

lecture 9: object detection

deep learning for vision

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Inria Rennes-Bretagne Atlantique

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outline

background

two-stage detection

object parts and deformation*

scale and feature pyramids

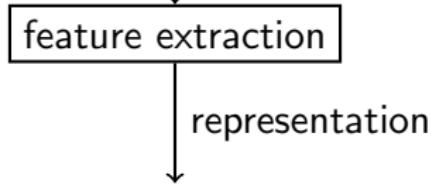
one-stage detection

background

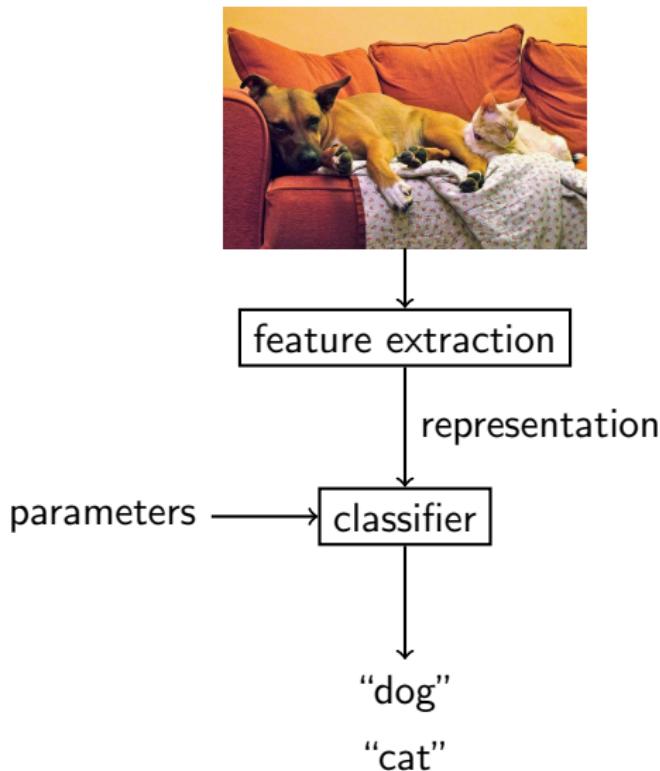
data-driven approach



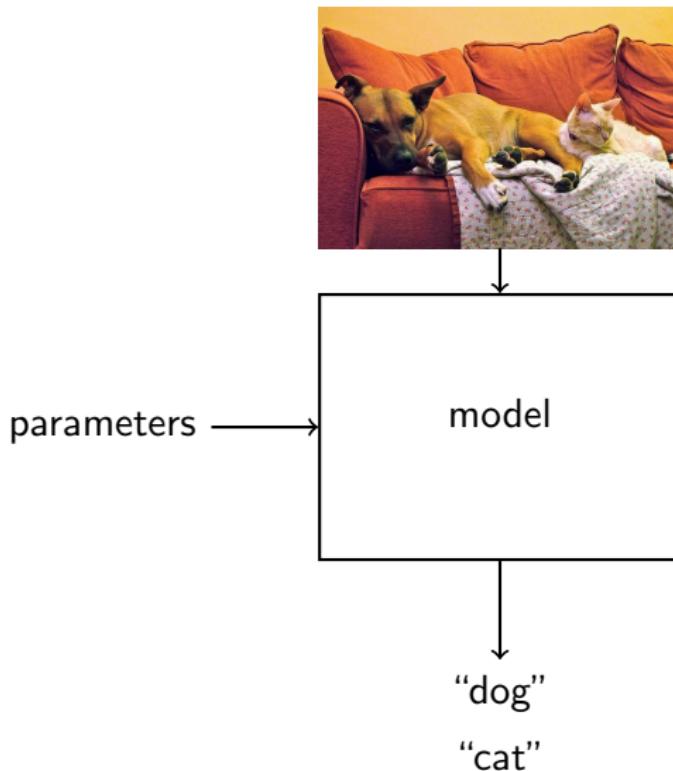
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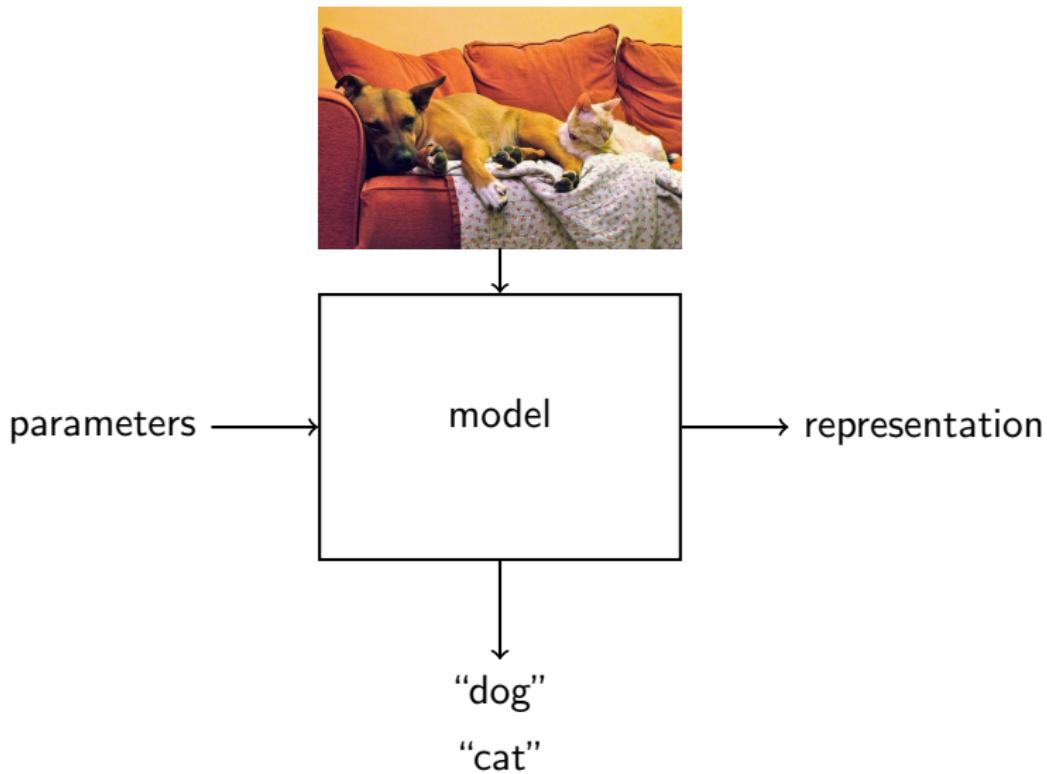
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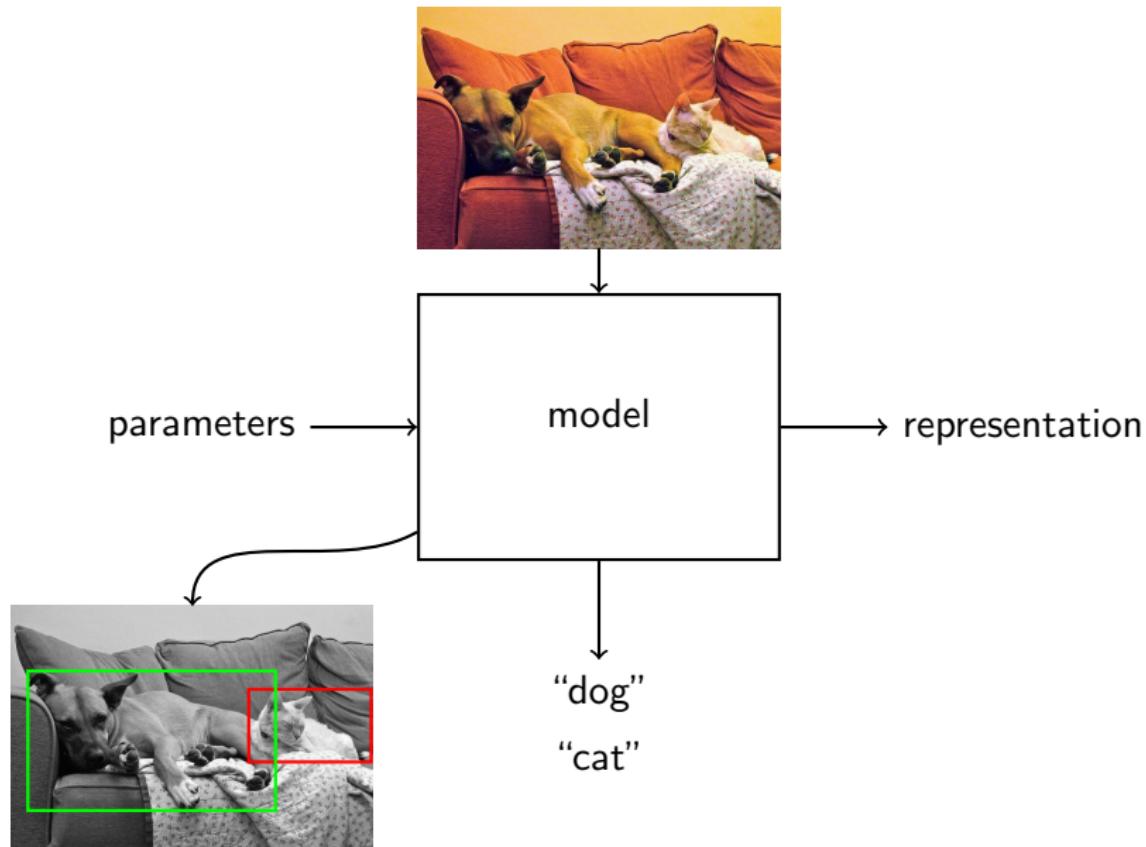
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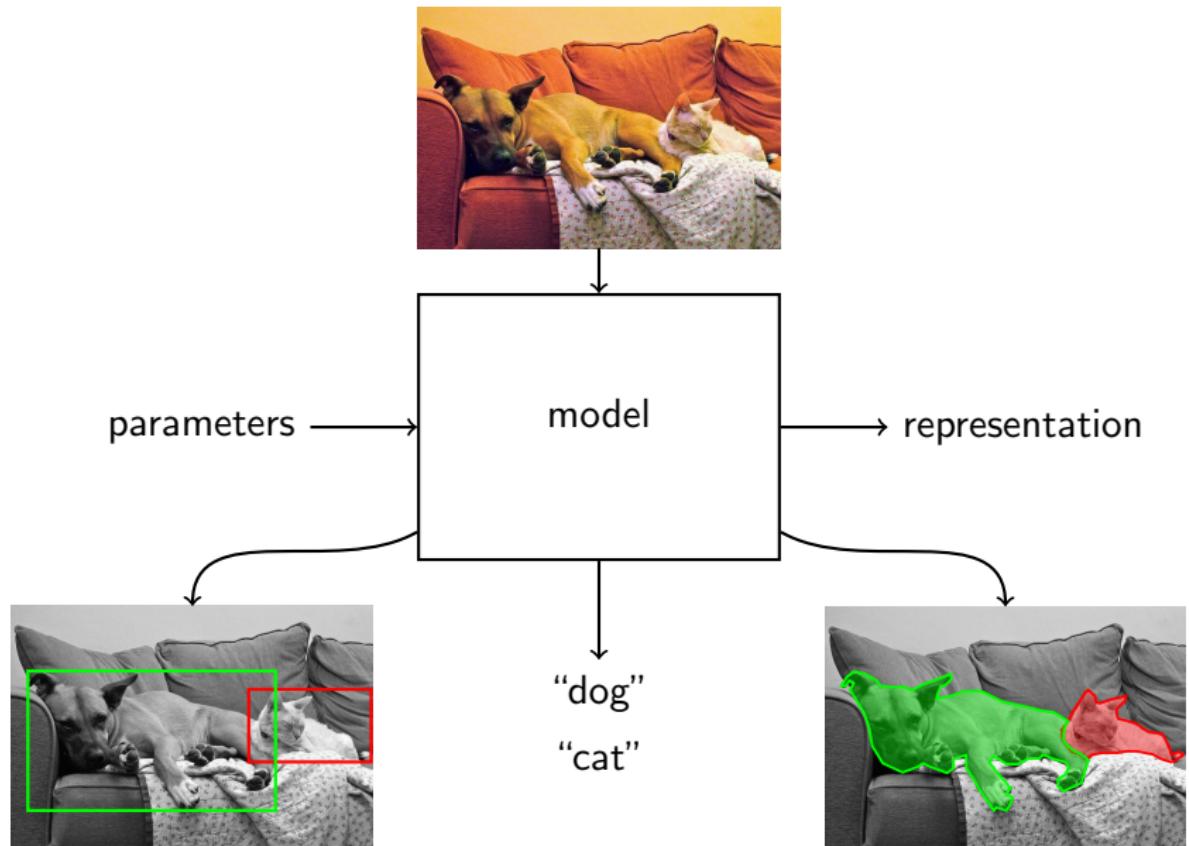
data-driven approach



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)



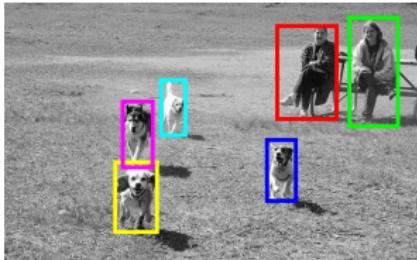
semantic segmentation
pixel-wise classify

beyond classification



object localization

classify + regress
bounding box (x, y, w, h)



object detection

per region: classify + regress
bounding box (x, y, w, h)

beyond classification



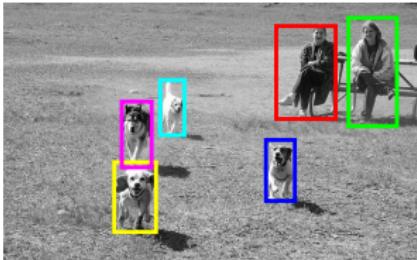
object localization

classify + regress
bounding box (x, y, w, h)



semantic segmentation

pixel-wise classify



object detection

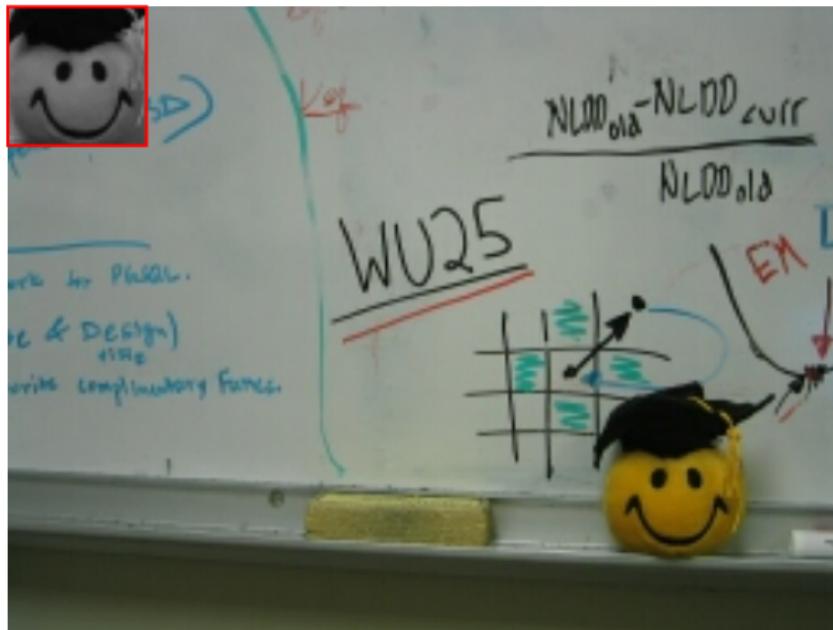
per region: classify + regress
bounding box (x, y, w, h)



instance segmentation

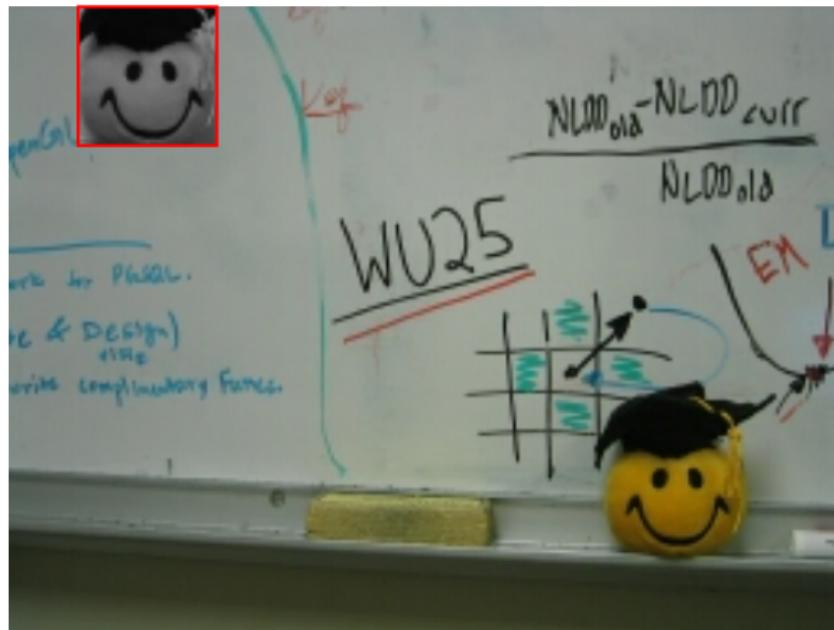
per region: pixel-wise classify

template matching, or sliding window



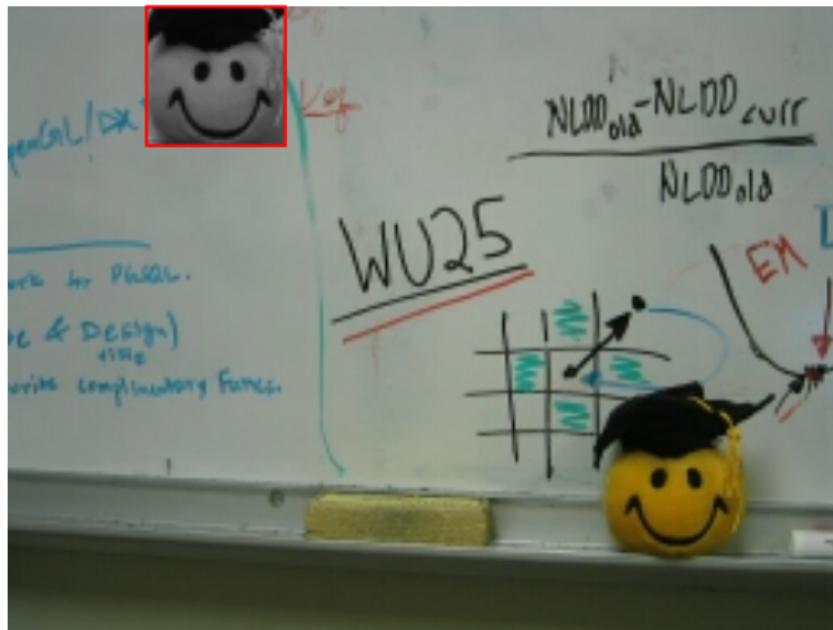
- slide template over image at multiple positions
- positions can be overlapping, or even **dense** (every pixel)
- seek maximum similarity score

