

Improving Semi-Supervised Object Detection by ROI-Enhanced Contrastive Learning

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Object Detection

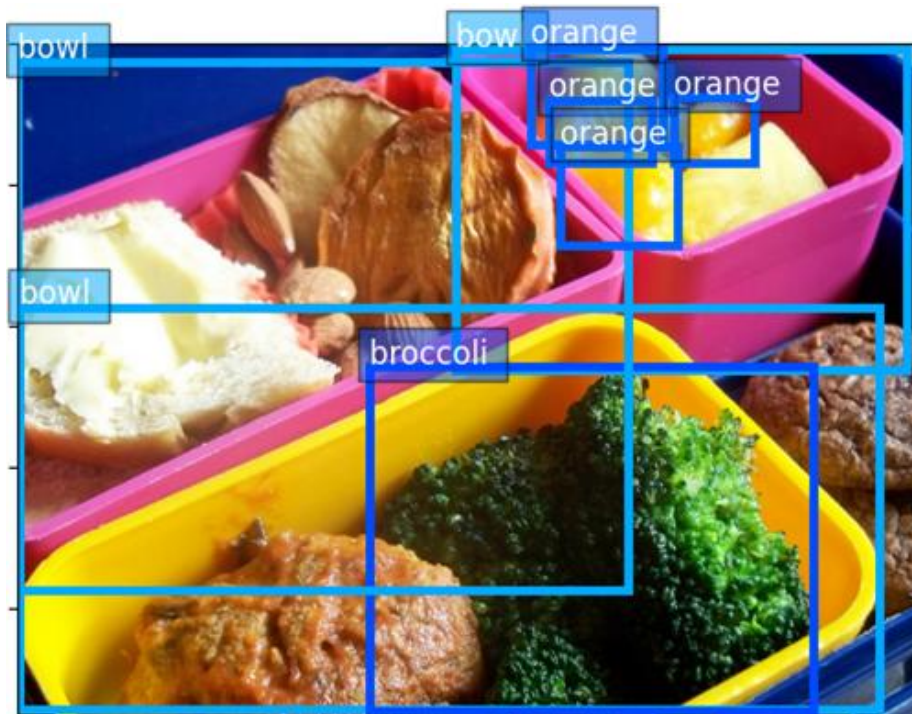
- Detects and locates objects of interest in an image



