CNNs for Segmentation, Localization, and detection

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Most slides have been adopted from Fei Fei Li and colleagues lectures, cs231n, Stanford 2017
and some from John Canny lectures, cs294-129, Berkeley, 2016. .

AlexNet

[Krizhevsky, Sutskever, Hinton, 2012]

- ImageNet Classification with Deep Convolutional Neural Networks

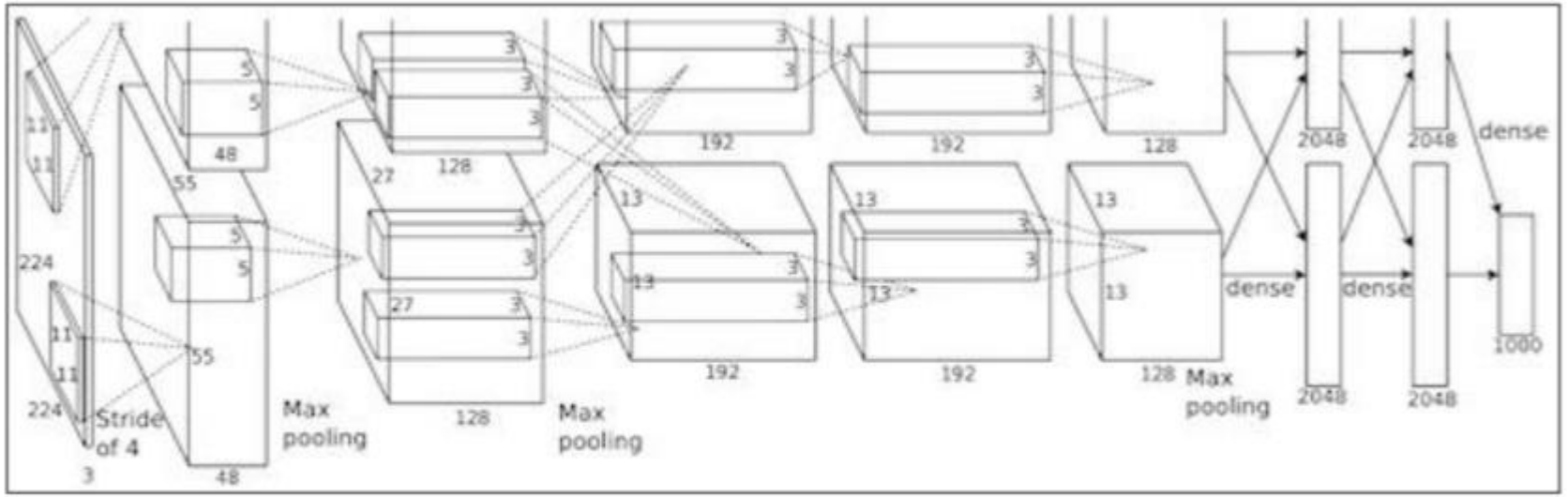

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Image classification

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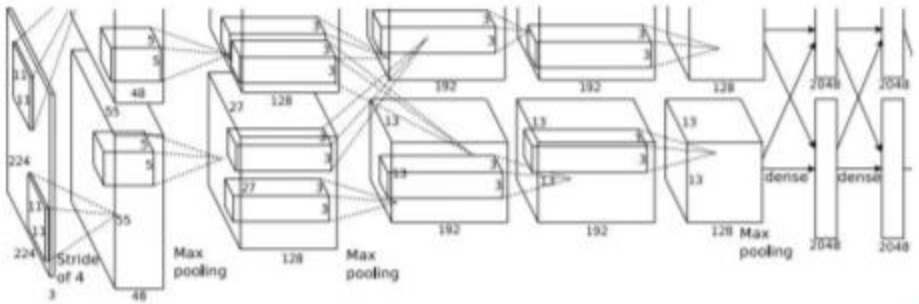

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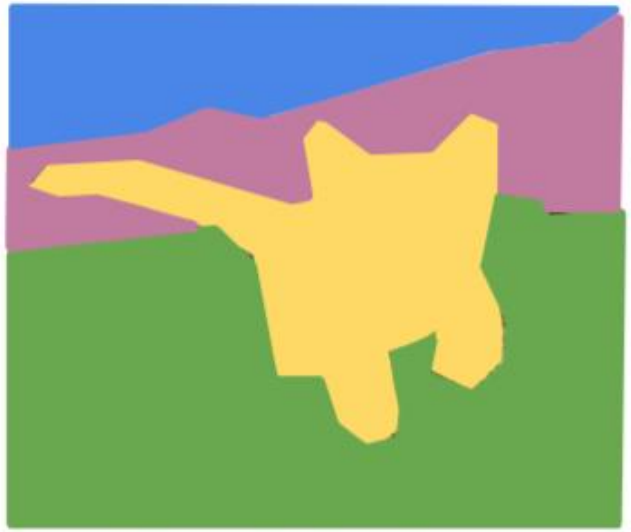
Vector:
4096

Fully-Connected:
4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Other Computer Vision Tasks

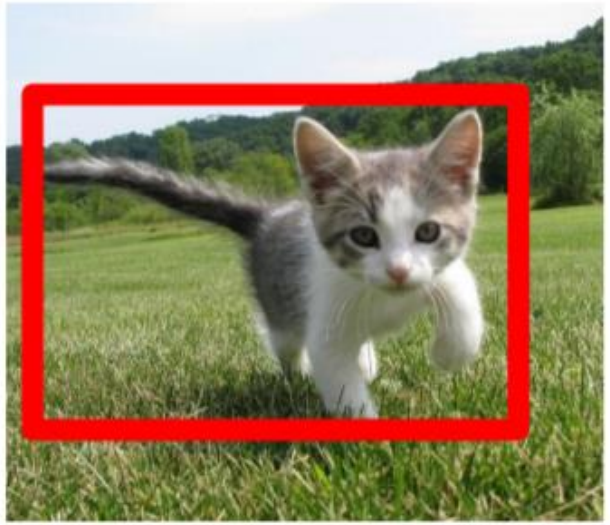
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

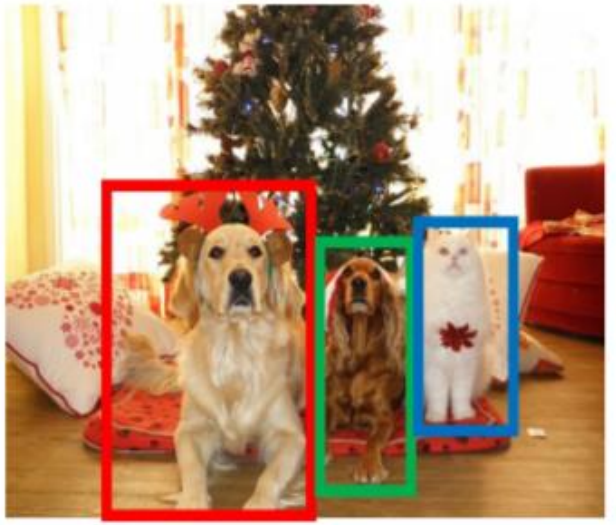
Classification + Localization



CAT

Single Object

Object Detection



DOG, DOG, CAT

Instance Segmentation

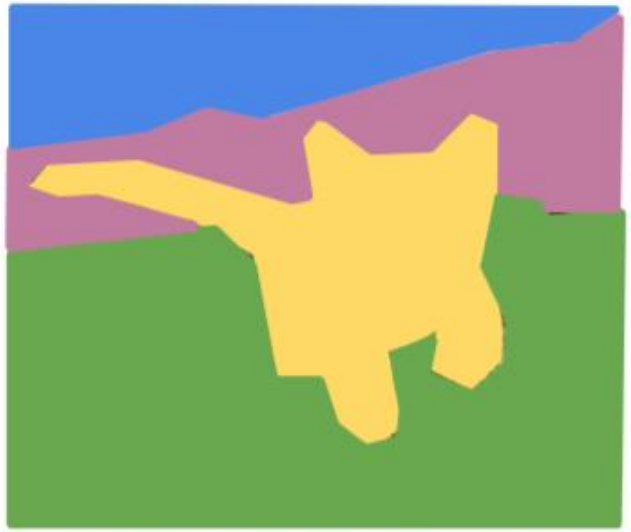
DOG, DOG, CAT

Multiple Object

Classification and localization

What & where

Semantic Segmentation



GRASS, CAT, TREE, SKY

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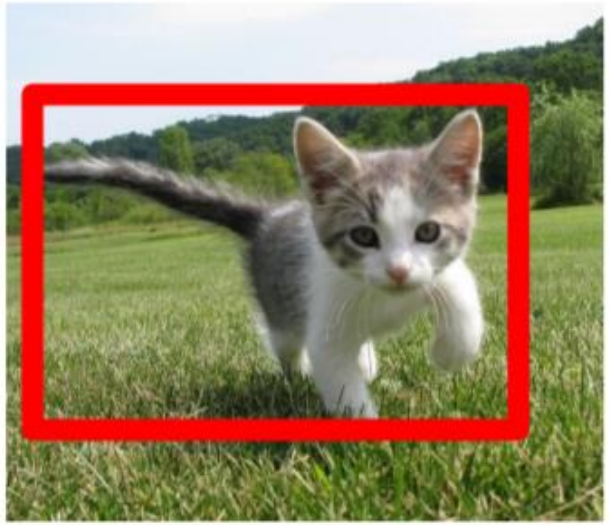
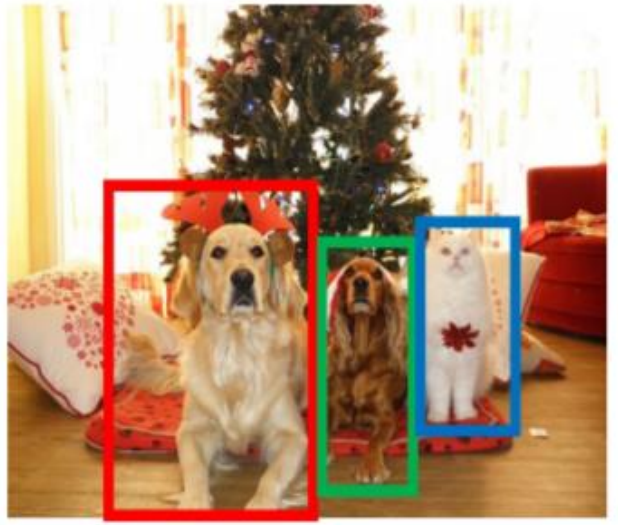
Classification + Localization



CAT

Single Object

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

Multiple Object

Classification + Localization

Classification: C classes

Input: Image

Output: Class label

Evaluation metric: Accuracy

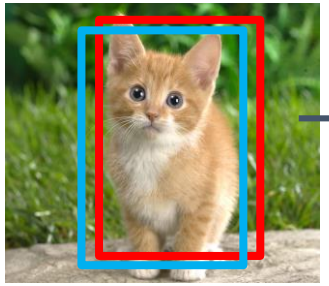
CAT

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

Idea #1: Localization as Regression

Input: image

Neural Net

Output:
Box coordinates
(4 numbers)

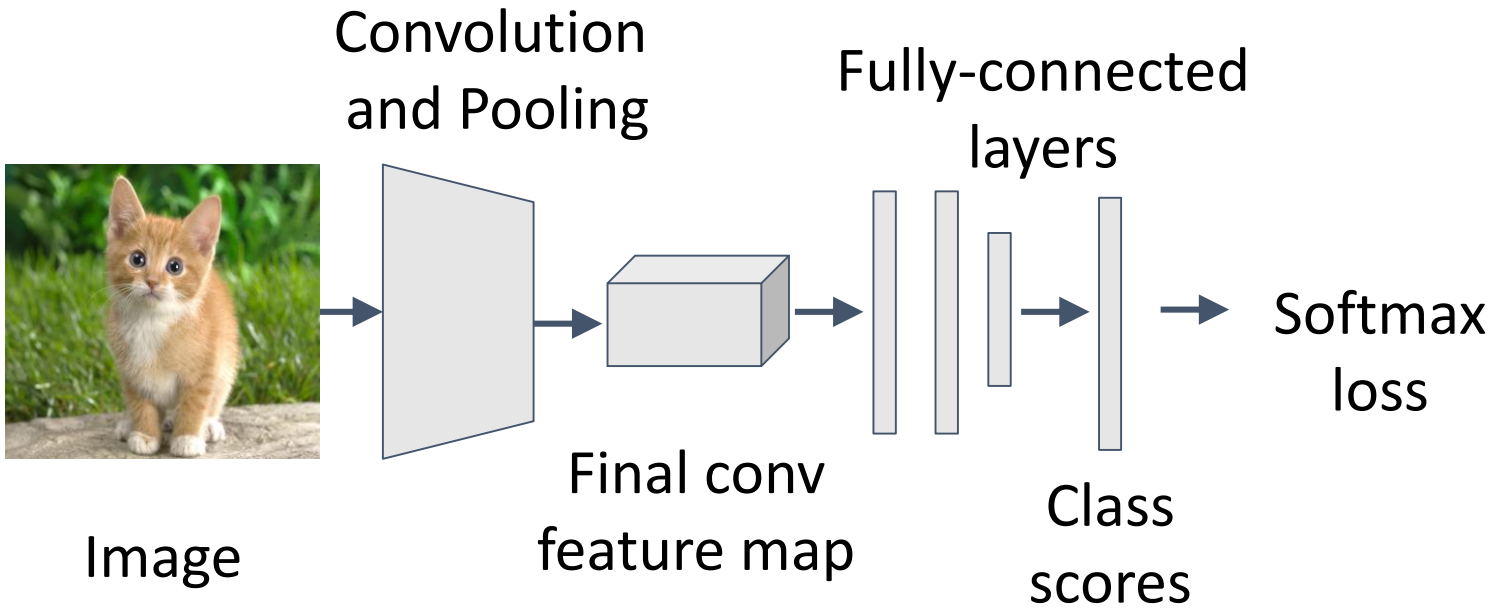
Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

