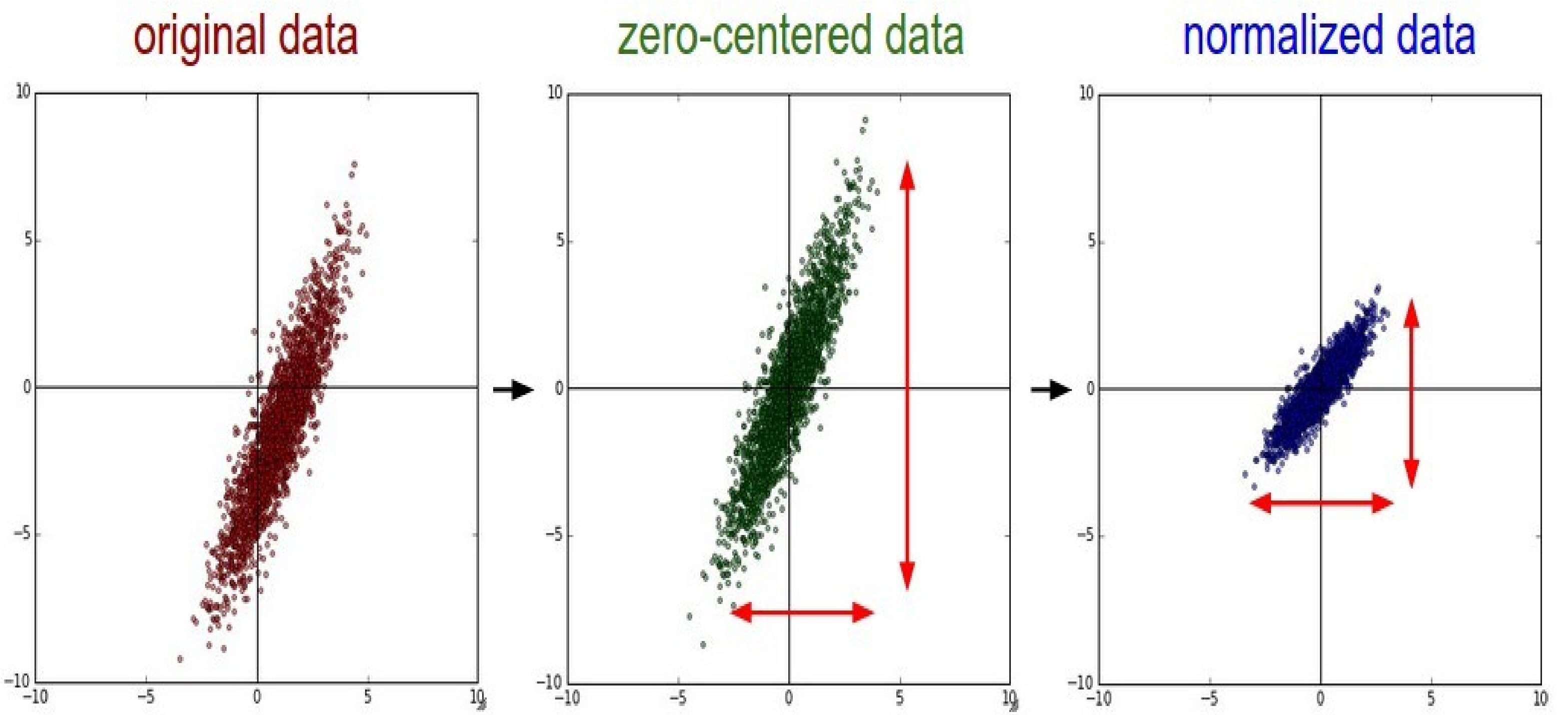
Lecture 22
Deep Learning:
Object Detection and Segmentation

COS 429: Computer Vision

PRINCETON UNIVERSITY

Thanks: most of these slides shamelessly adapted from
Stanford CS231n: Convolutional Neural Networks for Visual Recognition
Fei-Fei Li, Andrej Karpathy, Justin Johnson
http://cs231n.stanford.edu/

Step 1: Preprocess the data

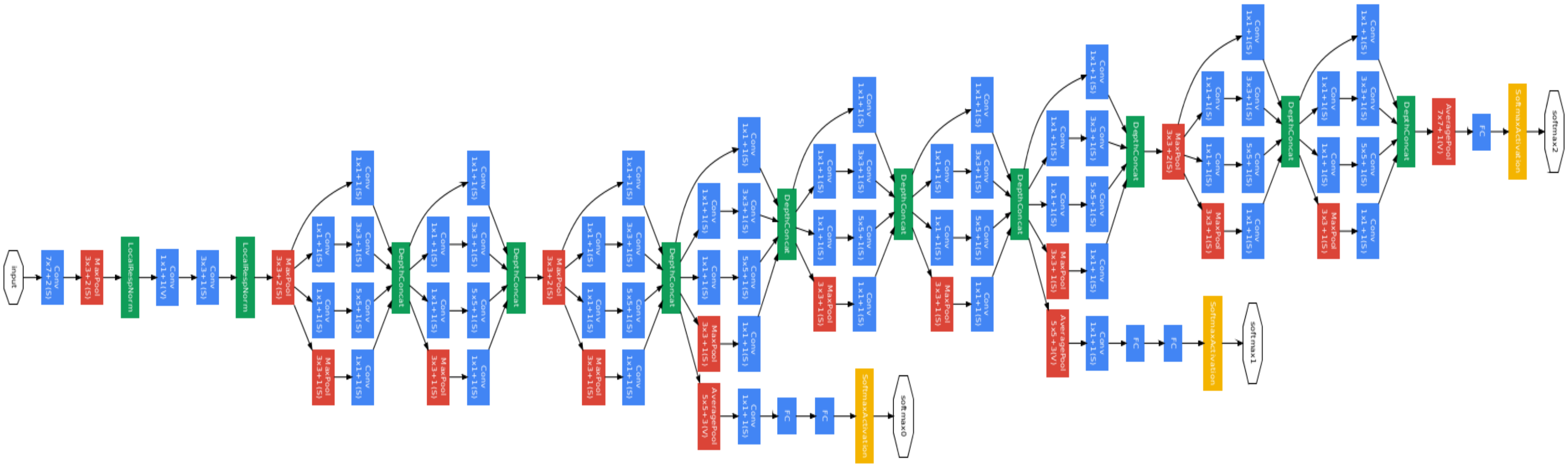



```
X -= np.mean(X, axis = 0)
```

```
X /= np.std(X, axis = 0)
```

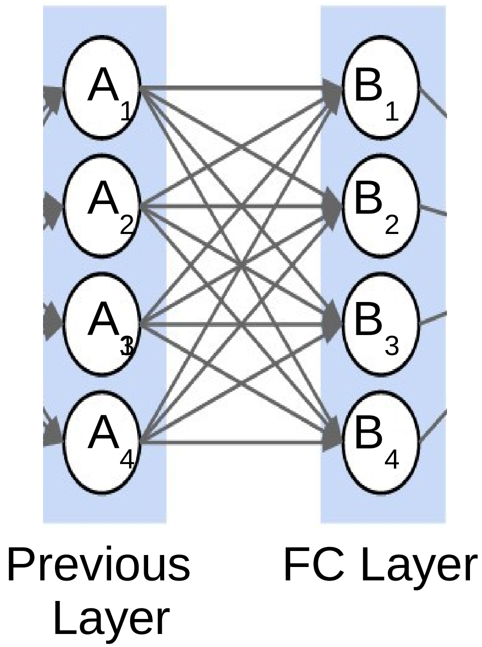
(Assume X [NxD] is data matrix,
each example in a row)

Define Network Architecture



Slide Credit:

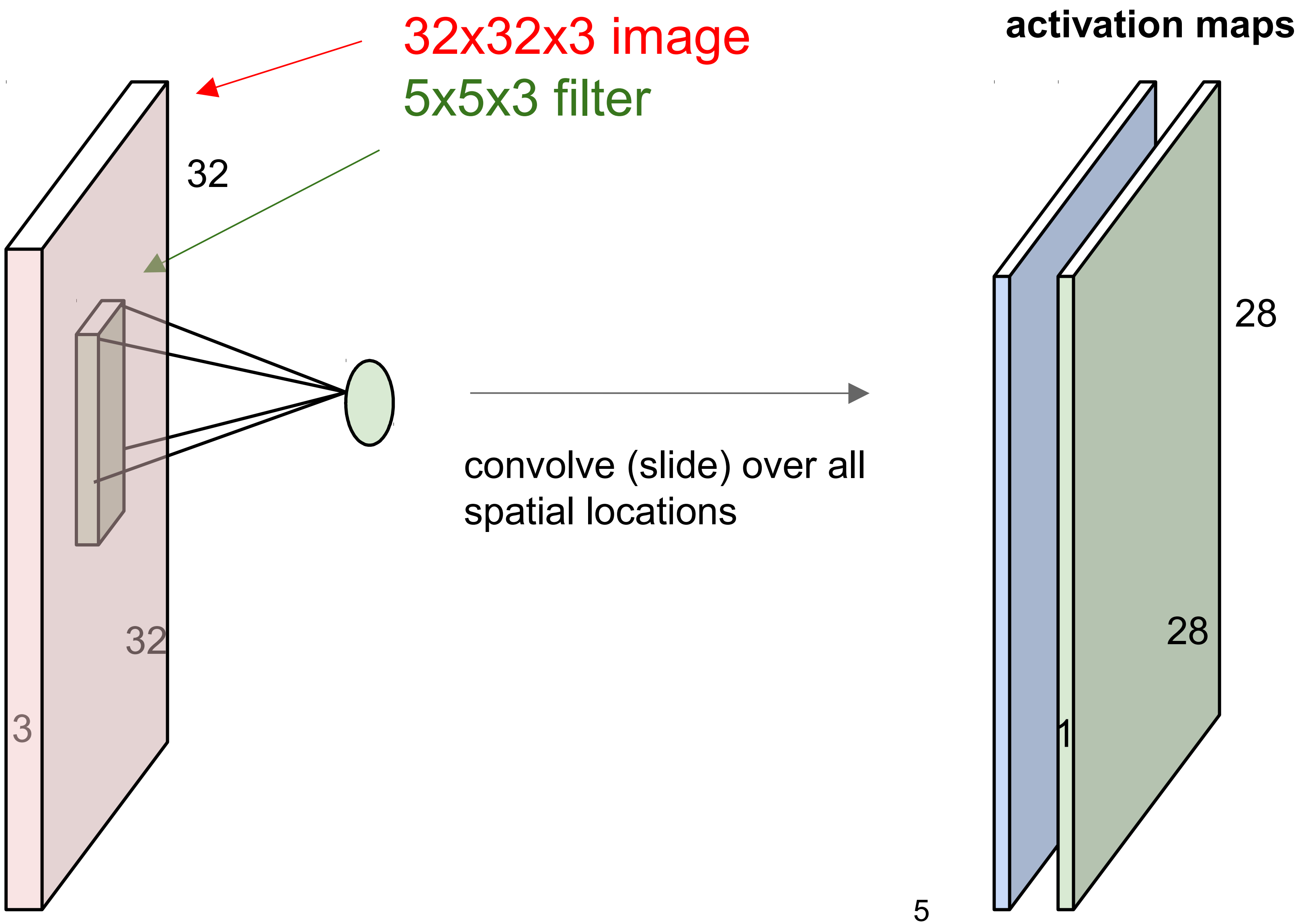
Fully Connected layer



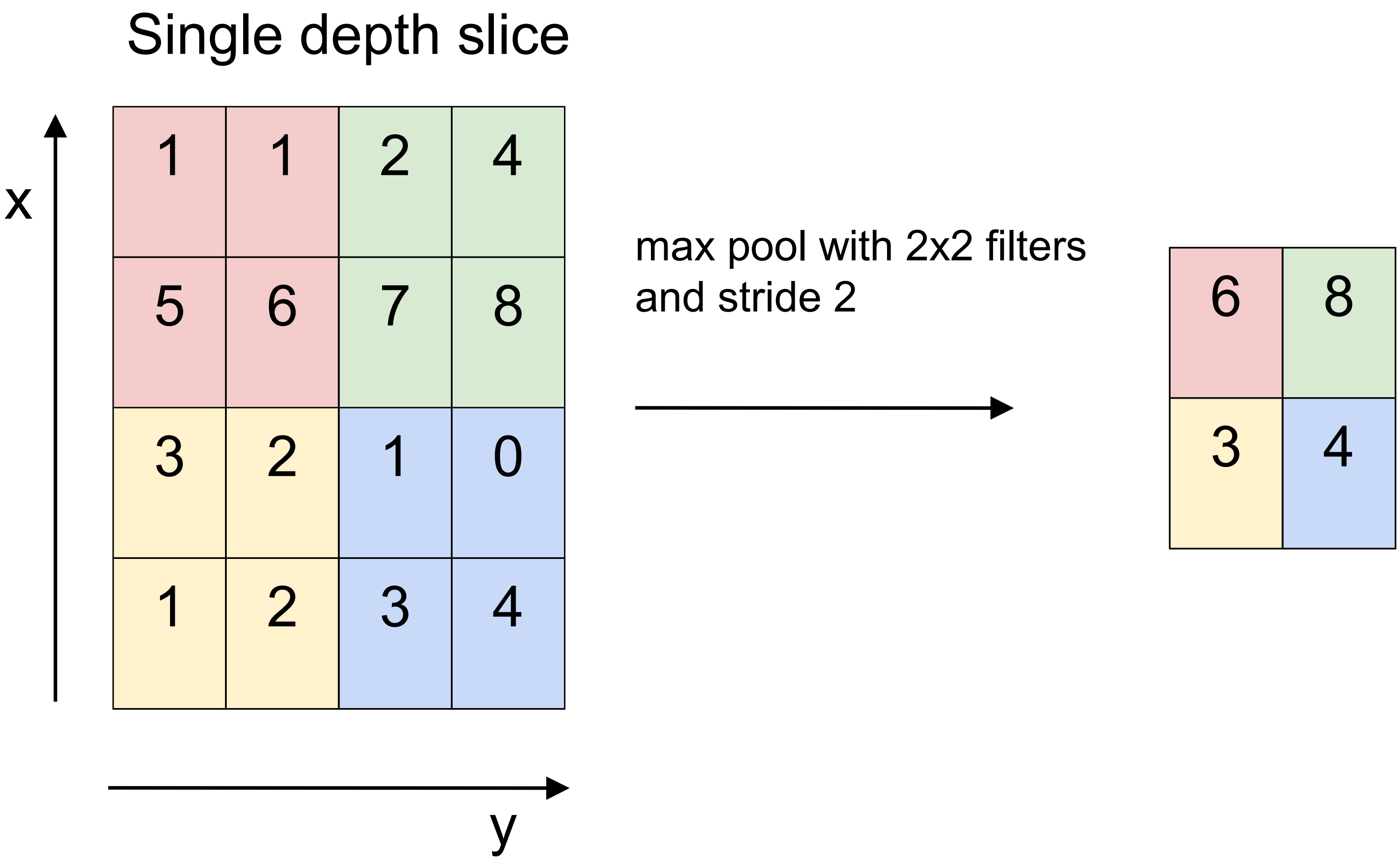
$$B_j = \sum_i \left(W_{ij} * A_i \right) + b_j$$

Slide Credit:

Convolution Layer



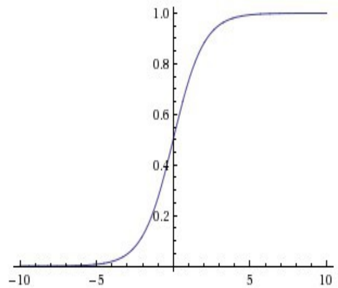
MAX POOLING


Single depth slice
x
y
1 1 2 4
5 6 7 8
3 2 1 0
1 2 3 4
max pool with 2x2 filters
and stride 2
6 8
3 4

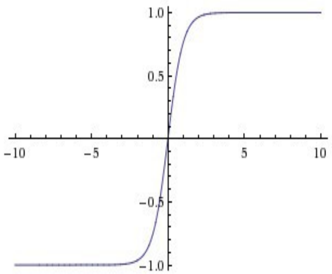
Activation Layer

Sigmoid

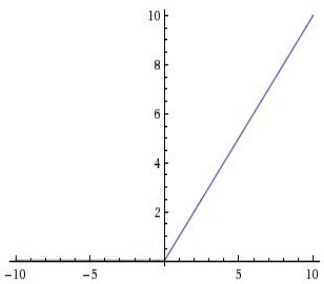
$$\sigma(x) = 1/(1+e^{-x})$$



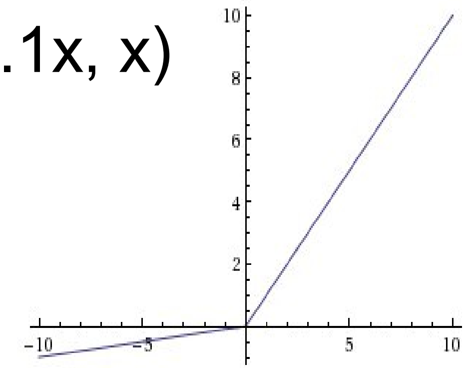
tanh tanh(x)



ReLU max(0,x)

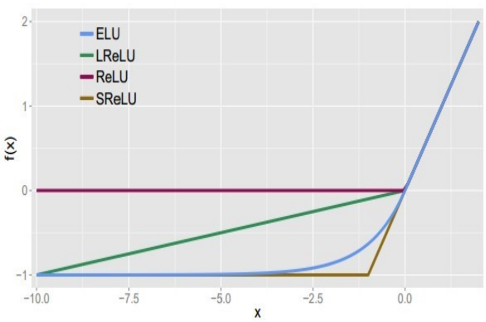


Leaky ReLU
max(0.1x, x)



Maxout $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU $f(x) = \begin{cases} x & \text{if } x > 0 \\ \alpha\,(\exp(x) - 1) & \text{if } x \le 0 \end{cases}$



Slide Credit:

Batch Normalization

[Ioffe and Szegedy, 2015]

Input: Values of x over a mini-batch: $\mathcal{B} = \{x_{1\ldots m}\}$;
Parameters to be learned: γ, β

Output: $\{y_i = \mathrm{BN}_{\gamma,\beta}(x_i)\}$

$$\mu_{\mathcal{B}} \leftarrow \frac{1}{m}\sum_{i=1}^{m} x_i \qquad \text{// mini-batch mean}$$

$$\sigma_{\mathcal{B}}^2 \leftarrow \frac{1}{m}\sum_{i=1}^{m} (x_i - \mu_{\mathcal{B}})^2 \qquad \text{// mini-batch variance}$$

$$\widehat{x}_i \leftarrow \frac{x_i - \mu_{\mathcal{B}}}{\sqrt{\sigma_{\mathcal{B}}^2 + \epsilon}} \qquad \text{// normalize}$$

$$y_i \leftarrow \gamma \widehat{x}_i + \beta \equiv \mathrm{BN}_{\gamma,\beta}(x_i) \qquad \text{// scale and shift}$$

- Improves gradient flow through the network
- Allows higher learning rates
- Reduces the strong dependence on initialization
- Acts as a form of regularization in a funny way, and slightly reduces the need for dropout, maybe

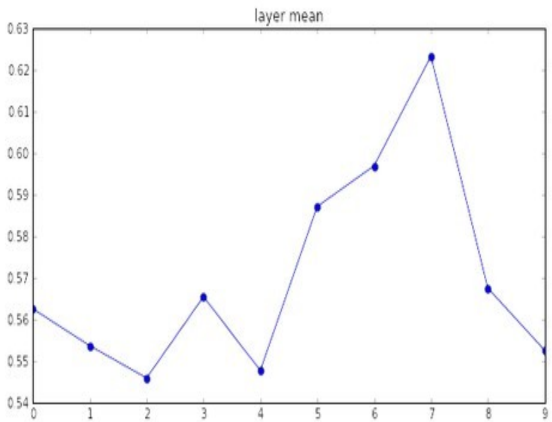
Slide Credit:

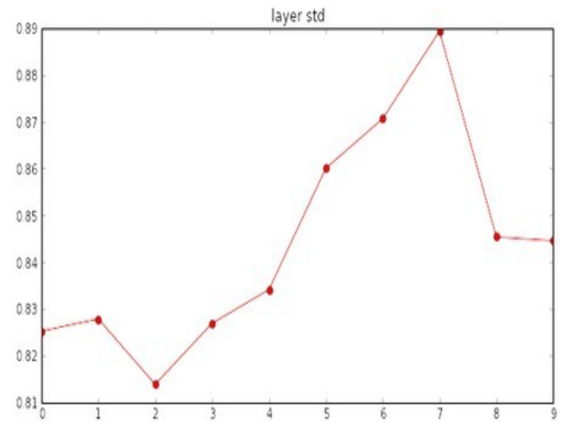
Weight Initialization

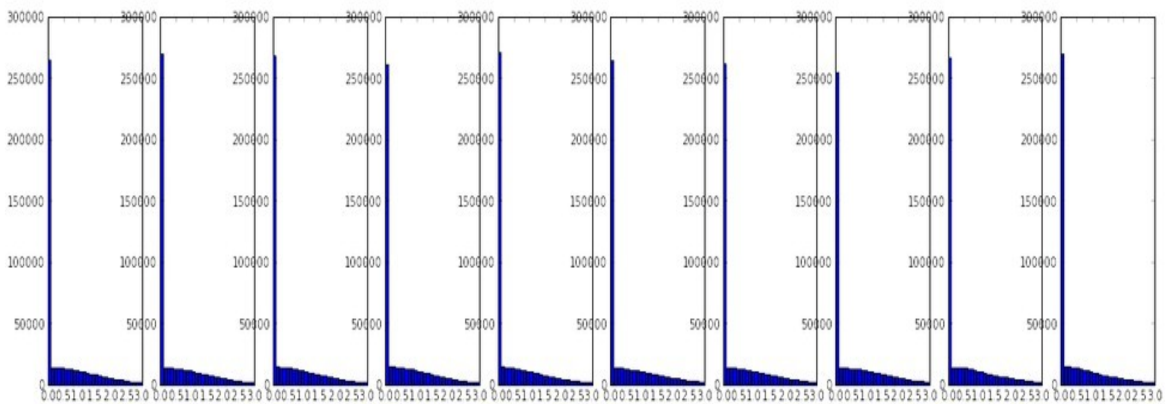
```
input layer had mean 0.000501 and std 0.999444
hidden layer 1 had mean 0.562488 and std 0.825232
hidden layer 2 had mean 0.553614 and std 0.827835
hidden layer 3 had mean 0.545867 and std 0.813855
hidden layer 4 had mean 0.565396 and std 0.826902
hidden layer 5 had mean 0.547678 and std 0.834092
hidden layer 6 had mean 0.587103 and std 0.860035
hidden layer 7 had mean 0.596867 and std 0.870610
hidden layer 8 had mean 0.623214 and std 0.889348
hidden layer 9 had mean 0.567498 and std 0.845357
hidden layer 10 had mean 0.552531 and std 0.844523
```

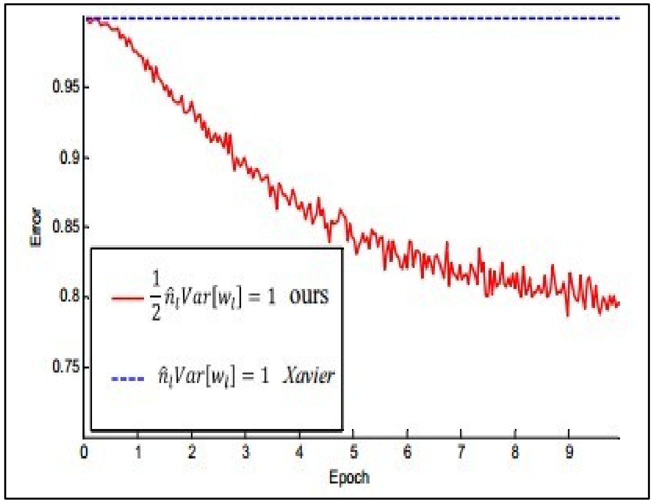
He et al., 2015
(note additional /2)

```
W = np.random.randn(fan_in, fan_out) / np.sqrt(fan_in/2) # layer initialization
```





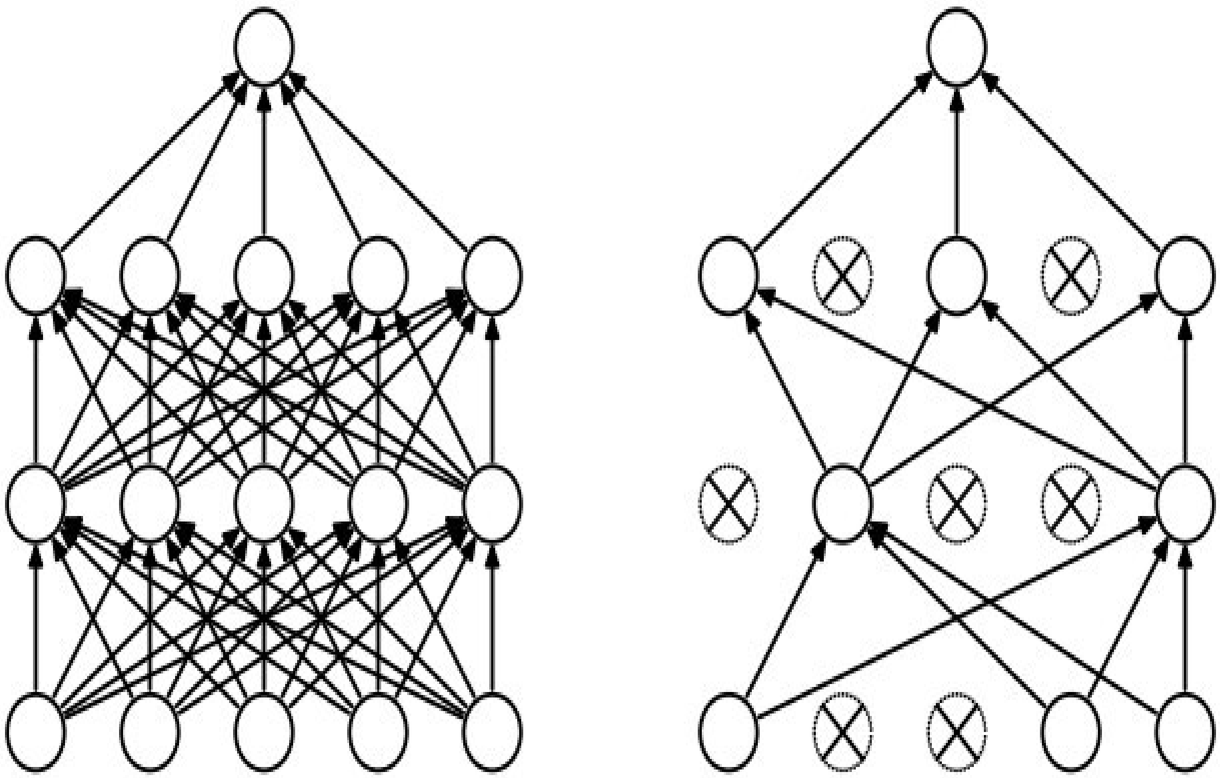




Slide Credit:

Regularization: **Dropout**

"randomly set some neurons to zero in the forward pass"



(a) Standard Neural Net (b) After applying dropout.

