

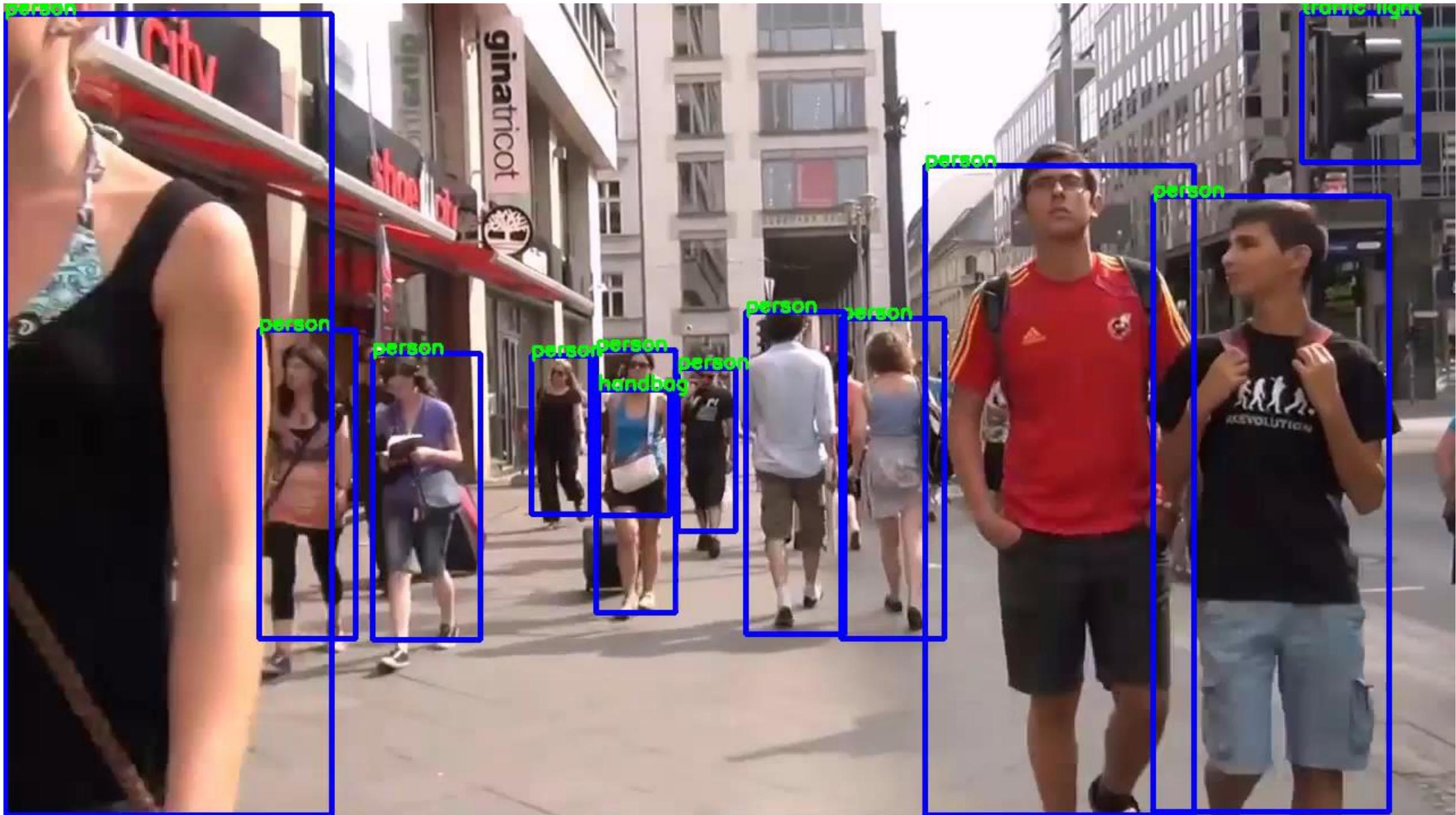
# RON: Reverse Connection with Objectness Prior Networks for Object Detection

Tao Kong<sup>1</sup>, Fuchun Sun<sup>1</sup>, Anbang Yao<sup>2</sup>, Huaping Liu<sup>1</sup>, Ming Lu<sup>3</sup>, Yurong Chen<sup>2</sup>

