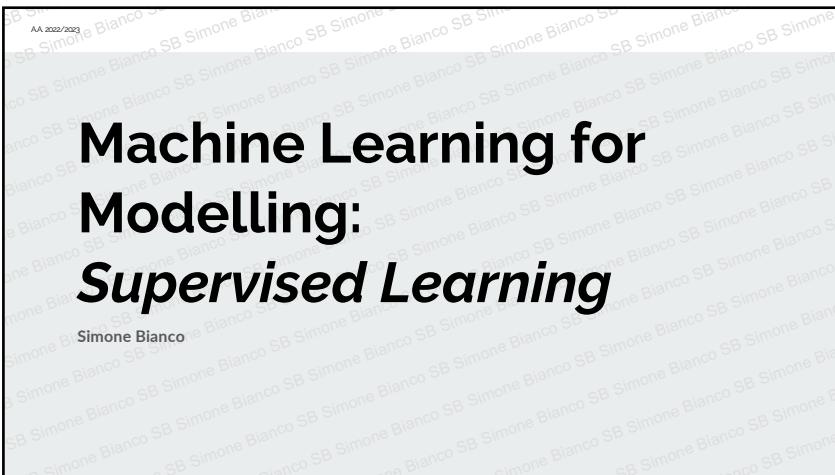


Machine Learning for Modelling: *Supervised Learning*

Simone Bianco



1

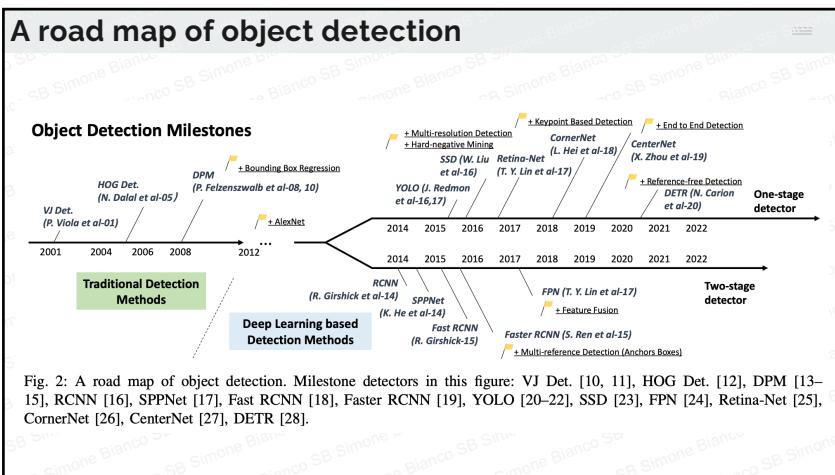
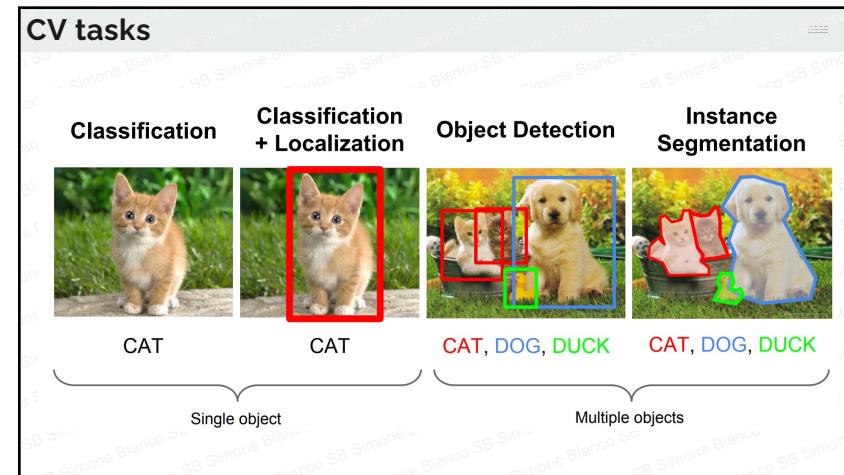
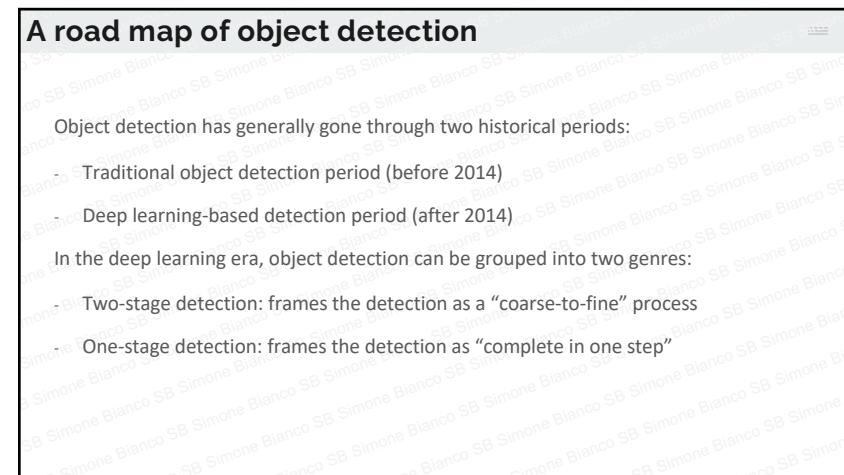


Fig. 2: A road map of object detection. Milestone detectors in this figure: VJ Det. [10, 11], HOG Det. [12], DPM [13–15], RCNN [16], SPPNet [17], Fast RCNN [18], Faster RCNN [19], YOLO [20–22], SSD [23], FPN [24], Retina-Net [25], CornerNet [26], CenterNet [27], DETR [28].



2



4

A road map of object detection

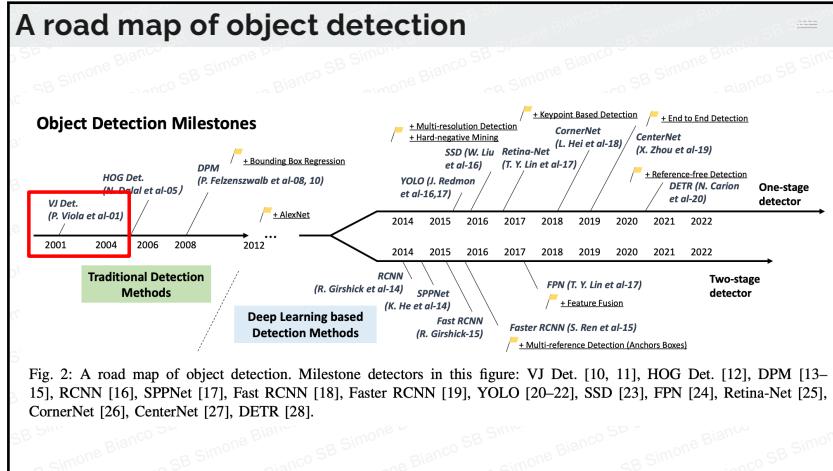


Fig. 2: A road map of object detection. Milestone detectors in this figure: VJ Det. [10, 11], HOG Det. [12], DPM [13–15], RCNN [16], SPPNet [17], Fast RCNN [18], Faster RCNN [19], YOLO [20–22], SSD [23], FPN [24], Retina-Net [25], CornerNet [26], CenterNet [27], DETR [28].

