Boulder

Computer Vision; Object Detection; Two Stage Detectors

YouTube Playlist

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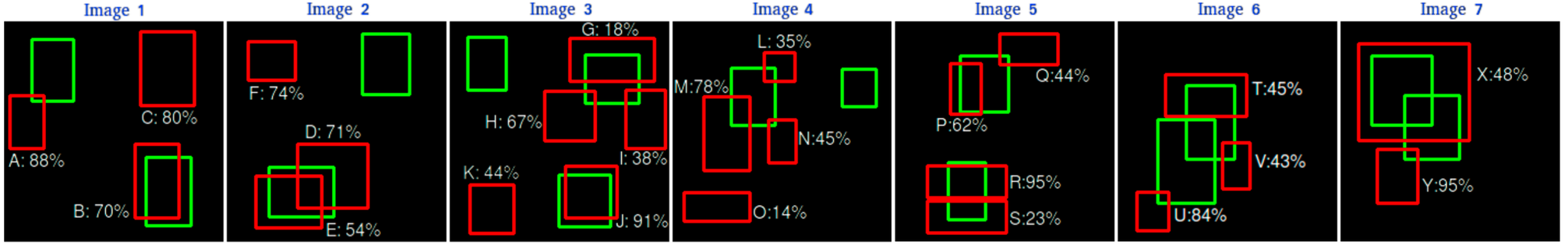
A Survey on Performance Metrics for Object-Detection Algorithms

YouTube Playlist



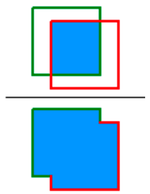
"In the object detection context, a true negative (TN) result does not apply, as there are infinite number of bounding boxes that should not be detected within any given image."

- True positive (TP): A correct detection of a ground-truth bounding box;
- False positive (FP): An incorrect detection of a nonexistent object or a misplaced detection of an existing object;
- False negative (FN): An undetected ground-truth bounding box;

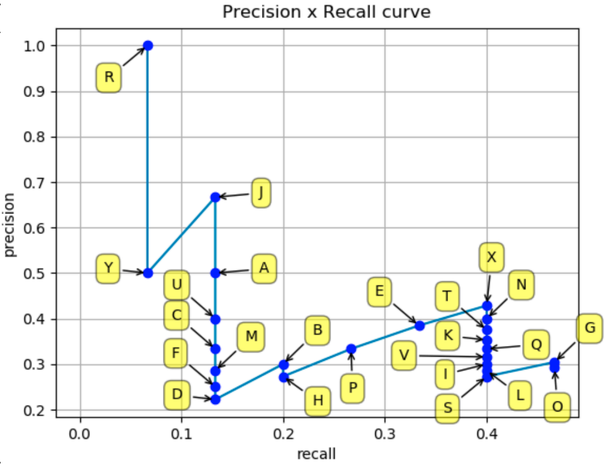
predicted bounding box, ground-truth bounding box

$$J(B_p, B_{gt}) = \text{IOU} = \frac{\text{area}(B_p \cap B_{gt})}{\text{area}(B_p \cup B_{gt})}$$

Jaccard Index; Intersection over Union



detection	confidence	TP	FP	acc TP	acc FP	precision	recall
R	95%	1	0	1	0	1	0.0666
Y	95%	0	1	1	1	0.5	0.0666
J	91%	1	0	2	1	0.6666	0.1333
A	88%	0	1	2	2	0.5	0.1333
U	84%	0	1	2	3	0.4	0.1333
C	80%	0	1	2	4	0.3333	0.1333
M	78%	0	1	2	5	0.2857	0.1333
F	74%	0	1	2	6	0.25	0.1333
D	71%	0	1	2	7	0.2222	0.1333
B	70%	1	0	3	7	0.3	0.2
H	67%	0	1	3	8	0.2727	0.2
P	62%	1	0	4	8	0.3333	0.2666
E	54%	1	0	5	8	0.3846	0.3333
X	48%	1	0	6	8	0.4285	0.4
N	45%	0	1	6	9	0.4	0.4
T	45%	0	1	6	10	0.375	0.4
K	44%	0	1	6	11	0.3529	0.4
Q	44%	0	1	6	12	0.3333	0.4
V	43%	0	1	6	13	0.3157	0.4
I	38%	0	1	6	14	0.3	0.4
L	35%	0	1	6	15	0.2857	0.4
S	23%	0	1	6	16	0.2727	0.4
G	18%	1	0	7	16	0.3043	0.4666
O	14%	0	1	7	17	0.2916	0.4666



$t \rightarrow$ threshold

$\text{IOU} > t \rightarrow$ correct

$\text{IOU} < t \rightarrow$ incorrect

$$P = \frac{\text{TP}}{\text{TP} + \text{FP}} = \frac{\text{TP}}{\text{all detections}},$$

$$R = \frac{\text{TP}}{\text{TP} + \text{FN}} = \frac{\text{TP}}{\text{all ground truths}}$$

$$\text{AP}_{11} = \frac{1}{11} \sum_{R \in \{0, 0.1, \ldots, 0.9, 1\}} P_{\text{interp}}(R)$$

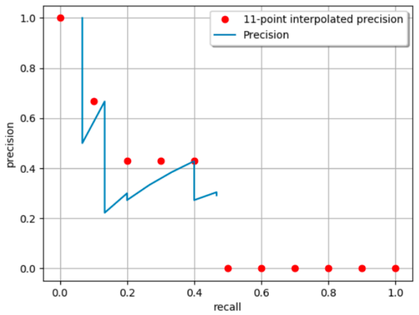
$$P_{\text{interp}}(R) = \max_{\tilde{R}:\tilde{R} \geq R} P(\tilde{R})$$

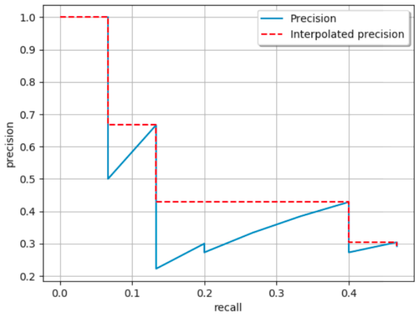
$$\text{AP}_{\text{all}} = \sum_{n} (R_{n+1} - R_n) P_{\text{interp}}(R_{n+1})$$

$$P_{\text{interp}}(R_{n+1}) = \max_{\tilde{R}:\tilde{R} \geq R_{n+1}} P(\tilde{R})$$

$$\text{mAP} = \frac{1}{N} \sum_{i=1}^{N} \text{AP}_i$$

$\text{AP}_i \rightarrow i$-th class



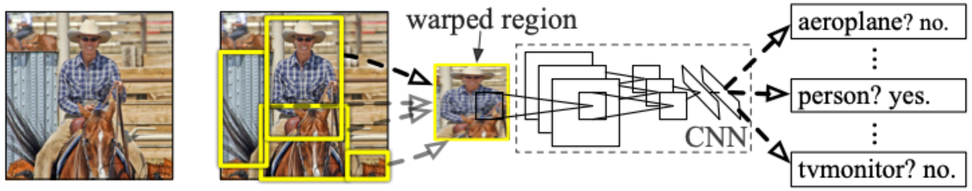


Padilla, Rafael, Sergio L. Netto, and Eduardo AB da Silva. "A Survey on Performance Metrics for Object-Detection Algorithms." *2020 International Conference on Systems, Signals and Image Processing (IWSSIP)*. IEEE, 2020.

Rich feature hierarchies for accurate object detection and semantic segmentation

YouTube Playlist

R-CNN: *Regions with CNN features*



1. Input image | 2. Extract region proposals (~2k) | 3. Compute CNN features | 4. Classify regions

Region proposals: selective search

Feature extraction: 4096-dimensional feature vector from AlexNet

Warped training samples

Classify regions: class-specific linear SVM

Greedy Non-maximum Suppression

For each class independently reject a region if it has an intersection-over-union (IoU) overlap with a higher scoring selected region larger than a learned threshold.