Only one object, simpler than detection

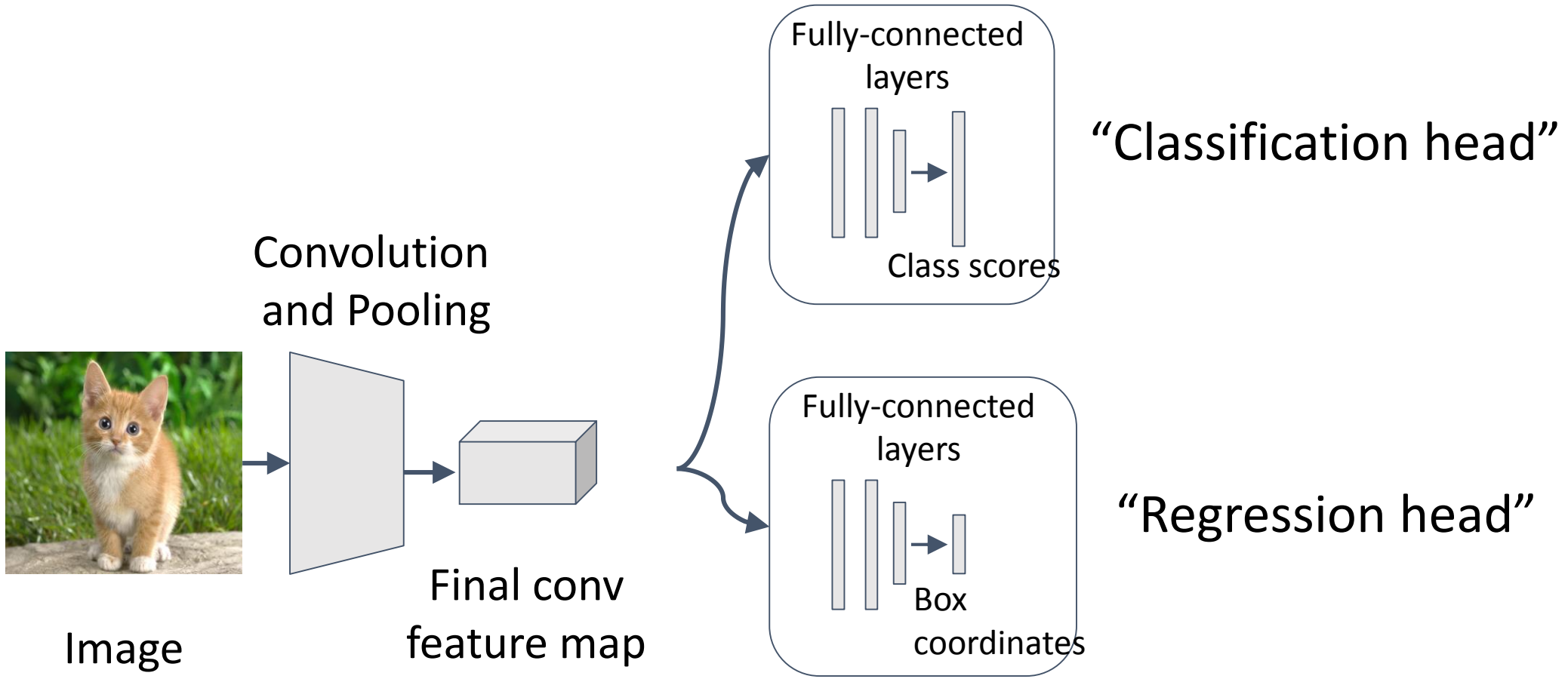
Simple Recipe for Classification + Localization

- **Step 1**: Train (or download) a classification model (e.g., VGG)



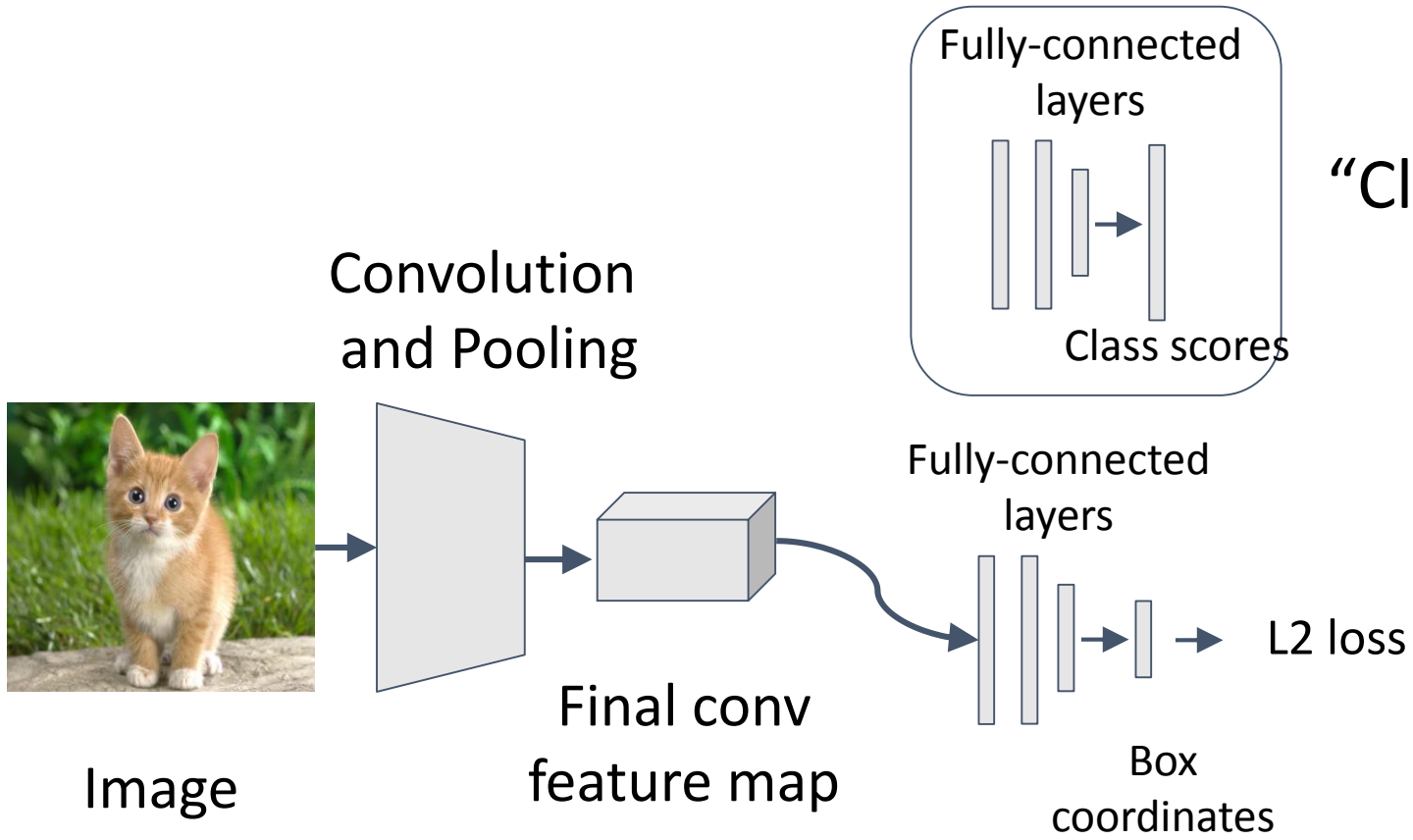
Simple Recipe for Classification + Localization

- **Step 1**: Train (or download) a classification model (e.g., VGG)
- **Step 2**: Attach new fully-connected "regression head" to the network



Simple Recipe for Classification + Localization

- **Step 1**: Train (or download) a classification model (e.g., VGG)
- **Step 2**: Attach new fully-connected "regression head" to the network
- **Step 3**: Train the regression head only with SGD and L2 loss



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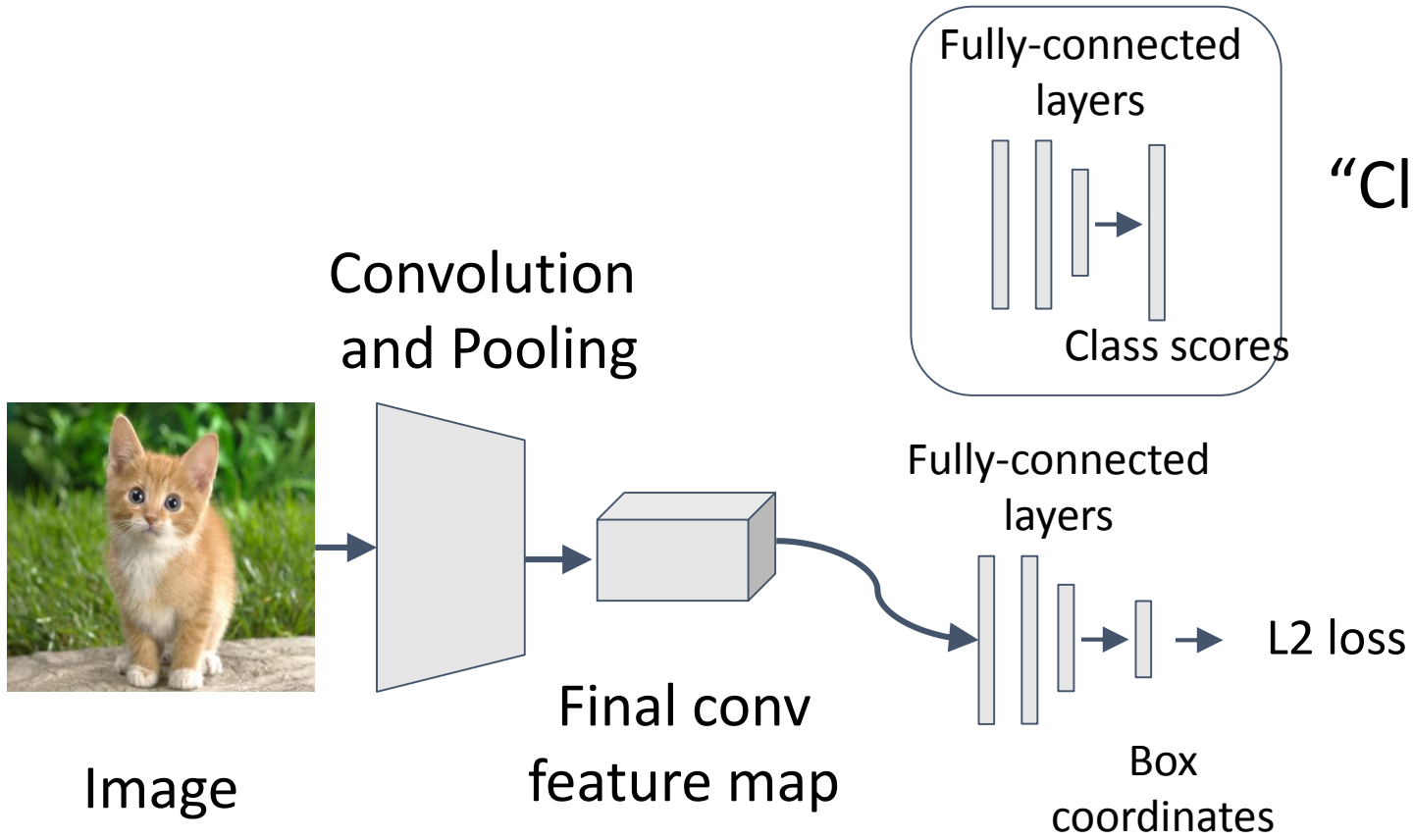

