

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

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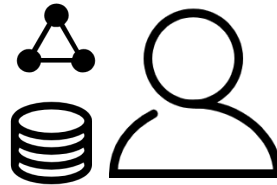
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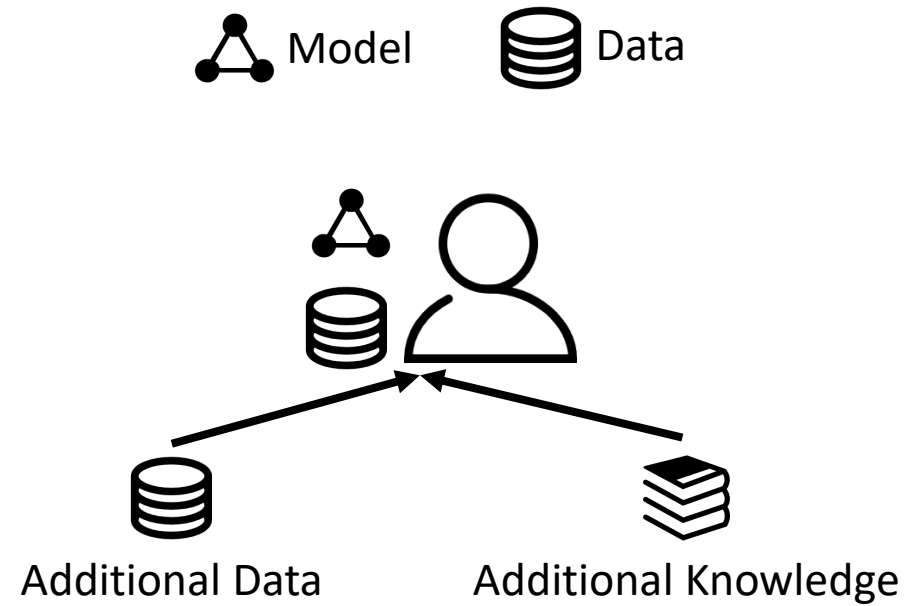
Data shortage

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



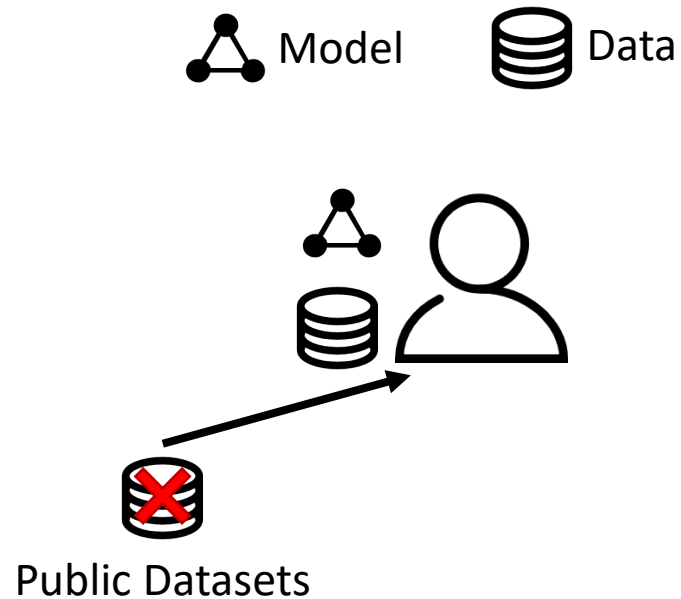
Data shortage

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



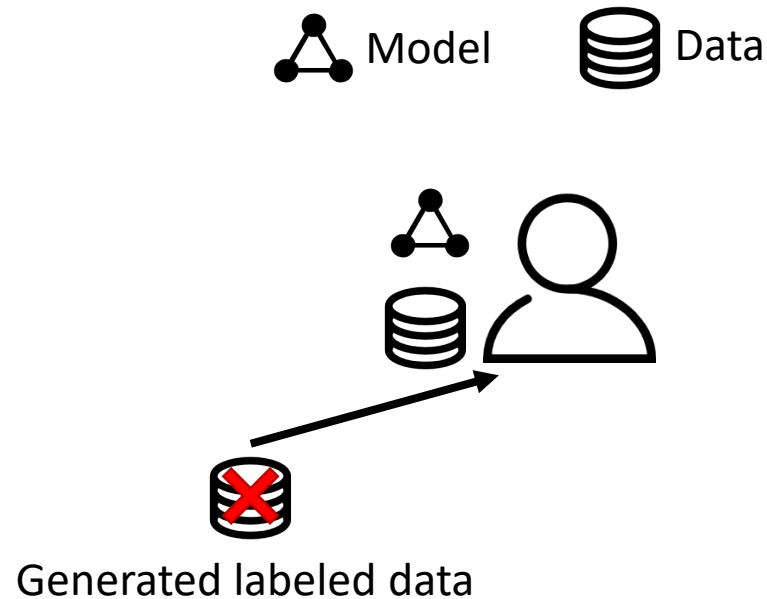
Public datasets

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



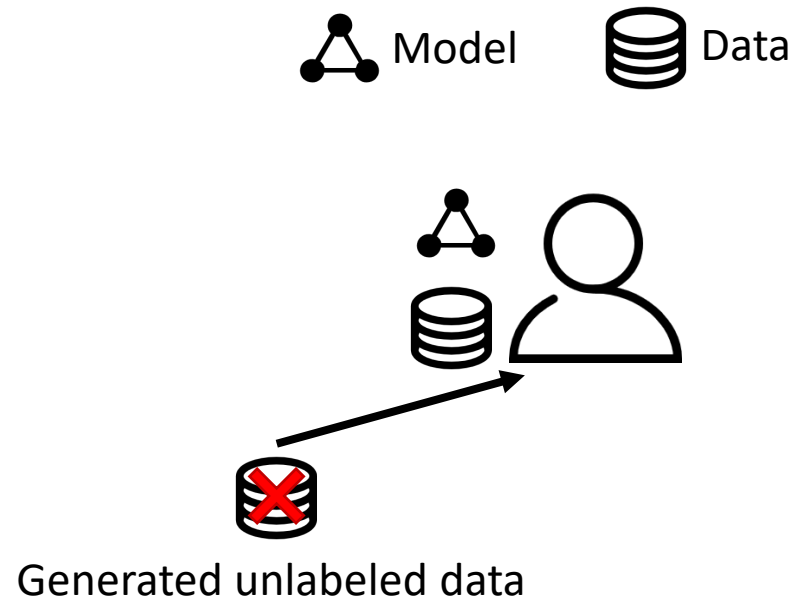
Generated labeled data

- Transmitting human-readable information, e.g., semantics of labels, about the client's task to the generator raises **privacy concerns**.



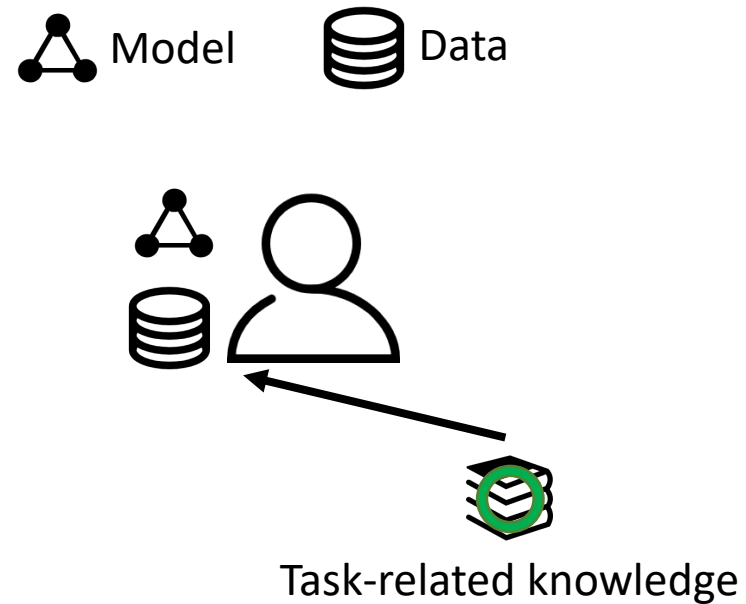
Generated unlabeled data

- The generated **unlabeled data** belongs to the **generator's output domain**, which is not naturally related to the client's task.
- Utilizing unlabeled data is **challenging**.



