Negative Evidence Matters in Interpretable Histology Image Classification (#179)

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Context

Class Activation Maps (CAMs) methods allow a classifier to classify the image content and localize ROI using only image class as label.

Due to histology image properties such as visual similarity between foreground/background, these methods yield poor ROI localization results causing:

- CAMs under-activation, leading to high false negative.
- CAMs over-activation, leading to high false positive.

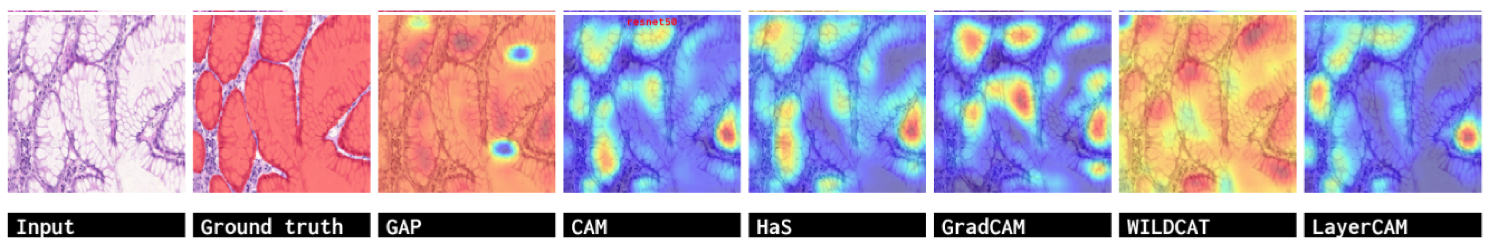

Figure 1. Example of a CAM ROI localization over histology images: under/over activation issue.

Our Proposal: Negative Evidence

Guide CAMs learning at pixel level from available negative and positive knowledge. We exploit two sources of negative knowledge:

- Fully negative samples ($\mathbb{D}^-$).
- CAMs from pre-trained classifier.

