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FedSeg: Class-Heterogeneous Federated Learning for Semantic Segmentation

GRADUATION REPORT TEMPLE FOR ZHEJIANG UNIVERSITY

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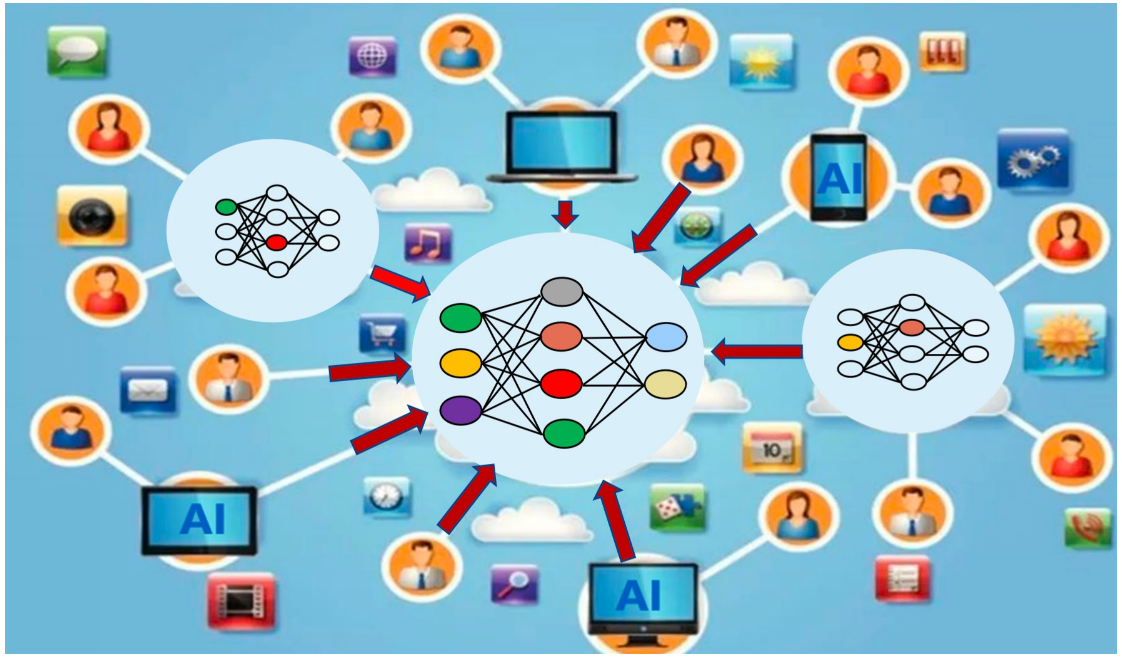
AI & Data Privacy



AI models require large amounts of data, collected from **a variety of sources**.

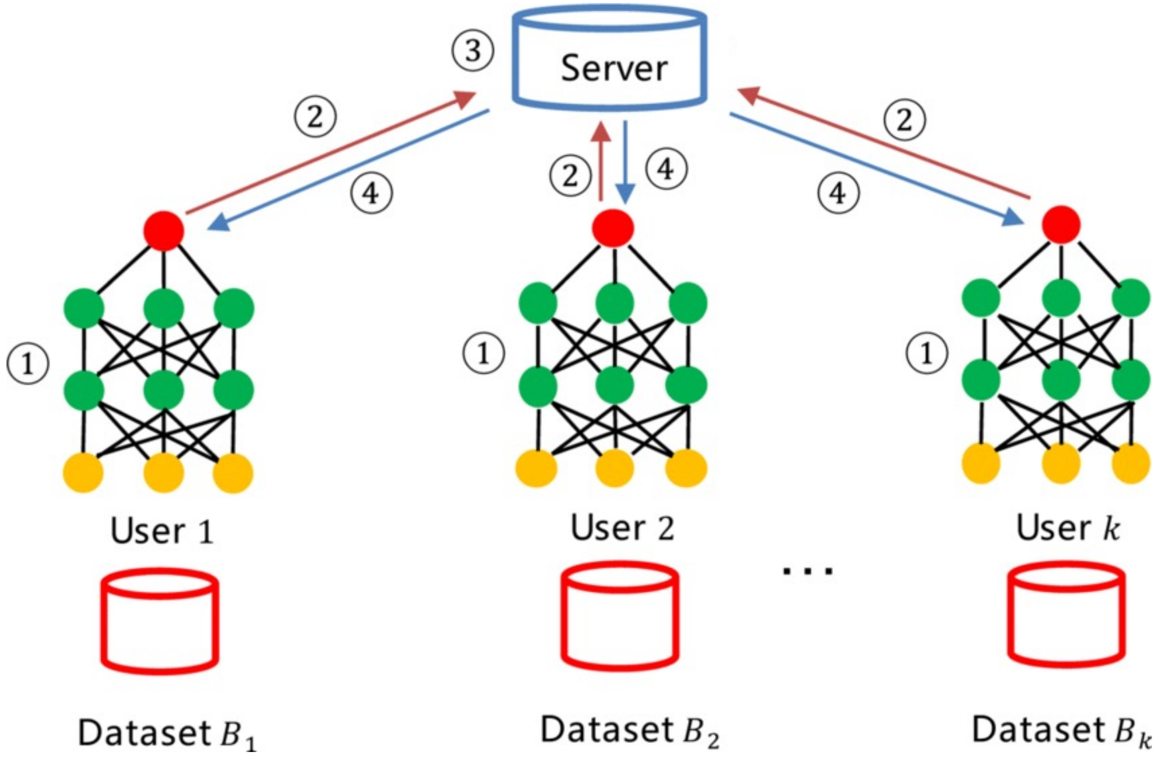
A risk of data privacy leakage will be compromised if AI models **use sensitive or personal data directly**.

