# Boosting Weakly Supervised Object Detection via Learning Bounding Box Adjusters


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2021 ICCV OCTOBER 11-17 VIRTUAL


## Motivation:

- In terms of **localization performance**, there remains a huge gap between WSOD methods and their fully-supervised counterparts.
- The class-agnostic object localization ability of an object detector can be **transferred into objects from novel categories**.
- We can pretrain a detector with **public well-annotated datasets**, and then guide training of WSOD using the **pretrained detector**.

## Problem Setting:

- During LBBA training, a **publicly available** well-annotated auxiliary dataset $\mathbb{X}^{\text{aux}}$ is used to supervise LBBA $g$.
- During LBBA-boosted WSOD, $\mathbb{X}^{\text{aux}}$ is abandoned, we only use **pretrained LBBA** $g$ and image-level labels $\mathbf{y}$ from **any** weakly annotated dataset $\mathbb{X}$ to supervise WSOD network $f$.

## Baseline WSOD network:

- Baseline network: OICR with bounding box regression branch.
- Training objective function of our baseline network:

$$\mathcal{L}_{\text{wsod}} = \mathcal{L}_{\text{wsddn}} + \mathcal{L}_{\text{r}} + \mathcal{L}_{\text{rpn-cls}} + \mathcal{L}_{\text{rpn-det}} + \mathcal{L}_{\text{det}}$$

## Learnable Bounding Box Adjuster (LBBA):

- We adopt Faster R-CNN with ResNet-50 backbone as well as a class-agnostic bounding box regression branch as our LBBA.
- LBBA is trained on fully-annotated **auxiliary dataset**.

## Training of LBBA:

- **Initialization: optimizing parameter of LBBA by fully supervised object detection**
- **E-Step:**

$$\theta_g = \arg\min_{\theta_g} \mathcal{L}_{\text{bba}}(\{\mathbf{b}^{\text{aux}}\}, g(\mathbf{I}^{\text{aux}}, \mathbb{P}^{\text{aux}}; \theta_g))$$

Where $\mathcal{L}_{\text{bba}} = \sum_{\mathbf{p}^{\text{aux}}\in\mathbb{P}^{\text{aux}}} \text{Smooth}_{L1}(\mathbf{b}^{\text{aux}}, \hat{\mathbf{b}}^{\text{aux}}; \theta_g)$

- **M-Step:**

$$\theta_{f^{\text{aux}}} = \arg\min_{\theta_{f^{\text{aux}}}} (\mathcal{L}_{\text{wsod}} + \mathcal{L}_{\text{bbr}})(\hat{\mathbf{b}}^{\text{aux}}, f^{\text{aux}}(\mathbf{I}^{\text{aux}}, \mathbb{P}^{\text{aux}}; \theta_{f^{\text{aux}}}))$$

Where $\mathcal{L}_{\text{bbr}} = \sum_{\mathbf{p}^{\text{aux}}\in\mathbb{P}^{\text{aux}}} \text{Smooth}_{L1}(\hat{\mathbf{b}}^{\text{aux}}, \tilde{\mathbf{b}}^{\text{aux}}; \theta_f)$

- After T stages training on auxiliary dataset, we obtain a series of adjusters for final LBBA-boosted WSOD training.

