Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation

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PRESENTED BY: COLLIN MCCARTHY

Goal

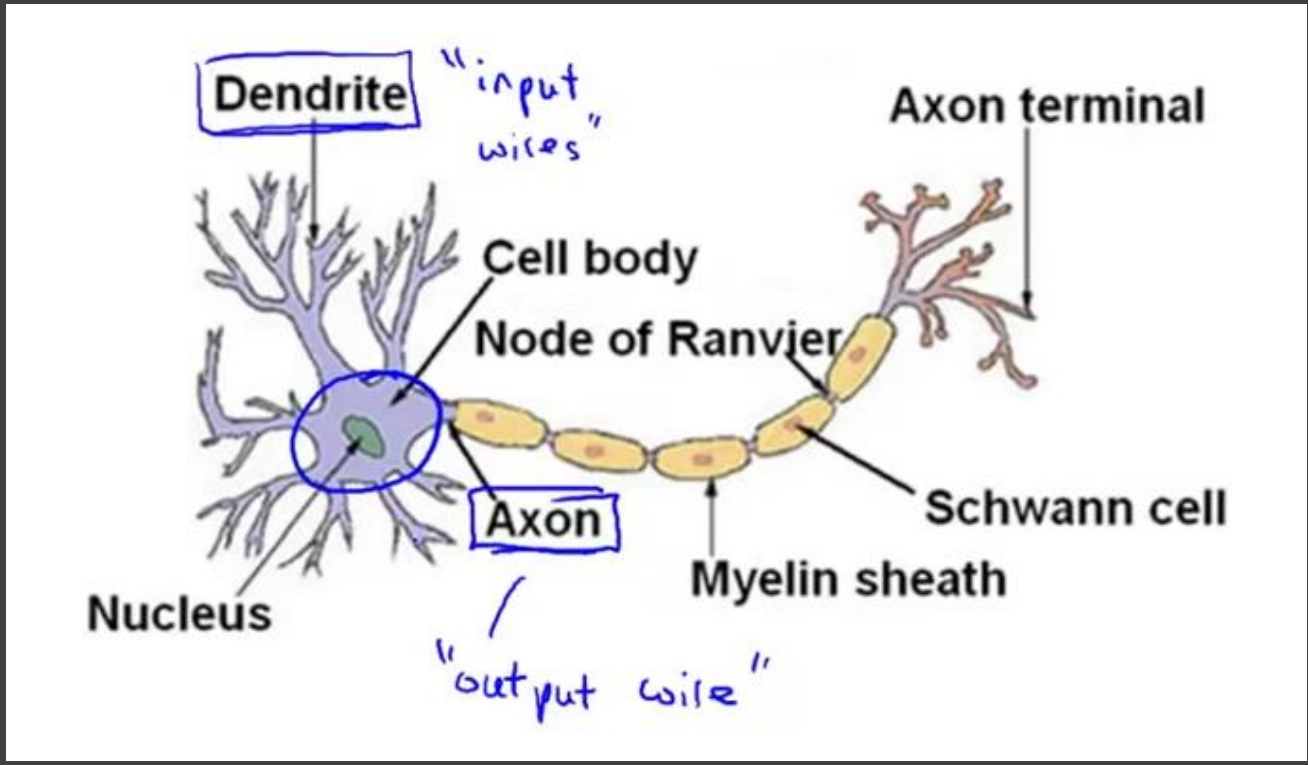
To produce a scalable, state-of-the-art detection algorithm

- CNN's using bottom-up regions
- Pre-training (general), fine-tuning (specific)

Background

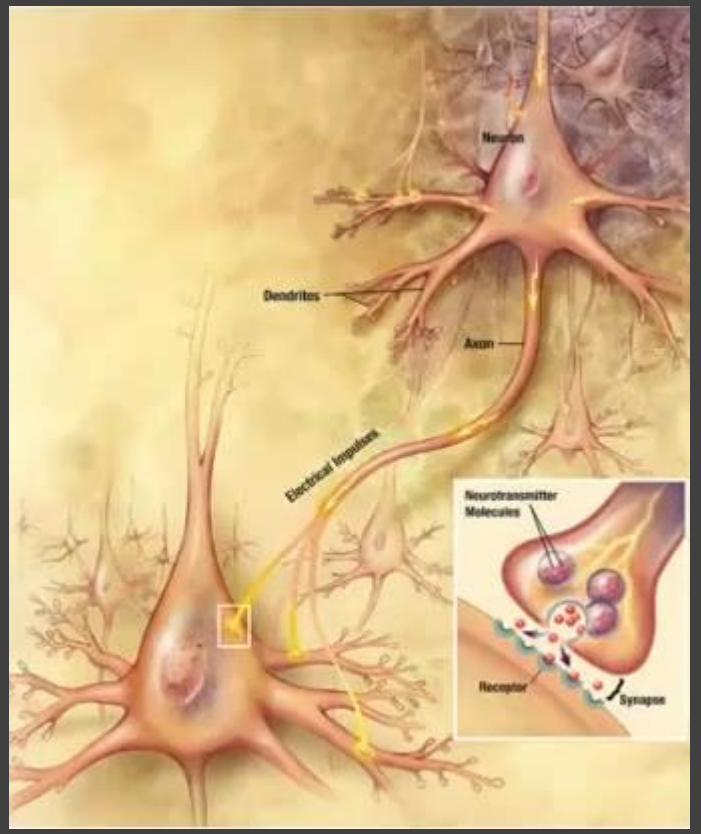
Neurons

Single Neuron



Ng, Andrew. Machine Learning, Lecture 8. Coursera.

Neural Network

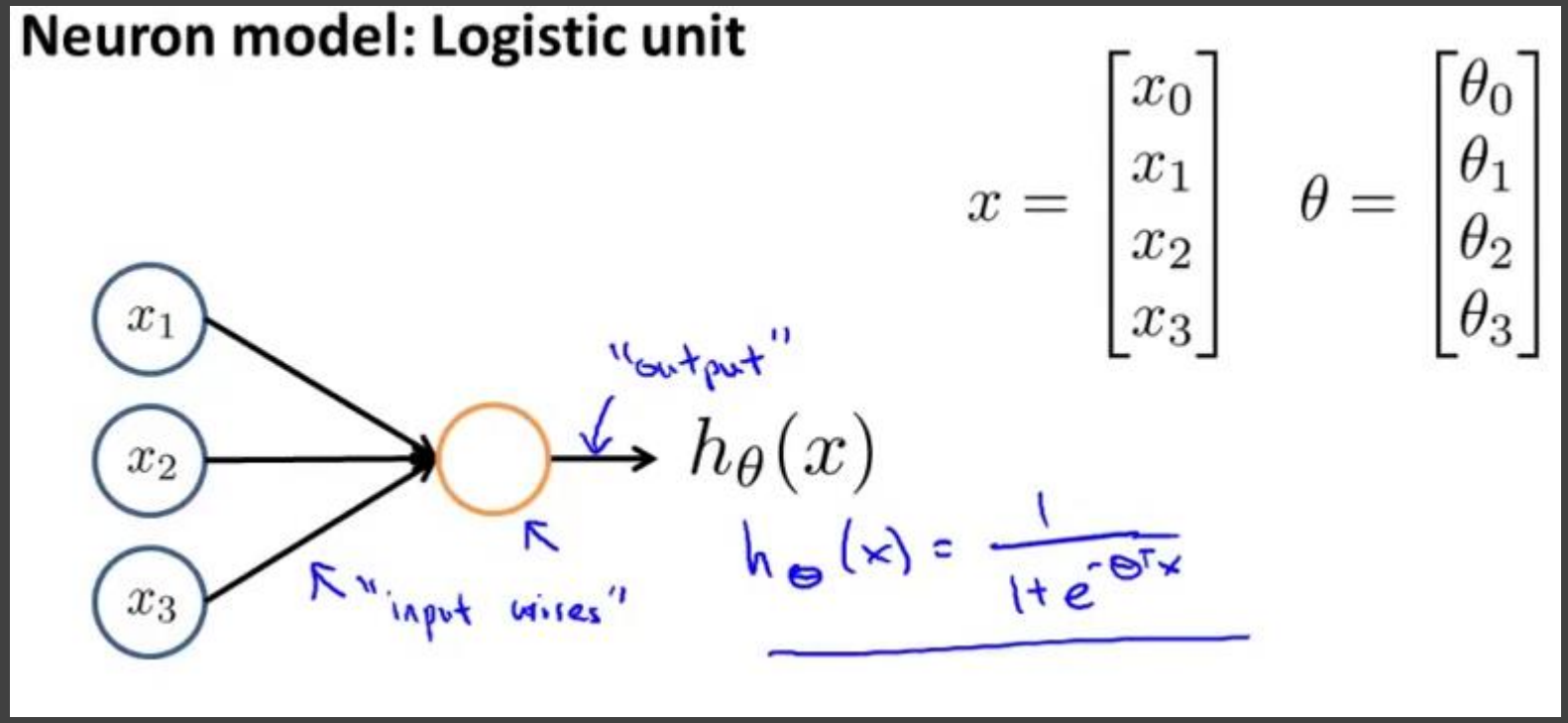


Ng, Andrew. Machine Learning, Lecture 8. Coursera.

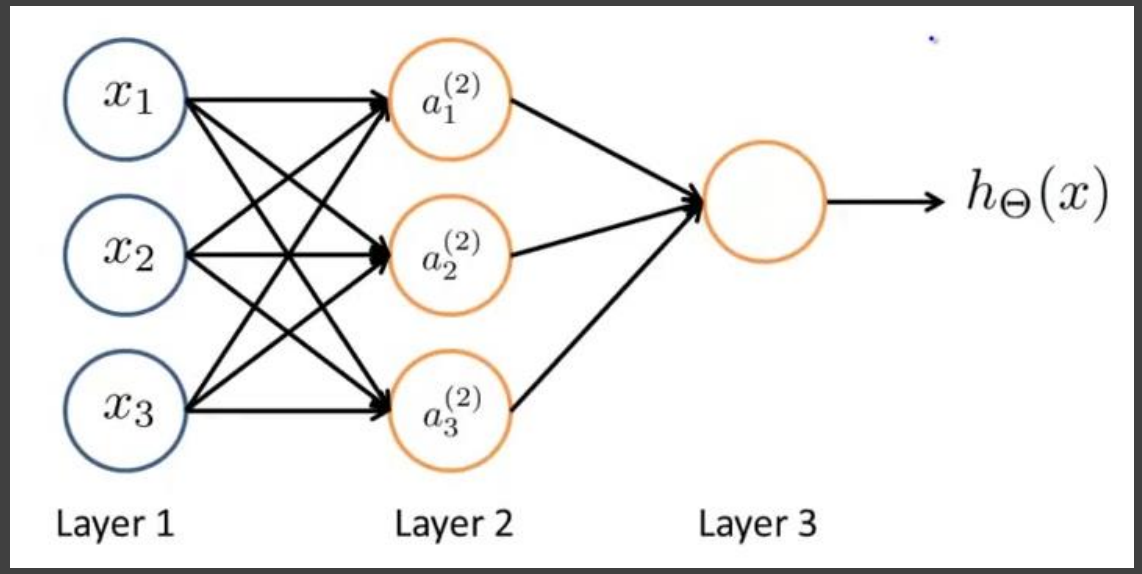
Artificial Neural Network

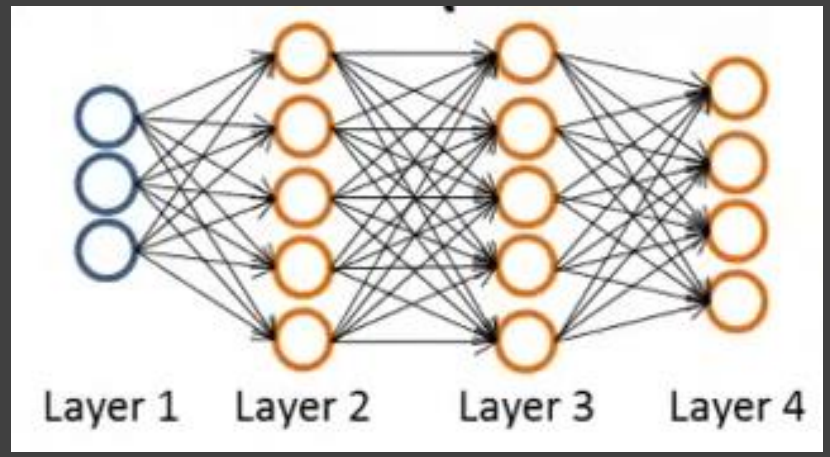
Sigmoid (logistic) activation function

- How much a neuron “fires”



