



### BoxTeacher: Exploring High-Quality Pseudo Labels for Weakly Supervised Instance Segmentation

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Poster Tag: TUE-AM-299





#### Overview



Box-supervised Instance Segmentation



Using bounding boxes to supervise instance masks: (1) mask projection and (2) pairwise relations



Tian et.al. BoxInst: High-Performance Instance Segmentation with Box Annotations. CVPR 2021

### Overview

BoxTeacher





- The Teacher generates and filters pseudo masks.
- 2. The Student learns from pseudo masks and updates the Teacher.

BoxTeacher leverages high-quality pseudo masks and bridges the gap between boxsupervised and fully-supervised methods!

#### Motivation



#### Key Observation: box-supervised methods generate high-quality masks!

✓ Accurate localization✓ Fine boundaries



Prediction

GT

Prediction

GT

Generated by BoxInst (30.7 AP on COCO val)

Can we leverage those **high-quality masks** to further improve box-supervised instance segmentation?

Tian et.al. BoxInst: High-Performance Instance Segmentation with Box Annotations. CVPR 2021

### Method



#### Naïve Self-Training

Firstly, we adopt a naïve self-training framework...



- 1. Using pre-trained and frozen BoxInst to generate pseudo masks for each image.
- 2. Training a new instance segmentation model with pseudo labeled samples

### Method

#### Naïve Self-Training

Firstly, we adopt a naïve self-training framework...



Method	AP	AP <sub>50</sub>	AP <sub>75</sub>
BoxInst, 1x	30.7	52.2	31.1
Self-Training, 1x	31.0	53.1	31.6
BoxInst, 3x	31.8	54.0	32.0
Self-Training, 3x	31.3↓	53.8	31.7





Pseudo masks do contain much noise!





Overall Architecture



An End-to-End Training Framework, including pseudo labeling and self-training

# JUNE 18-22, 2023



Pseudo Mask: Generation, Scoring, and Filtering



BoxTeacher

Mask-aware Confidence Score: estimate mask quality

$$s_{i} = \sqrt{c_{i} \cdot \frac{\sum_{x,y}^{H,W} \mathbb{1}(m_{i,x,y} > \tau_{m}) \cdot m_{i,x,y} \cdot m_{i,x,y}^{b}}{\sum_{x,y}^{H,W} \mathbb{1}(m_{i,x,y} > \tau_{m}) \cdot m_{i,x,y}^{b}}},$$

The Teacher:

- ✓ generates pseudo masks
- ✓ estimates mask confidence scores
- ✓ filters low quality masks





Box-based Mask Assignment



according to:

- ✓ IoU
- ✓ Confidence score





Training Student, Updating Teacher



The Student:

- ✓ Forwards with **perturbed** images
- ✓ Computes detection loss, box-supervised loss, and mask-supervised loss
- ✓ Updates the Teacher via **EMA** (Exponential Moving Average)







- End-to-end training, simple, efficient
- Flywheel: better student leads to better teacher, and better teacher leads to better student
- Better performance

#### JUNE 18-22, 2023 CVPR VANCOUVER, CANADA

#### COCO Instance Segmentation

Method	Backbone	Schedule	AP	$AP_{50}$	$AP_{75}$	$AP_s$	$AP_m$	$AP_l$
Mask-supervised methods.								
Mask R-CNN [23]	R-50-FPN	1×	35.5	57.0	37.8	19.5	37.6	46.0
CondInst [49]	R-50-FPN	1×	35.9	57.0	38.2	19.0	38.6	46.7
CondInst [49]	R-50-FPN	$3 \times$	37.7	58.9	40.3	20.4	40.2	48.9
CondInst [49]	R-101-FPN	$3 \times$	39.1	60.9	42.0	21.5	41.7	50.9
SOLO [54]	R-101-FPN	$6 \times$	37.8	59.5	40.4	16.4	40.6	54.2
SOLOv2 [54]	R-101-FPN	$6 \times$	39.7	60.7	42.9	17.3	42.9	57.4
Box-supervised meth	hods.							
BoxInst [51]	R-50-FPN	$3 \times$	32.1	55.1	32.4	15.6	34.3	43.5
DiscoBox [31]	R-50-FPN	3×	32.0	53.6	32.6	11.7	33.7	48.4
BoxTeacher <sup>†</sup>	R-50-FPN	1×	32.9	54.1	34.2	17.4	36.3	43.7
BoxTeacher	R-50-FPN	$3 \times$	35.0	56.8	36.7	19.0	38.5	45.9
BBTP [25]	R-101-FPN	1×	21.1	45.5	17.2	11.2	22.0	29.8
BBAM [32]	R-101-FPN	1×	25.7	50.0	23.3	-	-	-
BoxCaseg [53]	R-101-FPN	1×	30.9	54.3	30.8	12.1	32.8	46.3
BoxInst [51]	R-101-FPN	$3 \times$	33.2	56.5	33.6	16.2	35.3	45.1
BoxLevelSet [33]	R-101-FPN	$3 \times$	33.4	56.8	34.1	15.2	36.8	46.8
BoxLevelSet [33]	R-101-DCN-FPN	$3 \times$	35.4	59.1	36.7	16.8	38.5	51.3
DiscoBox [31]	R-101-DCN-FPN	3  imes	35.8	59.8	36.4	16.9	38.7	52.1
BoxTeacher	R-101-FPN	$3 \times$	36.5	59.1	38.4	20.1	40.2	47.9
BoxTeacher	R-101-DCN-FPN	$3\times$	37.6	60.3	39.7	21.0	41.8	49.3
BoxTeacher	Swin-Base-FPN	$3 \times$	40.6	65.0	42.5	23.4	44.9	54.2

