Mask Scoring R-CNN

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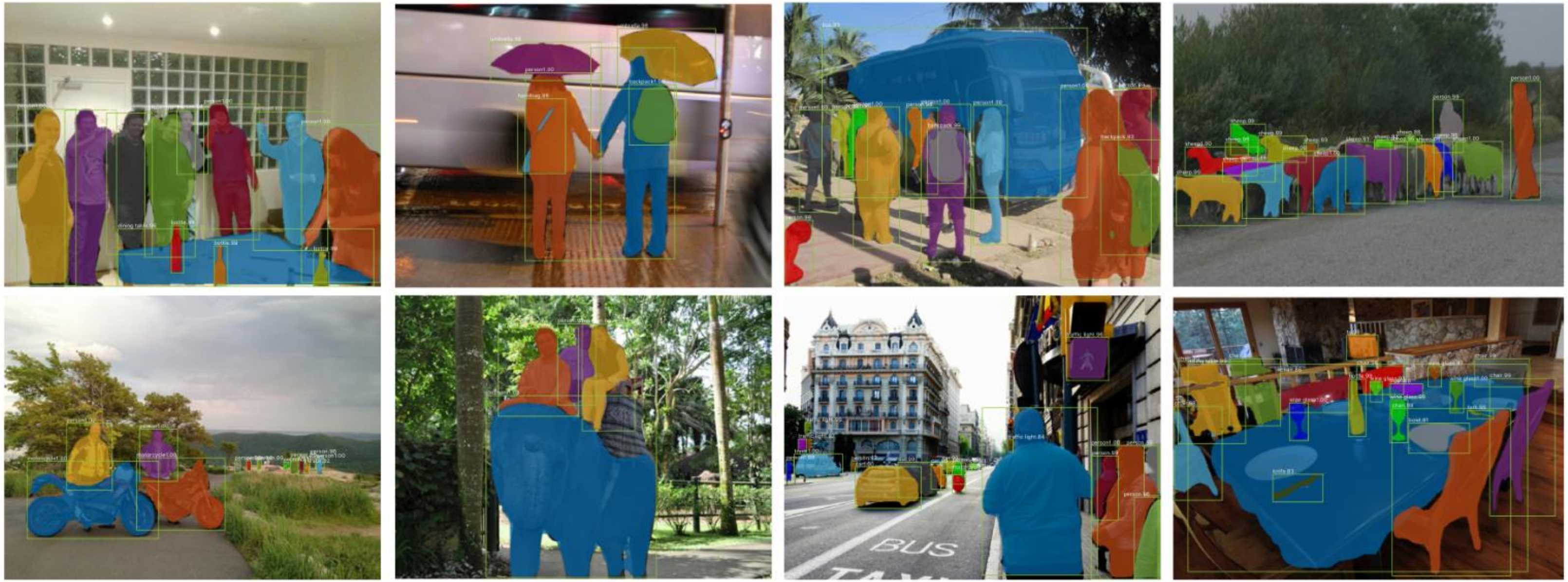
Instance Segmentation

Instance segmentation requires the correct **detection of all objects** in an image while also precisely **segmenting each instance**.



Related Work

Instance segmentation:

Detection based methods:

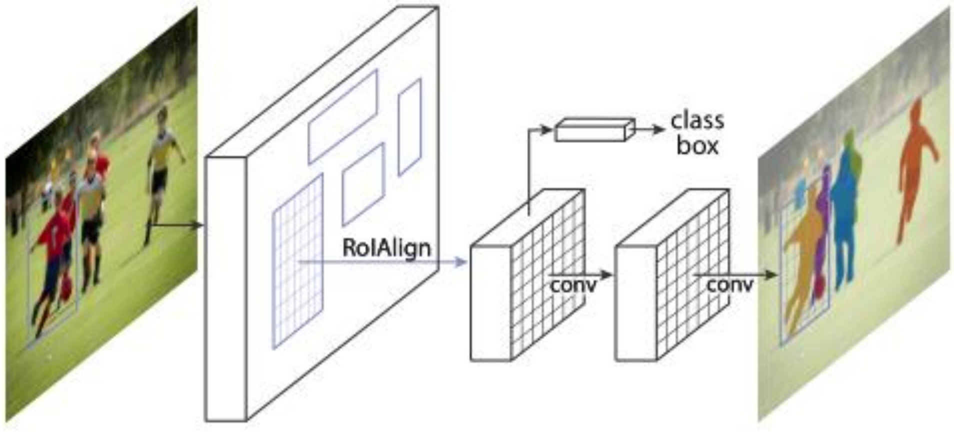
- FCIS [1] takes position-sensitive maps with inside/outside scores to generate the instance segmentation results.
- Mask R-CNN [2] builds on the top of Faster R-CNN by adding an instance level semantic segmentation branch.

