Negative Evidence Matters in Interpretable Histology Image Classification

#179

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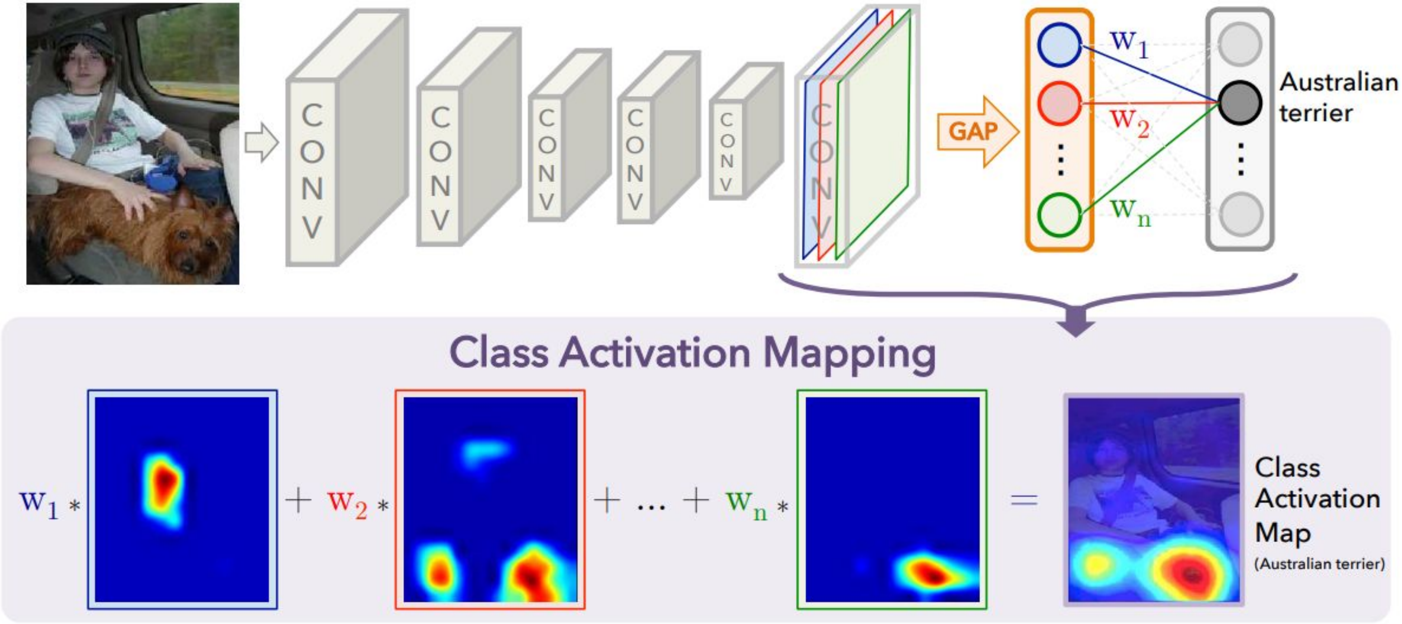
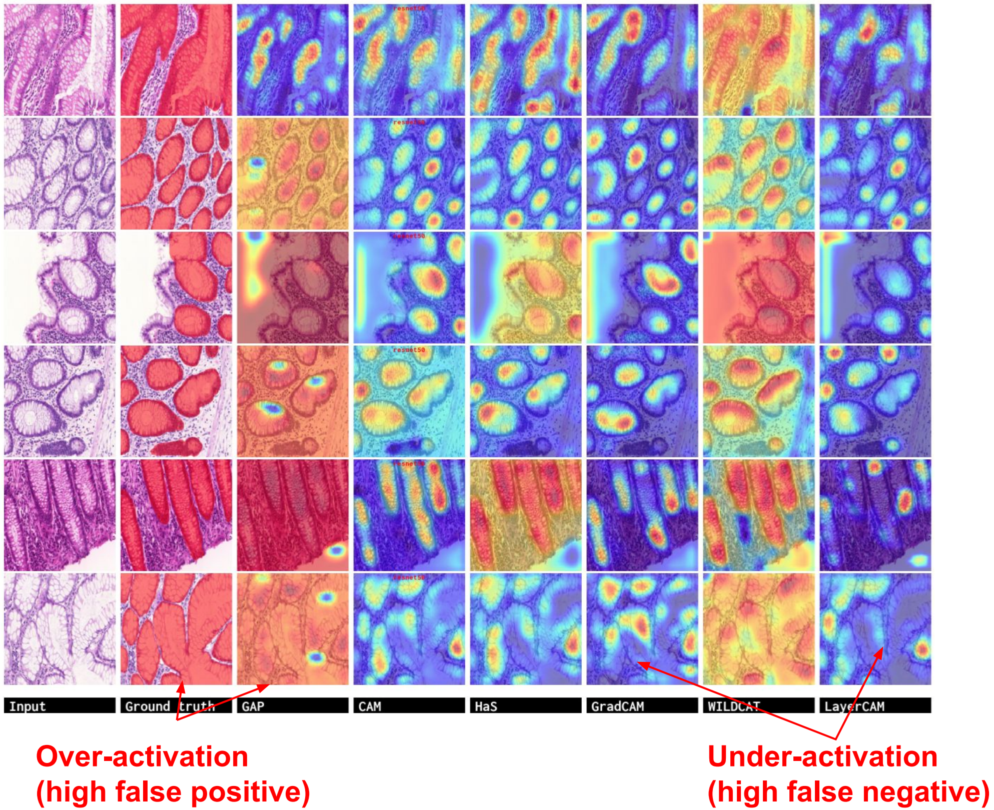
Classifier, ROI localization, and interpretability via global labels

