Omni-Fedge

Federated Algorithm With A Bayesian Approach

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॥ सा विद्या या विमुक्तये ॥
भारतीय प्रौद्योगिकी संस्थान धारवाड
Indian Institute of Technology Dharwad

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December 24, 2020

What is Federated Learning?

- Distributed machine learning architecture where edge-devices learn shared predictive model collaboratively

*https://blog.ml.cmu.edu/2019/11/12/federated-learning-challenges-methods-and-future-directions/

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Figure: FL Architecture *

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Where is FL being used?

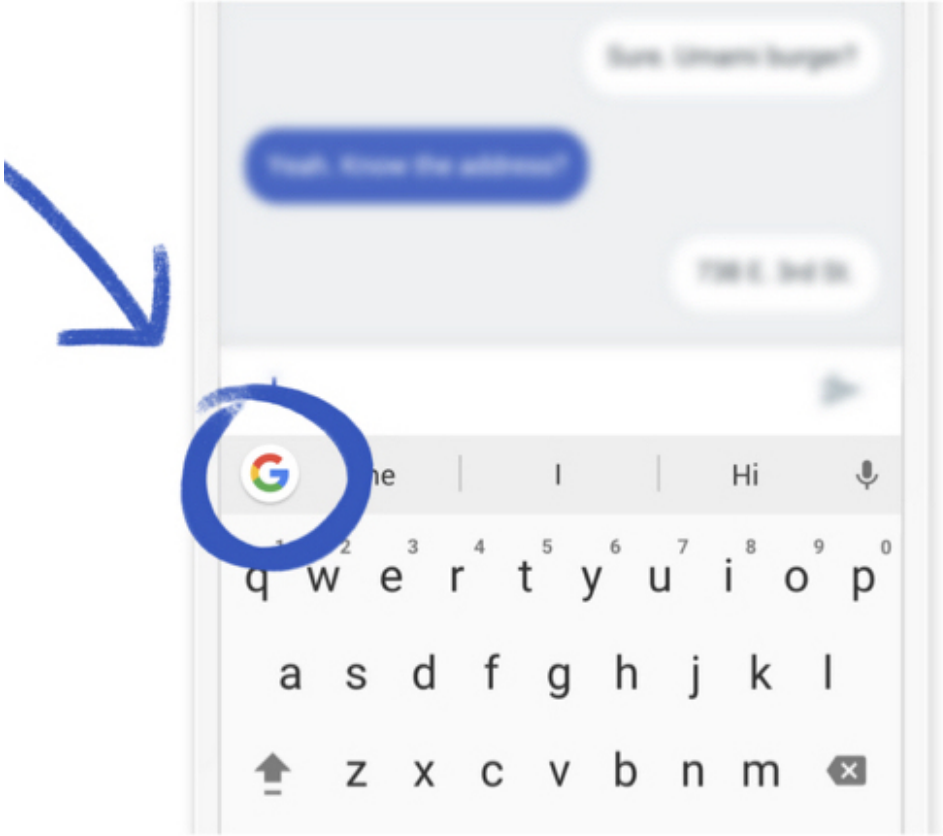

Figure: GBoard: Query prediction using FL †

† https://blog.google/products/search/gboard-now-on-android/

Where can FL be used?

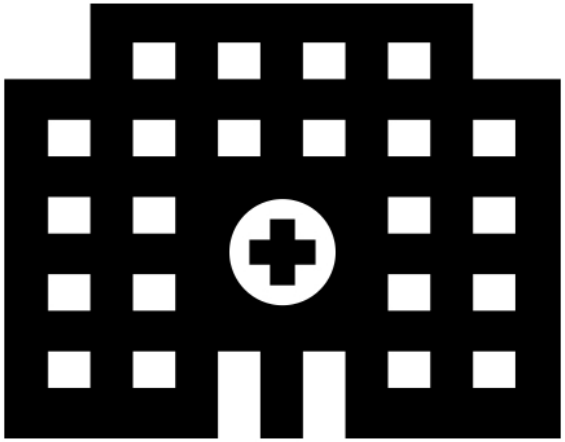

Figure: Private learning among hospitals [‡]

[‡] https://www.nature.com/articles/s41746-020-00323-1

Where can FL be used?

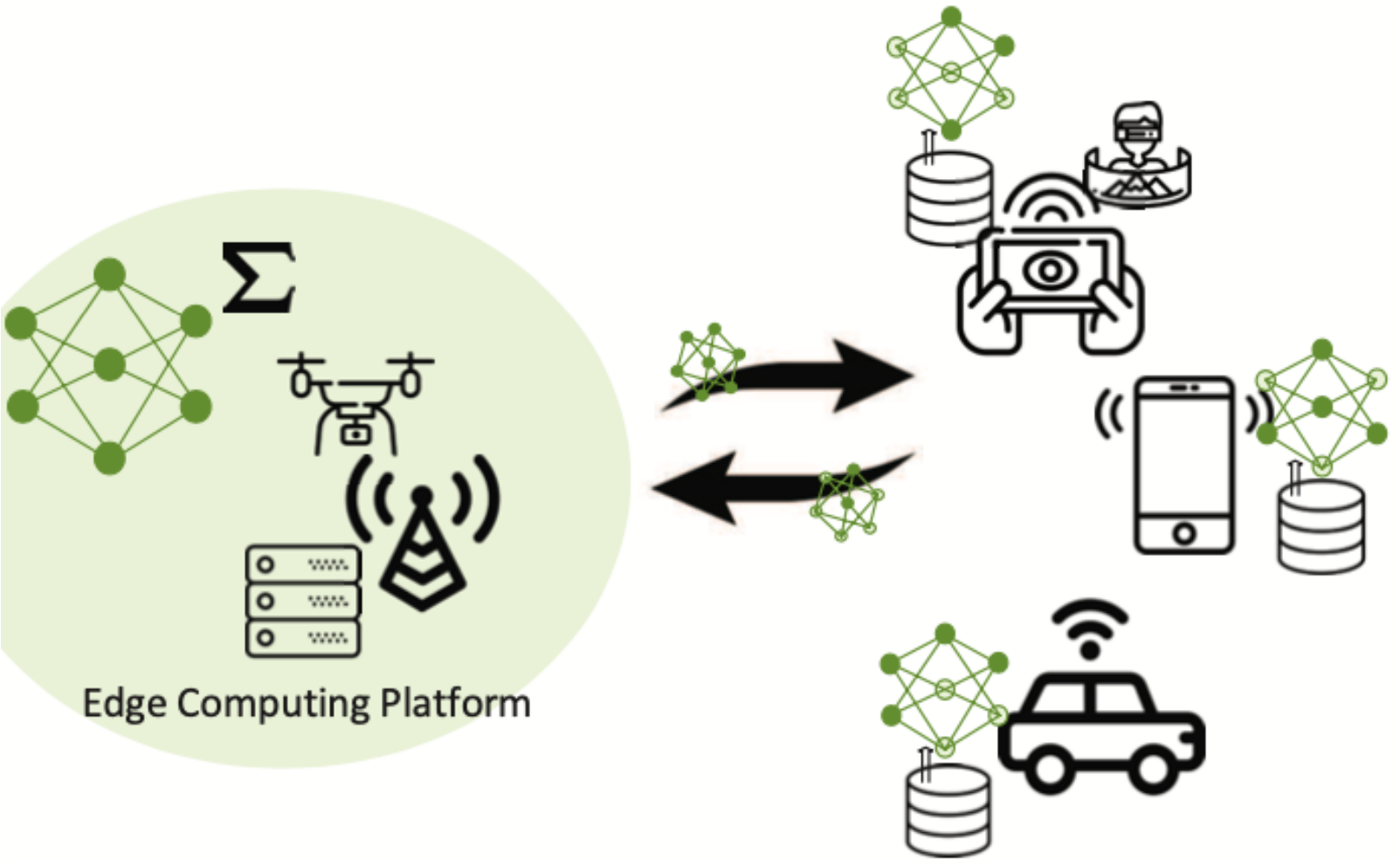

Figure: Self-driving cars in an autonomous vehicle network [§]

[§] https://ieeexplore.ieee.org/abstract/document/9141214

What are the fundamental challenges in FL?

- Implementing FL in practice imposes several challenges

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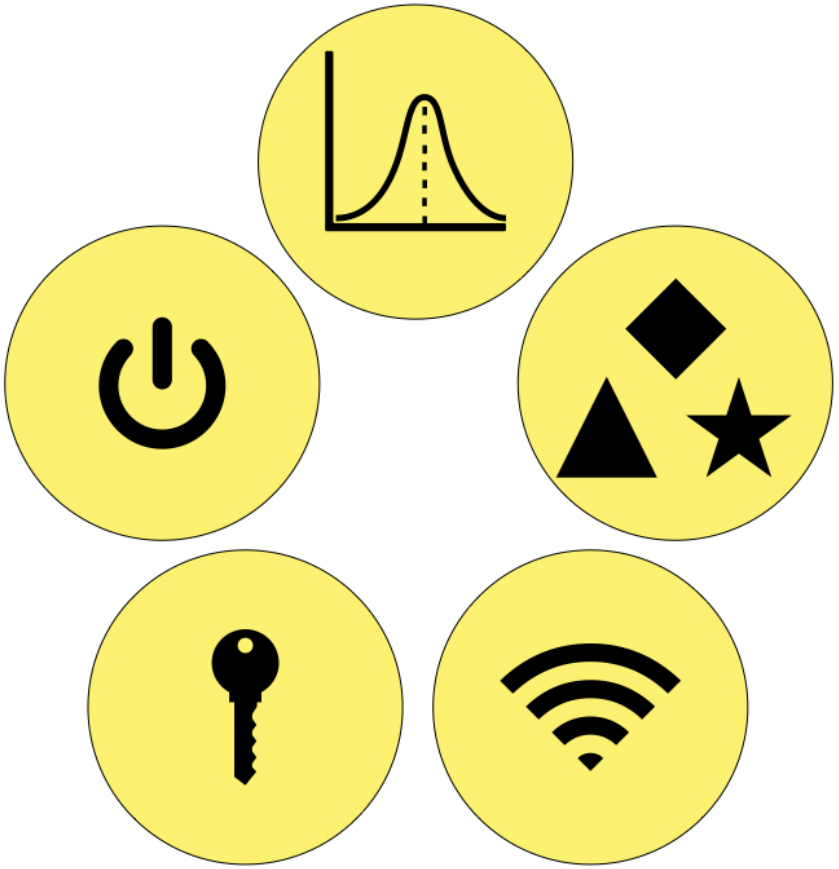

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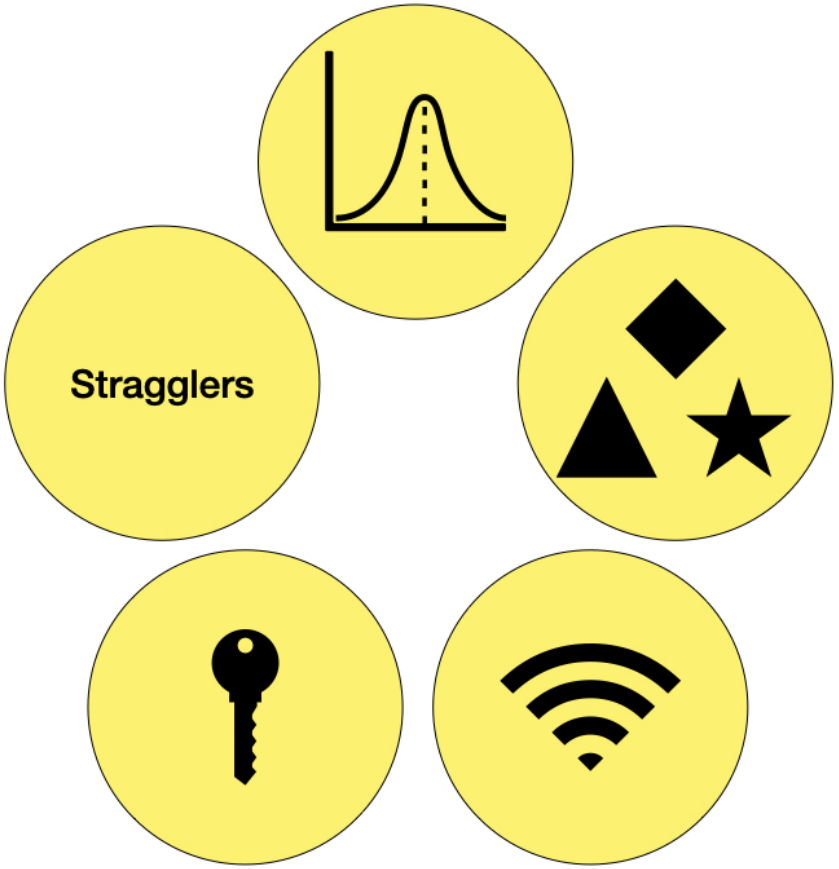

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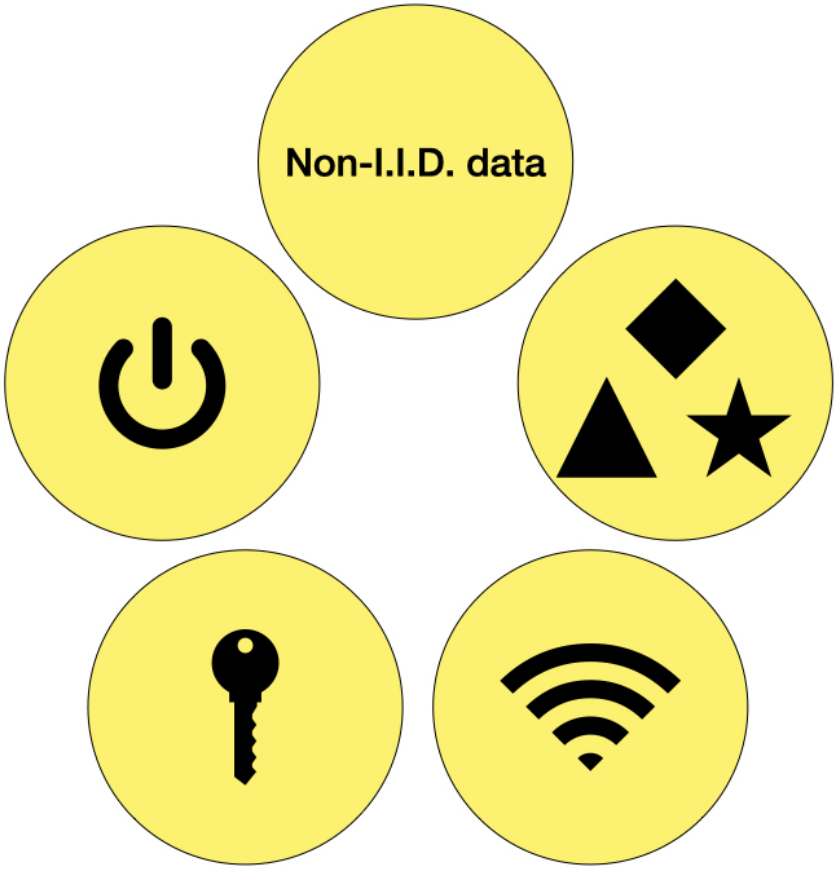

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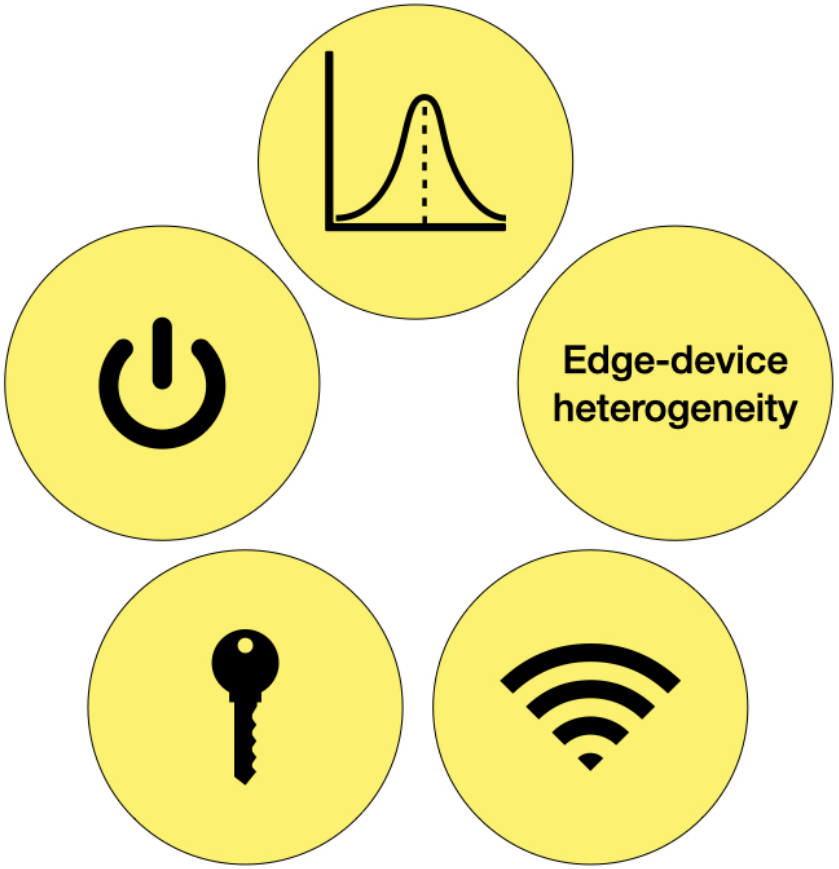

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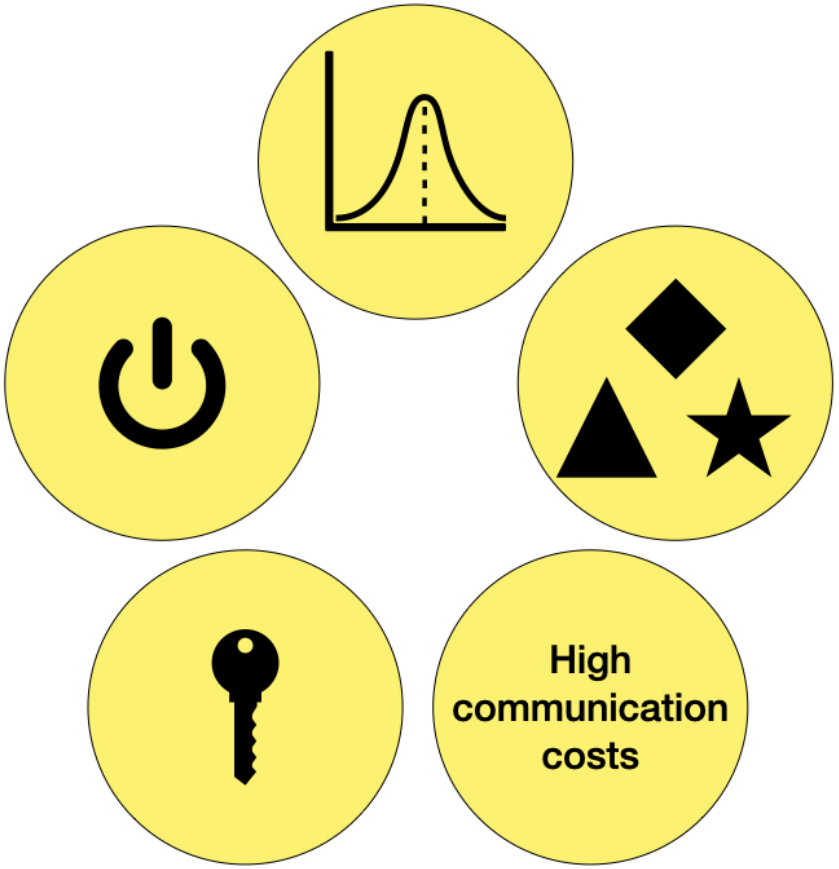

