



End Users

Outline

- Background on Oblivious Computation
- Our Approach
- Making the system work
- Results

Plaintext Analytics

Customer	AcctBalance
🤡	\$1000
😈	\$2000
🤡	\$500
🐸	\$60
😬	\$8000
😬	\$700
🐸	-\$200

`filter (Customer  $\neq$  🐸)`



Customer	AcctBalance
🤡	\$1000
😈	\$2000
🤡	\$500
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😬	\$700

Plaintext Analytics

Adversary View

Customer	AcctBalance

`filter (Customer  $\neq$  🐸)`

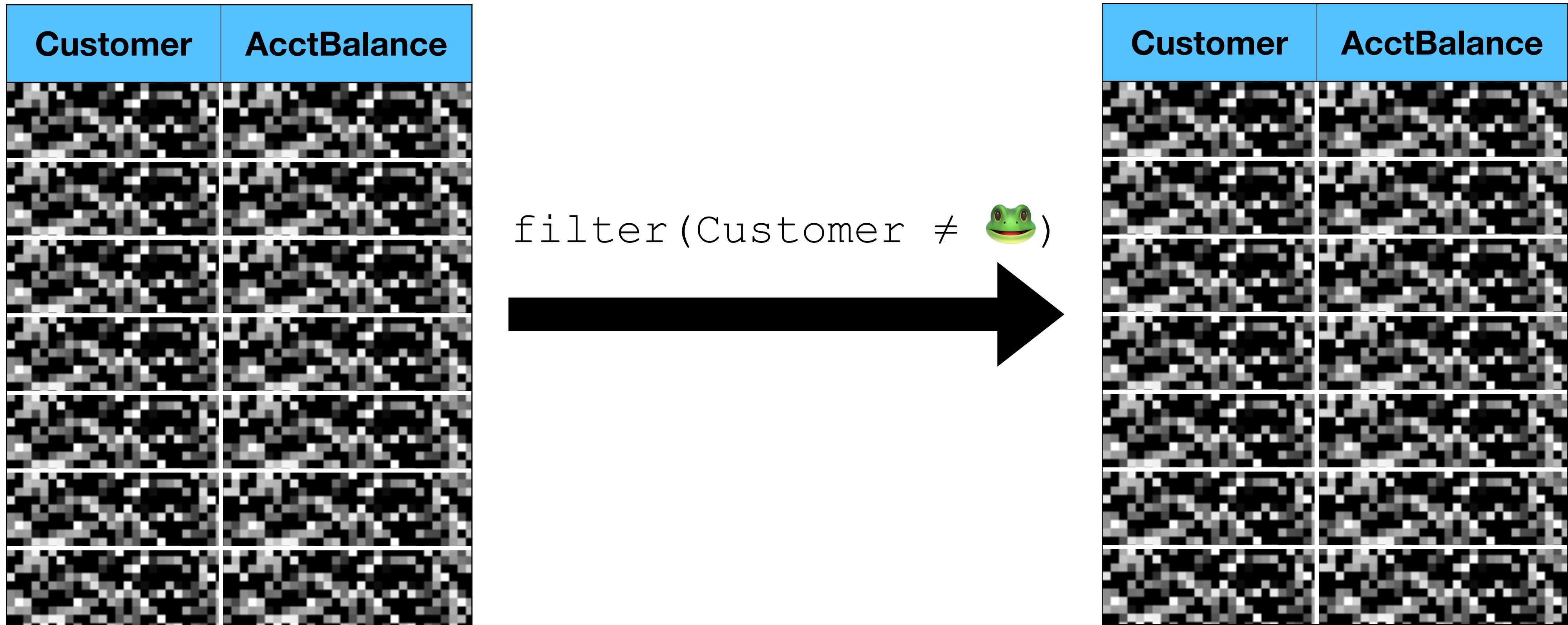


Customer	AcctBalance

Table sizes leak information!

Oblivious Analytics

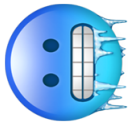
Complex oblivious operators must preserve **worst-case sizes**



Oblivious Joins with Cartesian Product

Customer	Order
Id	CustomerId
	
	
	
	
	
	
	

Oblivious Joins with Cartesian Product

Customer		Order						
Id		CustomerId						
								
								
								
								
								
								
								

Oblivious Joins with Cartesian Product

Cust \ Ord							



Oblivious Joins with Cartesian Product

Cust \ Ord							
	✗	✓	✗	✗	✓	✓	✗
	✗	✗	✗	✗	✗	✗	✓
	✗	✓	✗	✗	✓	✓	✗
	✓	✗	✗	✗	✗	✗	✗
	✗	✗	✓	✓	✗	✗	✗
	✗	✗	✓	✓	✗	✗	✗
	✓	✗	✗	✗	✗	✗	✗

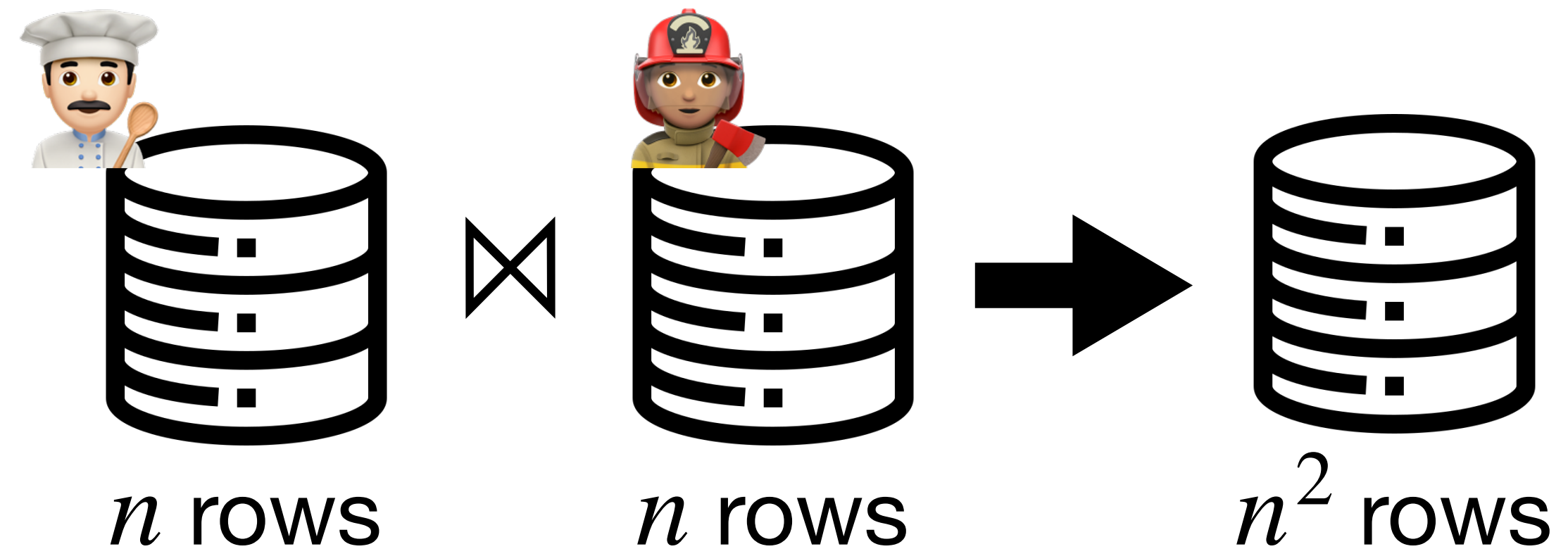
Oblivious Joins with Cartesian Product

Cust \ Ord							
	✗	✓	✗	✗	✓	✓	✗
	✗	✗	✗	✗	✗	✗	✓
	✗	✓	✗	✗	✓	✓	✗
	✓	✗	✗	✗	✗	✗	✗
	✗	✗	✓	✓	✗	✗	✗
	✗	✗	✓	✓	✗	✗	✗
	✓	✗	✗	✗	✗	✗	✗

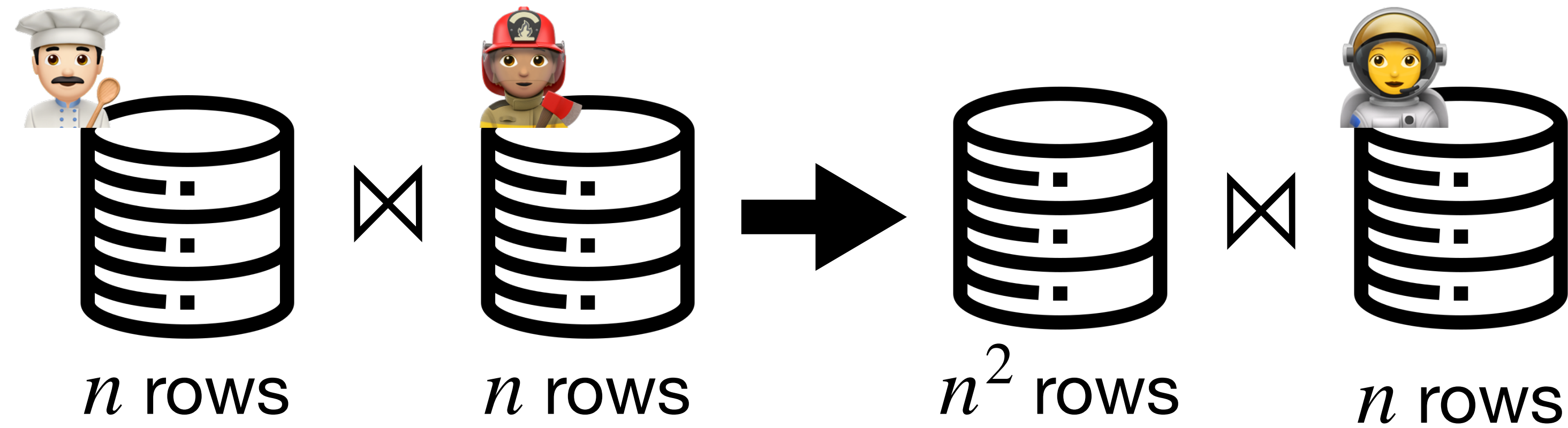


$O(n^2)$ work
 $O(n^2)$ output size

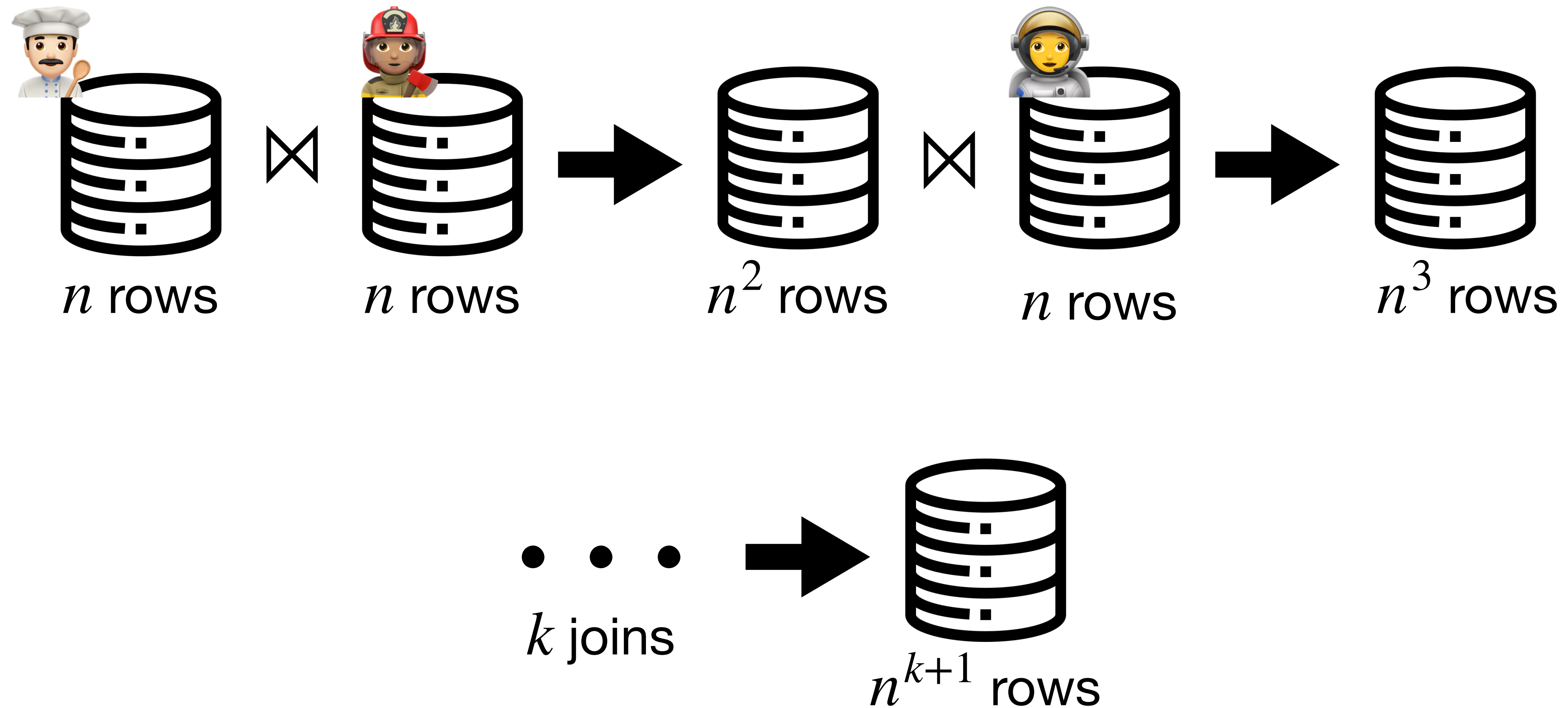
The Problem



The Problem

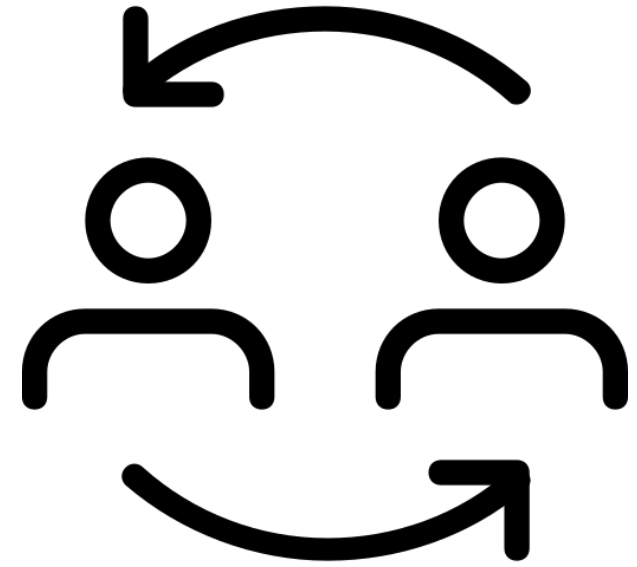


The Problem



Prior Approaches to Collaborative Analytics

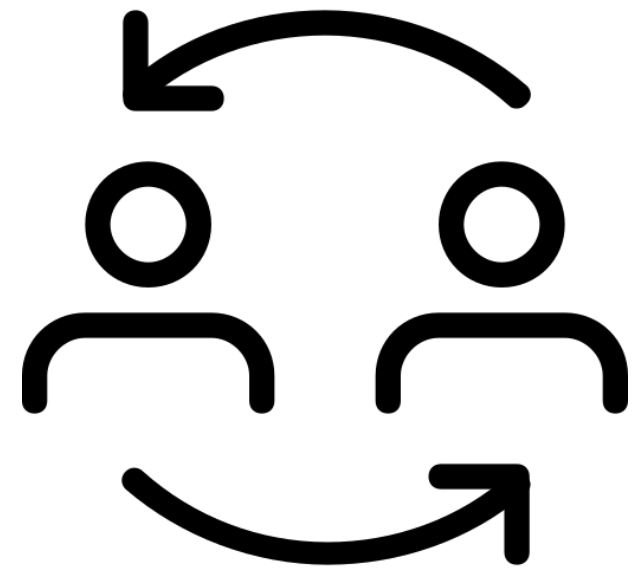
Prior Approaches to Collaborative Analytics



Peer-to-peer setting

e.g., Conclave (EuroSys'19),
Senate (Security'21), SMCQL (VLDB'17),
Shrinkwrap (VLDB'18)

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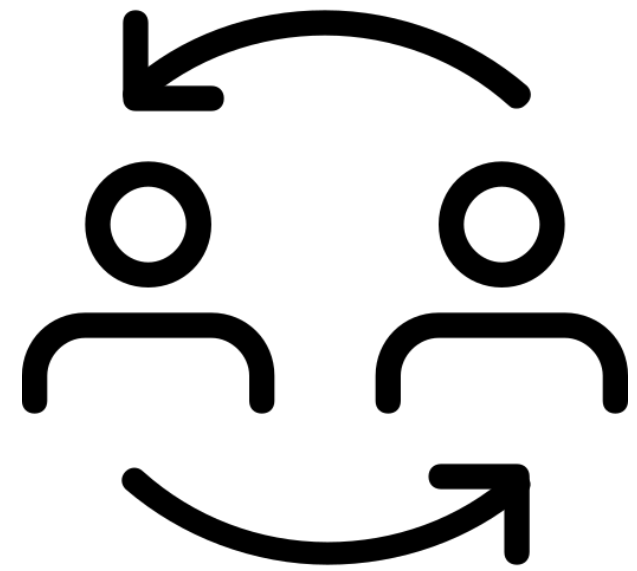


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✗ Doesn't scale with more parties

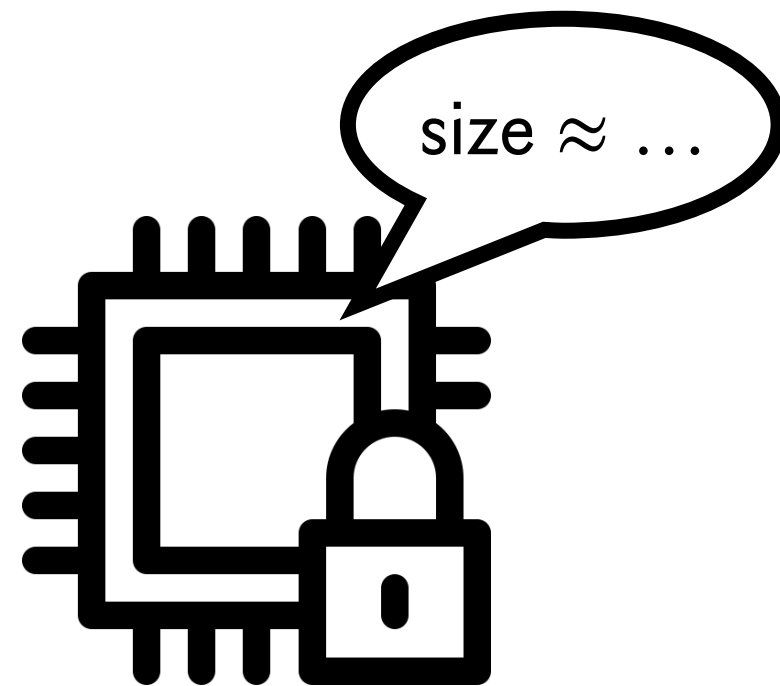
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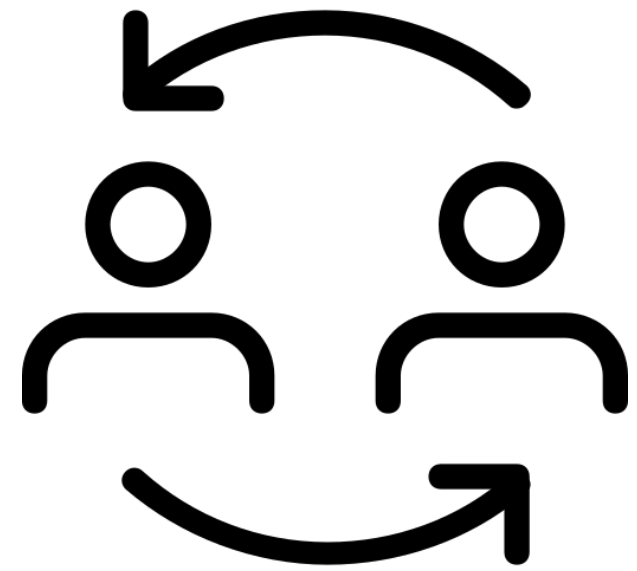
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Leakage or upper bounds

e.g., Opaque (NSDI'17), Oblivator (Security'25),
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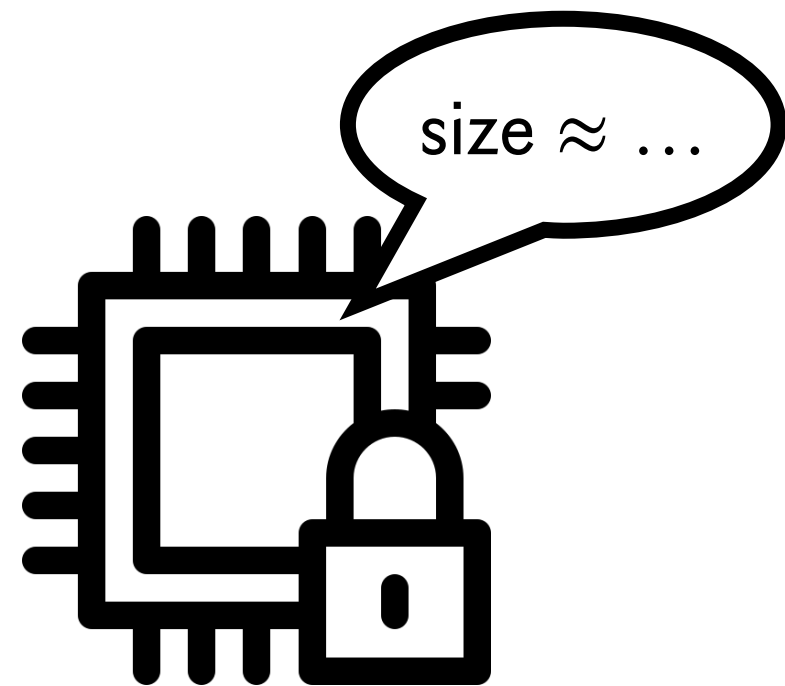
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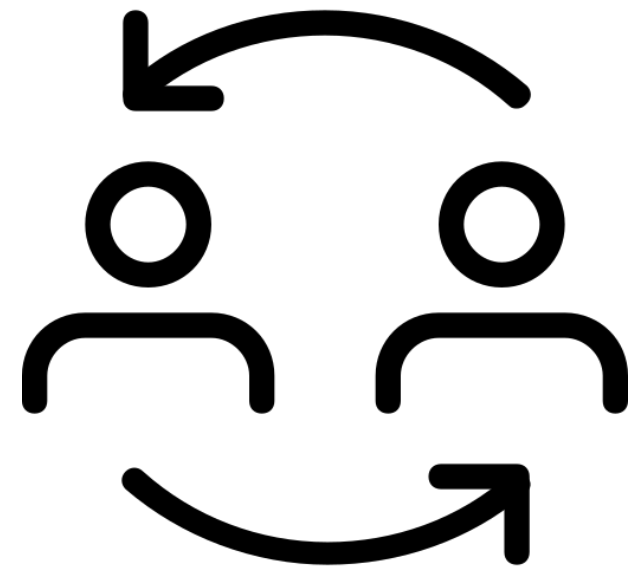


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✗ Only provides partial security