template matching, or sliding window



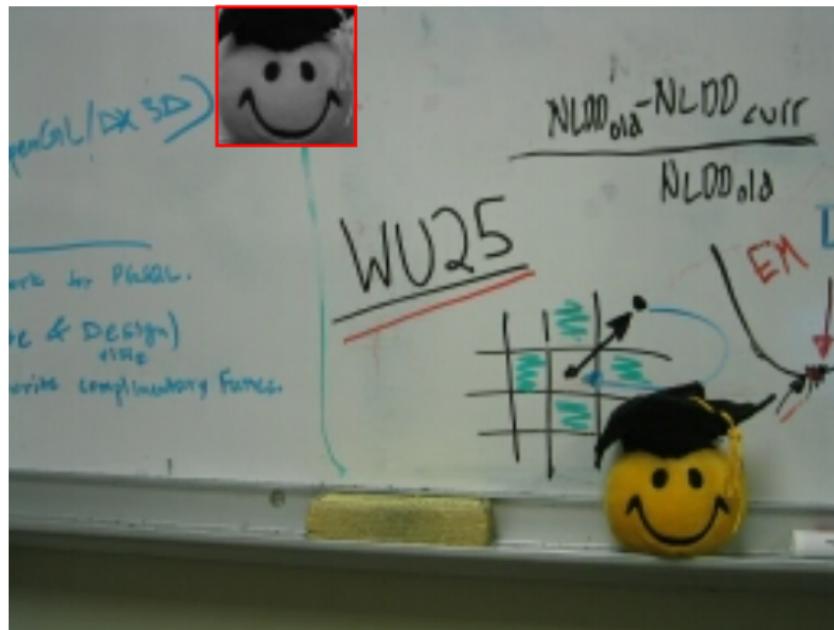
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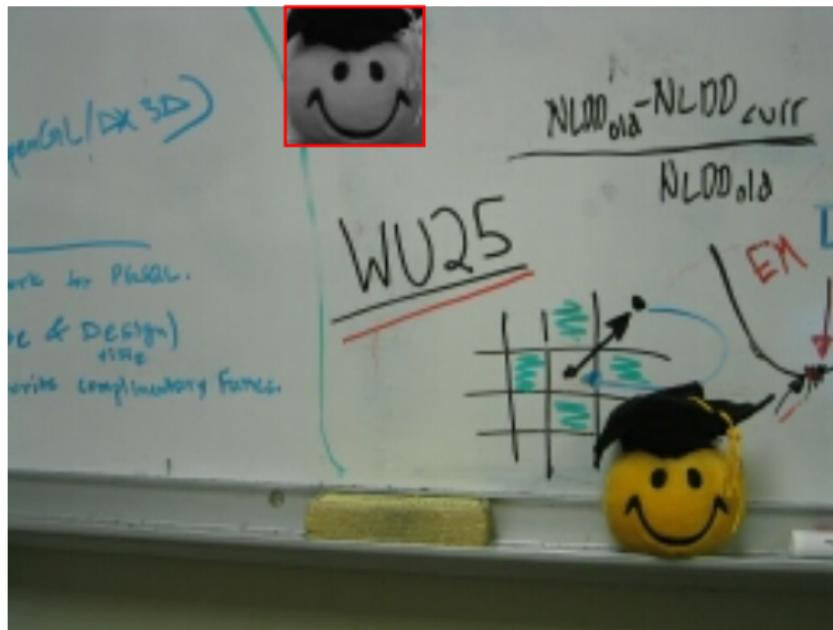
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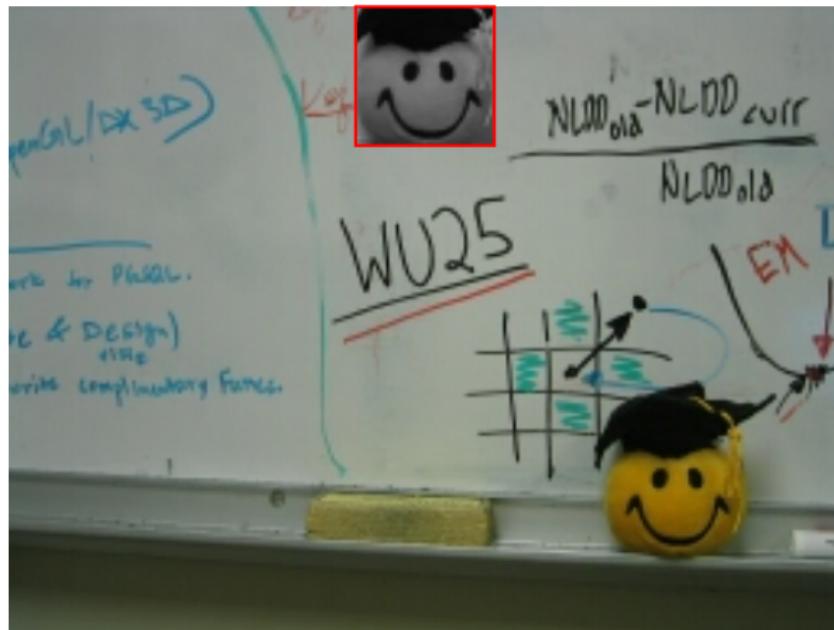
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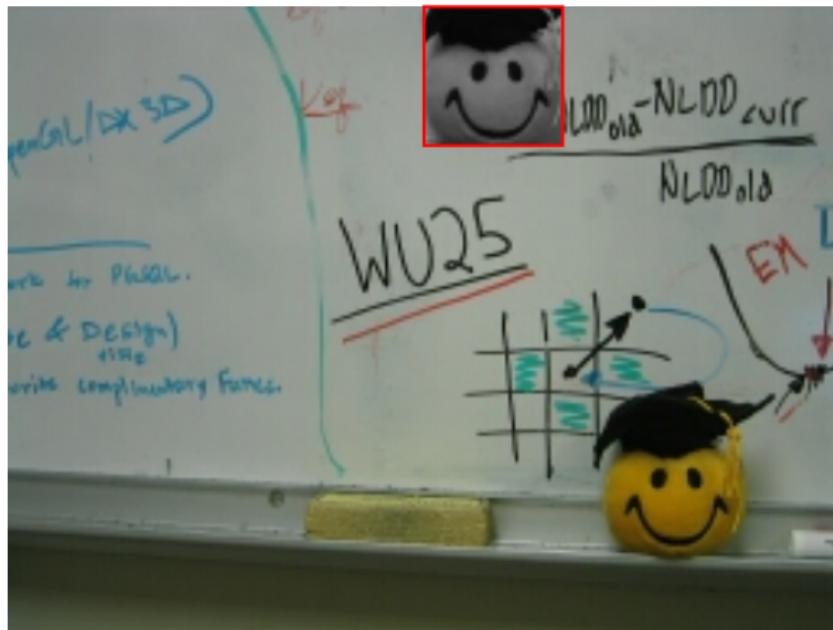
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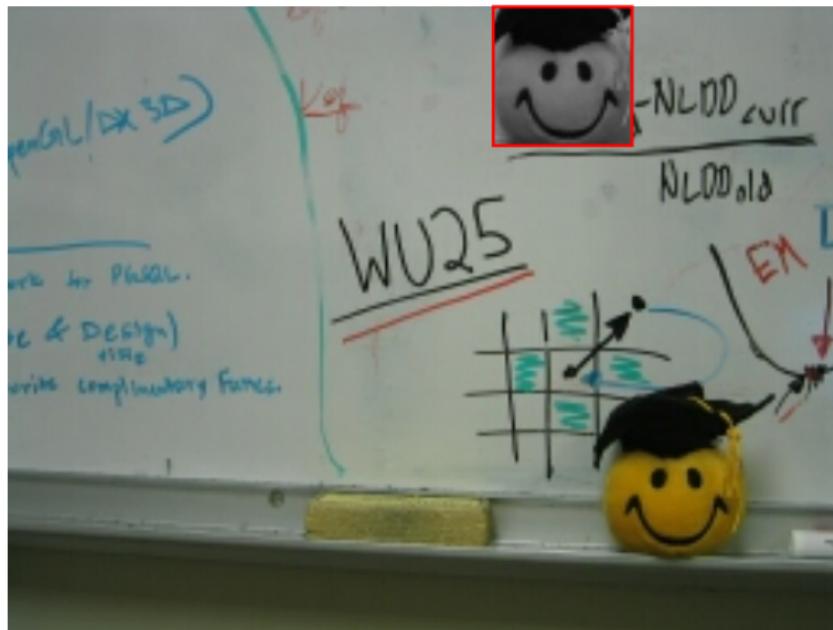
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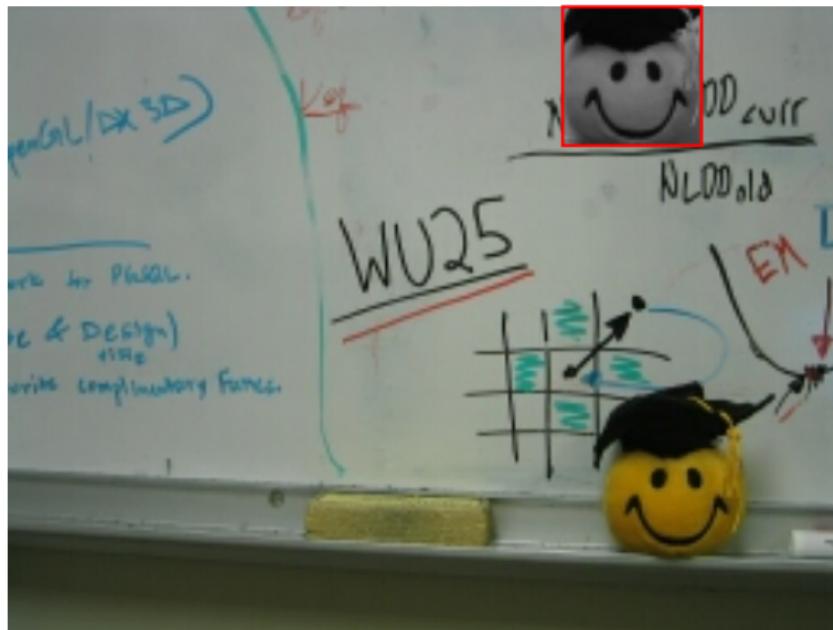
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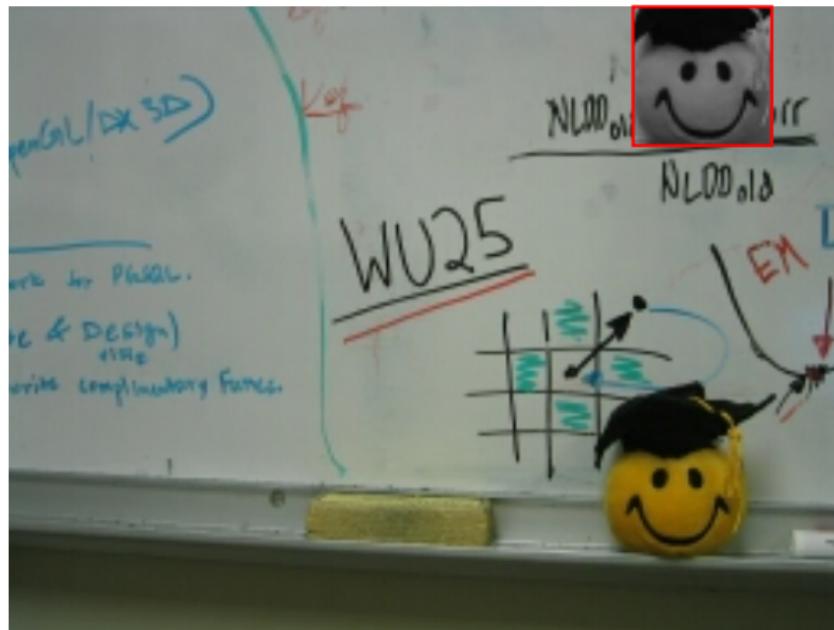
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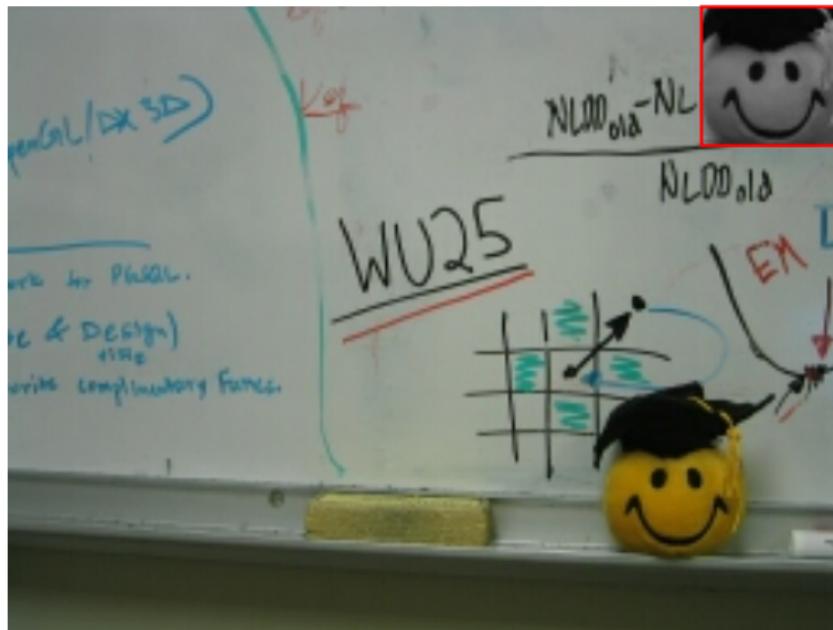
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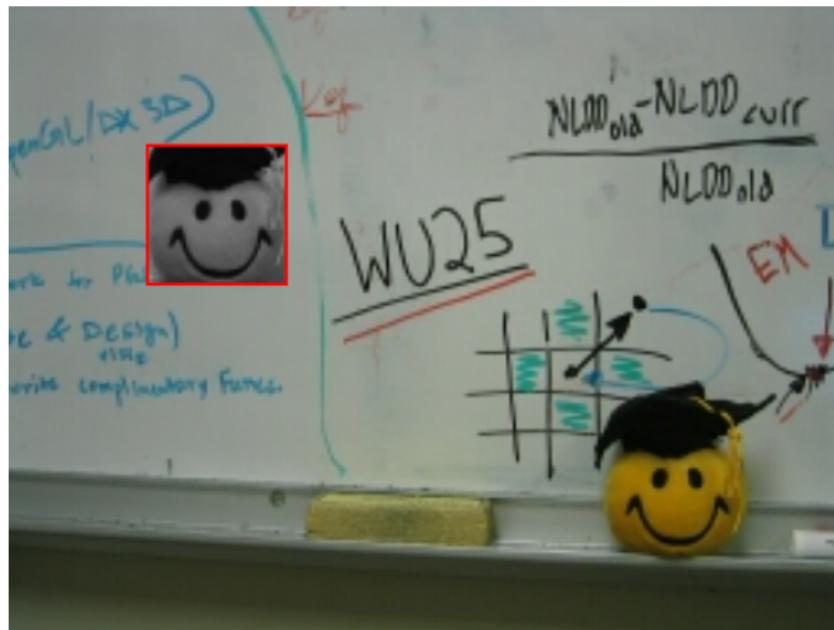
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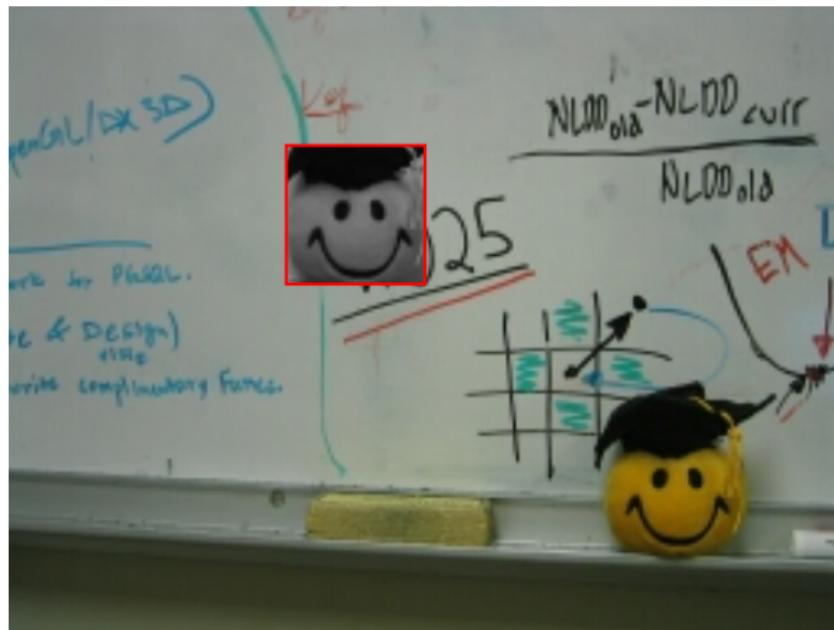
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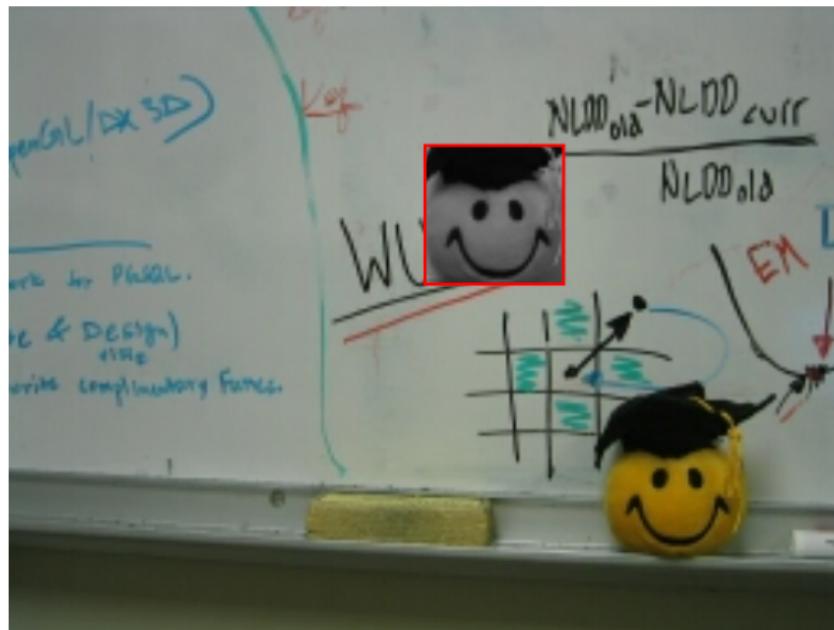
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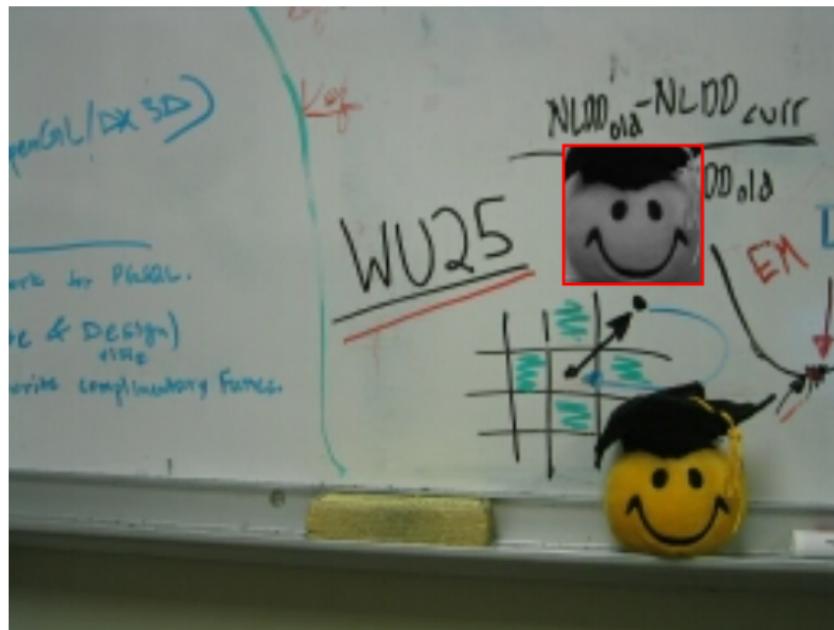
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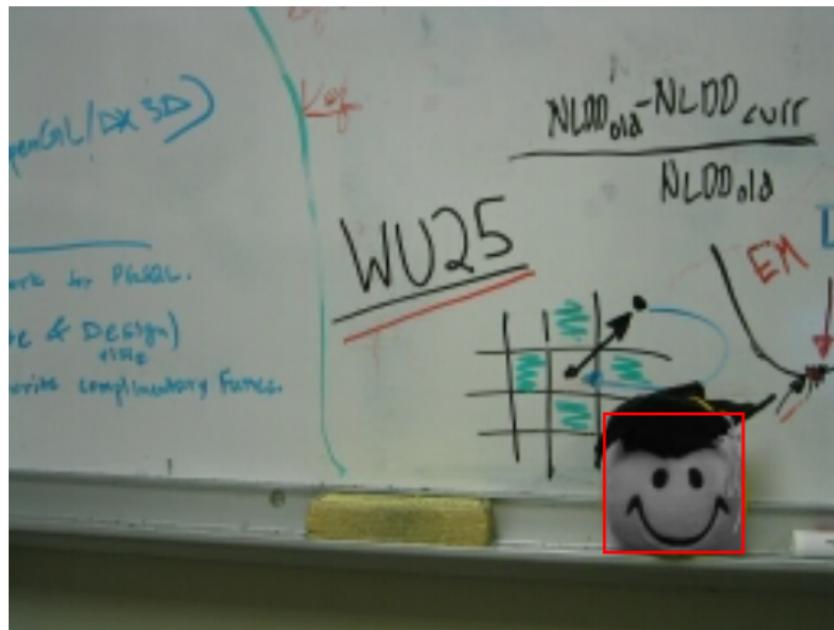
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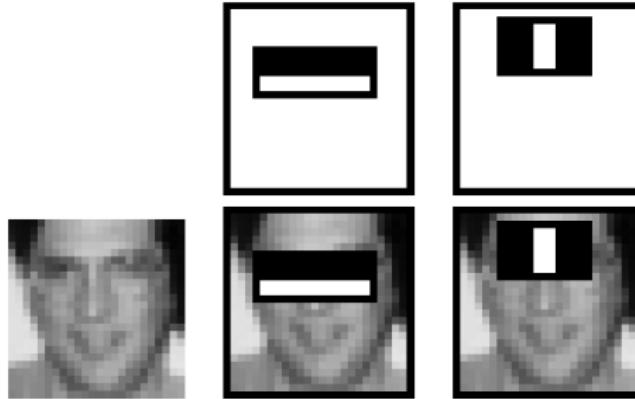
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- seek maximum similarity score (e.g. cross-correlation)

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

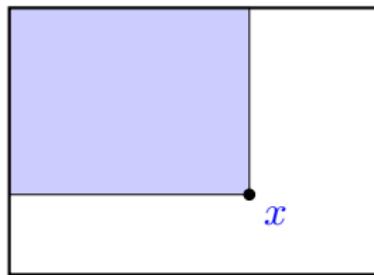
real-time face detection

[Viola and Jones 2001]



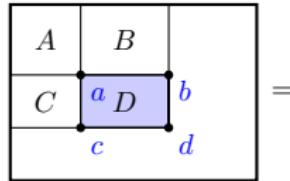
- millions of simple features exhaustively evaluated on integral image
- learning weak classifiers by AdaBoost
- classifier cascade provides a focus-of-attention mechanism

integral image: construction



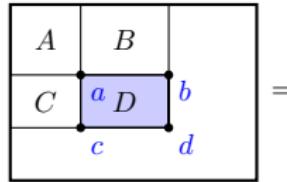
- given an image, precompute its sum over the rectangle with vertices the top-left corner and any point x in the image
- the collection of all sums is the **integral image**: it can be computed by one pass over the original image and takes the same space as the original image

integral image: use

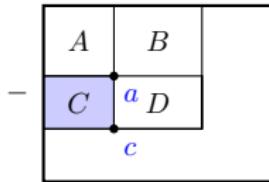
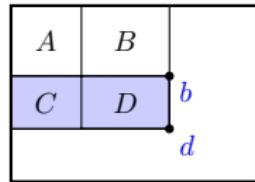


- then, the sum over any rectangle (D) can be evaluated by 3 scalar operations on its vertices (a, b, c, d)

integral image: use



=

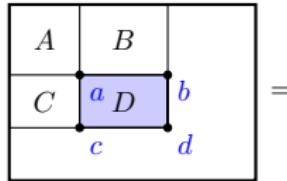


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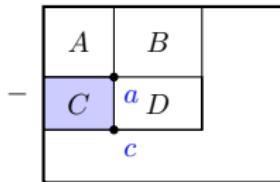
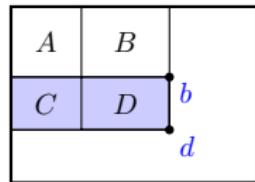
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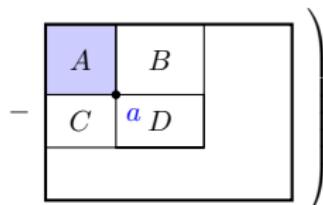
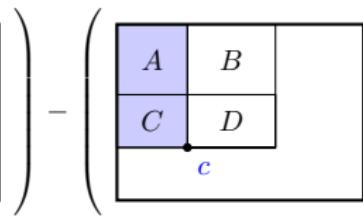
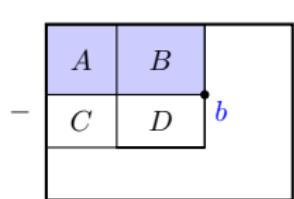
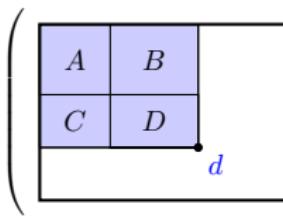
integral image: use



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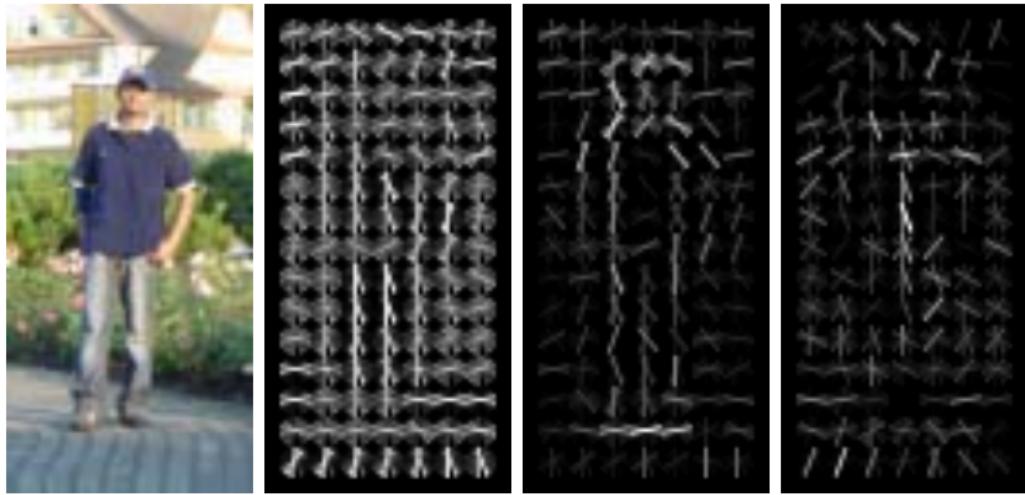
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histogram of oriented gradients (HOG)

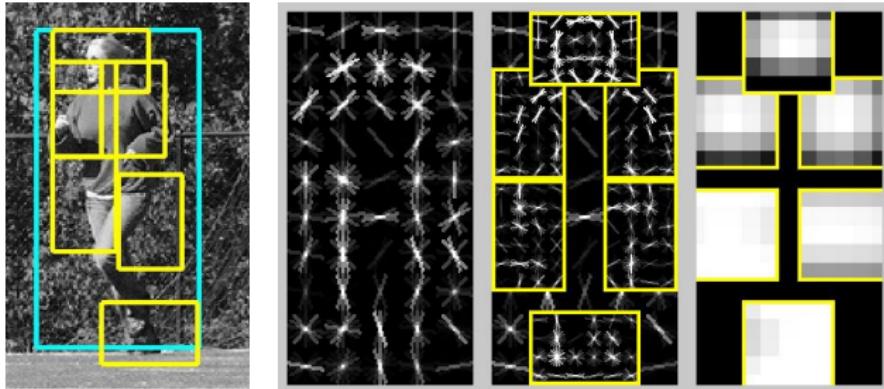
[Dalal and Triggs 2005]



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

deformable part model (DPM)

[Felzenszwalb et al. 2008]

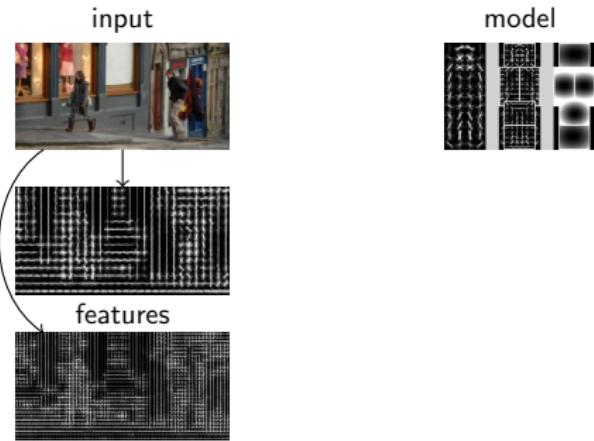


- appearance represented by HOG
- spatial configuration inspired by “pictorial structures”
- part locations treated as latent variables: **latent SVM**

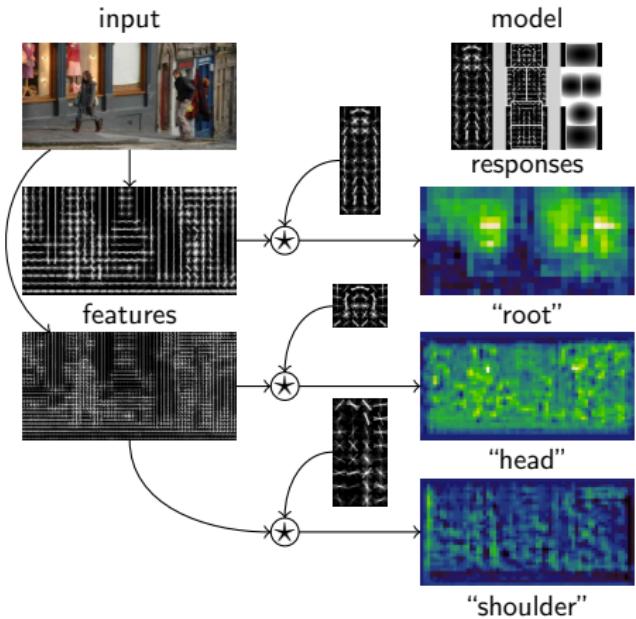
deformable part model: inference



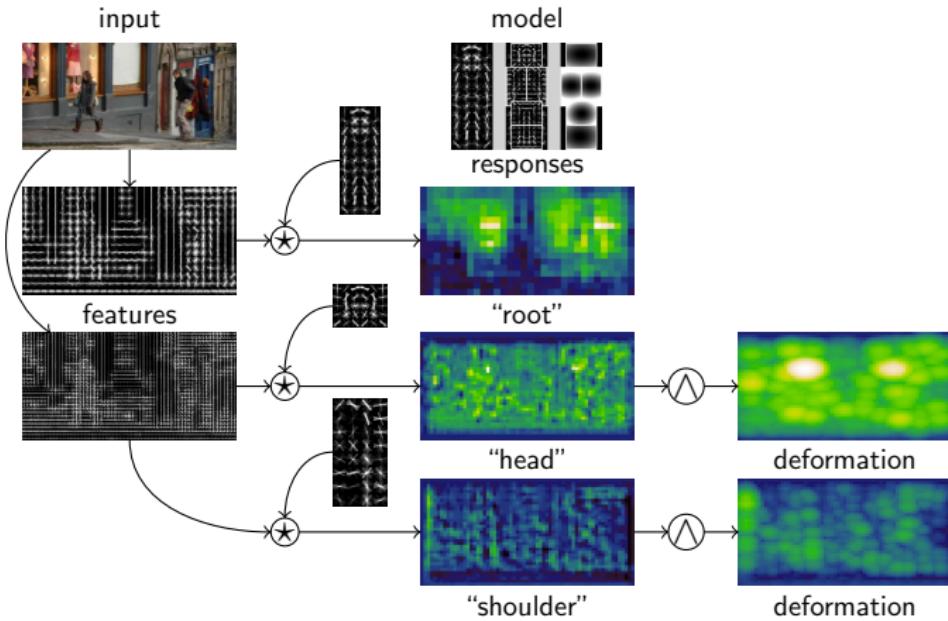
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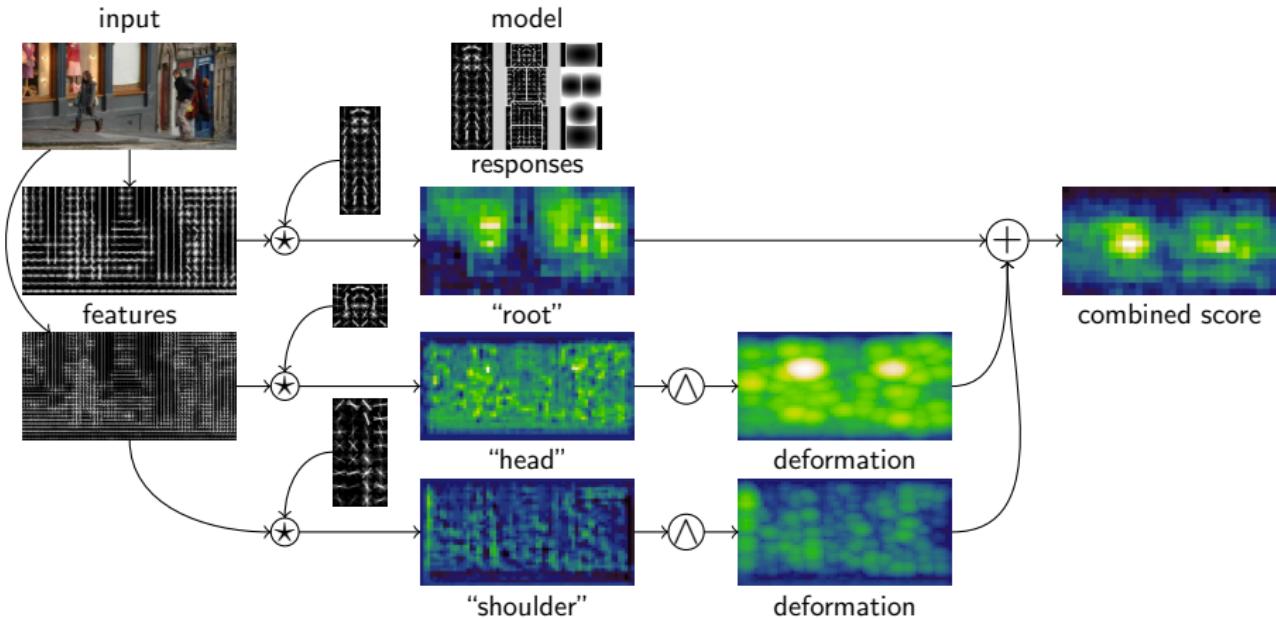
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hard example mining (bootstrapping)*

- an example is called **hard** for a model with parameters θ 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

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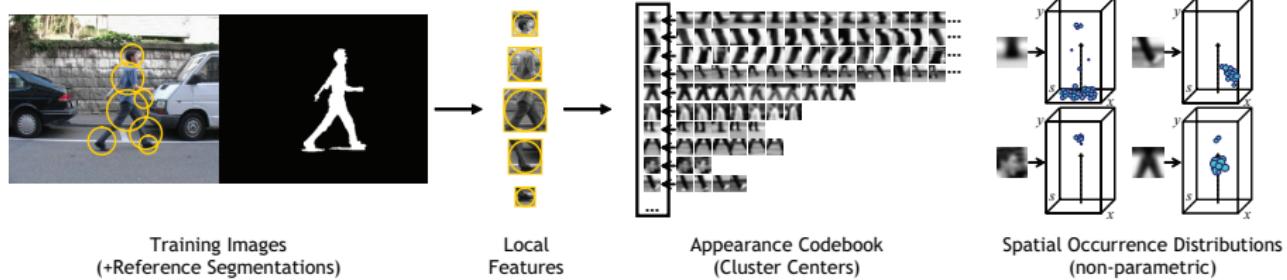
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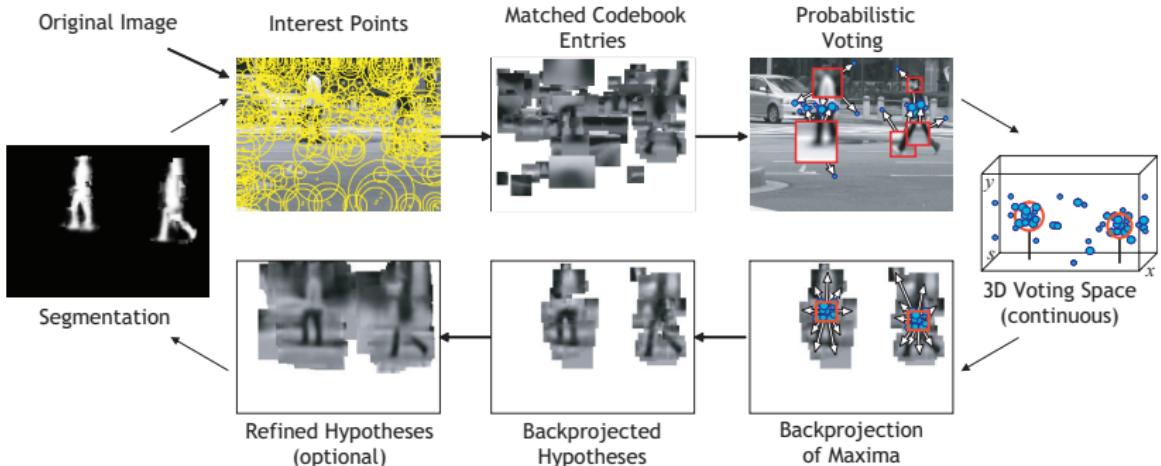
implicit shape model (ISM): training

[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

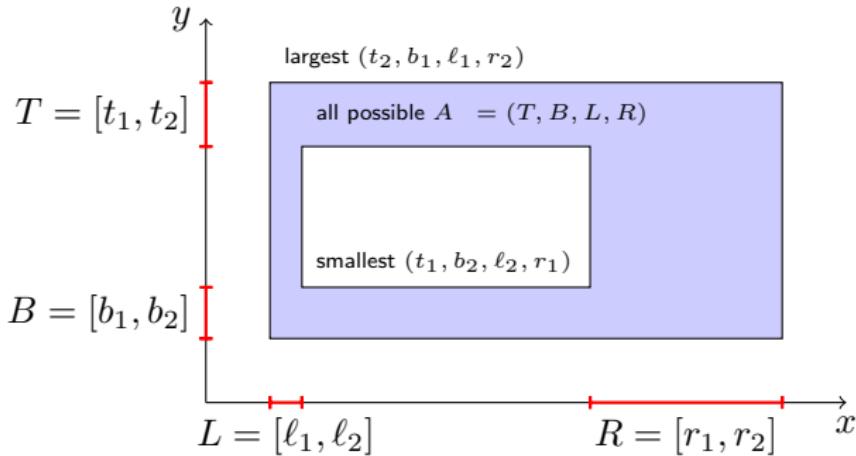
implicit shape model (ISM): inference



- 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**

efficient subwindow search (ESS)*

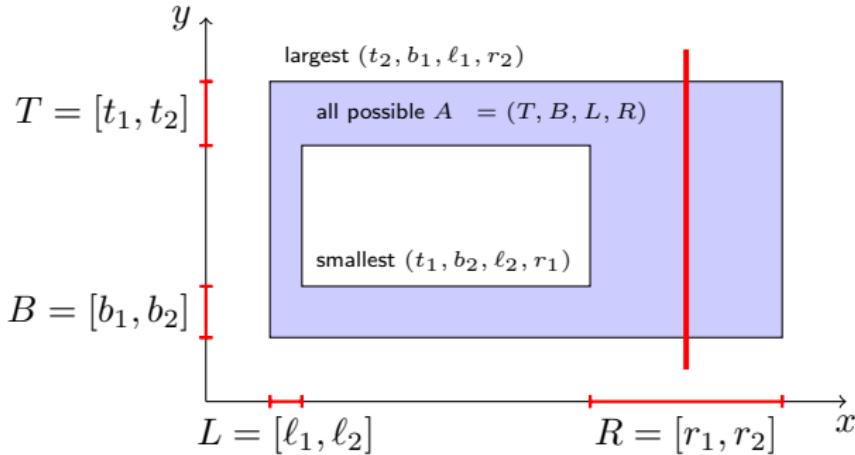
[Lampert et al. 2008]



