Federated Learning

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Outline

- ❑ Preliminary: deep learning and SGD
- ❑ Federated learning: FedSGD and FedAvg
- ❑ Related research in federated learning
- ❑ Open problems

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- ❑ Preliminary: deep learning and SGD
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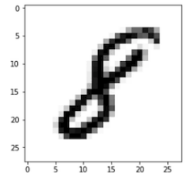
The goal of deep learning

- Find a function, which produces a desired output given a particular input.

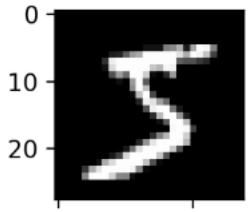
w is the set of parameters contained by the function

Example task	Given input	Desired output
Image classification		8
Next-word-prediction	*Looking forward to your **?***	*reply*
Playing GO		Next move

Finding the function: model training

- Given one input sample pair (x_0, y_0), the goal of deep learning model training is to find a set of parameters w, to maximize the probability of outputting y_0 given x_0.

Given input: x_0

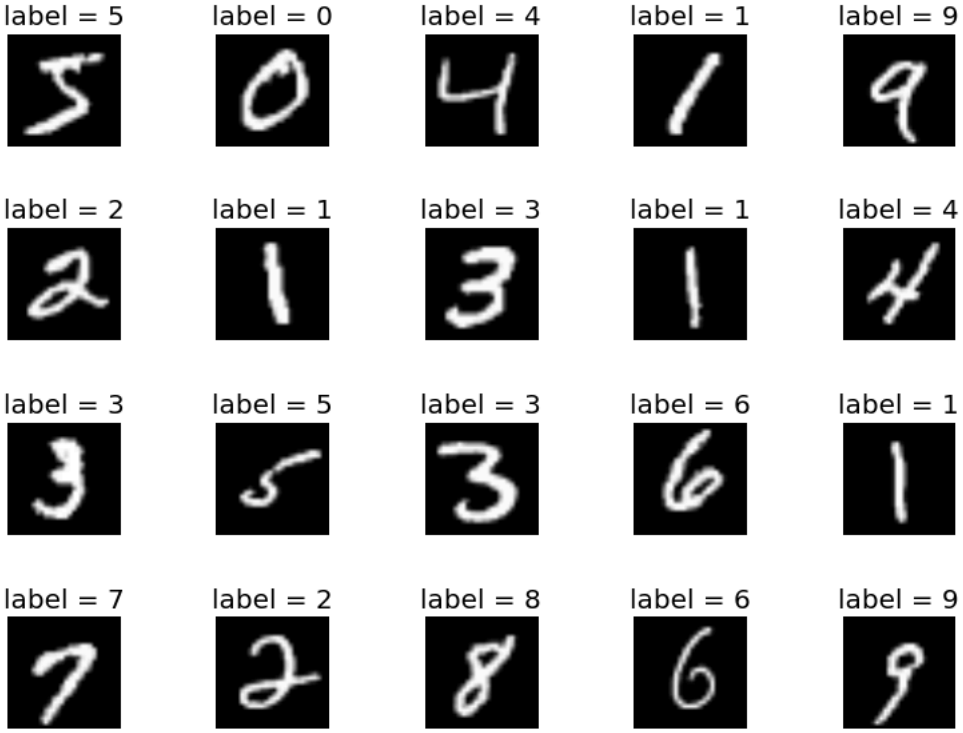


Maximize: $p(5|x_0, w)$

Finding the function: model training

- Given a training dataset containing n input-output pairs $(x_i, y_i), i \in [1, n]$, the goal of deep learning model training is to find a set of parameters w, such that the average of $p(y_i)$ is maximized given x_i.

Given input:



Output:

0
1
2
3
4
5
6
7
8
9

Finding the function: model training

- Given a training dataset containing n input-output pairs $(x_i, y_i), i \in [1, n]$, the goal of deep learning model training is to find a set of parameters w, such that the average of $p(y_i)$ is maximized given x_i.

- That is,

$$maximize \quad \frac{1}{n}\sum_{i=1}^{n} p(y_i|x_i, w)$$

Which is equivalent to

$$minimize \quad \frac{1}{n}\sum_{i=1}^{n} -\log(p(y_i|x_i, w))$$

A basic component for loss function $l(x_i, y_i, w)$ given sample (x_i, y_i):

Let $f_i(w) = l(x_i, y_i, w)$ denote the loss function.

Deep learning model training

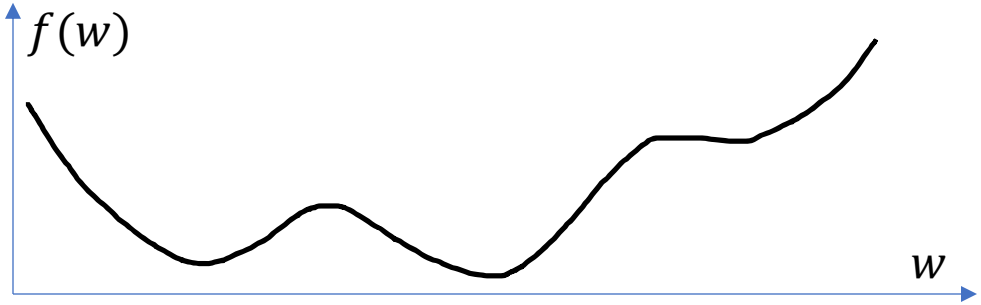
For a training dataset containing n samples $(x_i, y_i), 1 \leq i \leq n$, the training objective is:

$$\min_{w \in \mathbb{R}^d} f(w) \qquad \text{where } f(w) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^{n} f_i(w)$$

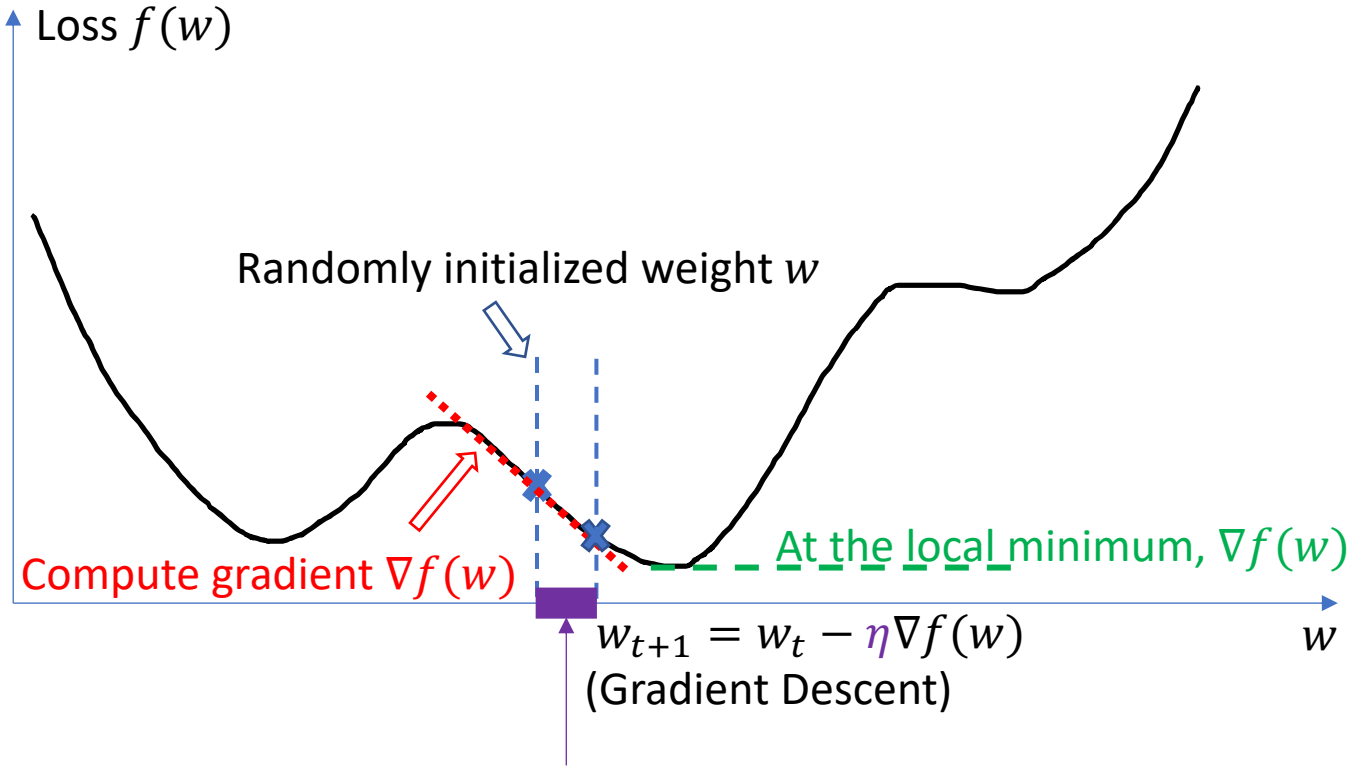
$f_i(w) = l(x_i, y_i, w)$ is the loss of the prediction on example (x_i, y_i)

No closed-form solution: in a typical deep learning model, w may contain millions of parameters.

Non-convex: multiple local minima exist.



Solution: Gradient Descent



How to stop? – when the update is small enough – converge.

$$\| w_{t+1} - w_t \| \leq \epsilon$$

or $$\| \nabla f(w_t) \| \leq \epsilon$$

***Problem**: Usually the number of training samples n is large – slow convergence*

Solution: Stochastic Gradient Descent (SGD)

- At each step of gradient descent, instead of compute for all training samples, randomly pick a small subset (mini-batch) of training samples (x_k, y_k).

$$w_{t+1} \leftarrow w_t - \eta \nabla f(w_t; x_k, y_k)$$

- Compared to gradient descent, SGD takes more steps to converge, but each step is much faster.

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The importance of data for ML

> “The biggest obstacle to using advanced data analysis isn’t skill base or technology; it’s plain old access to the data.”
>
> -Edd Wilder-James, Harvard Business Review

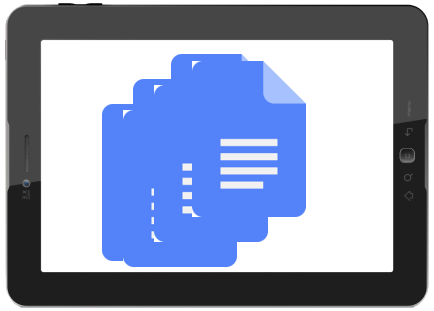
“Data is the New Oil”

PRIVACY

NETWORK OVERHEAD

image classification:
e.g. to predict which photos are most likely to be viewed multiple times in the future;

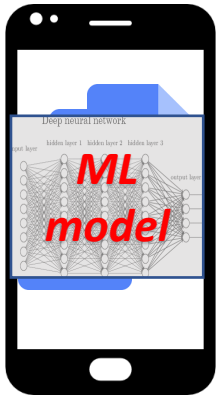
language models:
e.g. voice recognition, next-word-prediction, and auto-reply in Gmail

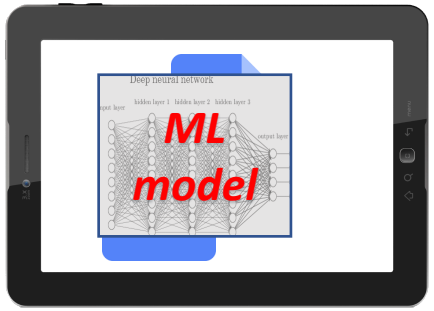


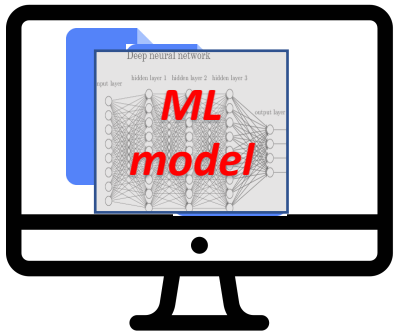
Private data: *all the* ***photos*** *a user takes and everything they type on their mobile keyboard, including* ***passwords, URLs, messages, etc.***

Addressing privacy:
Model parameters will never contain more information than the raw training data

Addressing network overhead:
The size of the model is generally smaller than the size of the raw training data







Instead of uploading the raw data,
train a model locally and upload the model.