- BoxTeacher achieves the State-of-the-Art performance!
- BoxTeacher bridges the gap between boxsupervised and fully-supervised methods,
  BoxTeacher (36.5) v.s. CondInst (39.1)



BoxTeacher on Other Datasets

#### **On PASCAL VOC**

Method	Backbone	AP	$AP_{25}$	$AP_{50}$	$AP_{70}$	$AP_{75}$
SDI [28]	VGG-16	-	-	44.8	-	16.3
BoxInst [51]	R-50	34.3	-	59.1	-	34.2
DiscoBox [31]	R-50	-	71.4	59.8	41.7	35.5
BoxLevelSet [33]	R-50	36.3	76.3	64.2	43.9	35.9
BoxTeacher	R-50	38.6	77.6	66.4	46.1	38.7
BBTP [25]	R-101	-	75.0	58.9	30.4	21.6
Arun <i>et al</i> . [2]	<b>R-101</b>	-	73.1	57.7	33.5	31.2
BBAM [32]	<b>R-101</b>	-	76.8	63.7	39.5	31.8
BoxInst [51]	<b>R-101</b>	36.4	-	61.4	-	37.0
DiscoBox [31]	<b>R-101</b>	-	72.8	62.2	45.5	37.5
BoxLevelSet [33]	<b>R-101</b>	38.3	77.9	66.3	46.4	38.7
BoxTeacher	<b>R-101</b>	40.3	78.4	67.8	48.0	41.3

#### **On Cityscapes**

Method	Data	AP	$AP_{50}$				
Mask-supervised methods.							
Mask R-CNN [23]	fine	31.5	-				
CondInst [49]	fine	33.0	59.3				
CondInst [49]	fine + COCO	37.8	63.4				
Box-supervised methods.							
BoxInst <sup>†</sup> [51]	fine	19.0	41.8				
BoxInst <sup>†</sup> [51]	fine + COCO	24.0	51.0				
BoxLevelSet <sup>†</sup> [33]	fine	20.7	43.3				
BoxLevelSet <sup>†</sup> [33]	fine + COCO	22.7	46.6				
BoxTeacher	fine	21.7	47.5				
BoxTeacher	fine + COCO	26.8	54.2				



Ablation Experiments

#### **Comparison to Naïve Self-Training**



#### **Strong Perturbation for Student**

Method	Schd.	weak	strong	$AP^b$	$AP^m$
CondInst	$1 \times$			39.6	36.2
CondInst	$1 \times$	$\checkmark$		39.6	$35.6^{-0.6}$
CondInst	$1 \times$		$\checkmark$	39.2	$35.3^{-0.9}$
BoxTeacher	$1 \times$			39.4	32.6
BoxTeacher	$1 \times$	$\checkmark$		39.1	$32.4^{-0.2}$
BoxTeacher	$1 \times$		$\checkmark$	38.8	$32.2^{-0.4}$
CondInst	$3 \times$			41.9	37.5
CondInst	3  imes		$\checkmark$	42.0	$37.6^{+0.1}$
BoxTeacher	3  imes			41.7	34.2
BoxTeacher	3  imes		$\checkmark$	41.8	$34.8^{+0.6}$

- 1. Strong perturbation is useless for fully-supervised training
- 2. Strong perturbation with longer schedule is beneficial to BoxTeacher

Qualitative Results





BoxTeacher can generate high-quality segmentation masks with fine-grained boundaries!





## Thanks

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Code