

# Summary of My Research

- **Name:** Jianqing Zhang
- **Age:** 26
- **Ph.D.:** Shanghai Jiao Tong University
- **Collaborations:**
  - Qiang Yang, HKUST, China
  - Yang Liu, Tsinghua University, China
  - Marco Canini, KAUST, Saudi Arabia
  - Yang Hua, Queen's University Belfast, UK

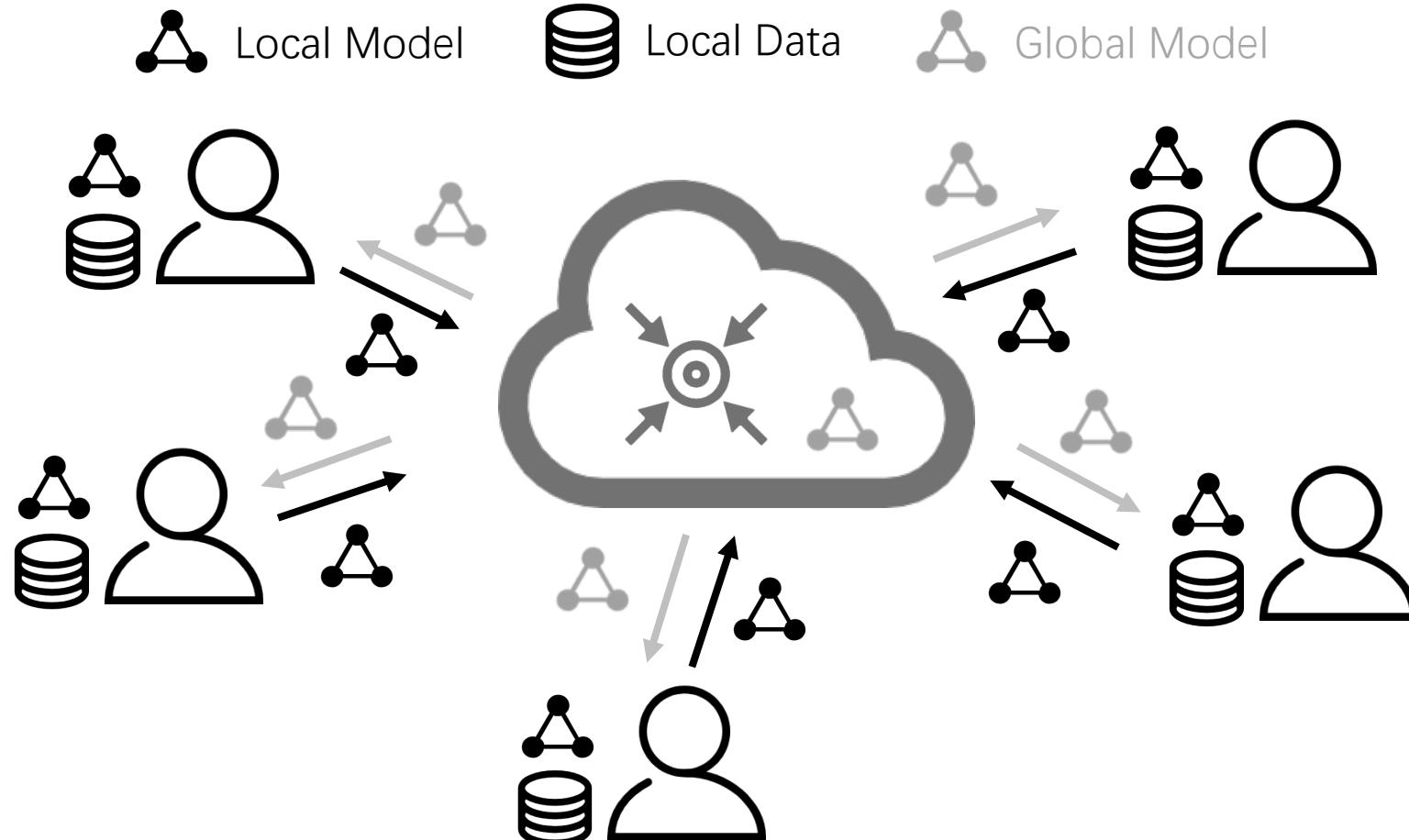


# Overview

- **Research interests**
  - Federated Learning
  - Cloud-Edge Collaboration
- **Open-sourced projects (initiator, main contributor)**
  - PFLlib (1400+ stars, 200+ forks), HtFLlib, FL-IoT, etc.
- **Featured publications (6 accepted papers, first author)**
  - Stage ① [Personalized Federated Learning]:
    - PFLlib, AAAI'23, KDD'23, ICCV'23, NeurIPS'23
  - Stage ② [Heterogeneous Federated Learning]:
    - HtFLlib, AAAI'24, CVPR'24
  - Stage ③ [Cloud-Edge Collaboration]:
    - CVPR'24

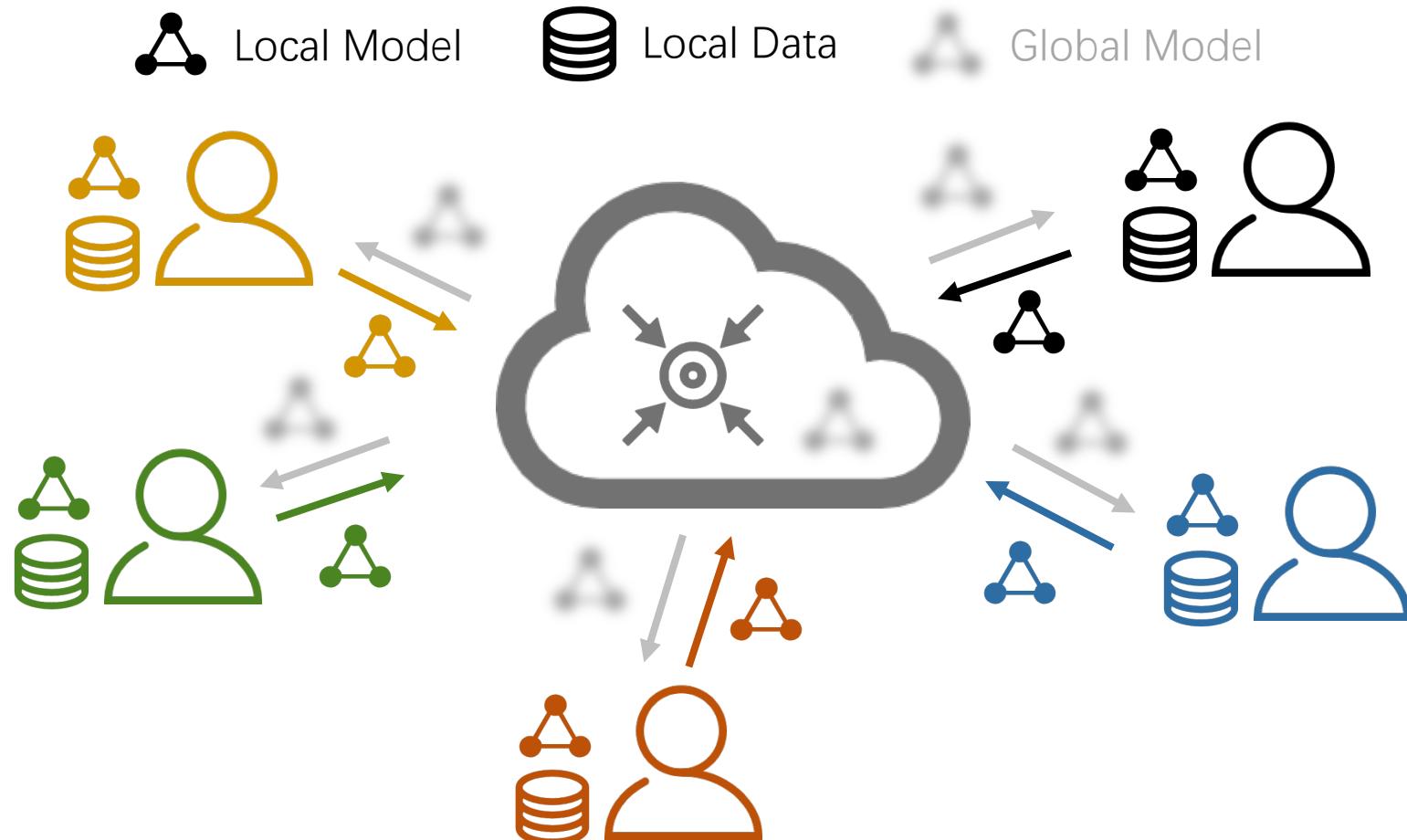
# Federated Learning (FL)

- A **collaborative** and **privacy-preserving** technique for AI model training
- Finally output **one global model** 



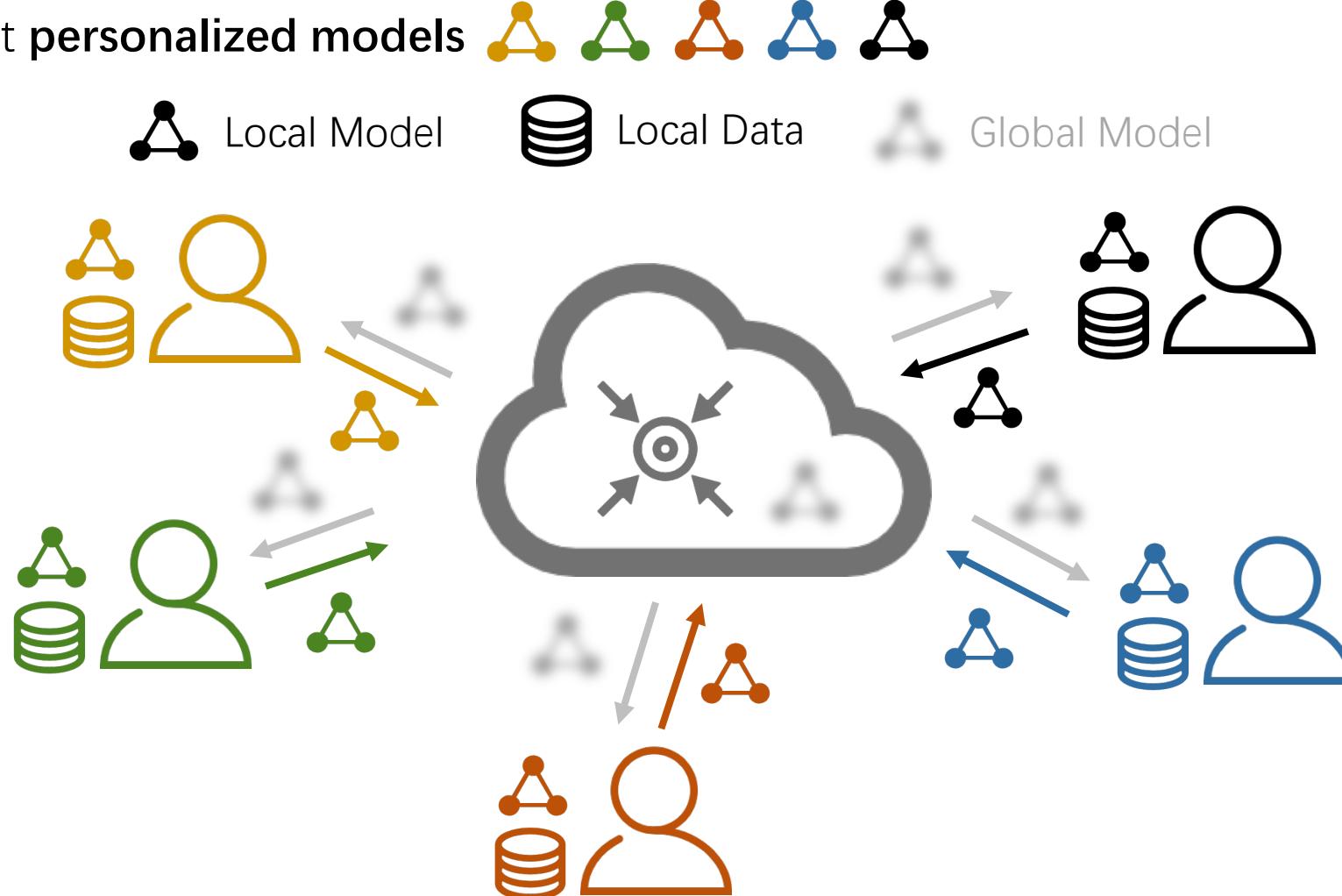
# ① Data Heterogeneity in FL

- Data is **generated in different ways on clients** and forbidden to be shared
- Each client also has **personalized preferences**



# ① [Personalized Federated Learning]

- Utilize the **intermediate** global model to **facilitate local training**
- Finally output **personalized models**



# ① PFLlib: personalized FL (pFL) algorithm library

- Beginner-friendly
- 37 FL&pFL, 3 scenarios, 20 datasets
- Popular (1400+ stars)
- Main contributor
- Rapidly developing:

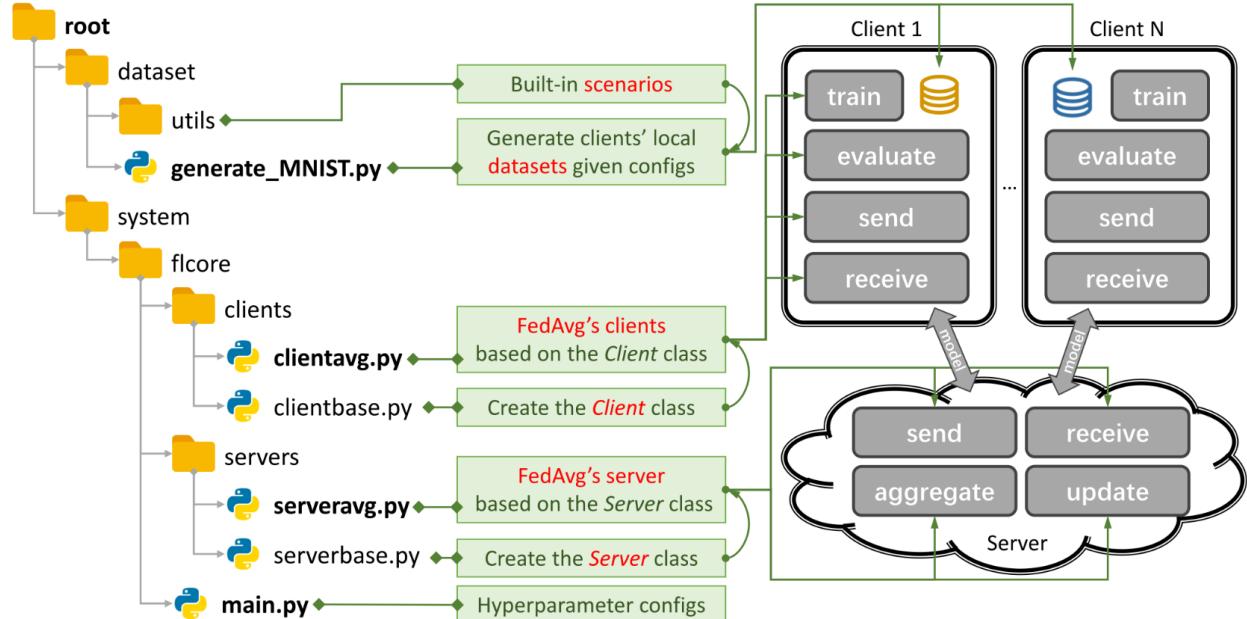
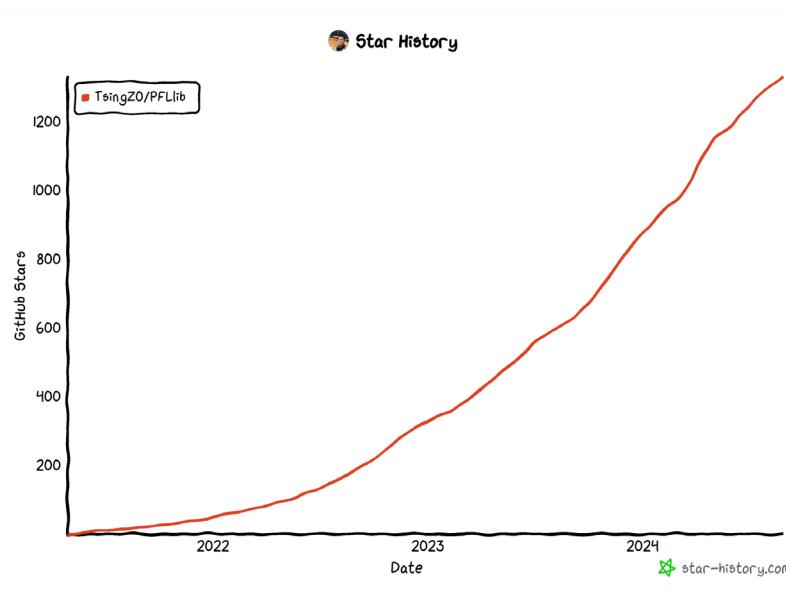


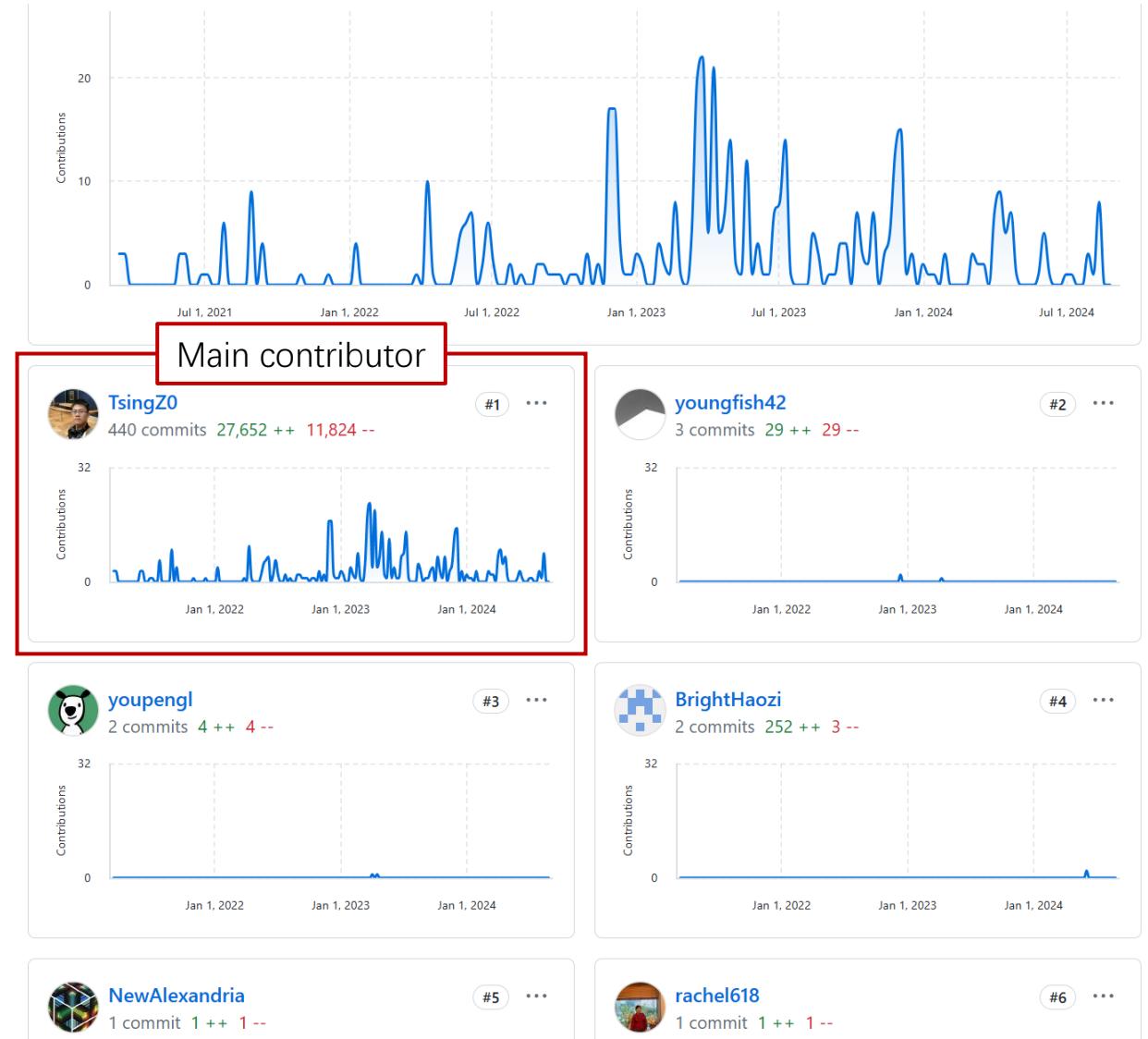
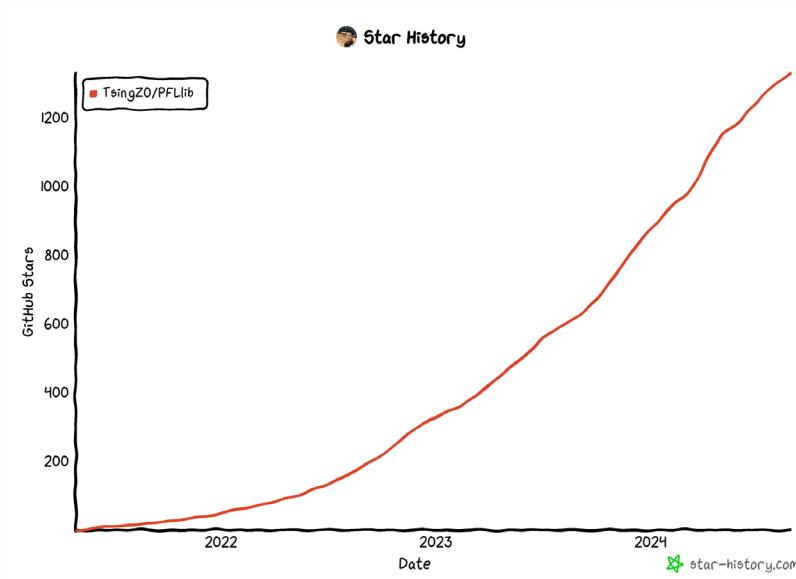
Figure 1: An Example for FedAvg. You can create a scenario using `generate_DATA.py` and run an algorithm using `main.py`, `clientNAME.py`, and `serverNAME.py`.

We've created a user-friendly algorithm library and evaluation platform for those new to federated learning. Join us in expanding the FL community by contributing your algorithms, datasets, and metrics to this project.

- 37 traditional FL ([tFL](#)) or personalized FL ([pFL](#)) algorithms, 3 scenarios, and 20 datasets.
- Some experimental results are available [here](#).
- Refer to [this guide](#) to learn how to use it.
- This library can simulate scenarios using the 4-layer CNN on Cifar100 for 500 clients on one NVIDIA GeForce RTX 3090 GPU card with only 5.08GB GPU memory cost.

# ① PFLlib: personalized FL (pFL) algorithm library

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- 37 FL&pFL, 3 scenarios, 20 datasets
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# ① Publications

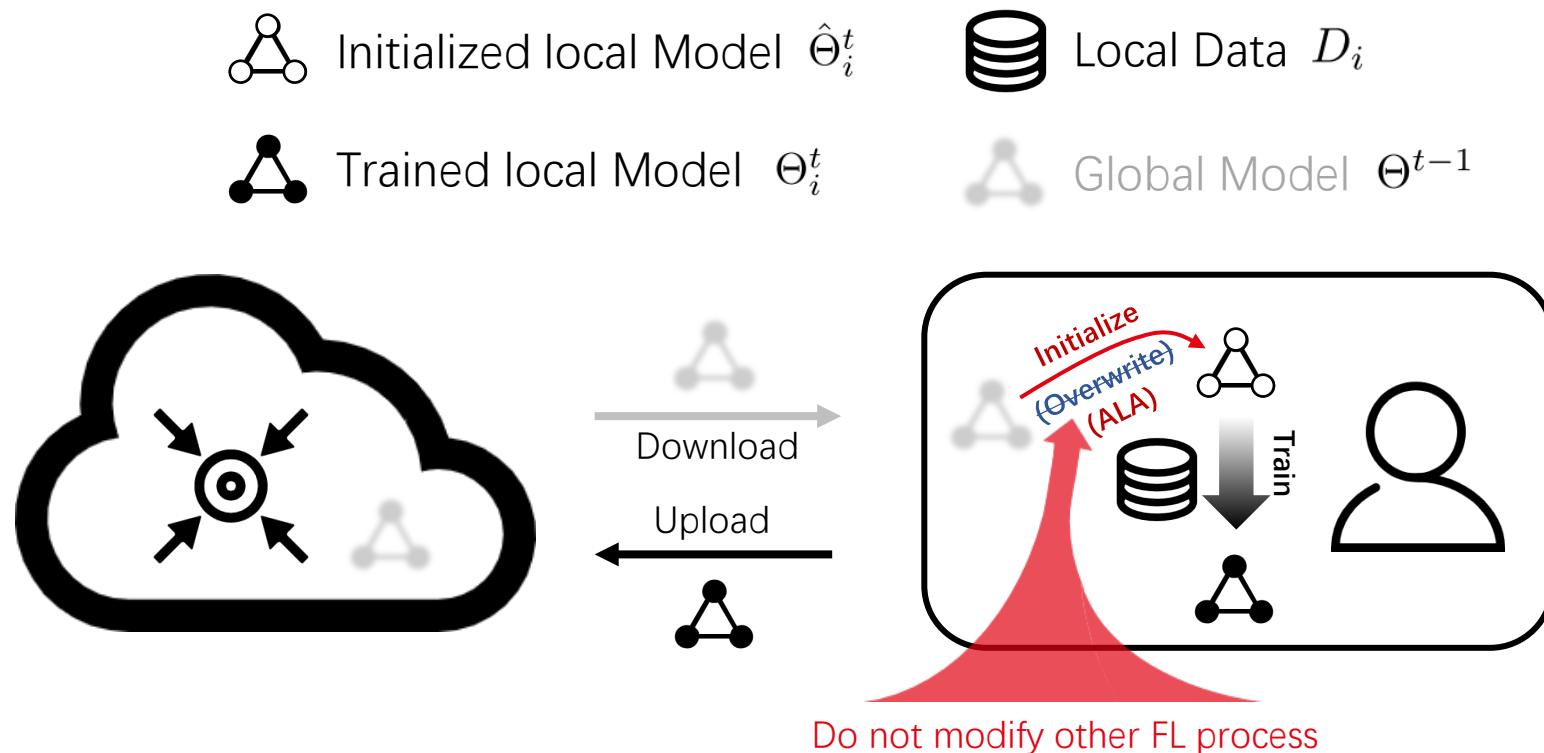
- [AAAI'23] FedALA: Adaptive Local Aggregation for Personalized Federated Learning.
- [KDD'23] FedCP: Separating Feature Information for Personalized Federated Learning via Conditional Policy.
- [ICCV'23] GPFL: Simultaneously Learning Generic and Personalized Feature Information for Personalized Federated Learning.
- [NeurIPS'23] Eliminating Domain Bias for Federated Learning in Representation Space.
- **How can we distinguish both generalization and personalization?**