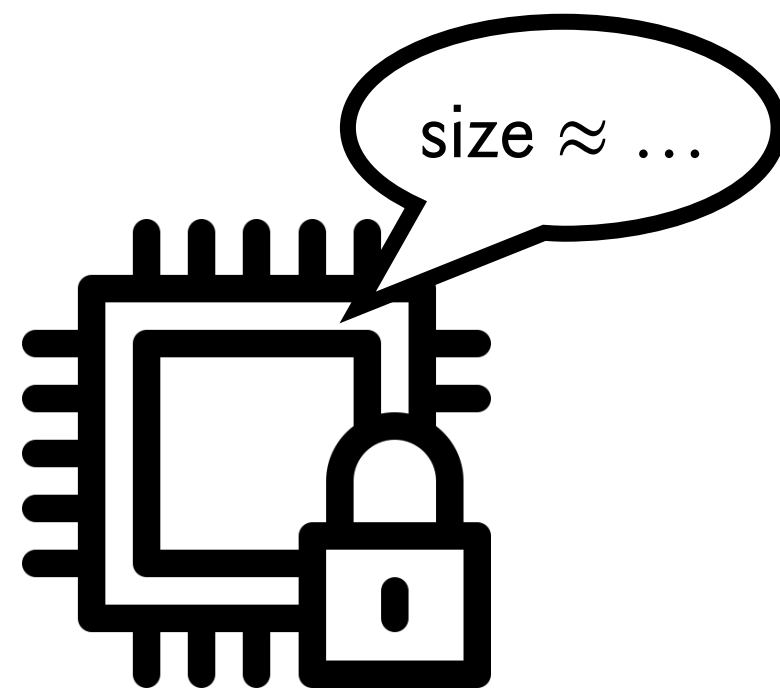
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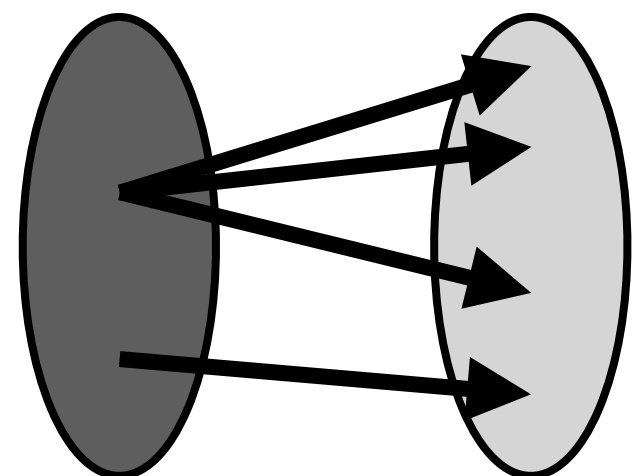
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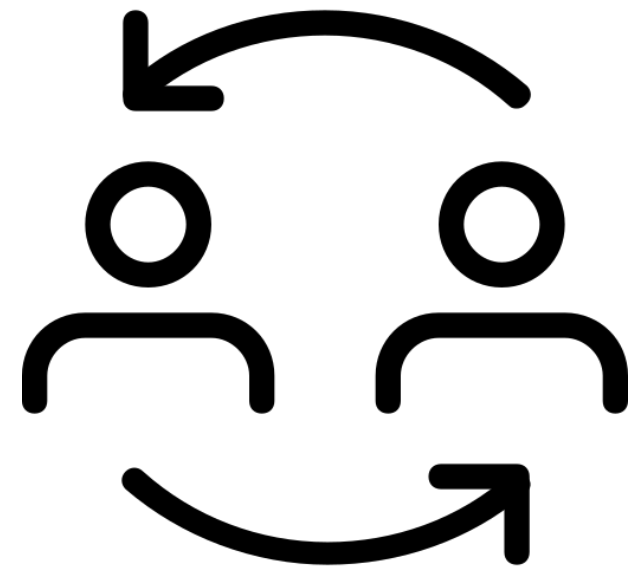
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Individual join operators

e.g., [MRR] (CCS'20), [BDG+] (CCS'22),
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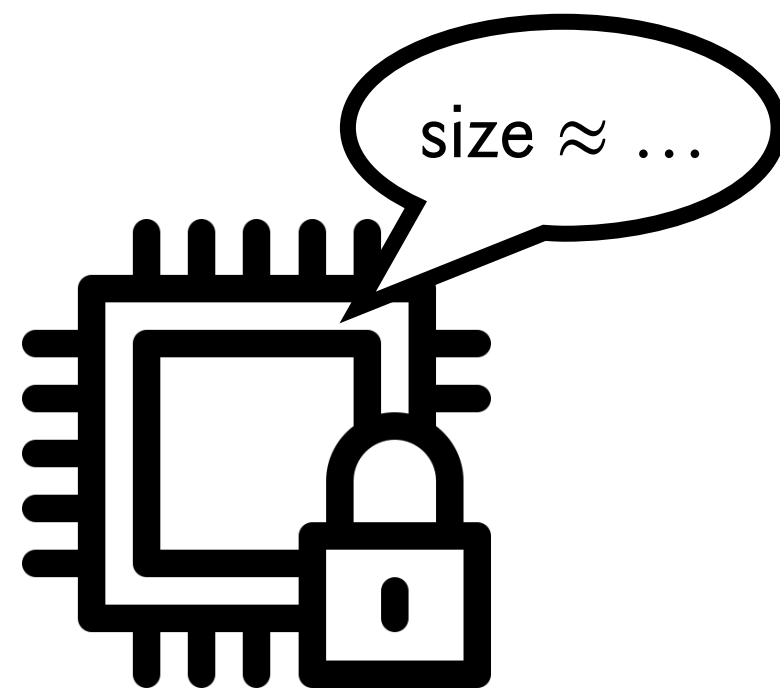
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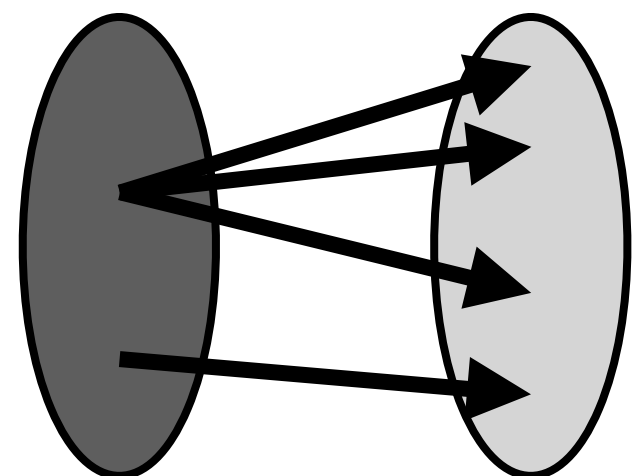
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Individual join operators

e.g., [MRR] (CCS'20), [BDG+] (CCS'22),
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✗ Cannot evaluate queries

*Can we efficiently evaluate complex analytics
without compromising security?*

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without compromising security?*

Yes!

*Can we efficiently evaluate complex analytics
without compromising security?*

Yes!

We are the first to show **multiple joins**
with no security compromises

...and run **all queries** from prior work,
with **orders-of-magnitude** larger inputs

What do real-world queries look like?

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We collect all **31 queries** from related work in MPC analytics

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All have output size bound $O(n)$ instead of $O(n^k)$!

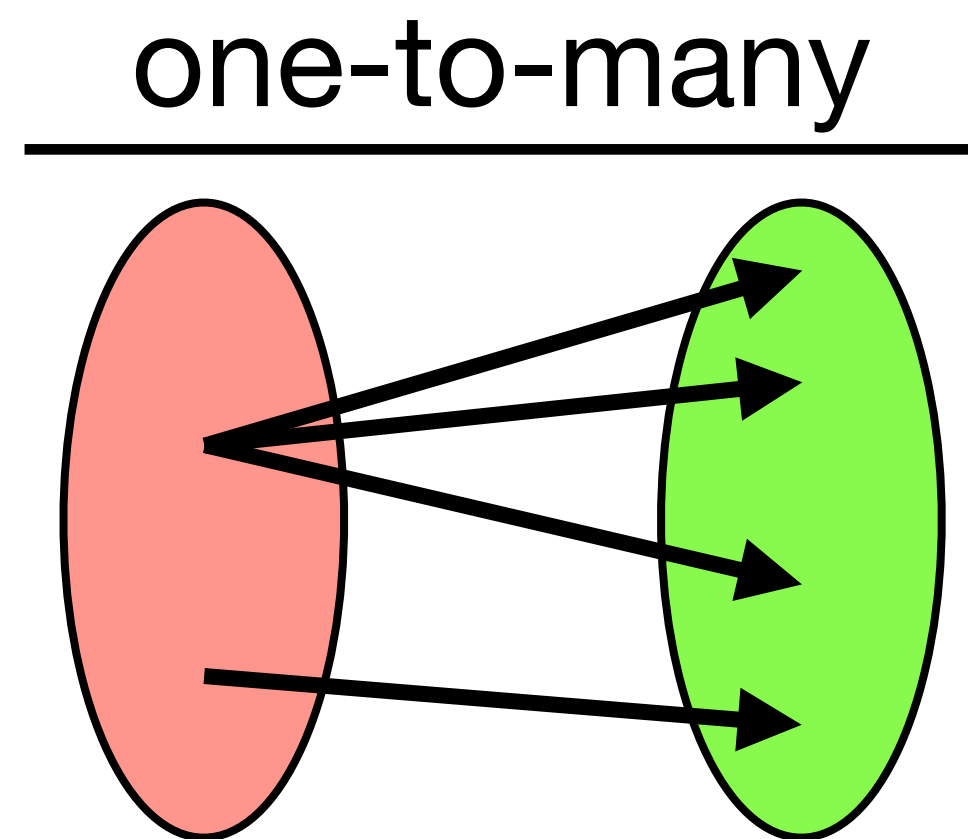
Why?

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Why?



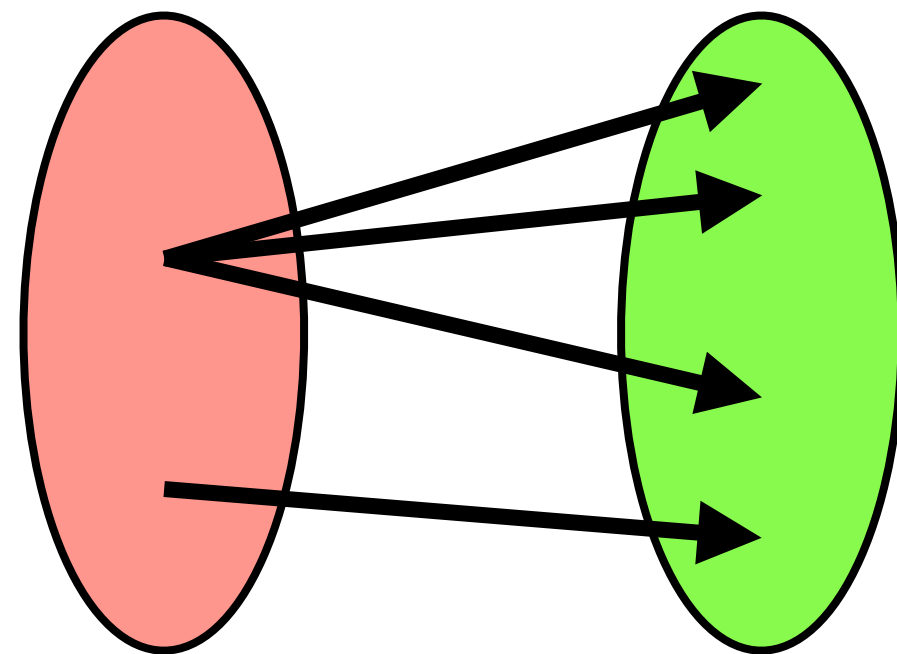
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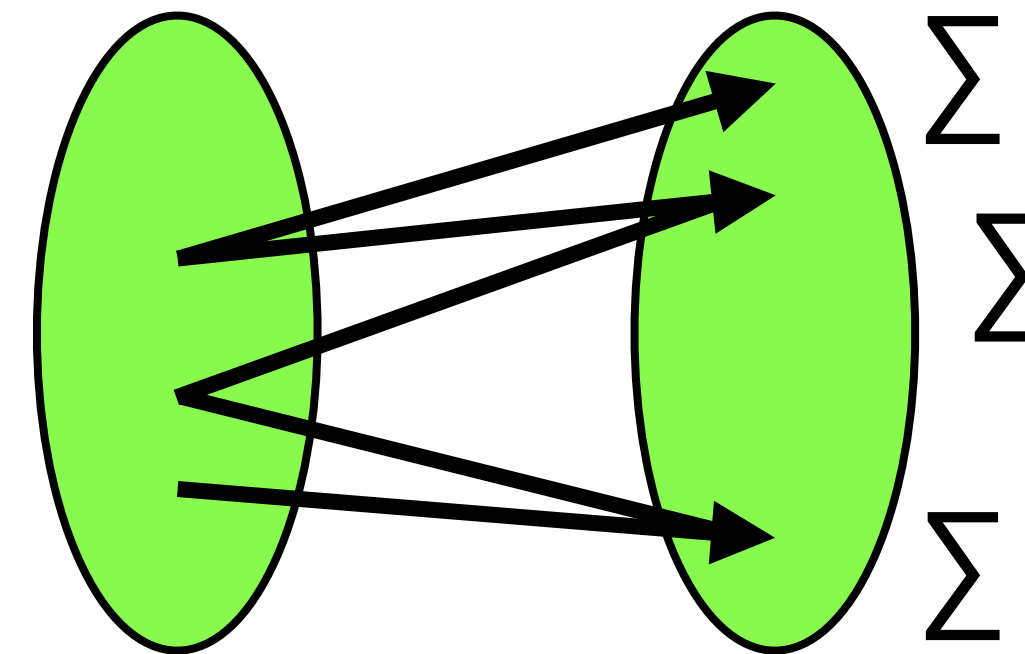
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Why?

one-to-many



many-to-many + aggregation



What do real-world queries look like?

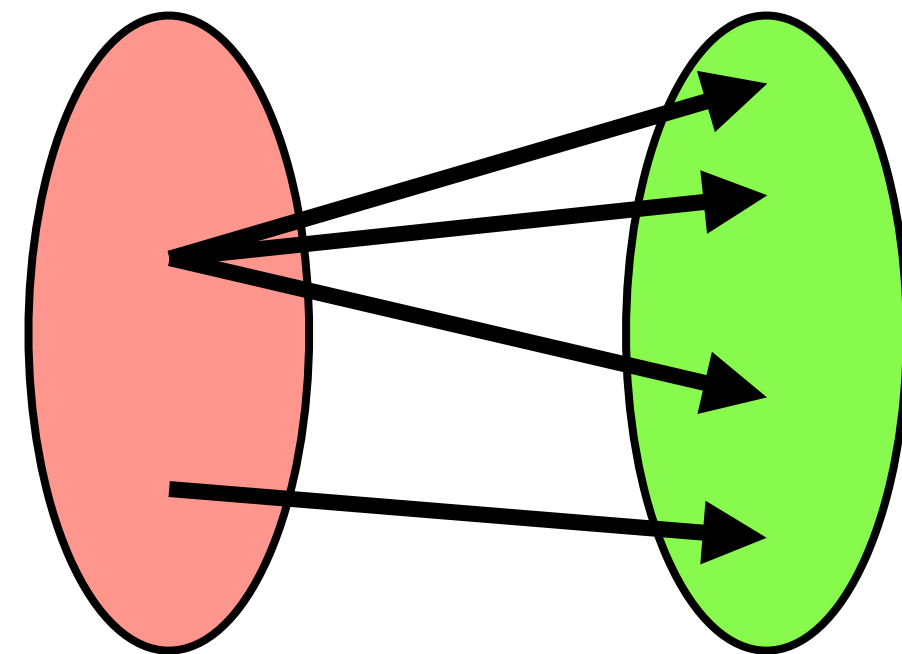
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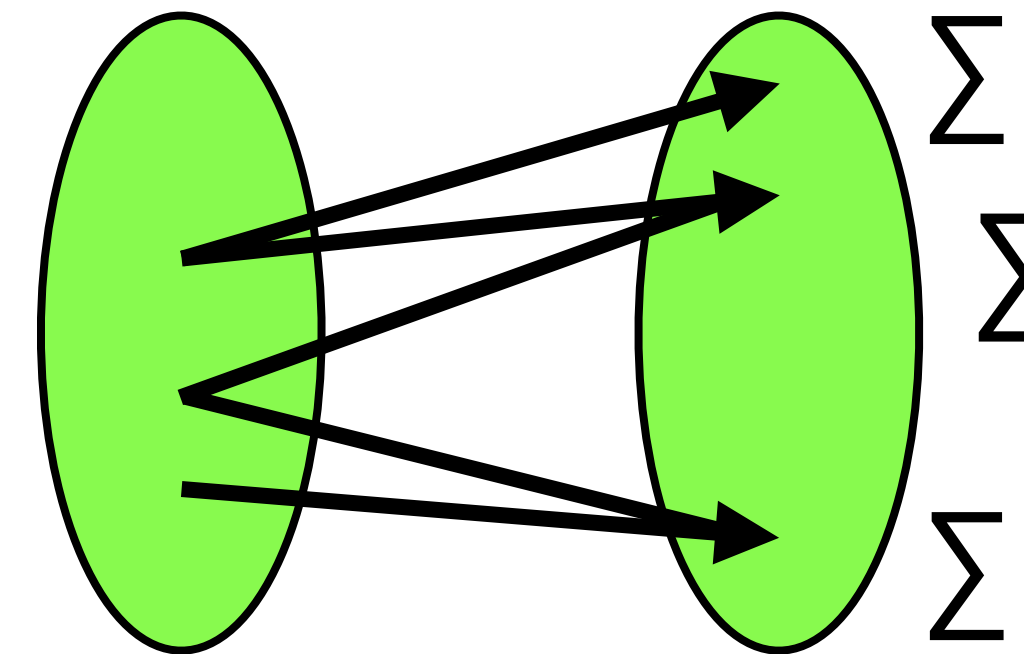
Why?

decomposable

one-to-many



many-to-many + aggregation



Our Insight

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The general problem is impractically difficult

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Practical instances are not!

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Common query semantics impose an
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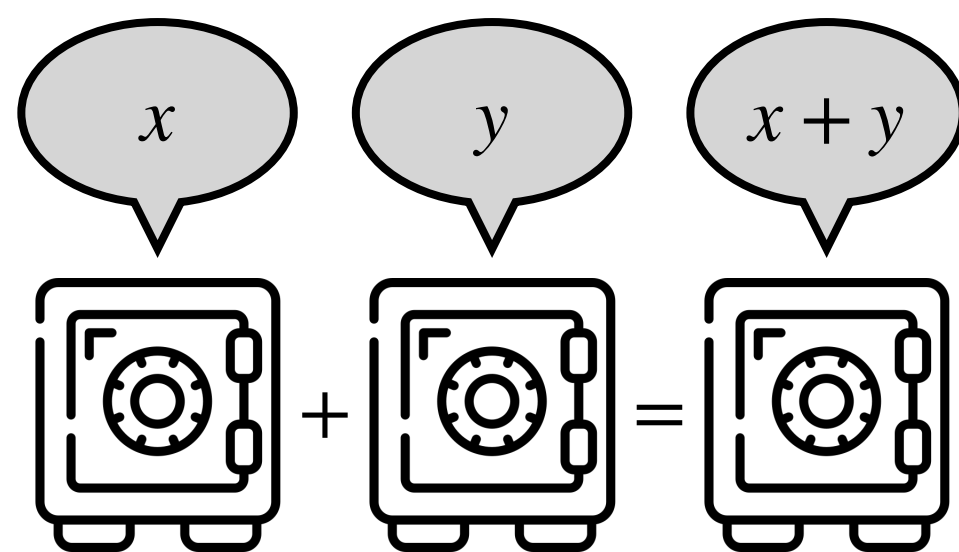
Decompose joins into sort + aggregation

Our Insight

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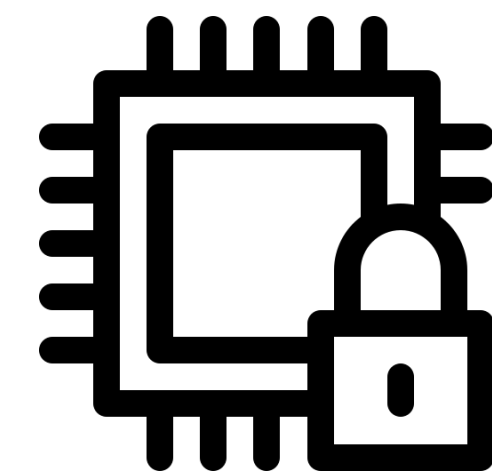
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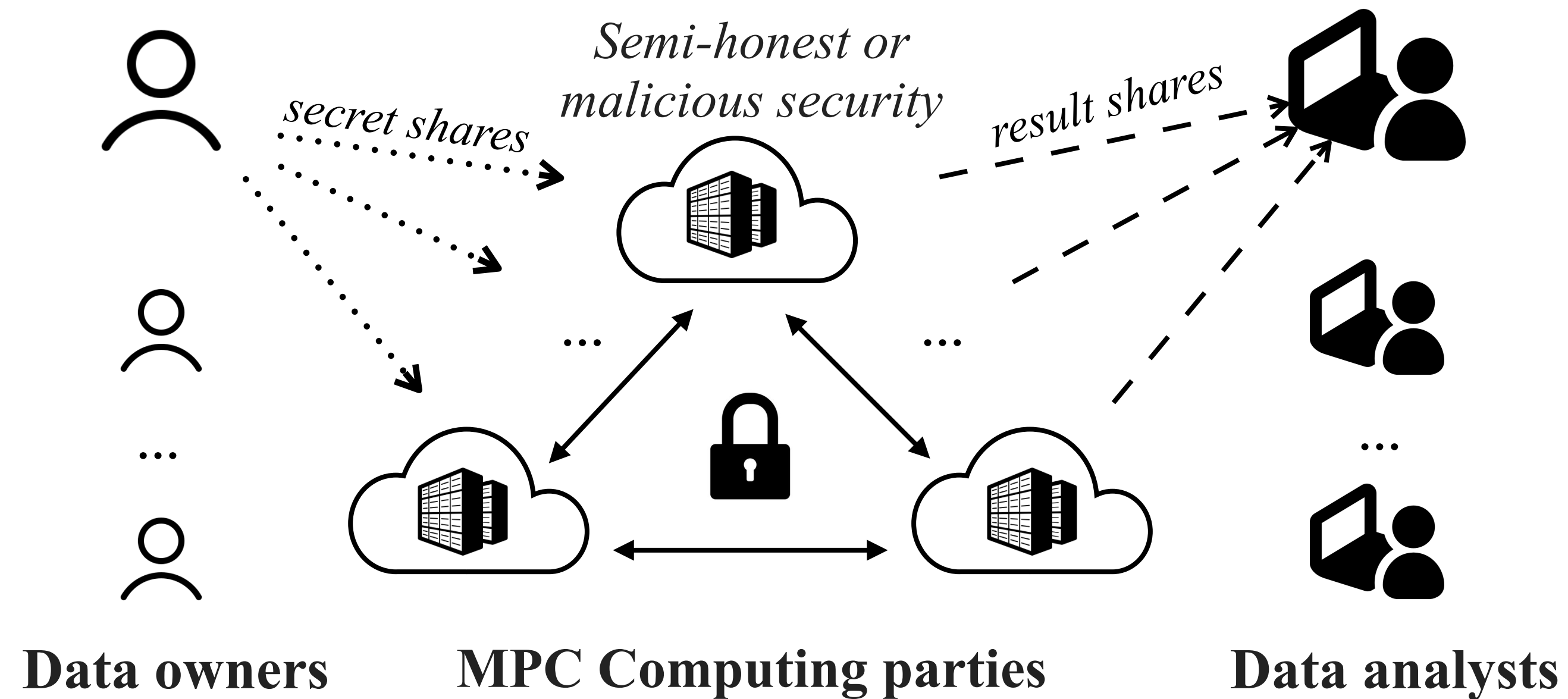
Decompose joins into sort + aggregation

Applies beyond multiparty computation!



