PriorsMatch: Prior-Level Pseudo-Labels for Semi-Supervised Object Detection on Medical Images

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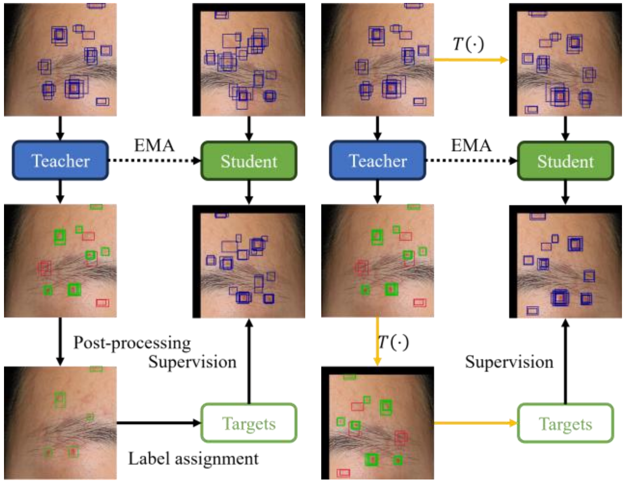
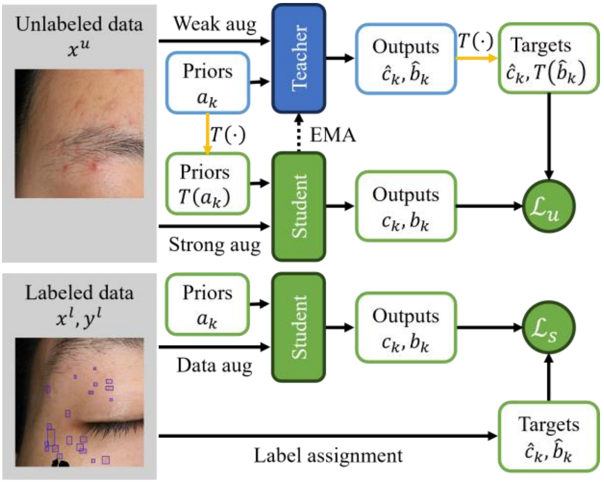
Problems & Ideas

- Problems of common pseudo-labels of SSOD for medical images:
  - Errors in pseudo-labels **weaken the consistency constraints** and destabilize model optimization.
  - Inaccurate pseudo boxes assigned to multiple student outputs **bias the box regression**.
- Ideas: Priors-Level Pseudo-Labels(PLPLs) were proposed to replace common pseudo-labels, jointly addressing the aforementioned issues with PriorsMatch framwork.



Comparison between common pseudo-labels and PLPLs



The overview of PriorsMatch

Main Contributions

- Contributions:
  - We identify how conventional pseudo-labels weaken consistency constraints and bias box regression, which substantially degrade the performance of SSOD methods on medical data;
  - We propose Prior-Level Pseudo-Labels (PLPLs) and further develop the PriorsMatch framework to address these issues;
  - We conducted extensive experiments on medical datasets and the results show that PriorsMatch achieves competitive results compared to state-of-the-art SSOD methods.

Methods	AcneSCU	BrainTumor
Supervised	34.02±0.24	56.29±0.62
MeanTeacher	34.55±0.59	57.46±1.08
UnbiasedTeacher [2]	35.10±1.14	57.64±1.08
SoftTeacher [3]	34.83±0.98	57.56±0.70
PseCo [4]	35.08±1.03	57.35±1.00
LabelMatch [5]	36.46±1.75	57.58±1.16
CPL-SAM [6]	36.96±1.01	58.41±0.96
MixPL [7]	37.11±1.50	58.91±1.00
PriorsMatch(Ours)	37.64±0.84	58.54±0.89
MixPL+	38.37±1.48	58.61±0.92
PriorsMatch+(Ours)	**38.65**±1.54	**60.38**±0.59

Table 1 Benchmark results for Faster R-CNN on medical detection datasets. "Supervised" means training only on labeled data. "+" means that RandomResize is added to the augmentation pipeline.