Masked R-CNN Paper Presentation

https://arxiv.org/abs/1703.06870

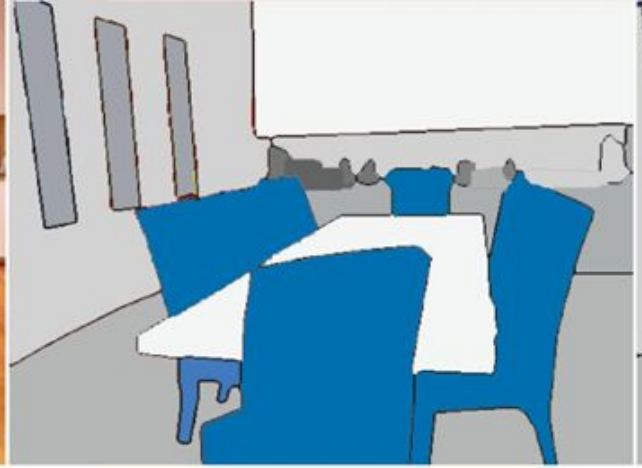
Mask RCNN

Simple to train

Small overhead to faster RCNN

Easy to generalize

Input Image



Semantic Segmentation

Instance Segmentation

Semantic Segmentation - Task of clustering parts of an image together which belong to the same class

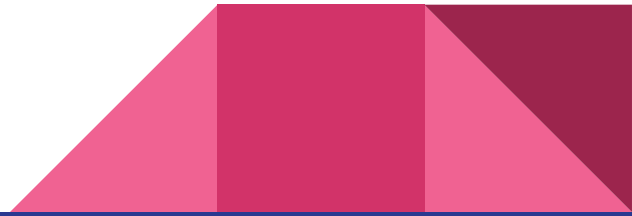
Instance segmentation - detecting and delineating each distinct object of interest appearing in an image

Faster RCNN : Fast RCNN + RPN

Mask RCNN : Faster RCNN + mask branch

Mask RCNN extends faster RCNN by adding a branch for detecting segmentation masks on ROI in **parallel**

Mask branch is a small FCN applied to each ROI in a pixel-to-pixel manner



ROIAlign vs ROIPool

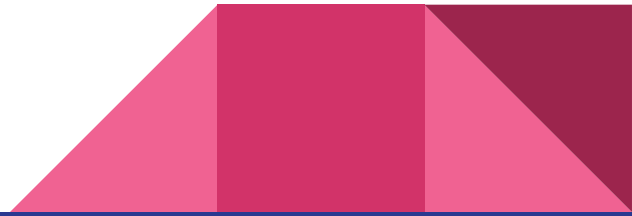
Faster RCNN not intended for pixel to pixel alignment

