# ION

# Inside-Outside Net: Detecting Objects in Context with Skip Pooling and Recurrent Neural Networks

Sean Bell[1], C. Lawrence Zitnick[2], Kavita Bala[1], Ross Girshick[2].

*[1]Cornell University. [2]Microsoft Research (now both at Facebook AI Research).*

Microsoft Research

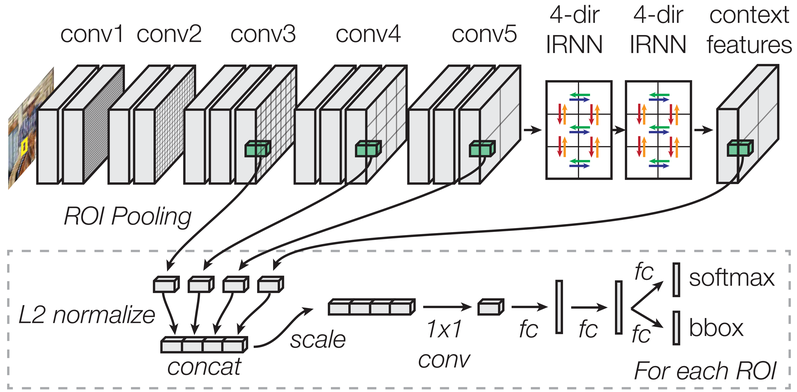
## Highlights

- New object detection architecture: "ION"
- Extensive experiments to validate design decisions
- MS COCO 2015: Won Best Student Entry (3rd overall)

## ION Architecture

- Based on Fast R-CNN [Girshick 2015]
- **Skip pooling:** pool from multiple layers (+3.8 mAP*)
- **Context features:** lateral stacked RNNs (+1.9 mAP*)
- **Normalization:** L2 normalize each pooled blob and re-scale [Liu 2015] (doesn't work without it)

**metric: object detection on PASCAL VOC 2007 test*

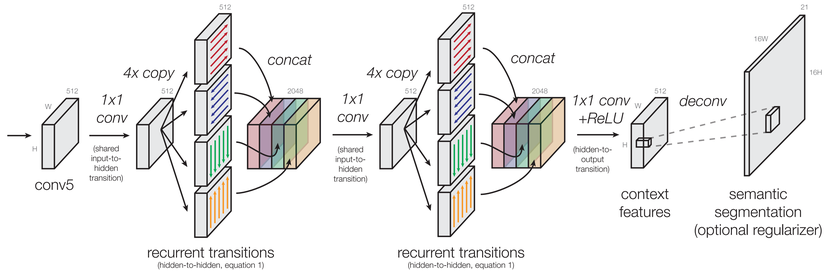



## Context Features

### 2x Stacked 4-Direction IRNN

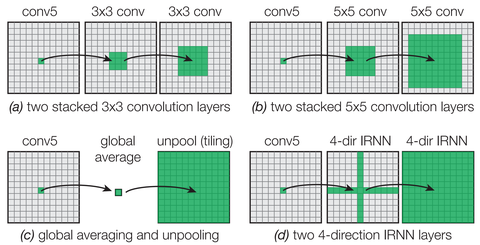
- 4 RNNs move in different directions, laterally across the feature map
- Stack multiple RNNs together (input/output have same shape)
- We use IRNNs: ReLU RNNs initialized with the identity
- Simplify the update rule using 1x1 convolutions:

$$h_{i,j}^{\text{right}} \leftarrow \max\left(\mathbf{W}_{hh}^{\text{right}} h_{i,j-1}^{\text{right}} + h_{i,j}^{\text{right}}, 0\right)$$




### Comparing approaches to adding context

2x stacked IRNN output is both "global" and "local": every cell in the output depends on every cell in the input, and it is spatially varying




| Context method | Seg. | mAP |
|---|---|---|
| Without context | | 74.6 |
| (a) 2x stacked 512x3x3 conv | | 74.8 |
| (b) 2x stacked 256x5x5 conv | | 74.6 |
| (c) Global average pooling | | 74.9 |
| (d) 2x stacked 4-dir IRNN | | **75.6** |
| (a) 2x stacked 512x3x3 conv | ✓ | 75.2 |
| (d) 2x stacked 4-dir IRNN | ✓ | **76.5** |

Table 7. **Comparing approaches to adding context.** All rows also pool out of conv3, conv4, and conv5. Metric: detection mAP on VOC07 test. **Seg:** if checked, the top layer received extra supervision from semantic segmentation labels.

