A²LC: Active and Automated Label Correction for Semantic Segmentation

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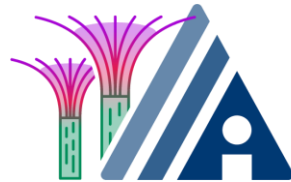
Yonsei University

Task: Label acquisition for semantic segmentation

Semantic segmentation is a task that
assigns a semantic class label to every pixel in an image.

Label acquisition for semantic segmentation is practically difficult
due to the high cost and labor-intensive nature of pixel-wise annotation.

Image   Ground Truth
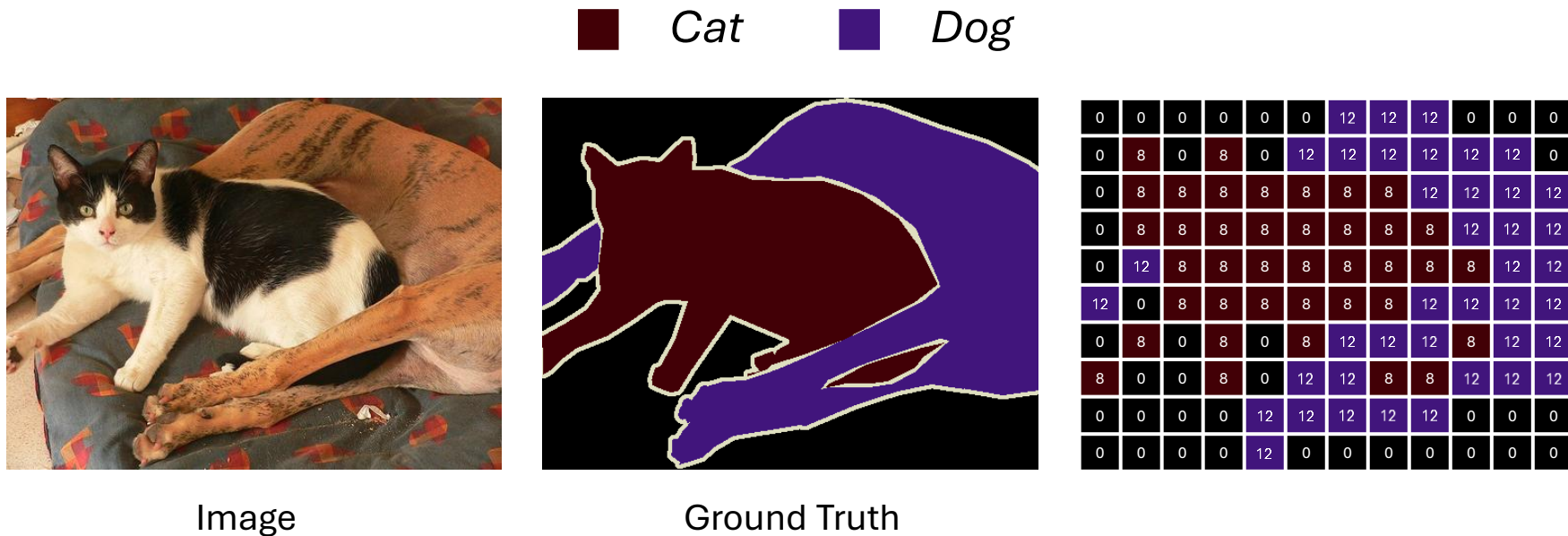
Preliminaries: Active Label Correction

Active Label Correction with foundation models (**ALC**) [1]
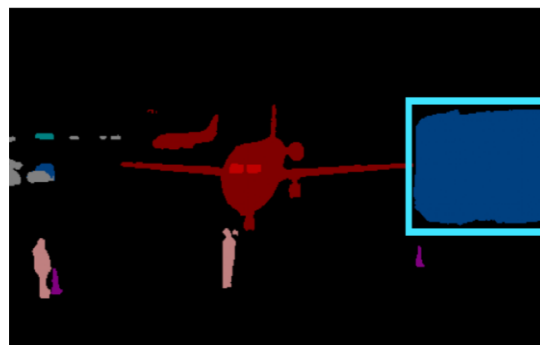   has emerged as a promising solution to the aforementioned difficulty.

