Sparse Object-level Supervision for Instance Segmentation with Pixel Embeddings

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Paper

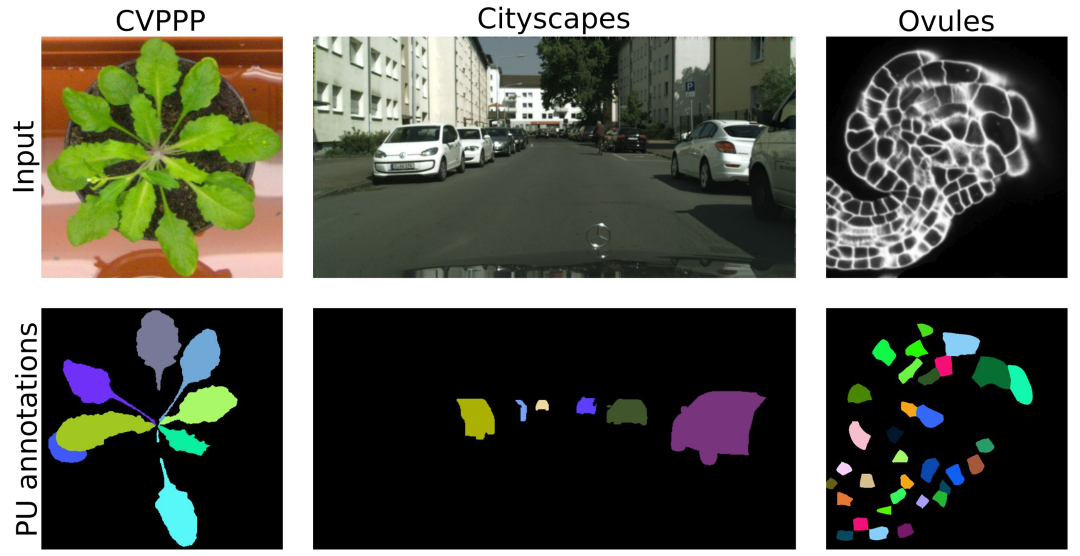
Code

Summary

- Problem: state-of-the-art instance segmentation methods require dense annotations
- Goal: an instance segmentation technique trainable from sparsely labeled instances
- Approach: embedding-based instance segmentation trained from positive-unlabeled (PU) supervision
- **Outperforms other embedding-based methods at a significantly reduced annotation cost**
- **Achieves state-of-the-art on the CVPPP benchmark**