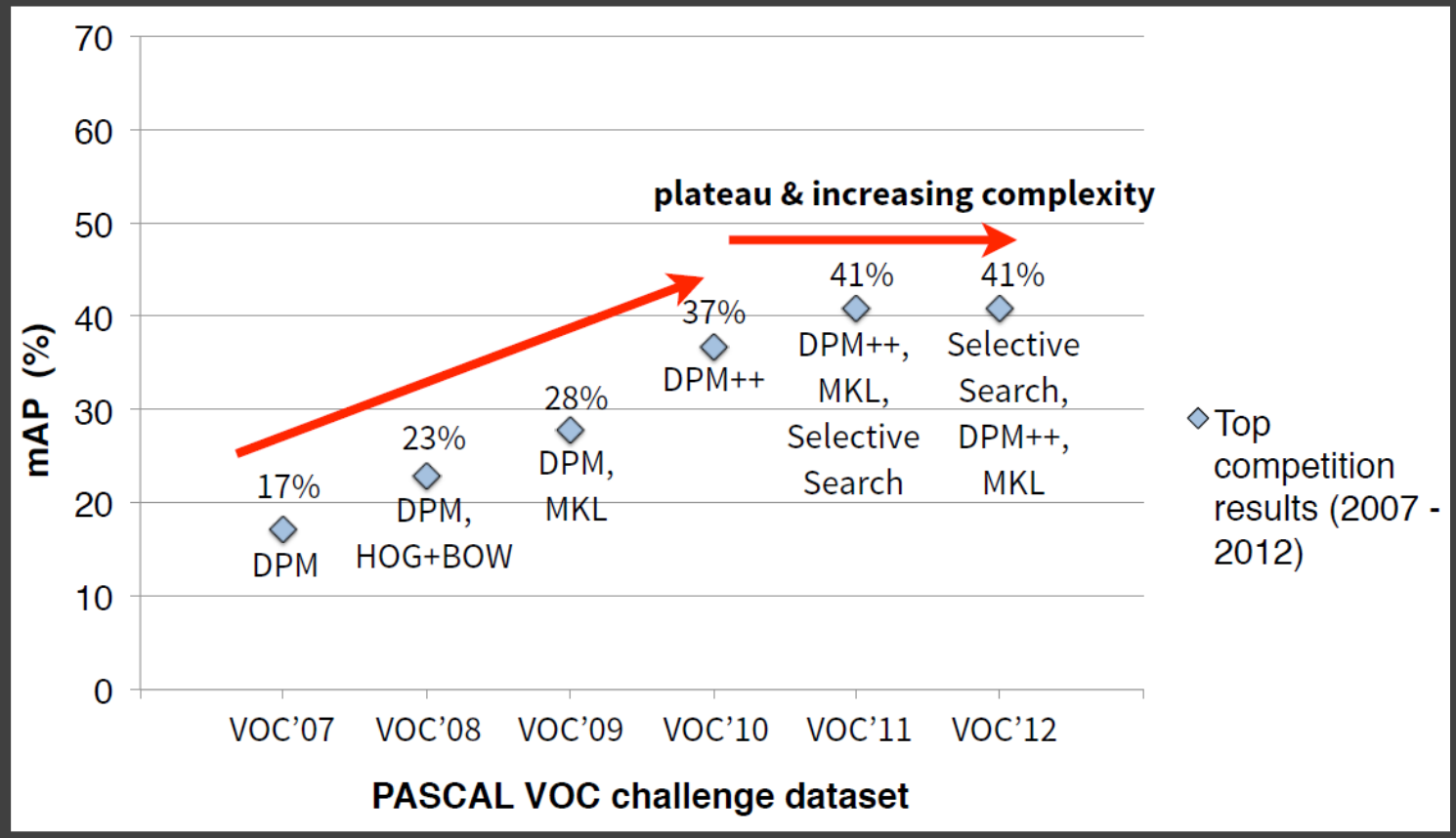
Artificial Neural Network



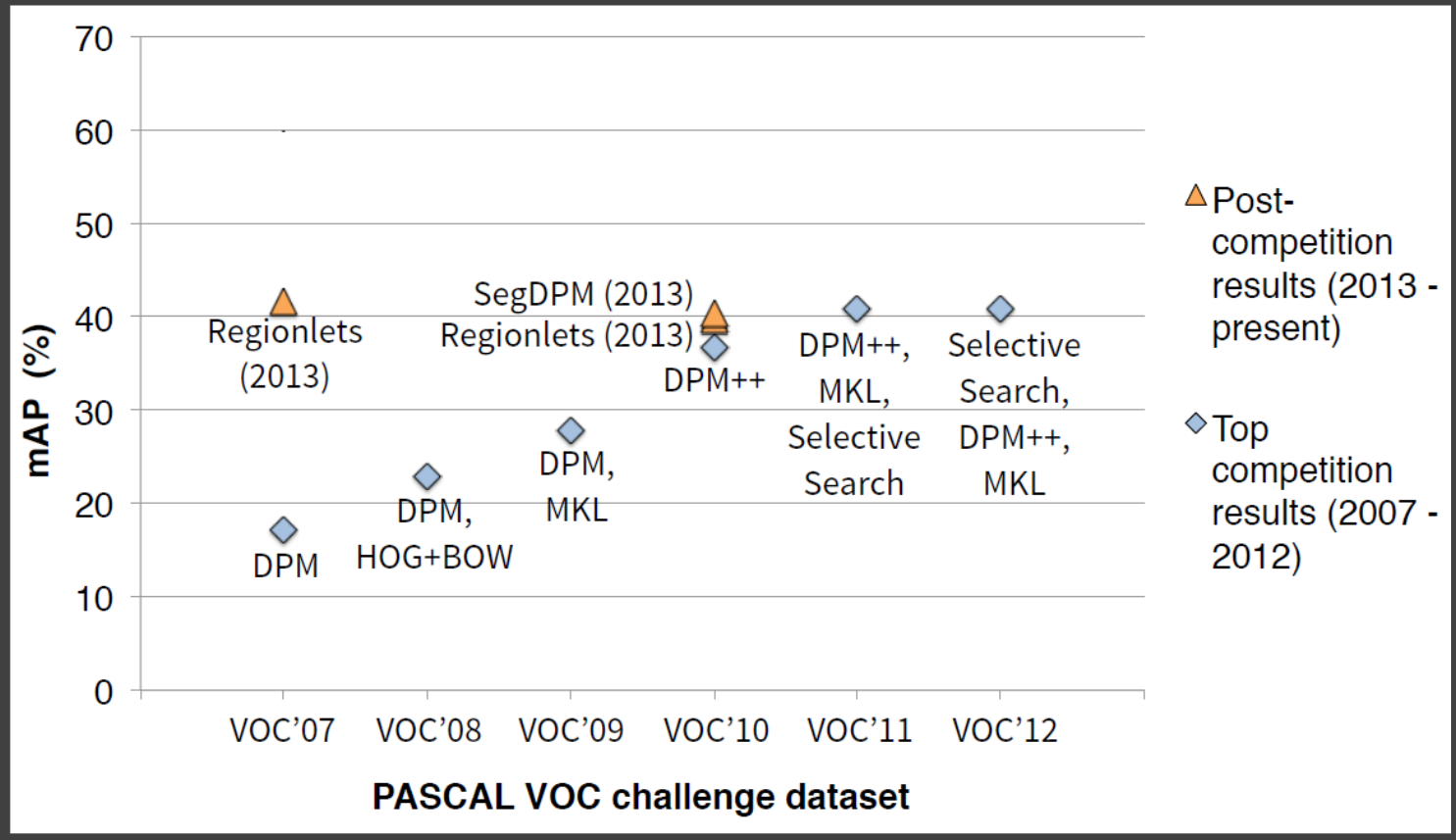


Previous Work

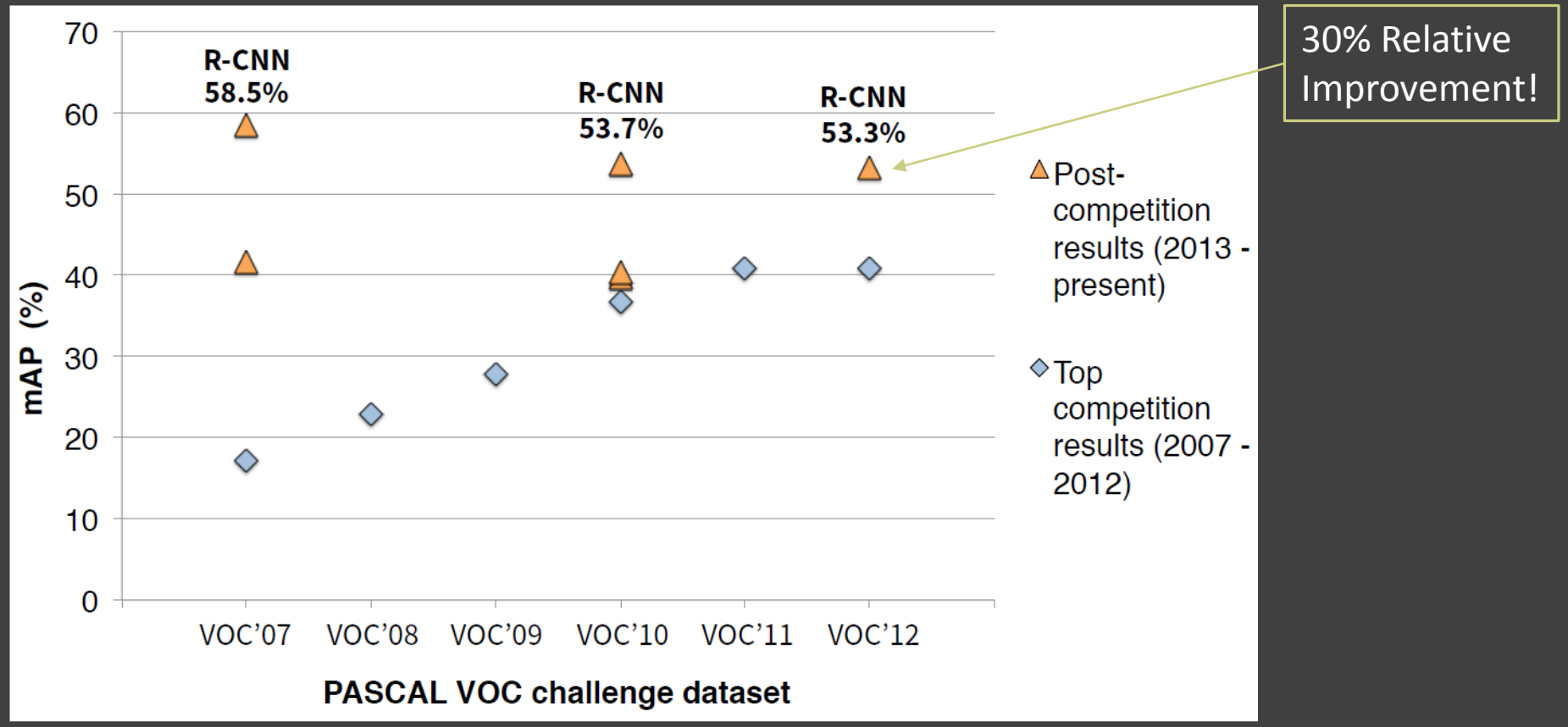
PASCAL VOC Challenge Results



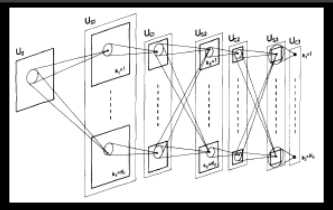
Post-Challenge Results (2013)



Regions with CNN Features (2014)

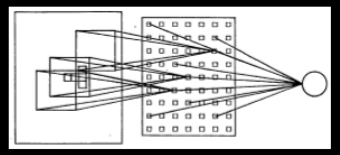


Previous Work on CNNs



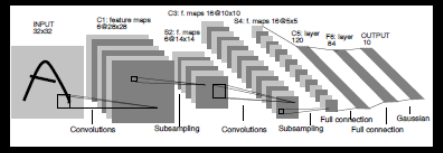
Fukushima 1980

Neocognitron



Rumelhart, Hinton, Williams 1986

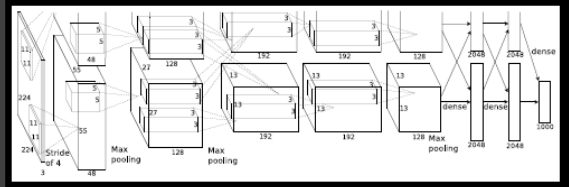
"T" versus "C" problem



LeCun et al. 1989-1998

Handwritten digit reading / OCR

...

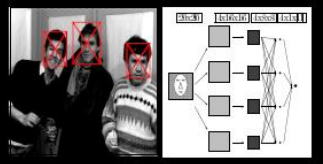


Krizhevksy, Sutskever, Hinton 2012

ImageNet classification breakthrough

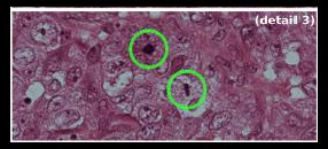
"SuperVision" CNN

Recent Work on CNNs for Object Detection



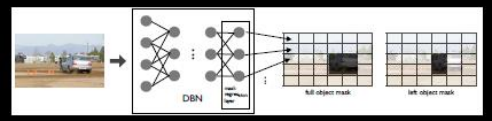
Vaillant, Monrocq, LeCun 1994
Multi-scale face detection

LeCun, Huang, Bottou 2004
NORB dataset



Cireşan et al. 2013
Mitosis detection

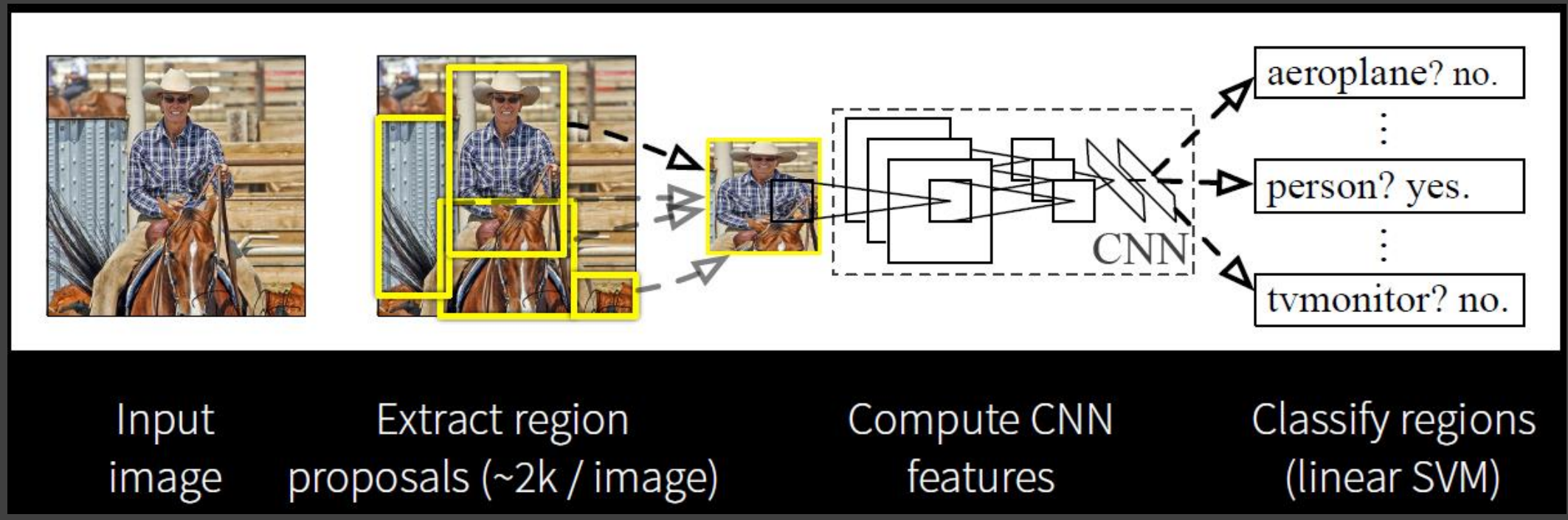
Sermanet et al. 2013
Pedestrian detection



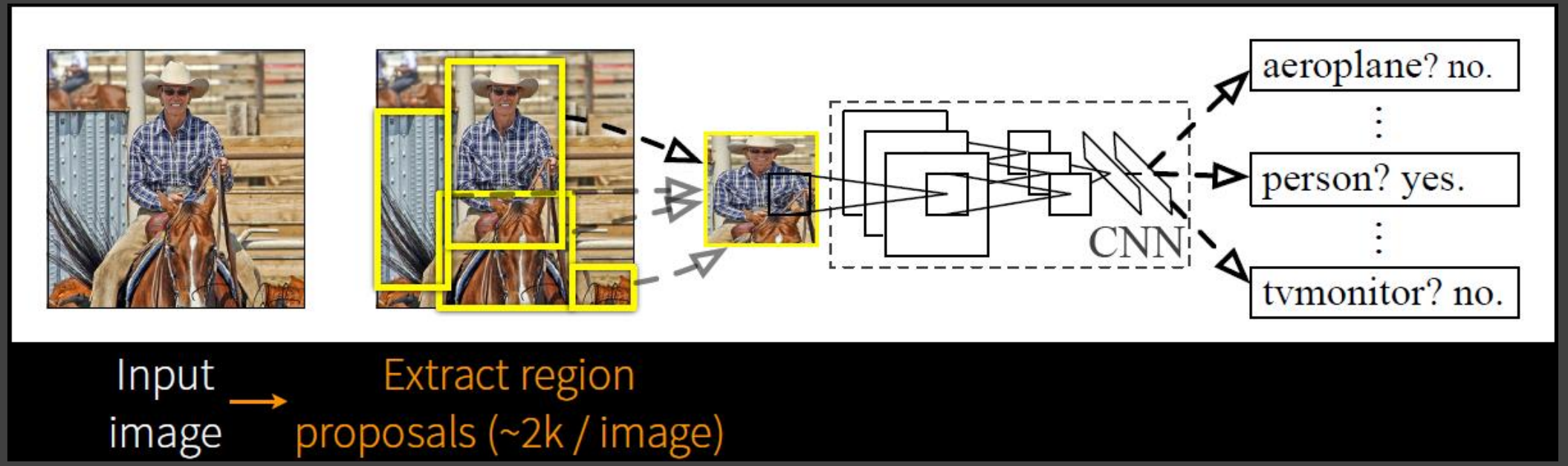
Szegedy, Toshev, Erhan 2013
PASCAL detection (VOC'07 mAP 30.5%)

Methods

Regions with CNN Features

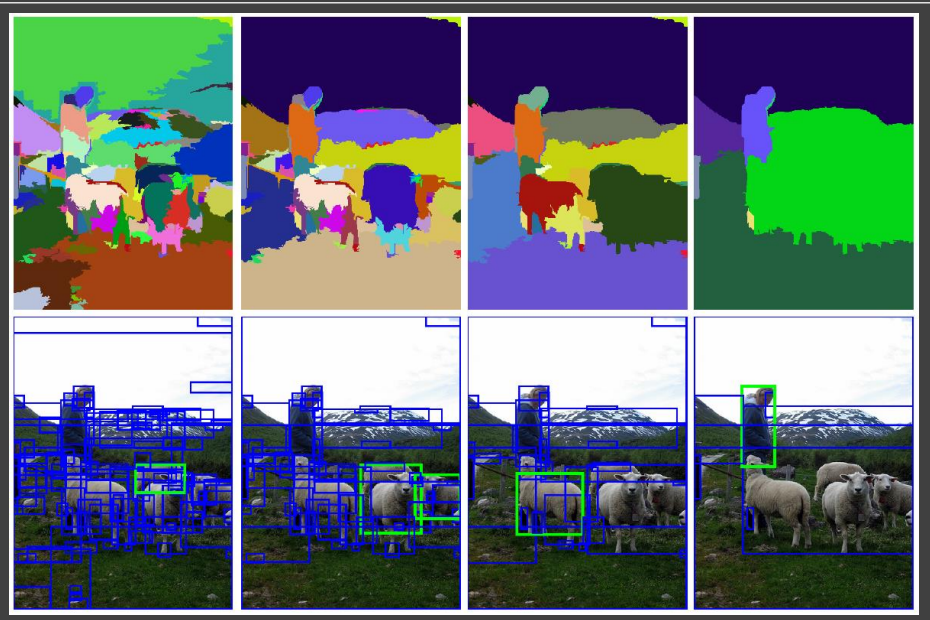


R-CNN: Step 1



Selective Search [van de Sande, Uijlings et al.]