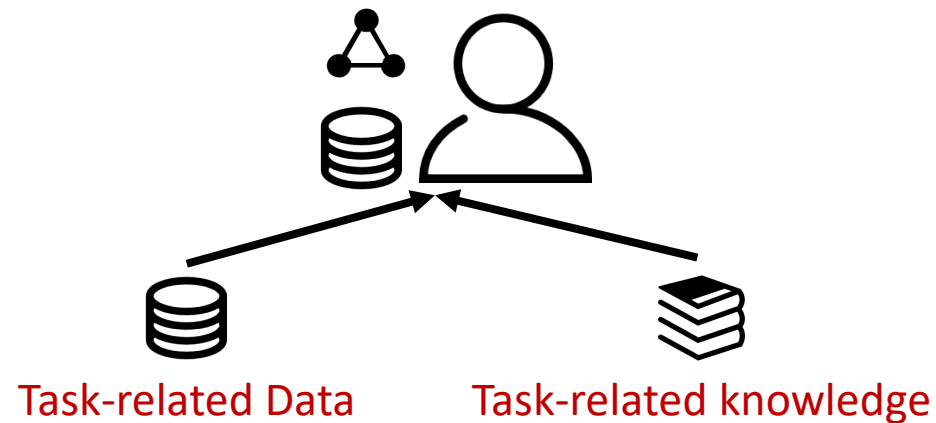
Knowledge from others

- Additional knowledge need to be **task-related**.
- Leveraging **knowledge from others** involved in similar tasks.



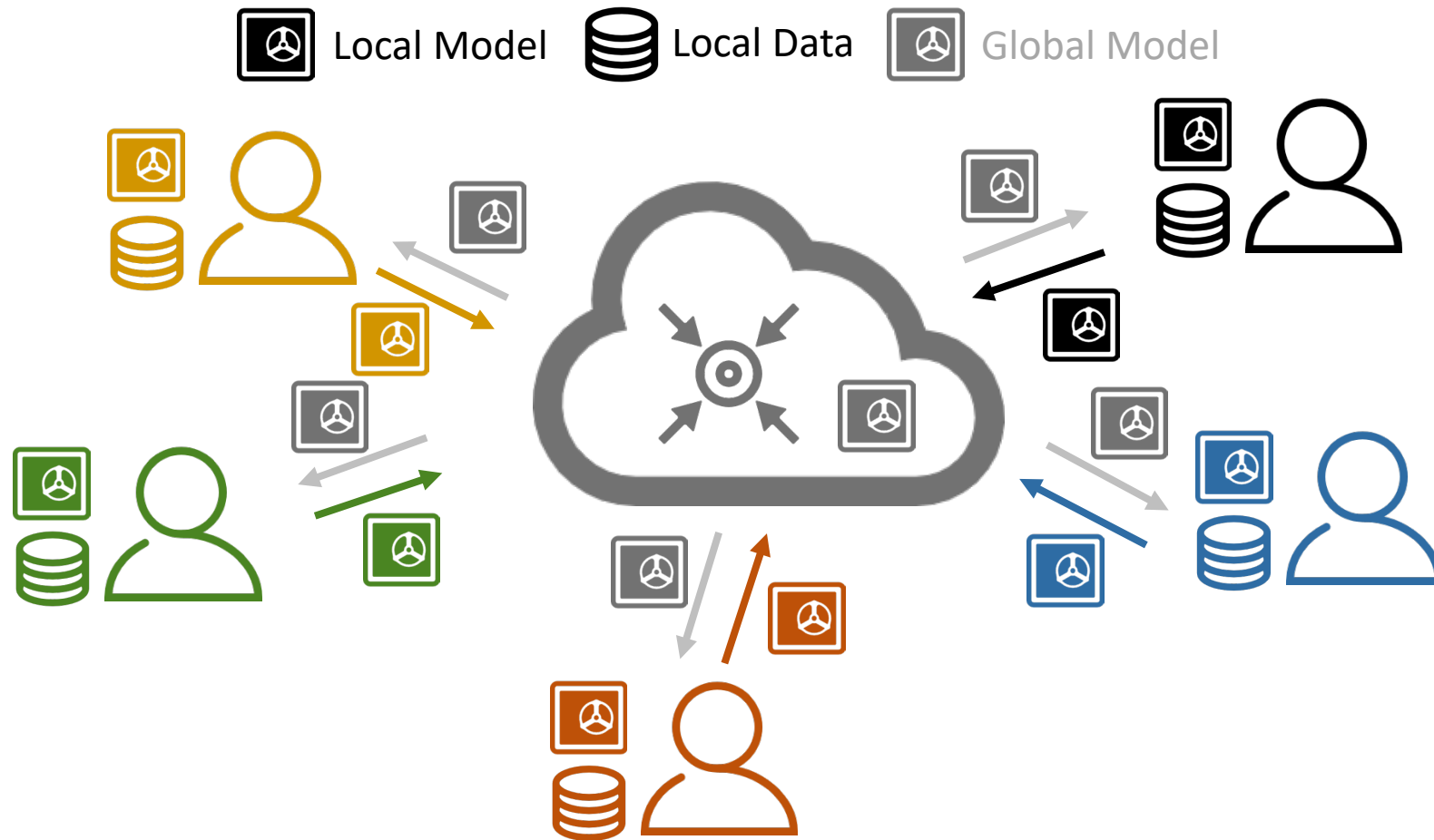
Our method

- Propose a **federated learning (FL) method** for sharing task-related (abstract) knowledge.
- Adapt a **large pre-trained generator** to produce images based on task-related knowledge.
- Transfer common and shared knowledge to each participant via **an additional supervised task**.



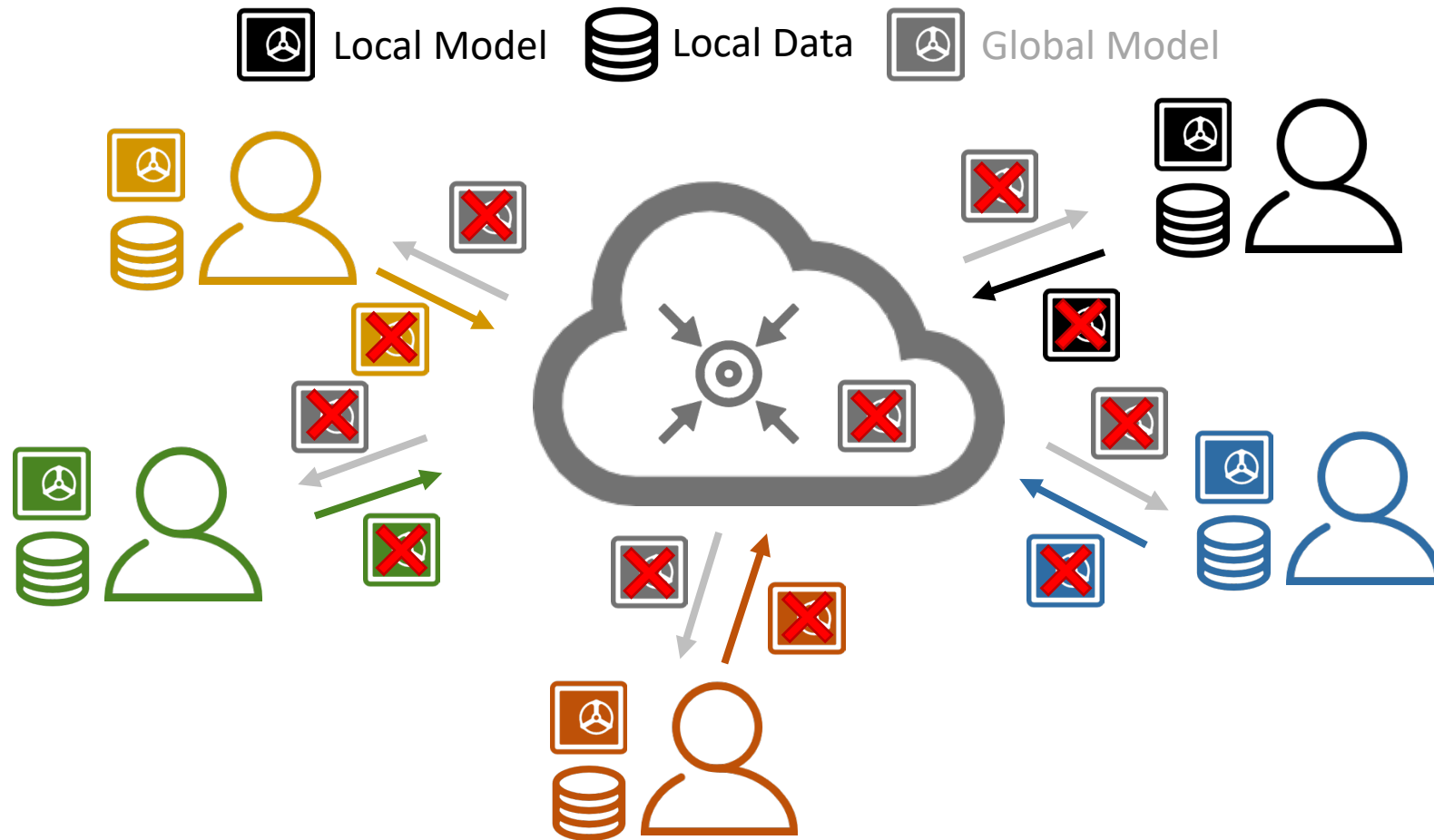
Heterogeneous Federated Learning (HtFL)