# ① Publications

- [AAAI'23] FedALA: Adaptive Local Aggregation for Personalized Federated Learning. (It has potential for pre-trained model merging[1])
- [KDD'23] FedCP: Separating Feature Information for Personalized Federated Learning via Conditional Policy.
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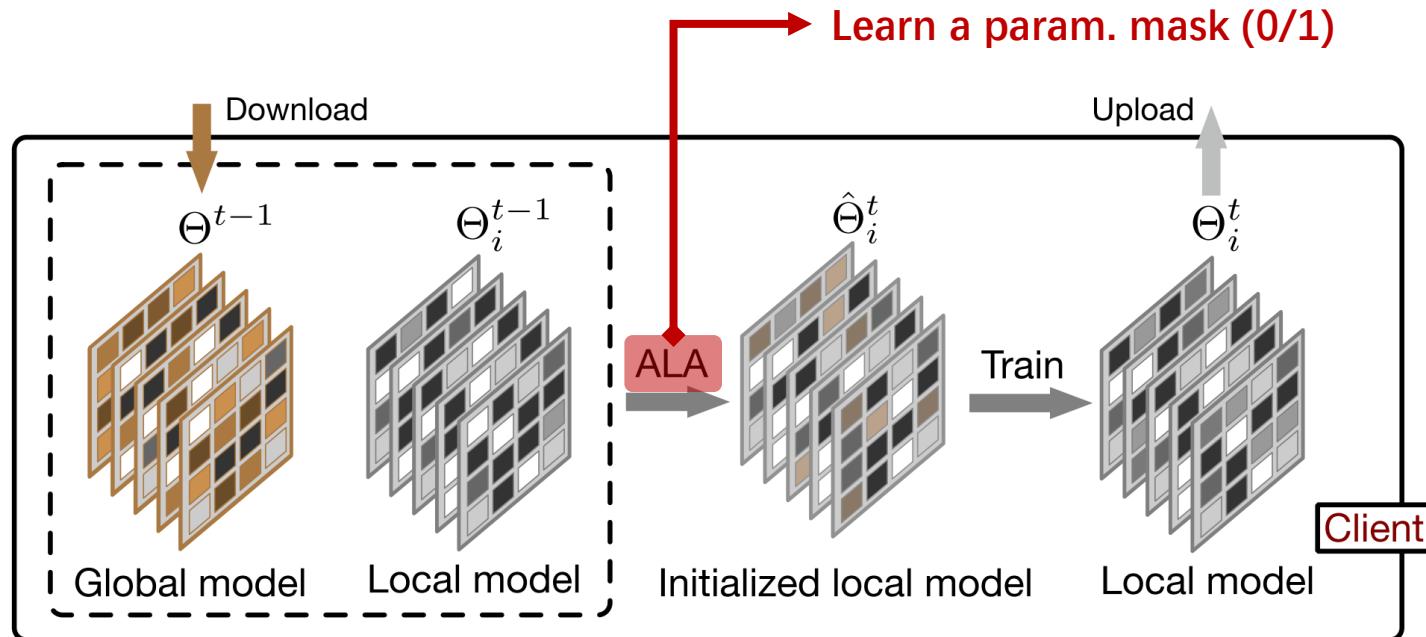
# Existing FL

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



# FedALA

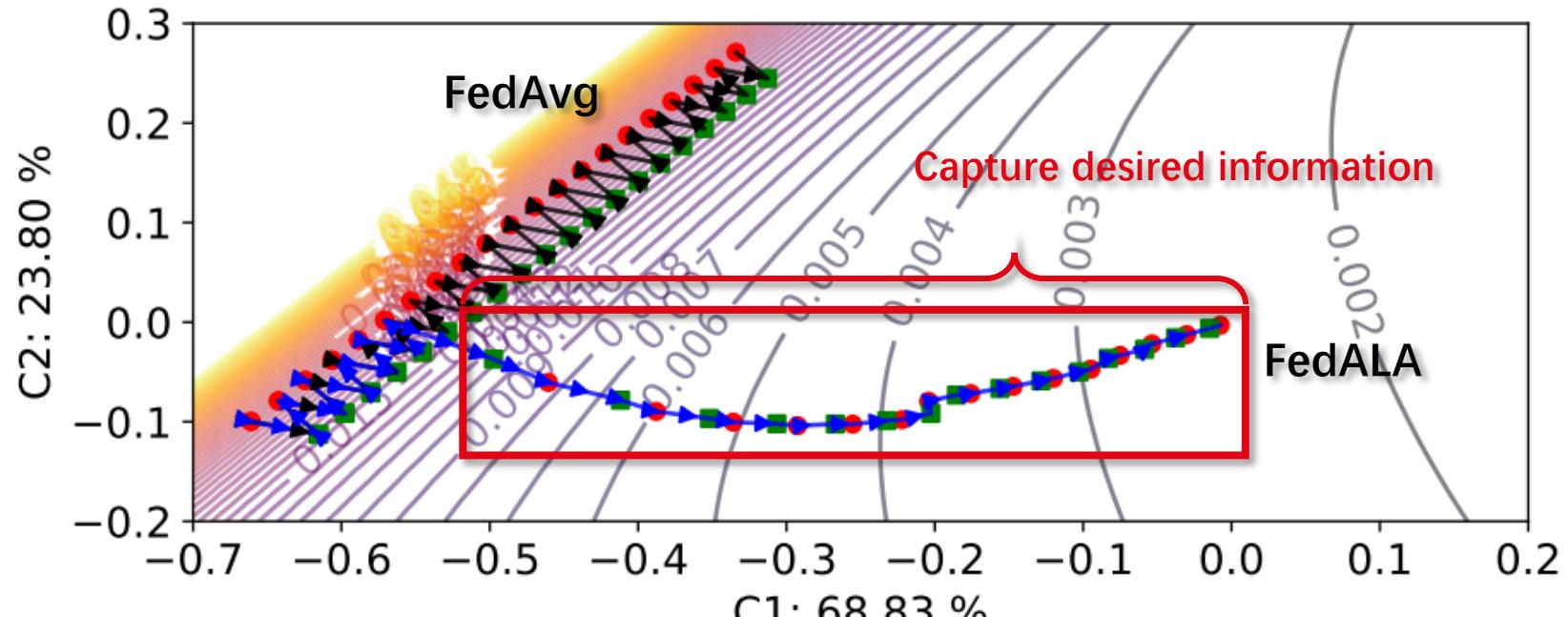
- Extract each client's desired information from the global model that facilitates local training
- Adaptively aggregate the information in the global and local model for initialization



Workflow on the client in one iteration

# FedALA

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



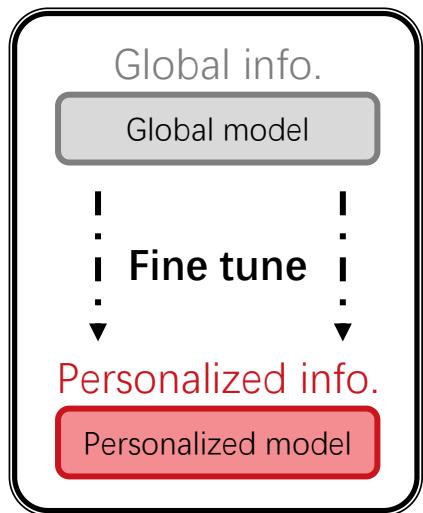
2D visualization of local learning trajectory

# ① Publications

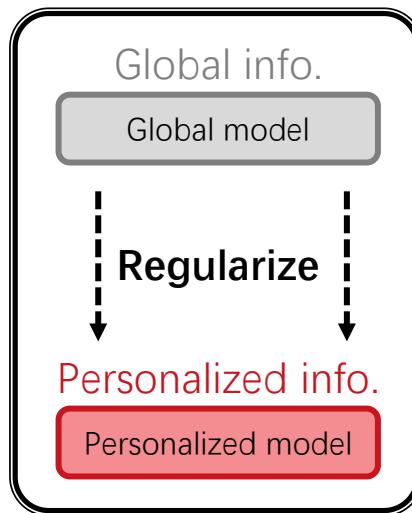
- [AAAI'23] FedALA: Adaptive Local Aggregation for Personalized Federated Learning.
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# Existing pFL

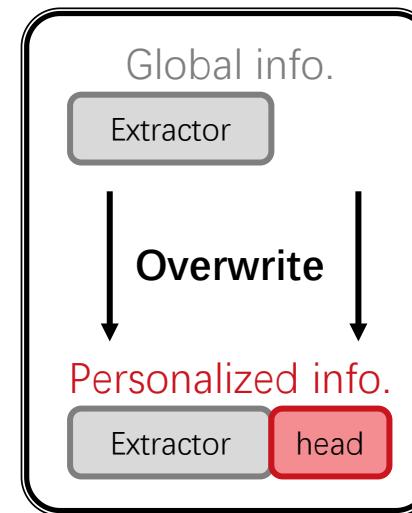
- **Consensus:** reasonably utilizing global and personalized information is the key for pFL.
  - meta-learning-based (Per-FedAvg), regularization-based (Ditto), and personalized-head-based (FedRep) pFL.



Per-FedAvg[1]



Ditto[2]



FedRep[3]

- They only focus on model parameters, but **ignore the source of information: data.**

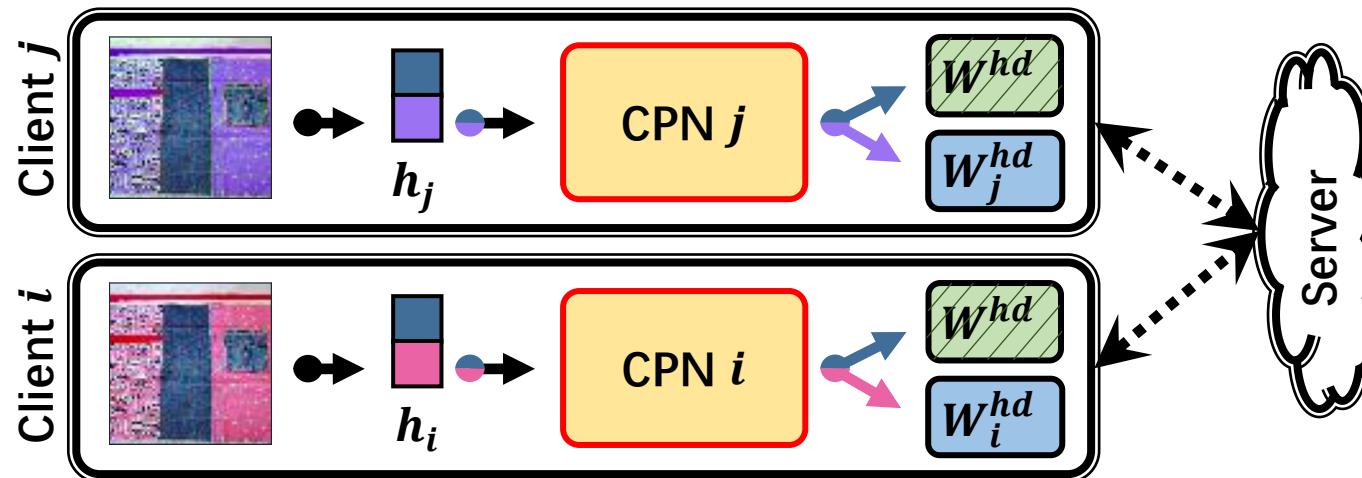
[1] Fallah A, Mokhtari A, Ozdaglar A. Personalized federated learning with theoretical guarantees: A model-agnostic meta-learning approach. NeurIPS, 2020.

[2] Li T, Hu S, Beirami A, et al. Ditto: Fair and robust federated learning through personalization. ICML, 2021.

[3] Collins L, Hassani H, Mokhtari A, et al. utilizing shared representations for personalized federated learning. ICML, 2021.

# FedCP

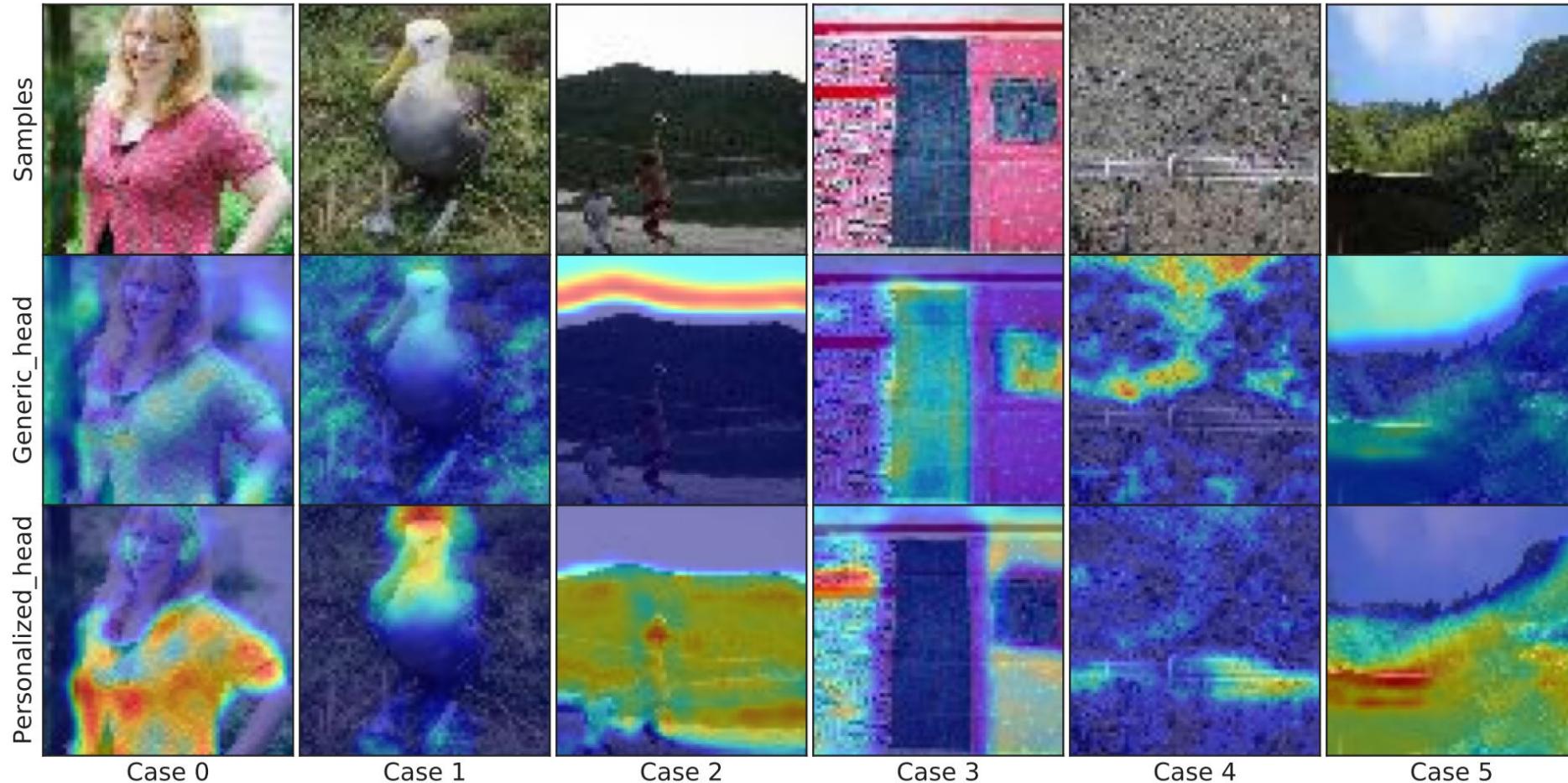
- We separate feature information via an auxiliary **Conditional Policy Network (CPN)**.
  - Sample-specific separation
  - Lightweight (e.g., 4.67% parameters of ResNet-18)



- Then, we utilize global and personalized information via global and personalized heads.