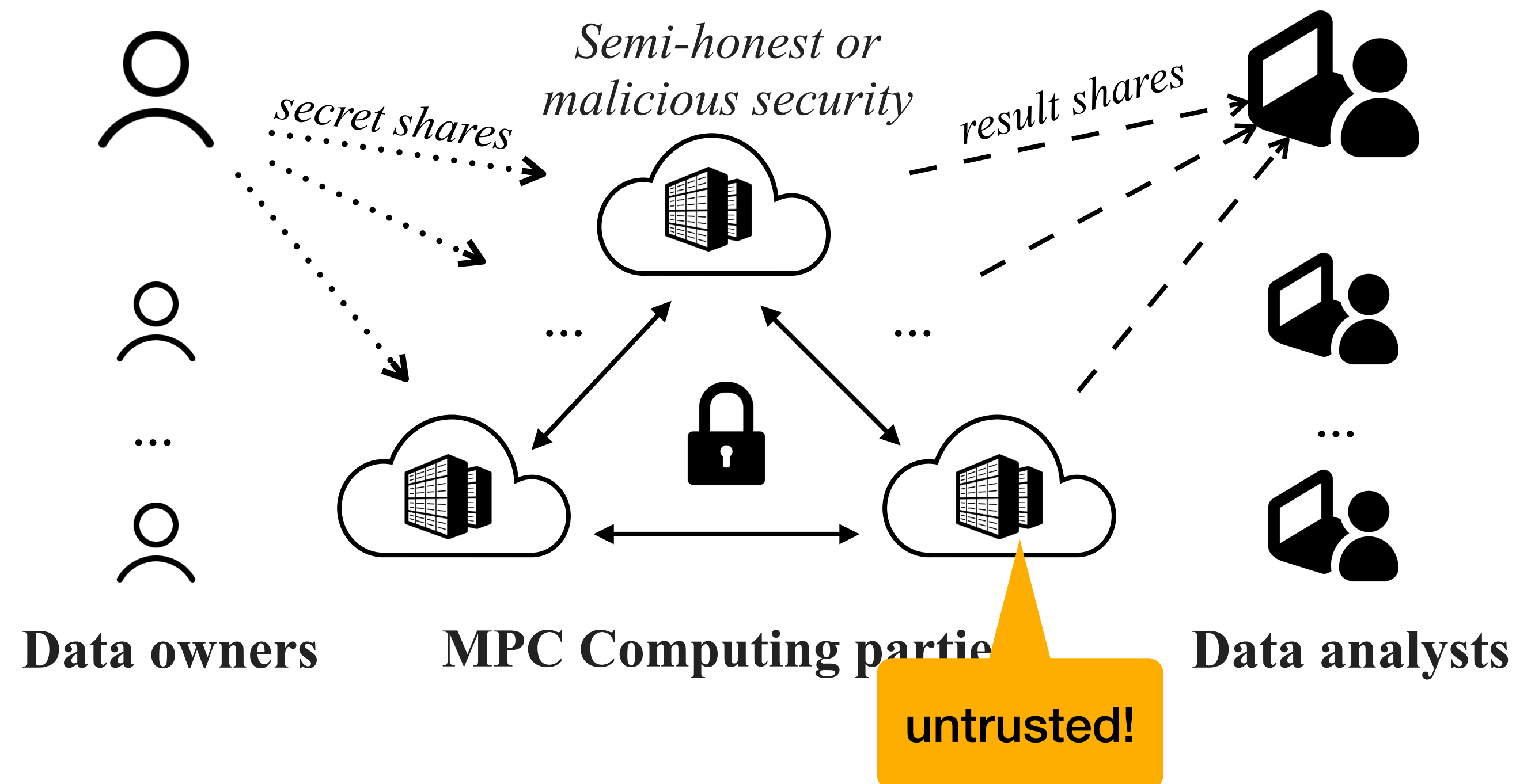
Secure Multiparty Computation (MPC)

Outsourced Setting



Secure Multiparty Computation (MPC)

Outsourced Setting



Secret Sharing: Data Owners



ID	Balance
1	\$100
4	\$50
9	\$25
7	-\$13



ID	Balance
3	\$814
2	\$312
7	\$60
6	-\$366



ID	Balance
14	\$82
12	\$14
0	-\$8
3	\$160

Secret Sharing: Data Owners



ID		Balance
Pr	N1	
nk	1799JtRkU	NV9MVqRf
qT	qicpdFpxn	ZgaoE7Hx
Rf	JtRkUmc5	FVwp7XTF
FV	qSiJ3nBG	vhnCMlo7j
P		
2g		



ID		Balance
CB	DF	
j8k	UW6m9tx	EABqfgpRi
3jfr	m6vQFTgb	9u19eWyV
0tv	qhQ2JFbe	hM2hOg8
Vy	MQeNGgyl	q1uon8xM
uR		

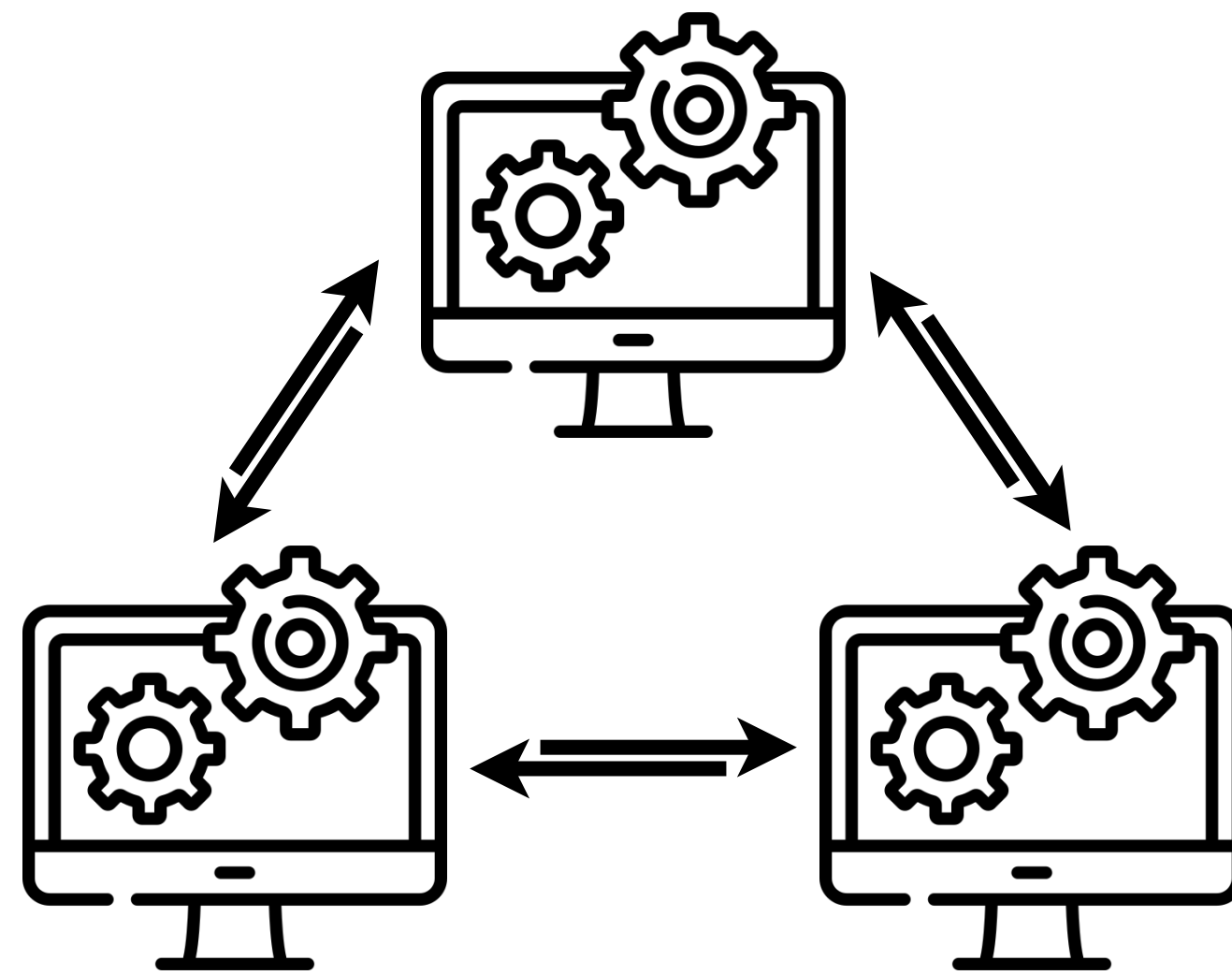


ID		Balance
Q8	MN	
as	hslcAgWLy	OUPgb2V
PQ	MVAJi4Vnt	FzI0j2hH8
91	8KsbVnN	YlaNhg5py
ajC	ehbzAtm6j	LmWp415
4n		
am		

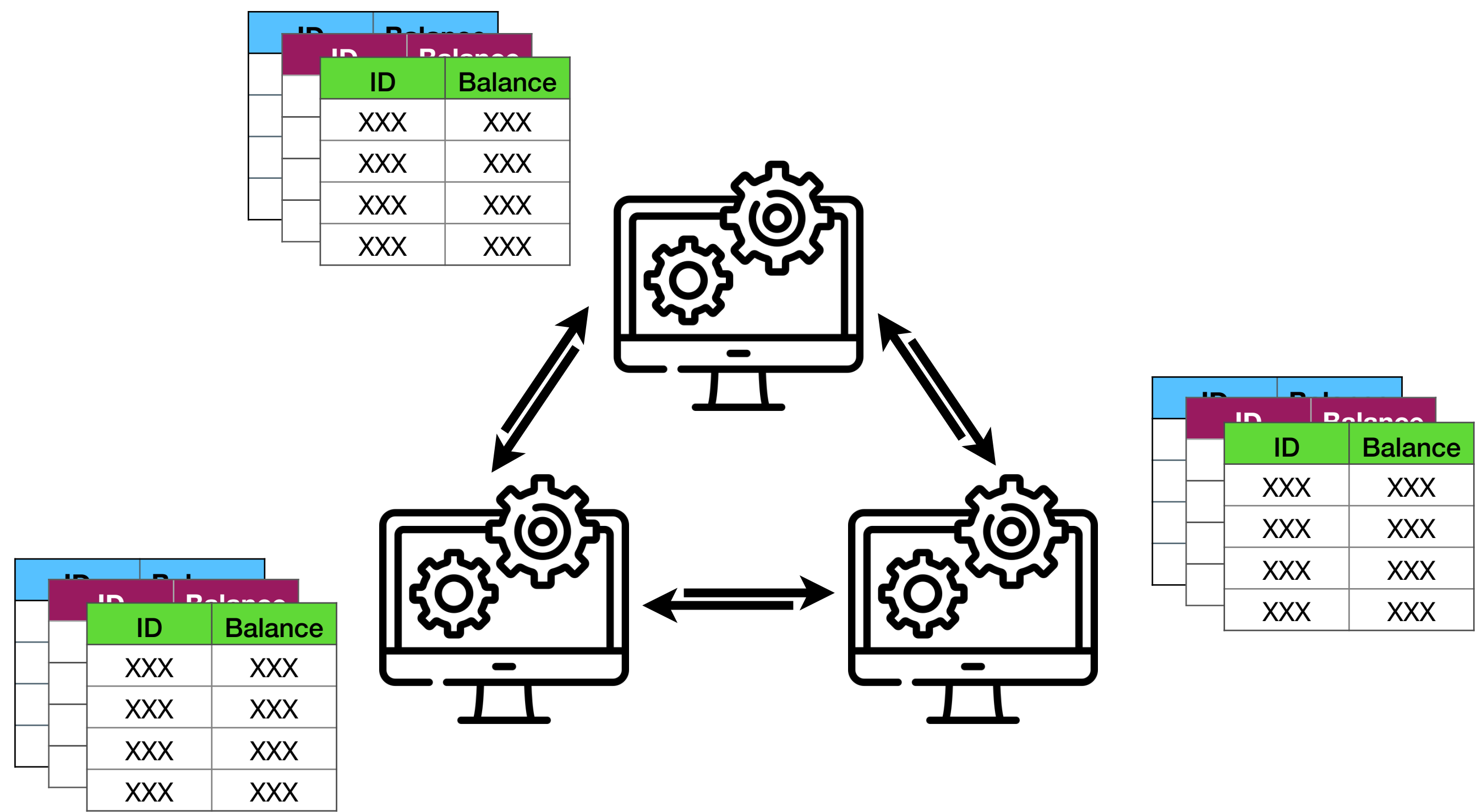
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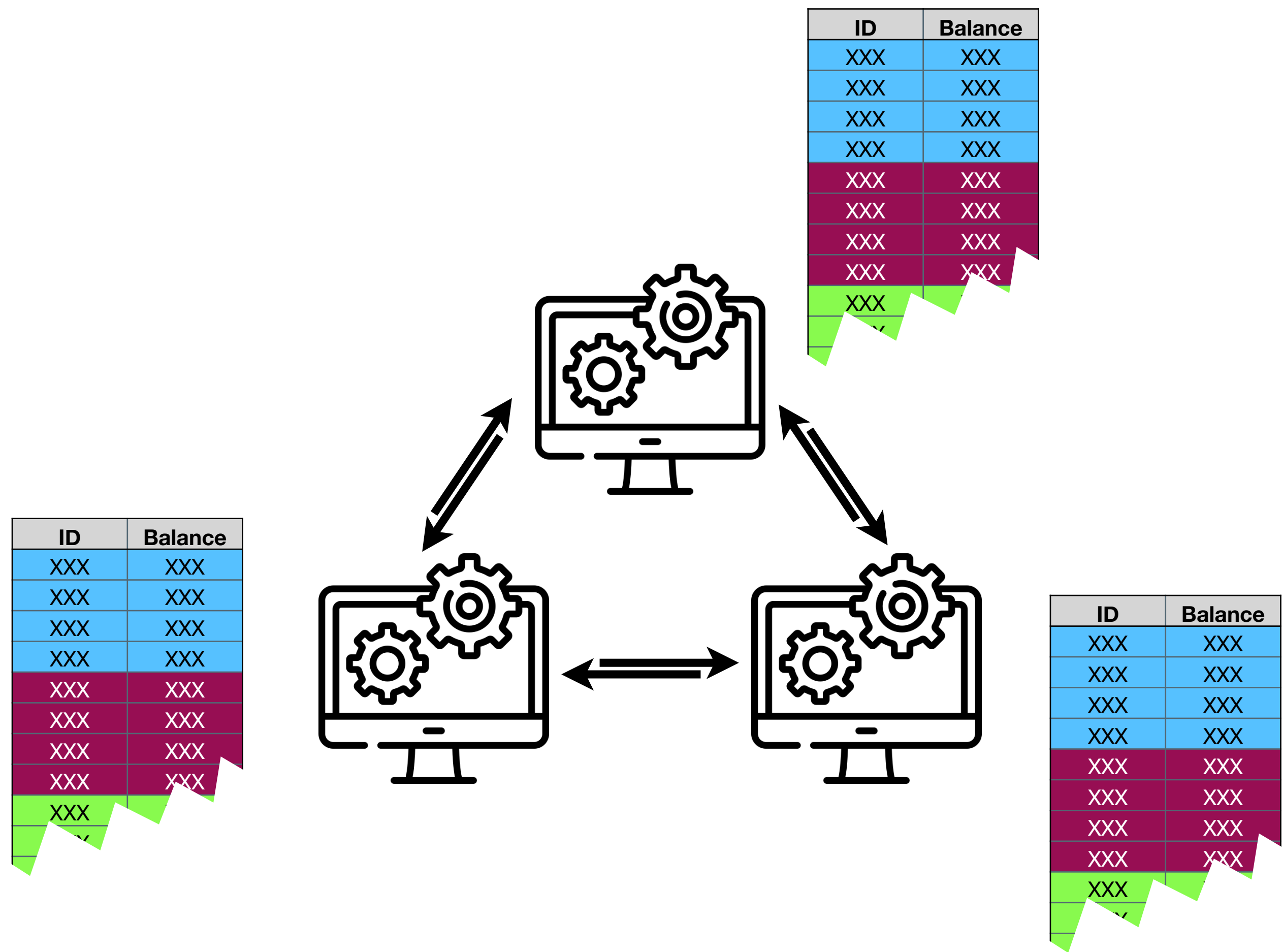
Secret Sharing: Computing Parties



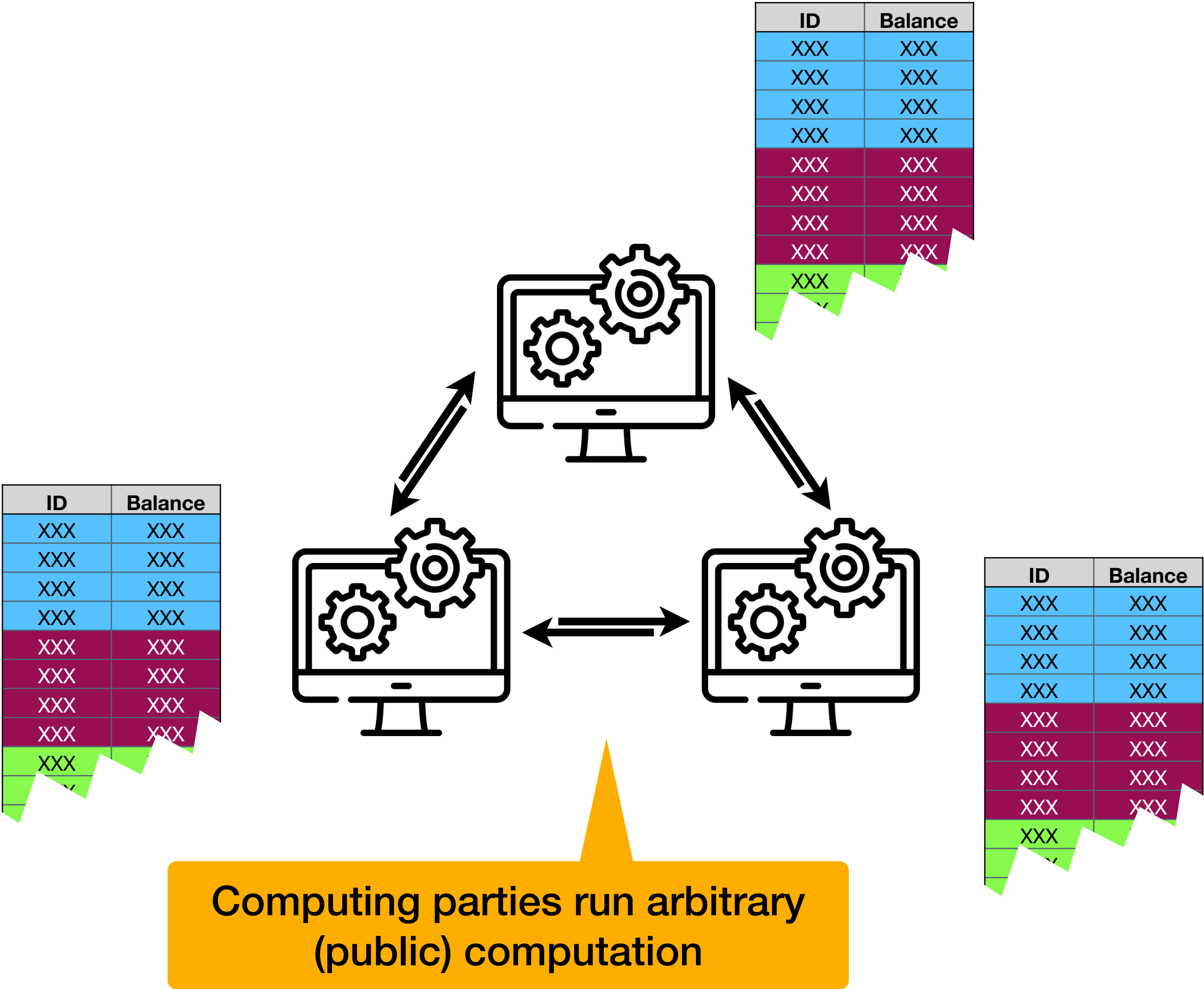
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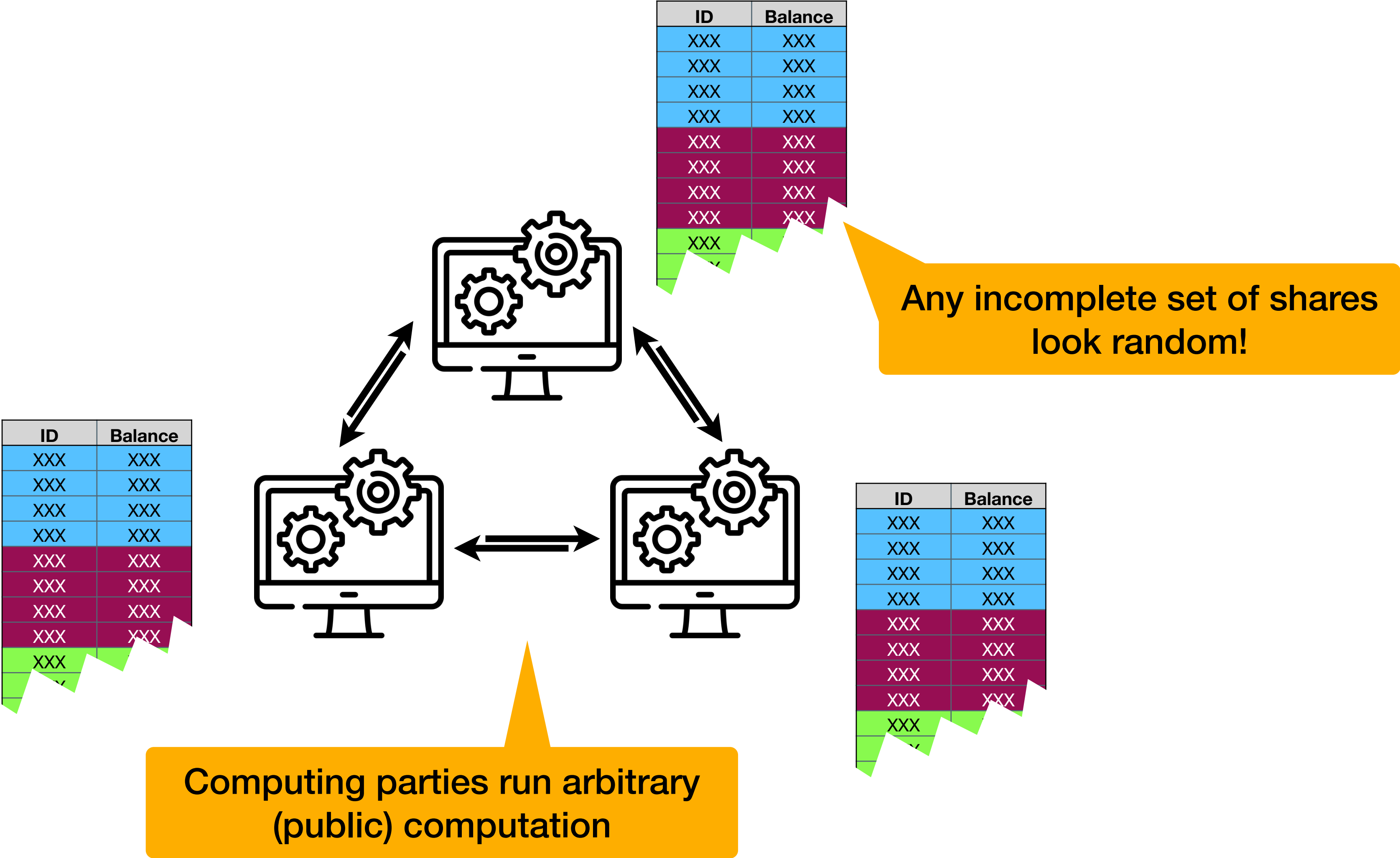
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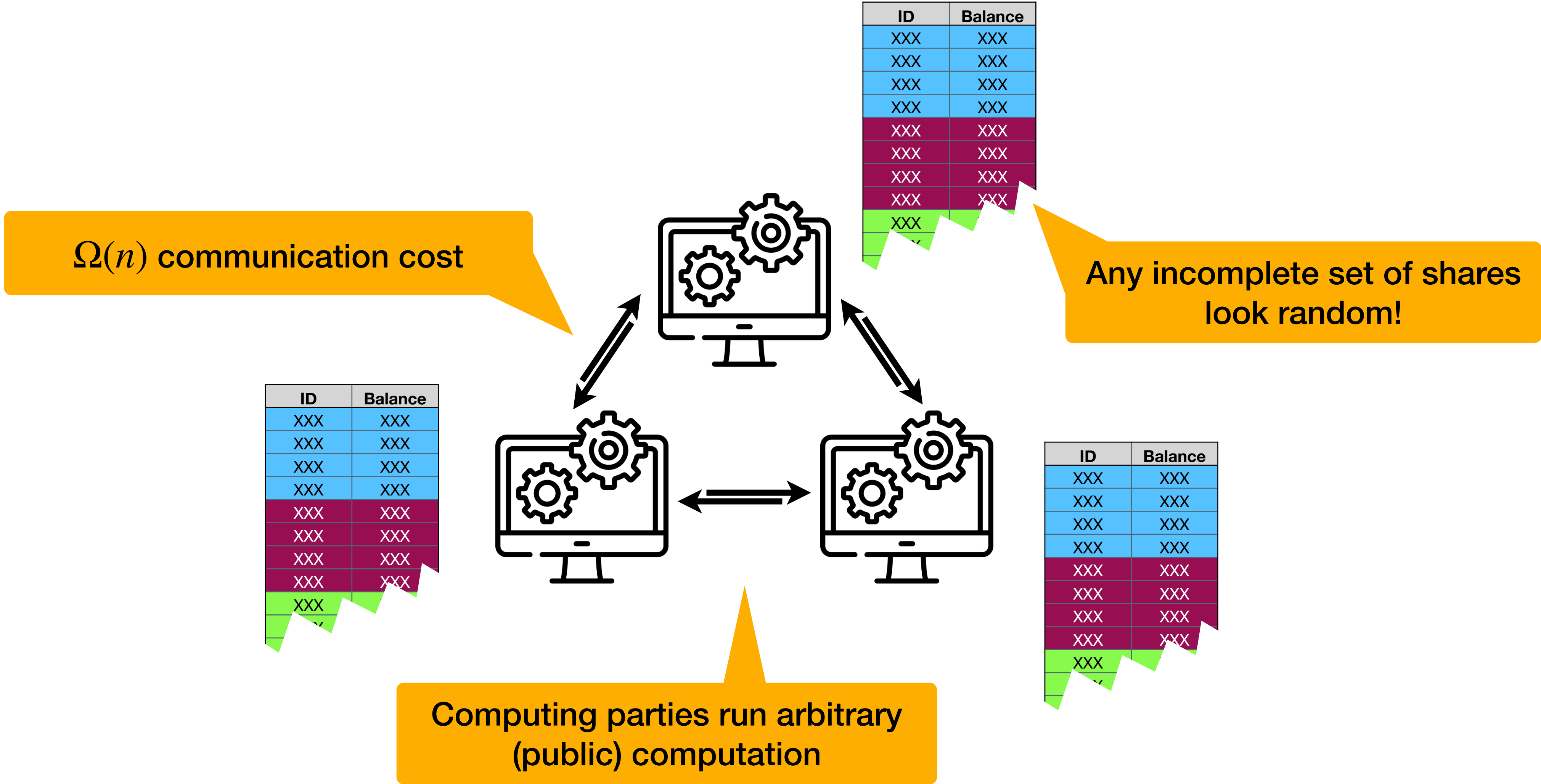
Secret Sharing: Computing Parties