5

A road map of object detection

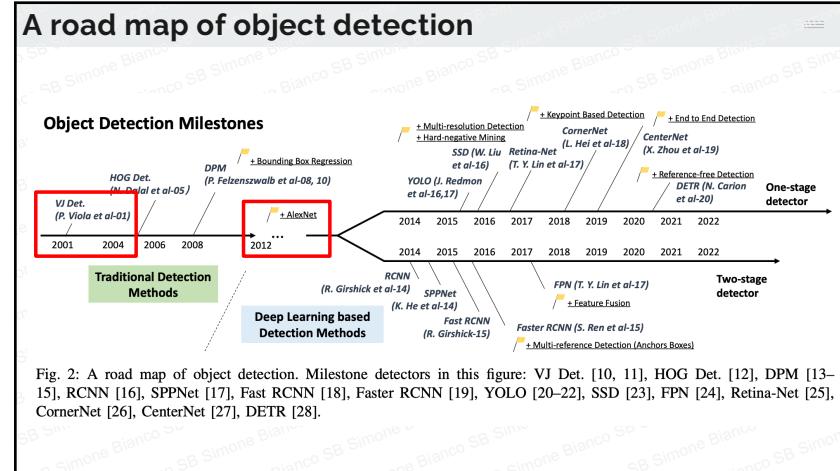
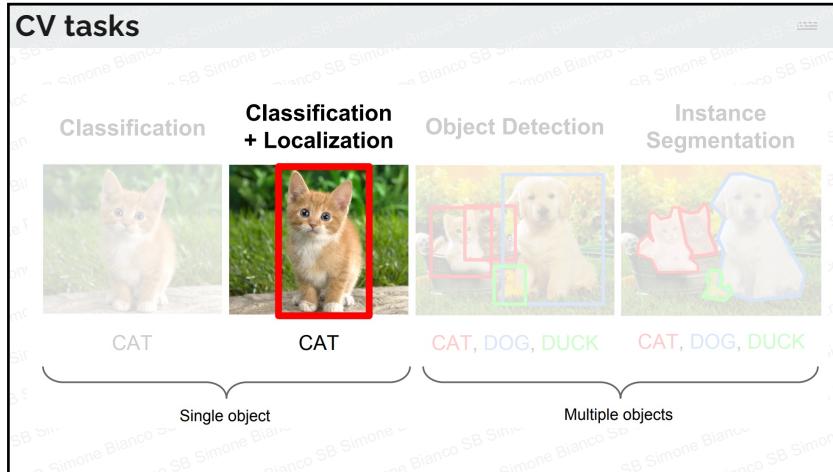


Fig. 2: A road map of object detection. Milestone detectors in this figure: VJ Det. [10, 11], HOG Det. [12], DPM [13–15], RCNN [16], SPPNet [17], Fast RCNN [18], Faster RCNN [19], YOLO [20–22], SSD [23], FPN [24], Retina-Net [25], CornerNet [26], CenterNet [27], DETR [28].

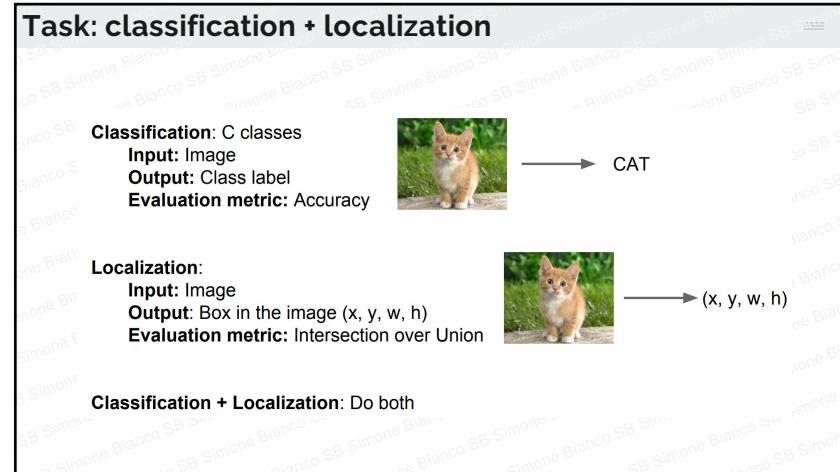
6

CV tasks



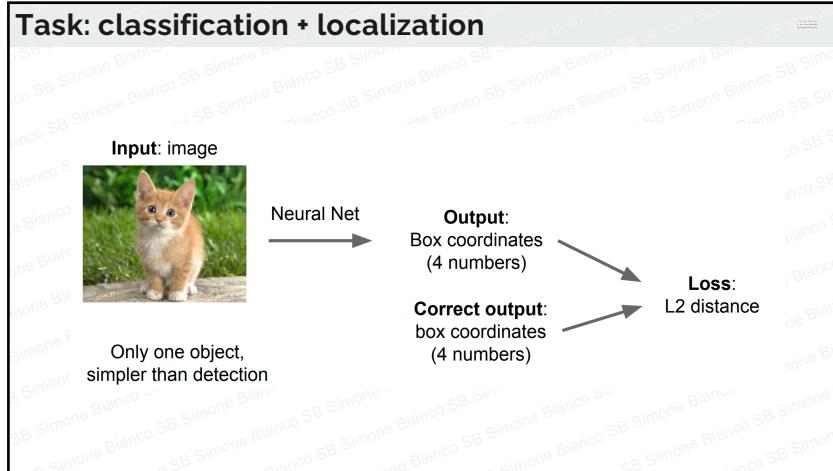
7

Task: classification + localization



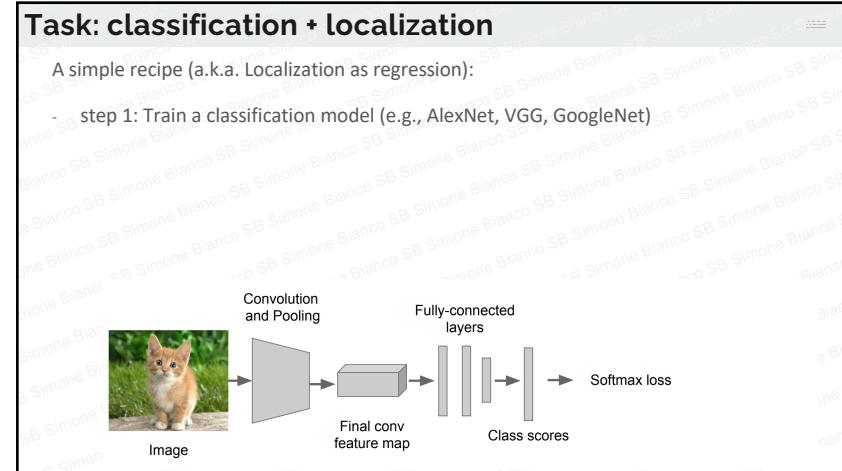
8

Task: classification + localization



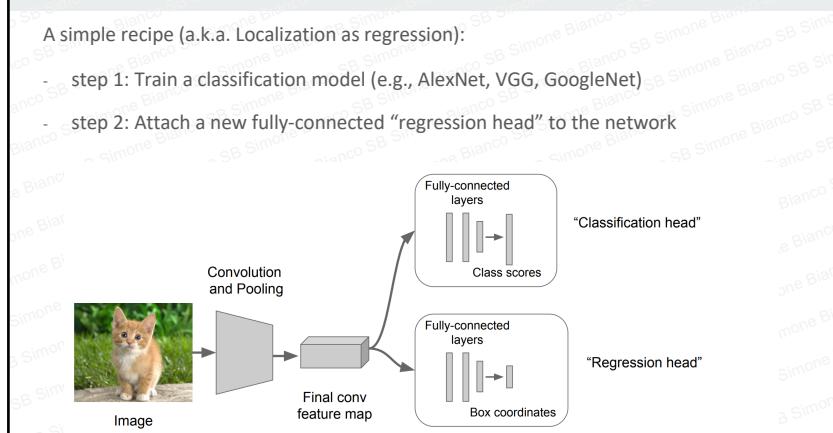
9

Task: classification + localization



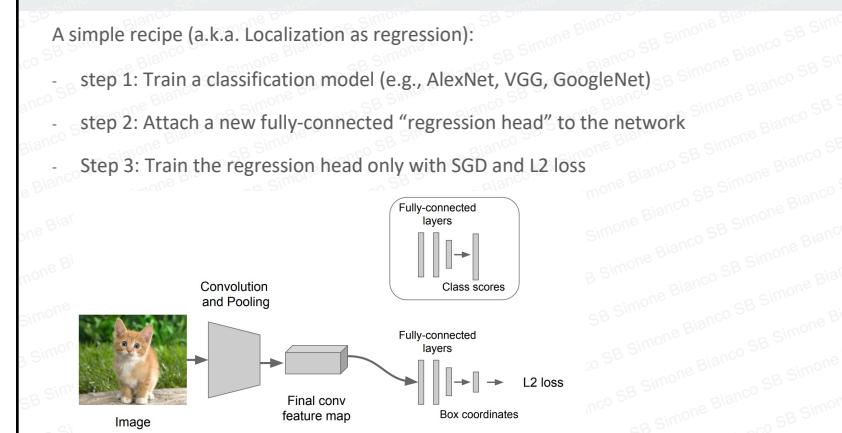
10

Task: classification + localization



11

Task: classification + localization

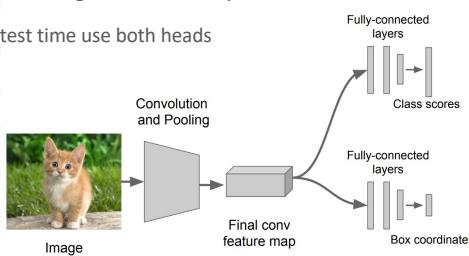


12

Task: classification + localization

A simple recipe (a.k.a. Localization as regression):

