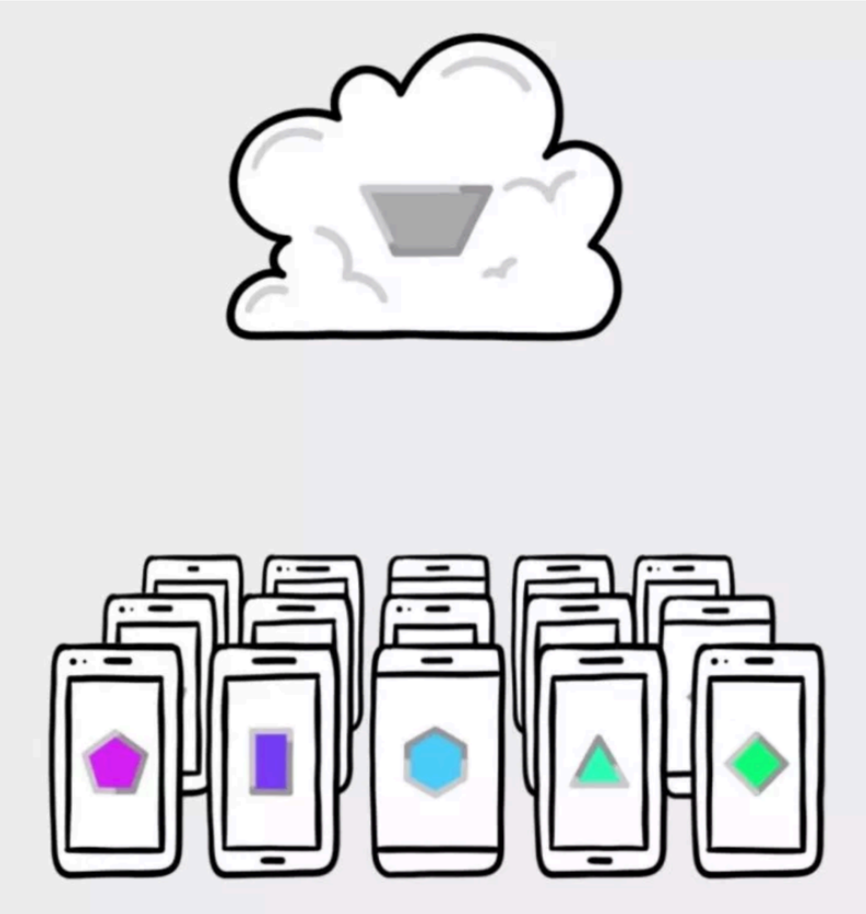
Federated Learning

Shusen Wang

Motivating Examples



Problem: Google wants to train a model using users' mobile data.

Possible solution: Centralized learning
- Collect users' data.
- Train a model on the cluster.

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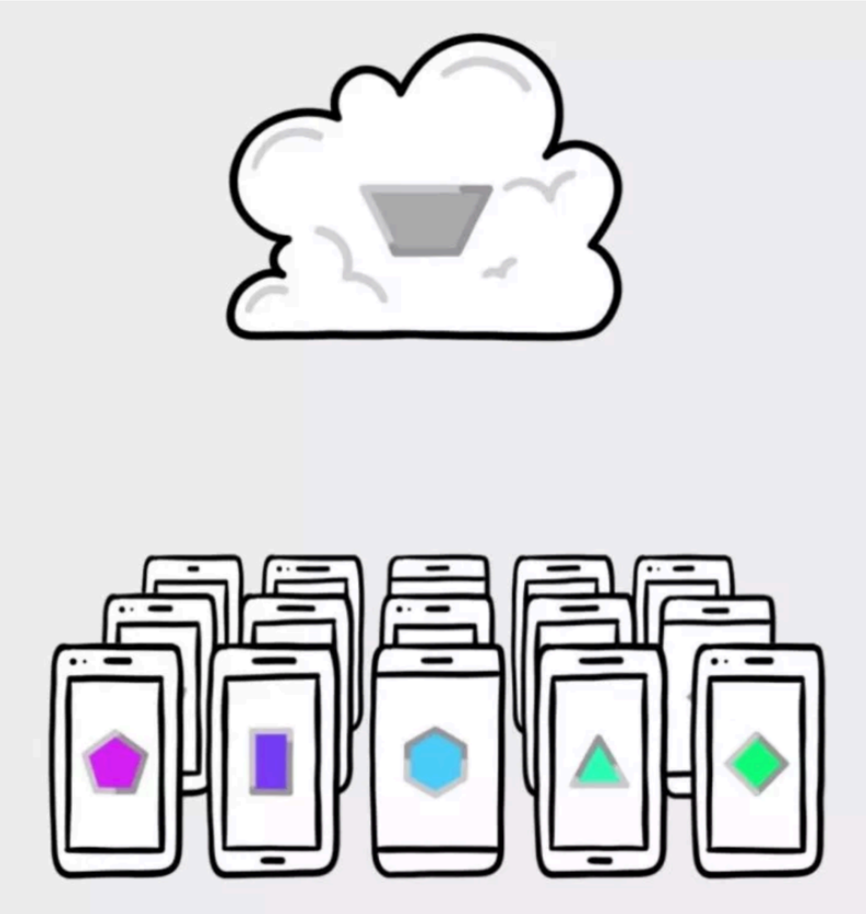


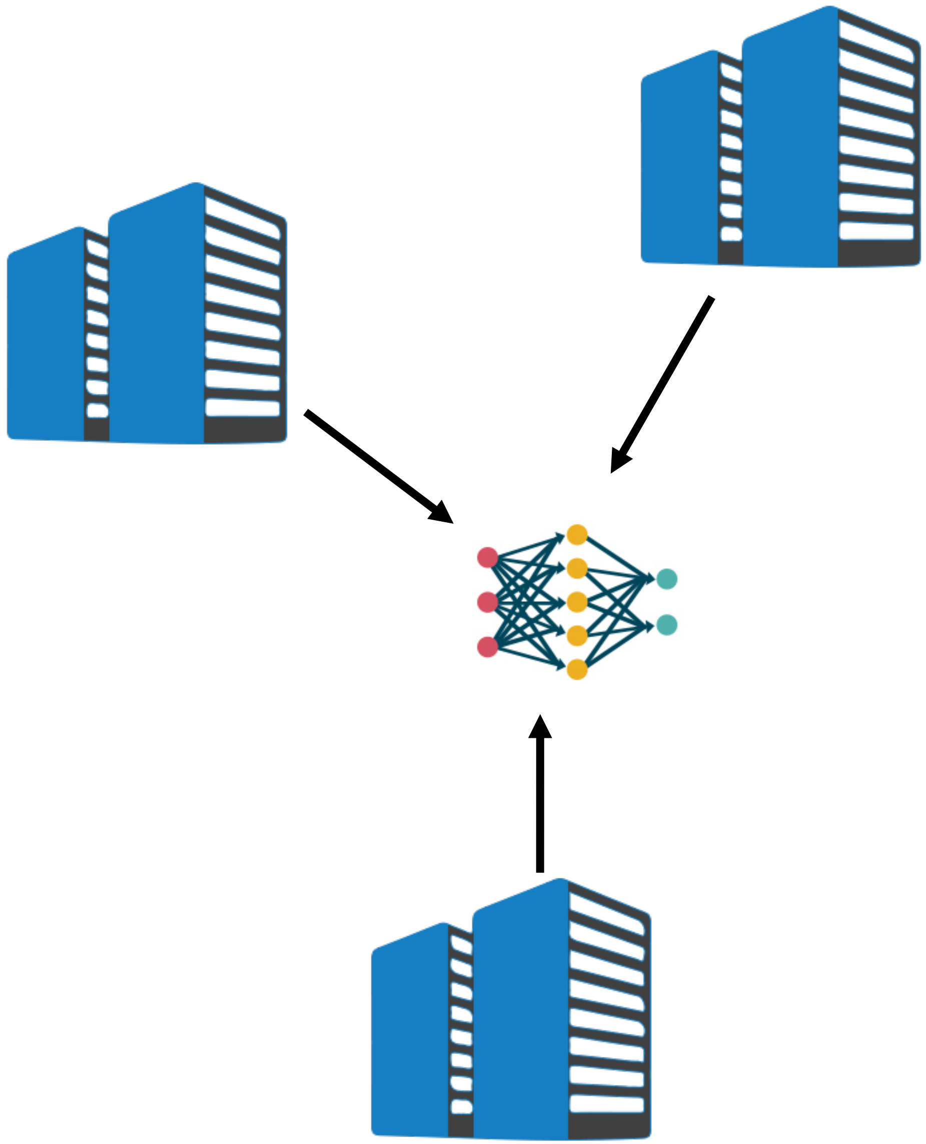
Problem: Google wants to train a model using users' mobile data.

Possible solution: Centralized learning

- Collect users' data.
- Train a model on the cluster.

Challenge: Users may refuse to upload their data, especially sensitive data, to Google's server.

Motivating Examples



Problem: Hospitals want to jointly train a model using medical data.

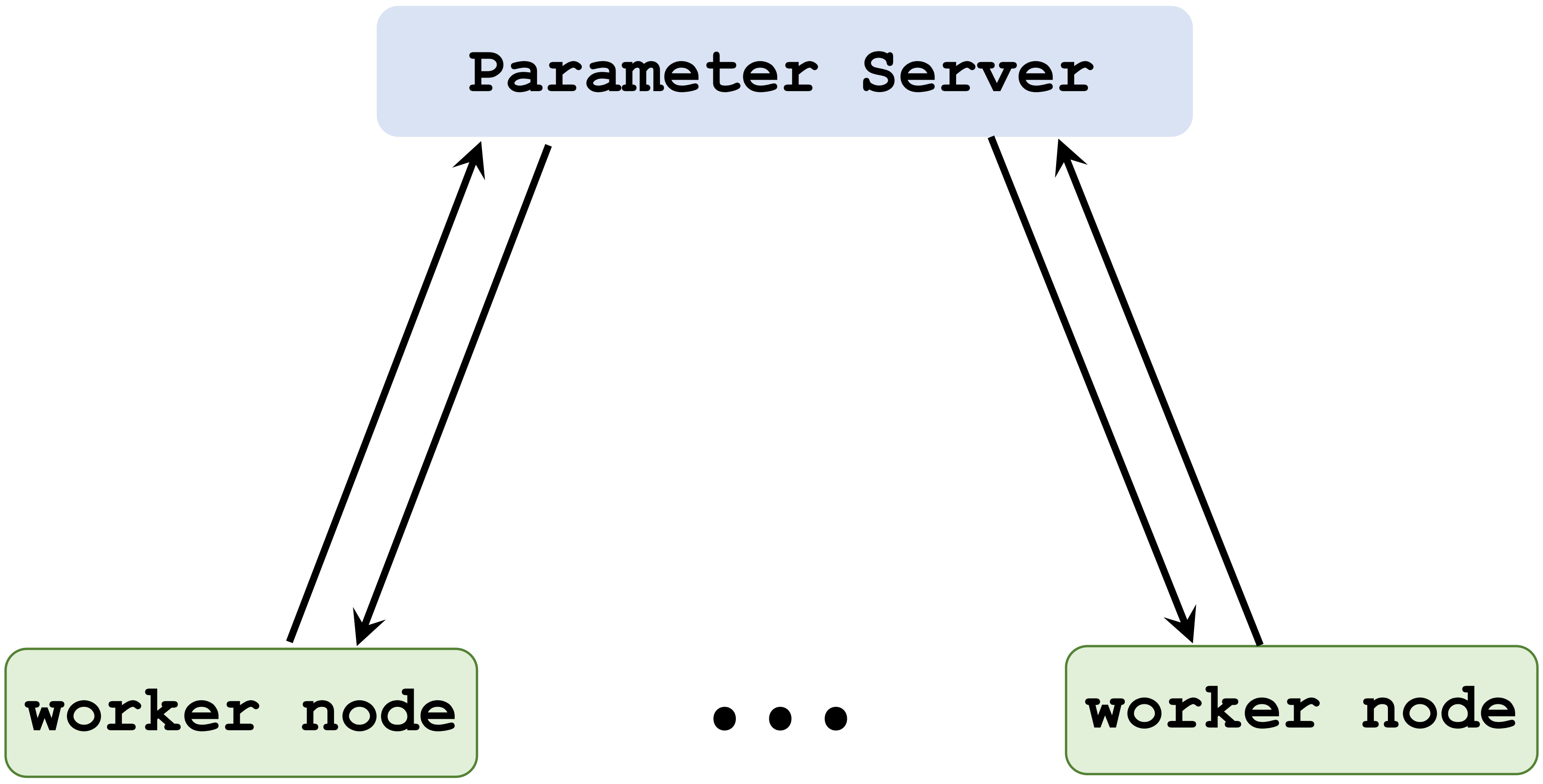
Possible solution: Centralized learning

- Aggregate the data.
- Train a model on the server.

