Self-similarity Student for Partial Label Histopathology Image Segmentation

Hsien–Tzu Cheng*[1], Chun–Fu Yeh*[1], Po–Chen Kuo[1,3], Andy Wei[1], Keng–Chi Liu[1], Mong–Chi Ko[1]
Kuan–Hua Chao[1], Yu–Ching Peng[2], Tyng–Luh Liu[1,4]

[1] Taiwan AI Labs
[2] Taipei Veterans General Hospital
[3] National Taiwan University College of Medicine
[4] Institute of Information Science, Academia Sinica, Taiwan

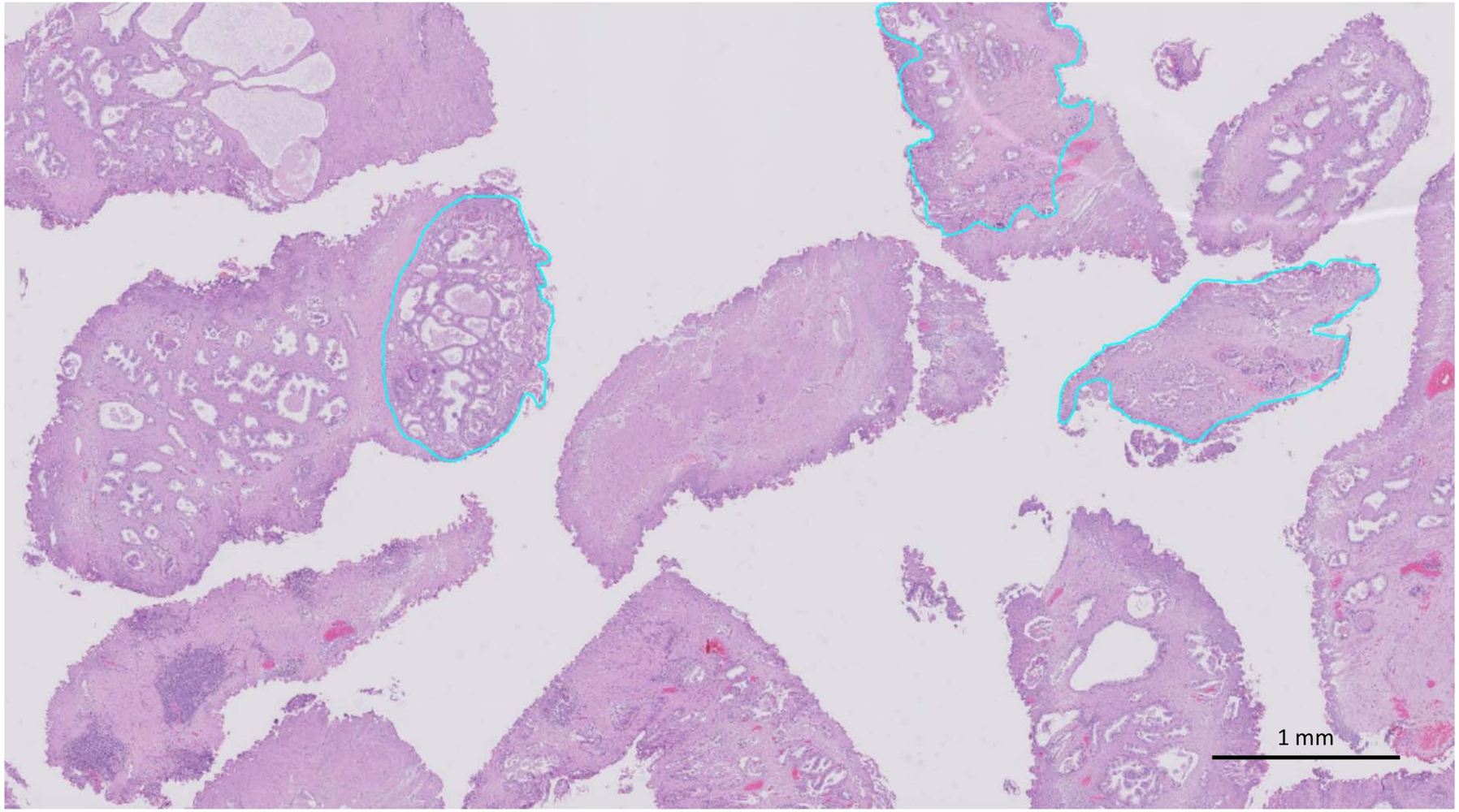
© Copyright Taiwan AI Labs. All Rights Reserved.

(*Both authors contributed equally to this work)

https://ailabstw.github.io/self-sim-student-pathology/

Motivation

Pathologists inspecting stained tissue specimens using microscopes.
The gold standard of cancer diagnosis.

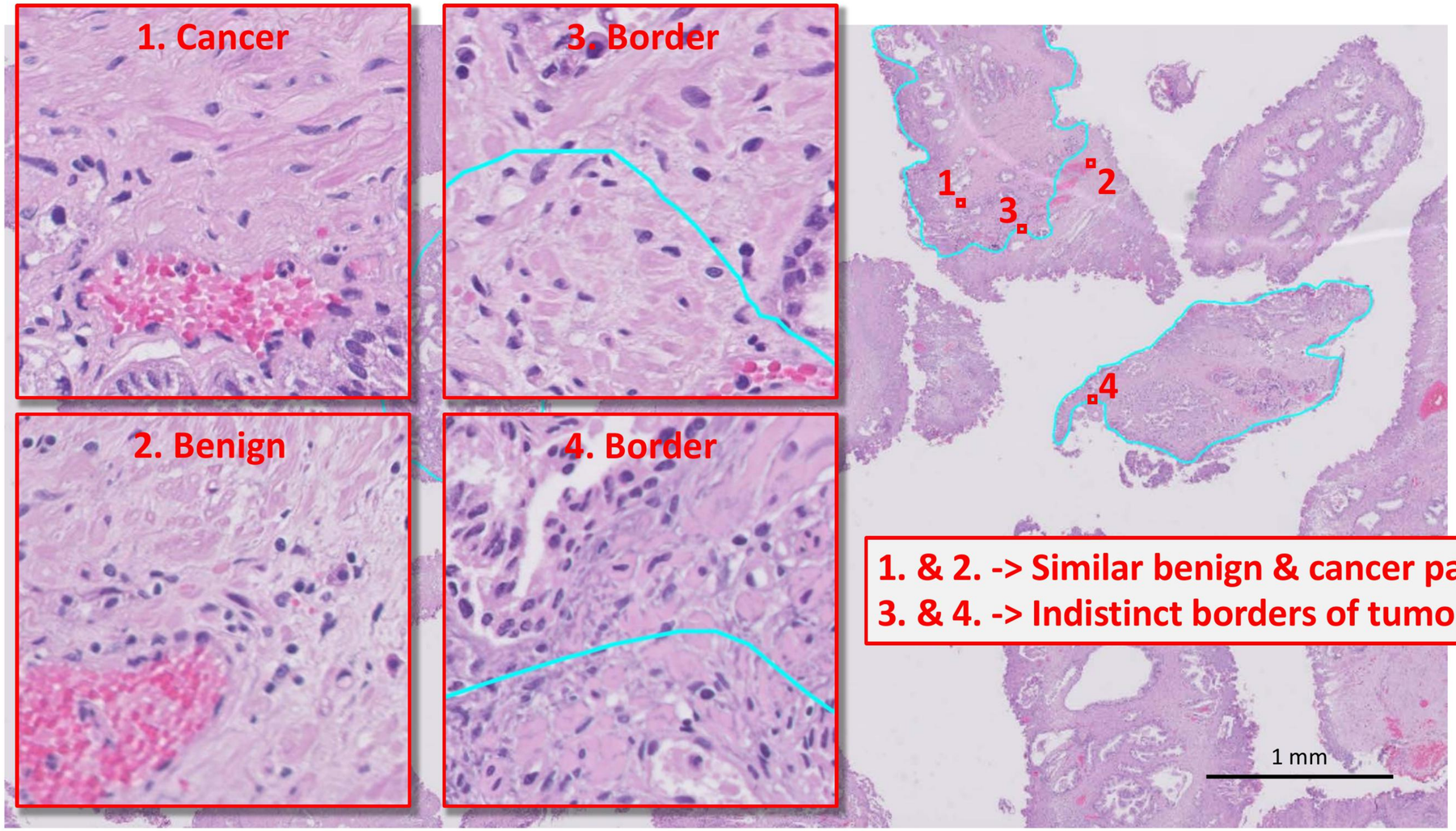


© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Motivation

Cancerous regions in gigapixel WSI are prone to be **partially labeled**, which generate benign and cancerous patches with **noisy label**.



