Adaptive Superpixel for Active Learning in Semantic Segmentation

Hoyoung Kim, Minhyeon Oh, Sehyun Hwang, Suha Kwak, Jungseul Ok

Pohang University of Science and Technology

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Active Learning in Semantic Segmentation

Pixel-wise Query in Semantic Segmentation

Query – "What is the class of a pixel?"

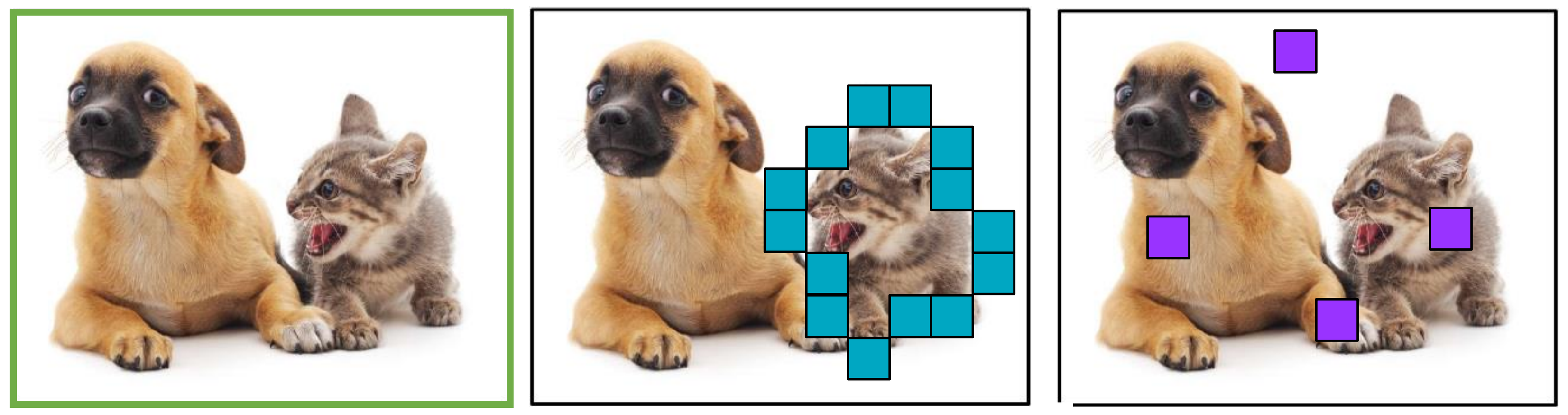
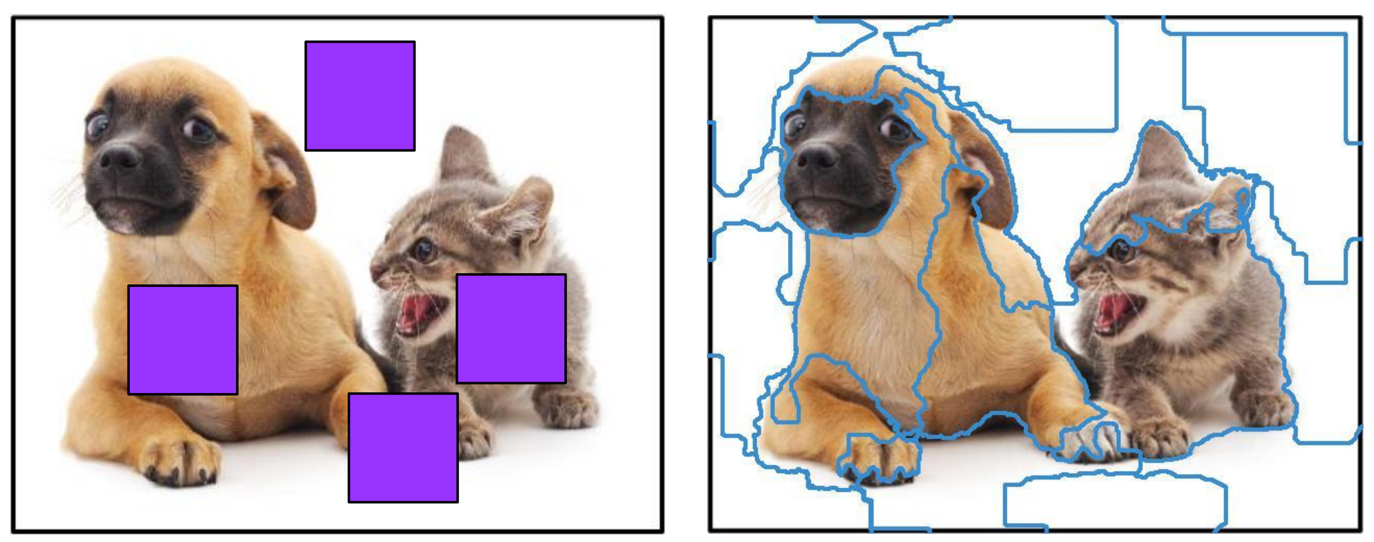


