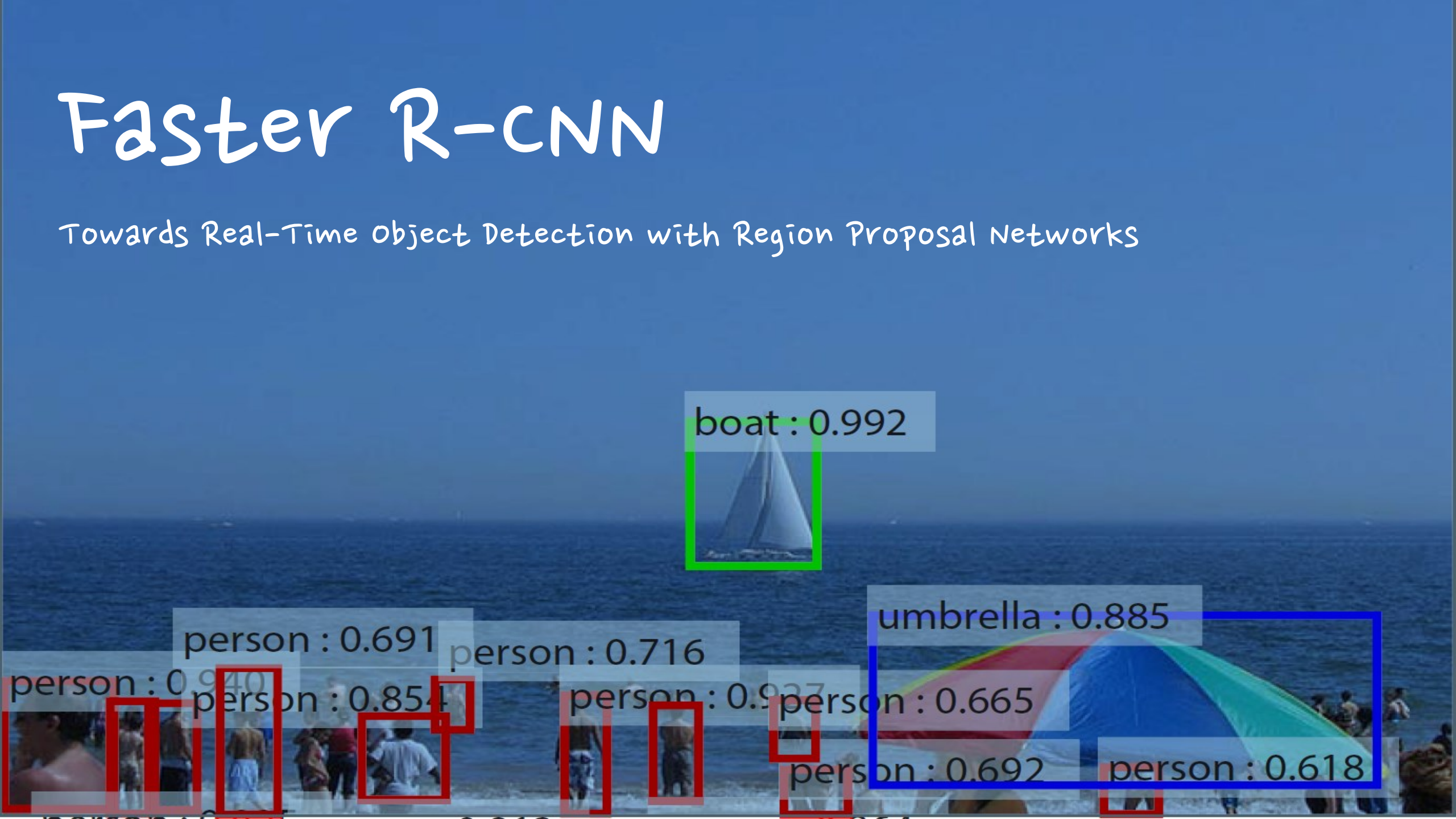
Faster R-CNN

Towards Real-Time Object Detection with Region Proposal Networks



Faster R-CNN(NIPS 2015)

Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks

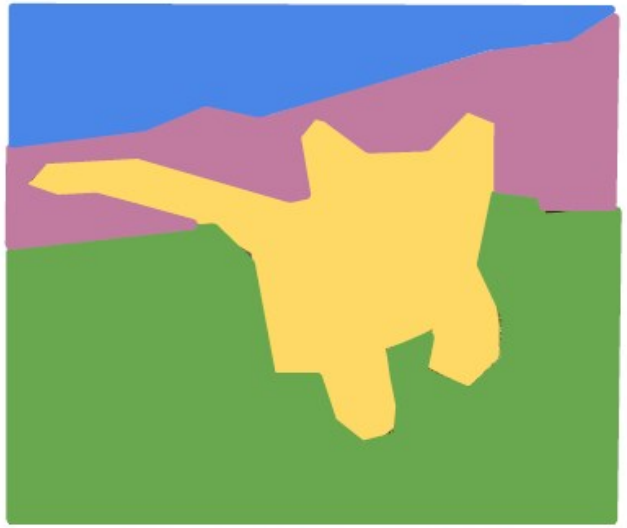
Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun

Abstract—State-of-the-art object detection networks depend on region proposal algorithms to hypothesize object locations. Advances like SPPnet [1] and Fast R-CNN [2] have reduced the running time of these detection networks, exposing region proposal computation as a bottleneck. In this work, we introduce a *Region Proposal Network* (RPN) that shares full-image convolutional features with the detection network, thus enabling nearly cost-free region proposals. An RPN is a fully convolutional network that simultaneously predicts object bounds and objectness scores at each position. The RPN is trained end-to-end to generate high-quality region proposals, which are used by Fast R-CNN for detection. We further merge RPN and Fast R-CNN into a single network by sharing their convolutional features—using the recently popular terminology of neural networks with "attention" mechanisms, the RPN component tells the unified network where to look. For the very deep VGG-16 model [3], our detection system has a frame rate of 5fps (*including all steps*) on a GPU, while achieving state-of-the-art object detection accuracy on PASCAL VOC 2007, 2012, and MS COCO datasets with only 300 proposals per image. In ILSVRC and COCO 2015 competitions, Faster R-CNN and RPN are the foundations of the 1st-place winning entries in several tracks. Code has been made publicly available.

Index Terms—Object Detection, Region Proposal, Convolutional Neural Network.

Computer Vision Task

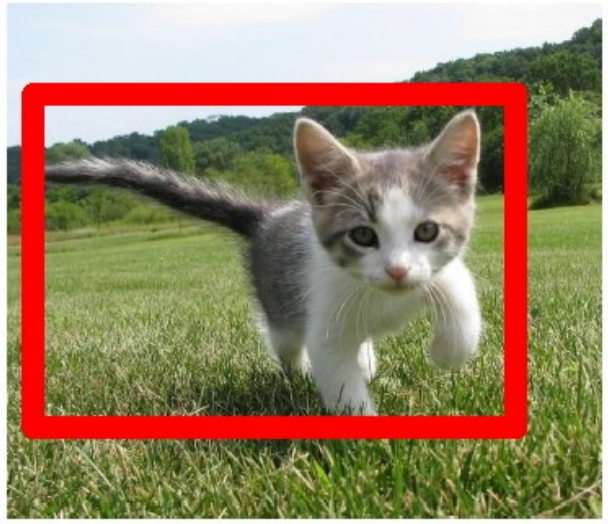
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