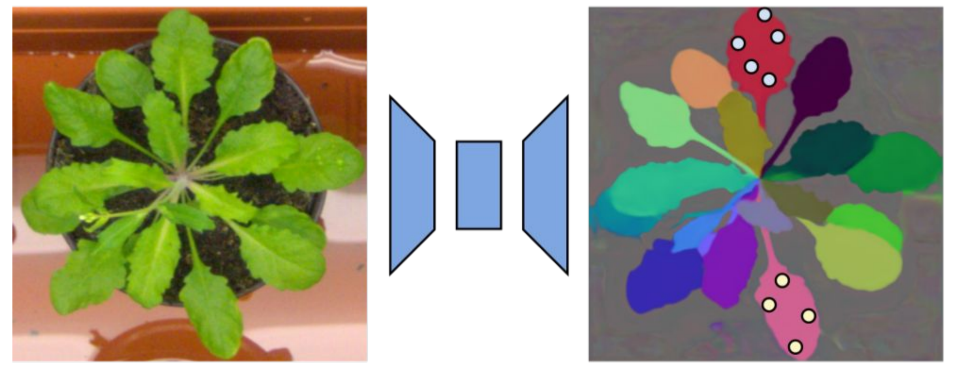
Positive-Unlabeled Supervision

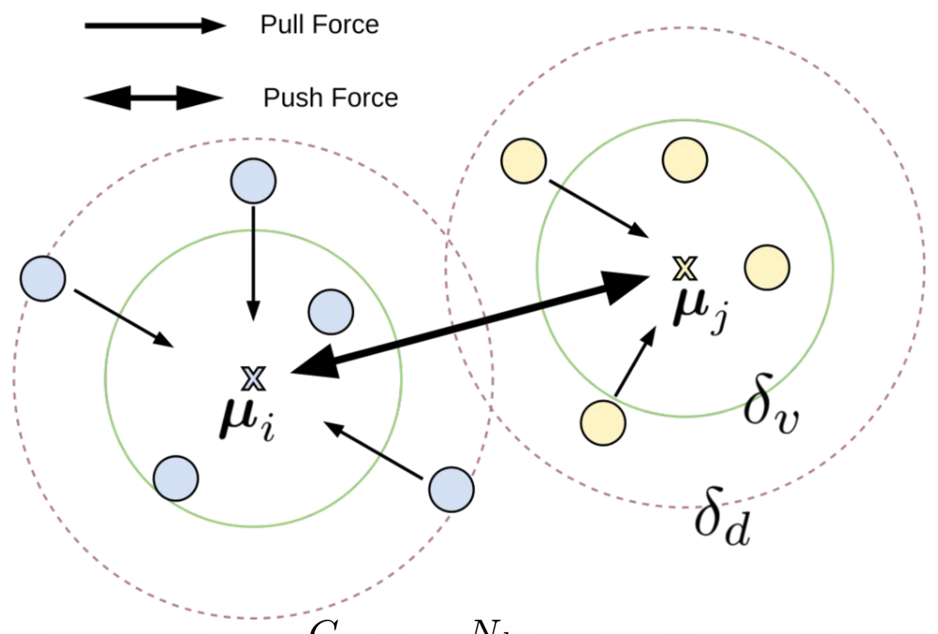
- Easier to create annotations
- More diverse training set



Embedding-based Instance Segmentation

Training [1]





Inference:

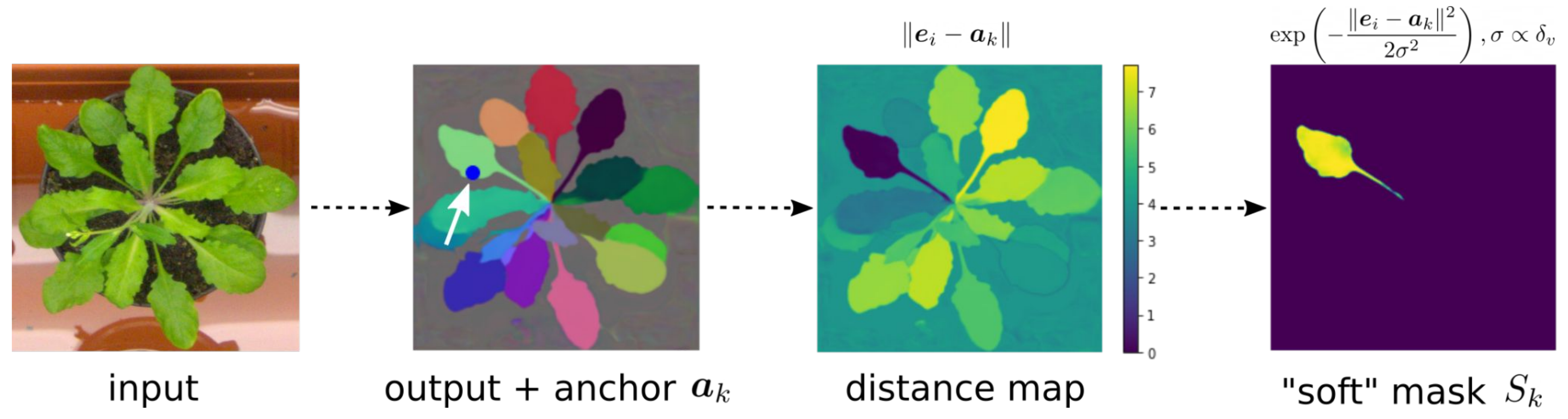
- HDBSCAN
- Mean-Shift
- **Consistency clustering**
- **Metric graph partitioning**

