FedALA: Adaptive Local Aggregation for Personalized Federated Learning

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Tao Song[1] Zhengui Xue[1] Ruhui Ma[1] Haibing Guan[1]

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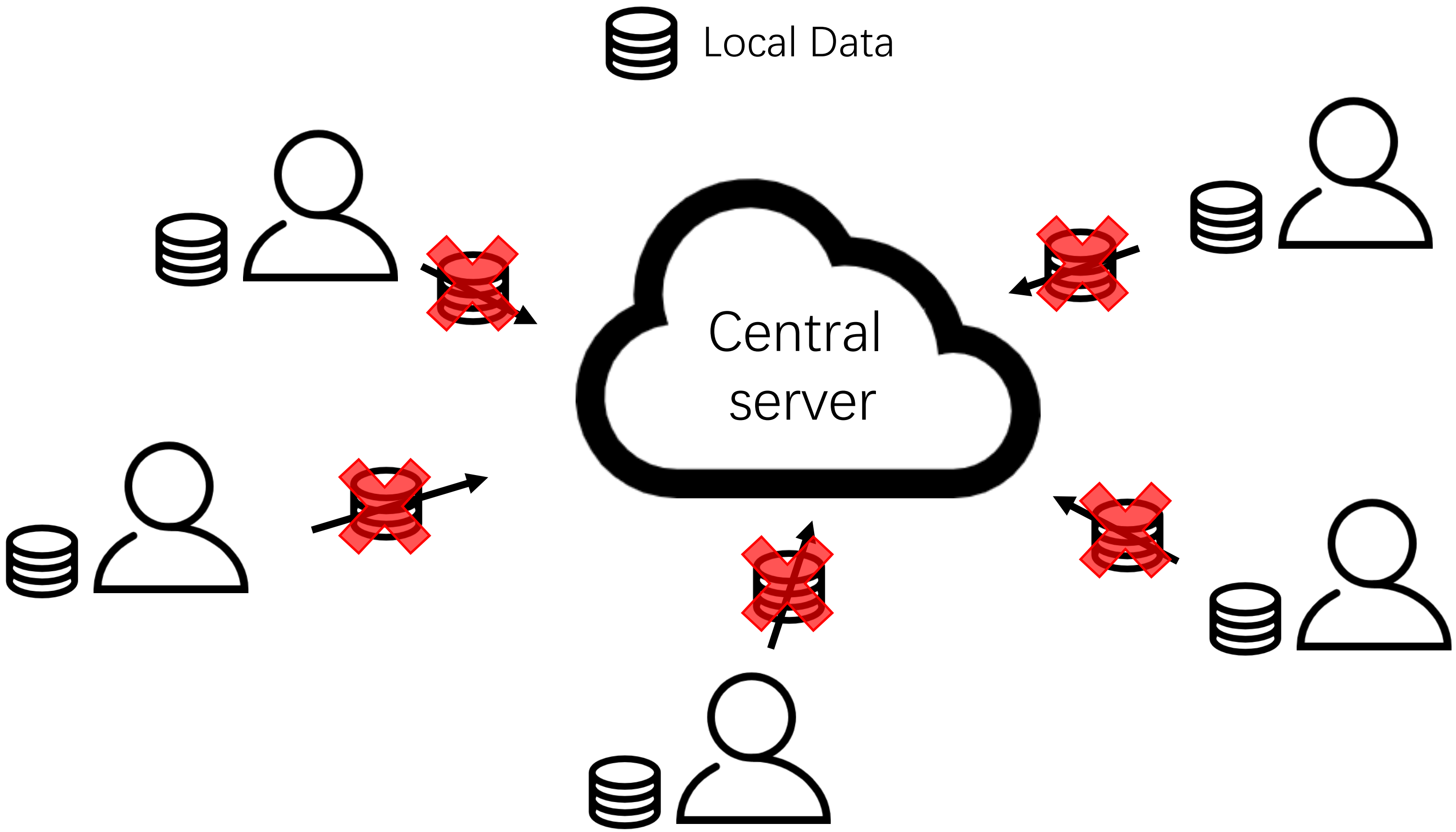
2 QUEEN'S UNIVERSITY BELFAST

3 LSU

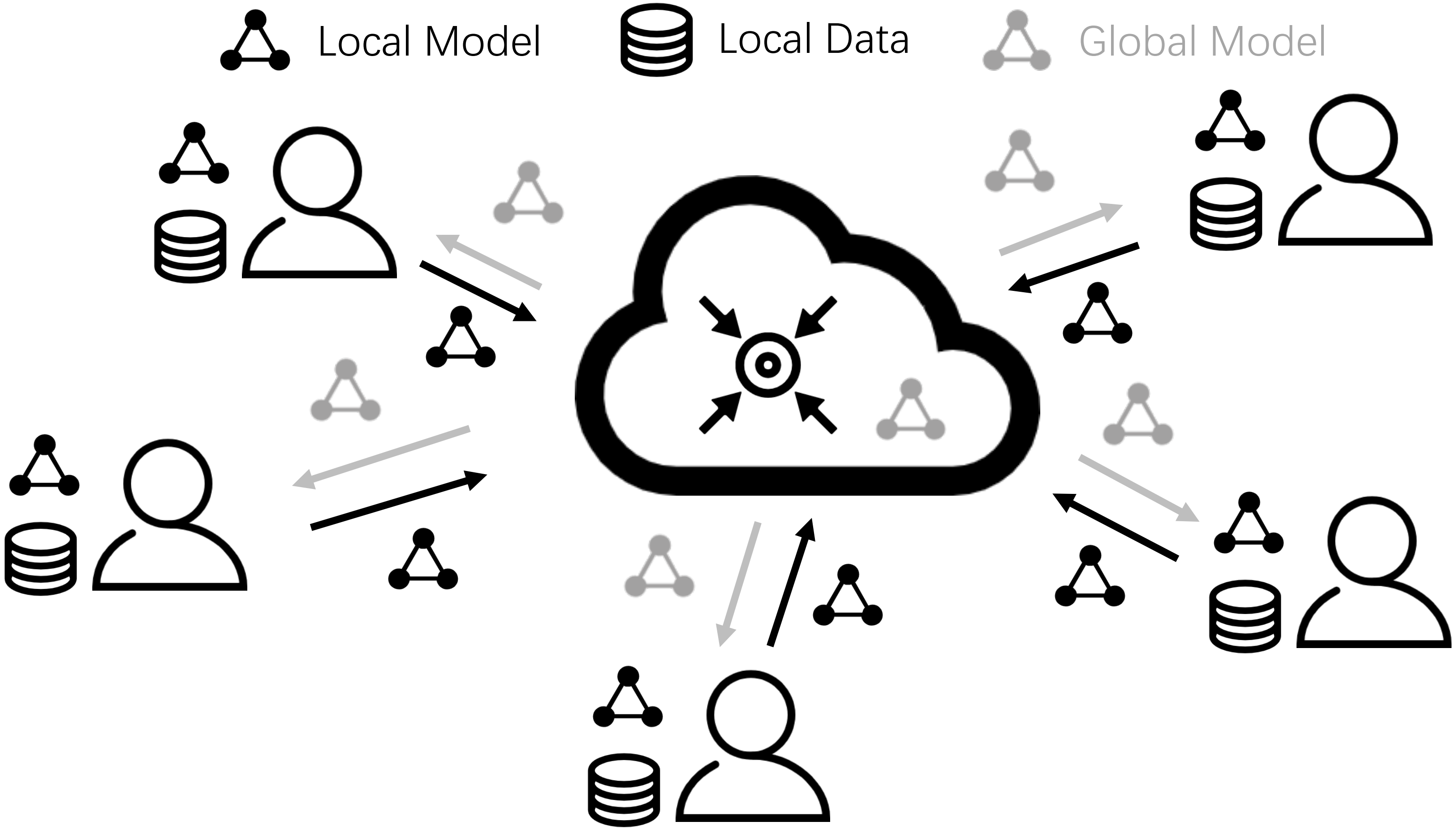
Federated Learning (FL)

- **Protect privacy** without uploading local data to the central server



Federated Learning (FL)

- Learn an **AI model** among clients by sharing models with the server.



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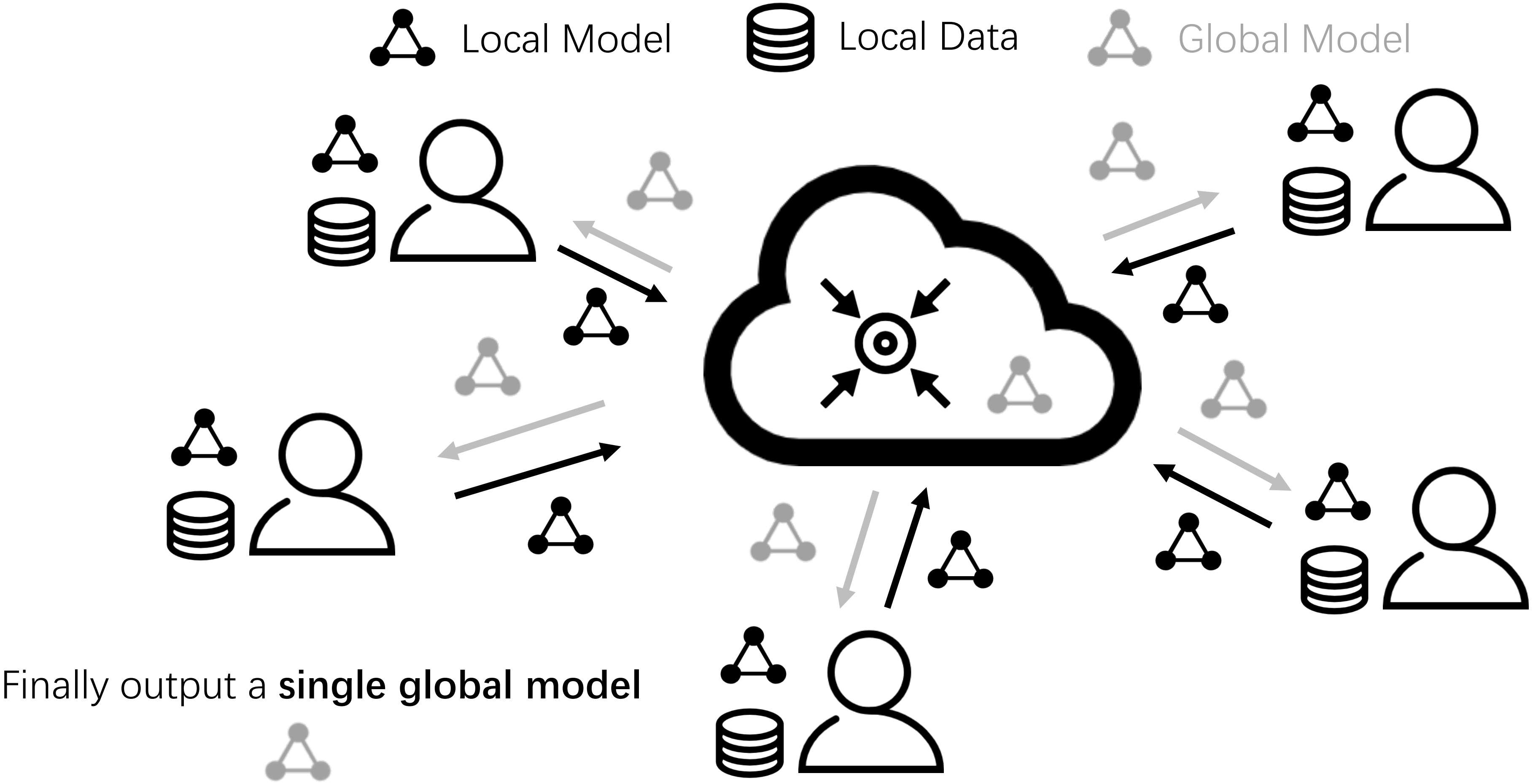


Local Model

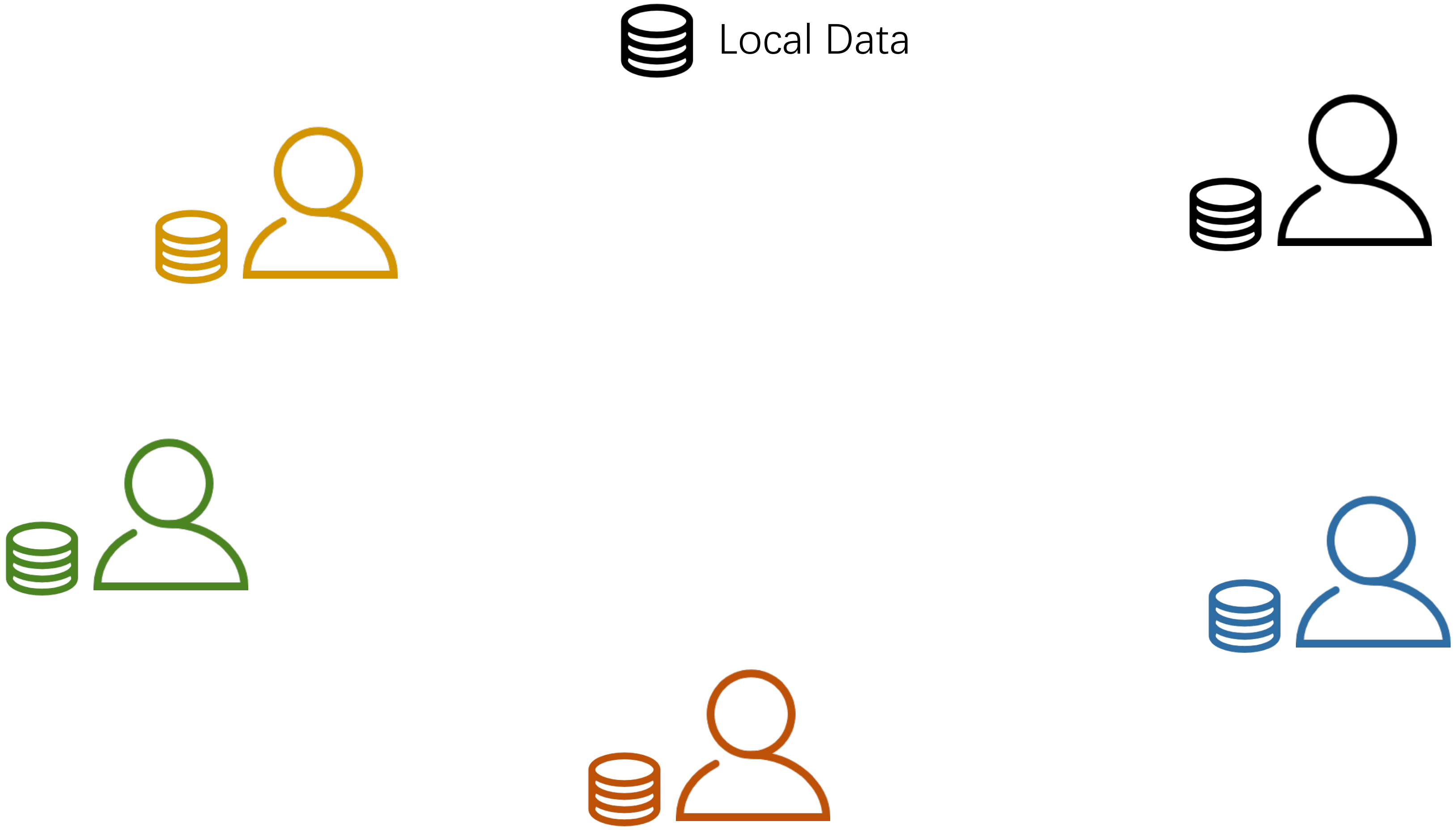
Local Data

Global Model

Finally output a **single global model**

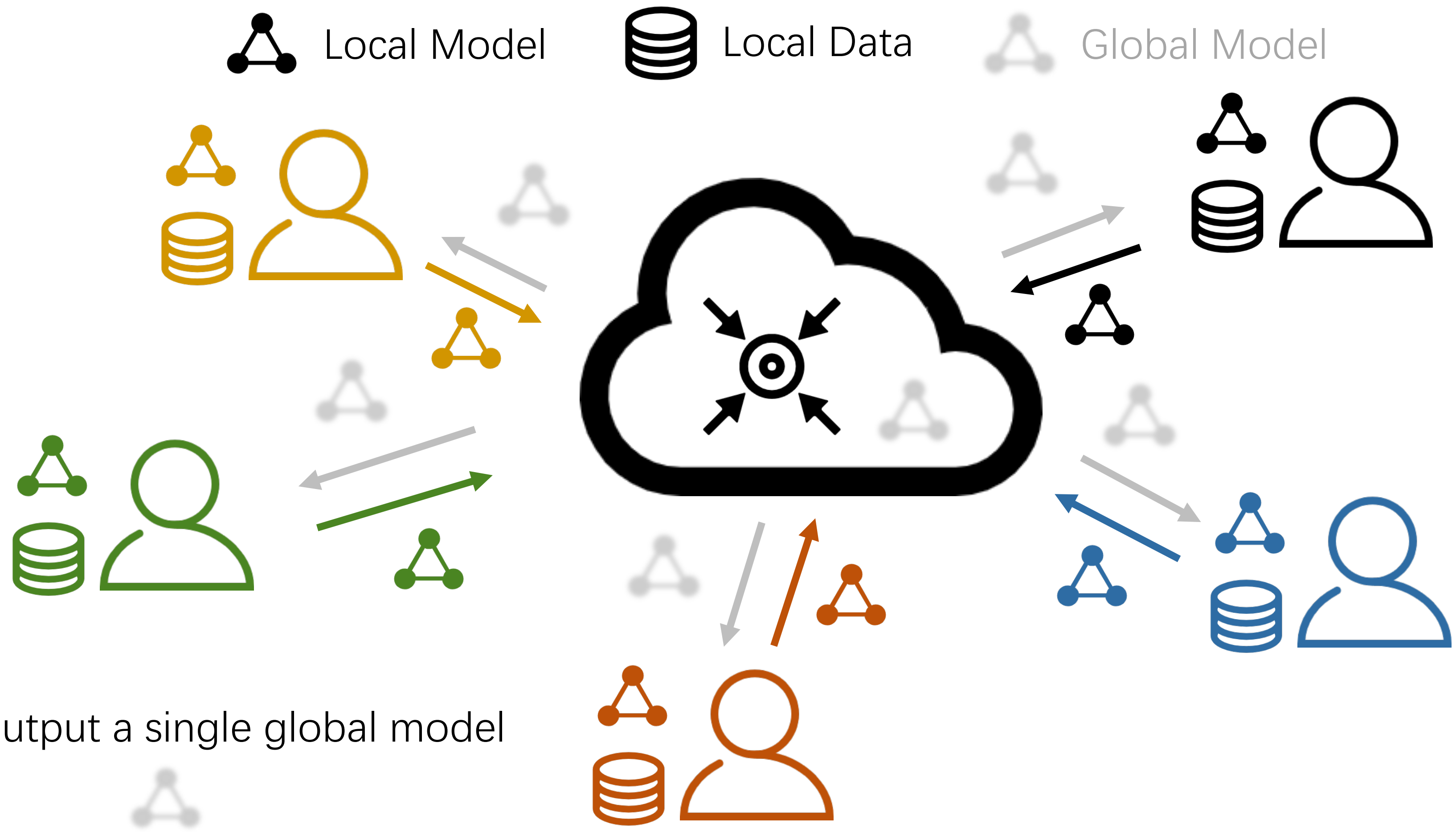
Issues in Federated Learning

- **Statistical heterogeneity**, such as non-IID and unbalanced data (colorful)