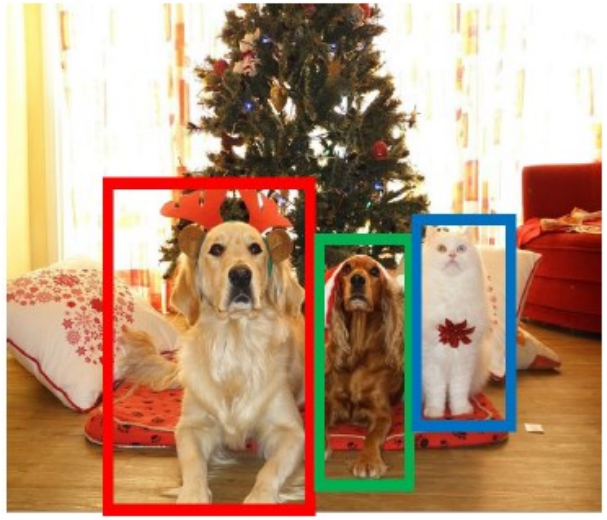
Classification + Localization



CAT

Single Object

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

Multiple Object

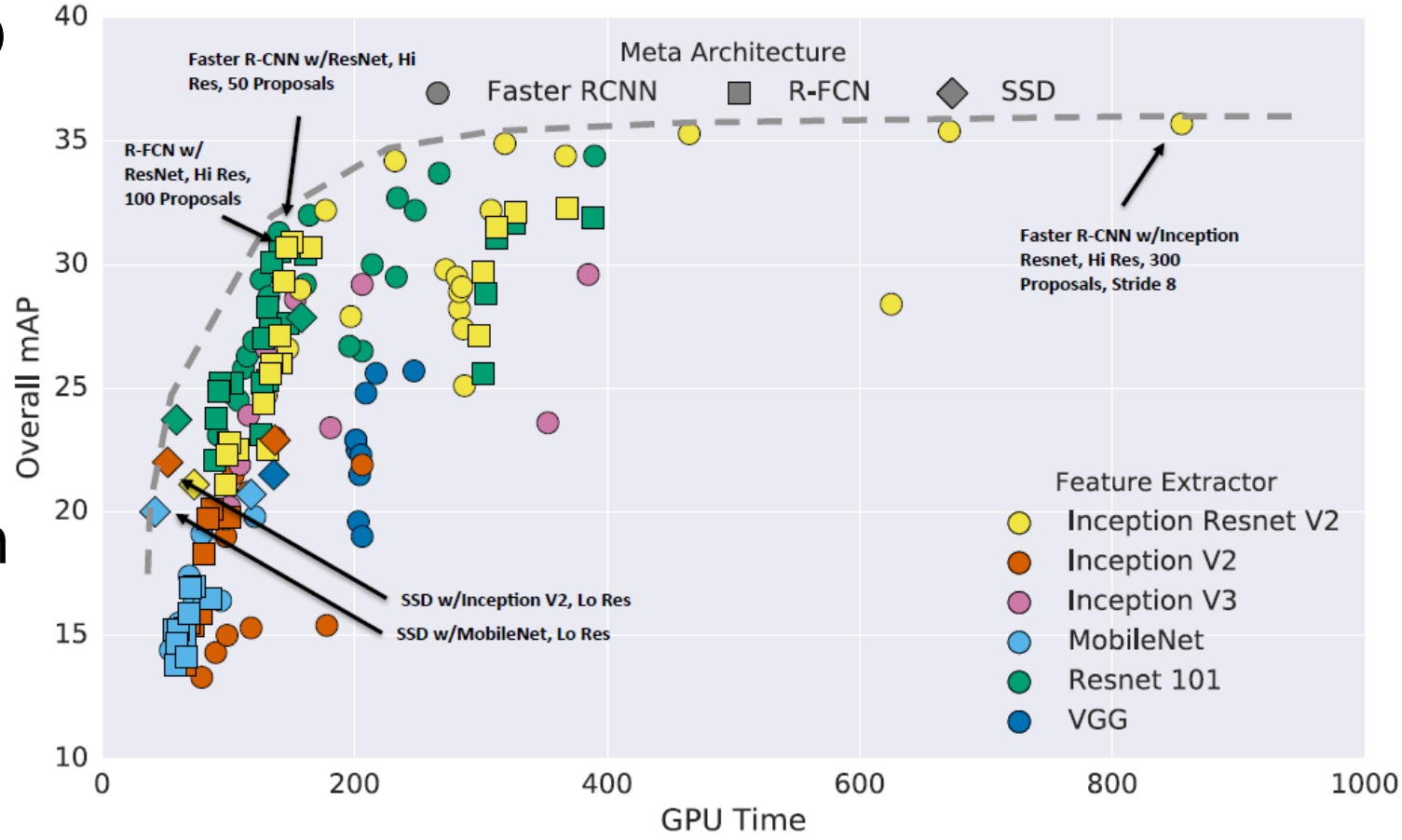
History(?) of R-CNN

- Rich feature hierarchies for accurate object detection and semantic segmentation(2013)
- Fast R-CNN(2015)
- Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks(2015)
- Mask R-CNN(2017)

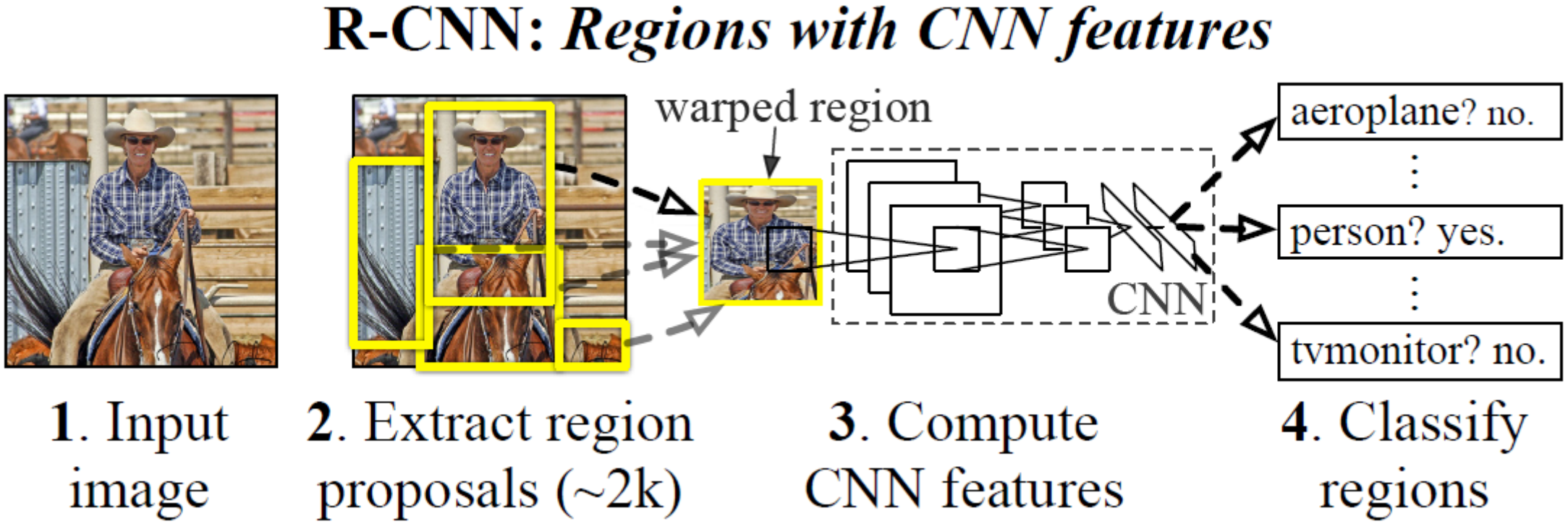
Is Faster R-CNN Really Fast?

- Generally R-FCN and SSD models are faster on average while Faster R-CNN models are more accurate

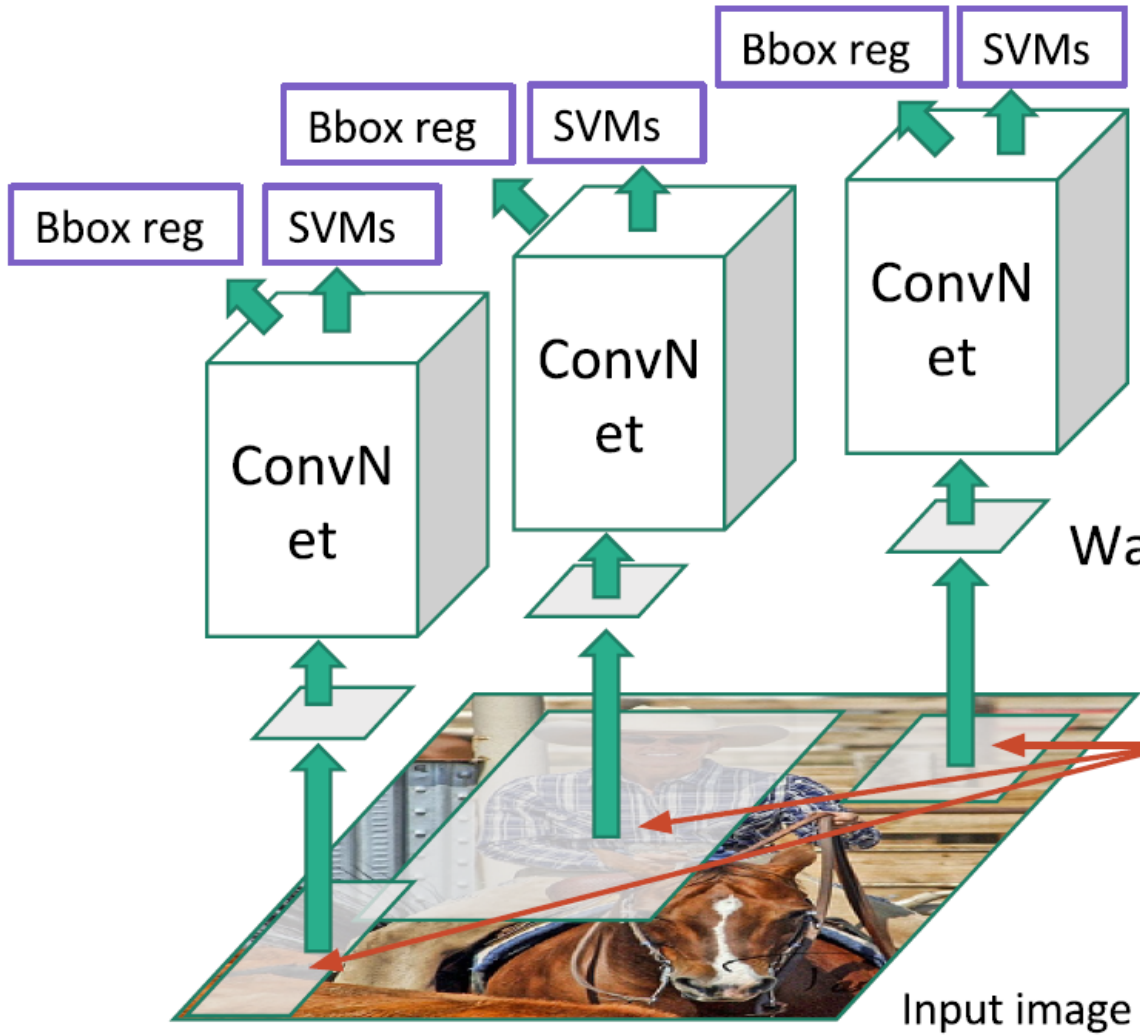
- Faster R-CNN models can be faster if we limit the number of regions proposed