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



Heterogeneous Federated Learning (HtFL)

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



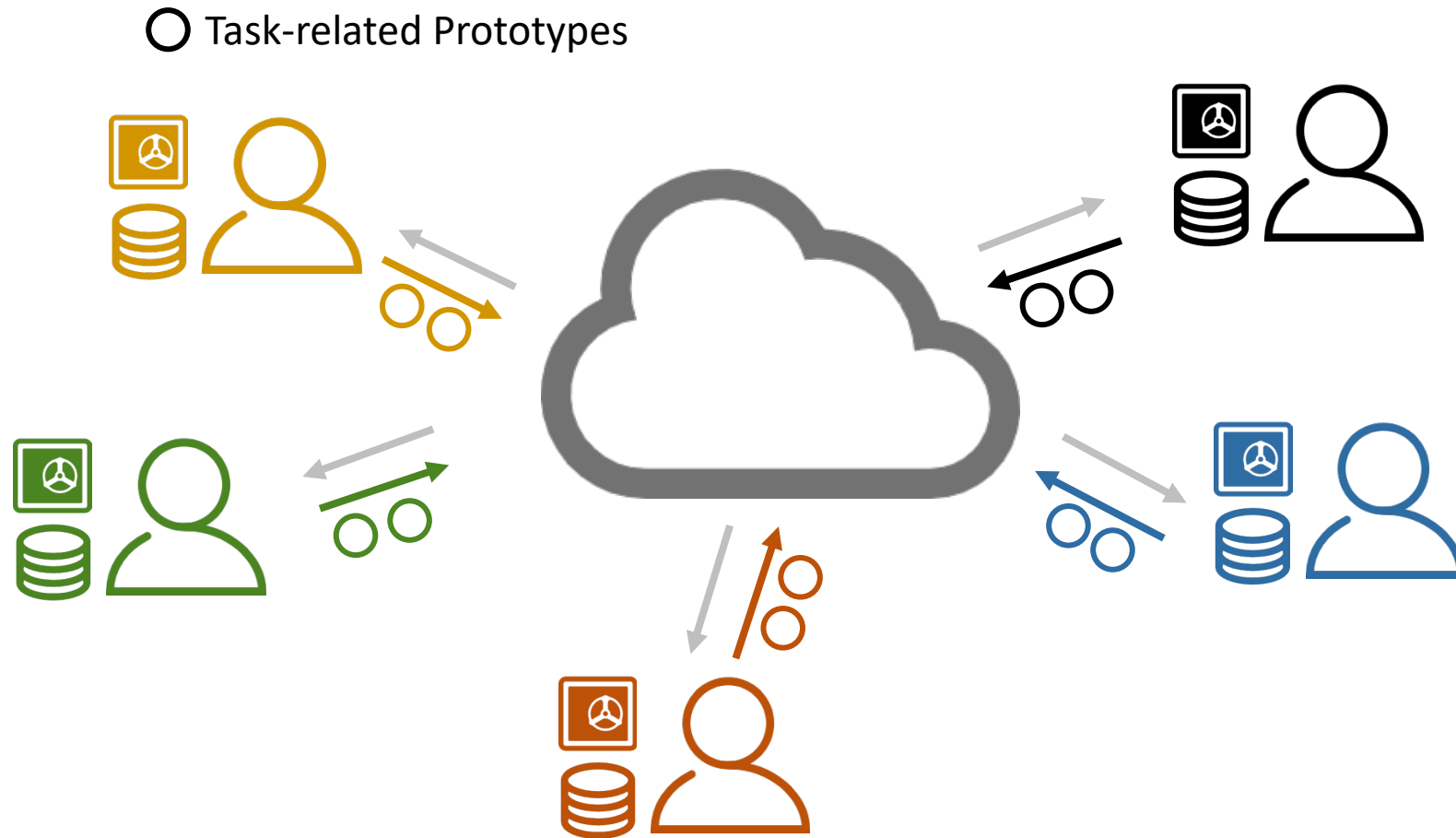
Heterogeneous Federated Learning (HtFL)

- Transmits **lightweight knowledge carriers** instead of exposing model parameters



Task-related prototypes

- Clients upload **task-related** prototypes ○ to the server.



Prototype aggregation

- The server aggregates client prototypes on the server.

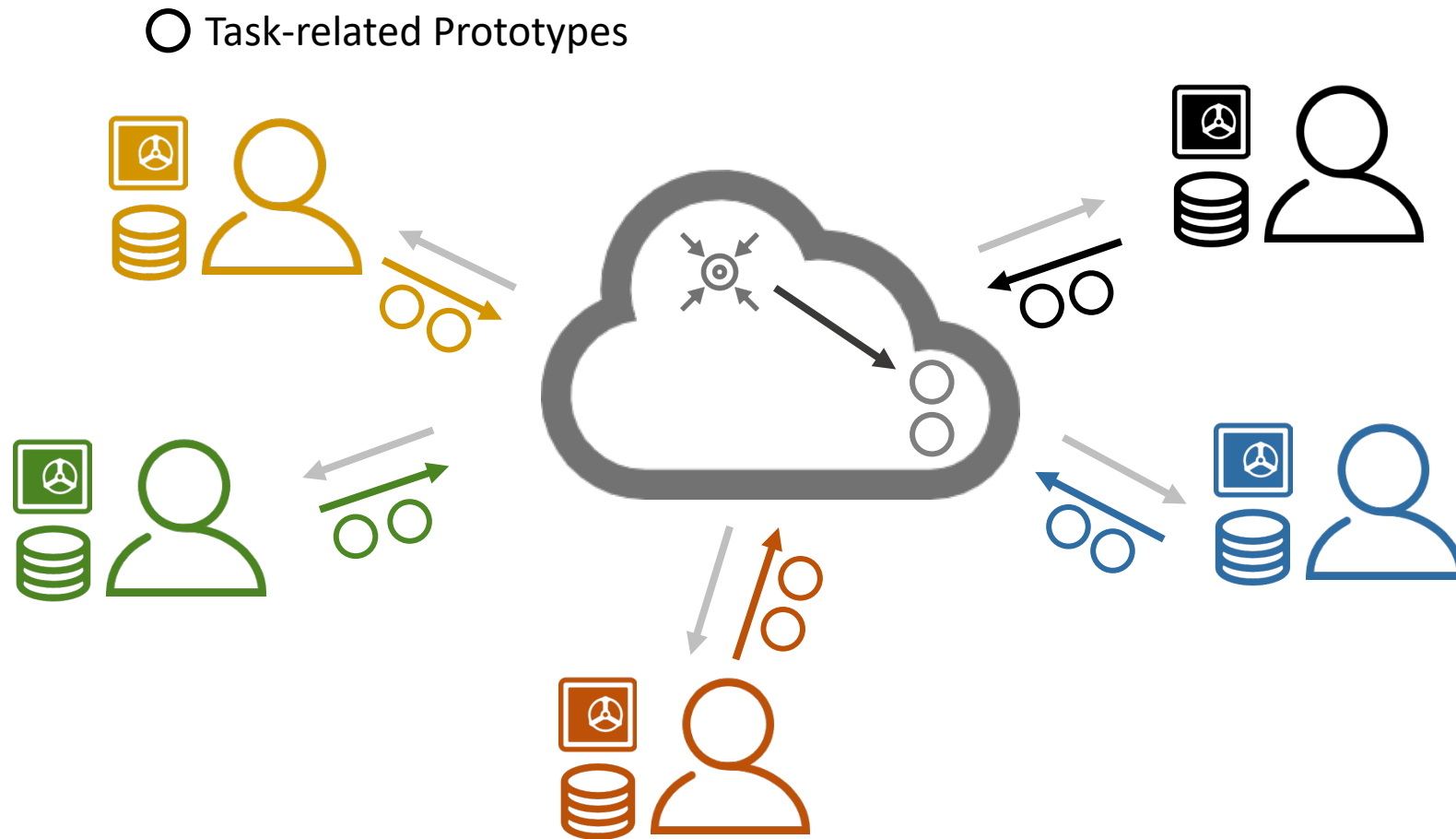


Image generation

- The server maps \bigcirc to **latent vectors** \triangle , and generates images \square .

