# Towards *Private* and *Efficient* Cross-Device **Federated Learning**

**PhD Thesis Defense** by **Zhifeng Jiang**

27 May 2024

香港科技大學
THE HONG KONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

Advisor: **Wei Wang**

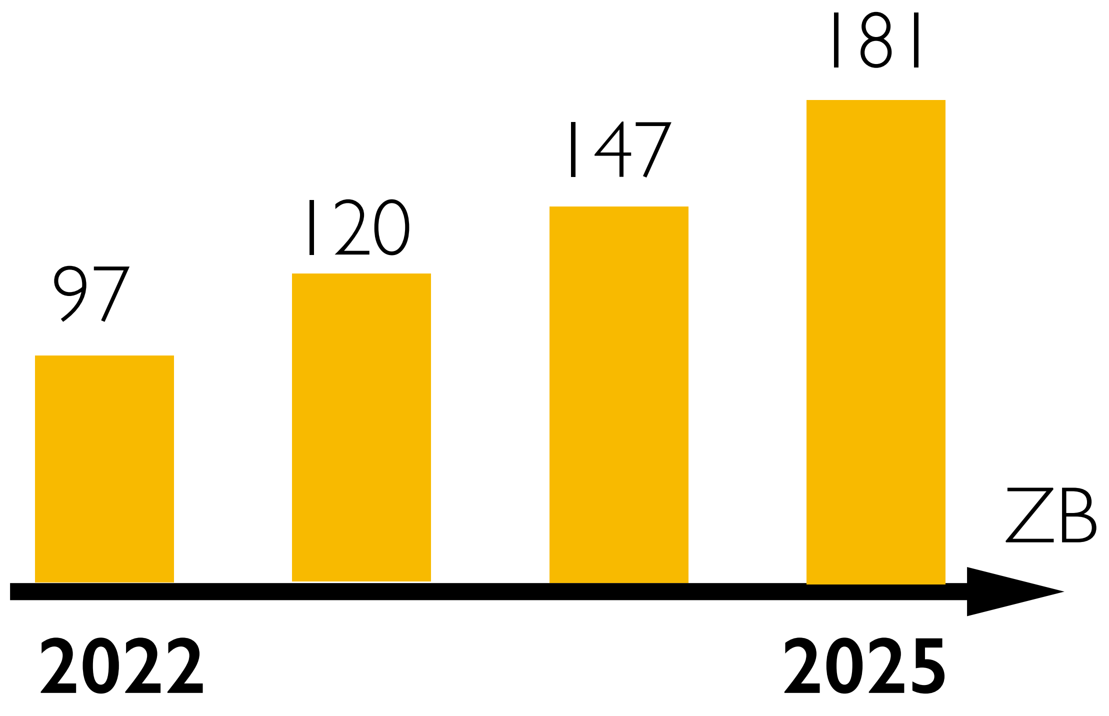
Chairperson: **Yi-Min Lin** (SOSC)

Committee: **Mo Li**, **Shuai Wang**, **Jun Zhang** (ECE), **Cong Wang** (CityU)

# Growth of edge computing

Edge devices generate
massive **data**

**Generated data volume**[1]

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Increasing **resource** on edge devices

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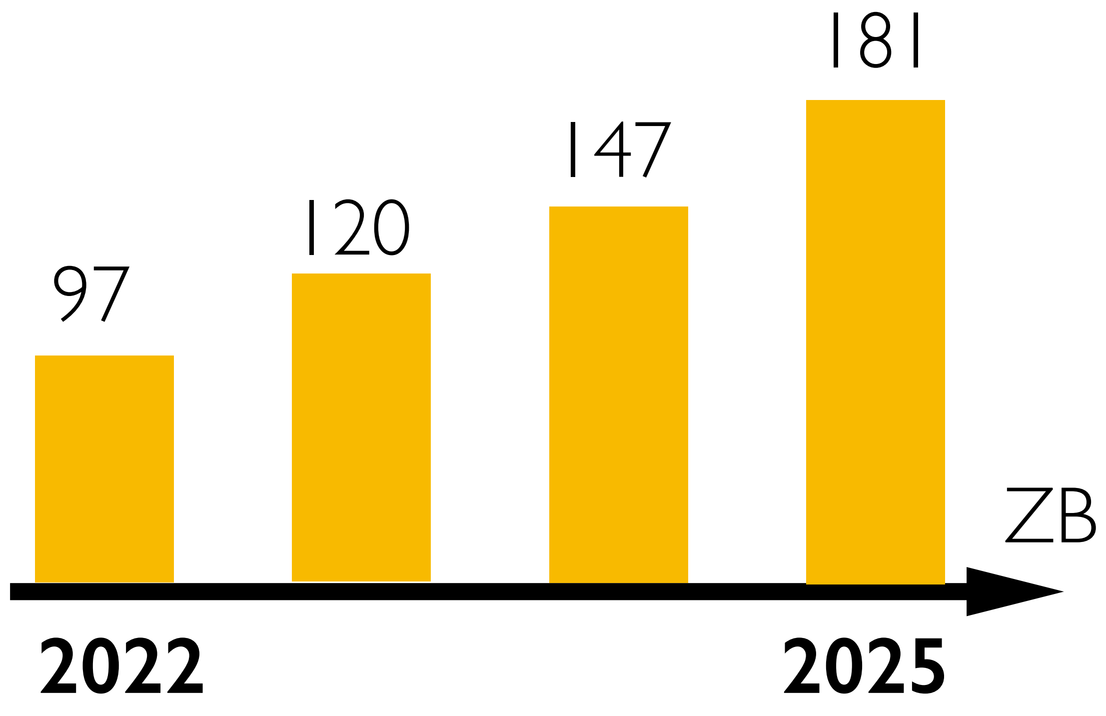


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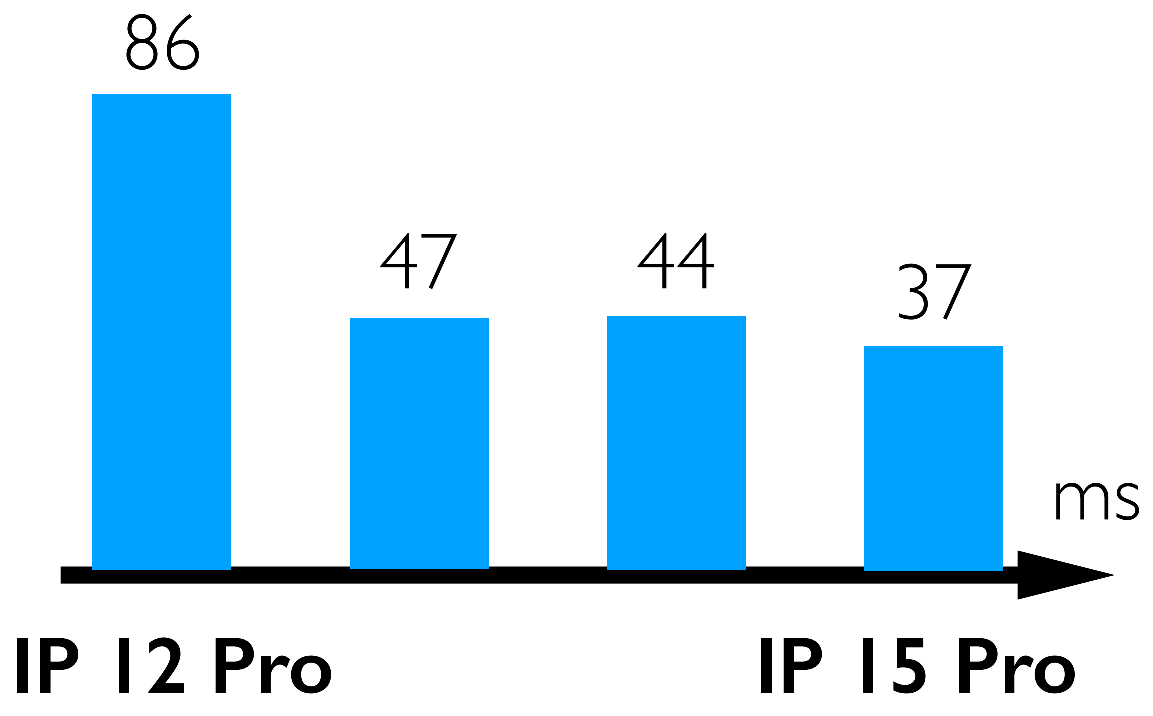
**Inference time**[2]

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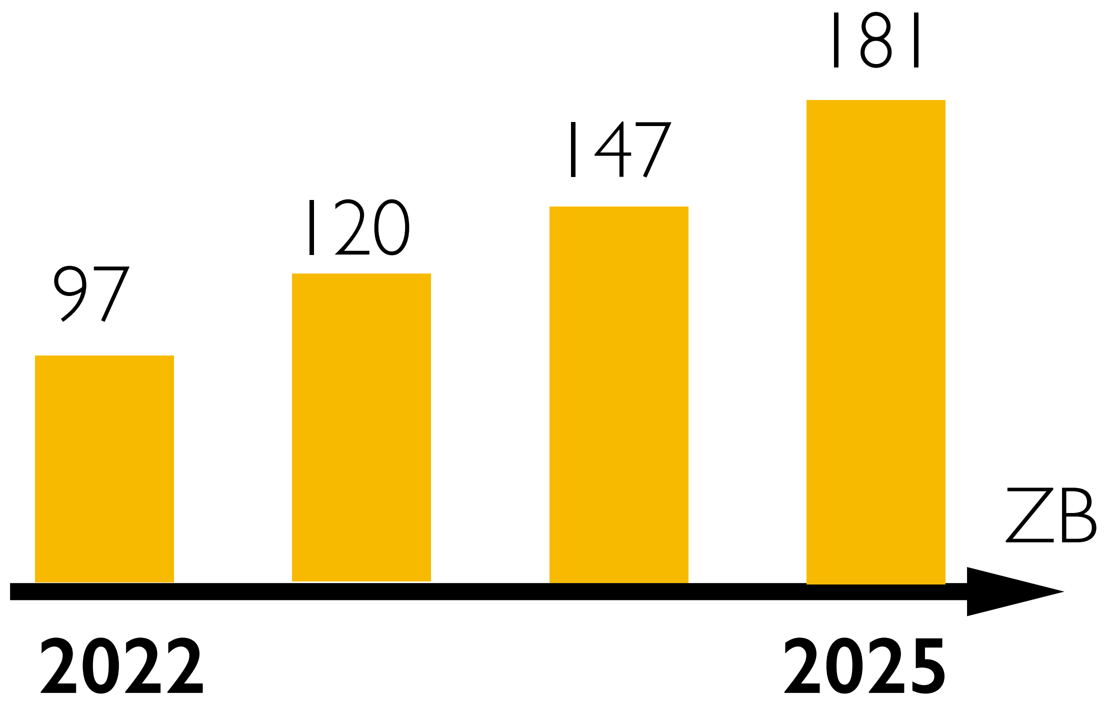


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Increasing **resource** on
edge devices

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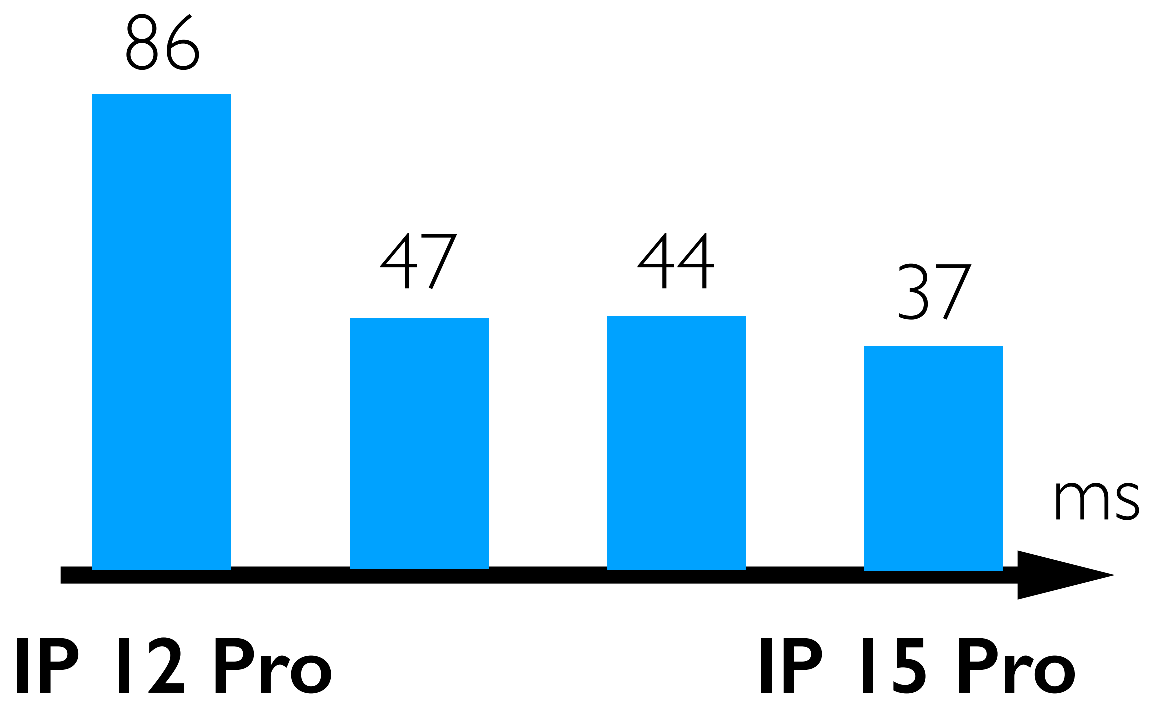
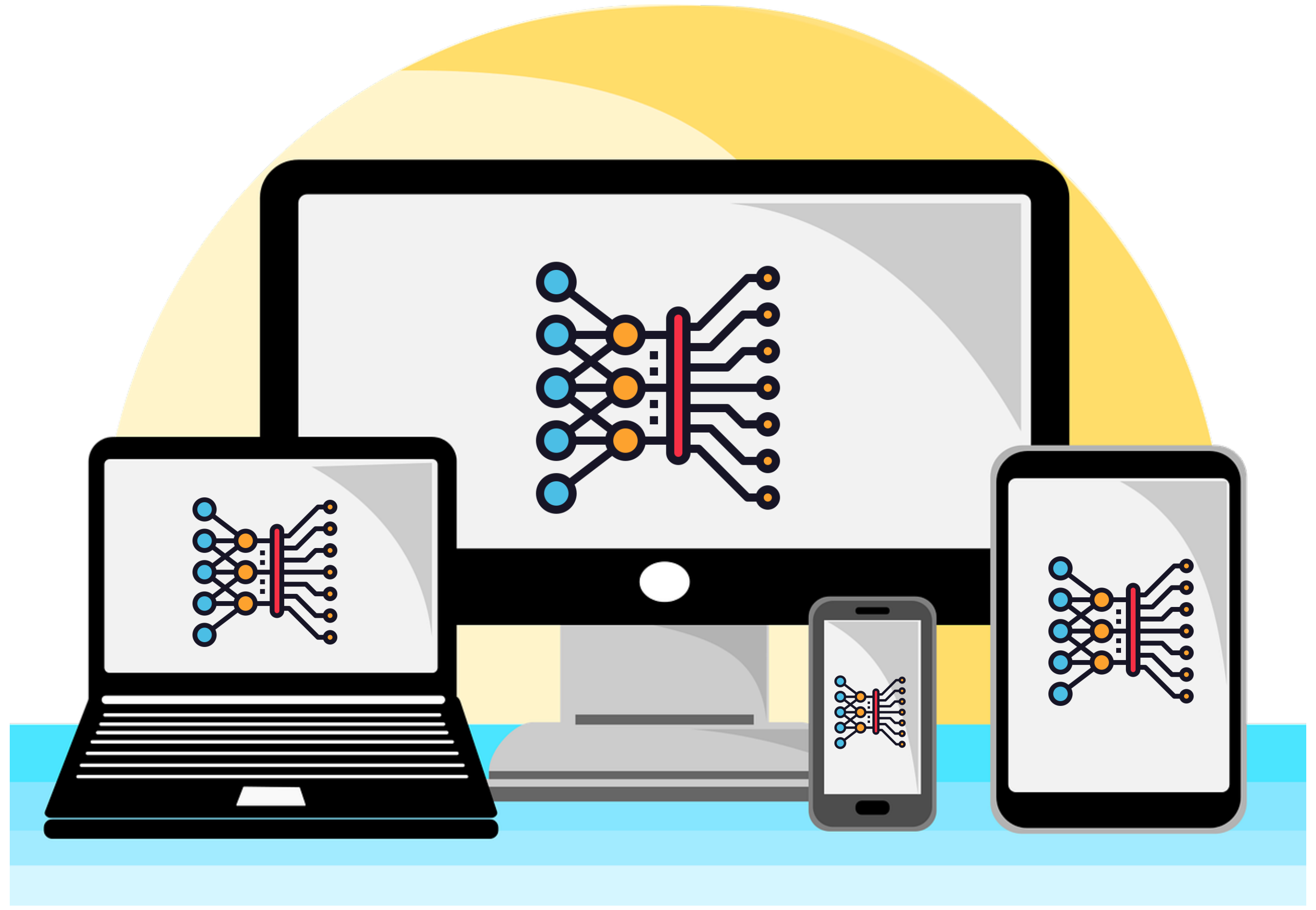



**machine learning**
driven to the edge



[1] Exploding topics blog, "Amount of Data Created Daily (2024)", 2023
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# Private learning on the edge

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| **Privacy Guarantee** | Data kept on premises |

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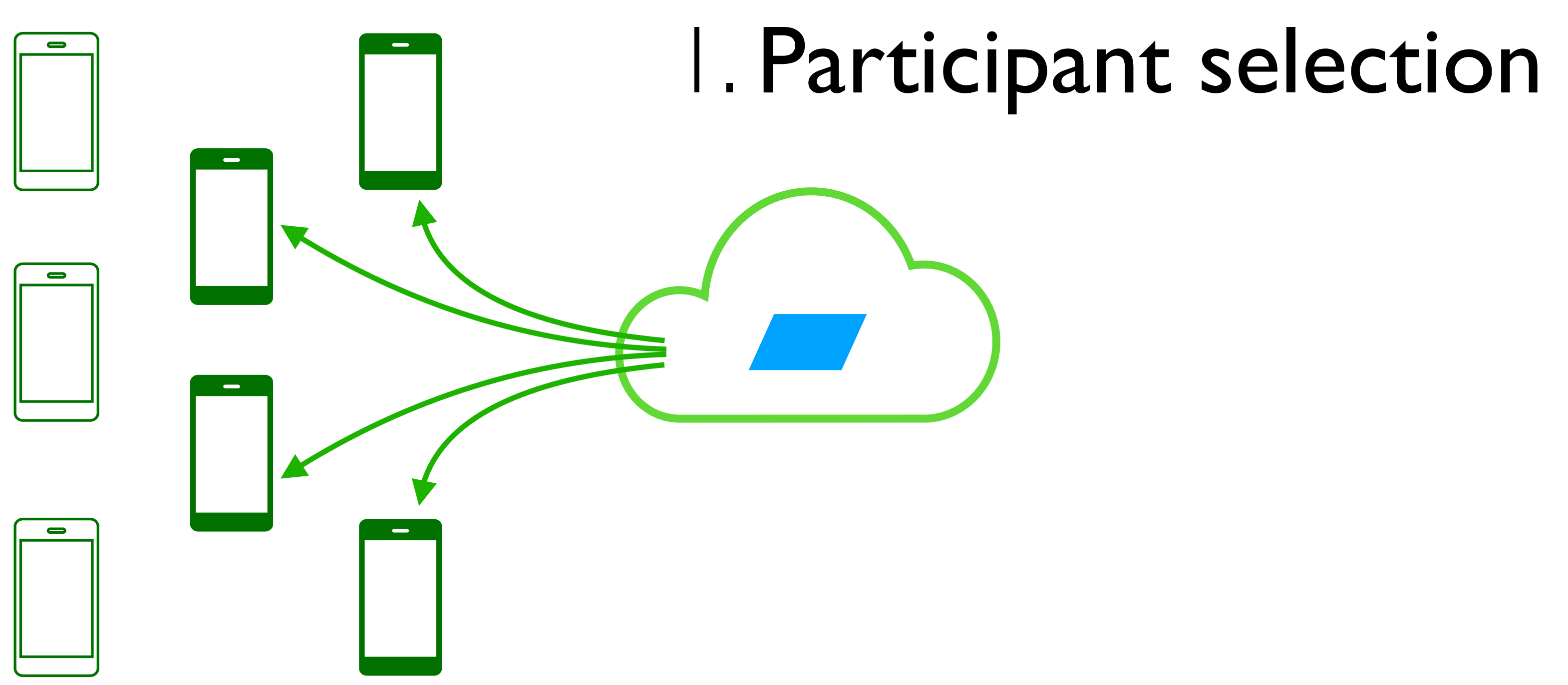


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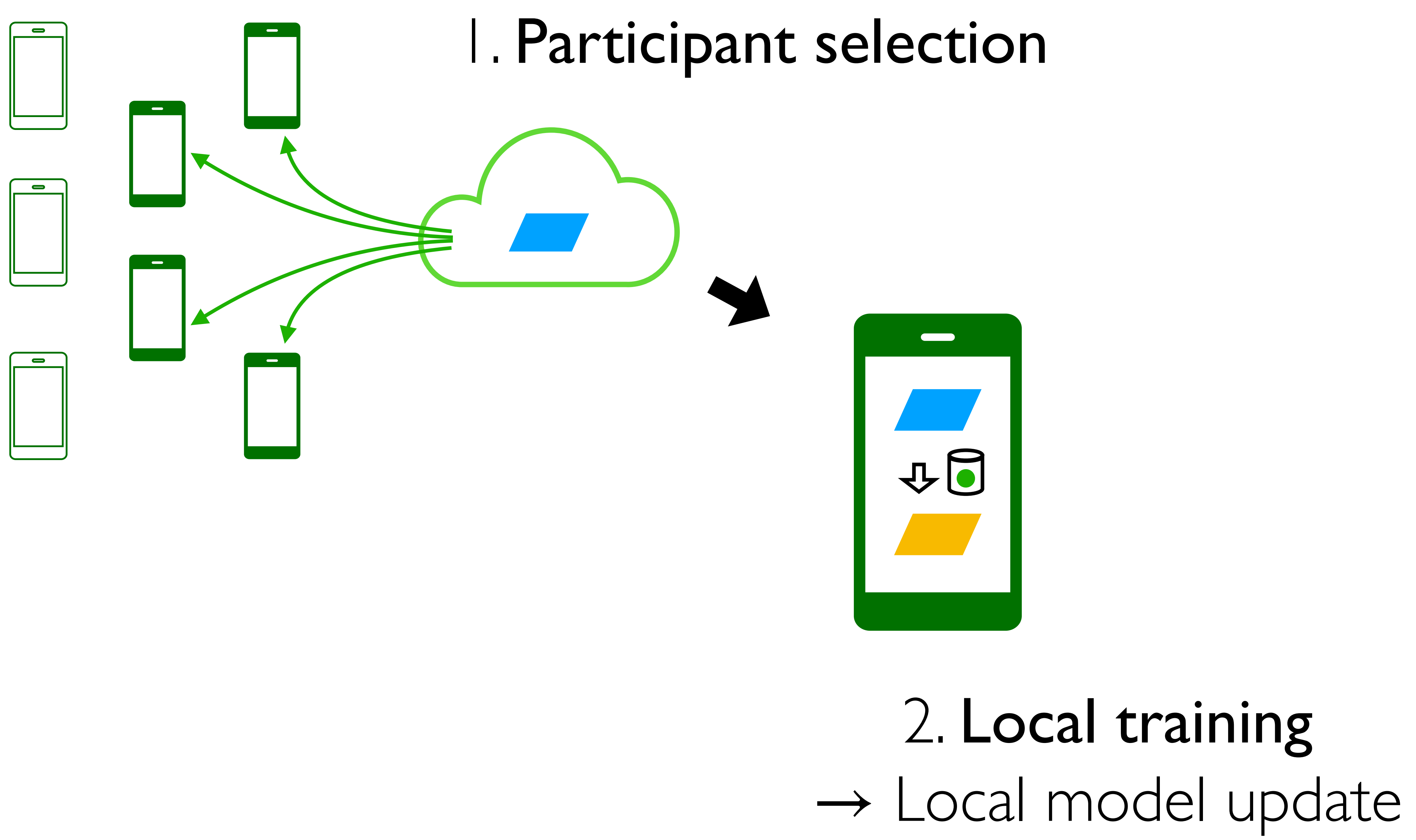


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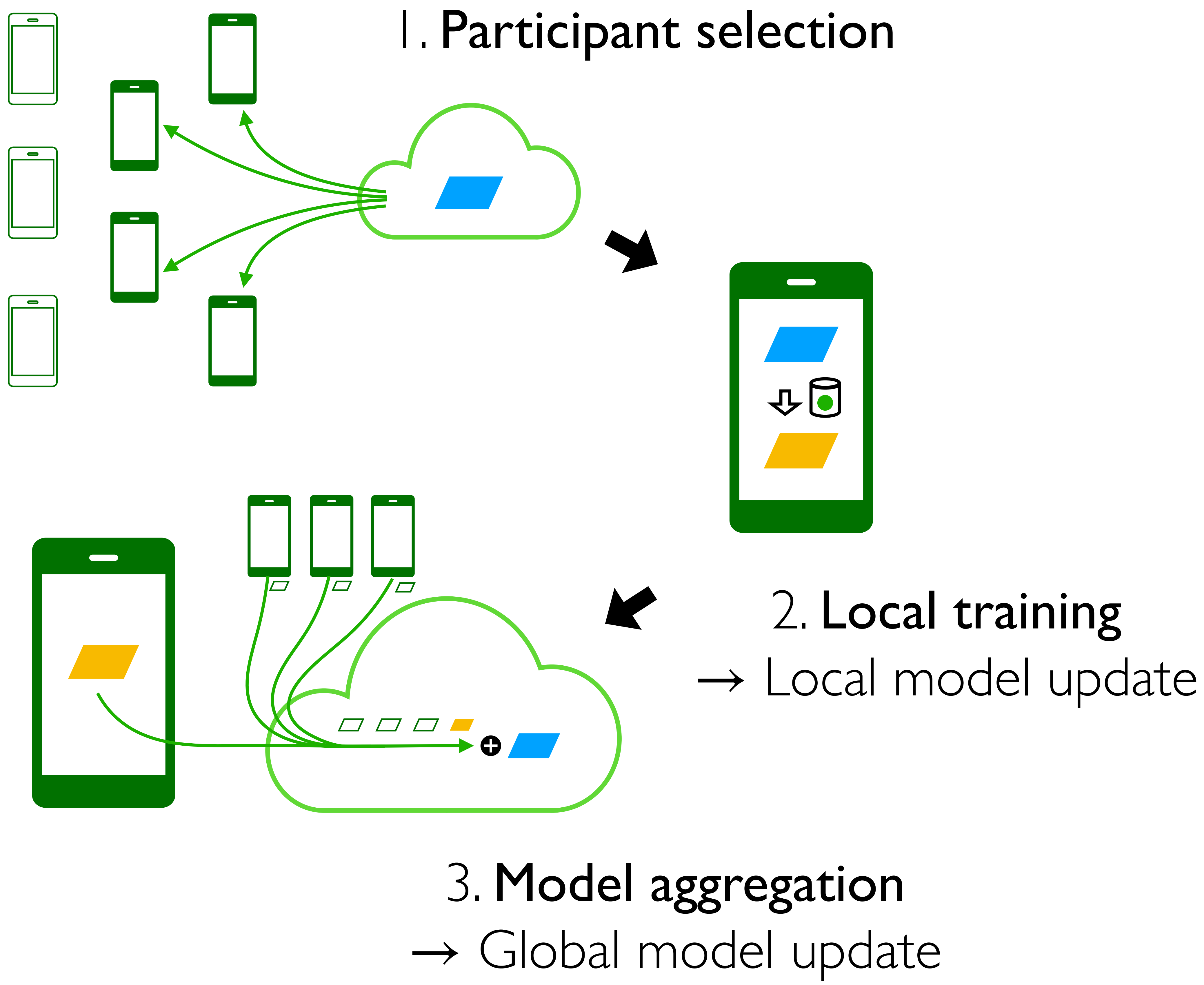


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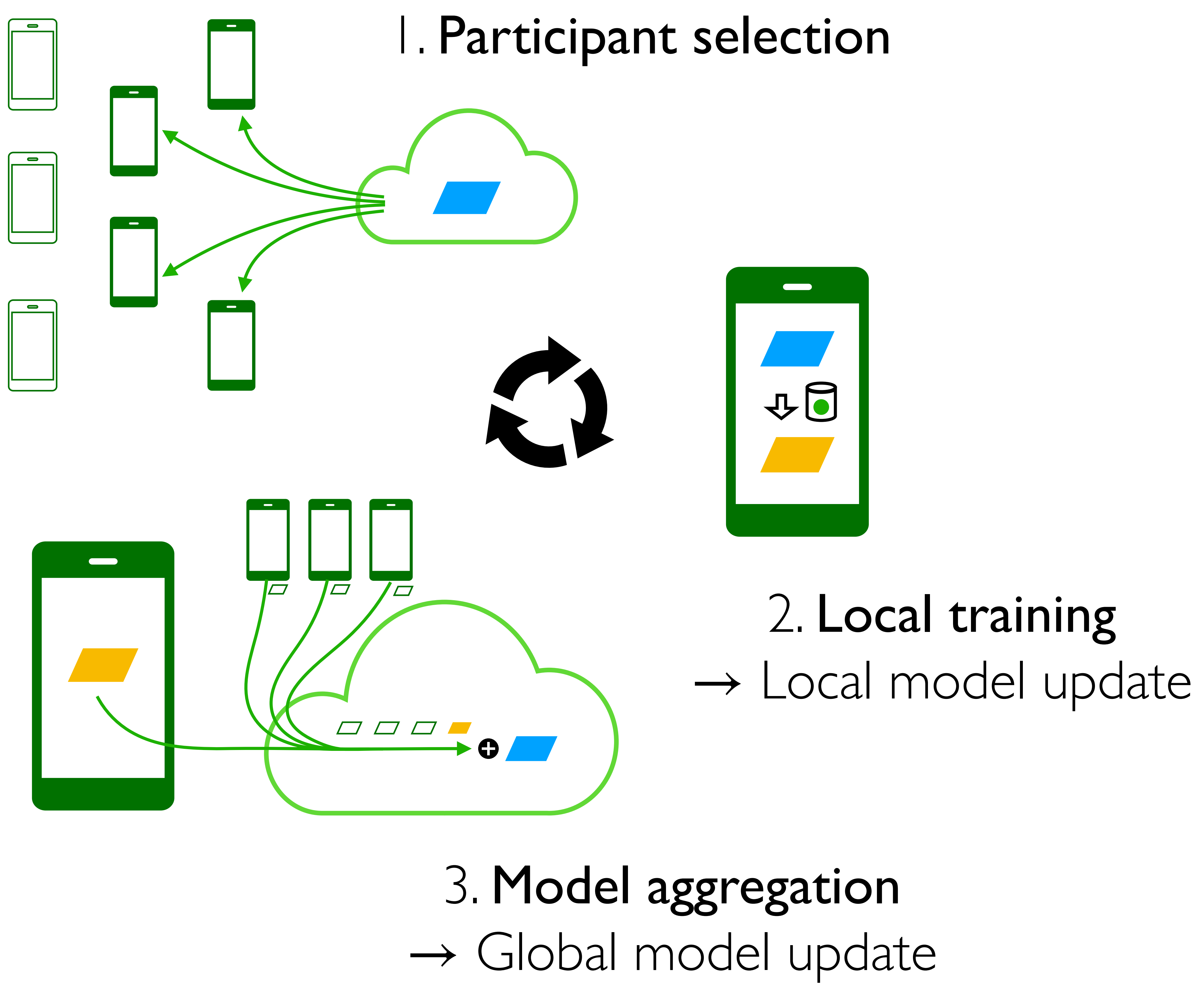


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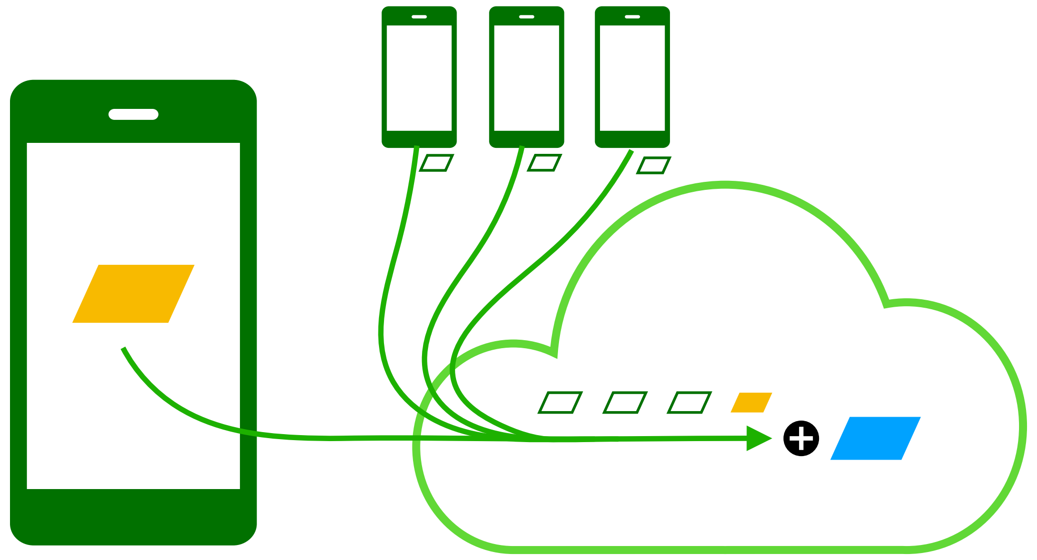

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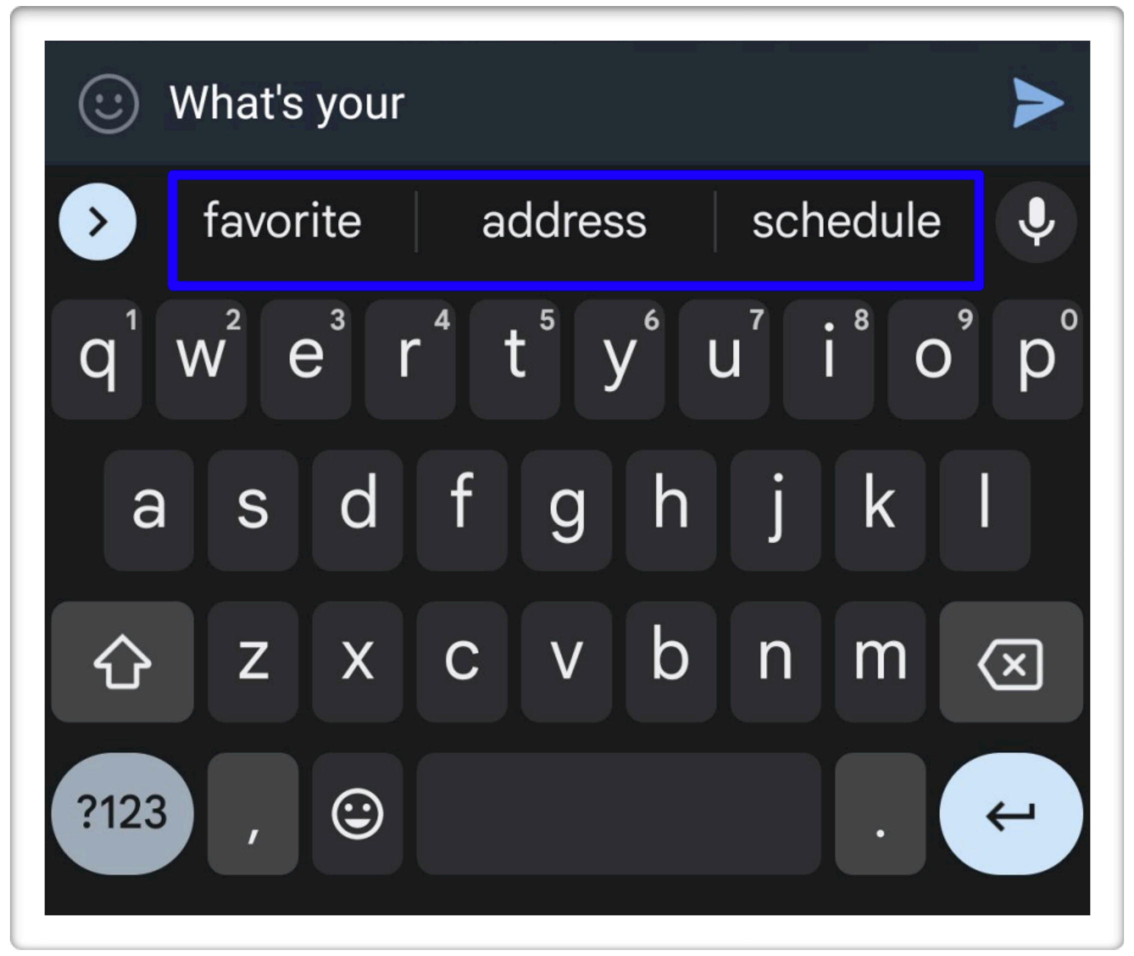


**Real application:**
Google's Keyboard

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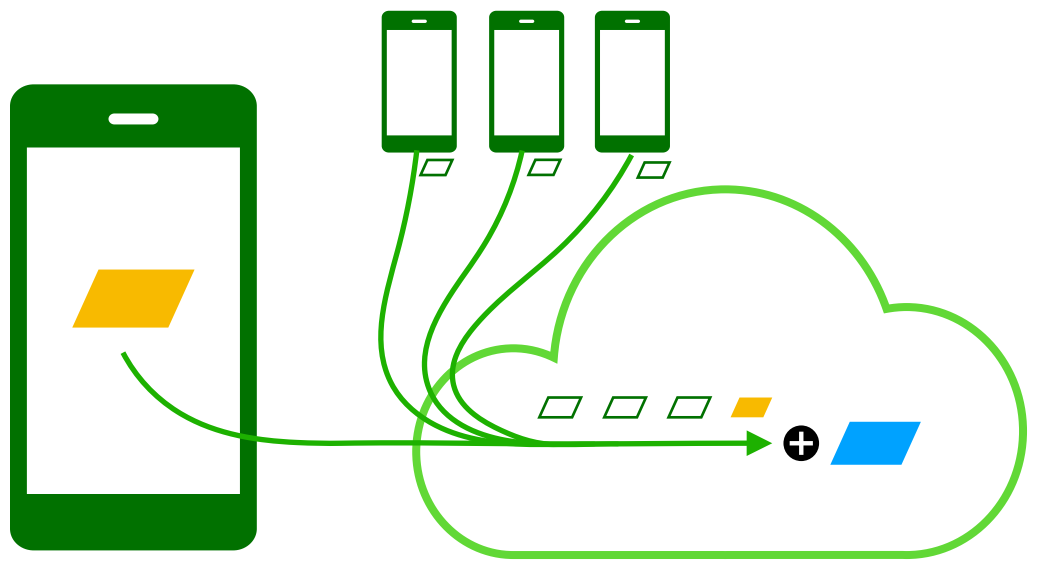

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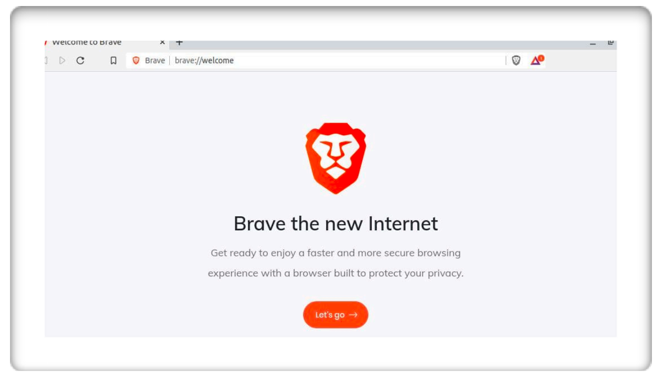


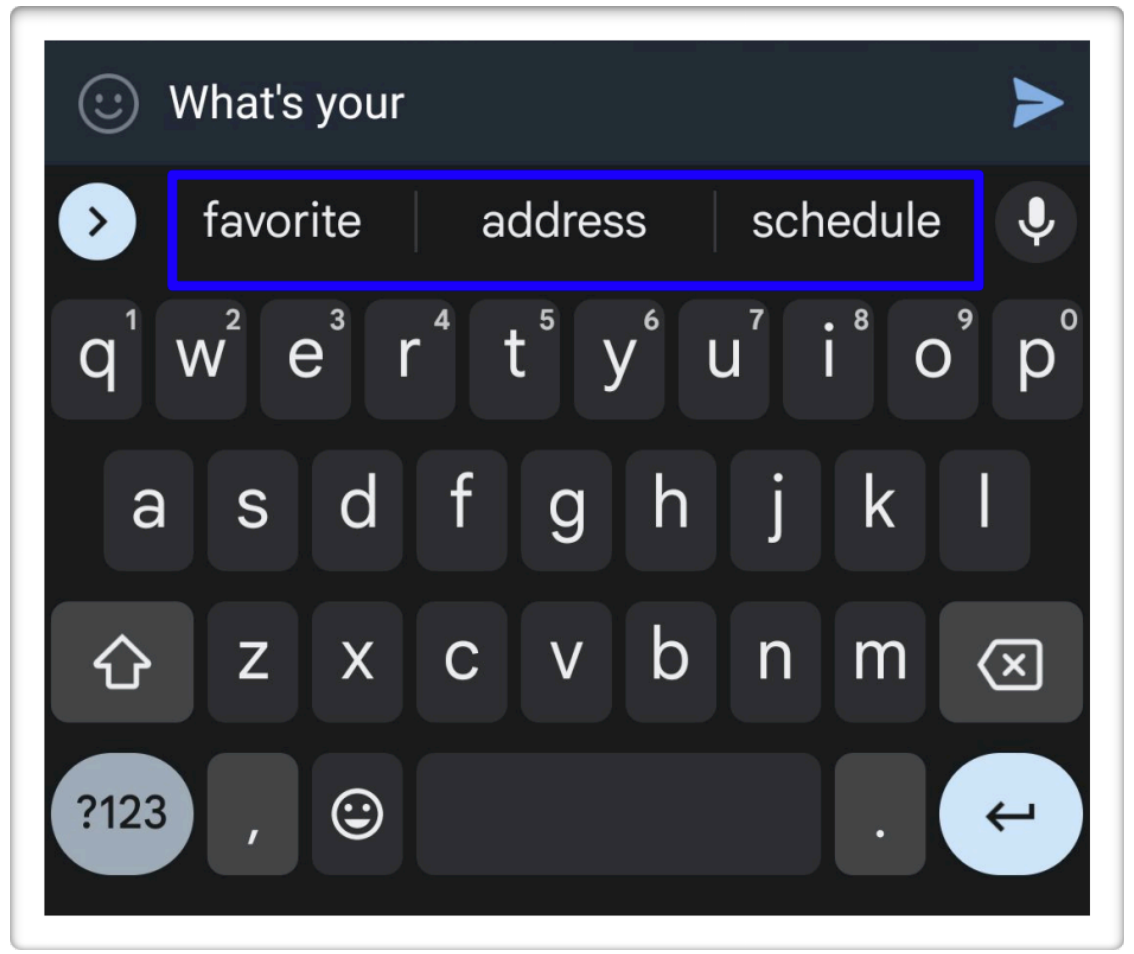


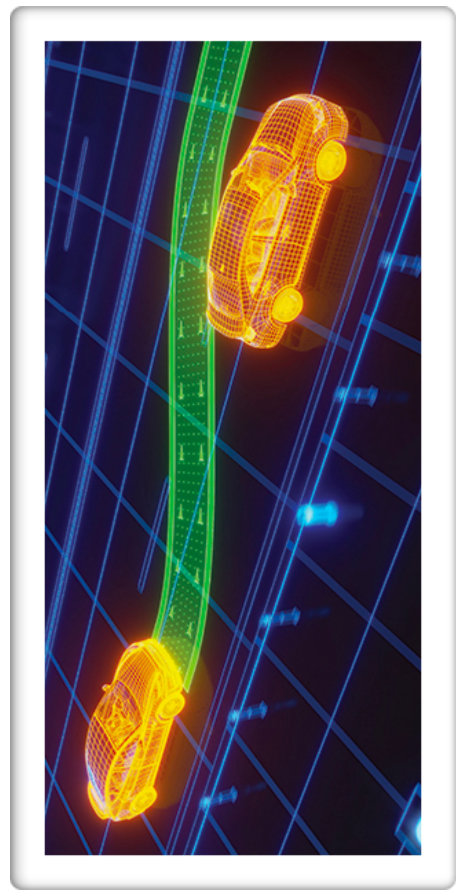

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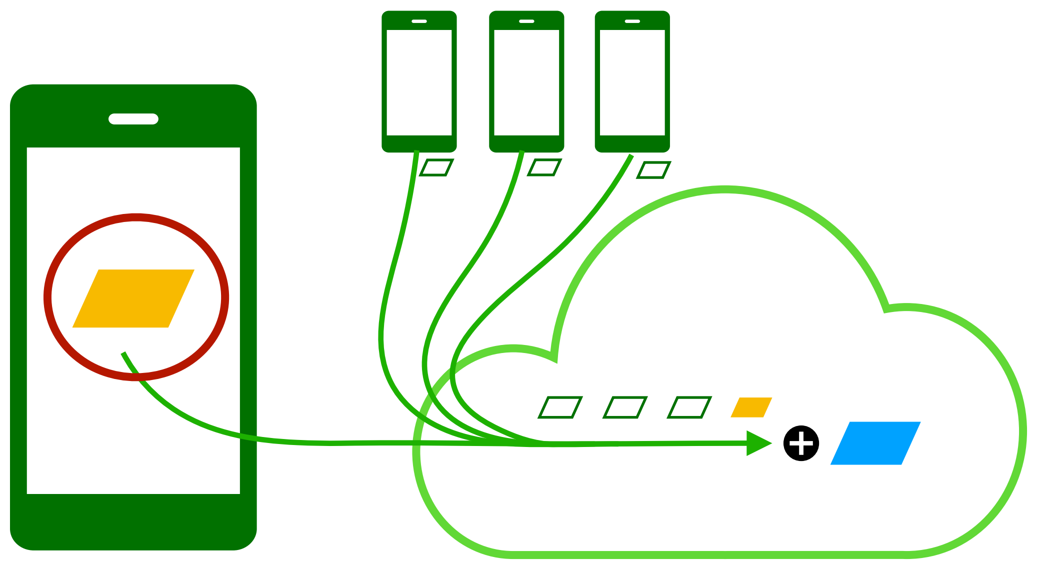

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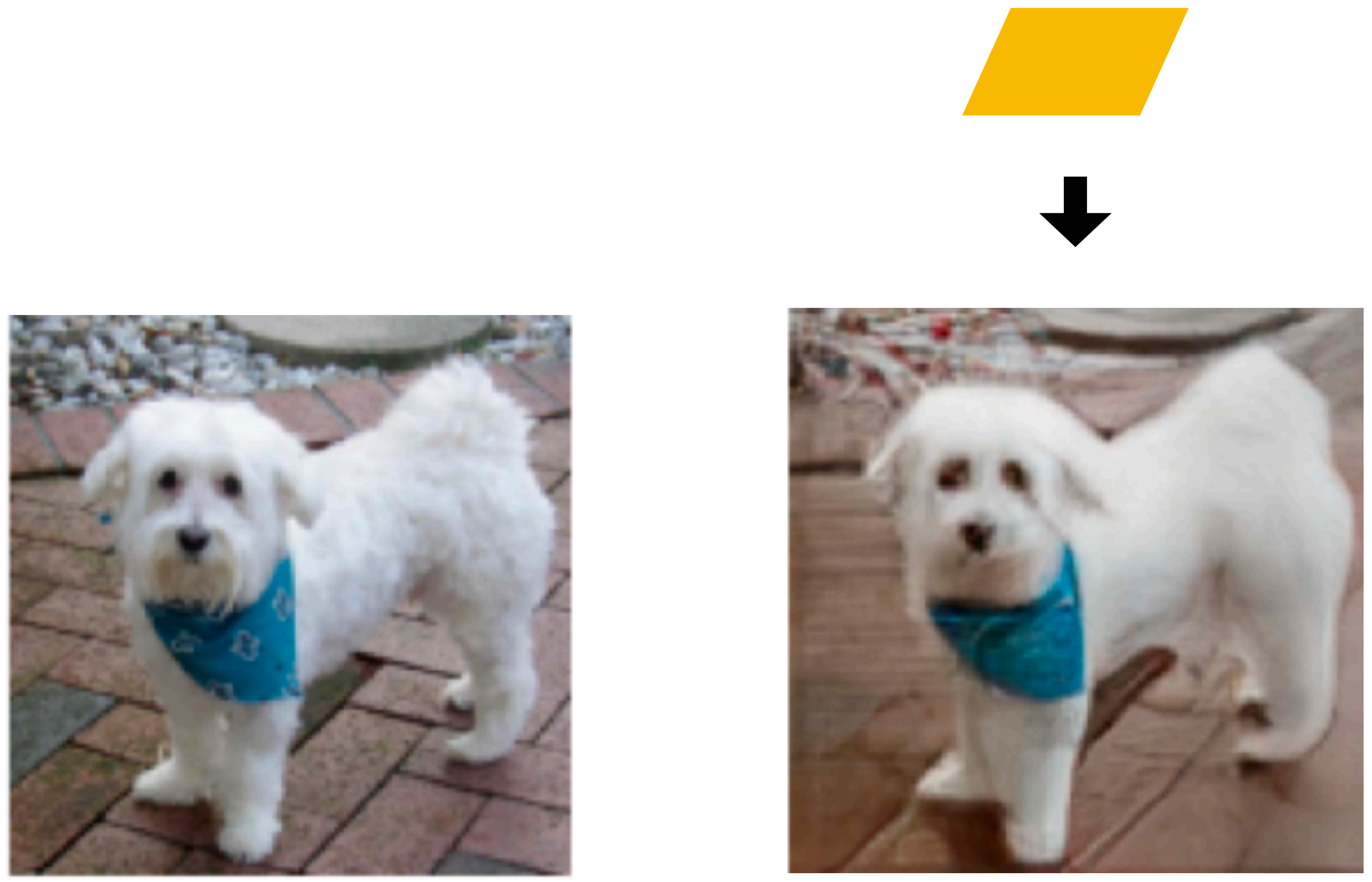

Ground truth | Reconstructed

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

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[2]Yue et al. "Gradient Obfuscation Gives a False Sense of Security in Federated Learning", In Security '23

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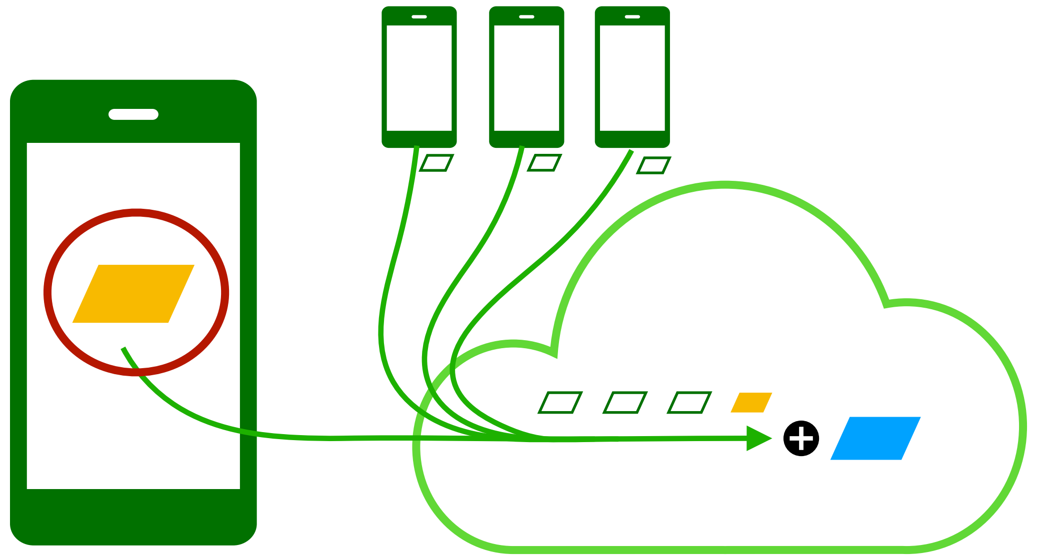

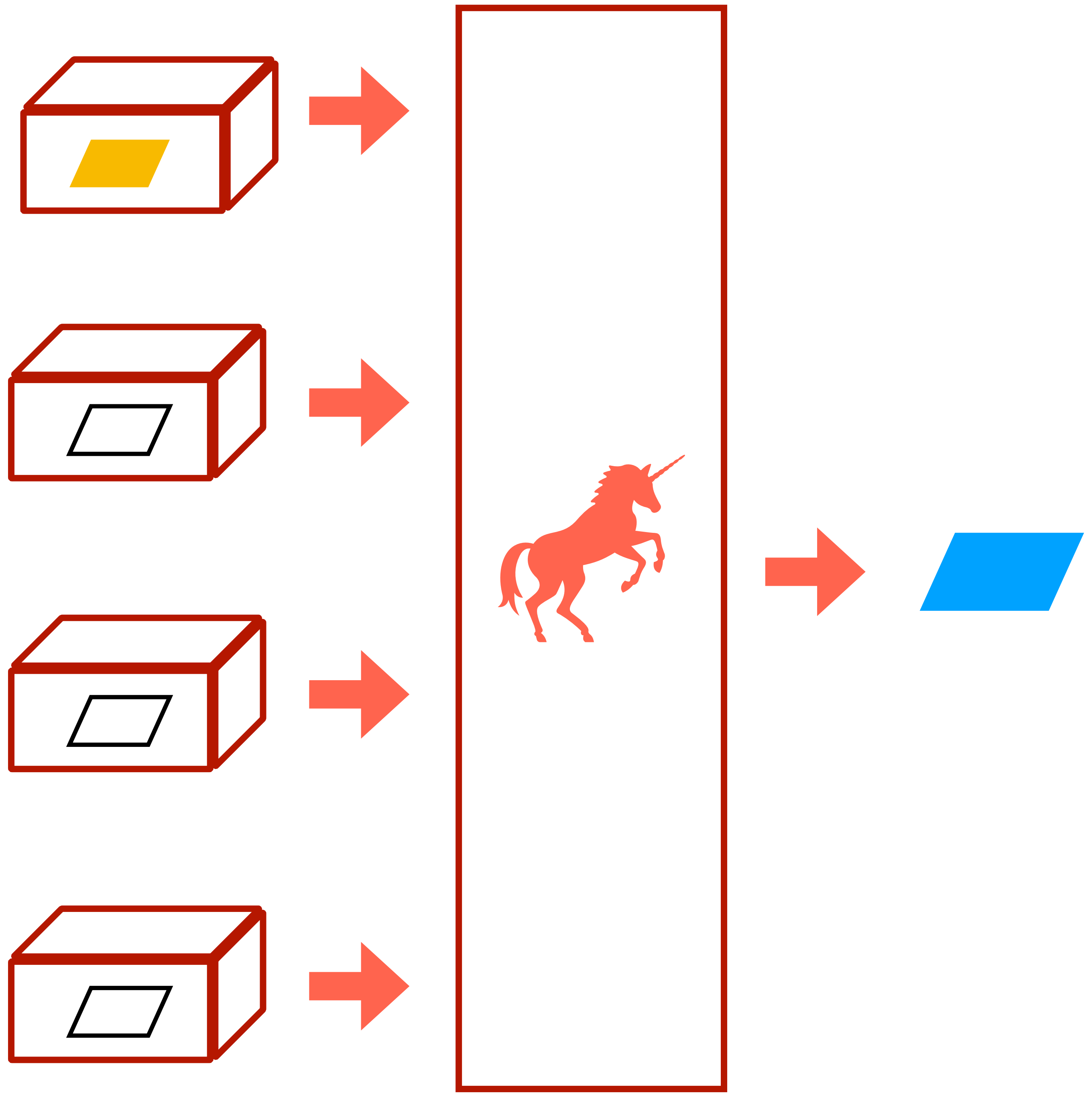

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| **Privacy-Enhancing Technique** | Federated Learning[1] | Secure Aggregation[3,4] |
| **Privacy Guarantee** | Data kept on premises | Local updates unseen |

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[3]Bonawitz et al. "Practical Secure Aggregation for Privacy-Preserving Machine Learning", In CCS '17
[4]Bell et al. "Secure Single-Server Aggregation with (Poly) Logarithmic Overhead", In CCS '20

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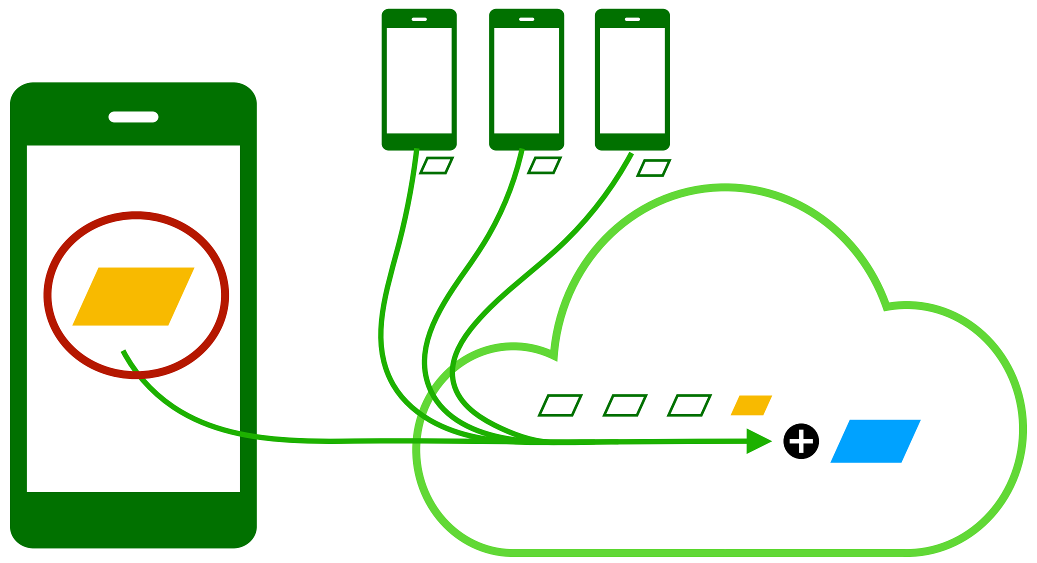

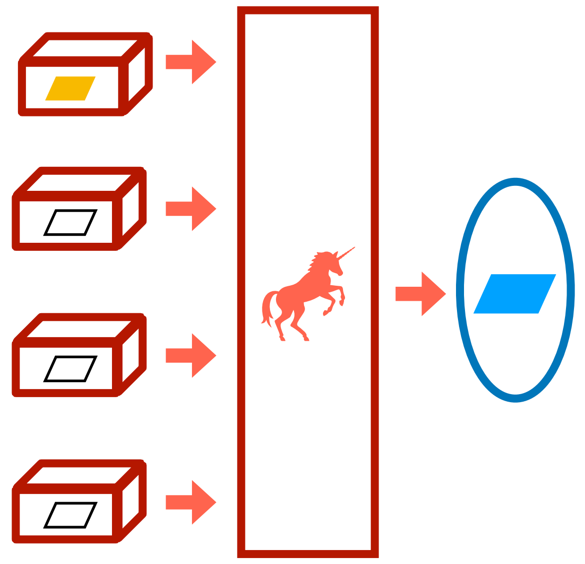

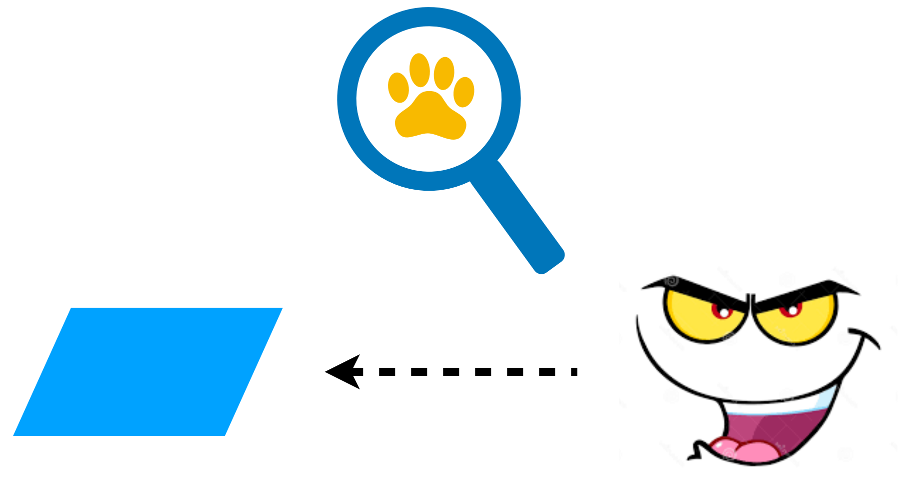

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**Problem**: Data still has footprints in **global model update**[5]

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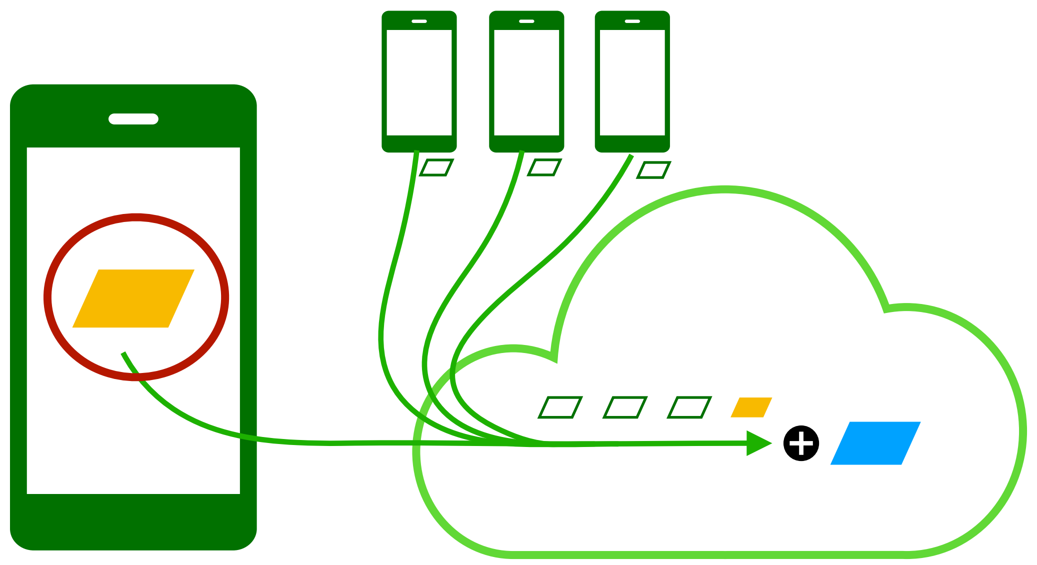
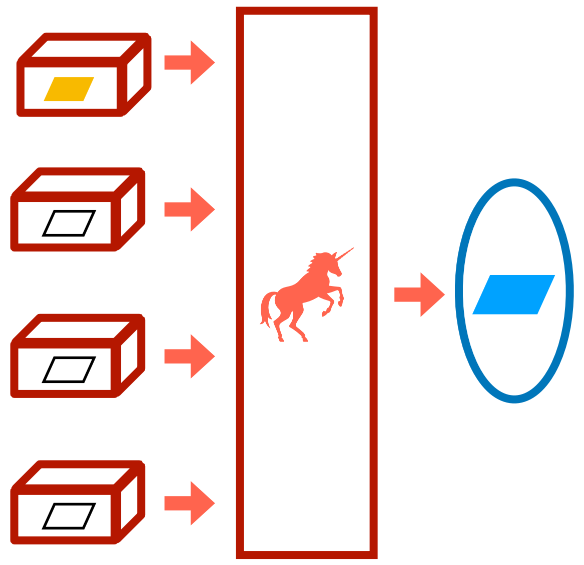
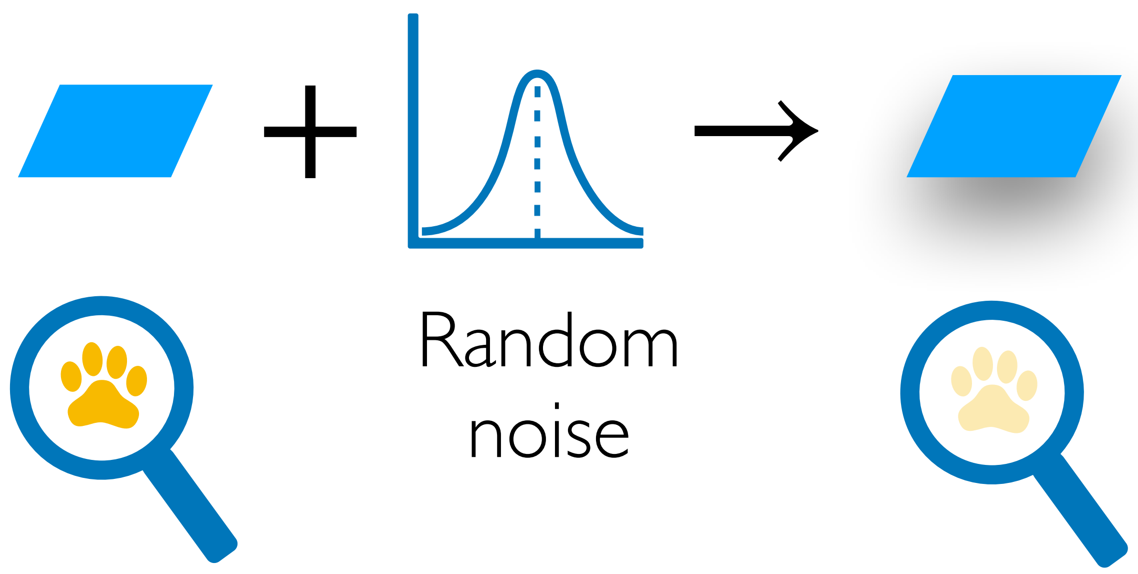
[5]Nasr et al. "Comprehensive Privacy Analysis of Deep Learning: Passive and Active White-box Inference Attacks against Centralized and Federated Learning", In S&P '19

# Private learning on the edge








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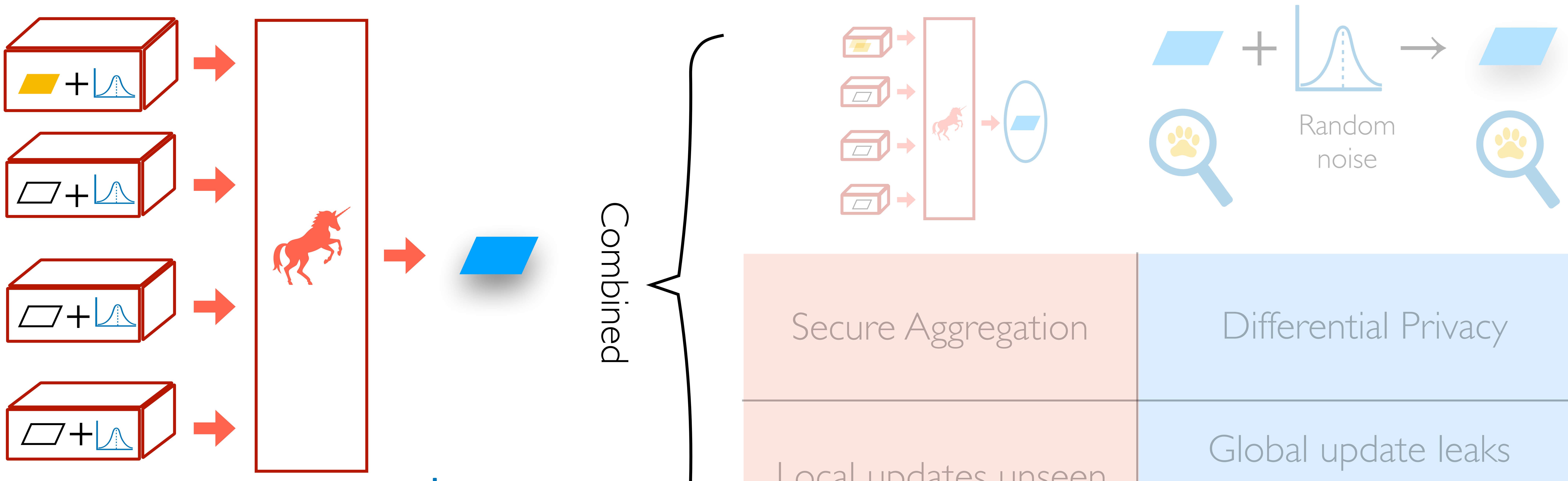
[6]Cynthia. "Differential Privacy", 06.