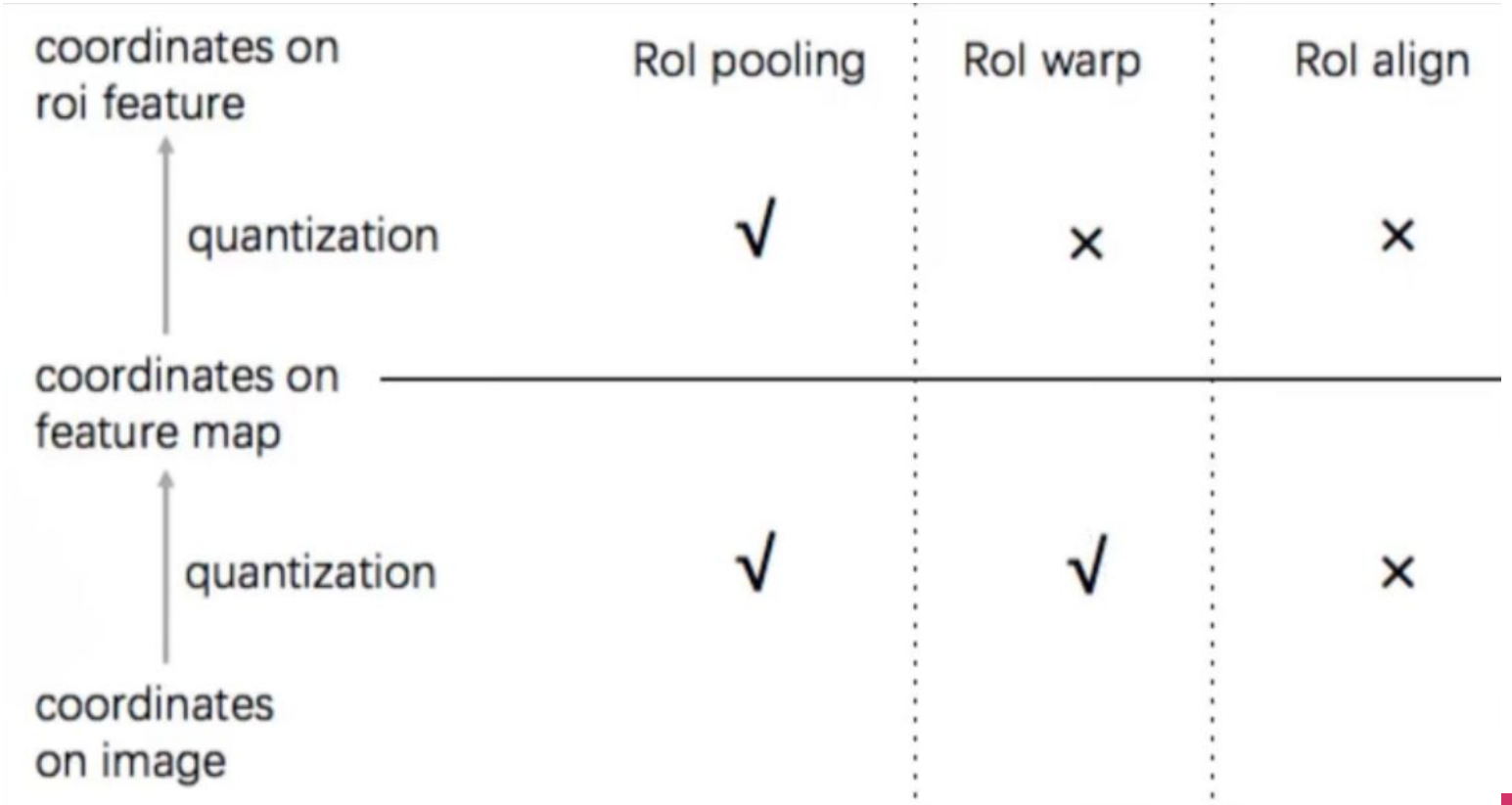
For mask RCNN, alignment is important

ROIAlign replaces ROIPool

Seems a small difference but has a large impact

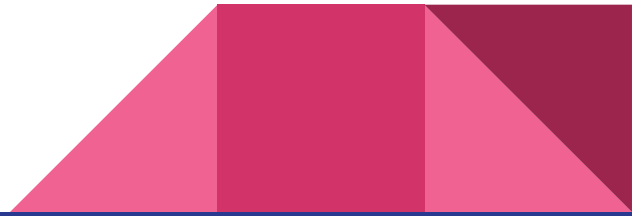
Improves mask accuracy from 10 to 50%



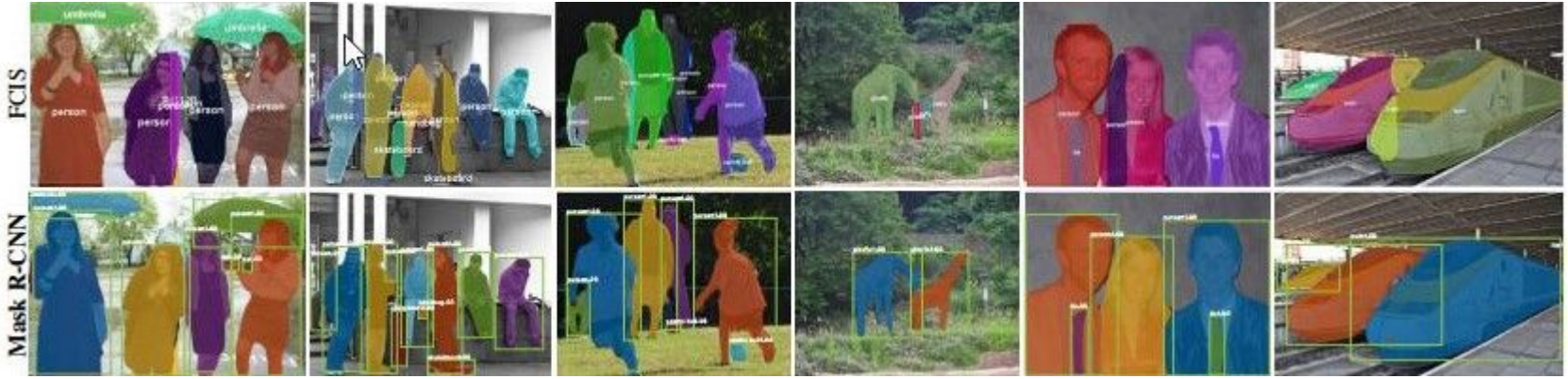

coordinates on roi feature
RoI pooling
RoI warp
RoI align
quantization
√
×
×
coordinates on feature map
quantization
√
√
×
coordinates on image

Decoupling of mask and class prediction

FCNs usually perform per pixel multi class categorization, which does segmentation and classification together



Related Work