ALC is a method that
        (1) generates **initial pseudo-labels** using a foundation model,
        (2) **selects** noisy labels through a deep learning model and
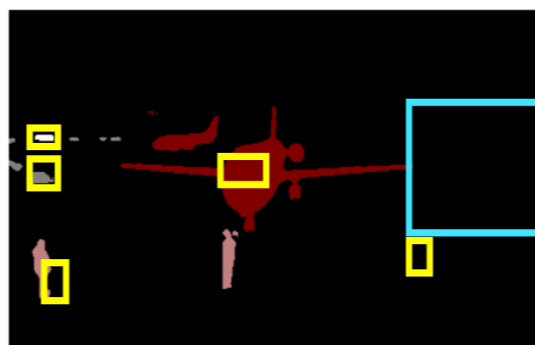   (3) **corrects** only those labels via human review in an iterative manner.

cf. Figures are from [1]

| Image | Initial Label (G-SAM [2]) | Corrected Label | Ground Truth |

[1] KIM, Hoyoung, et al. Active label correction for semantic segmentation with foundation models. In Forty-first International Conference on Machine Learning, 2024.
[2] REN, Tianhe, et al. Grounded sam: Assembling open-world models for diverse visual tasks. arXiv preprint arXiv:2401.14159, 2024.
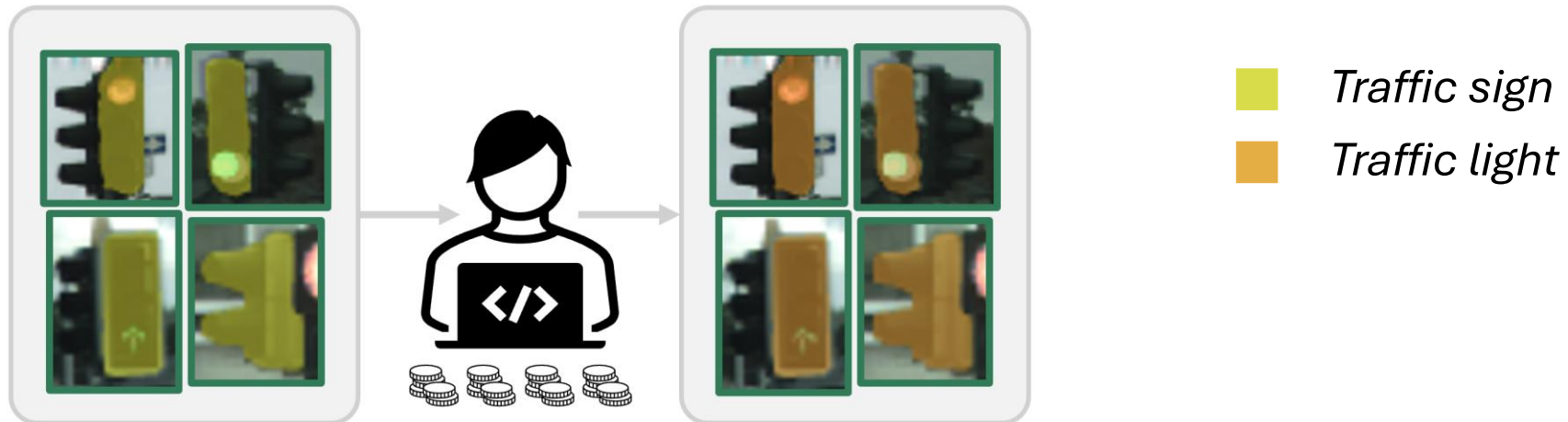
Two key challenges of ALC

The first challenge is
   redundant queries for similar patterns, leading to inefficient resource utilization.

What are redundant queries?
   Label confusion predominantly occurs among similar categories,
   that are naturally clustered within comparable acquisition score ranges
   and thus queried together.

Traffic sign
Traffic light

# Two key challenges of ALC

The second challenge is
sampling bias toward head classes, resulting in suboptimal corrections.

How does sampling bias affect the results?
Corrections overwhelmingly target head class pixels,
even when their performance is already saturated,
leaving noisy tail class labels uncorrected despite multiple correction rounds.