<sup>1</sup>Department of CST, Tsinghua University, <sup>2</sup>Intel Labs China

<sup>3</sup>Department of EE, Tsinghua University





person

traffic light

person

person

person

person

person

person

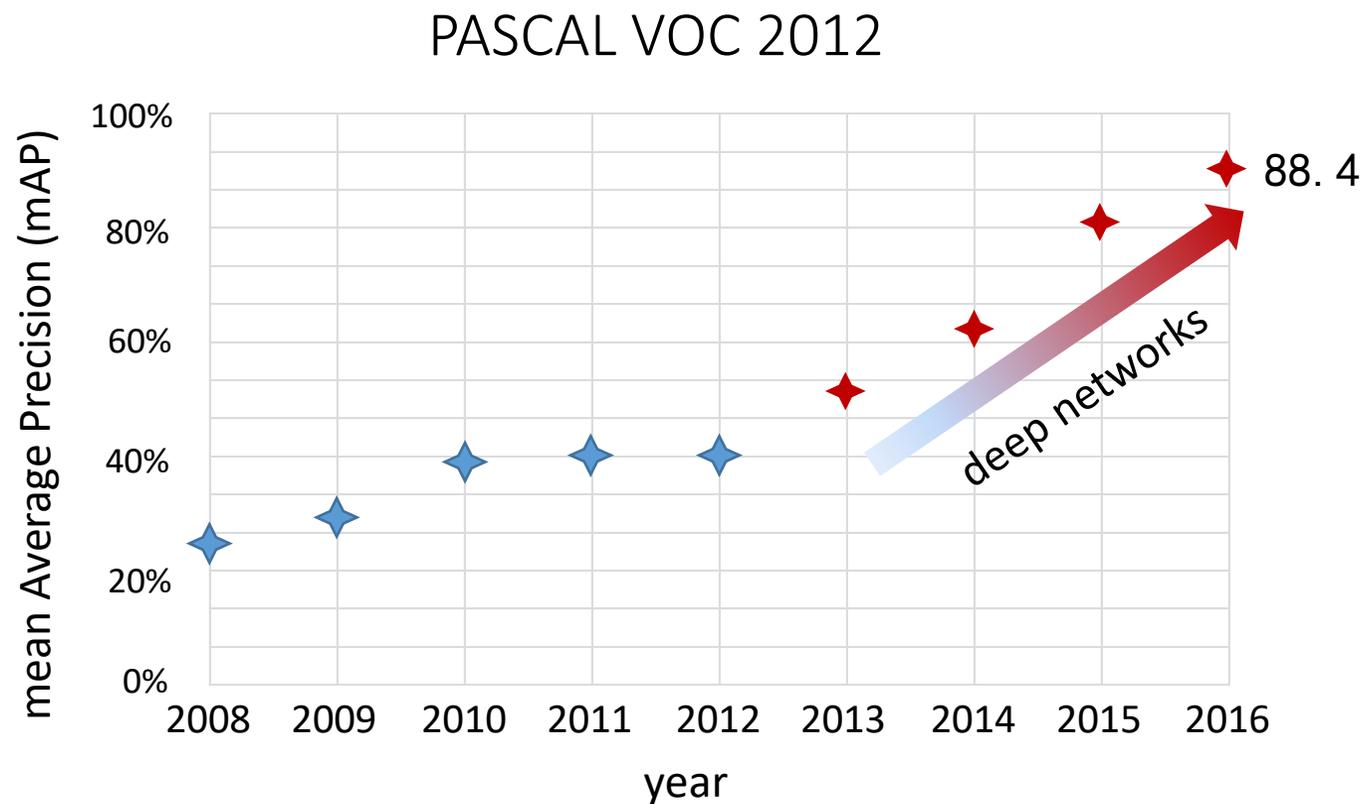
person

person

person

handbag

# The progress of object detection



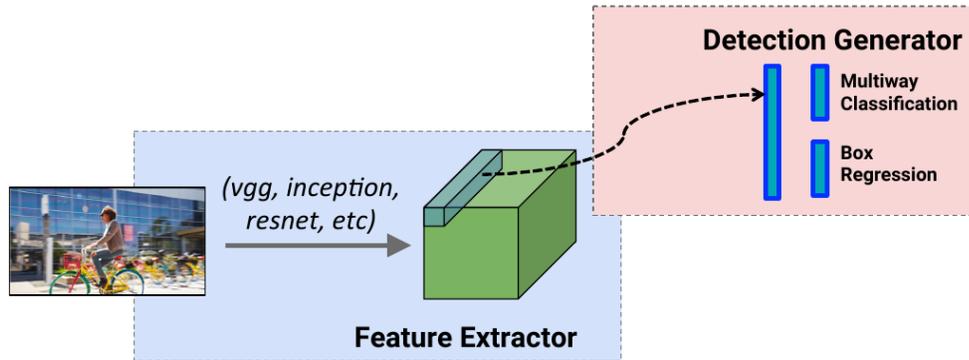
## Region Based.

R-CNN, Fast(er) R-CNN, R-FCN  
ION, HyperNet, OHEM, MR-CNN,  
etc.

## Region Free.

YOLO, SSD etc.

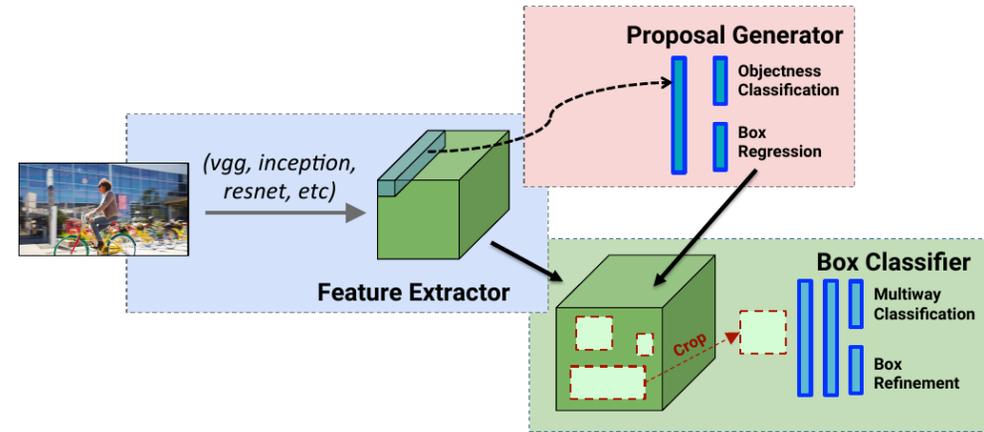
# Two object detection architectures



## SSD

- a) featurized image pyramid
- b) Single-shot detector with on CNN
- c) Multiple anchors at one level feature

- 1. High-speed
- 2. No repeated computations
- 3. Not easy to train
- 4. Struggle with small instances



## Faster R-CNN

- a) Region proposal network
- b) Region-wise object detection sub-network

- 1. High-accuracy, easy to train
- 2. Easy to follow
- 3. Resource/time consuming
- 4. Repeated computation with region-wise computing

# So, what is the lesson?

✓ Feature pyramid works better in locating all scales of objects  
from: SSD, HyperNet, ION, MR-CNN

✓ Using region proposal network to reduce searching space  
from: R-FCN, Faster R-CNN, Fast R-CNN

✓ A fully CNN pipeline with no repeated computation can achieve  
high detection performance.  
from: SSD, R-FCN