Image *[Desai & Ghose, 21]* Boundary *[P. Colling et al., 20]* Pixel *[G. Shin et al., 21]*

Such dense annotations are precise, but costly.

Clustered Query with Dominant Labeling

Query – "What is the dominant class of x?"

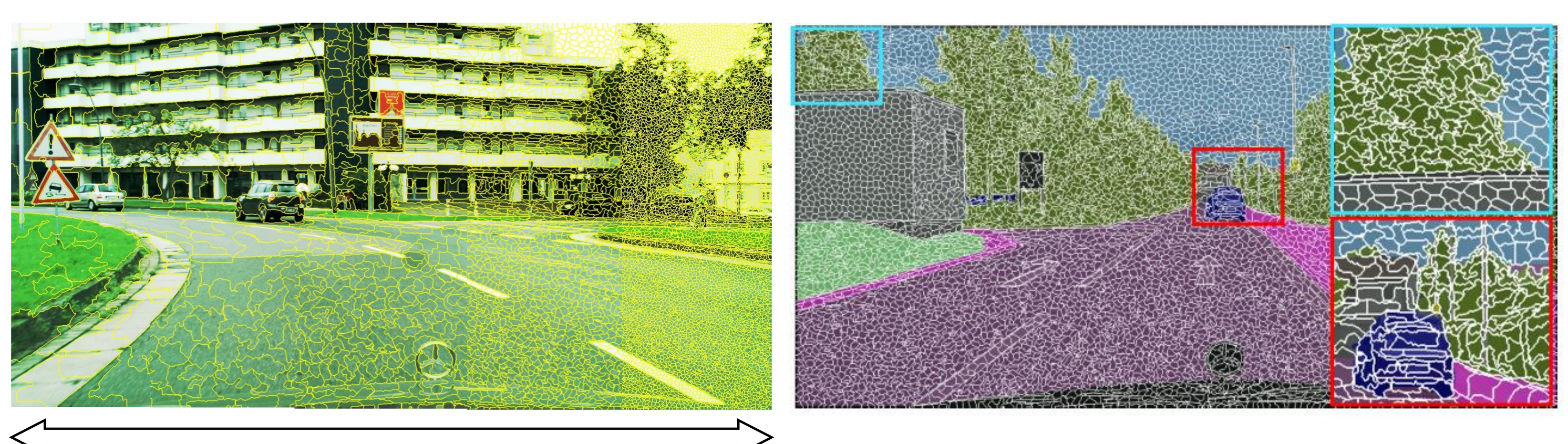


Patch *[L. Cai et al., 21]* Superpixel *[L. Cai et al., 21]*

Such clustered annotations are inaccurate, but economical.