Selective Search

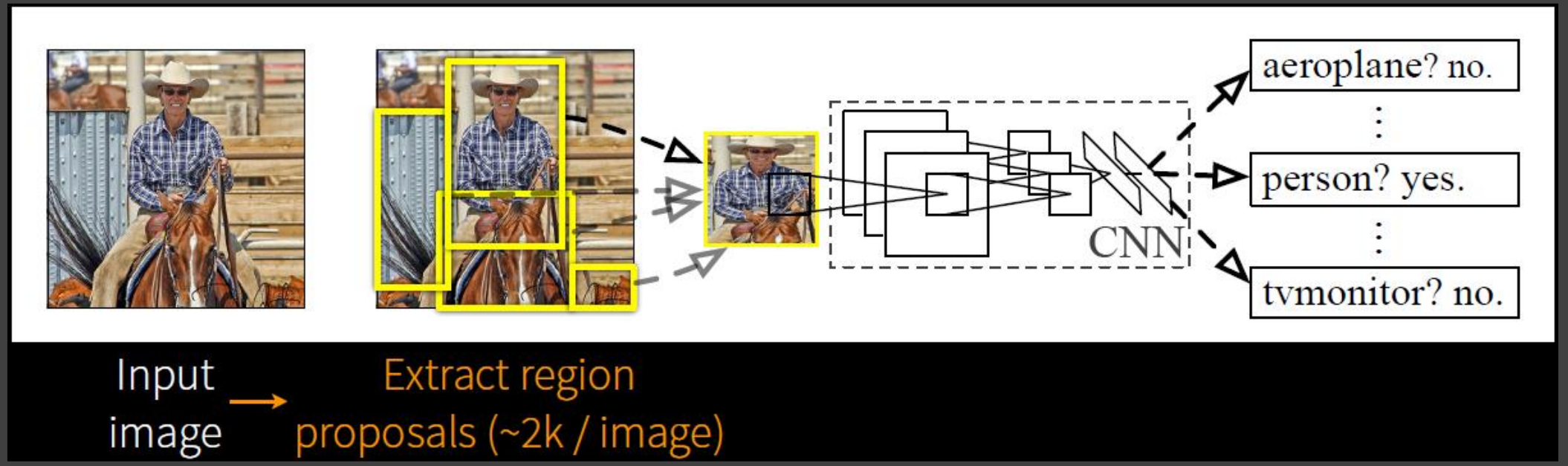


Approximate segmentation at multiple scales

- Capture more background
- Less expensive than exhaustive

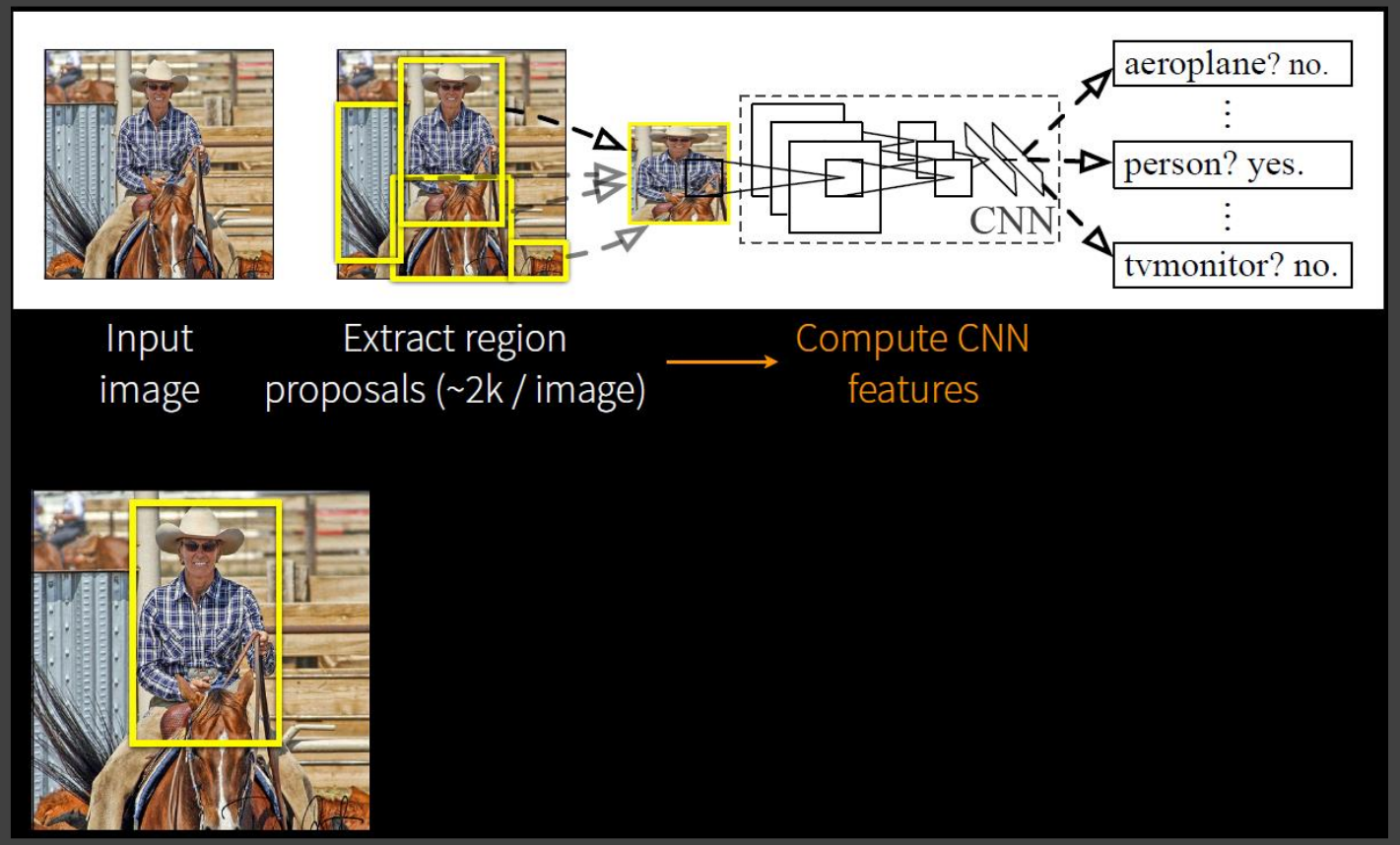
Uijlings, Jasper RR, et al. "Selective search for object recognition."*International journal of computer vision* 104.2 (2013): 154-171.

R-CNN: Step 1

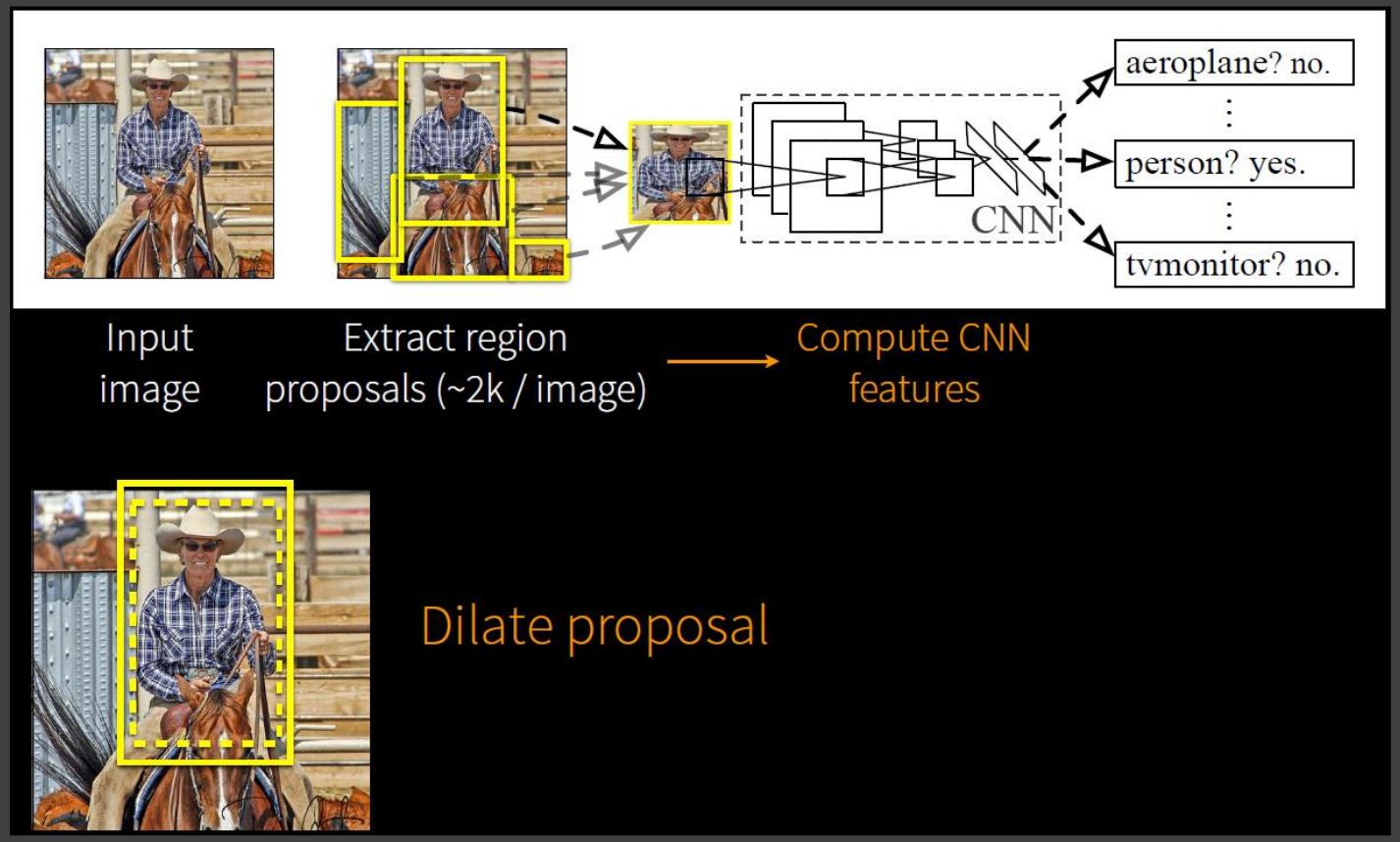


Selective Search [van de Sande, Uijlings et al.]

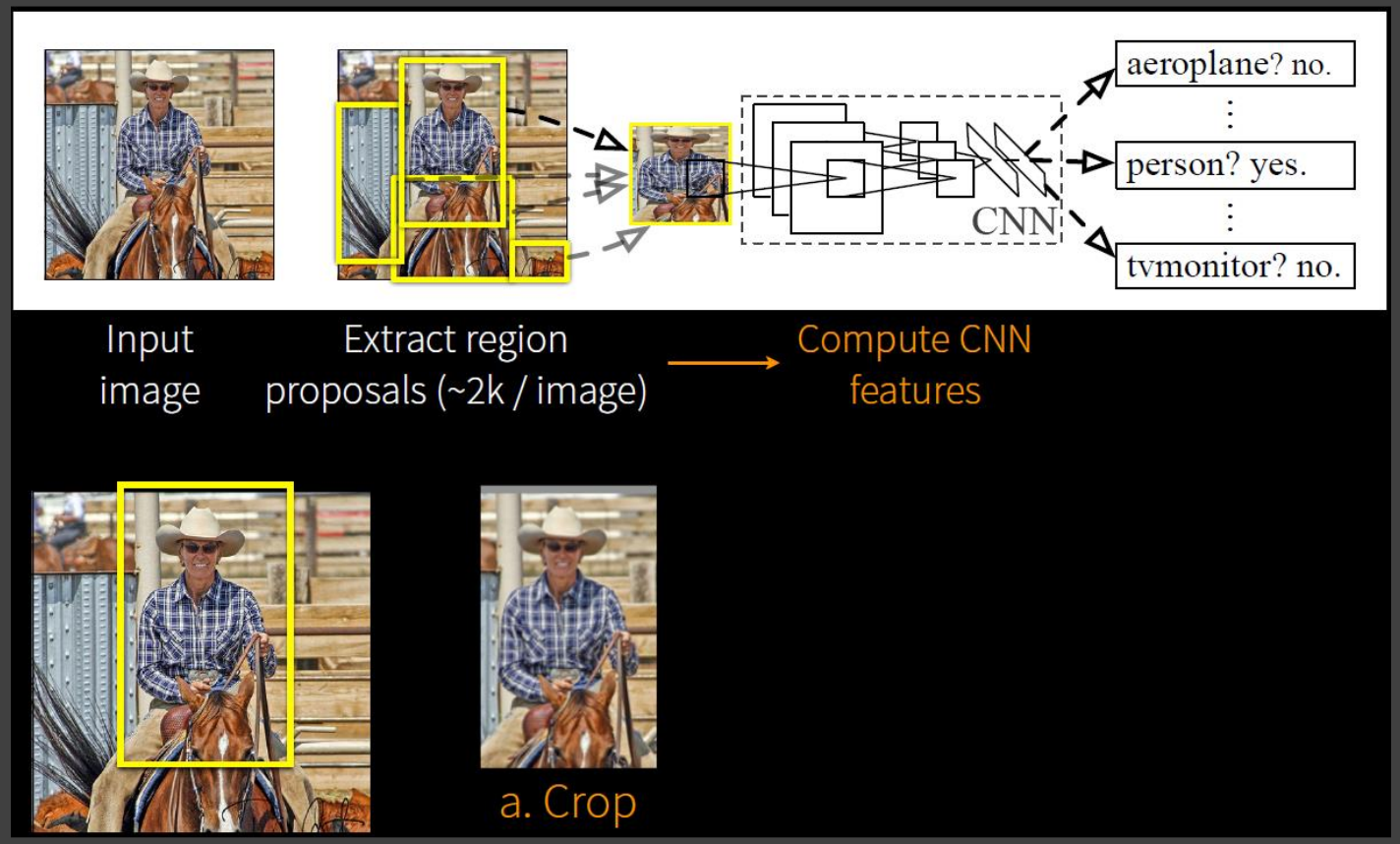
R-CNN: Step 2


aeroplane? no.
person? yes.
tvmonitor? no.
CNN
Input image
Extract region proposals (~2k / image)
Compute CNN features

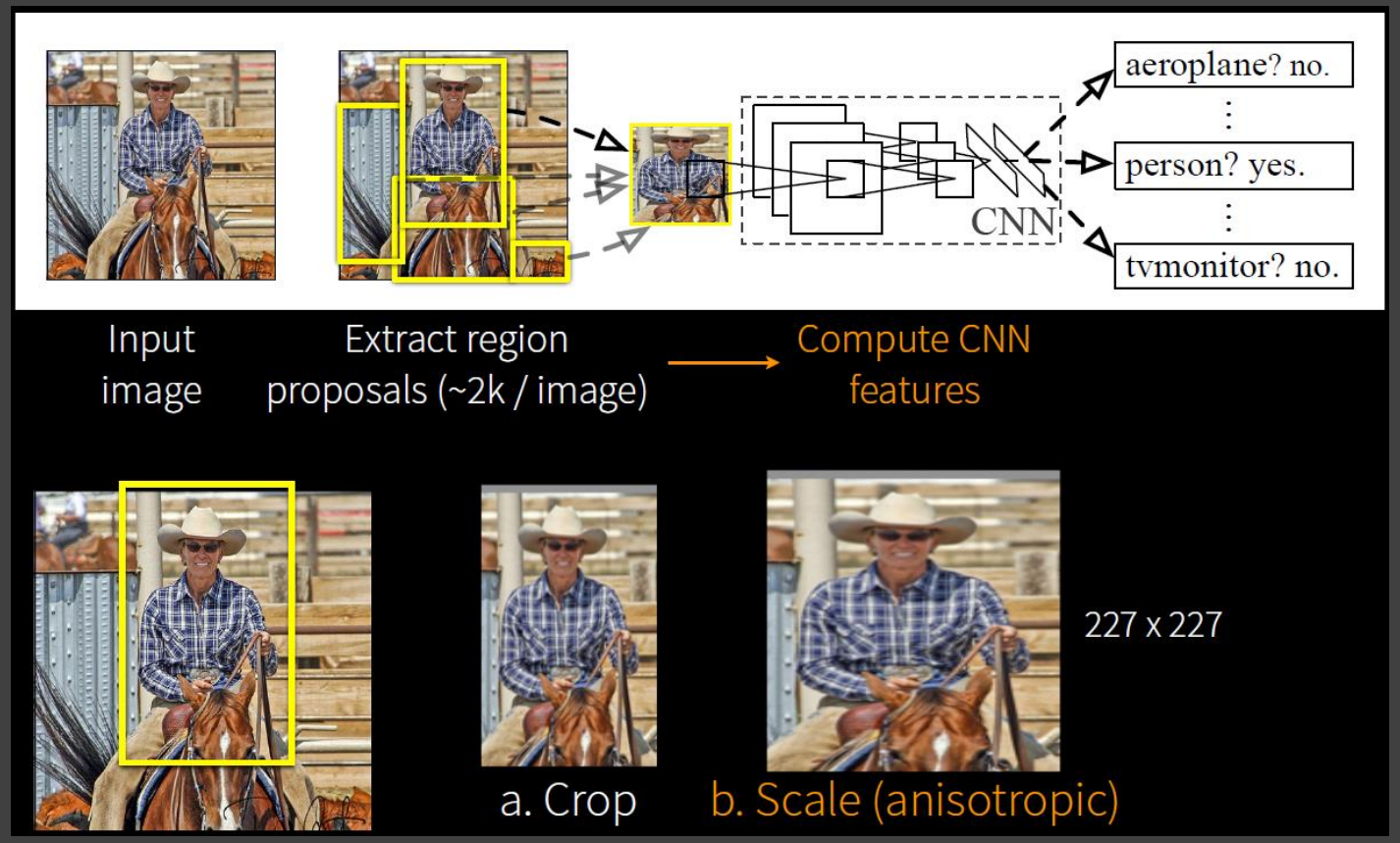
R-CNN: Step 2


aeroplane? no.
person? yes.
tvmonitor? no.
CNN
Input image
Extract region proposals (~2k / image)
Compute CNN features
Dilate proposal