Federated optimization

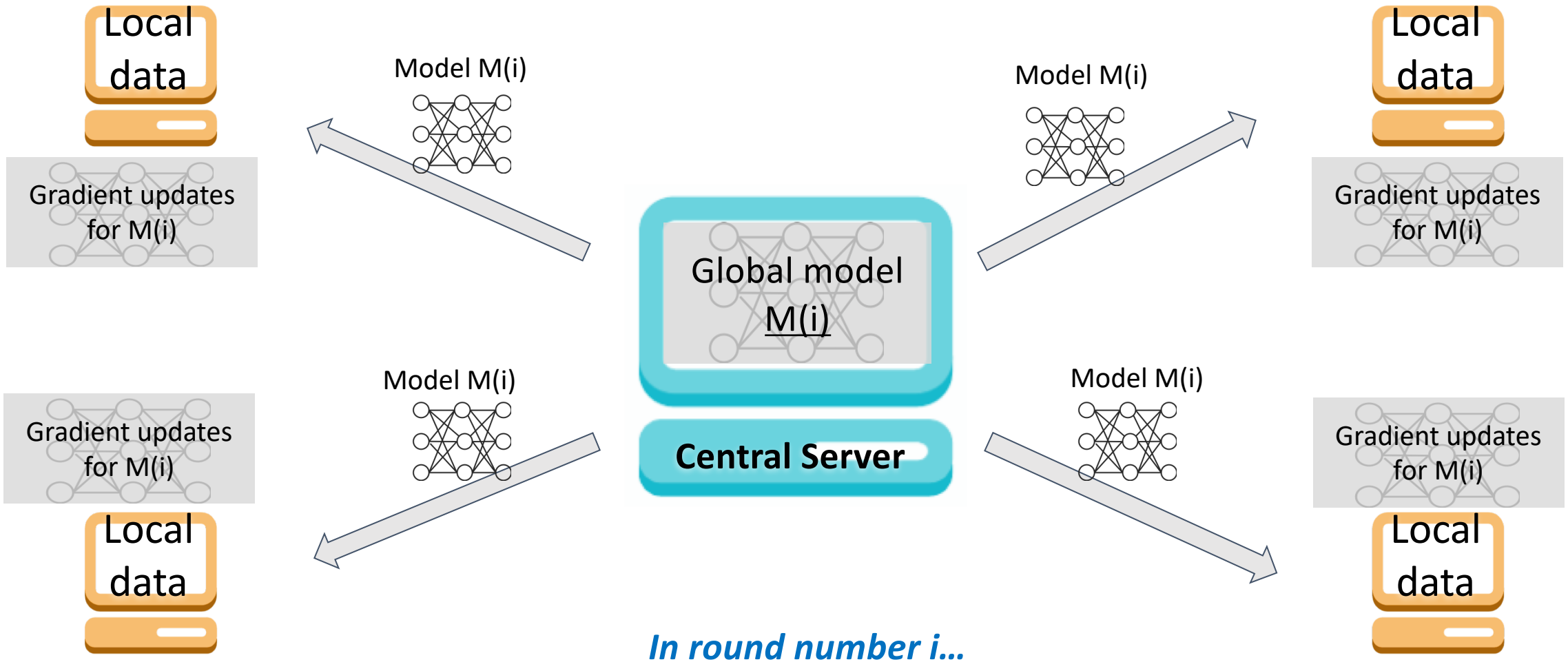
- Characteristics (Major challenges)
  - Non-IID
    - The data generated by each user are quite different
  - Unbalanced
    - Some users produce significantly more data than others
  - Massively distributed
    - # mobile device owners >> avg # training samples on each device
  - Limited communication
    - Unstable mobile network connections

A new paradigm – Federated Learning

a synchronous update scheme that proceeds in rounds of communication

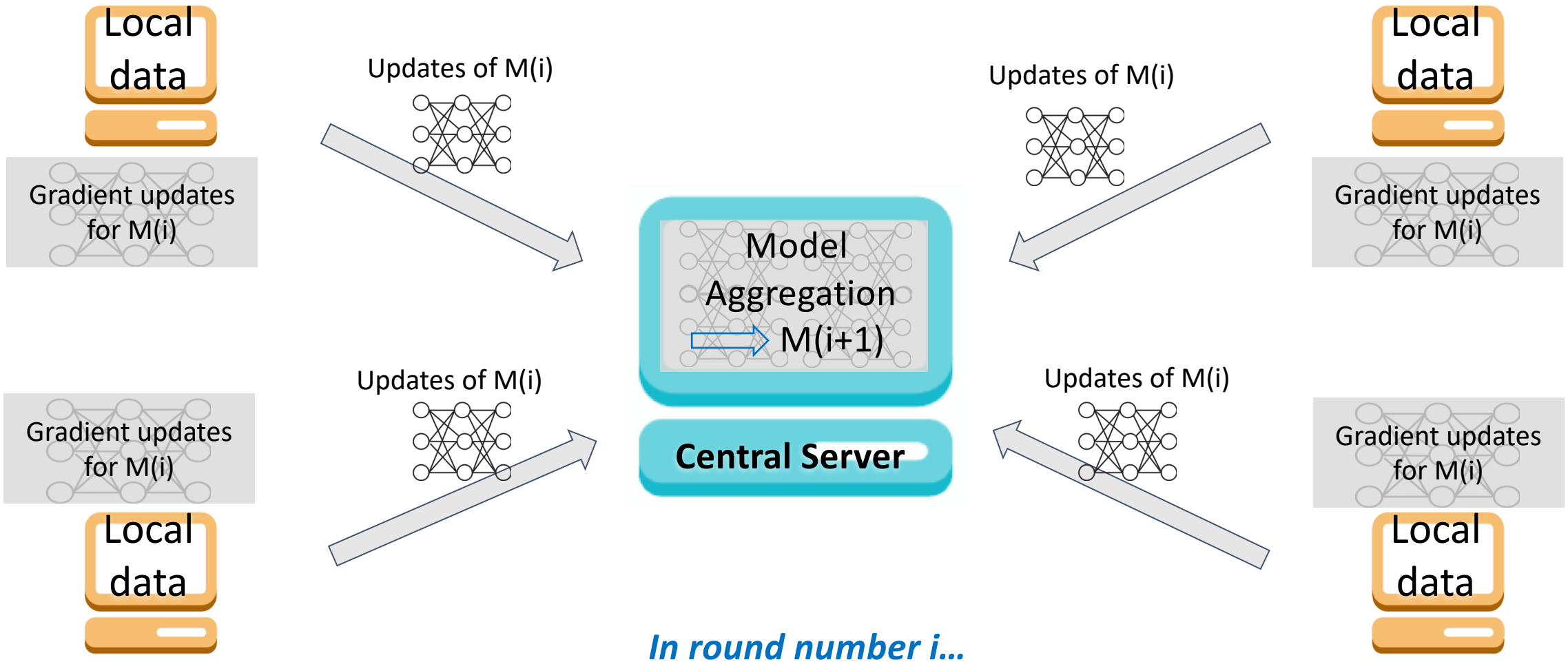
McMahan, H. Brendan, Eider Moore, Daniel Ramage, and Seth Hampson. "Communication-efficient learning of deep networks from decentralized data." *AISTATS, 2017*.

Federated learning – overview



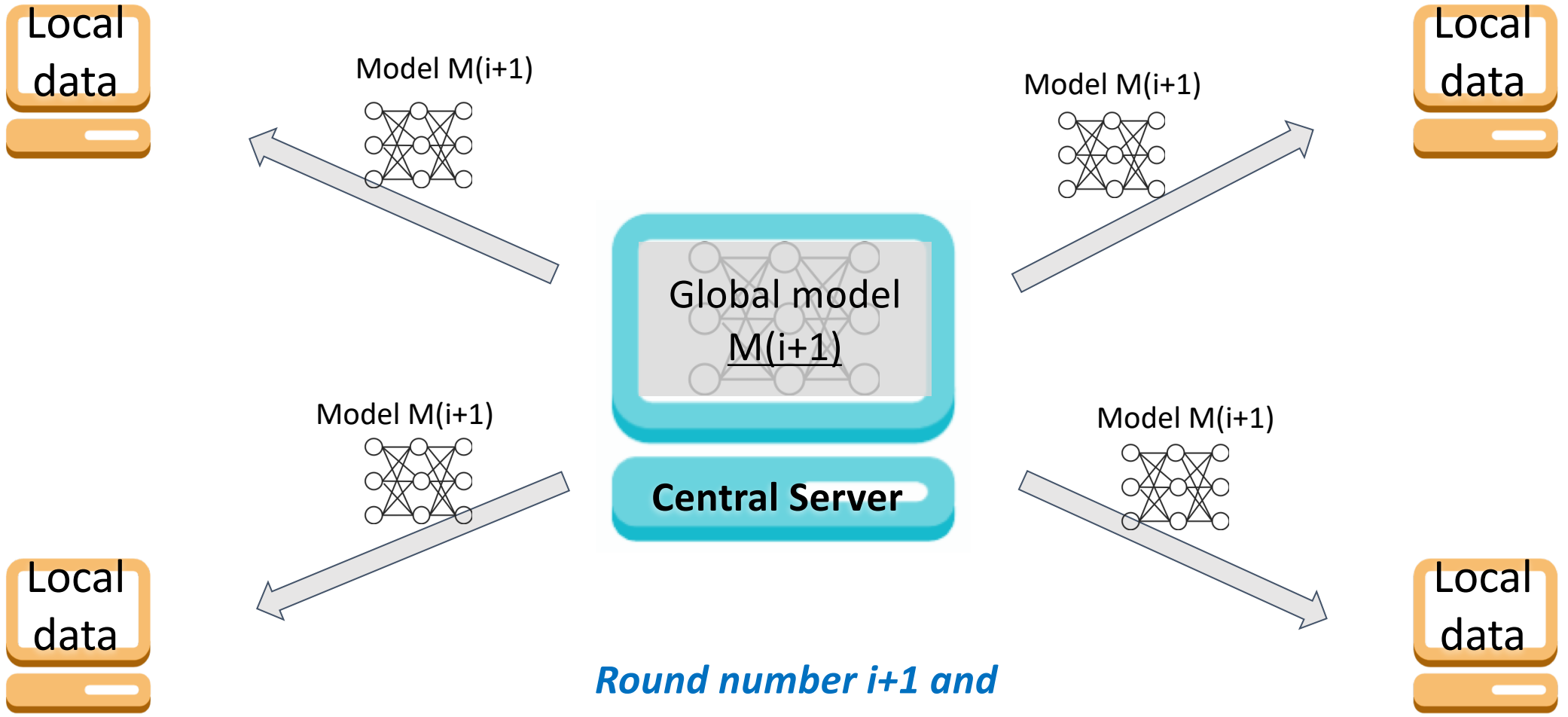
Deployed by Google, Apple, etc.

