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Federated Incremental Semantic Segmentation

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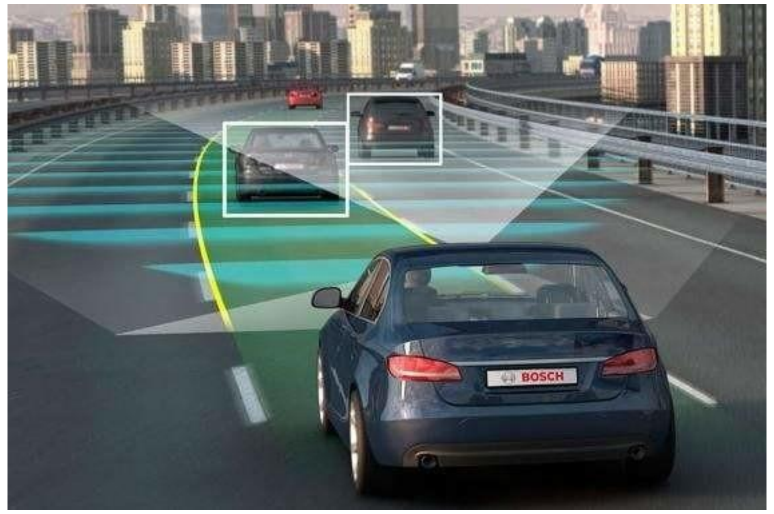
Federated Incremental Semantic Segmentation

◆ Background

- Federated learning (FL) has achieved rapid development in semantic segmentation, by training on multiple decentralized clients to **alleviate data island** that requires enormous pixel annotations.
- Federated learning-based semantic segmentation (FSS) significantly **economizes annotation costs** in data-scarce scenarios via training a global segmentation model on private data of different clients.



Autonomous Driving

Wearable Devices

Medical Diagnosis

Mobile Phones

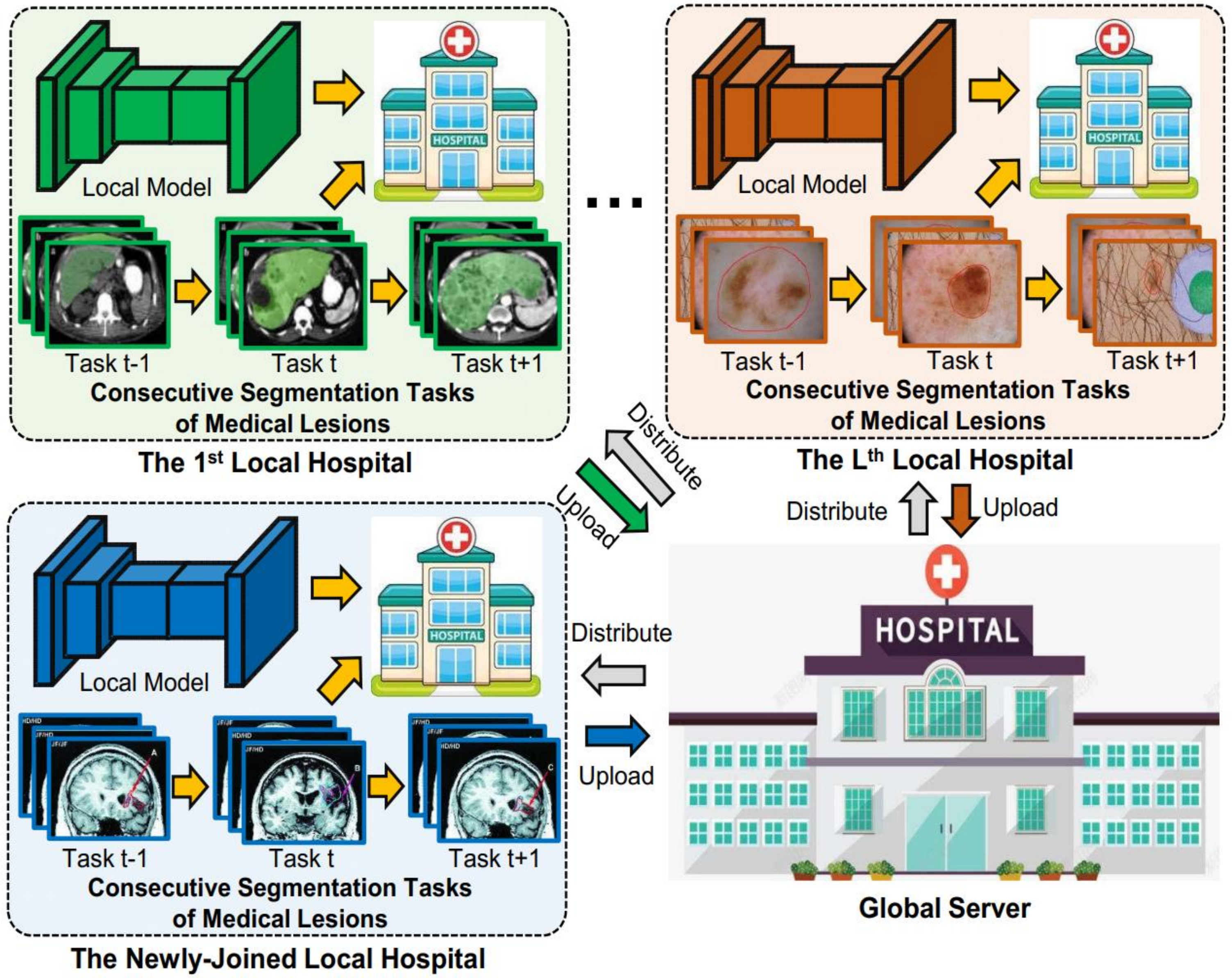
Federated Incremental Semantic Segmentation