Issues in Federated Learning

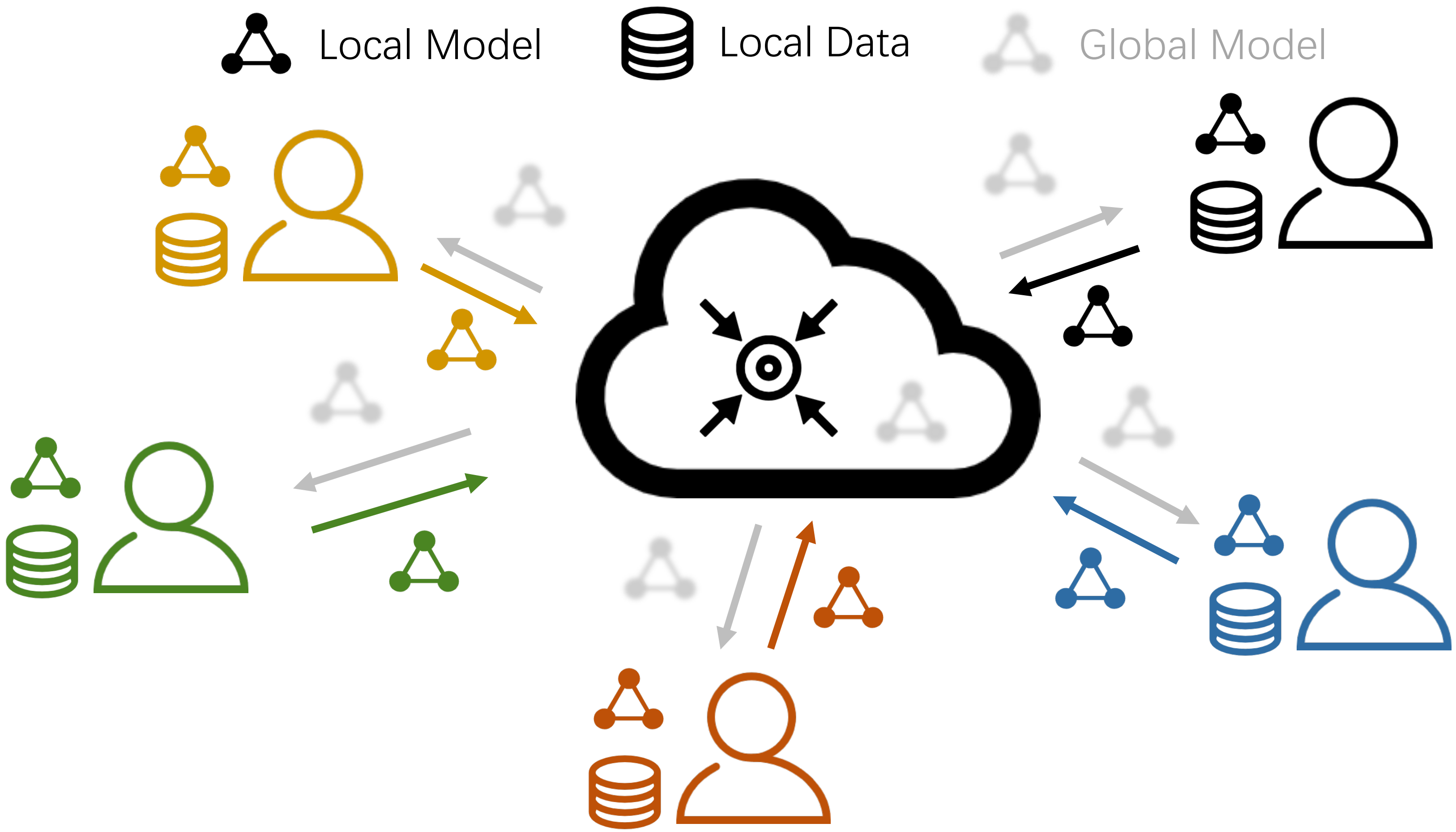
- **Poor generalization ability** (blurred) of the single global model on each client



Finally output a single global model

Personalized Federated Learning (pFL)

- Tackle the **statistical heterogeneity** issue
- Achieve **personalized requirements**



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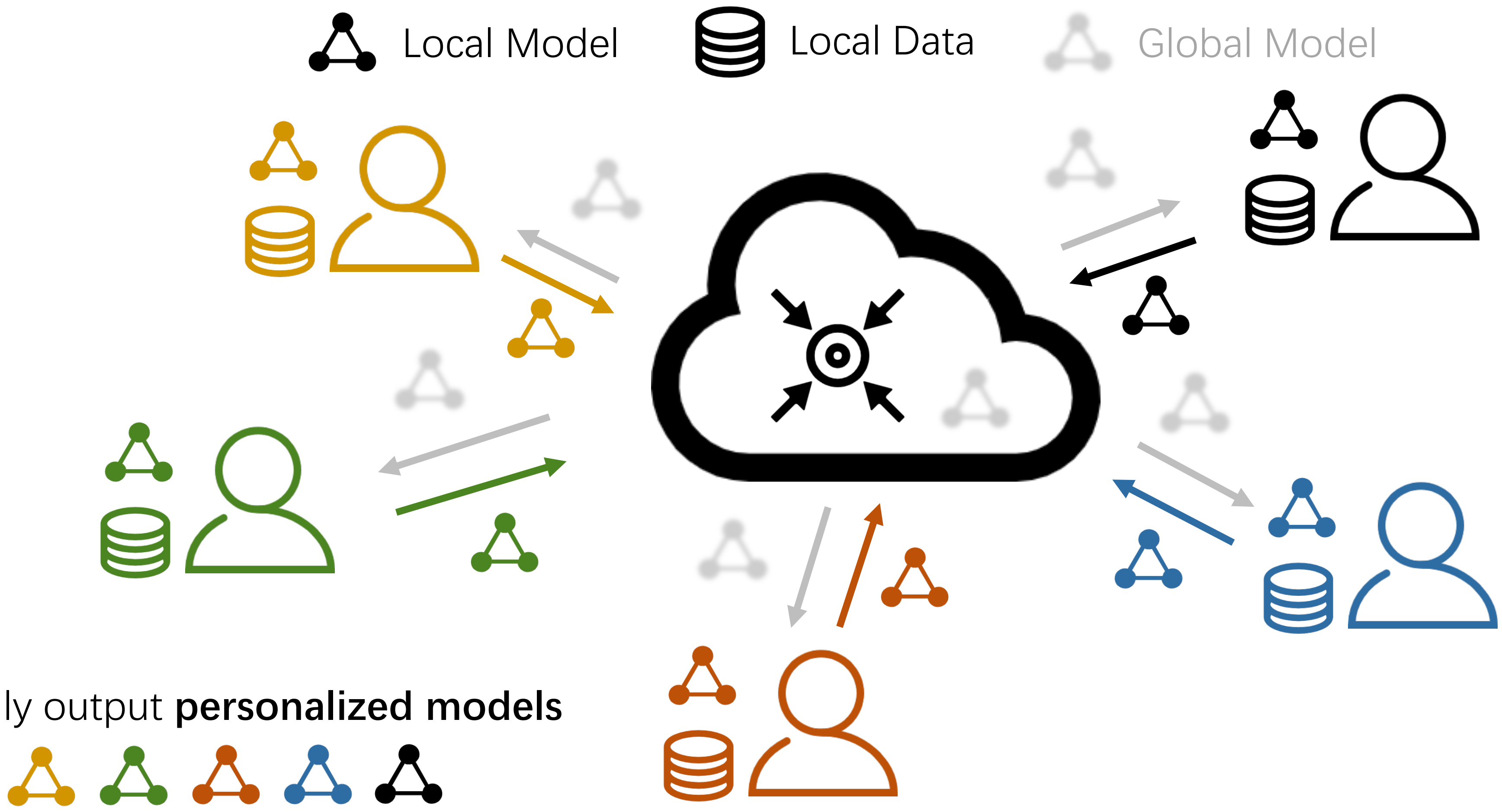


Local Model

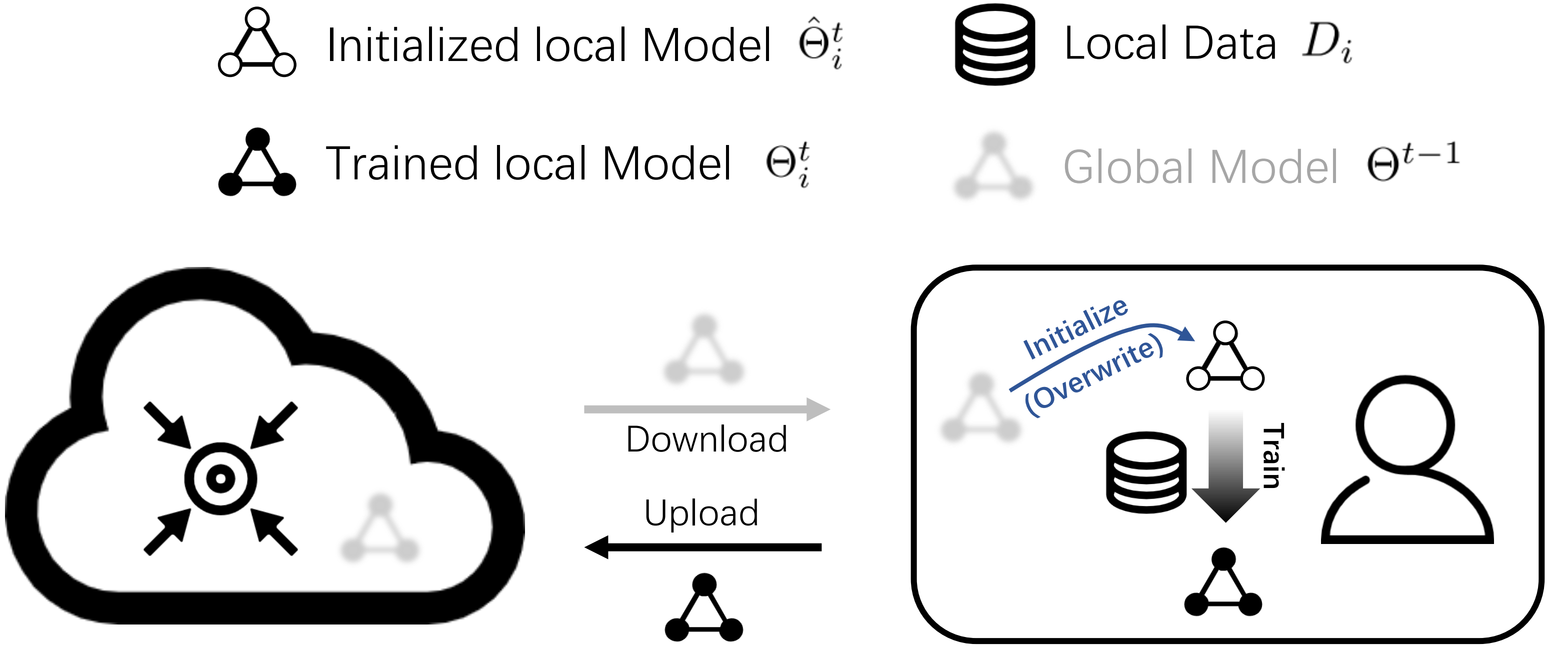
Local Data

Global Model

Finally output **personalized models**

Motivation of FedALA

- Original workflow in FL
  - **Overwrite** local model with the **entire global model** for local initialization in each iteration



Initialized local Model $\hat{\Theta}_i^t$

Local Data D_i

Trained local Model Θ_i^t

Global Model Θ^{t-1}

Download

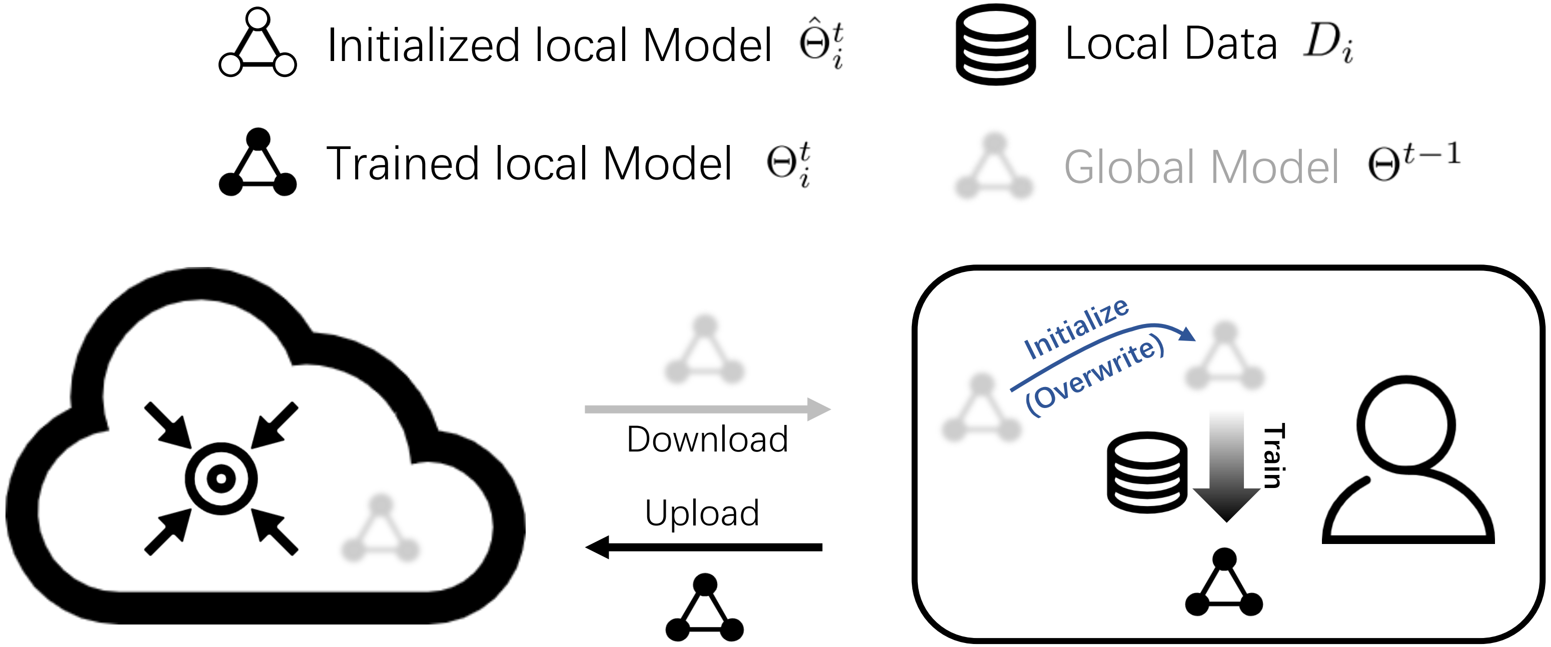
Upload

Initialize (Overwrite)

Train

Motivation of FedALA

- Original workflow in FL
  - However, only the desired information that improves the quality of the local model is beneficial for the client



Initialized local Model $\hat{\Theta}_i^t$

Local Data D_i

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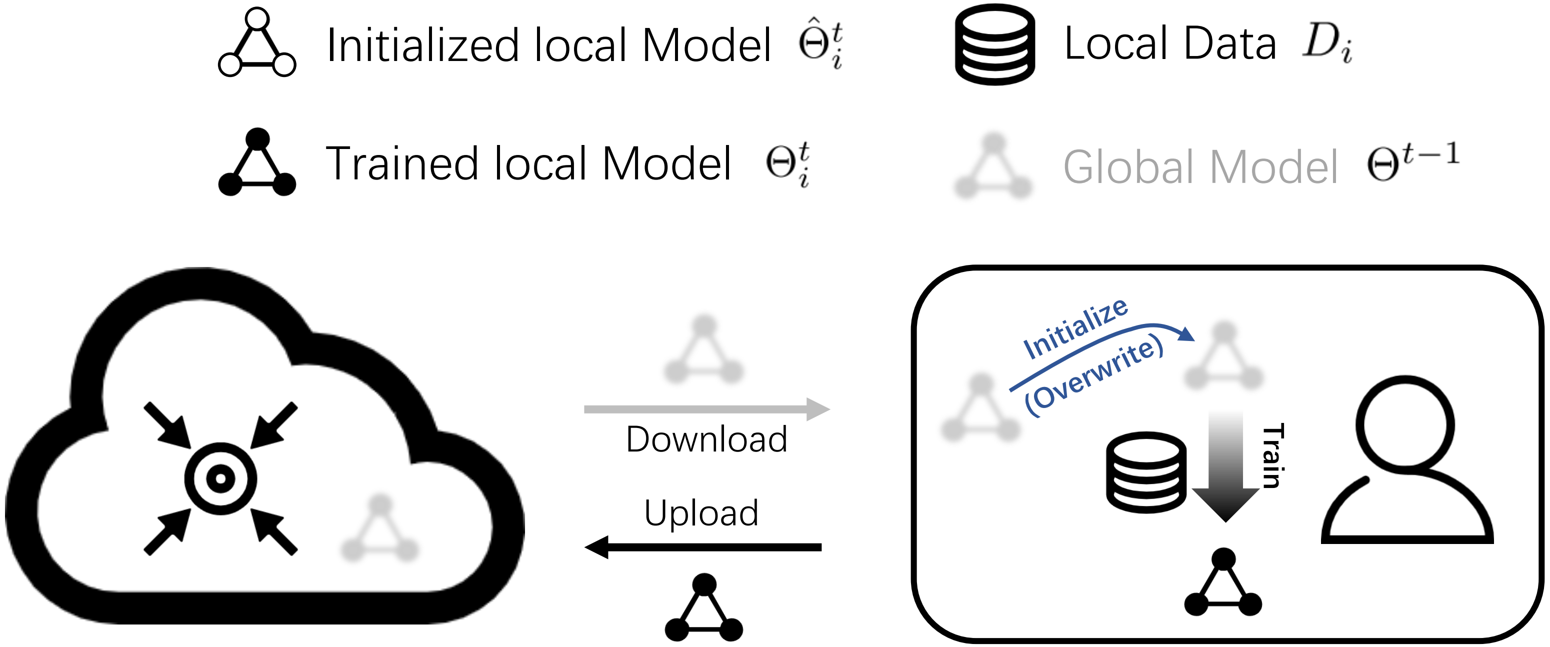
Motivation of FedALA