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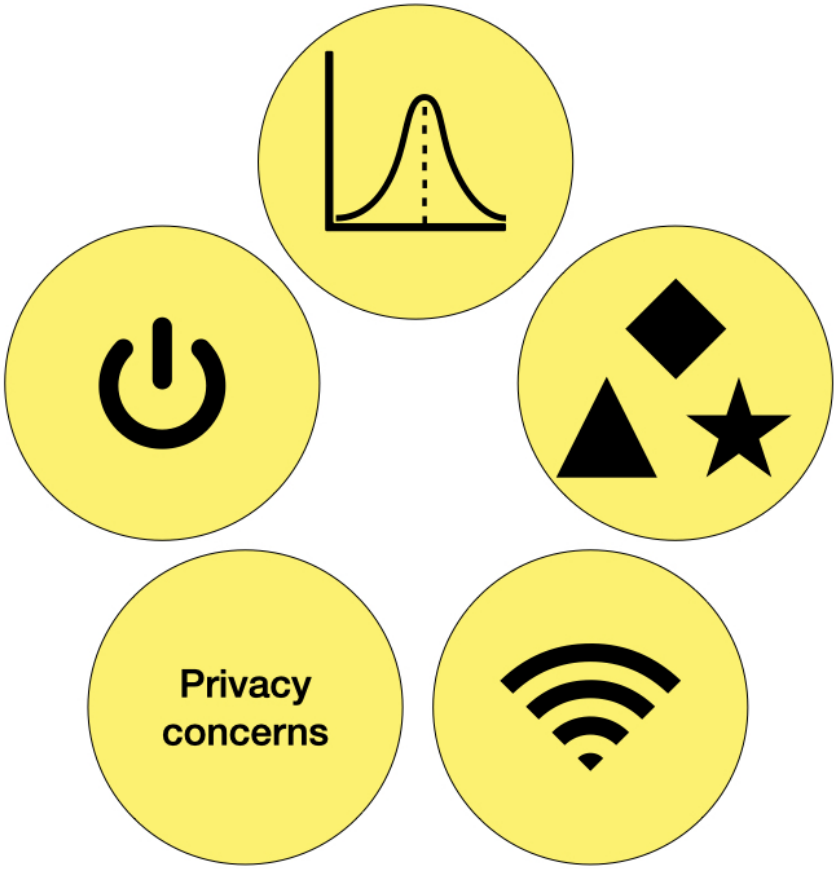

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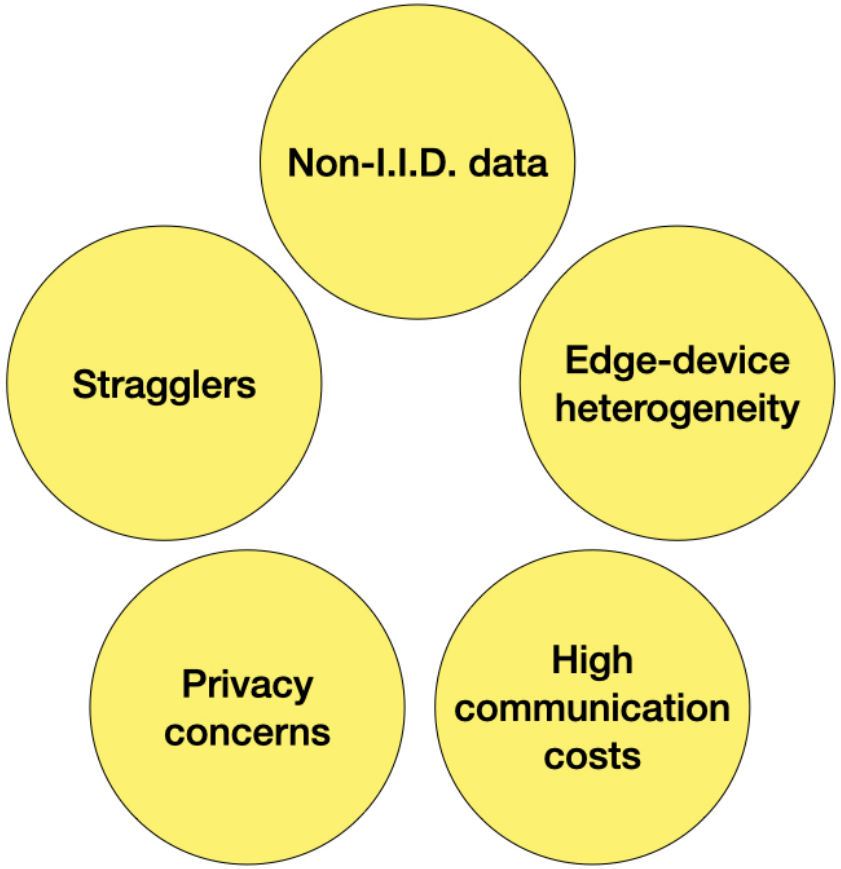

Recalling what is a neural network?

$z_{11} \longrightarrow$

$z_{12} \longrightarrow$

$z_{13} \longrightarrow$

$\vdots$

$z_{1n} \longrightarrow$

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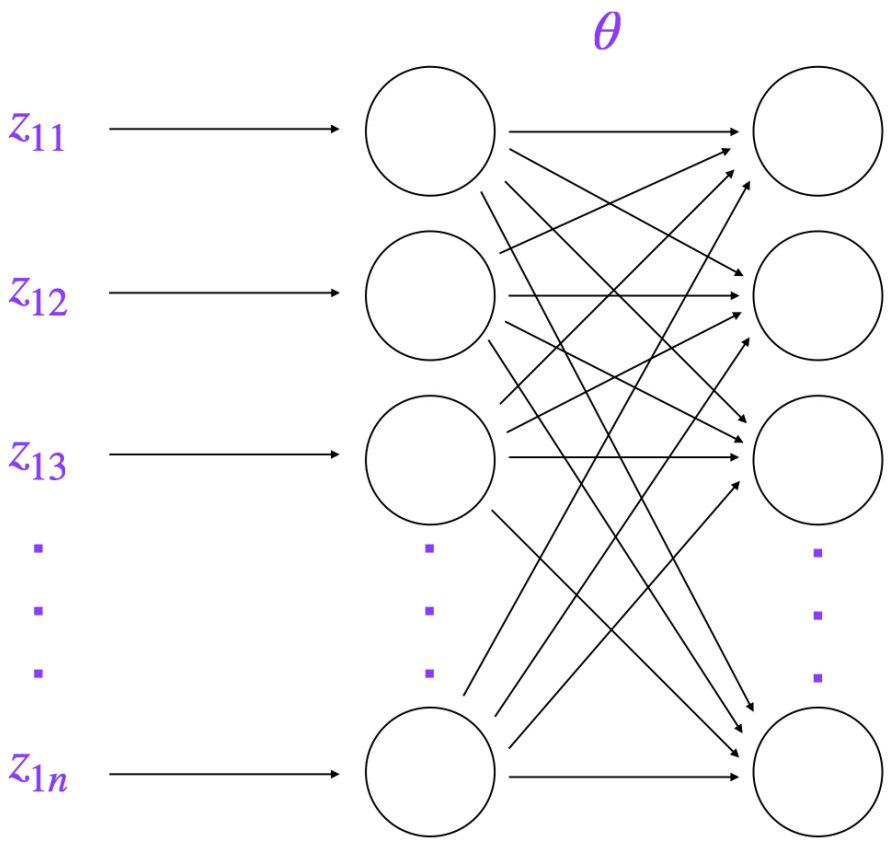

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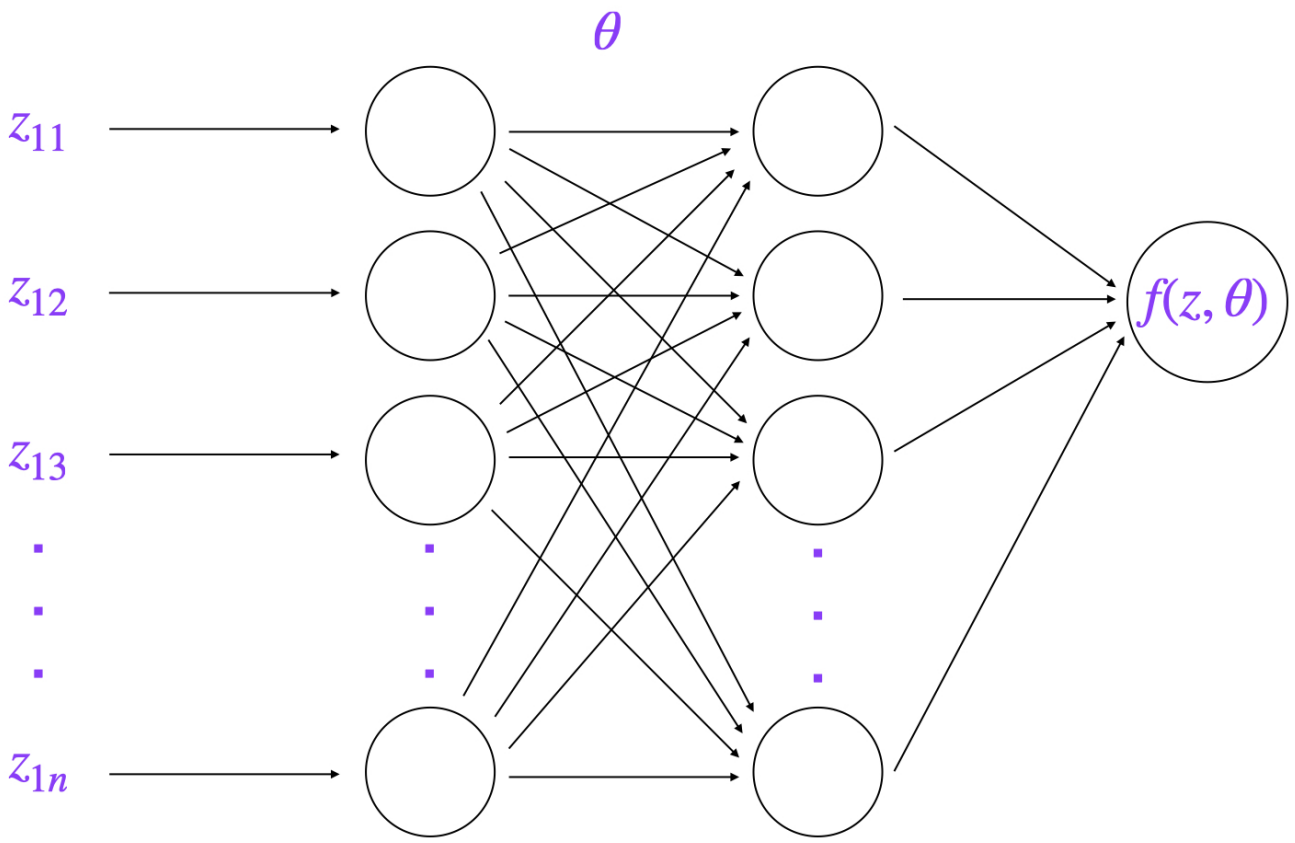

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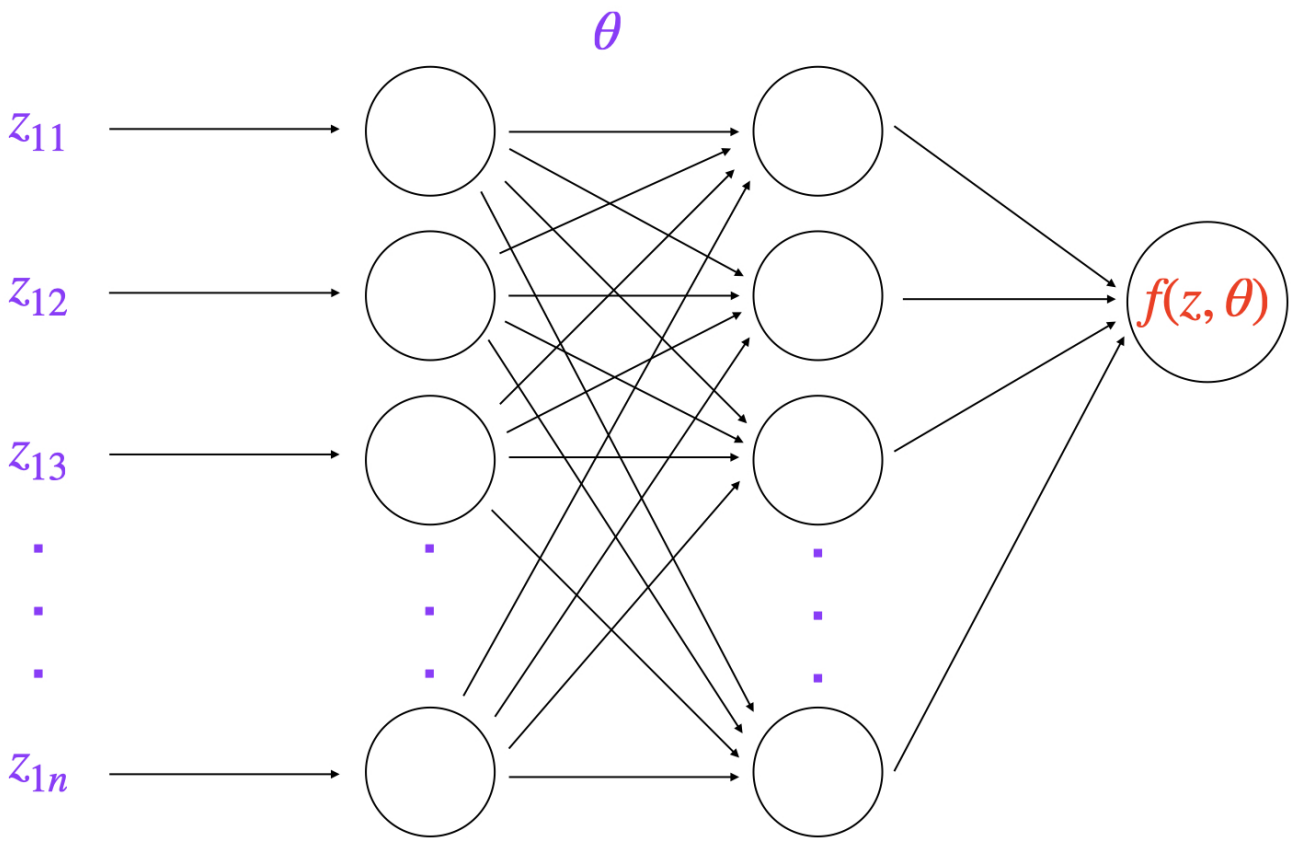

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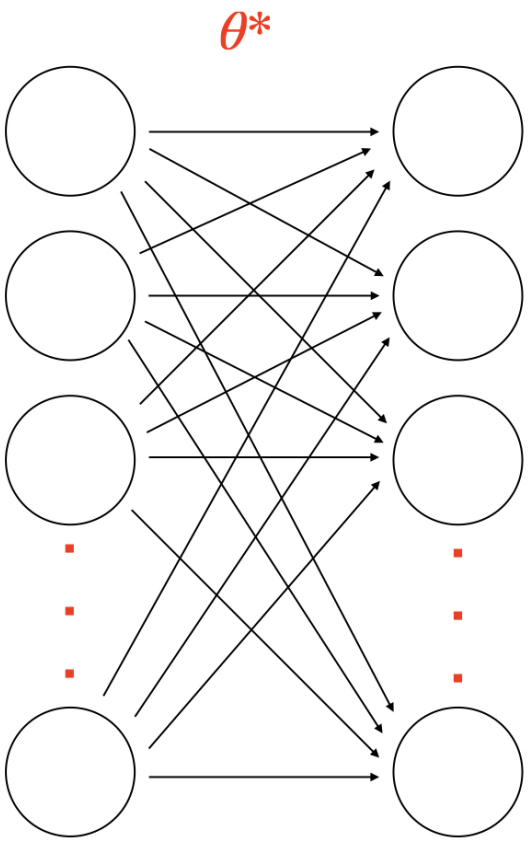

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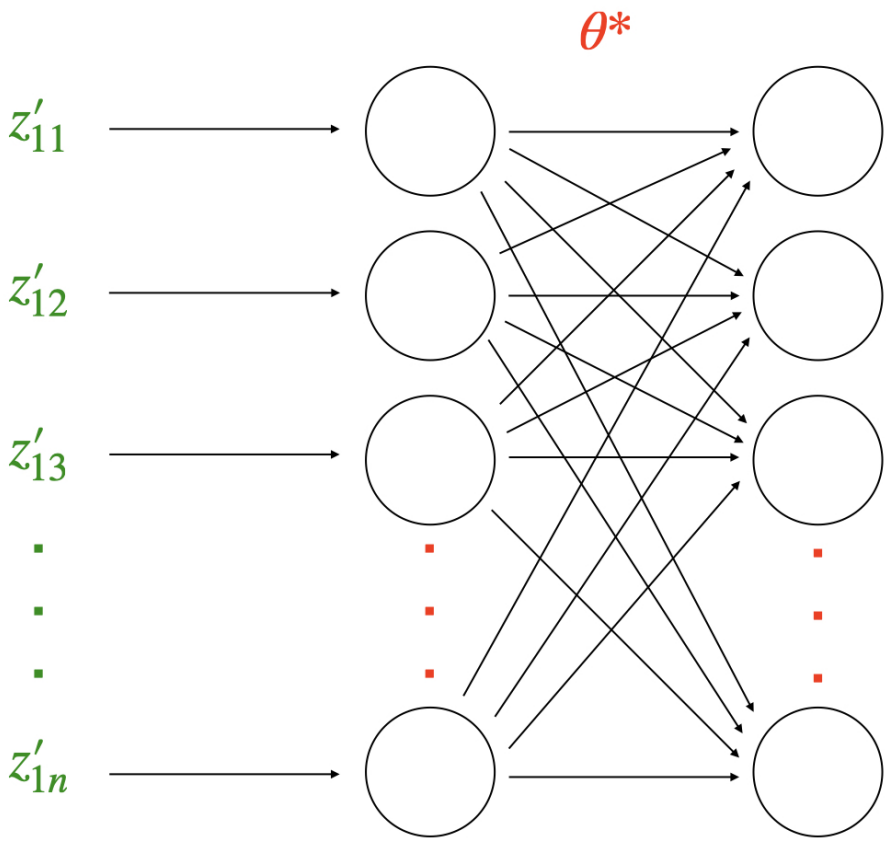