FedSeg: Class-Heterogeneous Federated Learning for Semantic Segmentation. In CVPR2023.

AI & Data Privacy – Federated Learning

Federated Learning - training across multiple **decentralized** edge devices or servers

- holding local data, **without exchanging them**



1. Local Training
2. Model Upload
3. Global Aggregation
4. Model Deployment

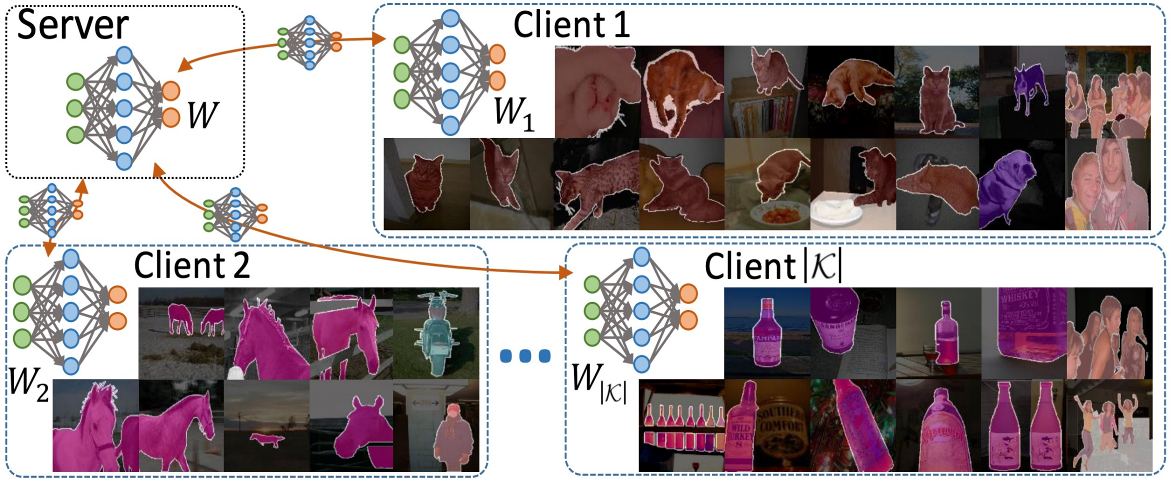
FedSeg: Class-Heterogeneous Federated Learning for Semantic Segmentation. In CVPR2023.

Federated Learning for Semantic Segmentation

Federated learning is needed in semantic segmentation

- Pixel-level annotations are hard to acquire – Data Insufficient
- Collaborative learning and privacy-preserving

