# Weakly Supervised Semantic Segmentation for Histopathology

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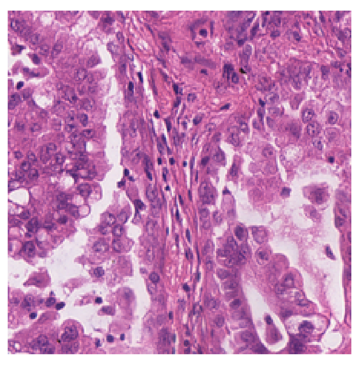
## Motivation

### Problem



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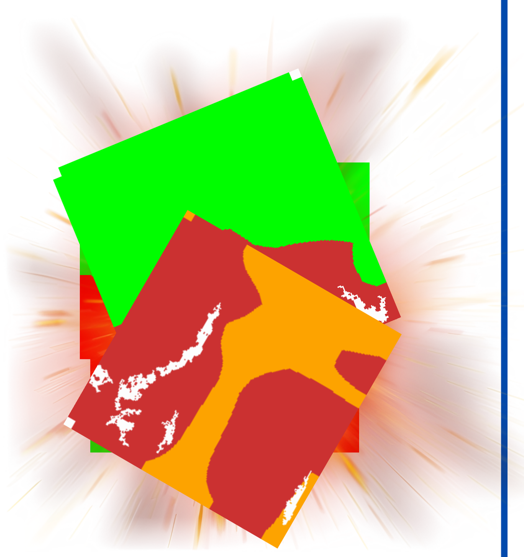
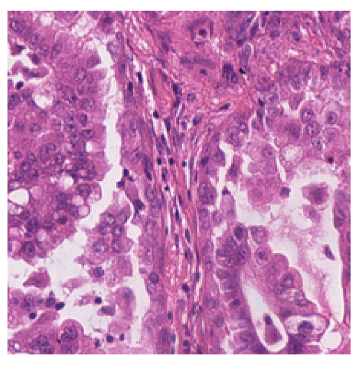


**Histopathology**
Diagnosis of disease via tissue microscopy

**Semantic Segmentation**
Machine-Learning approaches to identify tissue regions

**Annotation Burden**
Masks are large and require expertise

### Solution (Weakly Supervised Semantic Segmentation)



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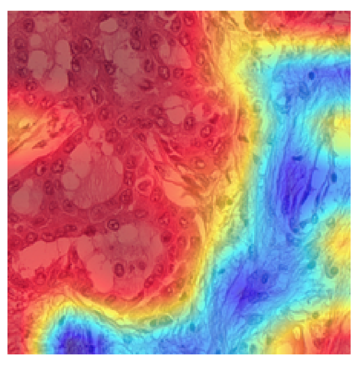


