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DIPARTIMENTO DI INFORMATICA

FEDERATED LEARNING
An Overview

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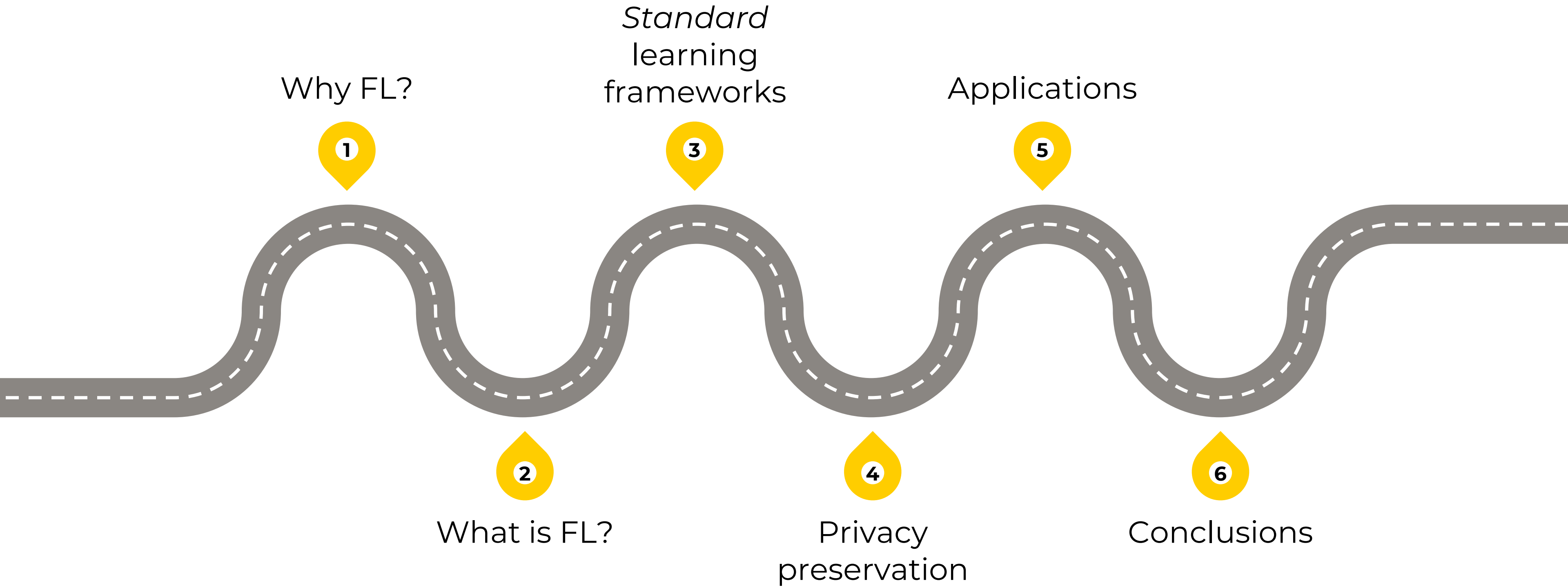
Roadmap

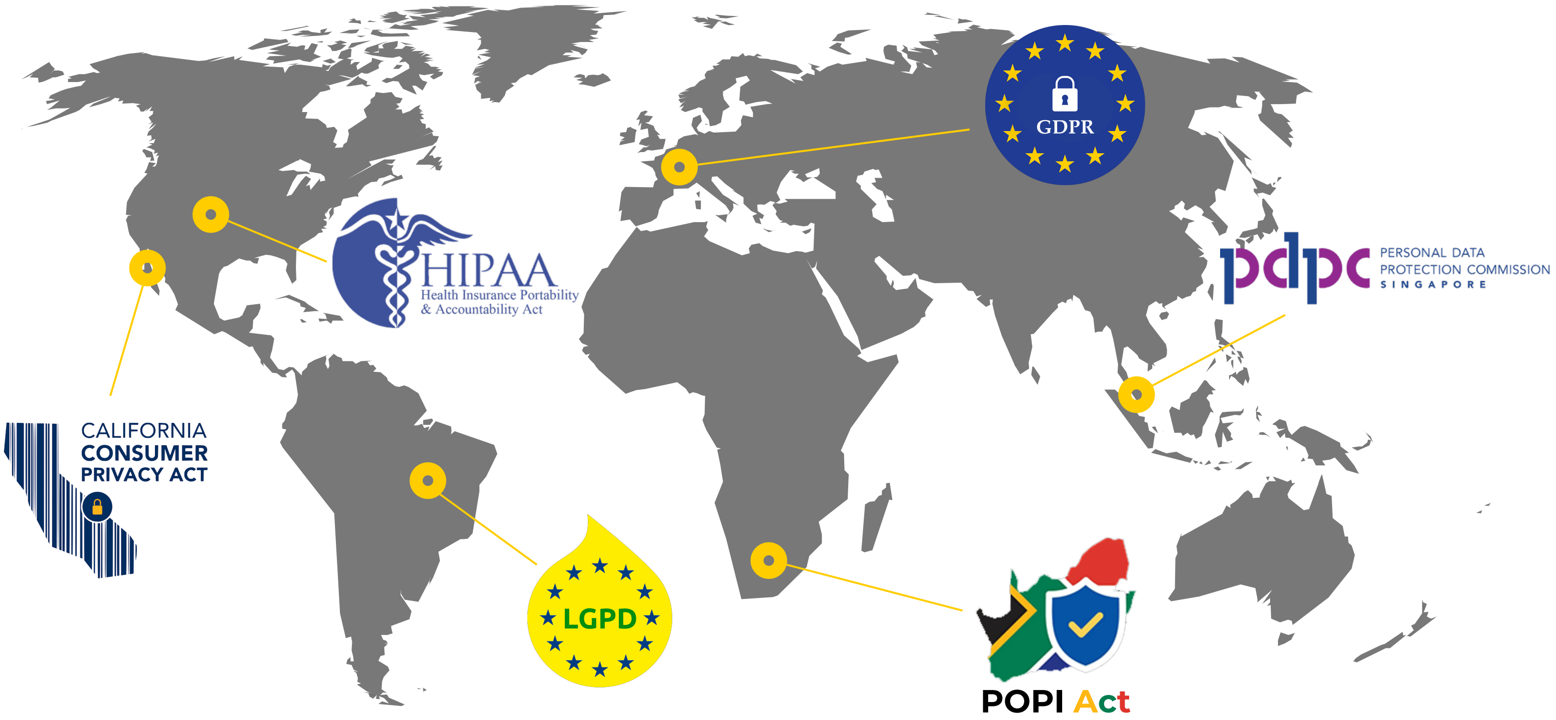

1 Why FL?
2 What is FL?
3 *Standard* learning frameworks
4 Privacy preservation
5 Applications
6 Conclusions

1

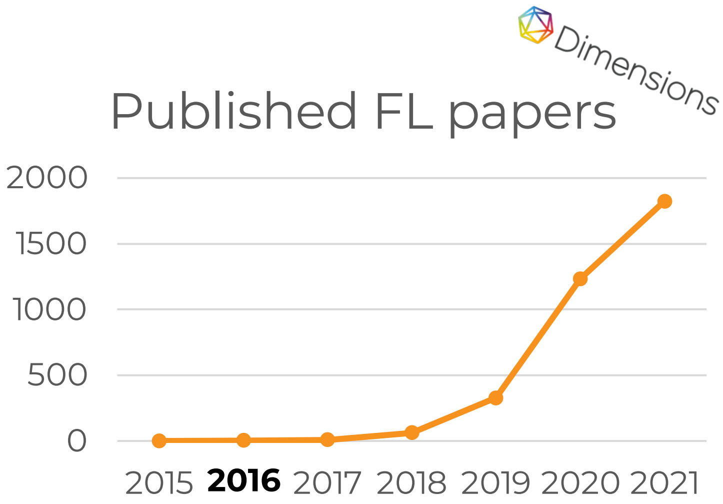
Why FL?

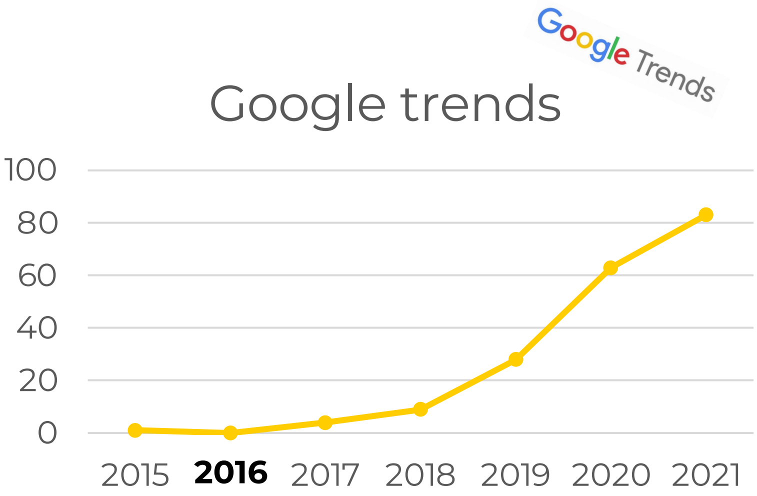
The main reasons behind this new learning paradigm

Data protection regulations



FL is on fire!





Google publishes the seminal work on FL

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What is FL?