RON

# So, what is the lesson?

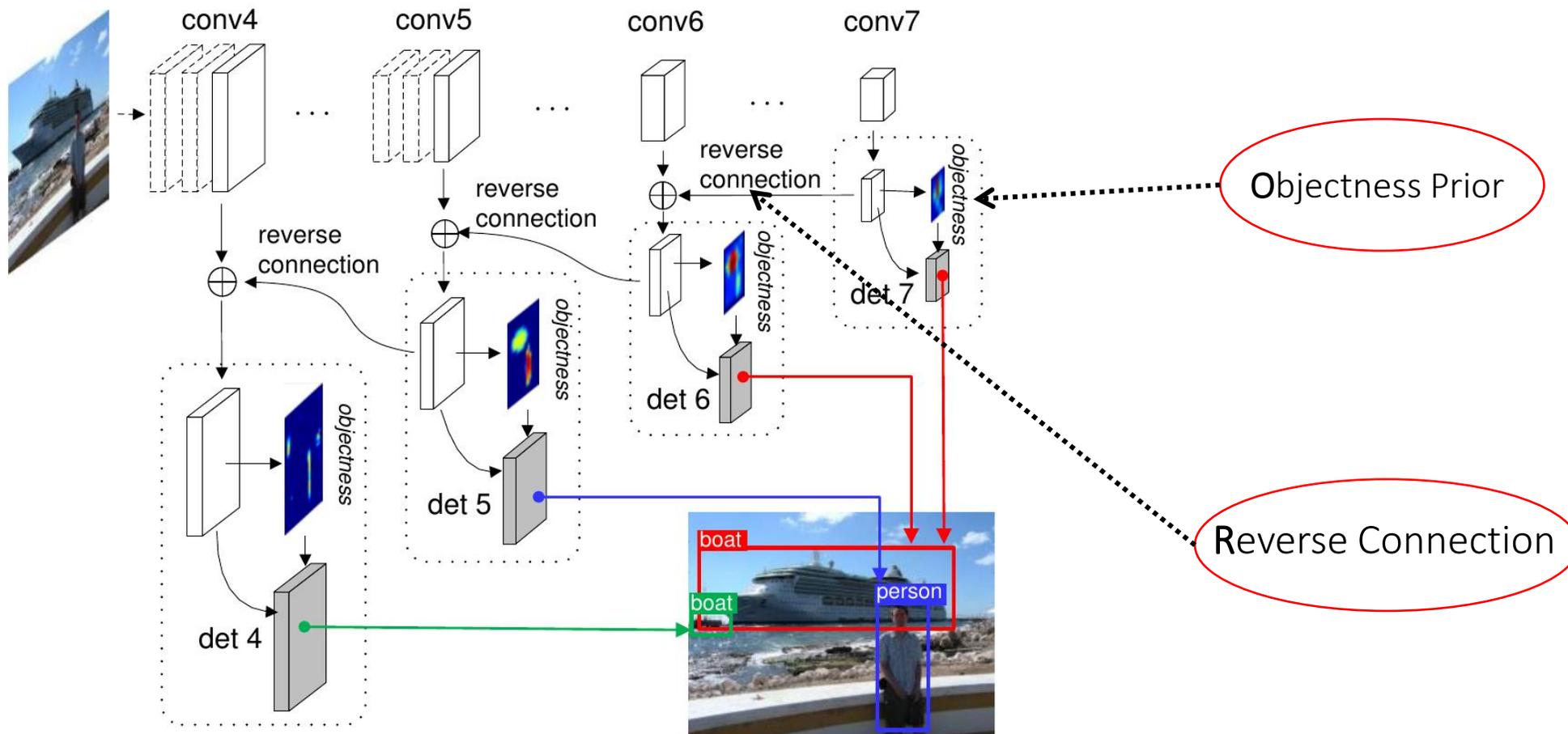
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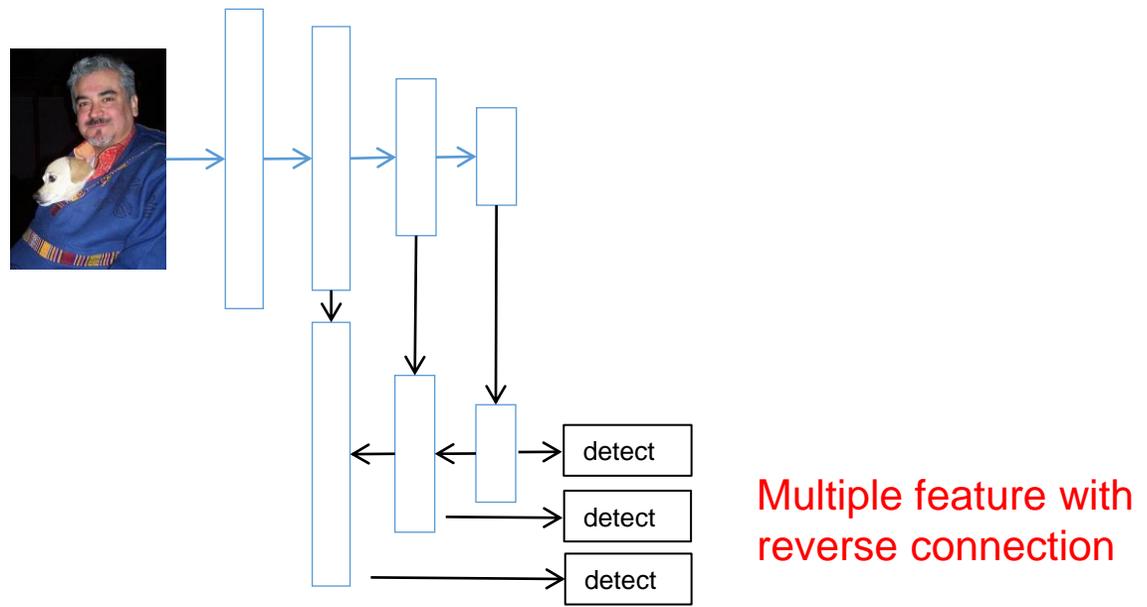
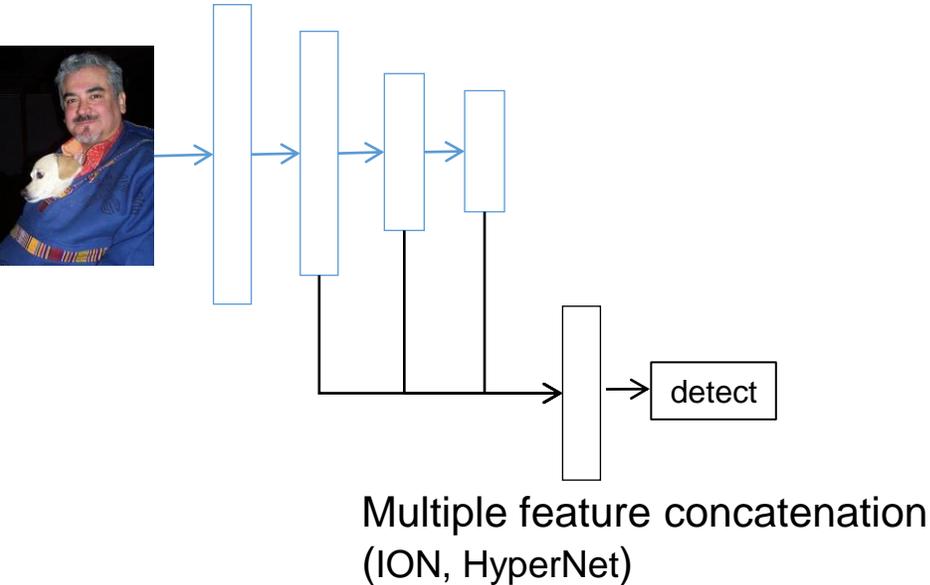
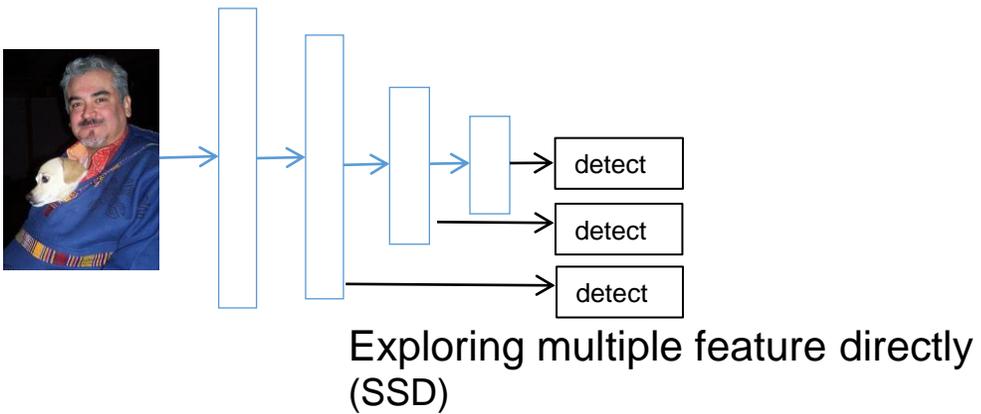
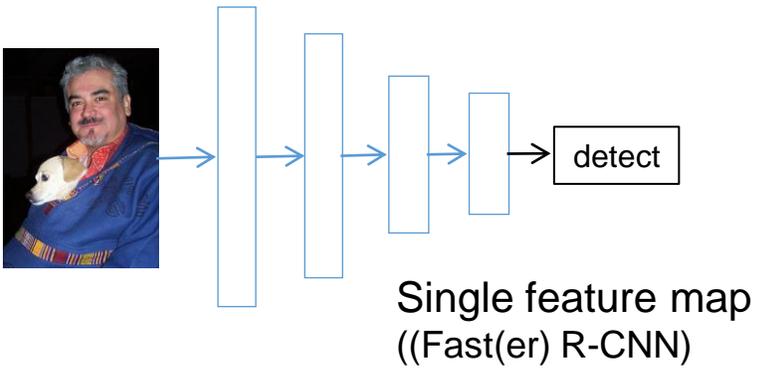
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RON