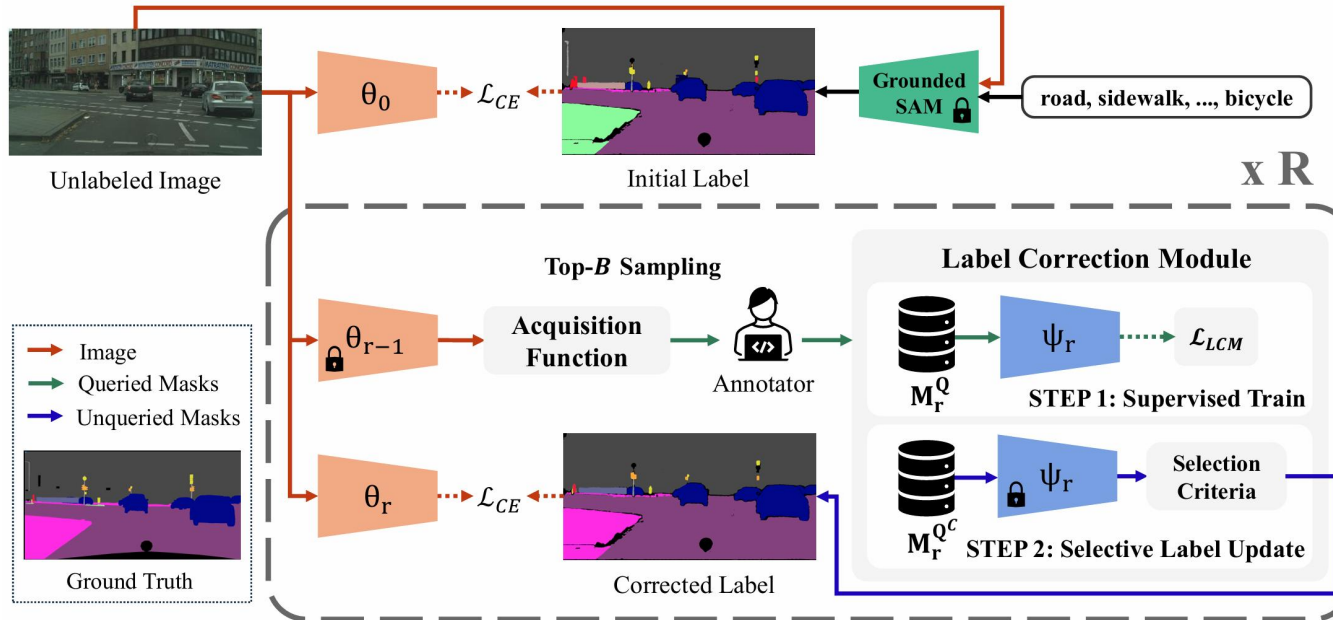← Tail class   Head class →
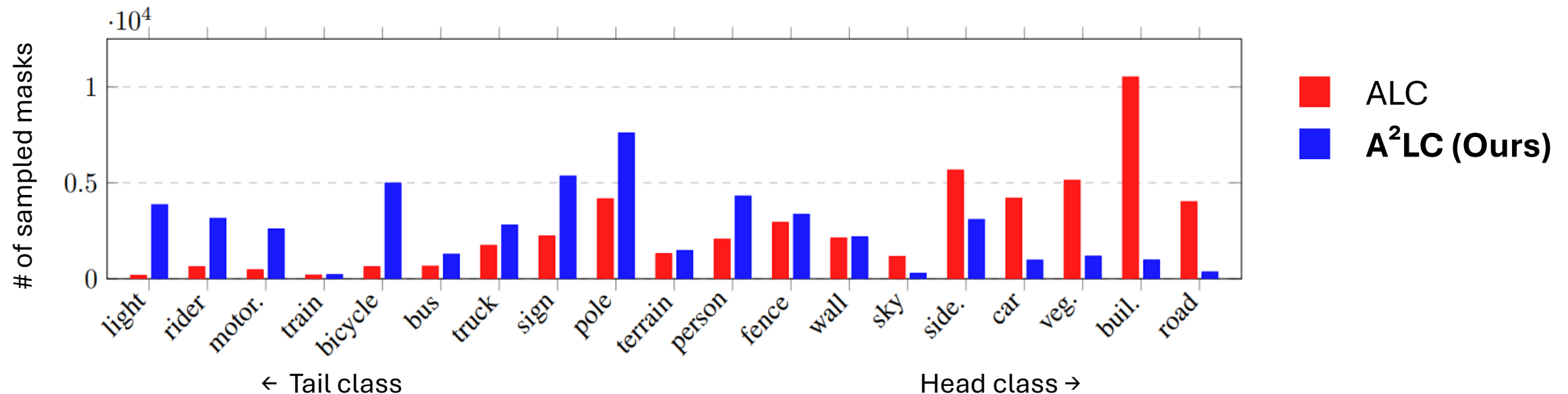
A²LC Framework

We introduce an Active and Automated Label Correction framework (**A²LC**),
that effectively addresses the two aforementioned challenges.

A²LC framework is
a **semi-automated label correction framework** for semantic segmentation,
where manual and automatic correction stages operate in a cascaded manner.