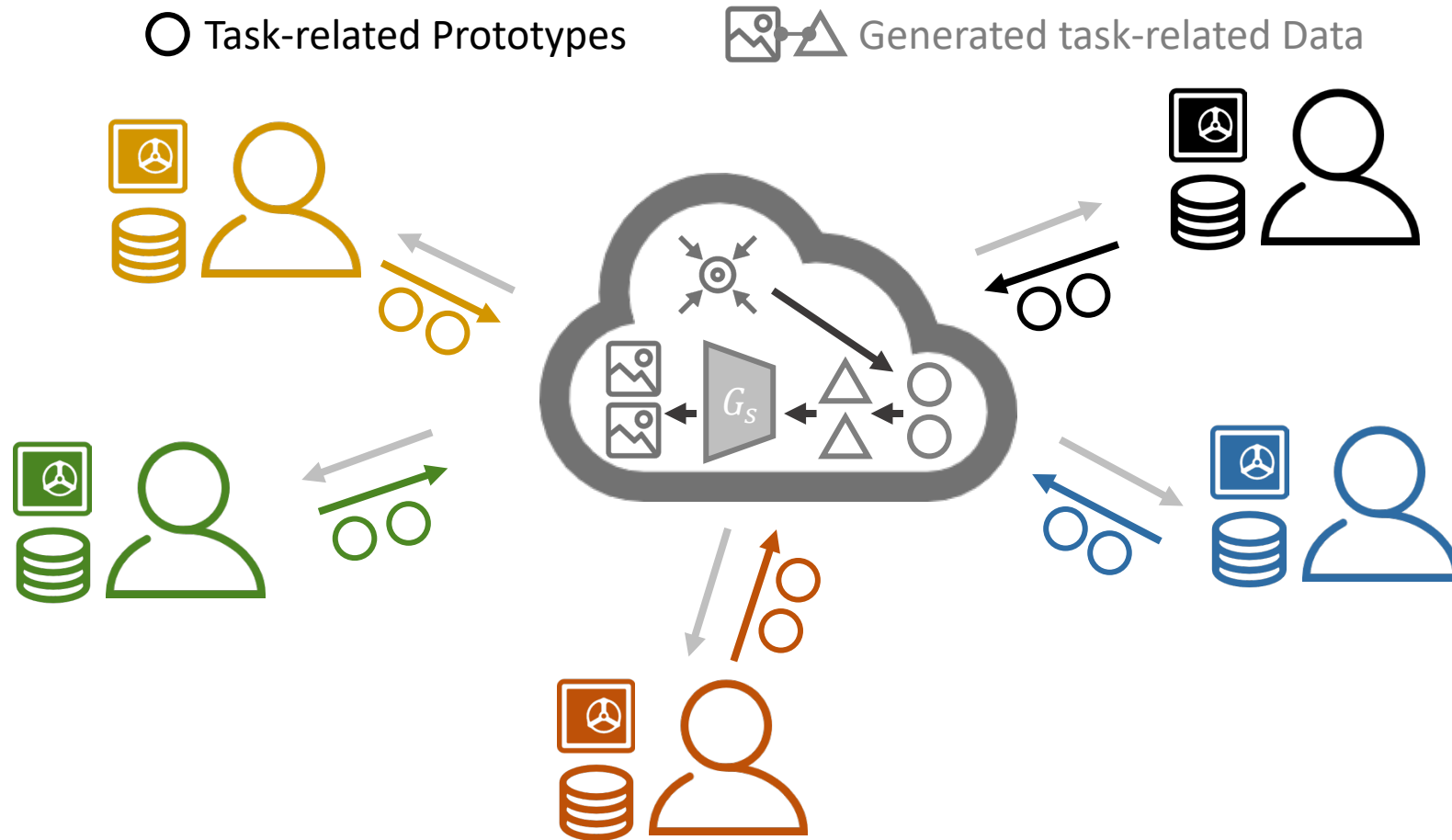


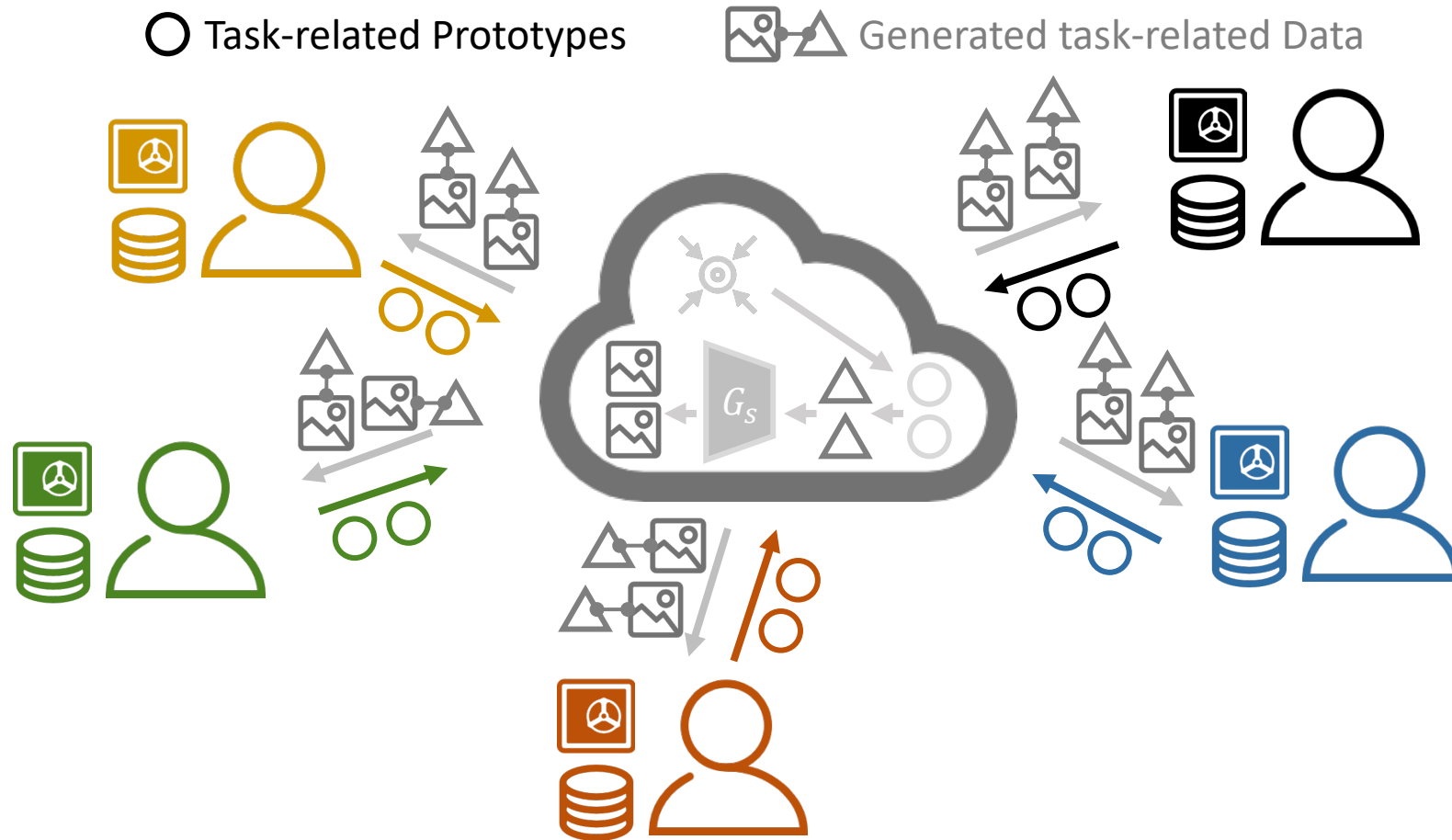
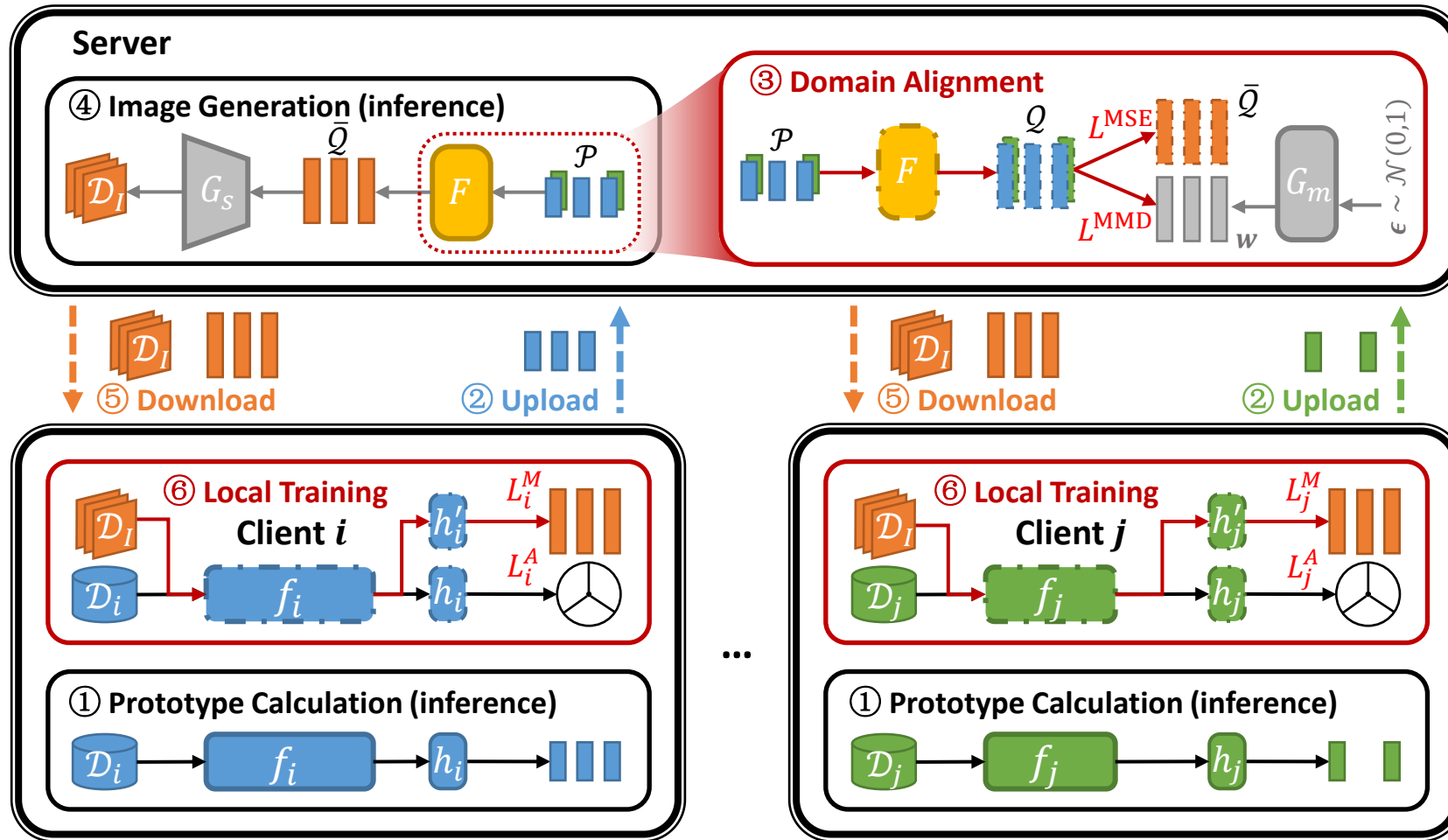