- 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**

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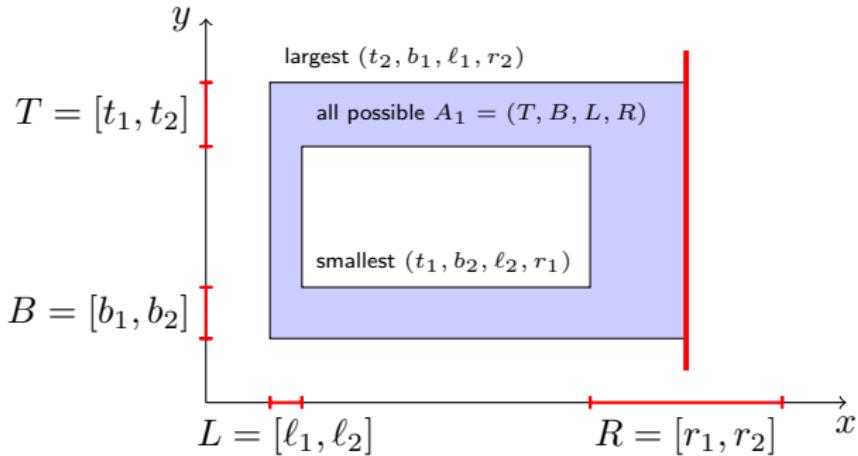
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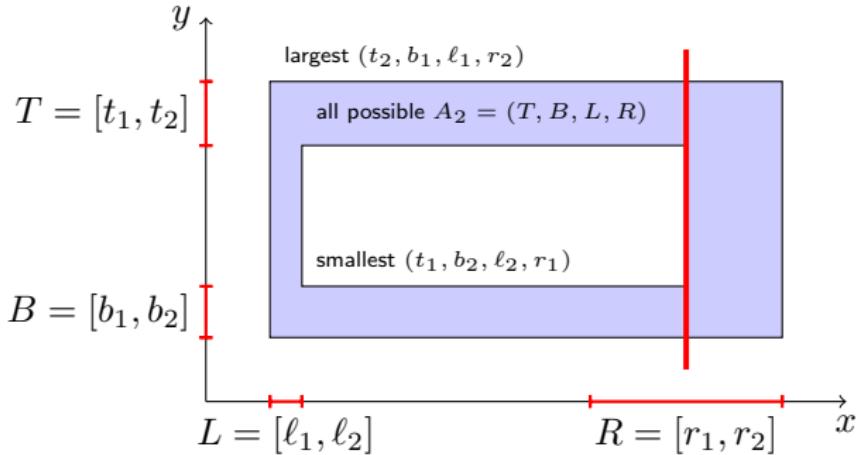
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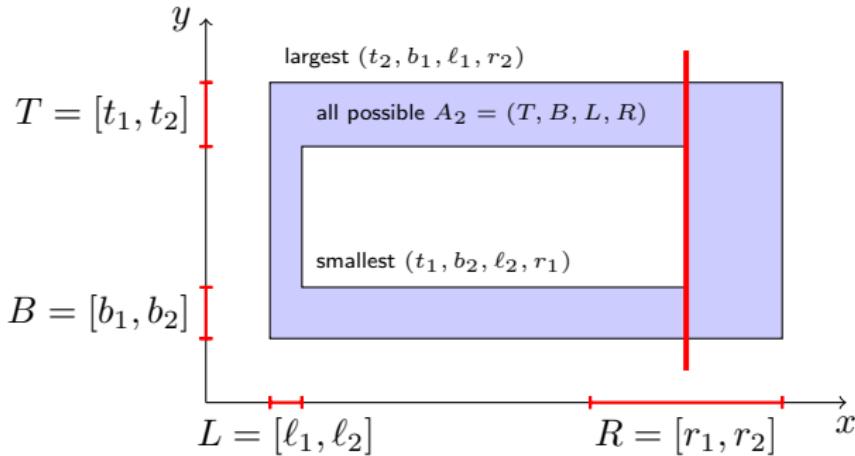
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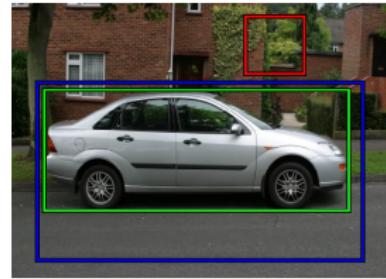
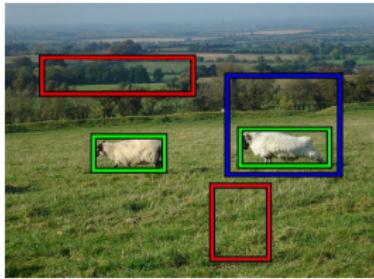
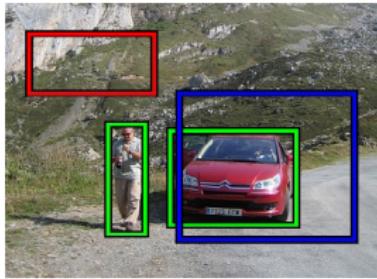
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what is an object?

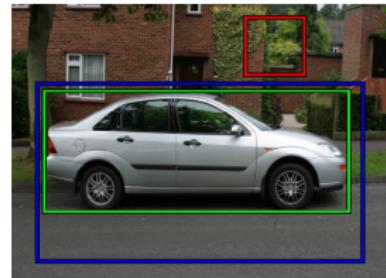
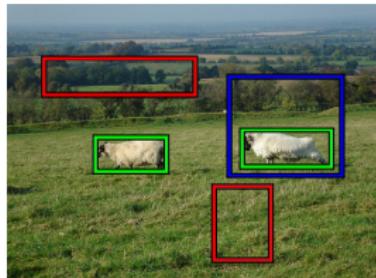
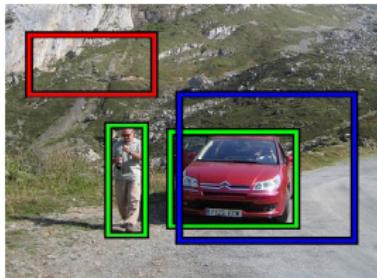
[Alexe et al. 2010]



- 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

what is an object?

[Alexe et al. 2010]



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selective search (SS)

[van de Sande et al. 2011]



input image



ground truth

selective search (SS)

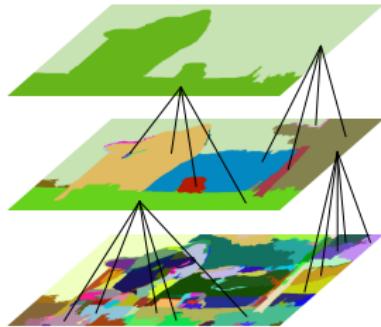
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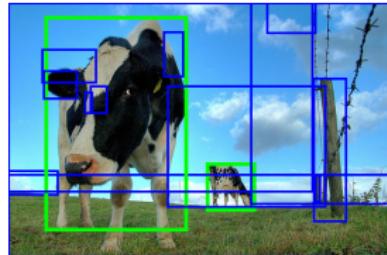
input image



ground truth



hierarchical grouping



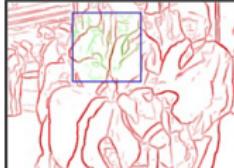
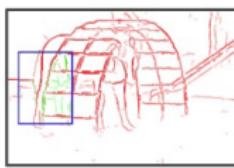
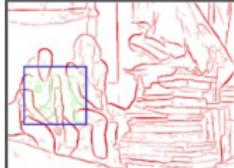
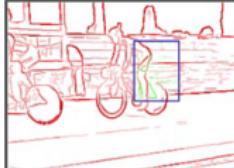
object proposals

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 $\sim 2-5\text{s}/\text{image}$

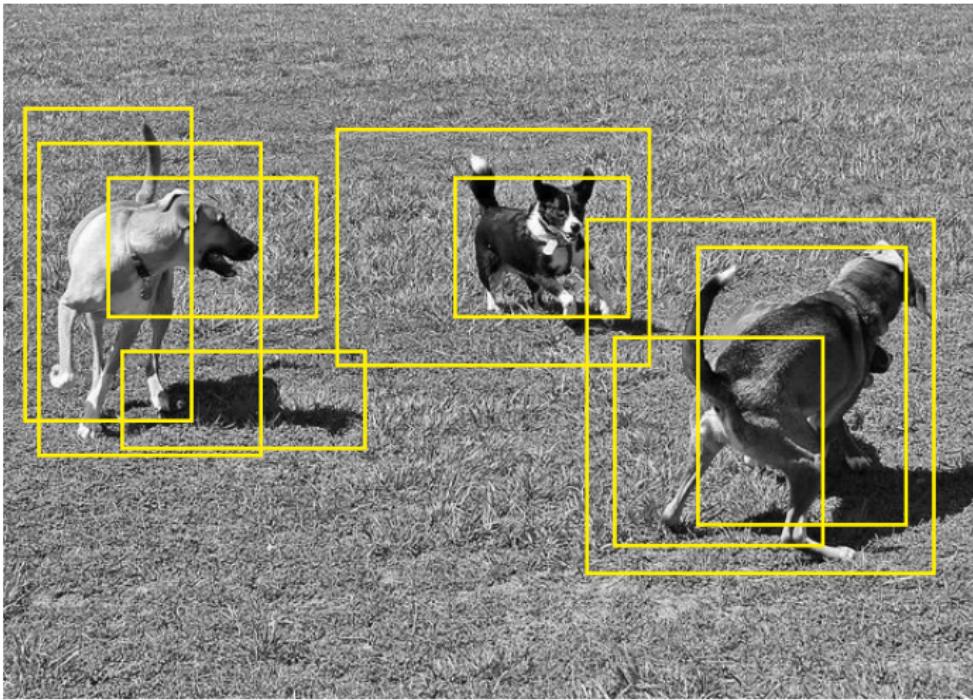
edge boxes (EB)

[Zitnick and Dollar 2014]

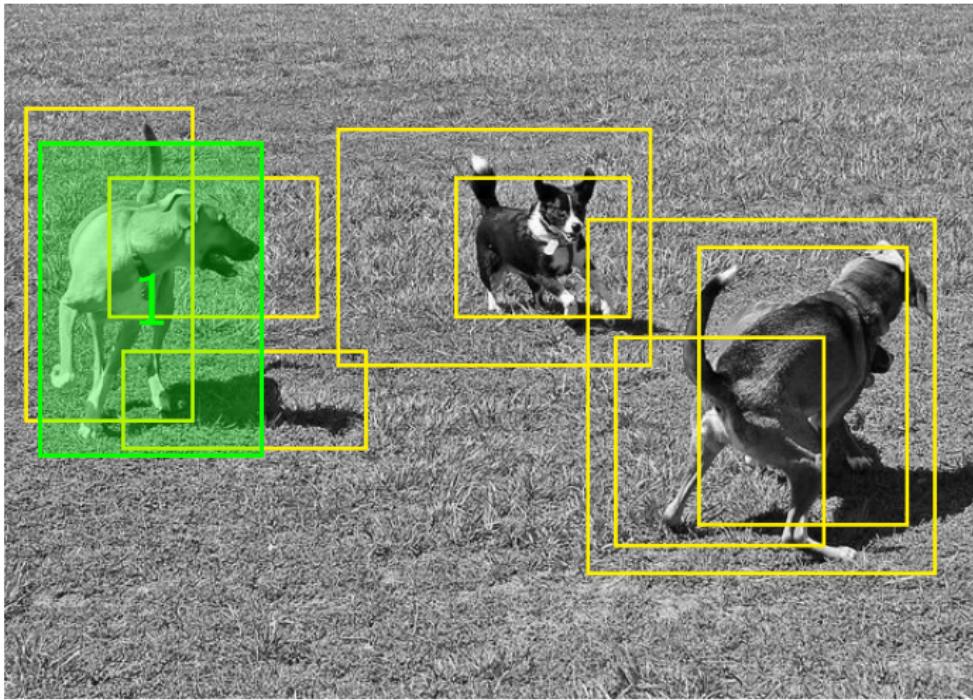


- fast evaluation of millions of regions of different scales/aspect ratios at different positions
- measures edges that are contained in a region and do not intersect its boundary
- performance similar to SS, but at $\sim 0.25\text{s}/\text{image}$ on average

non-maximum suppression (NMS)

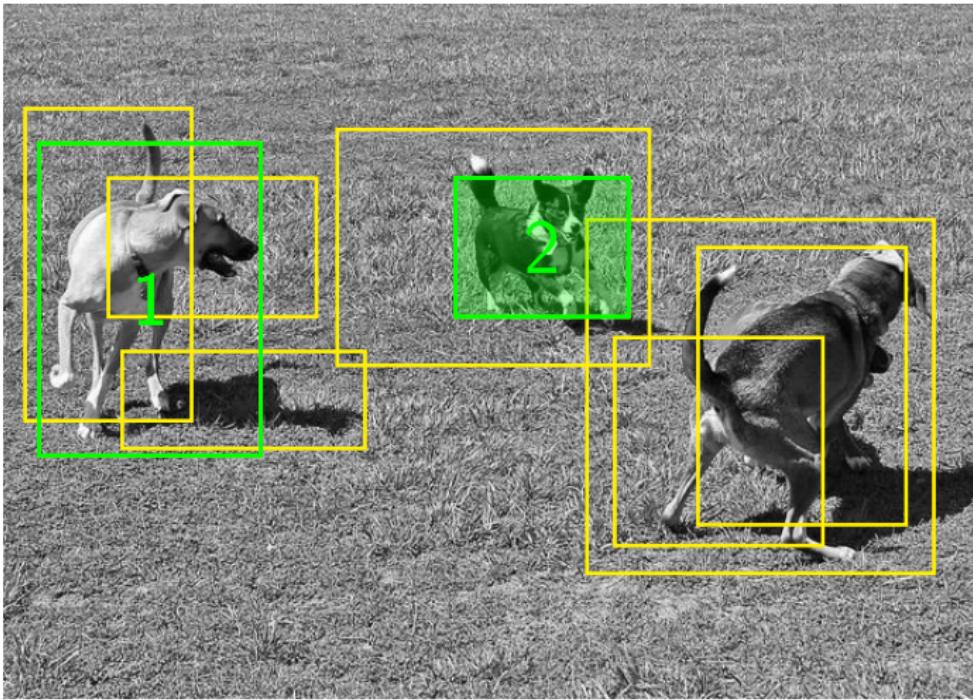


non-maximum suppression (NMS)



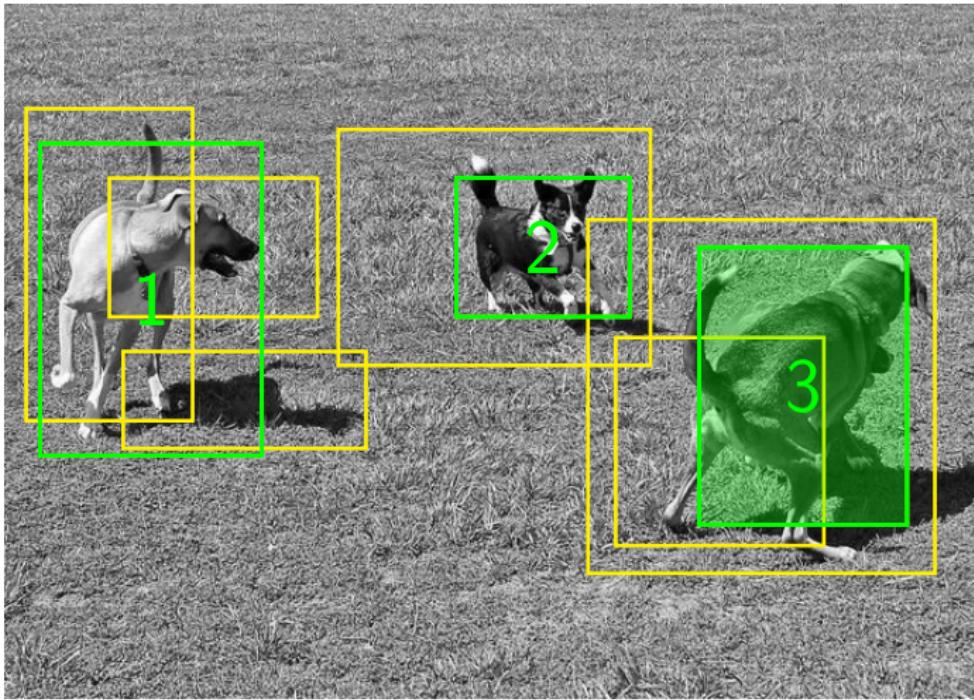
region 1 remains

non-maximum suppression (NMS)



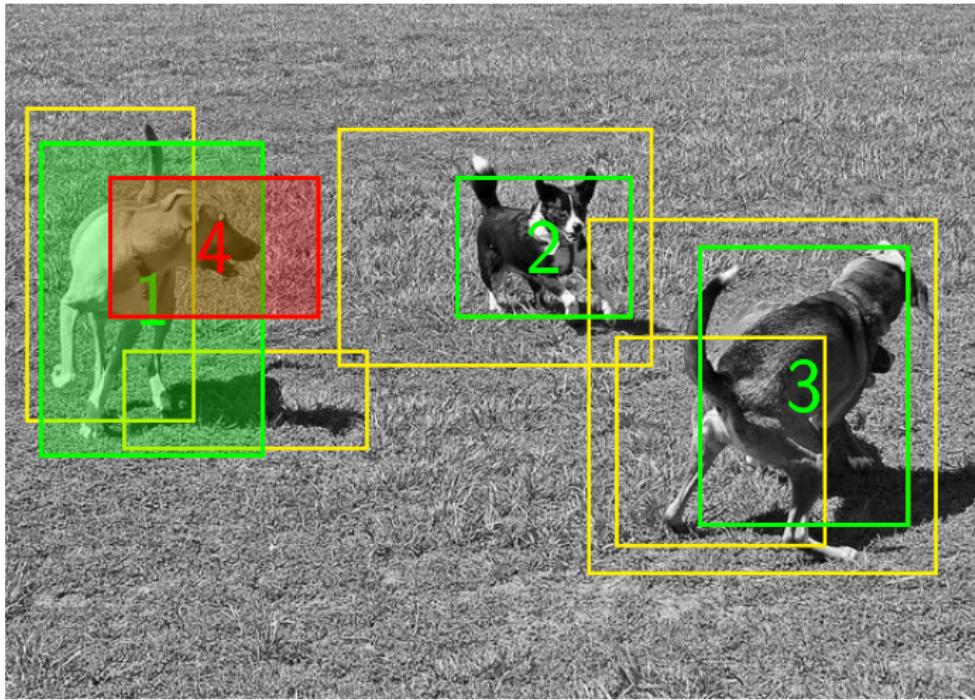
region 2 remains

non-maximum suppression (NMS)



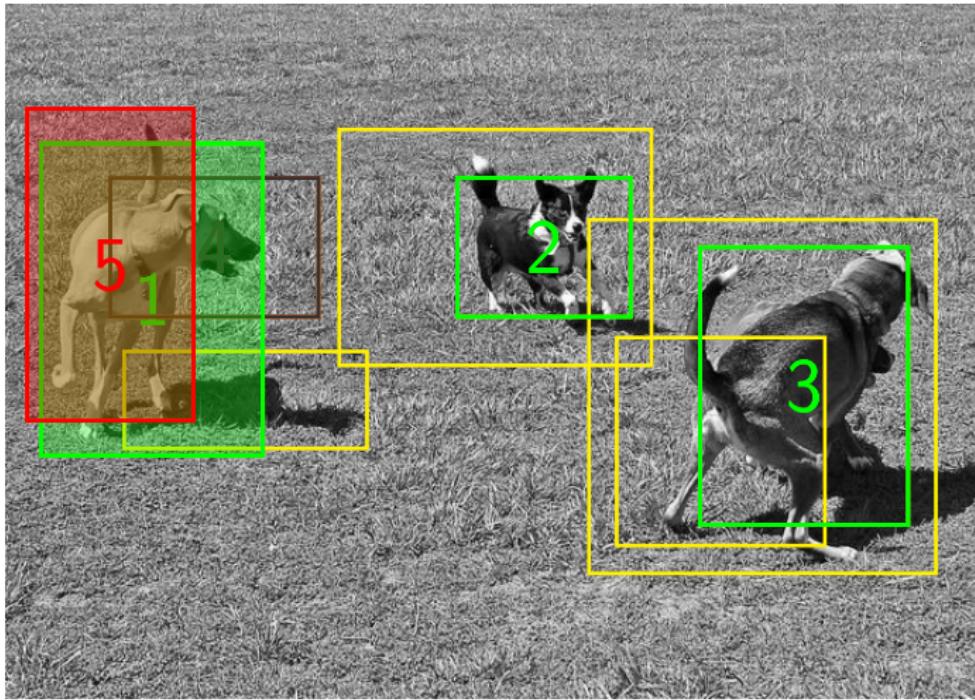
region 3 remains

non-maximum suppression (NMS)



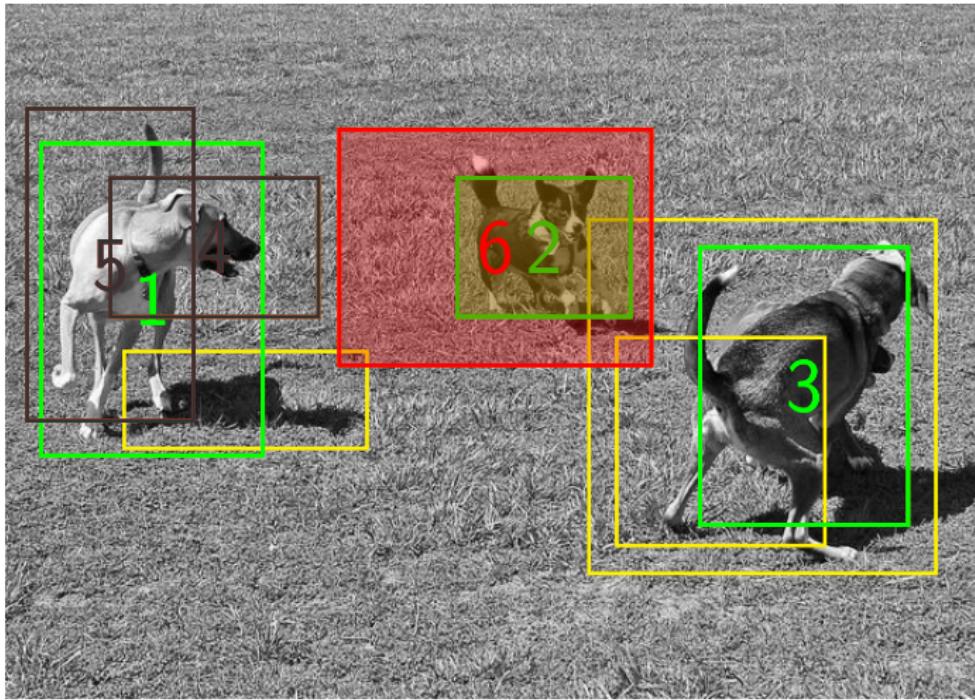
region 4 is rejected because $J(r_4, r_1) = 0.2750 > 0.25$

non-maximum suppression (NMS)



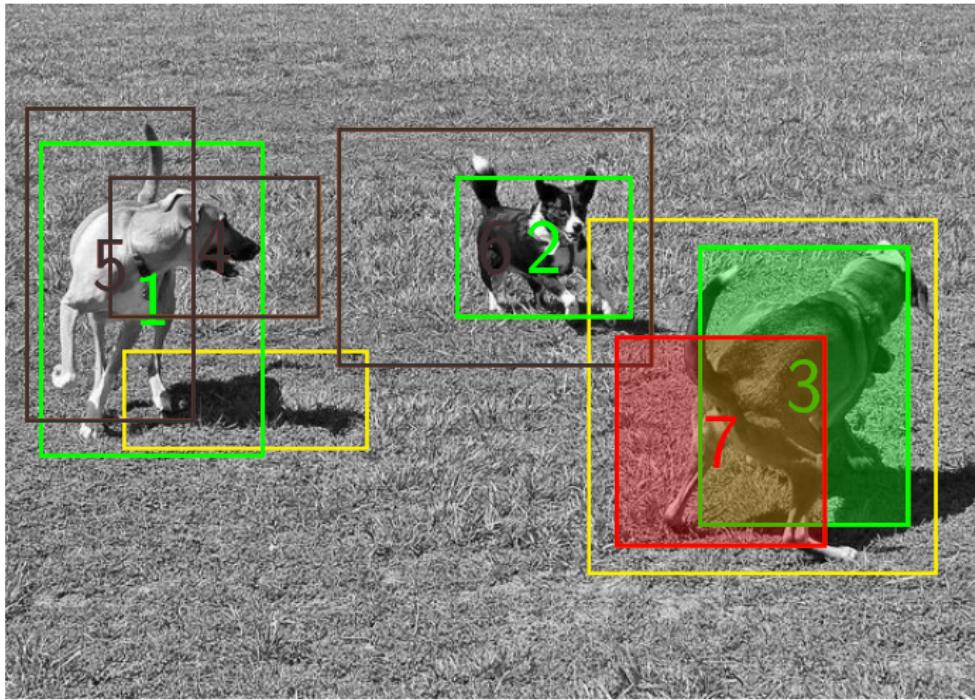
region 5 is rejected because $J(r_5, r_1) = 0.5366 > 0.25$

non-maximum suppression (NMS)



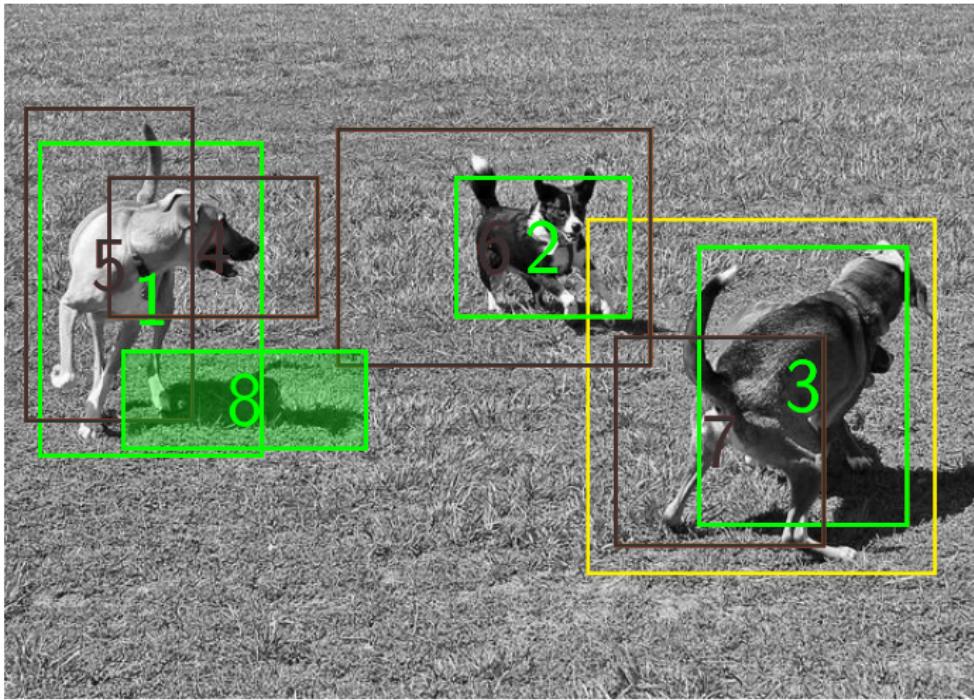
region 6 is rejected because $J(r_6, r_2) = 0.3268 > 0.25$

non-maximum suppression (NMS)



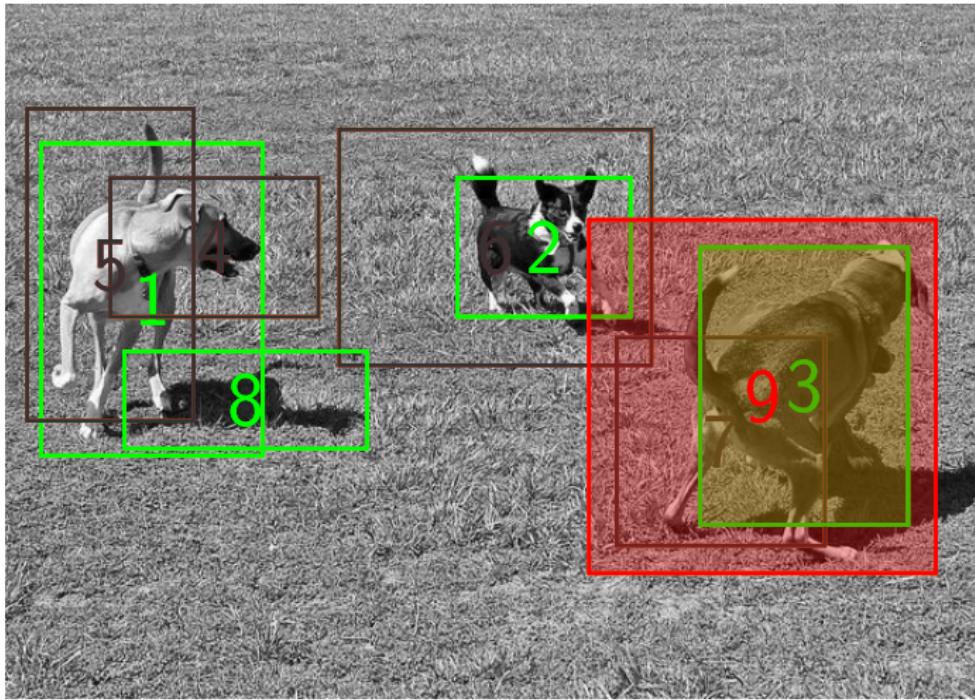
region 7 is rejected because $J(r_7, r_3) = 0.3011 > 0.25$

non-maximum suppression (NMS)