Proposed Approach: Architecture

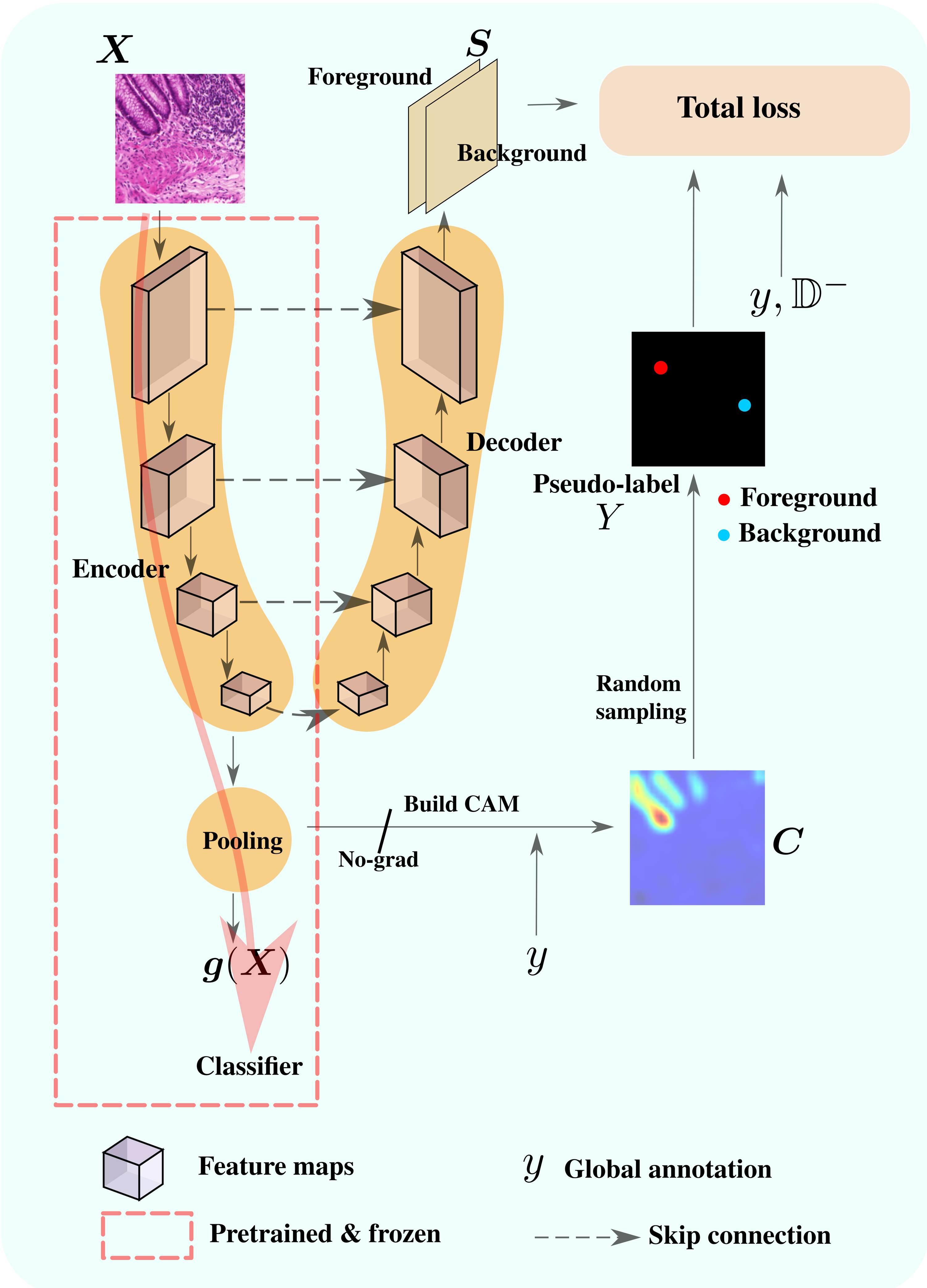

Figure 2. Our proposal.

Proposed Approach: Adaptive Training Loss

1. CAMs negative/positive evidence:

$$\min_{\boldsymbol{\theta}} \sum_{p \in \{\mathbb{C}^+ \cup \mathbb{C}^-\}} \boldsymbol{H}(Y_p, \boldsymbol{S}_p) \,. \tag{1}$$

2. Fully negative samples:

$$\min_{\boldsymbol{\theta}} \sum_{p \in \Omega} -\log(1 - \boldsymbol{S}_p^0) \,, \forall \boldsymbol{X} \in \mathbb{D}^- \,. \tag{2}$$

3. Total adaptive loss:

$$\begin{aligned} \min_{\boldsymbol{\theta}} \quad & \mathbb{1}_{\boldsymbol{X} \in \mathbb{D}^-} \Big(\sum_{p \in \Omega} -\log(1 - \boldsymbol{S}_p^0) \Big) \\ & + (1 - \mathbb{1}_{\boldsymbol{X} \in \mathbb{D}^-}) \Big(\lambda \sum_{p \in \{\mathbb{C}^+ \cup \mathbb{C}^-\}} \boldsymbol{H}(Y_p, \boldsymbol{S}_p) \Big) \,. \end{aligned} \tag{3}$$

Results

	GlaS				CAMELYON16			
	VGG	Inception	ResNet	Mean	VGG	Inception	ResNet	Mean
Metric	PxAP							
WSL								
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
GradCAM *(iccv,2017)*	75.7	56.9	70.0	67.5	40.2	34.4	29.1	34.5
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
GradCAM++ *(wacv,2018)*	**76.1**	65.7	70.7	70.8	41.3	43.9	25.8	37.0
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
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
TS-CAM *(corr,2021)*	00.0	00.0	00.0	00.0	00.0	00.0	00.0	00.0
NEGEV (ours)	**81.3**	**70.1**	**82.0**	**77.8**	**70.3**	**53.8**	52.6	**58.9**
Fully supervised								
U-Net *(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.