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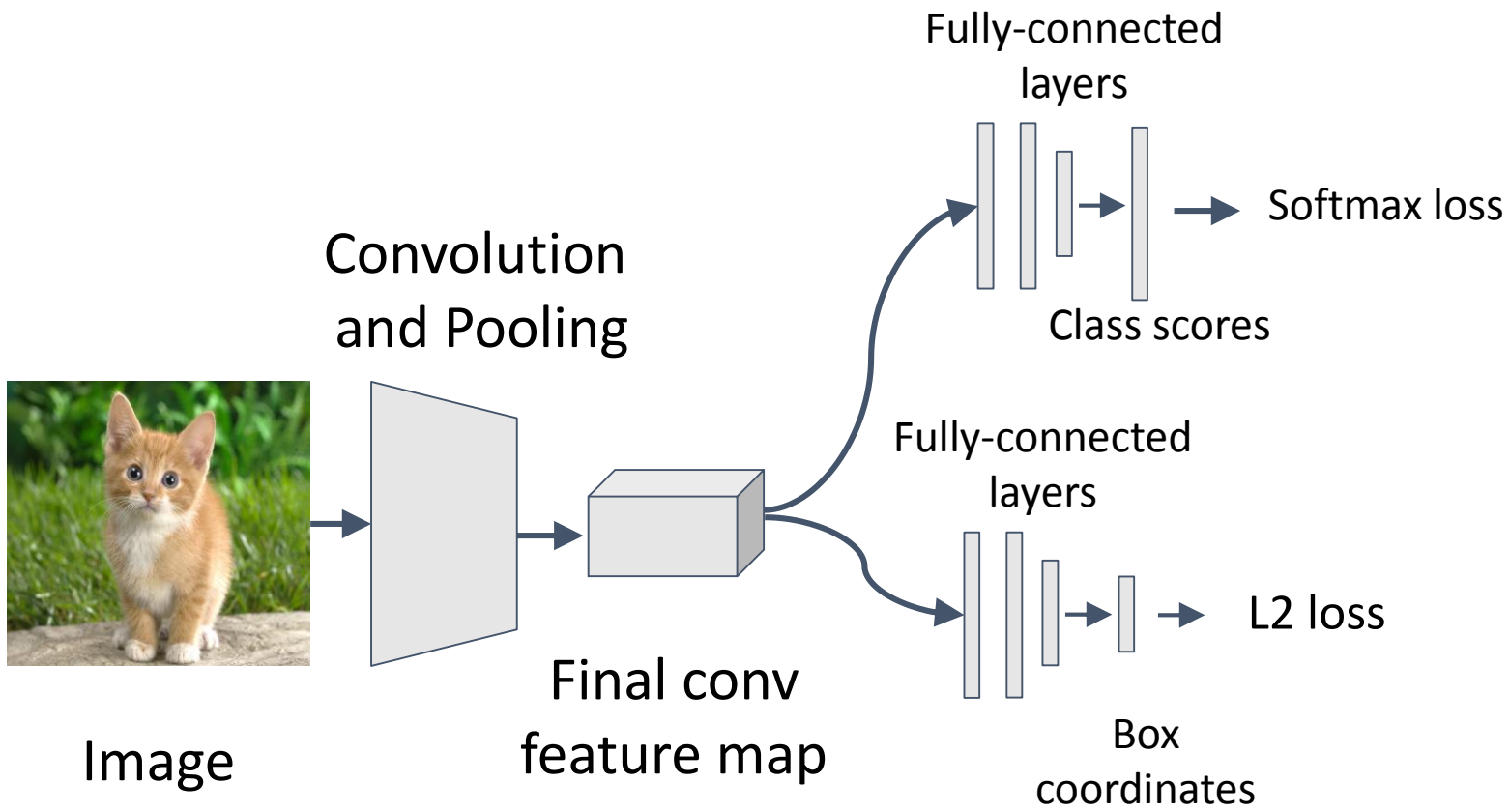

Classification + Localization

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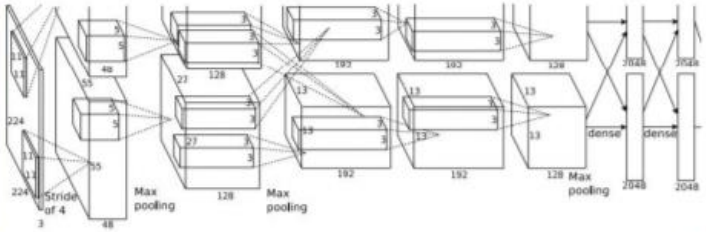


Often pretrained on ImageNet (Transfer learning)

Vector: 4096

Fully Connected: 4096 to 1000

Class Scores
Cat: 0.9
Dog: 0.05
Car: 0.01
...

Correct label:
Cat

Softmax Loss

Fully Connected: 4096 to 4

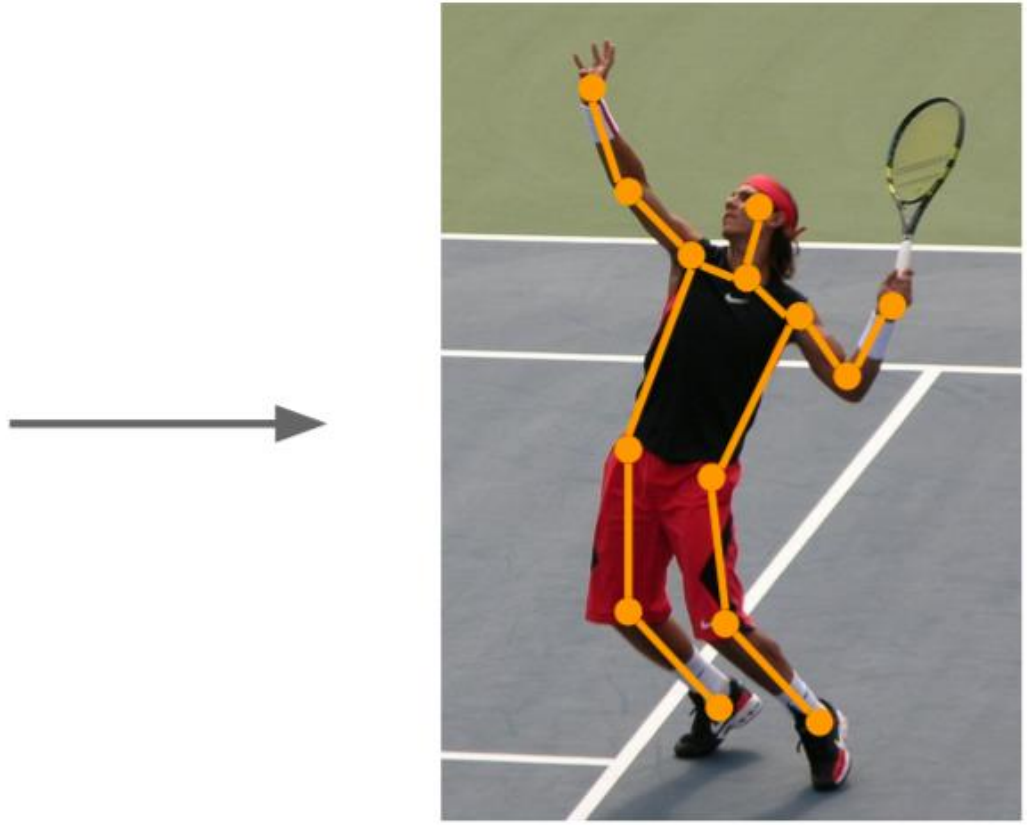
Box Coordinates
(x, y, w, h)

L2 Loss

Correct box:
(x', y', w', h')

+ → **Loss**

Aside: Human Pose Estimation

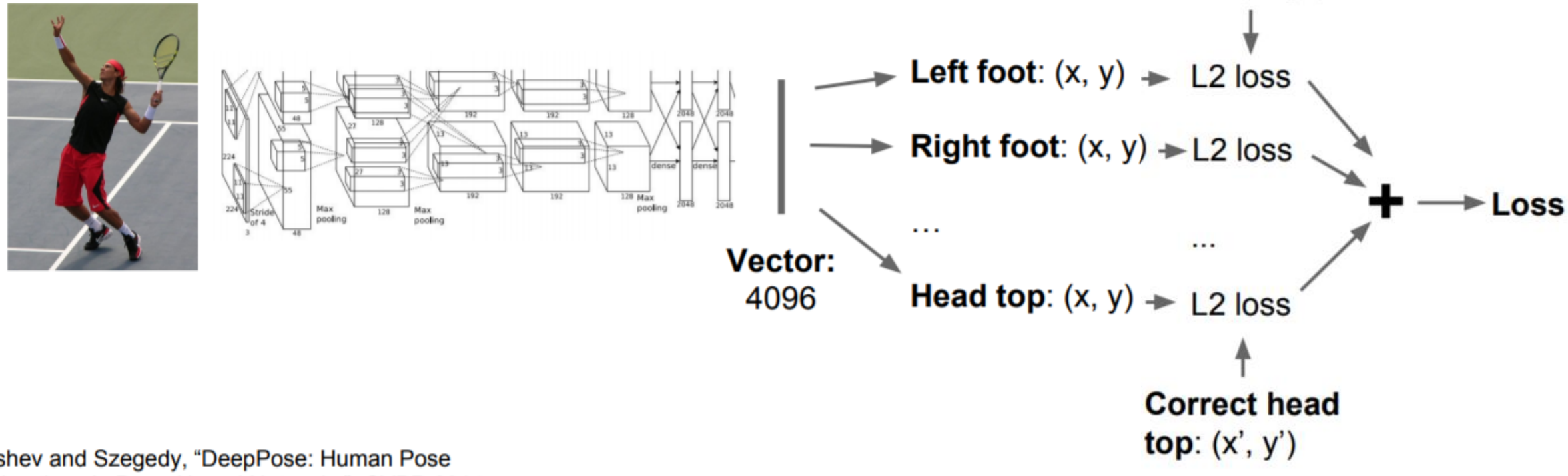


Represent pose as a set of 14 joint positions:

Left / right foot
Left / right knee
Left / right hip
Left / right shoulder
Left / right elbow
Left / right hand
Neck
Head top

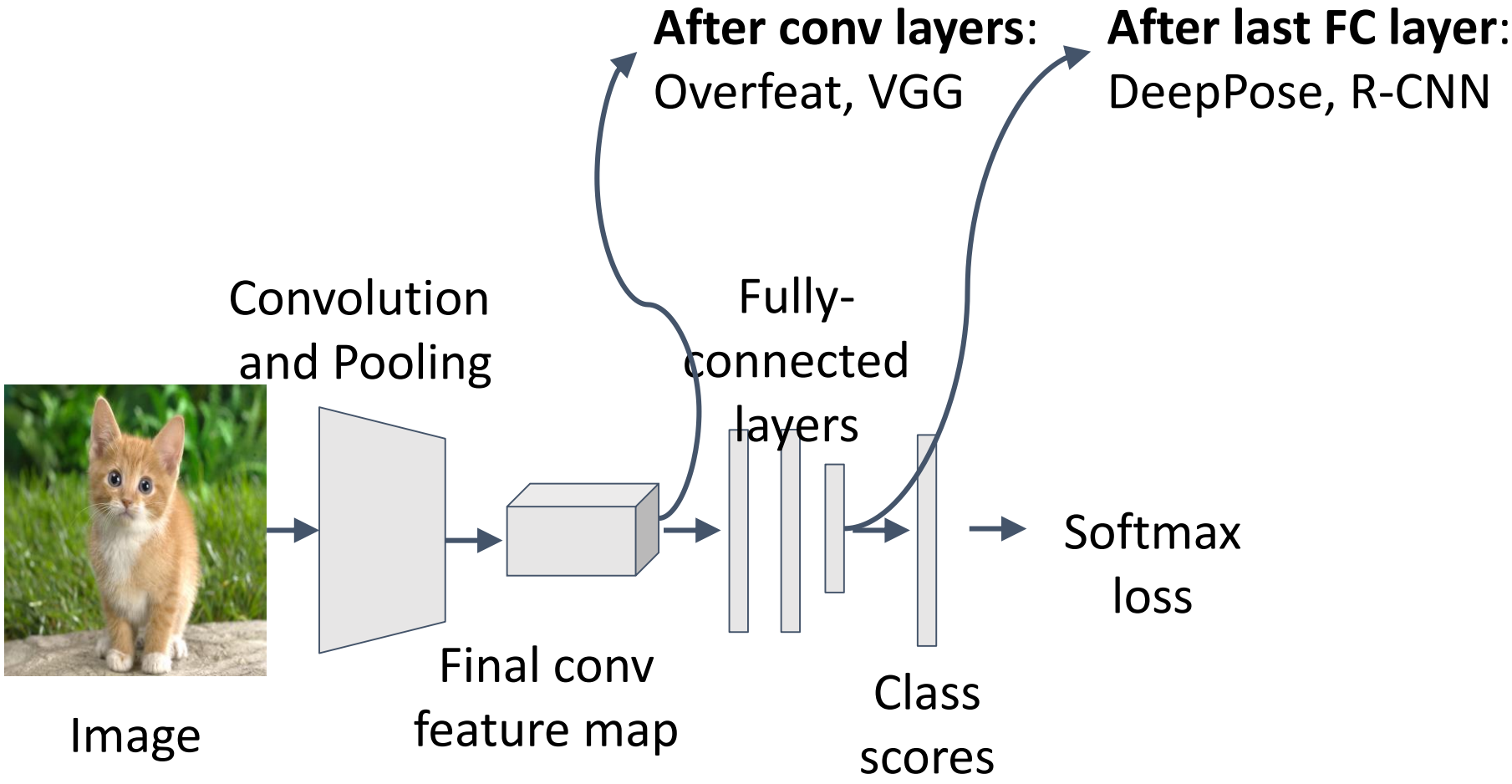
Johnson and Everingham, "Clustered Pose and Nonlinear Appearance Models for Human Pose Estimation", BMVC 2010

Aside: Human Pose Estimation



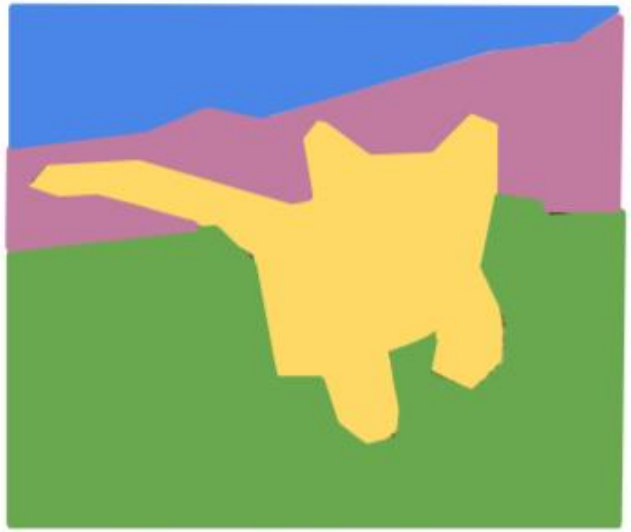
Toshev and Szegedy, "DeepPose: Human Pose Estimation via Deep Neural Networks", CVPR 2014

Where to attach the regression head?



