lecture 9: object detection

deep learning for vision

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outline

background
two-stage detection
object parts and deformation
scale and feature pyramids
one-stage detection

background

data-driven approach

data-driven approach

feature extraction

representation

data-driven approach

feature extraction

representation

parameters → classifier

"dog"

"cat"

data-driven approach

parameters

model

“dog”

“cat”

data-driven approach

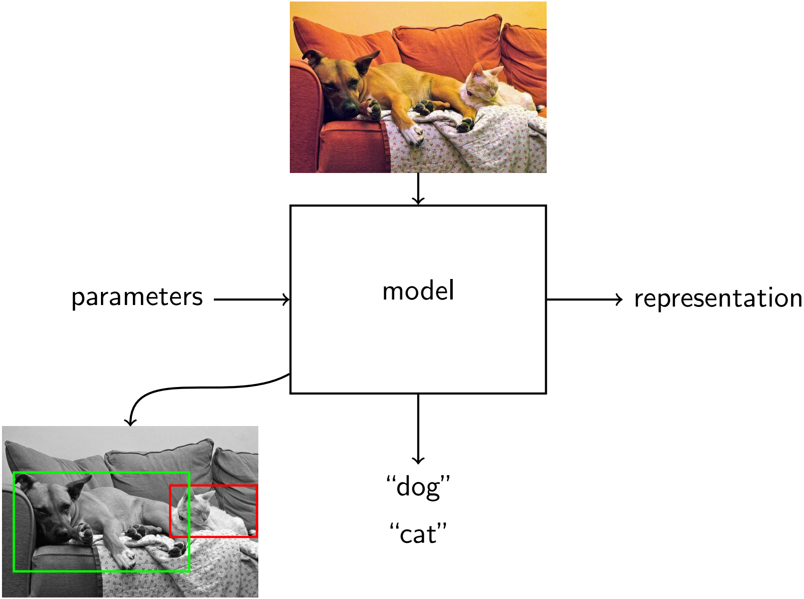
model

parameters → model → representation

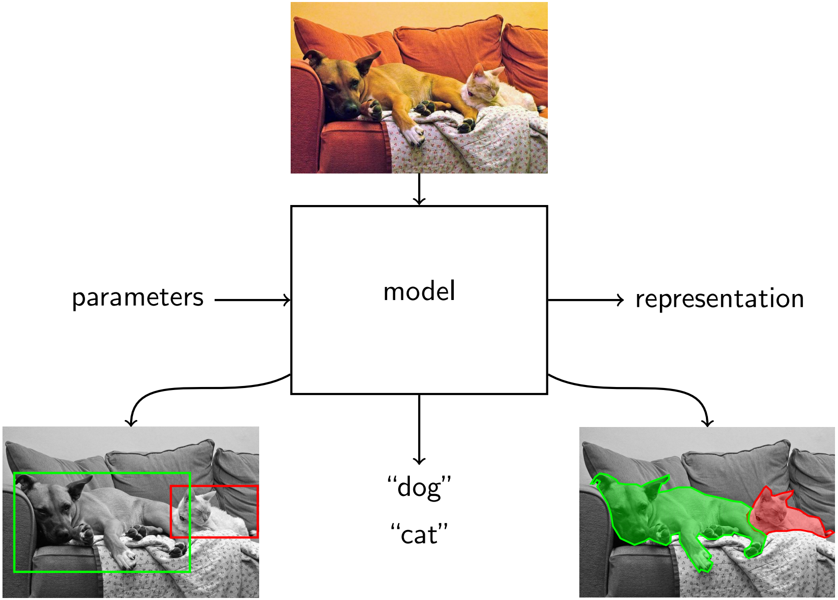
"dog"

"cat"

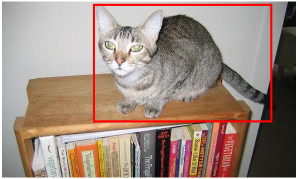
data-driven approach



data-driven approach



beyond classification

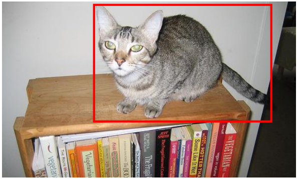


object localization

classify + regress

bounding box (x, y, w, h)

beyond classification



object localization

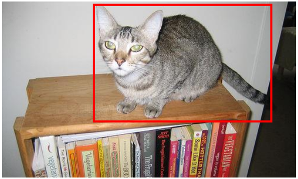
classify + regress

bounding box (x, y, w, h)

semantic segmentation

pixel-wise classify

beyond classification



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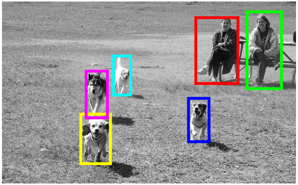
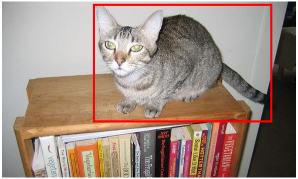


object detection

per region: classify + regress

bounding box (x, y, w, h)

beyond classification



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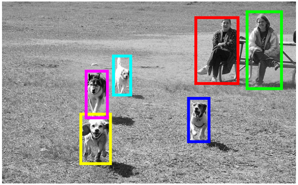

object detection

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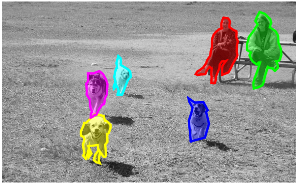
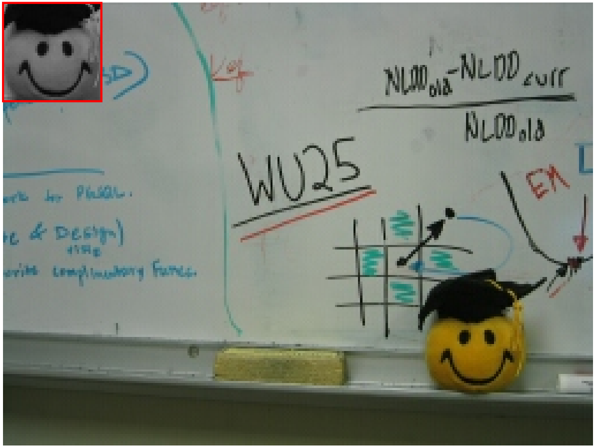


instance segmentation

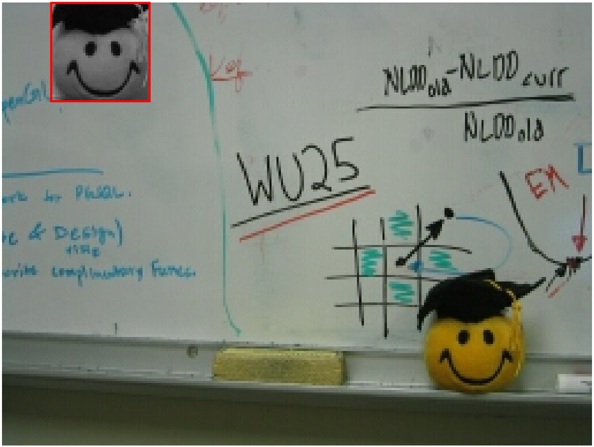
per region: pixel-wise classify

template matching, or sliding window



- slide template over image at multiple positions
- positions can be overlapping, or even dense (every pixel)
- seek maximum similarity score

template matching, or sliding window



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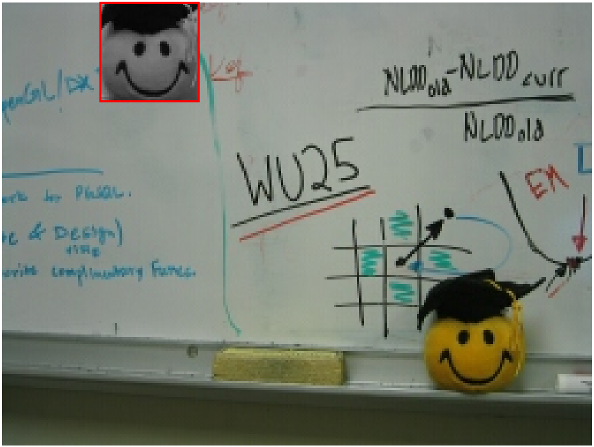

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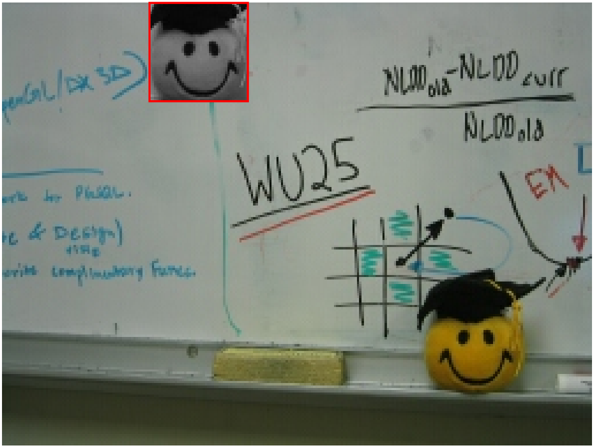

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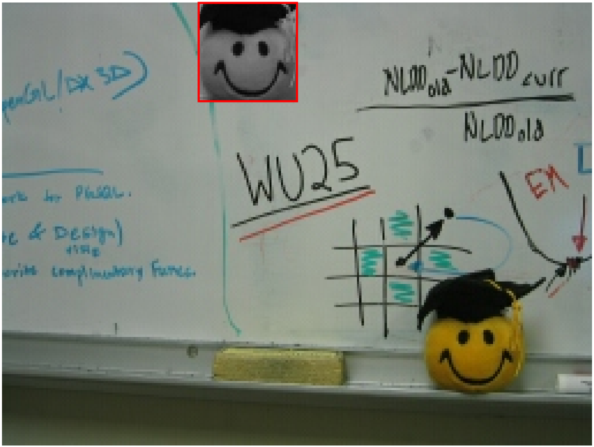

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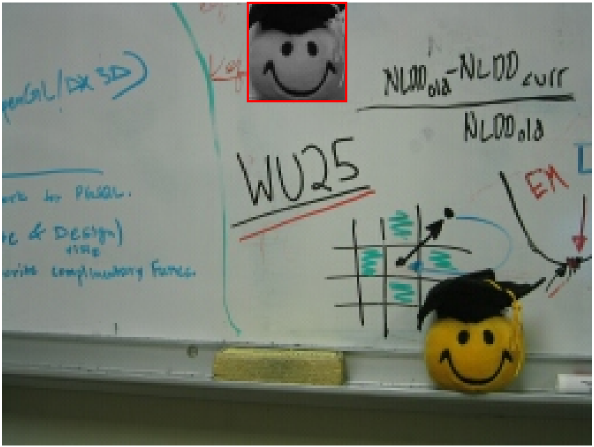

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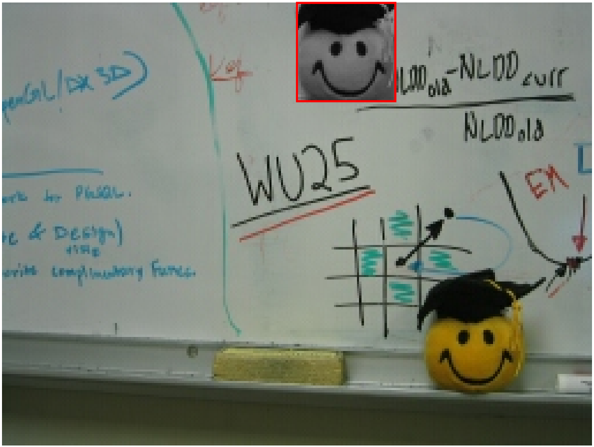

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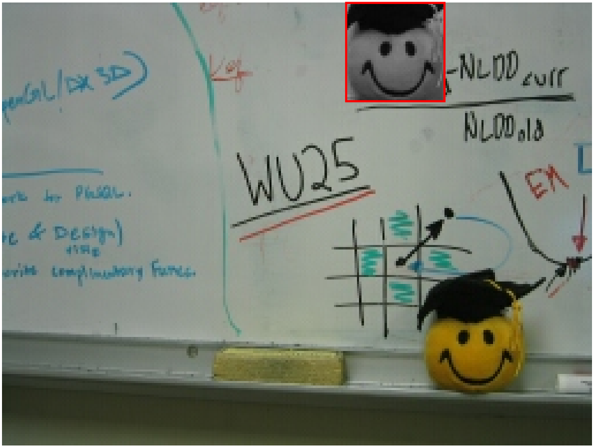

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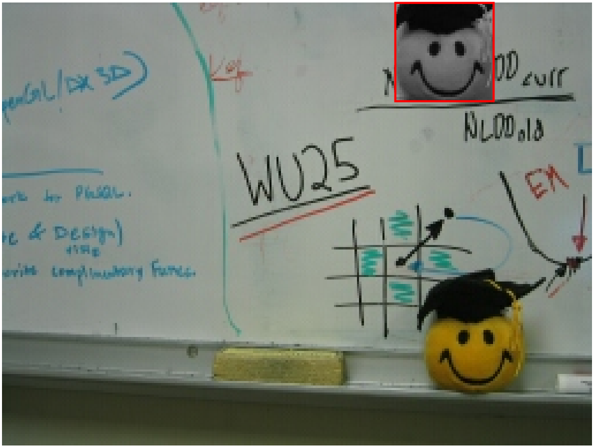

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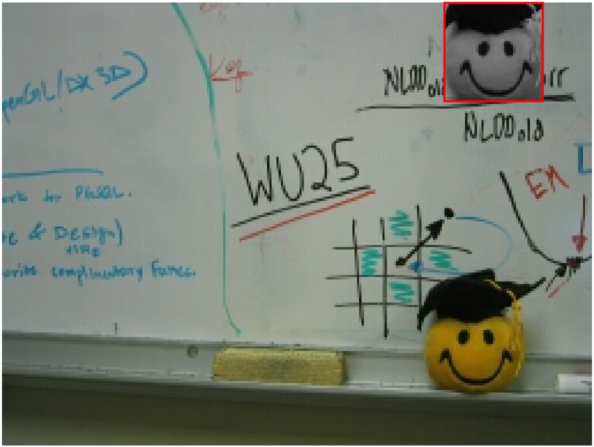

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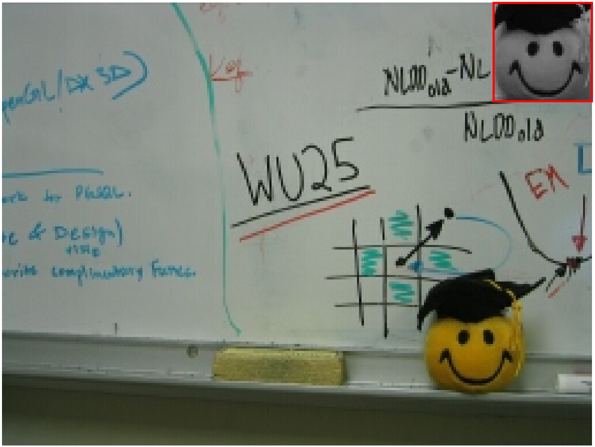

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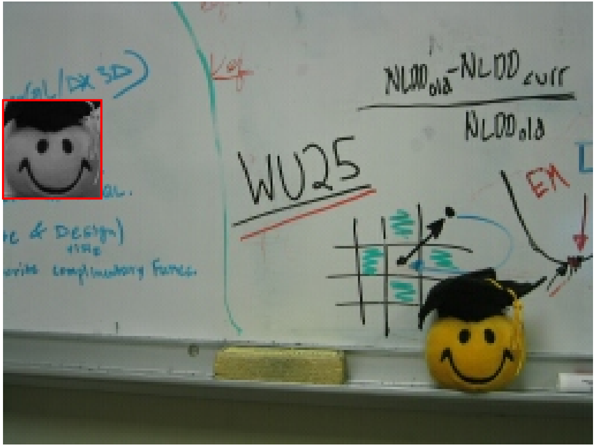

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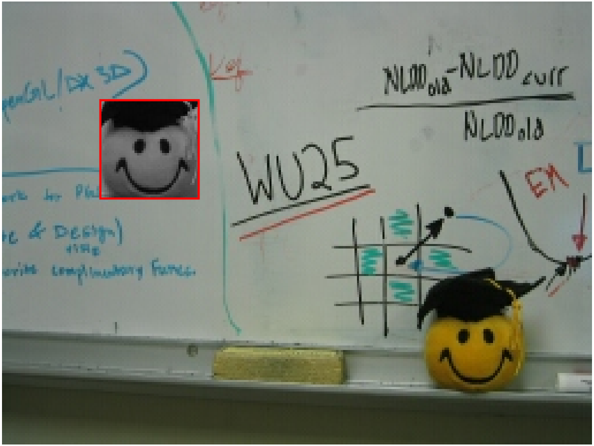

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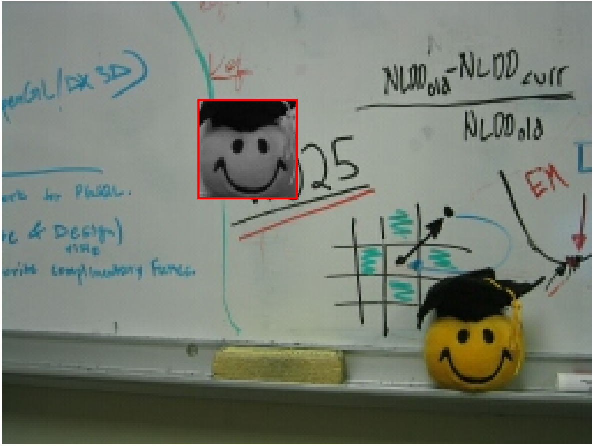

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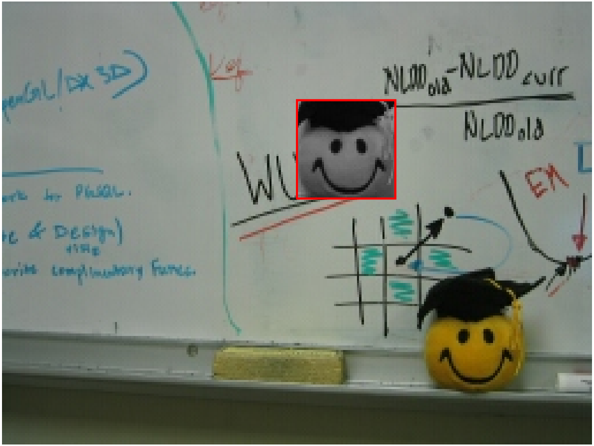

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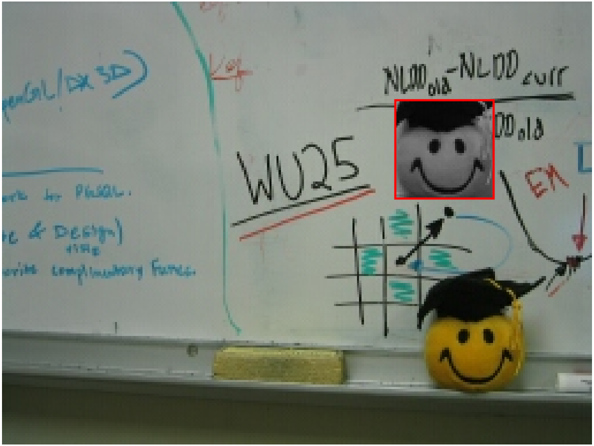

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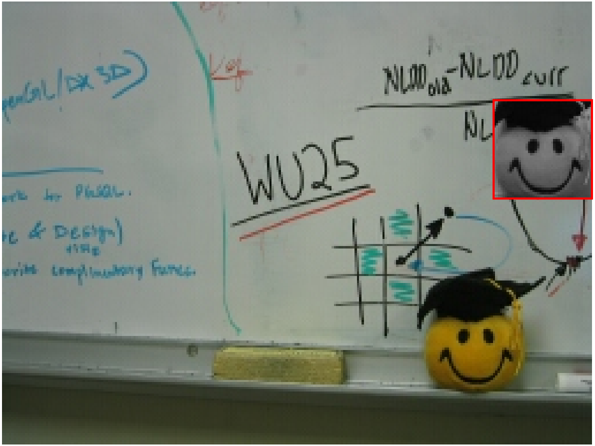