Semi-Supervised Object Detection

- Utilizes labeled and unlabeled images to train the object detection model

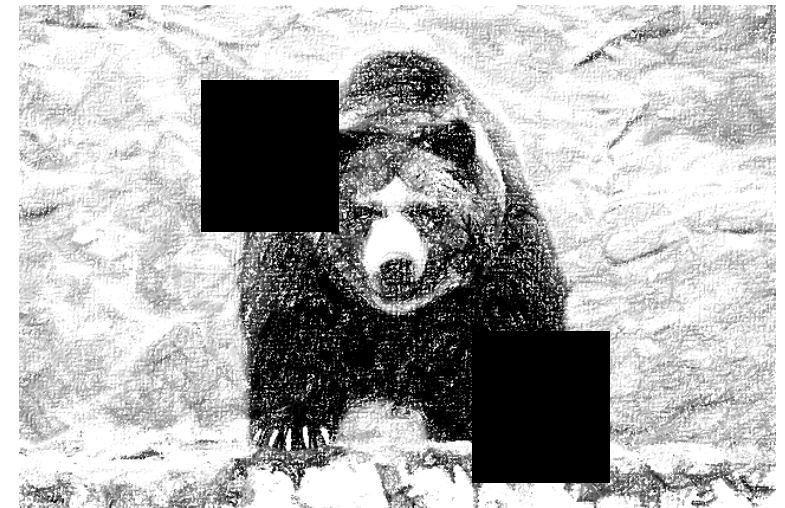
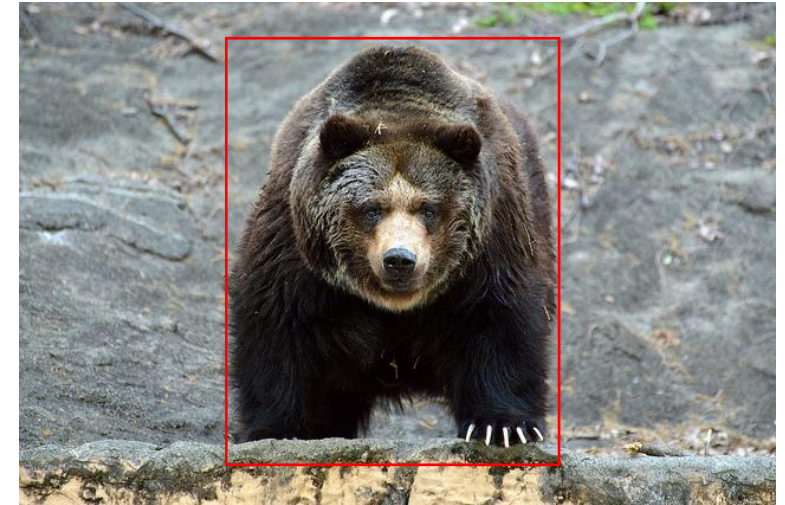
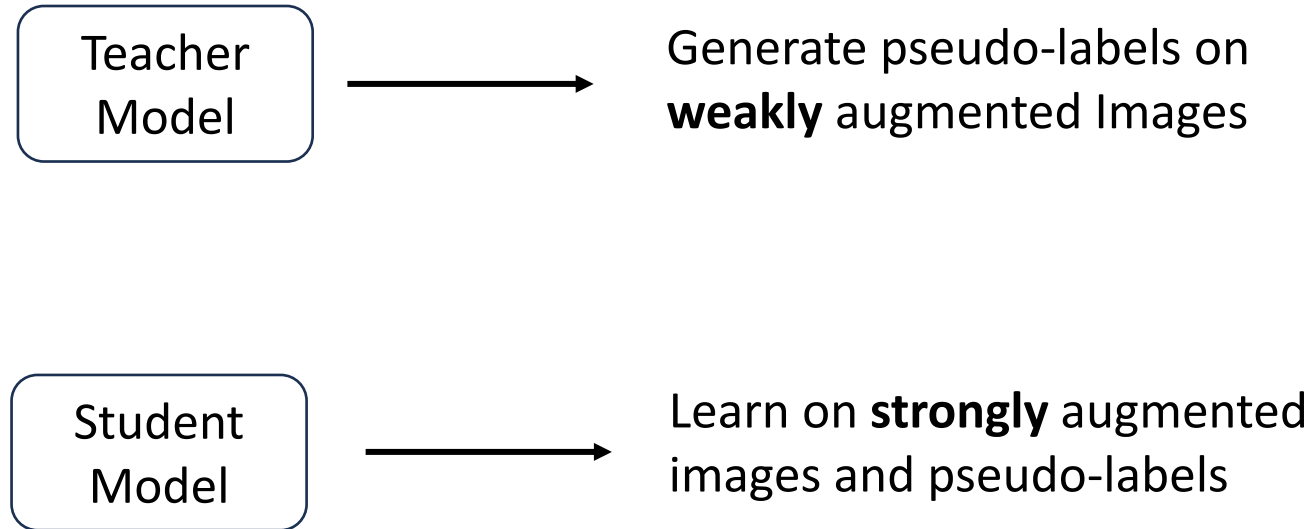
Labeled Images



Unlabeled Images



Teacher-Student Mutual Learning

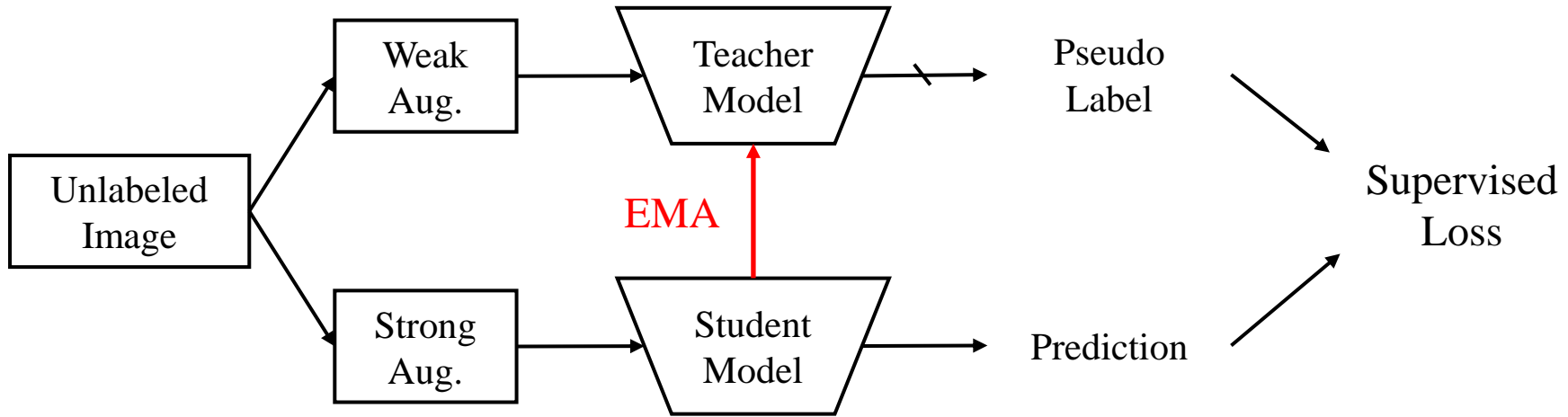


- Geoffrey Hinton, Oriol Vinyals, and Jeff Dean, “Distilling the knowledge in a neural network,” arXiv:1503.02531v1, 2015.
- Kihyuk Sohn *et al.*, “A simple semi-supervised learning framework for object detection,” arXiv:2005.04757v2, 2020.