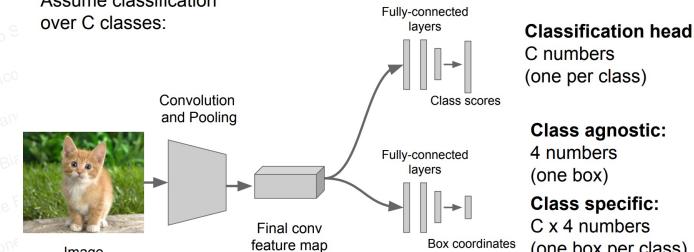
- step 1: Train a classification model (e.g., AlexNet, VGG, GoogleNet)
- step 2: Attach a new fully-connected “regression head” to the network
- Step 3: Train the regression head only with SGD and L2 loss
- Step 4: At test time use both heads



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Per-class vs class agnostic regression

Assume classification over C classes:

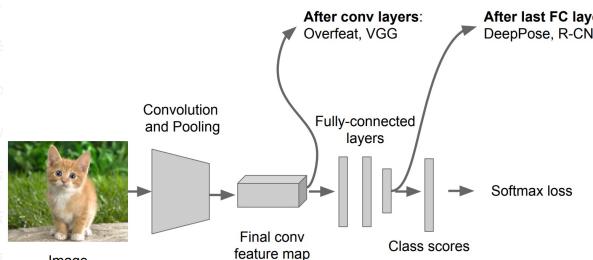


Classification head:
C numbers
(one per class)

Class agnostic:
4 numbers
(one box)
Class specific:
C x 4 numbers
(one box per class)

14

Where to attach the regression head?

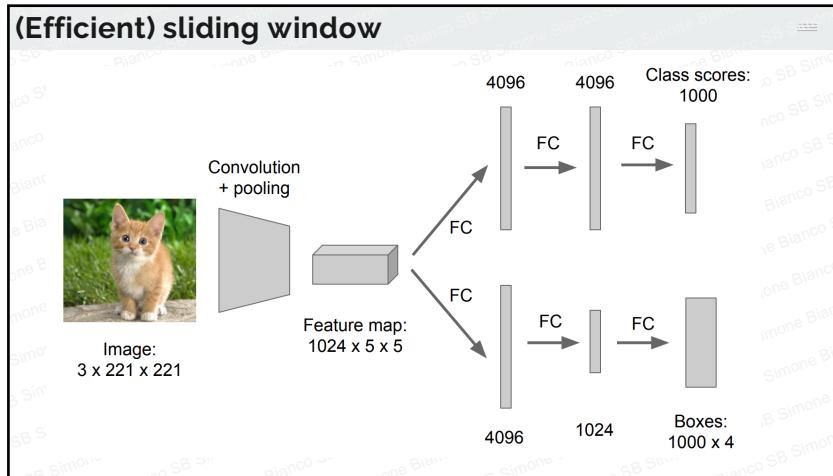


15

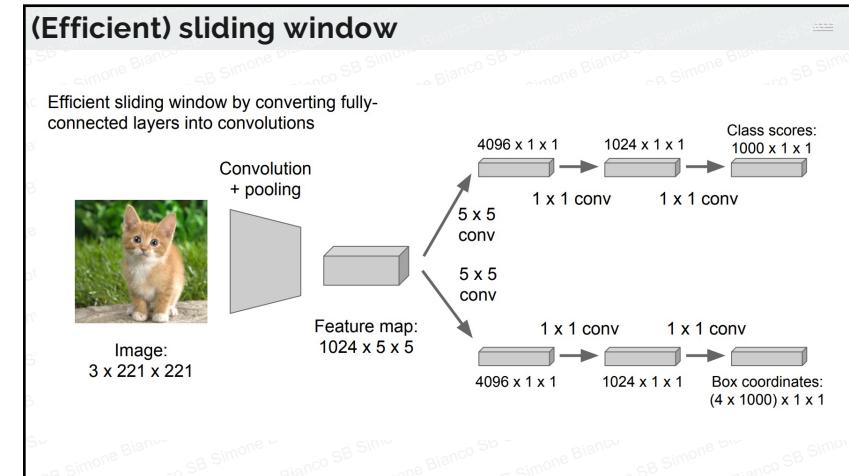
(Efficient) sliding window

- Run classification + regression network at multiple locations on a high-resolution image
- Convert fully-connected layers into convolutional layers for efficient computation
- Combine classifier and regressor predictions across all scales for final prediction

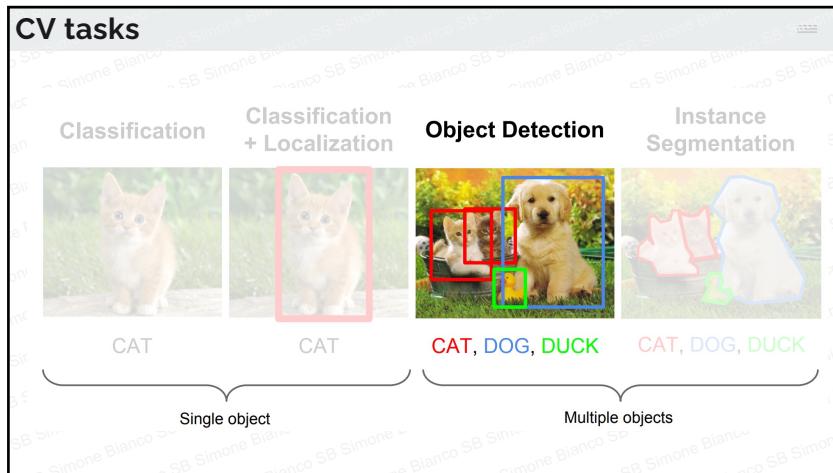
16



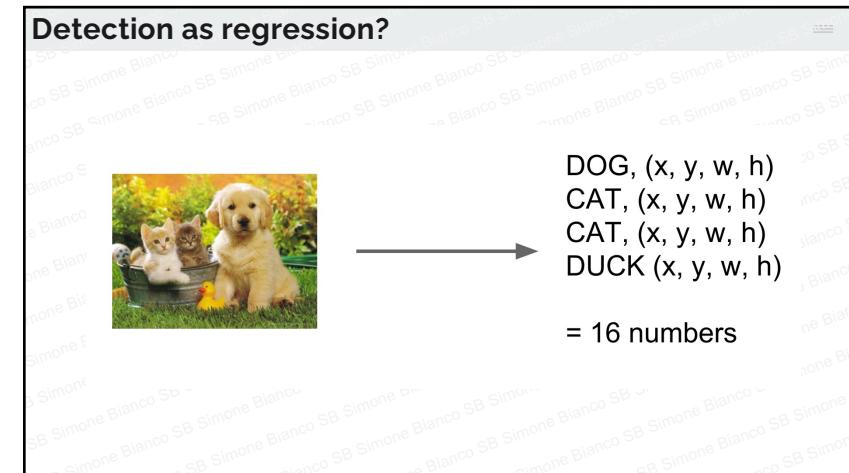
17



18



19



20

Detection as regression?

DOG, (x, y, w, h)
CAT, (x, y, w, h)

= 8 numbers

21

Detection as regression?

CAT, (x, y, w, h)
CAT, (x, y, w, h)
....
CAT (x, y, w, h)

= many numbers

We would need variable sized outputs...