$$L_{pull} = \frac{1}{C}\sum_{k=1}^{C}\frac{1}{N_k}\sum_{i=1}^{N_k}[\|\boldsymbol{\mu}_k - \mathbf{e}_i\| - \delta_v]_+^2$$

$$L_{push} = \frac{1}{C^2}\sum_{k=1}^{C}\sum_{l=1}^{C}[2\delta_d - \|\boldsymbol{\mu}_k - \boldsymbol{\mu}_l\|]_+^2$$

"SPOCO" Method

- Introduce differentiable instance selection

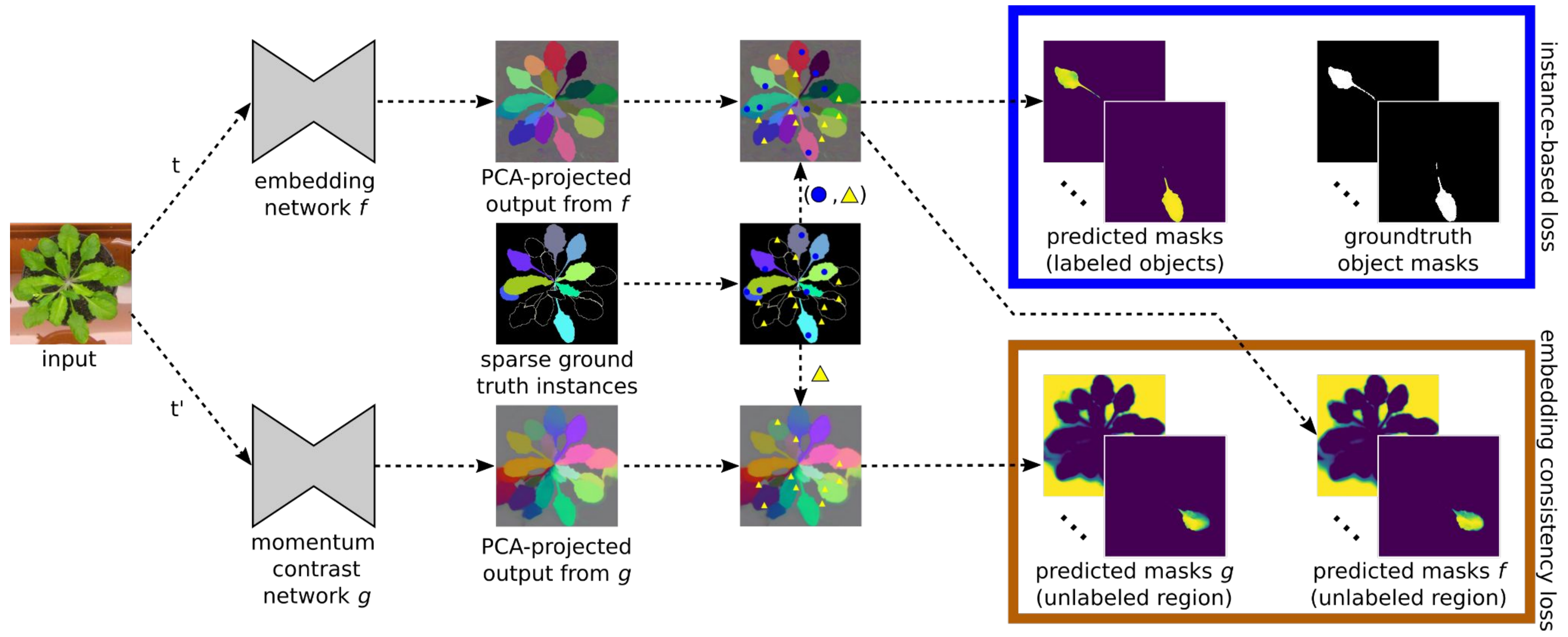


- Use differentiable instance selection in auxiliary losses:
  - **supervised instance-based loss (labeled set)**

