Deep Active Learning for Joint Classification & Segmentation with Weak Annotator

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Paper #1294

LIVIA LABORATOIRE D'IMAGERIE, DE VISION ET D'INTELLIGENCE ARTFICIELLE

ÉTS Le génie pour l'industrie

McCaffrey Lab CANCER CELL BIOLOGY

The Goodman Cancer Research Centre

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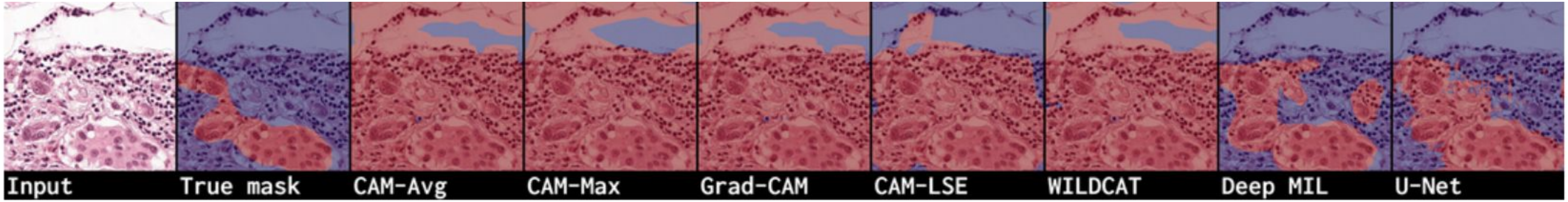
1. Challenges: CNN Visualization with CAMs

Application assumption: the image dataset for training is weakly annotated (with image labels)

Drawbacks [1]:

- Low resolution visualisation
- Accurate classifications, but inaccurate segmentations (object localizations)



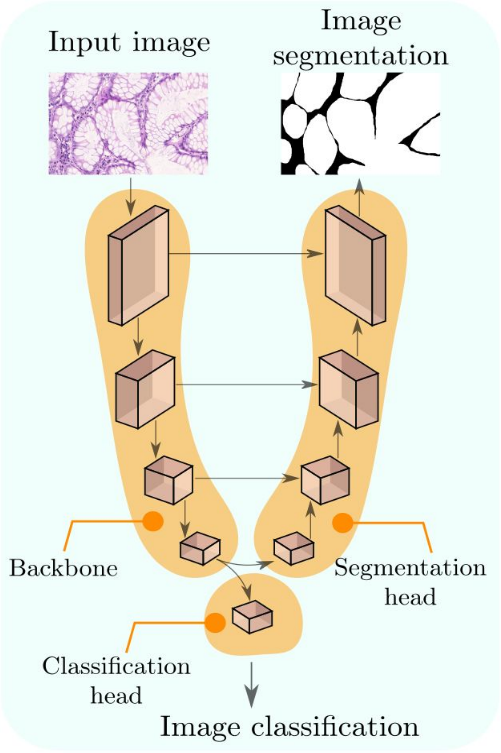
Our proposal:

- Provide full resolution CAMs
- Train CAMs with pixel-wise supervision under limited budget
- Rely on active learning and label propagation for pixel-wise annotations

[1] J. Rony, S. Belharbi, J. Dolz, I. Ben Ayed, L. McCaffrey, and E. Granger. Deep weakly-supervised learning methods for classification and localization in histology images: a survey. CoRR, abs/1909.03354, 2019.