## LBBA-boosted WSOD:

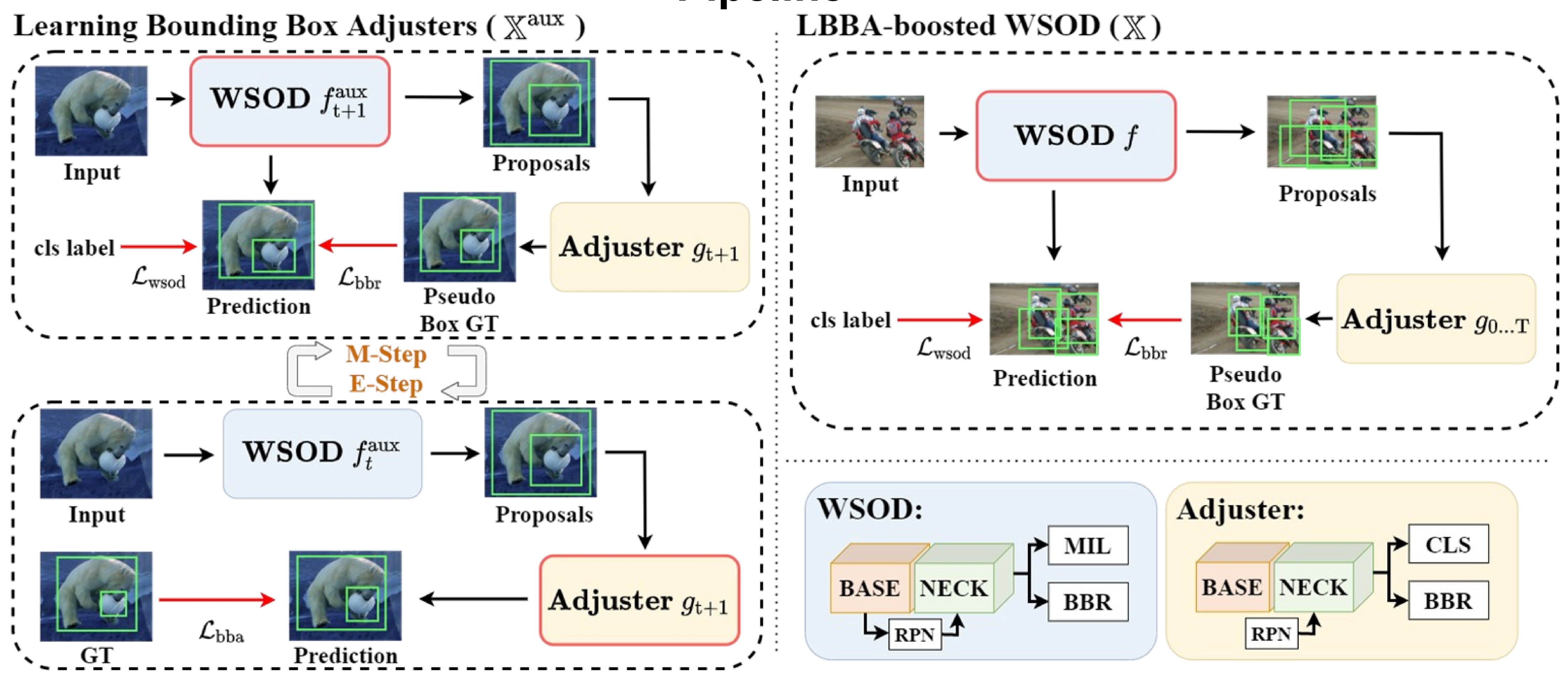
- Now, our WSOD network is supervised by both image level labels as well as a series of learnable bounding box adjusters.
- **Optimizing WSOD on target dataset:**

$$\theta_f = \arg\min_{\theta_f} (\mathcal{L}_{\text{wsod}} + \mathcal{L}_{\text{bbr}})(\hat{\mathbf{b}}, f(\mathbf{I}, \mathbb{P}; \theta_f))$$

Where $\mathcal{L}_{\text{bbr}} = \sum_{\mathbf{p}\in\mathbb{P}} \text{Smooth}_{L1}(\hat{\mathbf{b}}, \tilde{\mathbf{b}}; \theta_f)$

- Both training with the last LBBA and training with all LBBAs progressively are feasible.