Domain-specific fine-tuning

21-way classification layer

Treat all region proposals with ≥ 0.5 IoU overlap with a ground-truth box as positives for that box's class and the rest as negatives.

Object category classifiers

IoU $< 0.3 \rightarrow$ negative examples

ground-truth bounding boxes $\rightarrow$ positive examples

VOC 2010 test	aero	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv	mAP
DPM v5 [17]†	49.2	53.8	13.1	15.3	35.5	53.4	49.7	27.0	17.2	28.8	14.7	17.8	46.4	51.2	47.7	10.8	34.2	20.7	43.8	38.3	33.4
UVA [32]	56.2	42.4	15.3	12.6	21.8	49.3	36.8	46.1	12.9	32.1	30.0	36.5	43.5	52.9	32.9	15.3	41.1	31.8	47.0	44.8	35.1
Regionlets [35]	65.0	48.9	25.9	24.6	24.5	56.1	54.5	51.2	17.0	28.9	30.2	35.8	40.2	55.7	43.5	14.3	43.9	32.6	54.0	45.9	39.7
SegDPM [15]†	61.4	53.4	25.6	25.2	35.5	51.7	50.6	50.8	19.3	33.8	26.8	40.4	48.3	54.4	47.1	14.8	38.7	35.0	52.8	43.1	40.4
R-CNN	67.1	64.1	46.7	32.0	30.5	56.4	57.2	65.9	27.0	47.3	40.9	66.6	57.8	65.9	53.6	26.7	56.5	38.1	52.8	50.2	50.2
R-CNN BB	**71.8**	**65.8**	**53.0**	**36.8**	**35.9**	**59.7**	**60.0**	**69.9**	**27.9**	**50.6**	**41.4**	**70.0**	**62.0**	**69.0**	**58.1**	**29.5**	**59.4**	**39.3**	**61.2**	**52.4**	**53.7**

Visualizing learned features

The idea is to single out a particular unit (feature) in the network and use it as if it were an object detector in its own right.

Bounding-box regression

$G = (G_x, G_y, G_w, G_h) \rightarrow$ ground-truth bounding box

$P = (\underbrace{P_x, P_y}_{\text{center}}, \underbrace{P_w, P_h}_{\text{width \& height}}) \rightarrow$ proposal bounding box

$$\mathbf{w}_\star = \underset{\hat{\mathbf{w}}_\star}{\operatorname{argmin}} \sum_i^N (t_\star^i - \hat{\mathbf{w}}_\star^{\mathrm{T}} \boldsymbol{\phi}_5(P^i))^2 + \lambda \|\hat{\mathbf{w}}_\star\|^2$$

$$t_x = (G_x - P_x)/P_w$$
$$t_y = (G_y - P_y)/P_h$$
$$t_w = \log(G_w/P_w)$$
$$t_h = \log(G_h/P_h).$$

$$\hat{G}_x = P_w d_x(P) + P_x$$
$$\hat{G}_y = P_h d_y(P) + P_y$$
$$\hat{G}_w = P_w \exp(d_w(P))$$
$$\hat{G}_h = P_h \exp(d_h(P)).$$

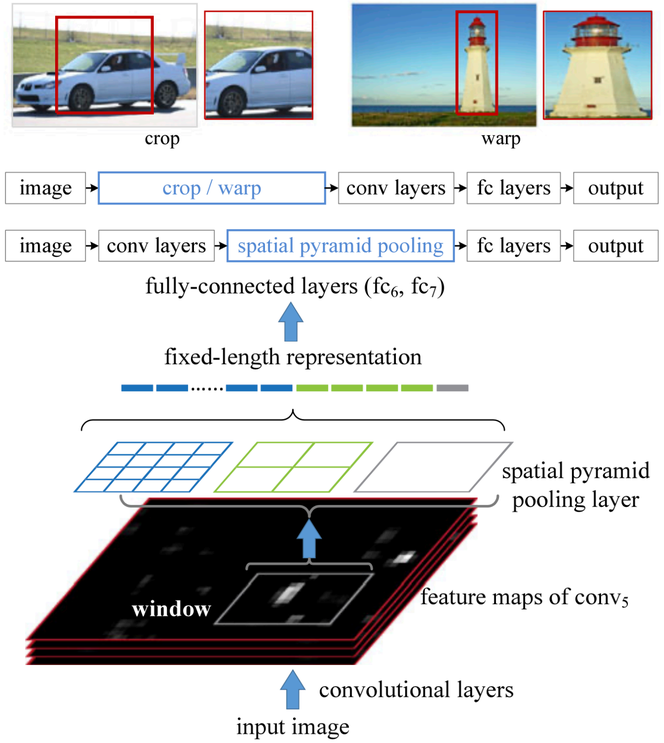
$d_\star(P) = \mathbf{w}_\star^{\mathrm{T}} \boldsymbol{\phi}_5(P)$

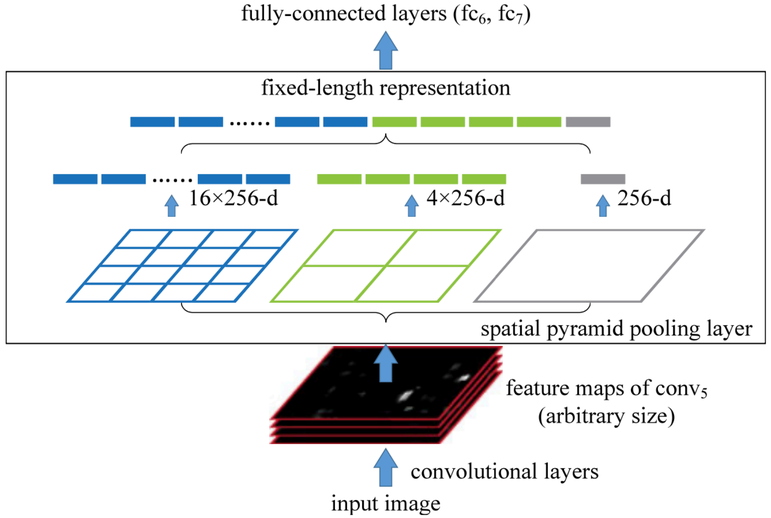
pool_5 features

Girshick, Ross, et al. "Rich feature hierarchies for accurate object detection and semantic segmentation." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014.

Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition

YouTube Playlist





$a \times a \rightarrow$ feature map size (e.g., 13×13)

