

Deep Weakly-Supervised Learning Methods for Classification and Localization in Histology Images: A Survey

(#M004)



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Context

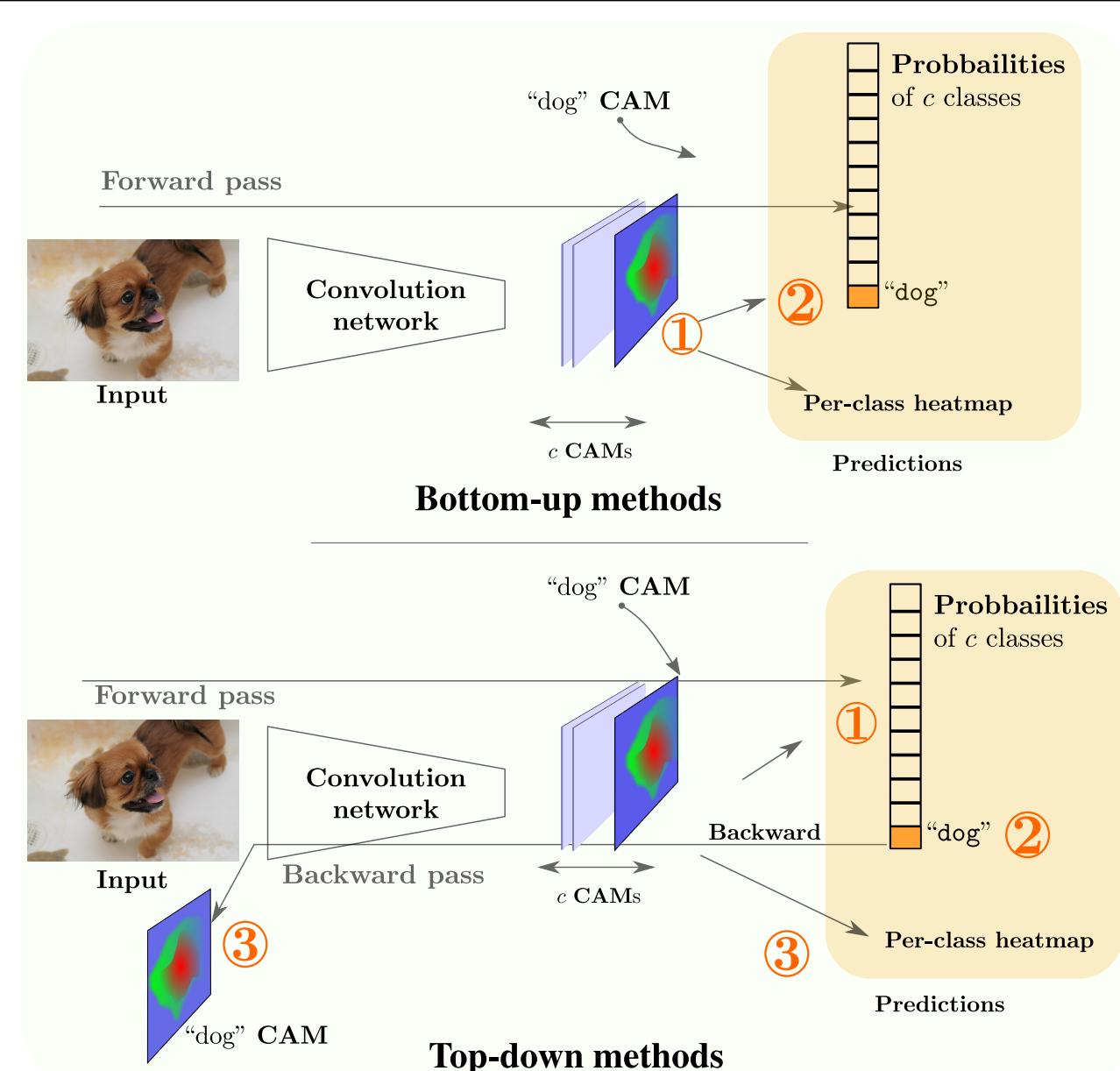
We explore weakly-supervised object localization methods in histology images and to what extent they are able to localize regions of interest (ROIs), i.e., cancerous regions, using only image label supervision.

Weak supervision: only global image class is available.