22

Detection as classification

CAT? NO
DOG? NO

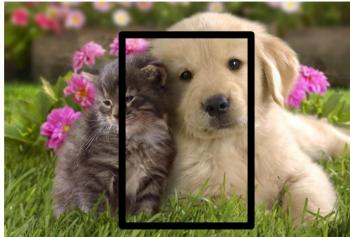
23

Detection as classification

CAT? YES!
DOG? NO

24

Detection as classification



CAT? NO
DOG? NO

25

Detection as classification

- **Problem:** Need to test many positions and scales
- **Solution:** If your classifier is fast enough, just do it

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Detection as classification

- **Problem:** Need to test many positions and scales
- **Solution:** If your classifier is fast enough, just do it

More likely:

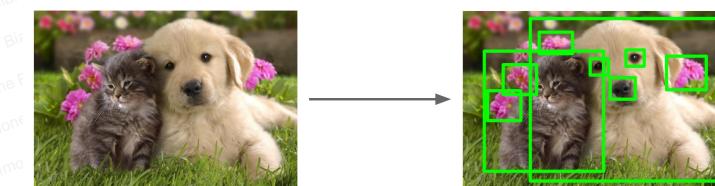
- **Problem:** Need to test many positions and scales, and need to use a computationally demanding classifier (e.g., CNN)
- **Solution:** Only look at a tiny subset of possible positions

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Detection as classification

Region proposals:

- Find “blobby” image regions as the are likely to contain objects
- “Class-agnostic” object detector
- Look for “blob-like” regions



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AA 2022/2023

Region proposals (object proposals)

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Selective search

1. Initial image regions
2. Similarity computation
3. Greedy bottom-up grouping

[1] Uijlings, J. R., van de Sande, K. E., Gevers, T., & Smeulders, A. W. (2013). Selective search for object recognition. *International journal of computer vision*, 104(2), 154-171.

30

Selective search: step 1. Initial image regions

- Graph-based segmentation of the input image
 - Felzenszwalb, P. F. and Huttenlocher, D. P. (2004). Efficient graph-based image segmentation. *International Journal of Computer Vision*, 59(2):167–181.
- Exploiting the concept of **superpixels**

31

Selective search: step 2. Similarity computation

- **Similarity between all pairs of neighboring regions**
- Criteria:
 - **Color:** A color histogram for each color channel is computed.
 - **Texture:** Gaussian derivatives are computed into orientation histograms.
 - **Size:** Smaller regions are given a larger incentive for merging.
 - **Fill:** A pair of regions where one encloses the other, is given higher merging likelihood.

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Selective search: step 3. Greedy bottom-up grouping

- The two most similar regions are merged
- Similarity with the other regions is updated
- The regions with lower rank are removed from the list of generated object proposals.
- Objective: produce multiple overlapping proposals
 - A wheel is an object by itself
 - It is also part of a bigger object «car»



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Selective search: see it in action



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Selective search: see it in action

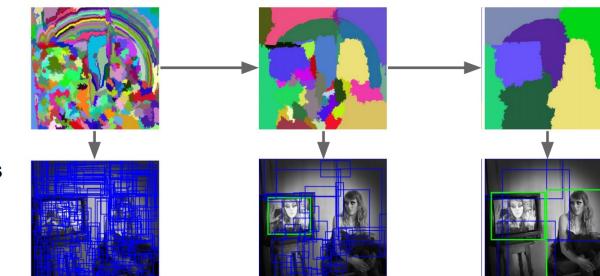


Results in approx. 2k proposals per image

35

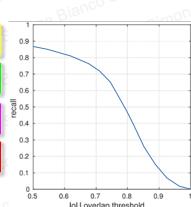
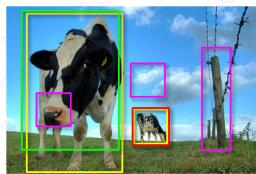
Selective search: see it in action

Bottom-up segmentation, merging regions at multiple scales



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Evaluating object proposals



- Recall only: $\frac{TP}{(TP+FN)}$
 - **True Positives:**
Counted when the proposal overlaps with the ground truth for more than a predefined threshold
 - **False Positives:**
Ignored: that's a problem for the classifier that comes next
- Overlap between 60% and 80% proved to be predictive of detector accuracy, for DPM [1].

[1] Hosang, J., Benenson, R., Dollár, P., & Schiele, B. (2015). What makes for effective detection proposals? arXiv preprint arXiv:1502.05082.

[2] Hosang, J., Benenson, R., & Schiele, B. (2014). How good are detection proposals, really? arXiv preprint arXiv:1406.6962.

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Comparison of object proposals

Method	Approach	Outputs Segments	Outputs Score	Control #proposals	Time (sec)	Repeatability	Recall Results	Detection Results
Bing [18]	Window scoring	✓	✓	✓	0.2	**	*	*
CPMC [19]	Grouping	✓	✓	✓	250	**	**	*
EdgeBoxes [20]	Window scoring	✓	✓	✓	0.3	**	***	***
Endres [21]	Grouping	✓	✓	✓	100	-	***	**
Geodesic [22]	Grouping	✓	✓	✓	1	*	***	**
MCS [23]	Grouping	✓	✓	✓	30	*	***	***
Objectness [24]	Window scoring	✓	✓	✓	3	.	*	.
Raihan [25]	Window scoring	✓	✓	✓	3	.	*	.
RandomizedRPN's [26]	Grouping	✓	✓	✓	1	*	*	**
Rantalanikka [27]	Grouping	✓	✓	✓	10	**	.	**
Rigor [28]	Grouping	✓	✓	✓	10	*	**	**
SelectiveSearch [29]	Grouping	✓	✓	✓	10	**	***	***
	Gaussian		✓		0	.	.	*
	SlidingWindow		✓		0	***	.	.
	Superpixels	✓			1	*	.	.
	Uniform				0	.	.	.

Table 1: Comparison of different detection proposal methods. Grey check-marks indicate that the number of proposals is controlled by indirectly adjusting parameters. Repeatability, quality, and detection rankings are provided as rough summary of the experimental results: “-” indicates no data, “*”, “**”, “***”, “****” indicate progressively better results. These guidelines were obtained based on experiments presented in sections §3, §4, and §5, respectively.

Summary and all citations from [1]:
[1] Hosang, J., Benenson, R., Dollár, P., & Schiele, B. (2015). What makes for effective detection proposals? arXiv preprint arXiv:1502.05082.

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R-CNN (Regions with CNN features)

- Semi-neural approach for object detection:
 - Object proposal from Selective Search (non-neural)
 - Classification of each candidate using neural features



Girshick, R., Donahue, J., Darrell, T., & Malik, J. (2014). Rich feature hierarchies for accurate object detection and semantic segmentation. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 580-587).

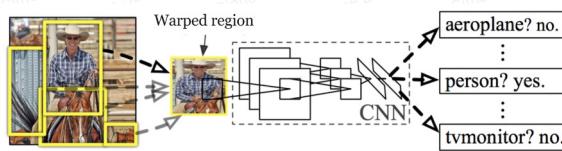
Region-based convolutional neural networks (R-CNN)

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R-CNN: Classification step

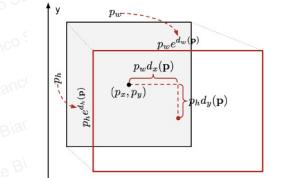
- Each candidate is warped to a common size
- Neural features are extracted from each candidate
 - Alexnet pretrained on IMAGENET (1000 classes)
 - Alexnet fine-tuned on the domain of interest
- Support Vector Machine (SVM) for final classification
 - Uses neural features as input
 - Binary classification for each possible class (+ unknown class)



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R-CNN: Extra step 1: Bounding box regression

- Estimate a correction for the candidate location:
 - Scale-invariant transformation for the bounding box center
 - Log-scale transformation for the bounding box sizes (height and width)



Input: candidate coordinates

$$\mathbf{p} = (p_x, p_y, p_w, p_h)$$

Output: corrected coordinates

$$\mathbf{g} = (g_x, g_y, g_w, g_h)$$

$$t_x = (g_x - p_x)/p_w$$

$$t_y = (g_y - p_y)/p_h$$

$$t_w = \log(g_w/p_w)$$

$$t_h = \log(g_h/p_h)$$

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R-CNN: Extra step 2: Non-maximum suppression

- Objective: remove multiple bounding boxes for the same object
- 1. Sort all the bounding boxes by confidence score
- 2. Discard boxes with low confidence scores
- 3. Greedily select the one with the highest score
- 4. Discard boxes with high overlap with previously selected one



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R-CNN: Extra step 3: Hard negative mining

- Automatically select useful negative samples
 - e.g., if I want to find a face:
 - A plain region in the sky is an **easy** negative (useless)
 - A face-looking pattern in foliage is a **hard** negative

1. Train the model with **random** negatives
2. Run the model on an annotated validation set
3. Select all false positives as (hard) negative examples

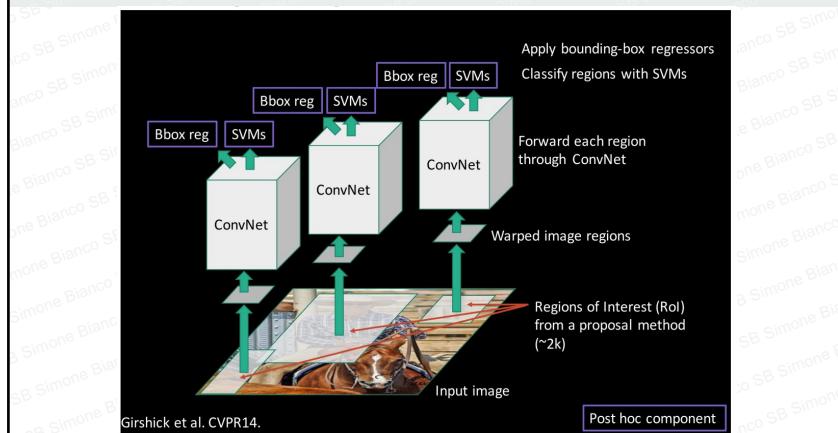
- Be careful!