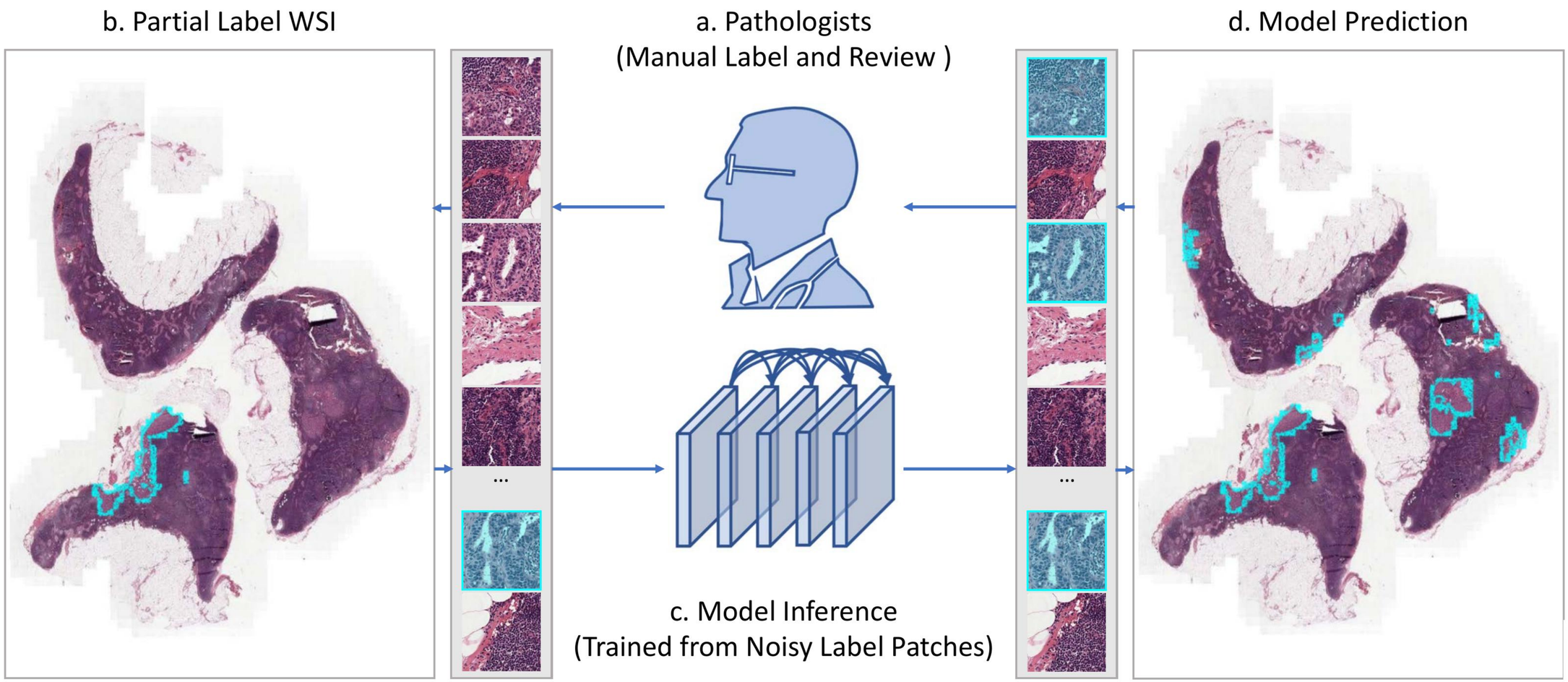
1. & 2. -> Similar benign & cancer patches
3. & 4. -> Indistinct borders of tumor lesions

© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Scenario

The model generates feasible prediction for review and diagnosis.



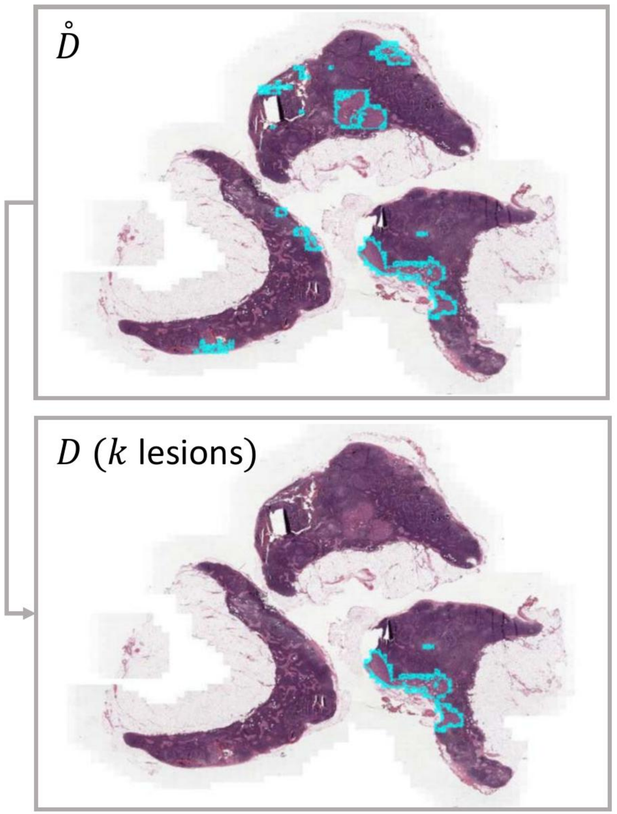
© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Sampling

D with k lesions remained is sampled from $\mathring{D}$.

Fully Annotated WSI

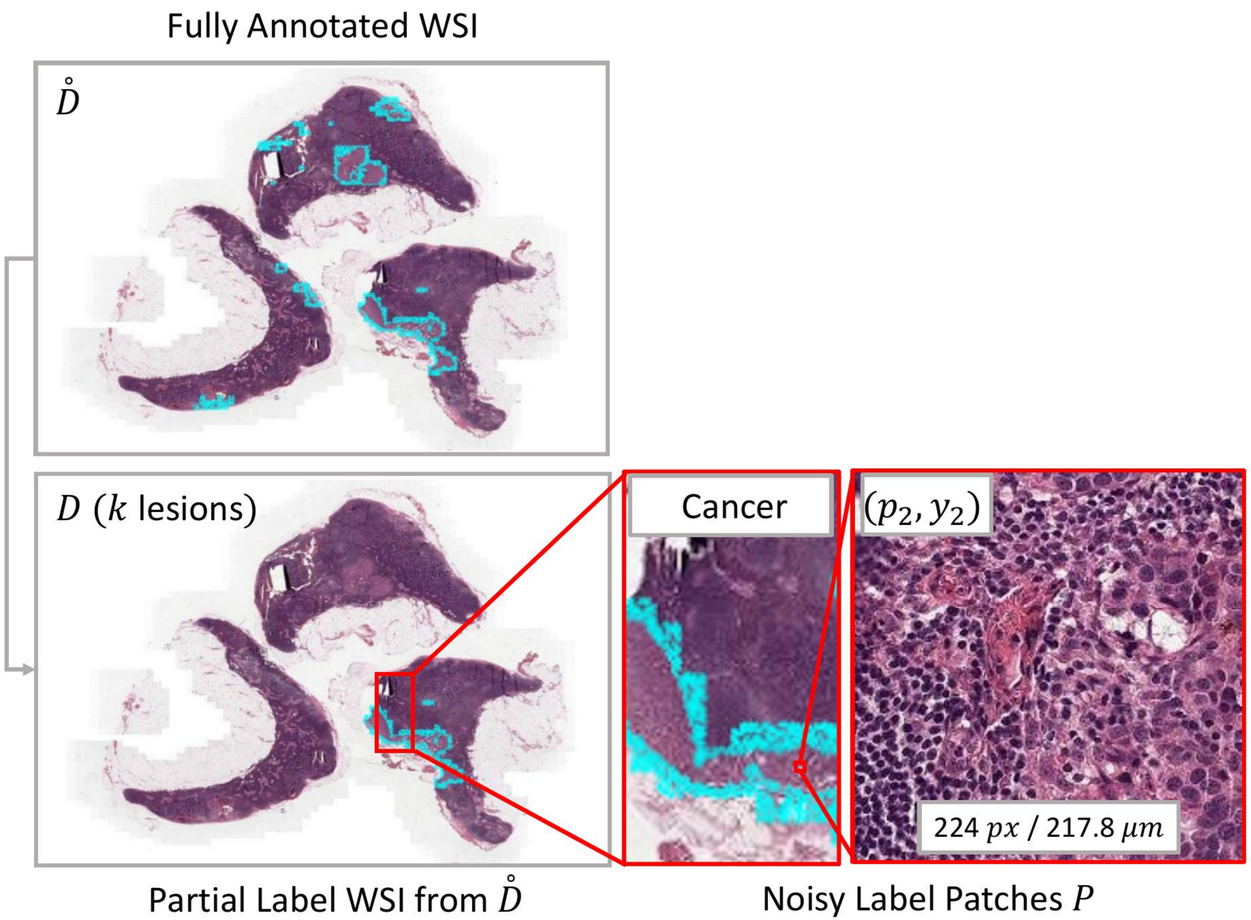


Partial Label WSI from $\mathring{D}$

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Sampling

Noisy label patches P are then sampled from D.