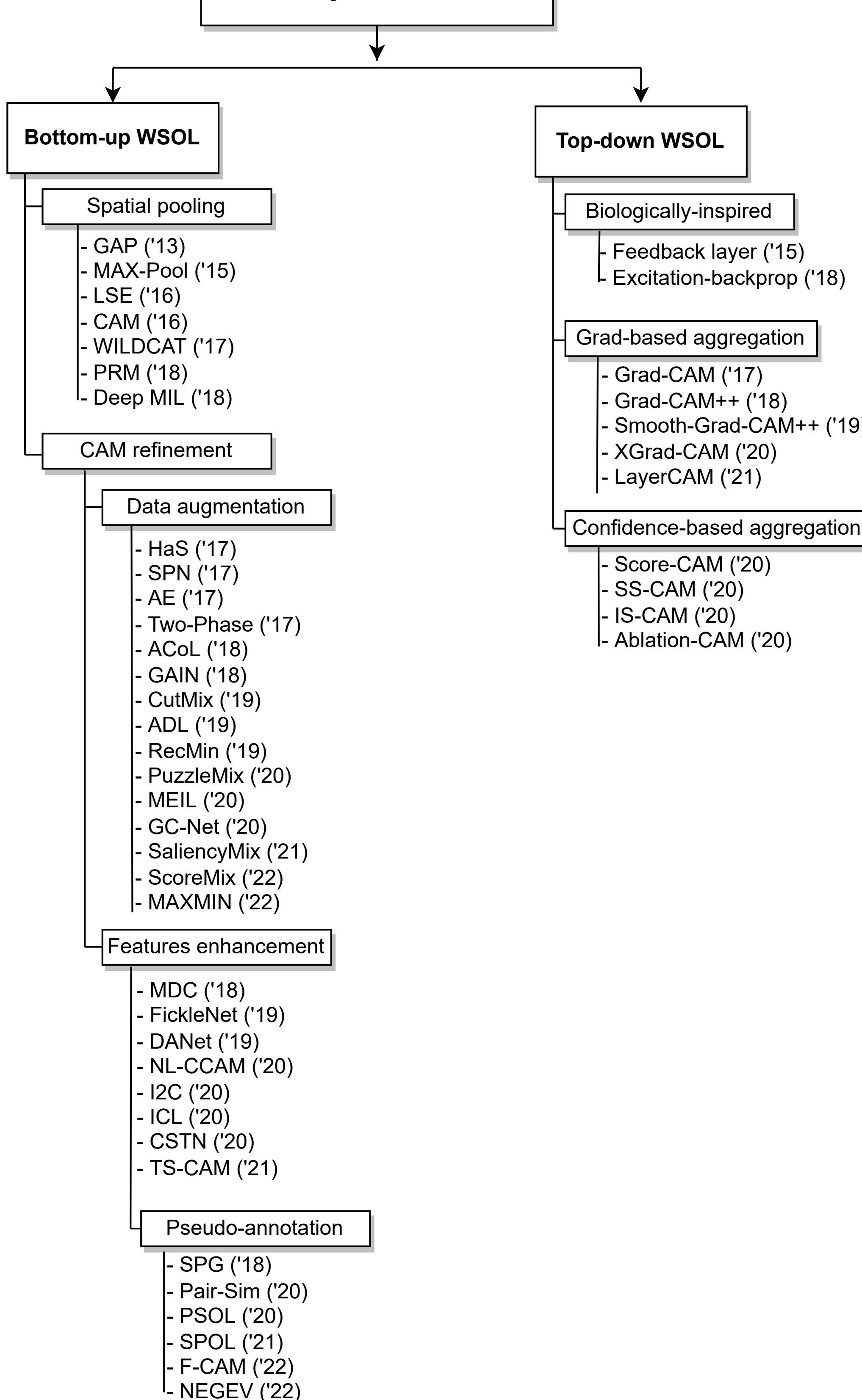
Challenges:

- ⌚ Large images
- ⌚ Label ambiguity
- ⌚ Large stain variability
- ⌚ Unstructured images
- ⌚ Similar foreground/background (no salient patterns)

Taxonomy



A taxonomy of WSOL methods



Empirical Results

Datasets: GLAS for colon cancer, and CAMELYON16 for breast cancer.

