ECEN 685 Machine Learning in CyberSecurity

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Talk Overview

1. Why Federated Learning?

Outline

Why Federated Learning?

Enables multiple actors to build a common machine learning systems without centralizing data and with privacy by default.

[1] https://www.slicktext.com/blog/2019/10/smartphone-addiction-statistics/

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- Mobile devices are personal computer
  - As of June 2019, 96% of Americans own a cellphone of some kind [1]
- Plethora of sensors
- Privacy issues.

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Challenges

- Deep Learning is non-convex
- millions of parameters
- complex structure

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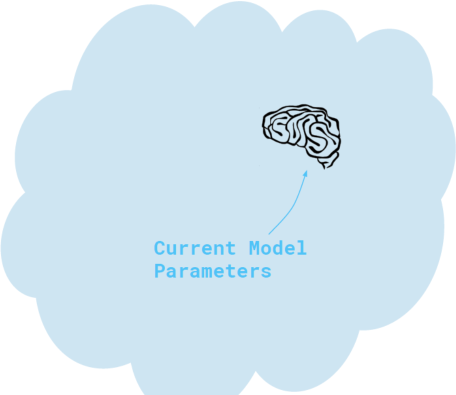
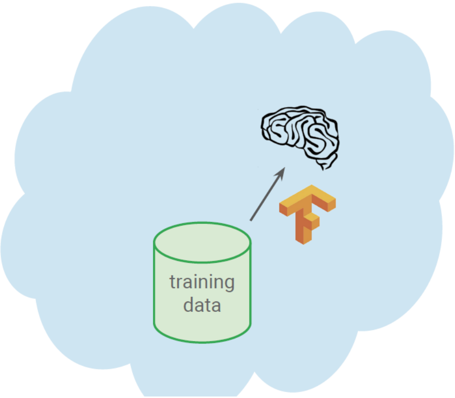
Current Machine Learning as a Service for Mobile Devices

The model lives in the cloud.



Current Machine Learning as a Service for Mobile Devices

We train models in the cloud.



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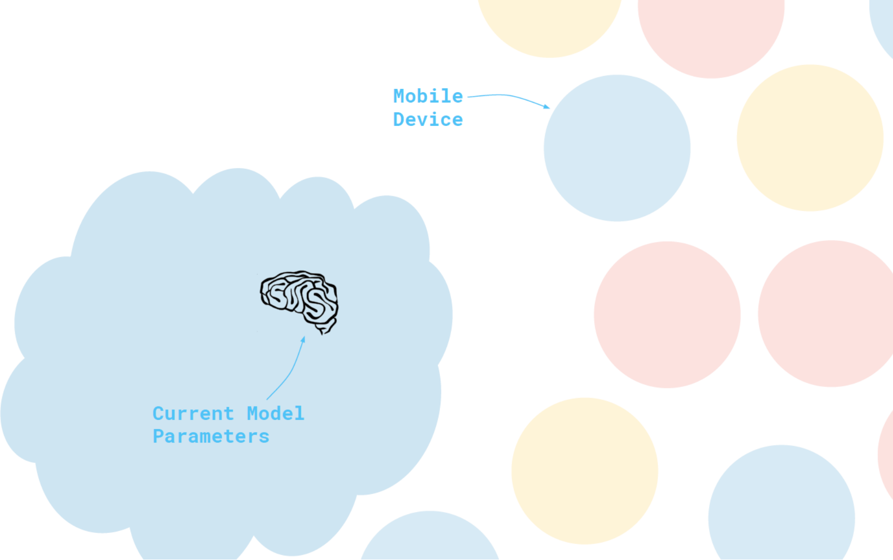

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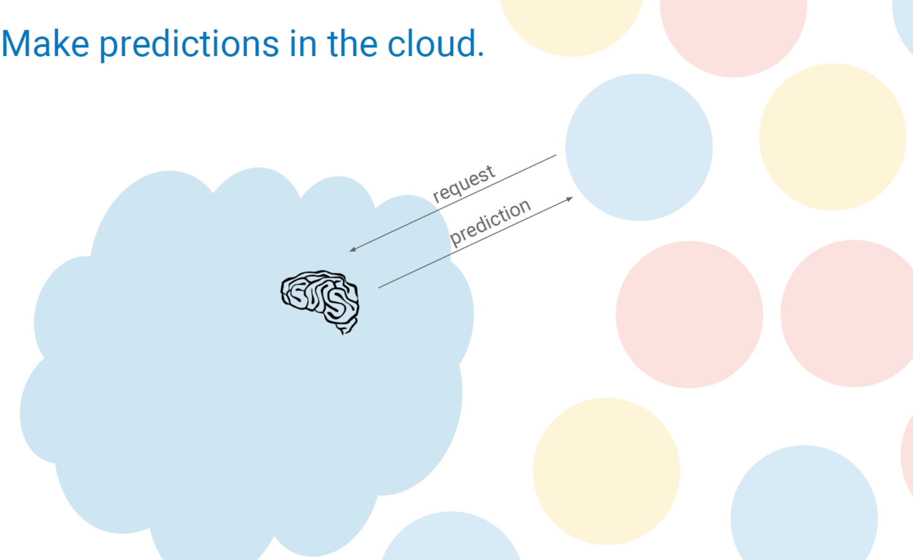

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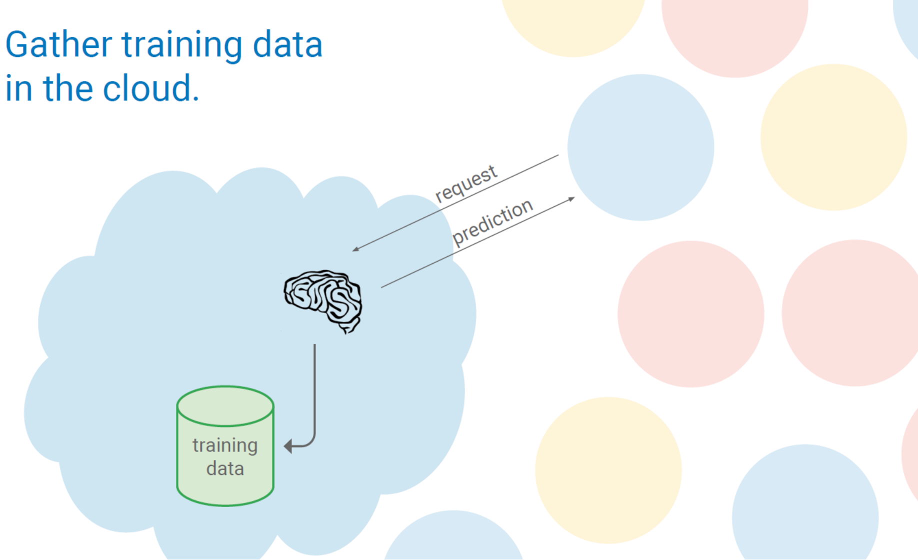
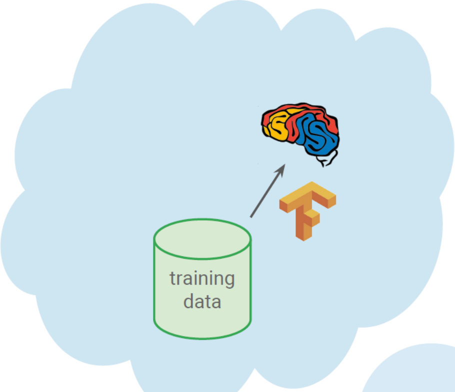


Current Machine Learning as a Service for Mobile Devices

And make the models better.

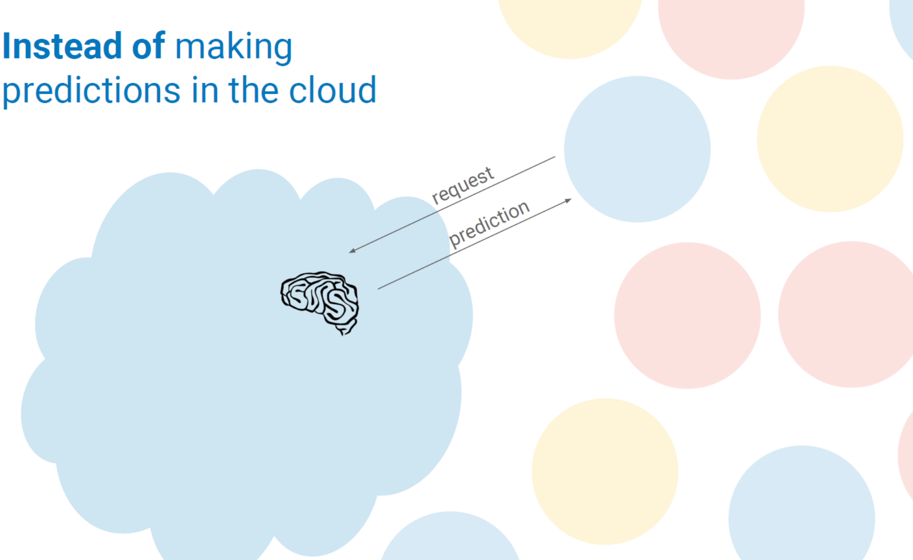


On-device inference

On-device inference is using a cloud-distributed model to make predictions directly on an edge device without a cloud round-trip

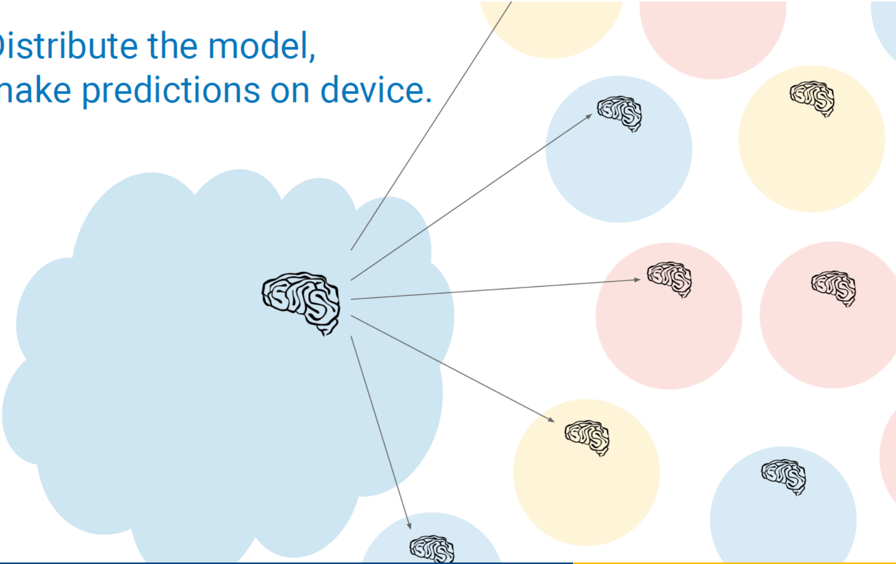
- ML models in the data center (e.g., Forecasting weather)
- ML models in the device (e.g., Keyboard suggestion)

On-device inference



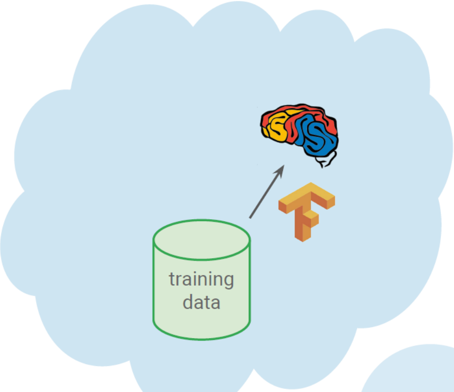
On-device inference

Distribute the model,
make predictions on device.