Image-vector pairs

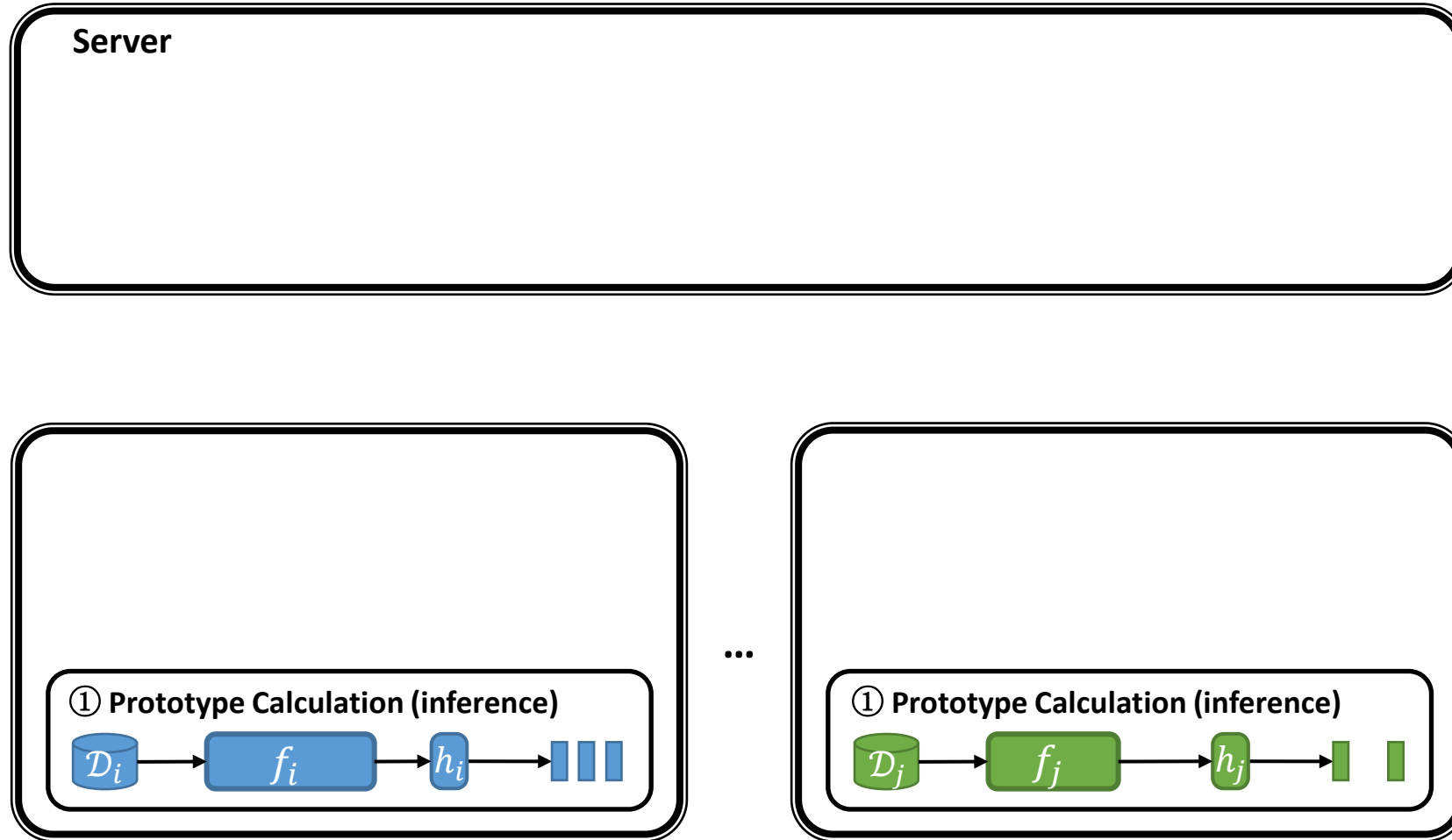
- The server sends **image-vector pairs**   to each client for an **additional supervised task**.