Dai et al. proposed complex multiple stage cascade predicting segment proposals from bounding box proposals , followed by classification

Doing this in parallel makes it simple and flexible

FCIS(Fully convolutional instance segmentation) - position sensitive output channels convolutionally. Overlap error

Mask

L = Lcls + Lbox + Lmask

First two terms same as in faster RCNN

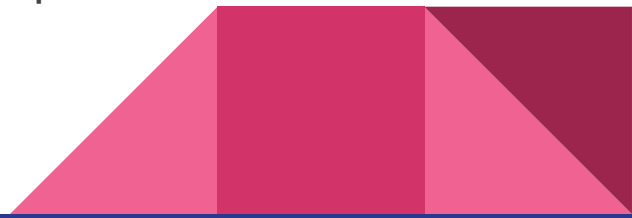
Mask branch has Km^2 dimensional output

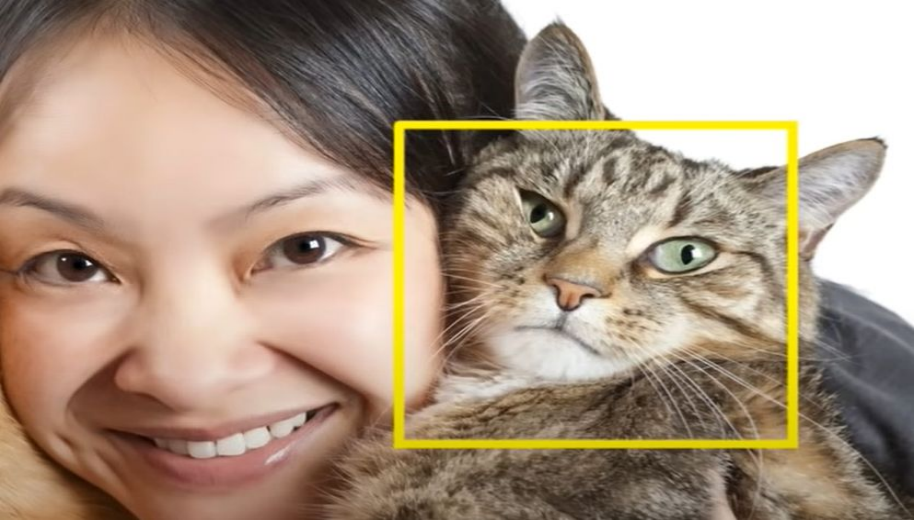
M x m for k classes

Lmask is the average cross entropy loss of the per pixel sigmoid defined only on the k-th mask(ground truth class is k)