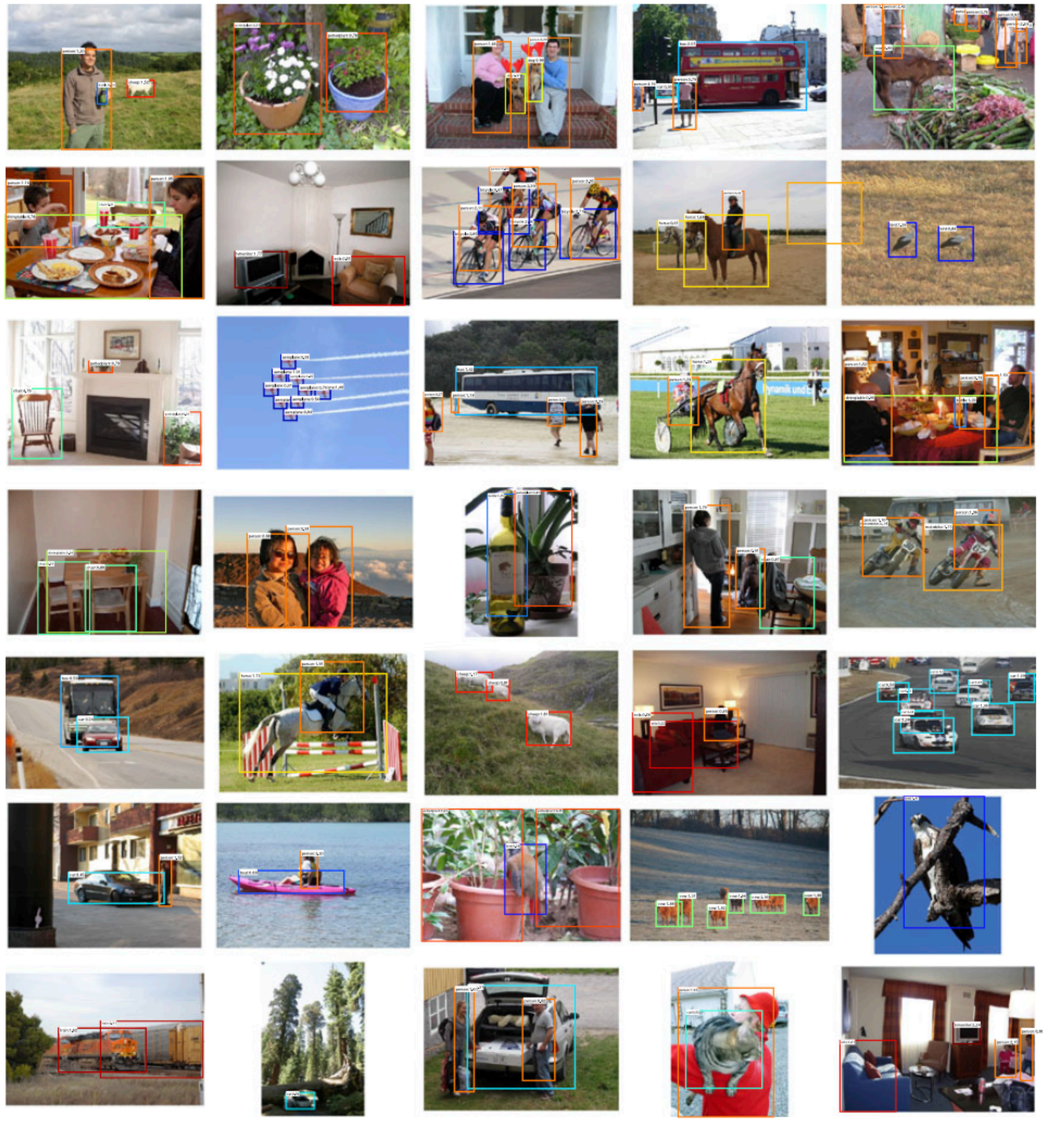
$n \times n \rightarrow$ pyramid level bins (e.g., 2×2)

$\text{win} = \lceil a/n \rceil \rightarrow$ window size

$\text{str} = \lfloor a/n \rfloor \rightarrow$ stride

Comparisons of Detection Results on Pascal VOC 2007

method	mAP	areo	bike	bird	boat	bottle	bus	car	cat	chair	cow	table	dog	horse	mbike	person	plant	sheep	sofa	train	tv
DPM [23]	33.7	33.2	60.3	10.2	16.1	27.3	54.3	58.2	23.0	20.0	24.1	26.7	12.7	58.1	48.2	43.2	12.0	21.1	36.1	46.0	43.5
SS [20]	33.8	43.5	46.5	10.4	12.0	9.3	49.4	53.7	39.4	12.5	36.9	42.2	26.4	47.0	52.4	23.5	12.1	29.9	36.3	42.2	48.8
Regionlet [39]	41.7	54.2	52.0	20.3	24.0	20.1	55.5	68.7	42.6	19.2	44.2	49.1	26.6	57.0	54.5	43.4	16.4	36.6	37.7	59.4	52.3
DetNet [40]	30.5	29.2	35.2	19.4	16.7	3.7	53.2	50.2	27.2	10.2	34.8	30.2	28.2	46.6	41.7	26.2	10.3	32.8	26.8	39.8	47.0
RCNN ftfc7 (A5)	54.2	64.2	69.7	50.0	41.9	32.0	62.6	71.0	60.7	32.7	58.5	46.5	56.1	60.6	66.8	54.2	31.5	52.8	48.9	57.9	64.7
RCNN ftfc7 (ZF5)	55.1	64.8	68.4	47.0	39.5	30.9	59.8	70.5	65.3	33.5	62.5	50.3	59.5	61.6	67.9	54.1	33.4	57.3	52.9	60.2	62.9
SPP ftfc7 (ZF5)	55.2	65.5	65.9	51.7	38.4	32.7	62.6	68.6	69.7	33.1	66.6	53.1	58.2	63.6	68.8	50.4	27.4	53.7	48.2	61.7	64.7
RCNN bb (A5)	58.5	68.1	72.8	56.8	**43.0**	36.8	**66.3**	74.2	67.6	34.4	63.5	54.5	61.2	69.1	68.6	58.7	33.4	62.9	51.1	62.5	64.8
RCNN bb (ZF5)	**59.2**	68.4	**74.0**	54.0	40.9	35.2	64.1	**74.4**	69.8	**35.5**	66.9	53.8	**64.2**	69.9	69.6	**58.9**	**36.8**	**63.4**	**56.0**	62.8	64.9
SPP bb (ZF5)	**59.2**	**68.6**	69.7	**57.1**	41.2	**40.5**	**66.3**	71.3	**72.5**	34.4	**67.3**	**61.7**	63.1	**71.0**	**69.8**	57.6	29.7	59.0	50.2	**65.2**	**68.0**



He, Kaiming, et al. "Spatial pyramid pooling in deep convolutional networks for visual recognition." *IEEE transactions on pattern analysis and machine intelligence* 37.9 (2015): 1904-1916.

Fast R-CNN

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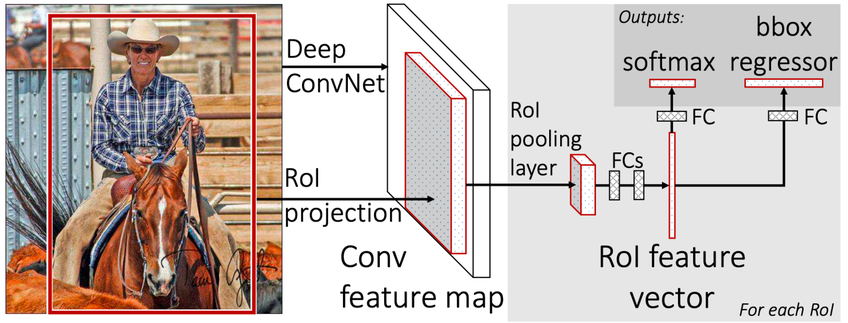
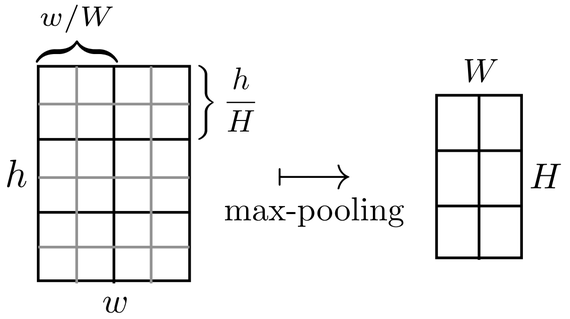


RoI pooling layer

$$(\underbrace{r, c}_{\text{top-left corner}}, \overbrace{h, w}^{\text{height \& width}}) \rightarrow \text{RoI (Regions of Interest)}$$



H & W are set to be compatible with the first fully connected layer

Fine-tuning

Mini-batches are sampled hierarchically, first by sampling N images and then by sampling R/N RoIs from each image (N=2, R = 128).