On-device inference

But how do we continue to improve the model?



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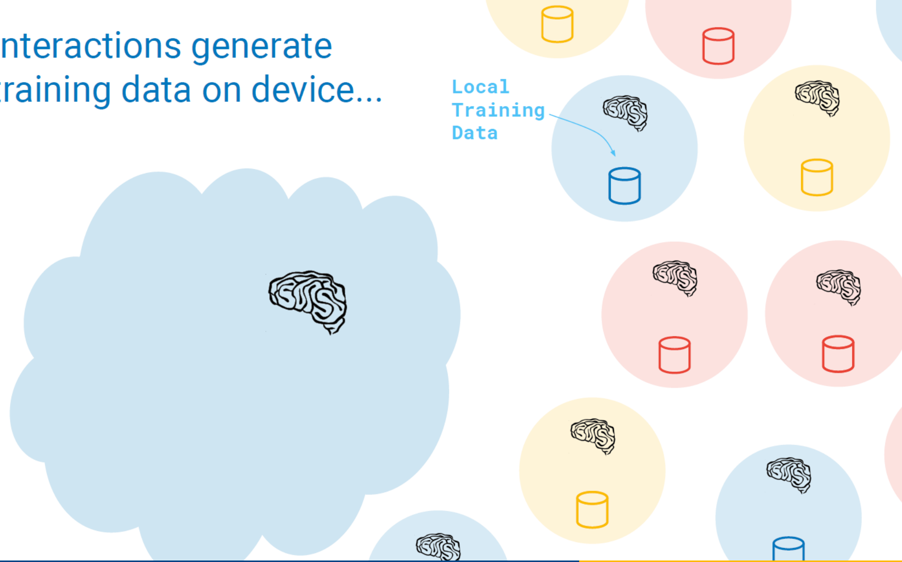
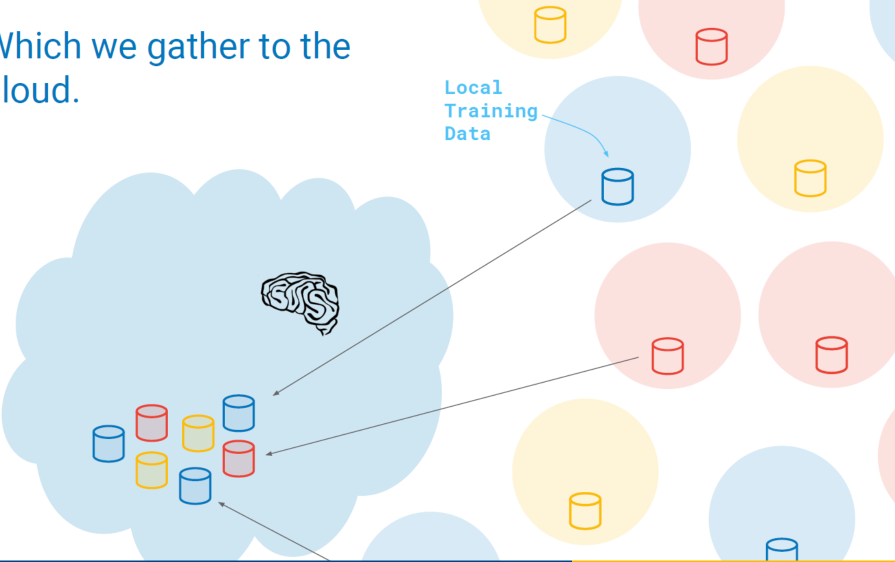
On-device inference

Interactions generate training data on device...



On-device inference

Which we gather to the cloud.



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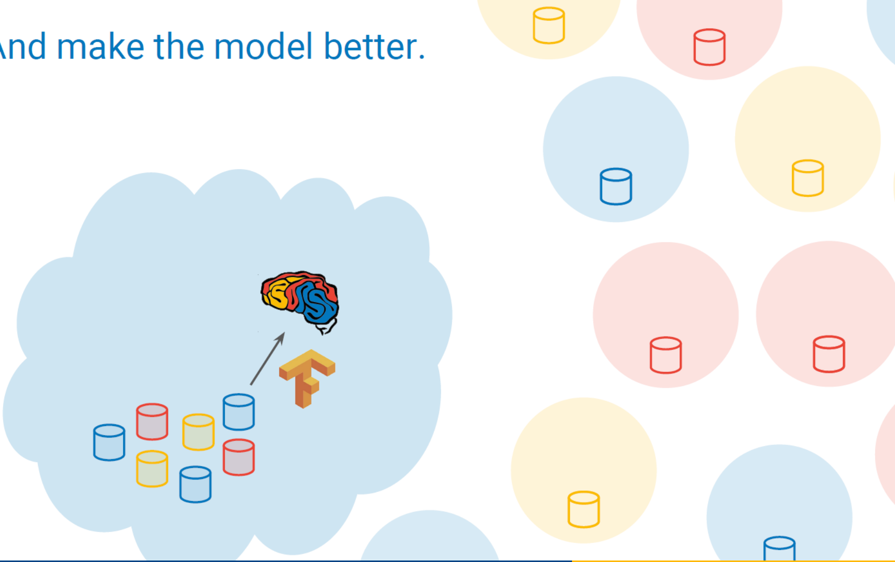

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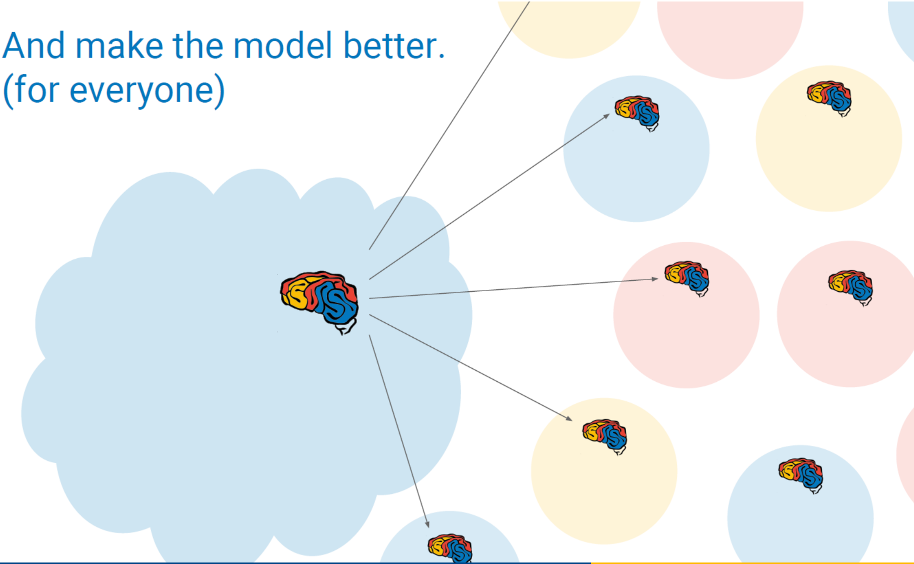
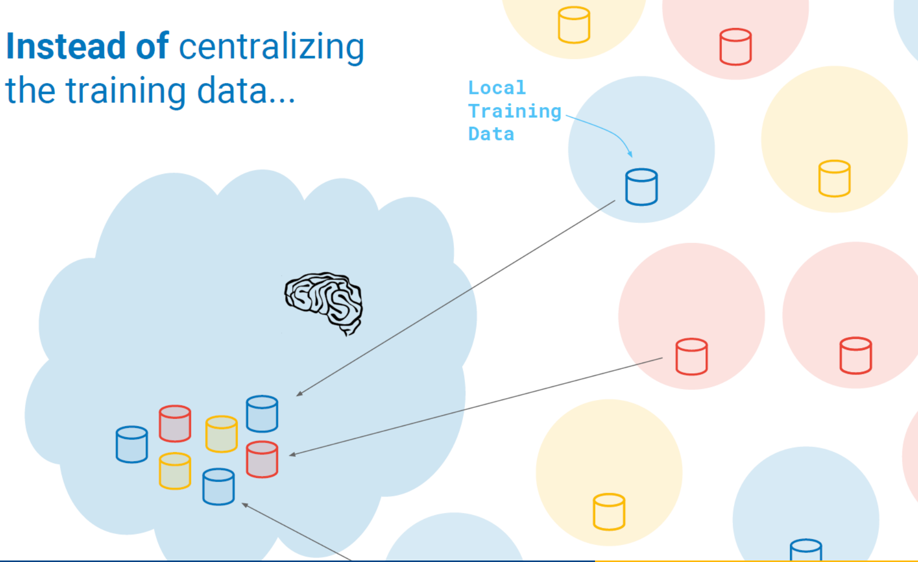


