

Instance segmentation with Mask R-CNN

Seminar: Current Works in Computer Vision

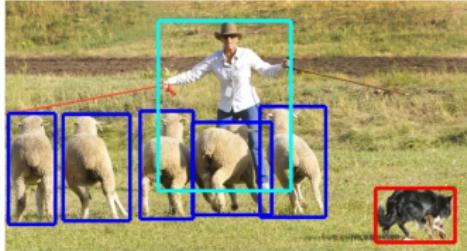
Silvio Galessio



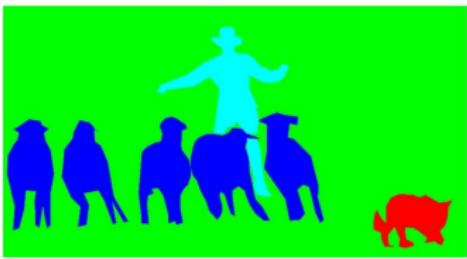
Scene understanding



Image classification



Object detection



Semantic segmentation



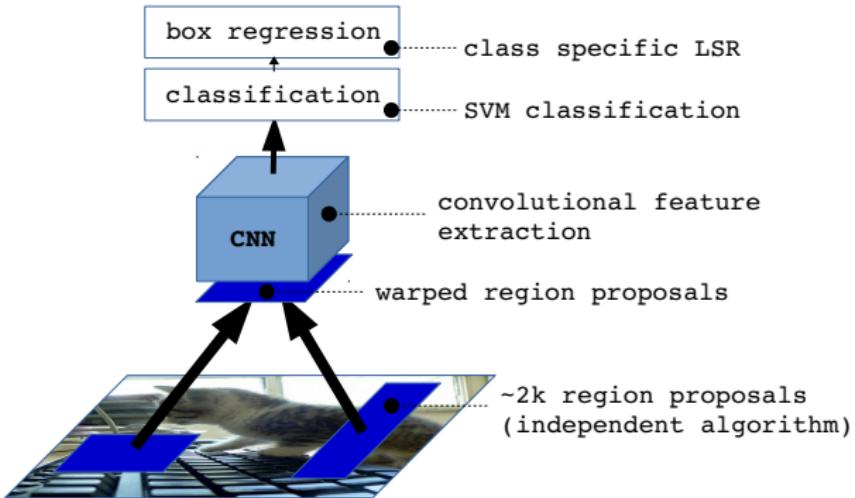
Instance segmentation

Source: Lin et al., Microsoft COCO: Common Objects in Context

Mask R-CNN: Motivation and goals

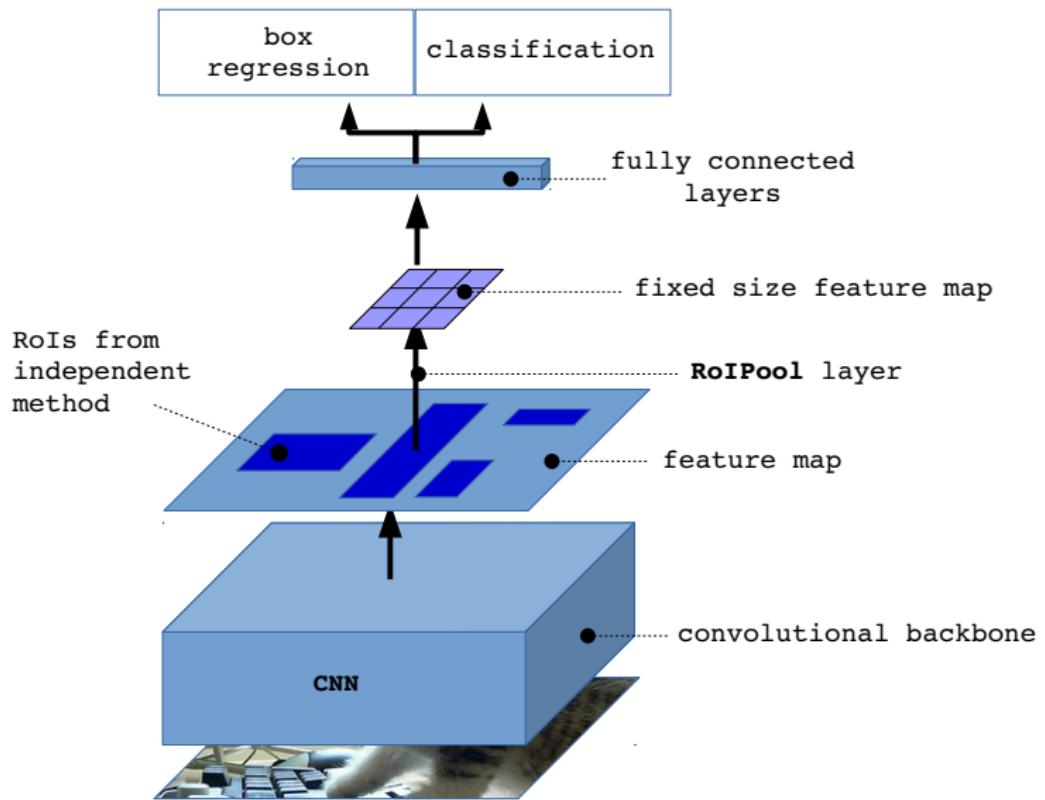
- State of the art multitask model for visual scene understanding:
 - object detection
 - classification
 - instance segmentation
- Highly modular and easy to train
- Flexible: e.g. human pose estimation with minor changes