Object detection

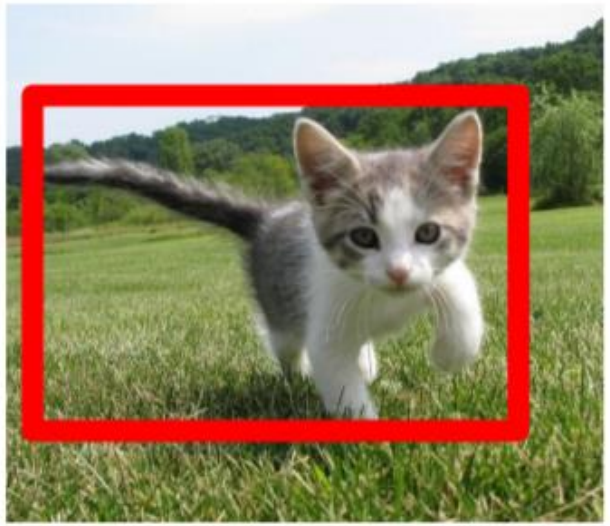
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

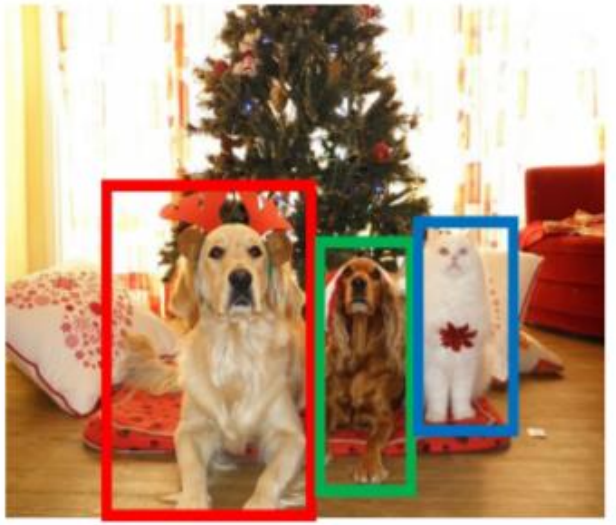
Classification + Localization



CAT

Single Object

Object Detection



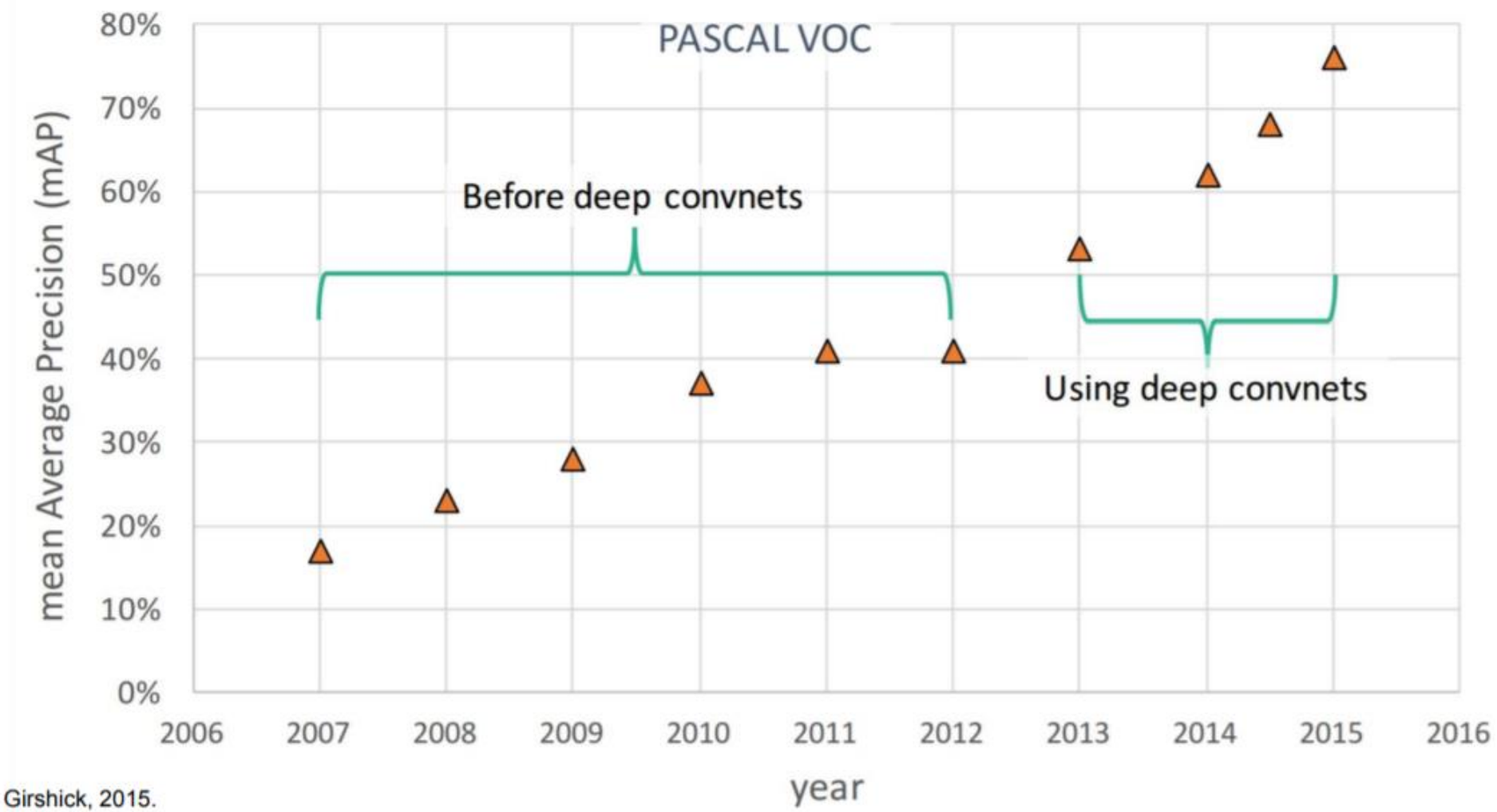
DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

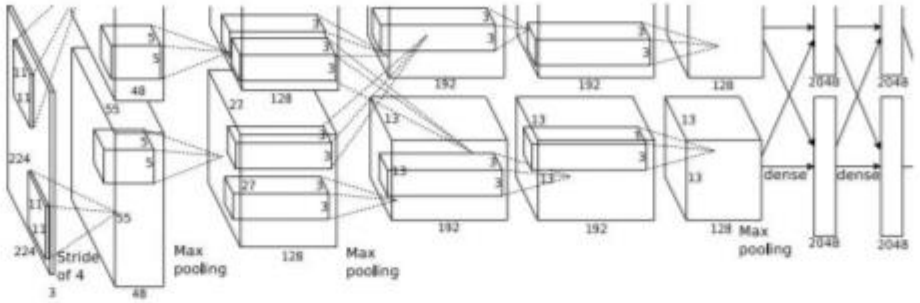
Multiple Object

Object Detection: Impact of Deep Learning

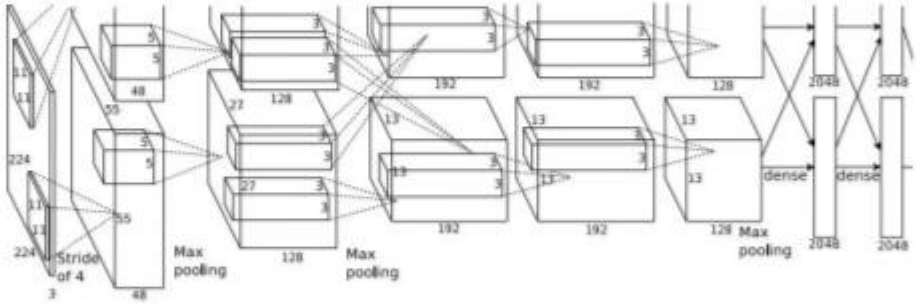


Object Detection as Regression?

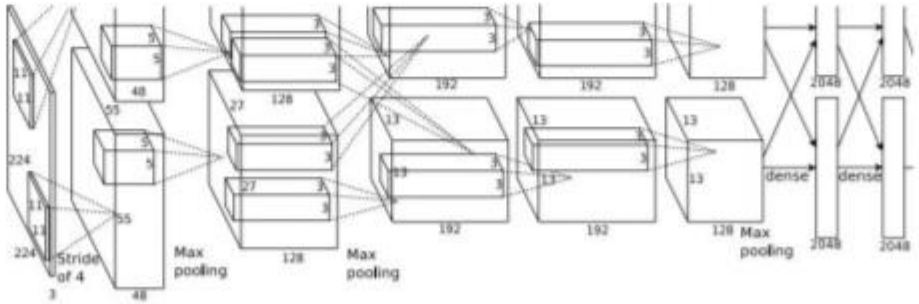
Each image needs a different number of outputs!



CAT: (x, y, w, h)



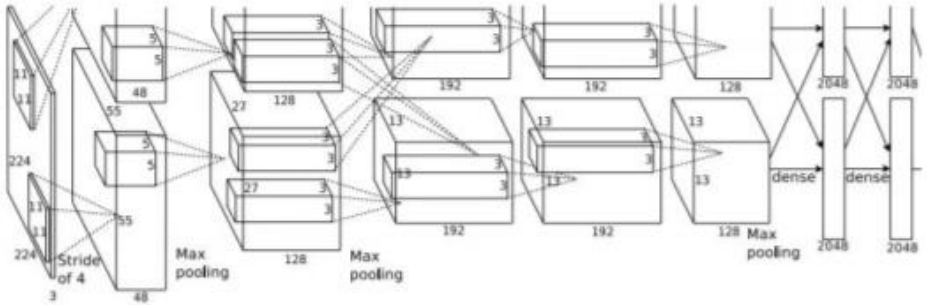
DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)



DUCK: (x, y, w, h)
DUCK: (x, y, w, h)
....

Object Detection as Classification: Sliding Window

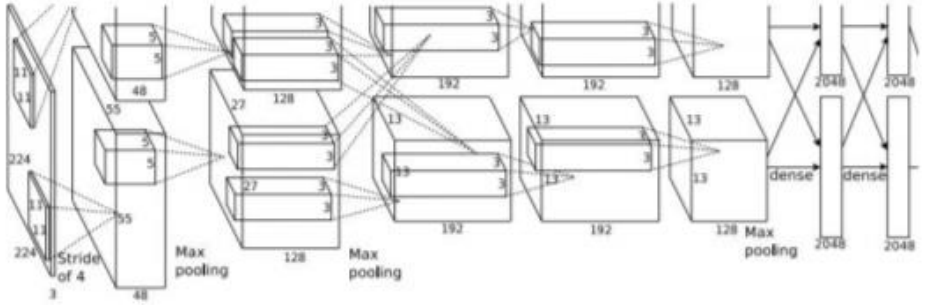
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection as Classification: Sliding Window

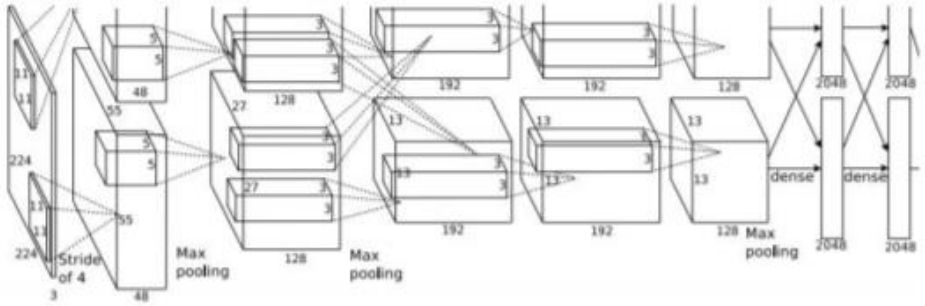
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection as Classification: Sliding Window

Apply a CNN to many different crops of the image, CNN classifies each crop as object or background

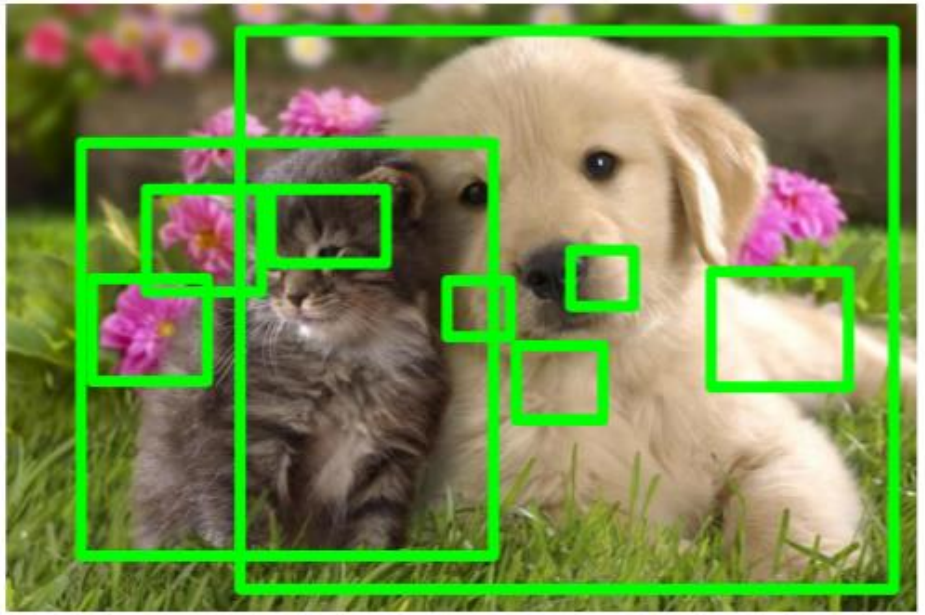


Dog? NO
Cat? YES
Background? NO

Problem: Need to apply CNN to huge number of locations and scales, very computationally expensive!