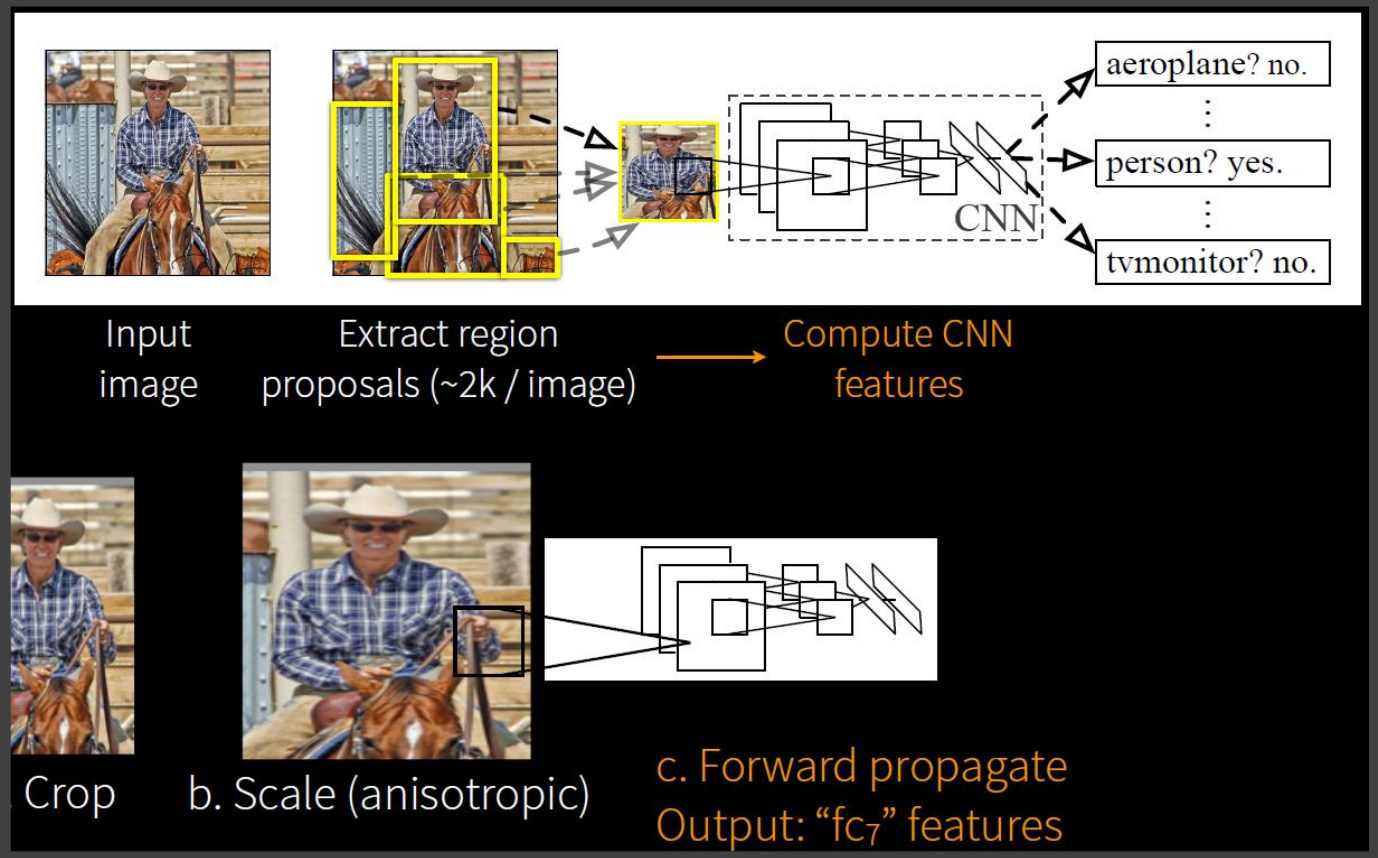
R-CNN: Step 2


aeroplane? no.
person? yes.
tvmonitor? no.
CNN
Input image
Extract region proposals (~2k / image)
Compute CNN features
a. Crop

R-CNN: Step 2

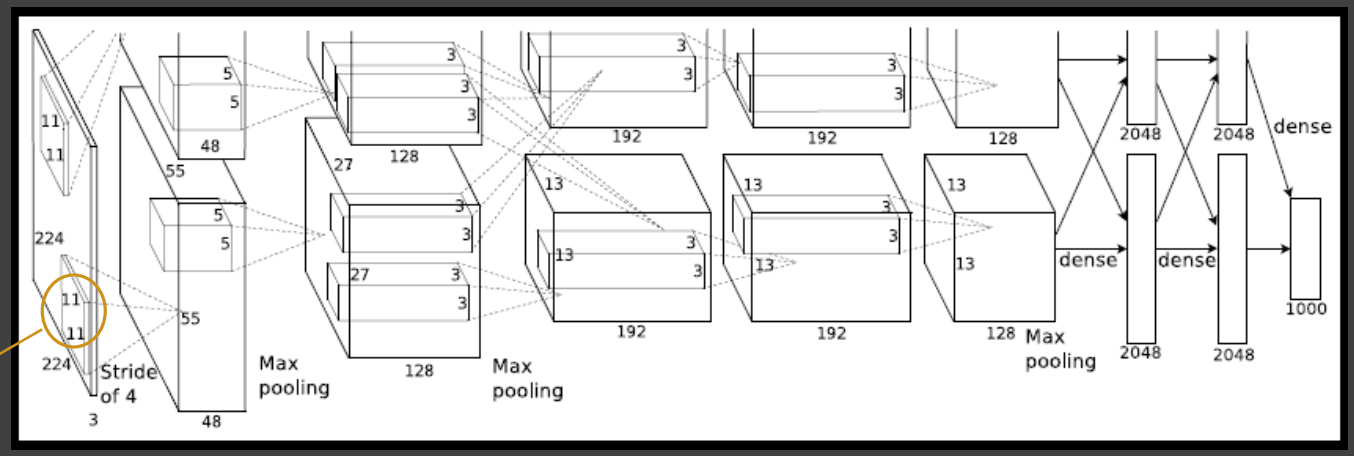

aeroplane? no.
person? yes.
tvmonitor? no.
CNN
Input image
Extract region proposals (~2k / image)
Compute CNN features
227 x 227
a. Crop
b. Scale (anisotropic)

R-CNN: Step 2


aeroplane? no.
person? yes.
tvmonitor? no.
CNN
Input image
Extract region proposals (~2k / image)
Compute CNN features
Crop
b. Scale (anisotropic)
c. Forward propagate
Output: "fc7" features

R-CNN: Step 2

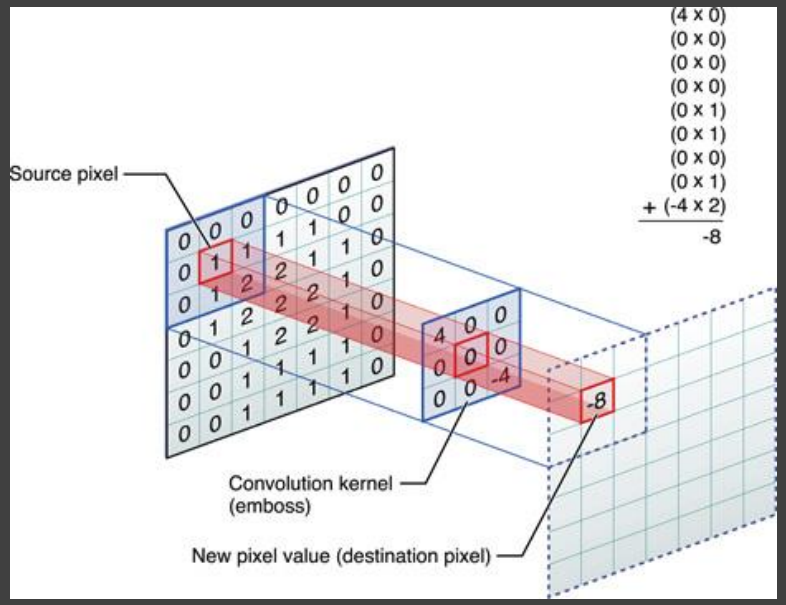
Forward Propagation



11x11 kernel size
w/ sliding window

R-CNN: Step 2

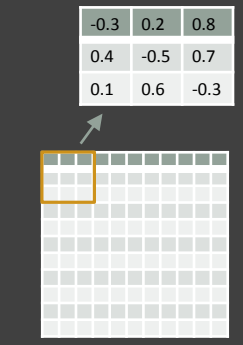
Kernel Convolution



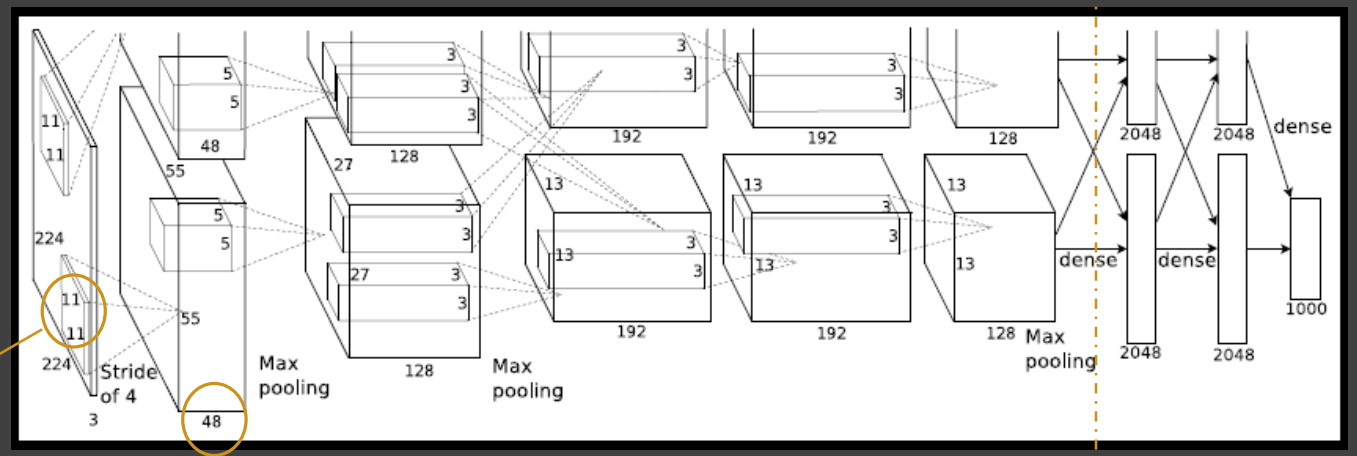
https://developer.apple.com/library/mac/documentation/Performance/Conceptual/vImage/ConvolutionOperations/ConvolutionOperations.html

R-CNN: Step 2

Forward Propagation



11x11 kernel size
w/ sliding window



48 kernels
(feature channels)

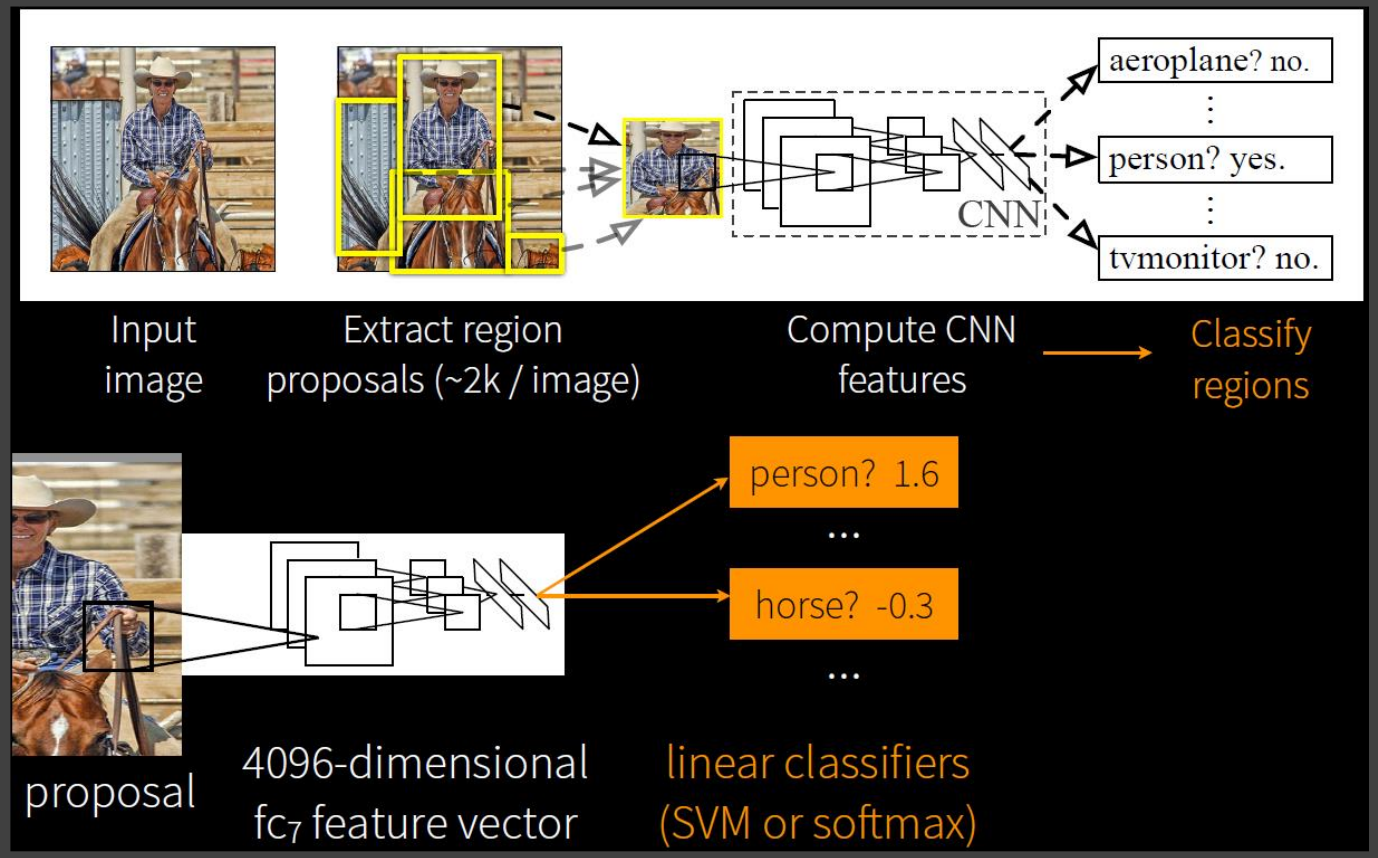
Feed-forward Convolutional Neural Net

Fully-connected Artificial Neural Net

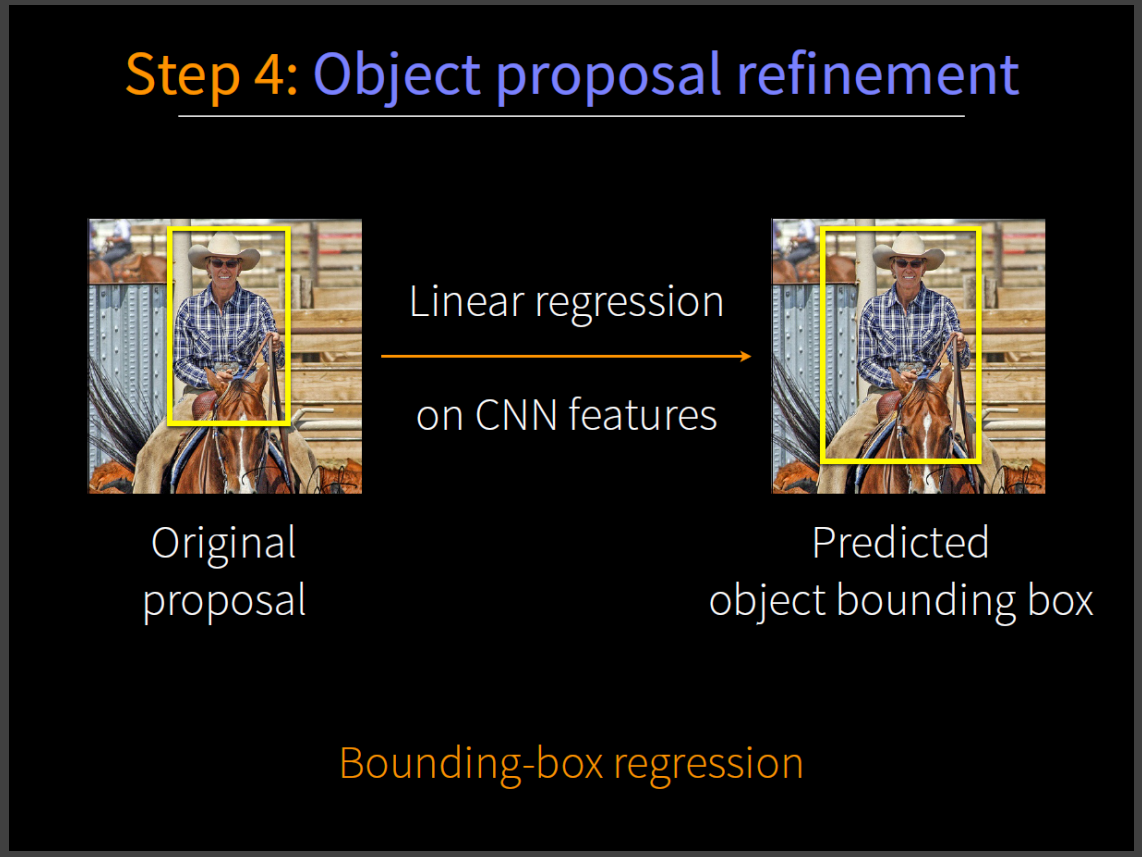
At each stage

- Higher level features, from convolution alone!
- Max pooling keeps best features
- Convolution kernels learned from training

