Lotto: Secure Participant Selection against Adversarial Servers in Federated Learning

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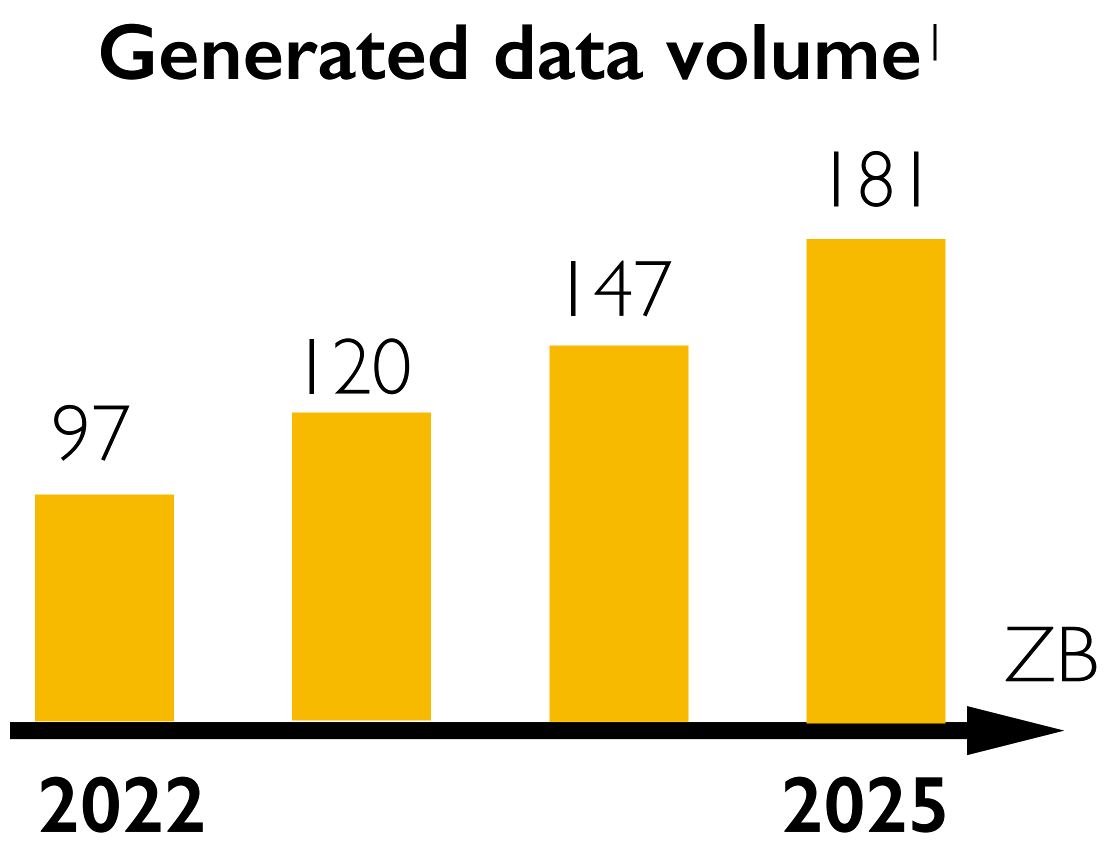
UNIVERSITY OF MICHIGAN
NOKIA BELL LABS

Growth of edge computing

Edge devices generate massive **data**



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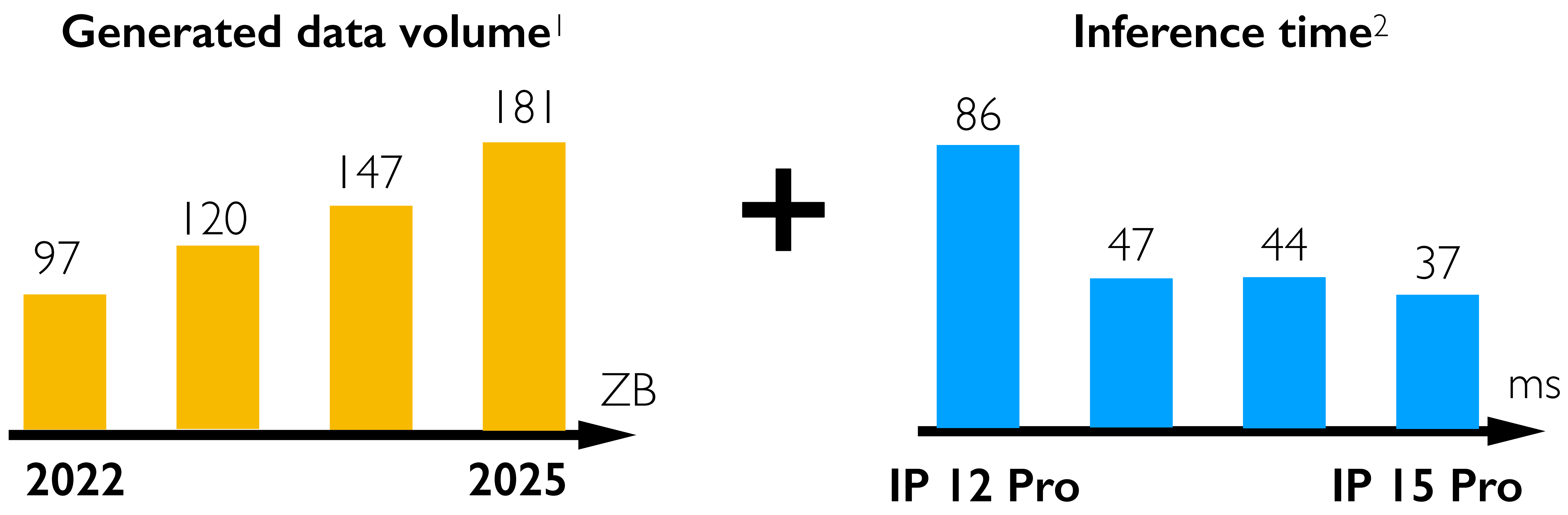
Increasing **resource** on edge devices



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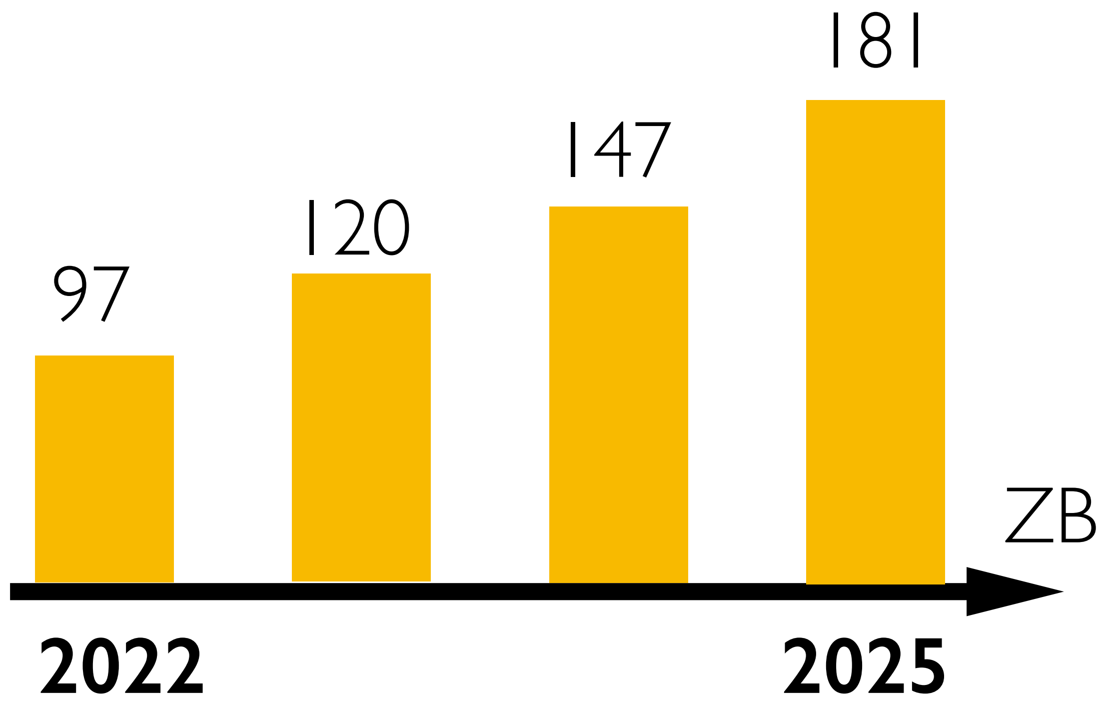
Growth of edge computing

Edge devices generate massive **data**

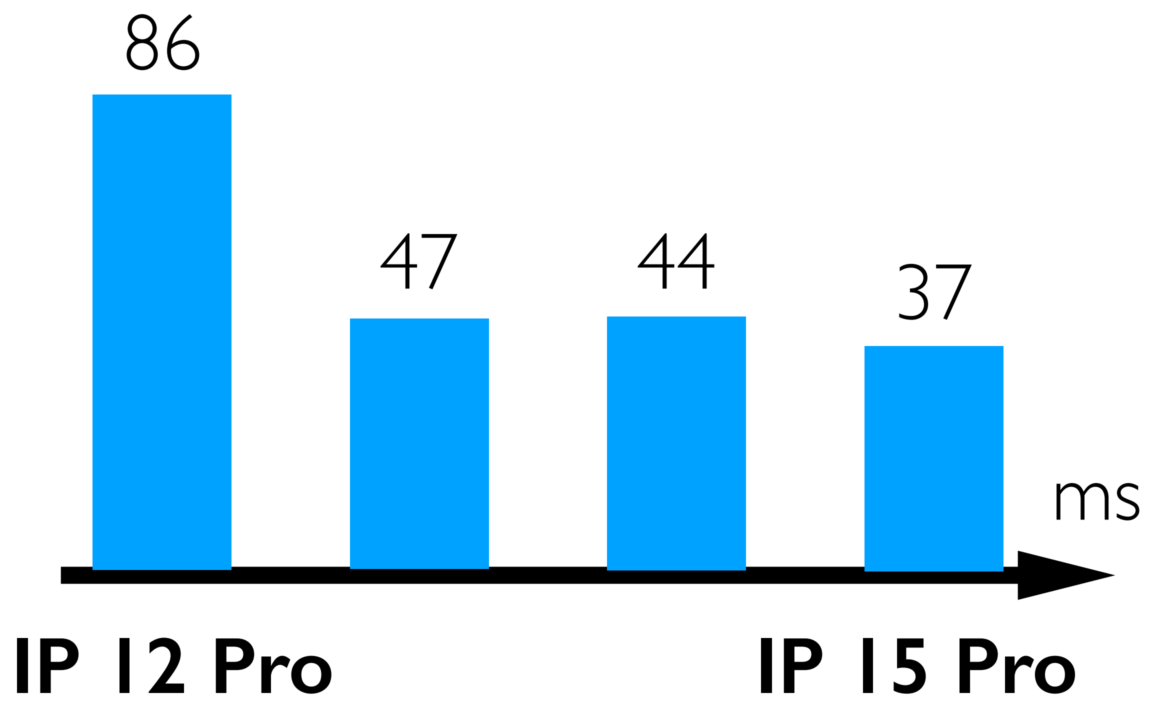
Generated data volume[1]



+

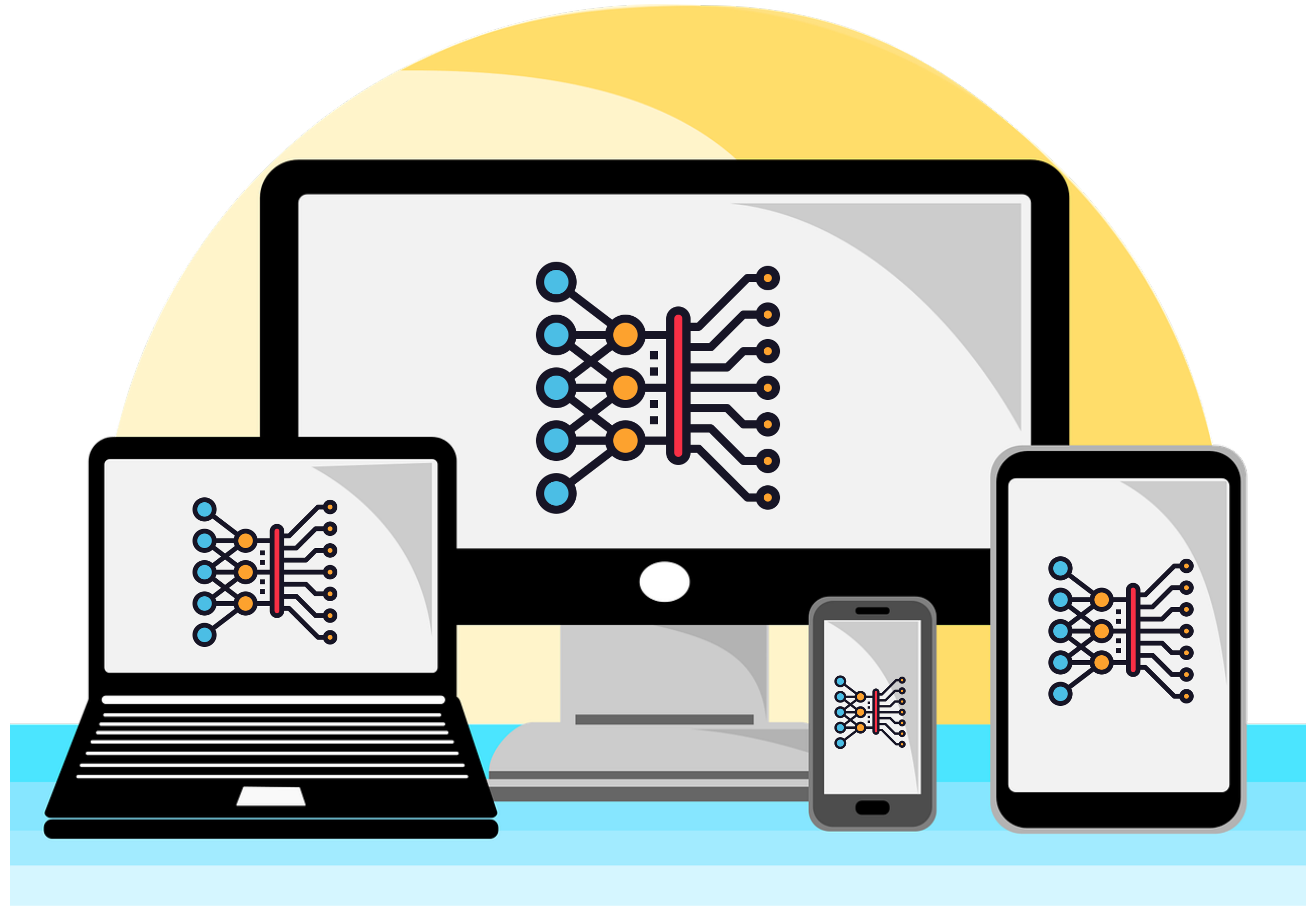
Increasing **resource** on edge devices

Inference time[2]



→

machine learning driven to the edge



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Private learning on the edge

Private learning on the edge

Privacy-Enhancing Technique	Federated Learning[1]
Privacy Guarantee	Data kept on premises

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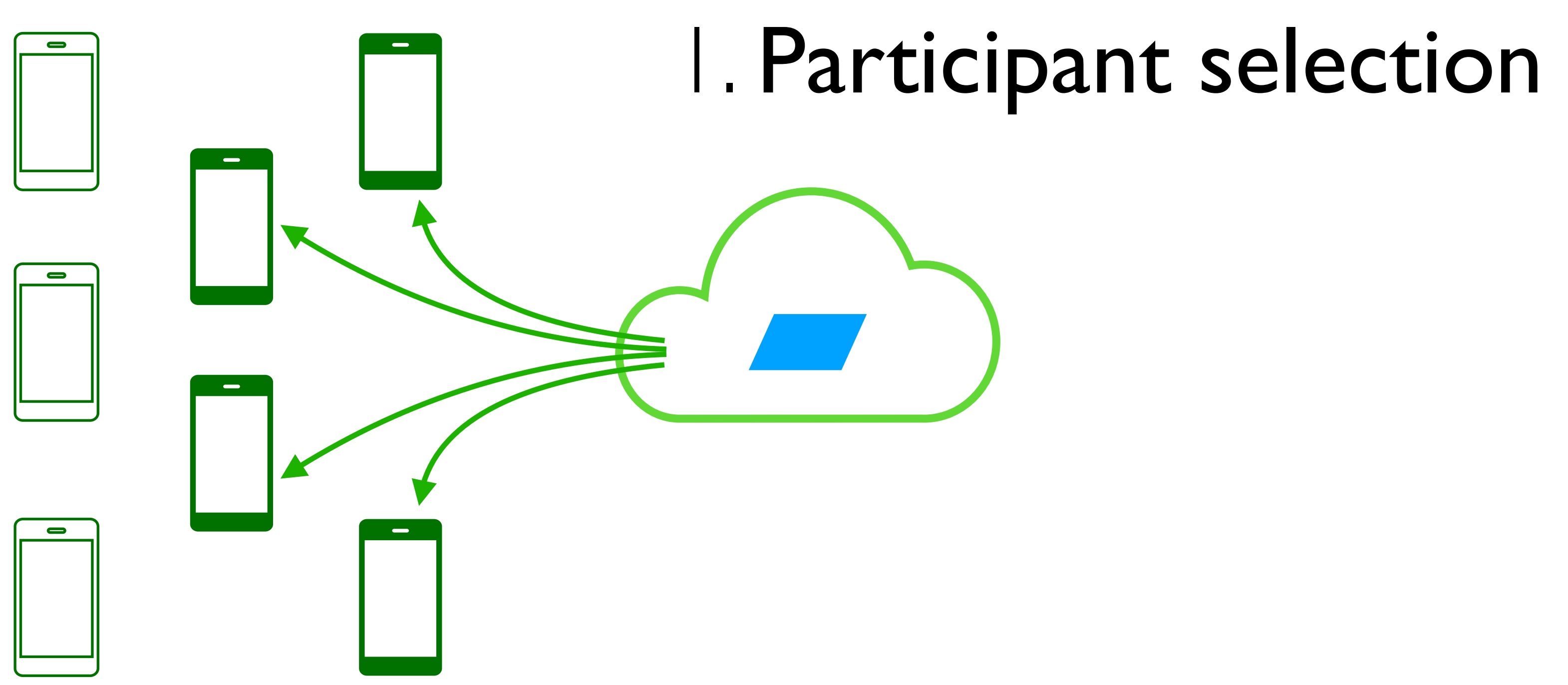

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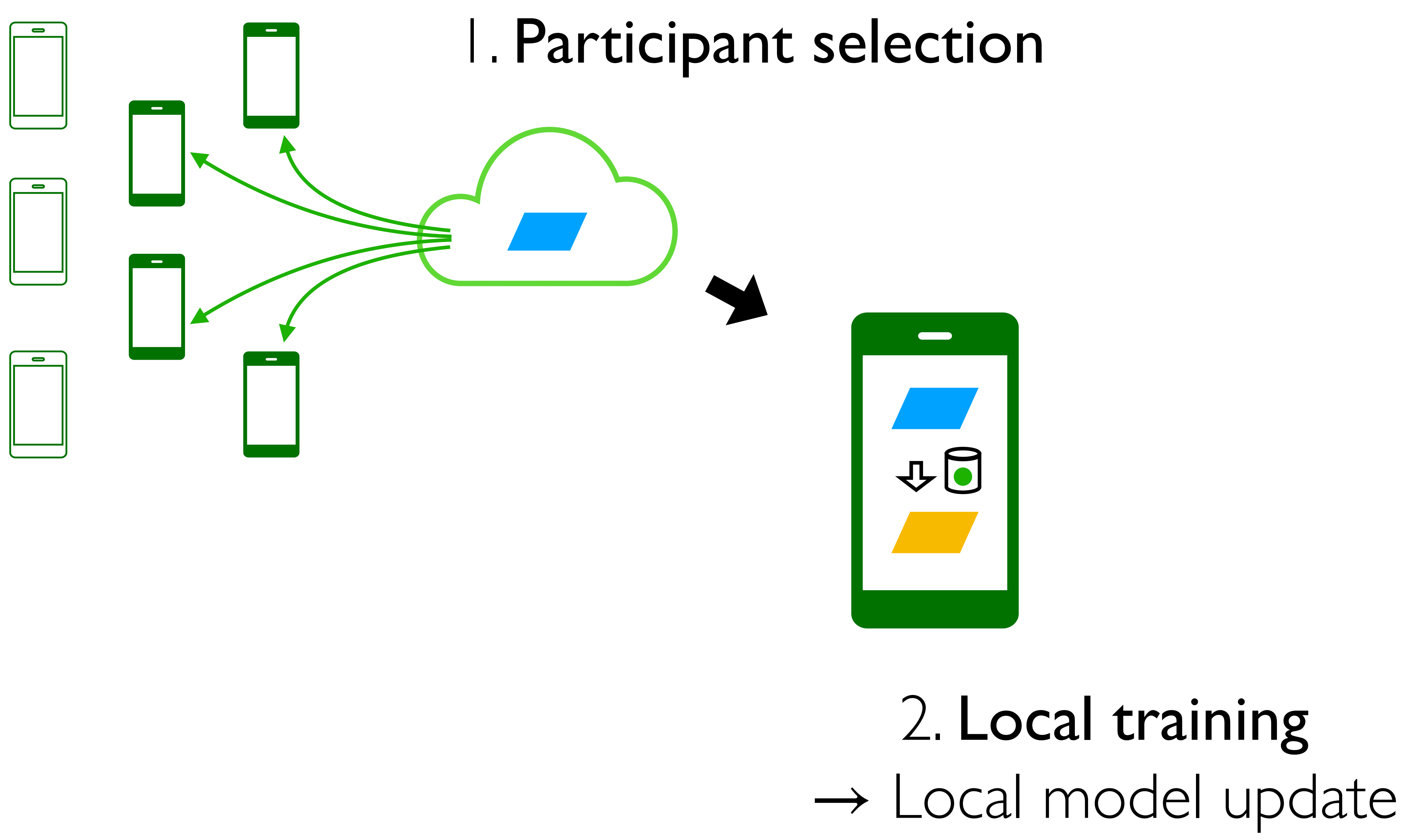

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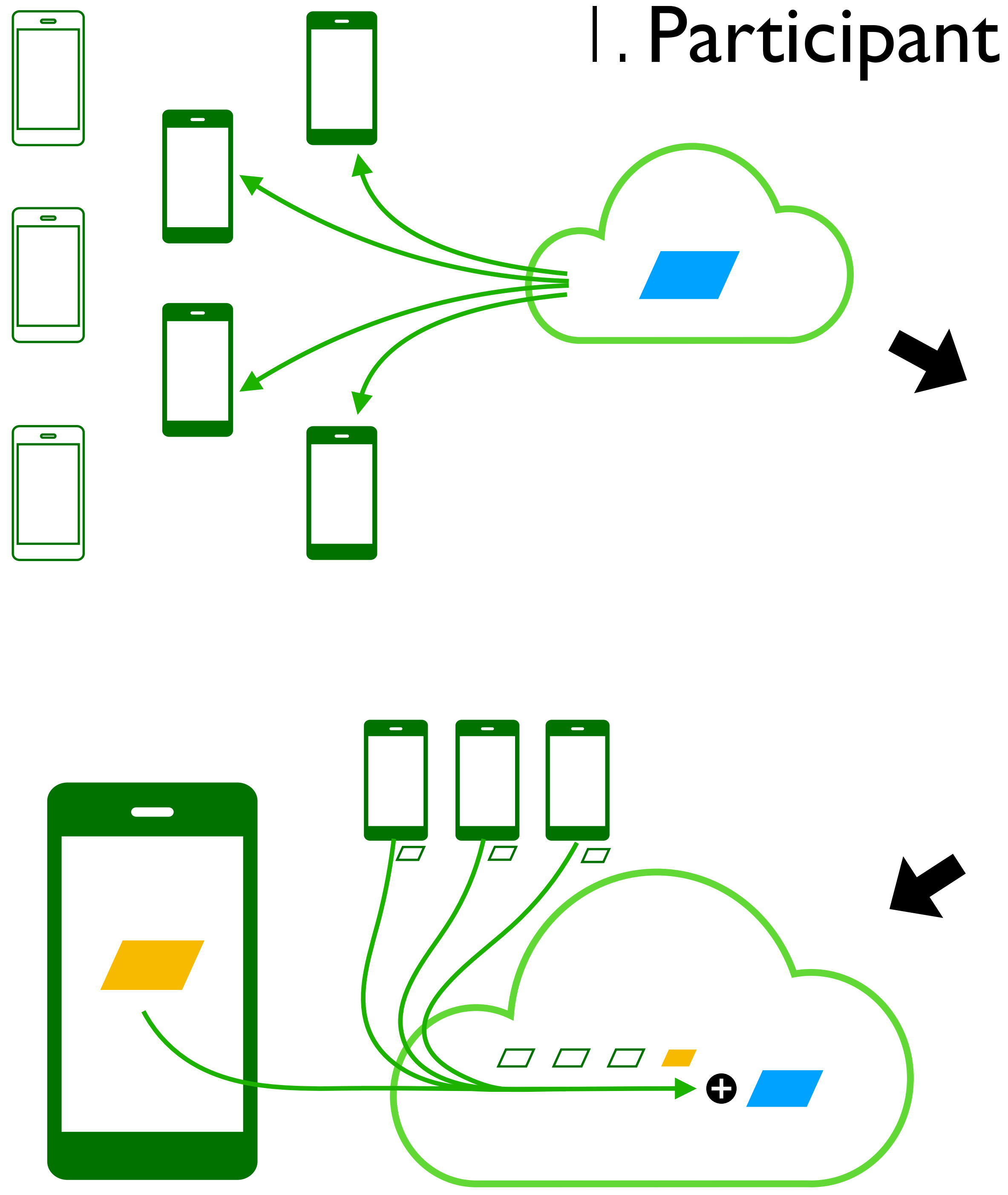

1. **Participant selection**

2. **Local training**
→ Local model update

3. **Model aggregation**
→ Global model update

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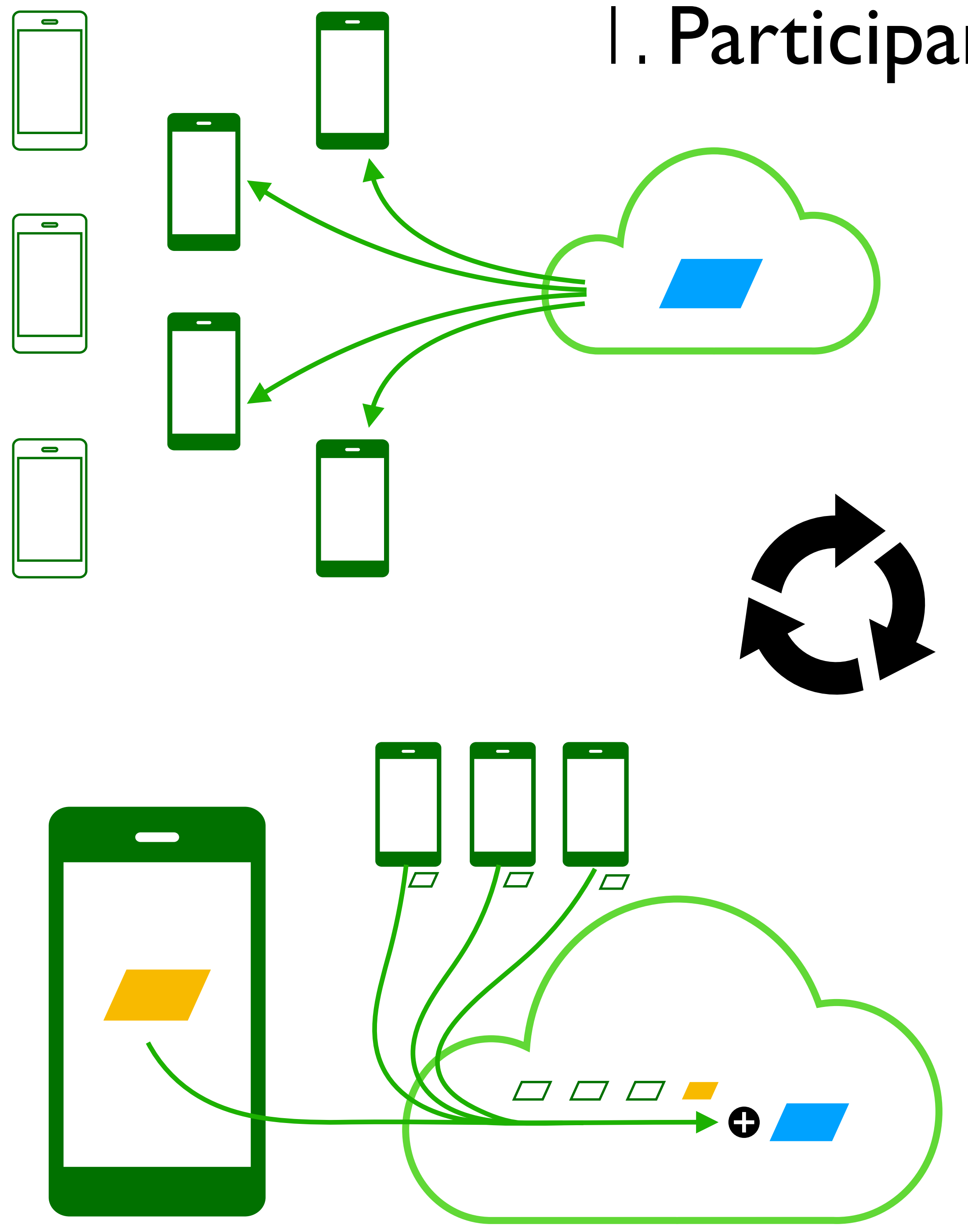