Region Proposals

- Find “blobby” image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 1000 region proposals in a few seconds on CPU



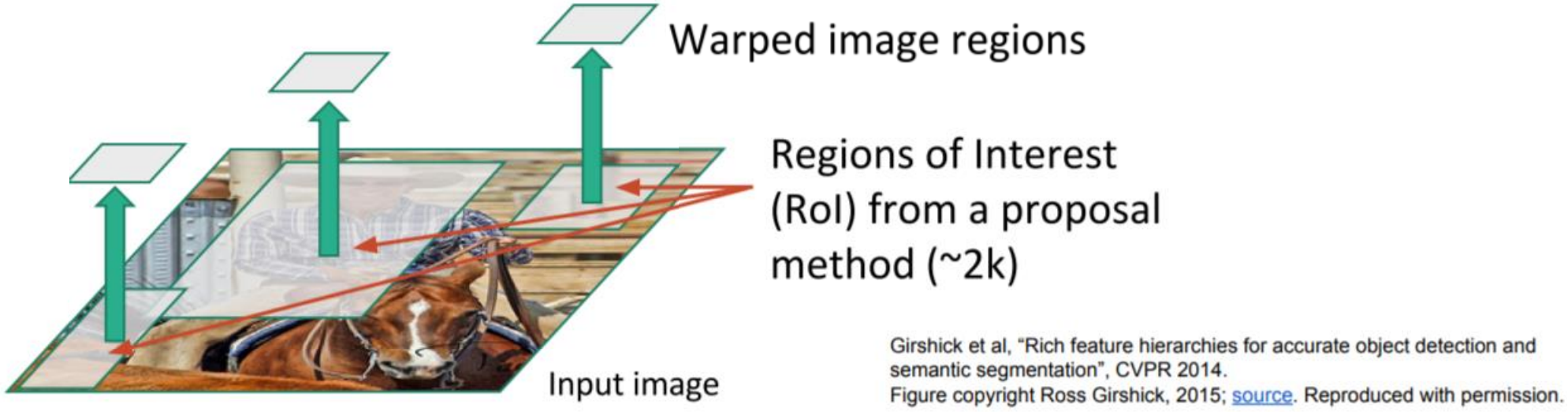
Alexe et al, “Measuring the objectness of image windows”, TPAMI 2012
Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013
Cheng et al, “BING: Binarized normed gradients for objectness estimation at 300fps”, CVPR 2014
Zitnick and Dollar, “Edge boxes: Locating object proposals from edges”, ECCV 2014

R-CNN

Input image

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

R-CNN



Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
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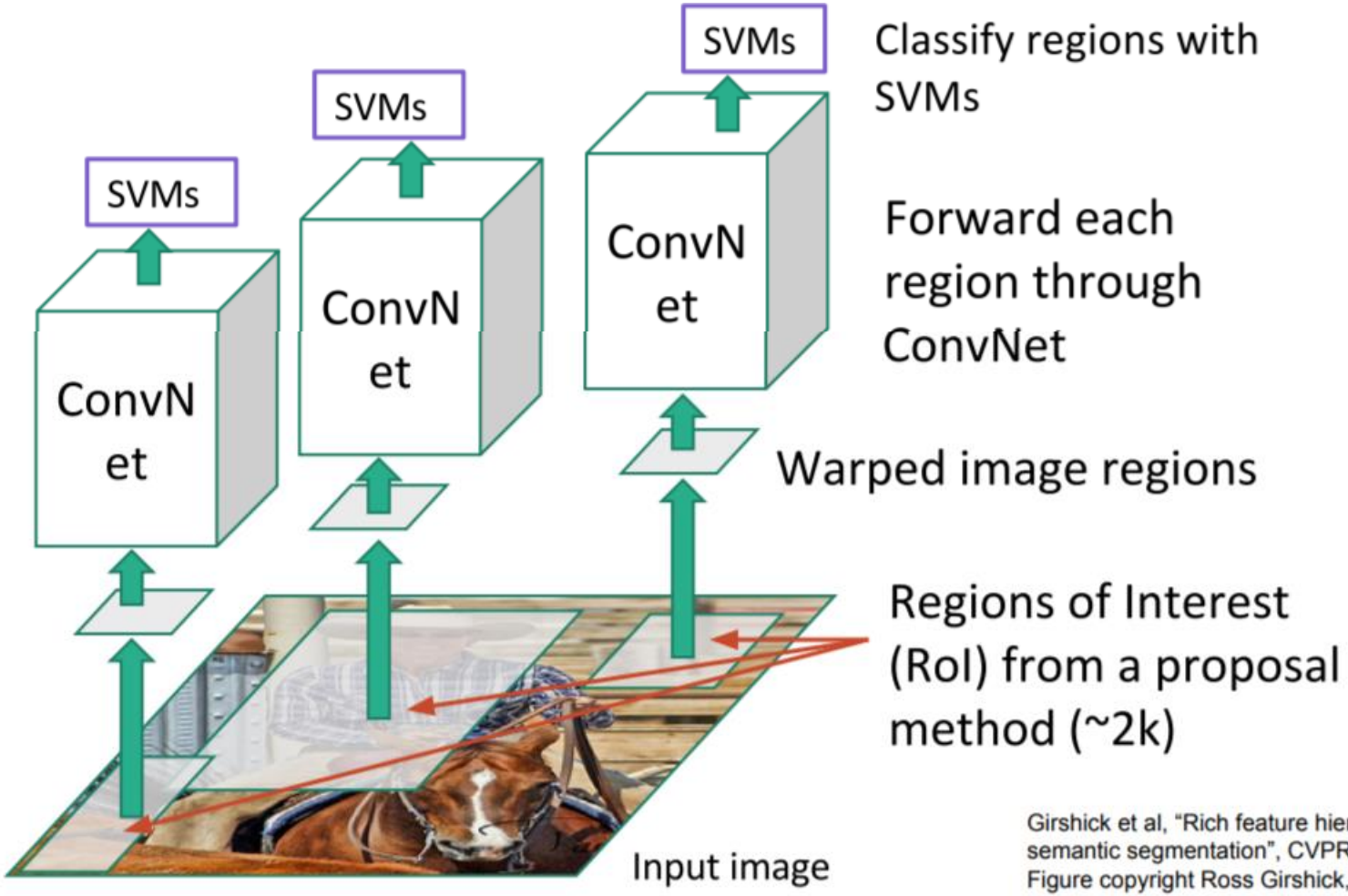
R-CNN



Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
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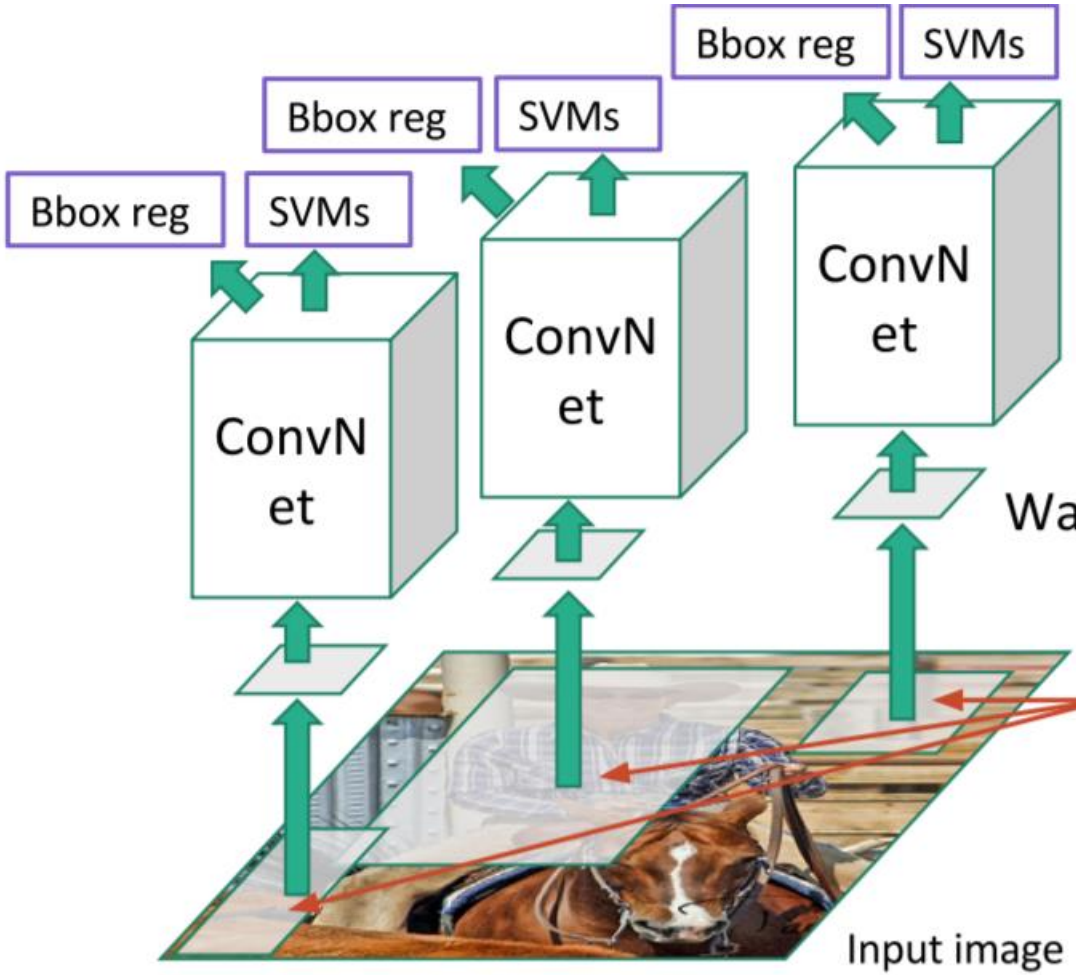
R-CNN



Linear Regression for bounding box offsets

Classify regions with SVMs

Forward each region through ConvNet

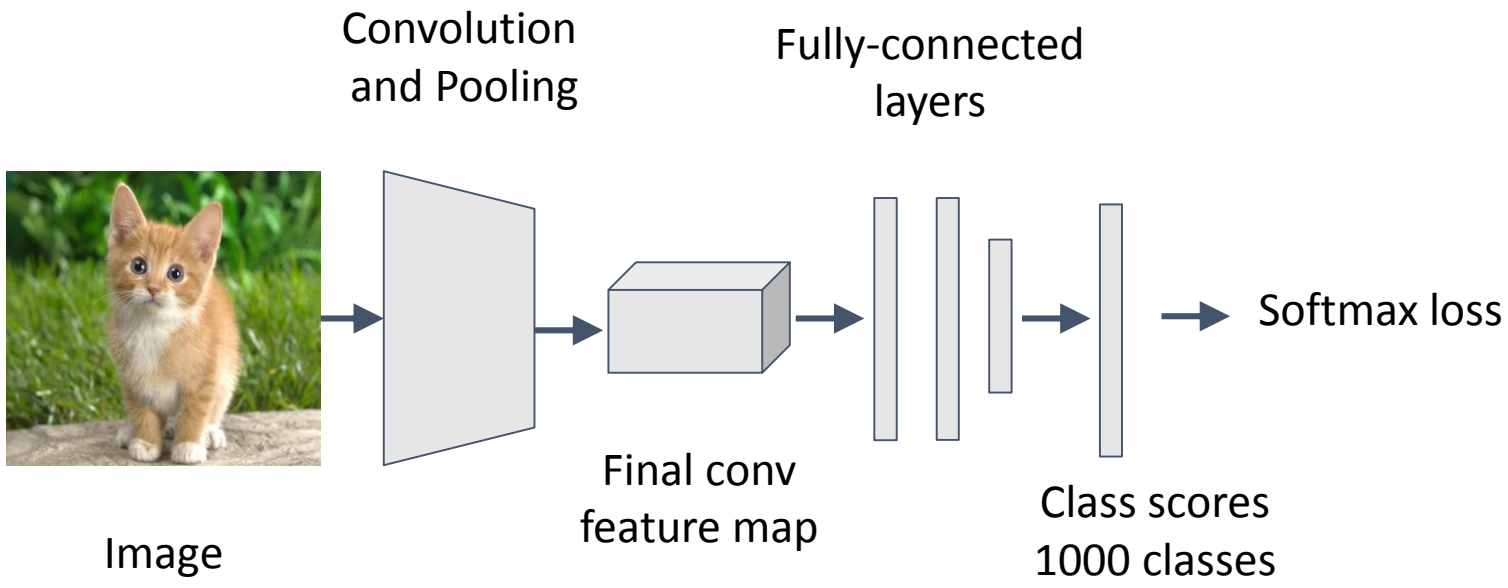
Warped image regions

Regions of Interest (RoI) from a proposal method (~2k)

Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.