- Original workflow in FL
  - Both the desired and undesired information exist in the global model, resulting in poor generalization ability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Download
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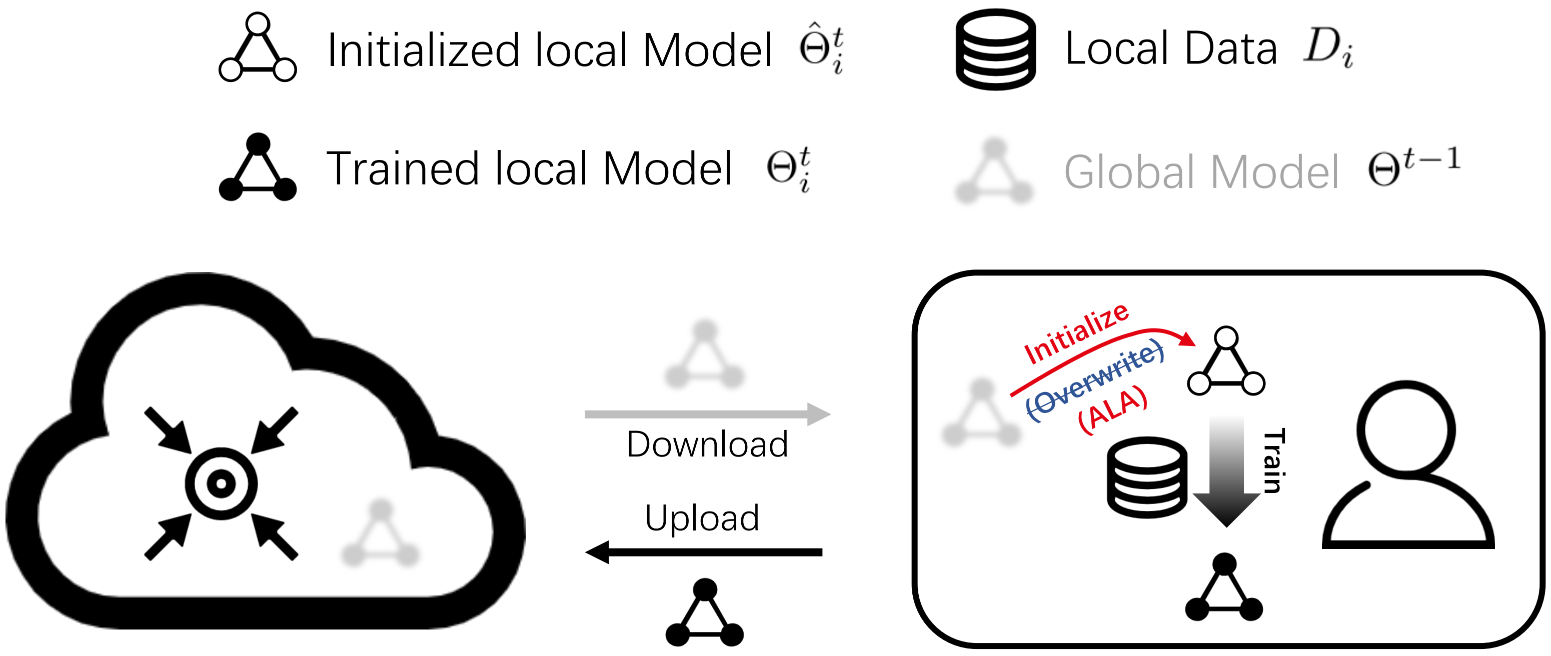

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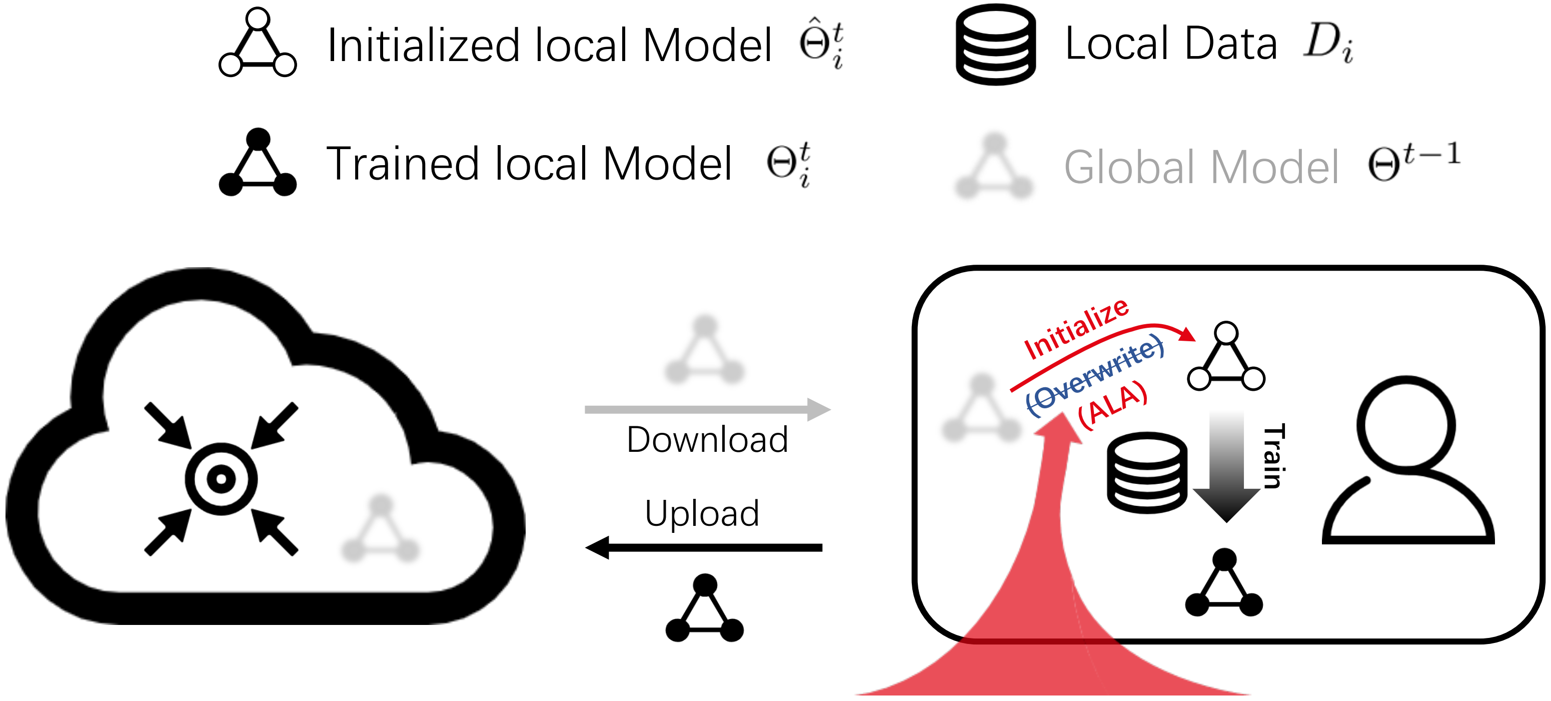
Initialized local Model $\hat{\Theta}_i^t$
Local Data D_i
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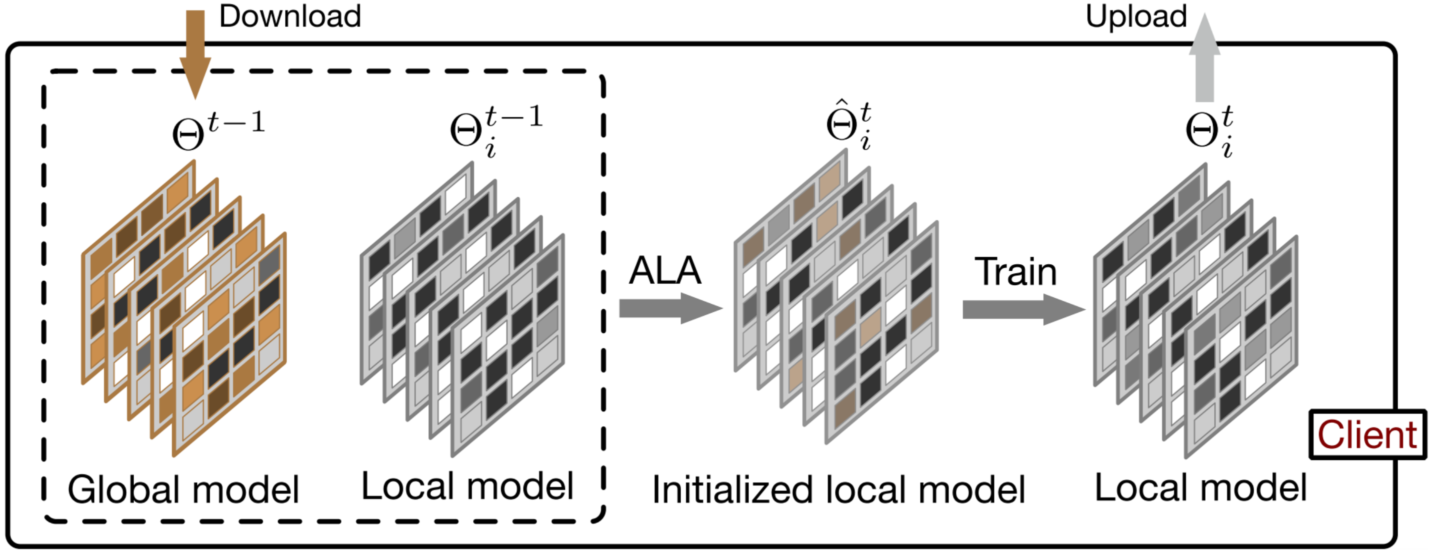
Initialize
~~(Overwrite)~~
(ALA)
Train

Do not modify other FL process

FedALA: overview

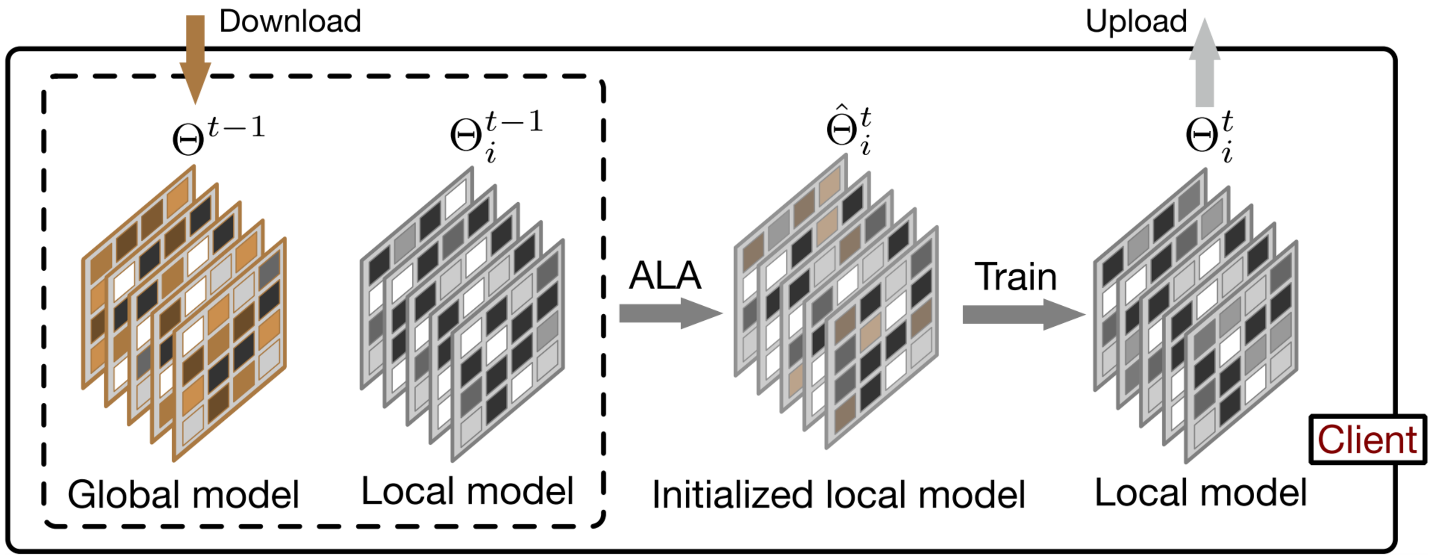
- **ALA**: adaptively aggregate the global model and local model for initialization



Workflow on the client in one iteration

FedALA: overview

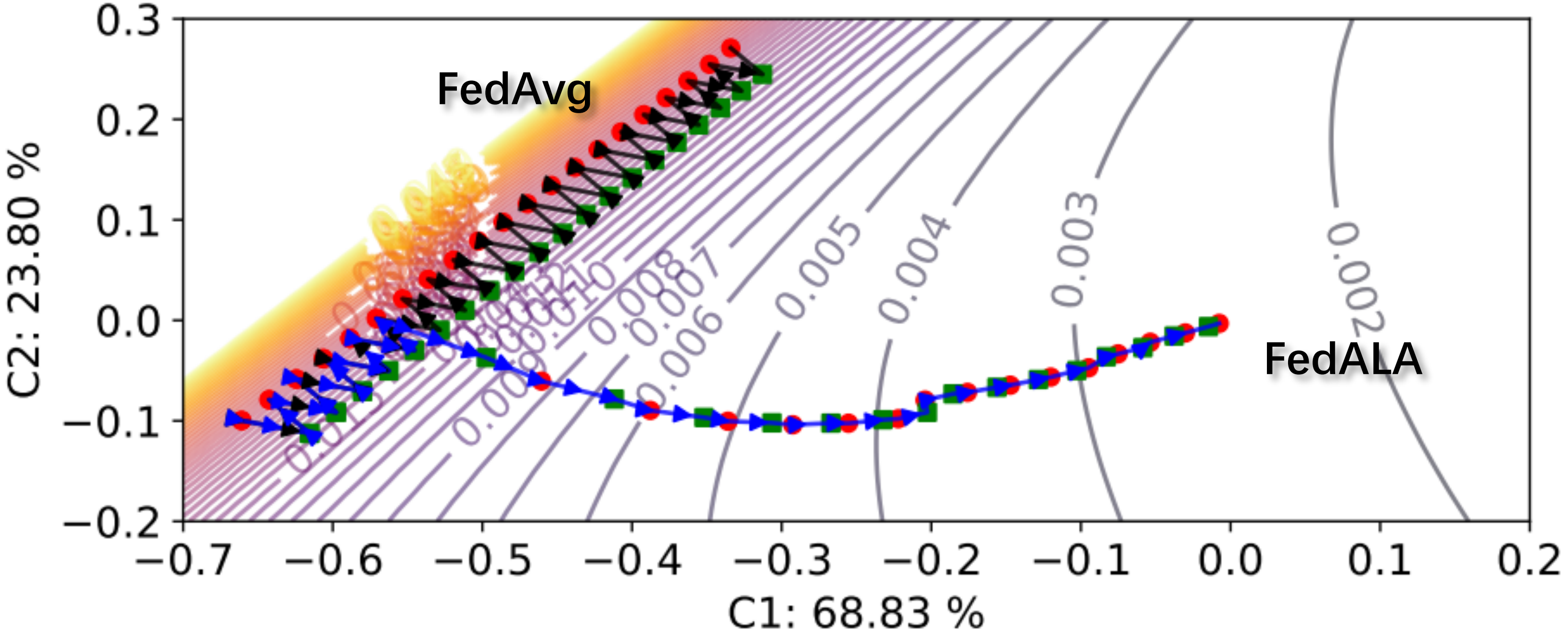
- **ALA**: adaptively aggregate the global model and local model for initialization
- **Train**: train the local model on the local data



