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# FedALA :Adaptive Local Aggregation for Personalized Federated Learning


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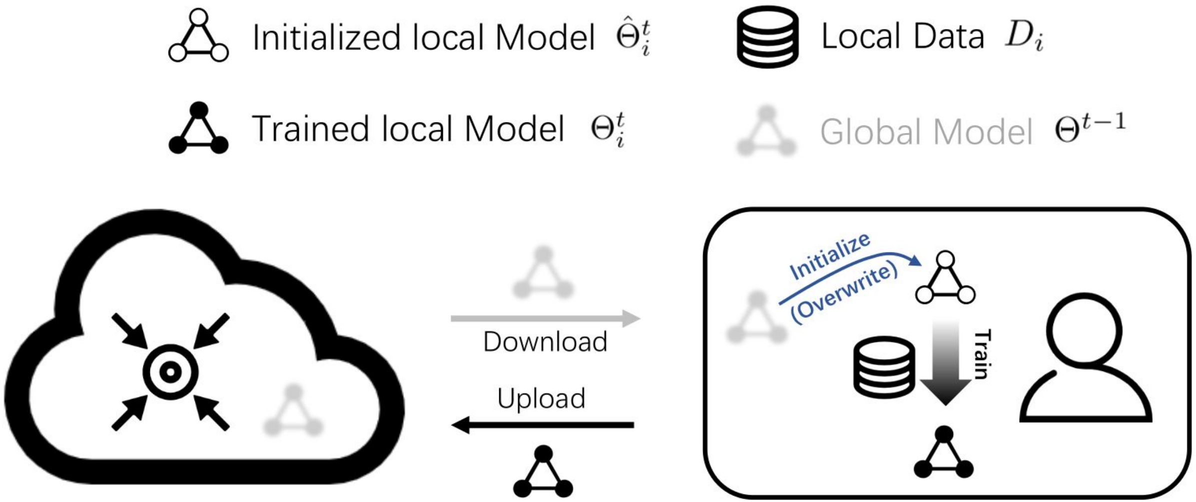
- Overview
- Issue in the current system
- Methodology used in the implementation
- Flow of the process
- Results of the implementation
- Novel idea
- Conclusion

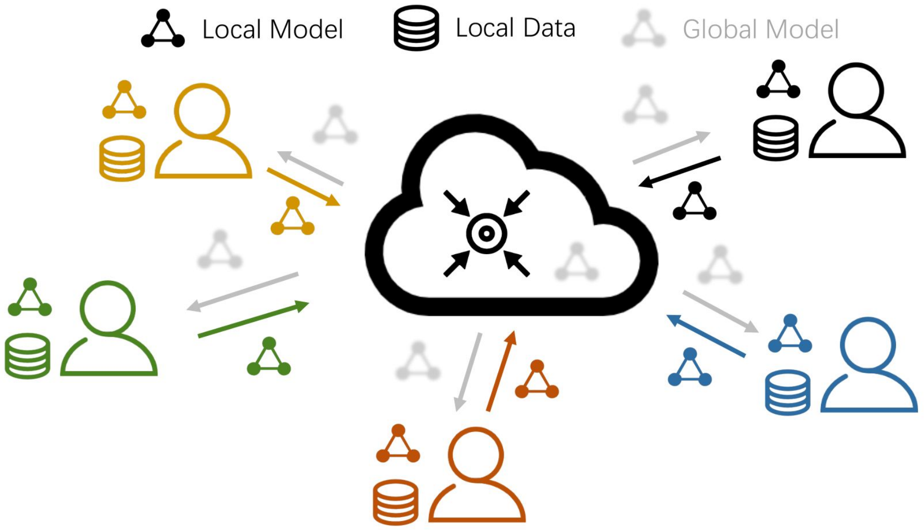
# Federated Learning

- ML technique in which model is trained across multiple devices.
- Protect privacy without uploading local data to central server.
- Learn AI model among clients by sharing model with server.
- Finally output single global model.