Contribution of other mask outputs do not contribute to the specific mask

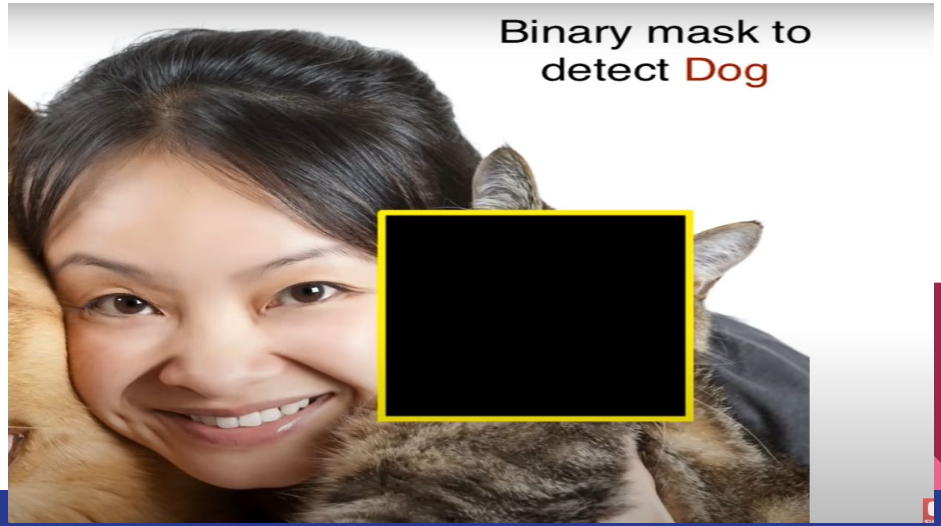
Mask for every class defined without competition






Binary mask to
detect Cat

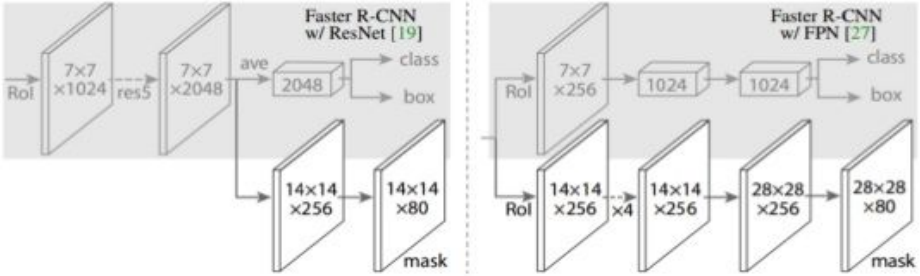

Binary mask t
detect Humar


Binary mask to
detect Dog

Architecture

Mask R-CNN

- Mask R-CNN extends Faster R-CNN by adding a branch for predicting segmentation masks on each Region of Interest (RoI), in parallel with the existing branch for classification and bounding box regression



Backbone : feature extraction over entire image

Head : bounding box recognition and mask prediction applied separately to each ROI

Demonstrates generality

Implementation

- RoI is positive it IoU >= 0.5 and –ve O.W.
- Ratio of +ve to –ve is 1:3 .
- At test time box prediction is run on proposals viz followed by non-max suppression.
- Mask is finally applied to the top 100 detection boxes.
- Only the k-th mask predicted by mask branch (k is predicted class by cls branch).

