Guarding user Privacy with Federated Learning and Differential Privacy

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2017.10.24

Federated Learning

Our Goal

Imbue **mobile devices** with **state of the art machine learning** systems **without centralizing data** and **with privacy** by default.

Federated Learning

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A very *personal* computer

```
2015: 79% away from phone ≤2 hours/day[1]
      63% away from phone ≤1 hour/day
      25% can't remember being away at all

2013: 72% of users within 5 feet of
          phone most of the time[2].
```

Plethora of sensors

Innumerable digital interactions

[1] 2015 Always Connected Research Report, IDC and Facebook
[2] 2013 Mobile Consumer Habits Study, Jumio and Harris Interactive.

Federated Learning

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Deep Learning

non-convex

millions of parameters

complex structure (eg LSTMs)

Federated Learning

Our Goal

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Distributed learning problem

Horizontally partitioned

Nodes: millions to billions

Dimensions: thousands to millions

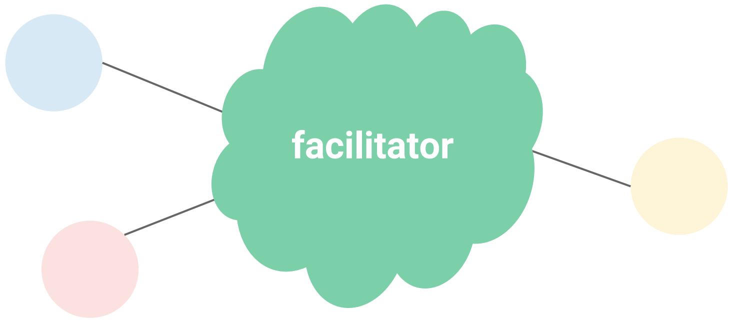
Examples: millions to billions

Federated Learning

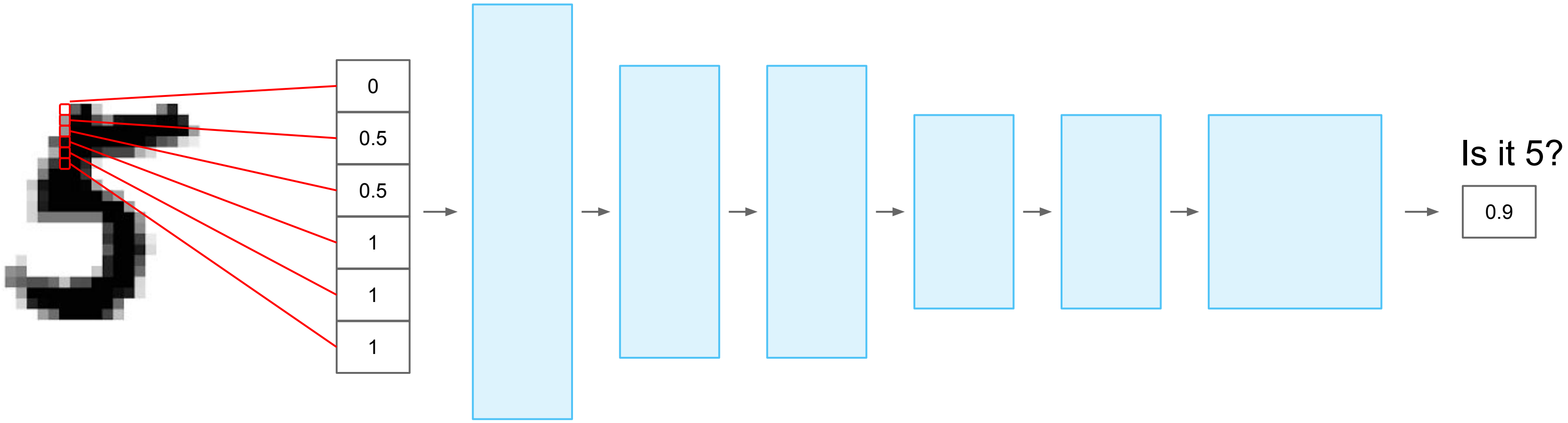
Our Goal

Imbue **mobile devices** with **state of the art machine learning** systems **without centralizing data** and **with privacy** by default.

Federated decentralization

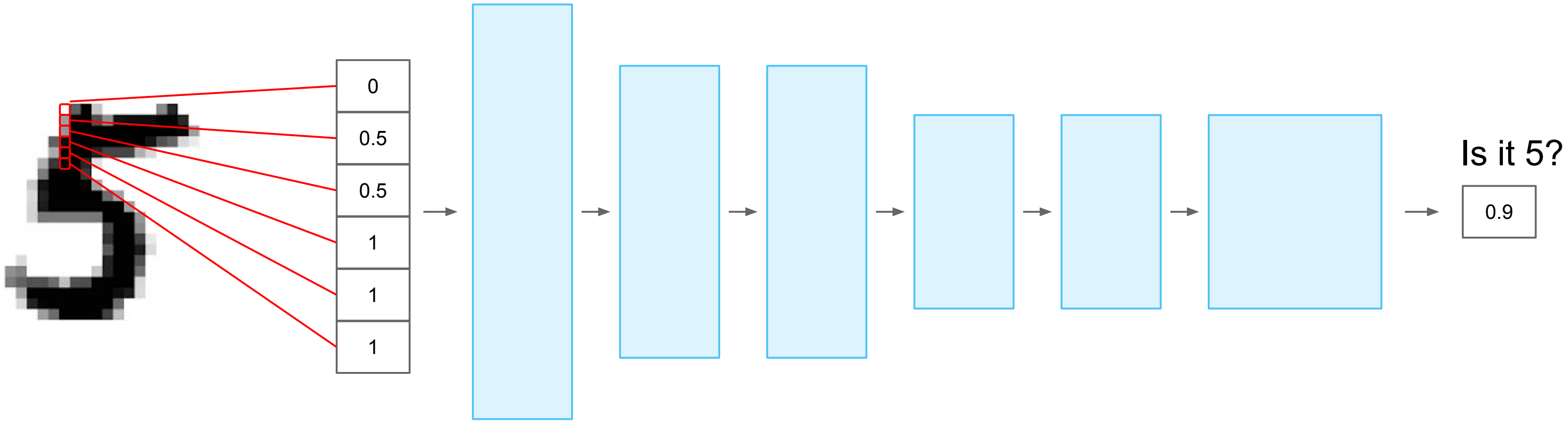


Deep Learning, the short short version



f(input, parameters) = output

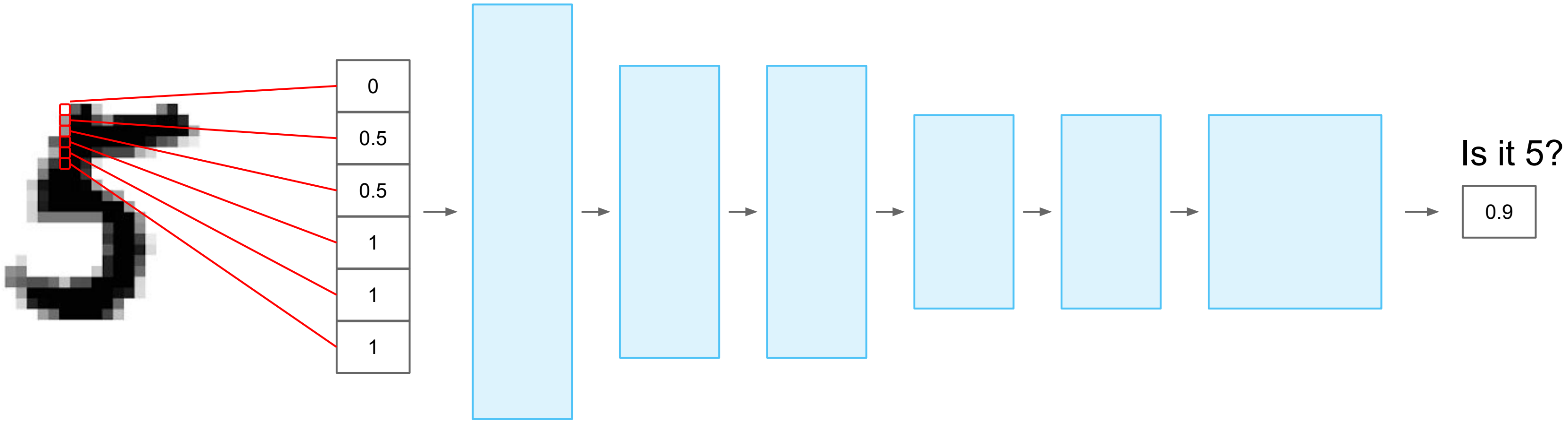
Deep Learning, the short short version



$\mathbf{f}$(input, parameters) = output

$\mathbf{loss}$(parameters) = $1/n \sum_i$ difference($\mathbf{f}$(input_i, parameters), desired_i)

Deep Learning, the short short version



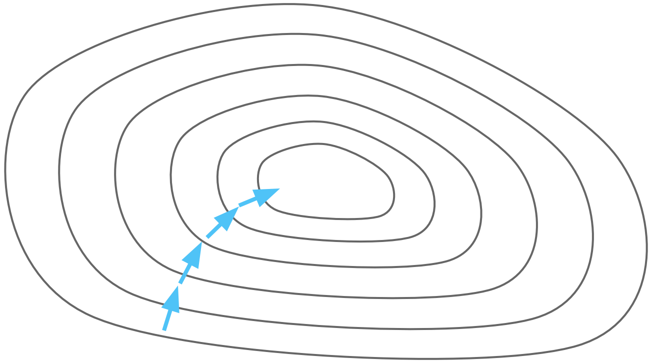
Adjust these

$$\mathbf{f}(\text{input}, \text{parameters}) = \text{output}$$

$$\mathbf{loss}(\text{parameters}) = 1/n \sum_i \text{difference}(\mathbf{f}(\text{input}_i, \text{parameters}), \text{desired}_i)$$

to minimize this

Deep Learning, the short short version



Stochastic Choose a random subset of training data

Gradient Compute the "down" direction on the loss function

Descent Take a step in that direction

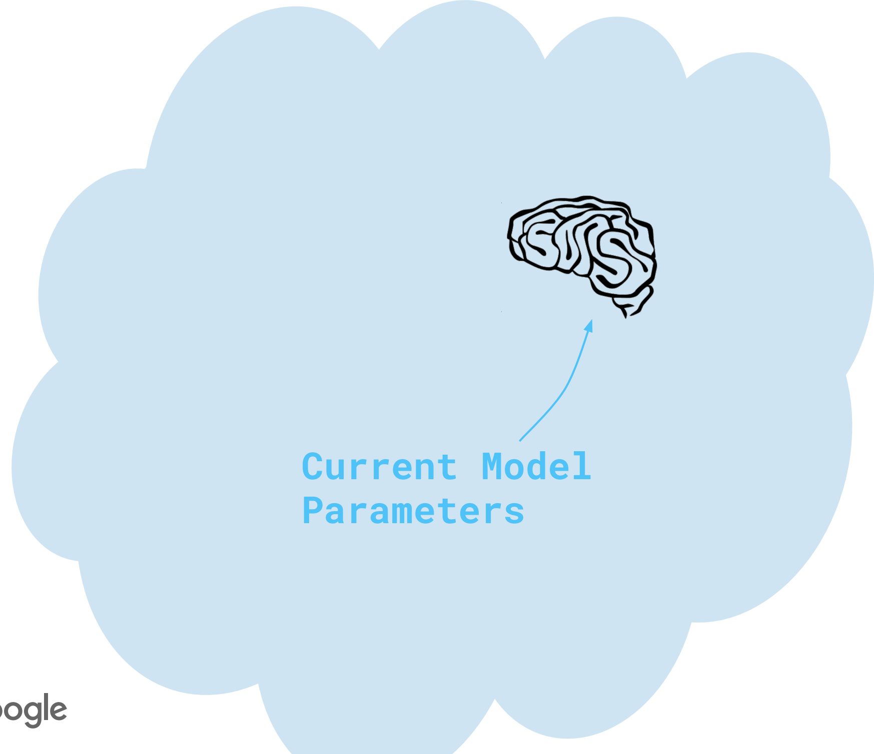
(Rinse & repeat)

$$\mathbf{f}(\text{input}, \text{parameters}) = \text{output}$$

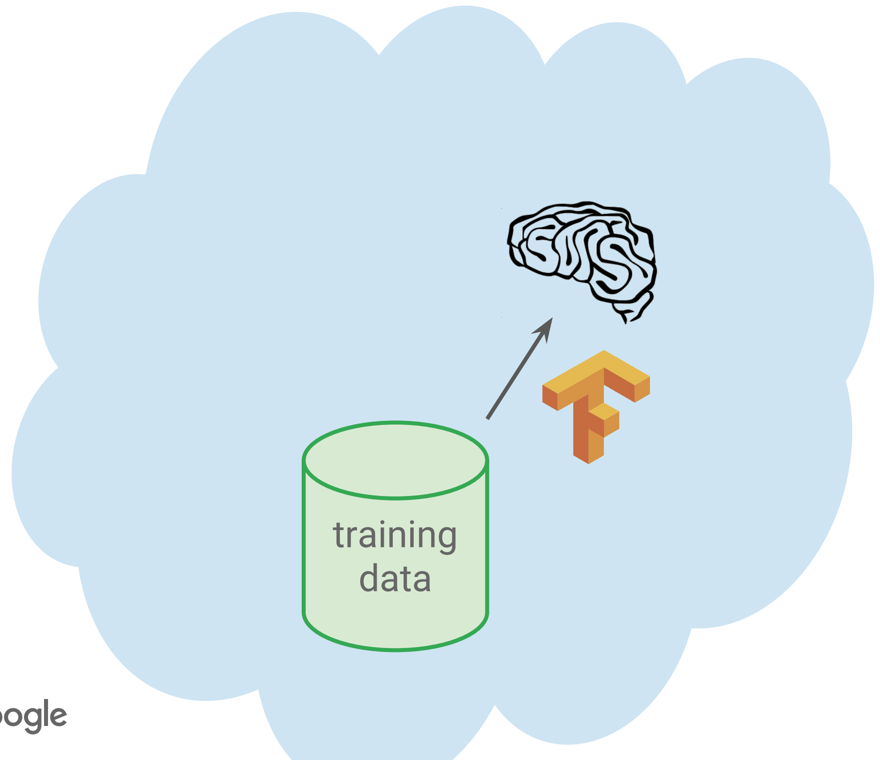
$$\mathbf{loss}(\text{parameters}) = 1/n \sum_i \text{difference}(\mathbf{f}(\text{input}_i, \text{parameters}), \text{desired}_i)$$

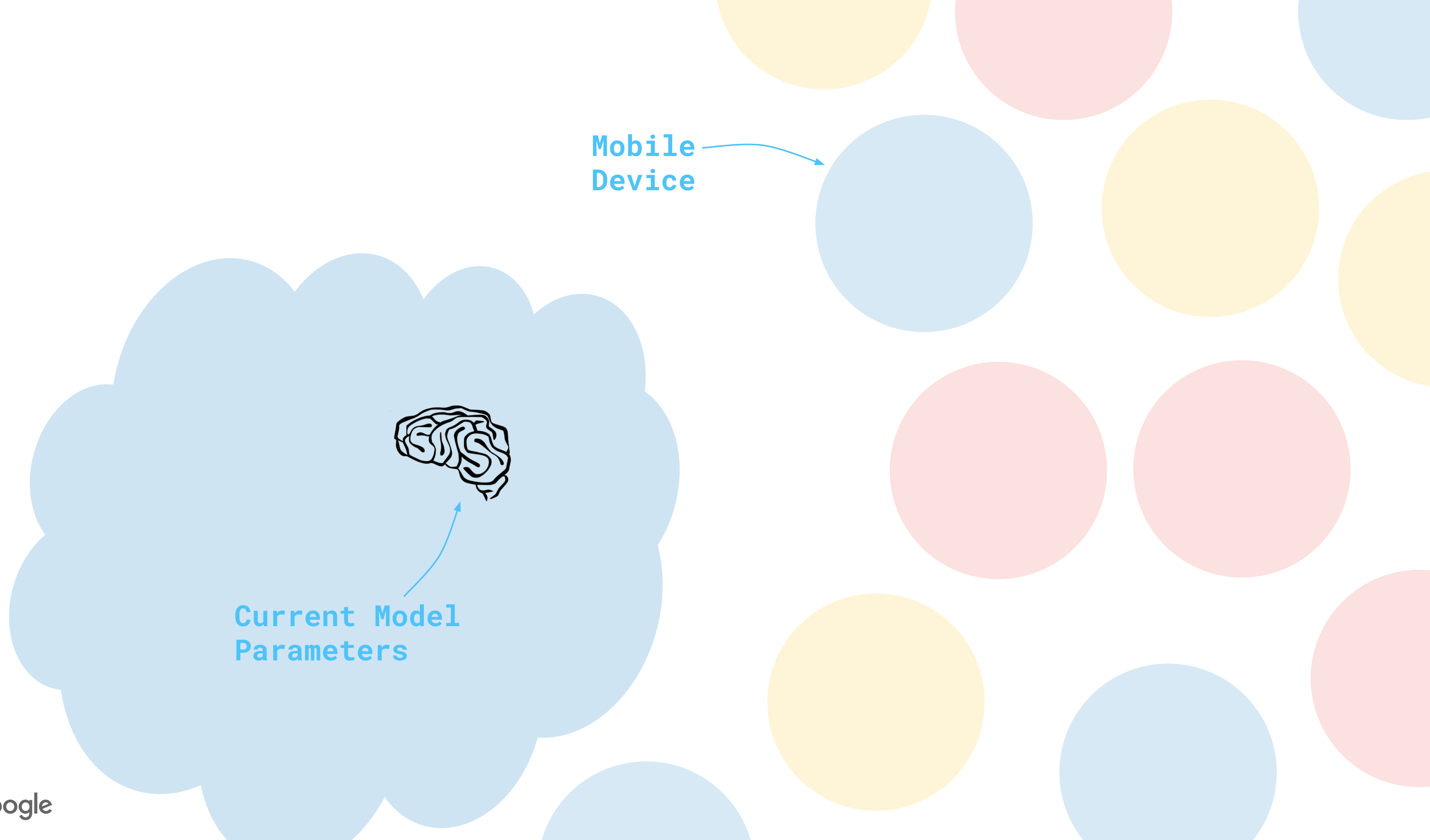
Cloud-centric ML for Mobile

The model lives in the cloud.