R-CNN Architecture



R-CNN



Linear Regression for bounding box offsets

Classify regions with SVMs

Forward each region through ConvNet

Warped image regions

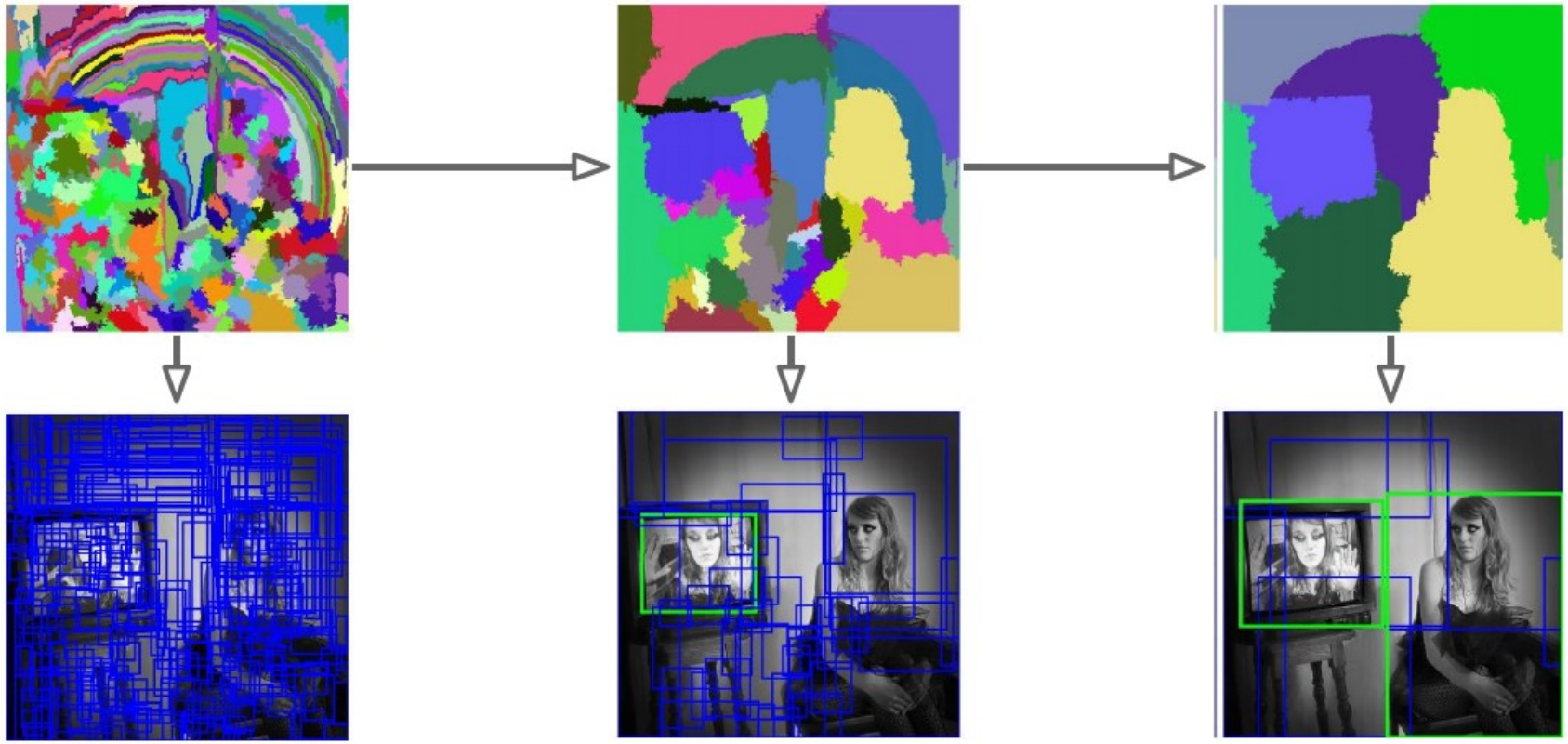
Regions of Interest (RoI) from a proposal method (~2k)

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

Region Proposals – Selective Search

- Bottom-up segmentation, merging regions at multiple scales

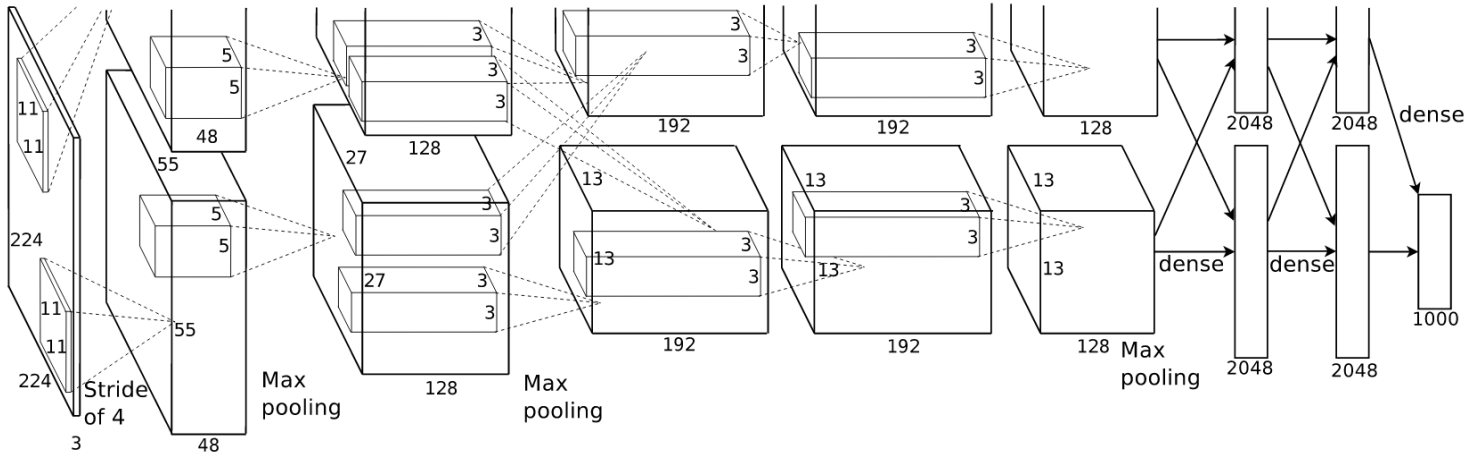
Convert regions to boxes



R-CNN Training

"Post hoc" means the parameters are learned after the ConvNet is fixed

- Pre-train a ConvNet(AlexNet) for ImageNet classification dataset
- Fine-tune for object detection(softmax + log loss)
- Cache feature vectors to disk
- Train post hoc linear SVMs(hinge loss)
- Train post hoc linear bounding-box regressors(squared loss)



Bounding-Box Regression

$P^i = (P^i_x, P^i_y, P^i_w, P^i_h)$ specifies the pixel coordinates of the center of proposal P^i's bounding box together with P^i's width and height in pixels

$G = (G_x, G_y, G_w, G_h)$ means the ground-truth bounding box

$$\hat{G}_x = P_w d_x(P) + P_x \quad (1)$$

$$\hat{G}_y = P_h d_y(P) + P_y \quad (2)$$

$$\hat{G}_w = P_w \exp(d_w(P)) \quad (3)$$

$$\hat{G}_h = P_h \exp(d_h(P)). \quad (4)$$

Bounding-Box Regression

Each function $d_\star(P)$ (where $\star$ is one of x, y, h, w) is modeled as a linear function of the pool_5 features of proposal P, denoted by $\phi_5(P)$. (The dependence of $\phi_5(P)$ on the image data is implicitly assumed.) Thus we have $d_\star(P) = \mathbf{w}_\star^{\mathrm{T}} \phi_5(P)$, where $\mathbf{w}_\star$ is a vector of learnable model parameters. We learn $\mathbf{w}_\star$ by optimizing the regularized least squares objective (ridge regression):

$$\mathbf{w}_\star = \underset{\hat{\mathbf{w}}_\star}{\operatorname{argmin}} \sum_i^N (t_\star^i - \hat{\mathbf{w}}_\star^{\mathrm{T}} \phi_5(P^i))^2 + \lambda \left\| \hat{\mathbf{w}}_\star \right\|^2 . \quad (5)$$

$$\hat{G}_x = P_w d_x(P) + P_x \quad (1)$$

$$\hat{G}_y = P_h d_y(P) + P_y \quad (2)$$

$$\hat{G}_w = P_w \exp(d_w(P)) \quad (3)$$

$$\hat{G}_h = P_h \exp(d_h(P)). \quad (4)$$

$$t_x = (G_x - P_x)/P_w \quad (6)$$

$$t_y = (G_y - P_y)/P_h \quad (7)$$

$$t_w = \log(G_w/P_w) \quad (8)$$

$$t_h = \log(G_h/P_h). \quad (9)$$

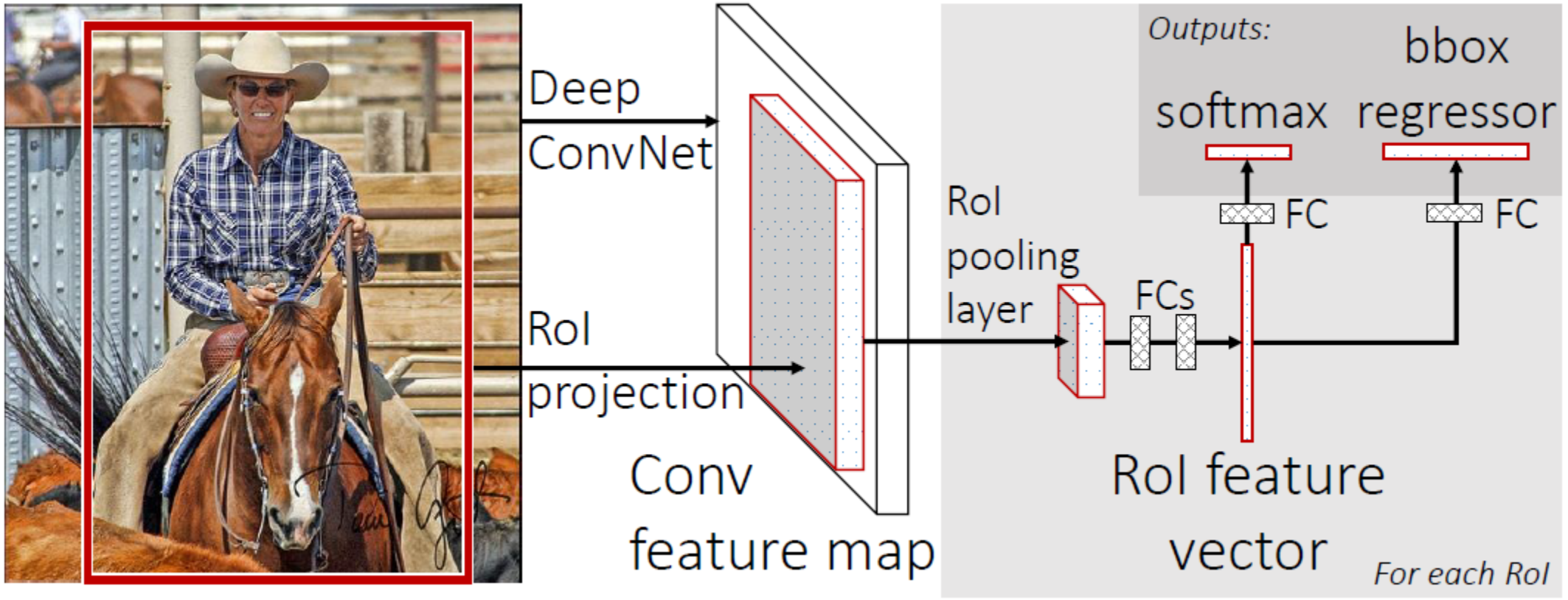
Problems of R-CNN

- Slow at test-time: need to run full forward path of CNN for each region proposal
  - 13s/image on a GPU(K40)
  - 53s/image on a CPU
- SVM and regressors are post-hoc: CNN features not updated in response to SVMs and regressors
- Complex multistage training pipeline (84 hours using K40 GPU)
  - Fine-tune network with softmax classifier(log loss)
  - Train post-hoc linear SVMs(hinge loss)
  - Train post-hoc bounding-box regressions(squared loss)