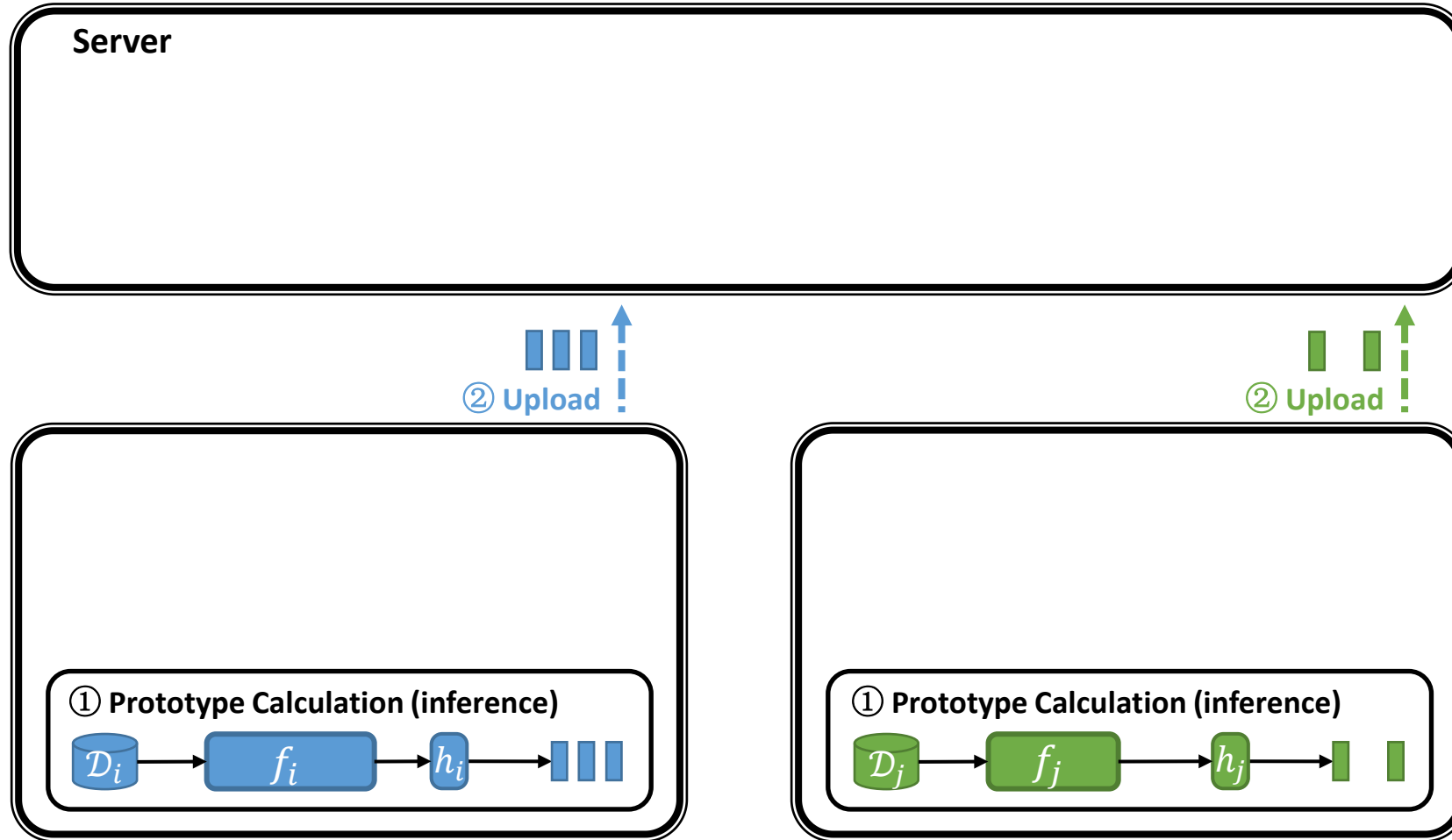
Overview



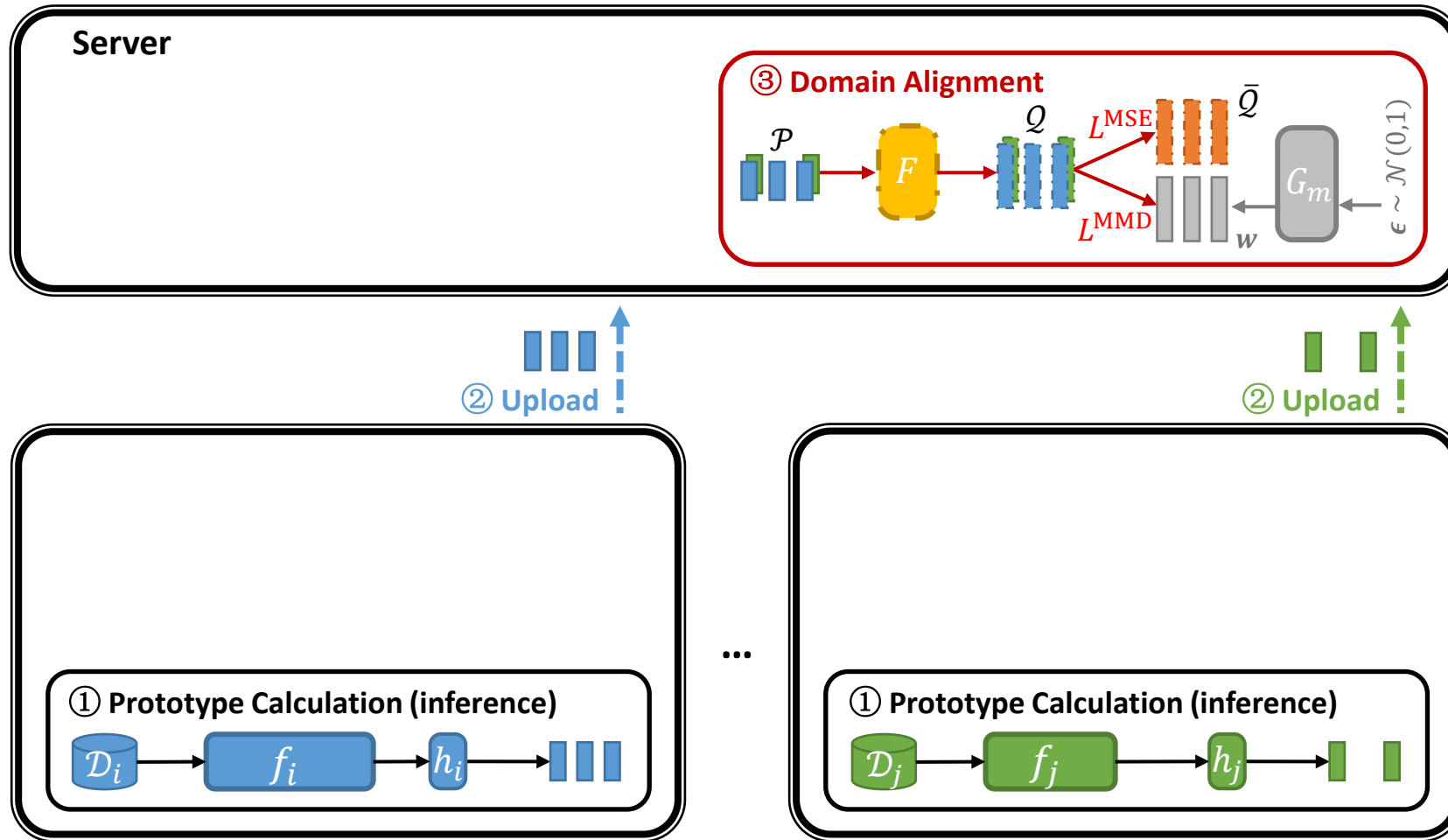
① Prototype Calculation (inference)



② Upload

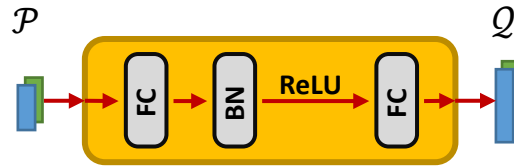


③ Domain Alignment



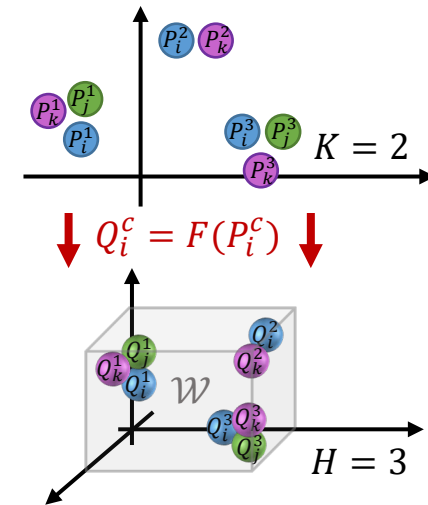
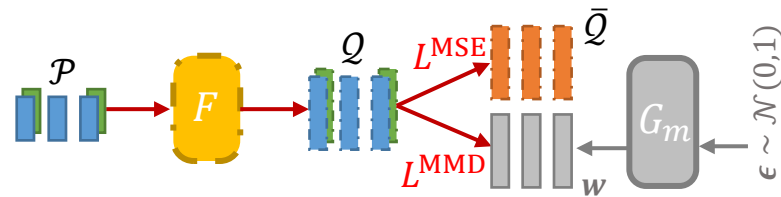
③ Domain Alignment

- The architecture of the feature transformer F .