On-device inference

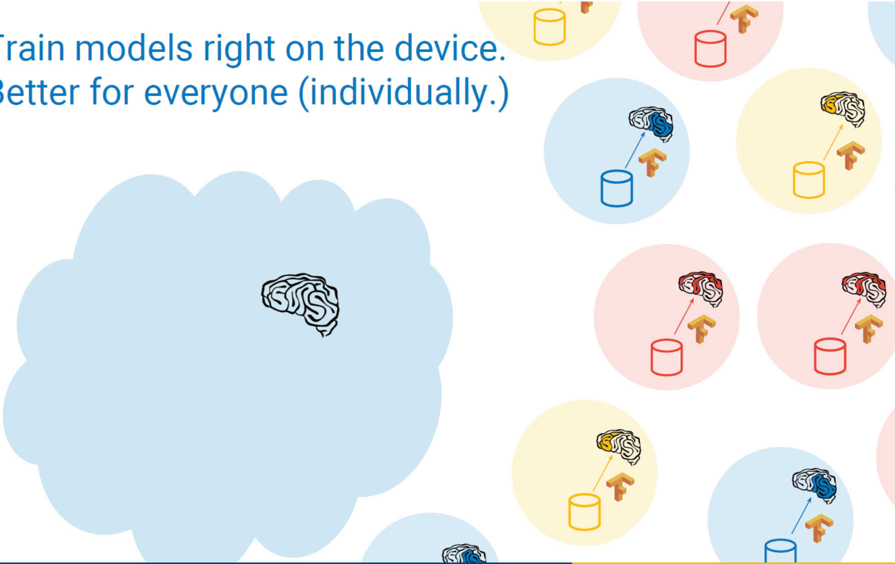
What about users privacy?

On-device inference



On-device inference

Train models right on the device.
Better for everyone (individually.)



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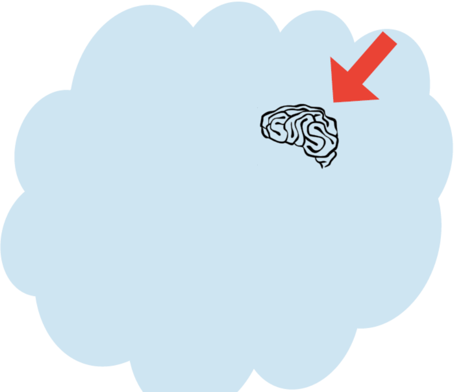


But what about...

1. New User Experience
2. Benefitting from peers' data

Federated Computation and Learning

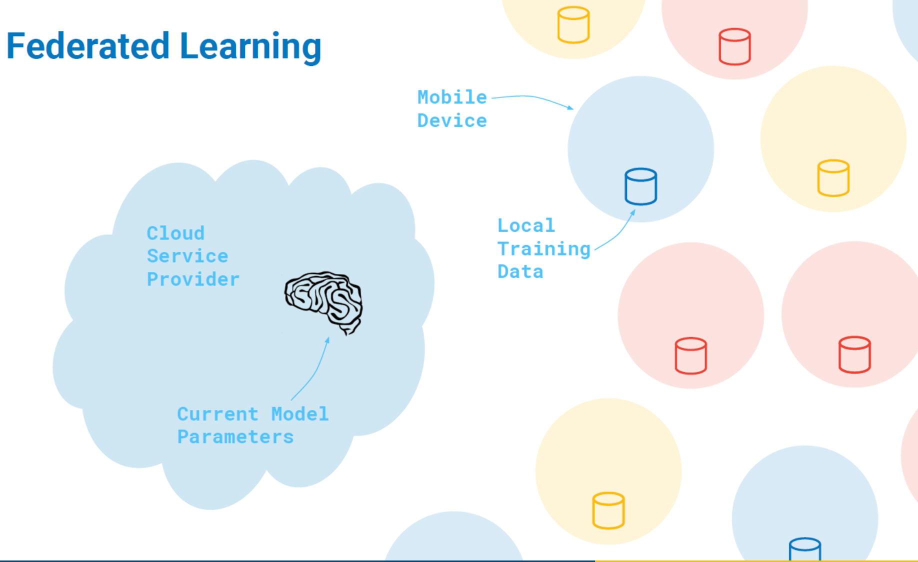
Federated learning

Where a server coordinates a fleet of participating devices to compute aggregated knowledge of devices private data.

Benefits:

- Privacy
- Global Model
- On device inference (Communication Friendly)

Federated Learning



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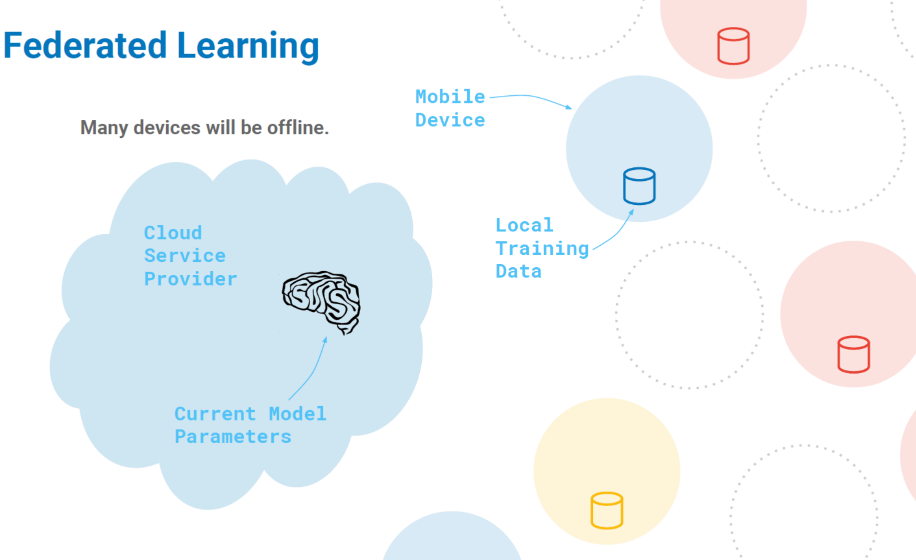

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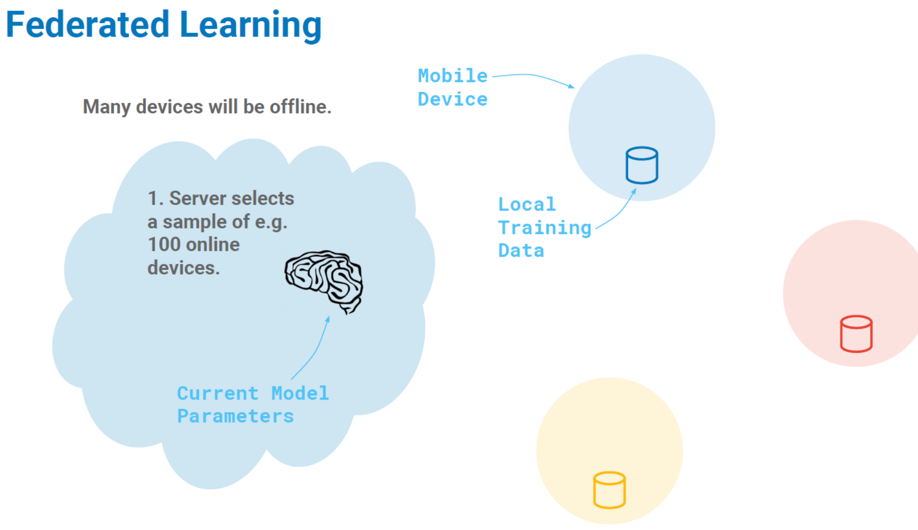

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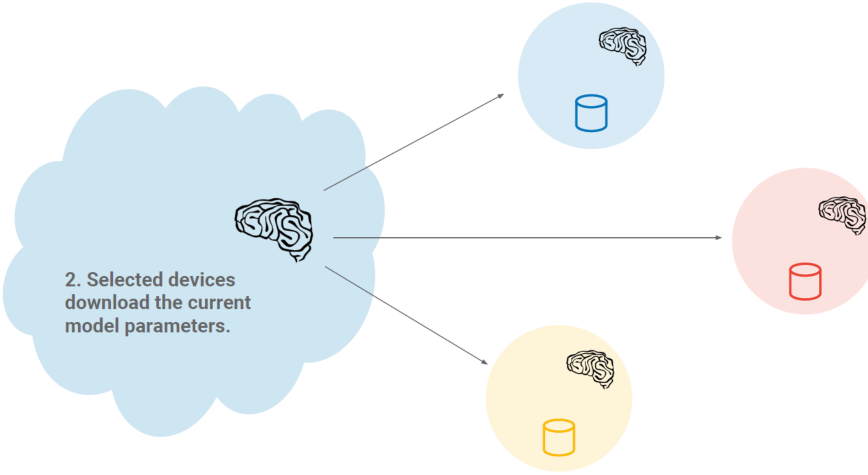

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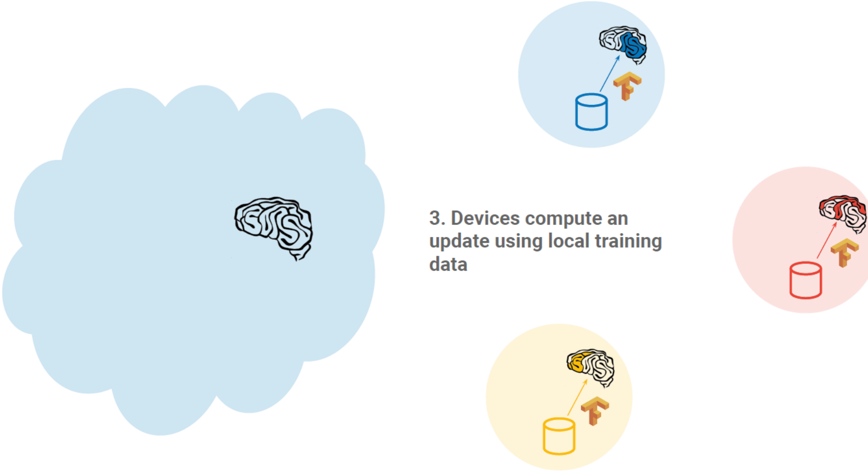