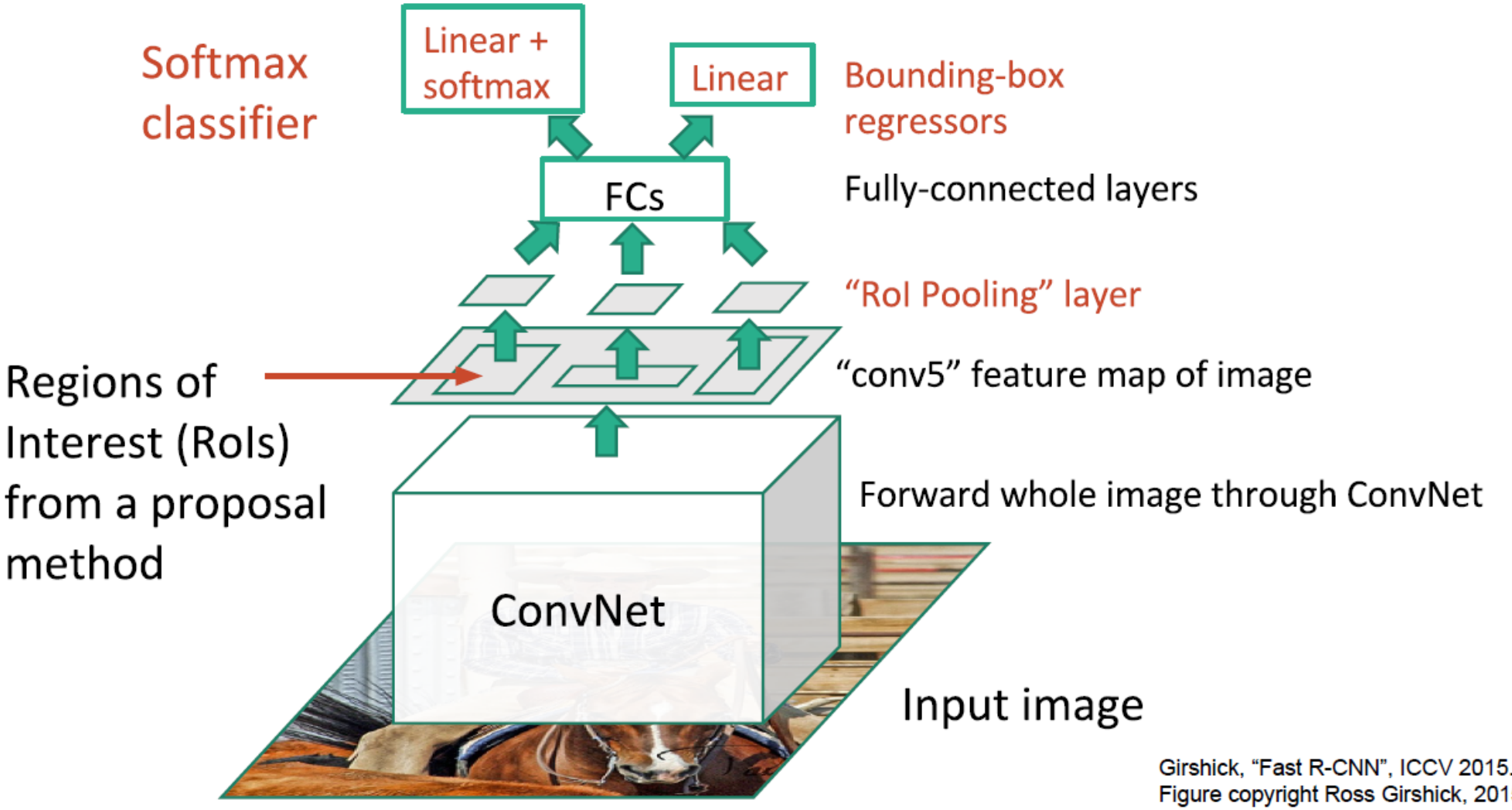
Fast R-CNN

- Fix most of what's wrong with R-CNN and SPP-net
- Train the detector in a single stage, end-to-end
  - No caching features to disk
  - No post hoc training steps
- Train all layers of the network

Fast R-CNN Architecture



Fast R-CNN

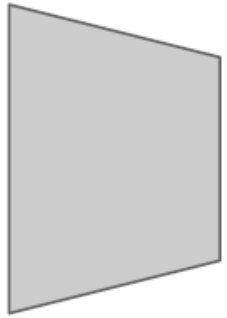


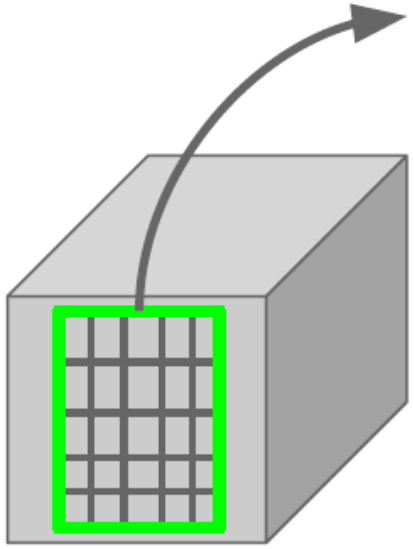
Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015;

RoI Pooling

Hi-res input image:
3 x 800 x 600
with region
proposal

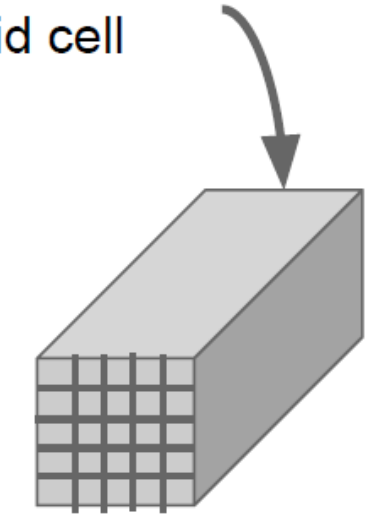
Convolution
and Pooling





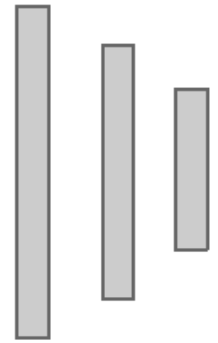
Hi-res conv features:
C x H x W
with region proposal

Max-pool within
each grid cell



RoI conv features:
C x h x w
for region proposal

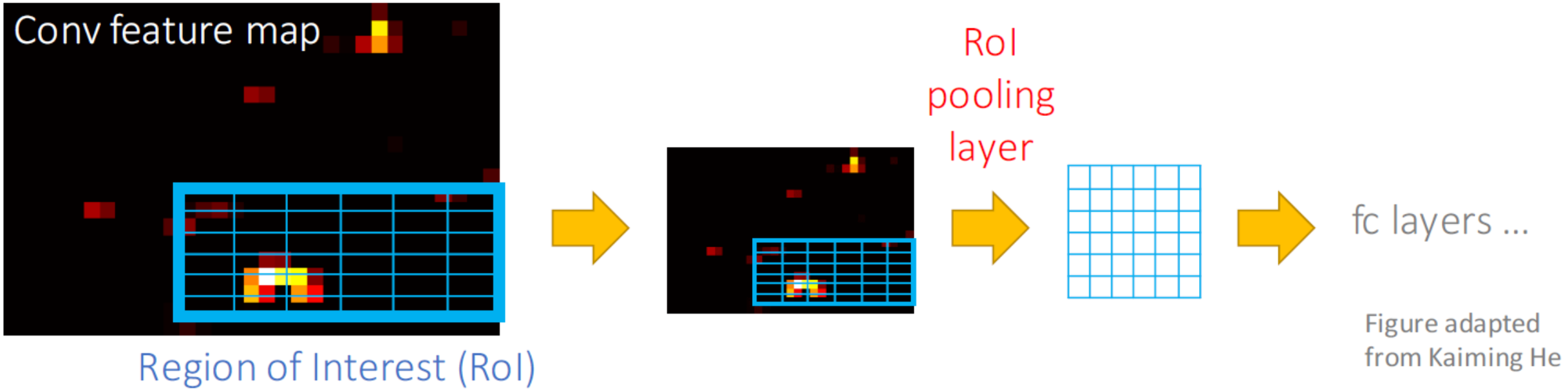
Fully-connected
layers



Fully-connected layers expect
low-res conv features:
C x h x w

RoI Pooling

VGG-16



Just a special case of the SPP layer with one pyramid level

RoI in Conv feature map : 21x14 → 3x2 max pooling with stride(3, 2) → output : 7x7
RoI in Conv feature map : 35x42 → 5x6 max pooling with stride(5, 6) → output : 7x7

Training & Testing

1. Takes an input and a set of bounding boxes
2. Generate convolutional feature maps
3. For each bbox, get a fixed-length feature vector from RoI pooling layer
4. Outputs have two information
   - K+1 class labels
   - Bounding box locations

- Loss function

True box coordinates

Predicted box coordinates

$$L(p, u, t^u, v) = L_{\text{cls}}(p, u) + \lambda[u \geq 1]L_{\text{loc}}(t^u, v)$$