R-CNN: Step 3


aeroplane? no.
person? yes.
tvmonitor? no.
CNN
Input image
Extract region proposals (~2k / image)
Compute CNN features
Classify regions
person? 1.6
horse? -0.3
proposal
4096-dimensional fc_7 feature vector
linear classifiers (SVM or softmax)

R-CNN: Step 4


Step 4: Object proposal refinement
Linear regression
on CNN features
Original proposal
Predicted object bounding box
Bounding-box regression

R-CNN: Step 4

Predicting Object Bounding Box

Ground Truth
Bounding Box

R-CNN: Step 4

Predicting Object Bounding Box

Ground Truth
Bounding Box

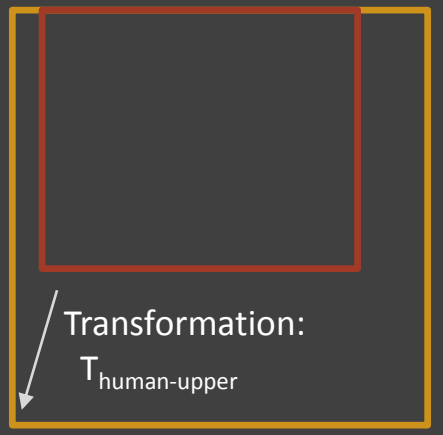
Features:
$F_{\text{human-upper}}$

R-CNN: Step 4

Predicting Object Bounding Box

Ground Truth
Bounding Box

Features:
$F_{human\text{-}upper}$



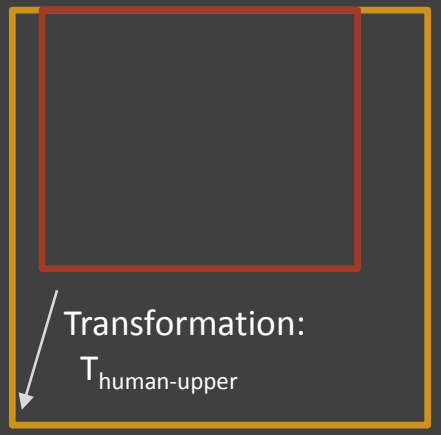
R-CNN: Step 4

Predicting Object Bounding Box

Ground Truth Bounding Box

Features: $F_{human\text{-}upper}$

Features: $F_{human\text{-}lower}$

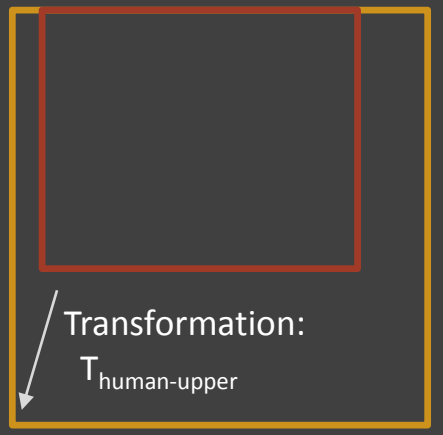


R-CNN: Step 4

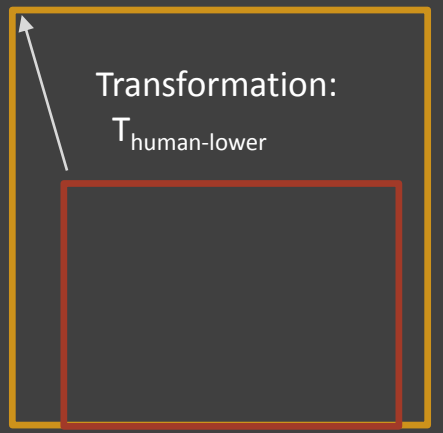
Predicting Object Bounding Box

Ground Truth Bounding Box

Features: $F_{human\text{-}upper}$



Features: $F_{human\text{-}lower}$

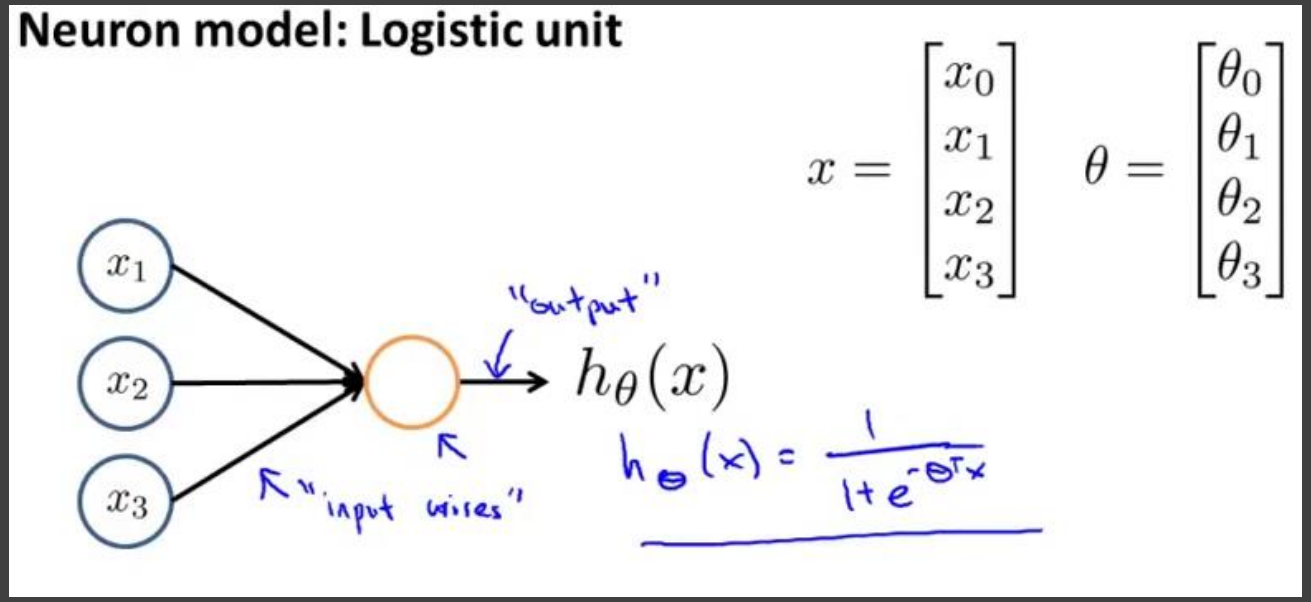


Training

Train What?

Convolution kernels

- To minimize a cost function
- Update kernels after every training image



Cost Function

Cost function

Logistic regression:

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m} y^{(i)} \log h_\theta(x^{(i)}) + (1-y^{(i)}) \log(1-h_\theta(x^{(i)}))\right] + \frac{\lambda}{2m}\sum_{j=1}^{n} \theta_j^2$$

Neural network:

$$h_\Theta(x) \in \mathbb{R}^K \quad (h_\Theta(x))_i = i^{th} \text{ output}$$

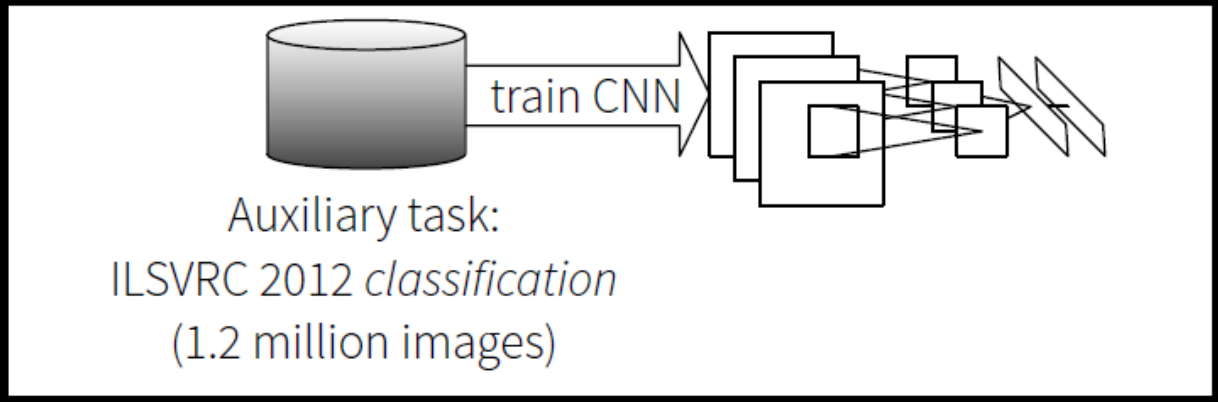
$$J(\Theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{k=1}^{K} y_k^{(i)} \log((h_\Theta(x^{(i)}))_k + (1-y_k^{(i)}) \log(1-(h_\Theta(x^{(i)}))_k)\right]$$

$$+\frac{\lambda}{2m}\sum_{l=1}^{L-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}(\Theta_{ji}^{(l)})^2$$

R-CNN Training: Step 1

Supervised pre-training

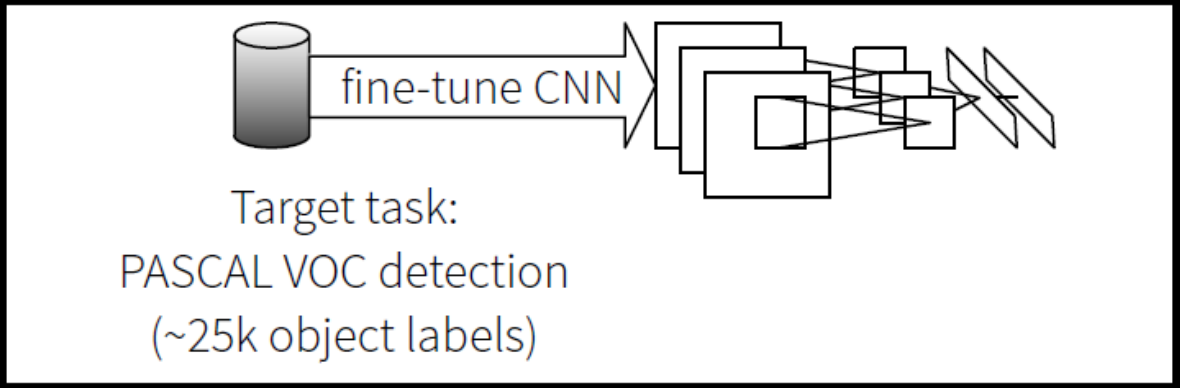
Train a SuperVision CNN* for the 1000-way ILSVRC image classification task



R-CNN Training: Step 2

Fine-tune the CNN for detection

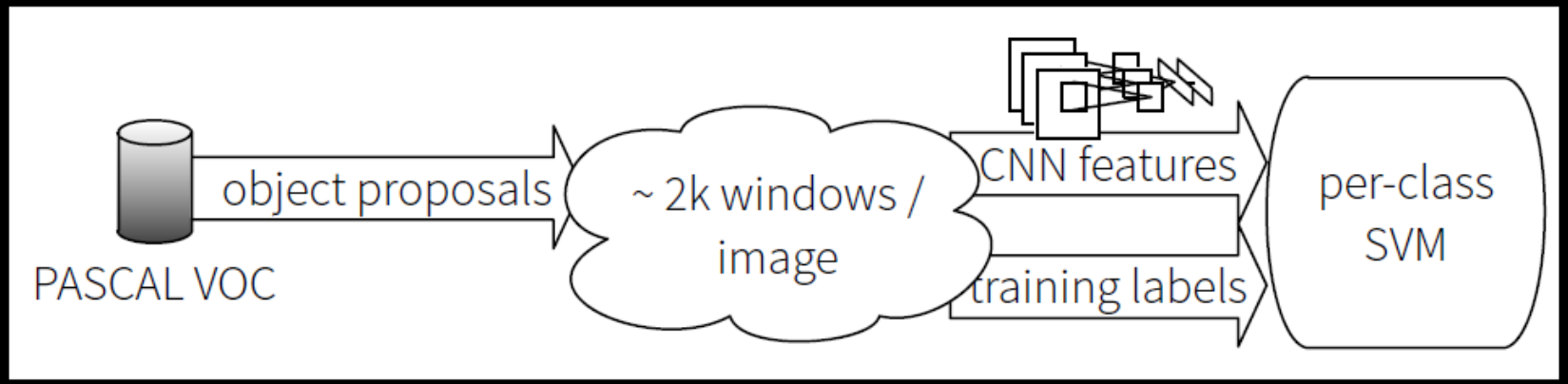
Transfer the representation learned for ILSVRC classification to PASCAL (or ImageNet detection)



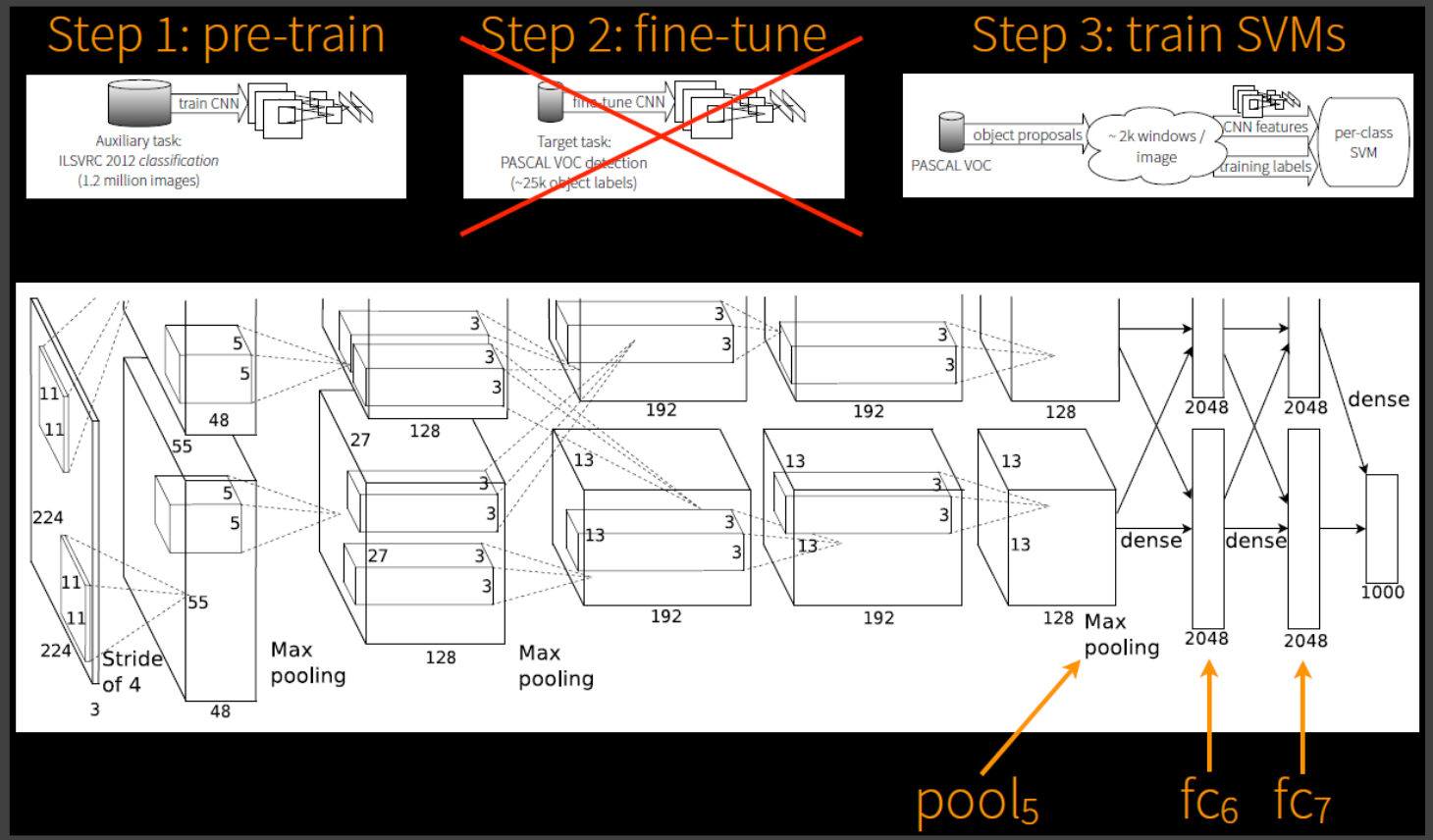
R-CNN Training: Step 3

Train detection SVMs

(With the softmax classifier from fine-tuning mAP decreases from 54% to 51%)