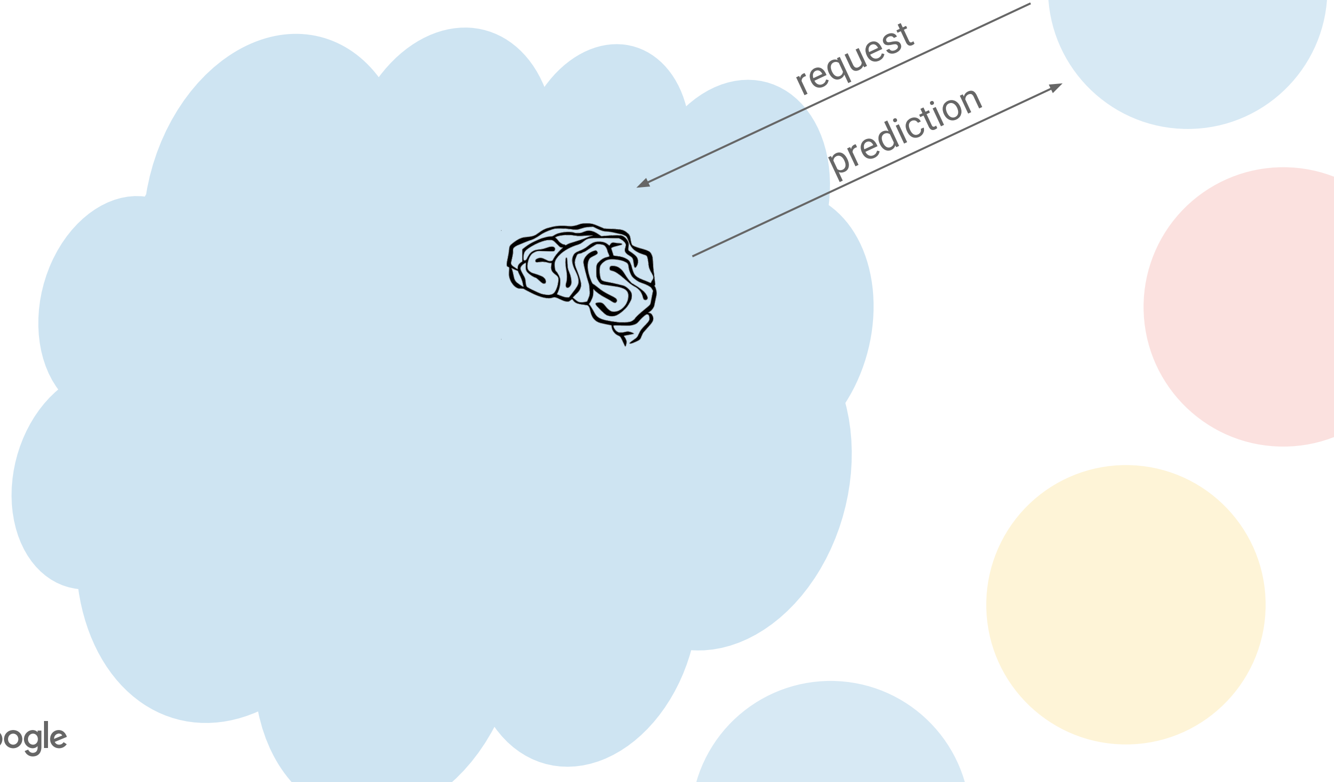


We train models in the cloud.

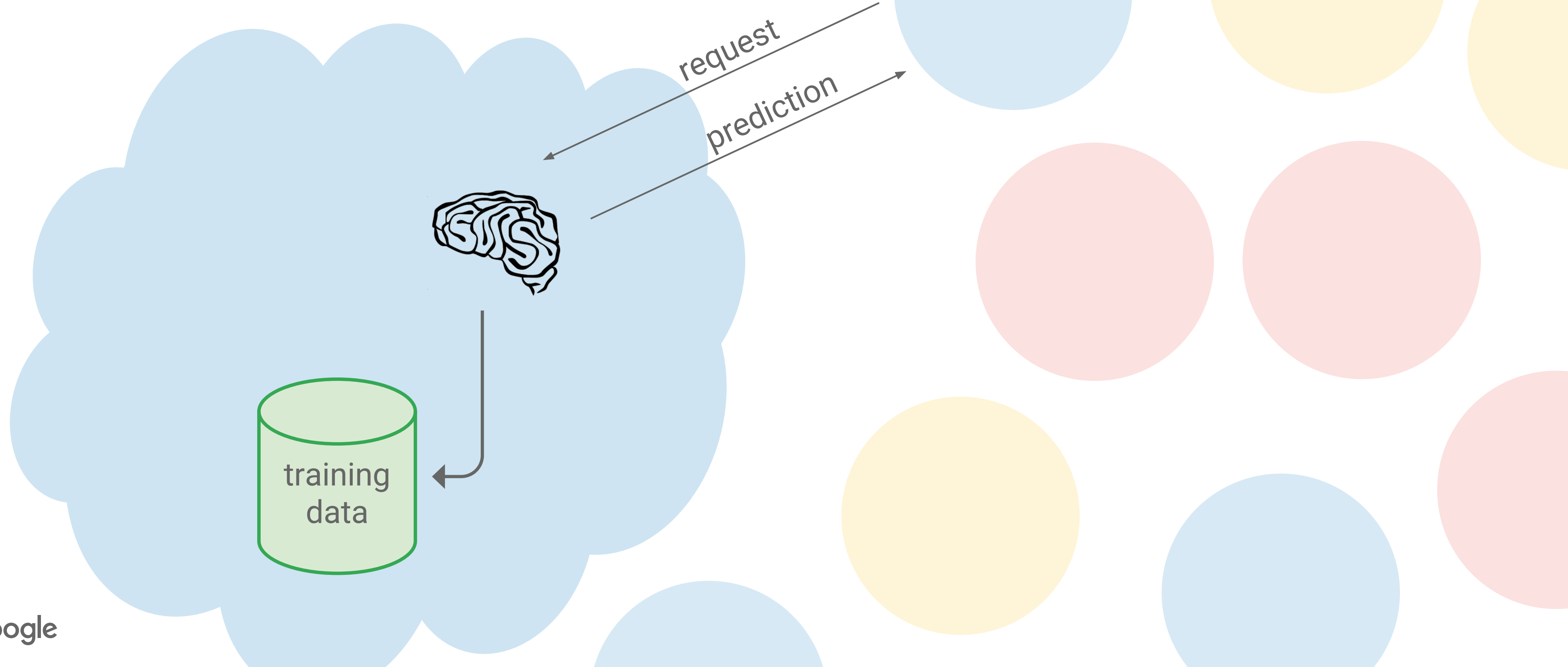



Mobile
Device
Current Model
Parameters

Make predictions in the cloud.

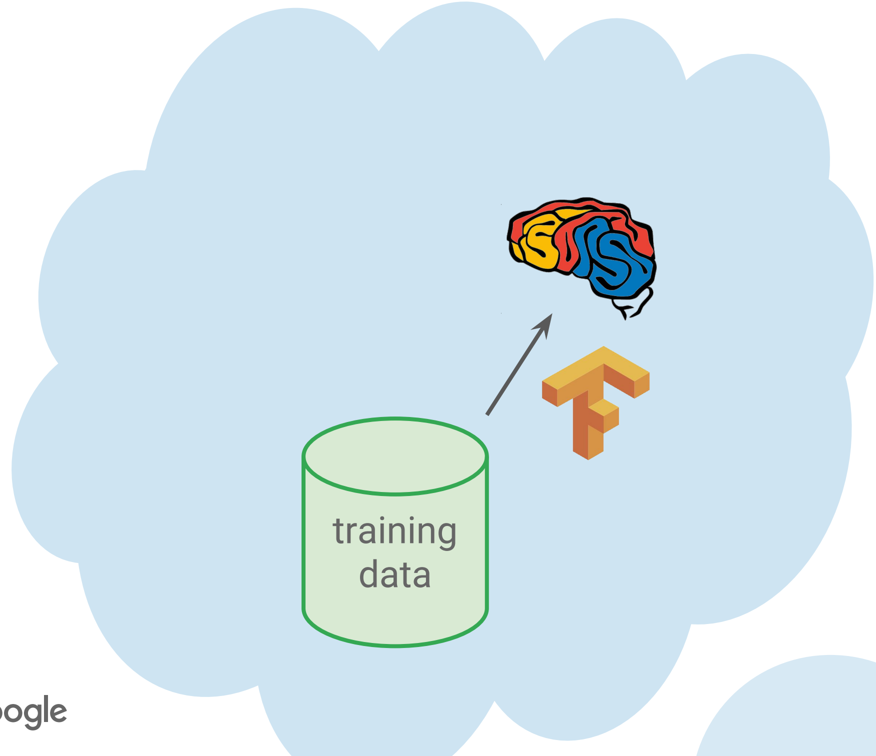


Gather training data in the cloud.



Google

And make the models better.

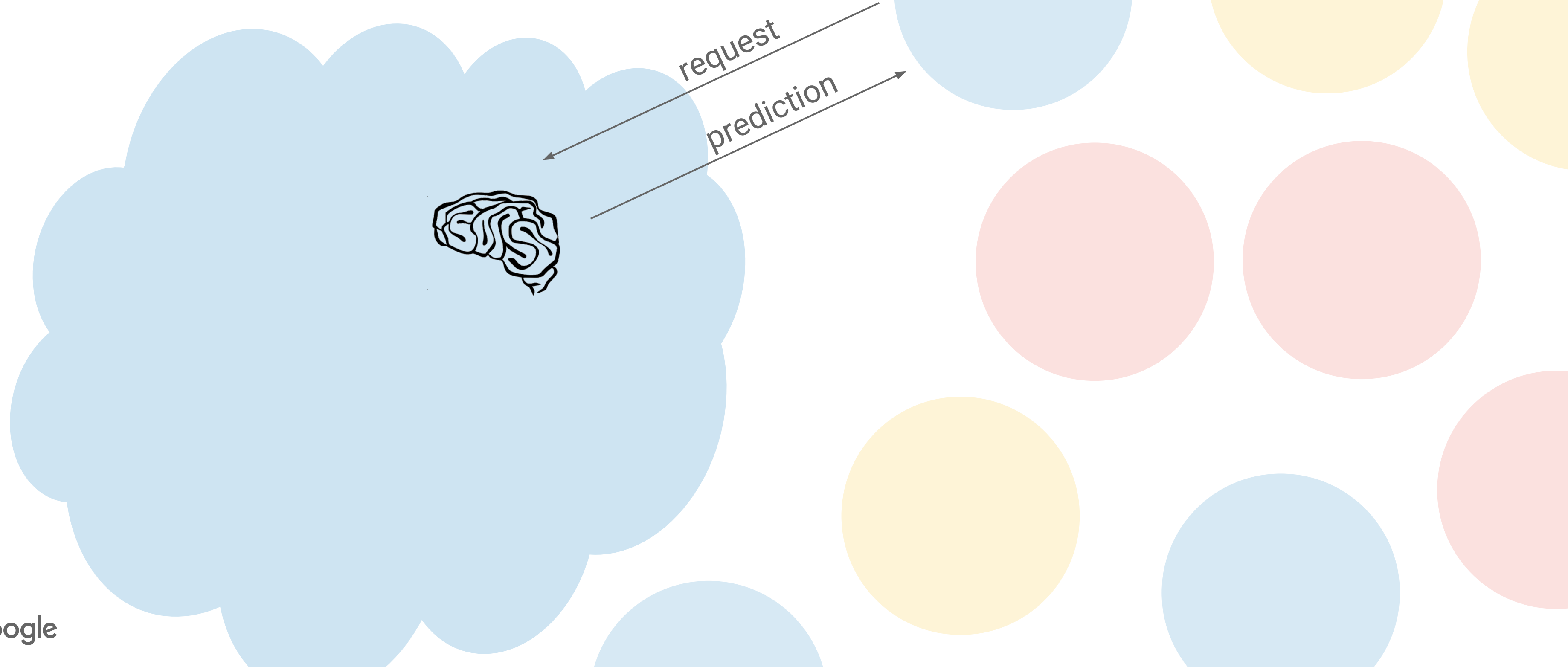


Google

On-Device **Predictions**
(Inference)

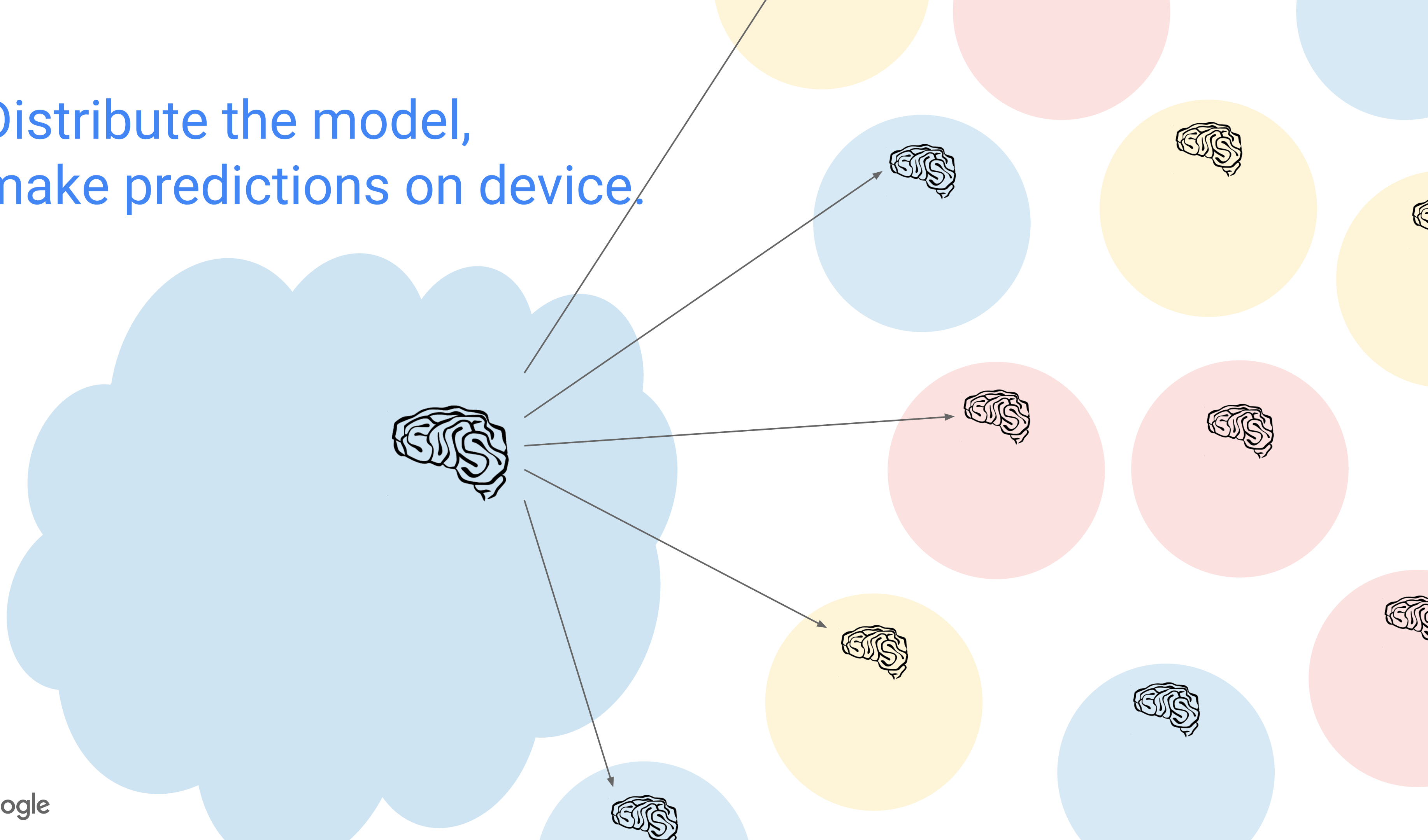
Google

Instead of making predictions in the cloud



Google

Distribute the model, make predictions on device.



On-device inference

User Advantages

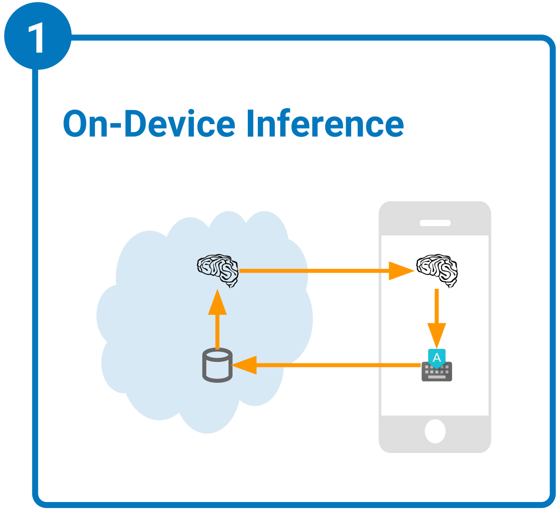
- Low latency
- Longer battery life
- Less wireless data transfer
- Better offline experience
- Less data sent to the cloud

Developer Advantages

- Data is already localized
- New product opportunities

World Advantages

- Raise privacy expectations for the industry



On-device training

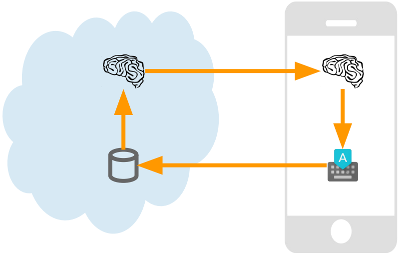
User Advantages

- Low latency
- Longer battery life
- Less wireless data transfer
- Better offline experience
- **Less data sent to the cloud (training data stays on device)**

Bringing
model training
onto mobile devices.