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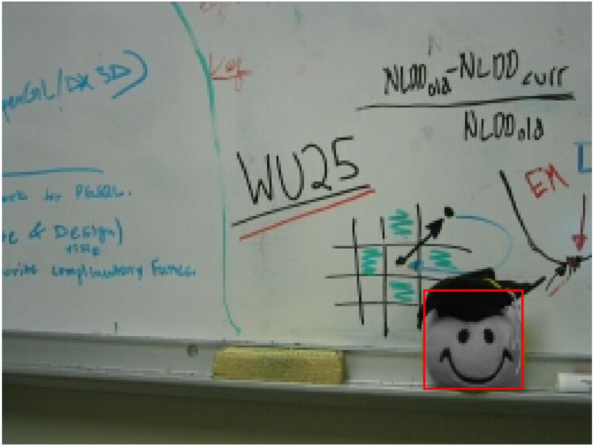

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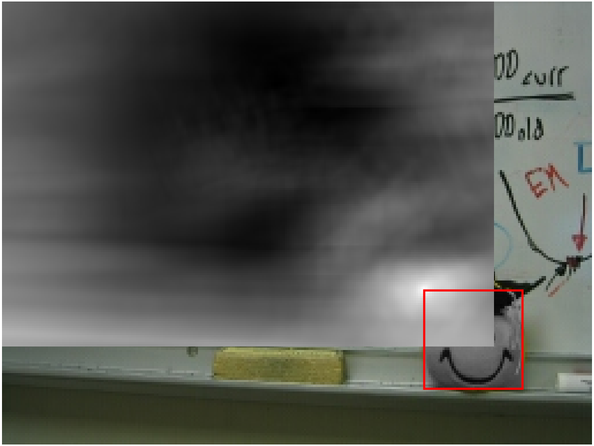


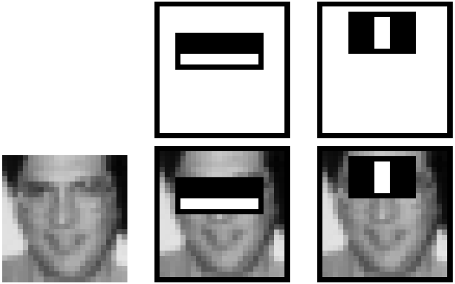
- slide template over image at multiple positions
- positions can be overlapping, or even dense (every pixel)
- seek maximum similarity score (*e.g.* cross-correlation)

two problems

- to detect a given instance (template), a similarity score may be enough; but to detect an object of a given class, we need strong features and a good classifier
- with unknown position, scale and aspect ratio, the search space is 4-dimensional: to search efficiently, we need something better than exhaustive search

real-time face detection

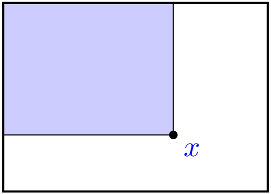
[Viola and Jones 2001]



- millions of simple features exhaustively evaluated on integral image
- learning weak classifiers by AdaBoost
- classifier cascade provides a focus-of-attention mechanism

Viola and Jones. CVPR 2001. Rapid Object Detection Using a Boosted Cascade of Simple Features.

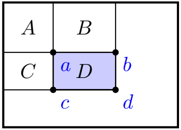
integral image: construction



- given an image, precompute its sum over the rectangle with vertices the top-left corner and any point x in the image
- the collection of all sums is the integral image: it can be computed by one pass over the original image and takes the same space as the original image

Viola and Jones. CVPR 2001. Rapid Object Detection Using a Boosted Cascade of Simple Features.

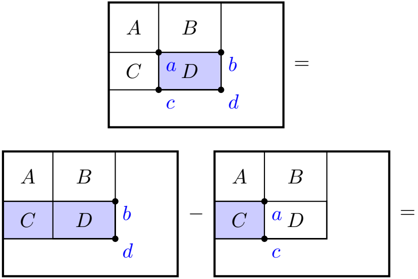
integral image: use



$=$

- then, the sum over any rectangle (D) can be evaluated by 3 scalar operations on its vertices (a, b, c, d)

integral image: use



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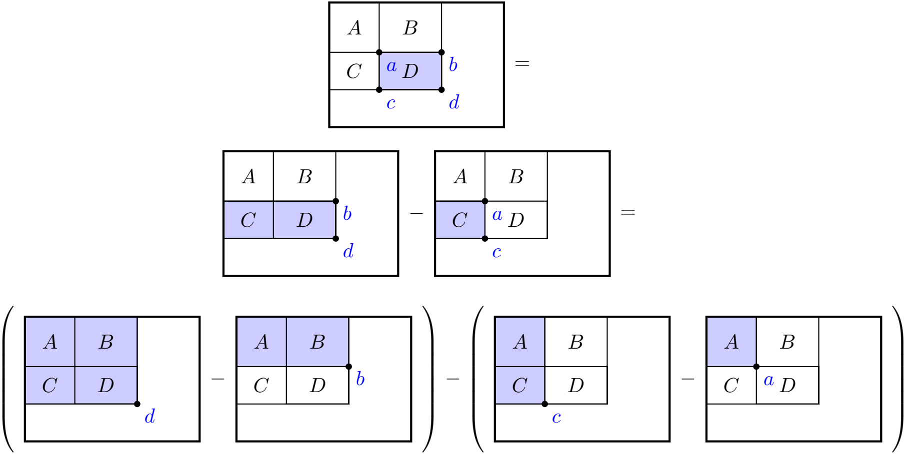

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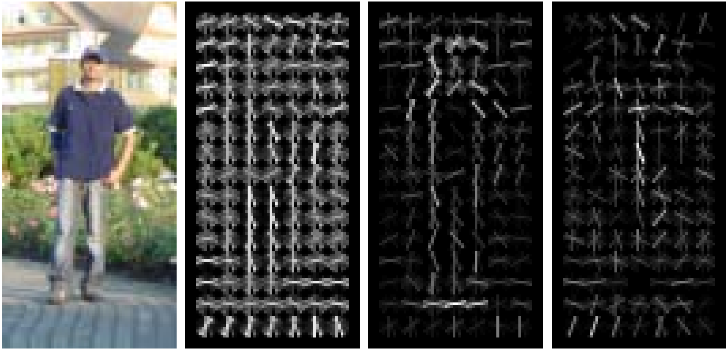
histogram of oriented gradients (HOG)

[Dalal and Triggs 2005]

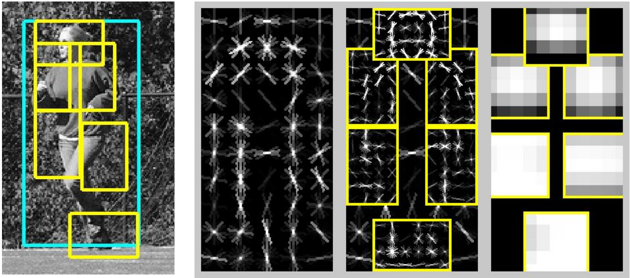


- dense, SIFT-like descriptors
- SVM classifier
- sliding window detection at all positions and scales

Dalal and Triggs. CVPR 2005. Histograms of Oriented Gradients for Human Detection.

deformable part model (DPM)

[Felzenszwalb et al. 2008]



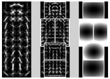
- appearance represented by HOG
- spatial configuration inspired by "pictorial structures"
- part locations treated as latent variables: latent SVM

Felzenszwalb, Mcallester and Ramanan. CVPR 2008. A Discriminatively Trained, Multiscale, Deformable Part Model.

deformable part model: inference

input

model



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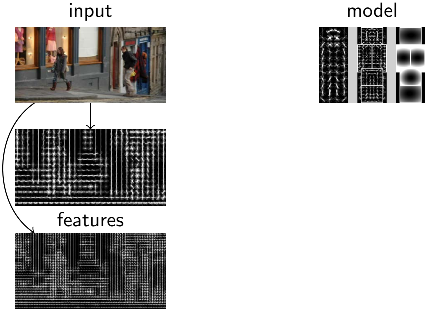

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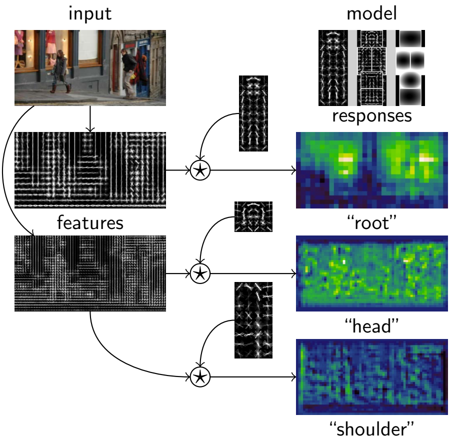

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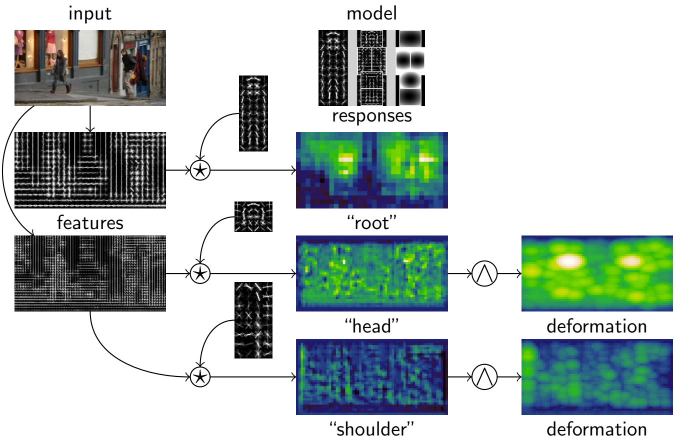

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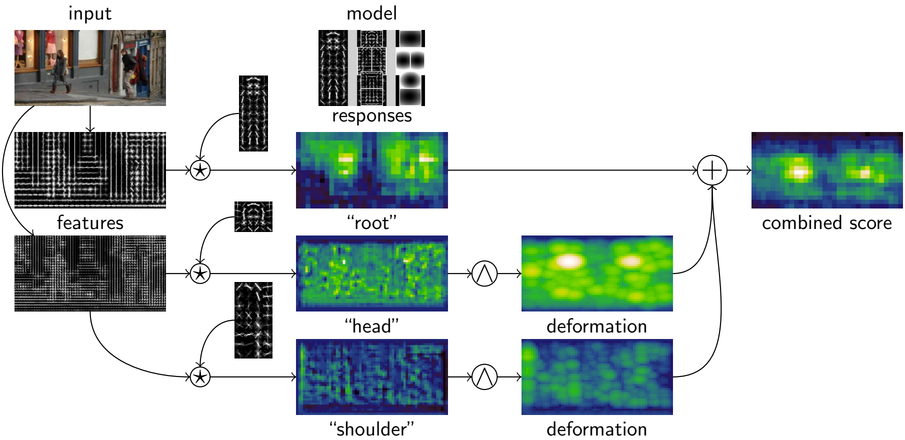

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hard example mining (bootstrapping)

- an example is called hard for a model with parameters $\boldsymbol{\theta}$ if it contributes non-zero loss (is incorrectly classified or inside the margin); otherwise easy
- repeat:
  1. optimize the model θ on a subset C (cache) of the training set D
  2. if all hard examples of D are included in C, stop
  3. shrink: remove any number of easy examples from C
  4. grow: add to C any number of new samples from D, including at least a new hard one
- this algorithm terminates and finds the optimal model for D

Felzenszwalb, Mcallester and Ramanan. CVPR 2008. A Discriminatively Trained, Multiscale, Deformable Part Model.
Sung and Poggio. PAMI 1998. Example-Based Learning for View-Based Human Face Detection.

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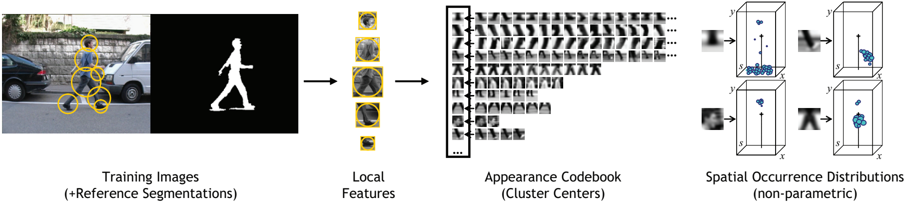
implicit shape model (ISM): training

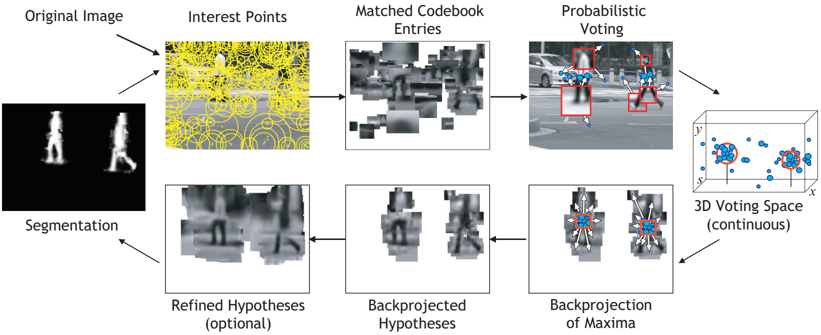
[Leibe et al. 2008]



- local features and descriptors extracted on training images
- appearance codebook built
- spatial occurrence distribution of features learned, relative to ground truth bounding boxes

Leibe, Leonardis and Schiele. IJCV 2008. Robust Object Detection With Interleaved Categorization and Segmentation.

implicit shape model (ISM): inference

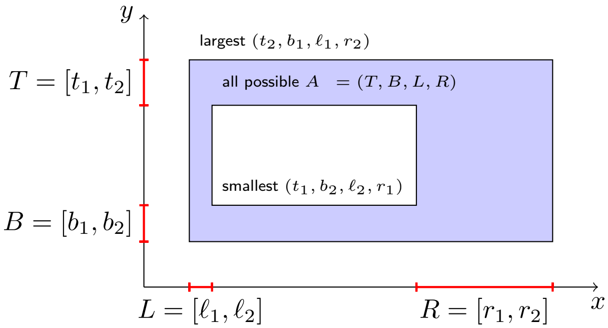


- local features and descriptors extracted on test image
- descriptors assigned to visual words
- generalized Hough transform: probabilistic class-specific votes for the object center
- optionally, back-project hypotheses for top-down segmentation

Leibe, Leonardis and Schiele. IJCV 2008. Robust Object Detection With Interleaved Categorization and Segmentation.

efficient subwindow search (ESS)

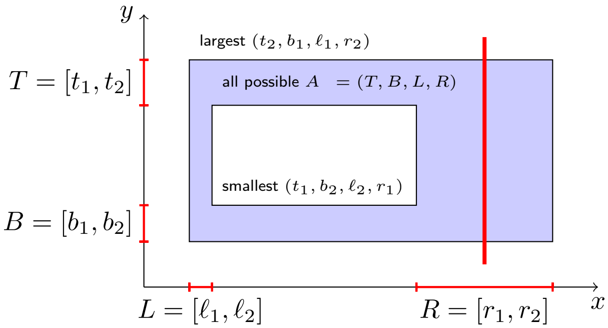
[Lampert et al. 2008]



- the filled area A represents the set of all rectangles lying in this area
- this set is split as $A = A_1 \cup A_2$ along the largest side and bounds of the objective function are estimated for both subsets
- optimization is performed by branch-and-bound

efficient subwindow search (ESS)

[Lampert et al. 2008]



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Lampert, Blaschko and Hofmann. CVPR 2008. Beyond Sliding Windows: Object Localization By Efficient Subwindow Search.

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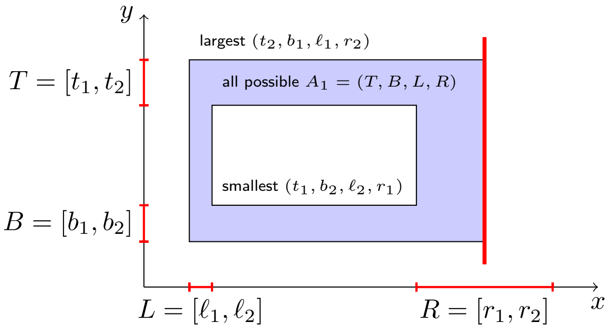

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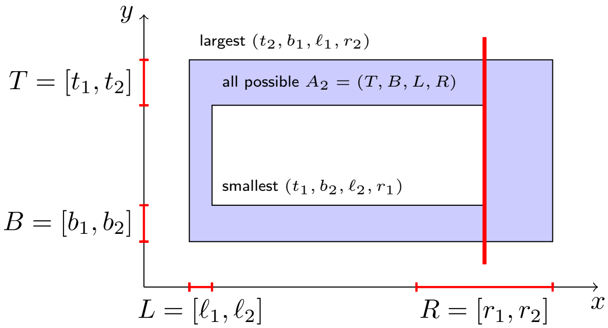

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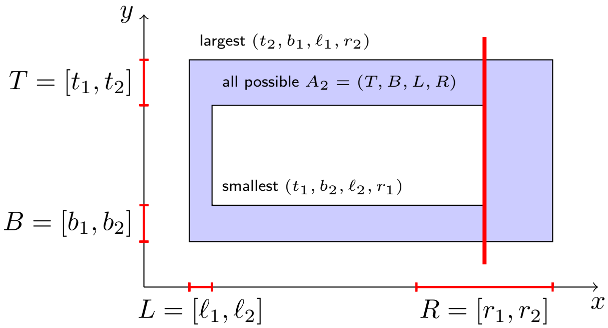

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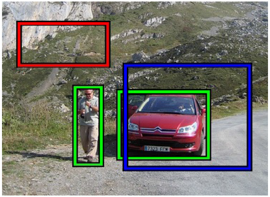
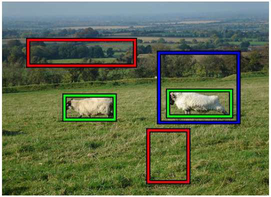
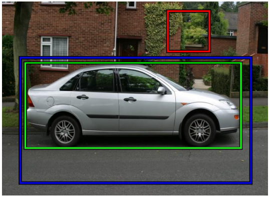
what is an object?

[Alexe et al. 2010]

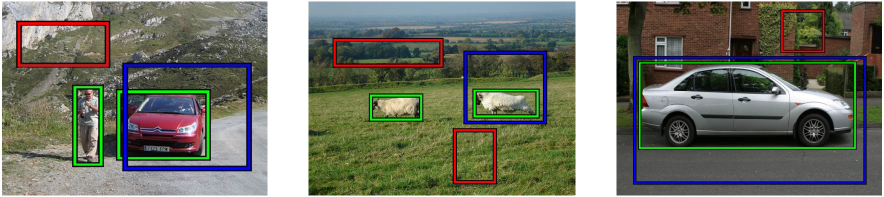




- seek a generic, class-agnostic objectness measure, quantifying how likely it is for an image region to contain an object
- if the measure is simple and fast to compute, it can yield a number of candidate object proposals or regions of interest (RoI) where to apply a more expensive classifier
- score the blue regions, partially covering the objects, lower than the green ground truth regions
- even lower the red regions containing only stuff or small object parts

Alexe, Deselaers and Ferrari. CVPR 2010. What is an Object?

what is an object?

[Alexe et al. 2010]



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Alexe, Deselaers and Ferrari. CVPR 2010. What is an Object?

selective search (SS)

[van de Sande et al. 2011]

input image

ground truth

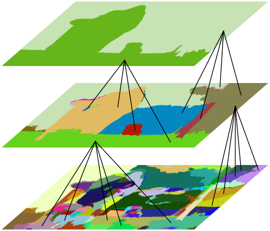
van de Sande, Uijlings, Gevers and Smeulders. ICCV 2011. Segmentation As Selective Search for Object Recognition.

selective search (SS)

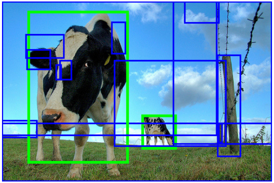
[van de Sande et al. 2011]

input image

ground truth



hierarchical grouping



object proposals

van de Sande, Uijlings, Gevers and Smeulders. ICCV 2011. Segmentation As Selective Search for Object Recognition.