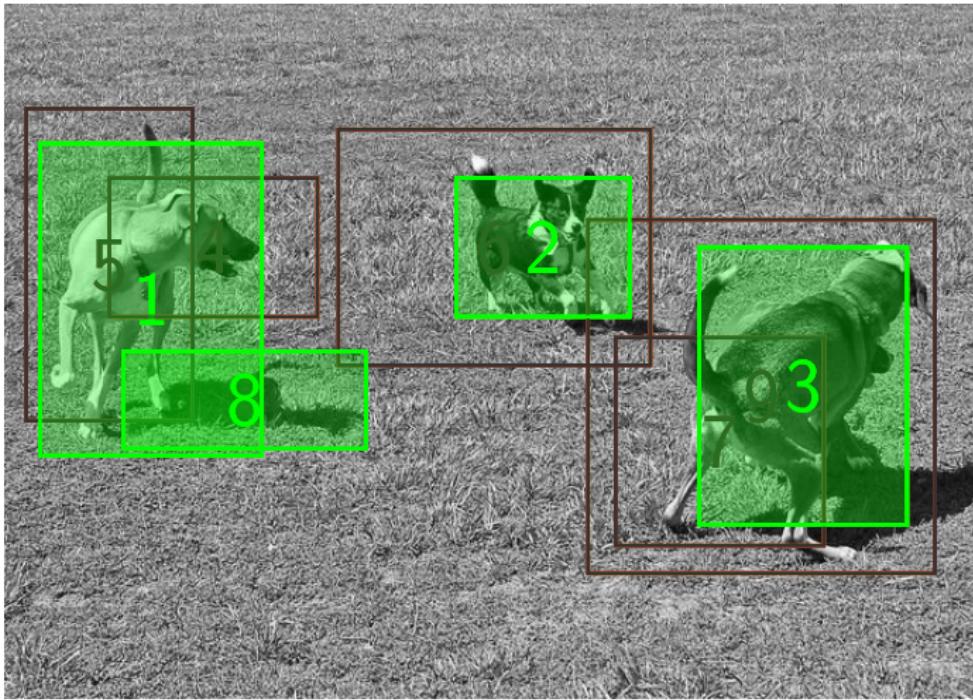
region 8 remains

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

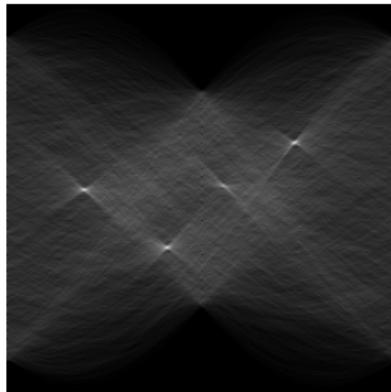
non-maximum suppression on regions

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



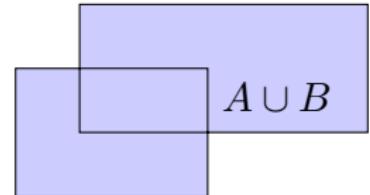
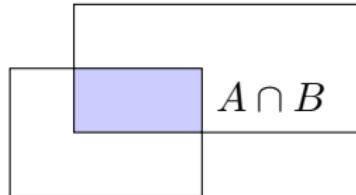
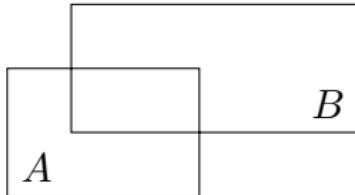
accumulator



local maxima

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

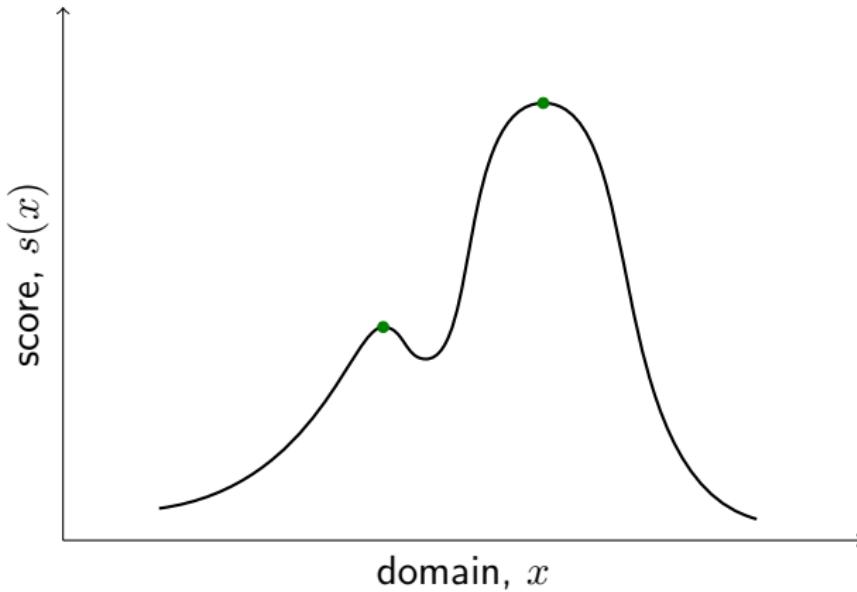
region overlap



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

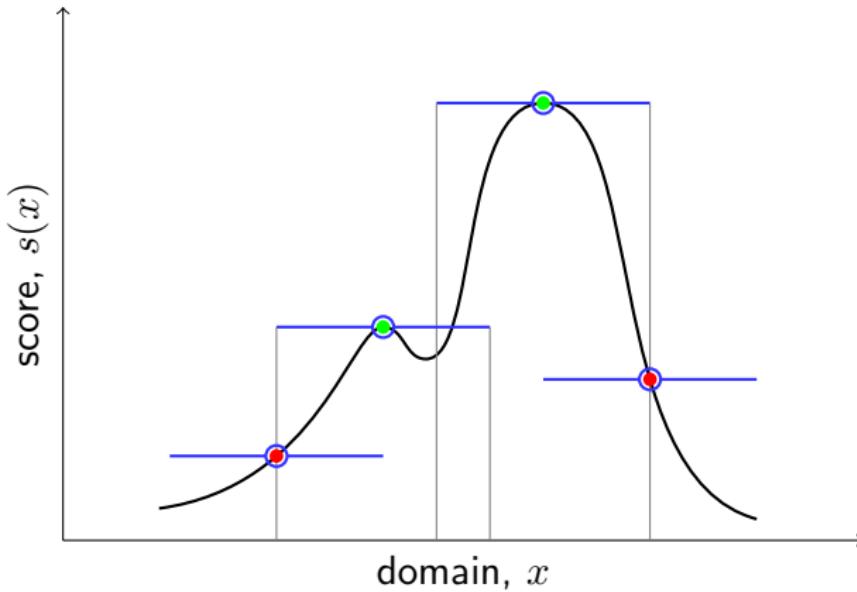
$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

the problem of non-maximum suppression



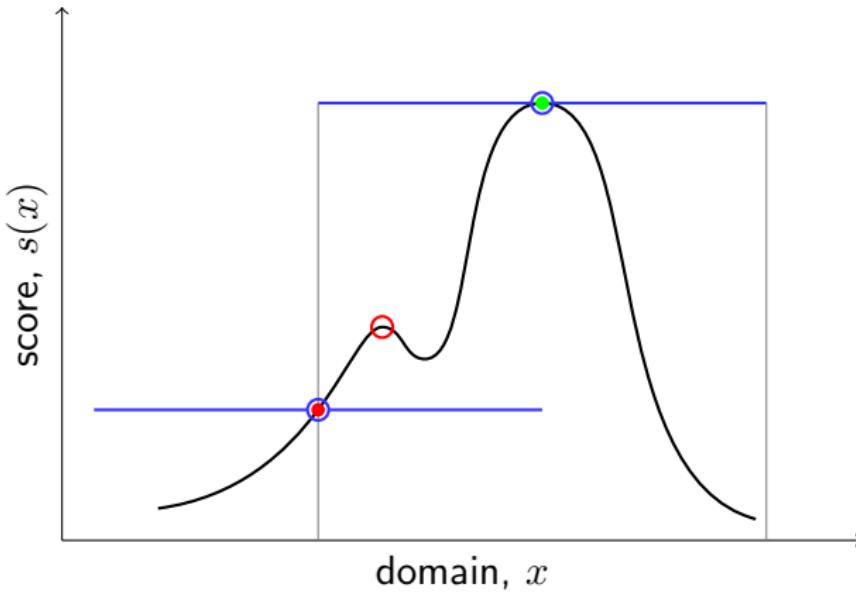
- ground truth positions

the problem of non-maximum suppression



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

the problem of non-maximum suppression



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

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

detection evaluation

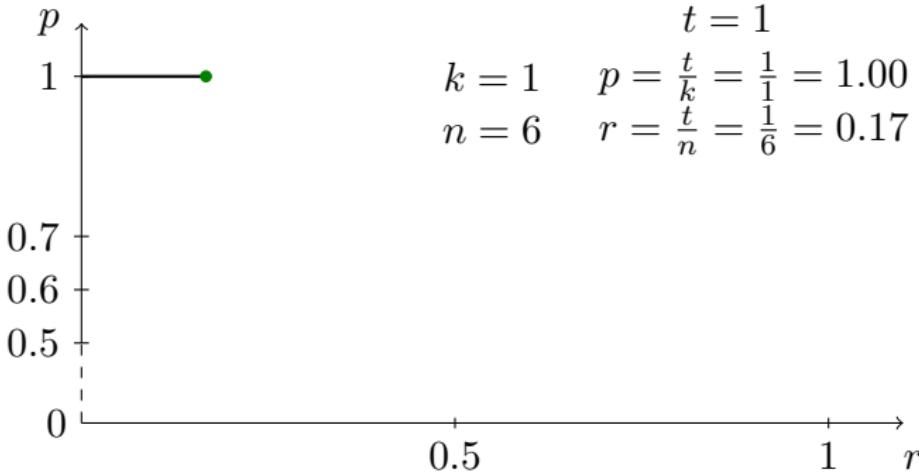
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average precision (AP)

- 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

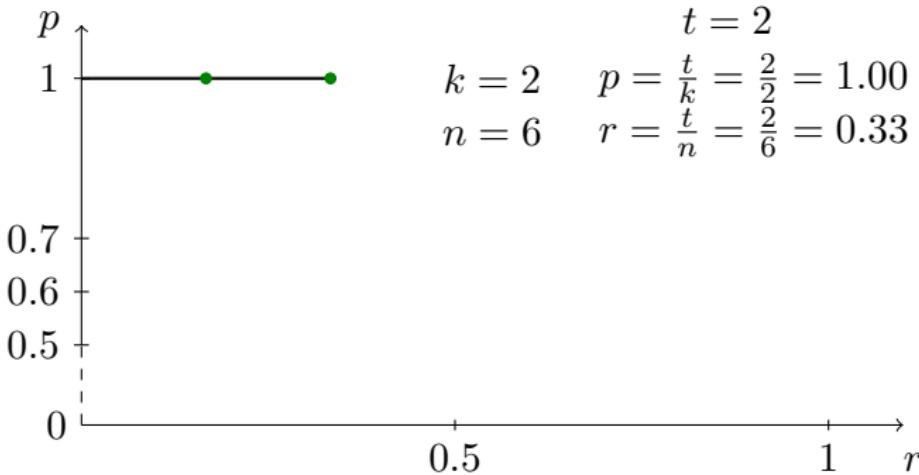


- # total ground truth n , current rank k , # true positives t
- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

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

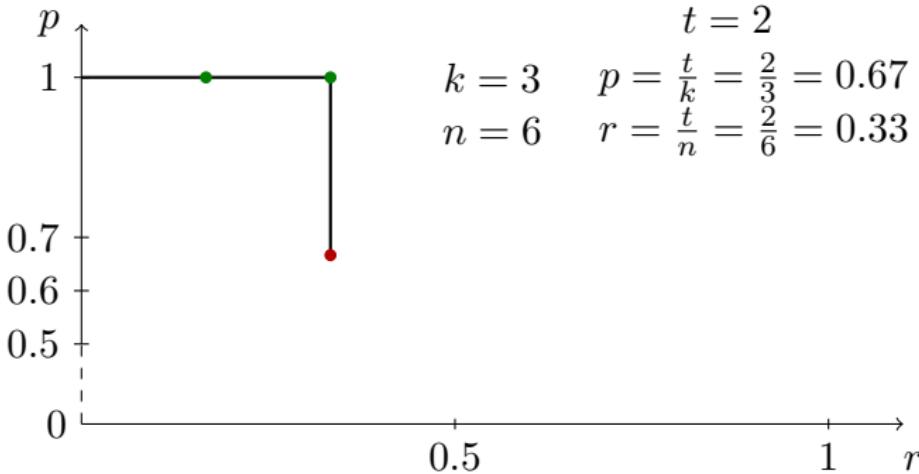


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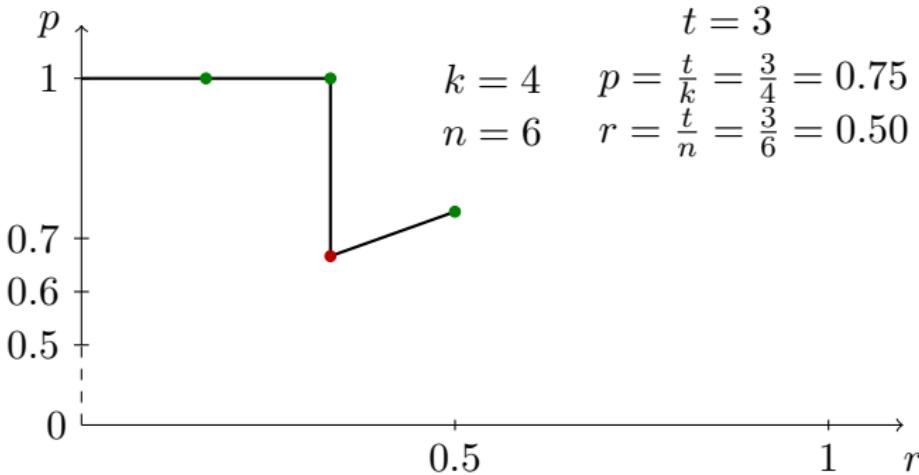


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T	T	F	T	F	F	T	F	T	T	F	F

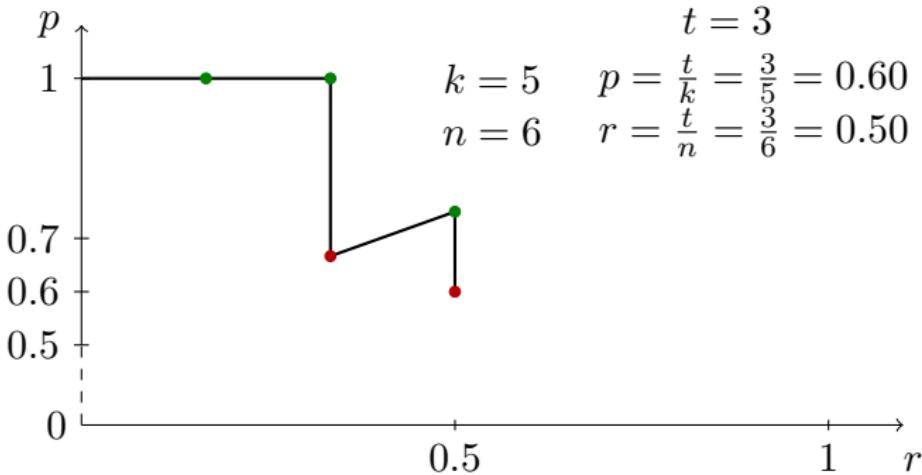


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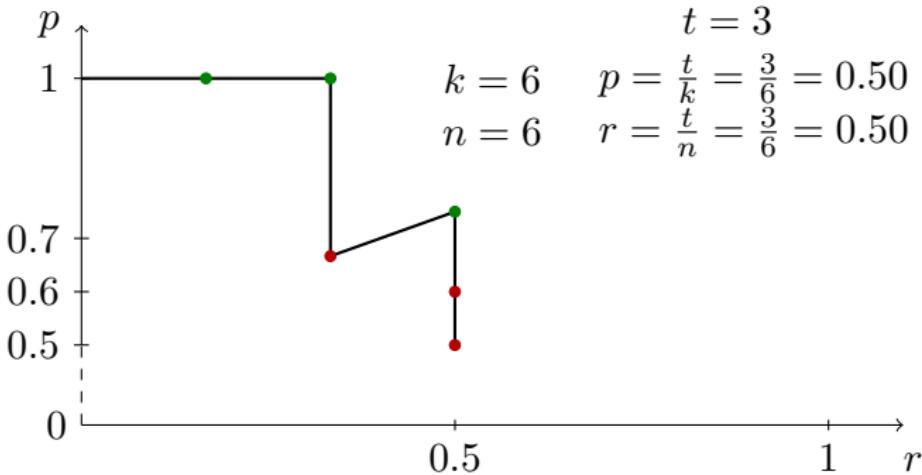


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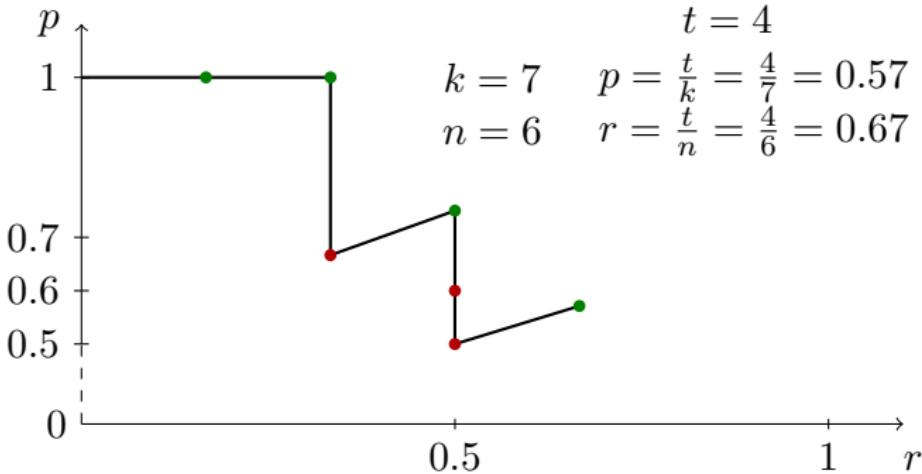


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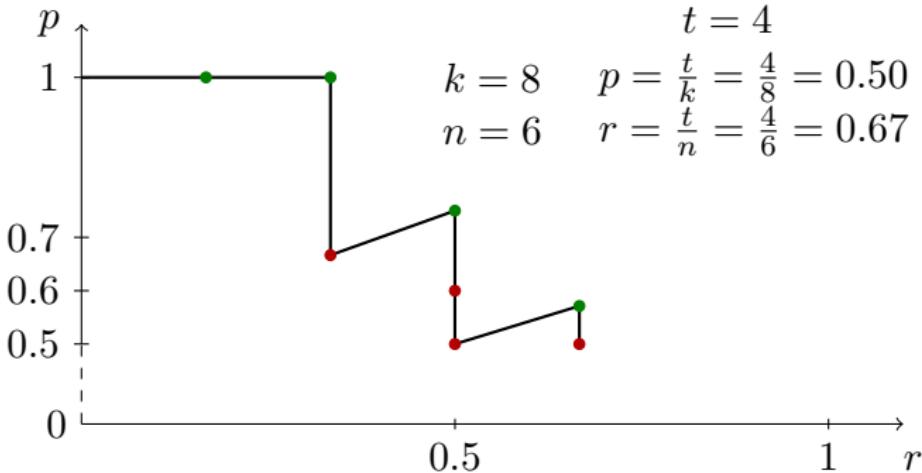


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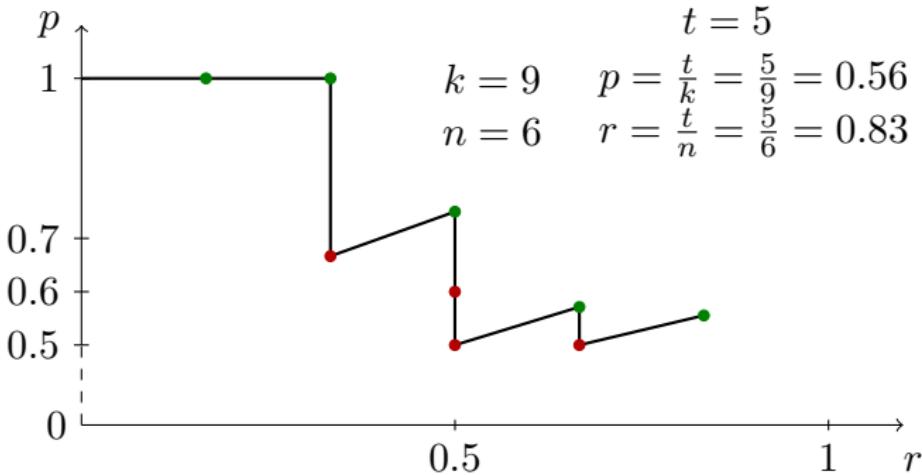


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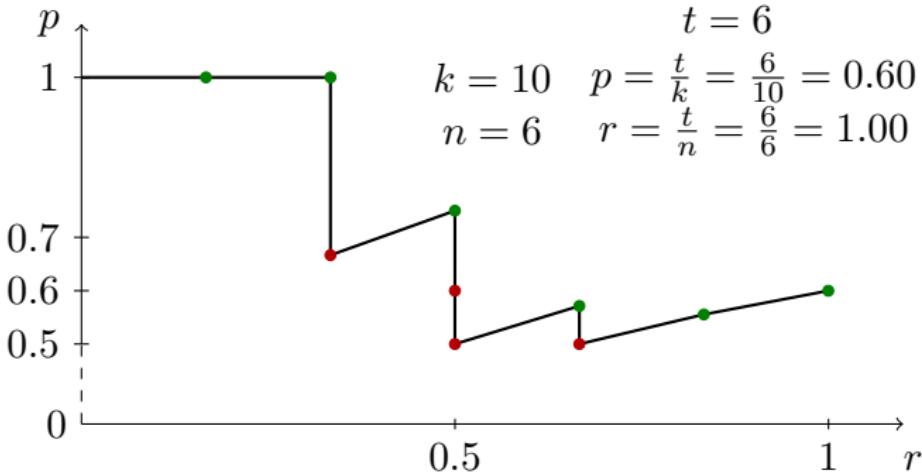


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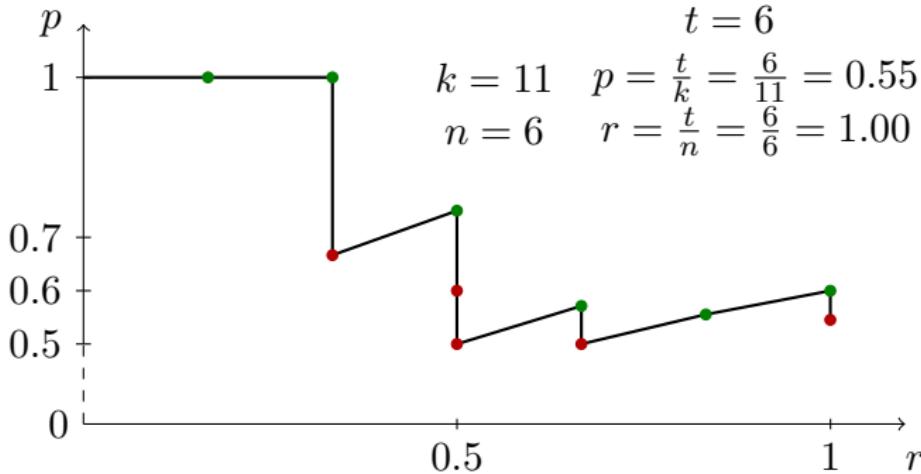


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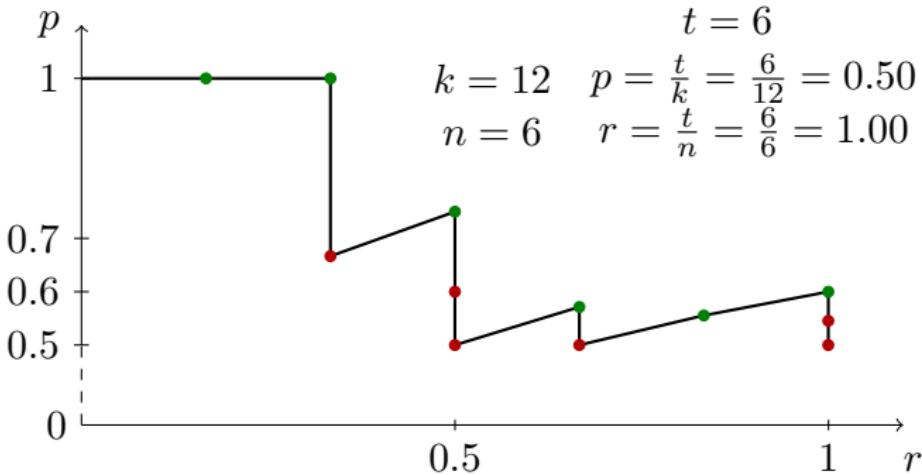


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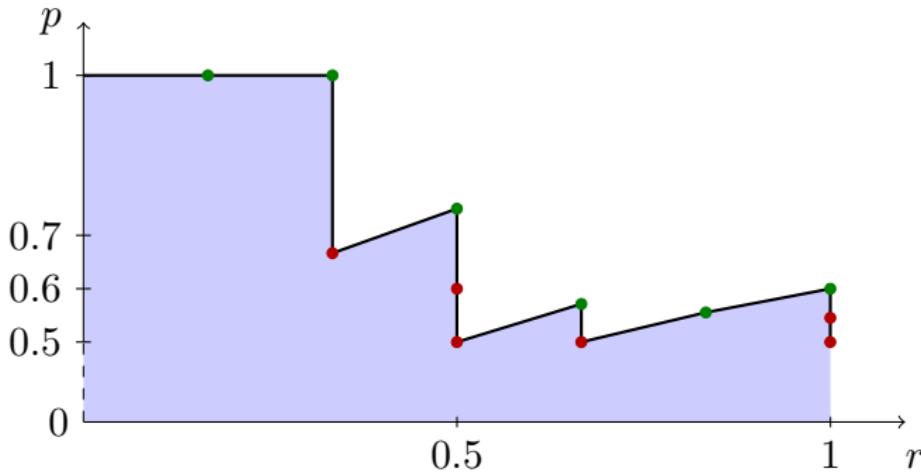


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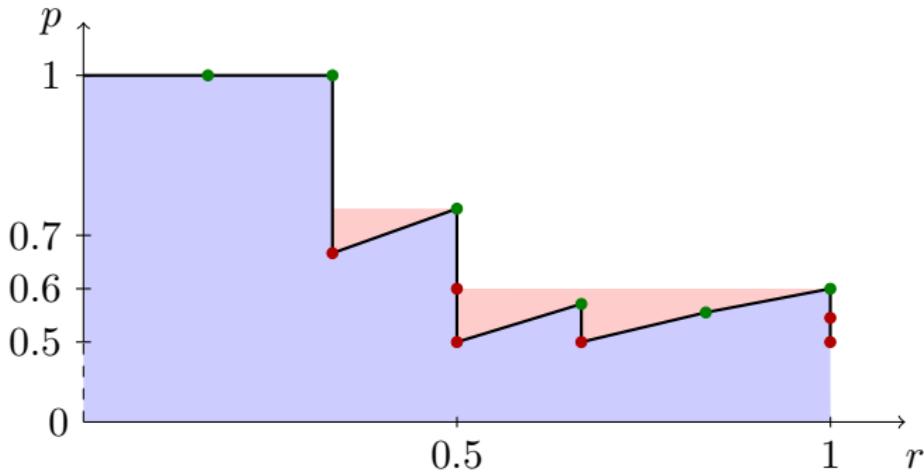
- average precision = area under curve

- precision $p = \frac{t}{k}$, recall $r = \frac{t}{n}$

average precision (AP)

- ranked list of items with true/false labels

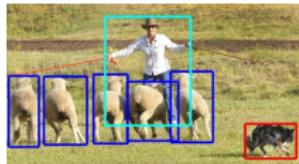
1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



- 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.

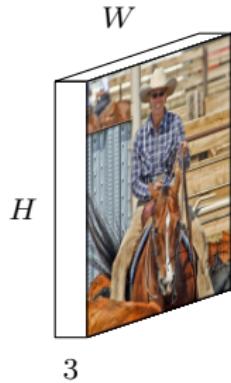
Lin *et al.* ECCV 2014. Microsoft COCO: Common Objects in Context.