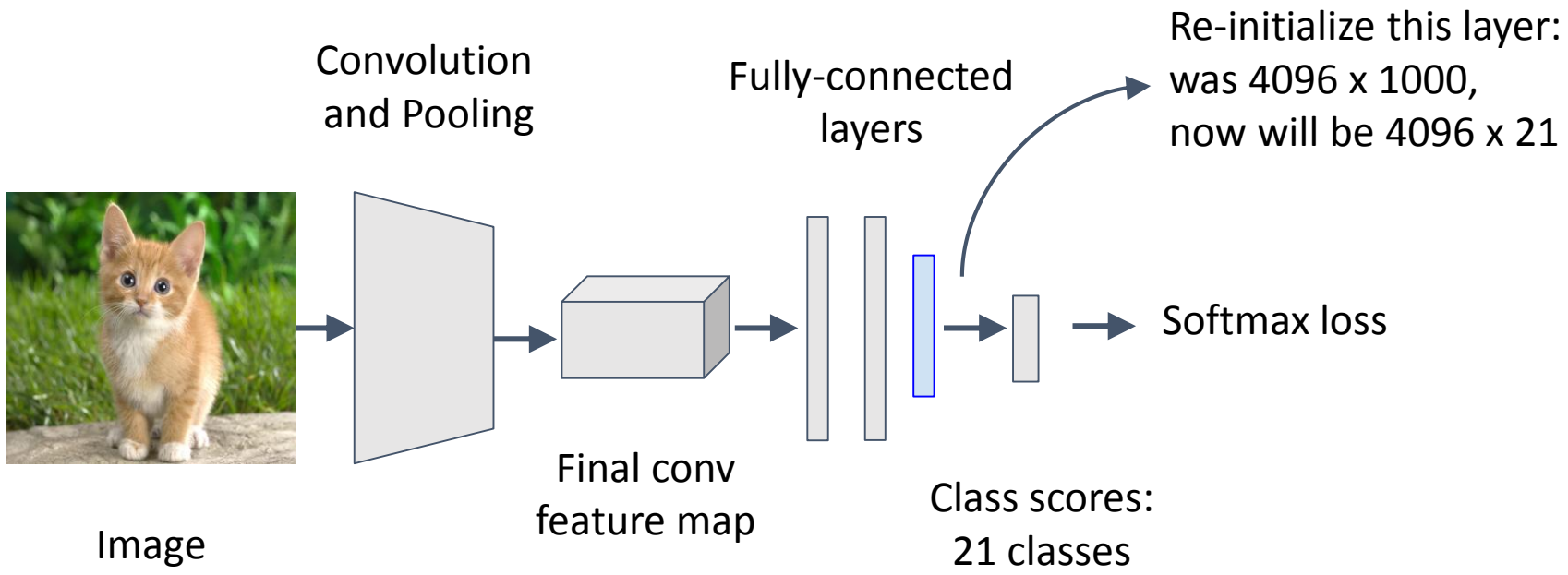
R-CNN Training

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



R-CNN Training

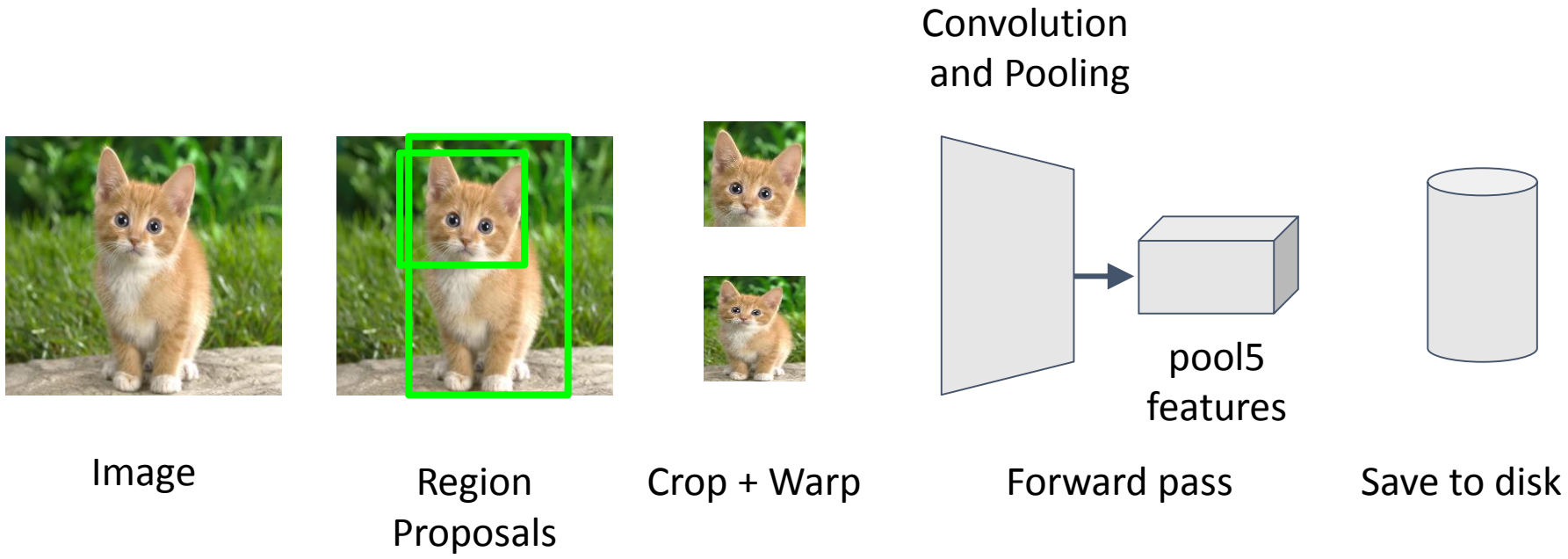
- **Step 2**: Fine-tune model for detection
  - Instead of 1000 ImageNet classes, want 20 object classes + background
  - Throw away final fully-connected layer, reinitialize from scratch
  - Keep training model using positive / negative regions from detection images



R-CNN Training

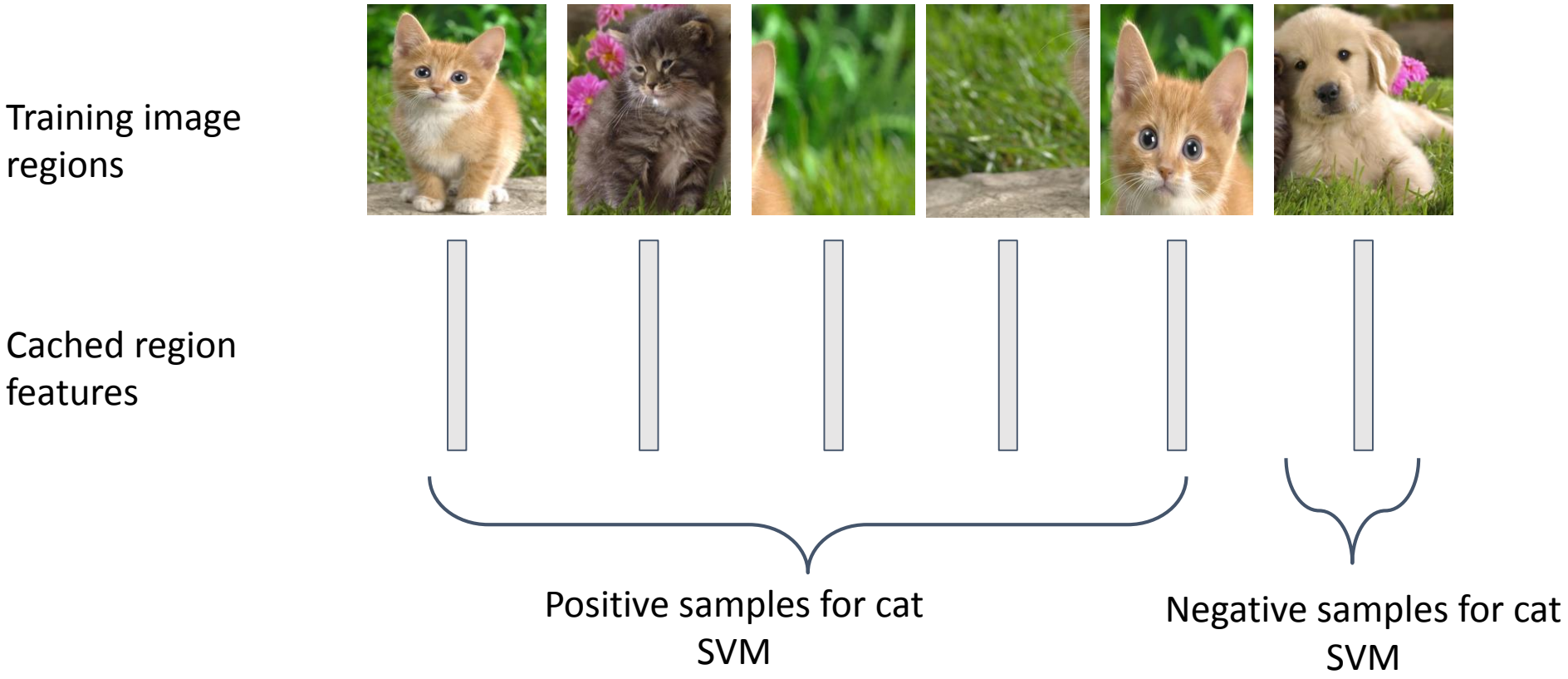
Step 3: Extract features

- 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



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

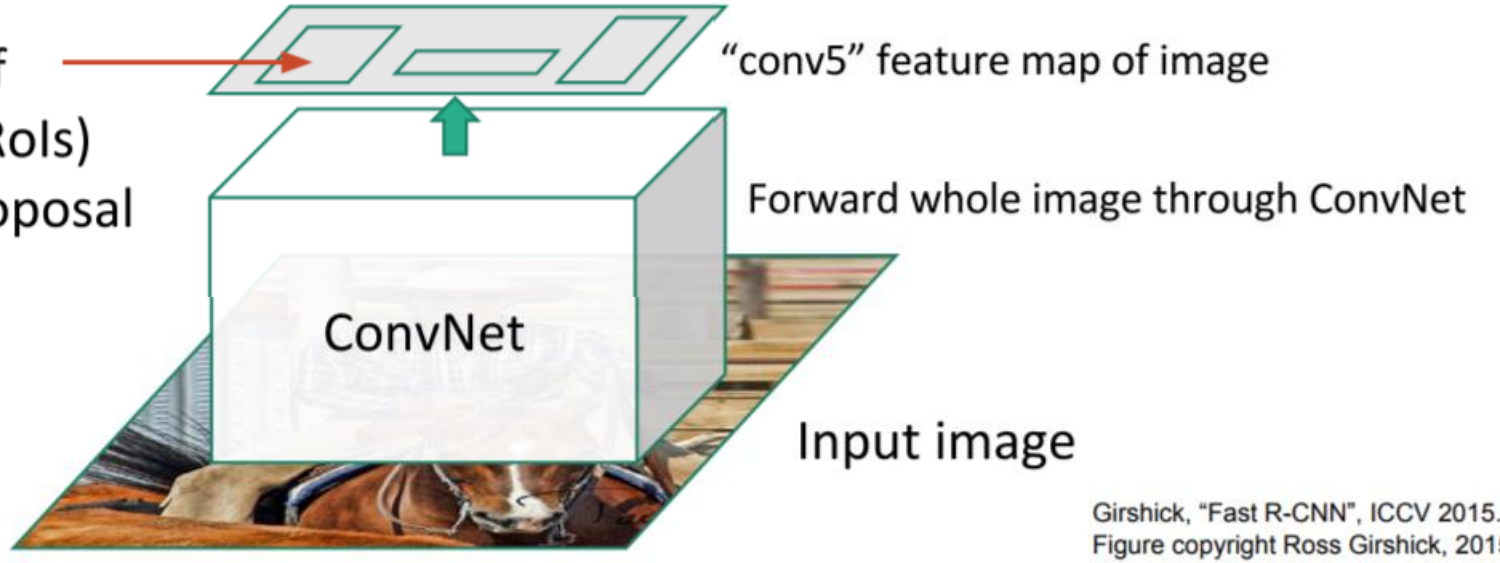
(.25, 0, 0, 0)
Proposal too far to left

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

R-CNN: Problems

- Ad hoc training objectives
  - Fine-tune network with softmax classifier (log loss)
  - Train post-hoc linear SVMs (hinge loss)
  - Train post-hoc bounding-box regressions (least squares)
- Training is slow (84h), takes a lot of disk space
- Inference (detection) is slow
  - 47s / image with VGG16 [Simonyan & Zisserman. ICLR15]
  - Fixed by SPP-net [He et al. ECCV14]

Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
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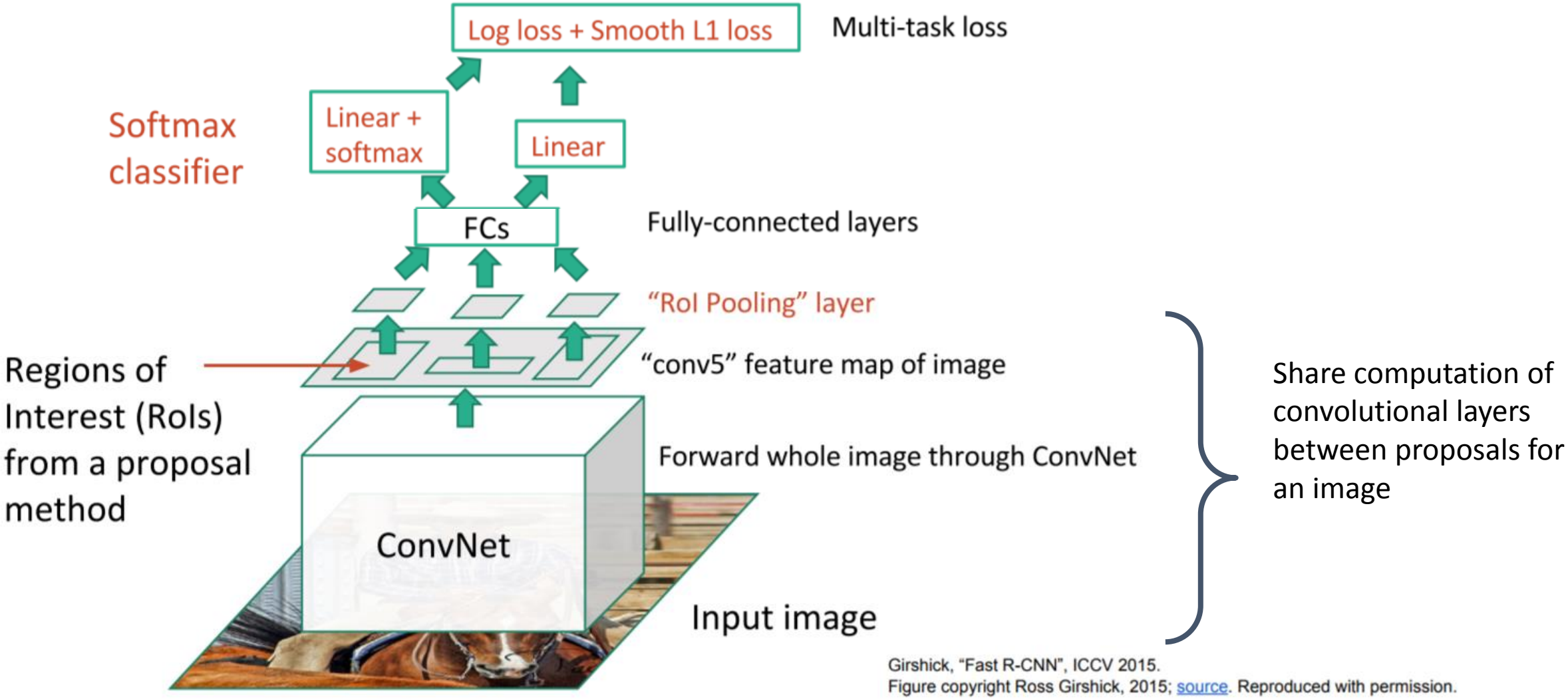
Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
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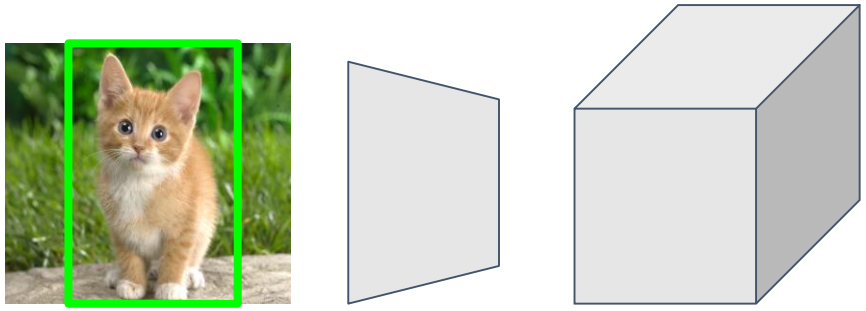
Fast R-CNN: Region of Interest Pooling

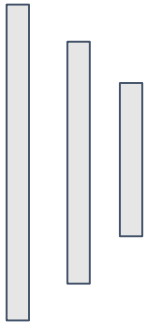
Convolution and Pooling



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

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

Fully-connected layers



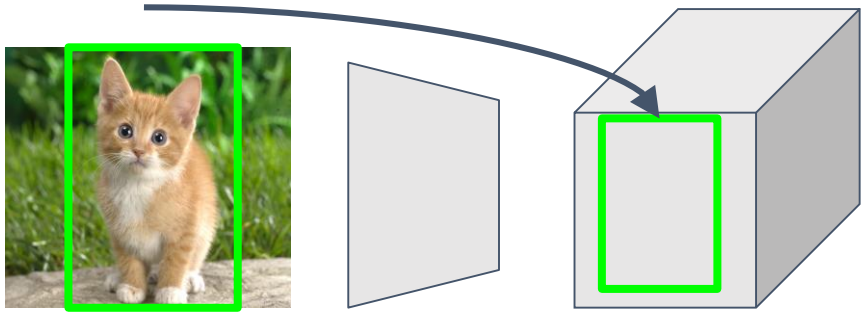
Problem: Fully-connected layers expect low-res conv features: C x h x w

Fast R-CNN: Region of Interest Pooling

Convolution and Pooling

Project region proposal onto conv feature map

Fully-connected layers



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

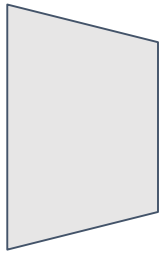
Hi-res conv features: C x H x W with region proposal

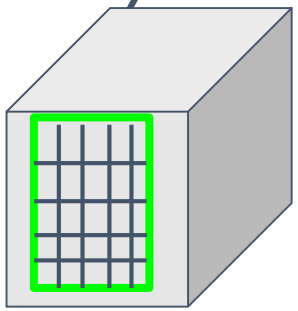
Problem: Fully-connected layers expect low-res conv features: C x h x w

Fast R-CNN: Region of Interest Pooling

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

Convolution and Pooling

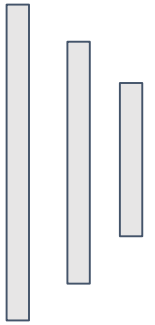




Hi-res conv features:
C x H x W
with region proposal

Divide projected region into h x w grid

Fully-connected layers

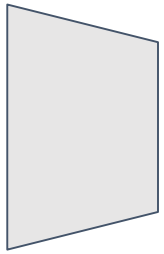


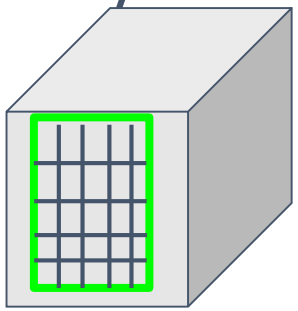
Problem: Fully-connected layers expect low-res conv features: C x h x w

Fast R-CNN: Region of Interest Pooling

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

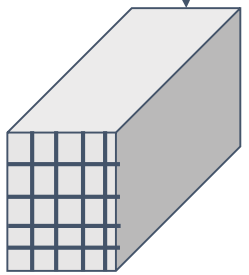
Convolution and Pooling





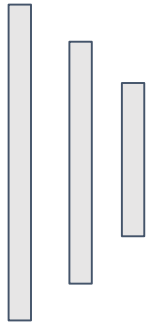
Hi-res conv features:
C x H x W
with region proposal

Max-pool within each grid cell



RoI conv features:
C x h x w
for region proposal

Fully-connected layers

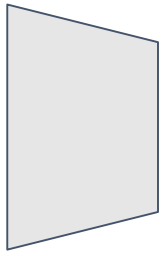


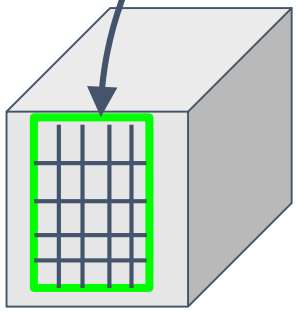
Fully-connected layers expect low-res conv features:
C x h x w

Fast R-CNN: Region of Interest Pooling

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

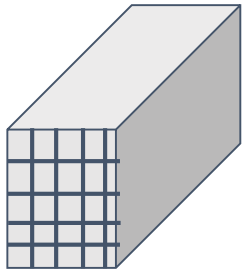
Convolution and Pooling





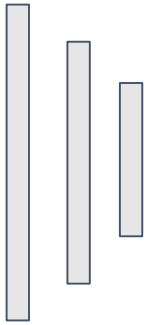
Hi-res conv features:
C x H x W
with region proposal

Can back propagate similar to max pooling



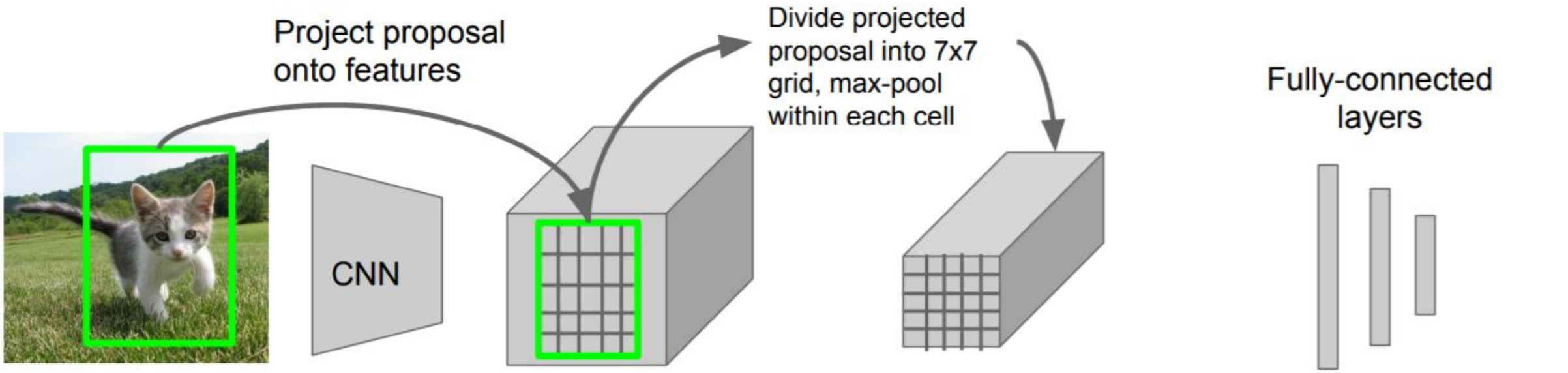
RoI conv features:
C x h x w
for region proposal

Fully-connected layers



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

Fast R-CNN: RoI Pooling



Hi-res input image:
3 x 640 x 480
with region proposal

Hi-res conv features:
512 x 20 x 15;

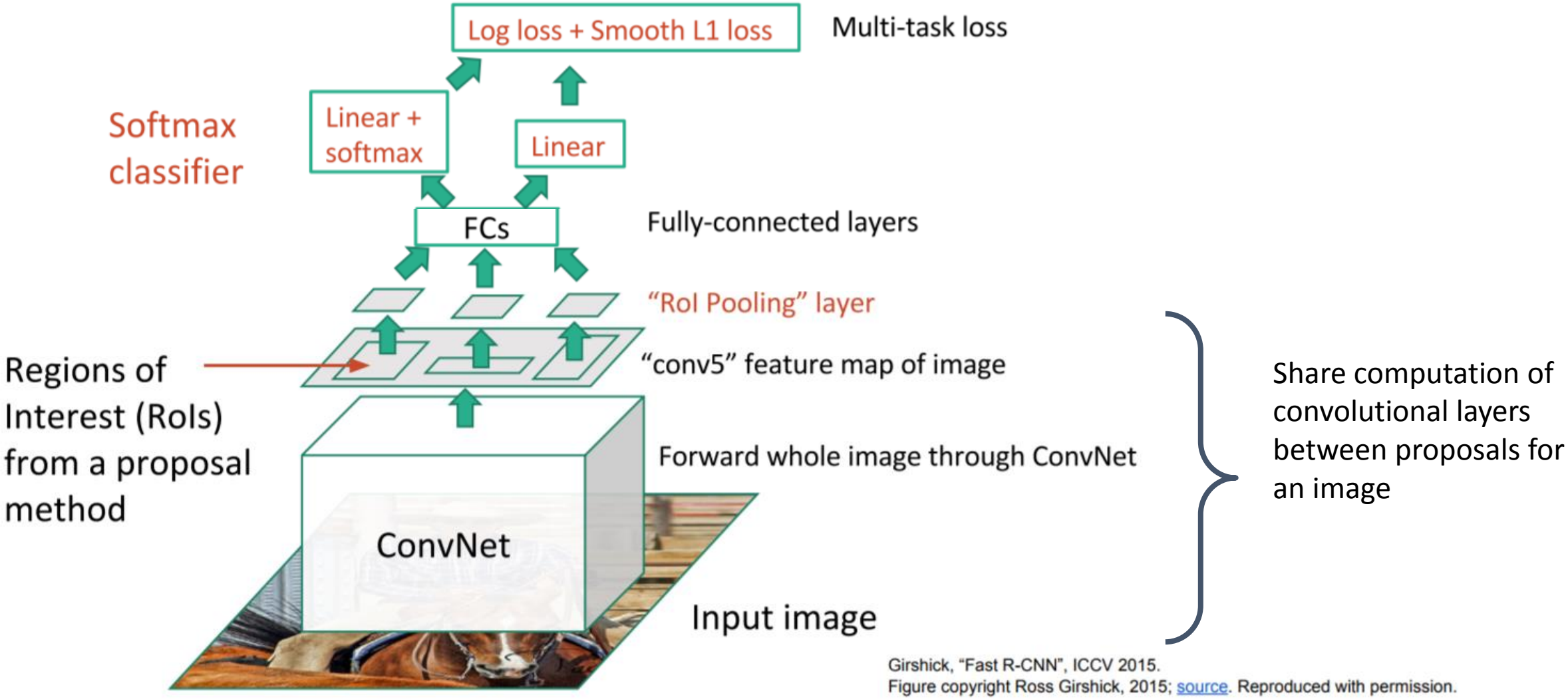
Projected region proposal is e.g.
512 x 18 x 8
(varies per proposal)

RoI conv features:
512 x 7 x 7
for region proposal

Fully-connected layers expect low-res conv features:
512 x 7 x 7

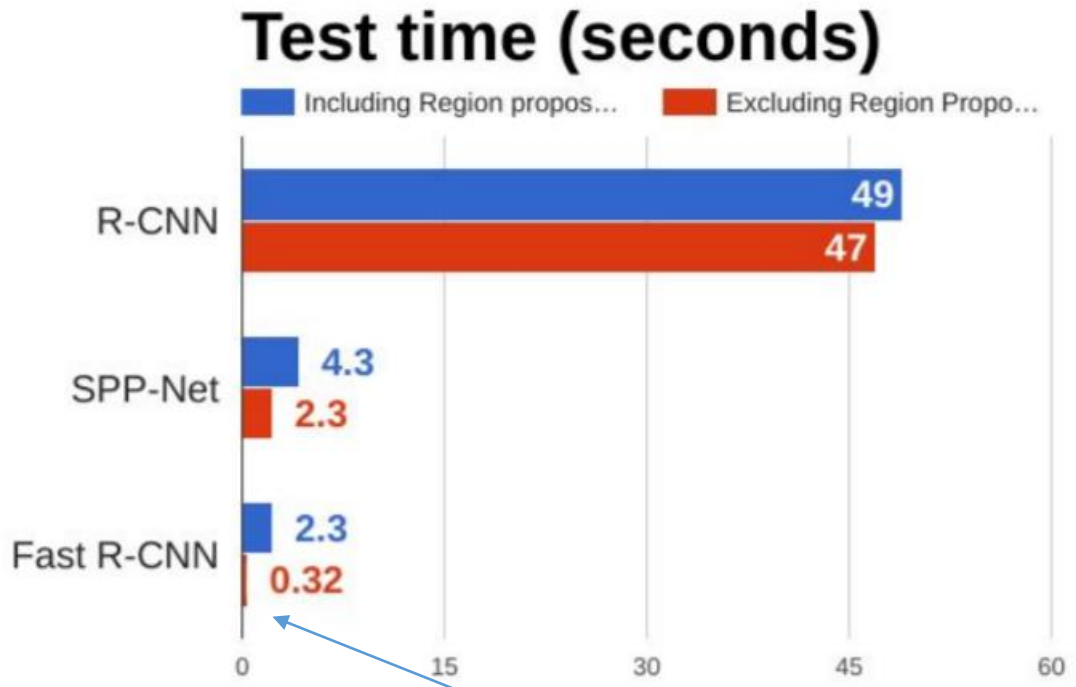
Girshick, "Fast R-CNN", ICCV 2015.