$$L_{obj} = \frac{1}{C}\sum_{k=1}^{C} L_{dice}(S_k, I_k)$$

  - **self-supervised embedding consistency loss (unlabeled set)**

$$L_{U\_con} = \frac{1}{K}\sum_{k=1}^{K} L_{dice}(S_k^f, S_k^g)$$



Final loss

$$L = \alpha L_{pull} + \beta L_{push} + \gamma L_{obj} + \lambda L_{U\_con}$$

References

[1] B. D. Brabandere et al. Semantic Instance Segmentation with a Discriminative Loss Function, CVPR '17
[2] M. Ren et al. End-to-End Instance Segmentation with Recurrent Attention, CVPR '17
[3] V. Kulikov et al., Instance Segmentation of Biological Images Using Harmonic Embeddings, CVPR '20
[4] A. Wolny et al., Accurate and versatile 3D segmentation of plant tissues at cellular resolution, eLife '20

Results

CVPPP test set

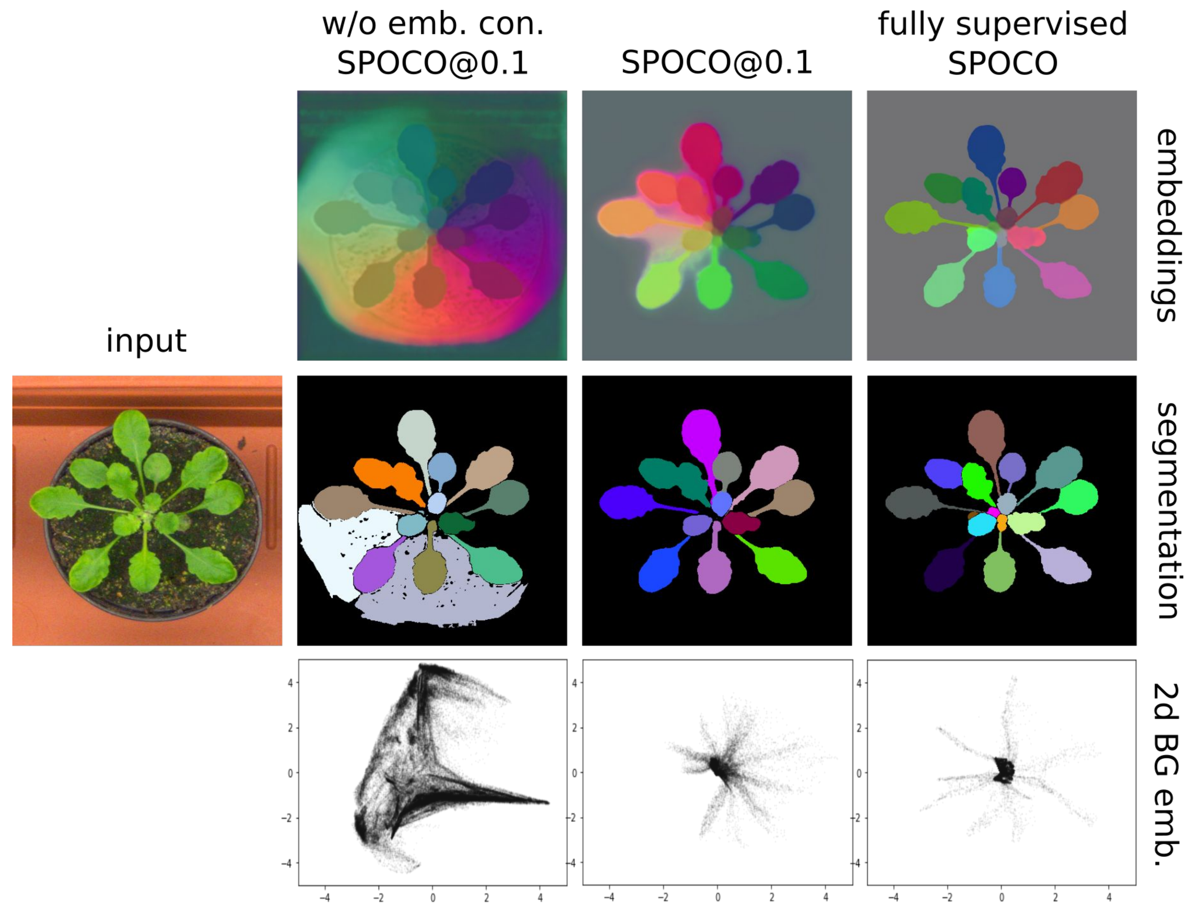
Method	SBD
Discriminative loss [1]	0.842
Recurrent attention [2]	0.849
Harmonic Embeddings [3]	0.899
SPOCO@0.1	0.788
SPOCO@0.4	0.824
SPOCO	**0.932**