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]

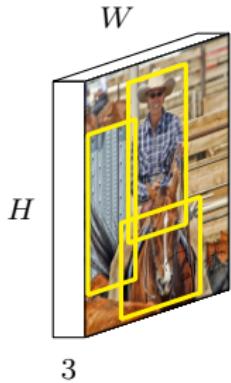


- 3-channel RGB input, fixed width $W = 500$ pixels
- ~ 2000 SS region proposals warped into fixed $w \times h = 227 \times 227$
- each proposal yields a $k = 4096$ dimensional feature by CaffeNet
- each feature is classified into c classes by c one-vs.-rest SVMs and localized by bounding box regression

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]

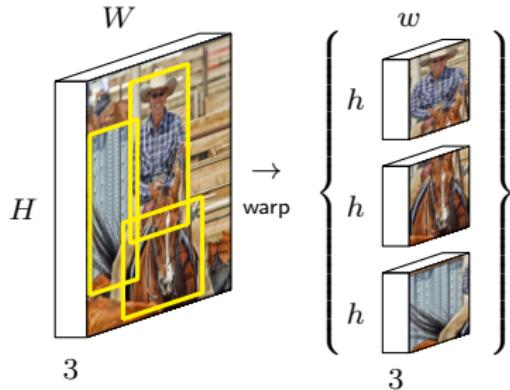


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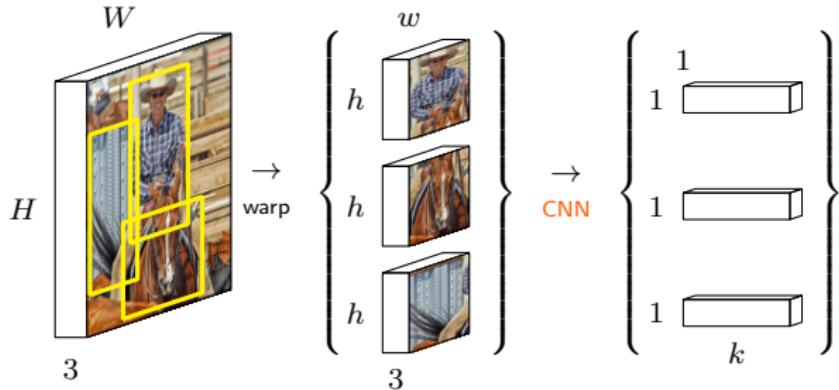
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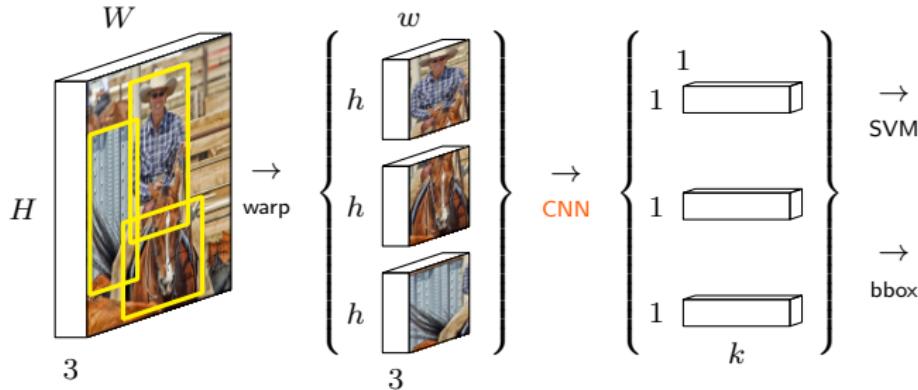
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regions with CNN features (R-CNN)

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)

$$\begin{aligned} t_x &= (g_x - p_x)/p_w & t_w &= \log(g_w/p_w) \\ t_y &= (g_y - p_y)/p_h & t_h &= \log(g_h/p_h) \end{aligned}$$

- 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

$$\begin{aligned} \hat{p}_x &= p_w f_x(p) + p_x & \hat{p}_w &= p_w \exp(f_w(p)) \\ \hat{p}_y &= p_h f_y(p) + p_y & \hat{p}_h &= p_h \exp(f_h(p)) \end{aligned}$$

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)

$$\begin{aligned} t_x &= (g_x - p_x)/p_w & t_w &= \log(g_w/p_w) \\ t_y &= (g_y - p_y)/p_h & t_h &= \log(g_h/p_h) \end{aligned}$$

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

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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

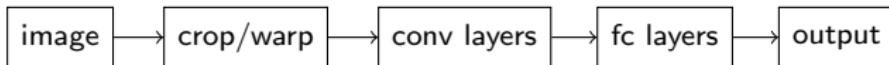
spatial pyramid pooling (SPP)

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crop

warp



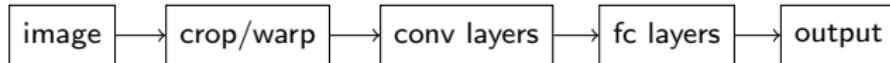
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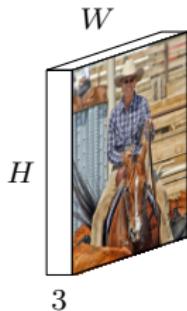


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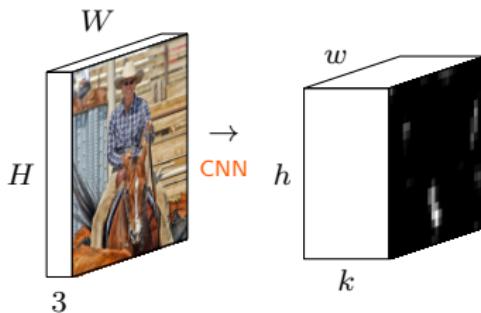
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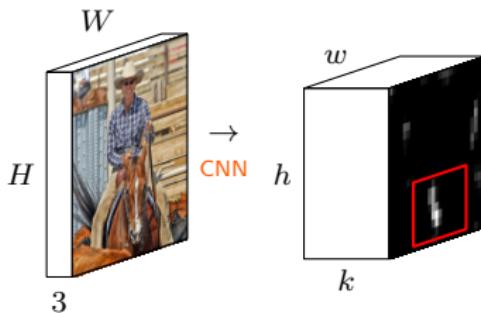
- 3-channel RGB input, arbitrary size
- input yields a single k dimensional feature map
- each region proposal projected onto feature maps
- then max-pooled into a number of fixed sizes $1 \times 1, 2 \times 2, 4 \times 4$ etc. and concatenated into fixed-length representation
- when the pyramid has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

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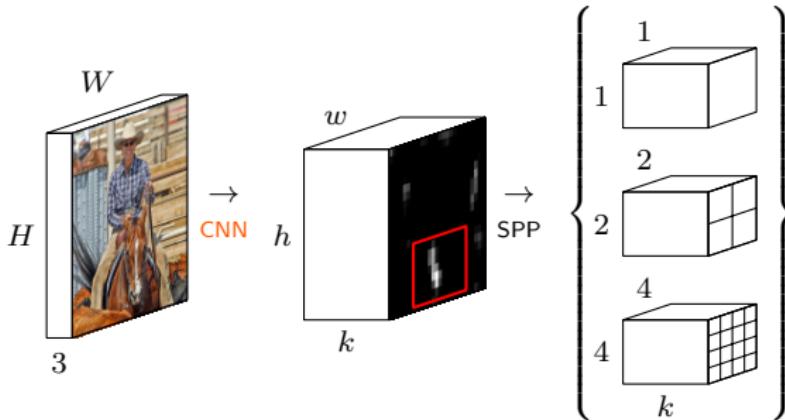
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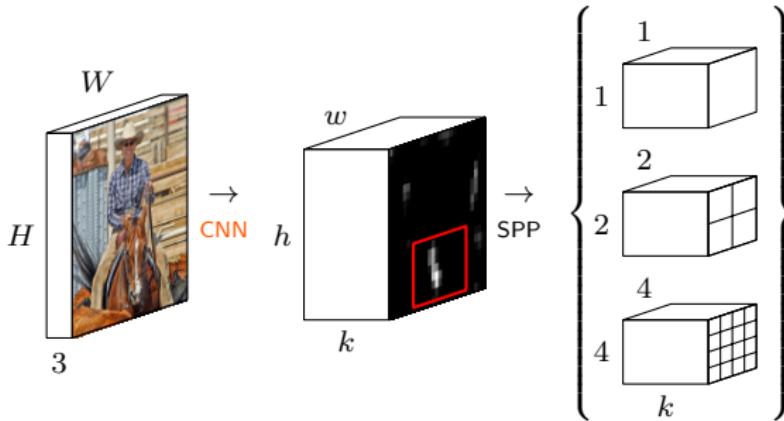
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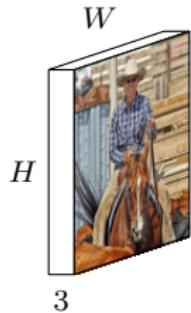
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fast R-CNN (FRCN)

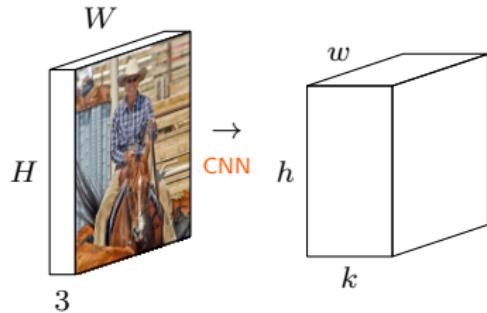
[Girshick 2015]



- 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

fast R-CNN (FRCN)

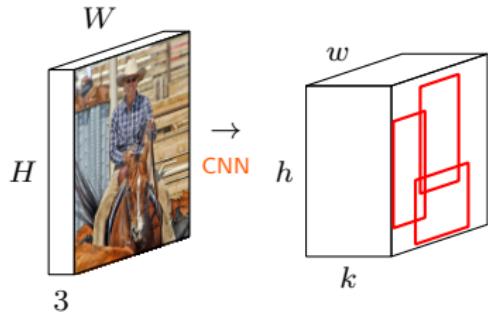
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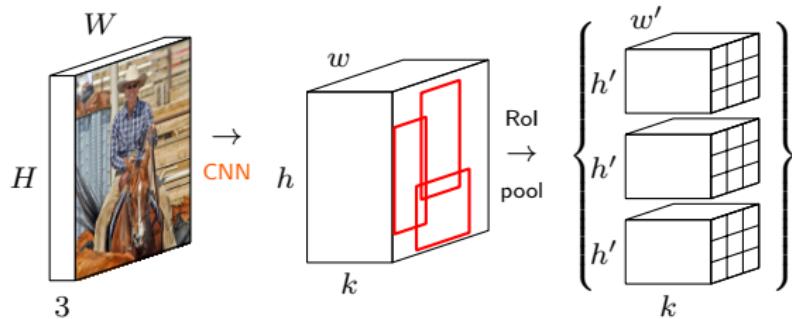
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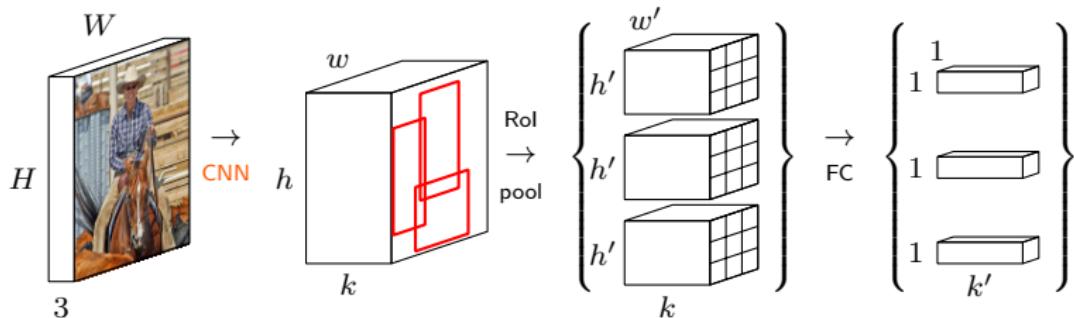
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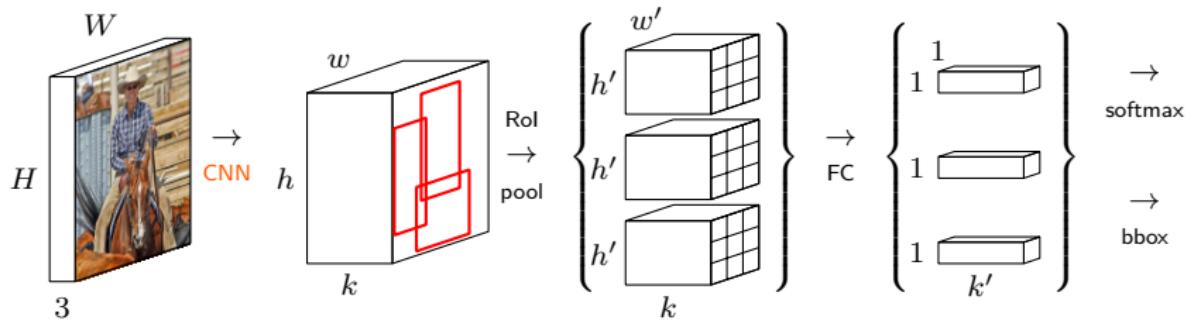
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fast R-CNN (FRCN)

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** (~ 2 s/image)
- **single-scale**

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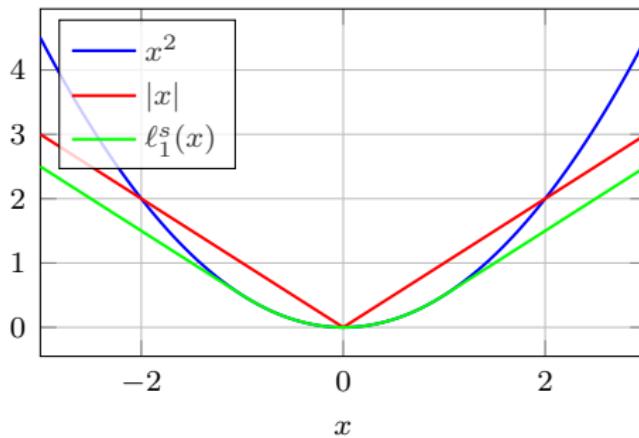
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regression loss*

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

$$L(y, t) = \sum_{j \in \{x, y, h, w\}} \ell_1^s(y_j - t_j)$$
$$\ell_1^s(x) = \begin{cases} \frac{x^2}{2}, & \text{if } |x| < 1 \\ |x| - \frac{1}{2}, & \text{otherwise} \end{cases}$$



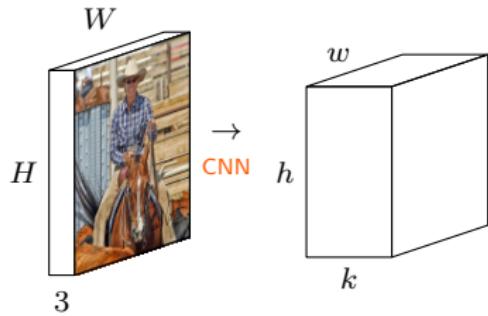
learning object proposals: MultiBox detector*

[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

faster R-CNN

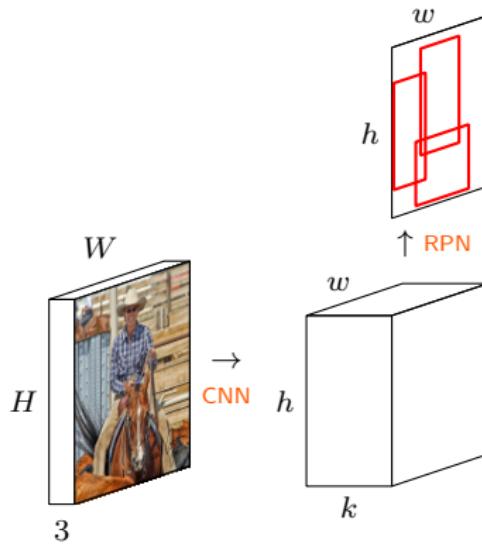
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- same input, same VGG-16 feature maps as Fast R-CNN
- proposals detected directly on feature maps by RPN and max-pooled
- same classifier, same bounding box regression, but now also for RPN

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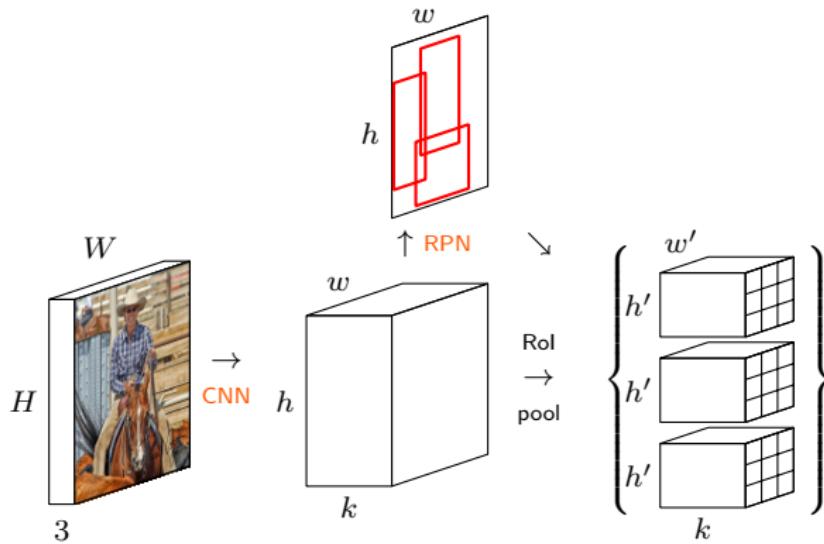
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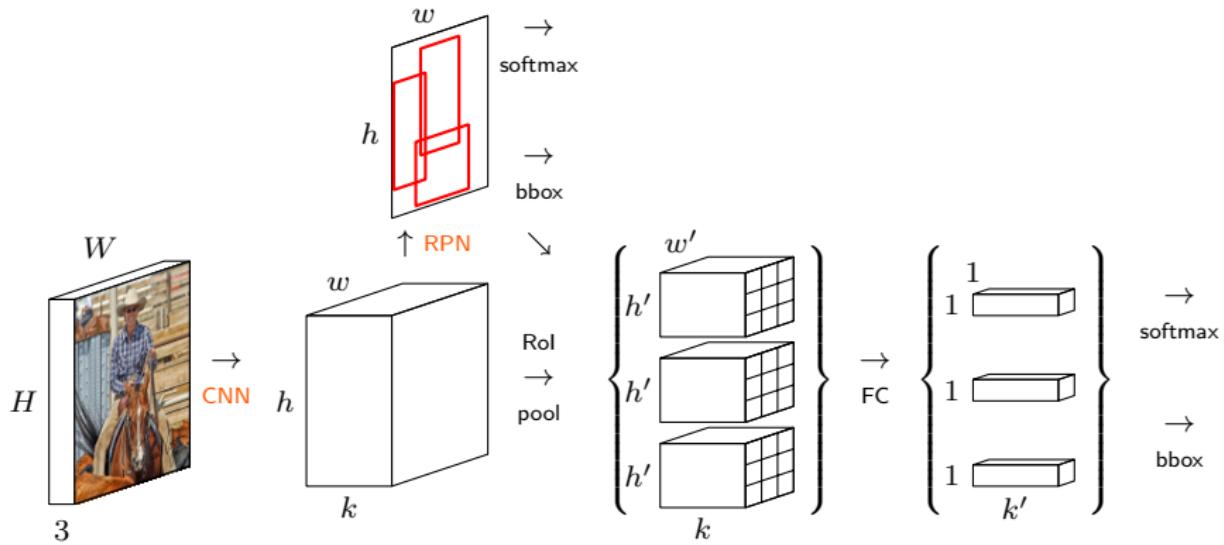
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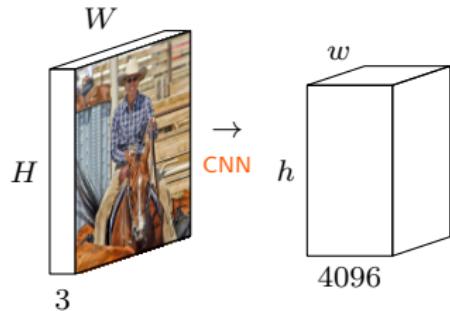
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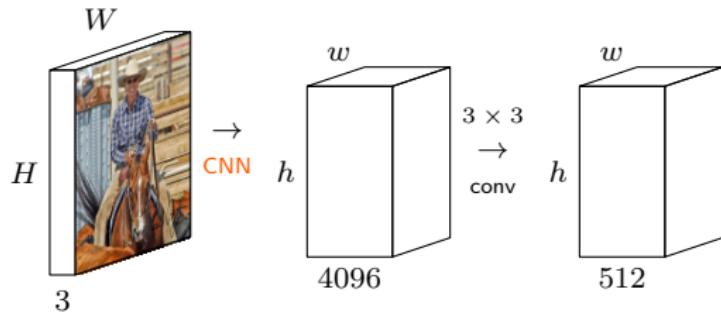
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region proposal network (RPN)



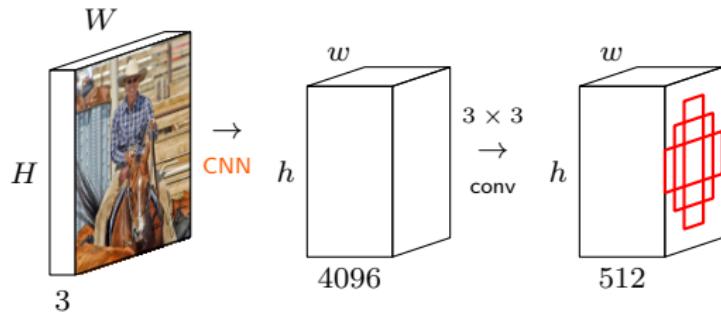
- same input, same feature maps, dimension reduced to 512
- $a = 9$ anchors at each position, for 3 scales and 3 aspect ratios
- $2a$ classification (object/non-object) scores and $4a$ bounding box coordinates relative to anchor at each position
- softmax on scores, regression loss on coordinates
- region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

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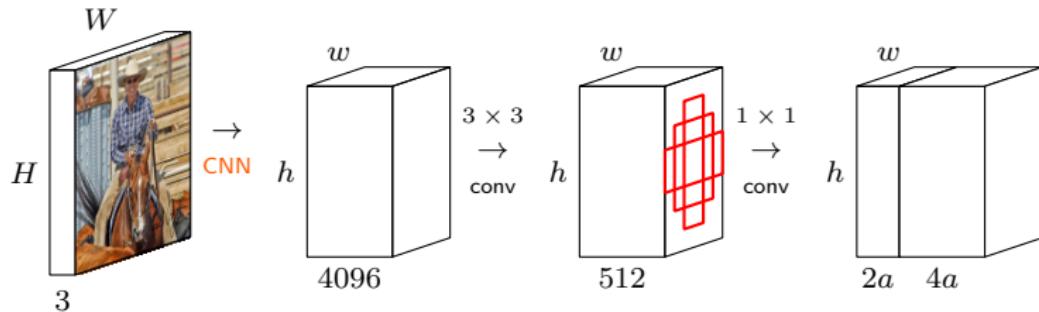
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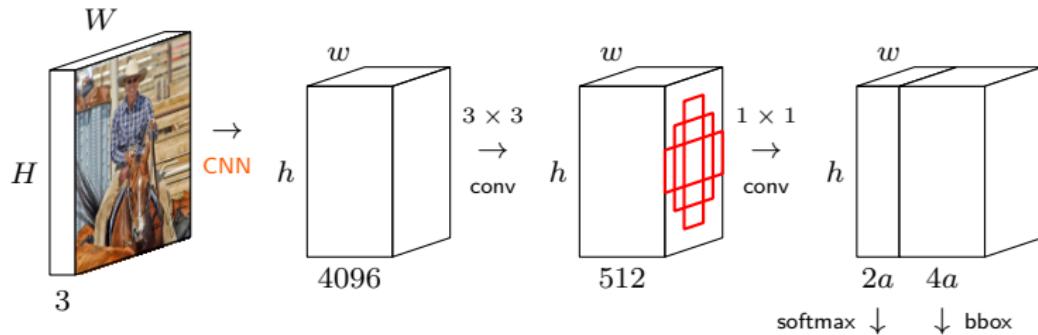
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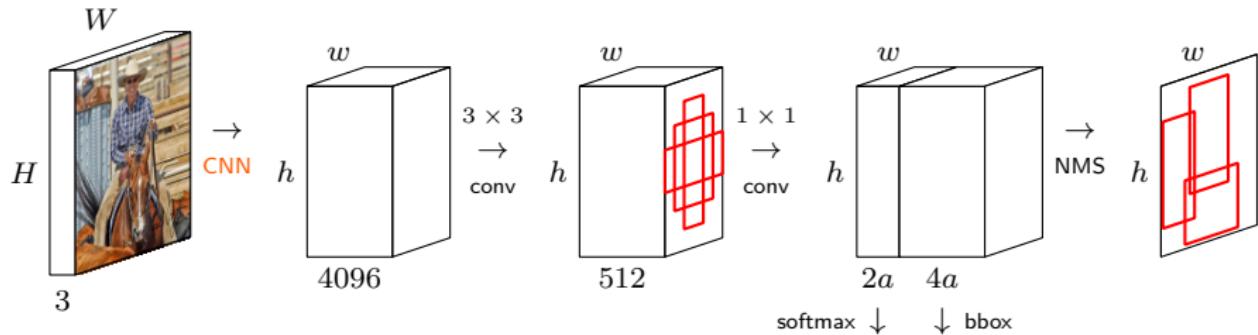
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pros

- faster (0.2s/image including proposals; 10× 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

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- 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 **Rol-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

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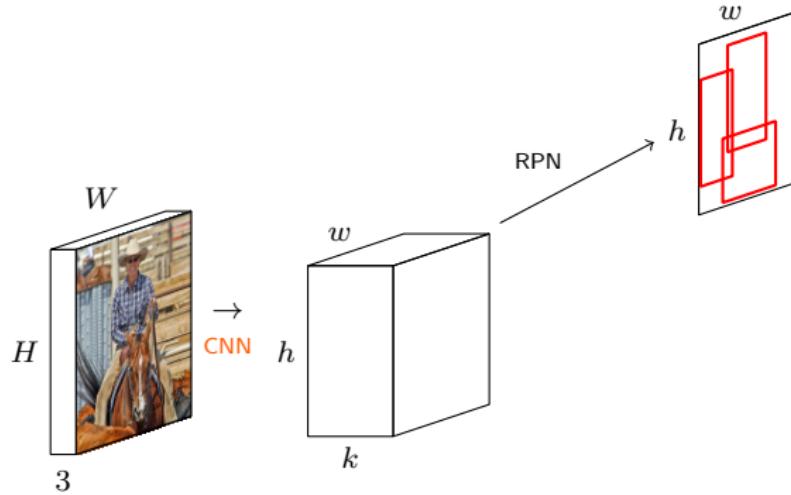
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object parts and deformation*

region-based fully convolutional network (R-FCN)

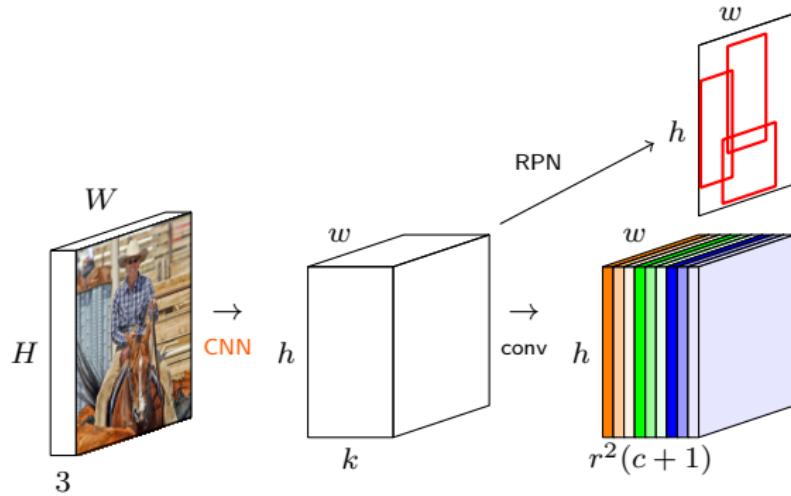
[Ren et al. 2016]