Federated learning – overview



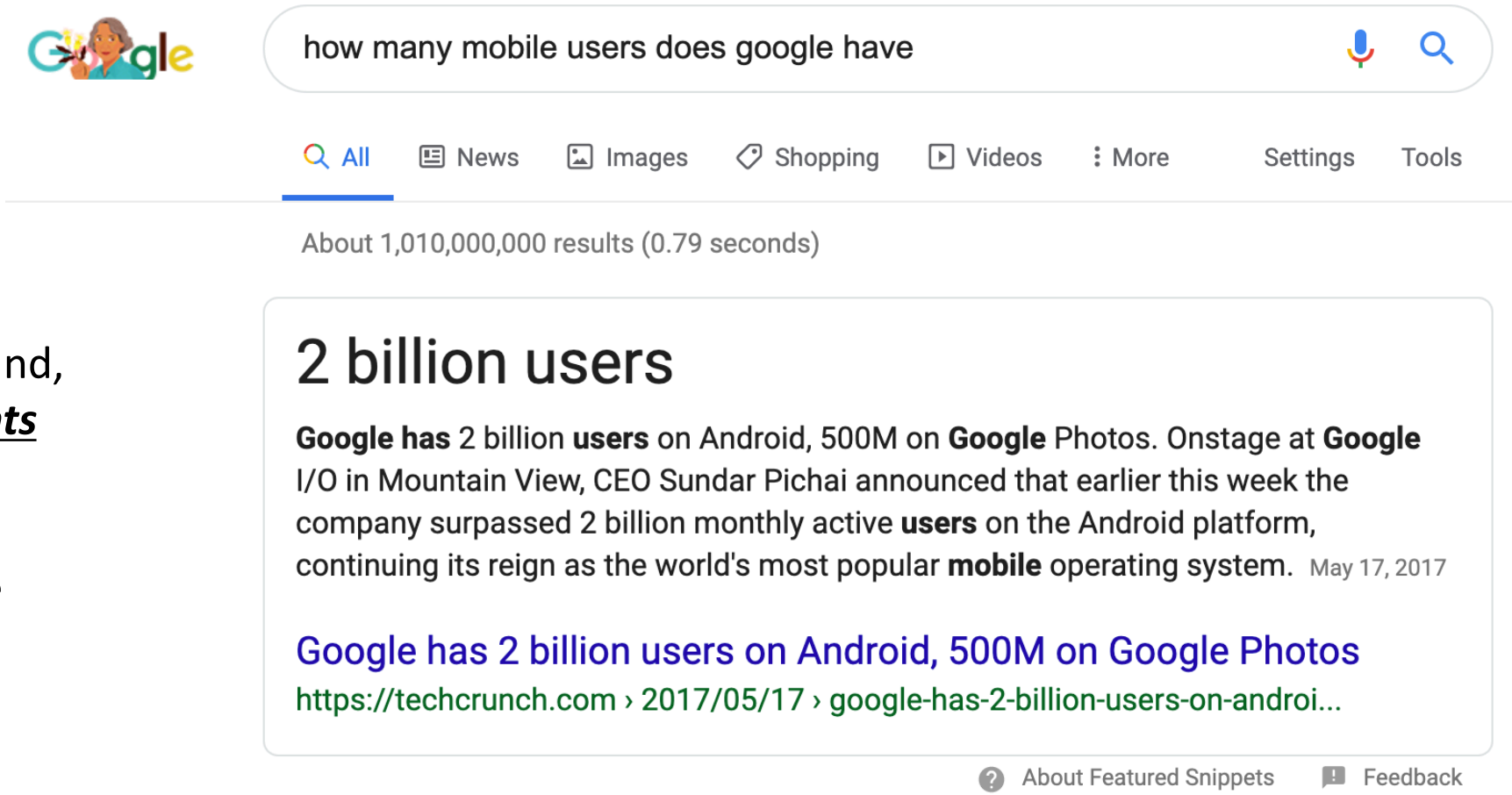
In round number i…

Federated learning – overview



Federated learning – detail

For efficiency,
at the beginning of each round,
a random fraction C of clients
is selected, and the server
sends the current model
parameters to each of these
clients.



Federated learning – detail

- Recall in traditional deep learning model training
  - For a training dataset containing n samples $(x_i, y_i), 1 \leq i \leq n$, the training objective is:

$$\min_{w \in \mathbb{R}^d} f(w) \qquad \text{where} \qquad f(w) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^{n} f_i(w)$$

$f_i(w) = l(x_i, y_i, w)$ is the loss of the prediction on example (x_i, y_i)

  - Deep learning optimization relies on SGD and its variants, through ***mini-batches***

$$w_{t+1} \leftarrow w_t - \eta \nabla f(w_t; x_k, y_k)$$

Federated learning – detail

- In federated learning
  - Suppose n training samples are distributed to K clients, where P_k is the set of indices of data points on client k, and $n_k = |P_k|$.
  - For training objective: $\min_{w \in \mathbb{R}^d} f(w)$

$$f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w) \qquad \text{where} \qquad F_k(w) \stackrel{\text{def}}{=} \frac{1}{n_k} \sum_{i \in P_k} f_i(w)$$

A baseline – *FederatedSGD (FedSGD)*

- A randomly selected client that has n_k training data samples in federated learning ≈ *A randomly selected sample in traditional deep learning*
- Federated SGD (FedSGD): a single step of gradient descent is done per round
- Recall in federated learning, a *C*-fraction of clients are selected at each round.
  - *C*=1: full-batch (non-stochastic) gradient descent
  - *C*<1: stochastic gradient descent (SGD)

A baseline – *FederatedSGD (FedSGD)*

Learning rate: η; total #samples: n; total #clients: K; #samples on a client k: n_k; clients fraction $C = 1$

- In a round t:
  - The central server broadcasts current model w_t to each client; each client k computes gradient: $g_k = \nabla F_k(w_t)$, on its local data.
    - Approach 1: Each client k submits g_k; the central server aggregates the gradients to generate a new model:
      - $w_{t+1} \leftarrow w_t - \eta \nabla f(w_t) = w_t - \eta \sum_{k=1}^{K} \frac{n_k}{n} g_k$.

Recall $f(w) = \sum_{k=1}^{K} \frac{n_k}{n} F_k(w)$

    - Approach 2: Each client k computes: $w_{t+1}^k \leftarrow w_t - \eta g_k$; the central server performs aggregation:
      - $w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$

For multiple times ⟹ FederatedAveraging (FedAvg)

Federated learning – deal with limited communication

- Increase computation
  - Select more clients for training between each communication round
  - Increase computation on each client

Federated learning – *FederatedAveraging (FedAvg)*

Learning rate: η; total #samples: n; total #clients: K; #samples on a client k: n_k; clients fraction C

- In a round t:
  - The central server broadcasts current model w_t to each client; each client k computes gradient: $g_k = \nabla F_k(w_t)$, on its local data.
    - Approach 2:
      - Each client k computes for *E* epochs: $w_{t+1}^k \leftarrow w_t - \eta g_k$
      - The central server performs aggregation: $w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$
      - Suppose *B* is the local mini-batch size, #updates on client *k* in each round: $u_k = E\frac{n_k}{B}$.

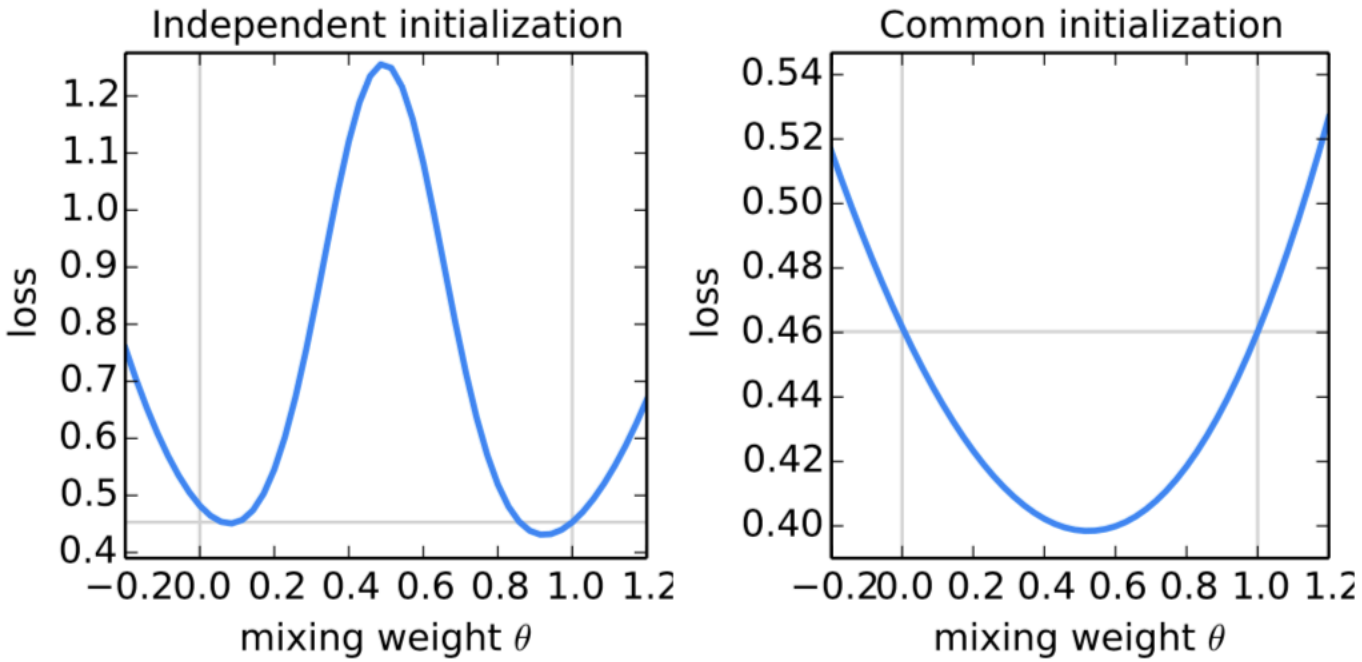
The amount of computation in each round is determined by:

Federated learning – *FederatedAveraging (FedAvg)*

Model initialization

- Two choices:
  - On the central server
  - On each client

Shared initialization works better in practice.



