An Upload-Efficient Scheme for Transferring Knowledge From a Server-Side Pre-trained Generator to Clients in Heterogeneous Federated Learning

Jianqing Zhang[1]   **Yang Liu**[2]   **Yang Hua**[3]   **Jian Cao**[1]

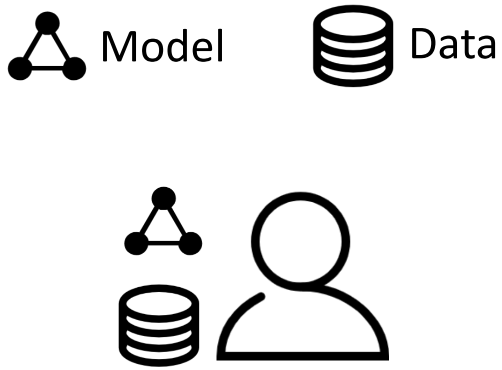
1 上海交通大学 SHANGHAI JIAO TONG UNIVERSITY

2 AIR 清華大學 智能产业研究院 Institute for AI Industry Research, Tsinghua University

3 QUEEN'S UNIVERSITY BELFAST

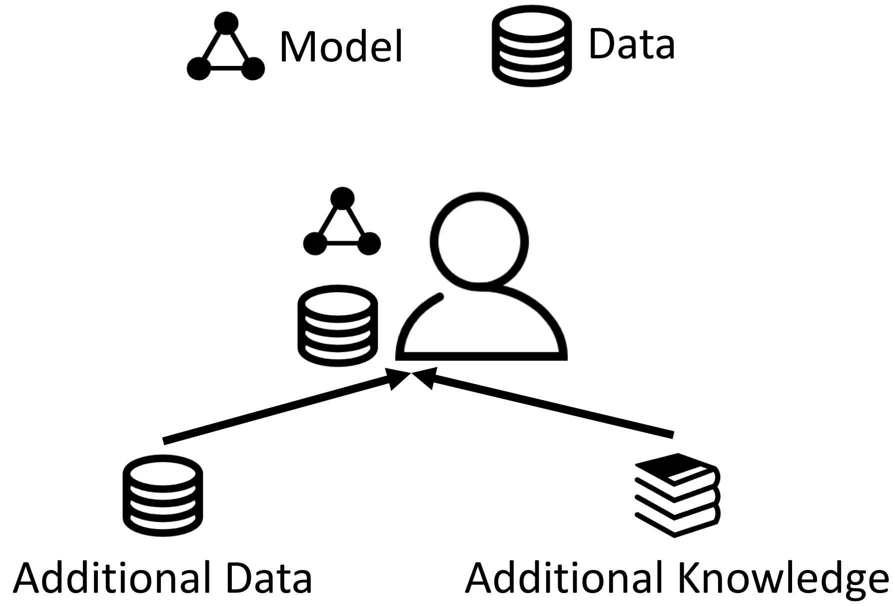
Data shortage

- Data shortage challenges AI model training for individuals and companies.



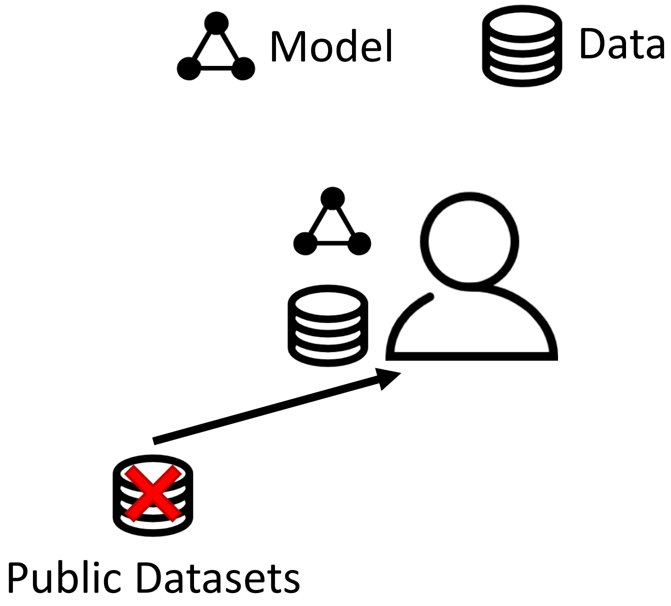
Data shortage

- Additional **data** and **knowledge** can mitigate this challenge.



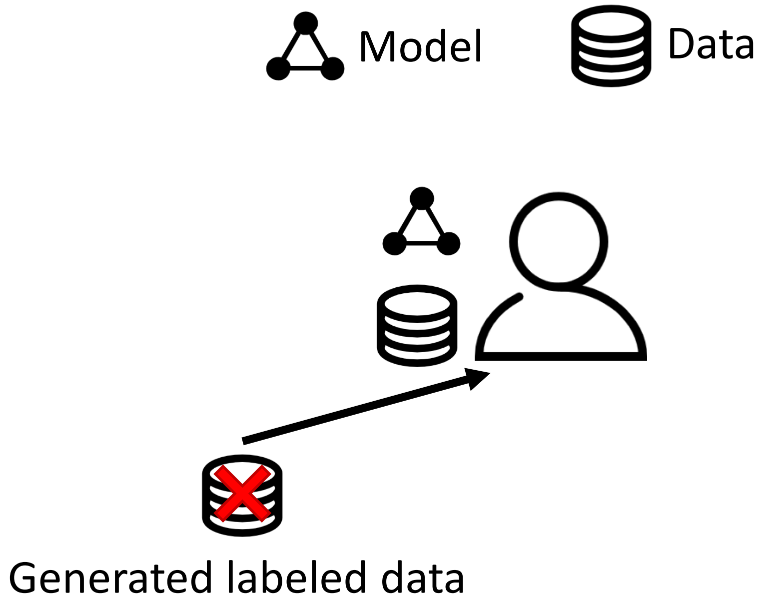
Public datasets

- Additional data need to be **task-related.**
- It is hard to extract such data from **public datasets**.



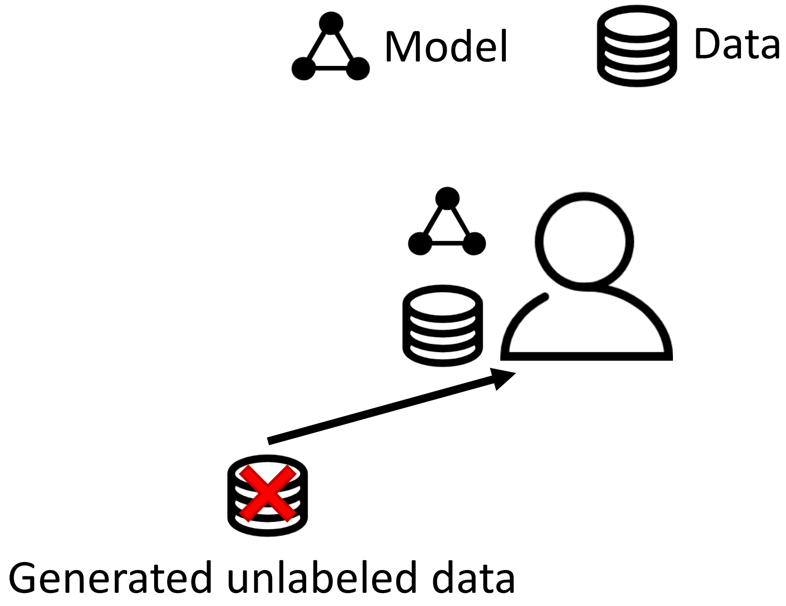
Generated labeled data

- Transmitting human-readable information, e.g., semantics of labels, about specific tasks to the generator raises **privacy concerns**.



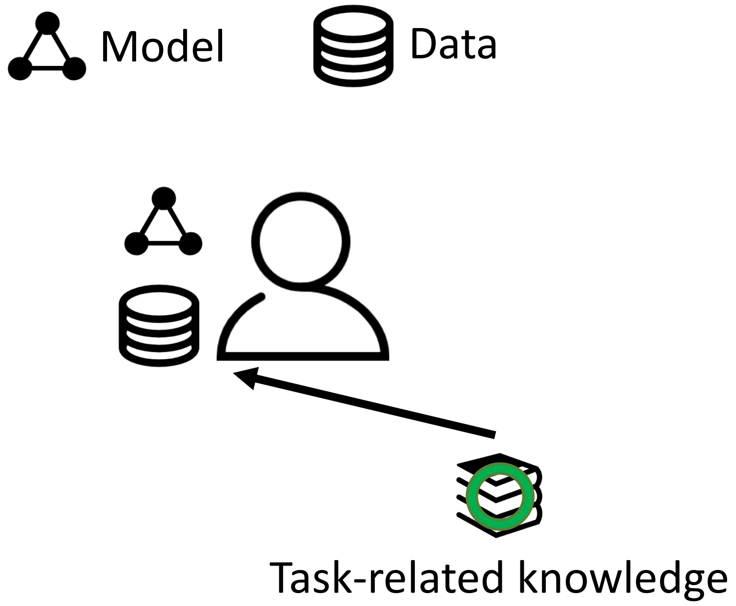
Generated unlabeled data

- Without exposing such information, the generated **unlabeled data** belongs to the **generator's output domain**, which is not naturally related to specific tasks.
- Fulfilling unlabeled data is **challenging** in deep learning.



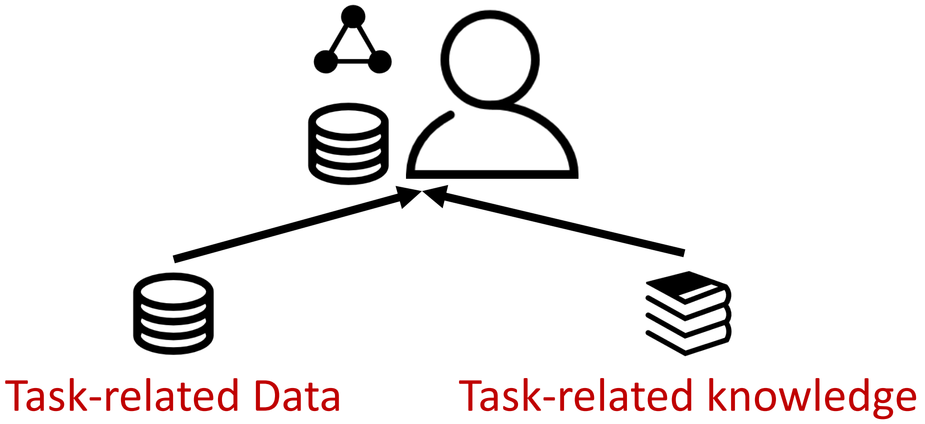
Knowledge from others

- Additional knowledge need to be **task-related.**
- Clients in federated learning (FL) intend to solve **similar tasks**, so we use FL techniques.