Background: R-CNN architechture

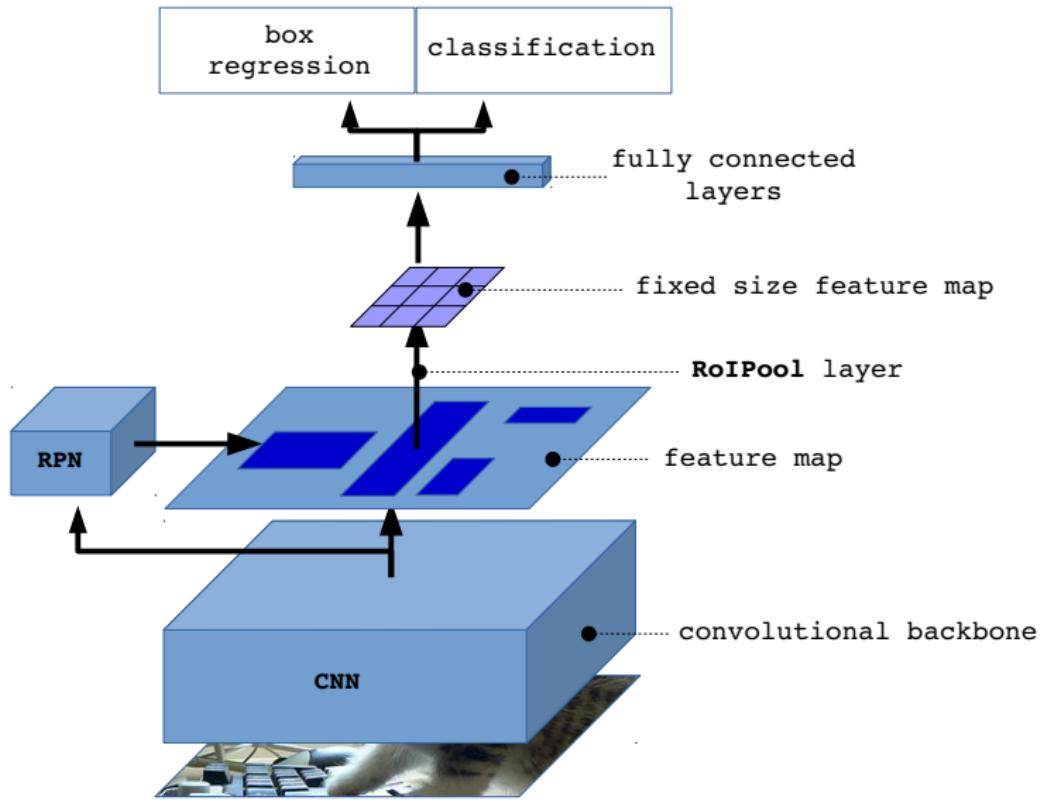


- Based on proposed Regions of Interest (RoI)
- Requires region warping for fixed size features
- Very inefficient pipeline