- 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 Rot pooling
 - similarly, $4r^2$ position-sensitive coordinates for regression
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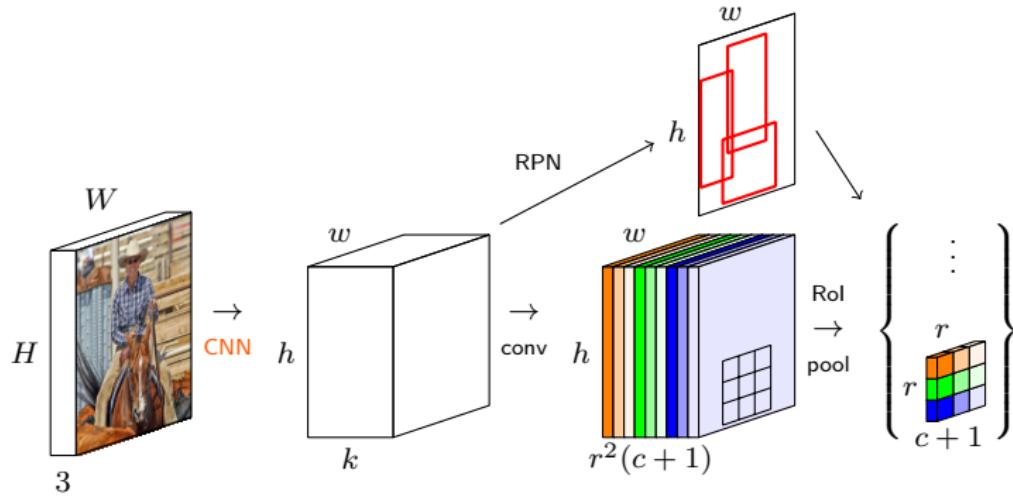
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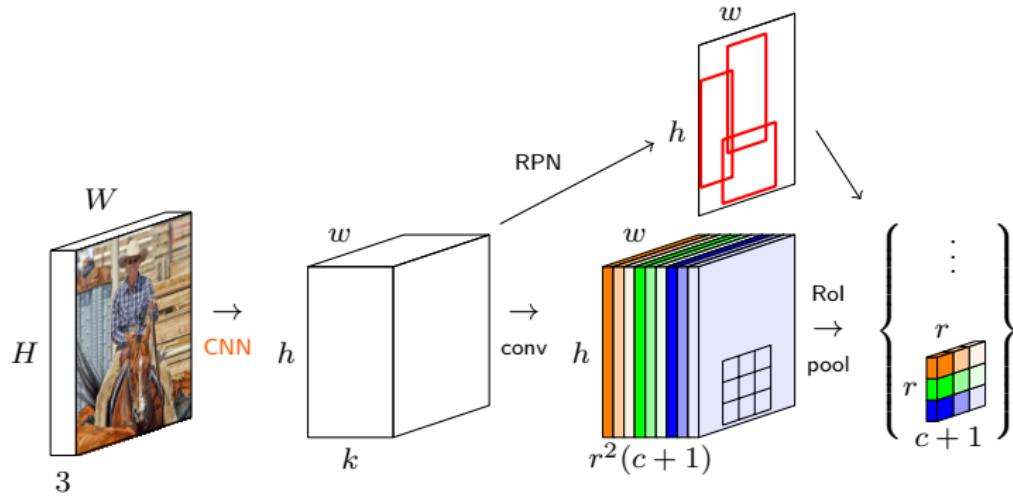
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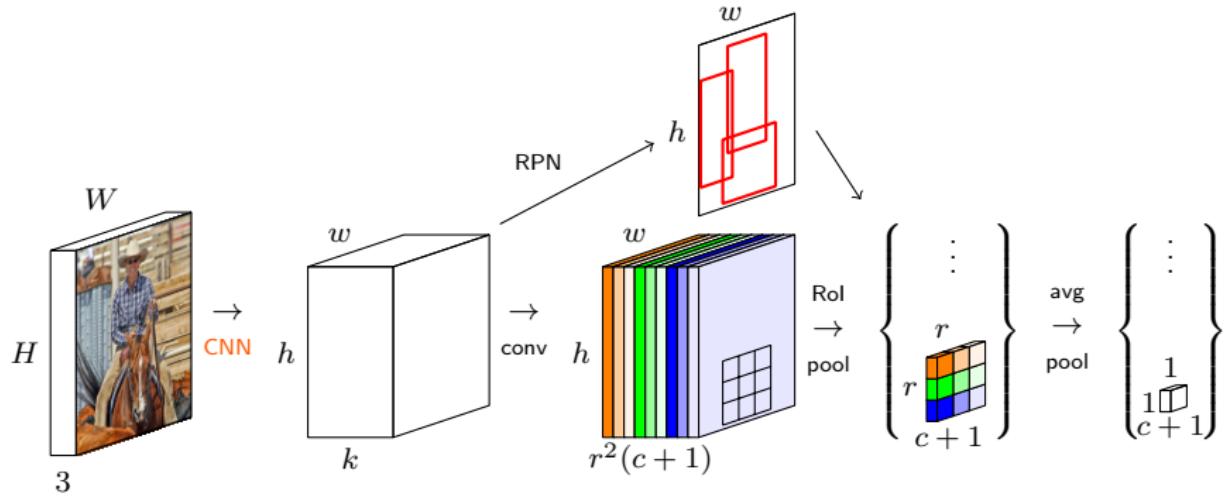
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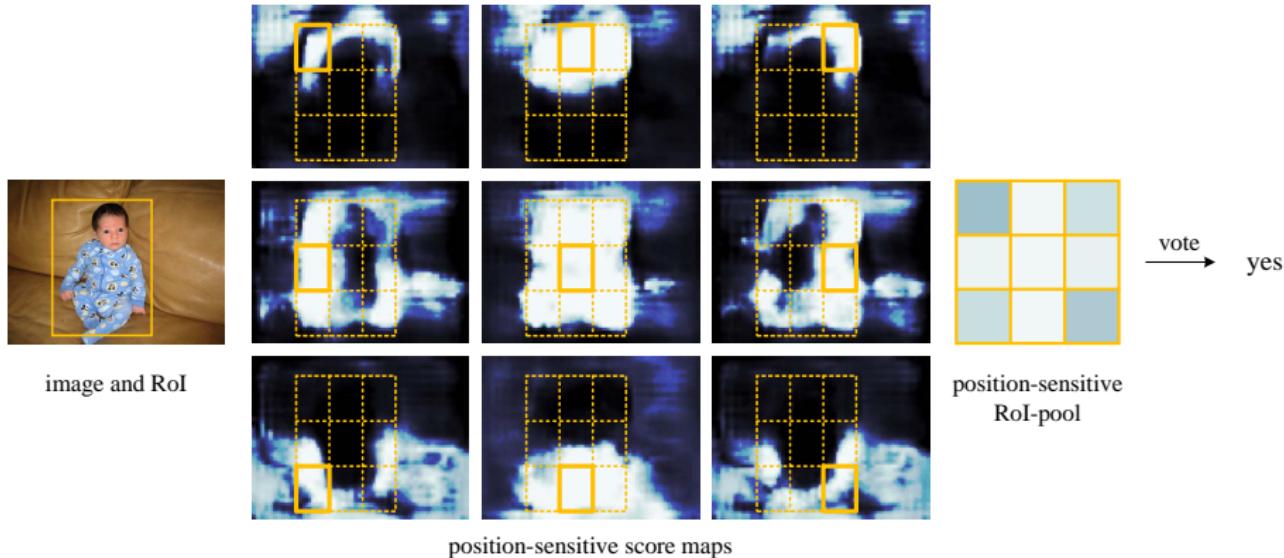
region-based fully convolutional network (R-FCN)

[Ren et al. 2016]



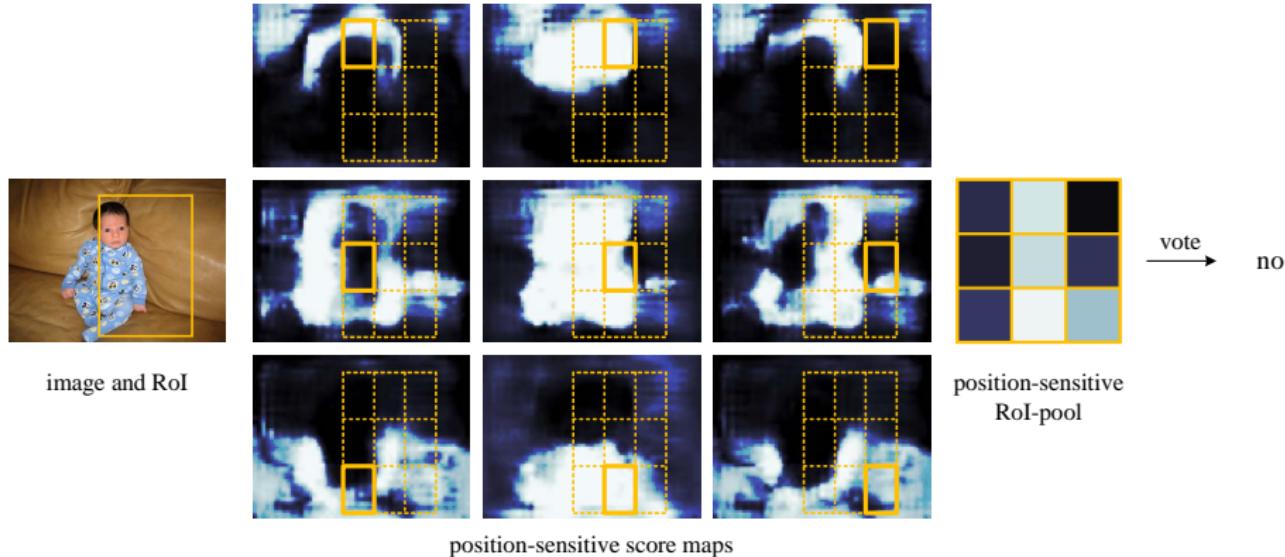
- 2048-d feature maps by ResNet-101, reduced to $k = 1024$, same RPN
 - $r \times r = 7 \times 7$ position-sensitive score maps per class, RoI pooling
 - similarly, $4r^2$ position-sensitive coordinates for regression
 - no FC, just average pooling

position-sensitive score maps and RoI pooling



- ROI is correctly aligned with the object

position-sensitive score maps and RoI pooling



- ROI is not correctly aligned with the object

region-based fully convolutional network (R-FCN)

pros

- **fully convolutional**: no more FC layers, maximum feature sharing between 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)

cons

- cells of position-sensitive RoI pooling are fixed
- still **single-scale**

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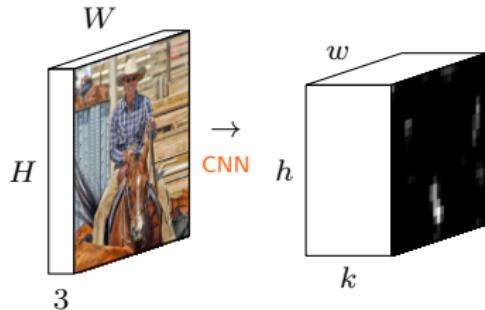
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spatial transformer networks (STN)

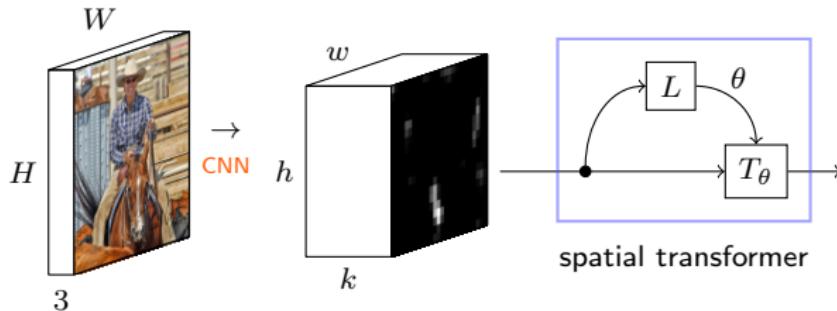
[Jaderberg et al. 2015]



- 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
- the localization network receives no supervision other than what is backpropagated from the end task

spatial transformer networks (STN)

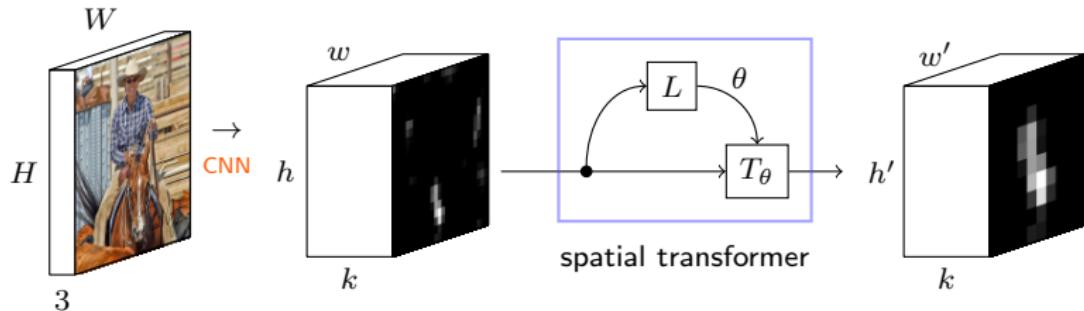
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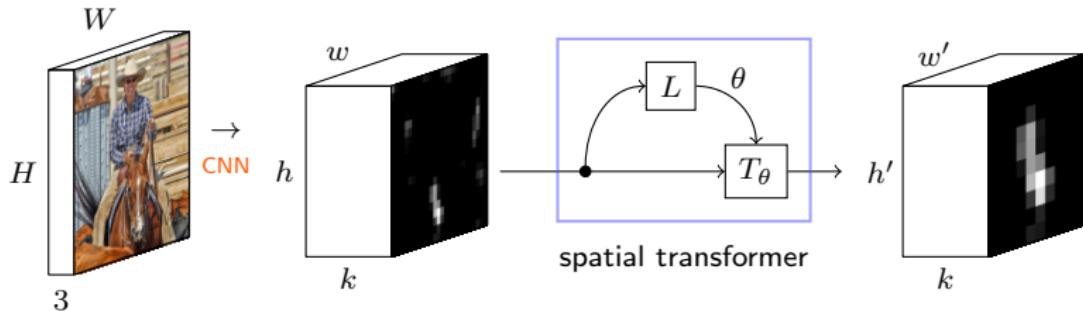
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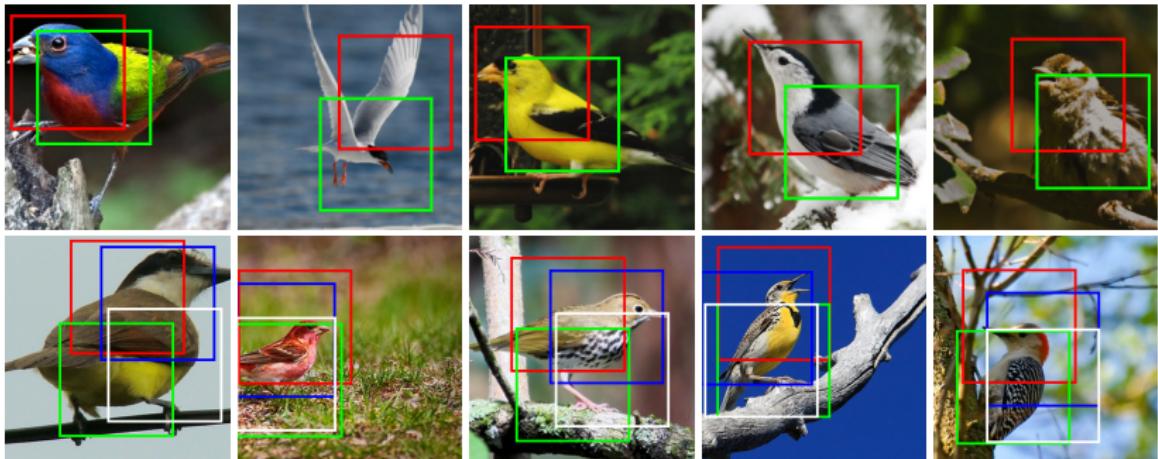
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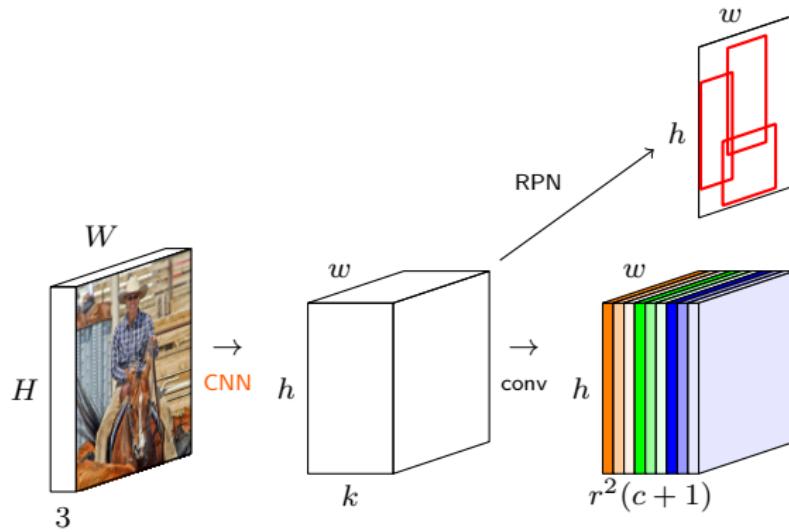
spatial transformer networks: part learning



- 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

deformable ROI pooling

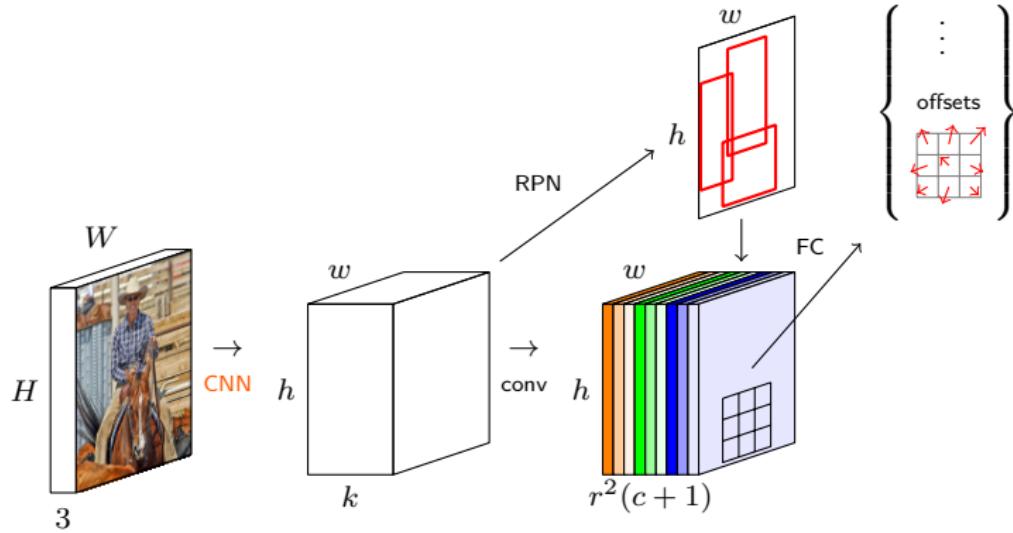
[Ren et al. 2017]



- same features, same RPN, same position-sensitive scores as R-FCN
 - cell offsets by FC on RoI-pooled features (demonstrated in figure)
 - same average pooling

deformable ROI pooling

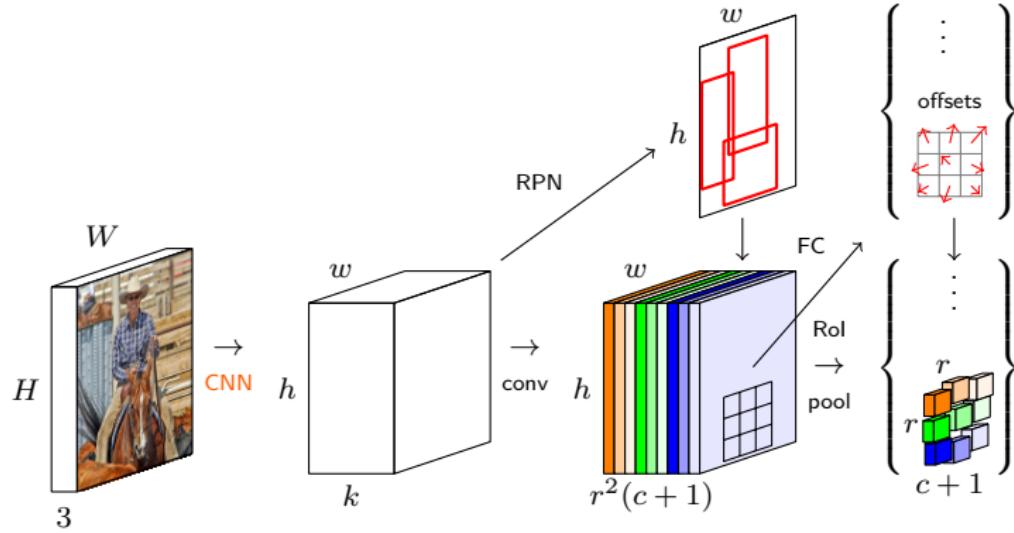
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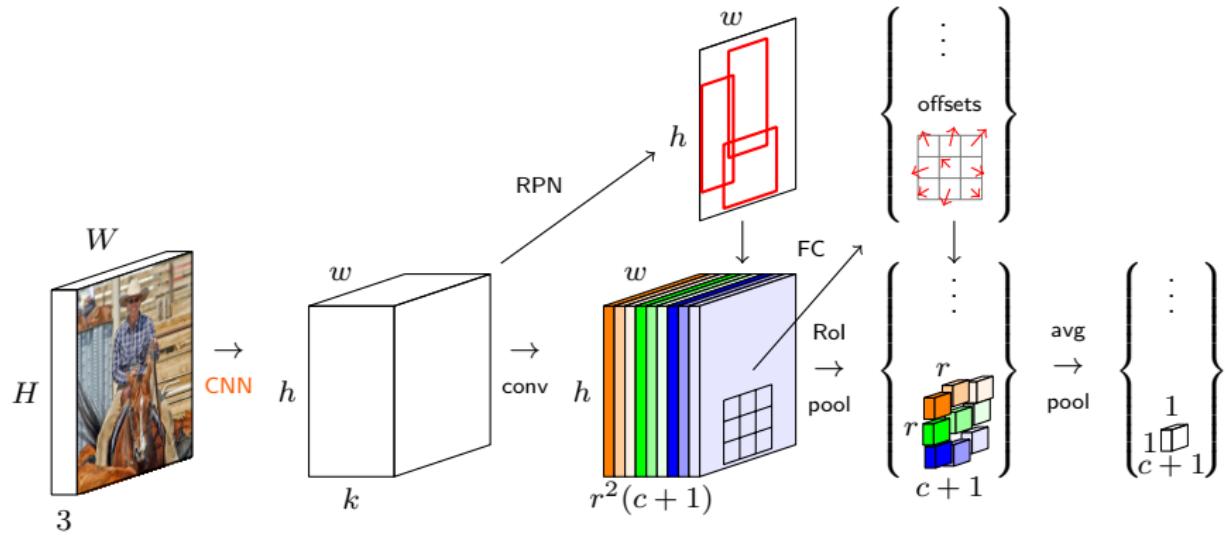
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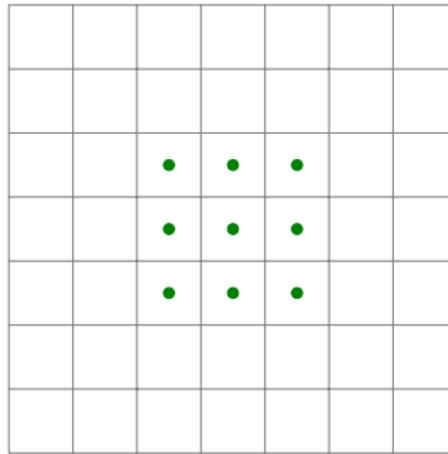
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- same features, same RPN, same position-sensitive scores as R-FCN
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deformable convolution

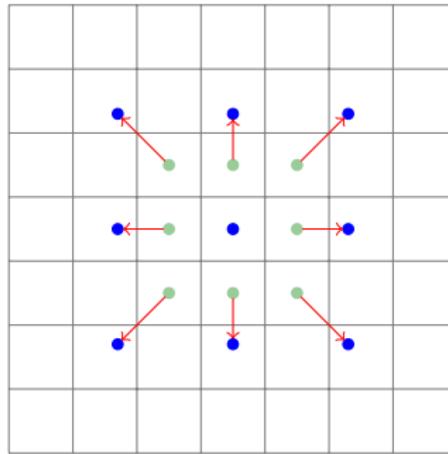
[Ren et al. 2017]



- standard convolution on 3×3 regular sampling grid

deformable convolution

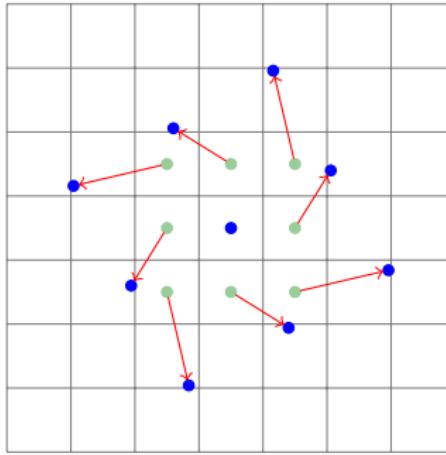
[Ren et al. 2017]



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

deformable convolution

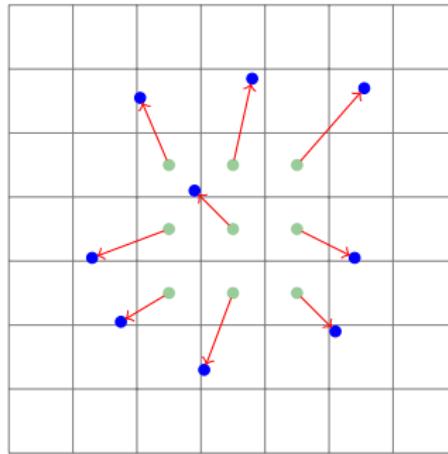
[Ren et al. 2017]



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

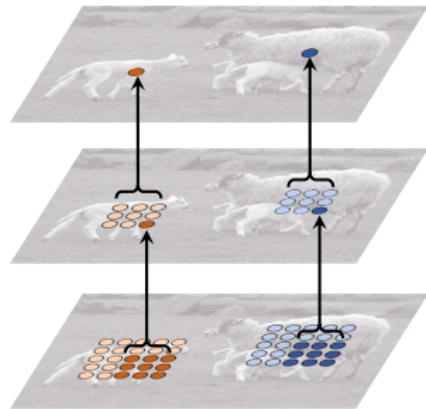
deformable convolution

[Ren et al. 2017]



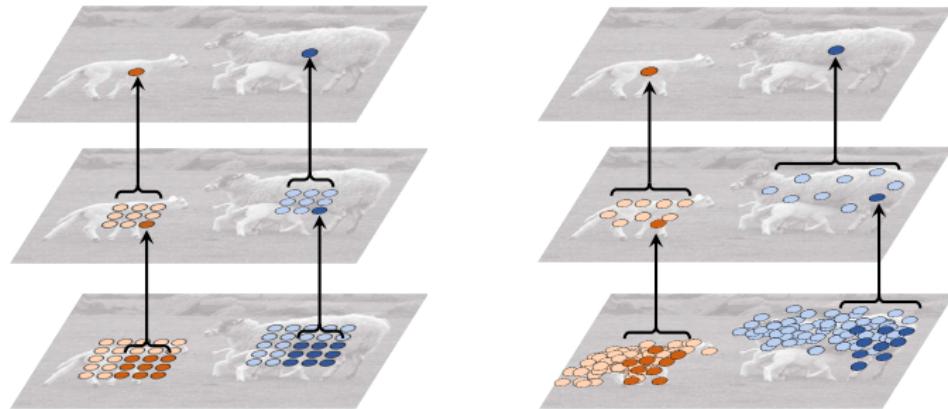
- deformed sampling grid where offsets are computed per pixel

deformable convolution: receptive field (2 layers)



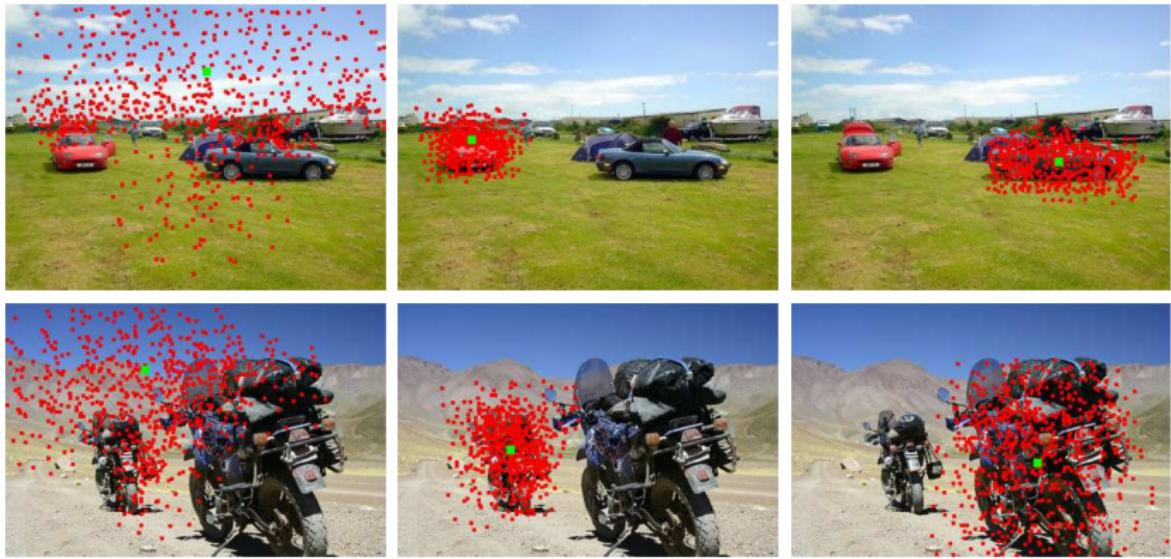
- **standard convolution**: receptive field grows with depth but only linearly, remains rectangular and is translation invariant
- **deformable convolution**: receptive field grows arbitrarily with depth, adapts per location and takes arbitrary shape

deformable convolution: receptive field (2 layers)



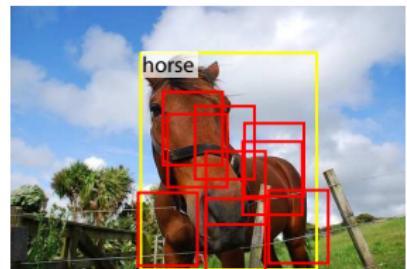
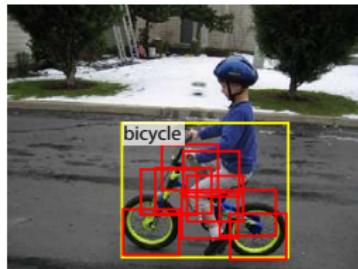
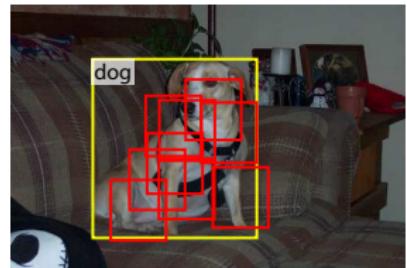
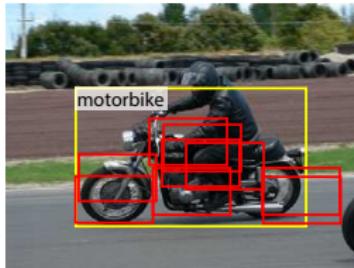
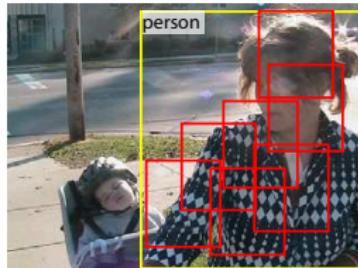
- **standard convolution**: receptive field grows with depth but only linearly, remains rectangular and is translation invariant
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deformable convolution: receptive field (2 layers)



- 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

deformable RoI pooling

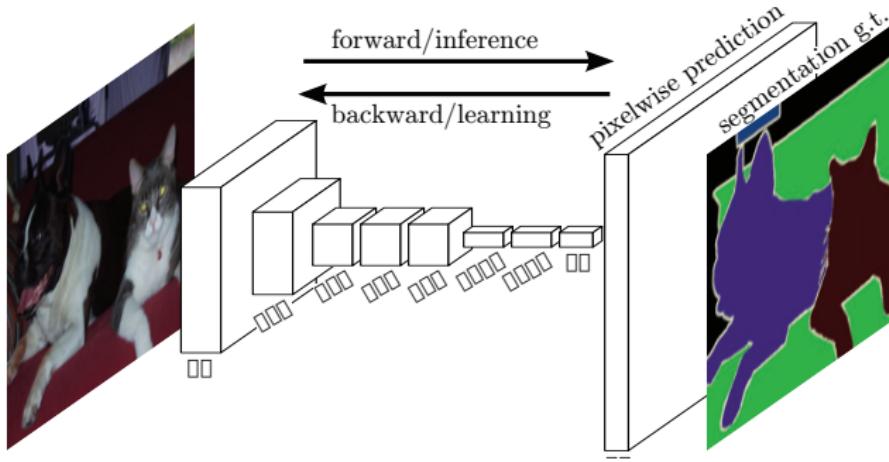


- deformed 3×3 cells (red) for an input RoI (yellow)
- cells adapt to part locations of non-rigid objects

scale and feature pyramids

fully convolutional networks (FCN)