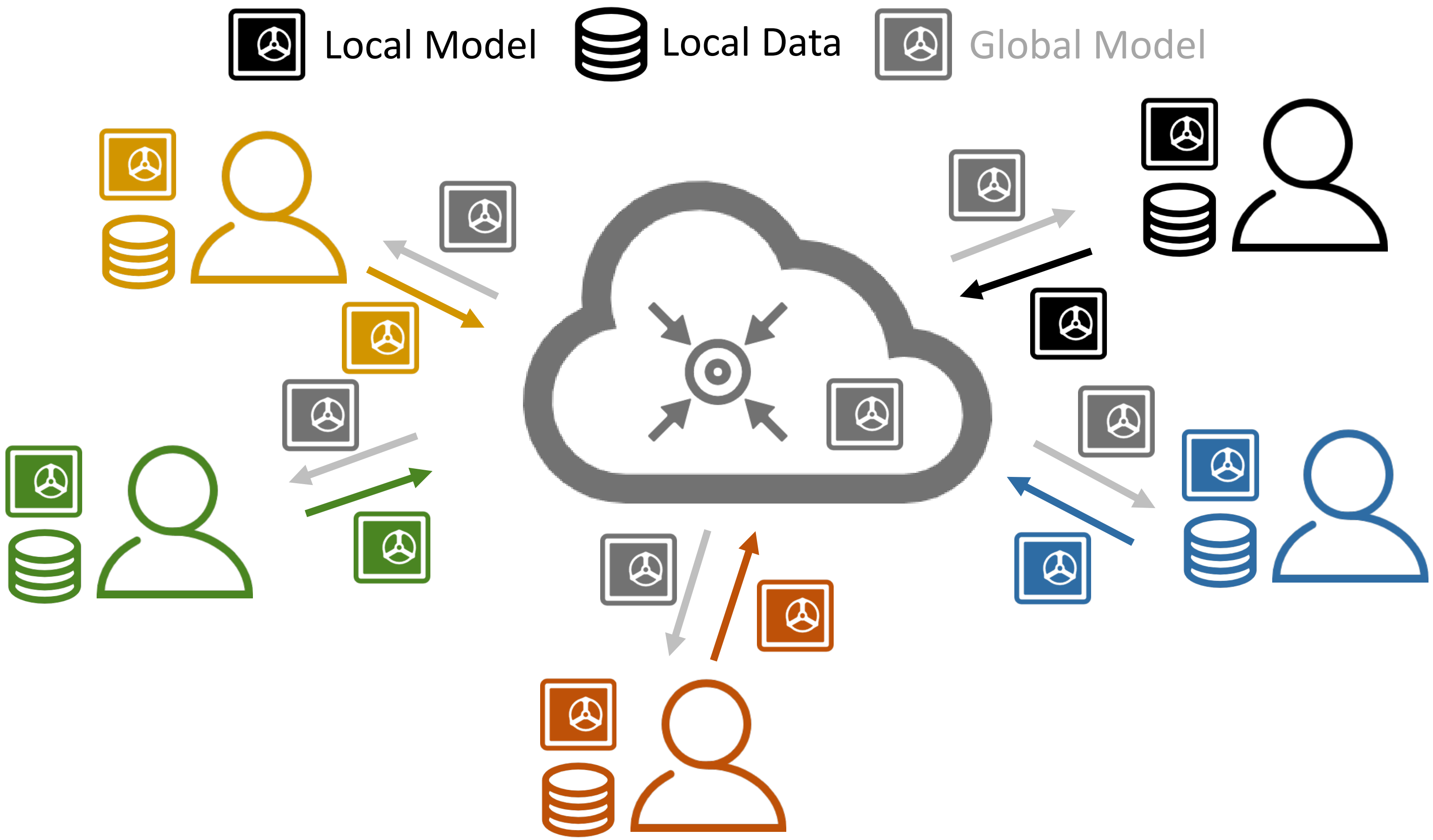
Our method

- Propose a **federated learning (FL) method** to share **task-related (abstract) knowledge**.
- **Adapt a pre-trained generator** to produce **task-related data** based on task-related knowledge.
- **Transfer** task-related knowledge and data **to each client** via **an additional supervised task**.



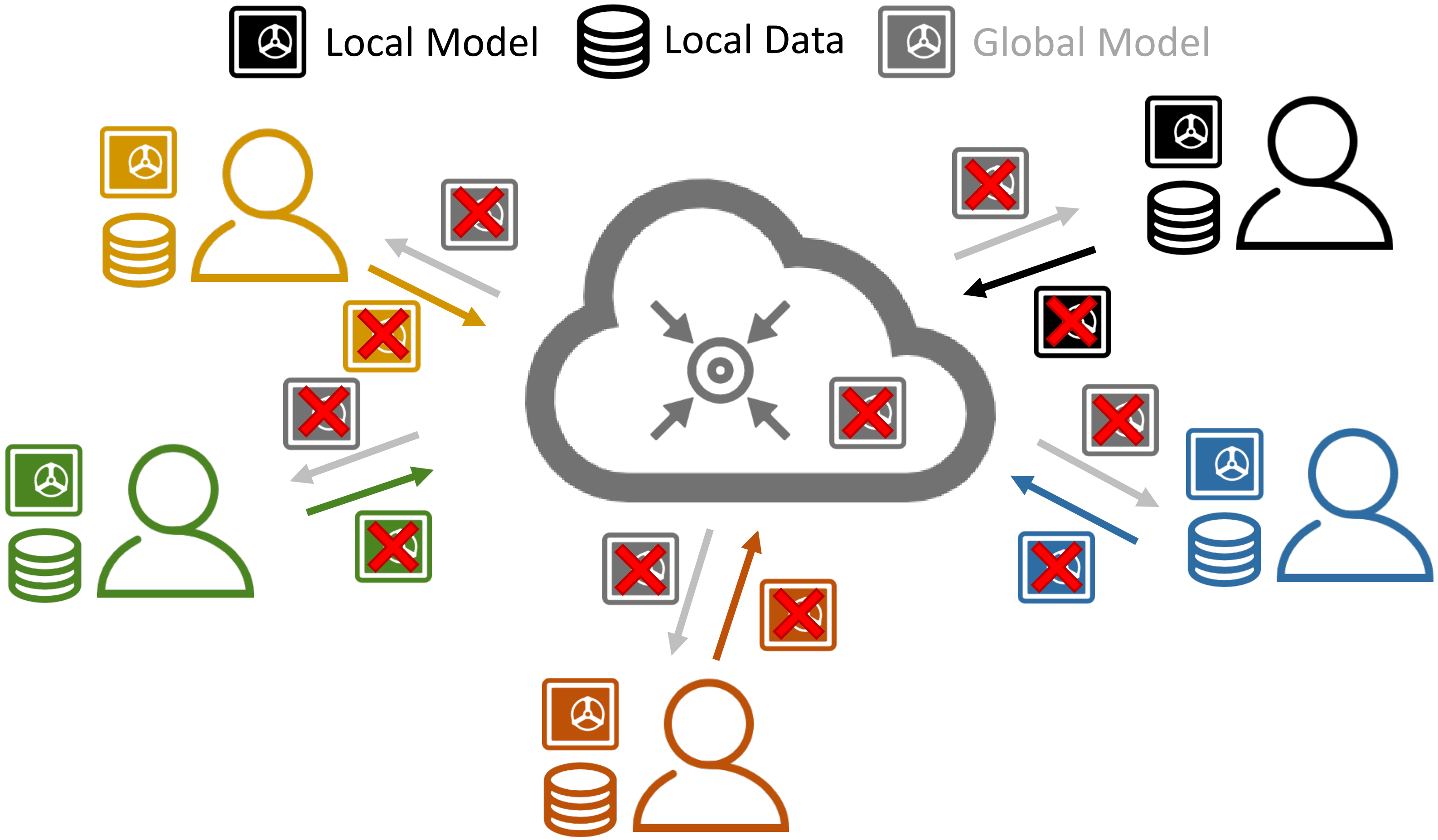
Heterogeneous Federated Learning (HtFL)

- **Data heterogeneity**, **model heterogeneity**, communication cost, **intellectual property**, etc.