Pixel-level annotations are hard to acquire



Collaborative learning and privacy-preserving

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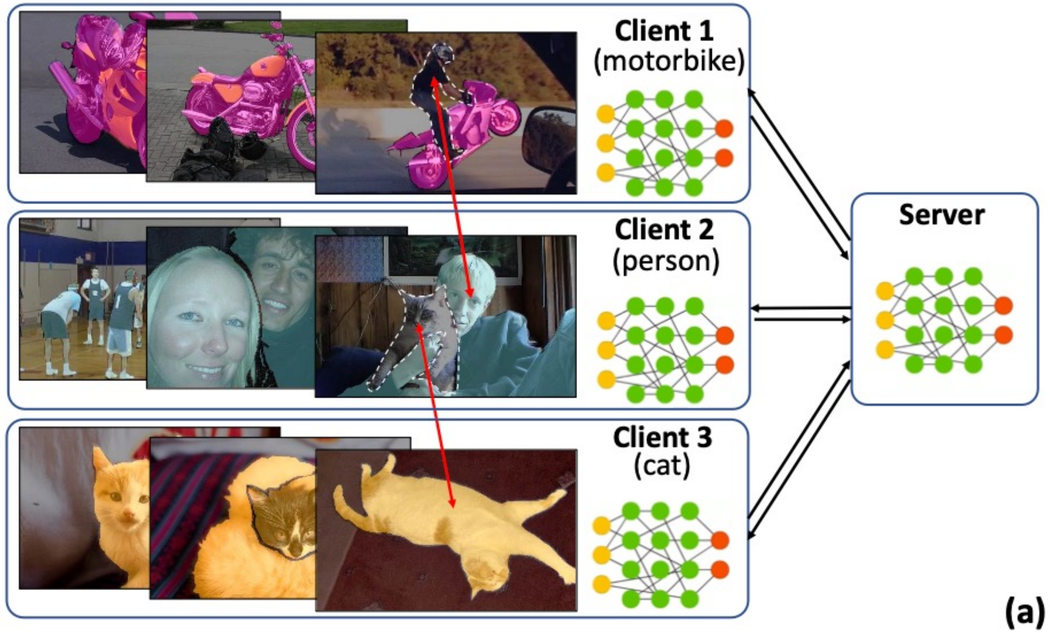
Federated Learning for Semantic Segmentation

Problems in semantic segmentation federated learning - **optimization direction diverging**

- **Foreground-background inconsistency**: “cat” is annotated in Client 3 but not in Client 2.
- **non-IID distribution:** makes the local optimization direction diverging to the global optimum.



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Federated Learning for Semantic Segmentation

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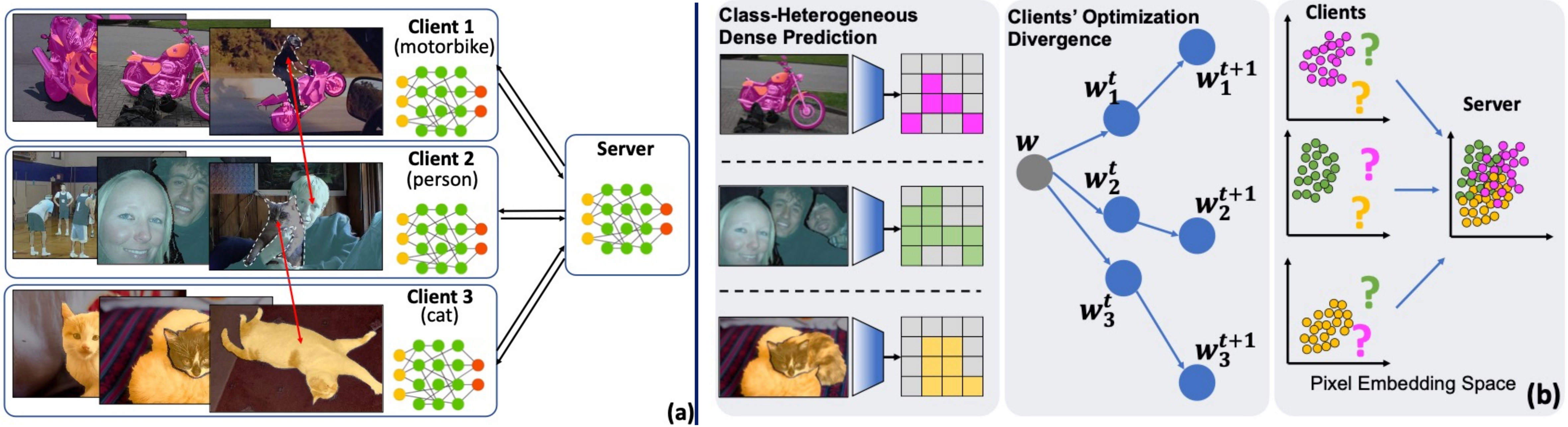