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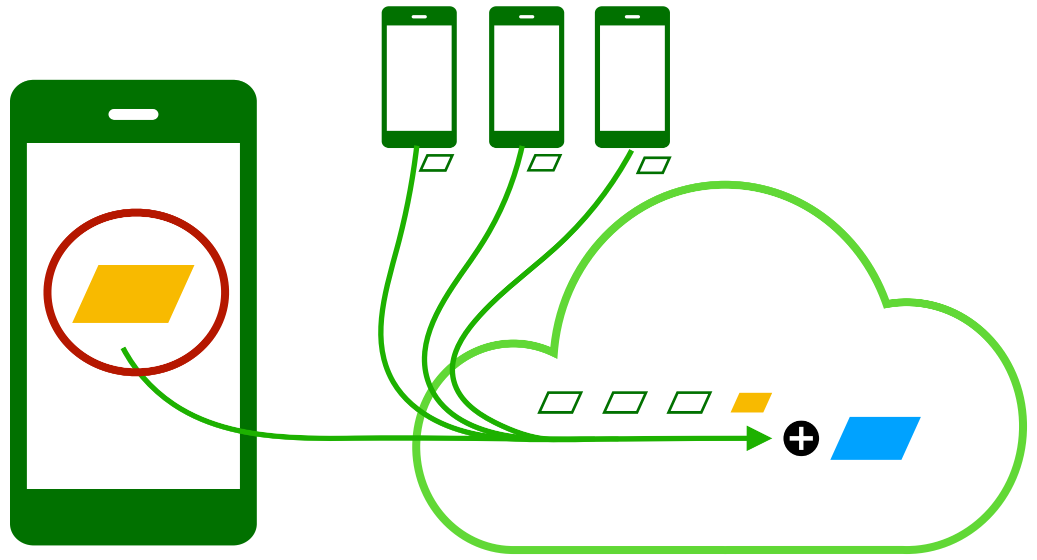

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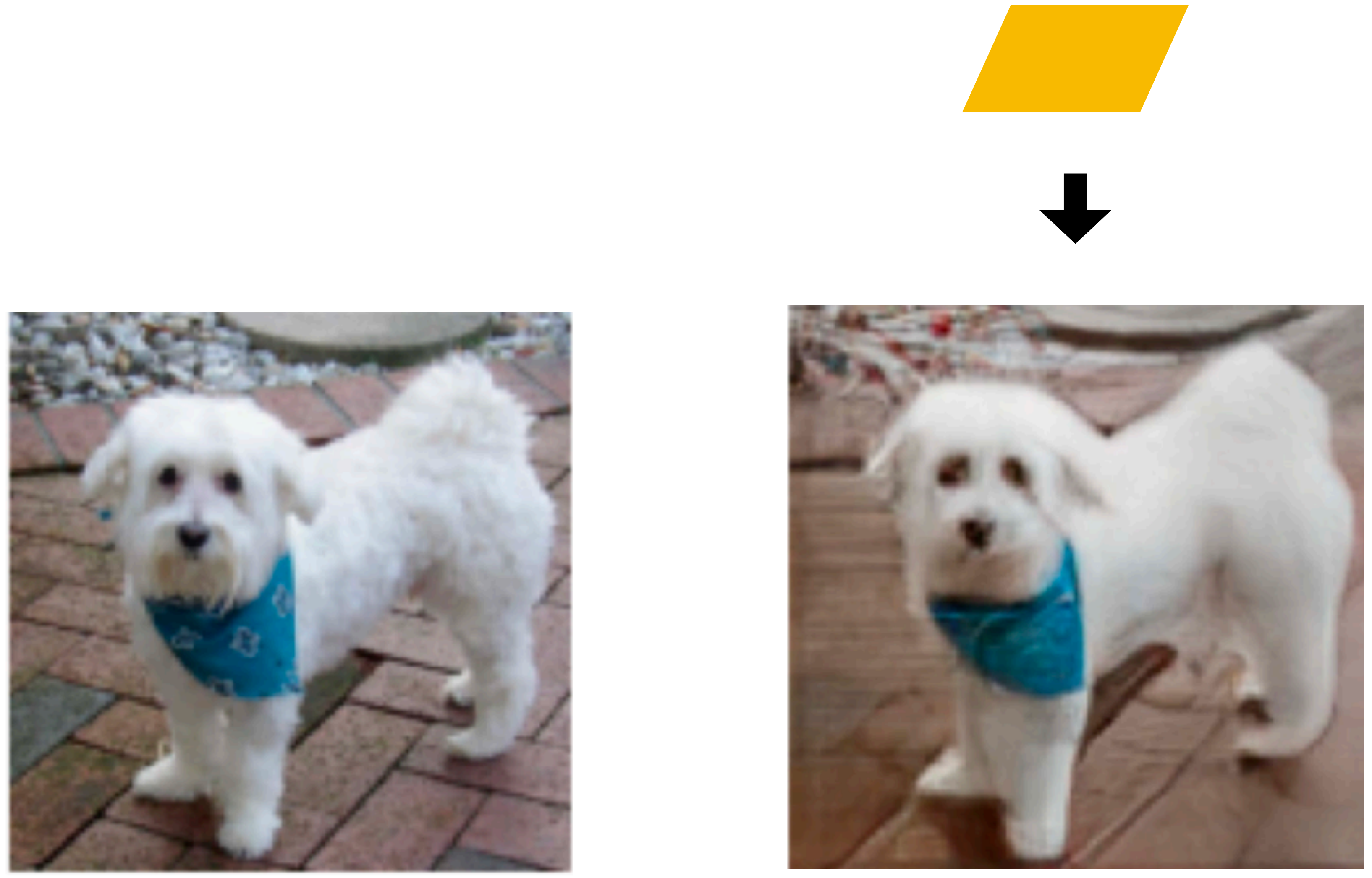

Ground truth   Reconstructed

Problem: Data can be reconstructed from **local model updates**[2]

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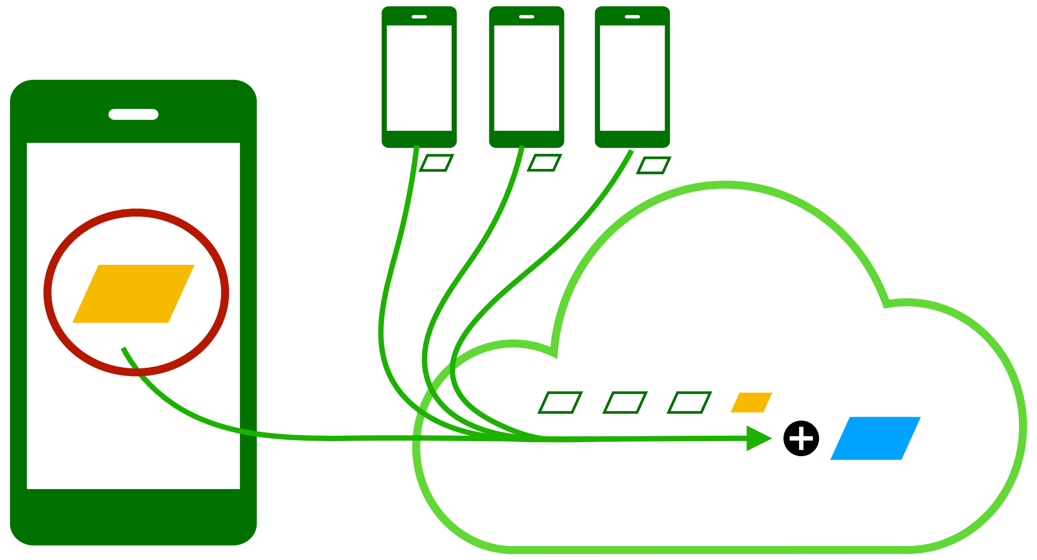

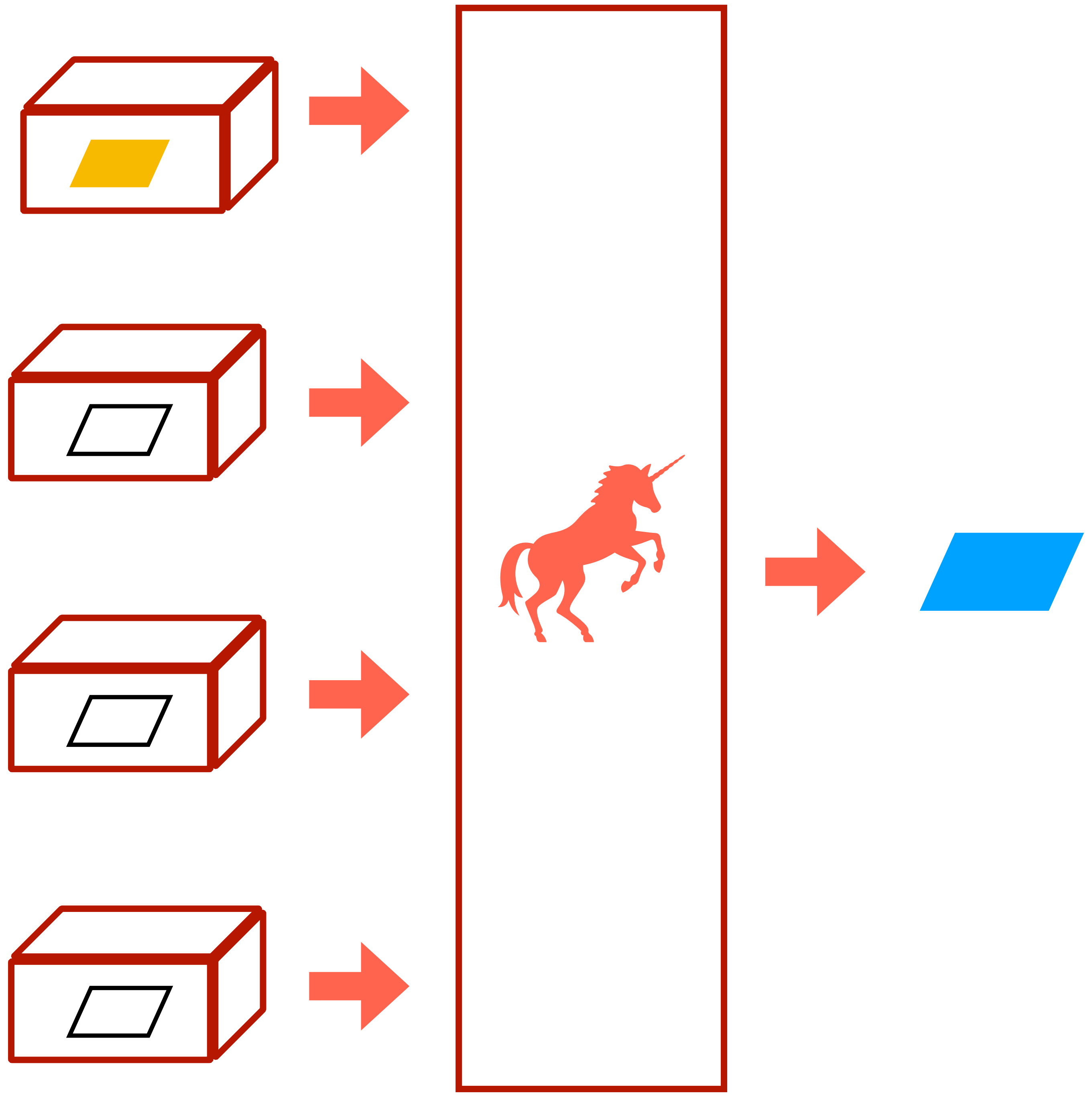

Privacy-Enhancing Technique	Federated Learning[1]	Secure Aggregation[3,4]
Privacy Guarantee	Data kept on premises	Local updates unseen

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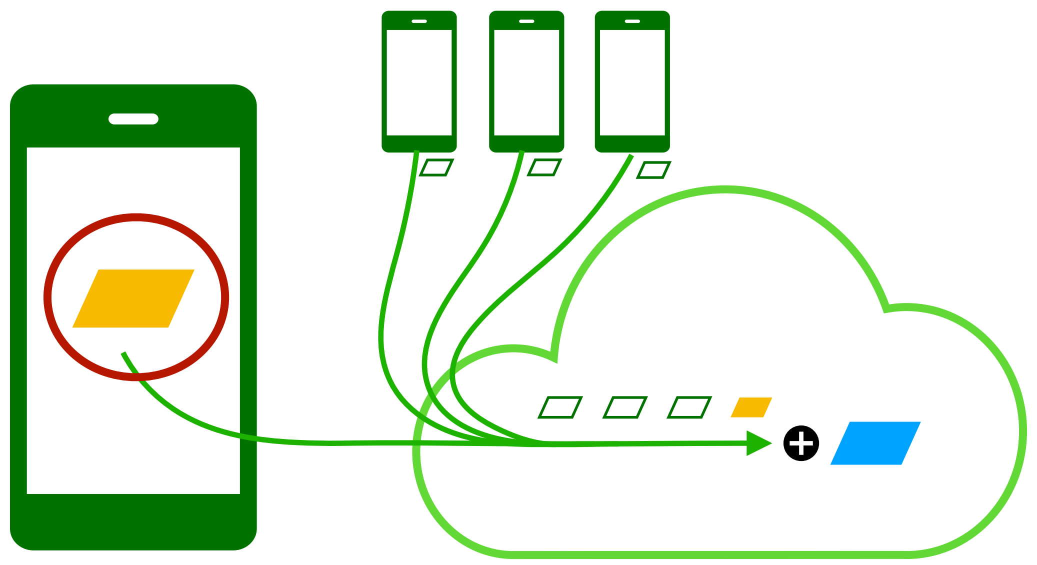

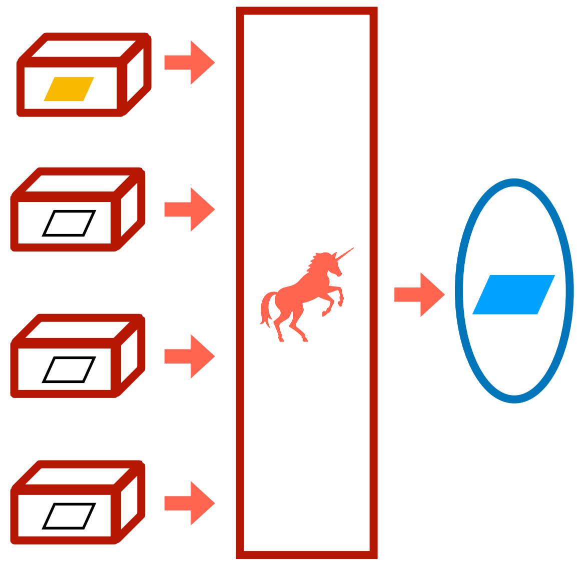

Privacy-Enhancing Technique	Federated Learning[1]	Secure Aggregation[3,4]
Privacy Guarantee	Data kept on premises	Local updates unseen

Problem: Data still has footprints in **global model update**[5]

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[5]Nasr et al. "Comprehensive Privacy Analysis of Deep Learning: Passive and Active White-box Inference Attacks against Centralized and Federated Learning", In S&P '19

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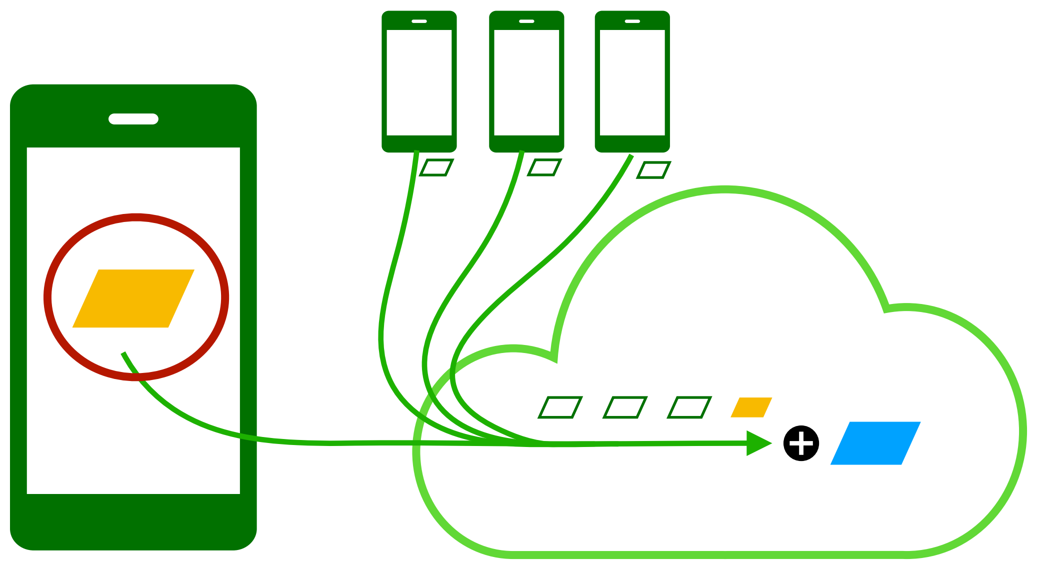

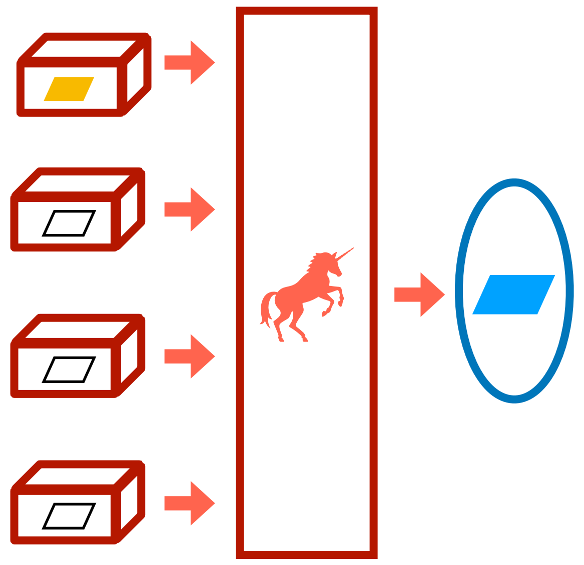

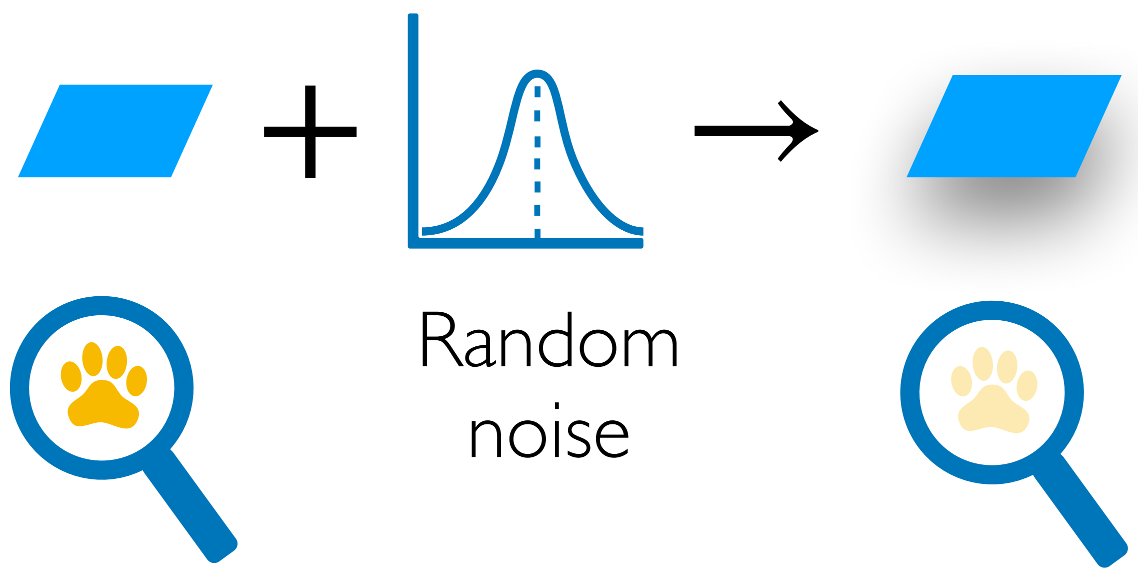

Privacy-Enhancing Technique	Federated Learning[1]	Secure Aggregation[3,4]	Differential Privacy[6]
Privacy Guarantee	Data kept on premises	Local updates unseen	Global update leaks little about any client

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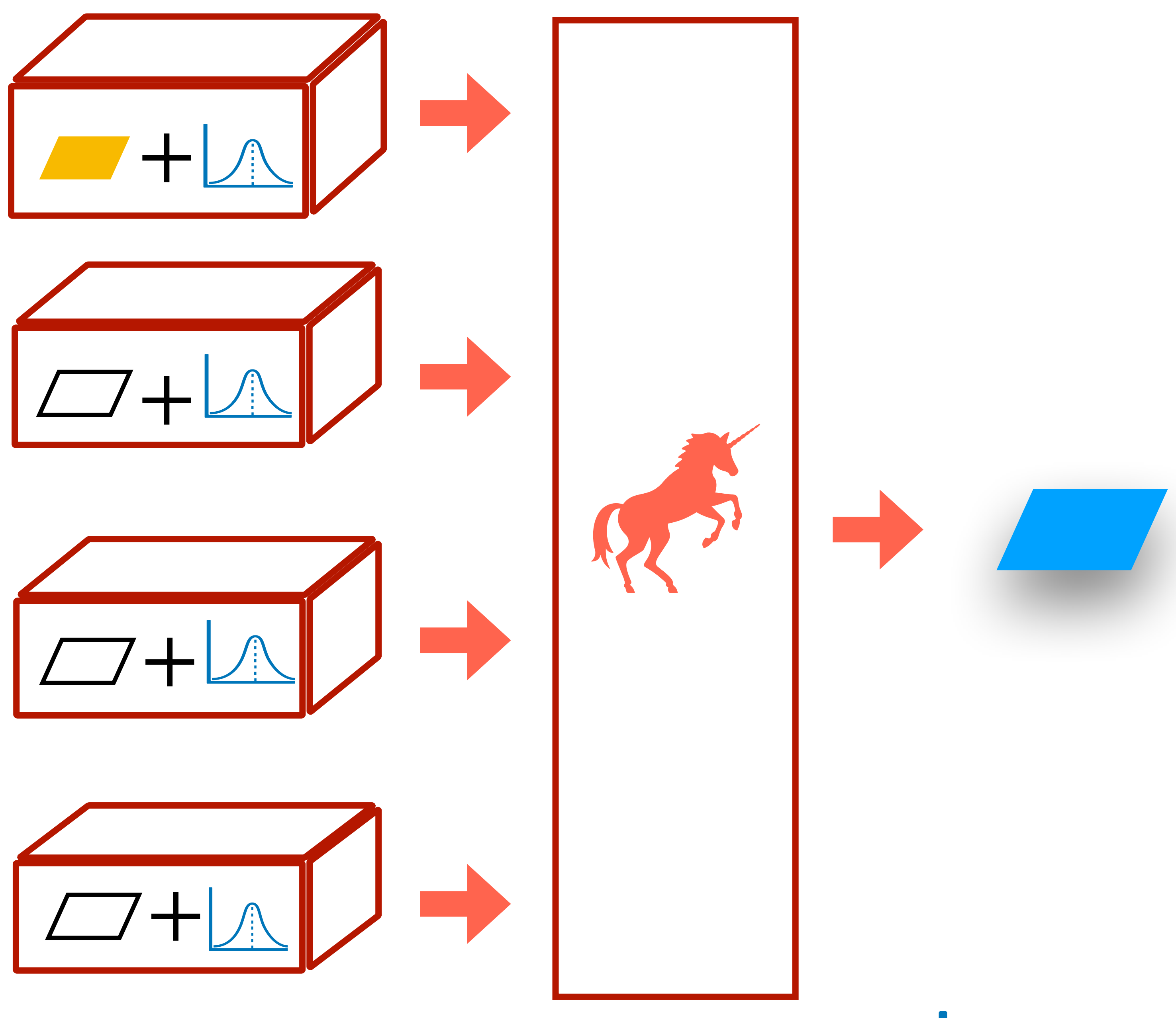
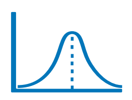
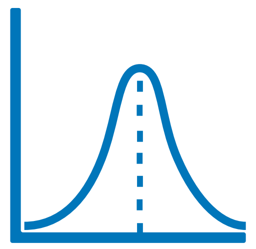
[6]Cynthia. "Differential Privacy", 06.