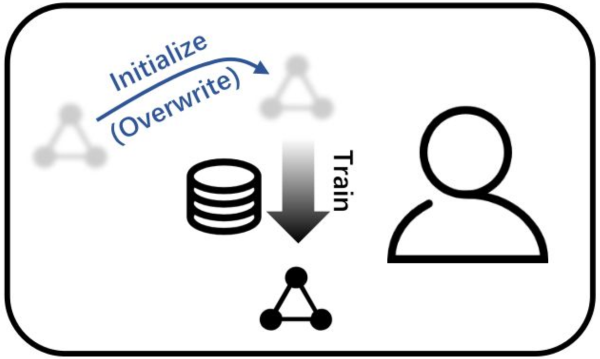
# Issues in Federated Learning

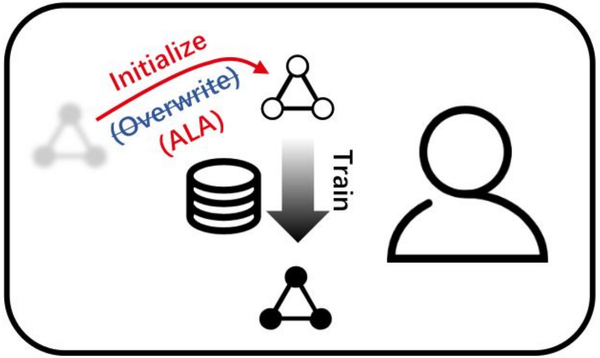
- Statistical heterogeneity
- Poor generalization ability of the global model on each client.



# Motivation of FedALA

- Almost all the other FL models overwrites local model with the entire global model for local initialization in each iteration.
- Only the desired information that improves the quality of the local model is beneficial for the client.
- Desired and undesired information exist in the global model resulting in poor generalization.

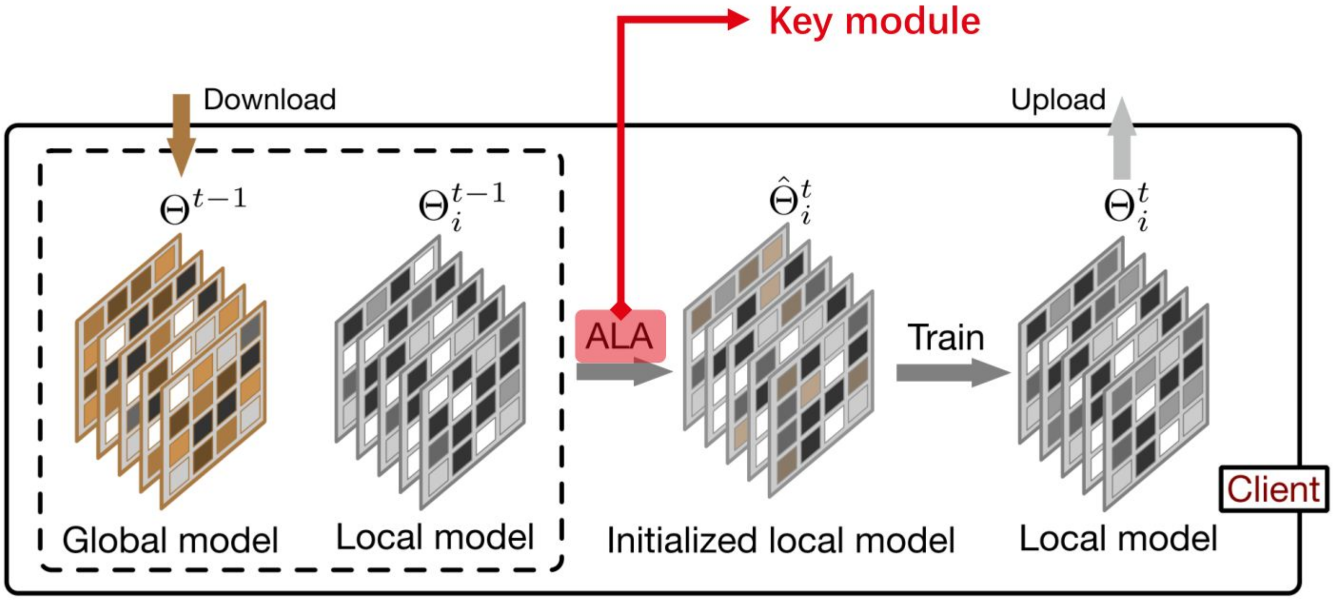


# FedALA

**ALA** : Adaptively aggregate the global model and local model for initialization.

**Train** : Train the local model on the local data.




Workflow on the client in one iteration

# FedALA : ALA module

- N clients
- Private training data $D_1, \ldots, D_N$, respectively.
- $D_1, \ldots, D_N$ are sampled from N distinct distributions.
- Individual local models $\hat{\Theta}_1, \ldots, \hat{\Theta}_N$
- Using $\{D_i\}_{i=1}^{N}$ for each client i.
- Objective:

Global loss $\sum_{i=1}^{N} k_i \mathcal{L}_i$

$$k_i = |D_i| / \sum_{j=1}^{N} |D_j|$$

$$\{\hat{\Theta}_1, \ldots, \hat{\Theta}_N\} = \arg\min \mathcal{G}(\mathcal{L}_1, \ldots, \mathcal{L}_N),$$

Total samples of client i

$$\mathcal{L}_i = \mathcal{L}(\hat{\Theta}_i, D_i; \Theta), \forall i \in [N]$$

Loss function

# FedALA : ALA module

- Element-wisely aggregate the global model and local model in an adaptive way

$$\hat{\Theta}_i^t := \Theta_i^{t-1} \odot \underbrace{W_{i,1}}_{\text{Trainable weights}} + \Theta^{t-1} \odot \underbrace{W_{i,2}}_{\text{Trainable weights}},$$

$$s.t. \quad \underbrace{w_1^q + w_2^q = 1, \forall \text{ valid } q}_{\text{Hard to learn weights with constraints}}$$

- Combine $W_{i,1}$ and $W_{i,2}$

$$\hat{\Theta}_i^t := \Theta_i^{t-1} + \underbrace{(\Theta^{t-1} - \Theta_i^{t-1})}_{\text{Called "update"}} \odot \underbrace{W_i}_{\text{Trainable weights}}$$

View the local aggregation as an **update process** for old local model

# FedALA : ALA module

- Element-wisely aggregate the global model and local model in an adaptive way

$$\hat{\Theta}_i^t := \Theta_i^{t-1} \odot W_{i,1} + \Theta^{t-1} \odot W_{i,2},$$
$$s.t. \quad w_1^q + w_2^q = 1, \forall \text{ valid } q$$

Trainable weights

Hard to learn weights with constraints

- Combine $W_{i,1}$ and $W_{i,2}$

$$\hat{\Theta}_i^t := \Theta_i^{t-1} + (\Theta^{t-1} - \Theta_i^{t-1}) \odot W_i$$

Trainable weights

Called "update"

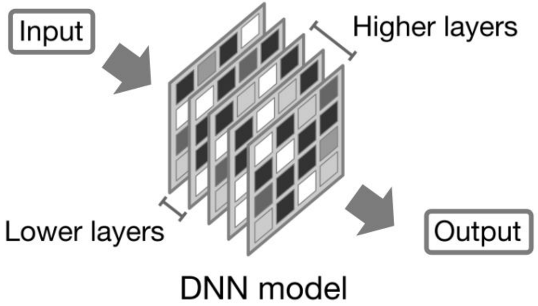
ALA covers the entire model

  - remove constraints
  - with weight clipping[1]

$$\boxed{\begin{aligned} \sigma(w) &= \max(0, \min(1, w)) \\ & w \in [0, 1], \forall w \in W_i \end{aligned}}$$

# FedALA : ALA module

- The lower layers in the DNN learn more general information than the higher layers[2]




- **Only apply ALA on $p$ higher layers**
- **Still overwrite the lower layers with global parameters**

$$\hat{\Theta}_i^t := \Theta_i^{t-1} + (\Theta^{t-1} - \Theta_i^{t-1}) \odot [\mathbf{1}^{|\Theta_i|-p}; W_i^p]$$

Fewer weights to train in ALA

Less computation overhead

# FedALA : ALA module

- Only apply ALA on $p$ higher layers
- Still overwrite the lower layers with global parameters