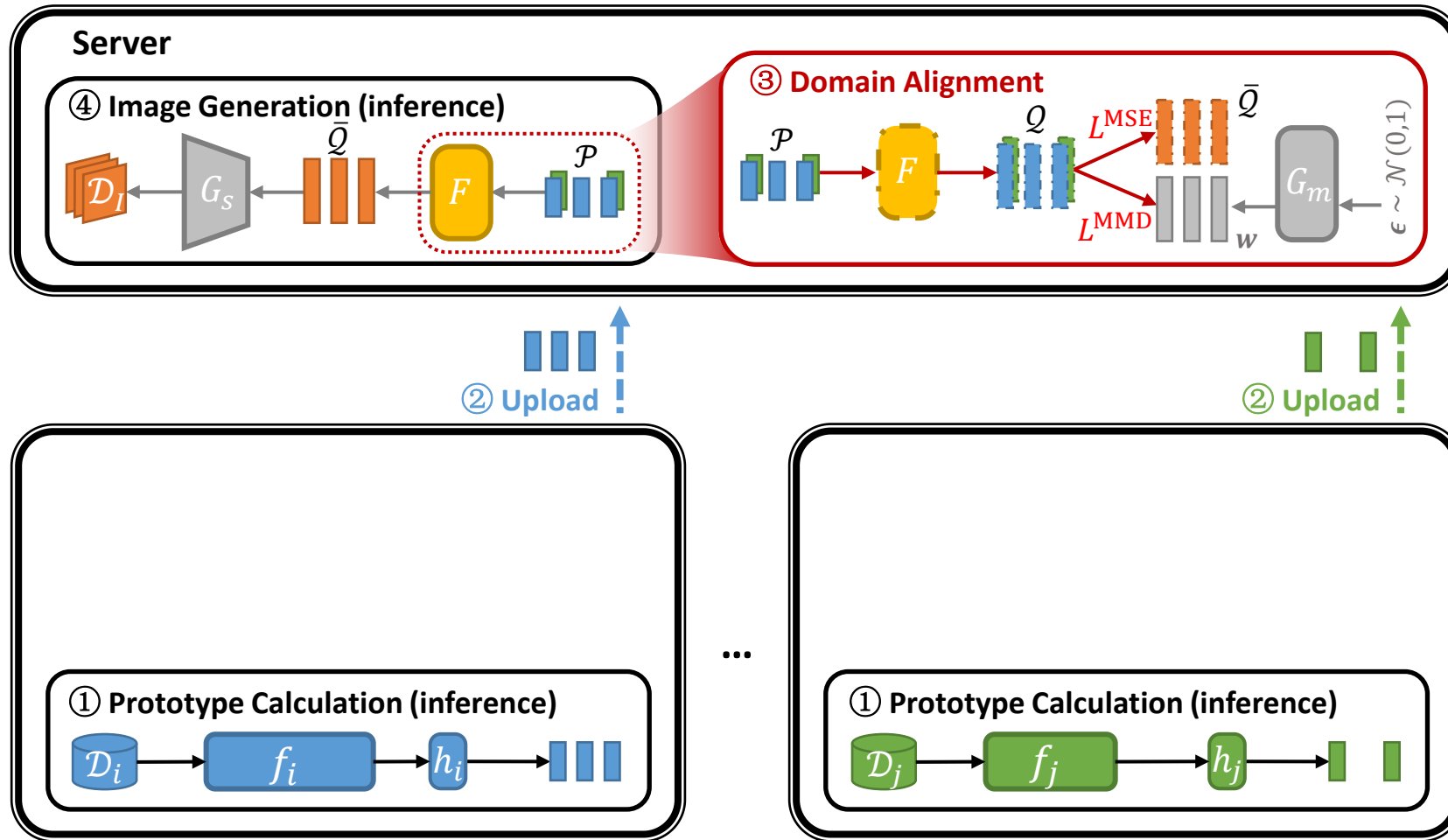


③ Domain Alignment

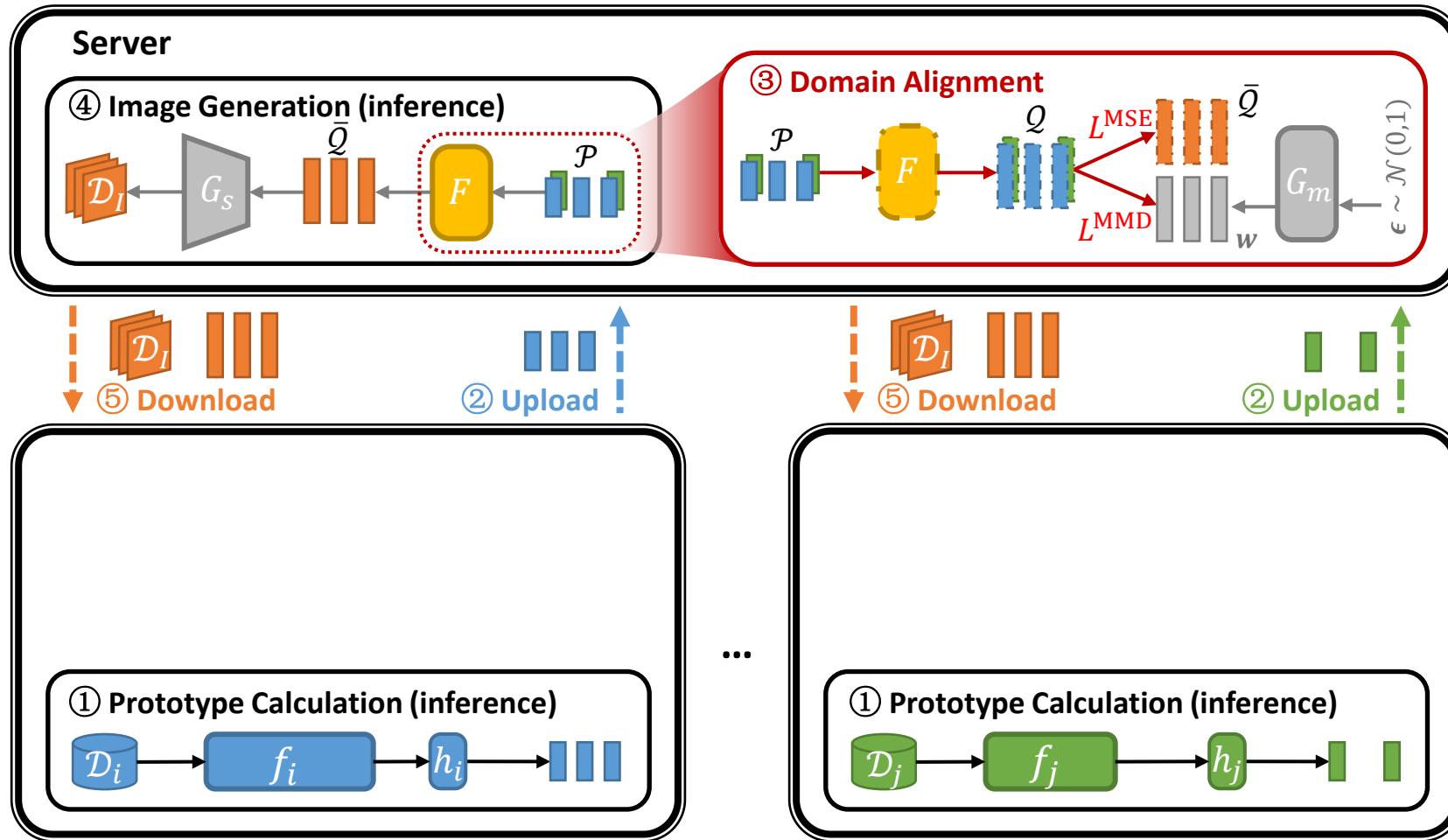
- A domain alignment example.