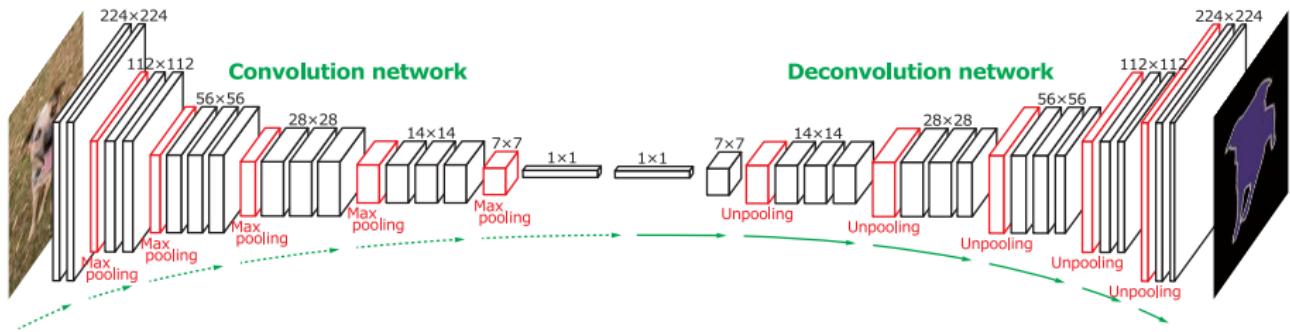
[Long et al. 2015]



- 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**”

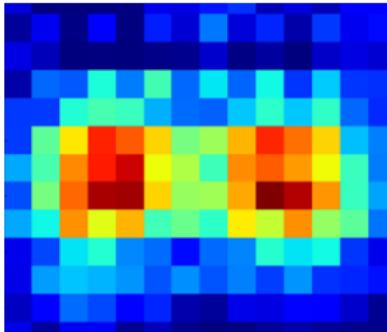
learning to upsample

[Noh et al. 2015]

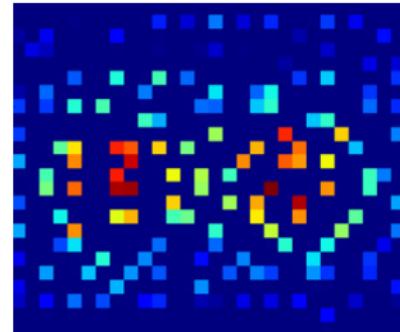


- the upsampling process is improved by learning to invert the max-pooling and convolution operations with unpooling and deconvolution
 - instance-wise segmentation is obtained by applying the network to individual object proposals, as in detection

learning to upsample



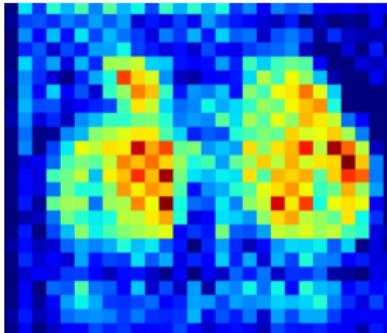
14×14 deconv



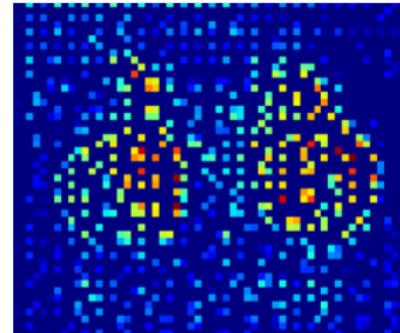
28×28 unpool

- 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

learning to upsample



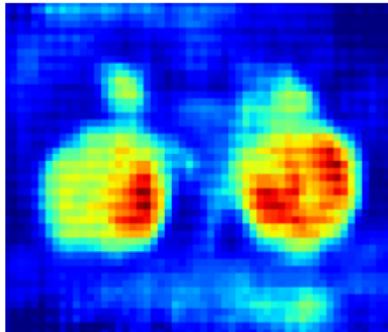
28×28 deconv



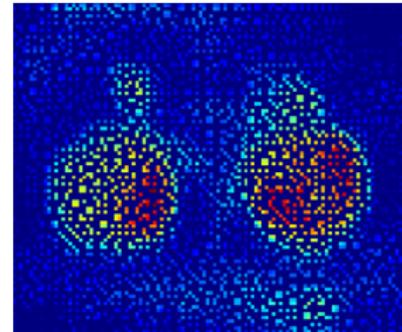
56×56 unpool

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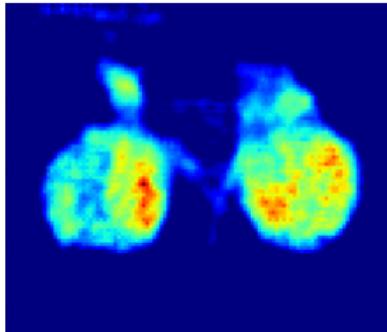
56×56 deconv



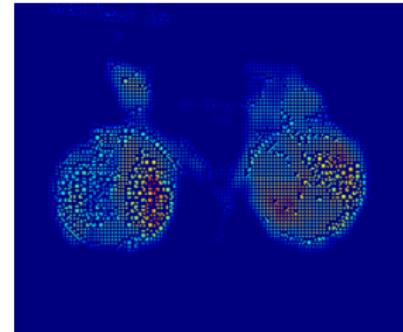
112×112 unpool

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learning to upsample



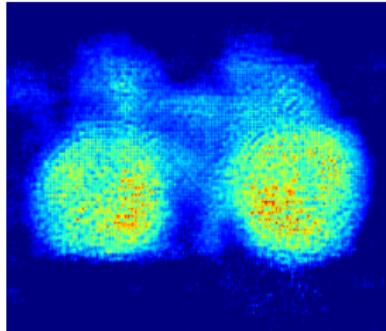
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224×224 unpool

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

network “stages” or “blocks”

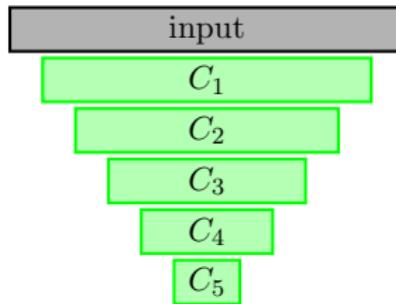
VGG-16

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

ResNet-101

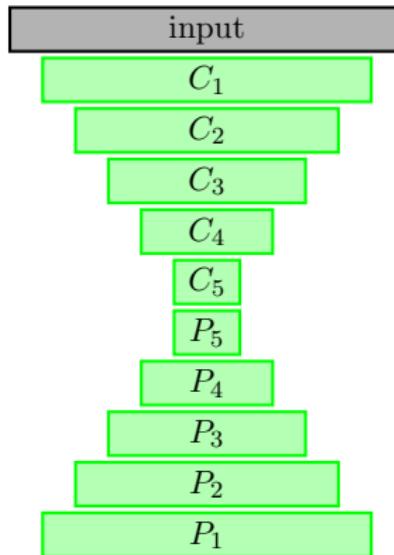
	volume	
	input(224, 3)	$224 \times 224 \times 3$
	conv(7, 64, p3, s2)	$112 \times 112 \times 64$
	pool(3, 2, p1)	$56 \times 56 \times 64$
	3× res(3, (64, 256))	$56 \times 56 \times 256$
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	22× res(3, (256, 1024))	$14 \times 14 \times 1024$
	res(3, (512,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

pyramid networks



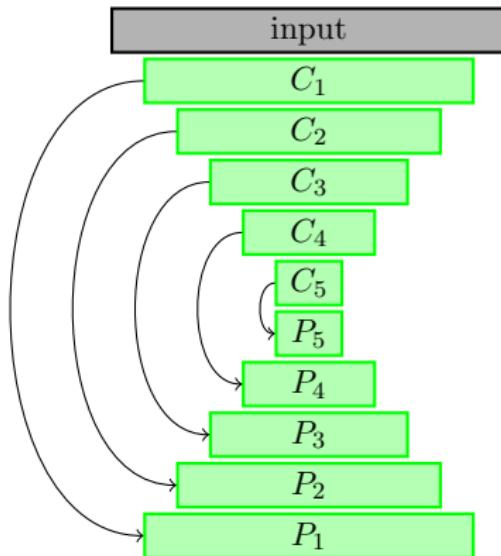
- **bottom-up** path: higher-level features, downsampling
- **top-down** path: still high-level, upsampling
- lateral connections
- predictions from multiple scales

pyramid networks



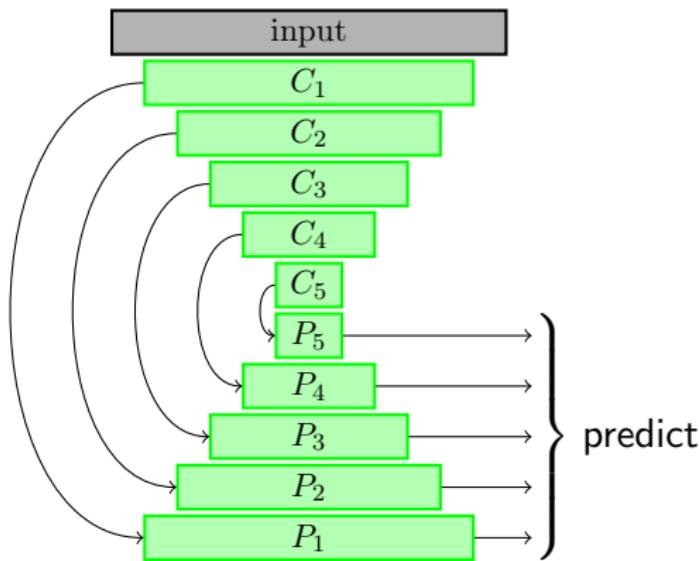
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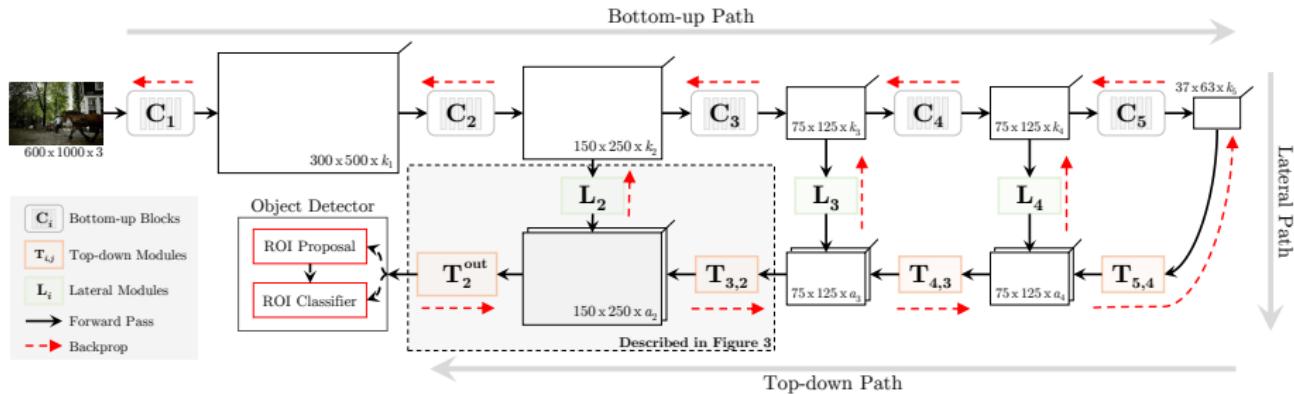
pyramid networks



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- predictions from multiple scales

top-down modulation (TDM)*

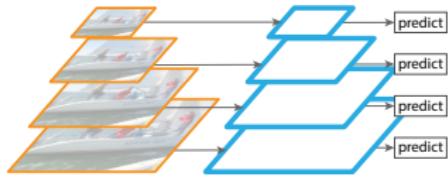
[Shrivastava et al. 2016]



- 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

feature pyramid networks (FPN)

[Lin et al. 2017]

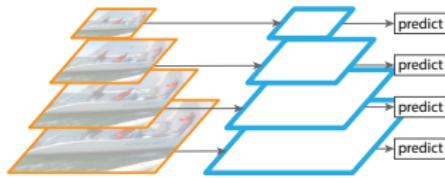


featurized image pyramid

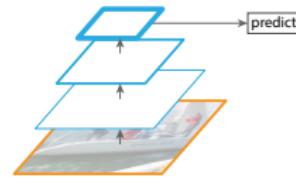
- features computed at each scale independently: **slow**
 - single scale for faster detection
 - reuse pyramidal feature hierarchy as if computed at different scales
 - still fast, but more accurate

feature pyramid networks (FPN)

[Lin et al. 2017]



featurized image pyramid

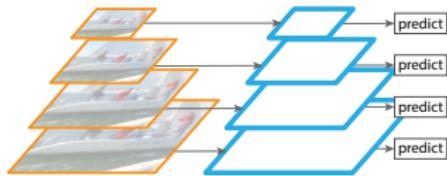


single feature map

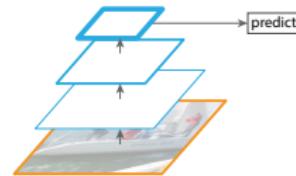
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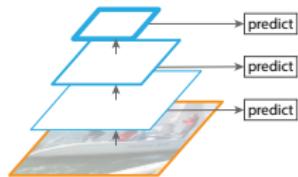
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featurized image pyramid



single feature map



pyramidal feature hierarchy

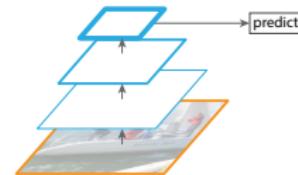
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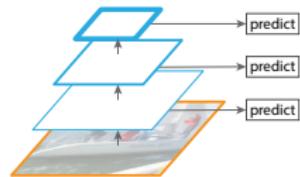
[Lin et al. 2017]



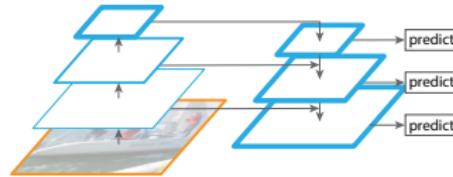
featurized image pyramid



single feature map



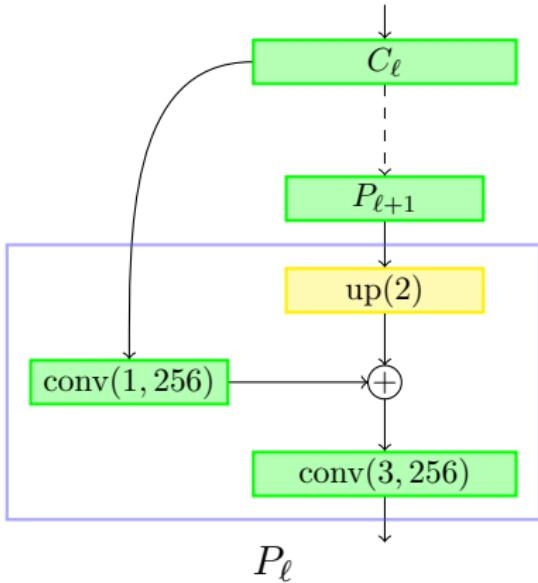
pyramidal feature hierarchy



feature pyramid network

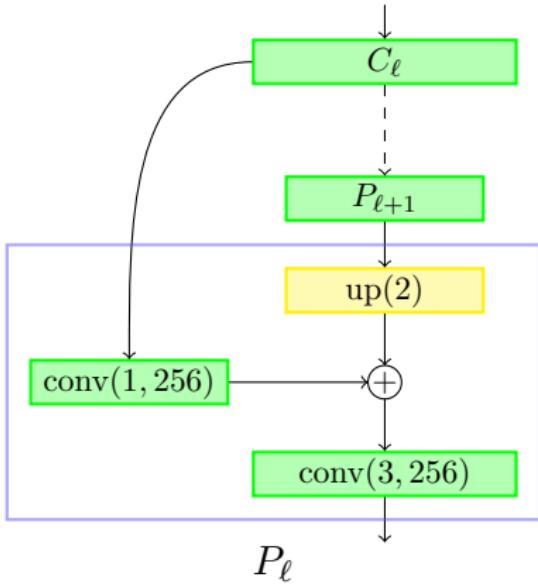
- features computed at each scale independently: **slow**
- single scale for faster detection
- reuse pyramidal feature hierarchy as if computed at different scales
- still fast, but more accurate

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
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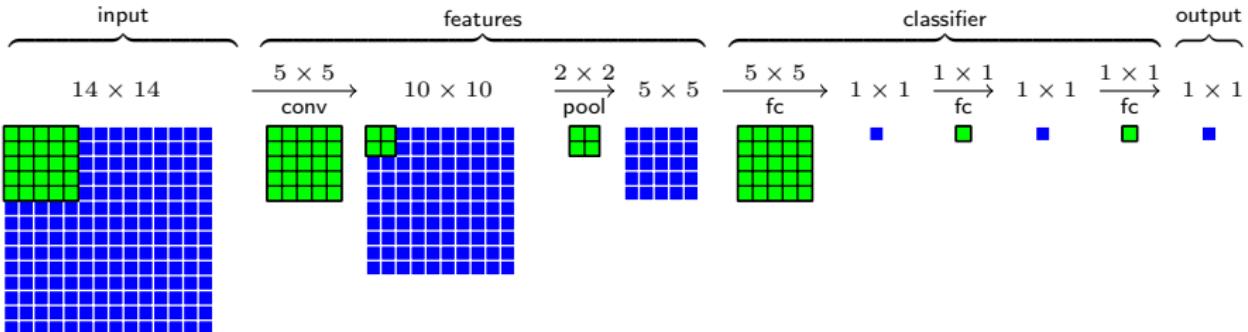
one-stage detection

OverFeat

[Sermanet et al. 2014]

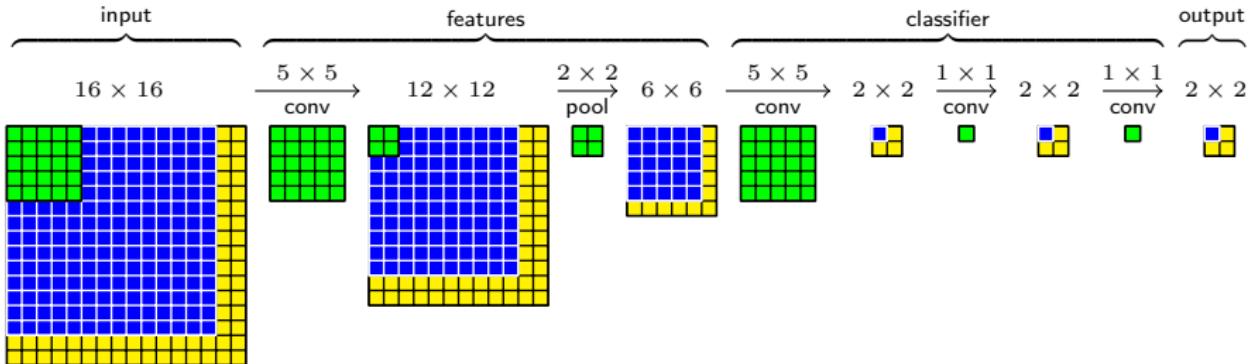
- won the ILSVRC2013 localization competition
- applied a classifier with fully connected layers densely as convolution, allowing region classification without cropping and warping
- increased output resolution with dilated convolution
- merged predictions instead of non-maxima suppression

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

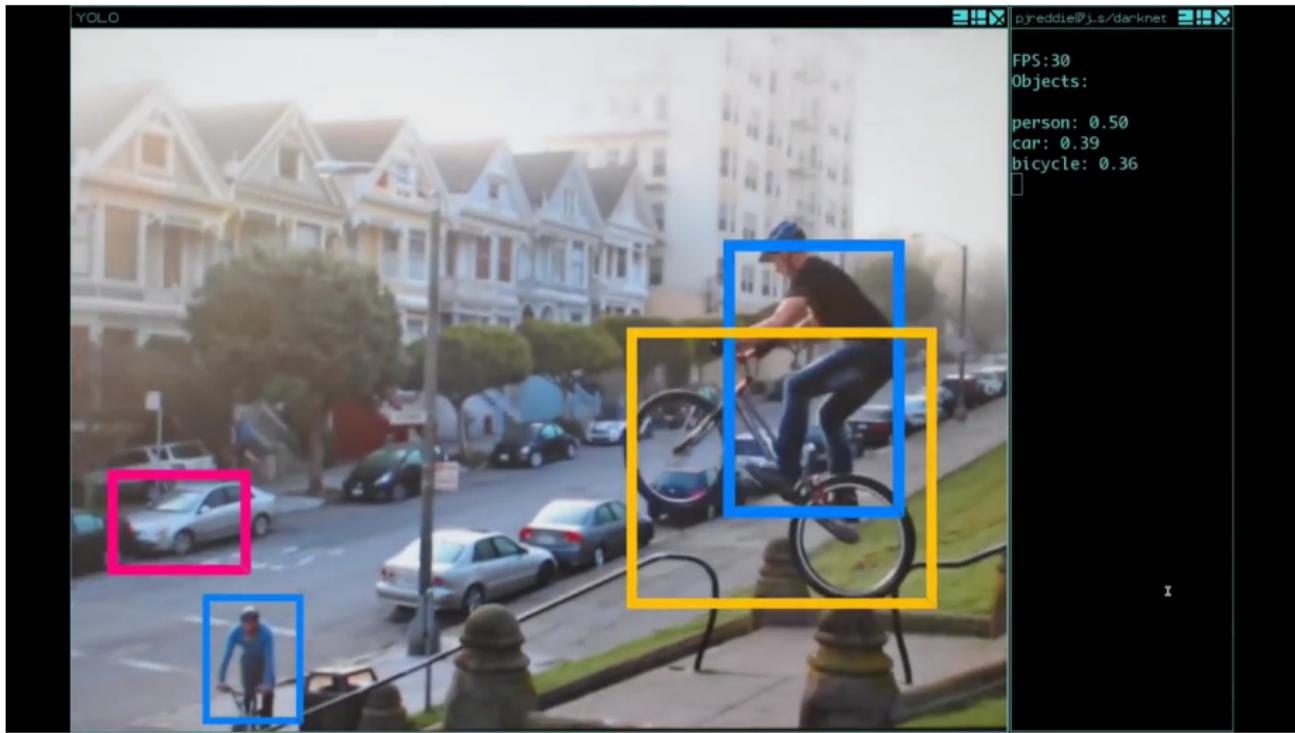
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“you only look once” (YOLO)

[Redmon et al. 2016]

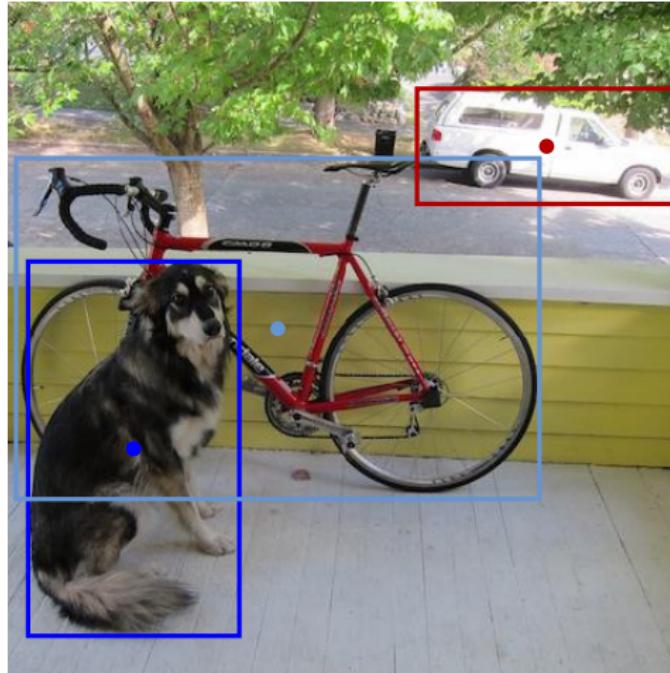


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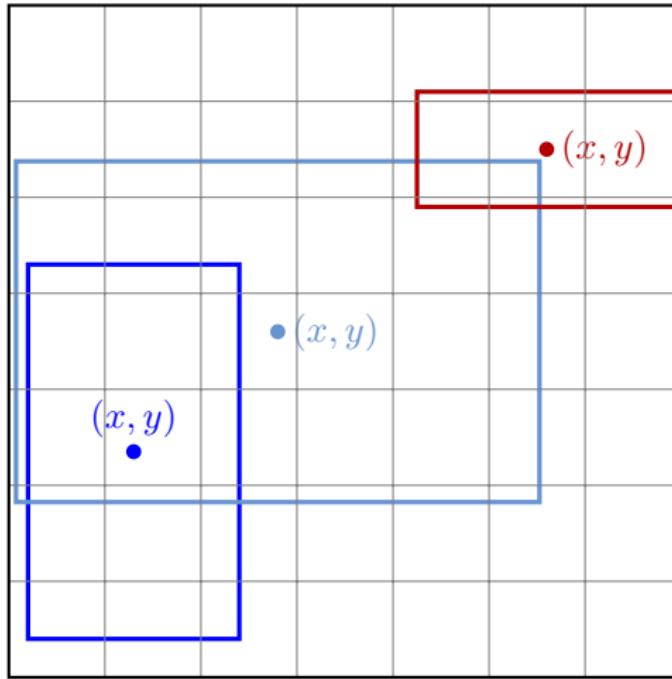
- input image

“you only look once” (YOLO)



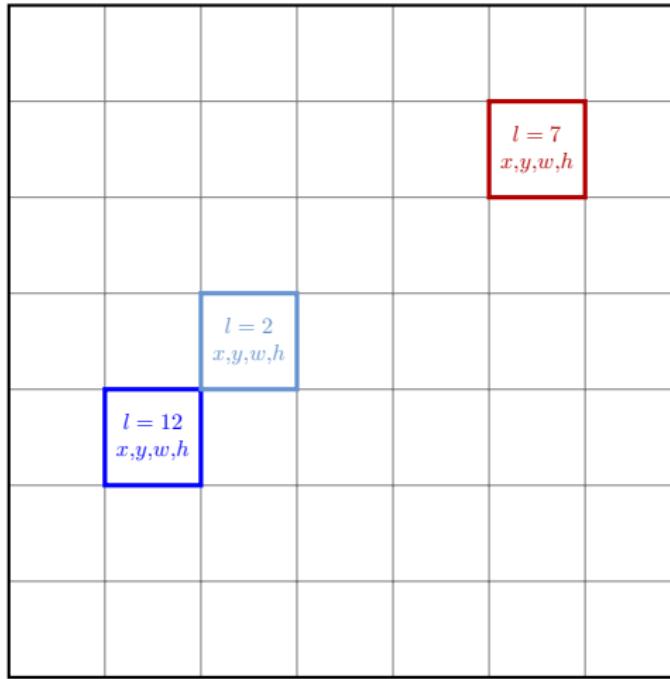
- ground truth bounding boxes and their centers

“you only look once” (YOLO)



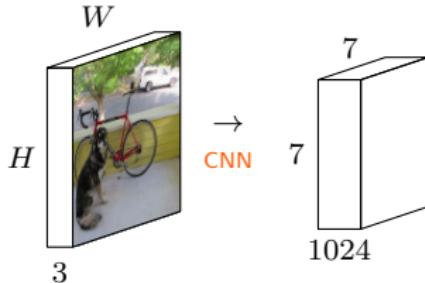
- image partitioned into 7×7 grid and center coordinates assigned to cells

“you only look once” (YOLO)



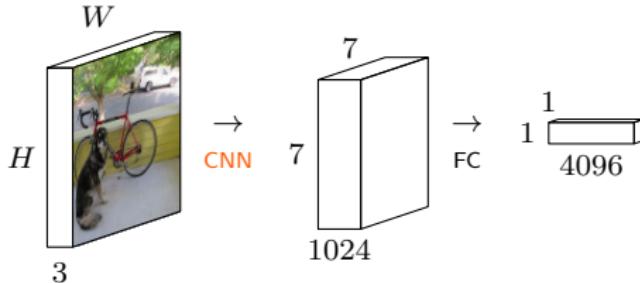
- network learns to predict up to one object per cell, including class label l , center coordinates x, y and bounding box size w, h

“you only look once” (YOLO)



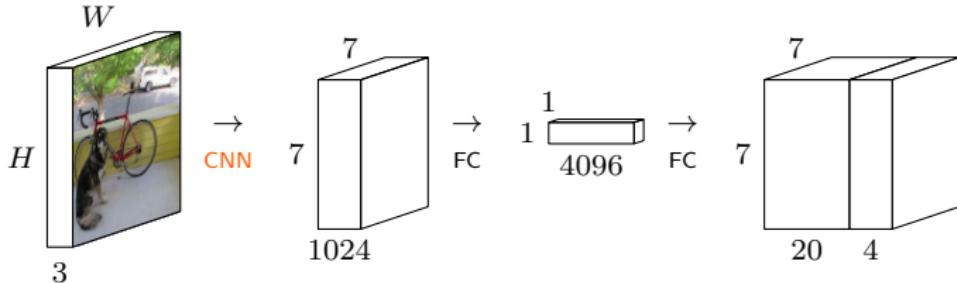
- 3-channel input $W = H = 448$, 24-layer NiN-like network
- fully connected layer, increasing to 4096 features
- $c = 20$ class scores and 4 bounding box coordinates at each position
- in a single stage, network performs regression from the image to a $7 \times 7 \times 24$ tensor encoding detected classes and positions
- regression (ℓ_2) loss on both class scores and coordinates
- “objectness” score makes it look like two-stage