Workflow on the client in one iteration

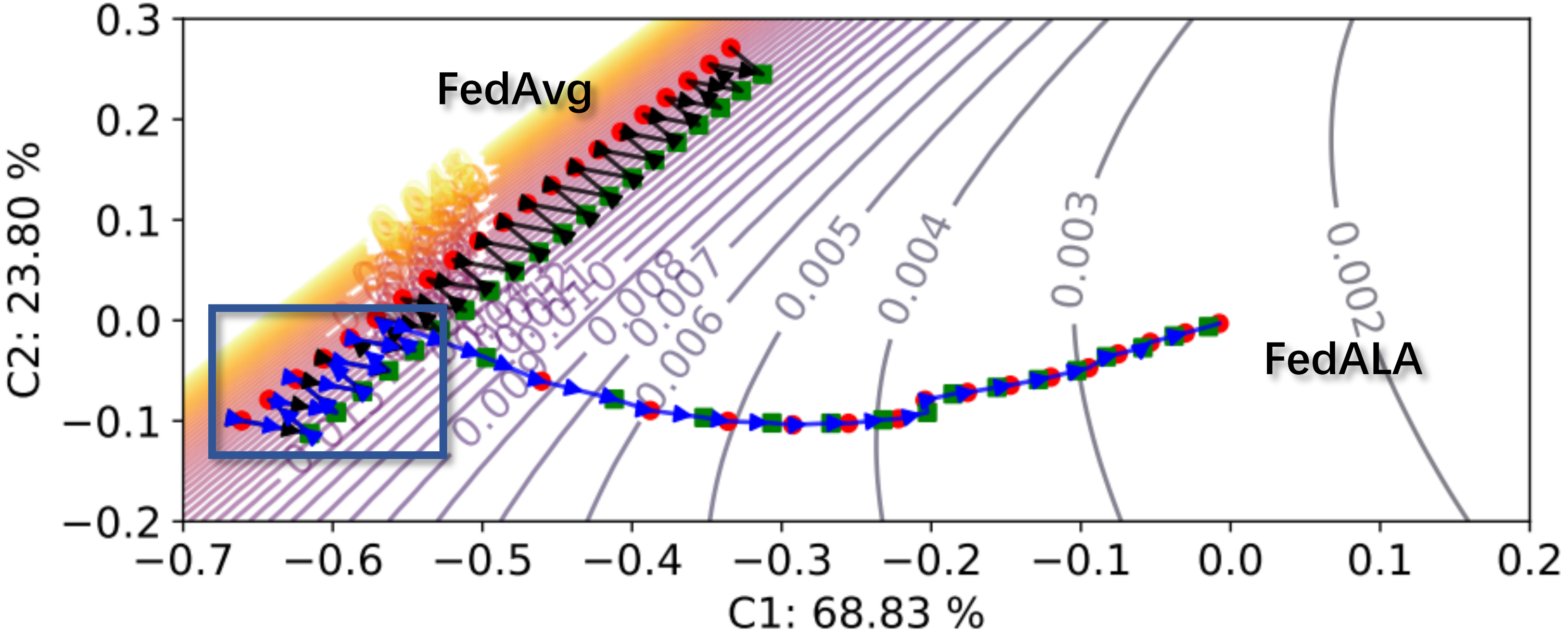
FedALA: overview

- Learning trajectory on one client: **FedAvg** vs. **FedALA**



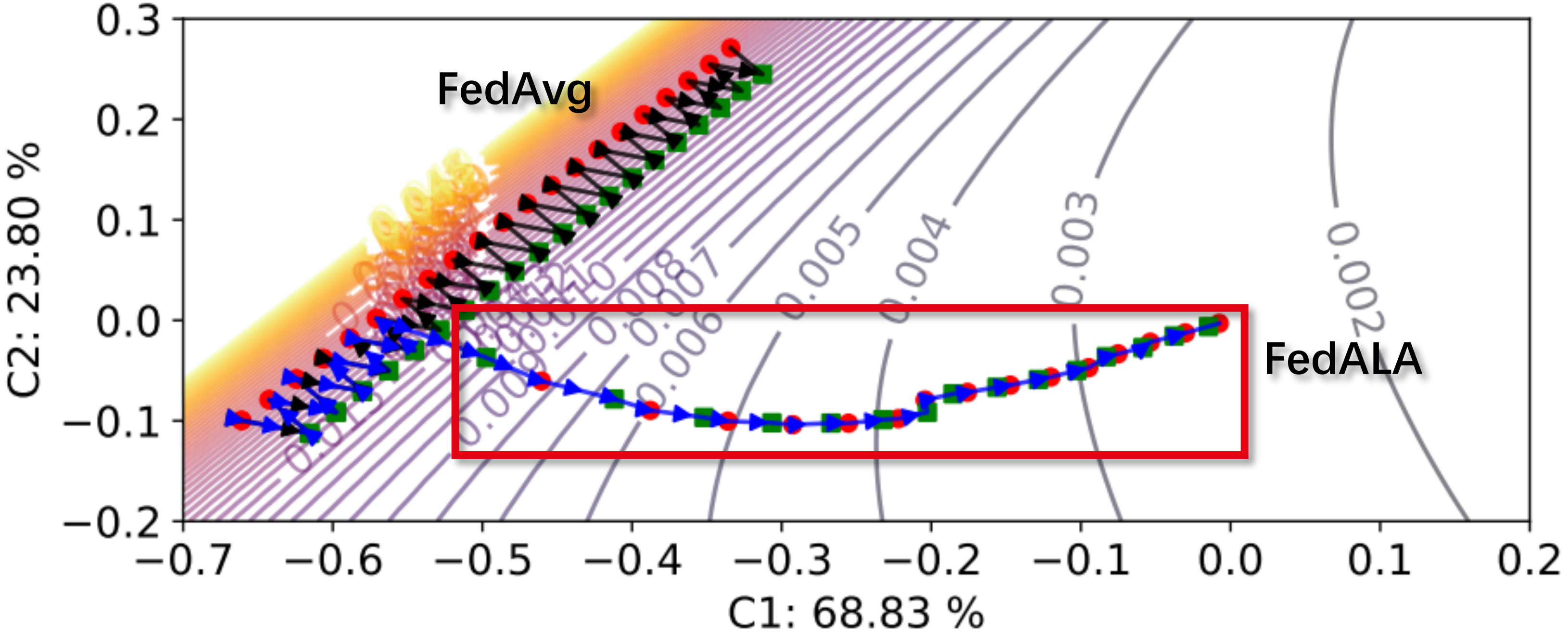
FedALA: overview

- Learning trajectory on one client: **FedAvg** vs. **FedALA**
- Deactivate **ALA** for **FedALA** in early iterations



FedALA: overview

- Learning trajectory on one client: **FedAvg** vs. **FedALA**
- Activate **ALA** in the subsequent iterations



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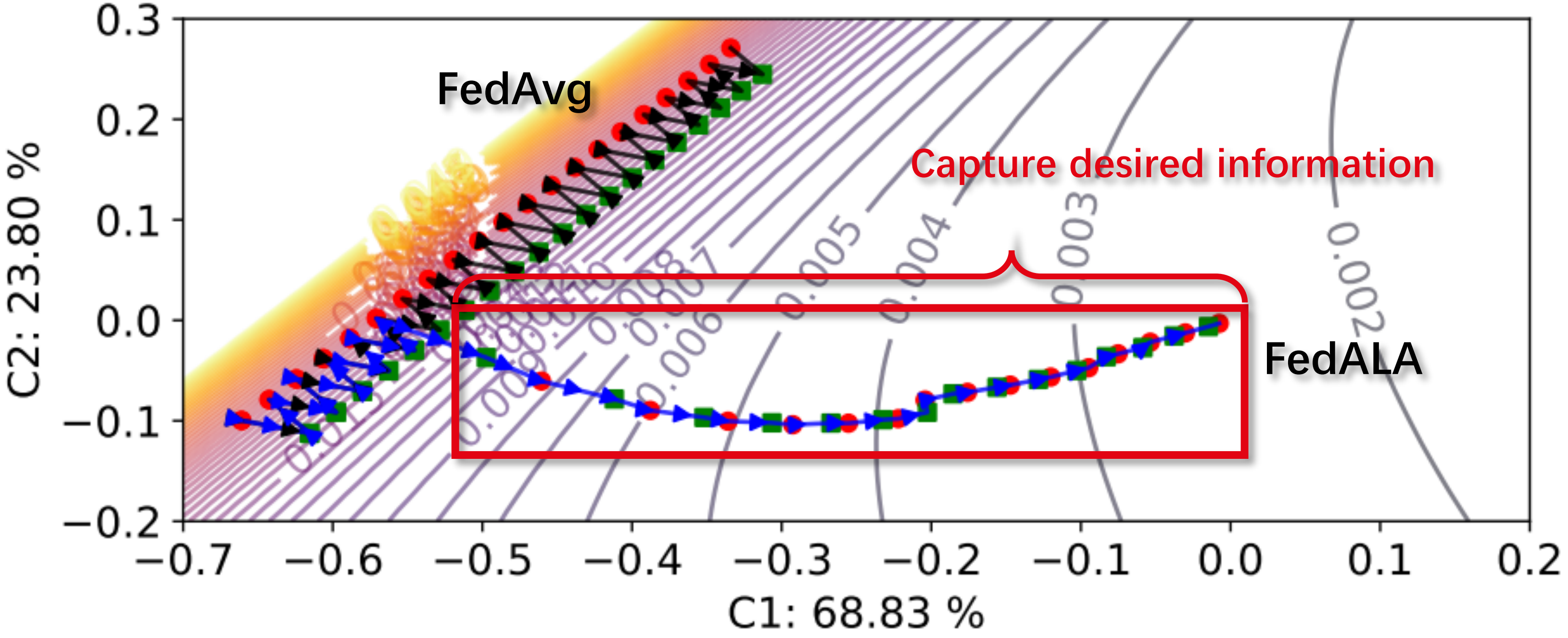
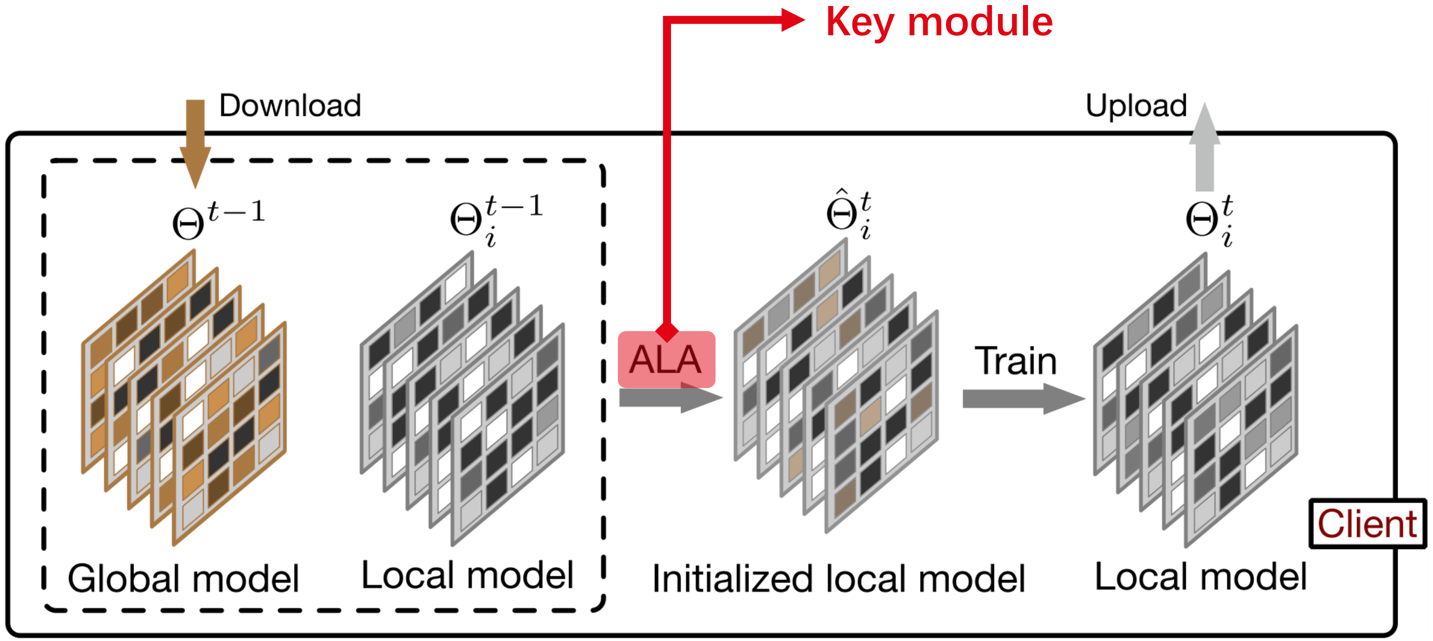


FedALA: overview

- **ALA**: adaptively aggregate the global model and local model for initialization
- **Train**: train the local model based on the initialized local model



Workflow on the client in one iteration

FedALA: ALA module

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

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

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Trainable weights

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Trainable weights

Hard to learn weights with constraints

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Trainable weights

Hard to learn weights with constraints

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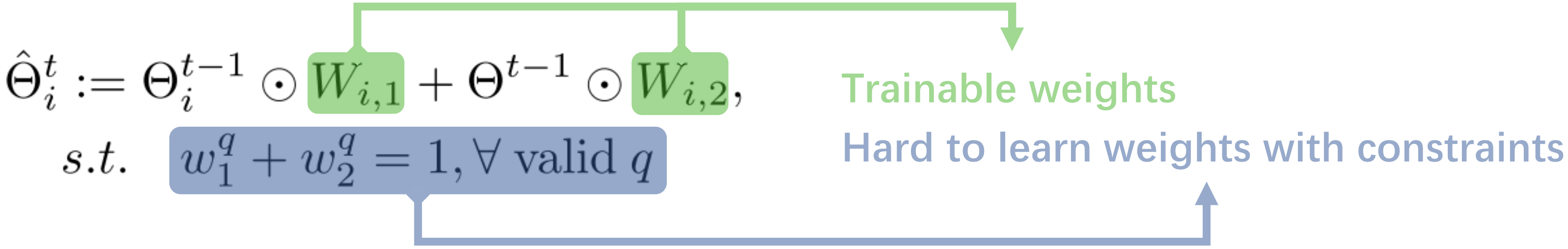

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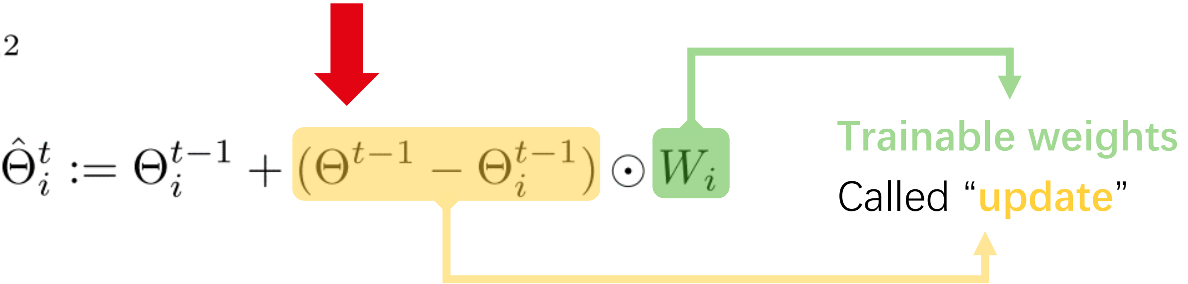

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Trainable weights

Called “update”

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

FedALA: ALA module

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  - remove constraints

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Trainable weights

Called “update”

  - remove constraints
  - with weight clipping[1]

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

[1] Arjovsky M, Chintala S, Bottou L. Wasserstein generative adversarial networks. ICLR, 2017.

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ALA covers the entire model

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ALA covers the entire model

How to reduce computation overhead?

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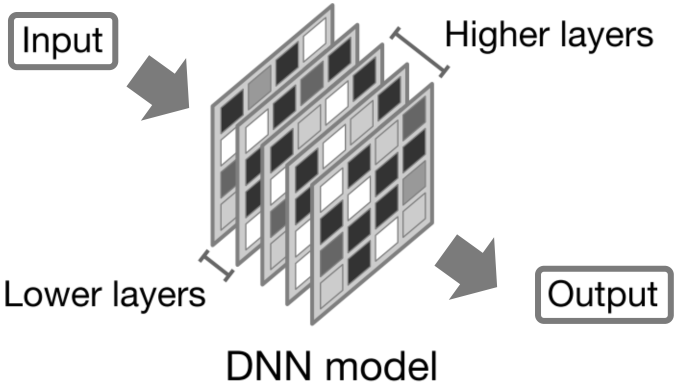
FedALA: ALA module

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



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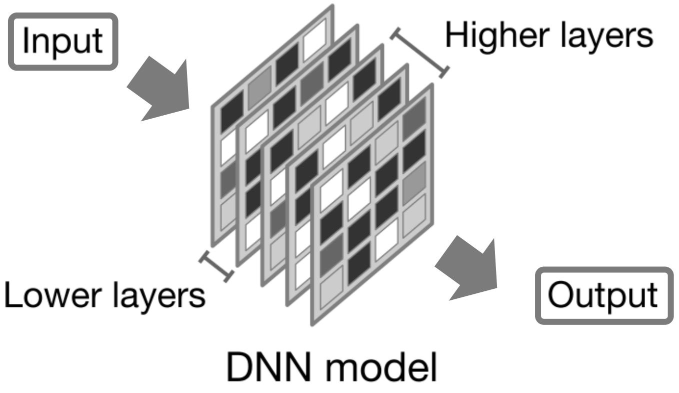

- **Only apply ALA on *p* higher layers**

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

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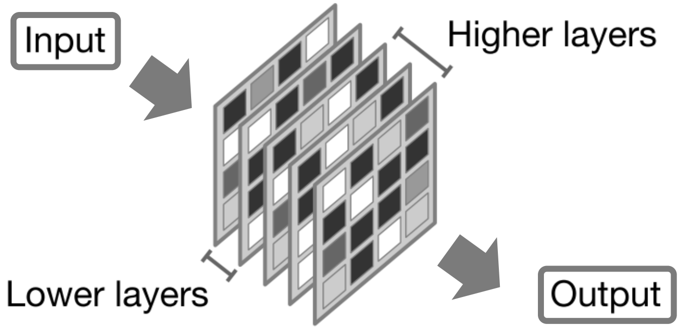

DNN model

- Only apply ALA on p higher layers
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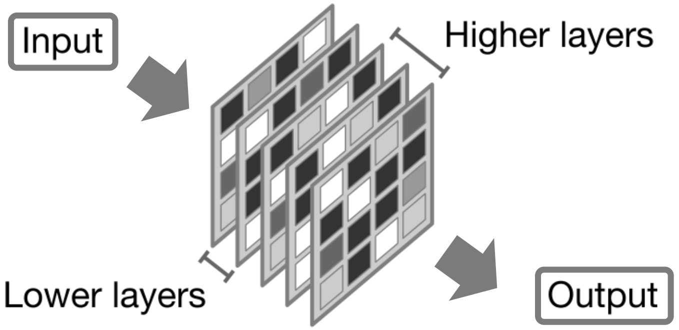

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Fewer weights to train in ALA

Less computation overhead

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FedALA: ALA module

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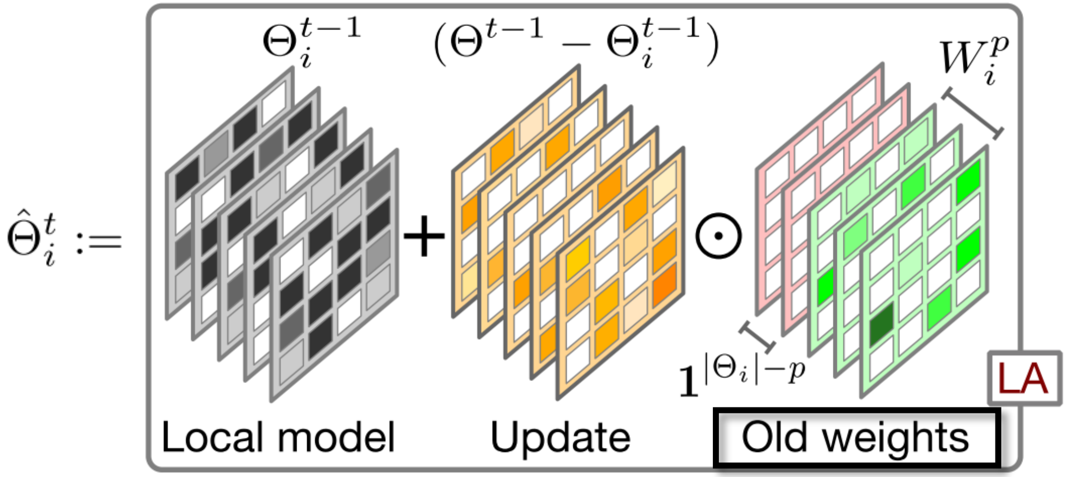

Local aggregation (LA)

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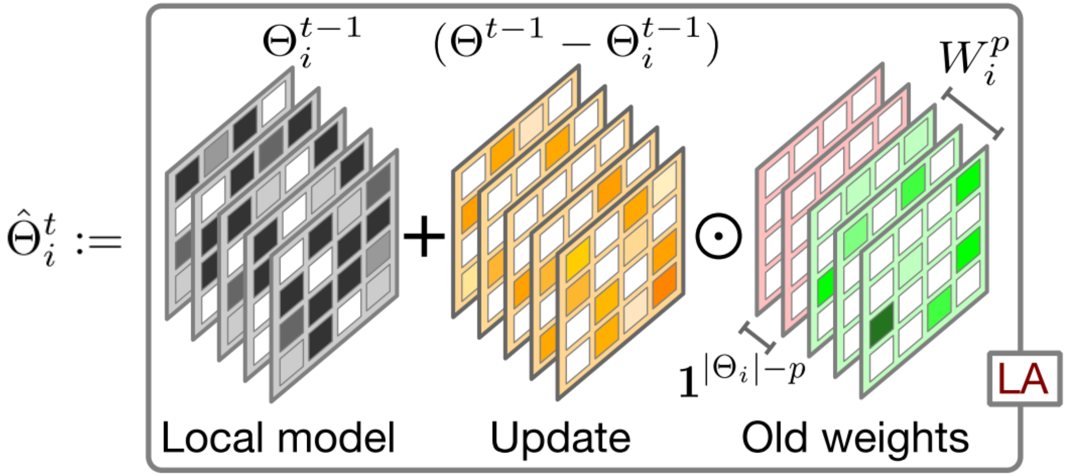

How to train weights?