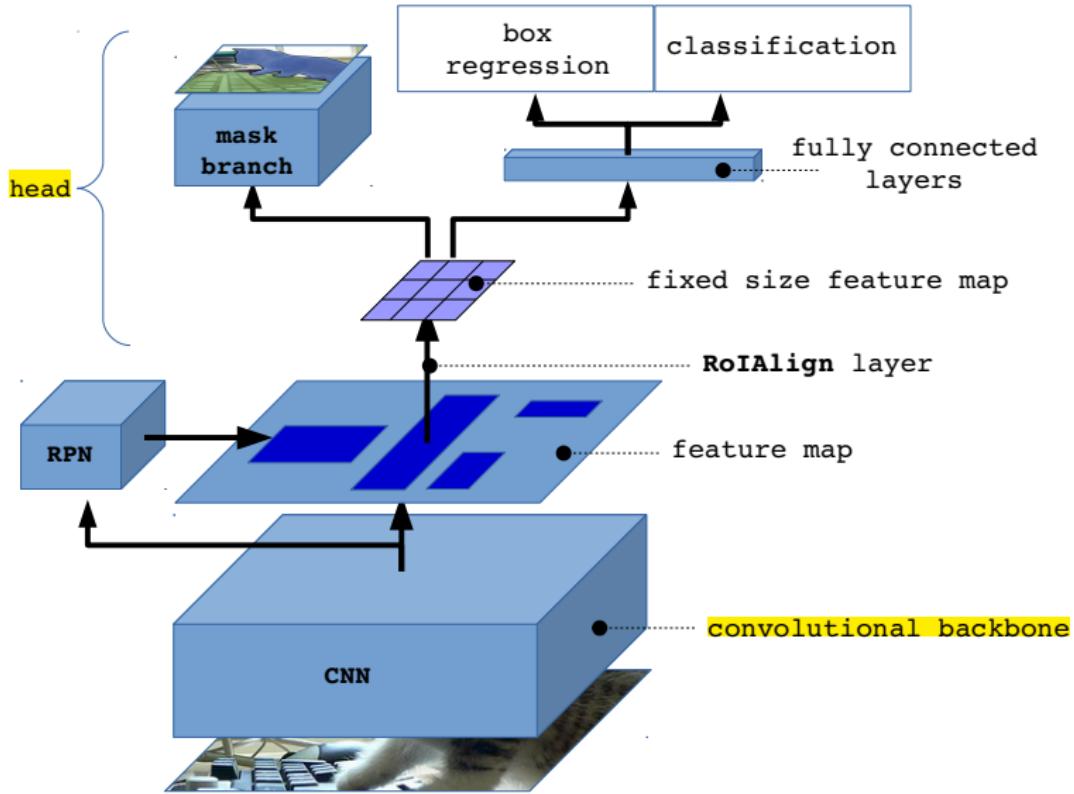
Background: Fast R-CNN



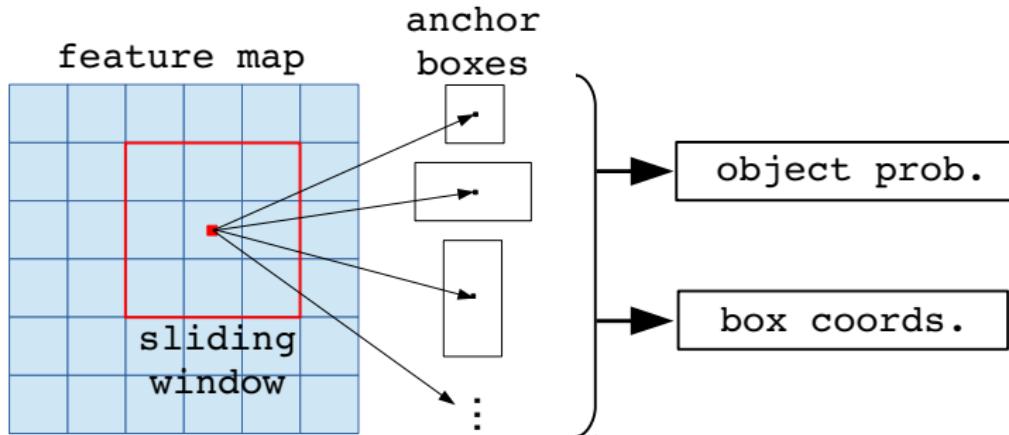
Background: Faster R-CNN



Mask R-CNN: overview

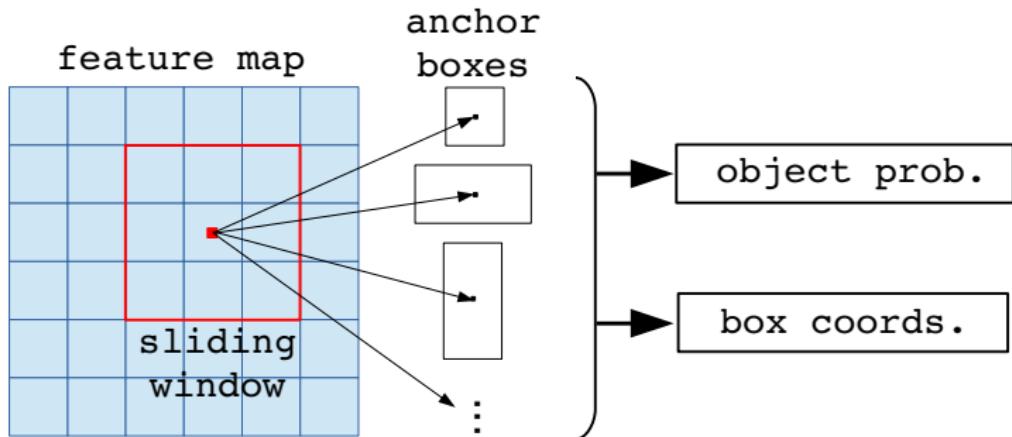


Region Proposal Network



- Shared conv layers with main model
- $n \times n$ sliding window, large receptive field
- Parallel branches:
 - object probability classification
 - box regression

Region Proposal Network

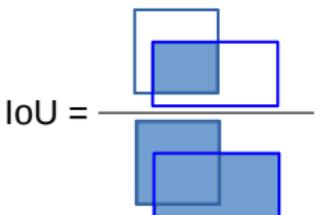


Anchor boxes:

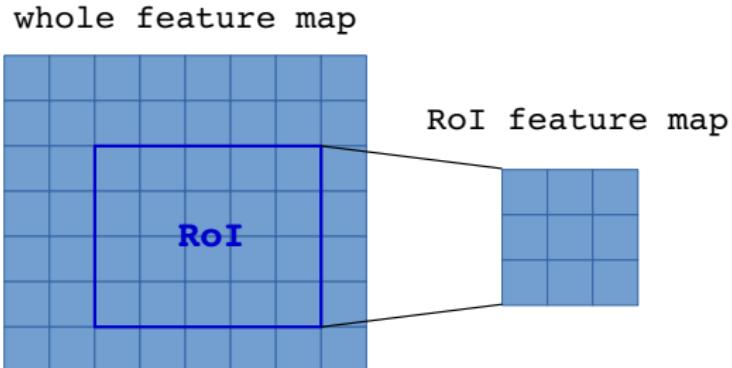
- for every window position, k region prototypes
- multiple scales, e.g. $128^2, 256^2, 512^2$
- multiple ratios, e.g. $1 : 1, 1 : 2, 2 : 1$