The loss on the full MNIST training set for models generated by

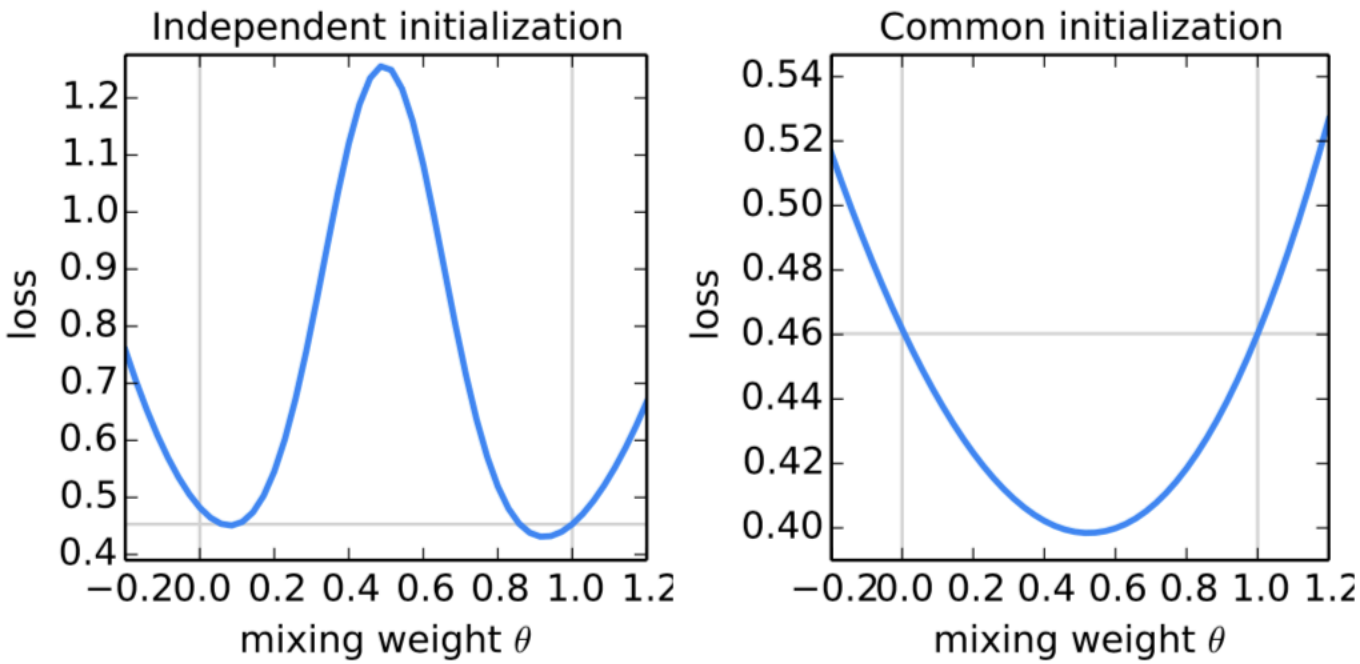
$$\theta w + (1 - \theta) w'$$

Federated learning – *FederatedAveraging (FedAvg)*

Model averaging

- As shown in the right figure:

In practice, naïve parameter averaging works surprisingly well.



The loss on the full MNIST training set for models generated by

$$\theta w + (1 - \theta) w'$$

Federated learning – *FederatedAveraging (FedAvg)*

Algorithm 1 `FederatedAveraging`. The K clients are indexed by k; B is the local minibatch size, E is the number of local epochs, and η is the learning rate.

Server executes:

initialize w_0

for each round $t = 1, 2, \dots$ **do**

$m \leftarrow \max(C \cdot K, 1)$

$S_t \leftarrow$ (random set of m clients)

for each client $k \in S_t$ **in parallel do**

$w_{t+1}^k \leftarrow \text{ClientUpdate}(k, w_t)$

$w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{n_k}{n} w_{t+1}^k$

ClientUpdate(k, w): *// Run on client k*

$\mathcal{B} \leftarrow$ (split $\mathcal{P}_k$ into batches of size B)

for each local epoch i from 1 to E **do**

for batch $b \in \mathcal{B}$ **do**

$w \leftarrow w - \eta \nabla \ell(w; b)$

return w to server

1. At first, a model is randomly initialized on the central server.
2. For each round *t:*
   - *i. A random set of clients are chosen;*
   - *ii. Each client performs local gradient descent steps;*
   - *iii. The server aggregates model parameters submitted by the clients.*

Federated learning – *Evaluation*

Impact of varying *C*

2NN	IID		Non-IID	
C	$B = \infty$	$B = 10$	$B = \infty$	$B = 10$
0.0	1455	316	4278	3275
0.1	1474 (1.0×)	87 (3.6×)	1796 (2.4×)	664 (4.9×)
0.2	1658 (0.9×)	77 (4.1×)	1528 (2.8×)	619 (5.3×)
0.5	— (—)	75 (4.2×)	— (—)	443 (7.4×)
1.0	— (—)	70 (4.5×)	— (—)	380 (8.6×)
CNN, $E = 5$				
0.0	387	50	1181	956
0.1	339 (1.1×)	18 (2.8×)	1100 (1.1×)	206 (4.6×)
0.2	337 (1.1×)	18 (2.8×)	978 (1.2×)	200 (4.8×)
0.5	164 (2.4×)	18 (2.8×)	1067 (1.1×)	261 (3.7×)
1.0	246 (1.6×)	16 (3.1×)	— (—)	97 (9.9×)

1 client

1 client

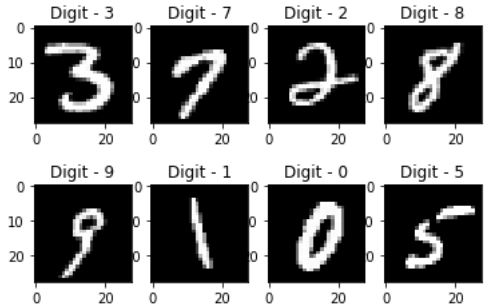
FedSGD FedAvg FedSGD FedAvg

#rounds required to achieve a target accuracy on test dataset.

In general, the higher C, the smaller #rounds to reach target accuracy.

Image classification

- #clients: 100
- Dataset: MNIST
  - IID: Random partition
  - Non-IID: each client only contains two digits
  - Balanced



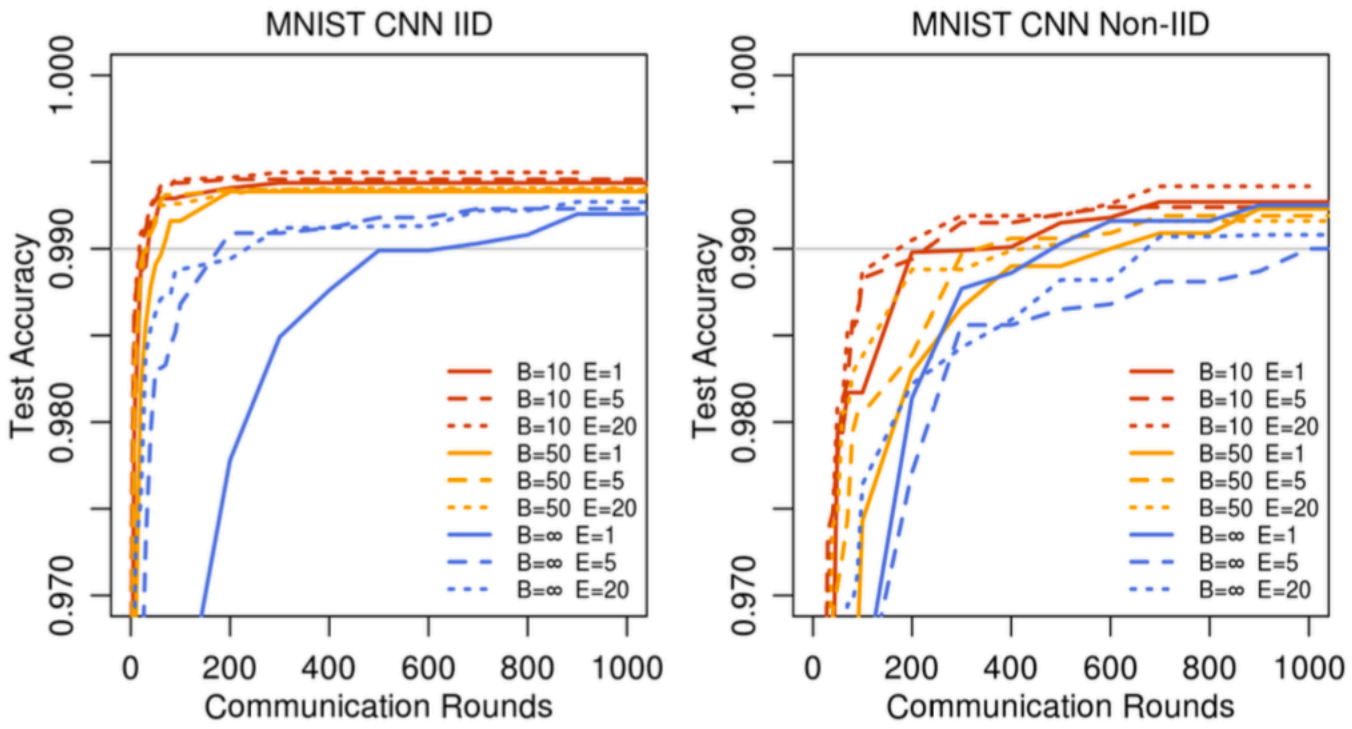
Federated learning – *Evaluation*

Language modeling

- Dataset from: *The Complete Works of Shakespeare*
  - #clients: 1146, each corresponding to a speaking role
  - Unbalanced: different #lines for each role
  - Train-test split ratio: 80% - 20%
  - A balanced and IID dataset with 1146 clients is also constructed
- Task: next character prediction
- Model: character-level LSTM language model