Overview of A²LC framework

Unlabeled Image

Initial Label

Ground Truth

Corrected Label

x R

Top-B Sampling

Label Correction Module

Acquisition Function

Annotator

$\mathcal{L}_{LCM}$

M_r^Q

STEP 1: Supervised Train

$M_r^{Q^C}$

STEP 2: Selective Label Update

Selection Criteria

Grounded SAM 🔒

road, sidewalk, ..., bicycle

θ_0

$\mathcal{L}_{CE}$

θ_{r-1}

θ_r

$\mathcal{L}_{CE}$

ψ_r

ψ_r

Image
Queried Masks
Unqueried Masks
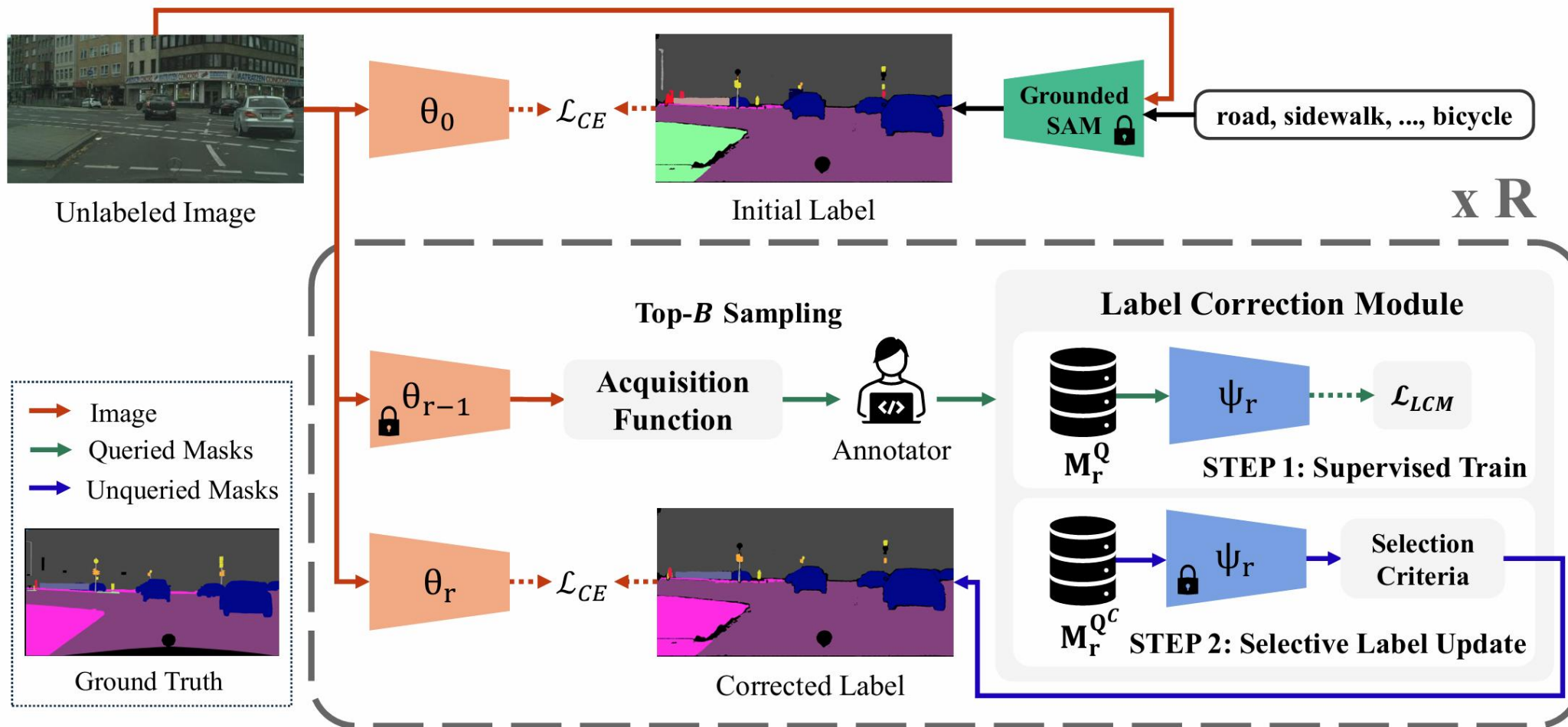
Main contributions of A^{2}LC

The first contribution is
   Label Correction Module (**LCM**) for additional automatic correction.