Region Proposal Network

- Multiple anchor scales and ratios → single scale images
- Proposal evaluation based on Intersection over Union with ground truth boxes:
 - best regions are kept as positive examples
 - worst ($\text{IoU} < 0.3$) are kept as negatives for training



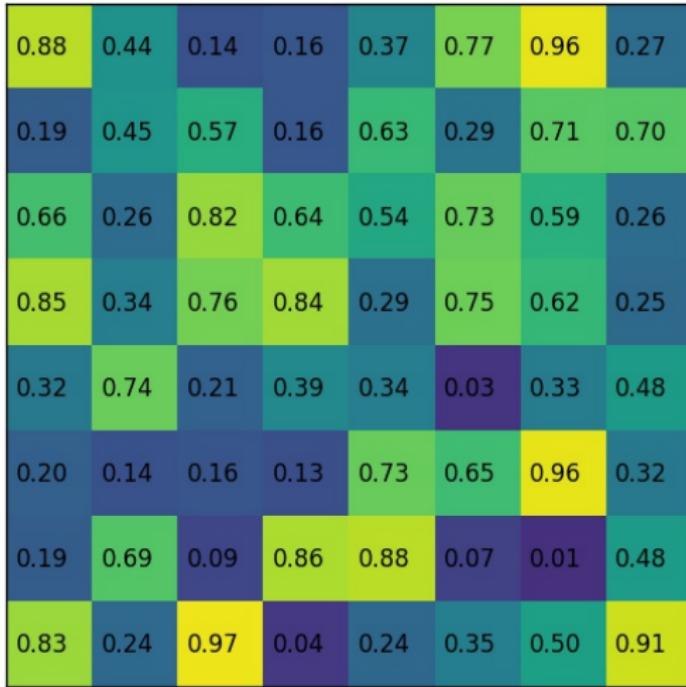
RoI feature extraction



- RoIPool: **quantized bins + pooling**
 - continuous roi feature map+
- RoIAvgPool: continuous bins + bilinear interpolation + pooling
⇒ better preserved spatial correspondence

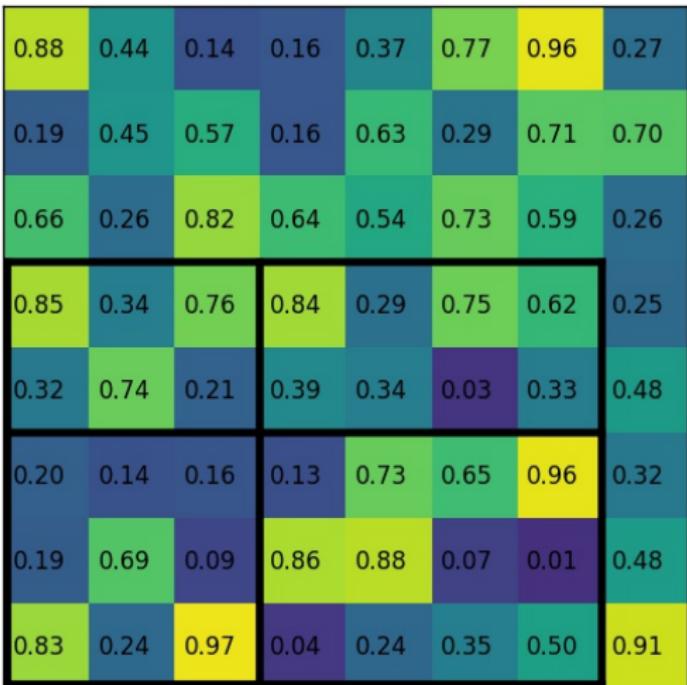
RoIPool (Faster R-CNN)

Source: <https://deepsense.io/region-of-interest-pooling-explained/>



Input activation

RoIPool (Faster R-CNN)



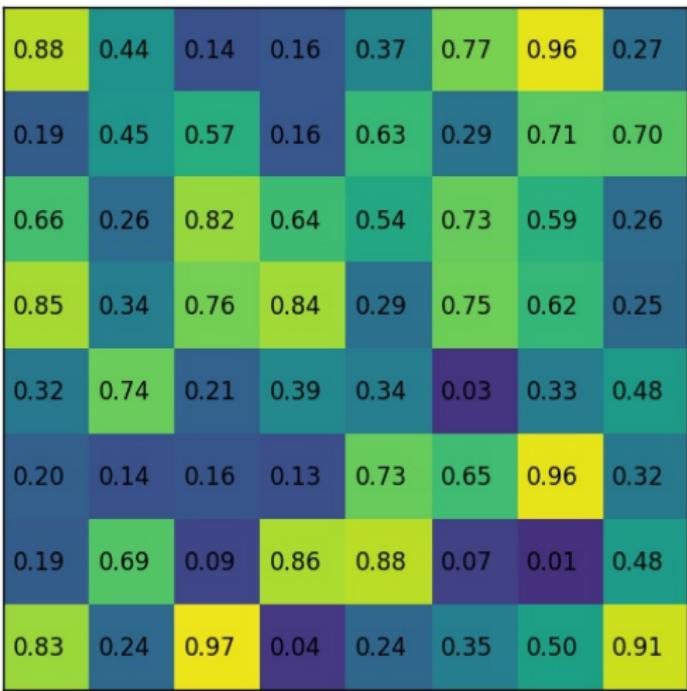
Region projection and pooling sections

RoIPool (Faster R-CNN)