Predicted class scores

True class scores

Log loss

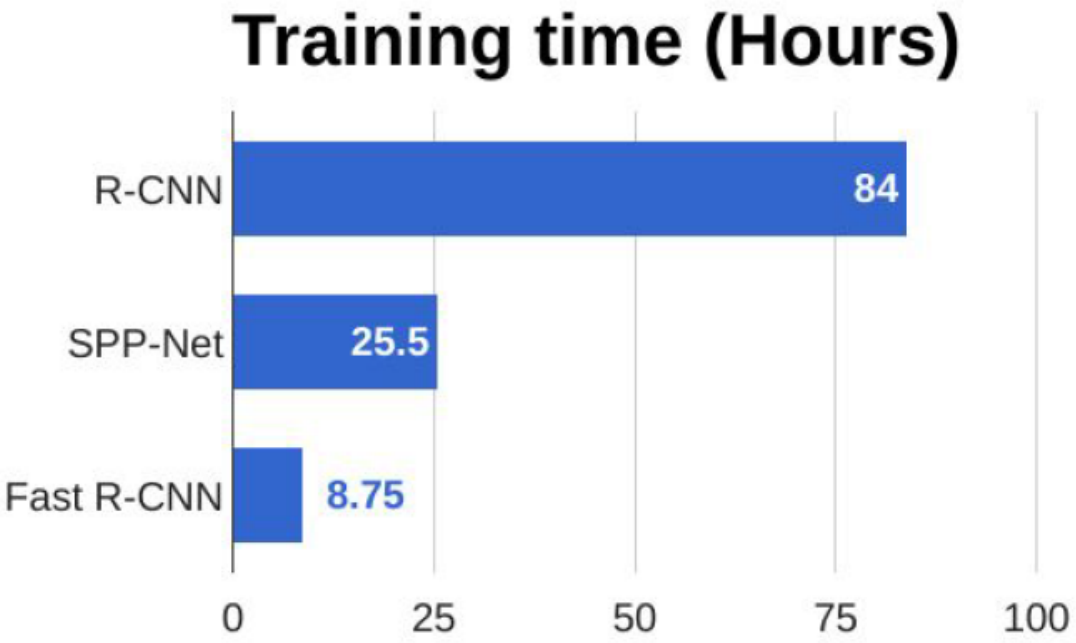
Smooth L1 loss

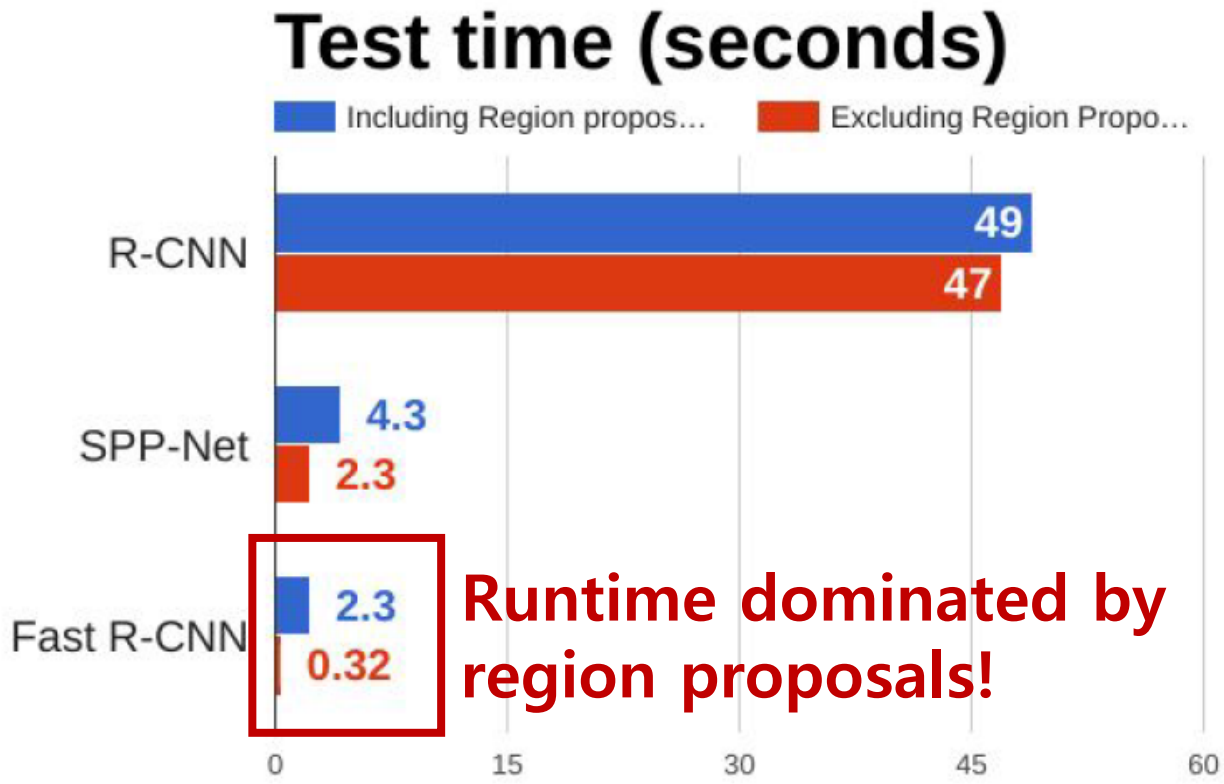
$$L_{\text{loc}}(t^u, v) = \sum_{i \in \{\text{x,y,w,h}\}} \text{smooth}_{L_1}(t_i^u - v_i),$$

in which

$$\text{smooth}_{L_1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise,} \end{cases}$$

R-CNN vs SPP-net vs Fast R-CNN



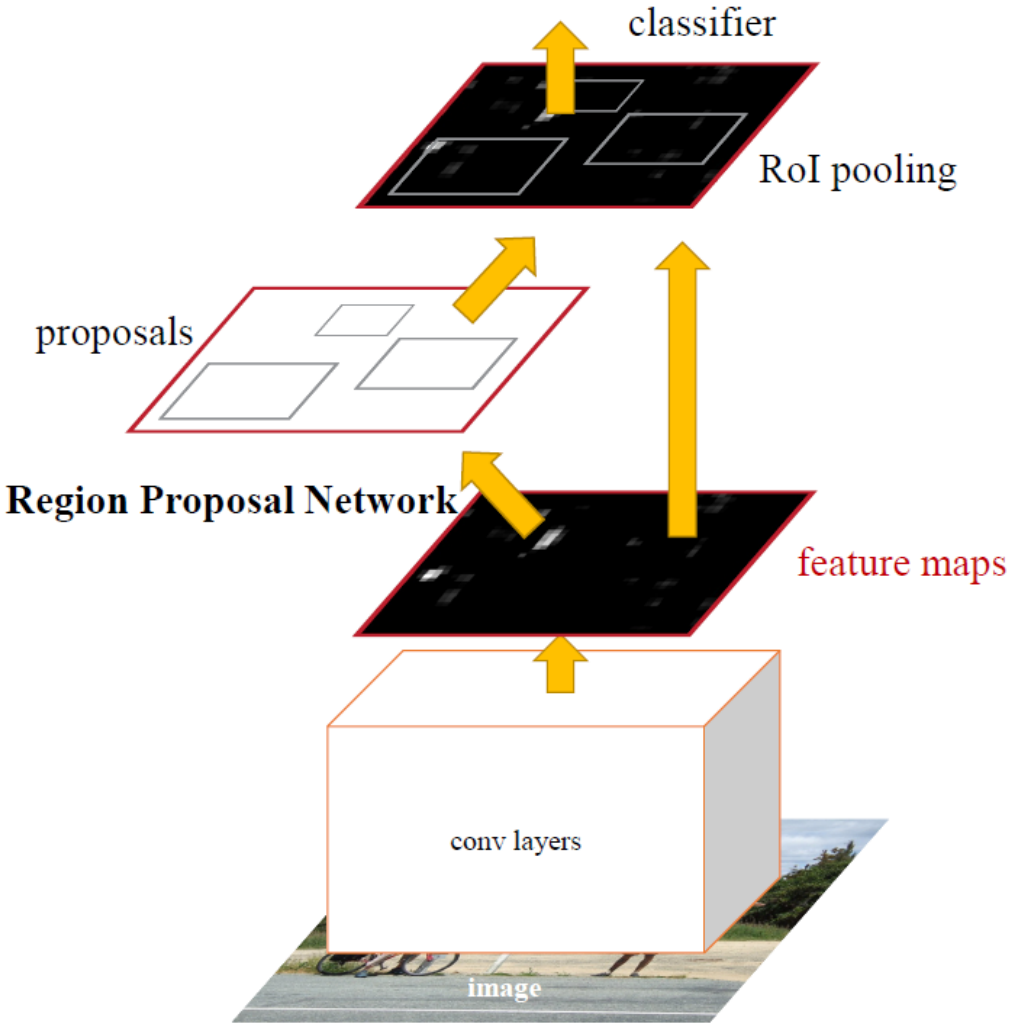


Problems of Fast R-CNN

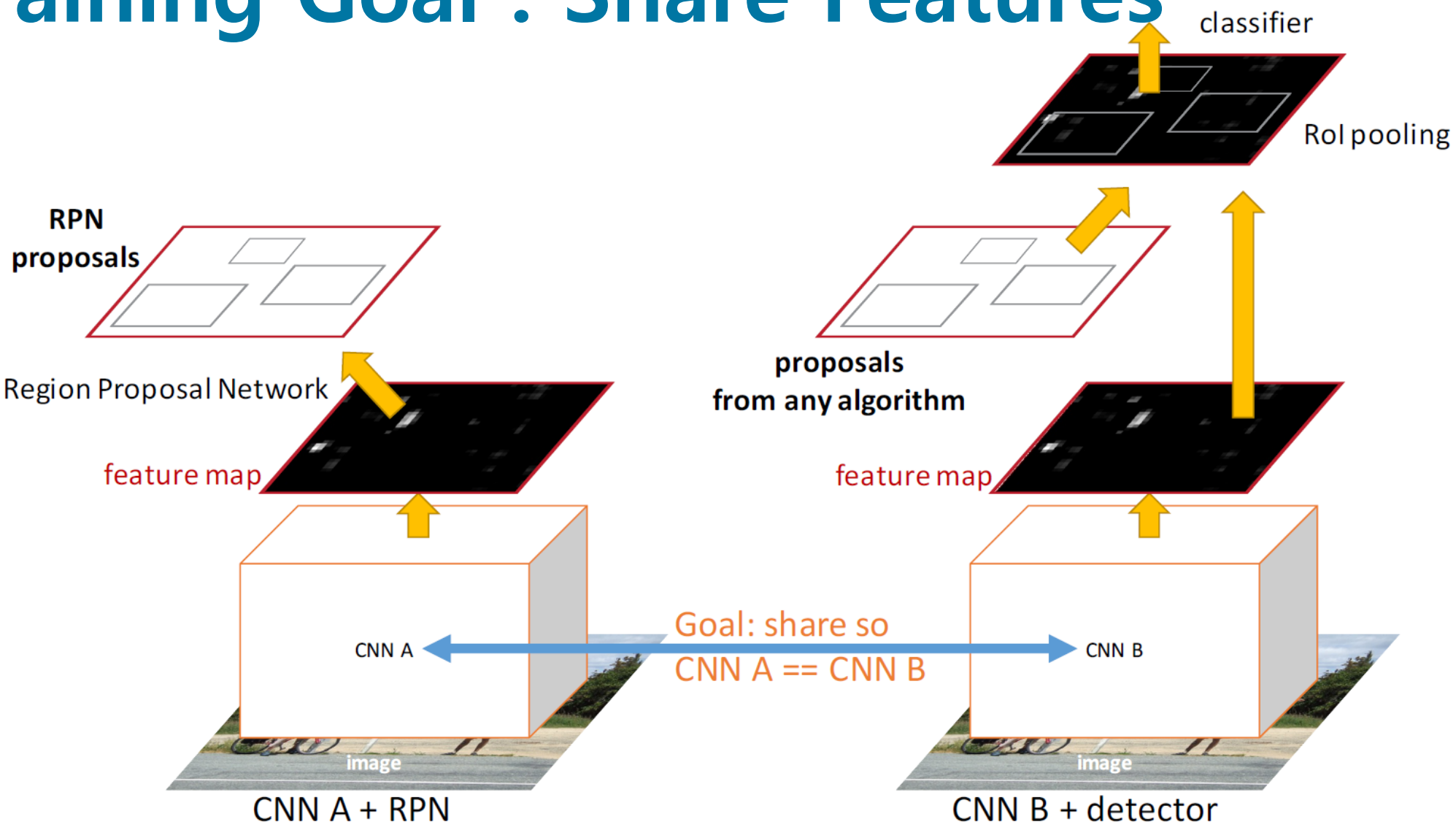
- Out-of-network region proposals are the test-time computational bottleneck
- Is it fast enough??