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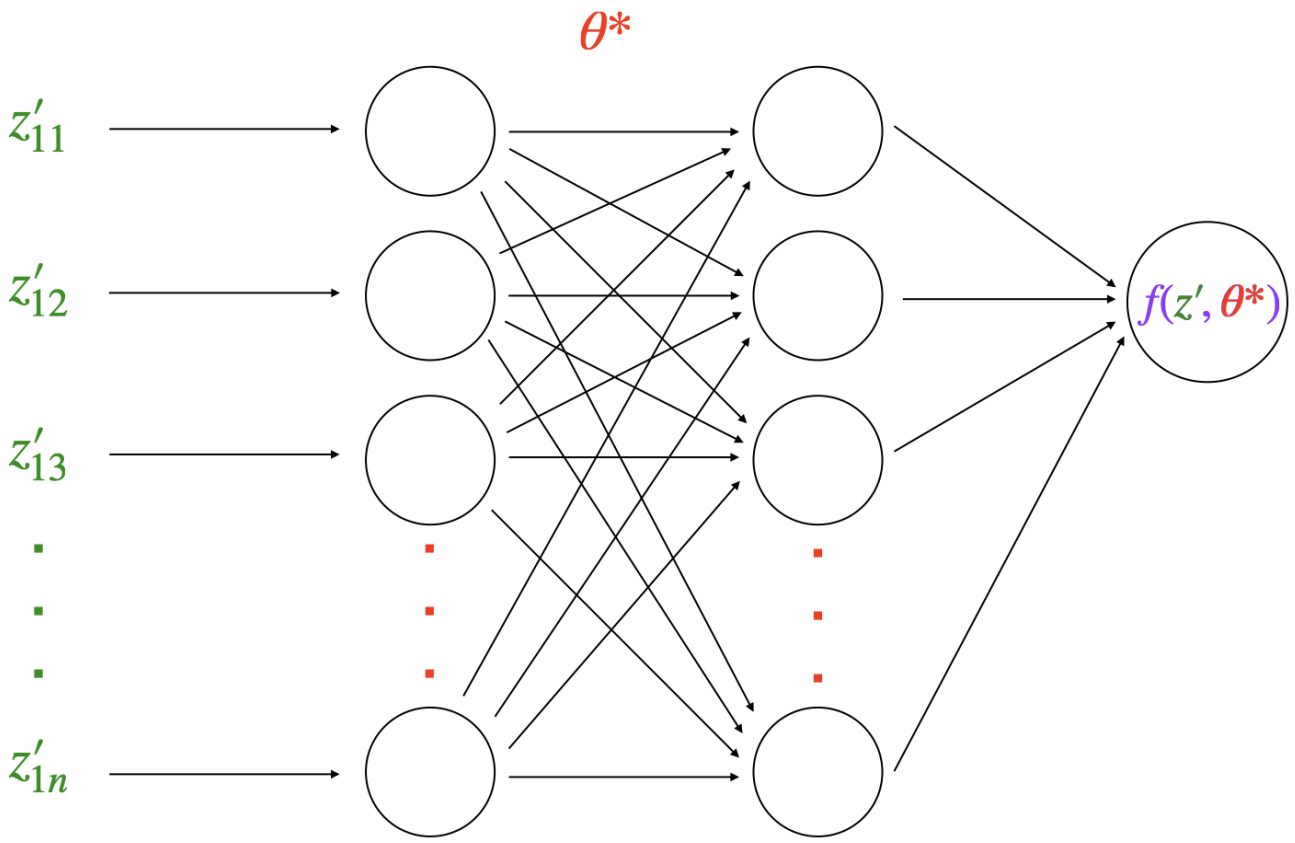

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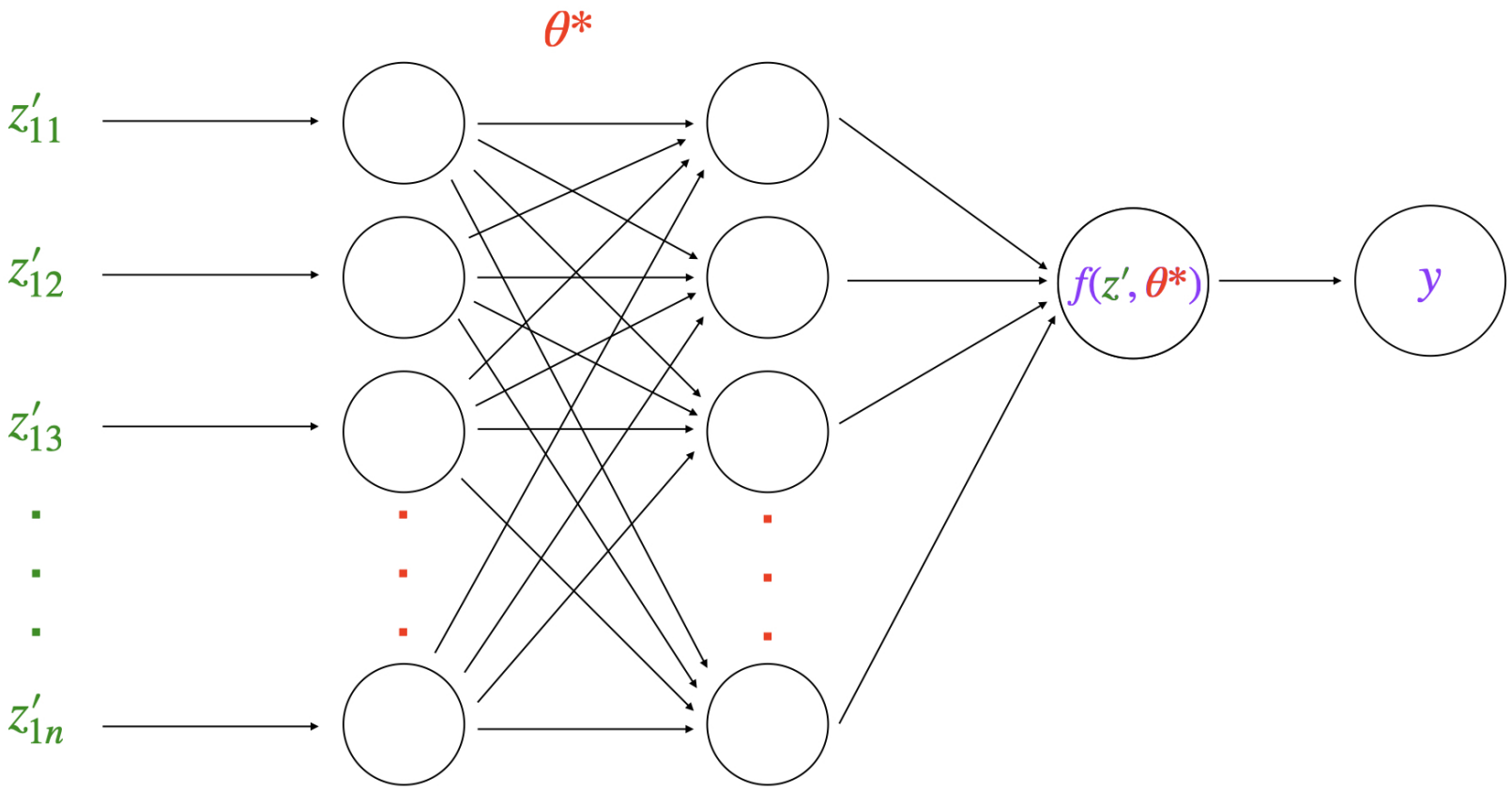

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$$\theta_1^{t+1} = \theta_1^t - \eta_1 \nabla_{\theta_1} f_1(\theta_1, z_1) \qquad \theta_2^{t+1} = \theta_2^t - \eta_2 \nabla_{\theta_2} f_2(\theta_2, z_2) \qquad \theta_3^{t+1} = \theta_3^t - \eta_3 \nabla_{\theta_3} f_3(\theta_3, z_3)$$

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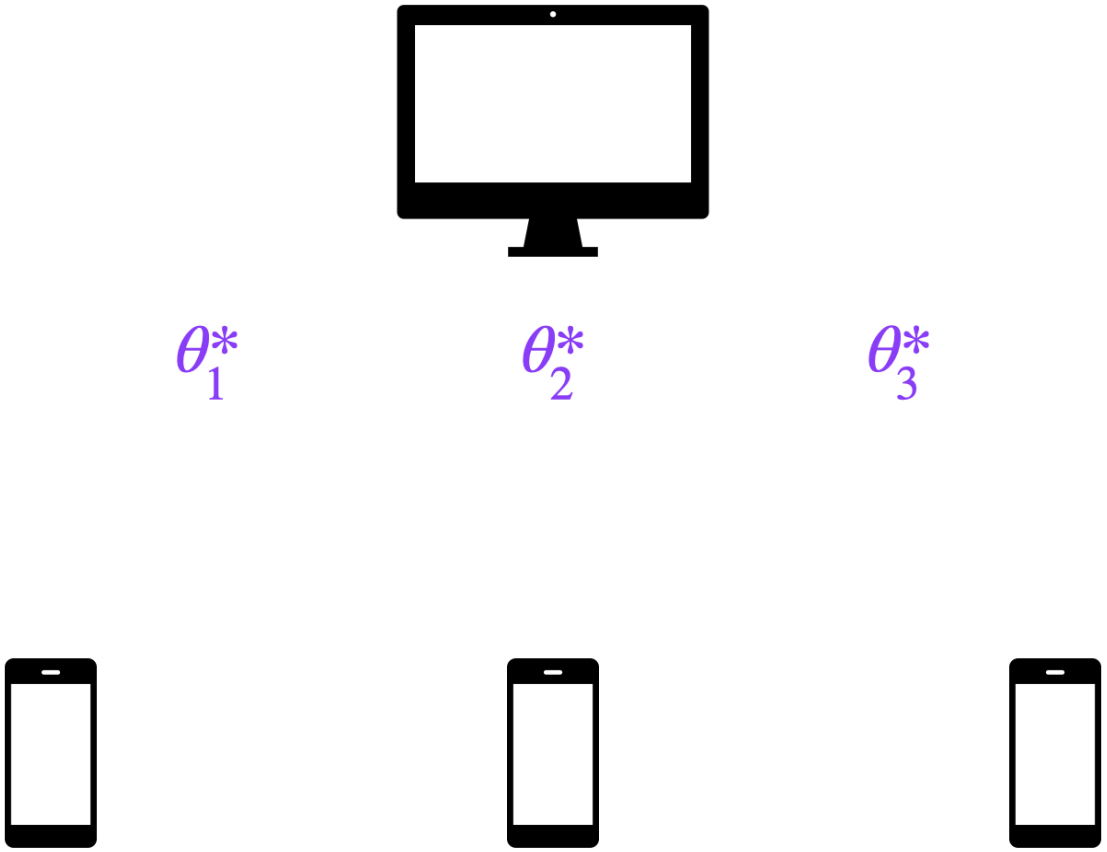

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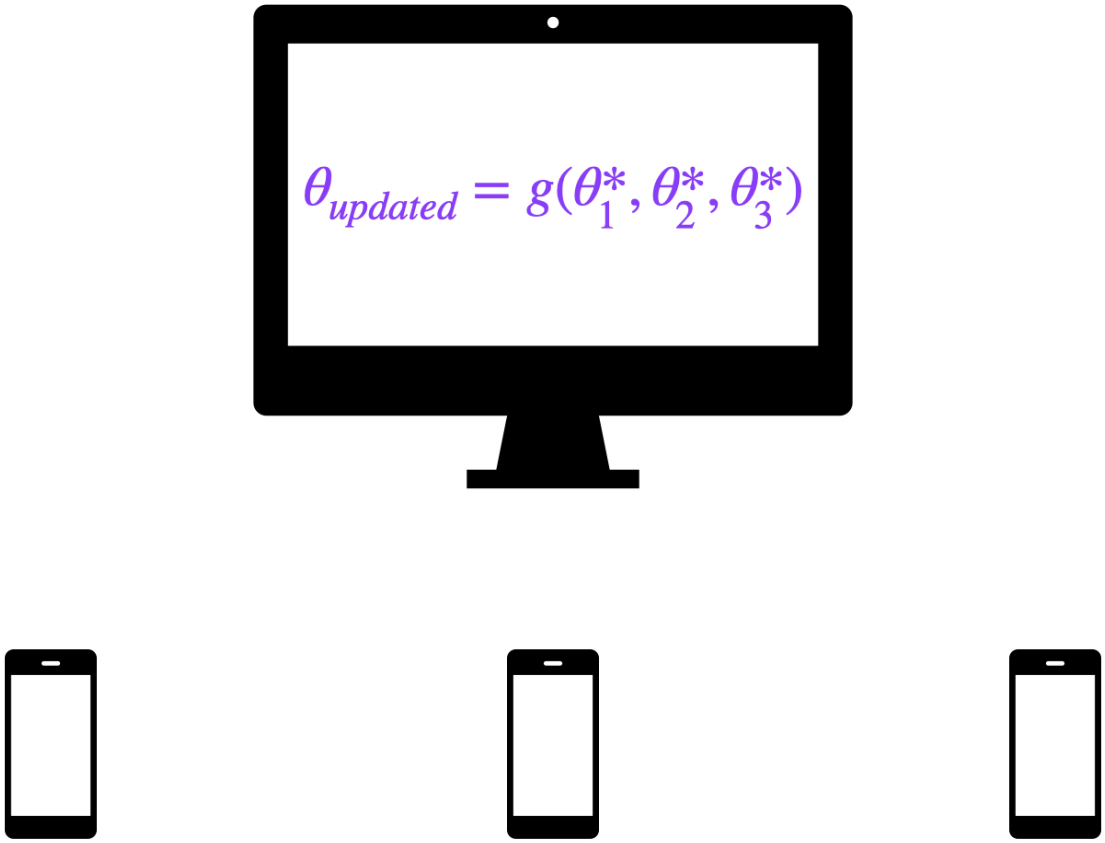

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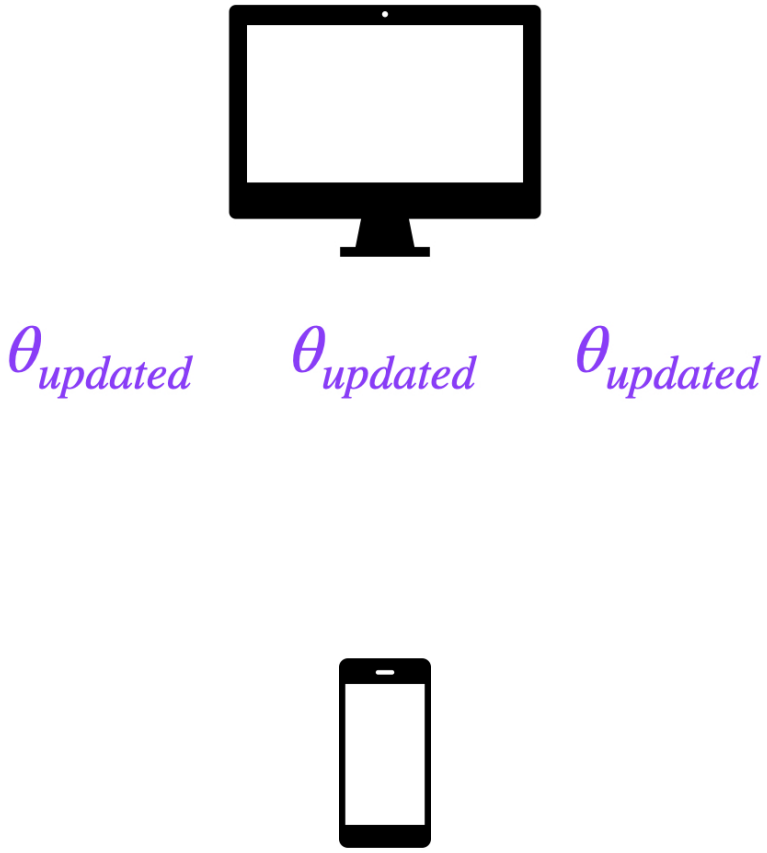

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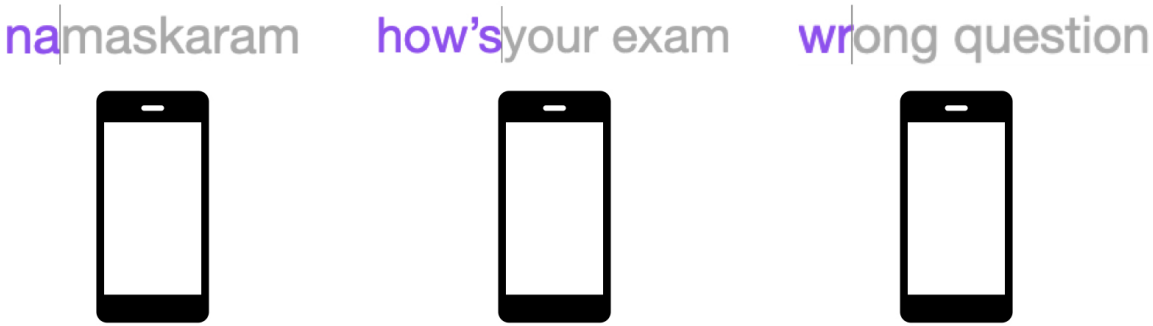

¶http://proceedings.mlr.press/v54/mcmahan17a/mcmahan17a.pdf

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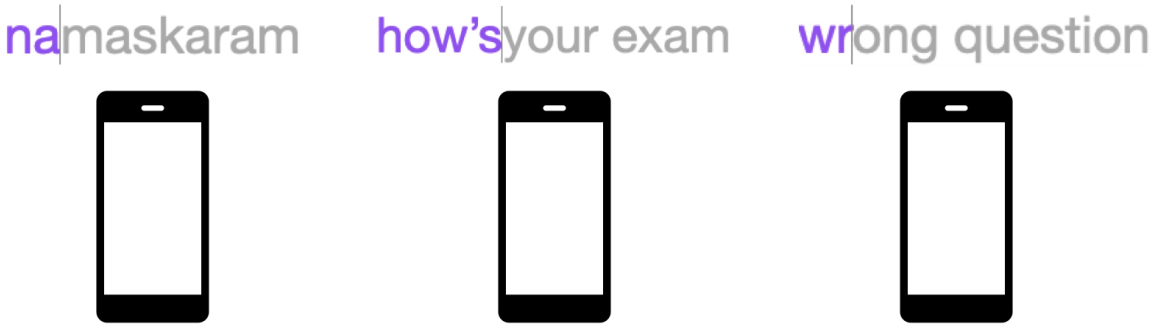

- FedAvg[¶]: $g(\theta_1^*, \theta_2^*, \theta_3^*) = \dfrac{\theta_1^* + \theta_2^* + \theta_3^*}{3}$

[¶] http://proceedings.mlr.press/v54/mcmahan17a/mcmahan17a.pdf

Our Work: Problem Setting

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$$\min_{\theta} \mathbb{E}_{z_1 \sim D_1}\{L_1(z_1, \theta)\}$$

$$\min_{\theta} \mathbb{E}_{z_3 \sim D_3}\{L_3(z_3, \theta)\}$$

$$\min_{\theta} \mathbb{E}_{z_2 \sim D_2}\{L_2(z_2, \theta)\}$$

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Our Work: Problem Setting

$$\min_{\theta} \hat{\mathbb{E}} L_1(z_1, \theta) \qquad \min_{\theta} \hat{\mathbb{E}} L_2(z_2, \theta) \qquad \min_{\theta} \hat{\mathbb{E}} L_3(z_3, \theta)$$

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Our Work: Problem Setting

$$\min_{\theta} \hat{\mathbb{E}} L_1(z_1, \theta^{(1)}, \theta^{(sh)})$$

$$\min_{\theta} \hat{\mathbb{E}} L_3(z_3, \theta^{(3)}, \theta^{(sh)})$$

$$\min_{\theta} \hat{\mathbb{E}} L_2(z_2, \theta^{(2)}, \theta^{(sh)})$$

Our Work: Neural Network

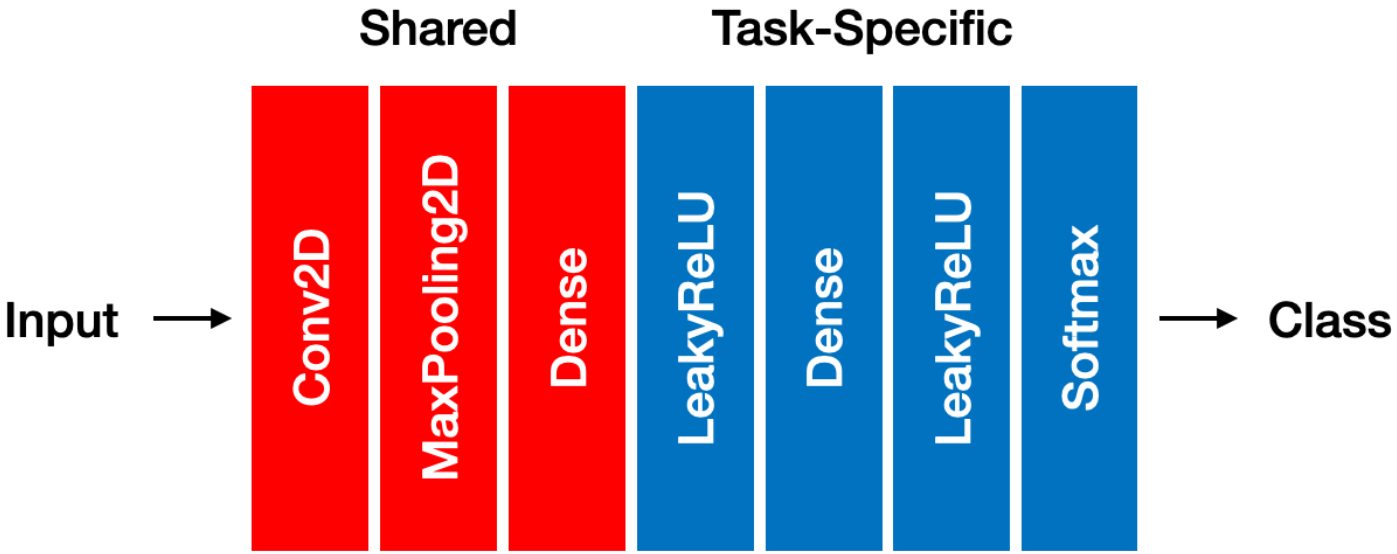

Figure: Shared and task-specific layers of the neural network.