◆ Challenges

- Assuming learned foreground classes are **fixed over time**, which is impractical in real-world applications where local clients receive streaming data of new classes consecutively.

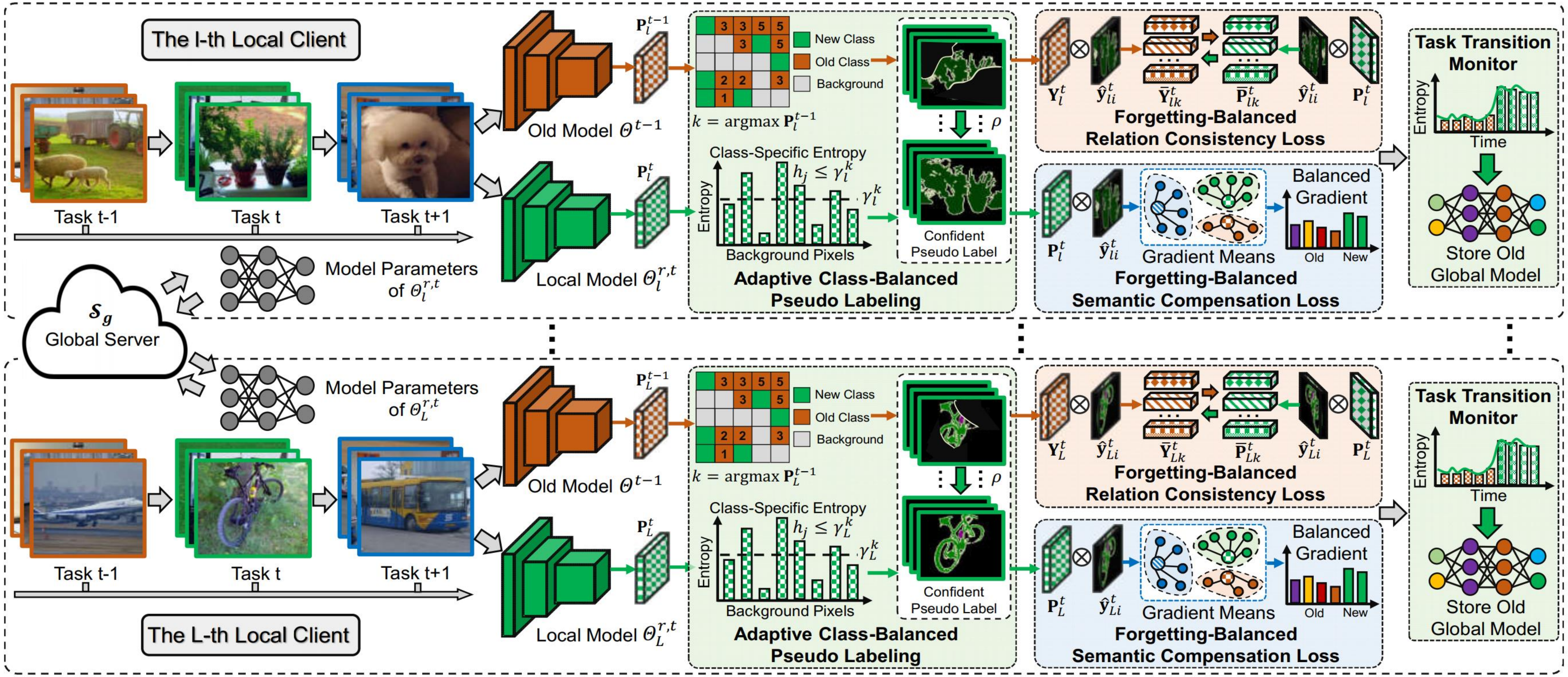
- If local clients have no memory to store old classes, existing FSS methods significantly degrade segmentation behavior on old classes (i.e., **catastrophic forgetting**).