Multi-task loss

$p = (p_0, \ldots, p_K) \rightarrow$ probability distribution over $K+1$ categories

$t^k = (t^k_x, t^k_y, t^k_w, t^k_h) \rightarrow$ bounding box regression offsets

$k = 1, \ldots, K \rightarrow$ object classes

category-specific bounding-box regressors

Each training RoI is labeled with:

$u \rightarrow$ ground-truth class

$v \rightarrow$ ground-truth bounding box regression target

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

$$L_{\text{cls}}(p, u) = -\log p_u$$

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

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

robust L_1 loss that is less sensitive to outliers

Back-propagation through RoI pooling layers

$x_i \in \mathbb{R} \rightarrow i$-th activation input into the RoI pooling layer

$y_{rj} \in \mathbb{R} \rightarrow$ layer's j-th output from the r-th RoI

$\mathcal{R}(r, j) \rightarrow$ sub-window over which the output unit y_{rj} max-pools

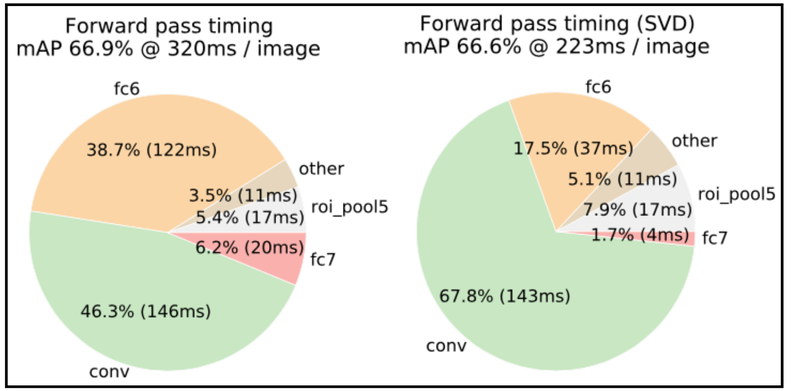
$$i^*(r, j) = \arg \max_{i' \in \mathcal{R}(r,j)} x_{i'}$$

$$y_{rj} = x_{i^*(r,j)}$$

$$\frac{\partial L}{\partial x_i} = \sum_r \sum_j [i = i^*(r, j)] \frac{\partial L}{\partial y_{rj}}$$

A single x_i may be assigned to several different outputs y_{rj}.

Truncated SVD $W \approx U \Sigma_t V^T$



	Fast R-CNN			R-CNN			SPPnet
	S	**M**	**L**	**S**	**M**	**L**	†**L**
train time (h)	**1.2**	2.0	9.5	22	28	84	25
train speedup	**18.3**×	14.0×	8.8×	1×	1×	1×	3.4×
test rate (s/im)	0.10	0.15	0.32	9.8	12.1	47.0	2.3
▷ with SVD	**0.06**	0.08	0.22	-	-	-	-
test speedup	98×	80×	146×	1×	1×	1×	20×
▷ with SVD	169×	150×	**213**×	-	-	-	-
VOC07 mAP	57.1	59.2	**66.9**	58.5	60.2	66.0	63.1
▷ with SVD	56.5	58.7	66.6	-	-	-	-

Girshick, Ross. "Fast r-cnn." Proceedings of the IEEE international conference on computer vision. 2015.

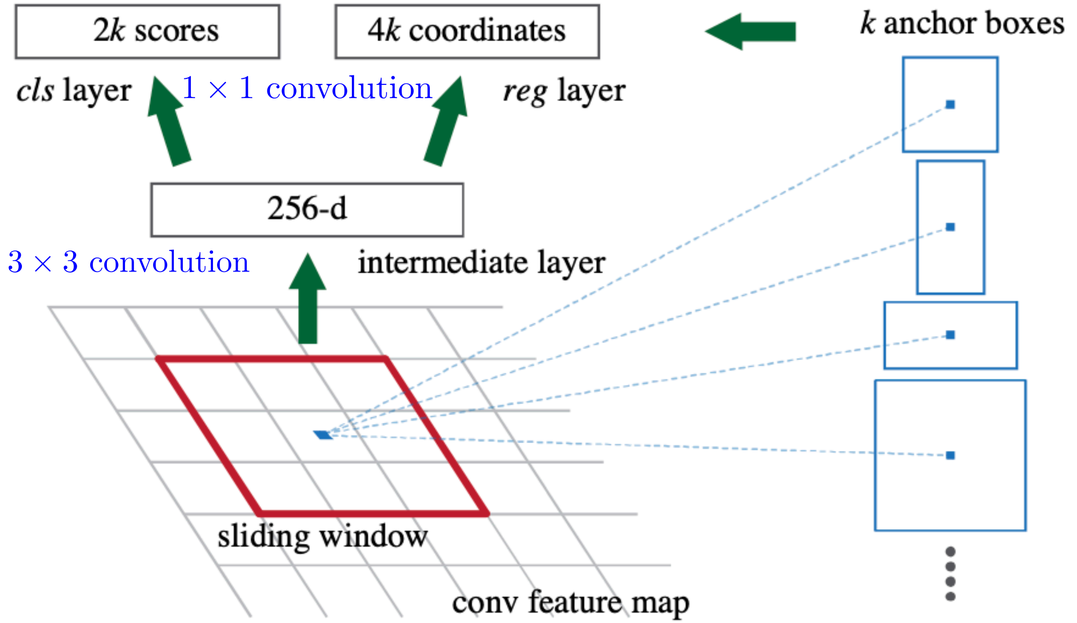
Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks

YouTube Playlist

Region Proposal Network (RPN)

An RPN is a fully-convolutional network that simultaneously predicts object bounds and objectness scores at each position.

RPN and Fast R-CNN can be trained using a simple alternating optimization to share convolutional features.



Translation-Invariant Anchors

9 anchors: 3 scales & 3 aspect ratios

$WHk \rightarrow$ total anchors for a feature map of size $H \times W$

Loss Function (Region Proposals)

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

$i \rightarrow$ index of an anchor in a minibatch

$p_i \rightarrow$ predicted probability of being an object

$p_i^* = 1 \rightarrow$ if anchor is positive

$p_i^* = 0 \rightarrow$ if anchor is negative

For anchors, use 3 scales with box areas of 128 x 128, 256 x 256, and 512 x 512 pixels, and 3 aspect ratios of 1:1, 1:2, and 2:1.

Positive label is assigned to two kinds of anchors: (i) the anchor/anchors with the highest Intersection- over-Union (IoU) overlap with a ground-truth box, or (ii) an anchor that has an IoU overlap higher than 0.7 with any ground-truth box. Negative label is assigned to a non-positive anchor if its IoU ratio is lower than 0.3 for all ground-truth boxes.

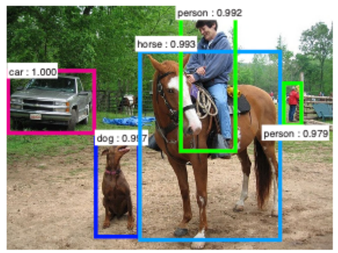
Alternating Training

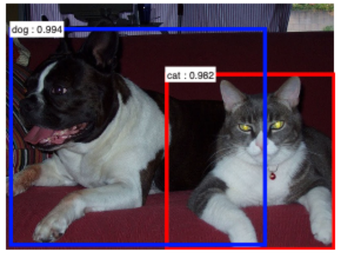
First step: Train the RPN initialized with an ImageNet-pre-trained model and fine-tuned end-to-end for the region proposal task.

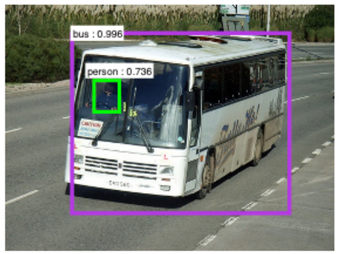
Second step: Train a separate detection network by Fast R-CNN using the proposals generated by the step-1 RPN. This detection network is also initialized by the ImageNet-pre-trained model.

Third step: Use the detector network to initialize RPN training, but we fix the shared conv layers and only fine-tune the layers unique to RPN.

Finally: Keeping the shared conv layers fixed, fine-tune the fc layers of the Fast R-CNN.