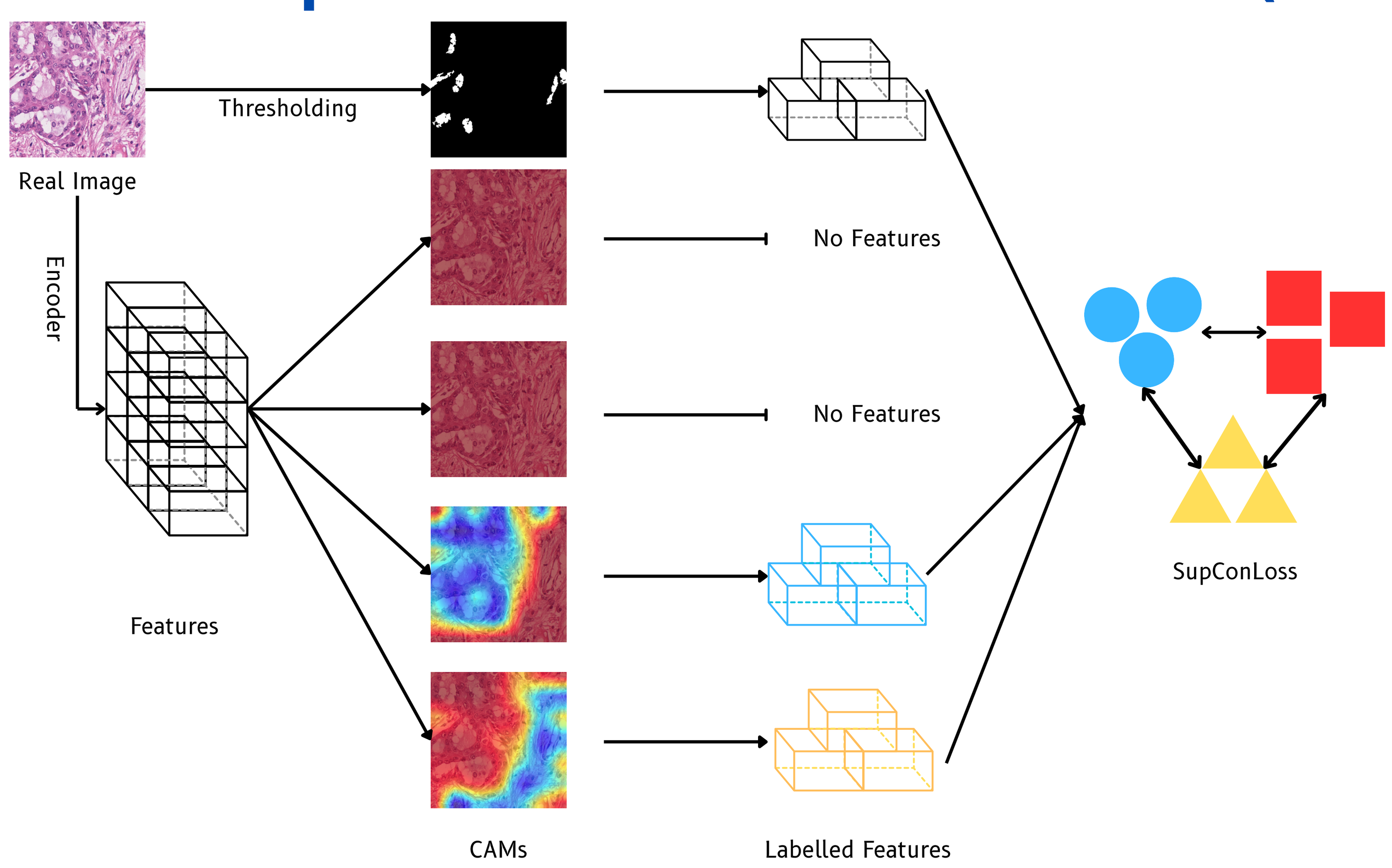
**Histopathology** **Global Patch Labels** **Class Activation Maps (CAMs)**

### Limitations of Existing Work

**1) CAMs suffer from Partial-Activation:** Only the most discriminative regions of an images are highlighted.

**2) Existing solutions often require many steps:** Complex work-arounds often involve many steps with additional approaches rather than it being an emergent property of a trained model.