CAMs



CAMs' challenges in histology images



Deep Weakly-Supervised Learning Methods for Classification and Localization in Histology Images: A Comparative Study. 2022. arxiv.org/abs/1909.03354

Our work: Using negative knowledge

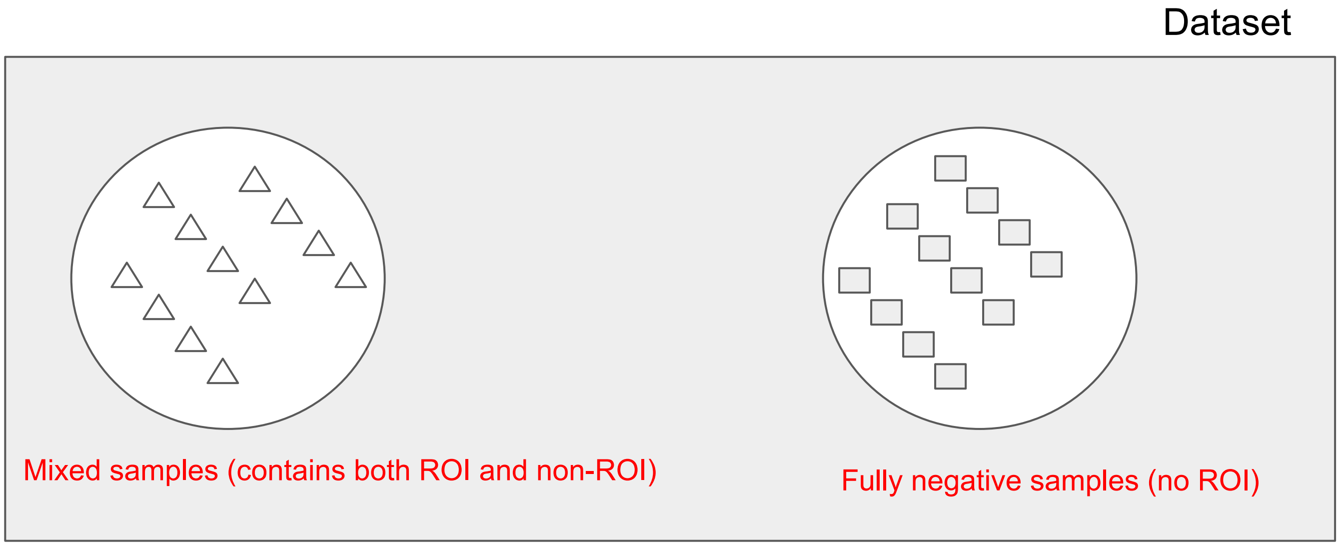
- To reduce mis-predictions, guide the CAM learning with available Negative knowledge.

