


# **Union-over-Intersections: Object Detection beyond Winner-Takes-All**

Aritra Bhowmik, Pascal Mettes, Martin R. Oswald, Cees G. M. Snoek

# Rethinking Regression: Collaboration not Competition

## Classical Regression

 Same target

 Out-of-scope

 Pick one

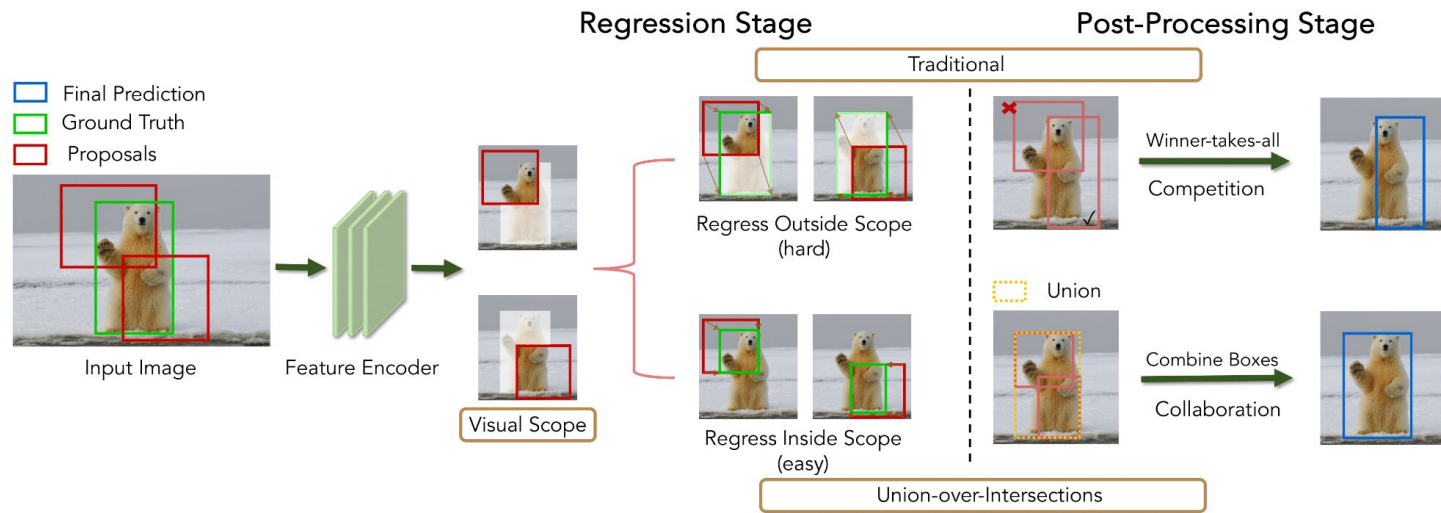
## Union-over-Intersections

 Different target

 Within scope

 Union of intersections

# Standard vs Our Pipeline



## STAGE 1

Regressing to Intersections



Easier task

## STAGE 2

Union-over-Intersections



Collaboration Better

# Proposed changes at a glance

## Regression Stage

**Input :**

Set of Proposals  $P = \{p_1, \dots, p_N\}$

Corresponding ground truths  $G = \{g_1, \dots, g_N\}$

Corresponding detection scores  $S = \{s_1, \dots, s_N\}$

Iou threshold  $k$

**Loss and Targets for Regression :**

Loss =  $|T - B|$ ,

where  $B = \{b_1, \dots, b_N\}$  are the set of box predictions.

$T = \{g_1, \dots, g_N\}$

**Traditional targets**

$T = \{p_1 \cap g_1, \dots, p_N \cap g_N\}$

**Our targets**

**Main Difference:** We regress only to the intersections, not the whole ground truth.

## Post-Processing Stage

**begin**

$D \leftarrow \{\}$

**while**  $P \neq \text{empty}$  **do**

$m \leftarrow \text{argmax } S$

$M \leftarrow b_m; H \leftarrow P_m; C \leftarrow \{H\}$

$B \leftarrow B \setminus M; P \leftarrow P \setminus H$

**for**  $i$  in range ( $\text{len}(P)$ ) **do**

**if**  $\text{iou}(M, b_i) \geq k$  **then**

$B \leftarrow B \setminus b_i; S \leftarrow S \setminus s_i$

**end**

**if**  $\text{iou}(H, p_i) \geq k$  **then**

$P \leftarrow P \setminus p_i; S \leftarrow S \setminus s_i; C \leftarrow C \cup b_i$