The second contribution is
   Adaptively Balanced Confidence in label (**ABC**) for class-balanced correction.
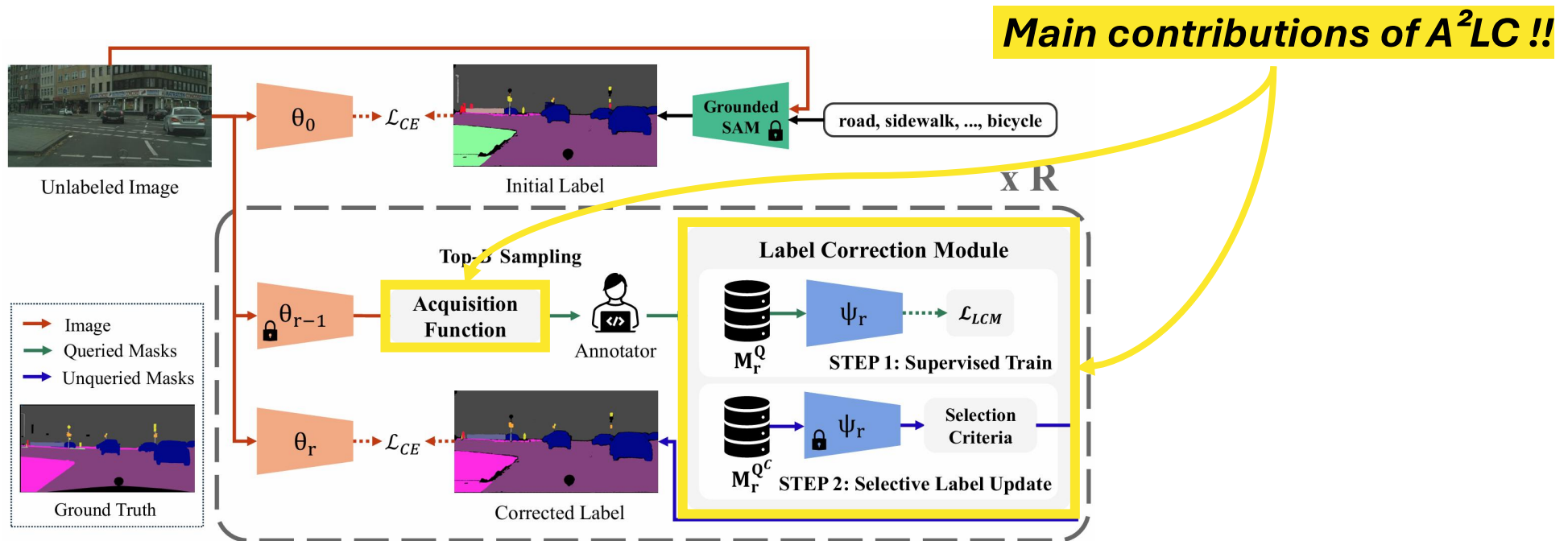

Main contributions of A^{2}LC !!
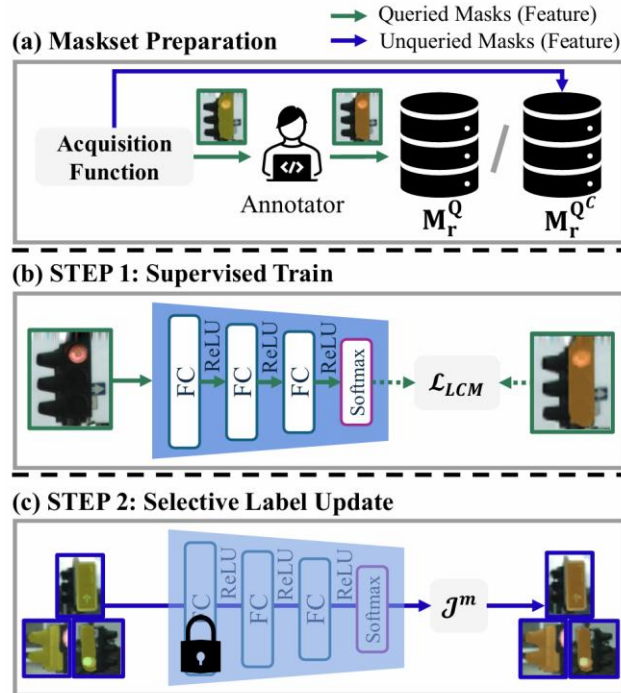
Label Correction Module (LCM)

LCM performs **automatic correction**
by propagating human-corrected labels beyond the queried samples.

LCM operates in two steps:
first, the model is **trained** using masks queried in the current round, and
second, it **corrects** masks that may be mislabeled but still remain unqueried.

(a) Maskset Preparation

→ Queried Masks (Feature)
→ Unqueried Masks (Feature)

Acquisition Function → Annotator → $\mathbf{M_r^Q}$ / $\mathbf{M_r^{Q^c}}$

(b) STEP 1: Supervised Train

FC ReLU FC ReLU FC ReLU Softmax → $\mathcal{L}_{LCM}$

(c) STEP 2: Selective Label Update

FC ReLU FC ReLU FC ReLU Softmax → $\mathcal{J}^m$

Algorithm 2: Label Correction Module (LCM)