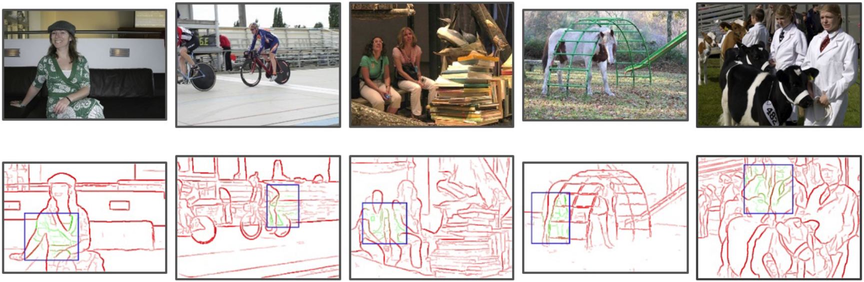
selective search (SS)

- hierarchical segmentation at all scales
- simple geometric and appearance features (*e.g.* size, texture)
- high recall: $\sim 97\%$ of ground truth objects found with $\sim 1000 - 2000$ proposals/image at ~ 2-5s/image

van de Sande, Uijlings, Gevers and Smeulders. ICCV 2011. Segmentation As Selective Search for Object Recognition.

edge boxes (EB)

[Zitnick and Dollar 2014]

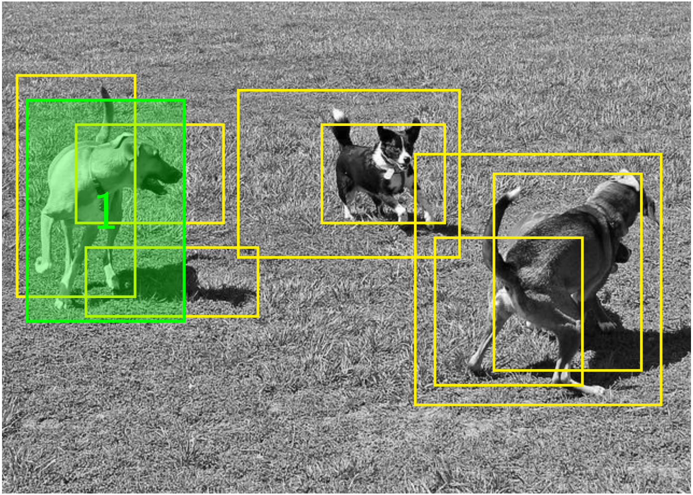


- fast evaluation of millions of regions of different scales/aspect ratios at different positions
- measures edges that are contained in a region and do not intersect its boundary
- performance similar to SS, but at ~ 0.25s/image on average

Zitnick and Dollar. ECCV 2014. Edge Boxes: Locating Object Proposals From Edges.

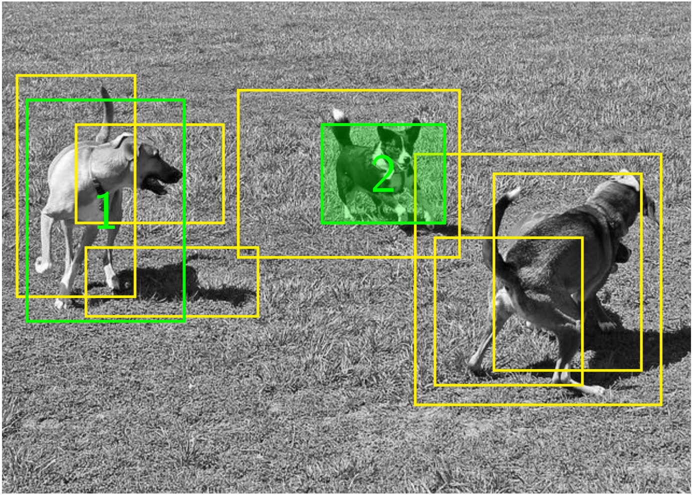
non-maximum suppression (NMS)

non-maximum suppression (NMS)



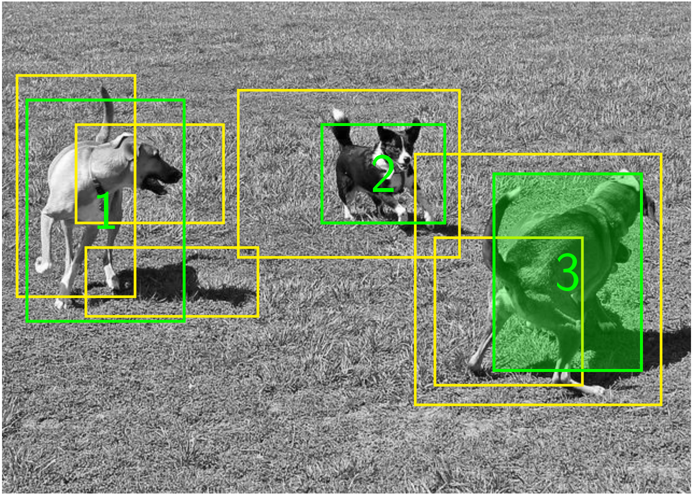
region 1 remains

non-maximum suppression (NMS)



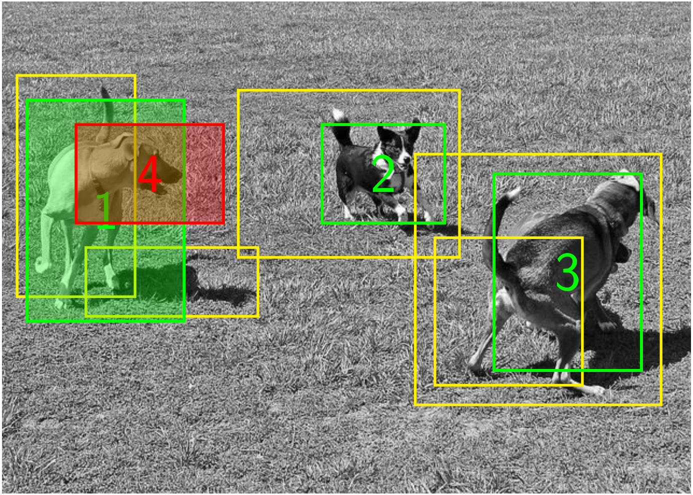
region 2 remains

non-maximum suppression (NMS)



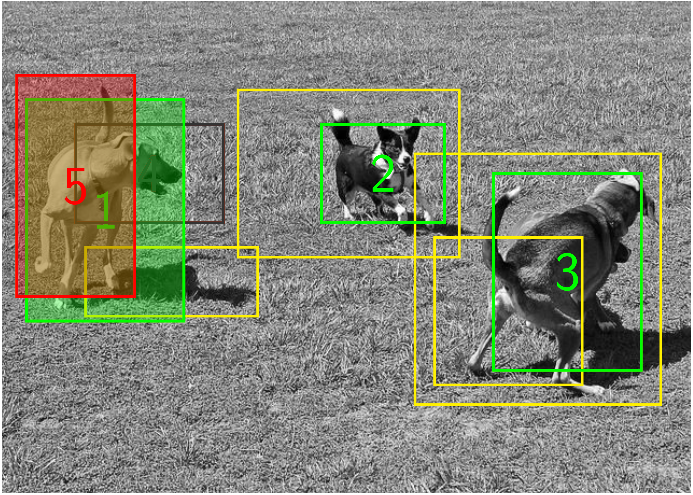
region 3 remains

non-maximum suppression (NMS)



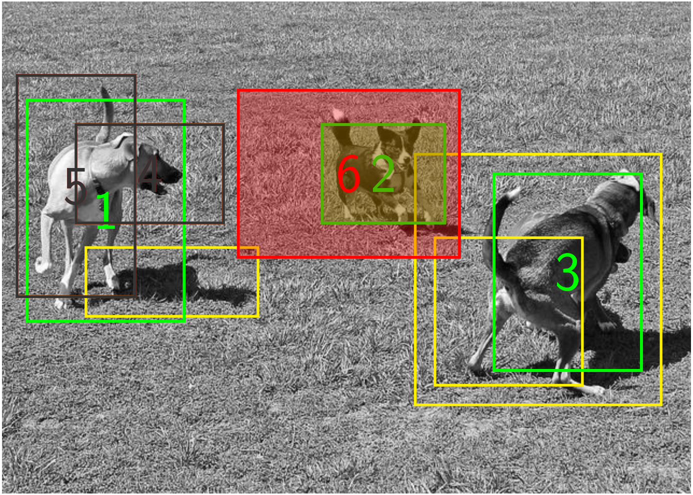
region 4 is rejected because $J(r_4, r_1) = 0.2750 > 0.25$

non-maximum suppression (NMS)



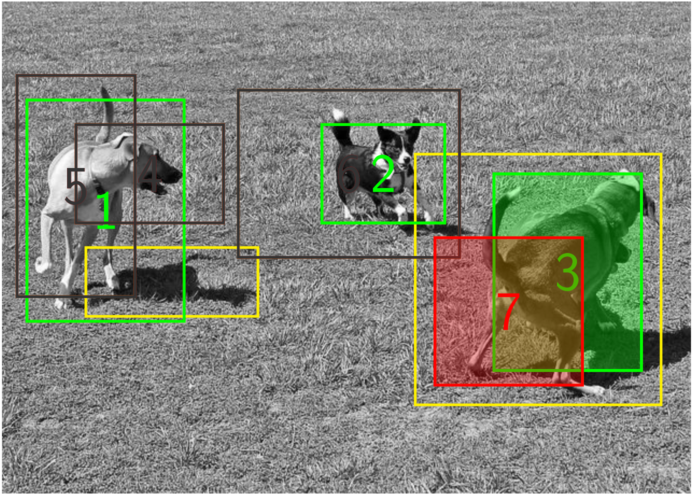
region 5 is rejected because $J(r_5, r_1) = 0.5366 > 0.25$

non-maximum suppression (NMS)



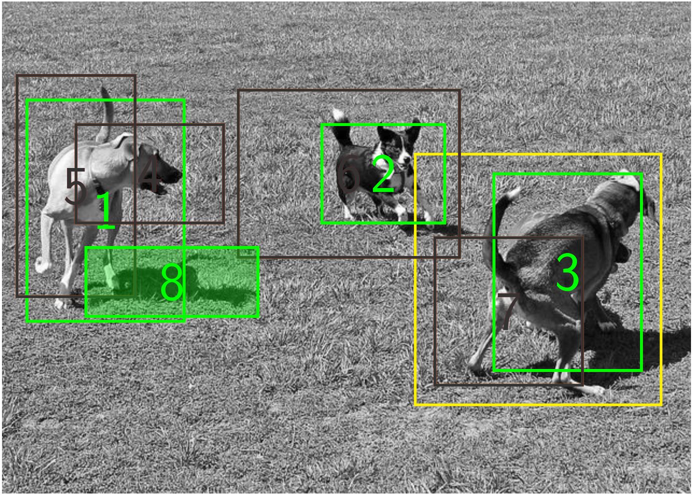
region 6 is rejected because $J(r_6, r_2) = 0.3268 > 0.25$

non-maximum suppression (NMS)



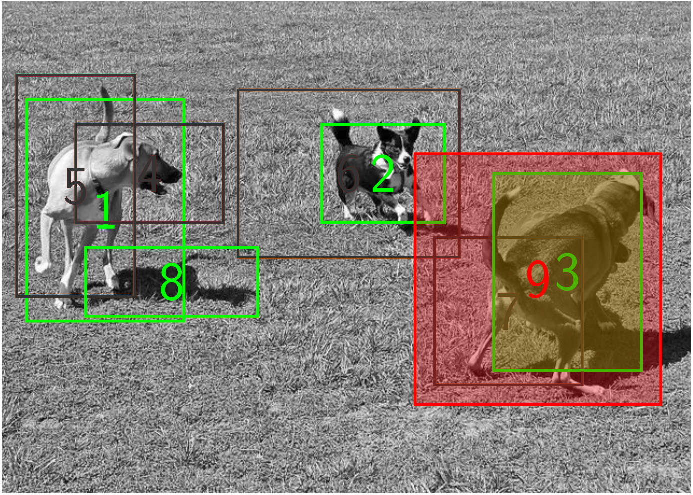
region 7 is rejected because $J(r_7, r_3) = 0.3011 > 0.25$

non-maximum suppression (NMS)



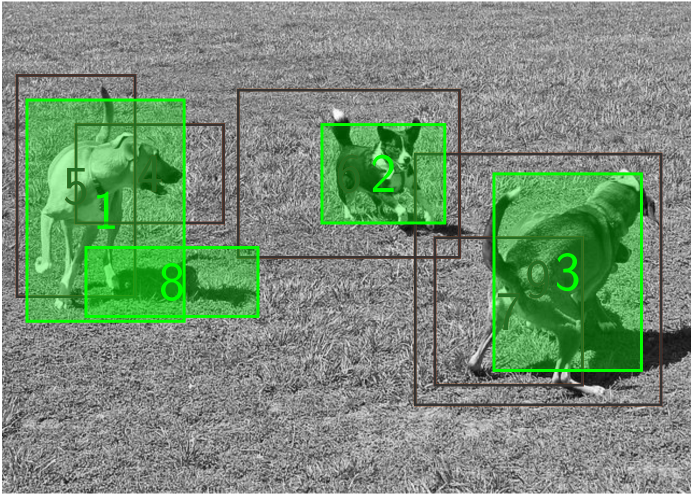
region 8 remains

non-maximum suppression (NMS)



region 9 is rejected because $J(r_9, r_3) = 0.4706 > 0.25$

non-maximum suppression (NMS)



in the end, regions 1, 2, 3, 8 remain

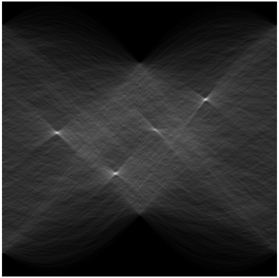
non-maximum suppression on regions

- given regions $r_1, r_2, \ldots$ of each class independently, ranked by decreasing order of confidence score
- for $i = 2, 3, \ldots$, reject region r_i if it has intersection-over-union (IoU) overlap higher then a threshold τ

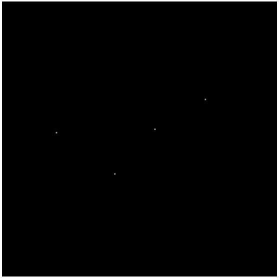
$$J(r_i, r_j) > \tau$$

  with some higher scoring region r_j with $j < i$ that has not been rejected

non-maximum suppression is everywhere



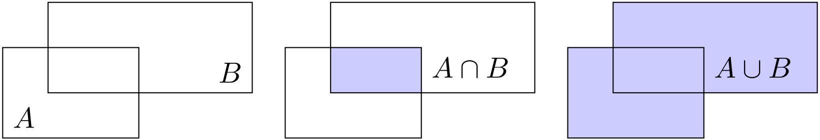
accumulator



local maxima

- we have used NMS to reject pixels or 1d-vector elements (rather than regions) accoding to some neighborhood relation, in
  - corner detection
  - feature point tracking
  - SIFT dominant orientation selection
  - Hough transform

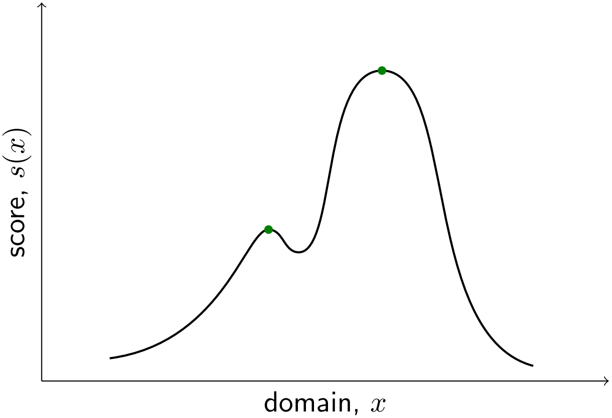
region overlap



- given regions $A, B \subset \mathbb{R}^2$ represented as planar point sets (including interior)
- their intersection over union (IoU) or Jaccard index is

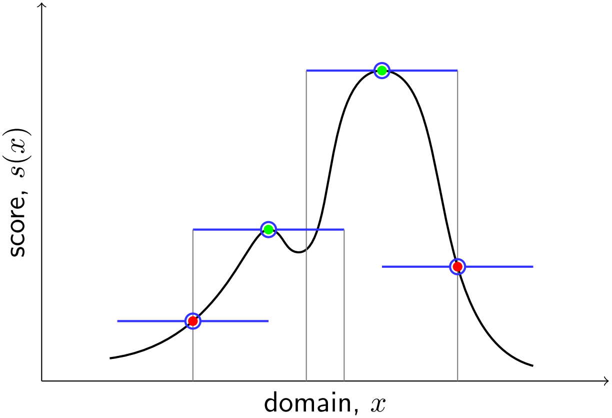
$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

the problem of non-maximum suppression



- ground truth positions

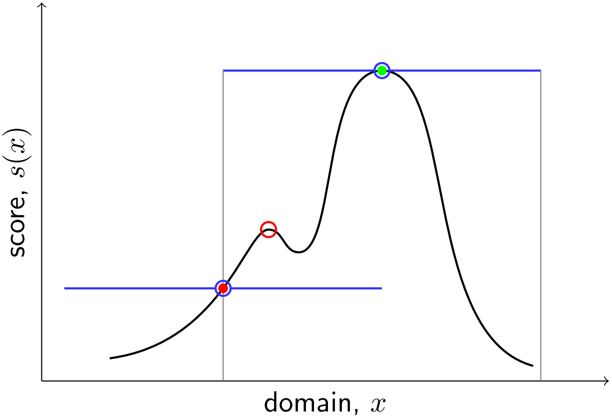
the problem of non-maximum suppression



- with a narrow neighborhood, there are two true positives (•) but also two false positives (•): precision is low

Hosang, Benenson and Schiele. 2015. A Convnet for Non-Maximum Suppression.

the problem of non-maximum suppression



- with a wide neighborhood, there is only one true positive (•), one false positive (•) and one false negative (○): recall is low

Hosang, Benenson and Schiele. 2015. A Convnet for Non-Maximum Suppression.

non-maximum suppression

- there are several recent attempts to improve NMS, *e.g.* merging or down-weighting instead of rejecting, replace it by a CNN, or integrate a differentiable version so that the entire pipeline is end-to-end trainable
- here we assume there is always NMS as the last post-processing stage after each detector

detection evaluation

[Russakovsky et al. 2015]

- for each image and for each class independently, rank predicted regions by descending order of confidence and assign each region r to the ground truth region $g^* = \arg\max_g J(r, g)$ of maximum overlap if $J(r, g^*) > \tau$ and mark it as true positive, else false
- each ground truth region can be assigned up to one predicted region
- now for each class independently, rank predicted regions of all images by descending order of confidence and compute average precision (AP) according to true/false labels
- the mean average precision (mAP) is the mean over classes

Russakovsky, Deng, Su, Krause, Satheesh, Ma, Huang, Karpathy, Khosla, Bernstein, Berg and Fei-Fei. IJCV 2015. Imagenet Large Scale Visual Recognition Challenge.