Definition and overview of the FL taxonomy

Informal definition

Federated Learning *is a machine learning setting where multiple entities (clients) collaborate in solving a machine learning problem, under the coordination of a central server. Each client's raw data is stored locally and not exchanged or transferred; instead, focused updates intended for immediate aggregation are used to achieve the learning objective.*

“Formal” definition

	Parties	Data	Learning	Performance
Centralized	Server	$\mathcal{D}$	On the server	P
Non-federated	Clients	$\mathcal{D} \equiv \cup_{i=1}^{N} \mathcal{D}_i$	On clients	$P_i \leq P$
Federated	Clients Server	$\mathcal{D} \equiv \cup_{i=1}^{N} \mathcal{D}_i$	Collaborative	$\hat{P}$

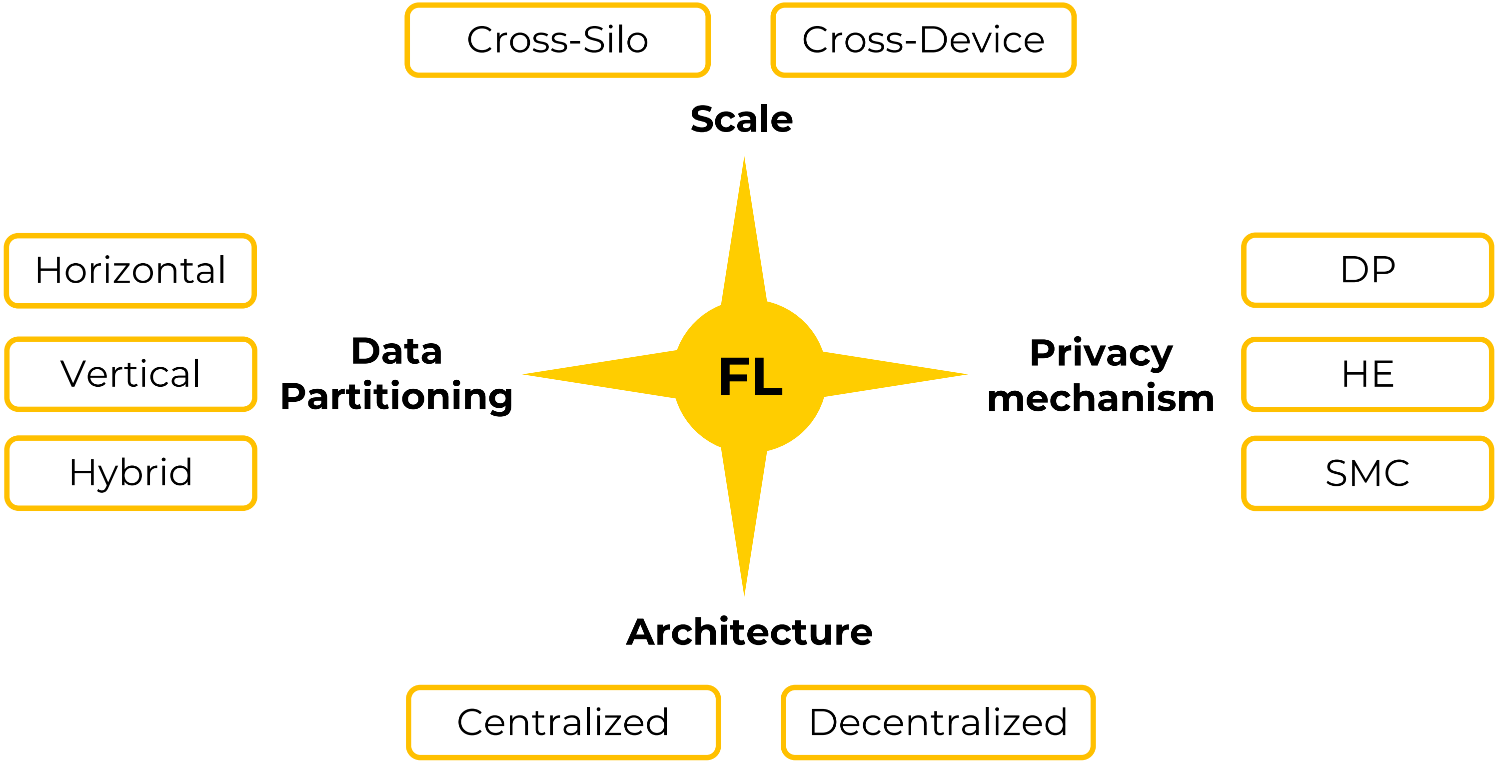
Goals

Clients do not share their data

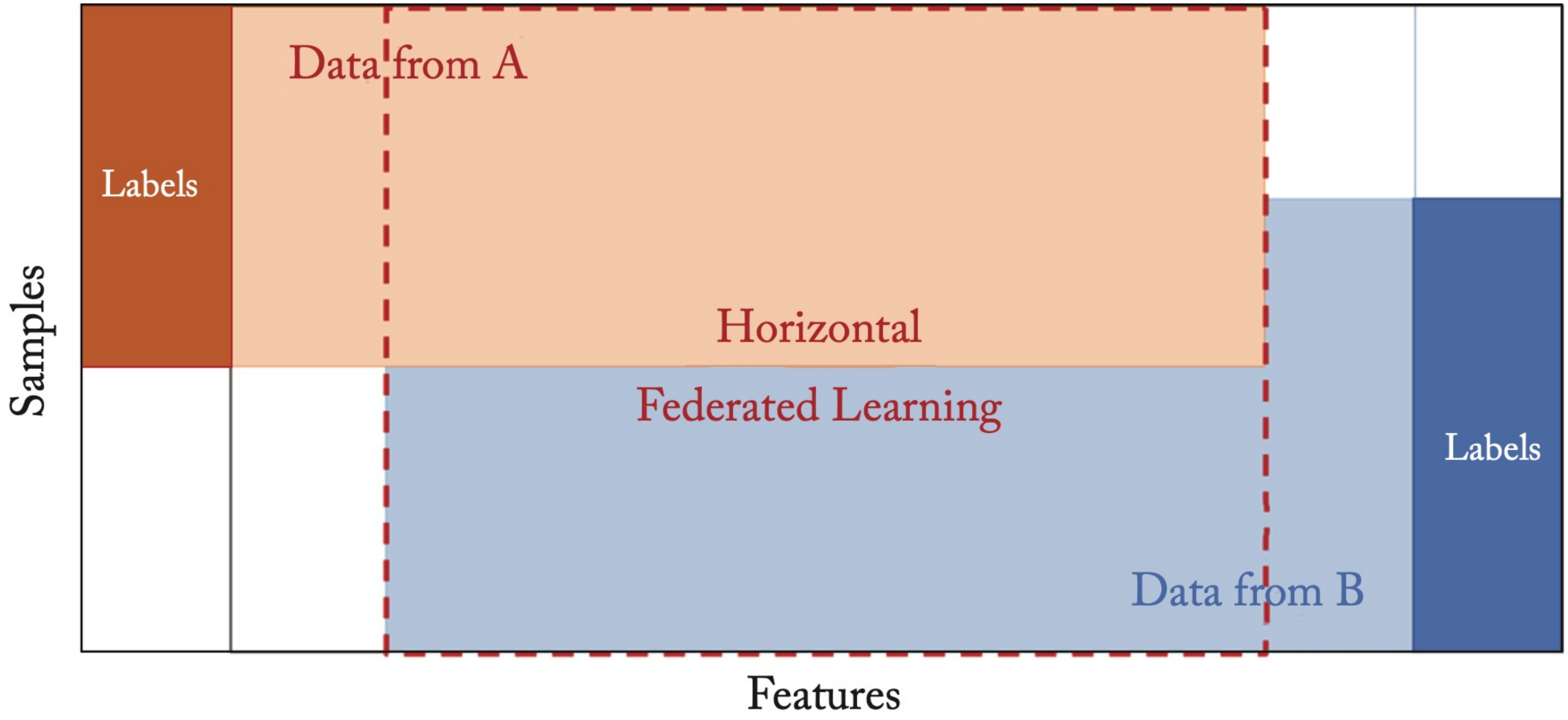
Clients benefit from the federation $\quad P_i \leq \hat{P}$

The federated model is close to the “ideal” one $\quad P - \hat{P} \leq \delta \quad \delta \to 0$