1

On-Device Inference



Developer Advantages

- Data is already localized
- **New product opportunities**
- **Straightforward personalization**
- **Simple access to rich user context**

World Advantages

- **Raise privacy expectations for the industry**

On-device training

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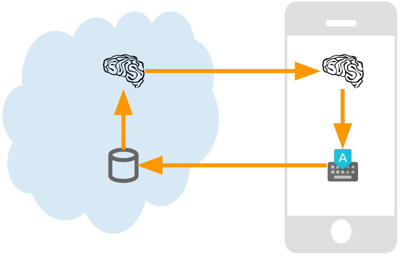
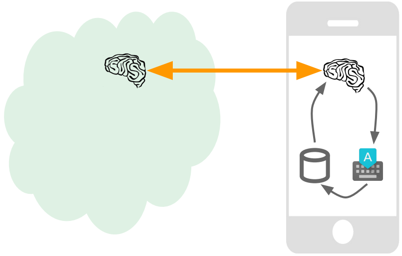
1

On-Device Inference



2

Federated Learning

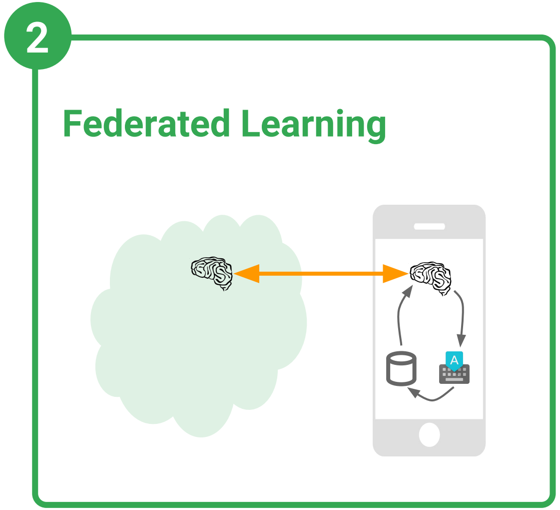


Google

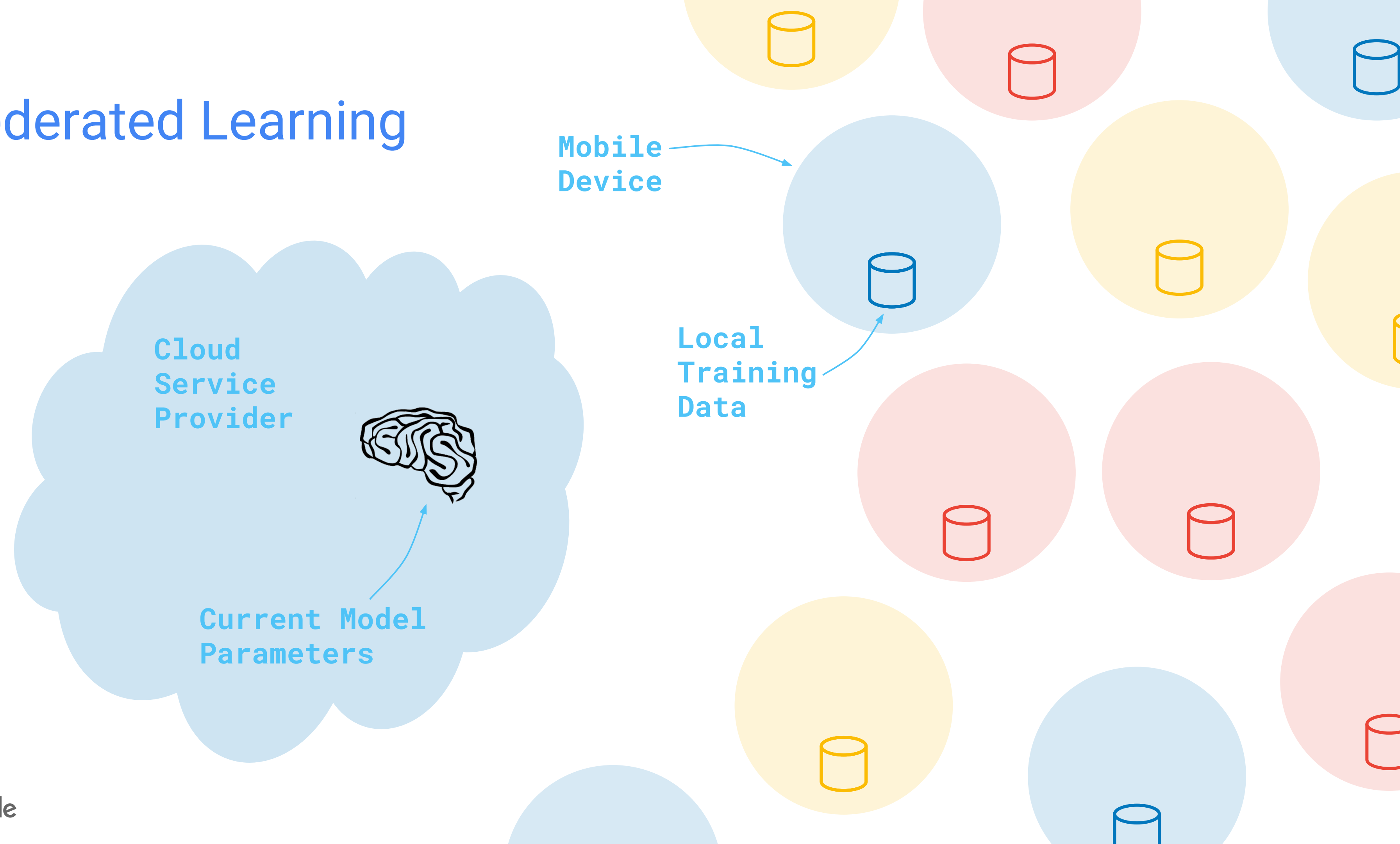
Federated Learning

Federated Learning

Federated Learning is the problem of training a shared global model under the coordination of a central server, from a federation of participating devices which maintain control of their own data.

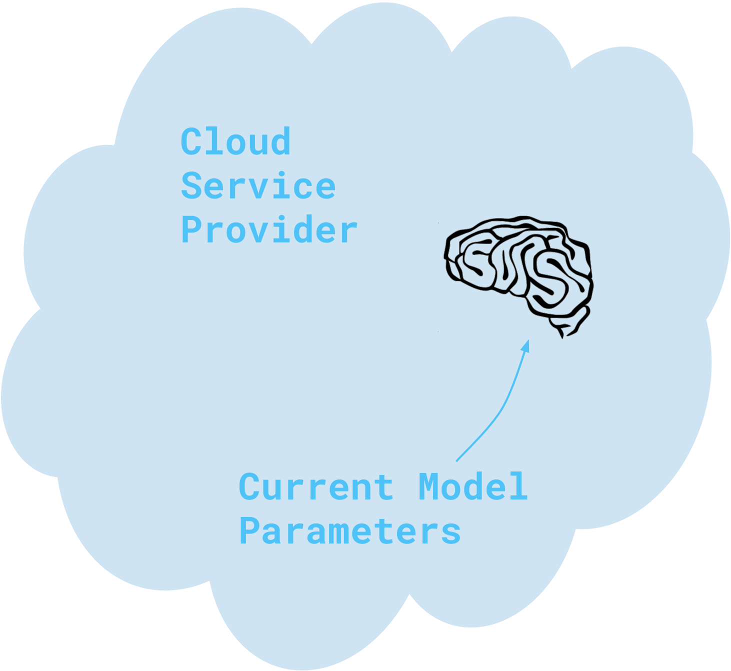


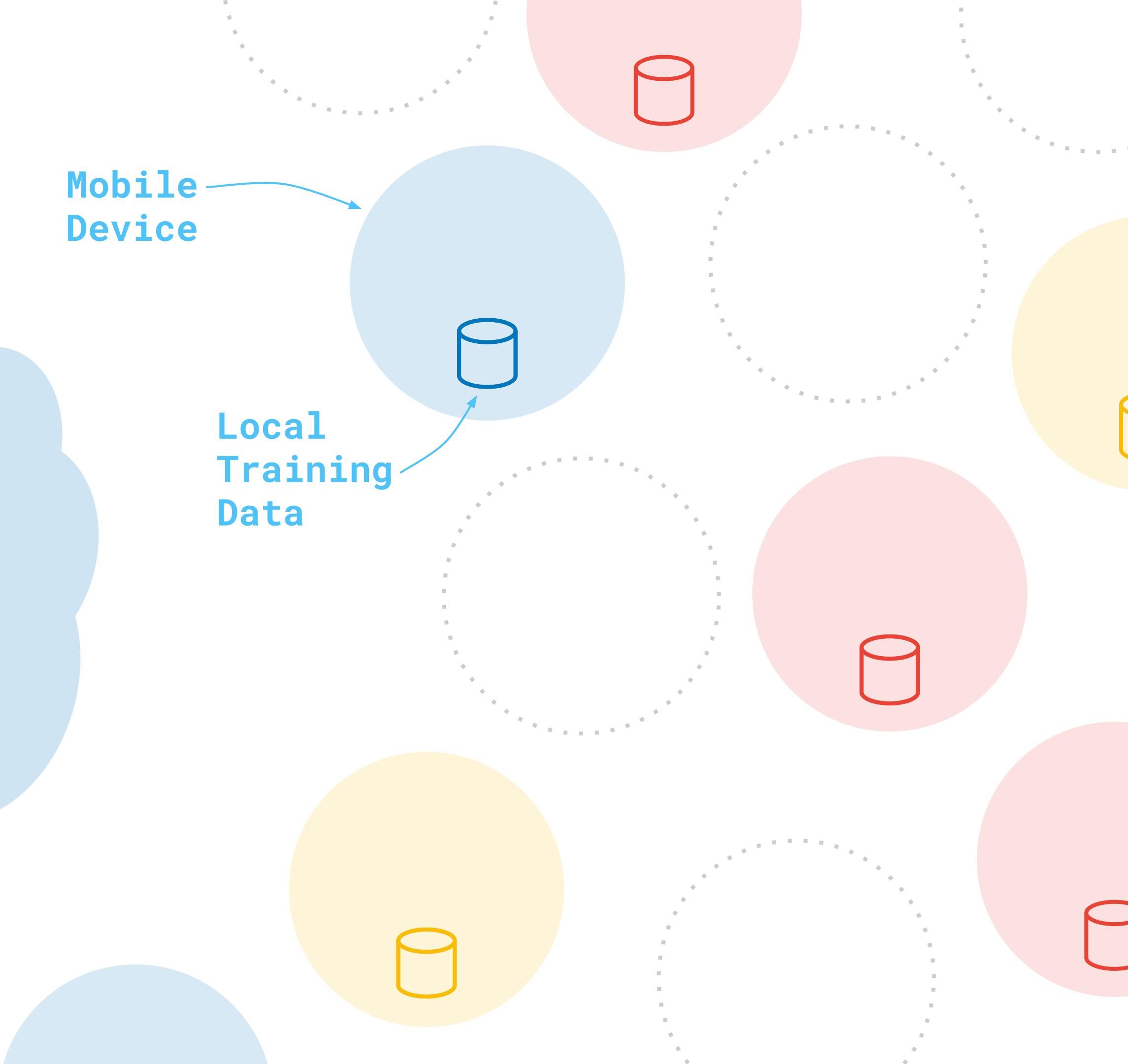
Federated Learning



Federated Learning

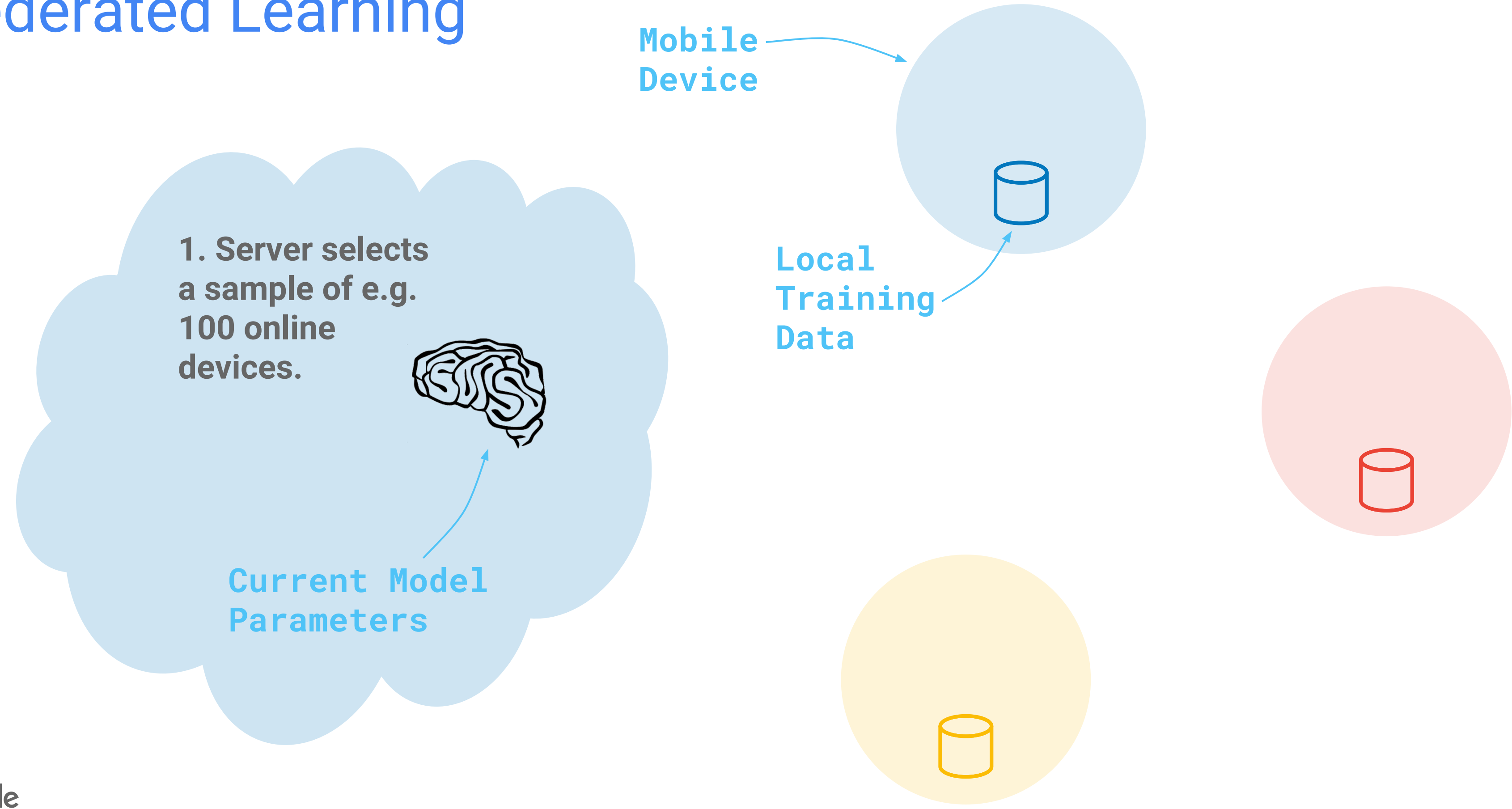
Many devices will be offline.