# FedCP

- Separating Feature Information



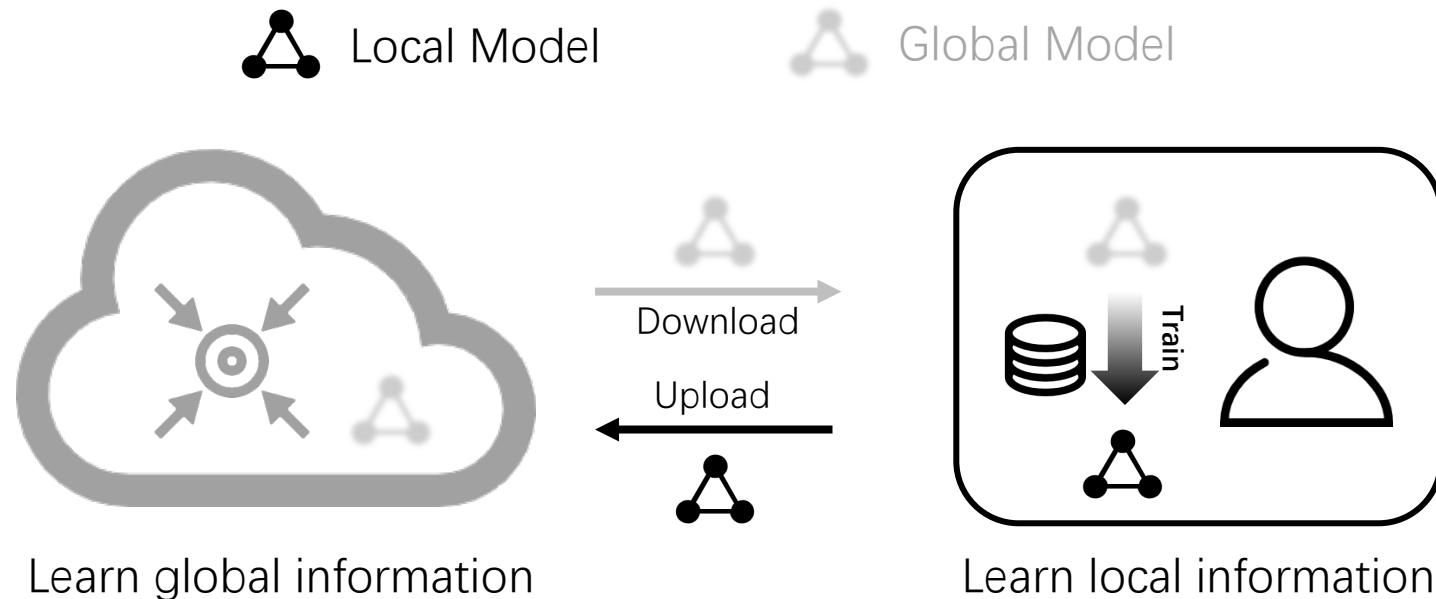
Six samples from the Tiny-ImageNet dataset

# ① Publications

- [AAAI'23] FedALA: Adaptive Local Aggregation for Personalized Federated Learning.
- [KDD'23] FedCP: Separating Feature Information for Personalized Federated Learning via Conditional Policy.
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# Existing pFL

- Most pFL learns global and personalized information **alternatively**
- **Catastrophic forgetting:** global knowledge is lost during local training



# GPFL

- GCE introduces more global information **simultaneously** with local training
- CoV **eliminates the interaction** between global and personalized feature learning

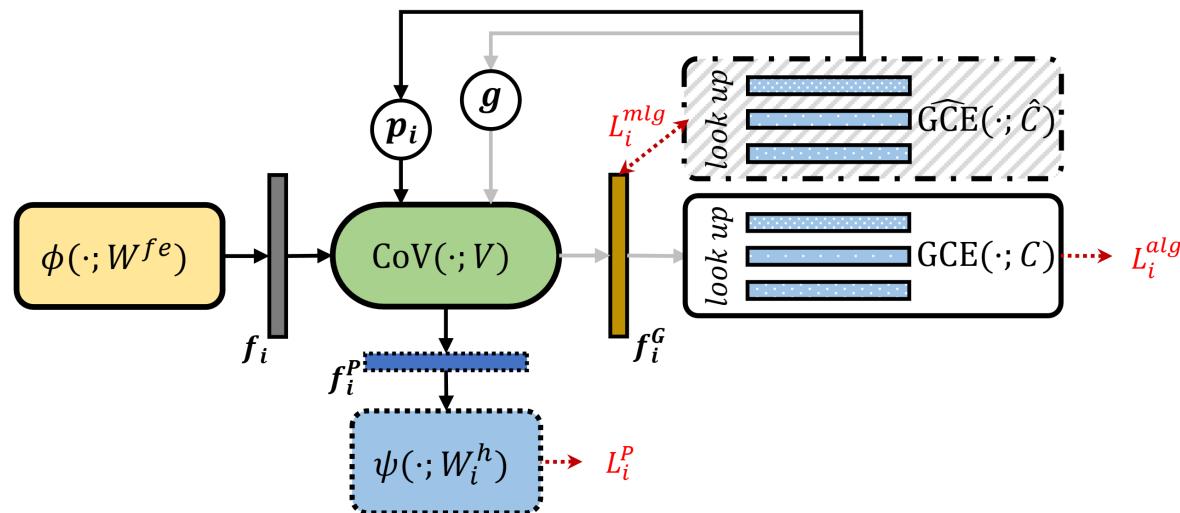
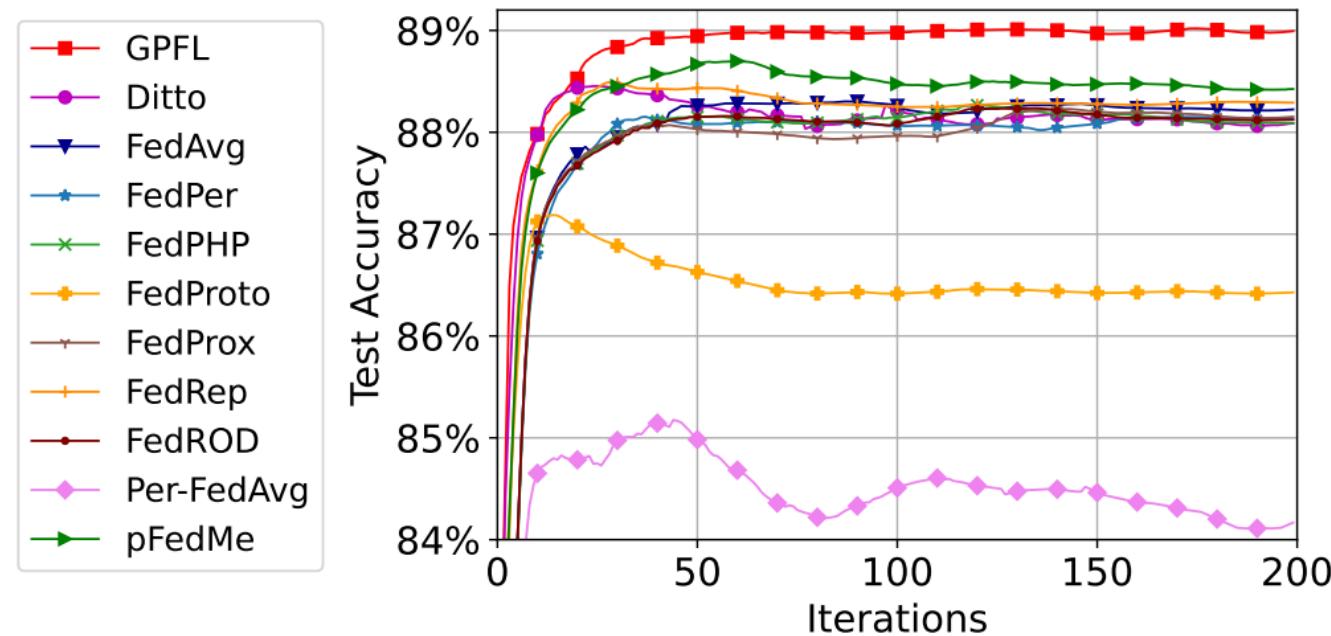


Illustration of client modules and data flow between them

# GPFL

- Relieve the **widely existed** overfitting issue in pFL



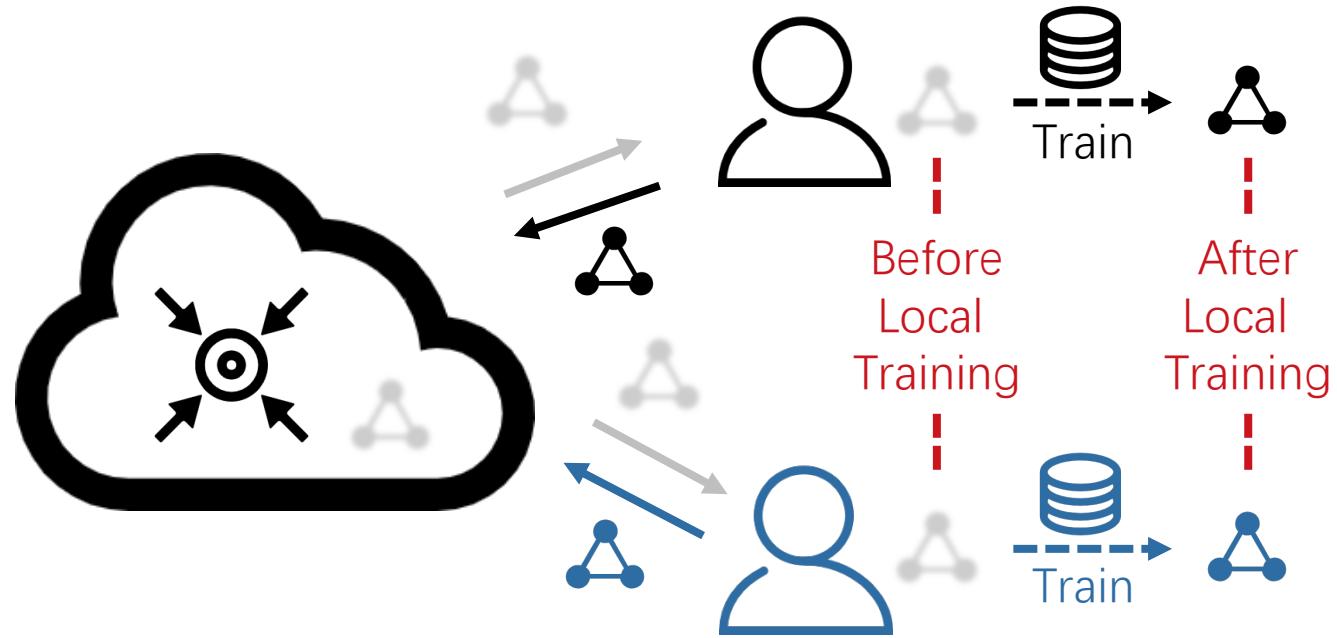
Test accuracy curves in the feature shift setting