# Private learning on the edge




| Secure Aggregation | Differential Privacy |
| --- | --- |
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**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

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# My Research

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|---|---|---|---|
| | Stragglers bottleneck time | Primitives heavy in comp. and comm. | Client dropout yields insufficient noise |
| **Privacy-Enhancing Technique** | Federated Learning | Secure Aggregation | Differential Privacy |
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# My Research

Can be a dishonest majority ⟷ Only or mostly works with honest participants

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# My Research

**Privacy**
Worst-case defense…

Can be a dishonest majority x ↔ Only or mostly works with honest participants

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| **Efficiency**<br>Time-to-accuracy… | Stragglers bottleneck time | Primitives heavy in comp. and comm. | Client dropout yields insufficient noise |
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# First work: Pisces[1]

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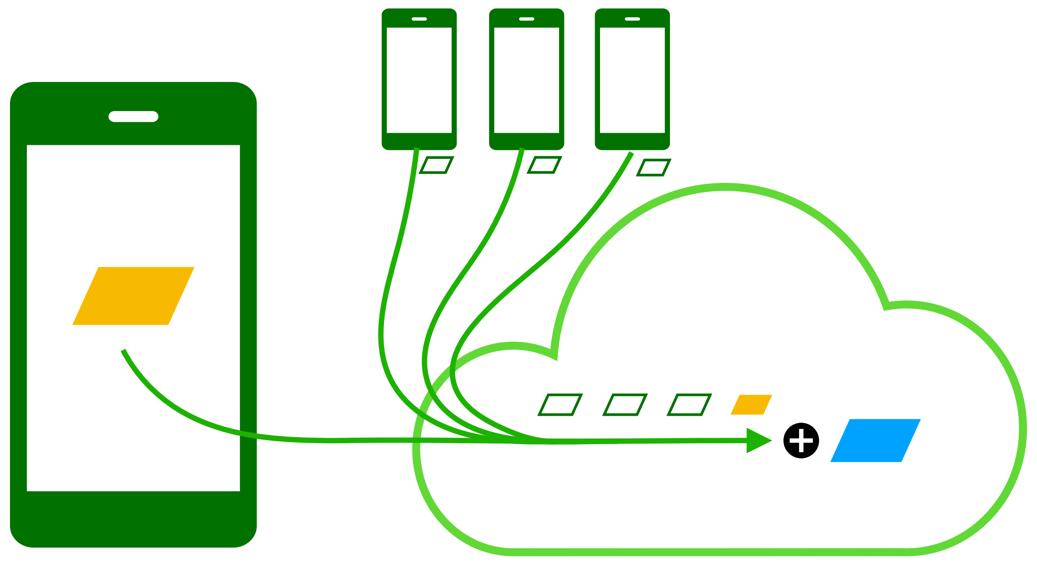
[1] Jiang et al. "Pisces: Efficient Federated Learning via Guided Asynchronous Training", In SoCC '22

# Need for Pisces



Synchronous

Federated Learning

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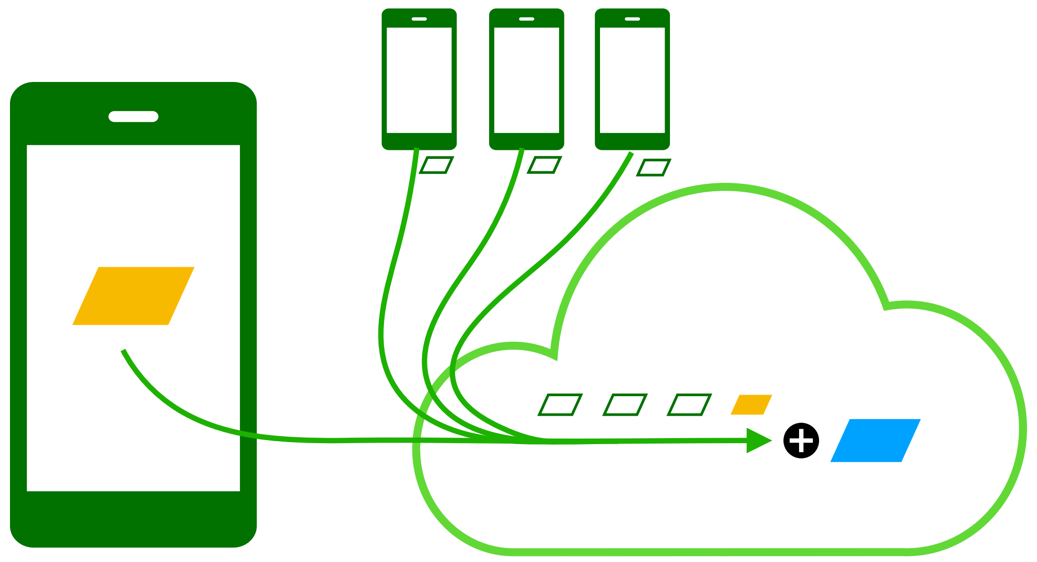

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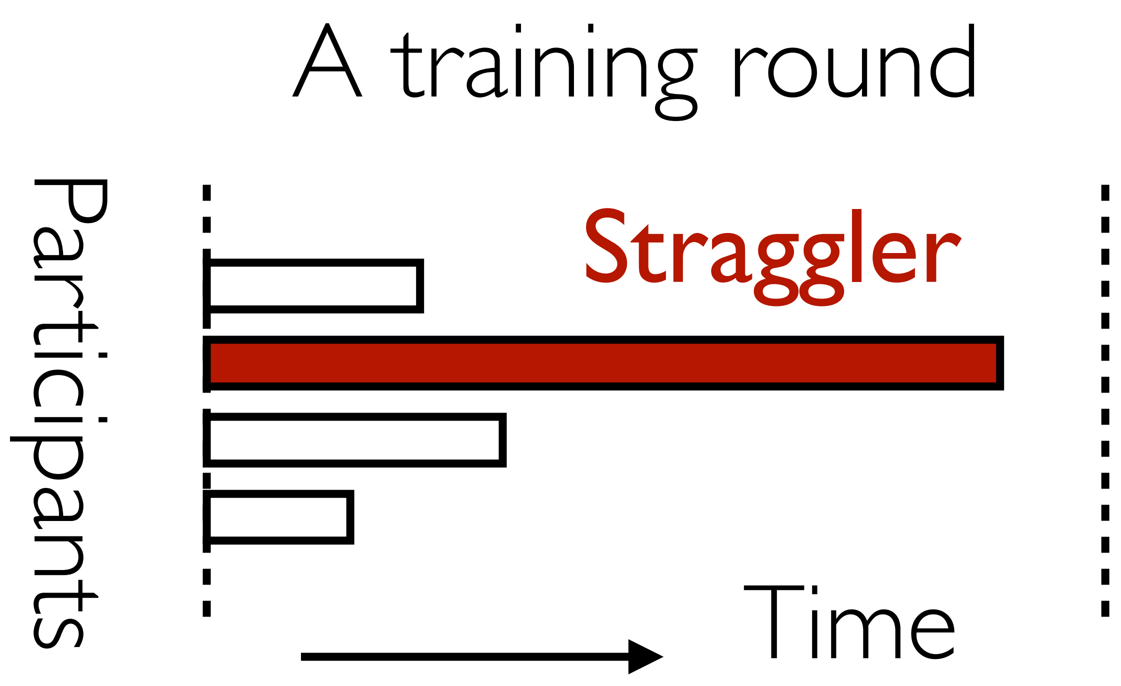


Federated Learning

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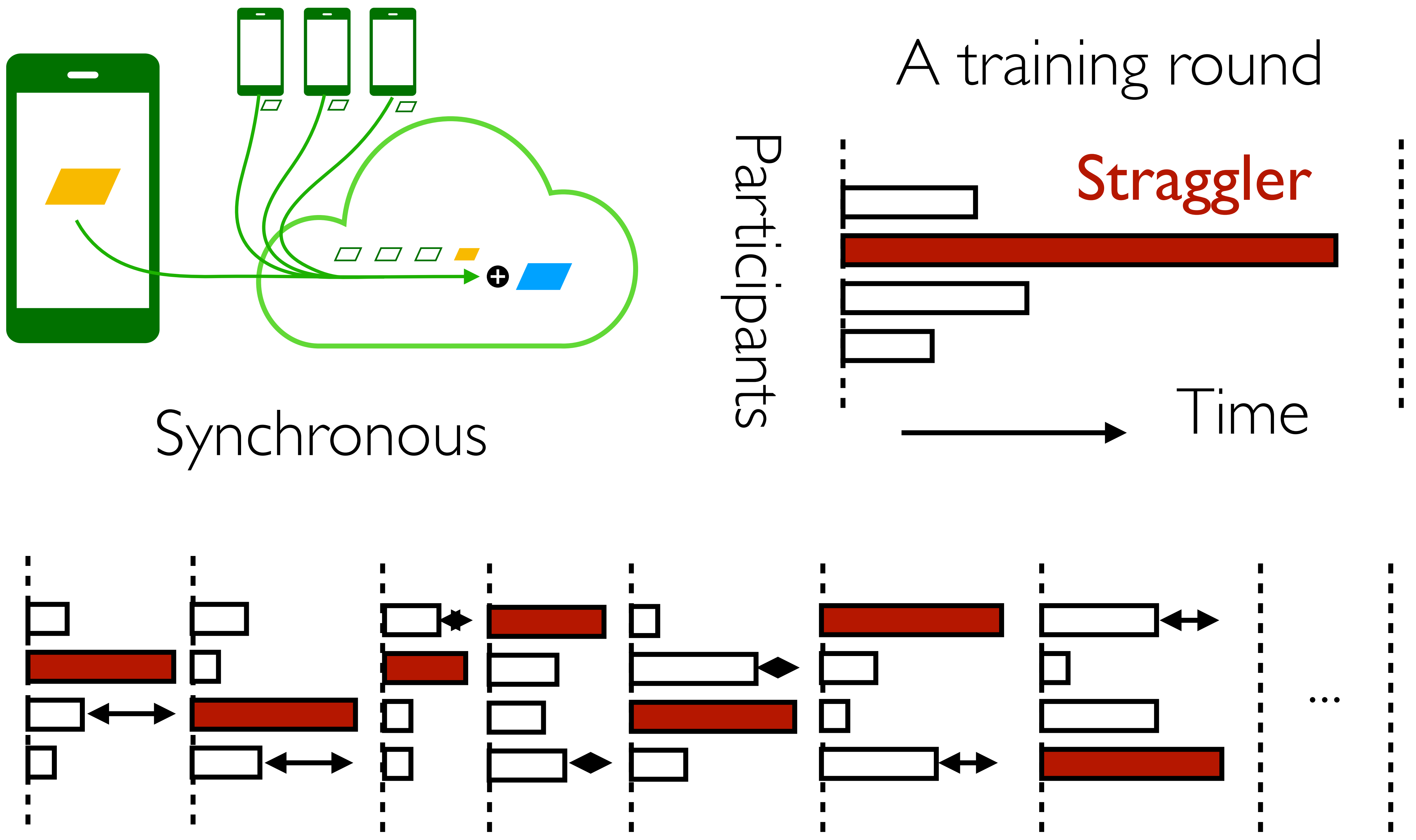


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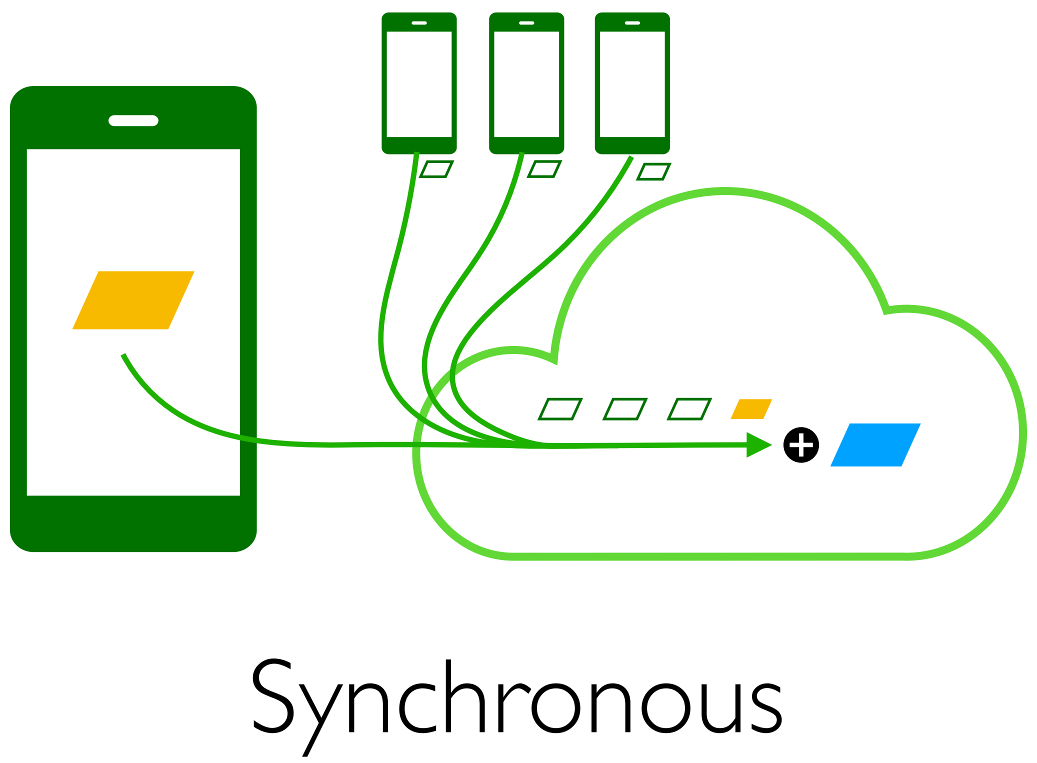


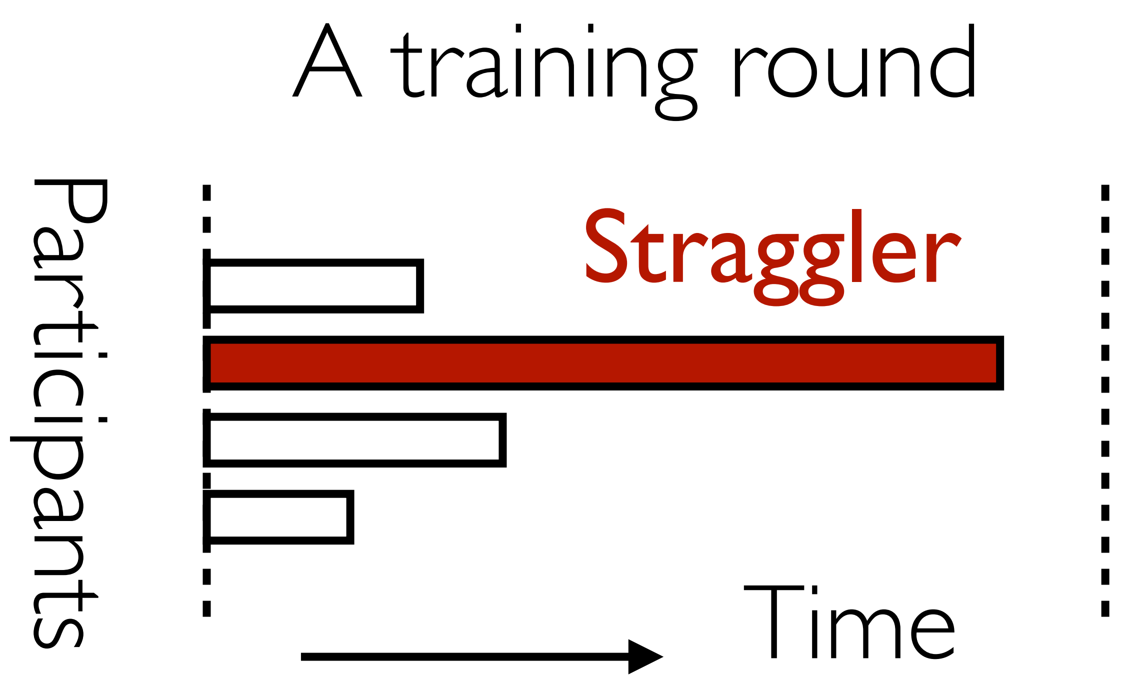


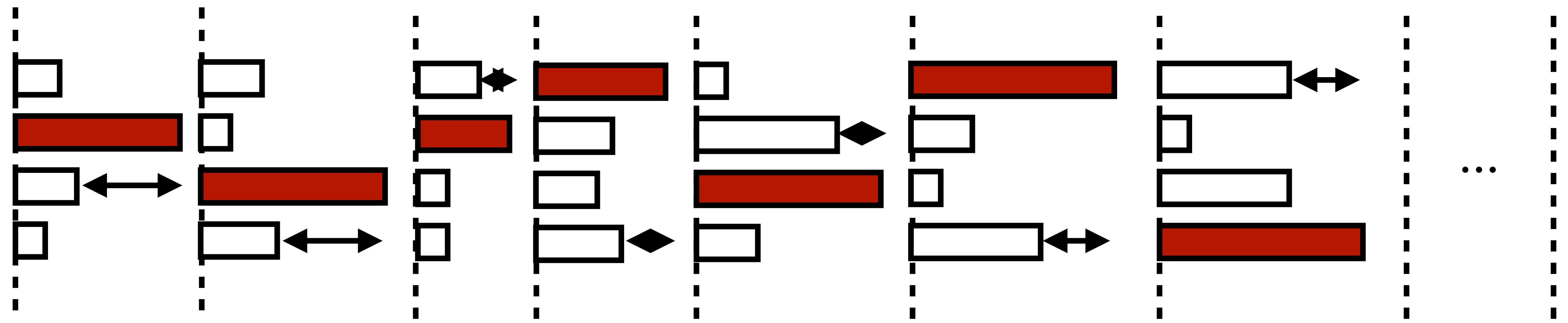


**Idle waiting**: 33.2% to 57.2%

Federated Learning

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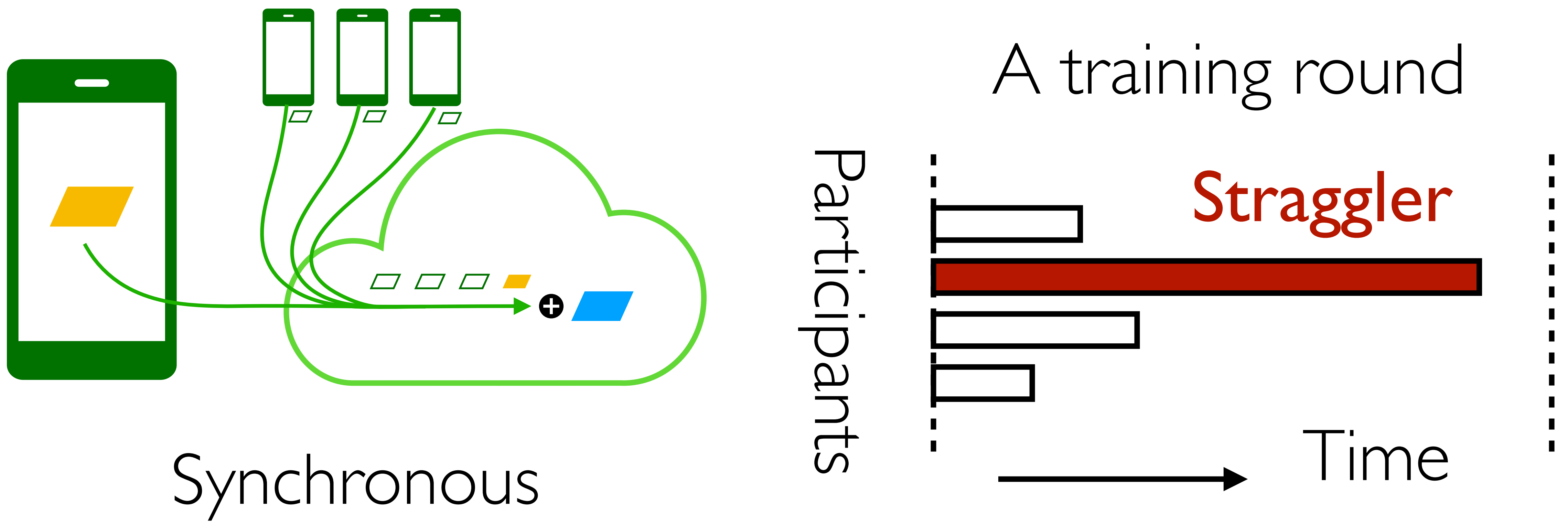


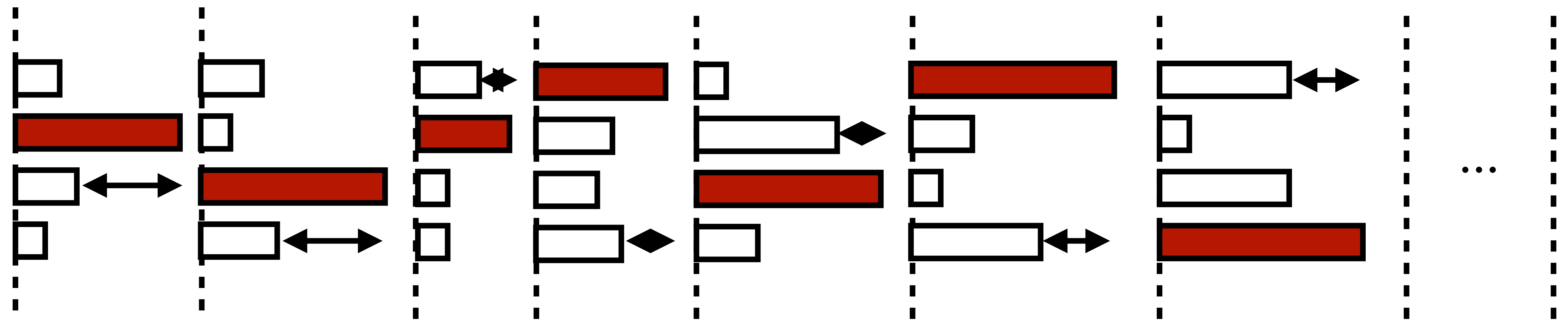

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Federated Learning

**Potential approach**:

- Prioritize fast clients in selection

Time-to-accuracy = mean round time × # rounds

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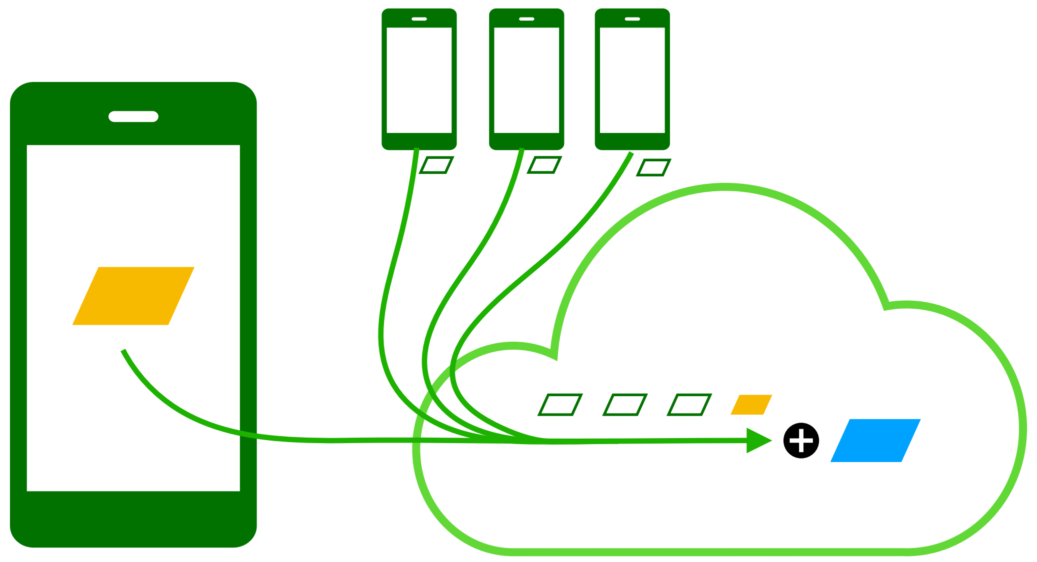
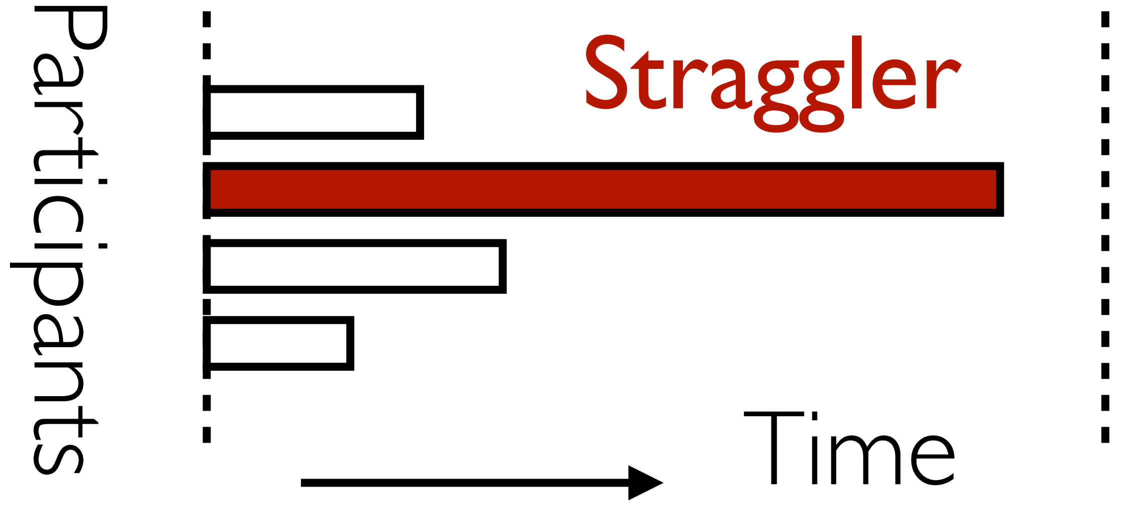
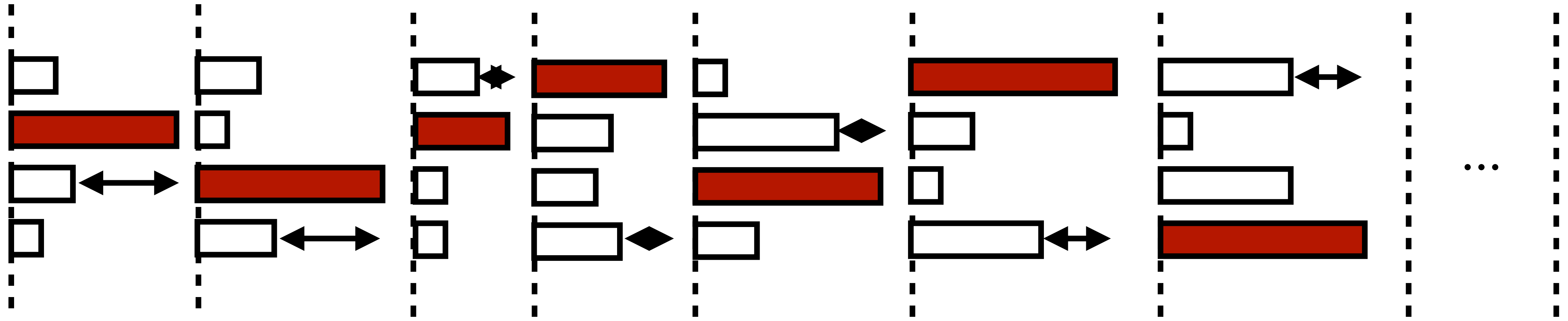


Synchronous

A training round

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Federated Learning

**Potential approach**:

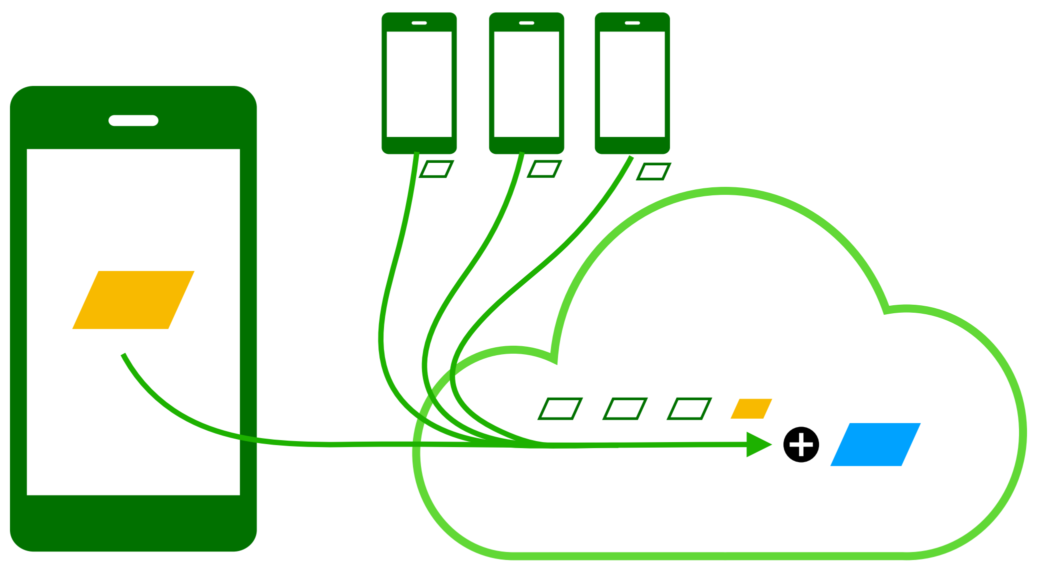
- Prioritize fast clients in selection

Selected clients have bad data quality…

Time-to-accuracy = mean round time × # rounds

?

# Need for Pisces



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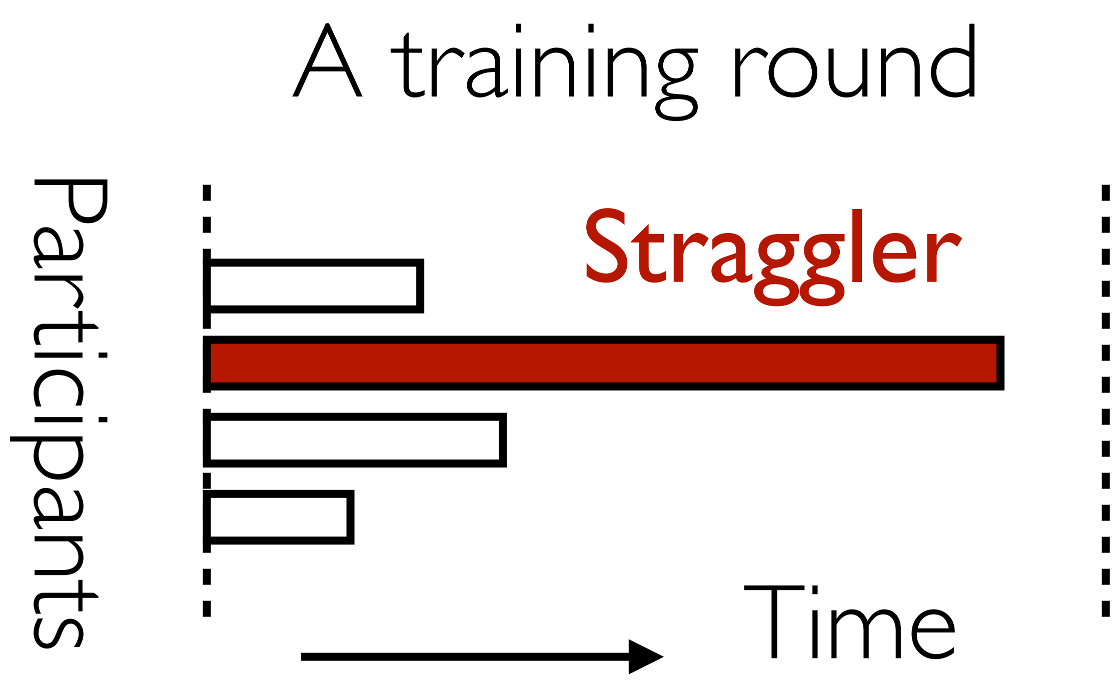


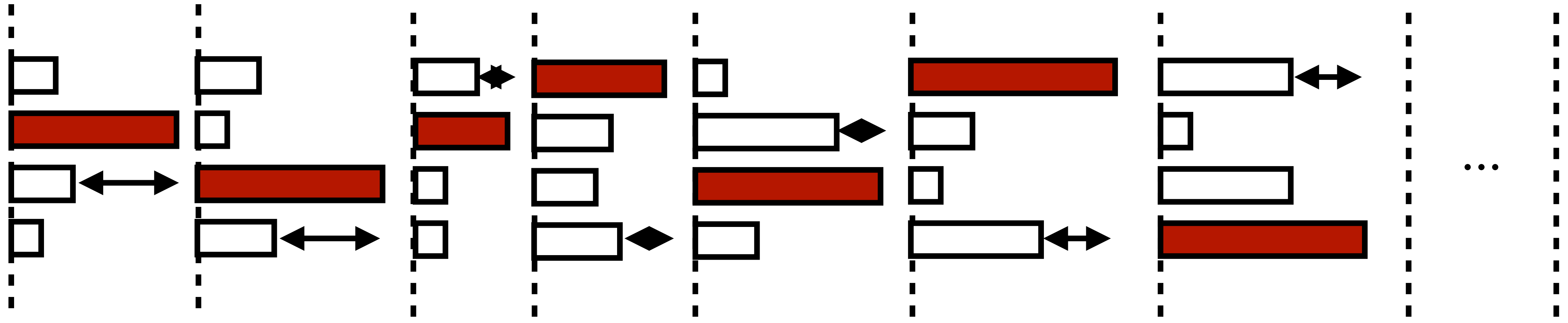


**Idle waiting**: 33.2% to 57.2%

Federated Learning

**Potential approach**:

- Prioritize fast clients in selection
- Also consider their data quality

Time-to-accuracy = mean round time × # rounds

# Need for Pisces

**SOTA - Oort**[1]

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

# Need for Pisces

**SOTA - Oort**[1]

- Definition of score for $U_i$ client $i$:

$$U_i = \underbrace{\left(\frac{T}{t_i}\right)^{\mathbf{1}(T<t_i)\times\alpha}}_{\text{speed}} \times \underbrace{|B_i|\sqrt{\frac{1}{|B_i|}\sum_{k\in B_i} Loss(k)^2}}_{\text{data quality}}$$

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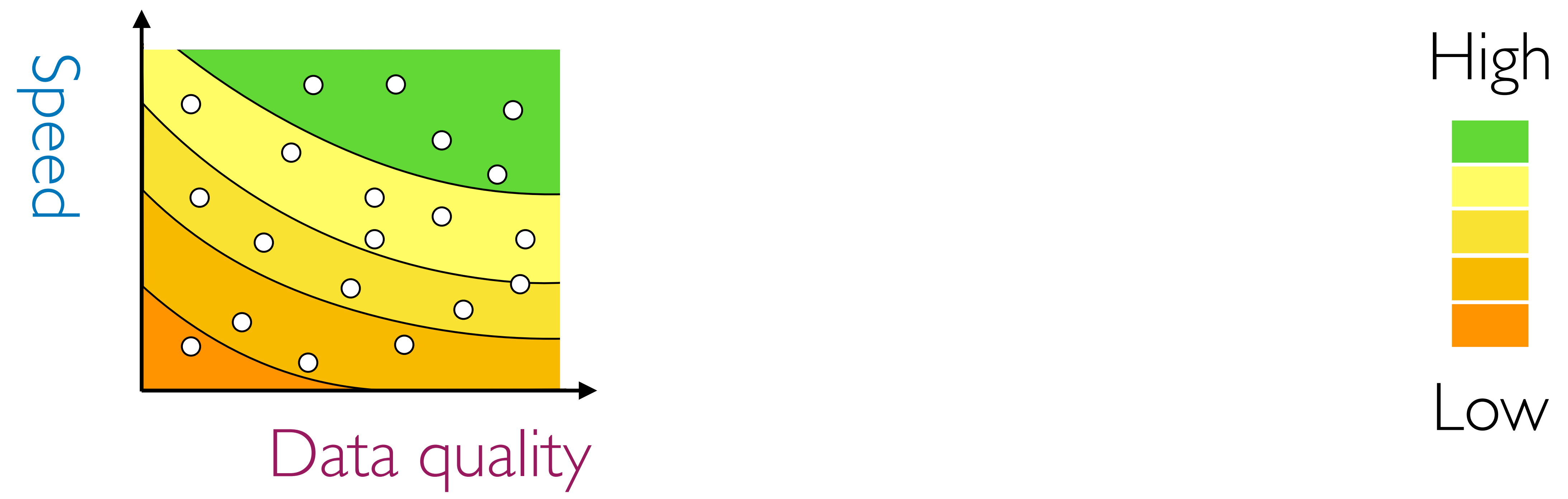
- Clients with higher score are selected




**Ideal**

→ High speed

& High data quality

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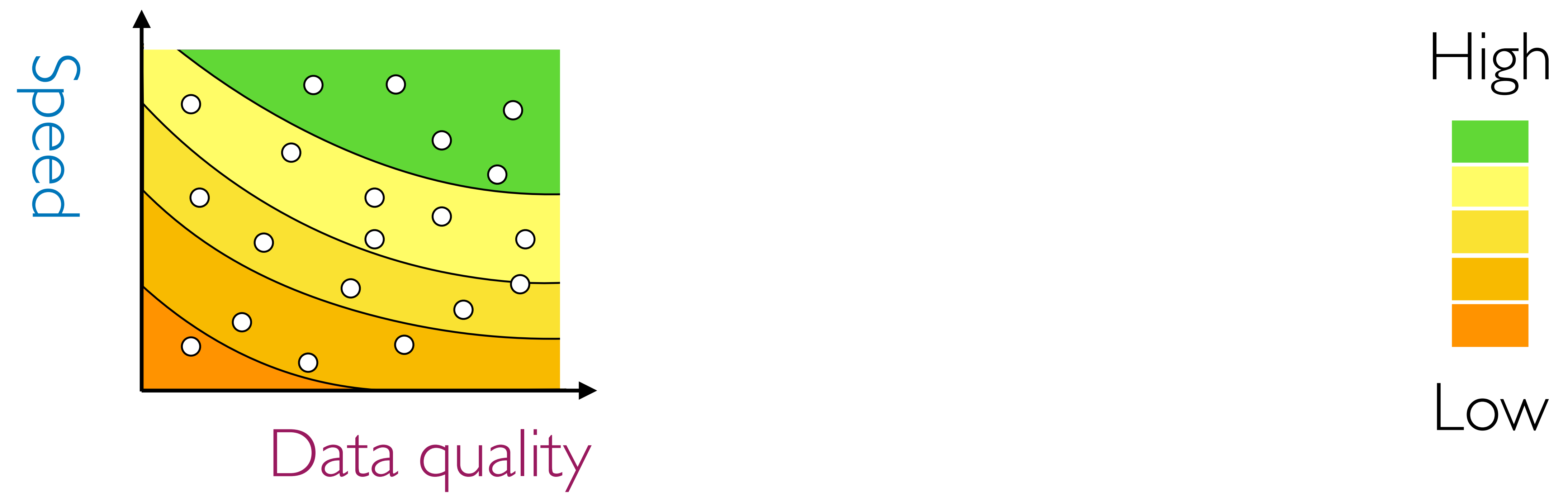


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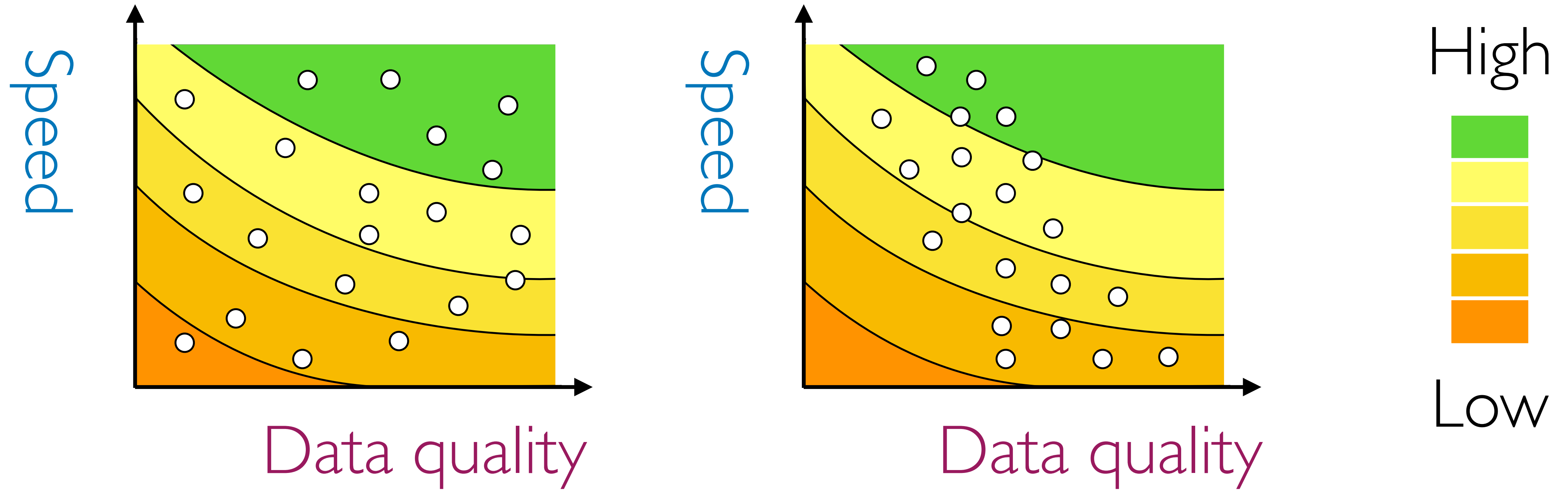


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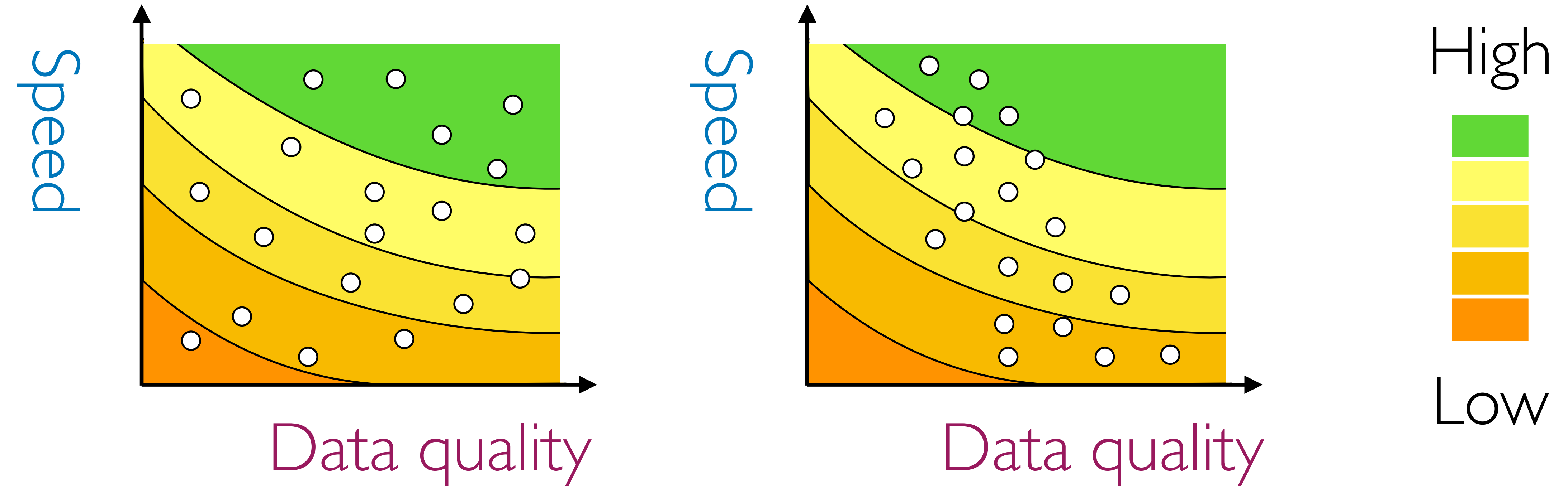


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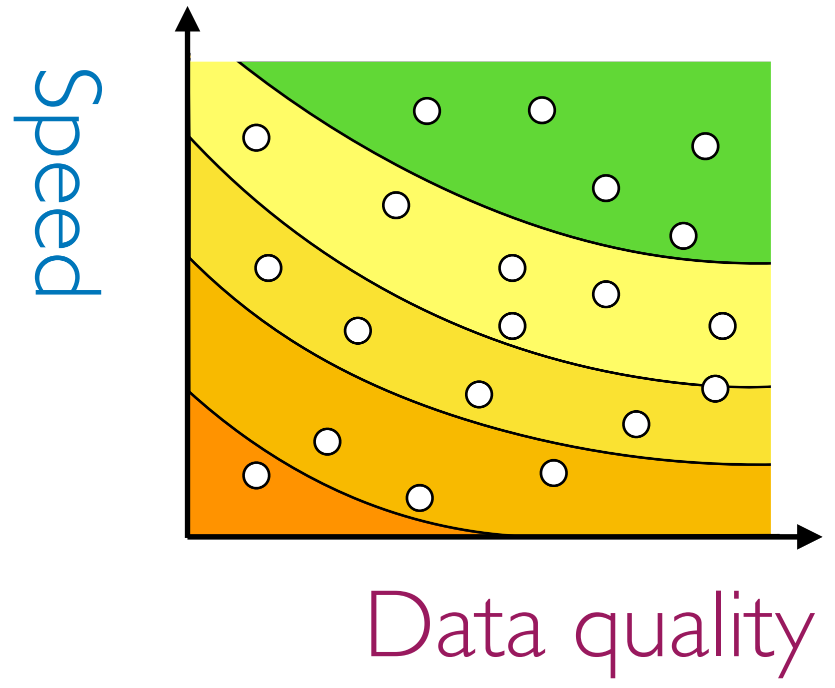


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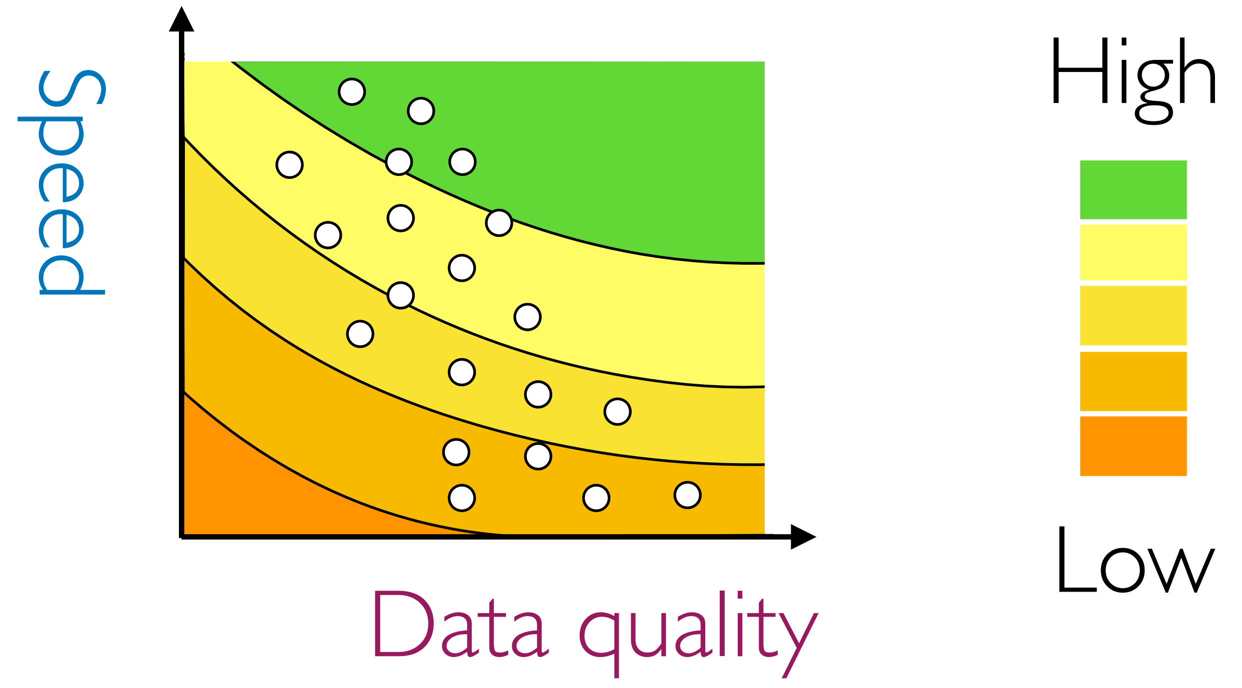


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**Problem**: Navigation between clients' **speed** and **data quality** is **inherently tricky**

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Easily Integrated to **production frameworks**

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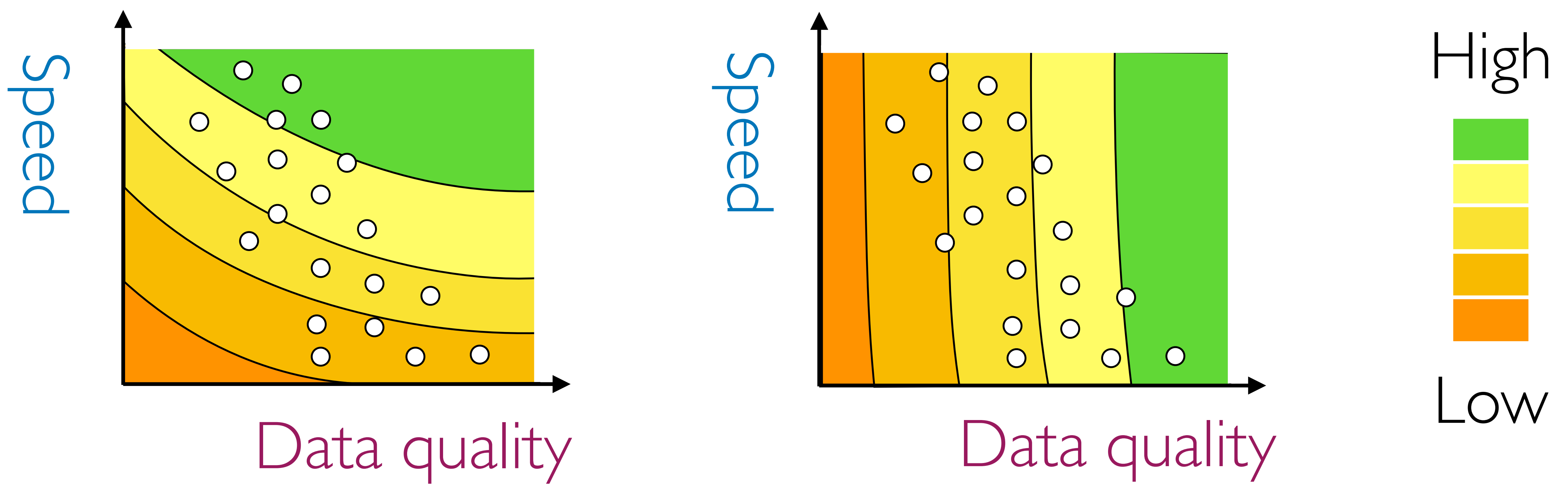


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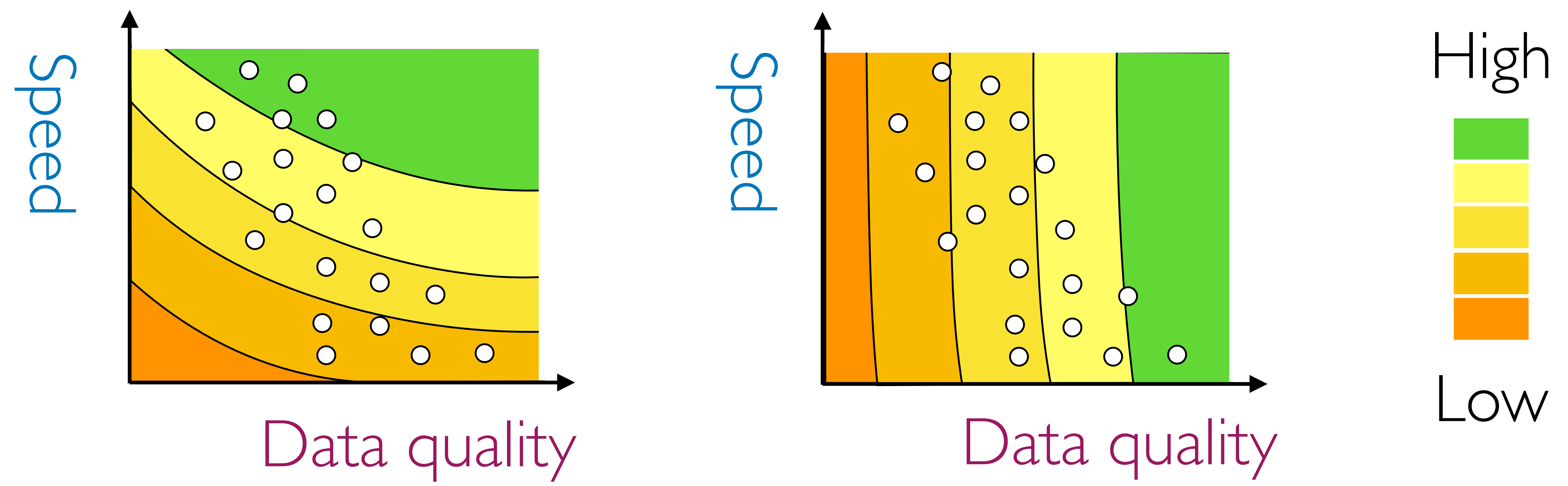


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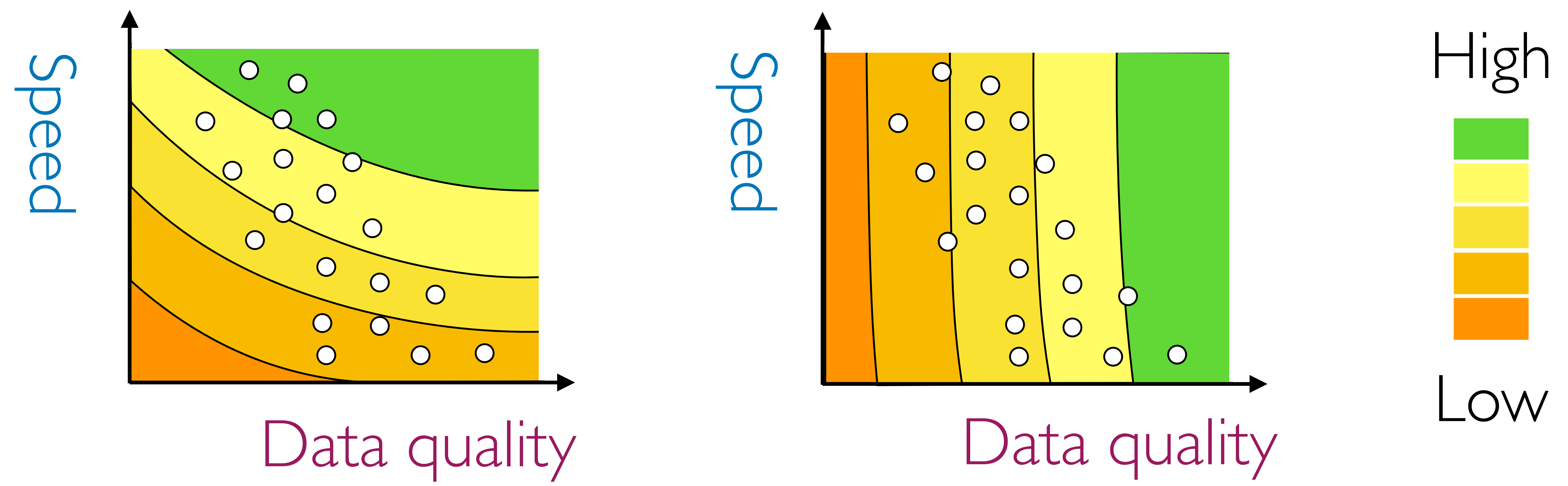


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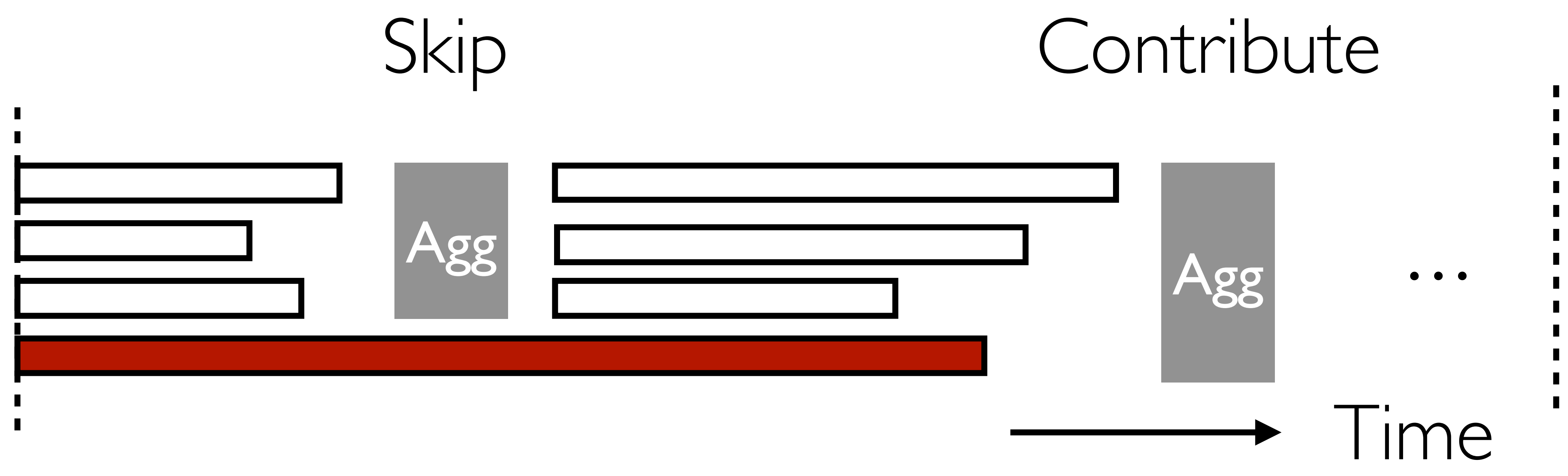

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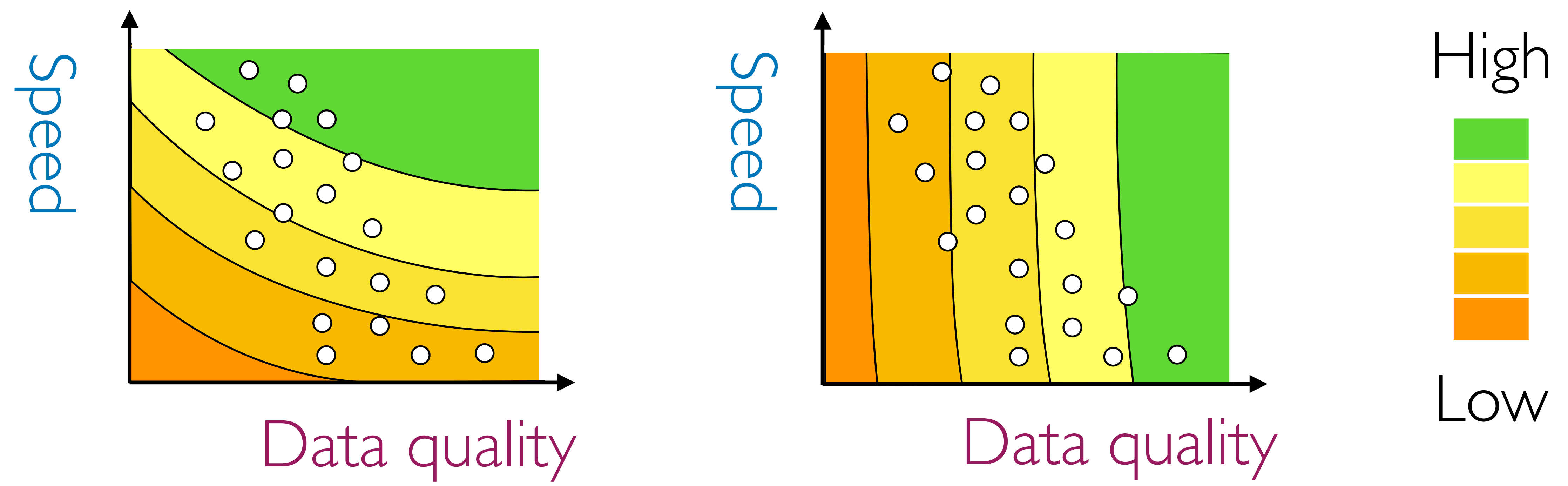


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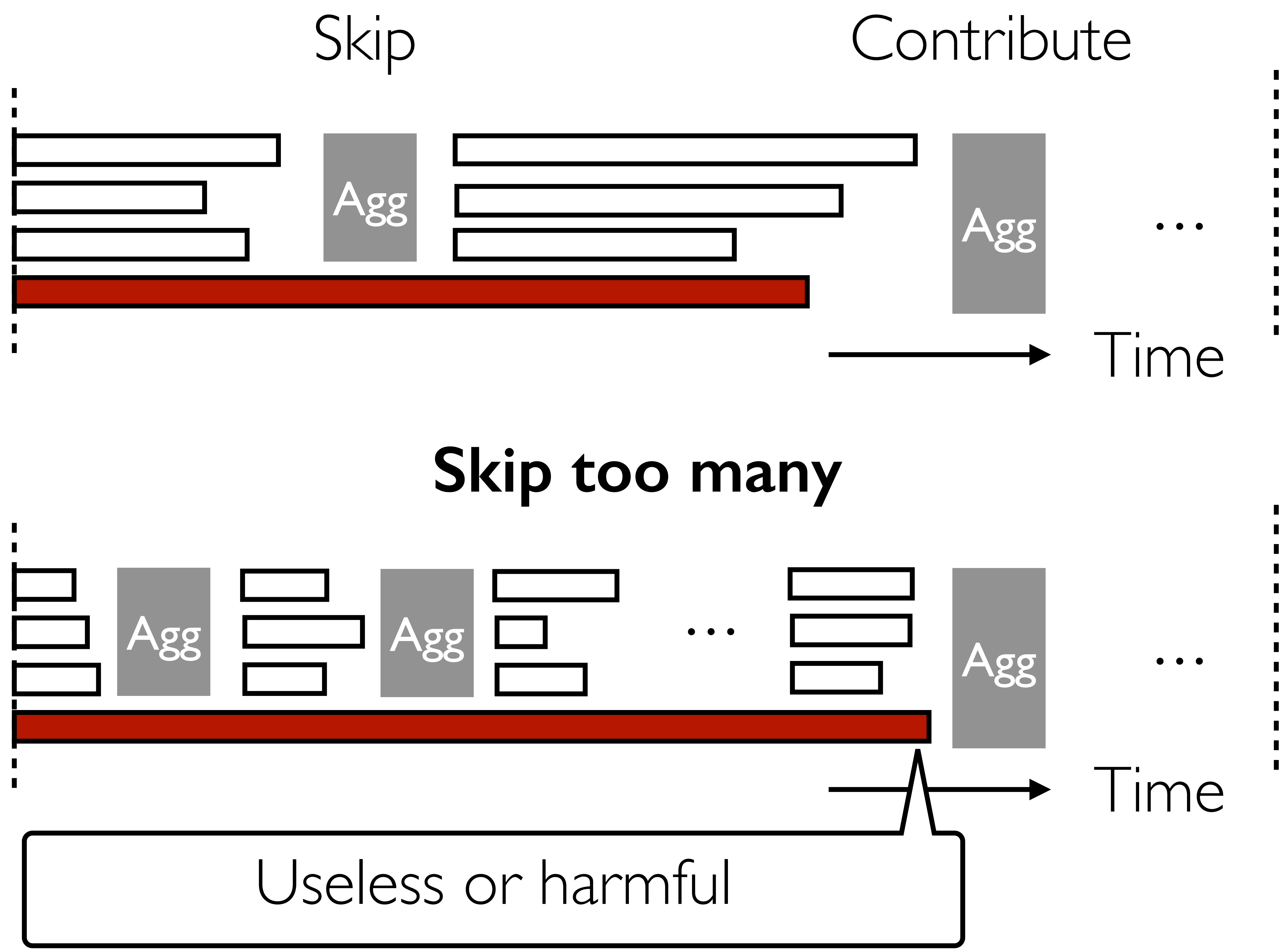

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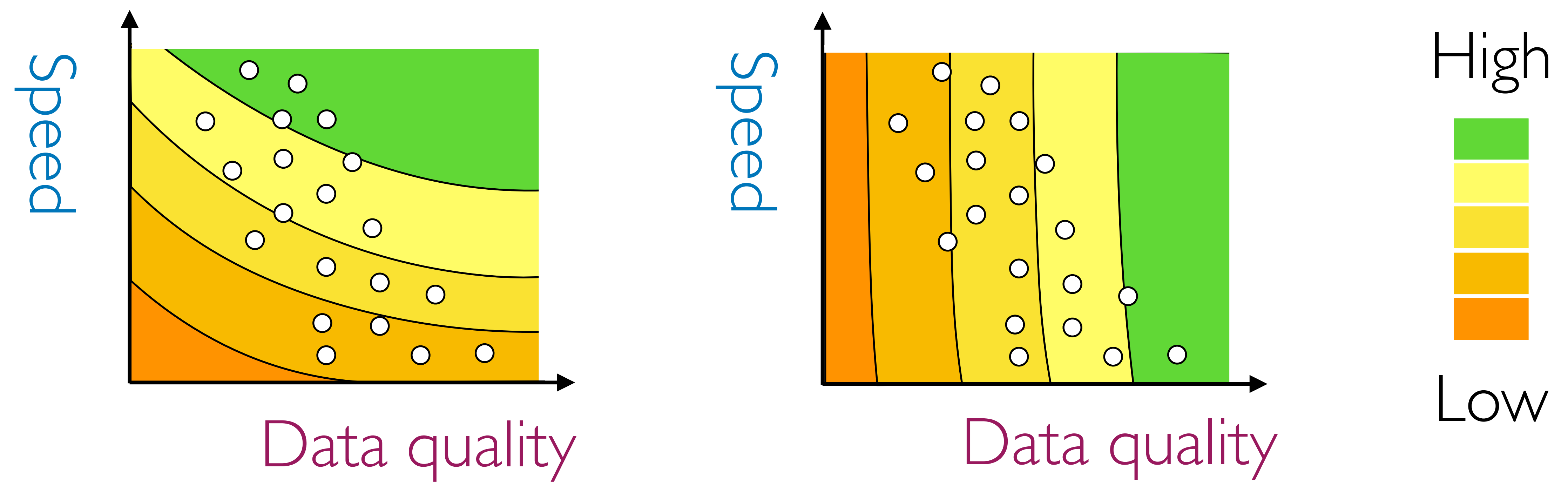


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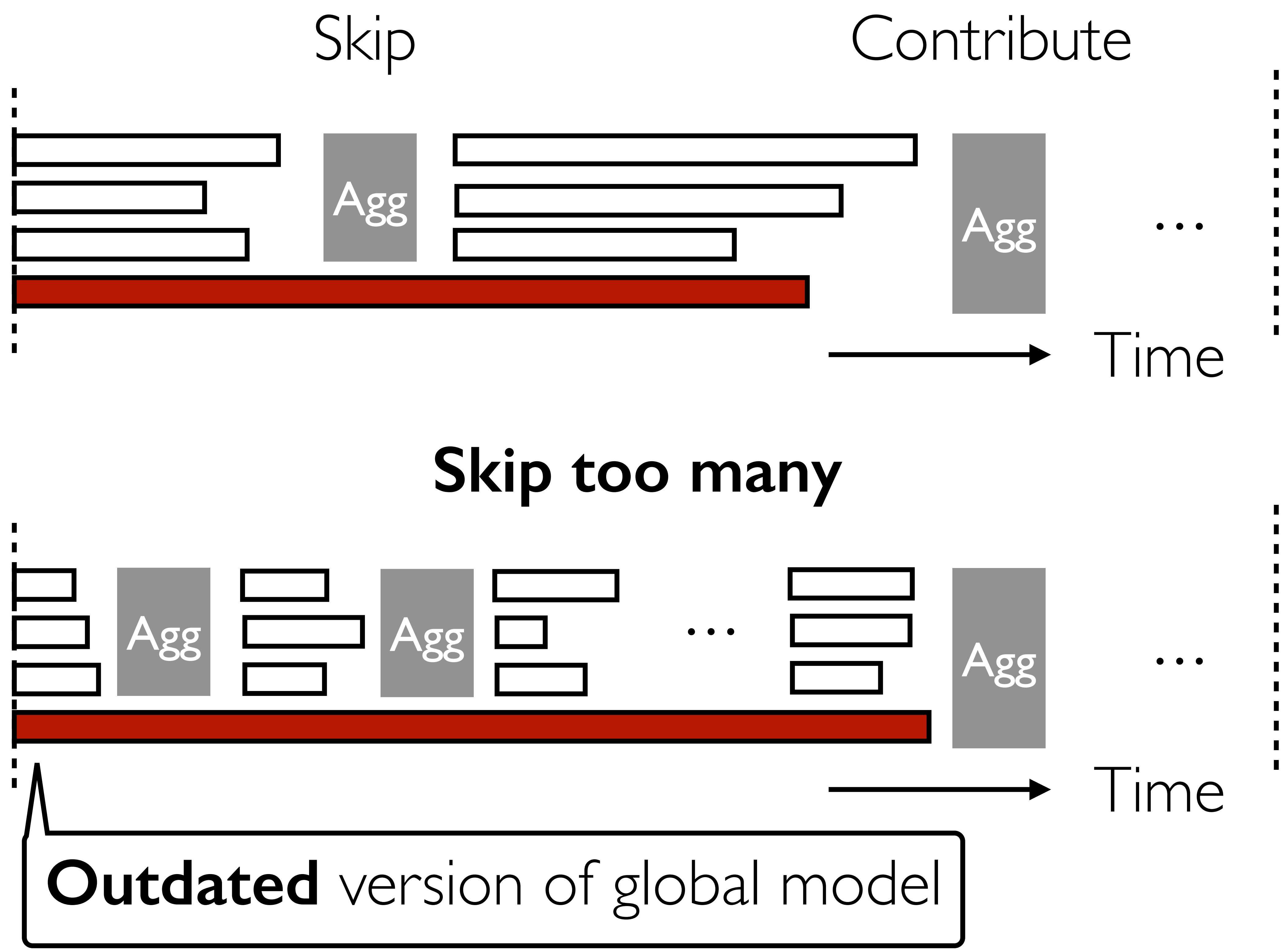

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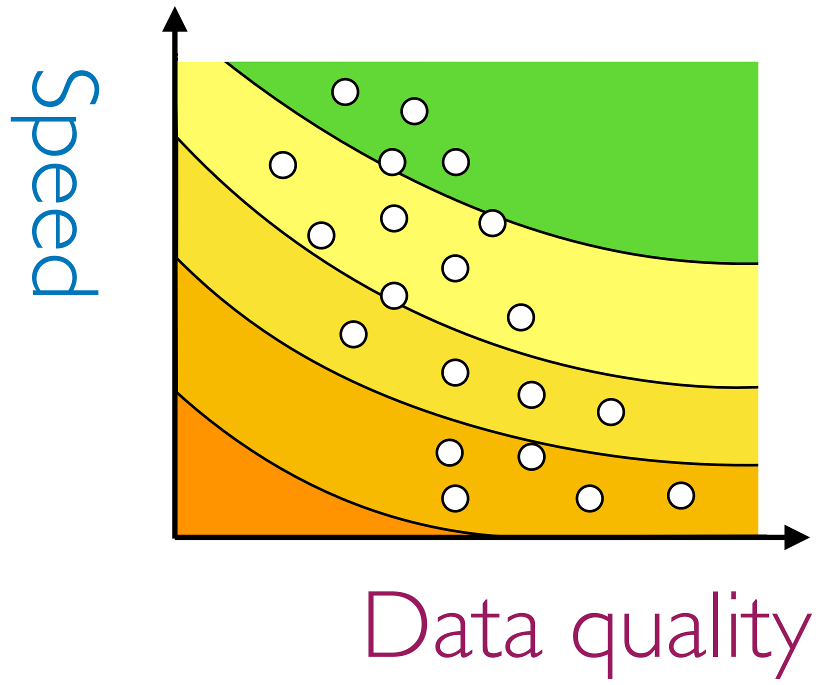


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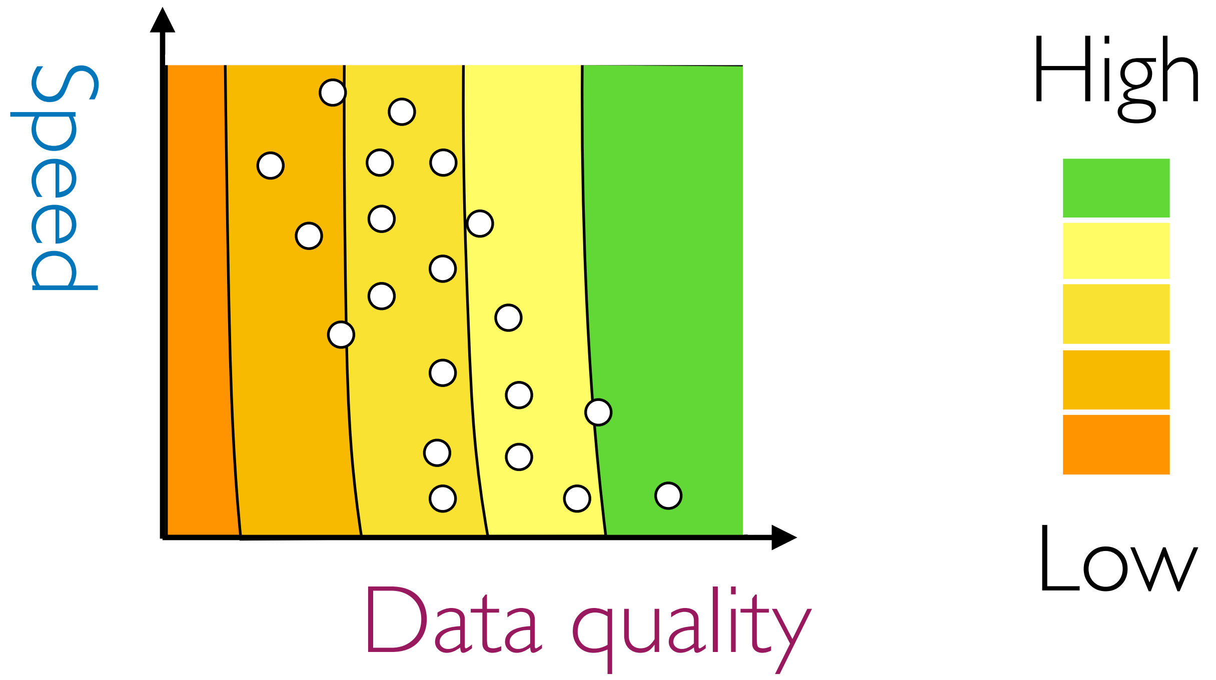


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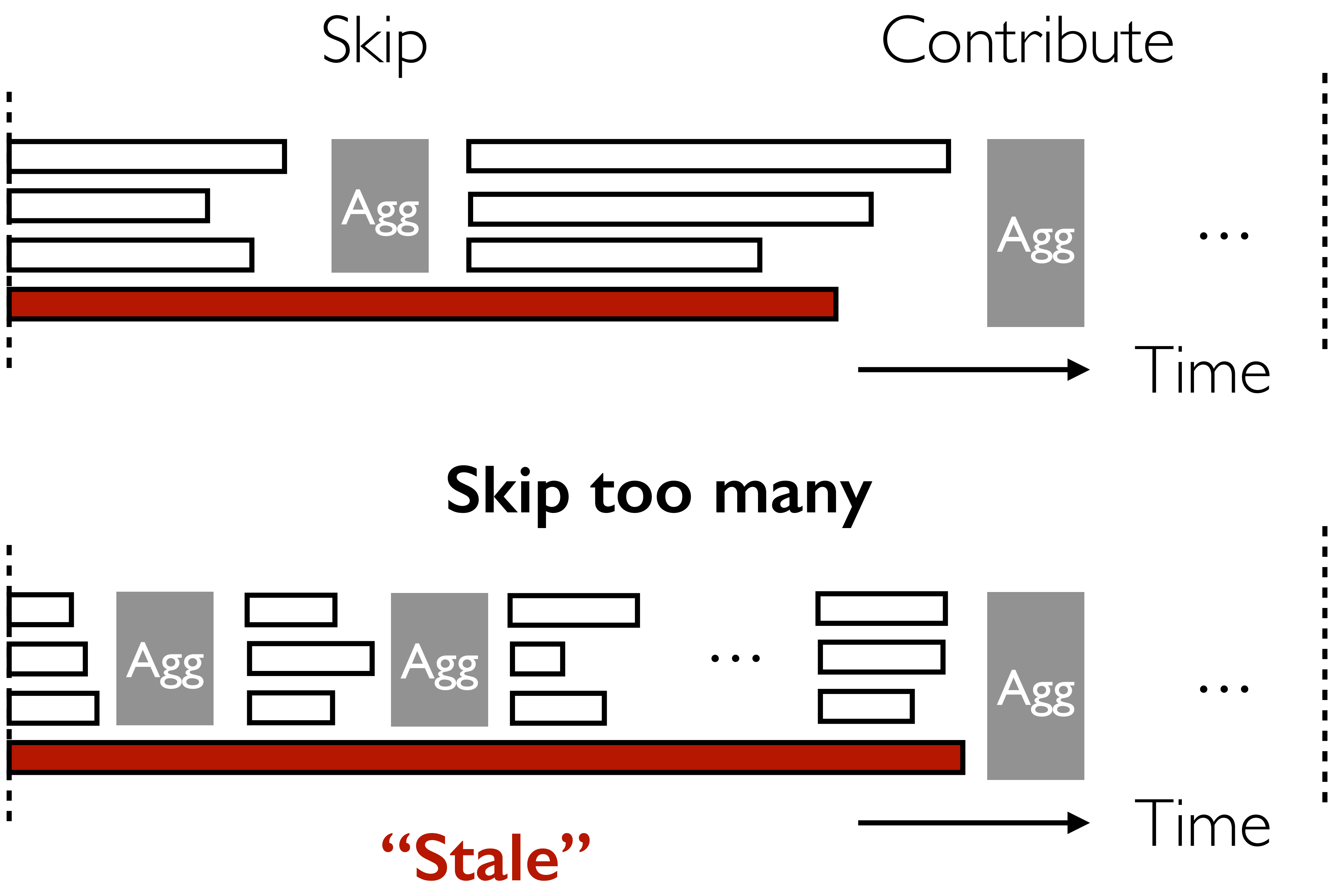

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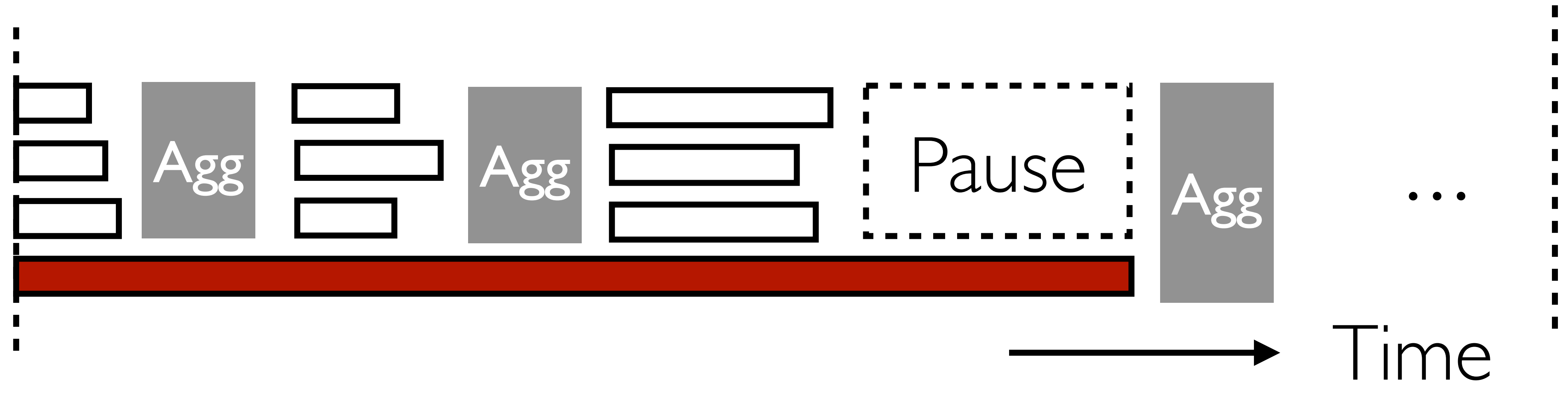