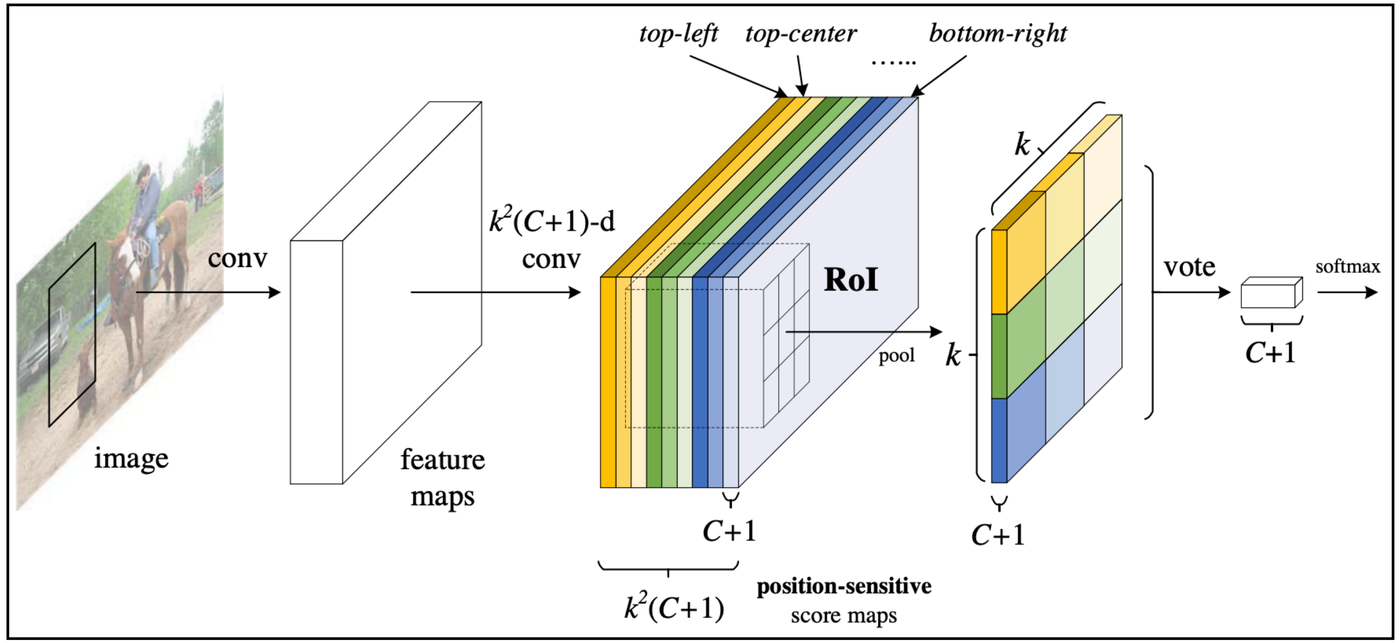


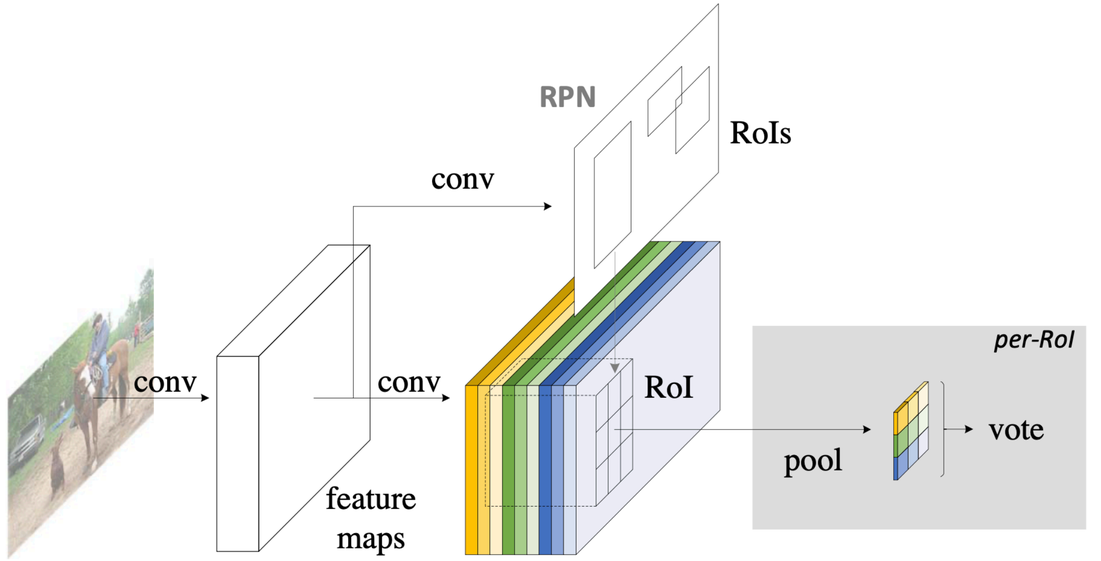
Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." *Advances in neural information processing systems*. 2015.

R-FCN: Object Detection via Region-based Fully Convolutional Networks

YouTube Playlist

There exists a dilemma between translation-invariance in image classification and translation-variance in object detection.





$$r_c(i,j \mid \Theta) = \sum_{(x,y)\in \text{bin}(i,j)} z_{i,j,c}(x + x_0, y + y_0 \mid \Theta)/n$$

$r_c(\Theta) = \sum_{i,j} r_c(i,j \mid \Theta) \rightarrow$ voting

Divide each RoI rectangle into $k \times k$ bins by a regular grid

For an RoI rectangle of a size $w \times h$, a bin is of a size $\approx \frac{w}{k} \times \frac{h}{k}$

$r_c(i,j) \rightarrow$ pooled response in the (i,j)-th bin for the c-th category

$z_{i,j,c} \rightarrow$ one score map out of the $k^2(C+1)$ score maps

$(x_0, y_0) \rightarrow$ top-left corner of an RoI

$n \rightarrow$ number of pixels in the bin

The (i,j)-th bin spans $\lfloor i\frac{w}{k} \rfloor \le x < \lceil (i+1)\frac{w}{k} \rceil$ and $\lfloor j\frac{h}{k} \rfloor \le y < \lceil (j+1)\frac{h}{k} \rceil$

Similarly, append a sibling $4k^2$-d convolutional layer for bounding box regression.

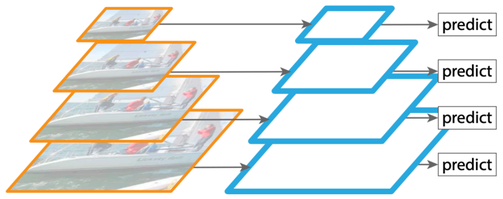
	depth of per-RoI subnetwork	training w/ OHEM?	train time (sec/img)	test time (sec/img)	mAP (%) on VOC07
Faster R-CNN	10		1.2	0.42	76.4
R-FCN	0		0.45	0.17	76.6
Faster R-CNN	10	✓(300 RoIs)	1.5	0.42	79.3
R-FCN	0	✓(300 RoIs)	0.45	0.17	**79.5**
Faster R-CNN	10	✓(2000 RoIs)	2.9	0.42	*N/A*
R-FCN	0	✓(2000 RoIs)	0.46	0.17	79.3

OHEM: Online Hard Example Mining

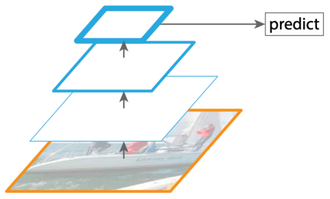
Dai, Jifeng, et al. "R-fcn: Object detection via region-based fully convolutional networks." *Advances in neural information processing systems*. 2016.