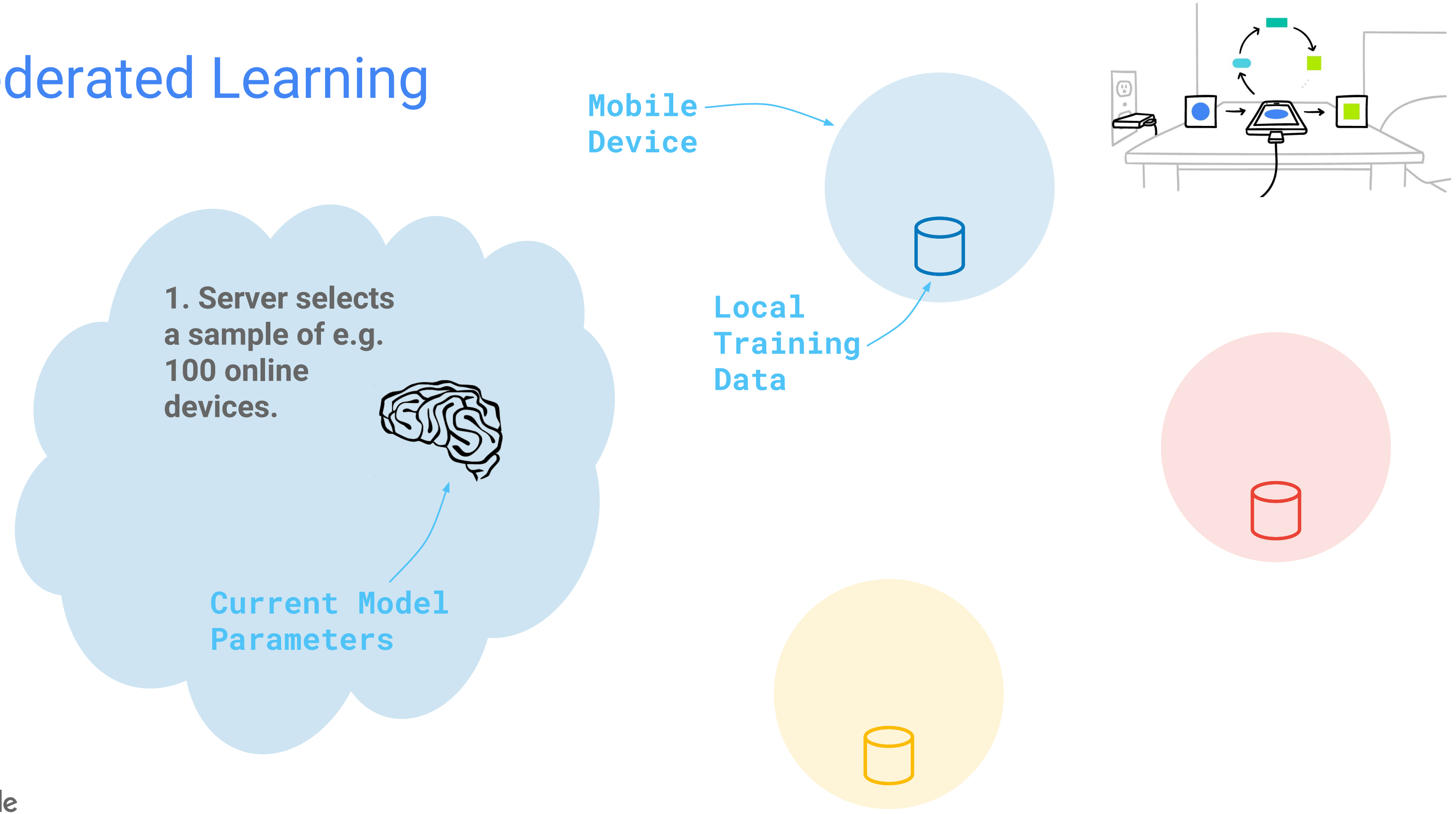


Google

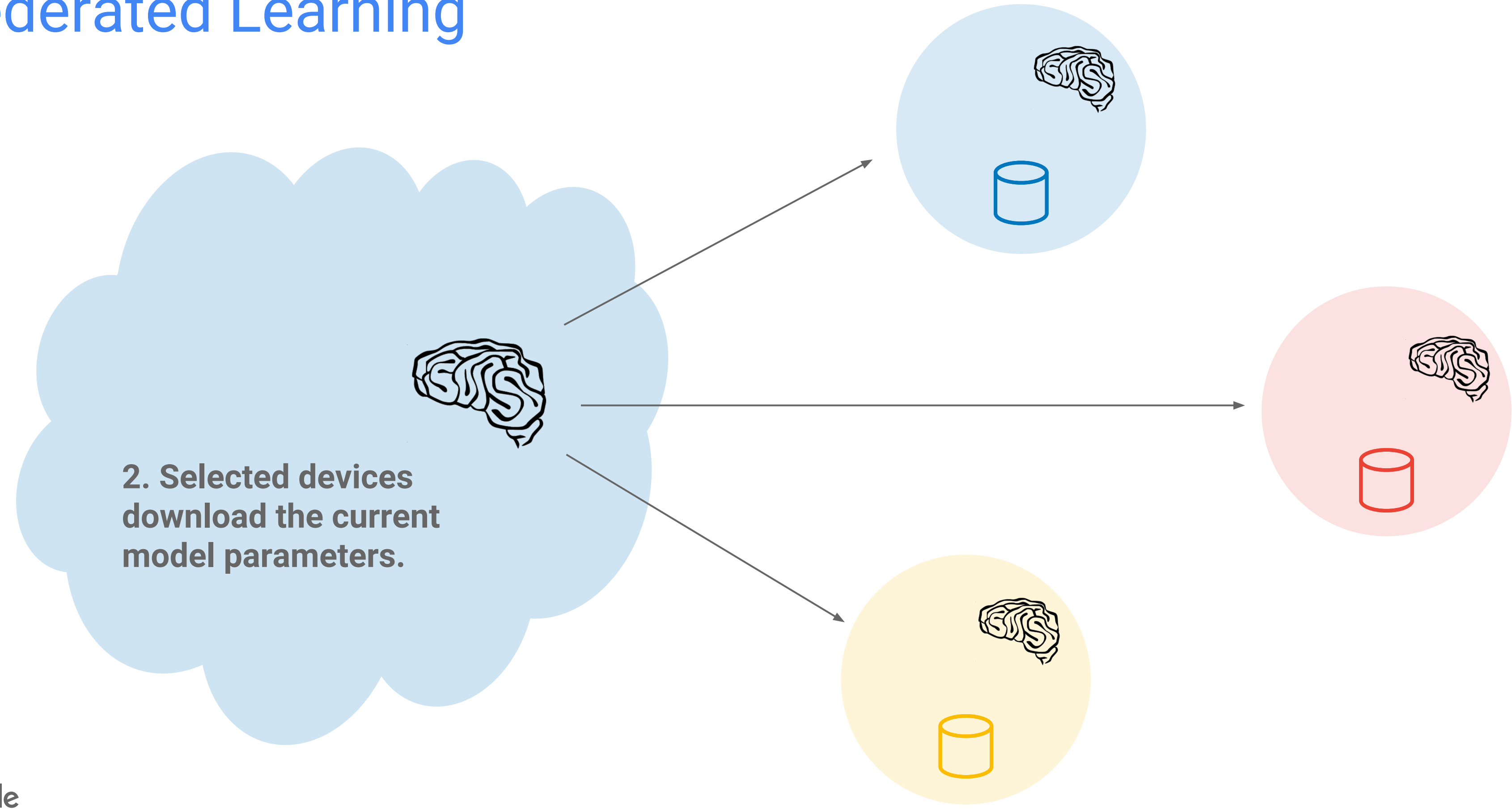
Federated Learning



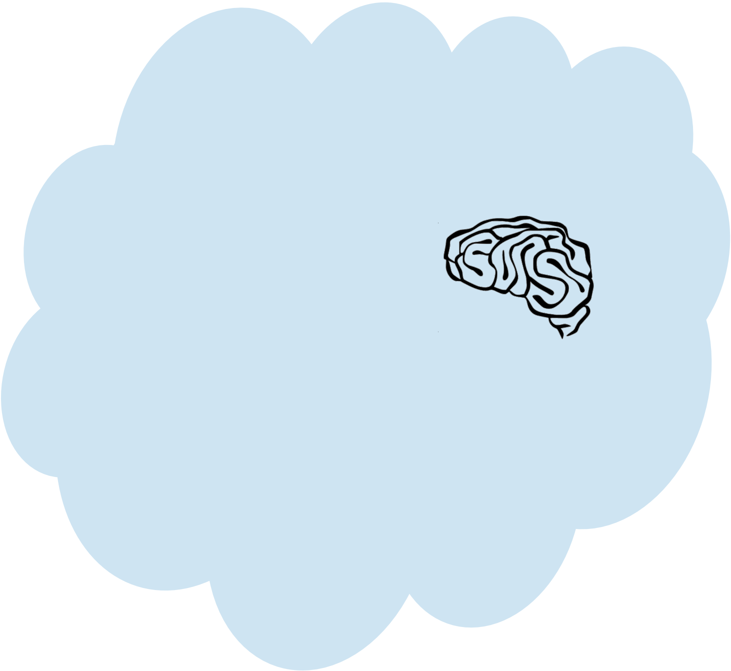
Federated Learning



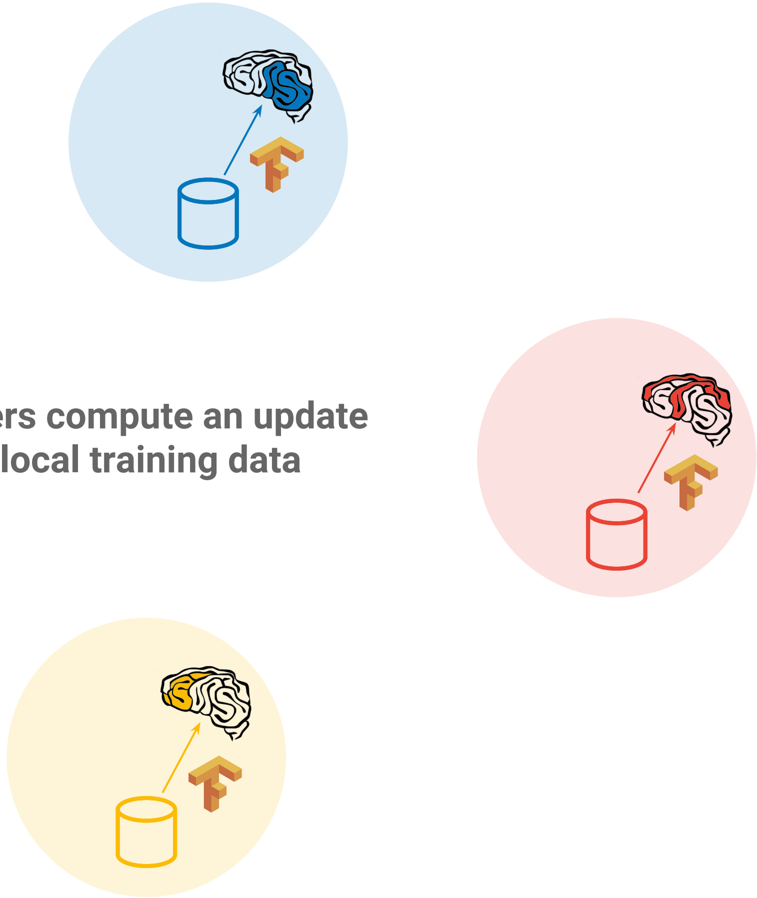
Federated Learning



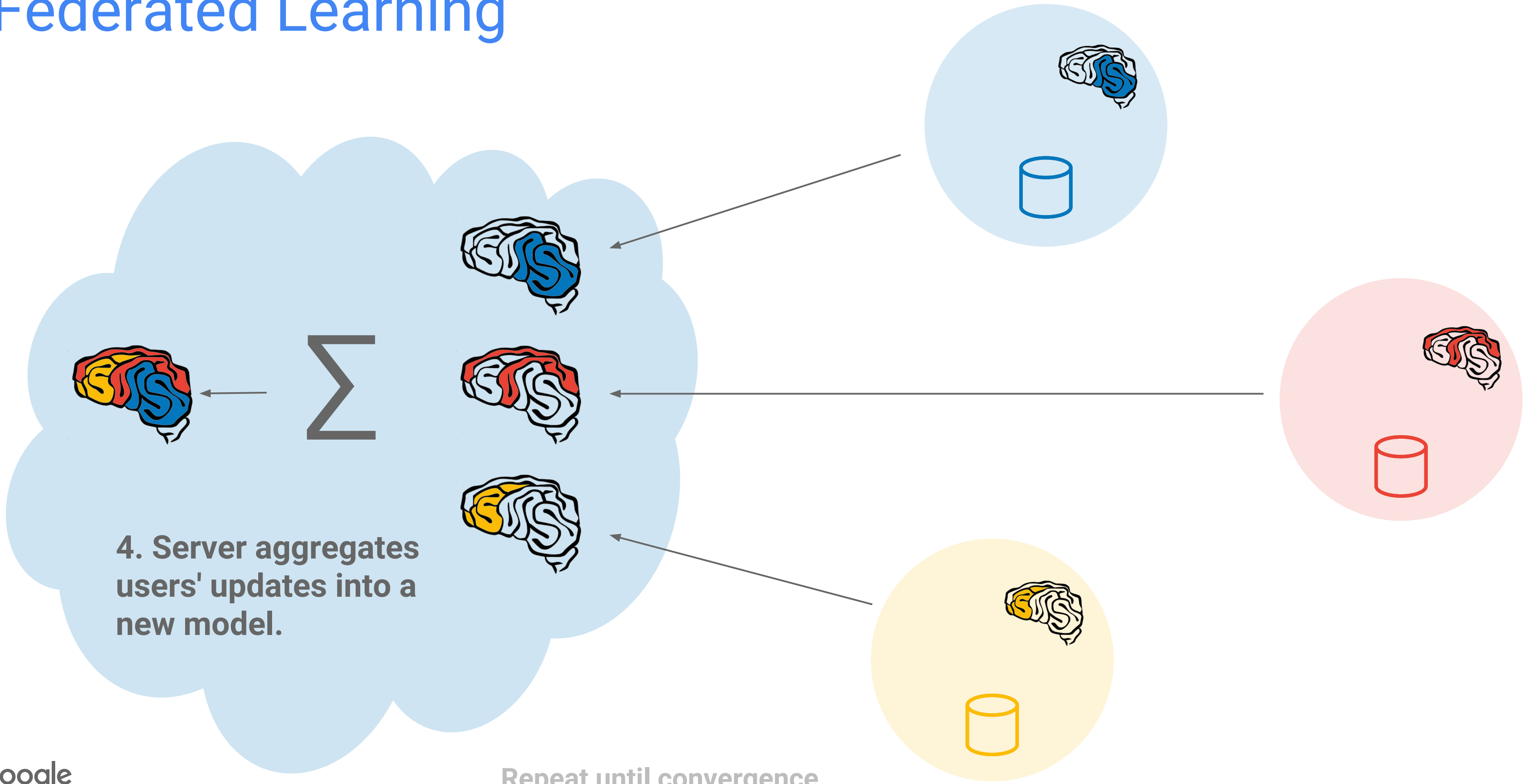
Federated Learning



3. Users compute an update using local training data



Federated Learning



Repeat until convergence.

Applications of federating learning

What makes a good application?

- On-device data is more relevant than server-side proxy data
- On-device data is privacy sensitive or large
- Labels can be inferred naturally from user interaction

Example applications

- Language modeling (e.g., next word prediction) for mobile keyboards
- Image classification for predicting which photos people will share
- ...

Challenges of Federated Learning

… or, why this isn't just "standard" distributed optimization

Massively Distributed

Training data is stored across a very large number of devices

Limited Communication

Only a handful of rounds of unreliable communication with each devices

Unbalanced Data

Some devices have few examples, some have orders of magnitude more

Highly Non-IID Data

Data on each device reflects one individual's usage pattern

Unreliable Compute Nodes

Devices go offline unexpectedly; expect faults and adversaries

Dynamic Data Availability

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

The Federated Averaging algorithm

Server

Until Converged:

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

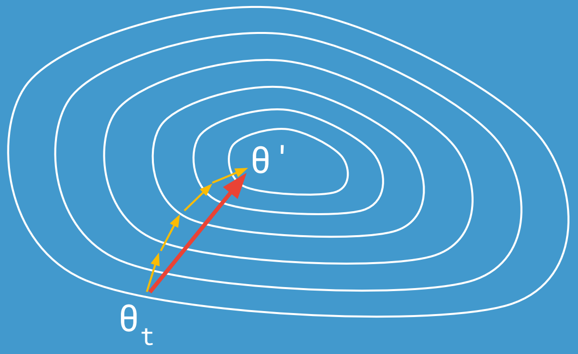
2. In parallel, send current parameters $\boldsymbol{\theta}_t$ to those clients

Selected Client k

1. Receive θ_t from server.

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

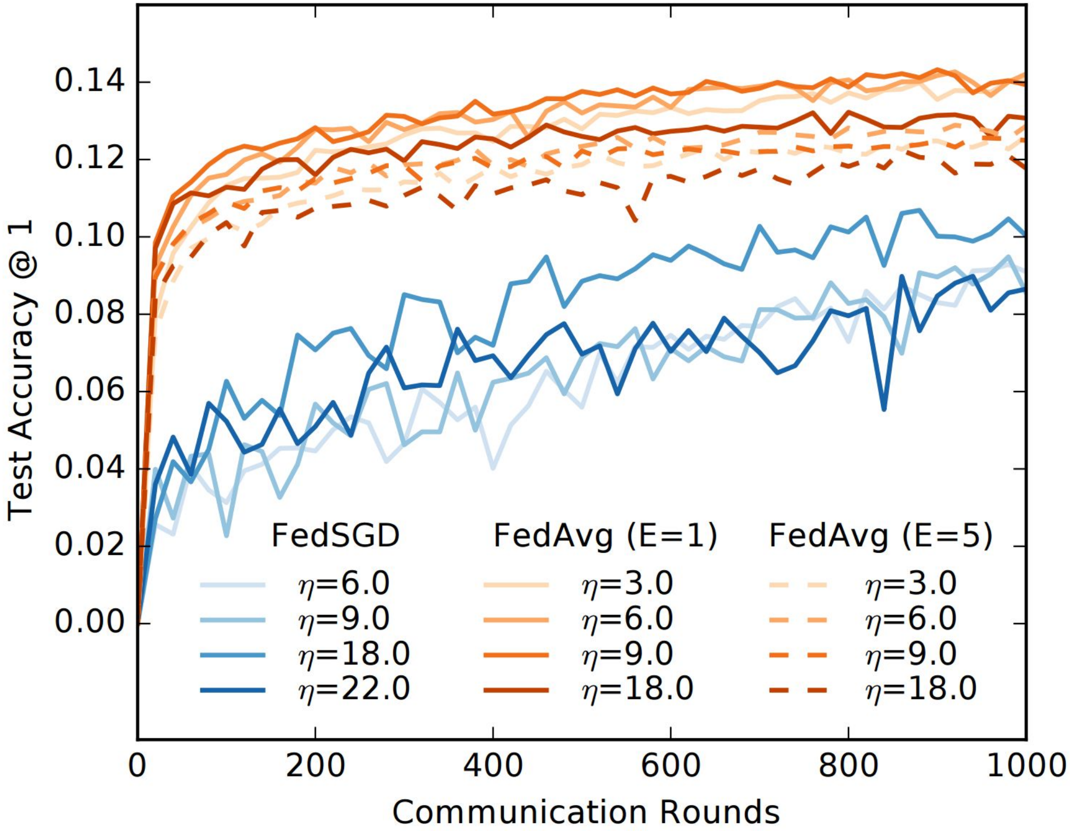
3. Return $\theta' - \theta_t$ to server.