Local aggregation (LA)

FedALA: ALA module

- Train weights to **reduce local loss** $\mathcal{L}(\hat{\Theta}_i^t, D_i; \Theta^{t-1})$ to find **client desired information**

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

FedALA: ALA module

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How to further reduce computation overhead?

FedALA: ALA module

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How to further reduce computation overhead?

- **Randomly** sample ***s***% data from **local dataset** D_i^t to form a **sub-dataset** $D_i^{s,t}$

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Covers all the data when *t* accumulates from 1 to *T*

FedALA: ALA module

- Randomly sample $\boldsymbol{s}\%$ data from local dataset D_i^t to form a sub-dataset $D_i^{s,t}$

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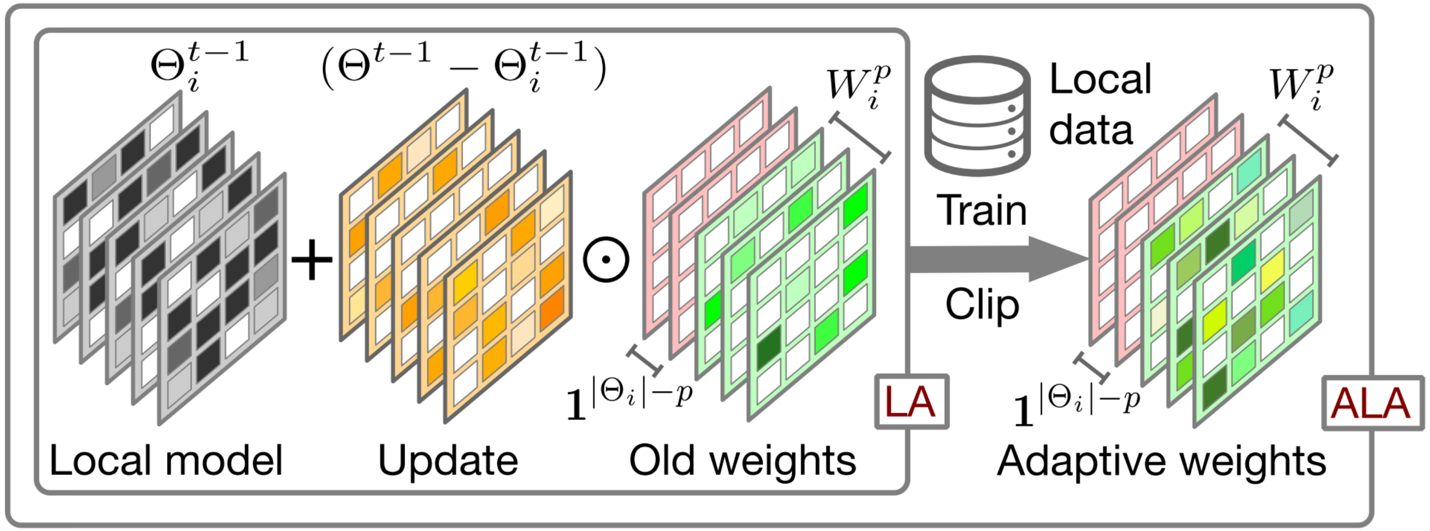
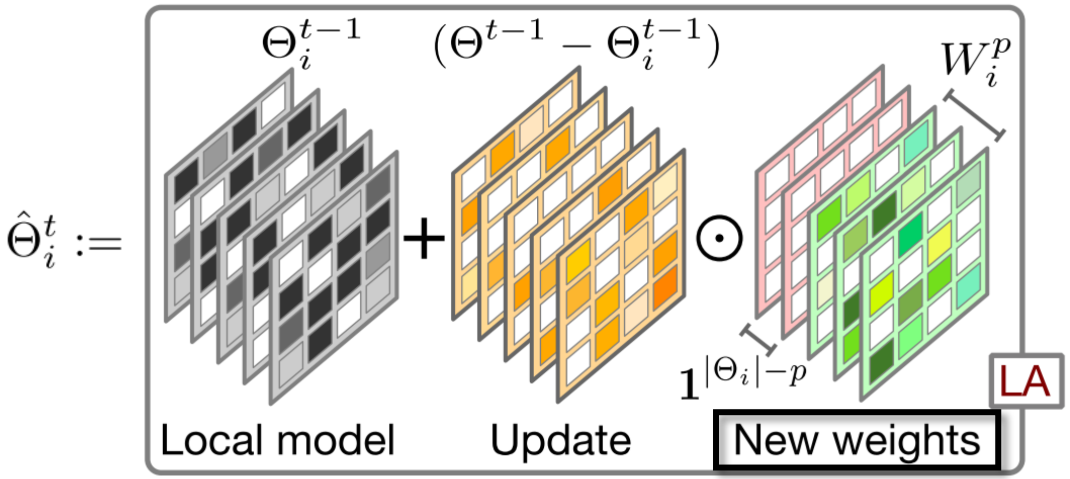


Adaptive local aggregation (ALA)

FedALA: ALA module

- Finally, obtain the initialized local model **with new weights**

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

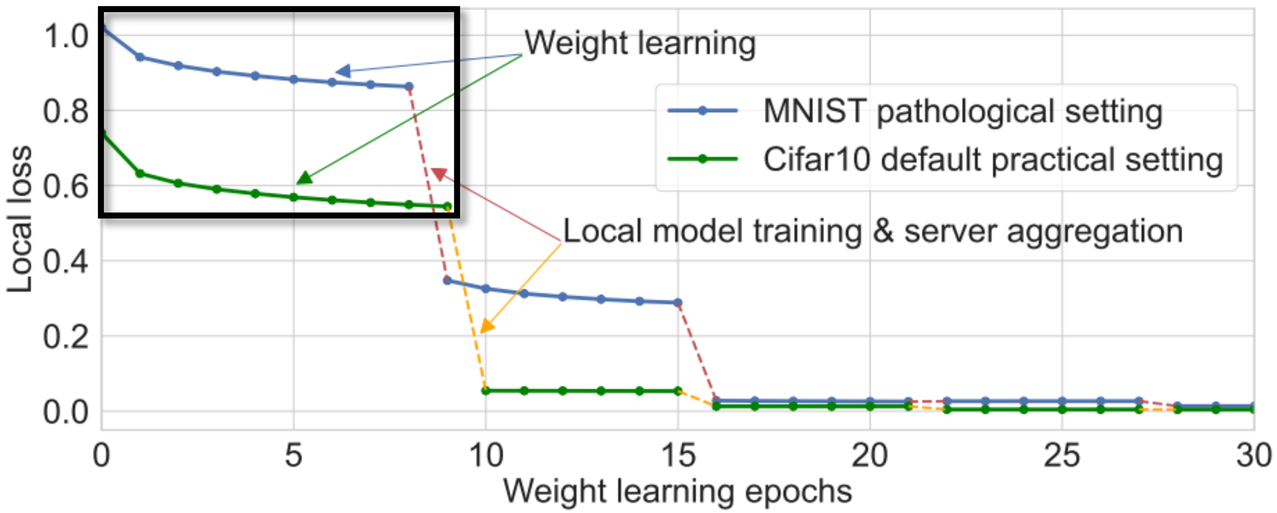


Local aggregation (LA)

FedALA: observations

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

- Once we train the weights to converge **in the first time**,

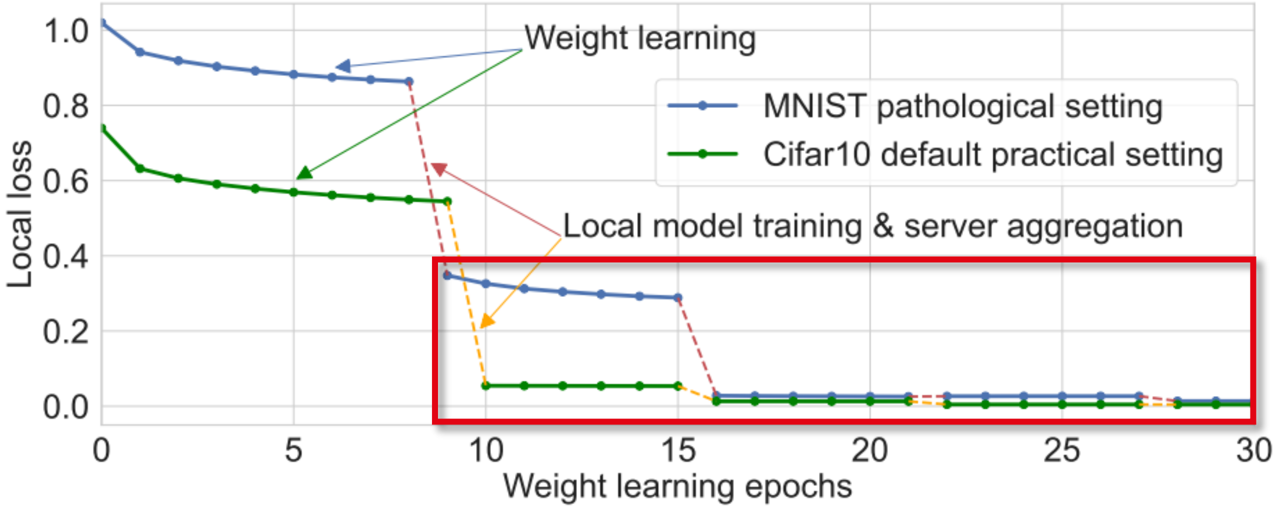


The local loss on client #8 regarding weight learning epochs in ALA on MNIST and Cifar10.

FedALA: observations

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

- Once we train the weights to converge in the first time, the weights hardly change in the subsequent iterations



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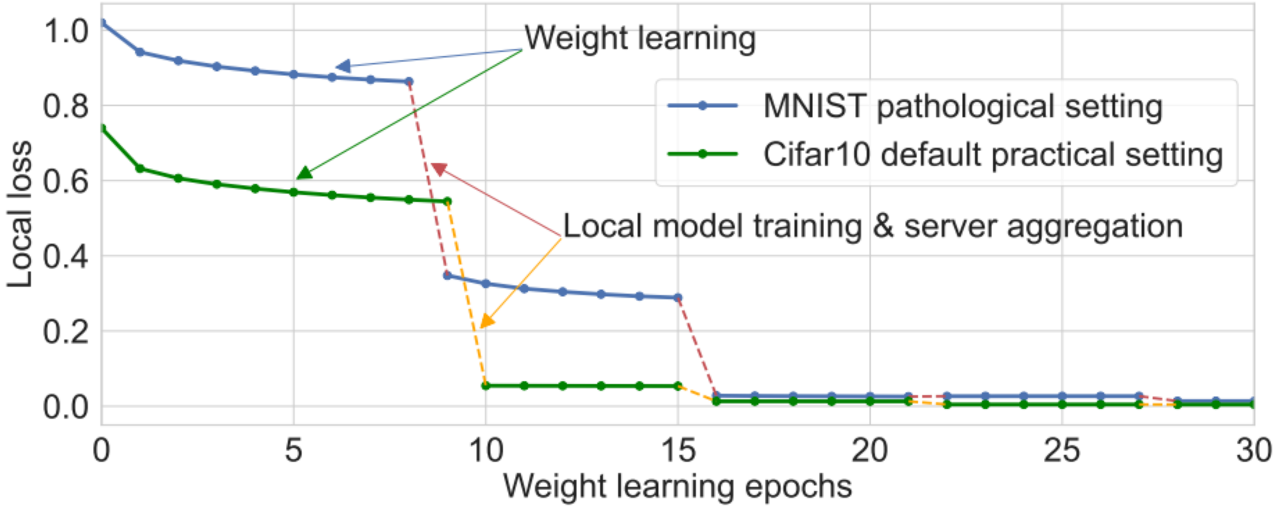
FedALA: observations

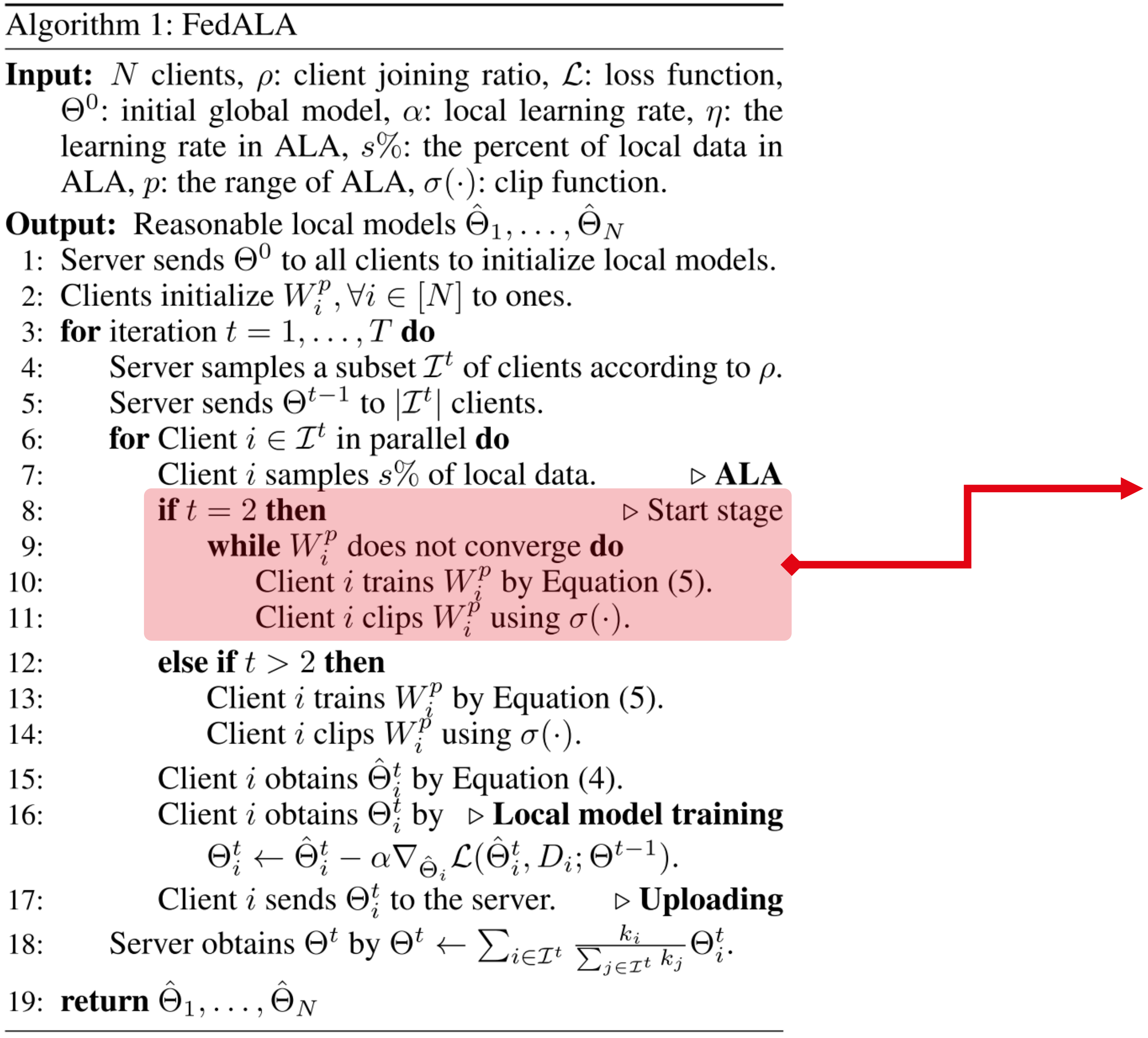
$$W_i^p \leftarrow W_i^p - \eta \nabla_{W_i^p} \mathcal{L}(\hat{\Theta}_i^t, D_i^{s,t}; \Theta^{t-1})$$

- The weights can be **reused** or just require few steps of fine-tuning for adaptation



The local loss on client #8 regarding weight learning epochs in ALA on MNIST and Cifar10.