The validation set must be exhaustively annotated!



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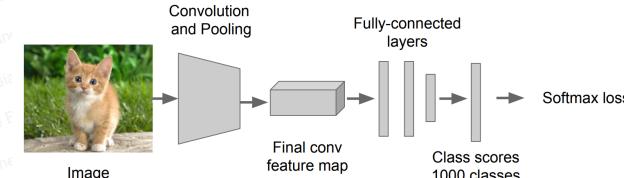
R-CNN: putting all together



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R-CNN training

Step 1: Train a classification model for ImageNet (AlexNet)



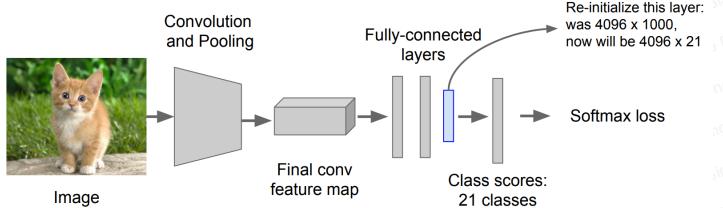
46

R-CNN training

Step 1: Train a classification model for ImageNet (AlexNet)

Step 2: Fine-tune model for detection:

- Instead of 1000 ImageNet classes, want 20 object classes + background
- Throw away final fully-connected layer, reinitialize from scratch
- Keep training model using positive/negative regions from detection images



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R-CNN training

Step 3: Extract features:

- Extract region proposals for all images
- For each region: warp to CNN input size, run forward through CNN, save pool5 features to disk

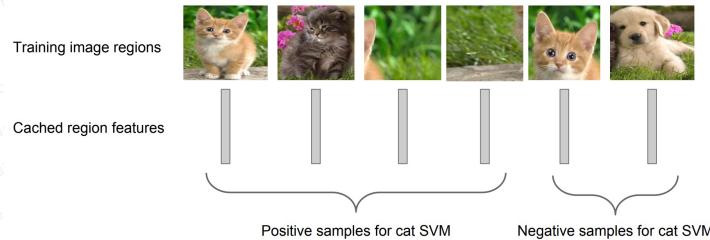


48

R-CNN training

Step 3: Extract features:

- Extract region proposals for all images
 - For each region: warp to CNN input size, run forward through CNN, save pool5 features to disk
- Step 4: Train one binary SVM per class (OVA) to classify region features

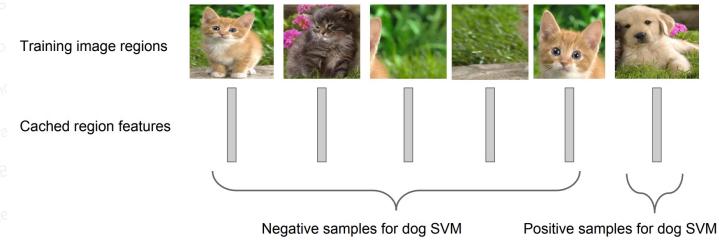


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R-CNN training

Step 3: Extract features:

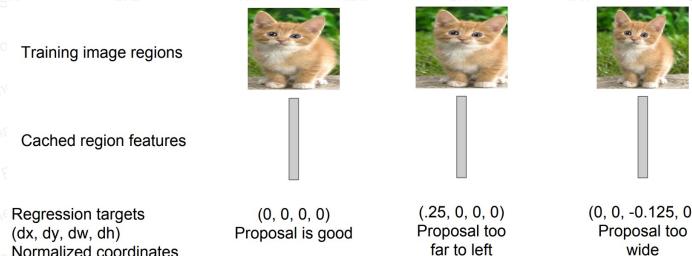
- Extract region proposals for all images
 - For each region: warp to CNN input size, run forward through CNN, save pool5 features to disk
- Step 4: Train one binary SVM per class (OVA) to classify region features



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R-CNN training

Step 5 (bbox regression): For each class, train a linear regression model to map from cached features to offsets to GT boxes to cope for "slightly wrong" proposals



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Object detection: Datasets

	PASCAL VOC (2010)	ImageNet Detection (ILSVRC 2014)	MS-COCO (2014)
Number of classes	20	200	80
Number of images (train + val)	~20k	~470k	~120k
Mean objects per image	2.4	1.1	7.2

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Object detection: Datasets

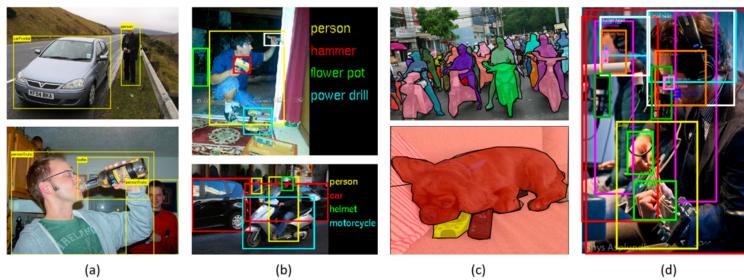


Fig. 4. Some example images and annotations in (a) PASCAL-VOC07, (b) ILSVRC, (c) MS-COCO, and (d) Open Images.

Object detection: Datasets

Dataset	train		validation		trainval		test	
	images	objects	images	objects	images	objects	images	objects
VOC-2007	2,501	6,301	2,510	6,307	5,011	12,608	4,952	14,976
VOC-2012	5,717	13,609	5,823	13,841	11,540	27,450	10,991	-
ILSVRC-2014	456,567	478,807	20,121	55,502	476,688	534,309	40,152	-
ILSVRC-2017	456,567	478,807	20,121	55,502	476,688	534,309	65,500	-
MS-COCO-2015	82,783	604,907	40,504	291,875	123,287	896,782	81,434	-
MS-COCO-2018	118,287	860,001	5,000	36,781	123,287	896,782	40,670	-
OID-2018	1,743,042	14,610,229	41,620	204,621	1,784,662	14,814,850	125,436	625,282

TABLE 1
Some well-known object detection datasets and their statistics.

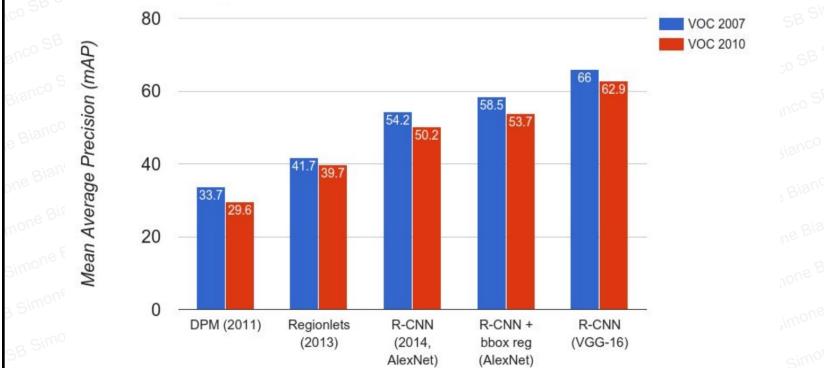
53

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Object detection: Evaluation