Federated learning – *Evaluation*

Image classification

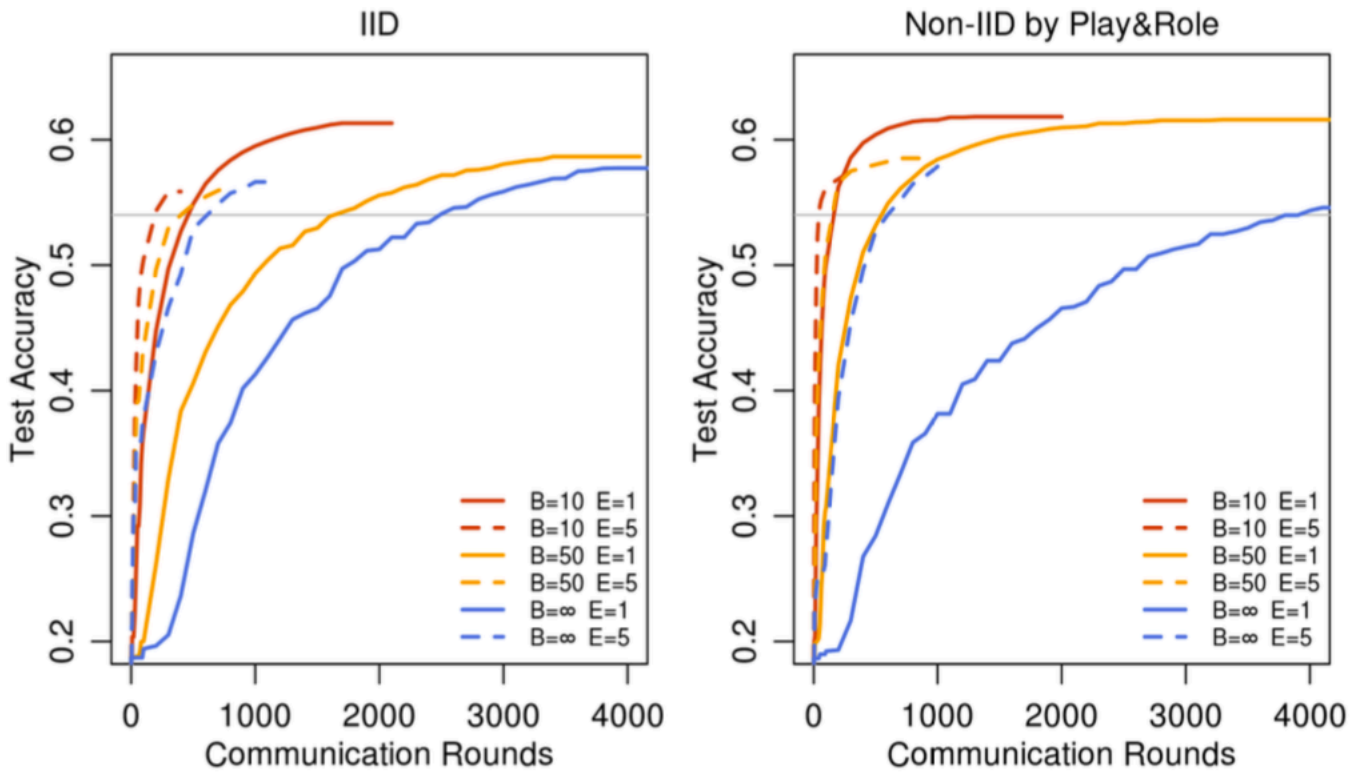


- The effect of increasing computation in each round (decrease B / increase E)
- Fix *C=0.1*

In general, the more computation in each round, the faster the model trains.
FedAvg also converges to a higher test accuracy (B=10, E=20).

Federated learning – *Evaluation*

Language modeling

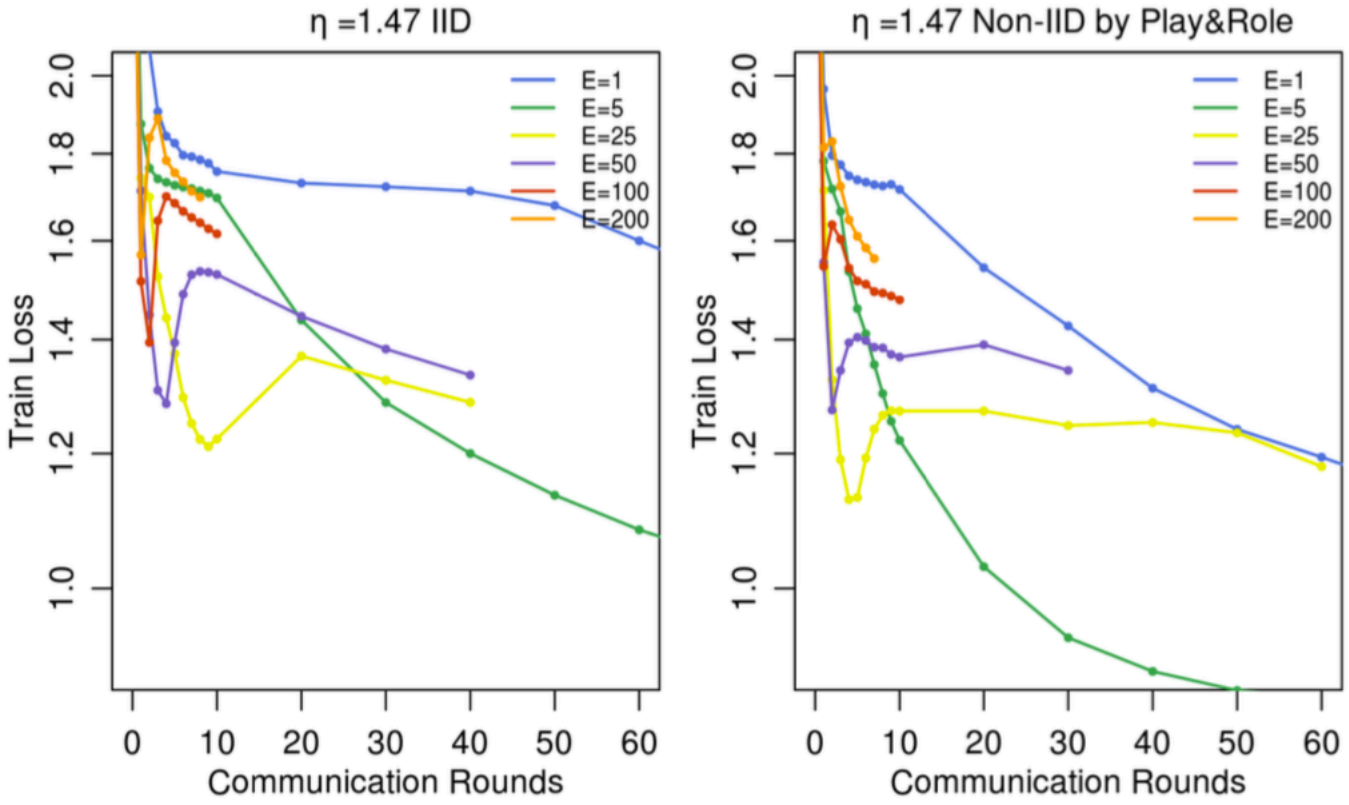


- The effect of increasing computation in each round (decrease B / increase E)
- Fix *C=0.1*

In general, the more computation in each round, the faster the model trains.
FedAvg also converges to a higher test accuracy (B=10, E=5).

Federated learning – *Evaluation*

- What if we maximize the computation on each client? $E \to \infty$



Best performance may achieve at earlier rounds; increasing #rounds do not improve.

Best practice: decay the amount of local computation when the model is close to converge.

Federated learning – *Evaluation*

Acc.	80%	82%	85%
SGD	18000 (—)	31000 (—)	99000 (—)
FedSGD	3750 (4.8×)	6600 (4.7×)	N/A (—)
FedAvg	280 (64.3×)	630 (49.2×)	2000 (49.5×)

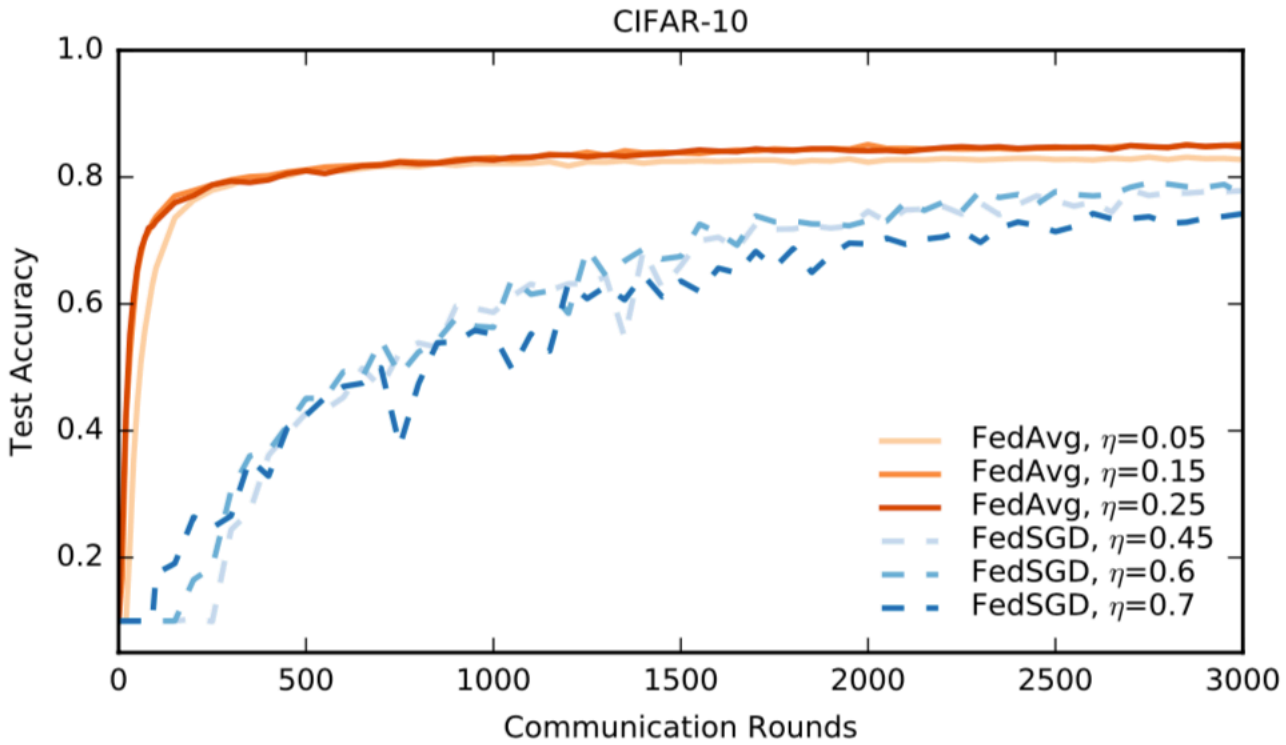
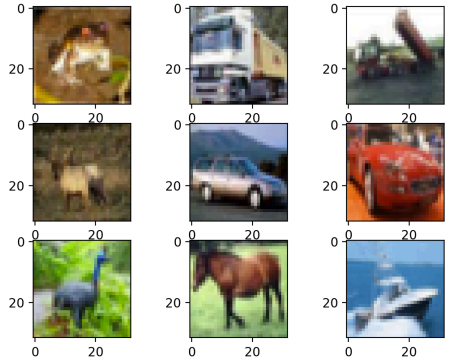