Cityscapes validation set

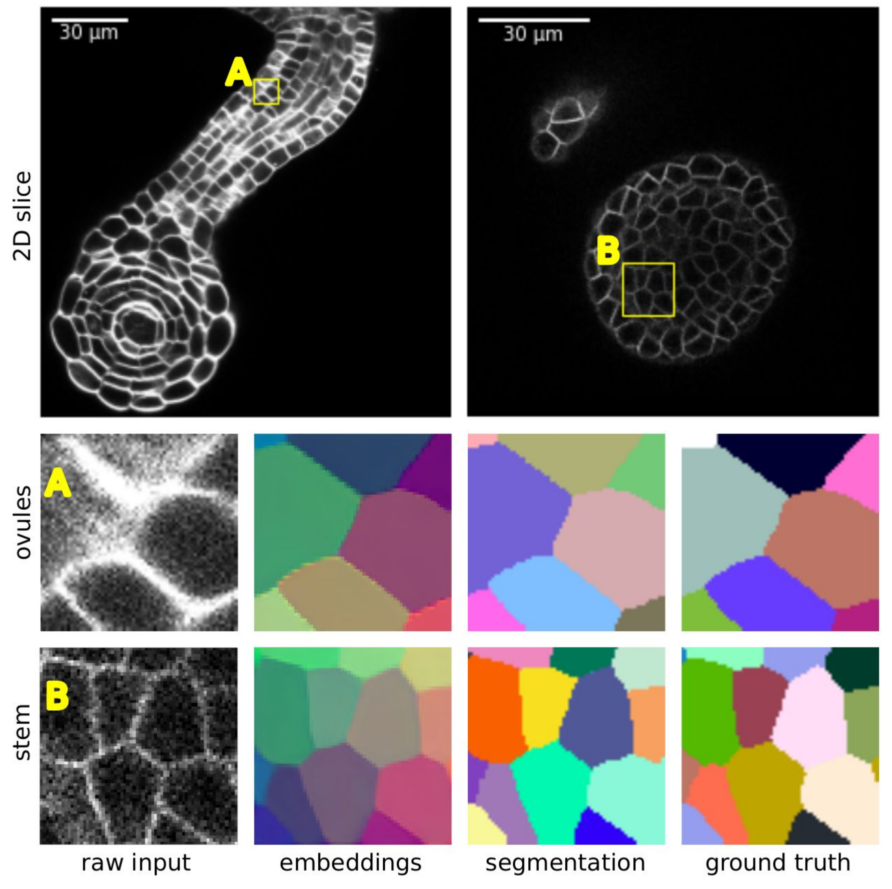
Method	mAP@0.5
Discriminative loss [1]	0.387
SPOCO@0.1	0.353
SPOCO@0.4	0.412
SPOCO	**0.459**