  Negative knowledge = all what is not ROI.

Our work: Using negative knowledge

- 2 sources of negative knowledge

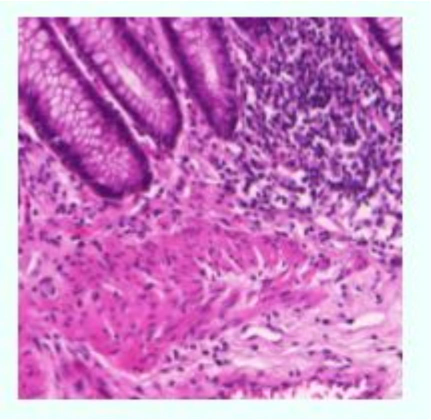
1 - Naturally occurring in dataset

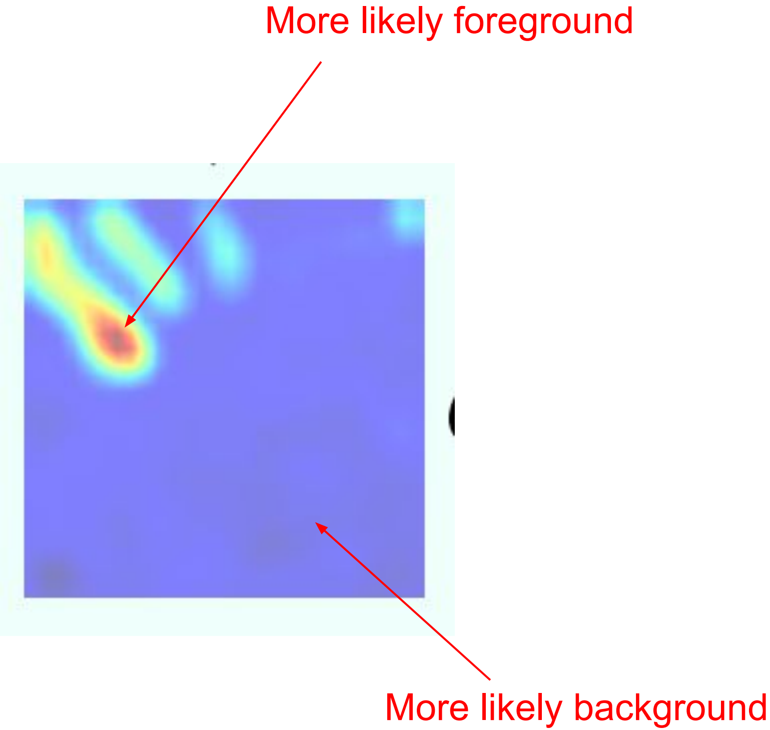


Our work: Using negative knowledge

- 2 sources of negative knowledge

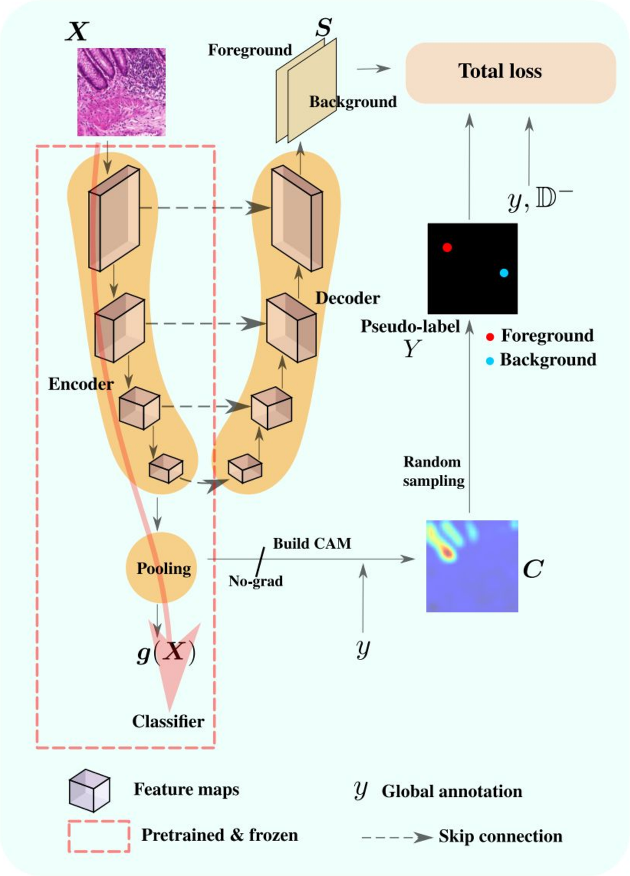