Private learning on the edge



Combined

Secure Aggregation	Differential Privacy
Local updates unseen	Global update leaks little about any client

Practice[1,2]:  = 1/4 

Each client adds an **even share** of the target noise to its local model update

[1] Kairouz et al. "The Distributed Discrete Gaussian Mechanism for Federated Learning with Secure Aggregation", In ICML '21
[2] Agarwal. "The Skellam Mechanism for Differentially Private Federated Learning", In NeurIPS '21

Private learning on the edge

Privacy-Enhancing Technique	Federated Learning[1]	Secure Aggregation	Differential Privacy
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Need for Lotto

Relied assumption

May **not** hold

Privacy-Enhancing Technique	Federated Learning	Secure Aggregation	Differential Privacy
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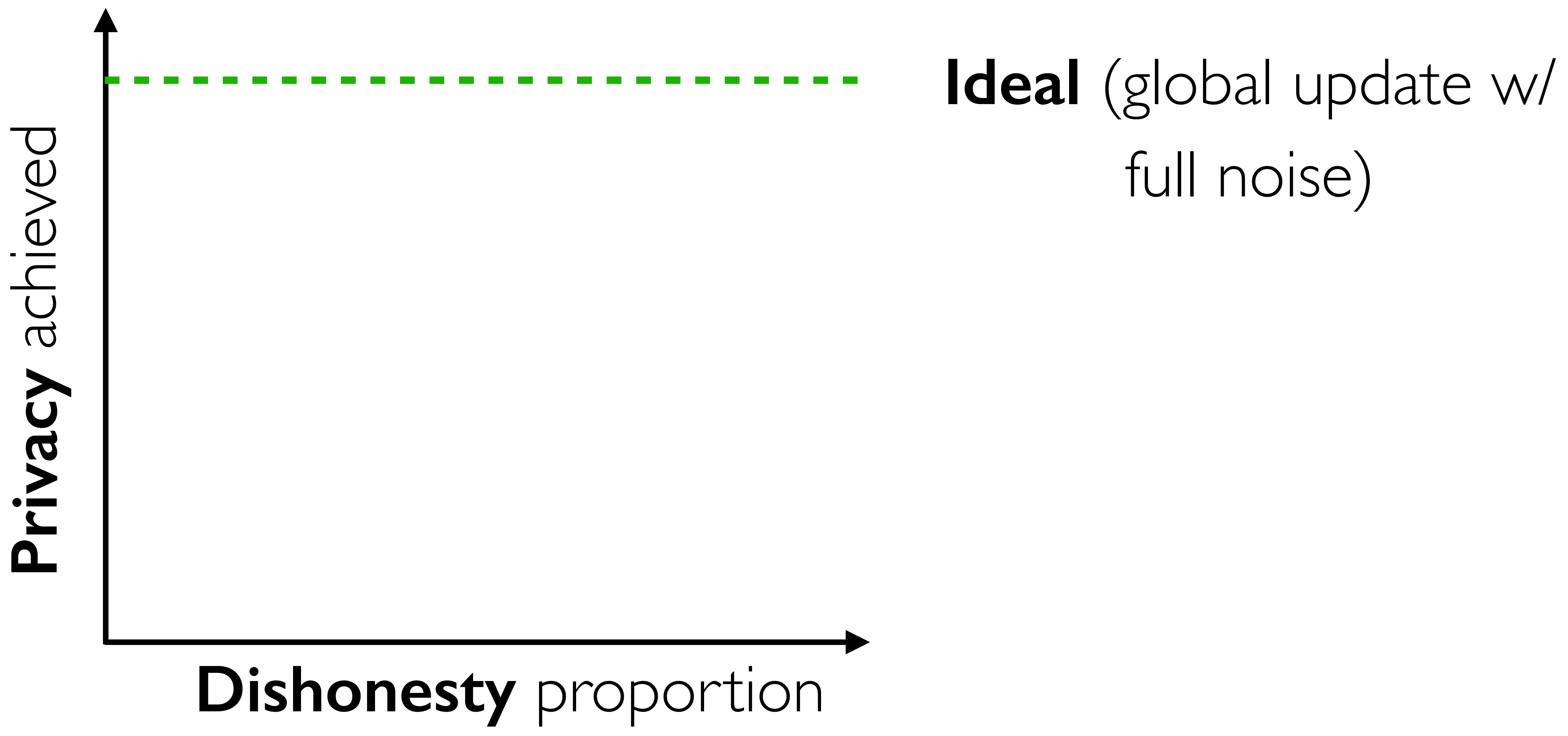

Secure Aggregation | Differential Privacy

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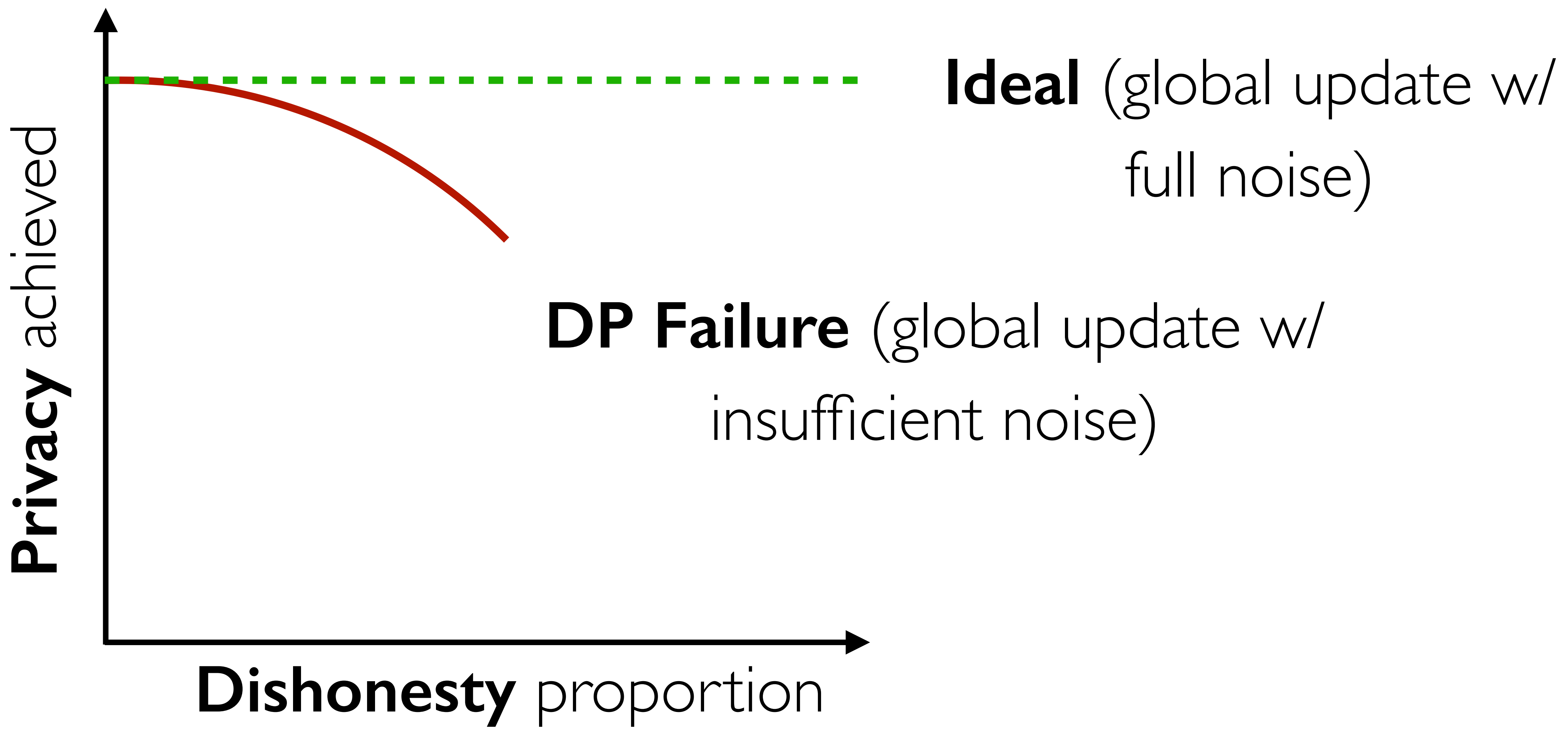

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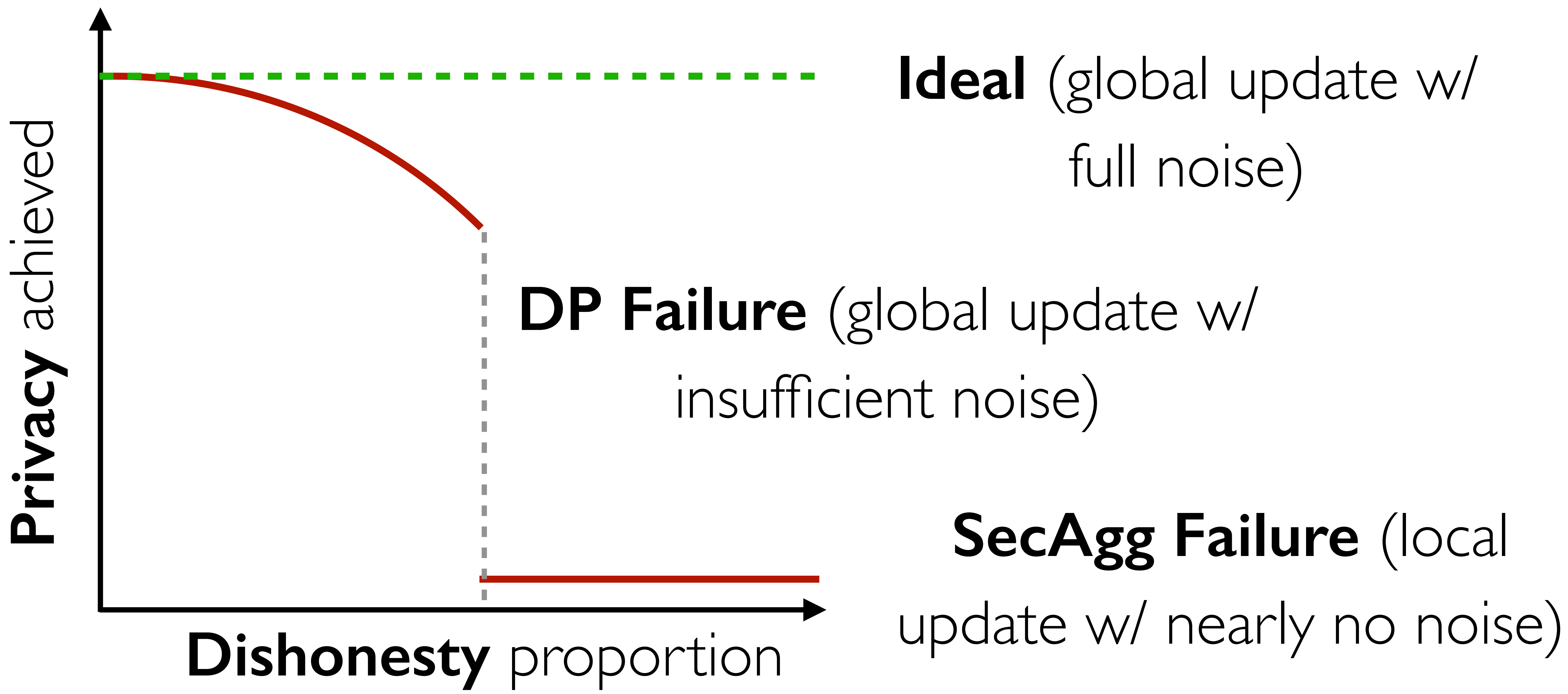

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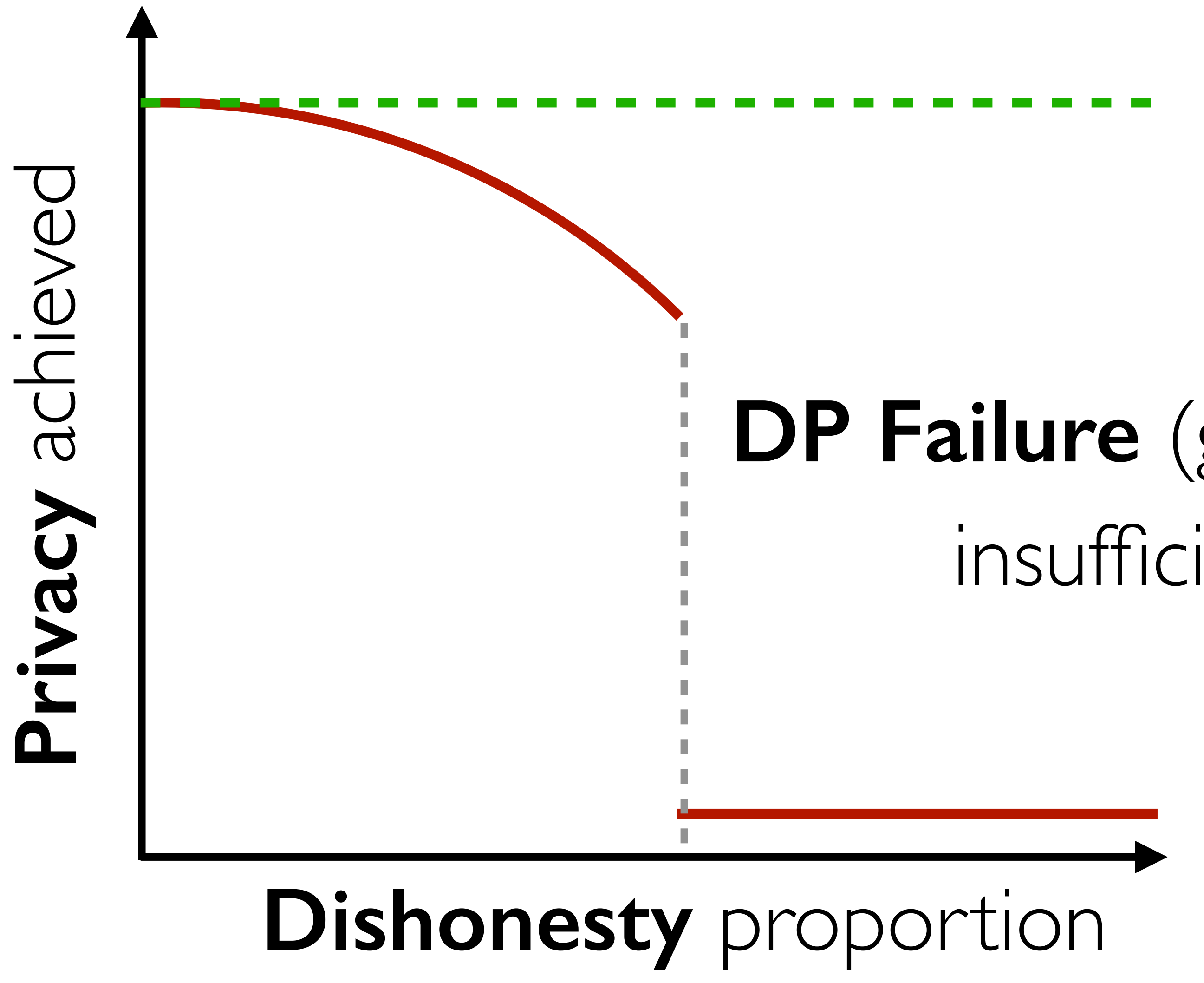

Ideal (global update w/ full noise)

DP Failure (global update w/ insufficient noise)

SecAgg Failure (local update w/ nearly no noise)

Assumption: honest participants

Secure Aggregation	Differential Privacy

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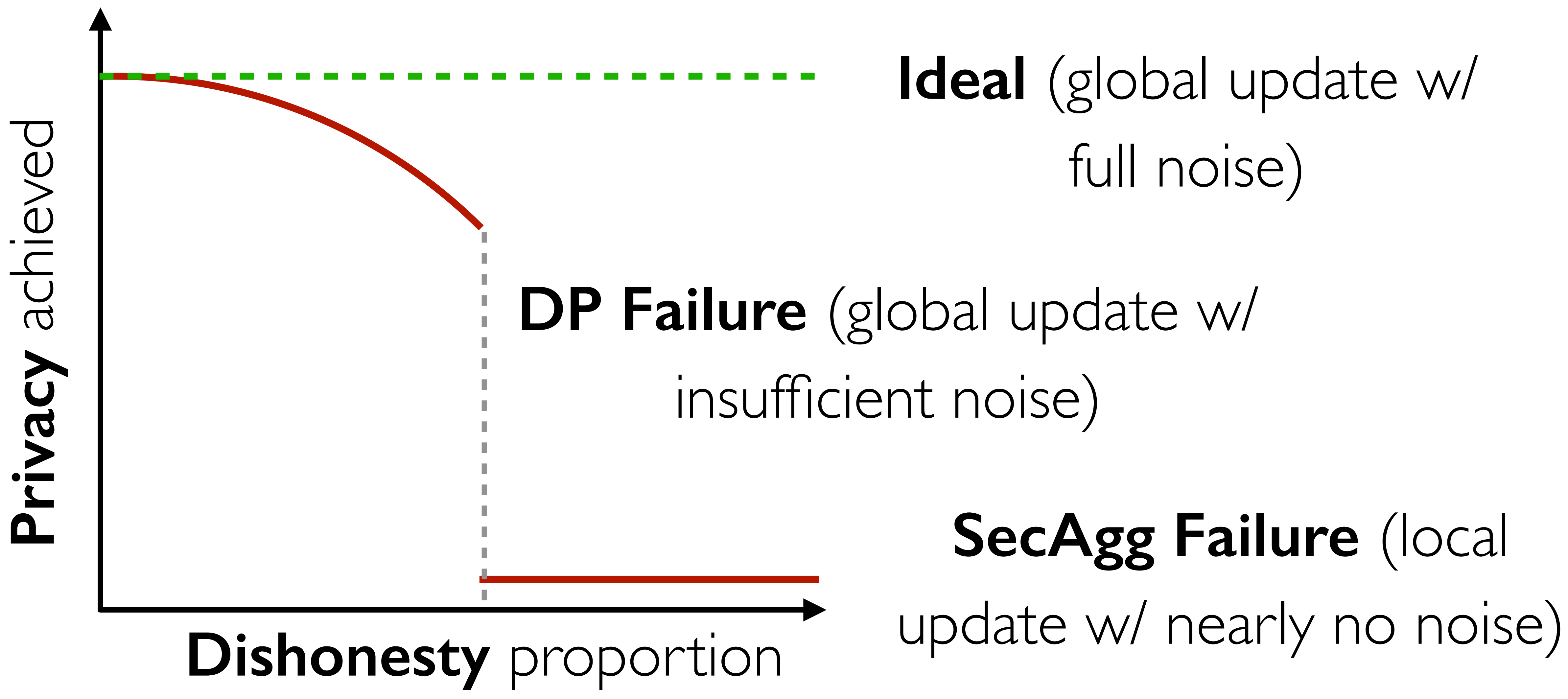

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Federated Learning

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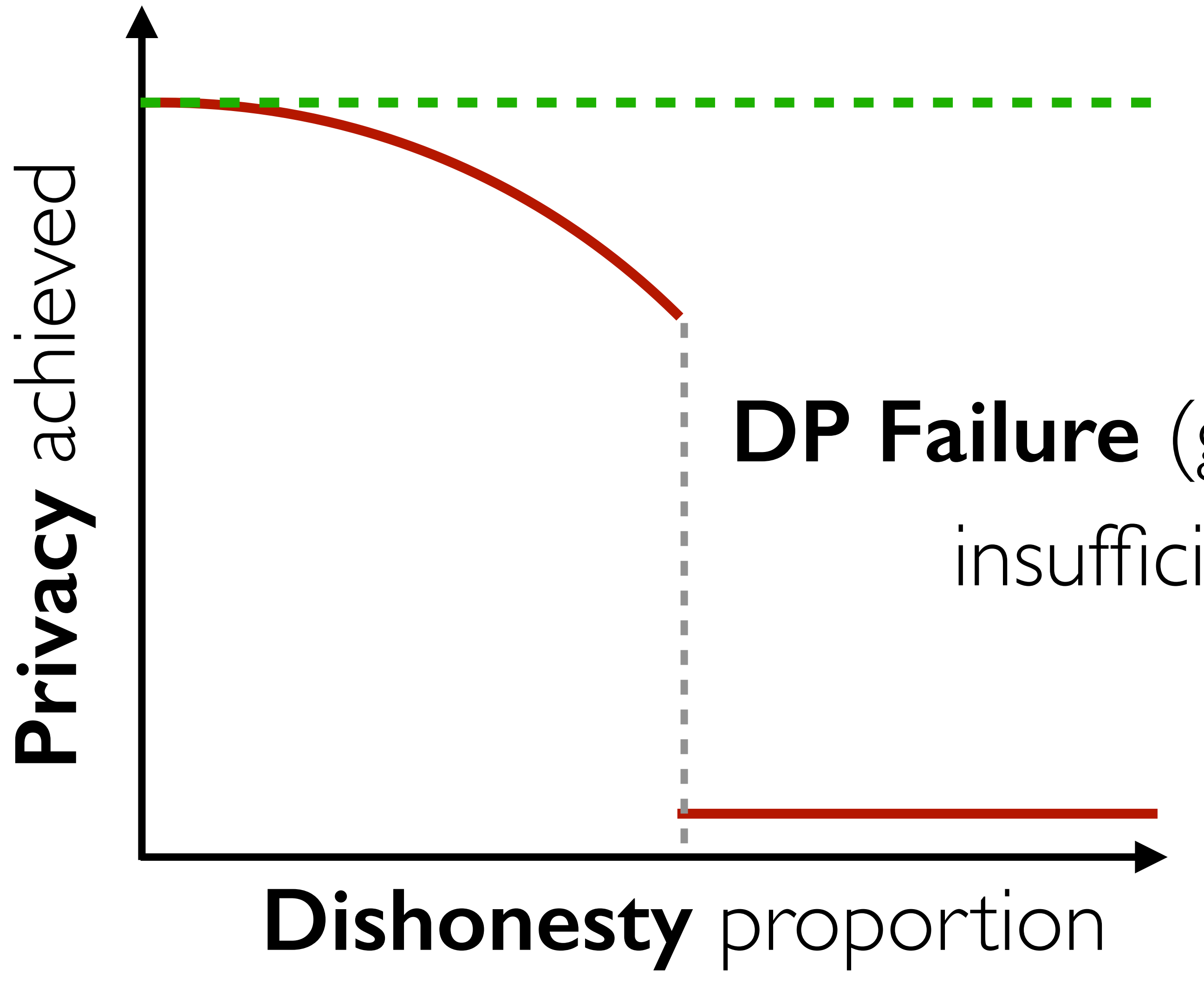

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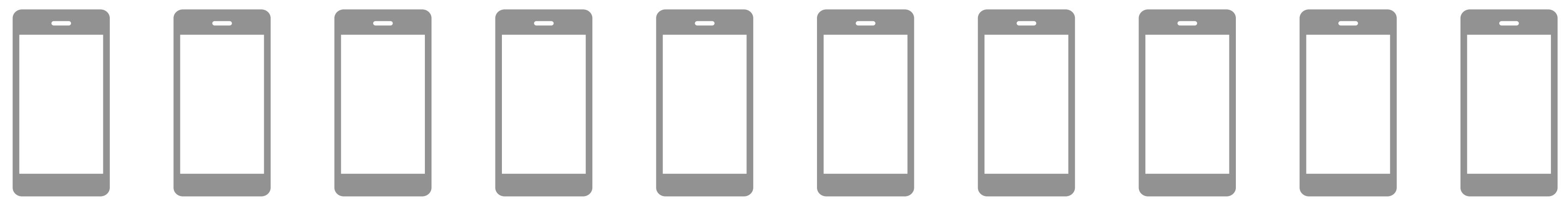
Secure Aggregation | Differential Privacy

Population (10^4 - 10^8)



Federated Learning

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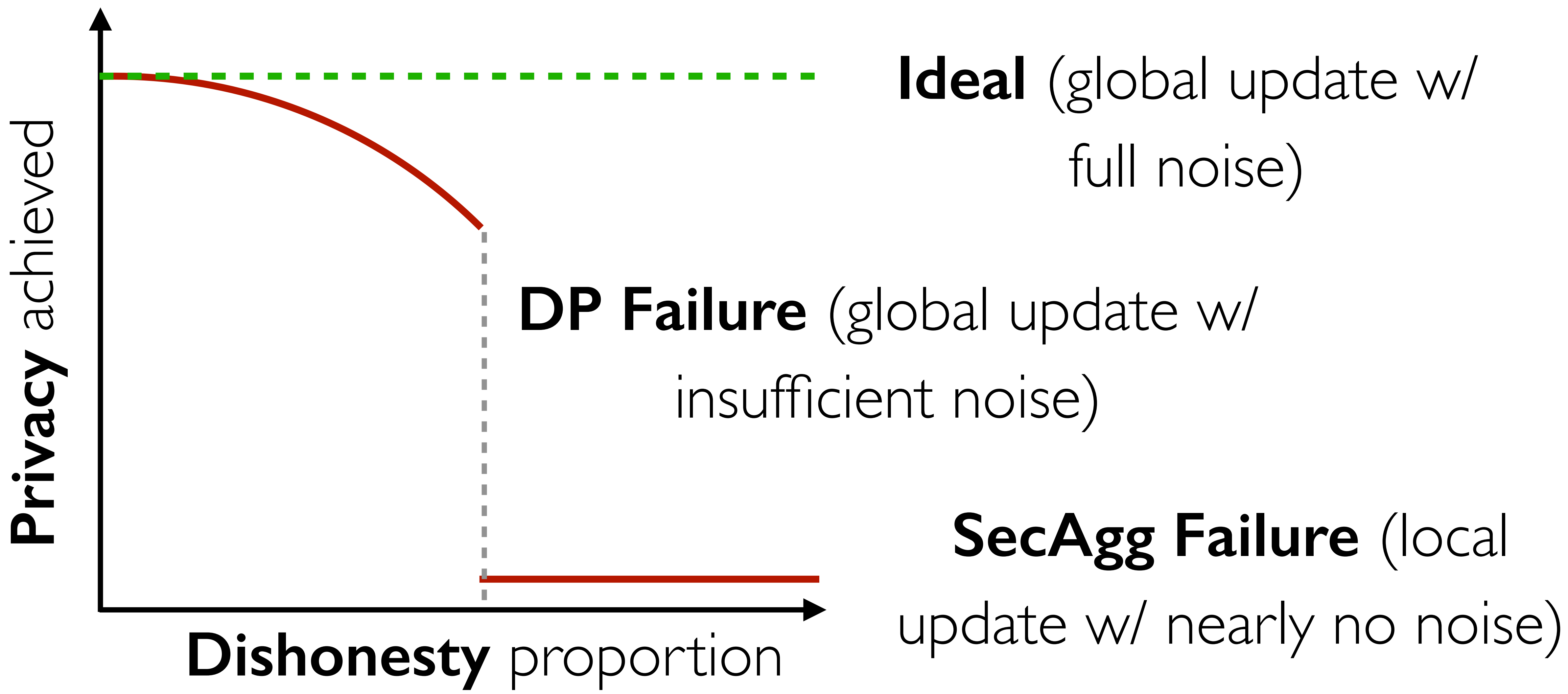

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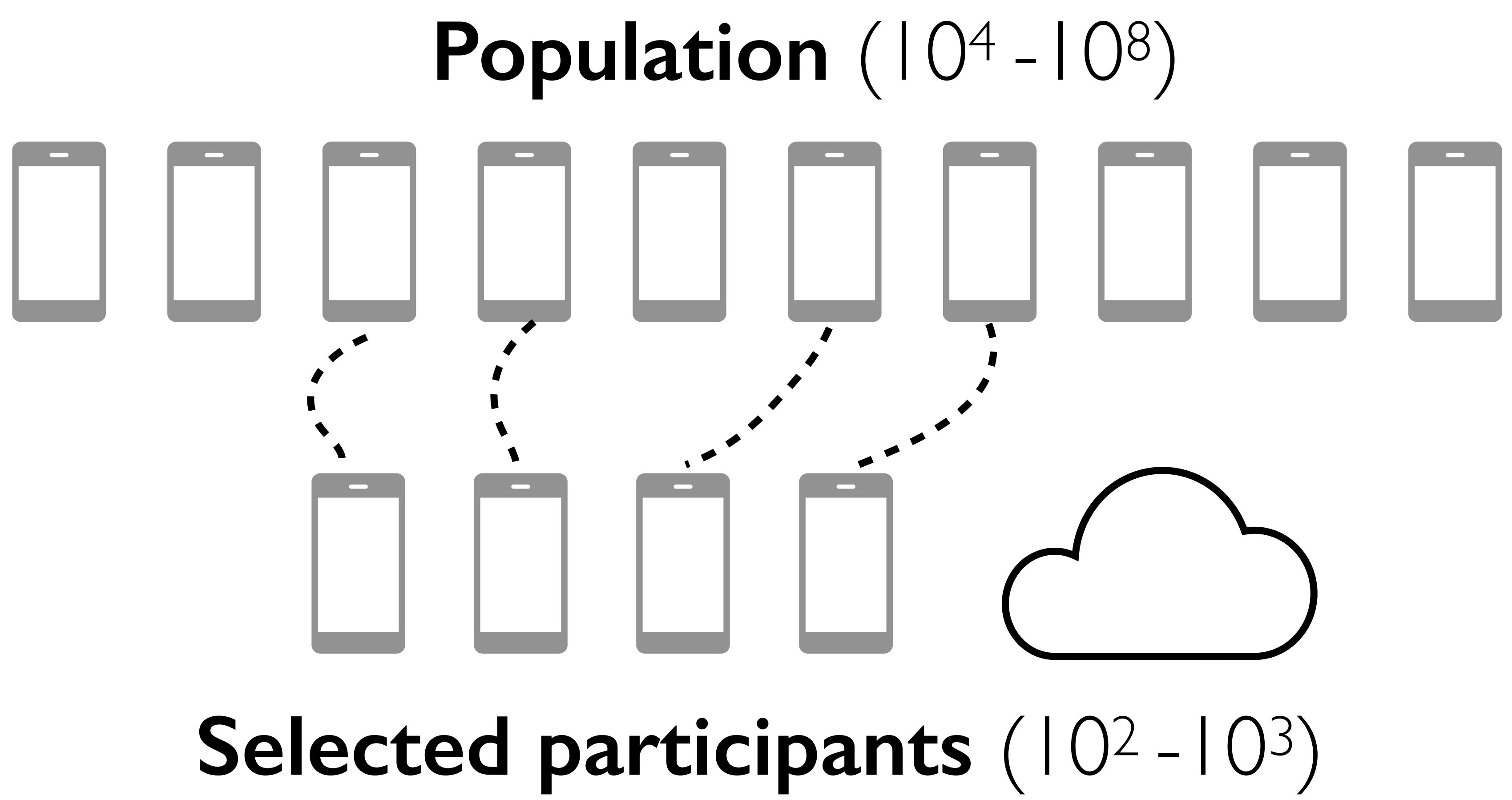