Faster R-CNN(RPN + Fast R-CNN)

- Insert a Region Proposal Network (RPN) after the last convolutional layer → using GPU!
- RPN trained to produce region proposals directly; no need for external region proposals
- After RPN, use RoI Pooling and an upstream classifier and bbox regressor just like Fast R-CNN

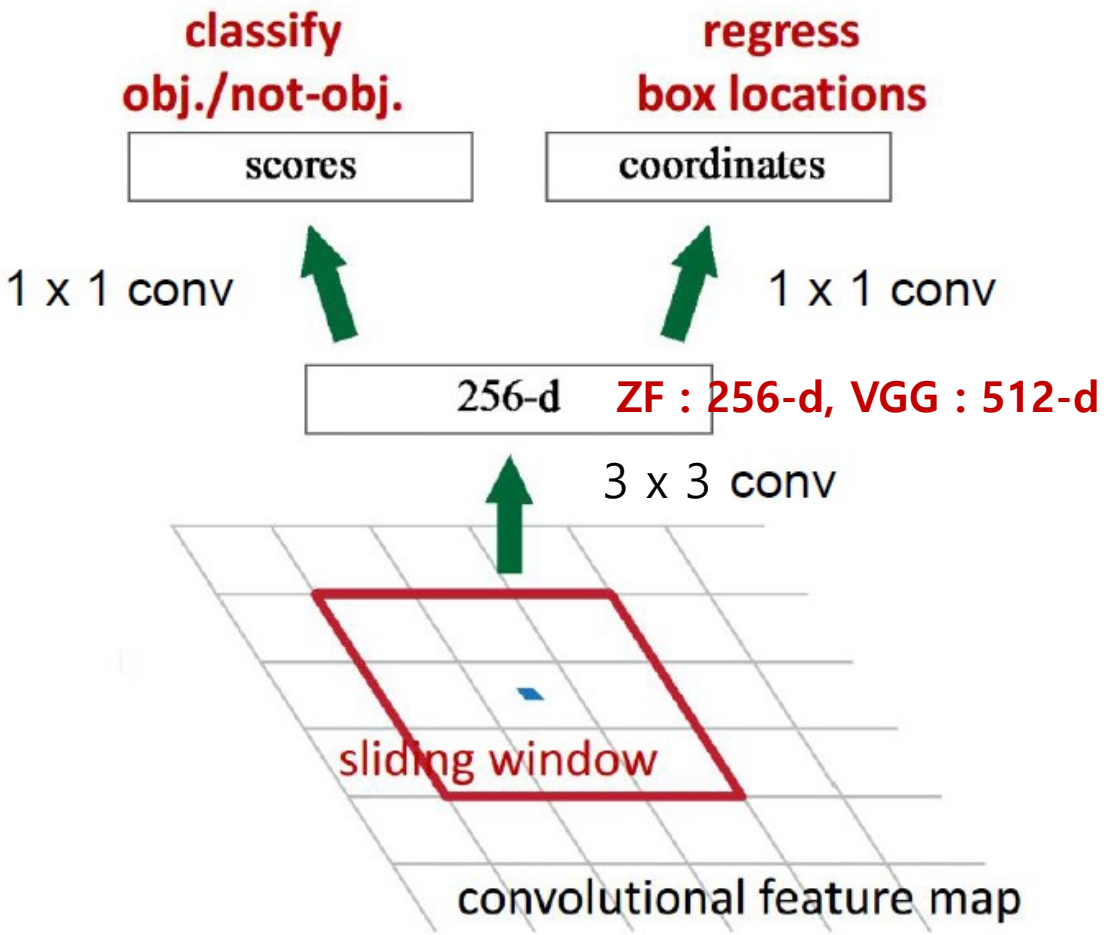


Training Goal : Share Features



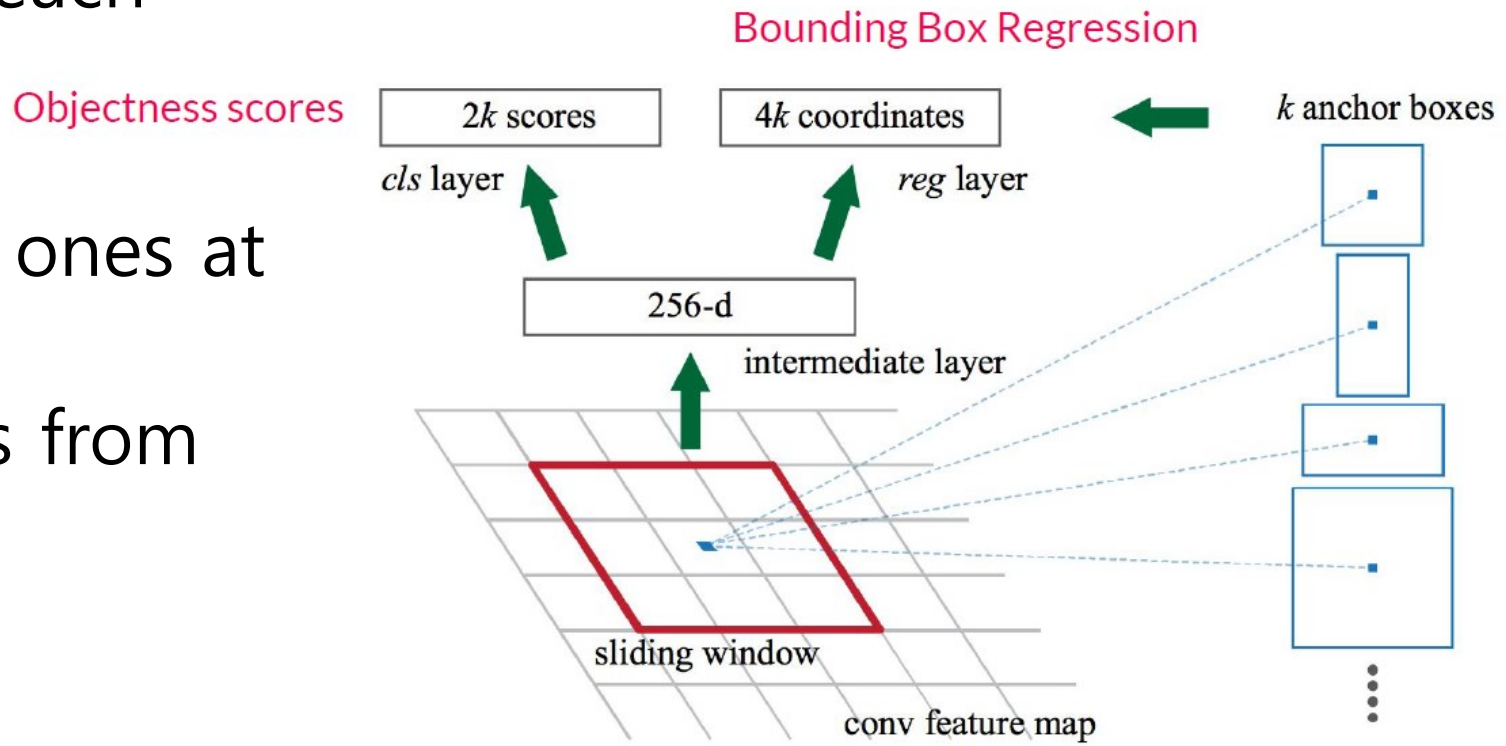
RPN

- Slide a small window on the feature map
- Build a small network for
  - Classifying object or not-object
  - Regressing bbox locations
- Position of the sliding window provides localization information with reference to the image
- Box regression provides finer localization information with reference to this sliding window