Test Results

	backbone	AP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L
MNC [10]	ResNet-101-C4	24.6	44.3	24.8	4.7	25.9	43.6
FCIS [26] +OHEM	ResNet-101-C5-dilated	29.2	49.5	-	7.1	31.3	50.0
FCIS+++ [26] +OHEM	ResNet-101-C5-dilated	33.6	54.5	-	-	-	-
Mask R-CNN	ResNet-101-C4	33.1	54.9	34.8	12.1	35.6	51.1
Mask R-CNN	ResNet-101-FPN	35.7	58.0	37.8	15.5	38.1	52.4
Mask R-CNN	ResNeXt-101-FPN	**37.1**	**60.0**	**39.4**	**16.9**	**39.9**	**53.5**

Table 1. **Instance segmentation** *mask* AP on COCO `test-dev`. MNC [10] and FCIS [26] are the winners of the COCO 2015 and 2016 segmentation challenges, respectively. Without bells and whistles, Mask R-CNN outperforms the more complex FCIS+++, which includes multi-scale train/test, horizontal flip test, and OHEM [38]. All entries are *single-model* results.

Test Results

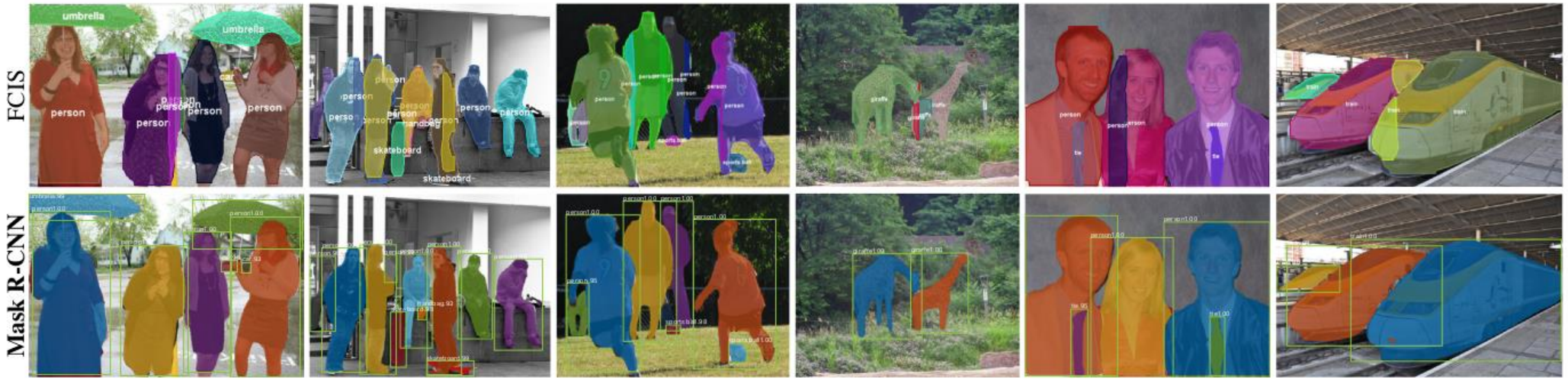


Figure 6. FCIS+++ [26] (top) *vs*. Mask R-CNN (bottom, ResNet-101-FPN). FCIS exhibits systematic artifacts on overlapping objects.

Test Results

net-depth-features	AP	AP_{50}	AP_{75}
ResNet-50-C4	30.3	51.2	31.5
ResNet-101-C4	32.7	54.2	34.3
ResNet-50-FPN	33.6	55.2	35.3
ResNet-101-FPN	35.4	57.3	37.5
ResNeXt-101-FPN	**36.7**	**59.5**	**38.9**

(a) **Backbone Architecture**: Better backbones bring expected gains: deeper networks do better, FPN outperforms C4 features, and ResNeXt improves on ResNet.