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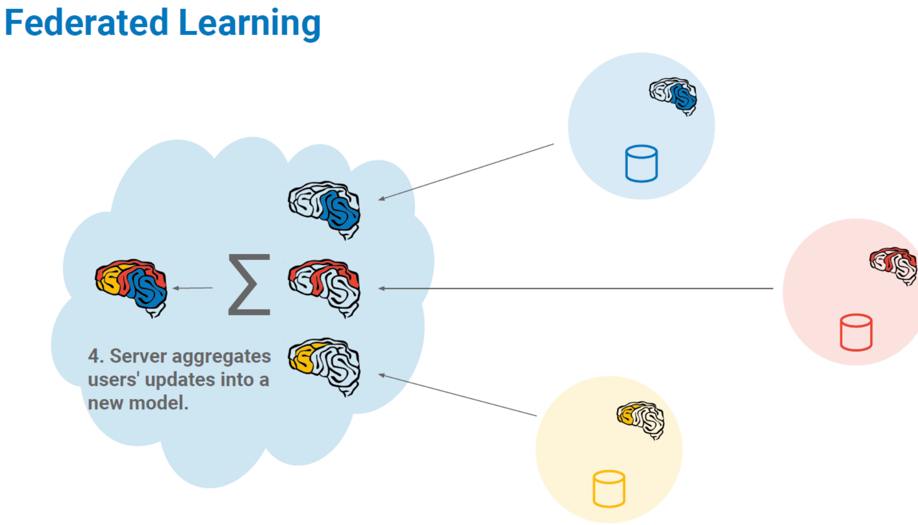

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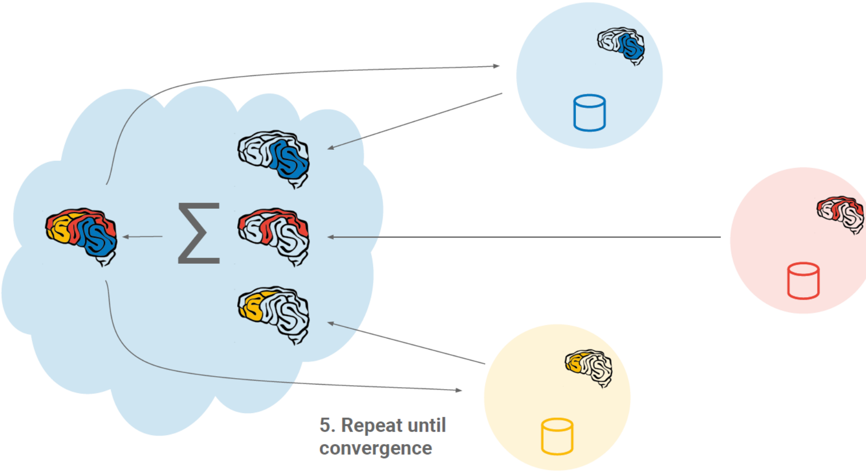
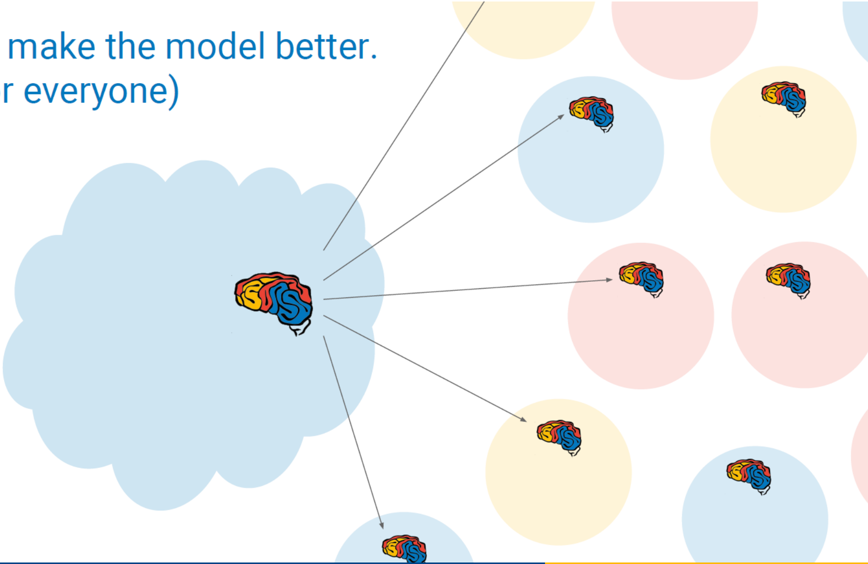


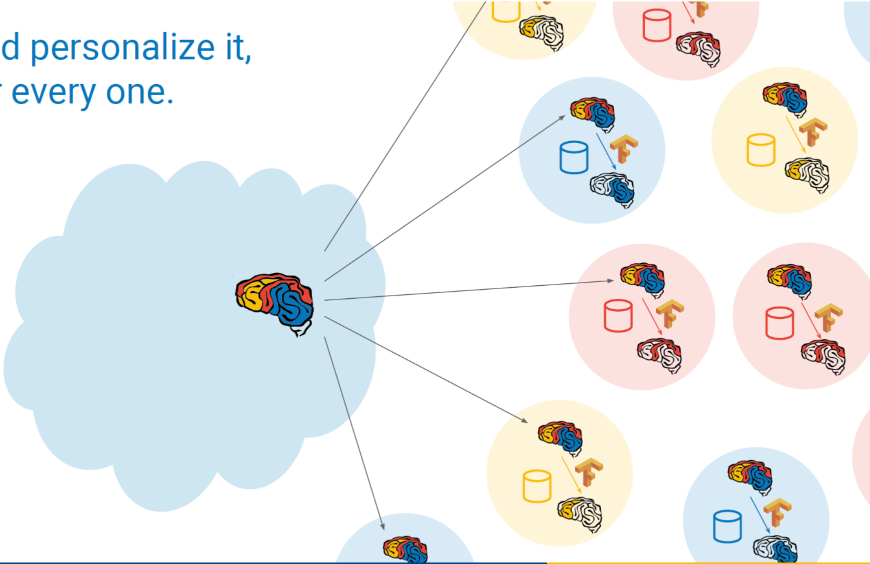
Federated Learning

To make the model better.
(for everyone)



Federated Learning

And personalize it,
for every one.



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- **Dynamic Data Availability**
  - The subset of data available is non-constant, e.g. time-of-day vs. country

Applications of Federating Learning

Federated learning will find a room to exist when:

- On-device data is more relevant than server-side proxy data
- On-device data is privacy sensitive or large

Examples of some application?

- Language modeling for mobile keyboards and voice recognition
- Medical diagnosis
- Mobile face recognition
- ...

The Federated Averaging Algorithm

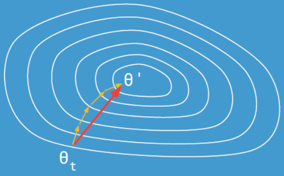
Server

Until Converged:

1. Select a random subset (e.g. 1000) of the (online) clients
2. In parallel, send current parameters θ_t to those clients

Selected Client k

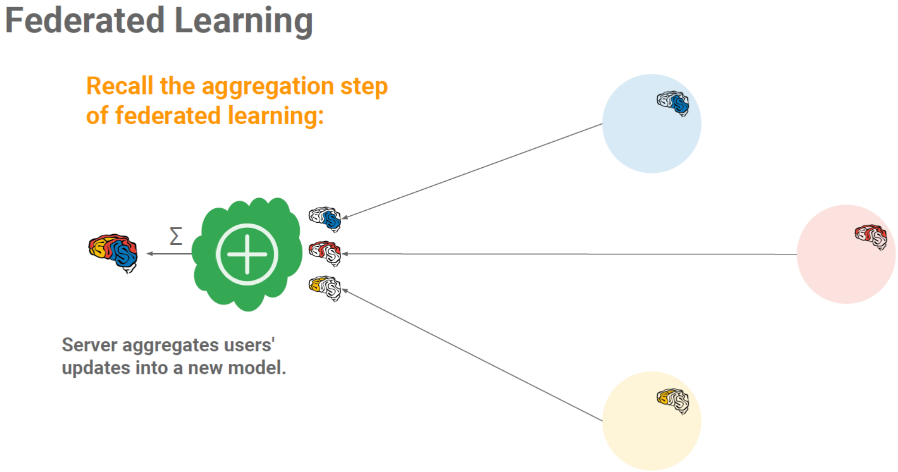
1. Receive θ_t from server.
2. Run some number of minibatch SGD steps, producing θ'
3. Return $\theta'-\theta_t$ to server.



3. $\theta_{t+1} = \theta_t$ + data-weighted average of client updates

H. B. McMahan, *et al.* **Communication-Efficient Learning of Deep Networks from Decentralized Data.** AISTATS 2017

Concerns in Federated Learning



Concerns in Federated Learning

Federated Learning

Might these updates contain privacy-sensitive data?

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1. Ephemeral

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Concerns in Federated Learning

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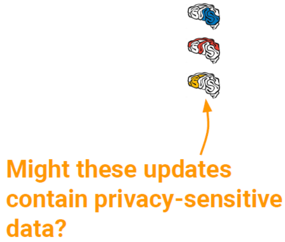

1. Ephemeral
2. **Focused**

Concerns in Federated Learning

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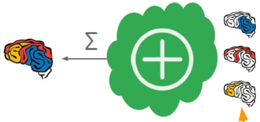
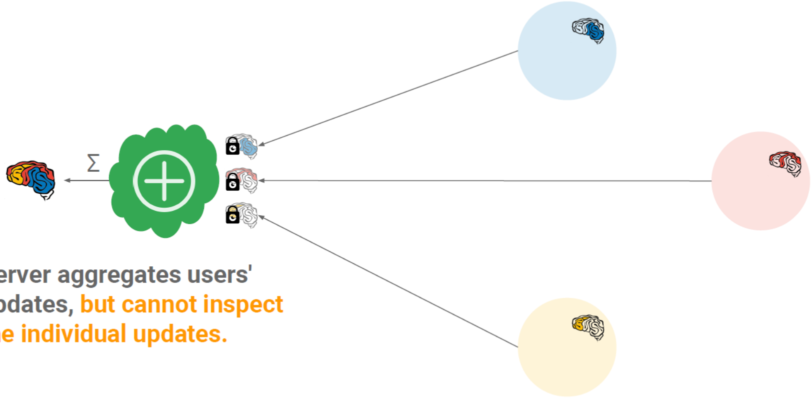


1. Ephemeral
2. Focused
3. **Only in Aggregate**

Secure Aggregation

Wouldn't it be great if...