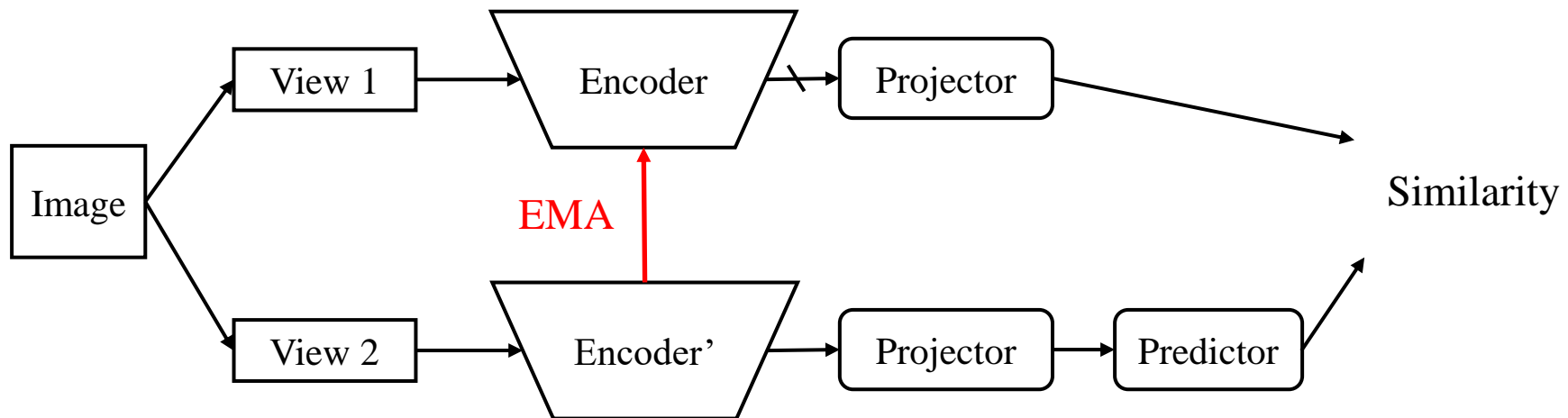
Motivations

- Pseudo-labels generated by the teacher model inevitably introduce label noise. However, deep neural networks have shown the ability to effectively memorize arbitrary noisy labels during training.
- We need a new strategy to utilize unlabeled data.

Semi-Supervised Learning



Self-Supervised Learning

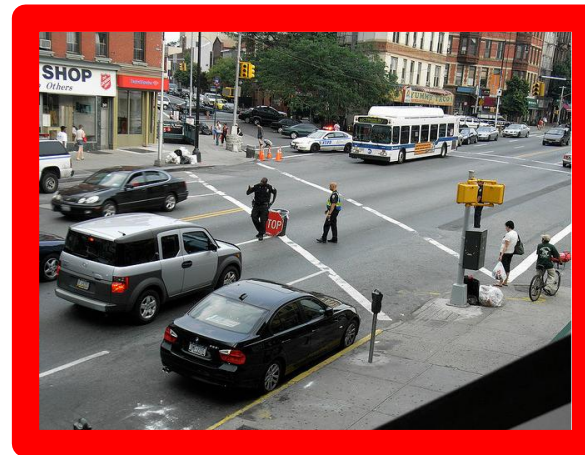


Motivations and Challenges

- Self-supervised learning diminishes the reliance on annotation.
- We incorporate this strategy to foster feature learning independent of (pseudo) labels in the context of semi-supervised object detection.
- Images are scene-centric, rather than object-centric.



