Evaluating the Resilience of Decentralized Federated Learning to Model Poisoning Attacks

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Federated Learning

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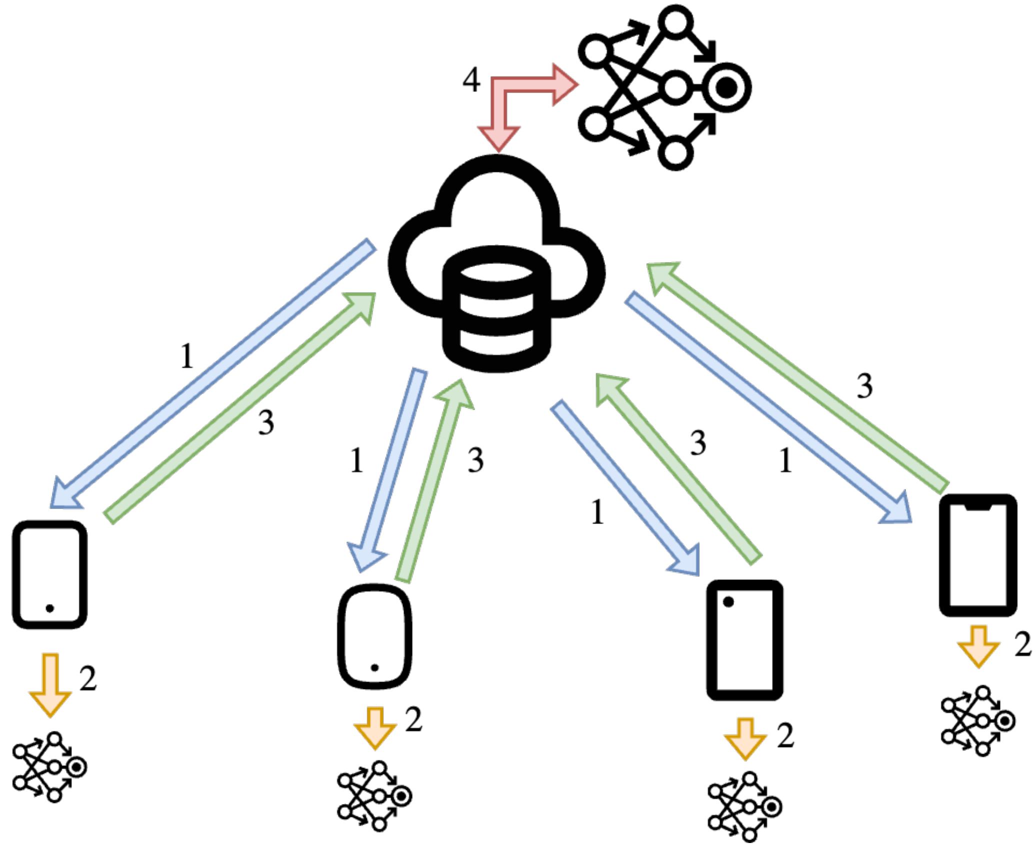

Federated Learning - Problems

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- Communication Efficiency
- Data and System Heterogeneity
- Incentive Mechanisms

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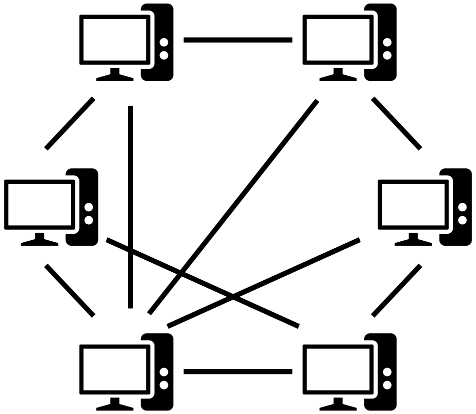
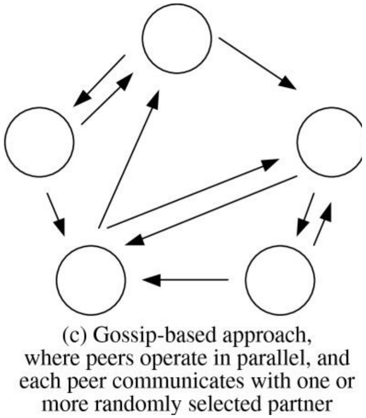
"Standard" Distributed Computing Techniques