Challenge: Laws or policies may forbid giving patients' data to others.

Distributed Learning vs. Federated Learning

Distributed Learning



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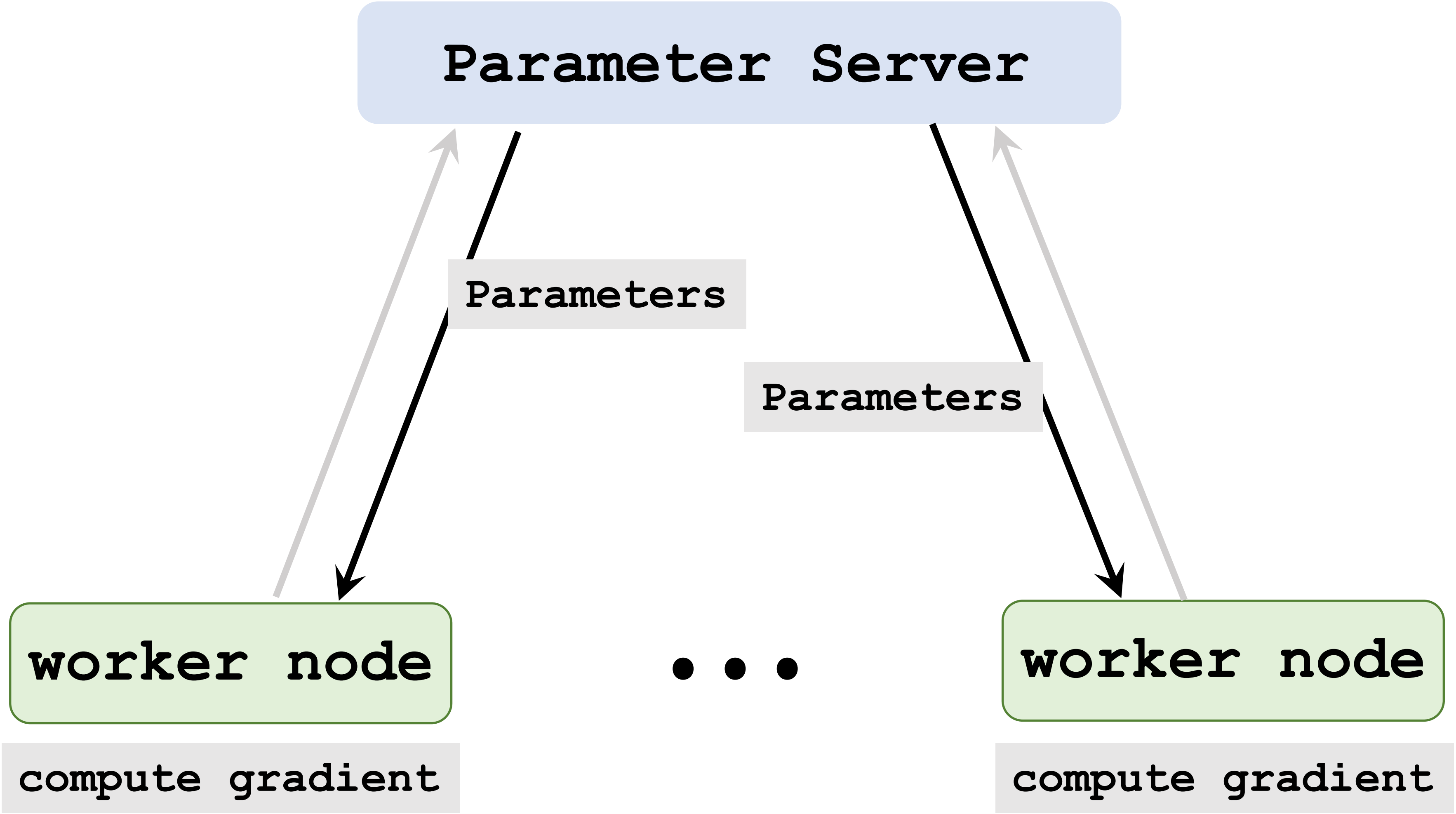

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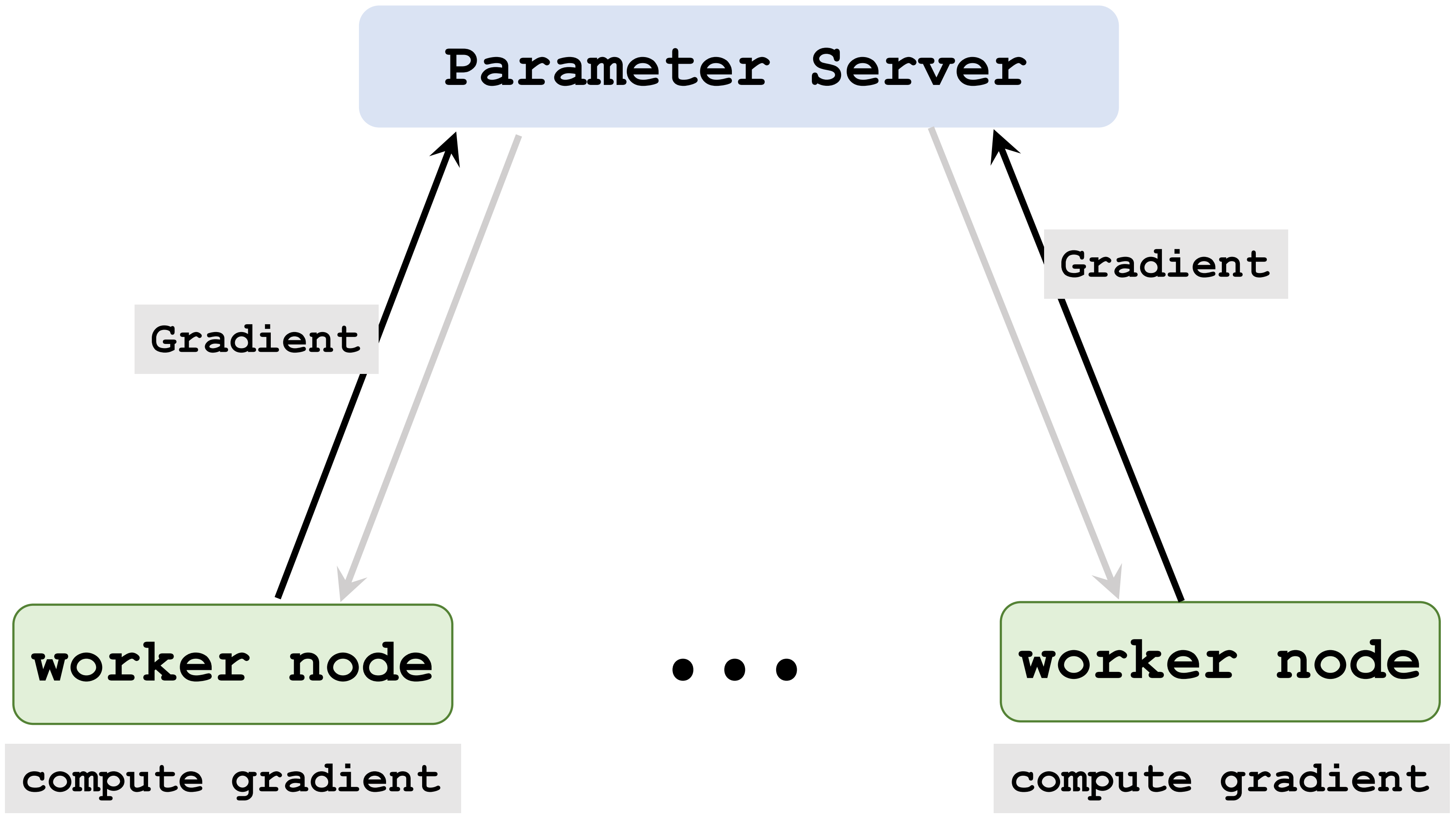

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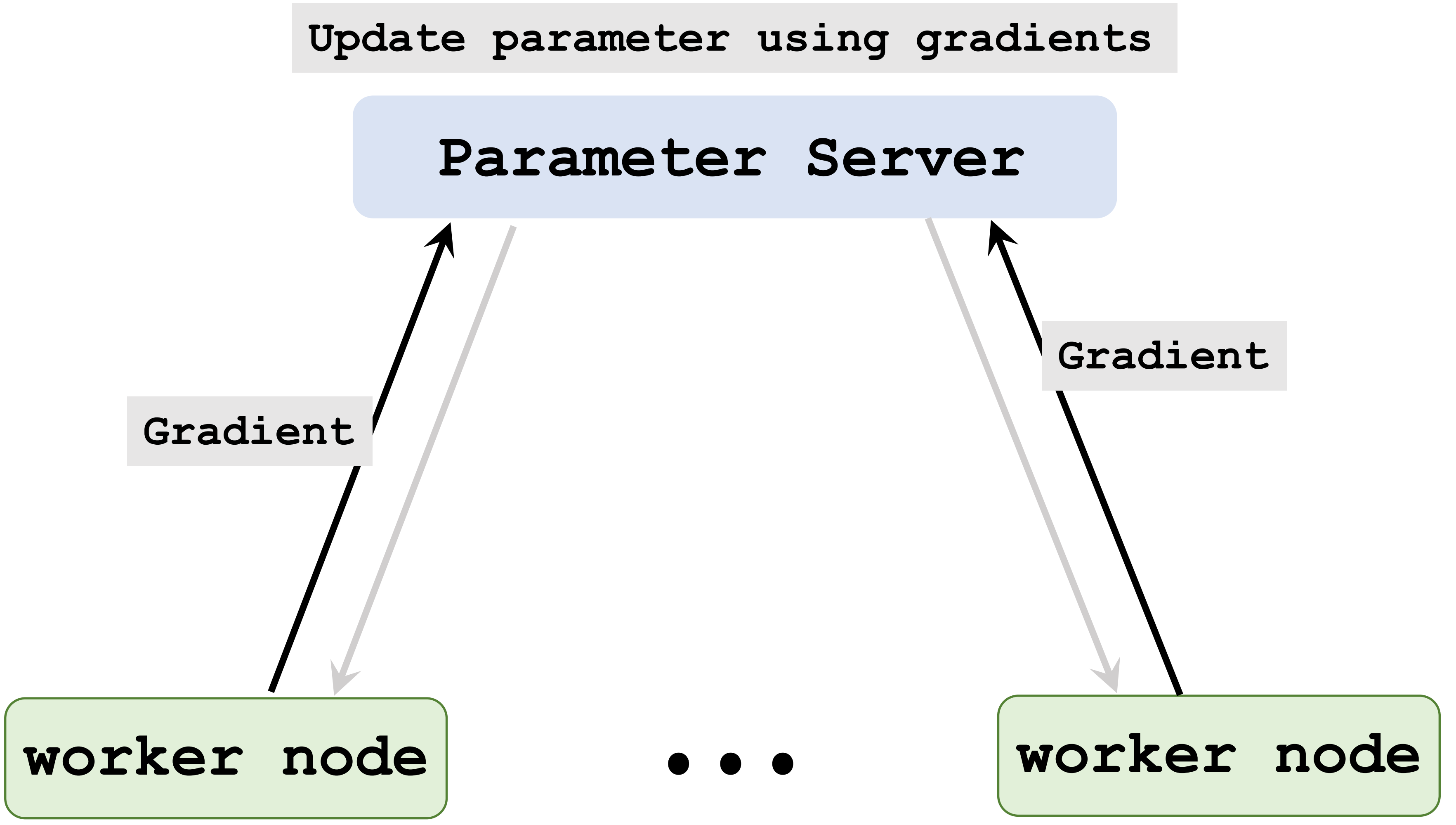