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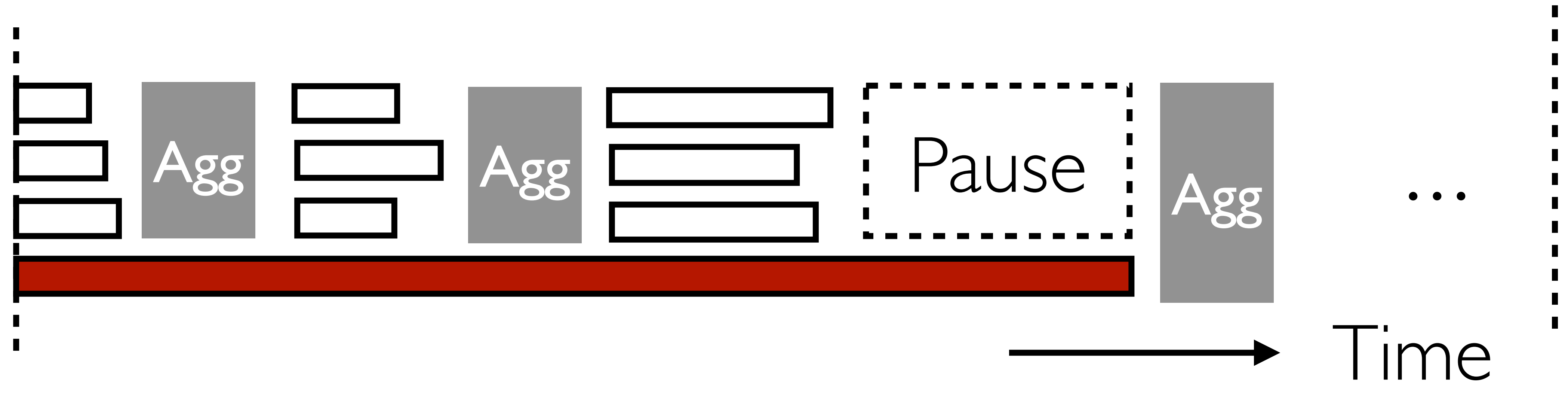


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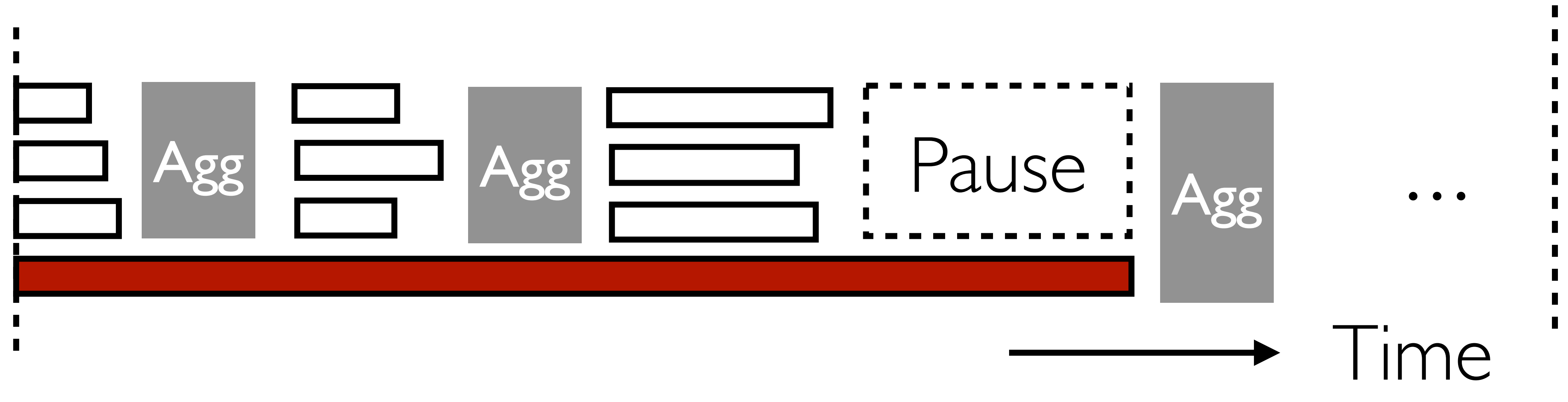


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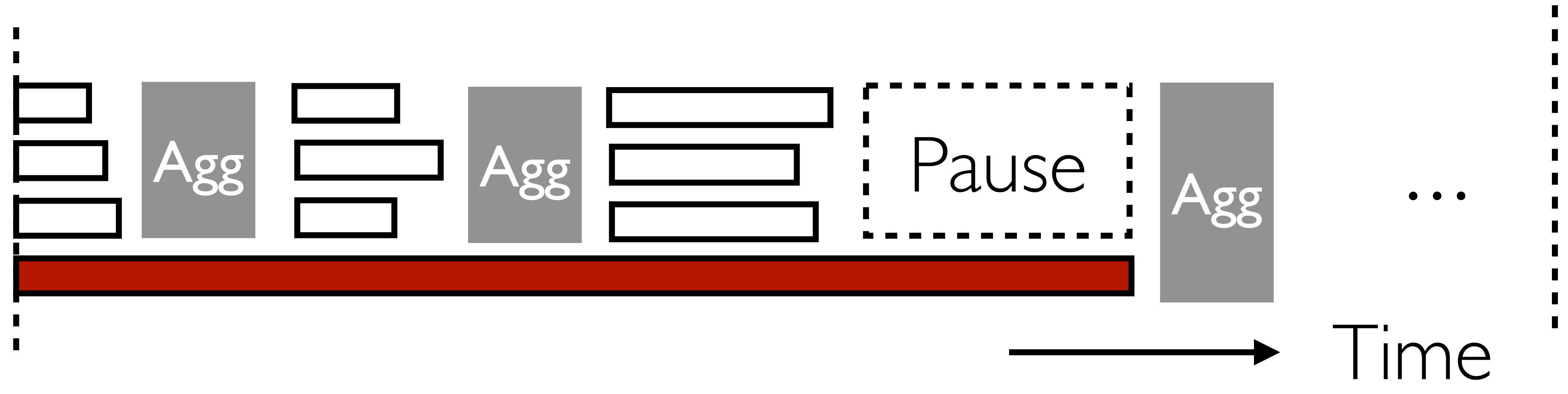


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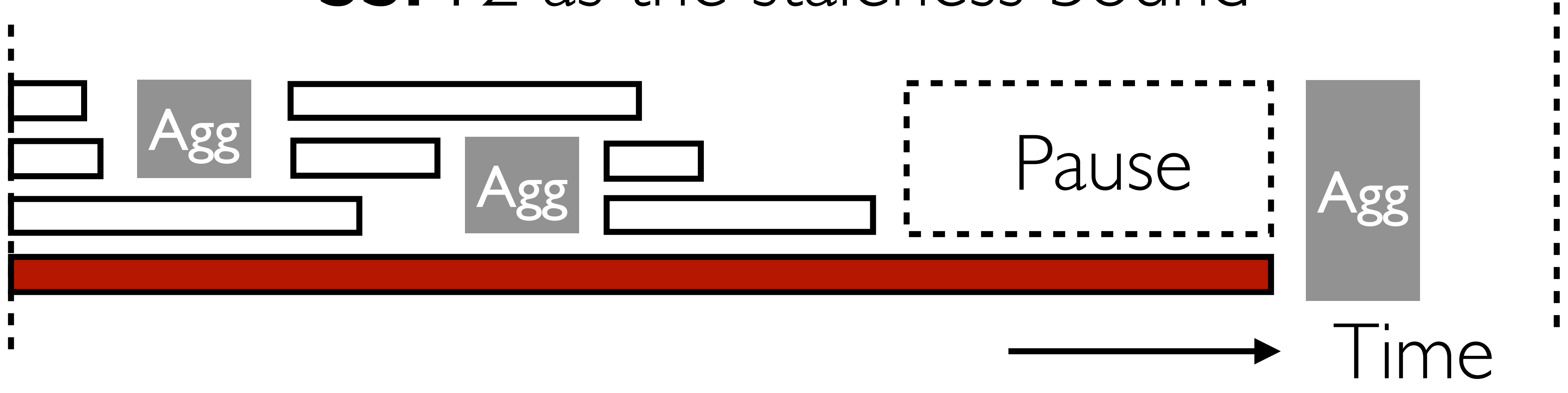


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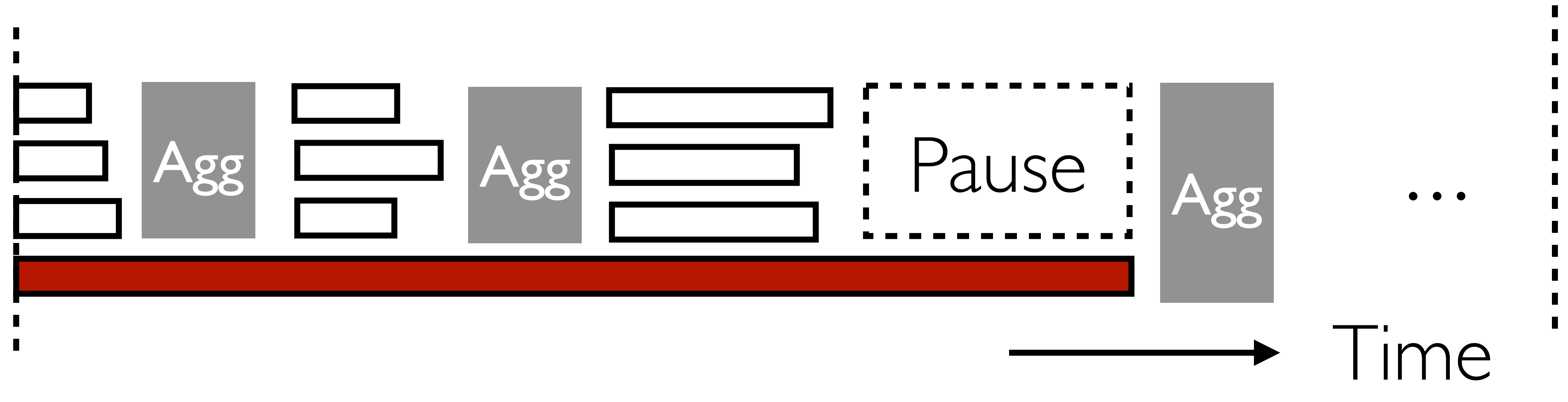


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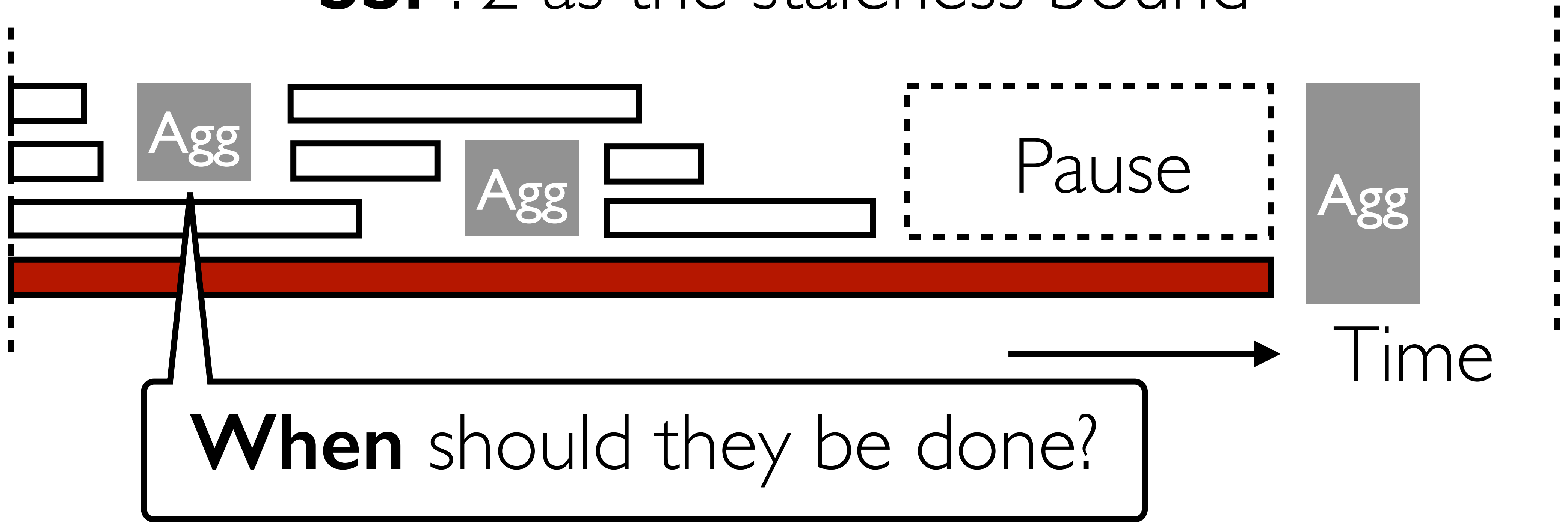


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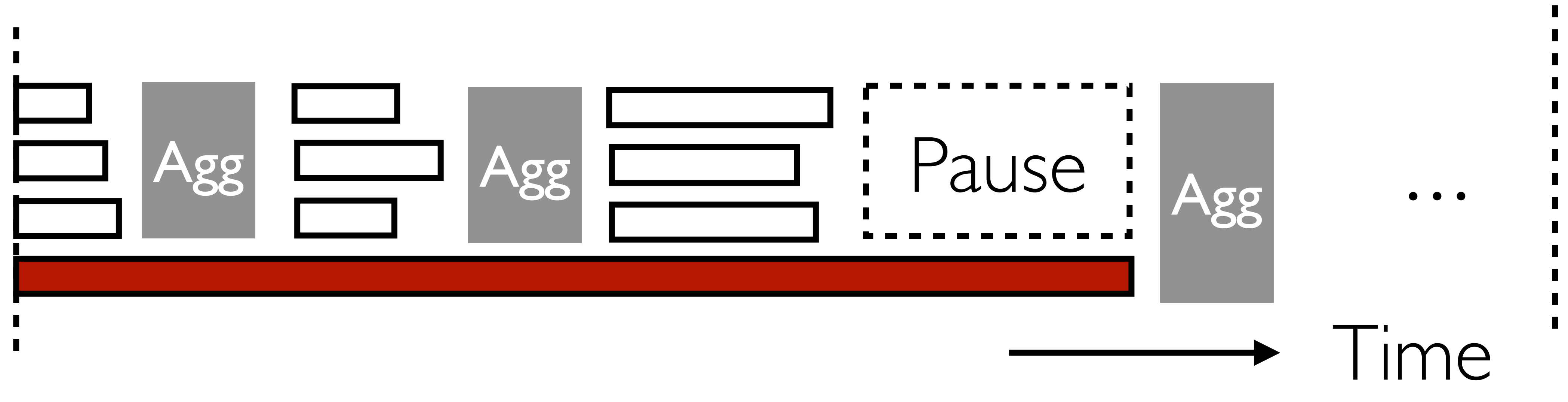


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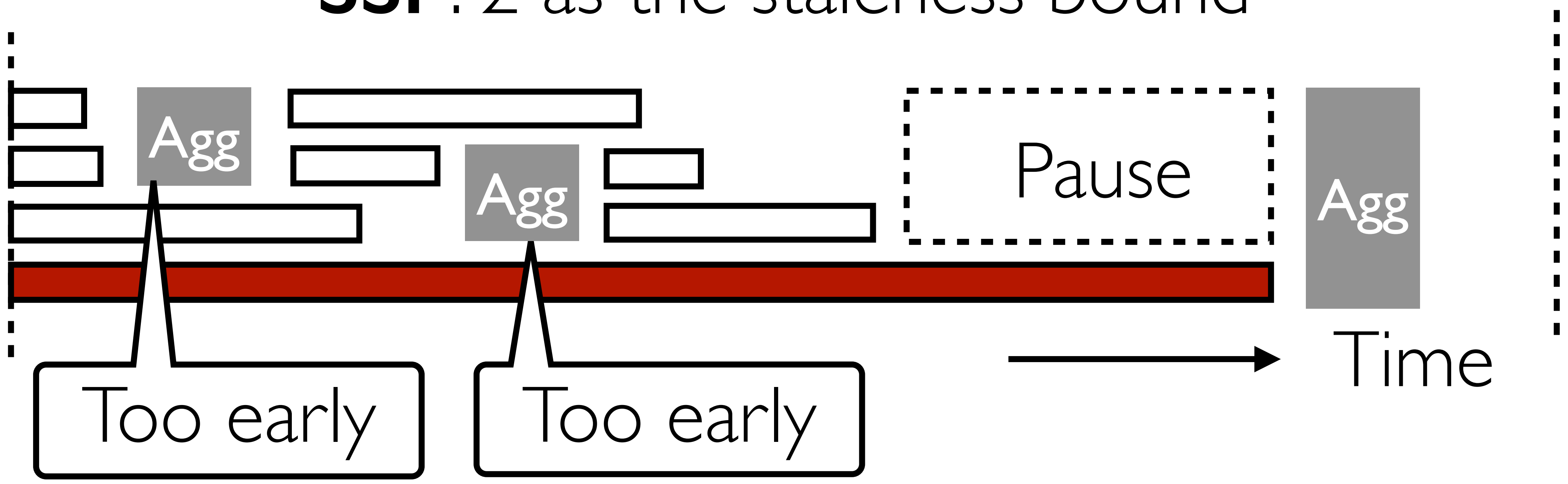
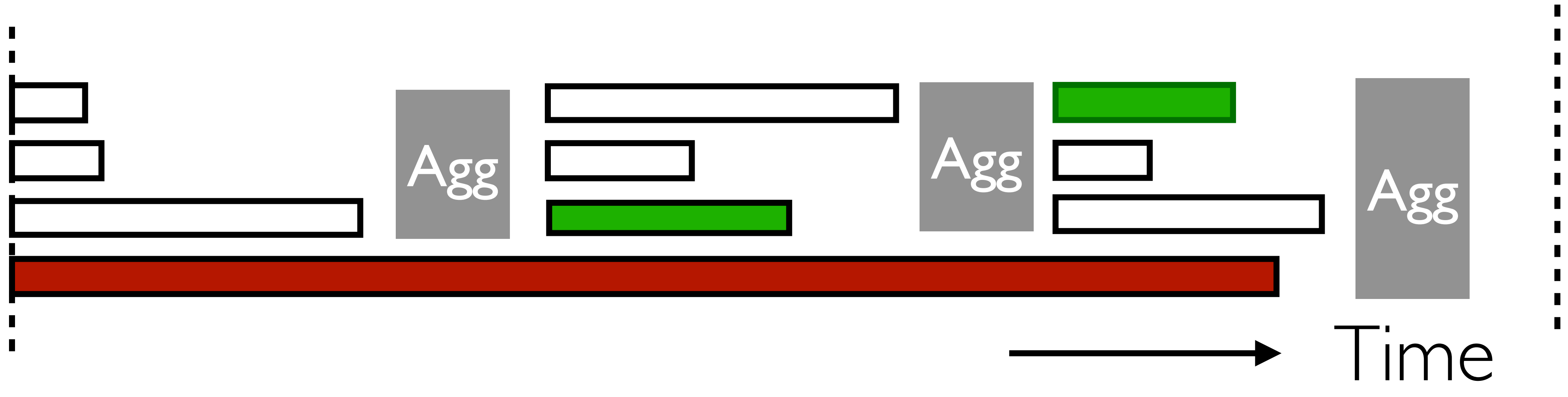



**Better case**: **more** contributions

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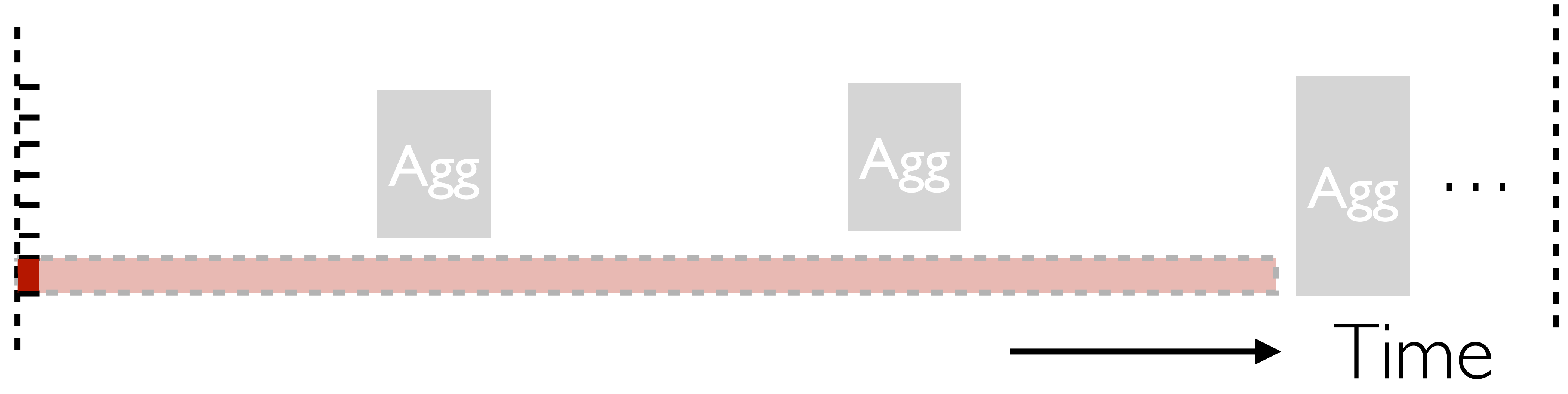


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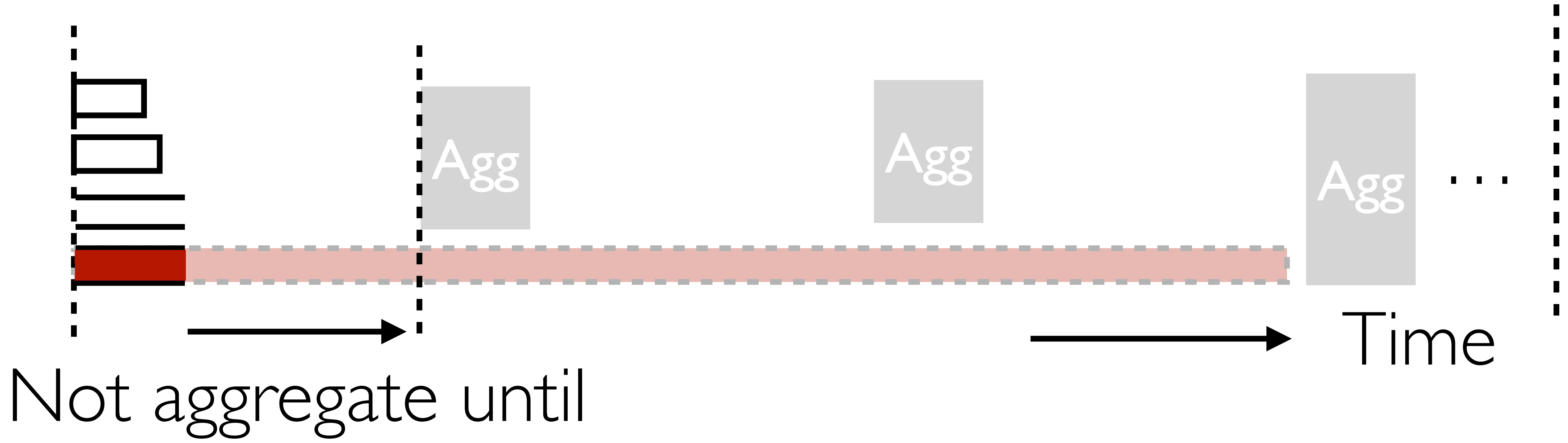


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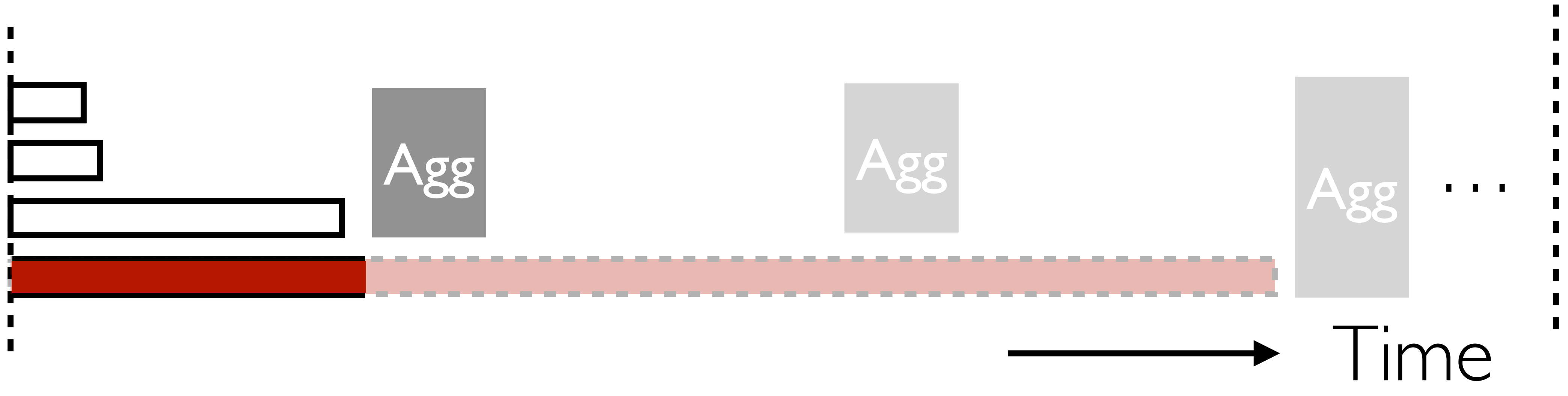


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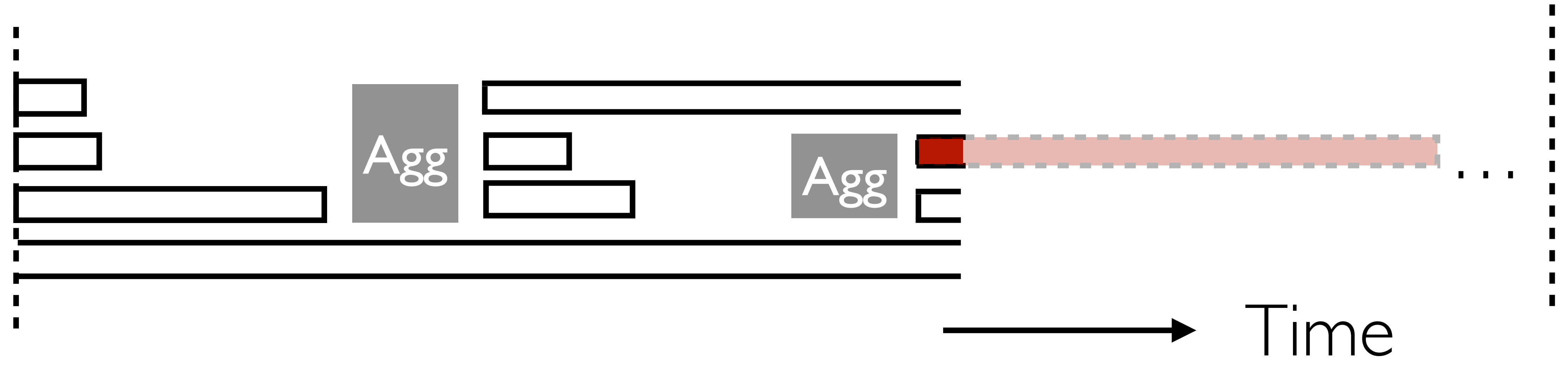


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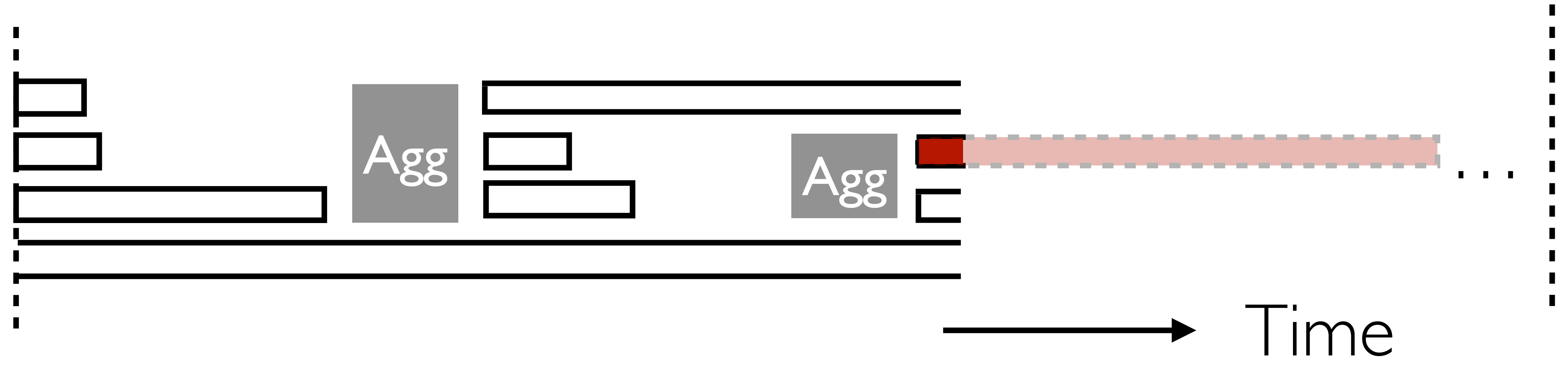


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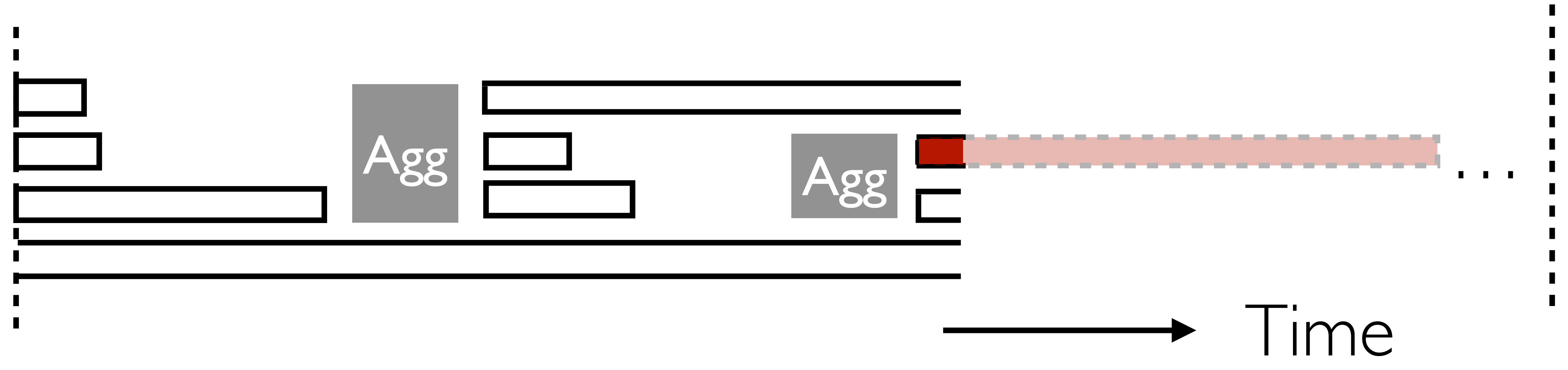


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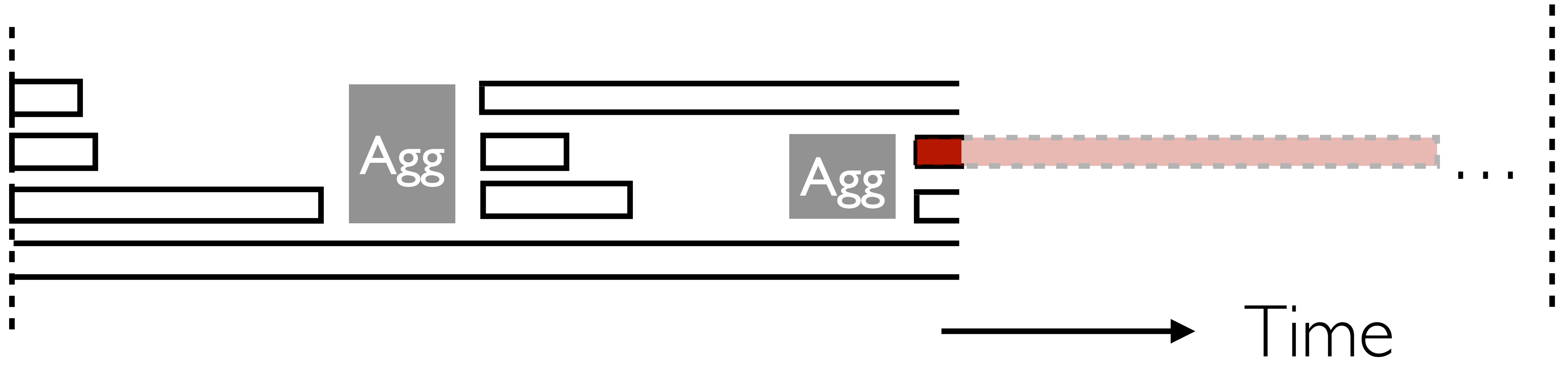


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Other designs on efficiency/robustness…

Please find more in the paper :)

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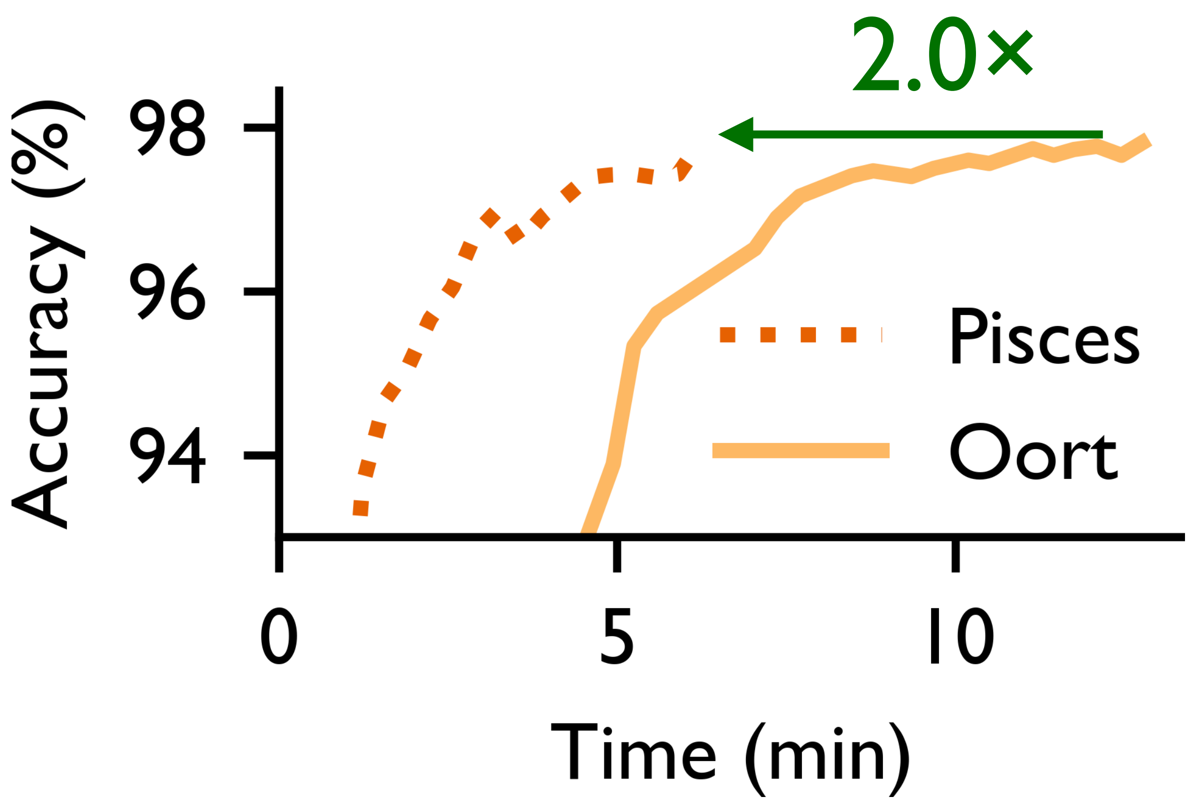


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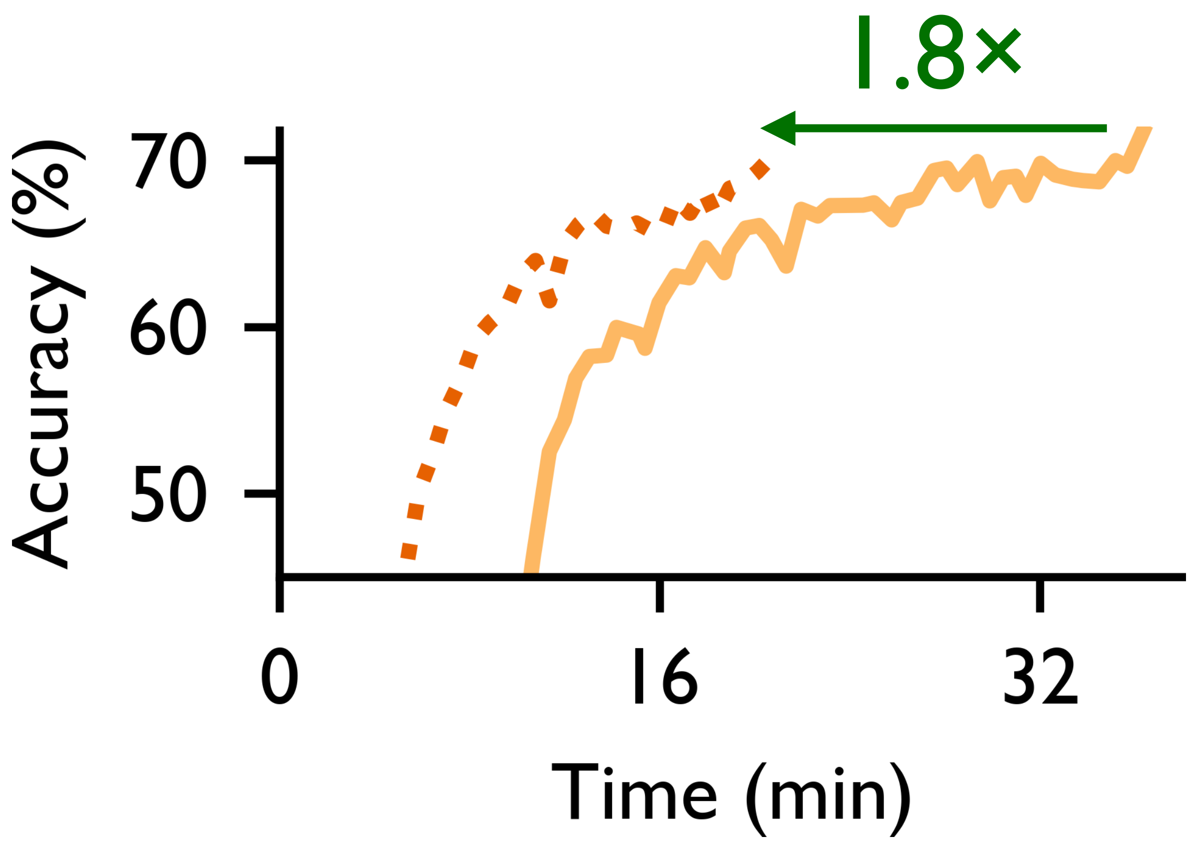


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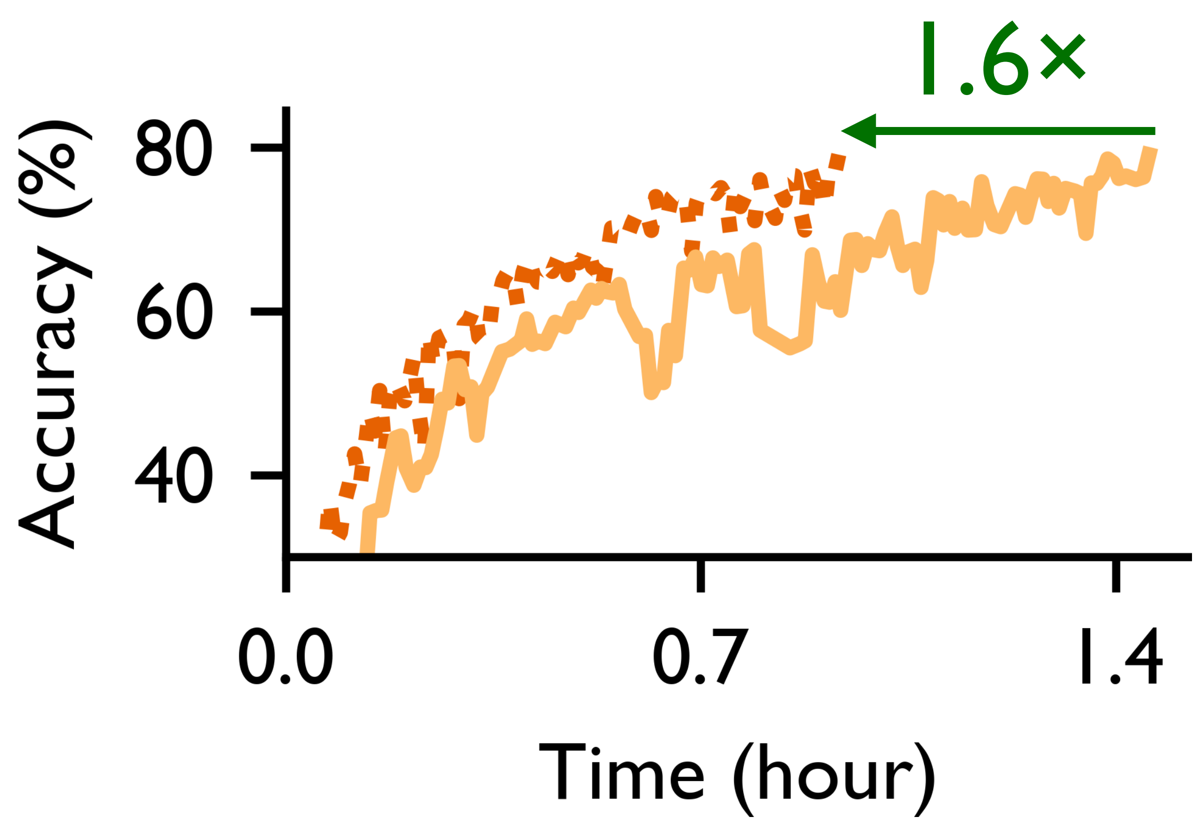


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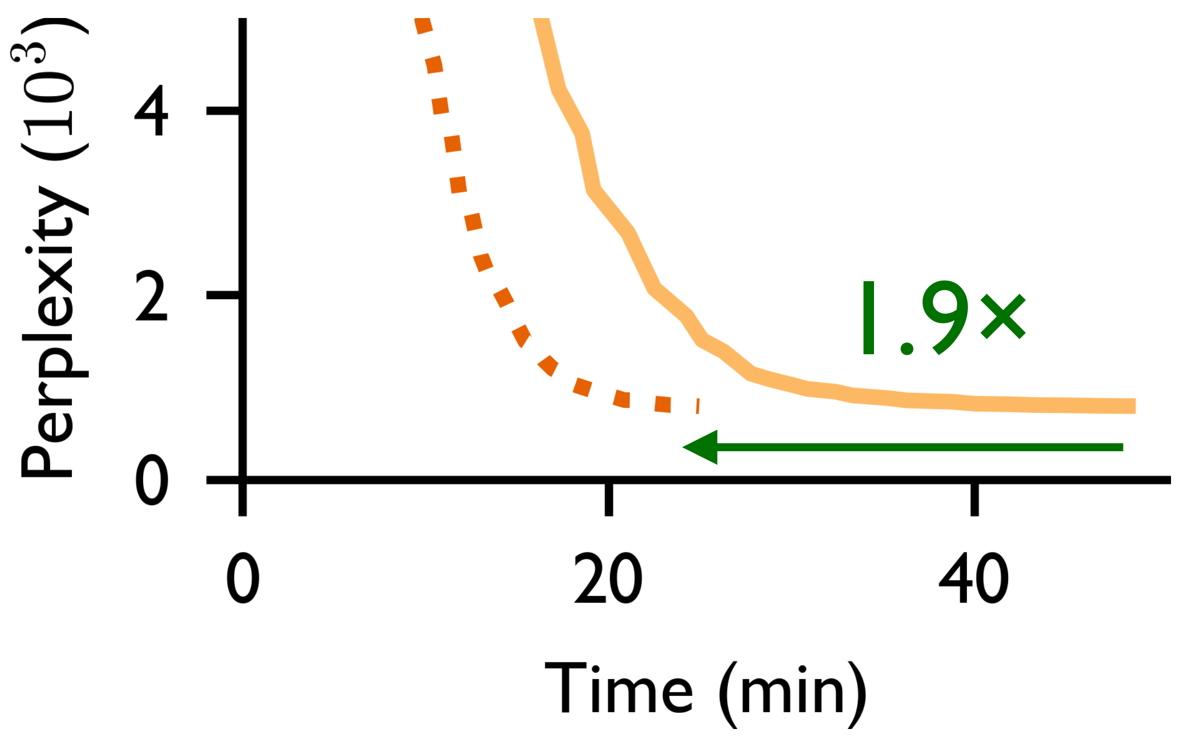


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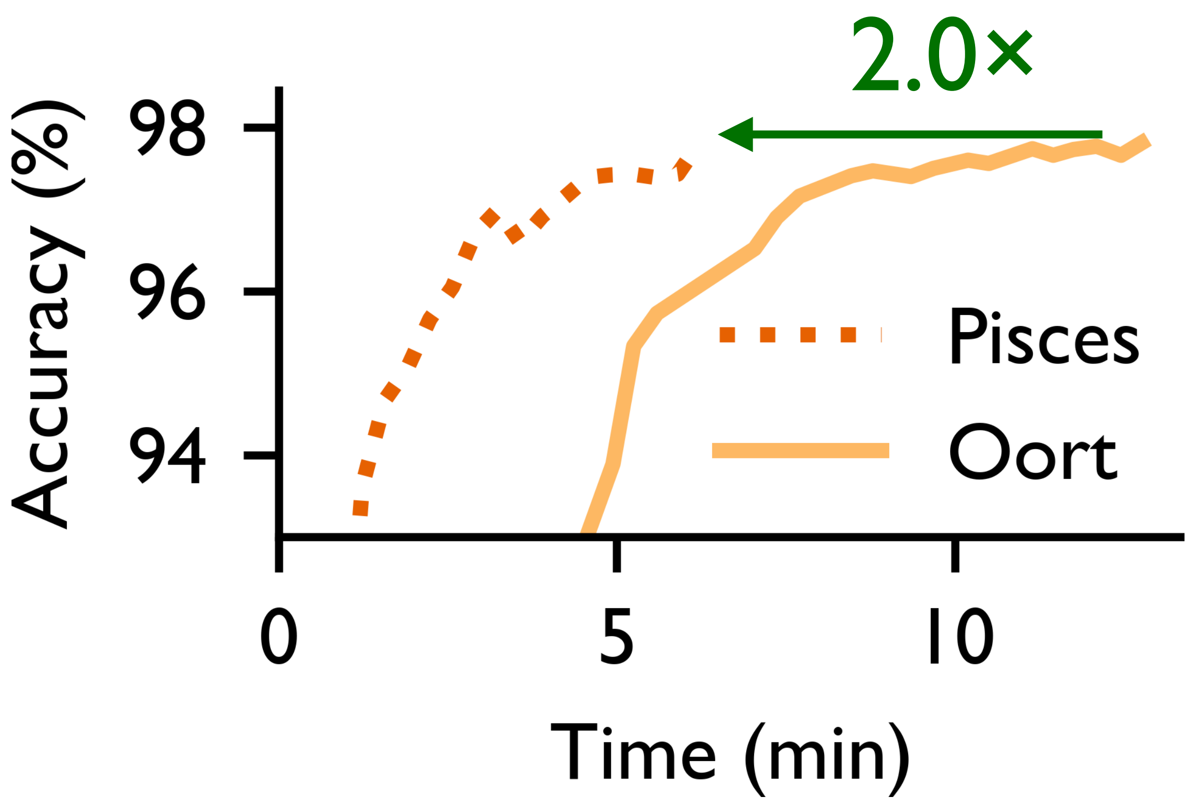


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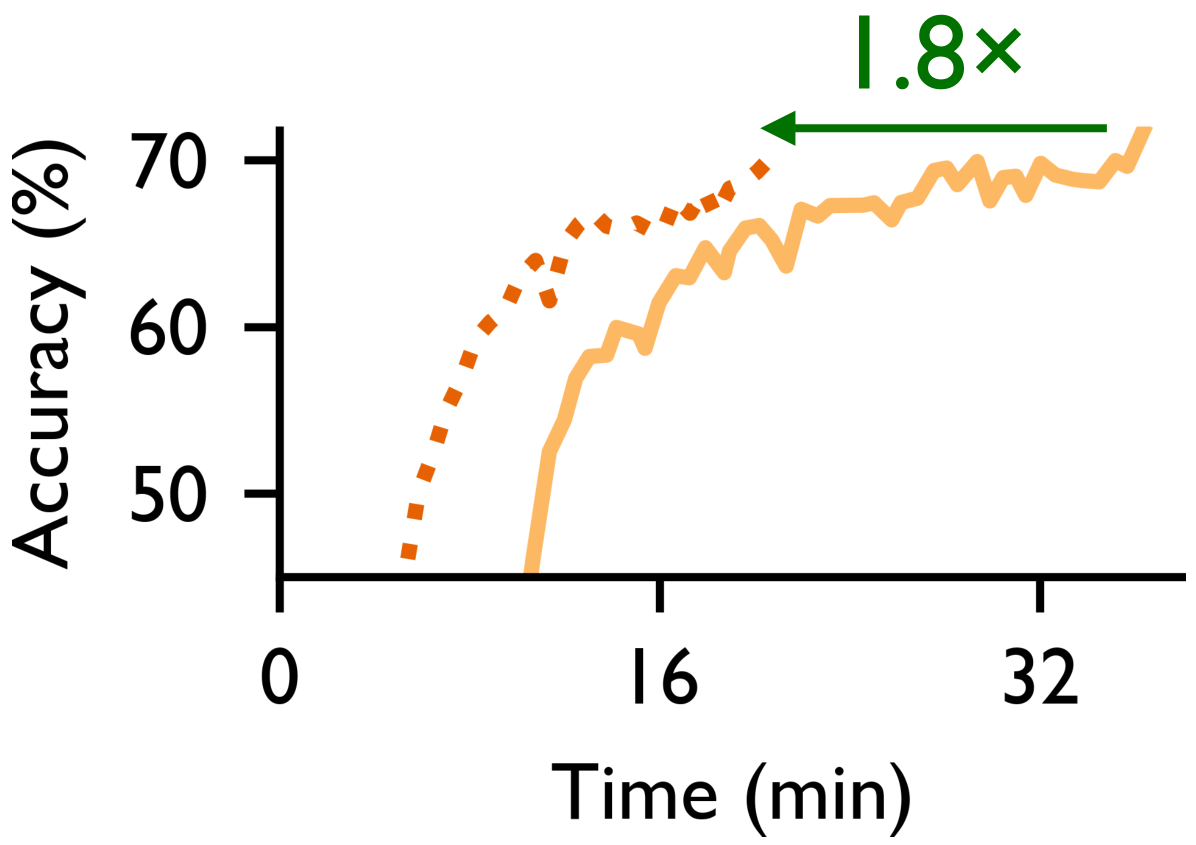


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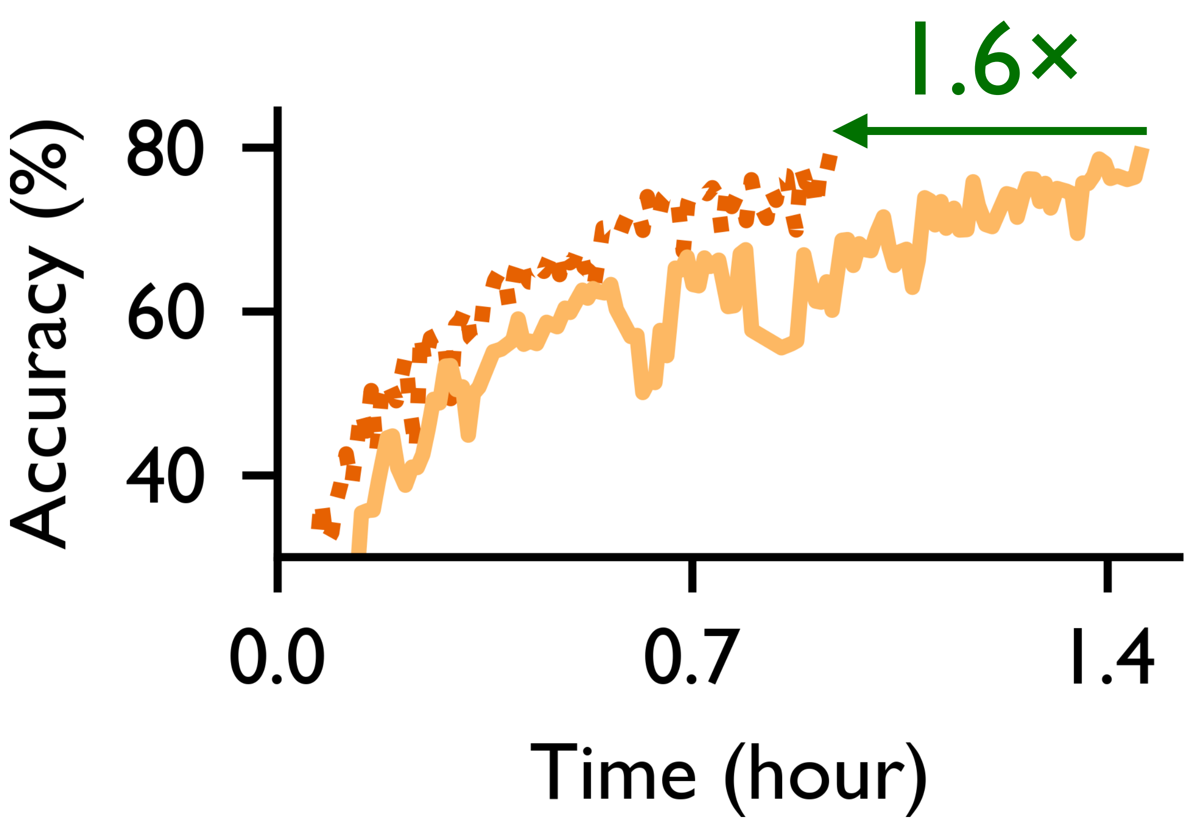


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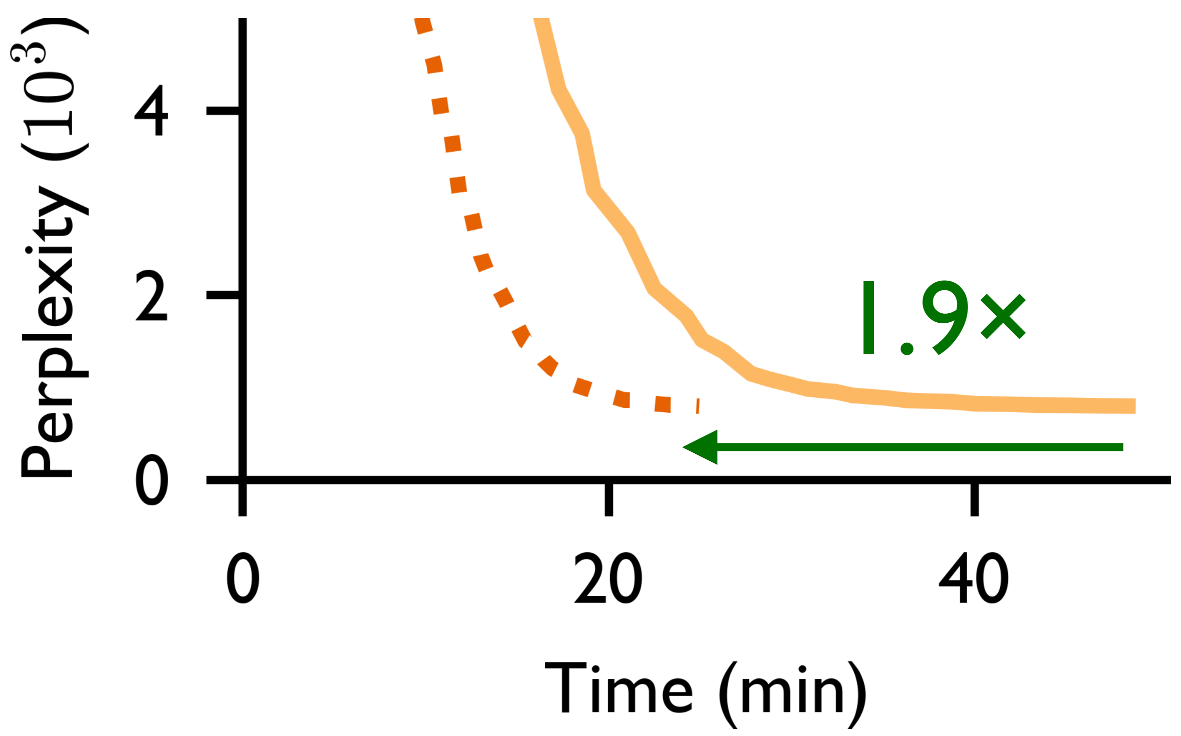
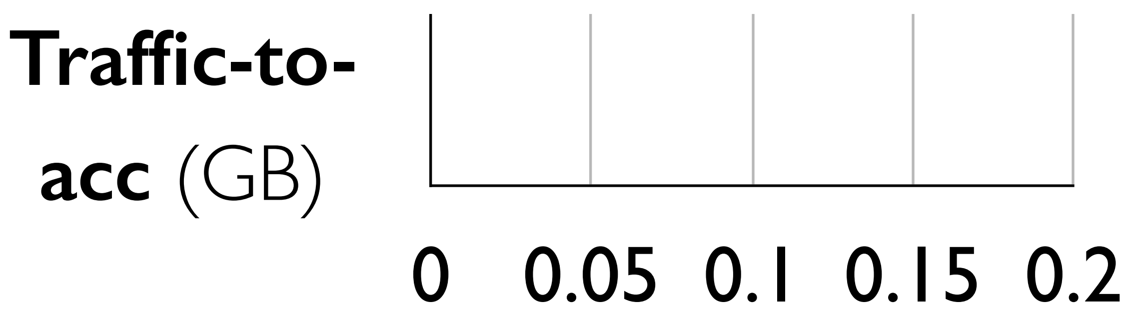
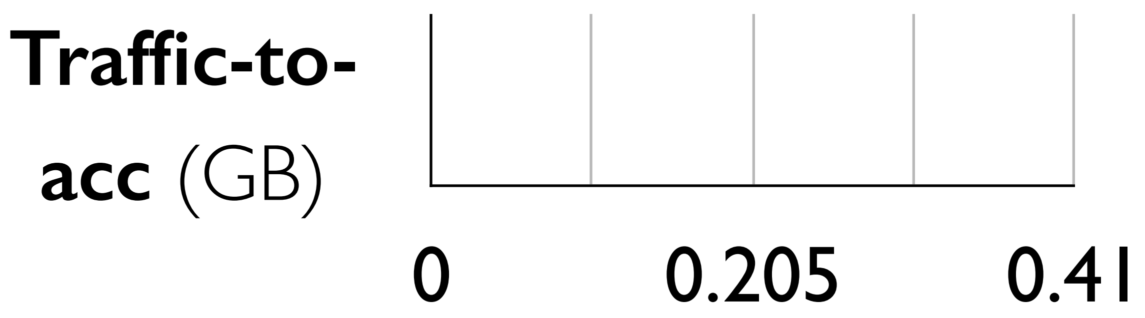
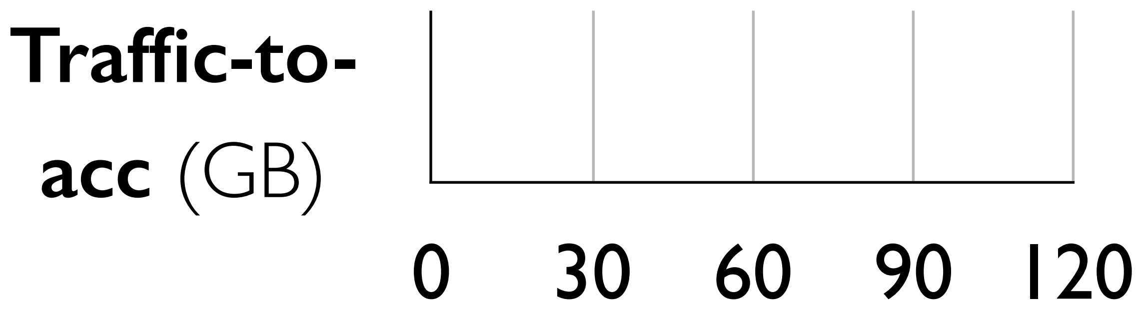



Reddit@Albert








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

# Pisces outperforms in time-to-accuracy

**Oort**[1] → State-of-the-art **synchronous** method: navigating the **speed-data tradeoff**


**Pisces accelerates** Oort by up to **2×**
**without** significant **network** cost

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

# Pisces: Results summary

**Theory**

**Provable convergence** for smooth non-convex problems based on **bounded staleness**

**Efficiency**

**2.0×** improvement in **time-to-accuracy** with **no network** overhead

**Practicality**

Easily integrated to **production frameworks** like Plato

github.com/SamuelGong/Pisces

# Second work: Dordis[1]

| | | | |
|---|---|---|---|
| **Privacy**<br>Worst-case defense… | Can be a dishonest majority | x ⟷ | Only or mostly works with honest participants |
| **Efficiency**<br>Time-to-accuracy… | Stragglers bottleneck time | Primitives heavy in comp. and comm. | Client dropout yields insufficient noise |

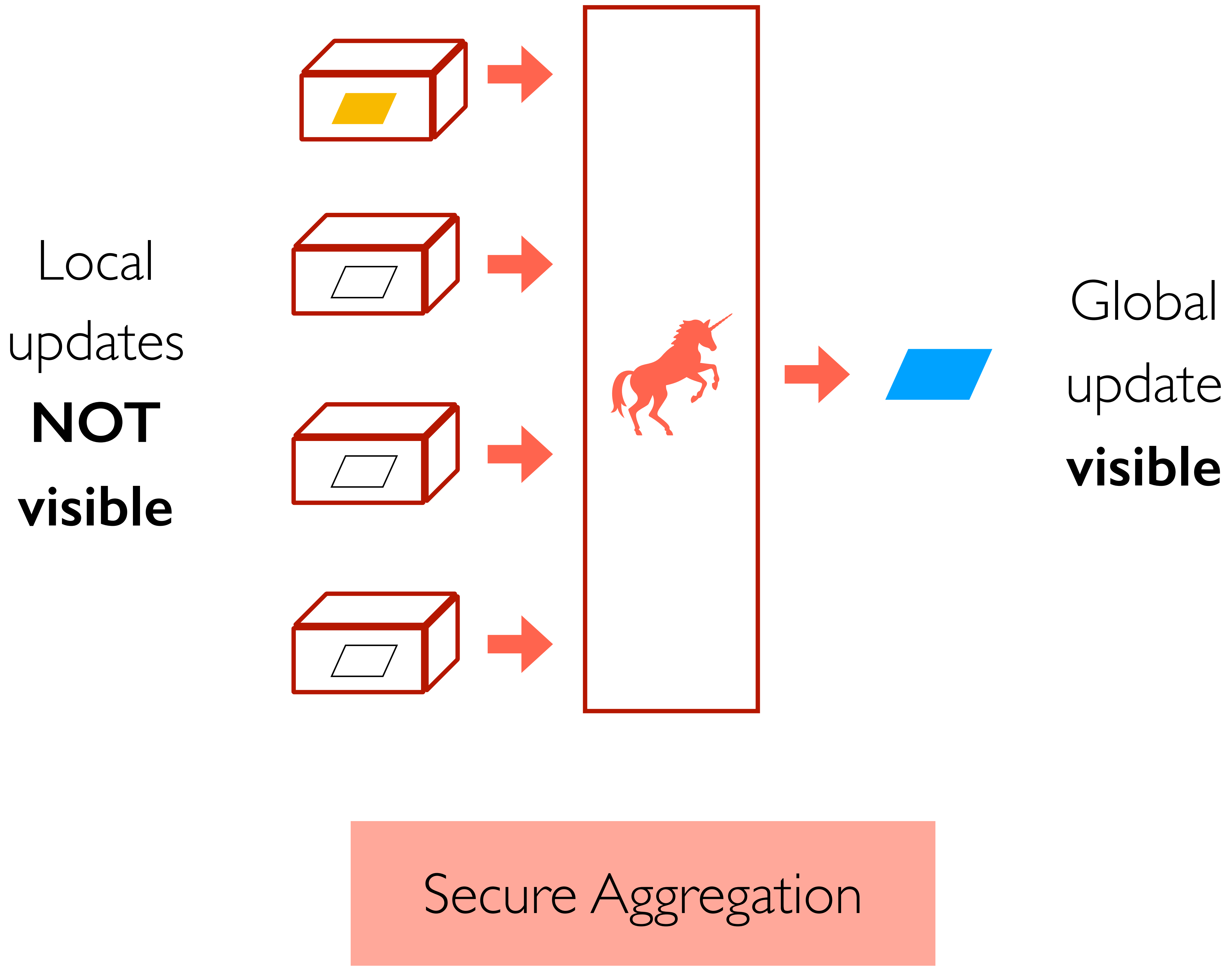
| | | | |
|---|---|---|---|
| **Privacy-Enhancing Technique** | Federated Learning | Secure Aggregation | Differential Privacy |
| **Privacy Guarantee** | Data kept on premises | Local updates unseen | Global update leaks little about any client |

[1] Jiang et al. "Dordis: Efficient Federated Learning with Dropout-Resilient Differential Privacy", In EuroSys '24

# Need for Dordis - 1

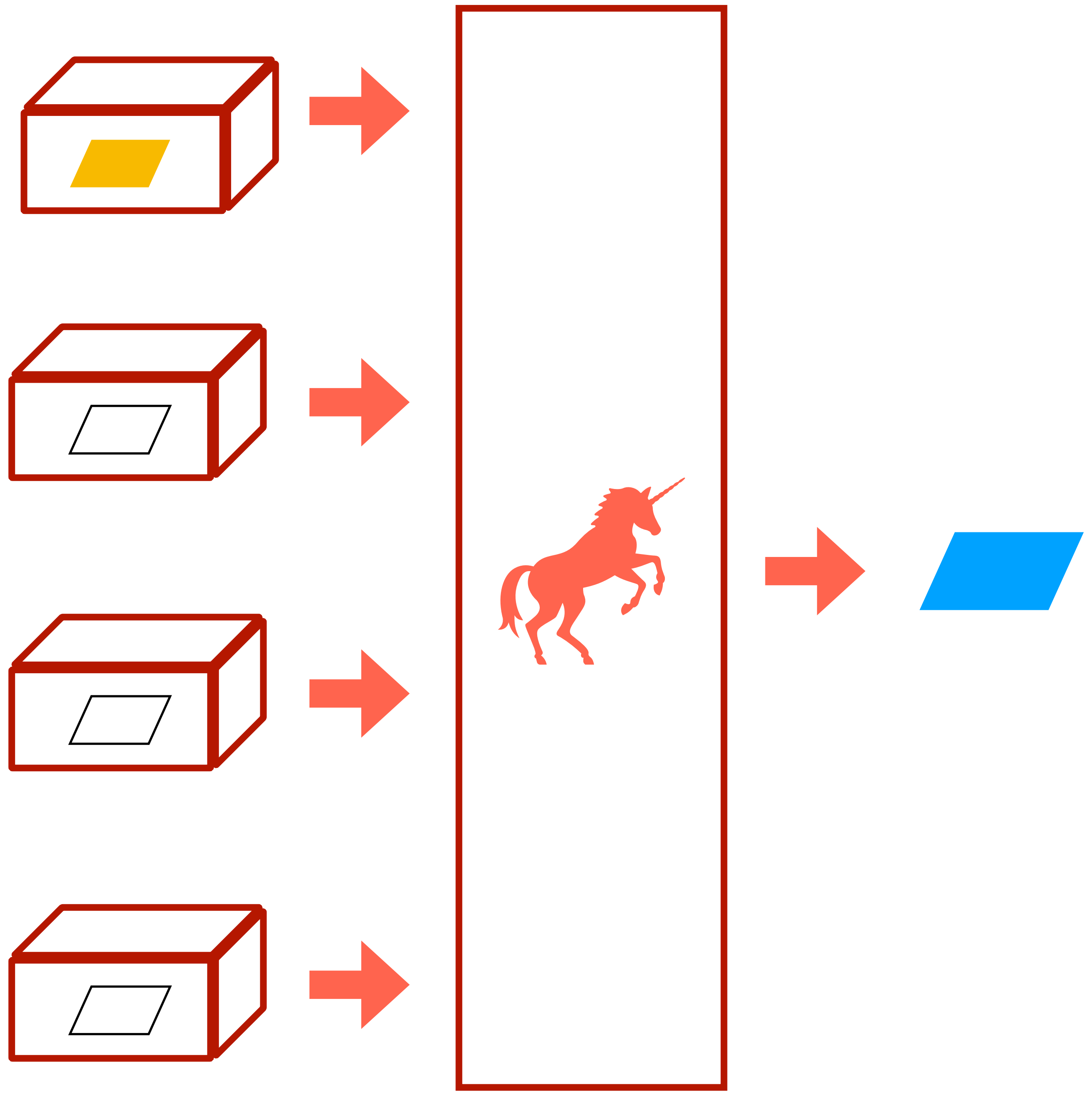
Secure Aggregation

# Need for Dordis - 1



# Need for Dordis - 1

Local
updates
**NOT**
**visible**



Global
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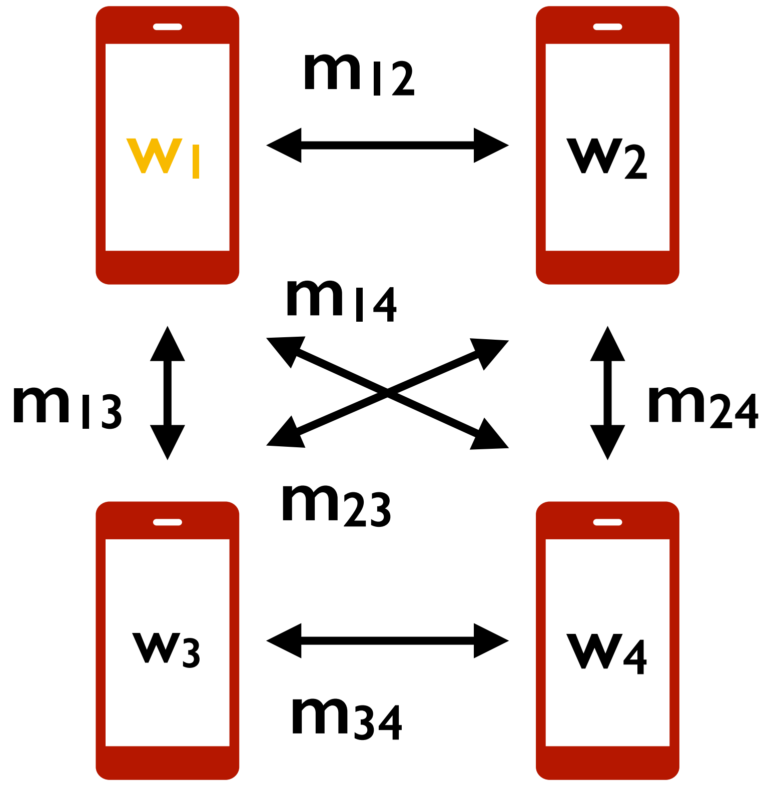
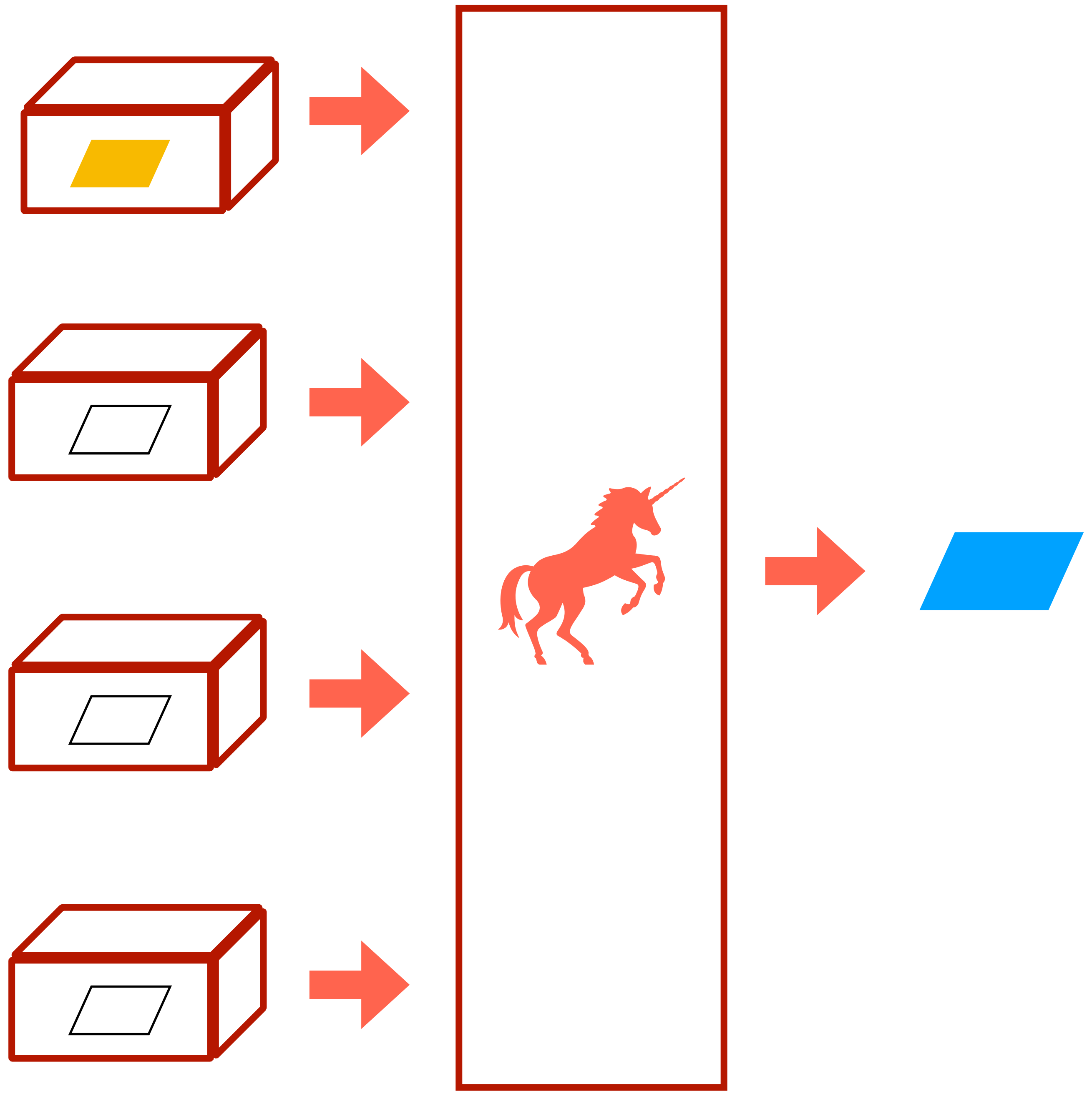