Our Work: Bayesian Approach

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$$\omega_{11} e^{-\omega_{11} \hat{\mathbb{E}} L_1(z_1, \theta^{(1)}, \theta^{(sh)})}$$

$$\omega_{13} e^{-\omega_{13} \hat{\mathbb{E}} L_3(z_3, \theta^{(1)}, \theta^{(sh)})}$$

$$\omega_{12} e^{-\omega_{12} \hat{\mathbb{E}} L_2(z_2, \theta^{(1)}, \theta^{(sh)})}$$

Our Work: Bayesian Approach

$$\omega_{11}\omega_{12}\omega_{13}e^{-(\omega_{11}\hat{\mathbb{E}}L_1(z_1,\theta^{(1)},\theta^{(sh)})+\omega_{12}\hat{\mathbb{E}}L_2(z_2,\theta^{(1)},\theta^{(sh)})+\omega_{13}\hat{\mathbb{E}}L_3(z_3,\theta^{(1)},\theta^{(sh)}))}$$

- We refer to the above distribution as $Q(\theta^{(1)}, \theta^{(sh)})$ and the true joint distribution as $P(\theta^{(1)}, \theta^{(sh)})$

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$$\omega_{21} e^{-\omega_{21} \hat{\mathbb{E}} L_1(z_1, \theta^{(2)}, \theta^{(sh)})}$$

$$\omega_{23} e^{-\omega_{23} \hat{\mathbb{E}} L_3(z_3, \theta^{(2)}, \theta^{(sh)})}$$

$$\omega_{22} e^{-\omega_{22} \hat{\mathbb{E}} L_2(z_2, \theta^{(2)}, \theta^{(sh)})}$$

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$$\omega_{21}\omega_{22}\omega_{23}e^{-(\omega_{21}\hat{\mathbb{E}}L_1(z_1,\theta^{(2)},\theta^{(sh)})+\omega_{22}\hat{\mathbb{E}}L_2(z_2,\theta^{(2)},\theta^{(sh)})+\omega_{23}\hat{\mathbb{E}}L_3(z_3,\theta^{(2)},\theta^{(sh)}))}$$

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$$\omega_{32} e^{-\omega_{32} \hat{\mathbb{E}} L_2(z_2, \theta^{(3)}, \theta^{(sh)})}$$

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- Our objective:
  For a given $\boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)}$

$$\min_{\boldsymbol{\omega}_i} \sum_{j=1}^{N} \omega_{ij} \hat{\mathbb{E}} L_j(z_j, \boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)}) - \sum_{j=1}^{N} \log \omega_{ij} \tag{1}$$

- So our algorithm roughly is:
  1. Given shared neural network weights $\boldsymbol{\theta}^{(sh)}$, each edge-device can use its local data to solve $\min_{\boldsymbol{\theta}^{(i)}} \hat{\mathbb{E}} L_i(z_i, \boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)})$ to obtain the updated task-specific neural network weights
  2. Given the updated task-specific weights, the next step is to solve the optimization problem in (1) to find $\boldsymbol{\omega}_i^*$
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Our Work: Theoretical Guarantees

Definition: $\log - \exp$ complexity of the neural network

$$\mathcal{R}_i(\boldsymbol{\theta}) := \log \mathbb{E}_Q \sup_{\boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)}} \frac{\exp\left\{\mathbb{E}_{z \sim \mathcal{D}_i} L_i(z, \boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)})\right\}}{\Pi_{i=1}^{N} \hat{\mathbb{E}} L_i(z_i, \boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)})}, \; i = \{1, \cdots, N\}$$

Our Work: Theoretical Guarantees

Theorem

For a given neural network $\boldsymbol{\theta}$, and the $\log - \exp$ complexity, the following bound holds with a probability of at least $1-\delta$, $(\delta > 0)$

$$\inf_{\boldsymbol{\theta}} \mathbb{E}_{z_i \sim \mathcal{D}_i}\{L_i(z_i, \boldsymbol{\theta})\} \leq \inf_{\boldsymbol{\theta}^{(sh)}} \Bigg[\mathtt{Obj}_i(\boldsymbol{\theta}^{(sh)}) + \mathcal{R}_i(\boldsymbol{\theta})$$

$$+ \sup_{\boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)}, \boldsymbol{\omega}_i} \mathtt{KL}(Q||P) + l_{max} \sqrt{\sum_{j=1}^{N} \frac{\omega_{ij}^2}{2n_j^2} \log\left(\frac{1}{\delta}\right)} - N \Bigg],$$

where $\mathtt{KL}(Q||P)$ is the KL-divergence between the distributions Q and P,

$\mathtt{Obj}_i(\boldsymbol{\theta}^{(sh)}) := \inf_{\boldsymbol{\omega}_i} \sum_{j=1}^{N} \left[\omega_{ij} \inf_{\boldsymbol{\theta}^{(i)}} \hat{\mathbb{E}} L_j(z_j, \boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)}) - \log \omega_{ij} \right]$

Our Work: Omni-Fedge

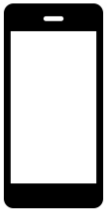
Algorithm 1: Omni-Fedge

1 `Omni-Fedge():`
2 INITIALIZE $\boldsymbol{\theta}_{sh}$ and BROADCAST (BC) to all nodes.
3 **for** $t \in \{1, 2, \ldots, \ldots\}$ **do**
4 **for** $i = 1, 2, \ldots, N$ **do**
5 $\boldsymbol{\theta}_t^{(i)} = \arg\min_{\boldsymbol{\theta}^{(i)}} \hat{\mathbb{E}} L_i(z_i, \boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)})$
6 Each device i BCs $\boldsymbol{\theta}_t^{(i)}$ to all other nodes $l = 1, 2, \ldots, N$ through FS.
7 COMPUTE AND SEND $\hat{\mathbb{E}} L_i(z_i, \boldsymbol{\theta}^{(j)}, \boldsymbol{\theta}^{(sh)})$ to all nodes.
8 `Minimize-Objective()`
9 to get $\boldsymbol{\omega}_i$ for all i.
10 At each node, COMPUTE $\sum_{j=1}^{N} \omega_{ji}^* \nabla_{\boldsymbol{\theta}_t^{(sh)}} \hat{\mathbb{E}} L_i(z_i, \boldsymbol{\theta}^{(j)}, \boldsymbol{\theta}^{(sh)})$ and BC it to all nodes through FS.
11 Perform GRADIENT UPDATE $\boldsymbol{\theta}_{t+1}^{(sh)} := \boldsymbol{\theta}_t^{(sh)} - \eta^{com} \gamma_t^{(i)}$, where $\gamma_t^{(i)} := \frac{1}{N}\left(\sum_{l=1}^{N} \sum_{j=1}^{N} \omega_{jl}^* \nabla_{\boldsymbol{\theta}_t^{(sh)}} \hat{\mathbb{E}} L_l(z_l, \boldsymbol{\theta}^{(j)}, \boldsymbol{\theta}^{(sh)})\right)$
12 GO TO step 3.
13 `Minimize-Objective():`
14 COMPUTE $\boldsymbol{\omega}_i^* = \arg\min_{\boldsymbol{\omega}_i} \left(\sum_{j=1}^{N} \omega_{ij} \hat{\mathbb{E}} L_j(z_j, \boldsymbol{\theta}^{(i)}, \boldsymbol{\theta}^{(sh)}) - \log \prod_{j=1}^{N} \omega_{ij}\right)$

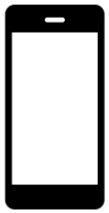
Figure: Omni-Fedge Algorithm

Our Work: Omni-Fedge

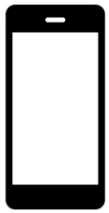
$$\hat{\theta}^{(1)} = arg \min_{\theta^{(1)}} \hat{\mathbb{E}} L_1(z_1, \theta^{(1)}, \theta^{(sh)}))$$



$$\hat{\theta}^{(2)} = arg \min_{\theta^{(2)}} \hat{\mathbb{E}} L_2(z_2, \theta^{(2)}, \theta^{(sh)}))$$



$$\hat{\theta}^{(3)} = arg \min_{\theta^{(3)}} \hat{\mathbb{E}} L_3(z_3, \theta^{(3)}, \theta^{(sh)}))$$



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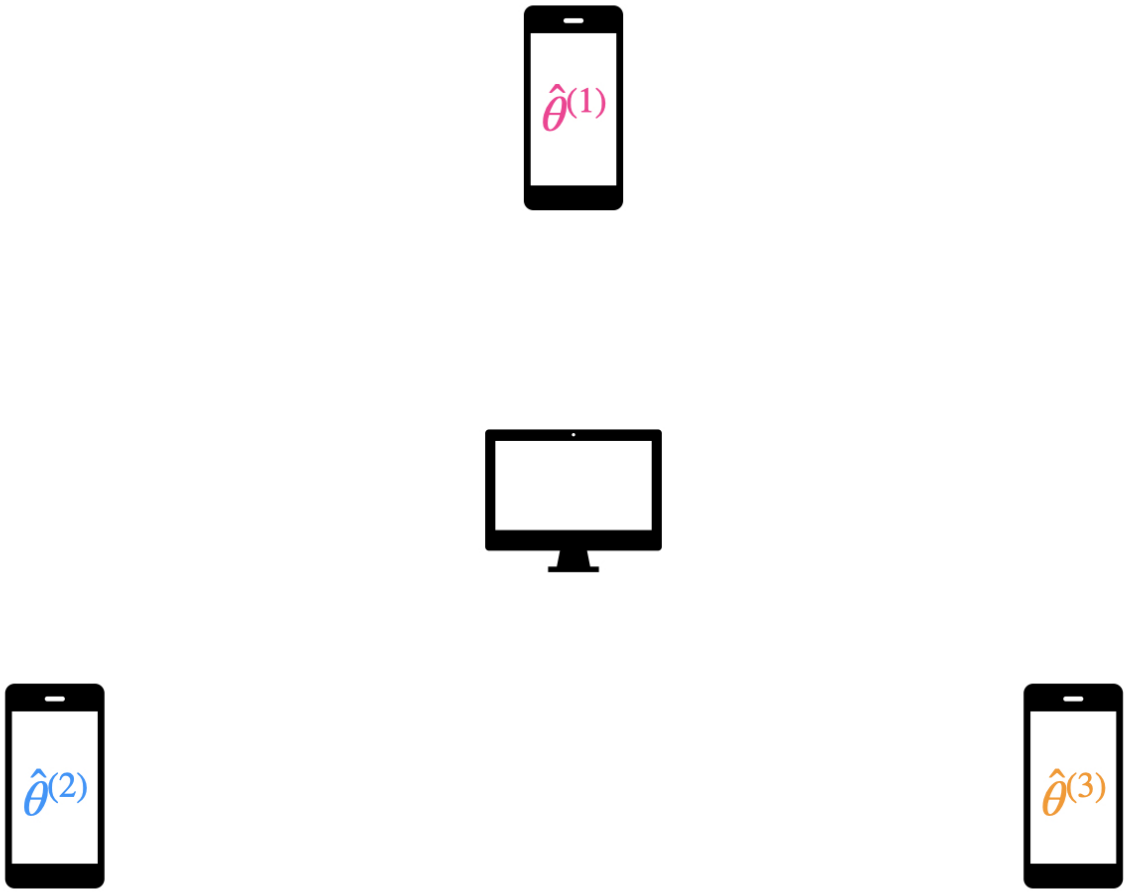

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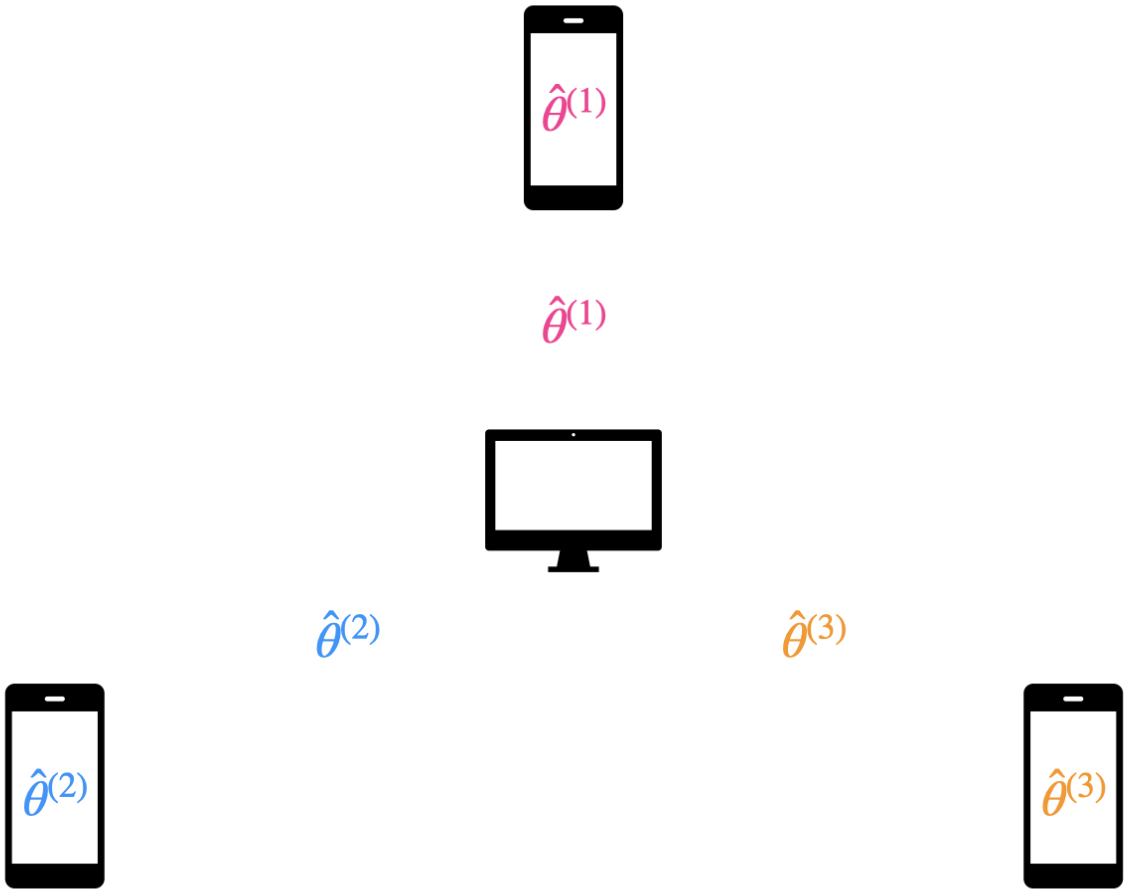

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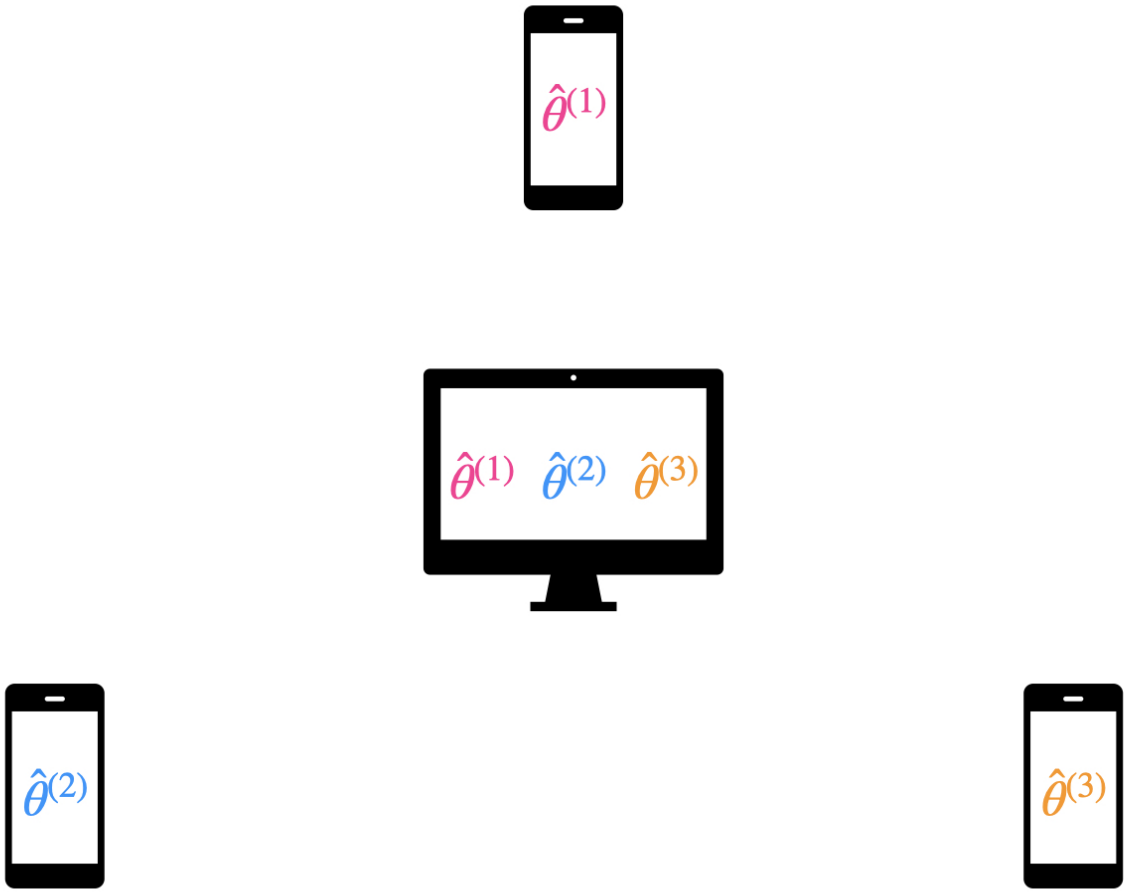