2 - Low activation in CAMs





Our architecture

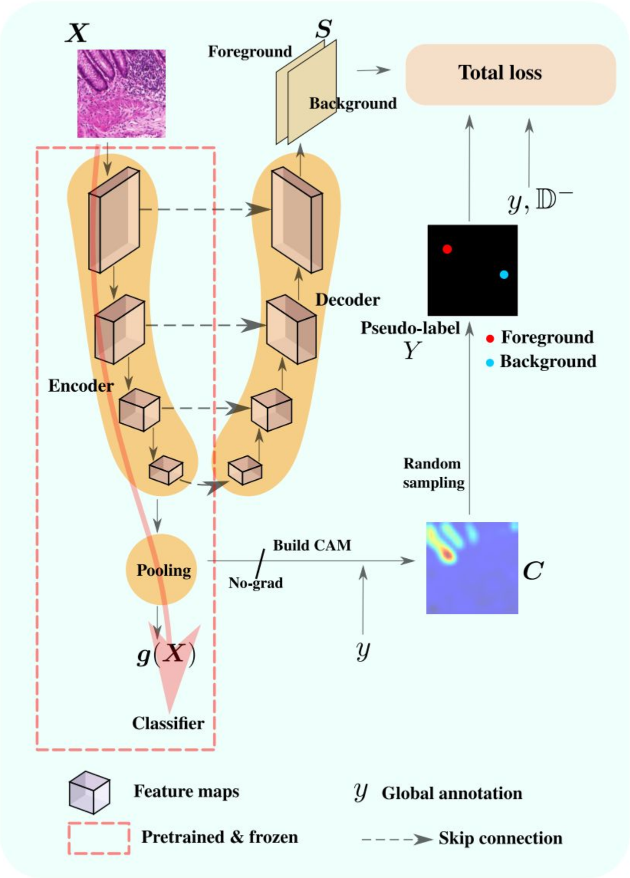
- Requires only image class for training



Training

1- Exploit CAM positive/negative information

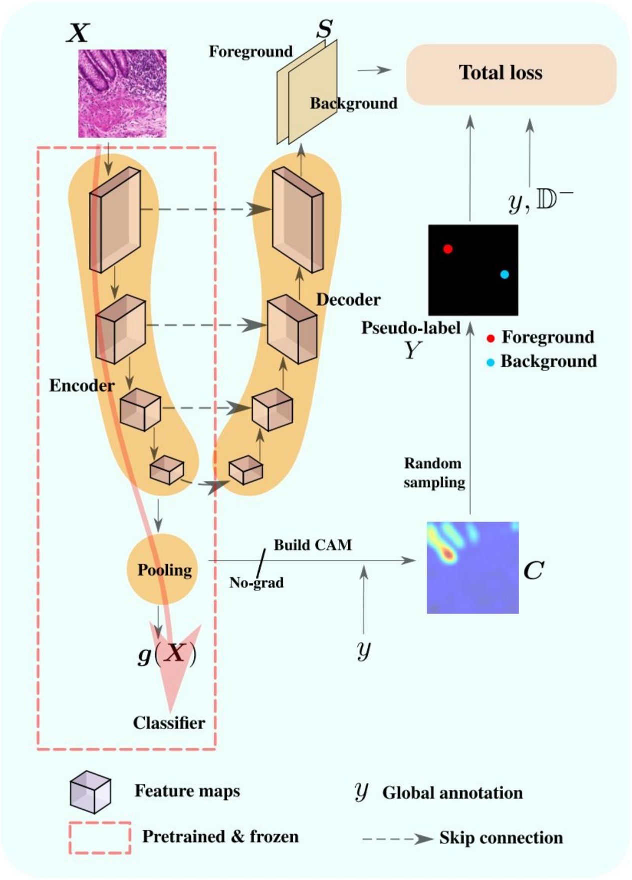
$$\min_{\boldsymbol{\theta}} \sum_{p \in \{\mathbb{C}^+ \cup \mathbb{C}^-\}} \boldsymbol{H}(Y_p, \boldsymbol{S}_p)\ .$$