1. **Pairwise** agreement

# Need for Dordis - 1

Local updates **NOT visible**



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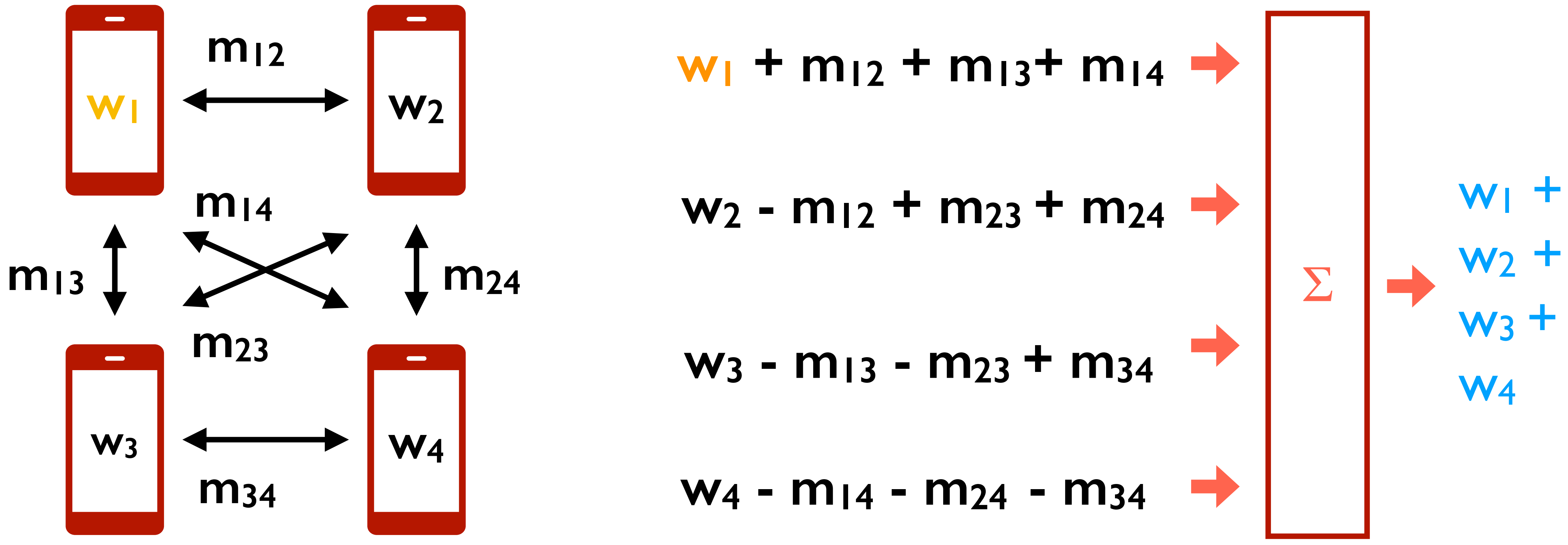
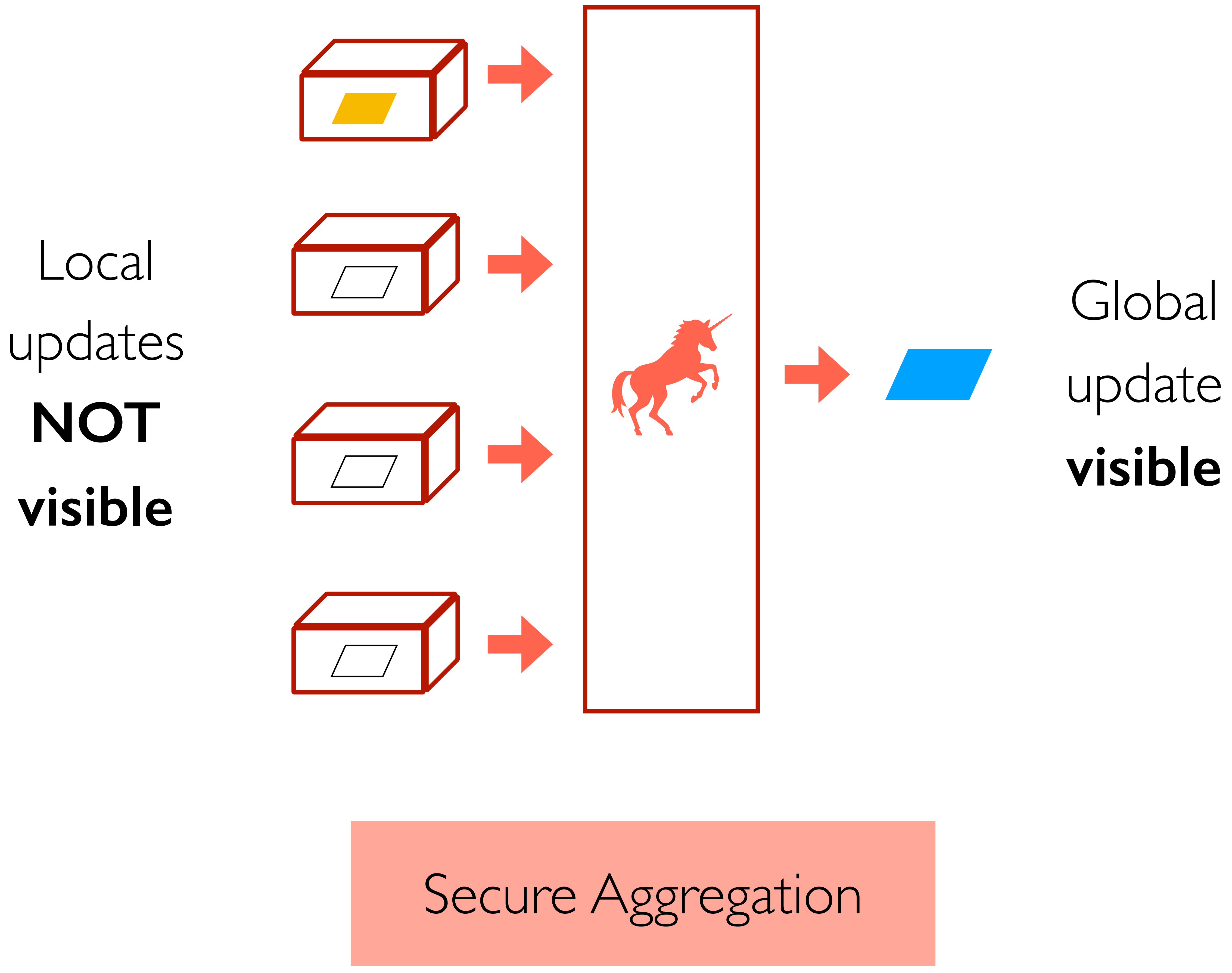
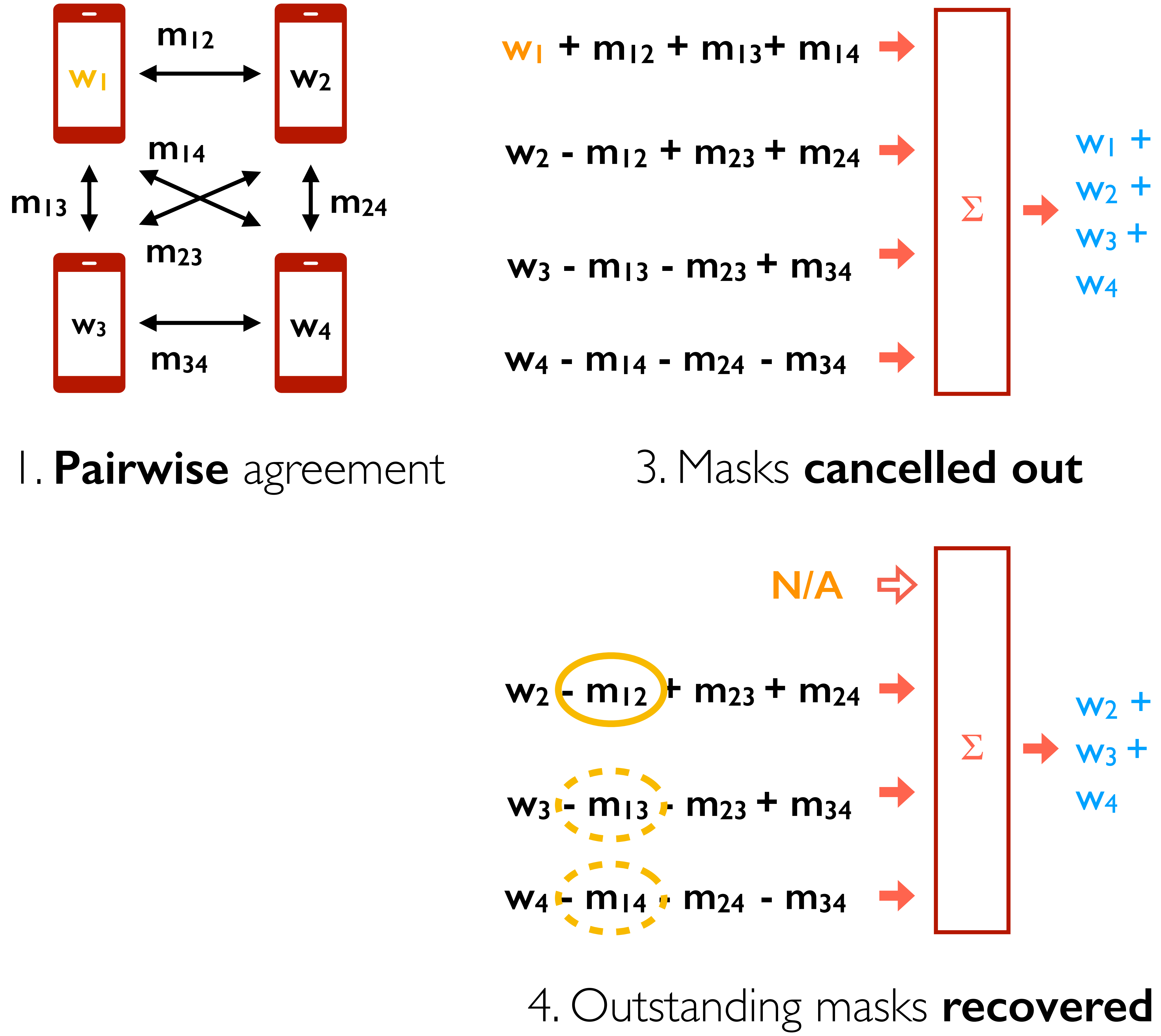



1. **Pairwise** agreement

3. Masks **cancelled out**

# Need for Dordis - 1



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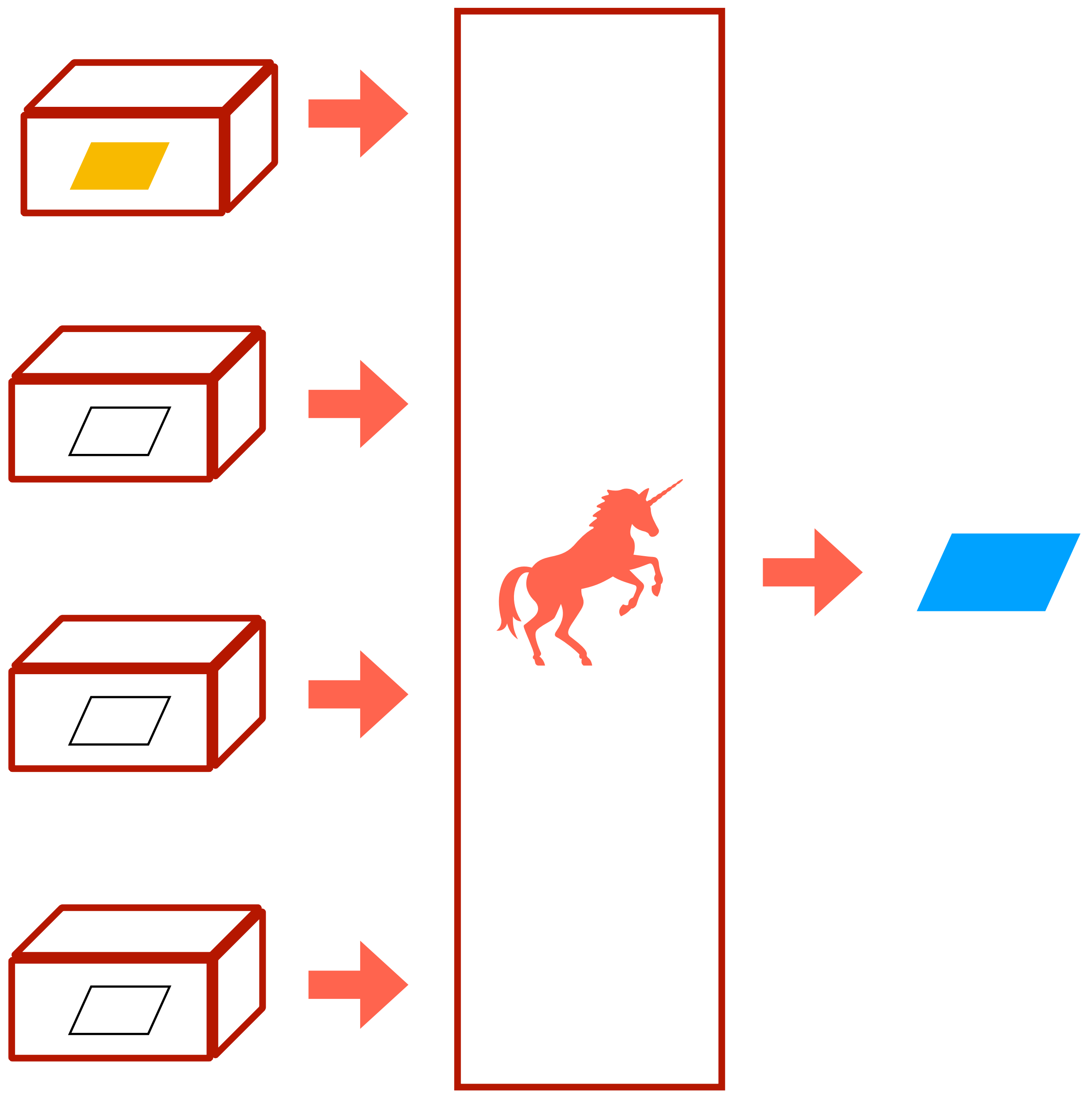
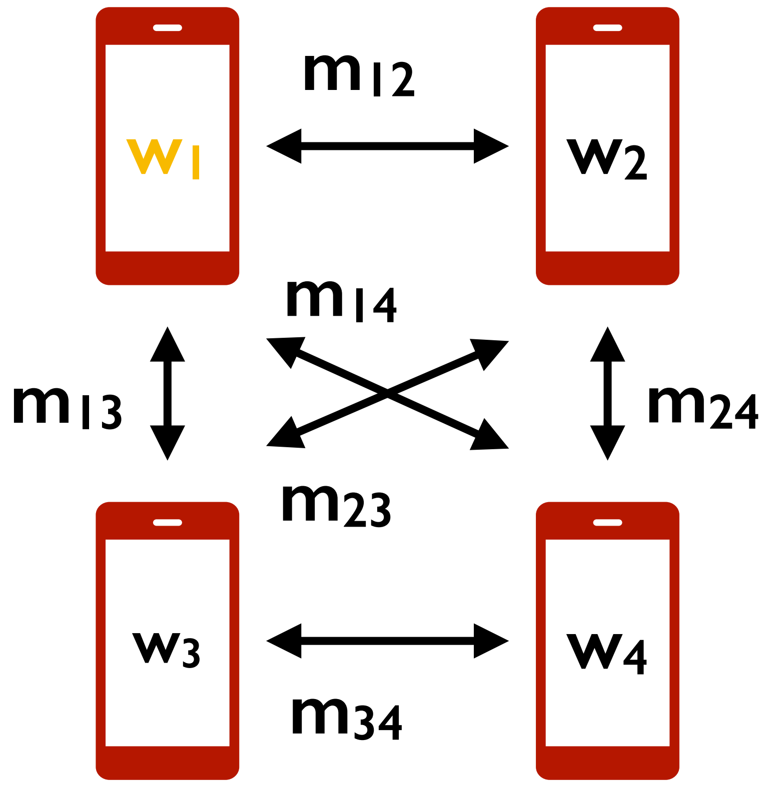


Global update **visible**

Secure Aggregation

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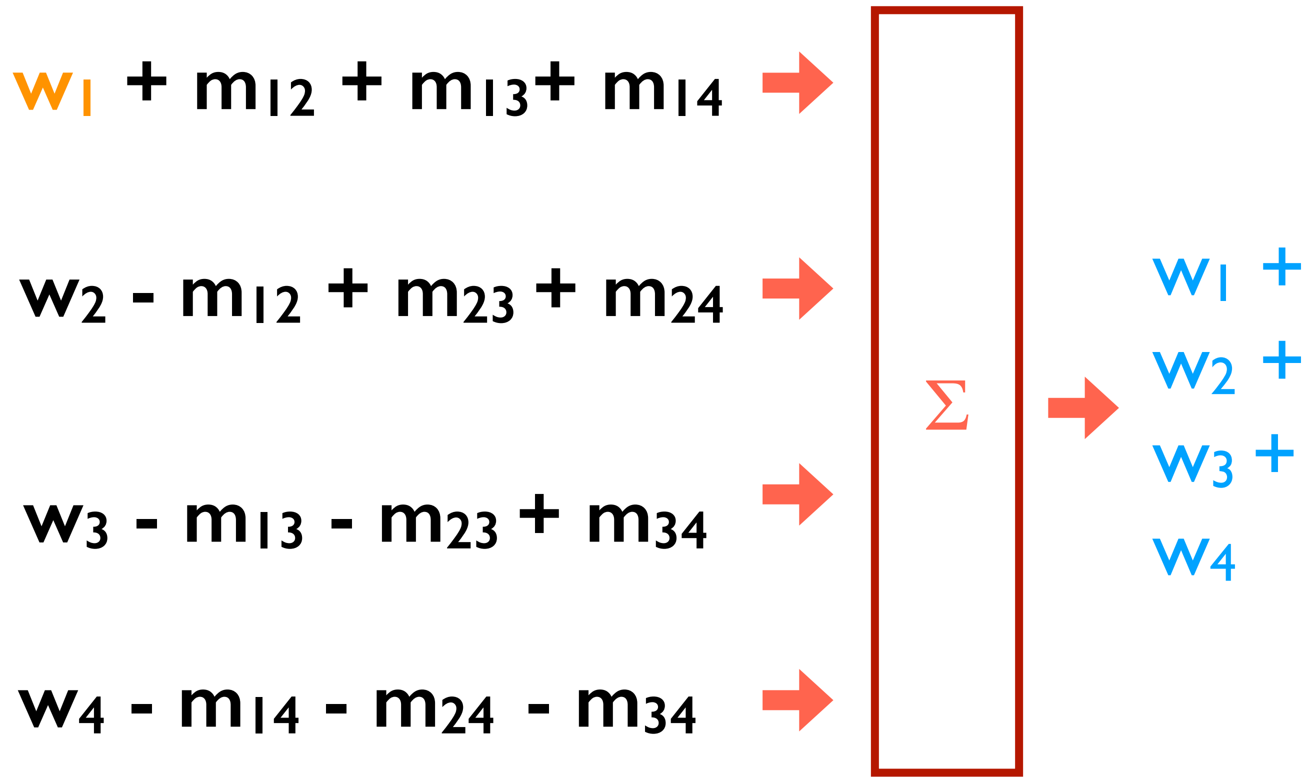


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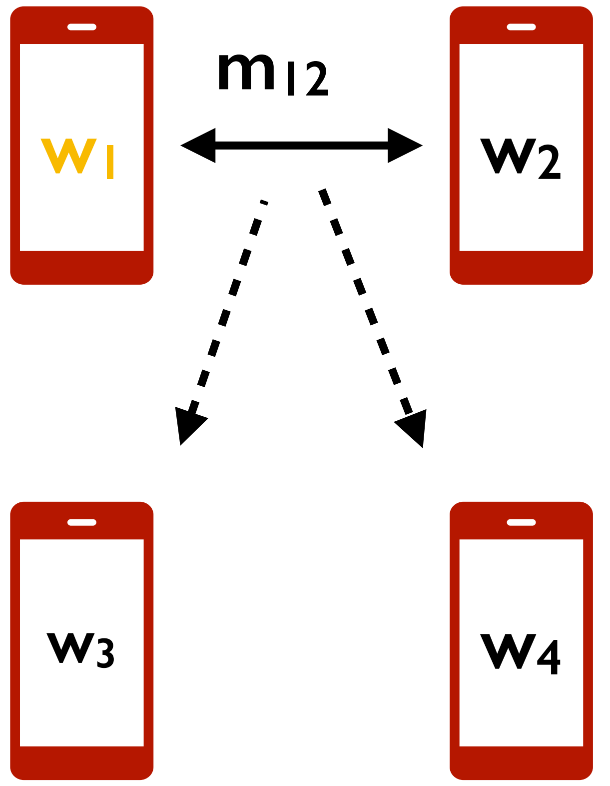
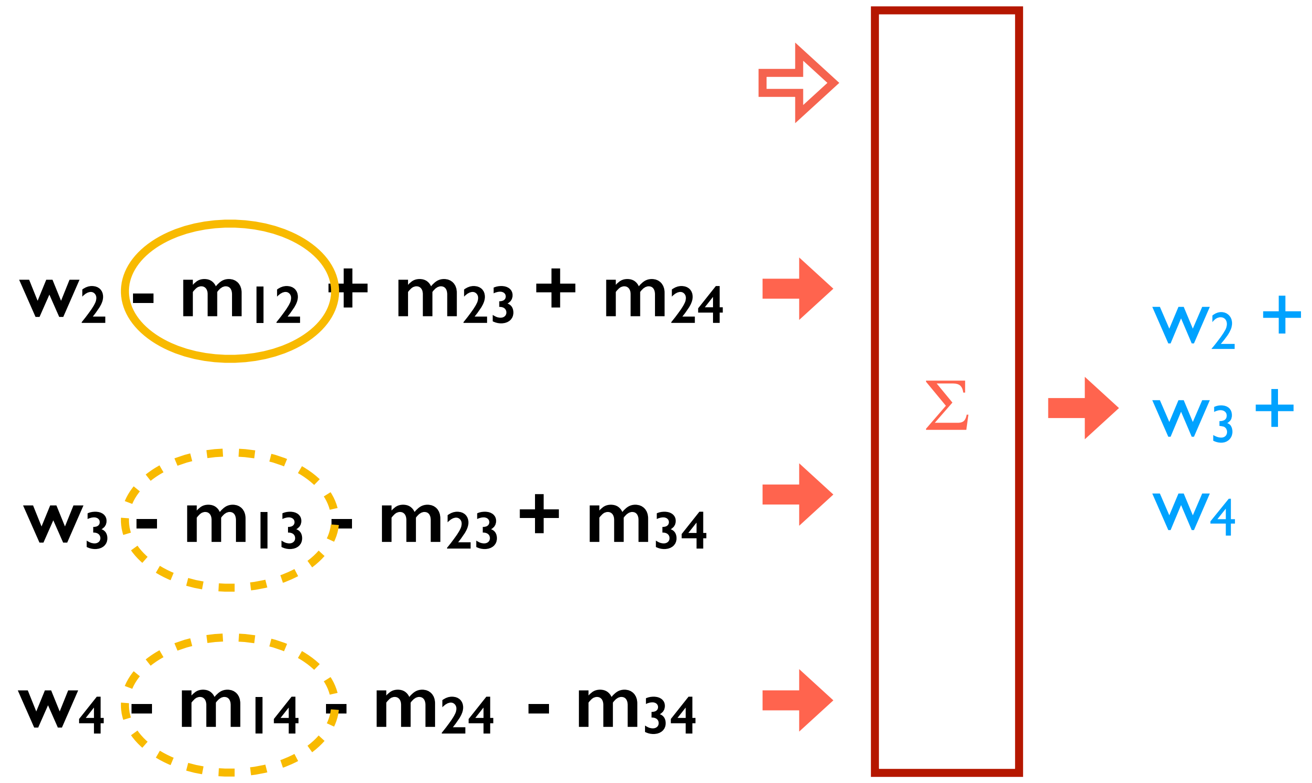



2. Masks **backed up**




4. Outstanding masks **recovered**

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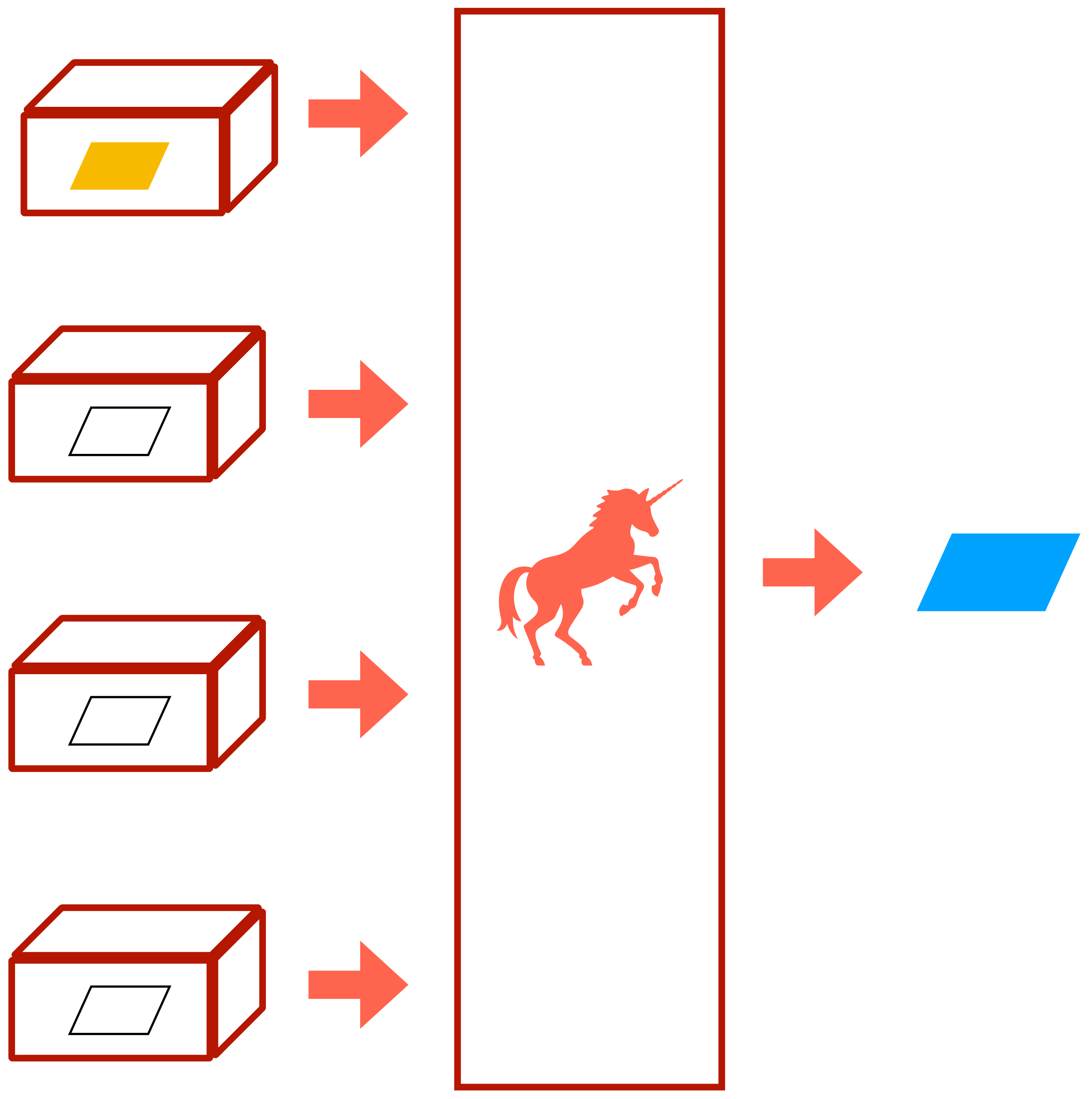

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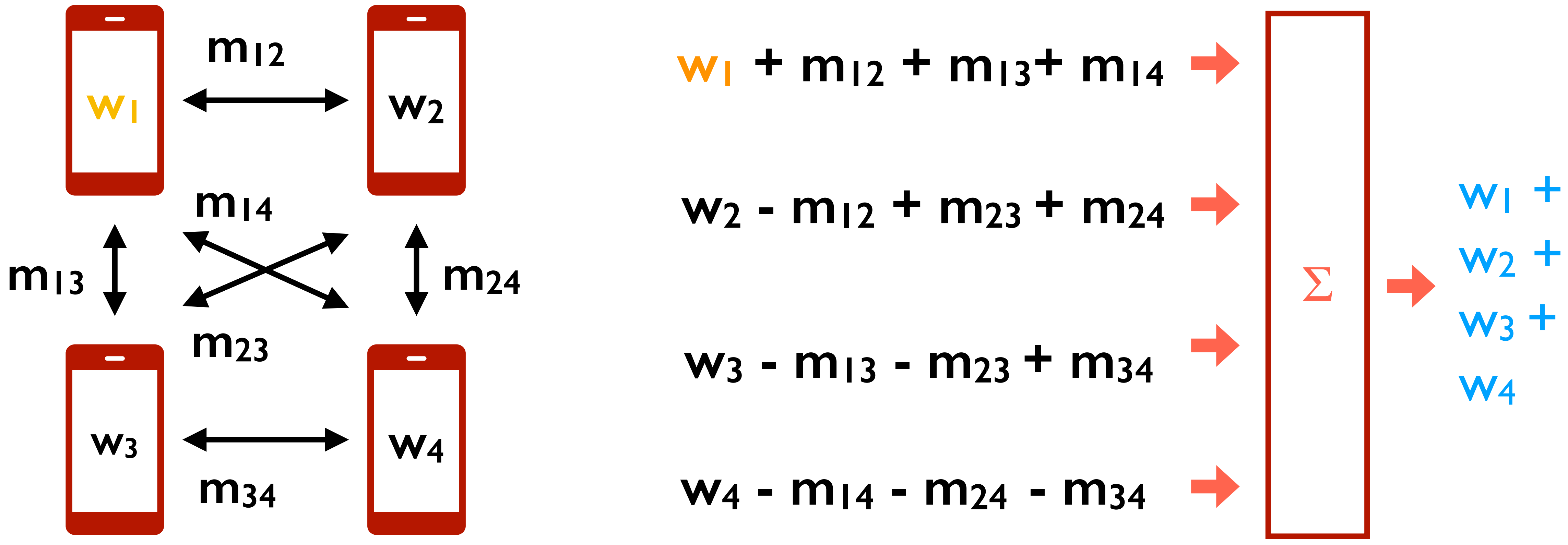
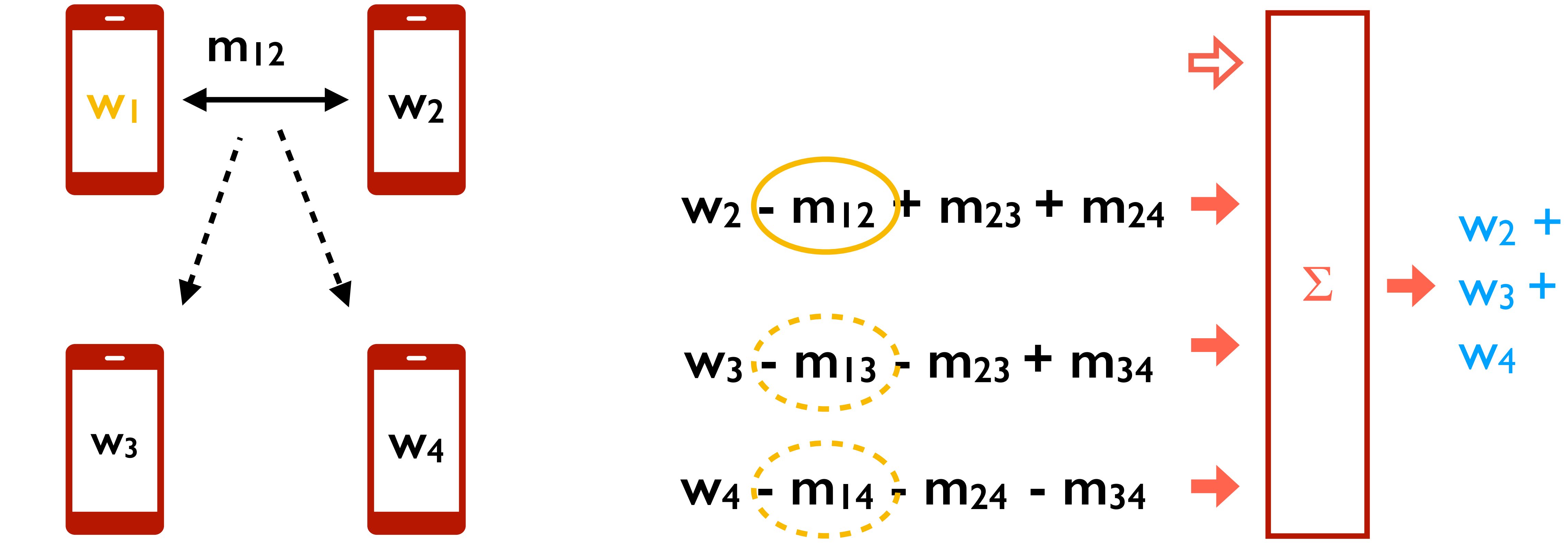
Secure Aggregation




Primitive 1: **Pairwise masking** (all-to-all)




Primitive 2: **Secret sharing** (all-to-all)

# Need for Dordis - 1

**Problem**: Pairwise masking and secret sharing are necessary but **expensive**

Secure Aggregation

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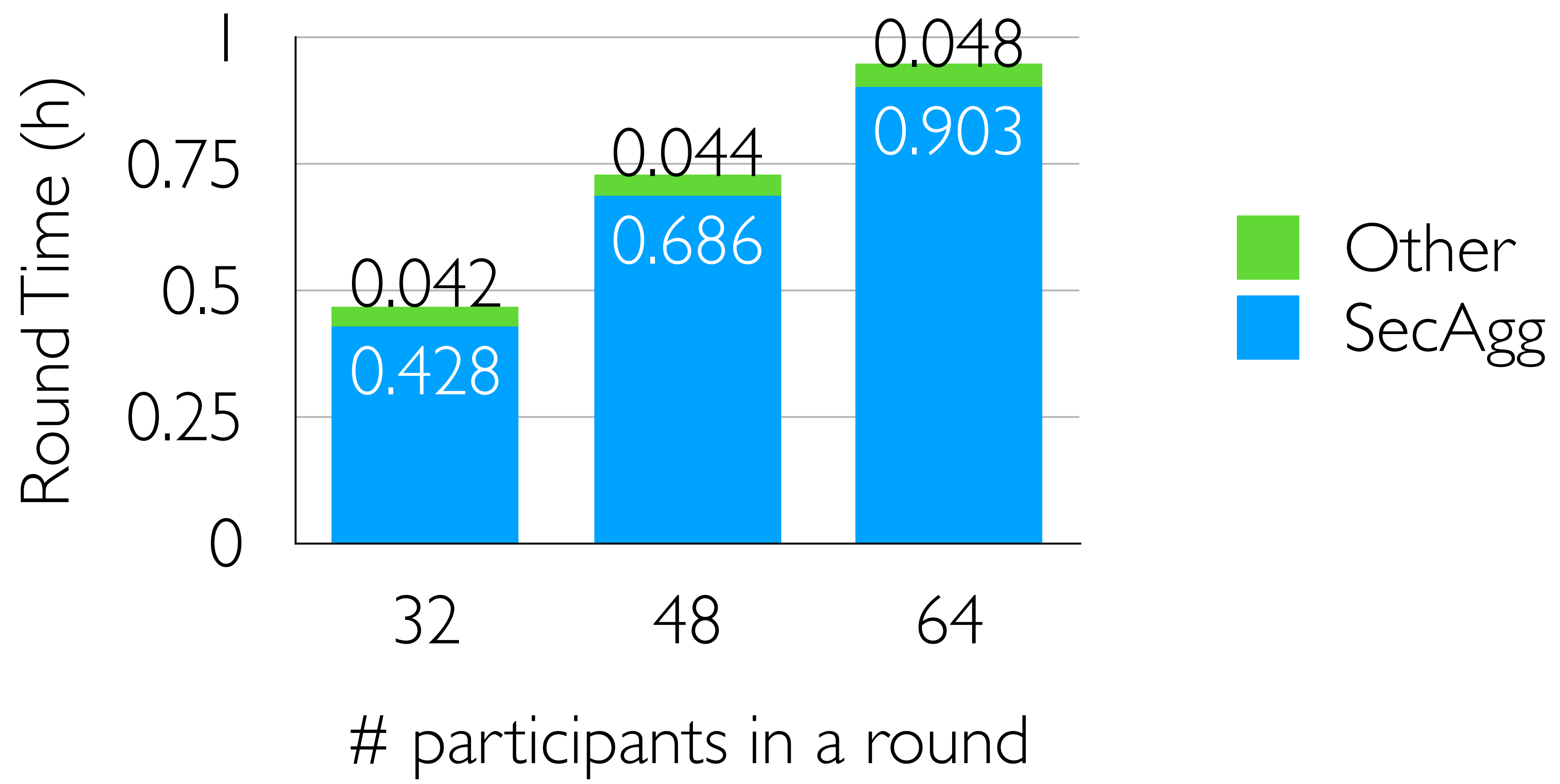


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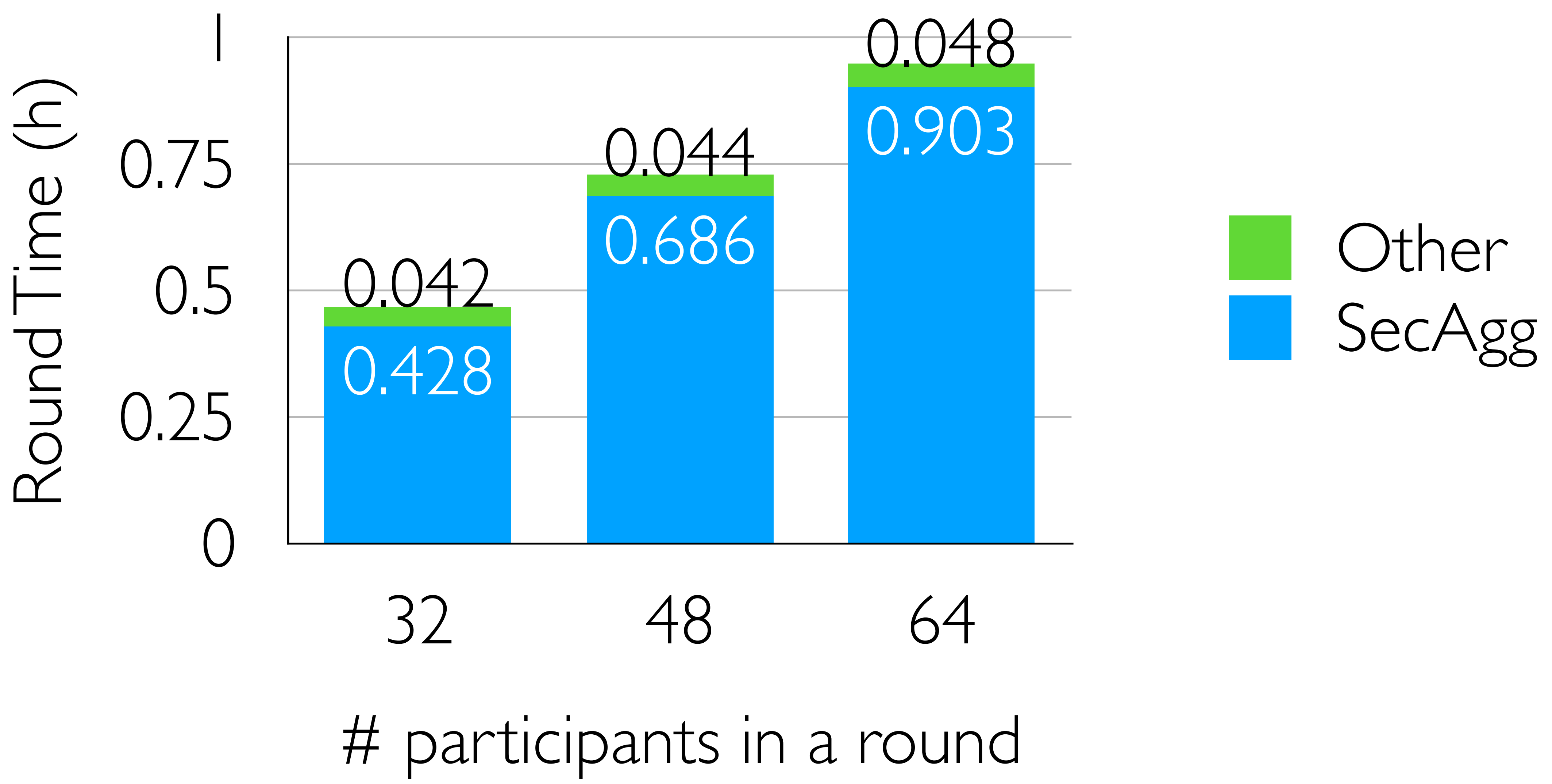


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New **algorithms** exist:

- E.g., **SecAgg+**[1]

[1] Bell et al. "Secure Single-Server Aggregation with (Poly) Logarithmic Overhead", In CCS '20

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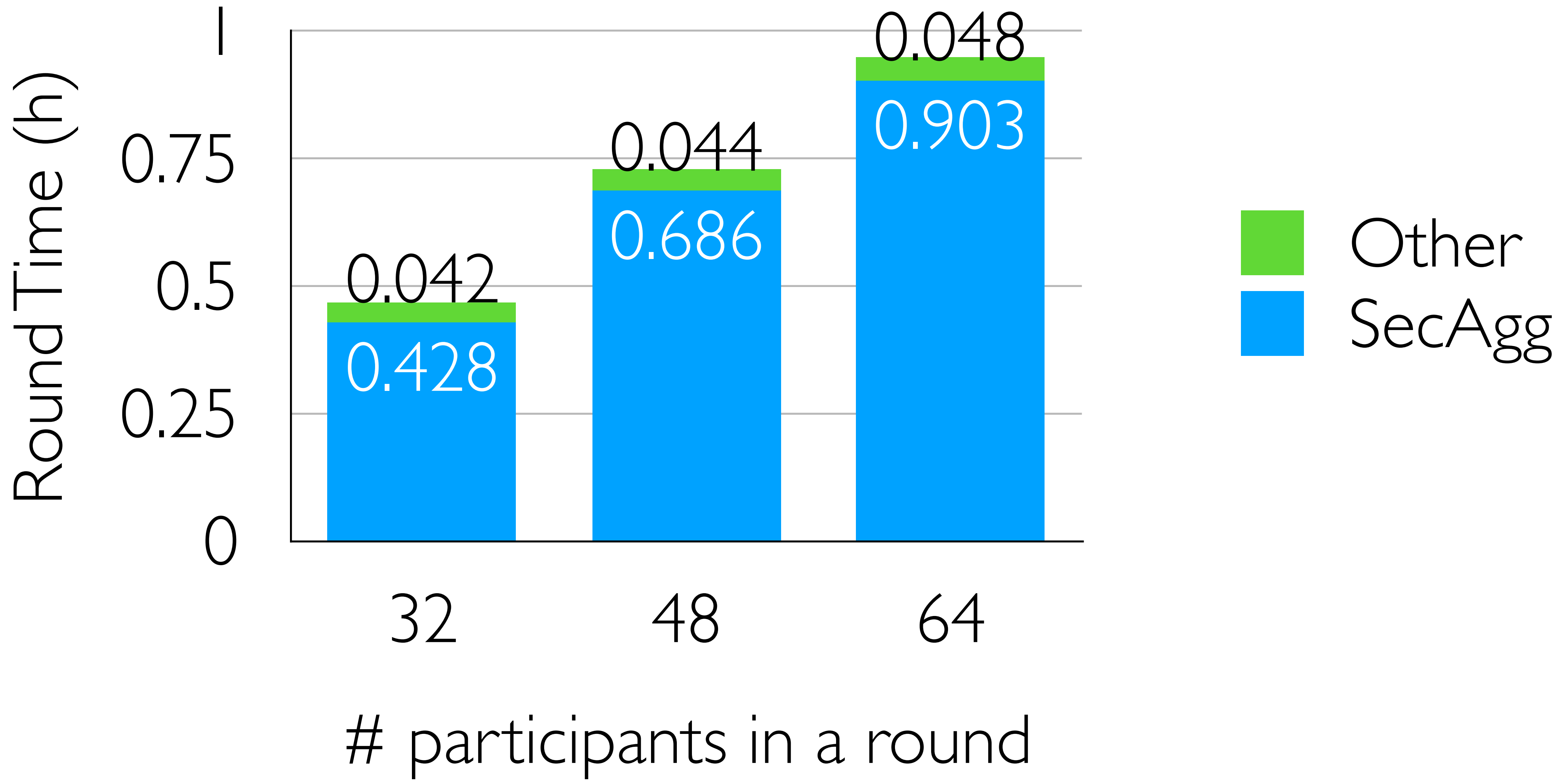


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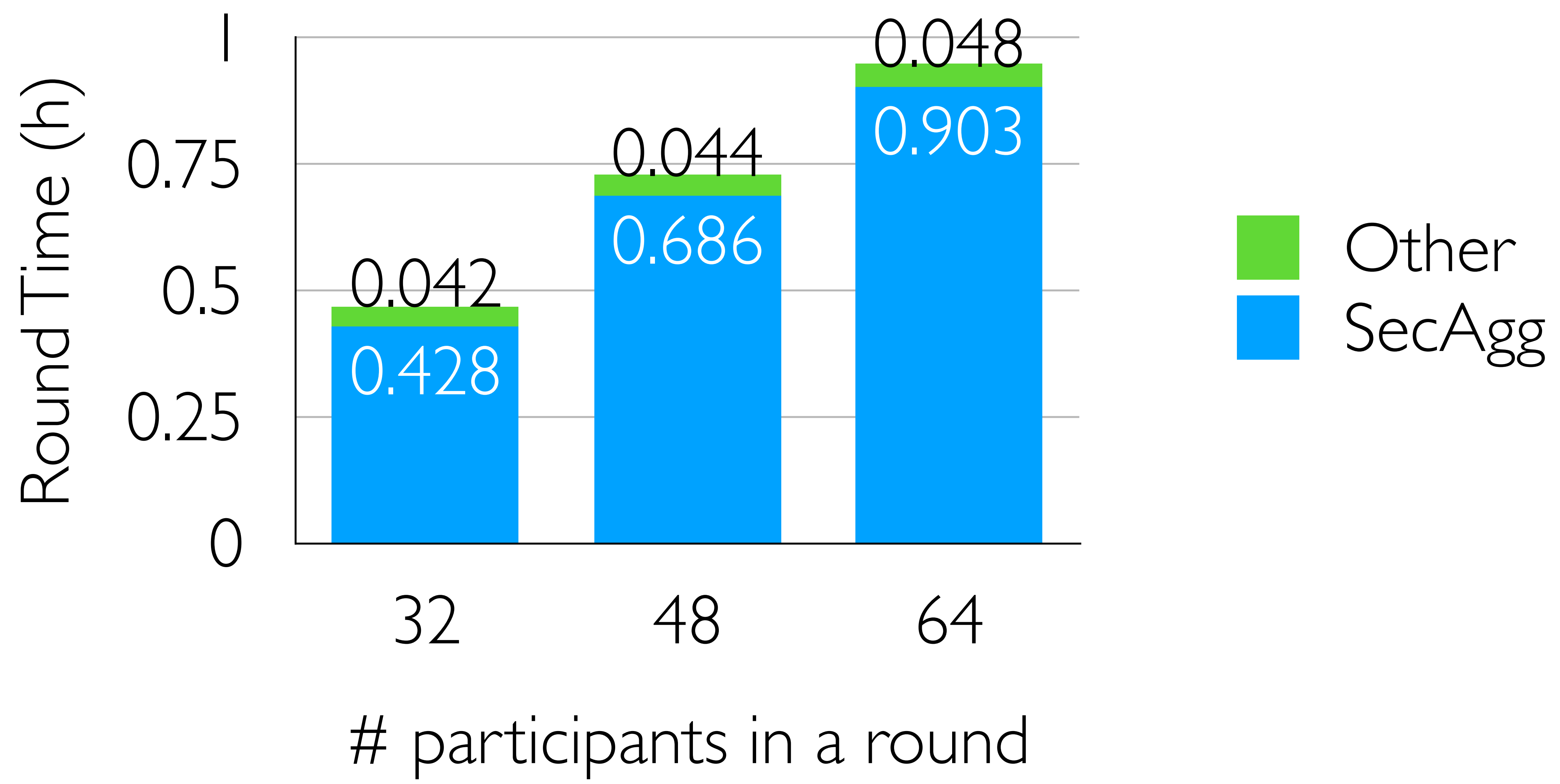


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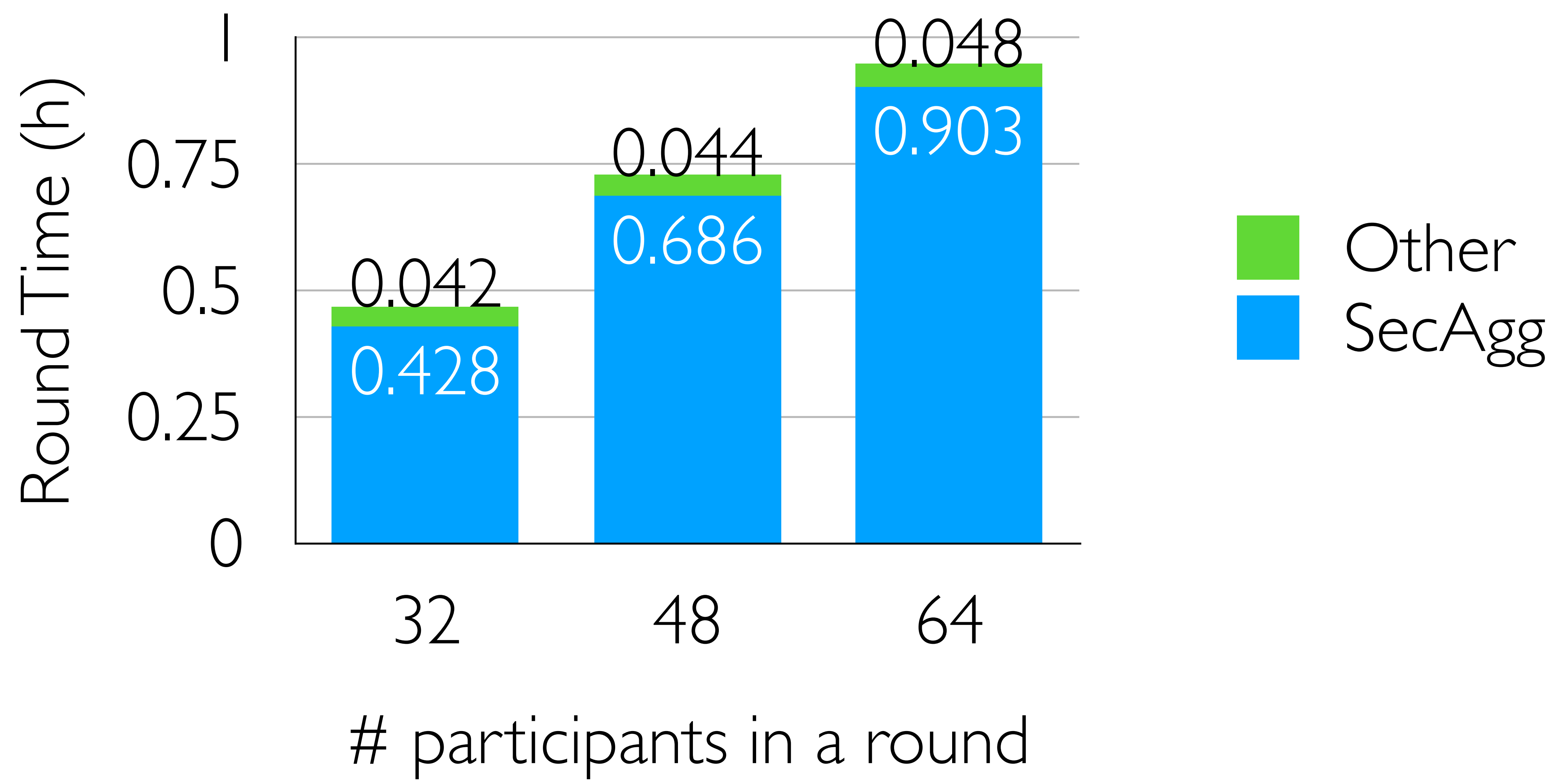


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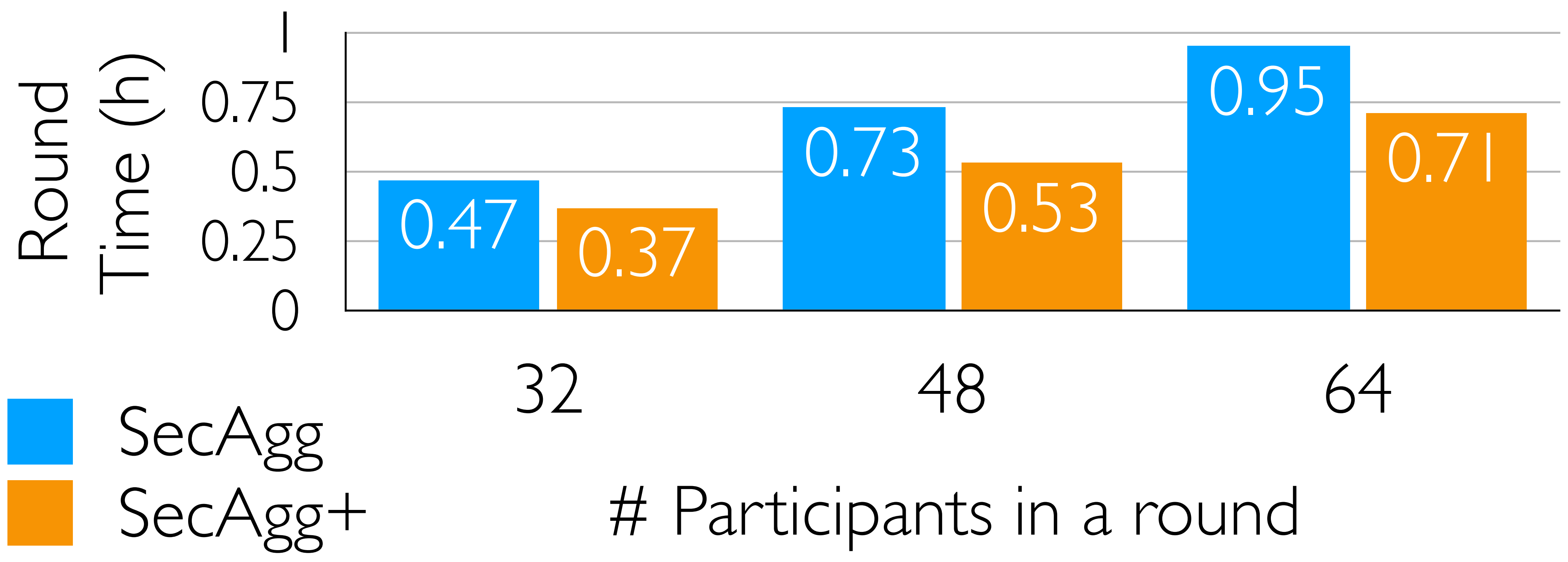


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# Need for Dordis - 2

Differential Privacy

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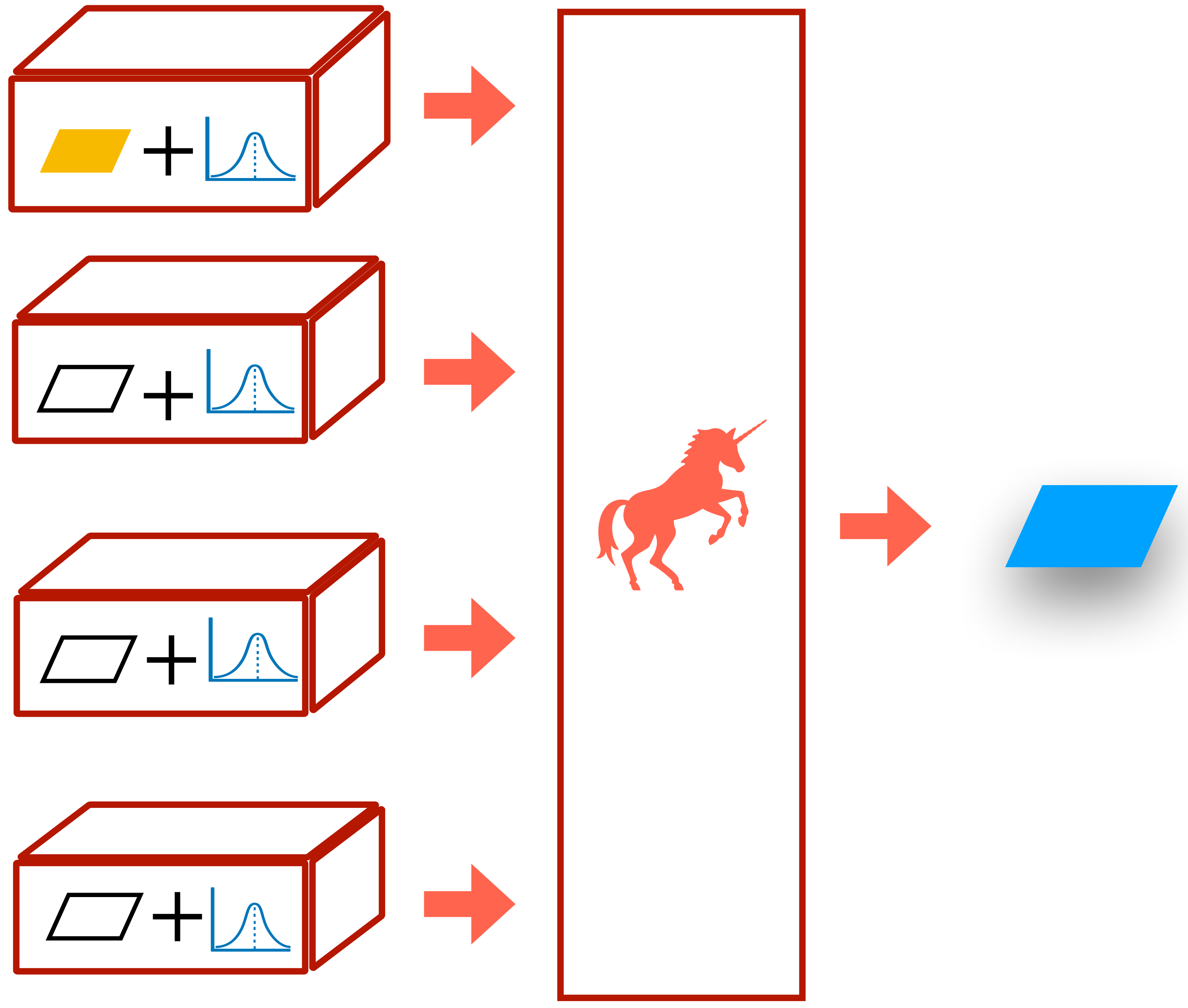

Each client adds an **even share** of the target noise to its local model update

Differential Privacy

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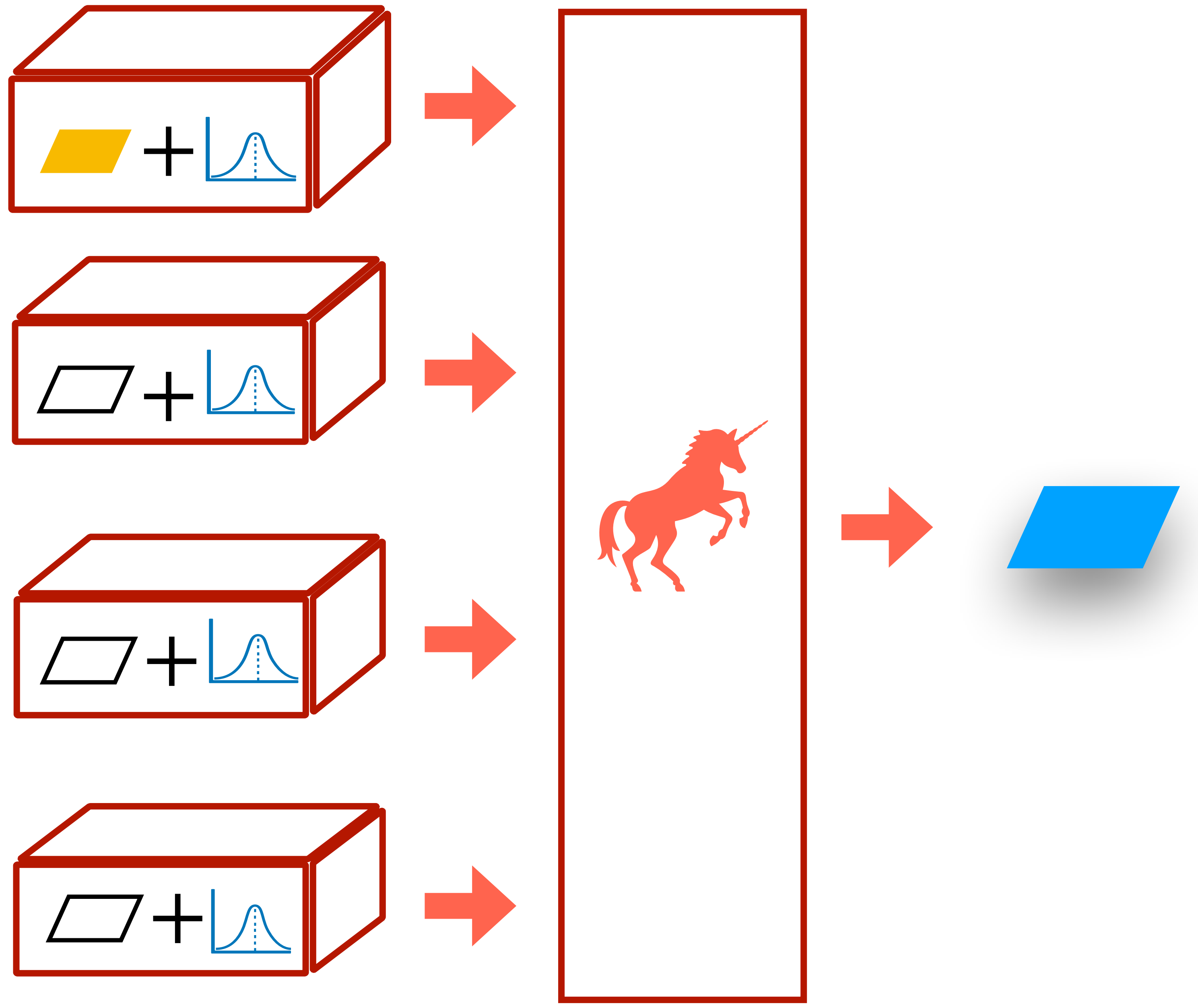

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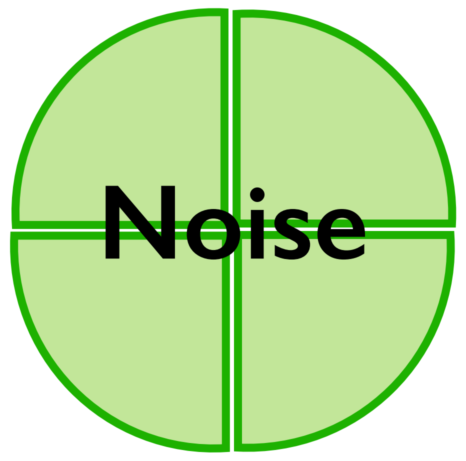
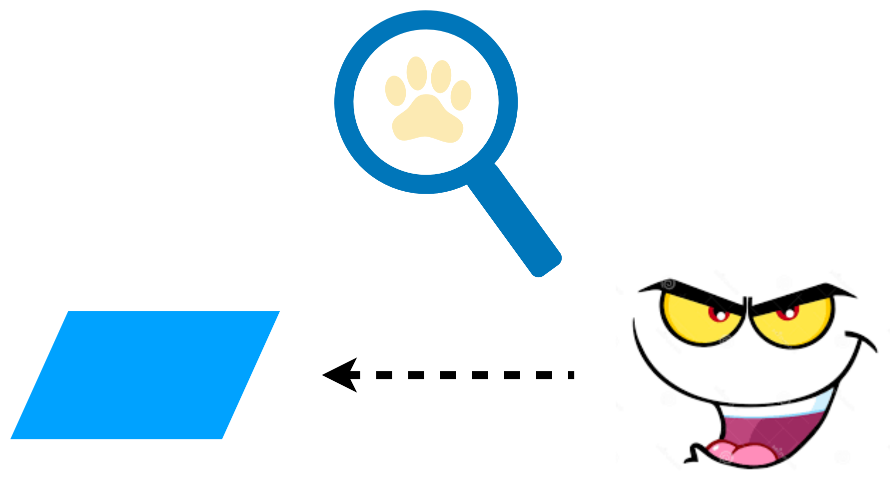



Dropout more severe



Data footprint clearer

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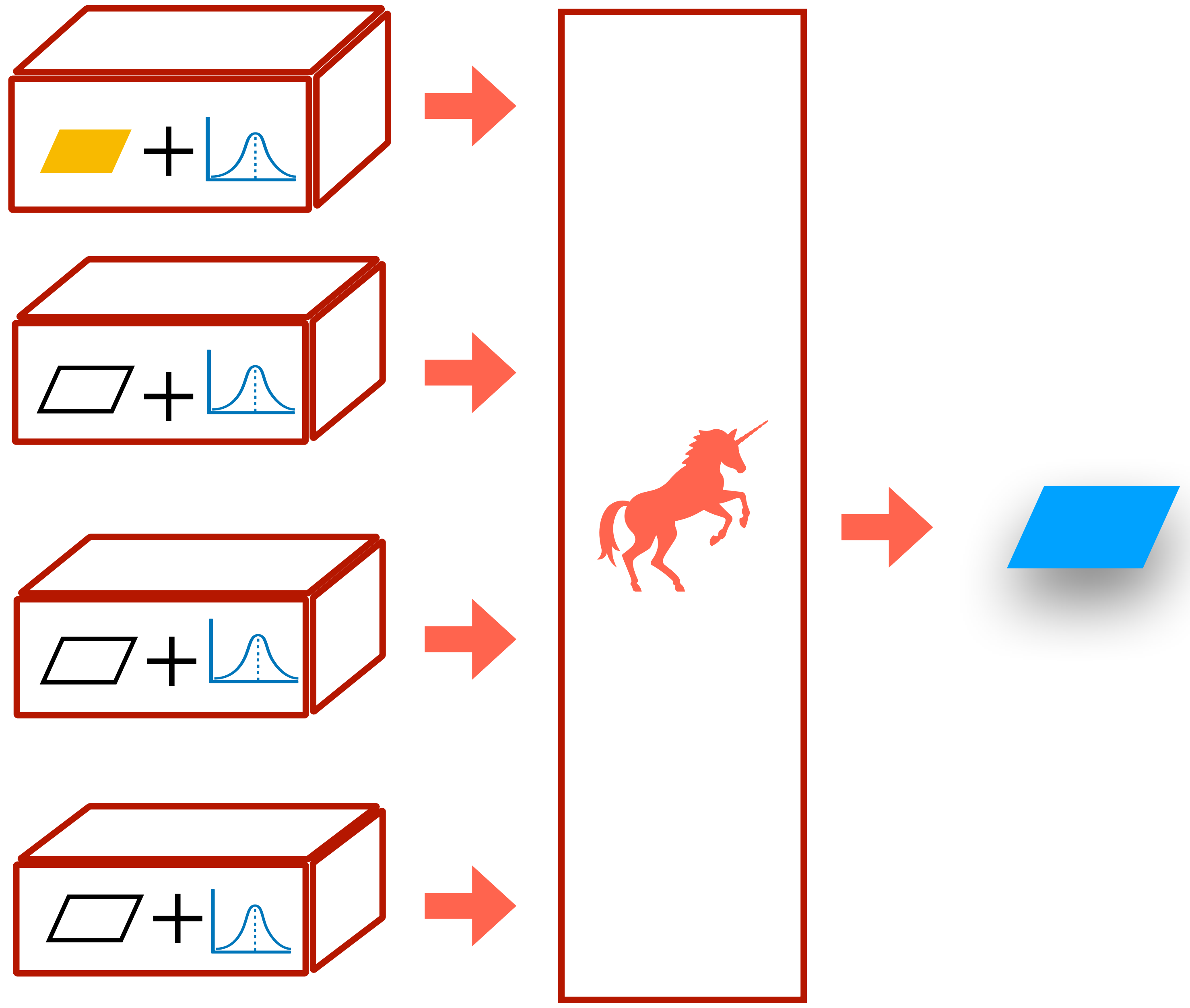

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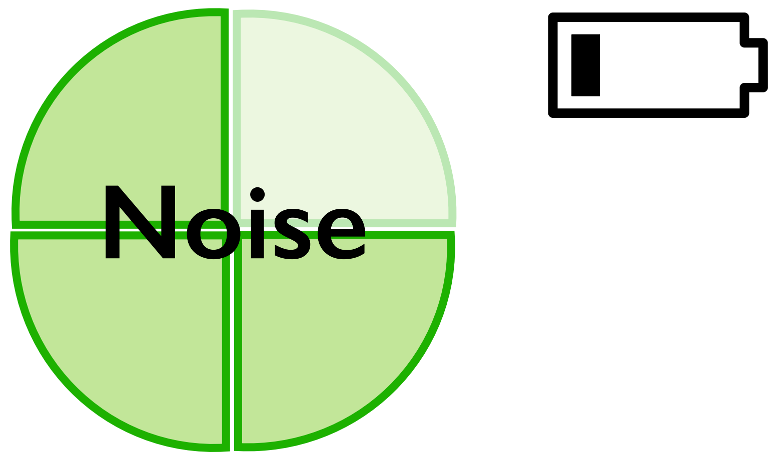


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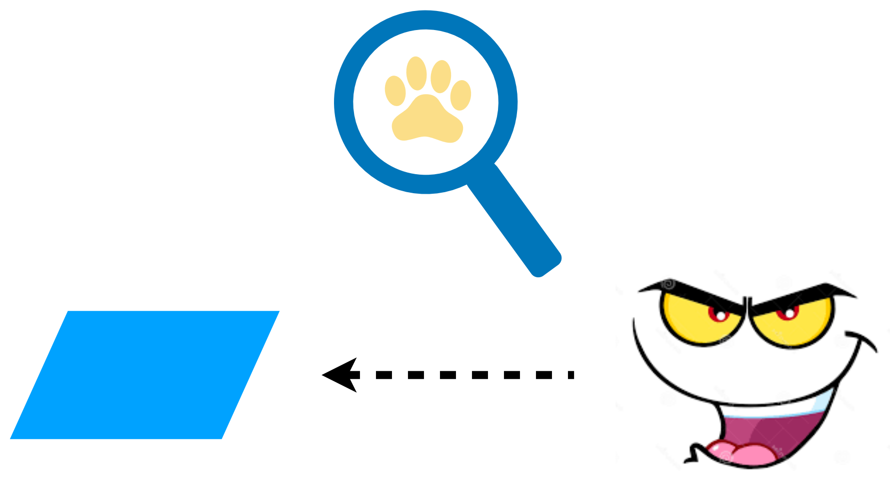

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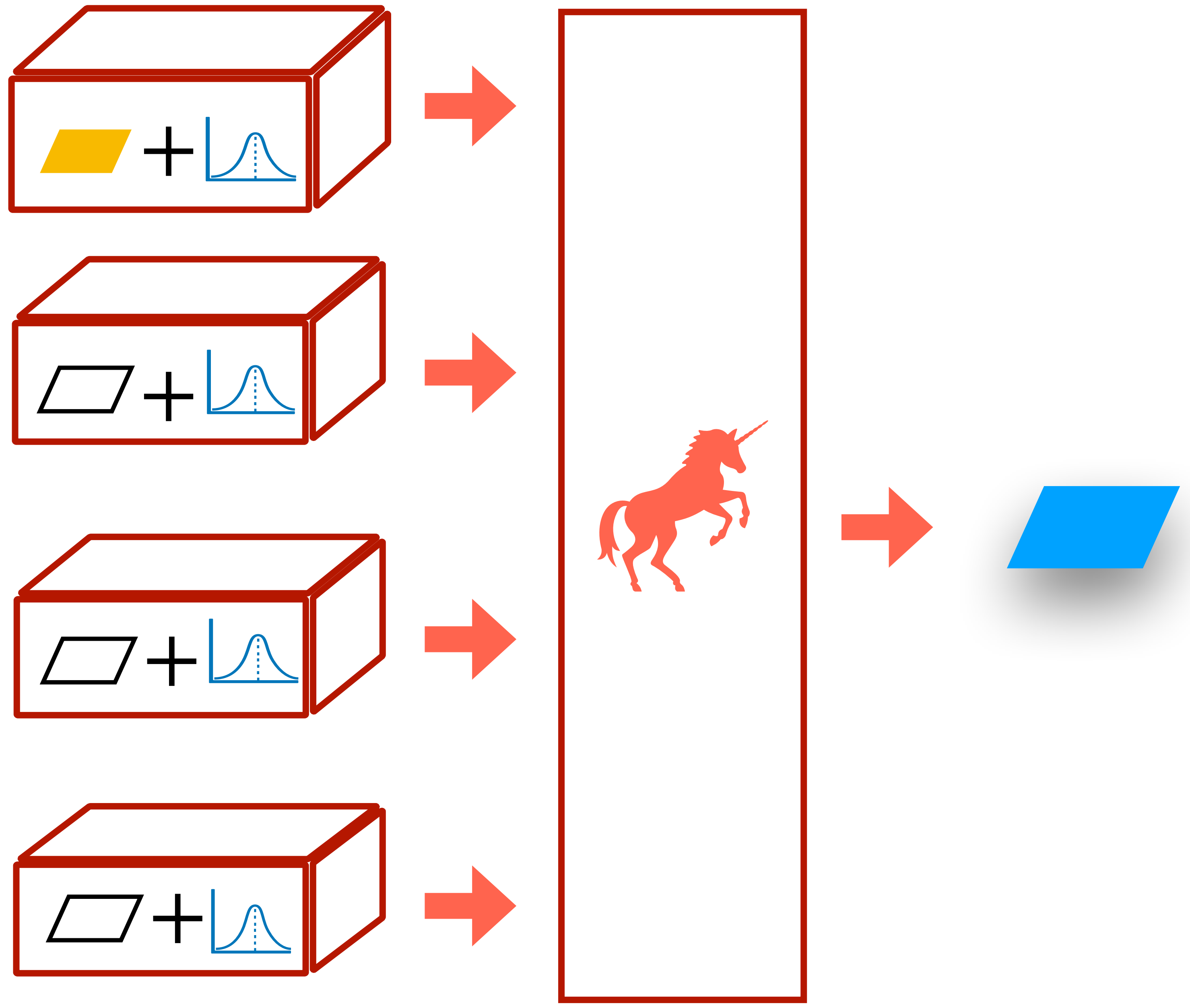