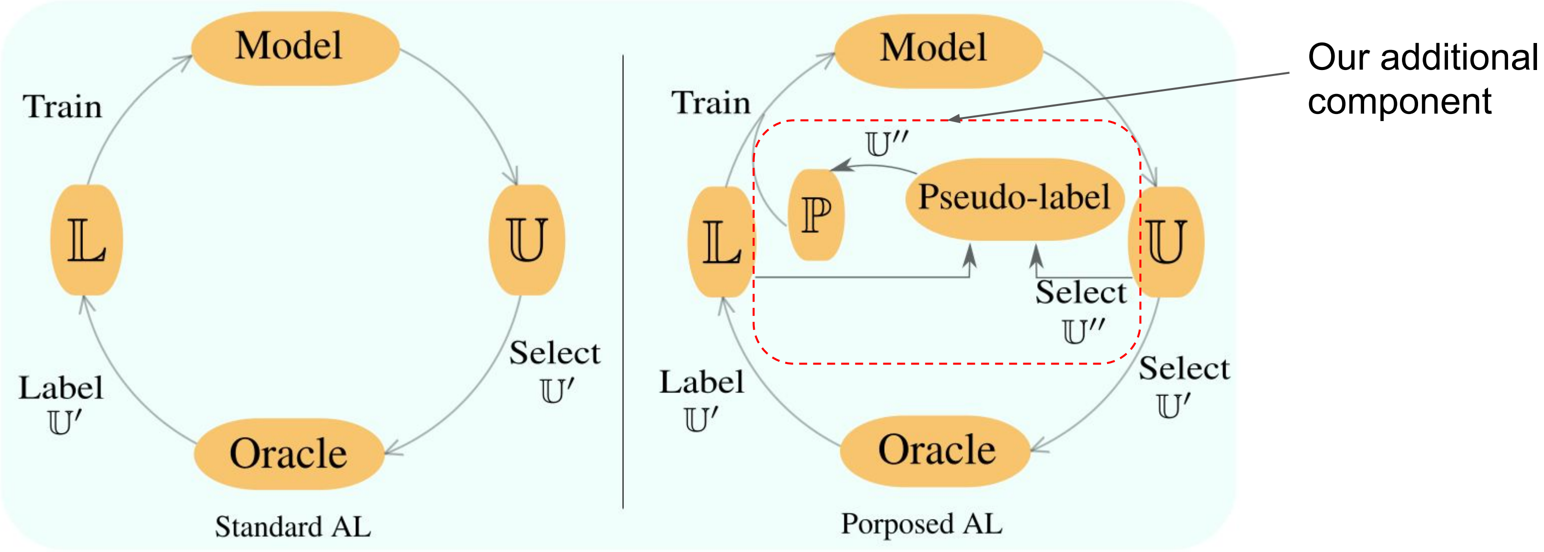
2. Deep architecture for supervised classification and segmentation

Proposed architecture.



3. Our proposal for active learning:

- label propagation based on randomly selected image



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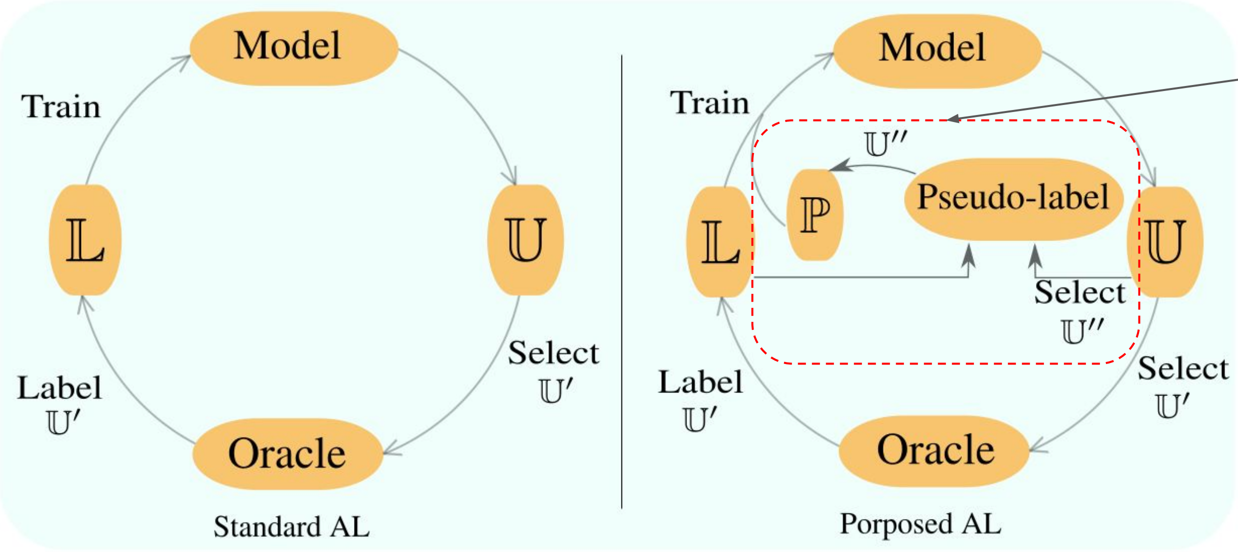