Segmentation based methods:

- Liang et al. [3] uses spectral clustering to cluster the pixels.
- Some works [4, 5] add boundary detection information during the clustering procedure.
- Other works [6, 7, 8, 9] cluster instance by the learned embedding.

Mask R-CNN

Mask R-CNN extends Faster R-CNN by adding a branch for predicting an object mask. It use classification score as instance segmentation score (called mask score).

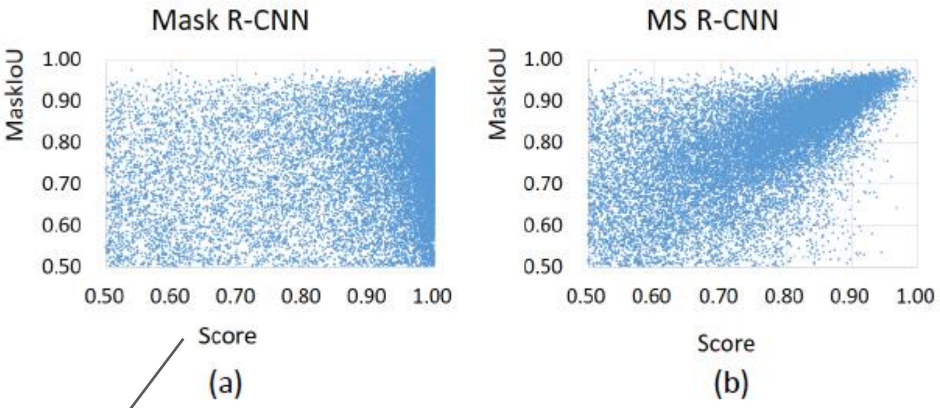


Problem

The mask quality, IoU between the predicted mask and its ground truth mask (**called MaskIoU**), is usually **not well correlated** with the mask score.

Motivation

Learning a calibrated mask score according to MaskIoU for every detection hypothesis.



The MaskIoU and mask score is not well correlated
in Mask R-CNN.

Related Work

IoU in detection:

- Fitness NMS [10] formulates box IoU prediction as a classification task.
- IoU-Net [11] regresses box IoU directly, and the predicted IoU was used for both NMS and bounding box refinement.

  Our method is similar to IoU-Net. Here we list some differences with IoU-Net:

  1. We use IoU for mask instead of box.
  2. The IoU is used for correcting score instead of for box refinement or NMS.

Method

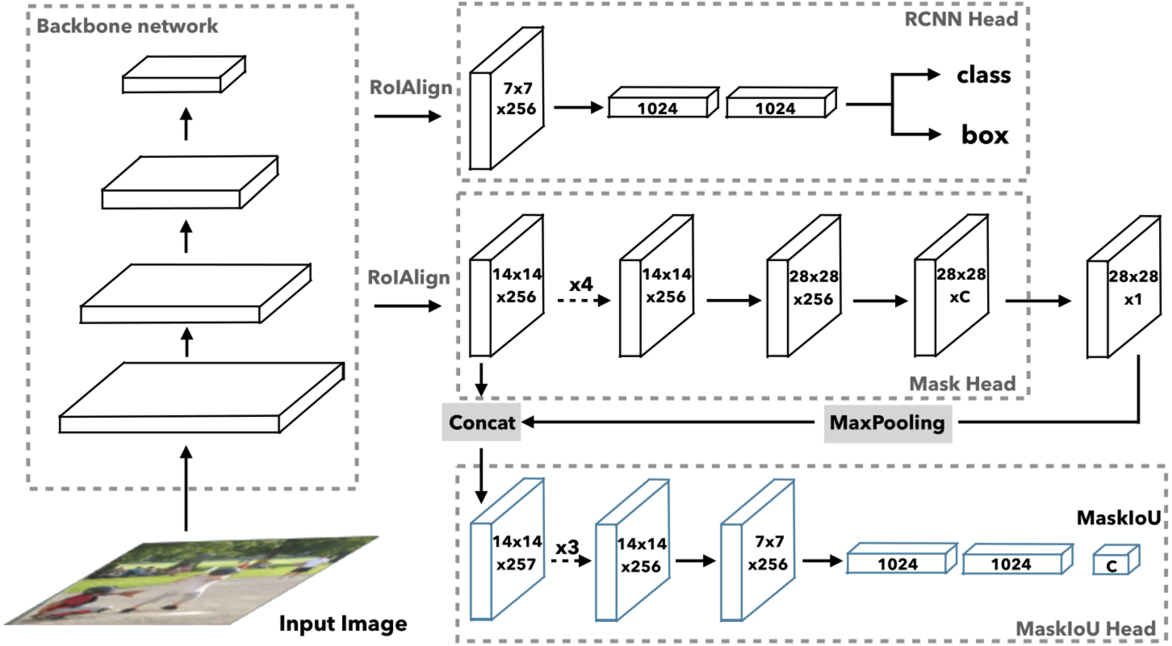
Mask scoring:

Decompose the mask score learning task into:

- **mask classification:** The mask classification score can directly take the corresponding classification score from R-CNN stage.
- **IoU regression**. The IoU can be learned by our propose MaskIoU head.

Method

Network: extends Mask R-CNN by adding a branch called MaskIoU head for predicting MaskIoU.



Method

Training:

- **Training samples for MaskIoU head**: the same with the training samples of the Mask head in Mask R-CNN.
- **Training targets**: the IoU between the predicted mask and its matched ground truth.
- **Training loss**: L2 loss for regression and the loss weight is set to 1.

Method

Inference:

1. Selecting top-k (i.e. k = 100) scoring boxes after SoftNMS.
2. The top-k boxes are fed into the Mask head to generate multi-class masks.
3. Feed the top-k target masks to MaskIoU head for predicting MaskIoU.
4. The predicted MaskIoU is multiplied with classification score, to get the new calibrated mask score as the final mask confidence.

1, 2 are the standard Mask R-CNN inference procedure.

Quantitative Results

Results in different backbone networks (ResNet/18/50/101).

Backbone	MaskIoU head	AP_m	AP_m@0.5	AP_m@0.75	AP_b	AP_b@0.5	AP_b@0.75
ResNet-18 FPN		27.7	46.9	29.0	31.2	50.4	33.2
	✓	29.3	46.9	31.3	31.5	50.8	33.5
ResNet-50 FPN		34.5	55.8	36.7	38.6	59.2	42.5
	✓	36.0	55.8	38.8	38.6	59.2	42.5
ResNet-101 FPN		36.6	58.6	39.0	41.3	61.7	45.9
	✓	38.2	58.4	41.5	41.4	61.8	46.3

We can get improvement in different backbone network!

Quantitative Results

Results in different frameworks (Faster R-CNN/FPN/DCN+FPN).

Backbone	MaskIoU head	FPN	DCN	AP_m	AP_m@0.5	AP_m@0.75	AP_b	AP_b@0.5	AP_b@0.75
ResNet-101				33.9	53.9	36.2	38.6	57.3	42.8
	✓			35.0	54.0	37.7	38.7	57.4	43.0
		✓		36.6	58.6	39.0	41.3	61.7	45.9
	✓	✓		38.2	58.4	41.5	41.4	61.8	46.3
		✓	✓	37.7	60.3	40.0	42.9	63.4	47.8
	✓	✓	✓	39.1	60.0	42.4	43.1	63.5	47.7

We can get improvement in different framework!

