Mask R-CNN

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Overview

- Framework name: Mask R-CNN
- Task type: Object instance segmentation
- Submission date: March, 2017
- Authors: Facebook Al Research (FAIR)
- Accolades: Won COCO Stuff Challenge 2017

facebook Artificial Intelligence

Problem Complexity

Instance Segmentation Object Detection Semantic Segmentation Complexity?

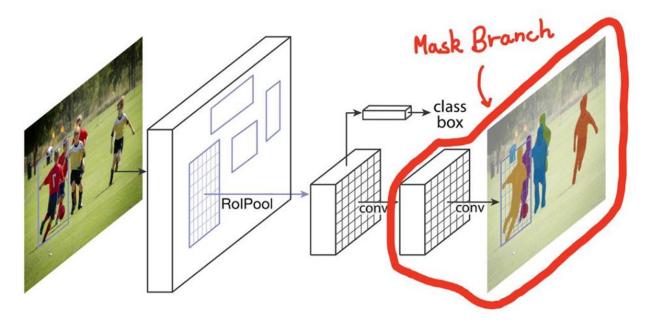
"[...] one might expect a complex method is required to achieve good results. However, we show that a surprisingly simple, flexible, and fast system can surpass prior state-of-the-art instance segmentation results."

Starting Point

Extending Fast R-CNN in order to predict a segmentation mask

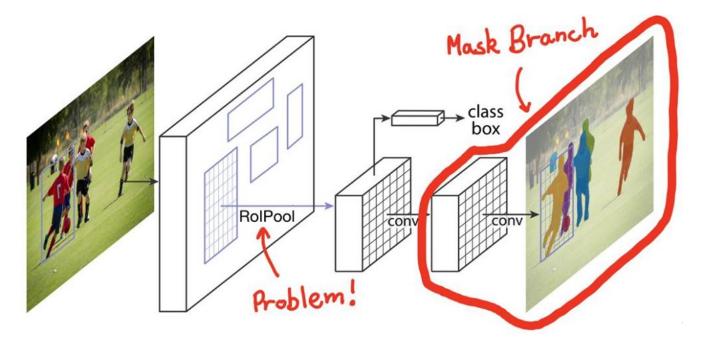
Proposal

Apply a **parallel** *fully convolutional network* (FCN) mask branch to each *region of interest* (RoI)



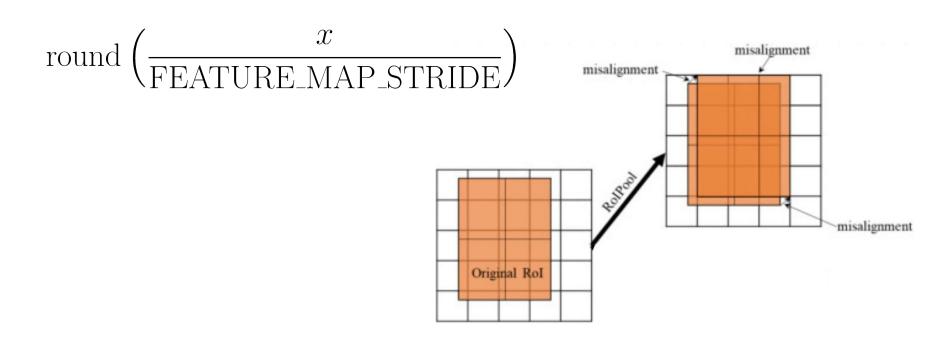
Problem

RolPool introduces a misalignment of input vs. output during quantization into spatial bins.

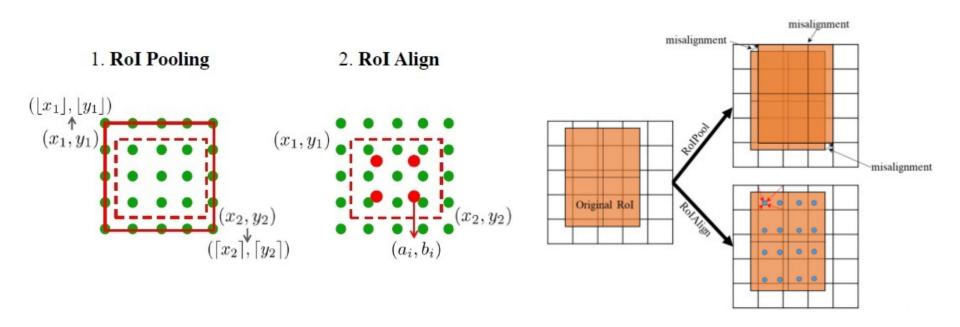


RolPool Quantization

RolPool quantizes a continuous coordinate *x* by computing:

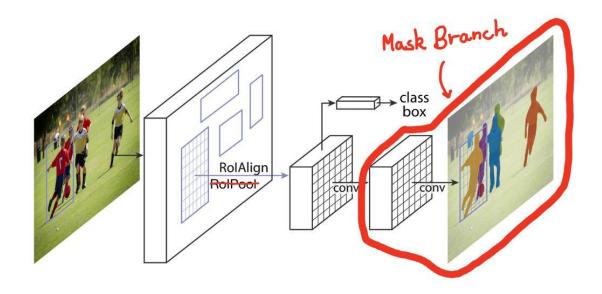


Solution - Bilinear Interpolation



RolPool → RolAlign

"[...] RolAlign has a large impact: it improves mask accuracy by relative 10% to 50%, showing bigger gains under stricter localization metrics."