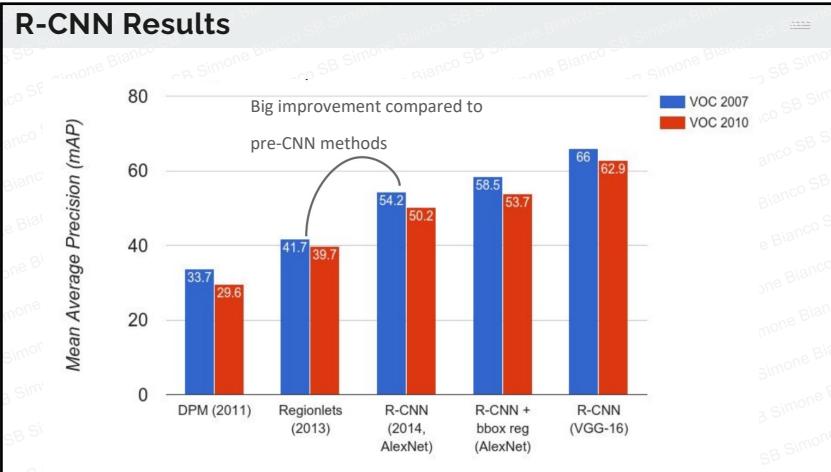
- We use a metric called “mean average precision” (mAP)
- Compute average precision (AP) separately for each class, then average over classes
- (Combine all detections from all test images to draw a precision/recall curve for each class; AP is area under the curve)
- A detection is a true positive if it has an IoU with a ground-truth box greater than some threshold (usually 0.5) → we talk about mAP @ 0.5
- mAP is a number from 0 to 100, where higher is better

R-CNN Results

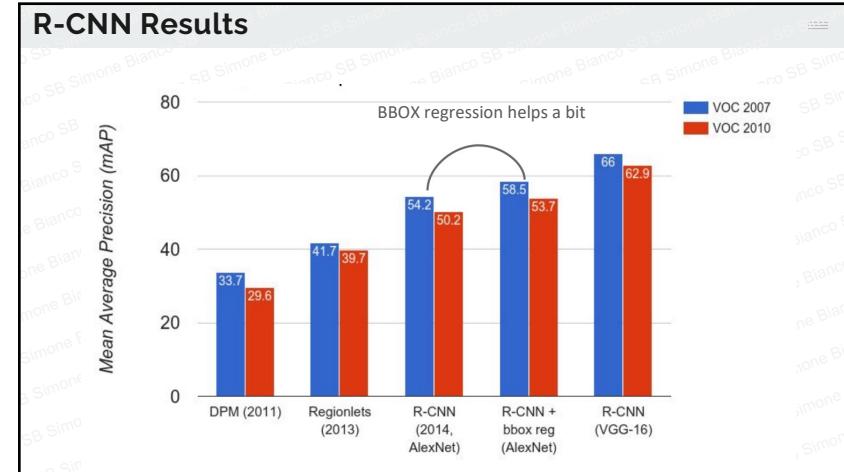


55

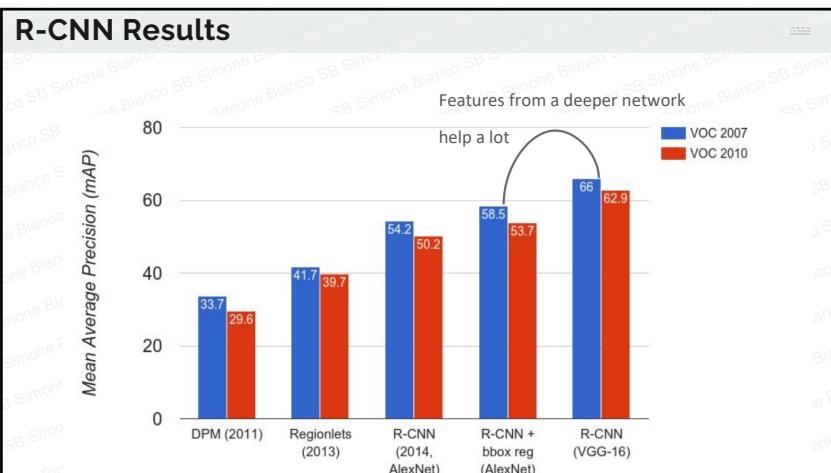
56



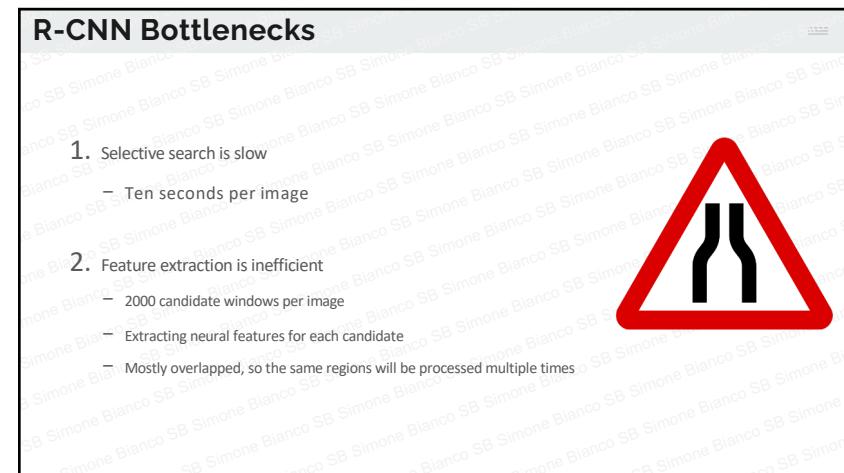
57



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59



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R-CNN Problems

1. SVMs and regressors are post-hoc: CNN features are not updated in response to SVMs and regressors
2. Complex multistage training pipeline

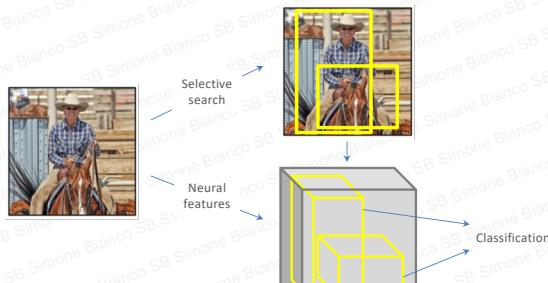
61

Fast R-CNN

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Fast R-CNN

- Compute dense features once, and sample them based on proposals

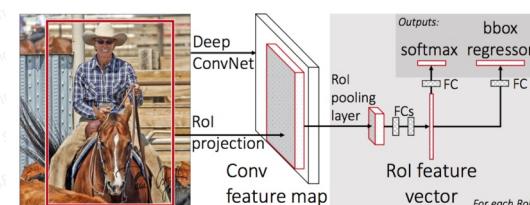


Girshick, R. (2015). Fast r-cnn. In Proceedings of the IEEE international conference on computer vision (pp. 1440-1448).

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Fast R-CNN

- Compute dense features once, and sample them based on proposals
- Bring sampled feature blocks to a common size
 - ROI pooling layer (Region of Interest)



Girshick, R. (2015). Fast r-cnn. In Proceedings of the IEEE international conference on computer vision (pp. 1440-1448).

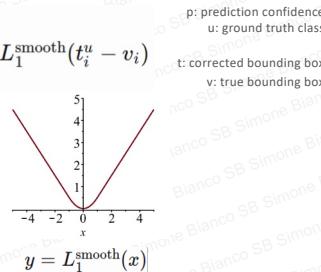
64

Fast R-CNN Classification

- Replace SVM with softmax (neural) classification
- Optimize the sum of two losses:

- Classification $\mathcal{L}_{\text{cls}}(p, u) = -\log p_u$

- BBox correction $\mathcal{L}_{\text{box}}(t^u, v) = \sum_{i \in \{x, y, w, h\}} L_1^{\text{smooth}}(t_i^u - v_i)$



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Fast R-CNN Bottleneck

- Selective search is slow

- Ten seconds per image

- Feature extraction is inefficient

- 2000 candidate windows per image
- Extracting neural features for each candidate
- Mostly overlapped, so the same regions will be processed multiple times