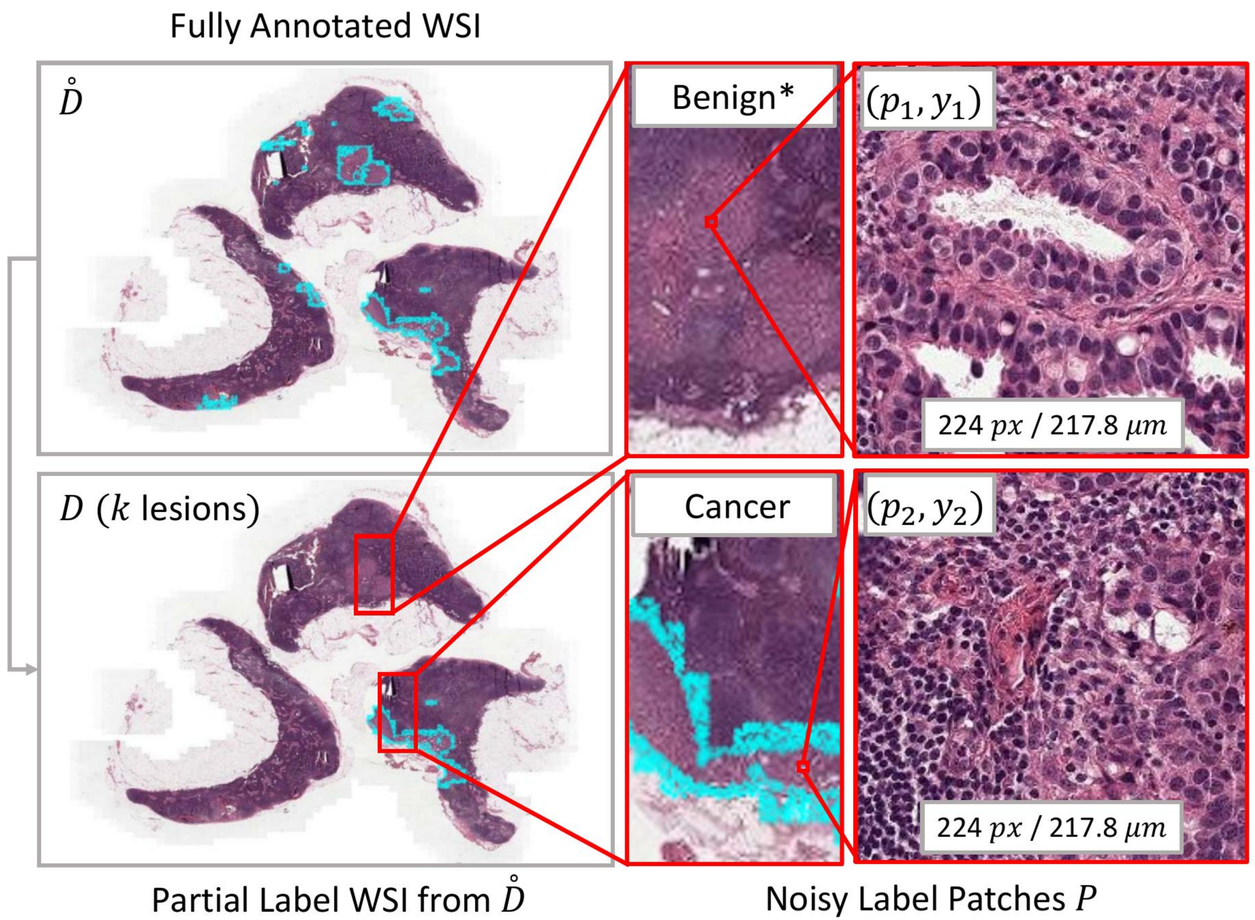


© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Sampling

These 2 sample patches demonstrate how the noisy label patches are created.

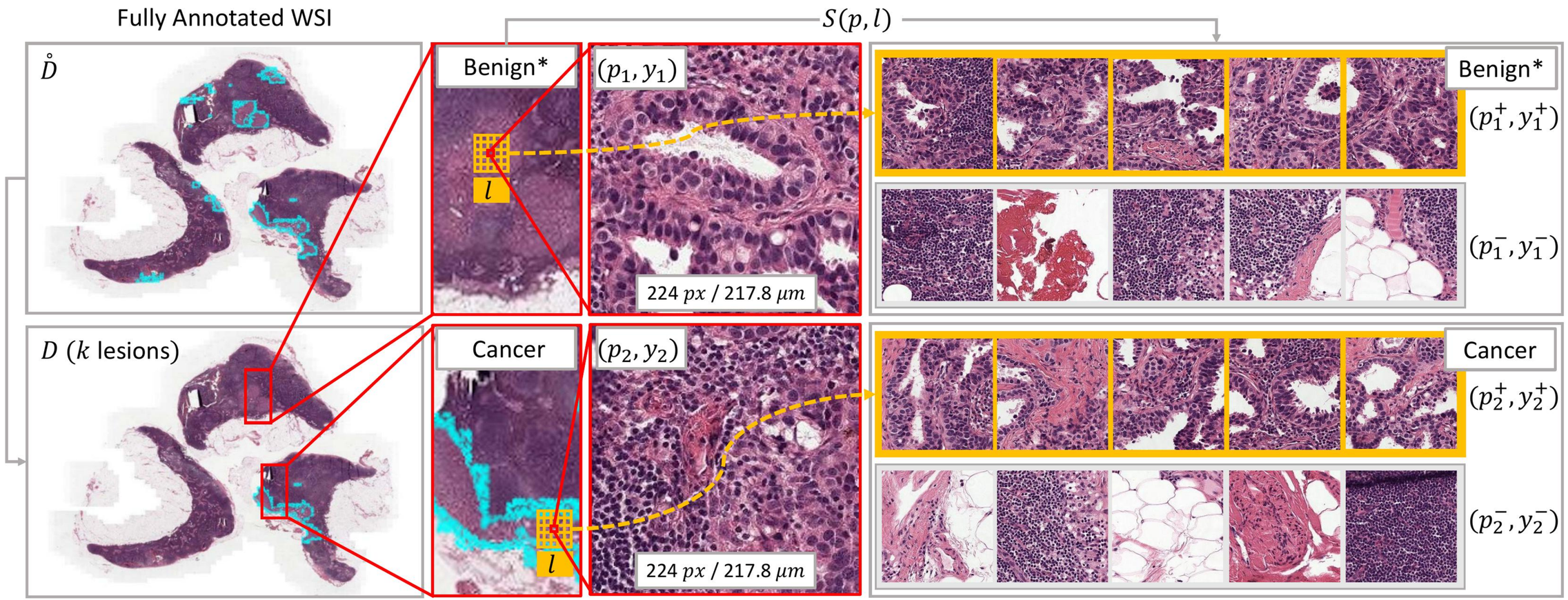


© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Sampling

Similar and dissimilar patches of any patch p are sampled by S according to distance l.



Partial Label WSI from $\mathring{D}$ | Noisy Label Patches P | Similar and Dissimilar Patches by $S(p,l)$

$$\mathcal{S}(p,l) = \begin{cases} p_i^+ \in p^+, i \in \{1, ..., N^+\}, & \text{if } \|coord(p) - coord(p_i)\| \leq l, \\ p_j^- \in p^-, j \in \{1, ..., N^-\}, & \text{otherwise.} \end{cases}$$

© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Sampling

Sampling statistics of CAMELYON16 dataset.

Label	Complete	k_{top}			k_{rand}		
		1	2	3	1	2	3
Benign	588286	597500	592454	590482	606342	604331	600122
Cancer	21730	12516	17562	19534	2819	5188	8358
Ratio of Correct Cancer Patches		57.60%	80.82%	89.89%	12.97%	23.87%	38.46%
Ratio of Noisiness		42.40%	19.18%	10.11%	87.03%	76.13%	61.54%
Number of Cancer Lesions		91	150	193	91	150	193
Average Size of Lesions (mm^2)		6.7814	5.7527	4.9959	2.0587	1.8747	2.5277

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Sampling

Sampling statistics of CAMELYON16 dataset.

Complete: Tasks using original $\mathring{D}$ with clean ground truth

Label	Complete	k_{top}			k_{rand}		
		1	2	3	1	2	3
Benign	588286	597500	592454	590482	606342	604331	600122
Cancer	21730	12516	17562	19534	2819	5188	8358
Ratio of Correct Cancer Patches		57.60%	80.82%	89.89%	12.97%	23.87%	38.46%
Ratio of Noisiness		42.40%	19.18%	10.11%	87.03%	76.13%	61.54%
Number of Cancer Lesions		91	150	193	91	150	193
Average Size of Lesions (mm^2)		6.7814	5.7527	4.9959	2.0587	1.8747	2.5277

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Sampling

Sampling statistics of CAMELYON16 dataset.

Complete: Tasks using original $\mathring{D}$ with clean ground truth
We sample P from D for k_{top} and k_{rand} tasks.

Label	Complete	k_{top}			k_{rand}		
		1	2	3	1	2	3
Benign	588286	597500	592454	590482	606342	604331	600122
Cancer	21730	12516	17562	19534	2819	5188	8358
Ratio of Correct Cancer Patches		57.60%	80.82%	89.89%	12.97%	23.87%	38.46%
Ratio of Noisiness		42.40%	19.18%	10.11%	87.03%	76.13%	61.54%
Number of Cancer Lesions		91	150	193	91	150	193
Average Size of Lesions (mm^2)		6.7814	5.7527	4.9959	2.0587	1.8747	2.5277

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Sampling

Sampling statistics of CAMELYON16 dataset.

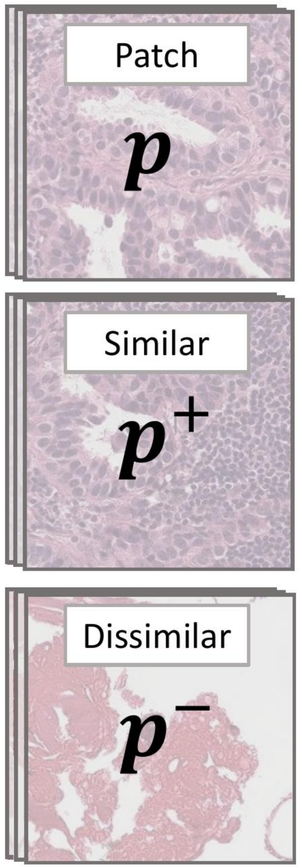
Complete: Tasks using original $\mathring{D}$ with clean ground truth
We sample P from D for k_{top} and k_{rand} tasks.
The ratio of noisiness declines as more lesions per WSI are correctly labeled.

Label	Complete	k_{top}			k_{rand}		
		1	2	3	1	2	3
Benign	588286	597500	592454	590482	606342	604331	600122
Cancer	21730	12516	17562	19534	2819	5188	8358
Ratio of Correct Cancer Patches		57.60%	80.82%	89.89%	12.97%	23.87%	38.46%
Ratio of Noisiness		42.40%	19.18%	10.11%	87.03%	76.13%	61.54%
Number of Cancer Lesions		91	150	193	91	150	193
Average Size of Lesions (mm^2)		6.7814	5.7527	4.9959	2.0587	1.8747	2.5277

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Overview

Given a WSI, we split all foreground regions into small patches.
For each patch, we sample its **similar and dissimilar patches** according to spatial distance.