Localization performance of different WSOL Methods

Methods / Metric	GLAS				CAMELYON16			
	VGG	Inception	ResNet	Mean	VGG	Inception	ResNet	Mean
Bottom-up WSOL								
GAP (corr,2013)	58.5	57.5	56.2	57.4	37.5	24.6	43.7	35.2
MAX-Pool (cvpr,2015)	58.5	57.1	46.2	53.9	42.1	40.9	20.2	34.4
LSE (cvpr,2016)	63.9	62.8	59.1	61.9	63.1	29.0	42.1	44.7
CAM (cvpr,2016)	68.5	50.5	64.4	61.1	25.4	48.7	27.5	33.8
HaS (iccv,2017)	65.5	65.4	63.5	64.8	25.4	47.1	29.7	34.0
WILDCAT (cvpr,2017)	56.1	54.9	60.1	57.0	44.4	31.4	31.0	35.6
ACoL (cvpr,2018)	63.7	58.2	54.2	58.7	31.3	39.3	31.3	33.9
SPG (eccv,2018)	63.6	58.3	51.4	57.7	45.4	24.5	22.6	30.8
Deep MIL (icml,2018)	66.6	61.8	64.7	64.3	53.8	51.1	57.9	54.2
PRM (cvpr,2018)	59.8	53.1	62.3	58.4	46.0	41.7	23.2	36.9
ADL (cvpr,2019)	65.0	60.6	54.1	59.9	19.0	46.0	46.0	37.0
CutMix (eccv,2019)	59.9	50.4	56.7	55.6	56.4	44.9	20.7	40.6
TS-CAM (tmi,2021)	t:54.5	b:57.8	s:55.1	52.8	t:46.3	b:21.6	s:42.2	36.7
MAXMIN (tmi,2022)	75.0	49.1	81.2	68.4	50.4	80.8	77.7	69.6
NEGEV (midl,2022)	81.3	70.1	82.0	77.8	70.3	53.8	52.6	58.9
Top-down WSOL								
GradCAM (iccv,2017)	75.7	56.9	70.0	67.5	40.2	34.4	29.1	34.5
GradCAM++ (wacv,2018)	76.1	65.7	70.7	70.8	41.3	43.9	25.8	37.0
Smooth-GradCAM++ (corr,2019)	71.3	67.6	75.5	71.4	35.1	31.6	25.1	30.6
XGradCAM (bmvc,2020)	73.7	66.4	62.6	67.5	40.2	33.0	24.4	32.5
LayerCAM (ieee,2021)	67.8	66.1	70.9	68.2	34.1	25.0	29.1	29.4
Fully supervised								
U-Net(miccai,2015)	96.8	95.4	96.4	96.2	83.0	82.2	83.6	82.9