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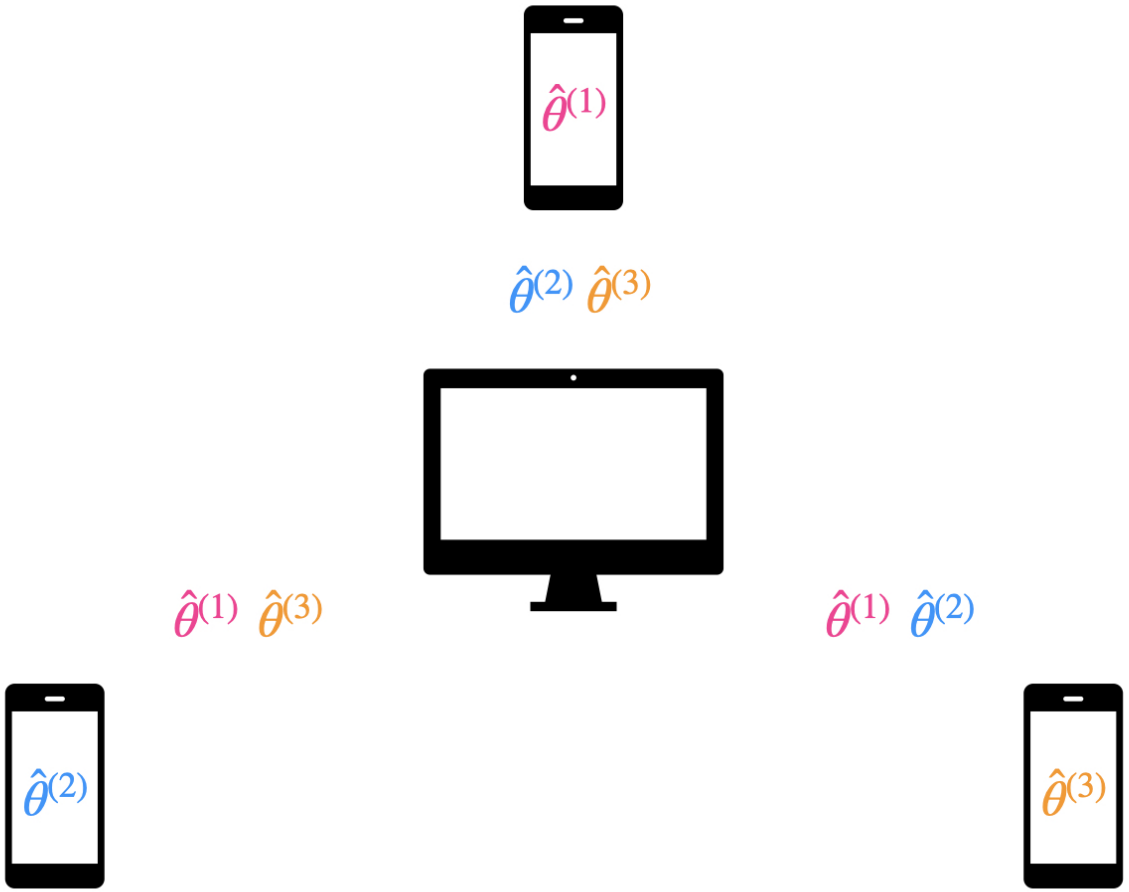
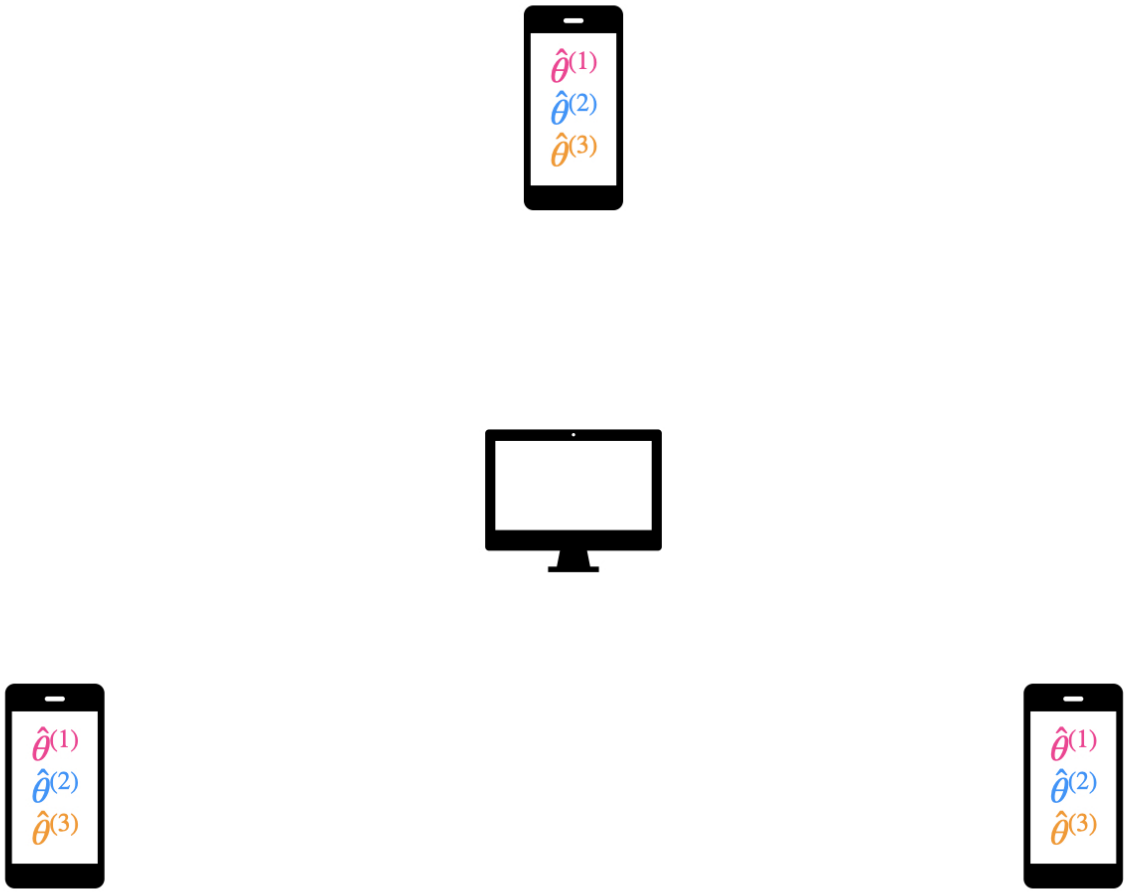


Our Work: Omni-Fedge



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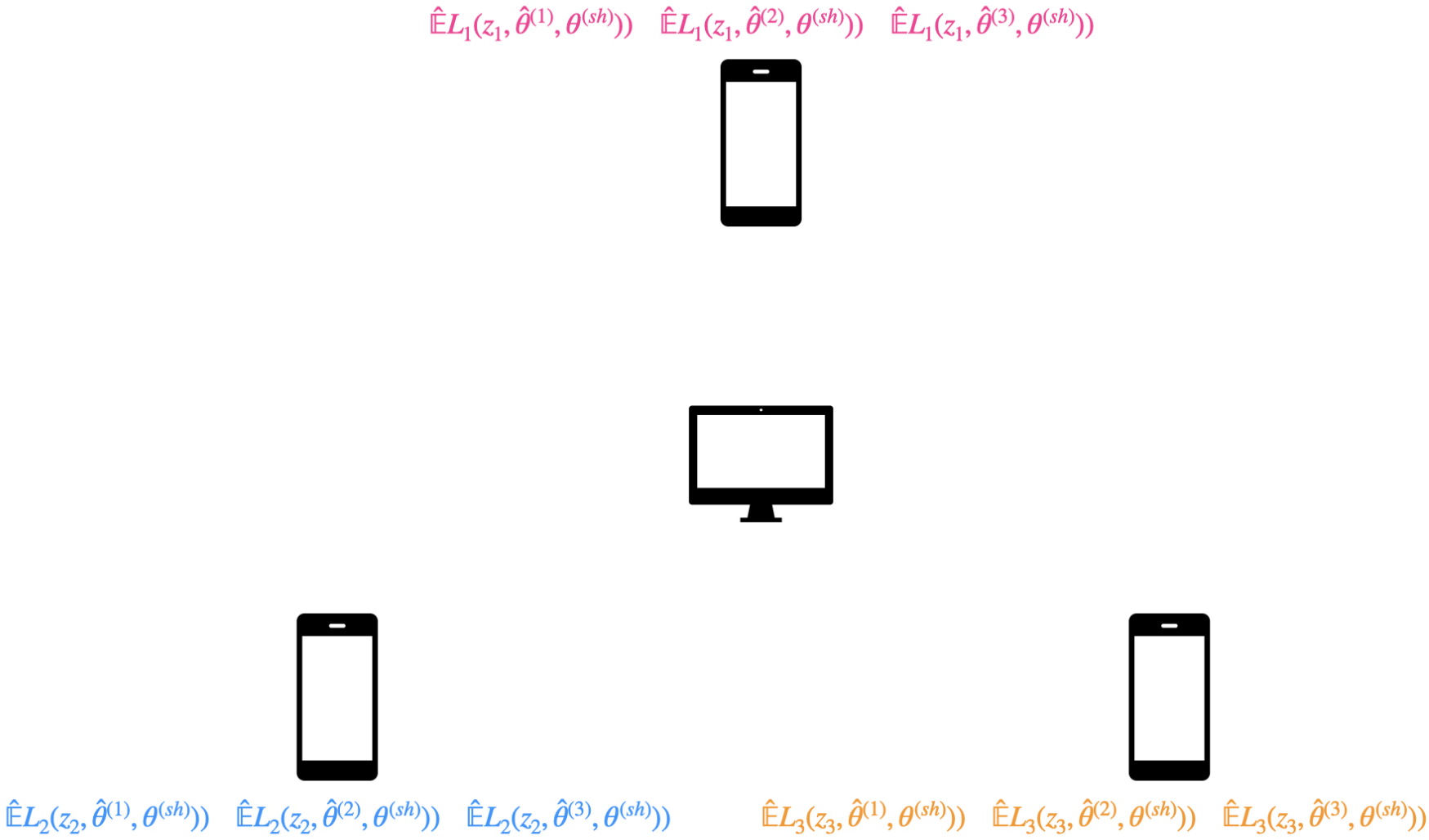

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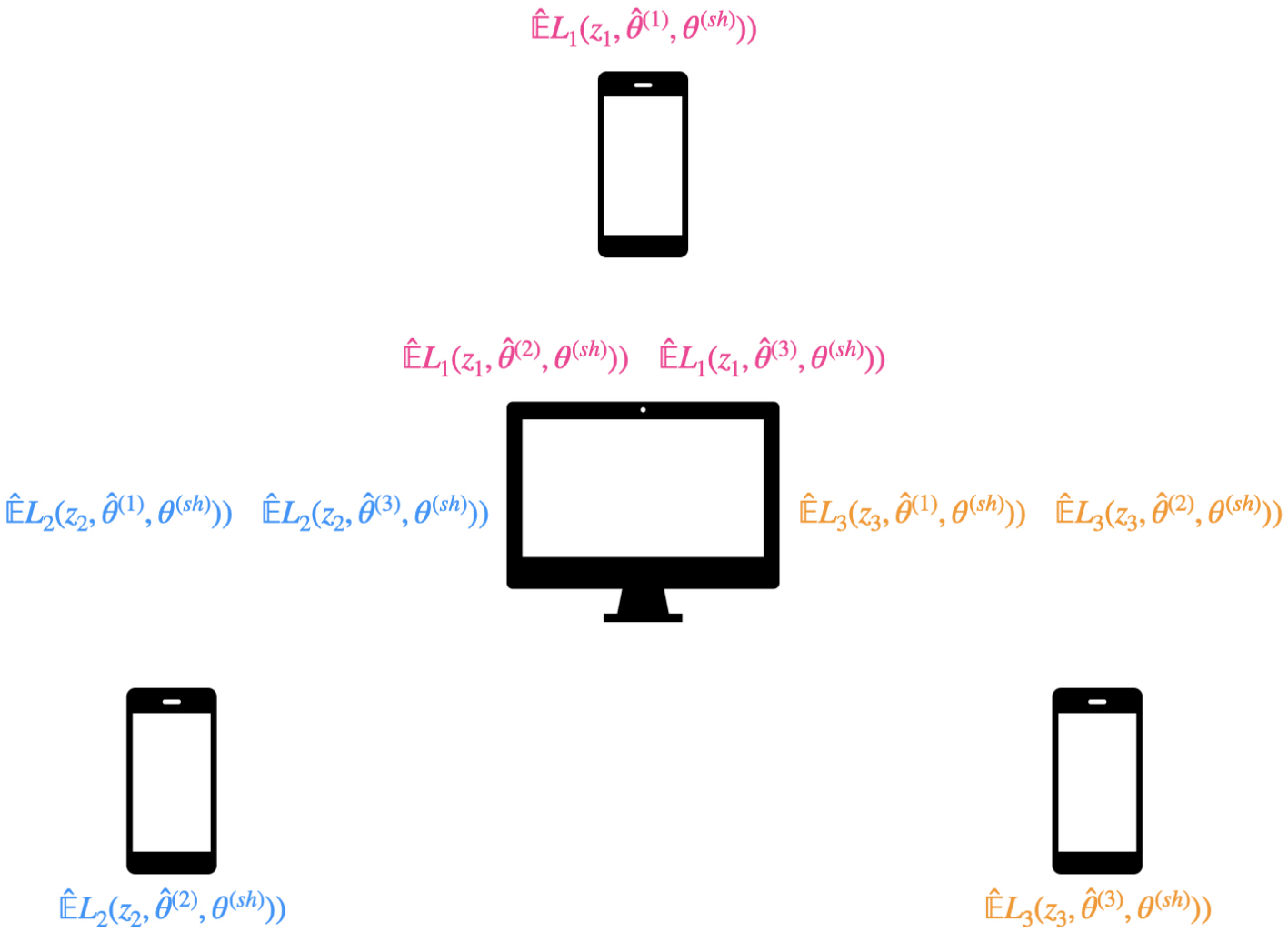

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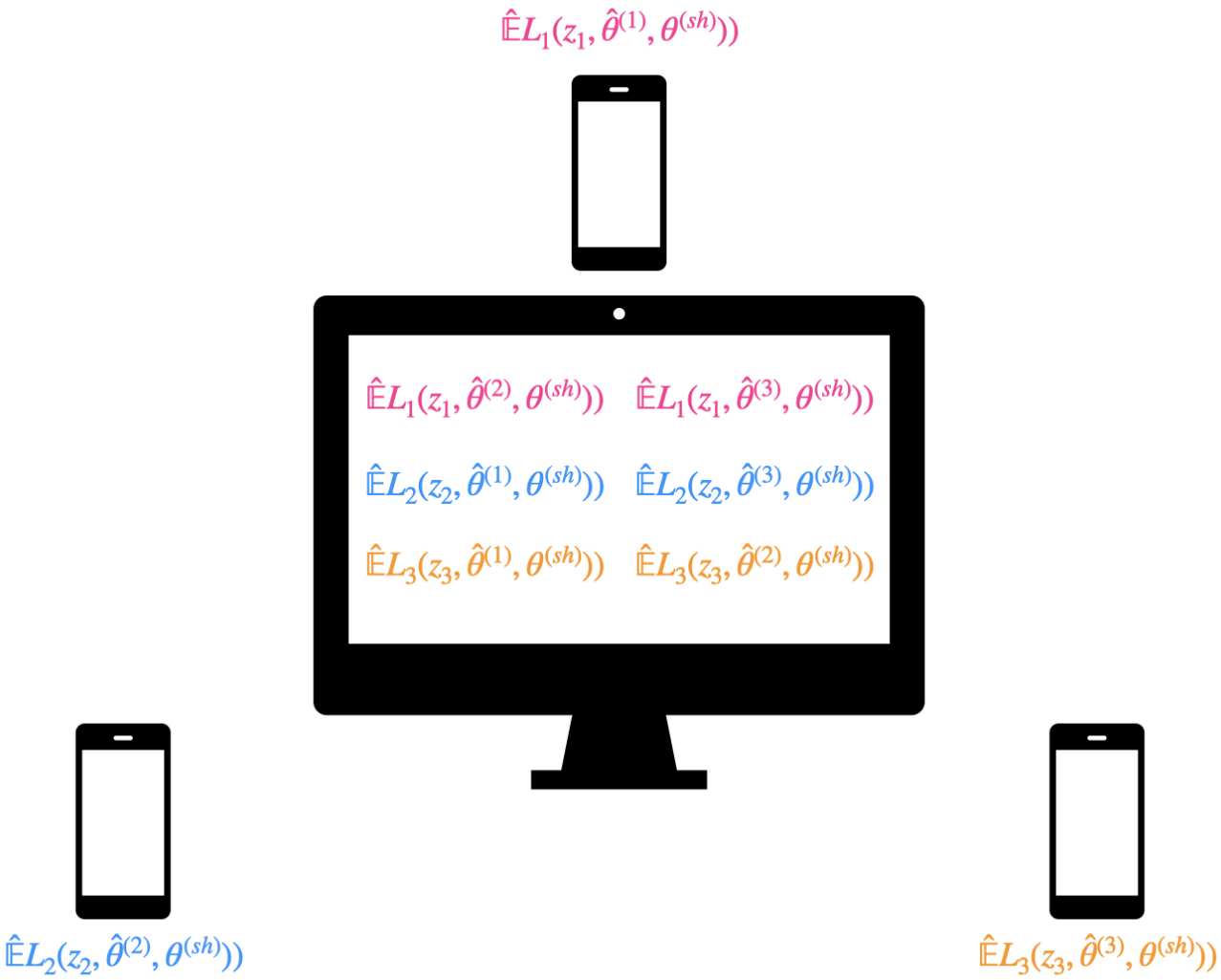