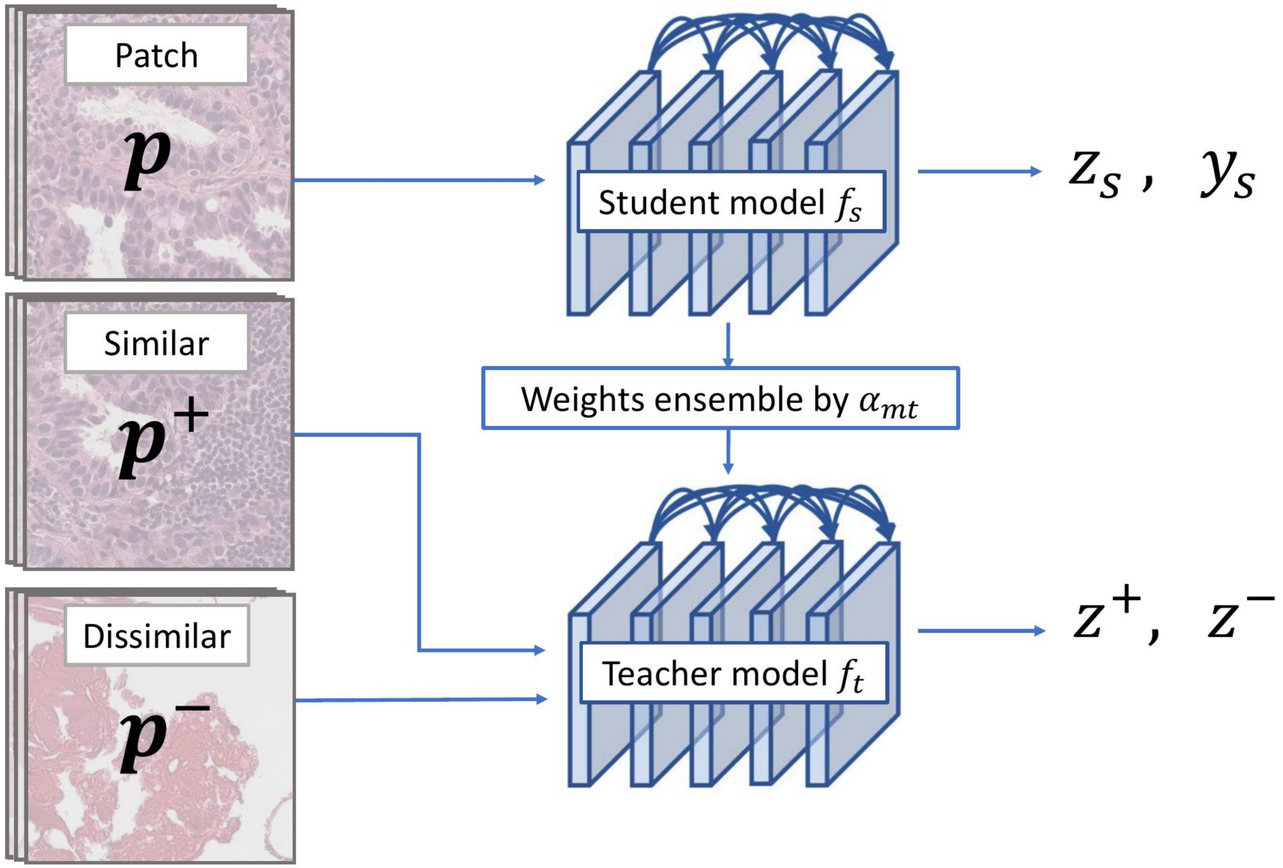


© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Overview

Our method is a teacher-student-based model. The student model takes patches.
The **teacher model** takes all their corresponding **similar and dissimilar patches.**

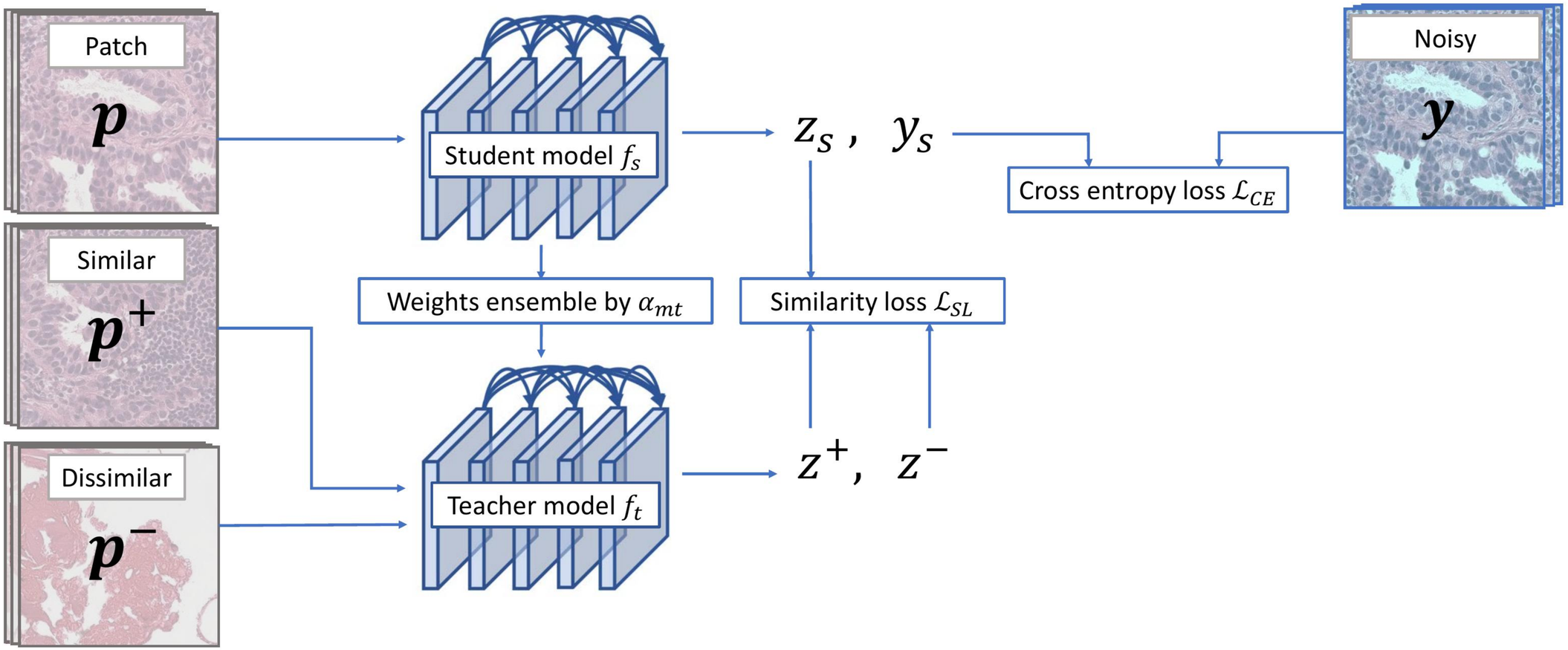


© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Overview

The **cross entropy loss** is for supervised learning from patches' label.
The **similarity loss** is for self-similarity learning with grouped representation.

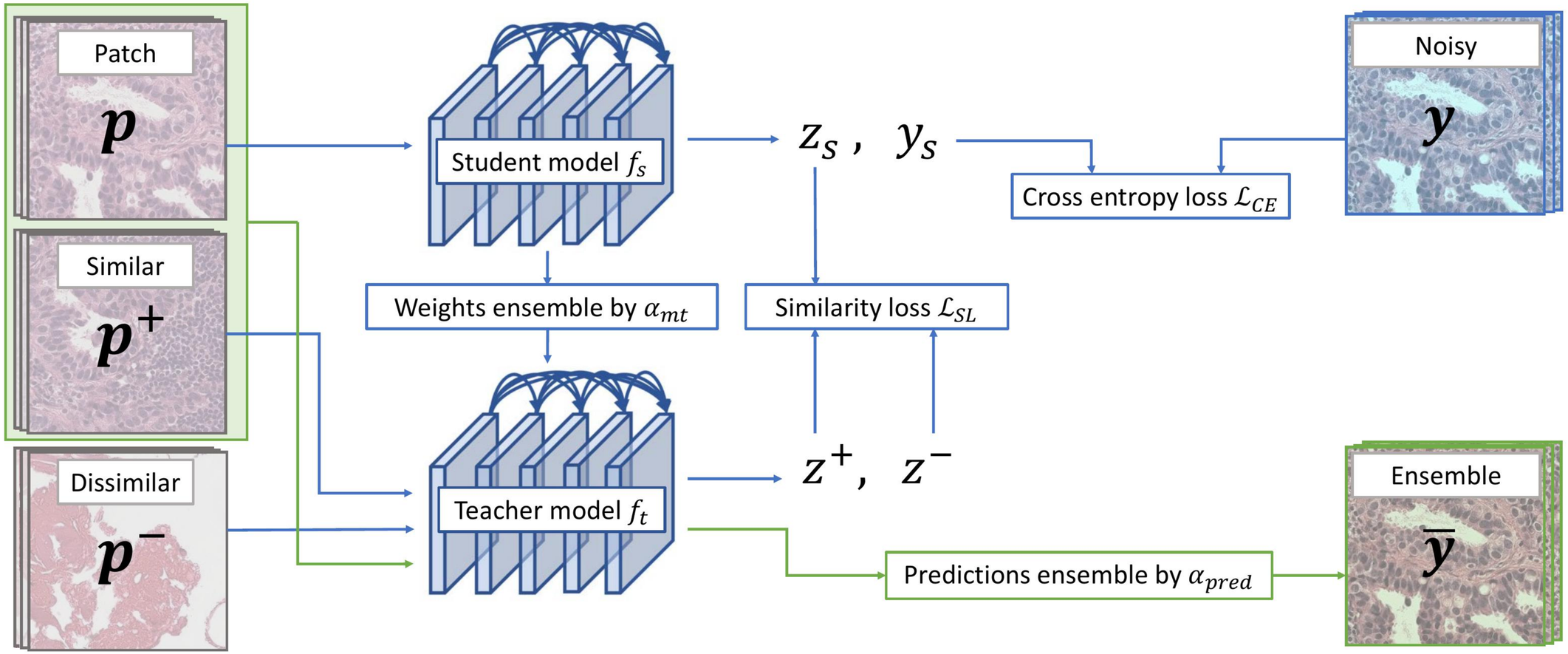


© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Overview

For **each epoch**, the teacher model generates **prediction ensemble** with previous predictions.