Server aggregates users' updates, but cannot inspect the individual updates.

Secure Aggregation

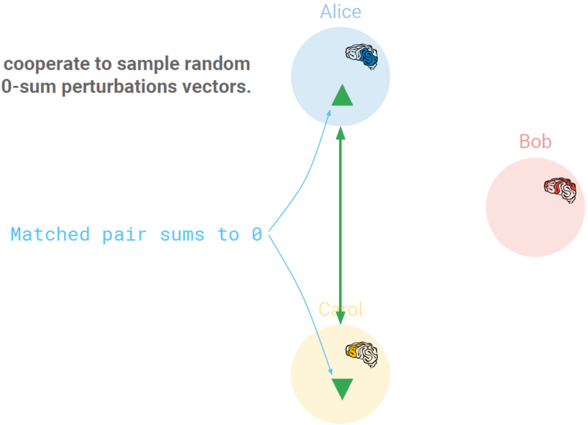
Secure Aggregation protocols aims to protect the privacy of the updates sent by the clients to the aggregator by letting the aggregator able only to calculate the aggregate update but not able to access the individual updates[2]

[2] https://storage.googleapis.com/pub-tools-public-publication-data/pdf/ae87385258d90b9e48377ed49d83d467b45d5776.pdf

Secure Aggregation

Random positive/negative pairs, *aka* antiparticles

Devices cooperate to sample random pairs of 0-sum perturbations vectors.



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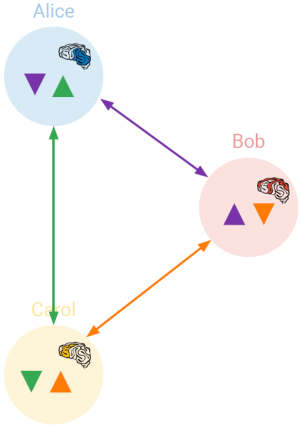
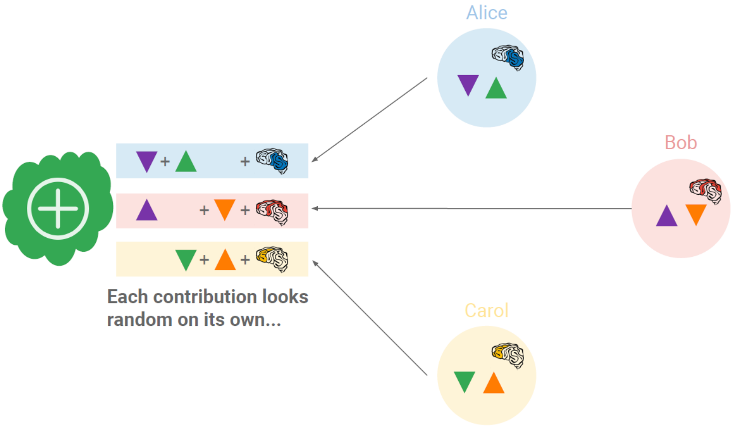


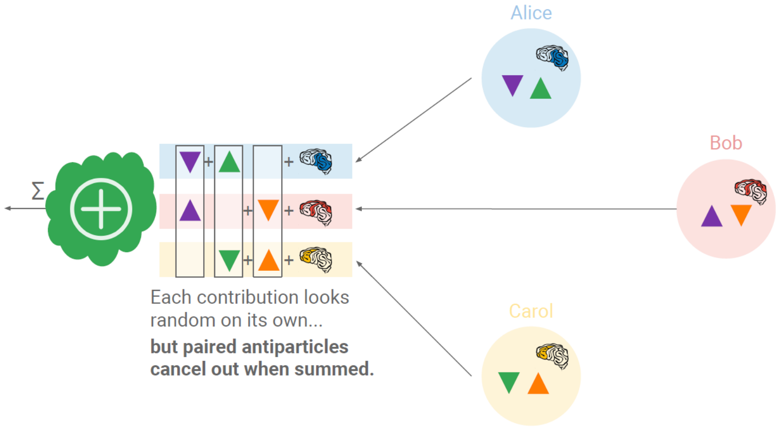
Secure Aggregation

Add antiparticles before sending to the server



Secure Aggregation

The antiparticles cancel when summing contributions



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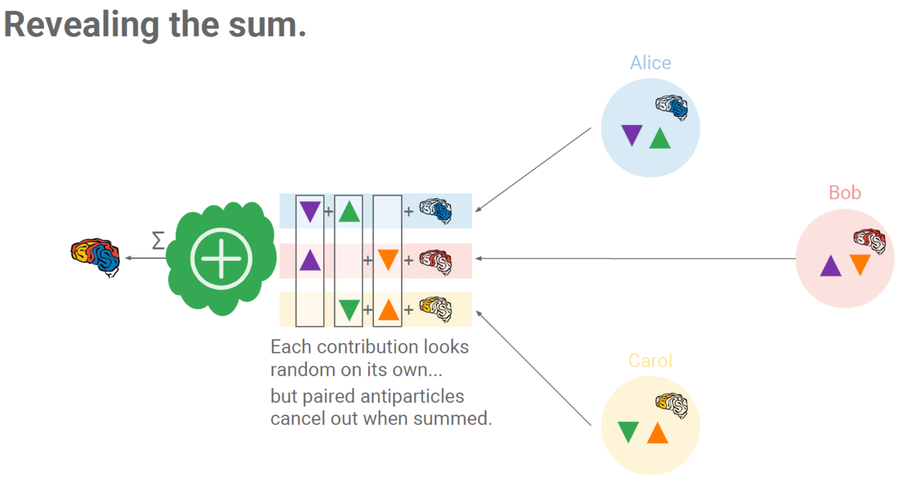
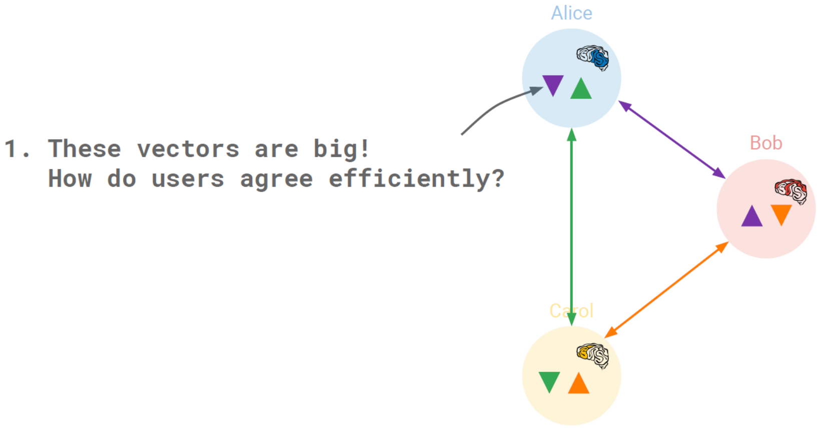


Problems in this approach

There are two main problems.



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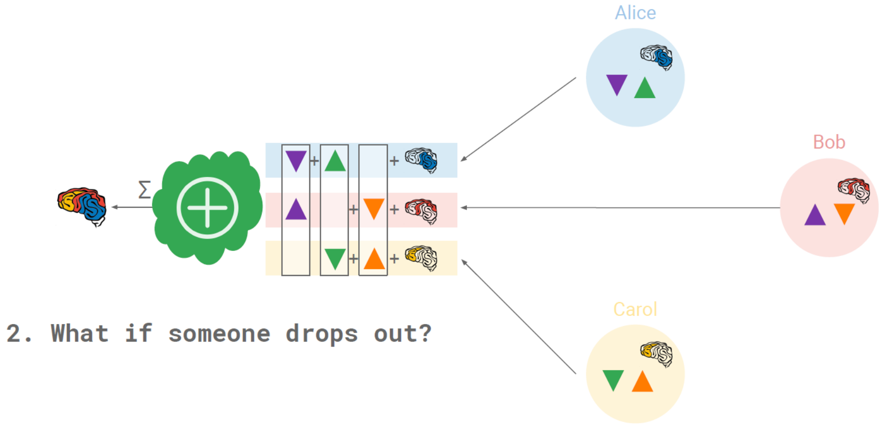

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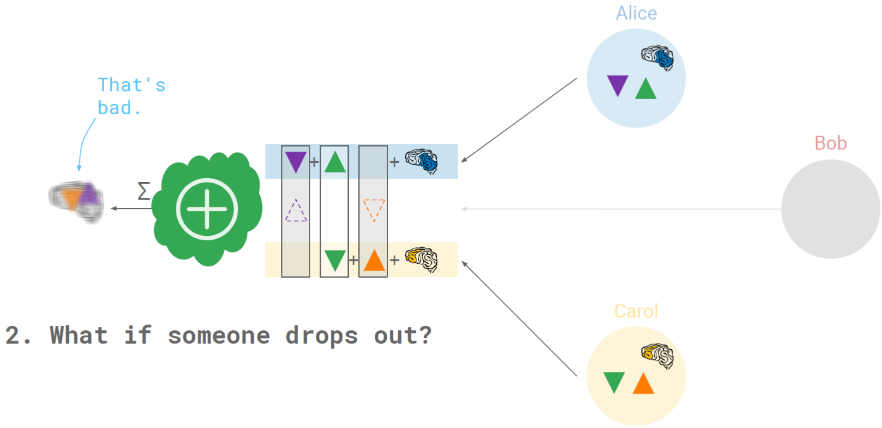
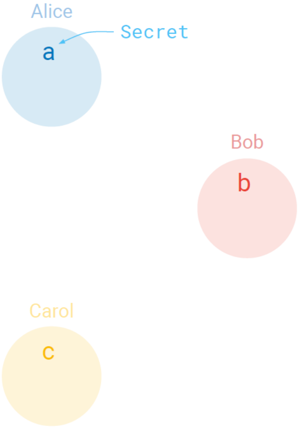


Secure Aggregation Protocol (Addressing First Problem)