P2P Networks

Image taken from wikipedia



Gossip communication

Image taken from https://haritibcoblog.wordpress.com/2018/11/01/what-is-a-gossip-protocol/

Decentralized Federated Learning

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Blockchain-based

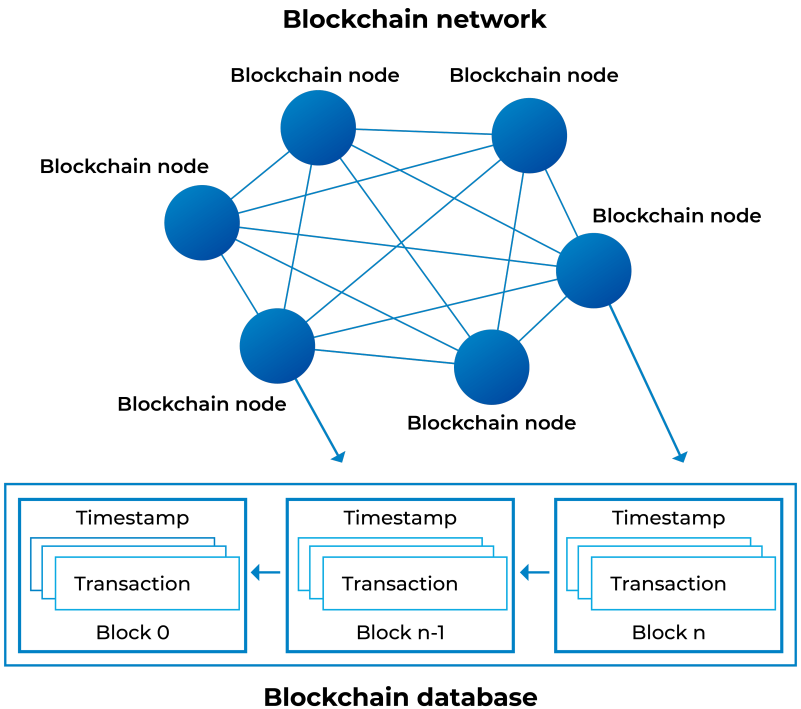

Image taken from https://unova.io/blockchain/

Decentralized Federated Learning - Problems?

- Centralized FL (and for extension decentralized FL) suffers **model poisoning** attacks.
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- Model poisoning exploits the inherent feature of federated learning, allowing malicious participants to directly influence the collective model.
- The centralized FL literature offers various strategies to address model poisoning attacks, with the goal of filtering out potentially malicious local updates during the server-side aggregation process.
- **However**, there is a notable absence of experimental studies examining model poisoning attacks on decentralized FL systems in the literature.

Research Questions

- **RQ1**: Does decentralized FL exhibit resilience against significant model poisoning attacks?
- **RQ2**: Do the adapted aggregation methods perform effectively in decentralized FL environments?

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- **FedAvg [5]**
- **Multi-Krum [6]**
- **Median [7]**

Proposed Method - PENS

- We decided to choose PENS [8] as decentralized FL framework to perform our analysis.
- PENS is divided in two parts:
    - Identification of peers with similar data distributions.
    - Selection of peers who have been chosen more frequently than expected. Thanks to Gossip Learning techniques.

Proposed Method - Threat Model

- **Adversarial Model**
- **Attacker’s Knowledge**
- **Attacker’s Behaviour**

Experiments - Setup

- We work with three datasets: MNIST, Fashion-MNIST, Spambase.
- We have used two ML models, Logistic Regression and MLP.
- As evaluation metric we use the average accuracy of all models of the nodes.
- To simulate our environment we use Gossipy. We set the number of clients as 50, and two parameters of PENS defined as number of received model set to 5 and number of top-performing clients set to 2.

Experiments - Evaluation

- We compare the robustness of the decentralized framework employed with the three aggregation schemes FedAvg, Multi-Krum and Median.
- And with the three attacks Gaussian, A Little Is Enough and Fall of Empires.
- Finally, we decided to set the number of malicious nodes as b = {3, 5, 15, 25}.
- The approach exhibits resilience against all the proposed attacks, whether employing other aggregation schemes.

