GFedCL: Graph-Based Federated Continual Learning with Spatial and Temporal Awareness

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1. Motivation

- Auxiliary conditioning helps in replay.

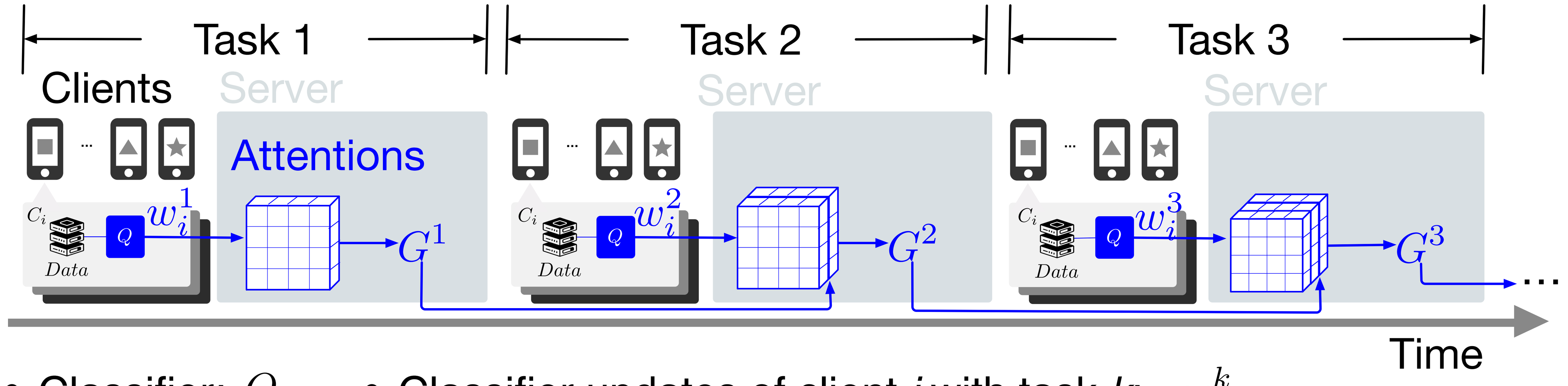
What auxiliary conditioning exists in FCL?

- Spatial and Temporal variation patterns.
- For example, patterns of client *i* of task *k* (represented as a graph row):