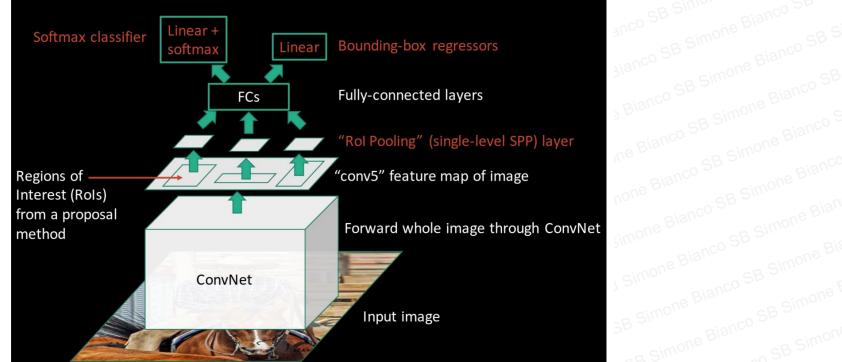


SOLVED

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Fast R-CNN

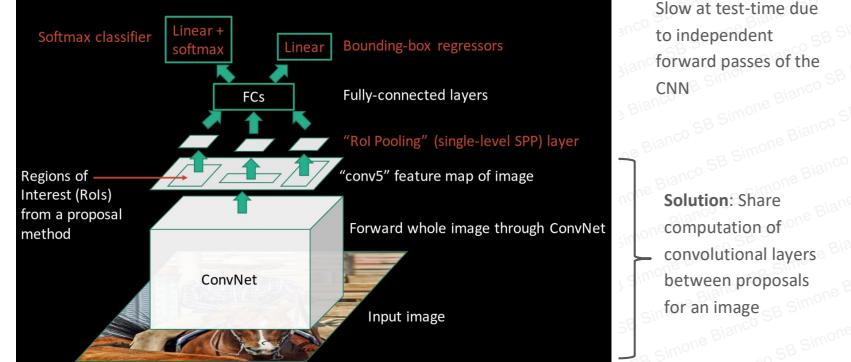
Fast R-CNN (test time)



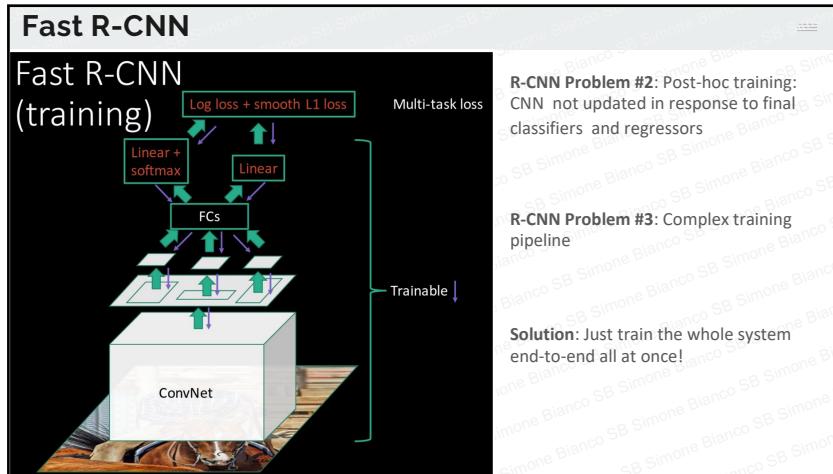
67

Fast R-CNN

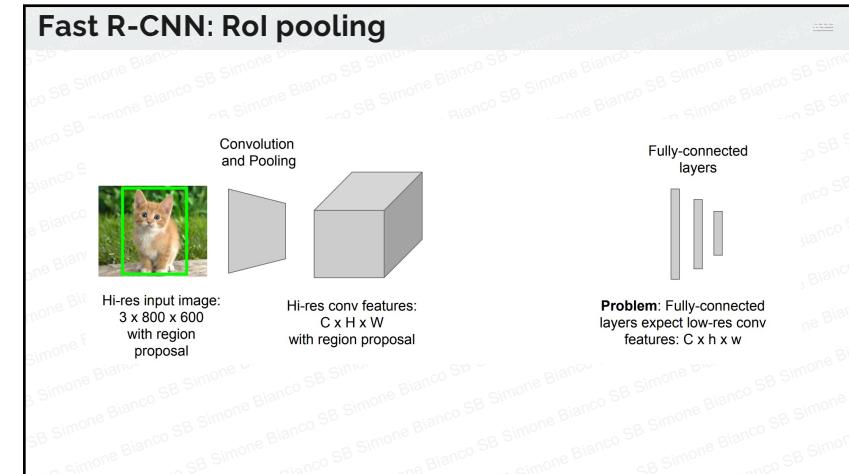
Fast R-CNN (test time)



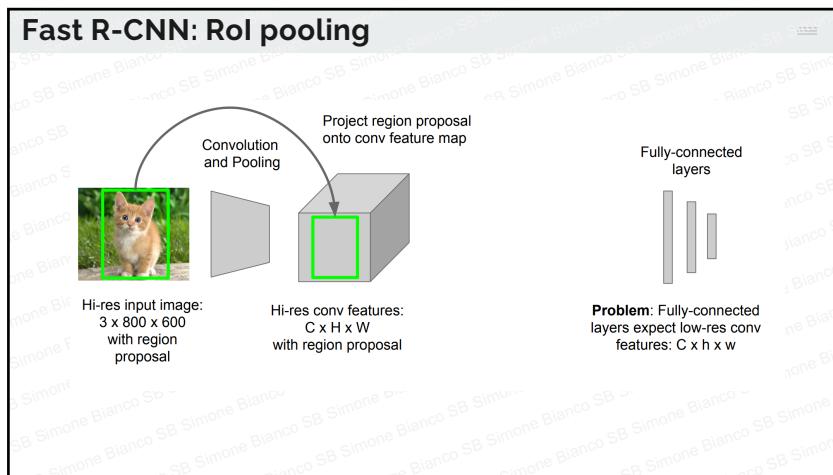
68



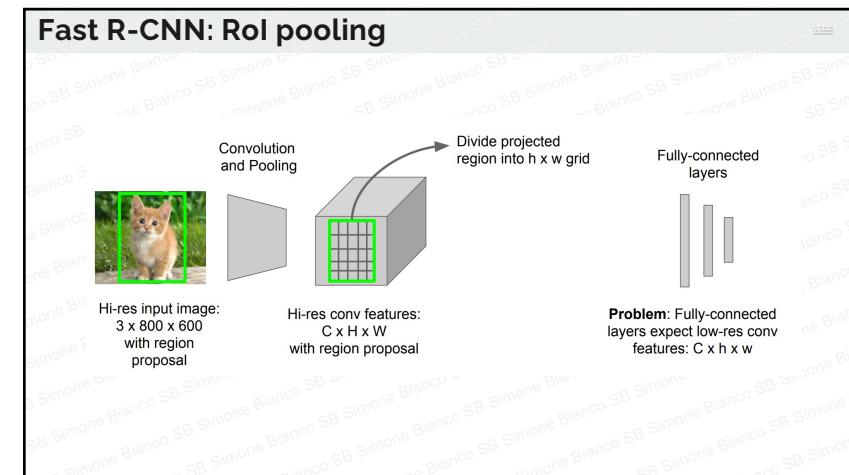
69



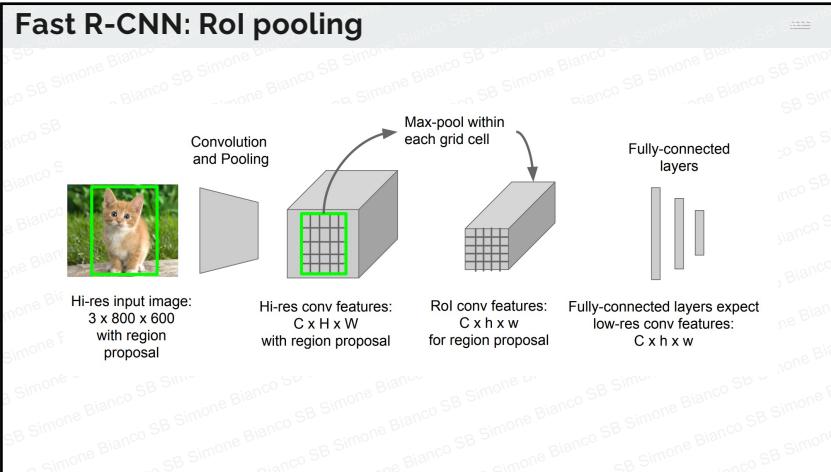
70



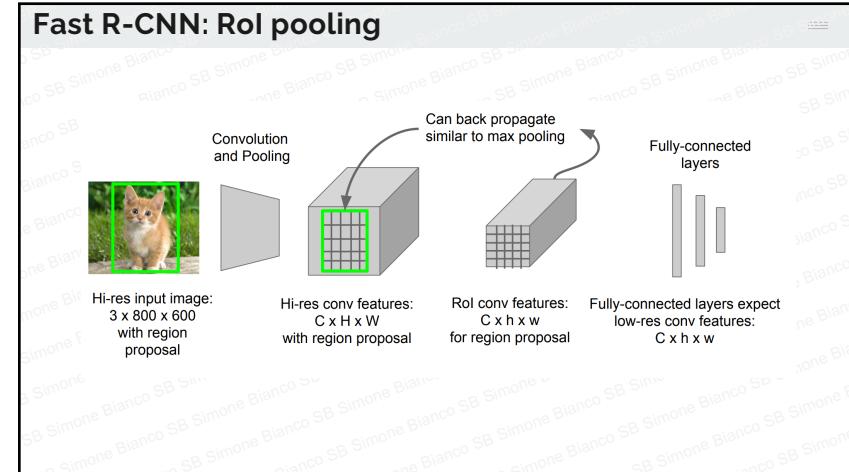
71



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Fast R-CNN: Results

Faster!