Standard AL

Porposed AL

Our additional component

lambda

pseudo-labeled

$$\min_{\boldsymbol{\theta}} \sum_{\boldsymbol{x}_i \in \mathbb{L}_{r-1}} \mathcal{L}(f(\boldsymbol{x}_i), \boldsymbol{m}_i) + \lambda \sum_{\boldsymbol{x}_i \in \mathbb{P}_{r-1}} \mathcal{L}(f(\boldsymbol{x}_i), \hat{\boldsymbol{m}}_i),$$

labeled

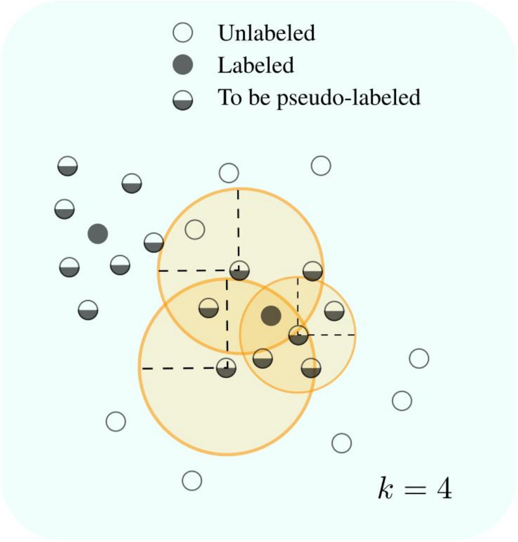
3. Our proposal for active learning:

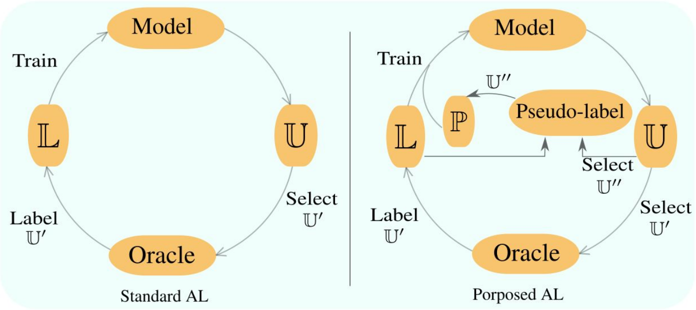
Few random images annotated by expert

Which images to pseudo-label U``?

- Use k-nn between samples of the same class
- Similarity: Jensen-Shannon div. between normalized color histograms

Key intuition: *The model is expected to provide good segmentation for images similar to the labeled ones.*





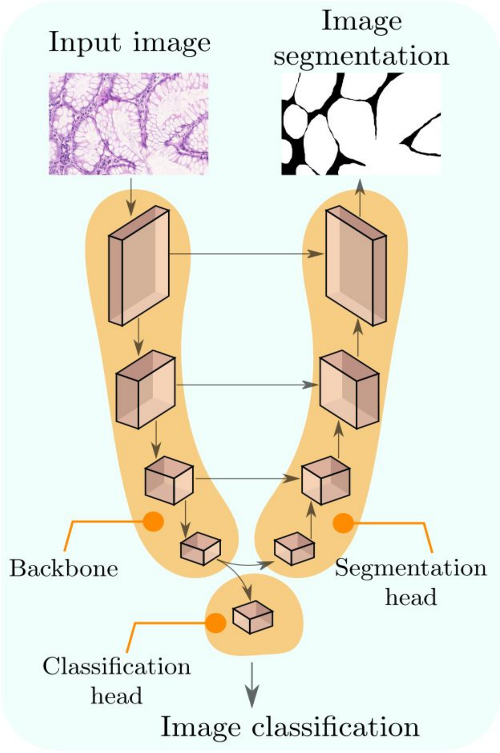
4. Deep architecture for supervised classification and segmentation

Training:

1. Train the backbone with classification head, then freeze it
2. Train the segmentation head

Why separate?