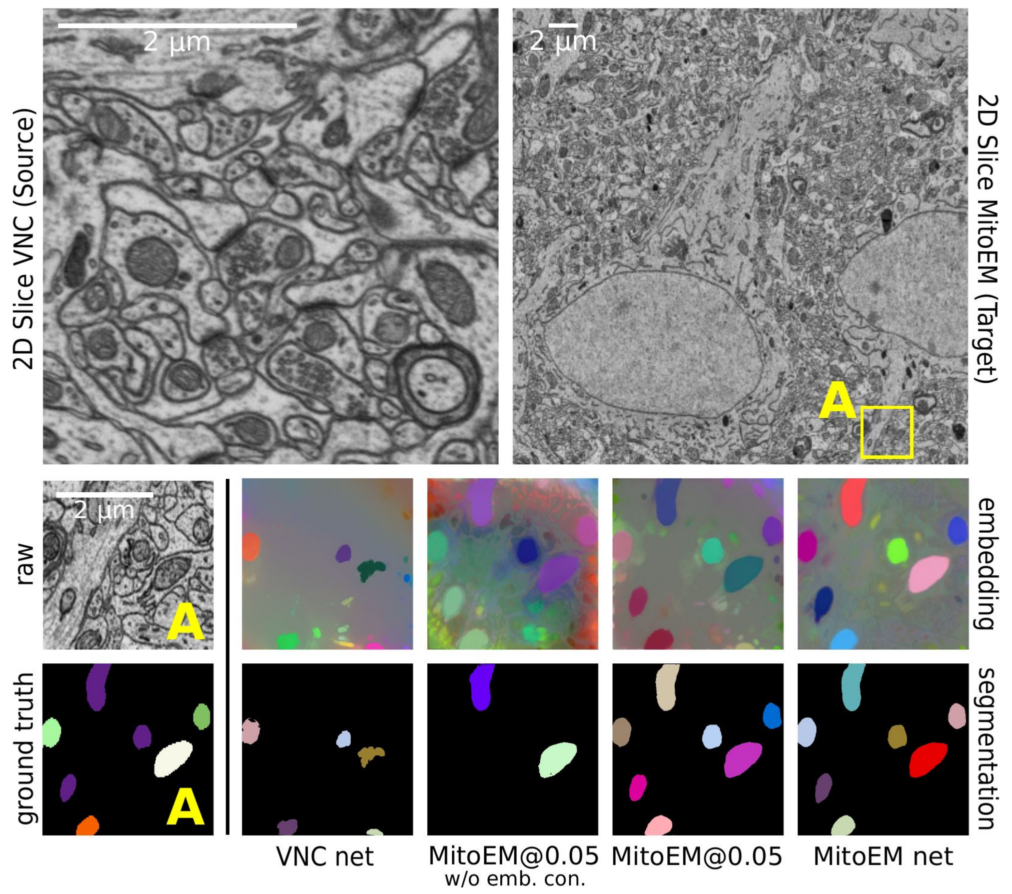
3D Ovules test set

Method	ARand Error
Discriminative loss [1]	0.074
PlantSeg [4]	0.046
SPOCO@0.1	0.069
SPOCO@0.4	0.060
SPOCO	0.048
SPOCO with L_{wgan}	**0.042**



Transfer Learning





3D Stem Cells

Method	ARand Error
Stem only	0.074
Ovules only	0.227
Ovules+Stem@0.01	0.141
Ovules+Stem@0.05	0.109
Ovules+Stem@0.1	0.106

MitoEM

Method	AP@0.5
VNC only	0.234
MitoEM only	0.560
VNC+MitoEM@0.01	0.368
VNC+MitoEM@0.05	0.398
VNC+MitoEM@0.10	0.389