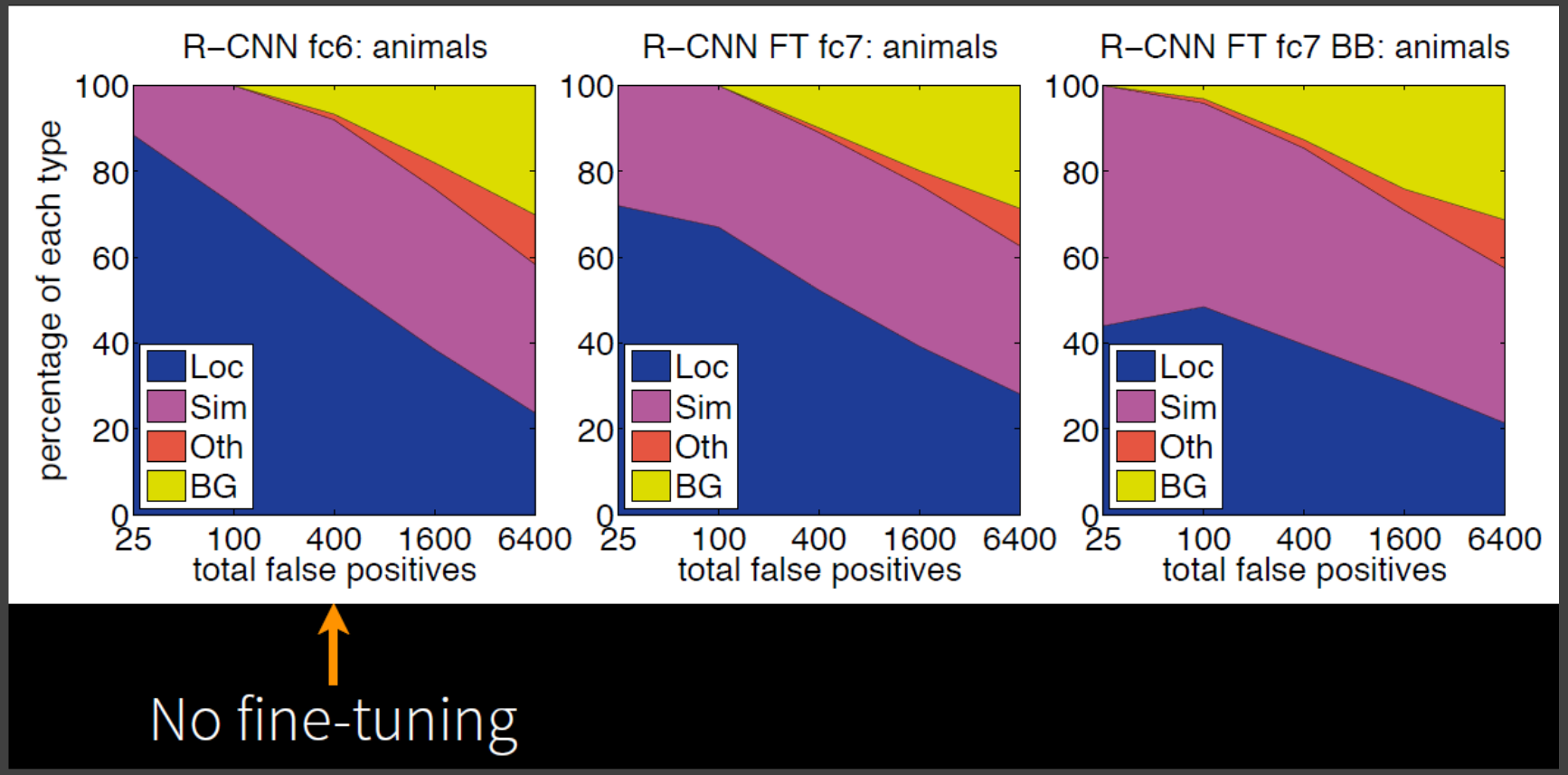
Tuning: Worth it?



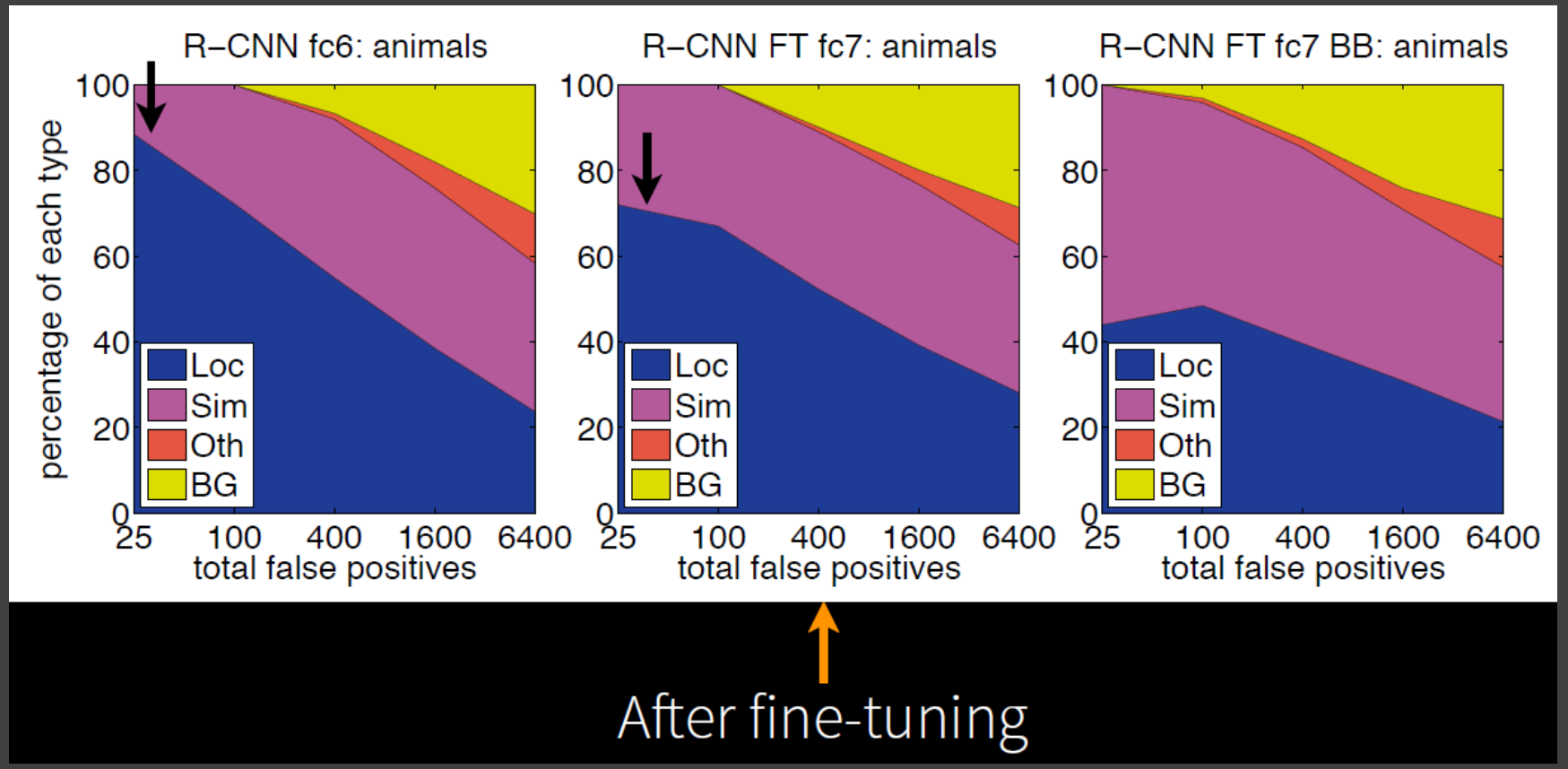
Tuning: Worth it?

fine-tuned		VOC 2007	VOC 2010
	Regionlets (Wang et al. 2013)	41.7%	39.7%
	SegDPM (Fidler et al. 2013)		40.4%
	R-CNN $pool_5$	44.2%	
	R-CNN fc_6	46.2%	
	R-CNN fc_7	44.7%	
✓	R-CNN FT $pool_5$	47.3%	
✓	R-CNN FT fc_6	53.1%	
✓	R-CNN FT fc_7	**54.2%**	**50.2%**

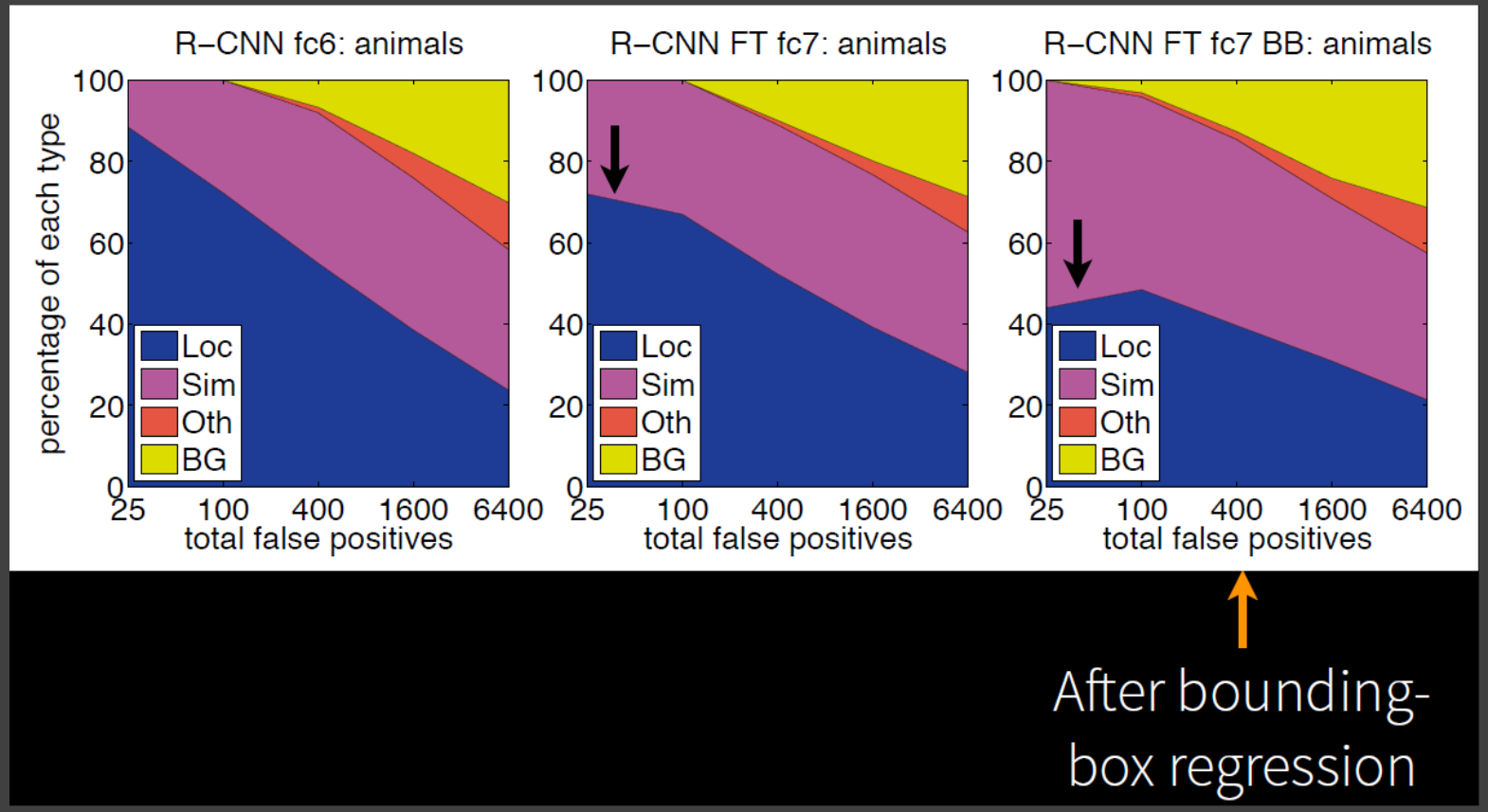
Tuning: Worth it?



Tuning: Worth it?



Tuning: Worth it?



Performance

R-CNN, PASCAL Results

	VOC 2007	VOC 2010
DPM v5 (Girshick et al. 2011)	33.7%	29.6%
UVA sel. search (Uijlings et al. 2013)		35.1%
Regionlets (Wang et al. 2013)	41.7%	39.7%
SegDPM (Fidler et al. 2013)		40.4%
R-CNN	54.2%	50.2%
R-CNN + bbox regression	**58.5%**	**53.7%**

ImageNet Detection

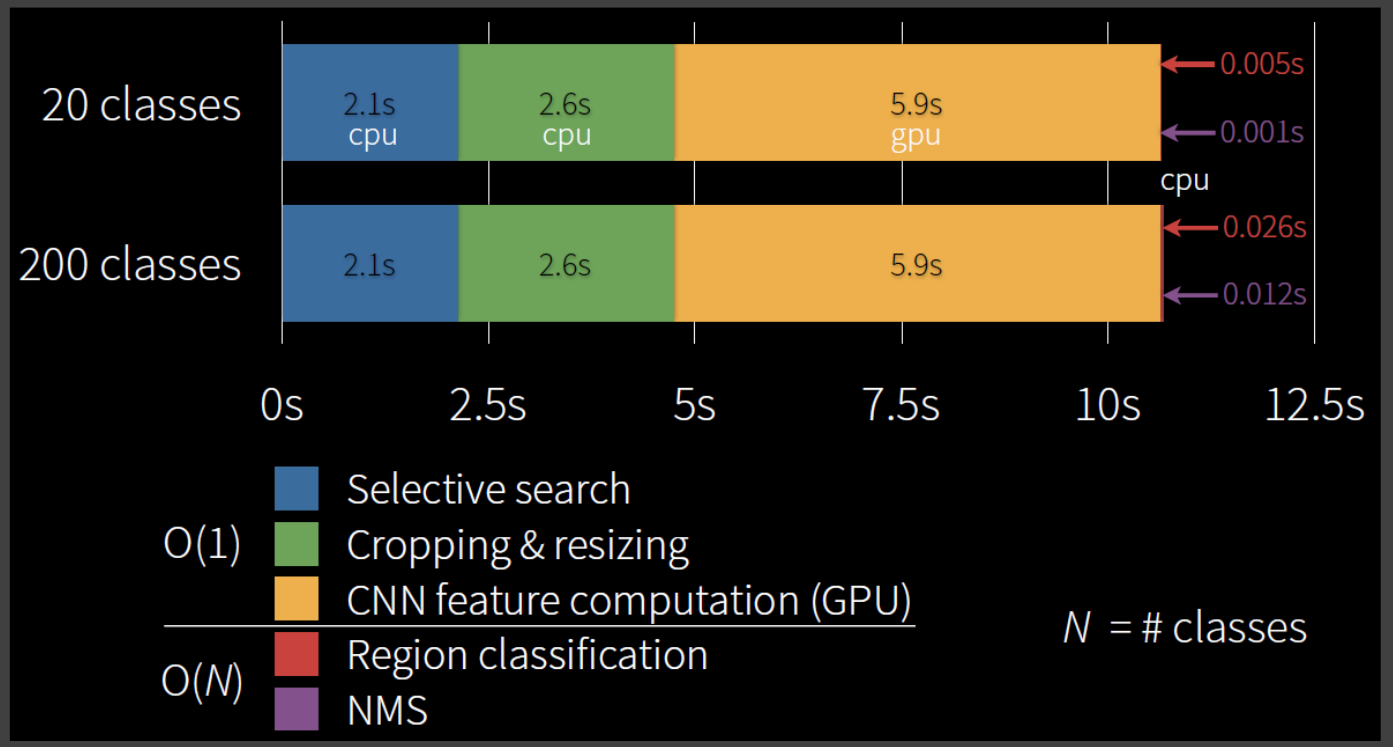
200 object categories instead of *20*

- Can this approach work?