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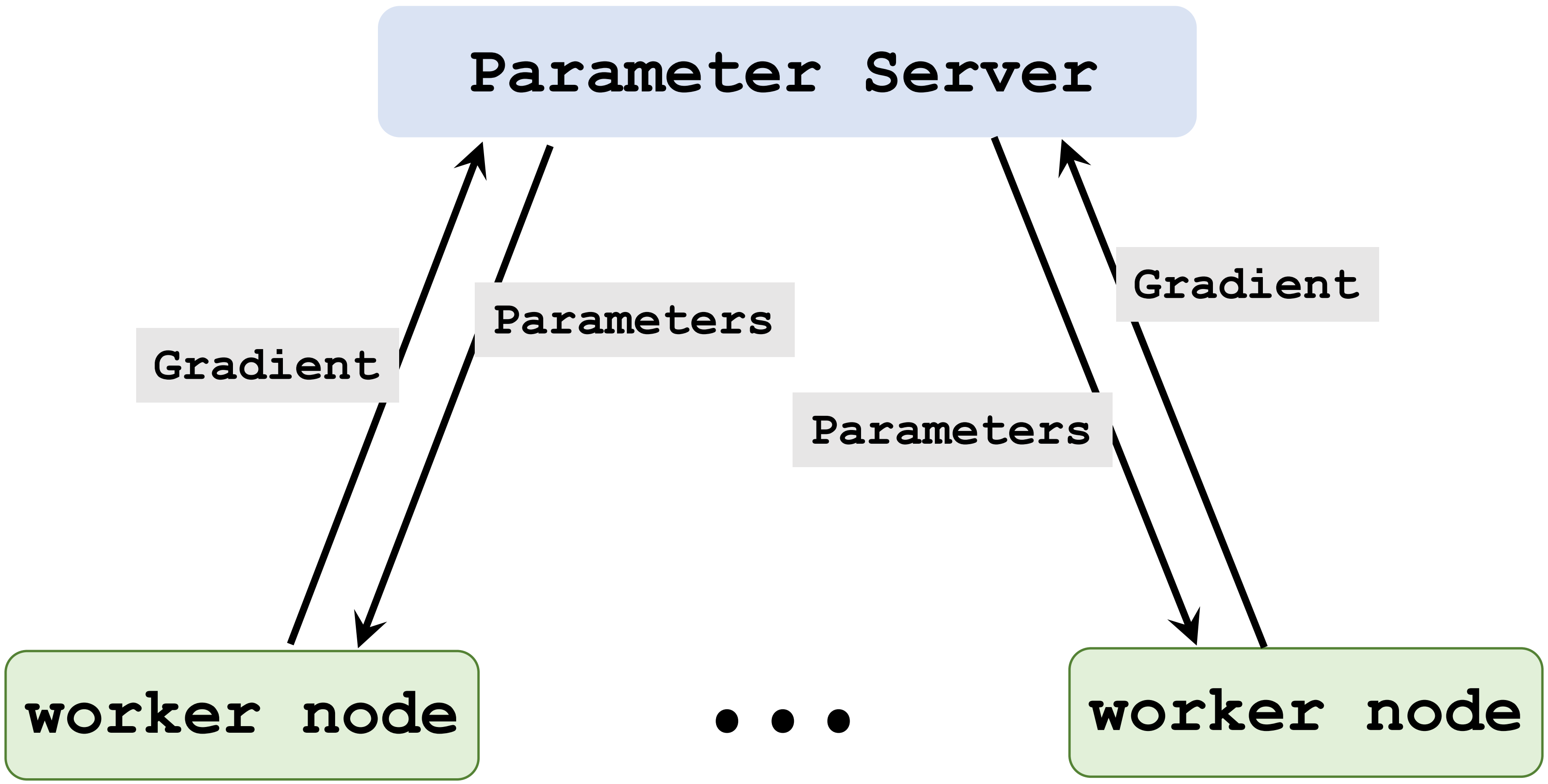

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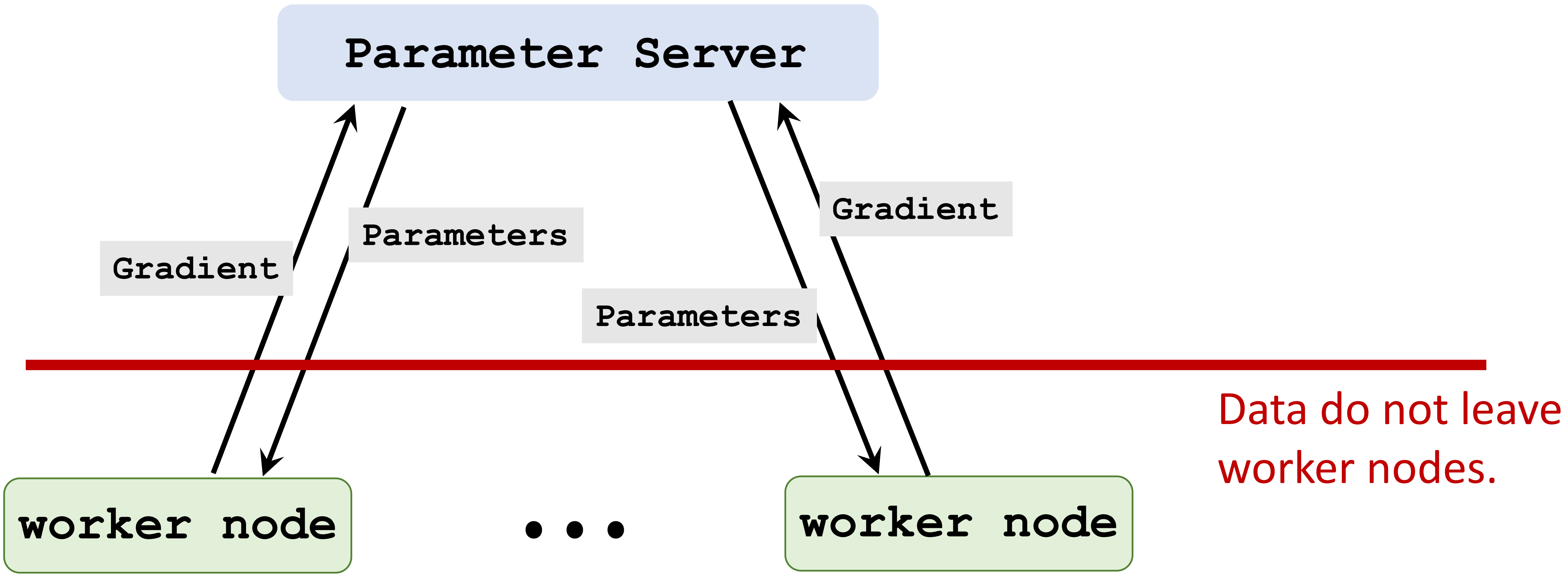

What is federated learning?

Federated learning [1, 2] is a kind of distributed learning.

References

1. McMahan and others: Communication-efficient learning of deep networks from decentralized data. In *AISTATS*, 2017.
2. Konevcny, McMahan, and Ramage: Federated optimization: distributed optimization beyond the datacenter. *arXiv:1511.03575*, 2015

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How does federated learning differ from traditional distributed learning?

1. Users have control over their device and data.

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2. Worker nodes are unstable.