Feature Pyramid Networks for Object Detection

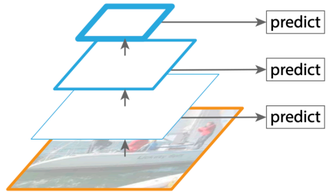
YouTube Playlist



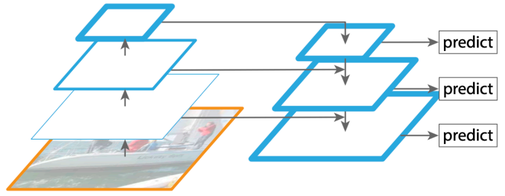
(a) Featurized image pyramid



(b) Single feature map

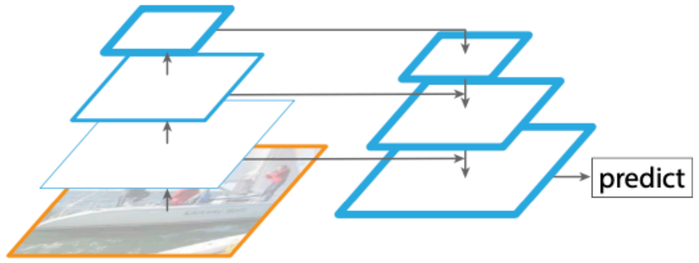


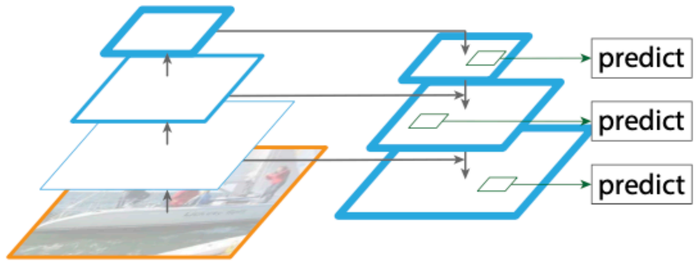
(c) Pyramidal feature hierarchy



(d) Feature Pyramid Network

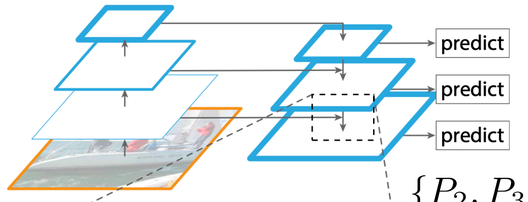
Thicker blue outlines denote semantically stronger features.



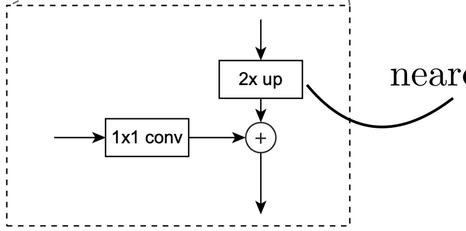


$\{C_2, C_3, C_4, C_5\} \rightarrow$ output of the last residual blocks for conv2, conv3, conv4 and conv5 in ResNets

$\{4, 8, 16, 32\} \rightarrow$ strides of pixels with respect to the input image



$\{P_2, P_3, P_4, P_5\} \rightarrow$ final set of feature maps



nearest neighbor upsampling

Region Proposal Network (RPN)

15 anchors over the pyramid:

$\{32^2, 64^2, 128^2, 256^2, 512^2\} \rightarrow$ areas of anchors on $\{P_2, P_3, P_4, P_5, P_6\}$, respectively

$\{1{:}2, 1{:}1, 2{:}1\} \rightarrow$ aspect ratio

Region-of-Interest (RoI) pooling

```
Intuition: If the RoI's scale becomes smaller
(say, 1/2 of 224), it should be mapped into a
finer-resolution level (say, k = 3).
```

w & $h \rightarrow$ width & height of RoI

$$k = \lfloor k_0 + \log_2(\sqrt{wh}/224) \rfloor$$

$k_0 = 4 \quad \Longrightarrow$ assign the RoI to P_k

COCO detection benchmark

Faster R-CNN	proposals	feature	head	lateral?	top-down?	AP@0.5	AP	AP_s	AP_m	AP_l
(*) baseline from He *et al.* [16]†	RPN, C_4	C_4	conv5			47.3	26.3	-	-	-
(a) baseline on conv4	RPN, C_4	C_4	conv5			53.1	31.6	13.2	35.6	**47.1**
(b) baseline on conv5	RPN, C_5	C_5	2*fc*			51.7	28.0	9.6	31.9	43.1
(c) **FPN**	RPN, $\{P_k\}$	$\{P_k\}$	2*fc*	✓	✓	**56.9**	**33.9**	**17.8**	**37.7**	45.8

method	backbone	competition	image pyramid	test-dev					test-std				
				$AP_{@.5}$	AP	AP_s	AP_m	AP_l	$AP_{@.5}$	AP	AP_s	AP_m	AP_l
ours, Faster R-CNN on **FPN**	ResNet-101	-		**59.1**	**36.2**	**18.2**	**39.0**	48.2	**58.5**	**35.8**	**17.5**	**38.7**	47.8
*Competition-winning **single-model** results follow:*													
G-RMI†	Inception-ResNet	2016		-	34.7	-	-	-	-	-	-	-	-
AttractioNet‡ [10]	VGG16 + Wide ResNet§	2016	✓	53.4	35.7	15.6	38.0	**52.7**	52.9	35.3	14.7	37.6	**51.9**
Faster R-CNN +++ [16]	ResNet-101	2015	✓	55.7	34.9	15.6	38.7	50.9	-	-	-	-	-
Multipath [40] (on minival)	VGG-16	2015		49.6	31.5	-	-	-	-	-	-	-	-
ION‡ [2]	VGG-16	2015		53.4	31.2	12.8	32.9	45.2	52.9	30.7	11.8	32.8	44.8

Lin, Tsung-Yi, et al. "Feature pyramid networks for object detection." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

Deformable Convolutional Networks

YouTube Video

geometric transformations: object scale, pose, view point, and part deformation

Convolution

2D convolution consists of two steps:

– sampling using a regular grid $\mathcal{R}$ over the input feature map x

– summation of sampled values weighted by w

$\mathcal{R} \rightarrow$ defines receptive field size & dilation

$\mathcal{R} = \{(-1,-1),(-1,0),\ldots,(0,1),(1,1)\} \rightarrow 3 \times 3$ convolution with dilation 1

$y \rightarrow$ output feature map

$$y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot x(p_0 + p_n)$$

Deformable Convolution

$\{\Delta p_n : n = 1,\ldots,|\mathcal{R}|\} \rightarrow$ offsets augmenting $\mathcal{R}$

$$y(p_0) = \sum_{p_n \in \mathcal{R}} w(p_n) \cdot x(p_0 + p_n + \Delta p_n)$$

$$x(p) = \sum_q G(q,p) \cdot x(q) \rightarrow \text{bilinear interpolation}$$

$p \rightarrow$ an arbitrary (fractional) location (e.g., $p = p_0 + p_n + \Delta p_n$)

$q \rightarrow$ enumerates all integral spatial locations in the feature map x

$G(q,p) = g(q_x,p_x) \cdot g(q_y,p_y) \rightarrow$ non-zero only for a few q's

$g(a,b) = \max(0, 1-|a-b|)$

RoI Pooling

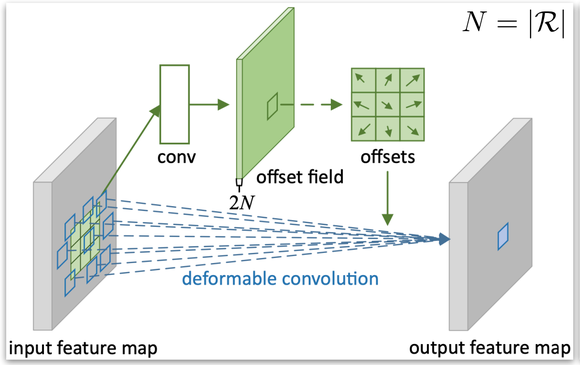
RoI of size $w \times h$ and top-left corner p_0