# ① Publications

- [AAAI'23] FedALA: Adaptive Local Aggregation for Personalized Federated Learning.
- [KDD'23] FedCP: Separating Feature Information for Personalized Federated Learning via Conditional Policy.
- [ICCV'23] GPFL: Simultaneously Learning Generic and Personalized Feature Information for Personalized Federated Learning.
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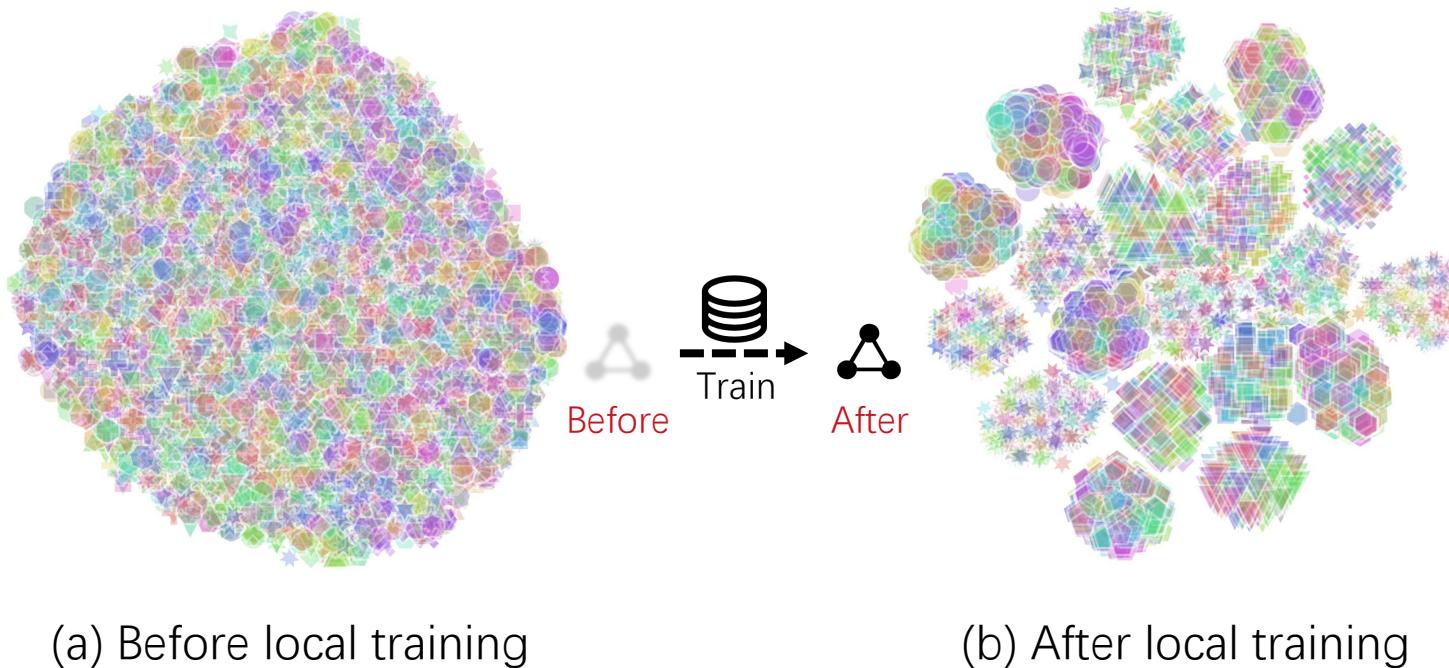
# Existing FL

- Clients' local training turns the received global model to client-specific local models



# Existing FL

- After local training, the feature representations are **biased** to client-specific domains

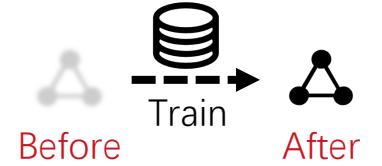


(a) Before local training

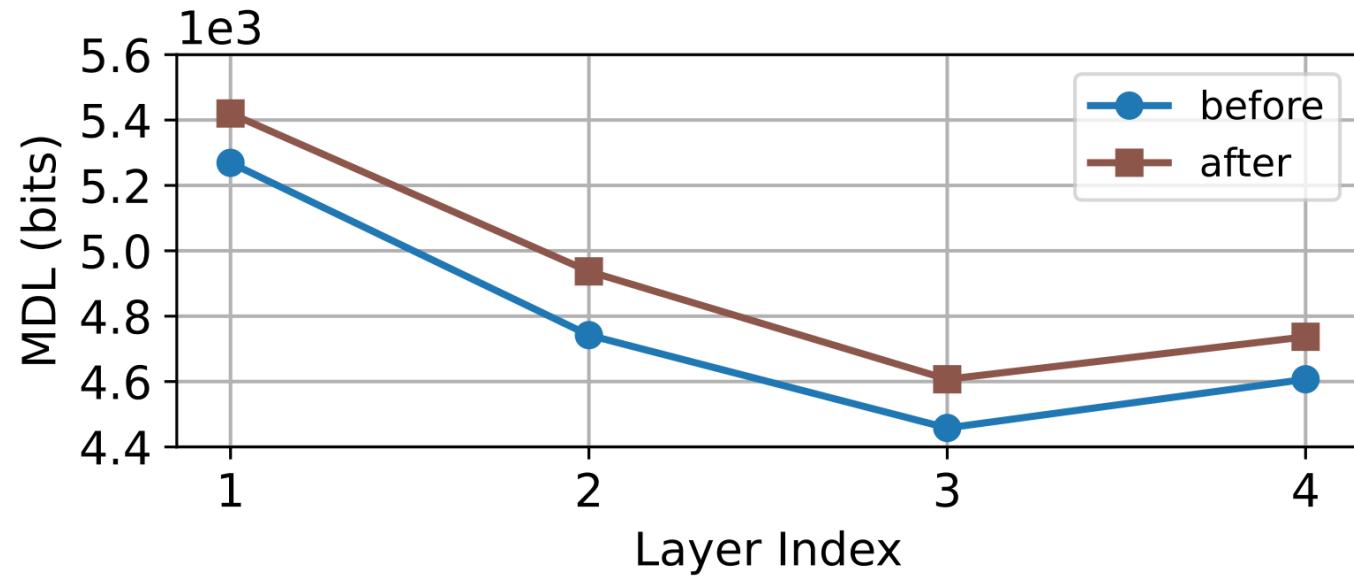
(b) After local training

We use *color* and *shape* to distinguish *labels* and *clients*, respectively.

# Existing FL



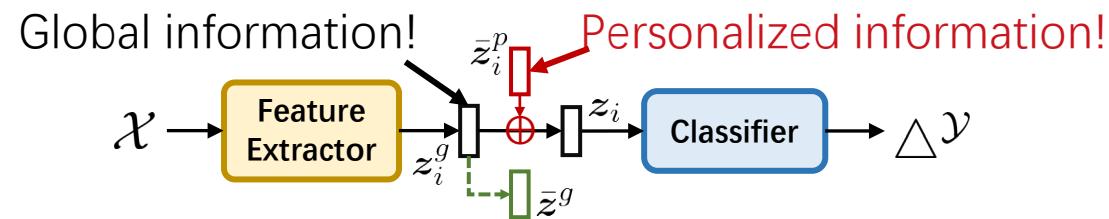
- At the same time, representations' quality is also **degenerated**



Per-layer MDL (bits) for representations before/after local training in FedAvg.  
A large MDL value means low representation quality.

# DBE

- Eliminate domain bias by store **personalized information** in **PRBM**
- Enhance **information disentanglement** by guiding feature extractor with **MR**



Local model (with PRBM and MR)

# DBE

- Improve bi-directional knowledge transfer
- Local-to-global knowledge transfer

**Corollary 1.** Consider a local data domain  $\mathcal{D}_i$  and a virtual global data domain  $\mathcal{D}$  for client  $i$  and the server, respectively. Let  $\mathcal{D}_i = \langle \mathcal{U}_i, c^* \rangle$  and  $\mathcal{D} = \langle \mathcal{U}, c^* \rangle$ , where  $c^* : \mathcal{X} \mapsto \mathcal{Y}$  is a ground-truth labeling function. Let  $\mathcal{H}$  be a hypothesis space of VC dimension  $d$  and  $h : \mathcal{Z} \mapsto \mathcal{Y}, \forall h \in \mathcal{H}$ . When using DBE, given a feature extraction function  $\mathcal{F}^g : \mathcal{X} \mapsto \mathcal{Z}$  that shared between  $\mathcal{D}_i$  and  $\mathcal{D}$ , a random labeled sample of size  $m$  generated by applying  $\mathcal{F}^g$  to a random sample from  $\mathcal{U}_i$  labeled according to  $c^*$ , then for every  $h^g \in \mathcal{H}$ , with probability at least  $1 - \delta$ :

$$\mathcal{L}_{\mathcal{D}}(h^g) \leq \mathcal{L}_{\hat{\mathcal{D}}_i}(h^g) + \sqrt{\frac{4}{m} \left( d \log \frac{2em}{d} + \log \frac{4}{\delta} \right)} + d_{\mathcal{H}}(\tilde{\mathcal{U}}_i^g, \tilde{\mathcal{U}}^g) + \lambda_i,$$

where  $\mathcal{L}_{\hat{\mathcal{D}}_i}$  is the empirical loss on  $\mathcal{D}_i$ ,  $e$  is the base of the natural logarithm, and  $d_{\mathcal{H}}(\cdot, \cdot)$  is the  $\mathcal{H}$ -divergence between two distributions.  $\lambda_i := \min_{h^g} \mathcal{L}_{\mathcal{D}}(h^g) + \mathcal{L}_{\mathcal{D}_i}(h^g)$ ,  $\tilde{\mathcal{U}}_i^g \subseteq \mathcal{Z}$ ,  $\tilde{\mathcal{U}}^g \subseteq \mathcal{Z}$ , and  $d_{\mathcal{H}}(\tilde{\mathcal{U}}_i^g, \tilde{\mathcal{U}}^g) \leq d_{\mathcal{H}}(\tilde{\mathcal{U}}_i, \tilde{\mathcal{U}})$ .  $\tilde{\mathcal{U}}_i^g$  and  $\tilde{\mathcal{U}}^g$  are the induced distributions of  $\mathcal{U}_i$  and  $\mathcal{U}$  under  $\mathcal{F}^g$ , respectively.  $\tilde{\mathcal{U}}_i$  and  $\tilde{\mathcal{U}}$  are the induced distributions of  $\mathcal{U}_i$  and  $\mathcal{U}$  under  $\mathcal{F}$ , respectively.  $\mathcal{F}$  is the feature extraction function in the original FedAvg without DBE.

# DBE

- Improve bi-directional knowledge transfer
- Global-to-local knowledge transfer

**Corollary 2.** Let  $\mathcal{D}_i$ ,  $\mathcal{D}$ ,  $\mathcal{F}^g$ , and  $\lambda_i$  defined as in Corollary 1. Given a translation transformation function PRBM :  $\mathcal{Z} \mapsto \mathcal{Z}$  that shared between  $\mathcal{D}_i$  and virtual  $\mathcal{D}$ , a random labeled sample of size  $m$  generated by applying  $\mathcal{F}'$  to a random sample from  $\mathcal{U}_i$  labeled according to  $c^*$ ,  $\mathcal{F}' = \text{PRBM} \circ \mathcal{F}^g : \mathcal{X} \mapsto \mathcal{Z}$ , then for every  $h' \in \mathcal{H}$ , with probability at least  $1 - \delta$ :

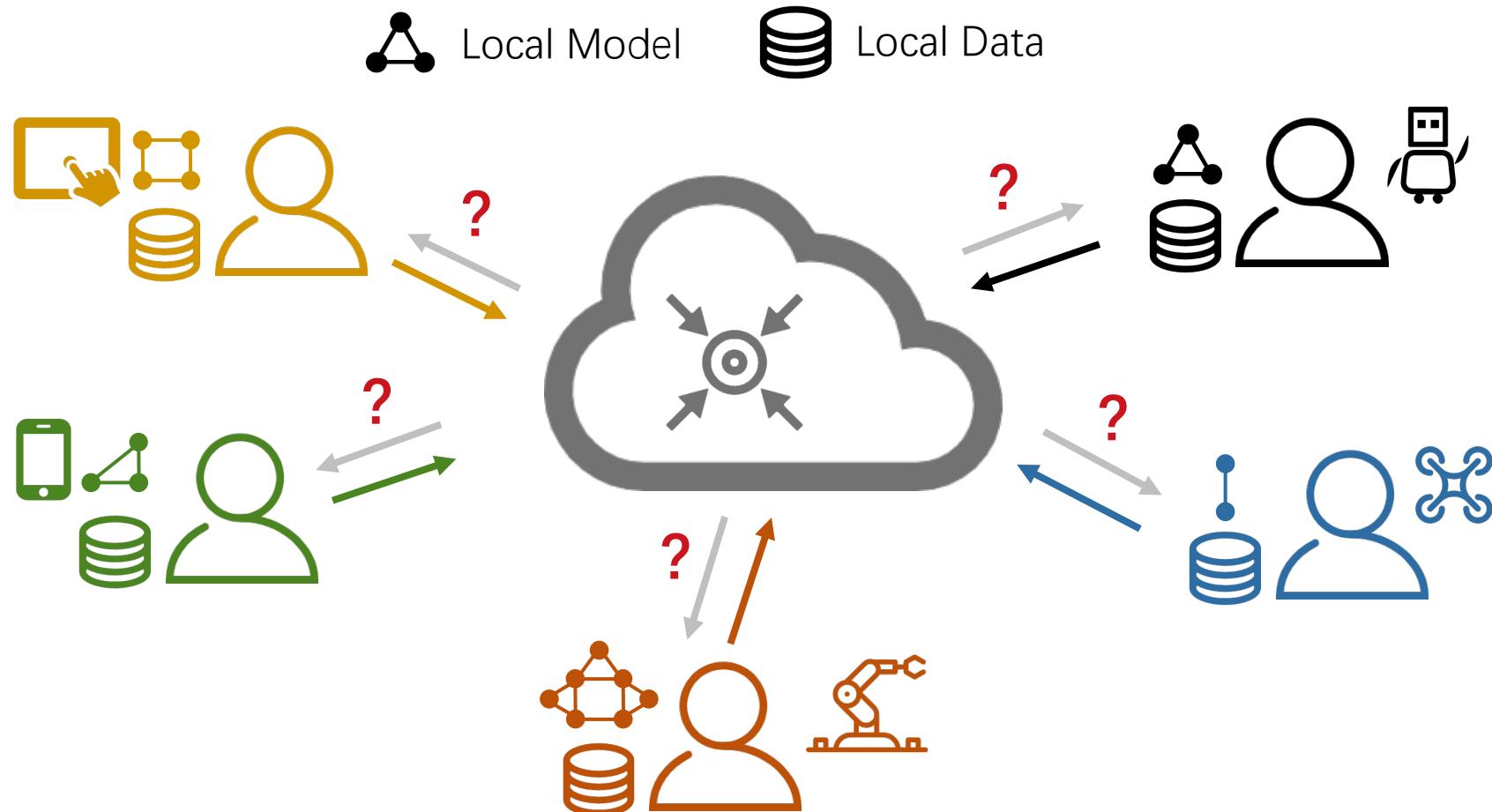
$$\mathcal{L}_{\mathcal{D}_i}(h') \leq \mathcal{L}_{\hat{\mathcal{D}}}(h') + \sqrt{\frac{4}{m} \left( d \log \frac{2em}{d} + \log \frac{4}{\delta} \right)} + d_{\mathcal{H}}(\tilde{\mathcal{U}}', \tilde{\mathcal{U}}'_i) + \lambda_i,$$

where  $d_{\mathcal{H}}(\tilde{\mathcal{U}}', \tilde{\mathcal{U}}'_i) = d_{\mathcal{H}}(\tilde{\mathcal{U}}^g, \tilde{\mathcal{U}}_i^g) \leq d_{\mathcal{H}}(\tilde{\mathcal{U}}, \tilde{\mathcal{U}}_i) = d_{\mathcal{H}}(\tilde{\mathcal{U}}_i, \tilde{\mathcal{U}})$ .  $\tilde{\mathcal{U}}'$  and  $\tilde{\mathcal{U}}'_i$  are the induced distributions of  $\mathcal{U}$  and  $\mathcal{U}_i$  under  $\mathcal{F}'$ , respectively.