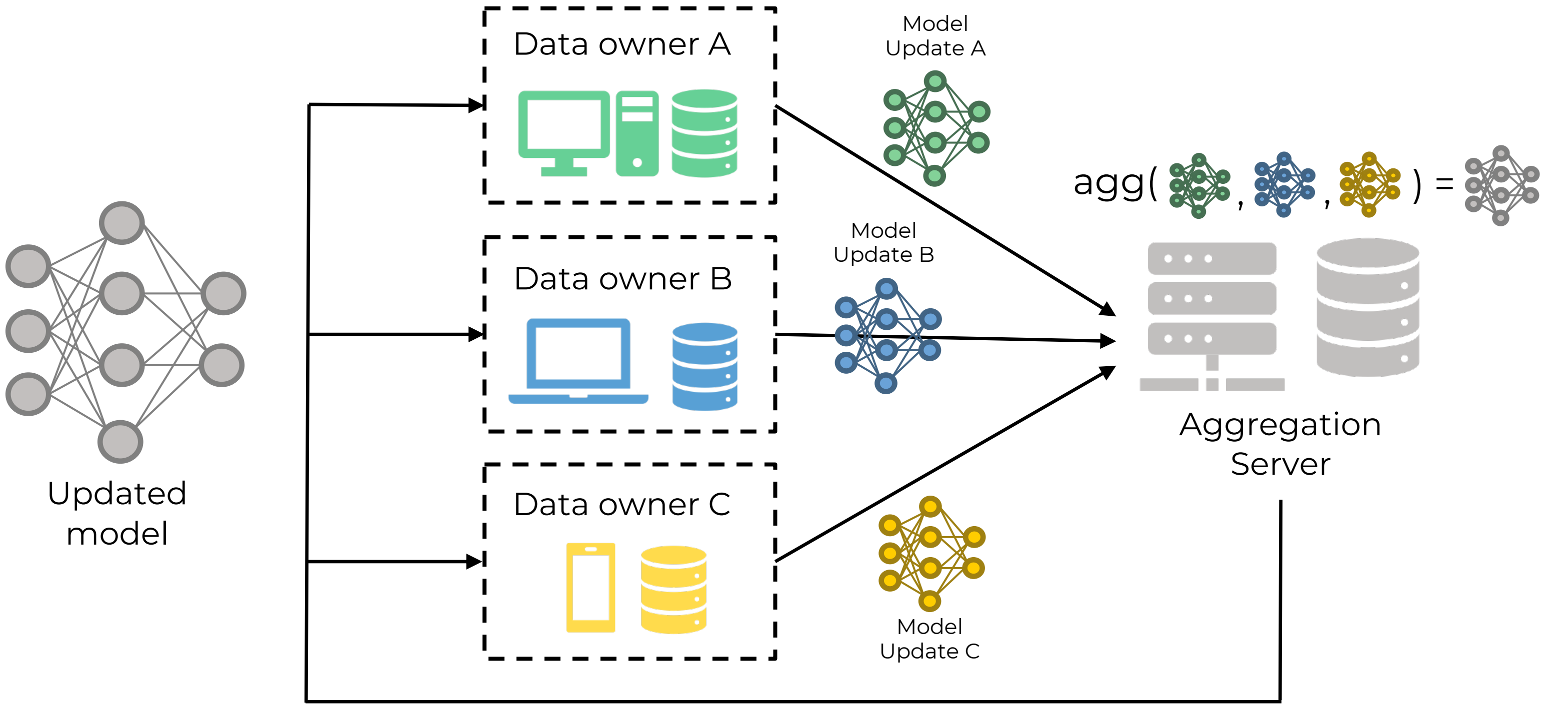
FL settings landscape



Horizontal FL



Standard HFL architecture

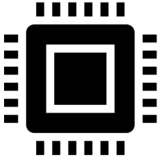


(Cross-device) FL characteristics

Large scale: thousands of devices

Unreliable connections

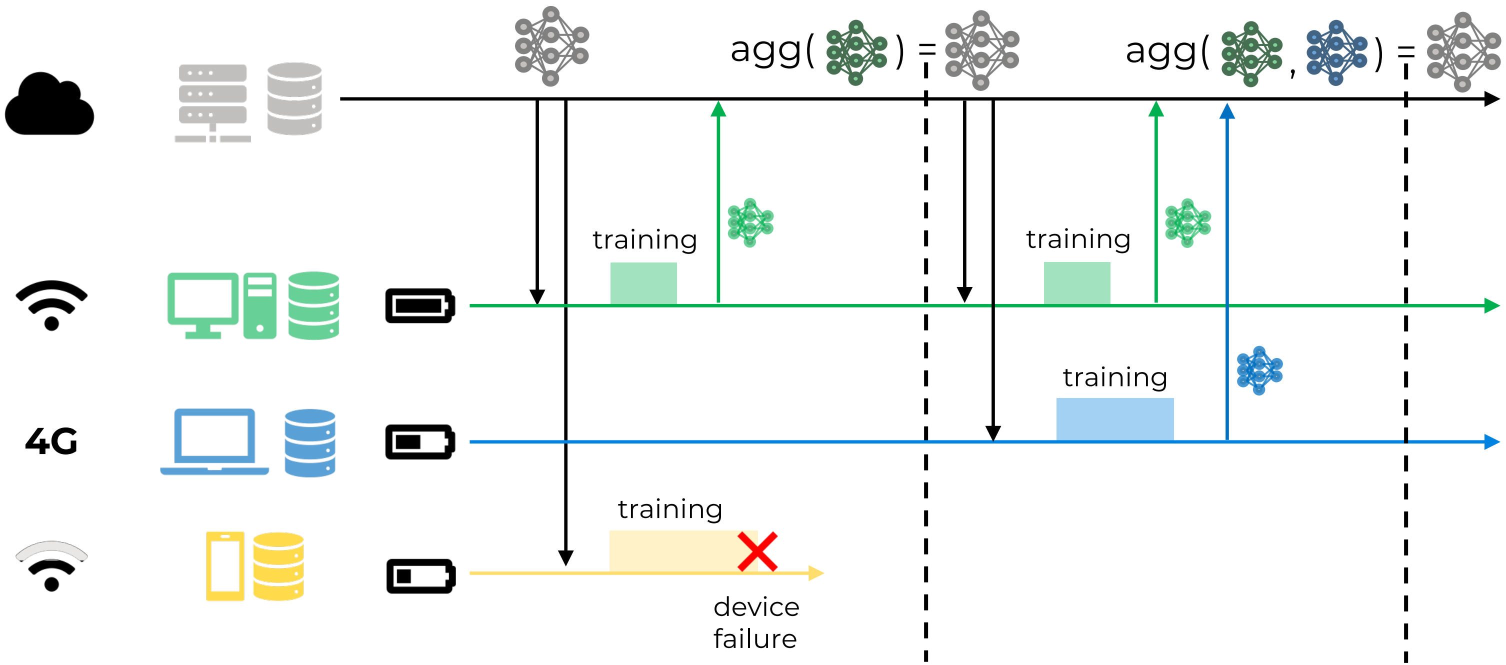
Limited computational capacity



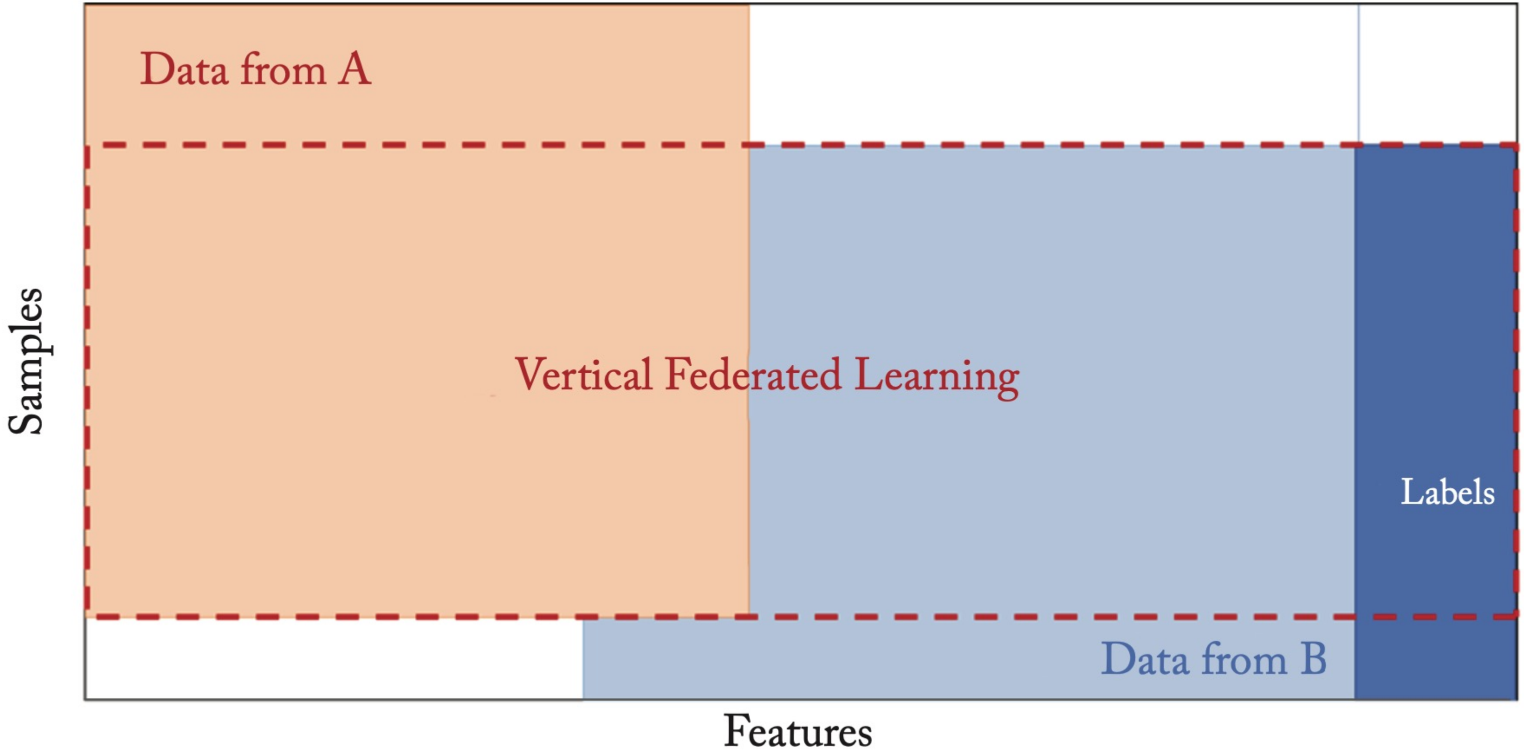
Power consumption

System heterogenity

System heterogenity

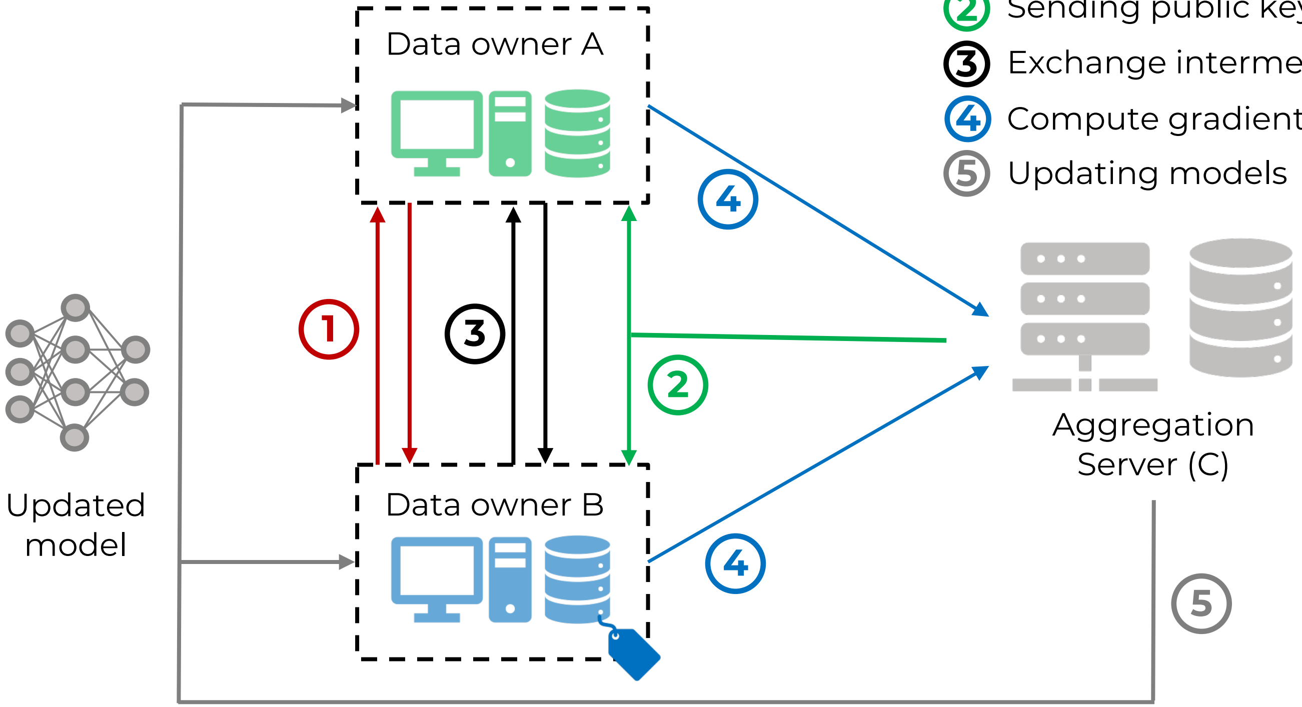


Vertical FL

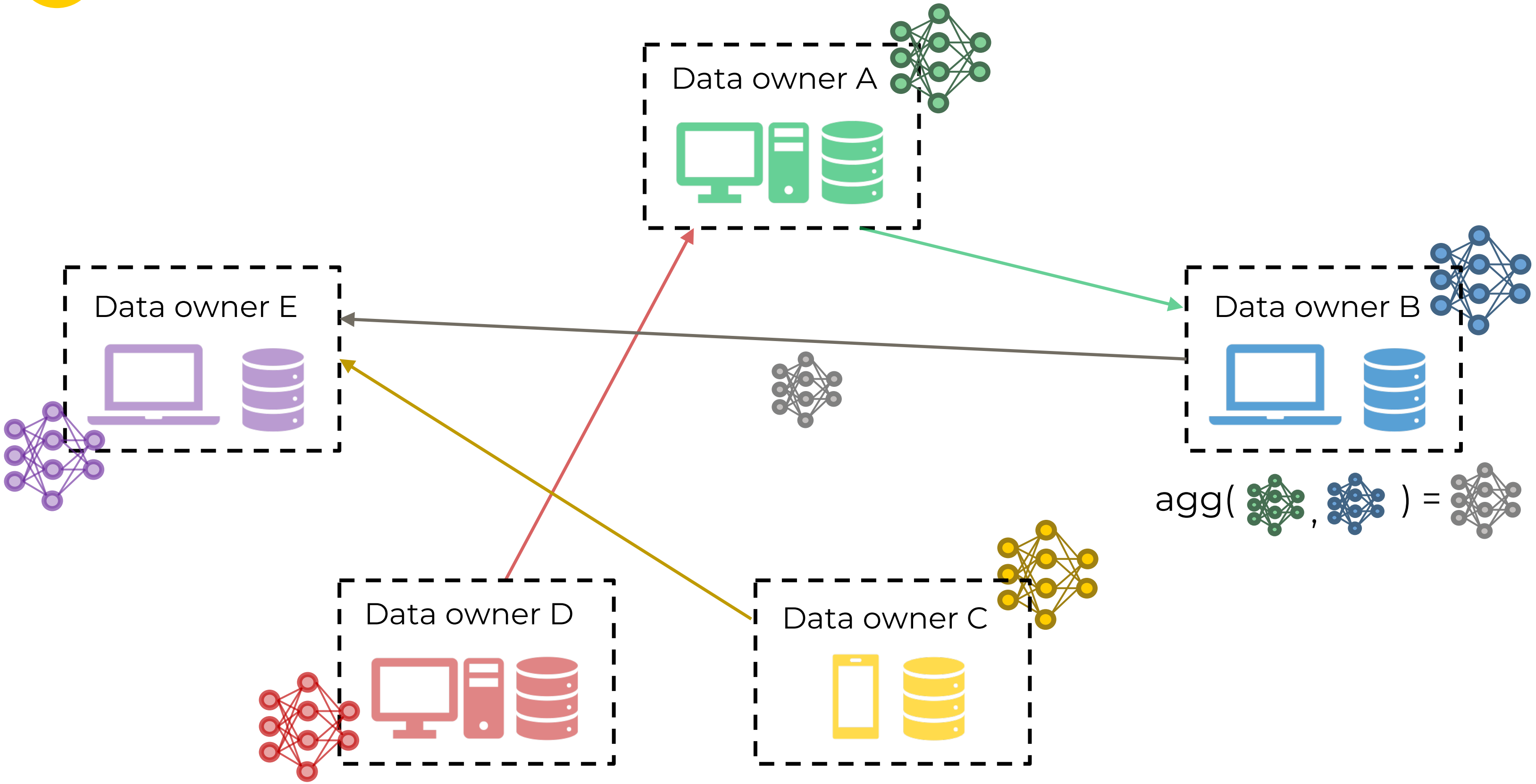

Data from A
Vertical Federated Learning
Labels
Data from B
Samples
Features

VFL Architecture

1. Encrypted entity alignment
2. Sending public keys
3. Exchange intermediate results
4. Compute gradient & loss
5. Updating models



Decentralized FL



Centralized vs Decentralized

	Centralized	Decentralized
Orchestration	Server	No centralized orchestration*
Topology	Hub-and-spoke	Peer-to-peer
Global model	Single	Many
Setup	Centralized	Consensus*

* A central authority might be needed!

Cross-Silo FL

Limited number of collaborators

Big local datasets

Reliable connection/ participation

- **Few organizations** share incentives to train a model without sharing their data
- Or, same organization cannot centralized its data (e.g., legal constraints)

Cross-Silo: incentives

Free-rider problem

Organizations/compatitors may benefit from the federation without contributing as much

Monetary payout

Assign FL model with performance commensurate with the contributions (game theory)

Cross-Silo vs Cross-Device

	Cross-Silo	Cross-Device
Availability	~Always	Small fraction available
Scale	2-100 clients	Up to 10^{10} clients
Addressability	Direct	No client identifier