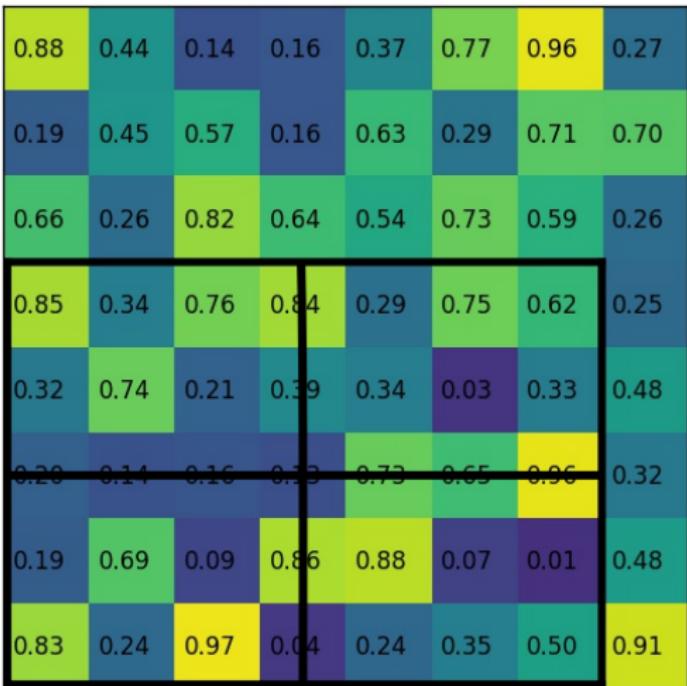
Max pooling output

RoIAlign (Mask R-CNN)



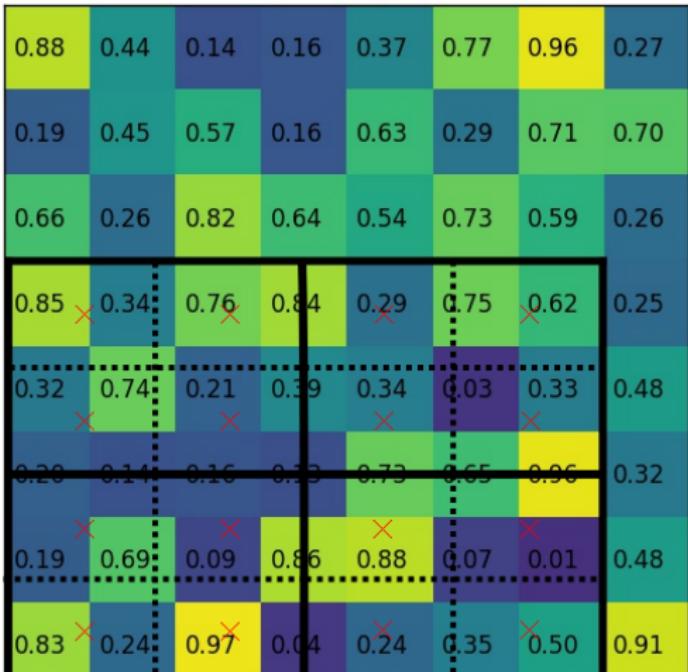
Input activation

RoIAlign (Mask R-CNN)



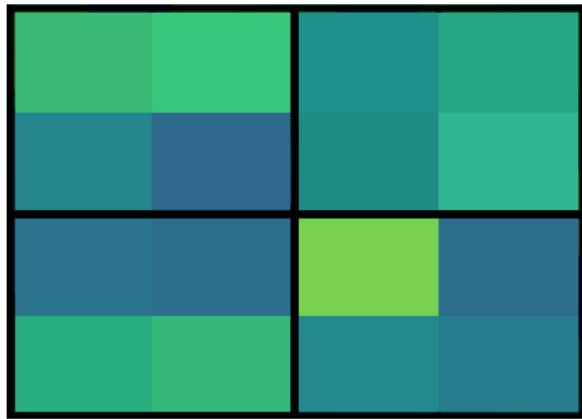
Region projection and pooling sections

RoIAlign (Mask R-CNN)



Sampling locations

RoIAlign (Mask R-CNN)



Bilinear interpolated values

RoIAlign (Mask R-CNN)



Max pooling output

Class prediction & box regression

- Fully connected branch:
 - $K + 1$ softmax for classification
 - $4 \cdot K$ box regression targets:
 $\mathbf{t}^k = (t_x^k, t_y^k, t_w^k, t_h^k)$
- Multitask loss:
 - L_{cls} : negative log likelihood
 - L_{reg} : smooth $L1$ loss

$$L_{box} = L_{cls} + \lambda \mathbf{1}_{[u=u^*]} L_{reg}$$

Mask branch features:

- Fully convolutional
- $K \cdot (m \times m)$ sigmoid outputs:
 - pixel-wise binary classification
 - one mask for each class, no competition
- L_{mask} : mean binary cross-entropy

Overall head loss:

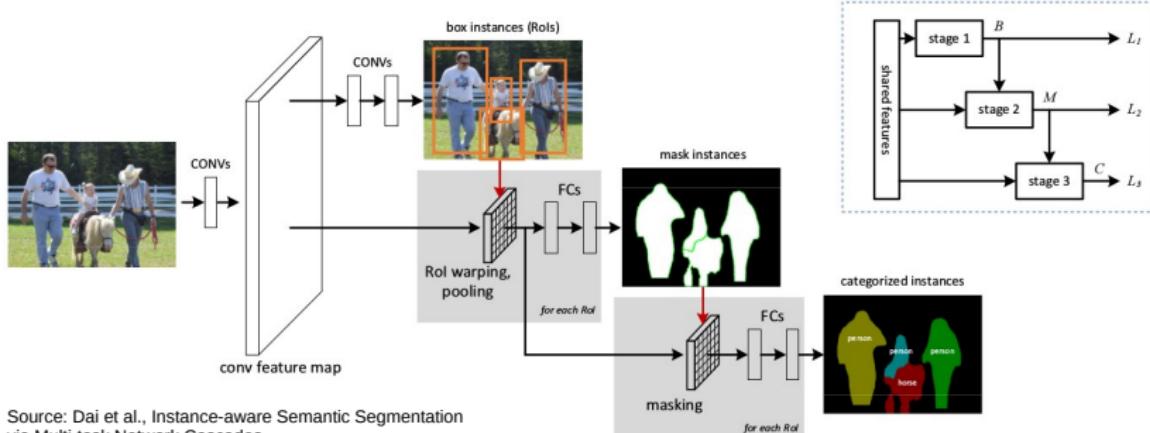
$$L = L_{box} + L_{mask}$$

Experiments

Dataset & metrics

- Main dataset: MS COCO
 - 80 classes
 - 115k training images
 - 5k images for ablation experiments
 - undisclosed ground truth test-dev for main results
- Similarity measure: Intersection over Union (IoU)
- AP_{50} & AP_{75} (PASCAL VOC metrics):
Average Precision: IoU threshold (.50, .75) for true positives
→ precision-recall curve → area under curve
- AP (MS COCO metric):
mean Average Precision over different IoU thresholds.

Related methods: MNC

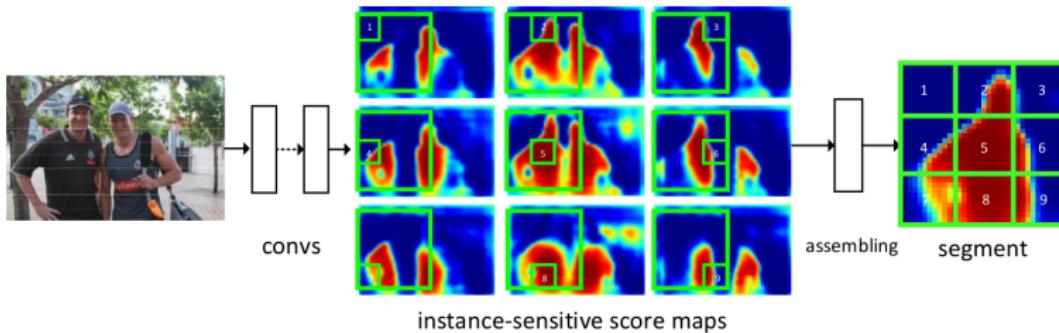


Source: Dai et al., Instance-aware Semantic Segmentation via Multi-task Network Cascades

Multi-task Network Cascade:

- bounding box regression
- mask estimation
- classification

Related methods: FCIS



Source: Dai et al., Instance-sensitive Fully Convolutional Networks

- Fully Convolutional Instance Segmentation
 - Challenge: translation invariance → no instance awareness
 - Proposed solution: positional aware sliding masks

Segmentation results

Model	backbone	AP	AP_{50}	AP_{75}
MNC	ResNet-101-C4	24.6	44.3	24.8
FCIS+++	ResNet-101-C5-dil.	33.6	54.5	-
Mask R-CNN	ResNet-101-C4	33.1	54.9	34.8
Mask R-CNN	ResNet-101-FPN	35.7	58.0	37.8
Mask R-CNN	ResNeXt-101-FPN	37.1	60.0	39.4

FPN (Feature Pyramid Network):