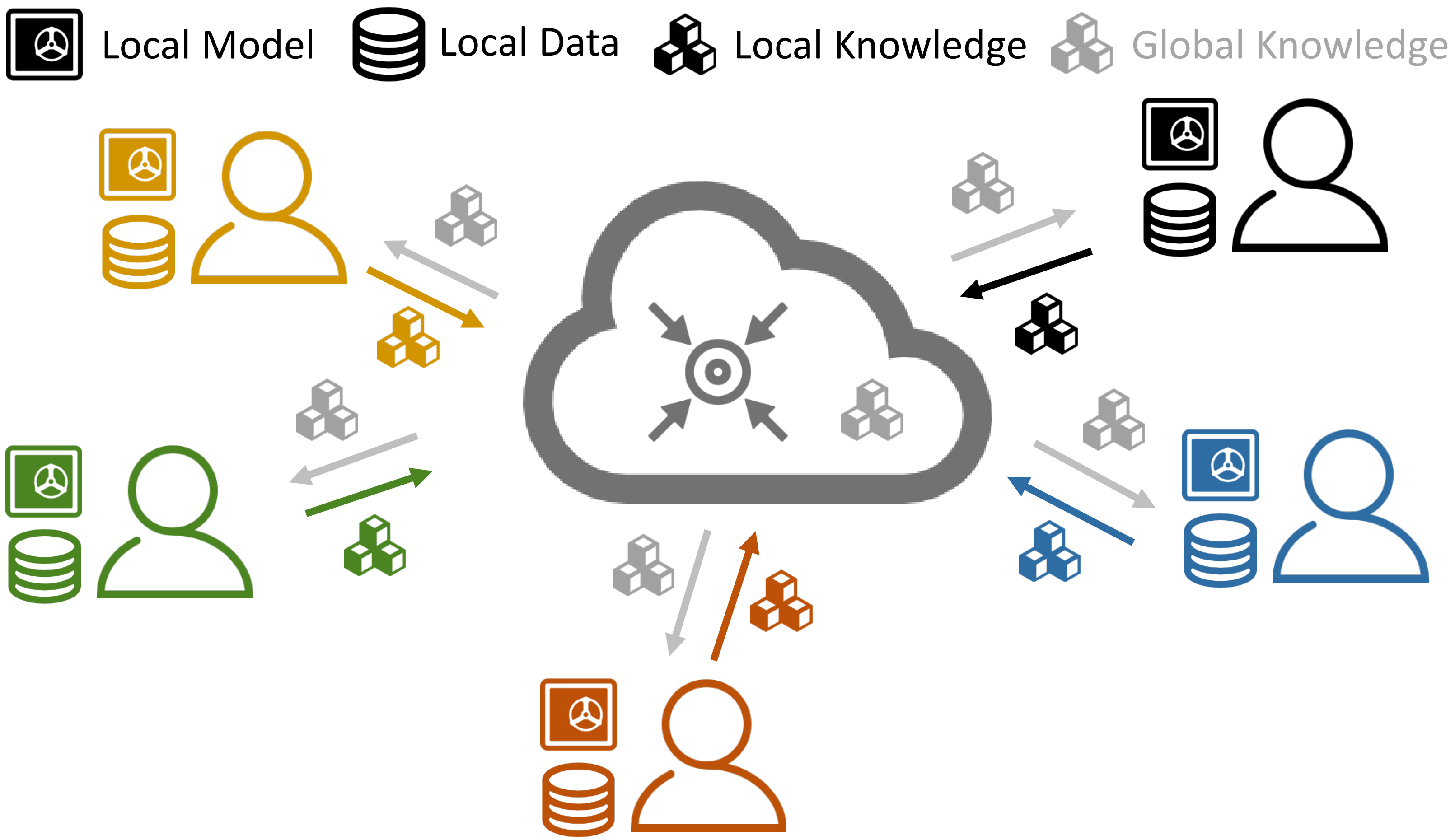
Heterogeneous Federated Learning (HtFL)

- The **intellectual property** is overlooked by most previous work.
- To protect intellectual property, we **cannot expose model parameters** among clients.



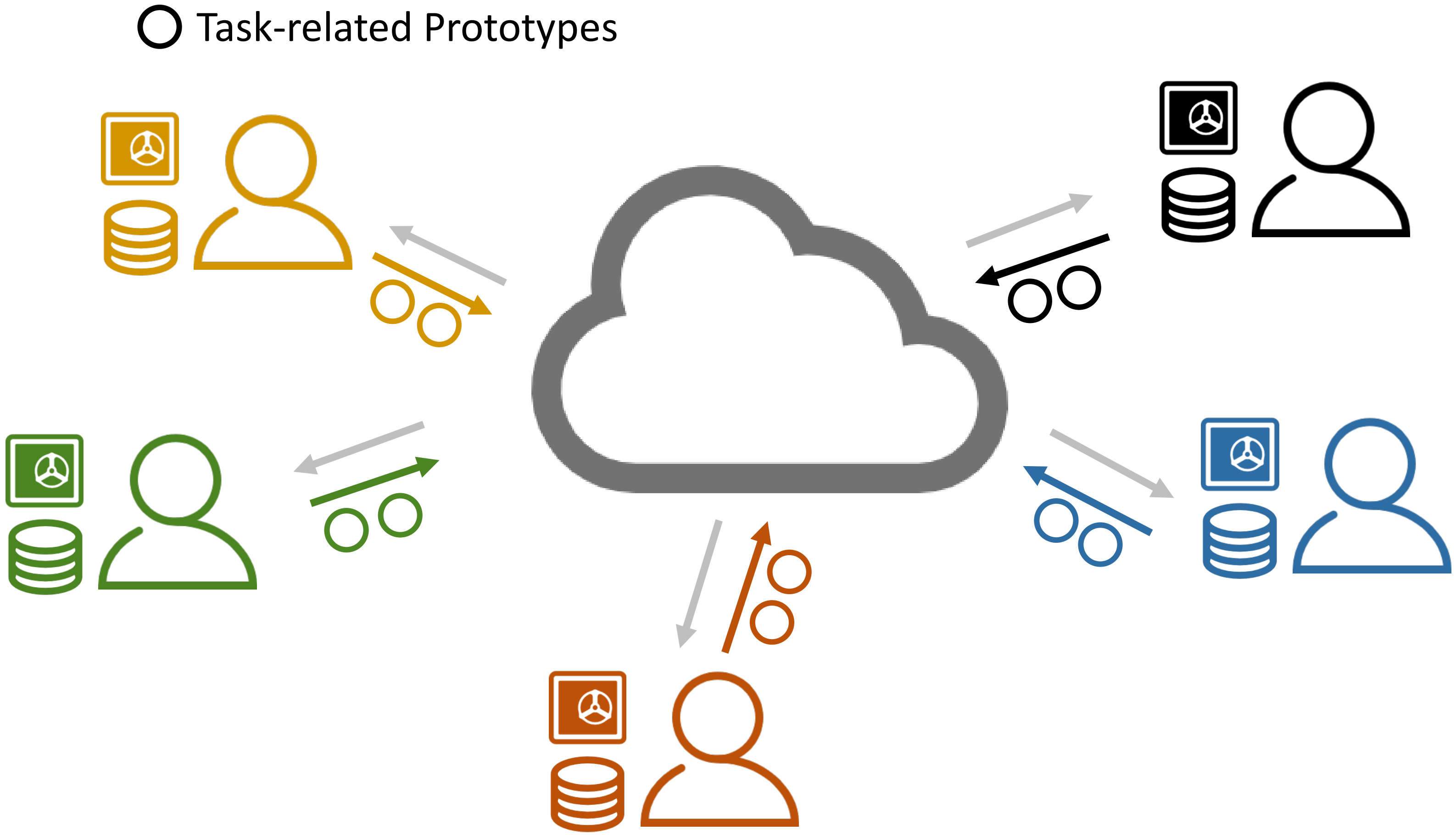
Heterogeneous Federated Learning (HtFL)

- Transmit **lightweight knowledge carriers** instead of exposing model parameters among clients



Task-related prototypes

- Specifically, in our work, clients upload **task-related** prototypes ○ to the server.



Prototype aggregation

- The server then aggregates client prototypes.

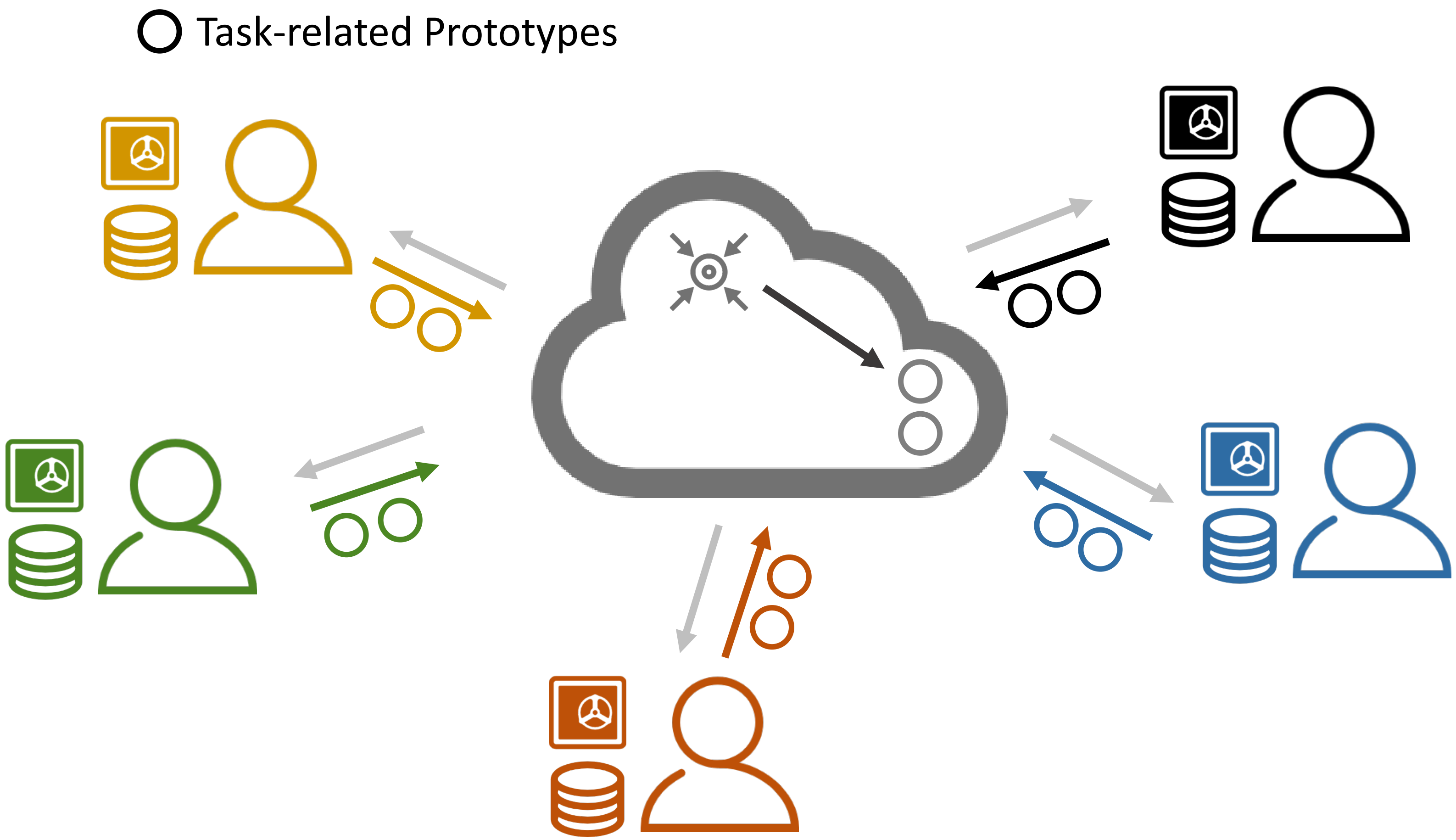


Image generation

- The server maps global prototypes ○ to **latent vectors** △, and generates images 🖼.