Inherent Limitations of Superpixels

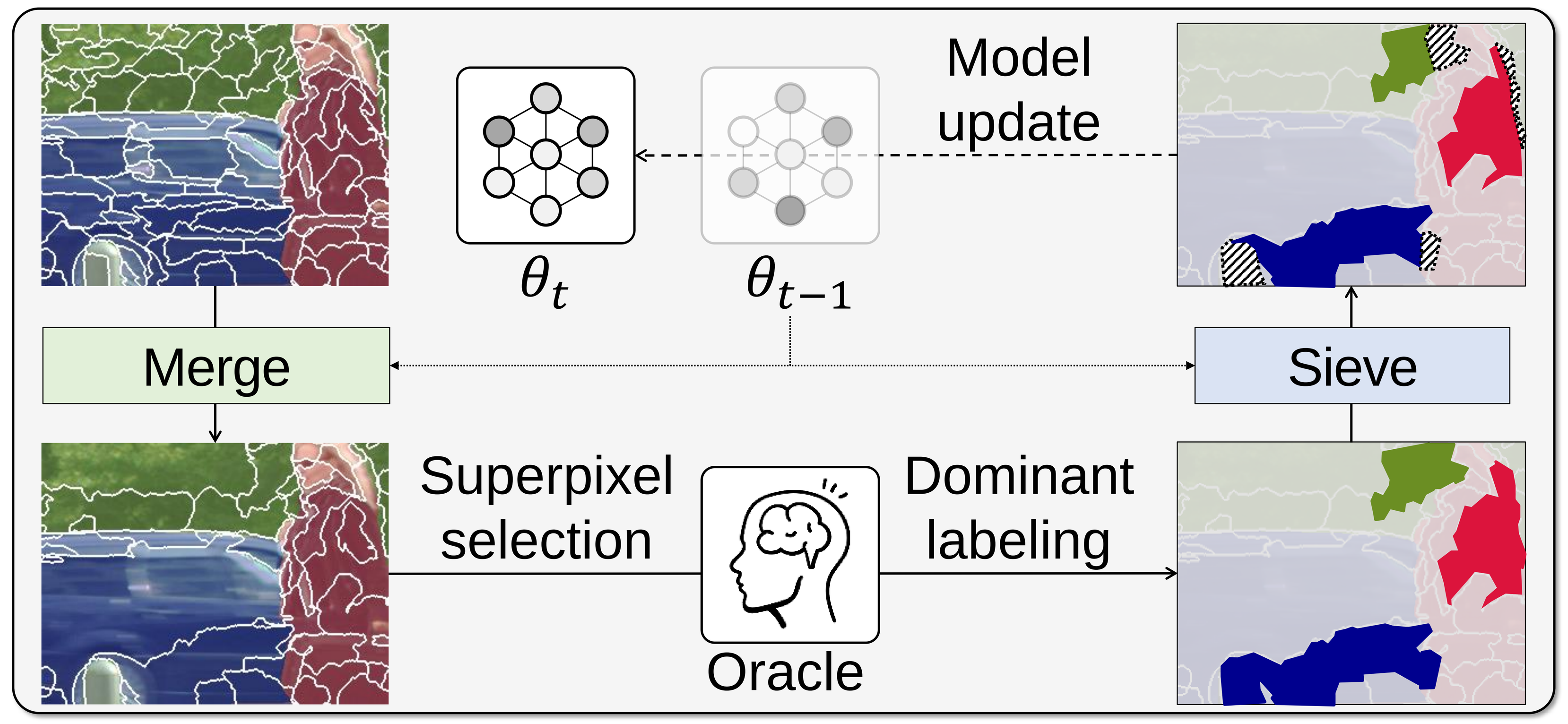
Hyperparameter sensitivity Oversegmentation issue