Visual results:

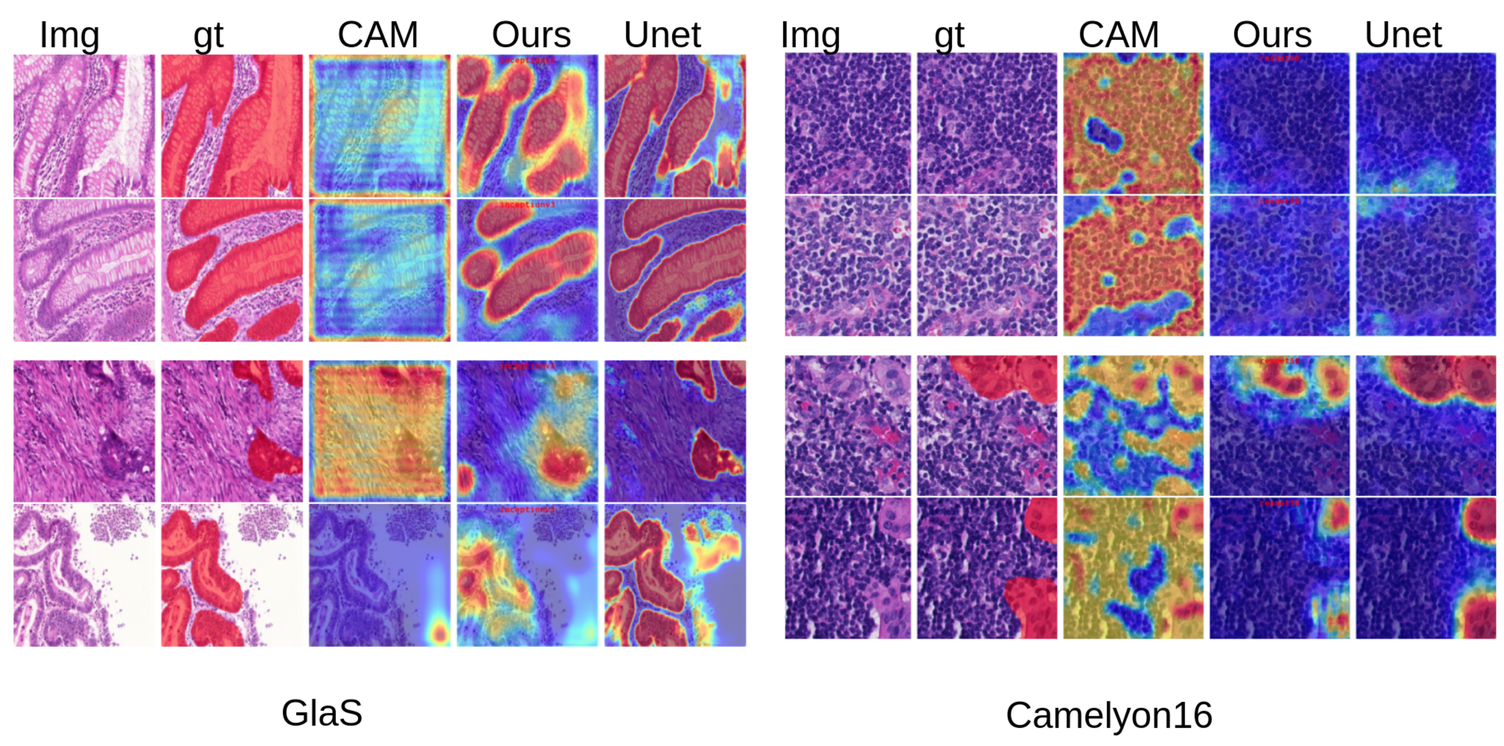

Figure 3. Test samples. Top 2 rows: normal. Bottom 2 rows: with cancer.

Ablation studies: see paper.