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

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

Large-scale LSTM for next-word prediction



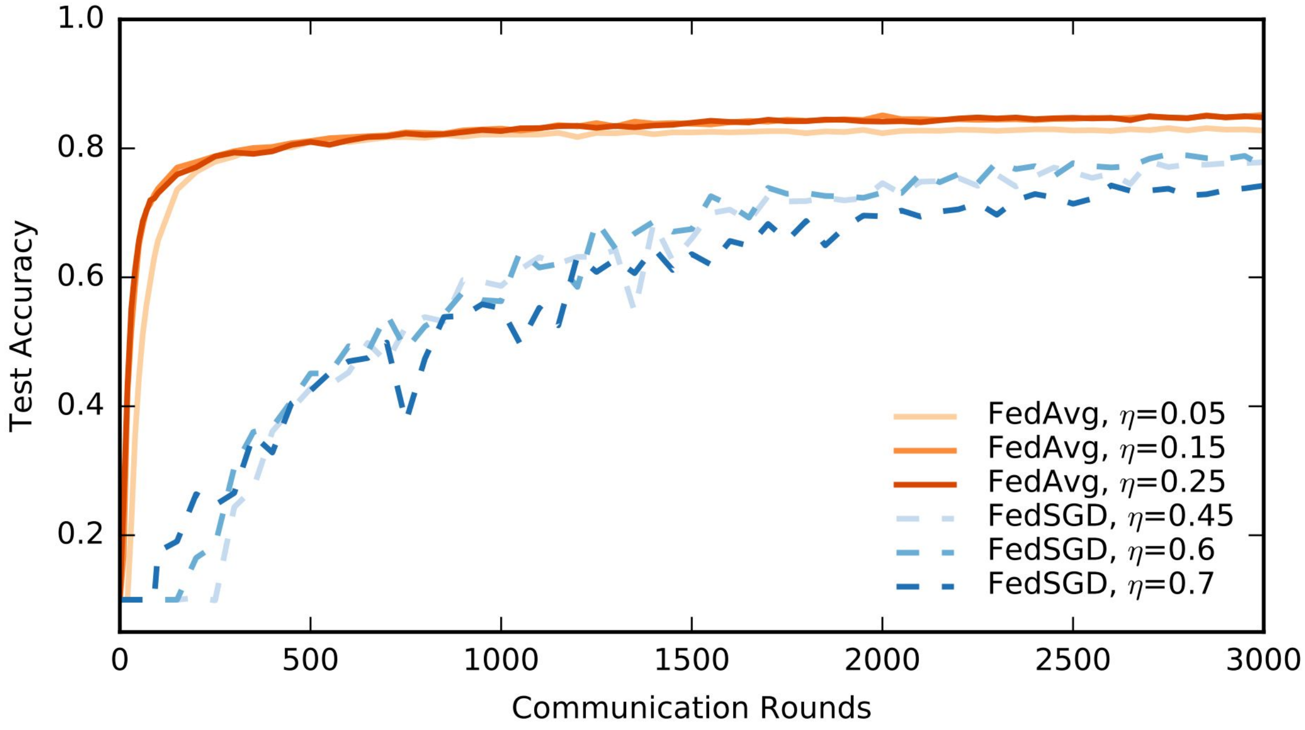
Rounds to reach 10.5% Accuracy

FedSGD	820
FedAvg	35

23x **decrease in communication rounds**

Model Details
1.35M parameters
10K word dictionary
embeddings $\in\mathbb{R}^{96}$, state $\in\mathbb{R}^{256}$
corpus: Reddit posts, by author

CIFAR-10 convolutional model



Updates to reach 82%

SGD	31,000
FedSGD	6,600
FedAvg	630

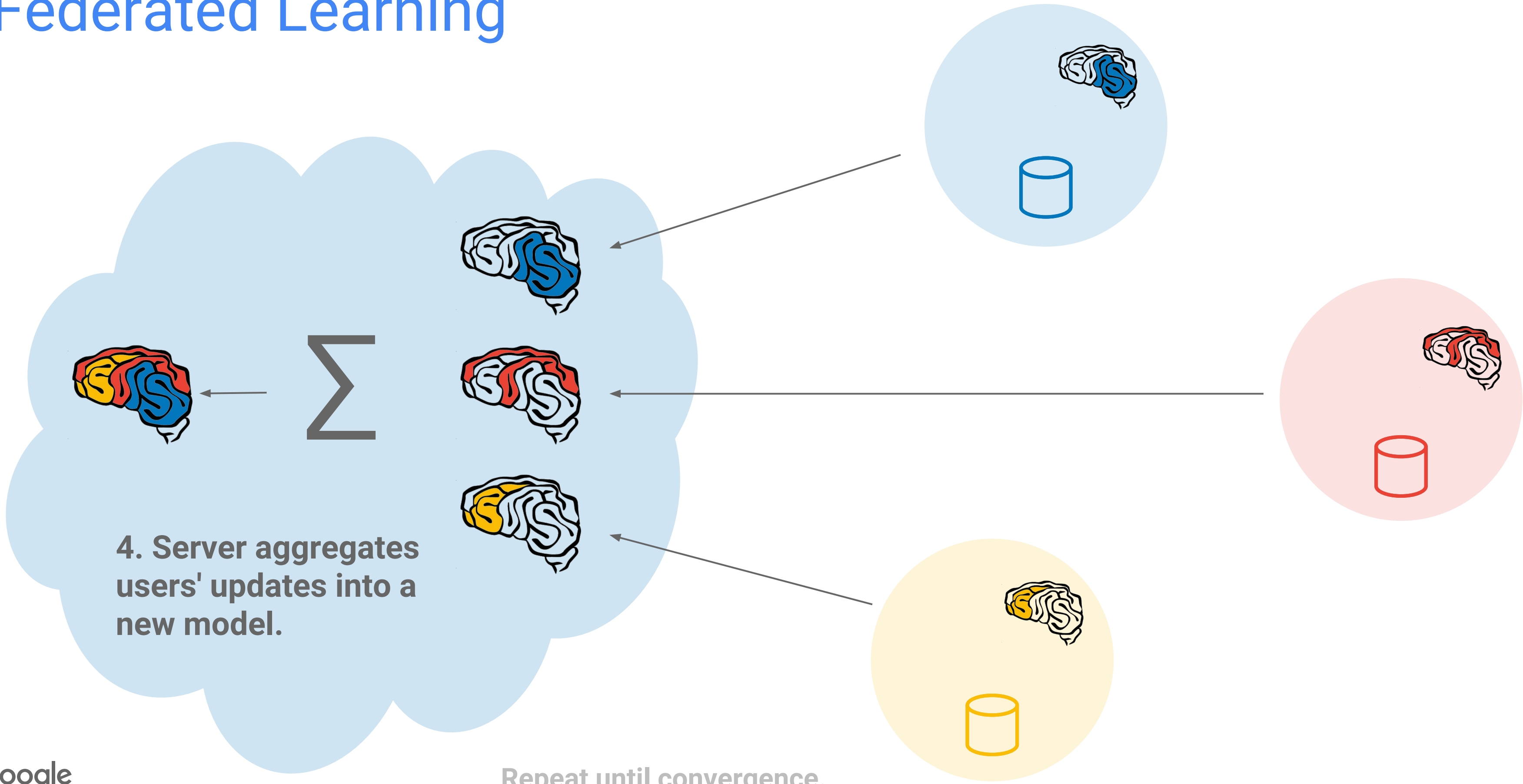
49x decrease in communication (updates) vs SGD

(IID and balanced data)

Federated Learning
&
Privacy

Google

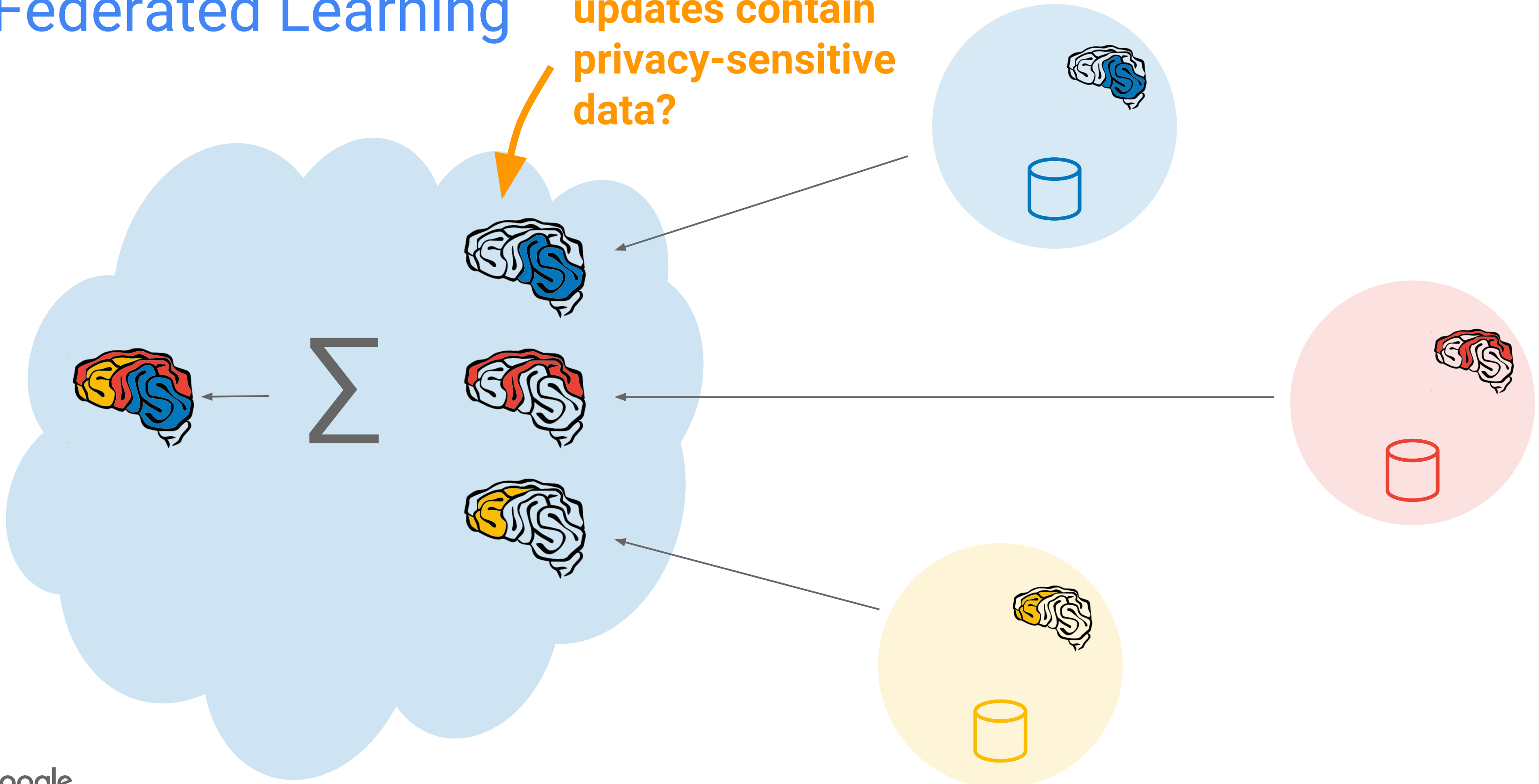
Federated Learning



Repeat until convergence.

Federated Learning

Might these updates contain privacy-sensitive data?



Google

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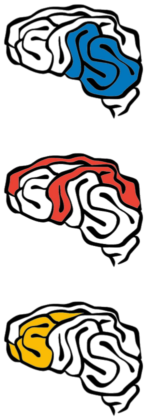

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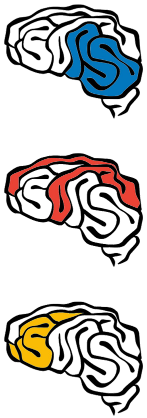


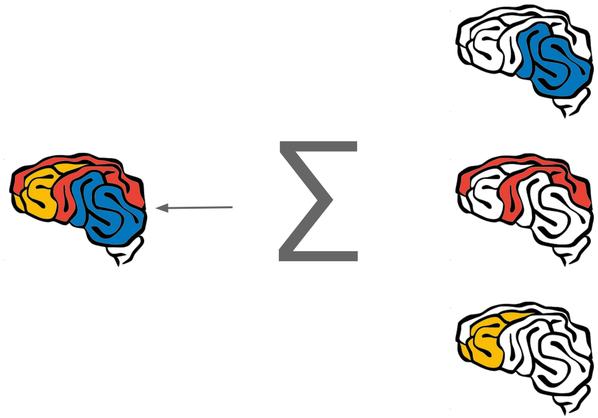
1. **Ephemeral**

Might these updates contain privacy-sensitive data?

1. Ephemeral
2. **Focussed**

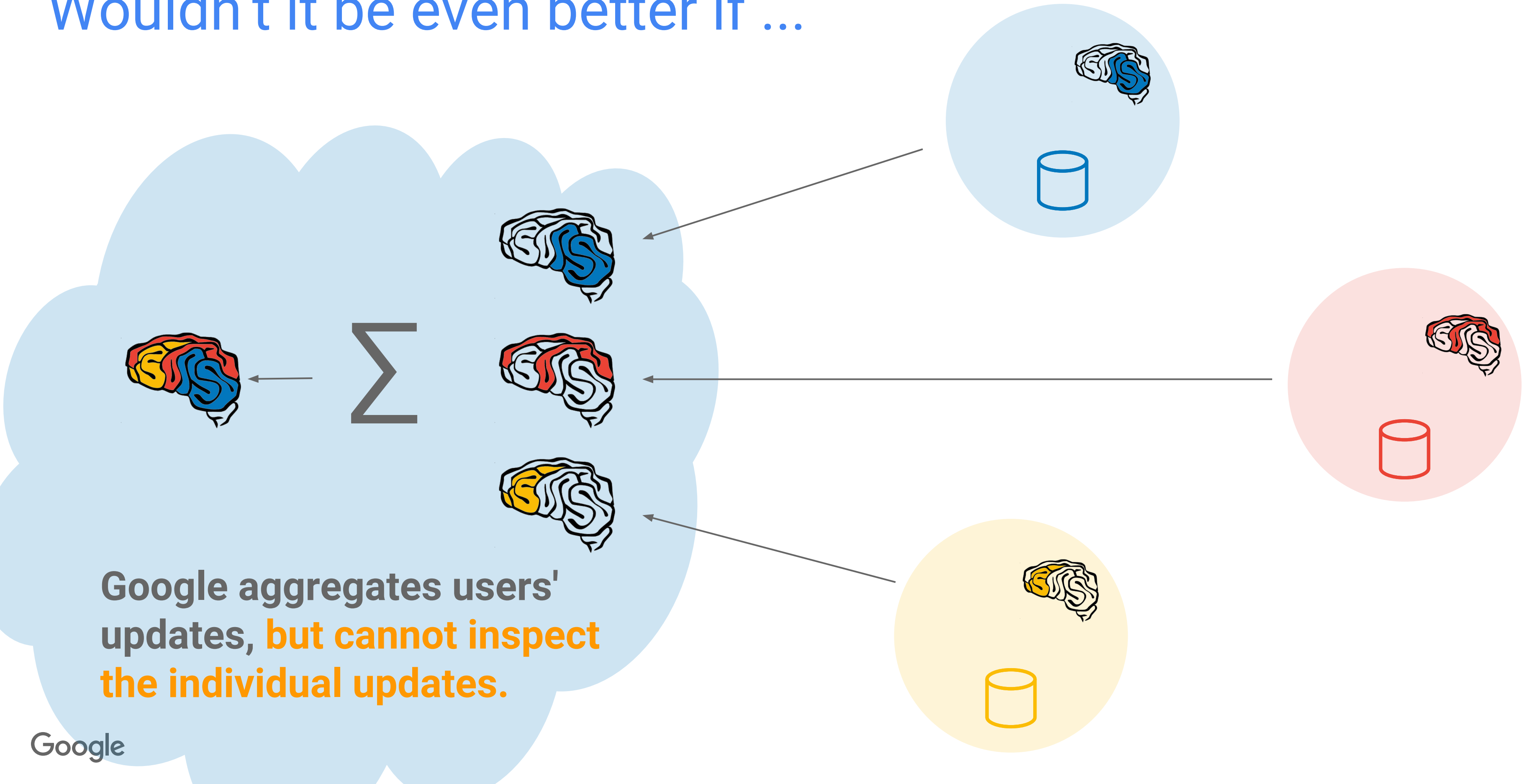
Improve privacy & security by minimizing the "attack surface"

Might these updates contain privacy-sensitive data?



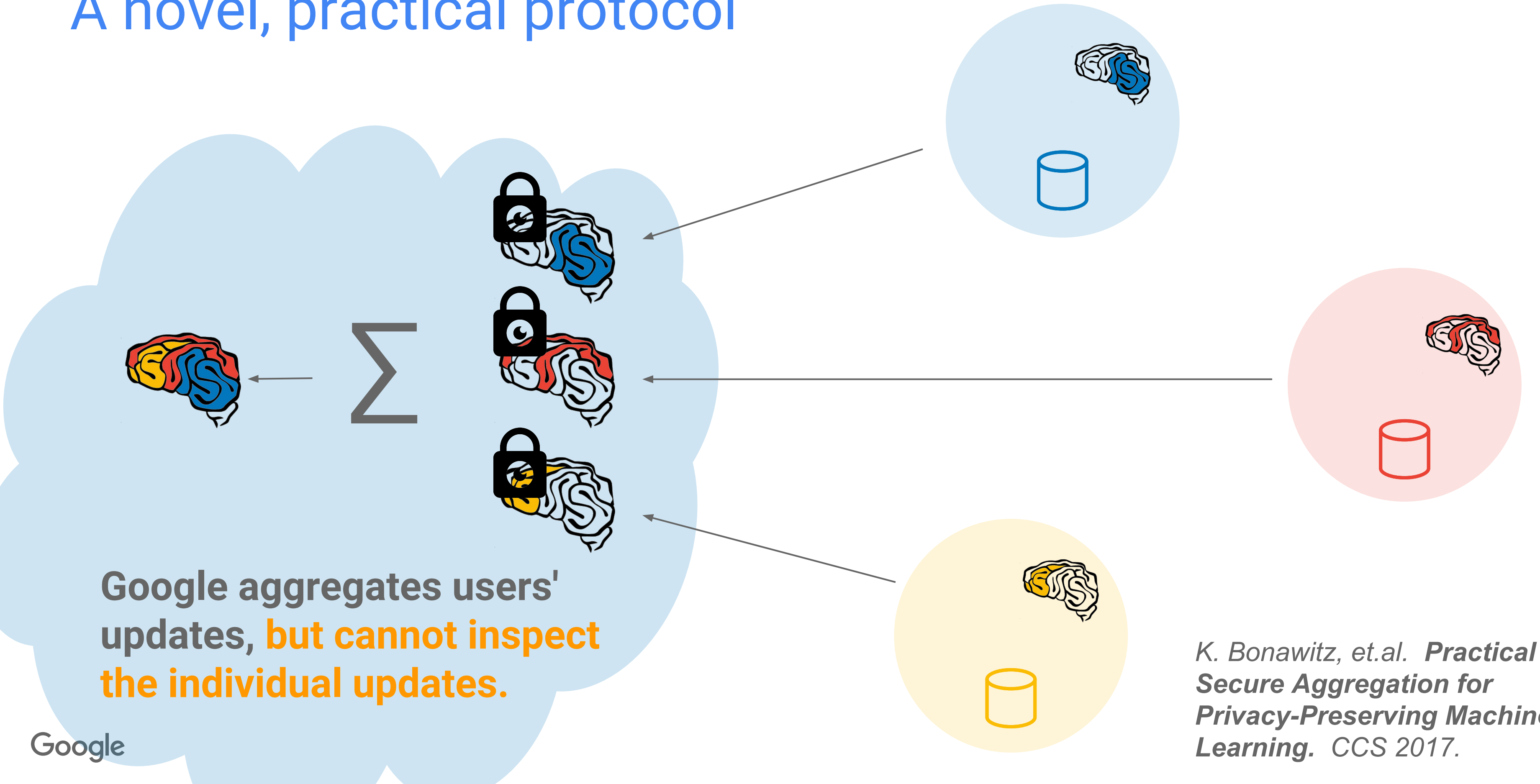
1. Ephemeral
2. Focussed
3. **Only in aggregate**

Wouldn't it be even better if ...