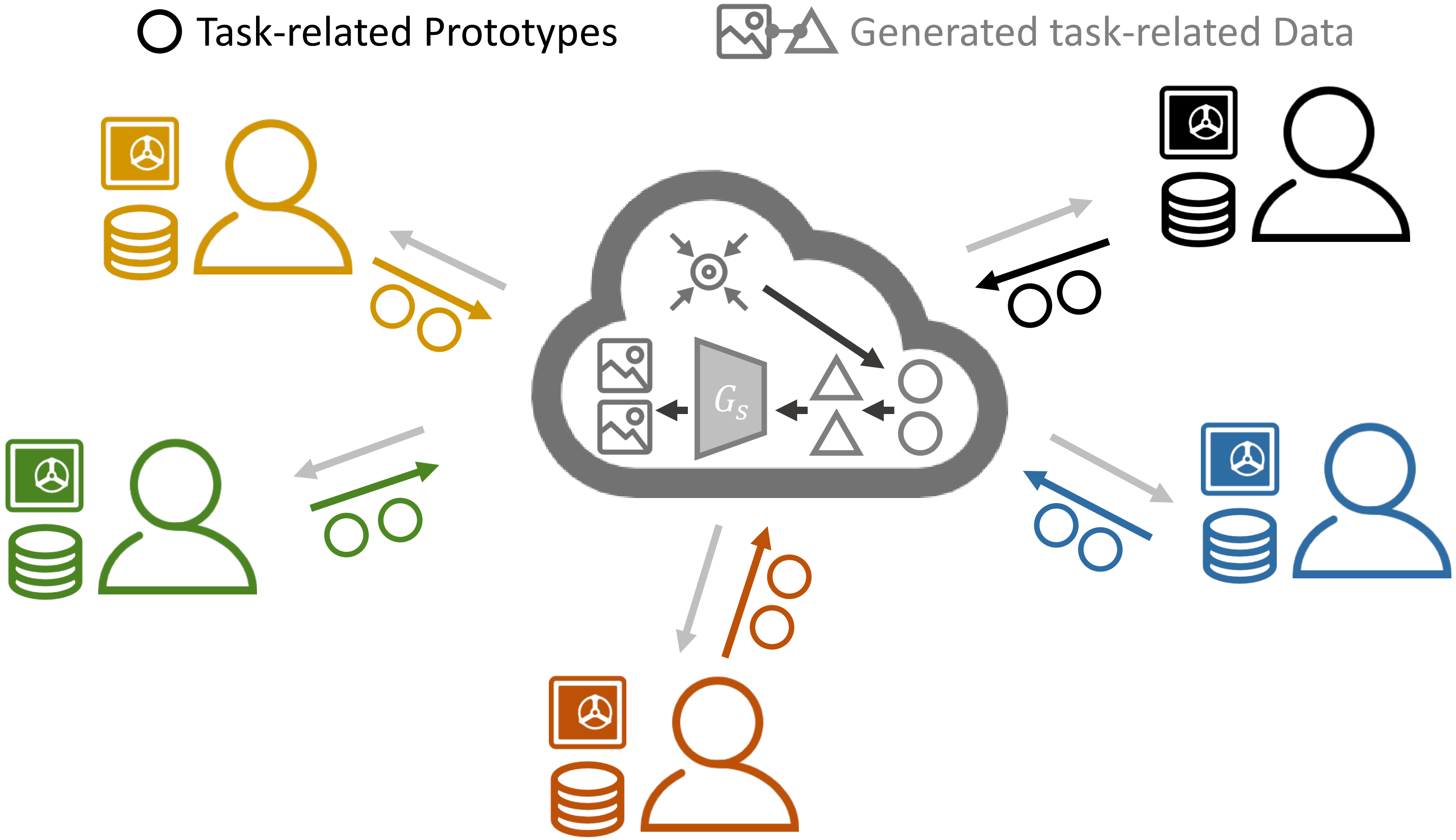
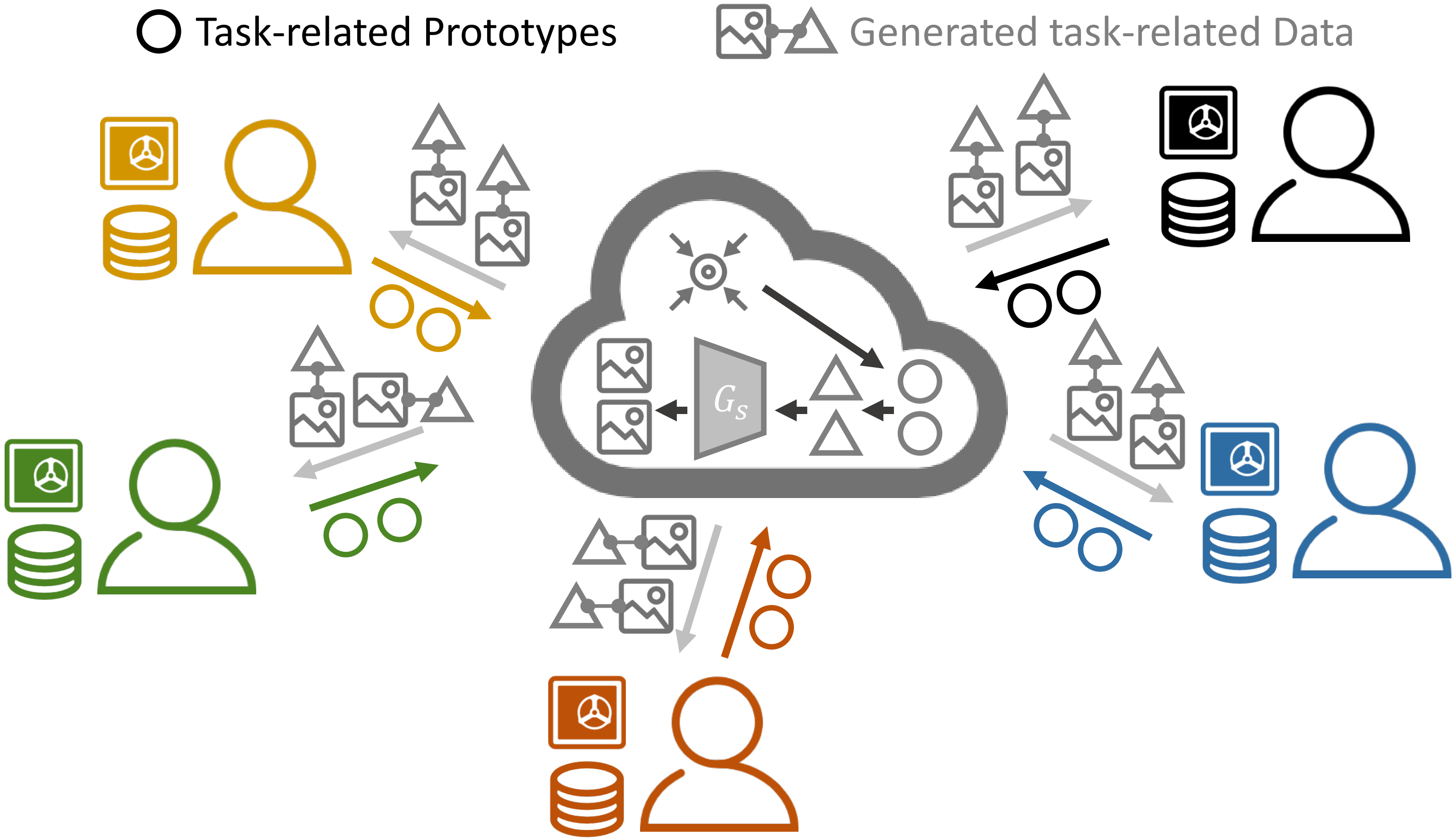
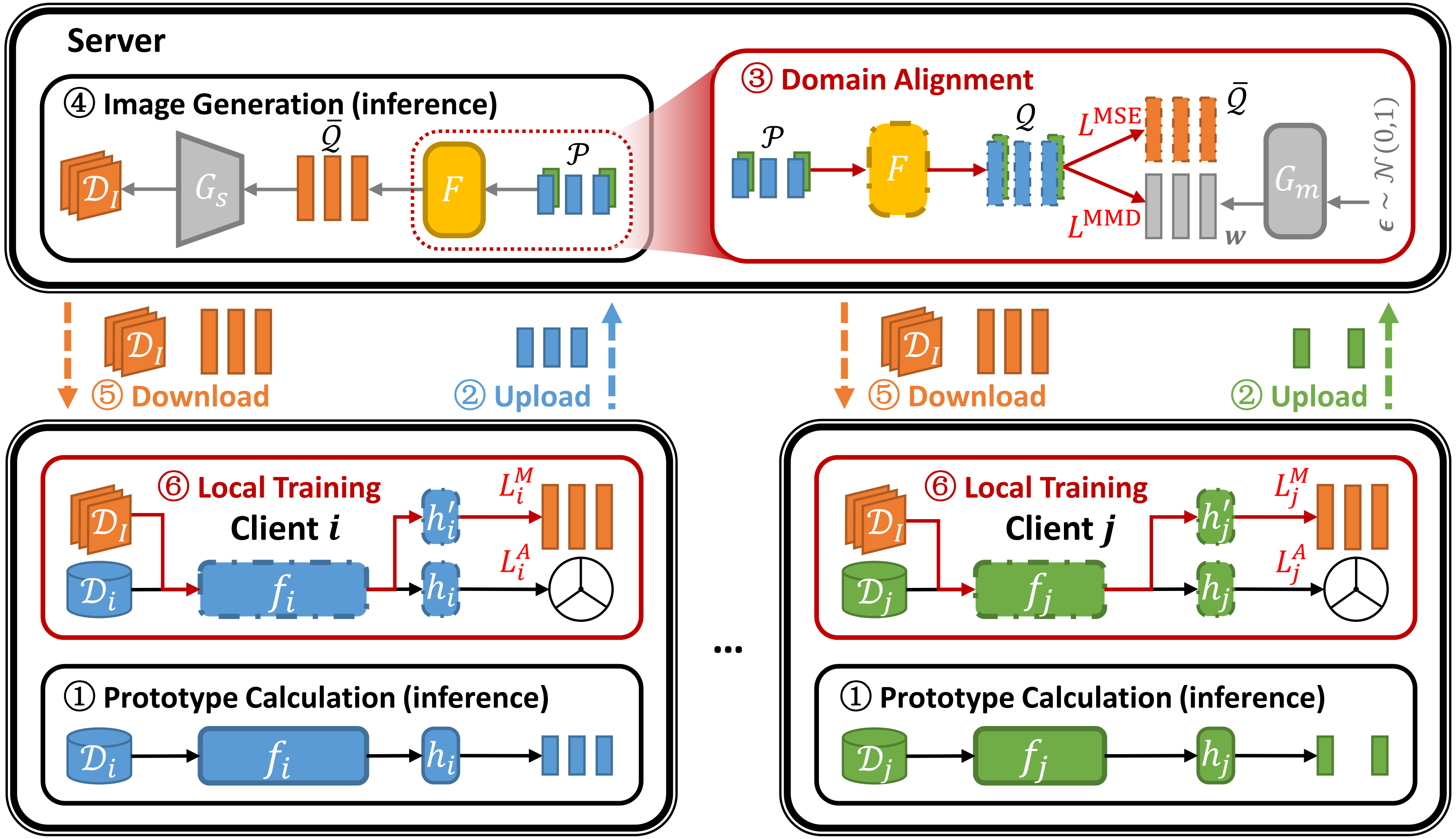