$$\mathbf{g}_i^k \triangleq G_{i,:}^k \in \mathbb{R}_+^N,$$

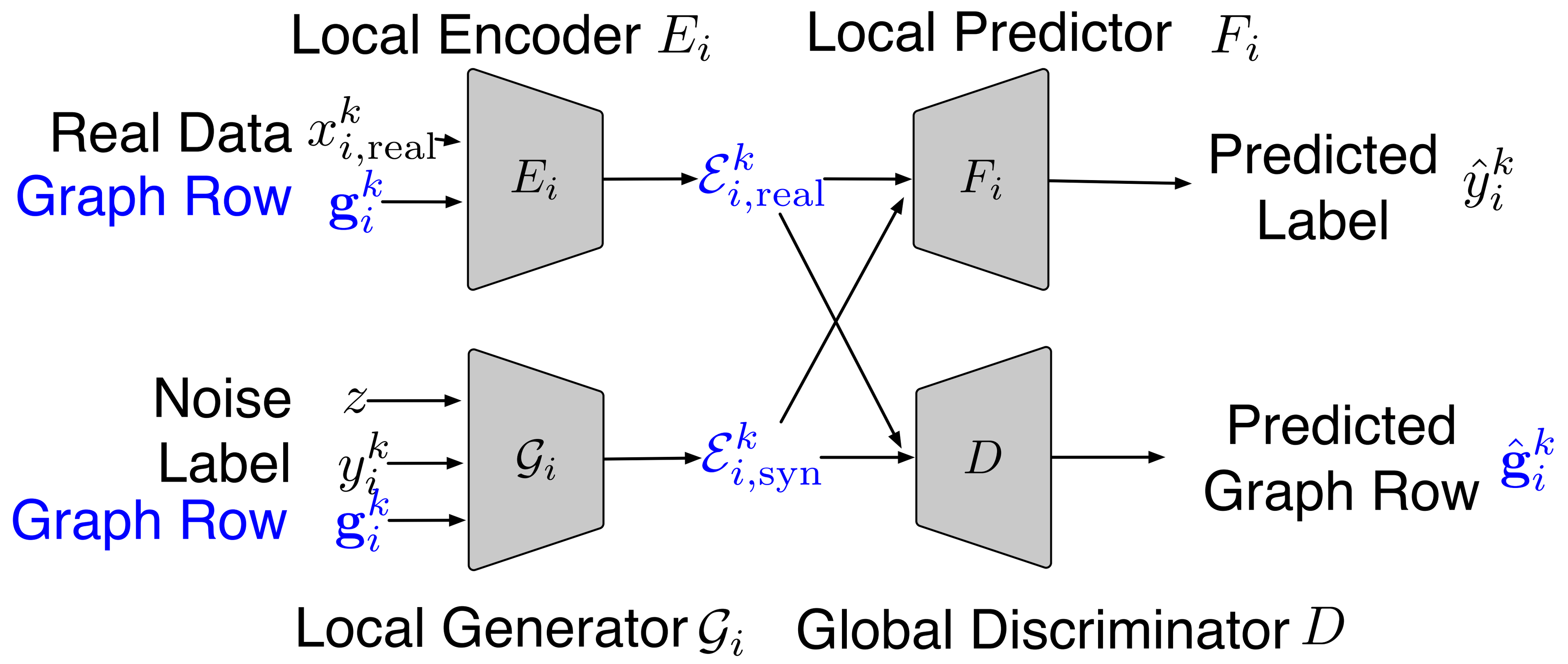
where $G_{ij}^k = \underbrace{\alpha_{ij}^k}_{\text{Spatial Attention}} \cdot \underbrace{\beta_{ij}^k}_{\text{Temporal Attention}} \in (0,1).$

2. Graph Generation



- Classifier: Q.
- Classifier updates of client *i* with task *k*: w_i^k.
- Spatial attention: $\alpha_{ij}^k = \mathrm{softmax}_j\left(a(w_i^k, w_j^k)\right) \in (0,1).$
- Temporal attention: $\beta_{ij}^k = \mathrm{softmax}_j\left(b(H_i^k, H_j^k, m)\right) \in (0,1)$, where $H_i^k = \{a_{i,:}^t\}_{t=1}^k$.

3. GFedCL



- Graph serves as conditioning in the adversarial training.

4. Representation Alignment between Real and Synthetic Data Embeddings

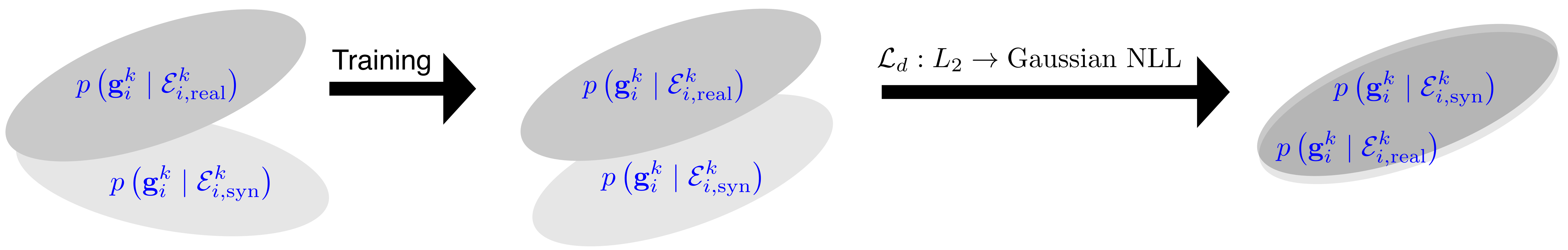
Before Training

After Training

Mean Alignment: $\forall i \in [N], \forall k \in [K],$

$$\mathbb{E}[\mathbf{g}_i^k | \mathcal{E}_{i,\mathrm{real}}^k] = \mathbb{E}[\mathbf{g}_i^k | \mathcal{E}_{i,\mathrm{syn}}^k] = \mathbb{E}[\mathbf{g}_i^k] = \mathbf{g}^*.$$