Object-centric



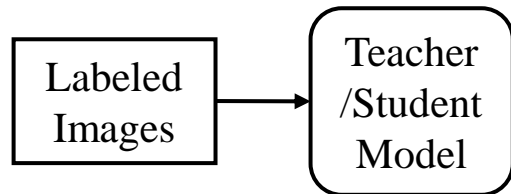
Scene-centric

Contributions

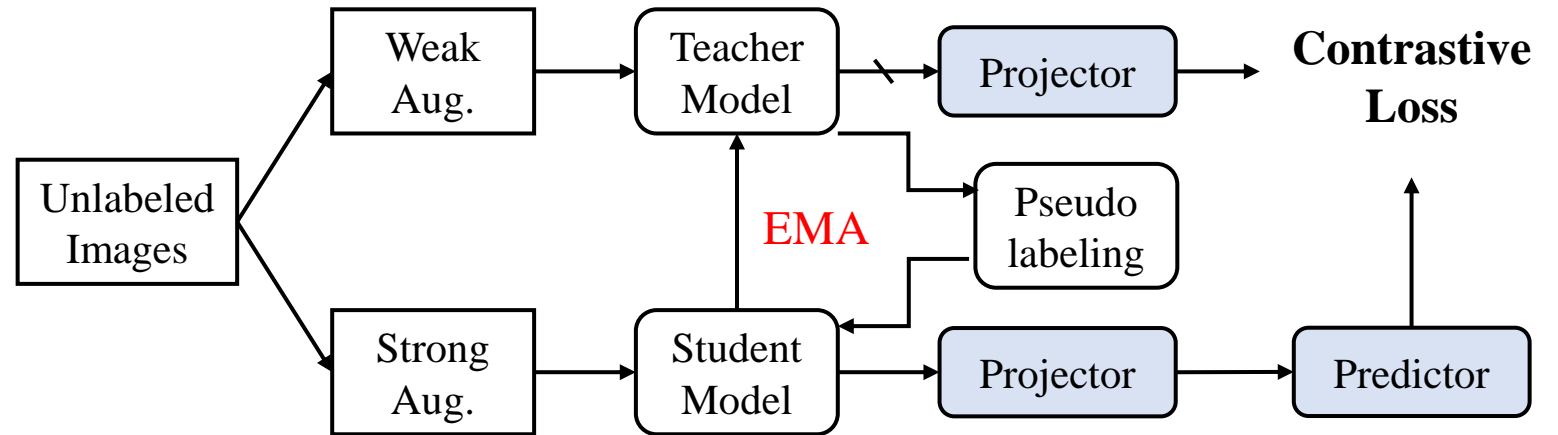
- We present a contrastive learning approach to improve semi-supervised object detection, performing consistency regularization not only by aligning the box predictions to pseudo boxes but also by considering feature-level representations.
- To address the challenge of object detection, the contrastive loss is computed at the box level, rather than on the entire image. Furthermore, the loss computation is spatially aware.
- Through experiments, we demonstrate that contrastive learning on RoI features can enhance the model's ability to gain additional information from unlabeled data.