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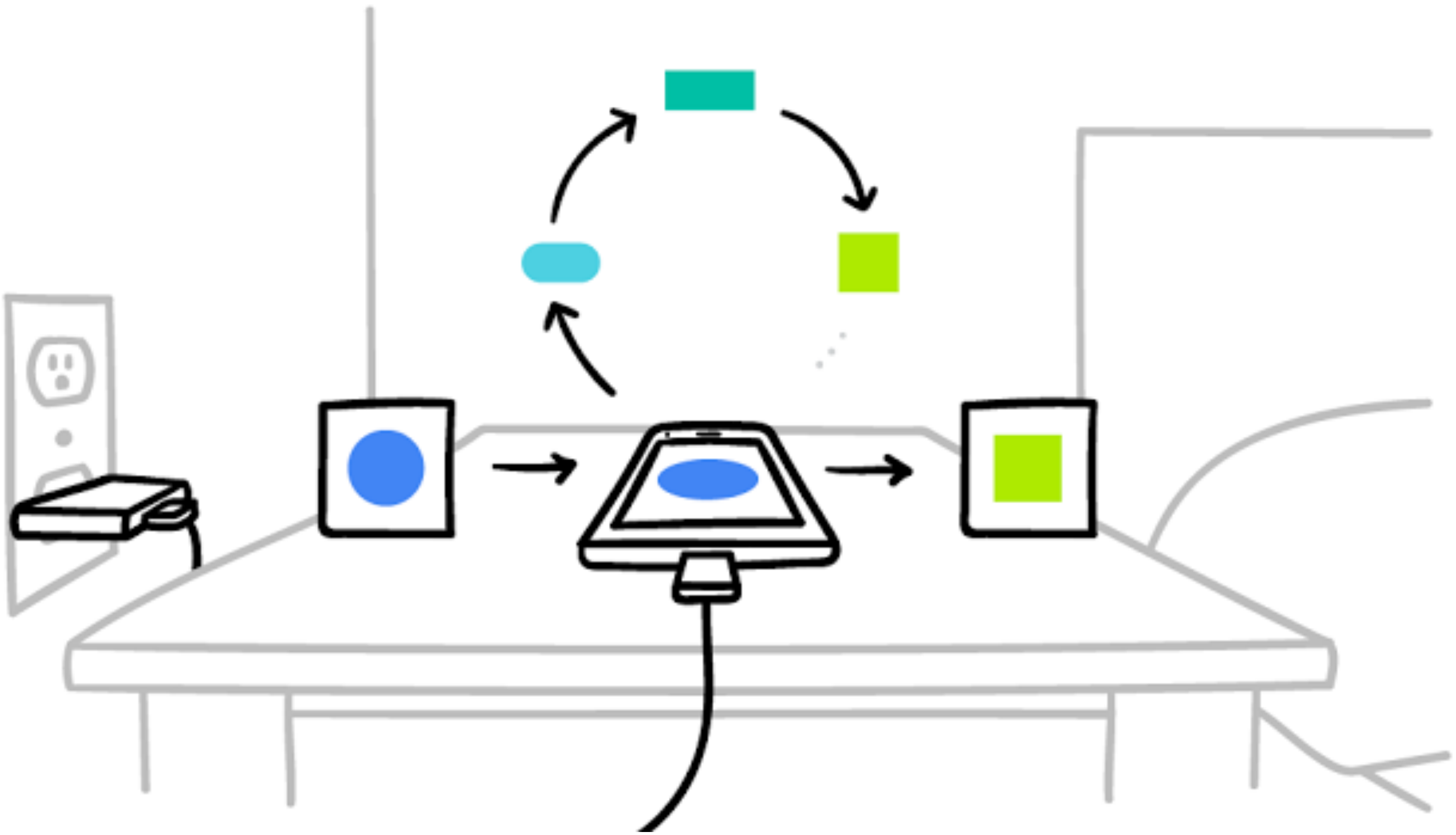
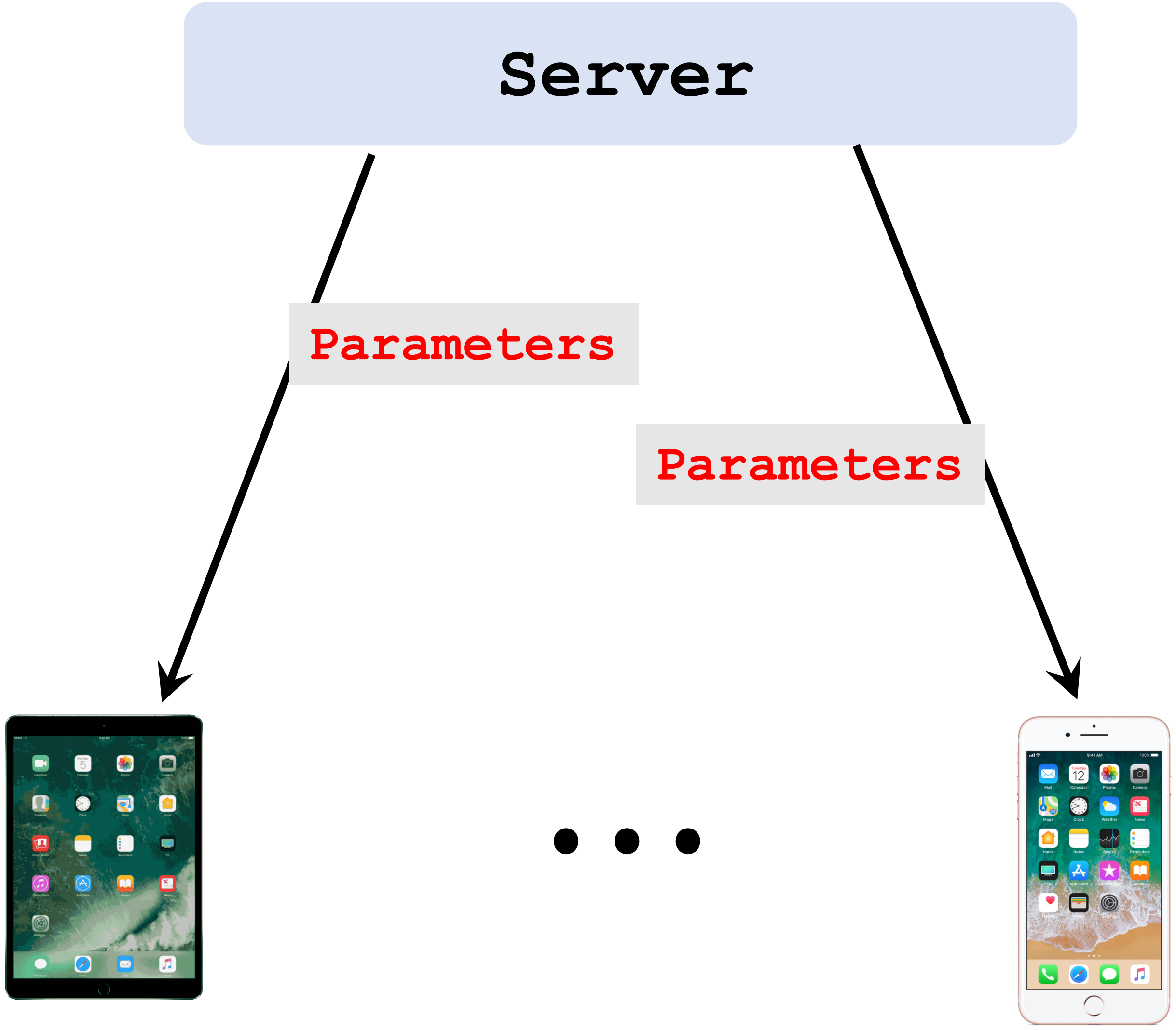
Research Direction 1: Communication-Efficiency

Trade computation for communication



The image is From Google Research Blog

Let us recall parallel gradient descent



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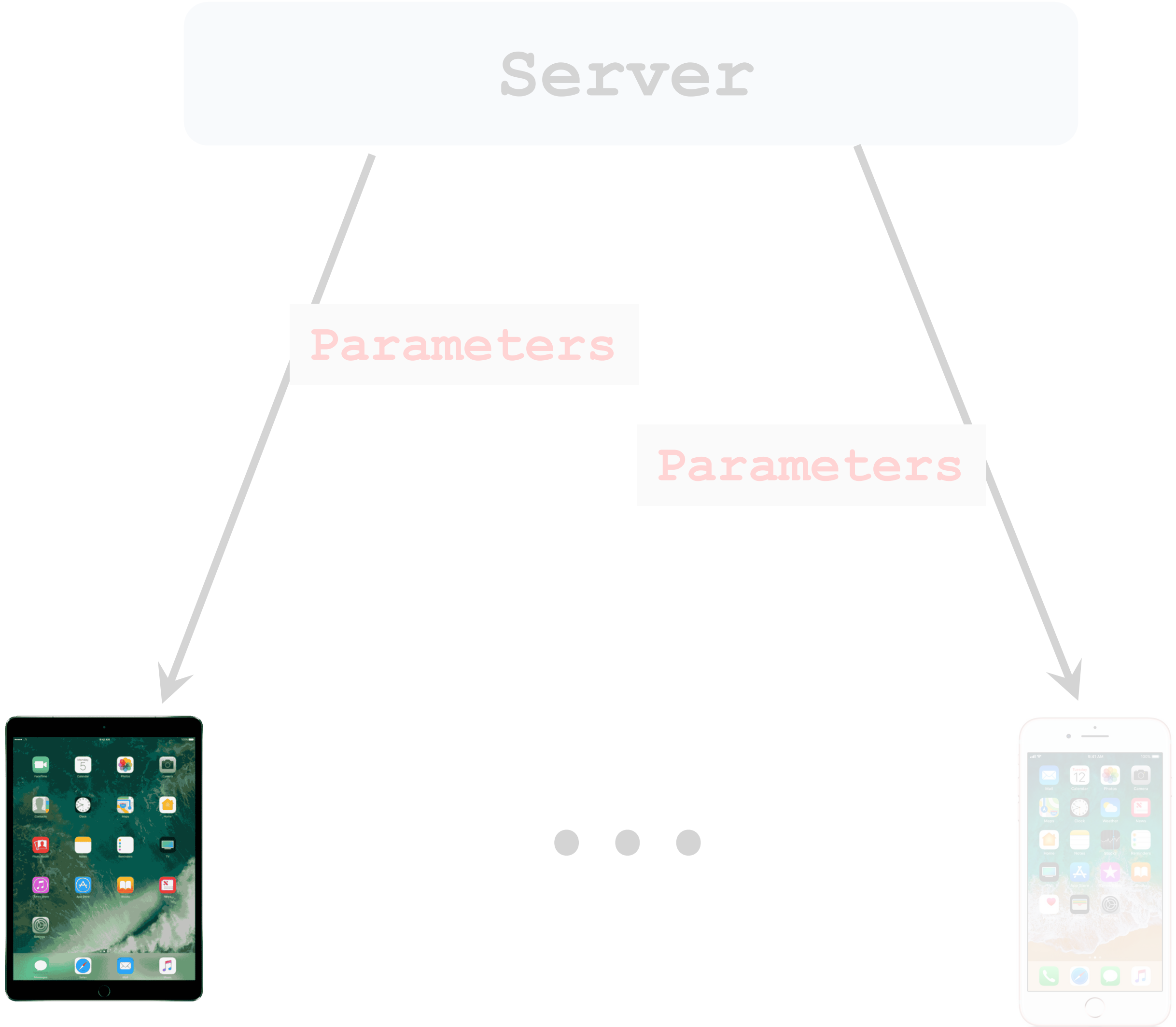