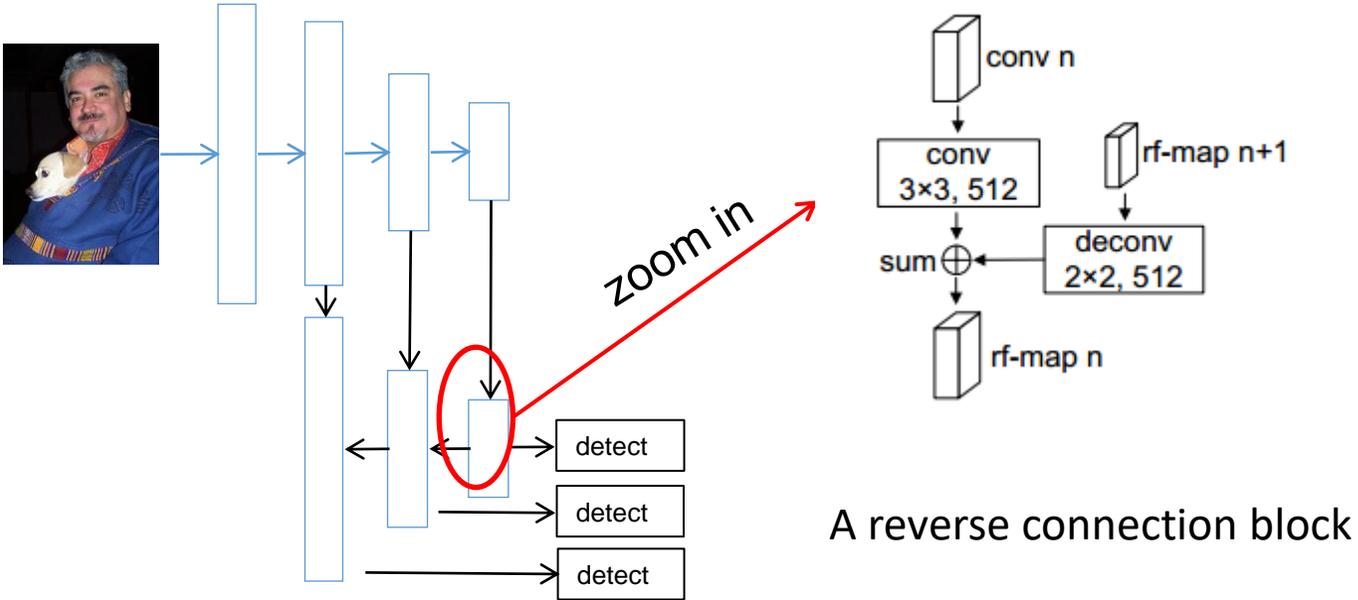
# RON: Reverse Connection with Objectness Prior Networks