## Pseudo-Supervised Contrastive Loss (PSCL)

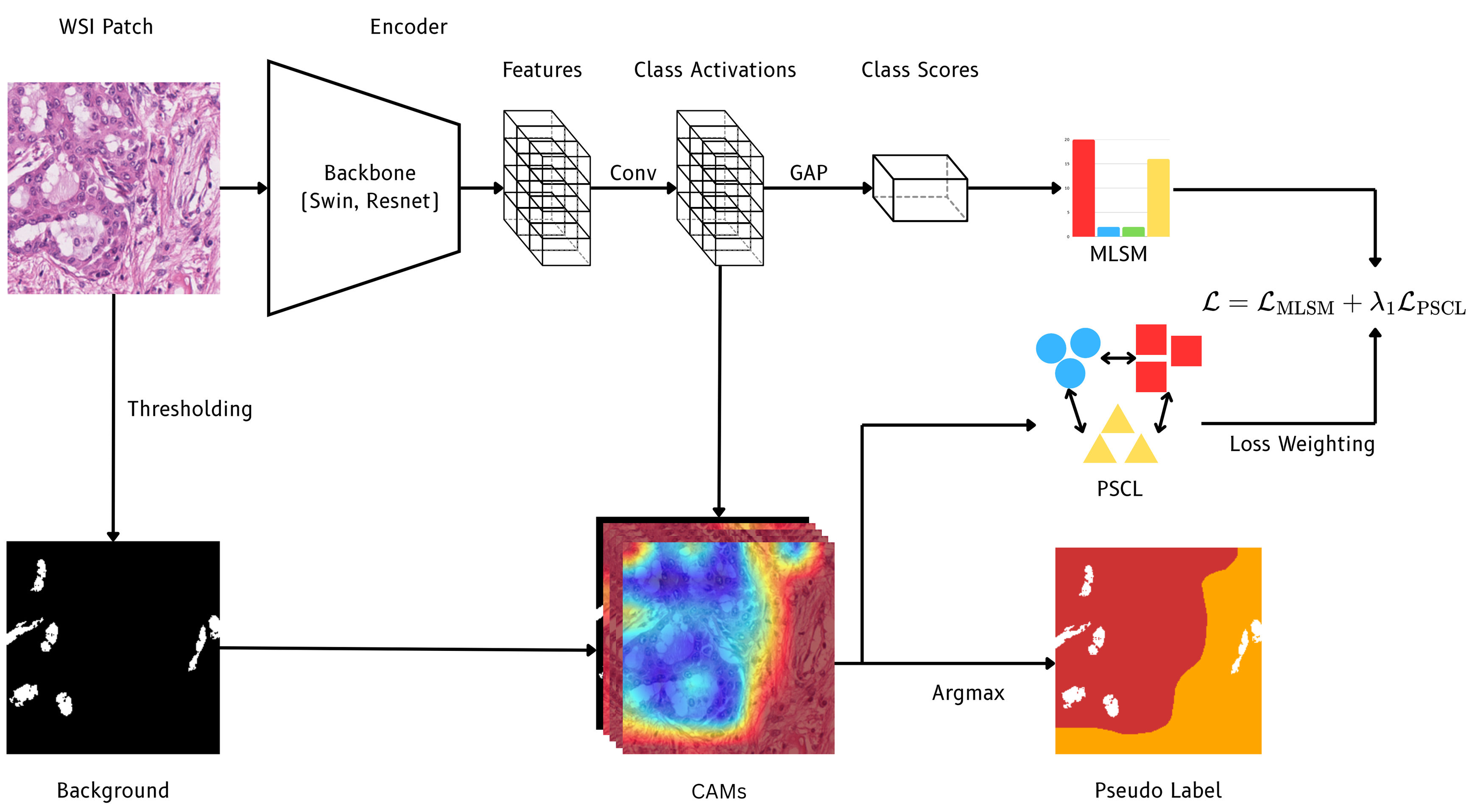



**1) Collect Features**
Extract features from last stage of encoder

**2) Filter Features**
Label features with pseudo-labels and remove poor responses

**3) Contrast Features**
Apply Supervised Contrastive Loss (SupConLoss)

## Method




**1) Classification Training:** We train a Swin Transformer Encoder on the patch classification task. We apply MLSM and our novel PSCL approach.

**2) Pseudo-Label Generation (Stage 1):** We take the trained model and produce Pseudo-Labels via argmax on the CAMs with a concatenated background map.

**3) Encoder-Decoder Supervised (Stage 2):** We attach a Mask2Former Decoder to the trained Swin Transformer backbone. We then train end-to-end using the pseudo-labels as ground truth.

## Results

### Strong Performance w.r.t SOTA

**We demonstrate performance that is comparable to state-of-the-art.** This is across both stages of training. In particular, **we rank 2nd on the BCSS-WSSS** dataset.

**Stage 1**

LUAD-HistoSeg

| Method | TE | NEC | LYM | TAS | fwIoU | mIoU |
|---|---|---|---|---|---|---|
| UAM (Kang et al., 2025) | **76.24** | **80.43** | **76.28** | **72.02** | **75.38** | **76.24** |
| TPRO (Zhang et al., 2023) | 74.82 | 77.55 | 76.40 | 70.98 | 73.81 | 74.94 |
| MLPS (Han et al., 2021) | 71.72 | 76.27 | 73.53 | 67.67 | 70.80 | 72.30 |
| Swin (Ours) | 67.49 | 72.39 | 69.82 | 65.28 | 67.35 | 68.75 |

BCSS-WSSS

| Method | TUM | STR | LYM | NEC | fwIoU | mIoU |
|---|---|---|---|---|---|---|
| UAM (Kang et al., 2025) | **78.97** | **71.72** | **58.16** | **63.59** | **72.20** | **68.11** |
| TPRO (Zhang et al., 2023) | 77.18 | 63.77 | 54.95 | 61.43 | 68.55 | 64.33 |
| MLPS (Han et al., 2021) | 70.76 | 61.07 | 50.87 | 52.94 | 63.89 | 58.91 |
| Swin (Ours) | 78.66 | 67.05 | 49.11 | 63.96 | 70.13 | 64.70 |