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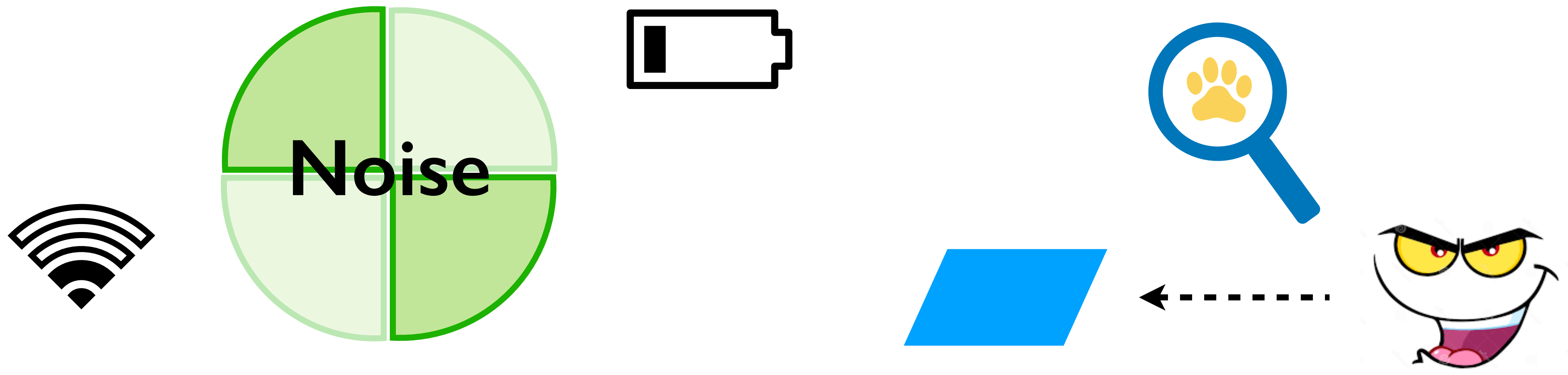


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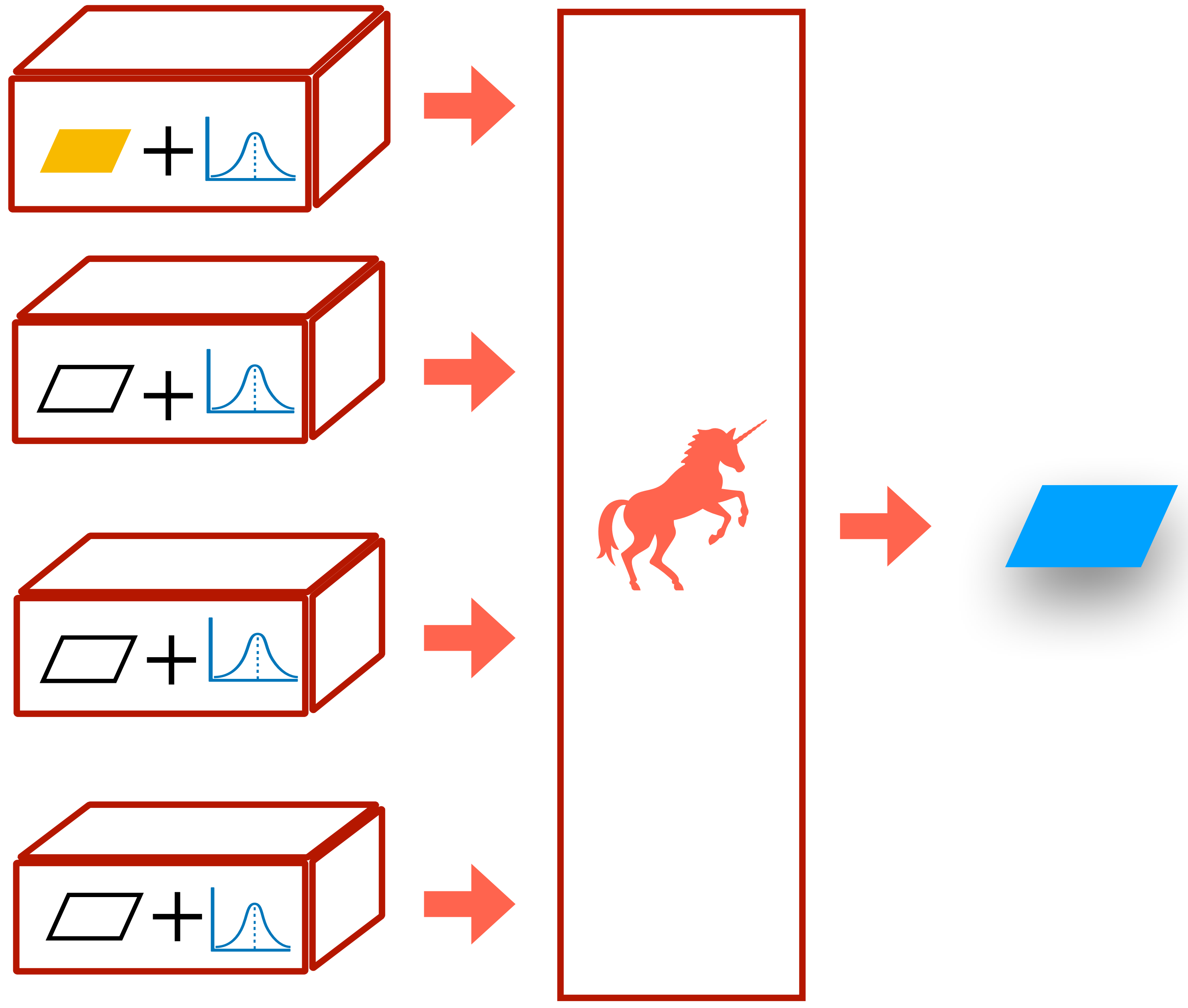

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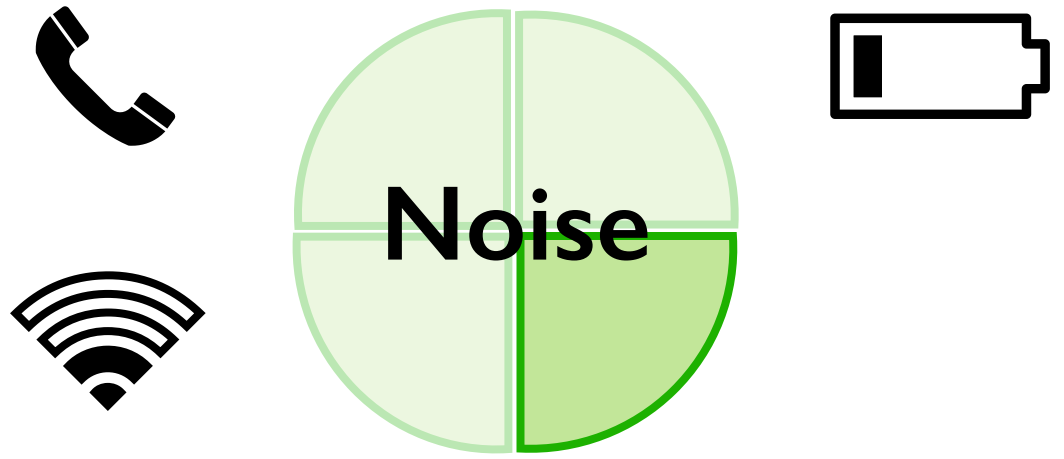


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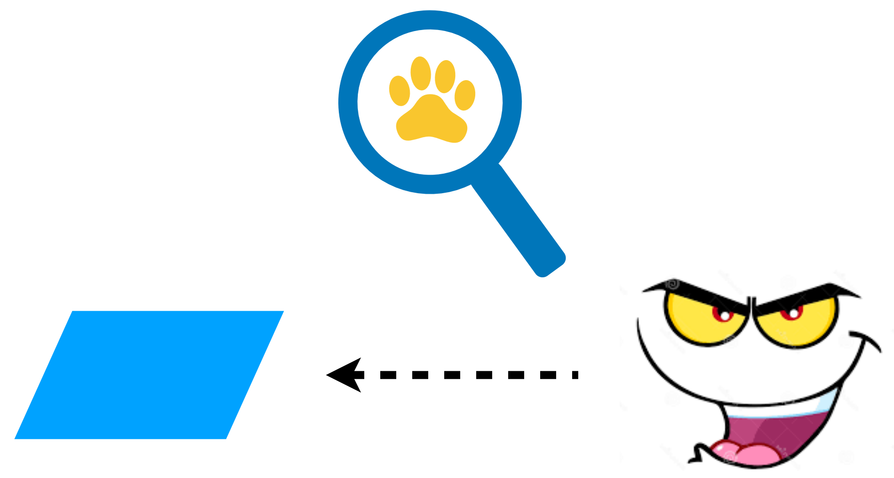

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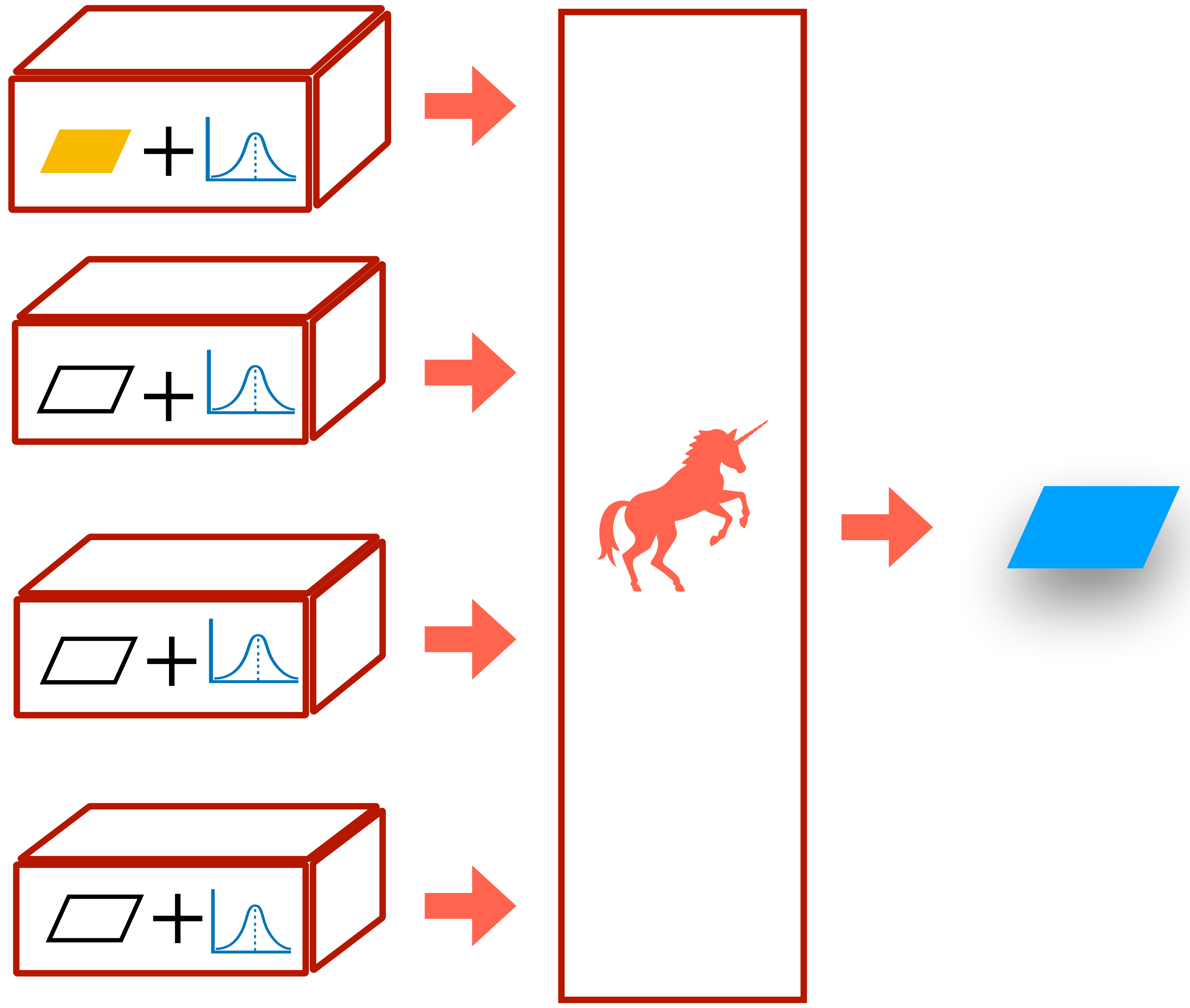

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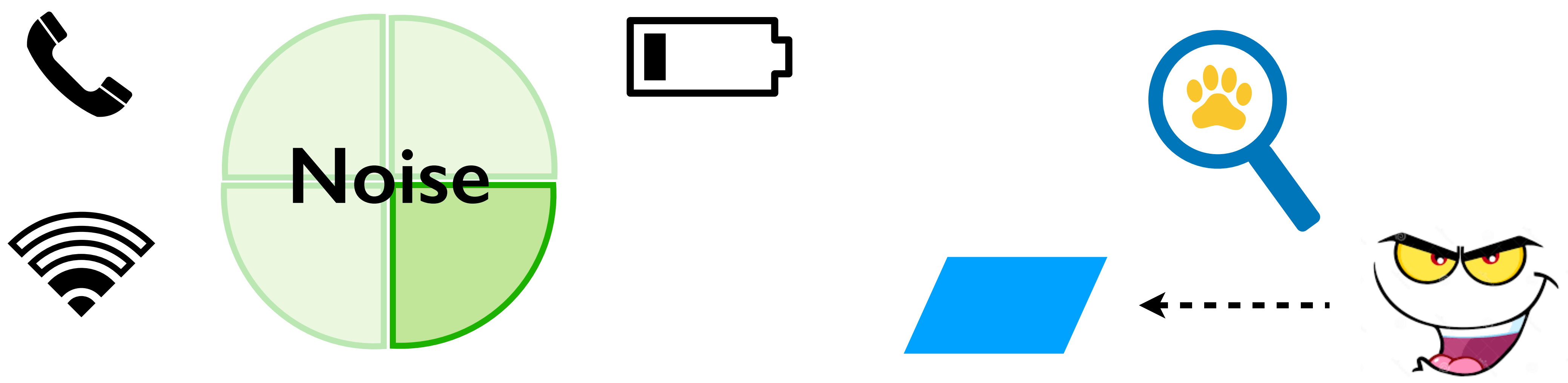


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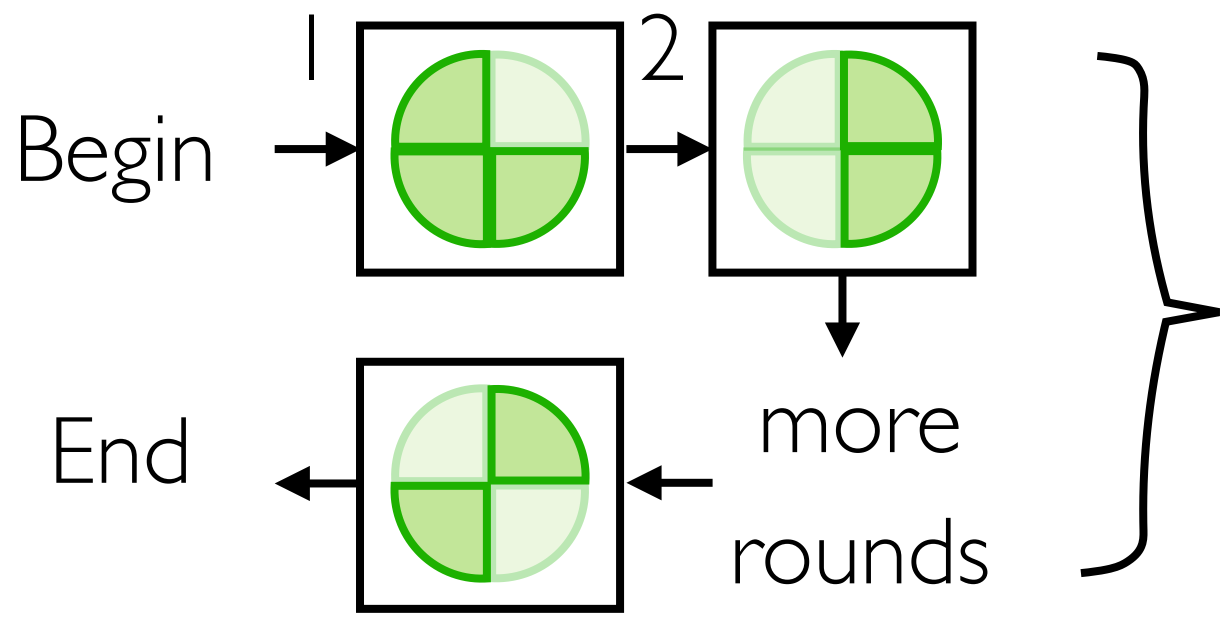


Even worse when **accumulated** across rounds

# Dordis - Overview

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**Substantial speedup** for

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**System-level** optimization:
FL-specific **pipeline parallelism**

Precise **noise enforcement**:
add-then-remove

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**Privacy preserved**
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Goal 1: **Efficient** secure aggregation

Goal 2: **Dropout-resilient** DP

**System-level** optimization:
FL-specific **pipeline parallelism**

Precise **noise enforcement**:
add-then-remove

**Efficiency**

**Integration**

**Resilience**

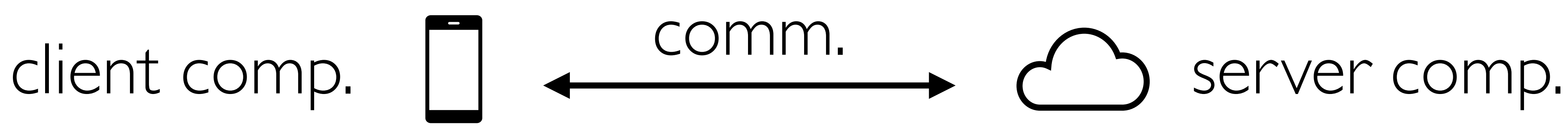
**Substantial speedup** for **general** workloads

**Seamlessly** packed in one **comprehensive** system

**Privacy preserved regardless** of client dropout

# Problem 1: Performance Bottleneck

**System opt.**: Utilize existing resources



# Problem 1: Performance Bottleneck

**System opt.**: Utilize existing resources

client comp. ⟷ comm. ⟷ server comp.

| Step | Operation | Resource |
|---|---|---|
| 1 | Clients encode updates | **client comp.** |
| 2 | Clients generate security keys | **client comp.** |
| 3 | Clients establish shared secrets | **client comp.** |
| 4 | Clients mask encoded updates | **client comp.** |
| 5 | Clients upload masked updates | **comm.** |
| 6 | Server deals with dropout | **server comp.** |
| 7 | Server computes the sum | **server comp.** |
| 8 | Server updates global model | **server comp.** |
| 9 | Server dispatches global model | **comm.** |
| 10 | Clients decode global model | **client comp.** |
| 11 | Clients use global model | **client comp.** |

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**Potential approach**:

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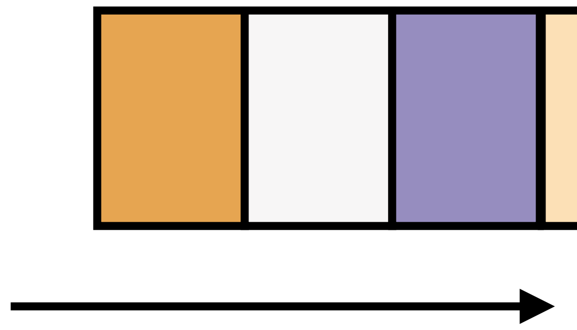
Diff. stages,
**diff** resources



Workflow

**Traditional ML**: Free data movement

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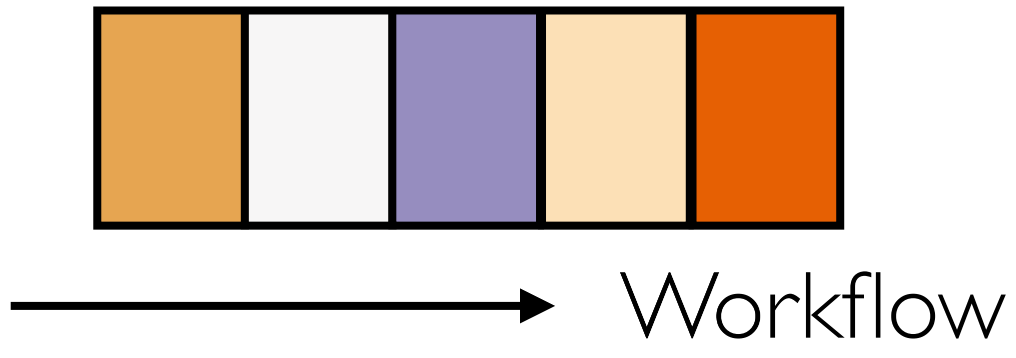
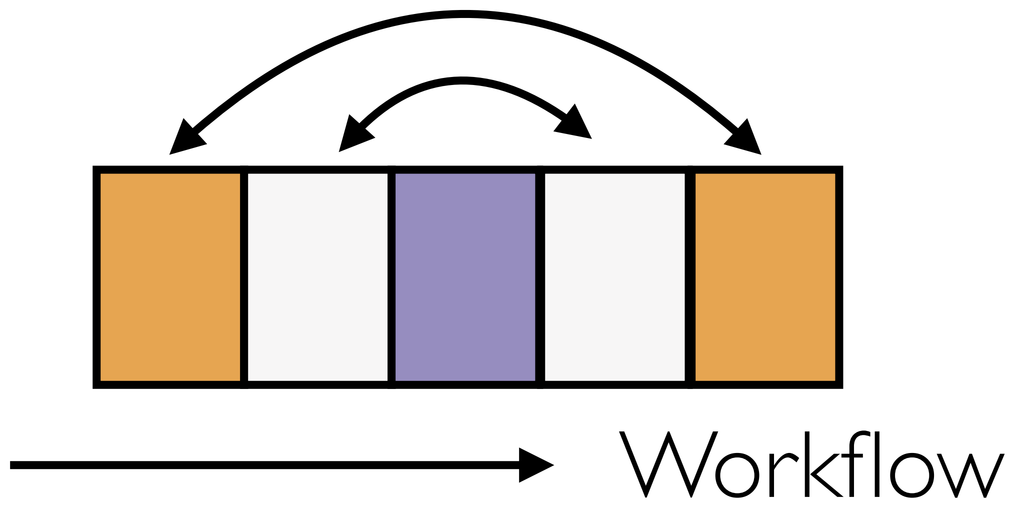



**Traditional ML**: Free data movement

Diff. stages, **same** resource




**FL**: Data movement restricted due to privacy

**Challenge**: New **constraints** in optimizing pipeline parallelism

# Problem 1: Performance Bottleneck

**Solution:** pipeline parallelism tailored for **FL**

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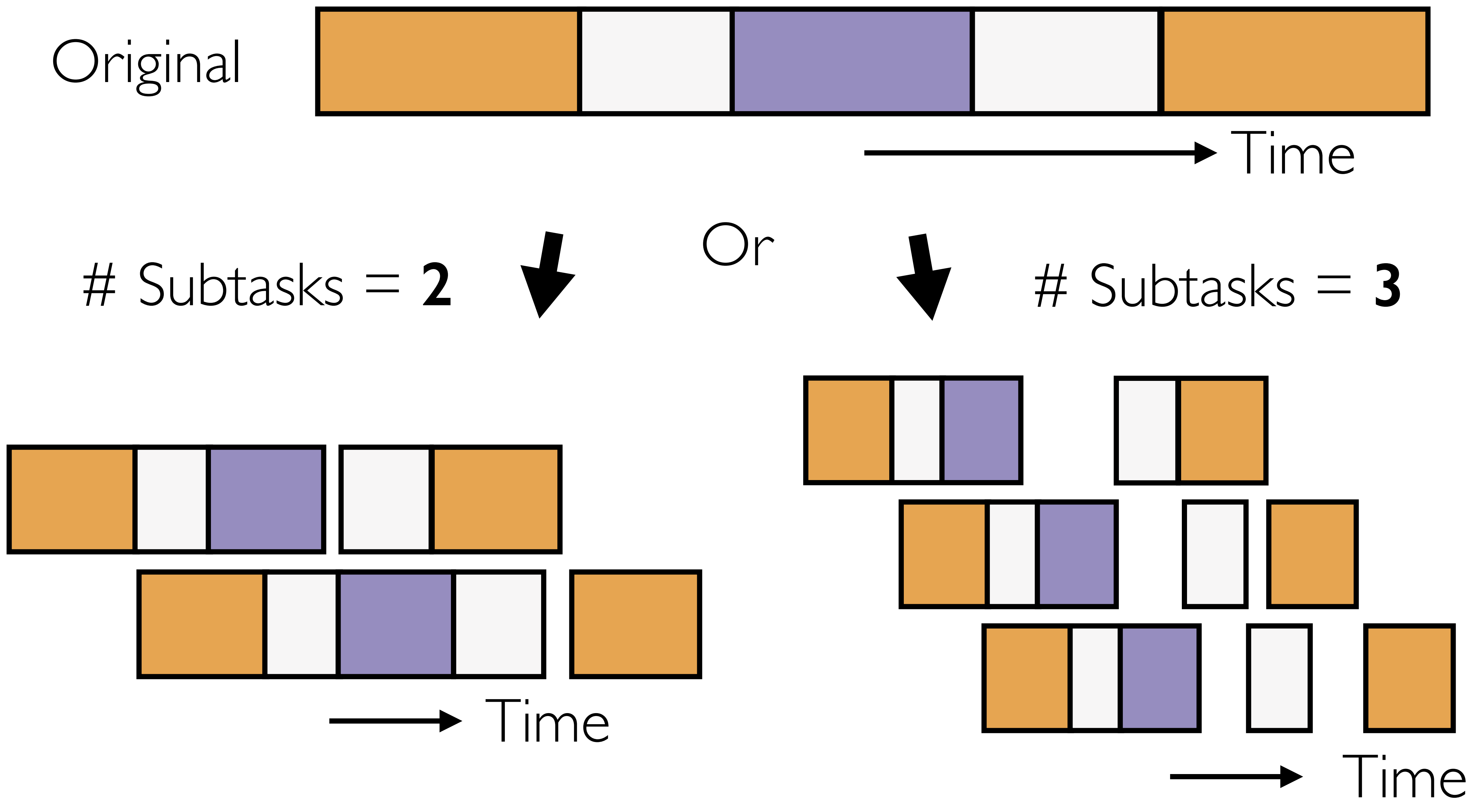


**Different time**

# Problem 1: Performance Bottleneck

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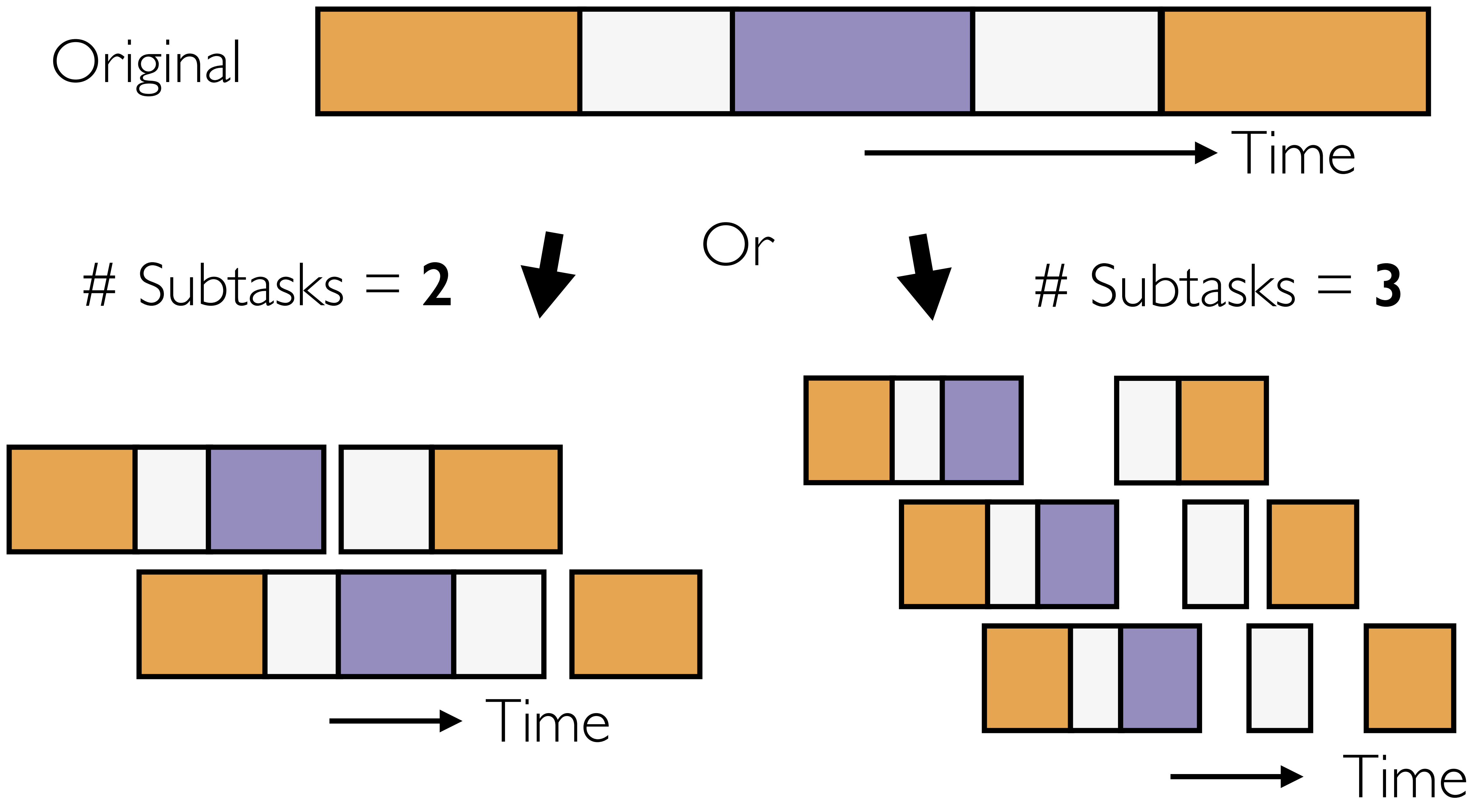
1. **Task partitioning**: enable parallelism

- # Subtasks: decision variable to optimize




**Different time**

2. **Constrained optimization**

$$m^* = \arg\min_{m \in N_+} f_{a,m}$$ Optimal # subtasks

$$s.t. \quad f_{s,c} = b_{s,c} + l_s$$

$$b_{s,c} = \max\{o_{s,c}, r_{s,c}\}$$

$$o_{s,c} = \begin{cases} 0, & \text{if } s = 0, \\ f_{s-1,c} & \end{cases}$$

**The FL constraint**

$$r_{s,c} = \begin{cases} 0, & \text{if } s = 0 \text{ and } c = 0, \\ f_{q,m} \text{ or } \perp, & \text{if } s \neq 0 \text{ and } c = 0, \\ f_{s,c-1}, & \text{otherwise} \end{cases}$$

Please find more in the paper :)

# Dordis generally boosts performance

**FEMNIST @ResNet18**

More participants

**CIFAR-10 @ResNet18**

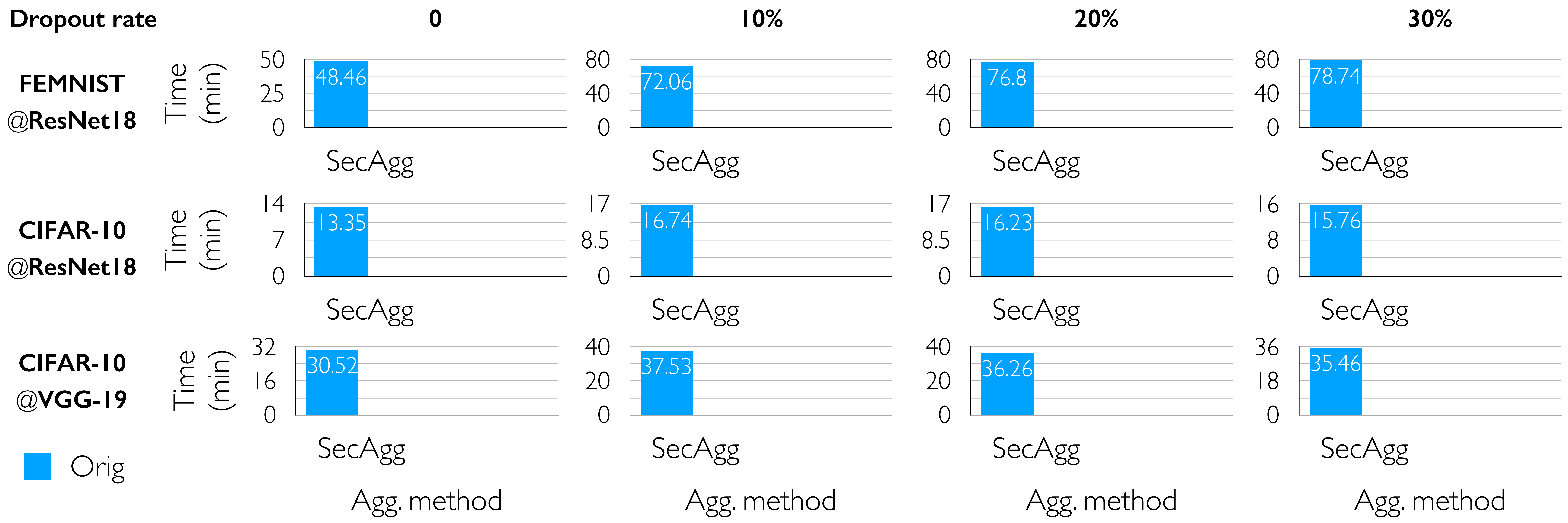
Larger model

**CIFAR-10 @VGG-19**

# Dordis generally boosts performance

| Dropout rate | 0 | 10% | 20% | 30% |
|---|---|---|---|---|
| FEMNIST @ResNet18 | | | | |
| CIFAR-10 @ResNet18 | | | | |
| CIFAR-10 @VGG-19 | | | | |

# Dordis generally boosts performance




**Orig** → Plain sequential execution

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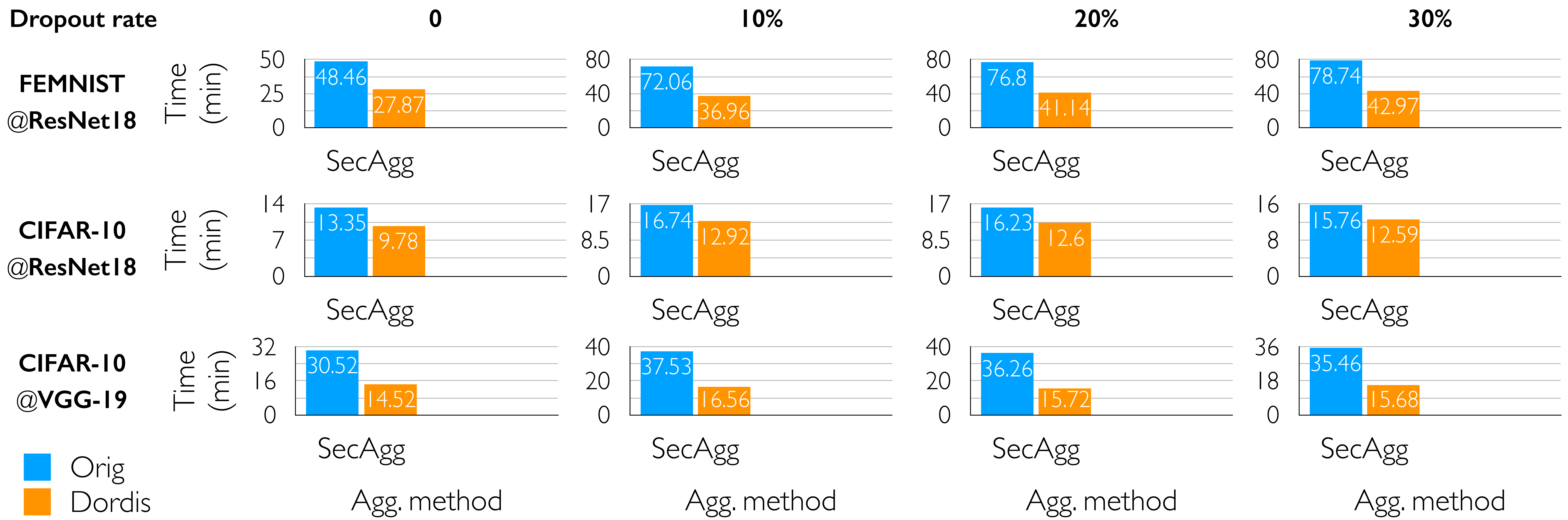


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**Dordis accelerates** by up to **2.4×** across different **participant** scale, **model** size, **dropout** situations

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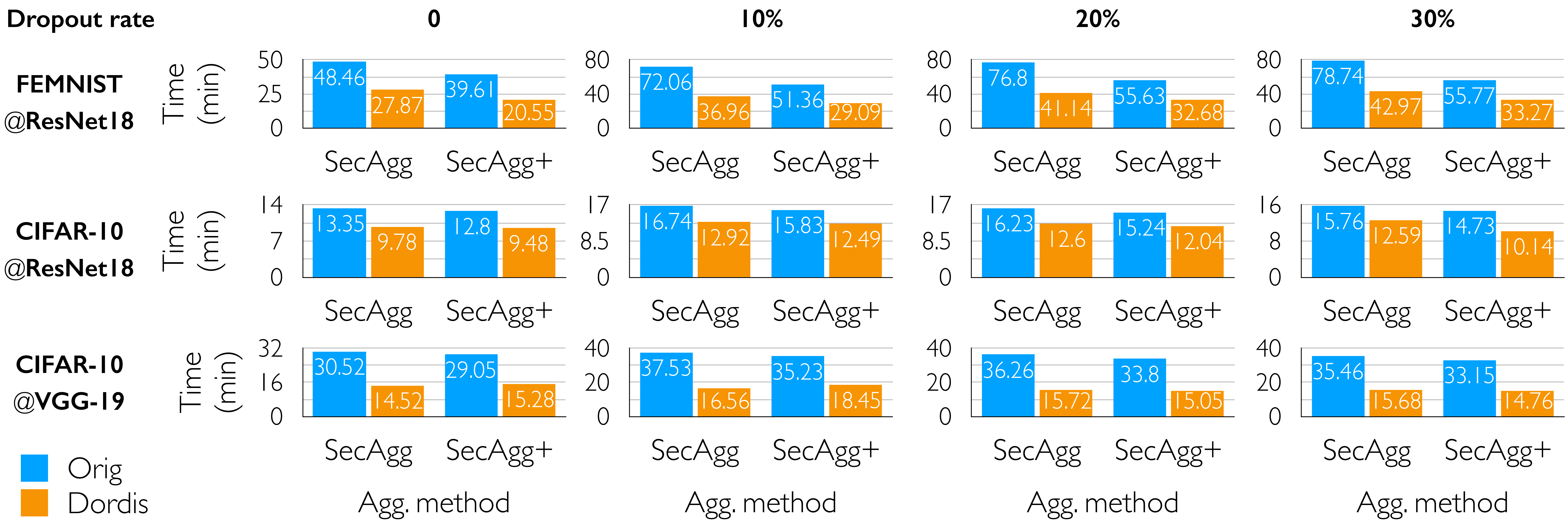


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**Dordis accelerates** by up to **2.4×** across different **participant** scale, **model** size, **dropout** situations, and **aggregation** methods

# Problem 2: Noise Deficiency

**Intuition** - Data privacy

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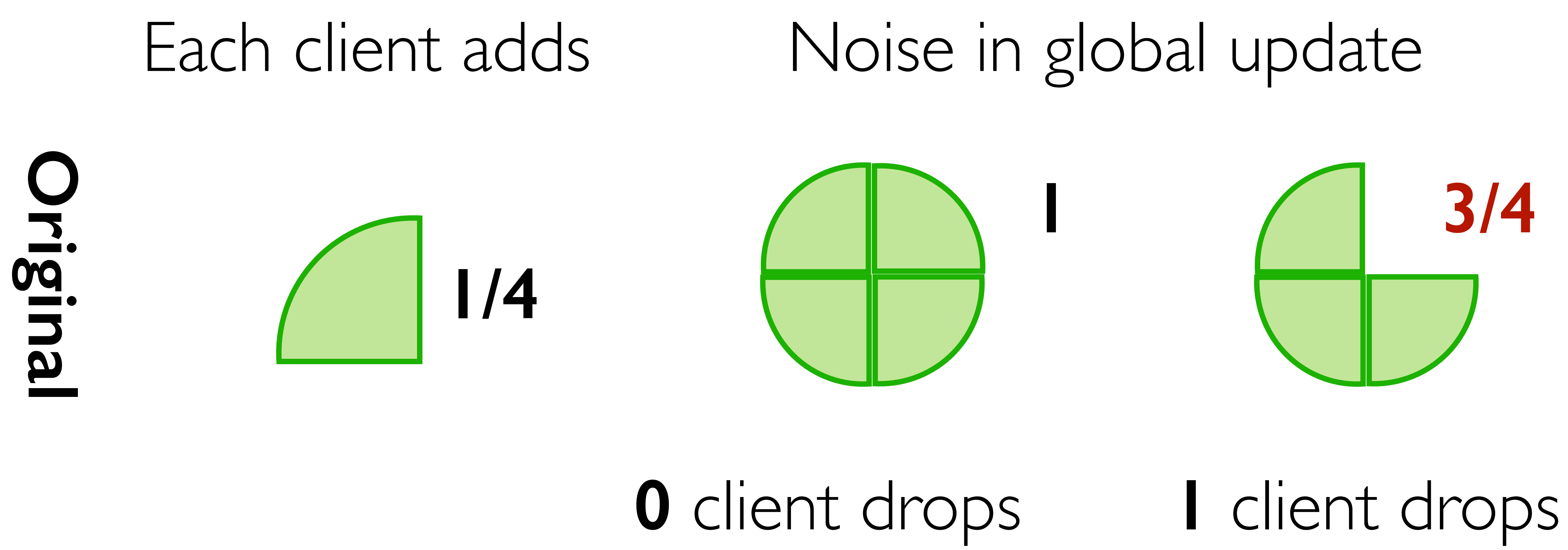
- Noise should **never** be **insufficient**



# Problem 2: Noise Deficiency

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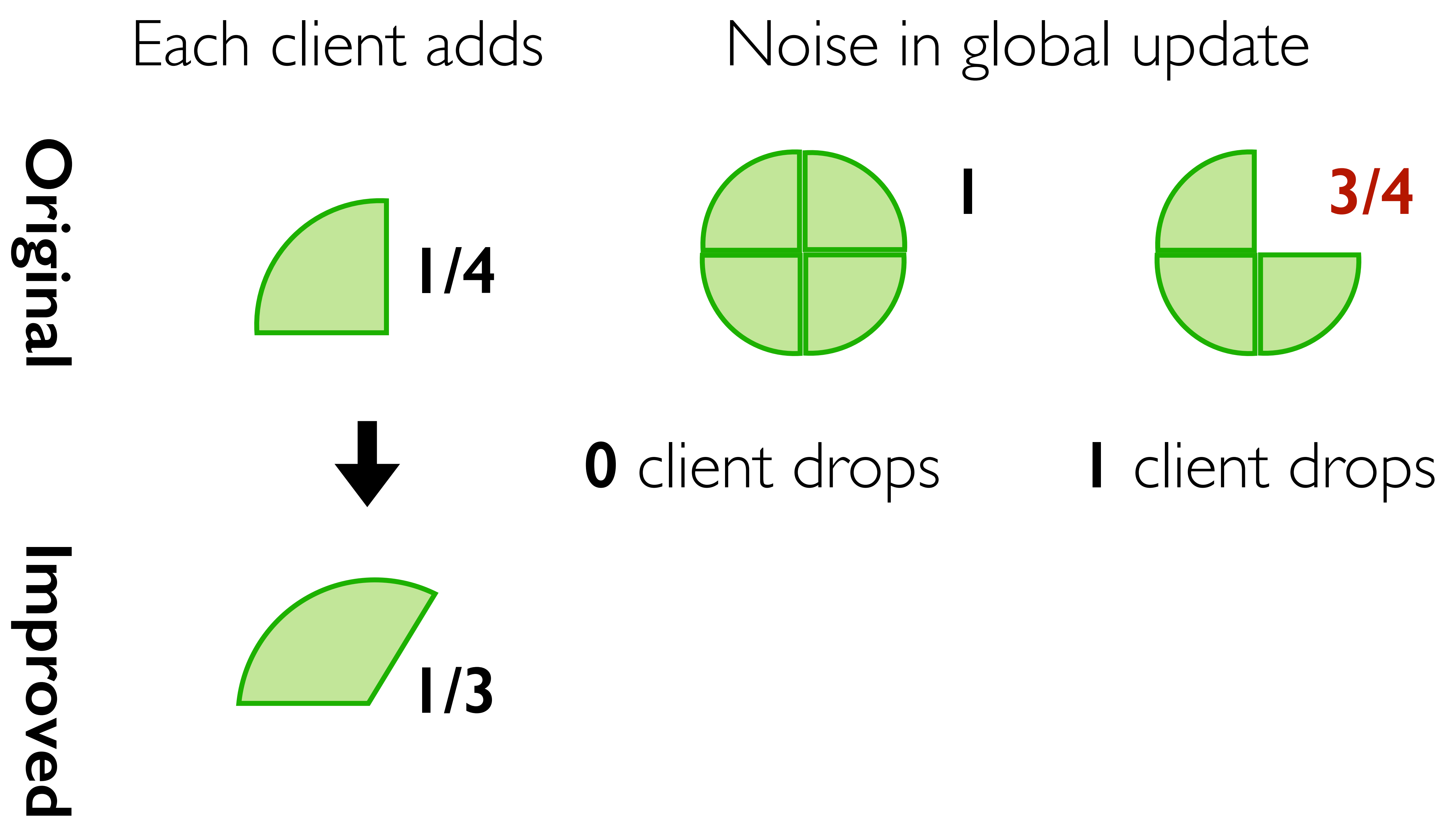
- Noise should **never** be **insufficient** → Proactively **add more** noise than needed



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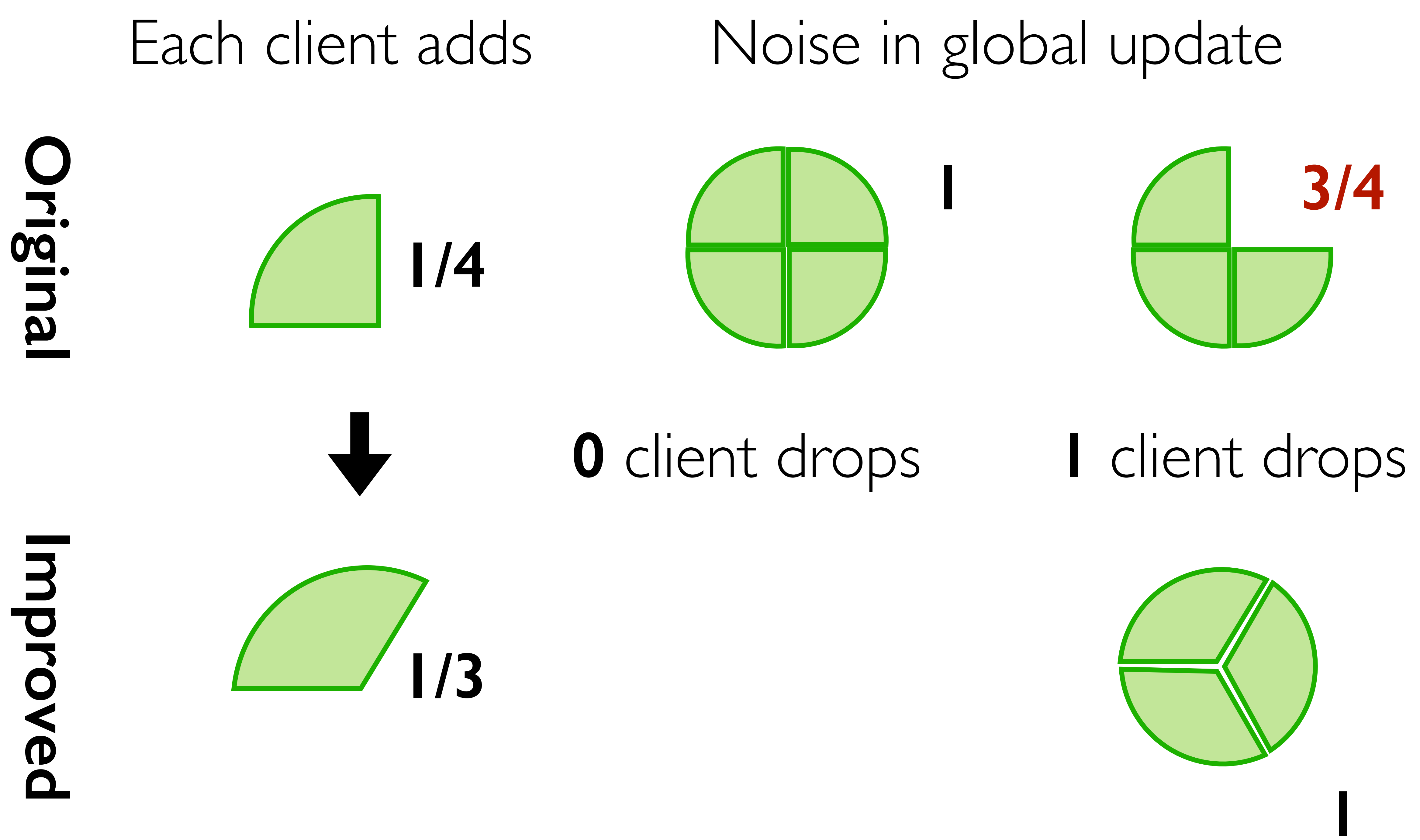

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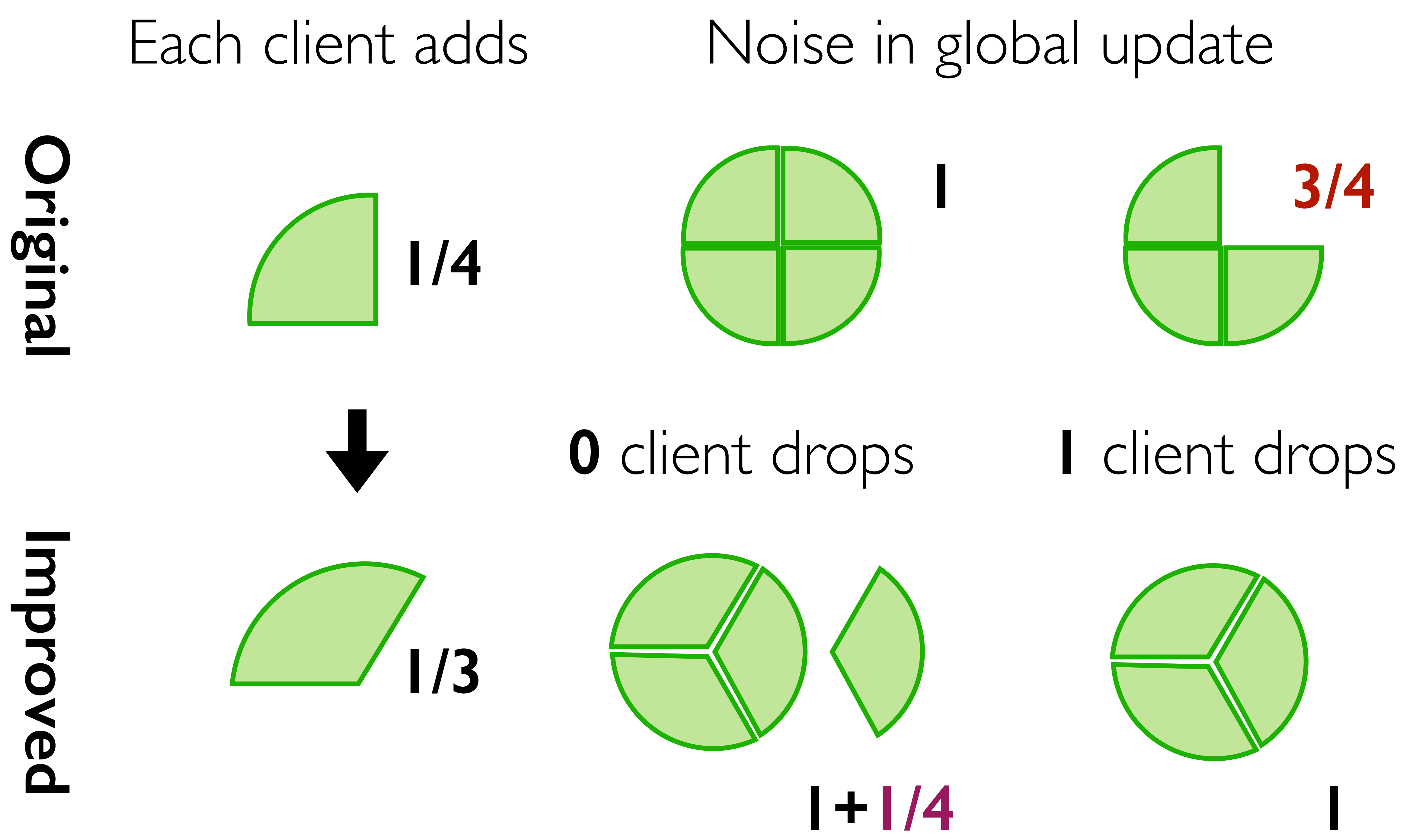


**Intuition** - Model Utility

- The **less** noise the **better**→**remove redundant** noise when dropout is settled

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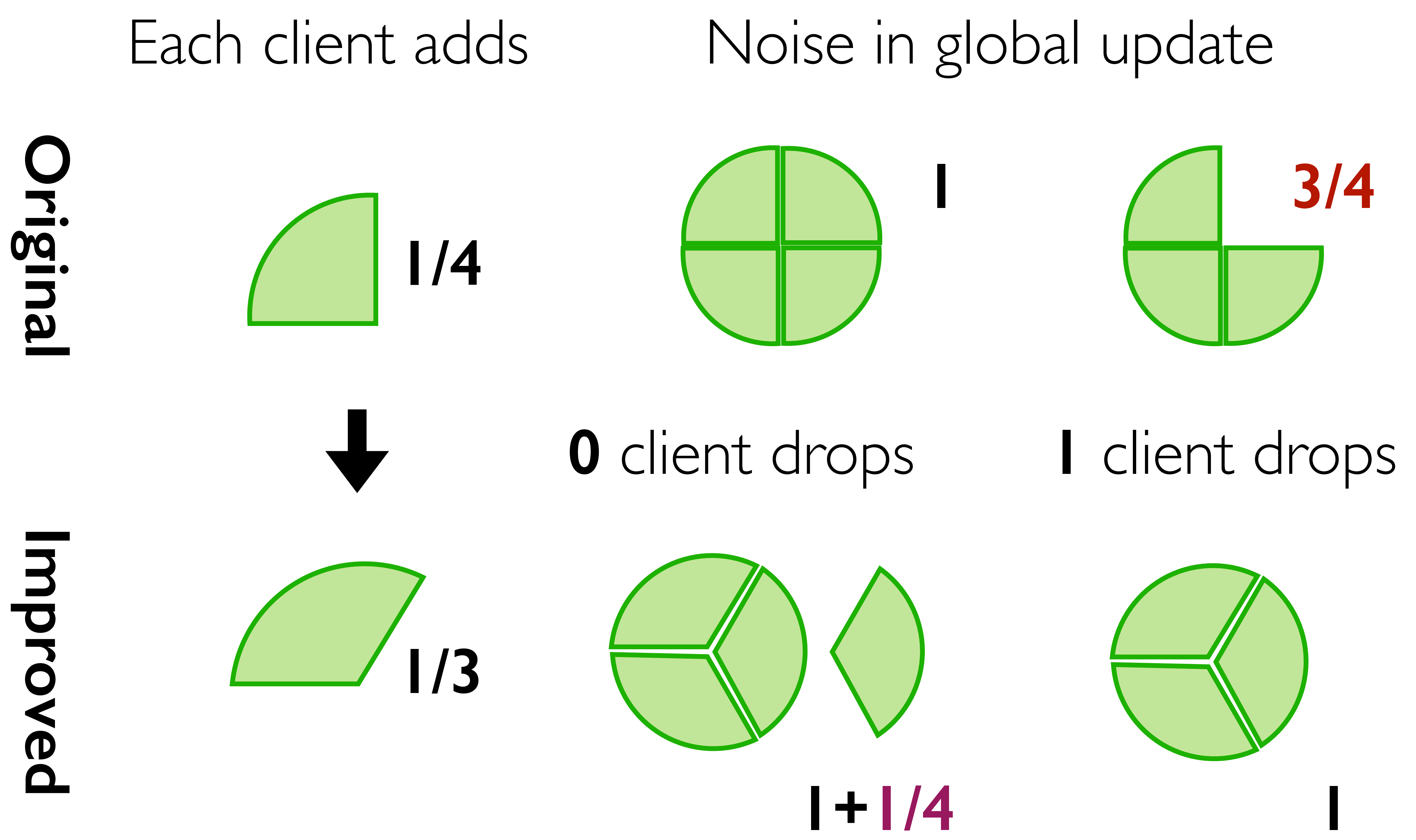


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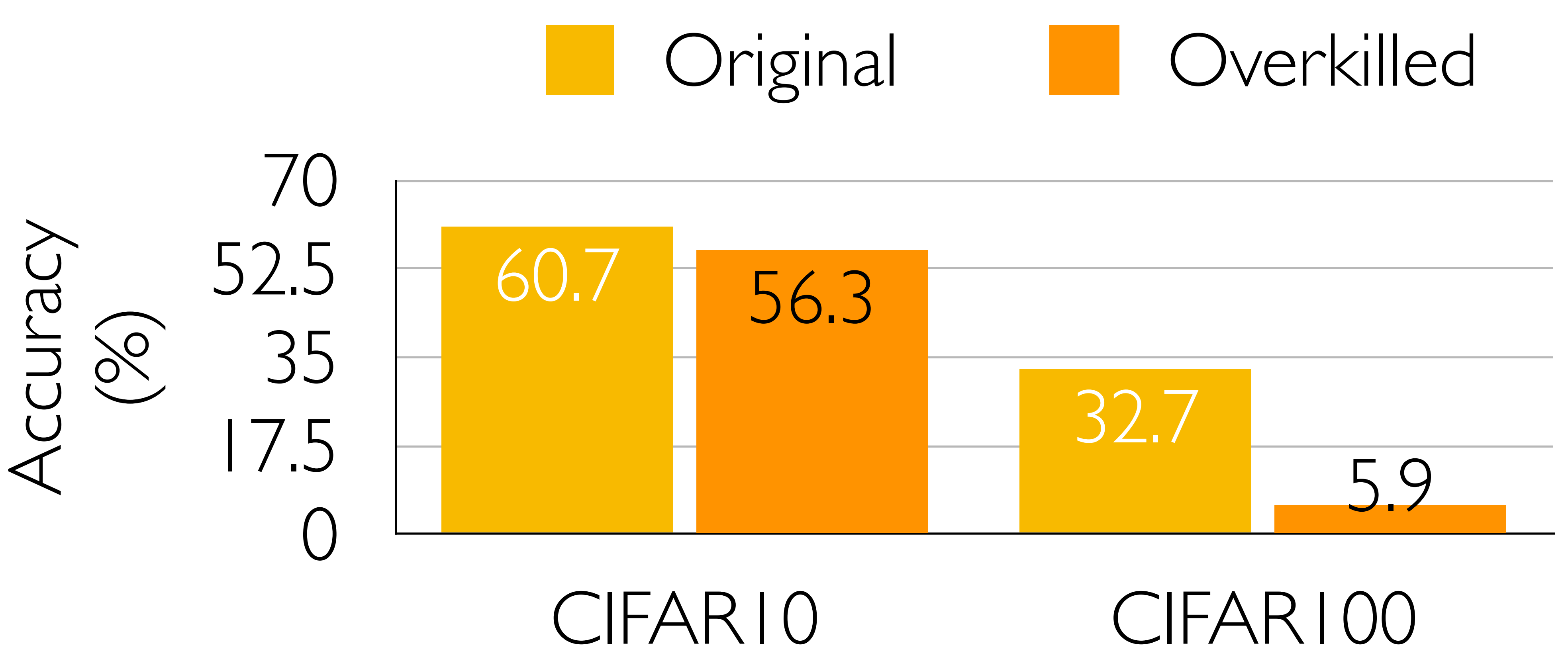
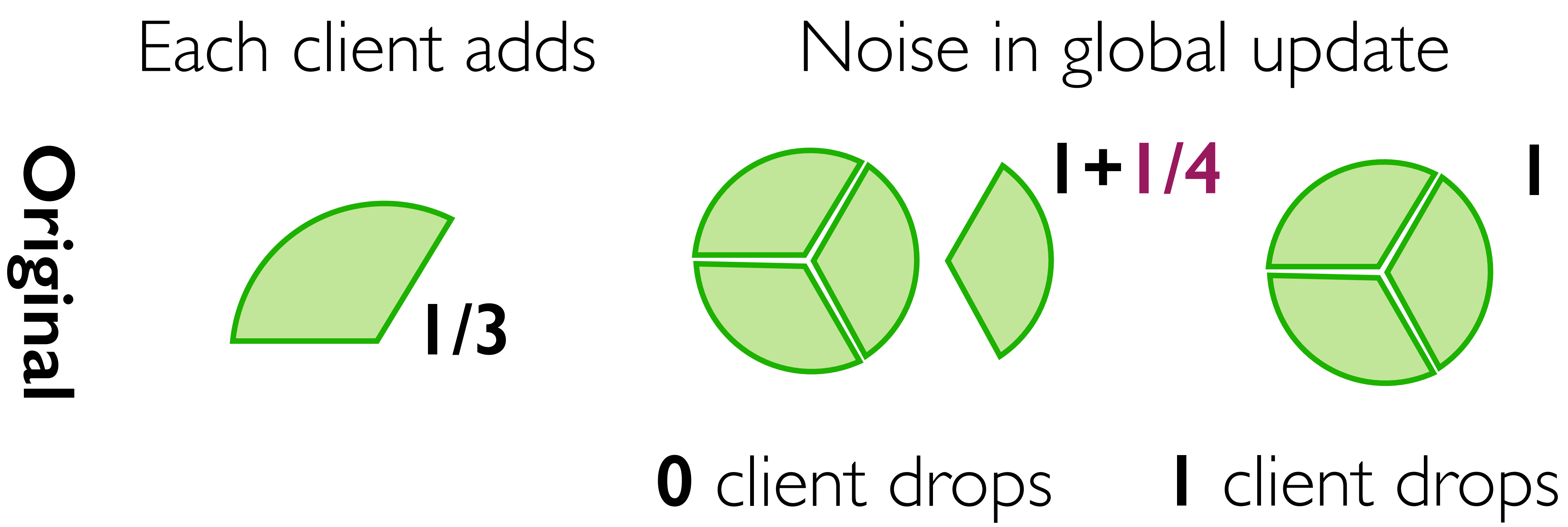


# Problem 2: Noise Deficiency

**Potential approach**

- Noise **decomposition** during addition



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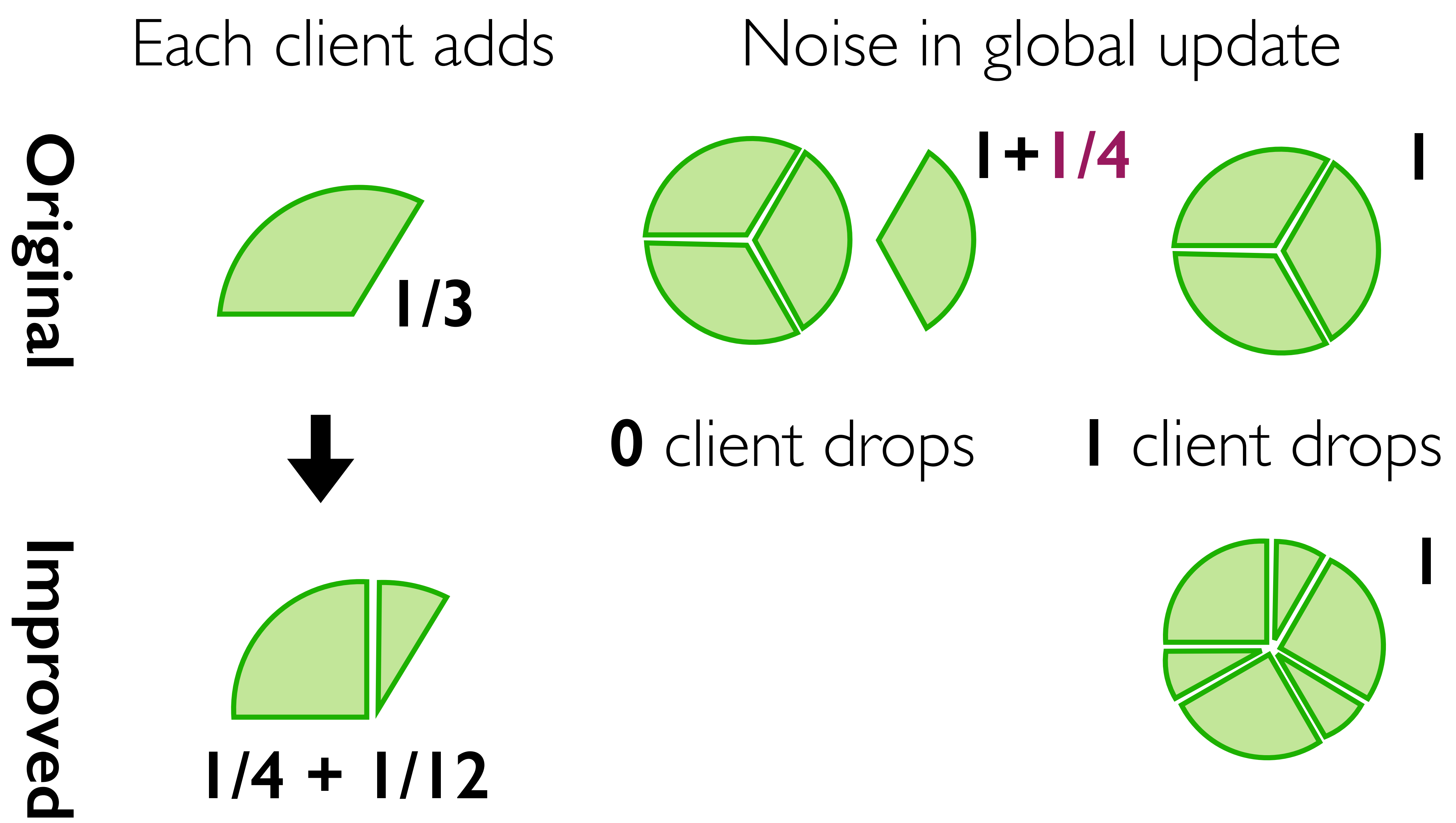

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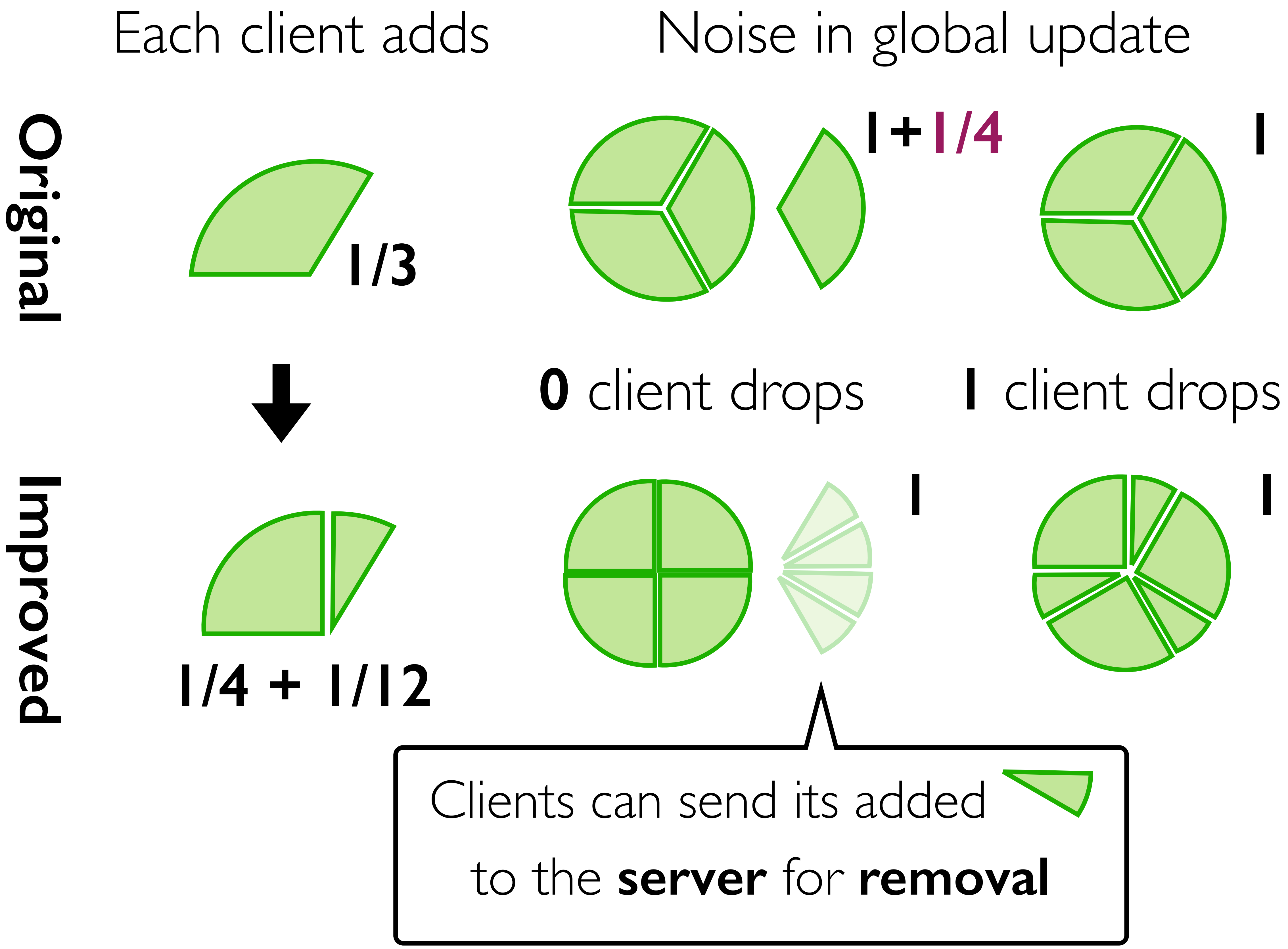

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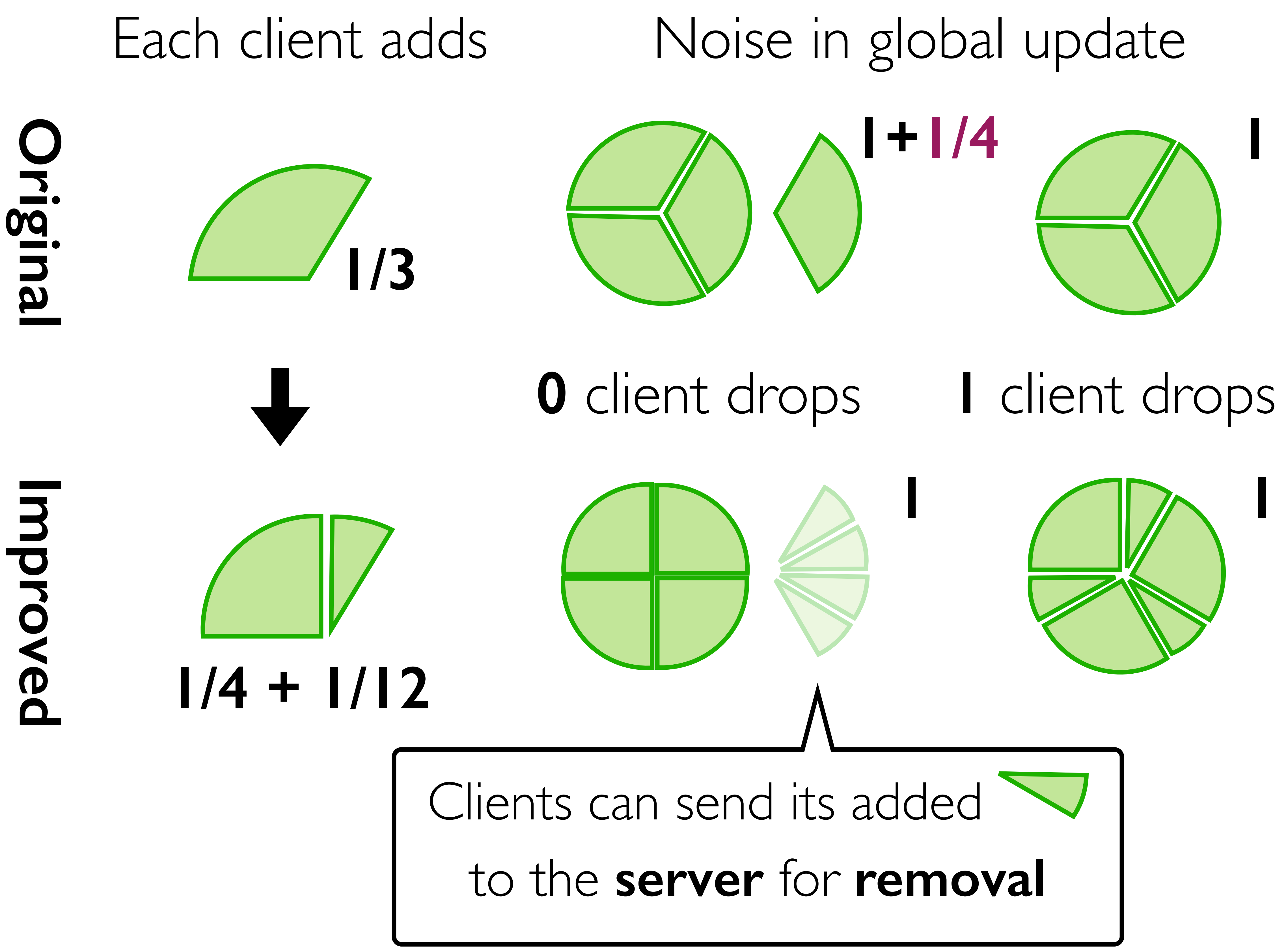