Quantitative Results

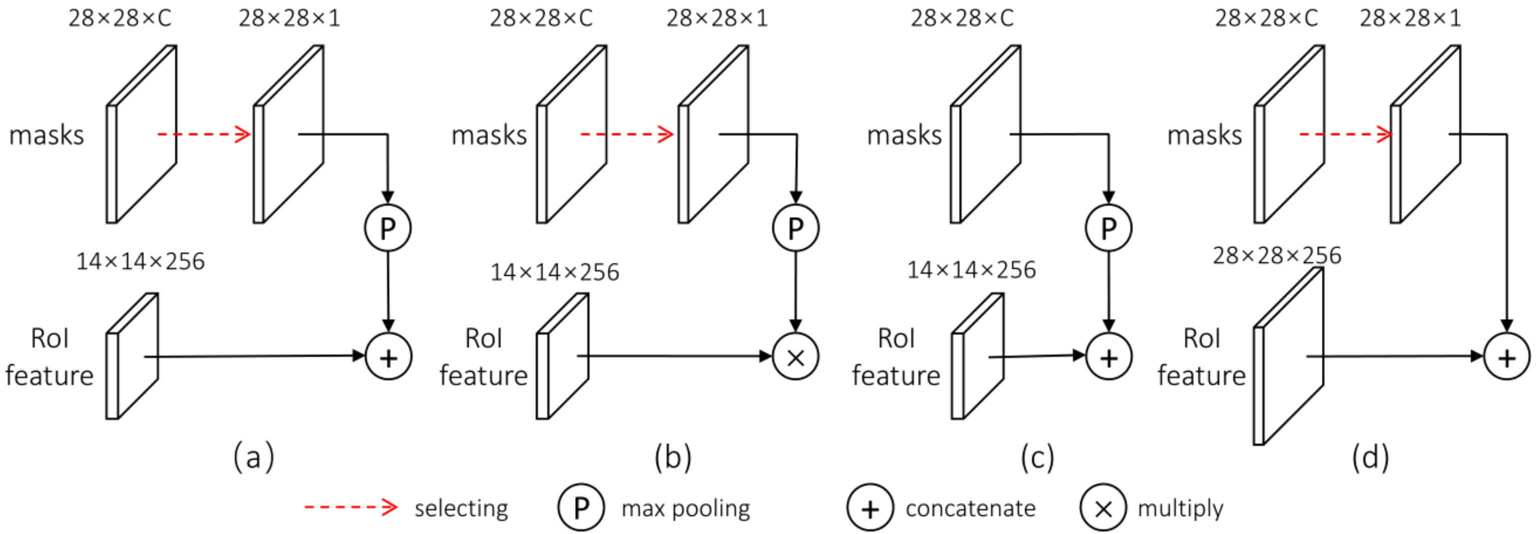
Comparing different instance segmentation methods on COCO 2017 test-dev.

Method	Backbone	AP	AP@0.5	AP@0.75	AP_S	AP_M	AP_L
MNC [7]	ResNet-101	24.6	44.3	24.8	4.7	25.9	43.6
FCIS [23]	ResNet-101	29.2	49.5	-	-	-	-
FCIS+++ [23]	ResNet-101	33.6	54.5	-	-	-	-
Mask R-CNN [15]	ResNet-101	33.1	54.9	34.8	12.1	35.6	51.1
Mask R-CNN [15]	ResNet-101 FPN	35.7	58.0	37.8	15.5	38.1	52.4
Mask R-CNN [15]	ResNeXt-101 FPN	37.1	60.0	39.4	16.9	39.9	53.5
MaskLab [3]	ResNet-101	35.4	57.4	37.4	16.9	38.3	49.2
MaskLab+ [3]	ResNet-101	37.3	59.8	36.6	19.1	40.5	50.6
MaskLab+ [3]	ResNet-101 (JET)	38.1	61.1	40.4	19.6	41.6	51.4
Mask R-CNN	ResNet-101	34.3	55.0	36.6	13.2	36.4	52.2
MS R-CNN	ResNet-101	35.4	54.9	38.1	13.7	37.6	53.3
Mask R-CNN	ResNet-101 FPN	37.0	59.2	39.5	17.1	39.3	52.9
MS R-CNN	ResNet-101 FPN	38.3	58.8	41.5	17.8	40.4	54.4
Mask R-CNN	ResNet-101 DCN+FPN	38.4	61.2	41.2	18.0	40.5	55.2
MS R-CNN	ResNet-101 DCN+FPN	39.6	60.7	43.1	18.8	41.5	56.2