Require: Previous round dataset $\mathcal{D}_{r-1}$, Queried maskset $\mathcal{M}_r^Q$, Unqueried maskset $\mathcal{M}_r^{Q^c}$, Epochs E
Ensure: Updated dataset $\mathcal{D}_r$
1: ▷ **Supervised train with queried masks**
2: **for** $e = 1, 2, \ldots, E$ **do**
3:     **for** each $(m, y(m)) \in \mathcal{M}_r^Q$ **do**
4:         Train the model ψ_r based on Eq. (2)
5:     **end for**
6: **end for**
7: ▷ **Selective label update for unqueried masks**
8: **for** each $(m, \hat{y}(m)) \in \mathcal{M}_r^{Q^c}$ **do**
9:     $\hat{y}_{\psi_r}(m) \leftarrow \arg\max_{c \in \mathcal{C}} \psi_r(c; m)$
10:    **if** m satisfies *Selection_Criteria* (Eq. (3)) **then**
11:       $\hat{y}(m) \leftarrow \hat{y}_{\psi_r}(m)$
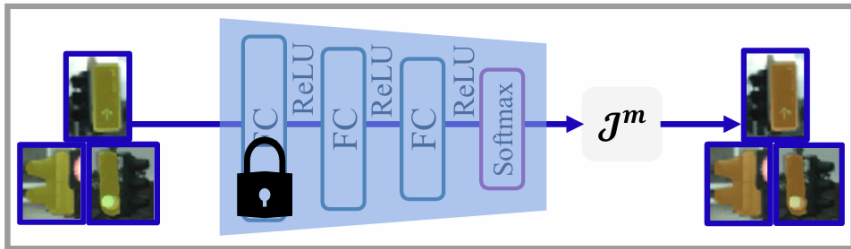12:   **end if**
13: **end for**

Label Correction Module (LCM)

LCM correction is applied only to the masks that satisfy all **selection criteria**.

What are selection criteria?
  Selection criteria detect highly reliable predictions,
  enabling automatic label updates exclusively for confidently inferred labels.

(c) STEP 2: Selective Label Update


```
 7: ▷ Selective label update for unqueried masks
 8: for each (m, ŷ(m)) ∈ M_r^{Q^c} do
 9:     ŷ_{ψ_r}(m) ← arg max_{c∈C} ψ_r(c; m)
10:     if m satisfies Selection_Criteria (Eq. (3)) then
11:         ŷ(m) ← ŷ_{ψ_r}(m)
12:     end if
13: end for
```

$$\mathcal{J}^m = \mathcal{J}_1^m \wedge \mathcal{J}_2^m \wedge \mathcal{J}_3^m$$

$$\mathcal{J}_1^m = \mathbb{I}\left(\max_{c\in\mathcal{C}} \psi_r(c; m) \geq \tau \right)$$

$$\mathcal{J}_2^m = \mathbb{I}\left(\hat{y}_{\psi_r}(m) \notin \{c \mid \text{rank}(c) \geq (1 - \alpha) \cdot |\mathcal{C}|, \, c \in \mathcal{C}\} \right)$$

$$\mathcal{J}_3^m = \mathbb{I}\left(\hat{y}(m) \neq \arg\max_{c\in\mathcal{C}} \text{rank}(c) \right)$$

Adaptively Balanced Confidence in Label (ABC)

ABC guides both correction stages toward **class-balanced correction** by incorporating pixel-wise **adaptive class weight** into the acquisition function.

Adaptive class weight consists of two components:
    (1) **class rarity score,** that prioritizes tail class pixels during sampling, and
    (2) **dataset imbalance score,** that adjusts this weighting based on label statistics.

$$a_{\text{ABC}}(m;\theta) := \sum_{x \in m} \frac{f_\theta(x) \cdot f_\theta(m')}{\|f_\theta(x)\|\|f_\theta(m')\|} \cdot a_{\text{ABC}}(x;\theta)$$

$$a_{\text{ABC}}(x;\theta) := w(x) \cdot a_{\text{CIL}}(x;\theta)$$

$$w(x) := \hat{w}(x)^{\text{KL}^3(\mathbb{P}_{\text{dist}} \| \mathbb{U}_{\text{dist}})}$$

$$\hat{w}(x) := \frac{\min_{c \in \mathcal{C}} |\{x' \in \mathcal{M} : \hat{y}(x') = c\}|}{|\{x' \in \mathcal{M} : \hat{y}(x') = \hat{y}(x)\}|}$$

$$\text{KL}(\mathbb{P}_{\text{dist}} \| \mathbb{U}_{\text{dist}}) = \sum_{c \in C} \mathbb{P}(c) \log \frac{\mathbb{P}(c)}{\mathbb{U}(c)}$$

Experiments: Quantitative results

- **High efficiency**: Requires only 20% (Cityscapes) and 60% (PASCAL) of the budget.

- **Strong effectiveness**: Achieves +27.23% (Cityscapes) and +14.30% (PASCAL) performance gains under the same budget.