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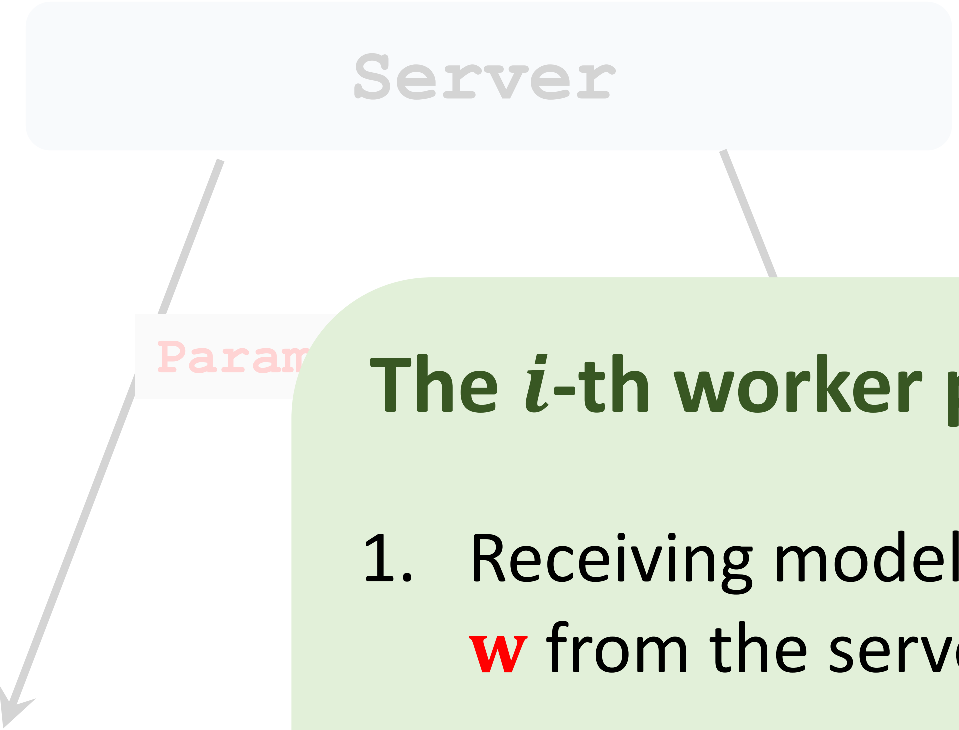
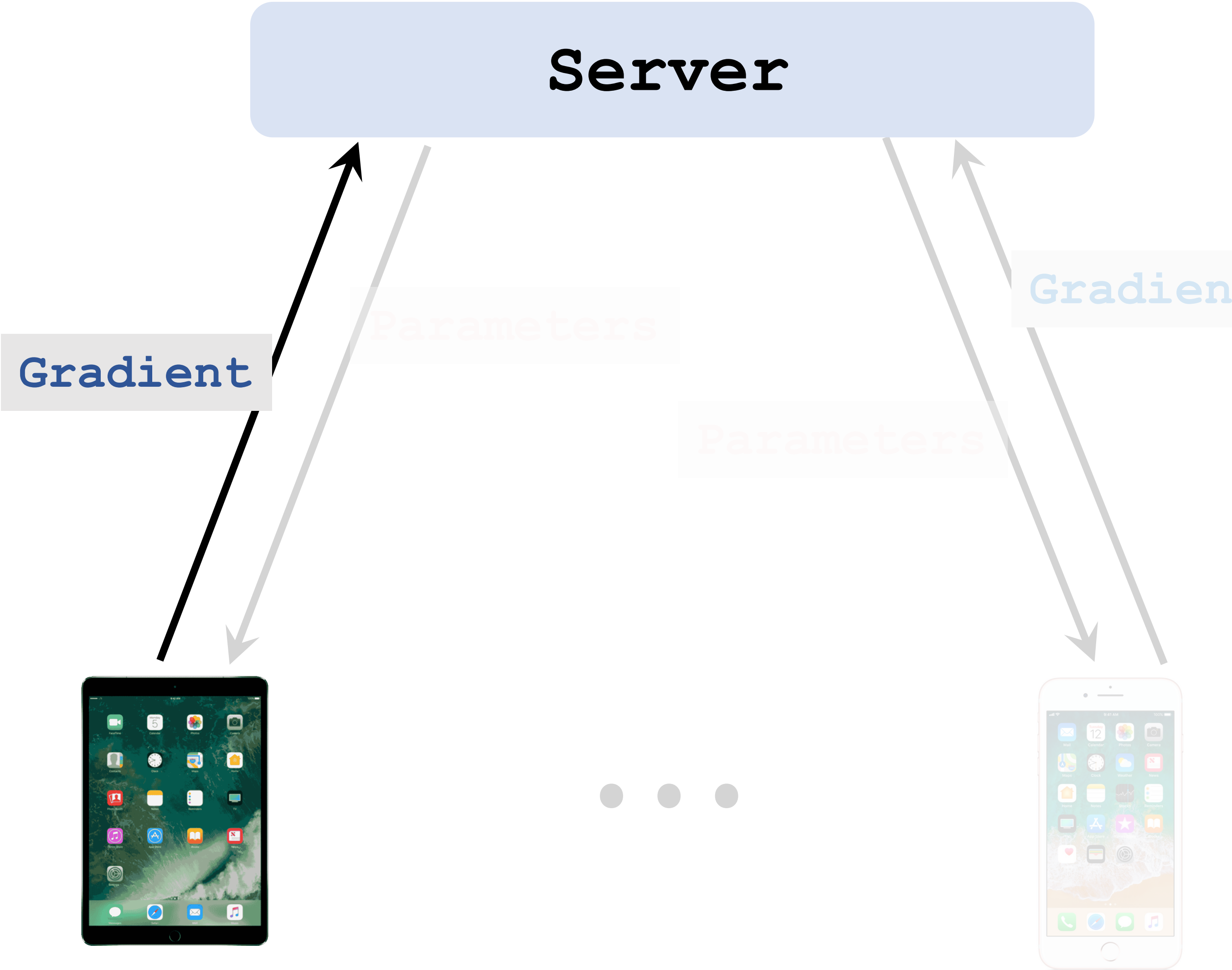


The i-th worker performs:

1. Receiving model parameters $\mathbf{w}$ from the server.
2. Using $\mathbf{w}$ and its local data to compute gradient $\mathbf{g}_i$.
3. Sending $\mathbf{g}_i$ to the server.

Let us recall parallel gradient descent

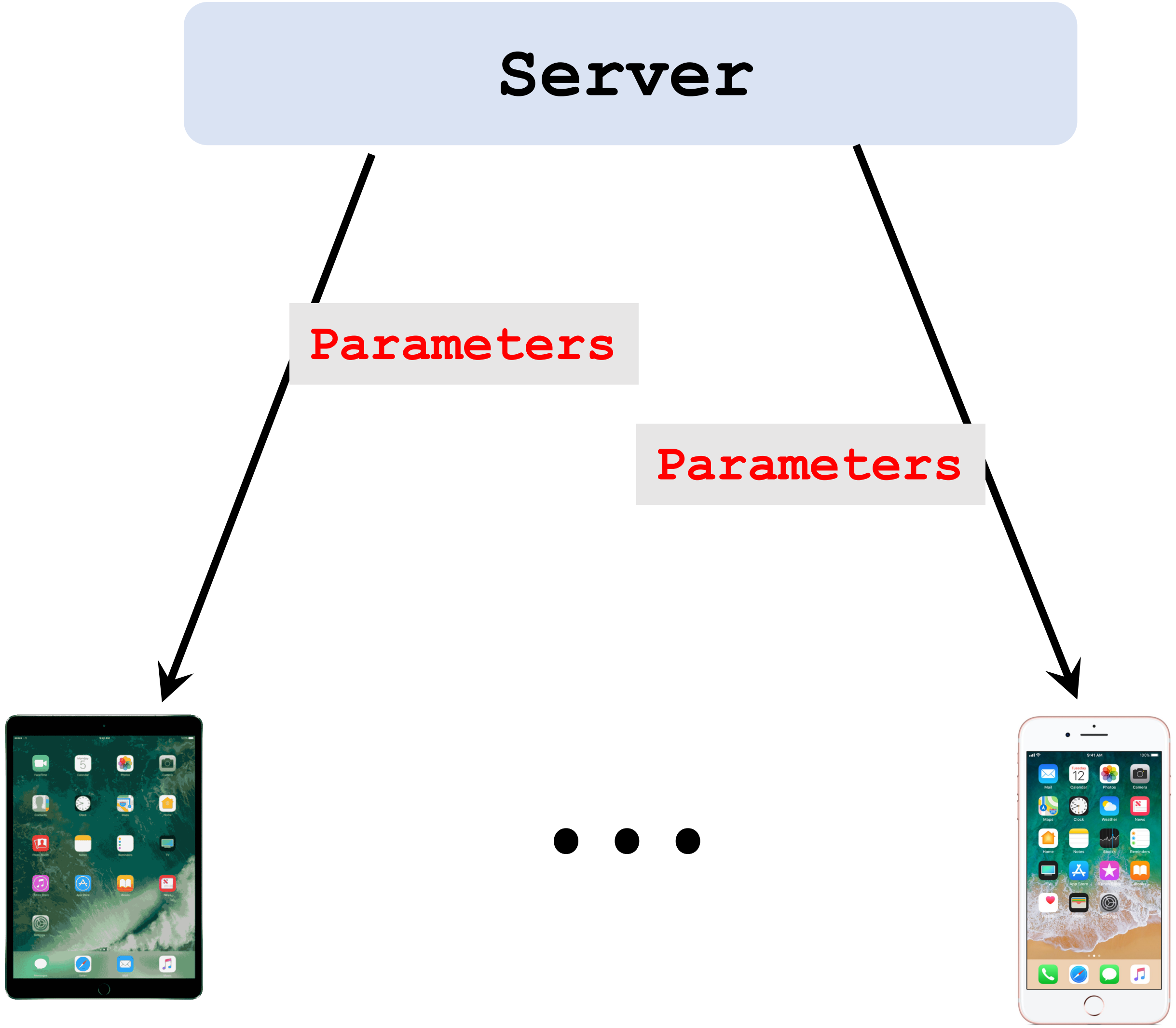


The server performs:

1. Receiving gradients $\mathbf{g}_1, \cdots, \mathbf{g}_m$ from all the m workers.
2. Computing $\mathbf{g} = \mathbf{g}_1 + \cdots + \mathbf{g}_m$.
3. Updating model parameters:

$$\mathbf{w} \leftarrow \mathbf{w} - \alpha \cdot \mathbf{g}.$$

Federated Averaging Algorithm



Federated Averaging Algorithm

Server

The i-th worker performs:

1. Receiving model parameters $\mathbf{w}$ from the server.
2. Repeating the followings:
   a) Using $\mathbf{w}$ and its local data to compute gradient $\mathbf{g}$.
   b) Local update: $\mathbf{w} \leftarrow \mathbf{w} - \alpha \cdot \mathbf{g}$.

Federated Averaging Algorithm

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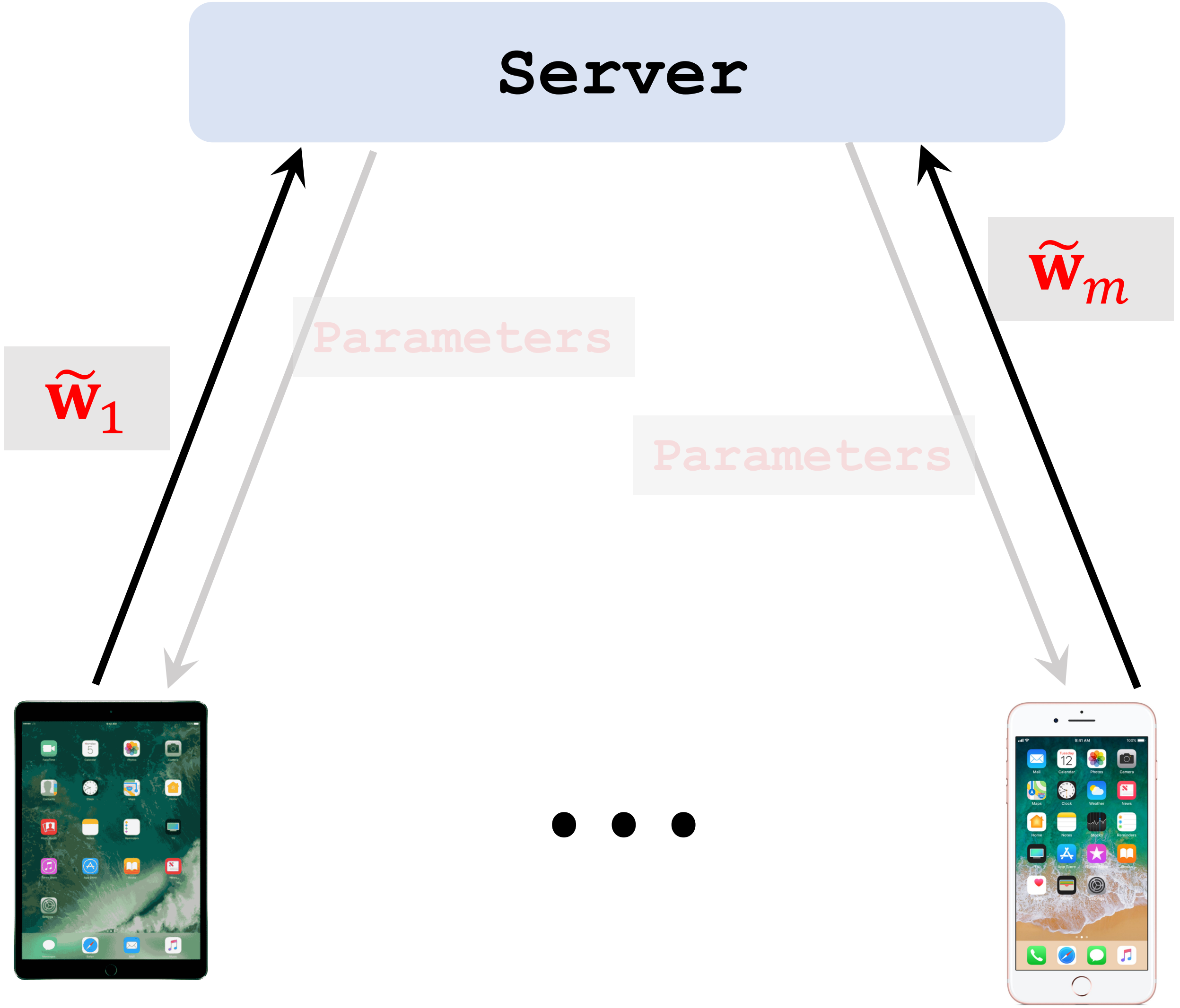
   b) Local update: $\mathbf{w} \leftarrow \mathbf{w} - \alpha \cdot \mathbf{g}$.
3. Sending $\tilde{\mathbf{w}}_i = \mathbf{w}$ to the server.