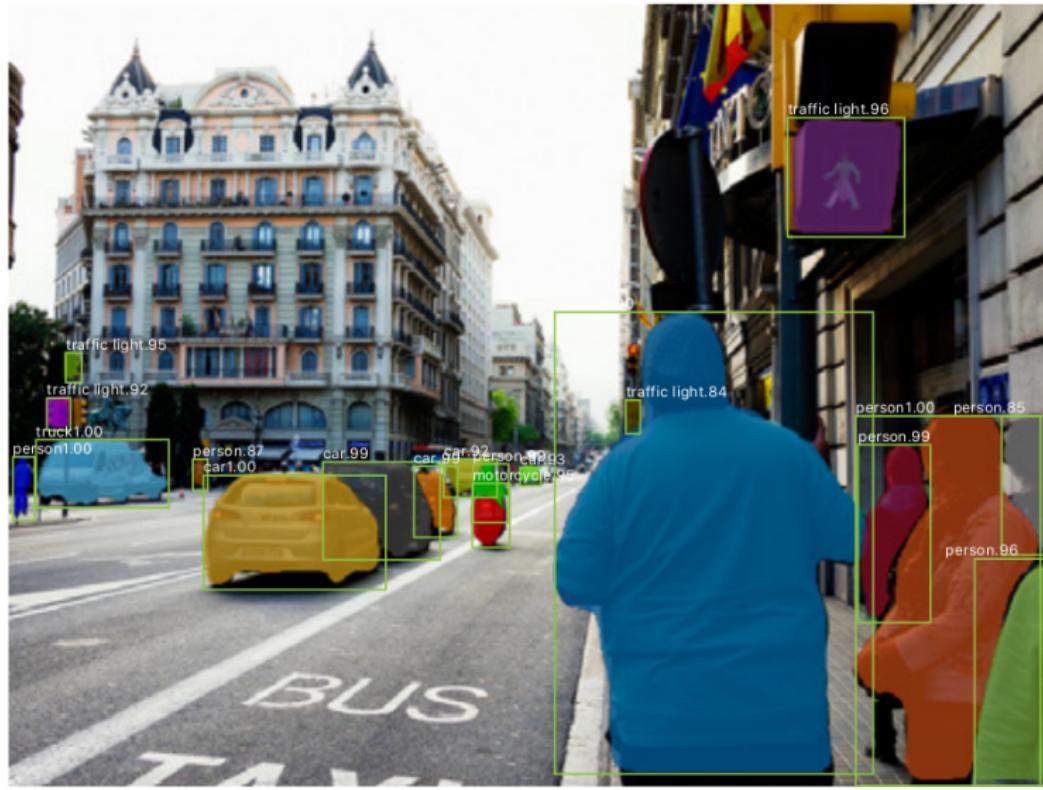
multi-scale hierarchical convolutional features, good for detection

Cityscape results

Cityscape dataset: smaller ($5k$ fine + $20k$ coarse), urban scenery for segmentation

Model	training set	AP	AP_{50}
SAIS	fine	17.4	36.7
DIN	fine+coarse	20.0	38.8
Mask R-CNN	fine	26.2	49.9
Mask R-CNN	fine+COCO pretrain	32.0	58.1

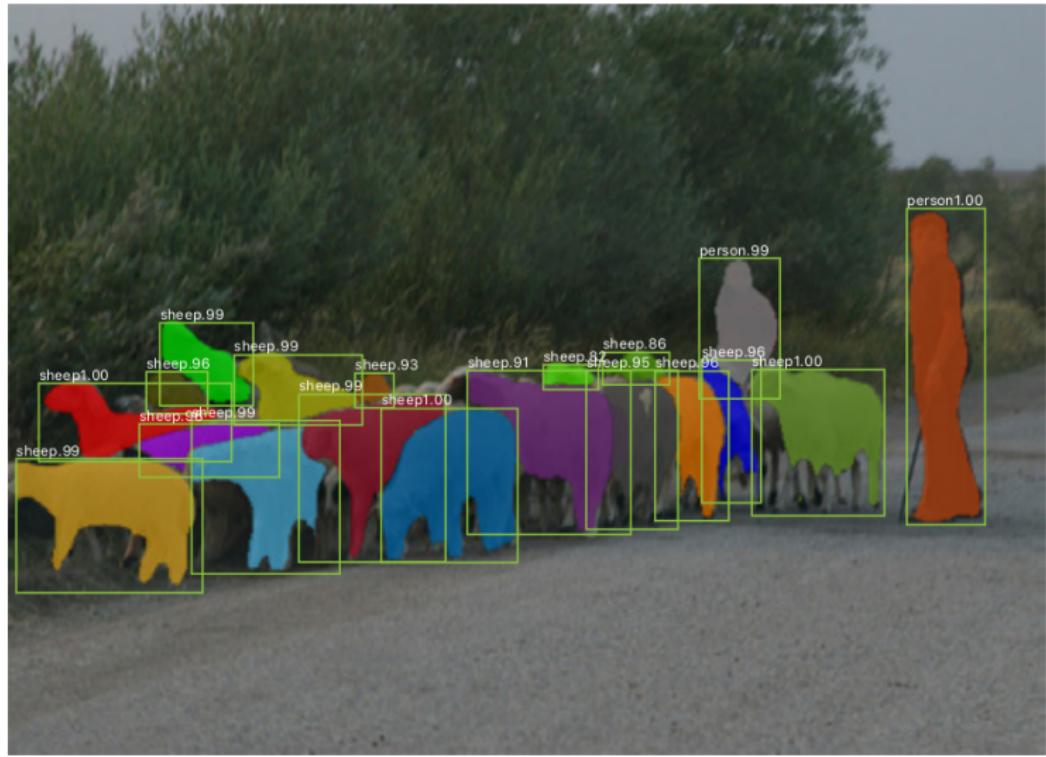
Example results



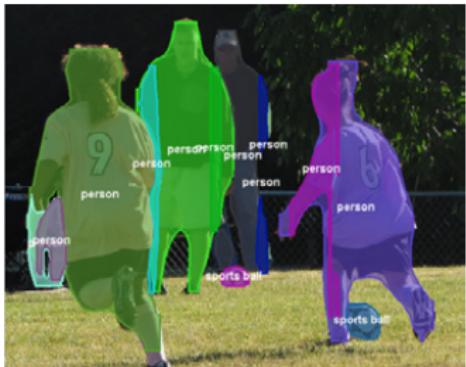
Example results



Example results



FCIS vs Mask R-CNN



Detection results

Model	backbone	AP^{bb}	AP_{50}^{bb}	AP_{75}^{bb}
Faster R-CNN	ResNet-101-FPN	36.2	59.1	39.0
Faster R-CNN	same + RoiAlign	37.3	59.6	40.3
Mask R-CNN	ResNet-101-FPN	38.2	60.3	41.7
Mask R-CNN	ResNeXt-101-FPN	39.8	62.3	43.4