Results

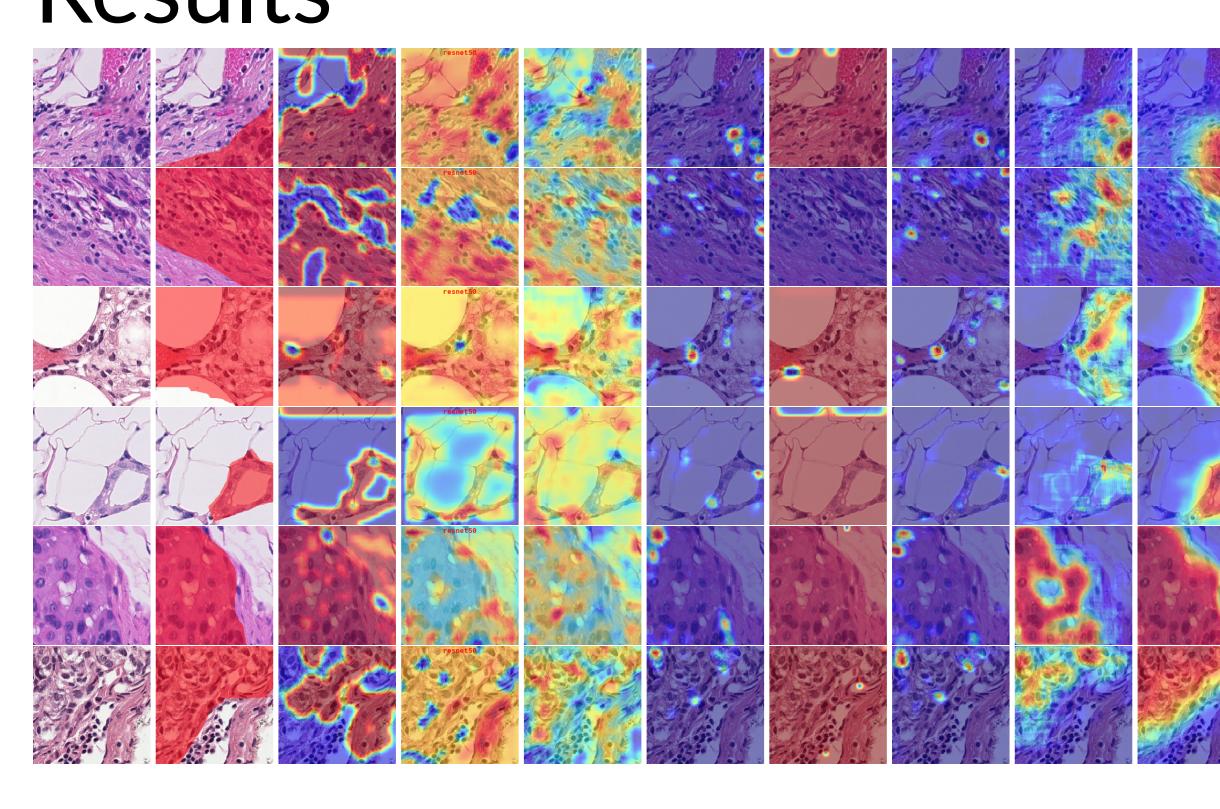


Figure 1. Predictions over metastatic test samples for CAMELYON16.

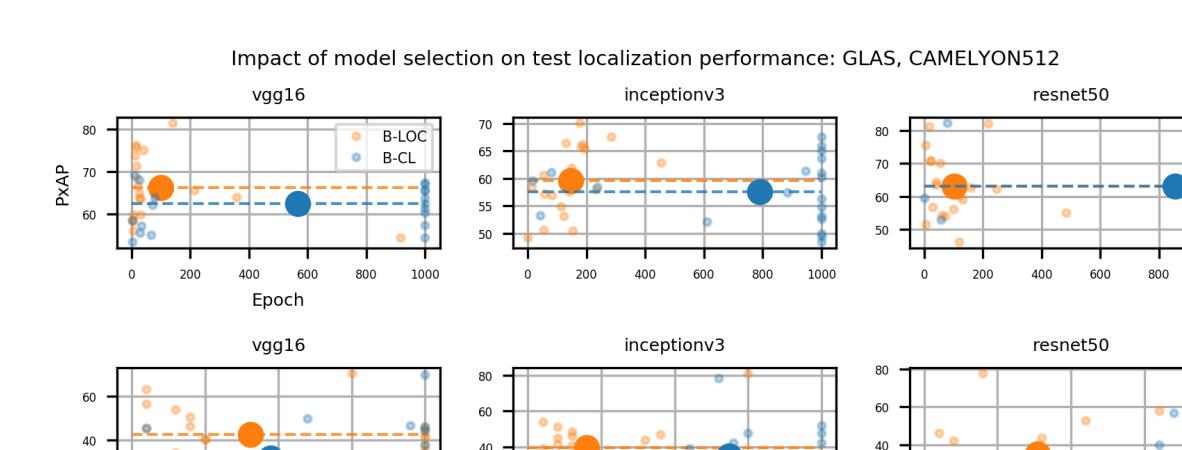


Figure 2. Localization: Impact of model selection (B-LOC: orange, vs. B-CL: blue) over test localization (PxAP) performance. Each point indicates the epoch (x-axis) at which the best model is selected and its corresponding localization performance (y-axis). Large circles indicate the average over all WSOL methods. Top: GLAS. Bottom: CAMELYON16.