**Solution**: **Generalized** design for noise decomposition

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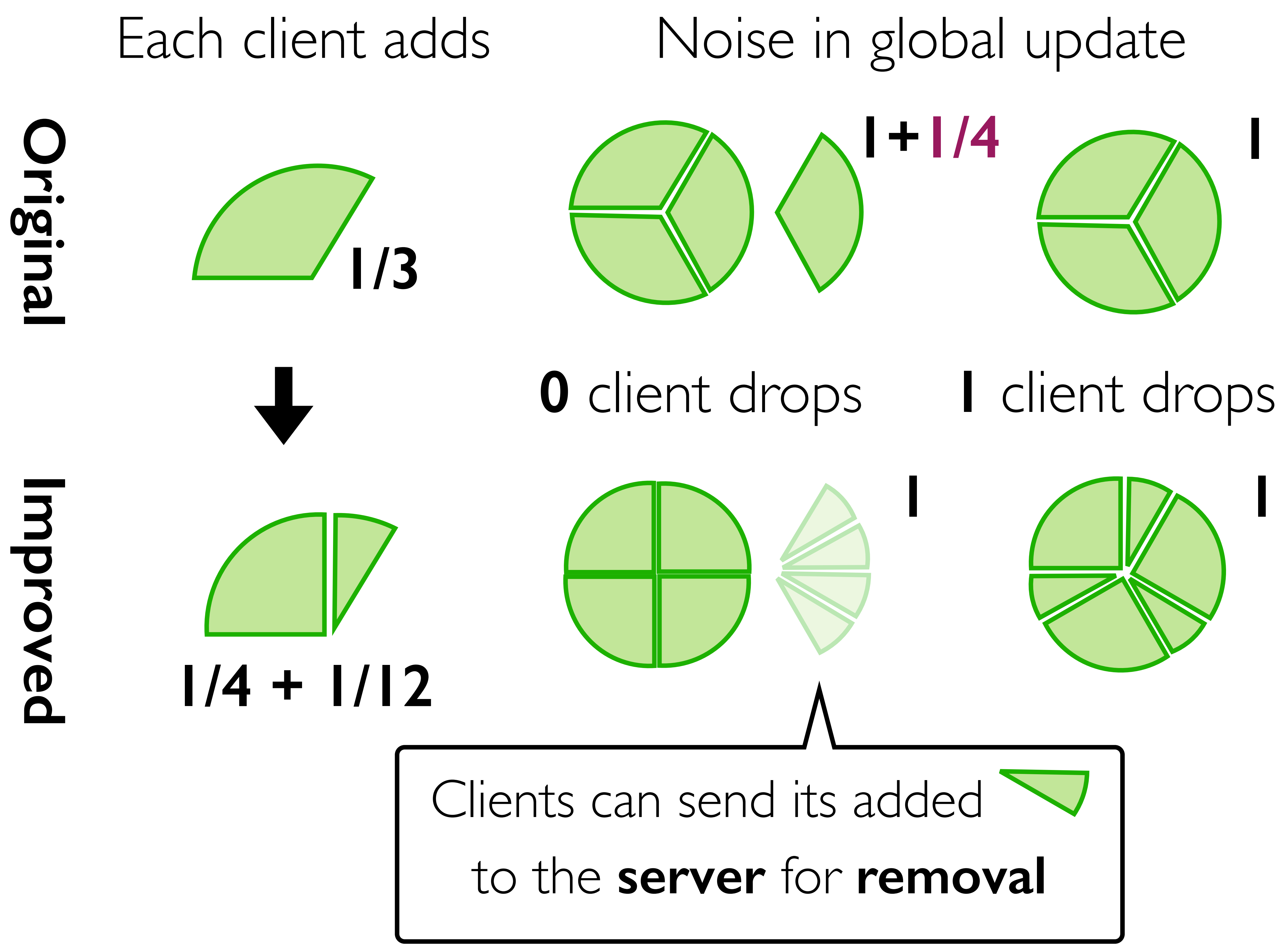
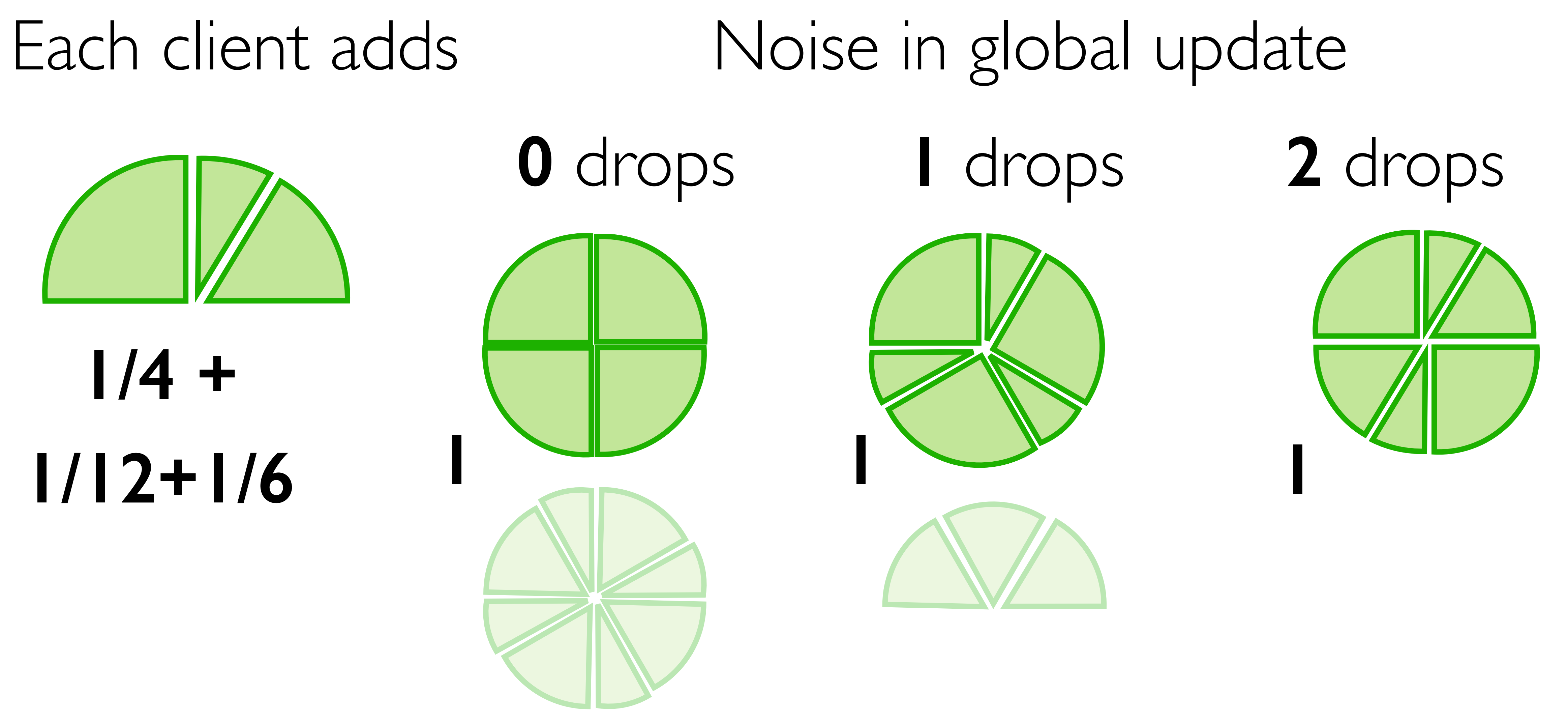



**Solution**: **Generalized** design for noise decomposition

E.g., 4 clients again, but tolerate up to **2** dropped clients



# Problem 2: Noise Deficiency

## Closed-form method

- **Noise addition**: Decompose Client $i$'s added noise $n_i \sim \chi\left(\frac{\sigma_*^2}{|S| - t}\right)$ into $t+1$ components: $n_i = \sum_{k=0}^{t} n_{i,k}$, $n_{i,0} \sim \chi\left(\frac{\sigma_*^2}{|S|}\right)$, and $n_{i,k} \sim \chi\left(\frac{\sigma_*^2}{(|S| - k + 1)(|S| - k)}\right)$ $(k \in [t])$
- **Noise removal**: when $|D|$ clients drop out, the noise components $n_{i,k}$ contributed by the surviving clients $i \in S \backslash D$ with the index $k > |D|$ becomes excessive and is removed by the server

# Dordis enforces the target noise

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**Guarantee**: **Dordis enforces the target noise** when all are semi-honest

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Please find more in the paper :)

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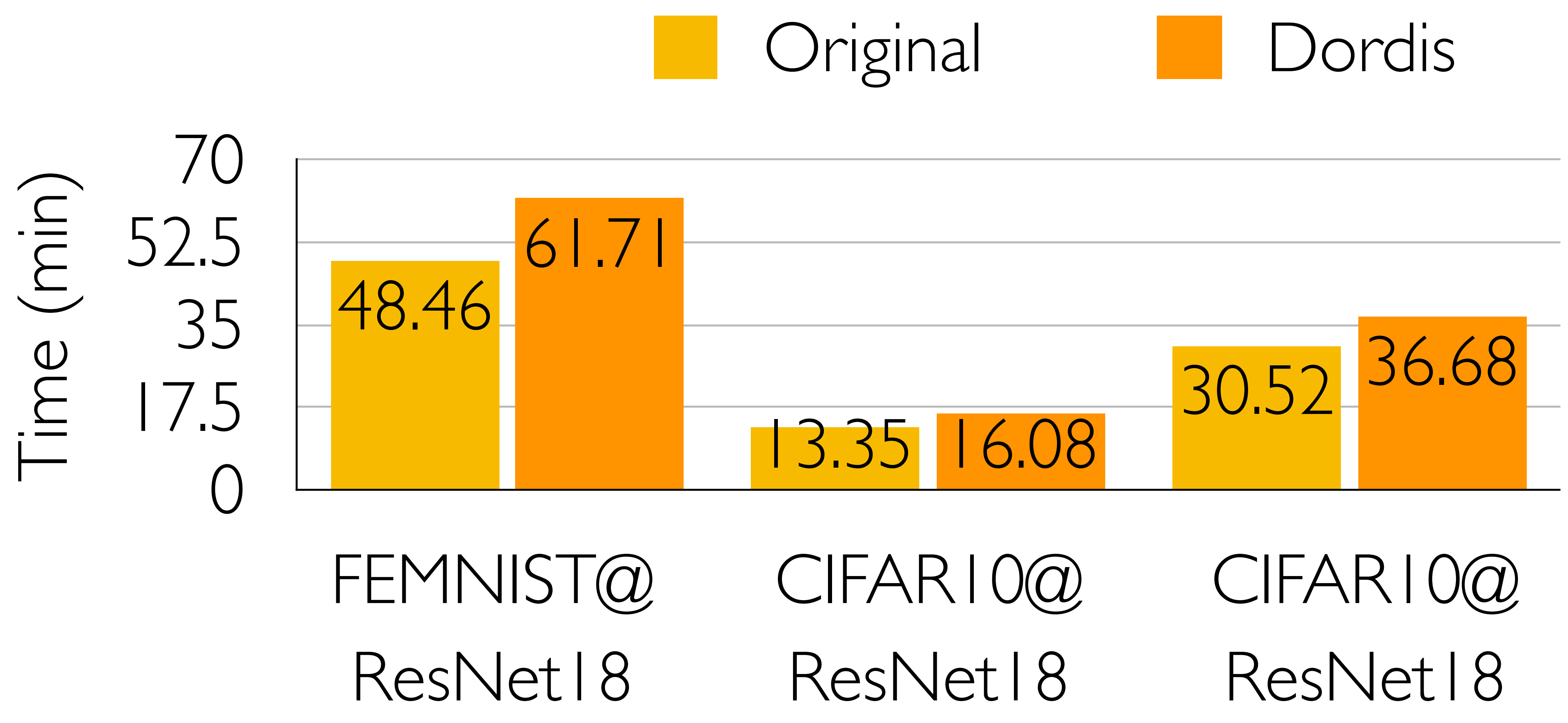
**Dordis runtime** overhead **≤34%**

**Guarantee**: **Dordis** enforces the target noise when all are **semi-honest**, or when even the server is **malicious**

Please find more in the paper :)



# Dordis: Results summary

**Efficiency**

**Substantial speedup** up to **2.4×** for **general** workloads

**Integration**

**Seamlessly** packed in one **comprehensive** system

**Resilience**

**Privacy preserved** with target noise **precisely** enforced **regardless** of client dropout

github.com/SamuelGong/Dordis

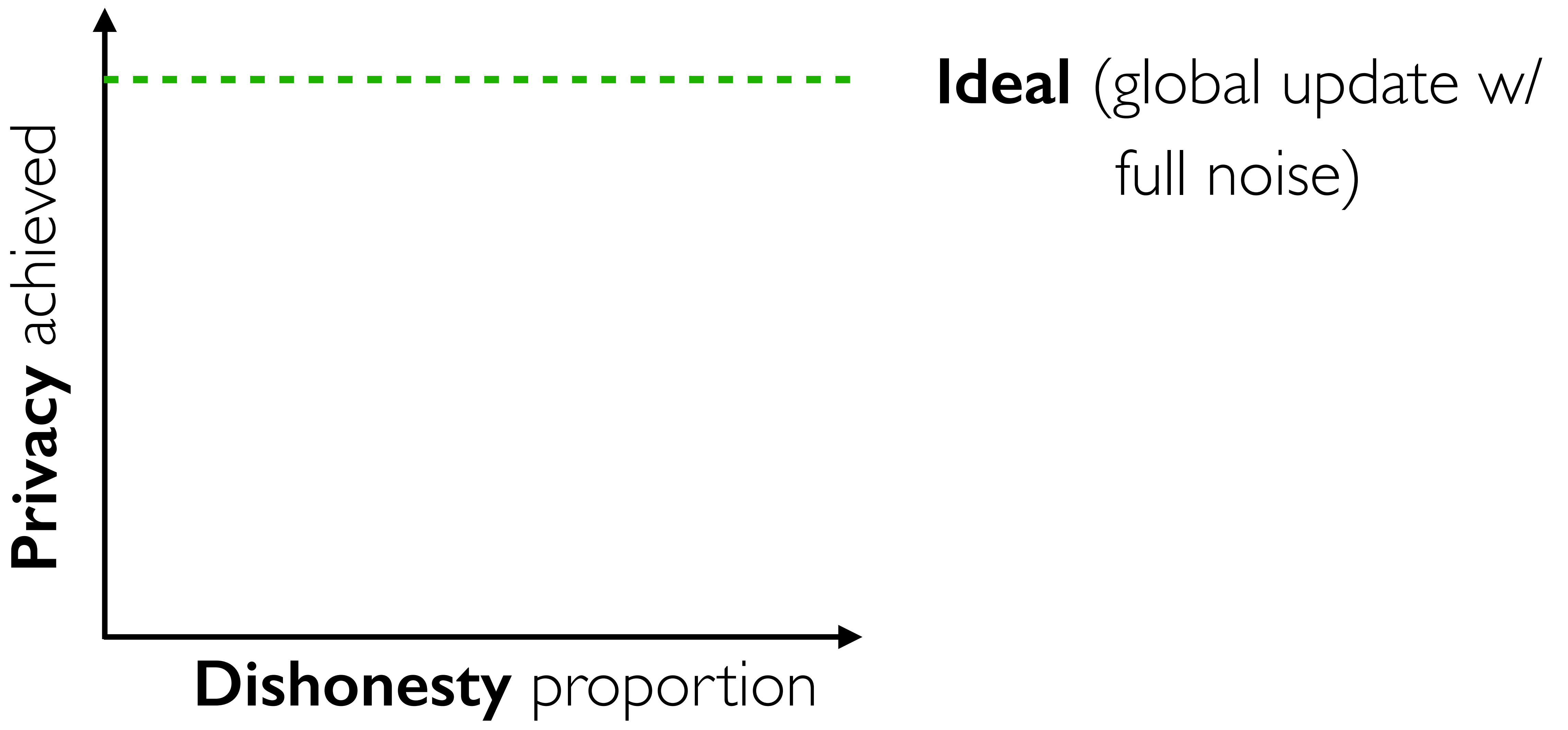
# Third work: Lotto [1]

| | | | |
|---|---|---|---|
| **Privacy** Worst-case defense… | Can be a dishonest majority | x ⟷ | Only or mostly works with honest participants |
| **Efficiency** Time-to-accuracy… | Stragglers bottleneck time | Primitives heavy in comp. and comm. | Client dropout yields insufficient noise |

| **Privacy-Enhancing Technique** | Federated Learning | Secure Aggregation | Differential Privacy |
|---|---|---|---|
| **Privacy Guarantee** | Data kept on premises | Local updates unseen | Global update leaks little about any client |

[1] Jiang et al. "Lotto: Secure Participant Selection against Adversarial Servers in Federated Learning", In Security '24

# Need for Lotto




Secure Aggregation | Differential Privacy

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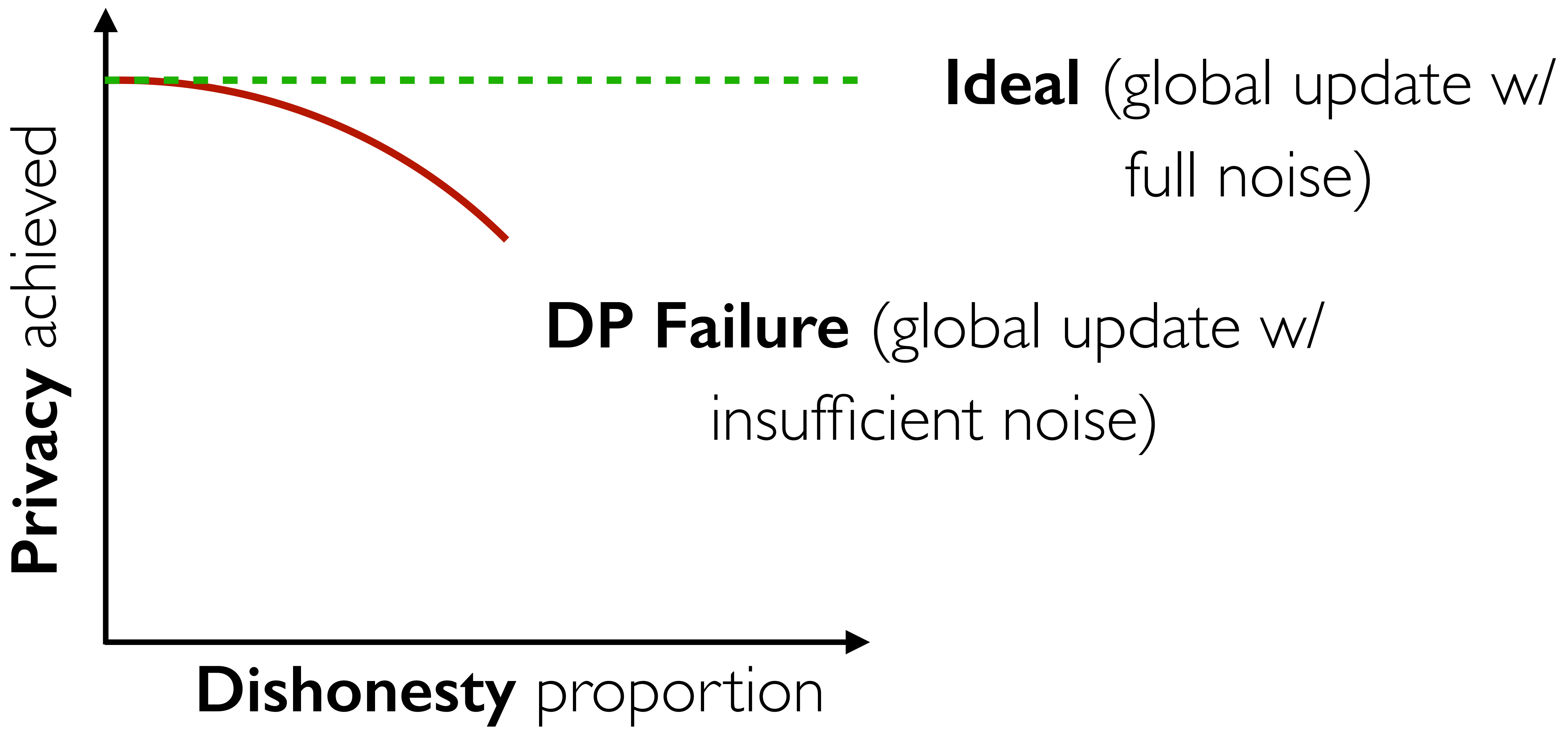


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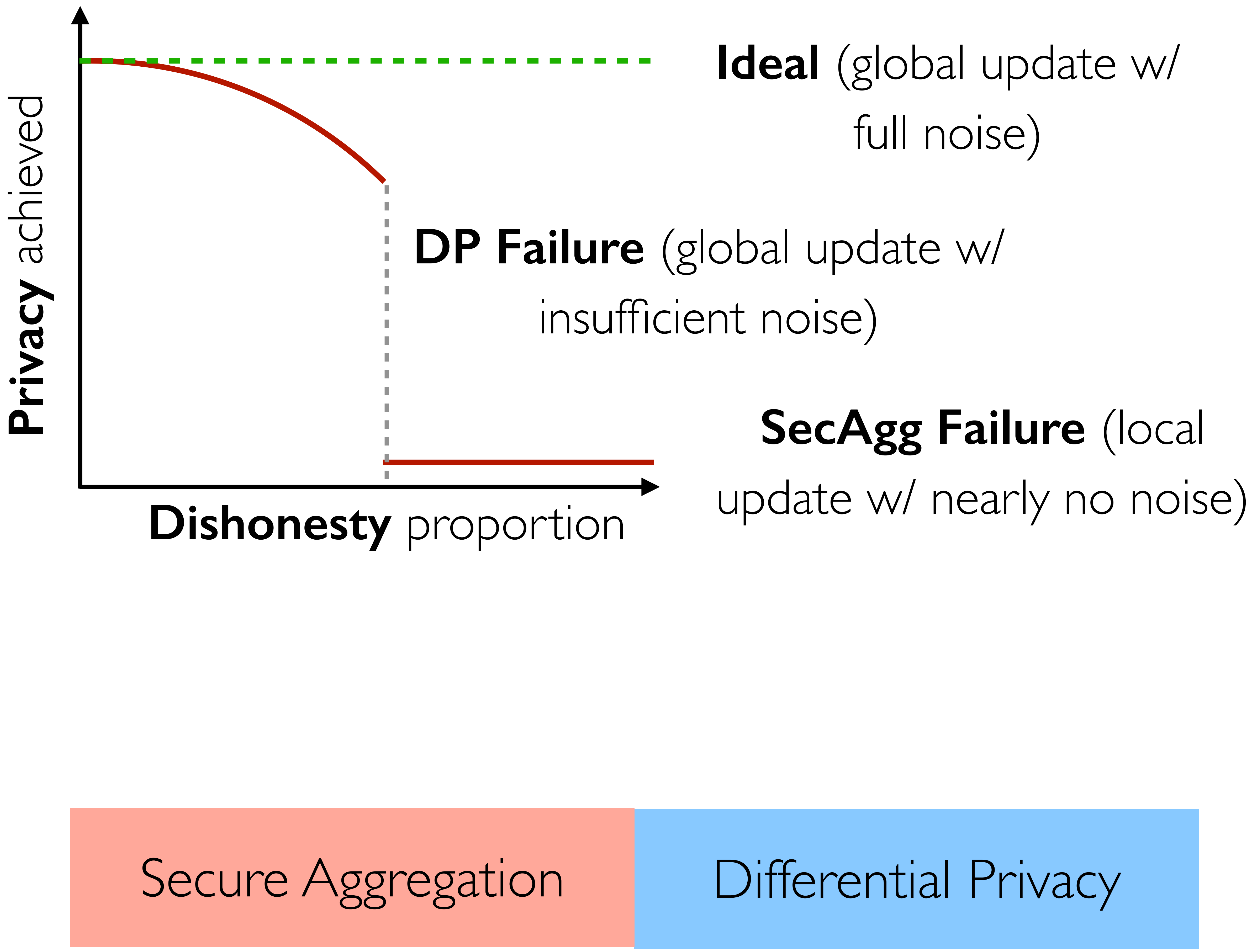

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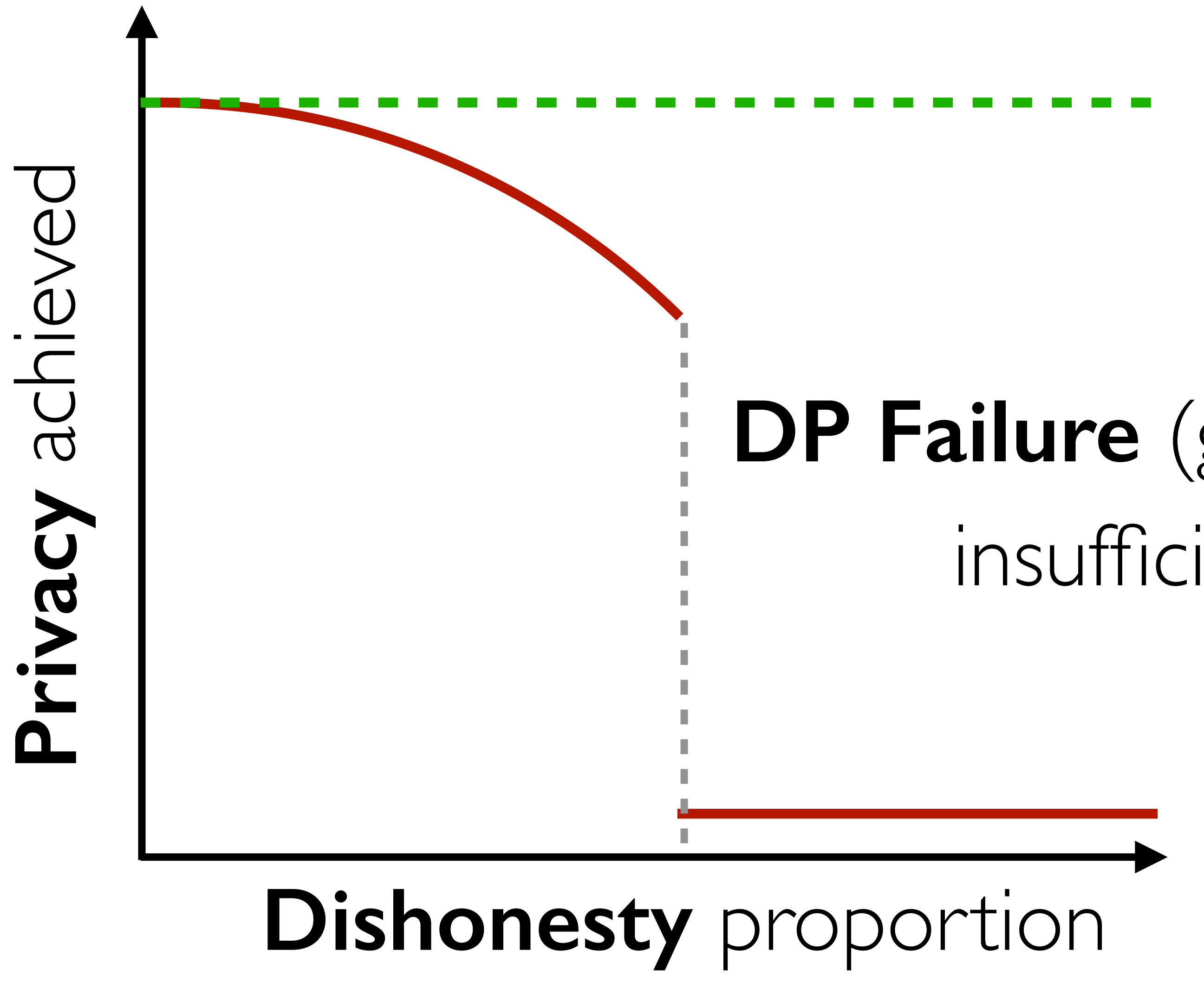



**Ideal** (global update w/ full noise)

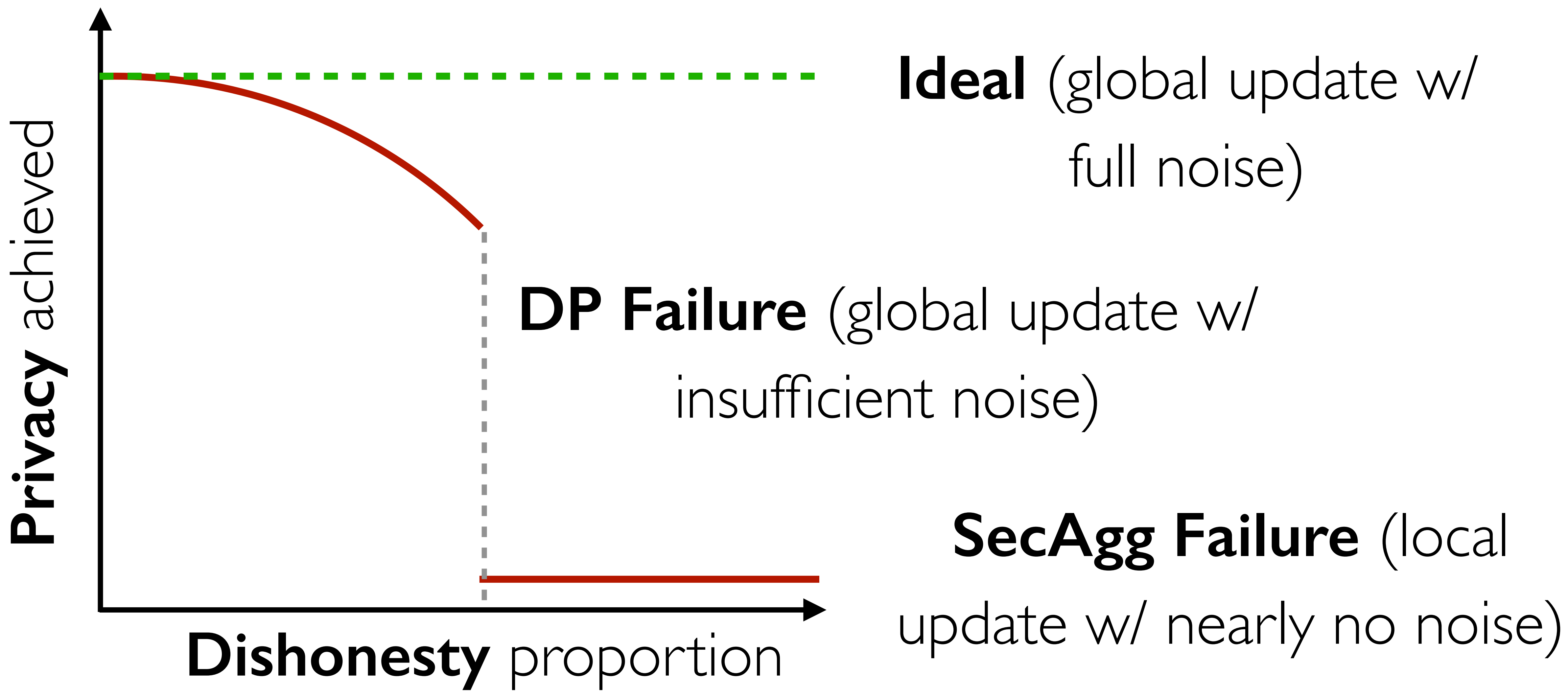
**DP Failure** (global update w/ insufficient noise)

**SecAgg Failure** (local update w/ nearly no noise)

**Assumption**: honest participants

| Secure Aggregation | Differential Privacy |
|---|---|

# Need for Lotto

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Federated Learning

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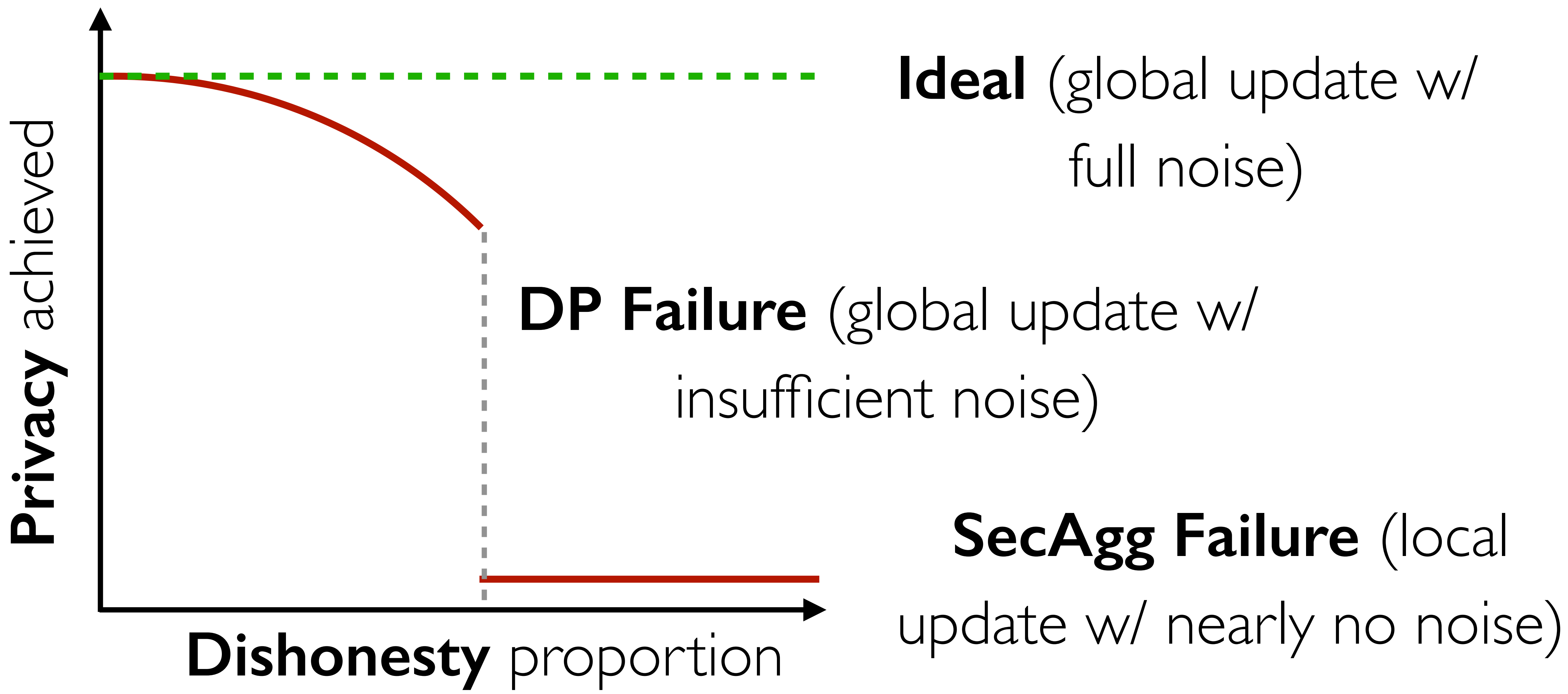
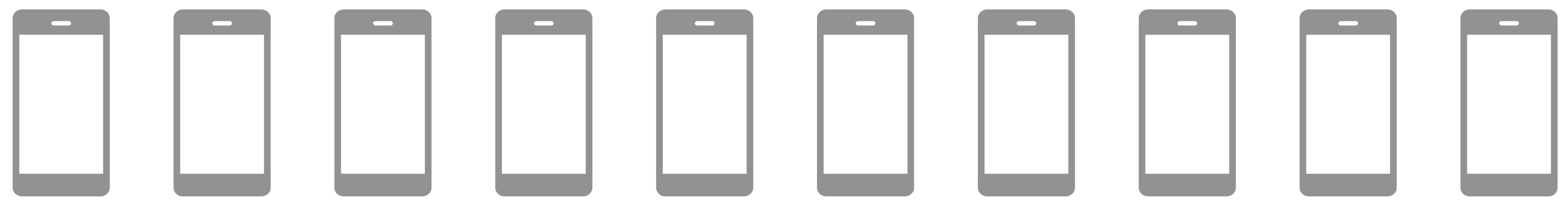



**Assumption**: honest participants

Secure Aggregation | Differential Privacy

**Population** ($10^4$ - $10^8$)



Federated Learning

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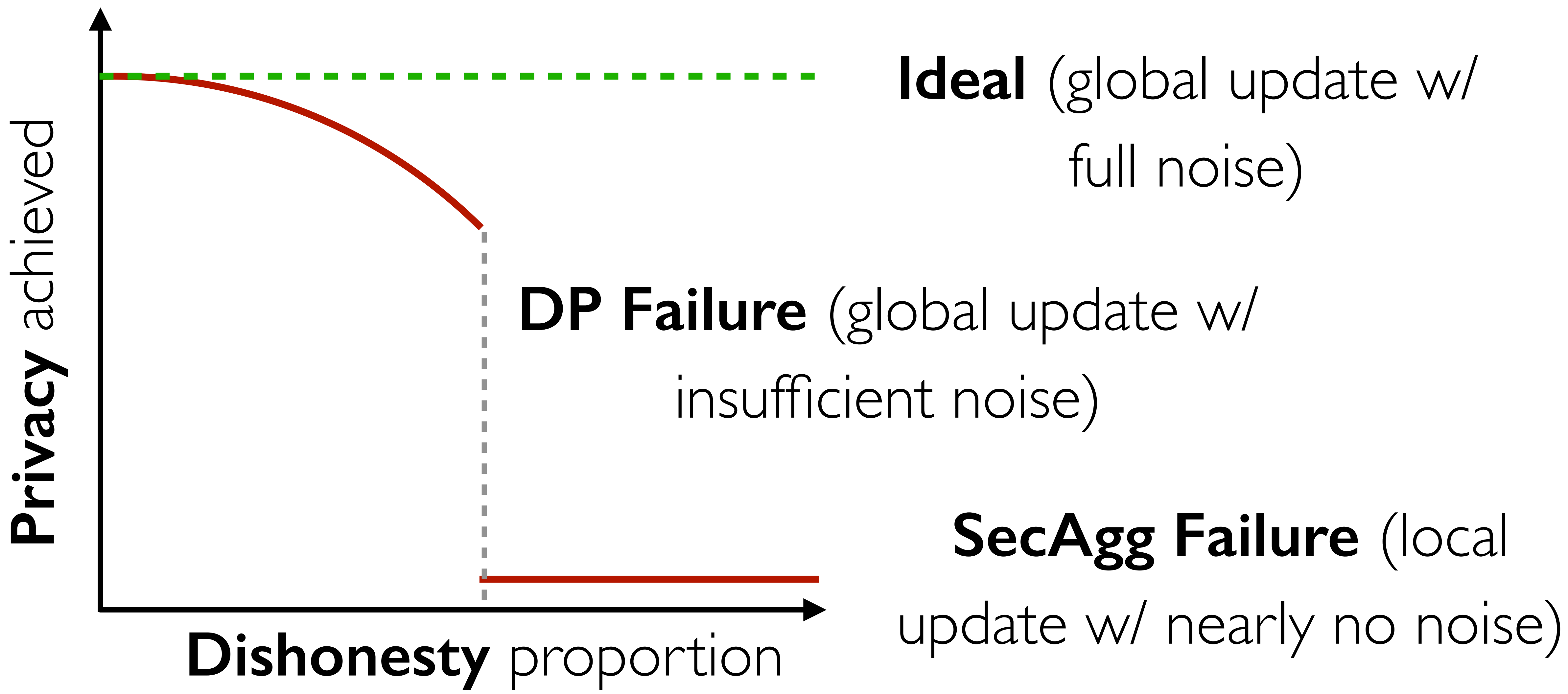


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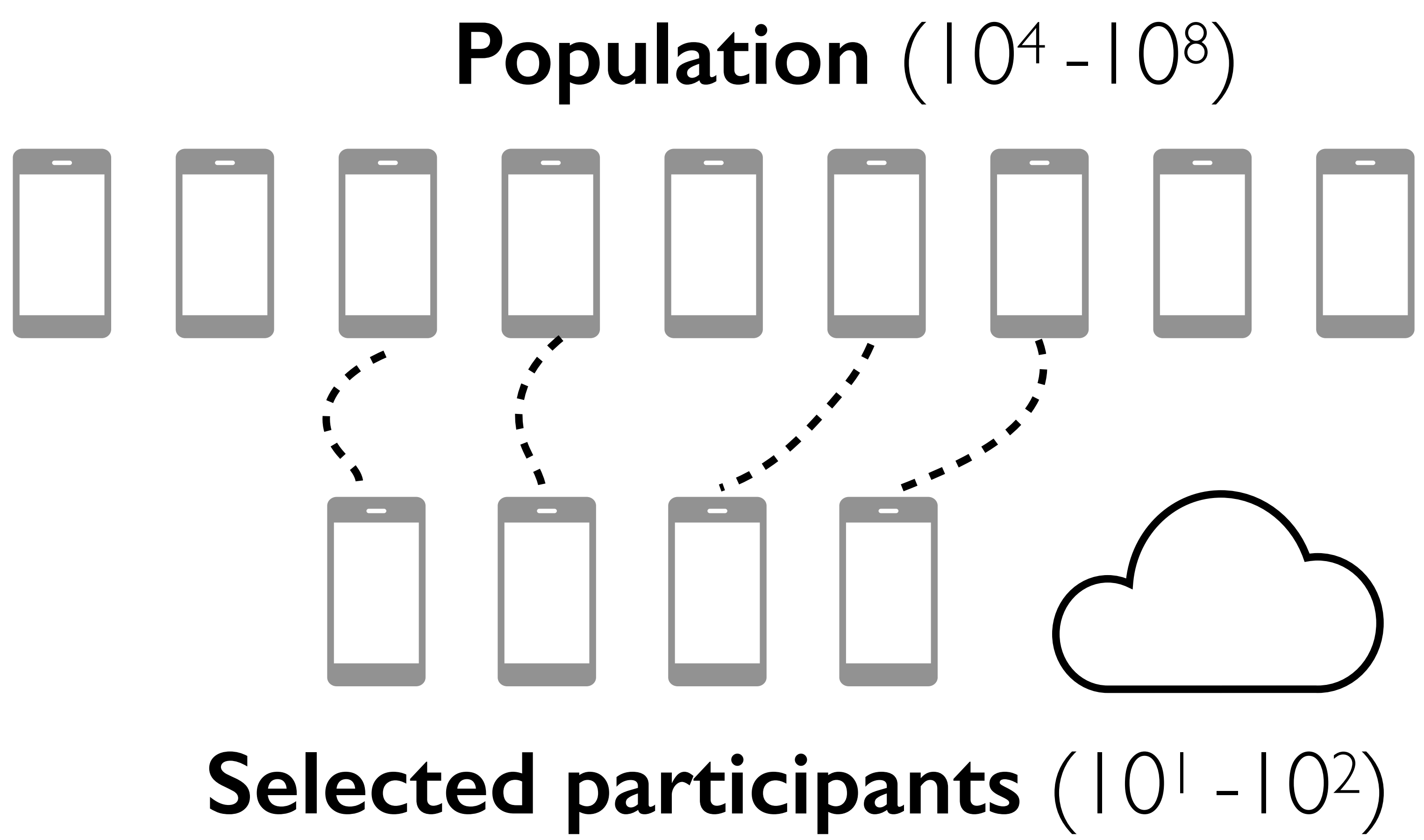


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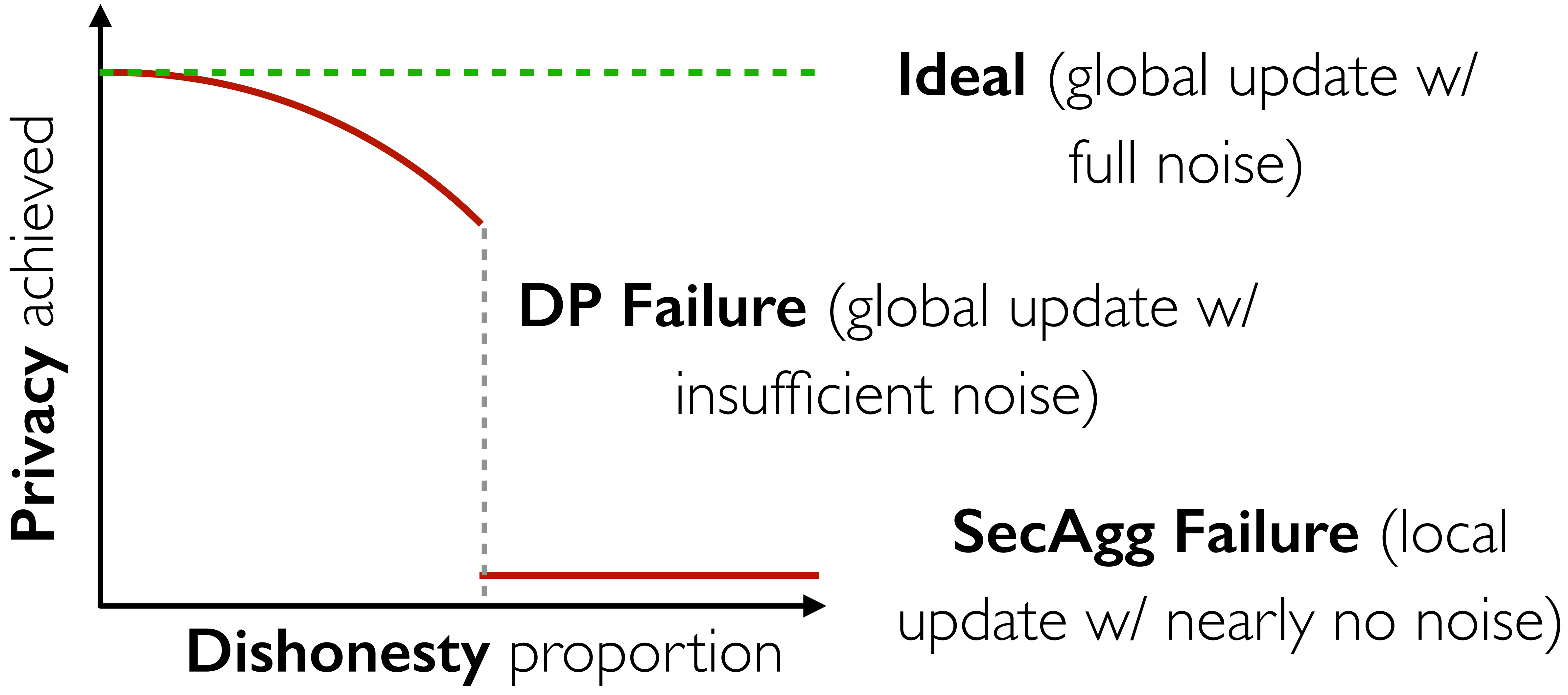


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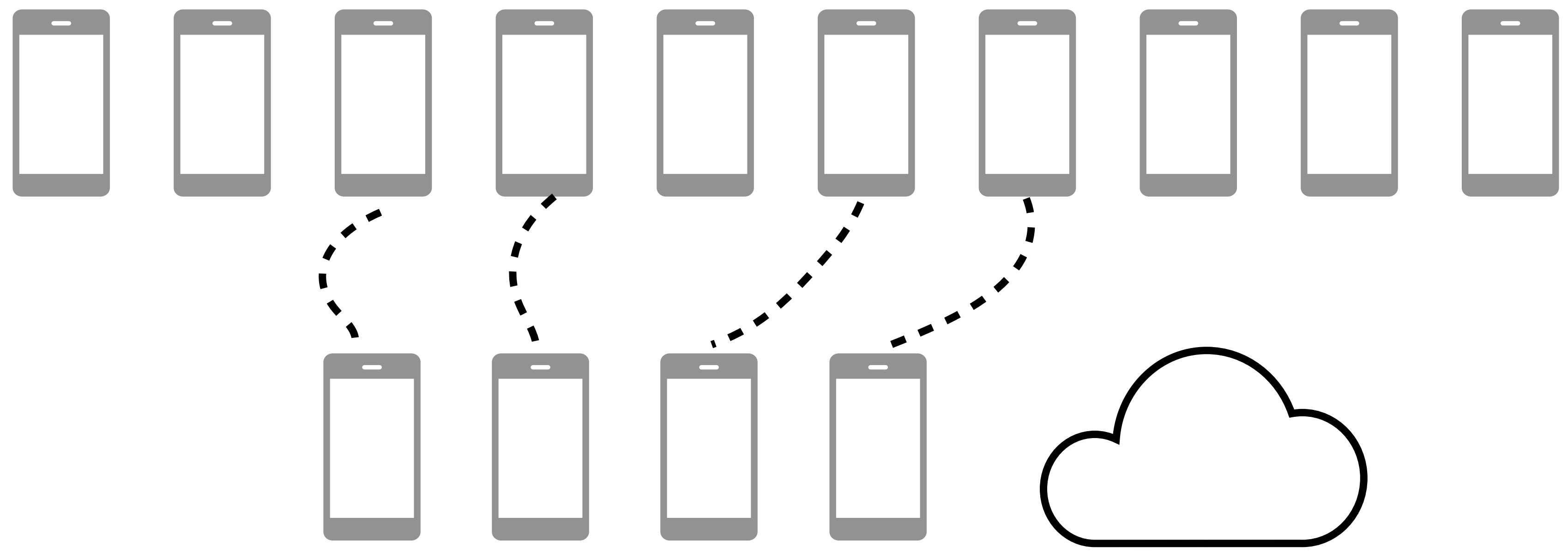
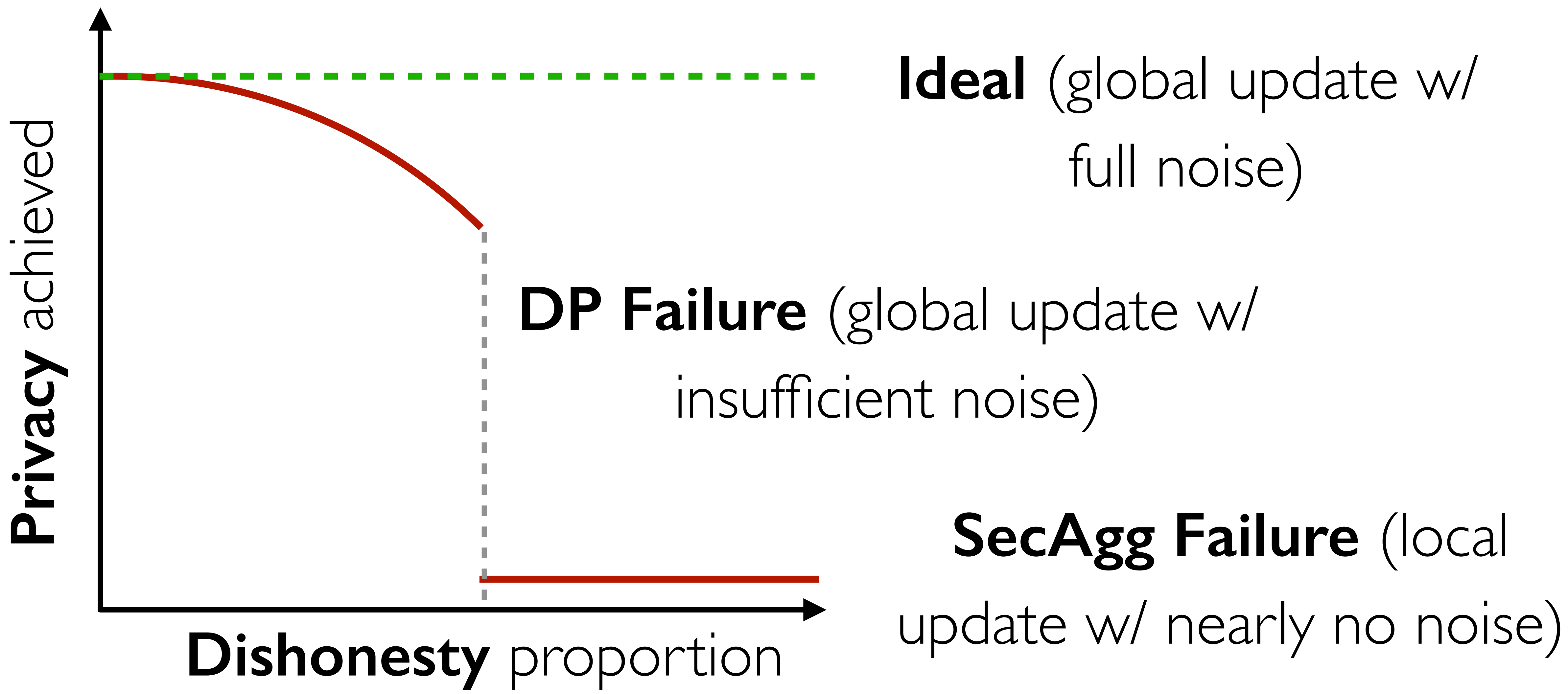


**Selected participants** ($10^1$ - $10^2$)

- **Random**: uniform chance

Federated Learning

# Need for Lotto

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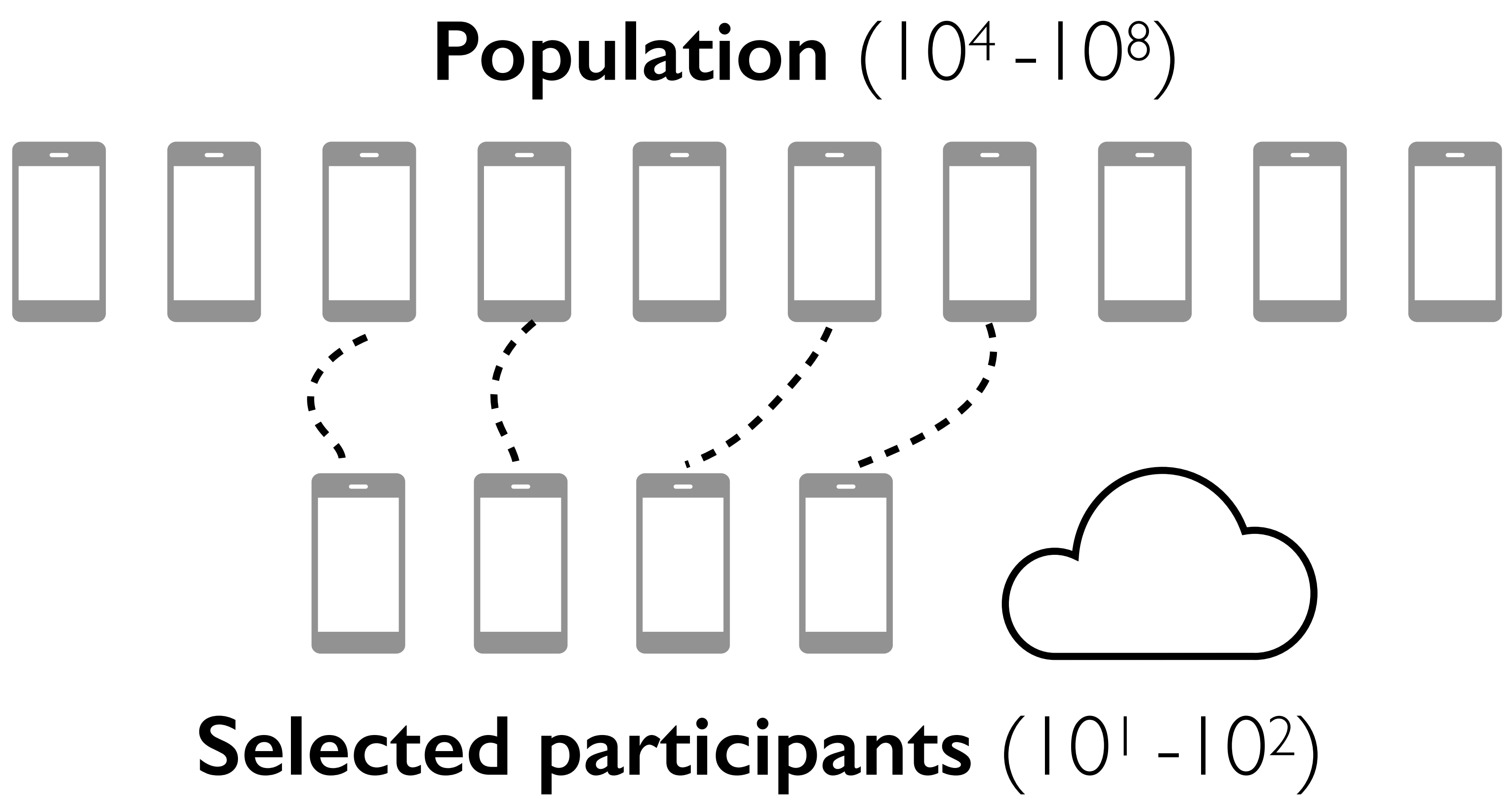


- **Random**: uniform chance
- **Informed**: "best-performing" clients are preferred (e.g., high speed and/or rich data)

Federated Learning

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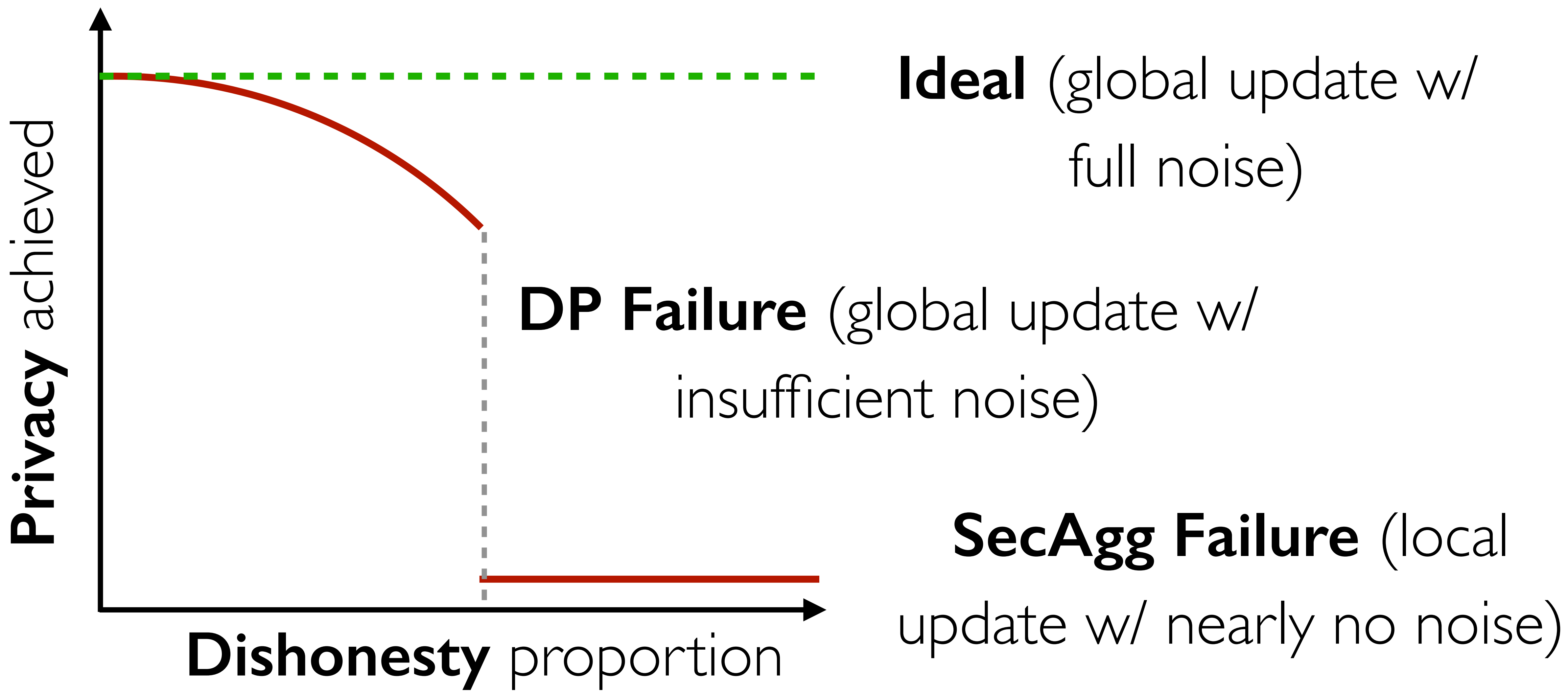


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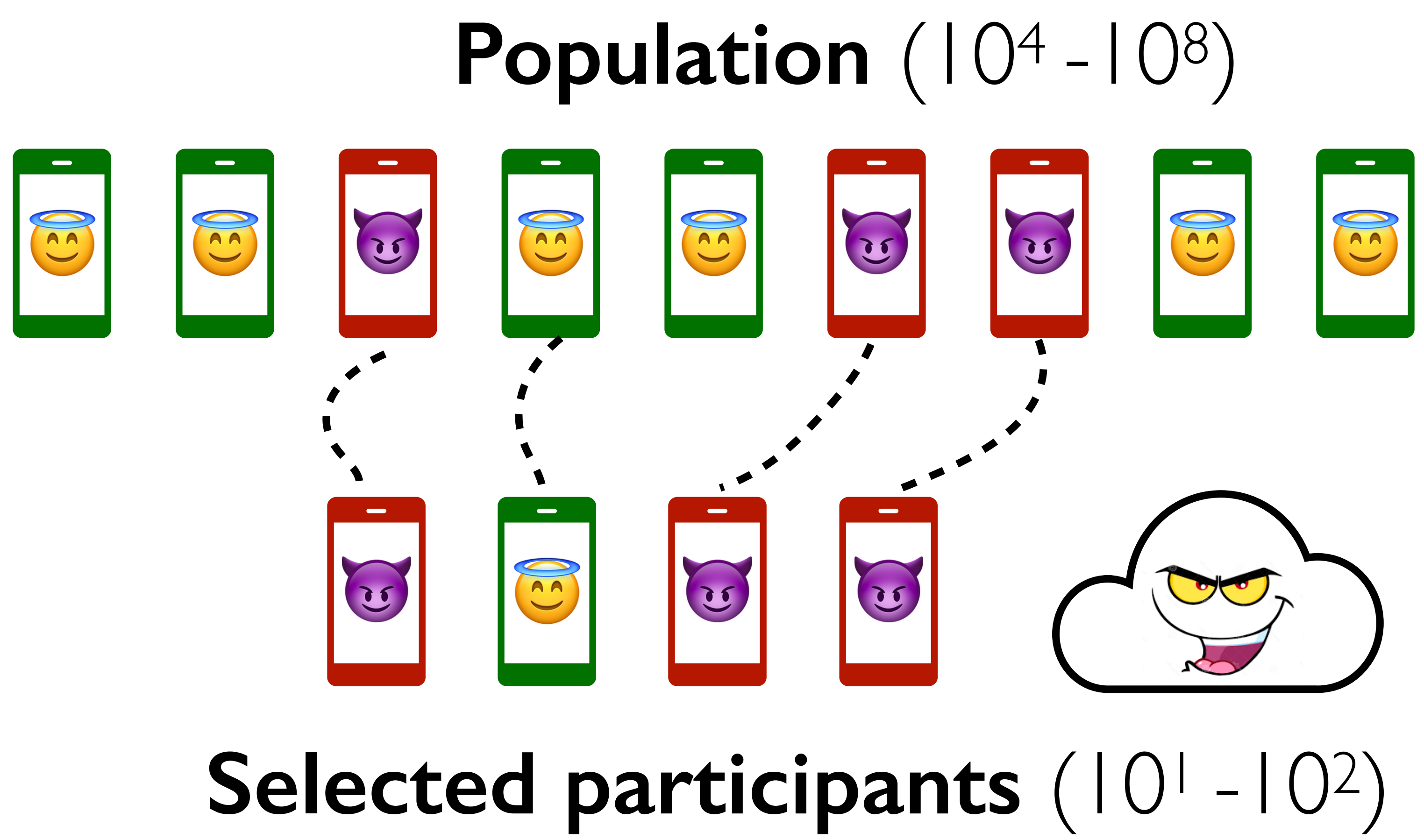


**Problem**: participant selection can be **manipulated** by the **malicious** server

Federated Learning

# Lotto - Overview

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

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

**Security**

**Theoretical guarantee** of preventing manipulation

**Efficiency**

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

# Problem: Random selection

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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

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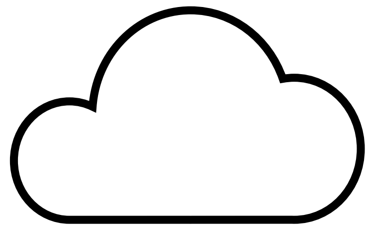

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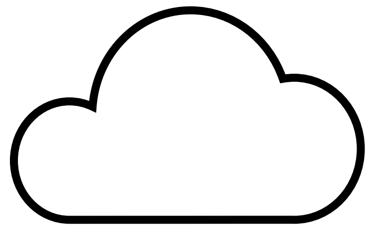

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For dishonest majority

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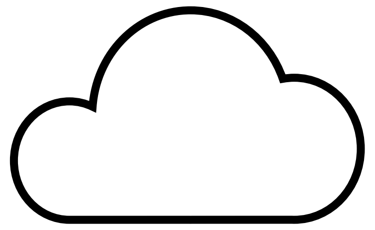

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**Potential approach**:

- Outcome verification

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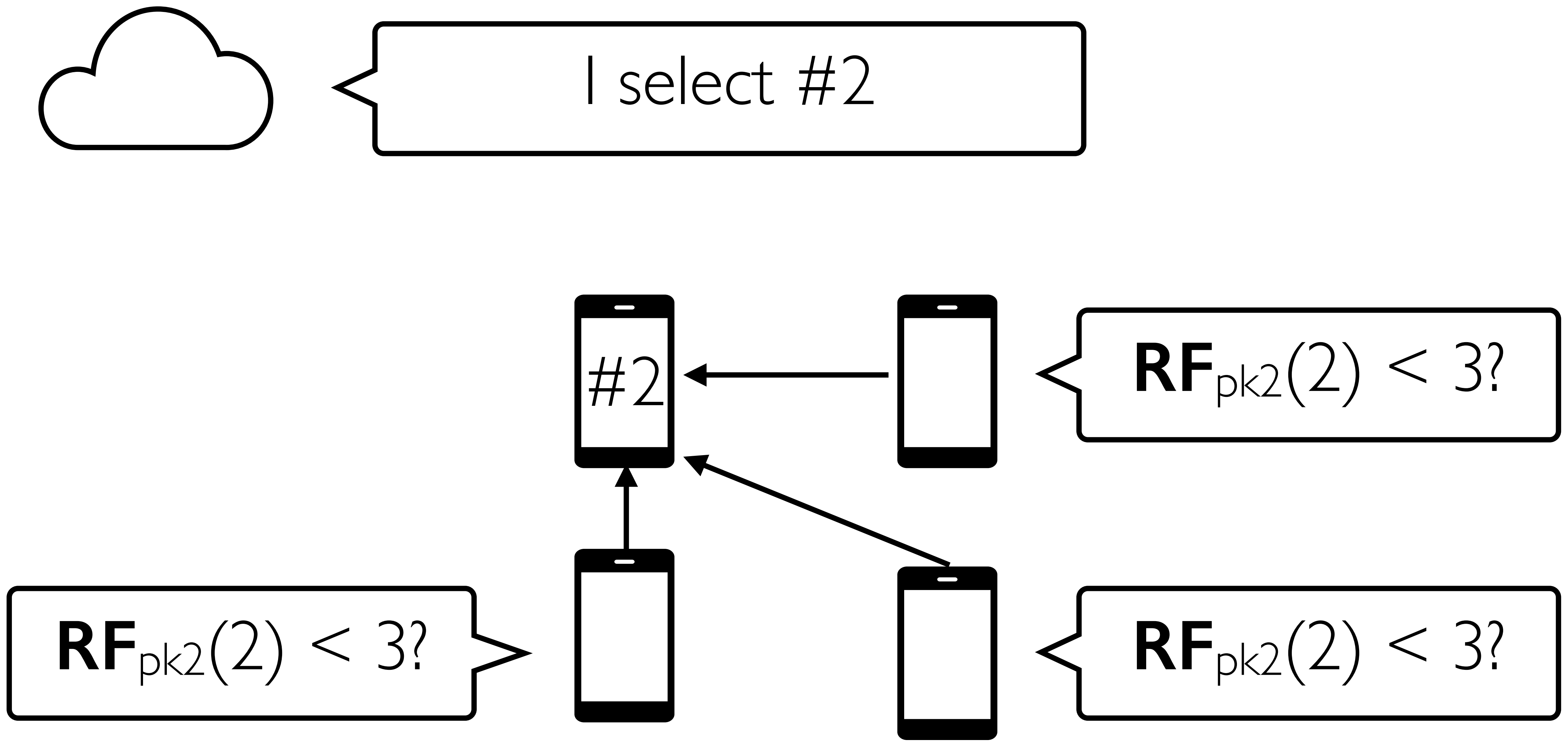

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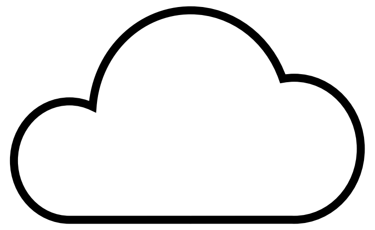

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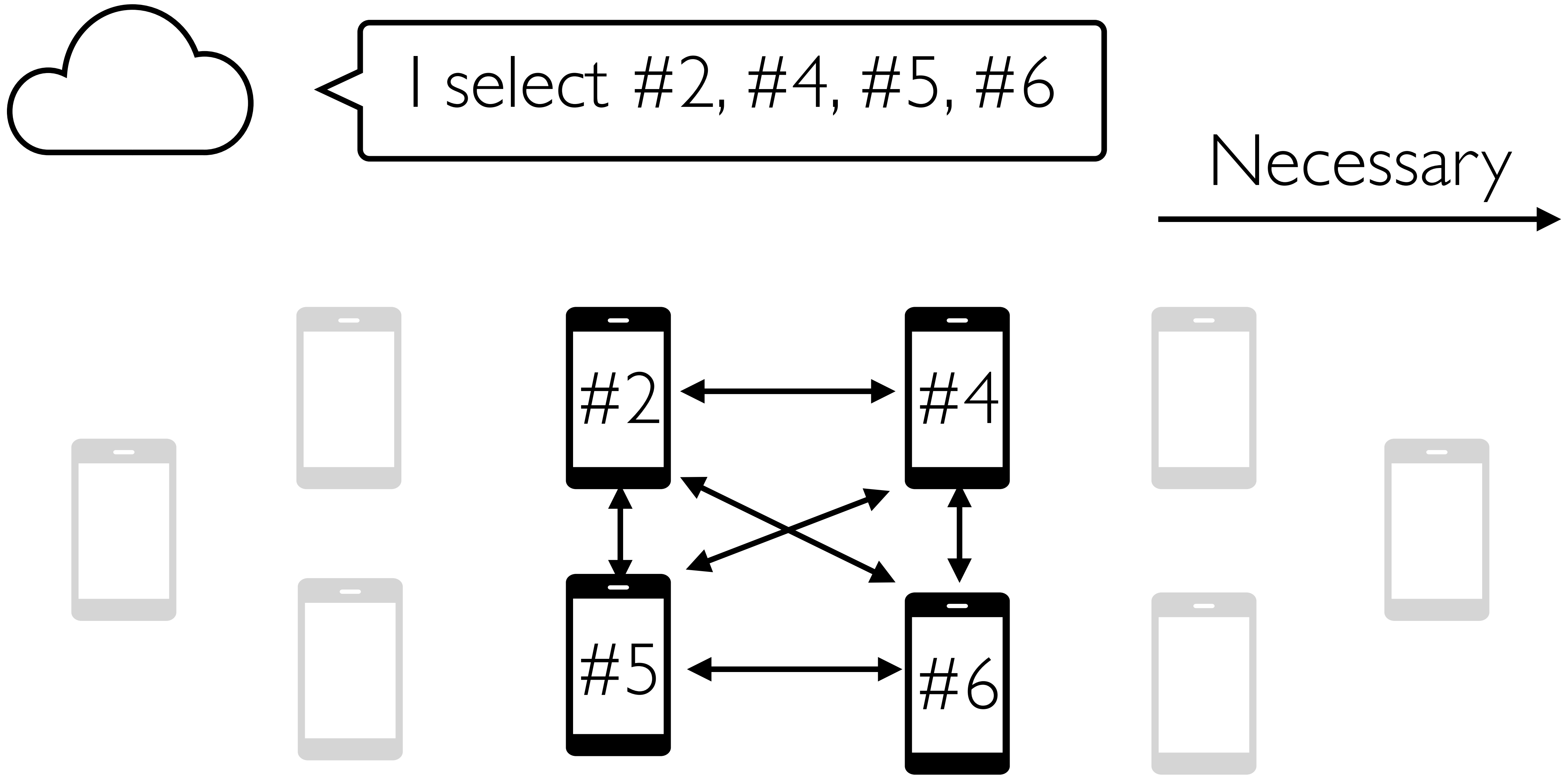

# Problem: Random selection

**What is achieved**:

Each participant
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**Potential approach**:

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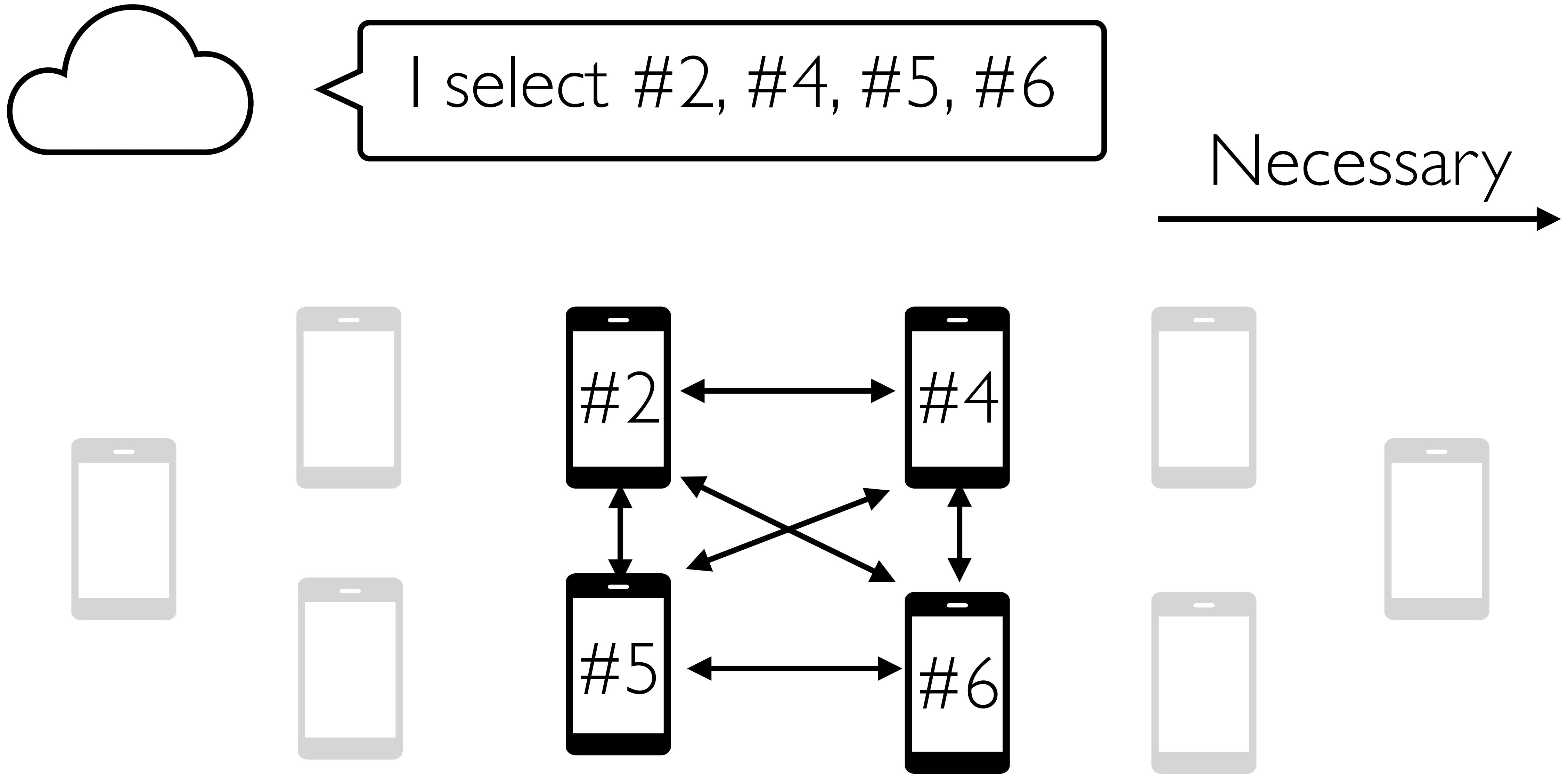
- Only within participants ($10^1$ - $10^2$)



# Problem: Random selection

**What is achieved**:

Each participant

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presents only by chance.