Secret Sharing: Computing Parties



Secret Sharing: Computing Parties



Secret Shared Tables 🔒



Pr		ID		Balance	
nk	N1	1799JtRkU	NV9MVqRf		
	qT	qicpdFpxn	ZgaoE7Hx		
	RV	JtRkUmc5	FVwp7XTF		
	FV	qSiJ3nBG	vhnCMlo7j		
	2g				



CB		ID		Balance	
j8k	DF	UW6m9tx	EABqfgpRi		
	3jfr	m6vQFTgb	9u19eWyV		
	0tv	qhQ2JFbe	hM2hOg8		
	ay	MQeNGgyl	q1uon8xM		
	Vy				



Q8		ID		Balance	
as	MN	hslcAgWLy	OUPgb2V		
	PQ	MVAJi4Vnt	FzI0j2hH8		
	ajC	8KsbVnN	YlaNhg5py		
	4n	ehbzAtm6j	LmWp415		
	am				

Secret Shared Tables 🔒



ID	Balance
1	\$100
4	\$50
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7	-\$13



ID	Balance
3	\$814
2	\$312
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ID	Balance
14	\$82
12	\$14
0	-\$8
3	\$160

Improving on Quadratic: Sort & Aggregate

One table must have unique keys

```
func join(L, R, keys) :  
    T := concat* (L, R)  
    T.sort(keys)  
    T.prefix_aggregate(...)  
    return T
```

Improving on Quadratic: Sort & Aggregate

One table must have unique keys

$O(n \log n)$

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func join(L, R, keys):  
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Improving on Quadratic: Sort & Aggregate

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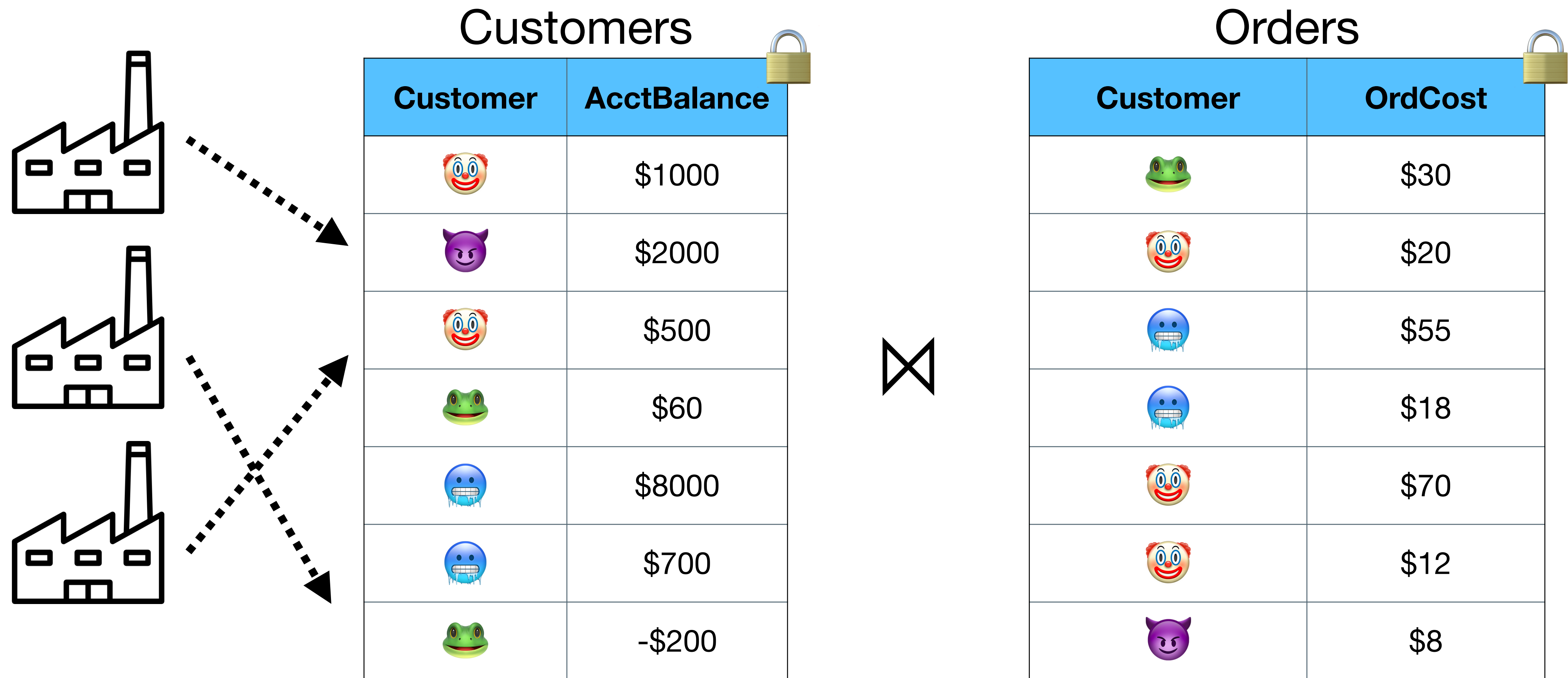
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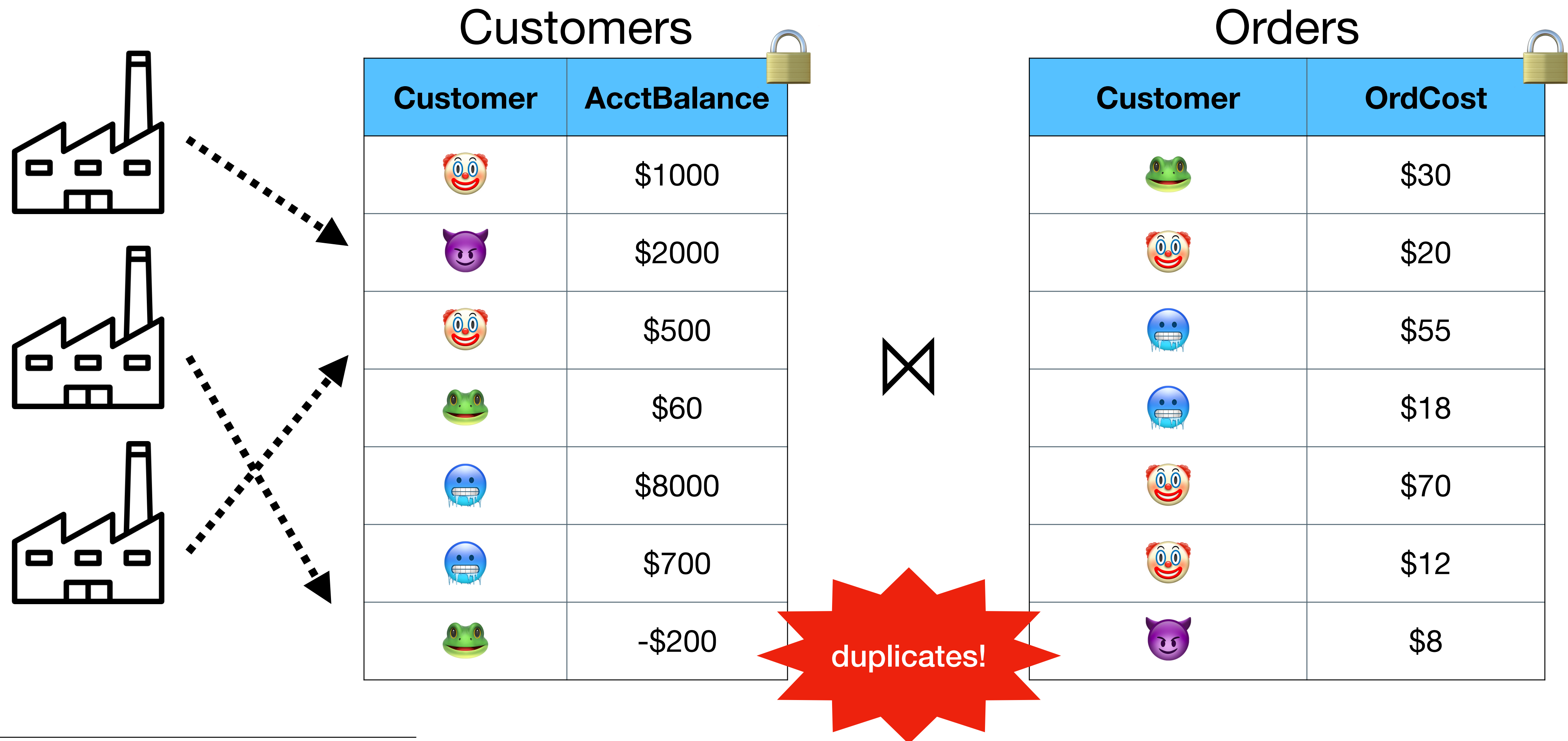
$O(n \log n)$

Extends to **inner**, **outer**, **anti**, and **semi** joins.

Example with Our Approach



Example with Our Approach



Example with Our Approach

```
SELECT
    SPECIES, SUM(ACCTBALANCE) / SUM(ORDCOST)
FROM
    ORDERS, CUSTOMERS
WHERE
    ORDER.CUSTOMER = CUSTOMERS.CUSTOMER
GROUP BY
    SPECIES
```

Per customer group, what is the ratio of account balance to order total?

Customers

Customer	AcctBalance
	\$1000
	\$2000
	\$500
	\$60
	\$8000
	\$700
	-\$200

Orders

Customer	OrdCost
	\$30
	\$20
	\$55
	\$18
	\$70
	\$12
	\$8

Pre-Aggregate

Customers

Customer	AcctBalance
🤡	\$1000
😈	\$2000
🤡	\$500
🐸	\$60
😬	\$8000
😬	\$700
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Orders

Customer	OrdCost
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🤡	\$70
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😈	\$8

Pre-Aggregate

Customers

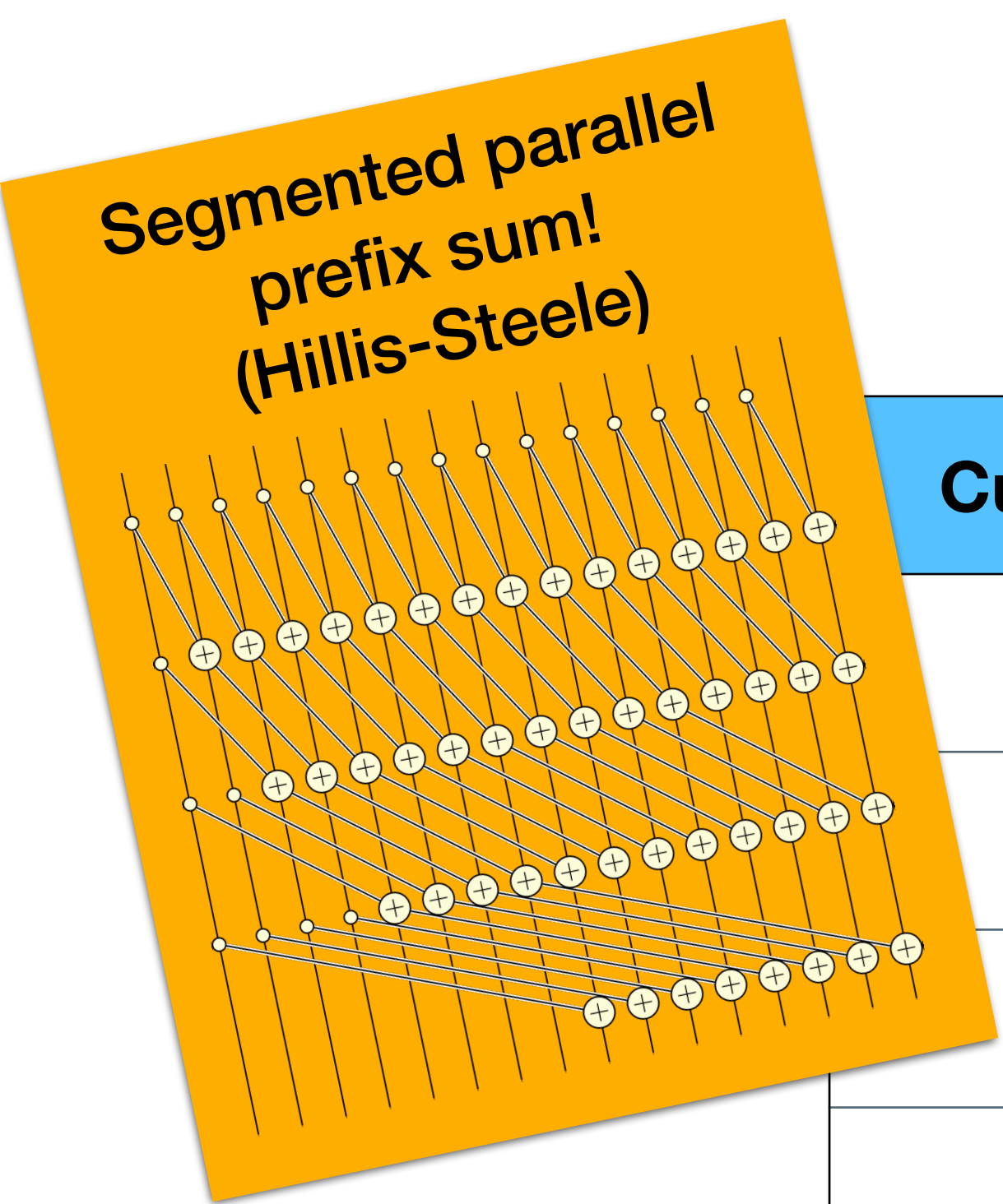
Customer	AcctBalance
	\$1000
	\$2000
	\$500
	\$60
	\$8000
	\$700
	-\$200

Orders

Customer	OrdCost
	\$30
	\$20
	\$55
	\$18
	\$70
	\$12
	\$8

After Pre-aggregation

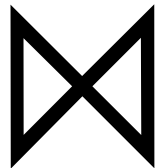
One-to-many join



Customers	
Customer	TotalAcctBalance
	\$1500
	\$2000
	-\$140
	\$8700

unique keys!

pre-aggregated values



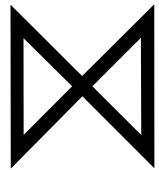
Orders	
Customer	OrdCost
	\$30
	\$20
	\$55
	\$18
	\$70
	\$12
	\$8

After Pre-aggregation

One-to-many join

Customers

Customer	TotalAcctBalance
🤡	\$1500
👹	\$2000
🐸	-\$140
🧊	\$8700



Orders

Customer	OrdCost
🐸	\$30
🤡	\$20
🧊	\$55
🧊	\$18
🤡	\$70
🤡	\$12
👹	\$8

Concatenate

```
func join(L, R, keys):  
    T := concat*(L, R)  
    T.sort(keys)  
    T.prefix_aggregate(...)  
    return T
```

Customer	C.Total	O.Cost
🤡	\$1500	
😈	\$2000	
🐸	-\$140	
🧊	\$8700	
🐸		\$30
🤡		\$20
🧊		\$55
🧊		\$18
🤡		\$70
🤡		\$12
😈		\$8

Sort

```
func join(L, R, keys):  
    T := concat*(L, R)  
    T.sort(keys)  
    T.prefix_aggregate(...)  
    return T
```

Customer	C.Balance	O.Cost
🤡	\$1500	
🤡		\$20
🤡		\$70
🤡		\$12
😈	\$2000	
😈		\$8
🐸	-\$140	
🐸		\$30
🥶	\$8700	
🥶		\$55
🥶		\$18

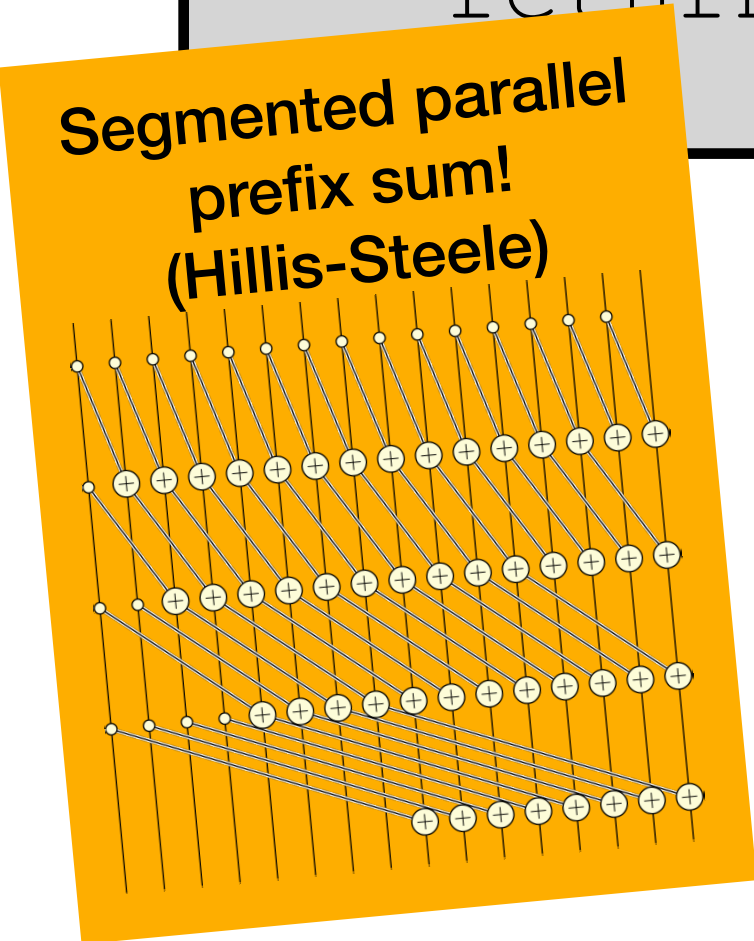
Group Aggregate

```
func join(L, R, keys):  
    T := concat*(L, R)  
    T.sort(keys)  
    T.prefix_aggregate(...)  
    return T
```

Customer	C.Balance	O.Cost	TotalCost
🤡	\$1500	∅	
🤡	\$1500	\$20	
🤡	\$1500	\$70	
🤡	\$1500	\$12	\$102
😈	\$2000	∅	
😈	\$2000	\$8	\$8
🐸	-\$140	∅	
🐸	-\$140	\$30	\$30
🥶	\$8700	∅	
🥶	\$8700	\$55	
🥶	\$8700	\$18	\$73

Group Aggregate

```
func join(L, R, keys):  
    T := concat*(L, R)  
    T.sort(keys)  
    T.prefix_aggregate(...)  
    return T
```



Customer	C.Balance	O.Cost	TotalCost
🤡	\$1500	∅	
🤡	\$1500	\$20	
🤡	\$1500	\$70	
🤡	\$1500	\$12	\$102
😈	\$2000	∅	
😈	\$2000	\$8	\$8
🐸	-\$140	∅	
🐸	-\$140	\$30	\$30
😬	\$8700	∅	
😬	\$8700	\$55	
😬	\$8700	\$18	\$73

Mark Invalid Rows

```
func join(L, R, keys):  
    T := concat*(L, R)  
    T.sort(keys)  
    T.prefix_aggregate(...)  
    T.mark_invalid()  
    return T
```

Customer	C.Balance	O.Cost	TotalCost
∅	∅	∅	∅
∅	∅	∅	∅
∅	∅	∅	∅
🤡	\$1500	\$12	\$102
∅	∅	∅	∅
😈	\$2000	\$8	\$8
∅	∅	∅	∅
🐸	-\$140	\$30	\$30
∅	∅	∅	∅
∅	∅	∅	∅
😬	\$8700	\$18	\$73

Join Output

```
SELECT
    SPECIES, SUM(ACCTBALANCE) / SUM(ORDCOST)
FROM
    ORDERS, CUSTOMERS
WHERE
    ORDER.CUSTOMER = CUSTOMERS.CUSTOMER
GROUP BY
    SPECIES
```

Customer	C.Balance	TotalCost	Species
	\$1500	\$102	Human
	\$8700	\$73	Human
	\$2000	\$8	NonHuman
	-\$140	\$30	NonHuman

Final Aggregation

```
SELECT
    SPECIES, SUM(ACCTBALANCE) / SUM(ORDCOST)
FROM
    ORDERS, CUSTOMERS
WHERE
    ORDER.CUSTOMER = CUSTOMERS.CUSTOMER
GROUP BY
    SPECIES
```

Species	Customer	C.Balance	TotalCost
Human	∅	∅	∅
Human	∅	\$10,200	\$175
NonHuman	∅	∅	∅
NonHuman	∅	\$1,860	\$38

Compute Ratio

```
SELECT
    SPECIES, SUM(ACCTBALANCE) / SUM(ORDCOST)
FROM
    ORDERS, CUSTOMERS
WHERE
    ORDER.CUSTOMER = CUSTOMERS.CUSTOMER
GROUP BY
    SPECIES
```

Species	C.Balance	TotalCost	Ratio
Human	\$10,200	\$174	58
NonHuman	\$1,860	\$38	48

Final Table

```
SELECT
    SPECIES, SUM(ACCTBALANCE) / SUM(ORDCOST)
FROM
    ORDERS, CUSTOMERS
WHERE
    ORDER.CUSTOMER = CUSTOMERS.CUSTOMER
GROUP BY
    SPECIES
```

Species	Ratio
Human	58
NonHuman	48

Final Table

```
SELECT
    SPECIES, SUM(ACCTBALANCE) / SUM(ORDCOST)
FROM
    ORDERS, CUSTOMERS
WHERE
    ORDER.CUSTOMER = CUSTOMERS.CUSTOMER
GROUP BY
    SPECIES
```

Still secret shared! More joins...



Species	Ratio
Human	58
NonHuman	48

Final Table

```
SELECT
  SPECIES, SUM(ACCTBALANCE) / SUM(ORDCOST)
FROM
  ORDERS, CUSTOMERS
WHERE
  ORDER.CUSTOMER = CUSTOMERS.CUSTOMER
GROUP BY
  SPECIES
```

Still secret shared! More joins...