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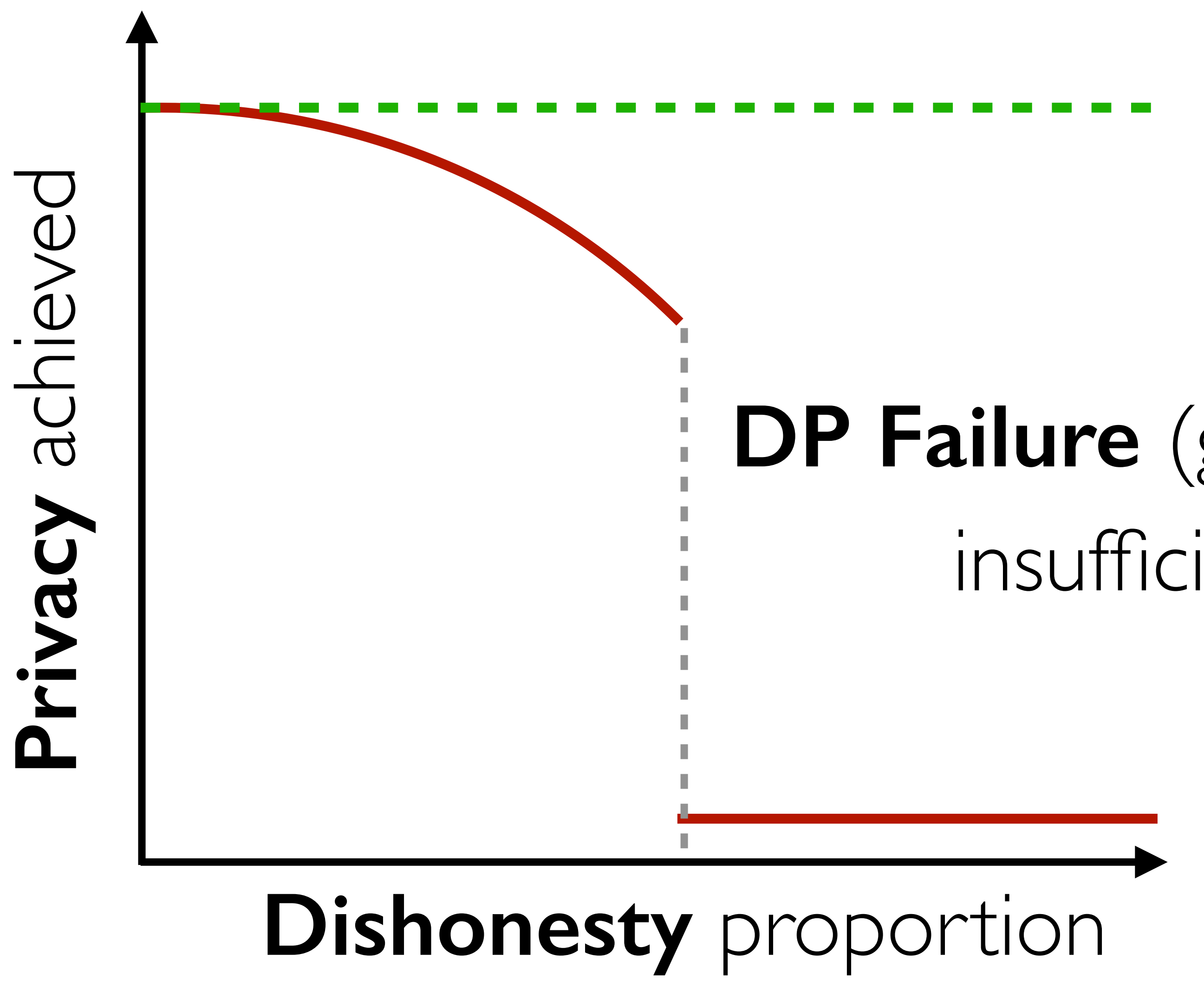

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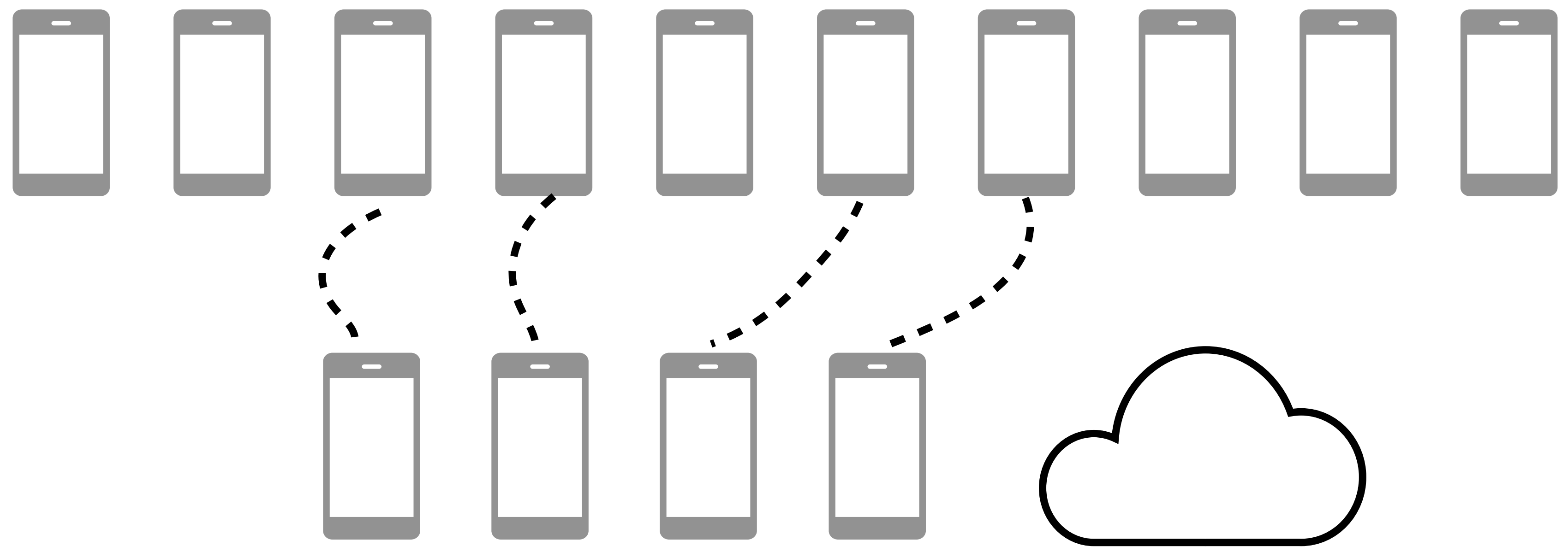
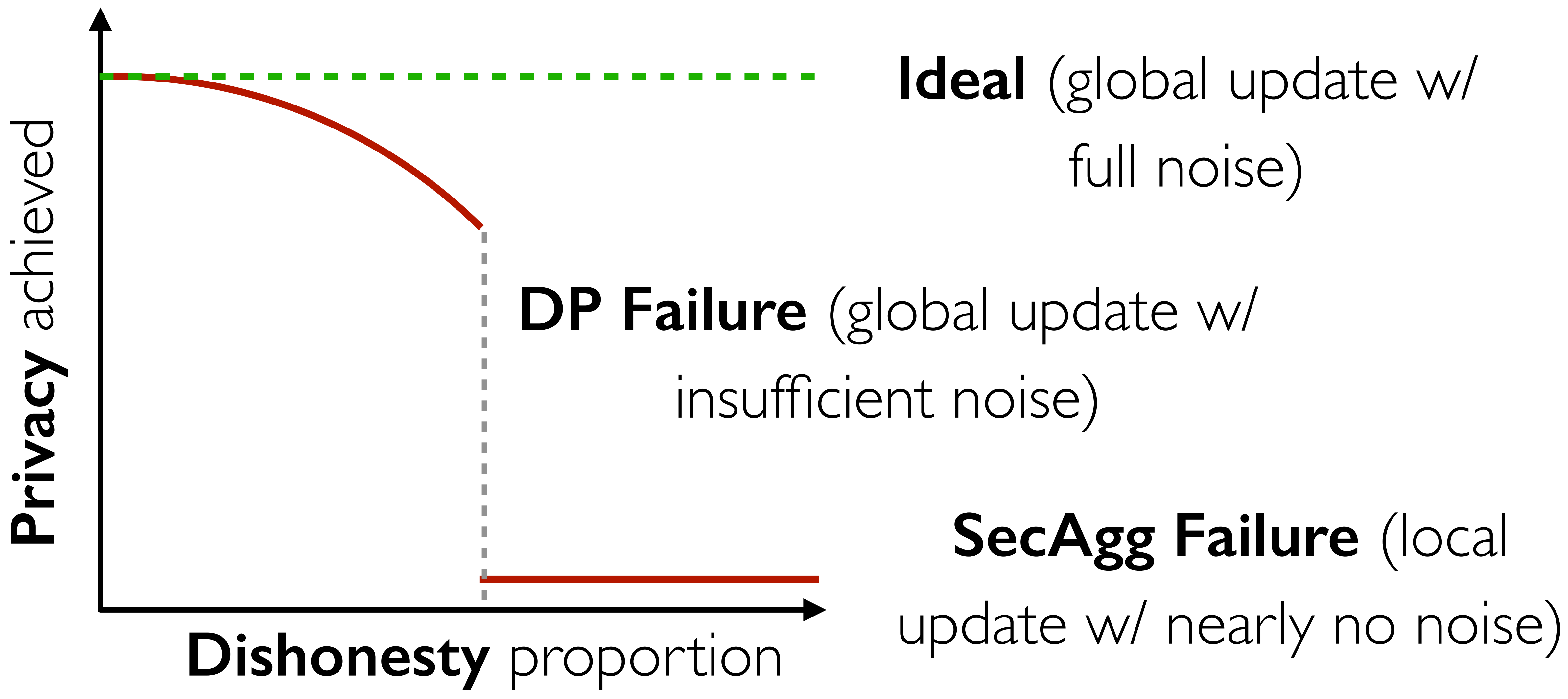


Selected participants (10^2 - 10^3)

- **Random**: uniform chance

Federated Learning

Need for Lotto



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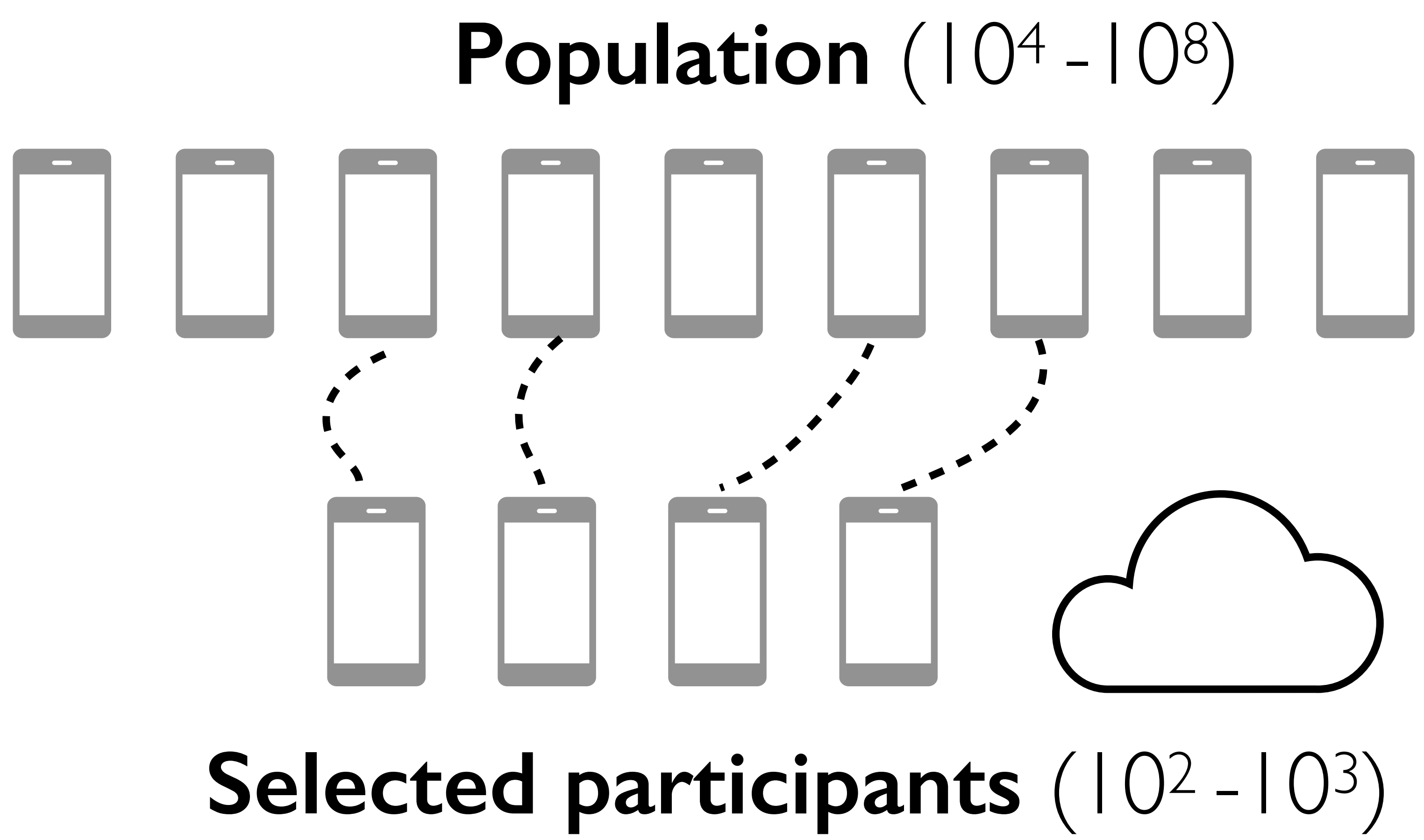
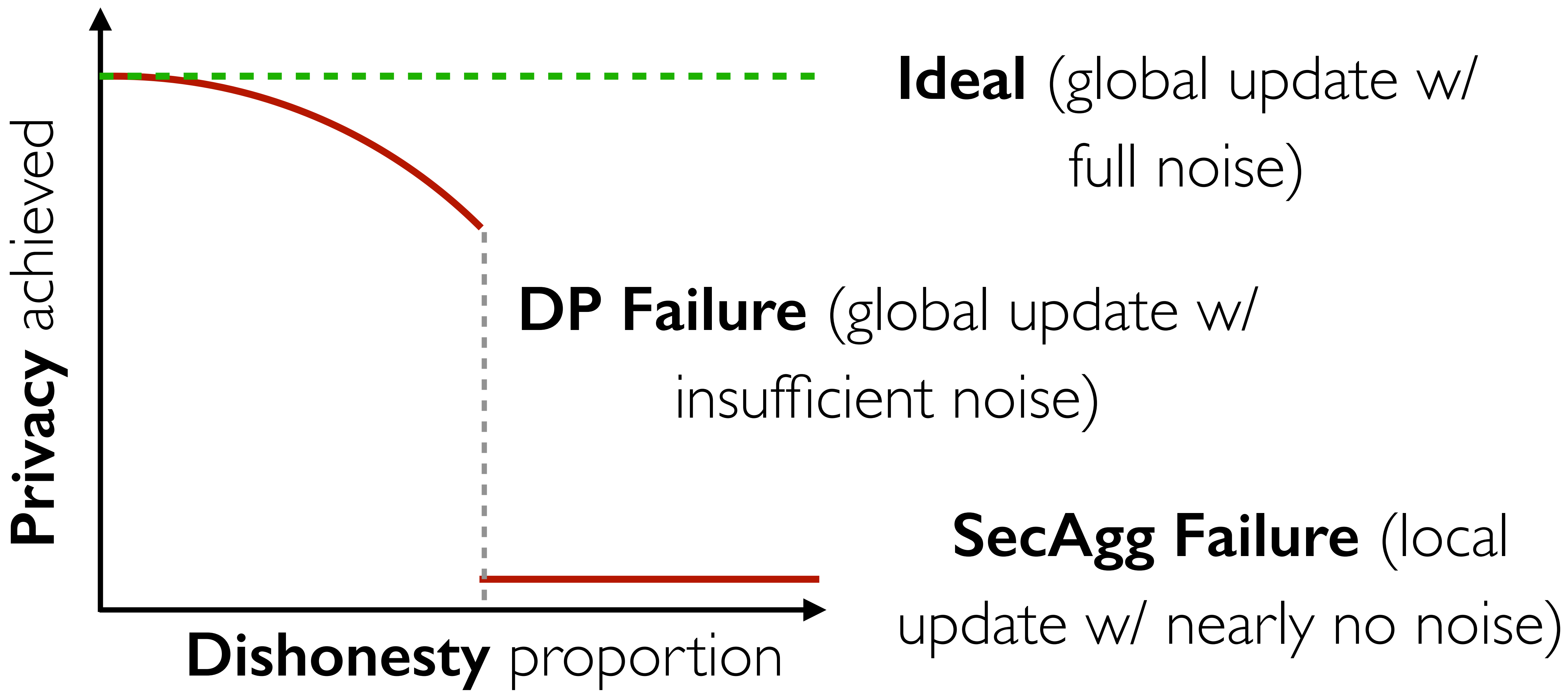


- **Random**: uniform chance
- **Informed**: "best-performing" clients are preferred (e.g., high speed and/or rich data)

Federated Learning

Need for Lotto



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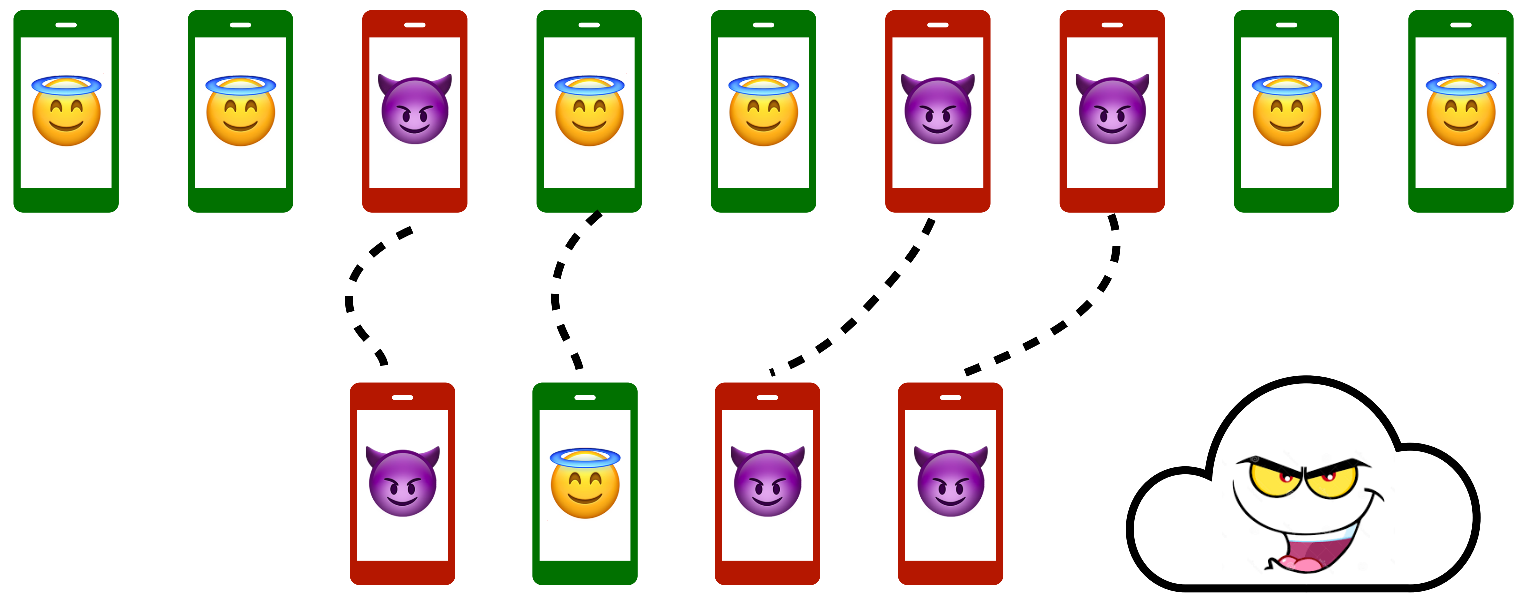

Selected participants (10^2 - 10^3)

Problem: participant selection can be **manipulated** by the **malicious** server

Federated Learning

Lotto - Overview

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No peer-to-peer network: all traffic relayed by the server

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Threat model: **malicious server colluding** with some clients, and a public key infrastructure (**PKI**)

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Functionality

Support both **random** and **informed** selection

Security

Theoretical guarantee of preventing manipulation

Efficiency

Mild **runtime overhead** with no **network cost**

Problem: Random selection

Problem: Random selection

Current round: 2

	Randomness
#1	$\mathbf{RF}_{pk1}(2) = 9$
#2	$\mathbf{RF}_{pk2}(2) = 1$
#3	$\mathbf{RF}_{pk3}(2) = 7$
…	…

Public keys

Selection criteria: <3

Problem: Random selection

Current round: 2

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#1	$\mathbf{RF}_{pk1}(2) = 9$	No
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…	…	…

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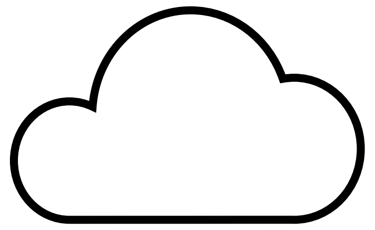

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Selection criteria: <3

For dishonest majority

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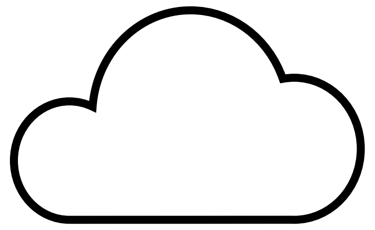
Current round: 2

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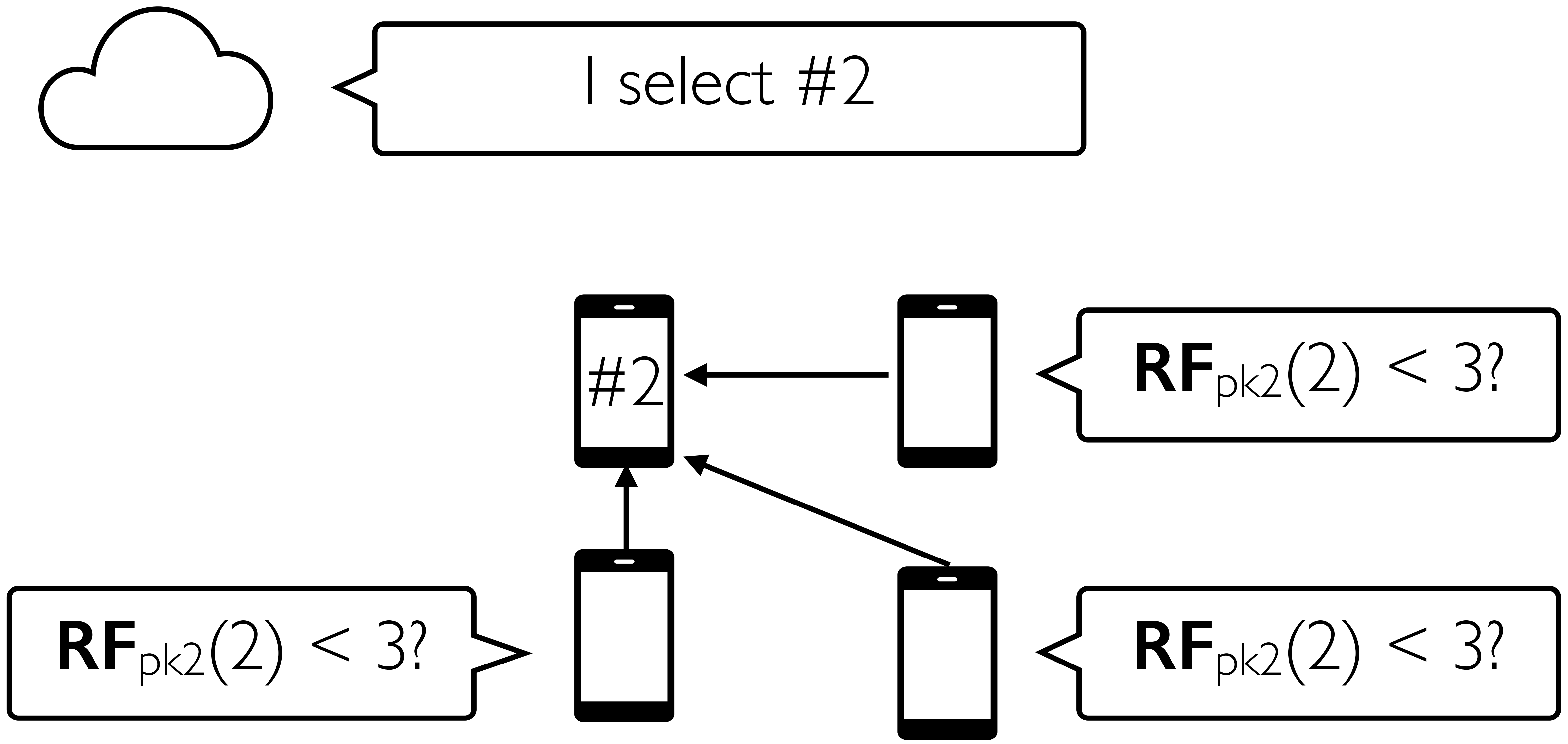

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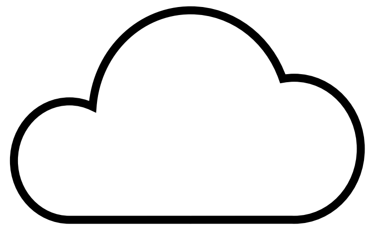


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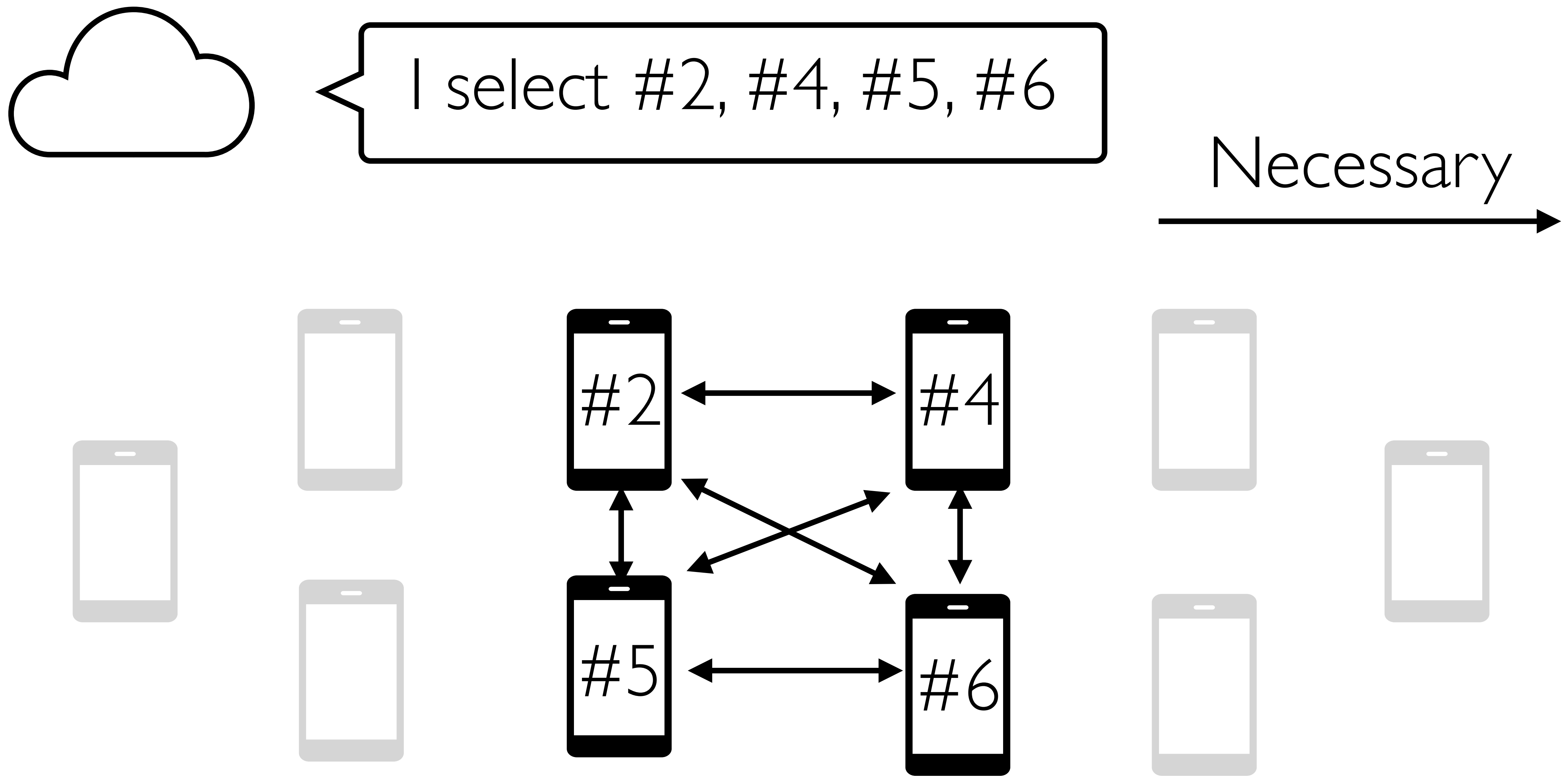

Problem: Random selection

What is achieved:

Each participant
 sees a list of peers

Potential approach:

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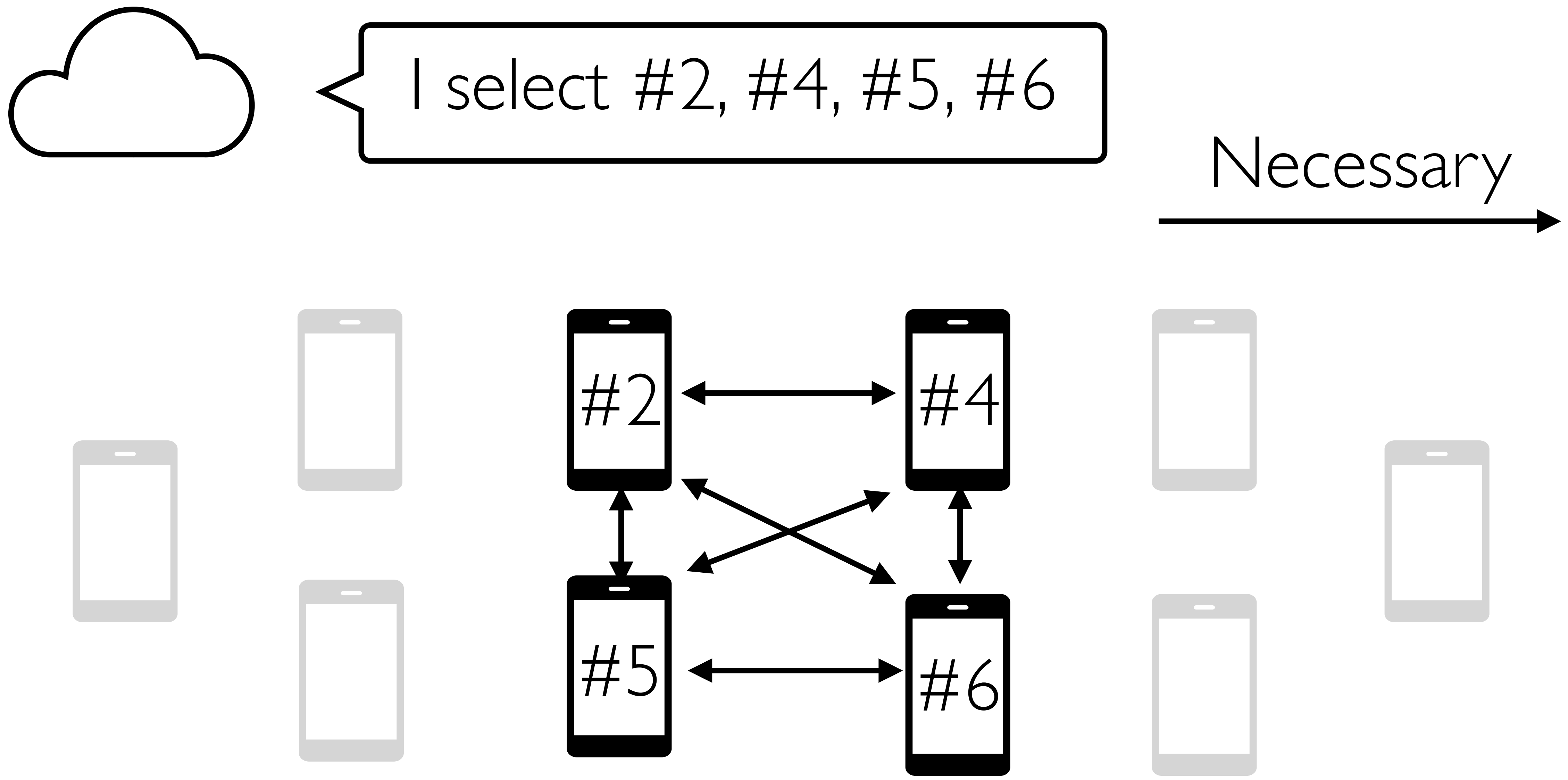

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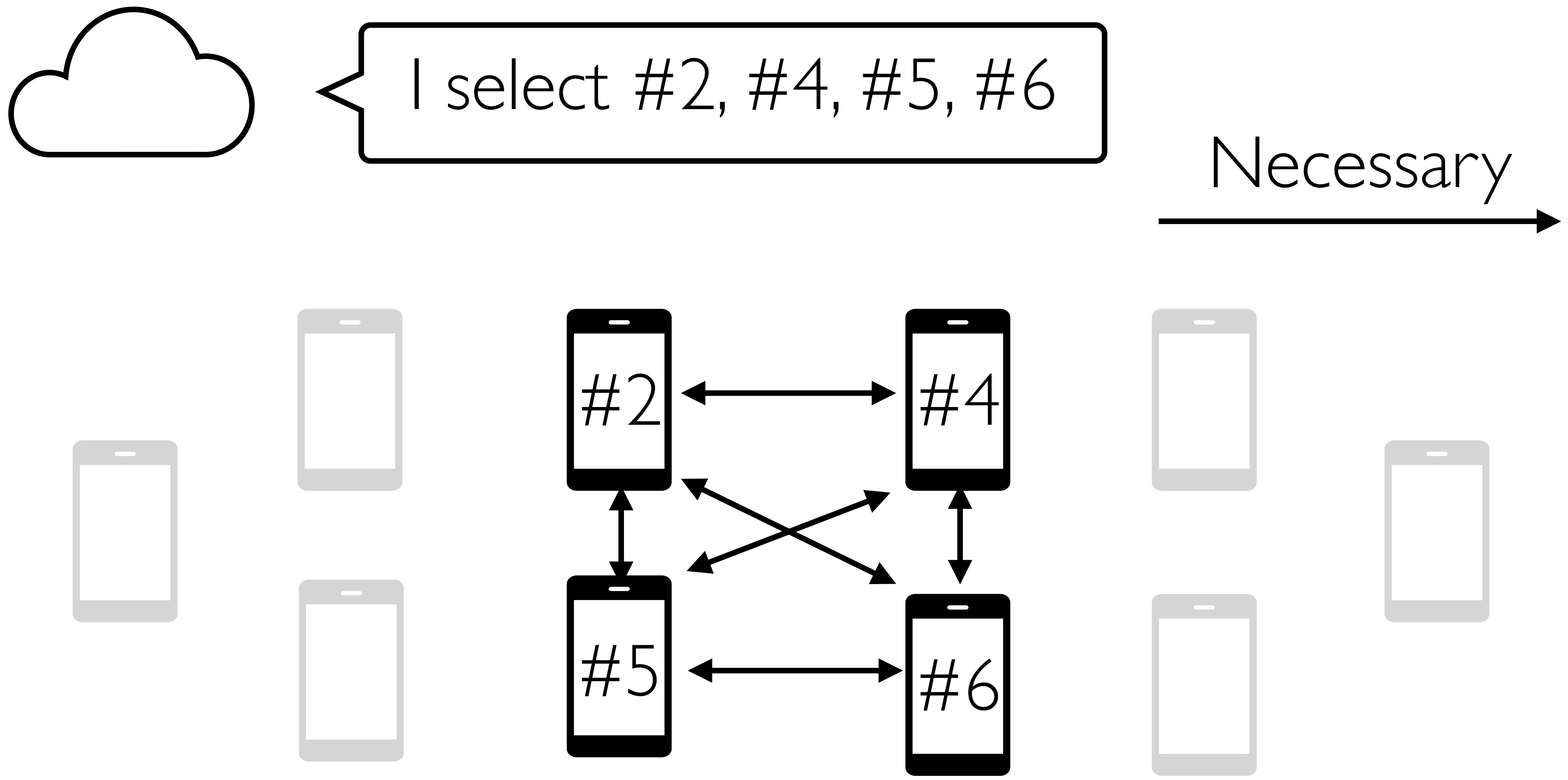

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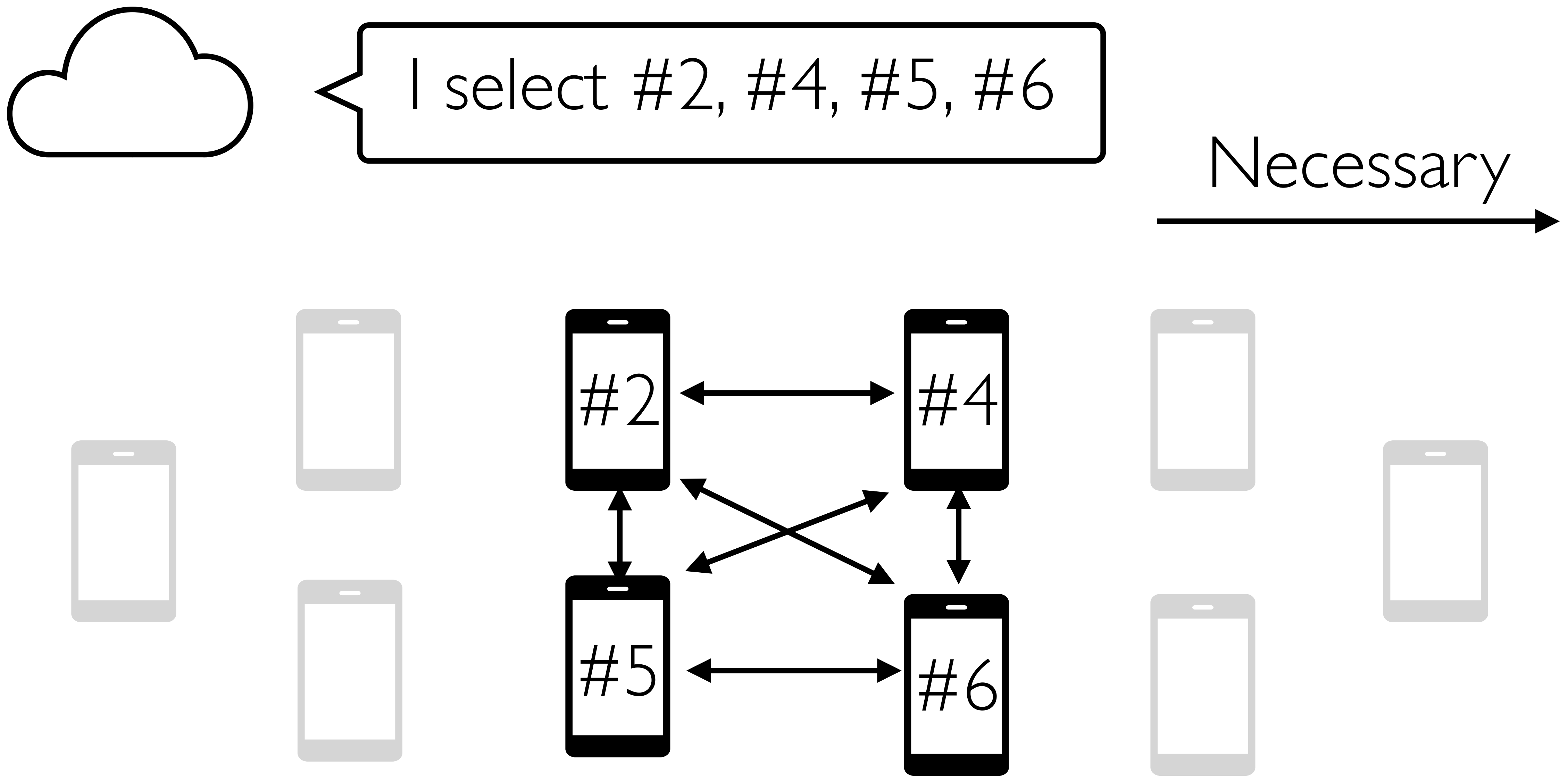

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What happens to the absent?

Problem: Random selection

What is achieved:

Each participant

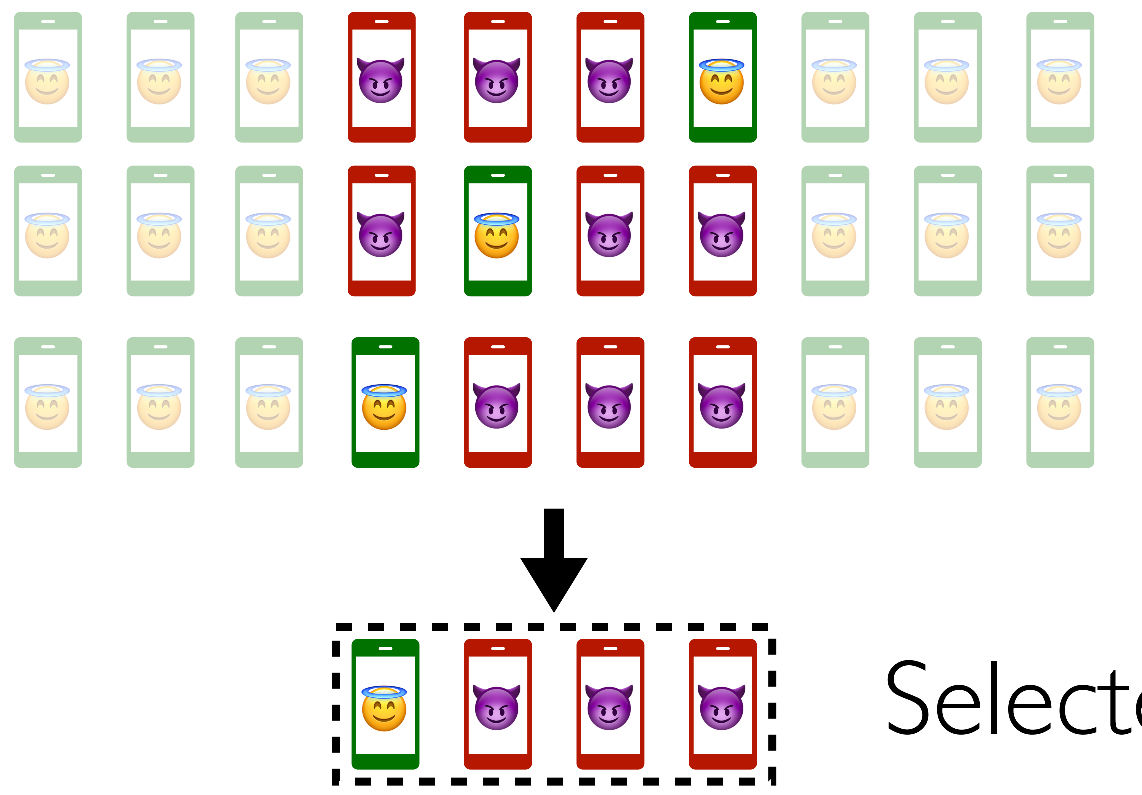
sees a list of peers who

presents only by chance.

What happens to the absent?

Problem: The server may arbitrarily **ignore honest** clients

Ignore **before** selection



Selected

Problem: Random selection

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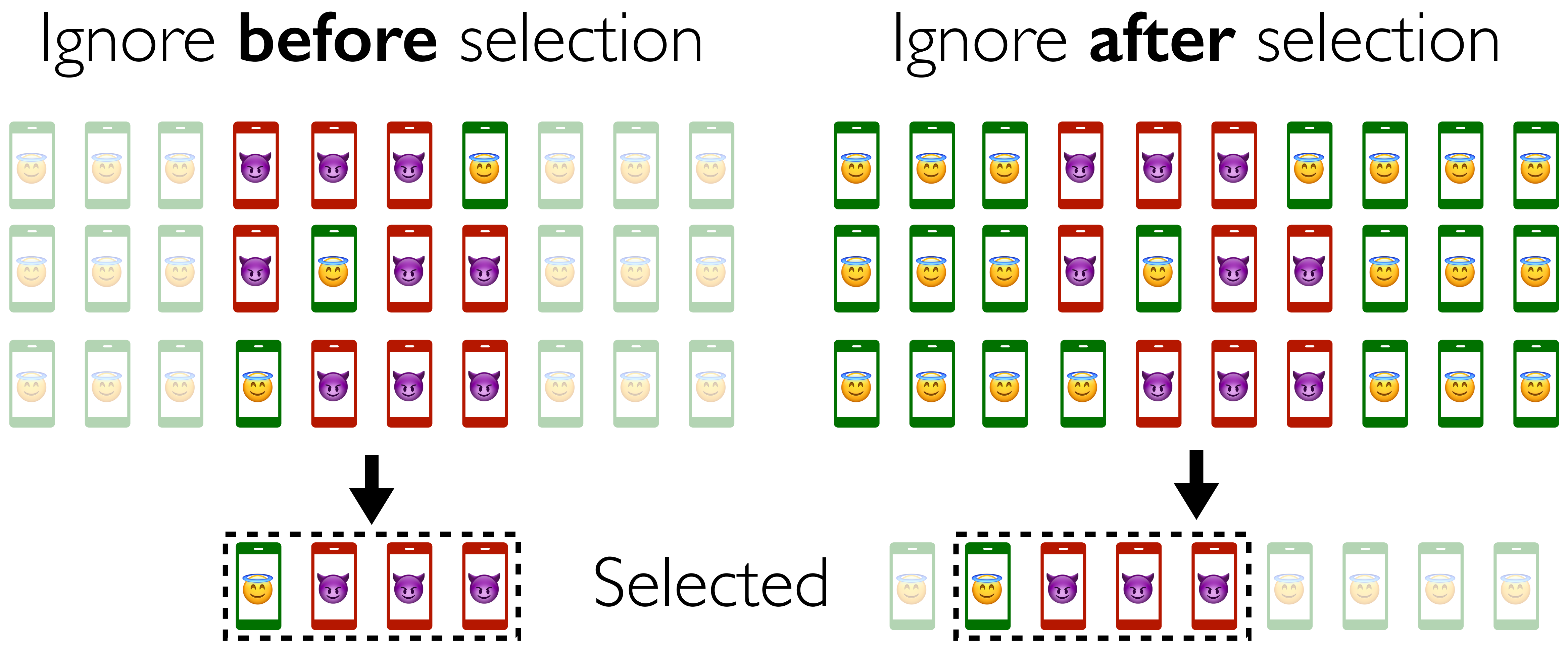

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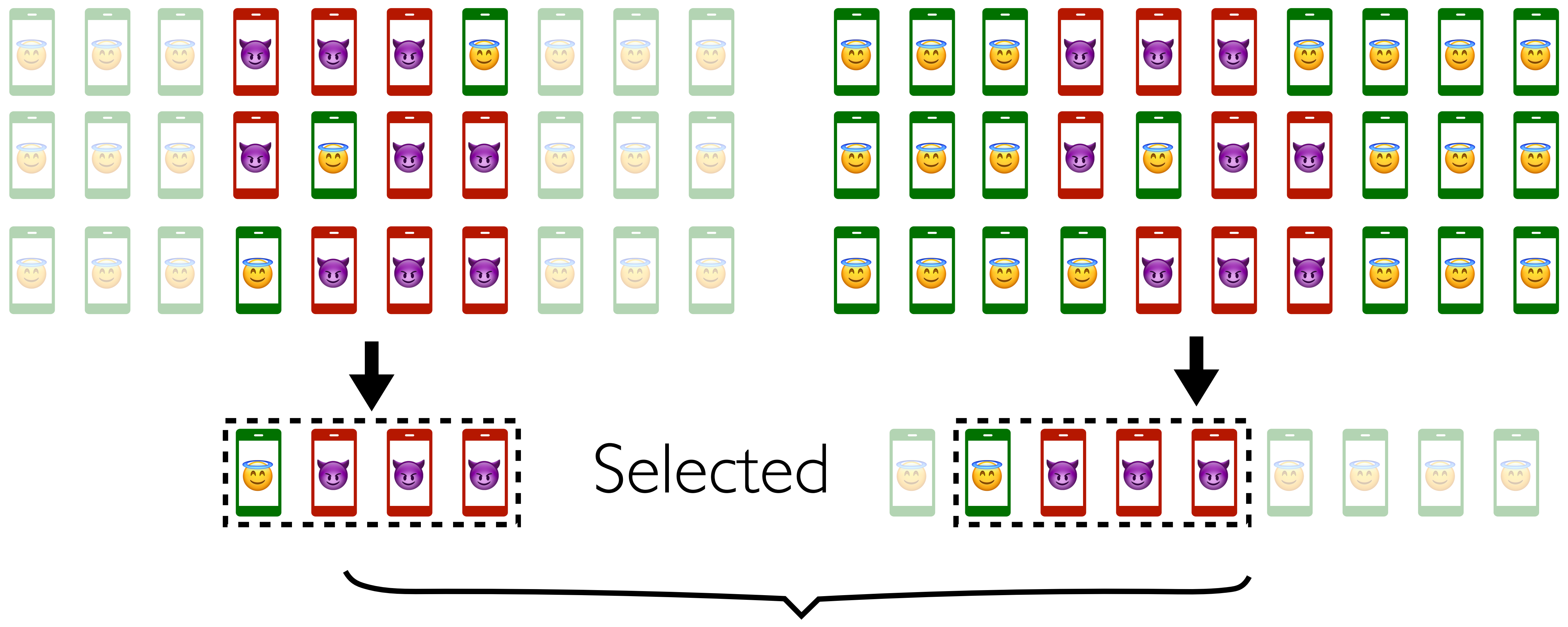
Ignore **before** selection

Ignore **after** selection



Unbounded advantage in growing dishonesty

Problem: Random selection

Solution: Enforce a **large enough list** and a **small enough chance**.

What is achieved:

Each participant

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What happens to the absent?

Problem: Random selection

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Solution: Enforce a **large enough list** and a **small enough chance**.

Example

- **len(list)**: ≥ 200
- **Chance**: ≤ 0.1%

Problem: Random selection

What is achieved:

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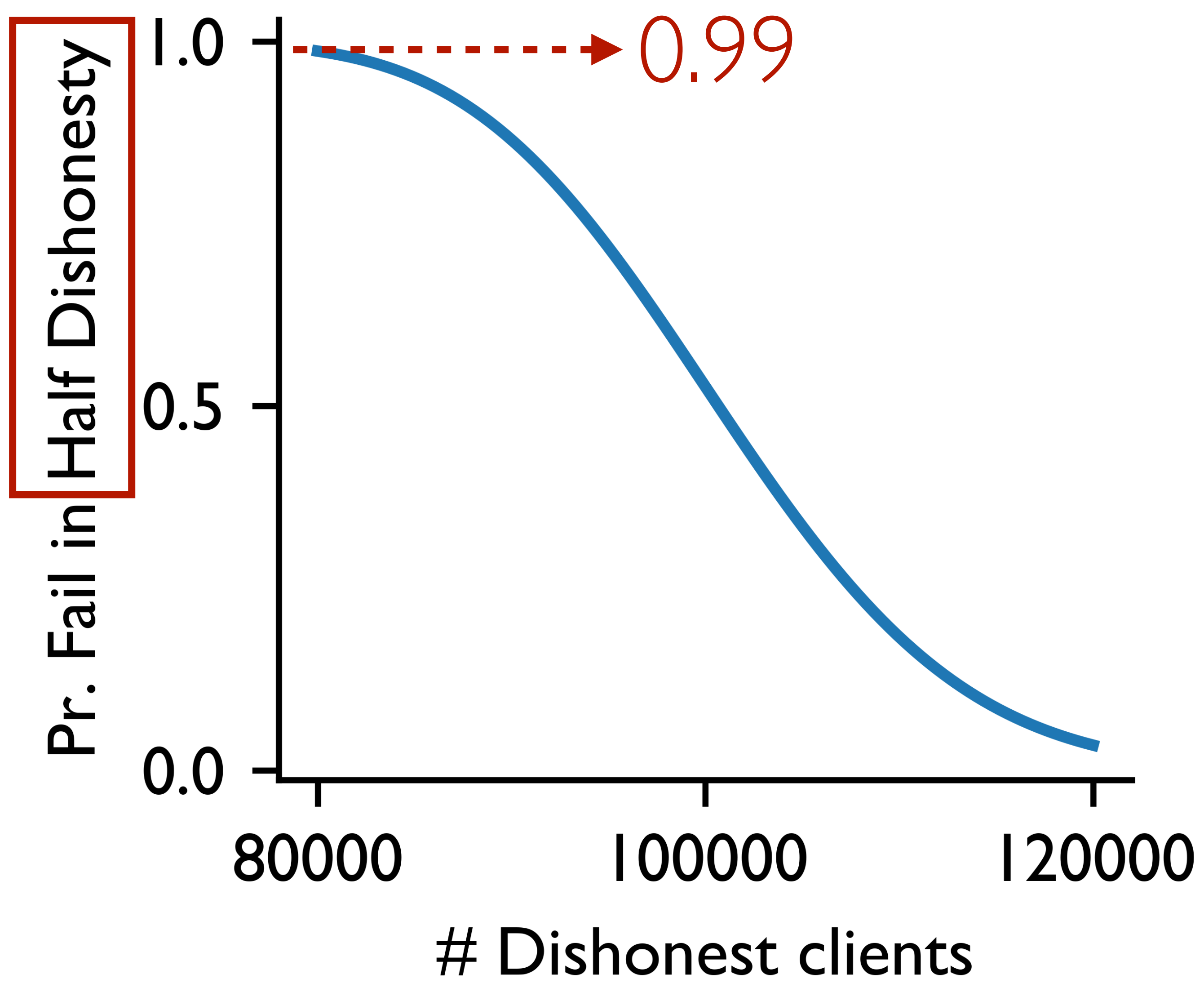
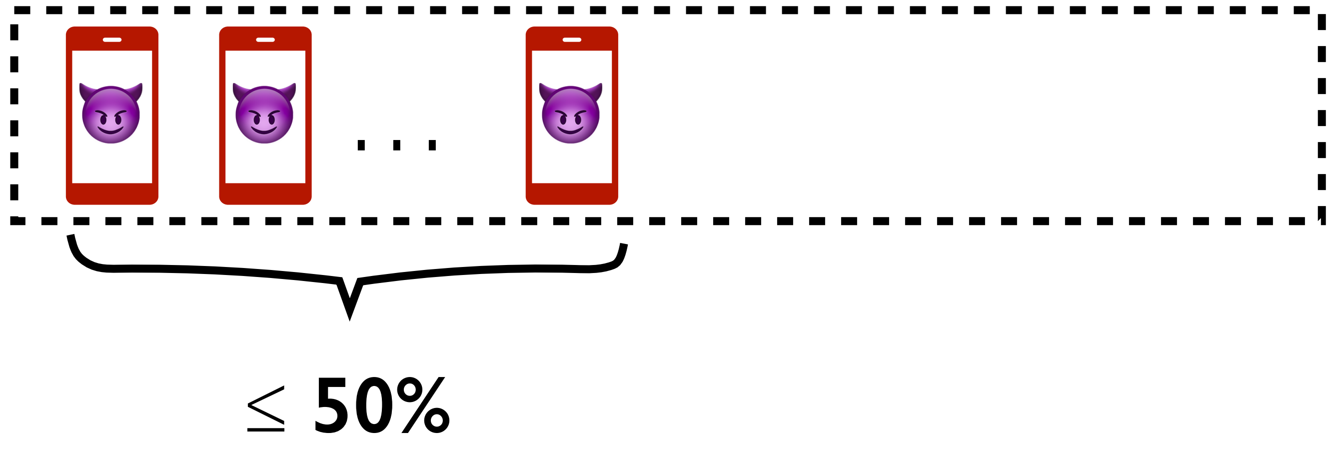


Selected



Problem: Random selection

What is achieved:

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The absent will not get arbitrarily ignored