Image-vector pairs

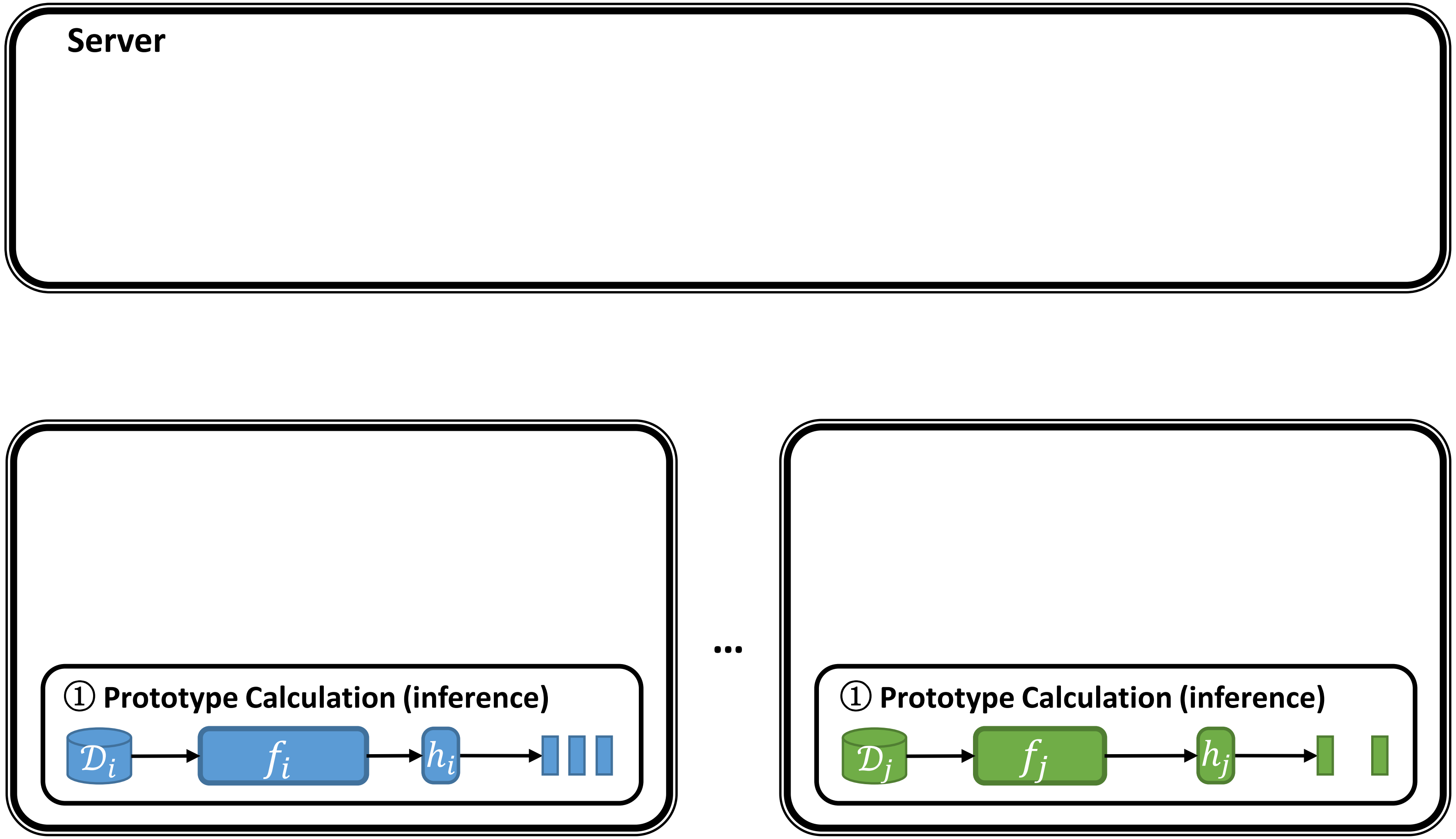
- The server sends **image-vector pairs**  to each client for an **additional supervised task**.



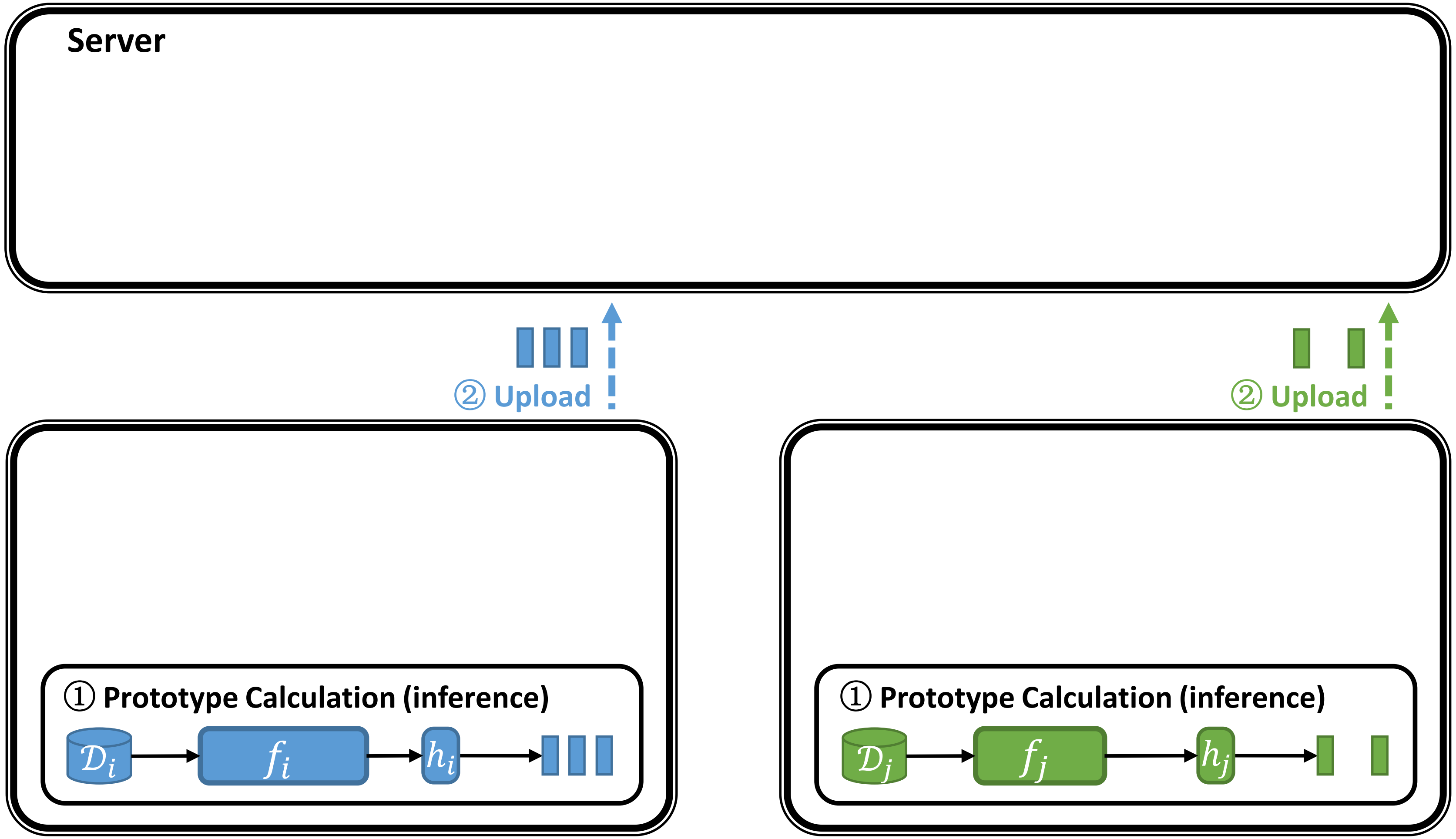
Federated Knowledge-Transfer-Loop (FedKTL)



① Prototype Calculation (inference)