	AP	AP_{50}	AP_{75}
softmax	24.8	44.1	25.1
sigmoid	**30.3**	**51.2**	**31.5**
	+5.5	*+7.1*	*+6.4*

(b) **Multinomial *vs.* Independent Masks** (ResNet-50-C4): *Decoupling* via per-class binary masks (sigmoid) gives large gains over multinomial masks (softmax).

	align?	bilinear?	agg.	AP	AP_{50}	AP_{75}
RoIPool [12]			max	26.9	48.8	26.4
RoIWarp [10]		✓	max	27.2	49.2	27.1
		✓	ave	27.1	48.9	27.1
RoIAlign	✓	✓	max	**30.2**	**51.0**	**31.8**
	✓	✓	ave	**30.3**	**51.2**	**31.5**

(c) **RoIAlign** (ResNet-50-C4): Mask results with various RoI layers. Our RoIAlign layer improves AP by ~3 points and AP_{75} by ~5 points. Using proper alignment is the only factor that contributes to the large gap between RoI layers.

	AP	AP_{50}	AP_{75}	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}
RoIPool	23.6	46.5	21.6	28.2	52.7	26.9
RoIAlign	**30.9**	**51.8**	**32.1**	**34.0**	**55.3**	**36.4**
	+7.3	*+ 5.3*	*+10.5*	*+5.8*	*+2.6*	*+9.5*

(d) **RoIAlign** (ResNet-50-**C5**, *stride 32*): Mask-level and box-level AP using *large-stride* features. Misalignments are more severe than with stride-16 features (Table 2c), resulting in big accuracy gaps.

	mask branch	AP	AP_{50}	AP_{75}
MLP	fc: $1024 \rightarrow 1024 \rightarrow 80 \cdot 28^2$	31.5	53.7	32.8
MLP	fc: $1024 \rightarrow 1024 \rightarrow 1024 \rightarrow 80 \cdot 28^2$	31.5	54.0	32.6
FCN	conv: $256 \rightarrow 256 \rightarrow 256 \rightarrow 256 \rightarrow 256 \rightarrow 80$	**33.6**	**55.2**	**35.3**

(e) **Mask Branch** (ResNet-50-FPN): Fully convolutional networks (FCN) *vs.* multi-layer perceptrons (MLP, fully-connected) for mask prediction. FCNs improve results as they take advantage of explicitly encoding spatial layout.

Table 2. **Ablations**. We train on `trainval35k`, test on `minival`, and report *mask* AP unless otherwise noted.