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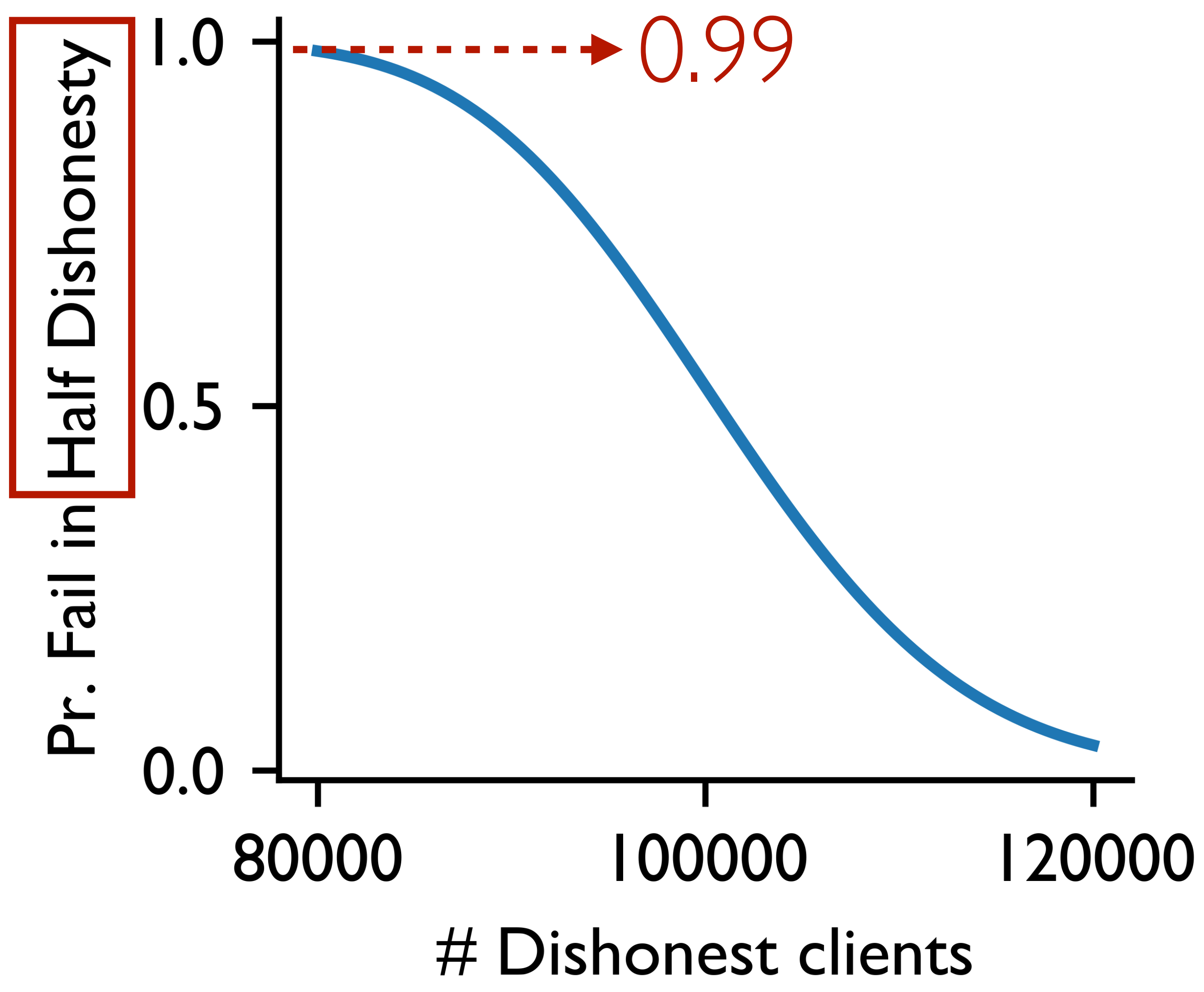

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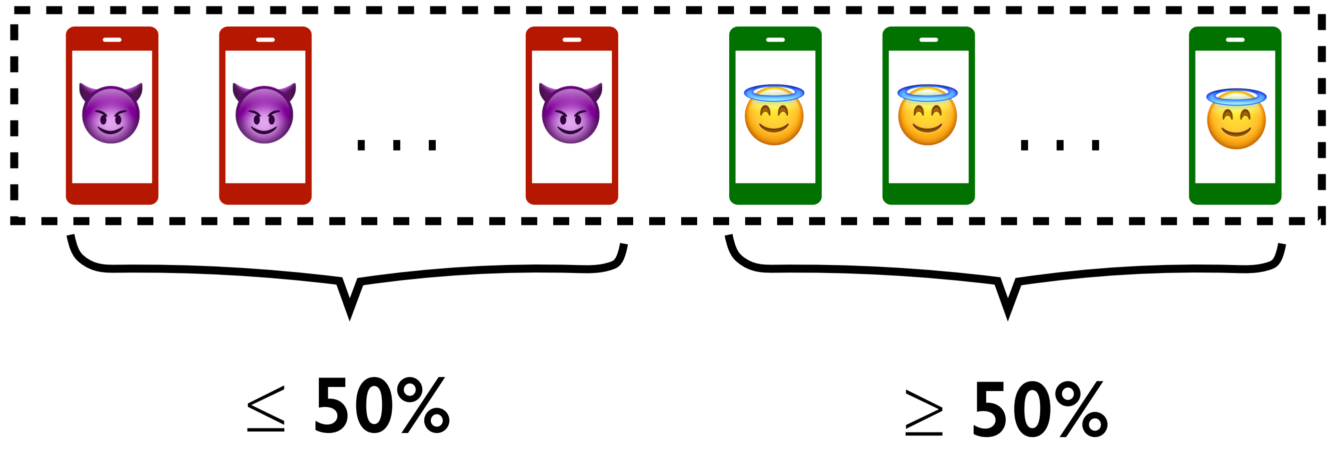

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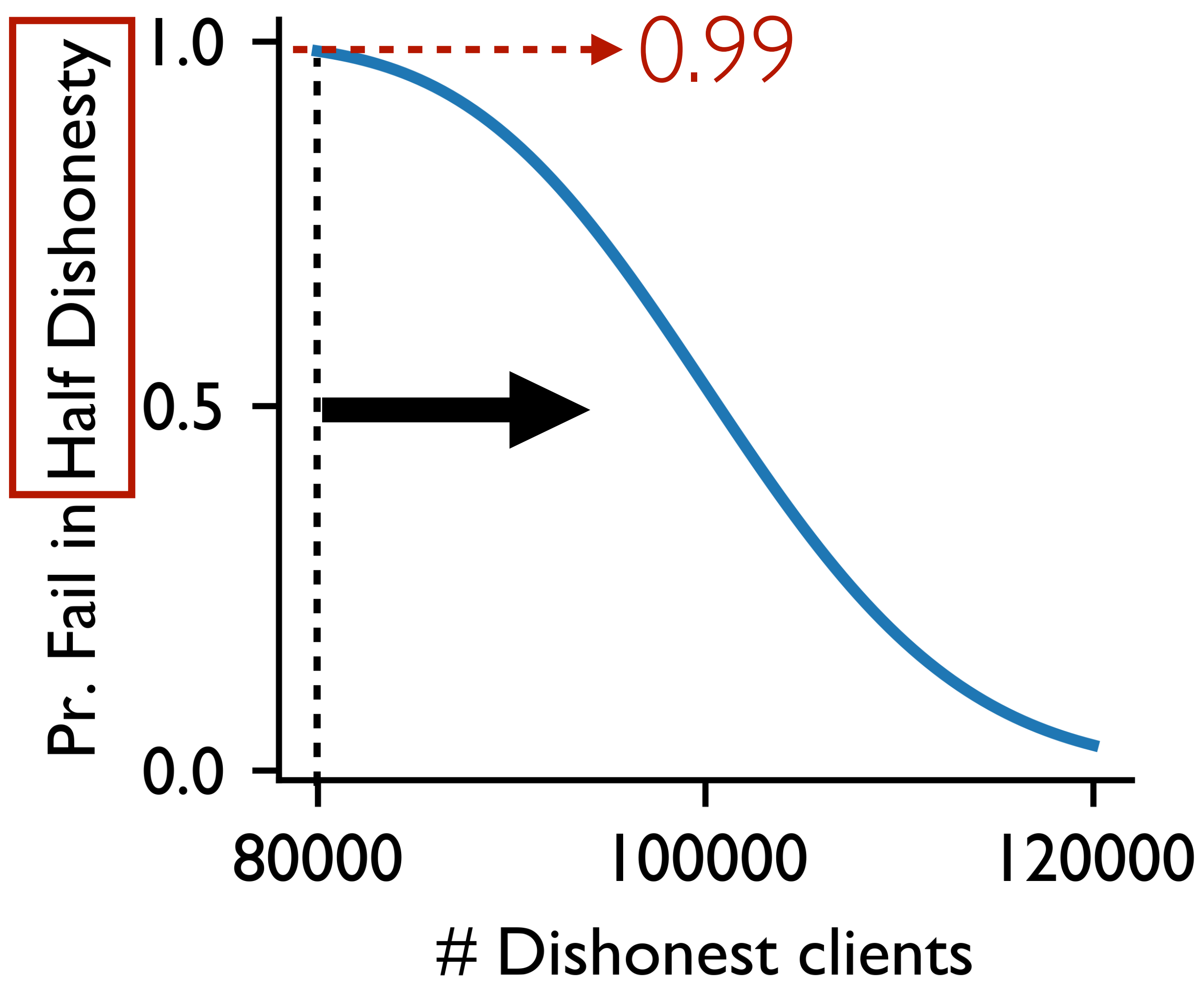

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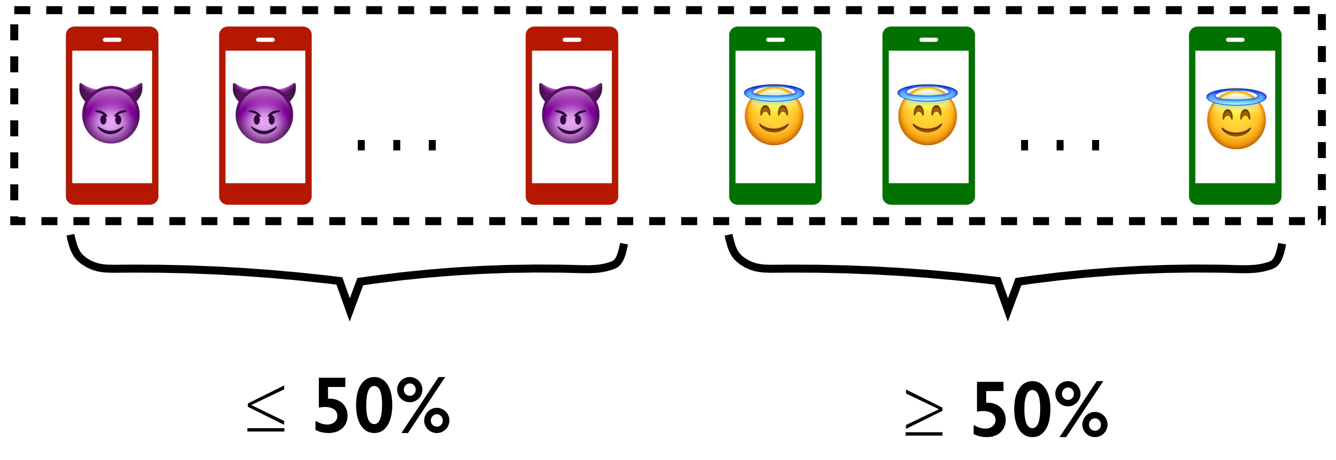

Problem: Random selection

What is achieved:

Each participant

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Predictable to server?

The absent will not get arbitrarily ignored

Public Round index

Examples: #2 will be selected as $\mathbf{RF}_{pk2}(2) = 1 < 3$.

Public Public keys

Problem: Random selection

What is achieved:
Each participant
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Predictable
to server?

The absent will not get
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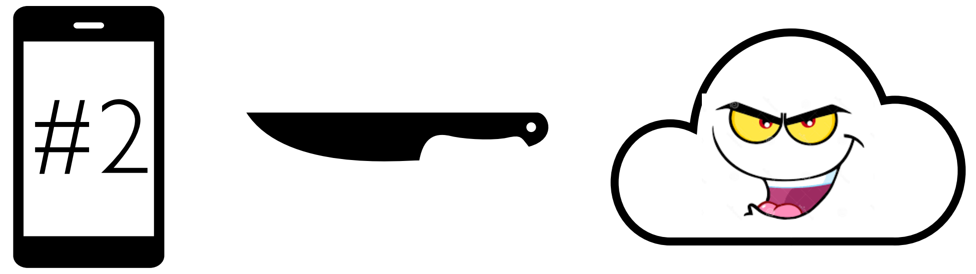
Problem: Attack surfaces **enlarged**!

Examples: #2 will be selected as $\mathbf{RF}_{pk2}(2) = 1 < 3$.
It's honest, so the server may grow its advantage by



Focused hacking

Problem: Random selection

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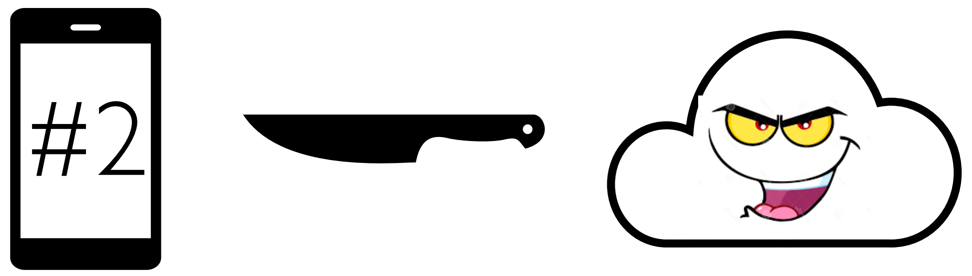
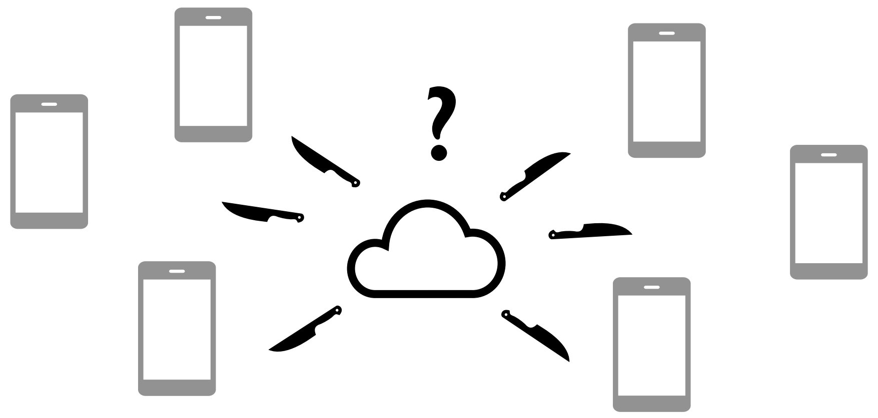


vs



Focused hacking

Random compromise

Problem: Random selection

What is achieved:

Each participant

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Predictable to server?

The absent will not get arbitrarily ignored

Solution: **Self-sampling** with verifiable random functions (**VRFs**)[1,2].

#2

Evaluation: $\mathbf{VRF.eval}_{sk2}(2) = (1, \quad)\ (\text{output}, \quad)$

Secret key

[1]Micali et al. "Verifiable random functions", In FOCS '99
[2]Dodis et al. "A verifiable random function with short proofs and keys", In PKC '05

Problem: Random selection

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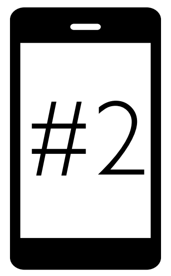

Evaluation: $\mathbf{VRF.eval}_{sk2}(2) = (\ 1, \boldsymbol{\pi_2}\ )$ (output, **proof**)

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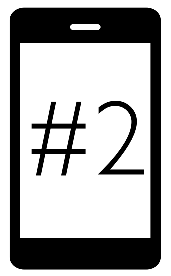

Evaluation: $\mathbf{VRF.eval}_{sk2}(2) = (\ 1, \boldsymbol{\pi_2}\ )$ (output, **proof**)

Verification: $\mathbf{VRF.ver}_{pk2}(\ 2, 1, \boldsymbol{\pi_2}\ ) = \text{True}$

Public key

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Problem: Random selection

What is achieved:
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Unpredictable
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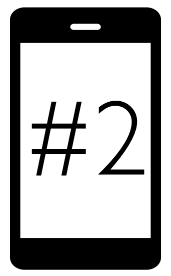
I self-sample with $(1, \pi_2)$



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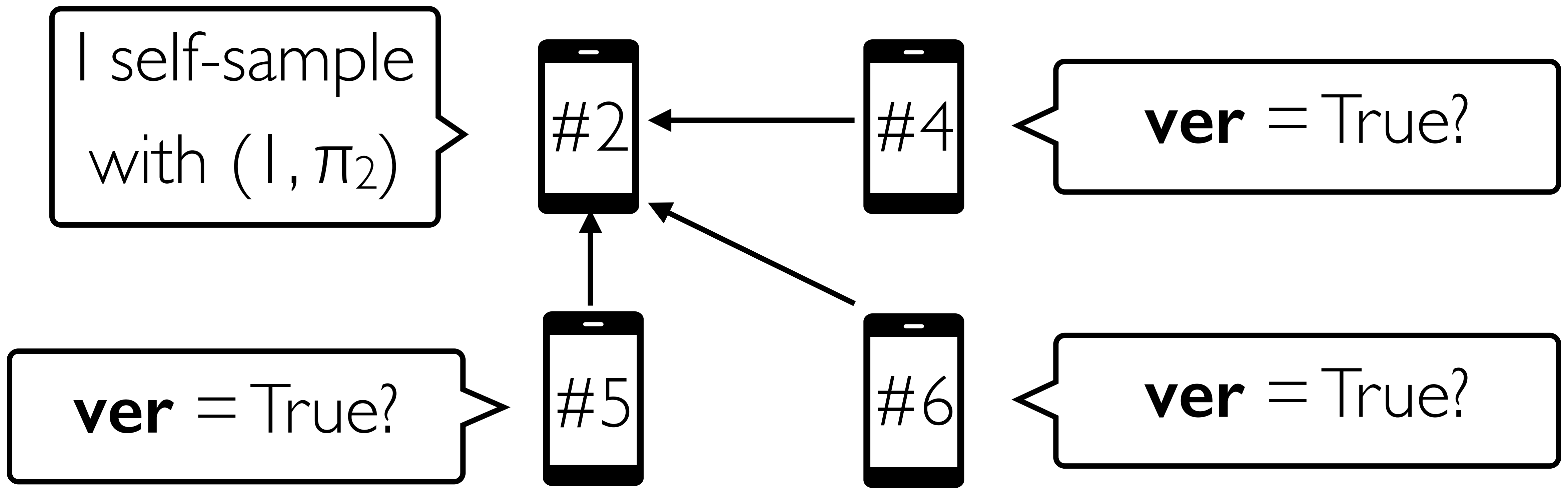

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Problem: Random selection

Actual participants
throughout the training?

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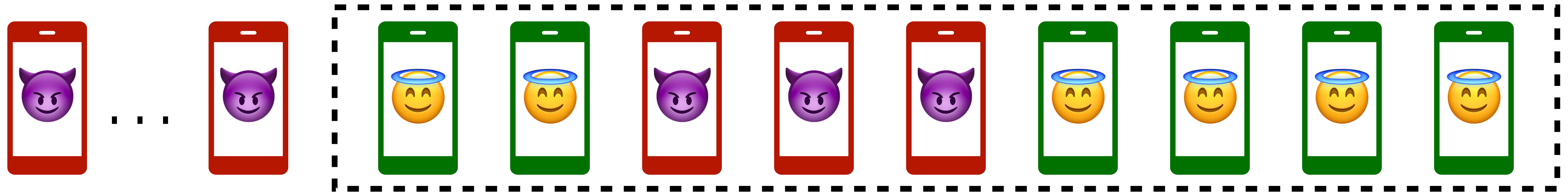
Problem: The server may **not follow**.

Involve **non-selected dishonest** ones



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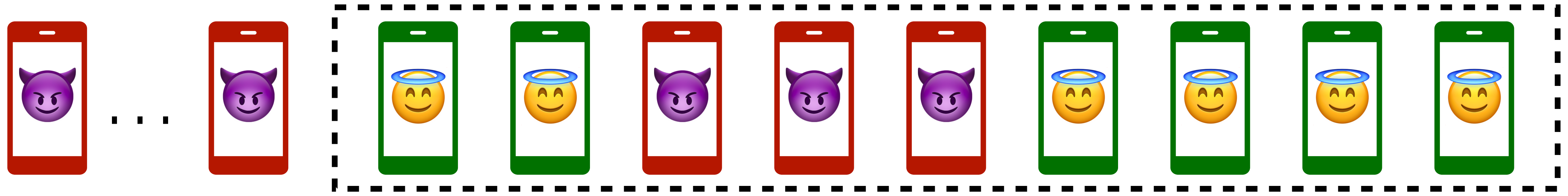
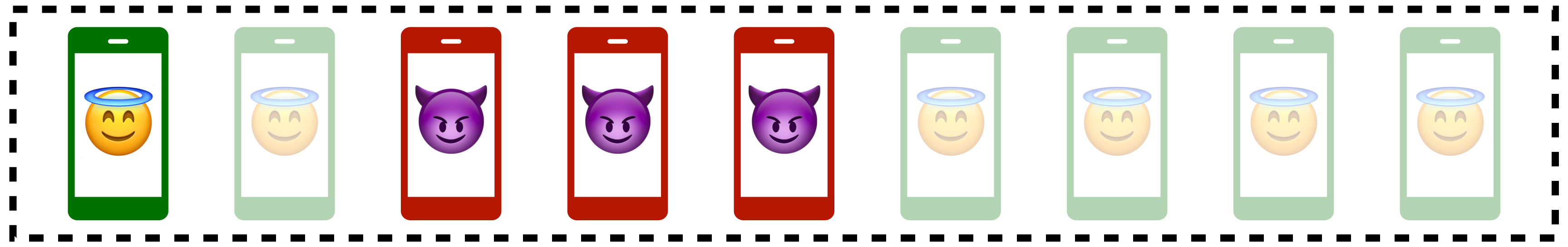


Disregard **selected honest** ones



Problem: Random selection

Actual participants throughout the training?

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[1]Thus also of distributed DP (other privacy-enhancing techniques may not have this feature and this is left for future work).

Solution: Utilize existing **secure semantics** of secure aggregation[1]

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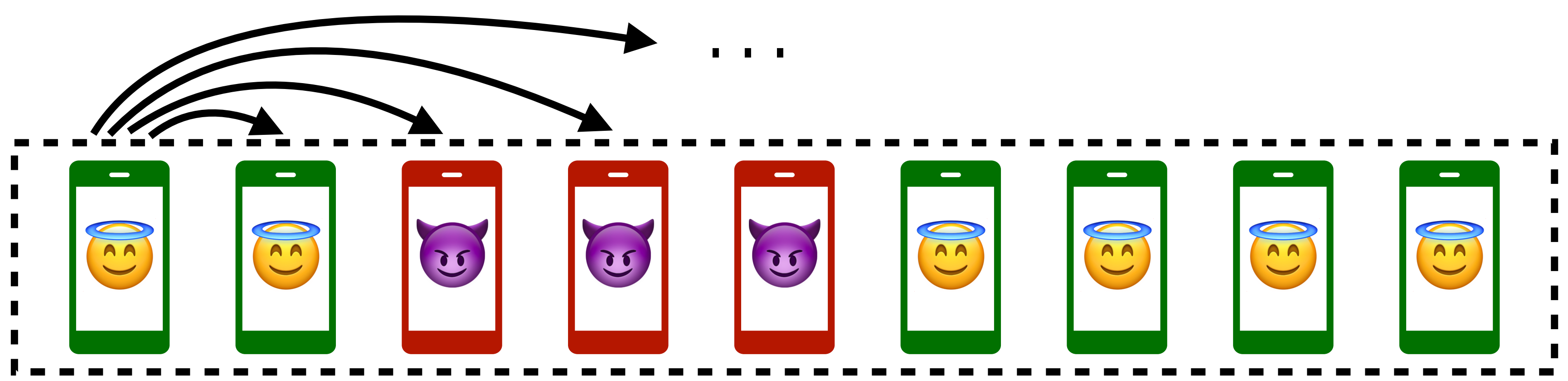
- **Commitment**: necessary info shared only once



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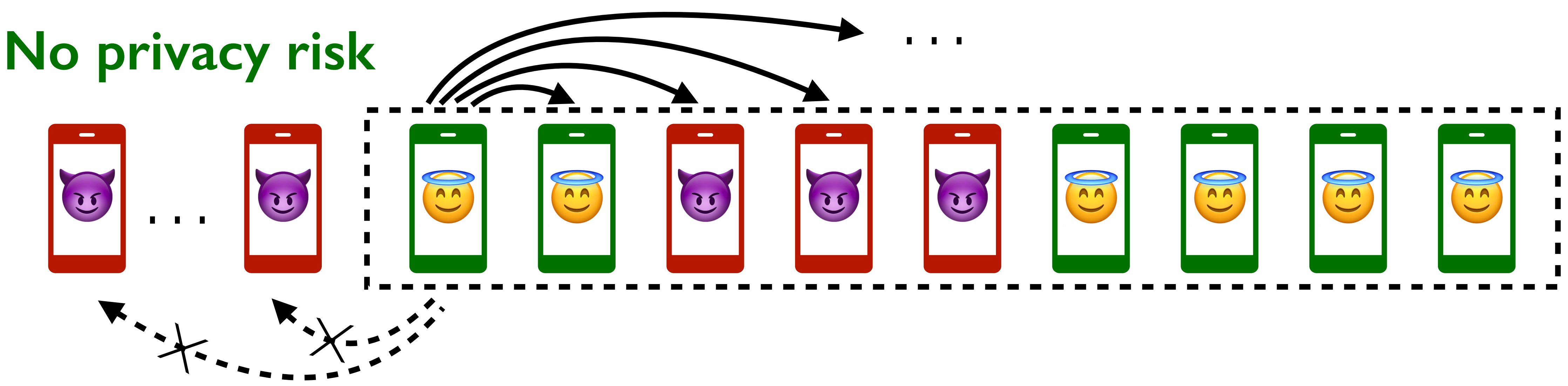
- **Commitment**: necessary info shared only once

No privacy risk



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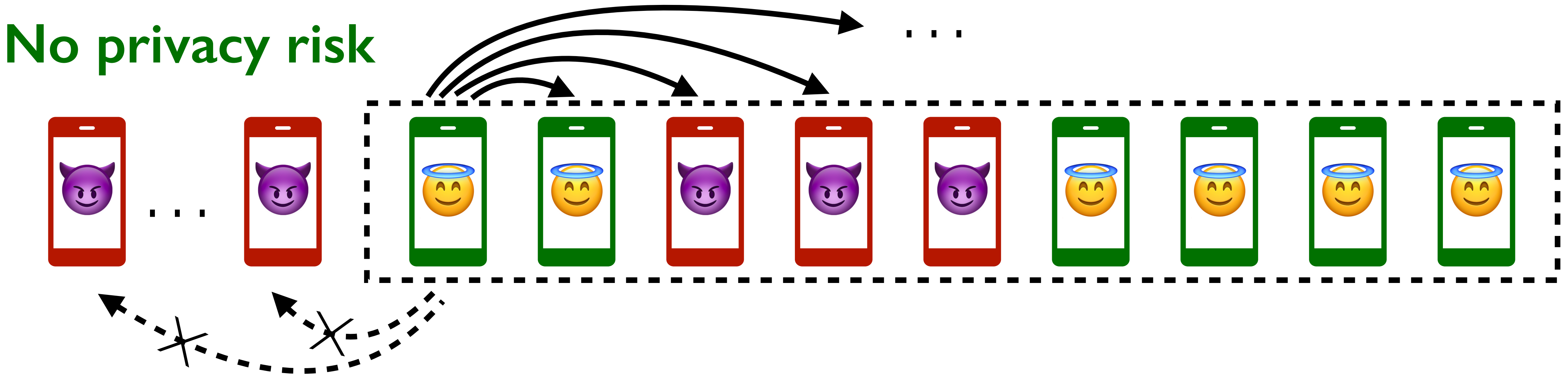
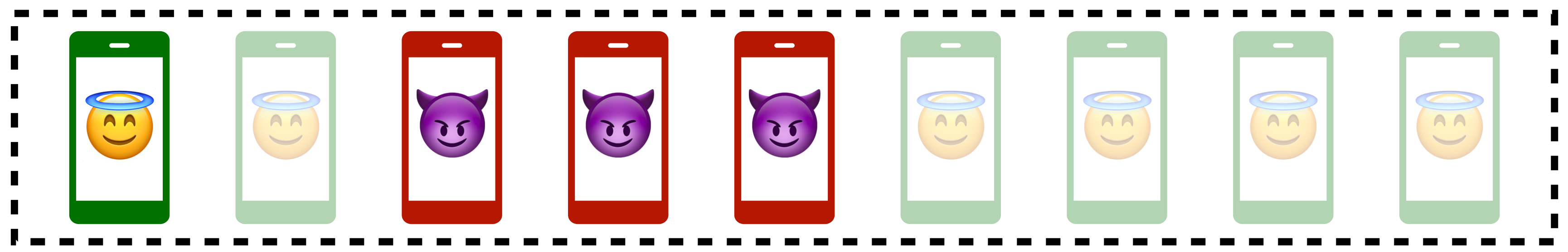