FedALA: overall algorithm



Algorithm 1: FedALA

Input: N clients, ρ: client joining ratio, $\mathcal{L}$: loss function, Θ^0: initial global model, α: local learning rate, η: the learning rate in ALA, $s\%$: the percent of local data in ALA, p: the range of ALA, $\sigma(\cdot)$: clip function.

Output: Reasonable local models $\hat{\Theta}_1, \ldots, \hat{\Theta}_N$

```
Server sends $\Theta^0$ to all clients to initialize local models.
Clients initialize $W_i^p, \forall i \in [N]$ to ones.
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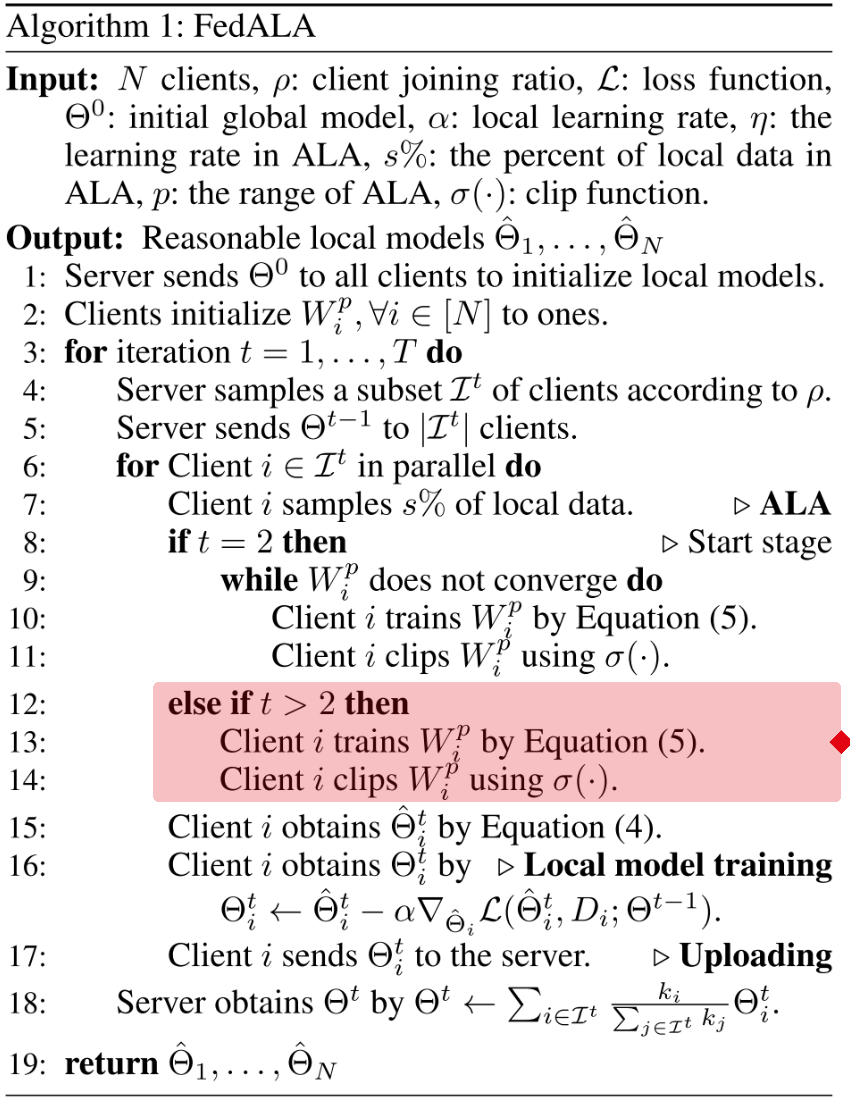
```