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

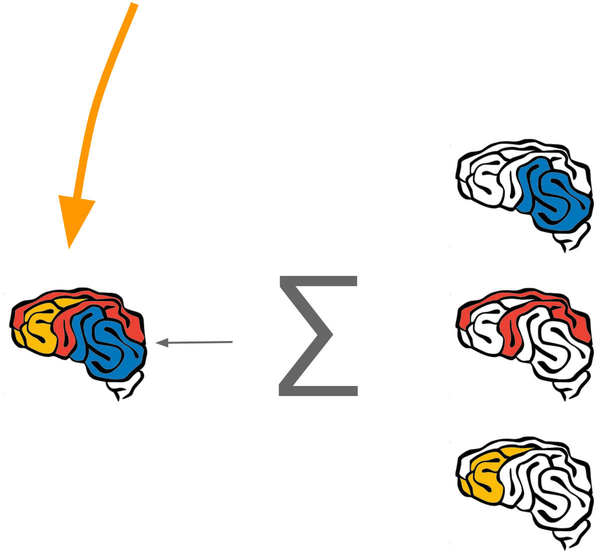
A novel, practical protocol



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

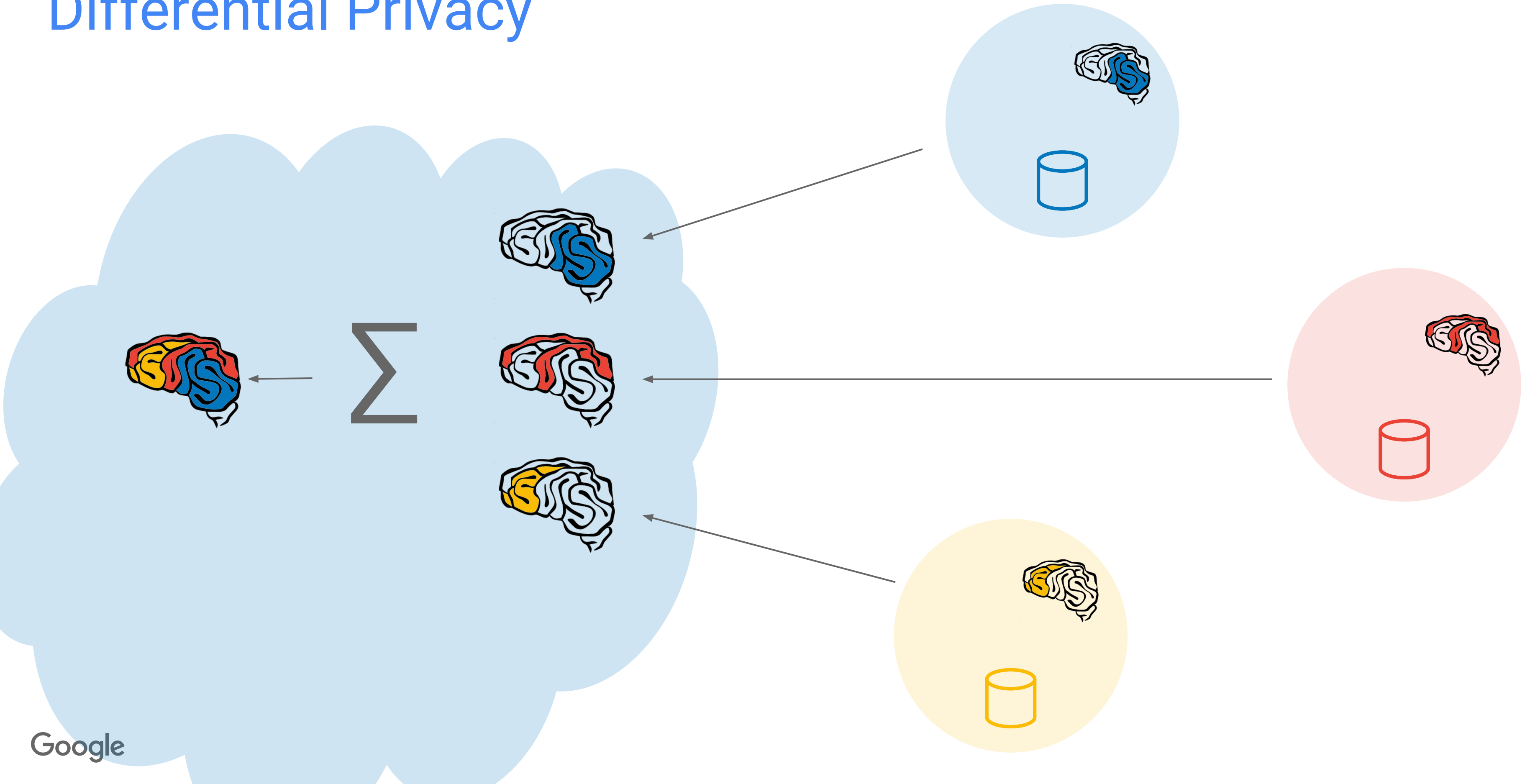
K. Bonawitz, et.al. ***Practical Secure Aggregation for Privacy-Preserving Machine Learning.*** *CCS 2017.*

Might the final model memorize a user's data?



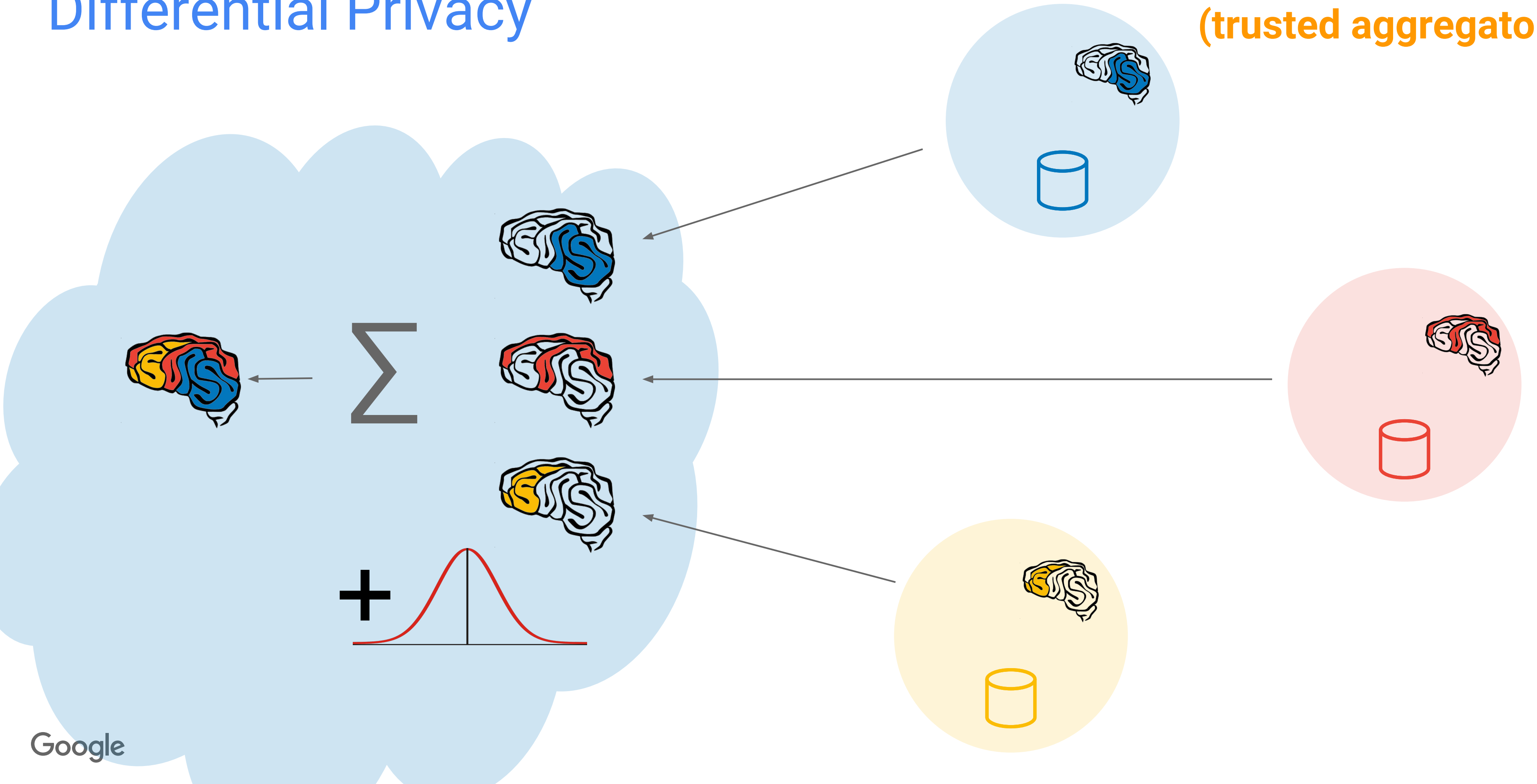
1. Ephemeral
2. Focussed
3. Only in aggregate
4. **Differentially private**

Differential Privacy



Differential Privacy

Differential Privacy (trusted aggregator)



Federated Averaging

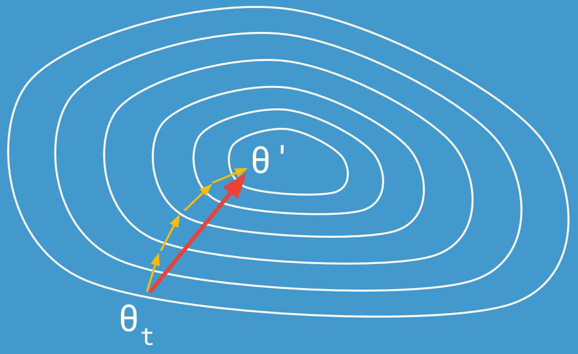
Server

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

Differentially-Private Federated Averaging

H. B. McMahan, *et al*. **Learning Differentially Private Language Models Without Losing Accuracy.**

Server

Until Converged:

1. Select each user **independently** with **probability q**, for say E[C]=1000 clients

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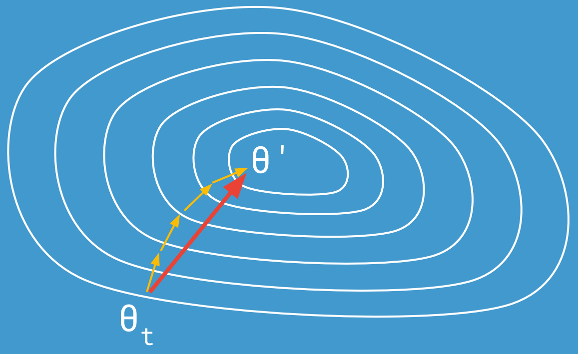

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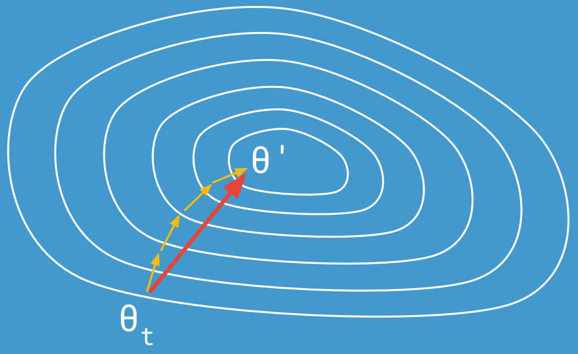
3. Return **Clip($\boldsymbol{\theta'-\theta_t}$)** to server.



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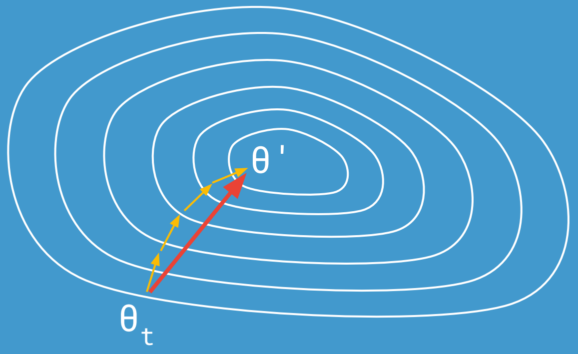

3. $\theta_{t+1} = \theta_t$ + **bounded sensitivity** data-weighted average of client updates

Differentially-Private Federated Averaging

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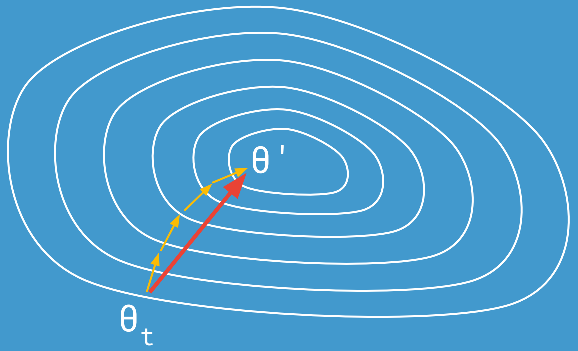
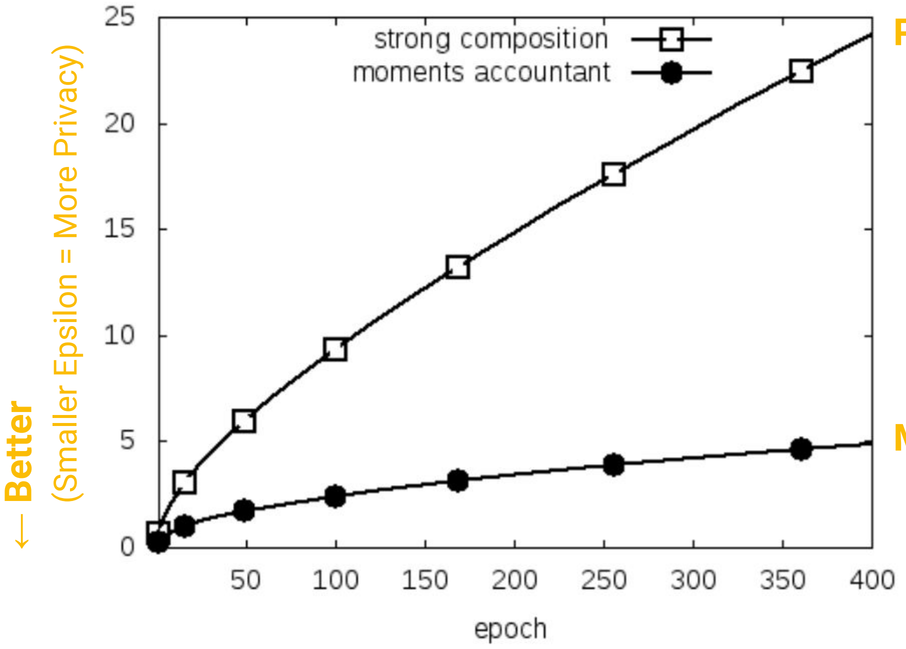


3. $\theta_{t+1} = \theta_t$ + **bounded sensitivity** data-weighted average of client updates
   \+ Gaussian noise **N(0, Iσ^2)**

Privacy Accounting for Noisy SGD: Moments Accountant

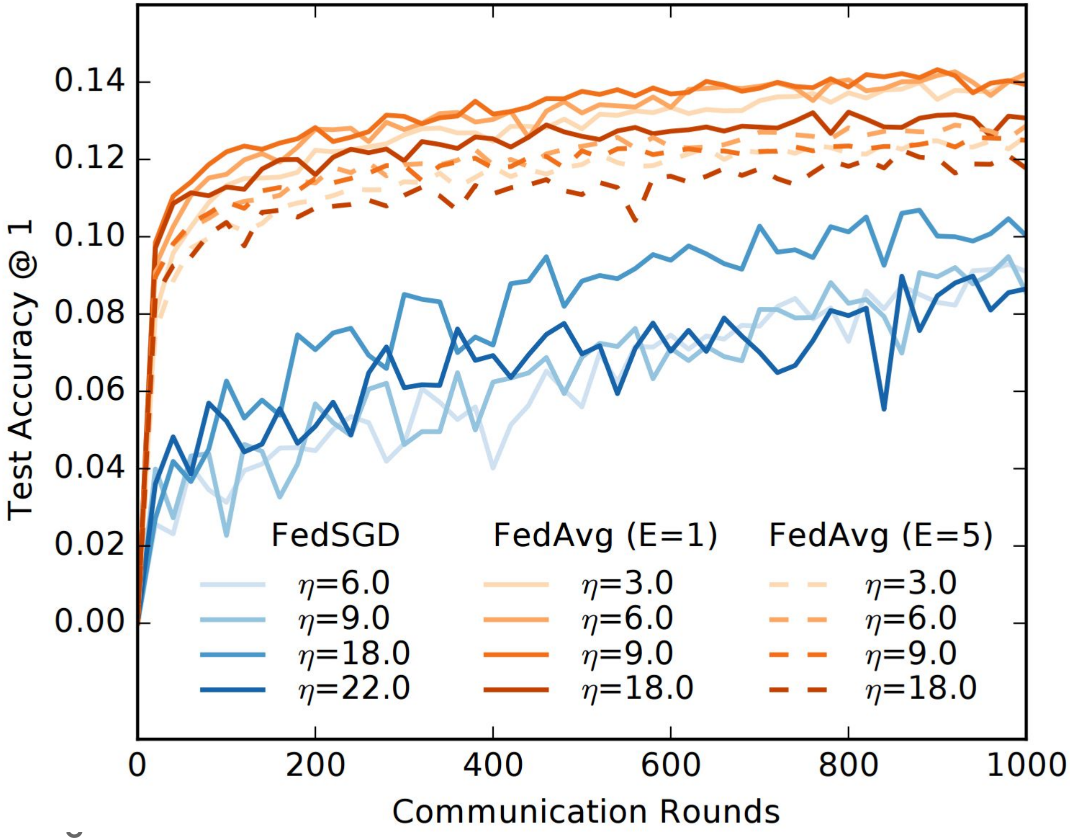


Previous composition theorems

Moments Accountant

M. Abadi, A. Chu, I. Goodfellow, H. B. McMahan, I. Mironov, K. Talwar, & L. Zhang. **Deep Learning with Differential Privacy**. CCS 2016.