**Potential approach**:

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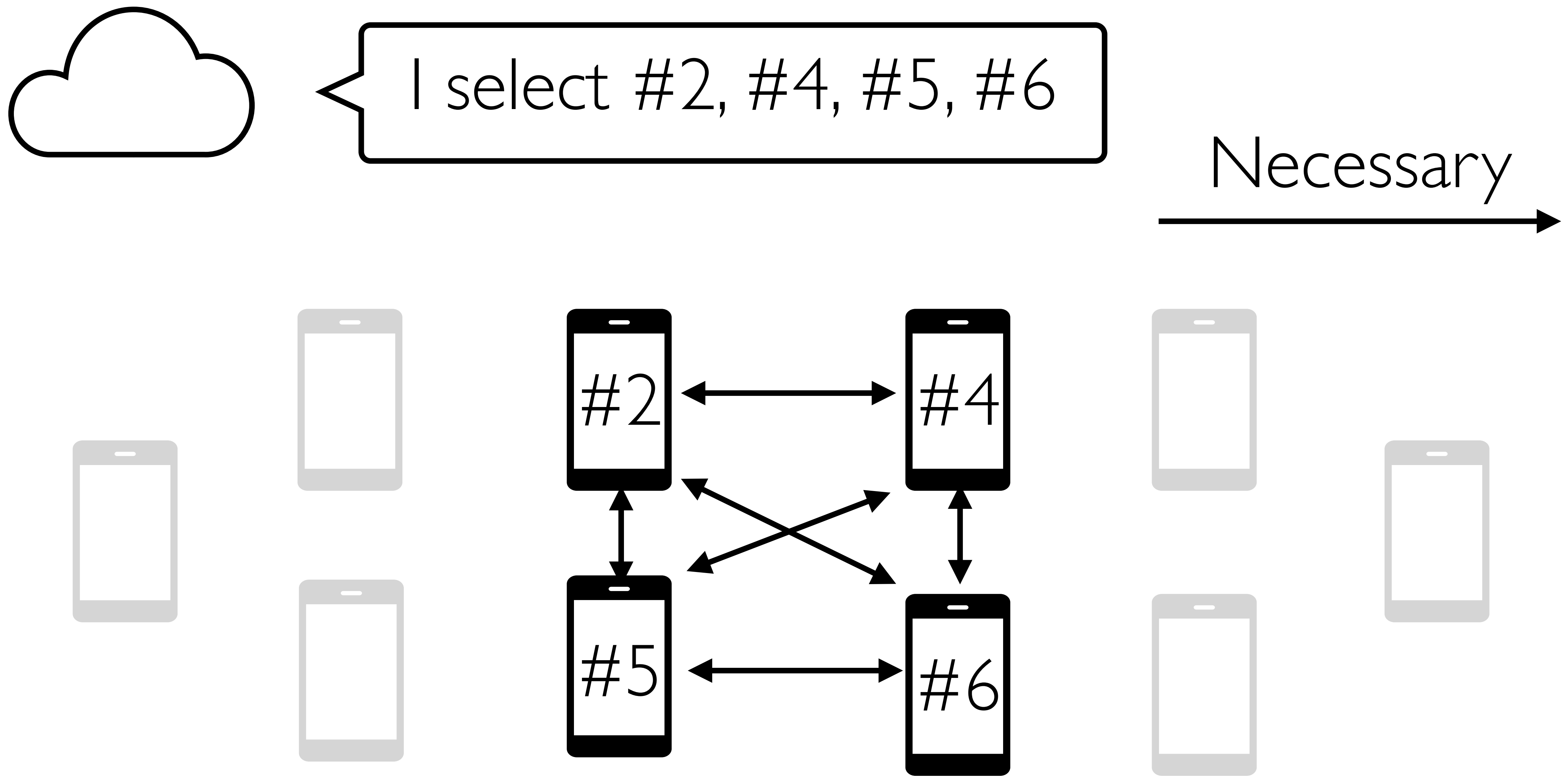
- Only within participants ($10^1$ - $10^2$)



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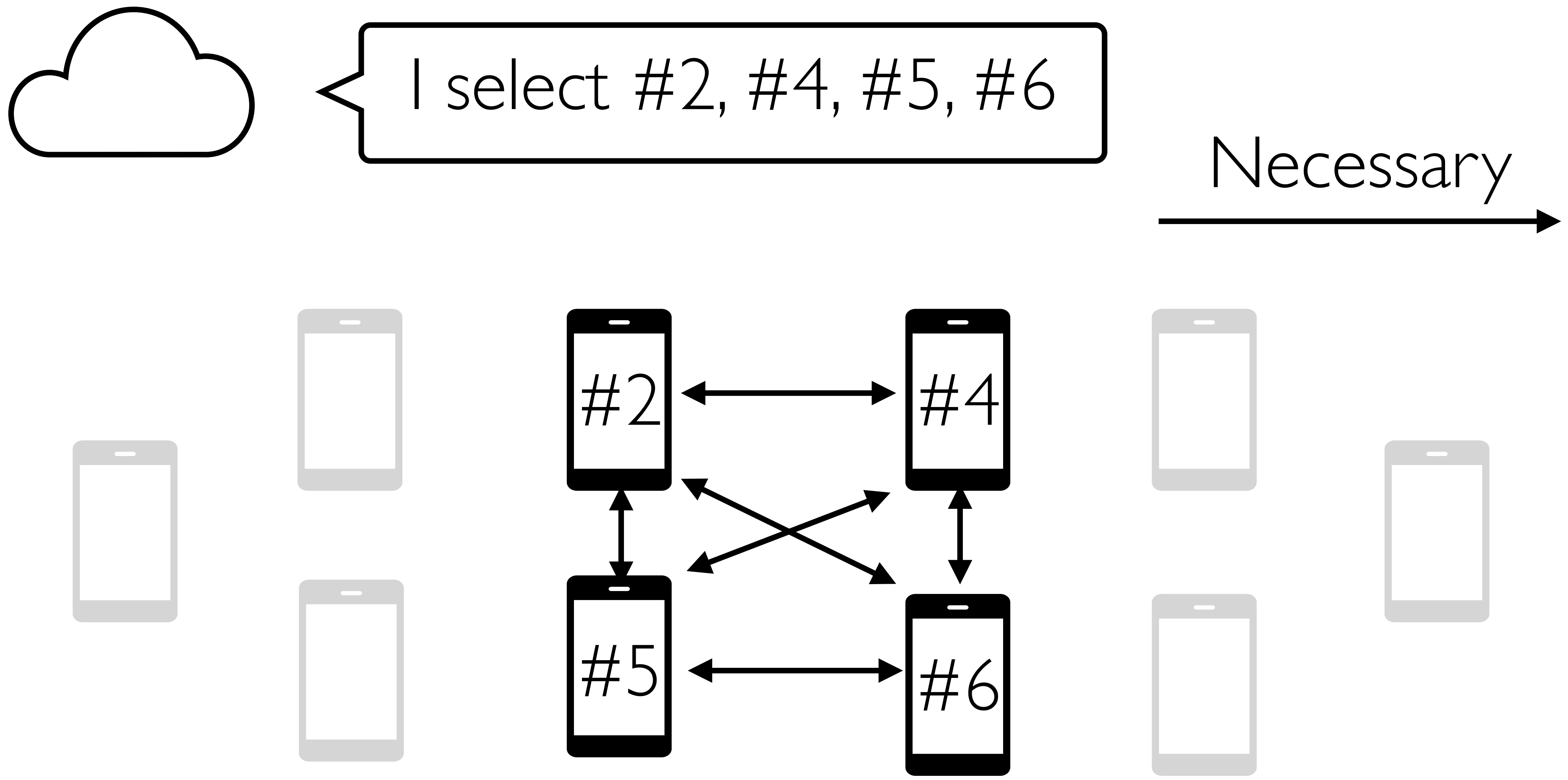
presents only by chance.

E.g., $\frac{\text{Selection criteria: } \mathbf{<3}}{\text{Output range: } \mathbf{[0,\ 10)}} = 3/10$

**Potential approach**:

- Outcome verification
- Only within participants ($10^1$ - $10^2$)



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What happens to the absent?

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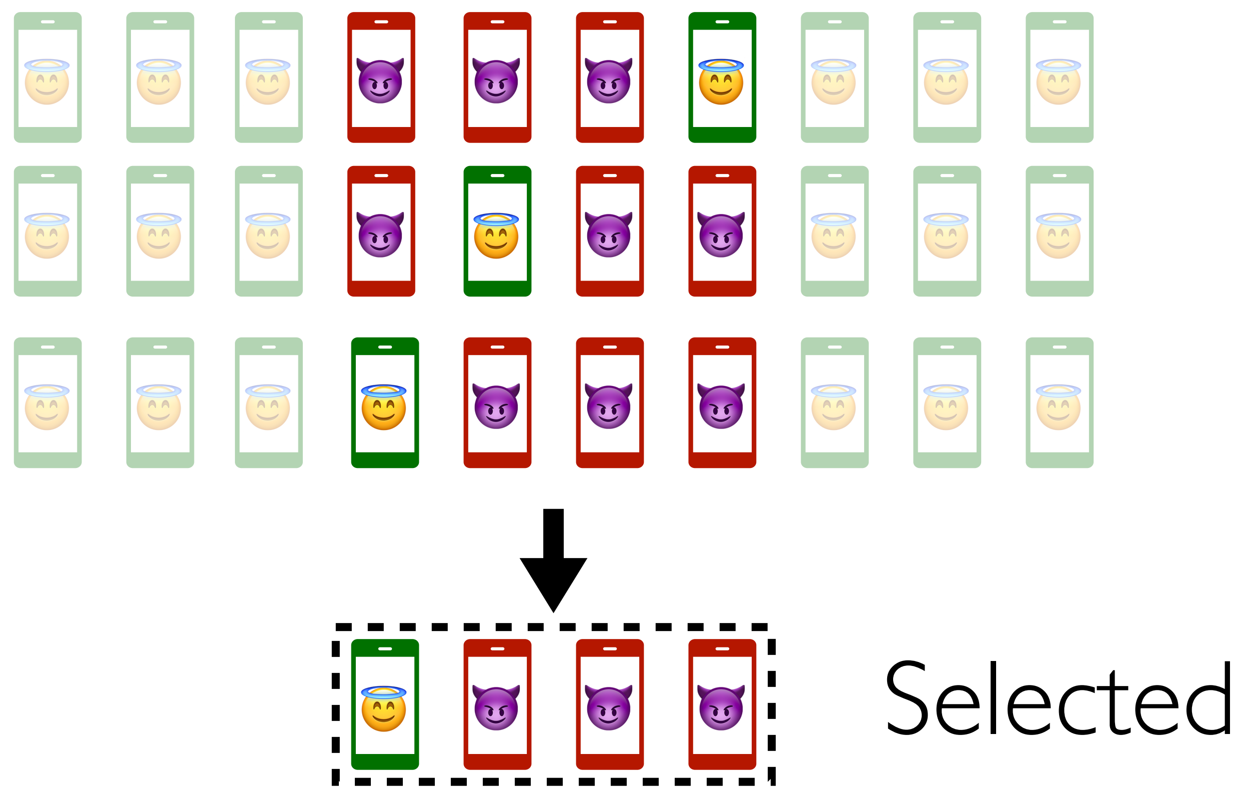
What happens to the absent?

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

Ignore **before** selection



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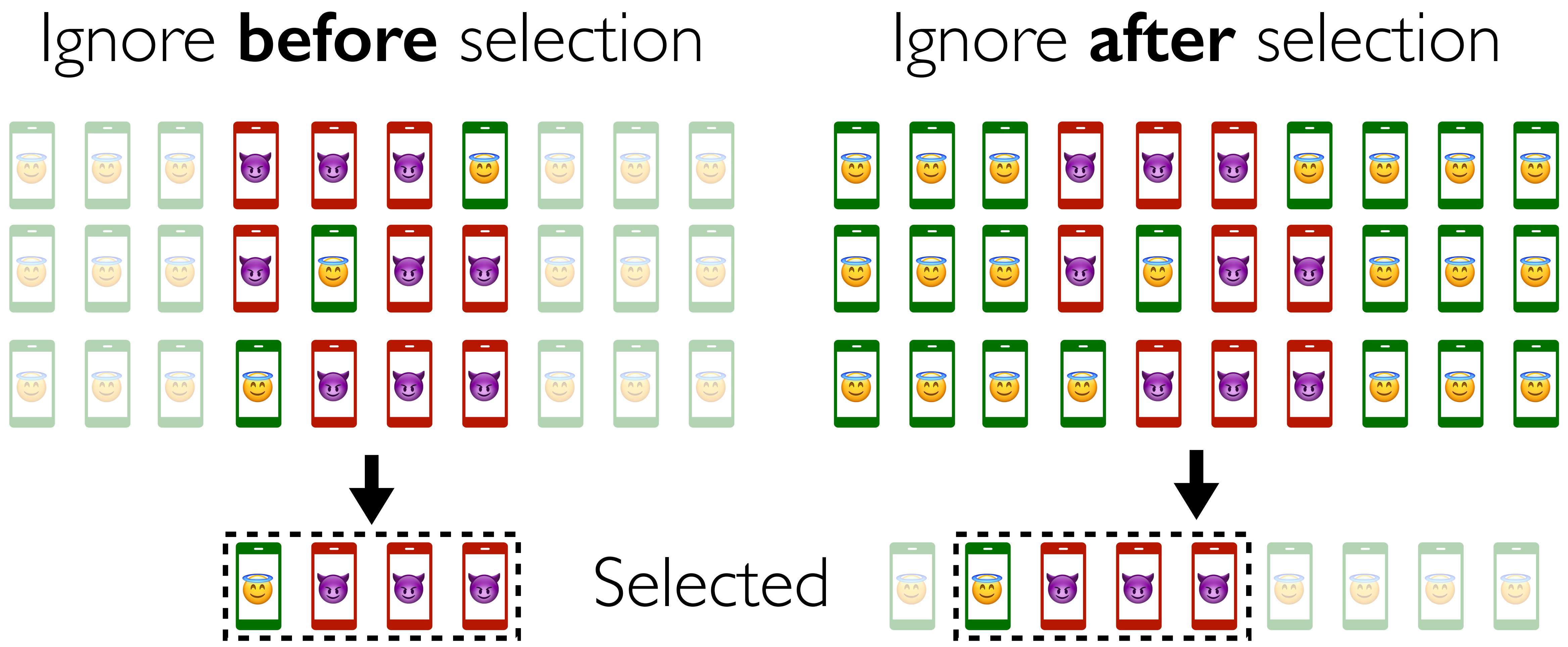

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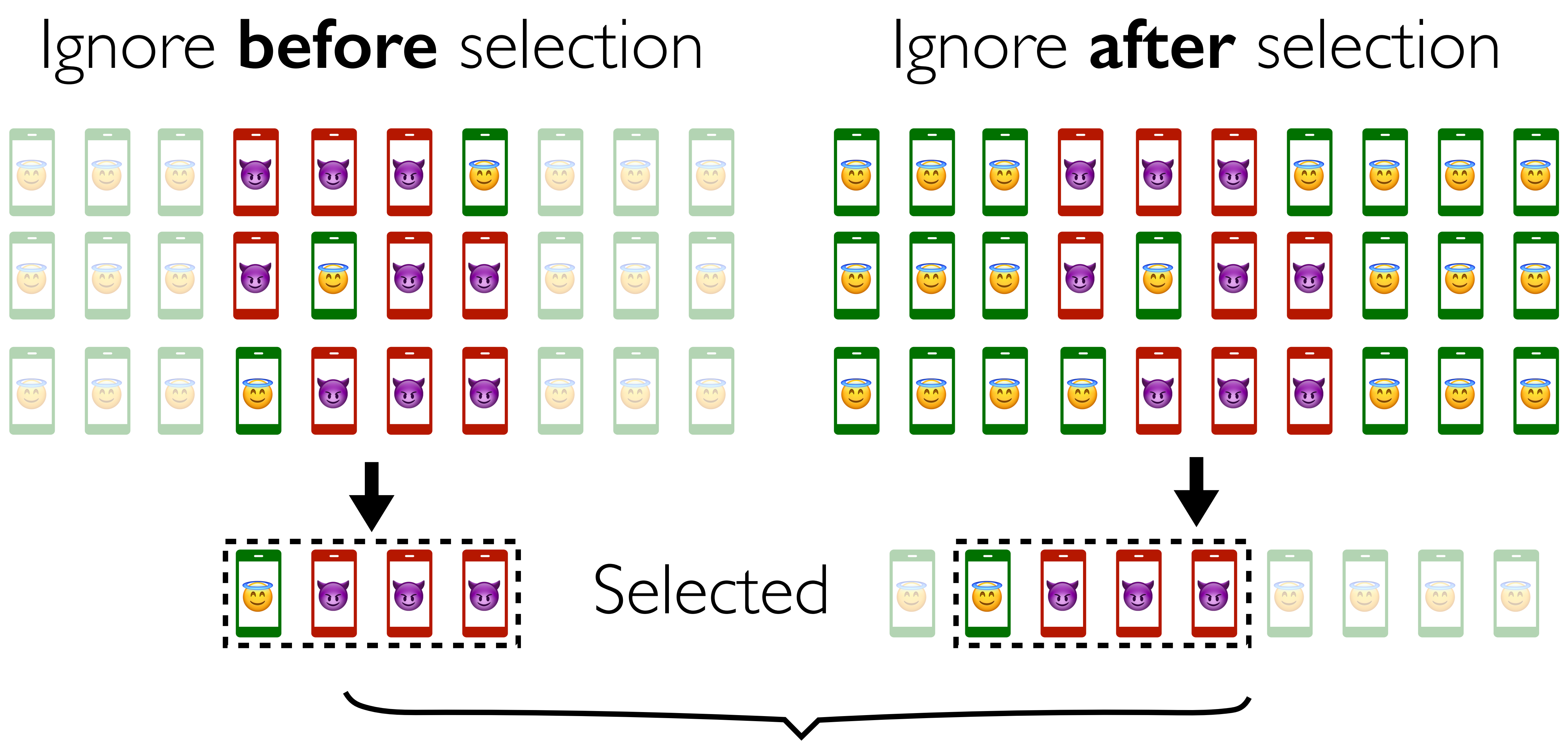


**Unbounded** advantage in growing dishonesty

# Problem: Random selection

**What is achieved**:

Each participant

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

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Example

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

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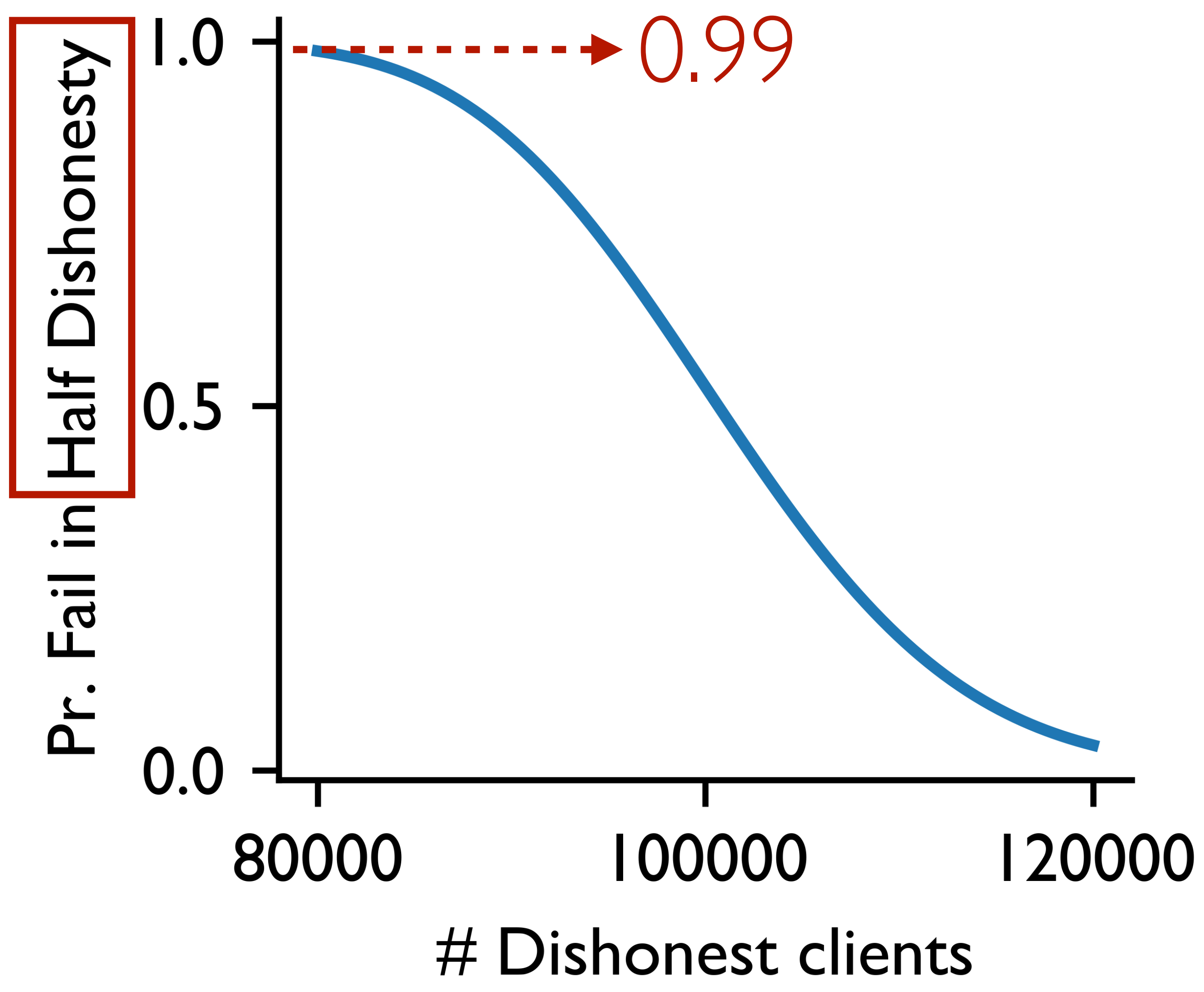
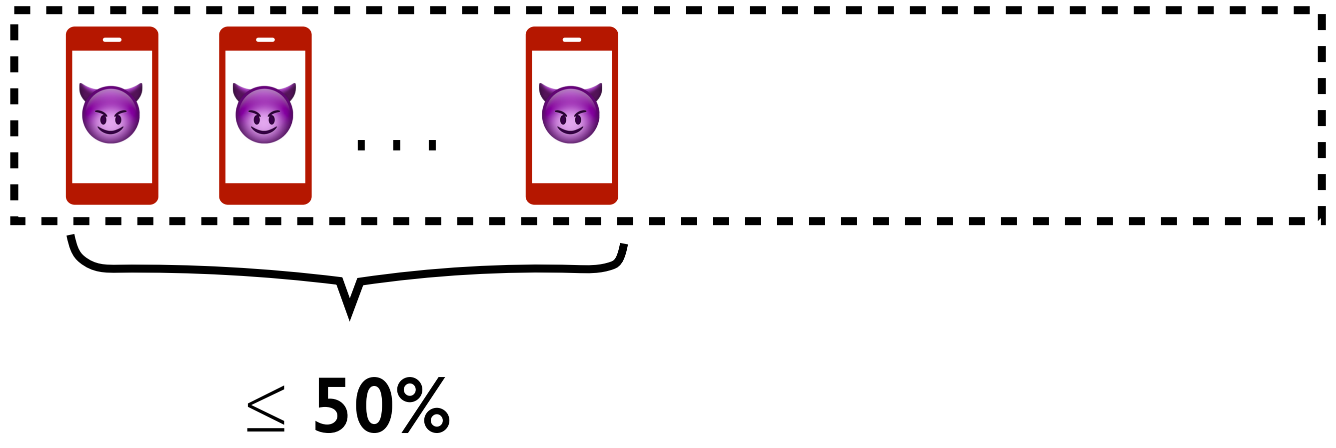



Selected



# Problem: Random selection

**What is achieved**:

Each participant

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The absent will not get arbitrarily ignored

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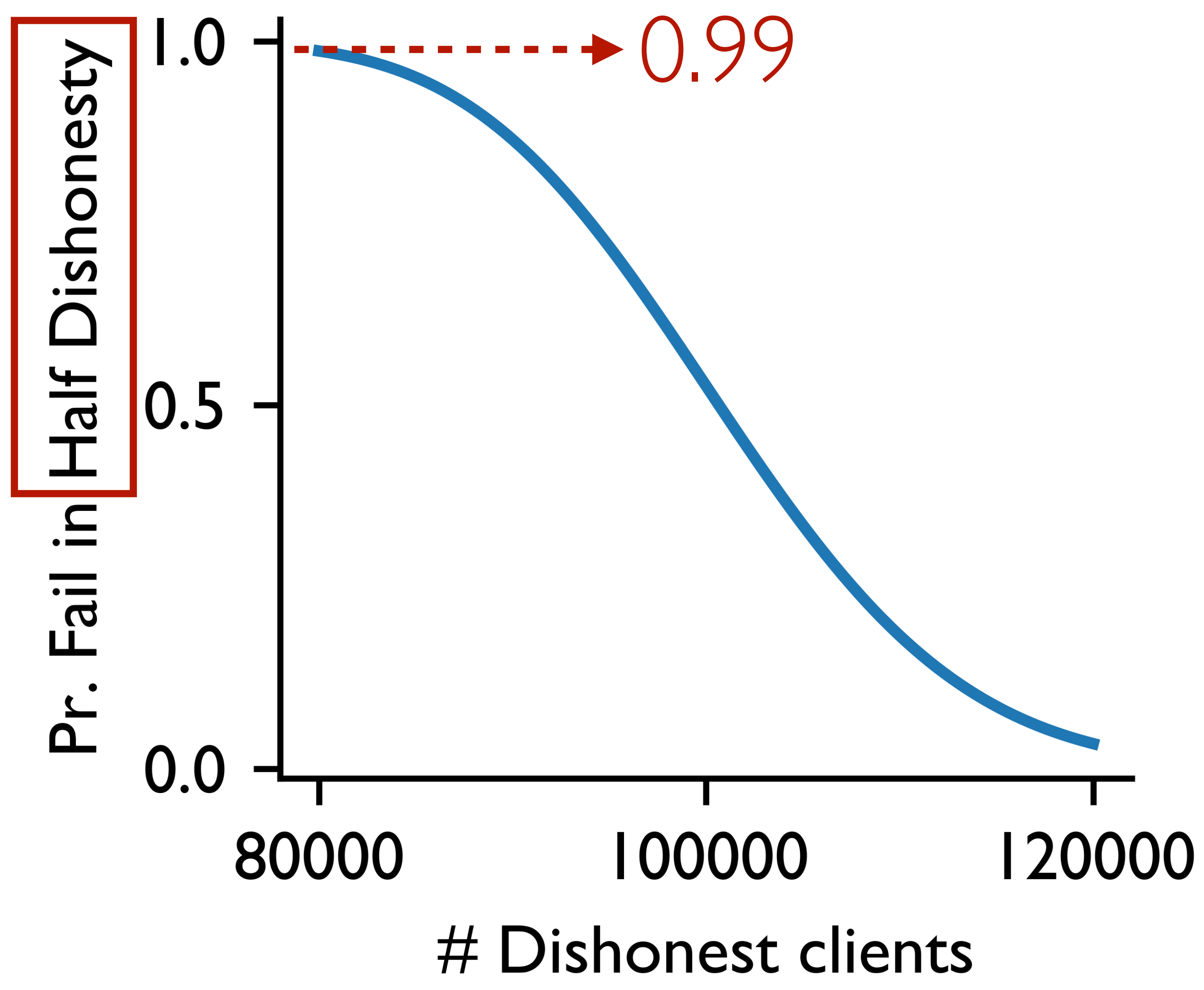


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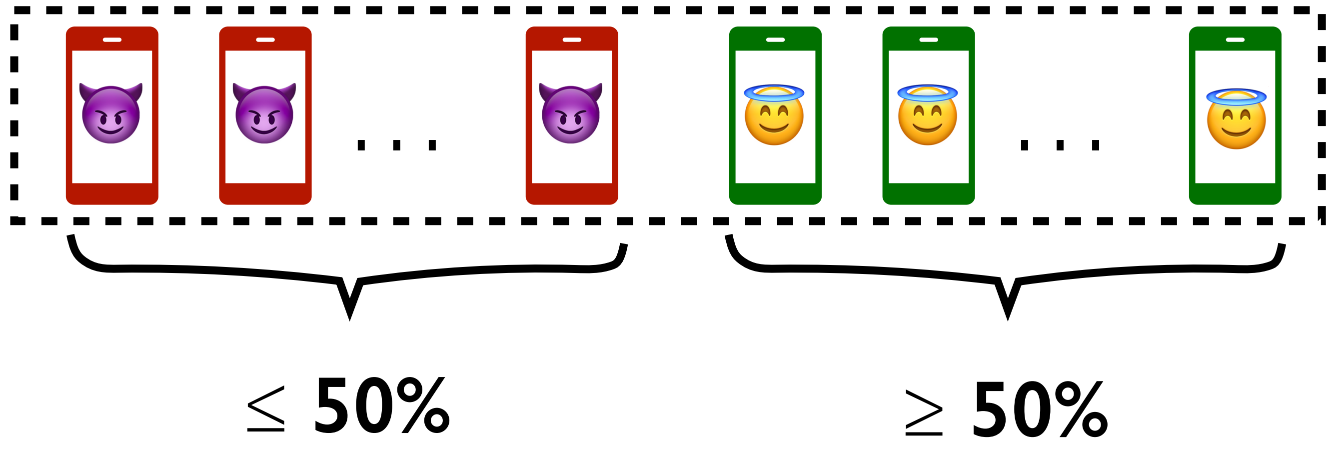

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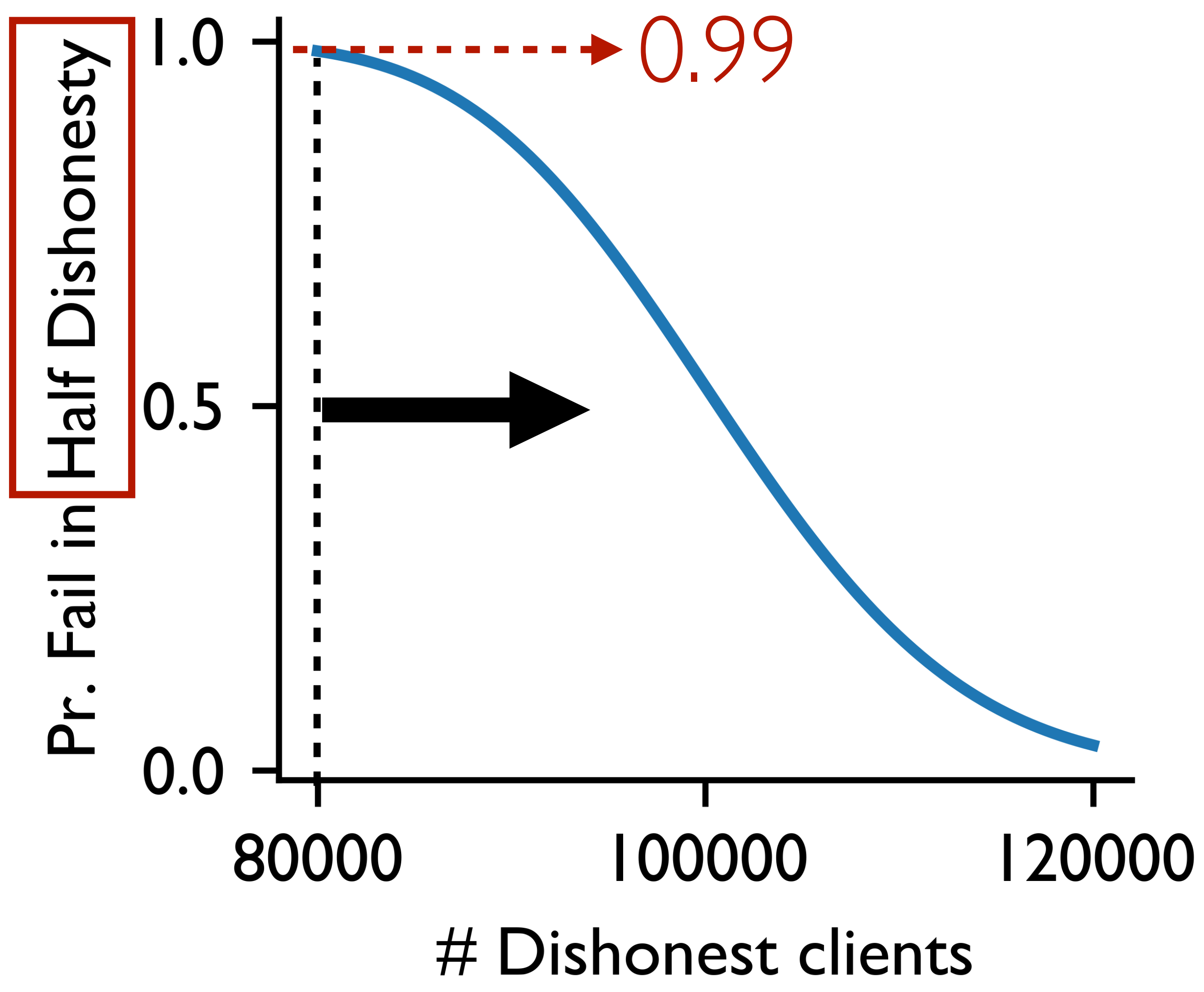


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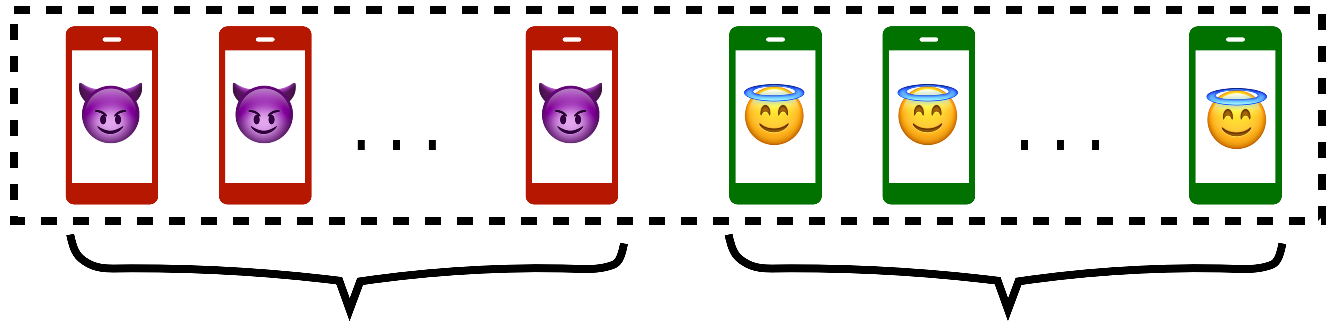


≤ **50%**

≥ **50%**

# Problem: Random selection

**What is achieved**:

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Predictable

to server?

The absent will not get

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Public Round index

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

Public Public keys

# Problem: Random selection

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**Problem**: Attack surfaces **enlarged**!

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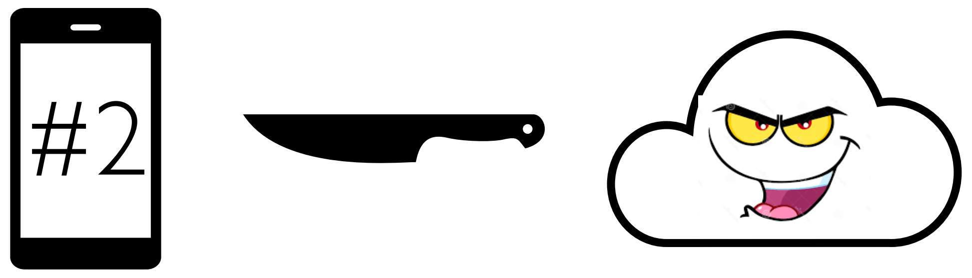
It's honest, so the server may grow its advantage by




Focused hacking

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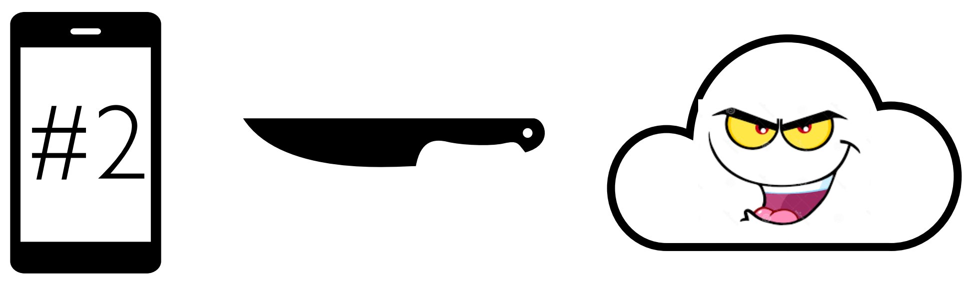
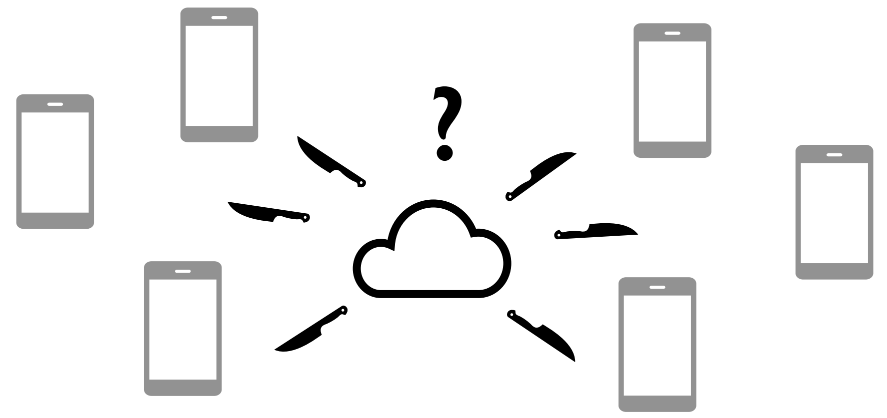



vs




Focused hacking

Random compromise

# Problem: Random selection

**What is achieved**:

Each participant sees a list of peers who presents only by chance.

Predictable to server?

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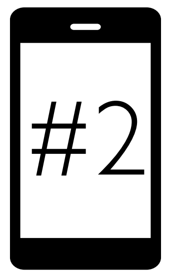
**Solution**: **Self-sampling** with verifiable random functions (**VRFs**)[1,2].




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

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

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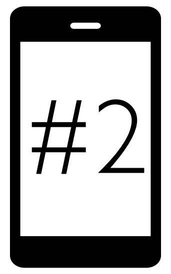


Evaluation: $\textbf{VRF.eval}_{sk2}(2) = (\ 1, \boldsymbol{\pi_2}\ )$ ( output, **proof** )

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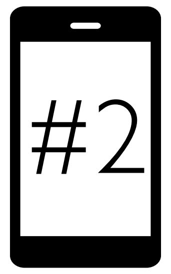


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Verification: $\mathbf{VRF.ver}_{pk2}(\ 2, 1, \boldsymbol{\pi_2}\ ) = \text{True}$

Public key

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I self-sample

with $(1, \pi_2)$

#2

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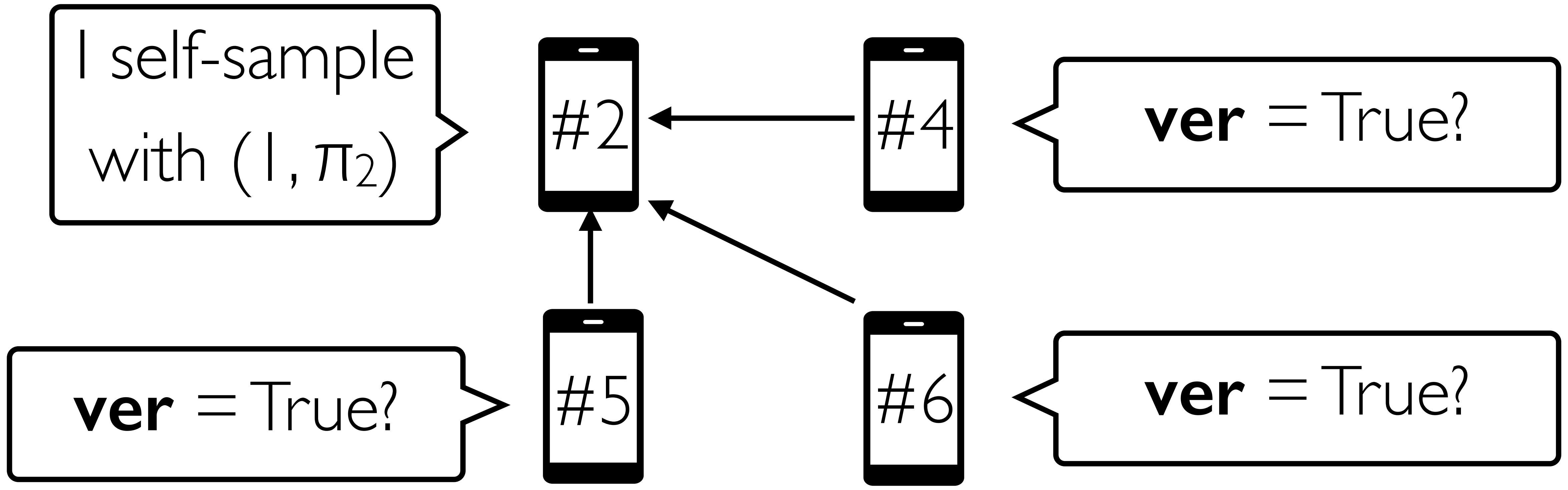


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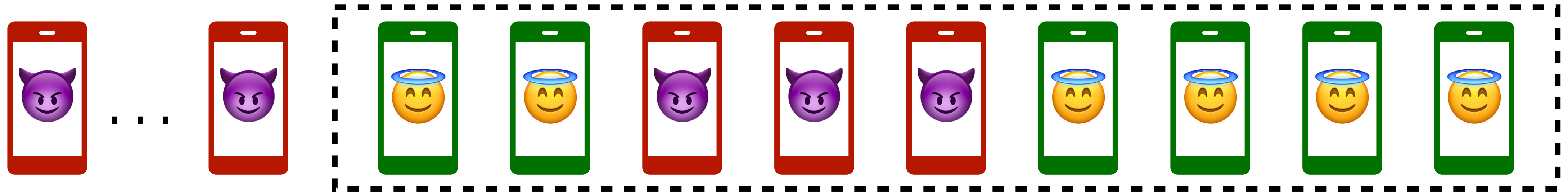
Involve **non-selected dishonest** ones



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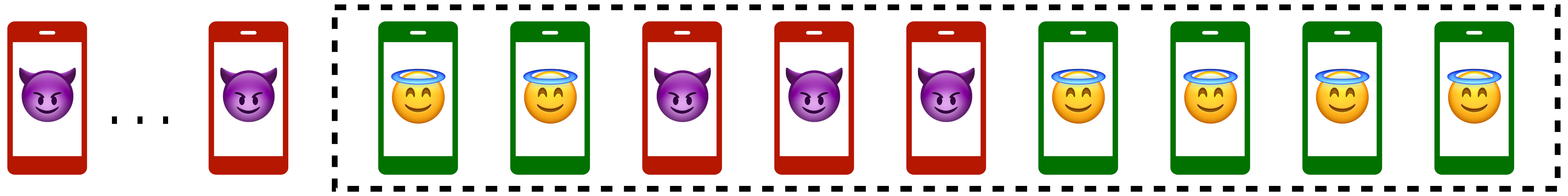
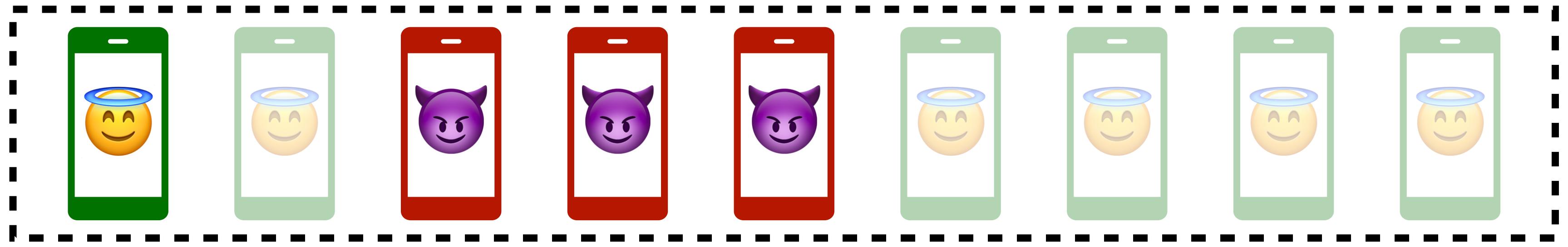


Disregard **selected honest** ones



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

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

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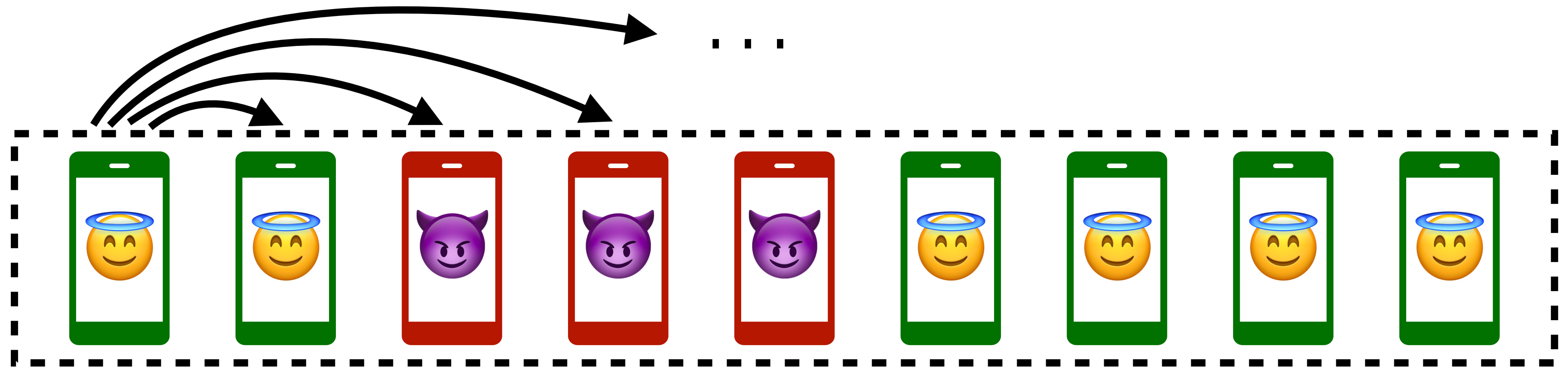


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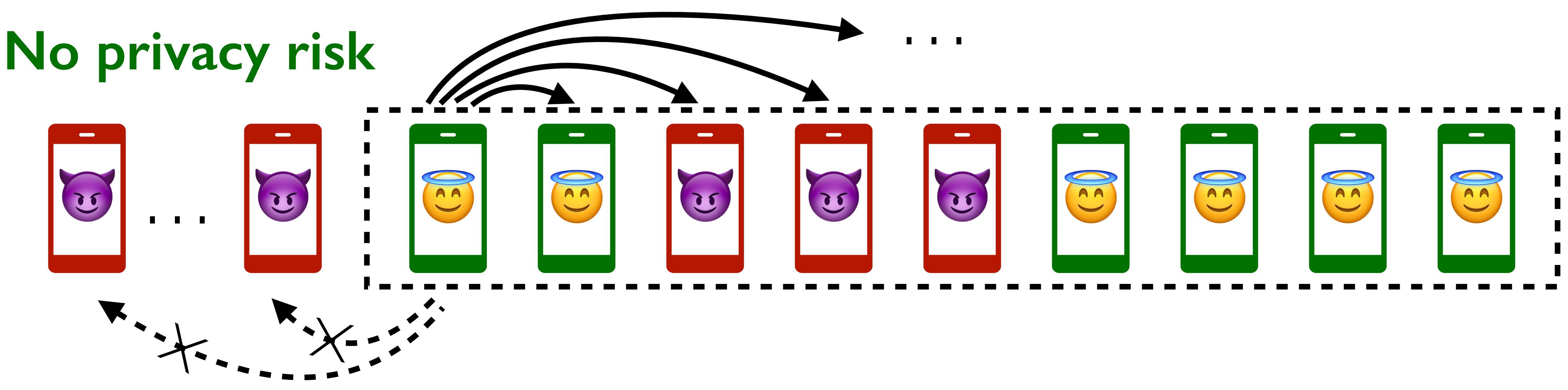
No privacy risk



# Problem: Random selection

Actual participants throughout the training?

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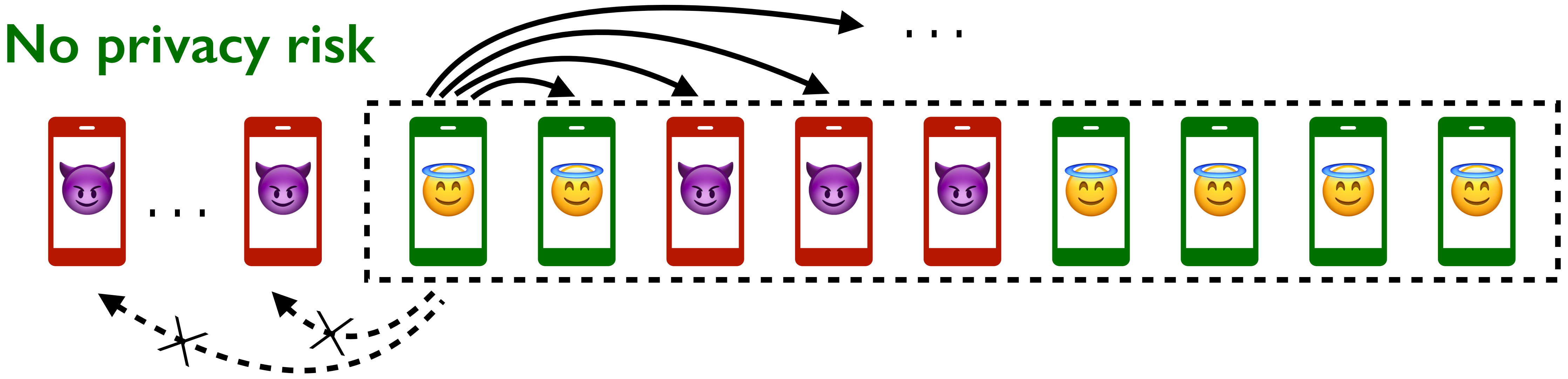
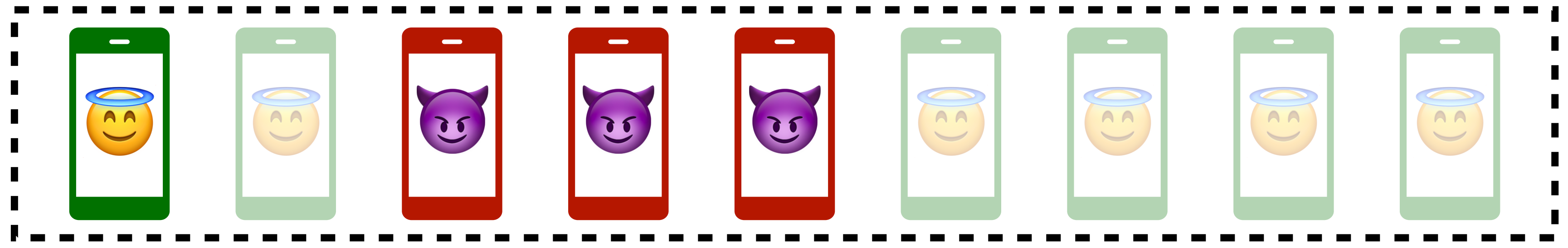



- **Consistency check**: to know remaining participants



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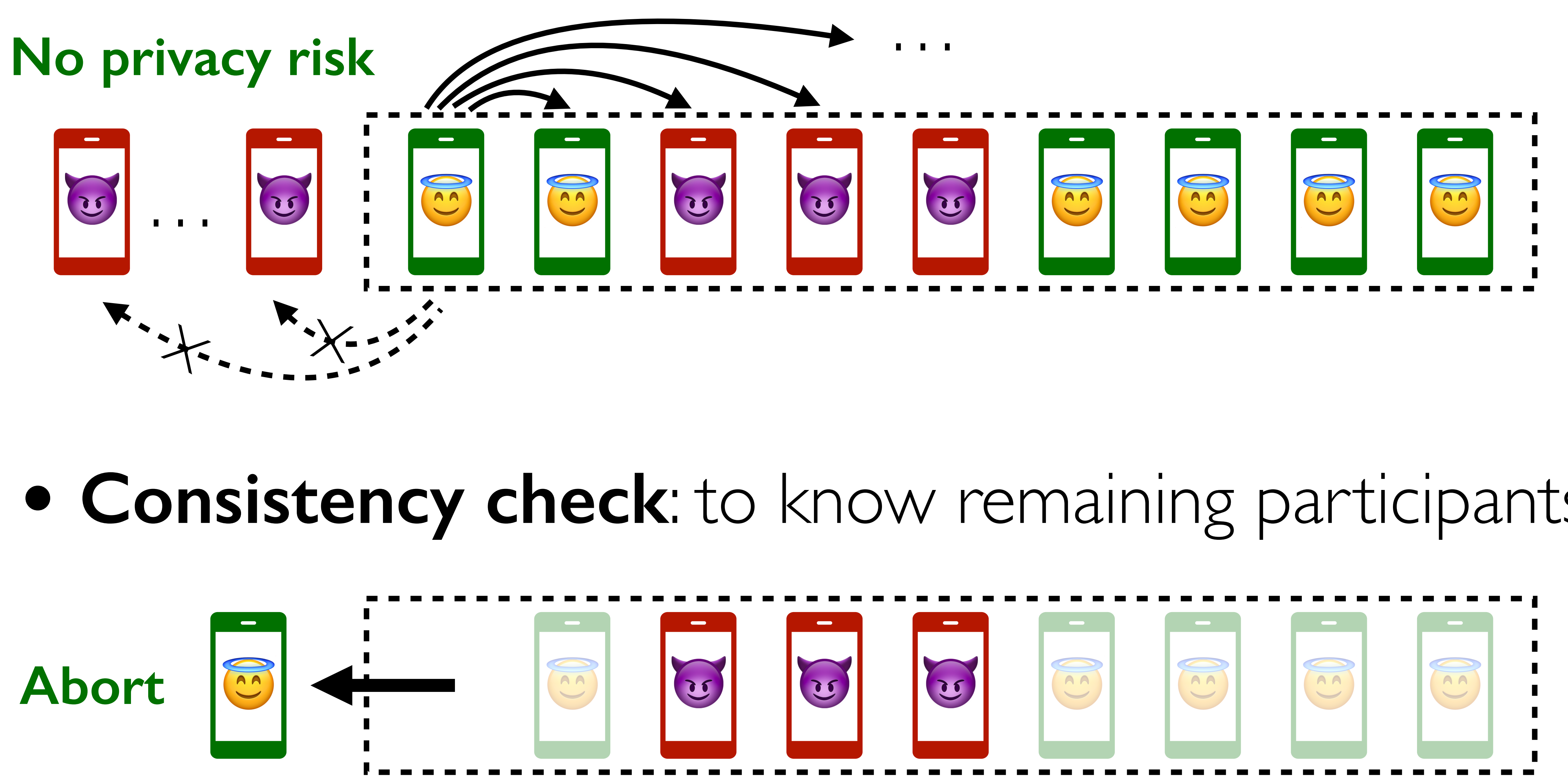


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Actual participants throughout the training

**What is achieved**:

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Minor issues:

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

…

Please find more in the paper :)

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# Problem: Informed selection

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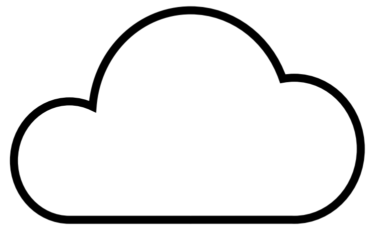
**Example**



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

# Problem: Informed selection

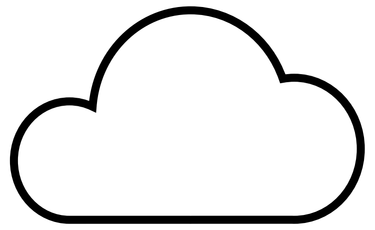
**Example**

| | (Est.) latency | Select |
|---|---|---|
| #1 | 1.2s | Yes |
| #2 | 2.7s | No |
| #3 | 1.6s | Yes |
| … | … | … |

Selection criteria: the fastest For dishonest majority

# Problem: Informed selection

**Example**



| | (Est.) latency | Select | (Est.) latency | Select |
|---|---|---|---|---|
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# Problem: Informed selection

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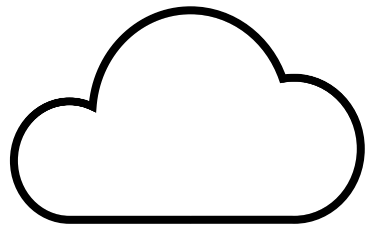
Selection criteria: the fastest

For dishonest majority

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

# Problem: Informed selection

**Example**



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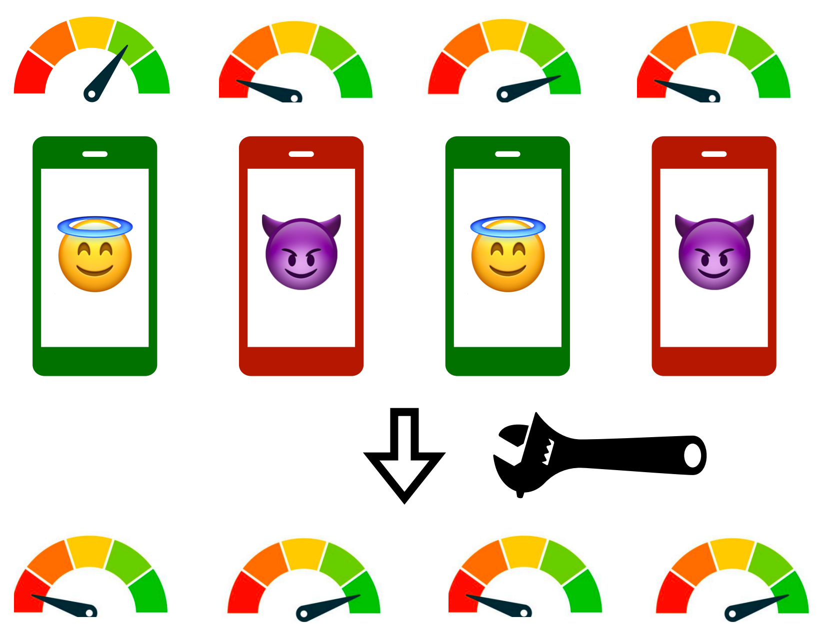
Selection criteria: the fastest

For dishonest majority

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

Metrics are fake



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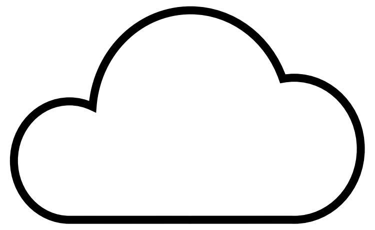

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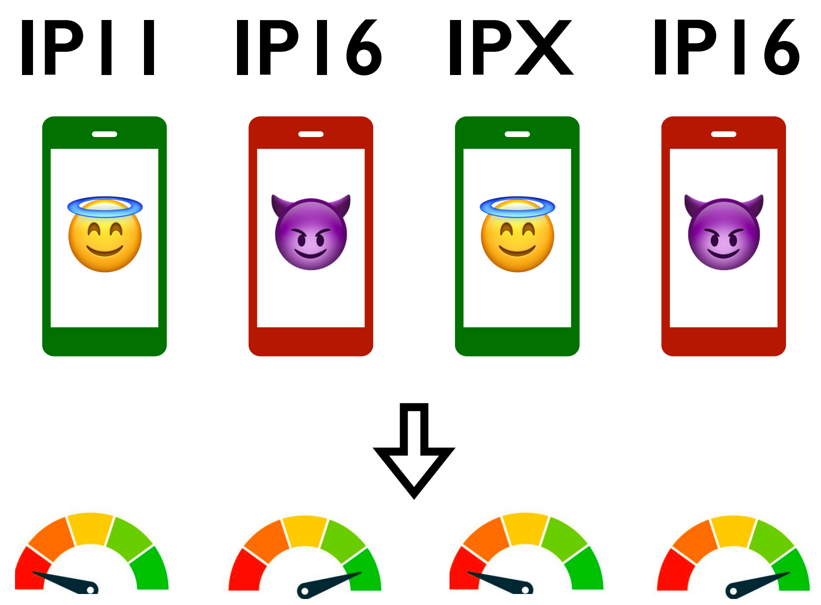
Selection criteria: the fastest For dishonest majority

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

Metrics are fake

Metrics are true, but…



# Problem: Informed selection

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|---|---|---|---|---|
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Selection criteria: the fastest    For dishonest majority

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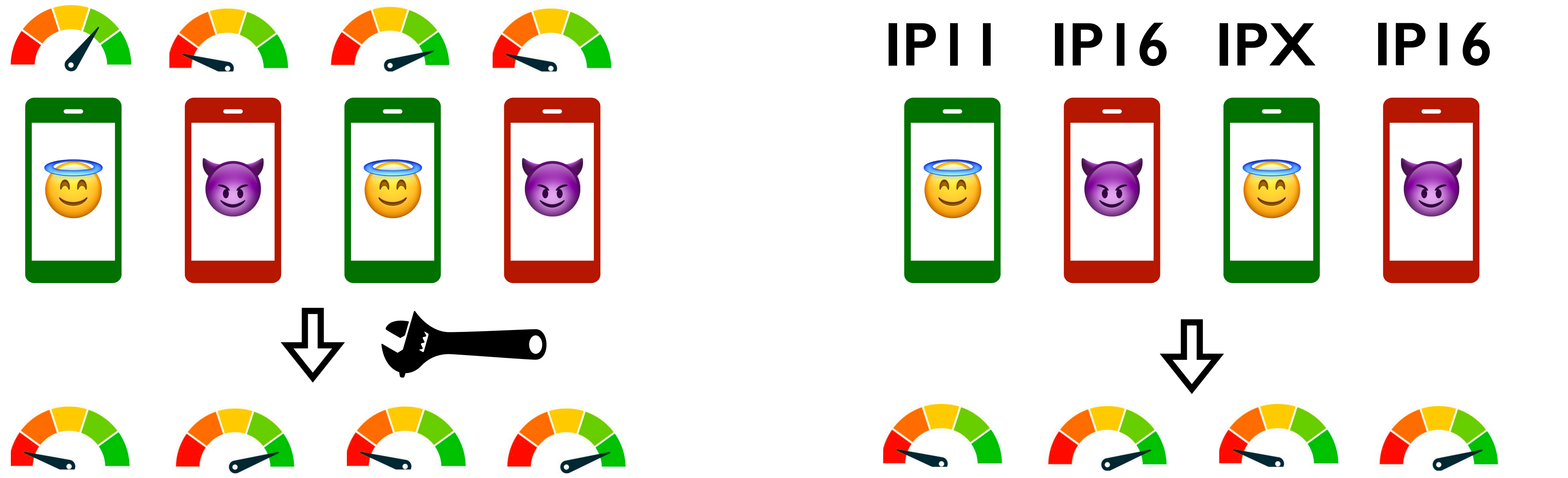


**Solution**: **Approximate** inform selection by **random** selection

Please find more in the paper :)

# Lotto prevents arbitrary manipulation

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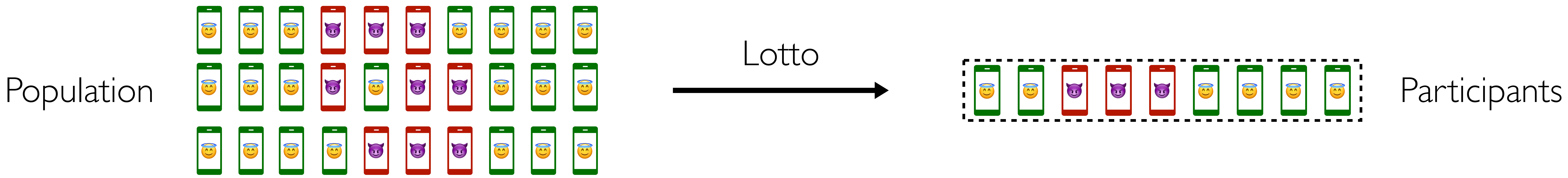
What can be **proven**:



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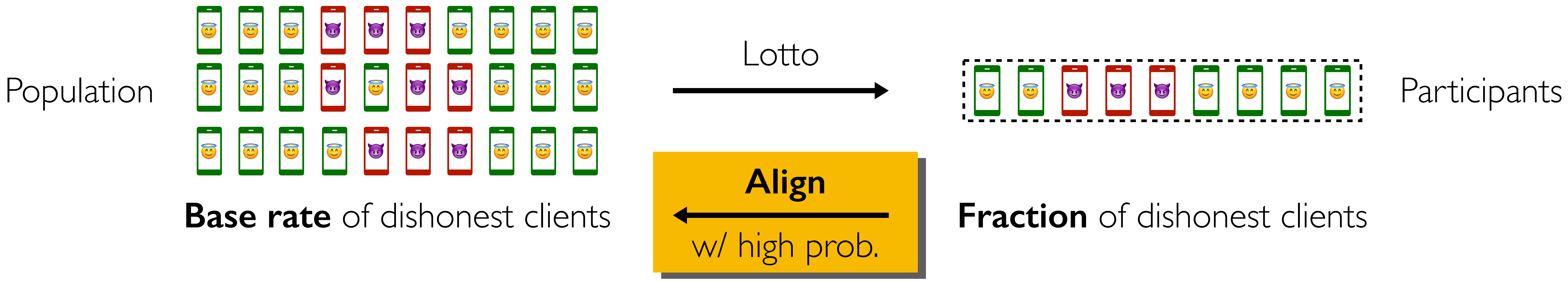

# Lotto prevents arbitrary manipulation

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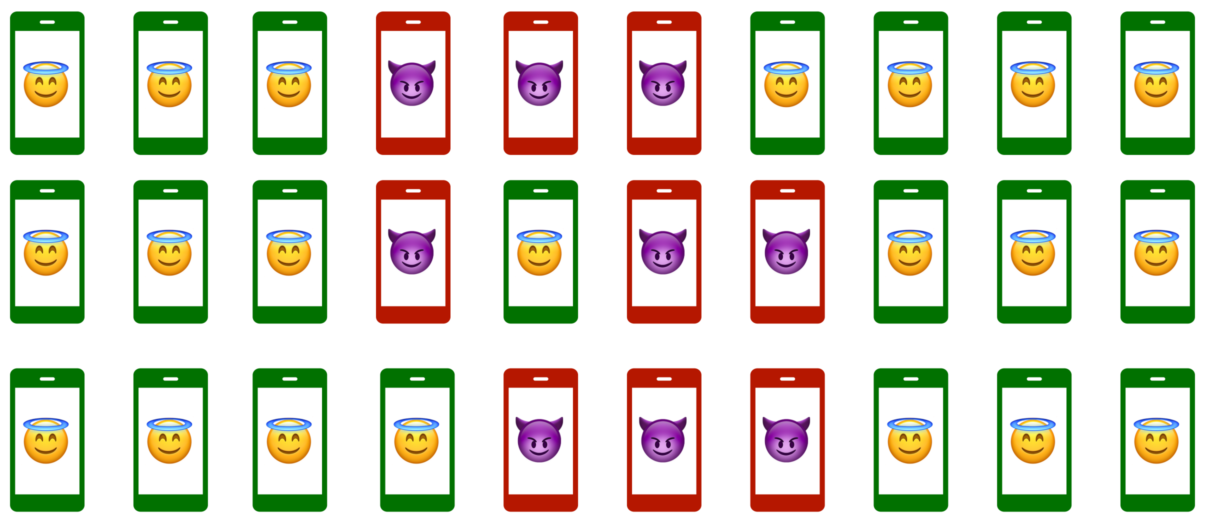
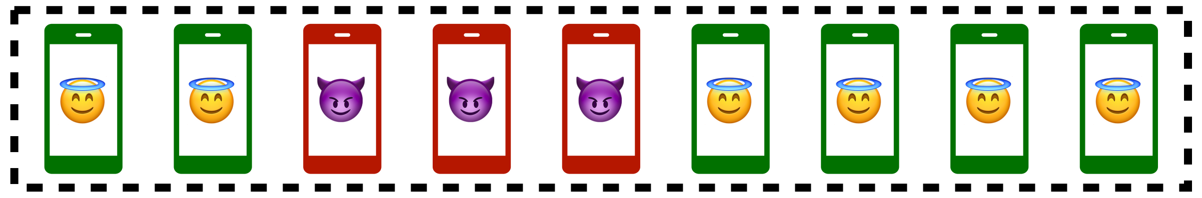
Population



**Base rate** of dishonest clients

Lotto →

**Align** ← w/ high prob.



Participants

**Fractions** of dishonest clients

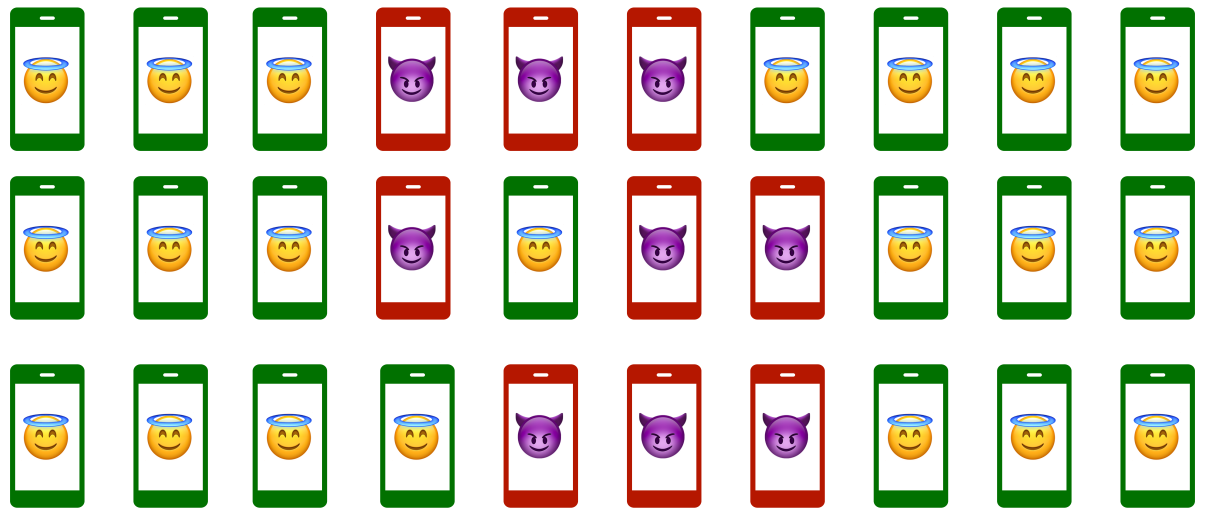
Example

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

# Lotto prevents arbitrary manipulation

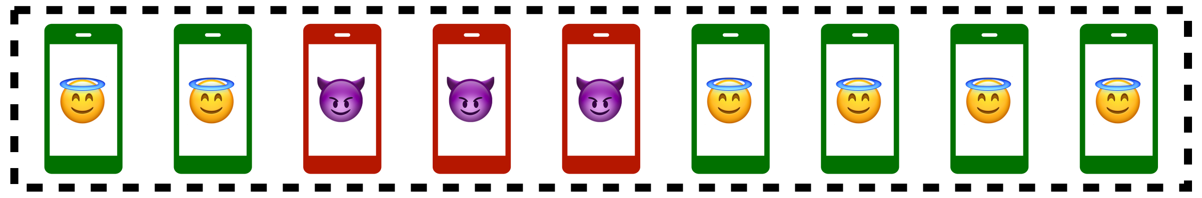
What can be **proven**:

Population



Lotto

Participants



**Align**

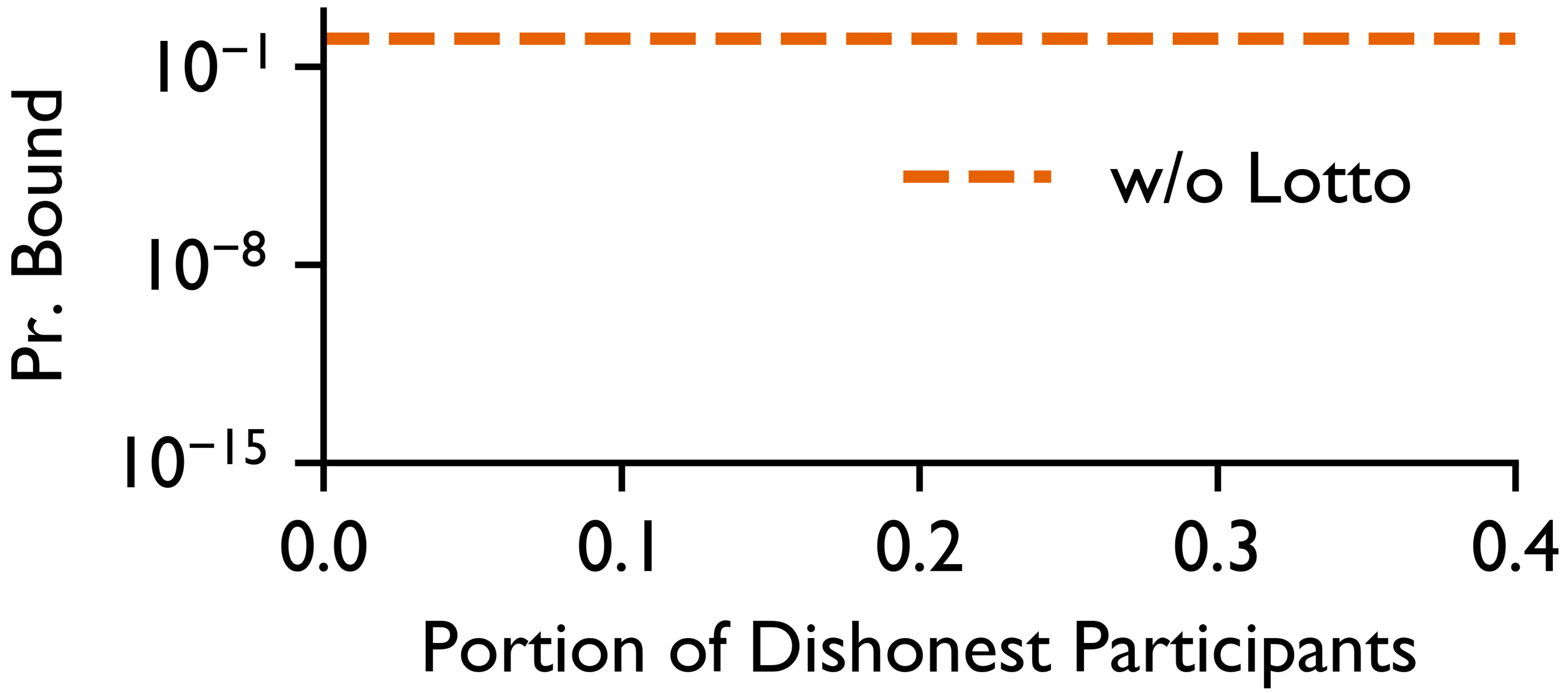
w/ high prob.