Only train weights to converge in the start stage

FedALA: overall algorithm



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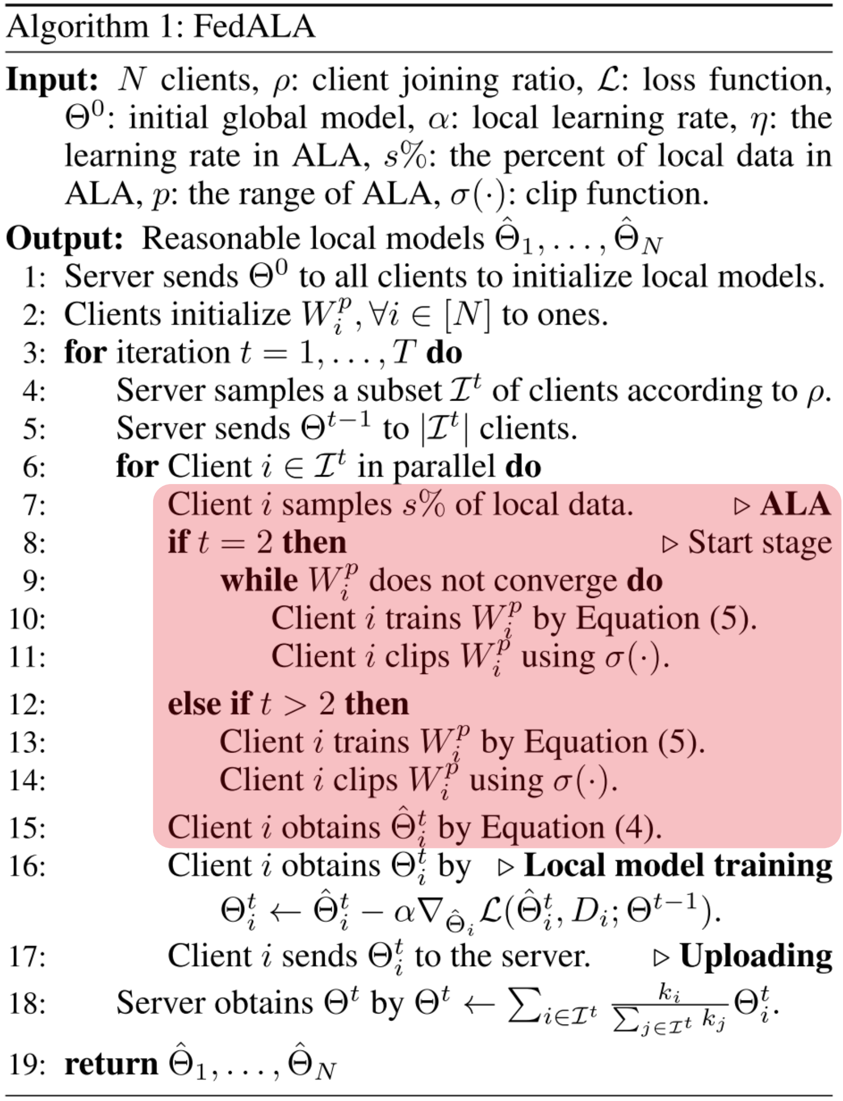
```

Fine-tune weights with only one step for adaptation

FedALA: overall algorithm



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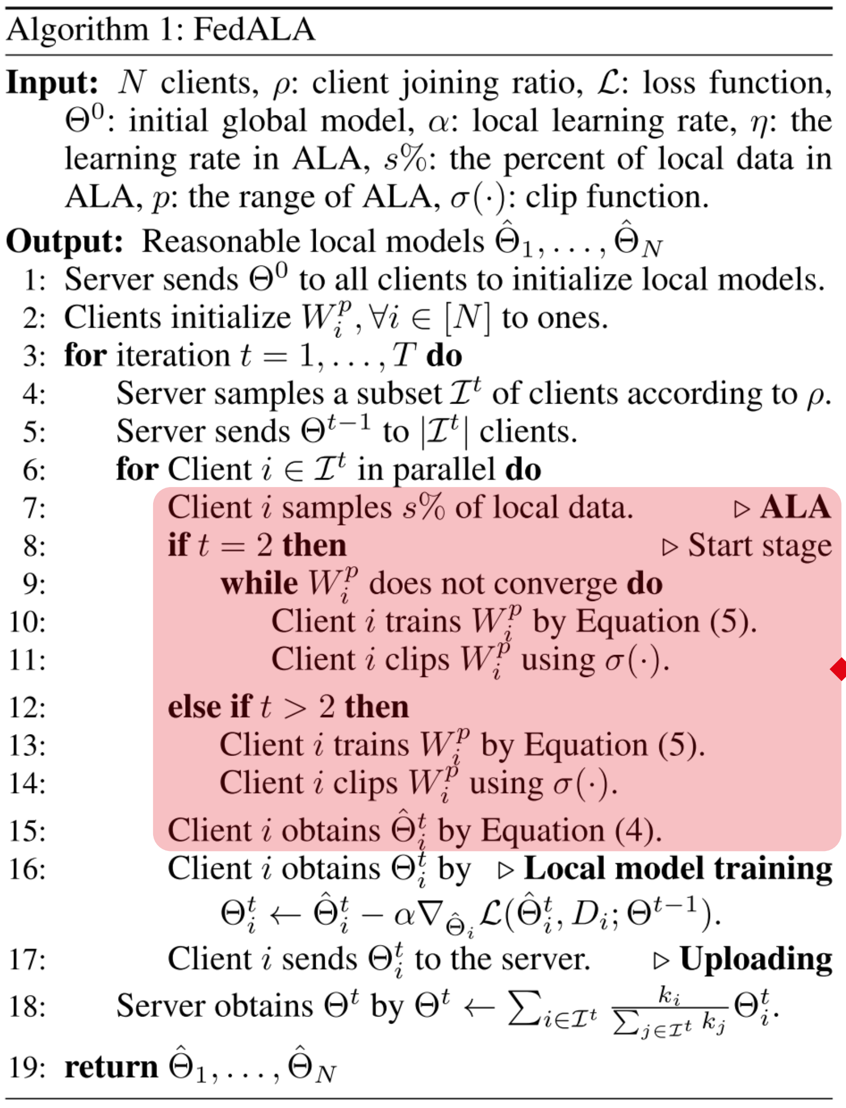

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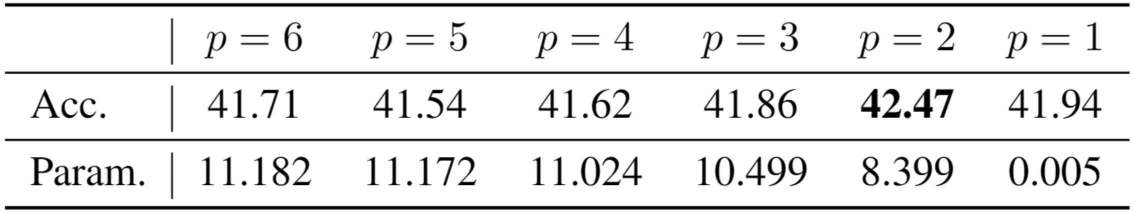
* **Capture desired information in global model**
without modifying other FL process

* **Reduce computation overhead with**
reused adaptive weights
small *p* (applying ALA on *p* higher layers)
small *s* (training weights with *s*% local data)

FedALA: results for computation reduction

- Reduce computation overhead with small $\boldsymbol{p}$ **(applying ALA on $\boldsymbol{p}$ 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 $\boldsymbol{p}$

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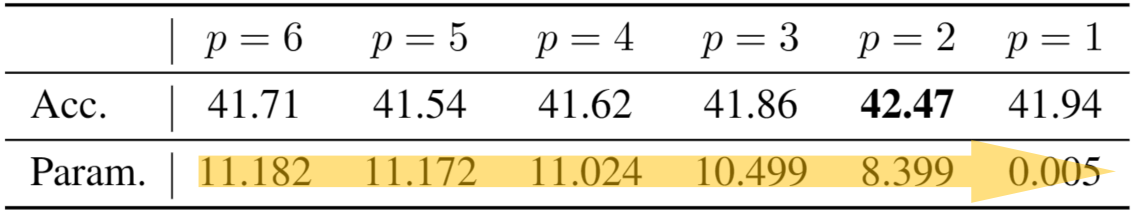

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Parameter amount decreases greatly with small $\boldsymbol{p}$

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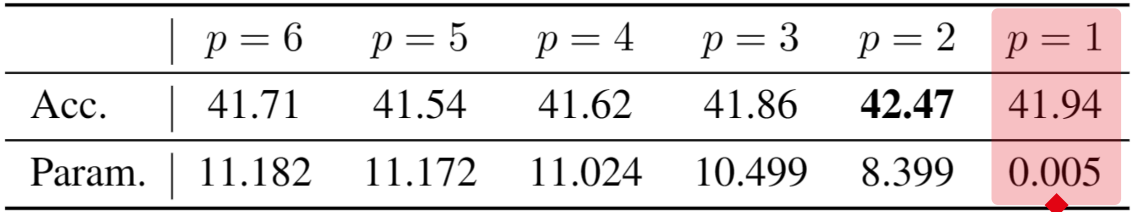

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Accuracy hardly changes with different $\boldsymbol{p}$

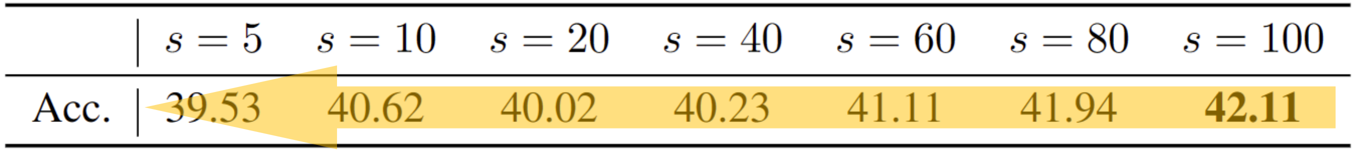
Parameter amount decreases greatly with small $\boldsymbol{p}$

Set $\boldsymbol{p} = \mathbf{1}$ to greatly reduce computation overhead

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*

FedALA: results for computation reduction

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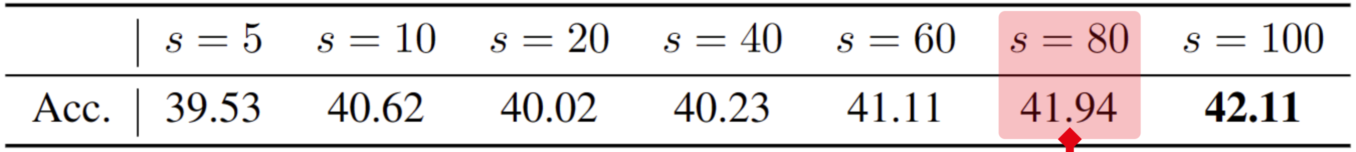

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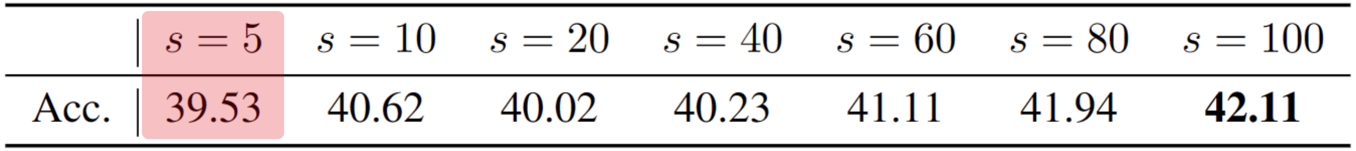

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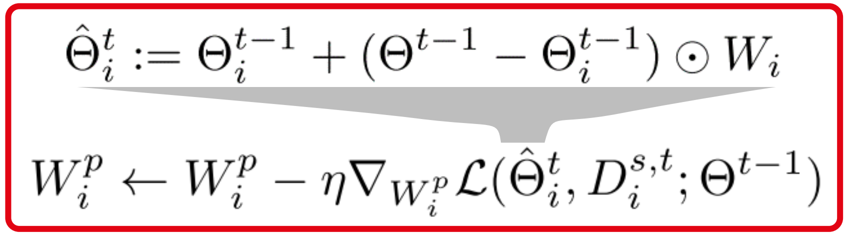
Accuracy decreases with smaller s

Set $s = 80$ to reduce computation overhead

FedALA performs well with only 5% local data for ALA

FedALA: analysis

- Two main equations (omitting $\boldsymbol{p}$):



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

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

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

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

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

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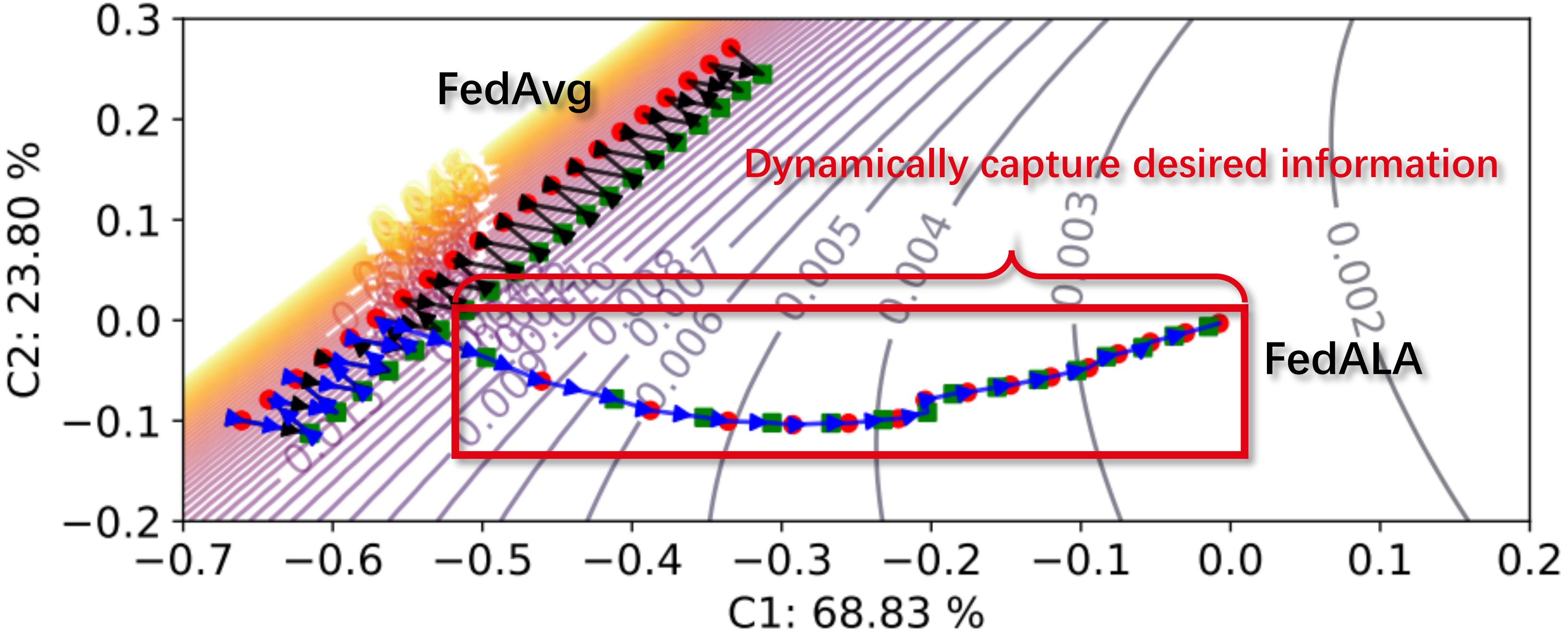
FedALA: overview (recall)

- Learning trajectory on one client: **FedAvg** vs. **FedALA**
- Activate **ALA** in the subsequent iterations



FedALA: applicability of ALA module

- Applying **ALA** to other FL methods

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  - only modifies the local initialization process

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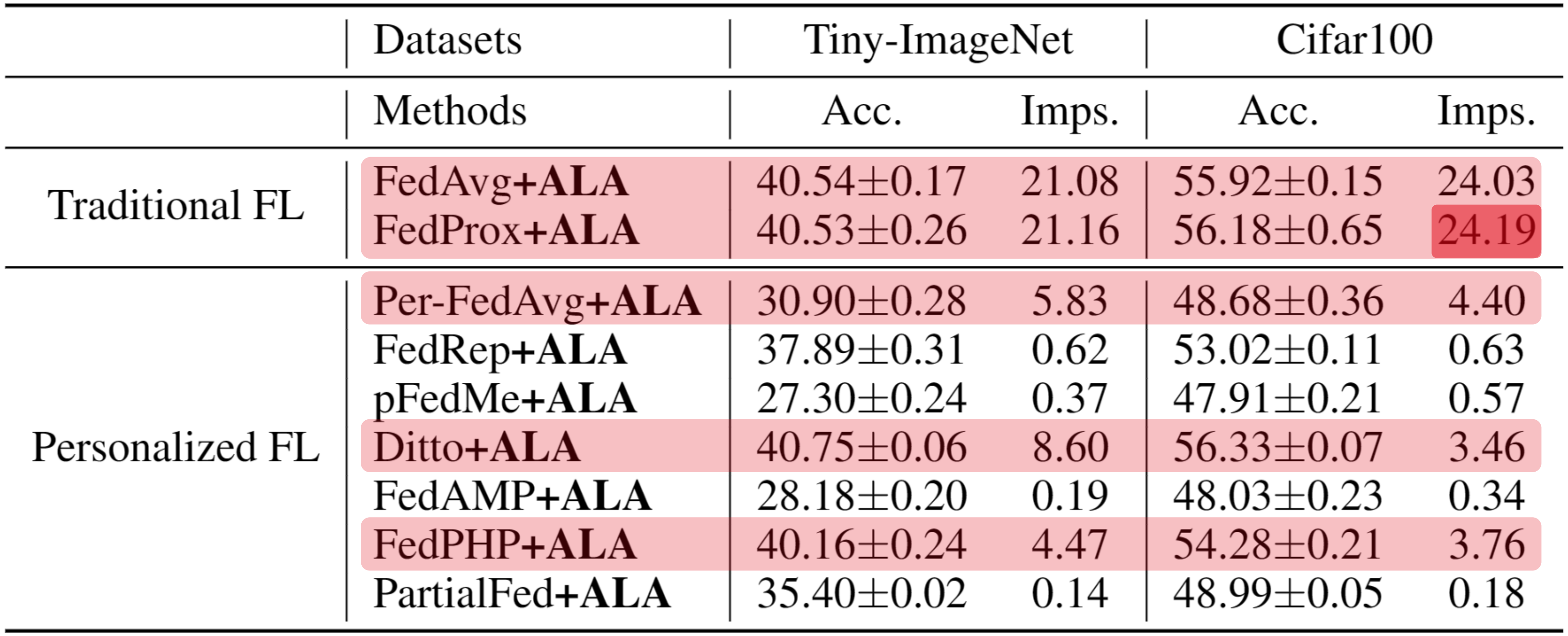
The test accuracy (%) and improvement (%)

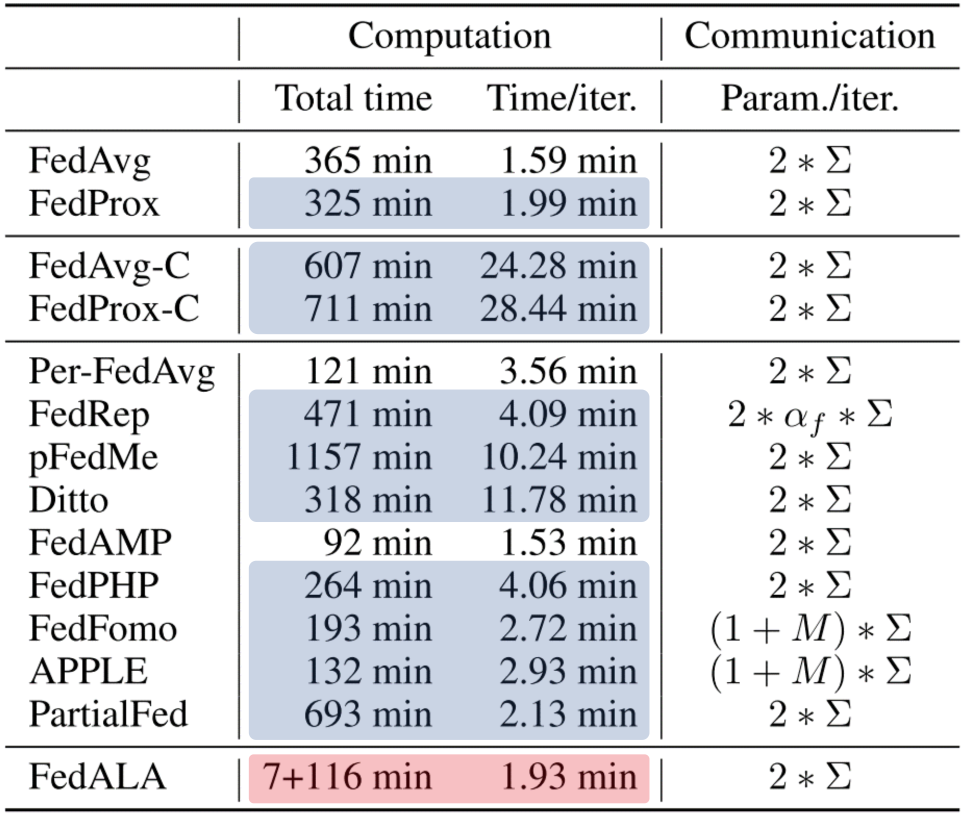


	Datasets	Tiny-ImageNet		Cifar100	
	Methods	Acc.	Imps.	Acc.	Imps.
Traditional FL	FedAvg+**ALA**	40.54±0.17	21.08	55.92±0.15	24.03
	FedProx+**ALA**	40.53±0.26	21.16	56.18±0.65	24.19
Personalized FL	Per-FedAvg+**ALA**	30.90±0.28	5.83	48.68±0.36	4.40
	FedRep+**ALA**	37.89±0.31	0.62	53.02±0.11	0.63
	pFedMe+**ALA**	27.30±0.24	0.37	47.91±0.21	0.57
	Ditto+**ALA**	40.75±0.06	8.60	56.33±0.07	3.46
	FedAMP+**ALA**	28.18±0.20	0.19	48.03±0.23	0.34
	FedPHP+**ALA**	40.16±0.24	4.47	54.28±0.21	3.76
	PartialFed+**ALA**	35.40±0.02	0.14	48.99±0.05	0.18

Performance comparison

- FedALA requires **less computation** than most FL methods

The computation and communication overhead, $M = 20$.

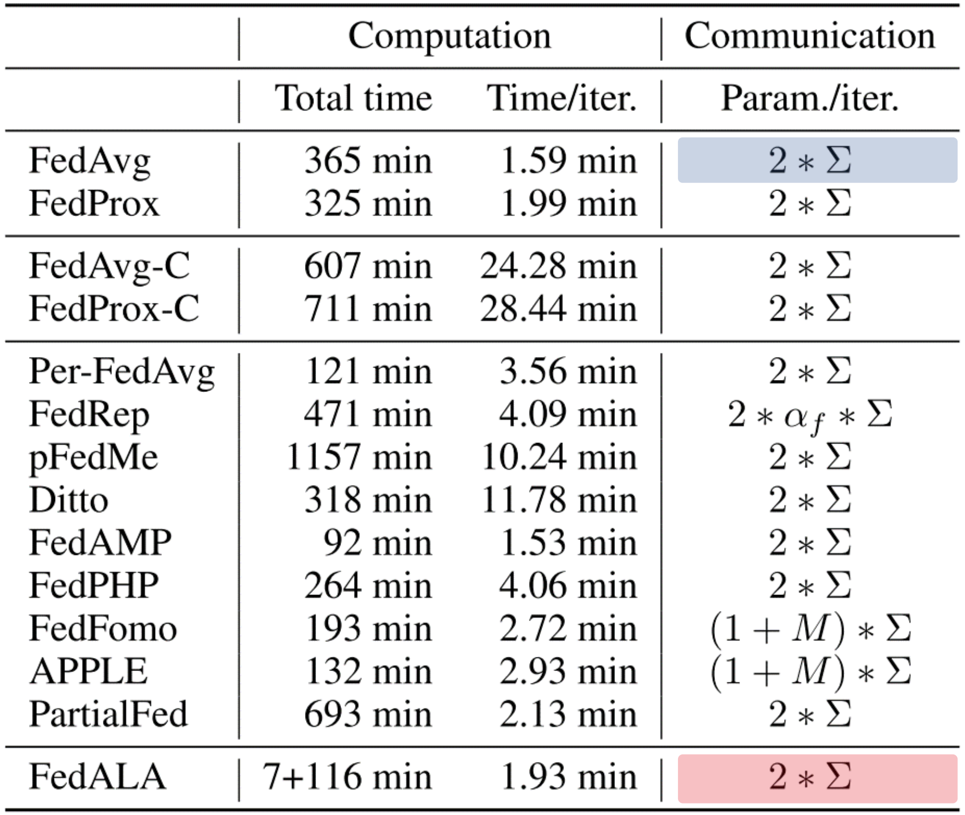


	Computation		Communication