	R-CNN	Fast R-CNN
Training Time:	84 hours	9.5 hours
(Speedup)	1x	8.8x

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Fast R-CNN: Results

Faster!

FASTER!

	R-CNN	Fast R-CNN
Training Time:	84 hours	9.5 hours
(Speedup)	1x	8.8x
Test time per image	47 seconds	0.32 seconds
(Speedup)	1x	146x

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Fast R-CNN: Results

	R-CNN	Fast R-CNN
Training Time:	84 hours	9.5 hours
(Speedup)	1x	8.8x
Test time per image	47 seconds	0.32 seconds
(Speedup)	1x	146x
Better!	mAP (VOC 2007)	66.9

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Fast R-CNN: Problem

	R-CNN	Fast R-CNN
Test time per image	47 seconds	0.32 seconds
(Speedup)	1x	146x
Test time per image with Selective Search	50 seconds	2 seconds
(Speedup)	1x	25x

Test-time speeds don't include region proposals

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Fast R-CNN: Solution

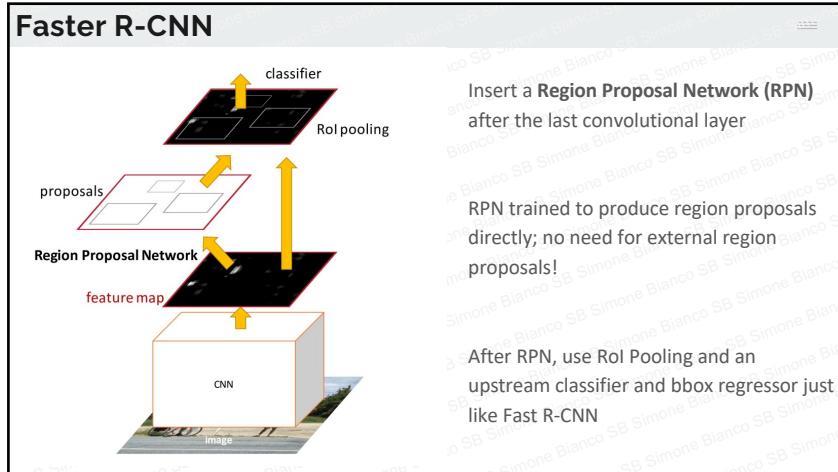
	R-CNN	Fast R-CNN
Test time per image	47 seconds	0.32 seconds
(Speedup)	1x	146x
Test time per image with Selective Search	50 seconds	2 seconds
(Speedup)	1x	25x

Test-time speeds don't include region proposals
 → Just make the CNN do region proposals too!

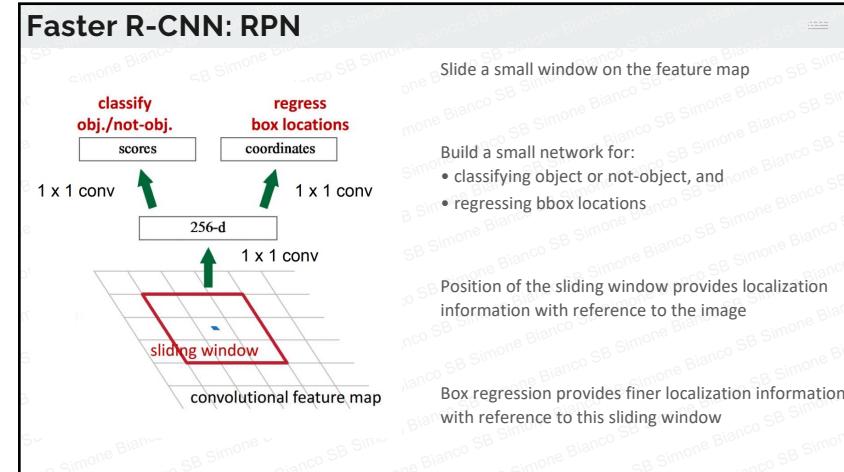
79

Faster R-CNN

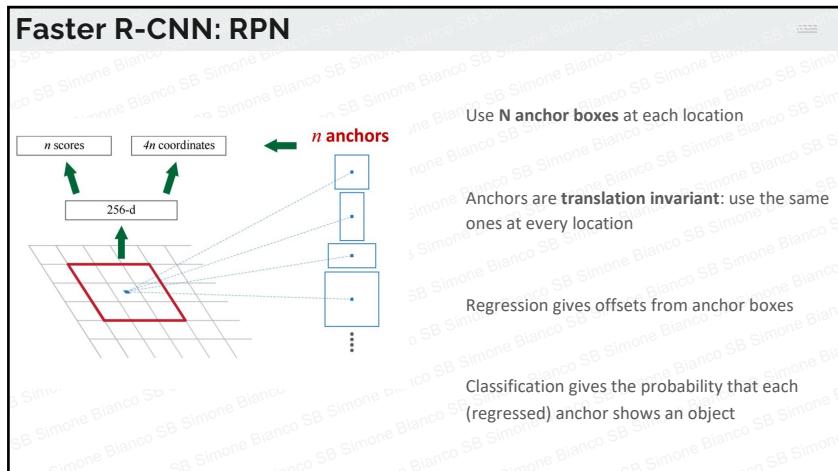
80



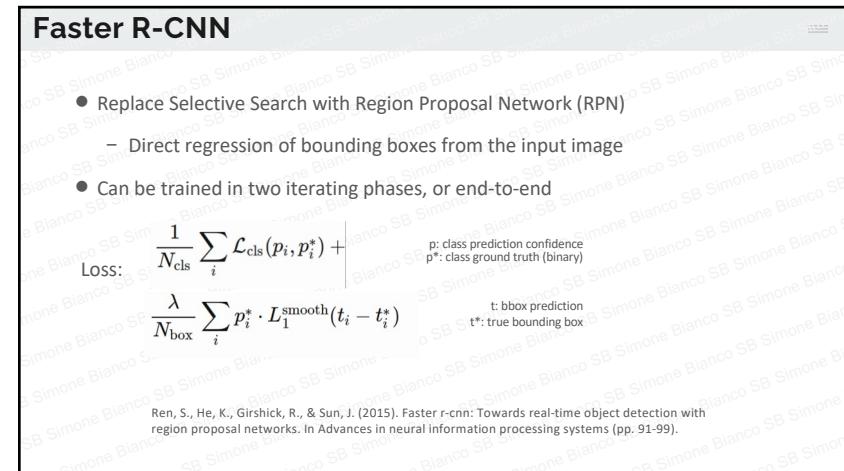
81



82

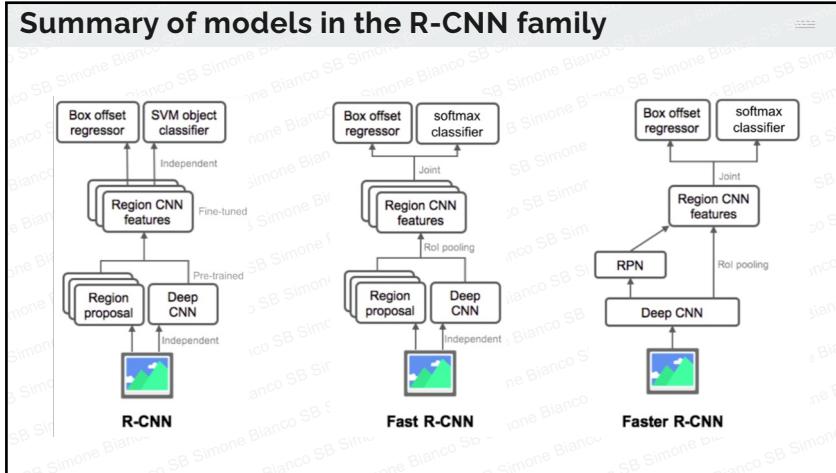


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Summary of models in the R-CNN family



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Faster R-CNN: Results

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

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