Method

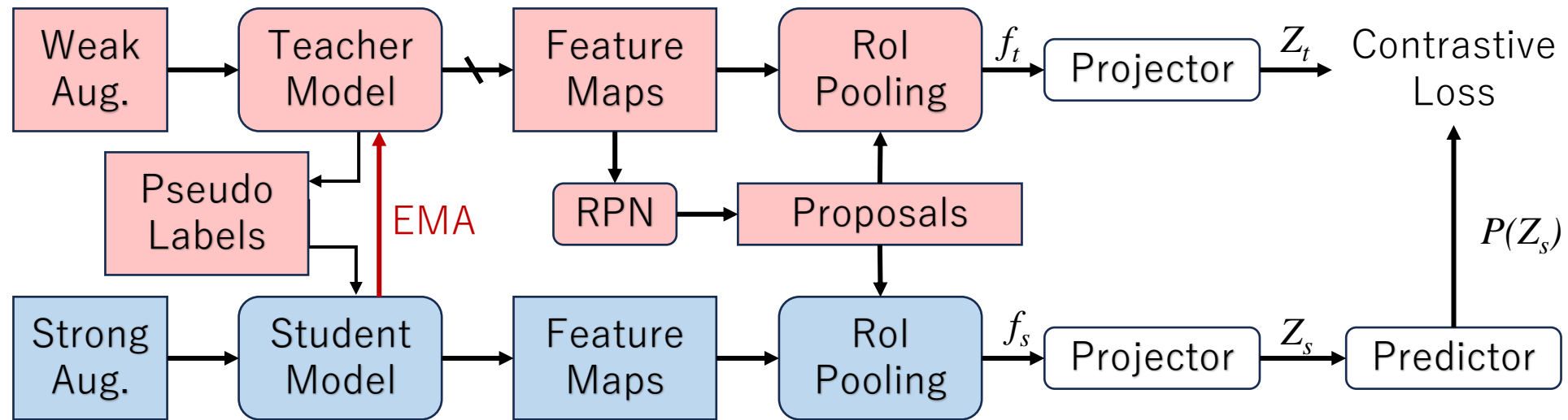
Burn-In Stage



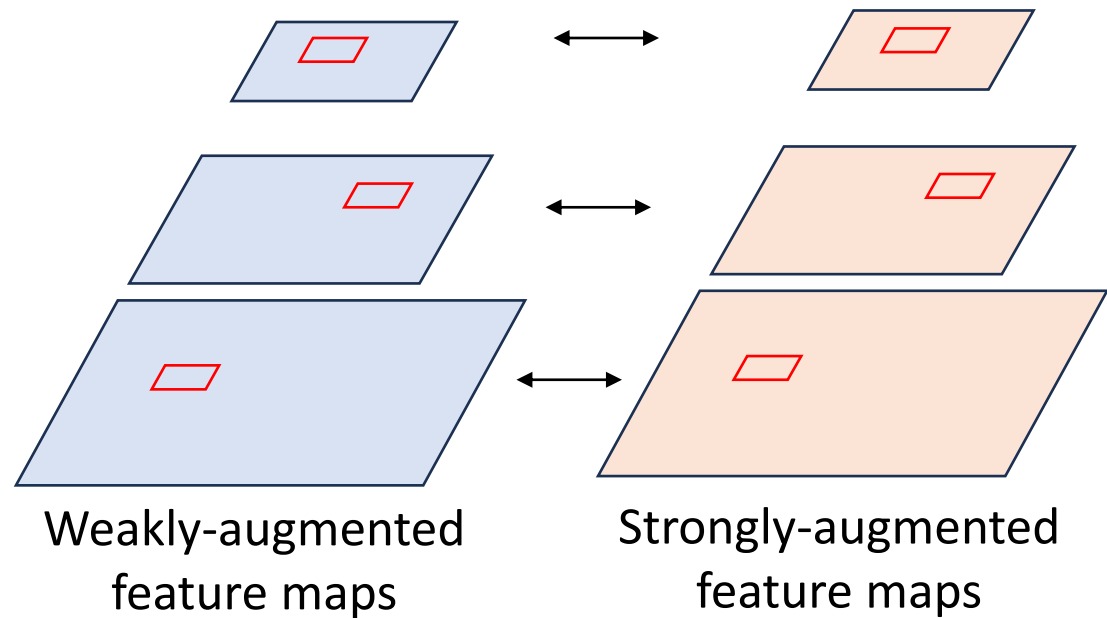
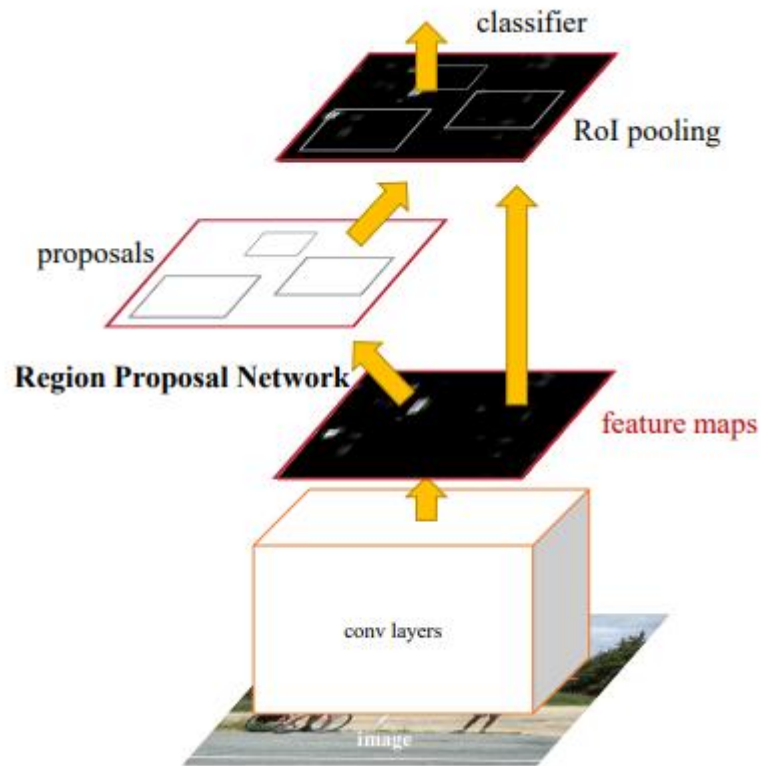
Teacher-Student Mutual Learning Stage