	Total time	Time/iter.	Param./iter.
FedAvg	365 min	1.59 min	$2 * \Sigma$
FedProx	325 min	1.99 min	$2 * \Sigma$
FedAvg-C	607 min	24.28 min	$2 * \Sigma$
FedProx-C	711 min	28.44 min	$2 * \Sigma$
Per-FedAvg	121 min	3.56 min	$2 * \Sigma$
FedRep	471 min	4.09 min	$2 * \alpha_f * \Sigma$
pFedMe	1157 min	10.24 min	$2 * \Sigma$
Ditto	318 min	11.78 min	$2 * \Sigma$
FedAMP	92 min	1.53 min	$2 * \Sigma$
FedPHP	264 min	4.06 min	$2 * \Sigma$
FedFomo	193 min	2.72 min	$(1 + M) * \Sigma$
APPLE	132 min	2.93 min	$(1 + M) * \Sigma$
PartialFed	693 min	2.13 min	$2 * \Sigma$
FedALA	7+116 min	1.93 min	$2 * \Sigma$

Performance comparison

- Compared to FedAvg, FedALA **does not introduce additional communication** per iteration

The computation and communication overhead, $M = 20$.



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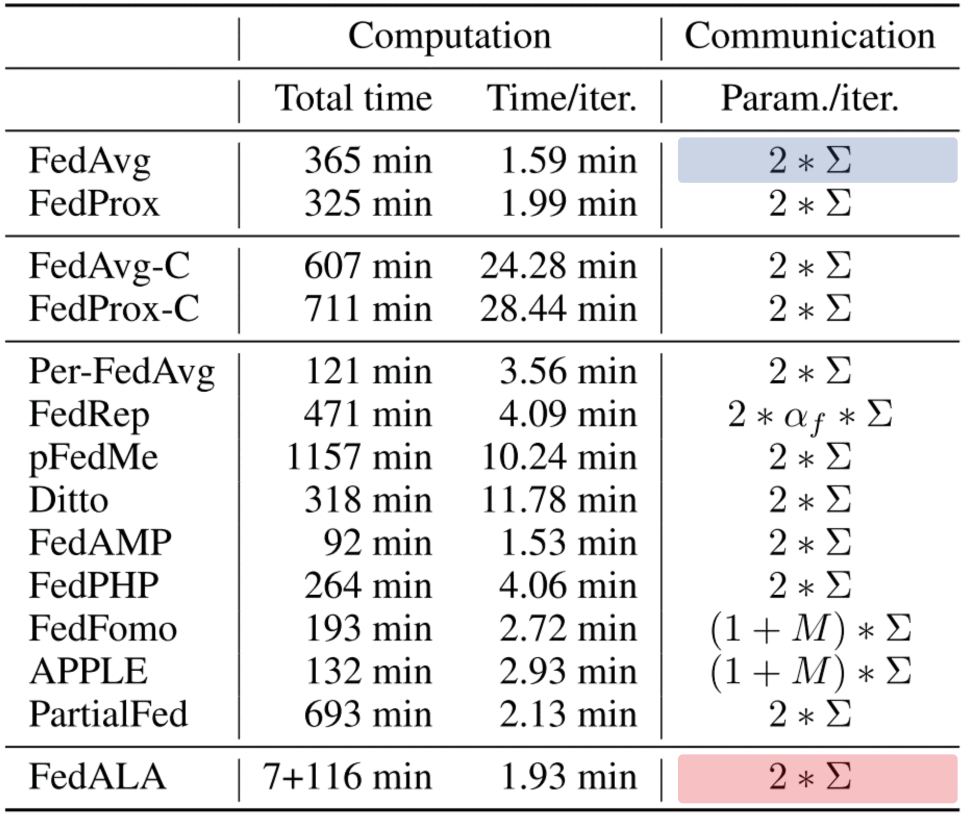
Performance comparison

- Compared to FedAvg, FedALA **does not introduce additional communication** per iteration
  - but **costs fewer iterations** to converge

The computation and communication overhead, $M = 20$.



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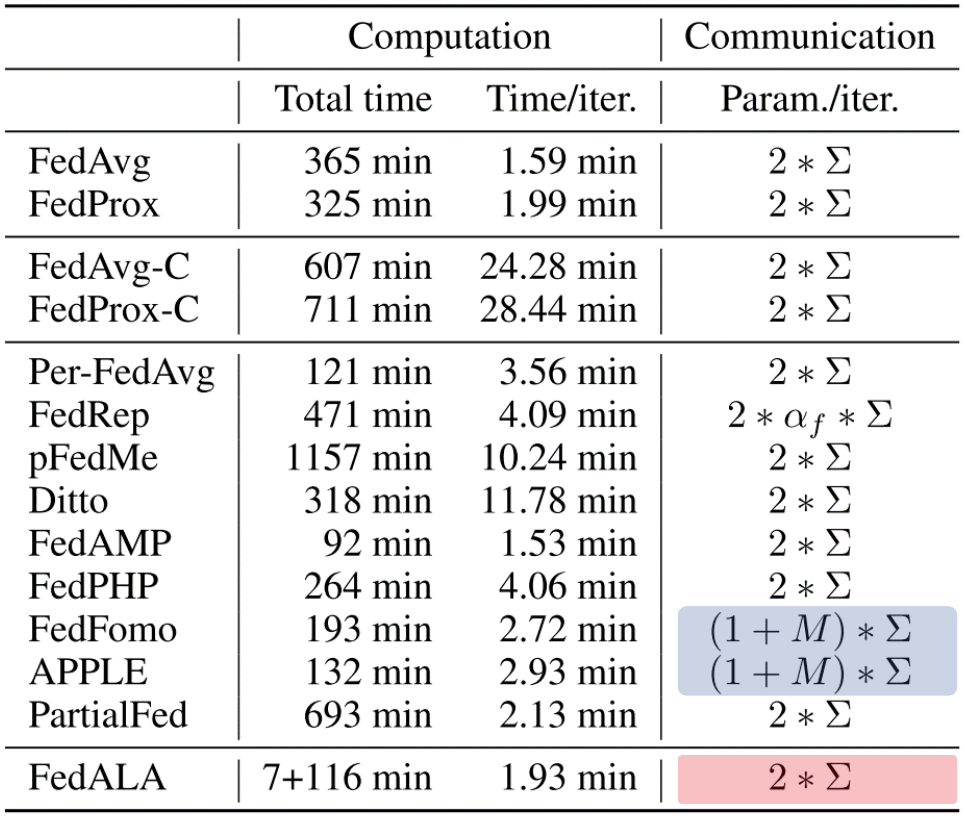
Performance comparison

- Compared to FedFomo and APPLE, FedALA **requires less communication** per iteration

The computation and communication overhead, $M = 20$.



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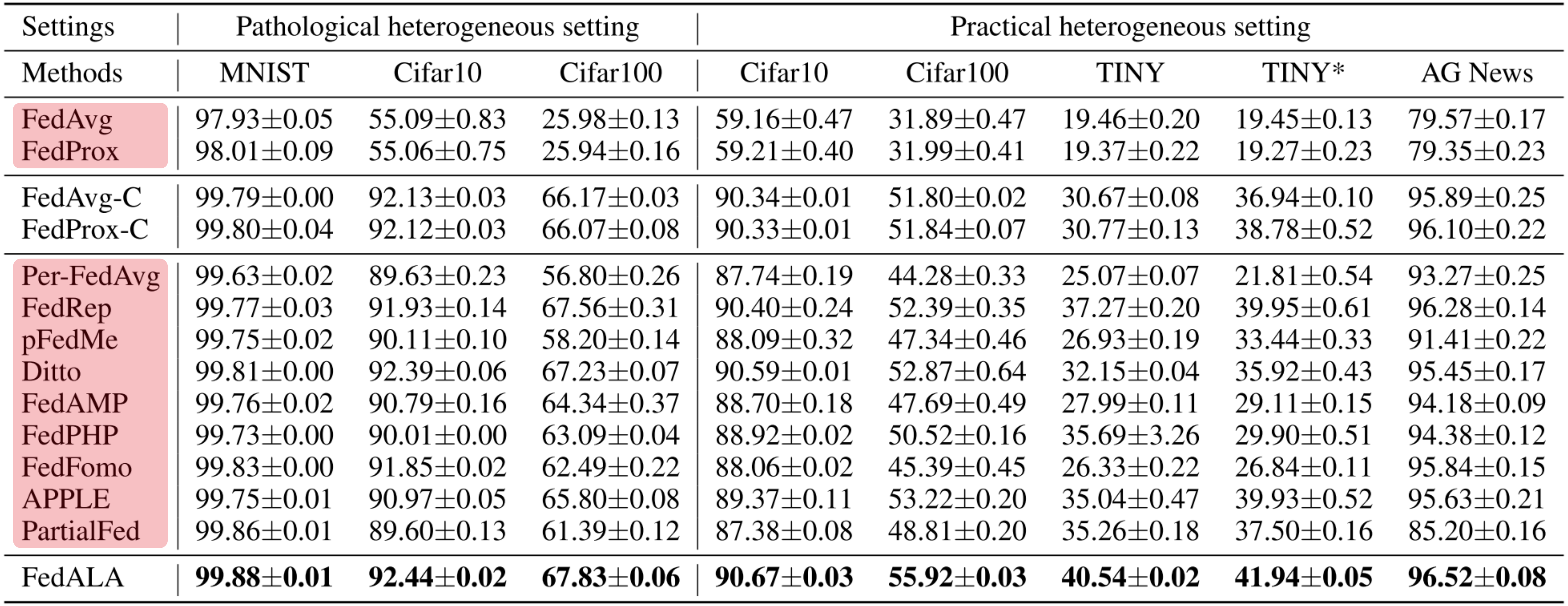
FedFomo	193 min	2.72 min	$(1 + M) * \Sigma$
APPLE	132 min	2.93 min	$(1 + M) * \Sigma$
PartialFed	693 min	2.13 min	$2 * \Sigma$
FedALA	7+116 min	1.93 min	$2 * \Sigma$

Performance comparison

- FedALA outperforms **11** SOTA 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
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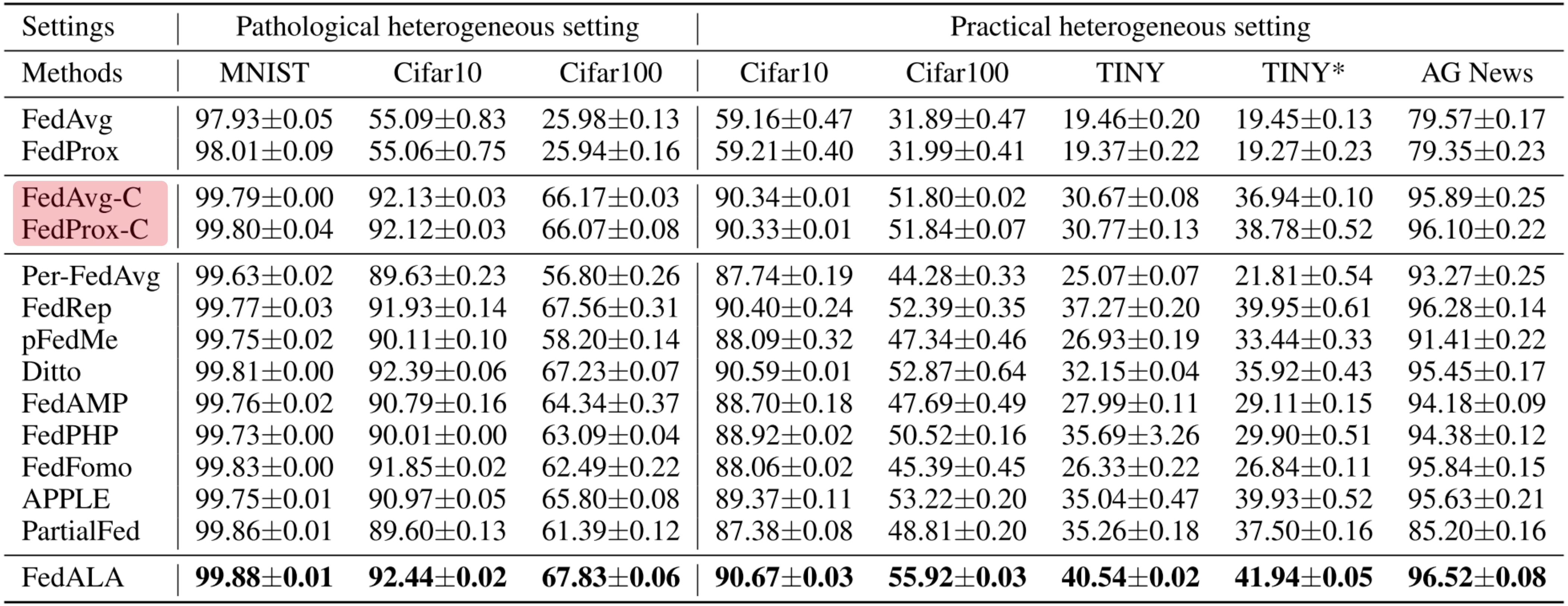
FedALA	**99.88±0.01**	**92.44±0.02**	**67.83±0.06**	**90.67±0.03**	**55.92±0.03**	**40.54±0.02**	**41.94±0.05**	**96.52±0.08**

Performance comparison

- FedALA outperforms **2** fine-tuning-based pFL methods

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



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Methods	MNIST	Cifar10	Cifar100	Cifar10	Cifar100	TINY	TINY*	AG News
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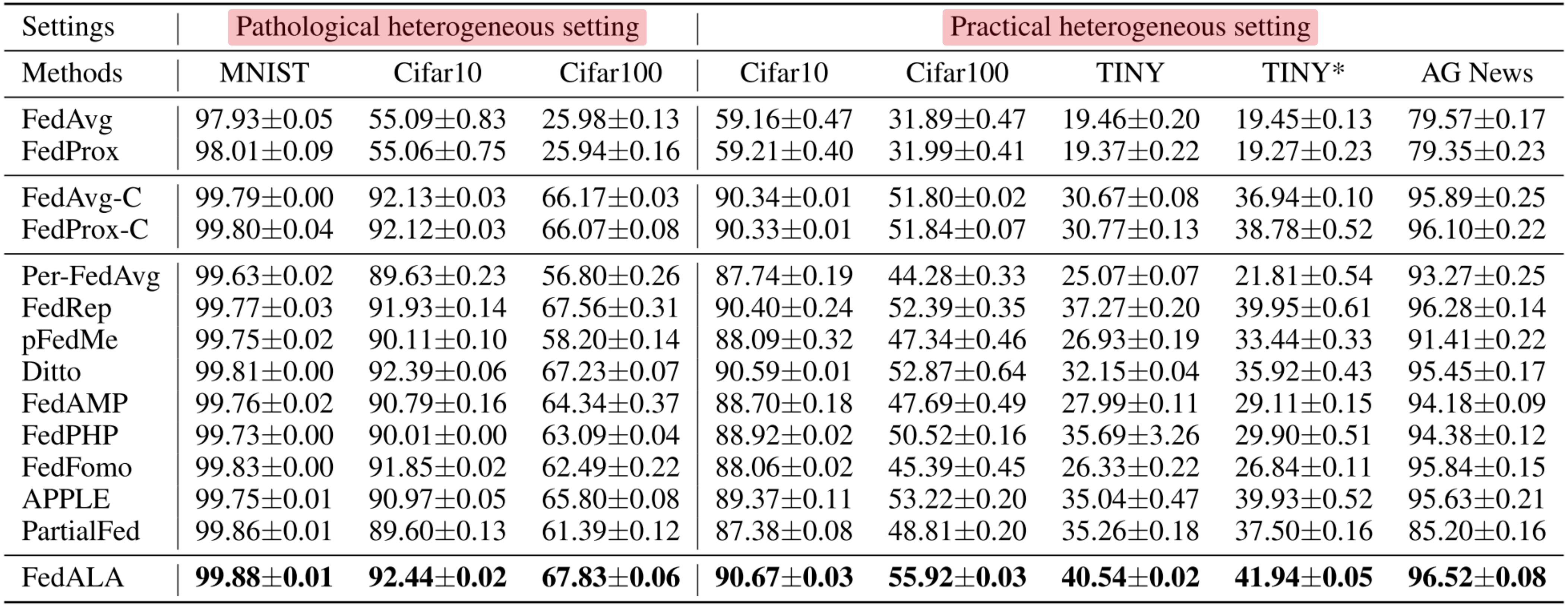
Performance comparison

- FedALA outperforms 13 traditional FL and pFL methods
  - in various settings

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



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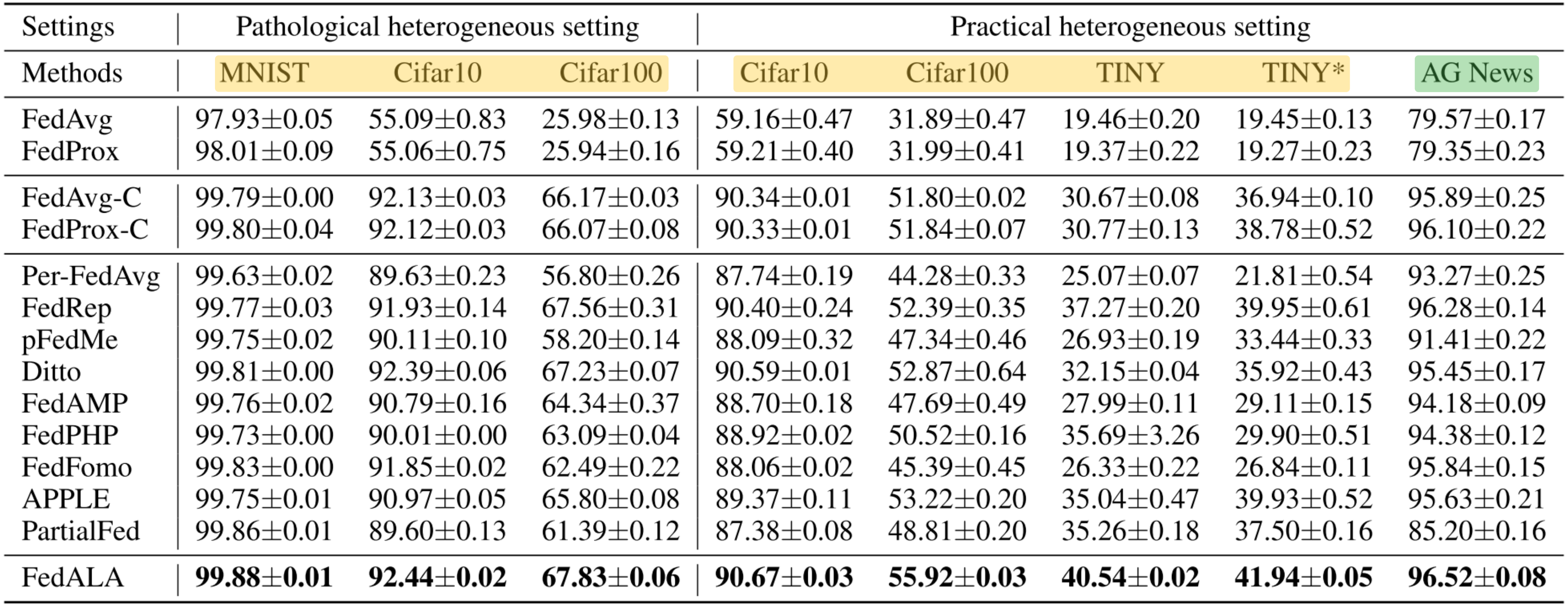
Performance comparison

- FedALA outperforms 13 traditional FL and pFL methods
  - in various settings and various datasets (CV and NLP domains)

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



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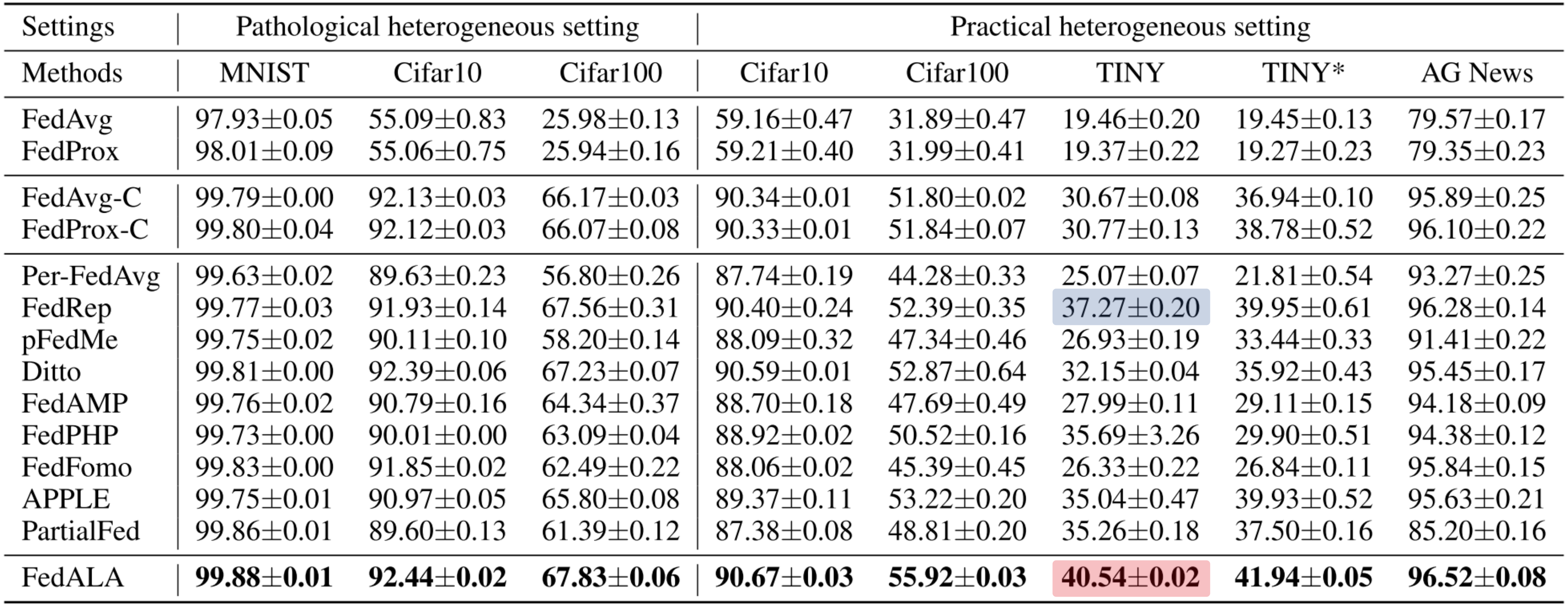
Performance comparison

- FedALA outperforms 13 traditional FL and pFL methods by up to **3.27%**

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



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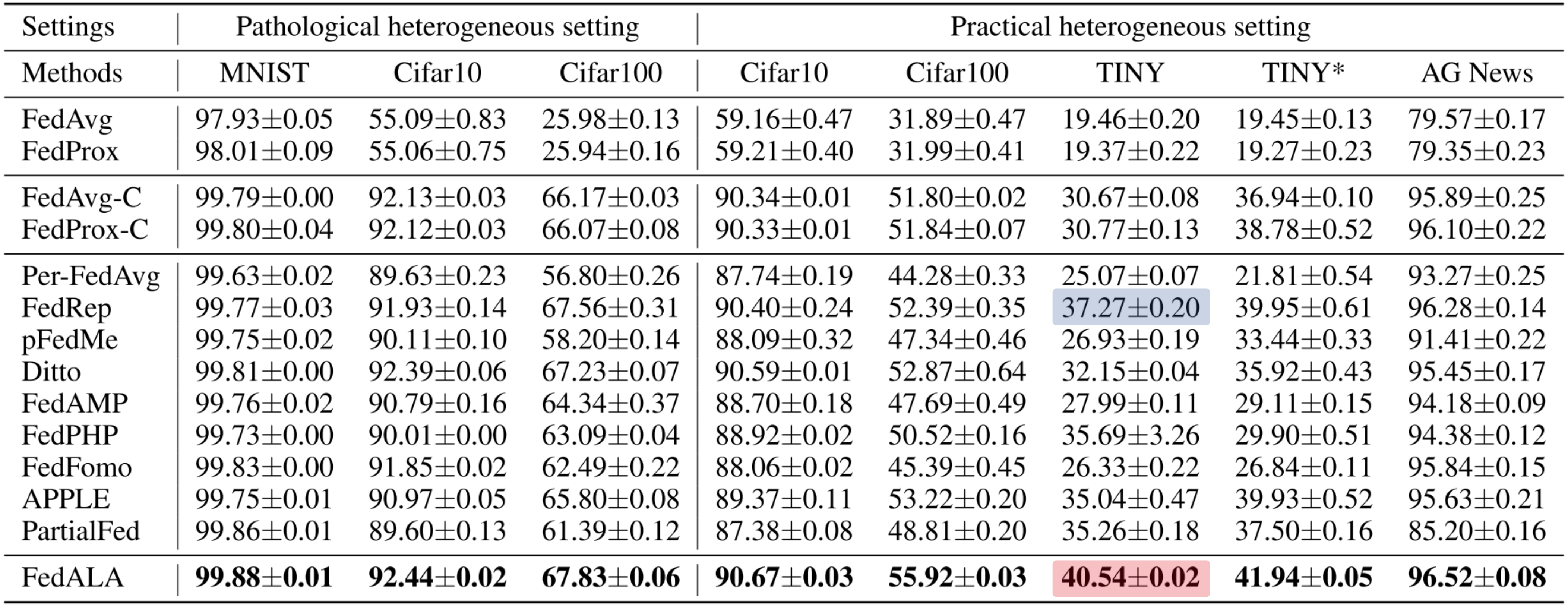
Performance comparison

- FedALA outperforms 13 traditional FL and pFL methods by up to **3.27%**
  - For more results, please refer to our paper

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



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Summary

- **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 3.27% 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%

- **Resources**:
  - Full paper: https://arxiv.org/abs/2212.01197
  - Code: https://github.com/TsingZ0/FedALA

FedALA: Adaptive Local Aggregation for Personalized Federated Learning

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Thanks!