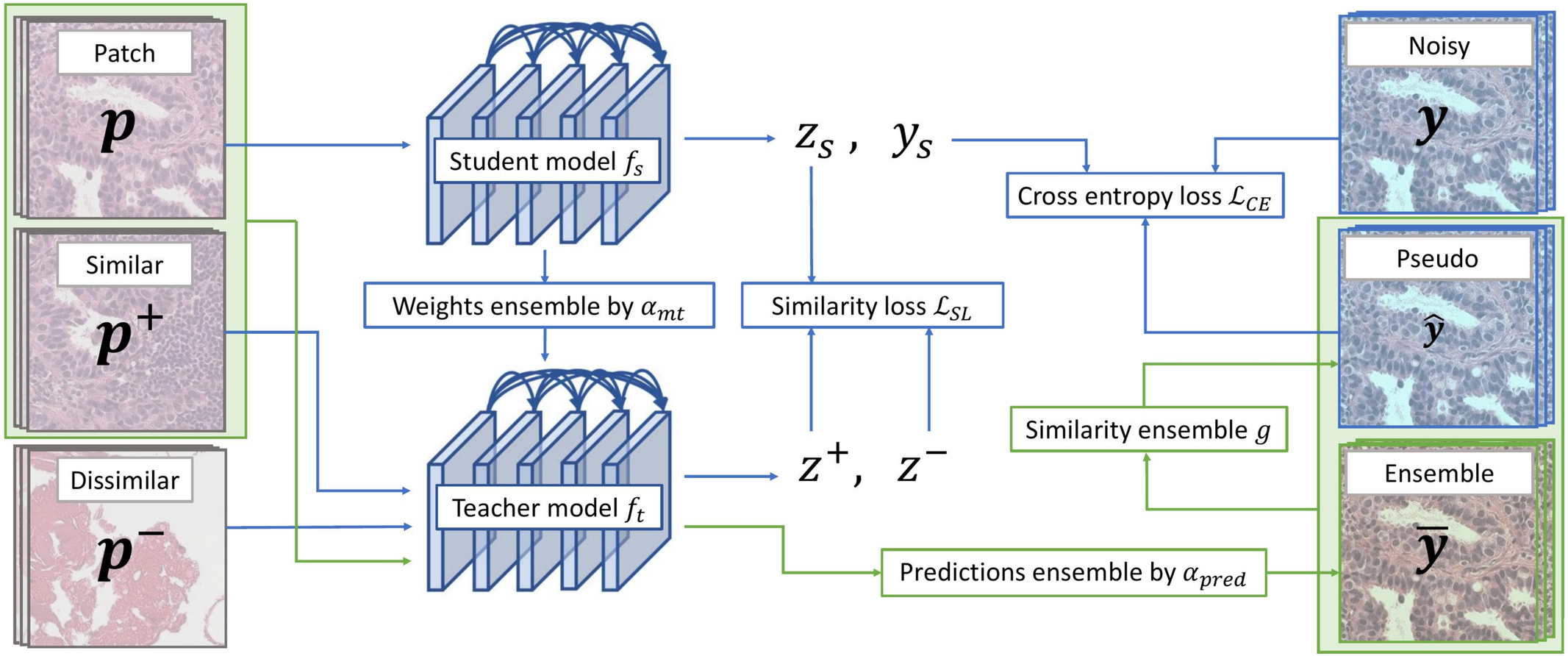


© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Overview

Then, the **similarity ensemble finds consensus of similar pairs** and generate pseudo label.



© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Algorithm

Algorithm 1 Overview of our Self-similarity Student algorithm

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Algorithm

Algorithm 1 Overview of our Self-similarity Student algorithm

Require: $\{P_{train}, P_{val}\} = P$ ▷ Noisy set of patches sampled from D
Require: $\alpha_{mt}, \alpha_{pred} \in (0, 1) \subset \mathbb{R}$ ▷ EMA momentum
Require: $l, ep_{max} \in \mathbb{N}$ ▷ Distance threshold and max epoch
Require: $\mathcal{O}$ = model weights gradient optimizer, e.g. Adam
Initialize $f_t(\theta_t, \eta_t)$ ▷ Initialize teacher model
Initialize $f_s(\theta_s, \eta_s)$ ▷ Initialize student model
$\hat{P} \leftarrow P_{train}$ ▷ Initialize all pseudo label $(p, \hat{y})$
$\bar{P} \leftarrow P_{train}$ ▷ Initialize all ensembled predictions $(p, \bar{y})$

Model and label initialization

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Algorithm

Algorithm 1 Overview of our Self-similarity Student algorithm

Require: $\{P_{train}, P_{val}\} = P$ ▷ Noisy set of patches sampled from D
Require: $\alpha_{mt}, \alpha_{pred} \in (0,1) \subset \mathbb{R}$ ▷ EMA momentum
Require: $l, ep_{max} \in \mathbb{N}$ ▷ Distance threshold and max epoch
Require: $\mathcal{O}$ = model weights gradient optimizer, e.g. Adam
Initialize $f_t(\theta_t, \eta_t)$ ▷ Initialize teacher model
Initialize $f_s(\theta_s, \eta_s)$ ▷ Initialize student model
$\hat{P} \leftarrow P_{train}$ ▷ Initialize all pseudo label $(p, \hat{y})$
$\bar{P} \leftarrow P_{train}$ ▷ Initialize all ensembled predictions $(p, \bar{y})$
for all $(p, y) \in P_{train}$ **do**
$P_{train} \ni ((p^+, y^+), (p^-, y^-)) \leftarrow \mathcal{S}(p, l)$ ➡ Similarity sampling (Eq. 1)
end for

Similarity sampling

$$\mathcal{S}(p,l) = \begin{cases} p_i^+ \in p^+, i \in \{1, ..., N^+\}, & \text{if } \|coord(p) - coord(p_i)\| \leq l, \\ p_j^- \in p^-, j \in \{1, ..., N^-\}, & \text{otherwise.} \end{cases}$$

© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Algorithm

Algorithm 1 Overview of our Self-similarity Student algorithm

Require: $\{P_{train}, P_{val}\} = P$ ▷ Noisy set of patches sampled from D
Require: $\alpha_{mt}, \alpha_{pred} \in (0,1) \subset \mathbb{R}$ ▷ EMA momentum
Require: $l, ep_{max} \in \mathbb{N}$ ▷ Distance threshold and max epoch
Require: $\mathcal{O}$ = model weights gradient optimizer, e.g. Adam
Initialize $f_t(\theta_t, \eta_t)$ ▷ Initialize teacher model
Initialize $f_s(\theta_s, \eta_s)$ ▷ Initialize student model
$\hat{P} \leftarrow P_{train}$ ▷ Initialize all pseudo label $(p, \hat{y})$
$\bar{P} \leftarrow P_{train}$ ▷ Initialize all ensembled predictions $(p, \bar{y})$
for all $(p, y) \in P_{train}$ **do**
  $P_{train} \ni ((p^+, y^+), (p^-, y^-)) \leftarrow \mathcal{S}(p, l)$ ▷ Similarity sampling (Eq. 1)
end for
for $ep \leftarrow 0, ep_{max}$ **do** ▷ Main training loop
  for all $(p, y) \in P_{train}$, $(p, \hat{y}) \in \hat{P}$ **do**
    $y_s, z_s \leftarrow f_s(p)$ ▷ **a.** Student forward
    $z_t^+ \leftarrow f_t(p^+)$ ▷ **b.** Teacher forward (Ignore y_t^+ and y_t^-)
    $z_t^- \leftarrow f_t(p^-)$
    $loss_{ce} \leftarrow \mathcal{L}_{CE}(y, y_s) + \mathcal{L}_{CE}(\hat{y}, y_s)$ ▷ **c.** Cross entropy loss (Eq. 3)
    $loss_{sl} \leftarrow \mathcal{L}_{SL}(z_s, z_t^+, z_t^-)$ ▷ **d.** Similarity embedding (Eq. 2)
    $\theta_s \leftarrow \mathcal{O}(\theta_s, loss_{ce} + loss_{sl})$ ▷ Update student's weights
    $\theta_t \leftarrow \alpha_{mt}\theta_t + (1 - \alpha_{mt})\theta_s$ ▷ **e.** Update teacher's weights
  end for

Teacher-student model update

$$\mathcal{S}(p, l) = \begin{cases} p_i^+ \in p^+, i \in \{1, ..., N^+\}, & \text{if } \|coord(p) - coord(p_i)\| \leq l, \\ p_j^- \in p^-, j \in \{1, ..., N^-\}, & \text{otherwise.} \end{cases}$$

$$\mathcal{L}_{CE}(y, f_s(p)) = -\log \sum_{k=0}^{N} y_k \log(f_s(p_k)) \,.$$

$$\mathcal{L}_{SL}(z_s, z_t^+, z_t^-) = -\log \frac{\sum_{i=1}^{N^+} \exp(z_s \cdot z_{t_i}^+ / \tau)}{\sum_{i=1}^{N^+} \exp(z_s \cdot z_{t_i}^+ / \tau) + \sum_{j=1}^{N^-} \exp(z_s \cdot z_{t_j}^- / \tau)}$$

$$\mathcal{L}_{overall} = \mathcal{L}_{CE}(y, f_s(p)) + \mathcal{L}_{CE}(\hat{y}, f_s(p)) + \mathcal{L}_{SL}(z_s, z_t^+, z_t^-) \,.$$

© Copyright Taiwan AI Labs. All Rights Reserved.