Experiments - Evaluation

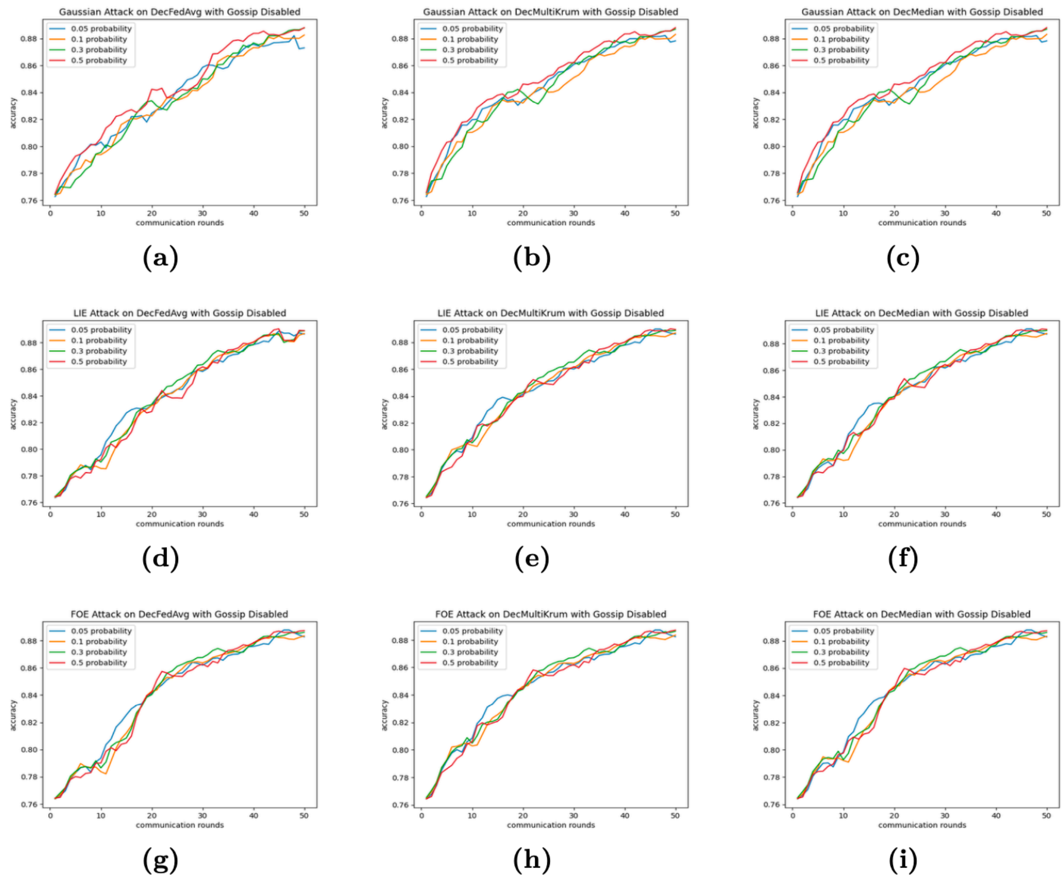

Figure 6.1. Comparing the robustness of PENS, with MNIST dataset. For each row we have the aggregation schemes, and for each column the attacks.