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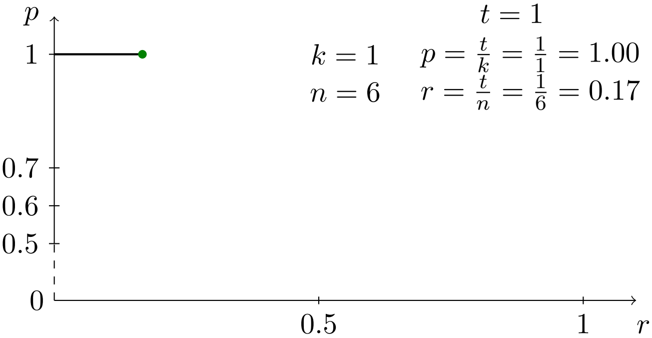
average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F

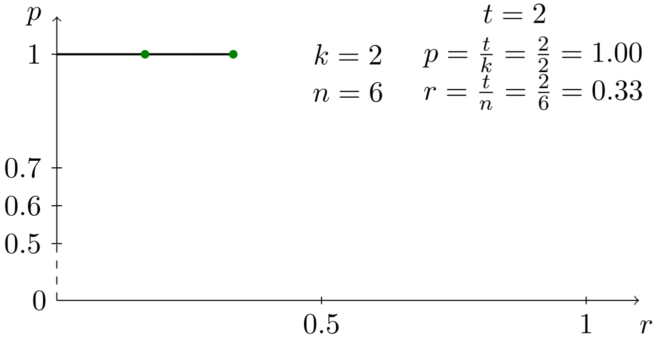


- # total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$t = 2$

$k = 2 \quad p = \frac{t}{k} = \frac{2}{2} = 1.00$

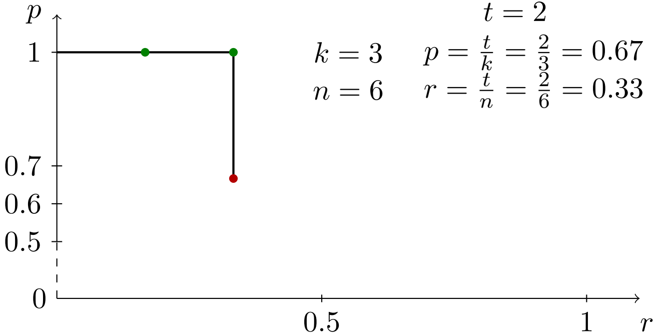
$n = 6 \quad r = \frac{t}{n} = \frac{2}{6} = 0.33$

- # total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$$t = 2$$

$$k = 3 \qquad p = \frac{t}{k} = \frac{2}{3} = 0.67$$

$$n = 6 \qquad r = \frac{t}{n} = \frac{2}{6} = 0.33$$

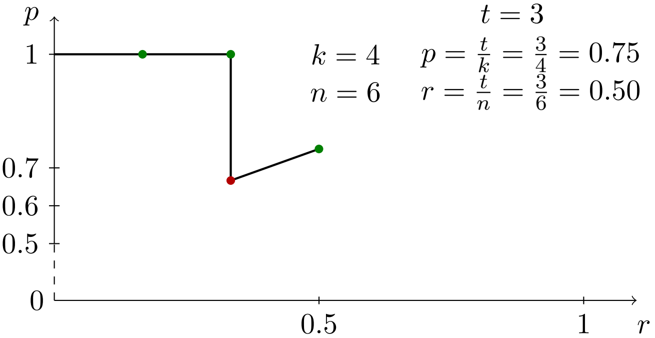
- # total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

Henderson and Ferrari. ACCV 2016. End-to-End Training of Object Class Detectors for Mean Average Precision

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F

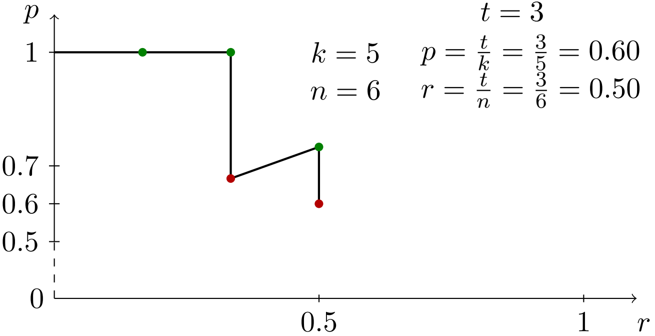


- \# total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$$t = 3$$

$$k = 5 \qquad p = \frac{t}{k} = \frac{3}{5} = 0.60$$

$$n = 6 \qquad r = \frac{t}{n} = \frac{3}{6} = 0.50$$

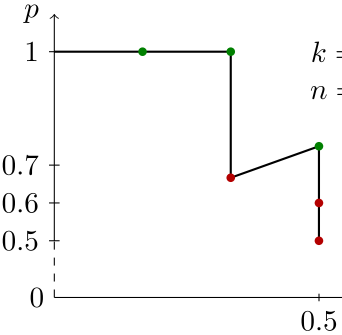
- \# total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

Henderson and Ferrari. ACCV 2016. End-to-End Training of Object Class Detectors for Mean Average Precision

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$$t = 3$$

$$k = 6 \qquad p = \frac{t}{k} = \frac{3}{6} = 0.50$$

$$n = 6 \qquad r = \frac{t}{n} = \frac{3}{6} = 0.50$$

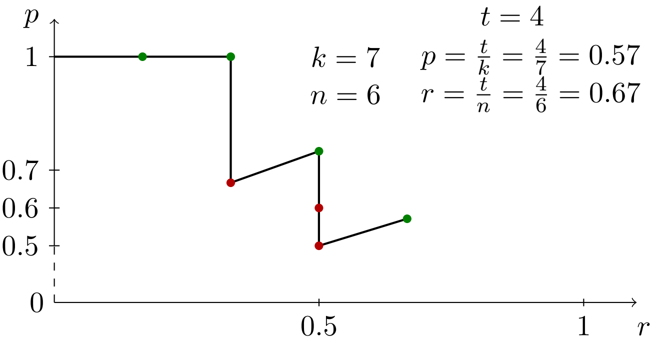
- # total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

Henderson and Ferrari. ACCV 2016. End-to-End Training of Object Class Detectors for Mean Average Precision

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



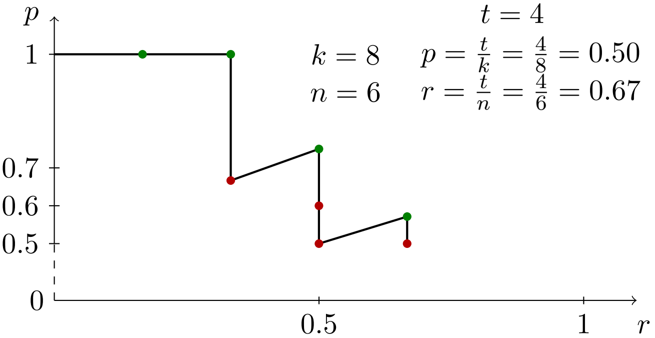
- $\#$ total ground truth n, current rank k, $\#$ true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

Henderson and Ferrari. ACCV 2016. End-to-End Training of Object Class Detectors for Mean Average Precision

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



$t = 4$

$k = 8 \qquad p = \frac{t}{k} = \frac{4}{8} = 0.50$

$n = 6 \qquad r = \frac{t}{n} = \frac{4}{6} = 0.67$

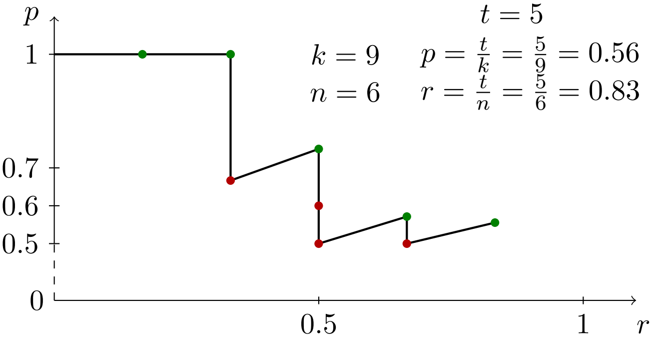
- \# total ground truth n, current rank k, \# true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

Henderson and Ferrari. ACCV 2016. End-to-End Training of Object Class Detectors for Mean Average Precision

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



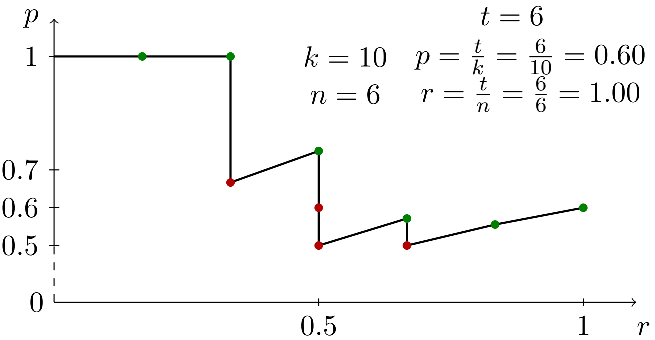
- # total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

Henderson and Ferrari. ACCV 2016. End-to-End Training of Object Class Detectors for Mean Average Precision

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



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average precision (AP)

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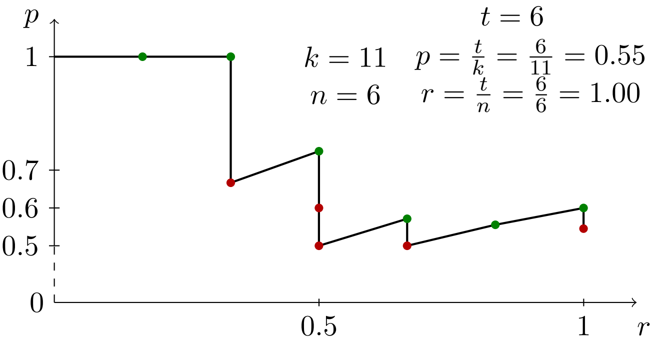
1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F

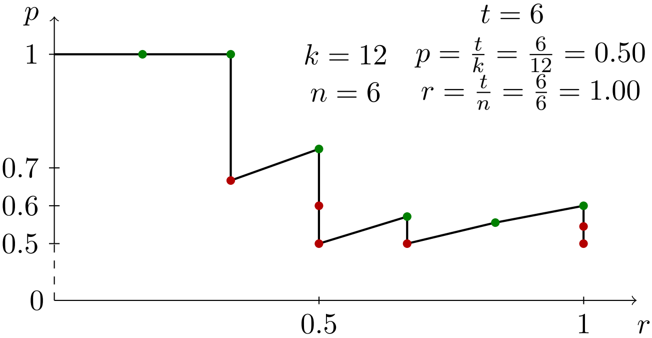


- \# total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F

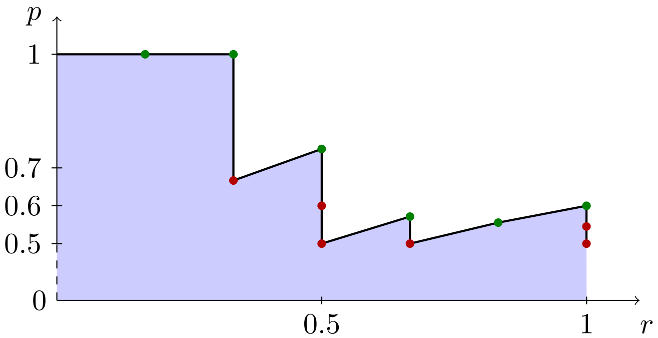


- # total ground truth n, current rank k, # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F

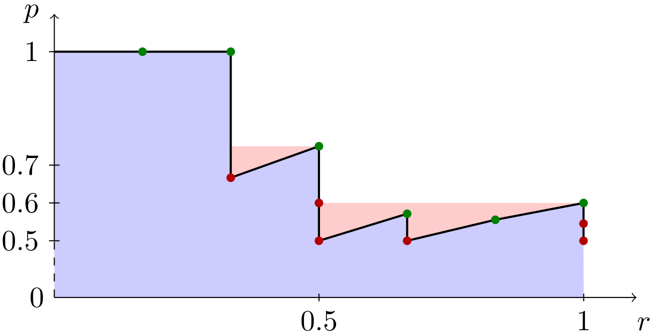


- average precision = area under curve
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

average precision (AP)

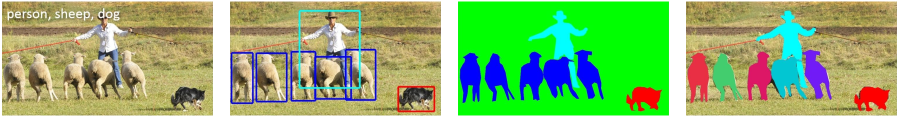
- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



- average precision = area under curve (filled-in curve)
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

object detection datasets



- **PASCAL** VOC 2007-12: 20 classes; images 5-11k train/val, 5-11k test (public for 2007)
- **ImageNet** ILSVRC 2010-17: 200 classes (subset or merged from classification task); images 400-450k train (partially annotated), 20k val, 40k test
- **COCO** 2015-: 80 classes; images 80k train, 40k val (115k/5k in 2017), 40k test, 120k unlabeled; smaller objects
- **Open Images** 2018-: 600 classes; images 1.74M train, 41k val, 125k test

Everingham *et al*. IJCV 2015. The PASCAL Visual Object Classes Challenge: a Retrospective.
Russakovsky *et al*. IJCV 2015. Imagenet Large Scale Visual Recognition Challenge.
Lin *et al*. ECCV 2014. Microsoft COCO: Common Objects in Context.
Kuznetsova *et al*. 2018. The Open Images Dataset V4: Unified image classification, object detection, and visual relationship detection at scale.

two-stage detection

regions with CNN features (R-CNN)

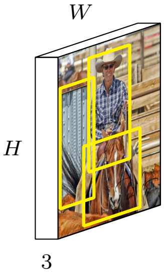
[Girshick et al. 2014]

- 3-channel RGB input, fixed width $W = 500$ pixels
- ~ 2000 SS region proposals warped into fixed $w \times h = 227 \times 227$
- each proposal yields a $k = 4096$ dimensional feature by CaffeNet
- each feature is classified into c classes by c one-*vs.* -rest SVMs and localized by bounding box regression

Girshick, Donahue, Darrell and Malik. CVPR 2014. Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation.

regions with CNN features (R-CNN)

[Girshick et al. 2014]



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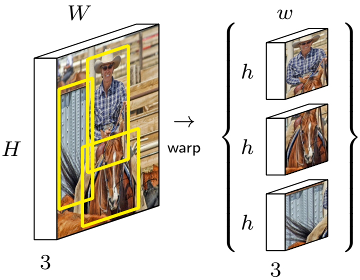

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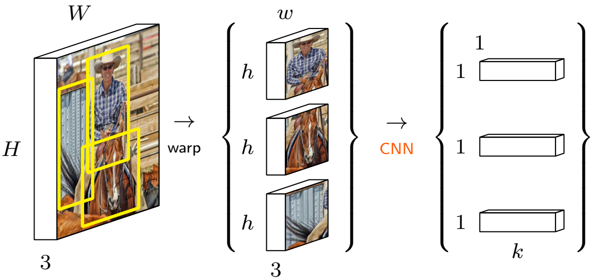

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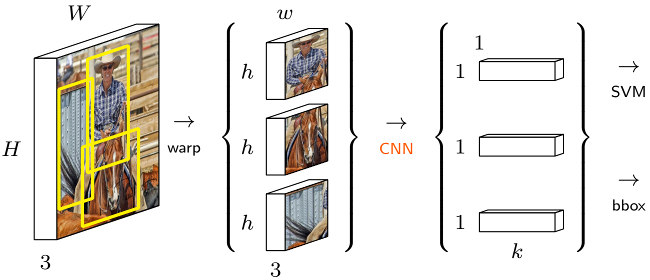

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pros

- region proposals, SVM classifier and NMS are standard; here one just replaces the features (*e.g.* HOG) by CNN
- CNN features are 4k-dimensional, compared *e.g.* to 360k dimensions of previous state of the art
- transfer learning: network pre-trained on 1.2M ImageNet images, then ImageNet-specific 1000-way classification layer replaced by randomly initialized $(c+1)$-way (c classes plus background) and fine-tuning

cons

- slow (13s/image): image warped and forwarded through network for each of the ~ 2000 region proposals
- 4 stages: region extraction, CNN features, SVM classifier, regressor
- positives/negatives defined differently in fine-tuning *vs.* SVM

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bounding box regression

- at training, given proposed and ground truth region $p, g \in \mathbb{R}^4$, define normalized target t for region center (x, y) and size (w, h)

$$t_x = (g_x - p_x)/p_w \qquad t_w = \log(g_w/p_w)$$
$$t_y = (g_y - p_y)/p_h \qquad t_h = \log(g_h/p_h)$$

- for $j \in \{x, y, w, h\}$, learn mapping $y_j = f_j(p)$ according to least squares loss

$$L(y_j, t_j) = (y_j - t_j)^2$$

- at inference, given proposal p, predict region $\hat{p}$ according to

$$\hat{p}_x = p_w f_x(p) + p_x \qquad \hat{p}_w = p_w \exp(f_w(p))$$
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spatial pyramid pooling (SPP)

[He et al. 2014]

- we need to extract features and classify each region
- we can crop or warp them to fixed size, then feed to CNN for both
- or we can extract features of arbitrary size with convolutions, max-pool features to fixed size, then classify

He, Zhang, Ren and Sun. ECCV 2014. Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition.

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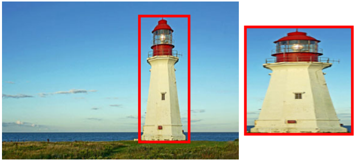
crop



warp

image → crop/warp → conv layers → fc layers → output

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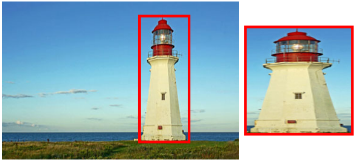

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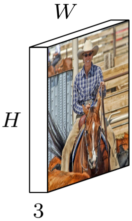

- 3-channel RGB input, arbitrary size
- input yields a single k dimensional feature map
- each region proposal projected onto feature maps
- then max-pooled into a number of fixed sizes $1 \times 1, 2 \times 2, 4 \times 4$ *etc.* and concatenated into fixed-length representation
- when the pyramid has only one level, we call this RoI pooling

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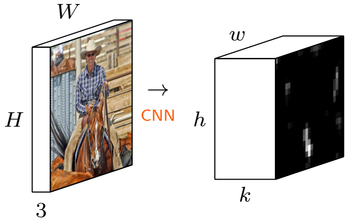

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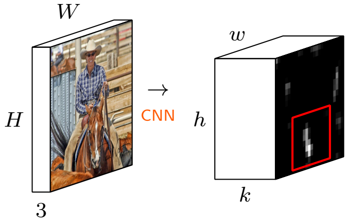

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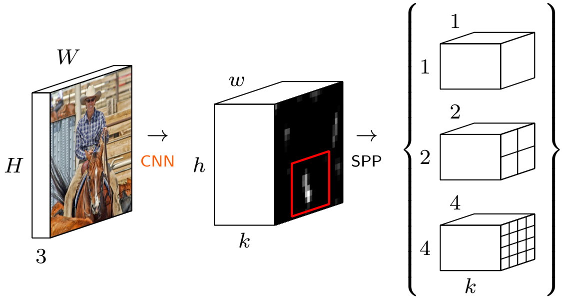

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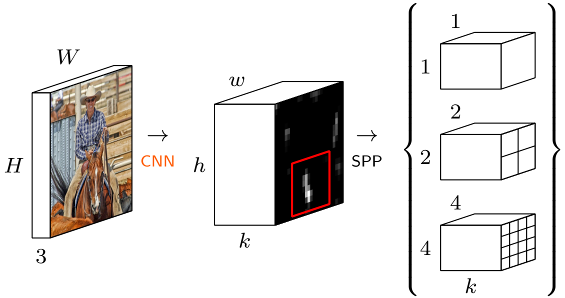

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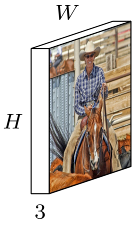

- 3-channel RGB input, arbitrary size
- input yields a single $k = 4096$ dimensional feature map by VGG-16
- ~ 2000 region proposals, projected onto feature maps and RoI-pooled into fixed size $w' \times h' \times k = 7 \times 7 \times k$
- several fully-connected layers follow, for each pooled map
- each pooled map is classified into $c + 1$ classes (c + background) by single softmax and localized by bounding box regression

Girshick. ICCV 2015. Fast R-CNN.