Reliability	Few failures	Highly unreliable
Dataset size	Big	Relatively small

Challenges

Hyper parameters tuning

Avoid overfitting

Model debugging

Malicious participants

Non-iidness

System heterogenity

Non-identical client distributions

$$P_i(x, y) = P_i(y|x)P_i(x) = P_i(x|y)P_i(y)$$

Covariate shift

$$P_i(y|x) = P_j(y|x)$$
$$P_i(x) \neq P_j(x)$$

Prior shift

$$P_i(x|y) = P_j(x|y)$$
$$P_i(y) \neq P_j(y)$$

Concept drift

$$P_i(y) = P_j(y)$$
$$P_i(x|y) \neq P_j(x|y)$$

Concept shift

$$P_i(y|x) \neq P_j(y|x)$$
$$P_i(x) = P_j(x)$$

Quantity skew

Clients hold hugely different amounts of data

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Standard Learning Frameworks

Learning in a federation

General Learning Scheme

1. Setup task – Model initialization

2. For each federated round:
    a. Broadcast the current global model

    b. In parallel:
        clients update and send back the local models

    c. Update global model with the users' ones

FedAvg (model averaging)

Aggregation Server

Algorithm: **FedAvg**

initialize model $\overline{w}_0$
for each round t=1,…:
  Broadcast $\overline{w}_{t-1}$
  select C eligible participants
  foreach|| participant p:
    $w_t^p \leftarrow$ LocalUpdate(p)
  $\overline{w}_t \leftarrow$ aggregate($\forall p\ w_t^p$)

Does not guarantee converge

Collaborator/Client

Algorithm: **LocalUpdate**

$w \leftarrow$ global model from Server
for each epoch $s \in 1, \dots, S$:
  for each batch b:
    $g_b \leftarrow$ compute gradient for b
    $w \leftarrow w - \eta g_b$
send w to the Server

Practically works most of the time

Efficient (communication-wise)

Not bound to SGD

FedSgd (gradient averaging)