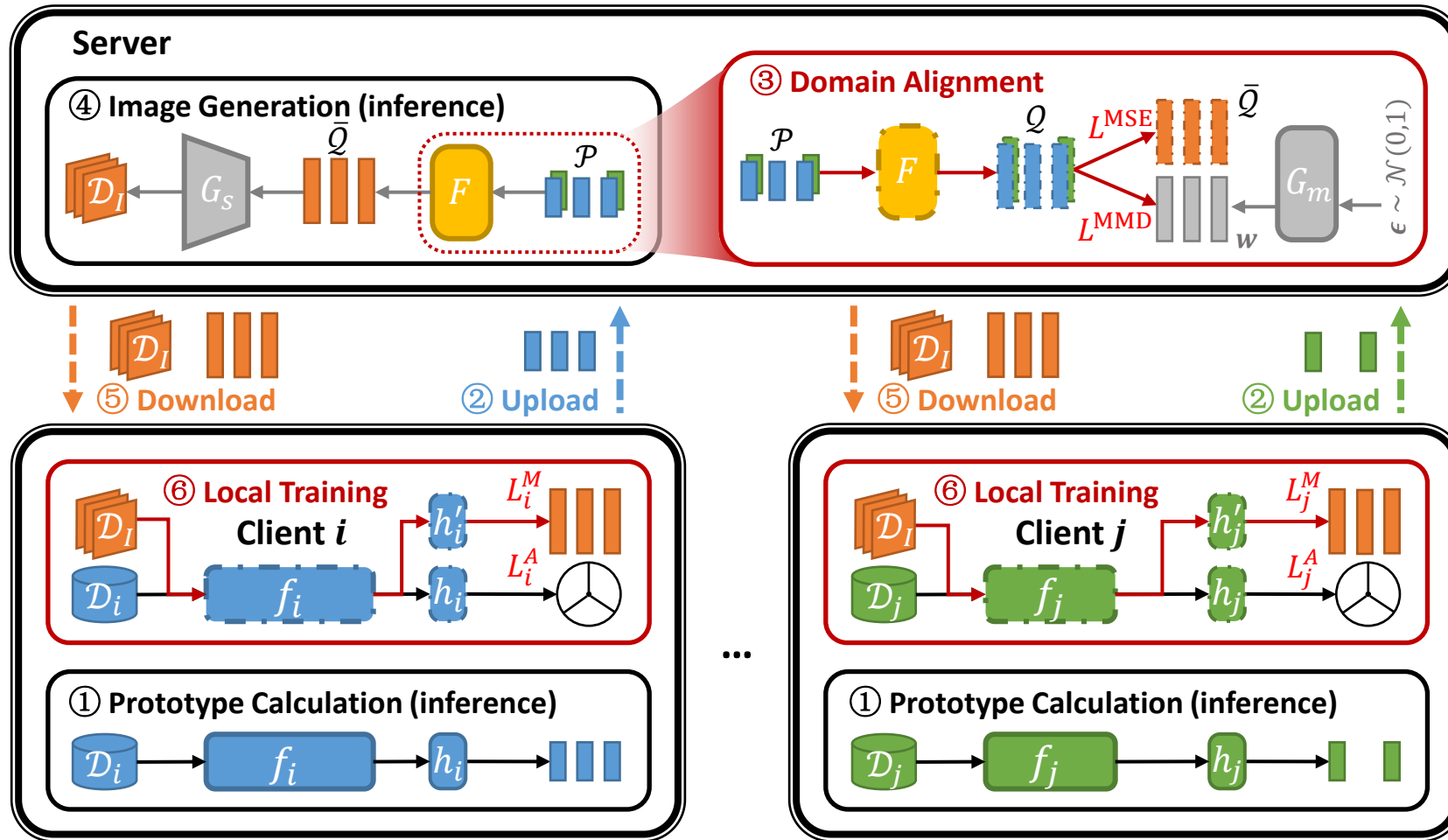
④ Image Generation (inference)



⑤ Download

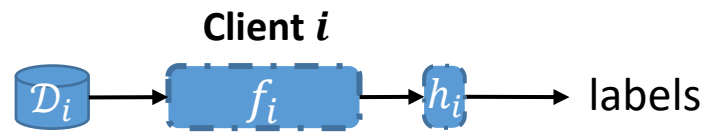


⑥ Local Training



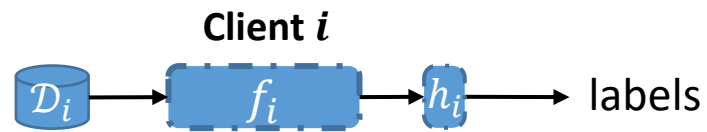
⑥ Local Training

- Original local task: **classification**.



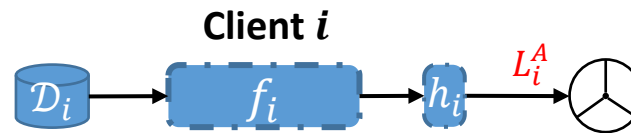
⑥ Local Training

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



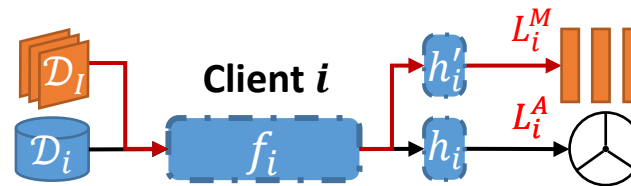
⑥ Local Training

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



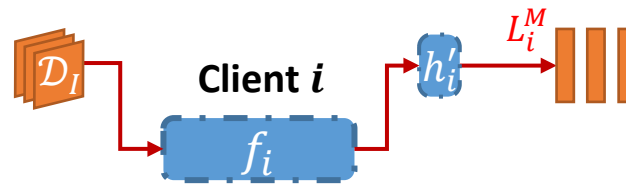
⑥ Local Training

- Transfer knowledge through an **additional supervised task**.



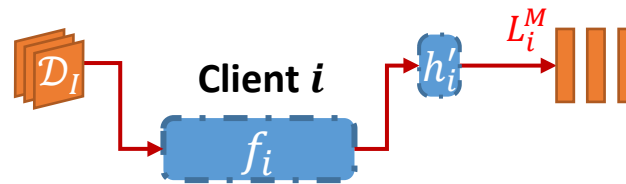
⑥ Local Training

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



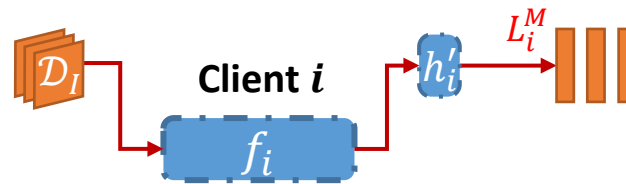
⑥ Local Training

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



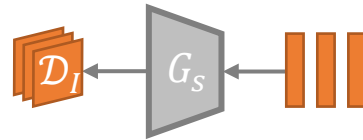
⑥ Local Training

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



Support for various pre-trained generators

- In other words, **generators pre-trained on any image datasets are applicable.**



Support for various pre-trained generators

- In other words, **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

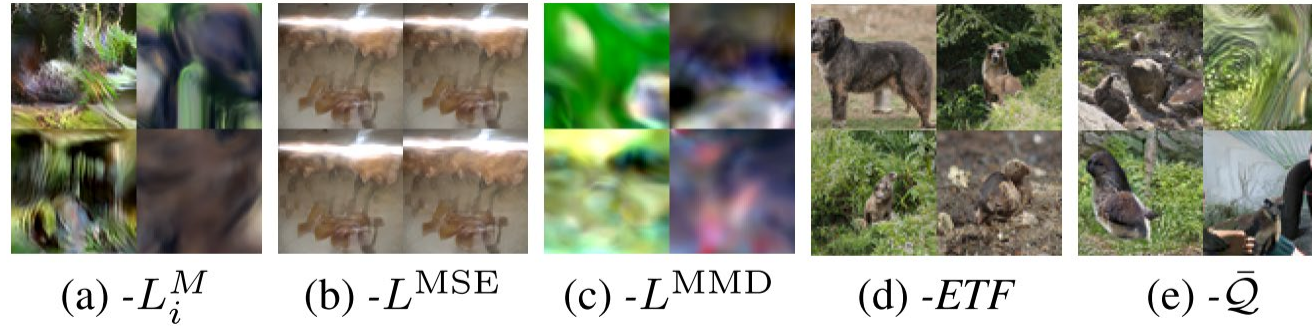
- In other words, **generators pre-trained on any image datasets are applicable.**

	$\lambda = 0.05$	$\lambda = 0.1$	$\lambda = 0.5$
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 HtFE₈ 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 can be omitted.



Excellent performance

- Experiment on four datasets using 14 kinds of models.

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 HtFE₈.

Excellent performance

- Experiment on four datasets 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 HtFE₈ 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 **various generators**, such as **StyleGAN** and **Stable Diffusion**, share similarities when generating contents, thus **they are all applicable** in our FedKTL.

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 HtFE₈.

The cloud-edge scenario

- Our **knowledge transfer scheme (KTL)** is also applicable in scenarios with **only one edge client**.
 - 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!