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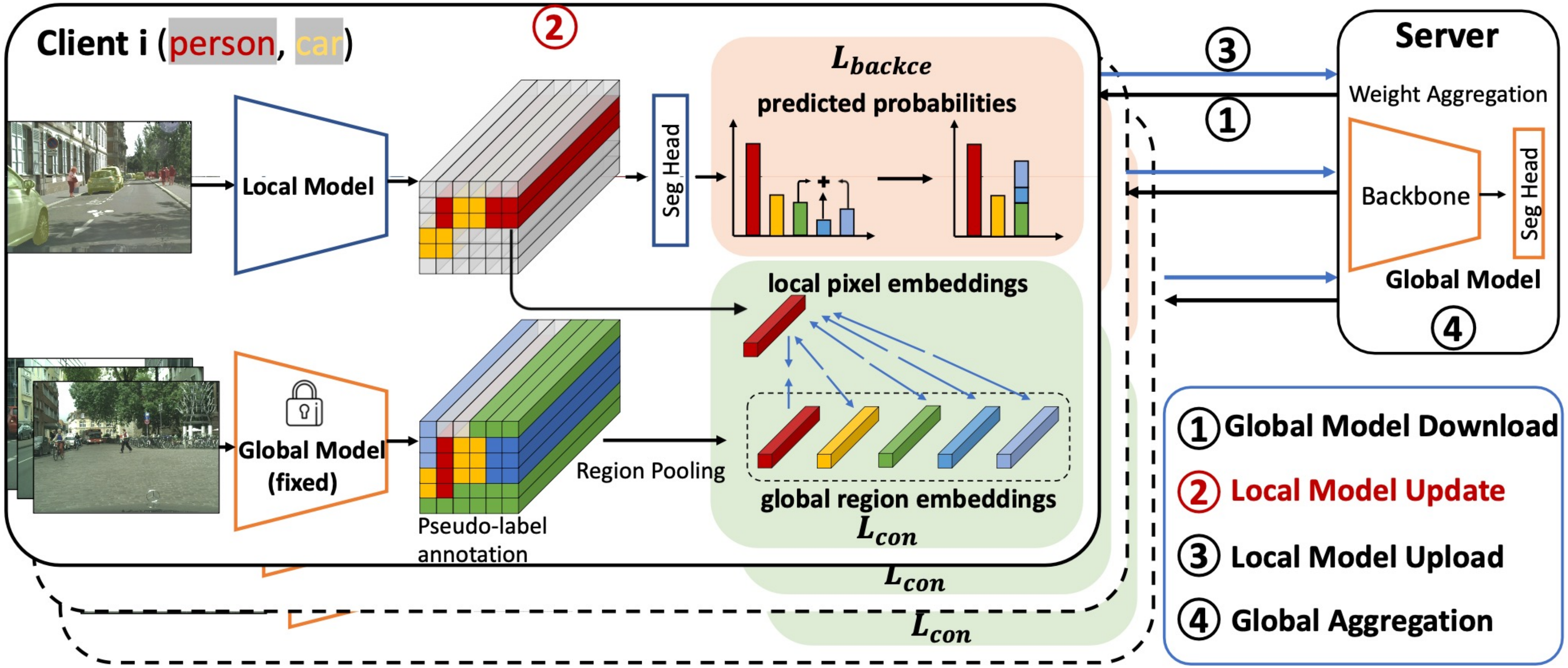
Federated Learning for Semantic Segmentation

Method: FedSeg – Use two local losses to **correct local drift** in local updates

- L_{backce} : modified CE loss - correct the local optimization direction
- L_{con} : local-to-global contrastive learning loss – local model close to global model



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Federated Learning for Semantic Segmentation

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Method: FedSeg – Use two local losses to **correct local drift** in local updates

- Proof of $\boldsymbol{L_{backce}}$: corrects local gradients to simulate the centralized learning

$$\mathcal{L}_{ce}(x,y) = -\frac{1}{|\mathcal{P}|}\sum_{j\in\mathcal{P}} \log q_x(j, y_j)$$

$$\downarrow$$

$$\frac{\partial \mathcal{L}_{ce}}{\partial z_c^j} = \begin{cases} p_c^j - 1 < 0 & \text{if } y_j = c \\ p_c^j > 0 & \text{if } y_j \neq c, \end{cases}$$