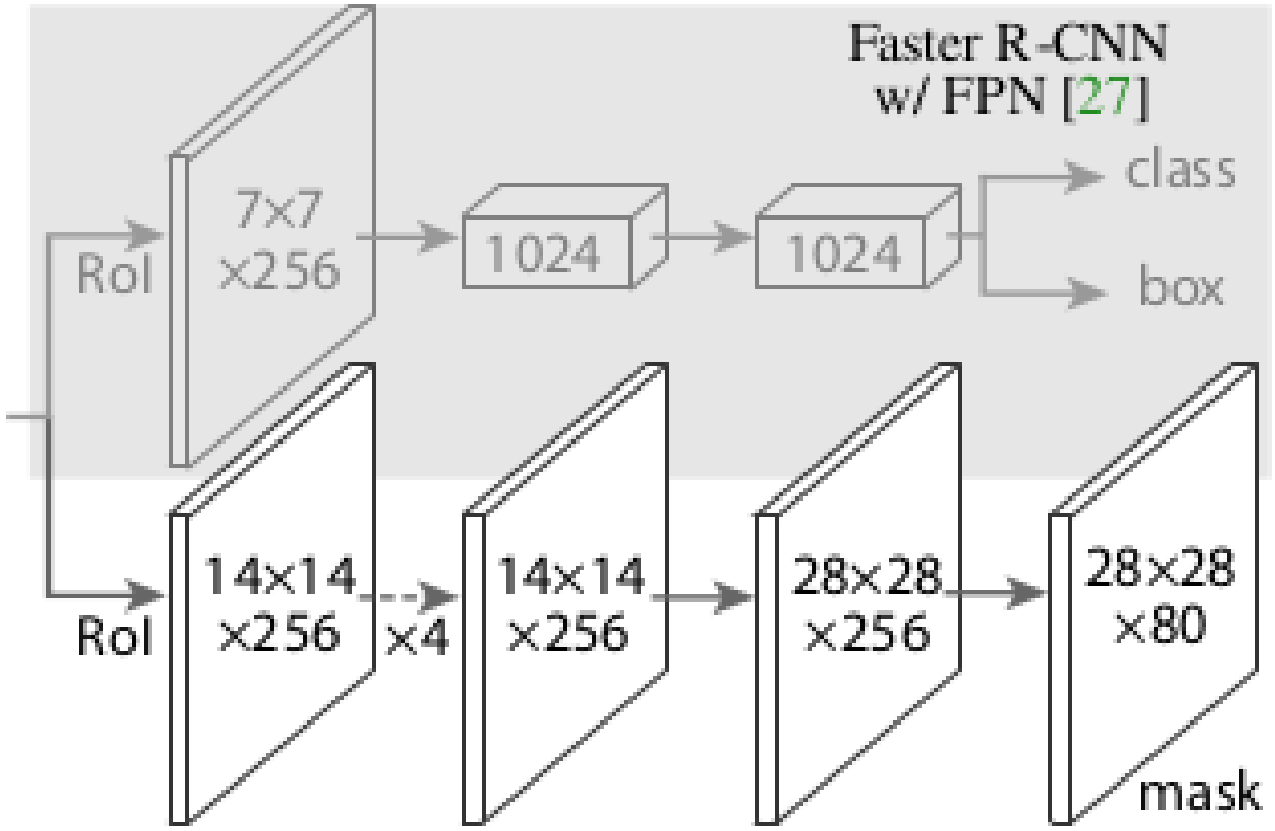
Test Results

	backbone	AP^{bb}	AP^{bb}_{50}	AP^{bb}_{75}	AP^{bb}_{S}	AP^{bb}_{M}	AP^{bb}_{L}
Faster R-CNN+++ [19]	ResNet-101-C4	34.9	55.7	37.4	15.6	38.7	50.9
Faster R-CNN w FPN [27]	ResNet-101-FPN	36.2	59.1	39.0	18.2	39.0	48.2
Faster R-CNN by G-RMI [21]	Inception-ResNet-v2 [41]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [39]	Inception-ResNet-v2-TDM	36.8	57.7	39.2	16.2	39.8	**52.1**
Faster R-CNN, RoIAlign	ResNet-101-FPN	37.3	59.6	40.3	19.8	40.2	48.8
Mask R-CNN	ResNet-101-FPN	38.2	60.3	41.7	20.1	41.1	50.2
Mask R-CNN	ResNeXt-101-FPN	**39.8**	**62.3**	**43.4**	**22.1**	**43.2**	51.2

Table 3. **Object detection** *single-model* results (bounding box AP), *vs.* state-of-the-art on `test-dev`. Mask R-CNN using ResNet-101-FPN outperforms the base variants of all previous state-of-the-art models (the mask output is ignored in these experiments). The gains of Mask R-CNN over [27] come from using RoIAlign (+1.1 AP^{bb}), multitask training (+0.9 AP^{bb}), and ResNeXt-101 (+1.6 AP^{bb}).

Mask R-CNN for Human Pose Estimation

- Model keypoint's location as a one-hot mask.
- Mask R-CNN is used to predict the K masks for K keypoints in the human body.
- For each keypoint instance segmentation training target is a one-hot m x m binary mask.