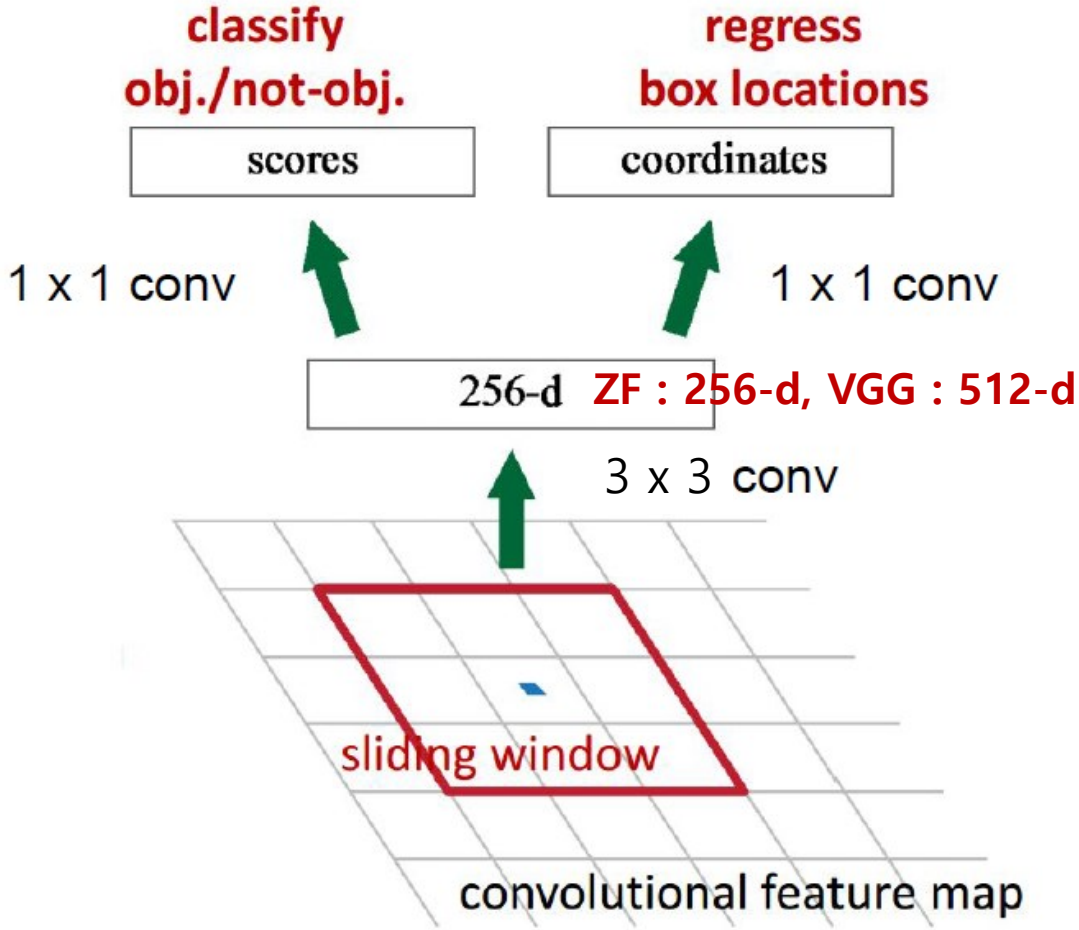
RPN

- Use k anchor boxes at each location
- Anchors are translation invariant: use the same ones at every location
- Regression gives offsets from anchor boxes
- Classification gives the probability that each (regressed) anchor shows an object



RPN(Fully Convolutional Network)

- Intermediate Layer – 256(or 512) 3x3 filter, stride 1, padding 1
- Cls layer – 18(9x2) 1x1 filter, stride 1, padding 0
- Reg layer – 36(9x4) 1x1 filter, stride 1, padding 0



Anchors as references

- Anchors: pre-defined reference boxes
- Multi-scale/size anchors:
  - Multiple anchors are used at each position:
    - 3 scale(128x128, 256x256, 512x512) and 3 aspect rations(2:1, 1:1, 1:2) yield 9 anchors
  - Each anchor has its own prediction function
  - Single-scale features, multi-scale predictions

Positive/Negative Samples

- An anchor is labeled as positive if
  - The anchor is the one with highest IoU overlap with a ground-truth box
  - The anchor has an IoU overlap with a ground-truth box higher than 0.7
- Negative labels are assigned to anchors with IoU lower than 0.3 for all ground-truth boxes
- 50%/50% ratio of positive/negative anchors in a minibatch

RPN Loss Function

i = anchor index in minibatch

Log loss

Ground truth objectness label

Smooth L1 loss

$$L(\{p_i\}, \{t_i\}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*).$$

True box coordinates

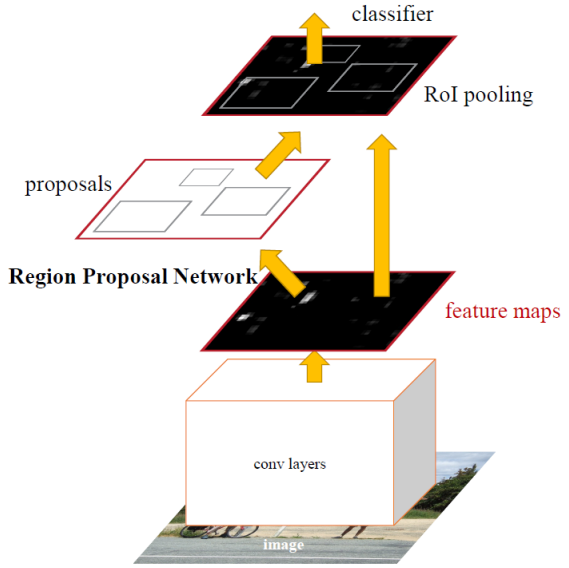
Coordinates of the predicted bounding box for anchor *i*

Predicted probability of being an object for anchor *i*

In practice λ= 10, so that both terms are roughly equally balanced

N_{cls} = Number of anchors in minibatch (~ 256)
N_{reg} = Number of anchor locations (~ 2400)

4-Step Alternating Training




```
# Let M0 be an ImageNet pre-trained network

1.  train_rpn(M0) → M1                  # Train an RPN initialized from M0, get M1

2.  generate_proposals(M1) → P1         # Generate training proposals P1 using RPN M1

3.  train_fast_rcnn(M0, P1) → M2        # Train Fast R-CNN M2 on P1 initialized from M0

4.  train_rpn_frozen_conv(M2) → M3      # Train RPN M3 from M2 without changing conv layers

5.  generate_proposals(M3) → P2

6.  train_fast_rcnn_frozen_conv(M3, P2) → M4   # Conv layers are shared with RPN M3

7.  return add_rpn_layers(M4, M3.RPN)          # Add M3's RPN layers to Fast R-CNN M4
```

Results

	R-CNN	Fast R-CNN	Faster R-CNN
Test time per image (with proposals)	50 seconds	2 seconds	**0.2 seconds**
(Speedup)	1x	25x	**250x**
mAP (VOC 2007)	66.0	**66.9**	**69.9**

Table 5: **Timing** (ms) on a K40 GPU, except SS proposal is evaluated in a CPU. "Region-wise" includes NMS, pooling, fully-connected, and softmax layers. See our released code for the profiling of running time.

model	system	conv	proposal	region-wise	total	rate
VGG	SS + Fast R-CNN	146	1510	174	1830	0.5 fps
VGG	RPN + Fast R-CNN	141	**10**	47	**198**	**5 fps**
ZF	RPN + Fast R-CNN	31	**3**	25	**59**	**17 fps**

Experiments

Table 1: the learned average proposal size for each anchor using the ZF net (numbers for $s = 600$).

anchor	128^2, 2:1	128^2, 1:1	128^2, 1:2	256^2, 2:1	256^2, 1:1	256^2, 1:2	512^2, 2:1	512^2, 1:1	512^2, 1:2
proposal	188×111	113×114	70×92	416×229	261×284	174×332	768×437	499×501	355×715

Table 8: Detection results of Faster R-CNN on PASCAL VOC 2007 test set using **different settings of anchors**. The network is VGG-16. The training data is VOC 2007 trainval. The default setting of using 3 scales and 3 aspect ratios (69.9%) is the same as that in Table 3.

settings	anchor scales	aspect ratios	mAP (%)
1 scale, 1 ratio	128^2	1:1	65.8
	256^2	1:1	66.7
1 scale, 3 ratios	128^2	{2:1, 1:1, 1:2}	68.8
	256^2	{2:1, 1:1, 1:2}	67.9
3 scales, 1 ratio	$\{128^2, 256^2, 512^2\}$	1:1	**69.8**
3 scales, 3 ratios	$\{128^2, 256^2, 512^2\}$	{2:1, 1:1, 1:2}	**69.9**

Table 9: Detection results of Faster R-CNN on PASCAL VOC 2007 test set using **different values of** λ in Equation (1). The network is VGG-16. The training data is VOC 2007 trainval. The default setting of using $\lambda = 10$ (69.9%) is the same as that in Table 3.

λ	0.1	1	10	100
mAP (%)	67.2	68.9	69.9	69.1

Experiments

Table 2: Detection results on **PASCAL VOC 2007 test set** (trained on VOC 2007 trainval). The detectors are Fast R-CNN with ZF, but using various proposal methods for training and testing.

train-time region proposals		**test-time region proposals**		
method	# boxes	method	# proposals	mAP (%)
SS	2000	SS	2000	58.7
EB	2000	EB	2000	58.6
RPN+ZF, shared	2000	RPN+ZF, shared	300	**59.9**
ablation experiments follow below				
RPN+ZF, unshared	2000	RPN+ZF, unshared	300	58.7
SS	2000	RPN+ZF	100	55.1
SS	2000	RPN+ZF	300	56.8
SS	2000	RPN+ZF	1000	56.3
SS	2000	RPN+ZF (no NMS)	6000	55.2
SS	2000	RPN+ZF (no *cls*)	100	44.6
SS	2000	RPN+ZF (no *cls*)	300	51.4
SS	2000	RPN+ZF (no *cls*)	1000	55.8
SS	2000	RPN+ZF (no *reg*)	300	52.1
SS	2000	RPN+ZF (no *reg*)	1000	51.3
SS	2000	RPN+VGG	300	59.2

Experiments

Table 3: Detection results on **PASCAL VOC 2007 test set**. The detector is Fast R-CNN and VGG-16. Training data: "07": VOC 2007 trainval, "07+12": union set of VOC 2007 trainval and VOC 2012 trainval. For RPN, the train-time proposals for Fast R-CNN are 2000. †: this number was reported in [2]; using the repository provided by this paper, this result is higher (68.1).

method	# proposals	data	mAP (%)
SS	2000	07	66.9†
SS	2000	07+12	70.0
RPN+VGG, unshared	300	07	68.5
RPN+VGG, shared	300	07	69.9
RPN+VGG, shared	300	07+12	**73.2**
RPN+VGG, shared	300	COCO+07+12	**78.8**