Training

2- Fully negative samples

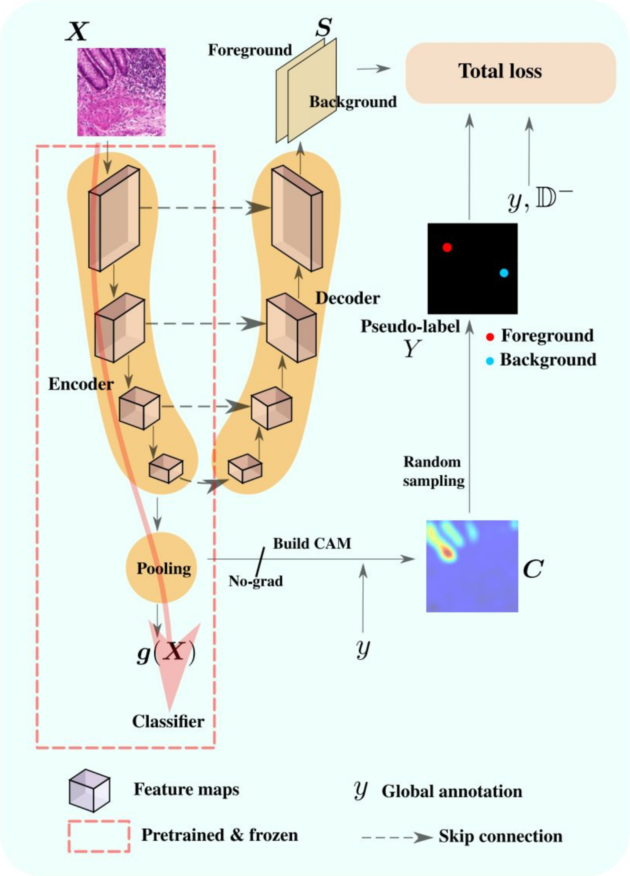
$$\min_{\boldsymbol{\theta}} \sum_{p \in \Omega} -\log(1 - \boldsymbol{S}_p^0) \ , \forall \boldsymbol{X} \in \mathbb{D}^- \ .$$



Training

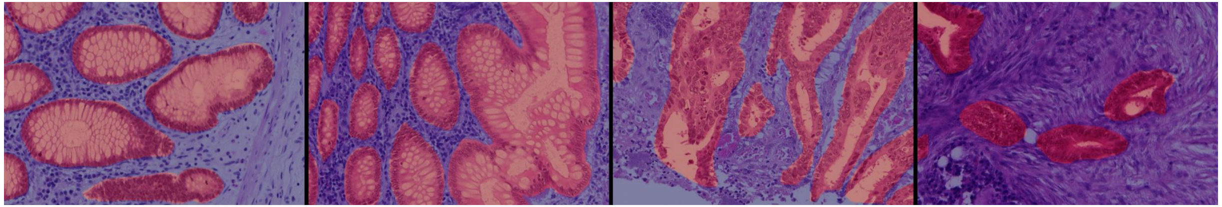
Total adaptive loss

$$\min_{\boldsymbol{\theta}} \quad \mathbb{1}_{\boldsymbol{X} \in \mathbb{D}^-} \Big(\sum_{p \in \Omega} - \log(1 - \boldsymbol{S}_p^0) \Big)$$
$$+ (1 - \mathbb{1}_{\boldsymbol{X} \in \mathbb{D}^-}) \Big(\lambda \sum_{p \in \{\mathbb{C}^+ \cup \mathbb{C}^-\}} \boldsymbol{H}(Y_p, \boldsymbol{S}_p) \Big) \; ,$$