- **Consistency check**: to know remaining participants



Problem: Random selection

Actual participants
throughout the training

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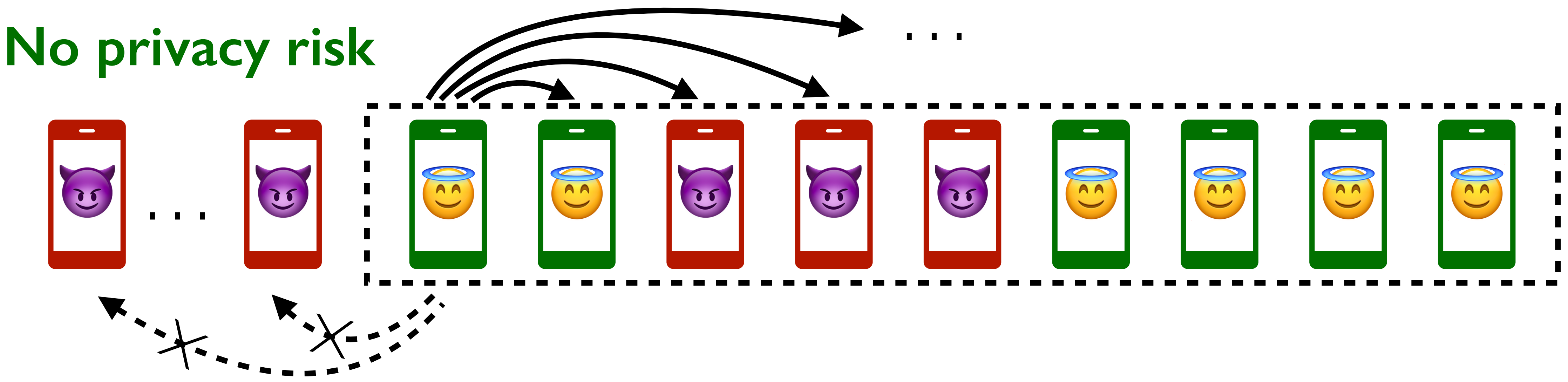
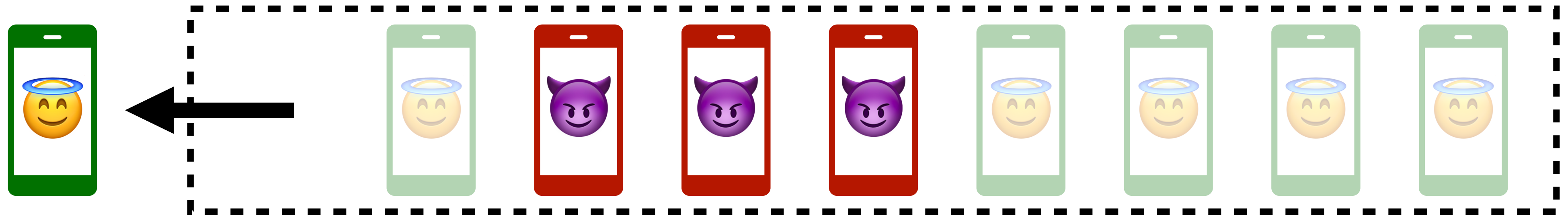


- **Consistency check**: to know remaining participants

Abort



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Minor issues:

- **Fixed sample size**: over-selection
- **Consistent round index**: uniqueness check

…

Please find more in the paper :)

Problem: Informed selection

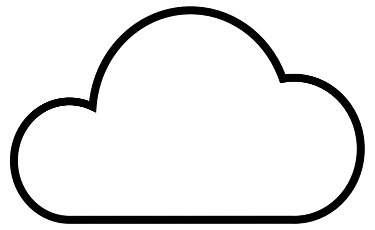
Problem: Informed selection

Example

	(Est.) latency
#1	1.2s
#2	2.7s
#3	1.6s
…	…

Problem: Informed selection

Example



	(Est.) latency	Select
#1	1.2s	Yes
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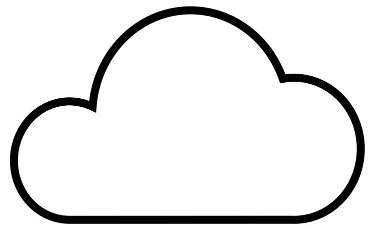
#3	1.6s	Yes
…	…	…

Selection criteria: the fastest For dishonest majority

Problem: Informed selection

Example



	(Est.) latency	Select	(Est.) latency	Select
#1	1.2s	Yes		Yes
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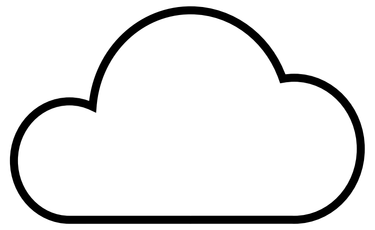
…	…	…		…

Selection criteria: the fastest For dishonest majority

Problem: Informed selection

Example



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Selection criteria: the fastest | For dishonest majority

Major Challenge: Client metrics are **hard to verify** by honest clients

Problem: Informed selection

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	(Est.) latency	Select	(Est.) latency	Select
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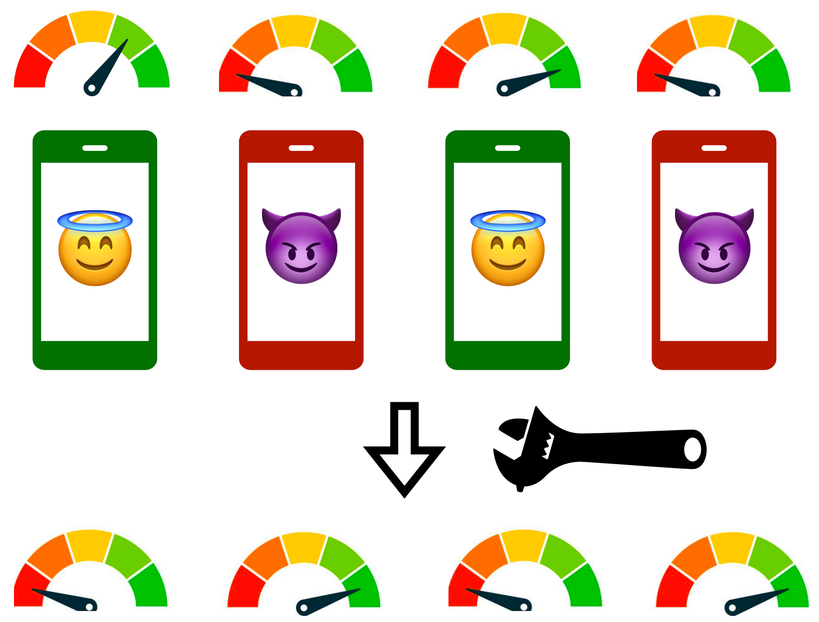
Selection criteria: the fastest — For dishonest majority

Major Challenge: Client metrics are **hard to verify** by honest clients

Metrics are fake



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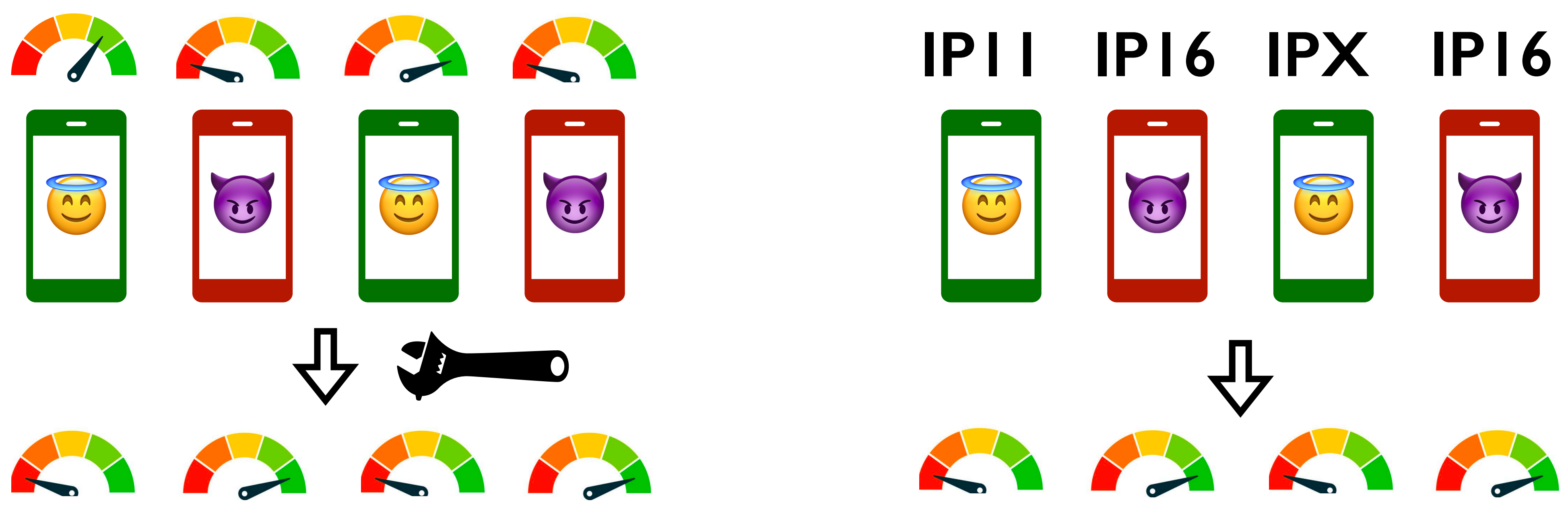
Selection criteria: the fastest For dishonest majority

Major Challenge: Client metrics are **hard to verify** by honest clients

Metrics are fake Metrics are true, but…



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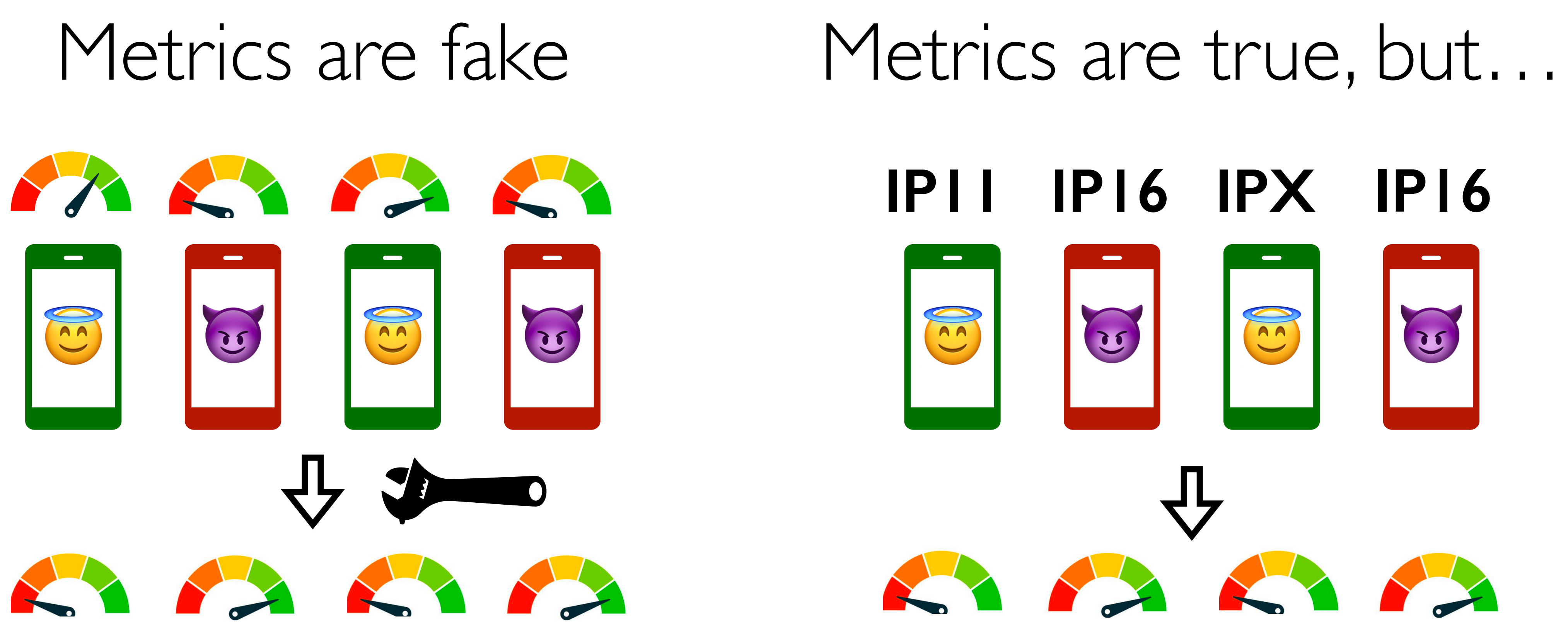
Selection criteria: the fastest

For dishonest majority

Major Challenge: Client metrics are **hard to verify** by honest clients



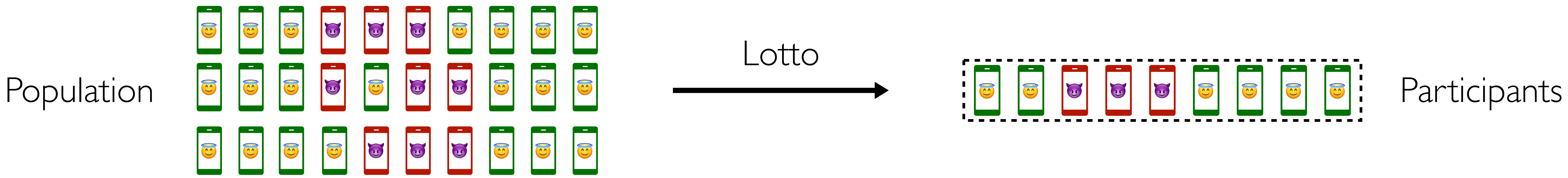
Solution: **Approximate** inform selection by **random** selection

Please find more in the paper :)

Lotto prevents arbitrary manipulation

Lotto prevents arbitrary manipulation

What can be **proven**:



Lotto prevents arbitrary manipulation

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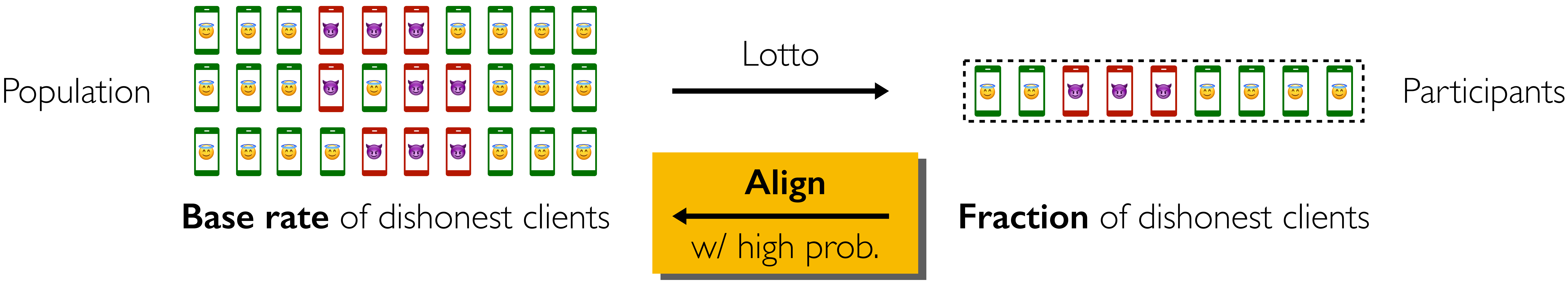

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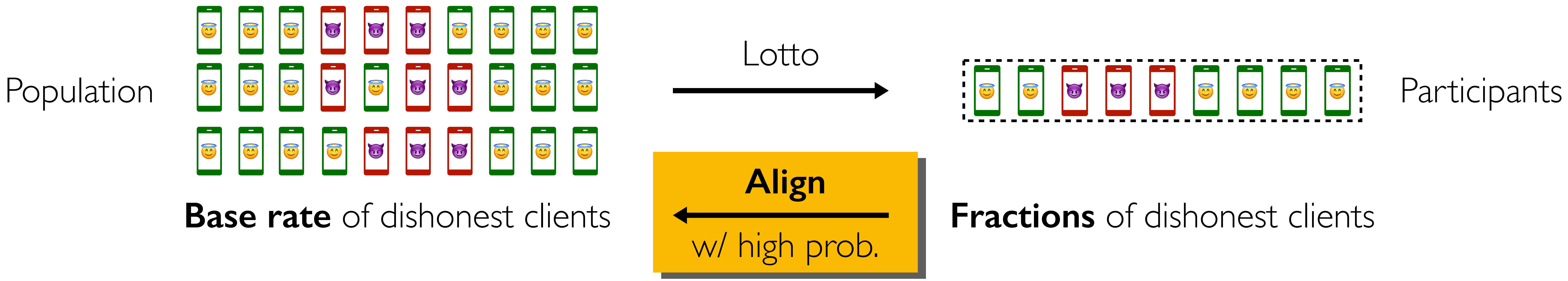

Example

- **Population**: 200,000
- **Dishonesty base rate**: 0.005

Lotto prevents arbitrary manipulation

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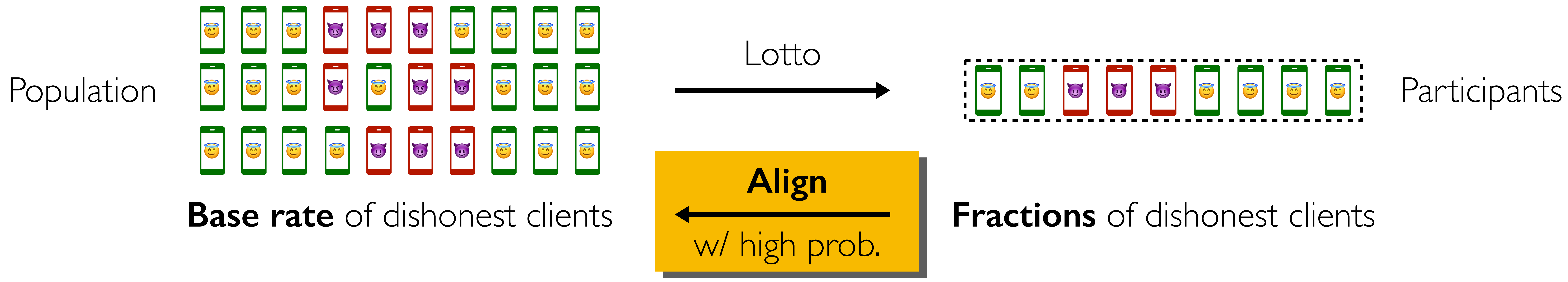

Example

- **Population**: 200,000
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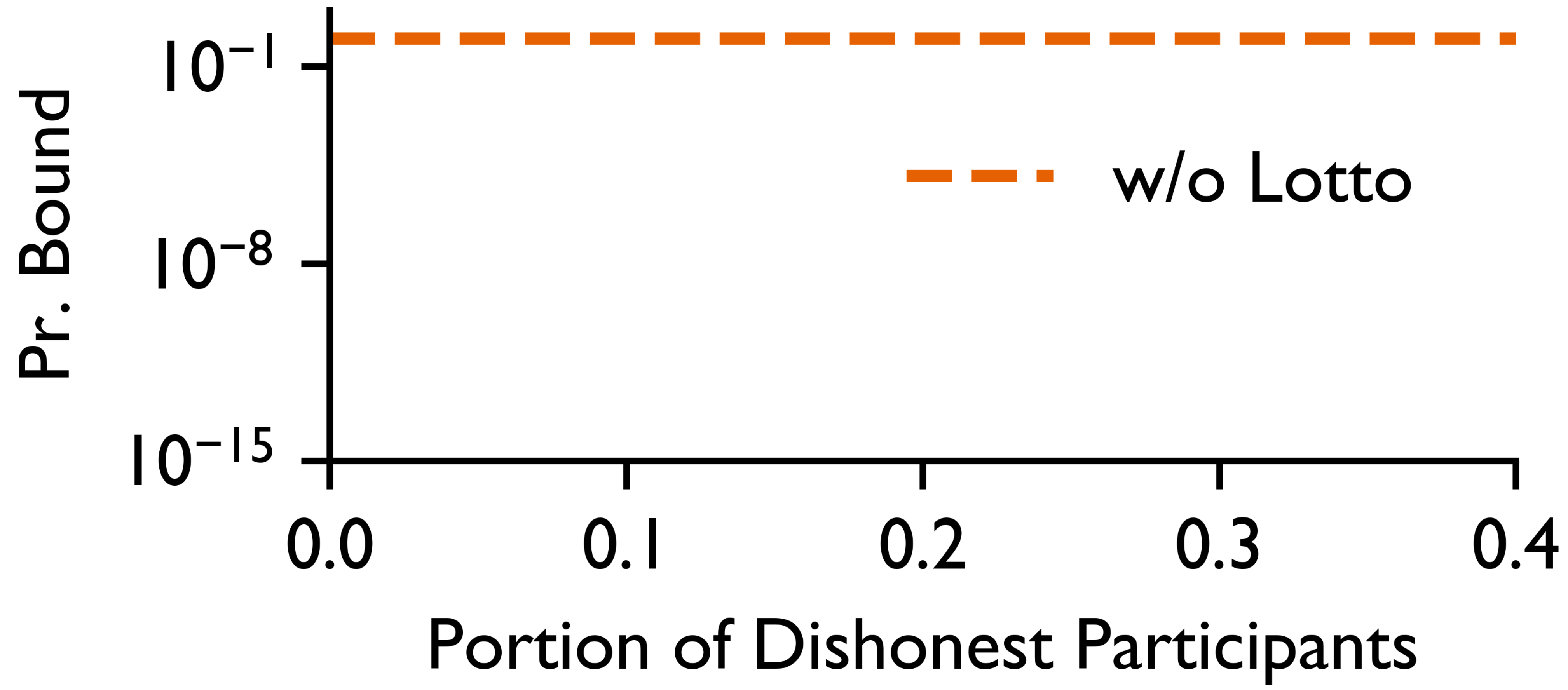
- **Target participants**: 200



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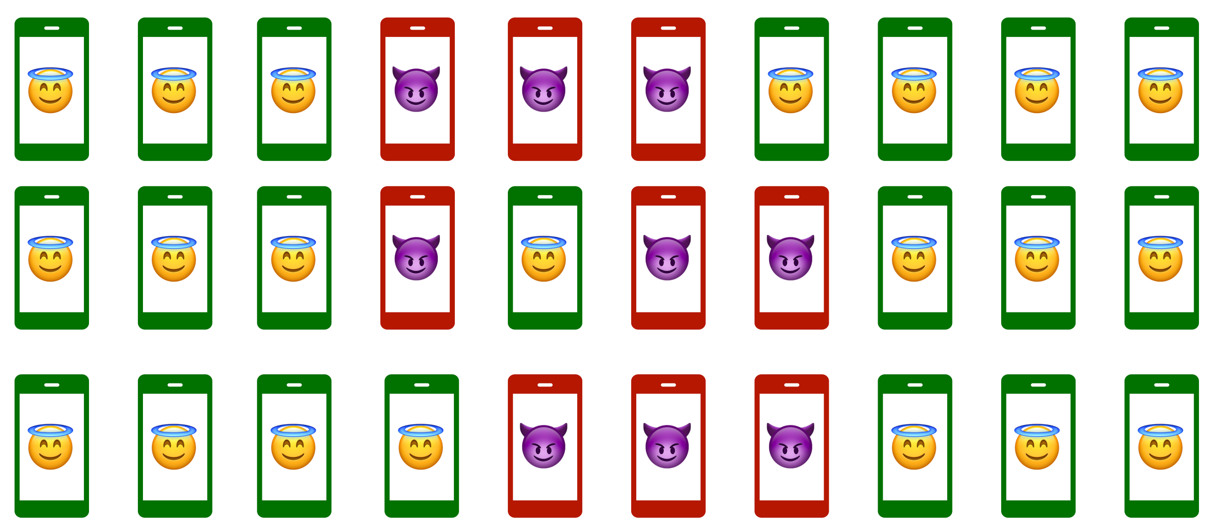
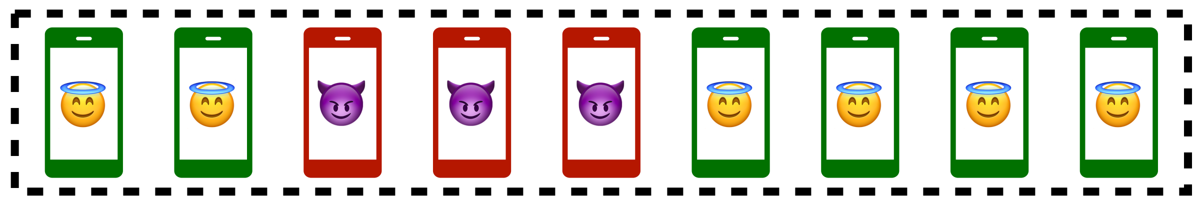
What can be **proven**:

Population



Base rate of dishonest clients

Lotto



Participants

Align

w/ high prob.

Fractions of dishonest clients

Example

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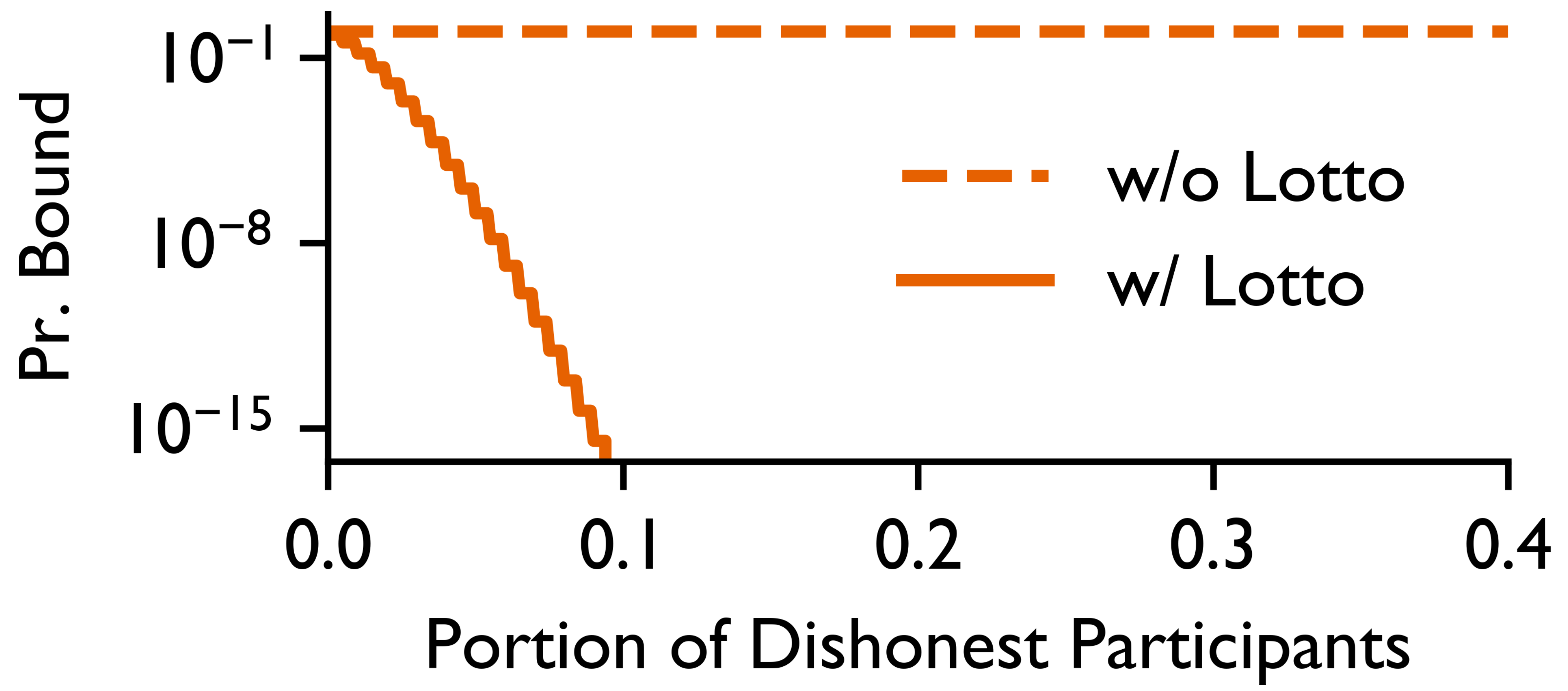
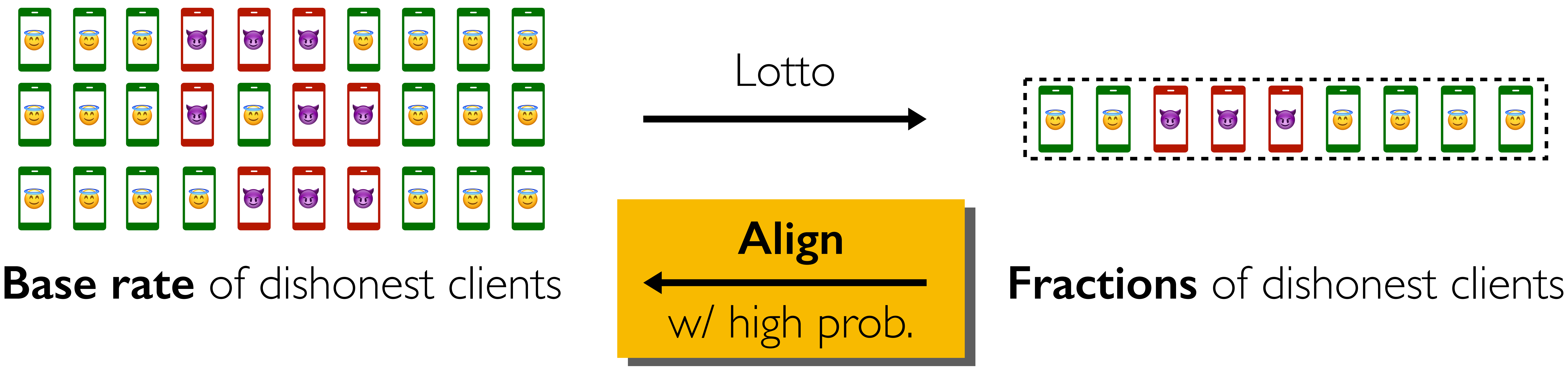
- **Dishonesty base rate**: 0.005
- **Target participants**: 200