Pairwise Diffie-Hellman Key Agreement



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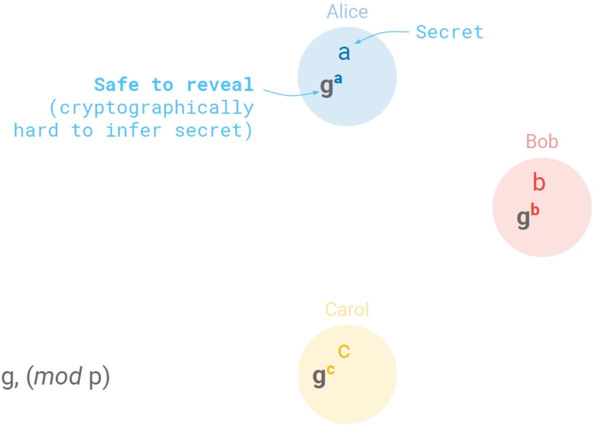

Public parameters: g, (*mod* p)

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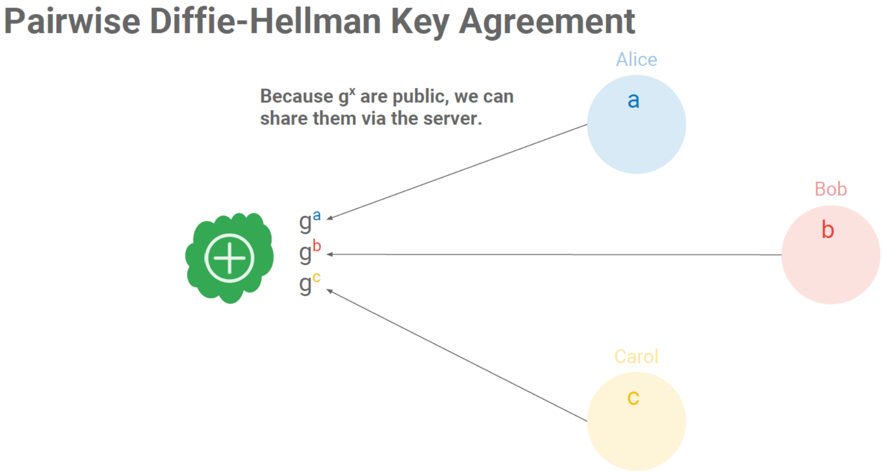

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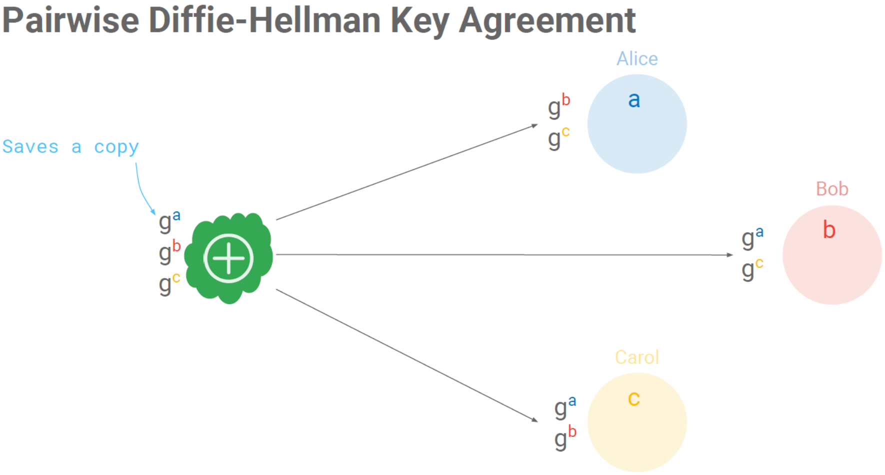

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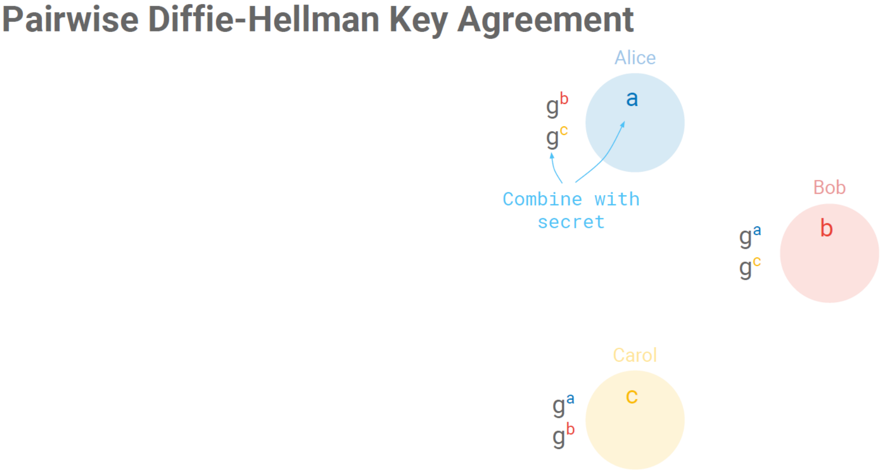

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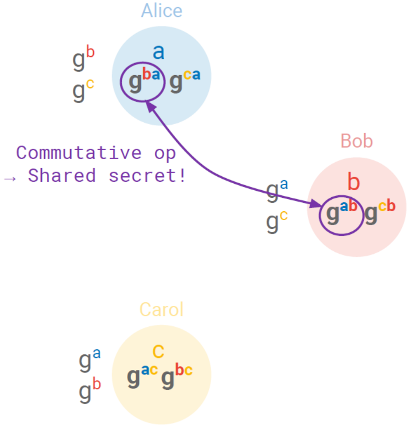


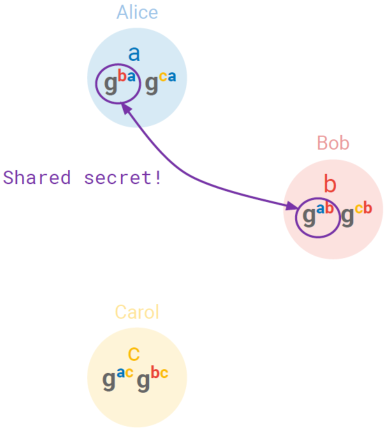
Secure Aggregation Protocol (Addressing First Problem)

Pairwise Diffie-Hellman Key Agreement + PRNG Expansion

Secrets are scalars, but....

Use each secret to seed a **pseudorandom number generator**, generate paired antiparticle vectors.

$\mathrm{PRNG}(g^{ba}) \rightarrow \vec{\blacktriangledown} = -\vec{\blacktriangle}$



Secure Aggregation Protocol (Addressing Second Problem)

How to enable online users to recover the secrets of any user that may go offline?

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Using k-out-of-n Threshold Secret Sharing

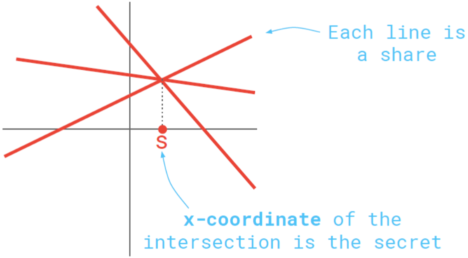
k-out-of-n Threshold Secret Sharing

k-out-of-*n* Threshold Secret Sharing

Goal: Break a secret into *n* pieces, called shares.

- **<k shares:** learn nothing
- **≥k shares**: recover *s* perfectly.

2-out-of-3 secret sharing:



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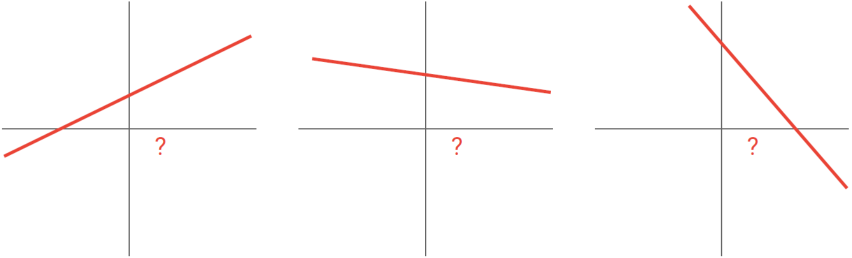

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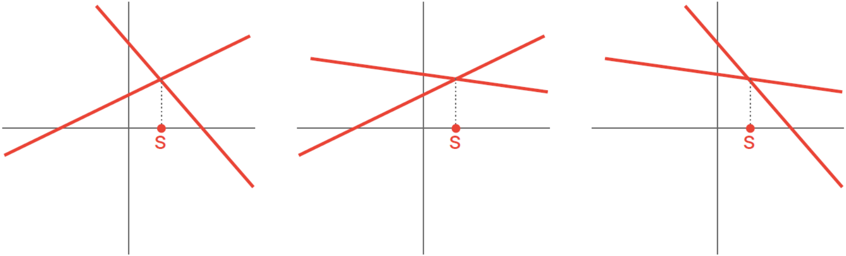
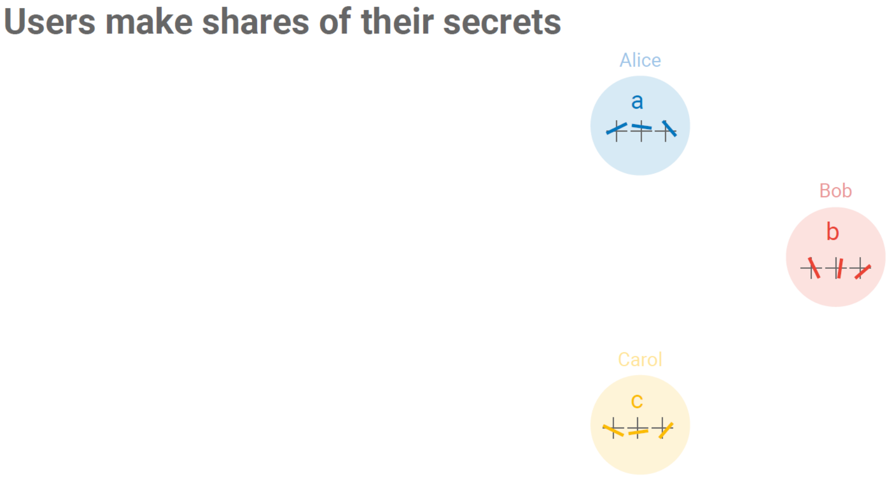