Federated Averaging Algorithm



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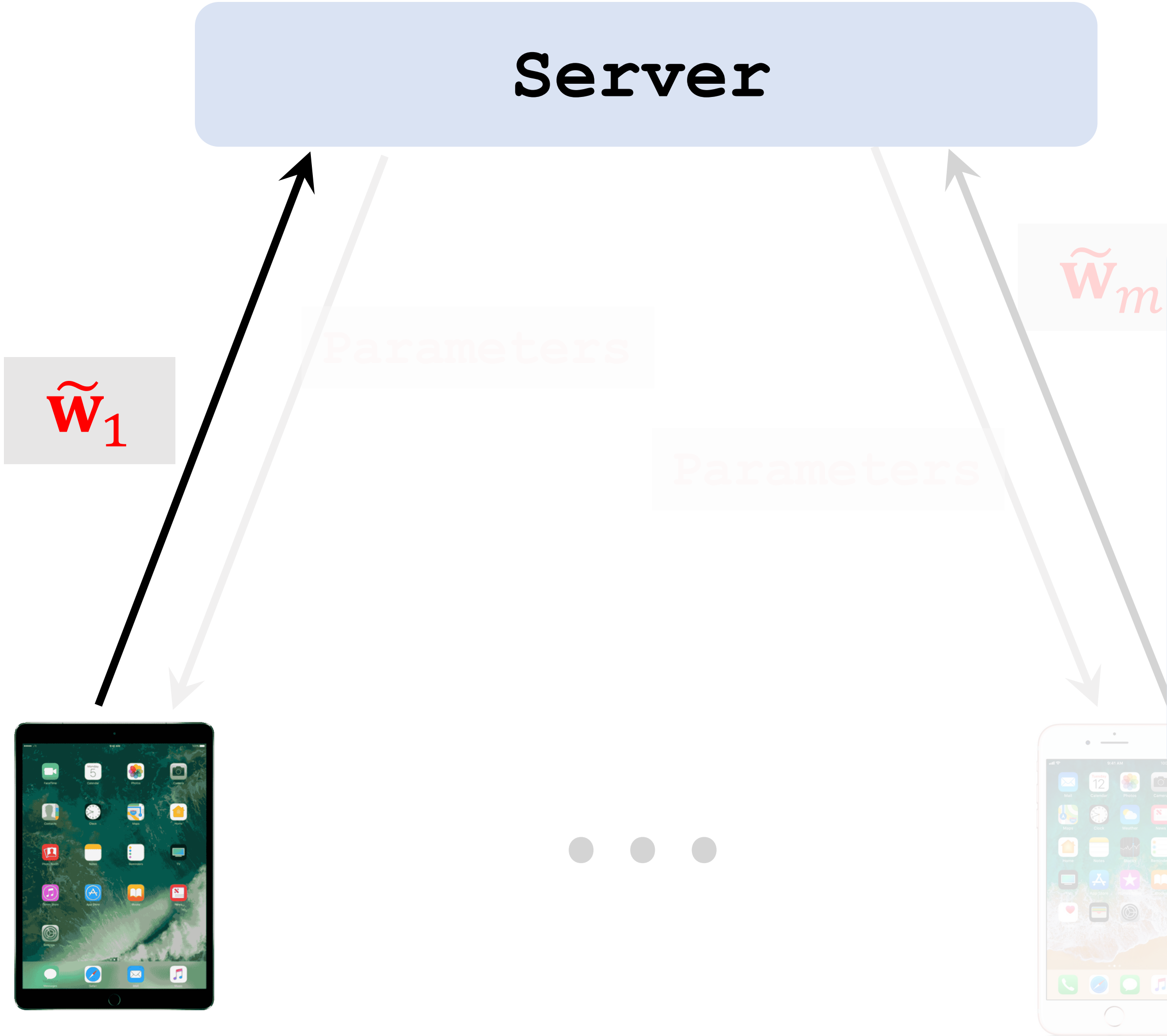


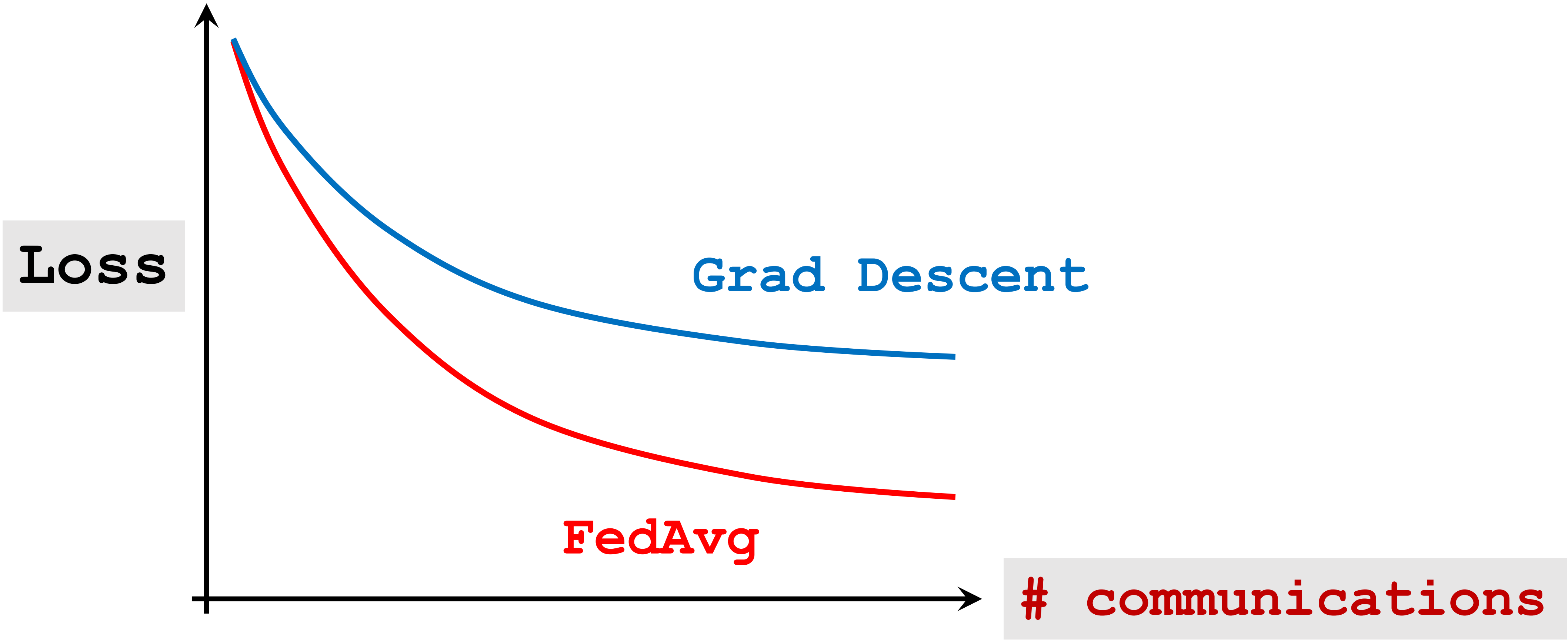
The server performs:

1. Receiving $\tilde{\mathbf{w}}_1, \cdots, \tilde{\mathbf{w}}_m$ from all the m workers.
2. Updating model parameters:

$$\mathbf{w} \leftarrow \frac{1}{m}(\tilde{\mathbf{w}}_1 + \cdots + \tilde{\mathbf{w}}_m).$$

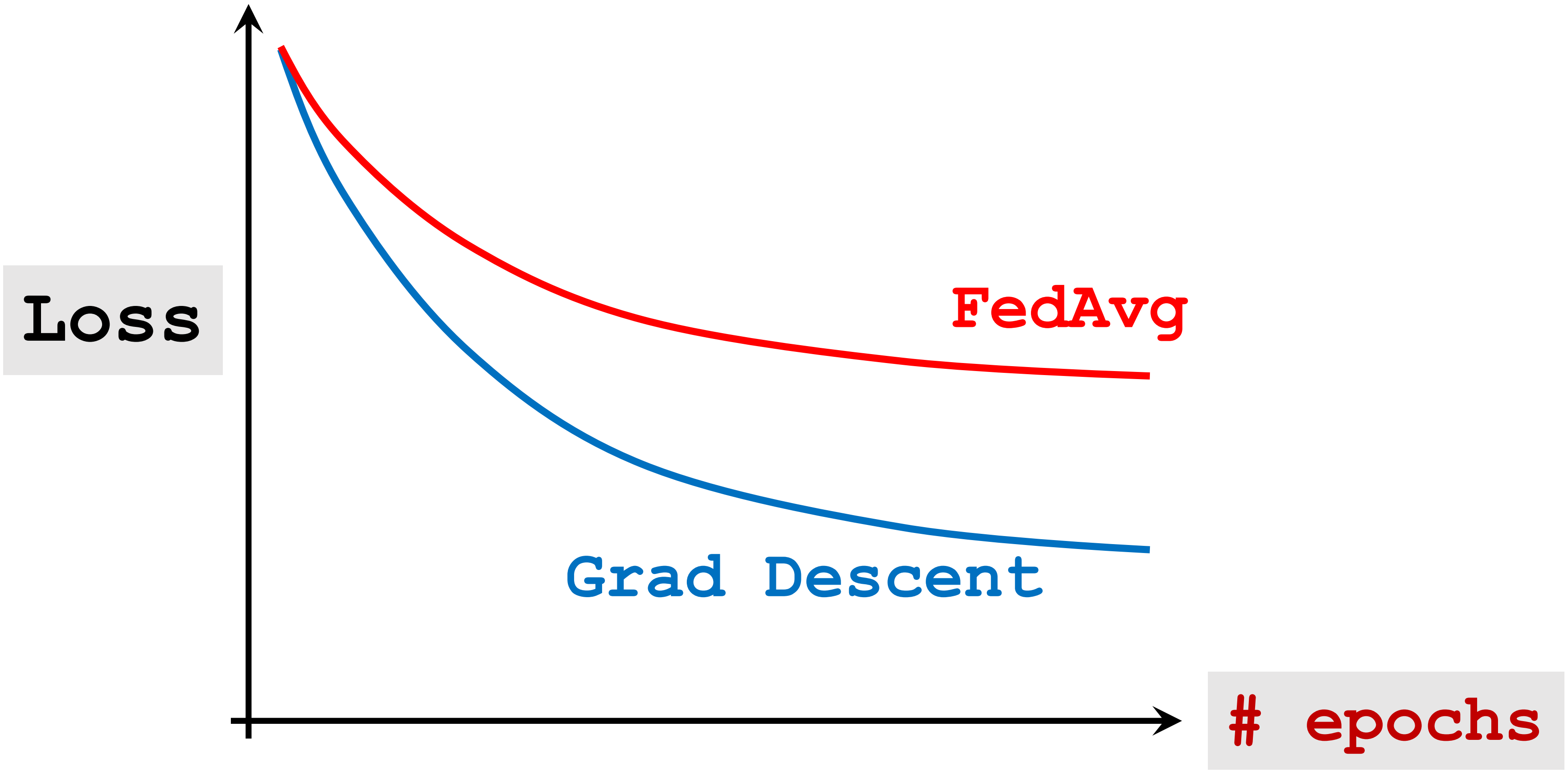
Computation vs. Communication

Measured by # communications, Federated Averaging is faster.