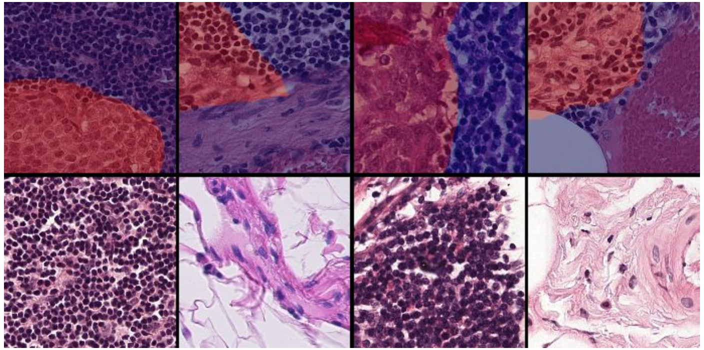


Experiments

- Task: classify and localize ROI
- 2 public datsets: GlaS, Camelyon16 patches.



GlaS: colon cancer diagnosis



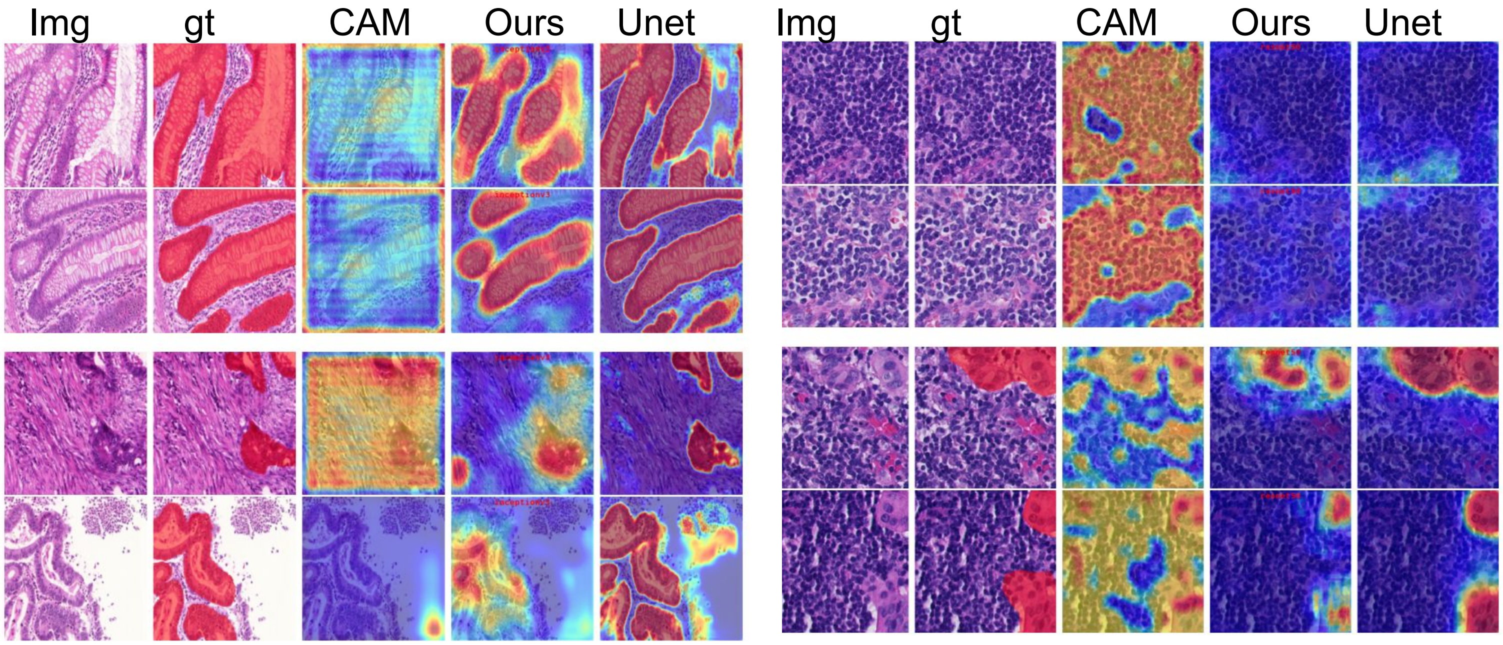
Camelyon16 patches: breast cancer

Results

	GlaS				CAMELYON16			
	VGG	Inception	ResNet	Mean	VGG	Inception	ResNet	Mean
Metric	PxAP							
WSL								
GAP (Lin et al., 2013) *(corr,2013)*	58.5	57.5	56.2	57.4	37.5	24.6	43.7	35.2
MAX-POOL (Oquab et al., 2015) *(cvpr,2015)*	58.5	57.1	46.2	53.9	42.1	40.9	20.2	34.4
LSE (Sun et al., 2016) *(cvpr,2016)*	63.9	62.8	59.1	61.9	**63.1**	29.0	42.1	44.7
CAM (Zhou et al., 2016) *(cvpr,2016)*	68.5	50.5	64.4	61.1	25.4	48.7	27.5	33.8
HaS (Singh and Lee, 2017) *(iccv,2017)*	65.5	65.4	63.5	64.8	25.4	47.1	29.7	34.0
GradCAM (Selvaraju et al., 2017) *(iccv,2017)*	75.7	56.9	70.0	67.5	40.2	34.4	29.1	34.5
WILDCAT (Durand et al., 2017) *(cvpr,2017)*	56.1	54.9	60.1	57.0	44.4	31.4	31.0	35.6
ACoL (Zhang et al., 2018a) *(cvpr,2018)*	63.7	58.2	54.2	58.7	31.3	39.3	31.3	33.9
SPG (Zhang et al., 2018b) *(eccv,2018)*	63.6	58.3	51.4	57.7	45.4	24.5	22.6	30.8
GradCAM++ (Chattopadhyay et al., 2018) *(wacv,2018)*	**76.1**	65.7	70.7	70.8	41.3	43.9	25.8	37.0
Deep MIL (Ilse et al., 2018) *(icml,2018)*	66.6	61.8	64.7	64.3	53.8	**51.1**	**57.9**	54.2