Aggregation Server

Algorithm: **FedSgd**

initialize model $\overline{w}_0$
for each round t=1,…:
  Broadcast $\overline{w}_{t-1}$
  select C eligible participants
  foreach|| participant p:
    $g_t^p \leftarrow$ LocalUpdate(p)
  $g_t \leftarrow$ aggregate($\forall p\ g_t^p$)
  $\overline{w}_t \leftarrow \overline{w}_{t-1} - \eta g_t$

Inefficient (communication-wise)

Collaborator/Client

Algorithm: **LocalUpdate**

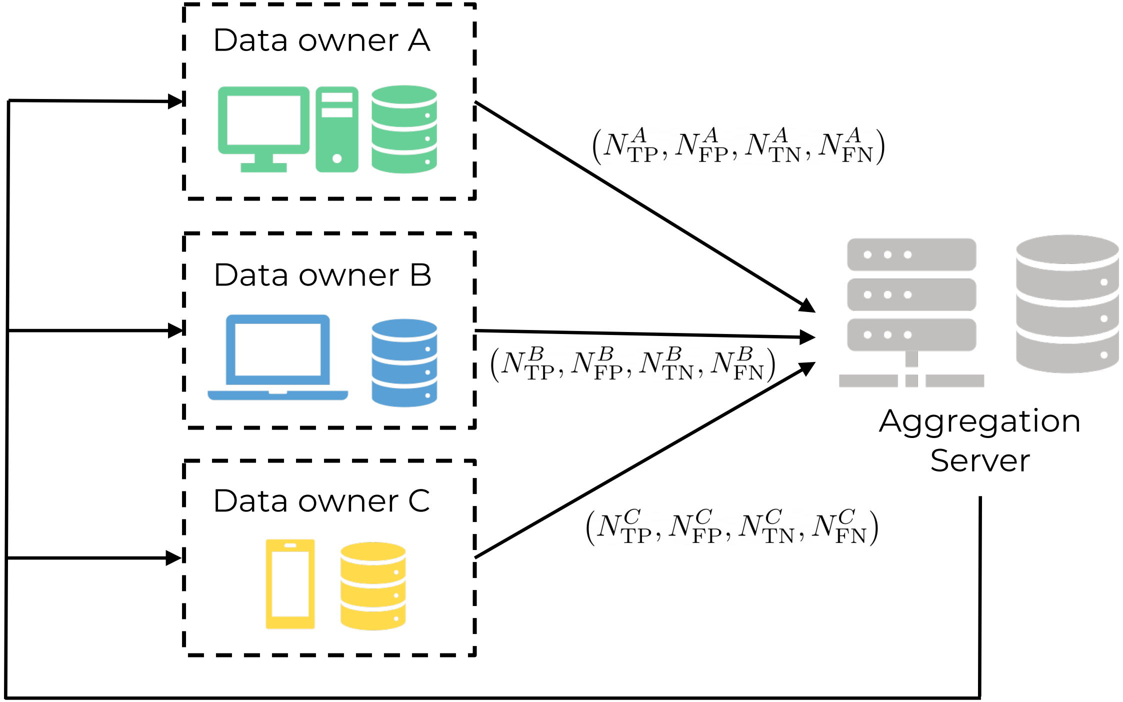
$w \leftarrow$ global model from Server
select batch b
$g_b \leftarrow$ compute gradient for b
send g_b to the Server

Guaranteed convergence

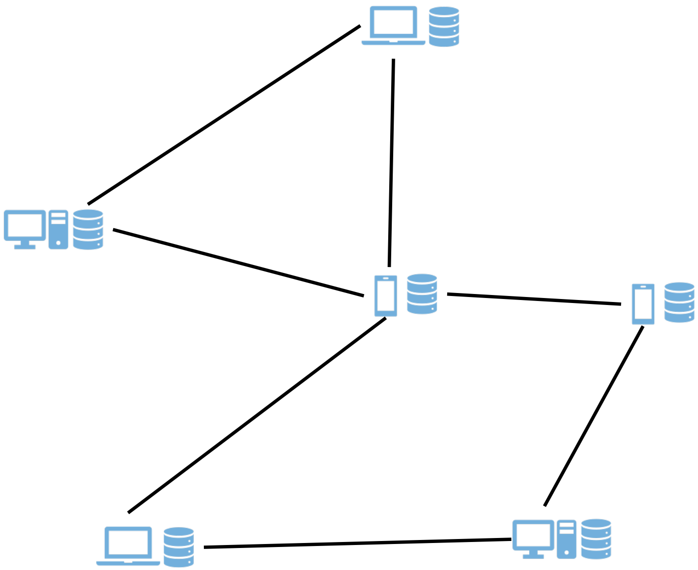
Model evaluation (classification)

$$\frac{\sum_{k\in\{A,B,C\}} N^k_{\mathrm{TP}}}{\sum_{k\in\{A,B,C\}} \left(N^k_{\mathrm{TP}} + N^k_{\mathrm{FN}}\right)}$$

e.g., global recall



Gossip Learning



Algorithm: **Main gossip loop (Push)**

1. initialize local model w
2. loop (forever)
3.   wait for a fixed time Δ
4.   select neighbor peer p
5.   send w to p

Algorithm: **On receive model**

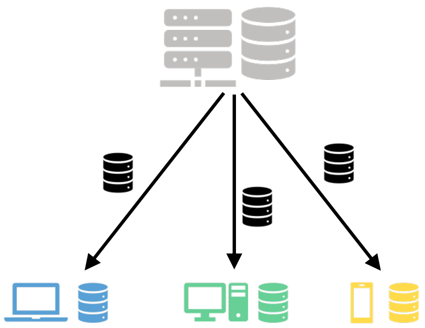
1. receive w_p from p
2. merge(w, w_p)
3. update(w)

e.g., gradient descent step on local data

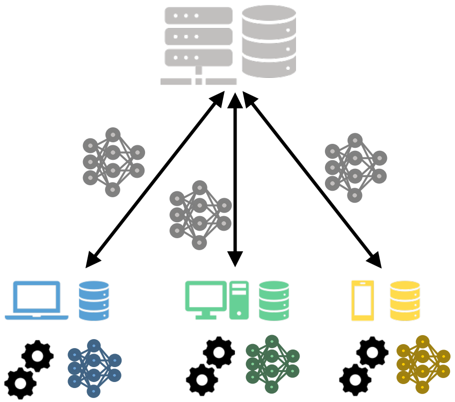
e.g., model averaging

Dealing with non-iidness

Data augmentation



Personalization: It's a feature not a bug!



- Ad hoc learning methods
- Hyper-parameter tuning

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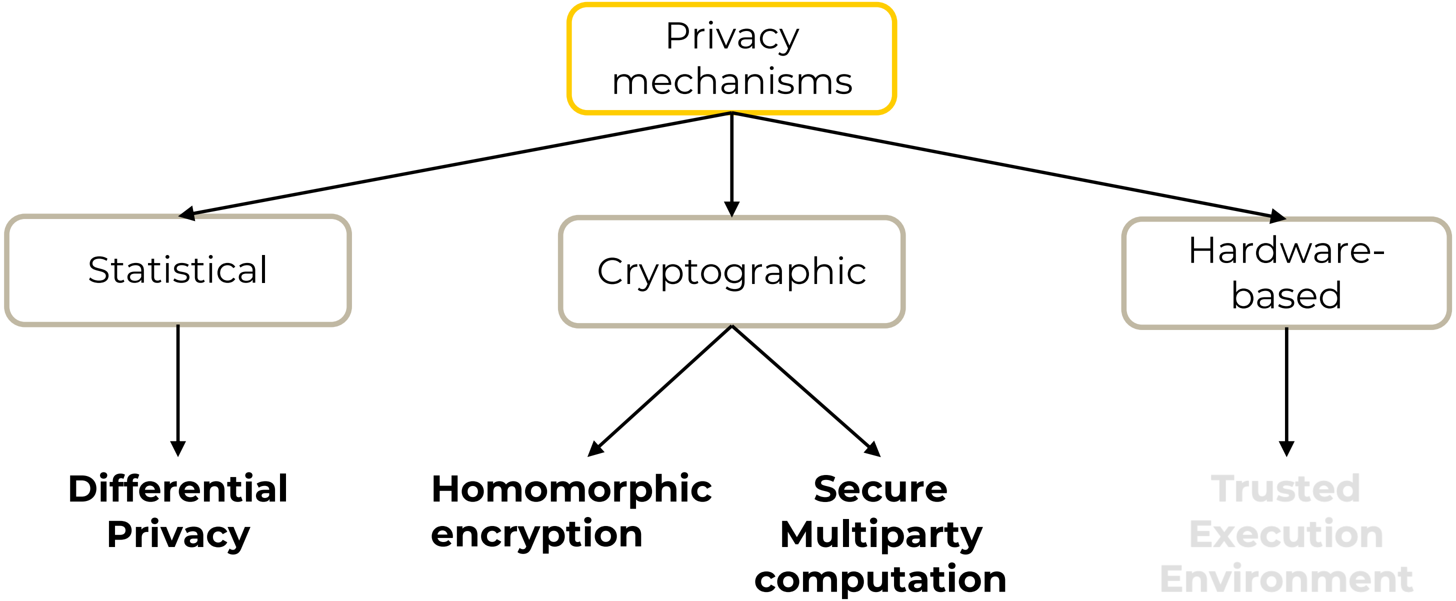
Privacy preservation