Please refer to our paper for proofs.

## ② Data and Model Heterogeneity in FL

- Device heterogeneity and intellectual property
- Low bandwidth: **What** should be transmitted?



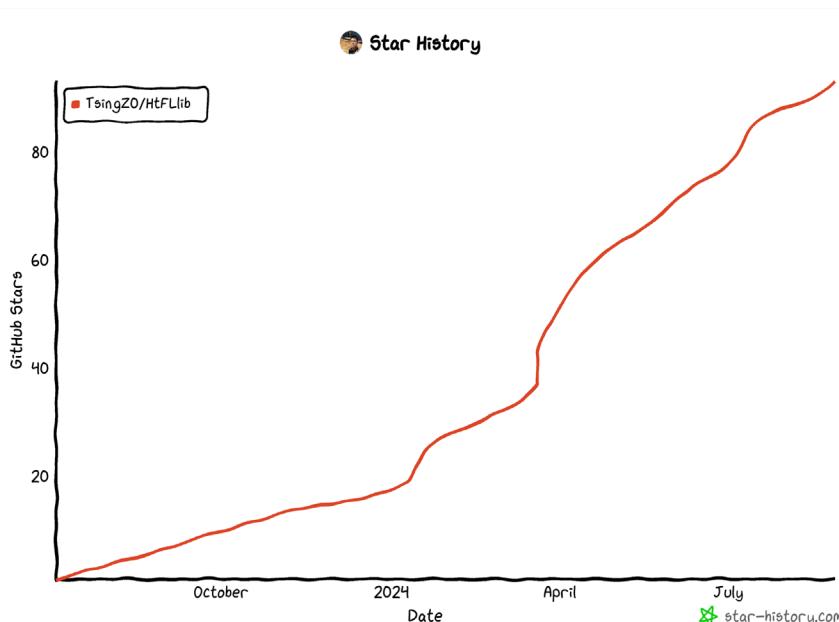
## ② [Heterogeneous Federated Learning]

- Transmits **lightweight information carriers** instead of exposing model parameters
- Typically uses **knowledge distillation**-based approaches



# ② HtFLlib: heterogeneous FL algorithm library

- Beginner-friendly
- PFLlib compatible
- 9 data-free HtFL, 21 types of models
- Main contributor
- Rapidly developing:



## Scenarios and datasets

Here, we only show the MNIST dataset in the *label skew* scenario generated via Dirichlet distribution for example. Please refer to my other repository [PFLlib](#) for more help.

You can also modify codes in PFLlib to support model heterogeneity scenarios, but it requires much effort. In this repository, you only need to configure `system/main.py` to support model heterogeneity scenarios.

**Note:** you may need to manually clean checkpoint files in the `temp/` folder via `system/clean_temp_files.py` if your program crashes accidentally. You can also set a checkpoint folder by yourself to prevent automatic deletion using the `-sfn` argument in the command line.

## Data-free algorithms with code (updating)

Here, "data-free" refers to the absence of any additional dataset beyond the clients' private data. We only consider data-free algorithms here, as they have fewer restrictions and assumptions, making them more valuable and easily extendable to other scenarios, such as the existence of public server data.

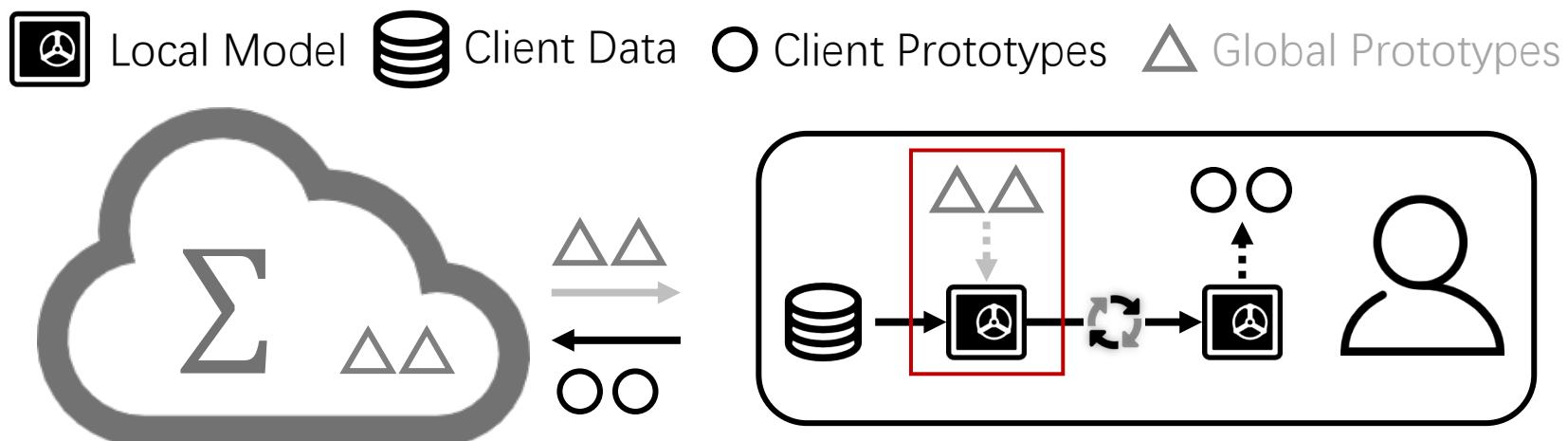
- Local — Each client trains its model locally without federation.
- FedDistill (FD) — [Communication-Efficient On-Device Machine Learning: Federated Distillation and Augmentation under Non-IID Private Data 2018](#)
- FML — [Federated Mutual Learning 2020](#)
- LG-FedAvg — [Think Locally, Act Globally: Federated Learning with Local and Global Representations 2020](#)
- FedGen — [Data-Free Knowledge Distillation for Heterogeneous Federated Learning ICML 2021](#)
- FedProto — [FedProto: Federated Prototype Learning across Heterogeneous Clients AAAI 2022](#)
- FedKD — [Communication-efficient federated learning via knowledge distillation Nature Communications 2022](#)
- FedGH — [FedGH: Heterogeneous Federated Learning with Generalized Global Header ACM MM 2023](#)
- FedTGP — [FedTGP: Trainable Global Prototypes with Adaptive-Margin-Enhanced Contrastive Learning for Data and Model Heterogeneity in Federated Learning AAAI 2024](#)
- FedKTL — [An Upload-Efficient Scheme for Transferring Knowledge From a Server-Side Pre-trained Generator to Clients in Heterogeneous Federated Learning CVPR 2024](#) (Note: FedKTL requires pre-trained generators to run, please refer to its [project page](#) for download links.)

## ② Publications

- [AAAI'24] FedTGP: Trainable Global Prototypes with Adaptive-Margin-Enhanced Contrastive Learning for Data and Model Heterogeneity in Federated Learning.
- [CVPR'24] ~~An Upload-Efficient Scheme for Transferring Knowledge From a Server-Side Pre-trained Generator to Clients in Heterogeneous Federated Learning. (It is also applicable in HtFL, but will be introduced later.)~~
- How can knowledge be shared and aggregated to benefit participants?

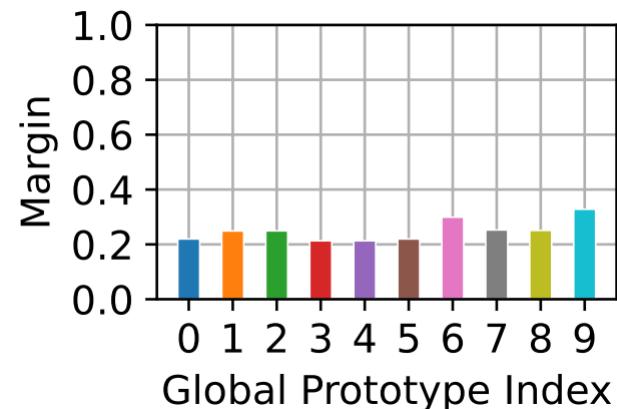
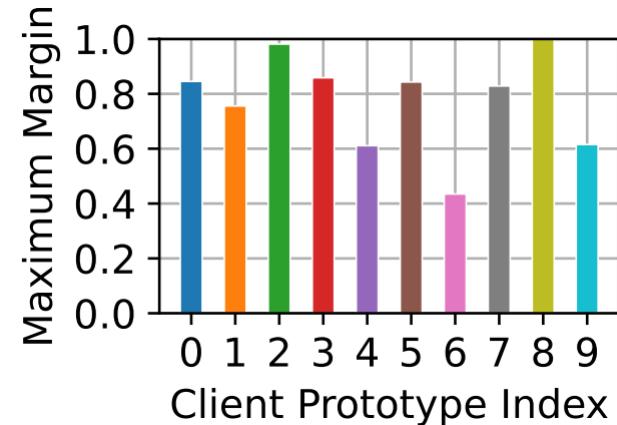
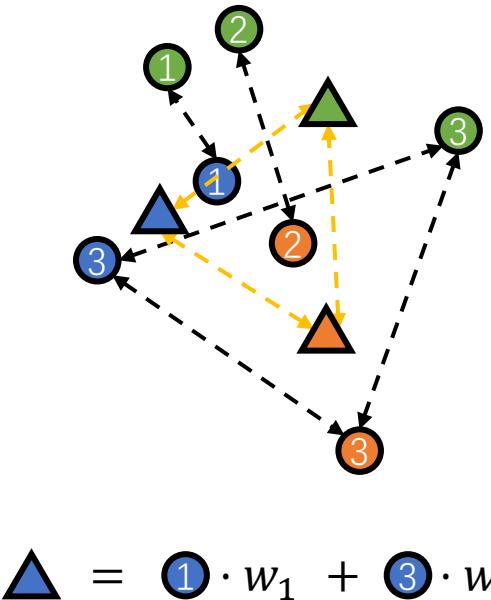
# Existing HtFL

- Share **client prototypes** (class representatives) with the server
- Aggregate client prototypes to generate **global prototypes**
- Train client models in a **knowledge distillation** manner in feature space



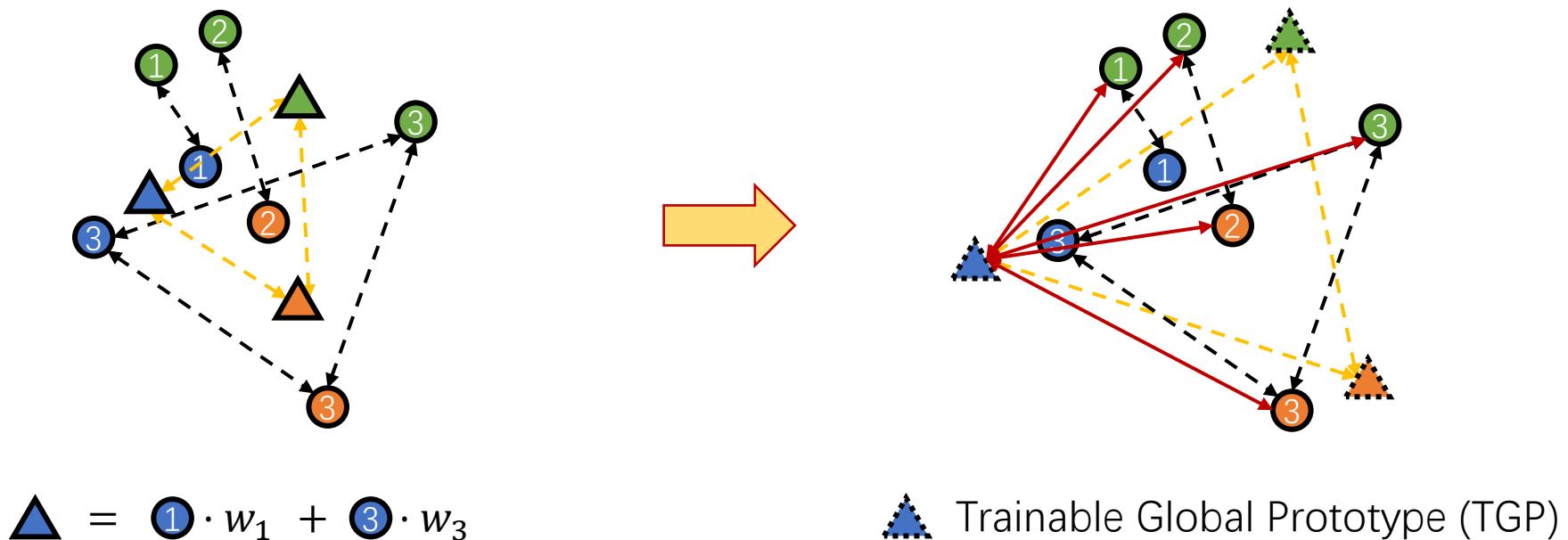
# Existing HtFL

- Global prototype ( $\Delta$ ) margin **shrinks** after weighted-averaging



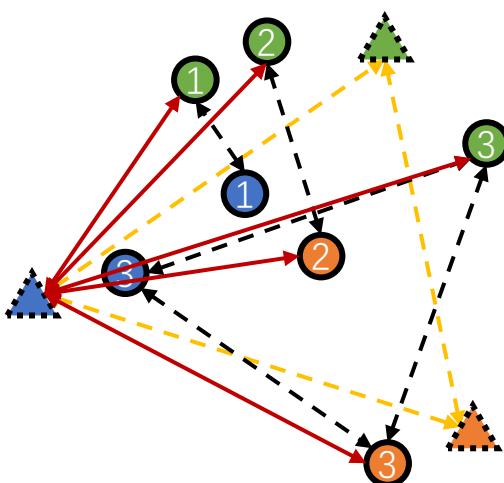
# FedTGP

- Remove weighted-averaging
- Consider the uploaded client prototypes as data
- **Enlarge** the global prototype margin