1. Isolate the segmentation training for analysis of active learning.
2. Avoid supervision unbalance: all images with global annotation versus only few images with pixel annotation



5. Experiments: protocol

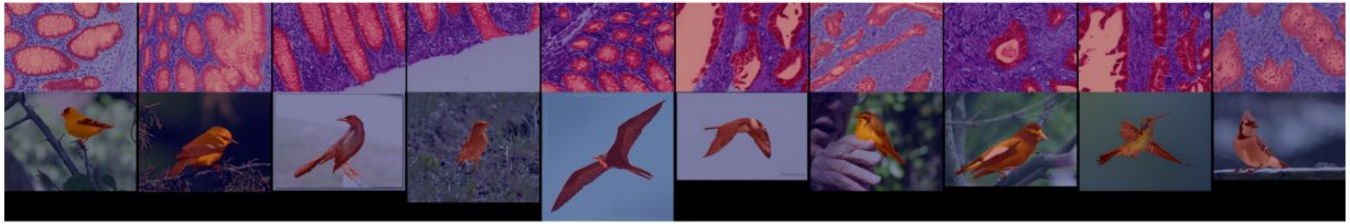
Active learning sampling

Datasets:

Dataset	#selected samples *per-class* ($r = 1$)	#selected samples *per-class* ($r > 1$)	Max AL rounds (`maxr` in Alg 1)
GlaS	4	1	25
CUB	1	1	20

Less load on the oracle (realistic)

Medical: GlaS dataset



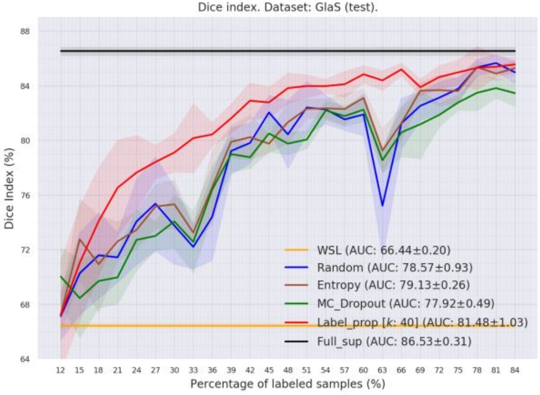
CUB-200-2011 dataset (CUB)

Our method uses random selection

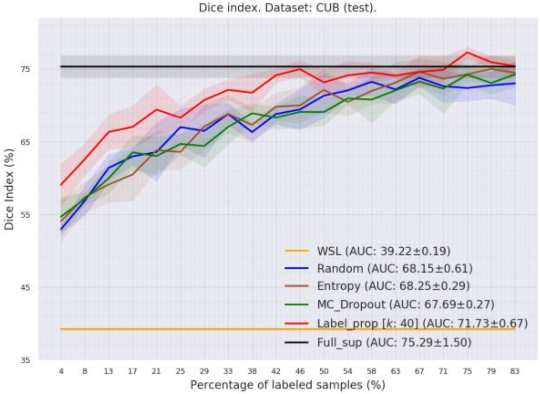
5. Experiments: results

AUC: Area Under the Curve

Dataset	GlaS	CUB
WSL	66.44 ± 0.20	39.22 ± 0.19
Random	78.57 ± 0.93	68.15 ± 0.61
Entropy	79.13 ± 0.26	68.25 ± 0.29
MC_Dropout	77.92 ± 0.49	67.69 ± 0.27
Label_prop (ours)	$\mathbf{81.48 \pm 1.03}$	$\mathbf{71.73 \pm 0.67}$
Full_sup	86.53 ± 0.31	75.29 ± 1.50