(RGB-based) Base superpixels

Adaptive Superpixel

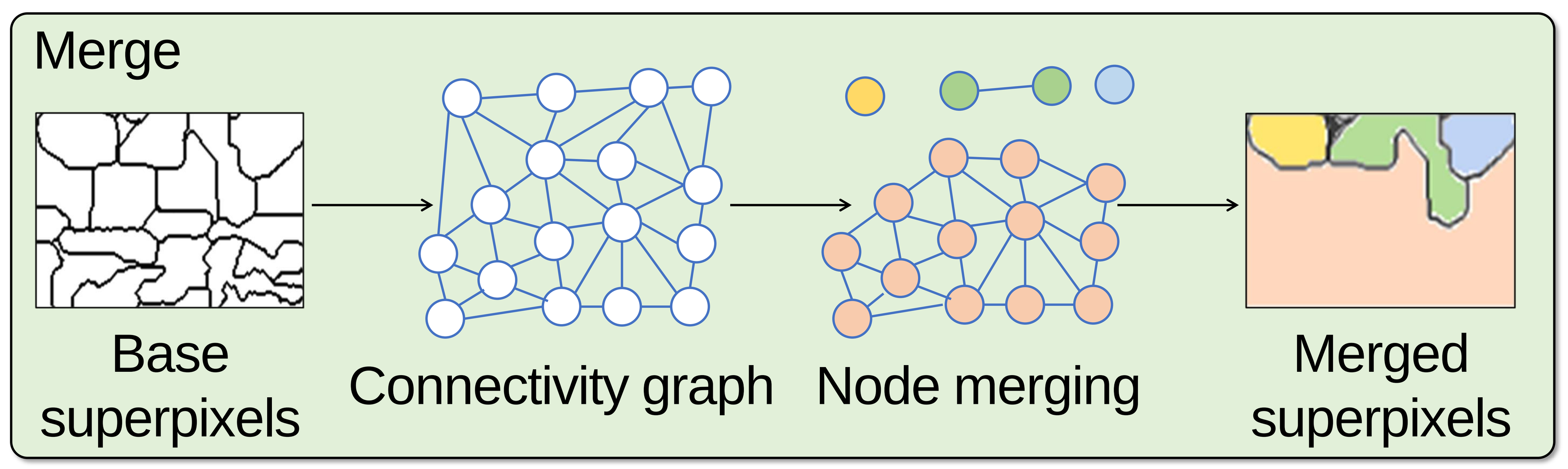
Proposed Active Learning Framework



Adaptive Merging

We merge neighboring superpixels of similar class predictions.

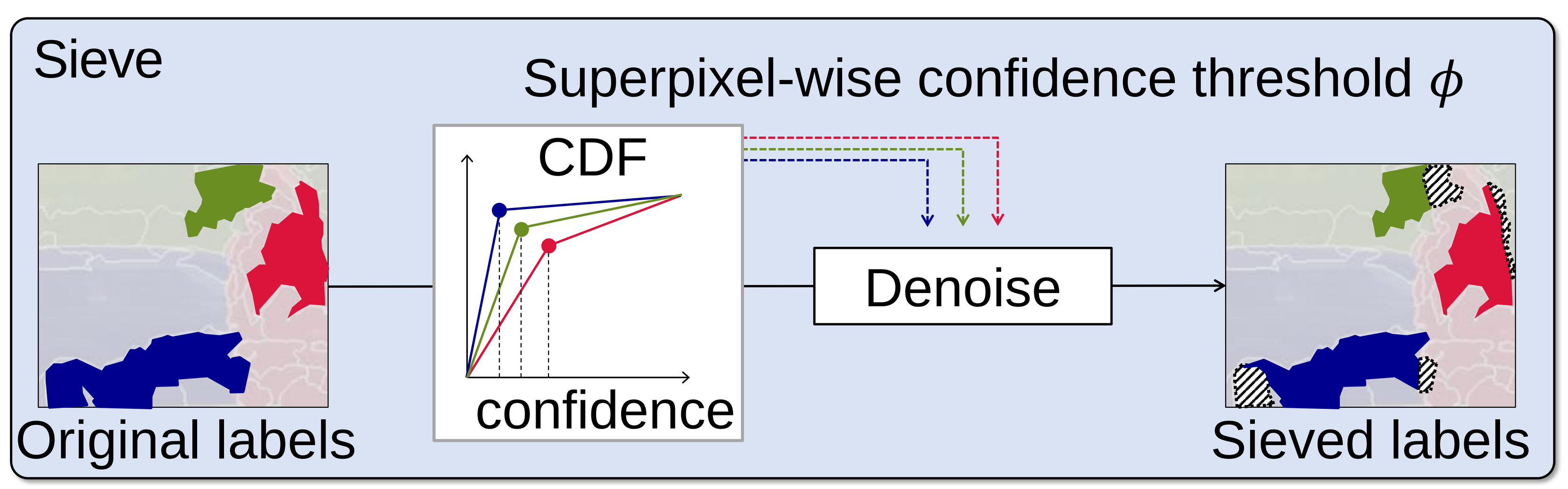
$$\underbrace{d_{\mathrm{JSD}}\big(f_\theta(n_1), f_\theta(n_2)\big)}_{\text{discrepancy between the class predictions of two superpixels}} < \epsilon$$