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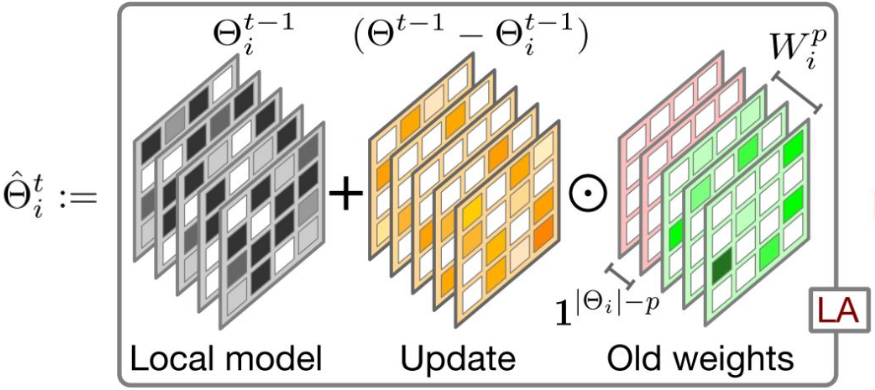
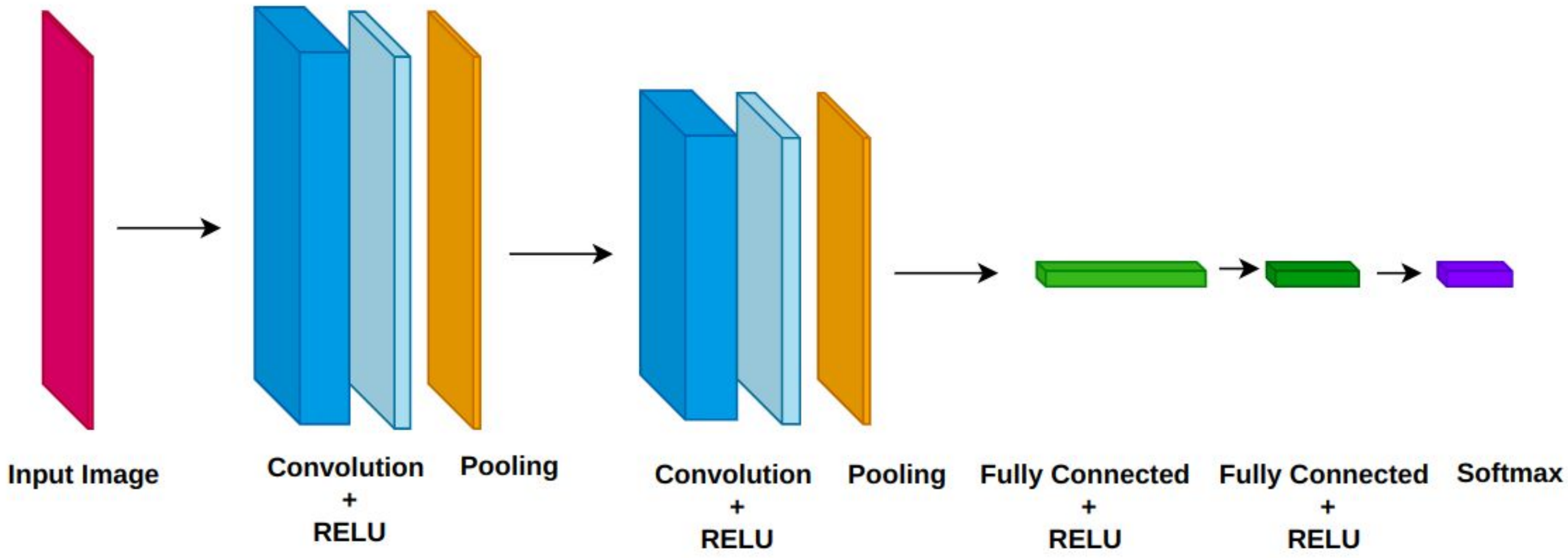



How to train weights?

Local aggregation (LA)

# FedAvgCNN



Input Image
Convolution
+
RELU
Pooling
Convolution
+
RELU
Pooling
Fully Connected
+
RELU
Fully Connected
+
RELU
Softmax