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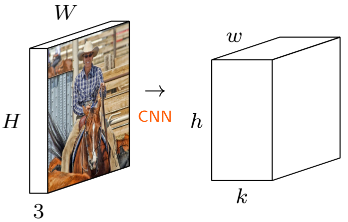

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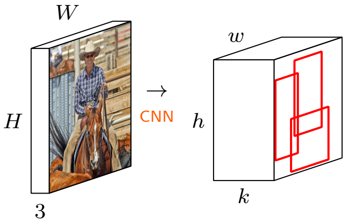

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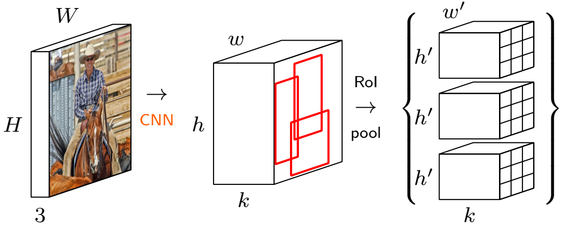

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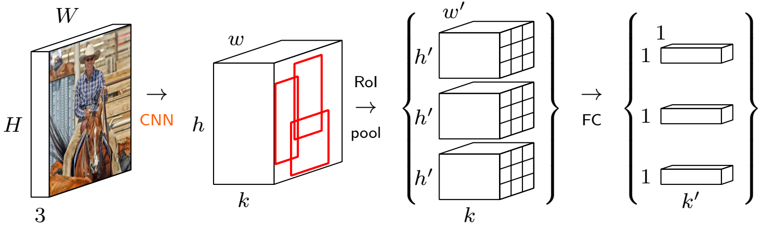

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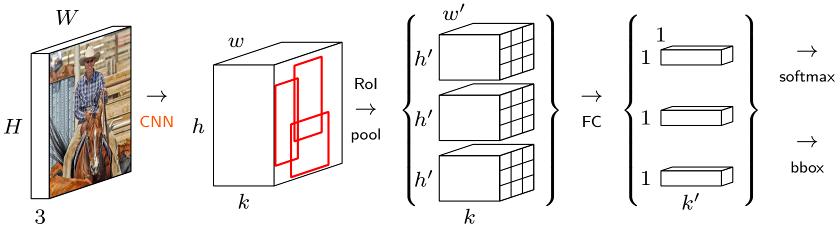

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pros

- fast (0.32s/image; $9\times$ training, $213\times$ test speedup *vs.* R-CNN): image forwarded through network only once, only few layers are region-specific
- 2 stages: only region proposals are separate; features, classifier and regressor are trained end-to-end with multi-task loss
- better performance

cons

- region proposals are still needed for performance, but are now the bottleneck (~ 2s/image)
- single-scale

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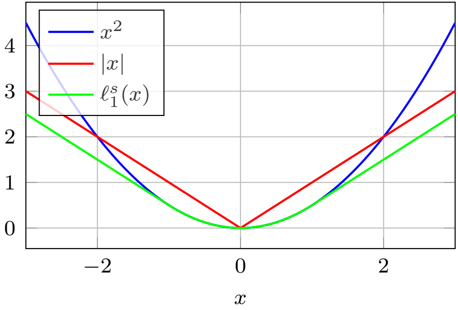
regression loss

- given region p and target t, learn mapping $y = f(p)$ according to smooth ℓ_1 or Huber loss, which prevents exploding gradients

$$L(y, t) = \sum_{j \in \{x,y,h,w\}} \ell_1^s(y_j - t_j)$$

$$\ell_1^s(x) = \begin{cases} \frac{x^2}{2}, & \text{if } |x| < 1 \\ |x| - \frac{1}{2}, & \text{otherwise} \end{cases}$$



Huber. AS 1964. Robust Estimation of a Location Parameter.

learning object proposals: MultiBox detector*

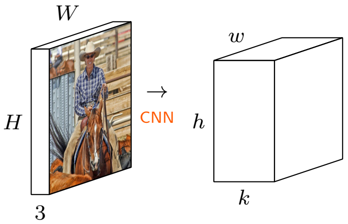
[Erhan et al. 2014]

- a fixed number (*e.g.* 100 or 200) of class-agnostic object proposals are learned by regression on image representation
- this is faster than *e.g.* selective search
- however, proposal generation is not convolutional, but rather based on a fully connected layer
- the next step would be to integrate object proposals and classifier, making the pipeline end-to-end trainable

Erhan, Szegedy, Toshev and Anguelov. CVPR 2014. Scalable Object Detection Using Deep Neural Networks.

faster R-CNN

[Ren et al. 2015]



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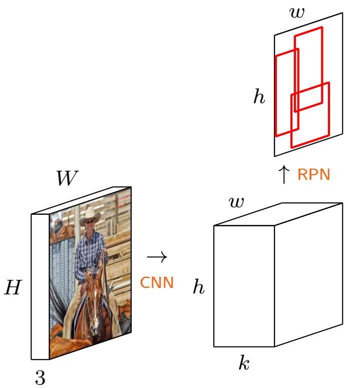
Ren, He, Girshick and Sun. NIPS 2015. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks.

faster R-CNN

[Ren et al. 2015]



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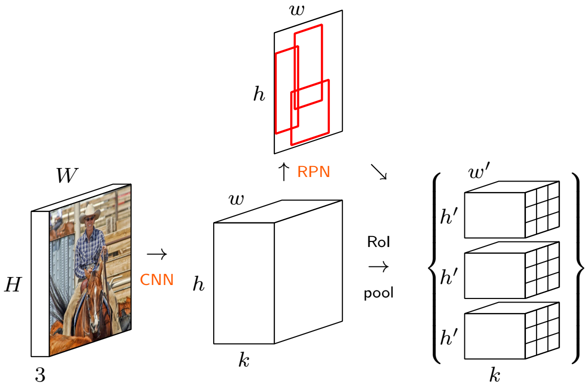
Ren, He, Girshick and Sun. NIPS 2015. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks.

faster R-CNN

[Ren et al. 2015]



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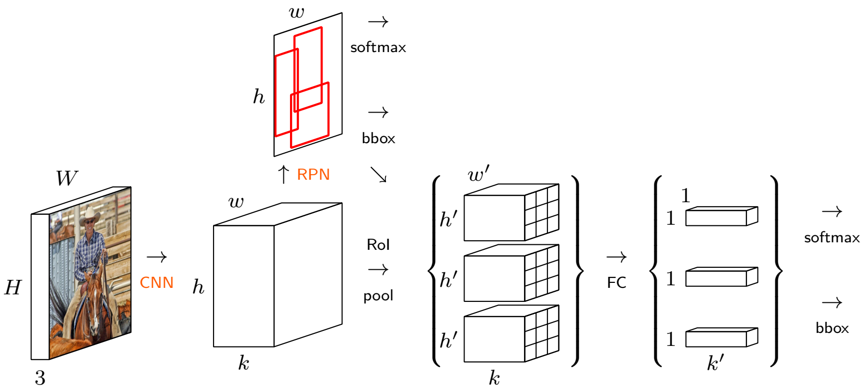

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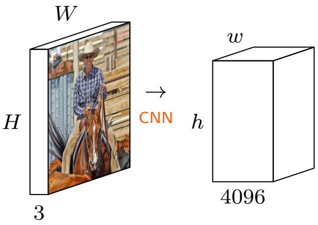

- same input, same feature maps, dimension reduced to 512
- $a = 9$ anchors at each position, for 3 scales and 3 aspect ratios
- $2a$ classification (object/non-object) scores and $4a$ bounding box coordinates relative to anchor at each position
- softmax on scores, regression loss on coordinates
- region proposals by non-maxima suppression

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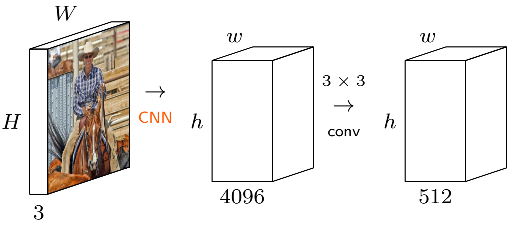

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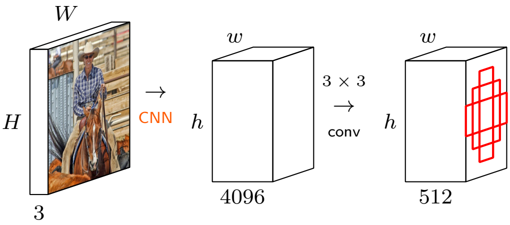

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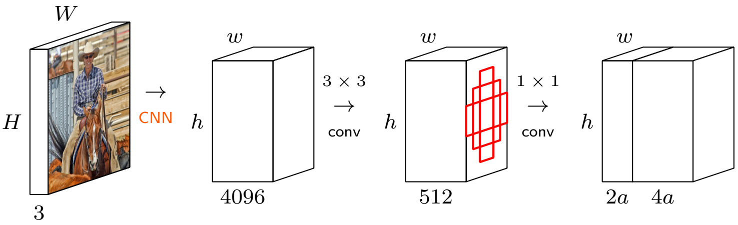

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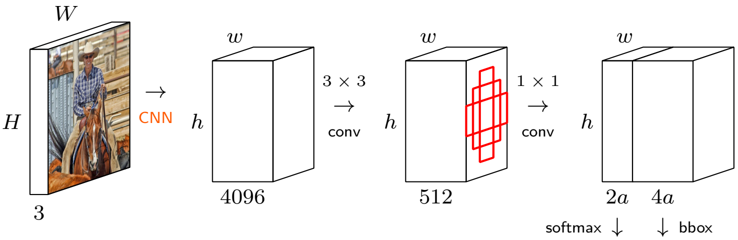

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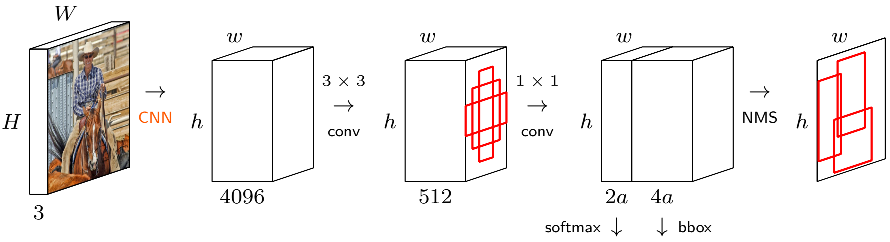

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faster R-CNN

pros

- faster (0.2s/image including proposals; $10\times$ test speedup *vs.* fast R-CNN): only few layers are used for RPN and region-specific classification and regression
- trained end-to-end including features, region proposals, classifier and regressor
- more accurate: region proposals are learned, RPN is convolutional

cons

- still, several fully-connected layers needed for region-specific tasks
- still single-scale

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online hard example mining (OHEM)*

[Shrivastava et al. 2016]

- models with separate SVM classifier (R-CNN, SPP) use RoI-centric mini-batches, sampled from all training images
- to enable end-to-end fine-tuning of all layers, image-centric mini-batches are used with very few images (1-2) but thousands of candidate regions
- most regions are negative: this class imbalance can overwhelm the classifier
- it is standard to use a fixed positive to negative ratio (*e.g.* 1:1 or 1:4)
- OHEM, instead, evaluates all candidate regions and samples the hardest ones, without any fixed ratio

Shrivastava, Gupta and Girshick. CVPR 2016. Training Region-Based Object Detectors with Online Hard Example Mining.

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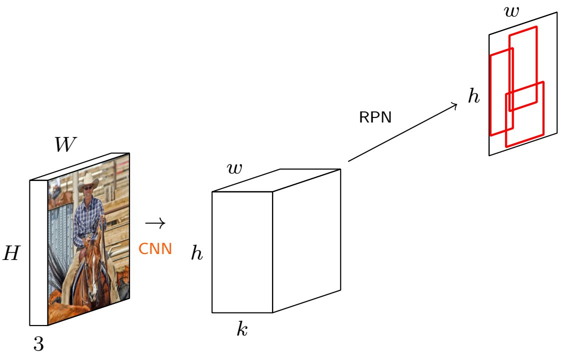
object parts and deformation

region-based fully convolutional network (R-FCN)

[Ren et al. 2016]



- 2048-d feature maps by ResNet-101, reduced to $k = 1024$, same RPN
- $r \times r = 7 \times 7$ position-sensitive score maps per class, RoI pooling
- similarly, $4r^2$ position-sensitive coordinates for regression
- no FC, just average pooling

Dai, Li, He and Sun. 2016. R-FCN: Object Detection via Region-Based Fully Convolutional Networks.

region-based fully convolutional network (R-FCN)

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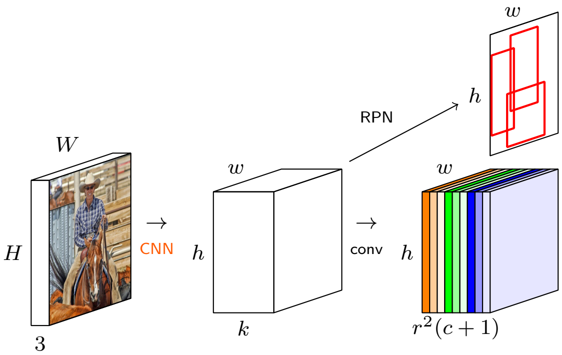

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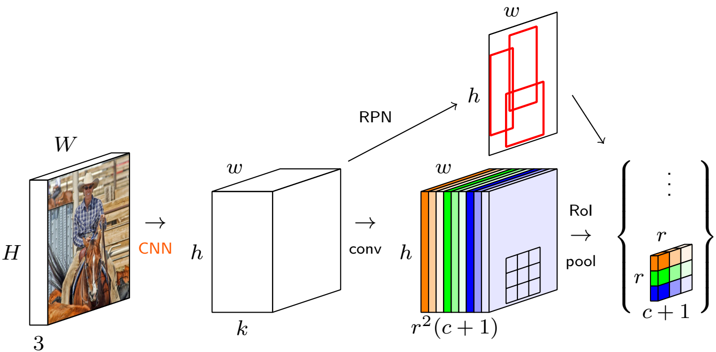

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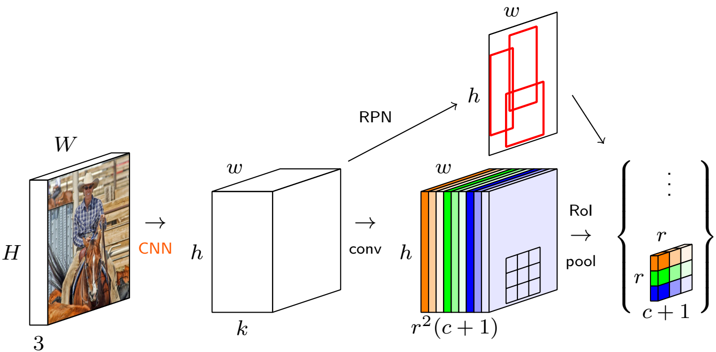

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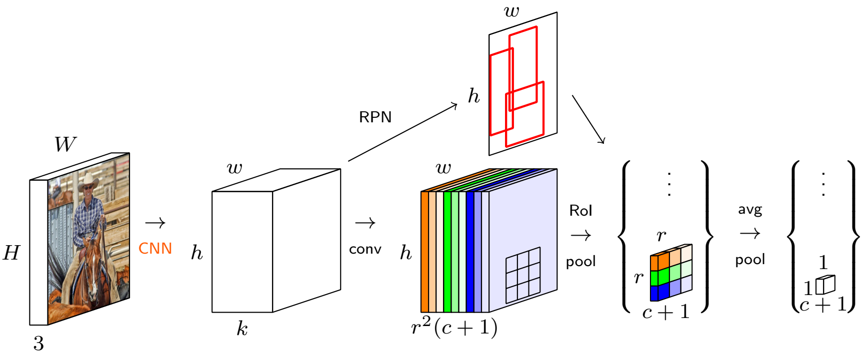

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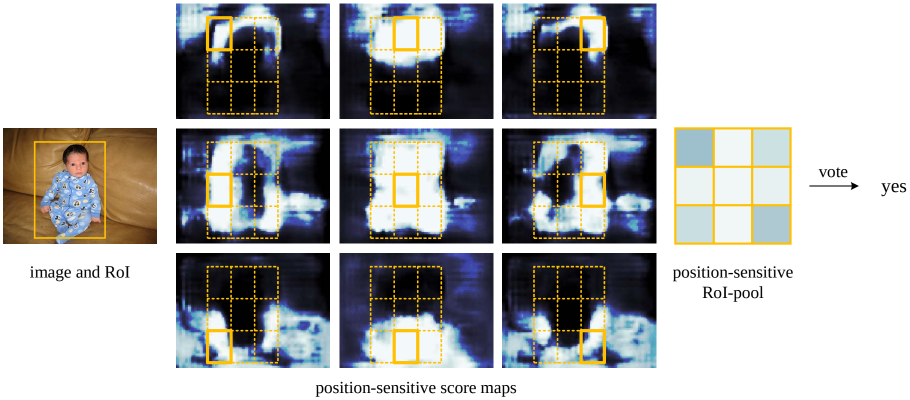
position-sensitive score maps and RoI pooling



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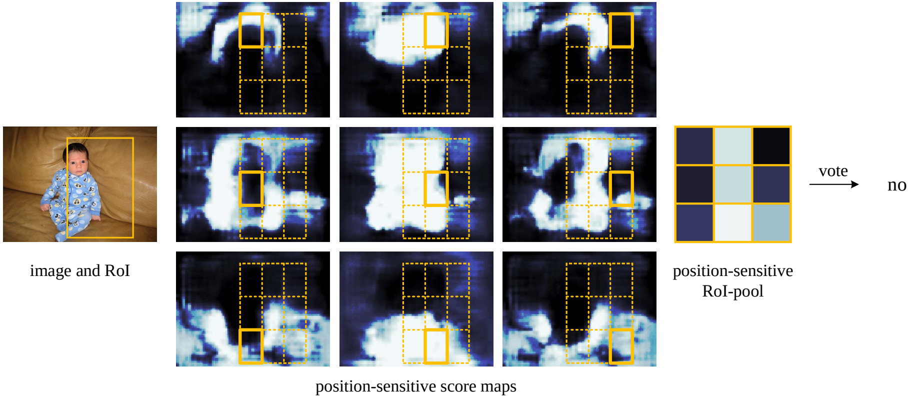

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region-based fully convolutional network (R-FCN)

pros

- fully convolutional: no more FC layers, maximum feature sharing bewteen all tasks (RPN, classification, regression)
- still, spatial information is preserved by position-sensitive layer, improving localization accuracy
- faster (0.17s/image *vs.* 0.42 for faster R-CNN on ResNet-101)

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- cells of position-sensitive RoI pooling are fixed
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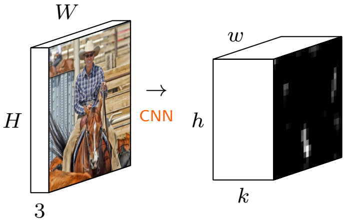
spatial transformer networks (STN)*

[Jaderberg et al. 2015]



- input image yields a k dimensional feature map
- a localization network L regresses a geometric transformation θ
- a transformer T_θ applies the transformation to the feature map
- the transformation can involve resampling, cropping, even deformation
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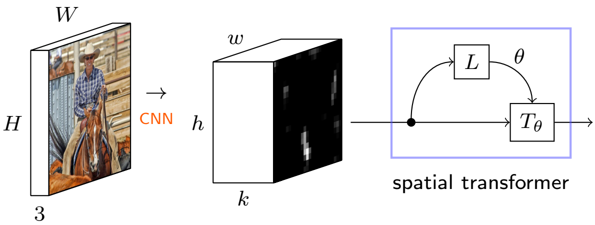

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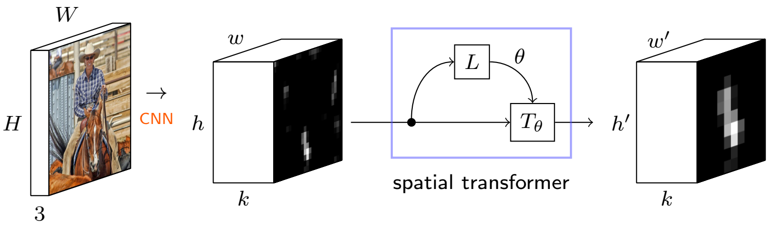