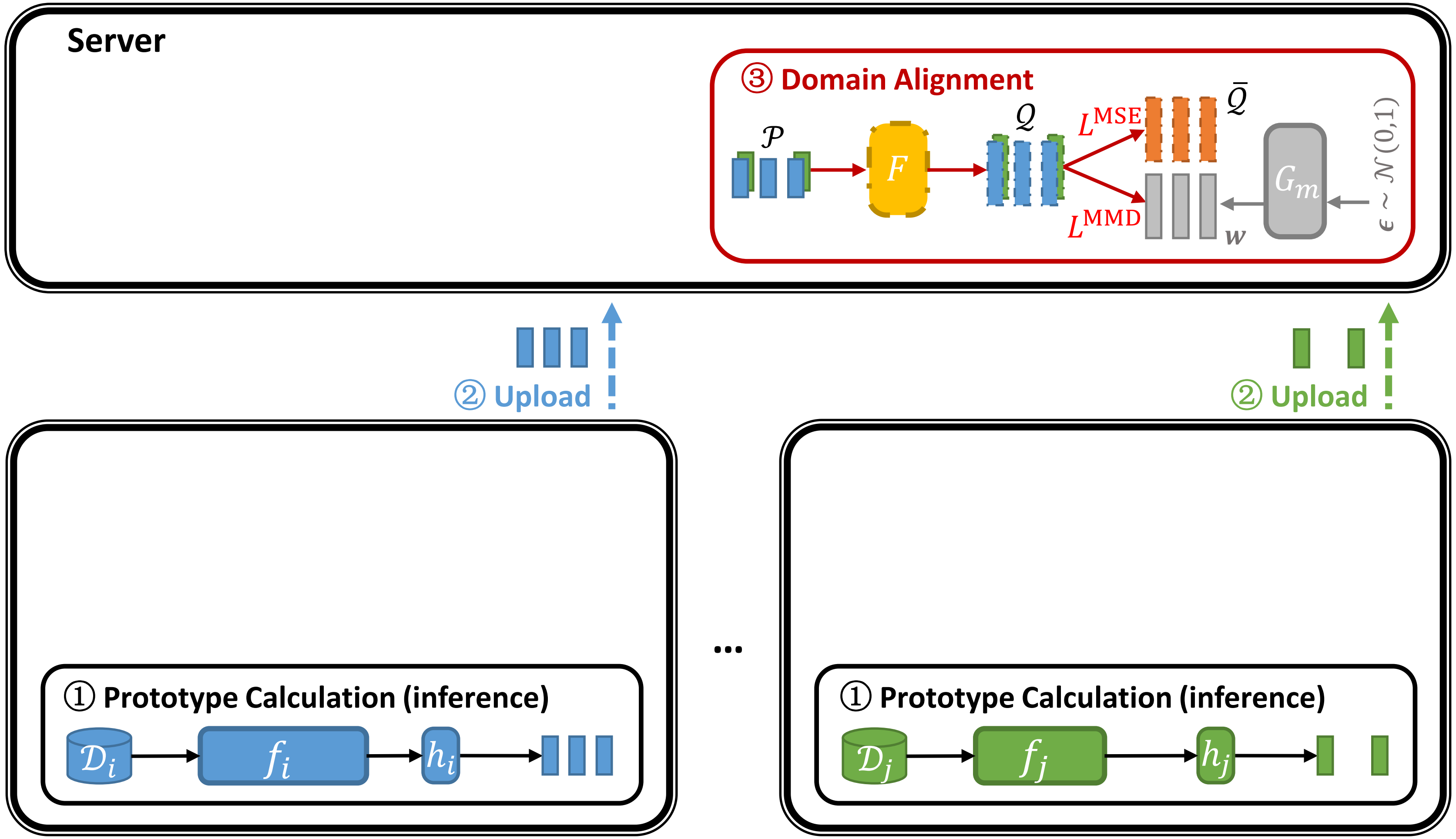


② Upload

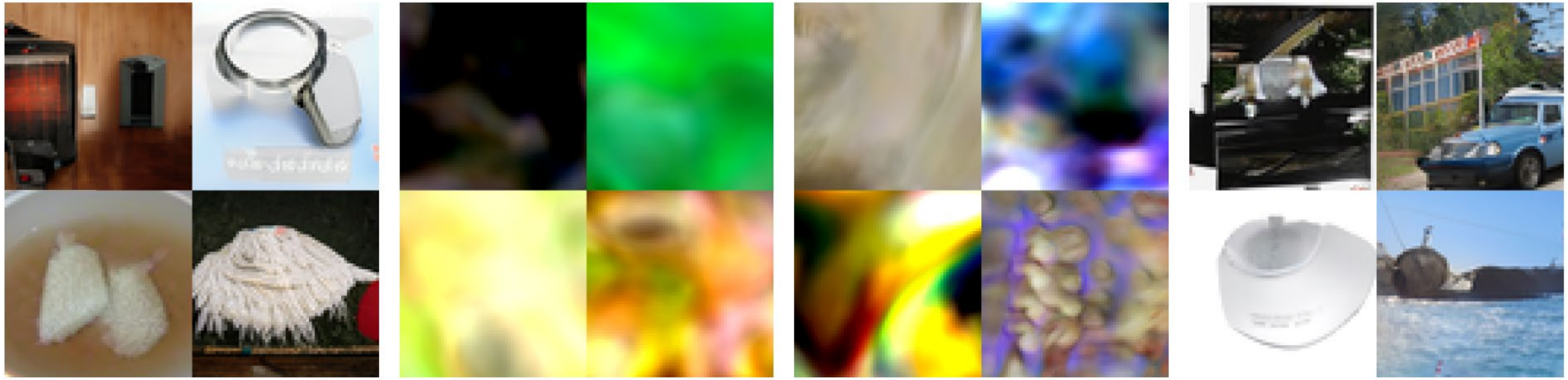


Server
② Upload
② Upload
① Prototype Calculation (inference)
$\mathcal{D}_i$
f_i
h_i
① Prototype Calculation (inference)
$\mathcal{D}_j$
f_j
h_j

③ Domain Alignment



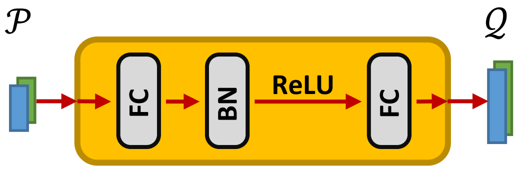
③ Domain Alignment



(a) Valid vecs (b) Random vecs (c) Prototypes (d) Aligned vecs

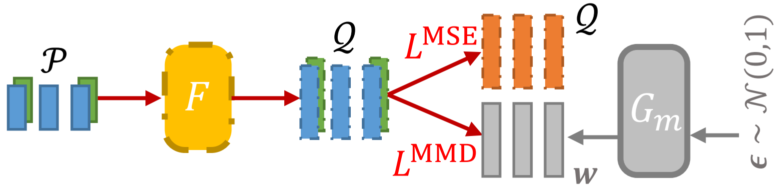
③ Domain Alignment

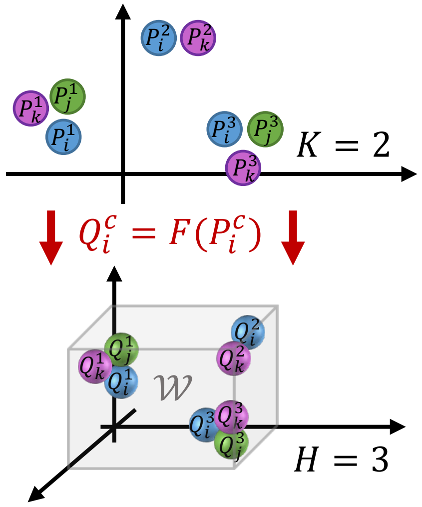
- The architecture of the feature transformer F.



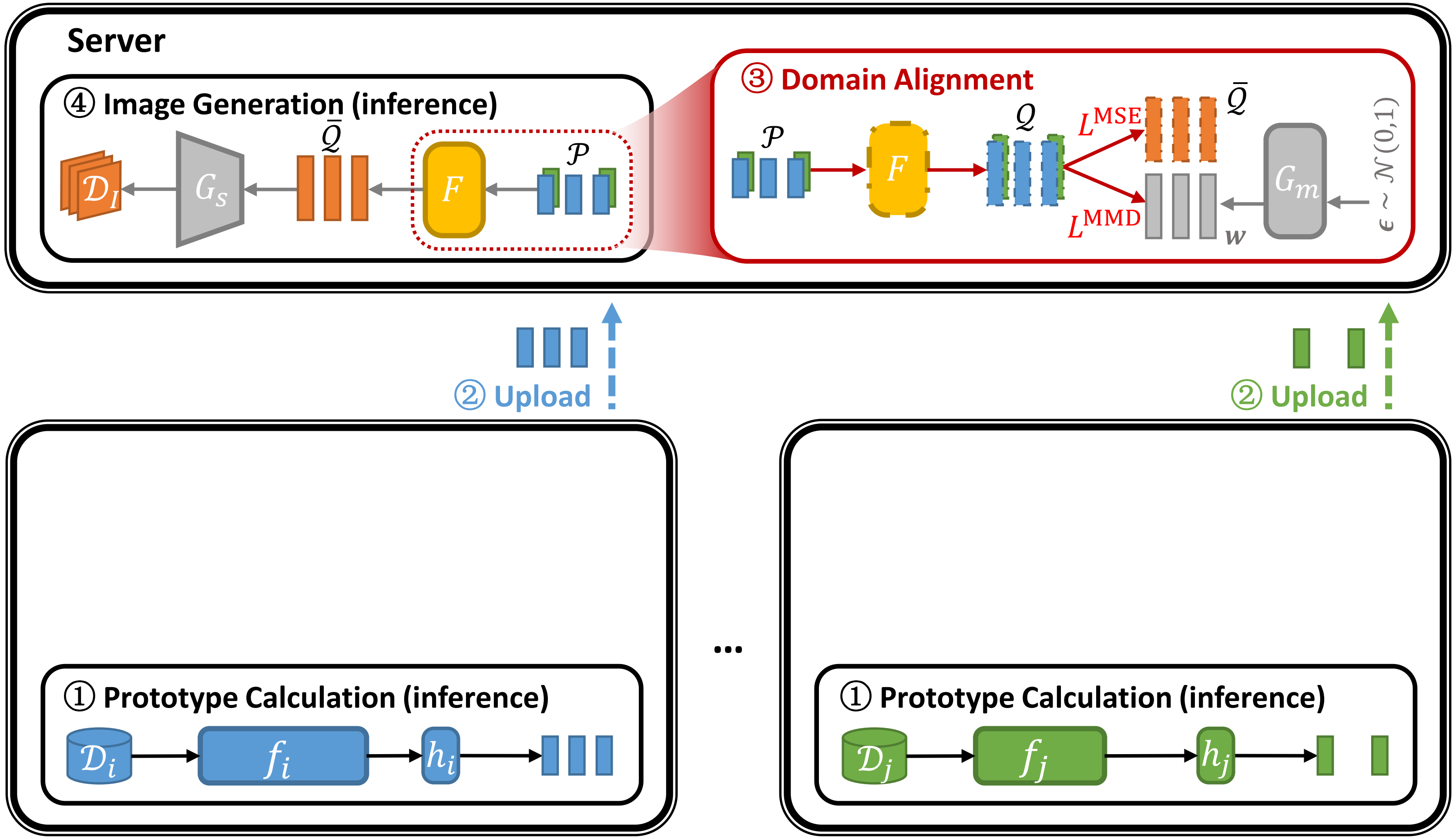
③ Domain Alignment

- A domain alignment example.