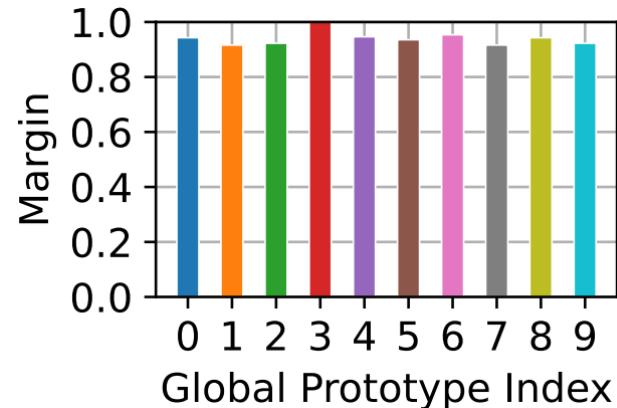
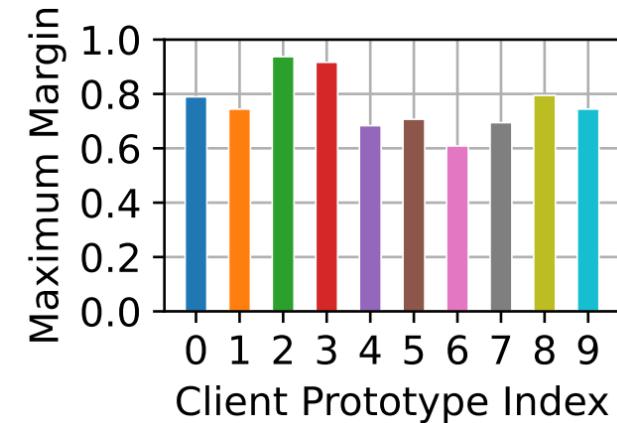


# FedTGP

- Remove weighted-averaging
- Consider the uploaded client prototypes as data
- **Enlarge** the global prototype margin



▲ Trainable Global Prototype (TGP)



# FedTGP

- Server objective: **Enlarge** the global prototype **margin** to improve discrimination
- **Train global prototypes** using **Adaptive-margin-enhanced Contrastive Learning (ACL)**

$$\min_{\hat{\mathcal{P}}} \sum_{c=1}^C \mathcal{L}_P^c,$$

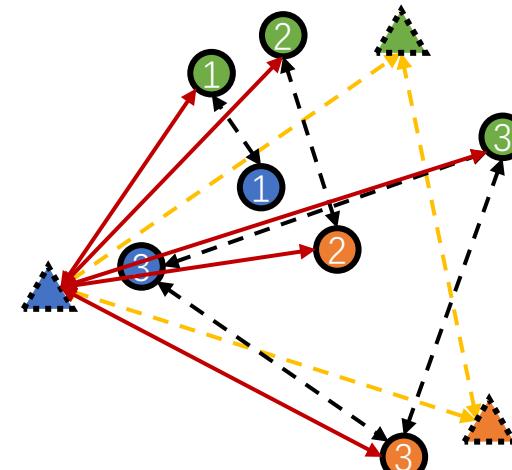
$$\mathcal{L}_P^c = \sum_{i \in \mathcal{I}^t} -\log \frac{e^{-(\phi(P_i^c, \hat{P}^c) + \delta(t))}}{e^{-(\phi(P_i^c, \hat{P}^c) + \delta(t))} + \sum_{c'} e^{-\phi(P_i^c, \hat{P}^{c'})}}$$

$$\delta(t) = \min(\max_{c \in [C], c' \in [C], c \neq c'} \phi(Q_t^c, Q_t^{c'}), \tau),$$

$$Q_t^c = \frac{1}{|\mathcal{P}_t^c|} \sum_{i \in \mathcal{I}^t} P_i^c, \forall c \in [C]$$

$\tau$  is a margin threshold

maximum cluster margin



- ▲  $\hat{P}^c$ : A TGP of class  $c$
- ▲  $\hat{\mathcal{P}}$ : All TGP
- $P_i^c$ : A prototype of class  $c$  from client  $i$

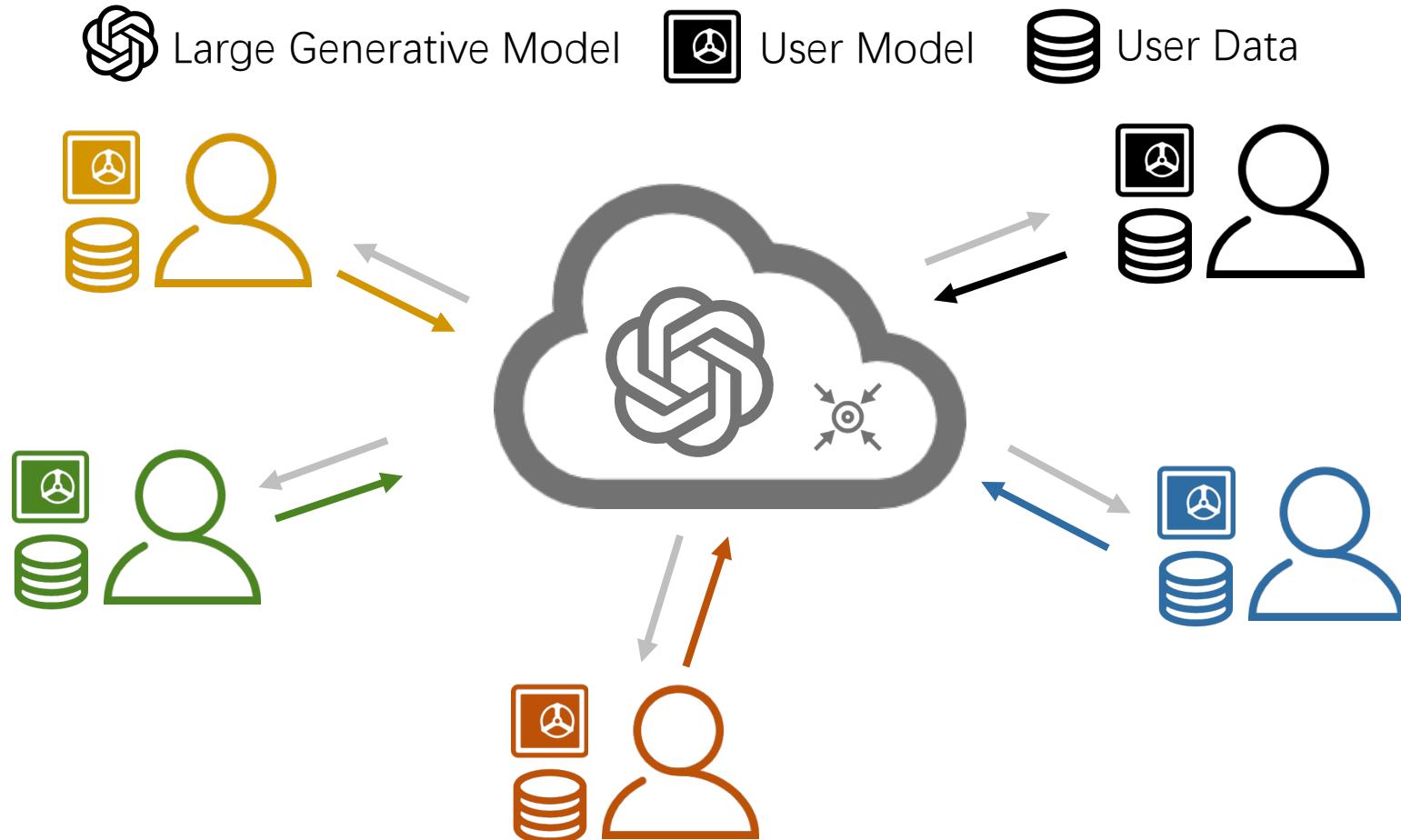
# FedTGP

- **ACL** can also be applied to other tasks and scenarios

$$\mathcal{L}_P^c = \sum_{i \in \mathcal{I}^t} -\log \frac{e^{-(\phi(P_i^c, \hat{P}^c) + \delta(t))}}{e^{-(\phi(P_i^c, \hat{P}^c) + \delta(t))} + \sum_{c'} e^{-\phi(P_i^c, \hat{P}^{c'})}}$$

# ③ Cloud-Edge Collaboration

- Transfer **common knowledge** from server to clients
- Transfer **task-specific knowledge** among clients

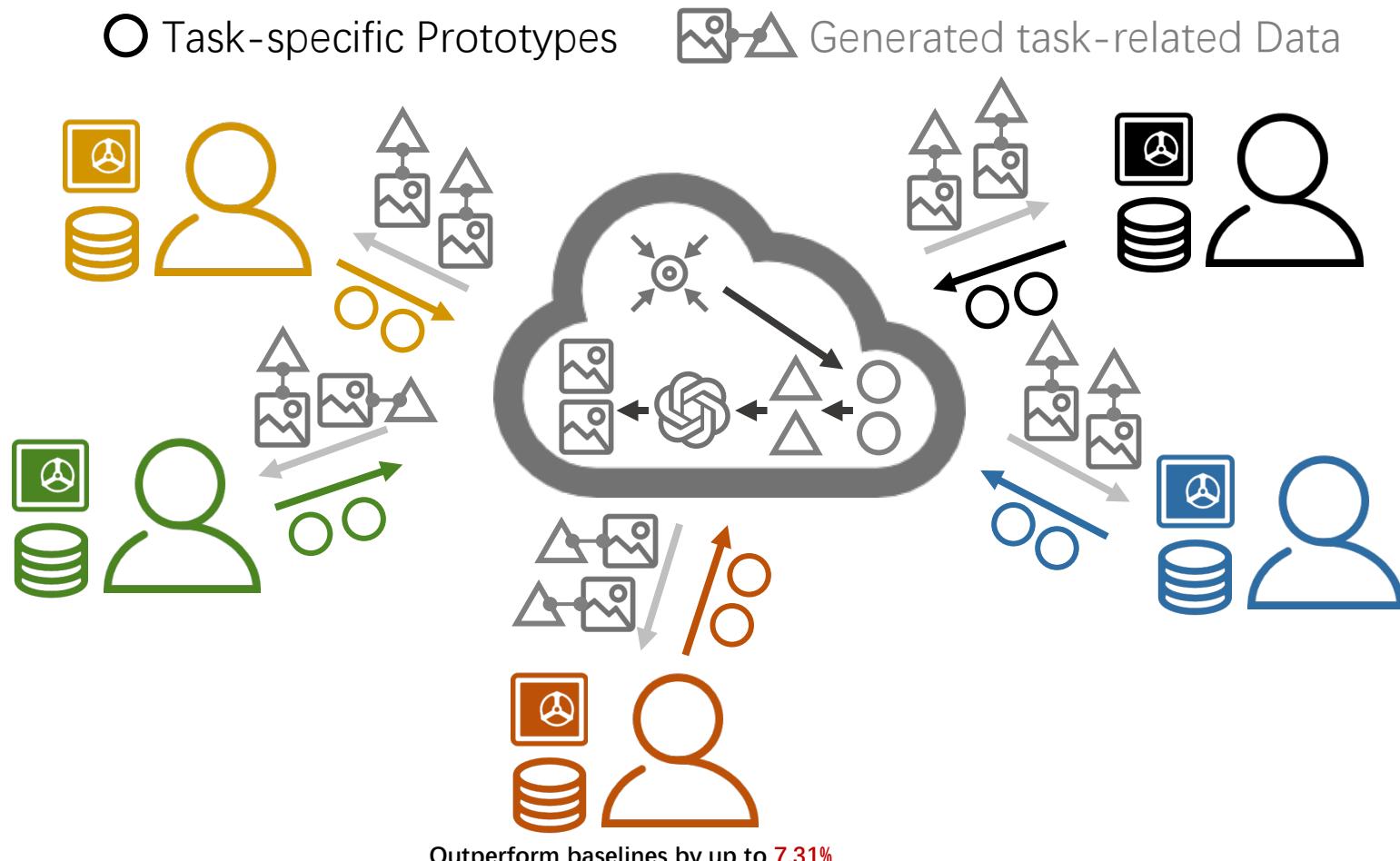


### ③ Publications

- [CVPR'24] An Upload-Efficient Scheme for Transferring Knowledge From a Server-Side Pre-trained Generator to Clients in Heterogeneous Federated Learning.
  - The **first one** that integrates a large generative model (Stable Diffusion, etc.) into heterogeneous small models (ResNets, ViTs, etc.) collaboration
- How to obtain and transfer common and task-specific knowledge?