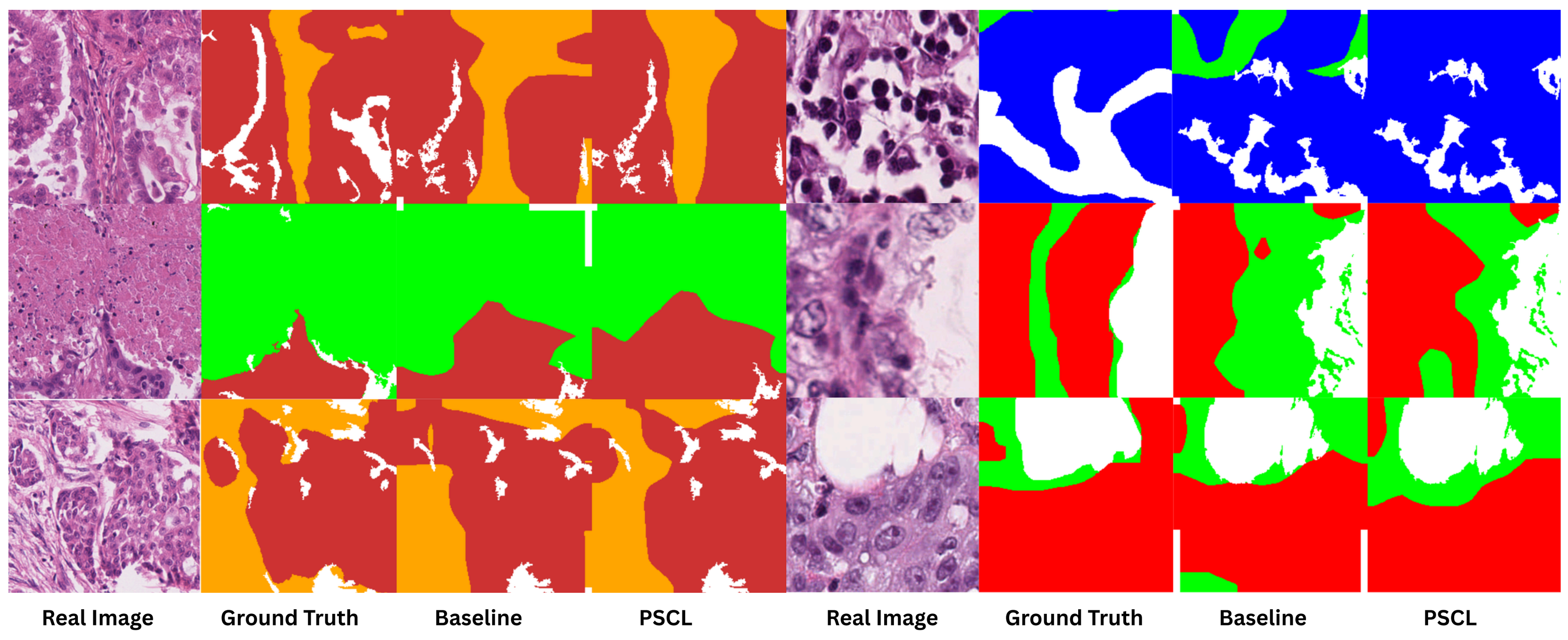
**Stage 2**

LUAD-HistoSeg

| Method | TE | NEC | LYM | TAS | fwIoU | mIoU |
|---|---|---|---|---|---|---|
| UAM (Kang et al., 2025) | **78.62** | **82.31** | **79.03** | **73.31** | **76.98** | **78.31** |
| TPRO (Zhang et al., 2023) | 75.80 | 80.56 | 78.14 | 72.69 | 75.31 | 76.80 |
| MLPS (Han et al., 2021) | 73.90 | 77.48 | 73.61 | 69.53 | 72.51 | 73.63 |
| Ours | 70.42 | 73.66 | 71.81 | 66.51 | 69.40 | 70.60 |