# Resnet 18

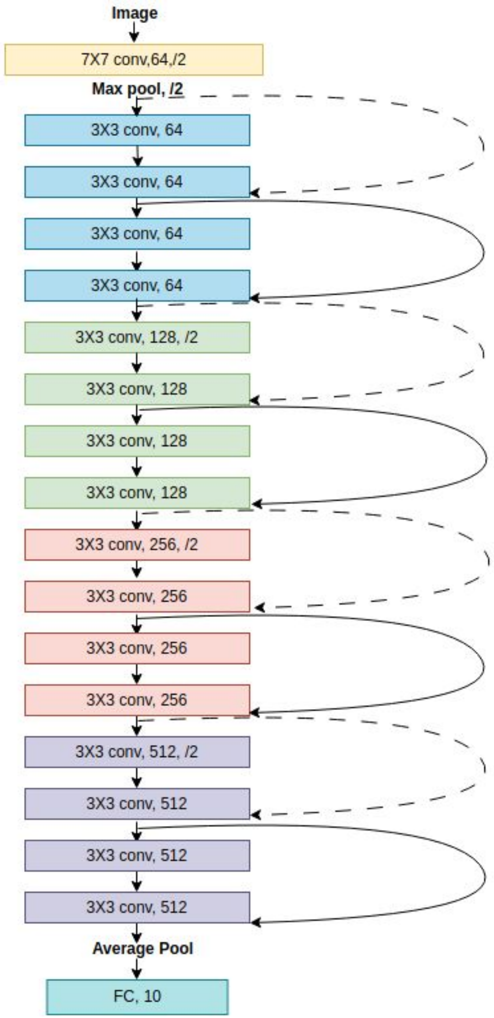
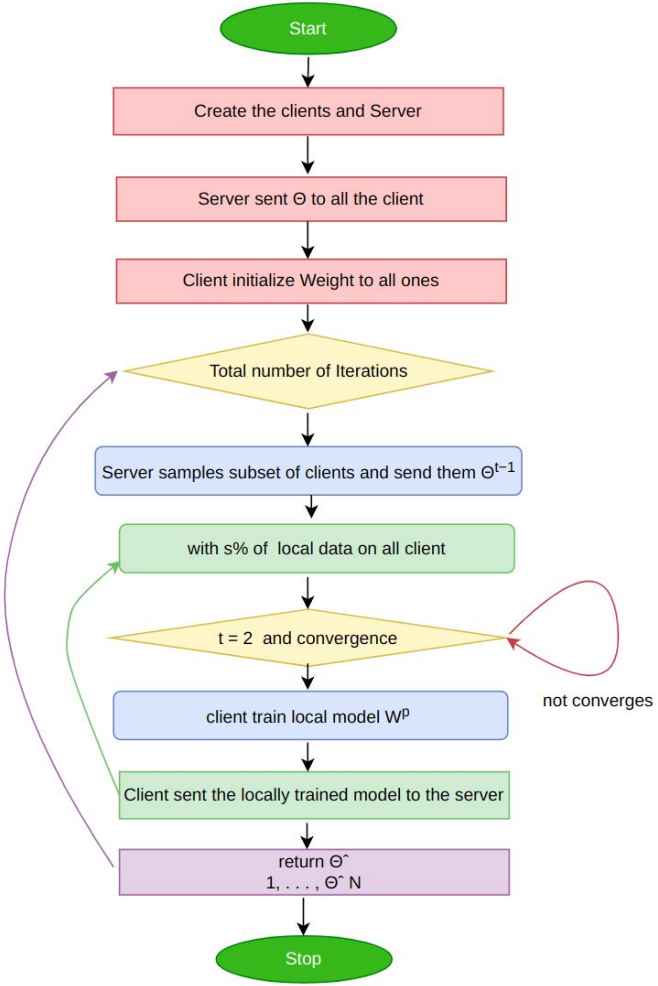


Image
7X7 conv,64,/2
Max pool, /2
3X3 conv, 64
3X3 conv, 64
3X3 conv, 64
3X3 conv, 64
3X3 conv, 128, /2
3X3 conv, 128
3X3 conv, 128
3X3 conv, 128
3X3 conv, 256, /2
3X3 conv, 256
3X3 conv, 256
3X3 conv, 256
3X3 conv, 512, /2
3X3 conv, 512
3X3 conv, 512
3X3 conv, 512
Average Pool
FC, 10

# Flow chart of FedALA



# FedALA: analysis

- Two main equations (omitting $p$):

$$\hat{\Theta}_i^t := \Theta_i^{t-1} + (\Theta^{t-1} - \Theta_i^{t-1}) \odot W_i$$

$$W_i^p \leftarrow W_i^p - \eta \nabla_{W_i^p} \mathcal{L}(\hat{\Theta}_i^t, D_i^{s,t}; \Theta^{t-1})$$

Denote $\mathcal{L}(\hat{\Theta}_i^t, D_i^{s,t}; \Theta^{t-1})$ as $\mathcal{L}_i^t$