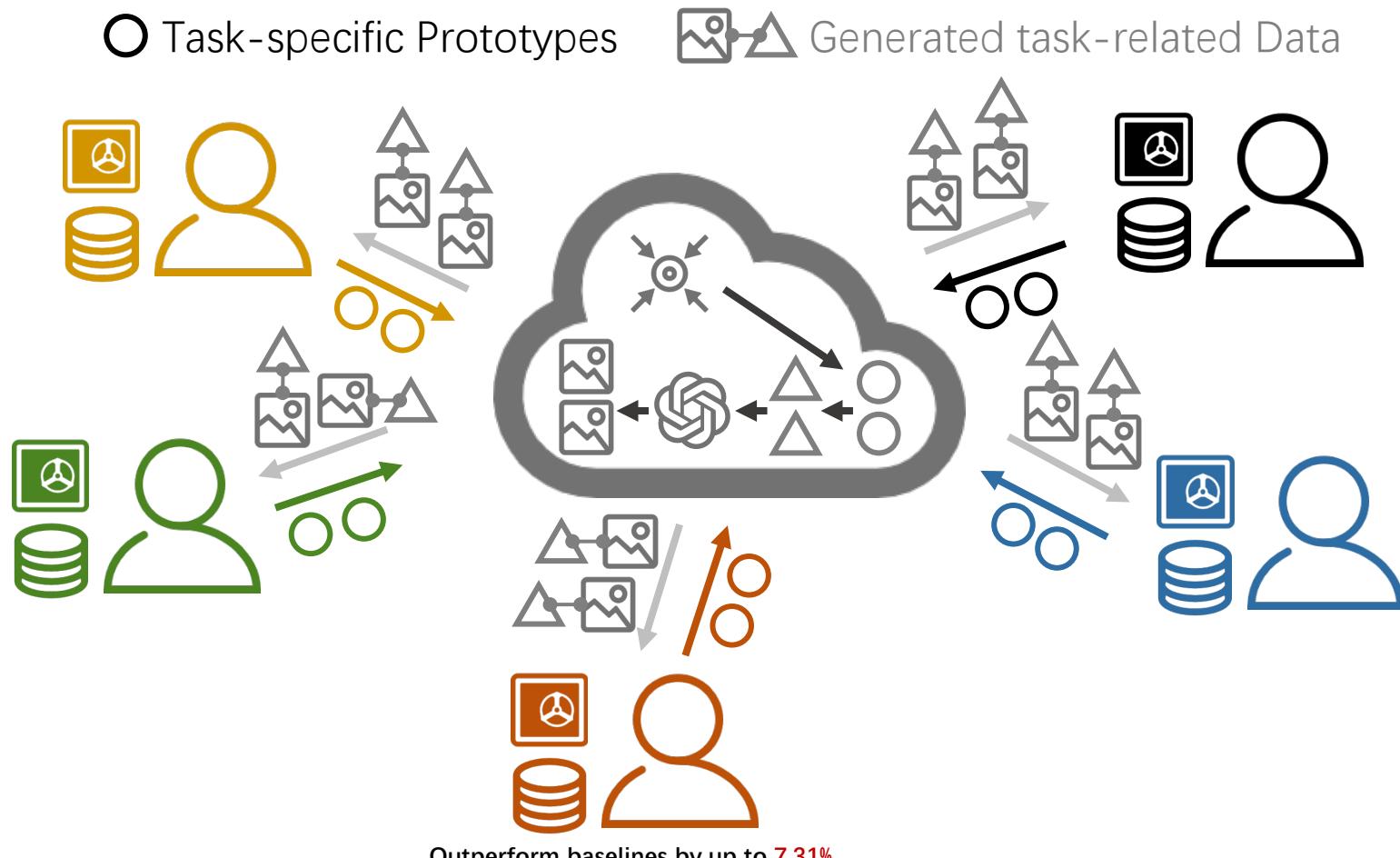
# FedKTL

- Transfer **common knowledge** from the generator to clients
- Obtain **task-specific knowledge** from other clients



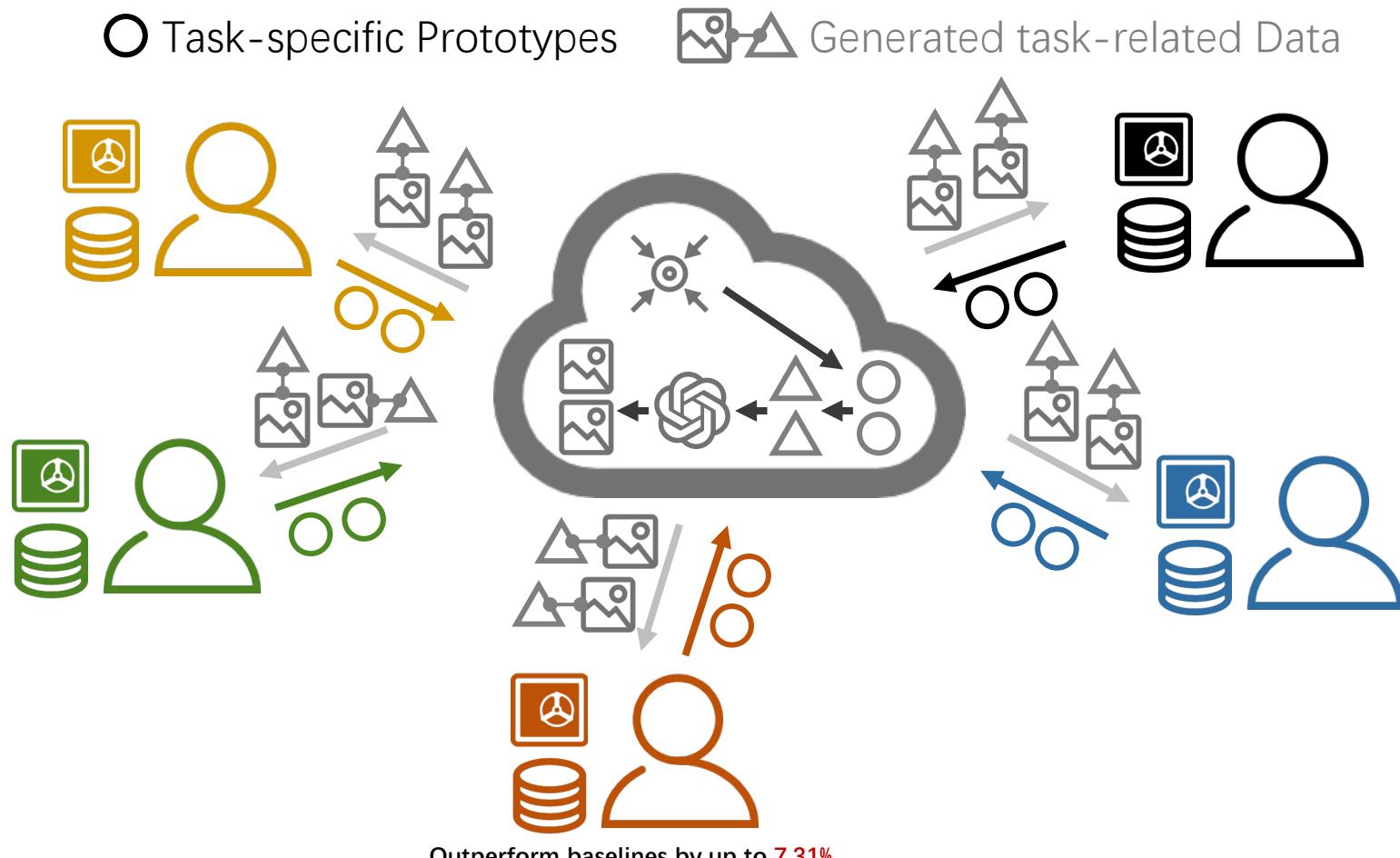
# FedKTL

- Common knowledge: **generated images**
- Task-specific knowledge: **prototype vectors**



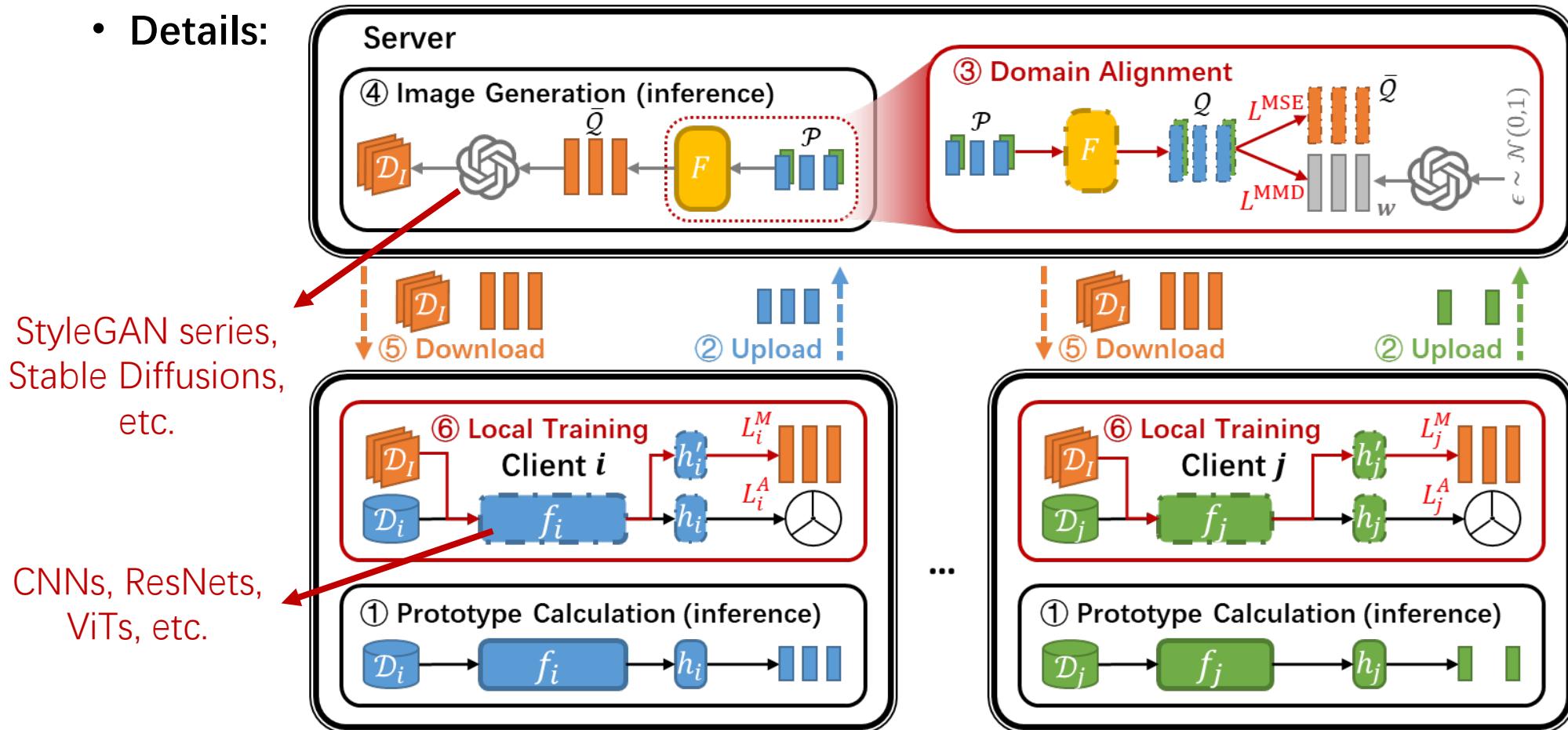
# FedKTL

- Generated Images are **induced by** prototype vectors
- Image-vector pairs** are **task-related** data that **contain common knowledge**



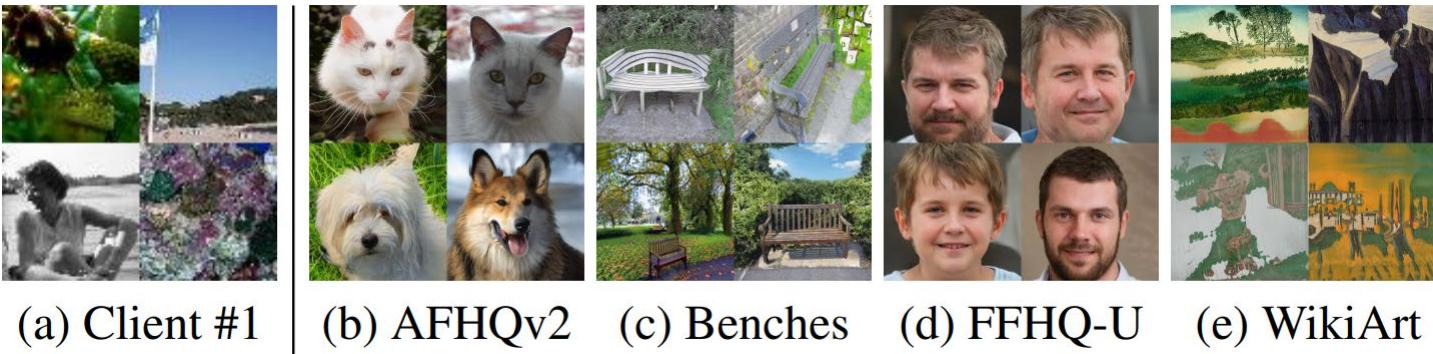
# FedKTL

- One image per class is sufficient for FedKTL
- Transfer knowledge using an **additional supervised local task**
- Details:



# FedKTL

- FedKTL can **adapt to various generators** that were pre-trained using various datasets
- The **semantics of the generated images** can be different from clients' data



Generators pre-trained on different image datasets

	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.5$
AFHQv2	$26.82 \pm 0.32$	<b><math>27.05 \pm 0.26</math></b>	$26.32 \pm 0.52$
Bench	$27.71 \pm 0.25$	<b><math>28.36 \pm 0.42</math></b>	$27.56 \pm 0.50$
FFHQ-U	<b><math>27.28 \pm 0.23</math></b>	$27.21 \pm 0.35$	$26.59 \pm 0.47$
WikiArt	$27.37 \pm 0.51$	<b><math>27.48 \pm 0.33</math></b>	$27.30 \pm 0.15$

# FedKTL

- **Knowledge transfer scheme (KTL)** is also applicable in scenarios with **only one edge client**.
- The **cloud-edge** scenario

Settings	100-way 23-shot	100-way 9-shot	100-way 2-shot
Client Data	12.53±0.39	7.55±0.41	4.44±1.66
Our KTL	13.02±0.43	8.88±0.62	8.76±2.25
Improvement	0.49	1.33	4.32
Improvement Ratio	3.91%	17.61%	97.29%

Table 9. The test accuracy (%) with Cifar100's subsets on a single client using a small model *i.e.*, the 4-layer CNN.

# Feel free to contact me!

Home page: <https://github.com/TsingZ0>



Thanks!