Ablation Study

The design choices of MaskIoU head input:

Setting	AP	AP@0.5	AP@0.75
Mask R-CNN baseline	27.7	46.9	29.0
(a) Target mask + RoI	29.3	46.9	31.3
(b) Target mask × RoI	29.1	46.6	30.9
(c) All masks + RoI	29.1	46.6	30.8
(d) Target mask + HR RoI	29.1	46.7	31.1



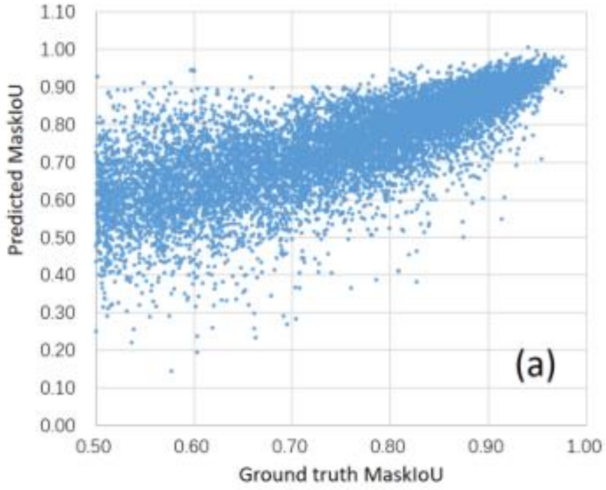
Ablation Study

How to select training samples: we use the samples whose MaskIoU are larger than τ to train the MaskIoU head.

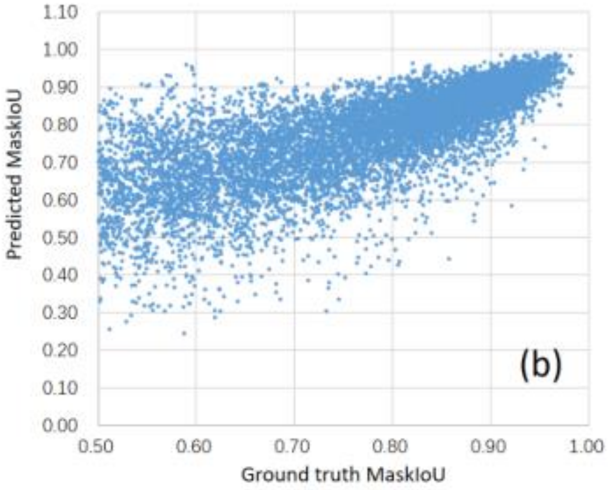
Threshold	AP	AP@0.5	AP@0.75
$\tau = 0.0$	29.3	46.9	31.3
$\tau = 0.3$	29.2	46.6	31.1
$\tau = 0.5$	29.0	46.5	30.9
$\tau = 0.7$	28.8	46.9	30.5

Discussion

The quality of the predicted MaskIoU: the correlation coefficient are both about 0.74.



ResNet-18 FPN



ResNet-101 DCN+FPN

Discussion

The upper bound performance of MS RCNN: use the ground truth MaskIoU to replace the predicted MaskIoU when the ground truth MaskIoU larger than 0.

Method	Backbone	AP
Mask R-CNN	ResNet-18 FPN	27.7
MS R-CNN		29.3
MS R-CNN*		31.5
Mask R-CNN	ResNet-101 DCN+FPN	37.7
MS R-CNN		39.1
MS R-CNN*		41.7

Discussion

- **FLOPs**: our MaskIoU head has about 0.39G FLOPs while Mask head has about 0.53G FLOPs for each proposal.
- **Running time**: the testing speed (sec./image) of MS R-CNN and Mask R-CNN is almost the same. ResNet-18 FPN: both about 0.132. ResNet-101 DCN+FPN: both about 0.202.

Codes

github: https://github.com/zjhuang22/maskscoring_rcnn (nearly 1000 stars)

Thanks

We are hiring(intern and full time): lichao.huang@horizon.ai

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