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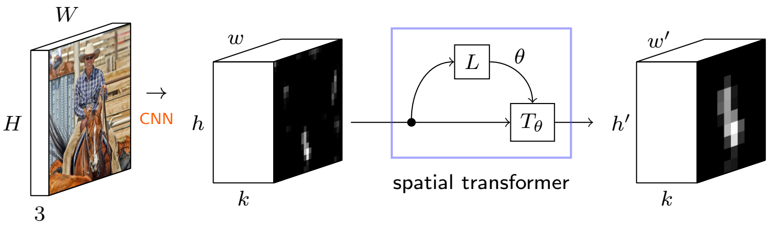

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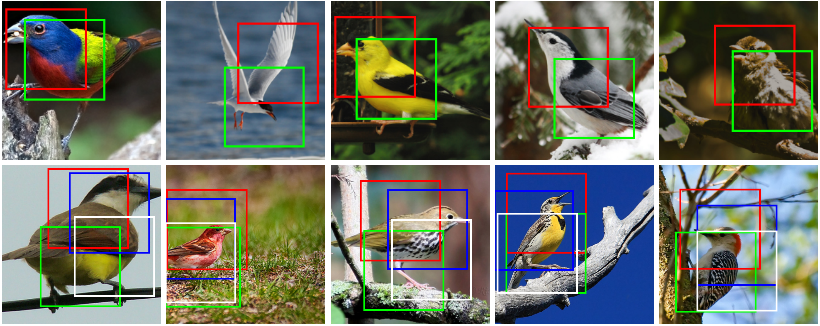
spatial transformer networks: part learning*

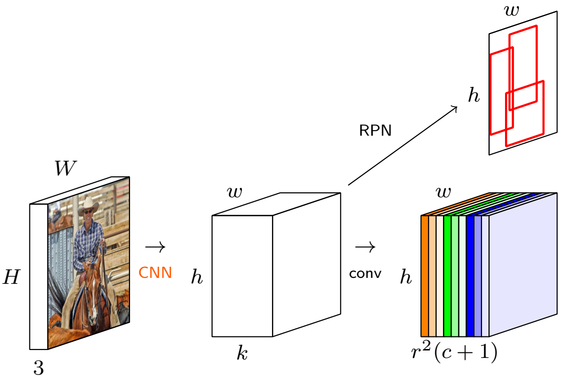


- 2 or 4 spatial transformers predict discriminative object parts with no supervision other than the class label
- the localization network is based on GoogLeNet and is shared across transformers; features are extracted by one GoogLeNet for each region
- features are concatenated and the image is classified by a single fully connected layer with softmax

Jaderberg, Simonyan, Zisserman and Kavukcuoglu. NIPS 2015. Spatial Transformer Networks.

deformable RoI pooling

[Ren et al. 2017]



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Dai, Qi, Xiong, Li, Zhang, Hu and Wei. ICCV 2017. Deformable Convolutional Networks.

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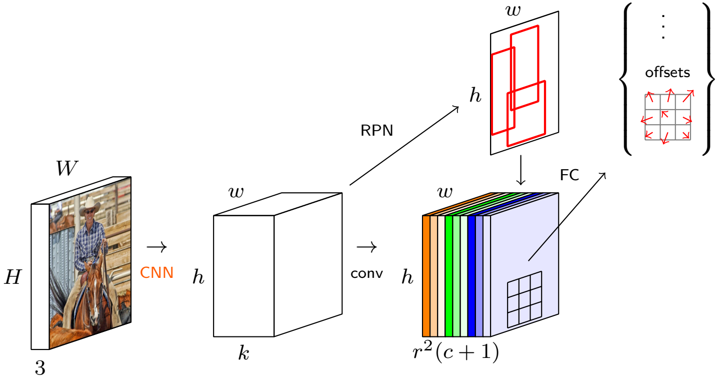

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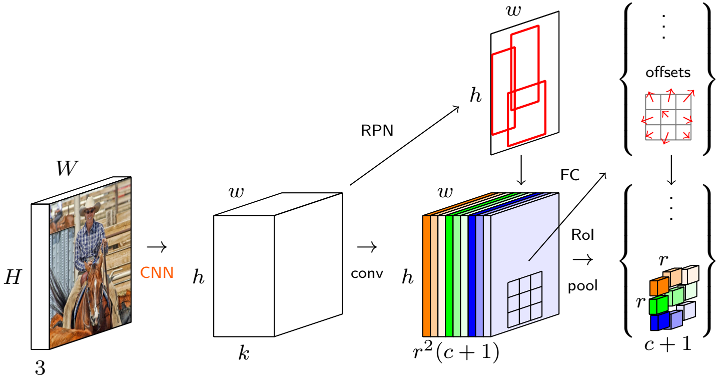

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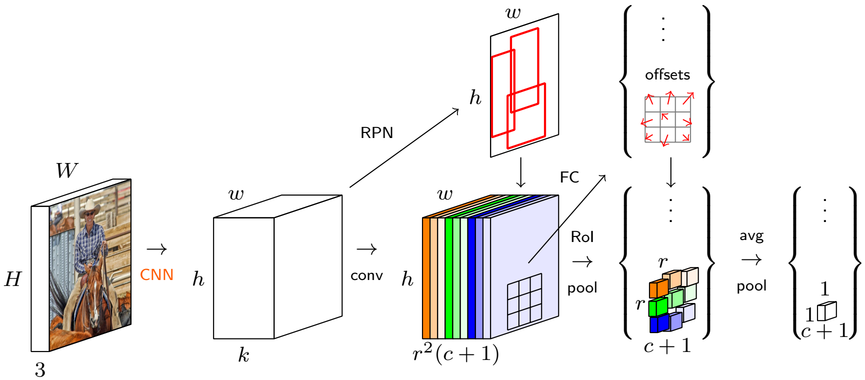

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deformable convolution

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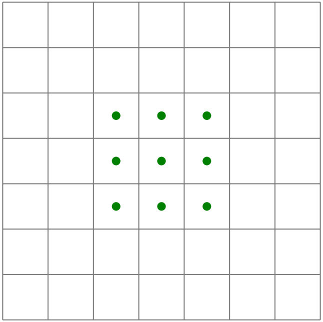

- standard convolution on 3×3 regular sampling grid

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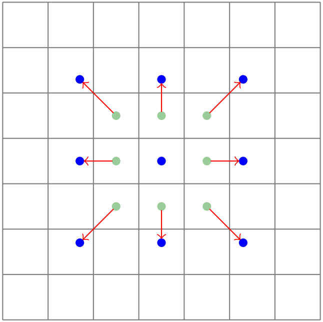
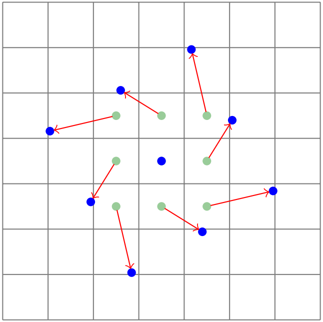


- scaled grid (as in automatic scale selection, but dense)

Dai, Qi, Xiong, Li, Zhang, Hu and Wei. ICCV 2017. Deformable Convolutional Networks.

deformable convolution

[Ren et al. 2017]



- rotated grid (as in dominant orientation selection, but dense)

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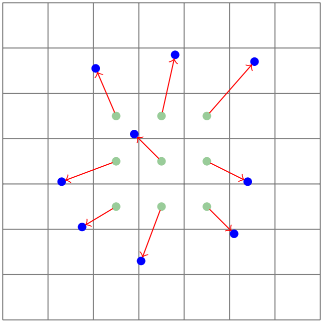
deformable convolution

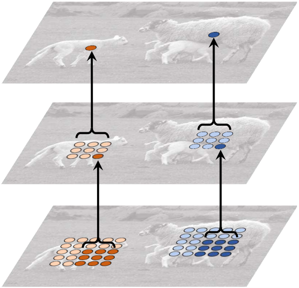
[Ren et al. 2017]



- deformed sampling grid where offsets are computed per pixel

Dai, Qi, Xiong, Li, Zhang, Hu and Wei. ICCV 2017. Deformable Convolutional Networks.

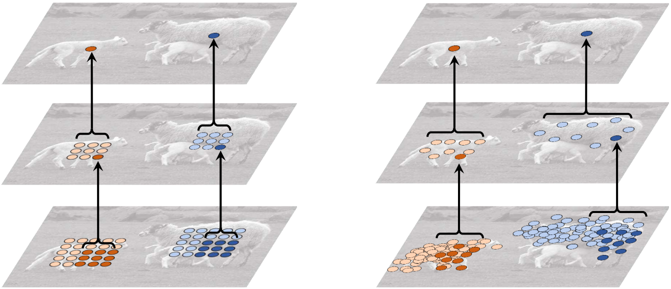
deformable convolution: receptive field (2 layers)



- standard convolution: receptive field grows with depth but only linearly, remains rectangular and is translation invariant
- deformable convolution: receptive field grows arbitrarily with depth, adapts per location and takes arbitrary shape

Dai, Qi, Xiong, Li, Zhang, Hu and Wei. ICCV 2017. Deformable Convolutional Networks.

deformable convolution: receptive field (2 layers)



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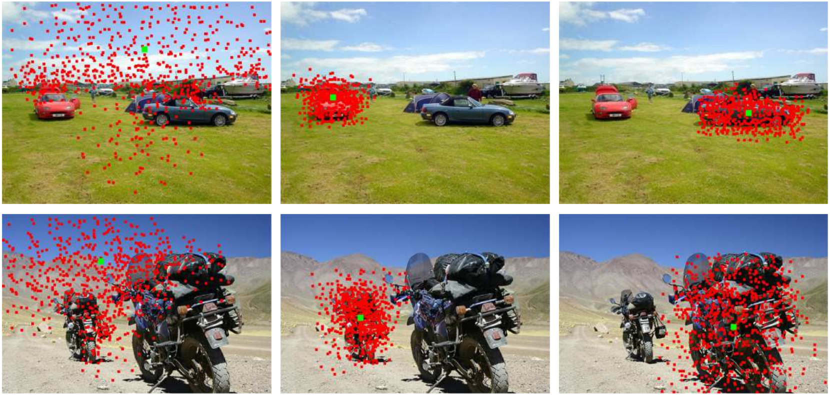
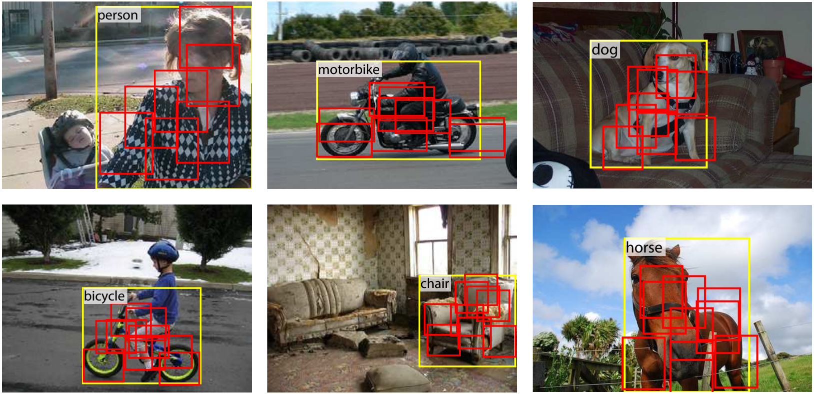
deformable convolution: receptive field (2 layers)



- red: $9^3 = 729$ sampling locations in 3 levels of 3×3 deformable filters for three units (green)
- receptive field adapts to object size and shape

Dai, Qi, Xiong, Li, Zhang, Hu and Wei. ICCV 2017. Deformable Convolutional Networks.

deformable RoI pooling



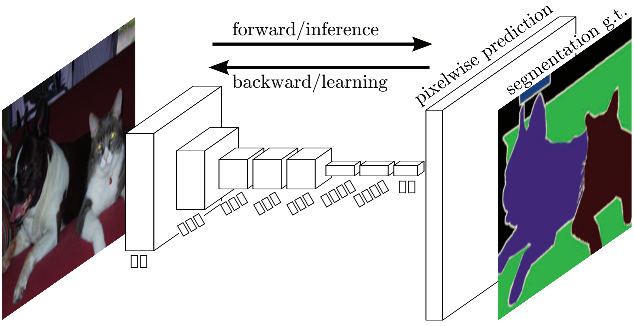
- deformed 3×3 cells (red) for an input RoI (yellow)
- cells adapt to part locations of non-rigid objects

Dai, Qi, Xiong, Li, Zhang, Hu and Wei. ICCV 2017. Deformable Convolutional Networks.

scale and feature pyramids

fully convolutional networks (FCN)*

[Long et al. 2015]

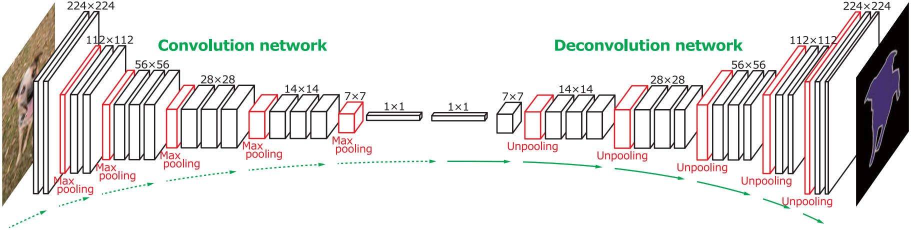


- feature maps capture high-level semantics but are of low resolution
- here, they are upsampled to original pixel resolution
- given pixel-wise class label supervision, the network learns pixel-wise prediction for semantic segmentation
- there are no fully-connected layers, hence "fully convolutional"

Long, Shelhamer and Darrell. CVPR 2015. Fully Convolutional Networks for Semantic Segmentation.

learning to upsample*

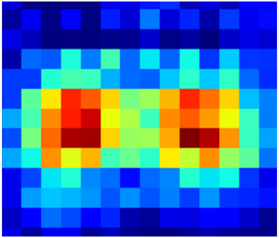
[Noh et al. 2015]



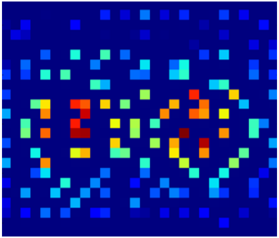
- the upsampling process is improved by learning to invert the max-pooling and convolution operations with unpooling and deconvolution
- instance-wise segmentations are obtained by applying the network to individual object proposals, as in detection

Noh, Hong, and Han. ICCV 2015. Learning Deconvolution Network for Semantic Segmentation.

learning to upsample



14×14 deconv

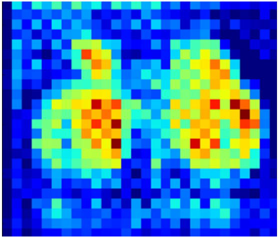


28×28 unpool

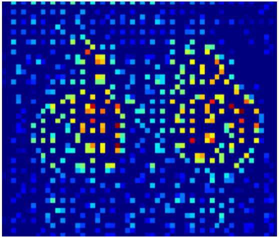
- resolution is decreased from 224×224 down to 7×7 by five 2×2 pooling layers and finally to 1×1 by fully connected layer
- it is then increased back to 7×7, 14×14 and finally up to 224×224 by five unpooling and deconvolution layers)
- the most appropriate feature map is chosen in each layer for visualization

Noh, Hong, and Han. ICCV 2015. Learning Deconvolution Network for Semantic Segmentation.

learning to upsample



28×28 deconv

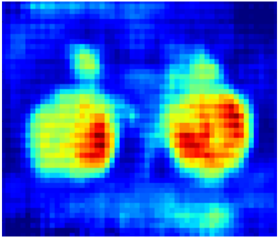


56×56 unpool

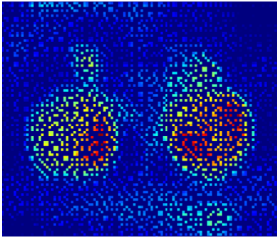
- resolution is decreased from 224×224 down to 7×7 by five 2×2 pooling layers and finally to 1×1 by fully connected layer
- it is then increased back to 7×7, 14×14 and finally up to 224×224 by five unpooling and deconvolution layers)
- the most appropriate feature map is chosen in each layer for visualization

Noh, Hong, and Han. ICCV 2015. Learning Deconvolution Network for Semantic Segmentation.

learning to upsample



56×56 deconv

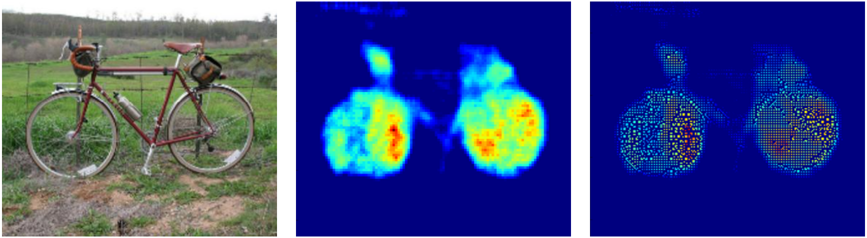


112×112 unpool

- resolution is decreased from 224×224 down to 7×7 by five 2×2 pooling layers and finally to 1×1 by fully connected layer
- it is then increased back to 7×7, 14×14 and finally up to 224×224 by five unpooling and deconvolution layers)
- the most appropriate feature map is chosen in each layer for visualization

Noh, Hong, and Han. ICCV 2015. Learning Deconvolution Network for Semantic Segmentation.

learning to upsample



112×112 deconv $\quad$ 224×224 unpool

- resolution is decreased from 224×224 down to 7×7 by five 2×2 pooling layers and finally to 1×1 by fully connected layer
- it is then increased back to 7×7, 14×14 and finally up to 224×224 by five unpooling and deconvolution layers)
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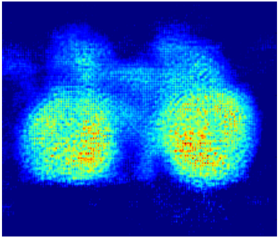
Noh, Hong, and Han. ICCV 2015. Learning Deconvolution Network for Semantic Segmentation.

learning to upsample



224×224 deconv

- resolution is decreased from 224×224 down to 7×7 by five 2×2 pooling layers and finally to 1×1 by fully connected layer
- it is then increased back to 7×7, 14×14 and finally up to 224×224 by five unpooling and deconvolution layers)
- the most appropriate feature map is chosen in each layer for visualization

Noh, Hong, and Han. ICCV 2015. Learning Deconvolution Network for Semantic Segmentation.

upsampling for detection

- we may not need pixel-wise prediction for detection, but we still higher resolution than *e.g.* 14×14 or 7×7 to detect and localize small objects accurately
- in fact, as we upsample, we will combine detections from multiple layers corresponding to multiple scales

network “stages” or “blocks”

VGG-16

		volume
	input$(224, 3)$	$224 \times 224 \times 3$
$2\times$	conv$(3, 64, p1)$	$224 \times 224 \times 64$
	pool(2)	$112 \times 112 \times 64$
$2\times$	conv$(3, 128, p1)$	$112 \times 112 \times 128$
	pool(2)	$56 \times 56 \times 128$
$3\times$	conv$(3, 256, p1)$	$56 \times 56 \times 256$
	pool(2)	$28 \times 28 \times 256$
$3\times$	conv$(3, 512, p1)$	$28 \times 28 \times 512$
	pool(2)	$14 \times 14 \times 512$
$3\times$	conv$(3, 512, p1)$	$14 \times 14 \times 512$
	pool(2)	$7 \times 7 \times 512$
$2\times$	fc(4096)	$4,096$
	fc(1000)	$1,000$
	softmax	$1,000$