Secure Aggregation Protocol (Addressing Second Problem)



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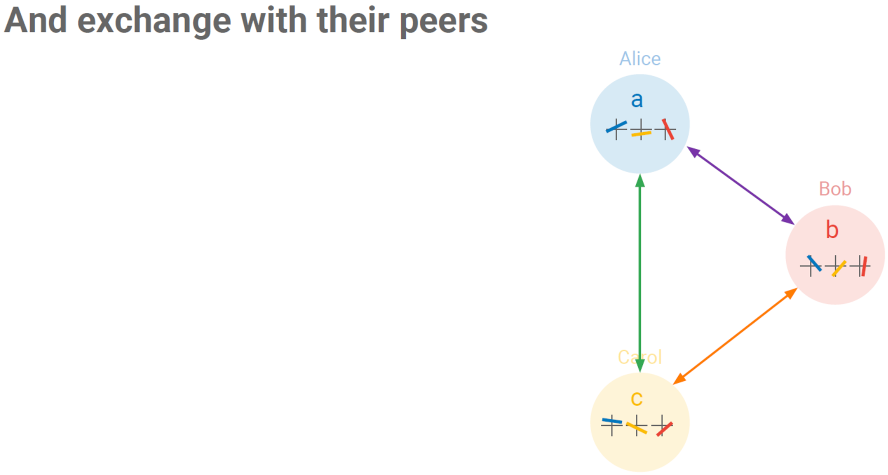

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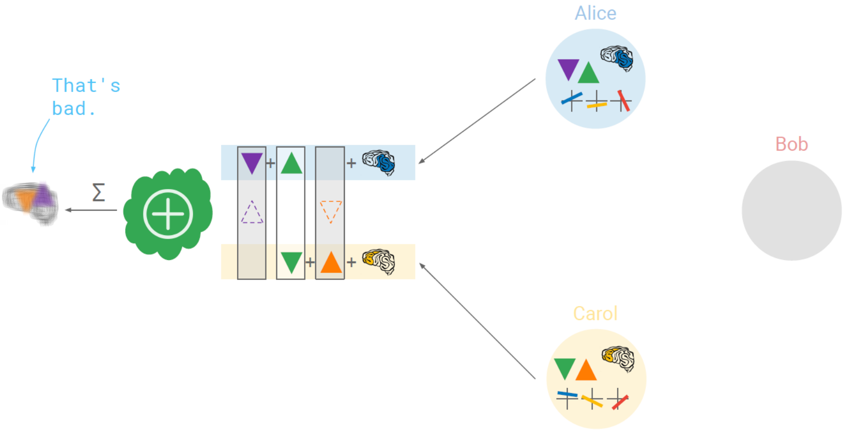

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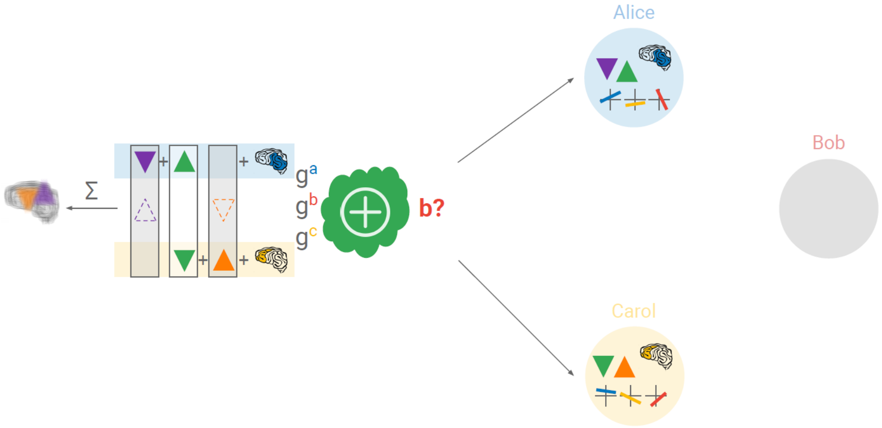

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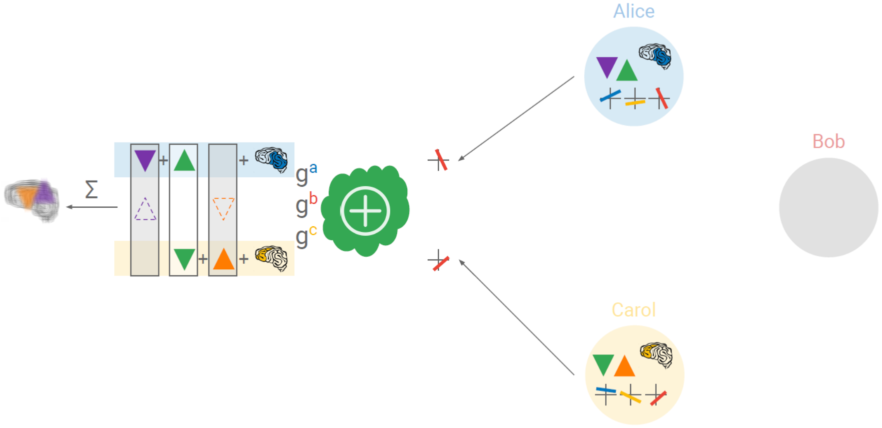

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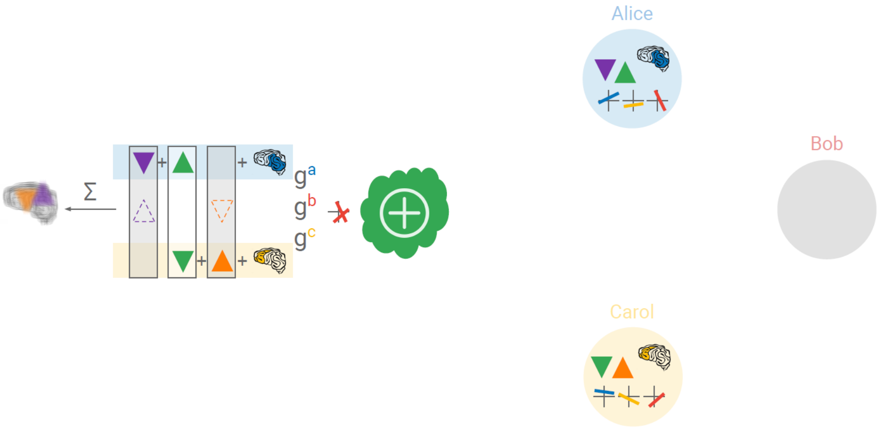

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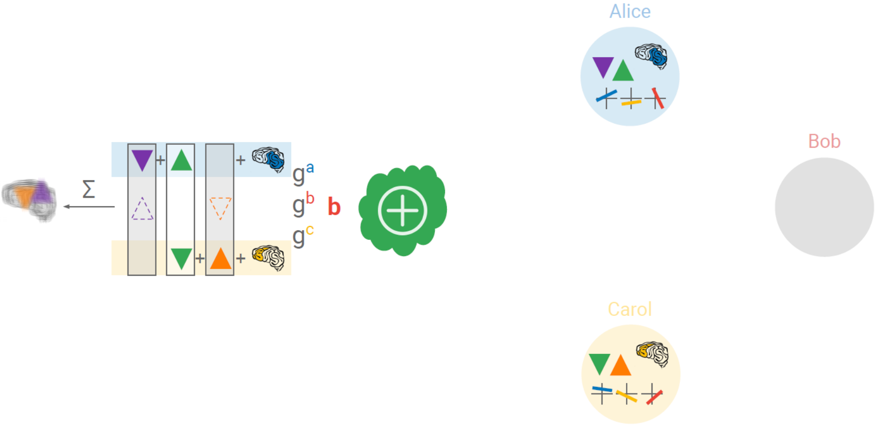

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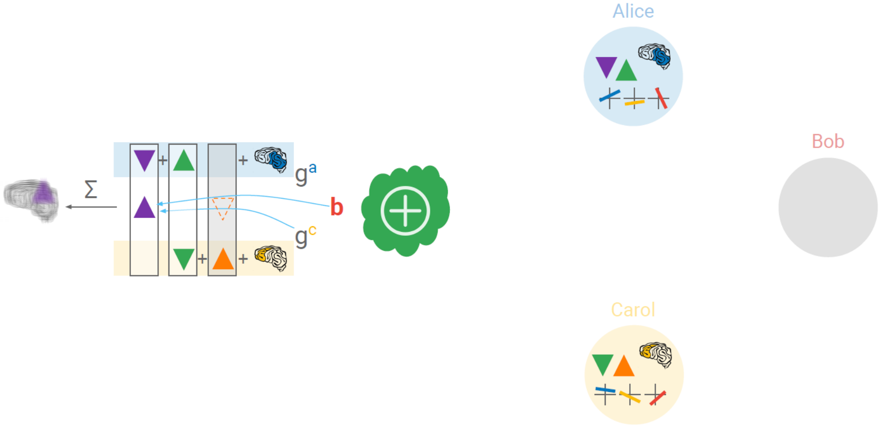

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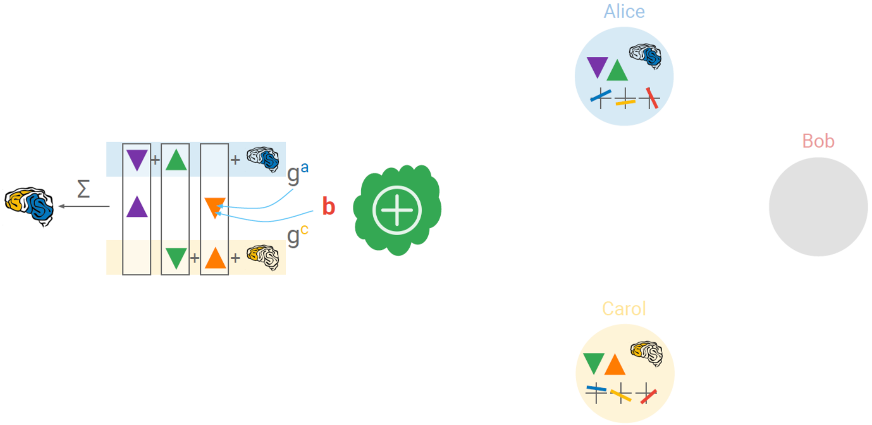

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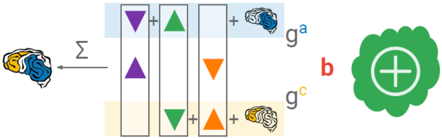
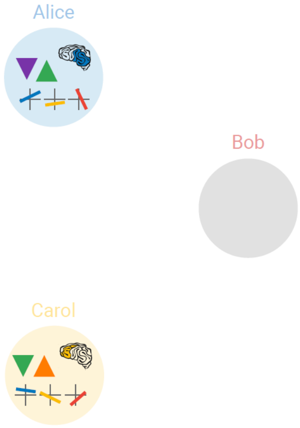


Enough honest users + a high enough threshold
⇒ dishonest users cannot reconstruct the secret.