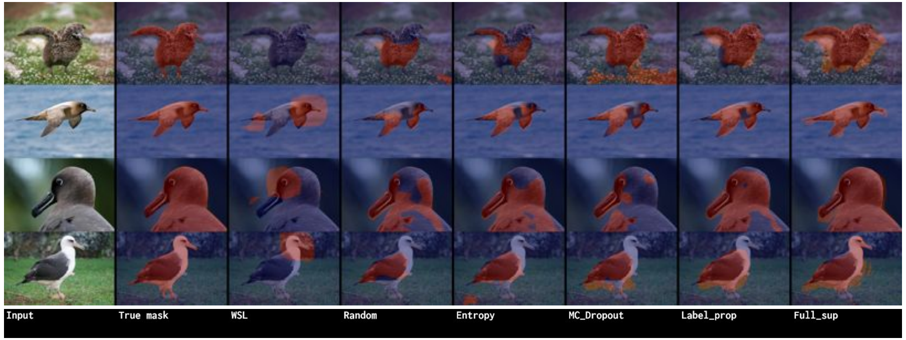


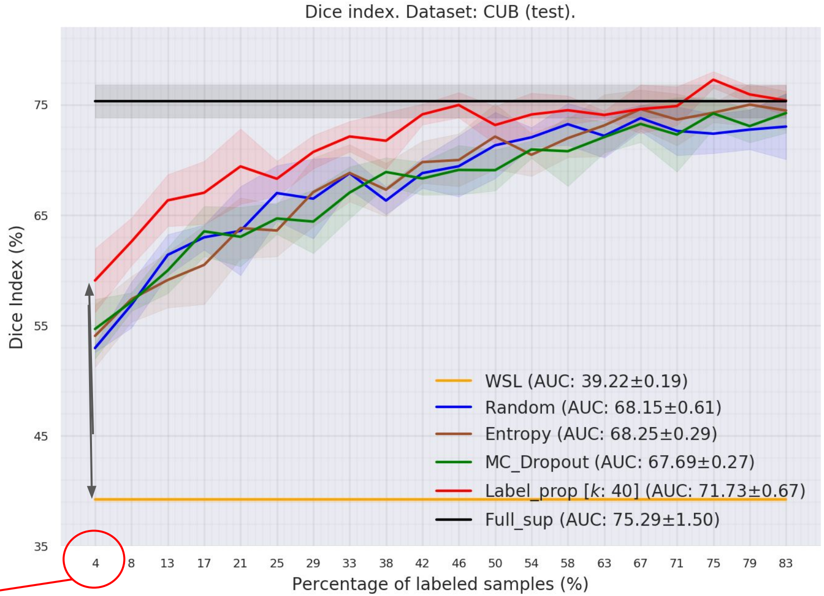
(a)



(b)