[Srivastava et al., 2014]

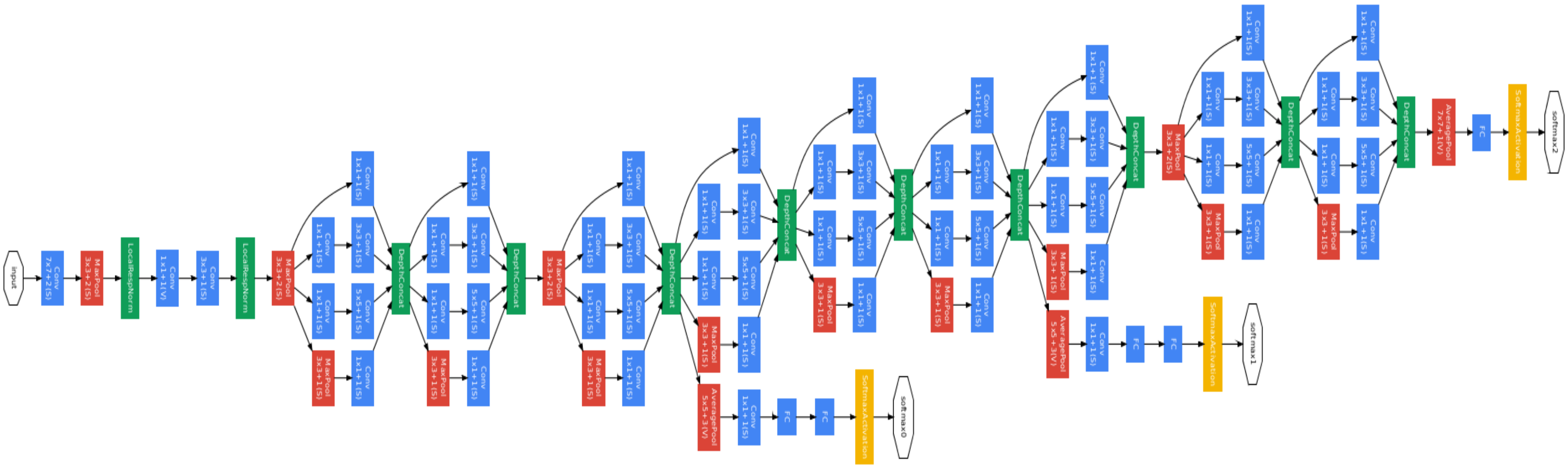
Regularization: **DisturbLabel**

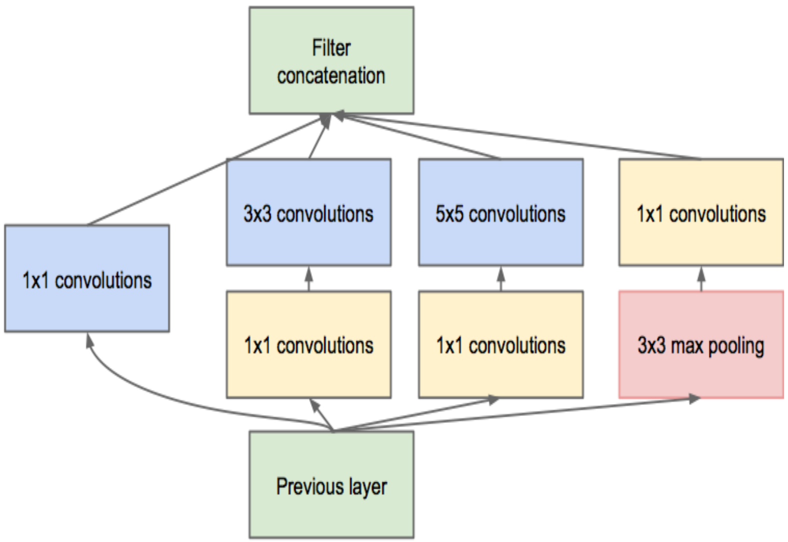
“randomly change ground truth label of small % of examples”

=>Improves generalization, reduces need for dropout

Case Study: GoogLeNet

[Szegedy et al., 2014]





Inception module

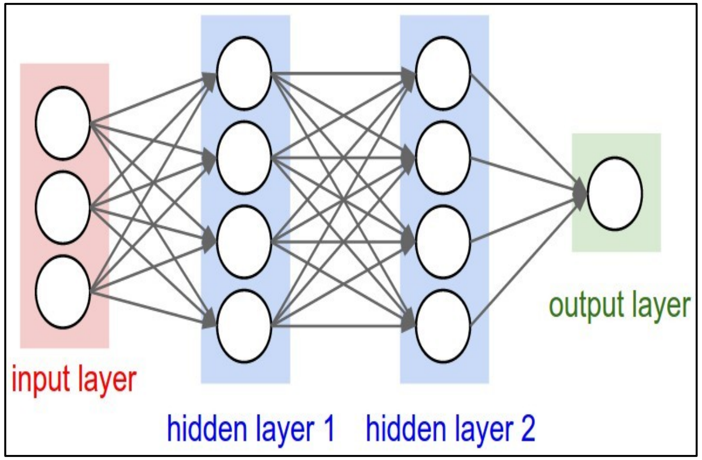
ILSVRC 2014 winner (6.7% top 5 error)

Slide Credit:

Mini-batch SGD

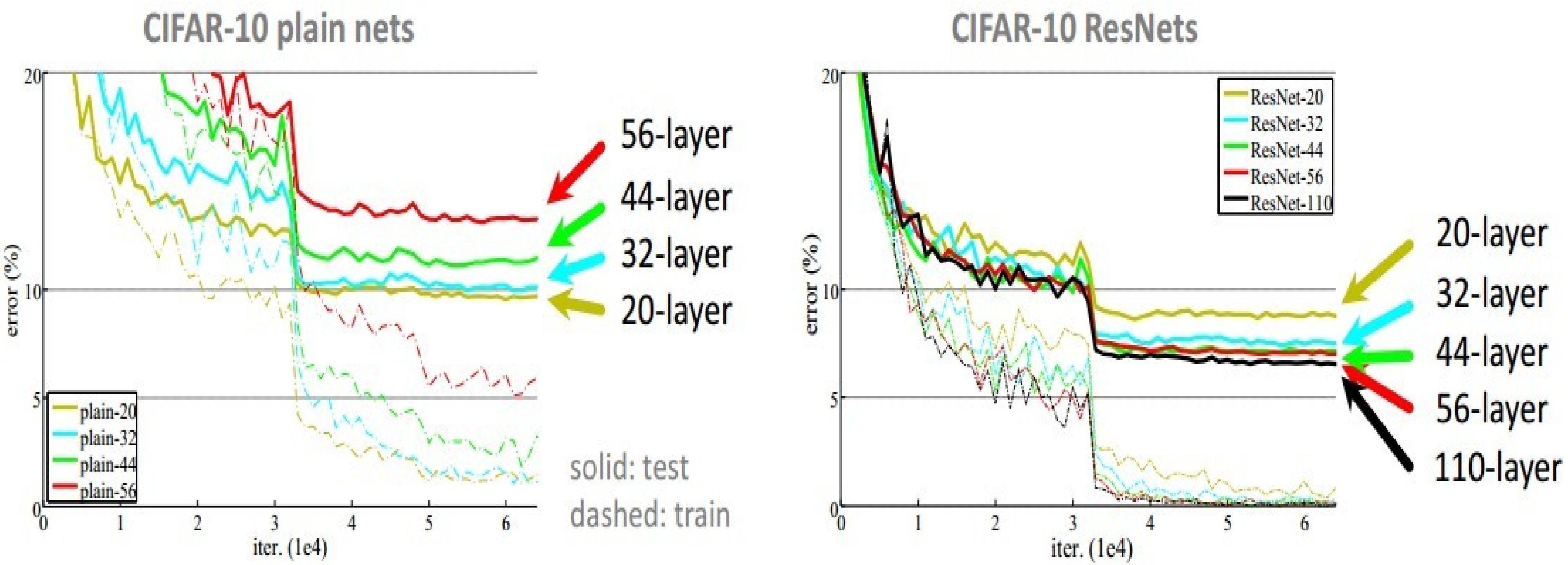
Loop:

1. **Sample** a batch of data
2. **Forward** prop it through the graph, get loss
3. **Backprop** to calculate the gradients
4. **Update** the parameters using the gradient



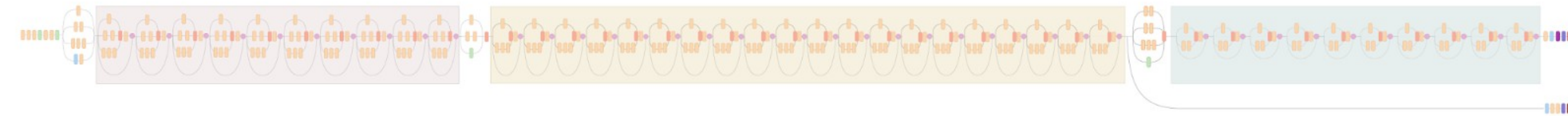
 Slide Credit:

CIFAR-10 experiments

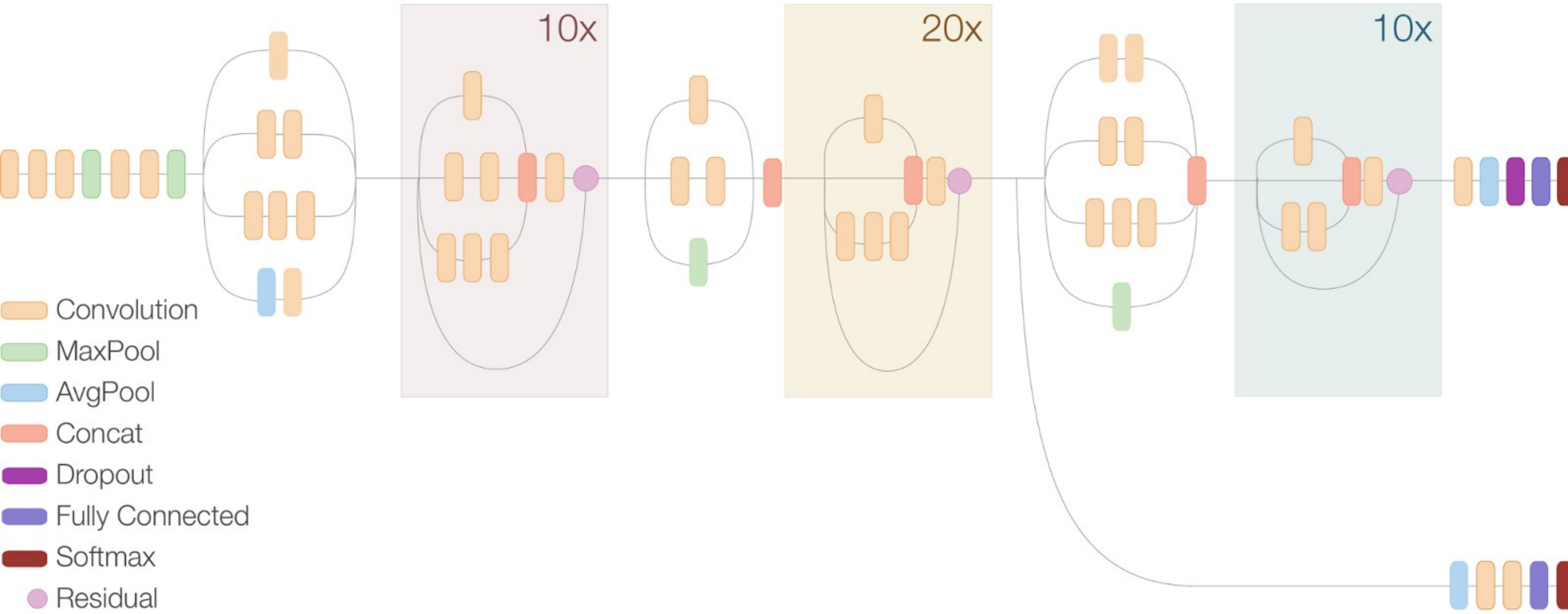


 Slide Credit:

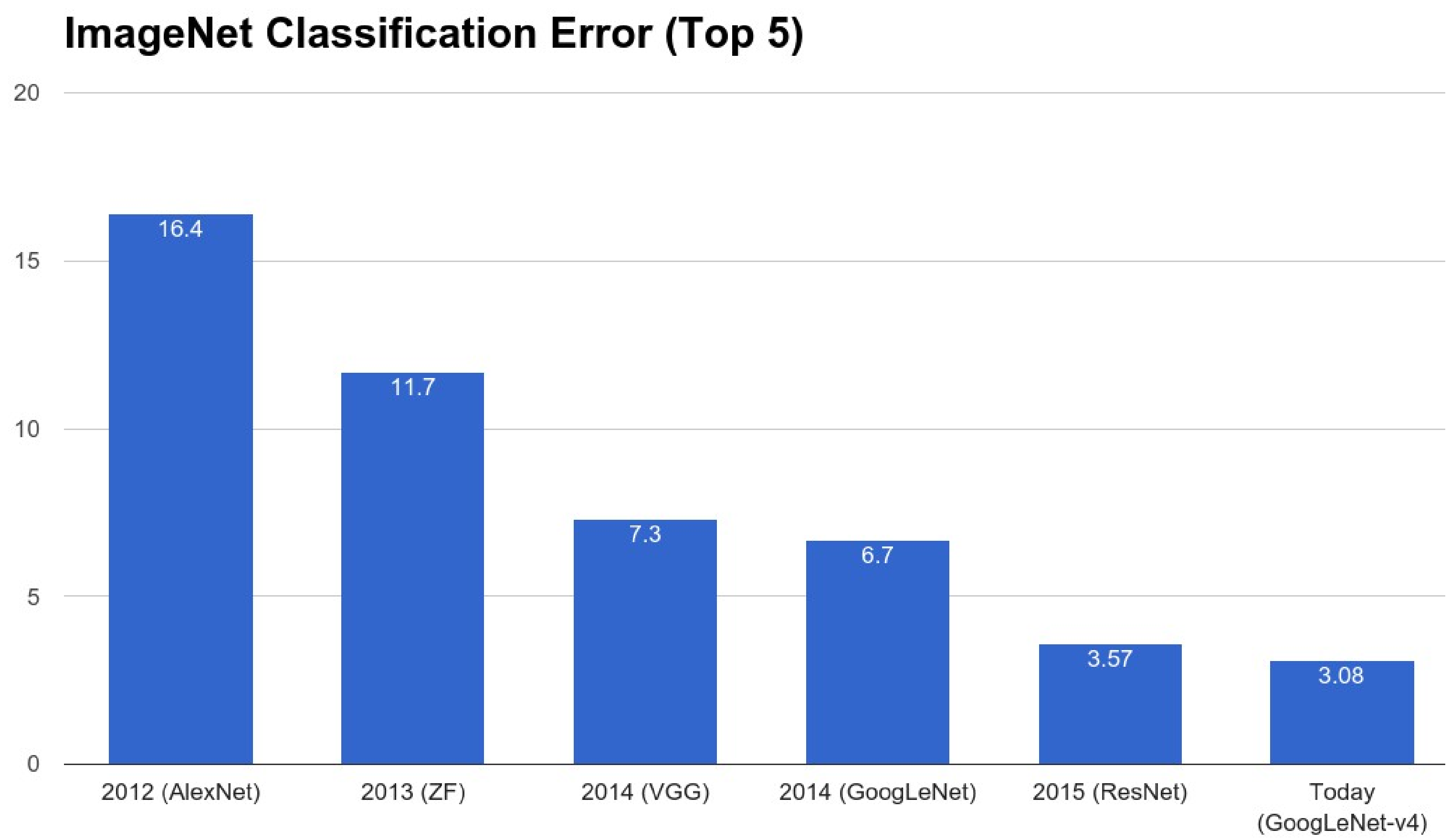
Inception Resnet V2 Network



Compressed View



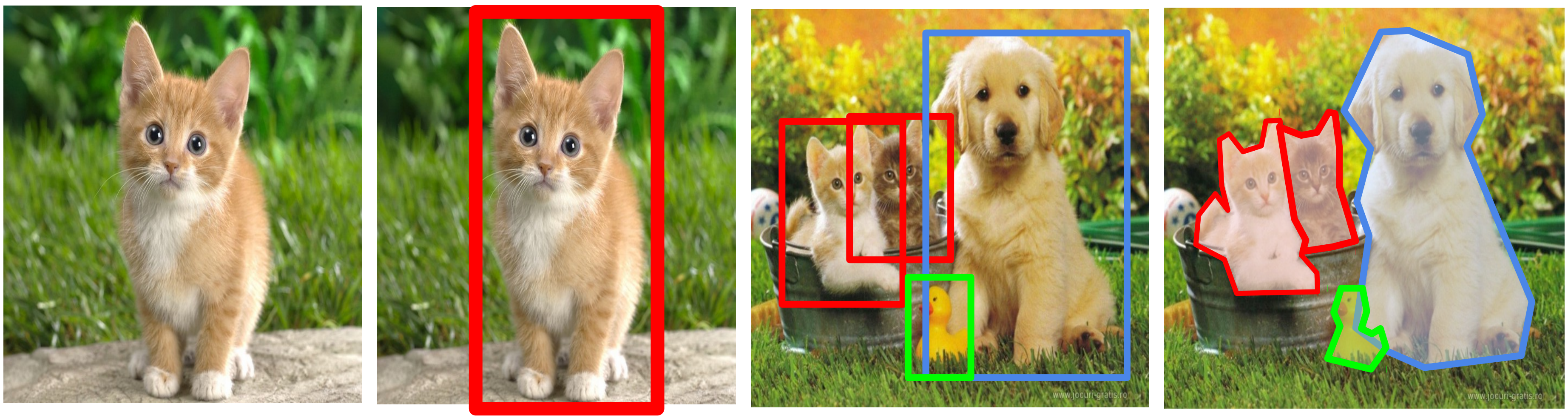
Slide Credit:



Szegedy et al, Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning, arXiv 2016

Computer Vision Tasks

Classification | **Classification + Localization** | **Object Detection** | **Instance Segmentation**



CAT | CAT | CAT, DOG, DUCK | CAT, DOG, DUCK

Single object | Multiple objects

Slide Credit:

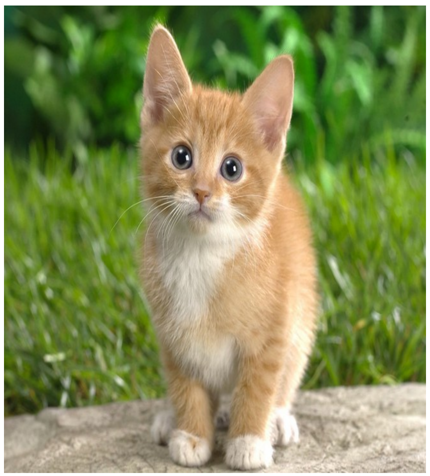
Computer Vision Tasks

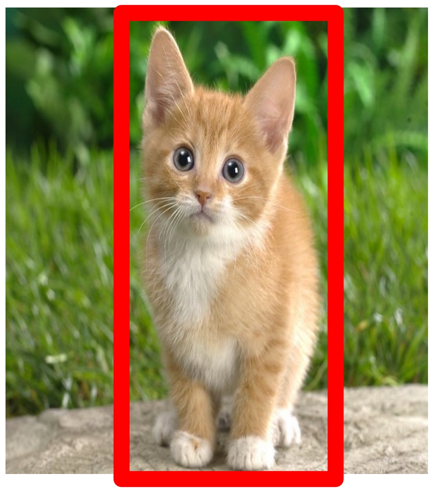
Classification

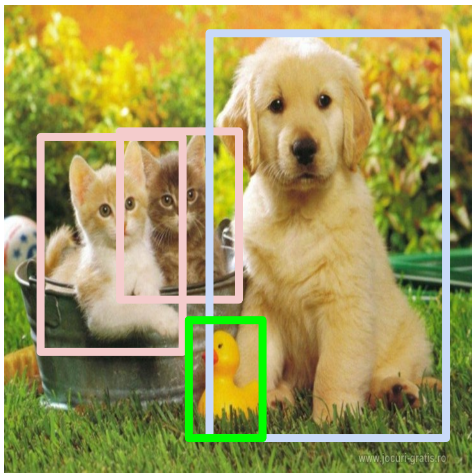
Classification + Localization

Object Detection

Instance Segmentation







Classification + Localization: Task

Classification: C classes
Input: Image
Output: Class label
Evaluation metric: Accuracy

CAT

Localization:
Input: Image
Output: Box in the image (x, y, w, h)
Evaluation metric: Intersection over Union

(x, y, w, h)

Classification + Localization: Do both

Classification + Localization: ImageNet

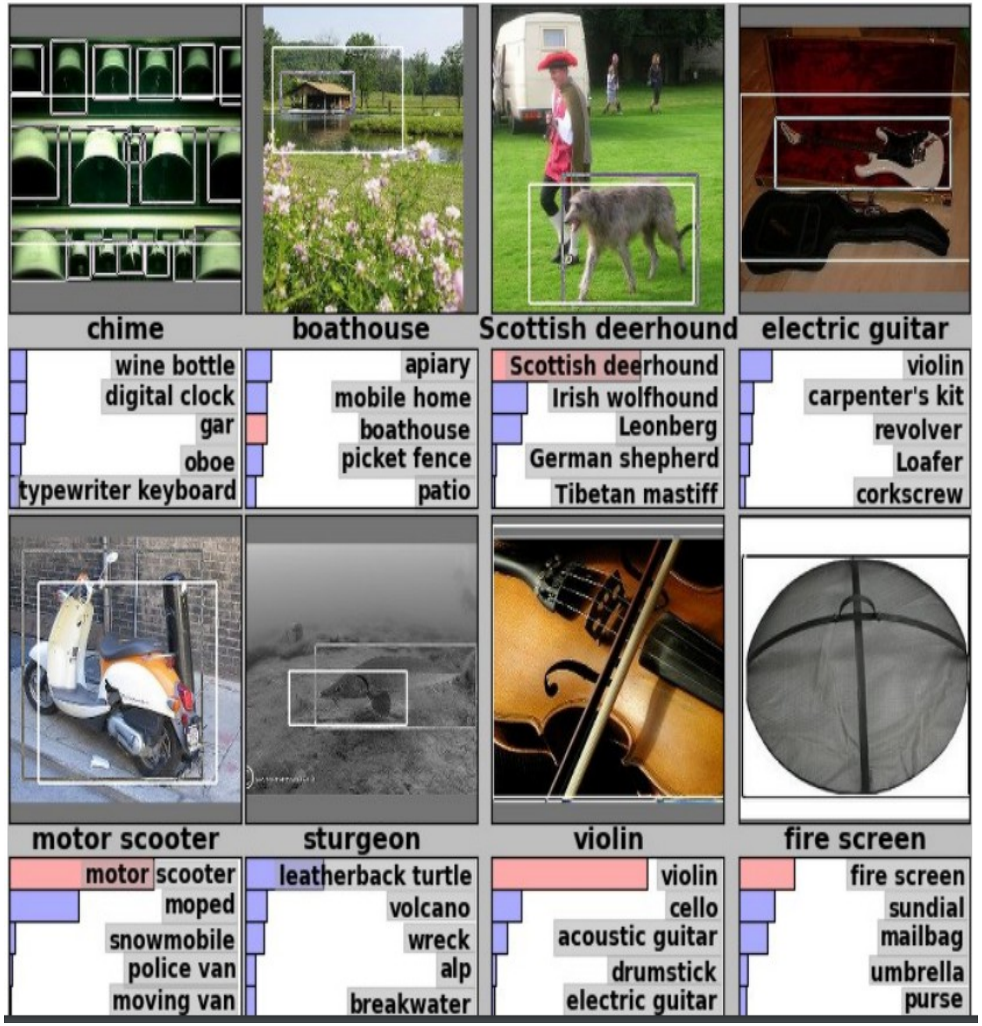
1000 classes (same as classification)

Each image has 1 class, at least one bounding box

~800 training images per class

Algorithm produces 5 (class, box) guesses

Example is correct if at least one one guess has correct class AND bounding box at least 0.5 intersection over union (IoU)



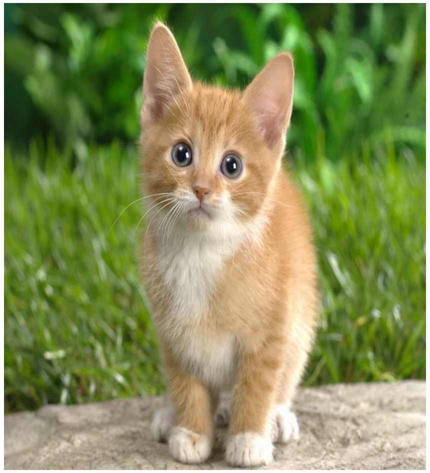
Krizhevsky et. al. 2012

20

Slide Credit:

Idea #1: Localization as Regression

Input: image



Neural Net

Output:
Box coordinates
(4 numbers)

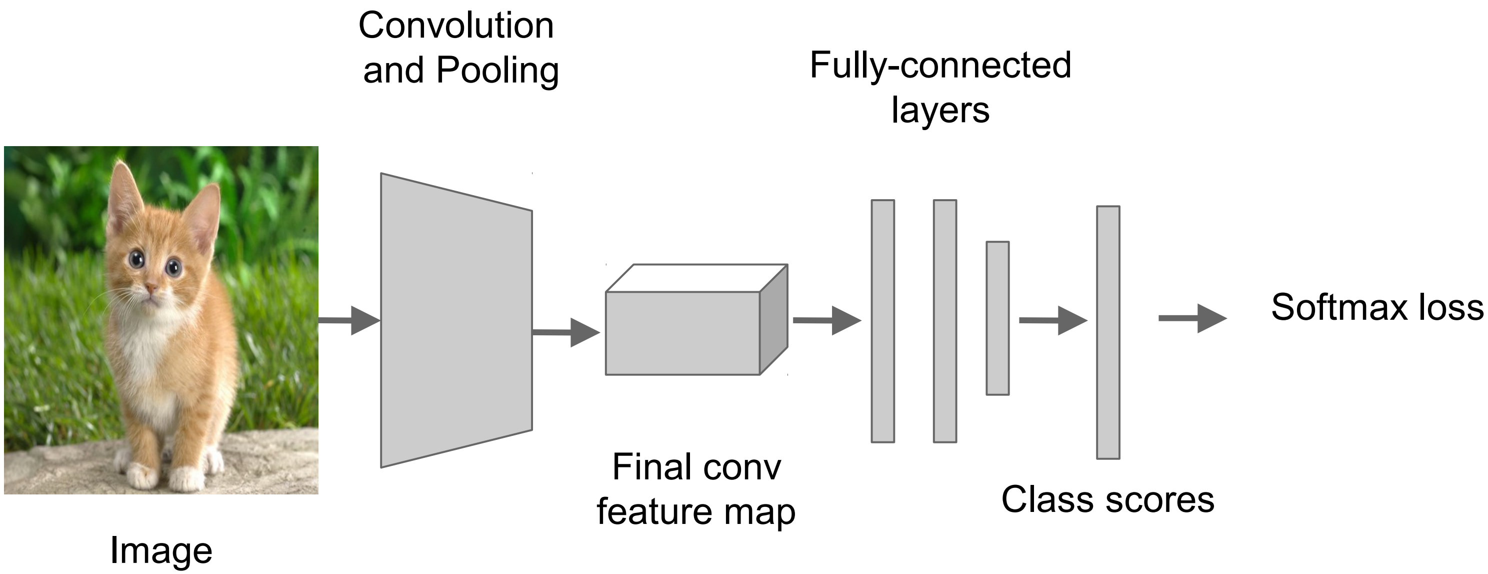
Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