- **Background shift** can heavily aggravate heterogeneous forgetting speeds on old classes.



Federated Incremental Semantic Segmentation

◆ Overview: Addressing **Heterogeneous Forgetting** From **Intra-Client and Inter-Client** Aspects



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1. Addressing Intra-Client Heterogeneous Forgetting

- **Adaptive Class-Balanced Pseudo Labeling:** Mine pseudo labels for old classes to tackle background shift

$$(\hat{\mathbf{y}}_{li}^{t})_j = \begin{cases} k, \ \text{if } (\mathbf{y}_{li}^{t})_j \notin \mathcal{Y}_l^b \text{ and } k = (\mathbf{y}_{li}^{t})_j; \\ k, \ \text{if } (\mathbf{y}_{li}^{t})_j \in \mathcal{Y}_l^b \text{ and } h_j \leq \gamma_l^k \\ \qquad \text{and } k = \arg\max \mathbf{P}_l^{t-1}(\mathbf{x}_{li}^{t}, \Theta^{t-1})_j; \\ 0, \ \text{otherwise}, \end{cases}$$

- **Forgetting-Balanced Semantic Compensation Loss:** Address heterogeneous forgetting speeds of different old classes

$$\mathcal{L}_{\mathrm{FS}} = \frac{1}{B}\sum_{i=1}^{B}\sum_{j=1}^{HW}\frac{\bar{\Gamma}_{ij}^{t}}{\bar{\Gamma}} \cdot \mathcal{D}_{\mathrm{CE}}\big(\mathbf{P}_l^t(\mathbf{x}_{li}^t, \Theta_l^{r,t})_j, (\hat{\mathbf{y}}_{li}^t)_j\big)$$

- **Forgetting-Balanced Relation Consistency Loss:** Tackle heterogeneous inter-class relations distillation

$$\mathcal{L}_{\mathrm{FR}} = \frac{1}{K^o + K^t}\sum_{k=1}^{K^o+K^t}\frac{\Gamma_k}{\bar{\Gamma}_{\mathrm{cls}}} \cdot \mathcal{D}_{\mathrm{KL}}(\bar{\mathbf{P}}_{lk}^t, \bar{\mathbf{Y}}_{lk}^t)$$

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2. Addressing Inter-Client Heterogeneous Forgetting

- Task Transition Monitor:
  1. Recognize new classes under privacy protection
  2. Store the latest old model from global aspect for relation distillation

$$\mathcal{I}_l^{r,t} = \frac{1}{N_l^t} \sum_{i=1}^{N_l^t} \sum_{j=1}^{HW} \mathcal{H}(P_l^t(\mathbf{x}_{li}^t, \Theta^{r,t})_j)$$