Experiments - Evaluation

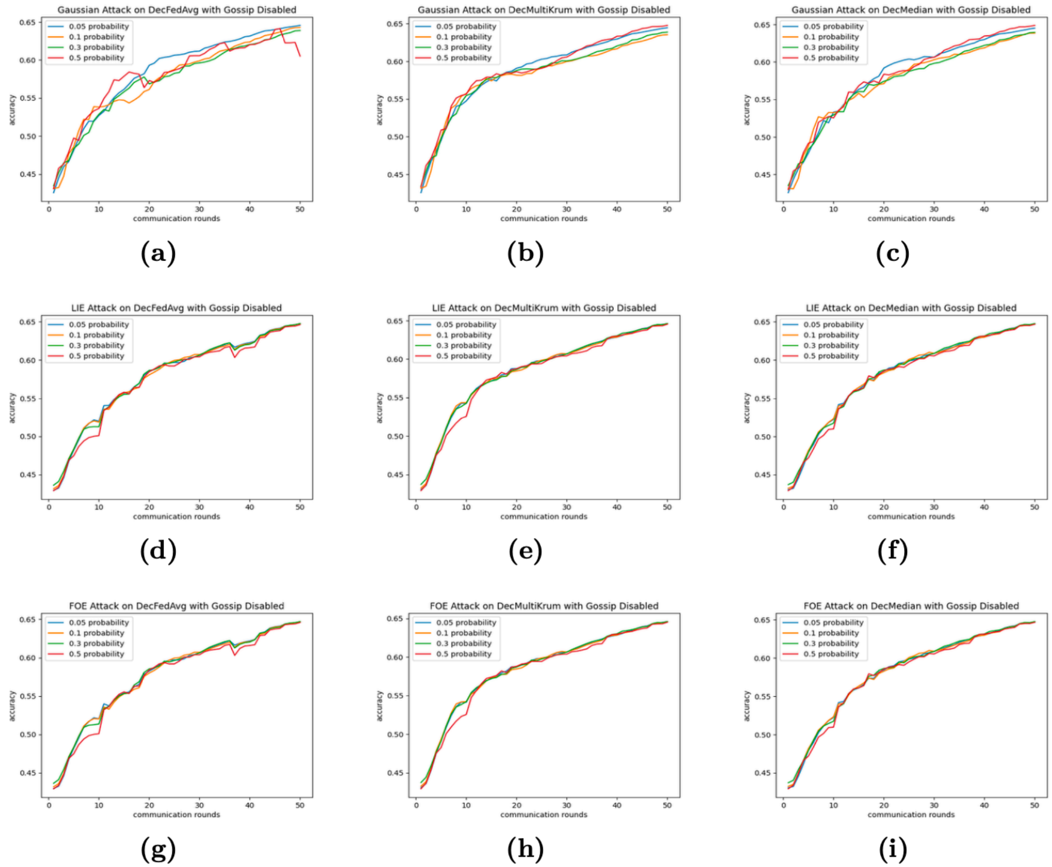

Figure 6.2. Comparing the robustness of PENS, with Fashion-MNIST dataset. For each row we have the aggregation schemes, and for each column the attacks.

Experiments - Evaluation

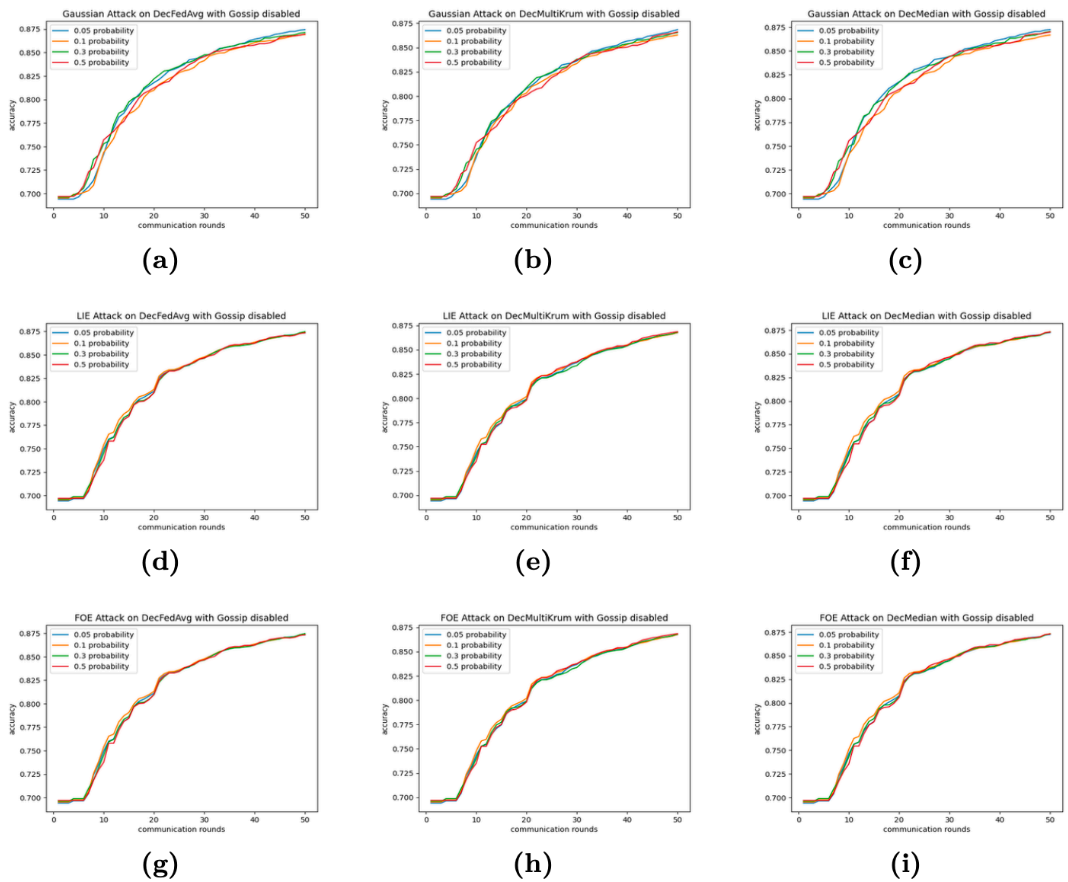

Figure 6.3. Comparing the robustness of PENS, with Spambase dataset. For each row we have the aggregation schemes, and for each column the attacks.