Adaptive Sieving

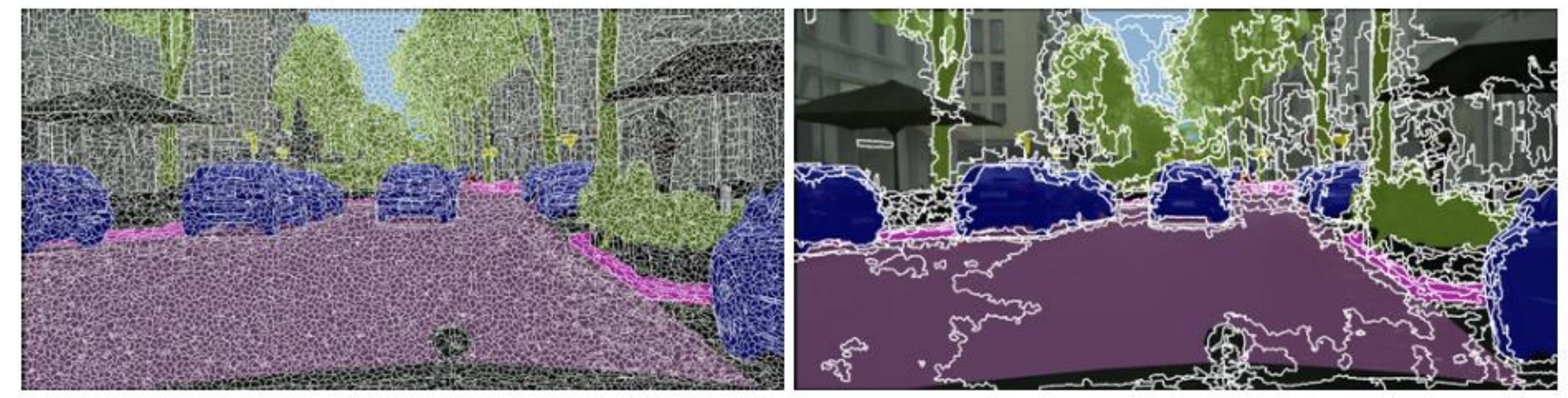
We sieve pixels with low confidence on acquired label $\mathrm{D}(s)$.

$$\underbrace{\{x \in s : f_\theta(\mathrm{D}(s); x) \geq \phi(s; \theta)\}}_{\text{the set of pixels with high confidence}}$$