RoI-Enhanced Contrastive Learning

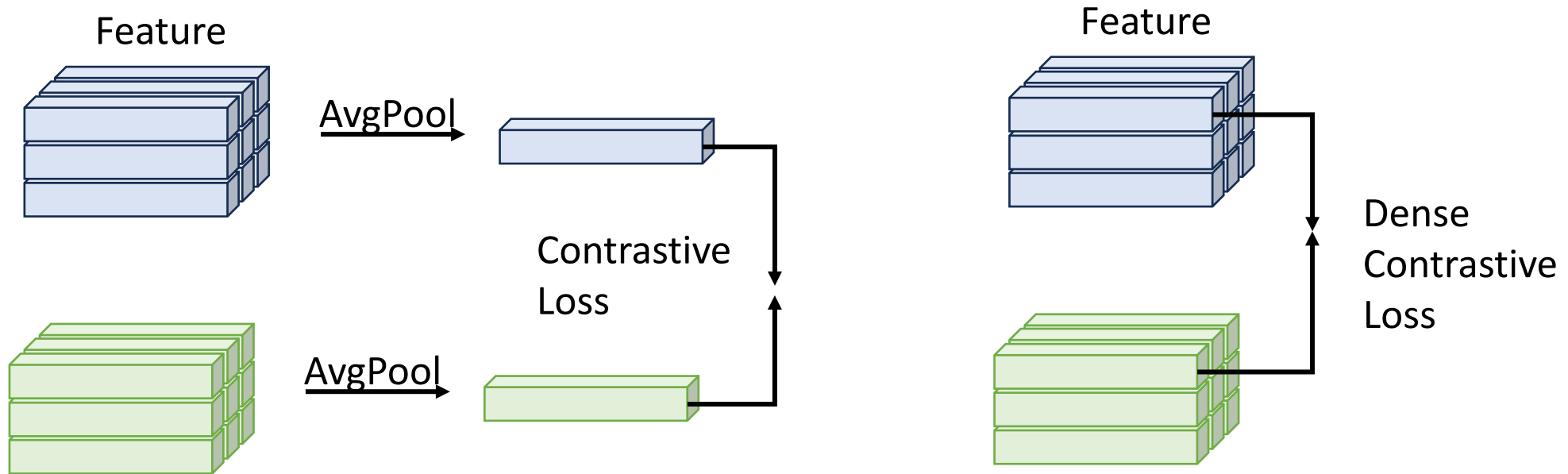


RoI-Enhanced Contrastive Learning



Shaoqing Ren *et al.*, “Faster r-cnn: Towards real-time object detection with region proposal networks,” *Advances in Neural Information Processing Systems*, 2015.

Dense Contrastive Learning



Xinlong Wang *et al.*, “Dense contrastive learning for self-supervised visual pre-training,” *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 2021.

Experimental Settings

- Dataset: COCO-Standard
 - Training: 118,000 images (train2017)
 - Test: 5,000 images (val2017)
- Evaluation protocol
 - Labeled Images: 1%, 5%, 10% training set
 - Metric: mAP
- Implementation details
 - Backbone: Faster-RCNN with ResNet50-FPN
 - Burn-in stage: 30k iterations
 - Batch size: 16 (smaller than other works)