- Rewrite the gradient term as $\nabla_{W_i} \mathcal{L}_i^t = \eta(\Theta^{t-1} - \Theta_i^{t-1}) \odot \nabla_{\hat{\Theta}_i} \mathcal{L}_i^t$

- We view updating $W_i$ as updating $\hat{\Theta}_i^t$

$$\hat{\Theta}_i^t \leftarrow \hat{\Theta}_i^t - \eta(\Theta^{t-1} - \Theta_i^{t-1}) \odot (\Theta^{t-1} - \Theta_i^{t-1}) \odot \nabla_{\hat{\Theta}_i} \mathcal{L}_i^t$$

# FedALA: analysis

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- We view updating $W_i$ as updating $\hat{\Theta}_i^t$

$$\hat{\Theta}_i^t \leftarrow \hat{\Theta}_i^t - \eta \underbrace{(\Theta^{t-1} - \Theta_i^{t-1}) \odot (\Theta^{t-1} - \Theta_i^{t-1})}_{\text{* Dynamic generic information}} \odot \nabla_{\hat{\Theta}_i} \mathcal{L}_i^t$$

# Hyperparameters

- **p: the range of ALA**

  To reduce computation overhead, we introduce a hyperparameter p to control the range of ALA by applying it on p higher layers and overwriting the parameters in the lower layers.

- **s%: the percent of local data in ALA**

  To further reduce computation overhead, we randomly sample s% of Di in iteration t for each client.

# FedALA: results for computation reduction

Reduce computation overhead with small p (applying ALA on p higher layers)

The test accuracy (%) and the number of trainable parameters (in millions) of FedALA on Tiny-ImageNet using ResNet-18 ($s = 80$)

| | $p=6$ | $p=5$ | $p=4$ | $p=3$ | $p=2$ | $p=1$ |
|---|---|---|---|---|---|---|
| Acc. | 41.71 | 41.54 | 41.62 | 41.86 | **42.47** | 41.94 |
| Param. | 11.182 | 11.172 | 11.024 | 10.499 | 8.399 | 0.005 |

**Accuracy hardly changes with different *p***

**Parameter amount decreases greatly with small *p***

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**Accuracy hardly changes with different $p$**

**Parameter amount decreases greatly with small $p$**

**Set $p = 1$ to greatly reduce computation overhead**

# FedALA: results for computation reduction

The test accuracy (%) of FedALA on Tiny-ImageNet using ResNet-18 ($p = 1$)

| | $s=5$ | $s=10$ | $s=20$ | $s=40$ | $s=60$ | $s=80$ | $s=100$ |
|---|---|---|---|---|---|---|---|
| Acc. | 39.53 | 40.62 | 40.02 | 40.23 | 41.11 | 41.94 | **42.11** |

Accuracy decreases with smaller $s$

# FedALA: results for computation reduction

Reduce computation overhead with small s (training weights with s% local data)

The test accuracy (%) of FedALA on Tiny-ImageNet using ResNet-18 ($p = 1$)

| | $s = 5$ | $s = 10$ | $s = 20$ | $s = 40$ | $s = 60$ | $s = 80$ | $s = 100$ |
|---|---|---|---|---|---|---|---|
| Acc. | 39.53 | 40.62 | 40.02 | 40.23 | 41.11 | 41.94 | **42.11** |

**Accuracy decreases with smaller $s$**

**Set $s = 80$ to reduce computation overhead**

**FedALA performs well with only 5% local data for ALA**

# Heterogeneity Setting:

- **Practical Heterogeneity Setting :**

  Clients are separated into groups, which is based on the similarity among clients.

- **Pathological Heterogeneity Setting :**

  controlled by dirichlet distribution denoted by Dir(**β**).

  The smaller the **β** is the more heterogeneous the setting is.