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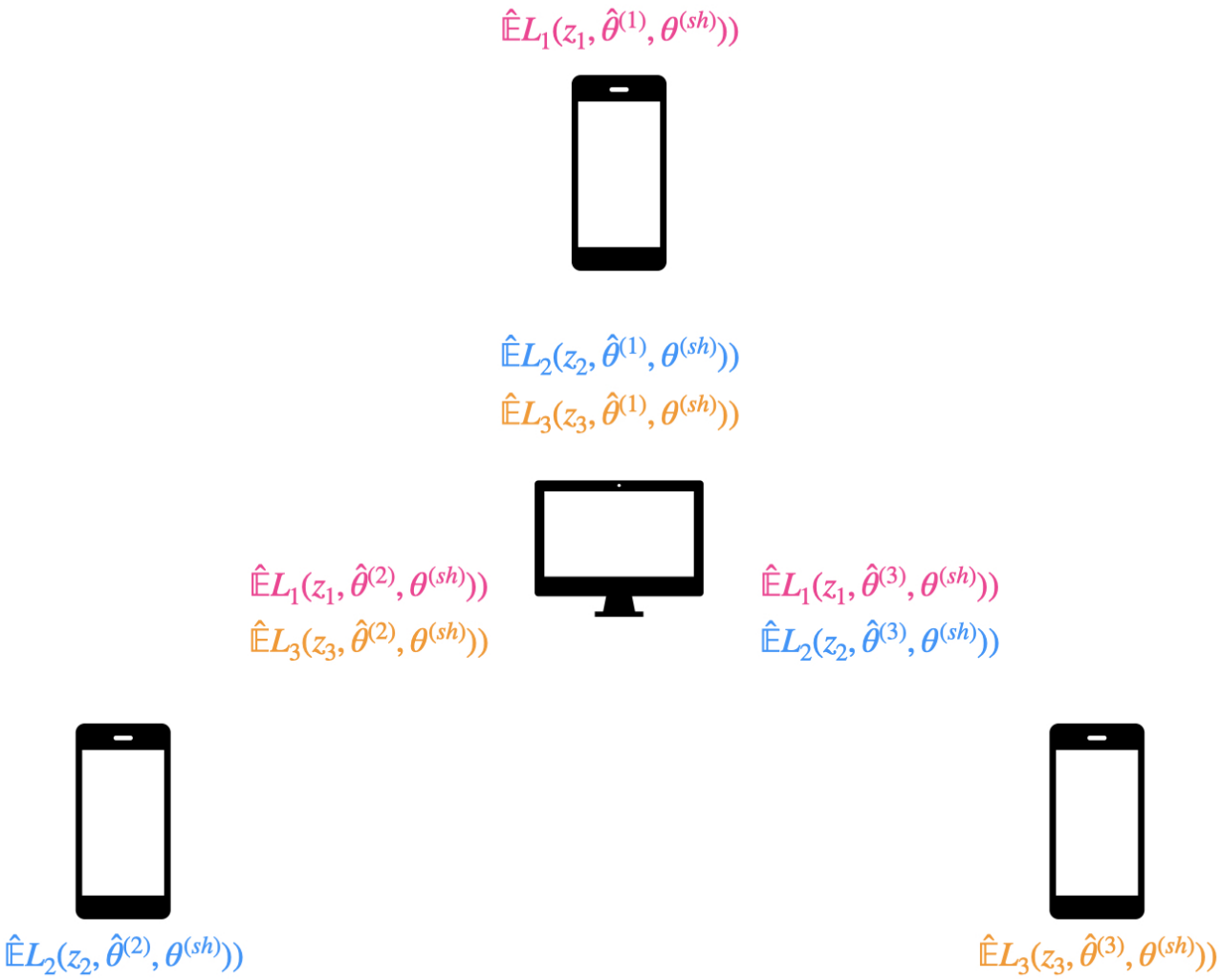
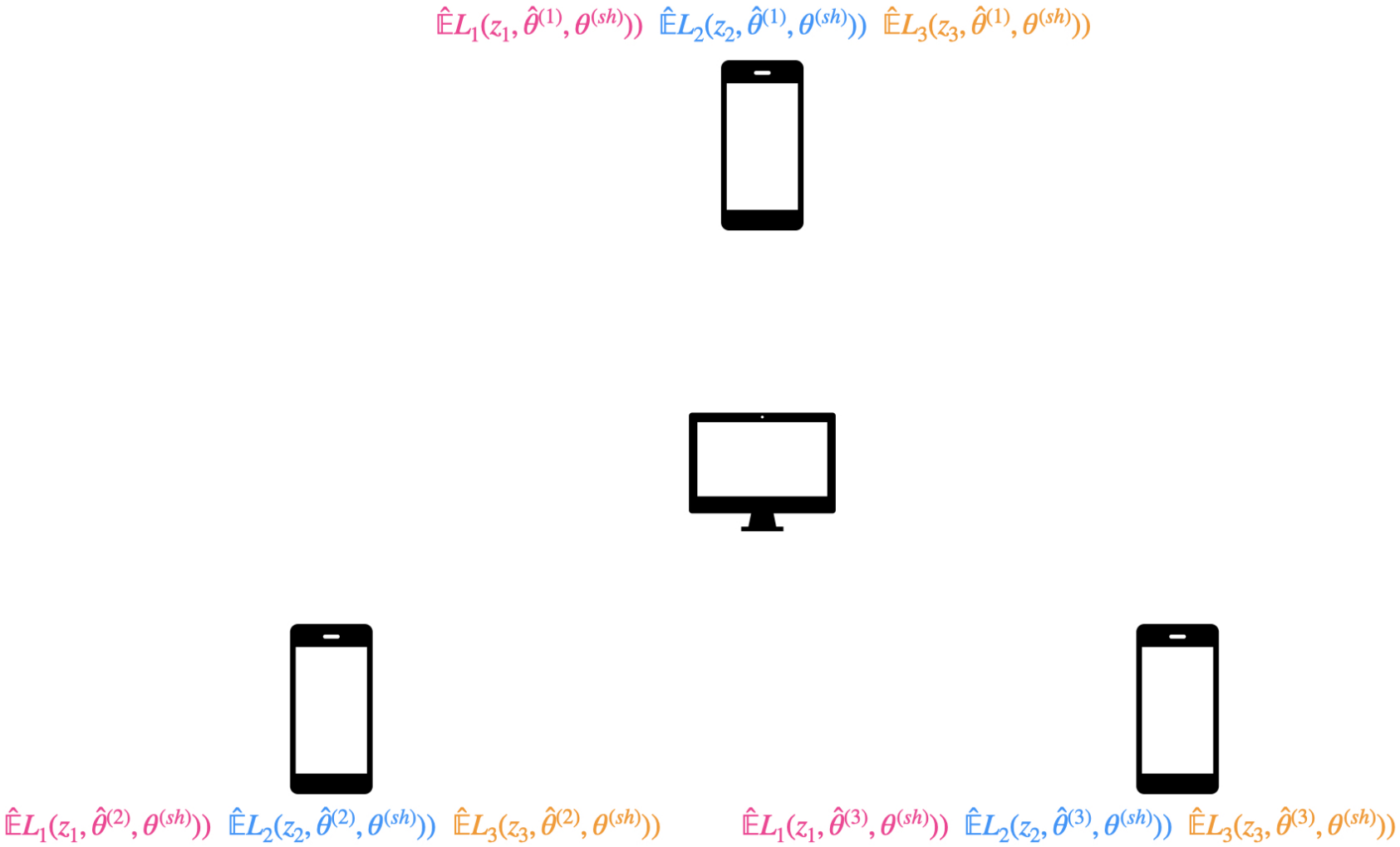
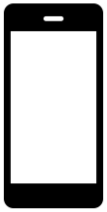


Our Work: Omni-Fedge

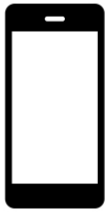


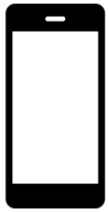
Our Work: Omni-Fedge

$$\omega_1^* = arg \min_{\omega_{11},\omega_{12},\omega_{13}} \left(\omega_{11}\hat{\mathbb{E}}L_1(z_1,\hat{\theta}^{(1)},\theta^{(sh)})) + \omega_{12}\hat{\mathbb{E}}L_2(z_2,\hat{\theta}^{(1)},\theta^{(sh)}) + \omega_{13}\hat{\mathbb{E}}L_3(z_3,\hat{\theta}^{(1)},\theta^{(sh)})) - \log \omega_{11}\omega_{12}\omega_{13} \right)$$



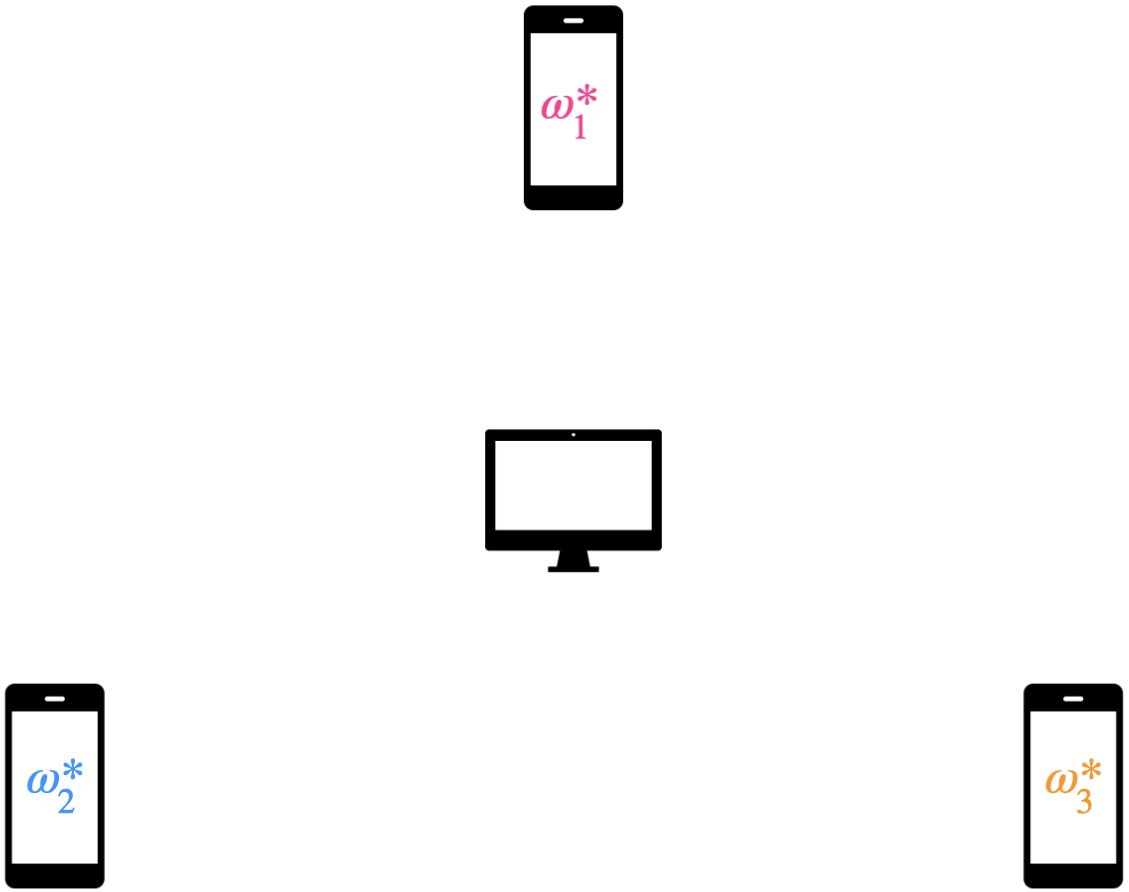
$$\omega_2^* = arg \min_{\omega_{21},\omega_{22},\omega_{23}} \left(\omega_{21}\hat{\mathbb{E}}L_1(z_1,\hat{\theta}^{(2)},\theta^{(sh)})) + \omega_{22}\hat{\mathbb{E}}L_2(z_2,\hat{\theta}^{(2)},\theta^{(sh)}) + \omega_{23}\hat{\mathbb{E}}L_3(z_3,\hat{\theta}^{(2)},\theta^{(sh)})) - \log \omega_{21}\omega_{22}\omega_{23} \right)$$





$$\omega_3^* = arg \min_{\omega_{31},\omega_{32},\omega_{33}} \left(\omega_{31}\hat{\mathbb{E}}L_1(z_1,\hat{\theta}^{(3)},\theta^{(sh)})) + \omega_{32}\hat{\mathbb{E}}L_2(z_2,\hat{\theta}^{(3)},\theta^{(sh)}) + \omega_{33}\hat{\mathbb{E}}L_3(z_3,\hat{\theta}^{(3)},\theta^{(sh)})) - \log \omega_{31}\omega_{32}\omega_{33} \right)$$

Our Work: Omni-Fedge



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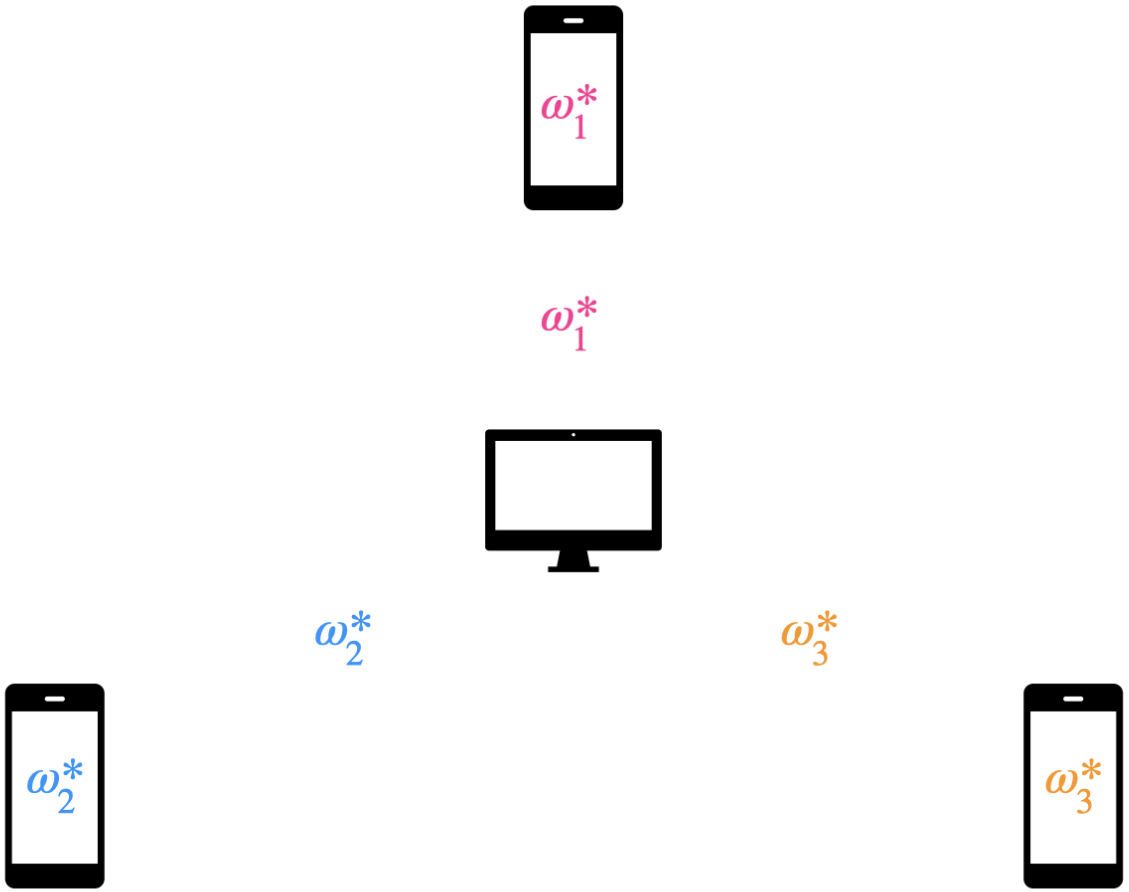

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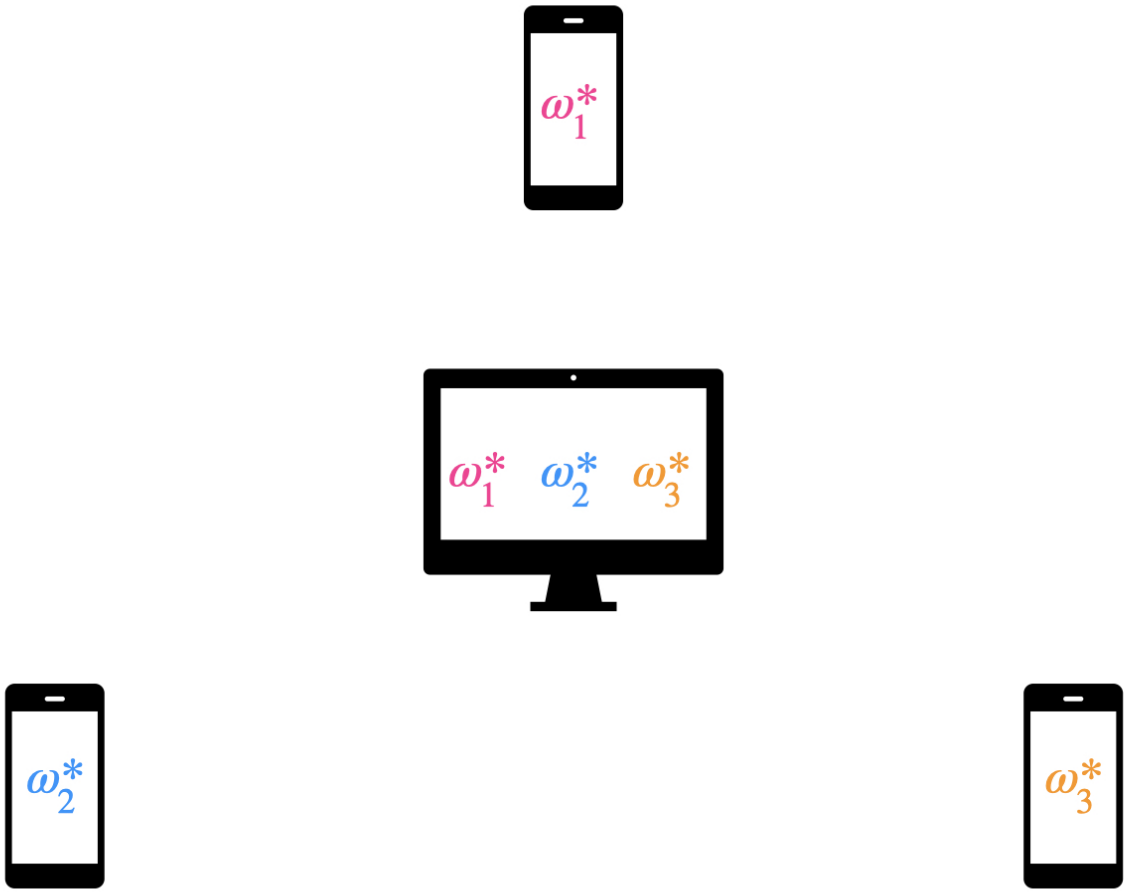

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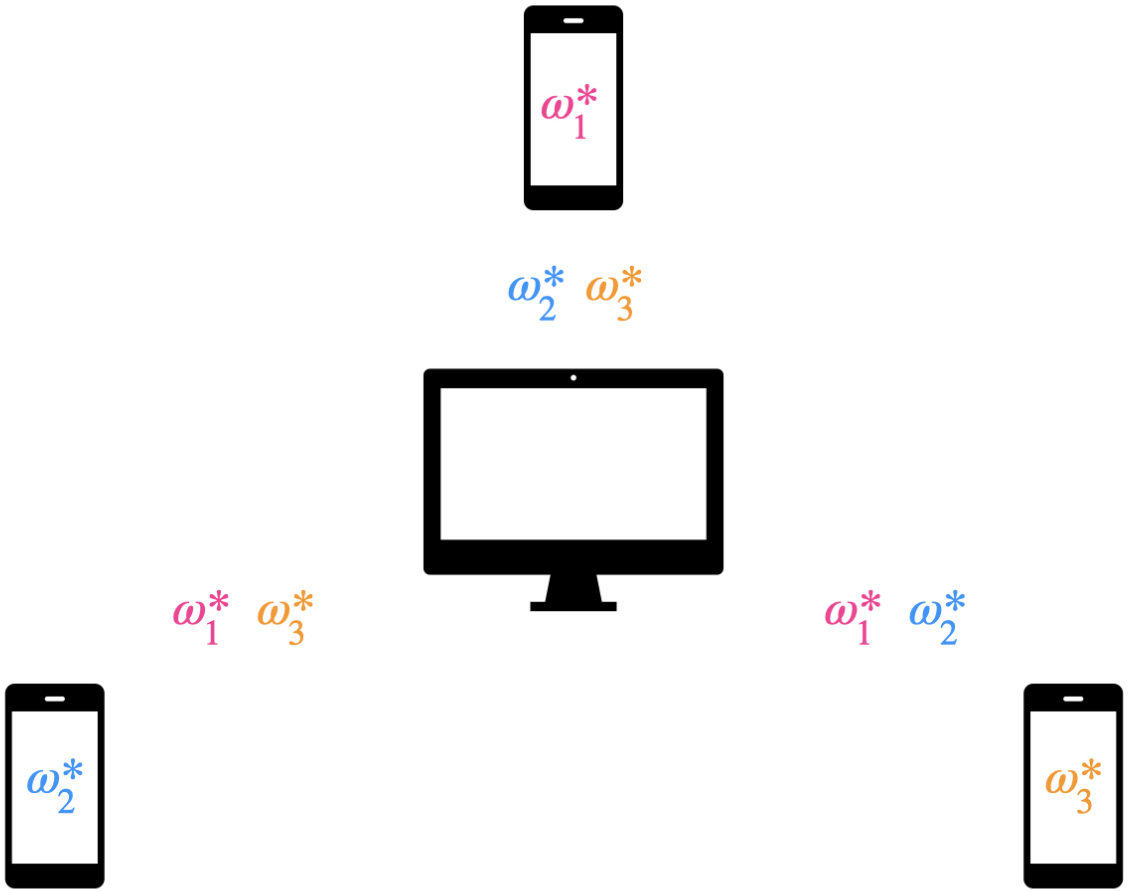