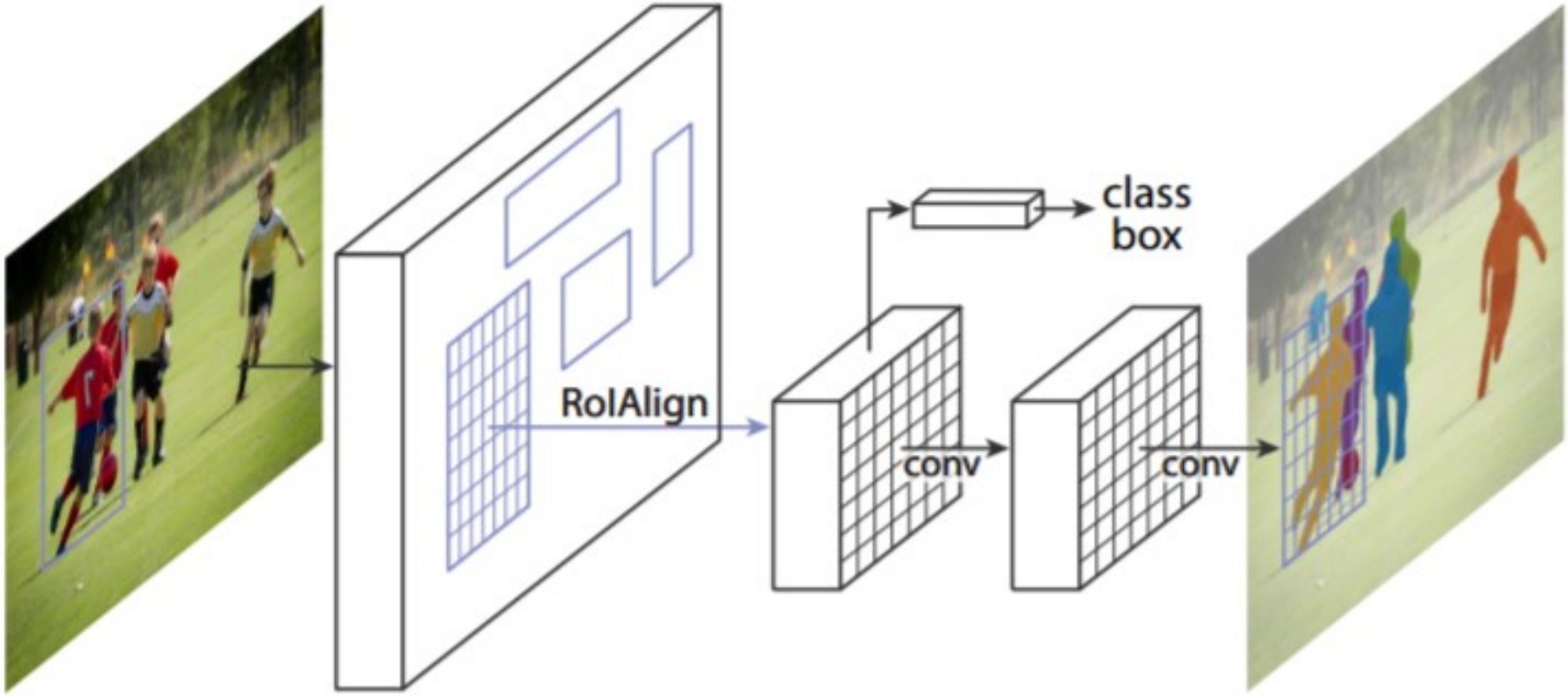
Table 4: Detection results on **PASCAL VOC 2012 test set**. The detector is Fast R-CNN and VGG-16. Training data: "07": VOC 2007 trainval, "07++12": union set of VOC 2007 trainval+test and VOC 2012 trainval. For RPN, the train-time proposals for Fast R-CNN are 2000. †: http://host.robots.ox.ac.uk:8080/anonymous/HZJTQA.html. ‡: http://host.robots.ox.ac.uk:8080/anonymous/YNPLXB.html. §: http://host.robots.ox.ac.uk:8080/anonymous/XEDH10.html.

method	# proposals	data	mAP (%)
SS	2000	12	65.7
SS	2000	07++12	68.4
RPN+VGG, shared†	300	12	67.0
RPN+VGG, shared‡	300	07++12	**70.4**
RPN+VGG, shared§	300	COCO+07++12	**75.9**

Is It Enough?

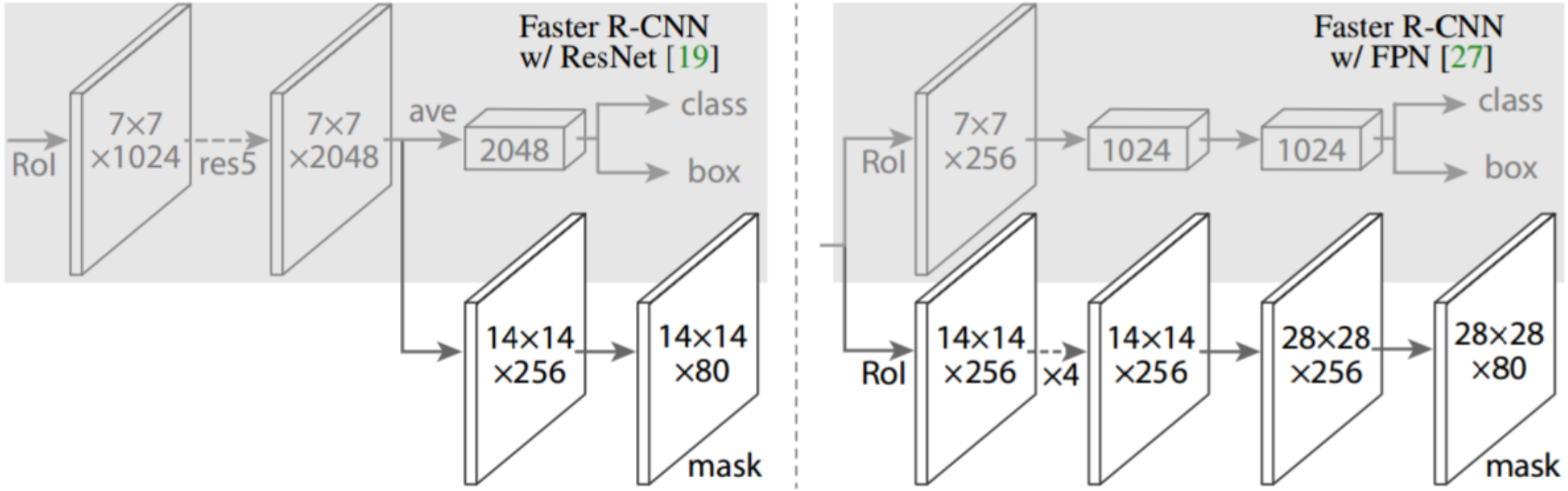
- RoI Pooling has some quantization operations
- These quantizations introduce misalignments between the RoI and the extracted features
- While this may not impact classification, it can make a negative effect on predicting bbox

Mask R-CNN



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



Loss Function, Mask Branch

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

- The mask branch has a K x m x m - dimensional output for each RoI, which encodes K binary masks of resolution m × m, one for each of the K classes.
- Applying per-pixel sigmoid
- For an RoI associated with ground-truth class k, Lmask is only defined on the k-th mask

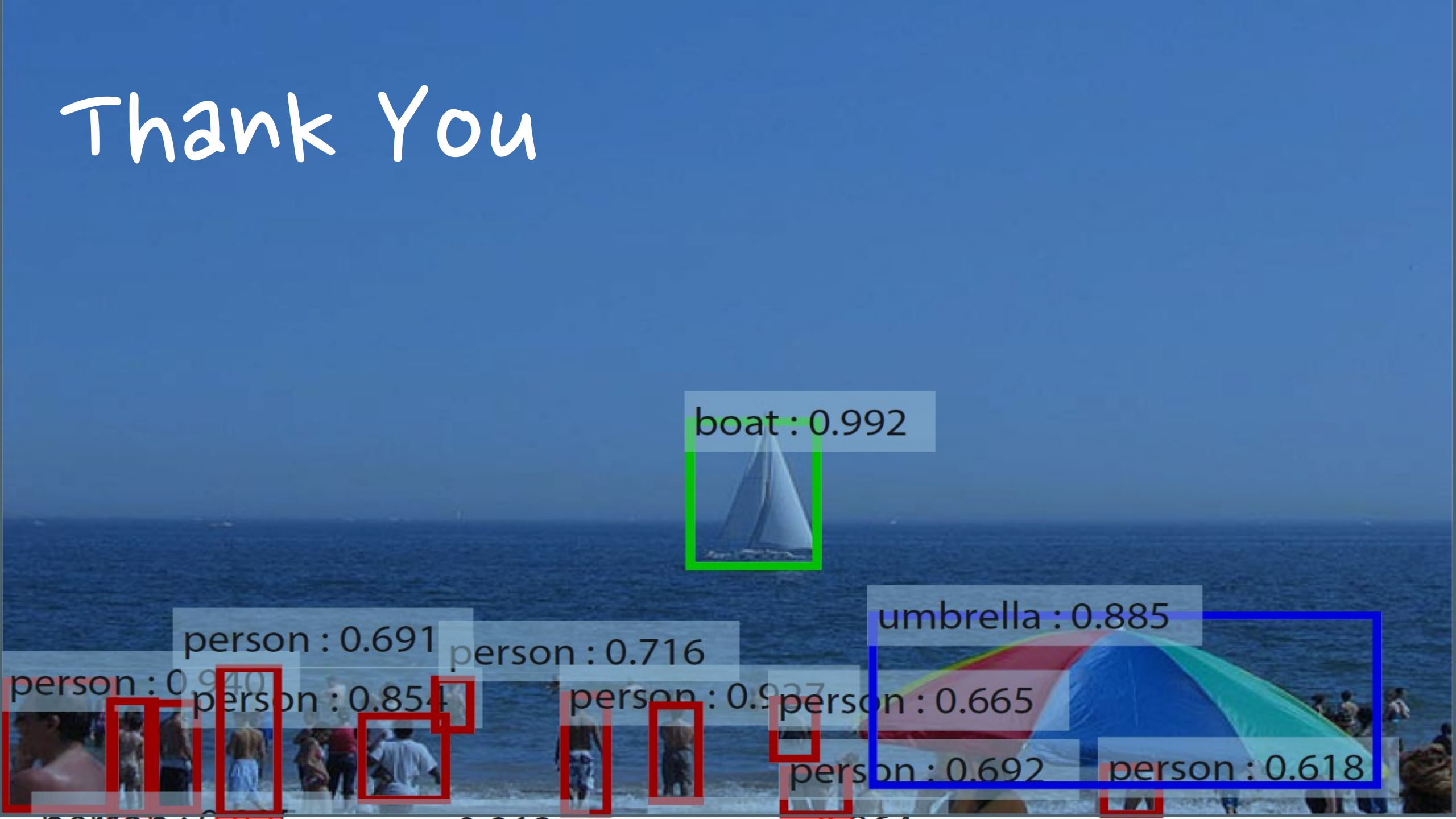
RoI Align

- RoI Align don’t use quantization of the RoI boundaries
- Bilinear interpolation is used for computing the exact values of the input features

Results – MS COCO

	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 [37]	34.7	55.5	36.7	13.5	38.1	52.0
Faster R-CNN w TDM [36]	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

Thank You


boat : 0.992
person : 0.691
person : 0.716
umbrella : 0.885
person : 0.665
person : 0.692
person : 0.618

Thank You