RoIPo	ol [12]			max	26.9	48.8	26.4
DoIWara [10]			\checkmark	max	27.2	49.2	27.1
RoIWarp [10]		\checkmark	ave	27.1	48.9	27.1	
RoIAlign		✓		max		51.0	31.8
		✓	\checkmark	ave	30.3	51.2	31.5
(c) RoIAlign (ResNet-50-C4): Mask results with various RoI							
layers. Our RoIAlign layer improves AP by \sim 3 points and							

align? | bilinear? | agg. | AP AP₅₀ AP₇₅

(c) **RoIAlign** (ResNet-50-C4): Mask results with various RoI layers. Our RoIAlign layer improves AP by \sim 3 points and AP₇₅ by \sim 5 points. Using proper alignment is the only factor that contributes to the large gap between RoI layers.

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) RoIAlig	n (ResNe	t-50- C5 ,	stride 32)): Mask-l	evel and	box-level

AP using *large-stride* features. Misalignments are more severe than

with stride-16 features (Table 2c), resulting in big accuracy gaps.

21.6

28.2

52.7

26.9

 AP_{50} AP_{75}

46.5

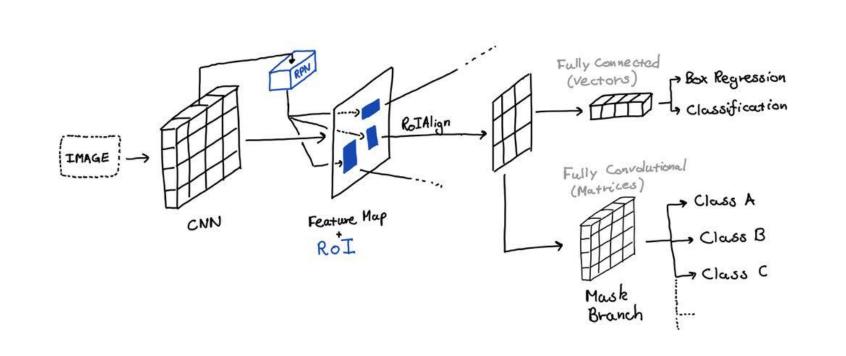
23.6

RoIPool

Decoupling Segmentation and Class Prediction

- Normal FCN approach Per-pixel multi-class categorization
 - Segmentation precedes recognition, which is slow and less accurate
 - Loss: Per-pixel softmax and a multinomial cross-entropy loss
 - "[...] based on our experiments works poorly for instance segmentation"

- Mask R-CNN Independent binary mask for each class
 - No class competition
 - Rol classification branch responsible for predicting the class of each pixel
 - Parallel prediction of masks and class labels, which is simpler and more flexible
 - Loss: Per-pixel sigmoid and a binary loss



Binary Masks

```
Kegion of Interest: m × m
Number of classes: K
          Mask: Km2
LOSS: Lols + Lbex + Lmask
       Faster R-CNN sigmoid
```

	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 perclass binary masks (sigmoid) gives large gains over multinomial masks (softmax).

MLP	fc: $1024 \rightarrow 1024 \rightarrow 80.28^2$	31.5	53.7	32.8		
MLP	fc: $1024 \rightarrow 1024 \rightarrow 1024 \rightarrow 80.28^2$	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 im-						
prove results as they take advantage of explicitly encoding spatial layout.						