Method - Algorithm

Algorithm 1 Overview of our Self-similarity Student algorithm

Require: $\{P_{train}, P_{val}\} = P$ ▷ Noisy set of patches sampled from D
Require: $\alpha_{mt}, \alpha_{pred} \in (0,1) \subset \mathbb{R}$ ▷ EMA momentum
Require: $l, ep_{max} \in \mathbb{N}$ ▷ Distance threshold and max epoch
Require: $\mathcal{O}$ = model weights gradient optimizer, e.g. Adam
Initialize $f_t(\theta_t, \eta_t)$ ▷ Initialize teacher model
Initialize $f_s(\theta_s, \eta_s)$ ▷ Initialize student model
$\hat{P} \leftarrow P_{train}$ ▷ Initialize all pseudo label $(p, \hat{y})$
$\bar{P} \leftarrow P_{train}$ ▷ Initialize all ensembled predictions $(p, \bar{y})$
for all $(p, y) \in P_{train}$ **do**
  $P_{train} \ni ((p^+, y^+), (p^-, y^-)) \leftarrow \mathcal{S}(p, l)$ ▷ Similarity sampling (Eq. 1)
end for
for $ep \leftarrow 0$, ep_{max} **do** ▷ Main training loop
  for all $(p, y) \in P_{train}$, $(p, \hat{y}) \in \hat{P}$ **do**
    $y_s, z_s \leftarrow f_s(p)$ ▷ **a.** Student forward
    $z_t^+ \leftarrow f_t(p^+)$ ▷ **b.** Teacher forward (Ignore y_t^+ and y_t^-)
    $z_t^- \leftarrow f_t(p^-)$
    $loss_{ce} \leftarrow \mathcal{L}_{CE}(y, y_s) + \mathcal{L}_{CE}(\hat{y}, y_s)$ ▷ **c.** Cross entropy loss (Eq. 3)
    $loss_{sl} \leftarrow \mathcal{L}_{SL}(z_s, z_t^+, z_t^-)$ ▷ **d.** Similarity embedding (Eq. 2)
    $\theta_s \leftarrow \mathcal{O}(\theta_s, loss_{ce} + loss_{sl})$ ▷ Update student's weights
    $\theta_t \leftarrow \alpha_{mt}\theta_t + (1 - \alpha_{mt})\theta_s$ ▷ **e.** Update teacher's weights
  end for
  for all $(p, \bar{y}) \in \bar{P}$ **do** ▷ **f.** Predictions ensemble
    $\bar{y} \leftarrow \alpha_{pred}\bar{y} + (1 - \alpha_{pred}) f_t(p)$ ▷ Update ensembled predictions per patch
  end for
  for all $(p, \bar{y}) \in \bar{P}$, $(p, \hat{y}) \in \hat{P}$ **do** ▷ **g.** Similarity ensemble as pseudo label
    $\hat{y} \leftarrow g(\bar{y}, \bar{y}^+)$ ▷ Consensus of nearby predictions
  end for
end for

Pseudo label update

$$\mathcal{S}(p, l) = \begin{cases} p_i^+ \in p^+, i \in \{1, ..., N^+\}, & \text{if } \|coord(p) - coord(p_i)\| \le l, \\ p_j^- \in p^-, j \in \{1, ..., N^-\}, & \text{otherwise.} \end{cases}$$

$$\mathcal{L}_{CE}(y, f_s(p)) = -\log \sum_{k=0}^{N} y_k \log(f_s(p_k)) .$$

$$\mathcal{L}_{SL}(z_s, z_t^+, z_t^-) = -\log \frac{\sum_{i=1}^{N^+} \exp(z_s \cdot z_{t_i}^+ / \tau)}{\sum_{i=1}^{N^+} \exp(z_s \cdot z_{t_i}^+ / \tau) + \sum_{j=1}^{N^-} \exp(z_s \cdot z_{t_j}^- / \tau)}$$

$$\mathcal{L}_{overall} = \mathcal{L}_{CE}(y, f_s(p)) + \mathcal{L}_{CE}(\hat{y}, f_s(p)) + \mathcal{L}_{SL}(z_s, z_t^+, z_t^-) .$$

© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Method - Algorithm

Algorithm 1 Overview of our Self-similarity Student algorithm

Require: $\{P_{train}, P_{val}\} = P$ ▷ Noisy set of patches sampled from D
Require: $\alpha_{mt}, \alpha_{pred} \in (0,1) \subset \mathbb{R}$ ▷ EMA momentum
Require: $l, ep_{max} \in \mathbb{N}$ ▷ Distance threshold and max epoch
Require: $\mathcal{O}$ = model weights gradient optimizer, e.g. Adam
Initialize $f_t(\theta_t, \eta_t)$ ▷ Initialize teacher model
Initialize $f_s(\theta_s, \eta_s)$ ▷ Initialize student model
$\hat{P} \leftarrow P_{train}$ ▷ Initialize all pseudo label $(p, \hat{y})$
$\bar{P} \leftarrow P_{train}$ ▷ Initialize all ensembled predictions $(p, \bar{y})$
for all $(p, y) \in P_{train}$ **do**
  $P_{train} \ni ((p^+, y^+), (p^-, y^-)) \leftarrow \mathcal{S}(p, l)$ ▷ Similarity sampling (Eq. 1)
end for
for $ep \leftarrow 0$, ep_{max} **do** ▷ Main training loop
  for all $(p, y) \in P_{train}$, $(p, \hat{y}) \in \hat{P}$ **do**
    $y_s, z_s \leftarrow f_s(p)$ ▷ **a.** Student forward
    $z_t^+ \leftarrow f_t(p^+)$ ▷ **b.** Teacher forward (Ignore y_t^+ and y_t^-)
    $z_t^- \leftarrow f_t(p^-)$
    $loss_{ce} \leftarrow \mathcal{L}_{CE}(y, y_s) + \mathcal{L}_{CE}(\hat{y}, y_s)$ ▷ **c.** Cross entropy loss (Eq. 3)
    $loss_{sl} \leftarrow \mathcal{L}_{SL}(z_s, z_t^+, z_t^-)$ ▷ **d.** Similarity embedding (Eq. 2)
    $\theta_s \leftarrow \mathcal{O}(\theta_s, loss_{ce} + loss_{sl})$ ▷ Update student's weights
    $\theta_t \leftarrow \alpha_{mt}\theta_t + (1 - \alpha_{mt})\theta_s$ ▷ **e.** Update teacher's weights
  end for
  for all $(p, \bar{y}) \in \bar{P}$ **do** ▷ **f.** Predictions ensemble
    $\bar{y} \leftarrow \alpha_{pred}\bar{y} + (1 - \alpha_{pred}) f_t(p)$ ▷ Update ensembled predictions per patch
  end for
  for all $(p, \bar{y}) \in \bar{P}$, $(p, \hat{y}) \in \hat{P}$ **do** ▷ **g.** Similarity ensemble as pseudo label
    $\hat{y} \leftarrow g(\bar{y}, \bar{y}^+)$ ▷ Consensus of nearby predictions
  end for
end for

$$\mathcal{S}(p, l) = \begin{cases} p_i^+ \in p^+, i \in \{1, ..., N^+\}, & \text{if } \|coord(p) - coord(p_i)\| \leq l, \\ p_j^- \in p^-, j \in \{1, ..., N^-\}, & \text{otherwise.} \end{cases}$$

$$\mathcal{L}_{CE}(y, f_s(p)) = -\log \sum_{k=0}^{N} y_k \log(f_s(p_k)) \,.$$

$$\mathcal{L}_{SL}(z_s, z_t^+, z_t^-) = -\log \frac{\sum_{i=1}^{N^+} \exp(z_s \cdot z_{t_i}^+ / \tau)}{\sum_{i=1}^{N^+} \exp(z_s \cdot z_{t_i}^+ / \tau) + \sum_{j=1}^{N^-} \exp(z_s \cdot z_{t_j}^- / \tau)}$$

$$\mathcal{L}_{overall} = \mathcal{L}_{CE}(y, f_s(p)) + \mathcal{L}_{CE}(\hat{y}, f_s(p)) + \mathcal{L}_{SL}(z_s, z_t^+, z_t^-) \,.$$

© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Result - Overall

CAMELYON16 270 WSIs training set
Result on 130 WSIs testing set

Method	$k_{top} = 1$		$k_{rand} = 1$	
	DSC	FROC	DSC	FROC
Baseline DenseNet121 [9]	83.08	29.99	63.08	28.09
Mean Teacher [22]	86.83	34.13	74.45	28.45
Noisy Student [25]	84.90	34.21	77.46	30.06
Prediction Ensemble [17]	88.60	33.41	75.59	30.20
Self-sim Student **(Ours)**	**93.76**	**36.90**	**85.56**	**31.88**

TVGH TURP 58 WSIs training set
Result on 13 WSIs testing set

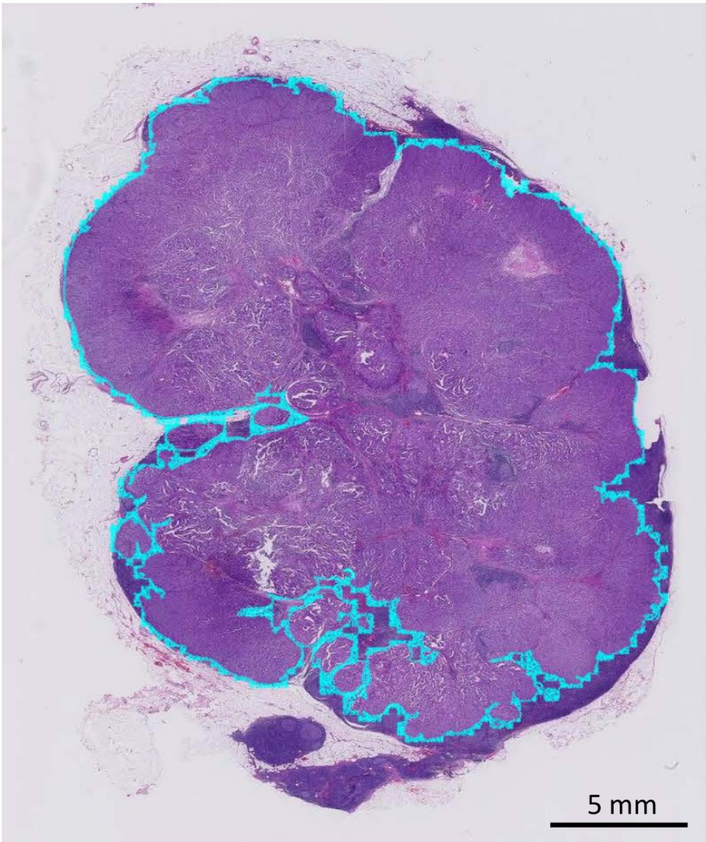
Method	DSC
Baseline DenseNet121 [9]	75.36
Self-sim Student **(Ours)**	**77.24**

© Copyright Taiwan AI Labs. All Rights Reserved.