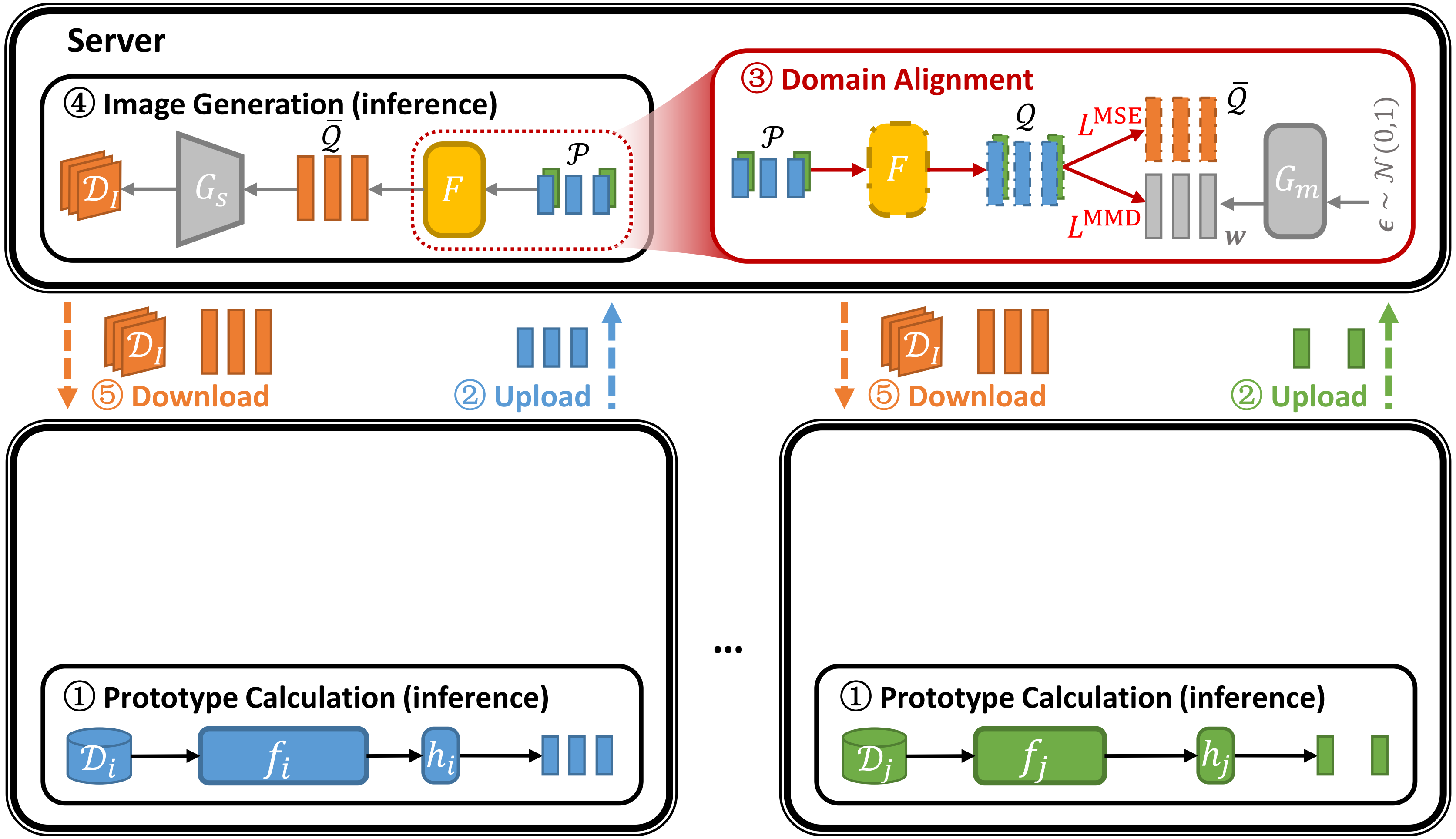




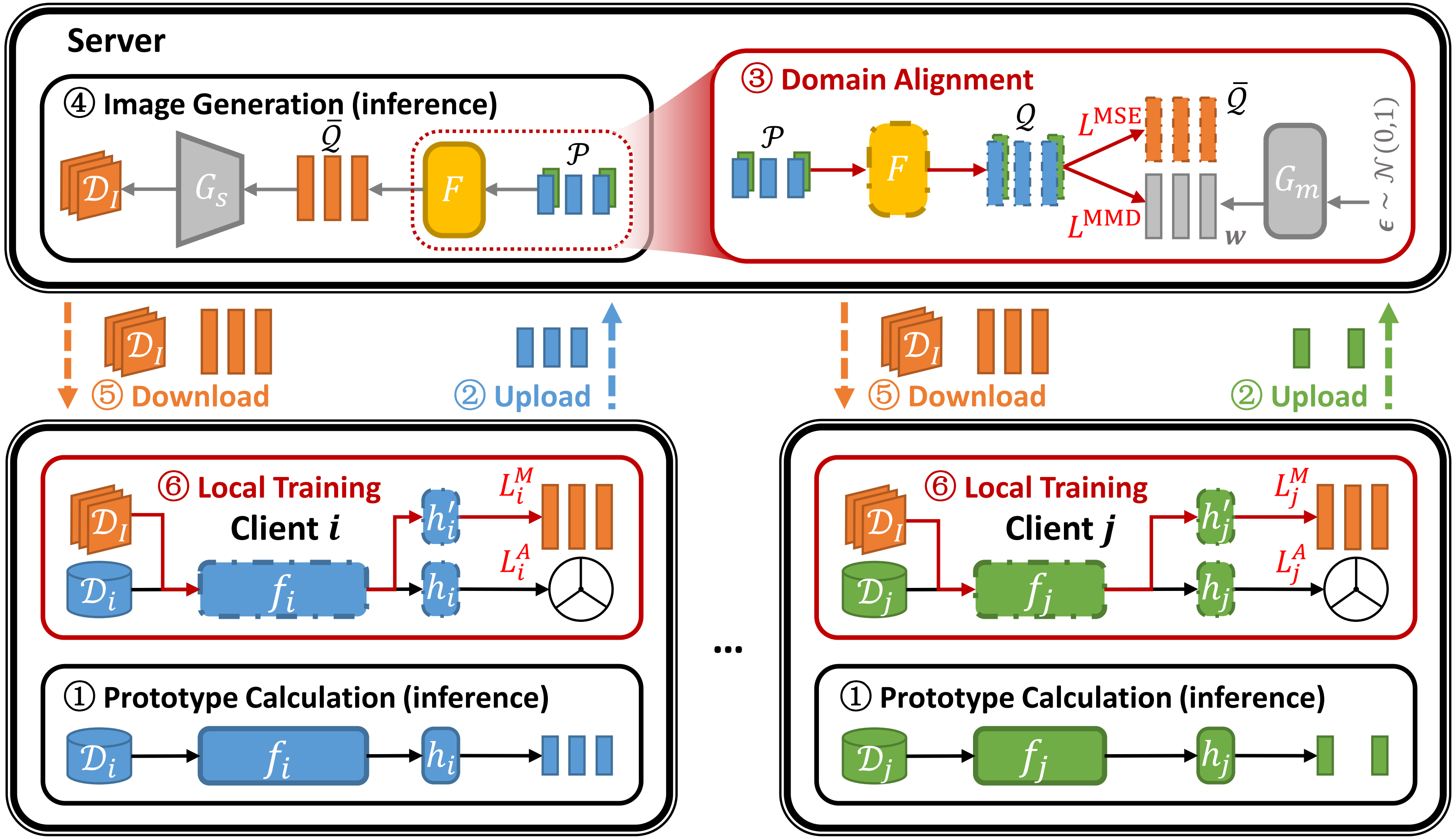
④ Image Generation (inference)



⑤ Download

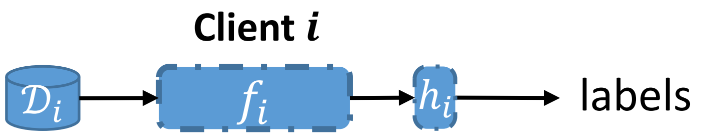

Server
④ Image Generation (inference)
$\mathcal{D}_I$
G_s
$\bar{Q}$
F
$\mathcal{P}$
③ Domain Alignment
$\mathcal{P}$
F
Q
L^{MSE}
L^{MMD}
$\bar{Q}$
w
G_m
$\epsilon \sim \mathcal{N}(0,1)$
⑤ Download
② Upload
⑤ Download
② Upload
① Prototype Calculation (inference)
$\mathcal{D}_i$
f_i
h_i
...
① Prototype Calculation (inference)
$\mathcal{D}_j$
f_j
h_j

⑥ Local Training



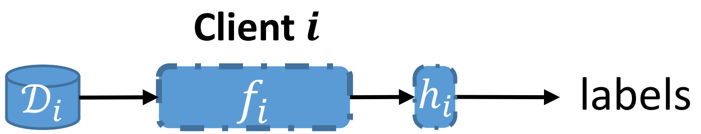
⑥ Local Training

- Original local task: **classification**.



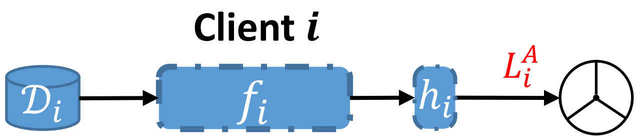
⑥ Local Training

- Heterogeneous models produce **biased prototypes** due to their divergent capabilities.