Human pose estimation

- Key point head is similar to architecture given here.
- The keypoint head consists of a stack of eight 3×3 512-d conv layers, followed by a deconv layer and 2× bilinear upscaling, producing an output resolution of 56×56.
- High resolution o/p increases key point localization accuracy.

Keypoint detection results

Figure 7. Keypoint detection results on COCO `test` using Mask R-CNN (ResNet-50-FPN), with person segmentation masks predicted from the same model. This model has a keypoint AP of 63.1 and runs at 5 fps.

	AP^{kp}	AP^{kp}_{50}	AP^{kp}_{75}	AP^{kp}_{M}	AP^{kp}_{L}
CMU-Pose+++ [6]	61.8	84.9	67.5	57.1	68.2
G-RMI [32]†	62.4	84.0	68.5	**59.1**	68.1
Mask R-CNN, keypoint-only	62.7	87.0	68.4	57.4	71.1
Mask R-CNN, keypoint & mask	**63.1**	**87.3**	**68.7**	57.8	**71.4**

Table 4. **Keypoint detection** AP on COCO `test-dev`. Ours is a single model (ResNet-50-FPN) that runs at 5 fps. CMU-Pose+++ [6] is the 2016 competition winner that uses multi-scale testing, post-processing with CPM [44], and filtering with an object detector, adding a cumulative ~5 points (clarified in personal communication). †: G-RMI was trained on COCO *plus* MPII [1] (25k images), using two models (Inception-ResNet-v2 for bounding box detection and ResNet-101 for keypoints).

single point to be detected). We note that as in instance seg-

	AP^{bb}_{person}	AP^{mask}_{person}	AP^{kp}
Faster R-CNN	52.5	-	-
Mask R-CNN, mask-only	**53.6**	**45.8**	-
Mask R-CNN, keypoint-only	50.7	-	64.2
Mask R-CNN, keypoint & mask	52.0	45.1	**64.7**

Table 5. **Multi-task learning** of box, mask, and keypoint about the *person* category, evaluated on `minival`. All entries are trained on the same data for fair comparisons. The backbone is ResNet-50-FPN. The entries with 64.2 and 64.7 AP on `minival` have `test-dev` AP of 62.7 and 63.1, respectively (see Table 4).

	AP^{kp}	AP^{kp}_{50}	AP^{kp}_{75}	AP^{kp}_{M}	AP^{kp}_{L}
RoIPool	59.8	86.2	66.7	55.1	67.4
RoIAlign	**64.2**	**86.6**	**69.7**	**58.7**	**73.0**

Table 6. **RoIAlign *vs.* RoIPool** for keypoint detection on `minival`. The backbone is ResNet-50-FPN.

Results on Cityscapes

	training data	AP [val]	AP	AP_{50}	person	rider	car	truck	bus	train	mcycle	bicycle
InstanceCut [23]	fine + coarse	15.8	13.0	27.9	10.0	8.0	23.7	14.0	19.5	15.2	9.3	4.7
DWT [4]	fine	19.8	15.6	30.0	15.1	11.7	32.9	17.1	20.4	15.0	7.9	4.9
SAIS [17]	fine	-	17.4	36.7	14.6	12.9	35.7	16.0	23.2	19.0	10.3	7.8
DIN [3]	fine + coarse	-	20.0	38.8	16.5	16.7	25.7	20.6	30.0	23.4	17.1	10.1
SGN [29]	fine + coarse	29.2	25.0	44.9	21.8	20.1	39.4	24.8	33.2	30.8	17.7	12.4
Mask R-CNN	fine	31.5	26.2	49.9	30.5	23.7	46.9	22.8	32.2	18.6	19.1	16.0
Mask R-CNN	fine + COCO	**36.4**	**32.0**	**58.1**	**34.8**	**27.0**	**49.1**	**30.1**	**40.9**	**30.9**	**24.1**	**18.7**

Table 7. Results on Cityscapes val ('AP [val]' column) and test (remaining columns) sets. Our method uses ResNet-50-FPN.