PRM (Zhou et al., 2018) *(cvpr,2018)*	59.8	53.1	62.3	58.4	46.0	41.7	23.2	36.9
ADL (Choe and Shim, 2019) *(cvpr,2019)*	65.0	60.6	54.1	59.9	19.0	46.0	46.0	37.0
CutMix (Yun et al., 2019) *(eccv,2019)*	59.9	50.4	56.7	55.6	56.4	44.9	20.7	40.6
Smooth-GradCAM (Omeiza et al., 2019) *(corr,2019)*	71.3	**67.6**	75.5	71.4	35.1	31.6	25.1	30.6
XGradCAM (Fu et al., 2020) *(bmvc,2020)*	73.7	66.4	62.6	67.5	40.2	33.0	24.4	32.5
LayerCAM (Jiang et al., 2021) *(ieee,2021)*	67.8	66.1	**70.9**	68.2	34.1	25.0	29.1	29.4
NEGEV (ours)	**81.3**	**70.1**	**82.0**	**77.8**	**70.3**	**53.8**	52.6	**58.9**
Fully supervised								
U-Net (Ronneberger et al., 2015)*(miccai,2015)*	96.8	95.4	96.4	96.2	83.0	82.2	83.6	82.9

Table 1: PxAP performance over GlaS and CAMELYON16 test sets.

Results



GlaS

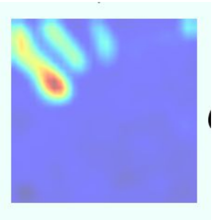
Camelyon16

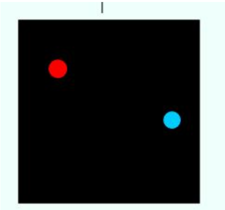
Ablations

Methods	GlaS VGG	GlaS Inception	GlaS ResNet	GlaS Mean	CAMELYON16 VGG	CAMELYON16 Inception	CAMELYON16 ResNet	CAMELYON16 Mean
CAM (Zhou et al., 2016)	68.5	50.5	64.4	61.1	25.4	48.7	27.5	20.3
Ours + $\mathbb{C}^+$	81.3	53.3	81.3	71.9	38.1	36.5	30.8	35.1
Ours + $\mathbb{C}^+$ + $\mathbb{C}^-$	81.3	70.1	82.0	77.8	38.1	35.3	30.2	34.5
Ours + $\mathbb{C}^+$ + $\mathbb{C}^-$ + $\mathbb{D}^-$	–	–	–	–	70.3	53.8	52.6	58.9
Improvement	+12.8	+19.6	+17.6	+16.6	+44.9	+5.0	+25.1	+25.0