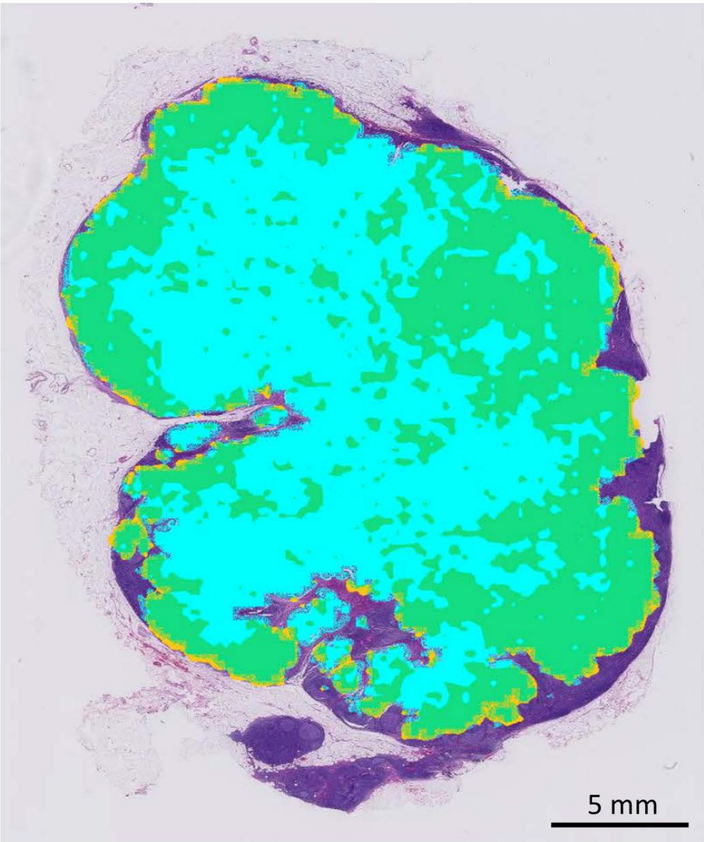
https://ailabstw.github.io/self-sim-student-pathology/

Result

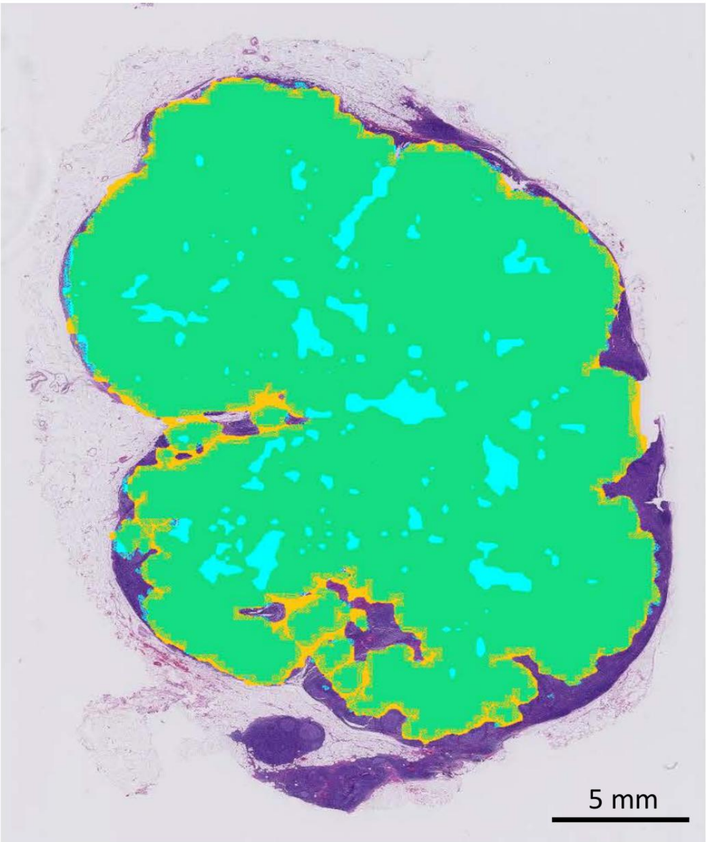
CAMELYON16 270 WSIs training set with Top-1 setting (42.4% wrong label)
Result on 130 WSIs testing set



Ground Truth



Supervised-trained Baseline



Self-similarity Student

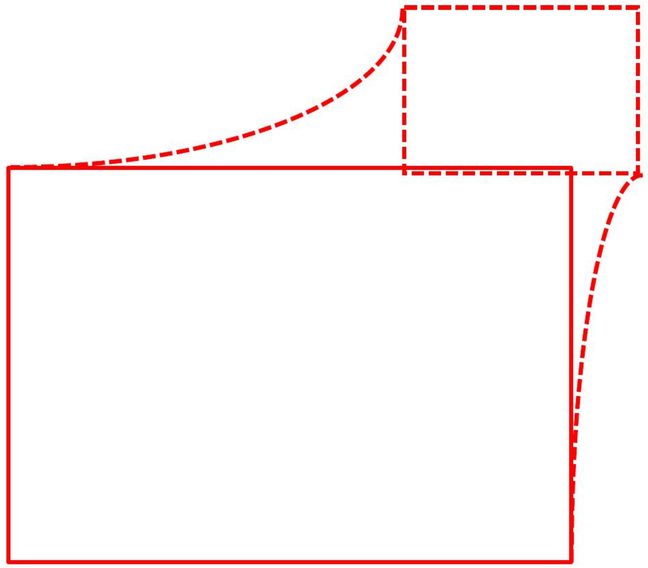
© Copyright Taiwan AI Labs. All Rights Reserved.

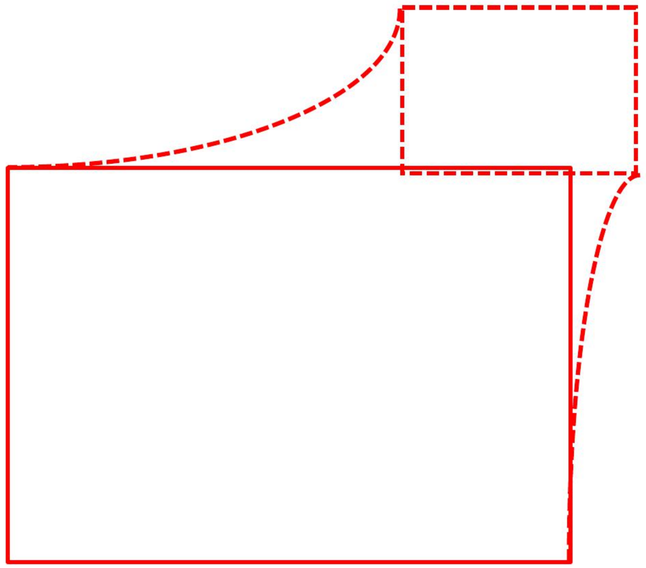
Legend: True Positive, False Positive, Ground Truth (False Negative)

https://ailabstw.github.io/self-sim-student-pathology/

+, -. /0

! " # $%& ( )* DEFGG A<$98 (5(5- 9$0''9+-('! 9/ #2-B$0''''(5- 9J DJ K9+-8/ 5- 9/ *0)L
>0$.)''9/ 59+-MFGG A<$90$''(5- 9$0''





C9 3 3

@8/ . 5499 8 "!

C9 3 3

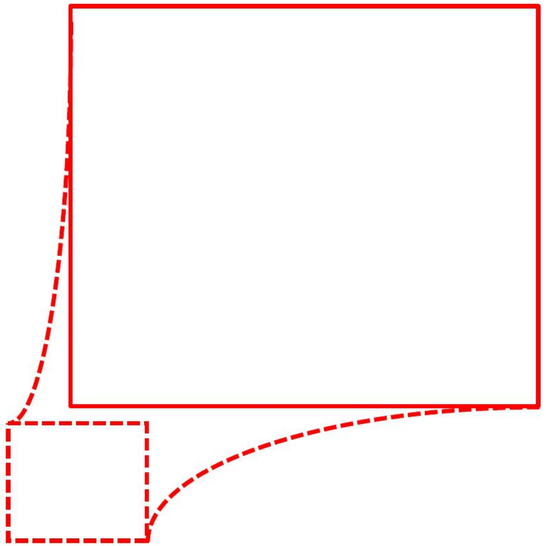
A #08?($042'8 (5049B' $0)(50

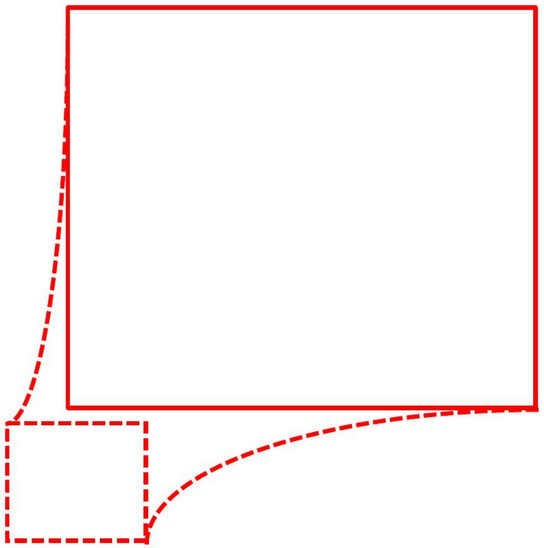
C9 3 3

A0)12$(3 ()' 8("69A". 405''

')*+,-

!"#$%&' (%DE +A0)"2/%%>'0-)'</)*'2444; - 4
C- 0$4'#%FGE +A0)- 0)/%>'0-)





8'6 6
8 6 6

! "#$%&("$)*

8'6 6
8 6 6

+$, - ". /0- &1)"2/% &'320- 4%

8'6 6
8 6 6

+ 4510/6 /42"/)7'+)$&- %)