Dataset	mIoU (%)	Methods	Init.	1R	2R	3R	4R	5R
Cityscapes	Data	ALC	$50.68_{\pm0.00}$	$62.28_{\pm1.25}$	$65.36_{\pm0.56}$	$66.19_{\pm0.60}$	$66.87_{\pm0.29}$	$67.01_{\pm0.30}$
		A^{2}LC (Ours)	$50.68_{\pm0.00}$	$\mathbf{70.01}_{\pm1.05}$	$\mathbf{75.60}_{\pm0.58}$	$\mathbf{80.84}_{\pm0.53}$	$\mathbf{82.69}_{\pm0.92}$	$\mathbf{85.26}_{\pm0.55}$
	Model	ALC	$51.55_{\pm0.71}$	$56.61_{\pm0.42}$	$58.27_{\pm0.63}$	$58.58_{\pm0.08}$	$58.52_{\pm0.26}$	$58.59_{\pm0.05}$
		A^{2}LC (Ours)	$51.55_{\pm0.71}$	$\mathbf{60.83}_{\pm0.66}$	$\mathbf{63.89}_{\pm0.44}$	$\mathbf{67.50}_{\pm0.31}$	$\mathbf{68.87}_{\pm0.78}$	$\mathbf{70.51}_{\pm0.32}$
PASCAL	Data	ALC	$58.63_{\pm0.00}$	$\mathbf{68.19}_{\pm0.34}$	$72.72_{\pm0.16}$	$74.84_{\pm0.29}$	$76.41_{\pm0.70}$	$77.06_{\pm0.73}$
		A^{2}LC (Ours)	$58.63_{\pm0.00}$	$67.49_{\pm2.03}$	$\mathbf{74.88}_{\pm1.45}$	$\mathbf{80.88}_{\pm0.83}$	$\mathbf{84.81}_{\pm0.48}$	$\mathbf{88.08}_{\pm0.44}$
	Model	ALC	$56.94_{\pm0.44}$	$\mathbf{62.11}_{\pm0.61}$	$\mathbf{64.12}_{\pm0.31}$	$64.15_{\pm0.68}$	$65.00_{\pm0.33}$	$65.48_{\pm0.83}$
		A^{2}LC (Ours)	$56.94_{\pm0.44}$	$60.87_{\pm2.93}$	$64.08_{\pm2.43}$	$\mathbf{66.45}_{\pm0.95}$	$\mathbf{67.76}_{\pm0.06}$	$\mathbf{68.42}_{\pm0.87}$

Table: Label correction is performed over five rounds with budgets of 10k/round (Cityscapes) and 1k/round (PASCAL).