**Base rate** of dishonest clients

**Fractions** of dishonest clients

Example

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



# Lotto prevents arbitrary manipulation

What can be **proven**:

Population


Participants

**Base rate** of dishonest clients

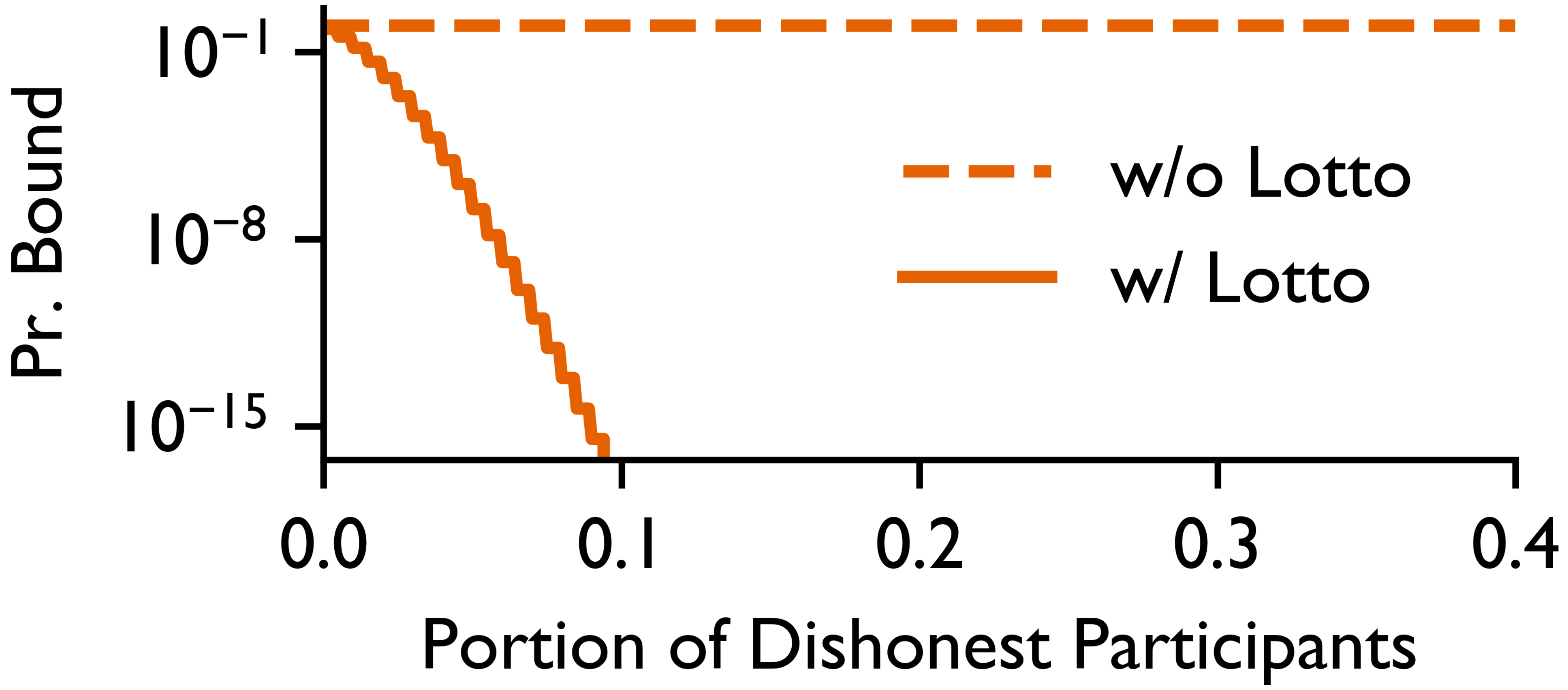
**Align**

w/ high prob.

**Fractions** of dishonest clients

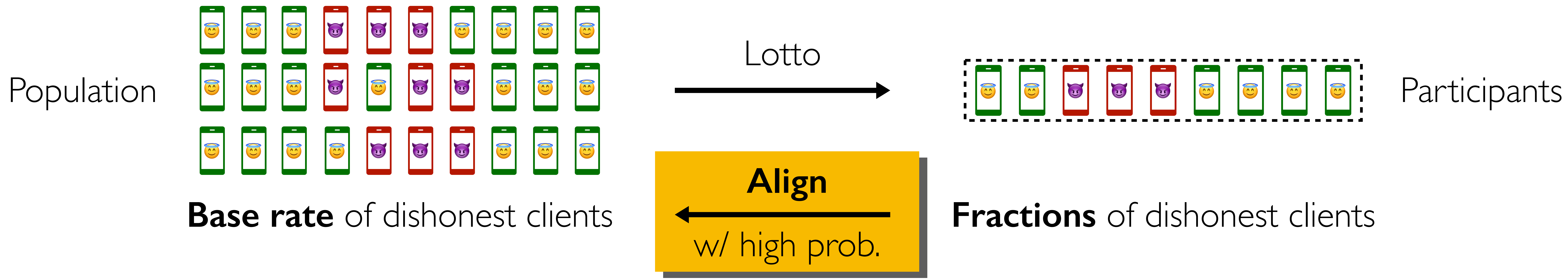
Example

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



# Lotto prevents arbitrary manipulation

What can be **proven**:




Example

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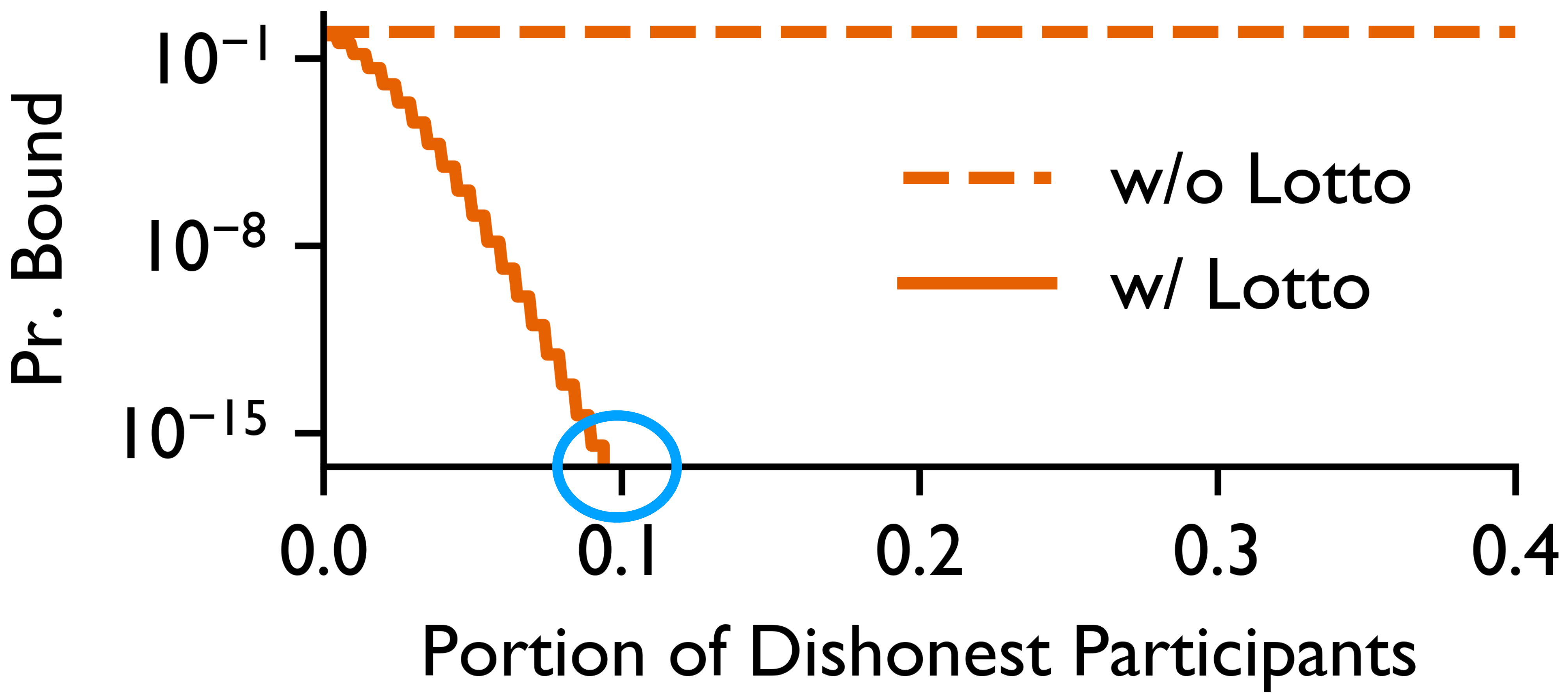


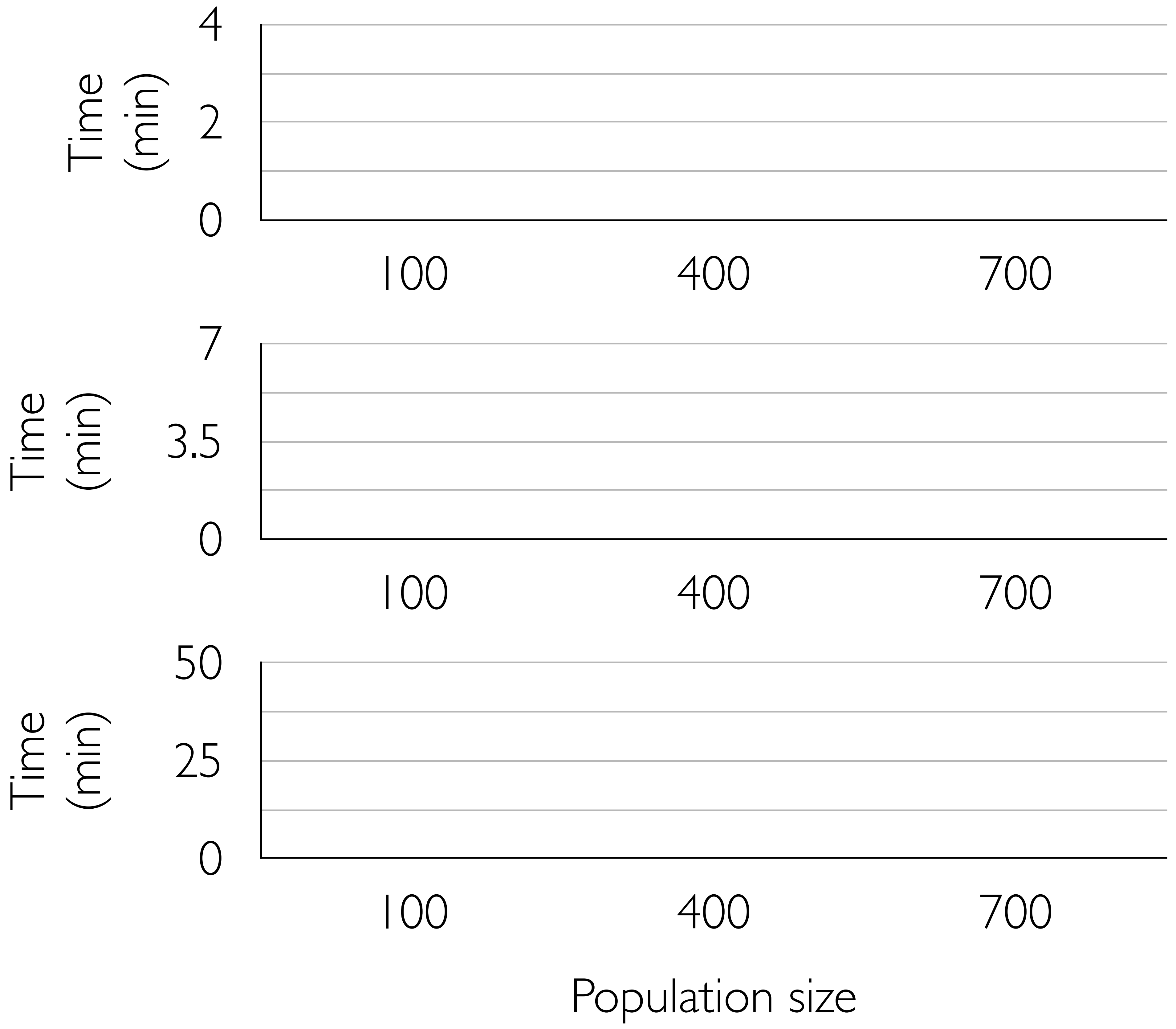
# Lotto induces no or mild overhead

# Lotto induces no or mild overhead

**FEMNIST**
**@CNN**

**OpenImage**
**@MobileNet**

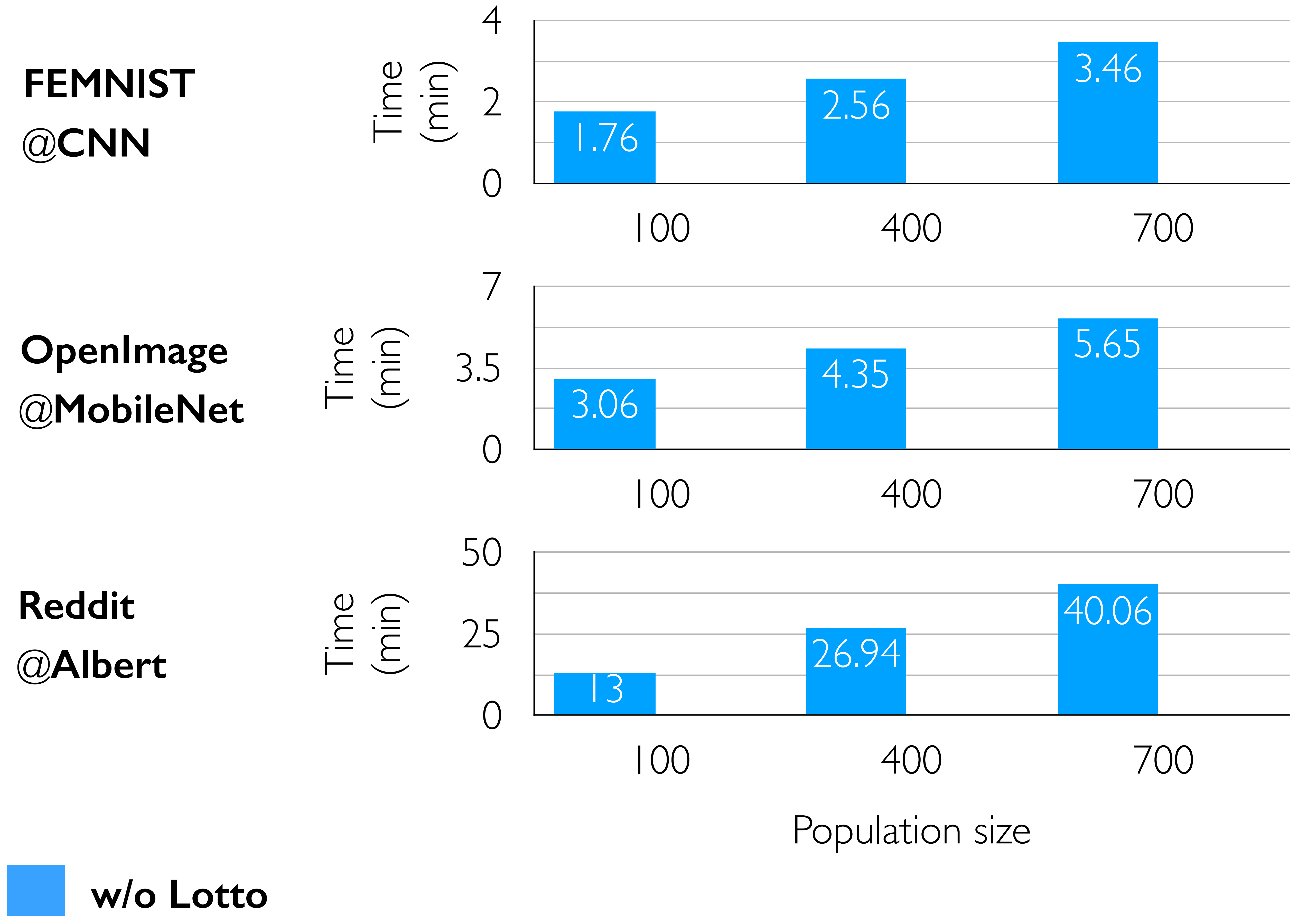
**Reddit**
**@Albert**






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

# Lotto induces no or mild overhead

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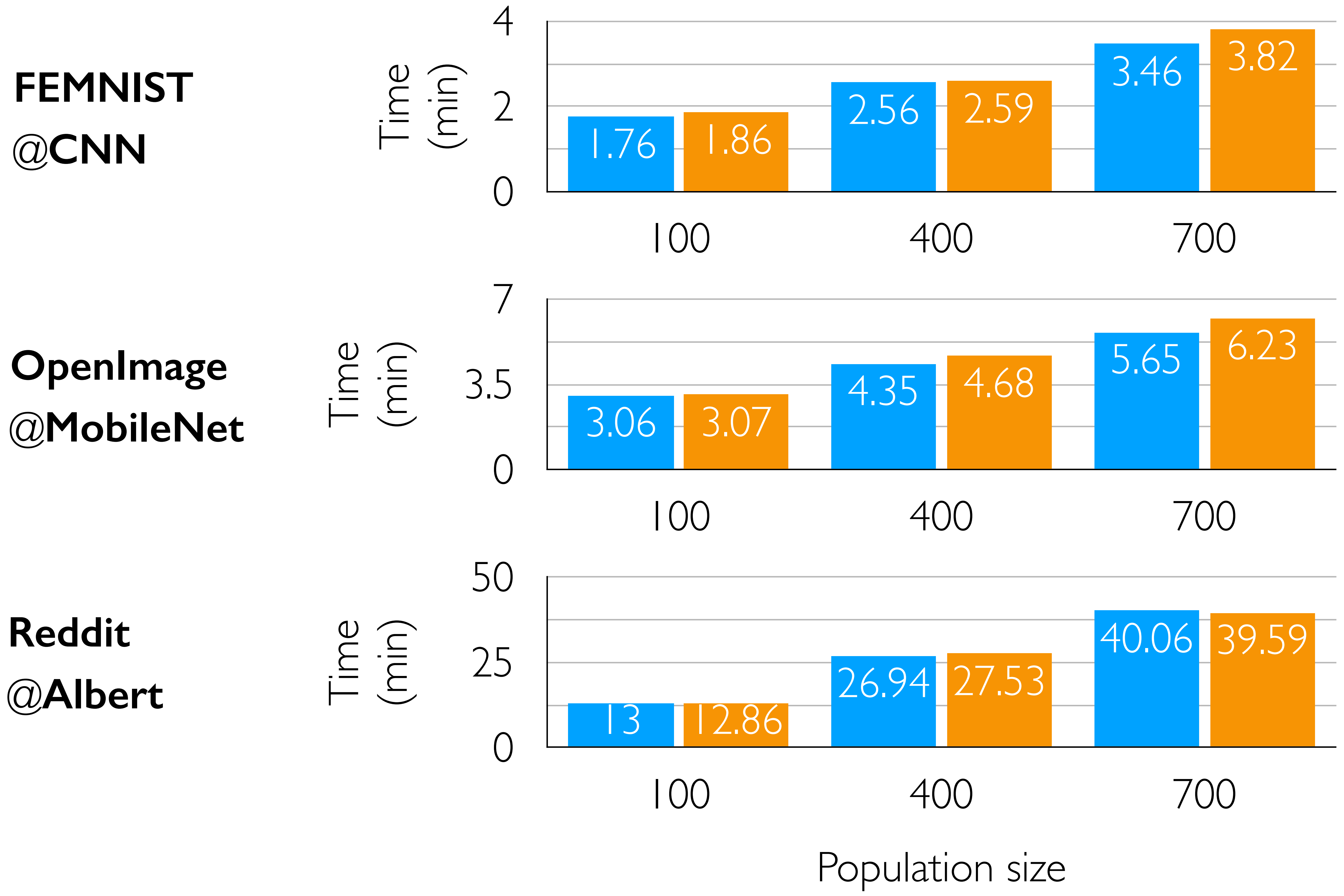
# Lotto induces no or mild overhead

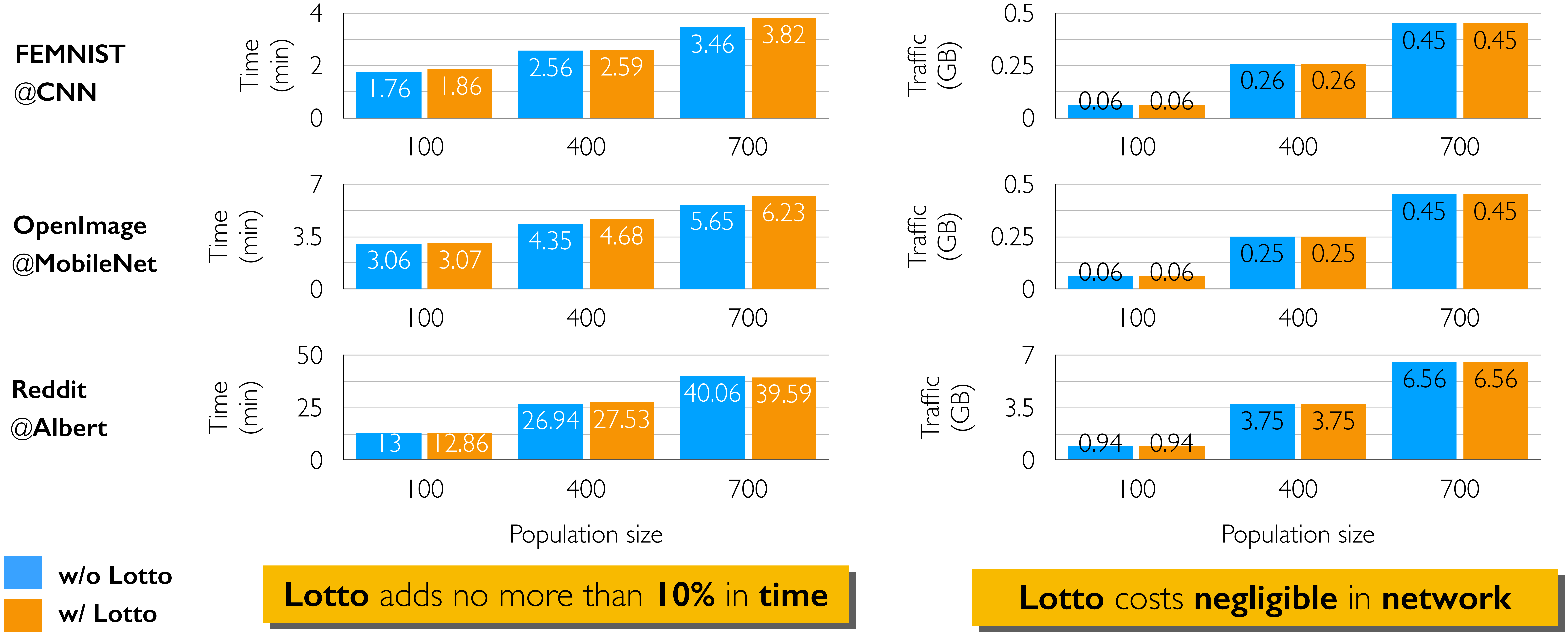



w/o Lotto
w/ Lotto

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

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

# Lotto induces no or mild overhead




**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

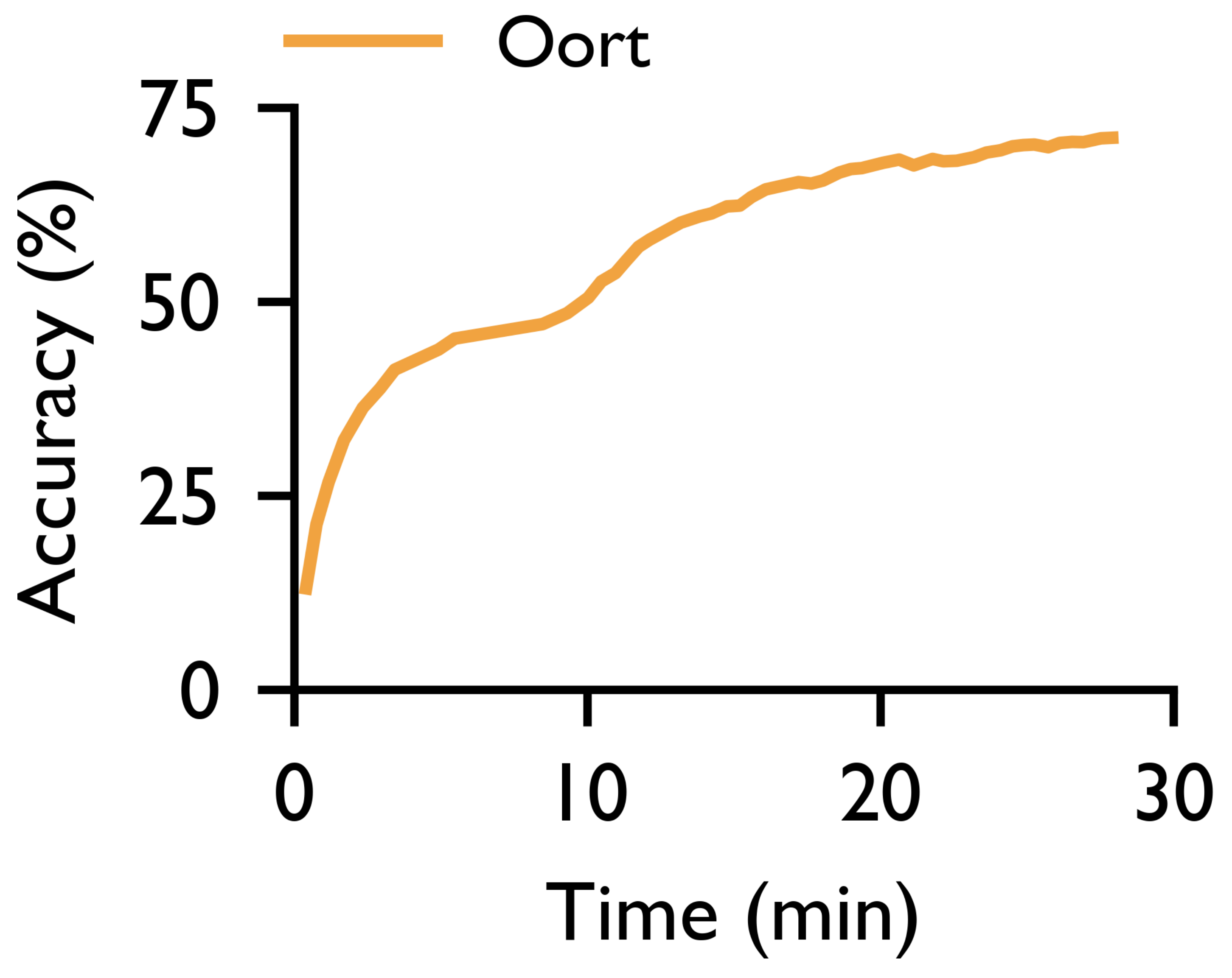
# Lotto functions as insecure selectors

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

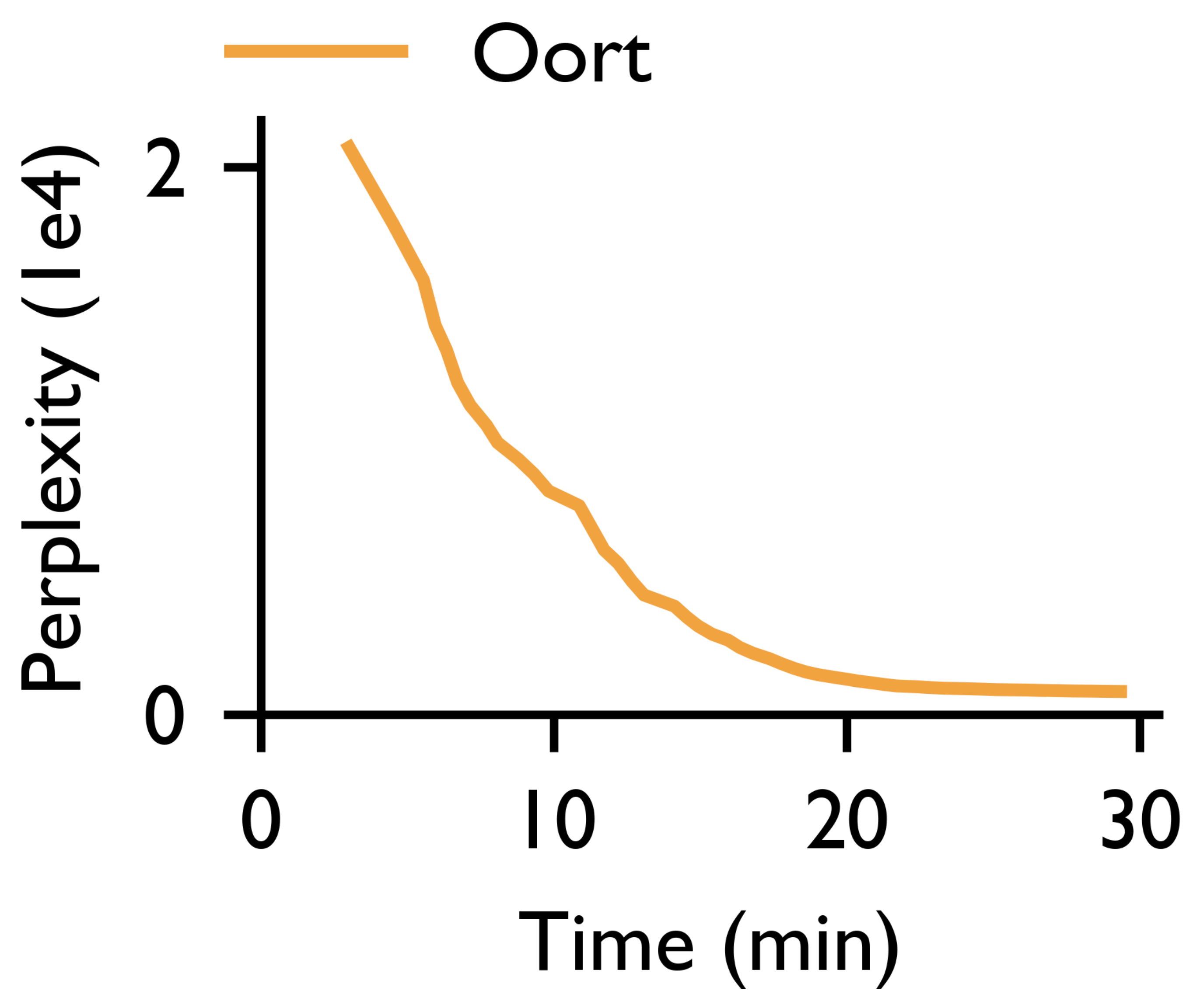
[1] Lai et al. "Oort: Efficient Federated Learning via Guided Participant Selection", In OSDI '21

# Lotto functions as insecure selectors

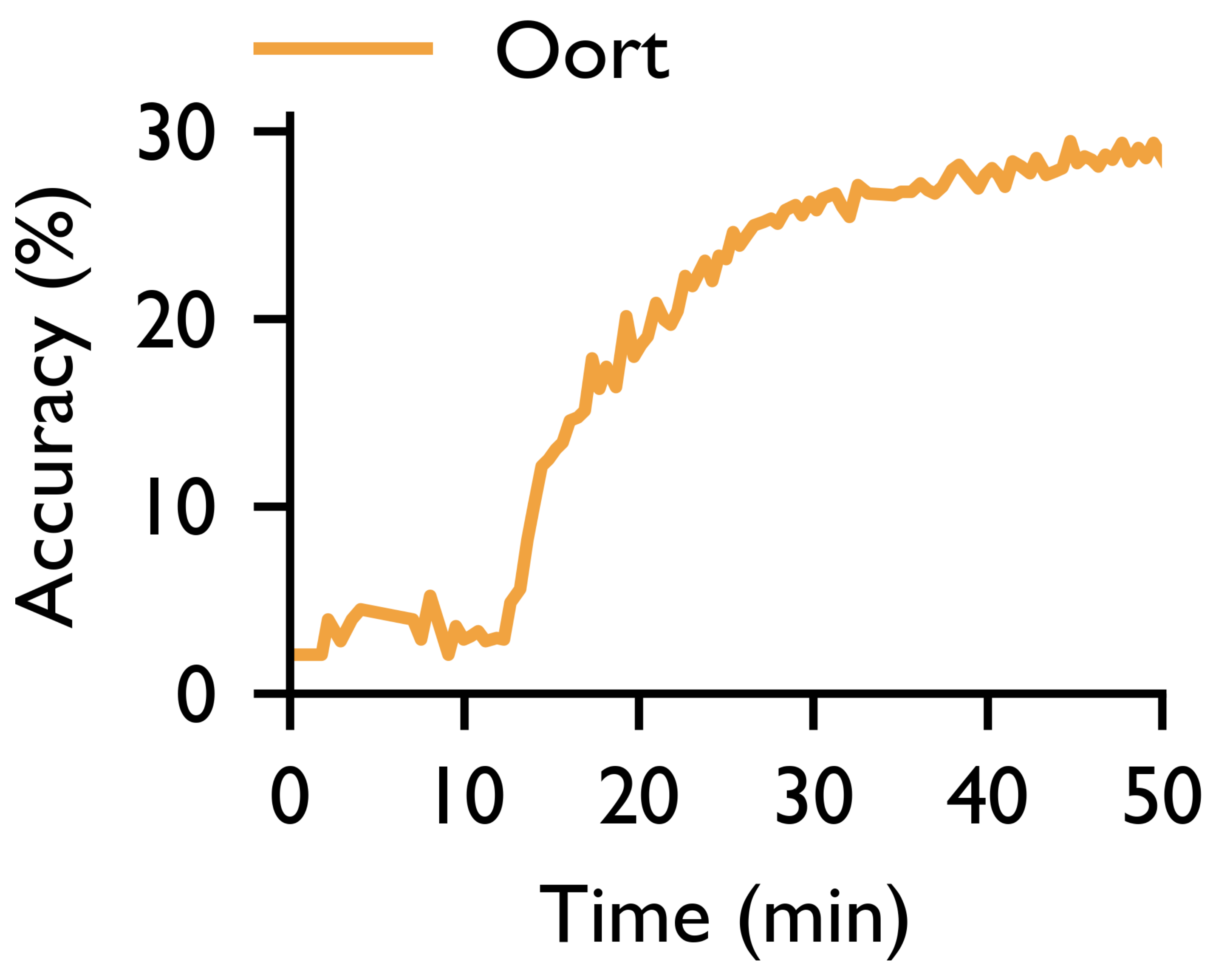
**Oort**[1] → State-of-the-art **informed** selector: optimized for **time-to-accuracy** of training




**FEMNIST@CNN**




**OpenImage@MobileNet**

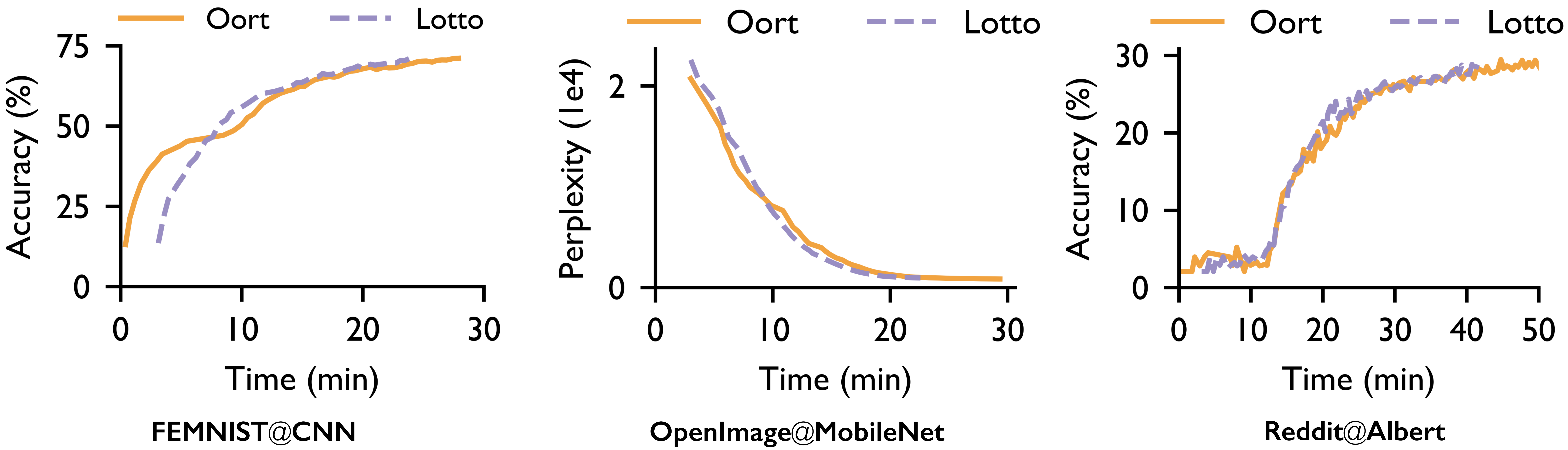



**Reddit@Albert**

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

# Lotto functions as insecure selectors

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




**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

# Summary: My efforts

**Privacy**
Worst-case defense…

**Lotto**

**Efficiency**
Time-to-accuracy…

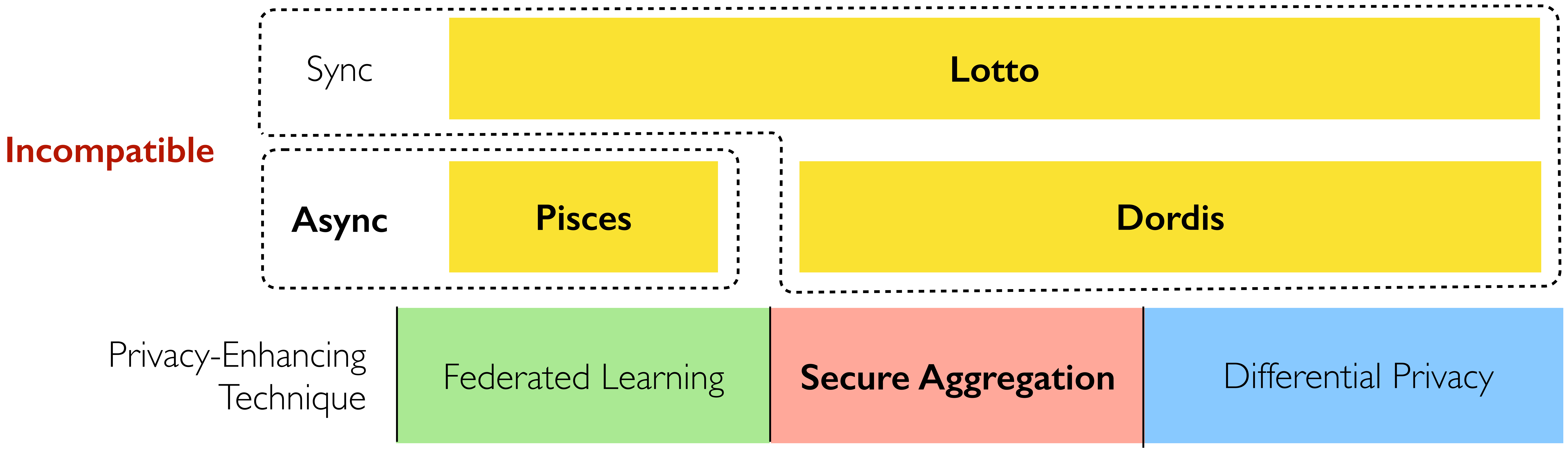
**Pisces**

**Dordis**

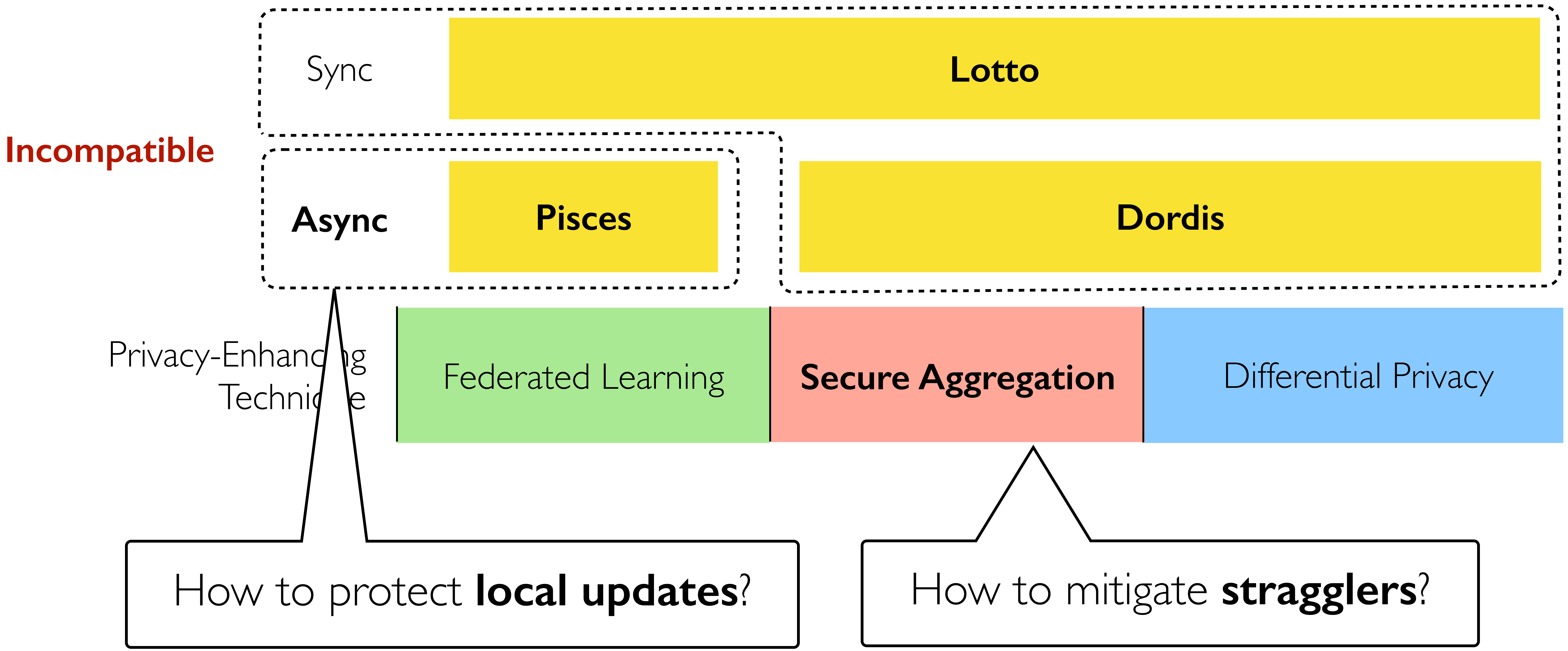
| | | | |
|---|---|---|---|
| **Privacy-Enhancing Technique** | Federated Learning | Secure Aggregation | Differential Privacy |
| **Privacy Guarantee** | Data kept on premises | Local updates unseen | Global update leaks little about any client |

# Future work

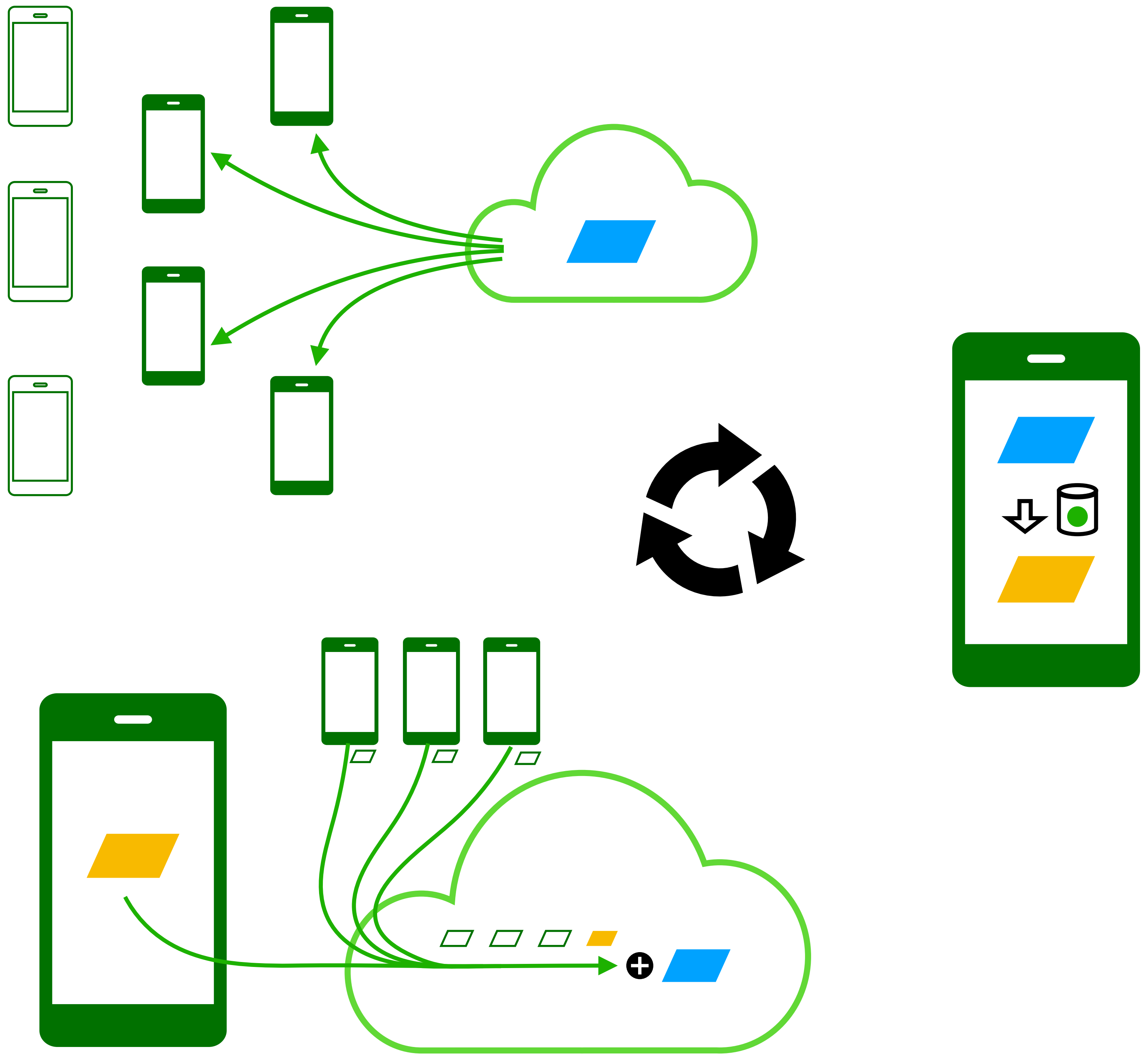
# 1. Better private learning on the edge



# 1. Better private learning on the edge

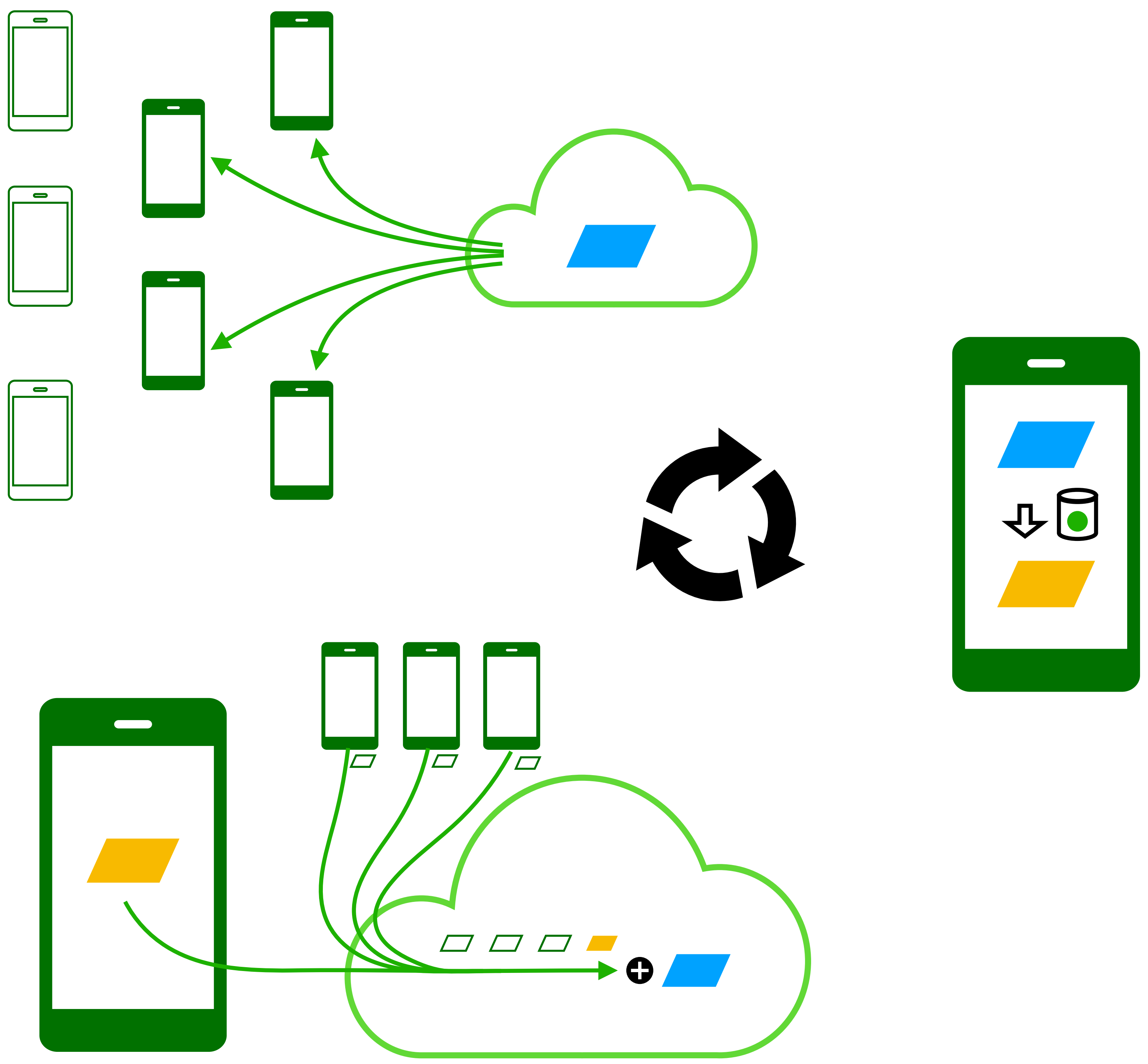


# 2. Private unlearning on the edge

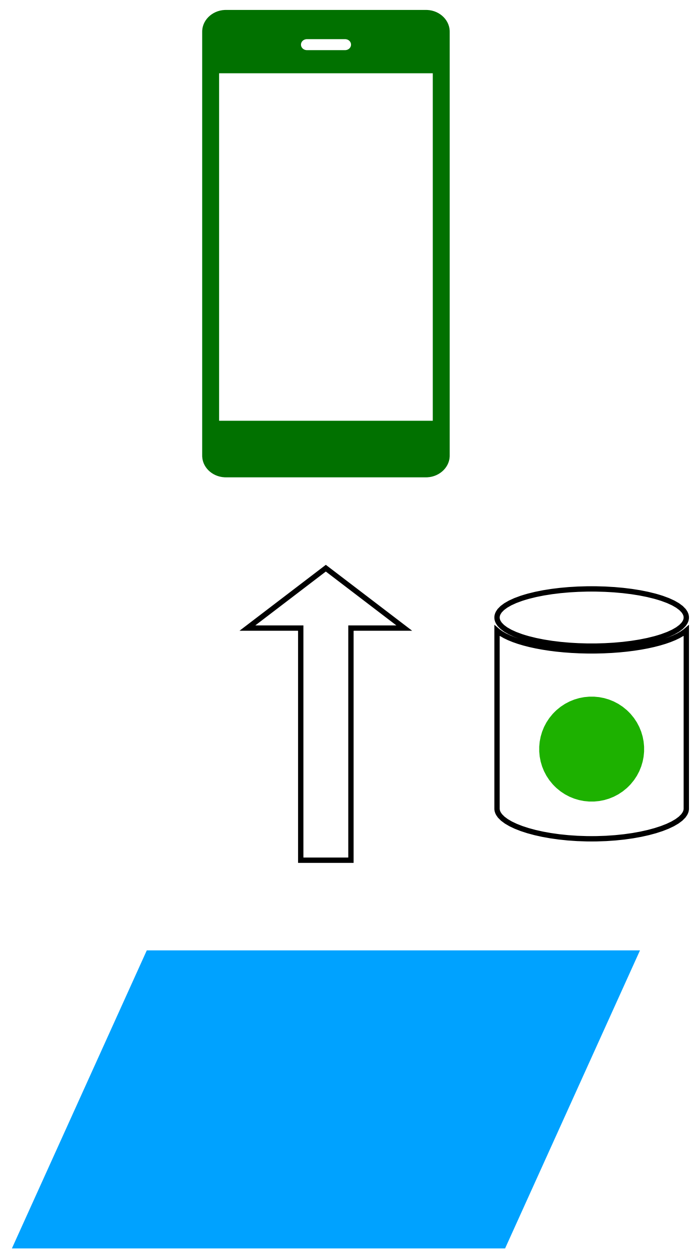


Learning

# 2. Private unlearning on the edge



Learning



**Unlearning**

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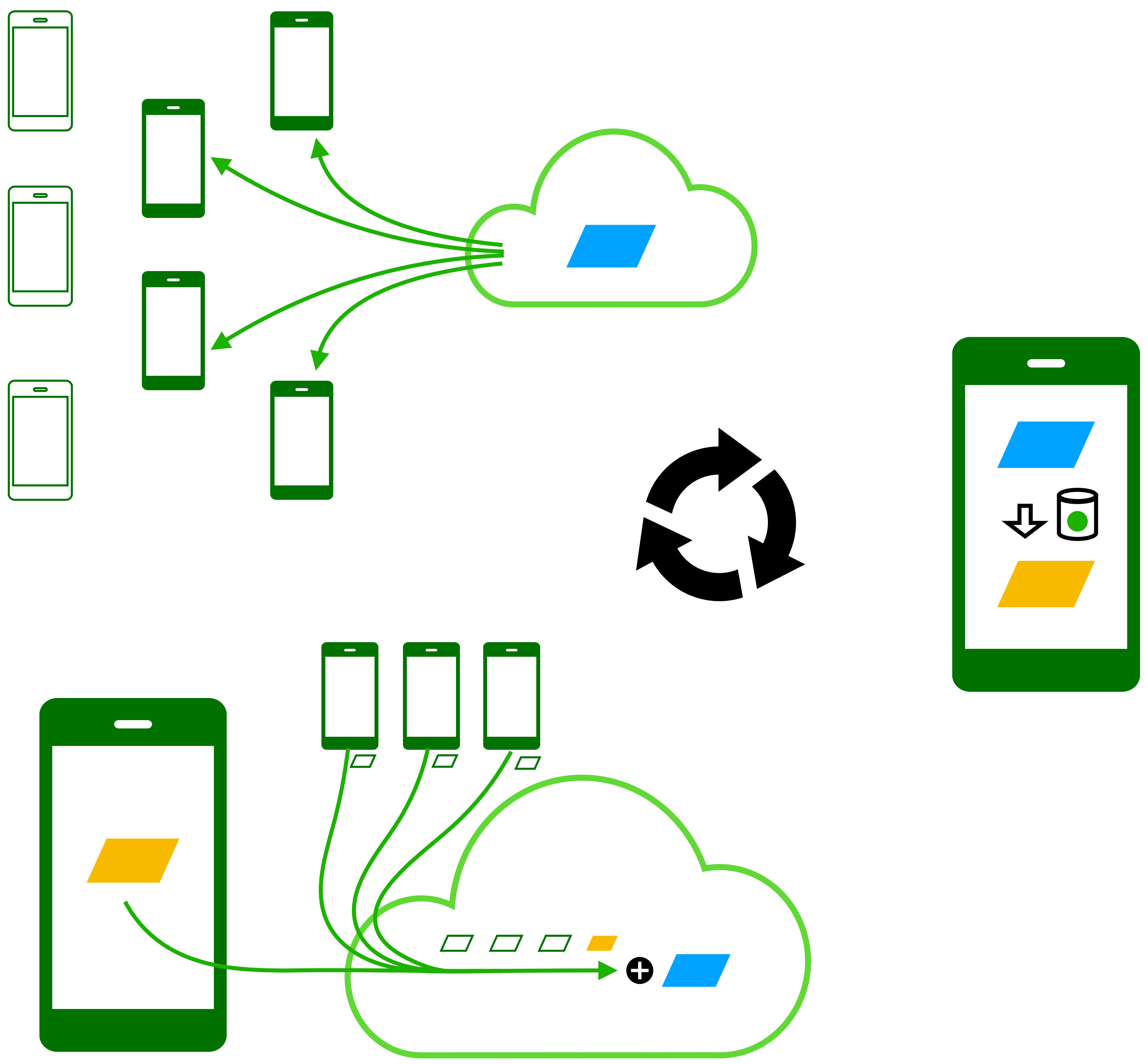
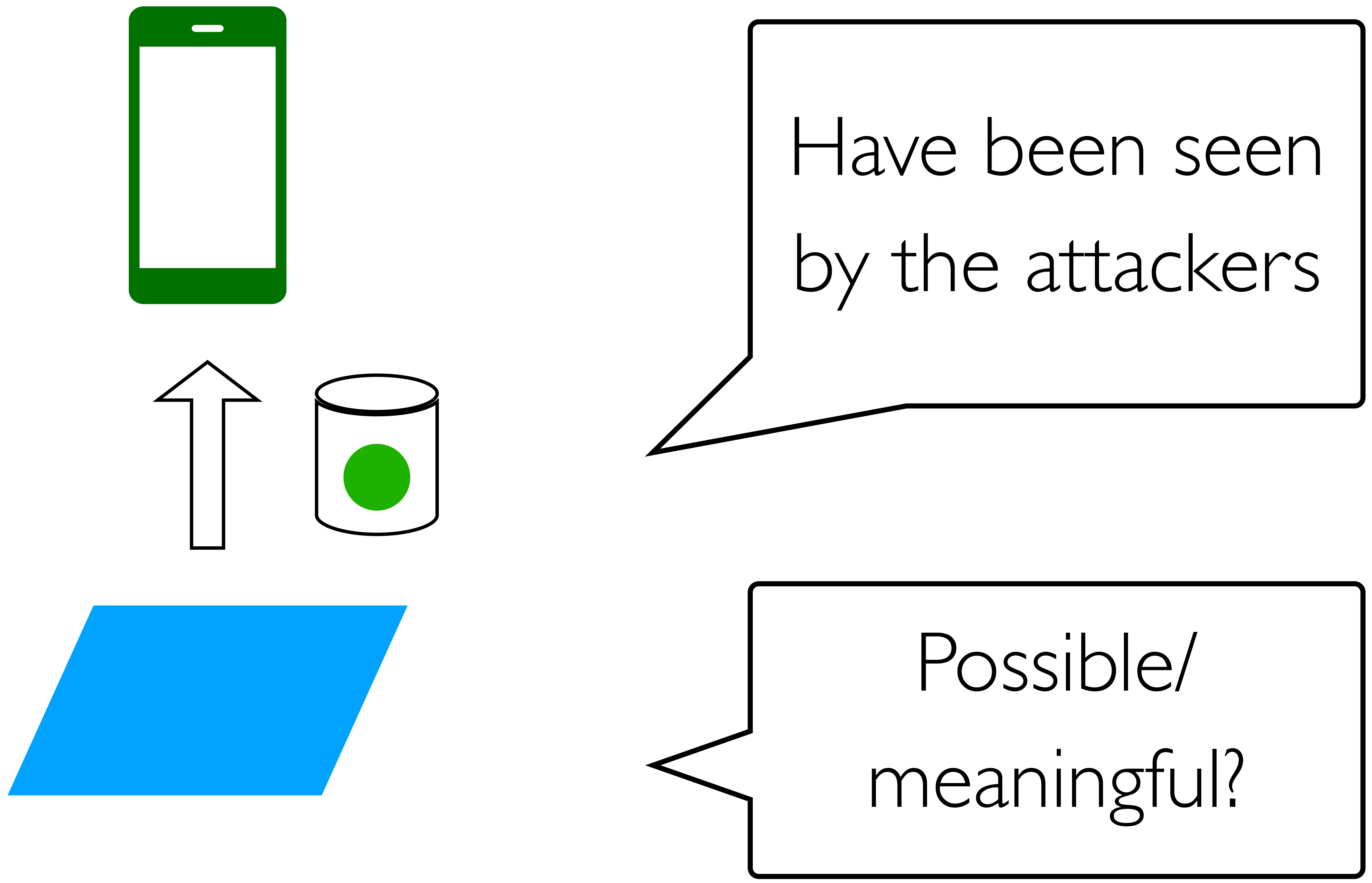
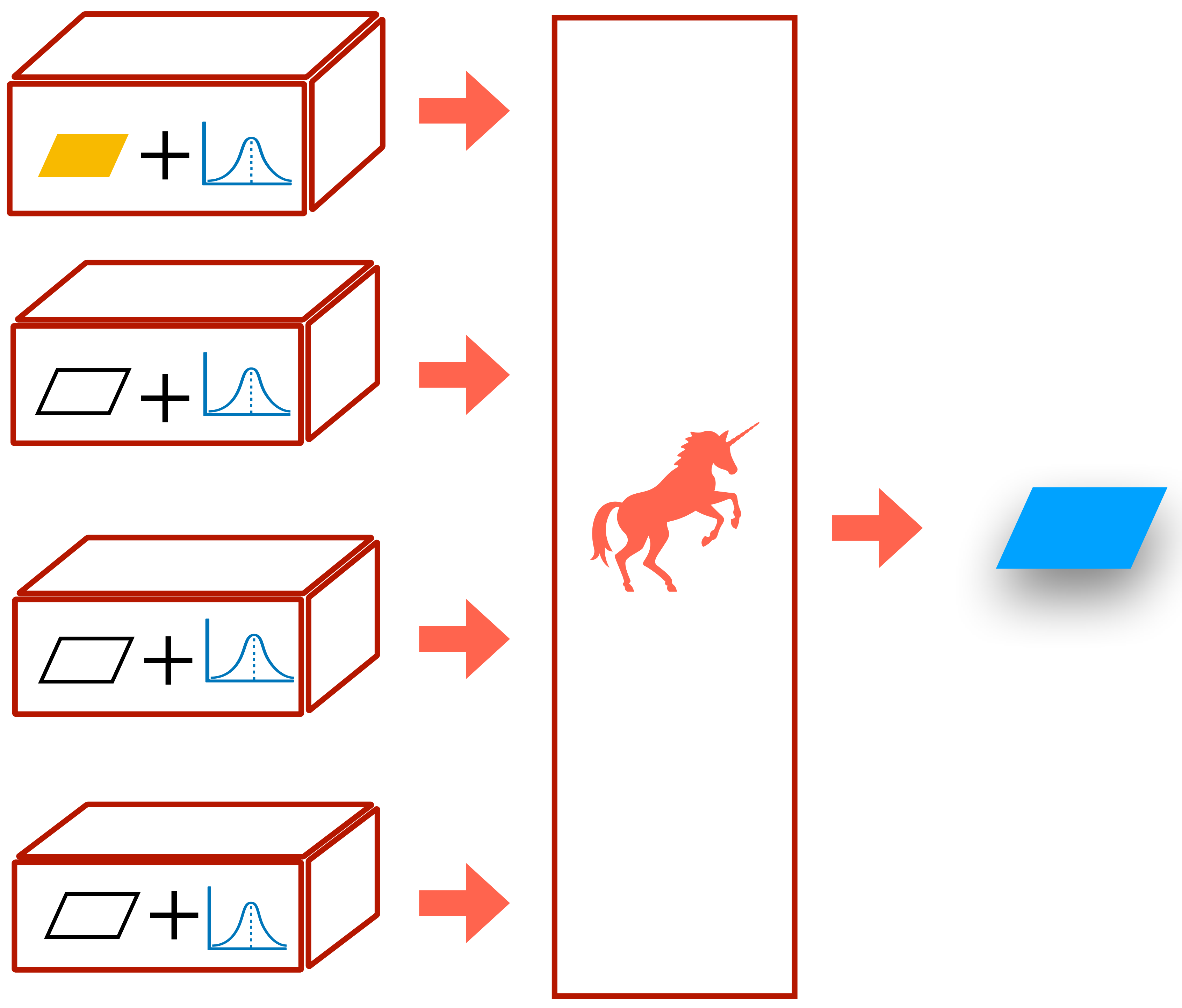


Learning



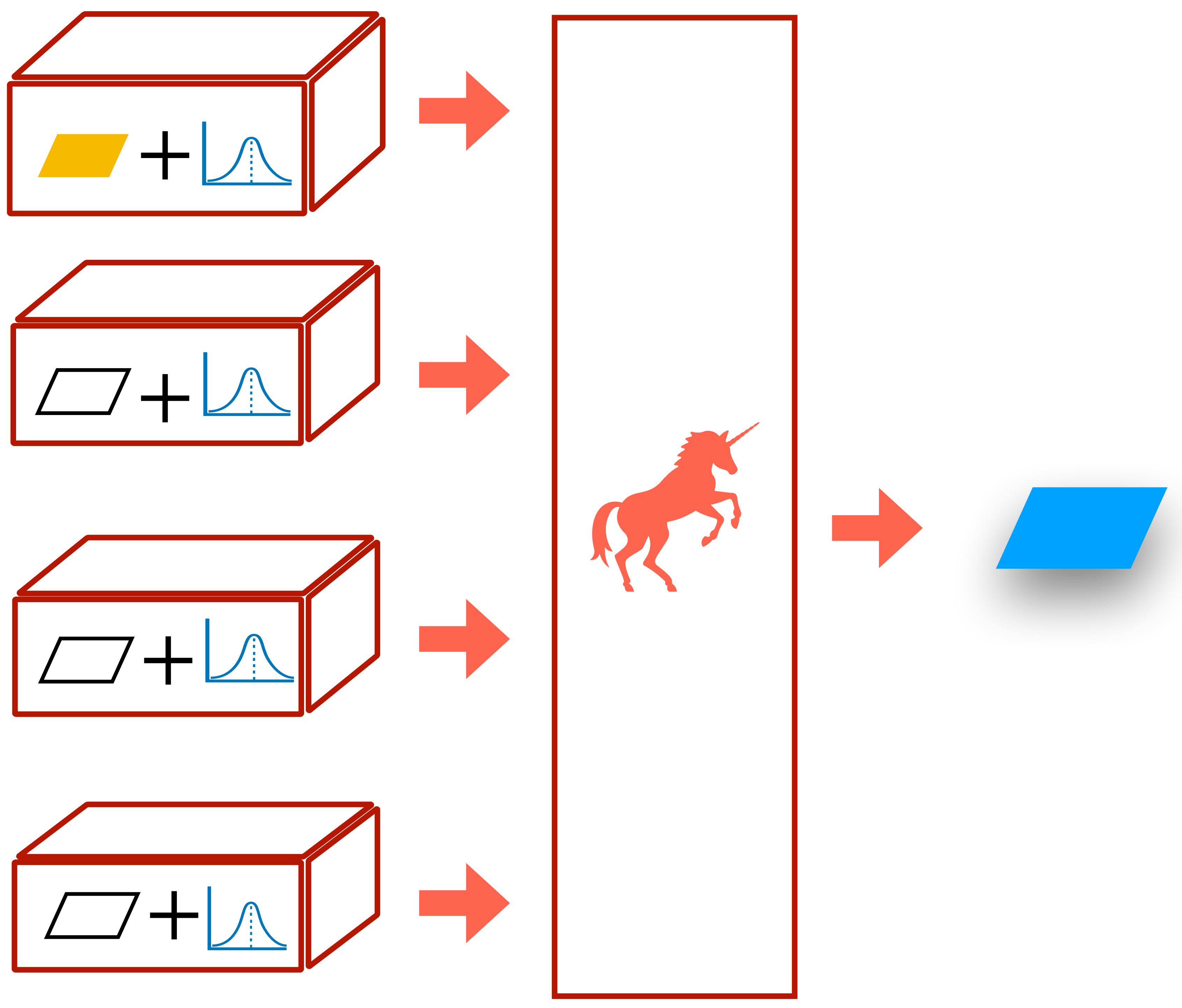

**Unlearning**

# 3. Security: Beyond privacy

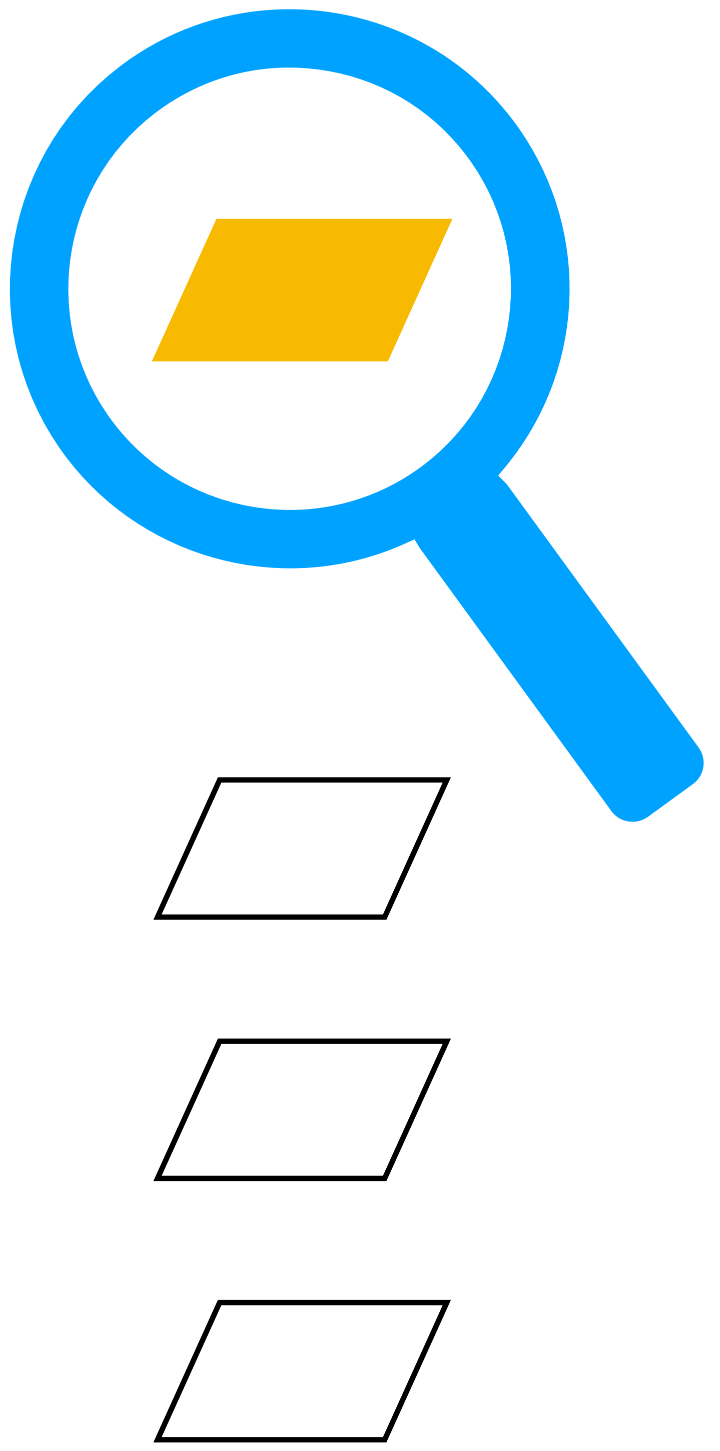


Data privacy

# 3. Security: Beyond privacy



Data privacy



Model security

# List of Publications

1. ☆ Lotto: Secure Participant Selection against Adversarial Servers in Federated Learning. **[Security 2024]**
   - Zhifeng Jiang, Peng Ye, Shiqi He, Wei Wang, Ruichuan Chen, Bo Li
2. ☆ Dordis: Efficient Federated Learning with Dropout-Resilient Differential Privacy. **[EuroSys 2024]**
   - Zhifeng Jiang, Wei Wang, Ruichuan Chen
3. ☆ Pisces: Efficient Federated Learning via Guided Asynchronous Training. **[SoCC 2022]**
   - Zhifeng Jiang, Wei Wang, Baochun Li, Bo Li
4. Towards Efficient Synchronous Federated Training: A Survey on System Optimization Strategies. **[IEEE Trans. Big Data 2022]**
   - Zhifeng Jiang, Wei Wang, Bo Li, Qiang Yang

The publications **covered by this thesis** is marked with ☆

5. Gillis: Serving Large Neural Networks in Serverless Functions with Automatic Model Partitioning. **[ICDCS 2021]**
   - Minchen Yu, Zhifeng Jiang, Hok Chun Ng, Wei Wang, Ruichuan Chen, Bo Li
6. Feature Reconstruction Attacks and Countermeasures of DNN Training in Vertical Federated Learning. **[IEEE TDSC 2024, Pending Major Revision]**
   - Peng Ye, Zhifeng Jiang, Wei Wang, Bo Li, Baochun Li
7. FedCA: Efficient Federated Learning with Client Autonomy. **[In Submission]**
   - Na Lv, Zhi Shen, Chen Chen, Zhifeng Jiang, Jiayi Zhang, Quan Chen, Minyi Guo
8. FLASHE: Additively Symmetric Homomorphic Encryption for Cross-Silo Federated Learning. **[arXiv 2021]**
   - Zhifeng Jiang, Wei Wang, Yang Liu