Experimental Result

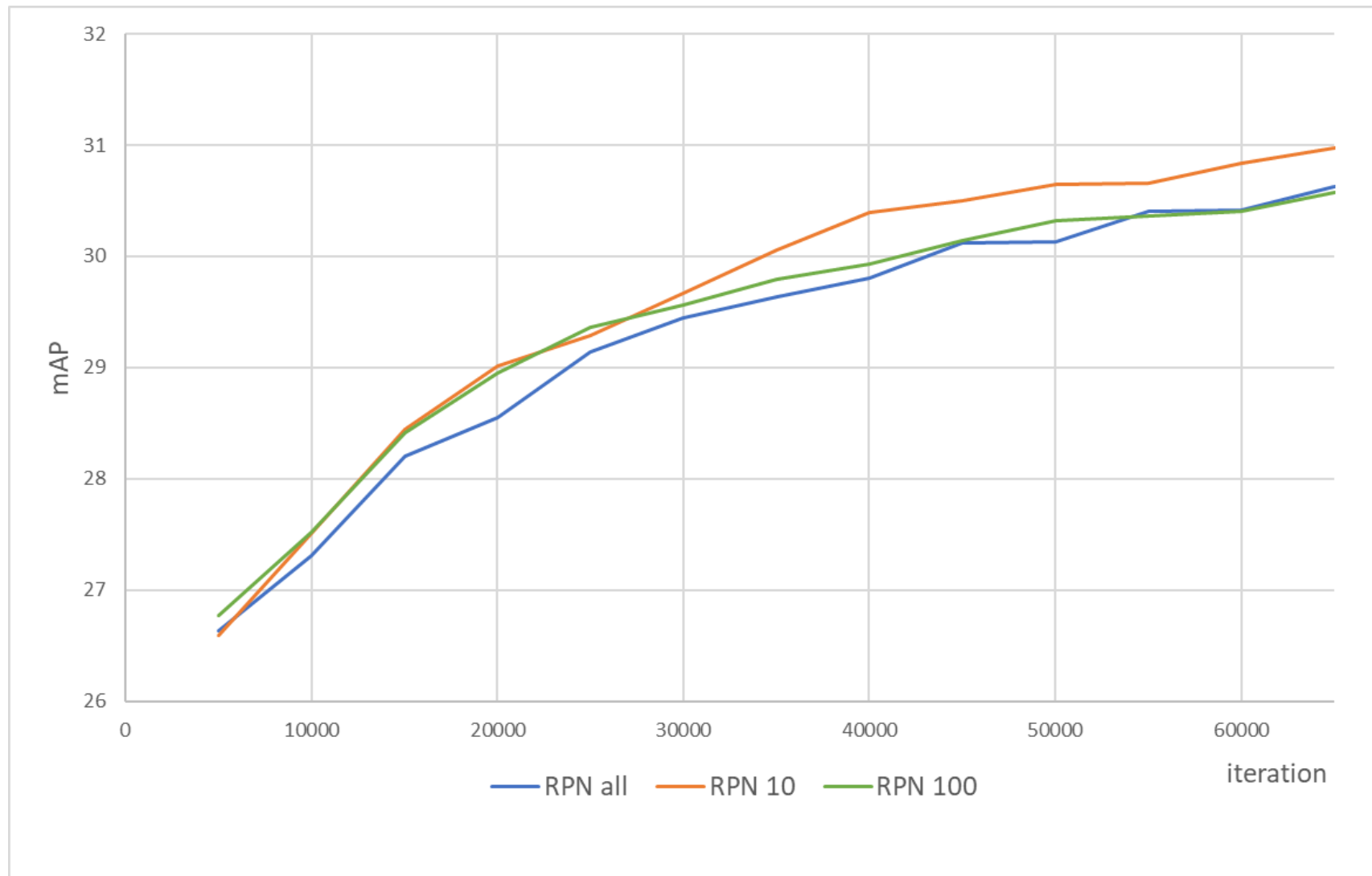
| Method | 1% | 5% | 10% |
|------------------|--------------|--------------|--------------|
| Supervised | 9.05 | 18.47 | 23.86 |
| Unbiased Teacher | 20.19 | 28.20 | 31.46 |
| Ours | 20.78 | 28.73 | 31.77 |