ResNet-101

		volume
	input$(224, 3)$	$224 \times 224 \times 3$
	conv$(7, 64, p3, s2)$	$112 \times 112 \times 64$
	pool$(3, 2, p1)$	$56 \times 56 \times 64$
$3\times$	res$(3, (64, 256))$	$56 \times 56 \times 256$
	res$(3, (128, 512), s2)$	$28 \times 28 \times 512$
$3\times$	res$(3, (128, 512))$	$28 \times 28 \times 512$
	res$(3, (256, 1024), s2)$	$14 \times 14 \times 1024$
$22\times$	res$(3, (256, 1024))$	$14 \times 14 \times 1024$
	res$(3, (512, 2048), s2)$	$7 \times 7 \times 2048$
$2\times$	res$(3, (512, 2048))$	$7 \times 7 \times 2048$
	avg(7)	2048
	fc(1000)	1000
	softmax	1000

network "stages" or "blocks"

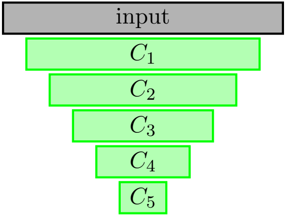
VGG-16

stage		layer	volume
		input(224, 3)	$224 \times 224 \times 3$
C_1	$2\times$	conv(3, 64, $p1$)	$224 \times 224 \times 64$
		pool(2)	$112 \times 112 \times 64$
C_2	$2\times$	conv(3, 128, $p1$)	$112 \times 112 \times 128$
		pool(2)	$56 \times 56 \times 128$
C_3	$3\times$	conv(3, 256, $p1$)	$56 \times 56 \times 256$
		pool(2)	$28 \times 28 \times 256$
C_4	$3\times$	conv(3, 512, $p1$)	$28 \times 28 \times 512$
		pool(2)	$14 \times 14 \times 512$
C_5	$3\times$	conv(3, 512, $p1$)	$14 \times 14 \times 512$
		pool(2)	$7 \times 7 \times 512$
	$2\times$	fc(4096)	4,096
		fc(1000)	1,000
		softmax	1,000

ResNet-101

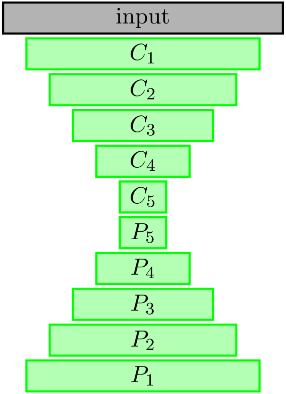
	layer	volume
	input(224, 3)	$224 \times 224 \times 3$
	conv(7, 64, $p3$, $s2$)	$112 \times 112 \times 64$
	pool(3, 2, $p1$)	$56 \times 56 \times 64$
$3\times$	res(3, (64, 256))	$56 \times 56 \times 256$
	res(3, (128, 512), $s2$)	$28 \times 28 \times 512$
$3\times$	res(3, (128, 512))	$28 \times 28 \times 512$
	res(3, (256, 1024), $s2$)	$14 \times 14 \times 1024$
$22\times$	res(3, (256, 1024))	$14 \times 14 \times 1024$
	res(3, (512, 2048), $s2$)	$7 \times 7 \times 2048$
$2\times$	res(3, (512, 2048))	$7 \times 7 \times 2048$
	avg(7)	2048
	fc(1000)	1000
	softmax	1000

pyramid networks



- bottom-up path: higher-level features, downsampling
- top-down path: still high-level, upsampling
- lateral connections
- predictions from multiple scales

pyramid networks



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- top-down path: still high-level, upsampling
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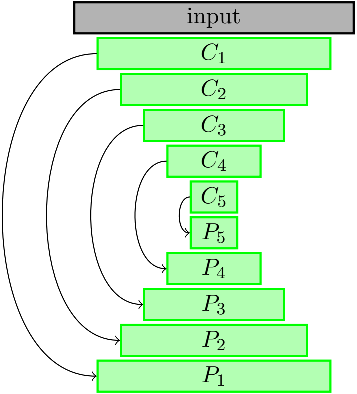
- predictions from multiple scales

pyramid networks



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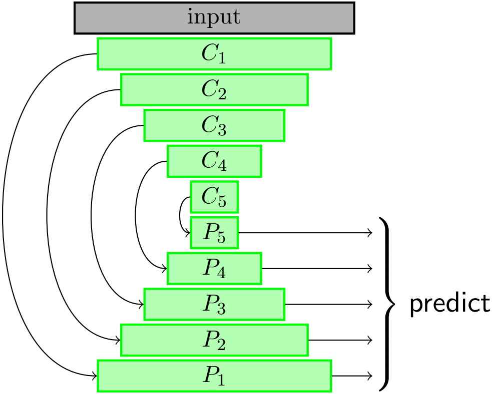
- lateral connections
- predictions from multiple scales

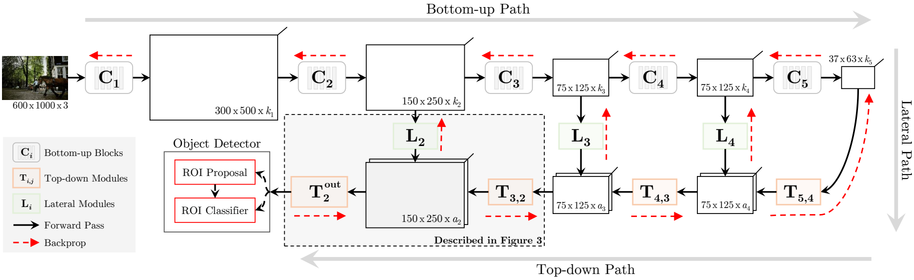
pyramid networks



- bottom-up path: higher-level features, downsampling
- top-down path: still high-level, upsampling
- lateral connections
- predictions from multiple scales

top-down modulation (TDM)*

[Shrivastava et al. 2016]

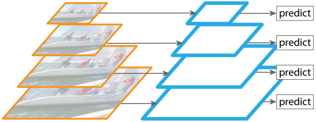


- the top-down network handles the integration of features and attempts to influence lower-level features
- detection (or any final task) now depends on high-resolution, high-level features
- applied to VGG-16 and ResNet-101 with faster R-CNN
- however, only the final top-down module collects features

Shrivastava, Sukthankar, Malik and Gupta 2016. Beyond Skip Connections: Top-Down Modulation for Object Detection.

feature pyramid networks (FPN)

[Lin et al. 2017]



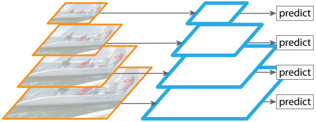
featurized image pyramid

- features computed at each scale independently: slow
- single scale for faster detection
- reuse pyramidal feature hierarchy as if computed at different scales
- still fast, but more accurate

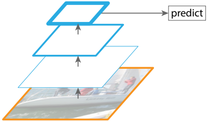
Lin, Dollar, Girshick, He, Hariharan and Belongie. CVPR 2017. Feature Pyramid Networks for Object Detection.

feature pyramid networks (FPN)

[Lin et al. 2017]



featurized image pyramid



single feature map

- features computed at each scale independently: slow
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Lin, Dollar, Girshick, He, Hariharan and Belongie. CVPR 2017. Feature Pyramid Networks for Object Detection.

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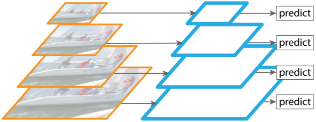
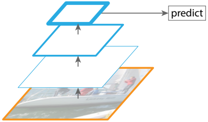
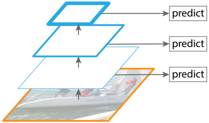


featurized image pyramid



single feature map



pyramidal feature hierarchy

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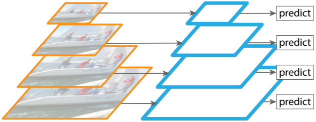
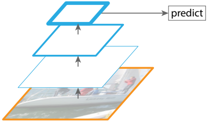
Lin, Dollar, Girshick, He, Hariharan and Belongie. CVPR 2017. Feature Pyramid Networks for Object Detection.

feature pyramid networks (FPN)

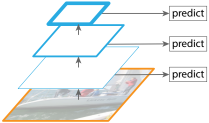
[Lin et al. 2017]



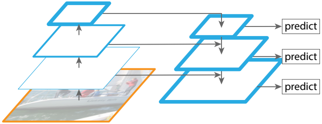
featurized image pyramid



single feature map



pyramidal feature hierarchy



feature pyramid network

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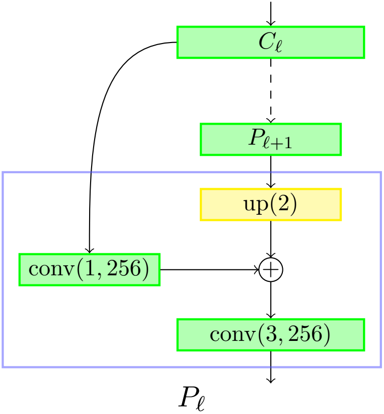
- single scale for faster detection
- reuse pyramidal feature hierarchy as if computed at different scales
- still fast, but more accurate

Lin, Dollar, Girshick, He, Hariharan and Belongie. CVPR 2017. Feature Pyramid Networks for Object Detection.

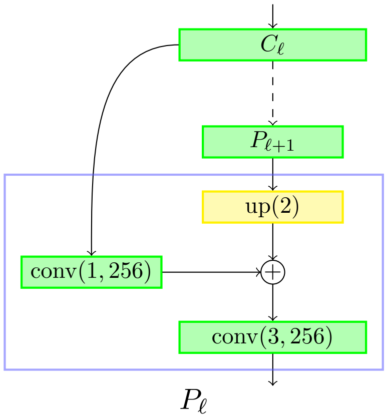
feature pyramid networks (FPN)



- all top-down layers have 256 features
- top-down network initialized at P_5 by 1×1 convolution on C_5
- 1×1 convolution on lateral connection reduces width
- 3×3 convolution on merged path reduces aliasing
- applied to ResNet-101 with fast/faster R-CNN
- regions are detected at all levels of top-down pyramid
- classifiers/regressors are shared across all levels

Lin, Dollar, Girshick, He, Hariharan and Belongie. CVPR 2017. Feature Pyramid Networks for Object Detection.

feature pyramid networks (FPN)



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Lin, Dollar, Girshick, He, Hariharan and Belongie. CVPR 2017. Feature Pyramid Networks for Object Detection.

one-stage detection

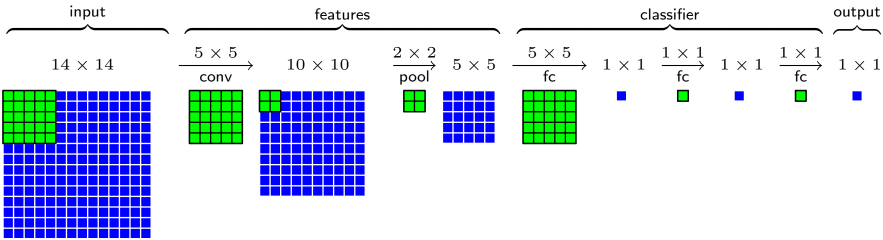
OverFeat*

[Sermanet et al. 2014]

- won the ILSVRC2013 localization competition
- applied a classifier with fully connected layers densely as convolution, allowing region classification without cropping and warping
- increased output resolution with dilated convolution
- merged predictions instead of non-maxima suppression

Sermanet, Eigen, Zhang, Mathieu, Fergus and LeCun. ICLR 2014. OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks.

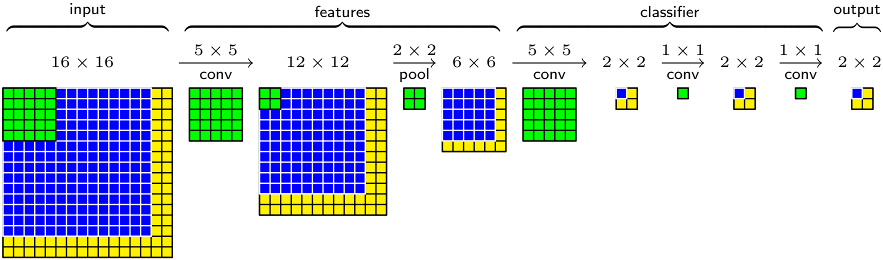
fully connected as convolutional



- a convolutional network with a fully connected classifier produces only one spatial output
- when applied densely over a bigger input image, it produces a spatial 2×2 output map
- since all layers are applied convolutionally, only the yellow region needs to be recomputed

Sermanet, Eigen, Zhang, Mathieu, Fergus and LeCun. ICLR 2014. OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks.

fully connected as convolutional



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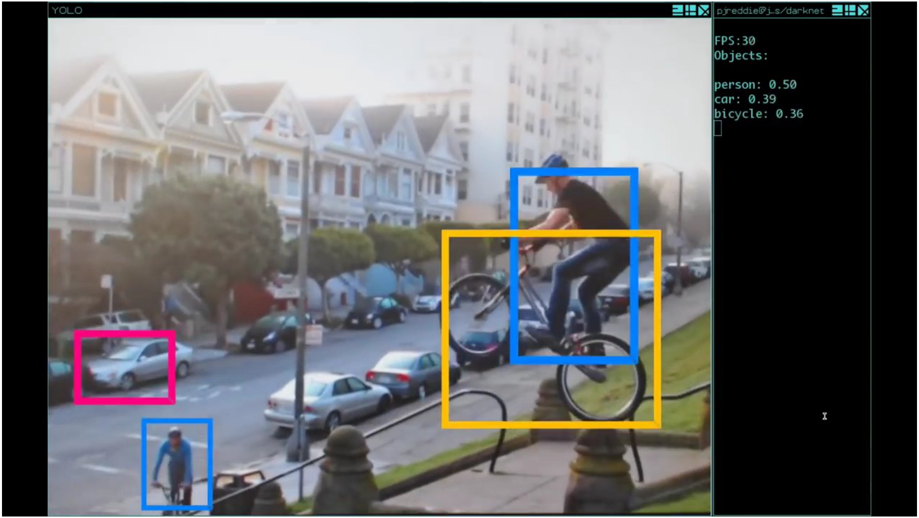
Sermanet, Eigen, Zhang, Mathieu, Fergus and LeCun. ICLR 2014. OverFeat: Integrated Recognition, Localization and Detection using Convolutional Networks.

“you only look once” (YOLO)

[Redmon et al. 2016]



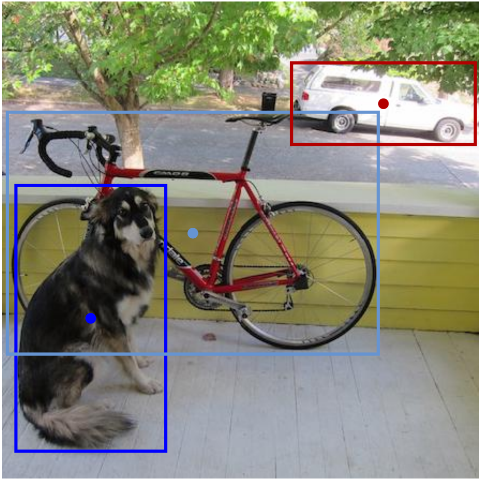
Redmon, Divvala, Girshick and Farhadi. CVPR 2016. You Only Look Once: Unified, Real-Time Object Detection.

“you only look once” (YOLO)

- input image

Redmon, Divvala, Girshick and Farhadi. CVPR 2016. You Only Look Once: Unified, Real-Time Object Detection.

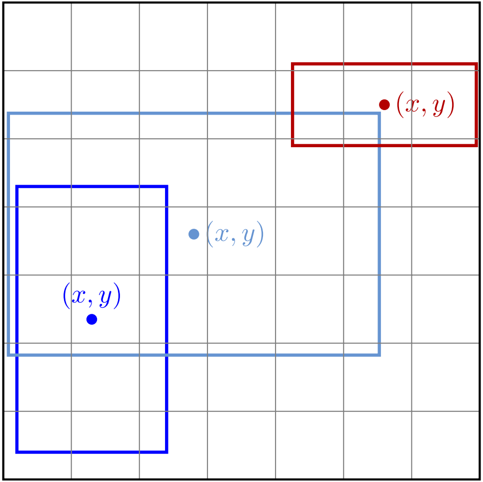
“you only look once” (YOLO)



- groung truth bounding boxes and their centers

Redmon, Divvala, Girshick and Farhadi. CVPR 2016. You Only Look Once: Unified, Real-Time Object Detection.

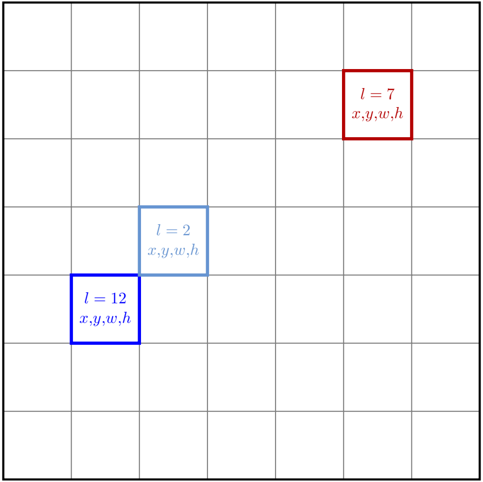
"you only look once" (YOLO)



- image partitioned into 7×7 grid and center coordinates assigned to cells

Redmon, Divvala, Girshick and Farhadi. CVPR 2016. You Only Look Once: Unified, Real-Time Object Detection.

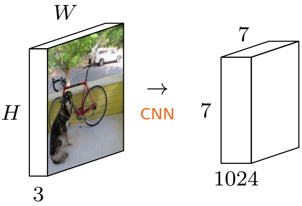
"you only look once" (YOLO)



- network learns to predict up to one object per cell, including class label l, center coordinates x, y and bounding box size w, h

Redmon, Divvala, Girshick and Farhadi. CVPR 2016. You Only Look Once: Unified, Real-Time Object Detection.

"you only look once" (YOLO)



- 3-channel input $W = H = 448$, 24-layer NiN-like network
- fully connected layer, increasing to 4096 features
- $c = 20$ class scores and 4 bounding box coordinates at each position
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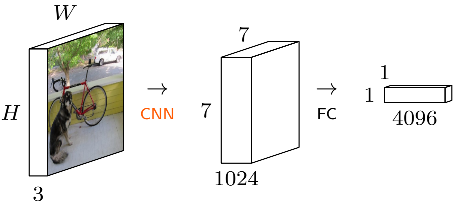
- "objectness" score makes it look like two-stage

Redmon, Divvala, Girshick and Farhadi. CVPR 2016. You Only Look Once: Unified, Real-Time Object Detection.