Large-scale LSTM for next-word prediction



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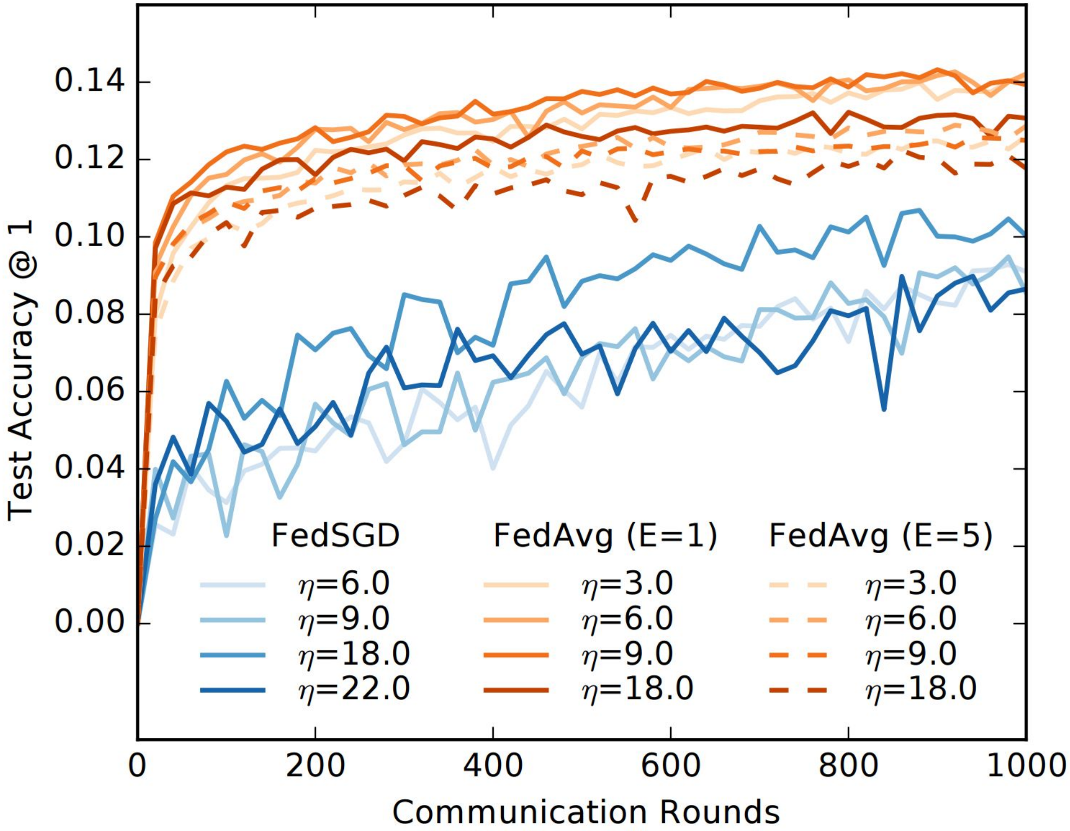
23x **decrease in communication rounds**

Large-scale LSTM for next-word prediction

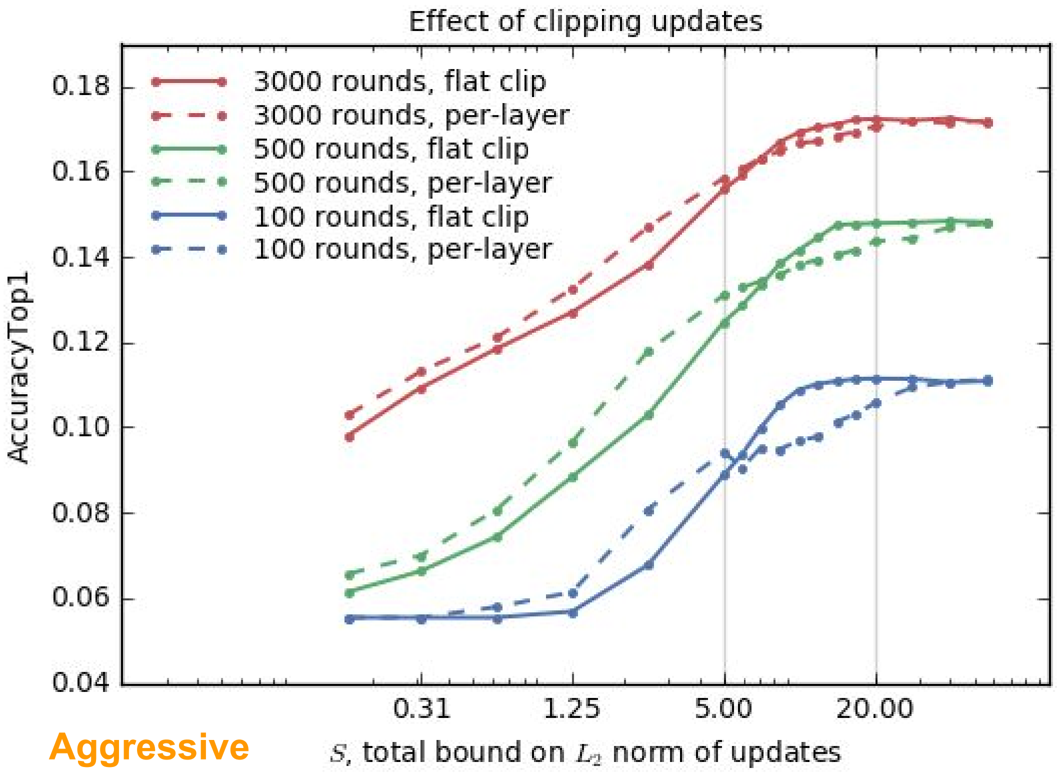


Rounds to reach 10.5% Accuracy

FedSGD	820
FedAvg	35

23x decrease in database queries

The effect of clipping updates

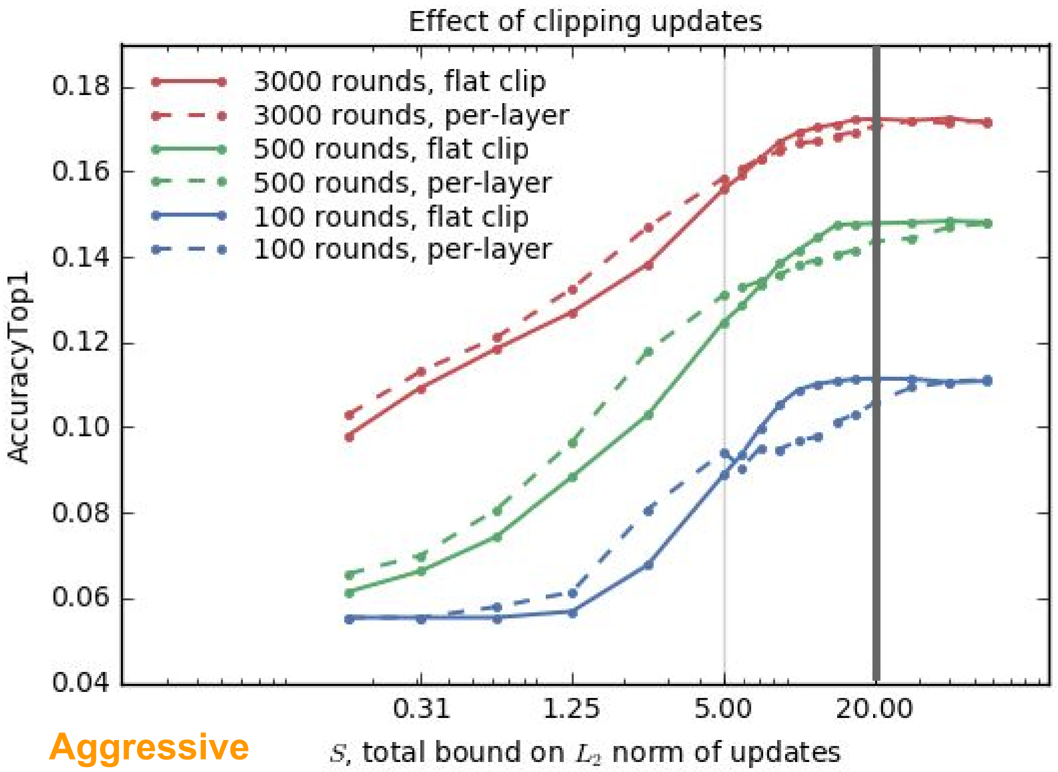


No Clipping

Aggressive Clipping

Sampling E[C] = 100 users per round.

The effect of clipping updates

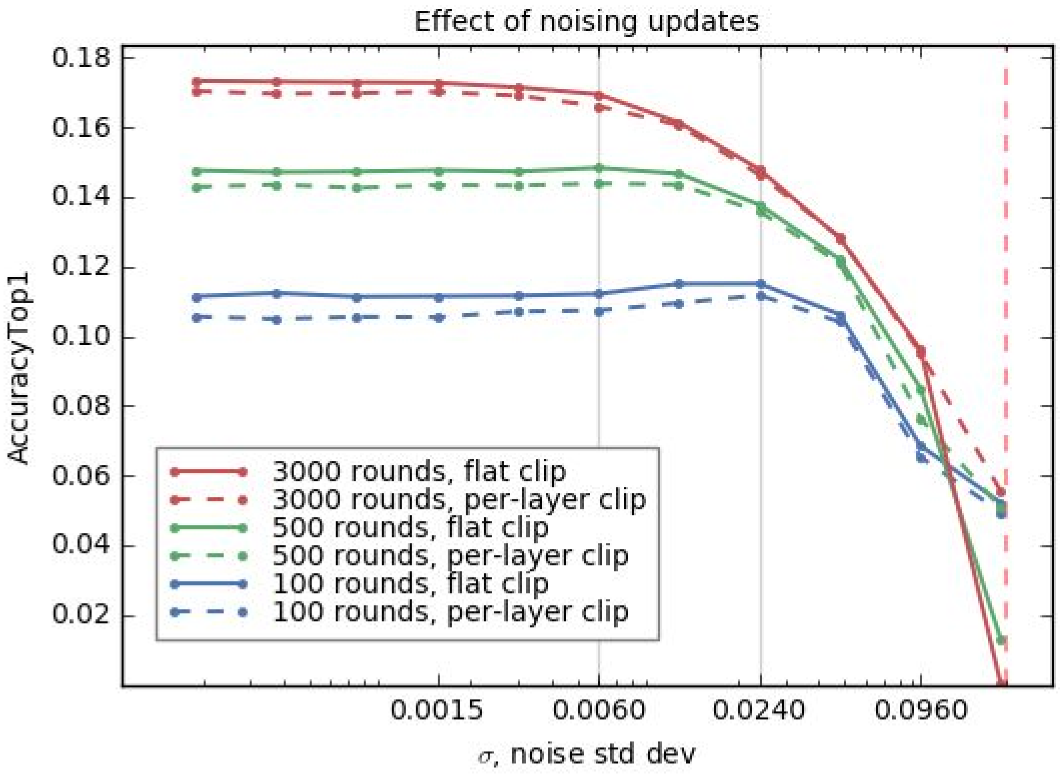


No Clipping

Aggressive Clipping

Sampling E[C] = 100 users per round.

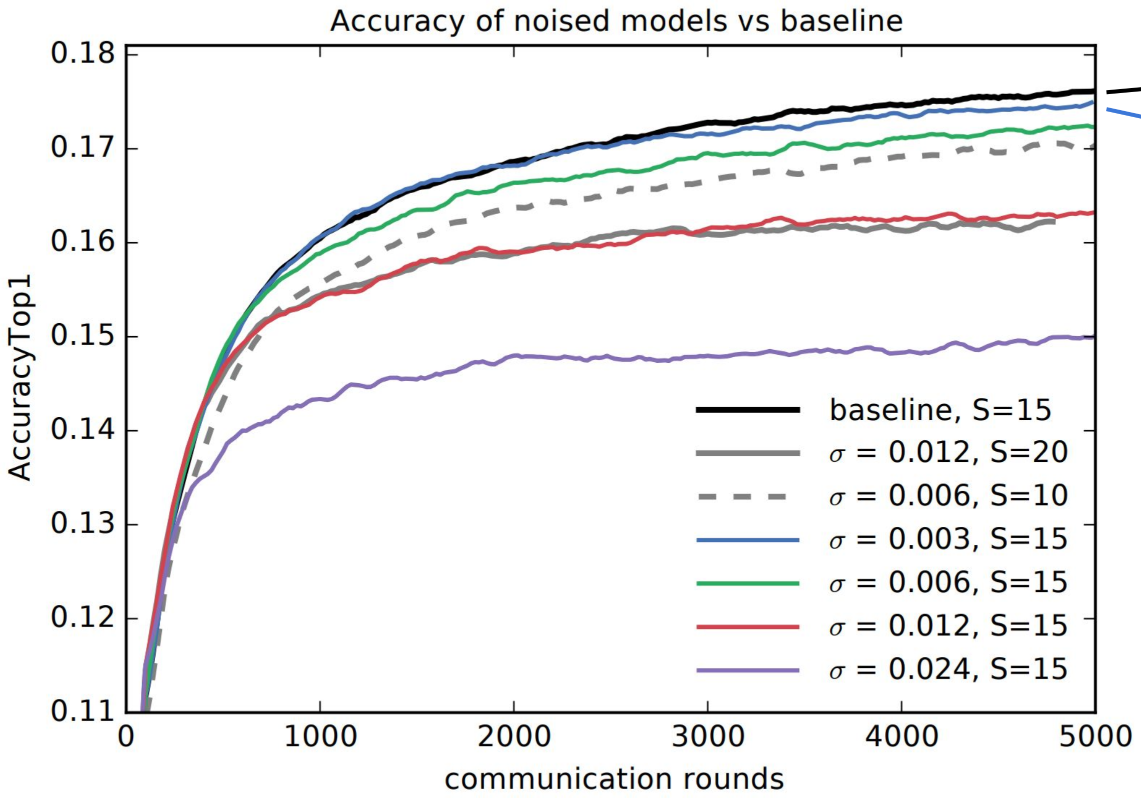
The effect of noising updates



Clipping at S=20

Sampling E[C] = 100 users per round.

Differential Privacy for Language Models

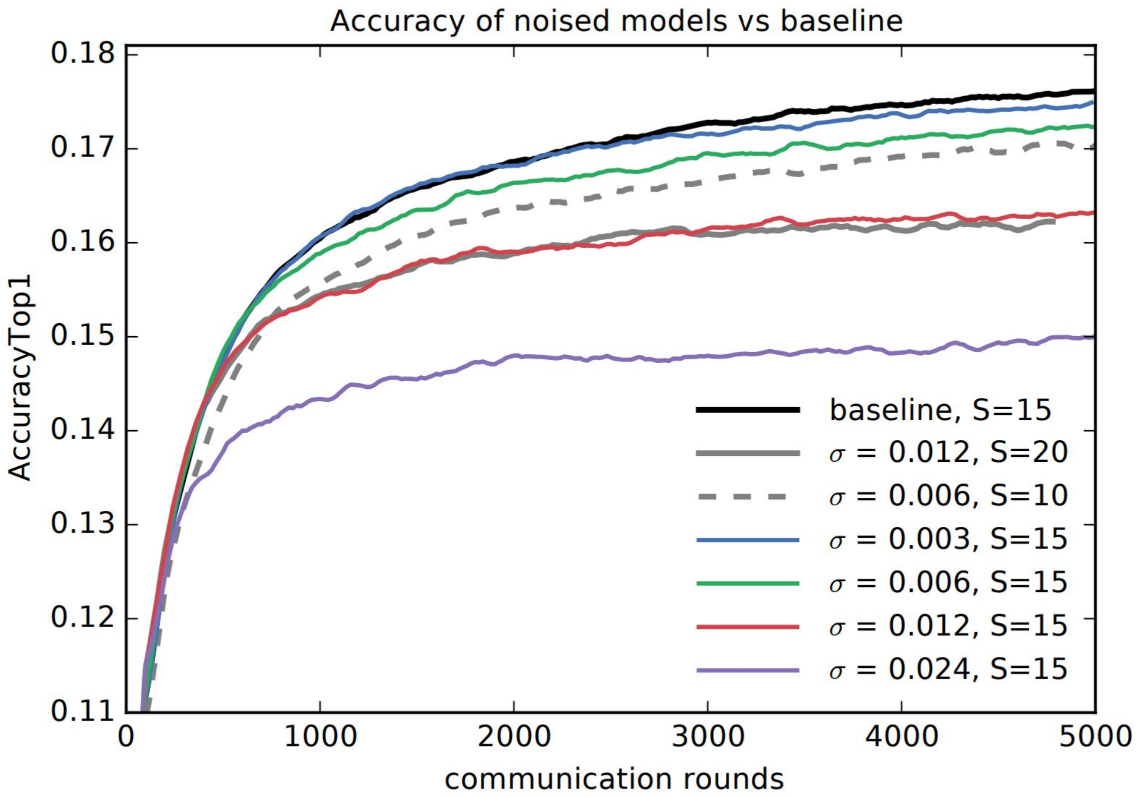


Non-private baseline

(4.634, 1e-9)-DP with 763k users
(1.152, 1e-9)-DP with 1e8 users

H. B. McMahan, *et al*. **Learning Differentially Private Language Models Without Losing Accuracy**.

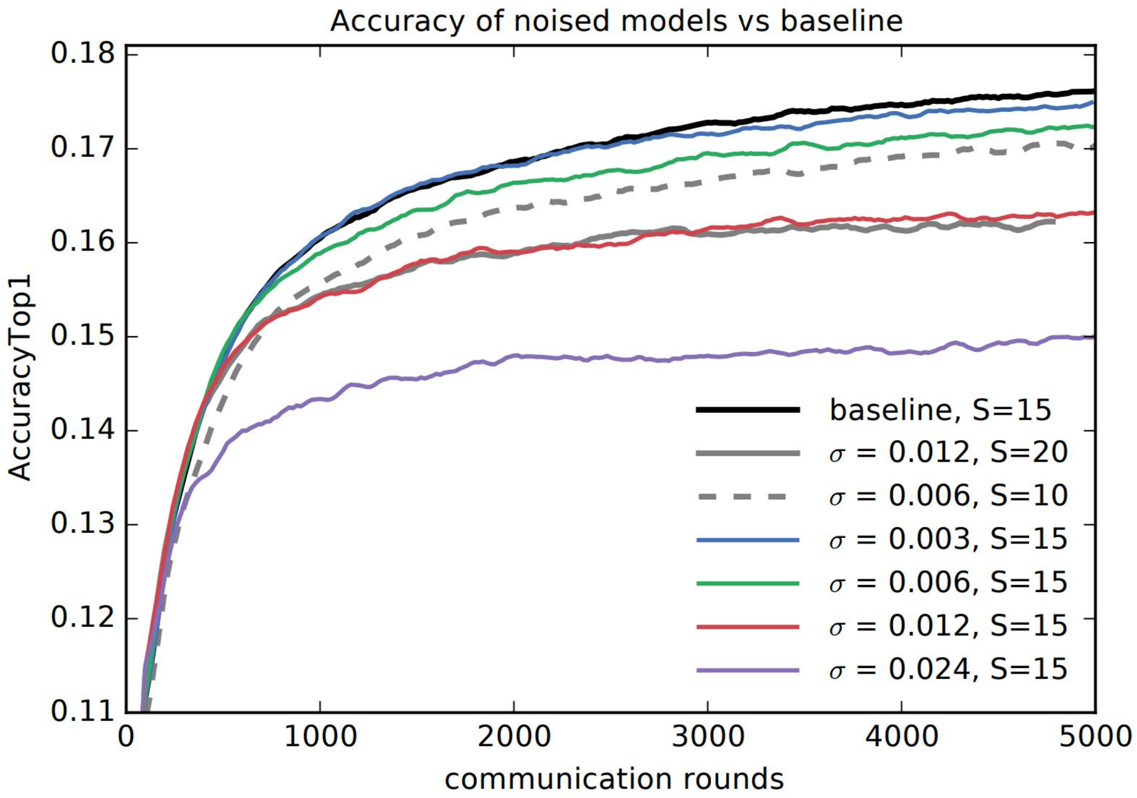
Differential Privacy for Language Models