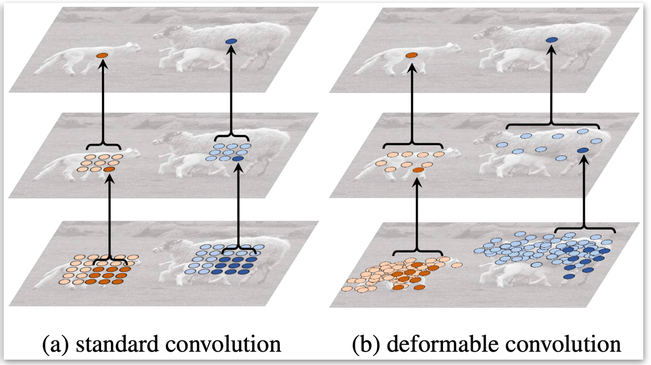
Divide the RoI into $k \times k$ bins

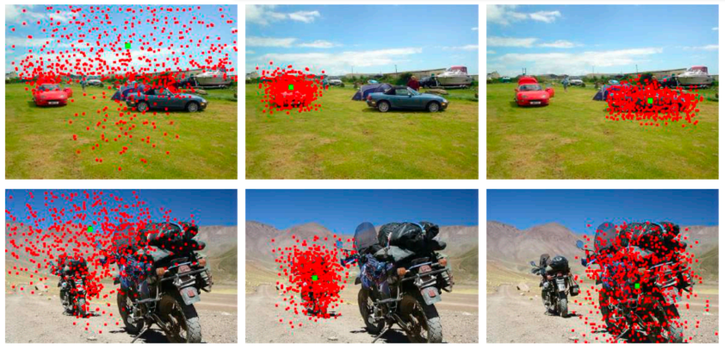
$y \rightarrow k \times k$ output feature map

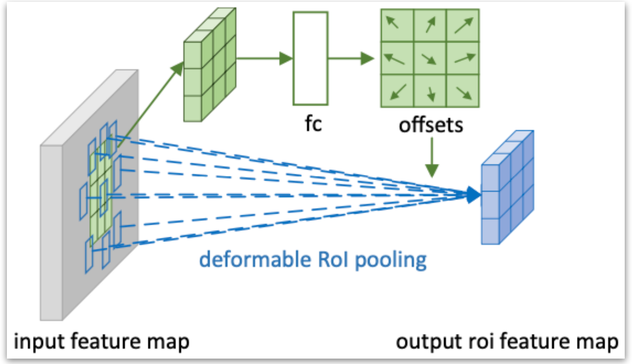
$n_{ij} \rightarrow$ number of pixels in the bin

$$y(i,j) = \sum_{p \in \text{bin}(i,j)} x(p_0 + p)/n_{ij} \text{ for } 0 \le j,j < k$$

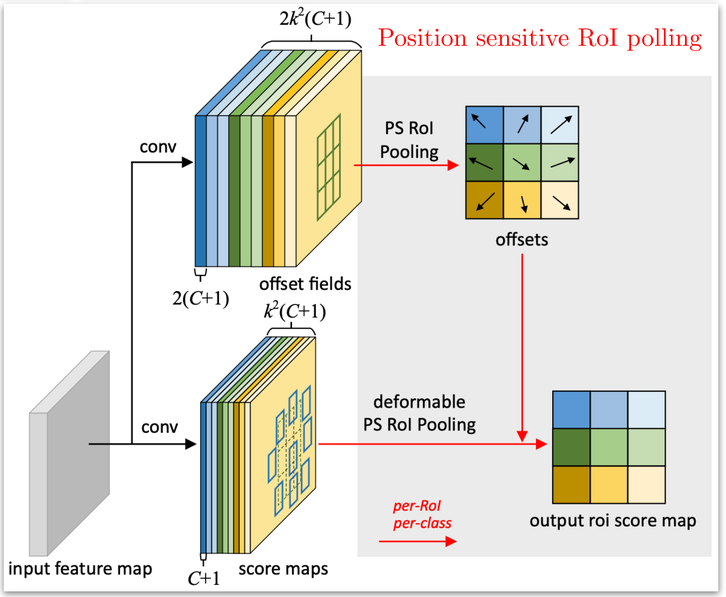








$\{\Delta p_{ij} : 0 \le i,j < k\} \rightarrow$ offsets



Deformable RoI Pooling

$$y(i,j) = \sum_{p \in \text{bin}(i,j)} x(p_0 + p + \Delta p_{ij})/n_{ij}$$

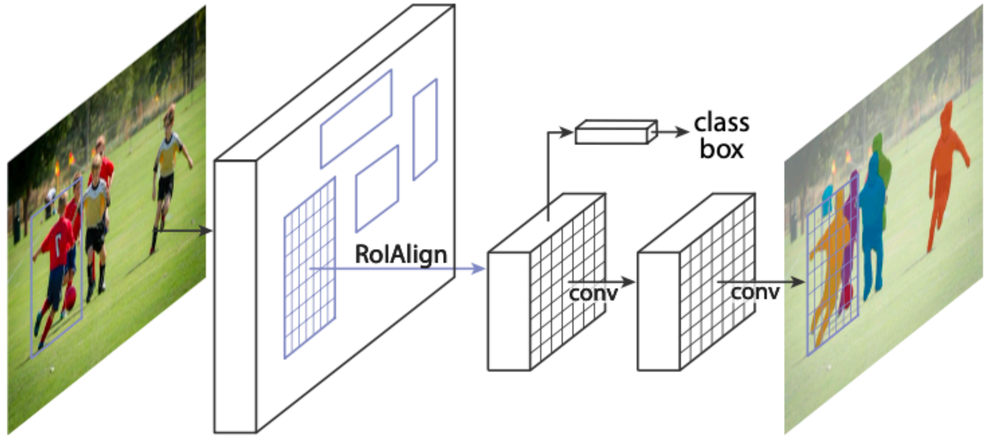
$\Delta p_{ij} = \gamma \Delta \hat{p}_{ij} \odot (w,h)$ $\Delta \hat{p}_{ij} \rightarrow$ normalized offsets

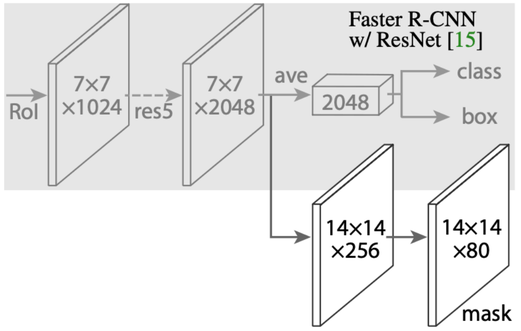
Dai, Jifeng, et al. "Deformable convolutional networks." Proceedings of the IEEE international conference on computer vision. 2017.