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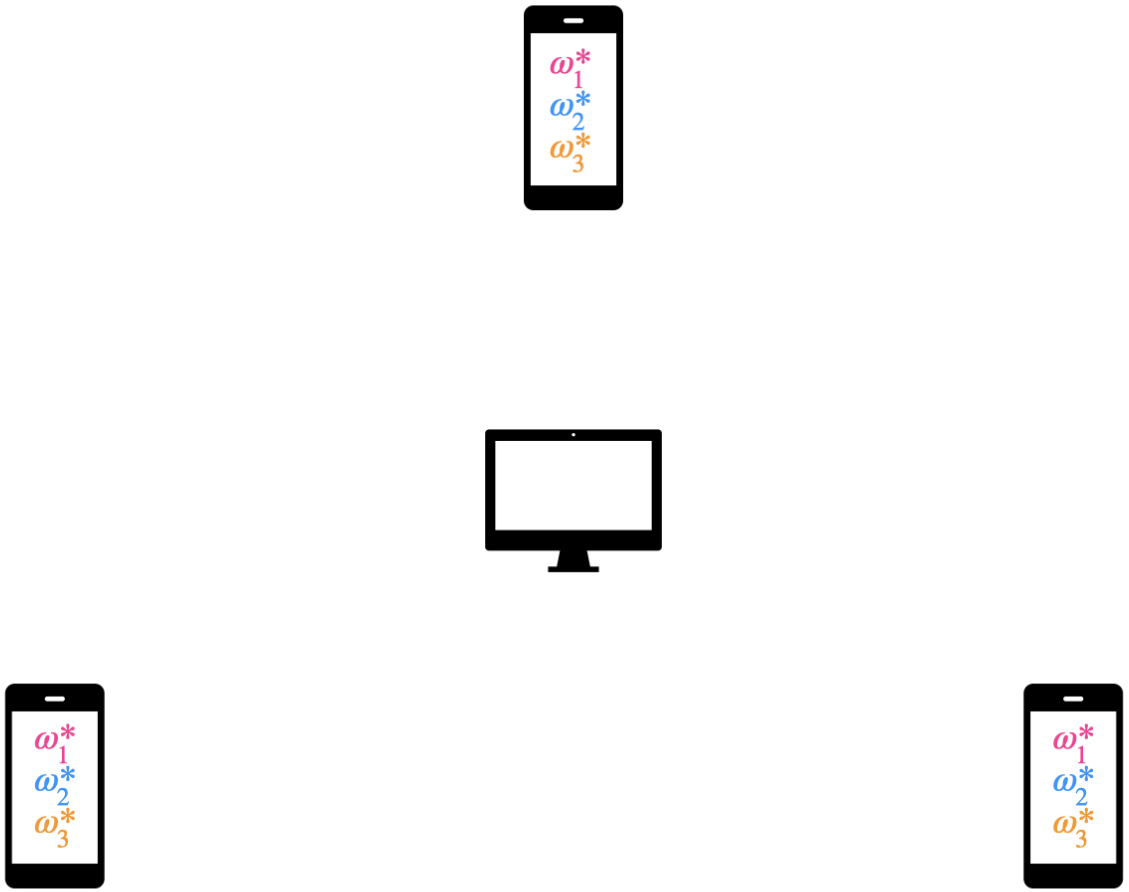
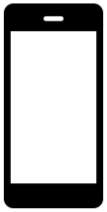
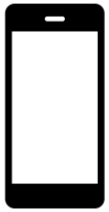


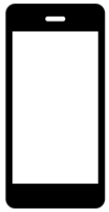
Our Work: Omni-Fedge

$$\alpha_1 = \omega_{11}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_1(z_1, \hat{\theta}^{(1)}, \theta^{(sh)})) + \omega_{21}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_1(z_1, \hat{\theta}^{(2)}, \theta^{(sh)}) + \omega_{31}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_1(z_1, \hat{\theta}^{(3)}, \theta^{(sh)}))$$



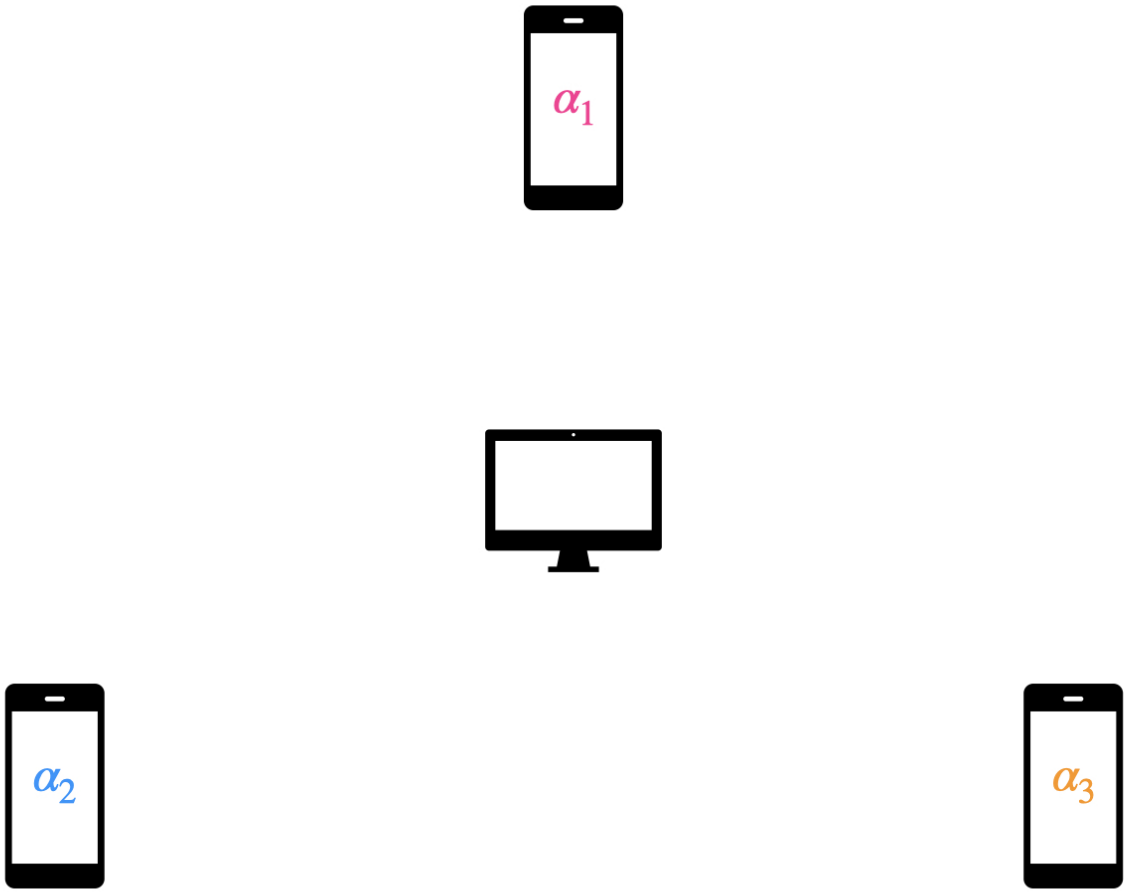
$$\alpha_2 = \omega_{12}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_2(z_2, \hat{\theta}^{(1)}, \theta^{(sh)})) + \omega_{22}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_2(z_2, \hat{\theta}^{(2)}, \theta^{(sh)}) + \omega_{32}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_2(z_2, \hat{\theta}^{(3)}, \theta^{(sh)}))$$





$$\alpha_3 = \omega_{13}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_3(z_3, \hat{\theta}^{(1)}, \theta^{(sh)})) + \omega_{23}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_3(z_3, \hat{\theta}^{(2)}, \theta^{(sh)}) + \omega_{33}^* \nabla_{\theta^{(sh)}} \hat{\mathbb{E}} L_3(z_3, \hat{\theta}^{(3)}, \theta^{(sh)}))$$

Our Work: Omni-Fedge



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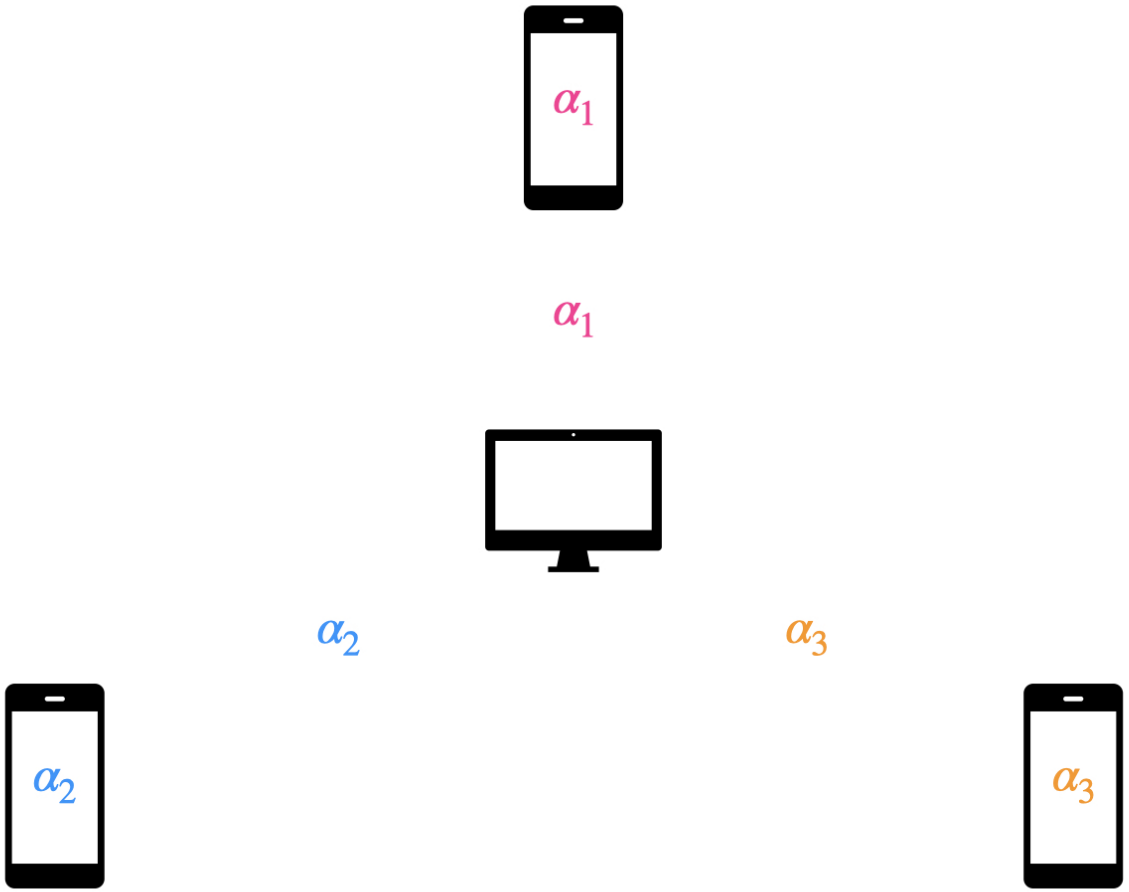

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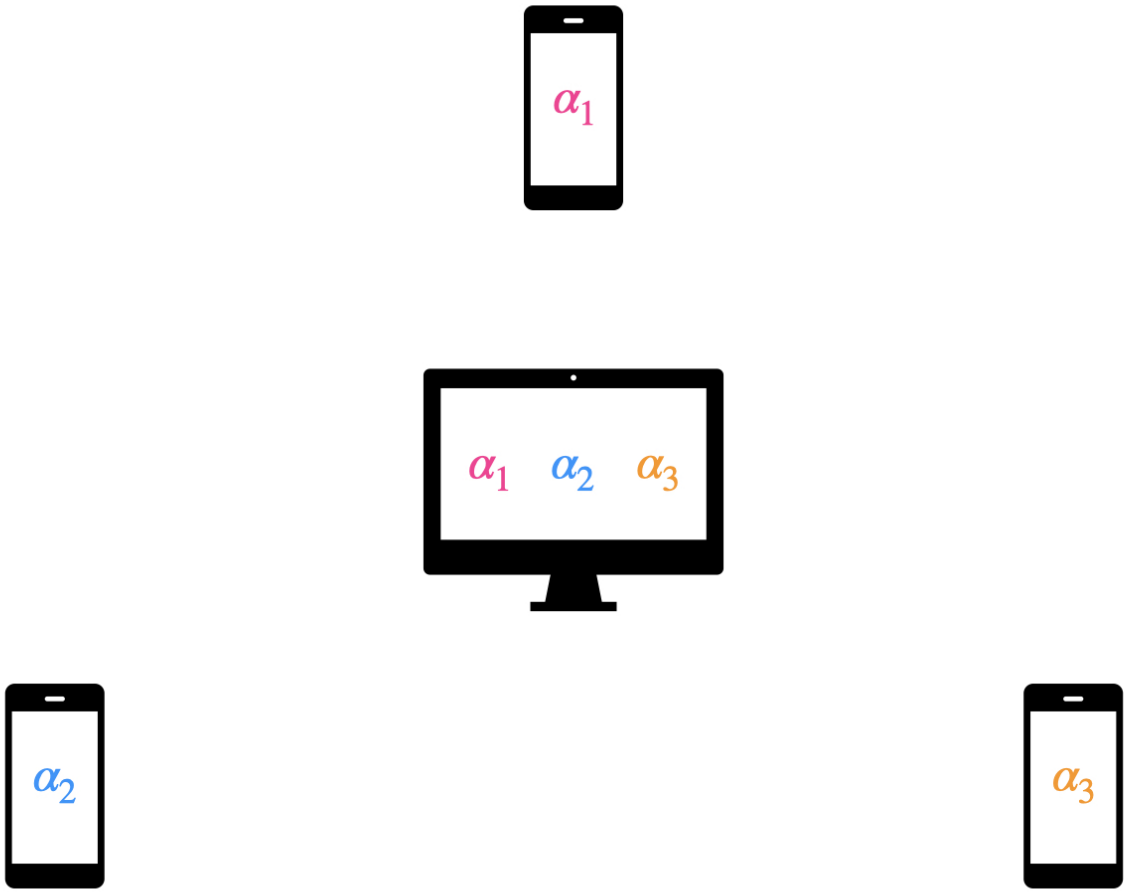

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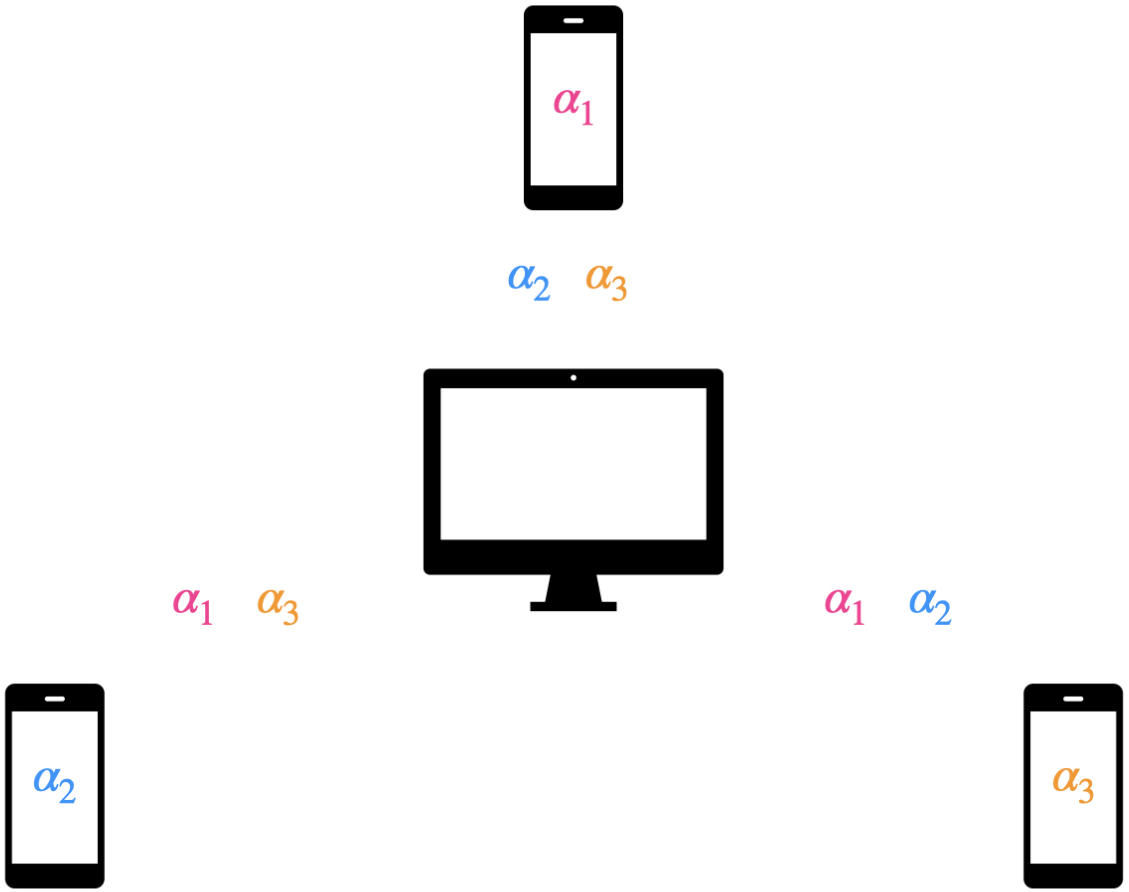

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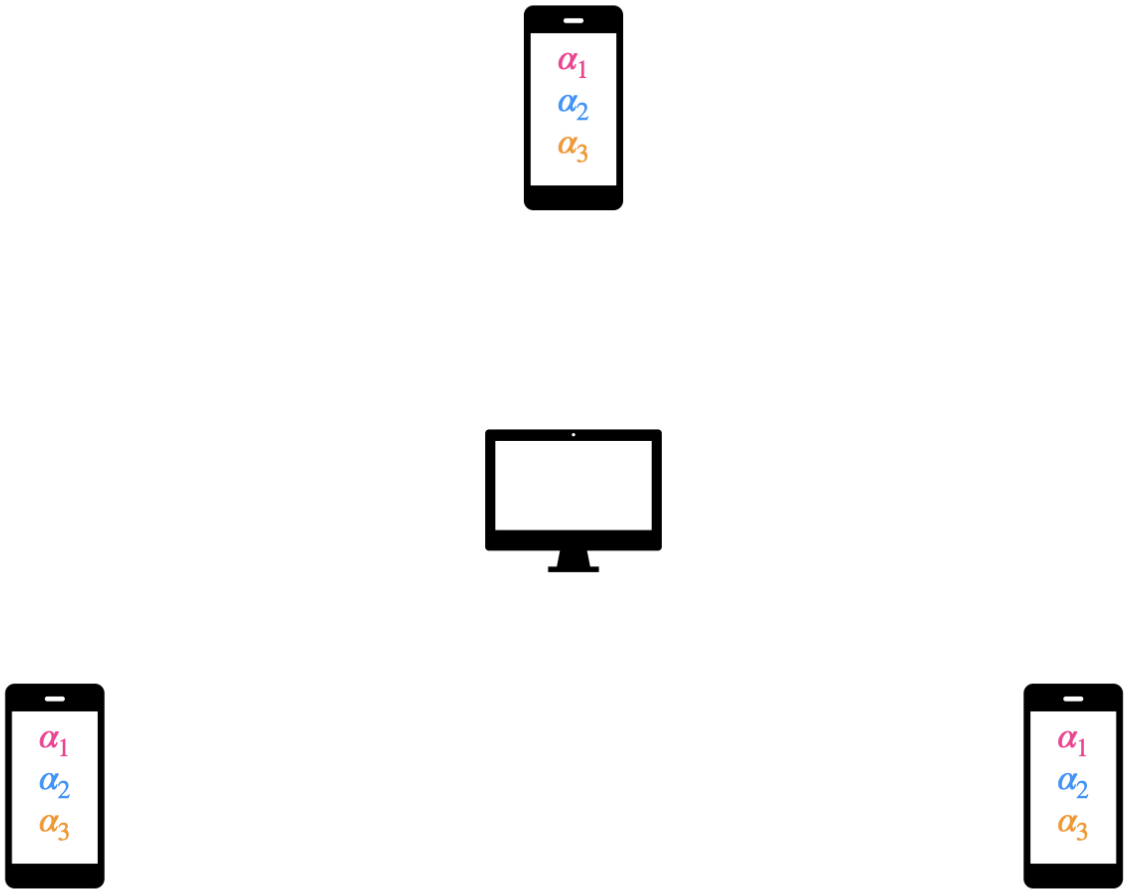
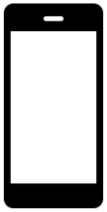