ImageNet Detection

200 object categories instead of *20*

- Can this approach work? Yes!



ImageNet Detection

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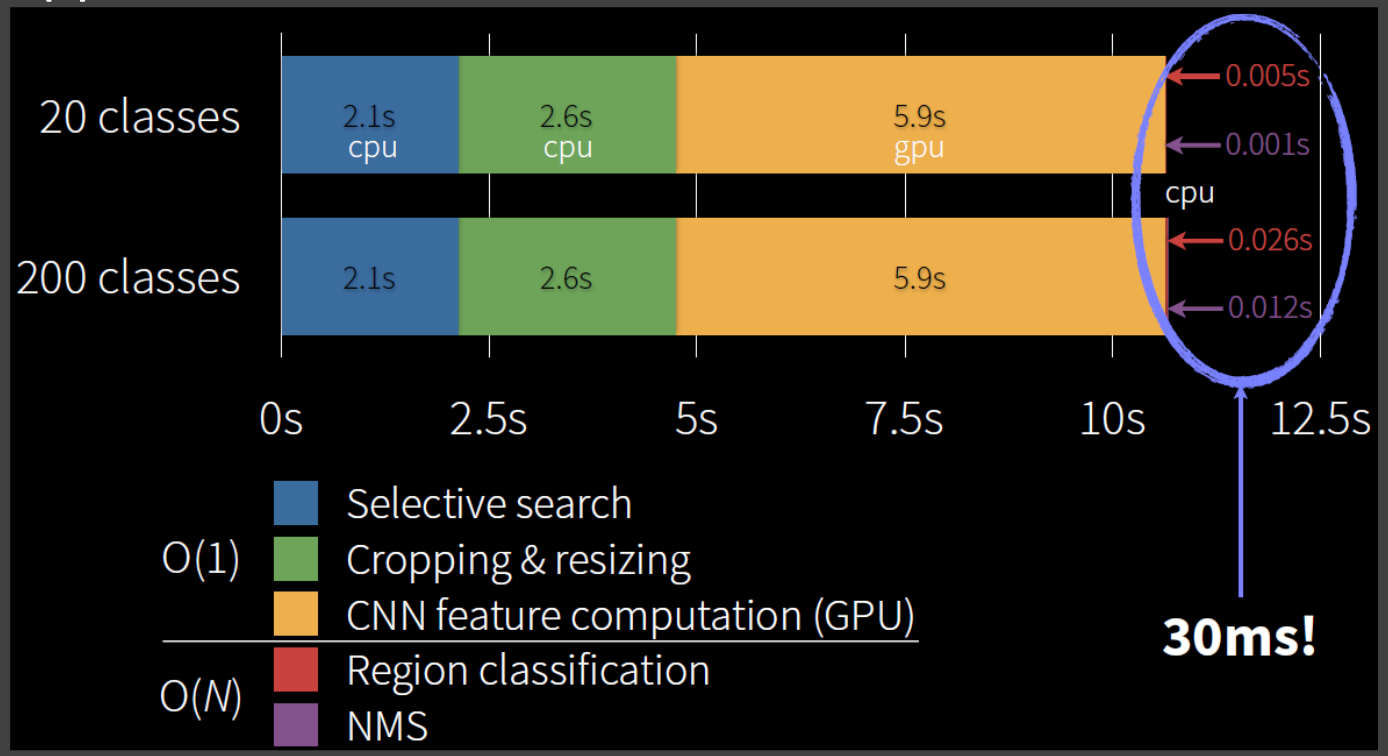
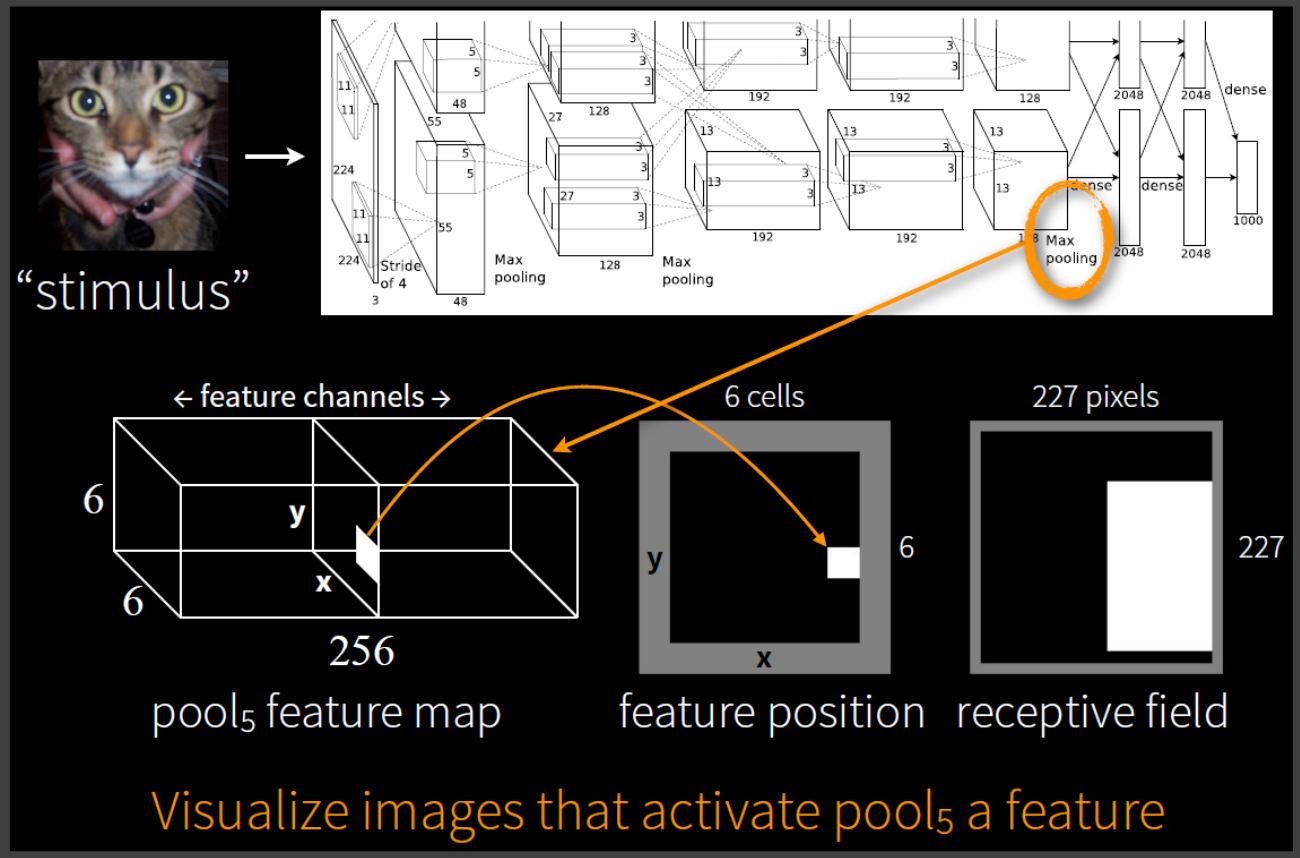
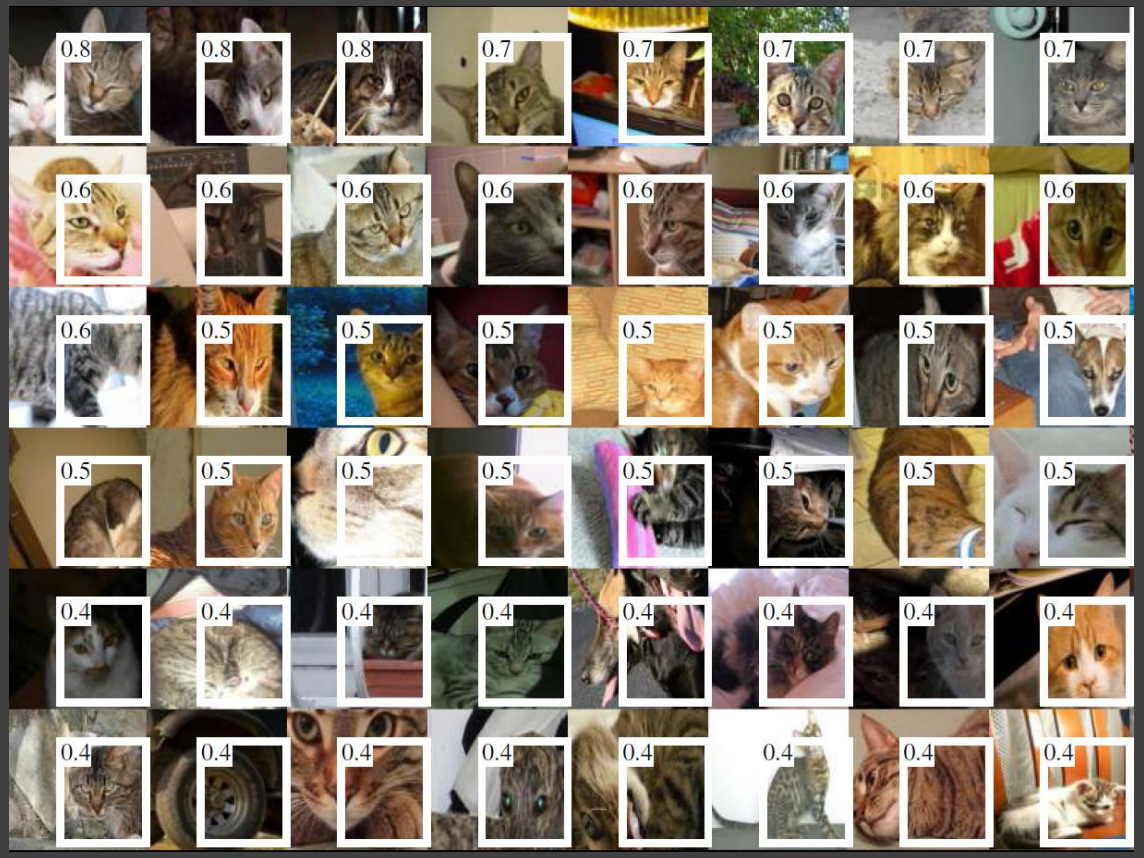


Results

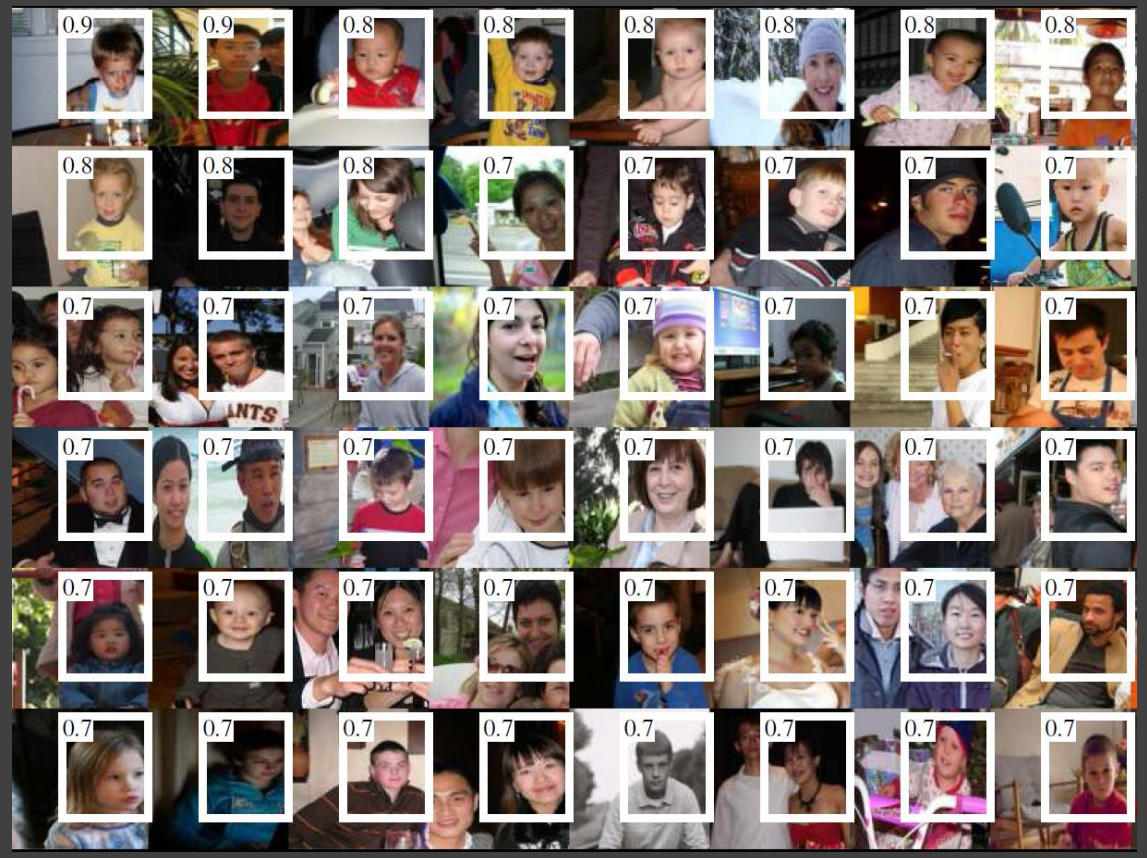
What did the CNN learn?



What did the CNN learn?



What did the CNN learn?



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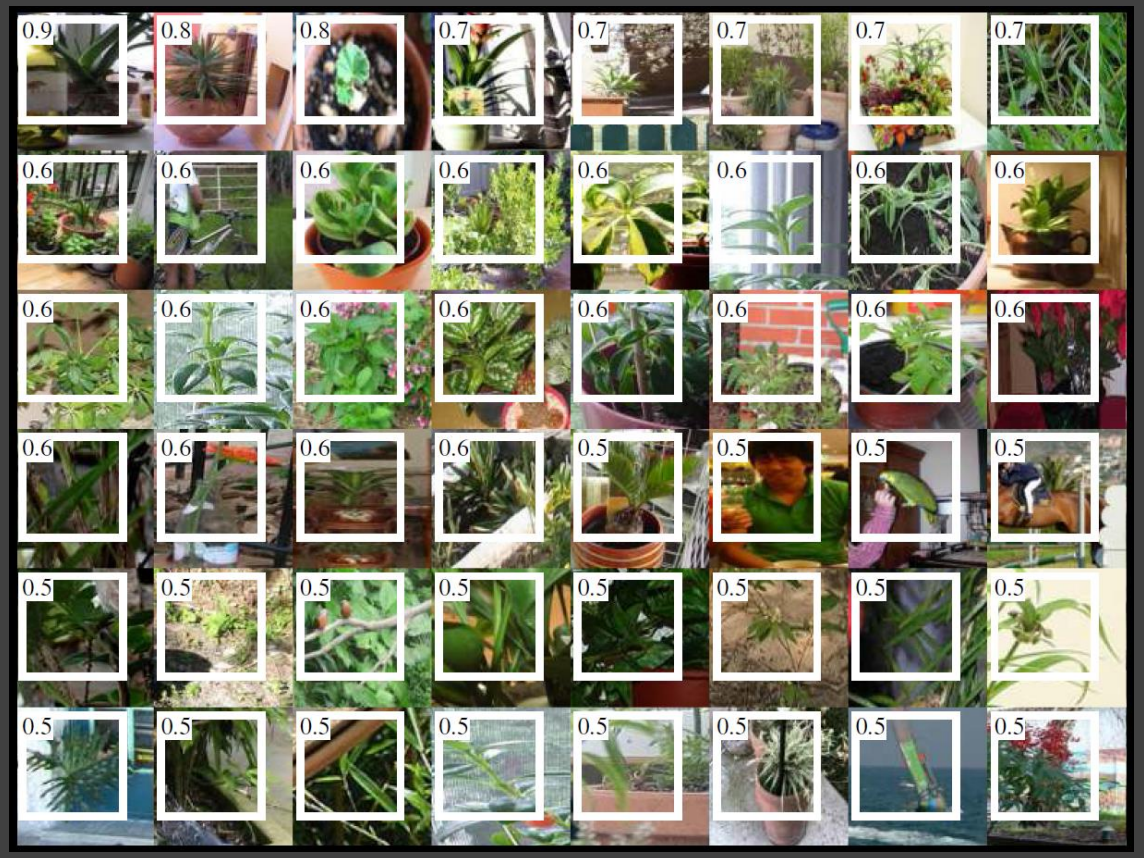
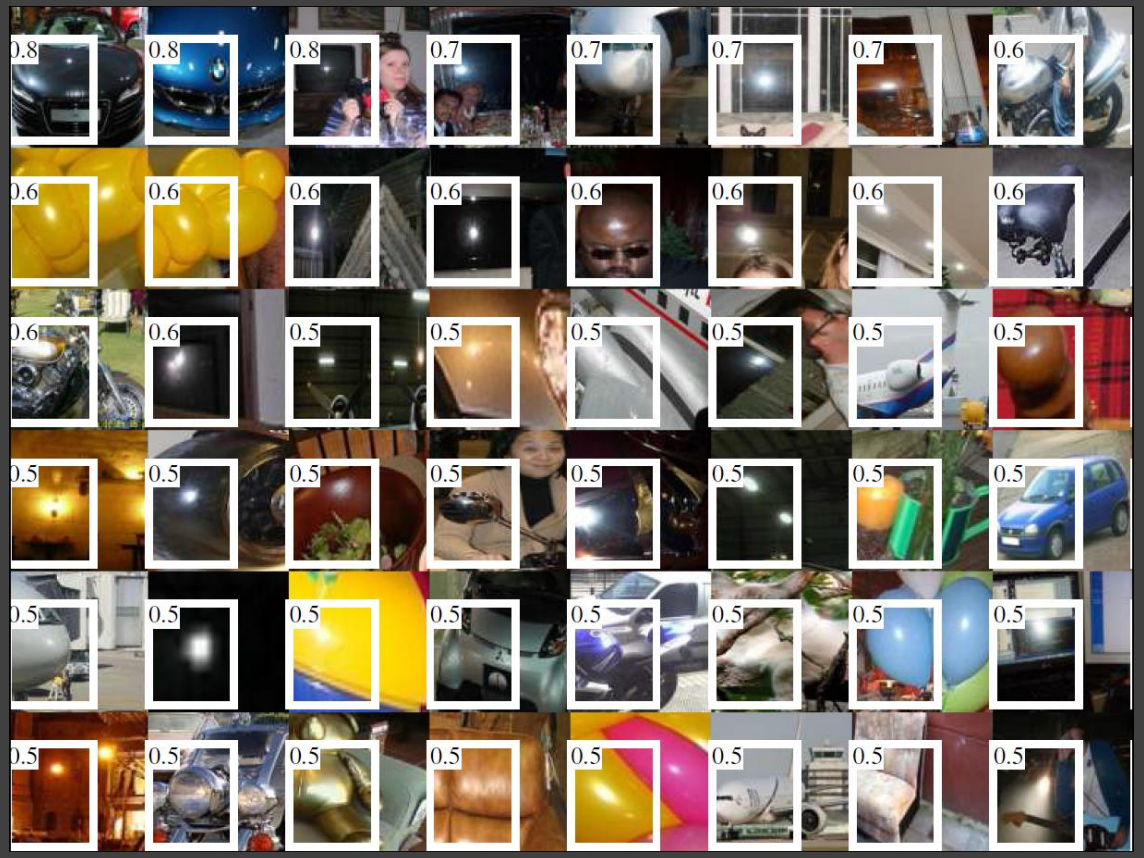