Computation vs. Communication

Measured by # epochs, Federated Averaging is slower.



Convergence of FedAvg

- The original paper [1] does not have theory.
- Paper [2] proved FedAvg converges for IID data.

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Convergence of FedAvg

- The original paper [1] does not have theory.
- Paper [2] proved FedAvg converges for IID data.
- Paper [3] is the first to prove FedAvg (with SGD) converges for non-IID data.
- Paper [4] proved FedAvg (with GD) converges for non-IID data.

References

1. McMahan and others: Communication-efficient learning of deep networks from decentralized data. In *AISTATS*, 2017.
2. Stich: Local SGD converges fast and communicates little. In *ICLR*, 2018.
3. Li and others: On the convergence of FedAvg on non-IID data. *arXiv*, 2019.
4. Khaled and others: First analysis of local GD on heterogeneous data. *arXiv*, 2019.

Communication-Efficient Algorithms

Communication-efficient algorithms for distributed learning, e.g.,

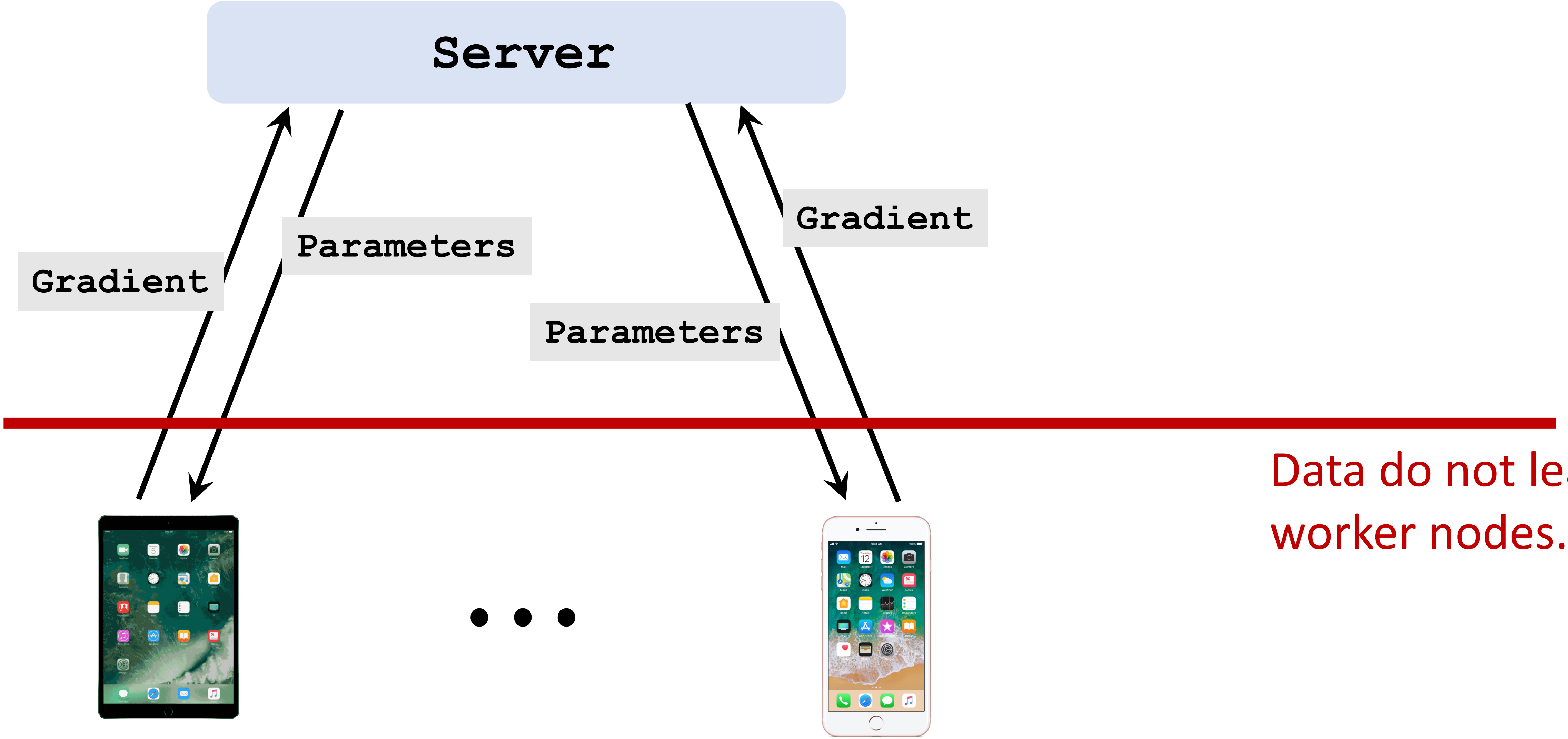
- Approximate Newton's algorithms [1, 2, 3].
- Primal-dual algorithms [4].
- One-shot averaging [5].

Reference:

1. Shamir, Srebro, & Zhang: Communication efficient distributed optimization using an approximate Newton-type method. In *ICML*, 2014.
2. Wang and others: GIANT: Globally improved approximate newton method for distributed optimization. In *NIPS*, 2018.
3. Mahajan and others: An efficient distributed learning algorithm based on effective local functional approximations. *Journal of Machine Learning Research*, 2019.
4. Smith and others: CoCoA: A general framework for communication-efficient distributed optimization. *Journal of Machine Learning Research*, 2018.
5. Zhang, Duchi, & Wainwright: Communication-efficient algorithms for statistical optimization. *Journal of Machine Learning Research*, 2013.

Research Direction 2: Privacy

Is federated learning (FL) safe?



Data do not leave worker nodes.

Is federated learning (FL) safe?

Gradient carries information in the training data.

- Least squares regression:

$$\min_{\mathbf{w}} \sum_{i=1}^{n} l(\mathbf{w}, \mathbf{x}_i, y_i), \quad \text{where } l(\mathbf{w}, \mathbf{x}_i, y_i) = \frac{1}{2}\left(\mathbf{x}_i^T \mathbf{w} - y_i\right)^2.$$

- Stochastic gradient:

$$\mathbf{g}_i = \frac{\partial\, l(\mathbf{w}, \mathbf{x}_i, y_i)}{\partial\, \mathbf{w}} = \left(\mathbf{x}_i^T \mathbf{w} - y_i\right) \mathbf{x}_i.$$

Is federated learning (FL) safe?

- If an ML model is useful, it must reveal information about the data on which it was trained [1].

References

1. Melis et al. Exploiting unintended feature leakage in collaborative learning. In *IEEE Symposium on Security & Privacy*, 2019.

Is federated learning (FL) safe?

- If an ML model is useful, it must reveal information about the data on which it was trained [1].
- Training data can be reversely inferred from the model [2].

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Is federated learning (FL) safe?

- If an ML model is useful, it must reveal information about the data on which it was trained [1].
- Training data can be reversely inferred from the model [2].
- In FL, gradients and model parameters leak users' data [1, 3].

References

1. Melis et al. Exploiting unintended feature leakage in collaborative learning. In *IEEE Symposium on Security & Privacy*, 2019.
2. Fredrikson et al. Model inversion attacks that exploit confidence information and basic countermeasures. In *CCS*, 2015.
3. Hitaj et al. Deep models under the GAN: information leakage from collaborative deep learning. In *ACM SIGSAC Conference on Computer and Communications Security*, 2017.

How is privacy disclosed?

References

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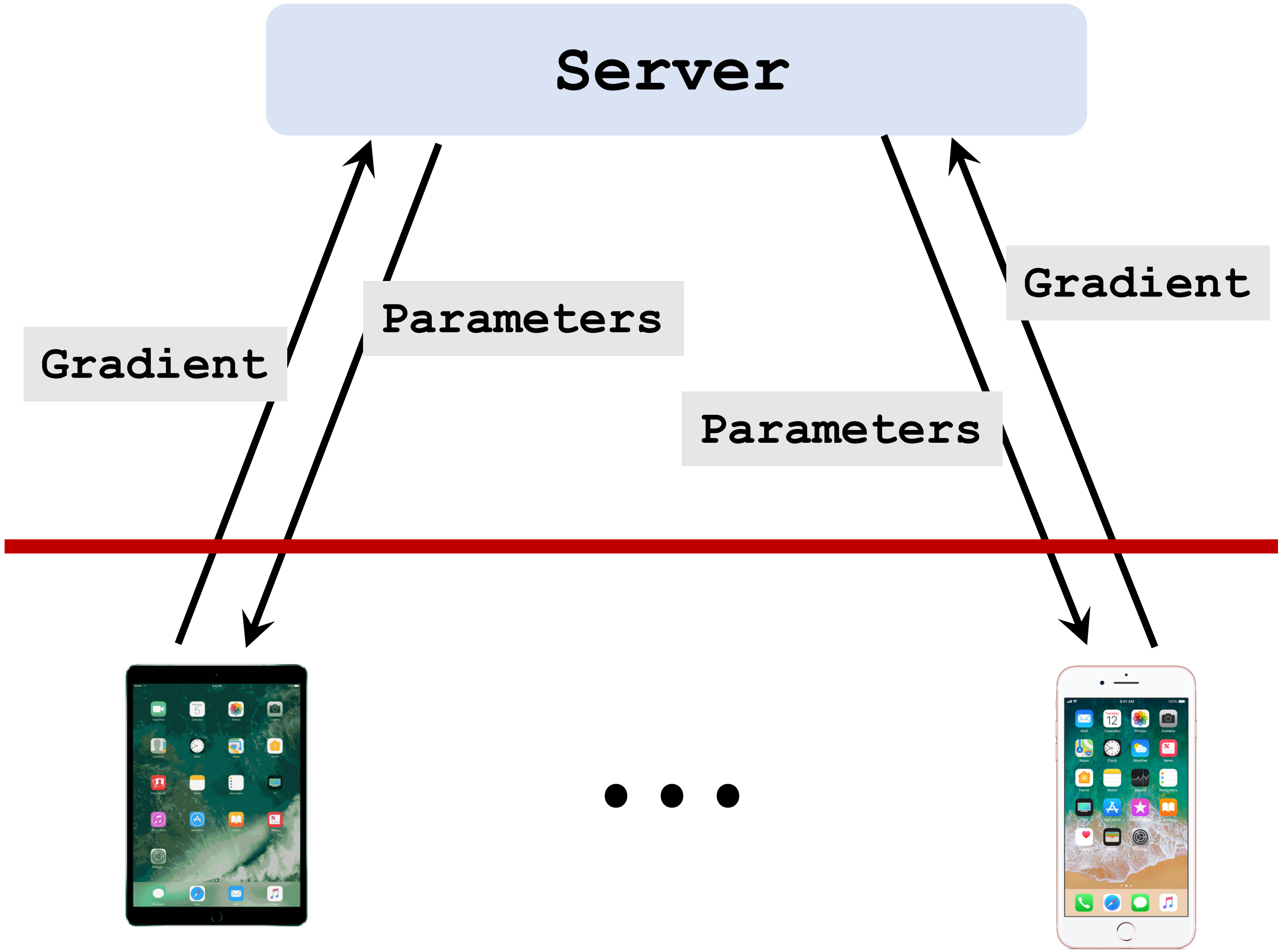
Can the attacks be defended?