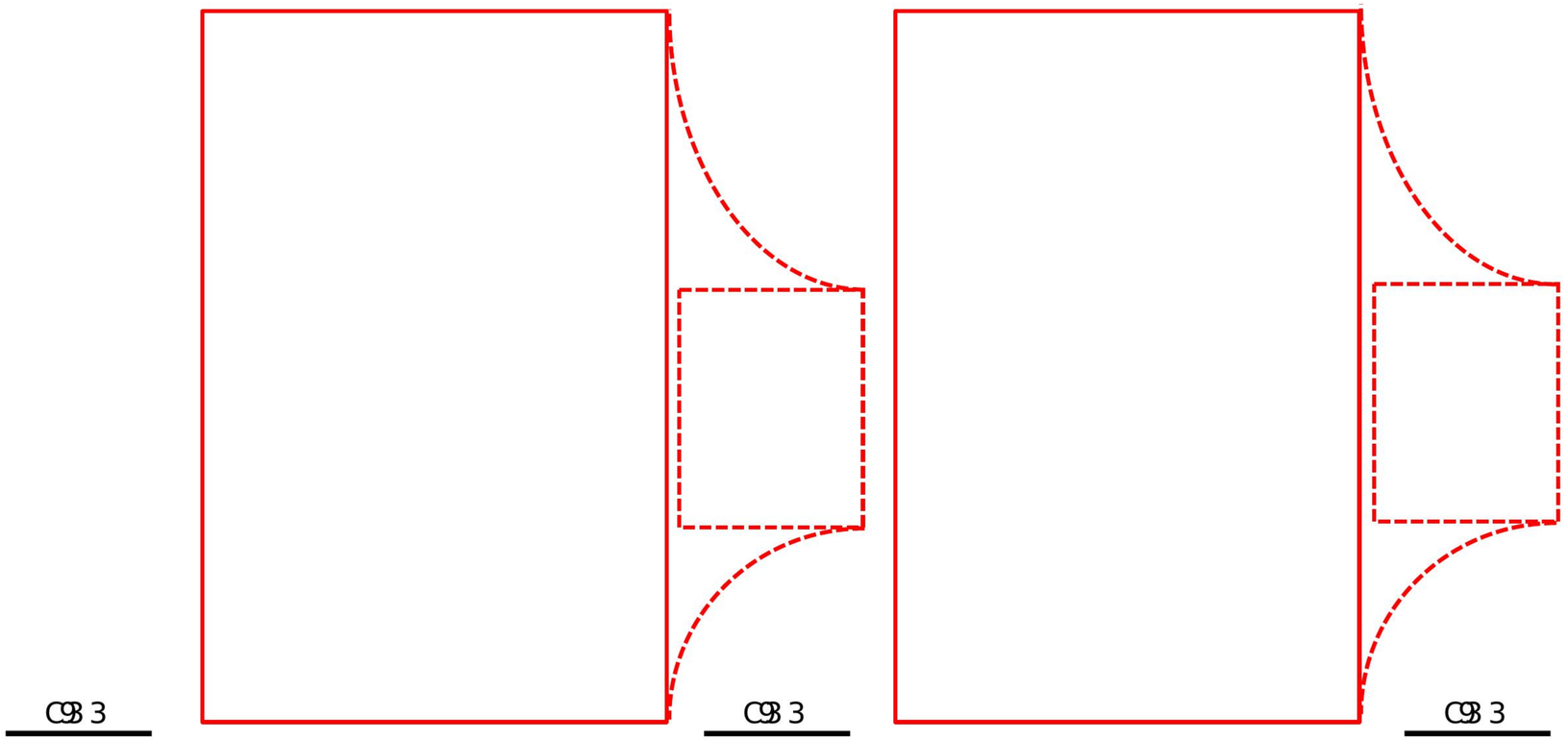
! ?#, 7"/>*)'(2/<2%@AB2; 0=@4C/>*)'0C- 0- ". - &=

.)/)012%3+) %(4*55) 7%89,*) %(4*55) 7%34+01%3+-: %89,*) %) / 9-5) =

)), 09:2/42; 0)<=>/)$; ##:0- 4510/6 10)$&- %)1, 2)* #4#>7:

')*+,-

!" #$%&' (%DE A<$98 (5(5- 9$0"9+-("! 9))9' *0)9
>0$.)"9 59FGE A<$90$"(5- 9$0"



@8 . 5498 "!

A #08?($042'8 (5049B' $0)(50

A0)12$(3 ()' 8("69A". 405"

Result – Ablation study

CAMELYON16 270 WSIs training set
Result on 130 WSIs testing set

Method	Metrics	Complete	k_{top}			k_{rand}		
			1	2	3	1	2	3
Baseline DenseNet121 [9]	DSC	92.68	83.08	87.40	90.41	63.08	70.02	78.39
	FROC	41.12	29.99	38.37	**40.18**	28.09	35.90	33.22
Self-sim Student **(Ours)**	DSC	90.49	**93.76**	**93.98**	**91.29**	**85.56**	**87.57**	**90.20**
	FROC	39.52	**36.90**	**38.94**	39.16	**31.88**	**36.54**	**35.08**

Ablation Study				DSC	FROC
Baseline	Sim-embedding	Pred-ensemble	Sim-ensemble		
✓				63.08	28.09
✓	✓			68.42	28.24
✓		✓		75.59	30.20
✓	✓	✓	✓	**85.56**	**31.88**

© Copyright Taiwan AI Labs. All Rights Reserved.

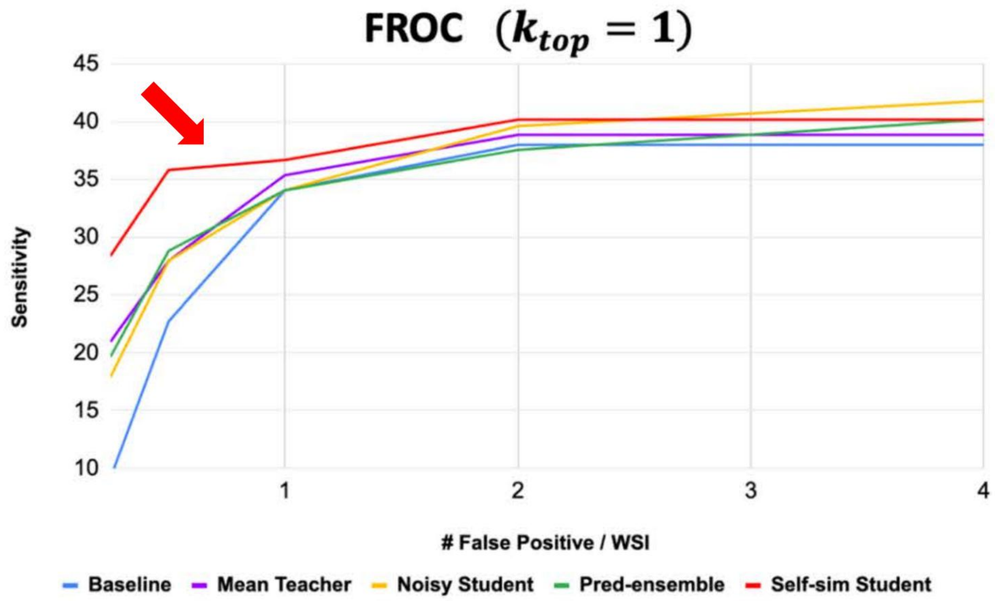
https://ailabstw.github.io/self-sim-student-pathology/

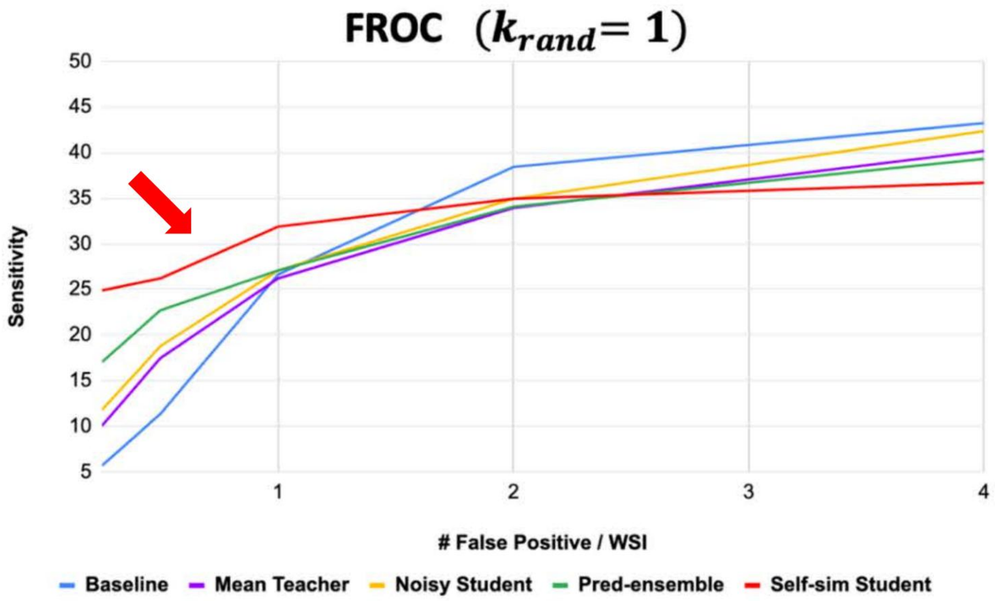
Result - FROC

CAMELYON16 270 WSIs training set
Result on 130 WSIs testing set

FROC of lesions over false positives

Our method prediction is more sensitive to cancer lesions with lower false positives.





© Copyright Taiwan AI Labs. All Rights Reserved.

https://ailabstw.github.io/self-sim-student-pathology/

Thank you for your watching!

For more information, please visit our website.

https://ailabstw.github.io/self-sim-student-pathology/

© Copyright Taiwan AI Labs. All Rights Reserved.