# What is reverse connection and why?



# What is reverse connection and why?



- a) Simple design
- b) The semantic information of former layers can be significantly enriched
- c) Keep the spatial sizes
- d) Easy to do multiple level detection

A reverse connection block

# So, what is the lesson?

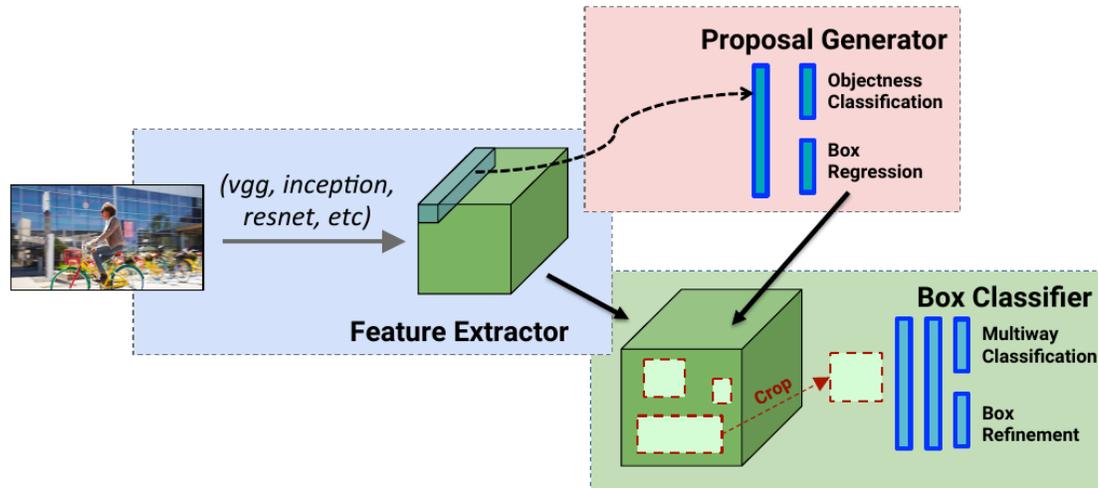
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RON

# From *region proposal boxes* to *region proposal maps*



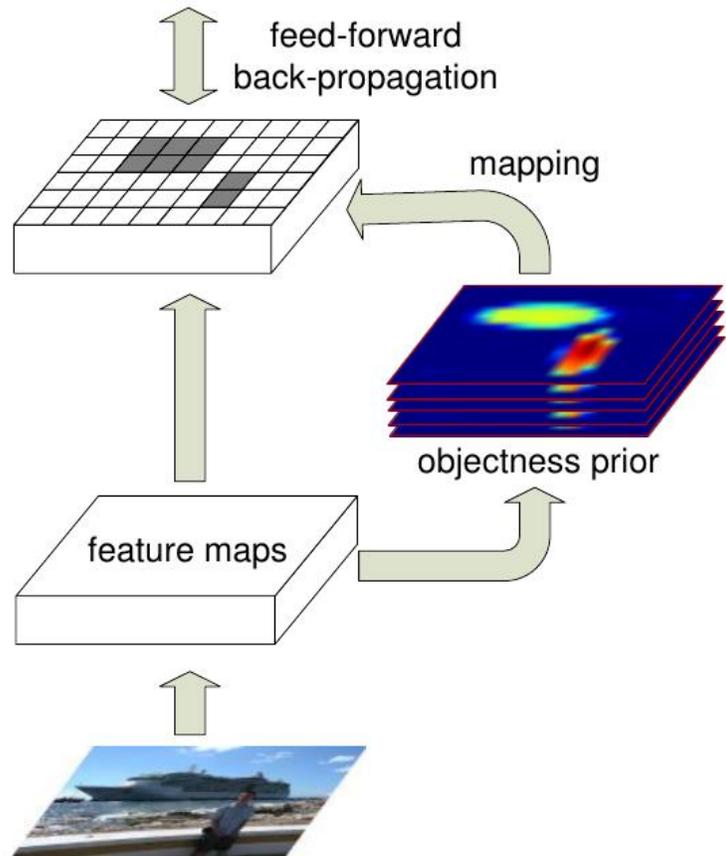
Faster R-CNN:

Region proposal network (RPN) is fully convolutional, but detection sub-network is with repeated computation (ROI-Pooling).

Why?

The bbox regression in RPN changes the spatial locations of all boxes, which breaks the anchor's relationship with its corresponding kernel.