- Backbone (ResNeXt): $+1.6AP^{bb}$
- RoiAlign: $+1.1AP^{bb}$
- Multitask training: $+0.9AP^{bb}$

Backbone architecture:

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

Ablation experiments

RoIAlign layer:

	stride 16			stride 32*		
	AP	AP_{50}	AP_{75}	AP	AP_{50}	AP_{75}
RoIPool	26.9	48.8	26.4	23.6	46.5	21.6
RoIAlign	30.2	51.0	31.8	30.9	51.8	32.1

* larger stride means larger misalignments

Ablation experiments

Mask branch independence:

last fc layer	AP	AP_{50}	AP_{75}
softmax + multinomial loss	24.8	44.1	25.1
sigmoid + binomial loss	30.3	51.2	31.5
	+5.5	+7.1	+6.4

Human pose estimation

- Task: localize anatomical keypoints
- K keypoint types (e.g. left shoulder, right elbow)
 $\rightarrow K$ one-hot masks \rightarrow cross-entropy loss, m^2 softmax
- No other domain knowledge employed

Model	AP^{kp}	AP_{50}^{kp}	AP_{75}^{kp}
CMU-Pose+++	61.8	84.9	67.5
G-RMI	62.4	84.0	68.5
Mask R-CNN, keypoint only	62.7	87.0	68.4
Mask R-CNN, keypoint & mask	63.1	87.3	68.7

Examples



Examples

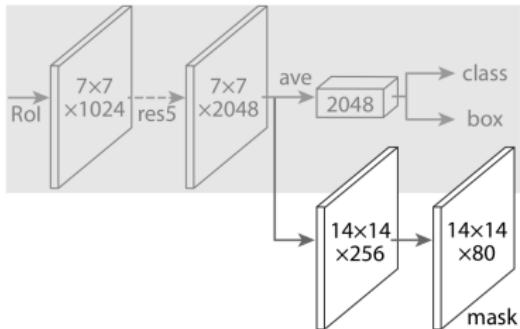


- Mask R-CNN does detection, classification and instance segmentation.
- Based on Faster R-CNN + mask branch, RoIAlign
- State of the art detection and instance segmentation on MS COCO and Cityscapes
- Can do human pose estimation with small adaptations

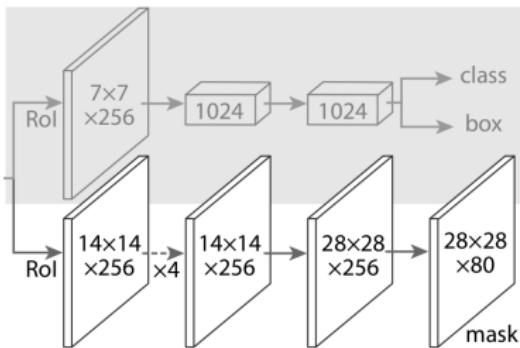
Literature

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- T. Lin, P. Dollr, R. Girshick, K. He, B. Hariharan, S. Belongie. Feature Pyramid Networks for Object Detection. In CoRR, 2016.

Mask R-CNN head architectures



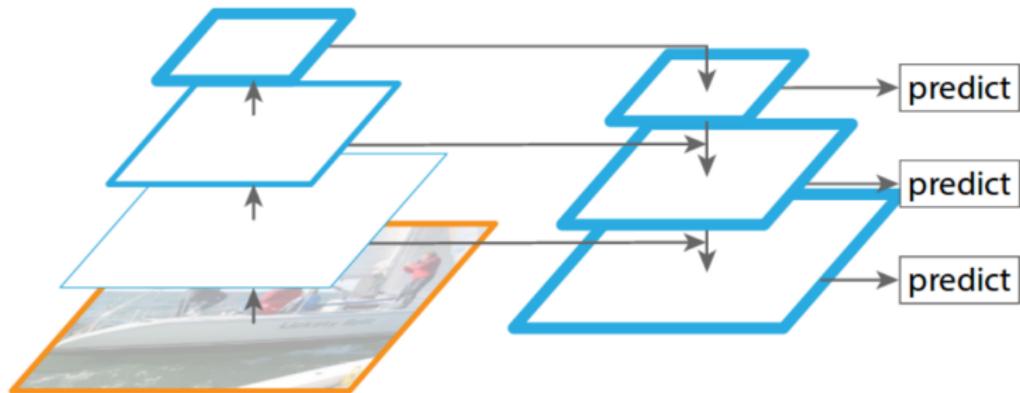
Extended Faster R-CNN head,
on ResNet-C4 feature map



Extended Faster R-CNN head,
on FPN feature map

Feature Pyramid Network

FPN exploits the inherent hierarchy of CNNs to compute multi-scale features:



Source: Lin et al., Feature Pyramid Networks for Object Detection