Image classification

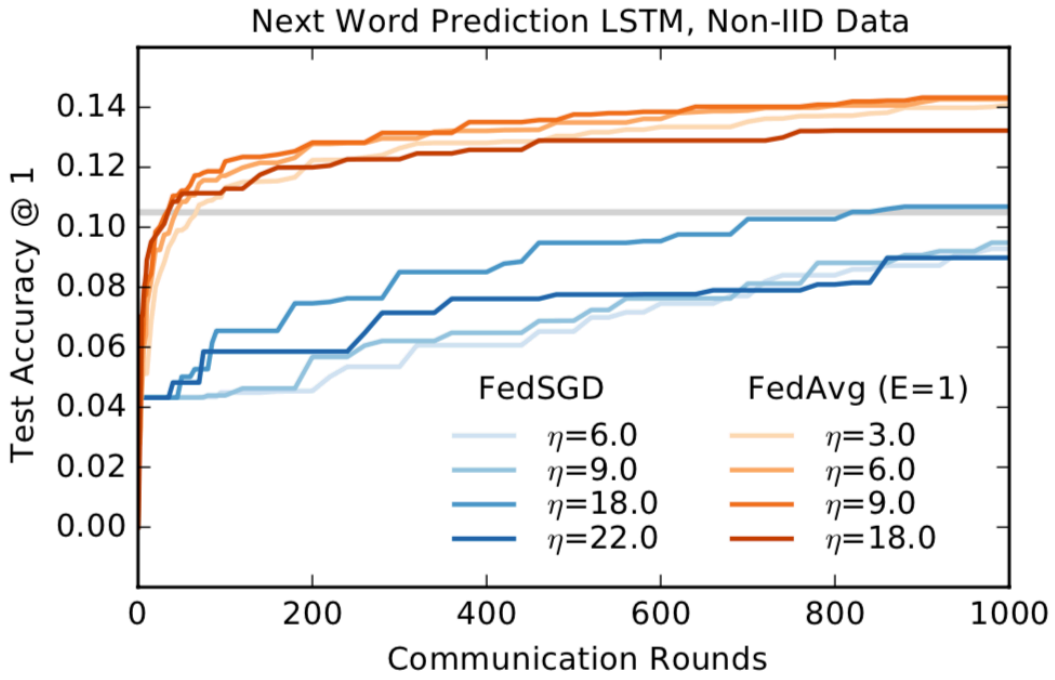
- #clients: 100
- Dataset: CIFAR-10
  - IID: Random partition
  - Non-IID: each client only contains two digits
  - Balanced



Federated learning – *Evaluation*

Language modeling
A real-world problem

- Dataset from: *10 million public posts from a large social network*
  - #clients: 500,000, each corresponding to an author
- Task: next word prediction
- Model: word-level LSTM language model



200 clients per round; *B*=8, *E*=1

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- ❑ Open problems

Federated learning – related research

Google FL Workshop: https://sites.google.com/view/federated-learning-2019/home

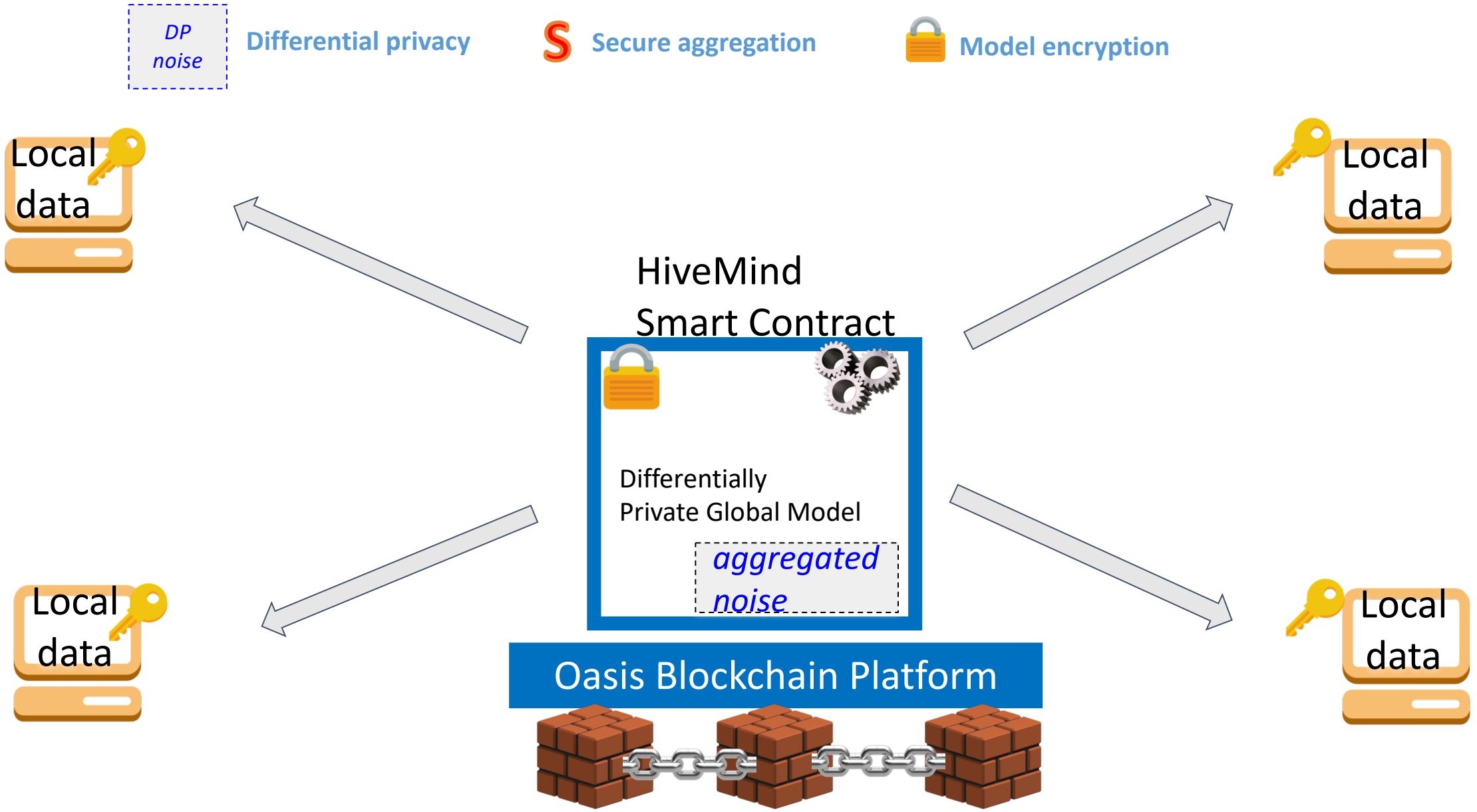
Data poisoning attacks. *How to backdoor federated learning, arXiv:1807.00459.*

Secure aggregation. *Practical Secure Aggregation for Privacy-Preserving Machine Learning, CCS'17*

Client-level differential privacy. *Differentially Private Federated Learning: A Client-level Perspective, ICLR'19*

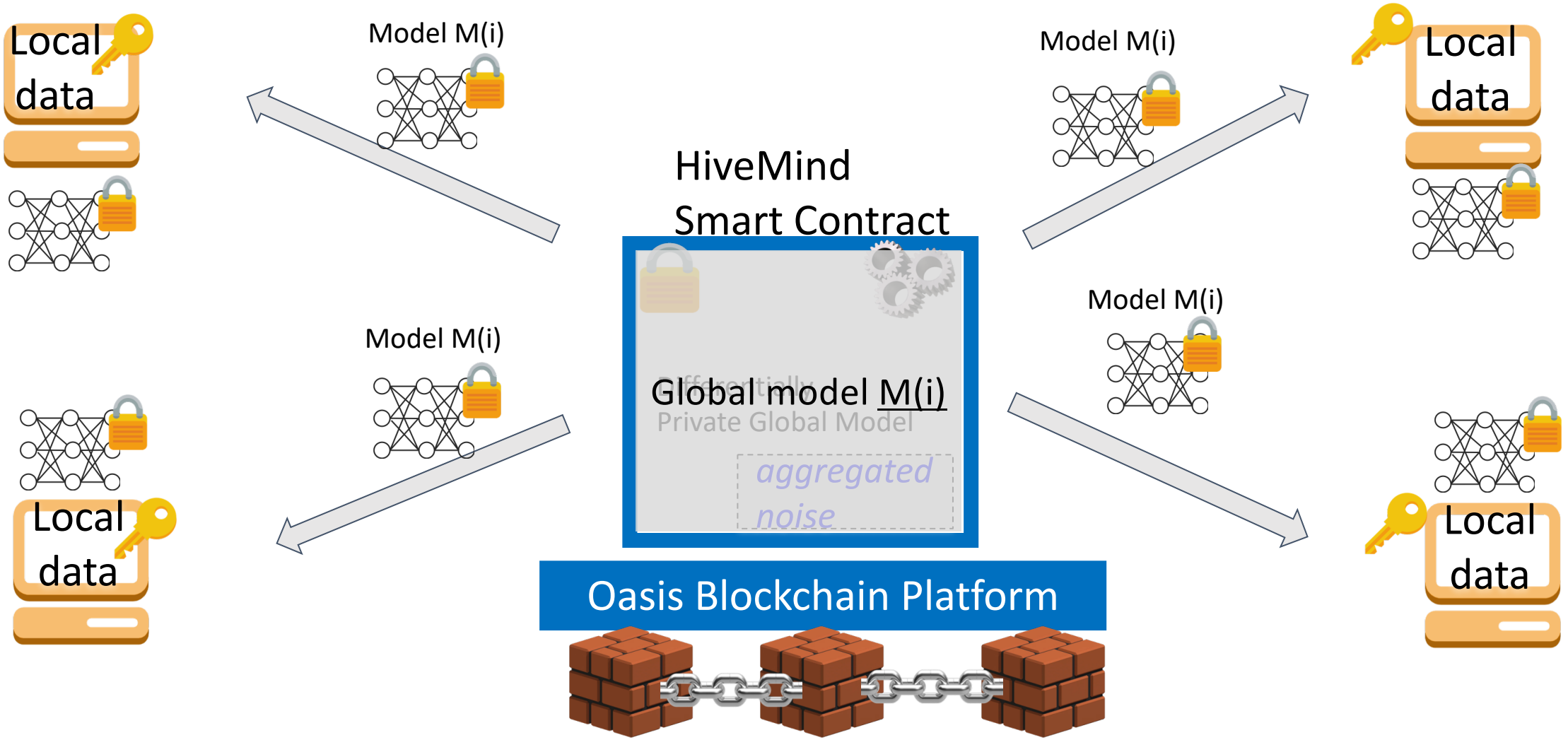
Decentralize the central server via blockchain.