## Results

### PASCAL VOC 2007

| Method | Boxes | R | W | D | Train | Time | mAP |
|---|---|---|---|---|---|---|---|
| FRCN [9] | SS | | | | 07+12 | 0.3s | 70.0 |
| Faster [32] | RPN | | | | 07+12 | 0.2s | 73.2 |
| MR-CNN [8] | SS+EB | ✓ | | | 07+12 | 30s | 78.2 |
| ION [ours] | SS | | | | 07+12 | 0.8s | 74.6 |
| ION [ours] | SS | ✓ | | | 07+12 | 0.8s | 75.6 |
| ION [ours] | SS | ✓ | ✓ | ✓ | 07+12 | 1.2s | 77.6 |
| ION [ours] | SS+EB | ✓ | ✓ | ✓ | 07+12 | 2.0s | 79.4 |
| ION [ours] | SS | ✓ | | | 07++12+S | 0.8s | 76.5 |
| ION [ours] | SS | ✓ | ✓ | | 07++12+S | 1.2s | 78.5 |
| ION [ours] | SS | ✓ | ✓ | ✓ | 07++12+S | 1.2s | 79.2 |
| ION [ours] | SS+EB | ✓ | ✓ | ✓ | 07++12+S | 2.0s | **80.1** |

### PASCAL VOC 2012

| Method | Boxes | R | W | D | Train | mAP |
|---|---|---|---|---|---|---|
| FRCN [9] | SS | | | | 07++12 | 68.4 |
| Faster [32] | RPN | | | | 07++12 | 70.4 |
| FRCN+YOLO [31] | SS | | | | 07++12 | 70.4 |
| HyperNet [21] | RPN | | | | 07++12 | 71.4 |
| MR-CNN [8] | SS+EB | ✓ | | | 07+12 | 73.9 |
| ION [ours] | SS | ✓ | ✓ | ✓ | 07+12 | 74.7 |
| ION [ours] | SS+EB | ✓ | ✓ | ✓ | 07+12 | 76.4 |
| ION [ours] | SS | ✓ | ✓ | ✓ | 07++12+S | 76.4 |
| ION [ours] | SS+EB | ✓ | ✓ | ✓ | 07++12+S | **77.9** |

**Legend**
**07+12:** 07 trainval + 12 trainval,
**07++12:** 07+12 + 07 test
**07++12+S:** 07+12 plus SBD segmentation labels [Hariharan 2011],
**R:** Use IRNN context features,
**W:** 2 rounds of bbox regression [Gidaris 2015],
**D:** no dropout,
**SS:** Selective Search [Uijlings 2013],
**EB:** Edge Boxes [Zitnick 2014],
**RPN:** Region Proposal Network [Ren 2015].
See paper for details.

### MS COCO 2015 Competition

| | test-comp. | test-dev | runtime | test scales | ensemble |
|---|---|---|---|---|---|
| Ours (competition) | 31.0 mAP | 31.2 mAP | 2.7s | 1 | 1 net |
| Ours (post-competition) | | 33.1 mAP | 5.5s | 1 | 1 net |
| ResNet [He 2015] | | 32.2 mAP | | 1 | 1 net |
| ResNet [He 2015] | | 34.9 mAP | | 2 | 1 net |
| ResNet [He 2015] (winner) | 37.1 mAP | 37.4 mAP | | 2 | 3 nets |

### Accuracy Breakdown (MS COCO 2015 test-dev, post-competition)

| | |
|---|---|
| +5.1 mAP: | New ION detection architecture |
| +3.9 mAP: | Better box proposals (RPN + MCG), more data (train+val) |
| +1.3 mAP: | Semantic segmentation (regularizer, not used for test) |
| +1.3 mAP: | Iterative bbox regression [Gidaris 2015] with new thresholds |
| +0.8 mAP: | Larger mini-batches (4 images/batch) and longer training |
| +0.8 mAP: | Left/right flips during inference (average results) |
| +0.6 mAP: | Remove dropout |
| +0.2 mAP: | Add two 3x3 convolution layers after conv5 |

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