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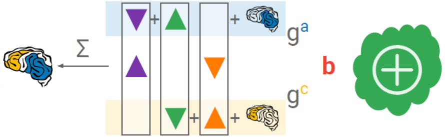

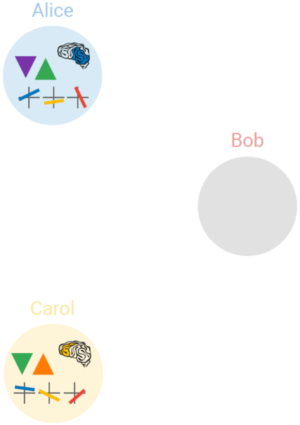

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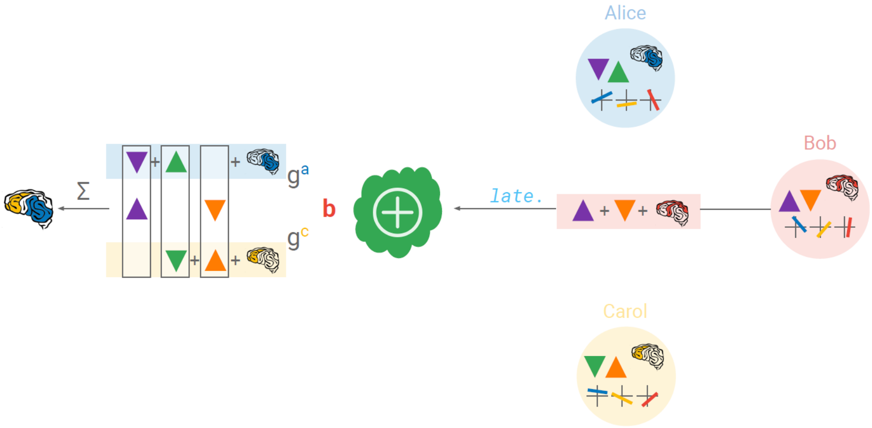
However....

Secure Aggregation Protocol (Addressing Second Problem)

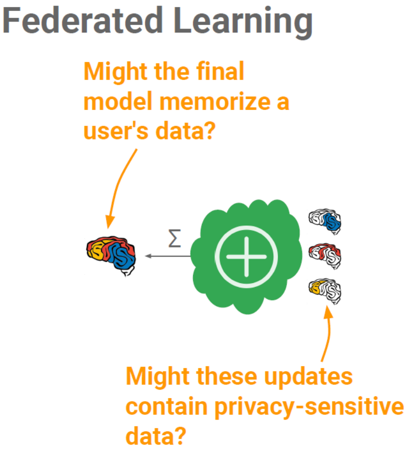


Secure Aggregation Protocol (Addressing Second Problem)

Summary for Secure Aggregation

- Diffie Hellman: Used for efficient keys (secrets) sharing among participants
- k-out-of-n Threshold secret sharing: Used to make the algorithm resilience to the drop out of any participant

Differential Privacy



1. Ephemeral
2. Focused
3. Only in Aggregate
4. **Differential Privacy**

Differential Privacy

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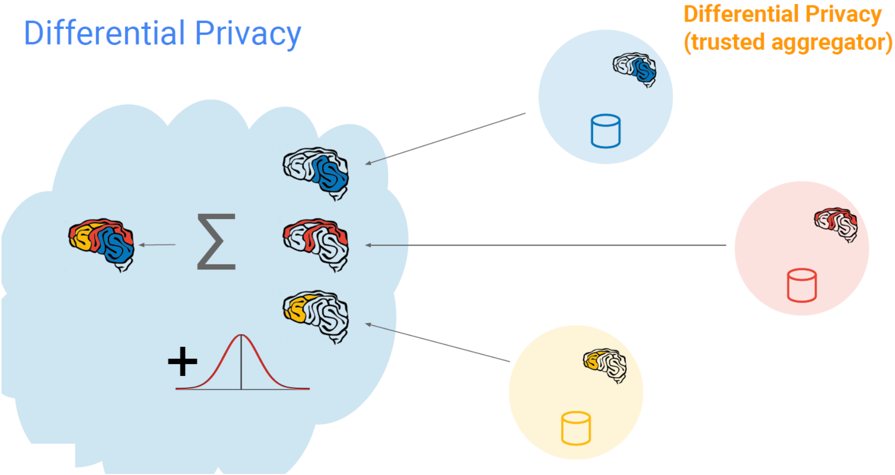
Note

Adding noise should be done with caution. We consider function Sensitivity.

Differential Privacy



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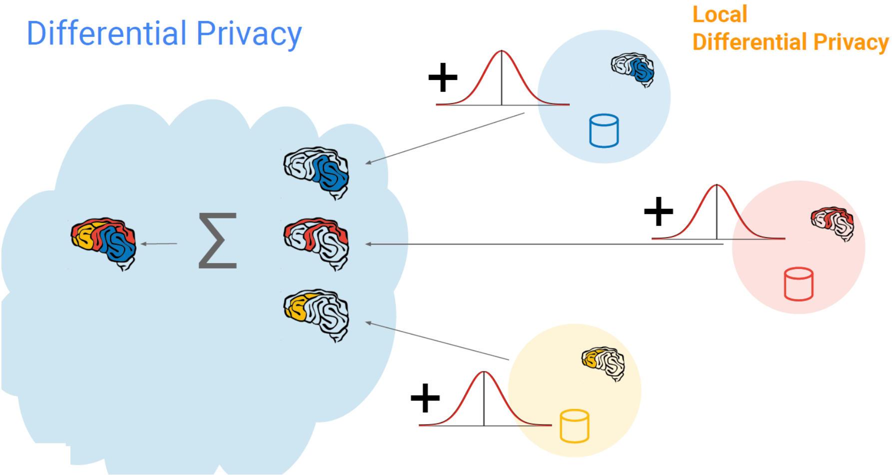

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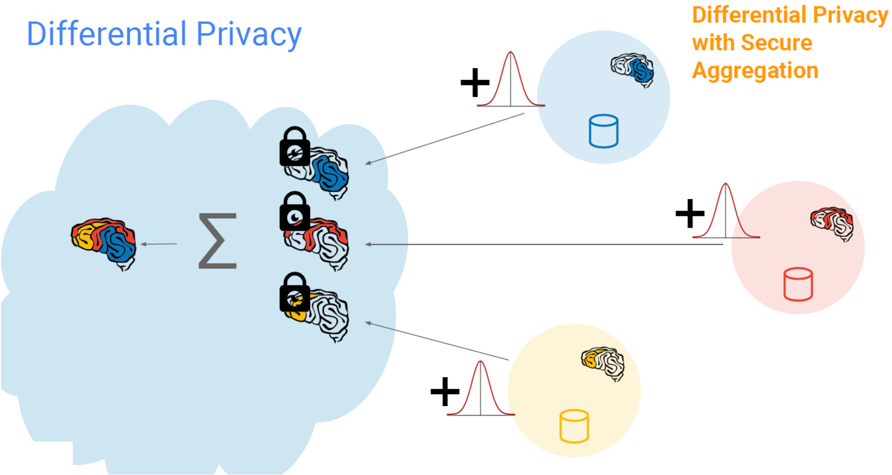


Differentially-Private Federated Averaging[3]

Server

Until Converged:

1. Select a random subset (e.g. C=100) of the (online) clients

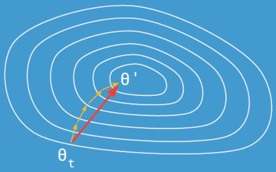
2. In parallel, send current parameters $\boldsymbol{\theta}_t$ to those clients

Selected Client k

1. Receive θ_t from server.

2. Run some number of minibatch SGD steps, producing θ'

3. Return $\theta' - \theta_t$ to server.



3. $\theta_{t+1} = \theta_t$ + data-weighted average of client updates

[3] McMahan, Ramage, Talwar, Zhang. Learning Differentially Private Recurrent Language Models.

Differentially-Private Federated Averaging[3]

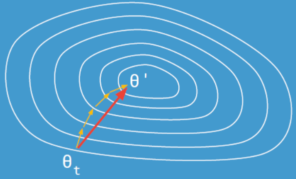
Server

Until Converged:

1. Select each user **independently** with **probability q**, for say E[C]=1000 clients
2. In parallel, send current parameters $\boldsymbol{\theta_t}$ to those clients

Selected Client k

1. Receive θ_t from server.
2. Run some number of minibatch SGD steps, producing θ'
3. Return **Clip(θ'-$\boldsymbol{\theta_t}$)** to server.



3. $\theta_{t+1} = \theta_t$ + **bounded sensitivity** data-weighted average of client updates + Gaussian noise **N(0, I$\boldsymbol{\sigma^2}$)**

[3] McMahan, Ramage, Talwar, Zhang. Learning Differentially Private Recurrent Language Models.

References

- Jakub Konecny, Federated Learning Privacy-Preserving Collaborative Machine Learning without Centralized Training Data
- H. B. McMahan, et al. Communication-Efficient Learning of Deep Networks from Decentralized Data. AISTATS 2017
- K. Bonawitz, V. Ivanov, B. Kreuter, A. Marcedone, H. B. McMahan, S. Patel, D. Ramage, A. Segal, K. Seth. Practical Secure Aggregation for Privacy-Preserving Machine Learning, CCS 2017.

Questions