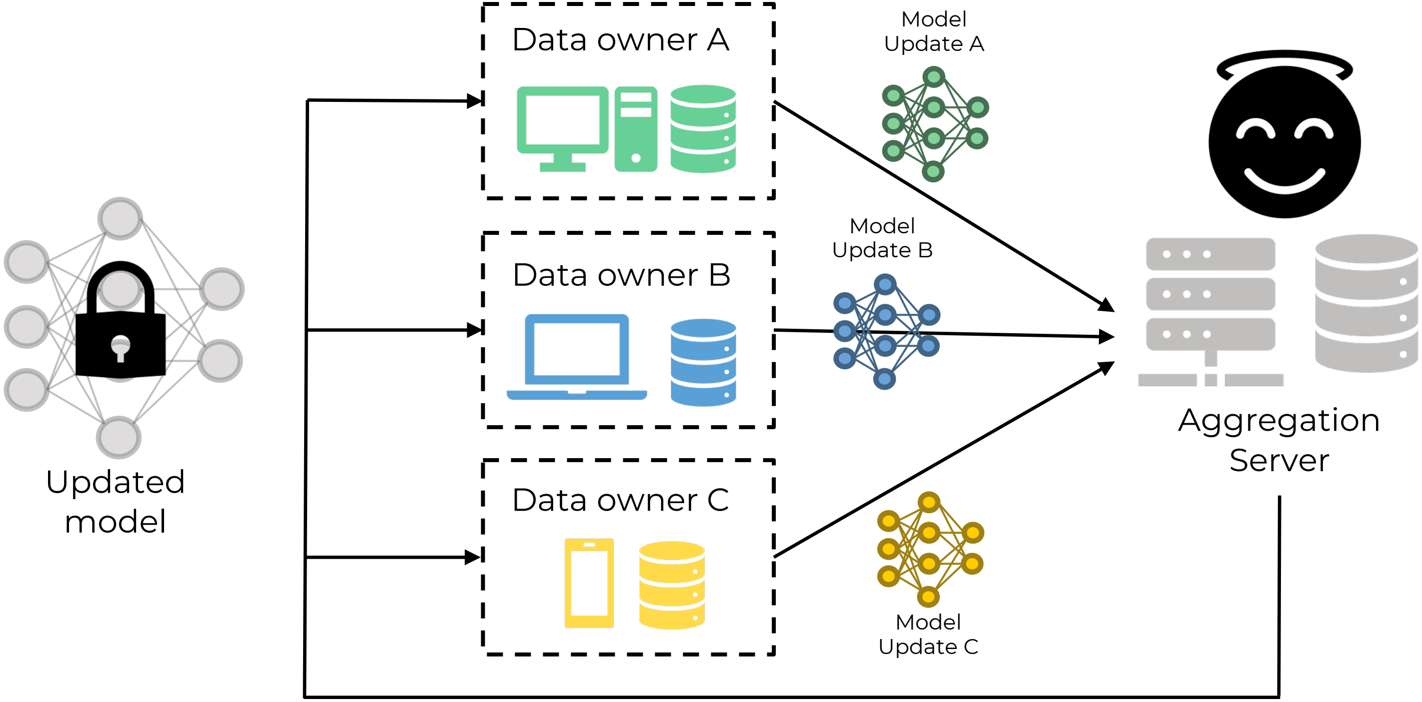
How to improve privacy in FL

FL may be not enough

Gradient/model updates may leak information about the user data!



Global Differential Privacy



FedAvg + Global DP

Aggregation Server

Algorithm: **FedAvg**

```
Initialize model w̄_0
for each round t=1,…:
    Broadcast w̄_{t−1} + noise
    select C eligible participants
    foreach|| participant p:
        w_t^p ← LocalUpdate(p)
    w̄_t ← aggregate(∀p w_t^p)
```

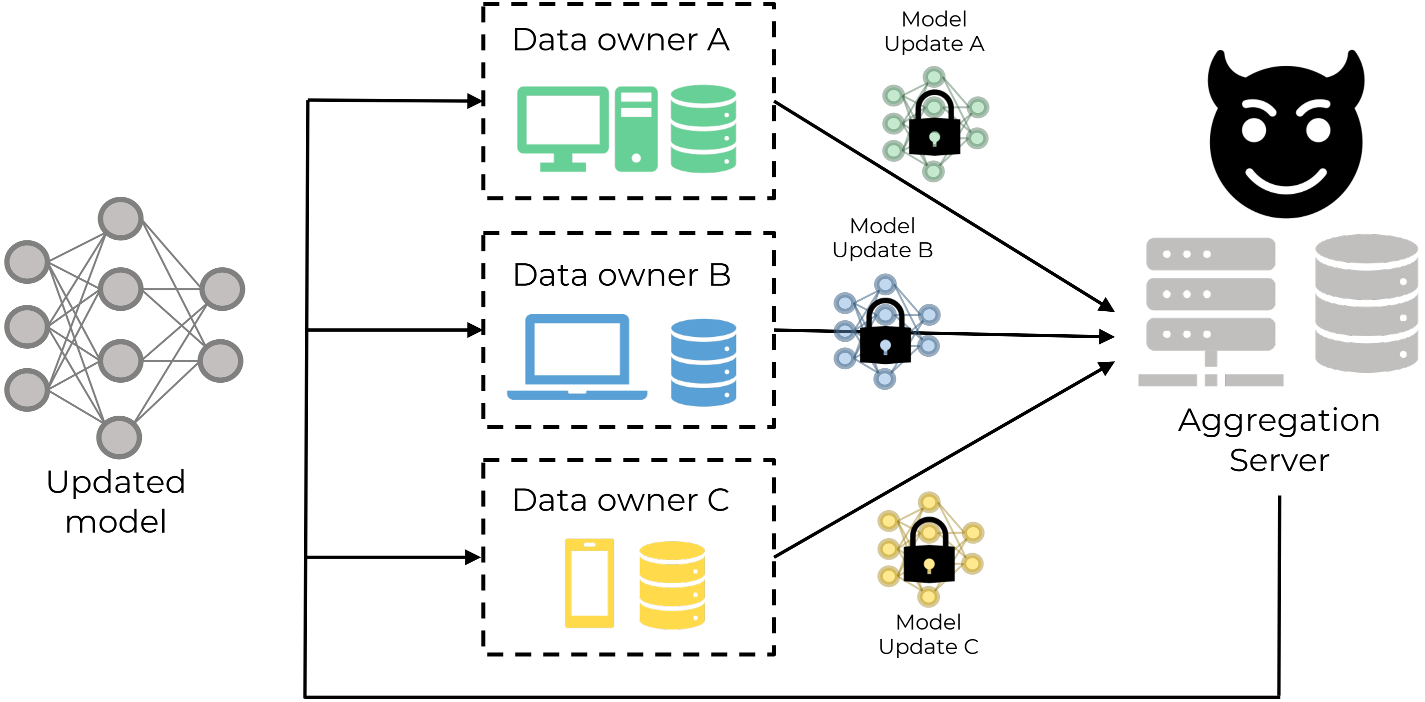
Collaborator/Client

Algorithm: **LocalUpdate**

```
w ← global model from Server
for each epoch s ∈ 1,…,S:
    for each batch b:
        g_b ← compute gradient for b
        w ← w − η g_b
send w to the Server
```

Not safe with honest-but-curious servers

Local Differential Privacy



FedAvg + Local DP

Aggregation Server

Algorithm: **FedAvg**

Initialize model $\overline{w}_0$
for each round t=1,…:
  Broadcast $\overline{w}_{t-1}$
  select C eligible participants
  foreach|| participant p:
    $w_t^p \leftarrow$ LocalUpdate(p)
  $\overline{w}_t \leftarrow$ aggregate($\forall p\ w_t^p$)

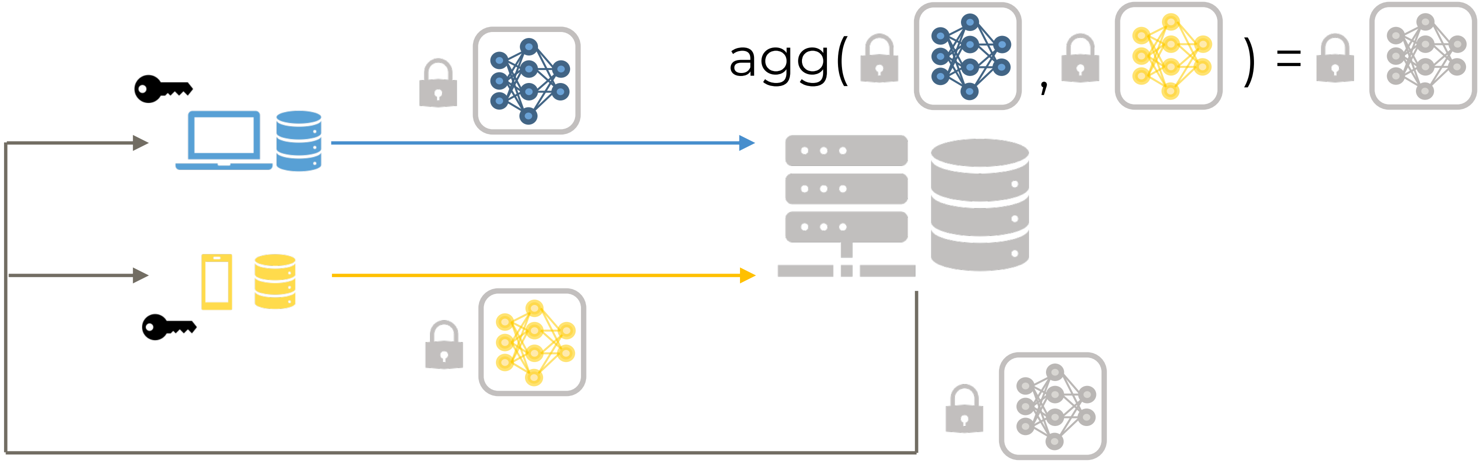
Collaborator/Client

Algorithm: **LocalUpdate**

$w \leftarrow$ global model from Server
for each epoch $s \in 1, \dots, S$:
  for each batch b:
    $g_b \leftarrow$ compute gradient for b
    $w \leftarrow w - \eta g_b$
send (w + noise) to the Server