Species	Ratio
Human	58
NonHuman	48

Oblivious output bound:
| Orders |

ORQ: an Oblivious Relational Query engine

ORQ: an Oblivious Relational Query engine

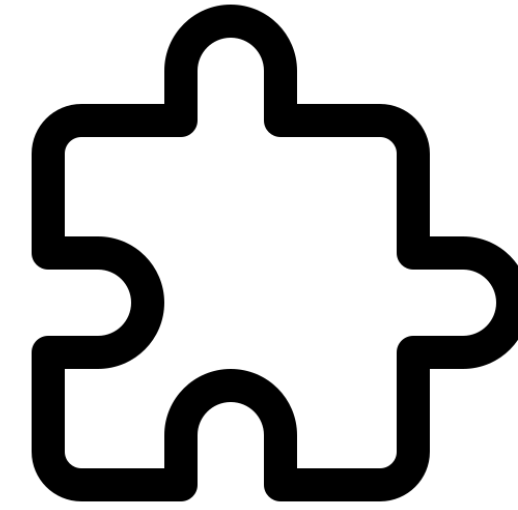


Familiar APIs &
simple orchestration

ORQ: an Oblivious Relational Query engine



Familiar APIs &
simple orchestration

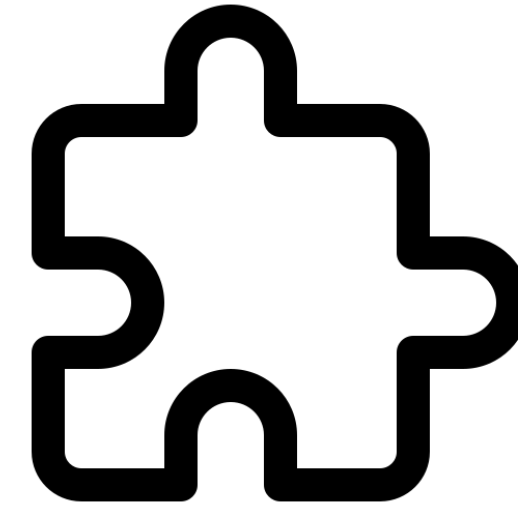


Support for multiple
protocols & threat models

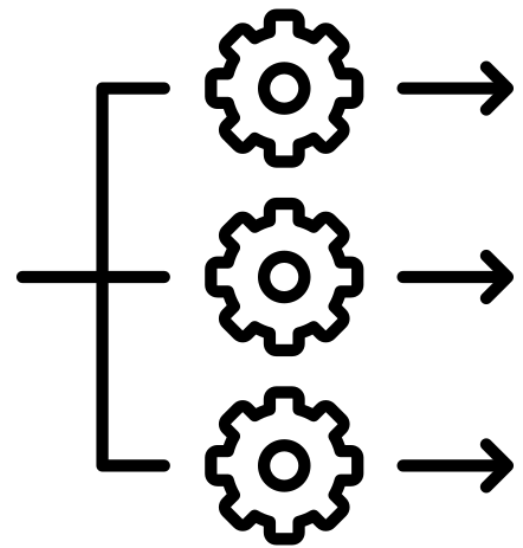
ORQ: an Oblivious Relational Query engine



Familiar APIs &
simple orchestration



Support for multiple
protocols & threat models

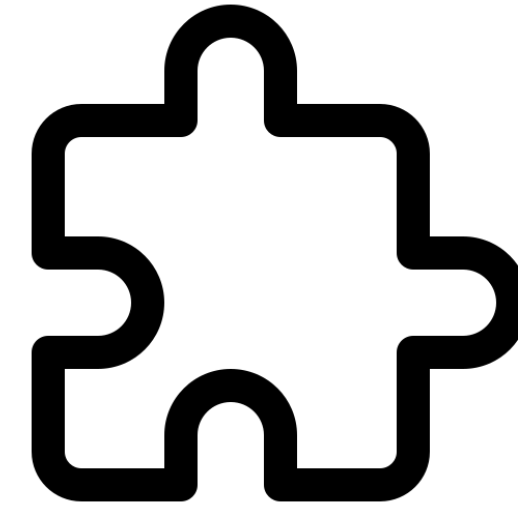


Data-parallel runtime

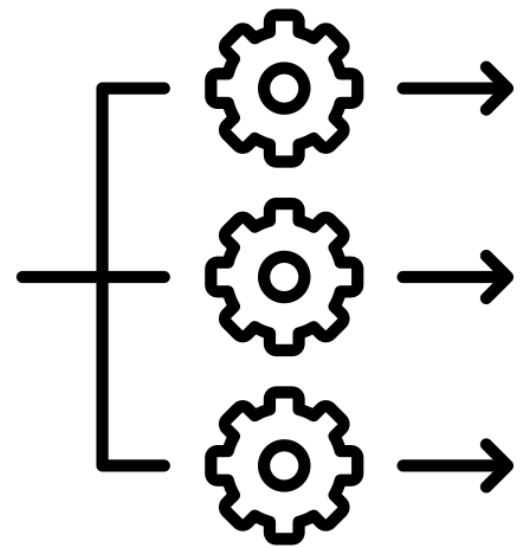
ORQ: an Oblivious Relational Query engine



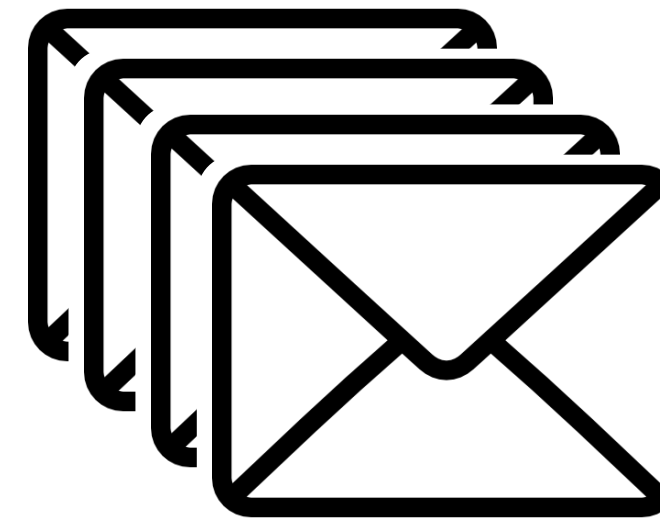
Familiar APIs &
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Support for multiple
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Data-parallel runtime

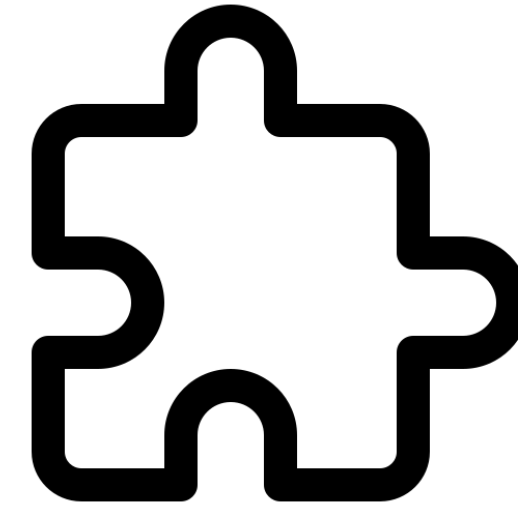


Vectorization &
message batching

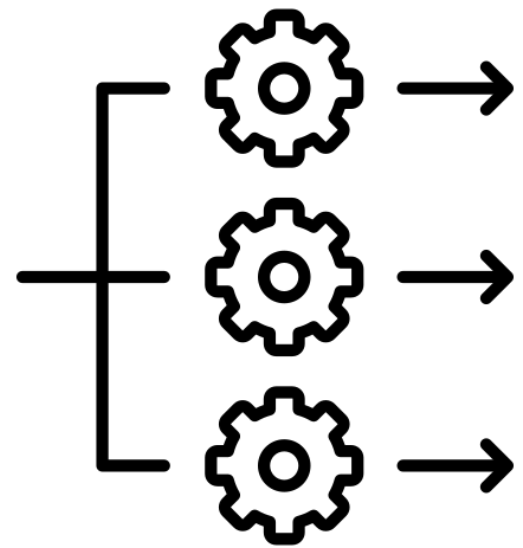
ORQ: an Oblivious Relational Query engine



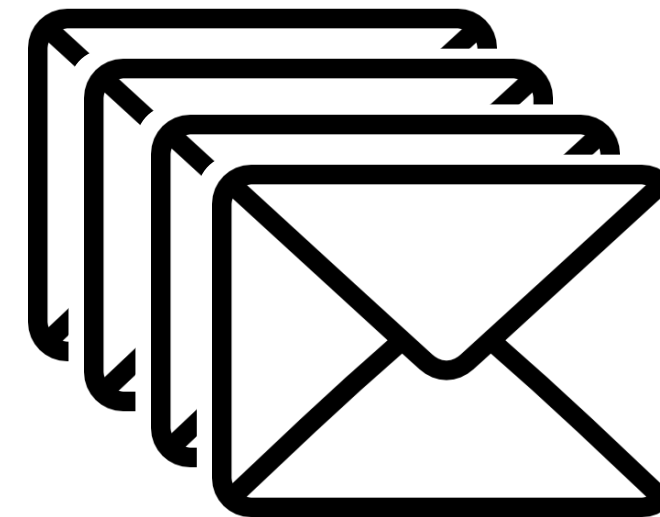
Familiar APIs &
simple orchestration



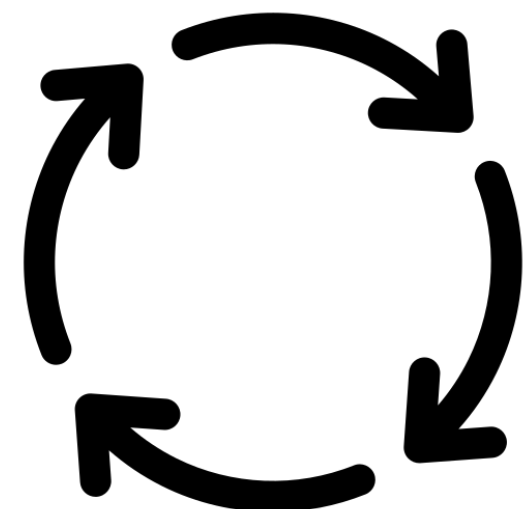
Support for multiple
protocols & threat models



Data-parallel runtime



Vectorization &
message batching

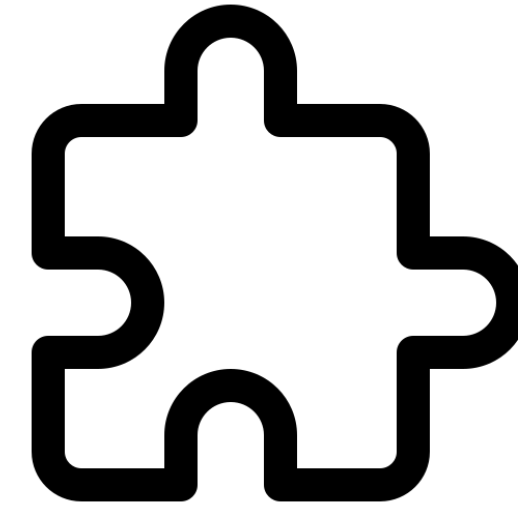


Custom TCP communicator

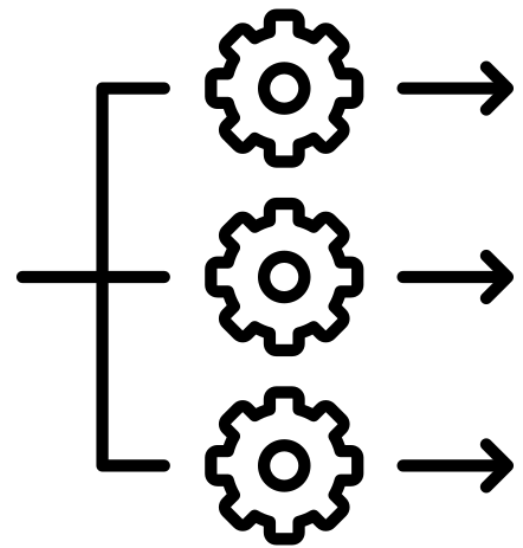
ORQ: an Oblivious Relational Query engine



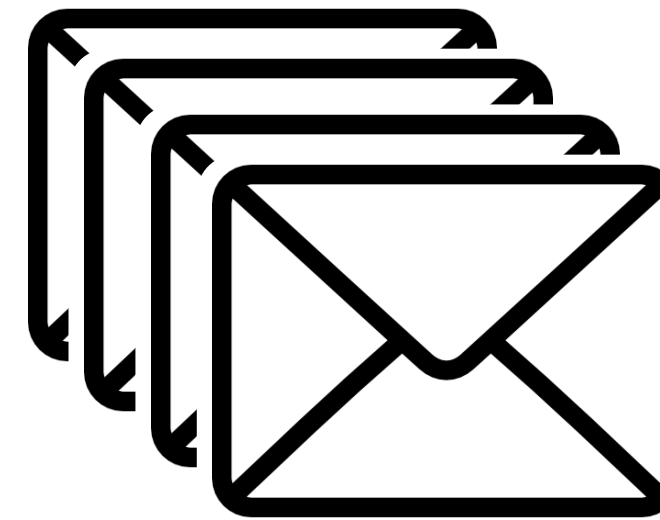
Familiar APIs &
simple orchestration



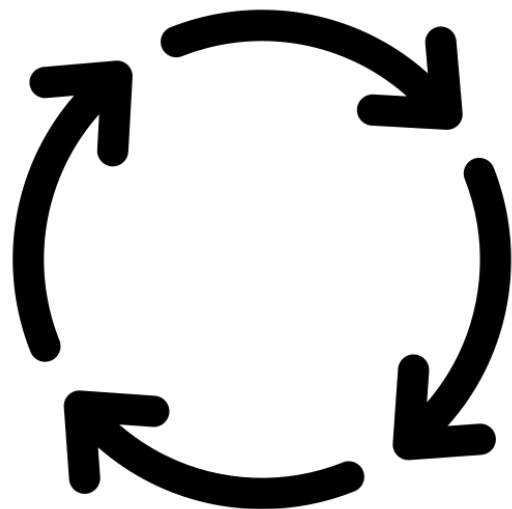
Support for multiple
protocols & threat models



Data-parallel runtime



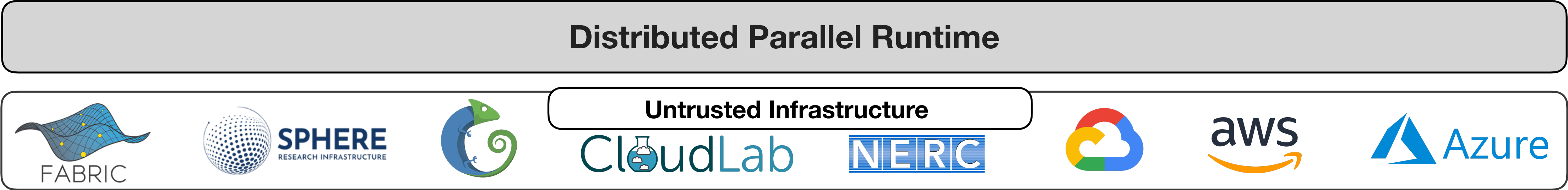
Vectorization &
message batching



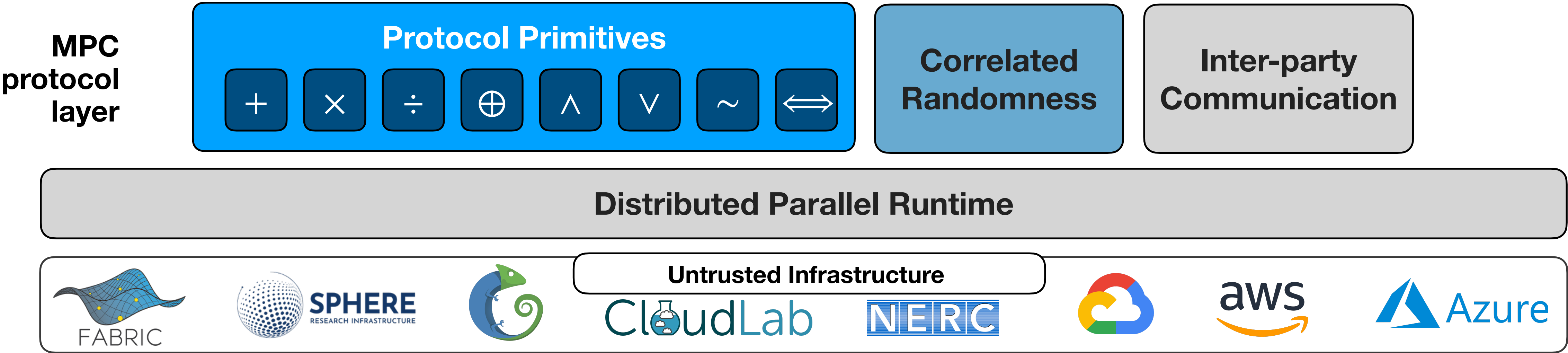
Custom TCP communicator

14,000 C++ LoC

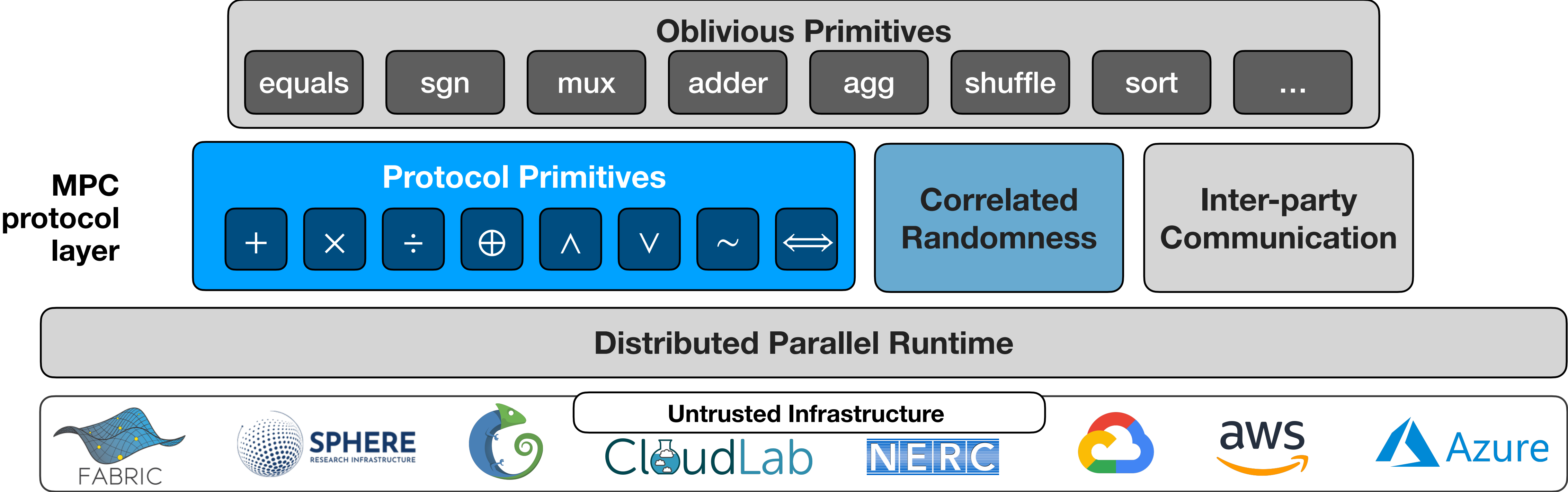
ORQ Stack



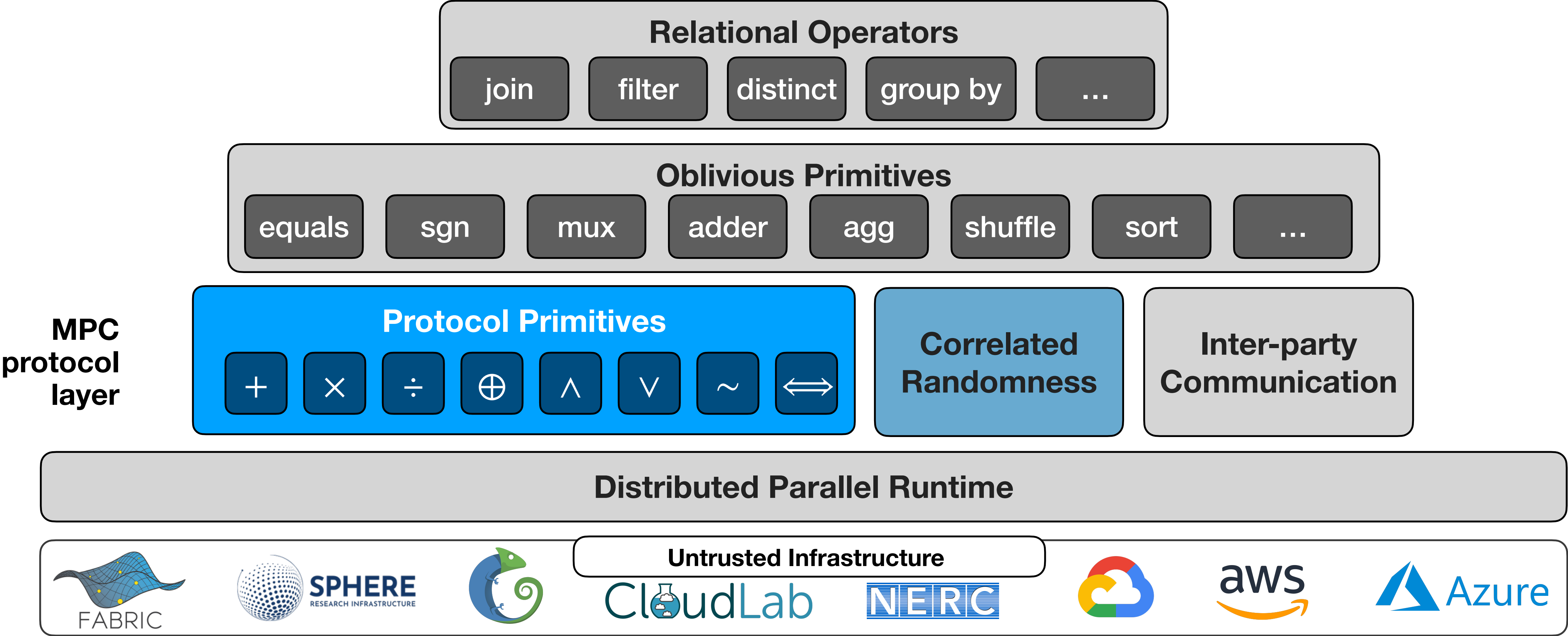
ORQ Stack



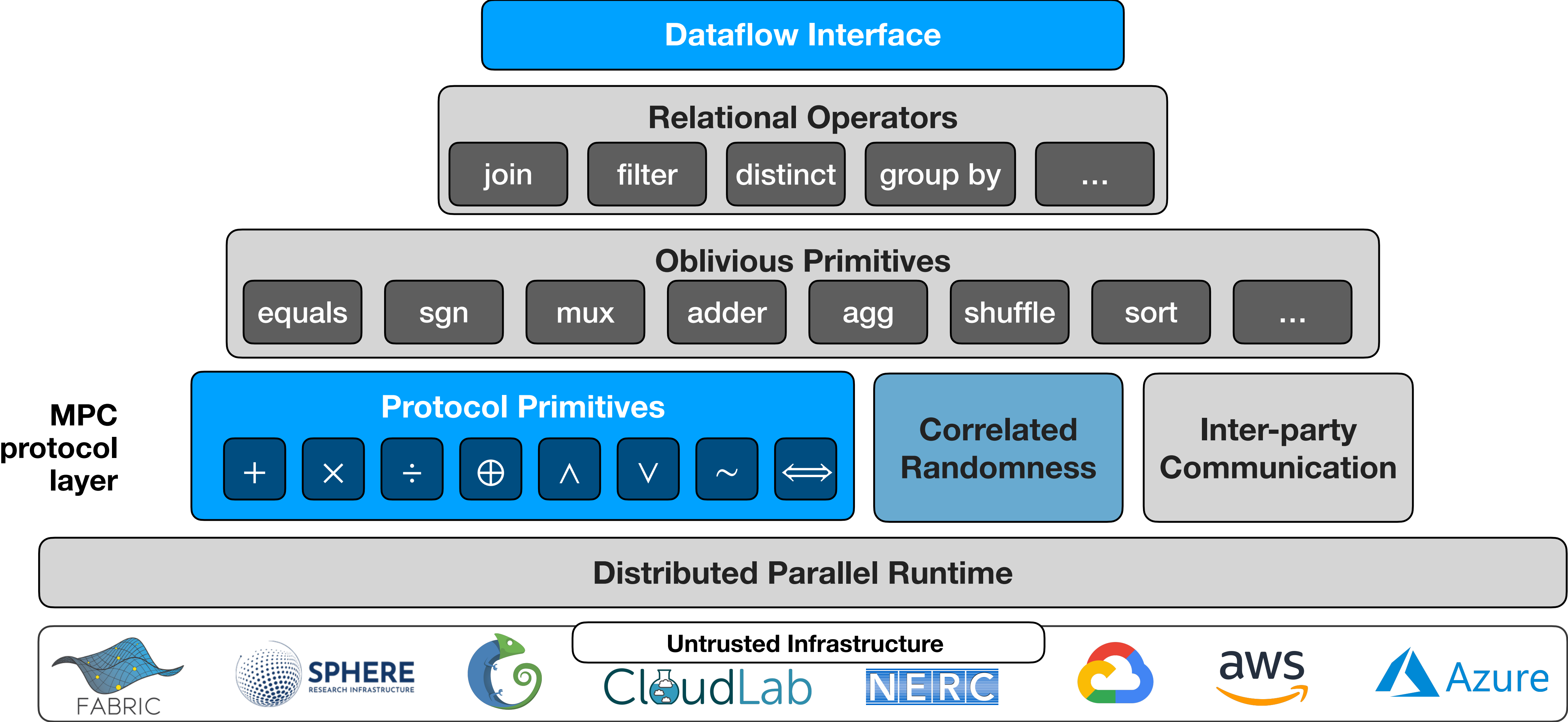
ORQ Stack



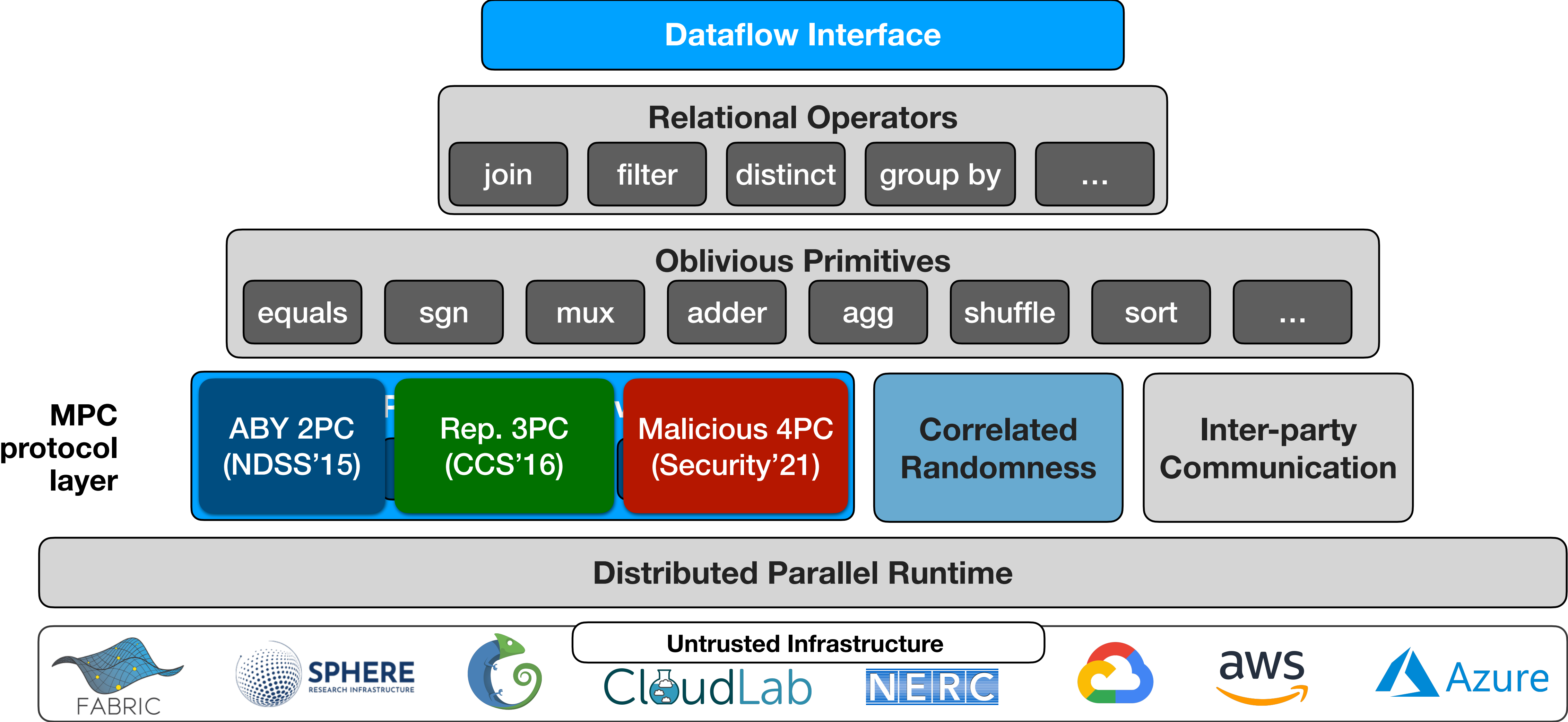
ORQ Stack



ORQ Stack



ORQ Stack



API Example

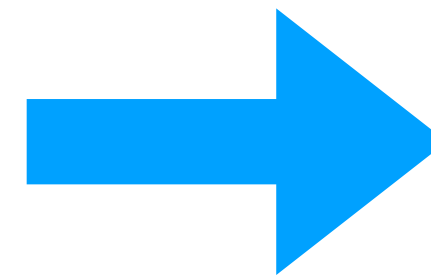
TPC-H Q13: SQL vs. ORQ Dataflow API

```
select
  c_count, count(*) as custdist
from (
  select
    c_custkey,
    count(o_orderkey)
  from
    customer left outer join orders on
      c_custkey = o_custkey
      and o_comment != 0
  group by
    c_custkey
) as c_orders (c_custkey, c_count)
group by
  c_count
order by
  custdist desc,
  c_count desc;
```