# From *region proposal boxes* to *region proposal maps*

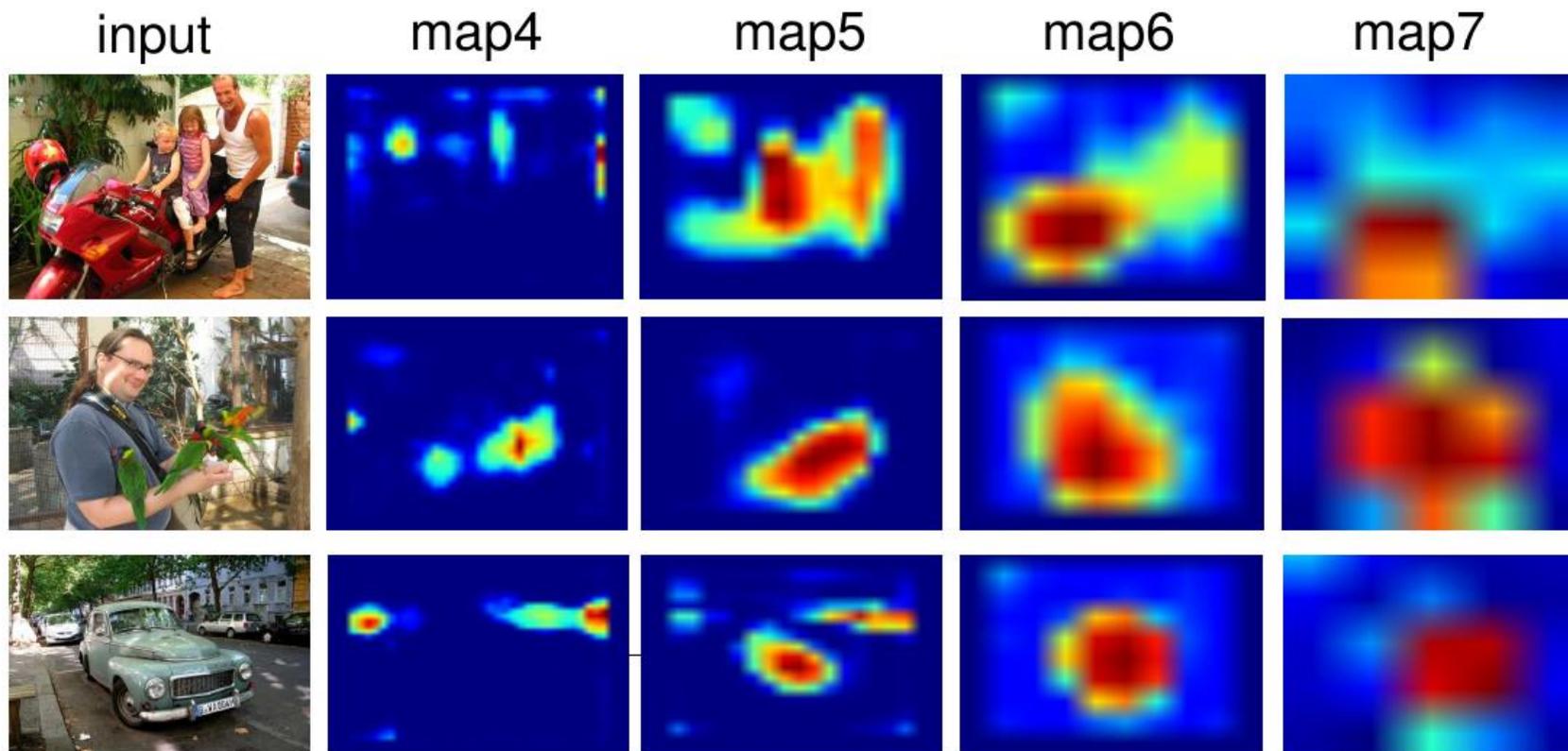


Objectness prior:

Share anchors between RPN and detector, make it possible to detect objects with fully ConvNet.

- ✓ No repeated computations, much faster
- ✓ The total network is fully convolutional
- ✓ There are one map for each type of anchors different from these mask-based methods.

# Region proposal maps



# So, what is the lesson?

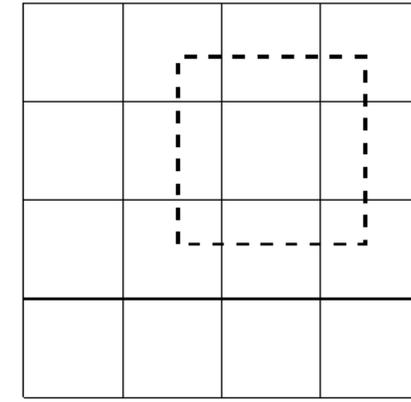
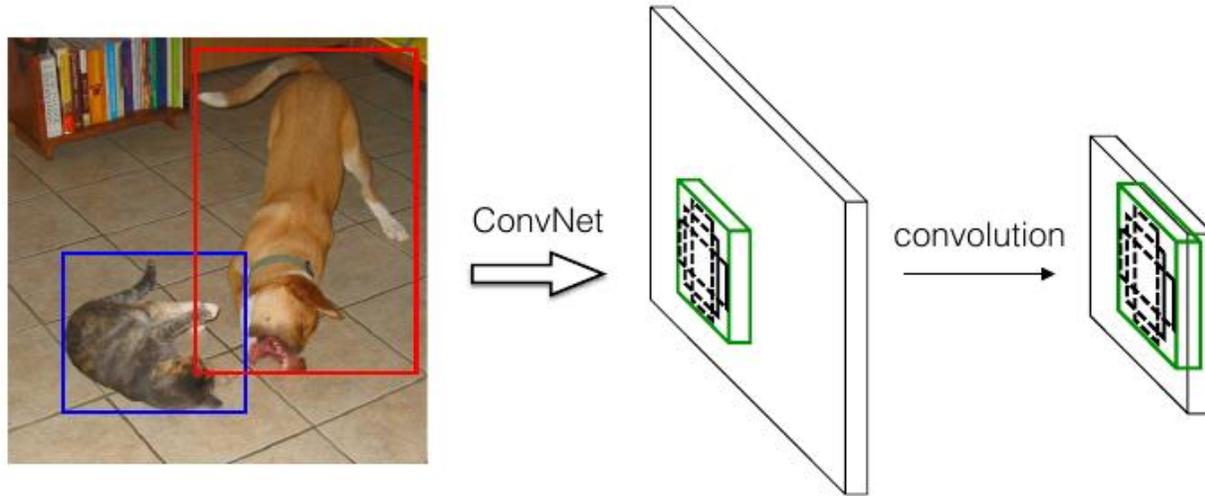
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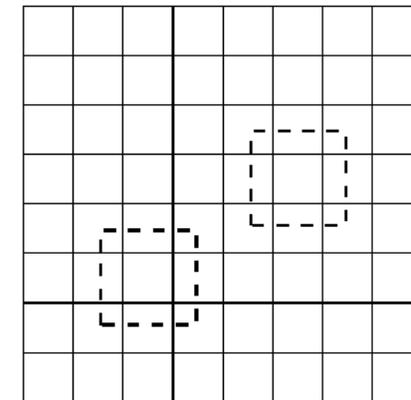
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RON