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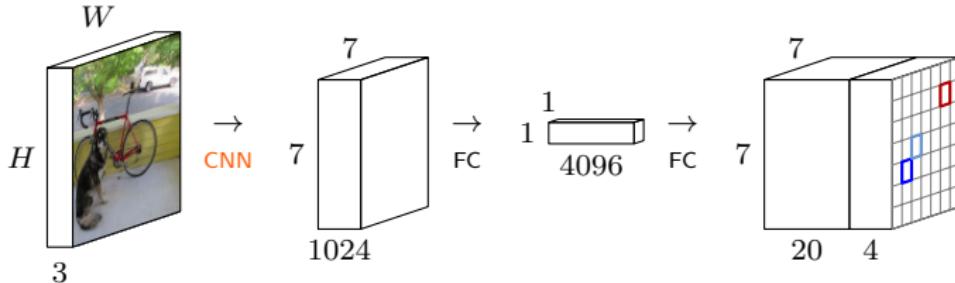
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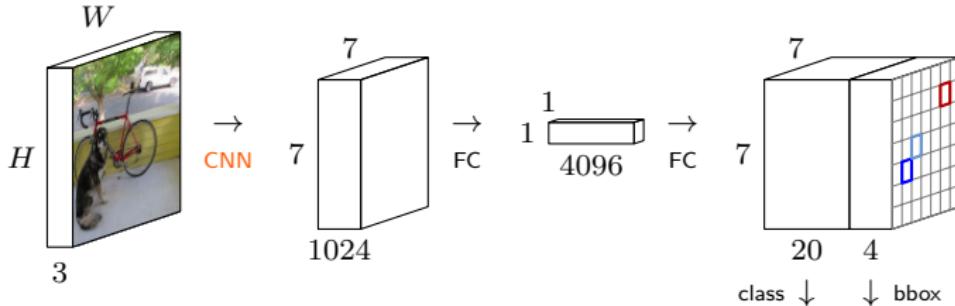
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pros

- **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)

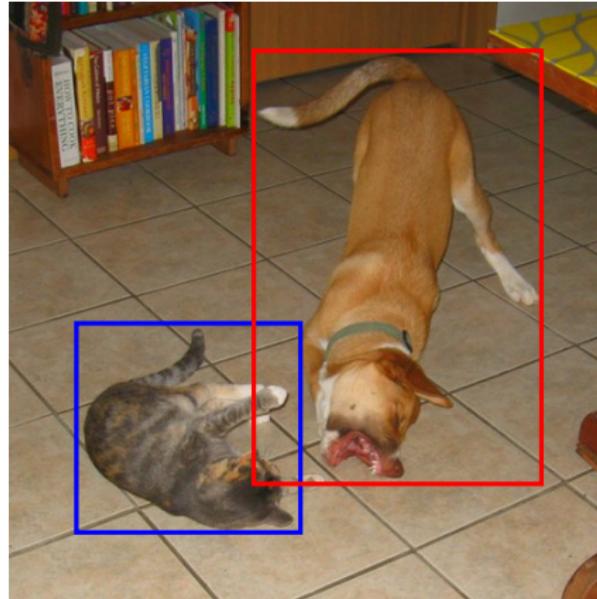
[Liu et al. 2016]



- input image

single shot detector (SSD)

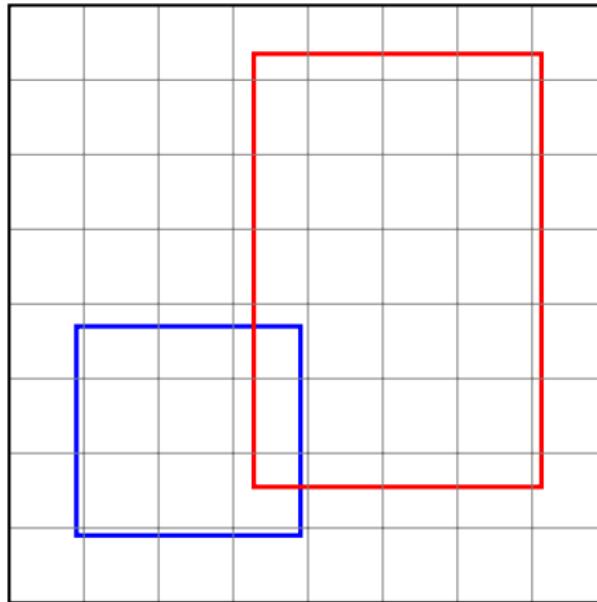
[Liu et al. 2016]



- ground truth bounding boxes

single shot detector (SSD)

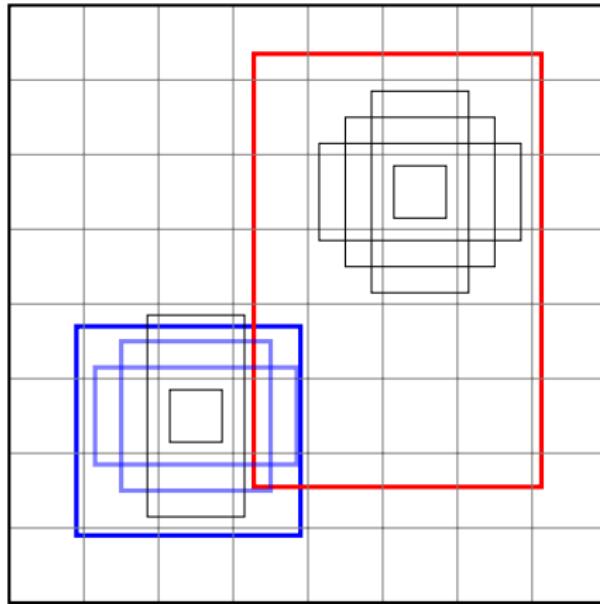
[Liu et al. 2016]



- image partitioned into 8×8 grid

single shot detector (SSD)

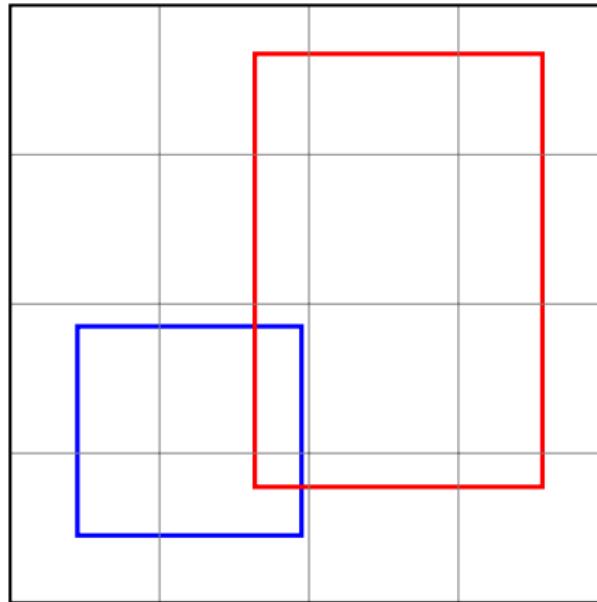
[Liu et al. 2016]



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

single shot detector (SSD)

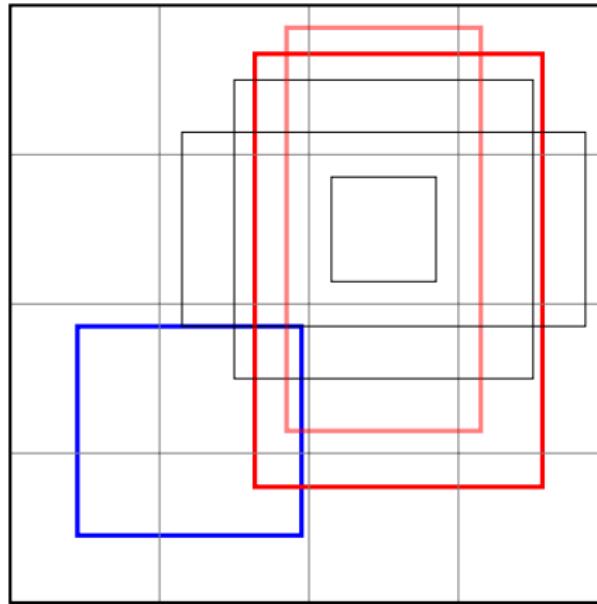
[Liu et al. 2016]



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

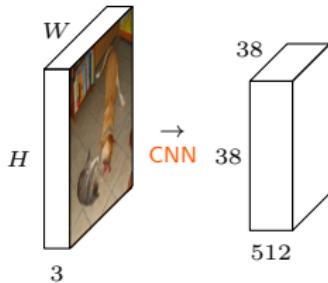
single shot detector (SSD)

[Liu et al. 2016]



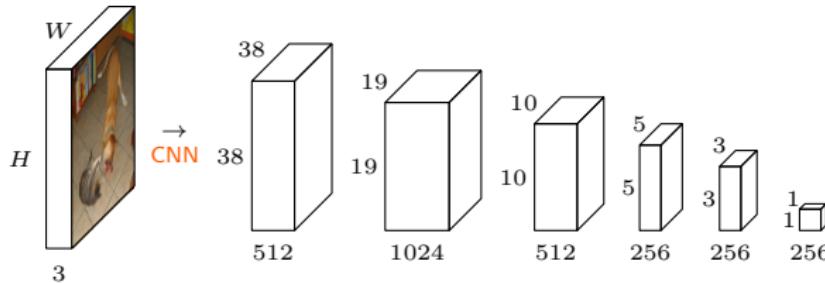
- anchor size is relative to feature map scale

single shot detector (SSD)



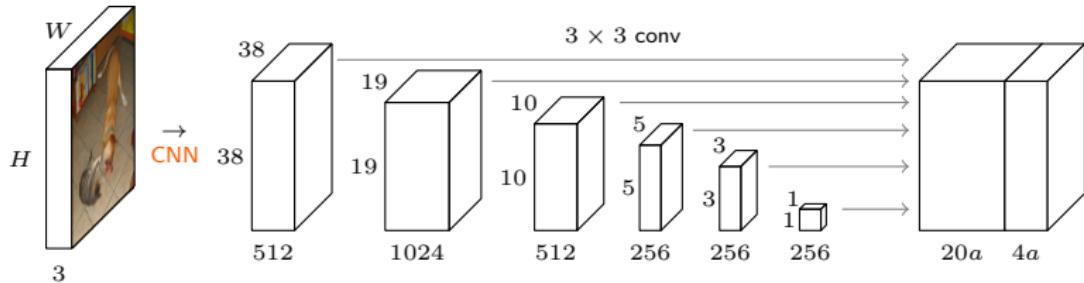
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 - multiple scales by convolutional layers with stride 2
 - $c = 20$ classification scores and 4 bounding box coordinates relative to each of $a = 6$ anchors at each position from each of 6 last layers: 7308 predictions per class
 - softmax on scores,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

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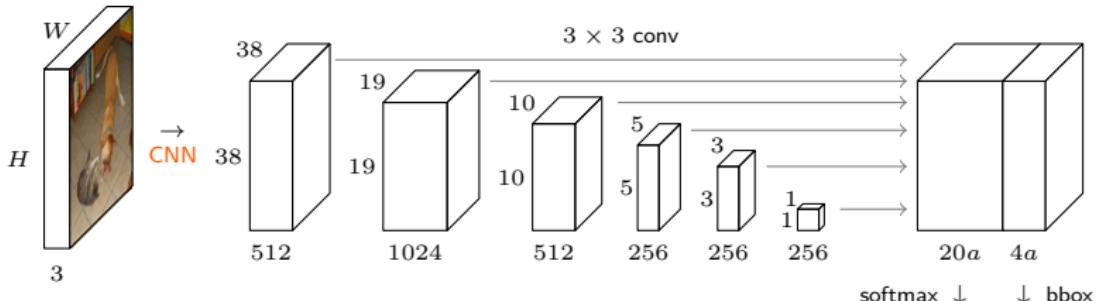
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- best trade-off: 23 (SSD500) or 58fps (SSD300) with performance closer (or superior) to faster R-CNN rather than YOLO
- **many scales** at no extra cost: many more detections compared to YOLO, no need for RoI pooling
- bounding box regression is **convolutional** 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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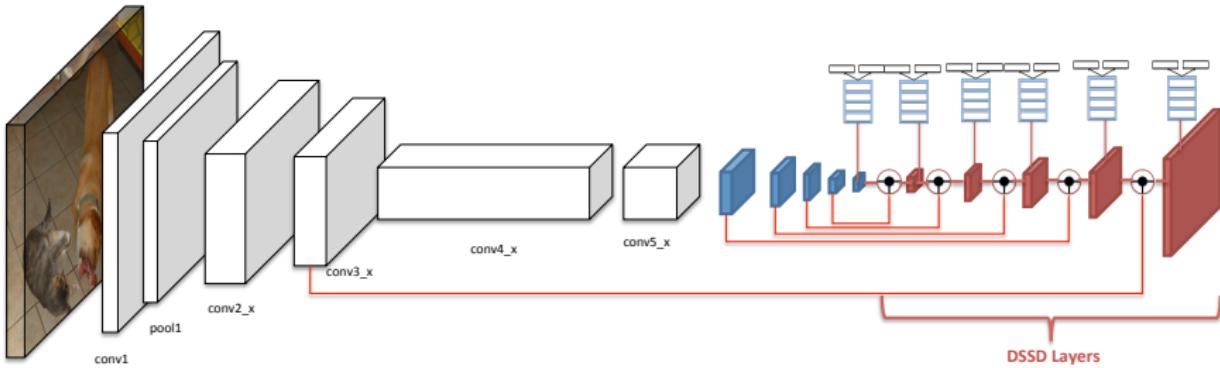
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deconvolutional single shot detector (DSSD)*

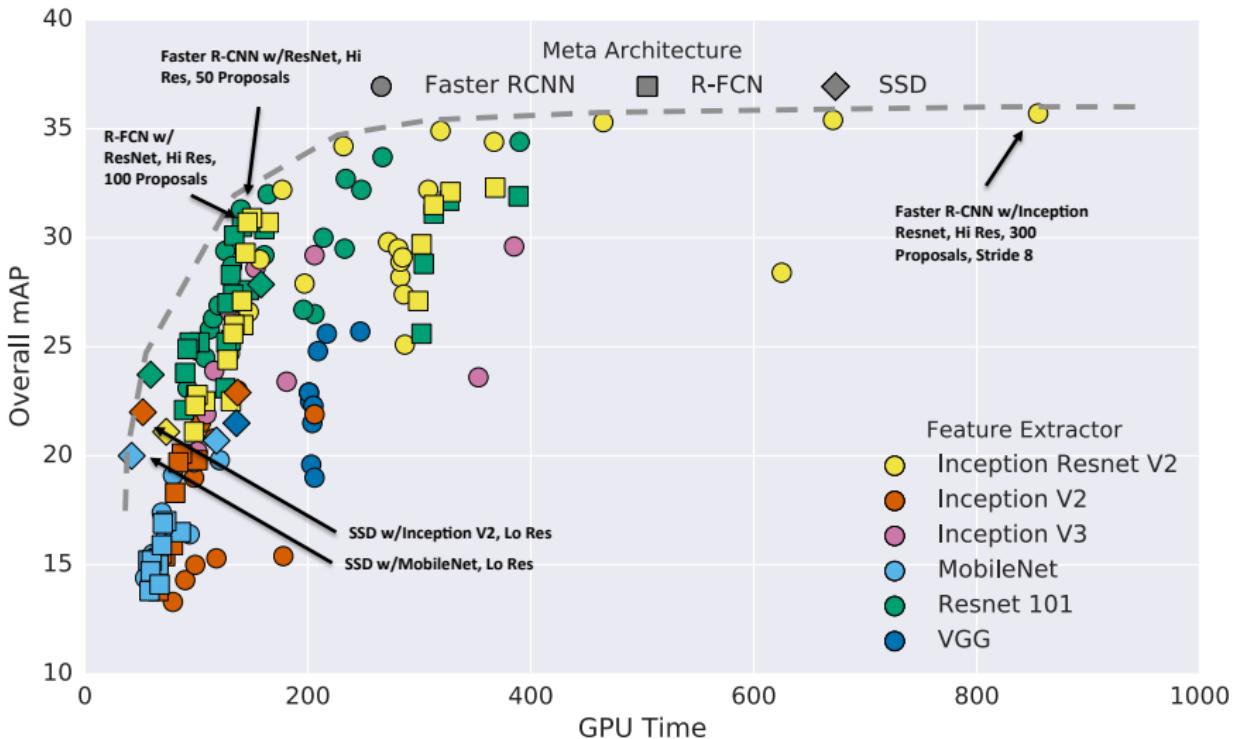
[Fu et al. 2017]



- 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

speed-accuracy trade-offs

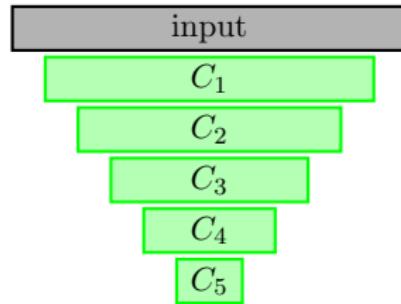
[Huang et al. 2016]



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

RetinaNet

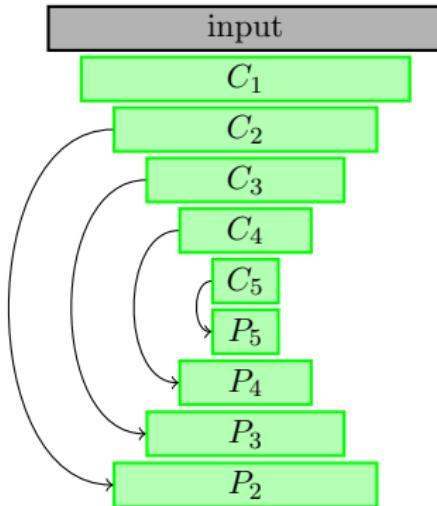
[Lin et al. 2017]



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

RetinaNet

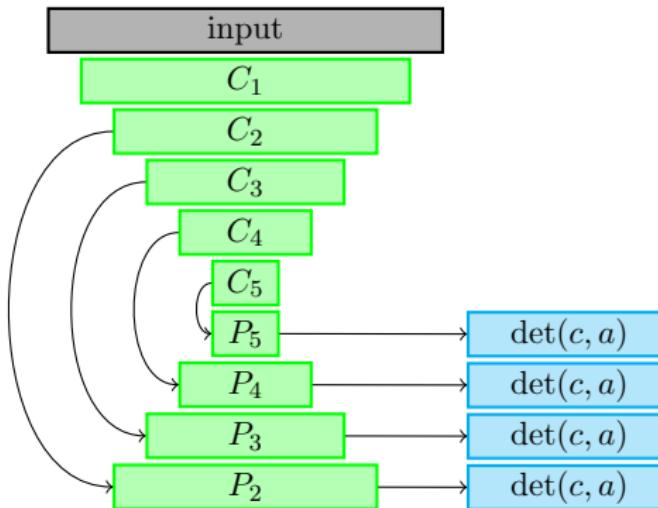
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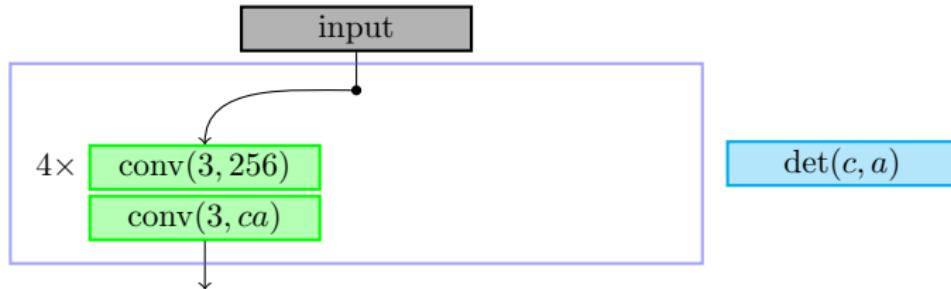
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[Lin et al. 2017]



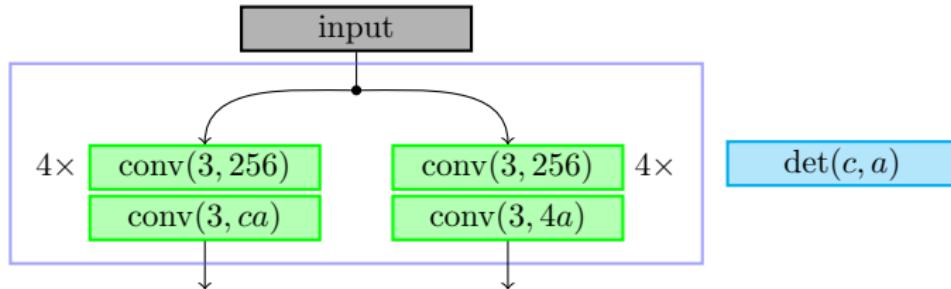
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RetinaNet: dense detection



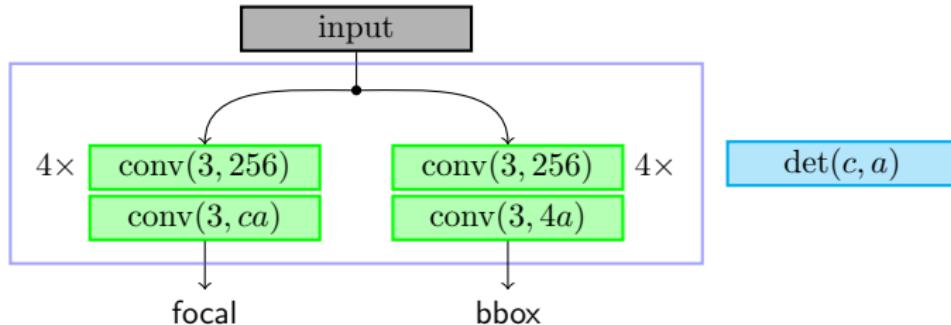
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 - parameters of detection subnets shared across all pyramid levels

RetinaNet: dense detection



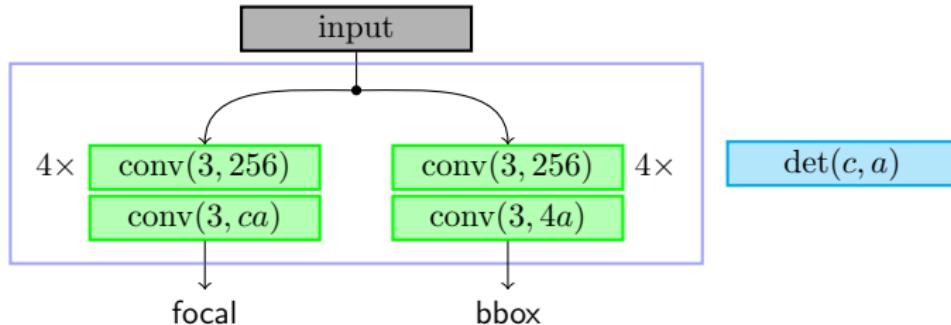
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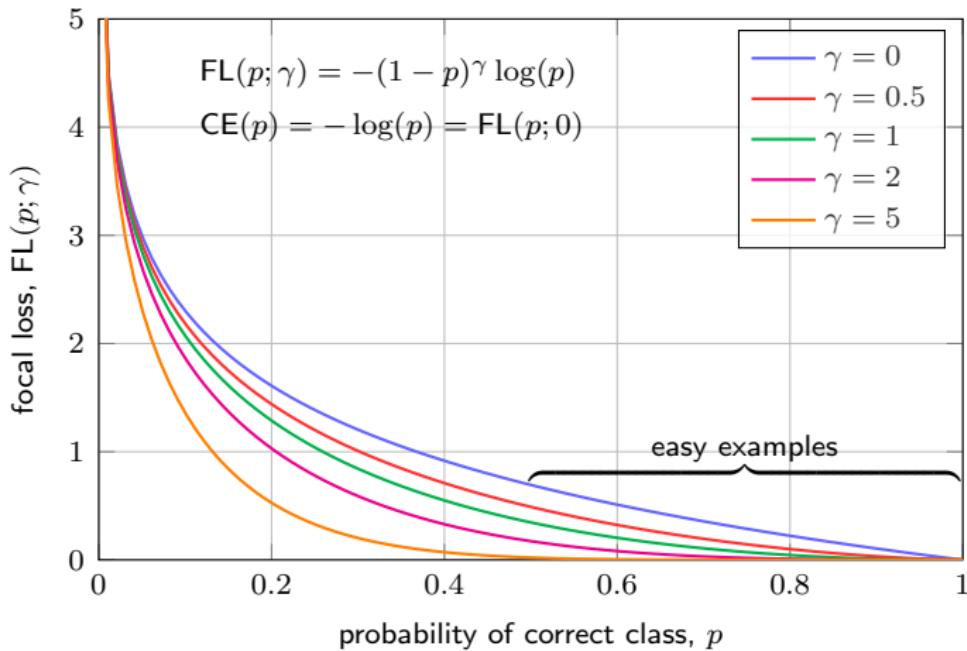
what is wrong with dense detection?

- 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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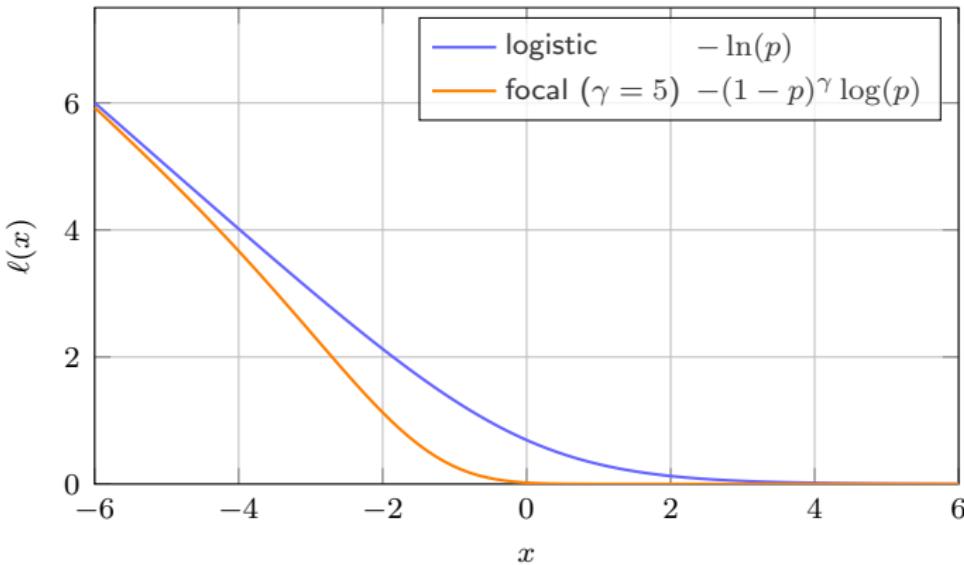
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focal loss



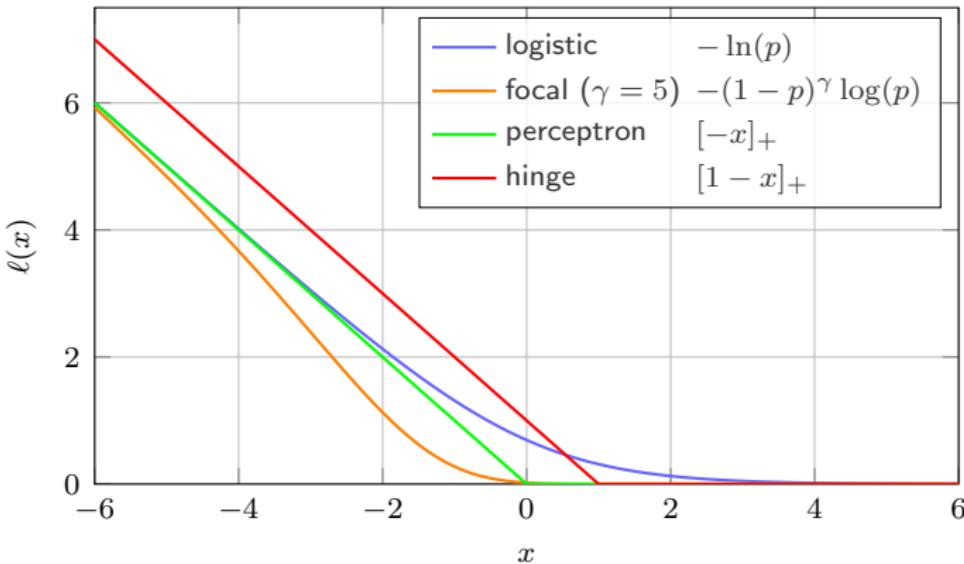
- reduces the relative loss for well-classified examples ($p > 0.5$), putting more focus on hard, misclassified examples

remember the perceptron loss? the margin?



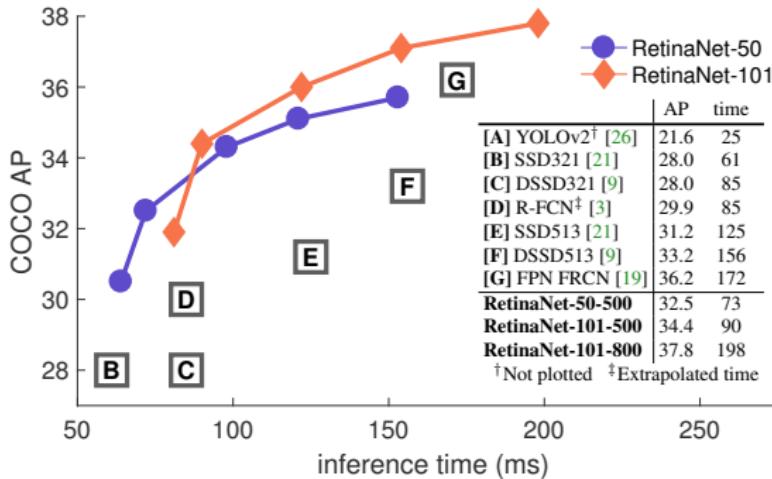
- the probability of the correct class is $p = \sigma(x) = \frac{1}{1+e^{-x}}$, where $x = sa$, $s \in \{-1, 1\}$ is the “sign” target variable, and a the activation
- easy example means $p > 0.5$, or $x > 0$
- perceptron loss is zero for such examples; logistic and hinge are not

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RetinaNet: performance



- 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

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

attention networks*



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

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