It may affect the performance

Homomorphic Encryption



FedAvg + HE

Aggregation Server

Algorithm: **FedAvg**

1. Initialize model $\overline{w}_0$
2. for each round t=1,…:
3. Broadcast $\overline{w}_{t-1}$
4. select C eligible participants
5. foreach|| participant p:
6. $\mathrm{enc}(w_t^p)$ ← LocalUpdate(p)
7. $\overline{w}_t$ ← aggregate_he($\forall p$ $\mathrm{enc}(w_t^p)$)

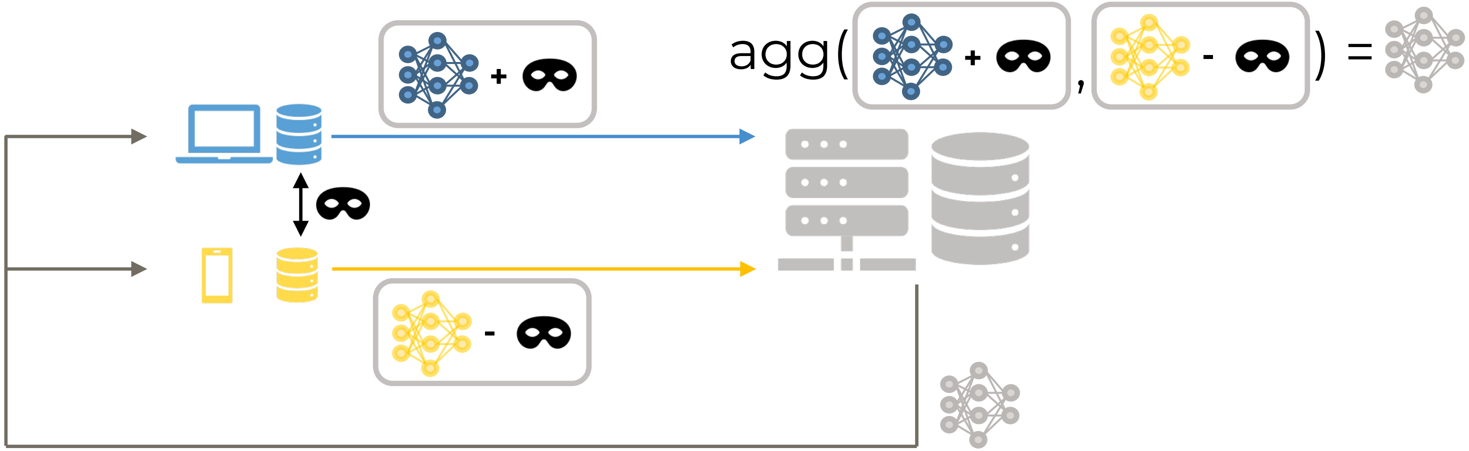
Collaborator/Client

Algorithm: **LocalUpdate**

1. w_{enc} ← global model from Server
2. w ← decrypt(w_{enc})
3. for each epoch $s \in 1,\ldots,S$:
4. for each batch b:
5. g_b ← compute gradient for b
6. $w \leftarrow w - \eta g_b$
7. send encrypt(w) to the Server

Computationally expensive

Secure Multiparty Computation



FedAvg + SMC

Aggregation Server

Algorithm: **FedAvg**

initialize model $\overline{w}_0$
for each round t=1,…:
  Broadcast $\overline{w}_{t-1}$
  select C eligible participants
  foreach|| participant p:
    $\mathrm{mask}(w_t^p) \leftarrow$ LocalUpdate(p)
  $\overline{w}_t \leftarrow$ agg_smc($\forall p$ $\mathrm{mask}(w_t^p)$)

Weigh down the communication protocol

Collaborator/Client

Algorithm: **OneTimePadAgreement**

For each active client p:
  agree on perturbation s_p

Algorithm: **LocalUpdate**

$w \leftarrow$ global model from Server
for each epoch $s \in 1, \dots, S$:
  for each batch b:
    $g_b \leftarrow$ compute gradient for b
    $w \leftarrow w - \eta g_b$
send mask(w,$\forall p$ s_p) to the Server

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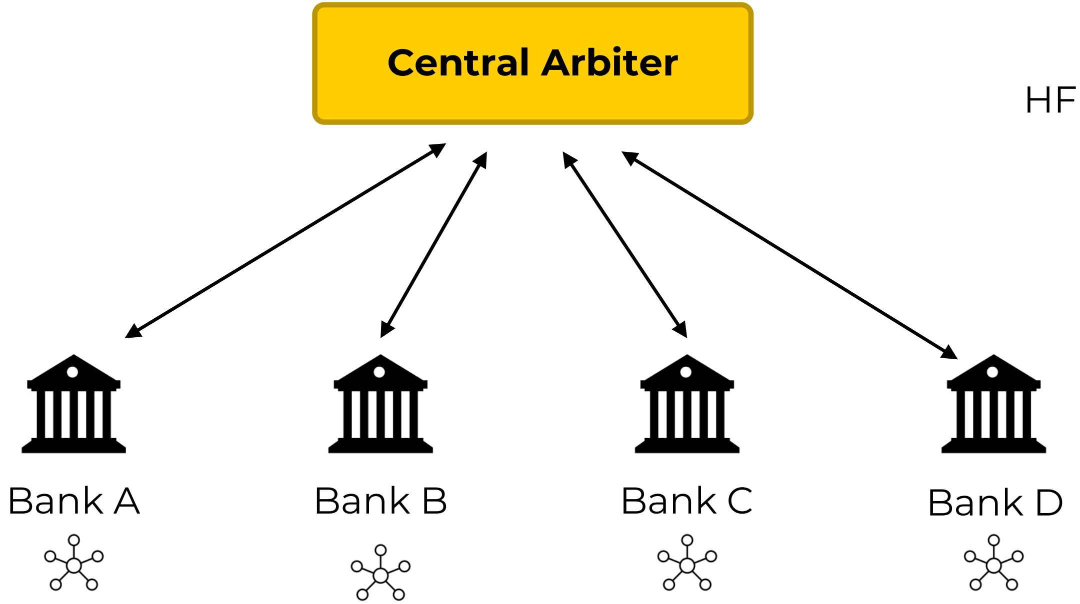
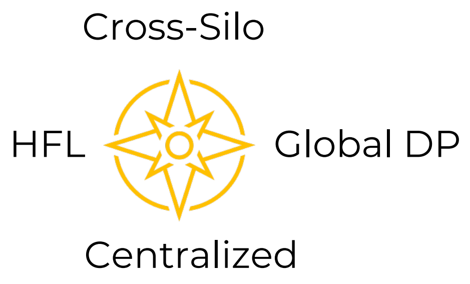
Applications