Our Work: Omni-Fedge

$$\theta_{t+1}^{(sh)} = \theta_t^{(sh)} - \eta_{com}\frac{(\alpha_1 + \alpha_2 + \alpha_3)}{3}$$



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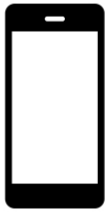
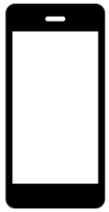


$$\theta_{t+1}^{(sh)} = \theta_t^{(sh)} - \eta_{com}\frac{(\alpha_1 + \alpha_2 + \alpha_3)}{3}$$



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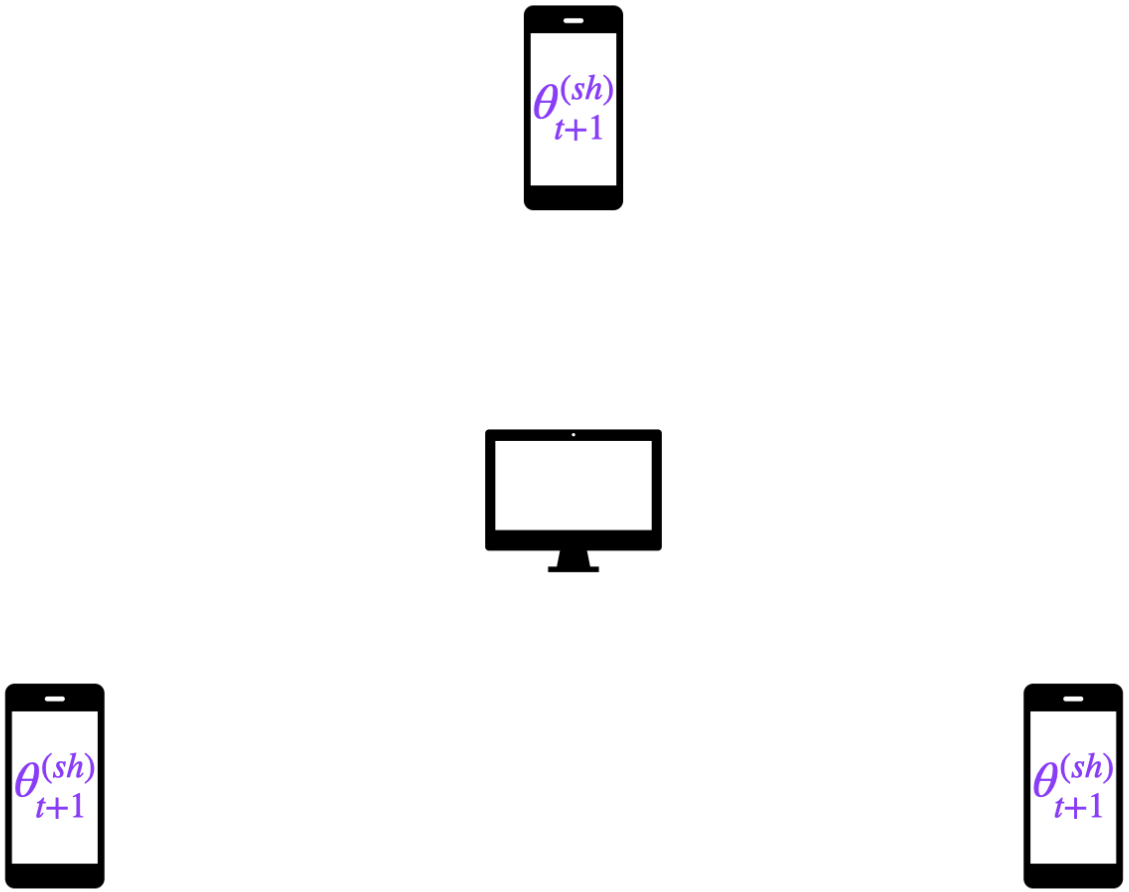

Our Work: Experimental Results with Omni-Fedge

Type of Data	Training samples per node	Testing samples per node
MNIST I.I.D.	622	778
MNIST non-I.I.D.	673	842
FMNIST I.I.D.	622	778
FMNIST non-I.I.D.	331	414

Our Work: Experimental Results with Omni-Fedge

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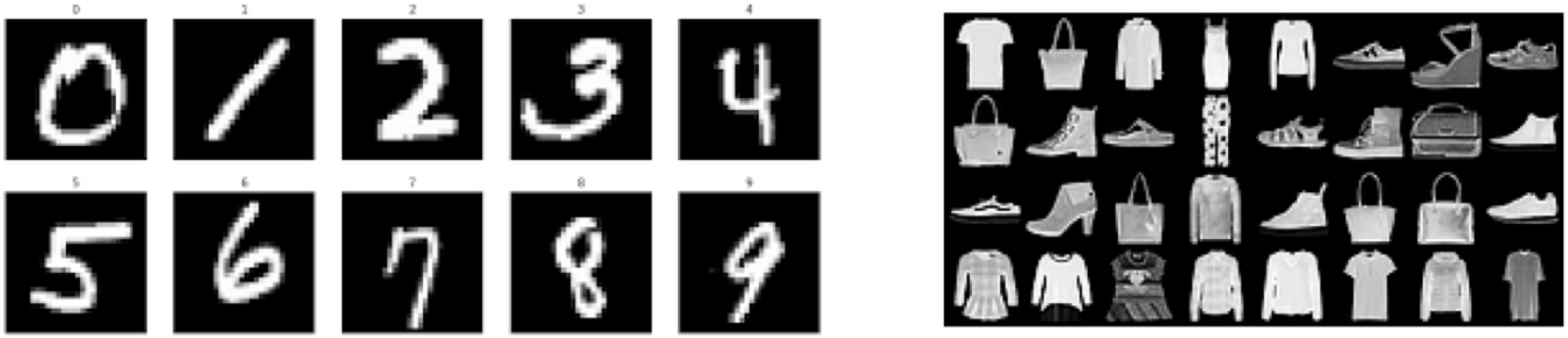

Figure: Sample MNIST and FMNIST images

Our Work: Experimental Results with Omni-Fedge

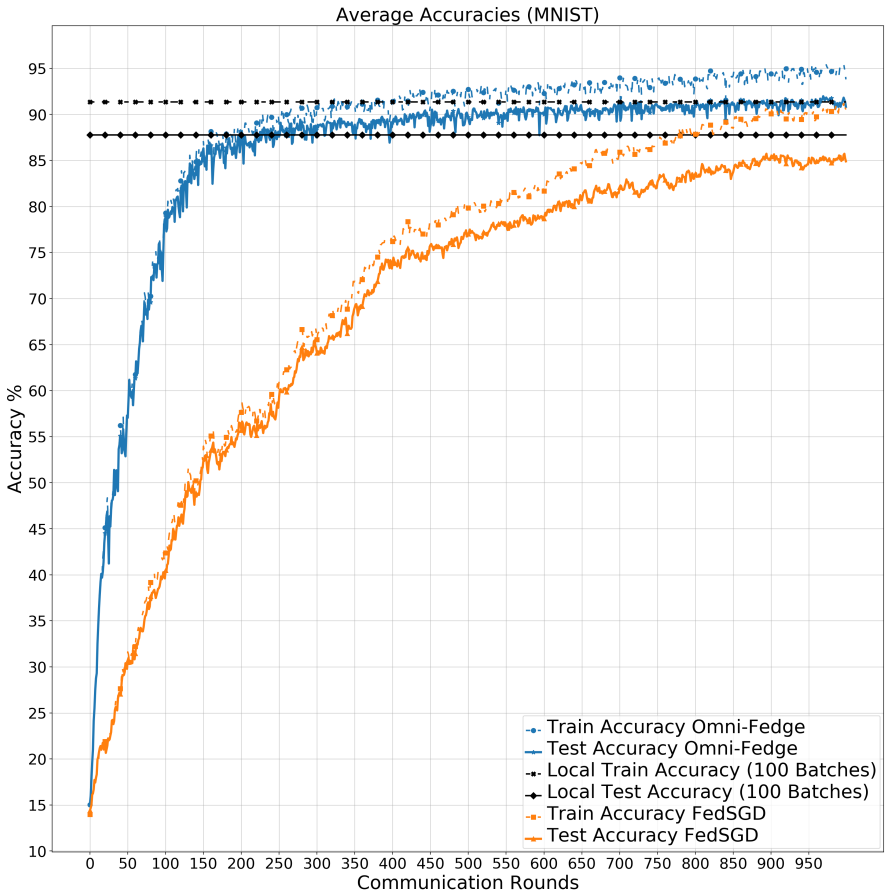

Figure: Results for non-IID data using MNIST

Our Work: Experimental Results with Omni-Fedge

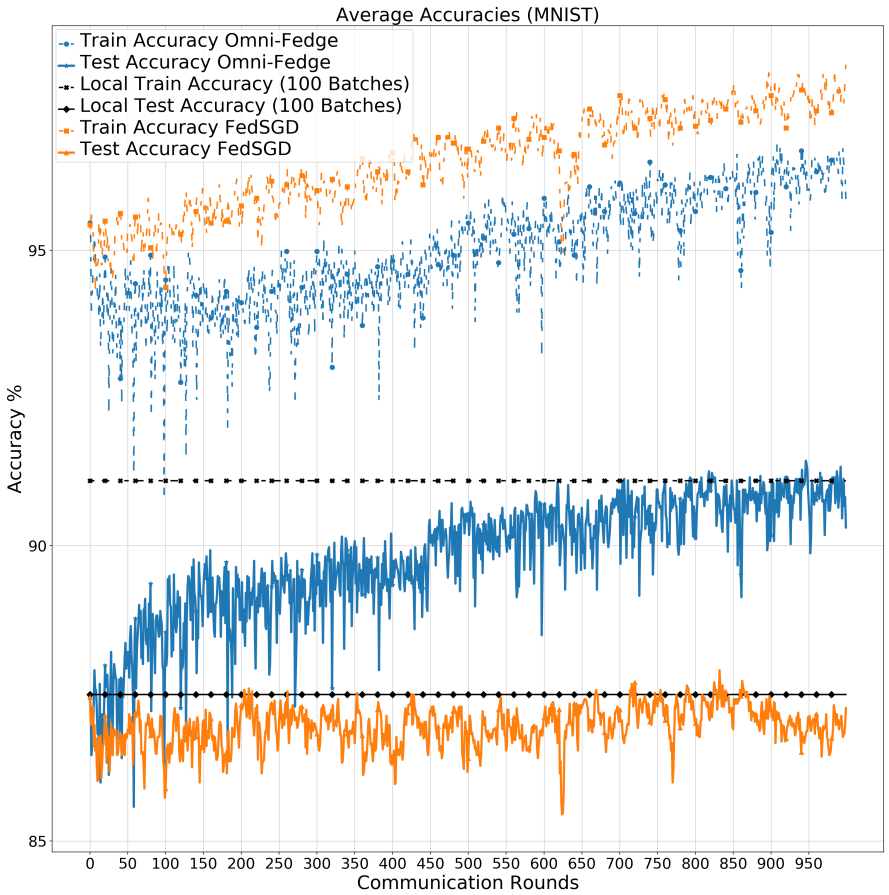

Figure: Results for IID data using MNIST

Our Work: Experimental Results with Omni-Fedge

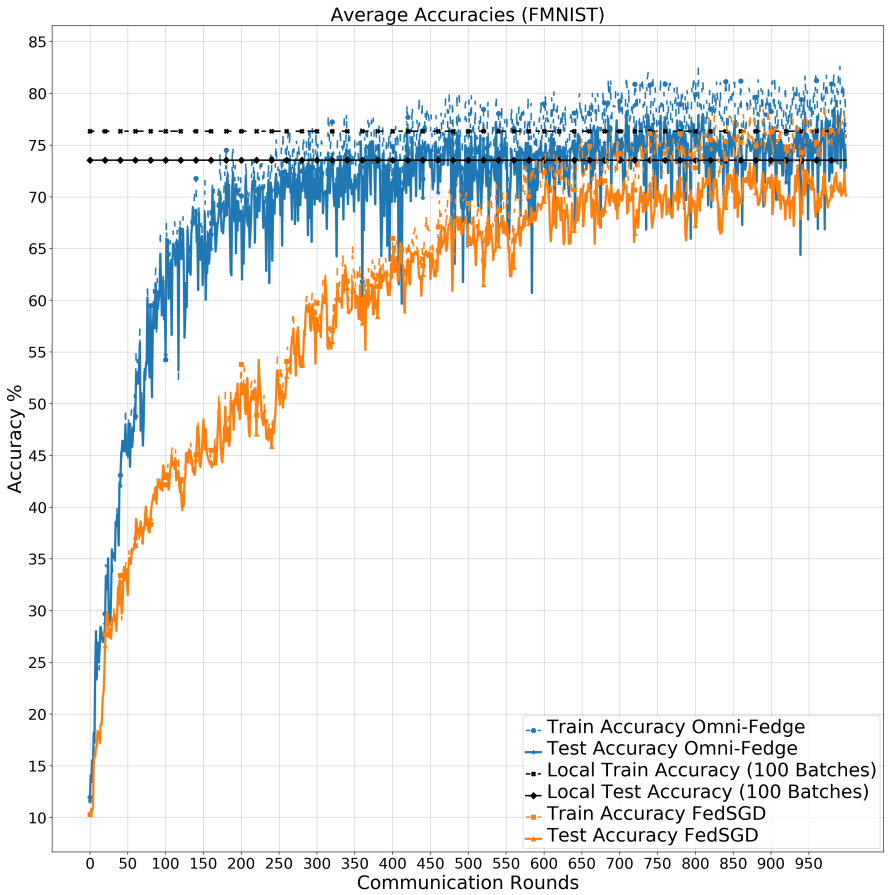

Figure: Results for non-IID data using FMNIST

Our Work: Experimental Results with Omni-Fedge

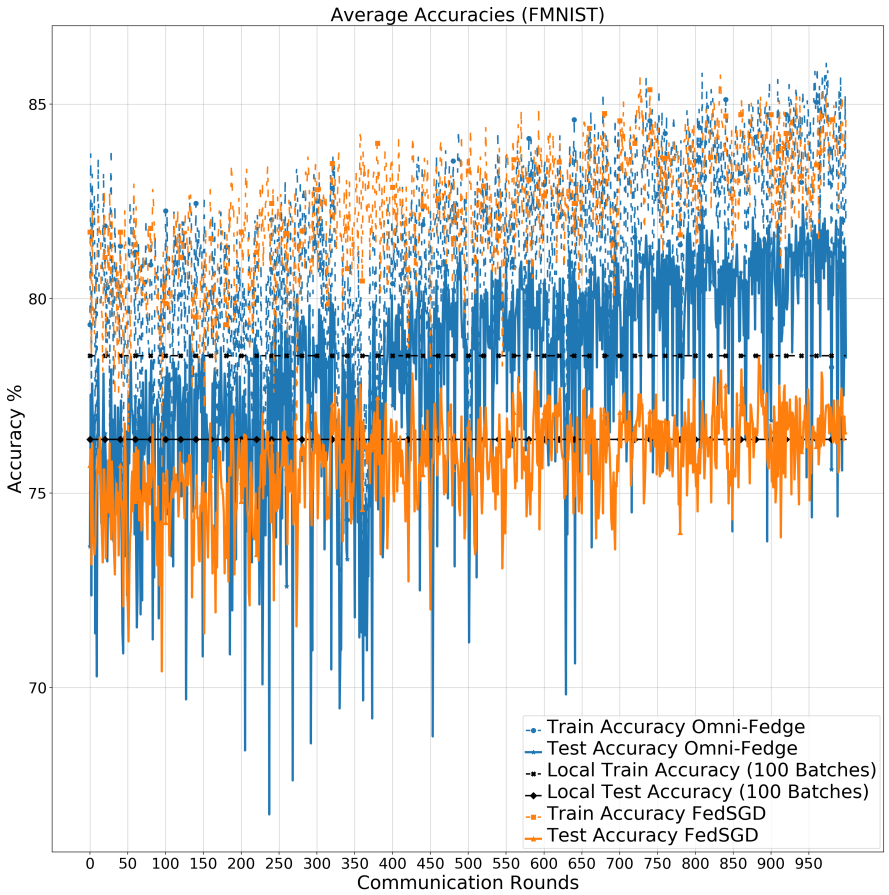

Figure: Results for IID data using FMNIST

Our Work: Experimental Results with Omni-Fedge

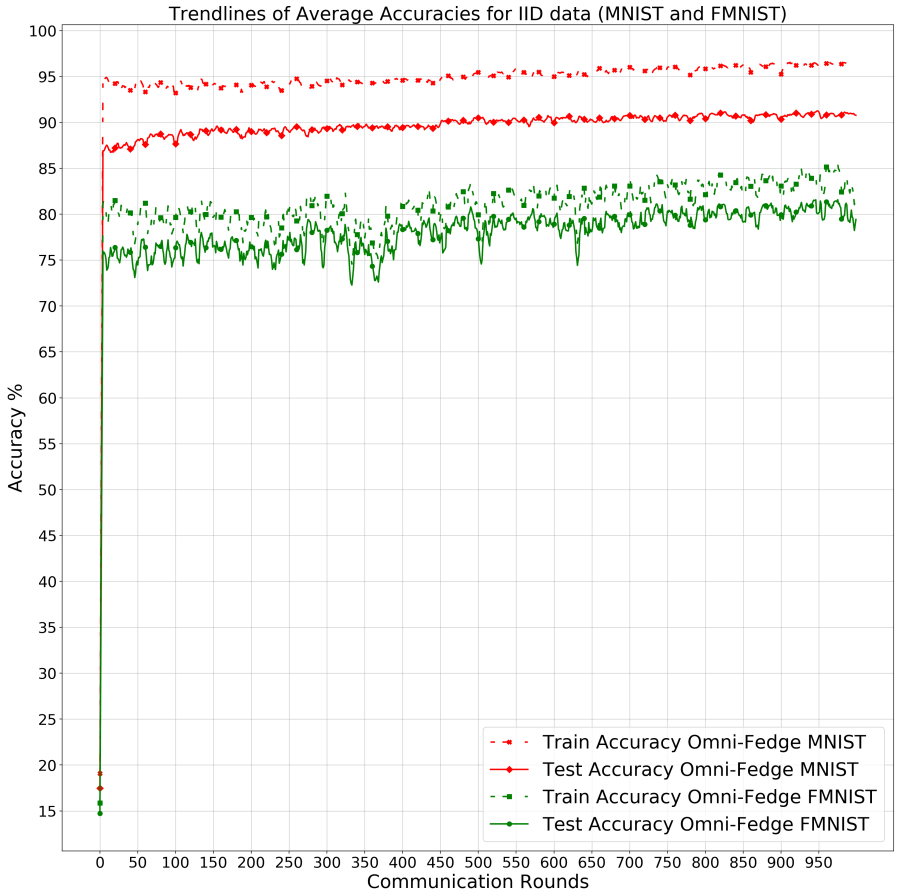

Figure: Trendlines of Average Accuracies for IID data using MNIST and FMNIST

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Thank you!