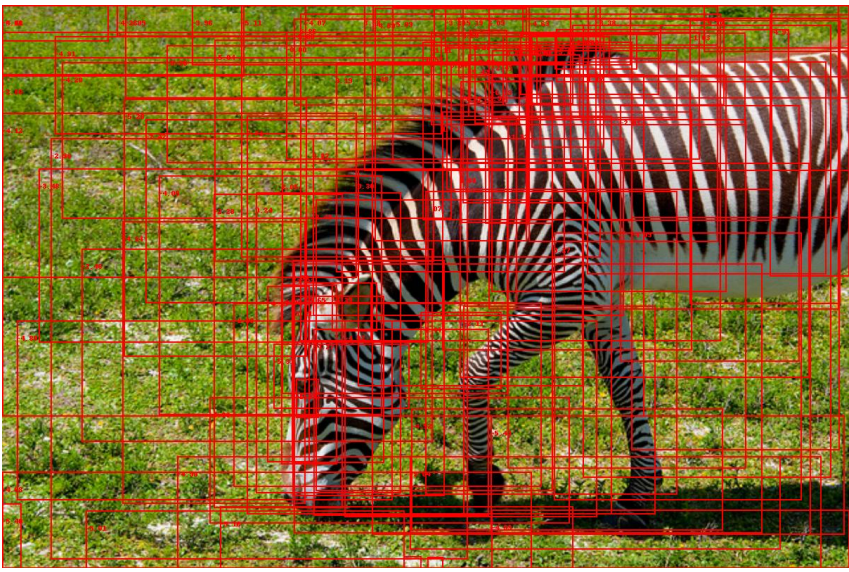
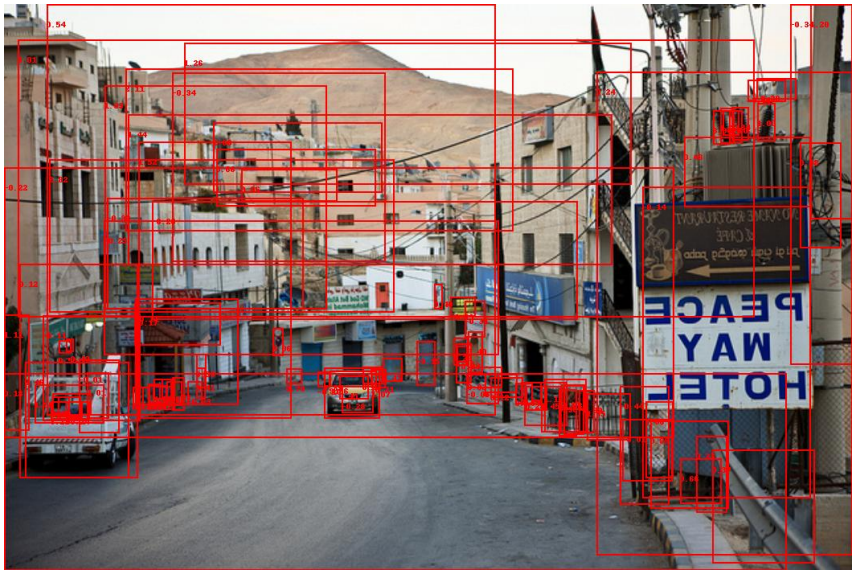
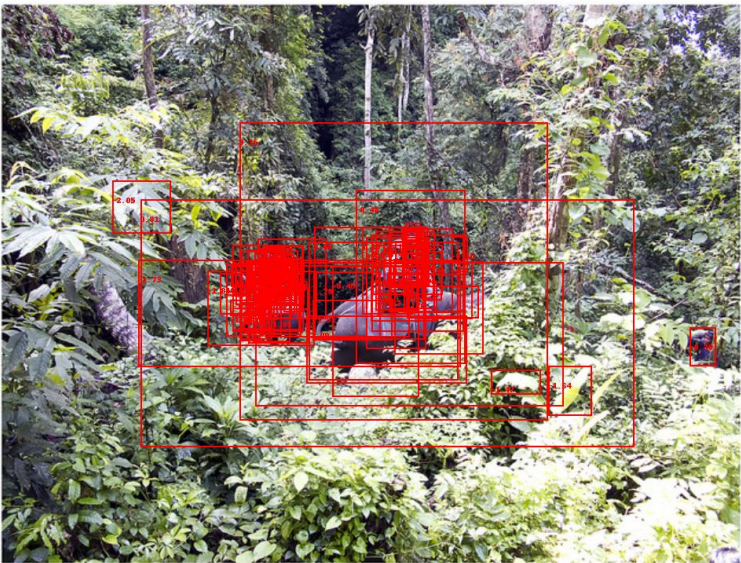
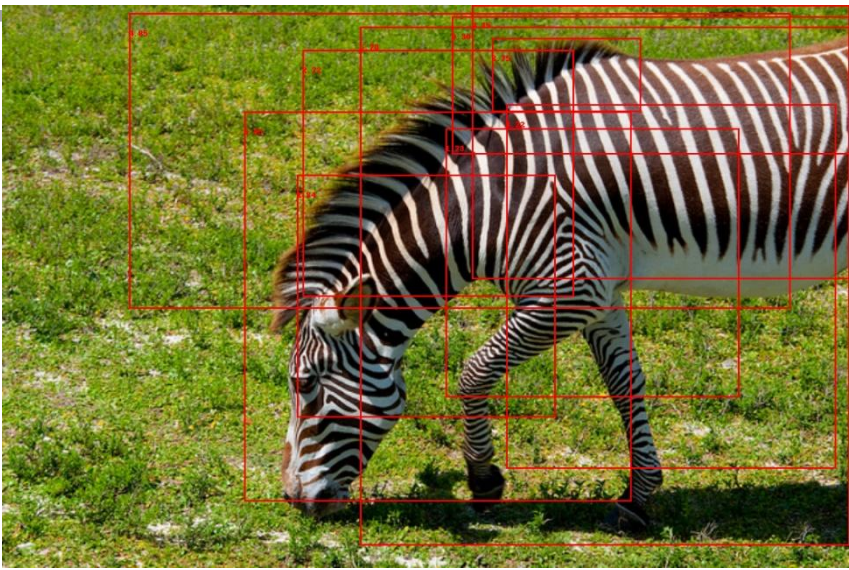
Y. -C. Liu *et al.*, “Unbiased teacher for semi-supervised object detection,” arXiv:2102.09480, 2021.

Effect of RoI-Enhanced Contrastive Learning



Number of RoI Proposals





Conventional Loss vs. Dense Loss



Conclusion

- We present a contrastive learning approach to enhance semi-supervised object detection.
 - Leveraging the candidate boxes selected by the Region Proposal Network (RPN) to facilitate RoI-based contrastive learning
 - Incorporating pixel-level comparisons to enable spatial-aware loss calculation
- We will validate the proposed plug-and-play method on alternative detection frameworks beyond Faster-RCNN.

Questions?

More Information:

<https://web.ntnu.edu.tw/~myeh/>