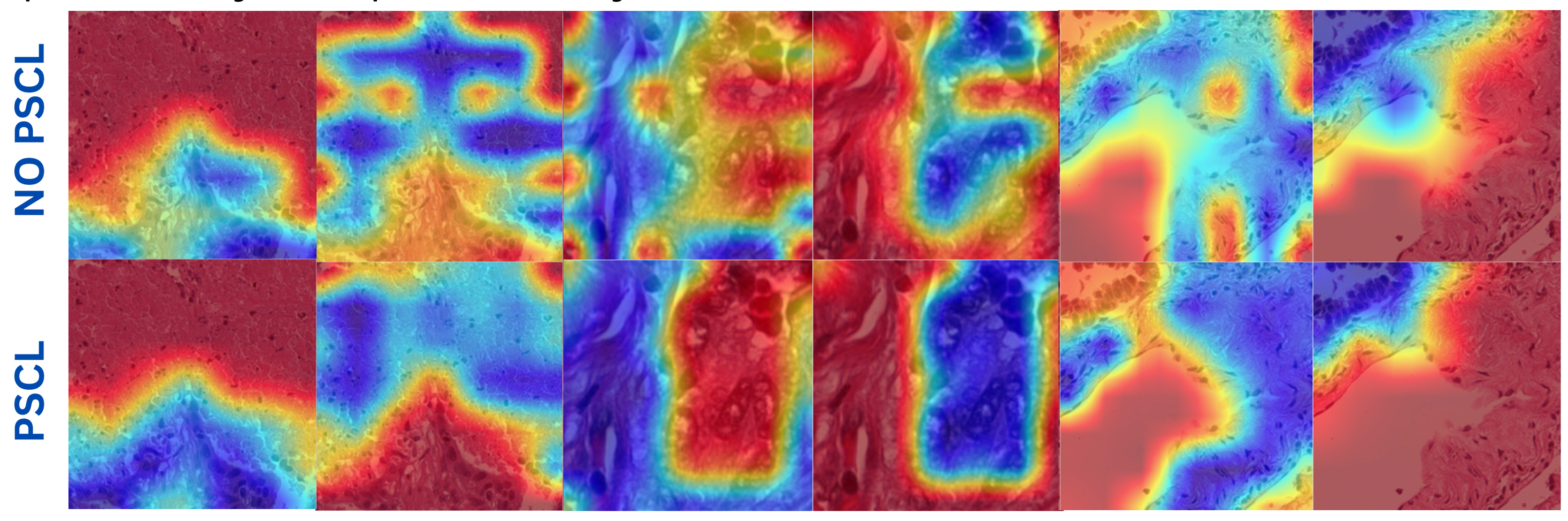
BCSS-WSSS

| Method | TUM | STR | LYM | NEC | fwIoU | mIoU |
|---|---|---|---|---|---|---|
| UAM (Kang et al., 2025) | **79.89** | **74.66** | **64.71** | **70.88** | **75.76** | **70.88** |
| TPRO (Zhang et al., 2023) | 77.95 | 65.10 | 54.55 | 64.96 | 67.36 | 65.64 |
| MLPS (Han et al., 2021) | 74.54 | 64.45 | 52.54 | 58.67 | 66.48 | 62.55 |
| Ours | 79.41 | 68.91 | 52.63 | 63.91 | 71.60 | 66.22 |




### More Complete Activations

**We demonstrate that PSCL helps to address the issue of partial activation.** Application of PSCL produces stronger, more consistent activations, both qualitatively and quantitatively.




### Faster and Simpler Training Schema

**Through conducting thorough evaluations we find:**

**1) Our method only requires 5 epochs of training to reach peak performance**. This is in comparison to other approaches which require up to 20 epochs.

**2) Using pre-trained weights significantly boosts performance.** Whether industry standard (ImageNet) or self-produced, pre-trained weights are necessary**.**

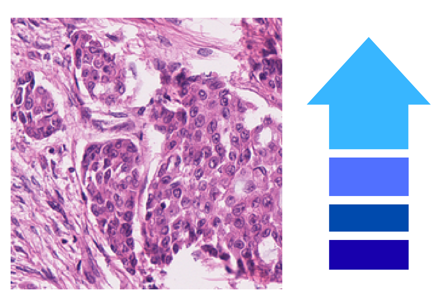
**3) Using pseudo-labels to train a supervised encoder-decoder boosts performance by ~2%.** A small performance win with little additional work

## Conclusion

**1) Novel Contrastive Learning Approach (PSCL):** We introduce and demonstrate the viability of a novel contrastive learning based approach to weakly supervised semantic segmentation for histopathology. This approach rivals state-of-the-art and **requires no further post-processing.**

**2) WSSS is a viable approach:** We conduct a thorough examination of the end-to-end WSSS pipeline and various modifications and demonstrate its viability in addressing the annotation burden.

### Further Work



**Improve LUAD Performance**
How can we bring LUAD performance gains to those of BCSS?

**More Classes**
Does PSCL generalise to more classes?

**Different Domain**
Can PSCL work on different domains?

## References

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