Experiments - Impact of Gossip Learning

- Notably, we have chosen to deactivate the second step of PENS, which involves gossip learning.
- This decision arises from the belief that, in the case of attacks, employing this algorithm would not yield significant benefits.

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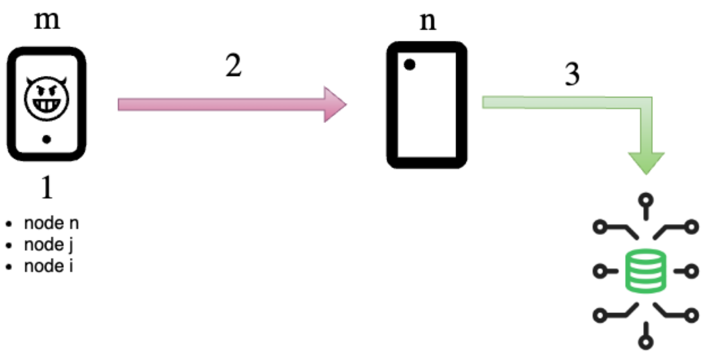
Algorithm 1 Gossip learning protocol

```
function MAIN
   while stopping criterion not met do
      WAIT(Δ)
      j ← RANDOMPEER() // select random peer
      SEND_{i→j}(w_i, j)
   end while
end function
function ONRECEIVEMODEL(w_i)
   SAVE(w_i)
   if no. of received models ≥ n_peers then
      w_j ← MERGE_SAVED_MODELS()
      w_j ← TRAIN(x; w_j) //update on local data x
   end if
end function
```

Image taken from PENS paper



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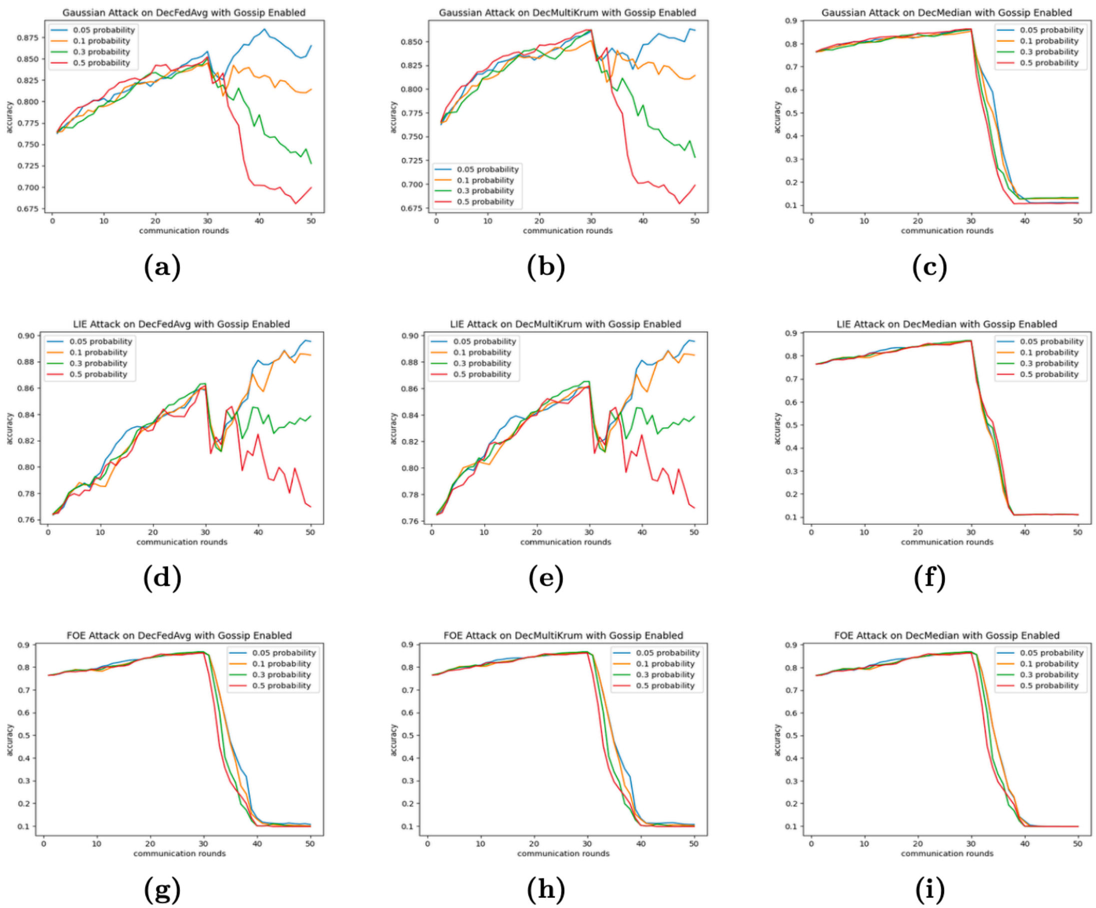