Only one object,
simpler than detection

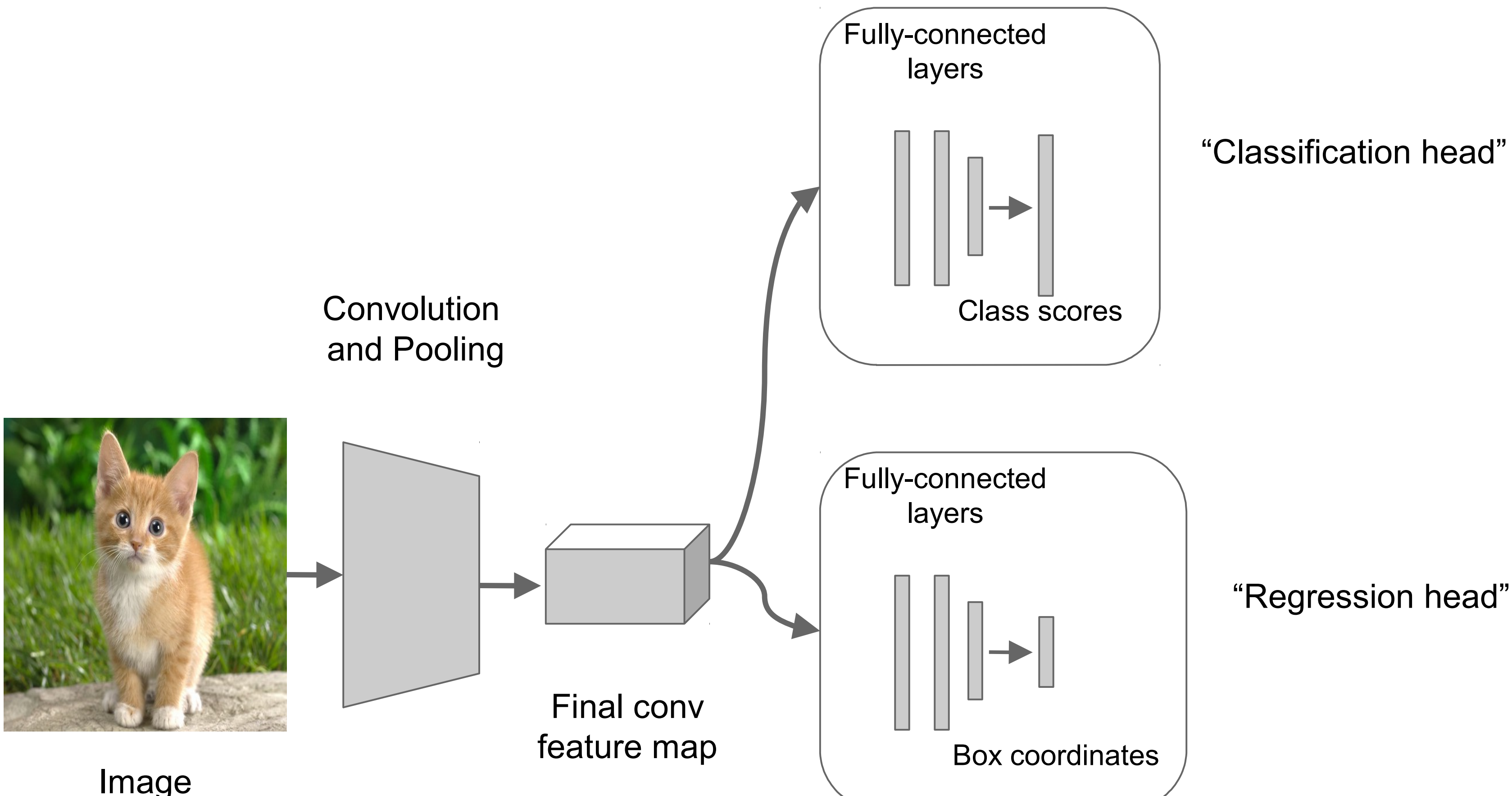
Simple Recipe for Classification + Localization

Step 1: Train (or download) a classification model (AlexNet, VGG, GoogLeNet)



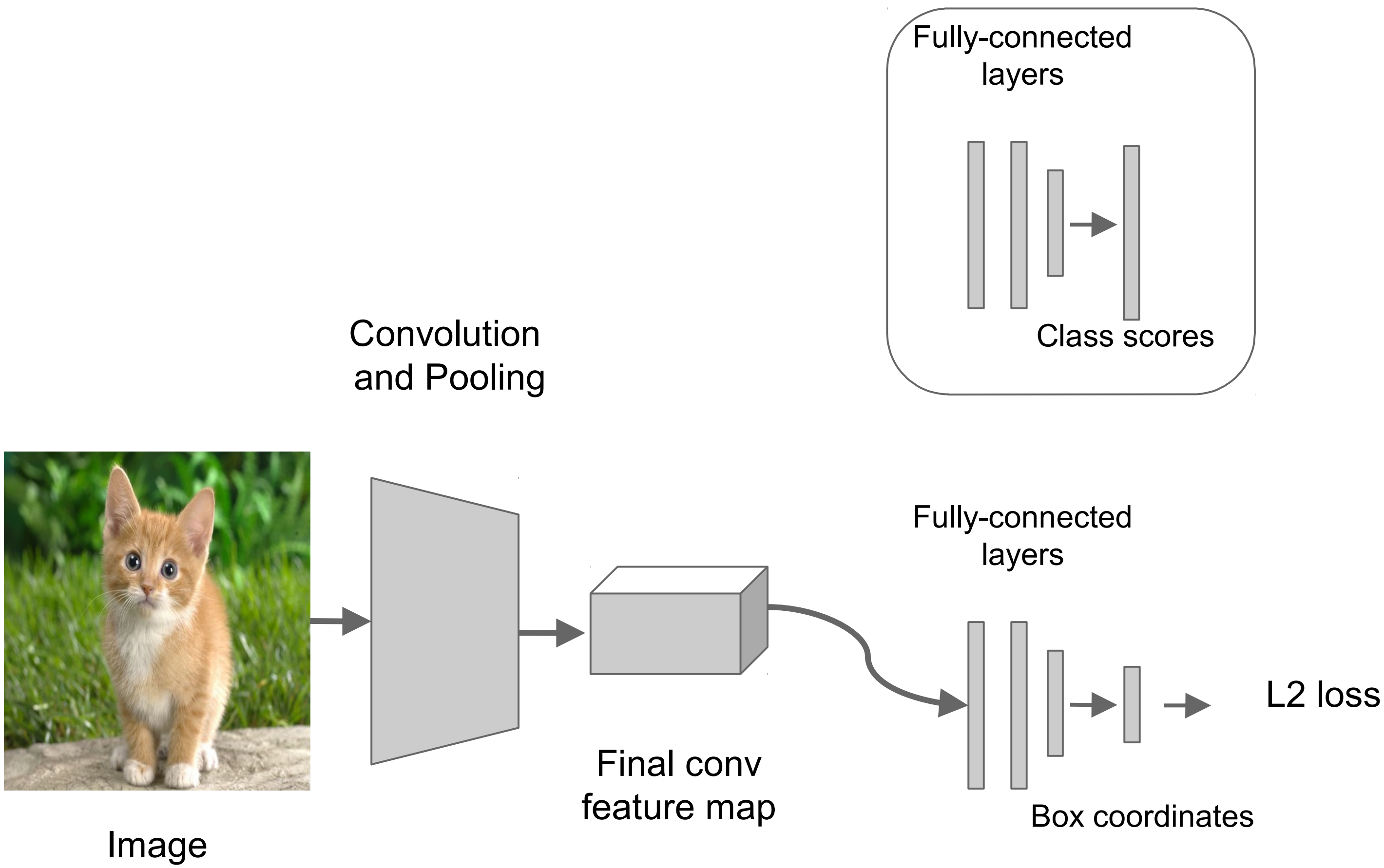
Simple Recipe for Classification + Localization

Step 2: Attach new fully-connected "regression head" to the network



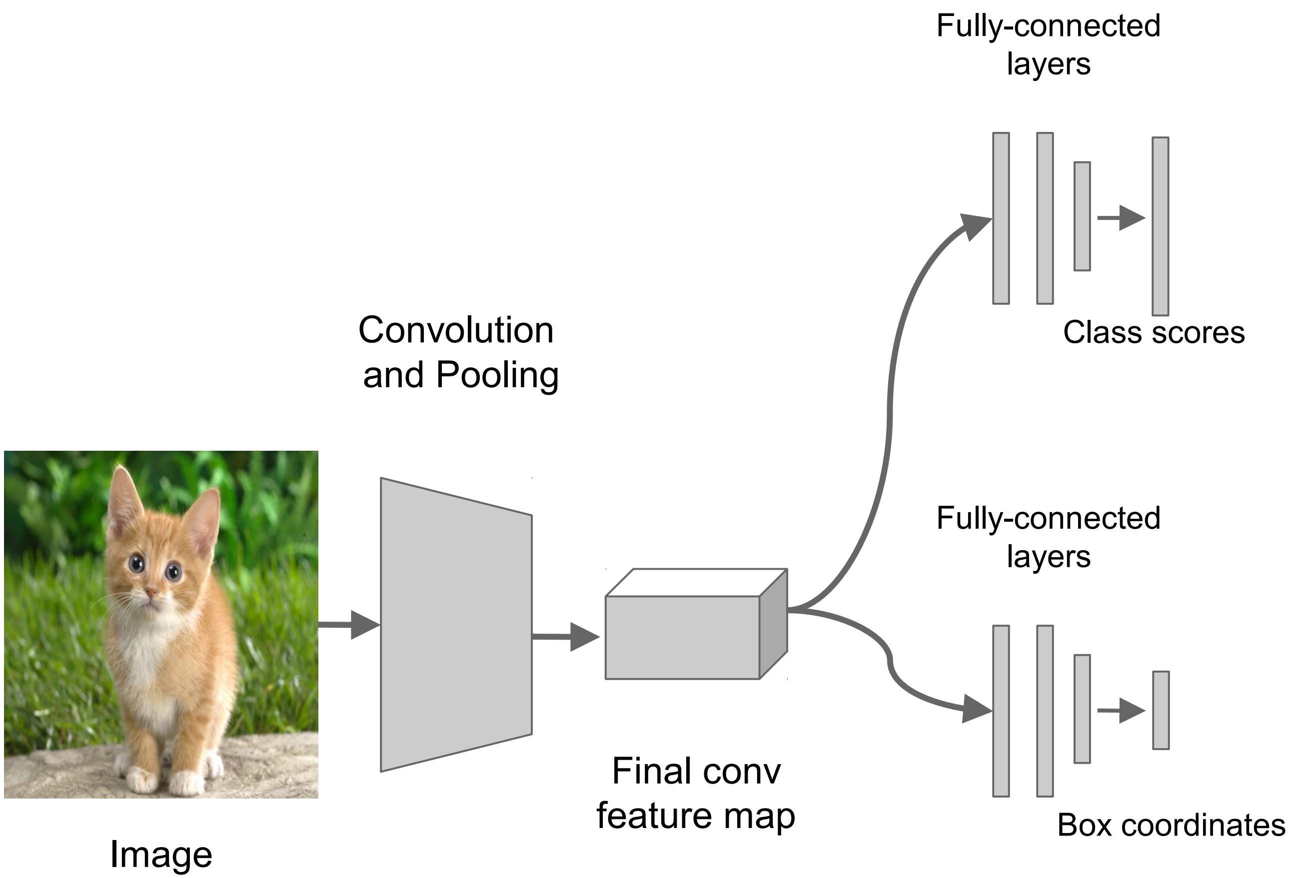
Simple Recipe for Classification + Localization

Step 3: Train the regression head only with SGD and L2 loss



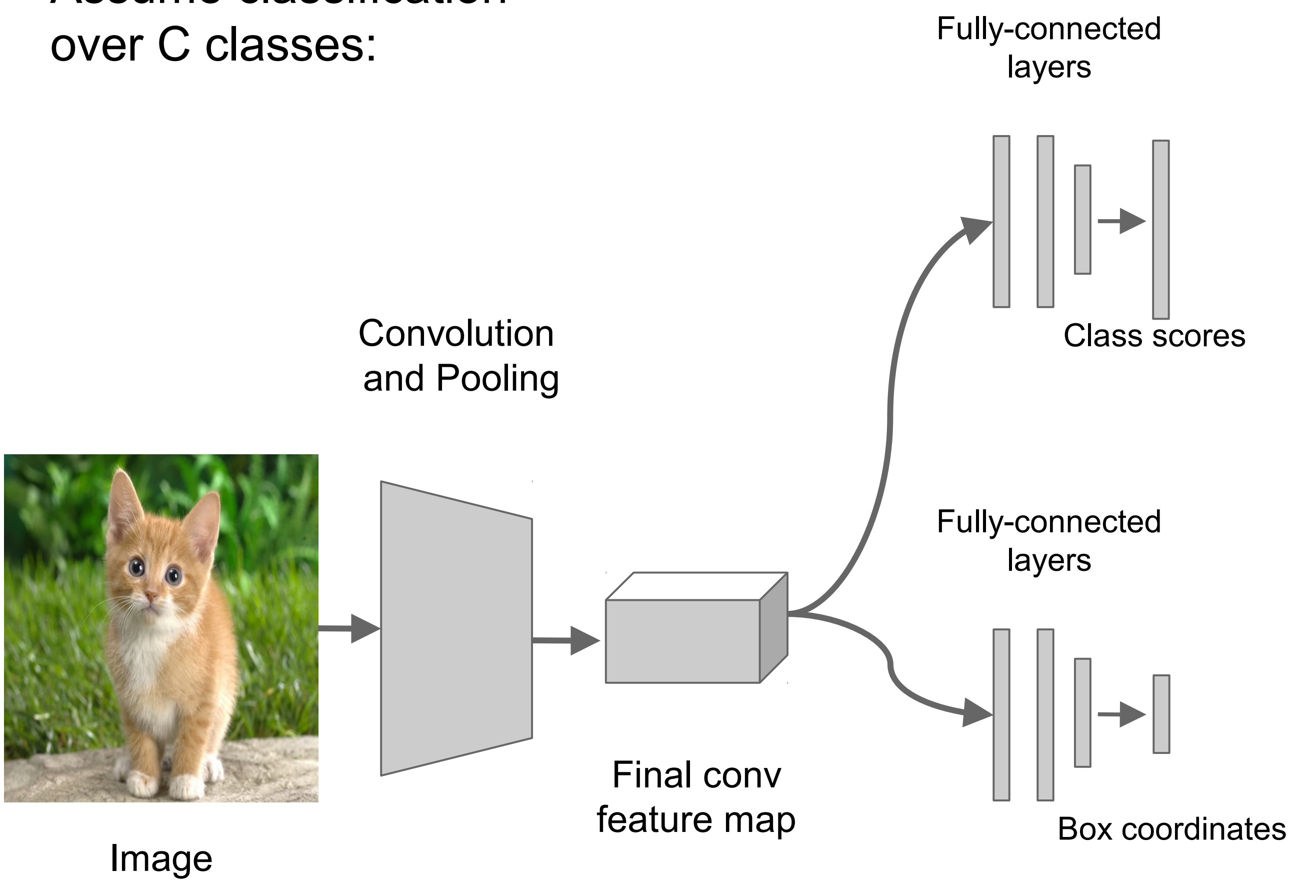
Simple Recipe for Classification + Localization

Step 4: At test time use both heads



Per-class vs class agnostic regression

Assume classification over C classes:

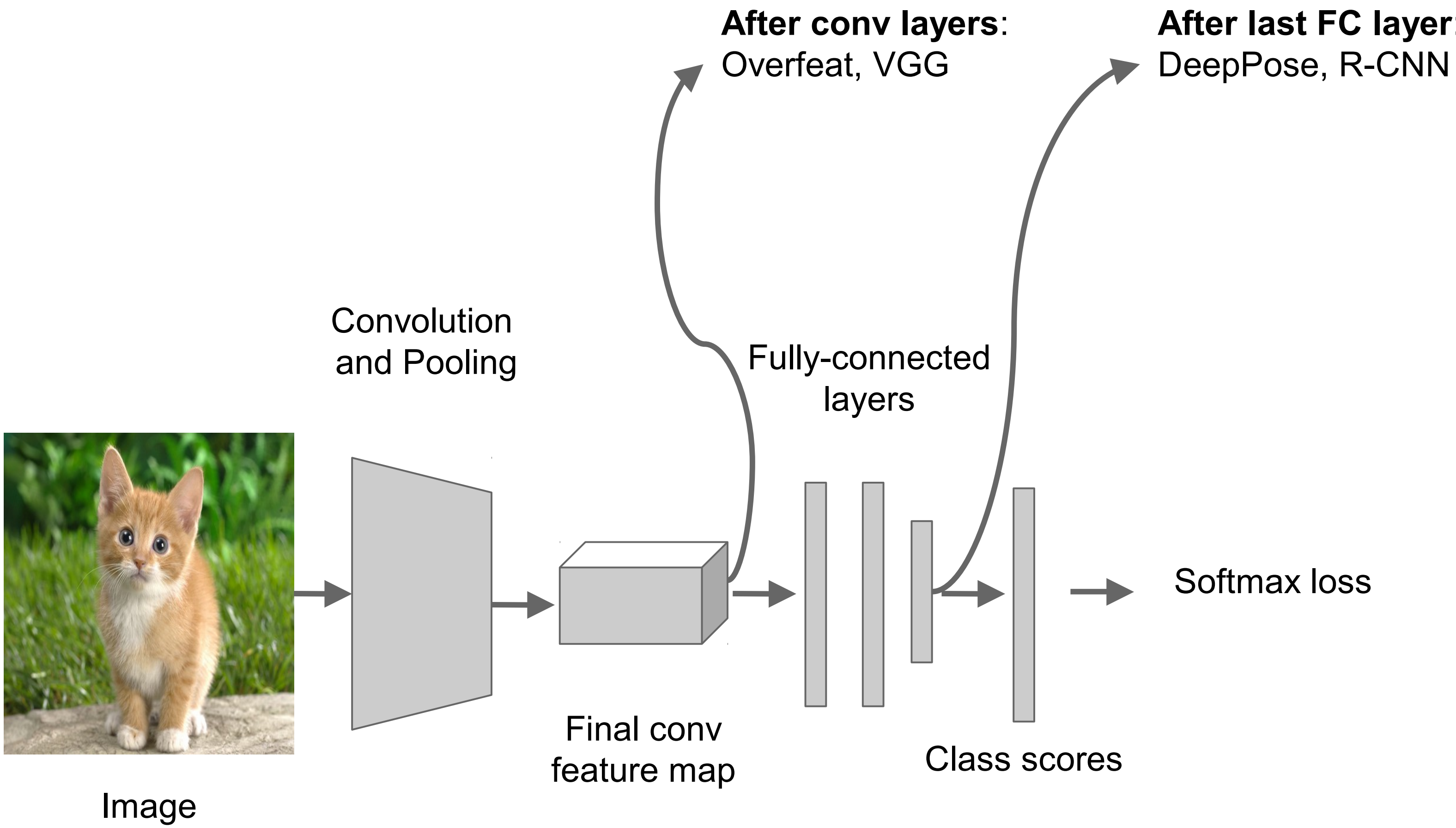


Classification head:
C numbers
(one per class)

Class agnostic:
4 numbers
(one box)

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

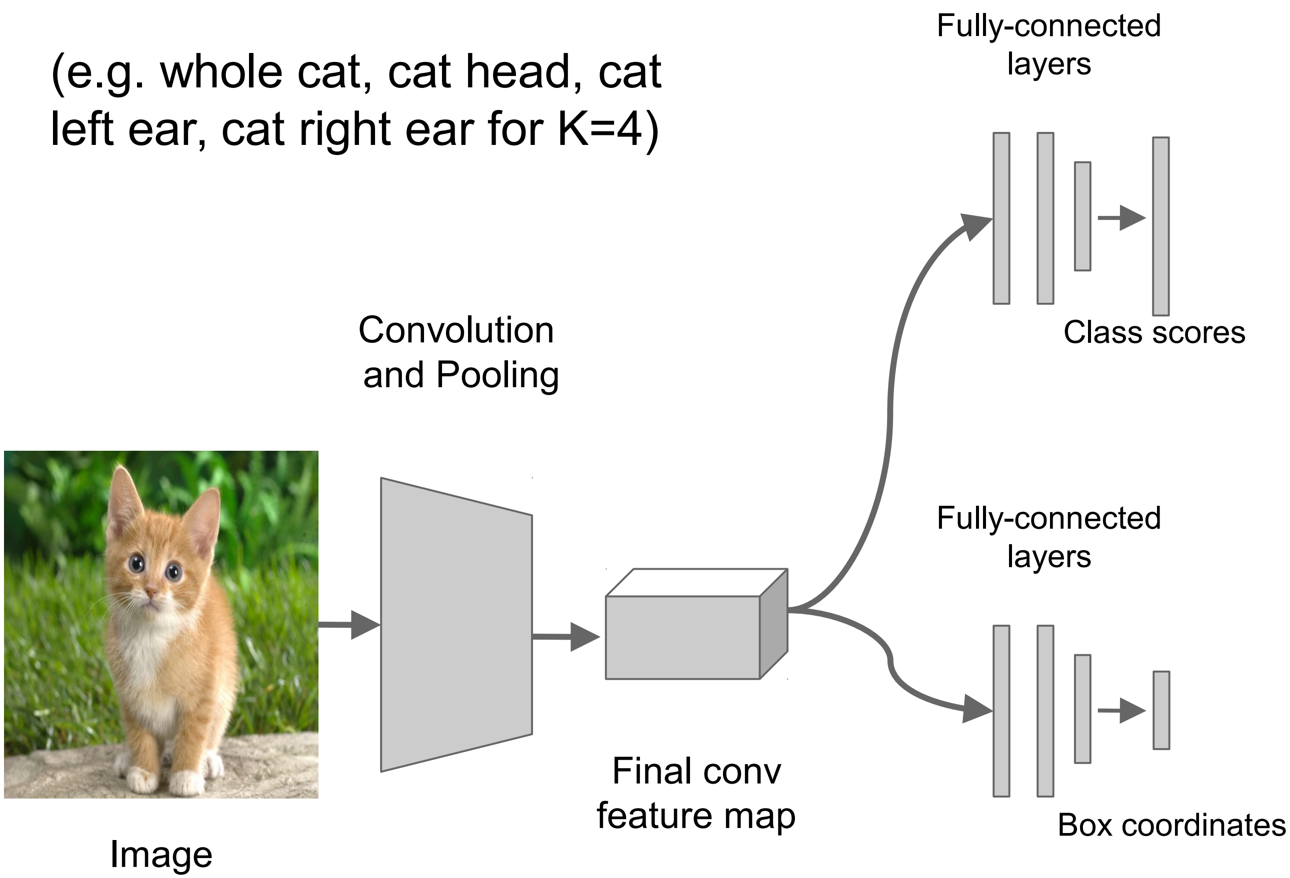
Where to attach the regression head?



Aside: Localizing multiple objects

Want to localize **exactly** K objects in each image

(e.g. whole cat, cat head, cat left ear, cat right ear for K=4)



K x 4 numbers (one box per object)

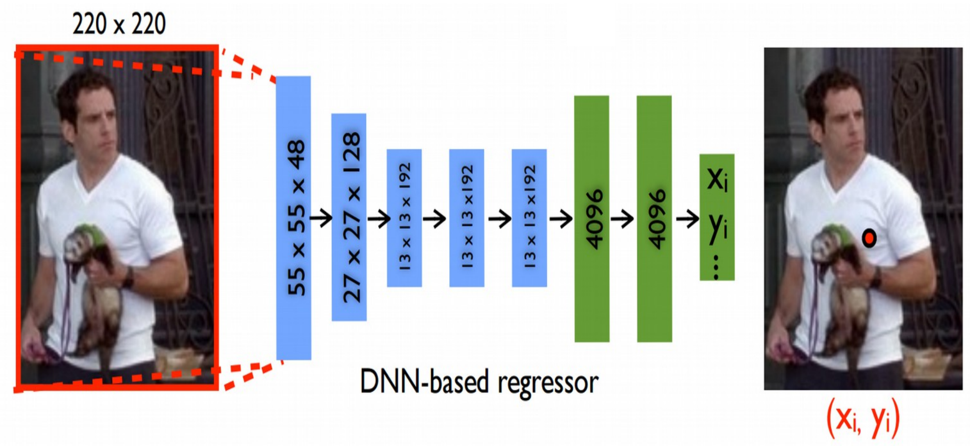
Slide Credit:

Aside: Human Pose Estimation

Represent a person by K joints

Regress (x, y) for each joint from last fully-connected layer of AlexNet

(Details: Normalized coordinates, iterative refinement)



Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014

Idea #2: Sliding Window

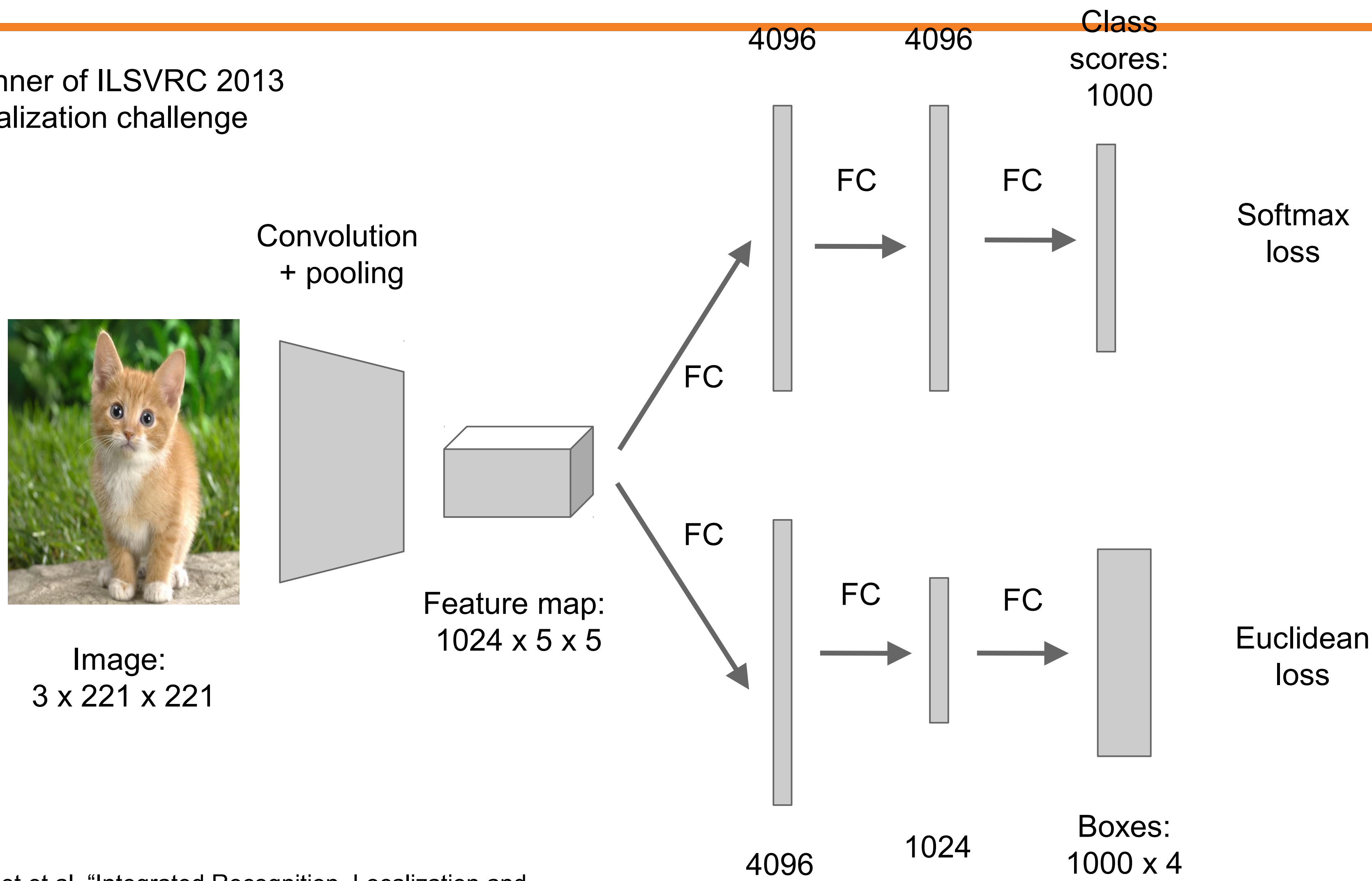
- Run classification + regression network at multiple locations on a high-resolution image

- Convert fully-connected layers into convolutional layers for efficient computation

- Combine classifier and regressor predictions across all scales for final prediction

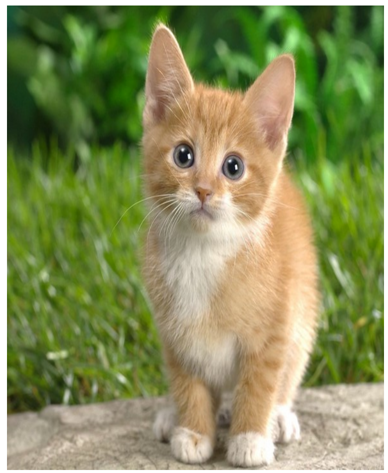
Sliding Window: Overfeat

Winner of ILSVRC 2013
localization challenge



Sermanet et al, “Integrated Recognition, Localization and Detection using Convolutional Networks”, ICLR 2014