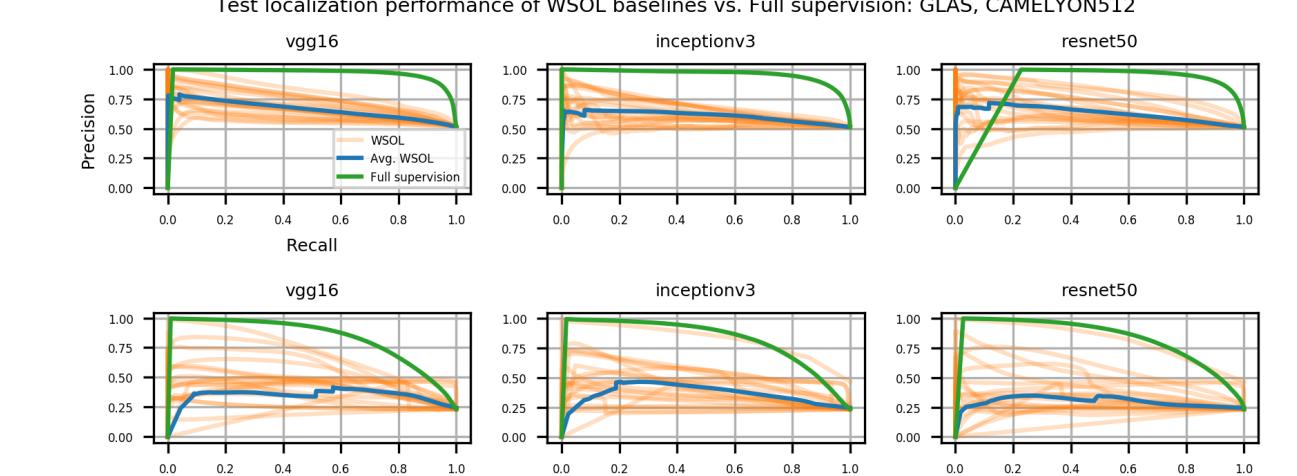


Figure 3. Localization sensitivity to thresholding: WSOL methods (orange), average WSOL methods (blue), fully supervised method (green). Top: GLAS. Bottom: CAMELYON16.

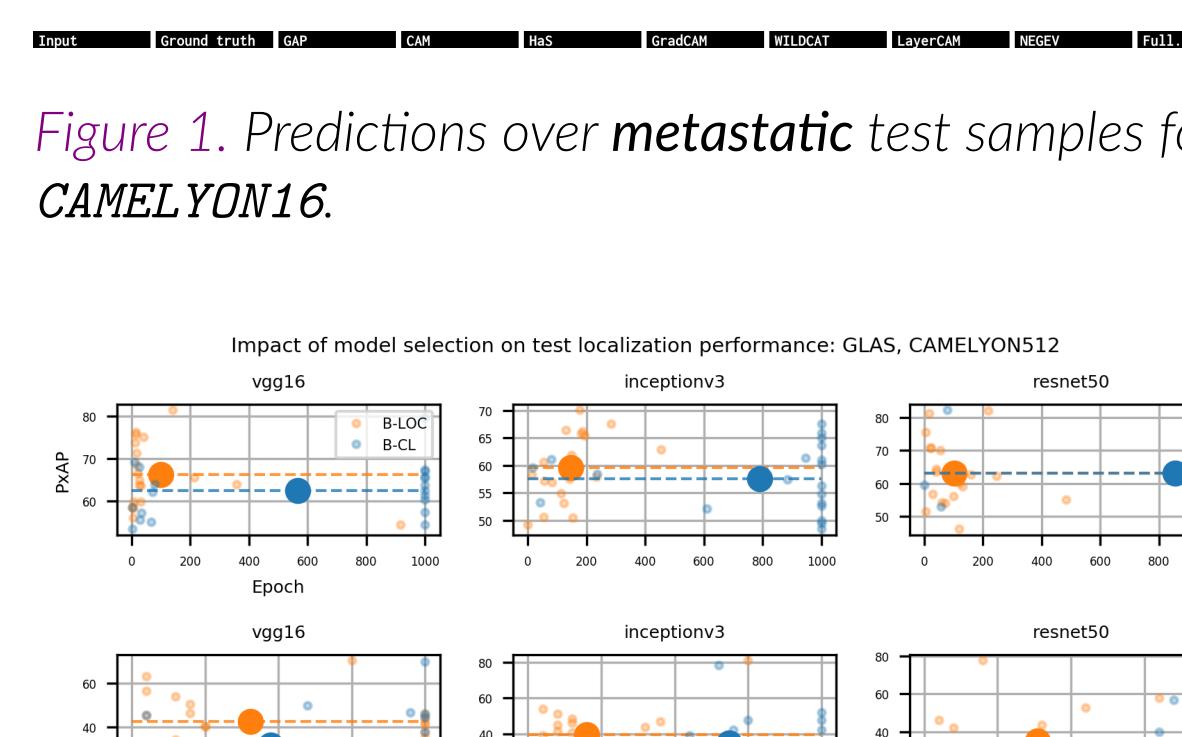


Figure 4. Classification: Impact of model selection (B-LOC: orange, vs. B-CL: blue) over test classification (CL) performance. Each point indicates the epoch (x-axis) at which the best model is selected and its corresponding classification performance (y-axis). Large circles indicate the average over all WSOL methods. Top: GLAS. Bottom: CAMELYON16.

Ongoing Challenges for WSOL in Histology Data

- ⌚ Under activation (high false negative), Over activation (high false positive)
- ⌚ Sensitivity to thresholding
- ⌚ Model selection

Directions:

- ⌚ Unsupervised size constraints
- ⌚ Pseudo-labels
- ⌚ Validation free