API Example

TPC-H Q13: SQL vs. ORQ Dataflow API

```
select
  c_count, count(*) as custdist
from (
  select
    c_custkey,
    count(o_orderkey)
  from
    customer left outer join orders on
      c_custkey = o_custkey
      and o_comment != 0
  group by
    c_custkey
) as c_orders (c_custkey, c_count)
group by
  c_count
order by
  custdist desc,
  c_count desc;
```



```
auto C = db.getCustomersTable();
auto O = db.getOrdersTable();

O.filter(O["Comment"] != 0);

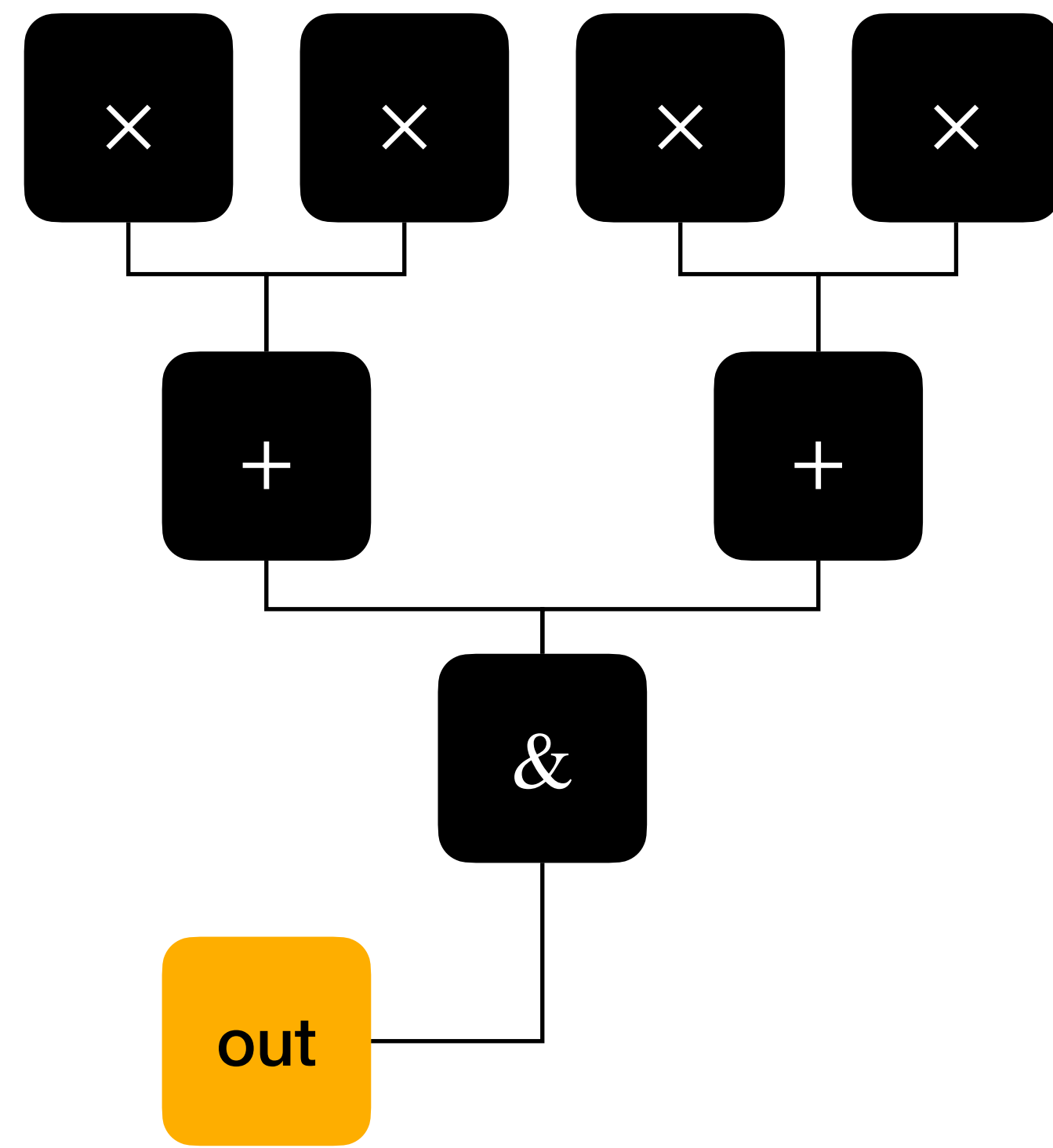
auto T = C.left_outer_join(O,
  {"CustKey"},
  {"Count", "Count", count});

T.convert_a2b("Count", "[Count]");

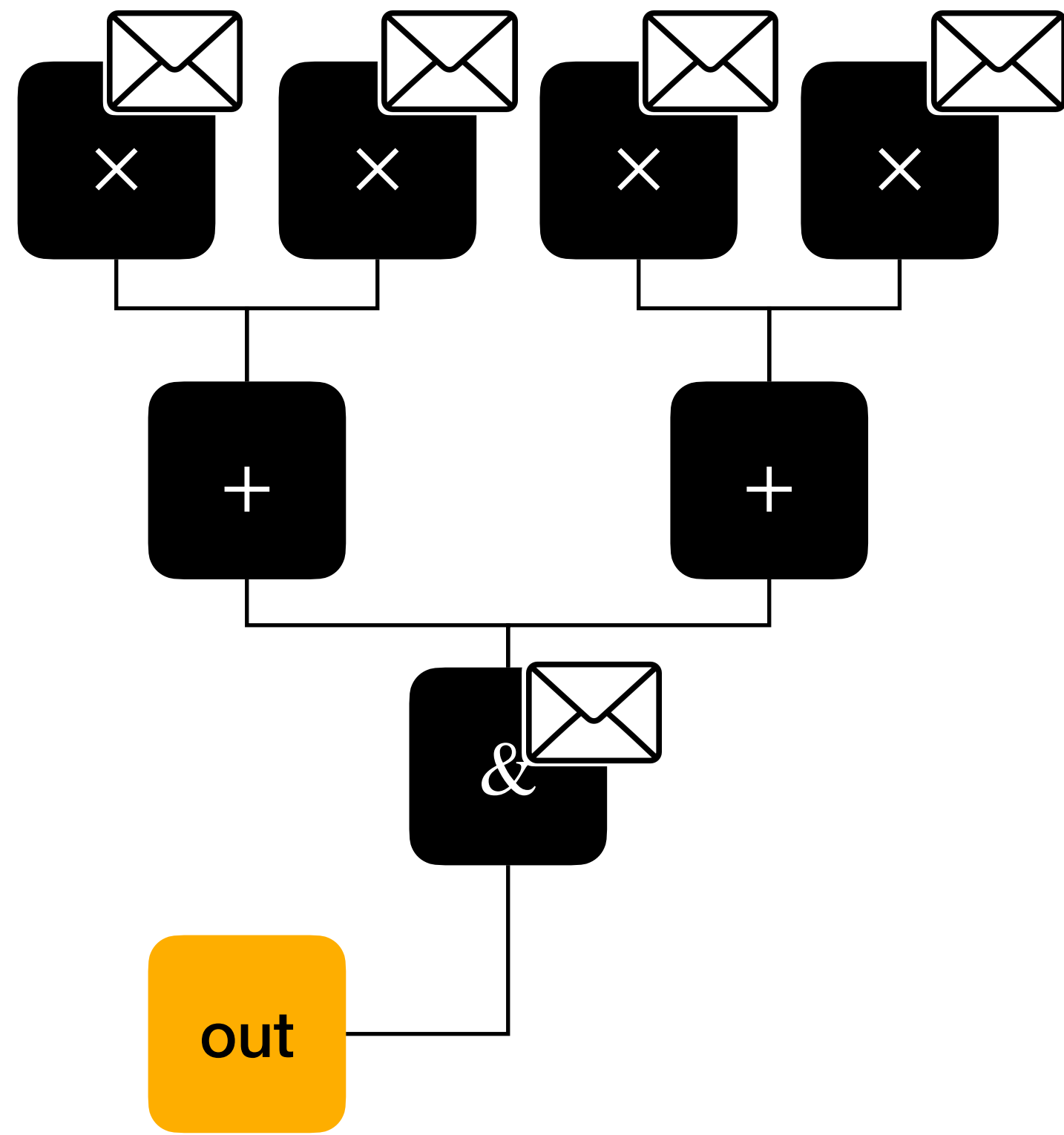
auto F = T.aggregate(
  {"Count"},
  {"CustDist", "CustDist", count});

F.convert_a2b("CustDist", "[CustDist]");
F.sort({"CustDist", "[Count]"}, DESC);
```

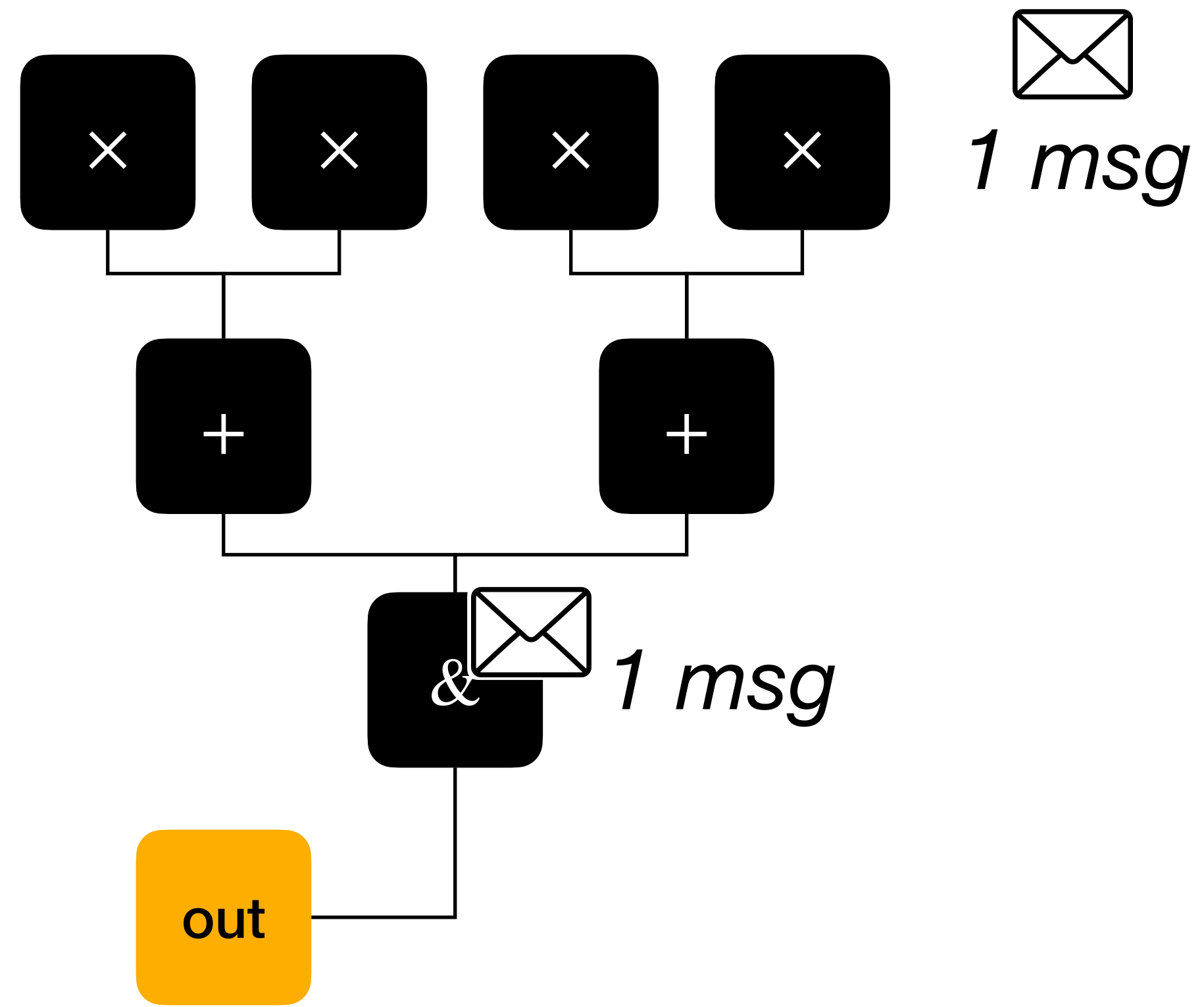
Vectorization & Message Batching



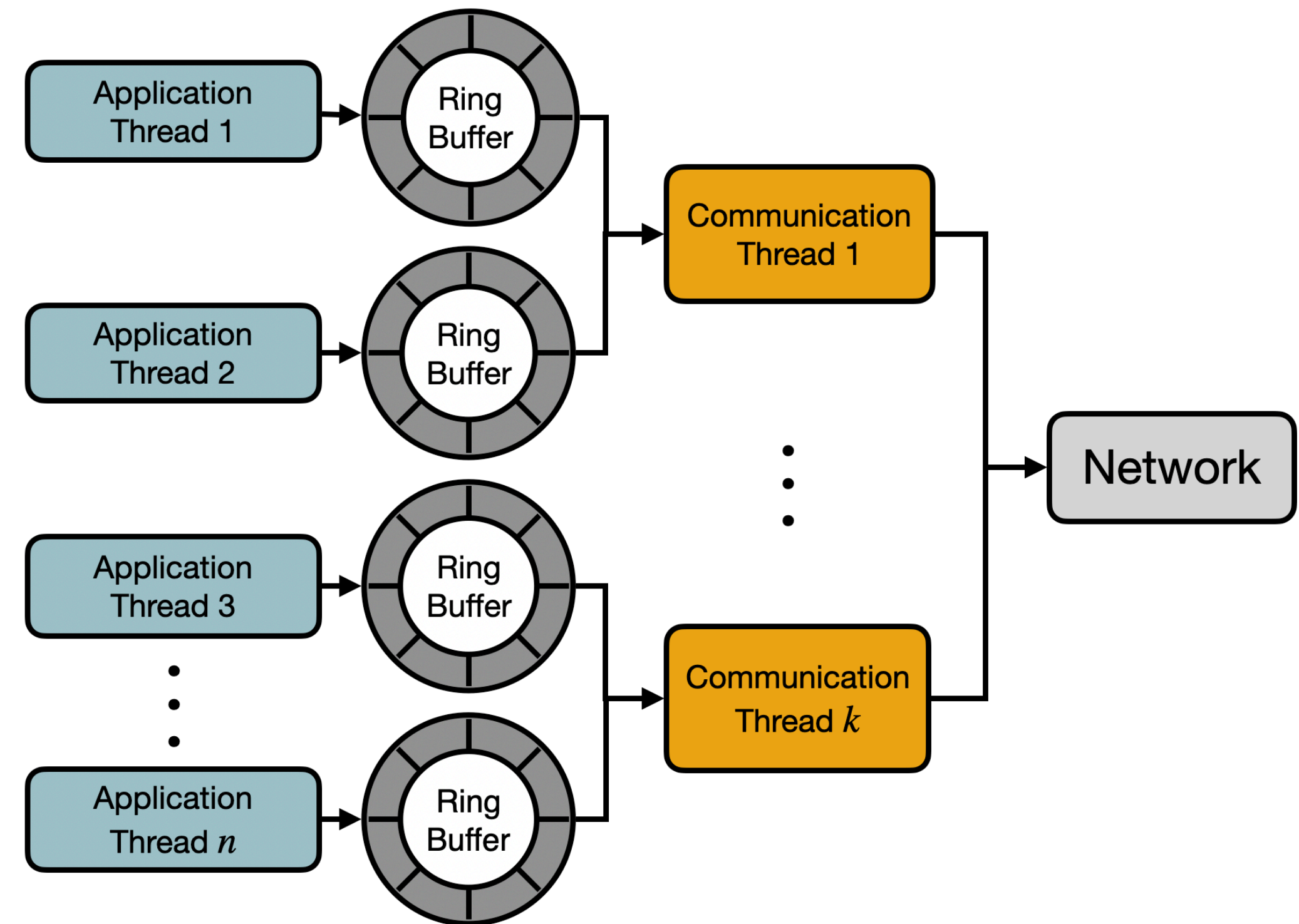
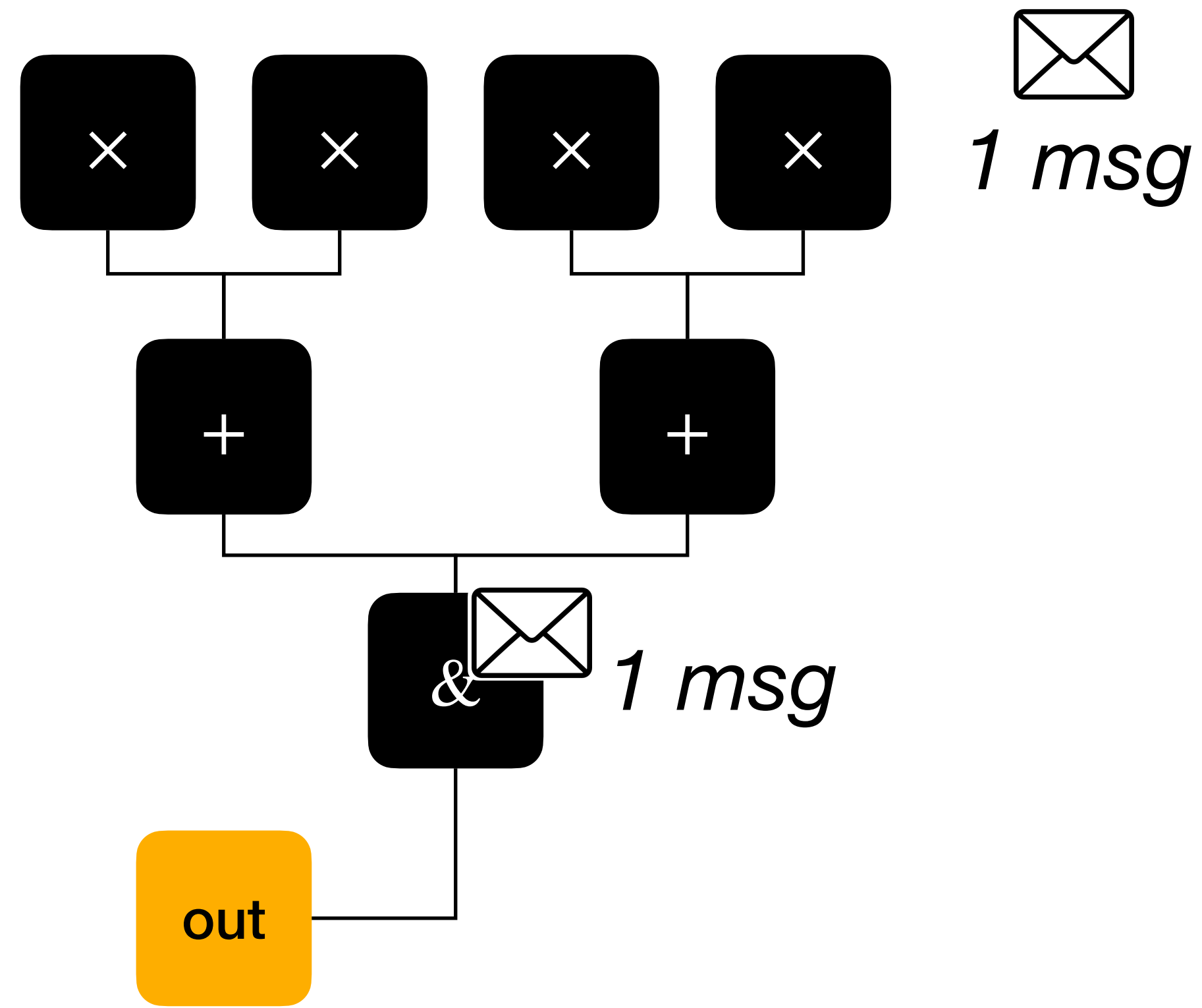
Vectorization & Message Batching