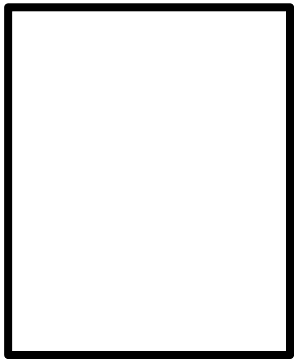
Sliding Window: Overfeat



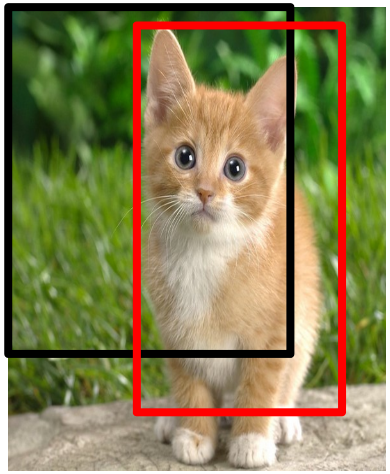
Network input:
3 x 221 x 221

Larger image:
3 x 257 x 257

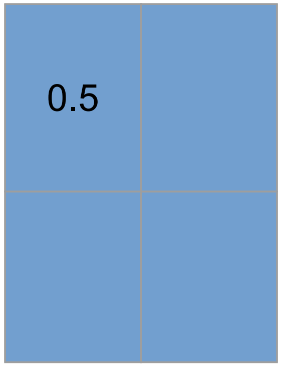
Sliding Window: Overfeat



Network input:
3 x 221 x 221



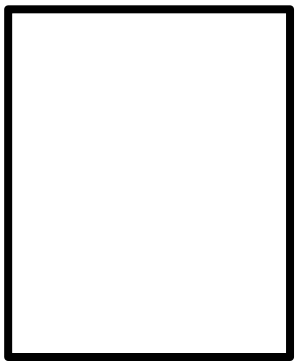
Larger image:
3 x 257 x 257



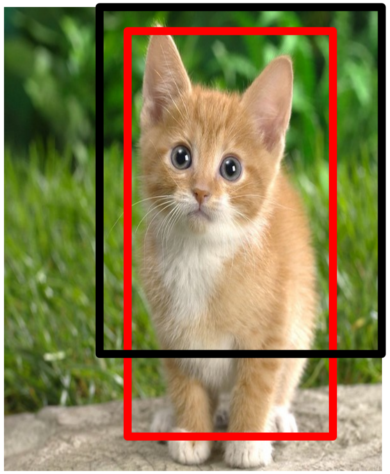
Classification scores:
P(cat)

Slide Credit:

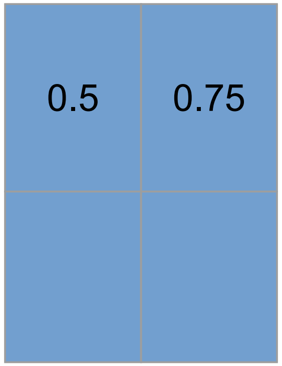
Sliding Window: Overfeat



Network input:
3 x 221 x 221



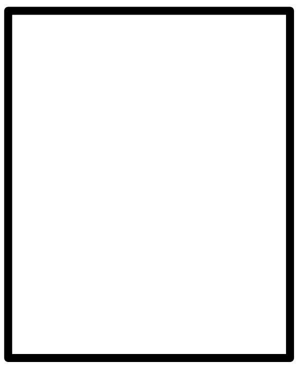
Larger image:
3 x 257 x 257



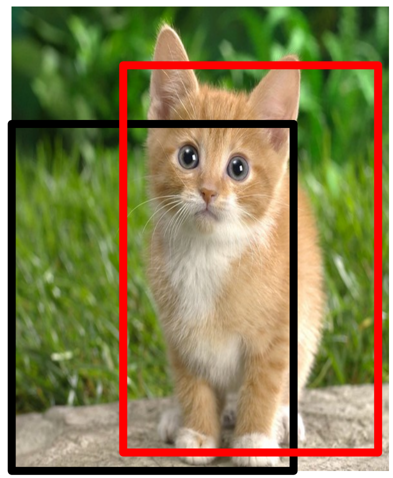
Classification scores:
P(cat)

Slide Credit:

Sliding Window: Overfeat



Network input:
3 x 221 x 221

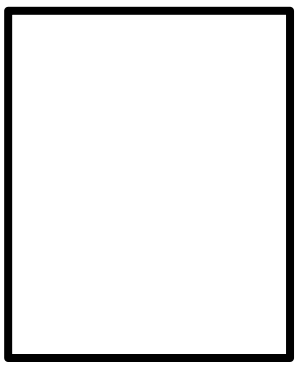


Larger image:
3 x 257 x 257

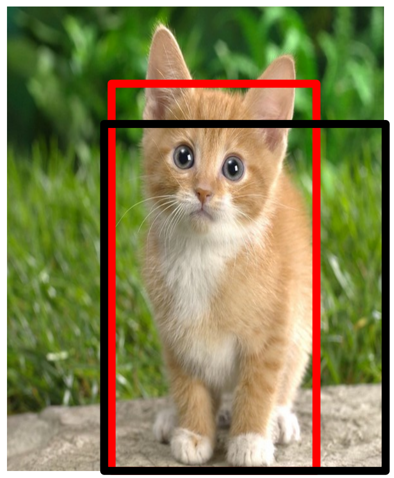
0.5	0.75
0.6	

Classification scores:
P(cat)

Sliding Window: Overfeat



Network input:
3 x 221 x 221

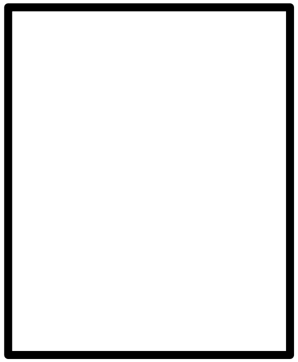


Larger image:
3 x 257 x 257

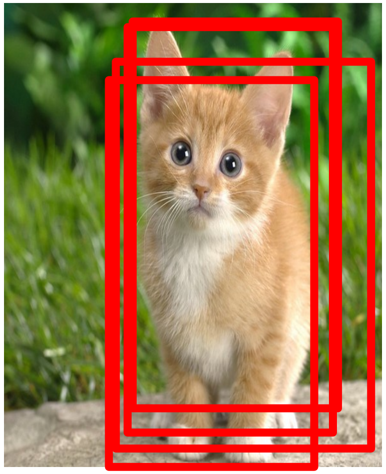
0.5	0.75
0.6	0.8

Classification scores:
P(cat)

Sliding Window: Overfeat



Network input:
3 x 221 x 221



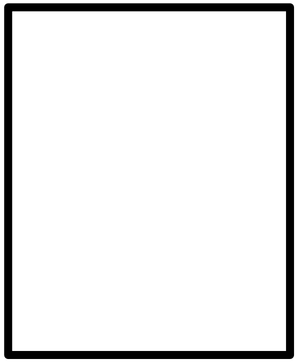
Larger image:
3 x 257 x 257

0.5	0.75
0.6	0.8

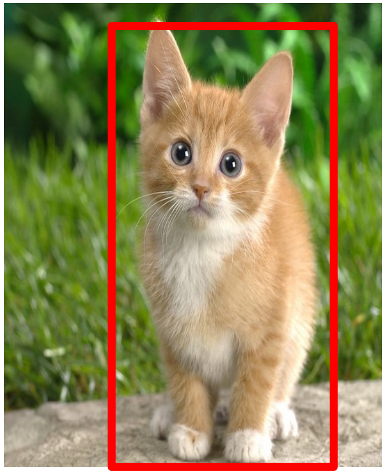
Classification scores:
P(cat)

Sliding Window: Overfeat

Greedily merge boxes and scores (details in paper)



Network input:
3 x 221 x 221



Larger image:
3 x 257 x 257

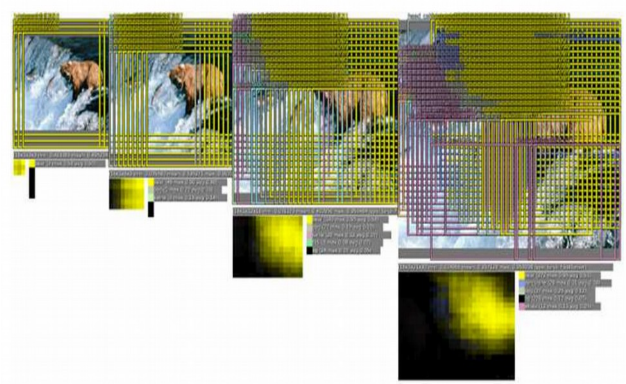
0.8

Classification score:
P(cat)

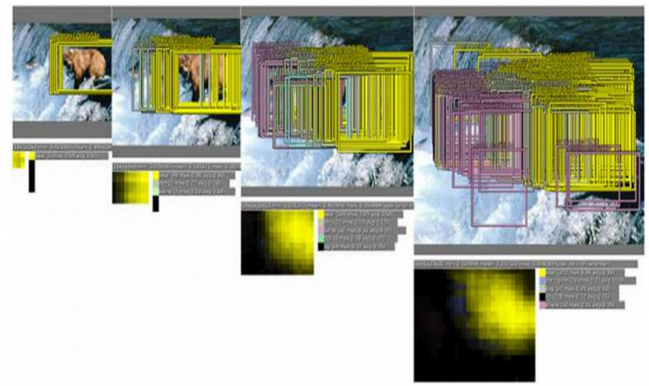
Sliding Window: Overfeat

In practice use many sliding window
locations and multiple scales

Window positions + score maps



Box regression outputs

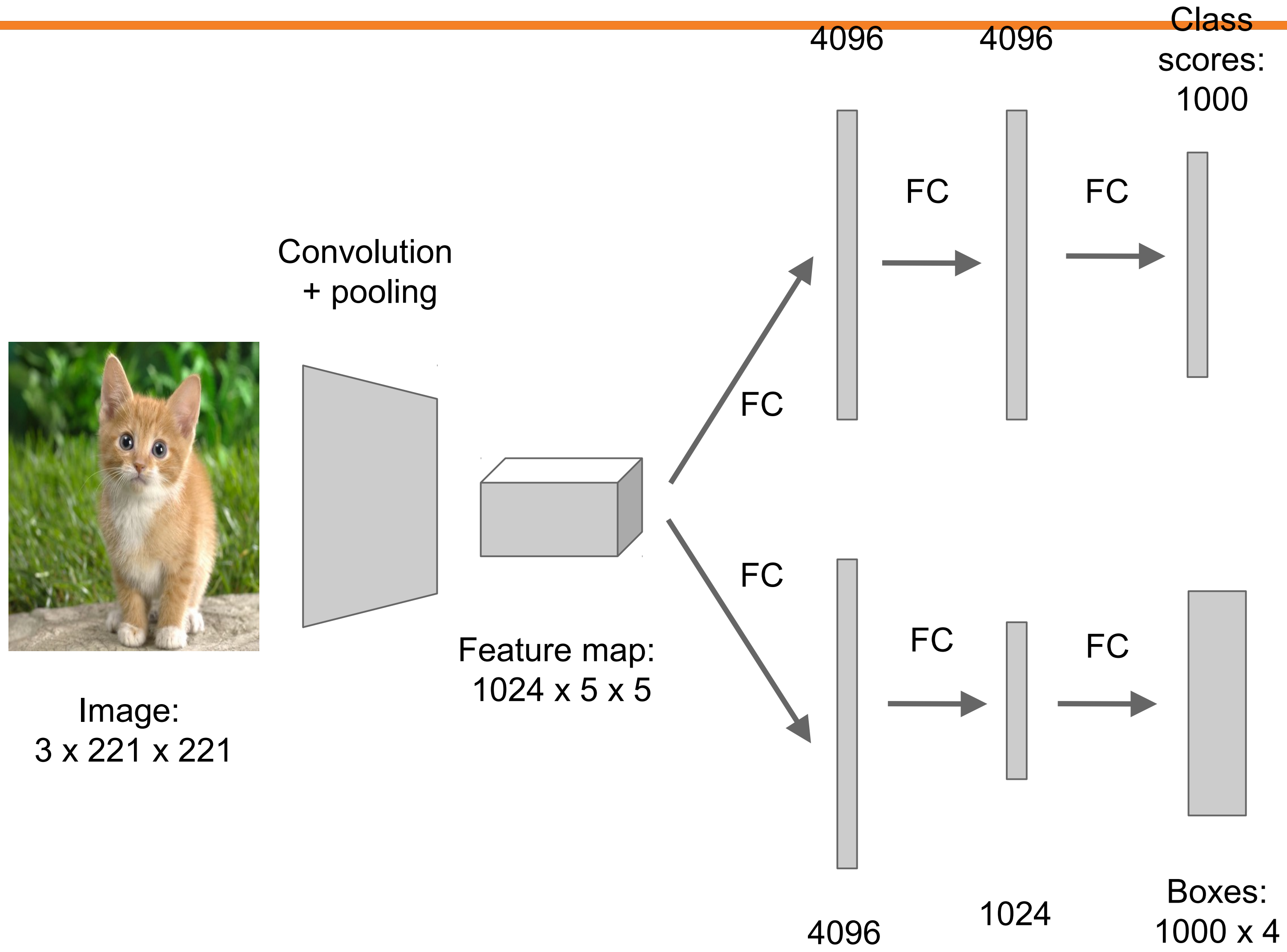


Final Predictions

Sermanet et al, “Integrated Recognition, Localization and Detection using Convolutional Networks”, ICLR 2014

Slide Credit:

Efficient Sliding Window: Overfeat

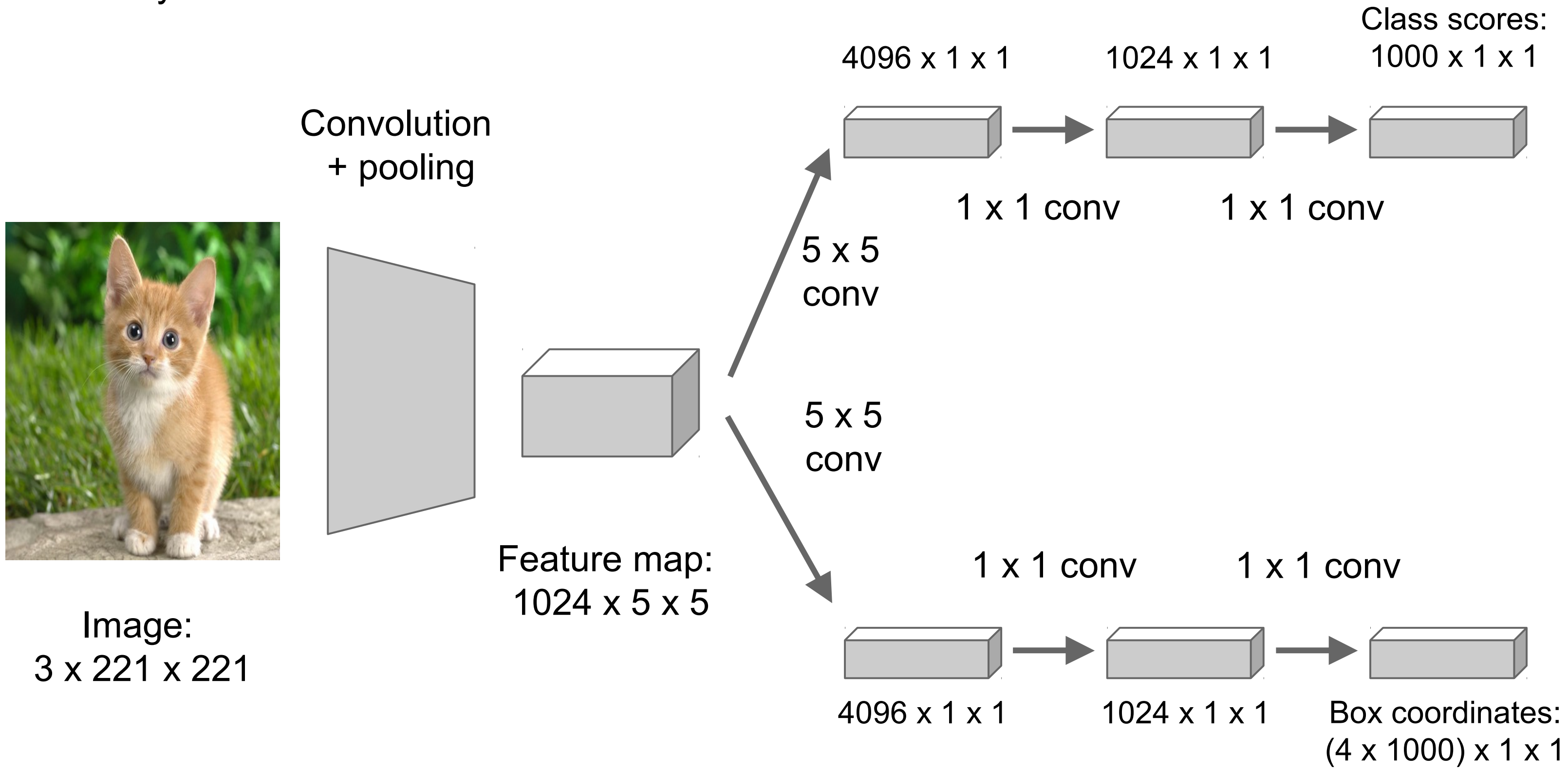


40

Slide Credit:

Efficient Sliding Window: Overfeat

Efficient sliding window by converting fully-connected layers into convolutions

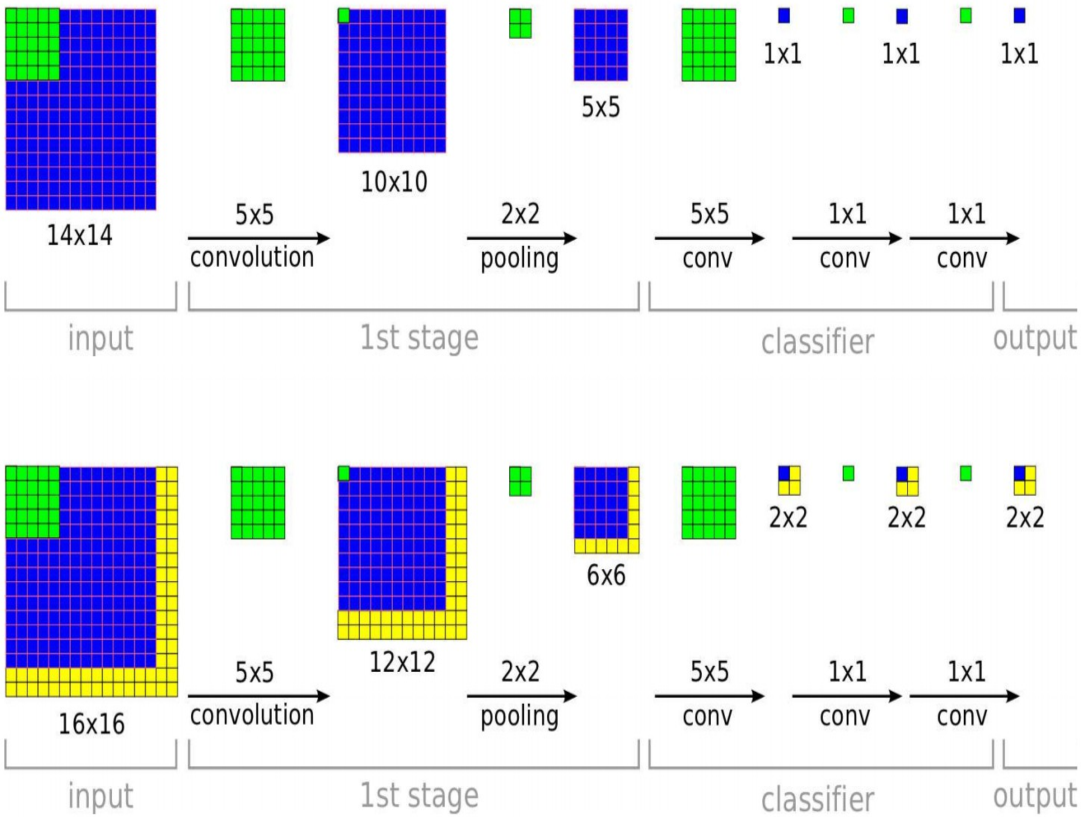


Slide Credit:

Efficient Sliding Window: Overfeat

Training time: Small image, 1 x 1 classifier output

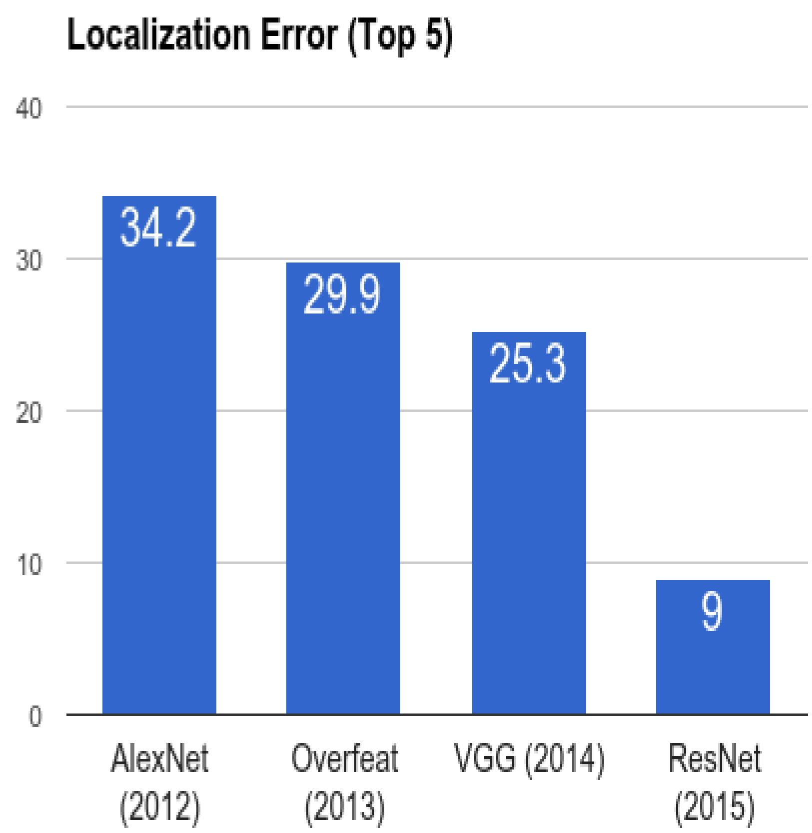
Test time: Larger image, 2 x 2 classifier output, only extra compute at yellow regions



Sermanet et al, “Integrated Recognition, Localization and Detection using Convolutional Networks”, ICLR 2014

Slide Credit:

ImageNet Classification + Localization



AlexNet: Localization method not published

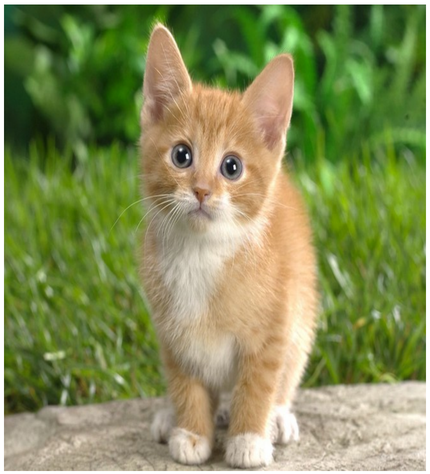
Overfeat: Multiscale convolutional regression with box merging

VGG: Same as Overfeat, but fewer scales and locations; simpler method, gains all due to deeper features

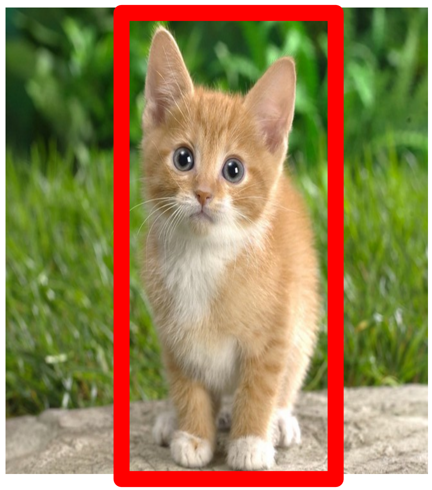
ResNet: Different localization method (RPN) and much deeper features

Computer Vision Tasks

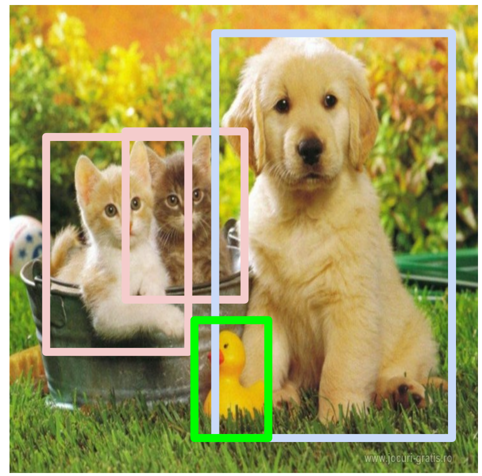
Classification



Classification + Localization



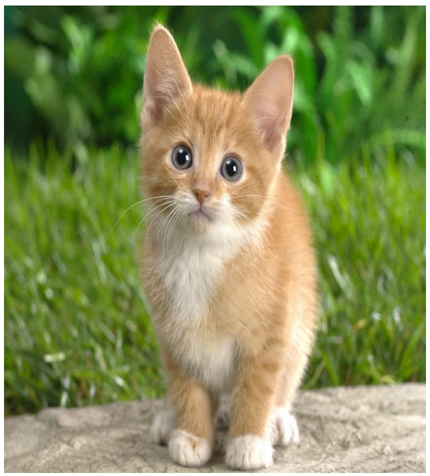
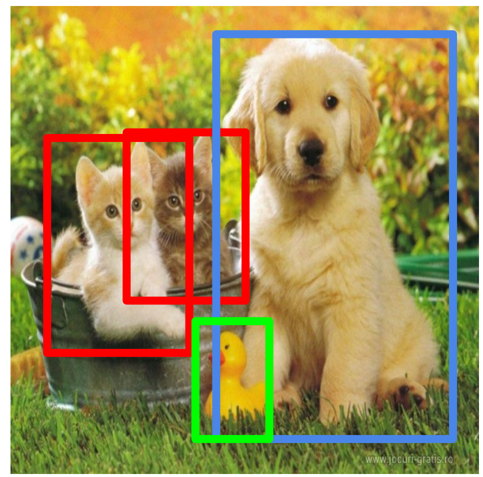
Object Detection



Instance Segmentation

Slide Credit:

Computer Vision Tasks

Classification	Classification + Localization	**Object Detection**	Instance Segmentation
			

Slide Credit:

Detection as Regression?

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

= 16 numbers

Detection as Regression?

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

= 8 numbers

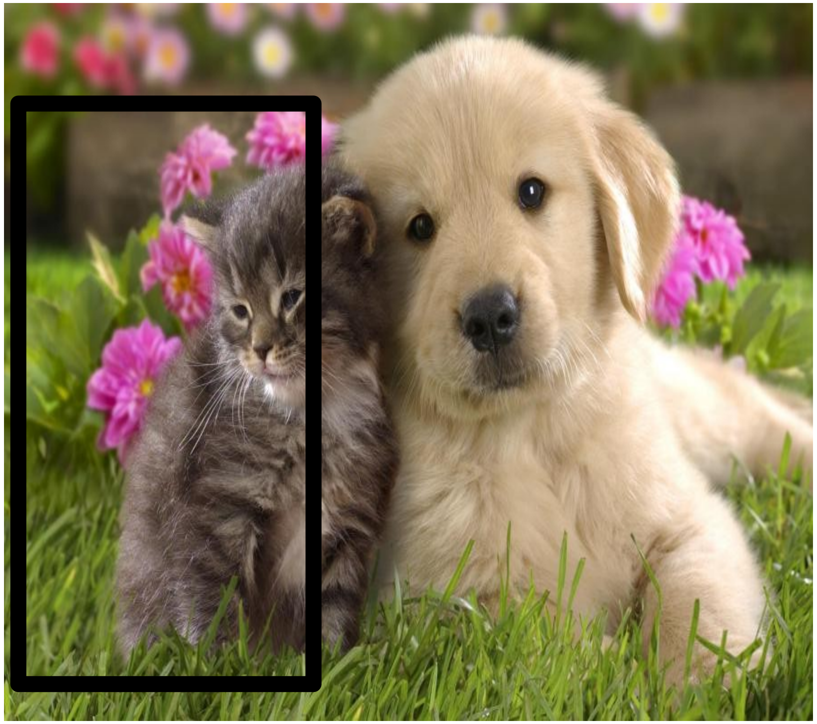
Detection as Regression?