Standard CE Loss: direction away from the global optimum

$$\mathcal{L}^i_{backce}(x,y) = -\frac{1}{|\mathcal{P}|}\sum_{j\in\mathcal{P}} \log \hat{q}_x(j, y_j)$$

$$\hat{q}_x(j,c) = \begin{cases} q_x(j,c) & \text{if } c \in \mathcal{C}_i \\ \sum_{k\in\mathcal{C}\setminus\mathcal{C}_i}^{K} q_x(j,k) & \text{if } c \notin \mathcal{C}_i. \end{cases}$$

$$\downarrow$$

$$\frac{\partial \mathcal{L}_{backce}}{\partial z_c} = -\frac{e^{z_c}}{\sum_{k=1}^{K} e^{z_k}} \cdot \frac{e^{z_l}}{\sum_{k\neq l}^{K} e^{z_k}} = -p_c \cdot \frac{e^{z_l}}{\sum_{k\neq l}^{K} e^{z_k}} \approx -p_c \cdot p_l;$$

BackCE Loss: Similar to the centralized learning

Federated Learning for Semantic Segmentation

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Experiments: Ablation study and comparisons with **state-of-the-art methods**

(a) Results of FedSeg(%) to show the effectiveness of $\mathcal{L}_{backce}$ and $\mathcal{L}_{con}$.

Method	Cityscapes				CamVID				VOC		ADE20k	
	non-IID$_1$		non-IID$_2$		non-IID$_1$		non-IID$_2$					
	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc
FedAvg [31]	10.40	31.90	28.60	73.76	19.06	51.71	32.12	69.55	8.56	34.44	6.91	59.25
FedAvg+$\mathcal{L}_{backce}$	45.08	87.98	47.67	89.48	58.38	88.51	62.13	90.00	32.28	54.83	8.31	61.60
FedAvg+$\mathcal{L}_{backce}$+$\mathcal{L}_{con}$	**50.24**	**90.06**	**52.18**	**91.38**	**63.50**	**90.68**	**64.67**	**91.25**	32.20	54.50	**8.64**	**62.10**

(b) Comparison with other FL methods(%). *All of them use $\mathcal{L}_{backce}$ as baseline.

	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc	mIoU	Acc
FedAvg* [31]	45.08	87.98	47.67	89.48	58.38	88.51	62.13	90.00	32.28	54.83	8.31	61.60
FedProx* [22]	44.85	87.50	47.17	89.81	58.29	87.28	62.04	90.61	32.17	55.19	8.25	61.01
FedDyn* [1]	45.19	88.26	47.69	90.38	59.44	89.32	62.18	90.20	32.20	54.59	-	-
MOON* [26]	45.84	88.58	47.87	89.59	58.90	87.96	62.77	90.98	30.92	53.91	-	-
FedSeg	**50.24**	**90.06**	**52.18**	**91.38**	**63.50**	**90.68**	**64.67**	**91.25**	32.20	54.50	**8.64**	**62.10**

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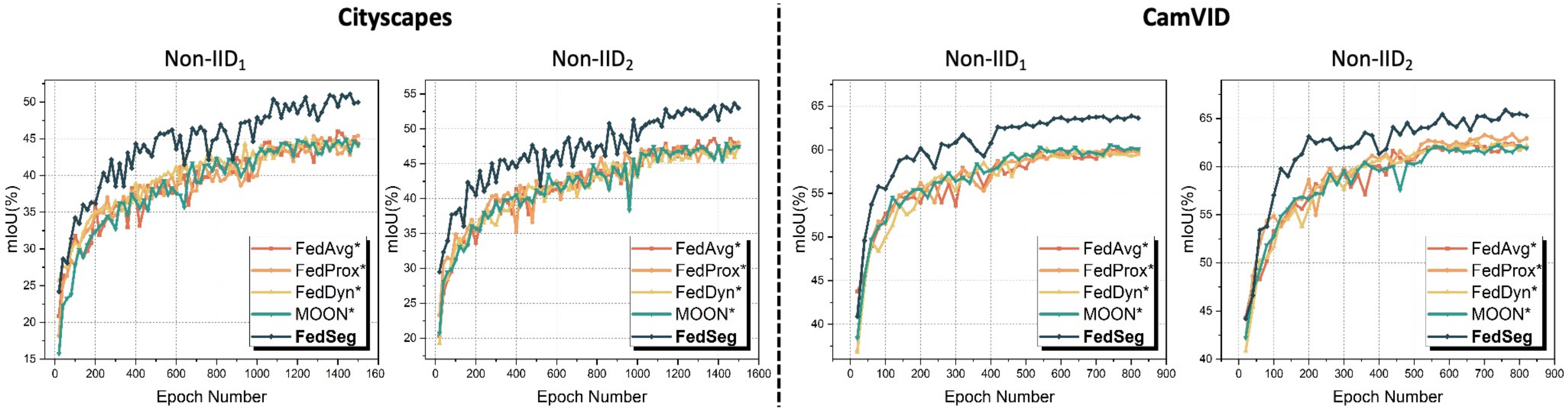
Federated Learning for Semantic Segmentation