Vectorization & Message Batching



Vectorization & Message Batching



Flexible TCP Communicator

Prior MPC Benchmarks

with ~5M input rows

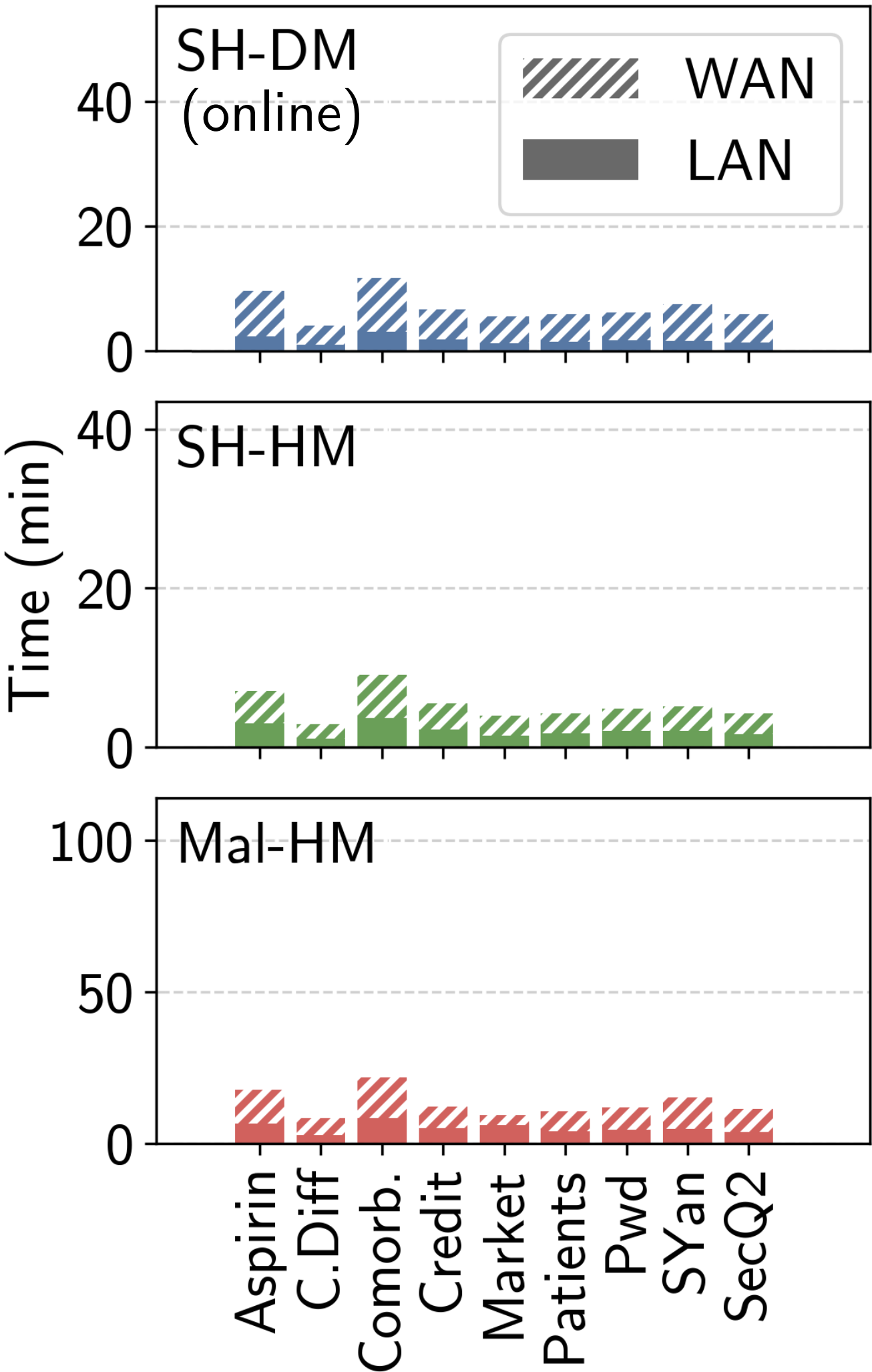
Prior MPC Benchmarks

with ~5M input rows

ABY 2PC
Semihonest / Dishonest Majority

Replicated 3PC
Semihonest / Honest Majority

Fantastic 4PC
Malicious / Honest Majority



all ≤ 3 min

all ≤ 4 min

all ≤ 9 min

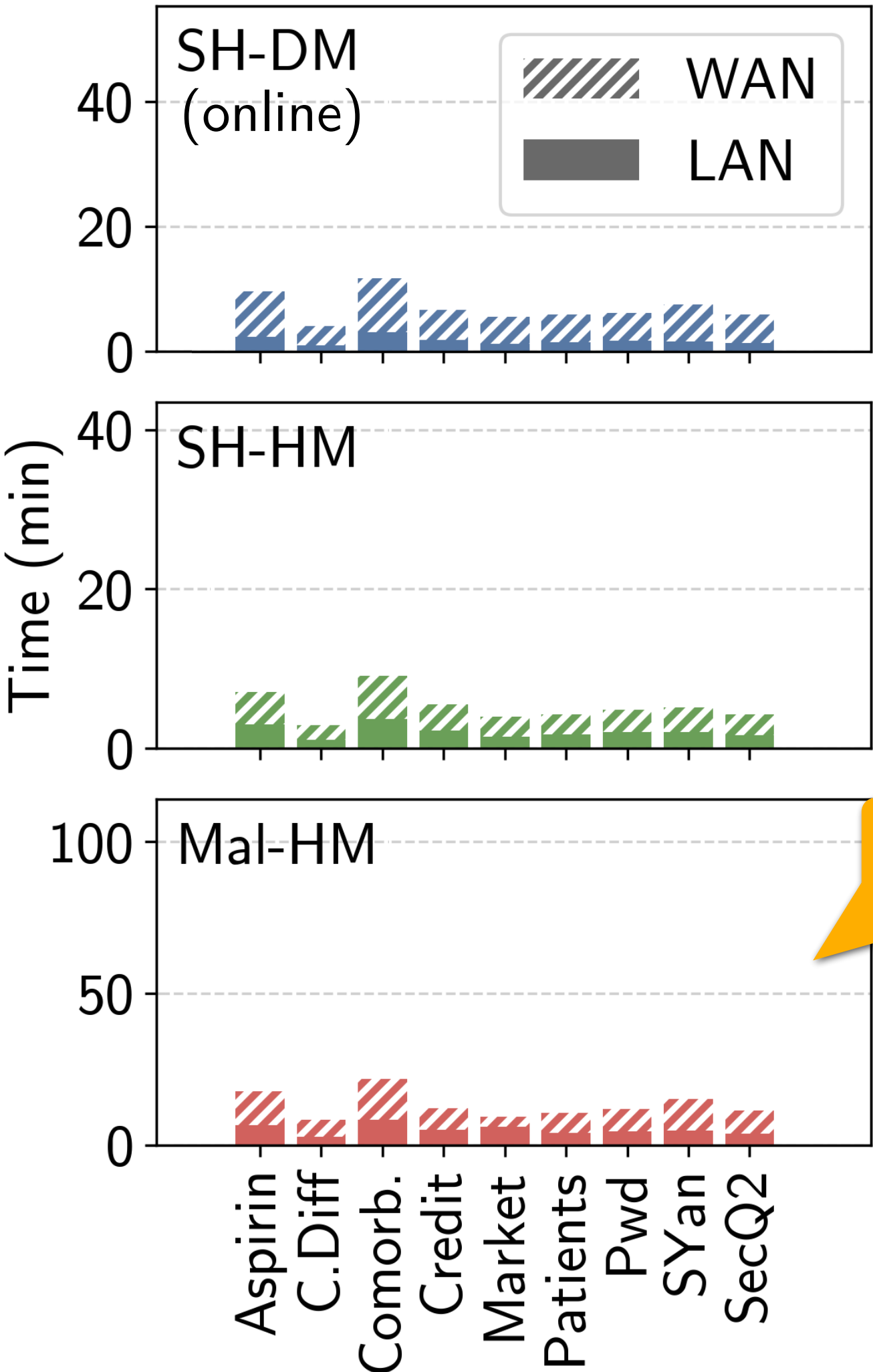
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Malicious / Honest Majority



all ≤ 3 min

all ≤ 4 min

all ≤ 9 min

Motivation for leakage!

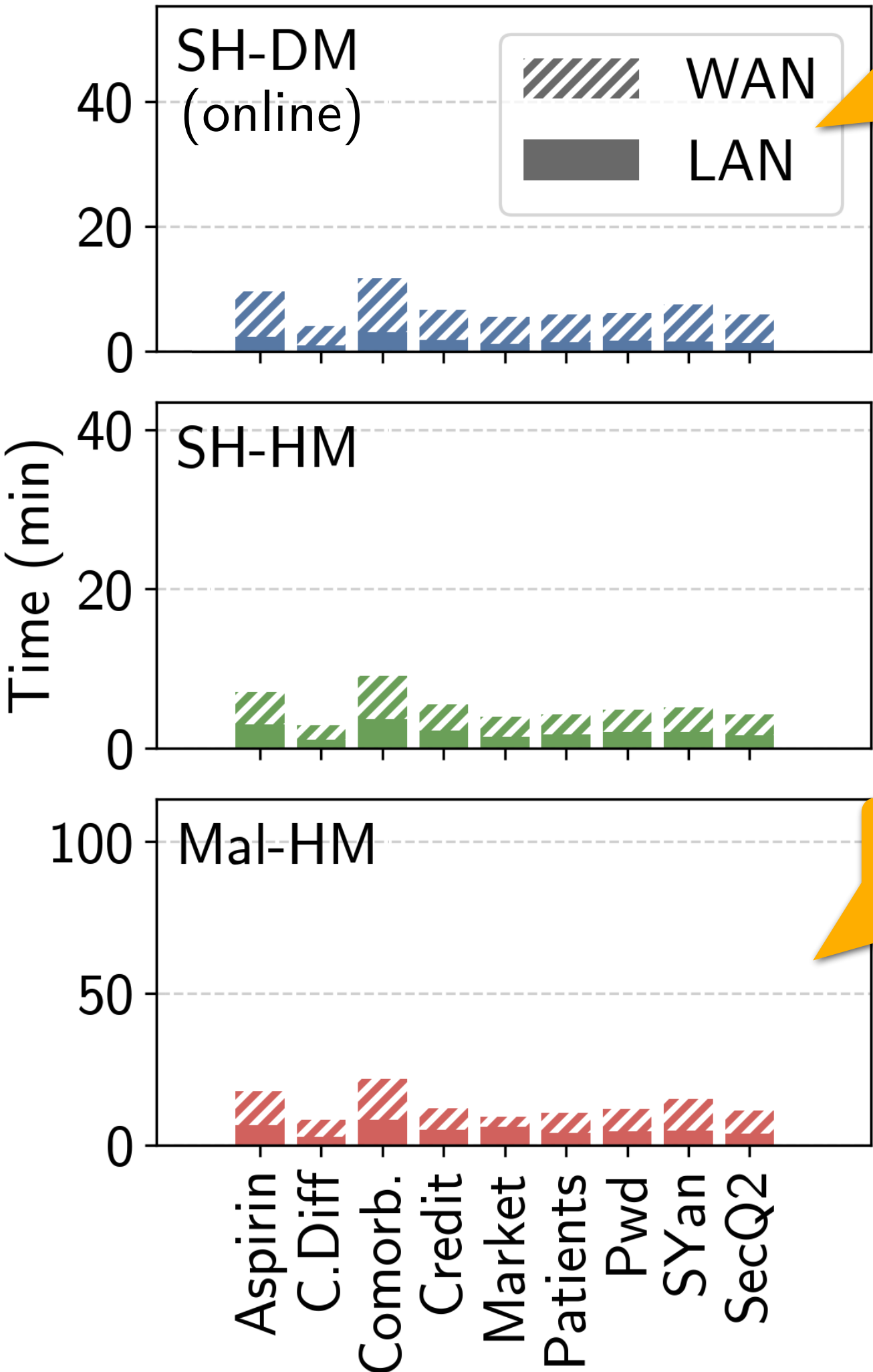
Prior MPC Benchmarks

with ~5M input rows

ABY 2PC
Semihonest / Dishonest Majority

Replicated 3PC
Semihonest / Honest Majority

Fantastic 4PC
Malicious / Honest Majority



6 Gbps 20 ms
25 Gbps 0.3 ms

all $\leq$ 3 min

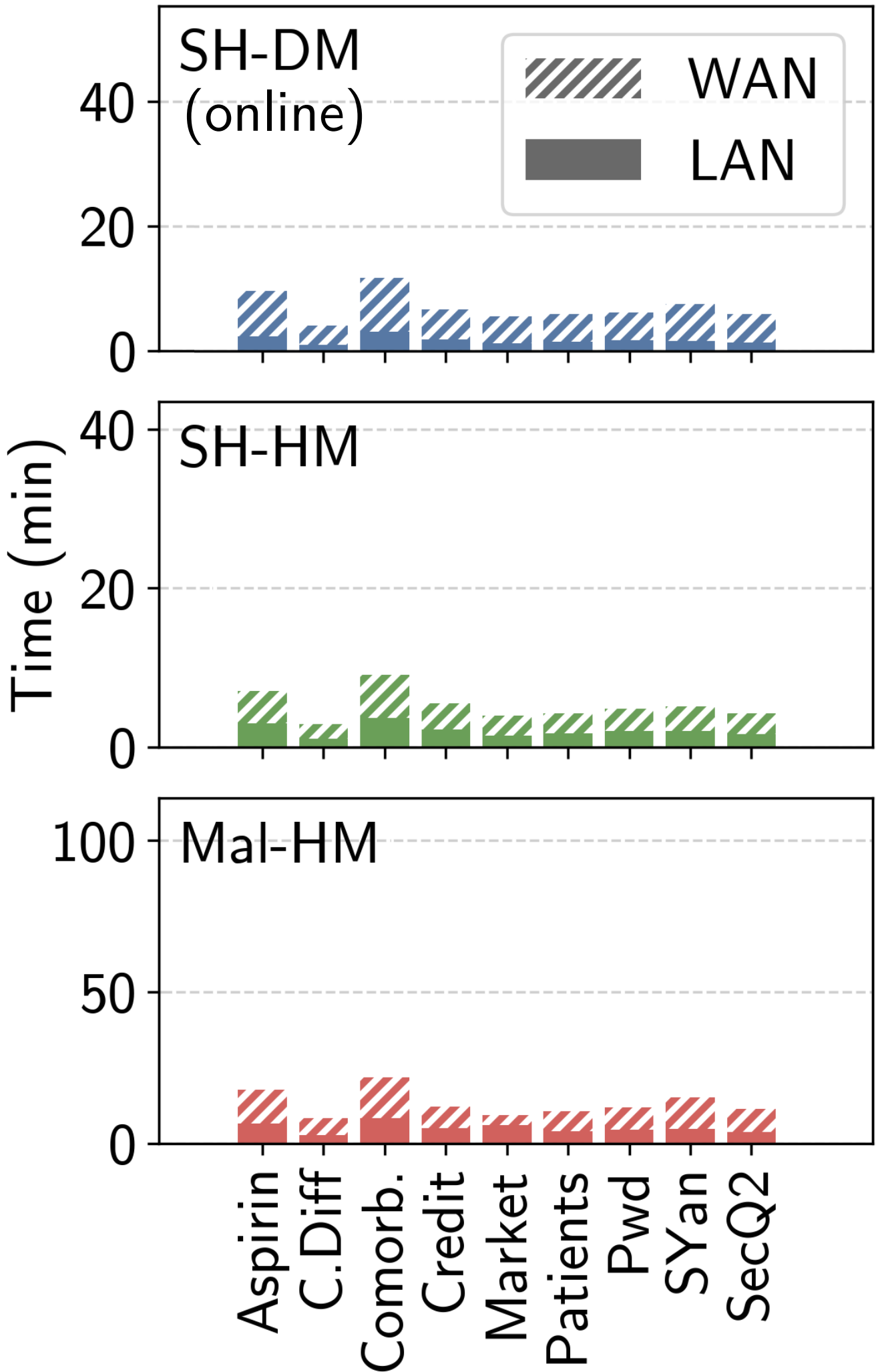
all $\leq$ 4 min

Motivation for leakage!

all $\leq$ 9 min

Prior MPC Benchmarks

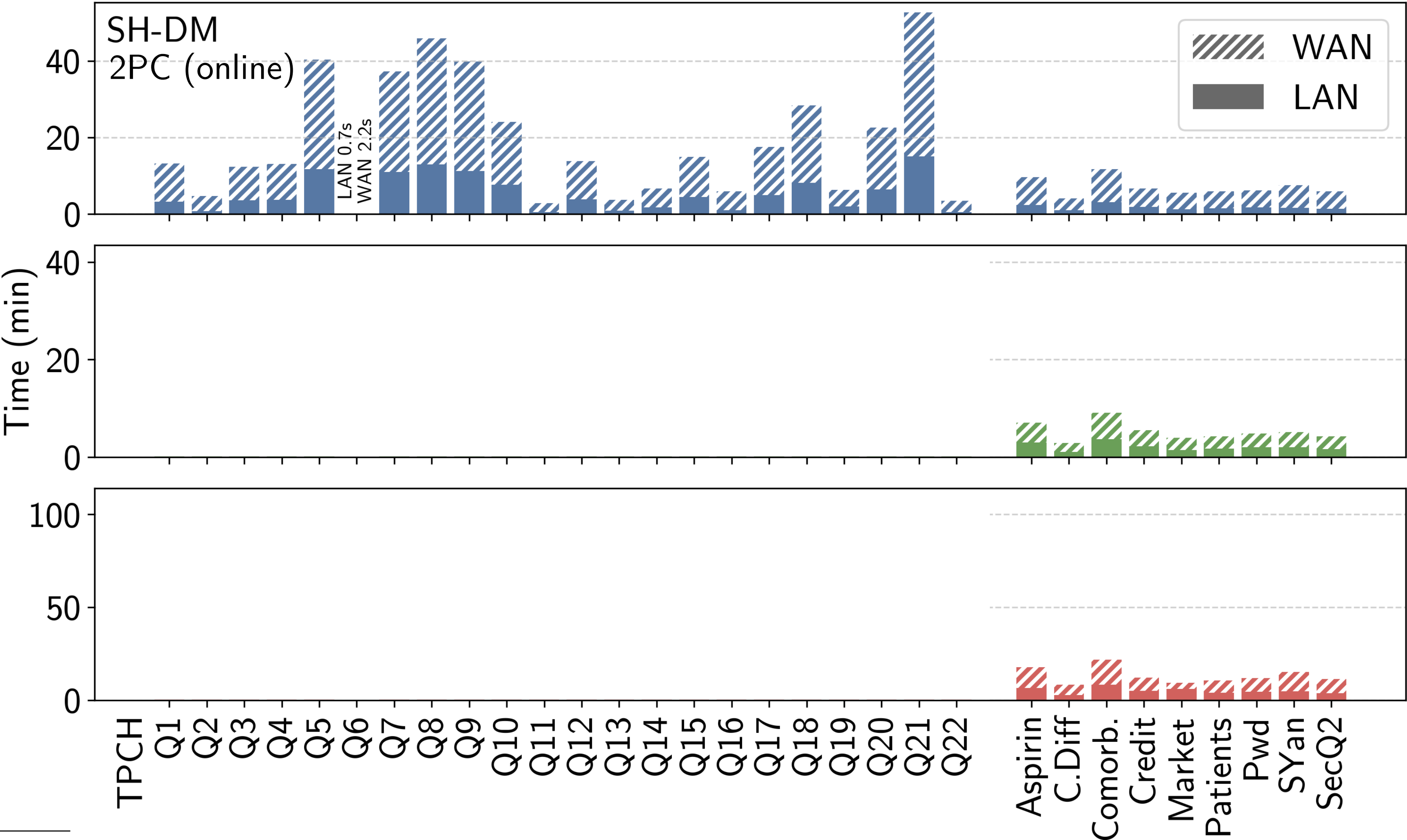
with ~5M input rows



Full TPC-H Benchmark under MPC

@ Scale Factor 1 ($\approx$ 1 GB input)

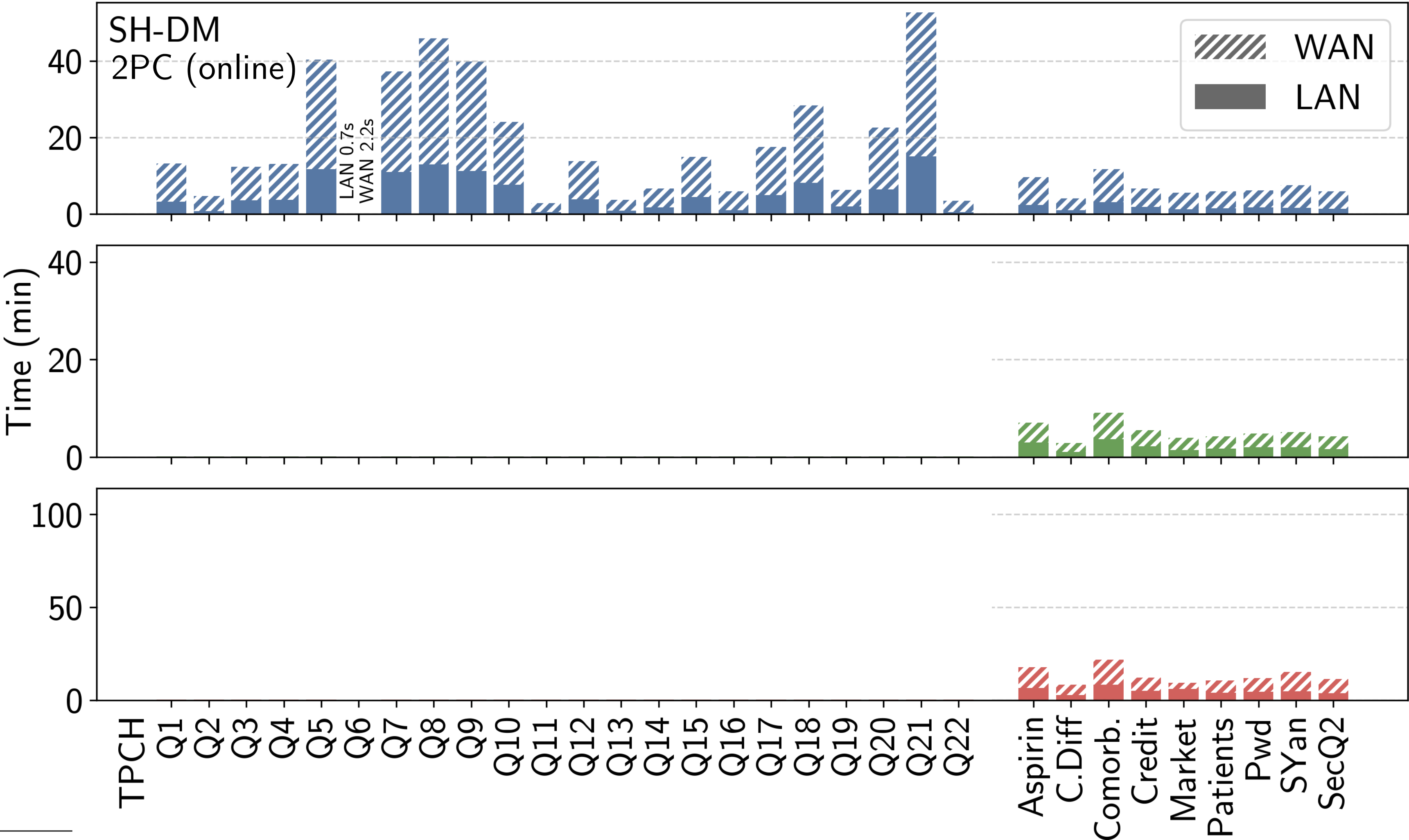
minutes	TPC-H	
	Median	Max
SH-DM LAN	3.8	15.0
WAN	13.5	52.7



Full TPC-H Benchmark under MPC

@ Scale Factor 1 ($\approx$ 1 GB input)

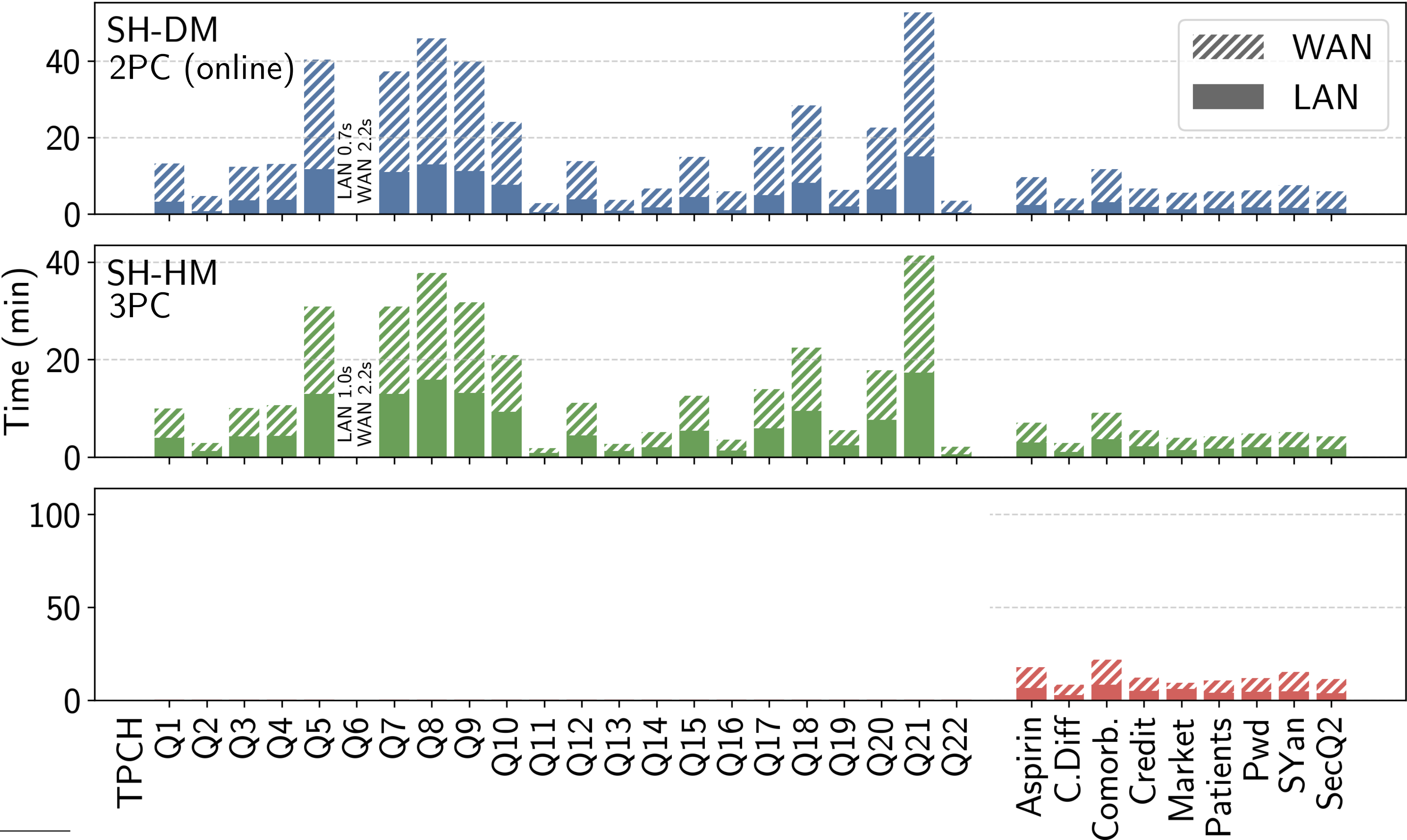
minutes	TPC-H	
	Median	Max
SH-DM LAN	3.8	15.0
WAN	13.5	52.7