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

= many numbers

Need variable sized outputs

Detection as Classification



CAT? NO

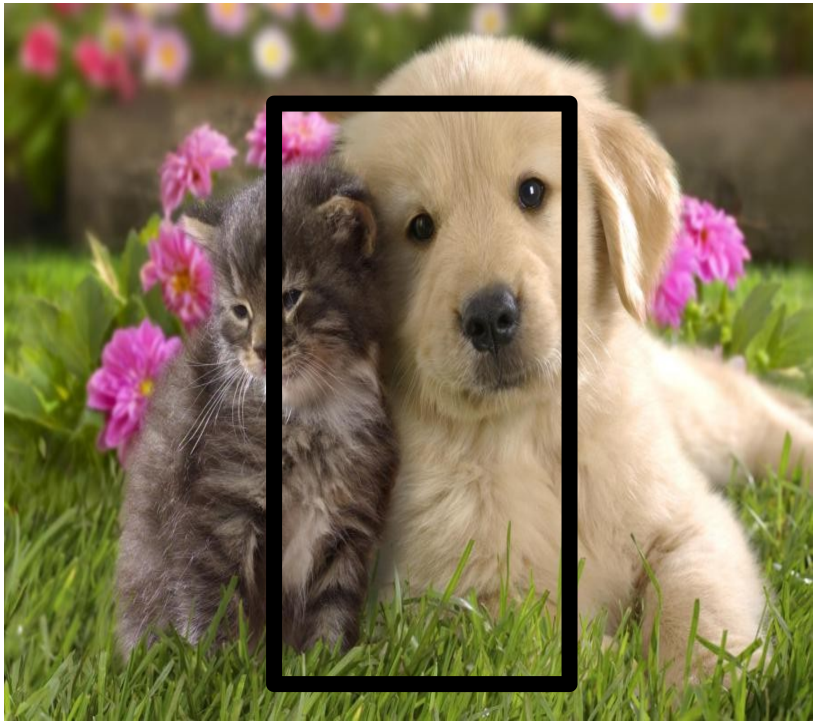
DOG? NO

Detection as Classification

CAT? YES!

DOG? NO

Detection as Classification



CAT? NO

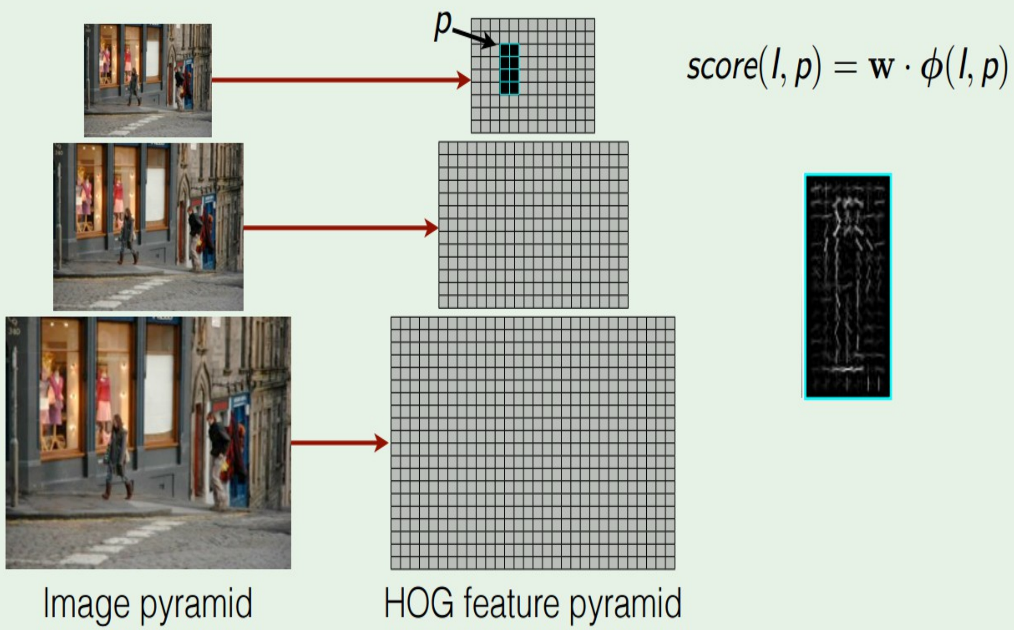
DOG? NO

Detection as Classification

Problem: Need to test many positions and scales

Solution: If your classifier is fast enough, just do it

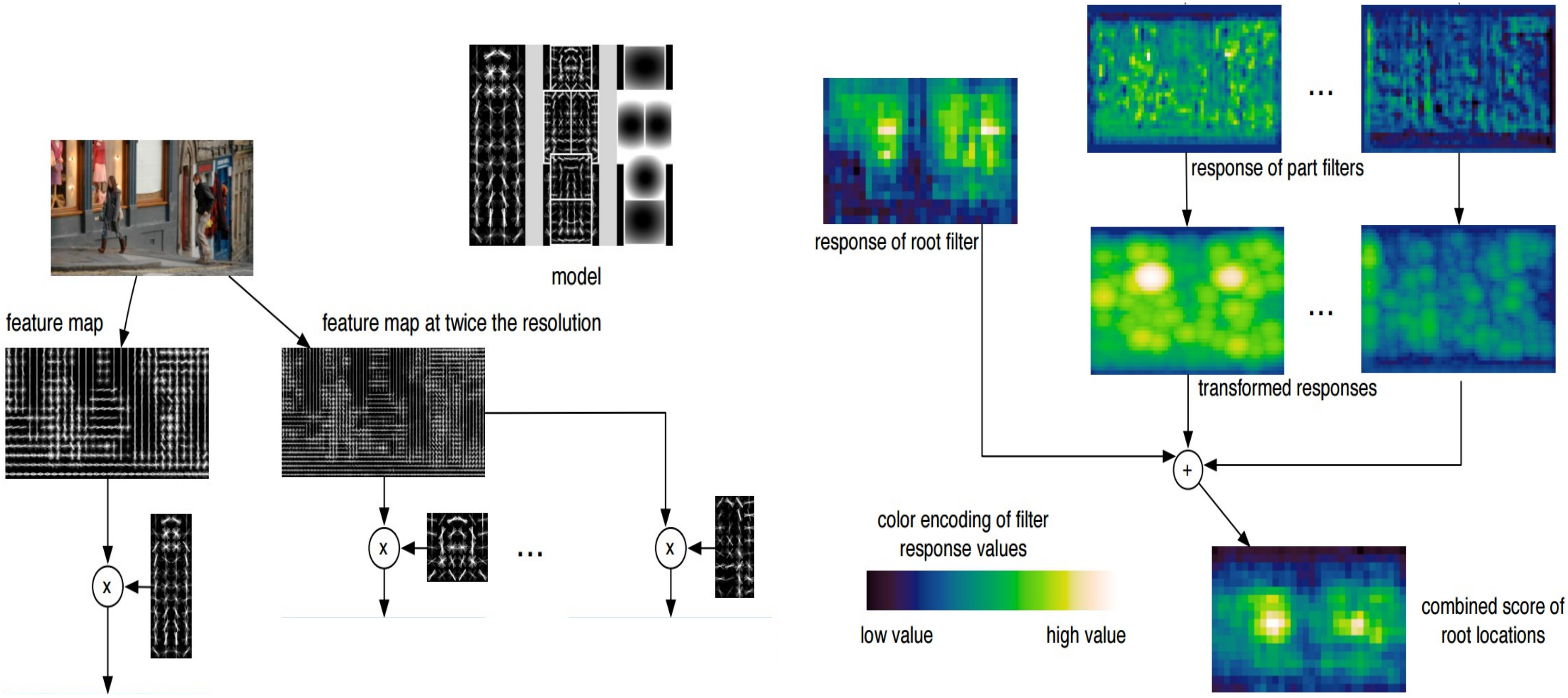
Histogram of Oriented Gradients



- Compute HOG of the whole image at multiple resolutions
- Score every subwindow of the feature pyramid
- Apply non-maxima suppression

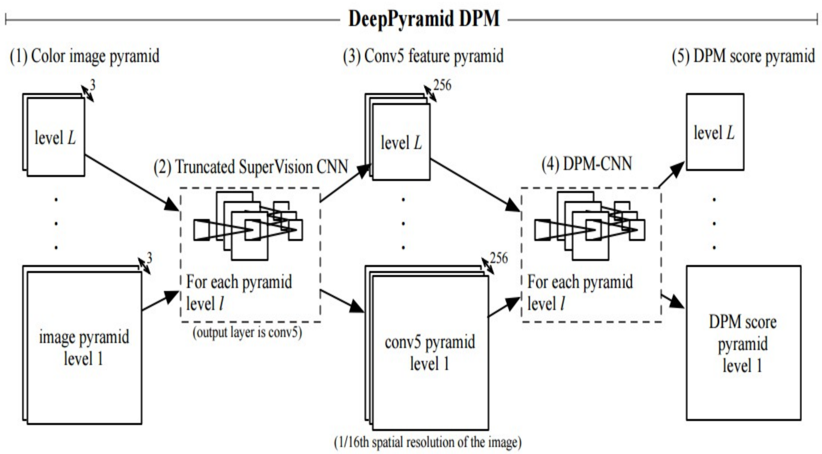
Dalal and Triggs, “Histograms of Oriented Gradients for Human Detection”, CVPR 2005
Slide credit: Ross Girshick

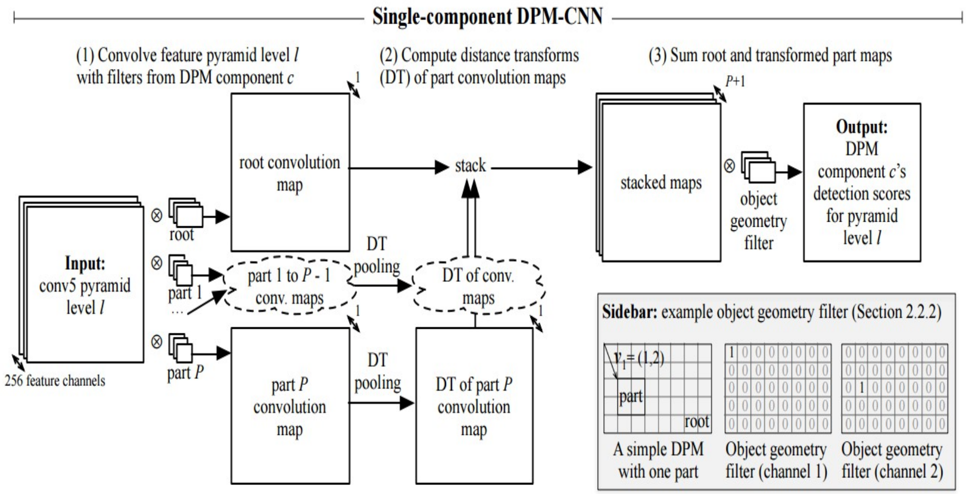
Deformable Parts Model (DPM)



Felzenszwalb et al, “Object Detection with Discriminatively Trained Part Based Models”, PAMI 2010

Aside: Deformable Parts Models are CNNs?





Girschick et al, “Deformable Part Models are Convolutional Neural Networks”, CVPR 2015

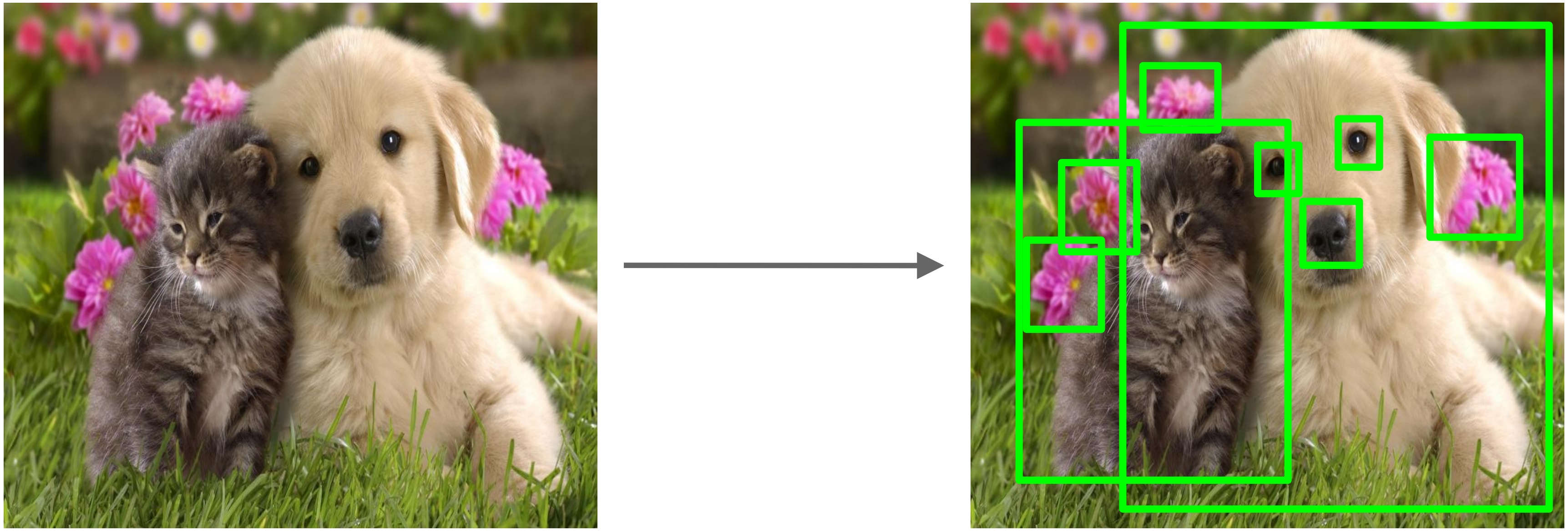
Detection as Classification

Problem: Need to test many positions and scales, and use a computationally demanding classifier (CNN)

Solution: Only look at a tiny subset of possible positions

Region Proposals

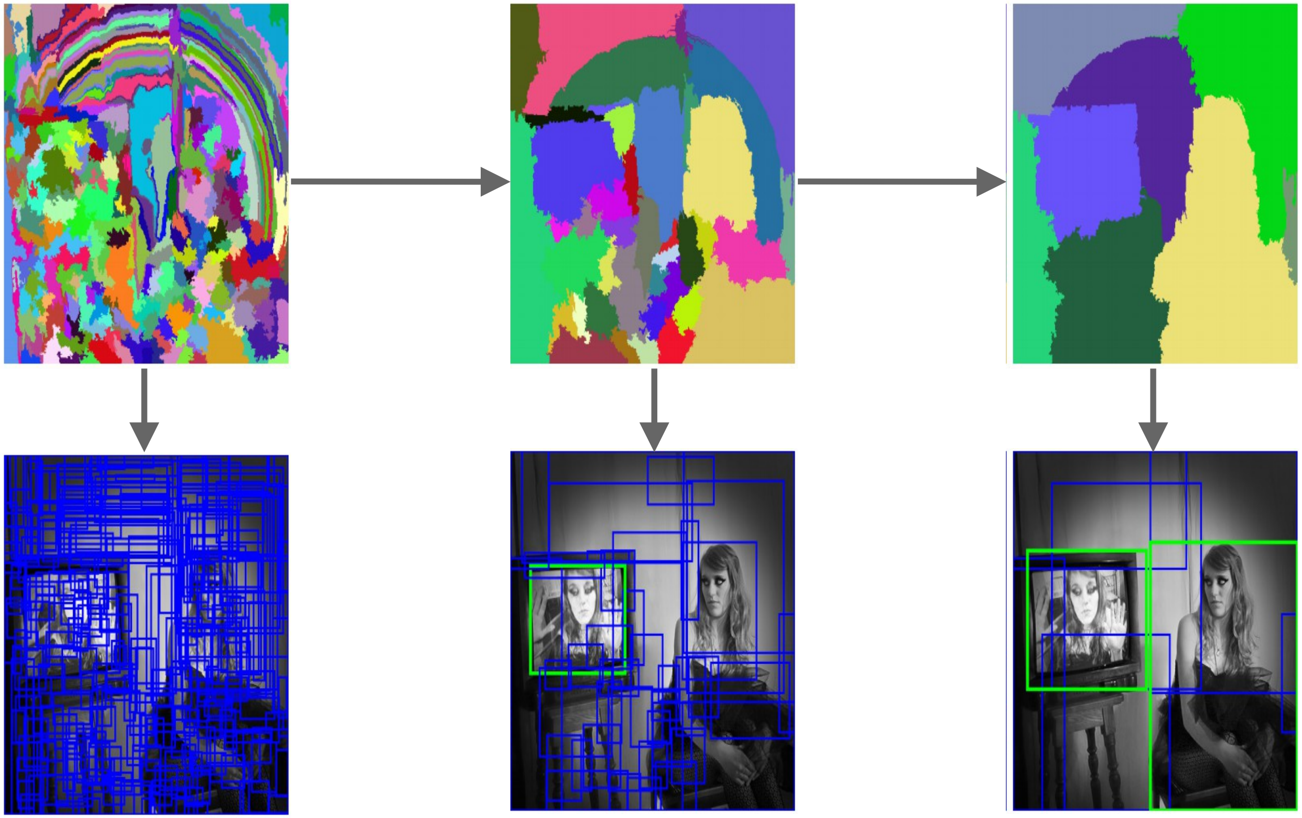
- Find “blobby” image regions that are likely to contain objects
- “Class-agnostic” object detector
- Look for “blob-like” regions



Region Proposals: Selective Search

Bottom-up segmentation, merging regions at multiple scales

Convert regions to boxes



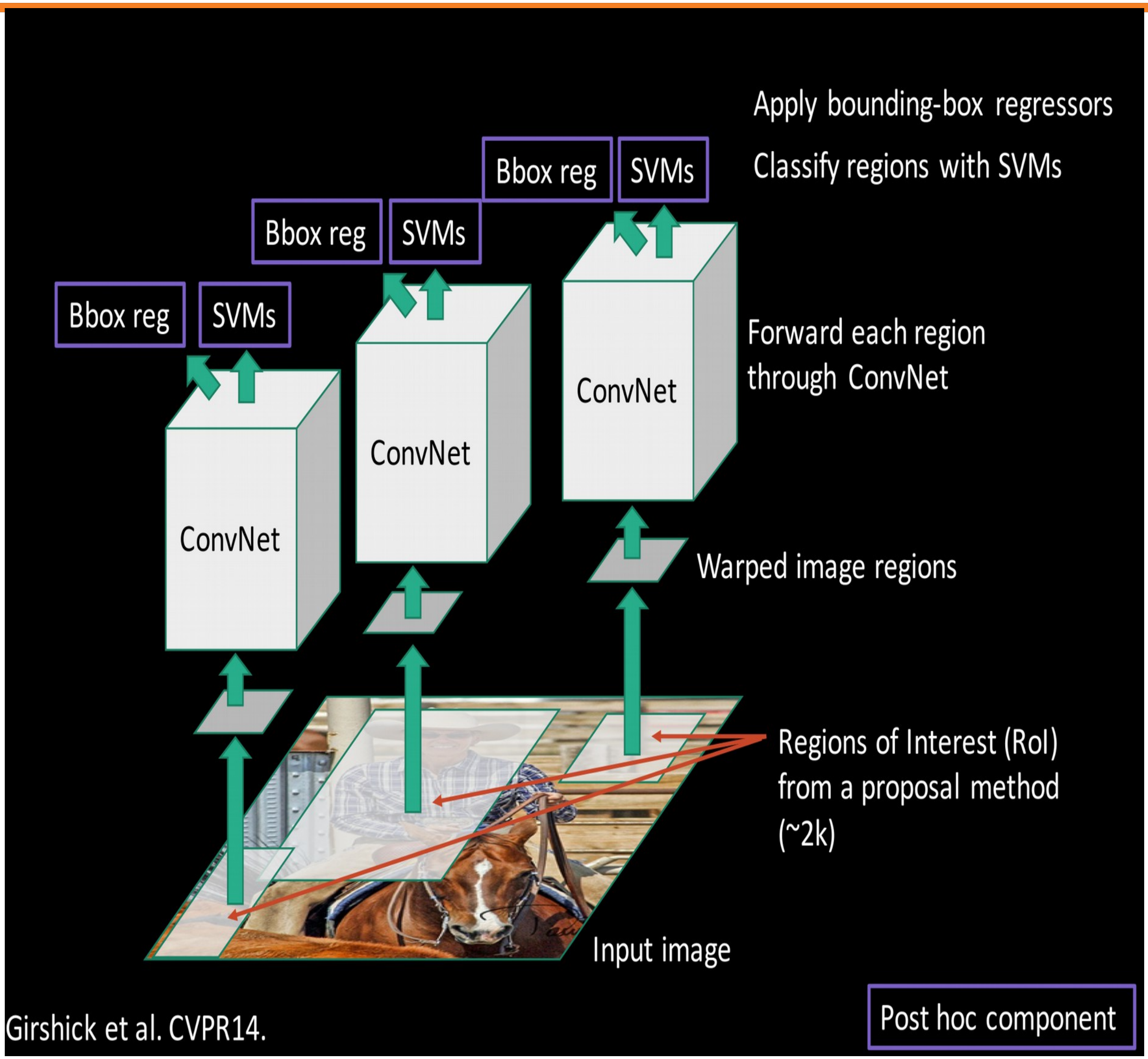
Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013

Region Proposals: Many other choices

Method	Approach	Outputs Segments	Outputs Score	Control #proposals	Time (sec.)	Repea-tability	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	⋆	⋆⋆⋆	⋆⋆
`MCG` [23]	Grouping	✓	✓	✓	30	⋆	⋆⋆⋆	⋆⋆⋆
`Objectness` [24]	Window scoring		✓	✓	3	·	⋆	·
`Rahtu` [25]	Window scoring		✓	✓	3	·	·	⋆
`RandomizedPrim's` [26]	Grouping	✓		✓	1	⋆	⋆	⋆⋆
`Rantalankila` [27]	Grouping	✓		✓	10	⋆⋆	·	⋆⋆
`Rigor` [28]	Grouping	✓		✓	10	⋆	⋆⋆	⋆⋆
`SelectiveSearch` [29]	Grouping	✓	✓	✓	10	⋆⋆	⋆⋆⋆	⋆⋆⋆
`Gaussian`				✓	0	·	·	⋆
`SlidingWindow`				✓	0	⋆⋆⋆	·	·
`Superpixels`		✓			1	⋆	·	·
`Uniform`				✓	0	·	·	·

Hosang et al, “What makes for effective detection proposals?”, PAMI 2015

Putting it together: R-CNN

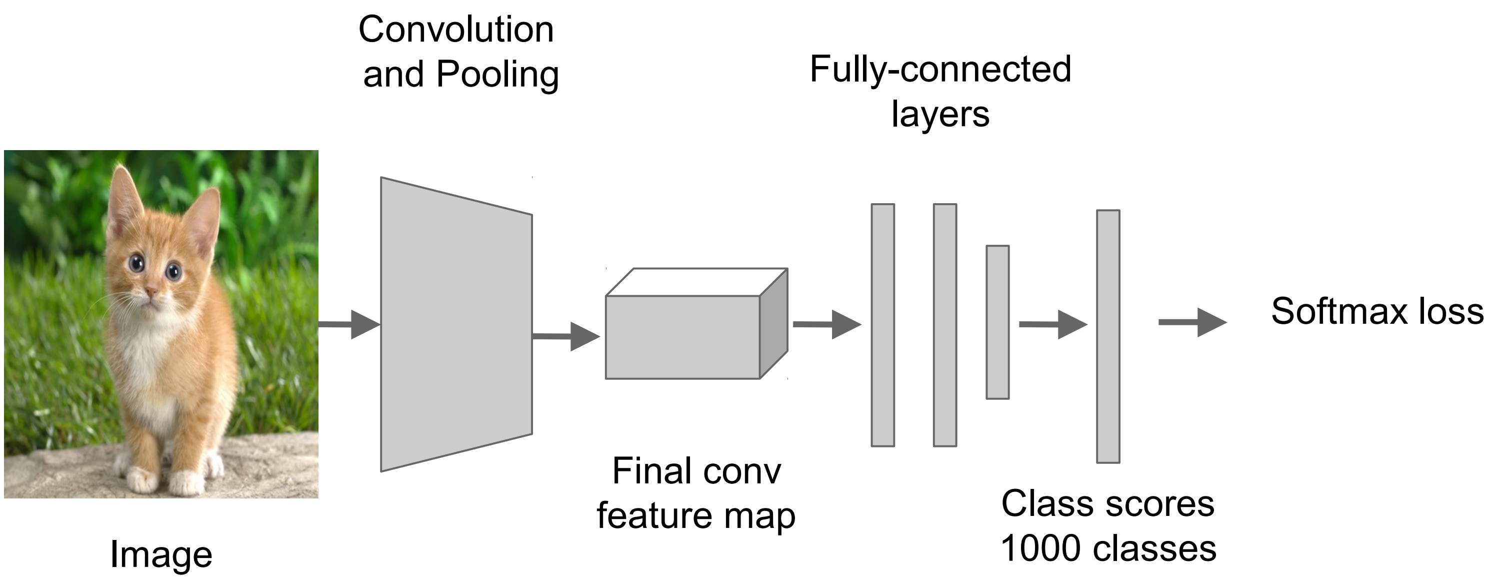


Girschick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014

Slide credit: Ross Girschick

R-CNN Training

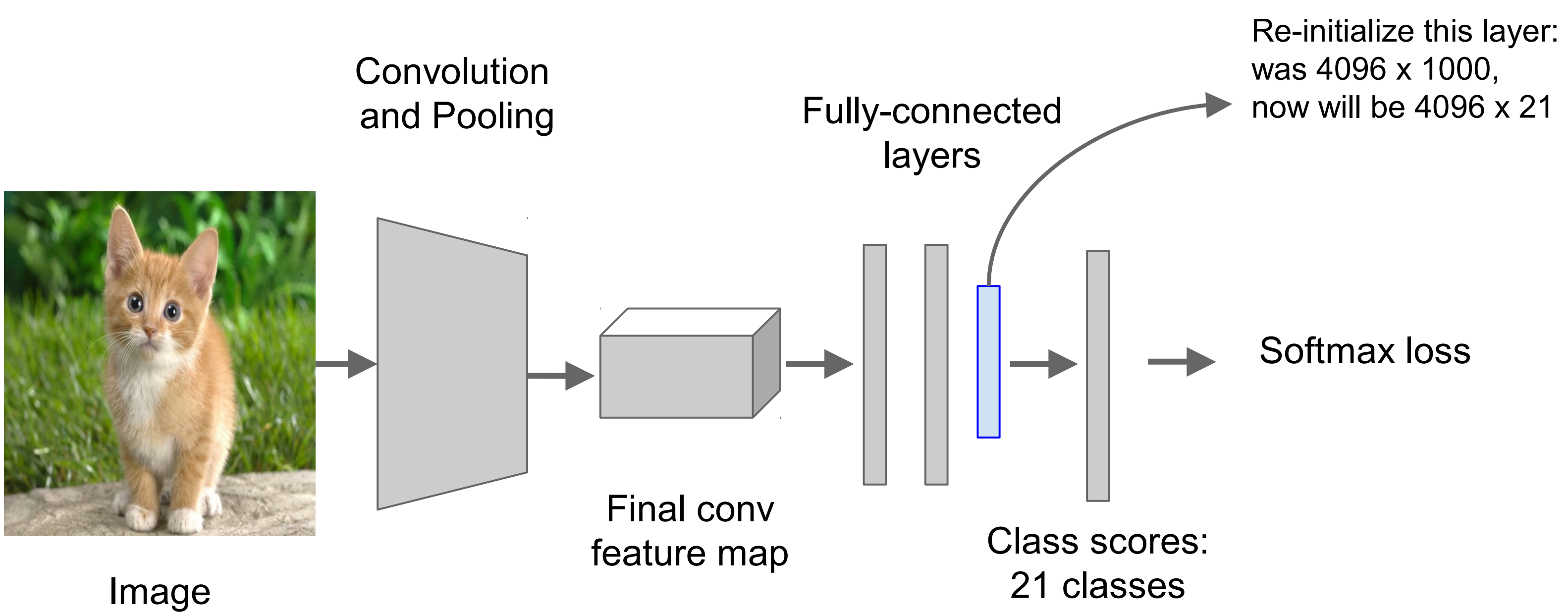
Step 1: Train (or download) a classification model for ImageNet (AlexNet)



Slide Credit:

R-CNN Training

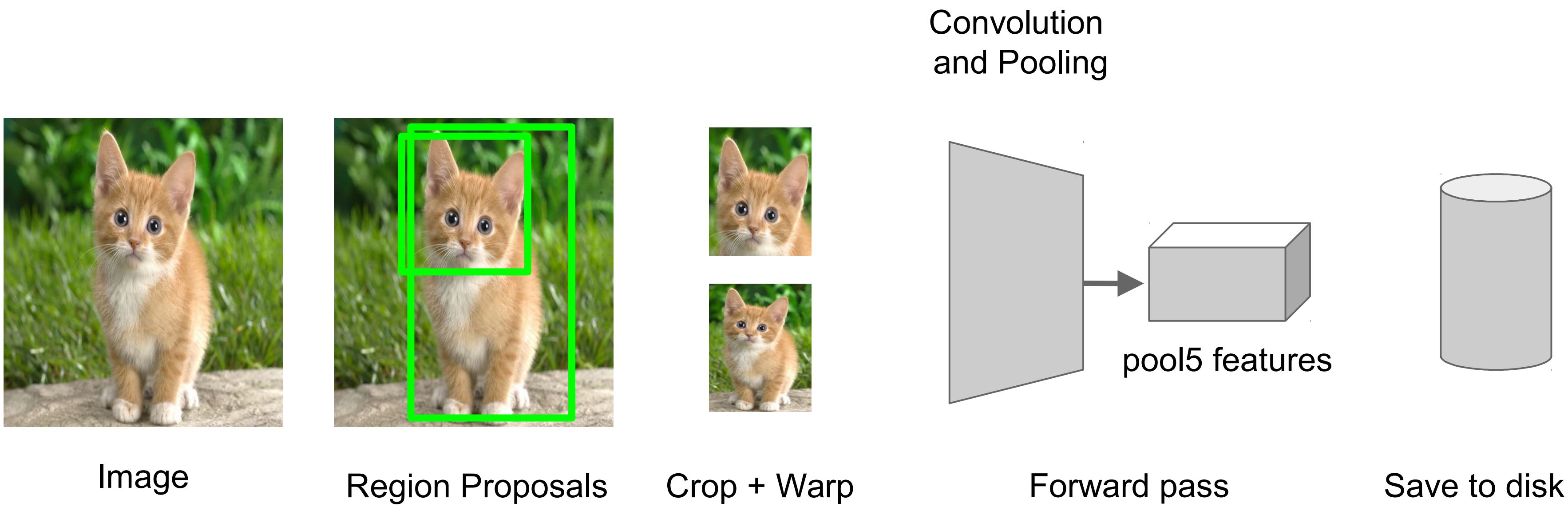
Step 2: Fine-tune model for detection
- Instead of 1000 ImageNet classes, want 20 object classes + background
- Throw away final fully-connected layer, reinitialize from scratch
- Keep training model using positive / negative regions from detection images



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
- Have a big hard drive: features are ~200GB for PASCAL dataset!