# RON bounding box generation



4\*4 feature map



8\*8 feature map

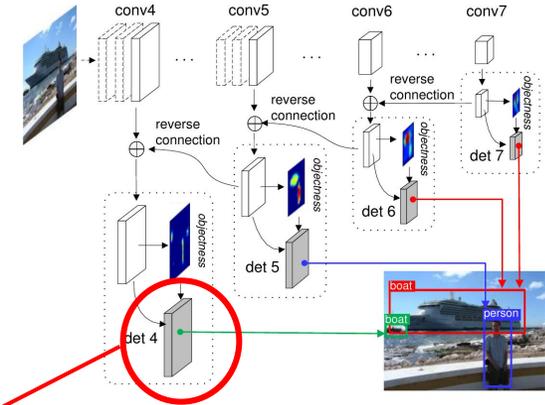
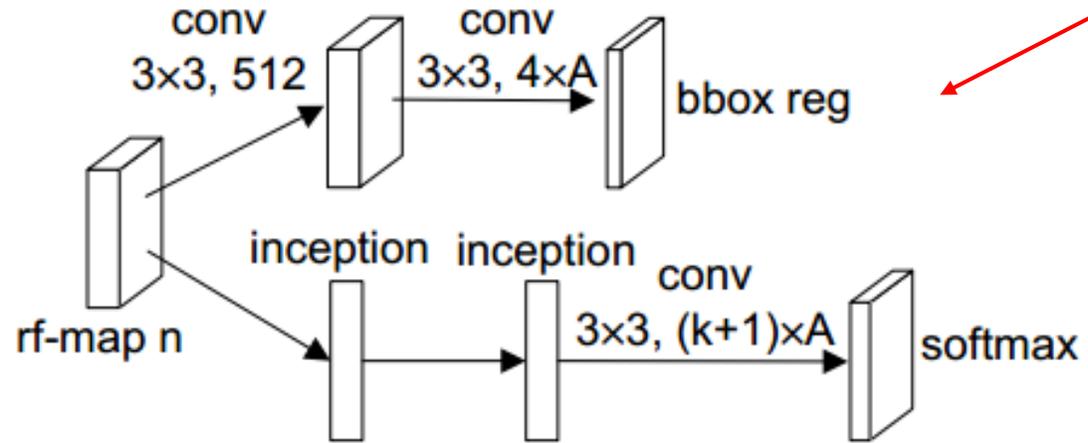
**Convolutinal output** in this position

a) sub-network for objectness

b) sub-network for detection with a)

c) sub-network for bounding box regression

# RON object detector



Object detection and bounding box regression modules. Top: bounding box regression; Bottom: object classification

# RON optimization

$$L = \alpha \frac{1}{N_{obj}} L_{obj} + \beta \frac{1}{N_{loc}} L_{loc} + (1 - \alpha - \beta) \frac{1}{N_{cls|obj}} L_{cls|obj}$$

objectness prior

bbox location

detection

optimize the network  
jointly

# Main results

Method	mAP	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
Fast R-CNN[10]	70.0	77.0	78.1	69.3	59.4	38.3	81.6	78.6	86.7	42.8	78.8	68.9	84.7	82.0	76.6	69.9	31.8	70.1	74.8	80.4	70.4
Faster R-CNN[23]	73.2	76.5	79.0	70.9	65.5	52.1	83.1	84.7	86.4	52.0	<b>81.9</b>	65.7	84.8	84.6	77.5	76.7	38.8	73.6	73.9	83.0	72.6
SSD300[19]	72.1	75.2	79.8	70.5	62.5	41.3	81.1	80.8	86.4	51.5	74.3	72.3	83.5	84.6	80.6	74.5	46.0	71.4	73.8	83.0	69.1
SSD500[19]	75.1	79.8	79.5	74.5	63.4	51.9	84.9	<b>85.6</b>	87.2	56.6	80.1	70.0	85.4	84.9	80.9	78.2	49.0	<b>78.4</b>	72.4	84.6	75.5
RON320	74.2	75.7	79.4	74.8	66.1	53.2	83.7	83.6	85.8	55.8	79.5	69.5	84.5	81.7	83.1	76.1	49.2	73.8	75.2	80.3	72.5
RON384	75.4	78.0	82.4	76.7	67.1	56.9	85.3	84.3	86.1	55.5	80.6	71.4	84.7	84.8	82.4	76.2	47.9	75.3	74.1	83.8	74.5
RON320++	76.6	79.4	<b>84.3</b>	75.5	<b>69.5</b>	56.9	83.7	84.0	<b>87.4</b>	57.9	81.3	<b>74.1</b>	84.1	85.3	<b>83.5</b>	77.8	49.2	76.7	<b>77.3</b>	<b>86.7</b>	77.2
RON384++	<b>77.6</b>	<b>86.0</b>	82.5	<b>76.9</b>	69.1	<b>59.2</b>	<b>86.2</b>	85.5	87.2	<b>59.9</b>	81.4	73.3	<b>85.9</b>	<b>86.8</b>	82.2	<b>79.6</b>	<b>52.4</b>	78.2	76.0	86.2	<b>78.0</b>

+2.5%

Table 1. Detection results on PASCAL VOC 2007 test set. The entries with the best APs for each object category are bold-faced.