Figure 6.4. Comparing the robustness of PENS, with MNIST dataset and gossip learning enabled. For each row we have the aggregation schemes, and for each column the attacks.

Conclusions

- In this research, we have presented a novel study investigating the resilience of decentralized approaches.
- Notably, we have demonstrated and answered to RQ1 that the decentralized approach exhibits robustness against three distinct types of attacks even when we are in the standard case with FedAvg.
- Also, we answered to RQ2 through the implementation of the other aggregation schemes, and the approach demonstrates its robustness also with them.
- Our future objectives include verifying the resilience of these approaches against newly developed attacks specifically tailored for this approach.
- Additionally, we aim to extend our experimental findings to envelop other datasets and various neural network architectures.
- Finally, we plan to expand our experiments to incorporate other decentralized FL approaches that do not have the requirement for gossip learning or incorporate a more generalized variant of it, and may not necessarily rely on neighbor selection.

Thank You!

For Your Attention

References

1. Gabrielli, E., Pica, G., and Tolomei, G. A survey on decentralized federated learning (2023). http://arxiv.org/abs/2308.04604
2. Fang, M., Cao, X., Jia, J., and Gong, N. Z. Local model poisoning attacks to byzantine-robust federated learning (2021). http://arxiv.org/abs/1911.11815
3. Baruch, G., Baruch, M., and Goldberg, Y. A Little Is Enough: Circumventing Defenses for Distributed Learning. In *Proc. of NeurIPS '19*, pp. 8632–8642 (2019). https://proceedings.neurips.cc/paper/2019/hash/ec1c59141046cd1866bbbcdfb6ae31d4-Abstract.html
4. Xie, C., Koyejo, S., and Gupta, I. Fall of empires: Breaking byzantine-tolerant sgd by inner product manipulation (2019). http://arxiv.org/abs/1903.03936
5. McMahan, B., Moore, E., Ramage, D., Hampson, S., and Arcas, B. A. y. Communication-Efficient Learning of Deep Networks from Decentralized Data. In *Proc. of AISTATS '17'* (edited by A. Singh and J. Zhu), vol. 54, pp. 1273–1282. PMLR (2017). https://proceedings.mlr.press/v54/mcmahan17a.html
6. Blanchard, P., El Mhamdi, E. M., Guerraoui, R., and Stainer, J. Machine learning with adversaries: Byzantine tolerant gradient descent. In *Adv. in NeurIPS* (edited by I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett), vol. 30. Curran Associates, Inc. (2017). https://proceedings.neurips.cc/paper_files/paper/2017/file/f4b9ec30ad9f68f89b29639786cb62ef-Paper.pdf
7. Yin, D., Chen, Y., Kannan, R., and Bartlett, P. Byzantine-robust distributed learning: Towards optimal statistical rates. In *Proceedings of the 35th International Conference on Machine Learning* (edited by J. Dy and A. Krause), vol. 80 of *Proceedings of Machine Learning Research*, pp. 5650– 5659. PMLR (2018). https://proceedings.mlr.press/v80/yin18a.html
8. Onoszko, N., Karlsson, G., Mogren, O., and Zec, E. L. Decentralized federated learning of deep neural networks on non-iid data (2021). http://arxiv.org/abs/2107.08517