$M = \text{top 5 } (C) \text{ combined}$

**end**

**Main Difference:** Union over discarding.

**end**

$D \leftarrow D \cup M$

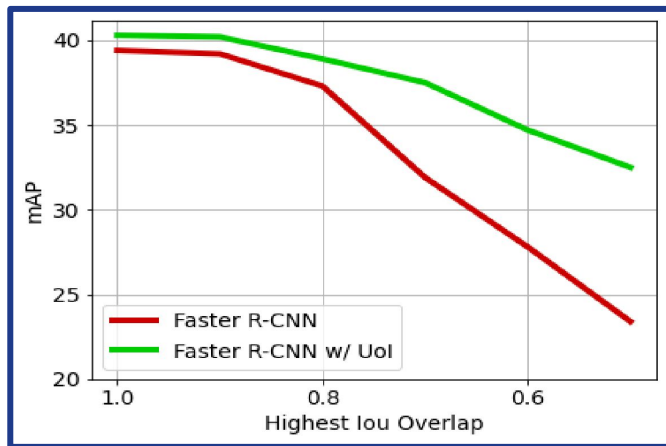
**end**

**return**  $D, S$

**end**

# Observations

(a) Robust to bad proposals

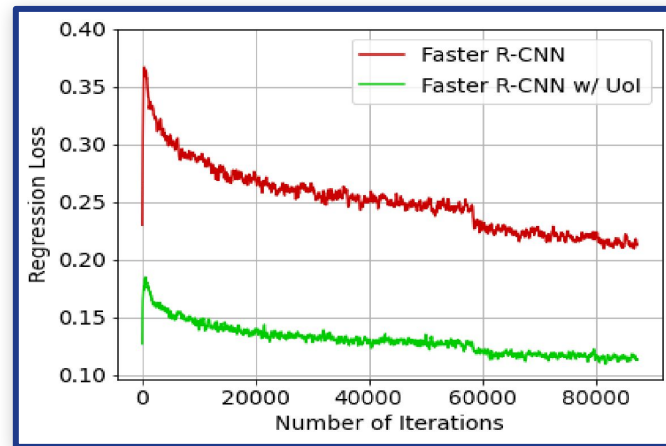


Only using bad proposals



Performance drops : much less

(b) Simpler target



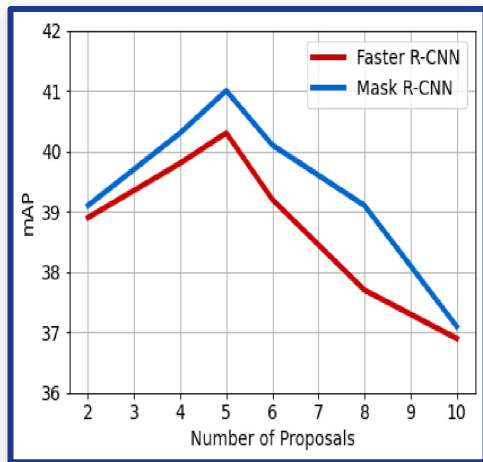
Regressing to Intersections



Half the loss at convergence

# Observations

(c) Top-K proposal

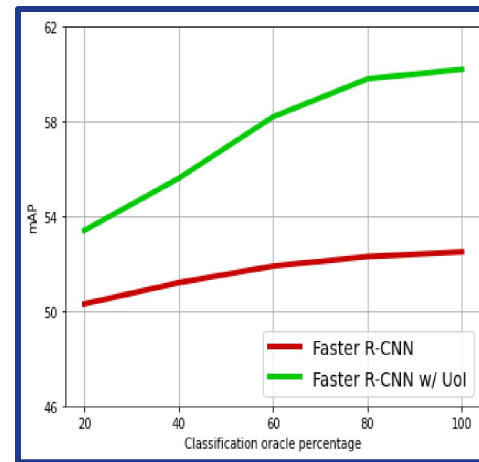


Depends on proposal number



5 is the best

(d) ↑ classifier, ↑ improvement



Classification accuracy improves



Higher relative improvement

## Detection comparison on MS COCO

Method	Backbone	mAP	AP <sub>50</sub>	AP <sub>75</sub>
Faster RCNN	R-50-fpn	37.4	58.1	40.4
<b>Faster RCNN w/ UoI</b>	R-50-fpn	<b>38.1</b>	<b>58.7</b>	<b>40.9</b>
-----				
YOLOv3	DarkNet-53	33.7	56.6	35.3
<b>YOLOv3 w/ UoI</b>	DarkNet-53	<b>34.5</b>	<b>57.5</b>	<b>35.9</b>
-----				
Def-DETR	R-50-fpn	44.3	63.2	48.6
<b>Def-DETR w/ UoI</b>	R-50-fpn	<b>44.8</b>	<b>63.9</b>	<b>49.1</b>

**UoI** works like a plug-and-play across architectures

## Segmentation comparison on MS COCO

Method	Backbone	mAP	AP <sub>s</sub>	AP <sub>M</sub>