Method	mAP	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
Fast R-CNN[10]	68.4	82.3	78.4	70.8	52.3	38.7	77.8	71.6	89.3	44.2	73.0	55.0	87.5	80.5	80.8	72.0	35.1	68.3	65.7	80.4	64.2
OHEM[26]	71.9	83.0	81.3	72.5	55.6	49.0	78.9	74.7	89.5	52.3	75.0	61.0	<b>87.9</b>	80.9	82.4	76.3	47.1	72.5	67.3	80.6	<b>71.2</b>
Faster R-CNN[23]	70.4	84.9	79.8	74.3	53.9	49.8	77.5	75.9	88.5	45.6	77.1	55.3	86.9	81.7	80.9	79.6	40.1	72.6	60.9	81.2	61.5
HyperNet[16]	71.4	84.2	78.5	73.6	55.6	53.7	78.7	79.8	87.7	49.6	74.9	52.1	86.0	81.7	83.3	<b>81.8</b>	48.6	73.5	59.4	79.9	65.7
SSD300[19]	70.3	84.2	76.3	69.6	53.2	40.8	78.5	73.6	88.0	50.5	73.5	61.7	85.8	80.6	81.2	77.5	44.3	73.2	66.7	81.1	65.8
SSD500[19]	73.1	84.9	82.6	74.4	55.8	50.0	80.3	78.9	88.8	53.7	76.8	59.4	87.6	83.7	82.6	81.4	47.2	75.5	65.6	84.3	68.1
RON320	71.7	84.1	78.1	71.0	56.8	46.9	79.0	74.7	87.5	52.5	75.9	60.2	84.8	79.9	82.9	78.6	47.0	75.7	66.9	82.6	68.4
RON384	73.0	85.4	80.6	71.9	56.3	49.8	80.6	76.8	88.2	53.6	78.1	60.4	86.4	81.5	83.8	79.4	48.6	77.4	67.7	83.4	69.5
RON320++	74.5	<b>87.1</b>	81.0	74.6	58.8	51.7	<b>82.1</b>	77.0	89.7	57.2	79.9	<b>62.6</b>	87.2	83.2	<b>85.0</b>	80.5	51.4	76.7	68.5	<b>84.8</b>	70.4
RON384++	<b>75.4</b>	86.5	<b>82.9</b>	<b>76.6</b>	<b>60.9</b>	<b>55.8</b>	81.7	<b>80.2</b>	<b>91.1</b>	<b>57.3</b>	<b>81.1</b>	60.4	87.2	<b>84.8</b>	84.9	81.7	<b>51.9</b>	<b>79.1</b>	<b>68.6</b>	84.1	70.3

+2.3%

Table 2. Results on PASCAL VOC 2012 test set. All methods are based on the pre-trained VGG-16 networks.

# Main results

Method	Train Data	Average Precision		
		0.5	0.75	0.5:0.95
Fast R-CNN[10]	train	35.9	-	19.7
OHEM[26]	trainval	42.5	22.2	22.6
OHEM++[26]	trainval	45.9	26.1	25.5
Faster R-CNN[23]	trainval	42.7	-	21.9
SSD300[19]	trainval35k	38.0	20.5	20.8
SSD500[19]	trainval35k	43.7	24.7	24.4
RON320	trainval	44.7	22.7	23.6
RON384	trainval	46.5	25.0	25.4
RON320++	trainval	47.5	25.9	26.2
<b>RON384++</b>	trainval	<b>49.5</b>	<b>27.1</b>	<b>27.4</b>

+3.7%

Table 3. MS COCO test-dev2015 detection results.

# Main results

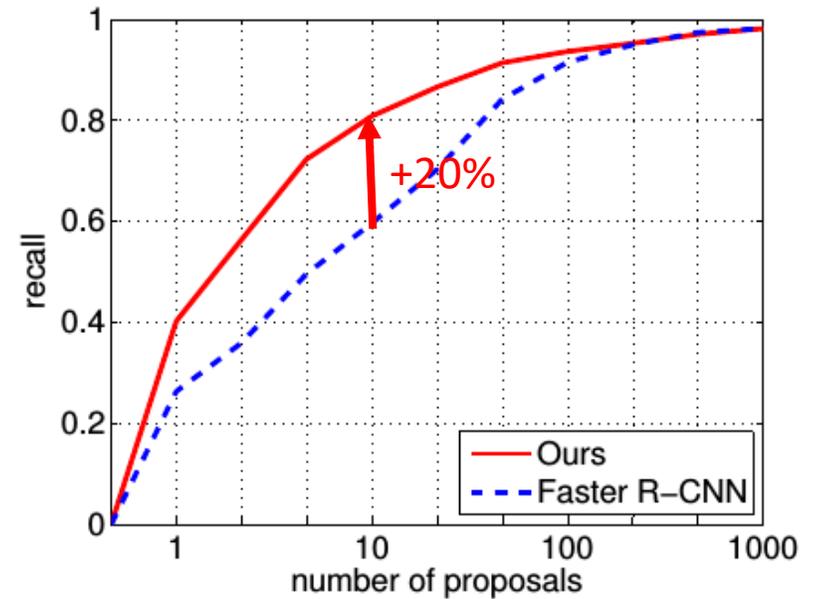
Method	2007 test	2012 test
Faster R-CNN[23]	78.8	75.9
OHEM++[26]	-	80.1
SSD512[19]	-	80.0
RON320	78.7	76.3
RON384	80.2	79.0
RON320++	80.3	78.7
RON384++	<b>81.3</b>	<b>80.7</b>

Table 4. The performance on PASCAL VOC datasets. All models are pre-trained on MS COCO, and fine-tuned on PASCAL VOC.

# Main results

detection from layer				mAP
4	5	6	7	
			✓	65.6
		✓	✓	68.3
	✓	✓	✓	72.5
✓	✓	✓	✓	74.2

Table 5. Combining features from different layers.



- Tao Kong, Fuchun Sun, Anbang Yao, Huaping Liu, Ming Lu, Yurong Chen. RON: Reverse Connection with Objectness Prior Networks for Object Detection, In *IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2017.
- Paper: <https://arxiv.org/abs/1707.01691>

Check out the code/models



<https://github.com/taokong/RON>

Thanks