HiveMind: Decentralized Federated Learning



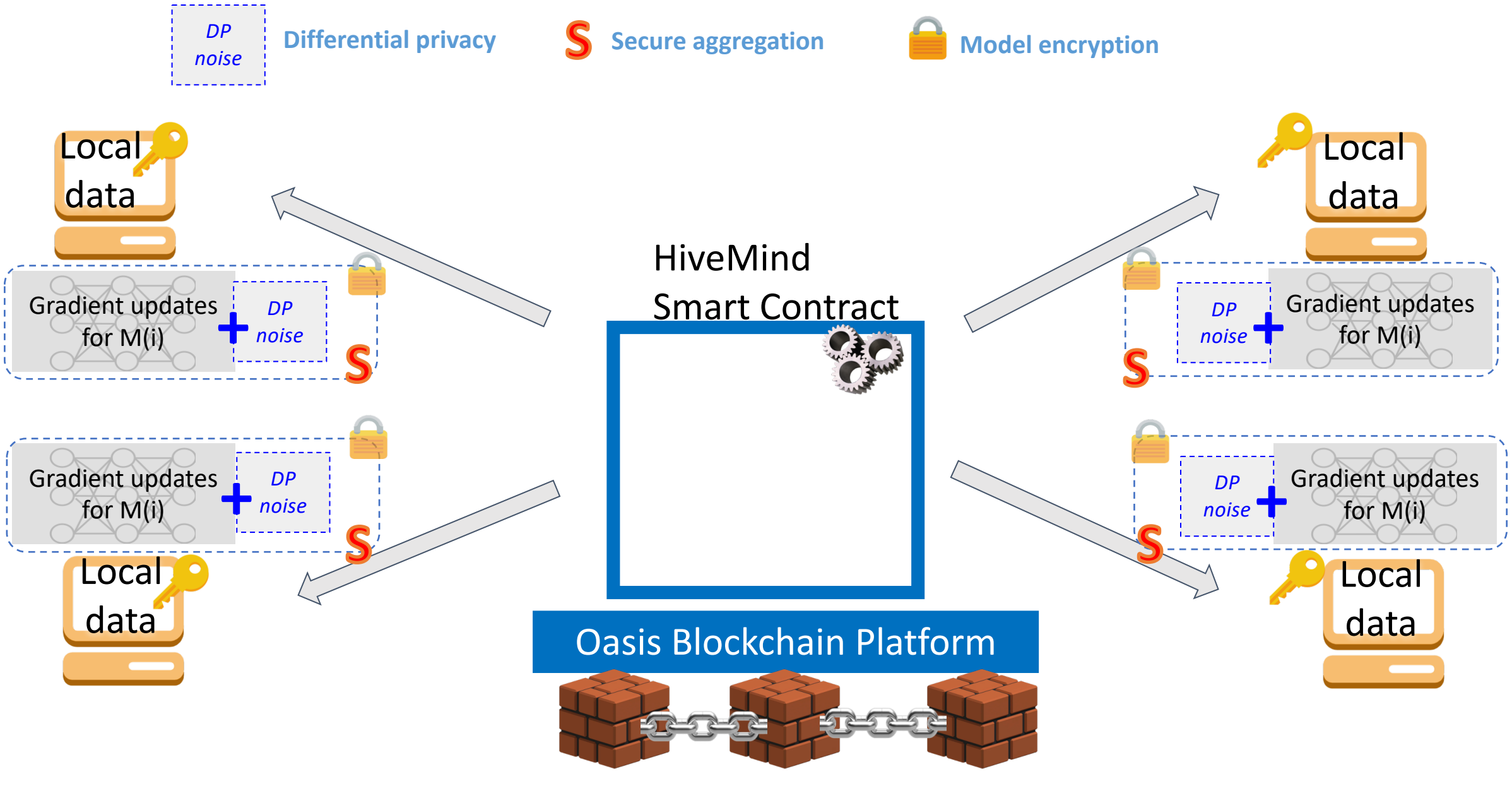
HiveMind: Decentralized Federated Learning

In round number i…



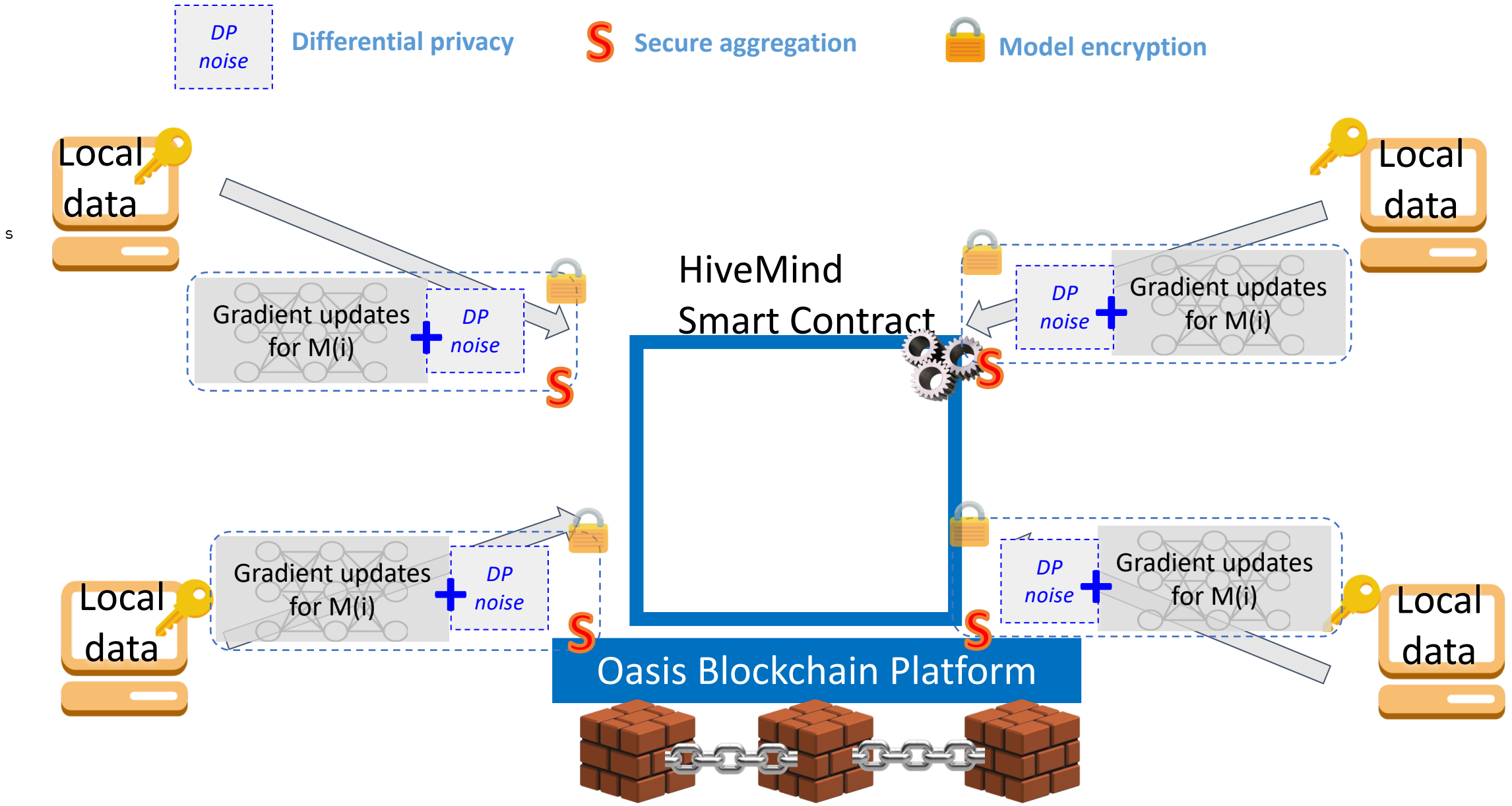
HiveMind: Decentralized Federated Learning

In round number i…



HiveMind: Decentralized Federated Learning

In round number i…



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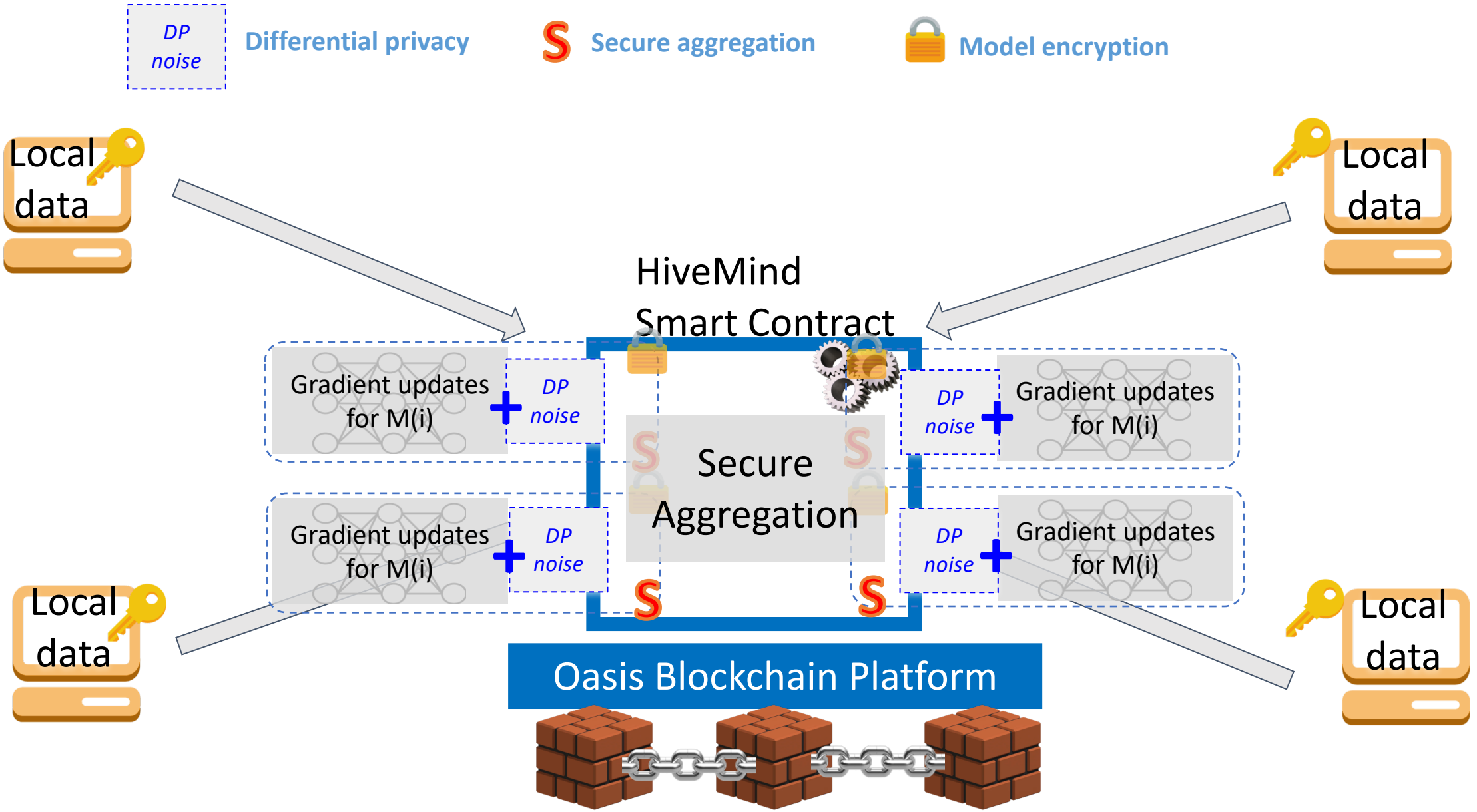
In round number i…