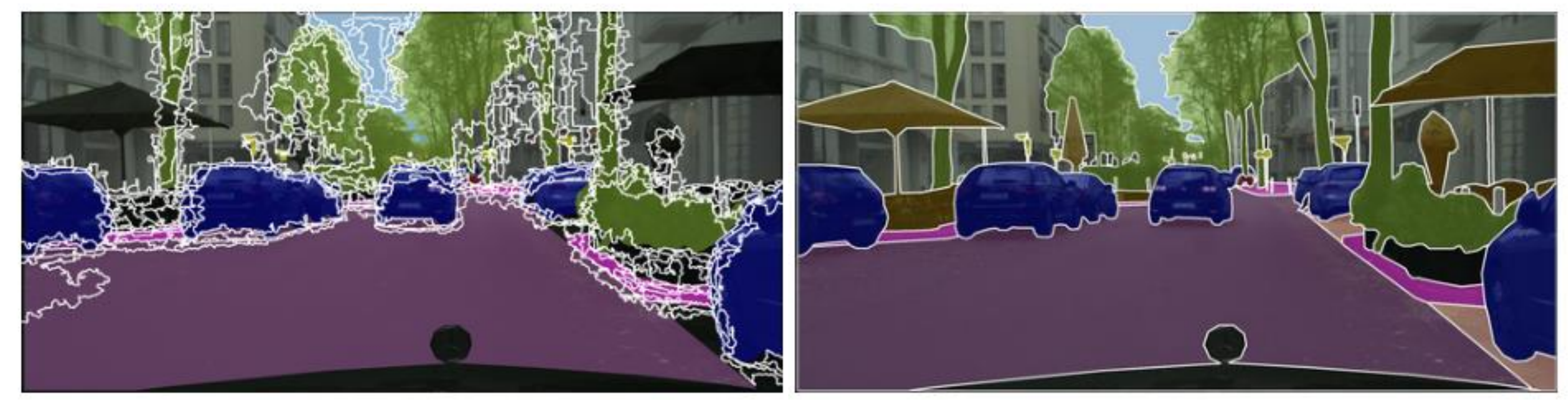


Experiments

Qualitative Results

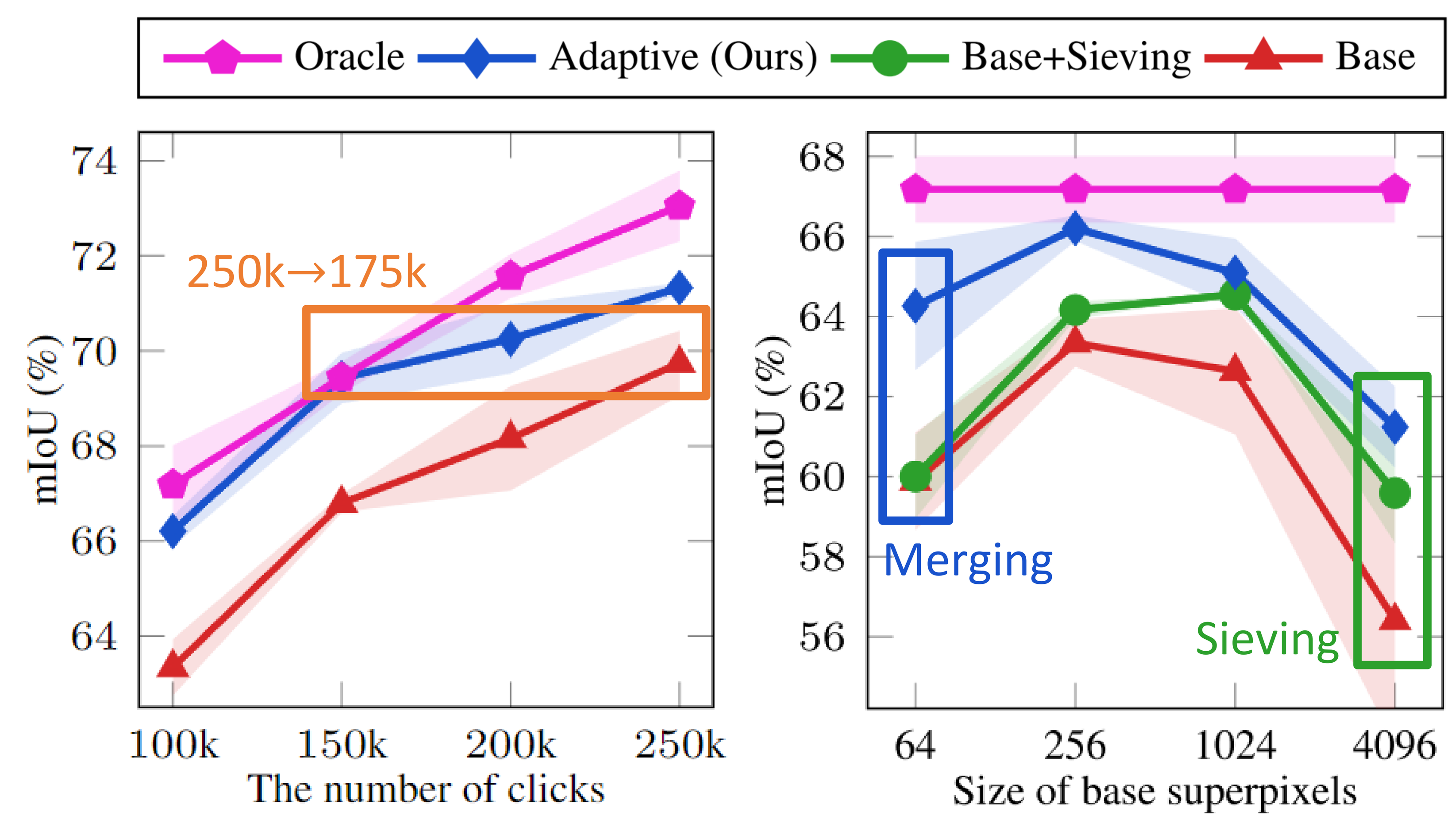


Base superpixels ($t = 1$) Adaptive superpixels ($t = 2$)



Adaptive superpixels ($t = 4$) Oracle superpixels

Effect of Adaptive Superpixels



Multi-round scenario Multi-size scenario

Conclusion

- Adaptively merged superpixels are cost-effective query for active learning requiring dense annotations.
- Adaptive sieving technique alleviates the side effect of noisy labels caused by dominant labeling.