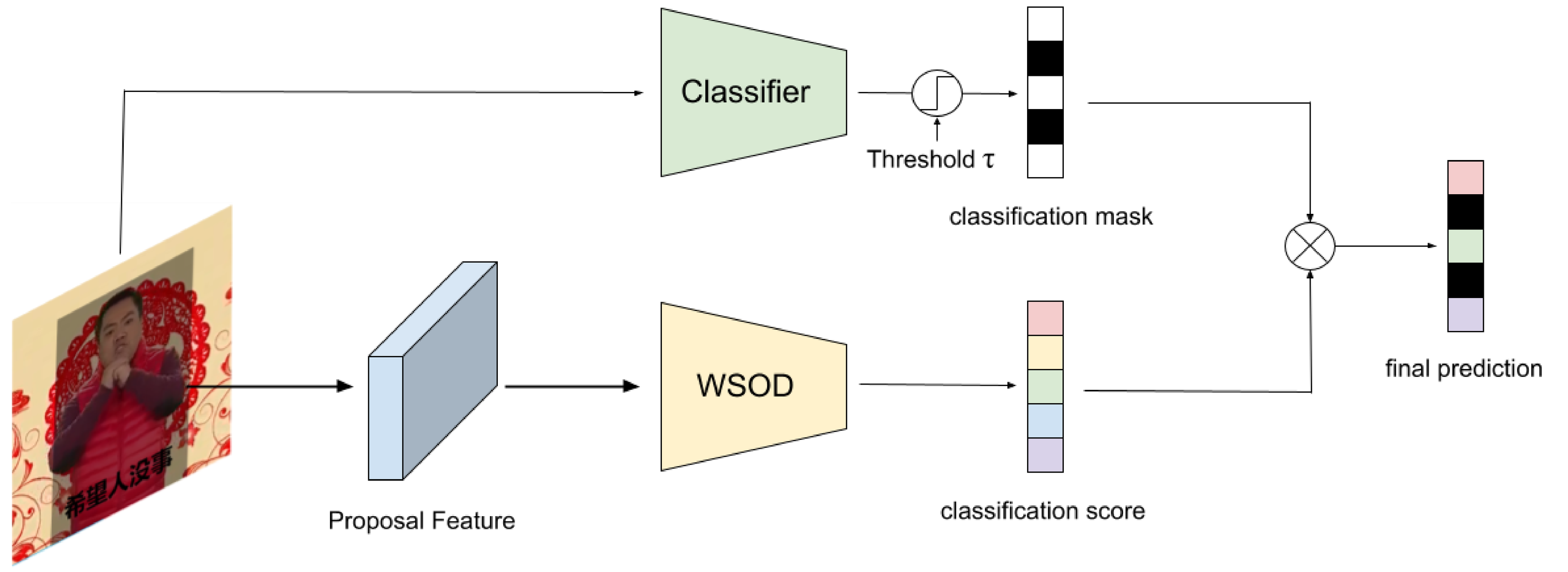
## Pipeline




## Visualization

## Masking Strategy:

- We introduce an additional multi-label image classifier and present a classification score masking strategy.




## Experiments:

- All LBBA methods **outperform the baseline** OICR and OICR+REG by improving the localization ability of WSOD methods.
- **LBBA with masking performs better**, which indicates that masking strategy can further improve detection ability of WSOD methods.
- Our LBBA method can be **generalized to multiple datasets**.

| Method | AP50(VOC07) | AP50(COCO-20) | AP50(ILSVRC) |
|---|---|---|---|
| OICR | 41.2 | 22.8 | 20.5 |
| OICR+REG | 51.4 | 23.9 | 22.4 |
| LBBA w/o masking | 55.8 | 27.5 | 28.0 |
| LBBA w/ masking | **56.5** | **29.9** | **30.1** |

## Conclusion

- **Multi-stage learnable bounding box adjusters** are presented for improving localization performance of WSOD.
- An **EM-like multi-stage training algorithm**, are suggested to learn LBBAs specified for optimizing WSOD.
- An **effective masking strategy** is introduced to improve the accuracy of the proposal classification branch.
- LBBA performs **favorably against the state-of-the-art** WSOD methods and knowledge transfer models.