5. Experiments: WSL vs. few supervision

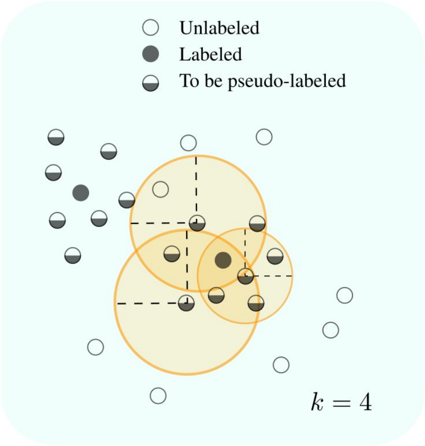


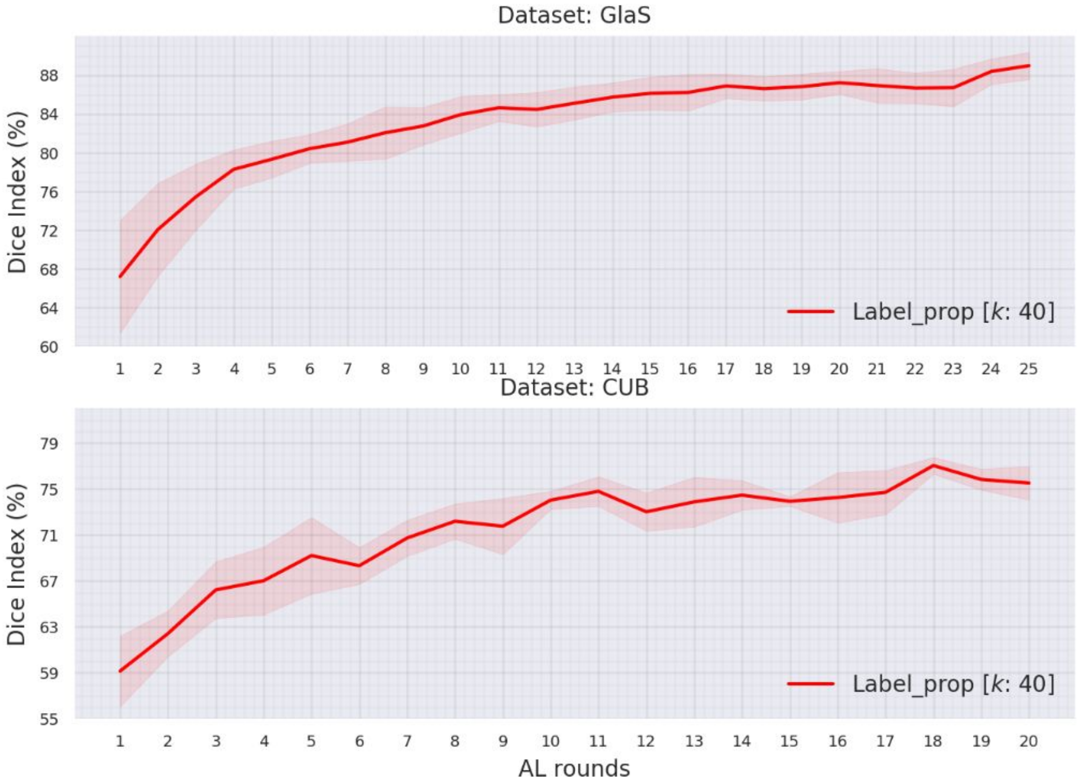


Label 1 sample per class

CUB

5. Experiments: Performance over pseudo-labeled samples

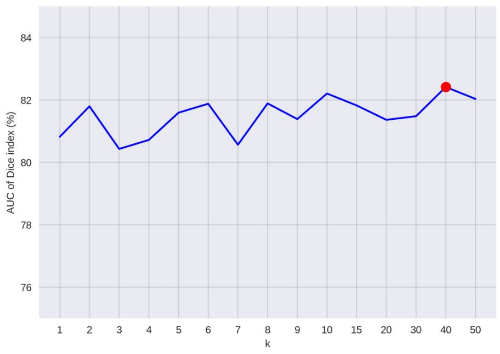




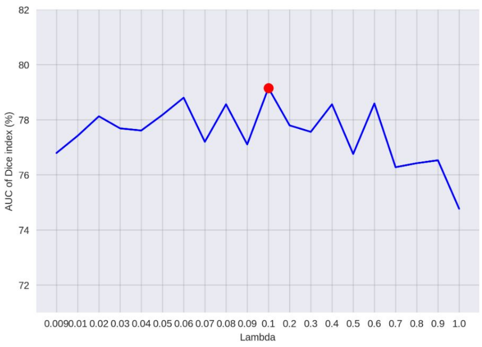
5. Experiments: Ablation study

Ablation study: impact on performance of *k* (for *k*-nn) and lambda.

Glas

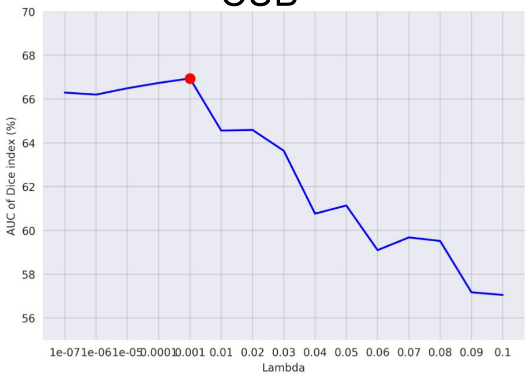


k



lambda

CUB



lambda

Our method is:

- Less sensitive to *k*
- Sensitive to lambda (depending of the difficulty of the dataset)

Thanks! Any Questions?
Please visit me at paper #1294

Code: https://github.com/sbelharbi/deep-active-learning-for-joint-classification-and-segmentation-with-weak-annotator

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