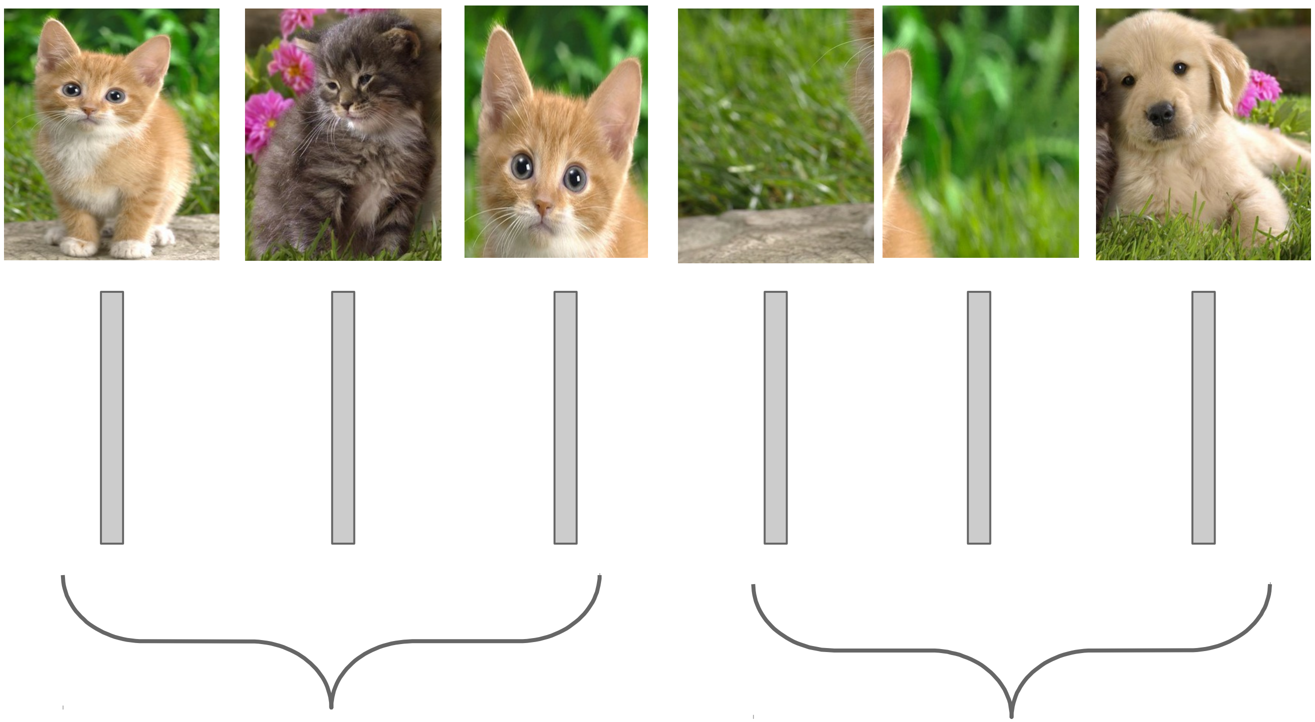


R-CNN Training

Step 4: Train one binary SVM per class to classify region features

Training image regions

Cached region features



Positive samples for cat SVM

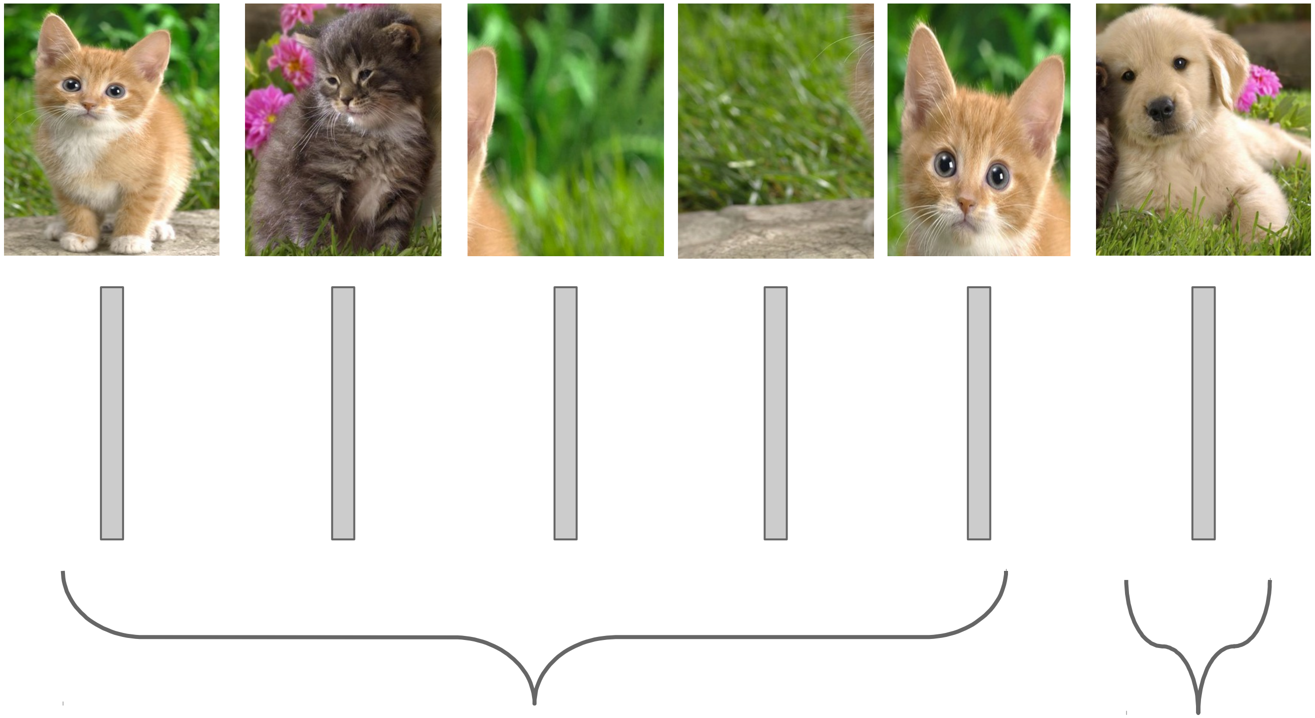
Negative samples for cat SVM

R-CNN Training

Step 4: Train one binary SVM per class to classify region features

Training image regions

Cached region features



Negative samples for dog SVM

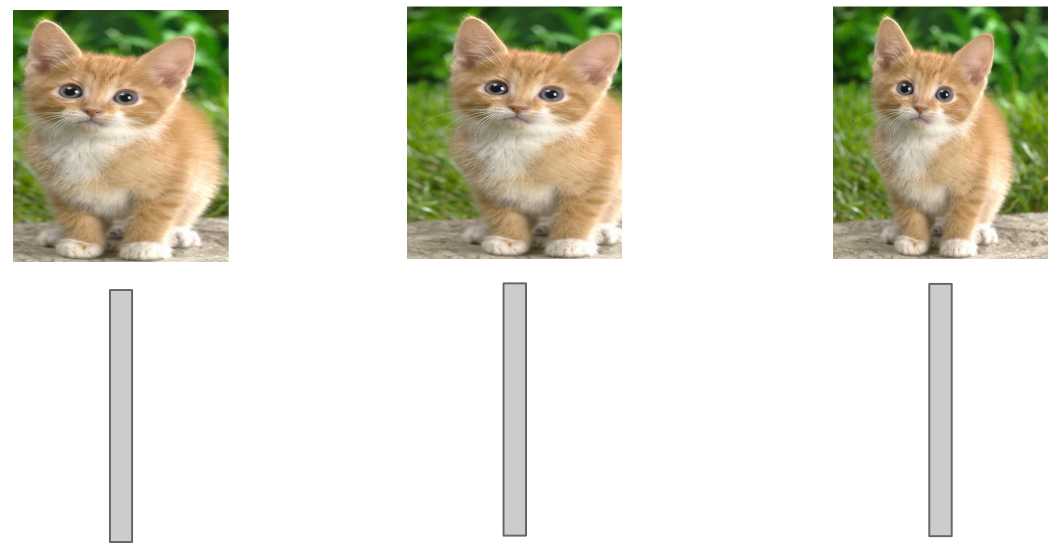
Positive samples for dog SVM

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 make up for “slightly wrong” proposals

Training image regions

Cached region features



Regression targets
(dx, dy, dw, dh)
Normalized coordinates

(0, 0, 0, 0)
Proposal is good

(.25, 0, 0, 0)
Proposal too
far to left

(0, 0, -0.125, 0)
Proposal too
wide

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**

Slide Credit:

Object Detection: Evaluation

We use a metric called “mean average precision” (mAP)

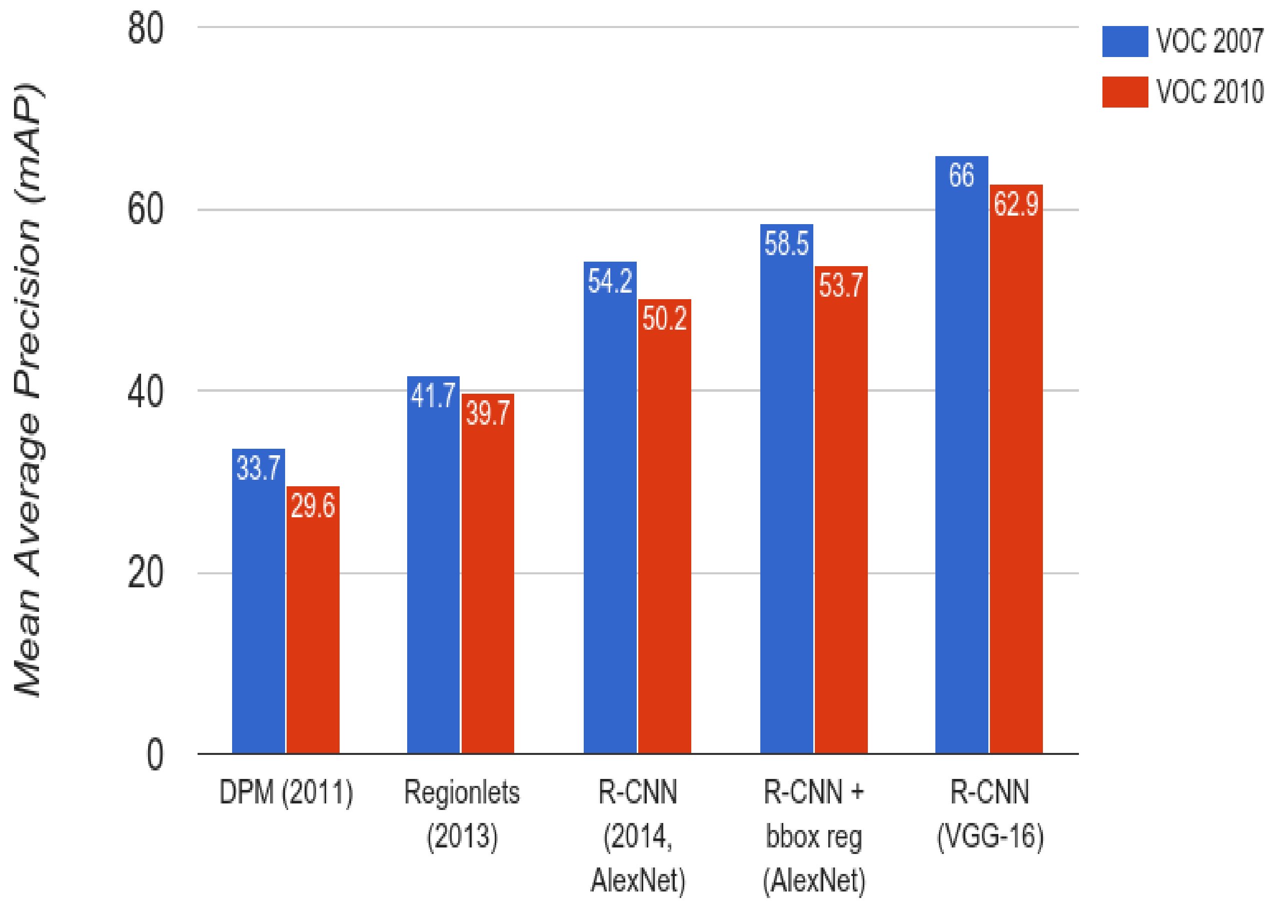
Compute average precision (AP) separately for each class, then average over classes

A detection is a true positive if it has IoU with a ground-truth box greater than some threshold (usually 0.5) (mAP@0.5)

Combine all detections from all test images to draw a precision / recall curve for each class; AP is area under the curve

TL;DR mAP is a number from 0 to 100; high is good

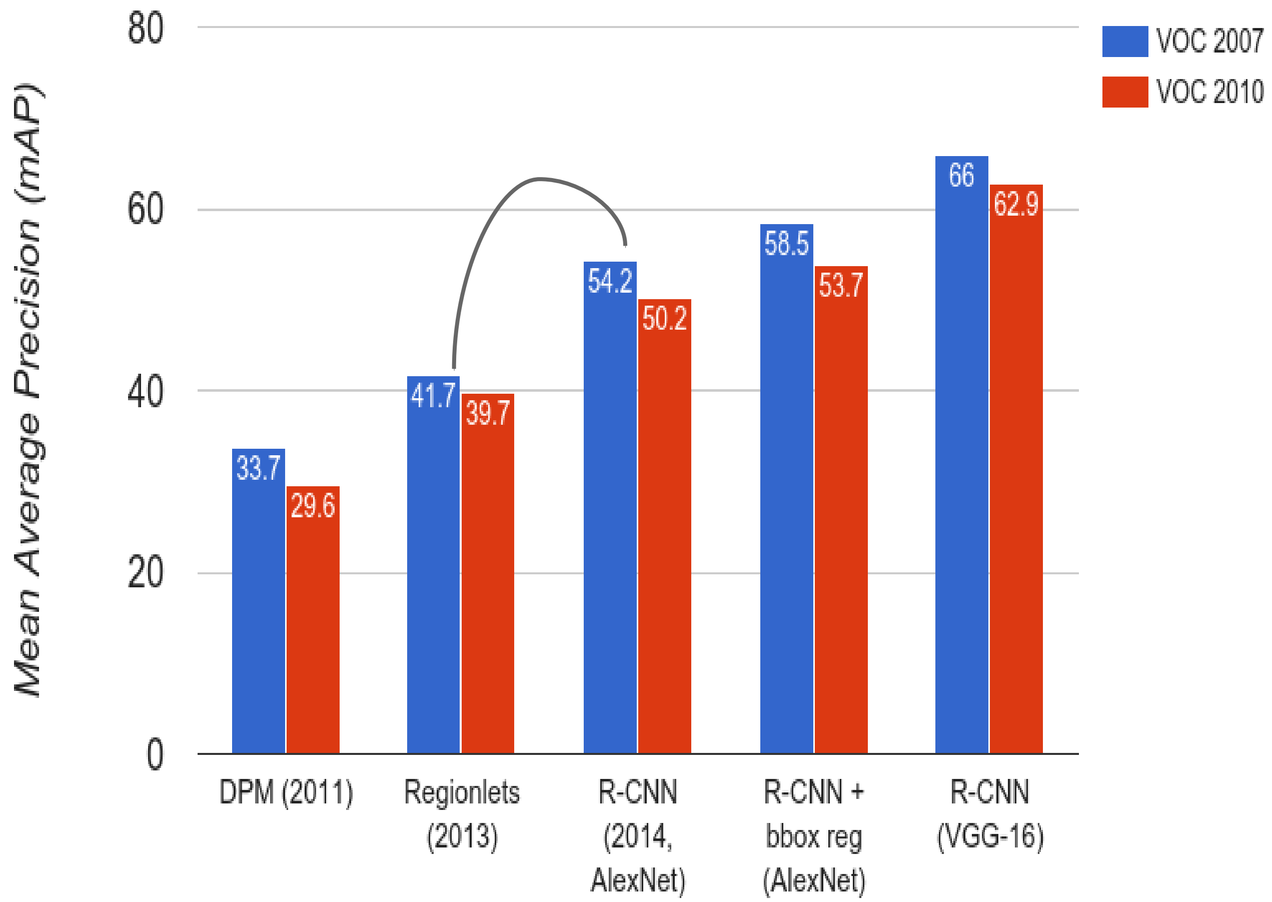
R-CNN Results



Wang et al, “Regionlets for Generic Object Detection”, ICCV 2013

R-CNN Results

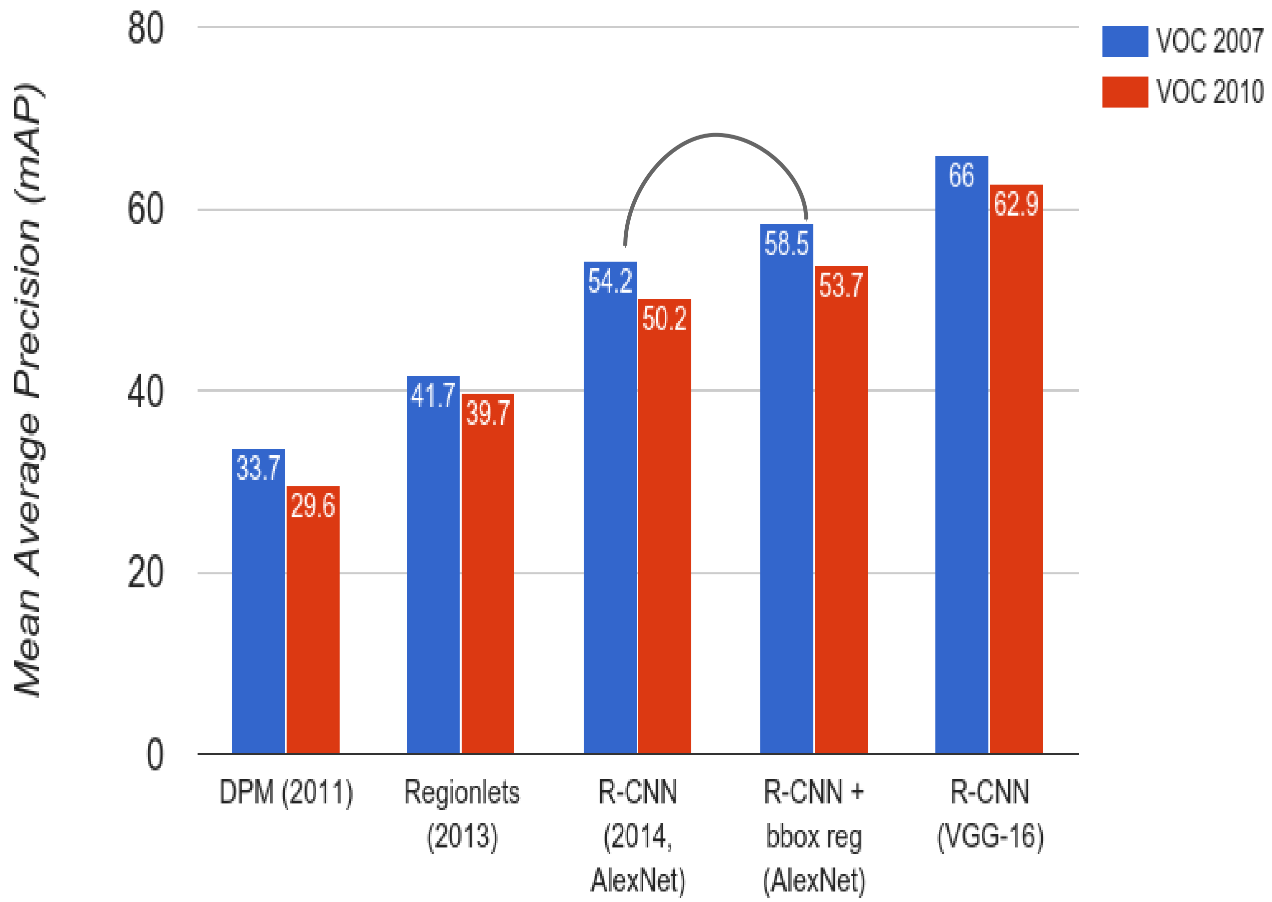
Big improvement compared
to pre-CNN methods



Slide Credit:

R-CNN Results

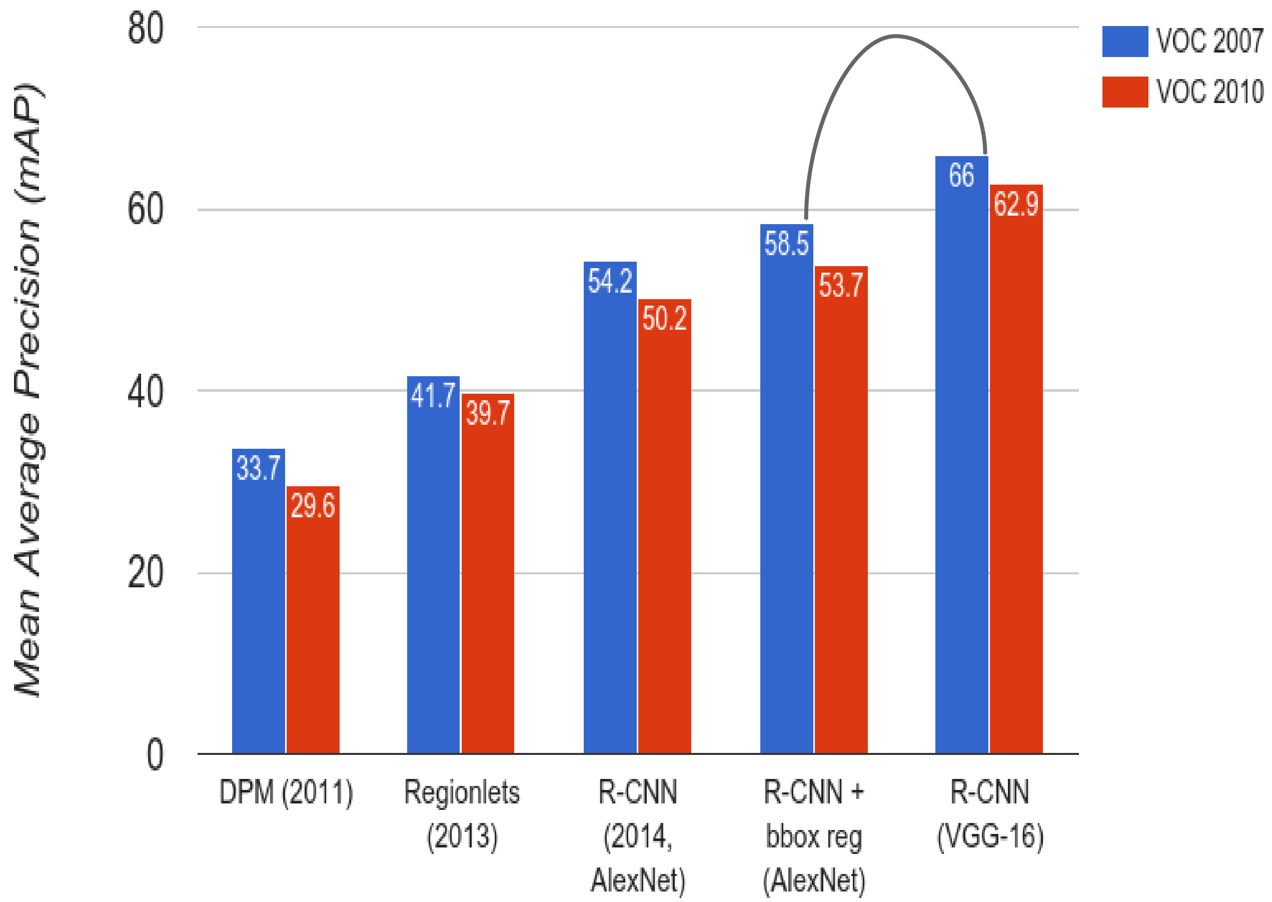
Bounding box regression helps a bit



Slide Credit:

R-CNN Results

Features from a deeper network help a lot



Slide Credit:

R-CNN Problems

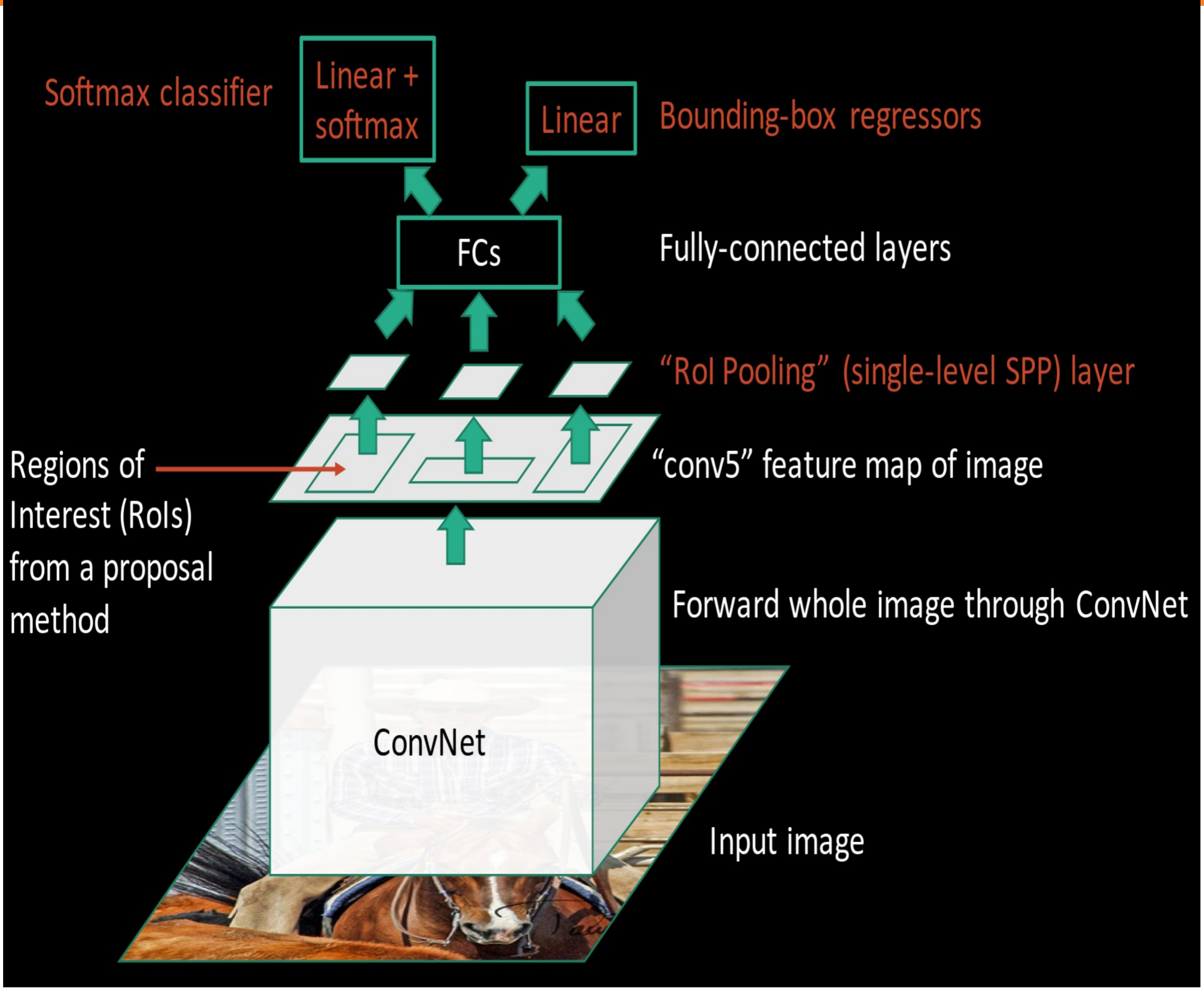
1. Slow at test-time: need to run full forward pass of CNN for each region proposal

2. SVMs and regressors are post-hoc: CNN features not updated in response to SVMs and regressors

3. Complex multistage training pipeline

Slide Credit:

Fast R-CNN (test time)

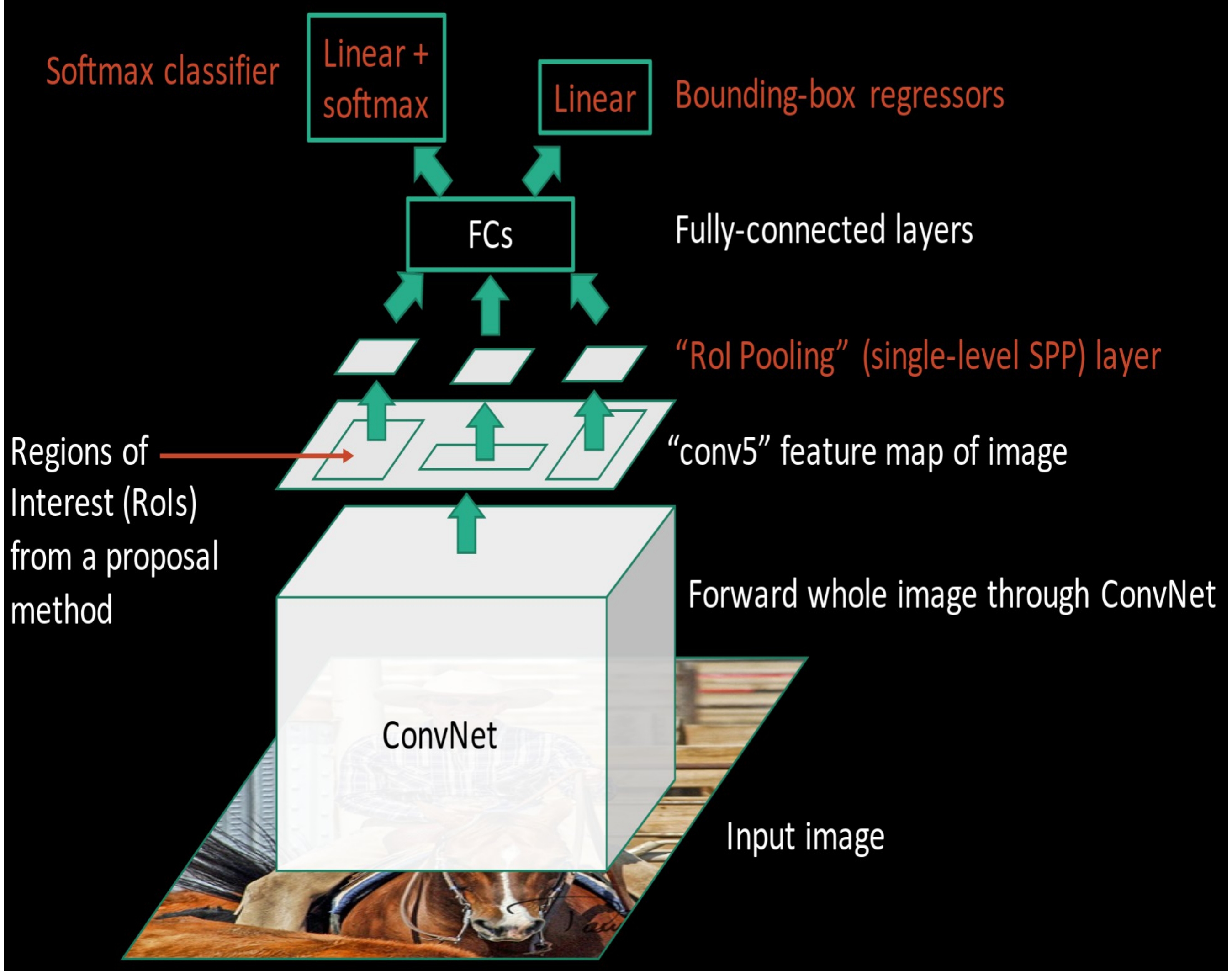


Girschick, "Fast R-CNN", ICCV 2015

Slide credit: Ross Girschick

Slide Credit:

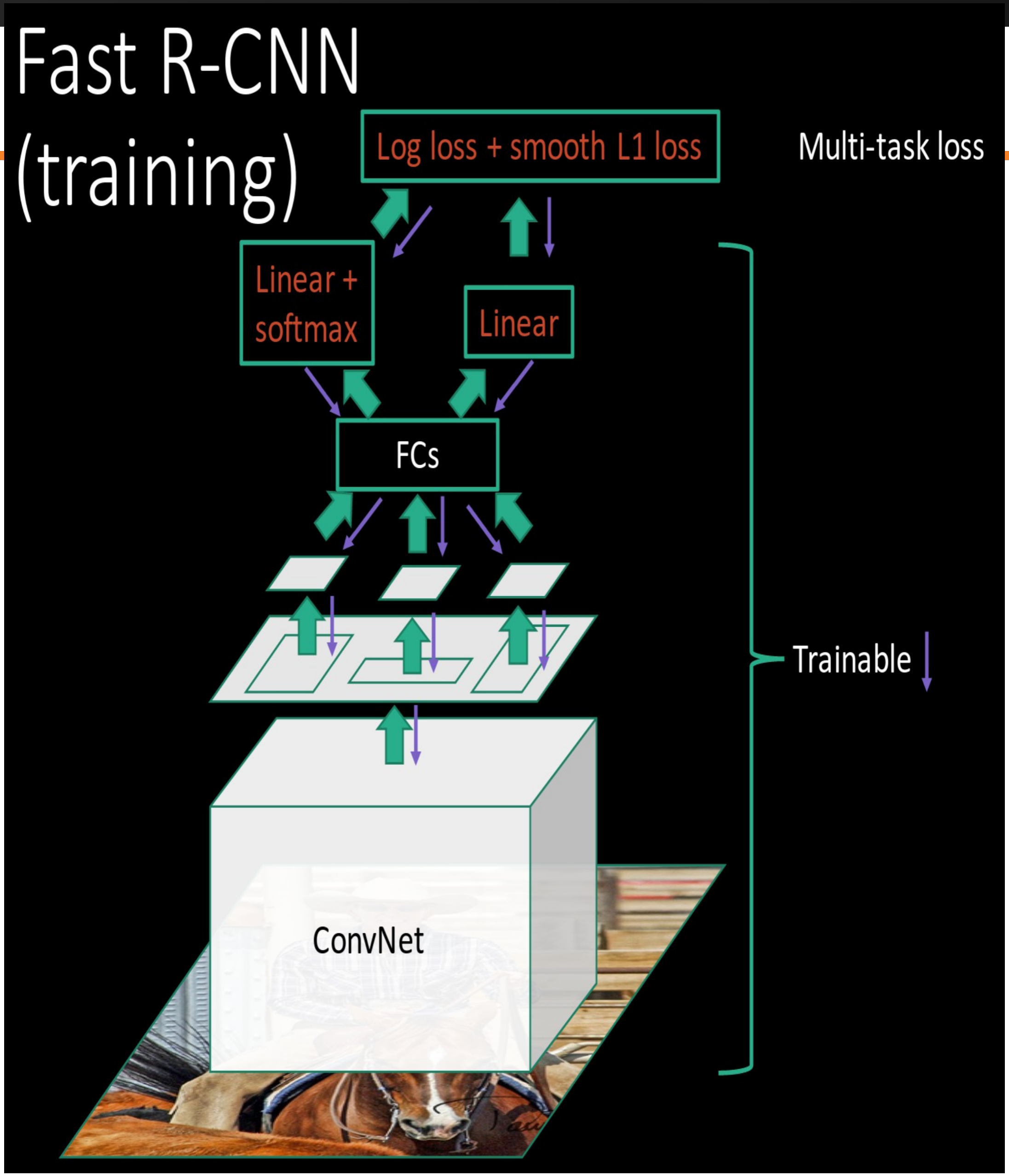
Fast R-CNN (test time)



R-CNN Problem #1:
Slow at test-time due to independent forward passes of the CNN

Solution:
Share computation of convolutional layers between proposals for an image

Slide Credit:



R-CNN Problem #2:
Post-hoc training: CNN not updated in response to final classifiers and regressors

R-CNN Problem #3:
Complex training pipeline

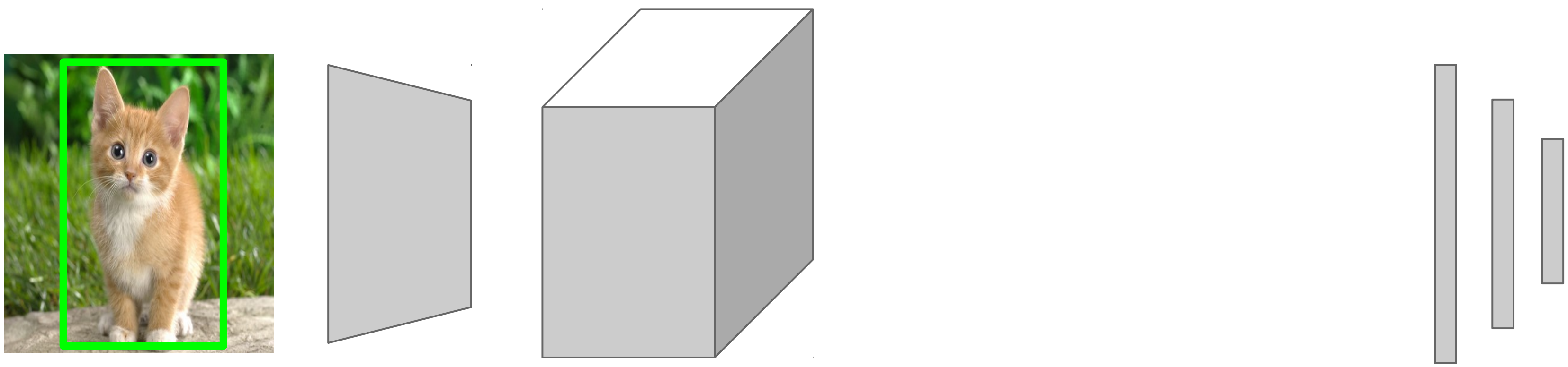
Solution:
Just train the whole system end-to-end all at once!

Slide credit: Ross Girschick

Fast R-CNN: Region of Interest Pooling

Convolution and Pooling

Fully-connected layers

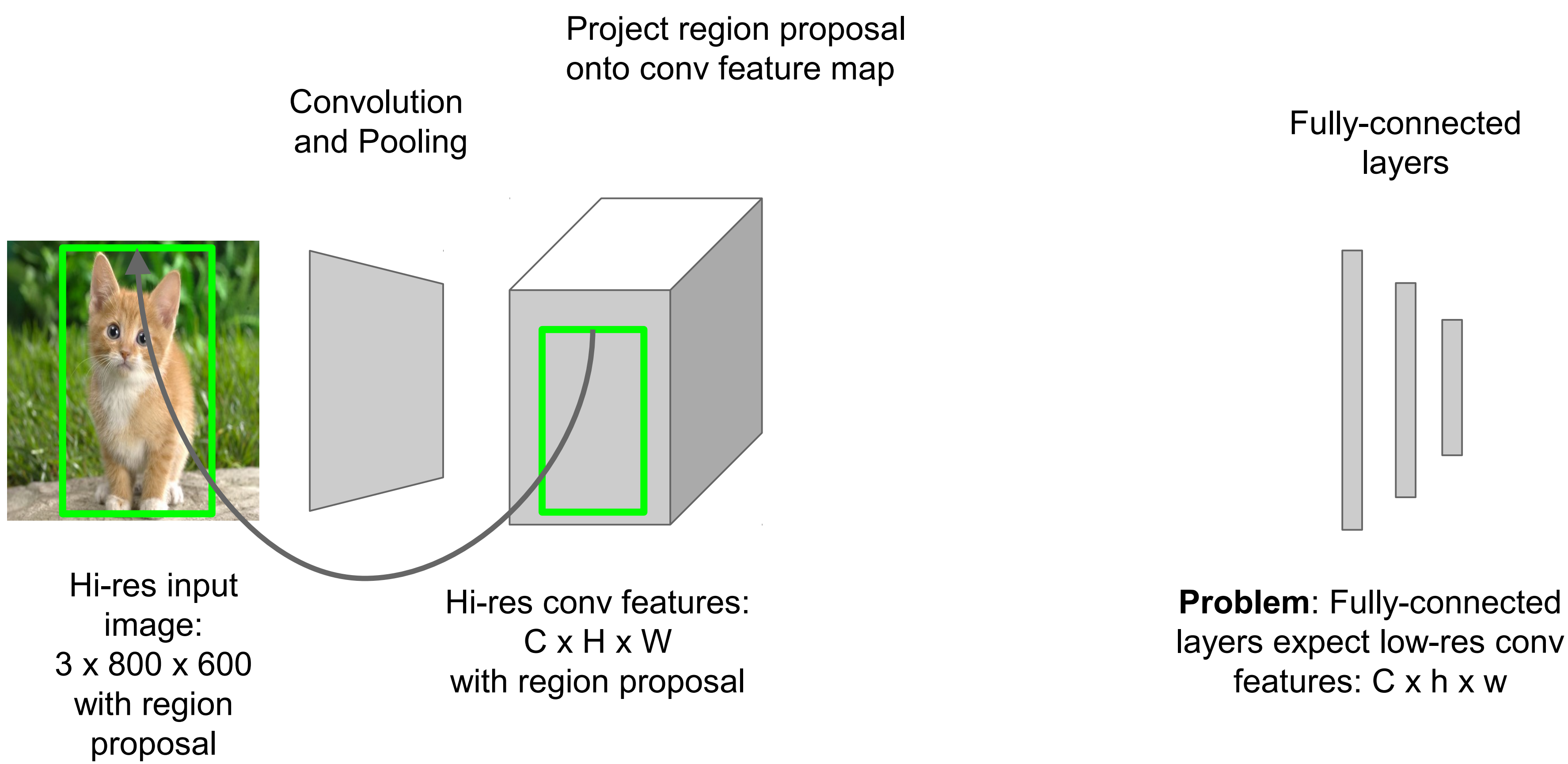


Hi-res input image:
3 x 800 x 600
with region proposal

Hi-res conv features:
C x H x W
with region proposal

Problem: Fully-connected layers expect low-res conv features: C x h x w

Fast R-CNN: Region of Interest Pooling

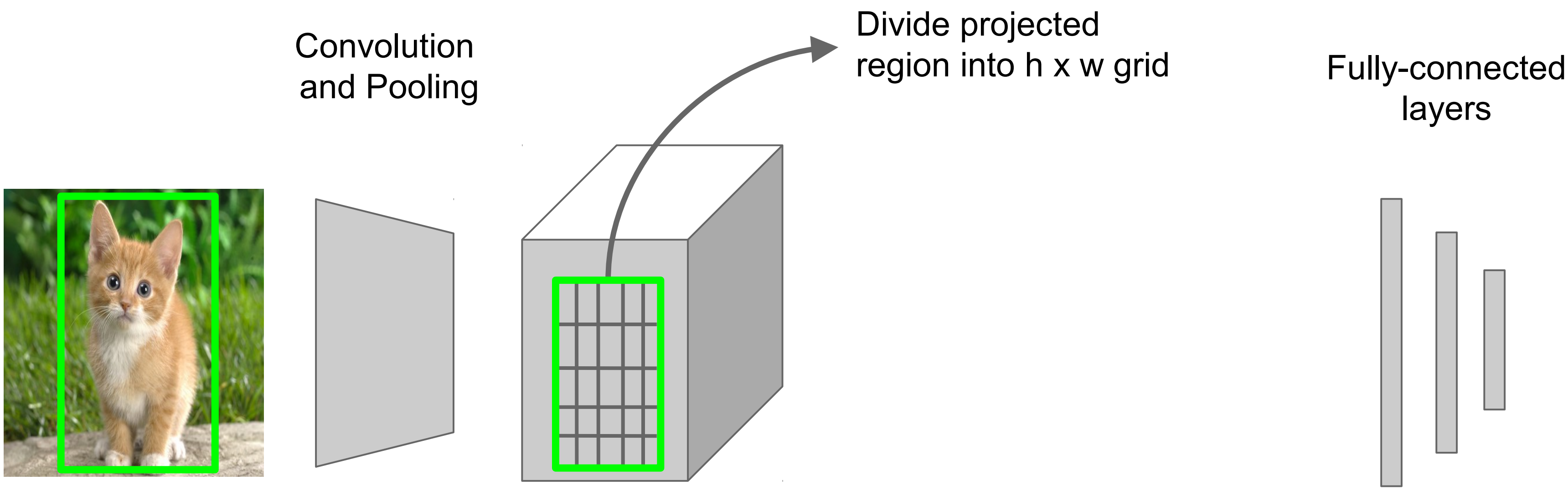


Problem: Fully-connected layers expect low-res conv features: C x h x w

78

Slide Credit:

Fast R-CNN: Region of Interest Pooling



Hi-res input image:
3 x 800 x 600
with region proposal

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C x H x W
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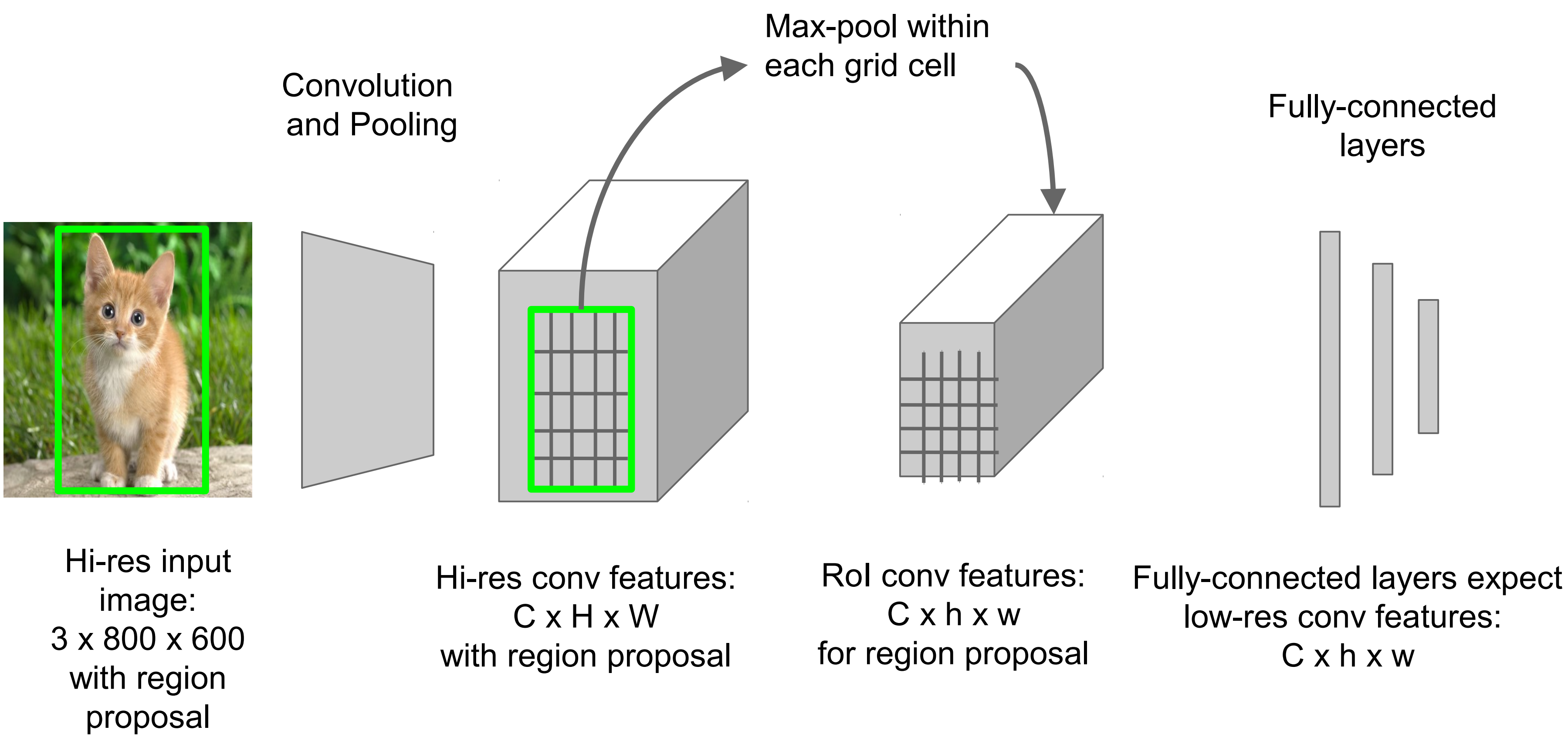
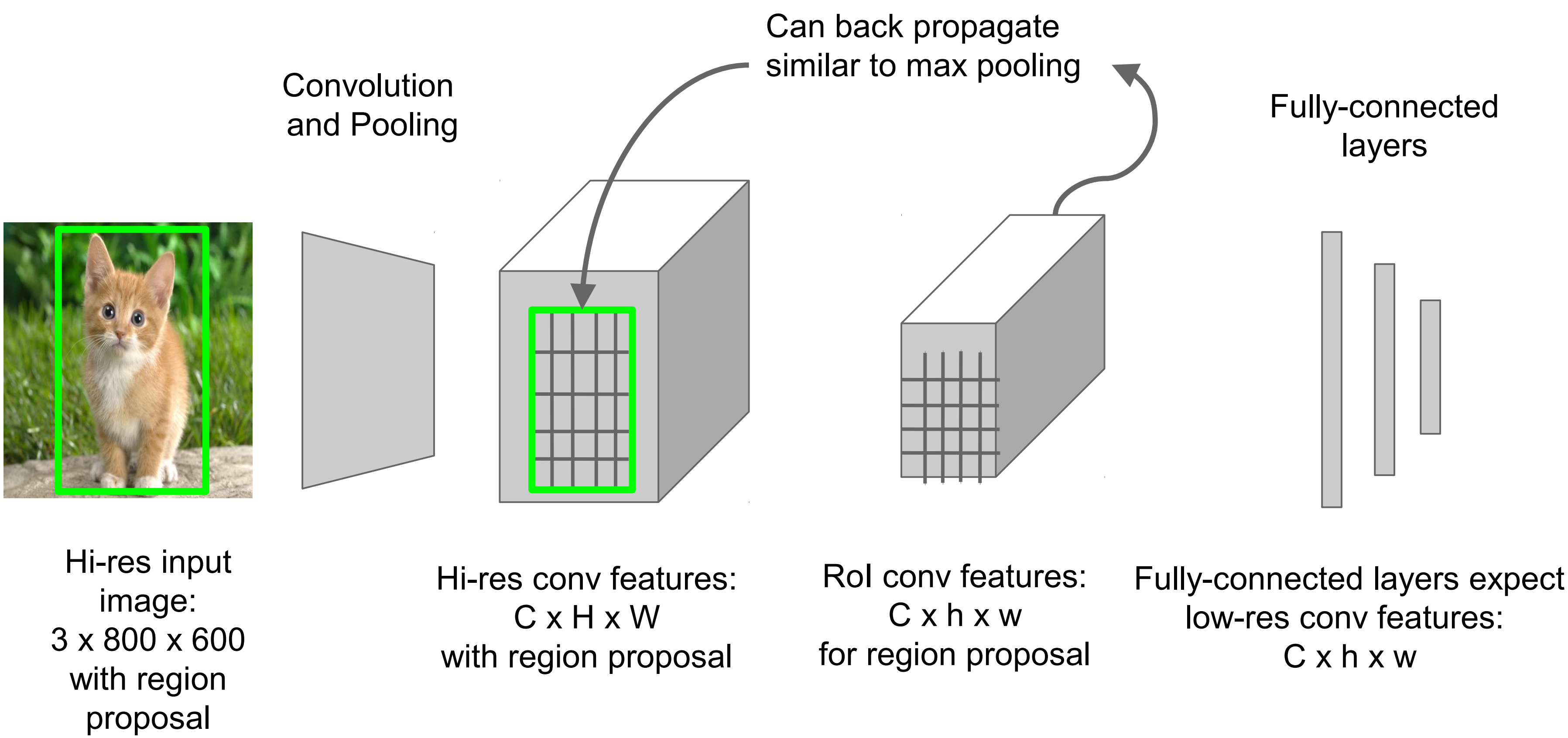
Fast R-CNN: Region of Interest Pooling



Fast R-CNN: Region of Interest Pooling



Fast R-CNN Results

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

Faster!

Using VGG-16 CNN on Pascal VOC 2007 dataset

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**

Faster!

FASTER!