Some use cases and real-world examples of FL

Use case 1
Anti-money laundering





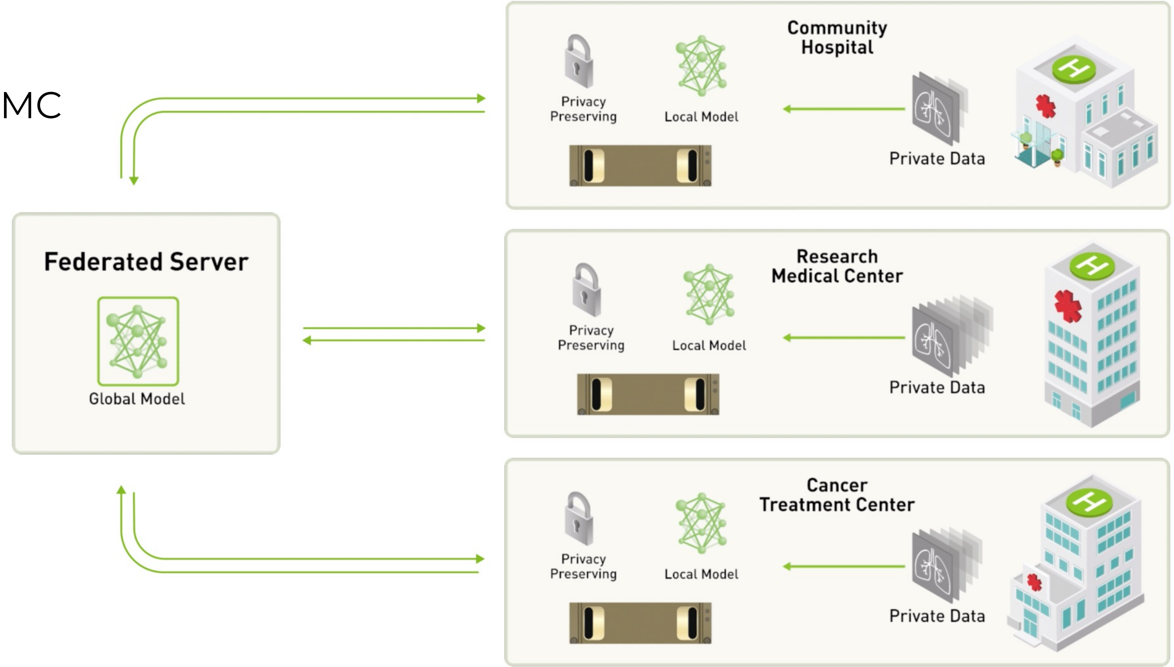
Use case 2
Medical diagnosis

Cross-Silo

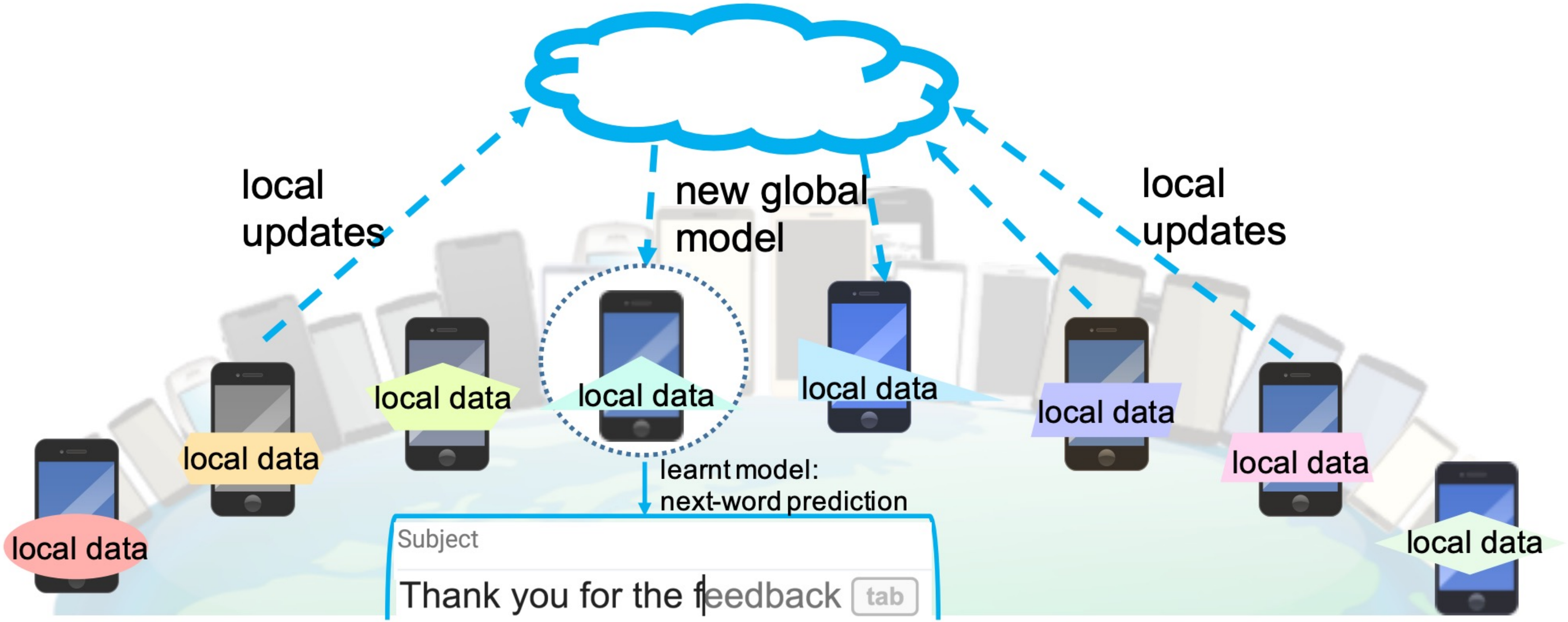
H/VFL

HE/SMC

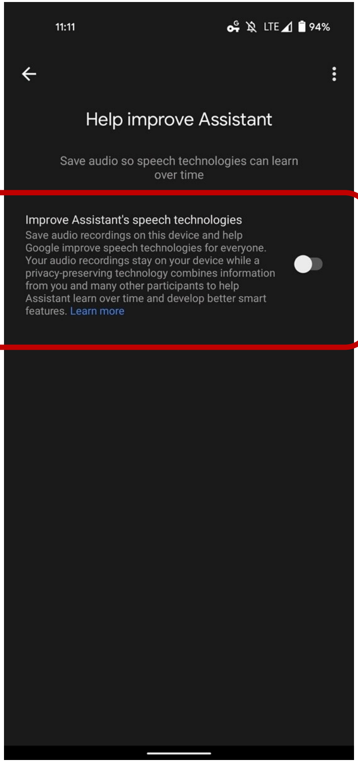
Centralized

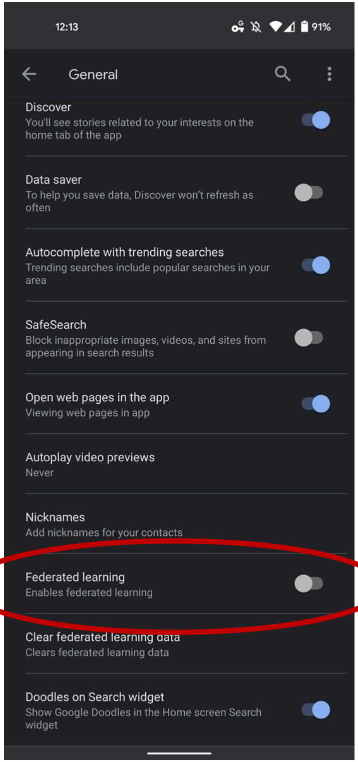


Google's GBoard

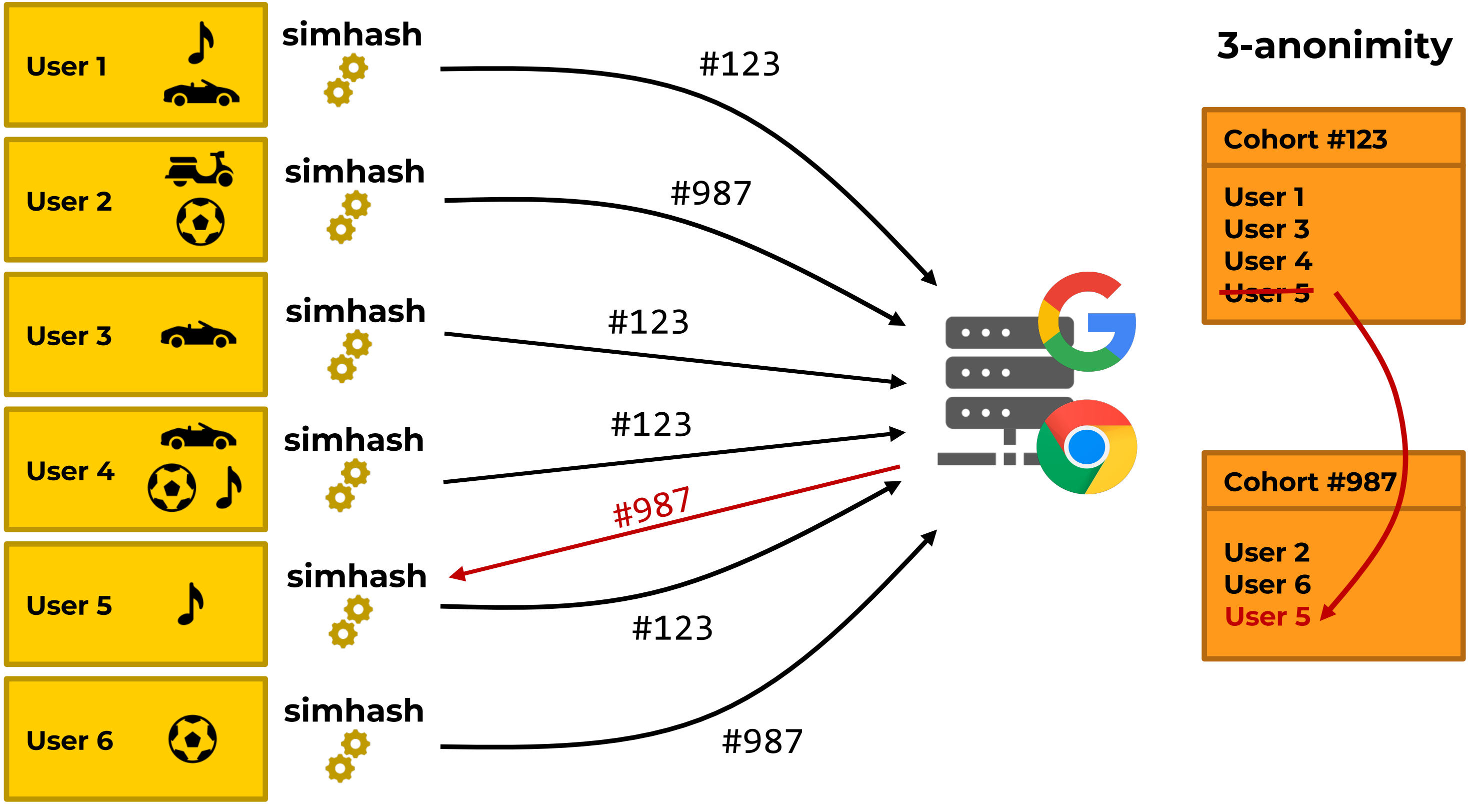


Google's "Hey Google!" recognition





Google's Federated Learning Of Cohorts



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Conclusions

The glorious “take home message”

What we did not cover

- Attacks to FL systems
- Federated Transfer Learning
- Improve communication efficiency, e.g., model quantization
- Fairness

Take home message ☺

- FL is a “novel” yet **interesting framework for privacy-preseving ML**
- FL methods must be designed considering the **communication-computation-privacy-effectiveness trade-off**
- FL is still in its infancy and there are **many open problems**

Thanks!

Any Questions?

The only stupid question is the one you were afraid to ask but never did.

Richard Sutton

Resources

- Li, et al. 'A Survey on Federated Learning Systems: Vision, Hype and Reality for Data Privacy and Protection', 2021. http://arxiv.org/abs/1907.09693.
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