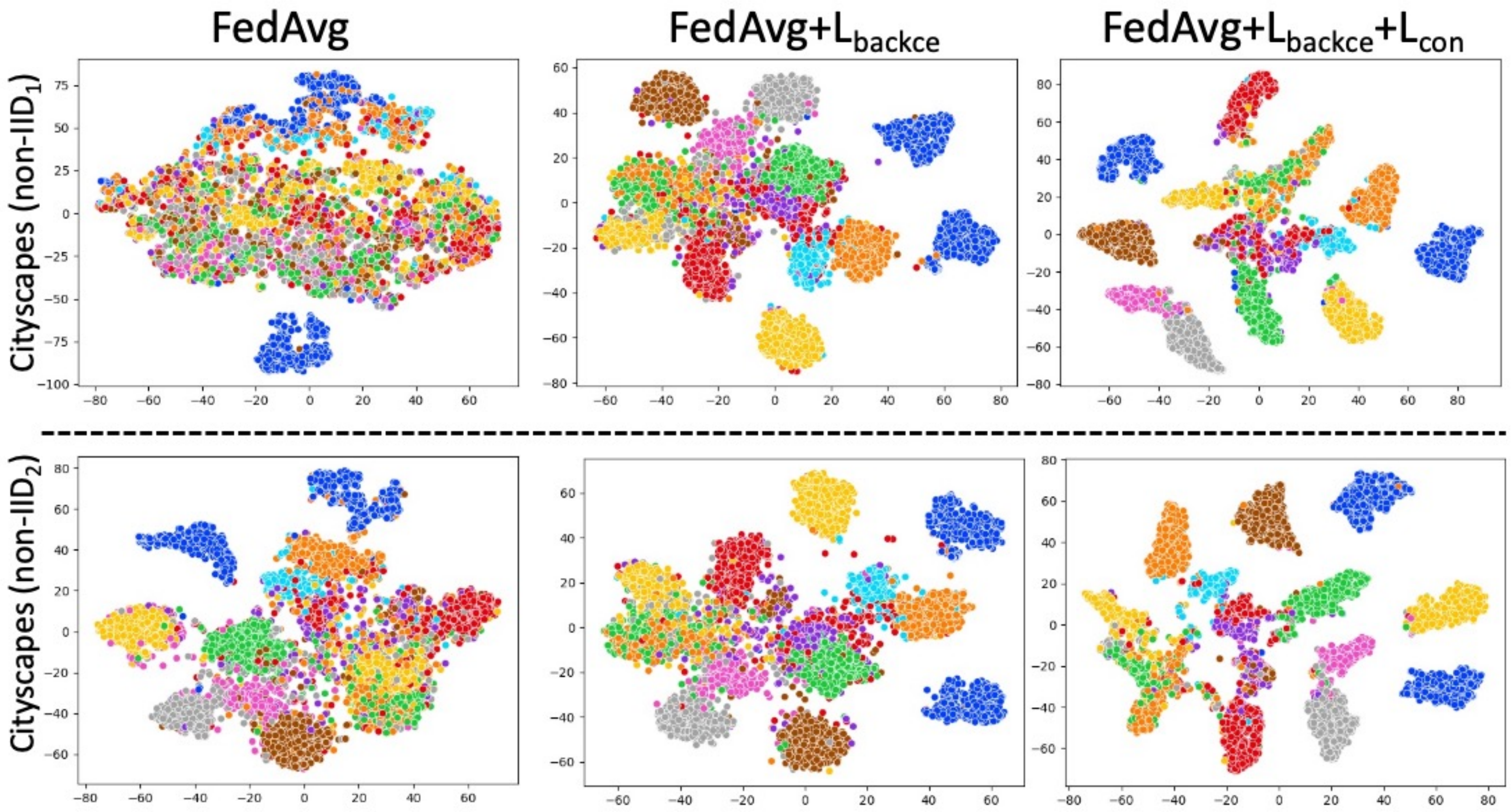
Experiments: Analysis of FedSeg

- The speed of mIoU improvement of FedSeg is faster - **communication efficiency**



Federated Learning for Semantic Segmentation

Experiments: Visualization of FedSeg



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