Using VGG-16 CNN on Pascal VOC 2007 dataset

Slide Credit:

Fast R-CNN Results

		R-CNN	Fast R-CNN
		R-CNN	**Fast R-CNN**
Faster!	Training Time:	84 hours	**9.5 hours**
	(Speedup)	1x	**8.8x**
FASTER!	Test time per image	47 seconds	**0.32 seconds**
	(Speedup)	1x	**146x**
Better!	mAP (VOC 2007)	66.0	**66.9**

Using VGG-16 CNN on Pascal VOC 2007 dataset

Fast R-CNN Problem:

Test-time speeds don't include region proposals

	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**

Slide Credit:

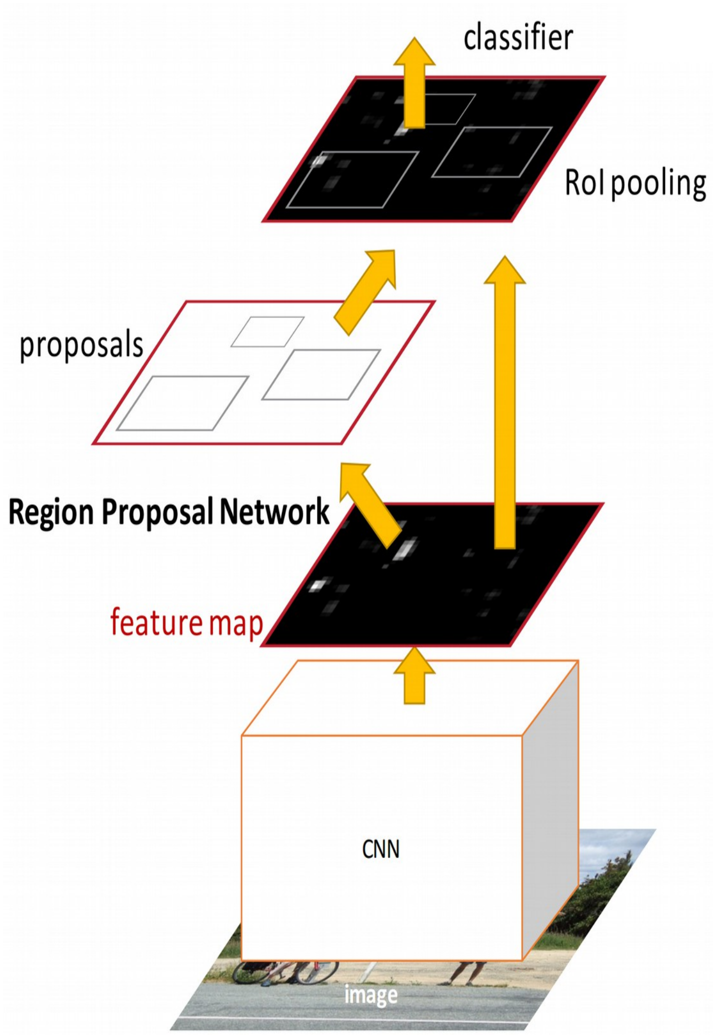
Fast R-CNN ~~Problem~~ Solution:

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

	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**

Slide Credit:

Faster R-CNN:



Insert a **Region Proposal Network (RPN)** after the last convolutional layer

RPN trained to produce region proposals directly; no need for external region proposals!

After RPN, use RoI Pooling and an upstream classifier and bbox regressor just like Fast R-CNN

Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015

Slide credit: Ross Girschick

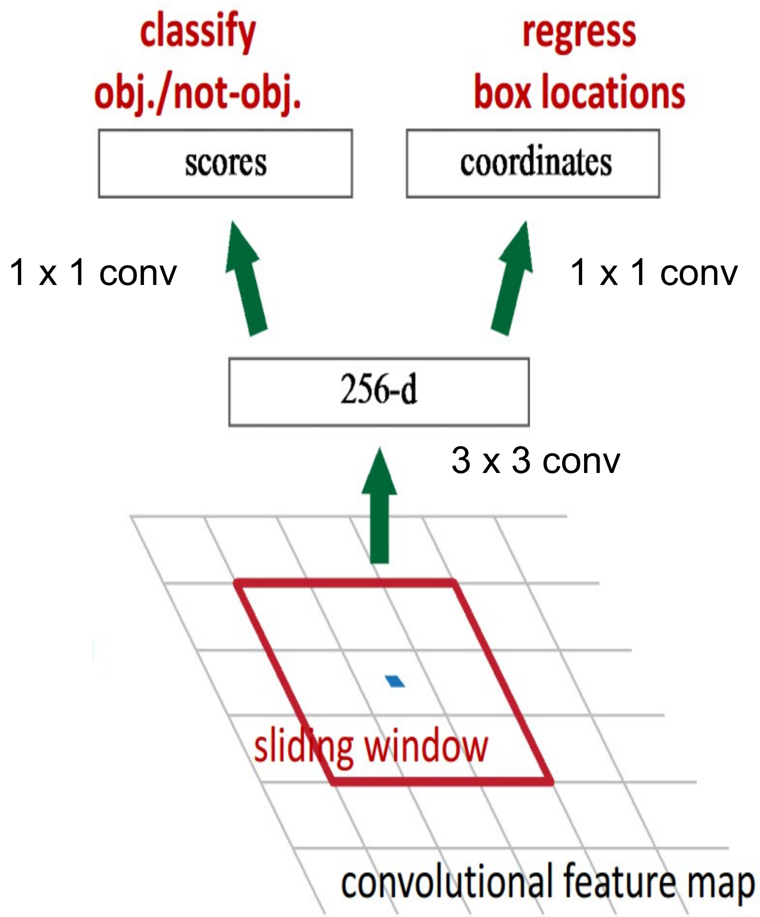
Faster R-CNN: Region Proposal Network

Slide a small window on the feature map

Build a small network for:
• classifying object or not-object, and
• regressing bbox locations

Position of the sliding window provides localization information with reference to the image

Box regression provides finer localization information with reference to this sliding window



Slide credit: Kaiming He

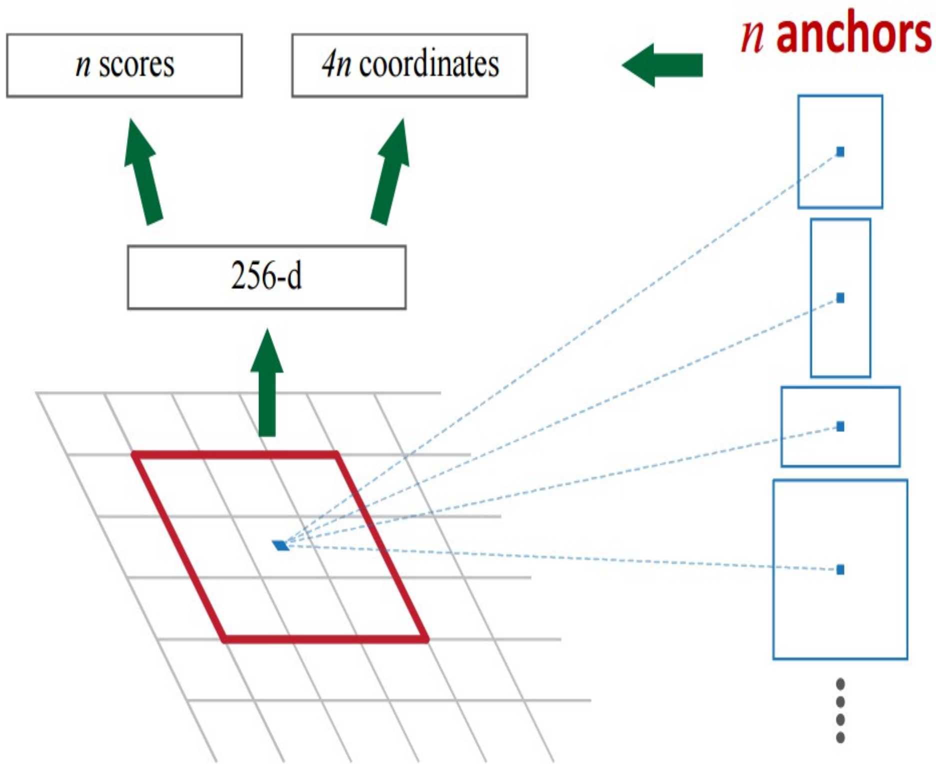
Faster R-CNN: Region Proposal Network

Use **N anchor boxes** at each location

Anchors are **translation invariant**: use the same ones at every location

Regression gives offsets from anchor boxes

Classification gives the probability that each (regressed) anchor shows an object



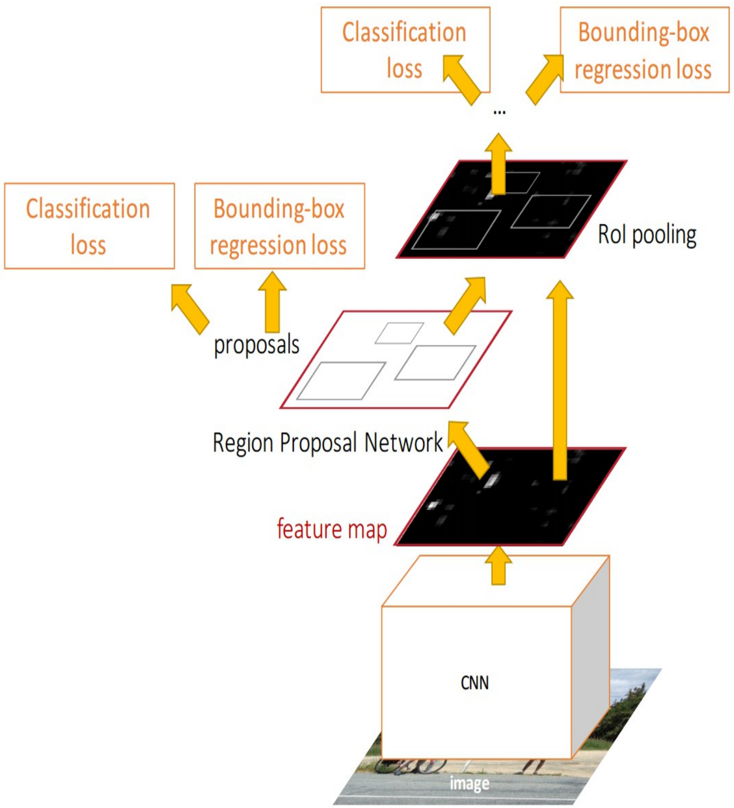
Faster R-CNN: Training

In the paper: Ugly pipeline

- Use alternating optimization to train RPN, then Fast R-CNN with RPN proposals, etc.
- More complex than it has to be

Since publication: Joint training!
One network, four losses

- RPN classification (anchor good / bad)
- RPN regression (anchor -> proposal)
- Fast R-CNN classification (over classes)
- Fast R-CNN regression (proposal -> box)



Slide credit: Ross Girschick

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**

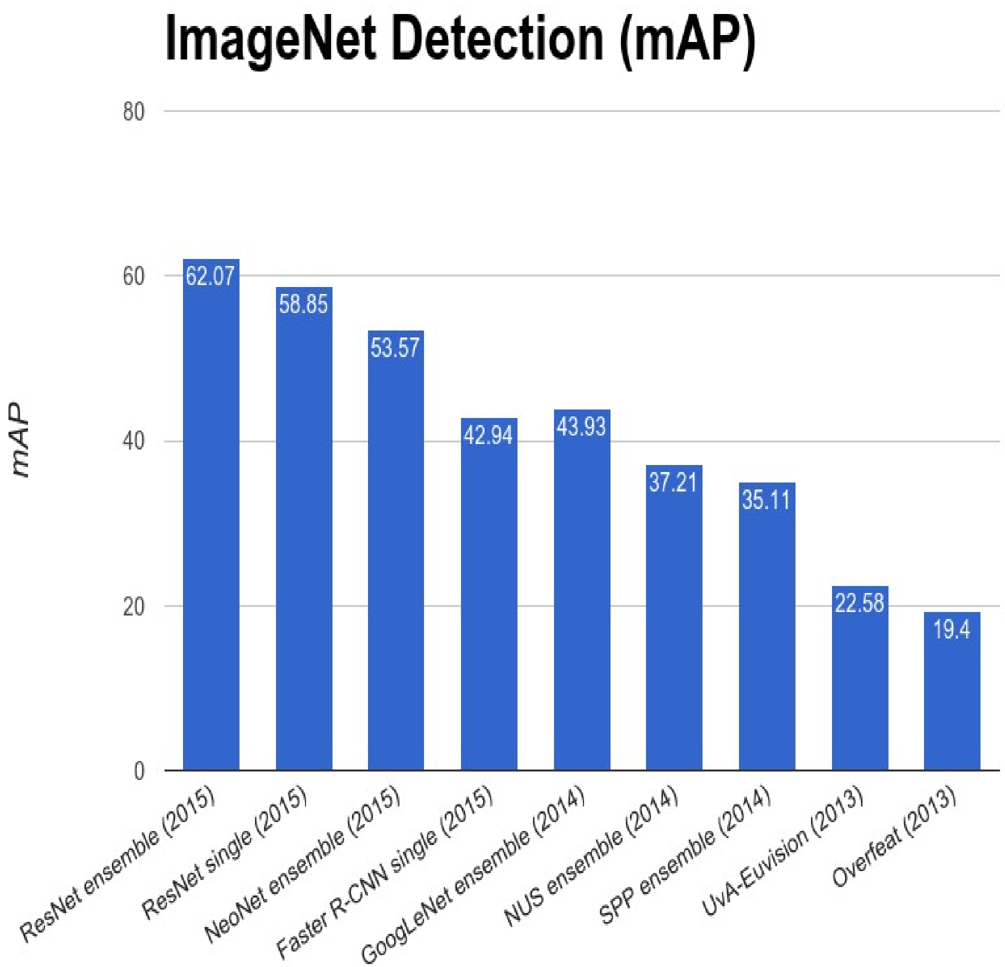
Slide Credit:

Object Detection State-of-the-art: ResNet 101 + Faster R-CNN + some extras

training data	COCO train		COCO trainval	
test data	COCO val		COCO test-dev	
mAP	@.5	@[.5, .95]	@.5	@[.5, .95]
baseline Faster R-CNN (VGG-16)	41.5	21.2		
baseline Faster R-CNN (ResNet-101)	48.4	27.2		
+box refinement	49.9	29.9		
+context	51.1	30.0	53.3	32.2
+multi-scale testing	53.8	32.5	**55.7**	**34.9**
ensemble			**59.0**	**37.4**

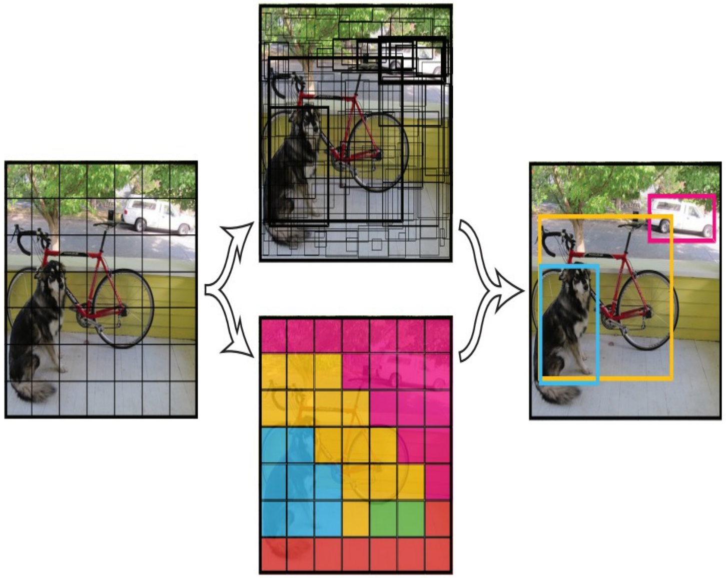
He et. al, "Deep Residual Learning for Image Recognition", arXiv 2015

ImageNet Detection 2013 - 2015



Slide Credit:

YOLO: You Only Look Once
Detection as Regression

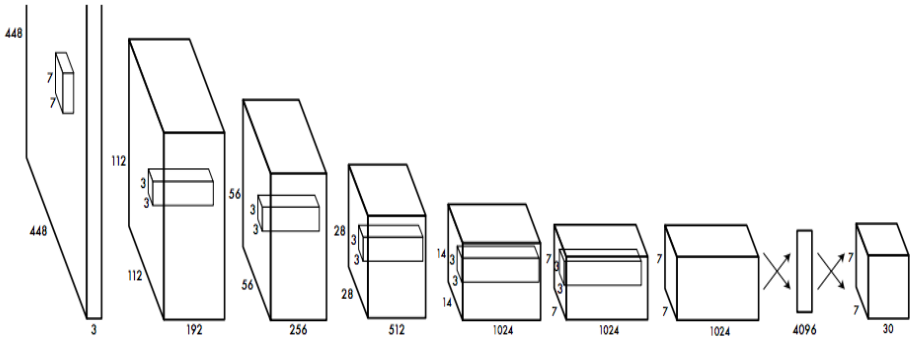


Divide image into S x S grid

Within each grid cell predict:
- B Boxes: 4 coordinates + confidence
- Class scores: C numbers

Regression from image to
7 x 7 x (5 * B + C) tensor

Direct prediction using a CNN



Redmon et al, “You Only Look Once:
Unified, Real-Time Object Detection”, arXiv 2015

YOLO: You Only Look Once
Detection as Regression

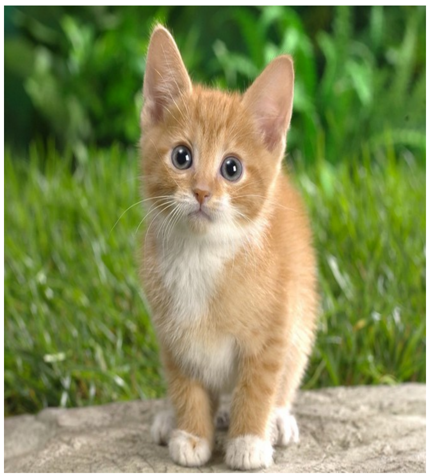
Faster than Faster R-CNN, but not as good

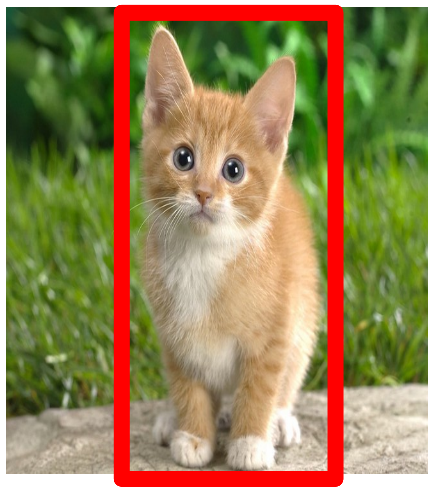
Redmon et al, "You Only Look Once:
Unified, Real-Time Object Detection", arXiv 2015

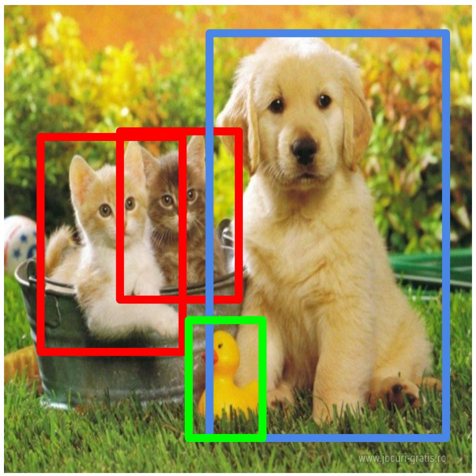
Real-Time Detectors	Train	mAP	FPS
100Hz DPM [30]	2007	16.0	100
30Hz DPM [30]	2007	26.1	30
Fast YOLO	2007+2012	52.7	**155**
YOLO	2007+2012	**63.4**	45
Less Than Real-Time			
Fastest DPM [37]	2007	30.4	15
R-CNN Minus R [20]	2007	53.5	6
Fast R-CNN [14]	2007+2012	70.0	0.5
Faster R-CNN VGG-16[27]	2007+2012	73.2	7
Faster R-CNN ZF [27]	2007+2012	62.1	18

Computer Vision Tasks

Classification	Classification + Localization	Object Detection	Segmentation







CAT	CAT	CAT, DOG, DUCK	CAT, DOG, DUCK

Single object

Multiple objects

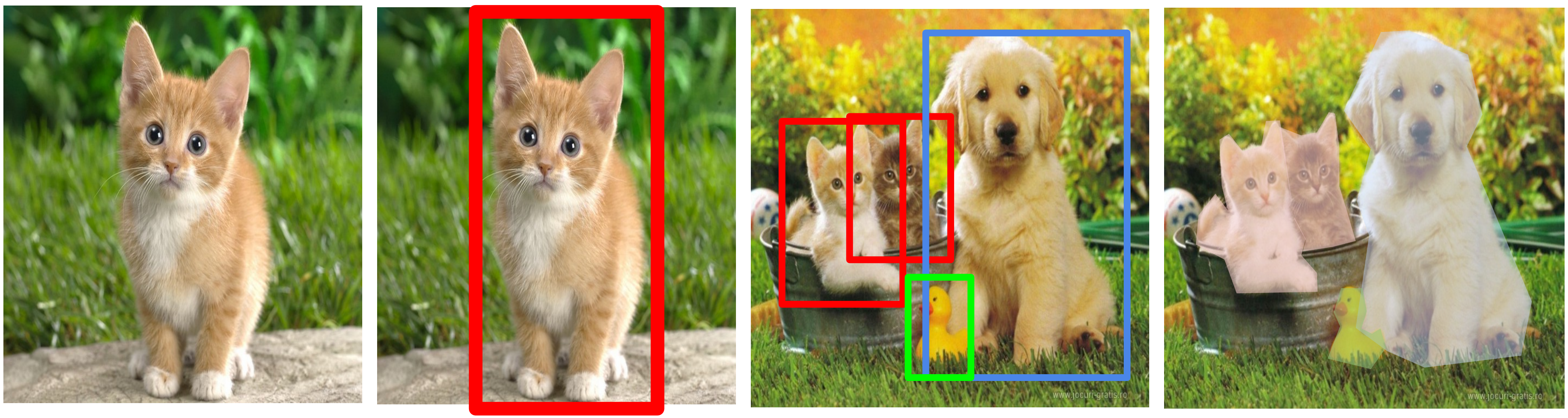
Computer Vision Tasks

Classification

Classification + Localization

Object Detection

Segmentation



Lecture 8

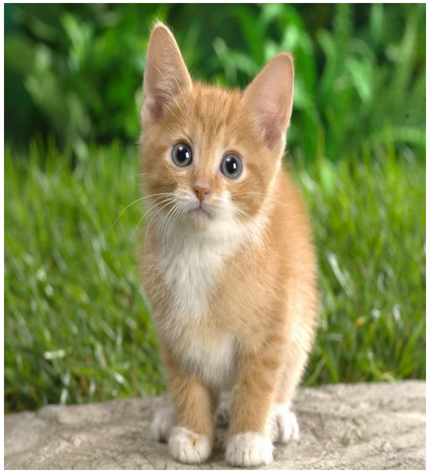
Computer Vision Tasks

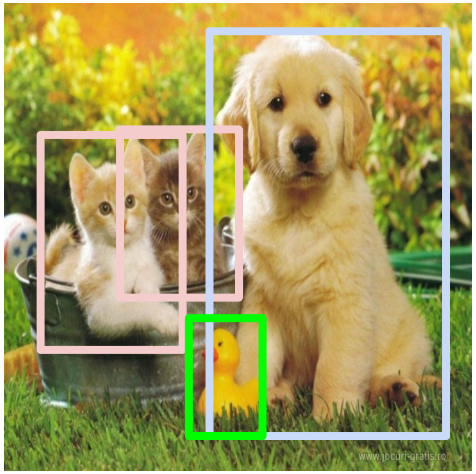
Classification

Classification
+ Localization

Object Detection

Segmentation





Today

Slide Credit:

Semantic Segmentation

Label every pixel!

Don't differentiate instances (cows)

Classic computer vision problem

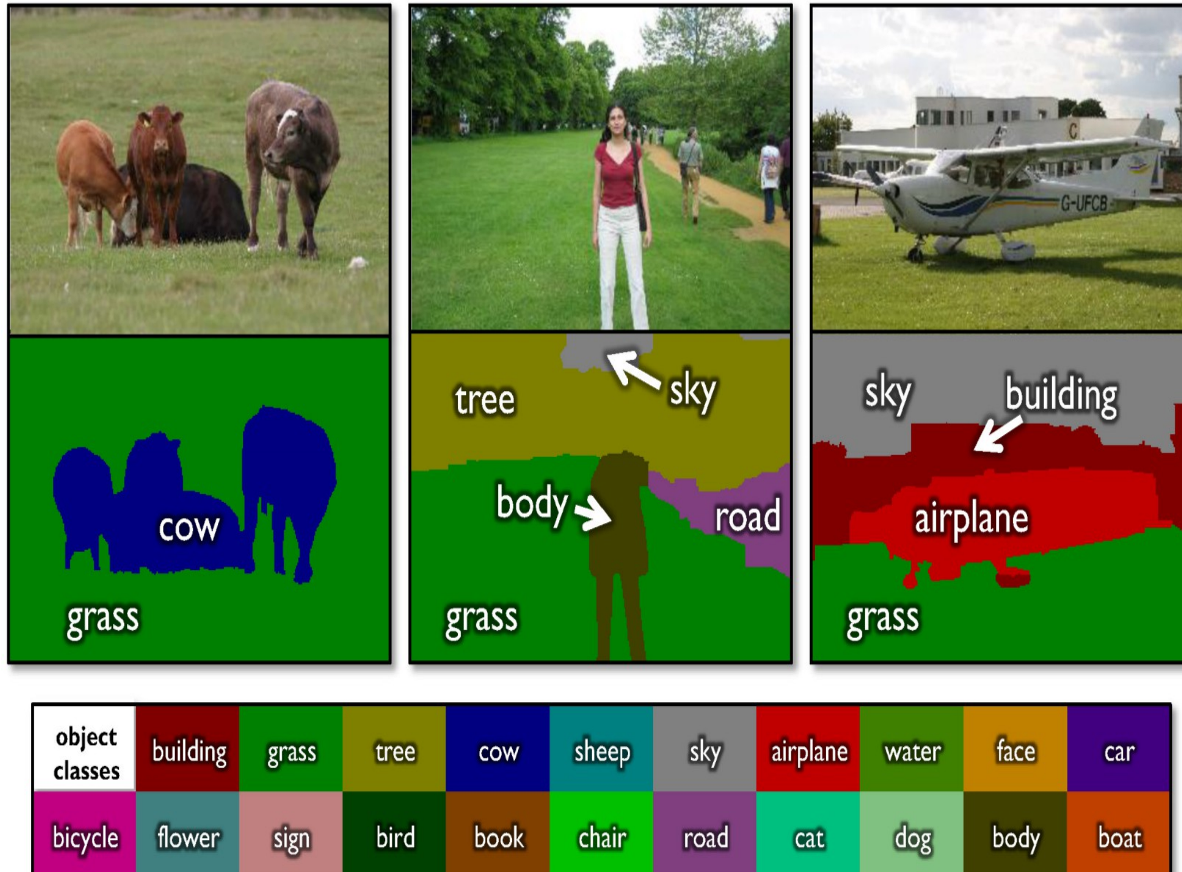


Figure credit: Shotton et al, "TextonBoost for Image Understanding: Multi-Class Object Recognition and Segmentation by Jointly Modeling Texture, Layout, and Context", IJCV 2007

Instance Segmentation

Detect instances, give category, label pixels

“simultaneous detection and segmentation” (SDS)

Lots of recent work (MS-COCO)

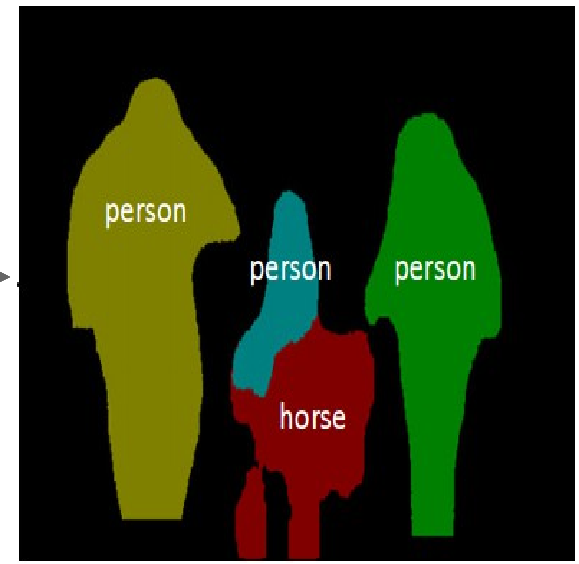


Figure credit: Dai et al, “Instance-aware Semantic Segmentation via Multi-task Network Cascades”, arXiv 2015