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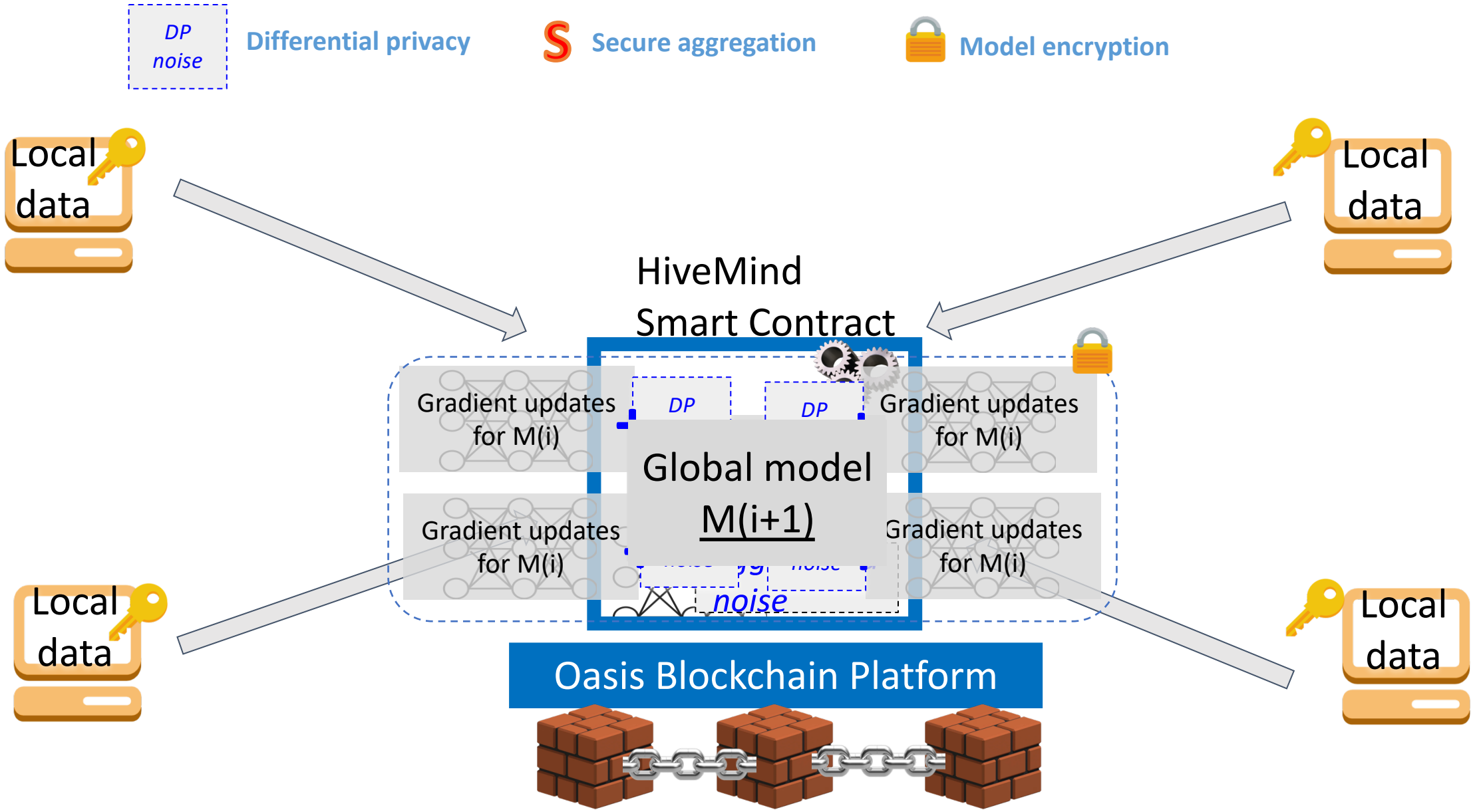
In round number i…



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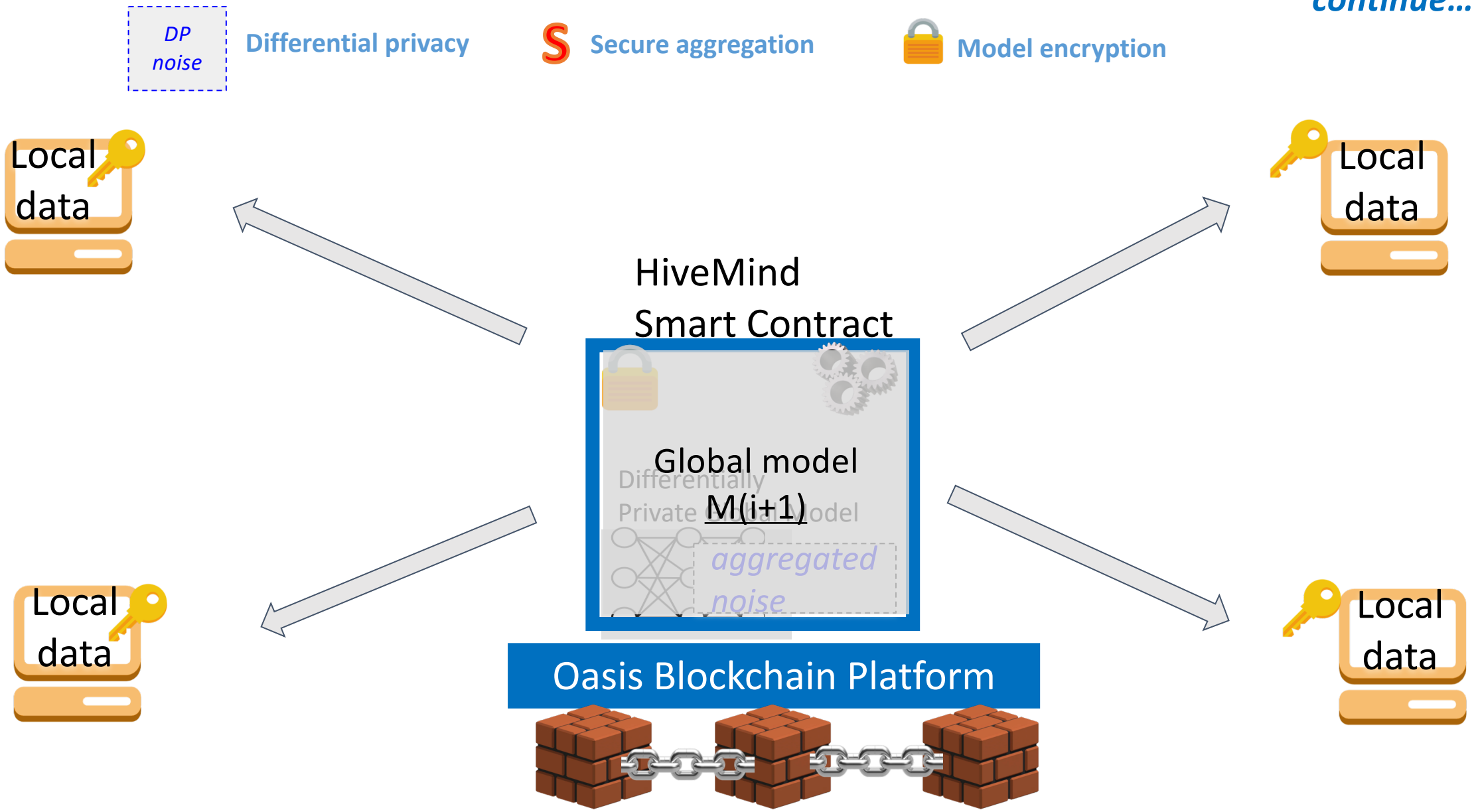
Round number i+1 and continue…



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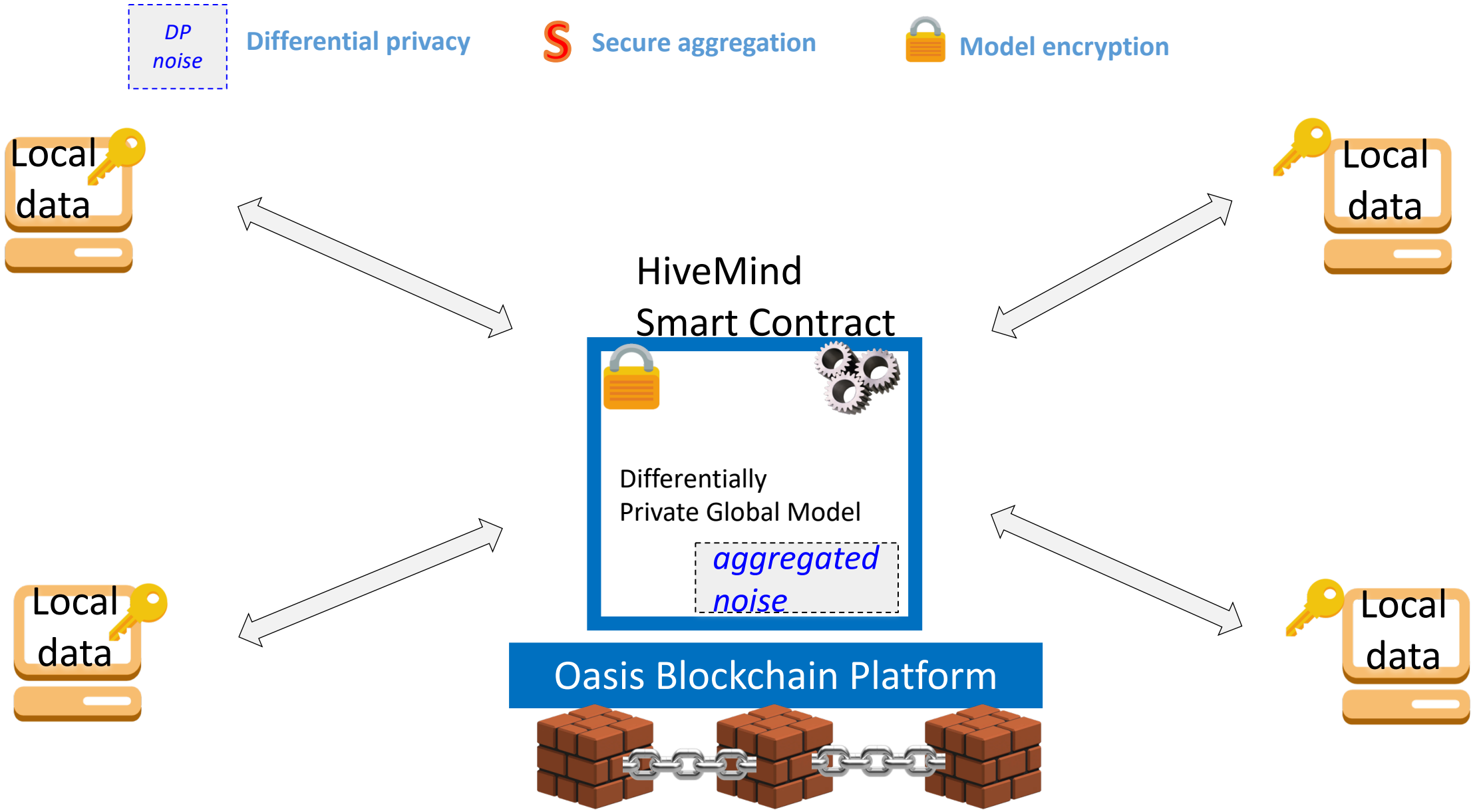

Outline

- ❑ Preliminary: deep learning and SGD
- ❑ Federated learning: FedSGD and FedAvg
- ❑ Related research in federated learning
- ❑ Open problems

Federated learning – open problems

- Detect data poisoning attacks, while secure aggregation is being used.
- Asynchronous model update in federated learning and its co-existence with secure aggregation.
- Further reduce communication overhead through quantization etc.
- The usage of differential privacy in each of the above settings.
- ……

Thank you!

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