Full TPC-H Benchmark under MPC

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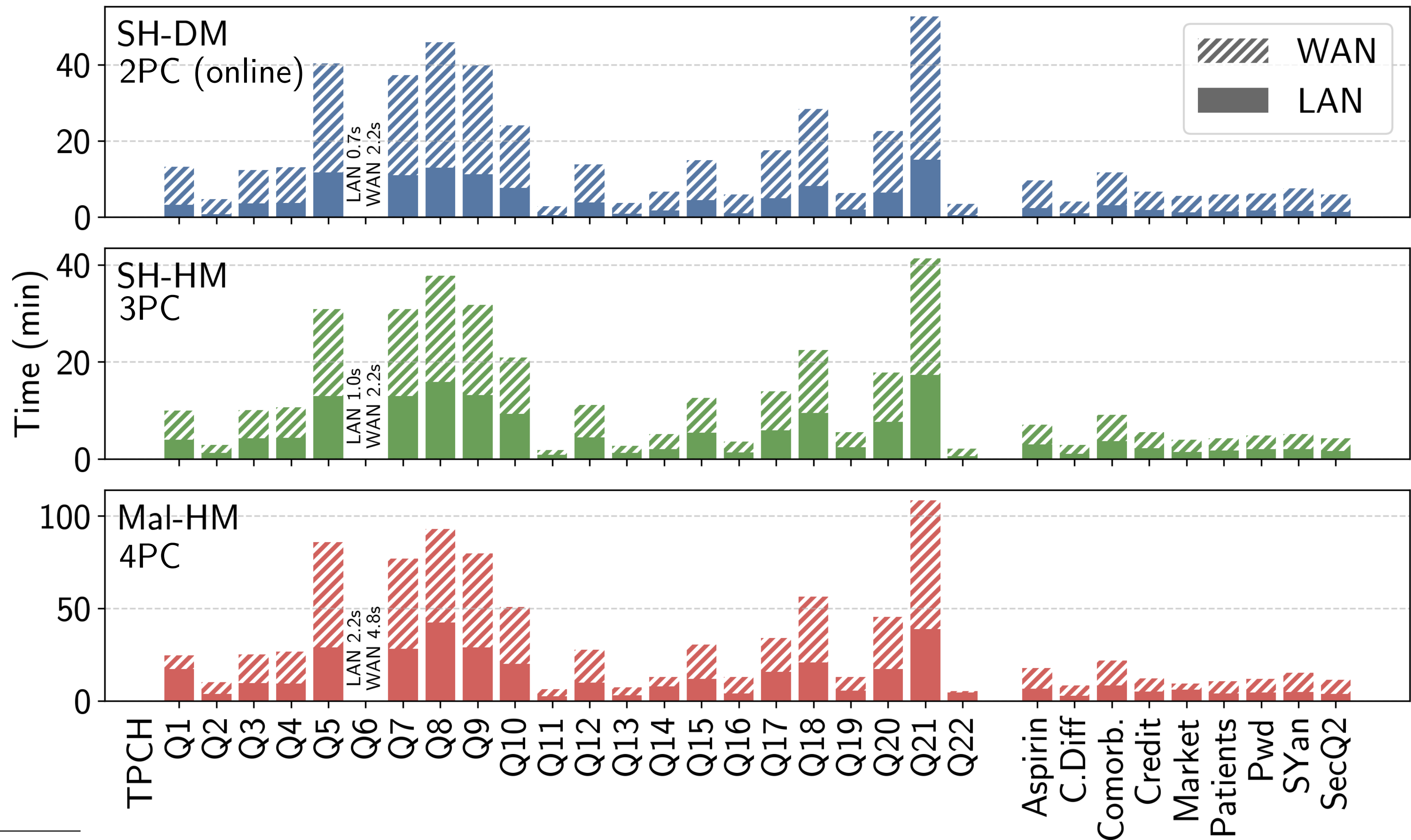
minutes	TPC-H	
	Median	Max
SH-DM LAN	3.8	15.0
WAN	13.5	52.7
SH-HM LAN	4.4	17.4
WAN	10.9	41.4



Full TPC-H Benchmark under MPC

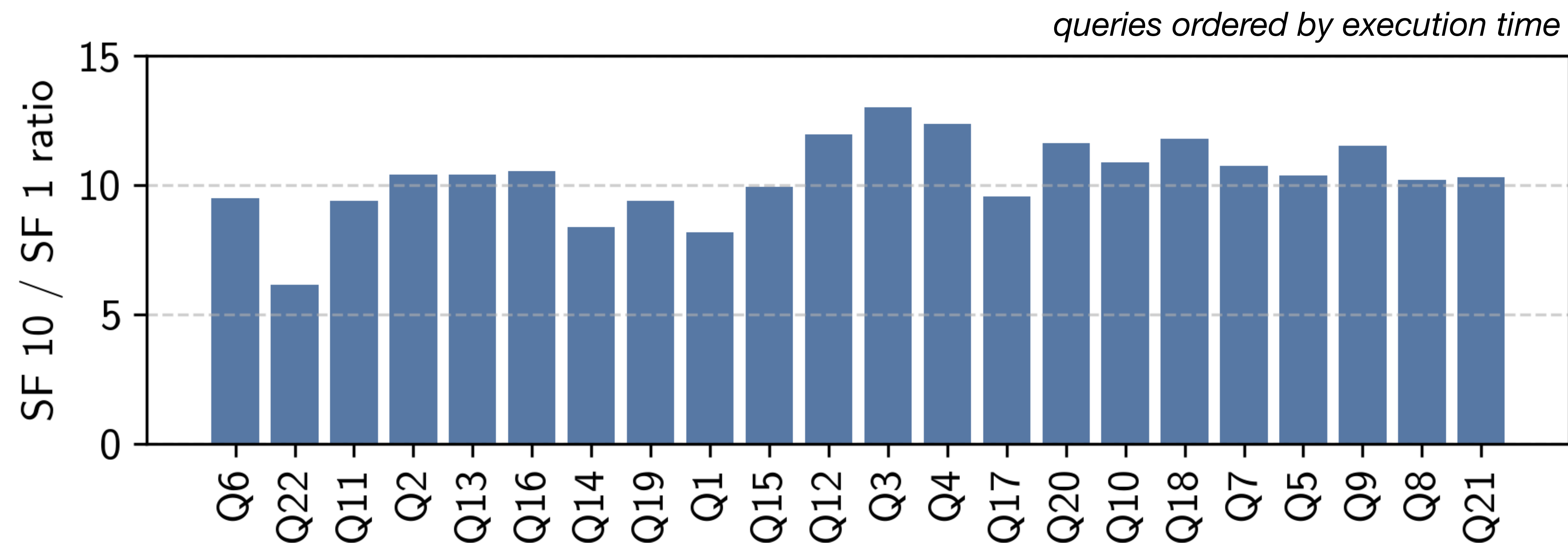
@ Scale Factor 1 ($\approx$ 1 GB input)

minutes	TPC-H	
	Median	Max
SH-DM LAN	3.8	15.0
WAN	13.5	52.7
SH-HM LAN	4.4	17.4
WAN	10.9	41.4
Mal-HM LAN	10.9	42.3
WAN	27.1	108.4



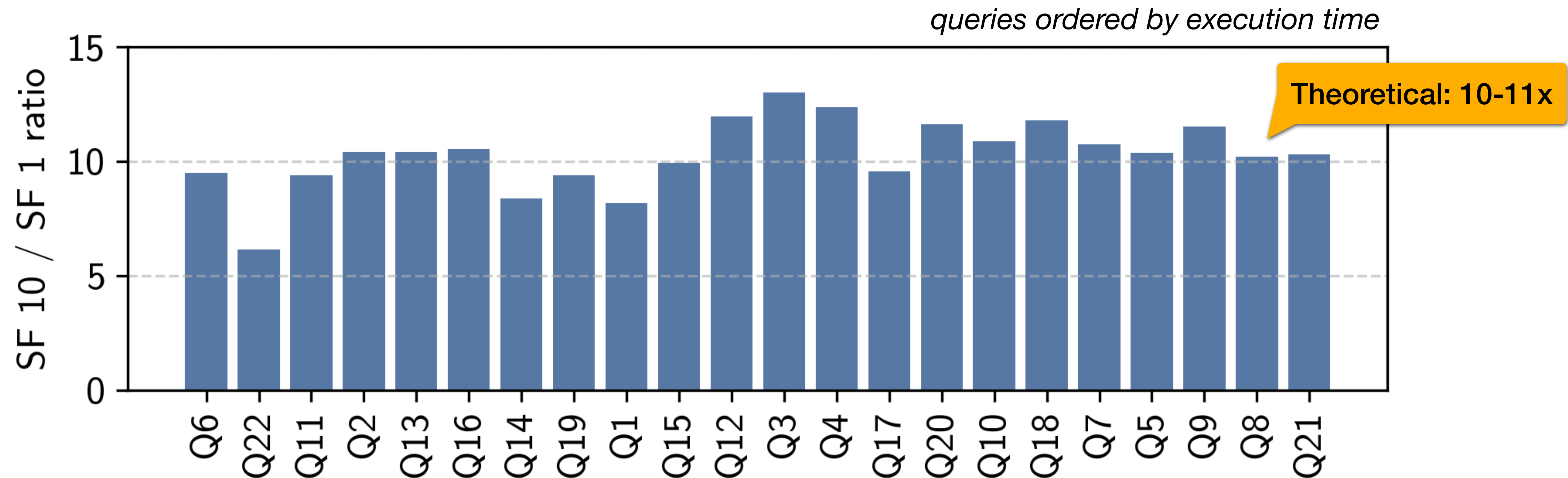
Scalability

10x larger inputs (SF 10)



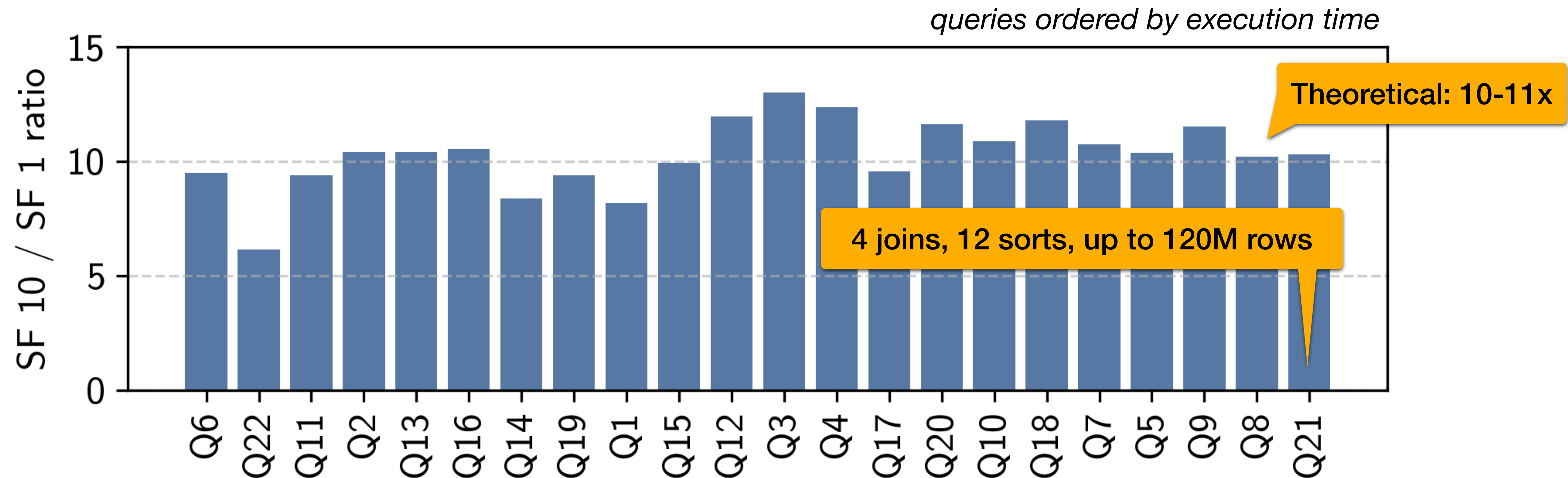
Scalability

10x larger inputs (SF 10)



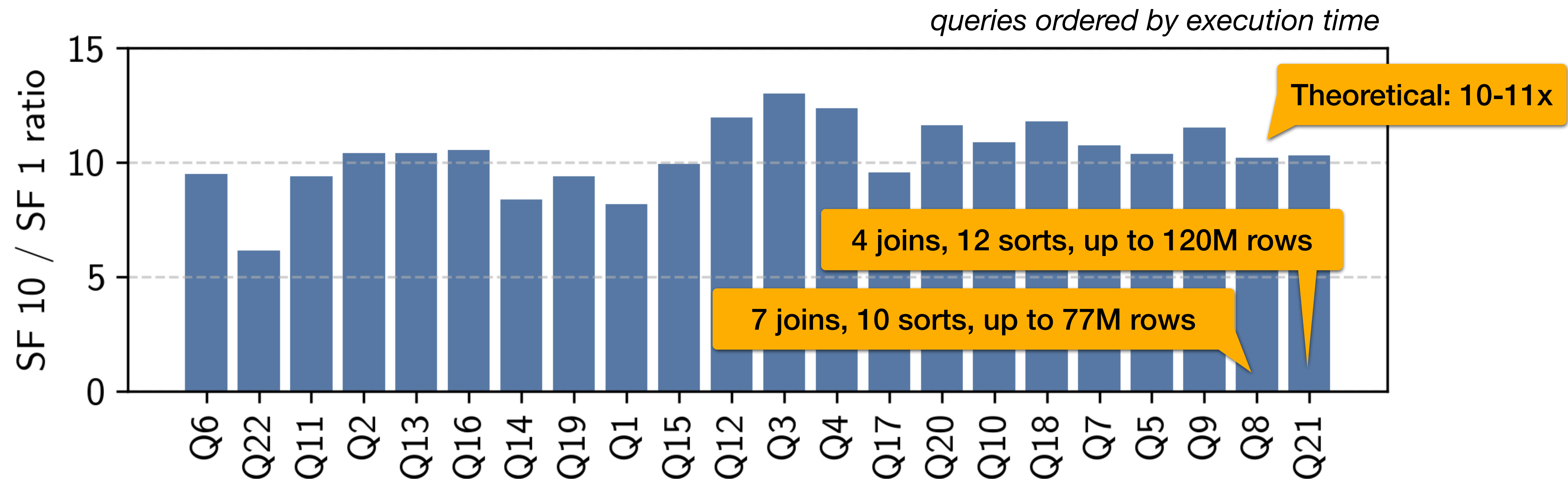
Scalability

10x larger inputs (SF 10)



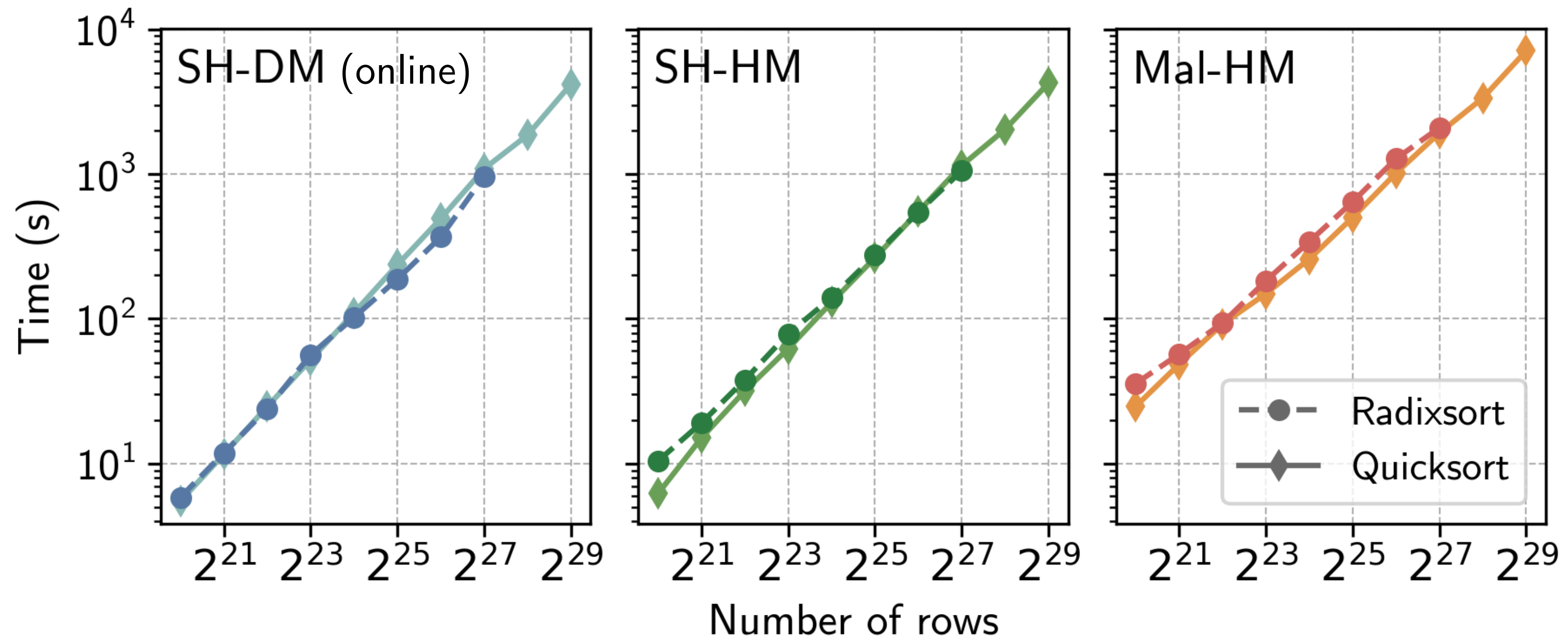
Scalability

10x larger inputs (SF 10)



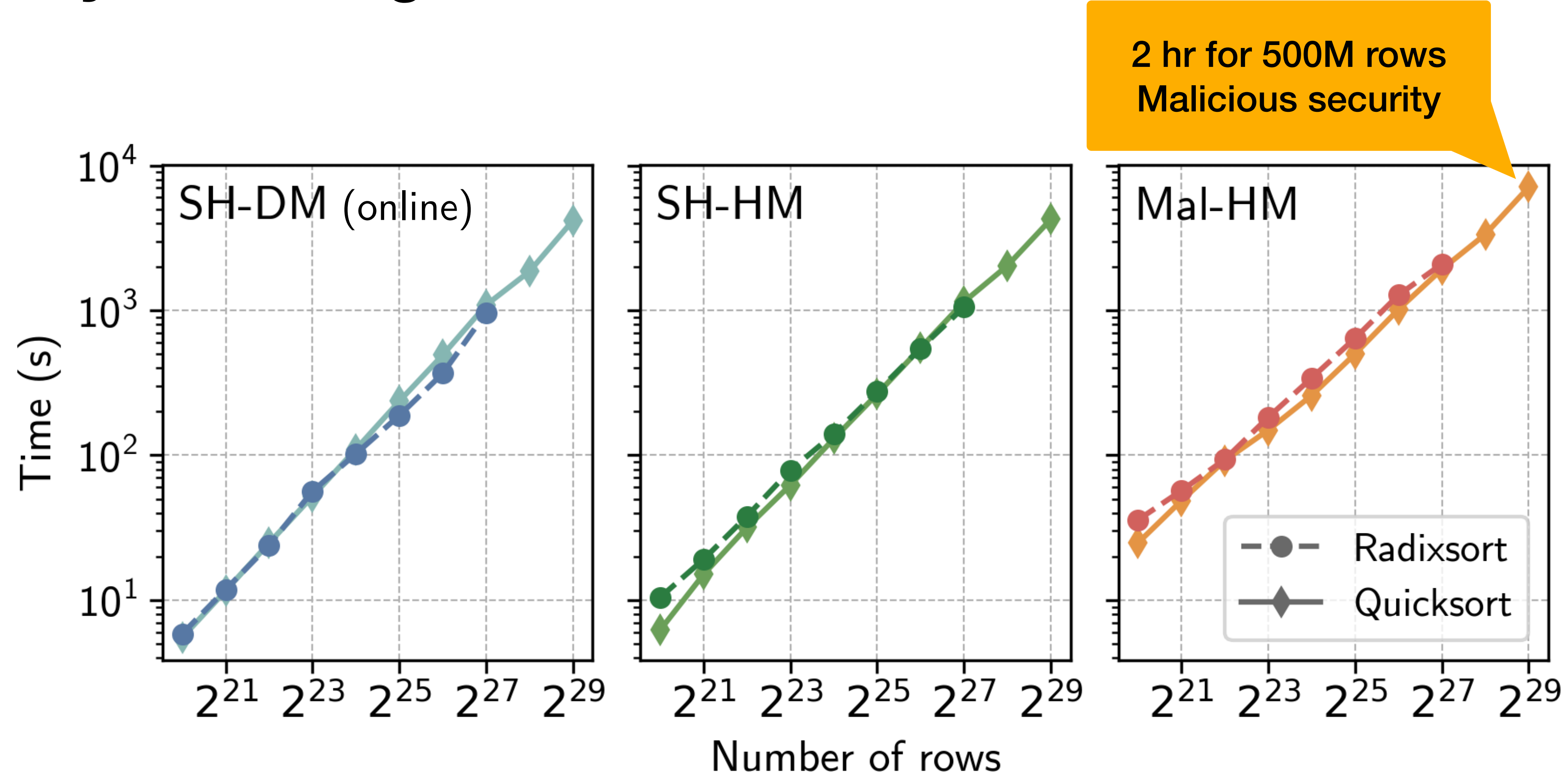
Going Even Further?

Scalability of Sorting



Going Even Further?

Scalability of Sorting



ORQ: Complex Analytics on Private Data with Strong Security Guarantees

email me: elibaum@bu.edu



Distinguished Artifact



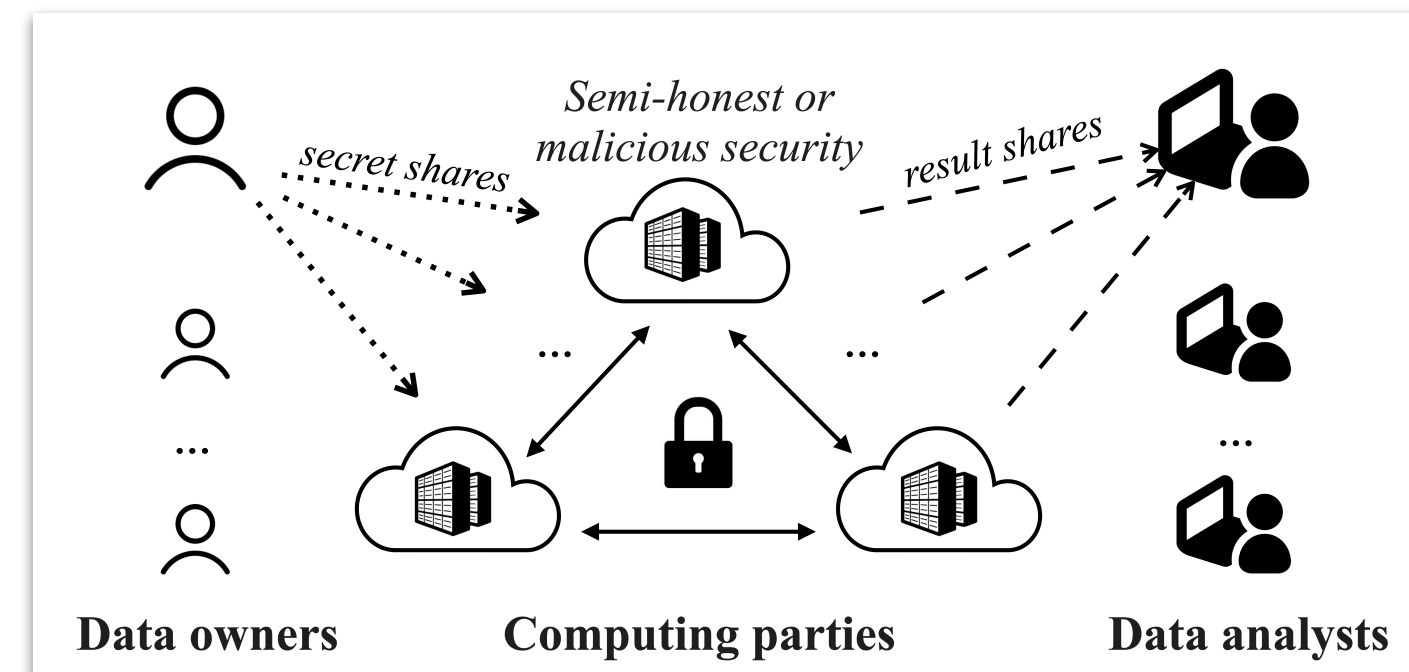
Paper/Code/Docs

elibaum.com



CASPLab

We're hiring!



Privacy

Runs on untrusted compute with end-to-end oblivious execution

Generality

Uses crypto protocols as a blackbox to meet different security requirements

Expressivity

Efficiently computes all queries from prior work & TPC-H, with no leakage

Scalability

Evaluates queries with millions of rows & efficiently uses available resources