# Performance Comparison

FedALA outperforms 13 traditional FL and pFL methods

The test accuracy (%) in the pathological heterogeneous setting and practical heterogeneous setting.

| Settings | Pathological heterogeneous setting | | | Practical heterogeneous setting | | | | |
|---|---|---|---|---|---|---|---|---|
| Methods | MNIST | Cifar10 | Cifar100 | Cifar10 | Cifar100 | TINY | TINY* | AG News |
| FedAvg | 97.93±0.05 | 55.09±0.83 | 25.98±0.13 | 59.16±0.47 | 31.89±0.47 | 19.46±0.20 | 19.45±0.13 | 79.57±0.17 |
| FedProx | 98.01±0.09 | 55.06±0.75 | 25.94±0.16 | 59.21±0.40 | 31.99±0.41 | 19.37±0.22 | 19.27±0.23 | 79.35±0.23 |
| FedAvg-C | 99.79±0.00 | 92.13±0.03 | 66.17±0.03 | 90.34±0.01 | 51.80±0.02 | 30.67±0.08 | 36.94±0.10 | 95.89±0.25 |
| FedProx-C | 99.80±0.04 | 92.12±0.03 | 66.07±0.08 | 90.33±0.01 | 51.84±0.07 | 30.77±0.13 | 38.78±0.52 | 96.10±0.22 |
| Per-FedAvg | 99.63±0.02 | 89.63±0.23 | 56.80±0.26 | 87.74±0.19 | 44.28±0.33 | 25.07±0.07 | 21.81±0.54 | 93.27±0.25 |
| FedRep | 99.77±0.03 | 91.93±0.14 | 67.56±0.31 | 90.40±0.24 | 52.39±0.35 | 37.27±0.20 | 39.95±0.61 | 96.28±0.14 |
| pFedMe | 99.75±0.02 | 90.11±0.10 | 58.20±0.14 | 88.09±0.32 | 47.34±0.46 | 26.93±0.19 | 33.44±0.33 | 91.41±0.22 |
| Ditto | 99.81±0.00 | 92.39±0.06 | 67.23±0.07 | 90.59±0.01 | 52.87±0.64 | 32.15±0.04 | 35.92±0.43 | 95.45±0.17 |
| FedAMP | 99.76±0.02 | 90.79±0.16 | 64.34±0.37 | 88.70±0.18 | 47.69±0.49 | 27.99±0.11 | 29.11±0.15 | 94.18±0.09 |
| FedPHP | 99.73±0.00 | 90.01±0.00 | 63.09±0.04 | 88.92±0.02 | 50.52±0.16 | 35.69±3.26 | 29.90±0.51 | 94.38±0.12 |
| FedFomo | 99.83±0.00 | 91.85±0.02 | 62.49±0.22 | 88.06±0.02 | 45.39±0.45 | 26.33±0.22 | 26.84±0.11 | 95.84±0.15 |
| APPLE | 99.75±0.01 | 90.97±0.05 | 65.80±0.08 | 89.37±0.11 | 53.22±0.20 | 35.04±0.47 | 39.93±0.52 | 95.63±0.21 |
| PartialFed | 99.86±0.01 | 89.60±0.13 | 61.39±0.12 | 87.38±0.08 | 48.81±0.20 | 35.26±0.18 | 37.50±0.16 | 85.20±0.16 |
| FedALA | **99.88±0.01** | **92.44±0.02** | **67.83±0.06** | **90.67±0.03** | **55.92±0.03** | **40.54±0.02** | **41.94±0.05** | **96.52±0.08** |

# Performance Comparison

The test accuracy (%) in the pathological heterogeneous setting and practical heterogeneous setting.

| Settings | Pathological heterogeneous setting | | | Practical heterogeneous setting | | | | |
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# Performance Comparison

| Sample setting | Dataset | Paper Results | Recreation Results |
|---|---|---|---|
| Pathological heterogeneous | MNIST | 99.88 | 99.63 |
| | Cifar10 | 92.44 | 91.40 |
| | Cifar100 | 67.83 | 52.93 |
| Practical heterogeneous | Cifar10 | 90.67 | 90.64 |
| | Cifar100 | 55.92 | 55.88 |
| | TINY(CNN) | 40.54 | 37.66 (136) |
| | TINY(Resnet-18) | 41.94 | 31.42 (12) |
| | AG News | 96.52 | 96.40 (696) |

# Novelty:

- Parallelizing the local client initialization on each client with the help of multithreading.
- This will be in contrast to the sequential initialization of client (using for loop in the current code).

# Conclusion

- Contributions of FedALA:
    - **Adaptively aggregates** the global model and local model towards the local objective to **capture the desired information** from the global model.
    - Outperforms **11 SOTA** methods by up to 3.2% in test accuracy **without additional communication overhead** in each iteration.
    - The ALA module in FedALA can be **directly applied to existing FL methods** to enhance their performance by up to 24.19%.

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Thankyou ….