Baseline Training
users per round = 100
tokens per round = 160k
17.5% accuracy in 4120 rounds

(1.152, 1e-9) DP Training
$\mathbb{E}$[users per round] = 5k
$\mathbb{E}$[tokens per round] = 8000k
17.5% **estimated** accuracy in 5000 rounds

Differential Privacy for Language Models



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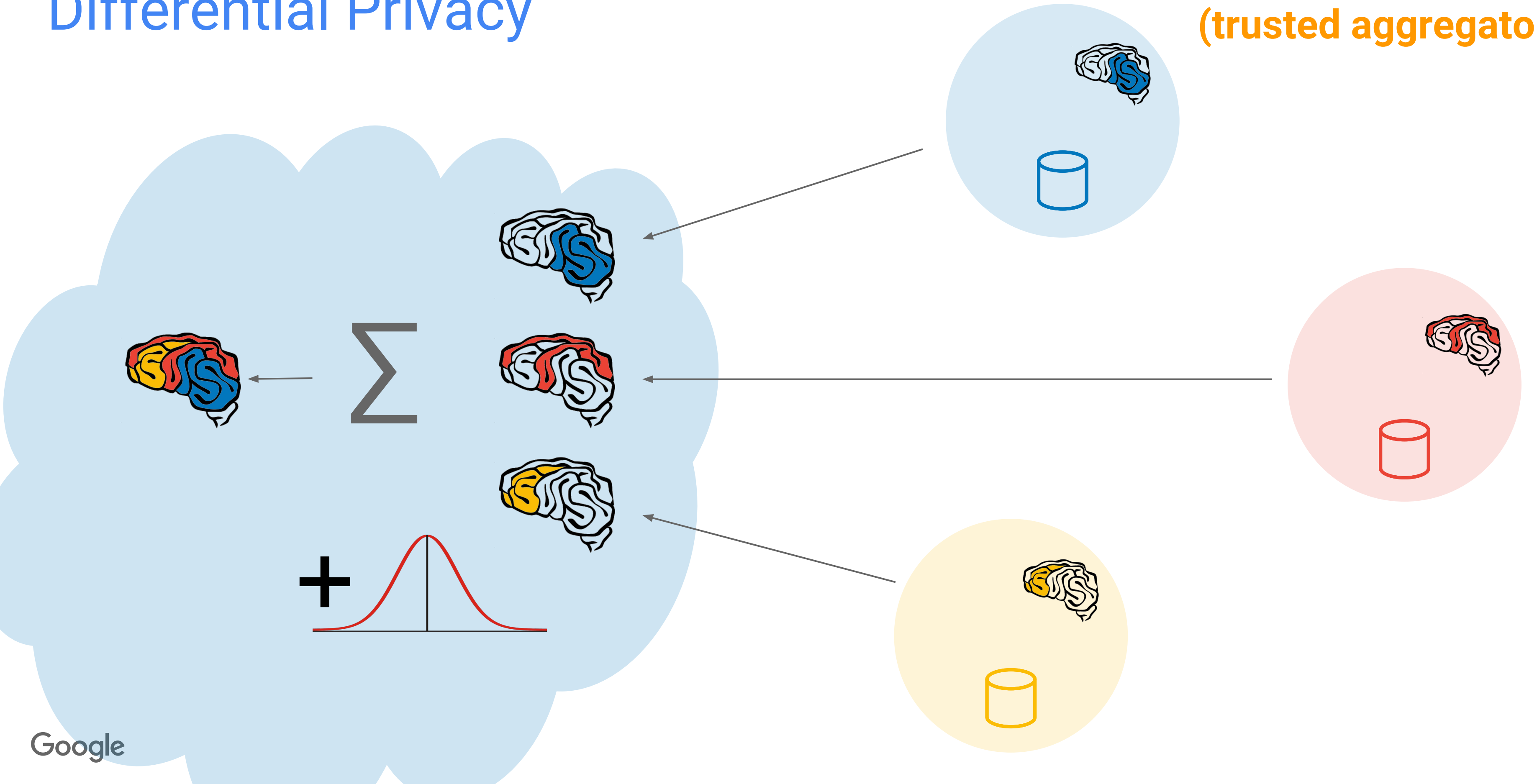
$\mathbb{E}$[users per round] = 5k
$\mathbb{E}$[tokens per round] = 8000k
17.5% **estimated** accuracy in 5000 rounds

Private training achieves **equal accuracy**, but using **60x more computation**.

Differential Privacy

Differential Privacy (trusted aggregator)



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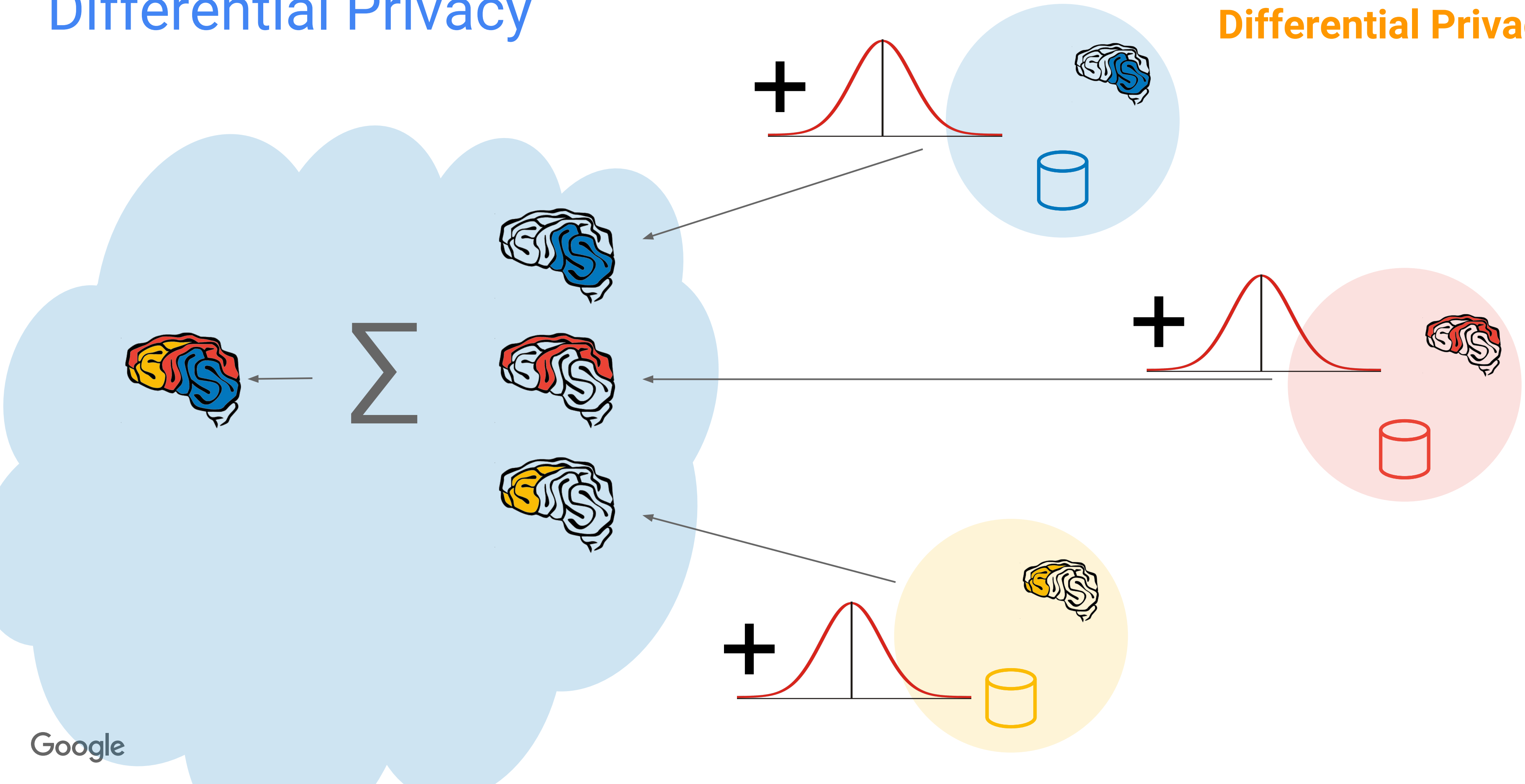
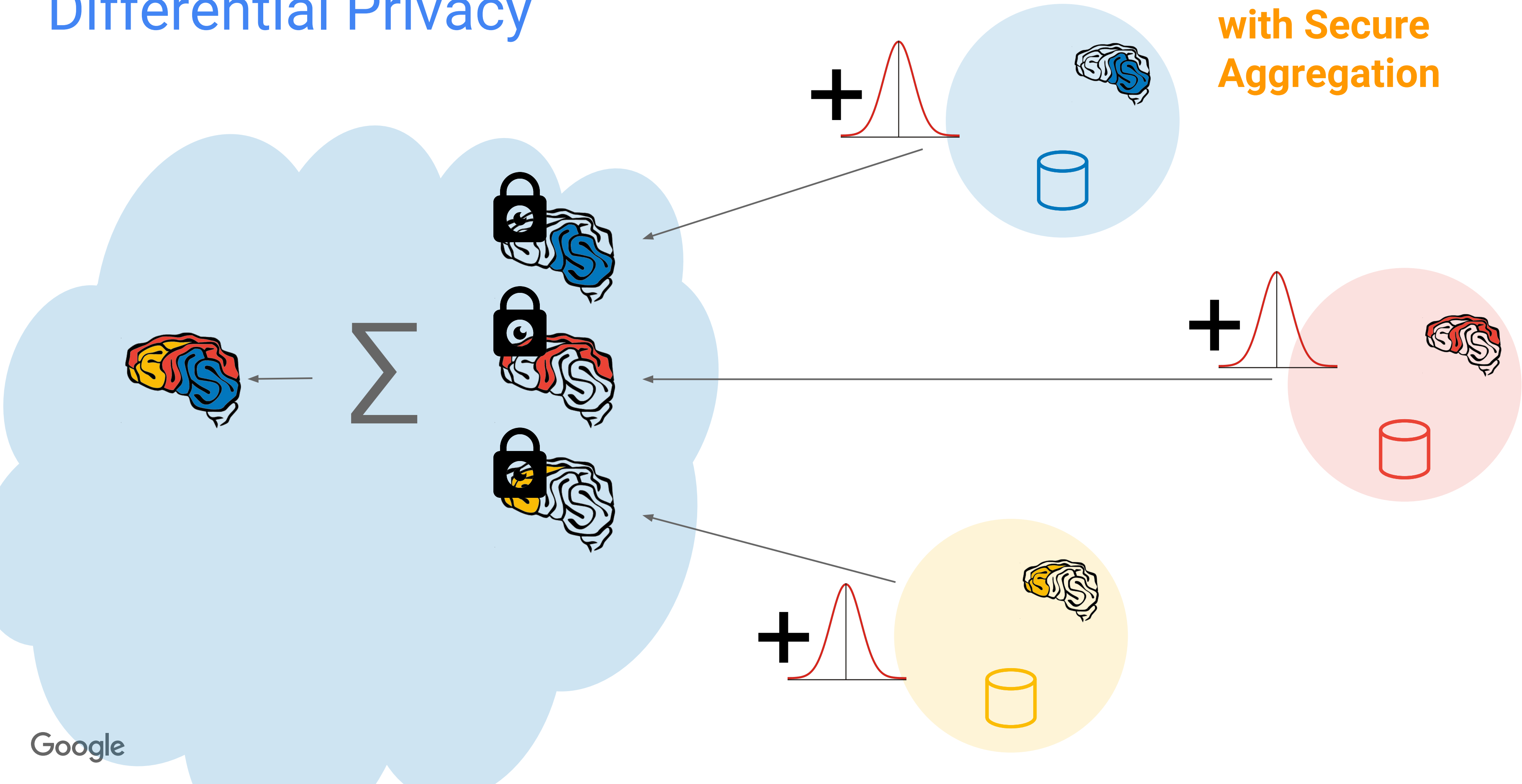
Differential Privacy

Local Differential Privacy



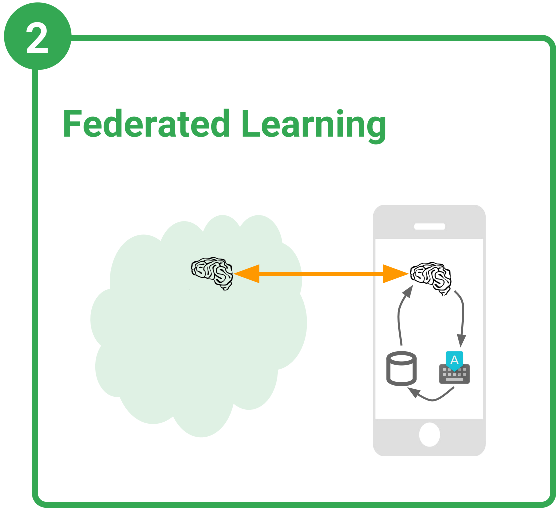
Differential Privacy

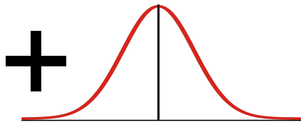
Differential Privacy with Secure Aggregation



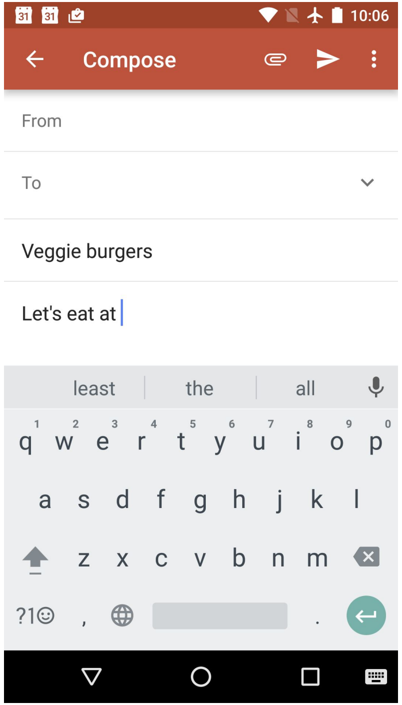
Differential Privacy is complementary to Federated Learning

- FL algorithms touch data one user (one device) at time --- natural algorithms for user-level privacy
- Communication constraints mean we want to touch the data as few times as possible --- also good for privacy.
- The DP guarantee is complementary to FL's focussed collection & ephemeral updates.





Federated Learning in Gboard



Google Research Blog

The latest news from Research at Google

Federated Learning: Collaborative Machine Learning without Centralized Training Data

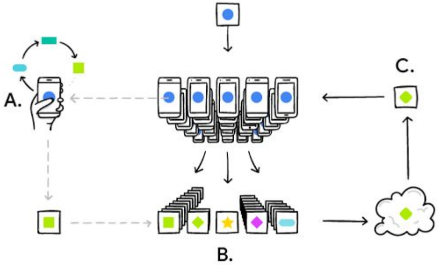
Thursday, April 06, 2017

Posted by Brendan McMahan and Daniel Ramage, Research Scientists

Standard machine learning approaches require centralizing the training data on one machine or in a datacenter. And Google has built one of the most secure and robust cloud infrastructures for processing this data to make our services better. Now for models trained from user interaction with mobile devices, we're introducing an additional approach: *Federated Learning*.

Federated Learning enables mobile phones to collaboratively learn a shared prediction model while keeping all the training data on device, decoupling the ability to do machine learning from the need to store the data in the cloud. This goes beyond the use of local models that make predictions on mobile devices (like the Mobile Vision API and On-Device Smart Reply) by bringing model *training* to the device as well.

It works like this: your device downloads the current model, improves it by learning from data on your phone, and then summarizes the changes as a small focused update. Only this update to the model is sent to the cloud, using encrypted communication, where it is immediately averaged with other user updates to improve the shared model. All the training data remains on your device, and no individual updates are stored in the cloud.



Your phone personalizes the model locally, based on your usage (A). Many users' updates are aggregated (B) to form a consensus change (C) to the shared model, after which the procedure is repeated.

Open Questions and Challenges

Showing privacy is possible

Many open research questions:

- Further lower computational and/or utility cost of differential privacy
- More communication-efficient algorithms for FL

Making privacy easy

Possible is not enough. Research to enable "privacy by default" in machine learning.

- Can federated learning be as easy as centralized learning?
- Differential privacy for deep learning without parameter tuning?
- How do we handle privacy budgets across time and across domains?

Google

Questions