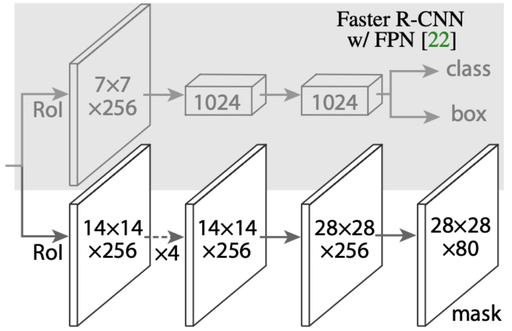
Mask R-CNN

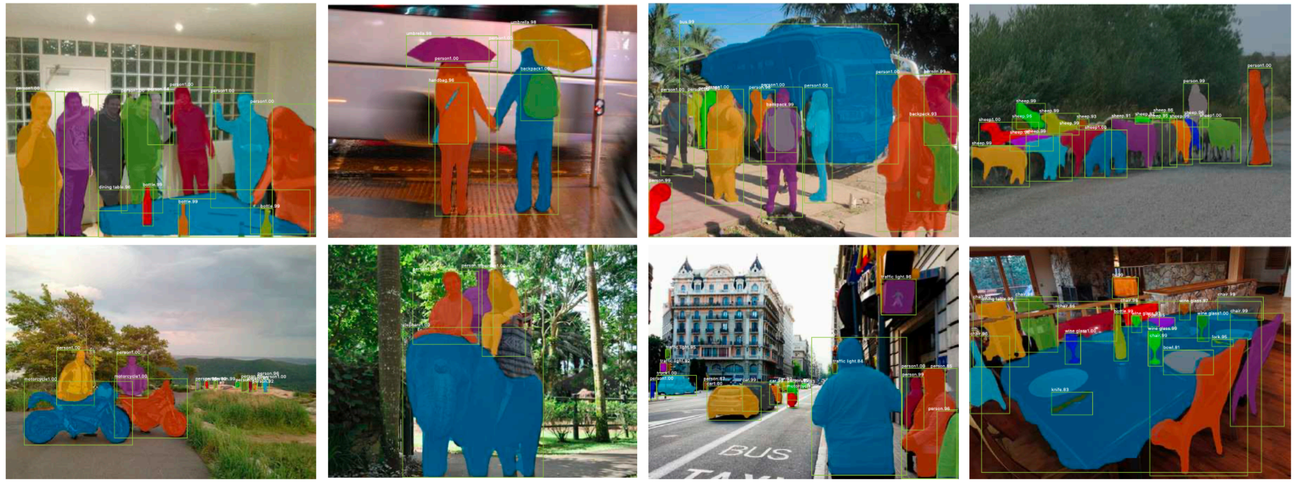
YouTube Playlist

Object detection: classify individual objects and localize each using a bounding box
Semantic segmentation: classify each pixel into a fixed set of categories
Instance segmentation









$L = L_{\text{cls}} + L_{\text{box}} + L_{\text{mask}} \rightarrow$ multi-task loss on each sampled RoI
The mask branch has a Km^2-dimensional output for each RoI
K binary masks of resolution $m \times m$, one for each of the K classes
per pixel sigmoid
$L_{\text{mask}} \rightarrow$ average binary cross-entropy loss
For an RoI associated with ground-truth class k, L_{mask} is only defined on the k-th mask (other mask outputs do not contribute to the loss).
RoIAlign $x \rightarrow$ a continuous coordinate
RoIPool $\rightarrow [x/16]$ (quantization)
Avoid any quantization of the RoI boundaries or bins (i.e., use $x/16$ instead of $[x/16]$)

Use bilinear interpolation to compute the exact values of the input features at four regularly sampled locations in each "RoI bin", and aggregate the result (using max or average).

Human Pose Estimation ←

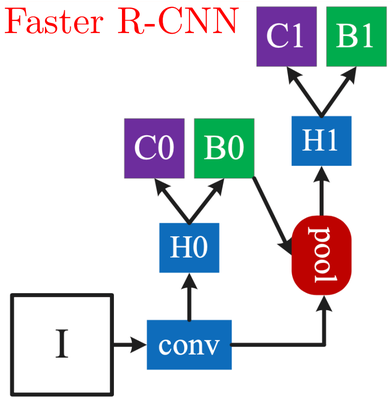
A keypoint's location can be modeled as a one-hot mask, and Mask R-CNN can be adopted to predict K masks, one for each of K keypoint types (e.g., left shoulder, right elbow).

He, Kaiming, et al. "Mask r-cnn." Proceedings of the IEEE international conference on computer vision. 2017.

Cascade R-CNN: Delving into High Quality Object Detection

YouTube Video

Faster R-CNN



$H0 \rightarrow$ proposal network (produce preliminary detection hypotheses) $\rightarrow$ object proposals

$H1 \rightarrow$ region-of-interest detection subnetwork (detection head)

$C \rightarrow$ classification score

$B \rightarrow$ bounding box

Bounding Box Regression

$b \rightarrow$ candidate bounding box

$b = (b_x, b_y, b_w, b_h) \rightarrow$ four coordinates of an image patch x

$g \rightarrow$ target bounding box

$f(x, b) \rightarrow$ regressor

$(g_i, b_i) \rightarrow$ training sample

$L_{\text{loc}}(f(x_i, b_i), g_i) \rightarrow$ bounding box L_1 loss function

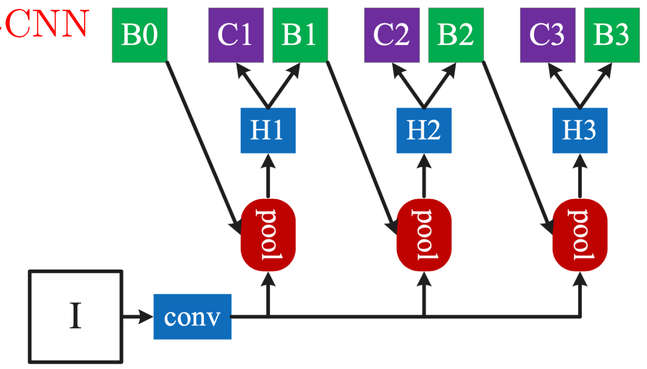
To encourage a regression invariant to scale and location:

$\Delta = (\delta_x, \delta_y, \delta_w, \delta_h) \rightarrow$ distance vector

$\delta_x = (g_x - b_x)/b_w, \delta_y = (g_y - b_y)/b_h \qquad \delta_w = \log(g_w/b_w), \delta_h = \log(g_h/b_h)$

Δ is usually normalized by its mean and variance (e.g., $\delta'_x = (\delta_x - \mu_x)/\sigma_x$)

Cascade R-CNN



$f(x, b) = f_T \circ f_{T-1} \circ \cdots \circ f_1(x, b)$

$\smile$ cascade of specialized regressors

$T \rightarrow$ total number of cascade stages

$L(x^t, g) = L_{cls}(h_t(x^t), y^t) + \lambda[y^t \geq 1] L_{loc}(f_t(x^t, \mathbf{b}^t), \mathbf{g})$

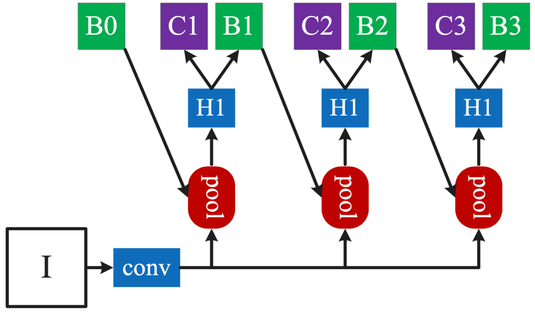
$\mathbf{b}^t = f_{t-1}(x^{t-1}, \mathbf{b}^{t-1})$

$u^t > u^{t-1} \rightarrow$ IoU theshold $\qquad t \rightarrow$ stage

multi-stage object detection architecture

Iterative BBox at inference

$f'(x, b) = f \circ f \circ \cdots \circ f(x, b)$



Detection Quality

$h(x) \rightarrow$ classifier (assigning an image patch x to one of $M + 1$ classes)

$(x_i, y_i) \rightarrow$ training set (y_i: label of patch x_i)

$L_{\text{cls}}(h(x_i), y_i) \rightarrow$ classification cross-entropy loss

$$y = \begin{cases} g_y, & IoU(x, g) \geq u \\ 0, & \text{otherwise} \end{cases}$$

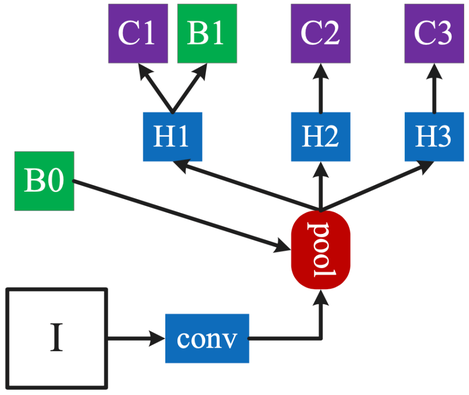
$u \rightarrow$ threshold (quality of a detector)

$g_u \rightarrow$ class label of the ground truth object g

Integral Loss

$$L_{cls}(h(x), y) = \sum_{u \in U} L_{cls}(h_u(x), y_u)$$

$U = \{0.5, 0.55, \cdots, 0.75\}$



Cai, Zhaowei, and Nuno Vasconcelos. "Cascade r-cnn: Delving into high quality object detection." *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2018.

Boulder

Questions?

YouTube Playlist