"you only look once" (YOLO)



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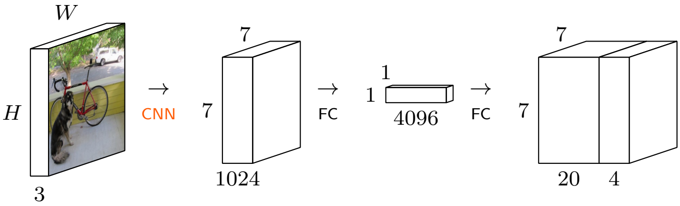

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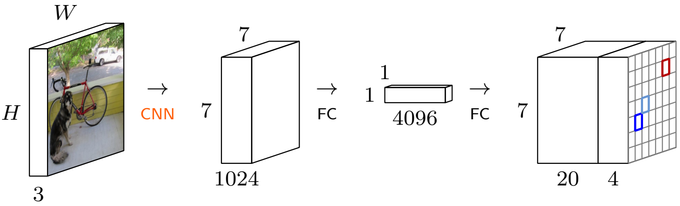

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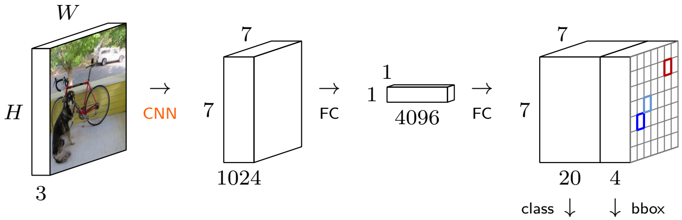

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pros

- extremely fast: 45fps; $93\times$ to $500\times$ test speedup *vs.* R-CNN on AlexNet, with similar performance
- end-to-end trainable, fully convolutional, one-stage detection

cons

- only up to one prediction per cell (fixed in later versions)
- trouble localizing small objects
- low-performance compared to two-stage detectors on strong networks

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single shot detector (SSD)

[Liu et al. 2016]

- input image

Liu, Anguelov, Erhan, Szegedy, Reed, Fu and Berg. ECCV 2016. SSD: Single Shot Multibox Detector.

single shot detector (SSD)

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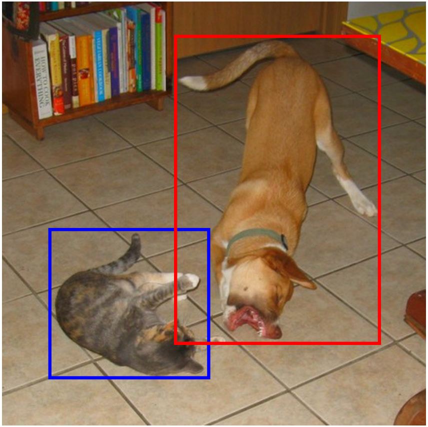
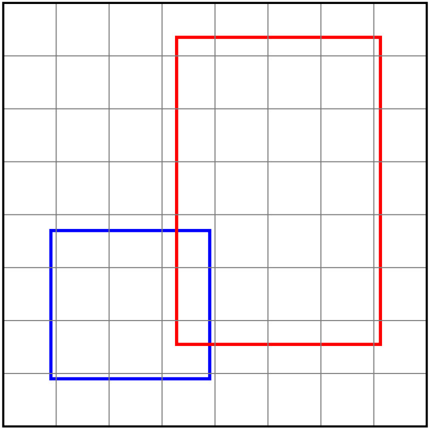


- groung truth bounding boxes

Liu, Anguelov, Erhan, Szegedy, Reed, Fu and Berg. ECCV 2016. SSD: Single Shot Multibox Detector.

single shot detector (SSD)

[Liu et al. 2016]



- image partitioned into 8×8 grid

Liu, Anguelov, Erhan, Szegedy, Reed, Fu and Berg. ECCV 2016. SSD: Single Shot Multibox Detector.

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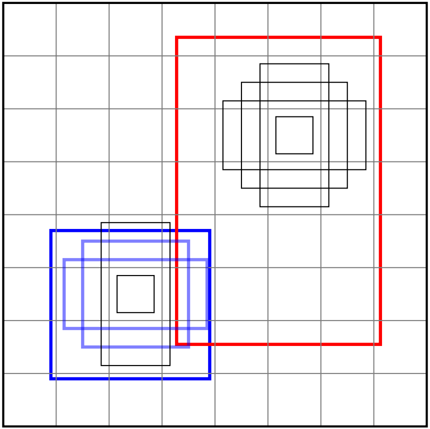
[Liu et al. 2016]



- set of anchors defined at each position, labeled as positive based on overlap with ground truth

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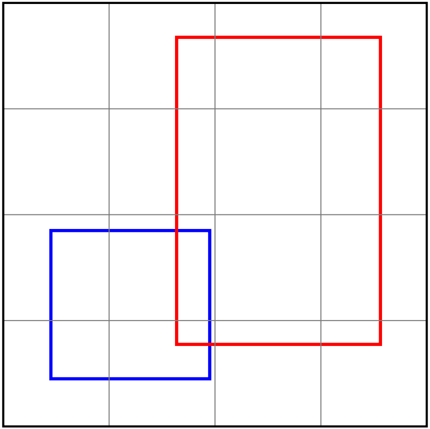

- same process at different scales, *e.g.* 4×4 grid

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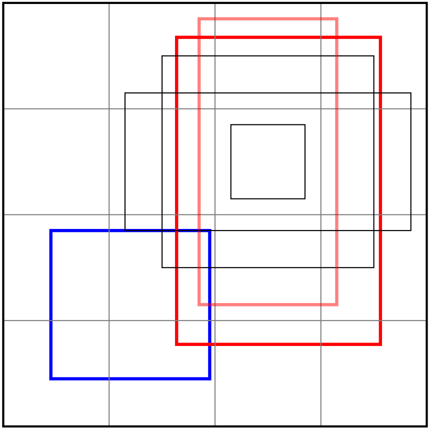
[Liu et al. 2016]



- anchor size is relative to feature map scale

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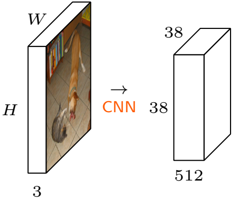

- 3-channel input $W = H = 300$, VGG-16 conv4-3 features
- multiple scales by convolutional layers with stride 2
- $c = 20$ classification scores and 4 bounding box coordinates relative to each of $a = 6$ anchors at each position from each of 6 last layers: 7308 predictions per class
- softmax on scores, regression loss on coordinates

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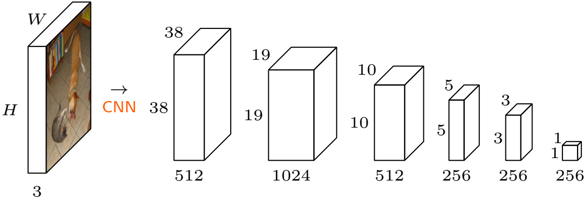

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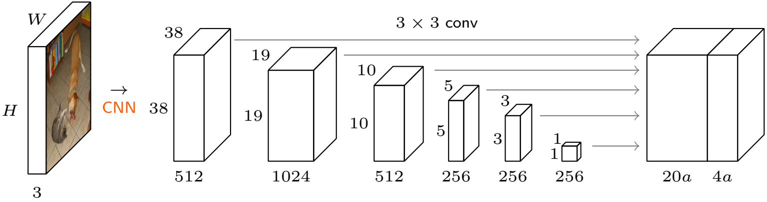

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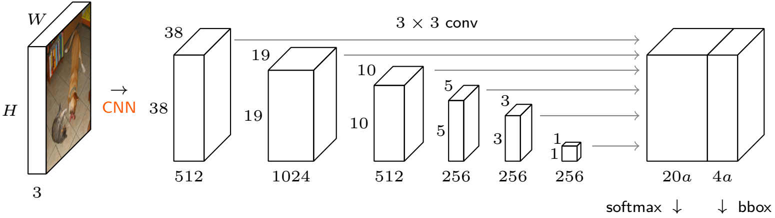

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pros

- best trade-off: 23 (SSD500) or 58fps (SSD300) with performance closer (or superior) to faster R-CNN rather than YOLO
- many scales at no extra cost: many more detections compared to YOLO, no need for RoI pooling
- bounding box regression is convolutional like RPN, but simpler pipeline like YOLO and more aspect ratios with same number of anchors

cons

- pyramid starts at low resolution: difficulty with small objects

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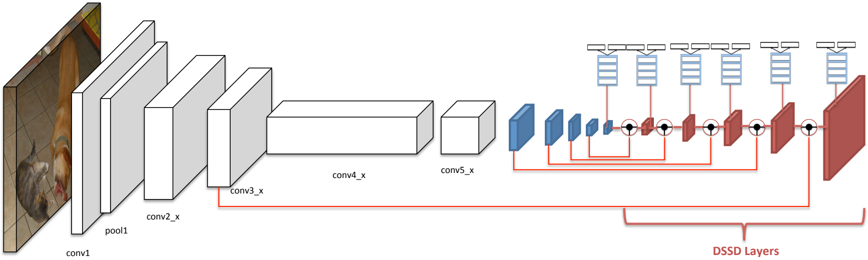
deconvolutional single shot detector (DSSD)*

[Fu et al. 2017]

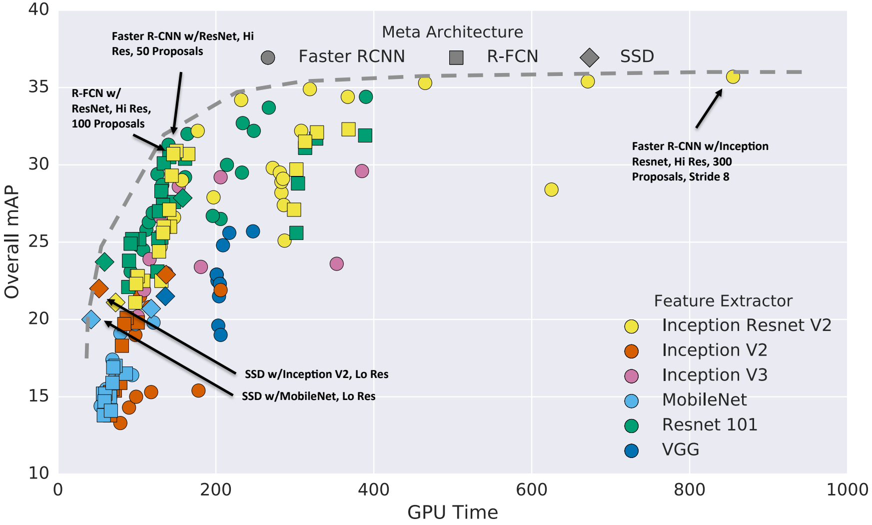


- builds on SSD on ResNet-101, introducing large-scale context
- similar to FPN, but one-stage:
  - deconvolution (⊕) upsamples: high-resolution, high-level features
  - prediction ( ) (classifier + regressor) at all top-down layers
- improves accuracy, especially on small objects
- only slightly slower than SSD

Fu, Liu, Ranga, Tyagi and Berg 2017. DSSD: Deconvolutional Single Shot Detector.

speed-accuracy trade-offs

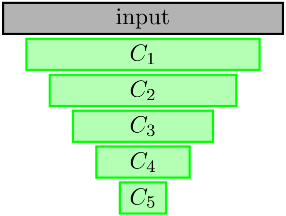
[Huang et al. 2016]



Huang, Rathod, Sun, Zhu, Korattikara, Fathi, Fischer, Wojna, Song, Guardarrama and Murphy 2016. Speed-Accuracy Trade-Offs for Modern Convolutional Object Detectors.

RetinaNet

[Lin et al. 2017]



- base network: ResNet-101
- feature pyramid network
- multi-scale dense detection

Lin, Goyal, Girshick, He and Dollar. ICCV 2017. Focal Loss for Dense Object Detection.

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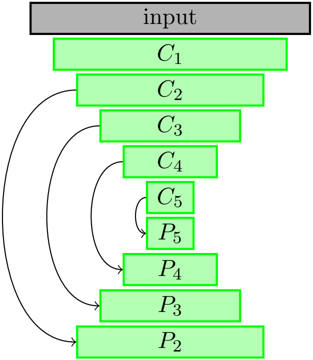

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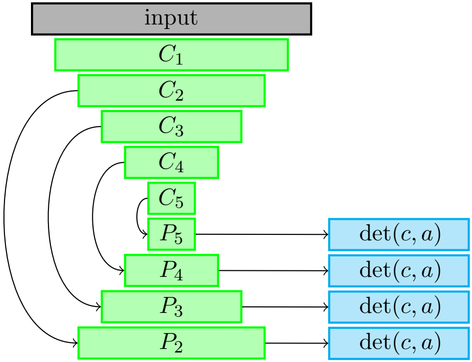

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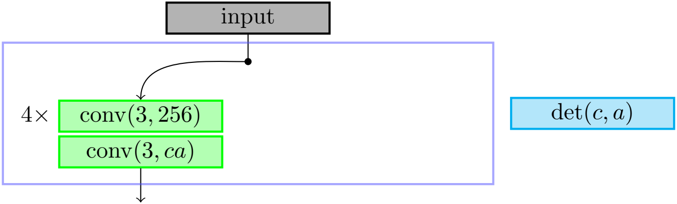

- c classification scores for each of $a = 9$ anchors at each position (3 scales, 3 aspect ratios)
- 4 bounding box coordinates relative to each anchor at each position
- focal loss on class scores, regression loss on coordinates
- no parameters shared between classification and regression branches
- parameters of detection subnets shared across all pyramid levels

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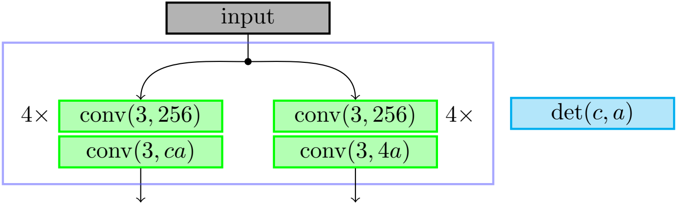

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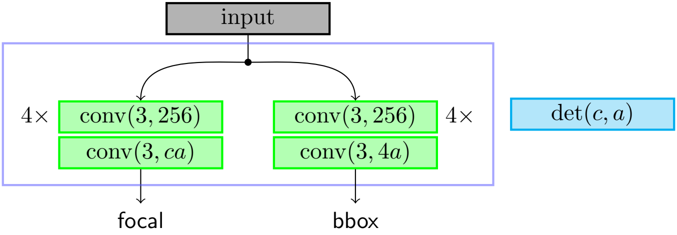

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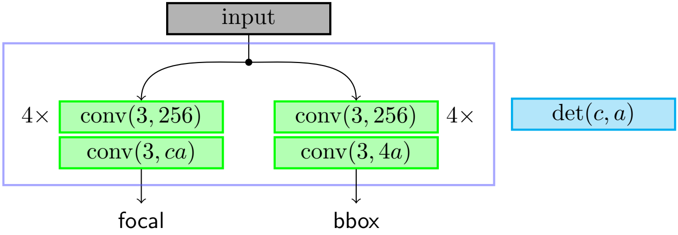

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what is wrong with dense detection?

- in a two-stage detector, the classifier is applied to a sparse set of candidate object locations, which are found by binary classification (object/non-object)
- in a one-stage detector, the classifier is applied to a dense set of locations (*e.g.* a regular grid), which introduces extreme class imbalance between foreground-background
- there is a vast number of easy negatives that can overwhelm the detector
- as an alternative to OHEM, design the loss function such that it does not penalize well-classified examples

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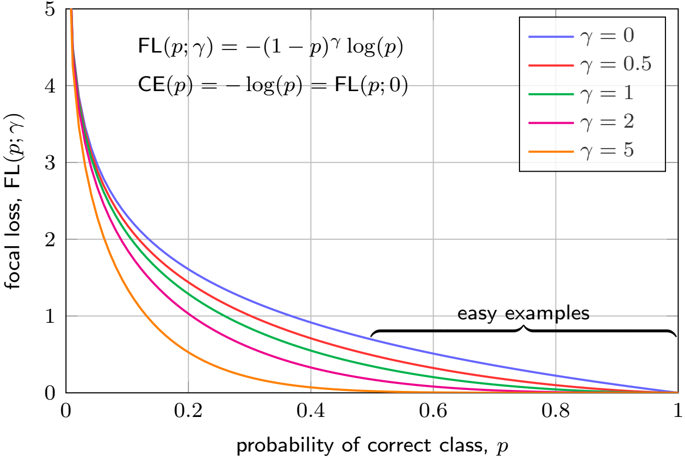
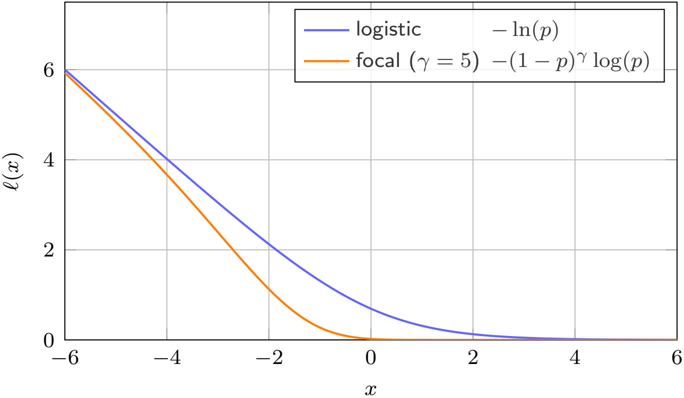
focal loss



- reduces the relative loss for well-classified examples ($p > 0.5$), putting more focus on hard, misclassified examples

Lin, Goyal, Girshick, He and Dollar. ICCV 2017. Focal Loss for Dense Object Detection.

remember the perceptron loss? the margin?



- the probability of the correct class is $p = \sigma(x) = \frac{1}{1+e^{-x}}$, where $x = sa$, $s \in \{-1, 1\}$ is the "sign" target variable, and a the activation
- easy example means $p > 0.5$, or $x > 0$
- perceptron loss is zero for such examples; logistic and hinge are not

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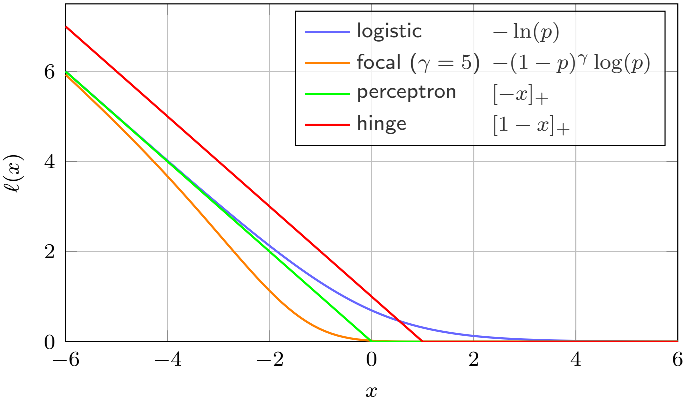

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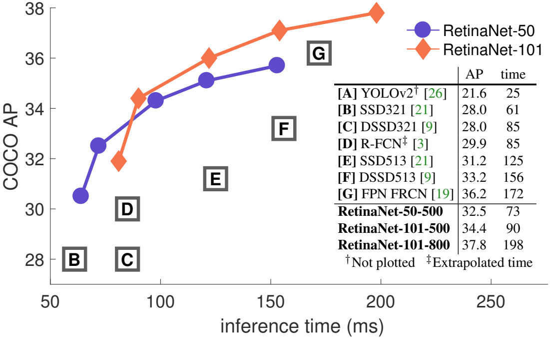
RetinaNet: performance



	AP	time
[A] YOLOv2† [26]	21.6	25
[B] SSD321 [21]	28.0	61
[C] DSSD321 [9]	28.0	85
[D] R-FCN‡ [3]	29.9	85
[E] SSD513 [21]	31.2	125
[F] DSSD513 [9]	33.2	156
[G] FPN FRCN [19]	36.2	172
RetinaNet-50-500	32.5	73
RetinaNet-101-500	34.4	90
RetinaNet-101-800	37.8	198

†Not plotted ‡Extrapolated time

- RetinaNet on ResNet-50-FPN and ResNet-101-FPN performance on COCO at five scales (400-800 pixels)
- outperforms all one-stage and two-stage detectors

Lin, Goyal, Girshick, He and Dollar. ICCV 2017. Focal Loss for Dense Object Detection.

one-stage vs. two-stage

- two-stage fights class imbalance; alternatively, use batch sampling, hard negative mining, or a better loss function
- two-stage defines regions at different scales; alternatively, use multiple scales from a feature pyramid
- two-stage resamples regions at different aspect ratios, or with deformable parts; this has not been explored with feature pyramids or one-stage detectors yet

Lin, Goyal, Girshick, He and Dollar. ICCV 2017. Focal Loss for Dense Object Detection.

attention networks*

- of course, there can be more stages!
- AttentionNet iterates bounding box regression and classification

Yoo, Park, Lee, Paek and Kweon. ICCV 2015. AttentionNet: Aggregating Weak Directions for Accurate Object Detection.

summary

- background: detectors (Viola & Jones, DPM, ISM, ESS), object proposals, NMS, evaluation
- two-stage detection: R-CNN, SPP, fast/faster R-CNN, RPN
- parts: R-FCN, spatial transformers, deformable convolution
- upsampling: FCN, feature pyramids, TDM, FPN
- one-stage detection: OverFeat, YOLO, SSD, DSSD, RetinaNet, focal loss
- with feature pyramids, multi-scale representation and appropriate loss, the gap between one- and two-stage detection is closing
- attentional cascade classifiers are developed in parallel