⑥ Local Training

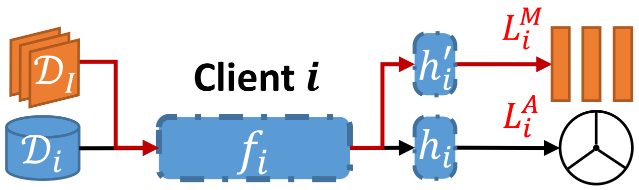
- Replace the original classifier part by an **ETF classifier**[1] to produce unbiased prototypes.



[1] Yang Y, Yuan H, Li X, et al. Neural Collapse Inspired Feature-Classifier Alignment for Few-Shot Class-Incremental Learning. *ICLR* 2022.

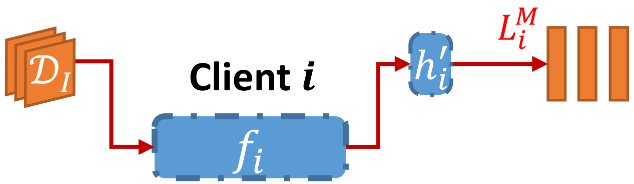
⑥ Local Training

- **Transfer task-related knowledge and data** to clients through an **additional supervised task**.



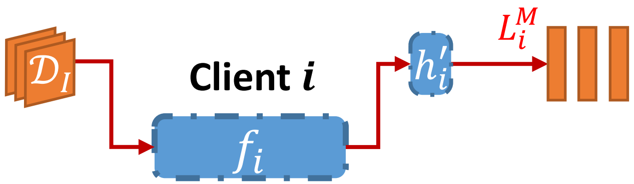
⑥ Local Training

- The image-vector pairs brings both **common** (from the pre-trained generator) and shared (from participating clients) **knowledge *only*** to the **feature extractor part**.



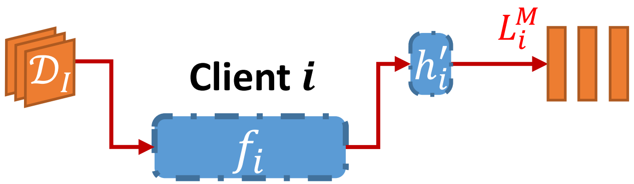
⑥ Local Training

- We only transfer knowledge to **enhance the general feature extraction capability**.



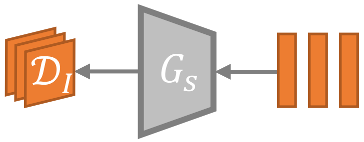
⑥ Local Training

- Thus, the **semantic relationship** between the generated images and local data is **insignificant**.



Support for various pre-trained generators

- Generators **pre-trained on any image datasets** are applicable.



Support for various pre-trained generators

- Generators **pre-trained on any image datasets** are applicable.

(a) Client #1 (b) AFHQv2 (c) Benches (d) FFHQ-U (e) WikiArt

Support for various pre-trained generators

- Generators **pre-trained on any image datasets** are applicable.

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

Table 6. The test accuracy (%) on Tiny-ImageNet in the practical setting using HtFE_8 with different pre-trained StyleGAN3s, which are represented by the names of the pre-training datasets.

Ablation study

- **Each** component plays a vital role, and none of them can be omitted.

(a) -L_i^M (b) -L^{MSE} (c) -L^{MMD} (d) -*ETF* (e) -$\bar{\mathcal{Q}}$

Excellent performance

- Experiments on four datasets.

Settings	Pathological Setting				Practical Setting			
Datasets	Cifar10	Cifar100	Flowers102	Tiny-ImageNet	Cifar10	Cifar100	Flowers102	Tiny-ImageNet
LG-FedAvg	86.82±0.26	57.01±0.66	58.88±0.28	32.04±0.17	84.55±0.51	40.65±0.07	45.93±0.48	24.06±0.10
FedGen	82.83±0.65	58.26±0.36	59.90±0.15	29.80±1.11	82.55±0.49	38.73±0.14	45.30±0.17	19.60±0.08
FedGH	86.59±0.23	57.19±0.20	59.27±0.33	32.55±0.37	84.43±0.31	40.99±0.51	46.13±0.17	24.01±0.11
FML	87.06±0.24	55.15±0.14	57.79±0.31	31.38±0.15	85.88±0.08	39.86±0.25	46.08±0.53	24.25±0.14
FedKD	87.32±0.31	56.56±0.27	54.82±0.35	32.64±0.36	86.45±0.10	40.56±0.31	48.52±0.28	25.51±0.35
FedDistill	87.24±0.06	56.99±0.27	58.51±0.34	31.49±0.38	86.01±0.31	41.54±0.08	49.13±0.85	24.87±0.31
FedProto	83.39±0.15	53.59±0.29	55.13±0.17	29.28±0.36	82.07±1.64	36.34±0.28	41.21±0.22	19.01±0.10
FedKTL	**88.43±0.13**	**62.01±0.28**	**64.72±0.62**	**34.74±0.17**	**87.63±0.07**	**46.94±0.23**	**53.16±0.08**	**28.17±0.18**

Table 1. The test accuracy (%) on four datasets in the pathological and practical settings using HtFE_8.

Excellent performance

- Experiments using 14 kinds of models including **CNNs and ViTs**.

Settings	Different Degrees of Model Heterogeneity					Large Client Amount ($\rho = 0.5$)		
	HtFE_2	HtFE_3	HtFE_4	HtFE_9	HtM_{10}	50 Clients	100 Clients	200 Clients
LG-FedAvg	46.61±0.24	45.56±0.37	43.91±0.16	42.04±0.26	—	37.81±0.12	35.14±0.47	27.93±0.04
FedGen	43.92±0.11	43.65±0.43	40.47±1.09	40.28±0.54	—	37.95±0.25	34.52±0.31	28.01±0.24
FedGH	46.70±0.35	45.24±0.23	43.29±0.17	43.02±0.86	—	37.30±0.44	34.32±0.16	29.27±0.39
FML	45.94±0.16	43.05±0.06	43.00±0.08	42.41±0.28	39.87±0.09	38.47±0.14	36.09±0.28	30.55±0.52
FedKD	46.33±0.24	43.16±0.49	43.21±0.37	42.15±0.36	40.36±0.12	38.25±0.41	35.62±0.55	31.82±0.50
FedDistill	46.88±0.13	43.53±0.21	43.56±0.14	42.09±0.20	40.95±0.04	38.51±0.36	36.06±0.24	31.26±0.13
FedProto	43.97±0.18	38.14±0.64	34.67±0.55	32.74±0.82	36.06±0.10	33.03±0.42	28.95±0.51	24.28±0.46
FedKTL	**48.06±0.19**	**49.83±0.44**	**47.06±0.21**	**50.33±0.35**	**45.84±0.15**	**43.16±0.82**	**39.73±0.87**	**34.24±0.45**

Table 2. The test accuracy (%) on Cifar100 in the practical setting with different degrees of model heterogeneity or large client amounts.

Excellent performance

- Our FedKTL outperforms counterparts by up to **7.31%**.

Settings	Different Degrees of Model Heterogeneity					Large Client Amount ($\rho = 0.5$)		
	HtFE_2	HtFE_3	HtFE_4	HtFE_9	HtM_{10}	50 Clients	100 Clients	200 Clients
LG-FedAvg	46.61±0.24	45.56±0.37	43.91±0.16	42.04±0.26	—	37.81±0.12	35.14±0.47	27.93±0.04
FedGen	43.92±0.11	43.65±0.43	40.47±1.09	40.28±0.54	—	37.95±0.25	34.52±0.31	28.01±0.24
FedGH	46.70±0.35	45.24±0.23	43.29±0.17	43.02±0.86	—	37.30±0.44	34.32±0.16	29.27±0.39
FML	45.94±0.16	43.05±0.06	43.00±0.08	42.41±0.28	39.87±0.09	38.47±0.14	36.09±0.28	30.55±0.52
FedKD	46.33±0.24	43.16±0.49	43.21±0.37	42.15±0.36	40.36±0.12	38.25±0.41	35.62±0.55	31.82±0.50
FedDistill	46.88±0.13	43.53±0.21	43.56±0.14	42.09±0.20	40.95±0.04	38.51±0.36	36.06±0.24	31.26±0.13
FedProto	43.97±0.18	38.14±0.64	34.67±0.55	32.74±0.82	36.06±0.10	33.03±0.42	28.95±0.51	24.28±0.46
FedKTL	**48.06±0.19**	**49.83±0.44**	**47.06±0.21**	**50.33±0.35**	**45.84±0.15**	**43.16±0.82**	**39.73±0.87**	**34.24±0.45**

Table 2. The test accuracy (%) on Cifar100 in the practical setting with different degrees of model heterogeneity or large client amounts.

Excellent performance

- Our FedKTL is **upload-efficient** (lowest upload communication cost)

	Upload	Download	Accuracy
LG-FedAvg	1.03M	1.03M	40.65±0.07
FedGen	1.03M	7.66M	38.73±0.14
FedGH	0.46M	1.03M	40.99±0.51
FML	18.50M	18.50M	39.86±0.25
FedKD	16.52M	16.52M	40.56±0.31
FedDistill	0.09M	0.20M	41.54±0.08
FedProto	0.46M	1.02M	36.34±0.28
FedKTL	0.09M	7.17M	**46.94±0.23**

Table 5. The upload and download overhead per iteration using $HtFE_8$ on Cifar100 with 20 clients in the practical setting. "M" is short for million. The accuracy column is referred from Tab. 1.

Using Stable Diffusion

- Several concepts in generators share similarities when generating contents, thus **they are all applicable** in our FedKTL, such as **StyleGAN** and **Stable Diffusion.**

Generator	StyleGAN-XL	Stable Diffusion
Accuracy	87.63	87.71

Table 8. The test accuracy (%) of our FedKTL with different pre-trained generators on Cifar10 in the practical setting using $HtFE_8$.

The cloud-edge scenario

- Our **knowledge transfer scheme (KTL)** is also applicable in scenarios with **only one edge client**.
  - Cloud-edge scenarios
  - No collaboration
  - Few-shot learning

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

Paper with code: https://github.com/TsingZ0/FedKTL

Thanks!