Mean and Variance Alignment

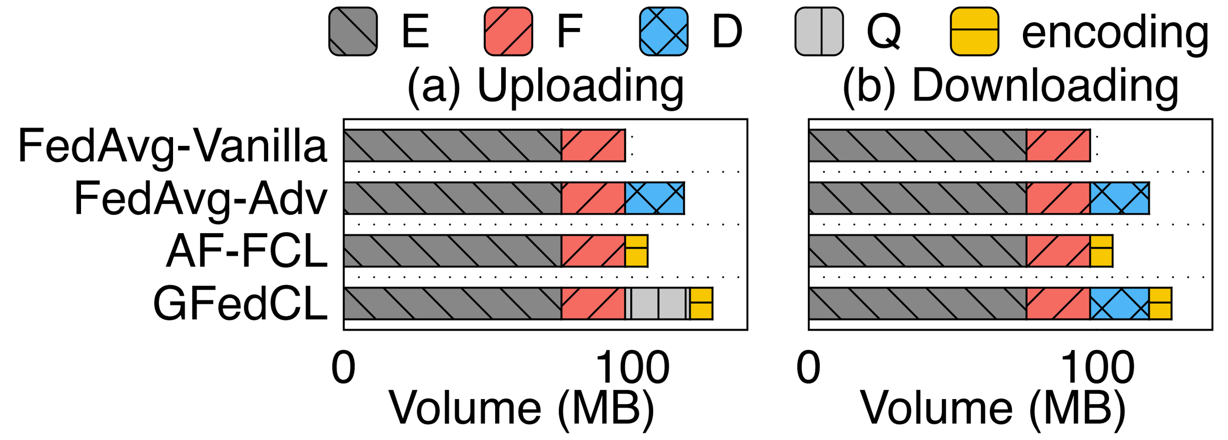


- Representation alignment alleviate catastrophic forgetting and data heterogeneity simultaneously.

6. Evaluation

Comm. Overhead

Main Results



Method	EMNIST-Letters		CIFAR-100		TinyImageNet	
	Acc (%)↑	Forgetting (%)↓	Acc (%)↑	Forgetting (%)↓	Acc (%)↑	Forgetting (%)↓
GLFC	43.47 ± 2.14	8.74 ± 2.78	46.08 ± 2.70	5.66 ± 1.74	42.93 ± 2.88	7.64 ± 2.91
FedAvg-Adv	25.67 ± 4.49	9.77 ± 3.17	32.05 ± 4.51	8.92 ± 2.01	25.41 ± 6.55	9.74 ± 3.29
FedCIL	38.95 ± 4.53	8.87 ± 2.31	39.47 ± 3.24	6.54 ± 1.72	45.75 ± 5.26	7.51 ± 1.33
MFCL	52.66 ± 3.24	6.76 ± 1.24	37.09 ± 3.76	5.26 ± 1.87	47.82 ± 3.09	8.11 ± 1.07
AF-FCL	41.22 ± 4.51	6.58 ± 1.44	43.27 ± 4.77	5.87 ± 2.35	54.91 ± 3.72	7.84 ± 2.02
C^2Prompt	68.47 ± 3.81	7.42 ± 1.80	<u>67.93</u> ± 5.19	6.94 ± 2.77	<u>72.41</u> ± 4.53	6.72 ± 1.84
AFL	<u>75.17</u> ± 1.31	**2.94** ± 0.79	55.33 ± 1.55	**3.47** ± 0.85	49.44 ± 1.35	**3.95** ± 1.59
GFedCL	**77.23** ± 2.76	<u>3.34</u> ± 1.21	**73.67** ± 3.42	<u>4.24</u> ± 1.45	**77.39** ± 3.02	<u>5.57</u> ± 1.88

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