What did the CNN learn?



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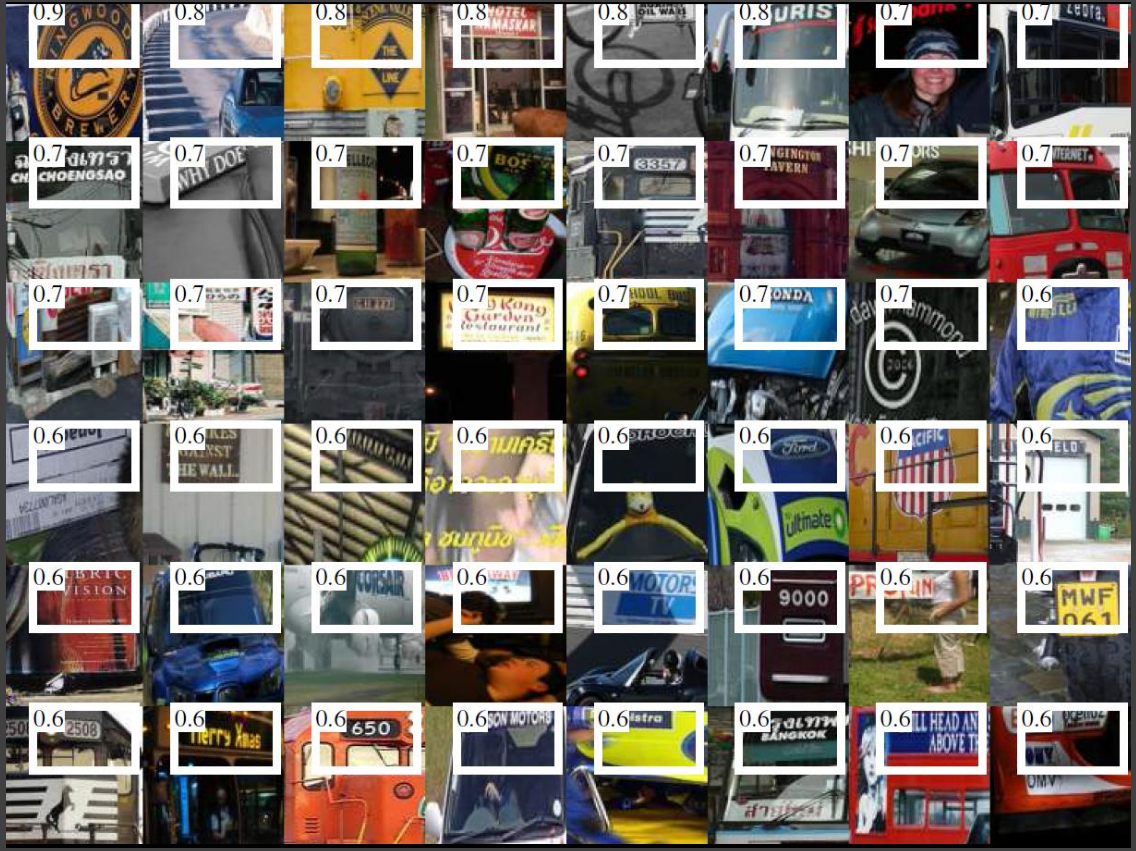
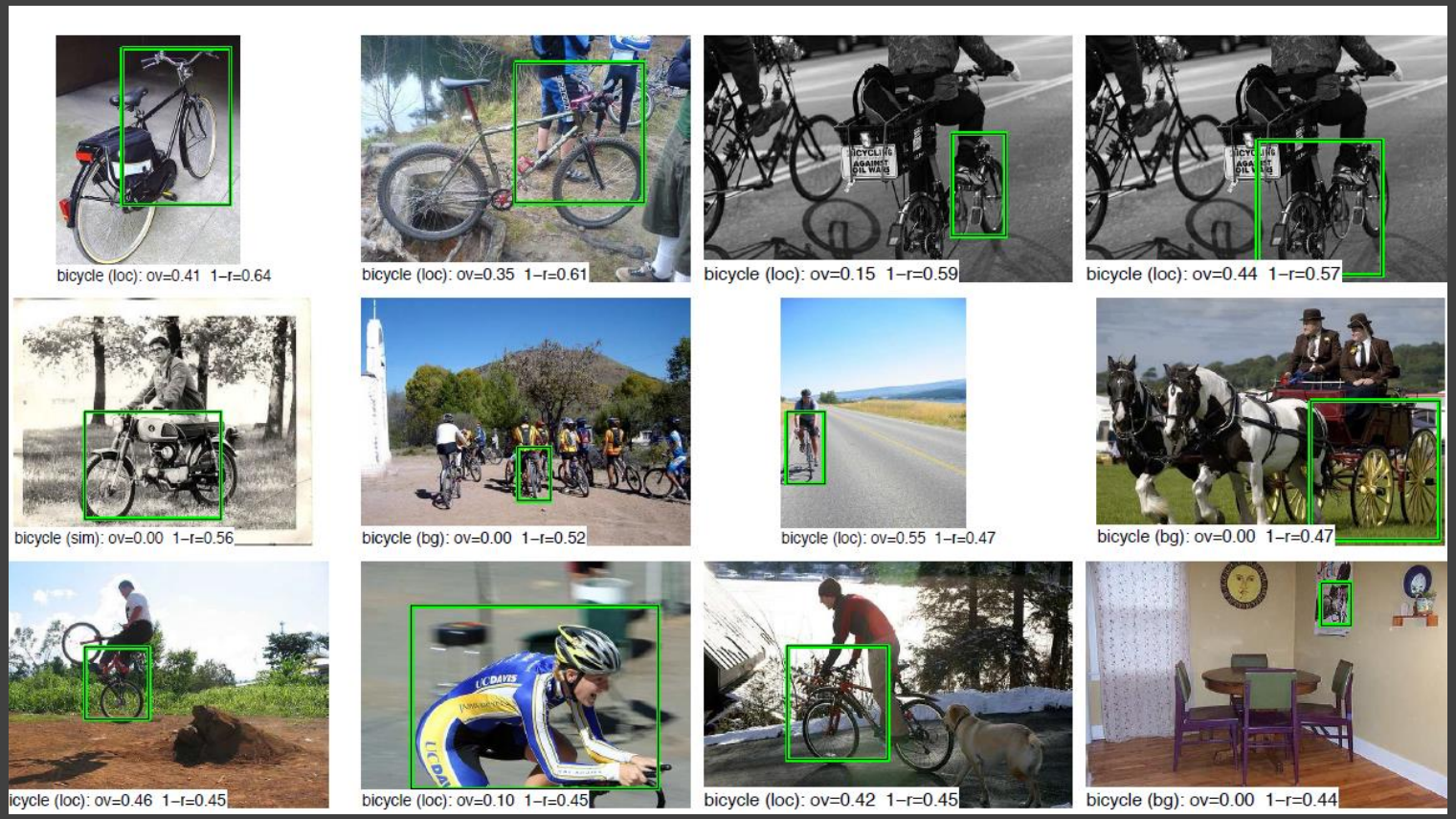
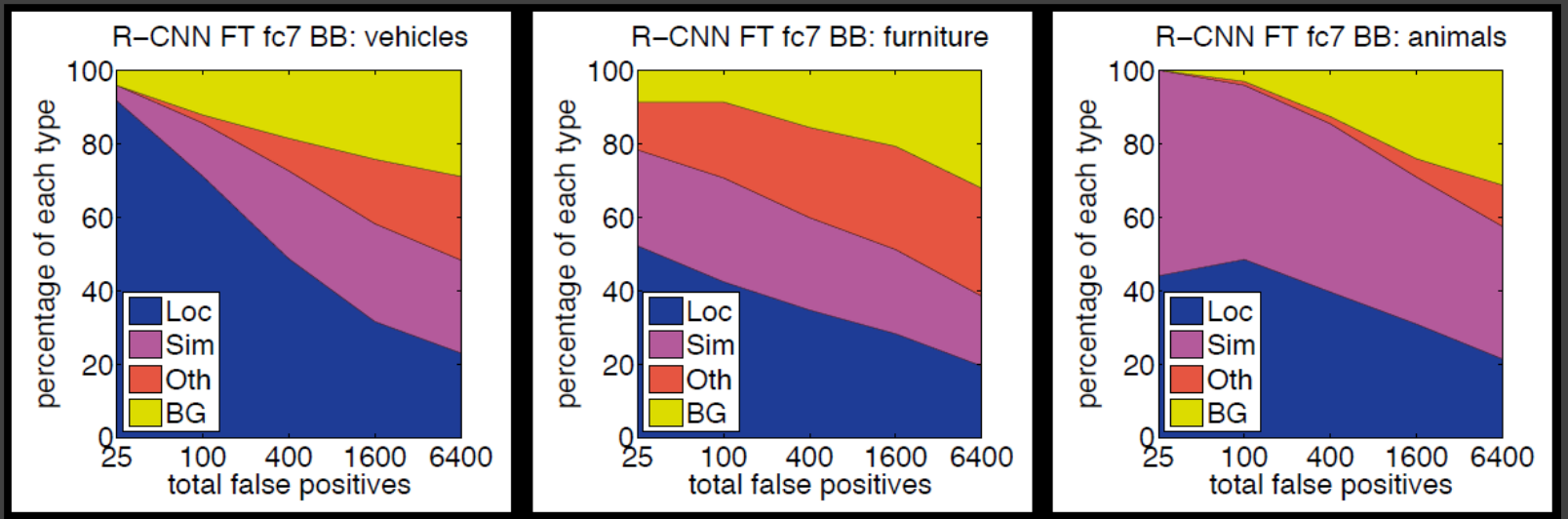


False-Positives

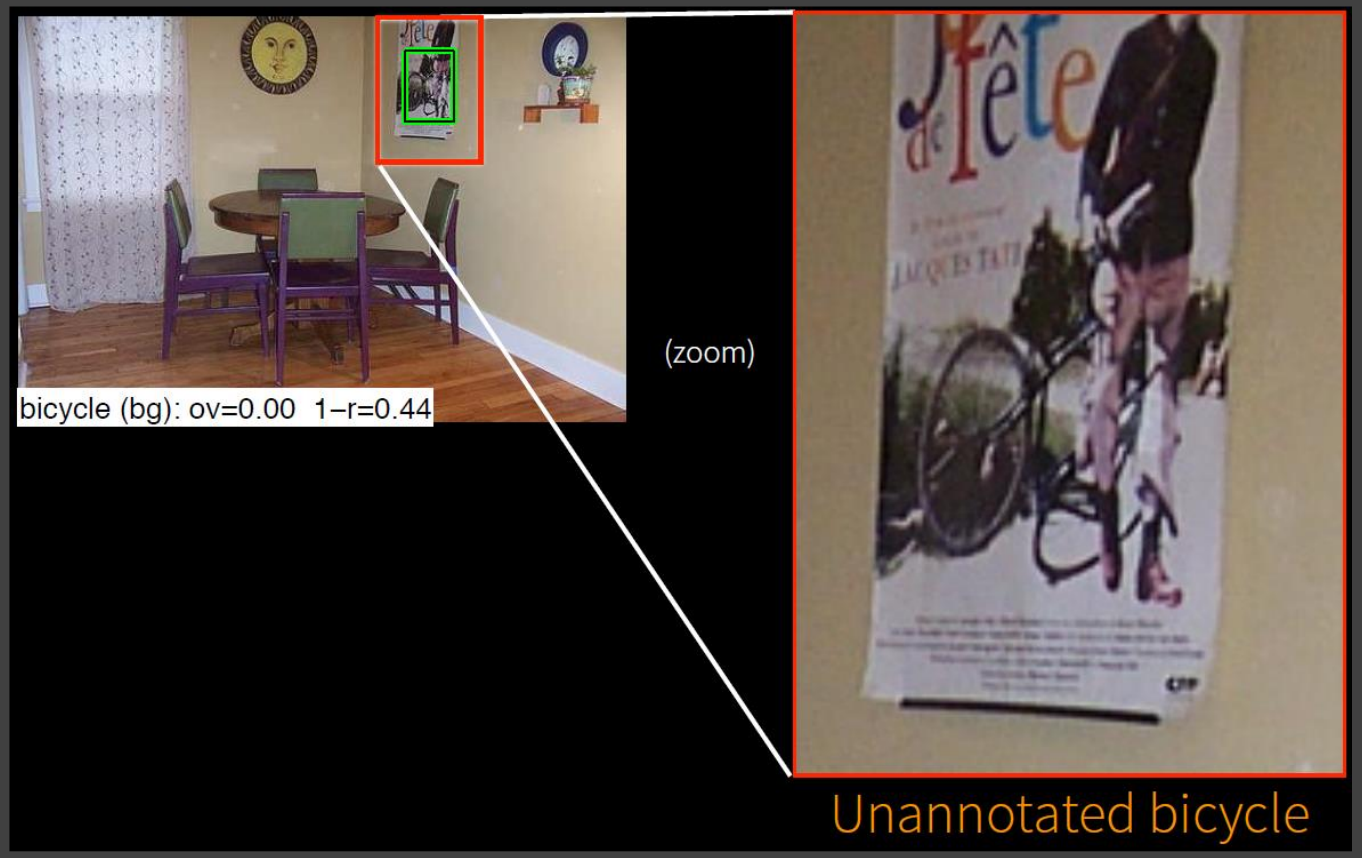


False-Positive Distribution



Analysis software: D. Hoiem, Y. Chodpathumwan, and Q. Dai. Diagnosing Error in Object Detectors. ECCV, 2012.

False-Positive?



False-Positive?

1949 French comedy by Jacques Tati

Conclusion

R-CNN Conclusion

- Dramatically better PASCAL mAP
- Outperforms other CNN-based methods
- Detection speed manageable (~11s/image on GPU)
- Scales very well (30ms for 20 → 200 classes!)
- Relatively simple and open source

Questions