Lotto prevents arbitrary manipulation

What can be **proven**:

Population



Participants

Base rate of dishonest clients

Fractions of dishonest clients

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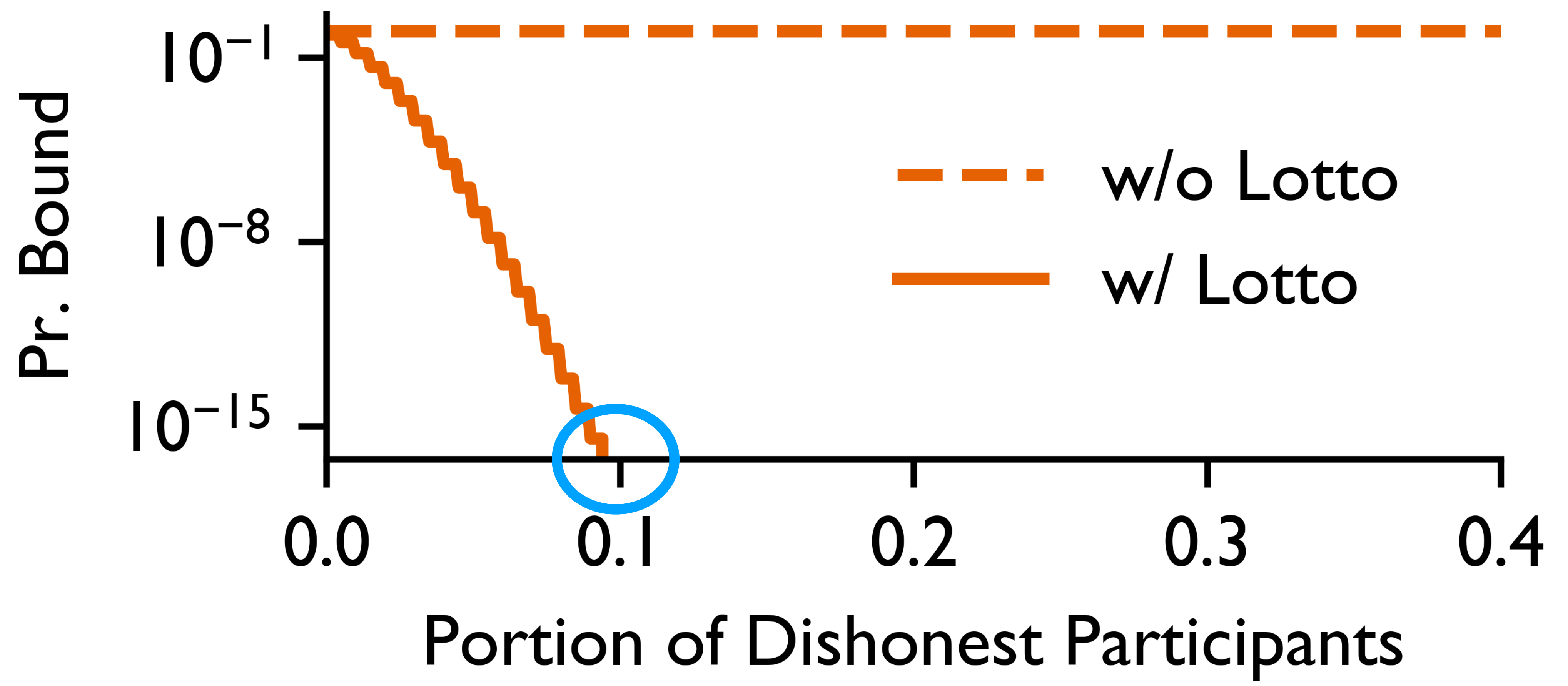

Lotto induces no or mild overhead

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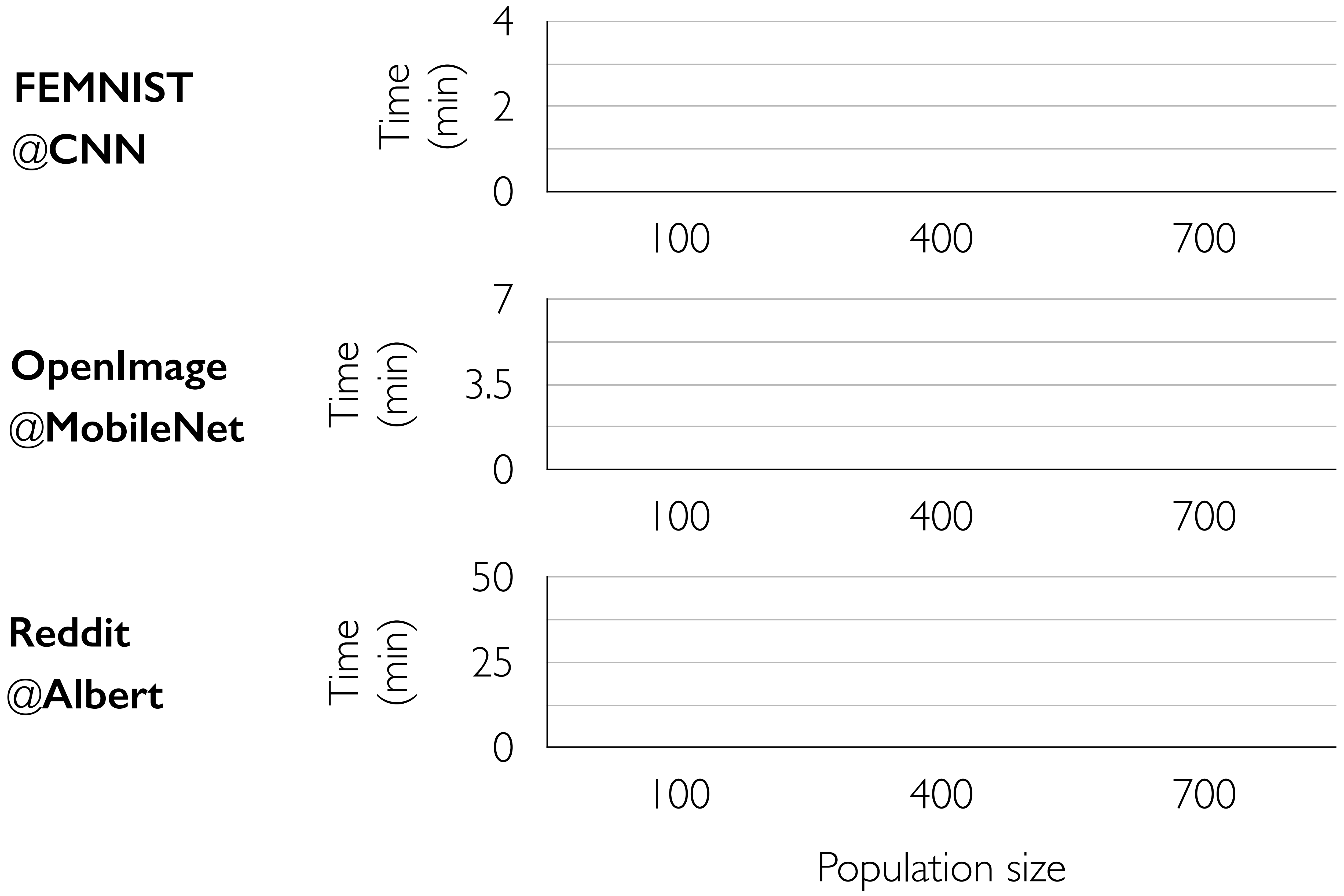
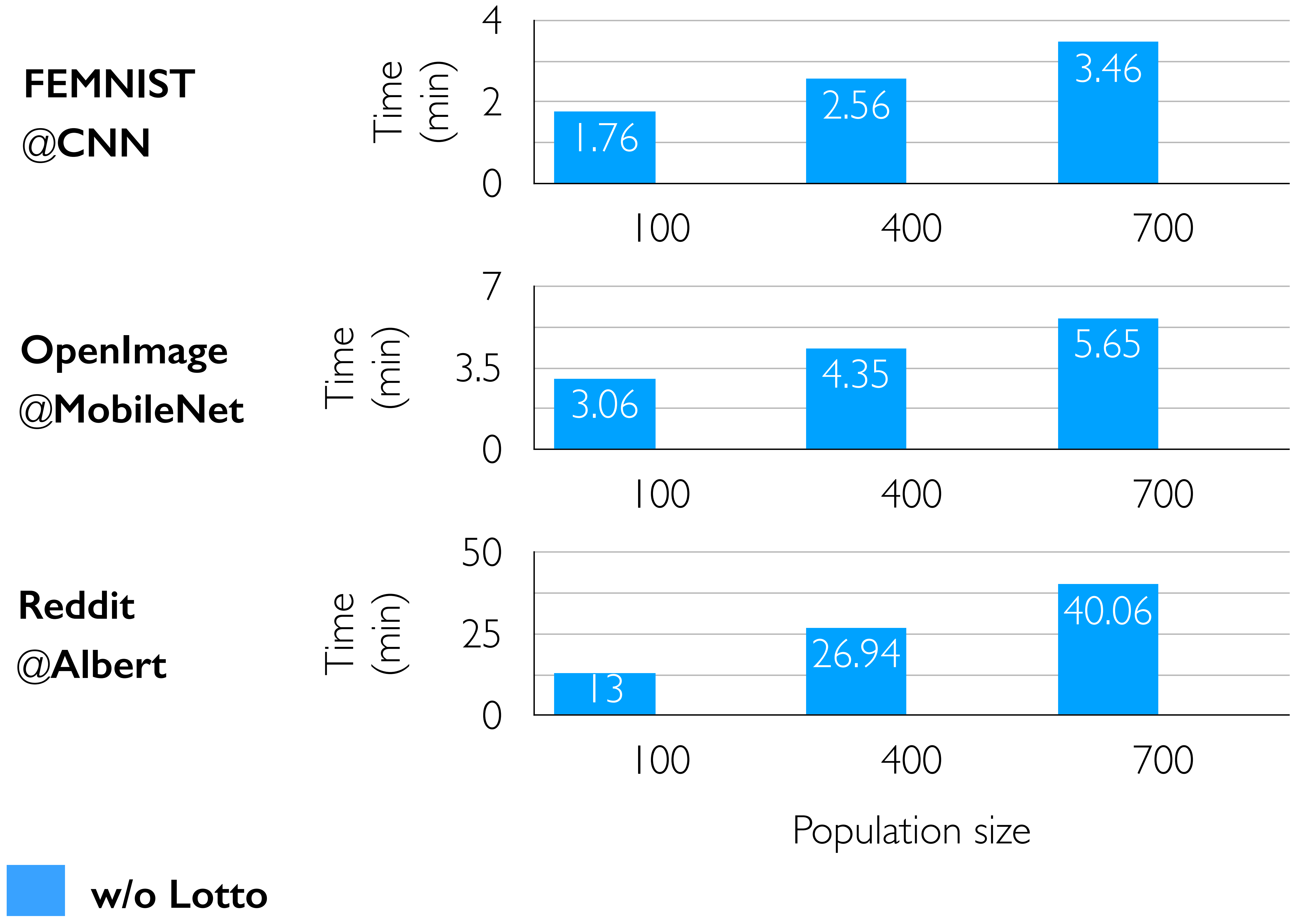


[1]Random selection as an example. See results for informed selection in the paper.

Lotto induces no or mild overhead



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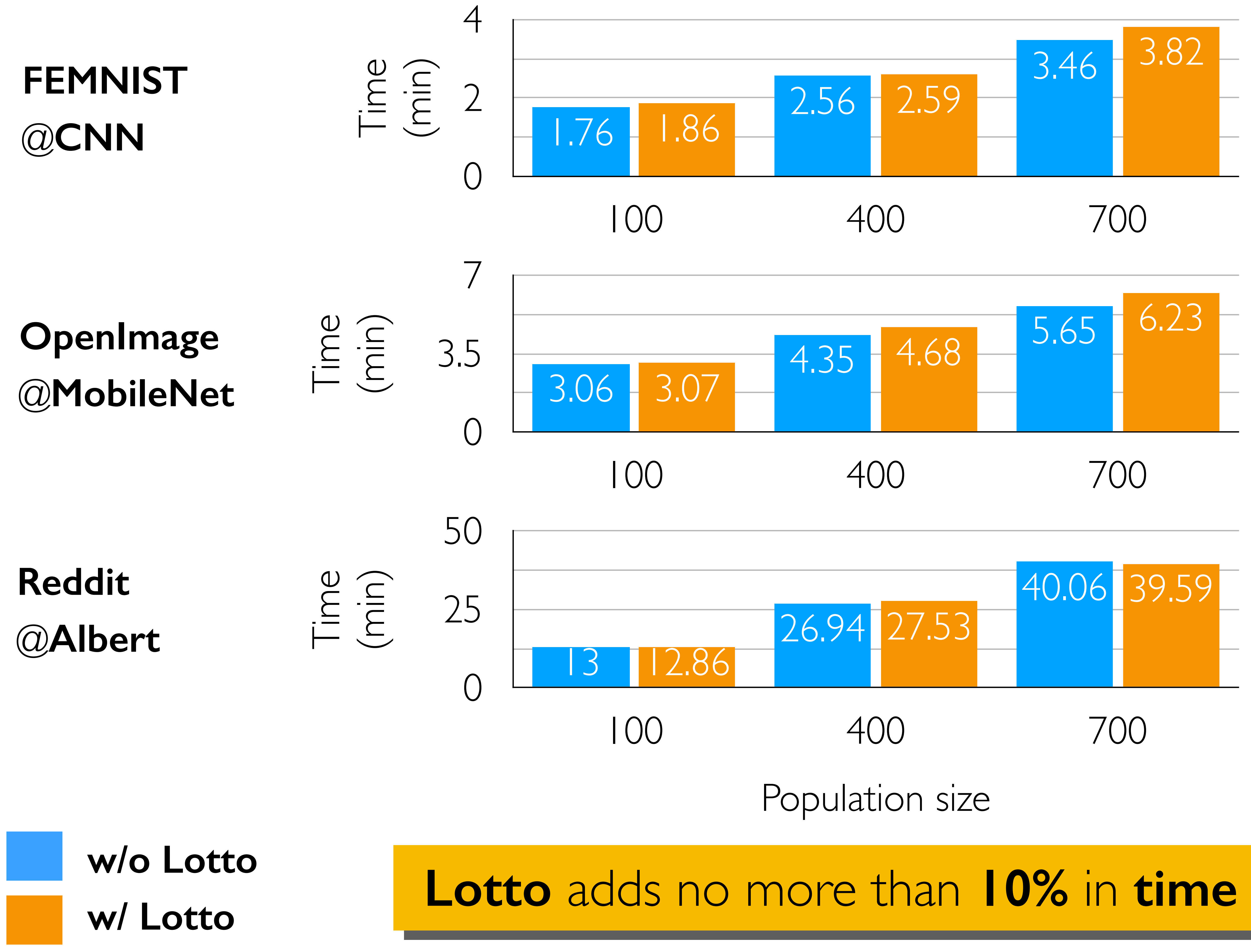

Lotto adds no more than **10%** in **time**

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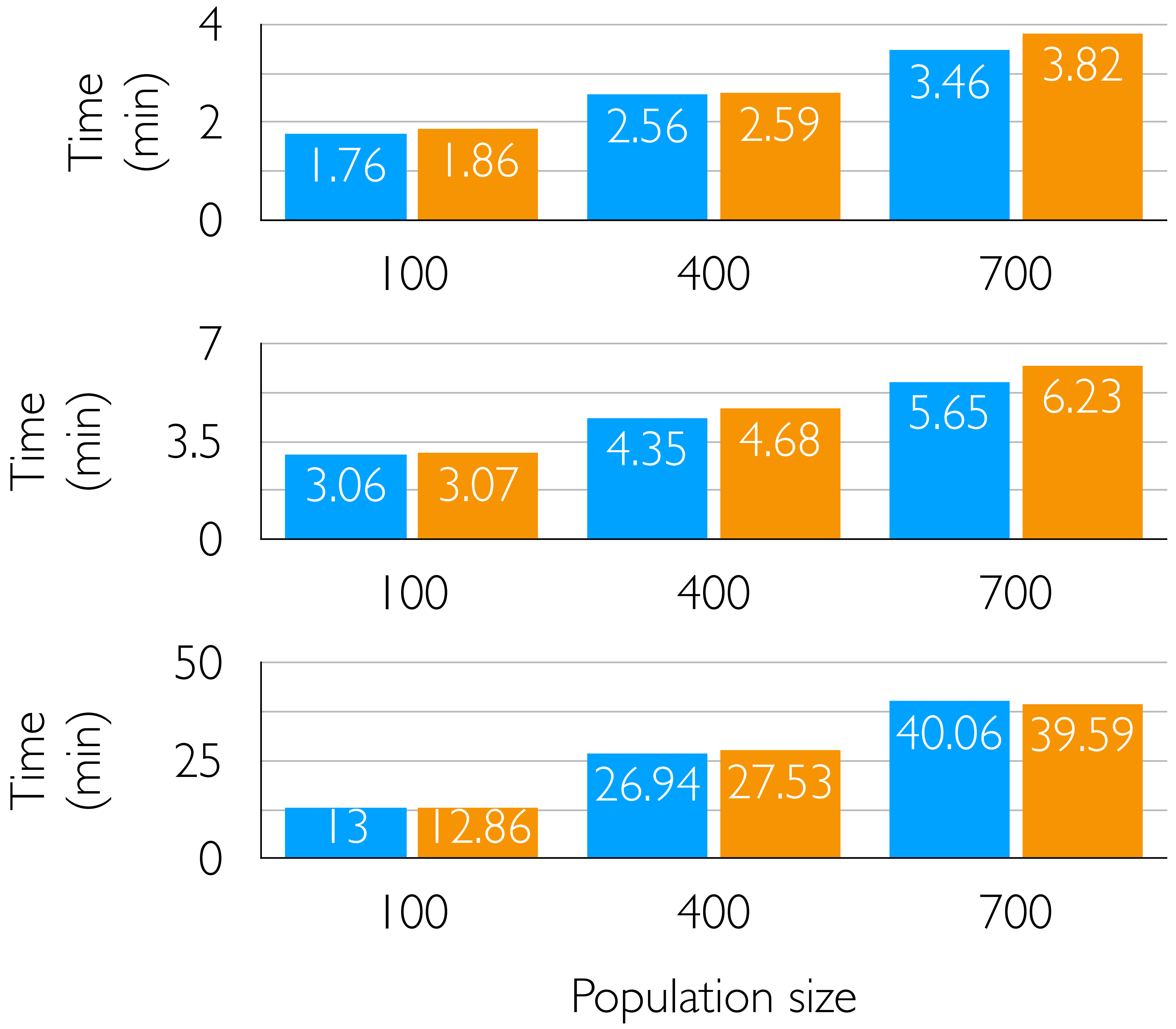
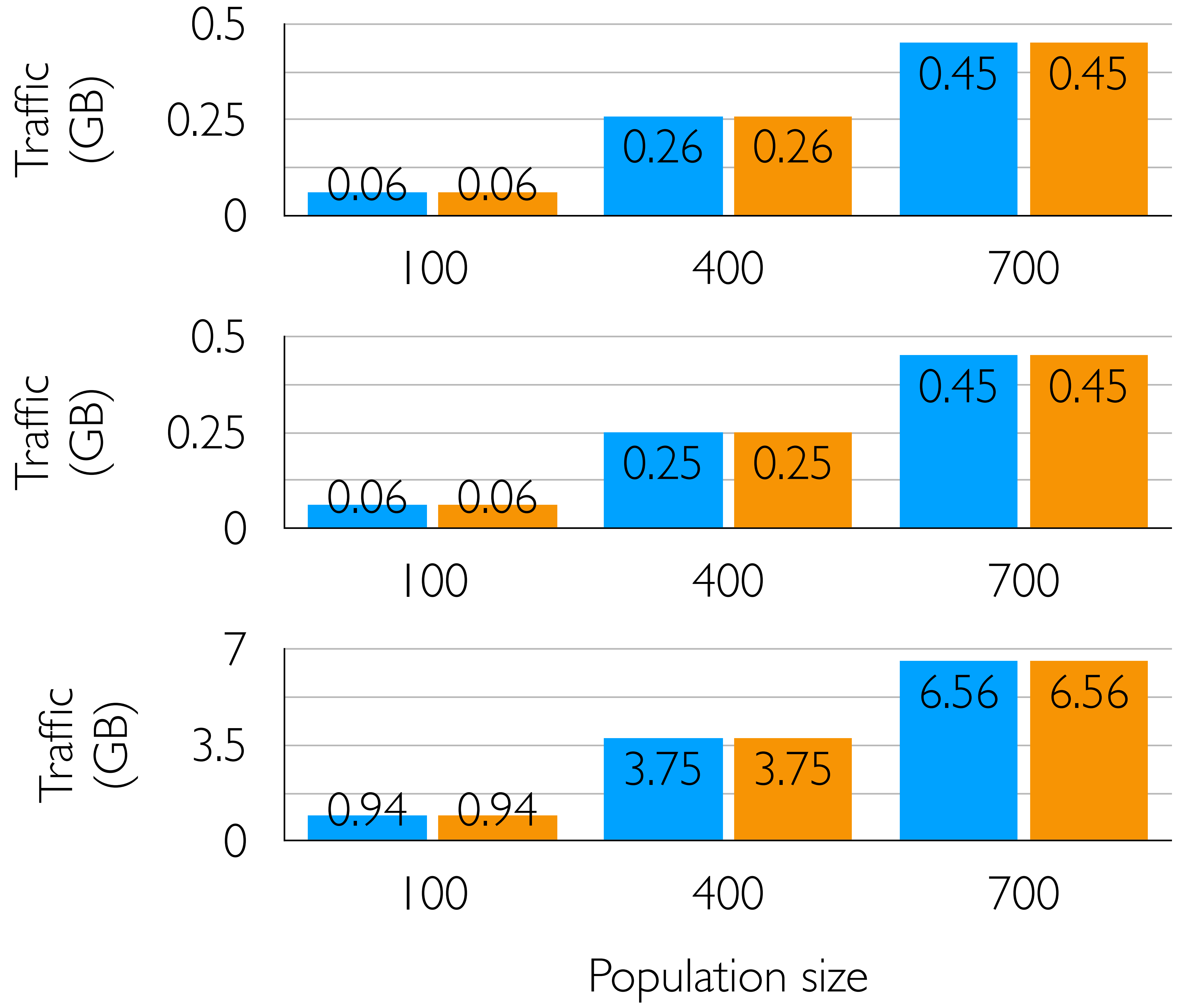
Lotto induces no or mild overhead

FEMNIST @CNN

OpenImage @MobileNet

Reddit @Albert





w/o Lotto
w/ Lotto

Lotto adds no more than **10%** in **time**

Lotto costs **negligible** in **network**

[1]Random selection as an example. See results for informed selection in the paper.

Lotto functions as insecure selectors

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Oort[1] → State-of-the-art **informed** selector: optimized for **time-to-accuracy** of training

[1] Lai et al. "Oort: Efficient Federated Learning via Guided Participant Selection", In OSDI '21

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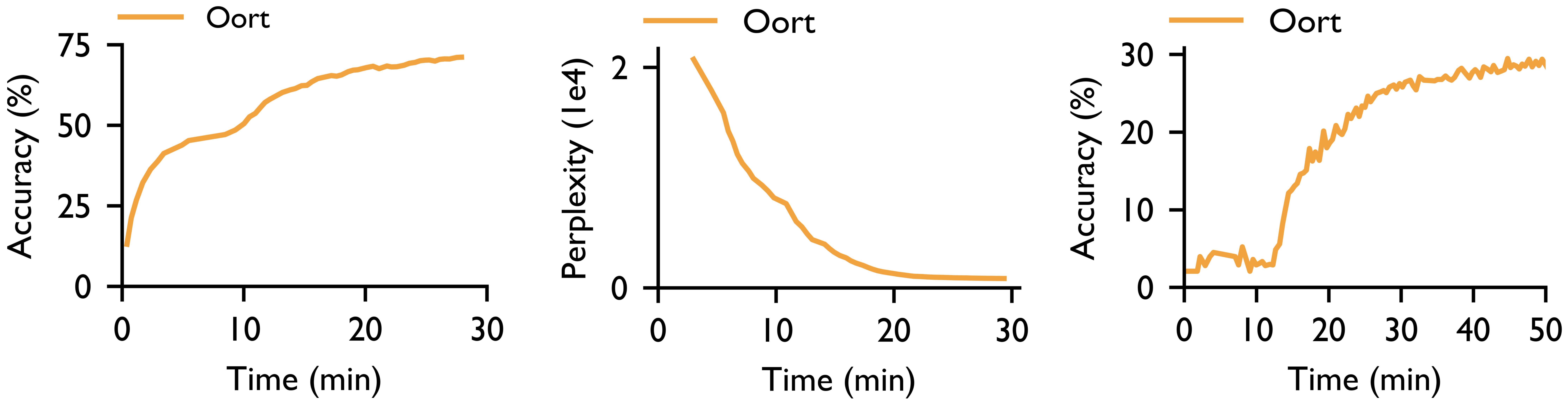

FEMNIST@CNN **OpenImage@MobileNet** **Reddit@Albert**

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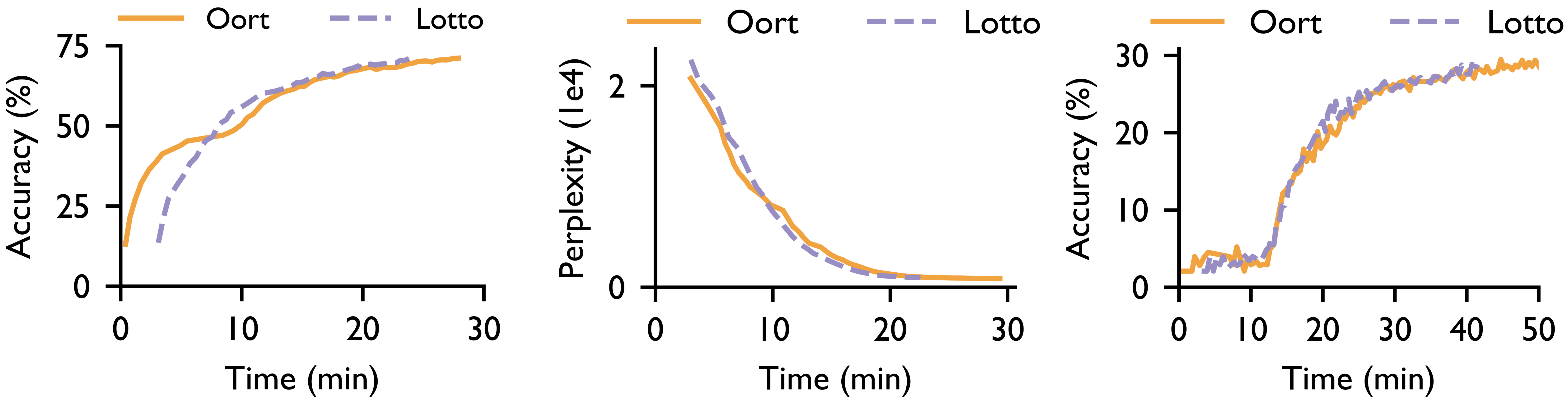

FEMNIST@CNN **OpenImage@MobileNet** **Reddit@Albert**

Lotto well approximate Oort with **no cost in time-to-accuracy** performance

[1]Lai et al. "Oort: Efficient Federated Learning via Guided Participant Selection", In OSDI '21

Lotto: Results summary

Functionality

Support both **random (exact)** and **informed (well approximated)** selection

Security

Theoretical guarantee (tight probability bound) of preventing manipulation

Efficiency

Mild **runtime overhead (≤10%)** with no **network cost (<1%)**

github.com/SamuelGong/Lotto

Thank you

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