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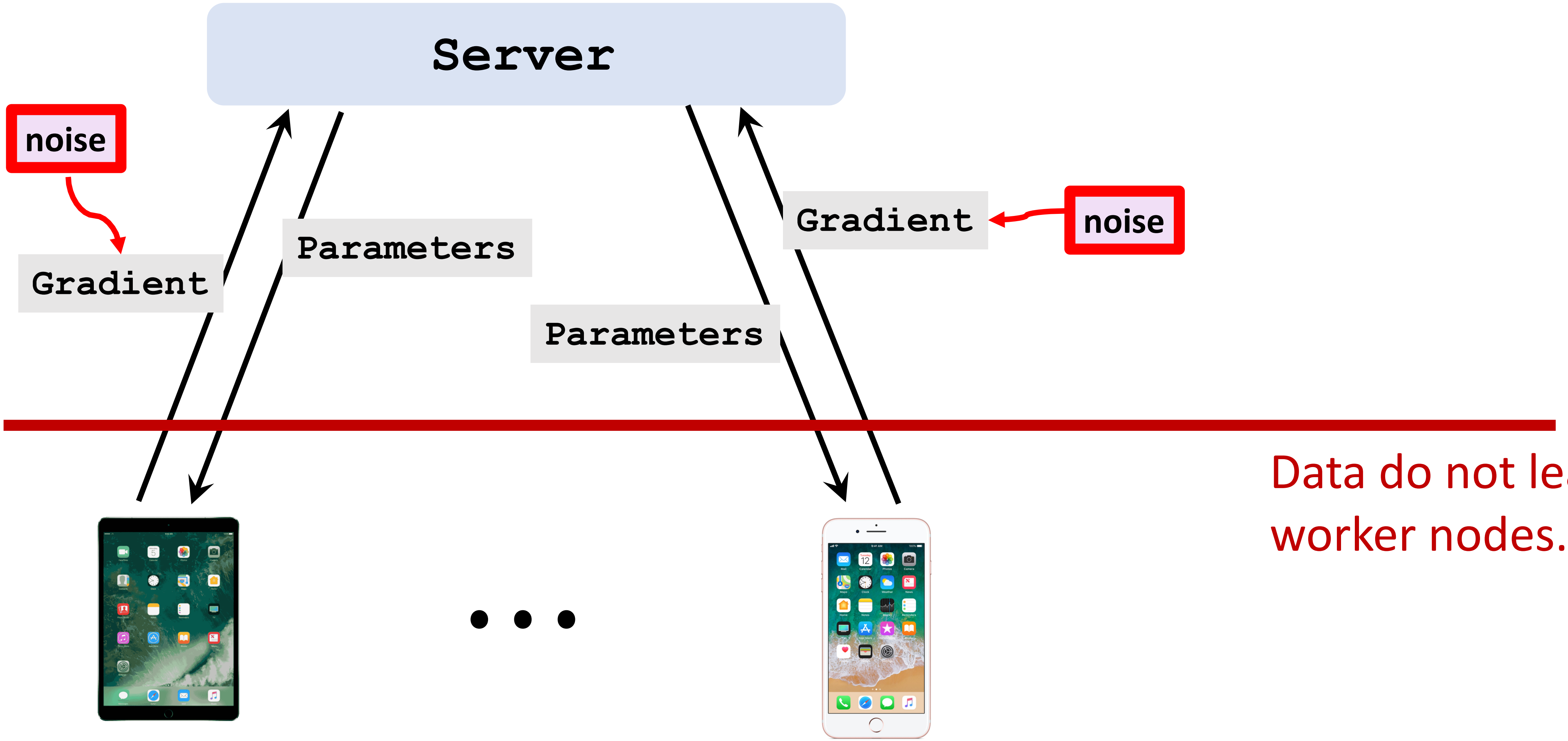
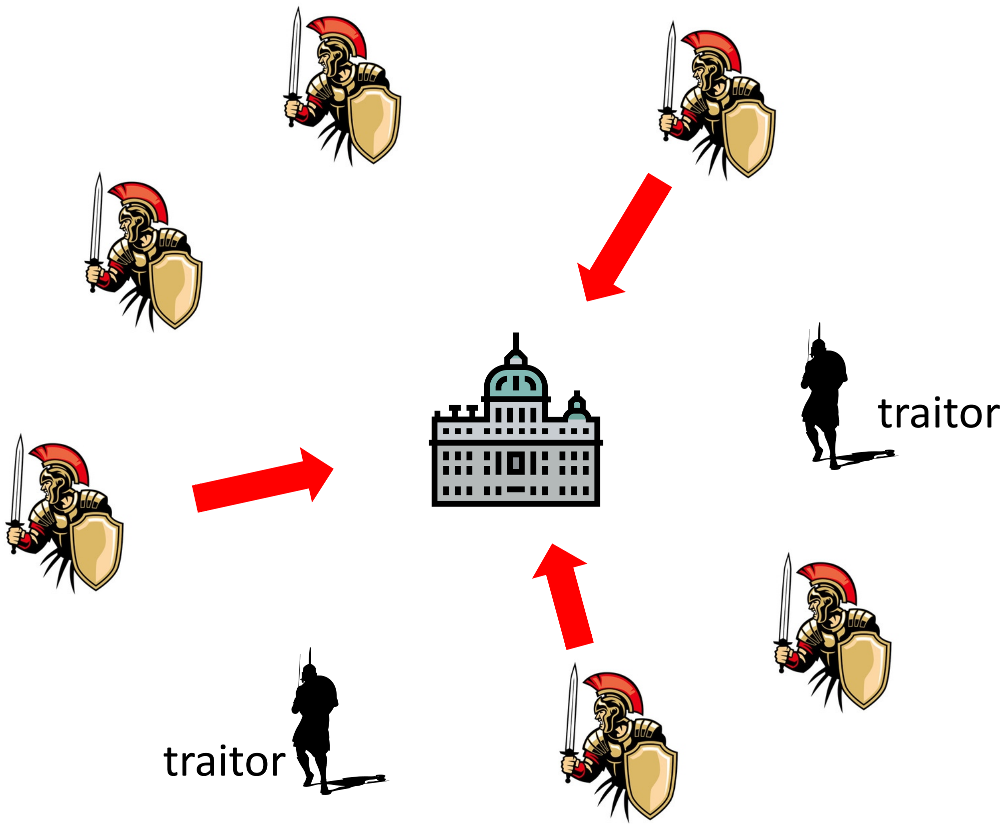


Data do not leave worker nodes.

Research Direction 3: Adversarial Robustness

Byzantine Generals Problem



Reference

- Lamport, Shostak, & Pease: The Byzantine Generals Problem. *ACM Transactions on Programming Languages and Systems*, 1982.

Attacks on Federated Learning

- Attack 1: Data poisoning attack [1].

References

1. Shafah and others: Poison frogs! targeted clean-label poisoning attacks on neural networks. In *NIPS*, 2018.

Attacks on Federated Learning

- Attack 1: Data poisoning attack [1].
- Attack 2: Model poisoning attack [2].

References

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- Attack 1: Data poisoning attack [1].
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- Defense 1: Server check validation accuracy.

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Attacks on Federated Learning

- Attack 1: Data poisoning attack [1].
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- Defense 1: Server check validation accuracy.
- Defense 2: Server check gradient statistics.
- Defense 3: Byzantine-tolerant aggregation [3, 4, 5].

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2. Bhagoji and others: Analyzing federated learning through an adversarial lens. In *ICML*, 2019.
3. Blanchard, Guerraoui, & Stainer: Machine learning with adversaries: Byzantine tolerant gradient descent. In *NIPS*, 2017.
4. Chen, Su, & Xu: Distributed statistical machine learning in adversarial settings: Byzantine gradient descent. *In Proceedings of the ACM on Measurement and Analysis of Computing Systems*, 2017.
5. Yin and others: Byzantine-robust distributed learning: Towards optimal statistical rates. In *ICML*, 2018.

Summary

What is federated learning (FL)?

- FL is a kind of distributed learning.
- Objective: jointly learn a model without sharing data.
- FL has unique challenges, e.g.,
  - non-IID data,
  - slow communication.

Research Directions

- Direction 1: Communication-efficient algorithms.

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- Direction 2: Defense against privacy leakage.

Research Directions

- Direction 1: Communication-efficient algorithms.
- Direction 2: Defense against privacy leakage.
- Direction 3: Robustness to Byzantine faults.

Thank you!

Reference (Communication Efficiency)

1. McMahan, Moore, Ramage, Hampson, & Arcas. Communication-efficient learning of deep networks from decentralized data. In *AISTATS*, 2017.
2. Stich. Local SGD converges fast and communicates little. In *ICLR*, 2018.
3. Li, Sahu, Talwalkar, & Smith. Federated optimization in heterogeneous networks. *arXiv*, 2018.
4. Wang & Joshi. Cooperative SGD: A unified framework for the design and analysis of communication-efficient SGD algorithms. *arXiv*, 2018.
5. Fan & Cong. On the convergence properties of a k-step averaging stochasticgradient descent algorithm for nonconvex optimization. In *IJCAI*, 2018.
6. Lin, Stich, and Jaggi. Don’t use large mini-batches, use local SGD. arXiv, 2018.
7. Li, Huang, Yang, Wang, & Zhang. On the convergence of FedAvg on non-IID data. *arXiv*, 2019.
8. Khaled, Mishchenko, Richtárik. First analysis of local GD on heterogeneous data. *arXiv*, 2019.
9. Yu, Yang, Zhu. Parallel restarted SGD with faster convergence and less communication: Demystifying why model averaging works for deep learning. In *AAAI*, 2019.

…

(And many other work which I am unaware of.)

Reference (Privacy Leakage)

1. Hitaj, Ateniese, & Perez-Cruz. Deep models under the GAN: information leakage from collaborative deep learning. In *ACM SIGSAC Conference on Computer and Communications Security*, 2017.
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3. Zhu, Liu, & Han. Deep leakage from gradients. In *NIPS*, 2019.
4. Orekondy, Oh, Zhang, Schiele, & Fritz. Gradient-Leaks: Understanding and controlling deanonymization in federated learning. *arXiv*, 2018.
5. Ateniese, Felici, Mancini, Spognardi, Villani, & Vitali. Hacking smart machines with smarter ones: How to extract meaningful data from machine learning classifiers. *International Journal of Security and Networks*, 2015.
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7. Ganju, Wang, Yang, Gunter, & Borisov. Property Inference Attacks on Fully Connected Neural Networks using Permutation Invariant Representations. In *CCS*, 2018.
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Reference (Adversarial Robustness)

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2. Bhagoji, Chakraborty, Mittal, & Calo. Analyzing federated learning through an adversarial lens. In *ICML*, 2019.
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