Mask RCNN	R-50-fpn	34.7	15.8	36.9
<b>Mask RCNN w/ UoI</b>	R-50-fpn	<b>35.3</b>	<b>16.2</b>	<b>37.5</b>

**UoI** works beyond detection task and improves segmentation



## IoU-type loss based comparison

IoU Loss Type	Base (mAP)	Base w/ <i>Uol</i> (mAP)	Base ( $AP_{75}$ )	Base w/ <i>Uol</i> ( $AP_{75}$ )
L1	37.4	<b>38.1</b>	40.4	<b>40.9</b>
G-IoU	38.0	<b>38.6</b>	41.1	<b>42.0</b>
Alpha-IoU	38.9	<b>39.4</b>	41.8	<b>42.6</b>

Our **Uol** approach does not depend upon the regression loss type

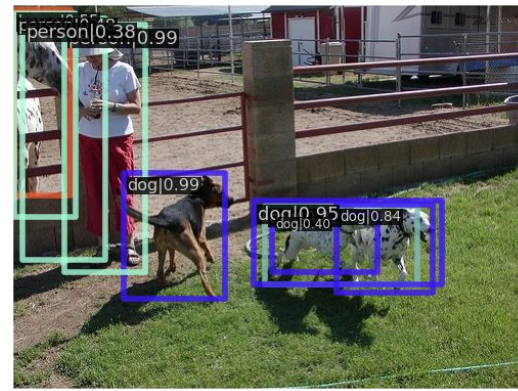
## Grouping method based comparison

NMS Type	Base (mAP)	Base w/ <i>UoI</i> (mAP)	Base (AP <sub>75</sub> )	Base w/ <i>UoI</i> (AP <sub>75</sub> )
NMS	37.4	<b>38.1</b>	40.4	<b>40.9</b>
Cluster-NMS	37.6	<b>38.4</b>	40.4	<b>41.0</b>
Soft-NMS	38.2	<b>38.8</b>	40.9	<b>41.7</b>

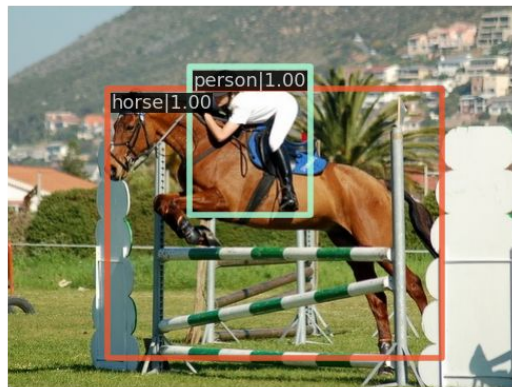
**UoI** performed with better grouping strategies makes it better

## Qualitative results

w/o Uol



w/ Uol



Corrects the stretch of the boxes via **Uol**

## Failure

w/o Uol



w/ Uol



**Uol** sometimes merges multiple instances into one in crowded cases

**THANK YOU**