Impact of different terms

Ablations





Methods	GlaS VGG	GlaS Inception	GlaS ResNet	GlaS Mean	CAMELYON16 VGG	CAMELYON16 Inception	CAMELYON16 ResNet	CAMELYON16 Mean
CAM (Zhou et al., 2016)	68.5	50.5	64.4	61.1	25.4	48.7	27.5	33.8
Ours ($n = 1$, random selection)	81.3	70.1	82.0	77.8	70.3	53.8	52.6	58.9
Ours ($n = 1$, static selection)	77.7	60.3	76.5	71.5	57.5	47.4	42.8	49.2
Performance drop	-3.6	-9.8	-5.5	-6.3	-12.8	-6.4	-9.8	-9.6

Fixed vs random seeds selection

Ablations

n	GlaS VGG	GlaS Inception	GlaS ResNet	GlaS Mean	CAMELYON16 VGG	CAMELYON16 Inception	CAMELYON16 ResNet	CAMELYON16 Mean
1	81.3	70.1	82.0	77.8	70.3	53.8	52.6	58.9
2	81.3	52.9	81.3	71.8	69.7	51.1	47.2	56.0
3	81.3	52.9	81.3	71.8	69.7	51.9	47.2	56.2
4	81.3	55.0	81.3	72.5	69.7	50.0	47.2	56.6
5	81.3	52.9	81.3	71.8	69.7	53.4	47.2	56.7
10	81.3	53.7	81.3	72.1	69.7	52.6	47.2	56.5
20	81.3	52.9	82.2	72.1	69.7	51.3	47.2	56.0
50	81.3	52.0	81.3	71.5	69.7	53.8	50.3	57.9
100	81.3	53.4	81.3	72.0	69.7	50.5	47.2	55.8
500	81.3	52.9	81.3	71.8	69.7	51.5	47.6	56.2
1k	81.3	53.7	81.3	72.1	69.7	51.2	48.5	56.4
2k	81.3	53.0	81.3	71.8	69.7	51.5	47.2	56.1
3k	81.3	54.2	81.3	72.2	69.7	50.4	48.5	56.2
4k	81.3	52.9	81.3	71.8	69.7	52.9	47.2	56.6
5k	81.3	53.2	82.7	72.4	69.7	51.4	47.7	56.2
10k	81.3	52.9	81.3	71.8	69.7	52.1	47.2	56.3
CAM (Zhou et al., 2016)	68.5	50.5	64.4	61.1	25.4	48.7	27.5	33.8

How many pixels to sample?

Ablations

λ	GlaS VGG	GlaS Inception	GlaS ResNet	GlaS Mean	CAMELYON16 VGG	CAMELYON16 Inception	CAMELYON16 ResNet	CAMELYON16 Mean
1	81.3	70.1	82.0	77.8	70.3	53.8	52.6	58.9
0.1	81.3	50.8	81.3	71.1	69.7	52.5	47.1	56.4
0.01	80.3	52.9	73.0	68.7	69.5	50.6	51.0	57.0
0.001	80.2	52.9	56.8	63.3	65.3	51.2	38.1	51.5
0.0001	64.7	52.9	55.0	57.5	45.2	42.6	23.4	37.0
CAM (Zhou et al., 2016)	68.5	50.5	64.4	61.1	25.4	48.7	27.5	33.8

$$\min_{\boldsymbol{\theta}} \quad \mathbb{1}_{\boldsymbol{X}\in\mathbb{D}^-}\Big(\sum_{p\in\Omega} -\log(1-\boldsymbol{S}_p^0)\Big) + (1-\mathbb{1}_{\boldsymbol{X}\in\mathbb{D}^-})\Big(\lambda \sum_{p\in\{\mathbb{C}^+\cup\,\mathbb{C}^-\}} \boldsymbol{H}(Y_p, \boldsymbol{S}_p)\Big),$$

Impact of lambda

Thanks! Questions?

Please visit us at #179

Code: https://github.com/sbelharbi/negev