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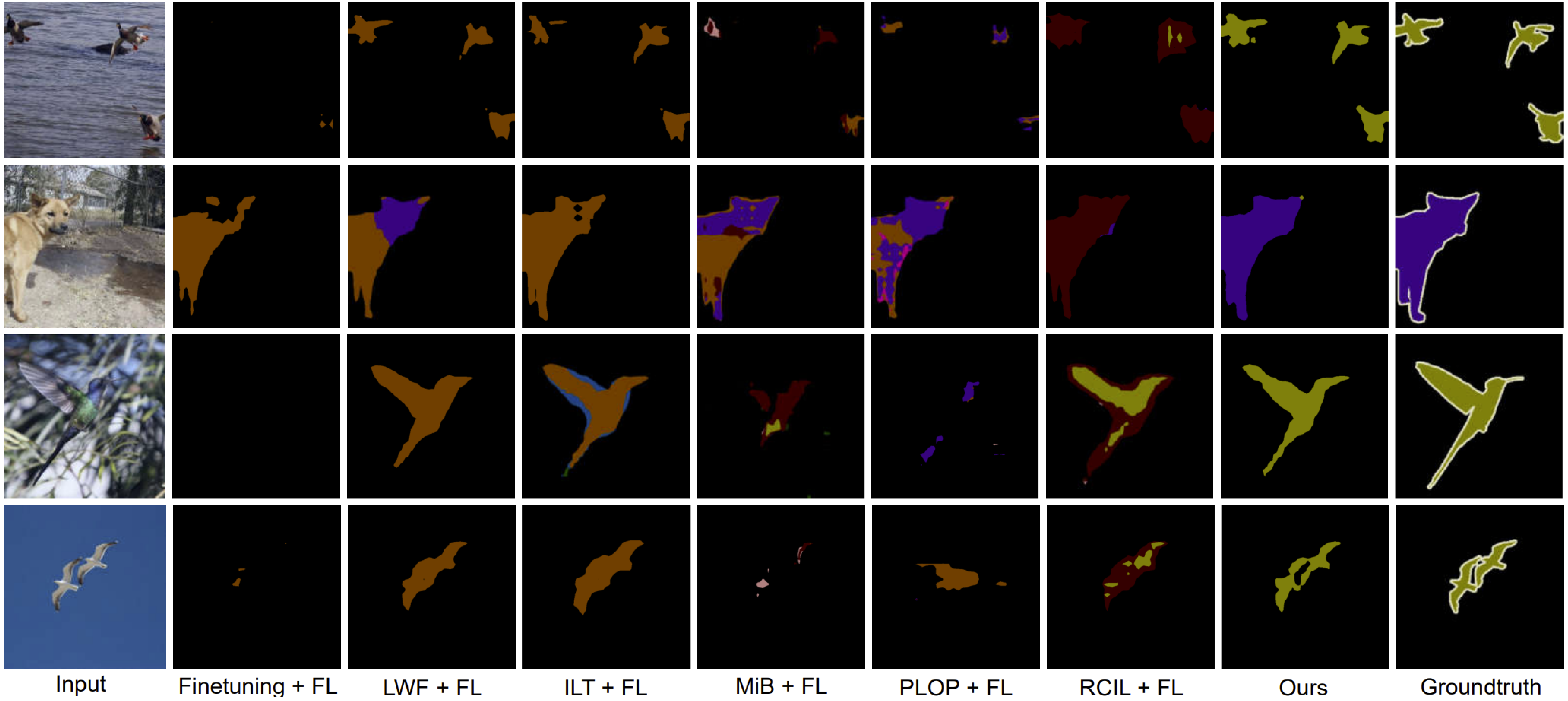
◆ Experiments

