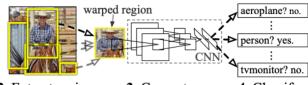


Rich feature hierarchies for accurate object detection and semantic segmentation



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 sinale 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

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

$$P = (\underbrace{P_x, P_y}, \quad \underbrace{P_w, P_h}) \rightarrow \text{proposal bounding box}$$

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

$$\mathbf{w}_{\star} = \underset{\hat{\mathbf{w}}_{\star}}{\operatorname{argmin}} \sum_{i}^{N} (t_{\star}^{i} - \hat{\mathbf{w}}_{\star}^{\mathsf{T}} \phi_{5}(P^{i}))^{2} + \lambda \|\hat{\mathbf{w}}_{\star}\|^{2}$$

$$\mathbf{w}_{\star} = \underset{i}{\operatorname{argmin}} \sum_{i}^{N} (t_{\star}^{i} - \hat{\mathbf{w}}_{\star}^{\mathsf{T}} \phi_{5}(P^{i}))^{2} + \lambda \|\hat{\mathbf{w}}_{\star}\|^{2}$$

$$t_{w} = \log(G_{w}/P_{w})$$

$$t_{h} = \log(G_{h}/P_{h}).$$

 $\hat{G}_x = P_w d_x(P) + P_x$ $\hat{G}_y = P_h d_y(P) + P_y$

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.