AP

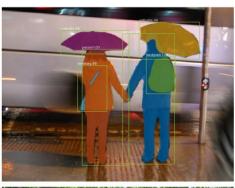
 AP_{50}

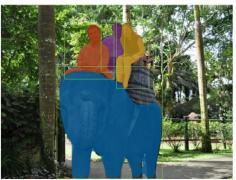
 AP_{75}

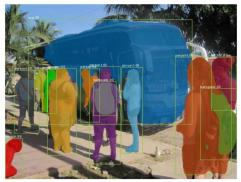
mask branch

Results



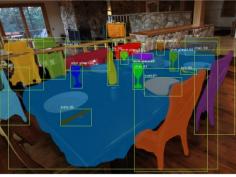


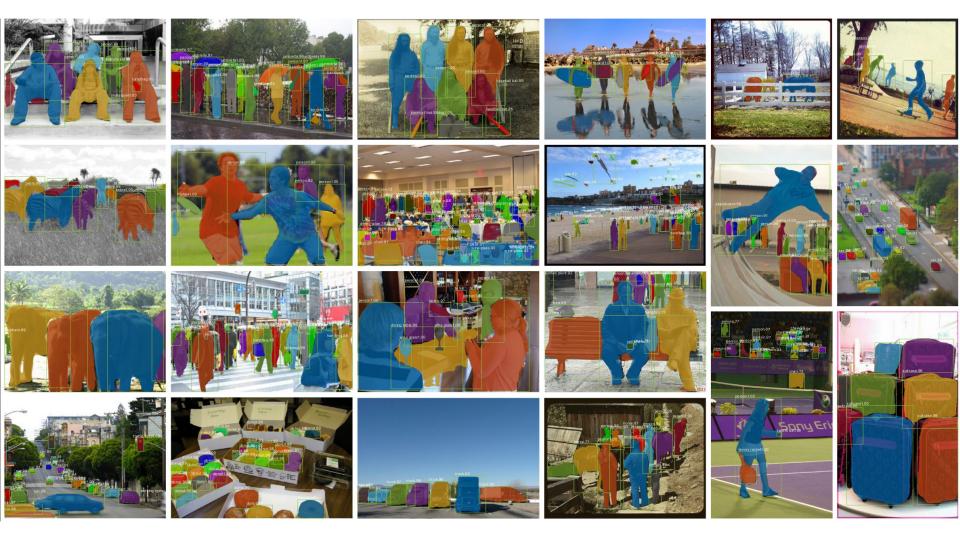












Generalizes to CityScapes

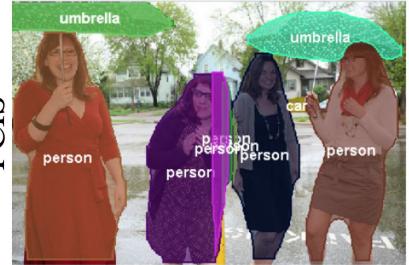


Generalizes to Keypoint Detection



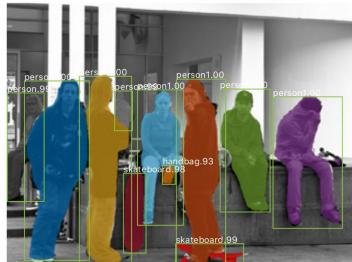
Comparison with FCIS+++

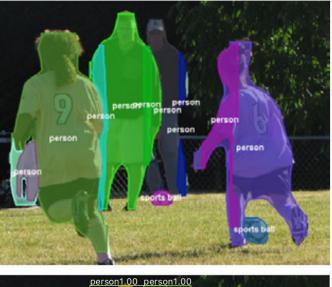
- Position-sensitive output channels by full convolution
- Channels are responsible for *(no decoupling)*:
 - Object classification
 - Bounding box regression
 - Segmentation masks
- Fast but systematic errors on overlapping instances and spurious edges





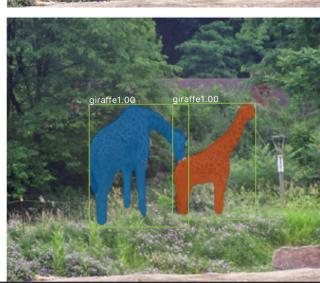






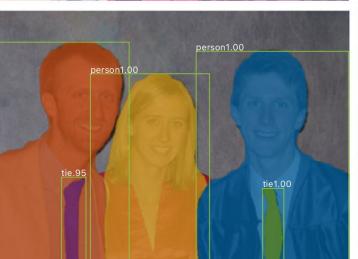


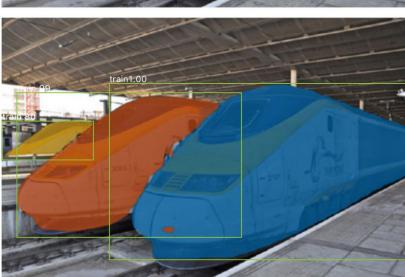












Benefits from Deeper Networks

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.

Accolades

- Outperformed every single-model entry on every task in the COCO 2017
 Challenge at time of publication in March
 - Instance segmentation
 - Bounding-box object detection
 - Person keypoint detection
- FAIR still won "COCO Stuff" competition at the end of 2017
- Won "ICCV 2017 Best Paper Award"

Key Contributions

Rol alignment

Preservation of pixel alignment in order to predict pixel-accurate segmentation masks.

Independent masks

Decouples mask and class prediction. Mask branch segments independently for each class, while box branch decides on final labels. Negligible computational overhead and less complexity.

Use FCN and not FC layers in mask branch

Using fully convolutional network in mask prediction captures spatial information.

Class-agnostic masks

A single binary mask regardless of class can be nearly as effective provided proper division of labor.