Comparison Results on Pascal VOC Under 4-4 Setting



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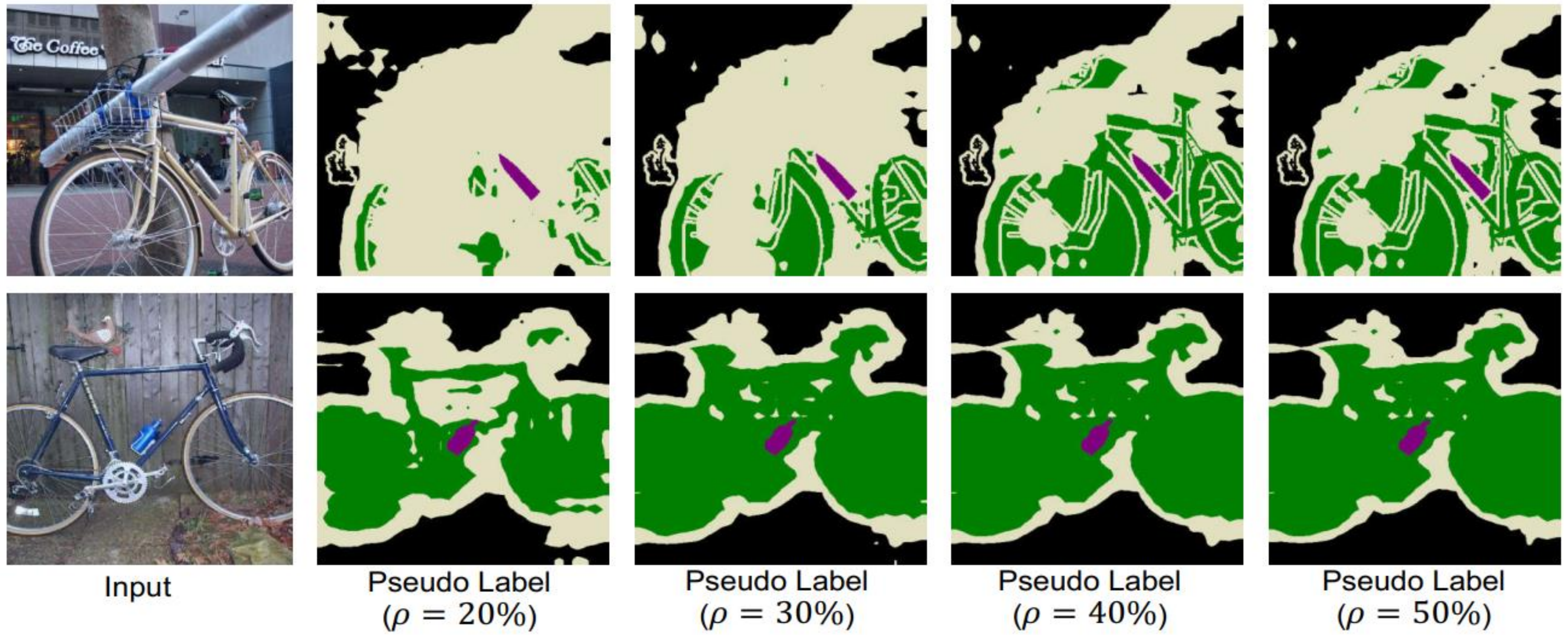
◆ Experiments

Task ID	t=1 (Base)	t=2	t=3	t=4	t=5
Finetuning + FL	70.4	43.1	21.3	19.0	9.1
LWF [27] + FL	70.4	59.8	38.7	39.1	23.8
ILT [36] + FL	70.4	56.4	36.9	35.3	22.7
MiB [1] + FL	70.4	**64.8**	**52.8**	**47.2**	**33.0**
PLOP [11] + FL	70.4	54.2	38.3	29.4	28.1
RCIL [53] + FL	70.5	60.3	40.1	36.8	32.4
FBL (Ours)	70.4	**66.6**	**53.6**	**49.6**	**43.9**

Task-Wise Comparisons on Pascal VOC
Under 4-4 Setting



Analysis of Pseudo Labels on Pascal VOC
Under 4-4 Setting

Thanks for your attention!

Code Link: https://github.com/JiahuaDong/FISS

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