Experiments: Qualitative results

- Constructed pseudo-labels

| Image | Initial Label [1] | ALC [2] | A²LC (Ours) | Ground Truth |
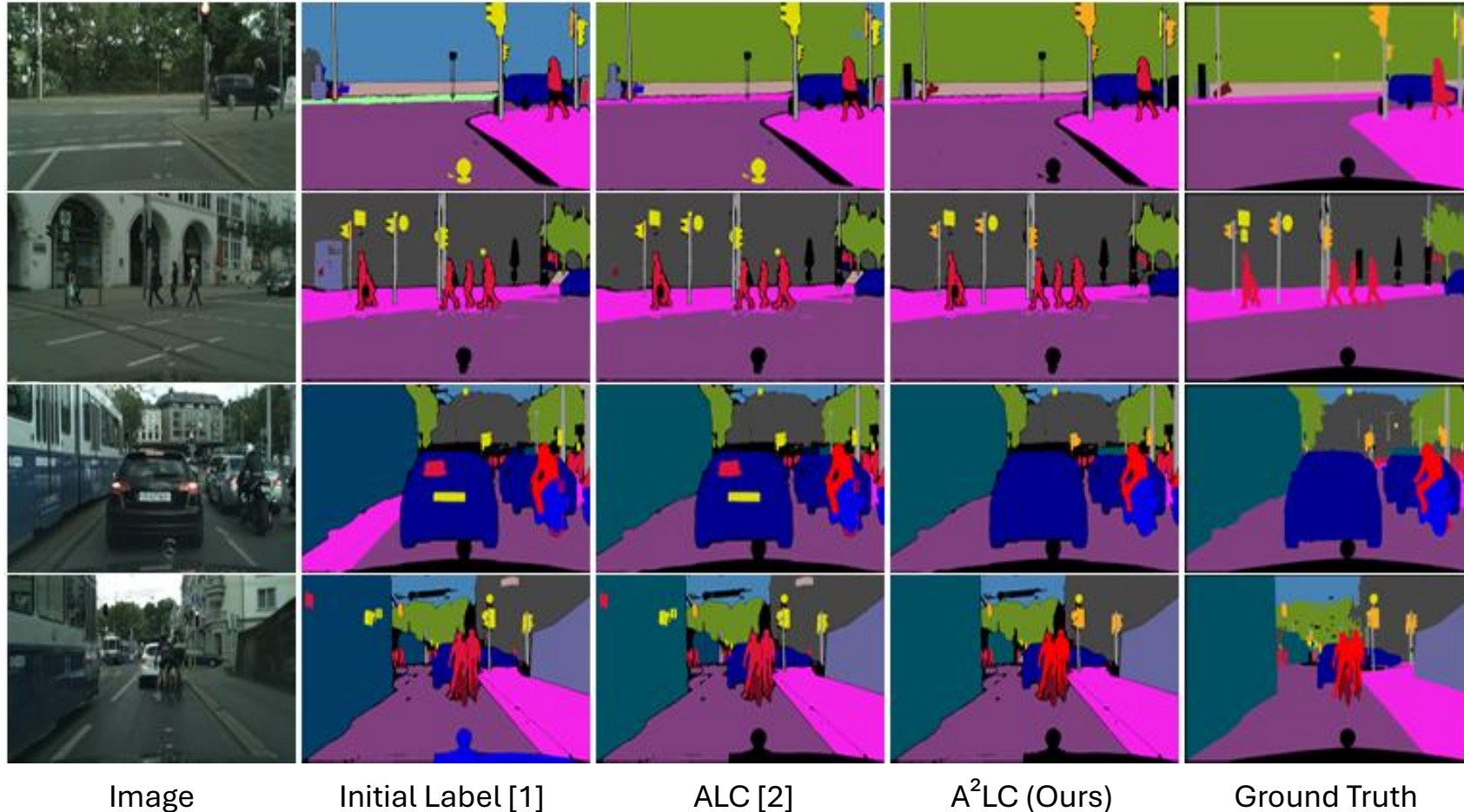
[1] REN, Tianhe, et al. Grounded sam: Assembling open-world models for diverse visual tasks. arXiv preprint arXiv:2401.14159, 2024.
[2] KIM, Hoyoung, et al. Active label correction for semantic segmentation with foundation models. In Forty-first International Conference on Machine Learning, 2024.

Experiments: Qualitative results

- Visualization of LCM-corrected masks

Experiments: Ablation study

Each component individually improves performance, while the best results are obtained when all are combined.

Notably, combining LCM and ABC yields greater gains than using either alone, highlighting the complementary and synergistic nature of these two components.

LCM	ABC	Mask	Data mIoU (%)					Model mIoU (%)				
			1R	2R	3R	4R	5R	1R	2R	3R	4R	5R
			62.60	65.20	66.03	66.85	66.86	56.86	58.93	58.63	58.59	58.59
✓			65.66	71.53	76.00	78.38	80.59	59.02	61.39	64.19	65.58	66.94
	✓		67.31	70.06	74.49	78.32	81.58	59.09	60.86	62.05	65.27	67.75
✓	✓		70.62	**77.29**	80.39	82.80	84.15	60.32	**65.09**	67.36	68.71	70.11
✓	✓	✓	**71.04**	76.08	**81.13**	**83.53**	**85.57**	**61.06**	64.39	**67.83**	**69.63**	**70.88**

Table: Label correction is performed over five rounds with budgets of 10k/round (Cityscapes).

Conclusion

We introduce **A^{2}LC**,
    an Active and Automated Label Correction framework for semantic segmentation,
    built upon cascading stages of manual and automatic correction.

The A^{2}LC framework incorporates two key components:
    (1) **LCM**, which performs automatic correction, and
    (2) **ABC**, which steers adaptively class-balanced correction.

Extensive experiments on Cityscapes and PASCAL VOC 2012 show that
    our method achieves state-of-the-art performance with superior cost efficiency,
    highlighting its potential for real-world deployment.

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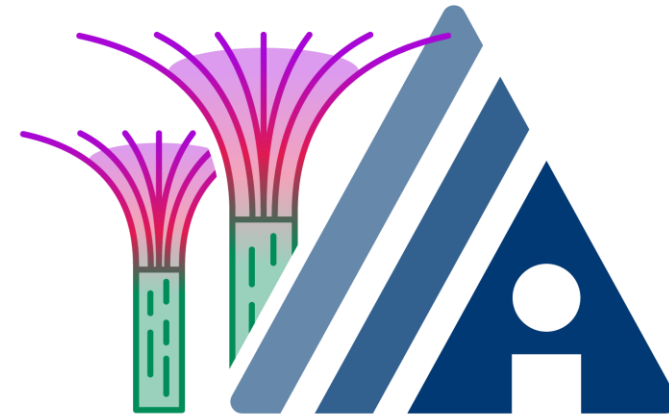
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