Fast R-CNN



Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

R-CNN vs SPP vs Fast R-CNN

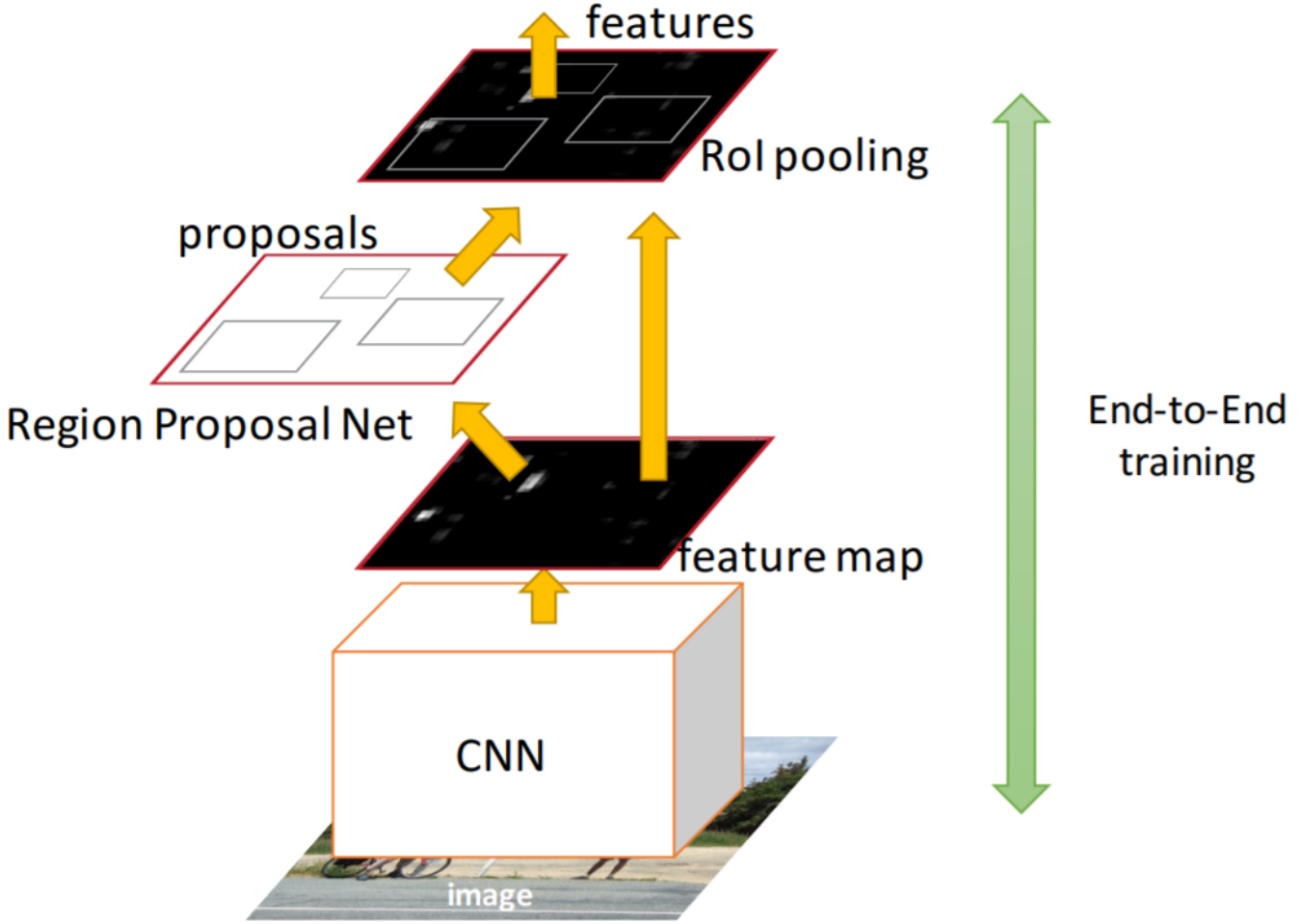


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

Problem: Runtime dominated by region proposals!

Faster R-CNN

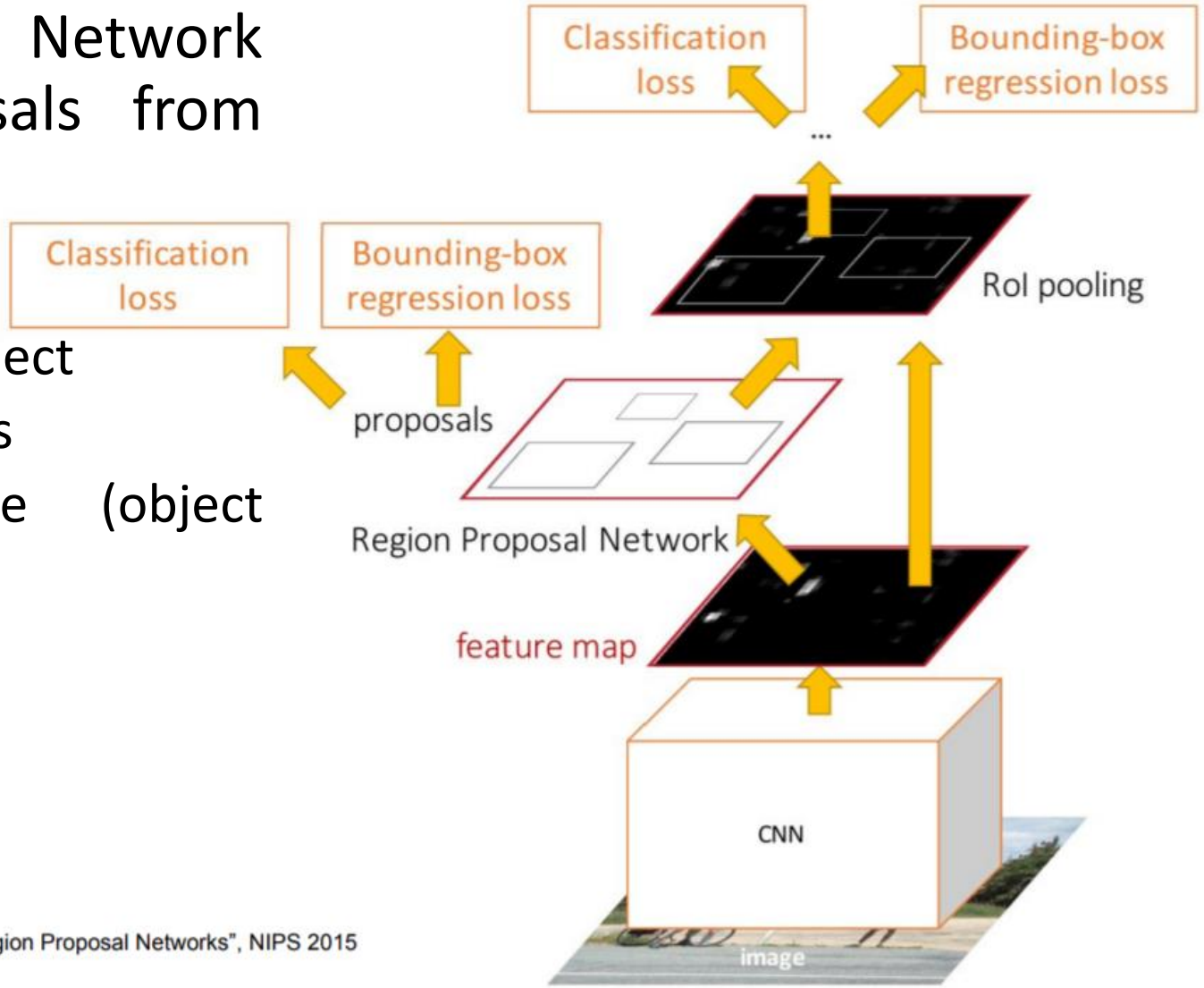
- Make CNN do proposals!
  - Solely based on CNN
  - No external modules
- Each step is end-to-end



Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. “Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks”. NIPS 2015

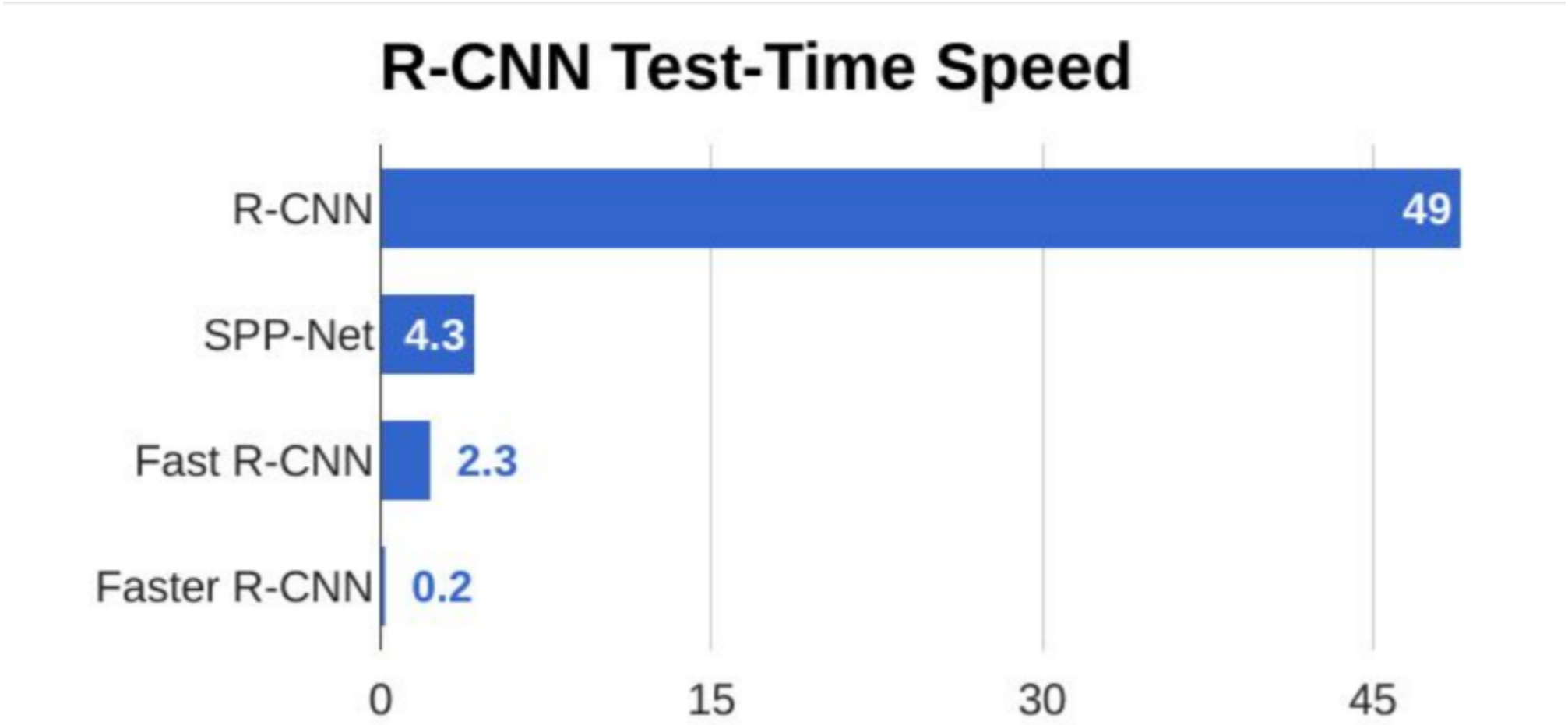
Faster R-CNN

- Insert Region Proposal Network (RPN) to predict proposals from features Jointly
- Train with 4 losses:
  - RPN classify object / not object
  - RPN regress box coordinates
  - Final classification score (object classes)
  - Final box coordinates

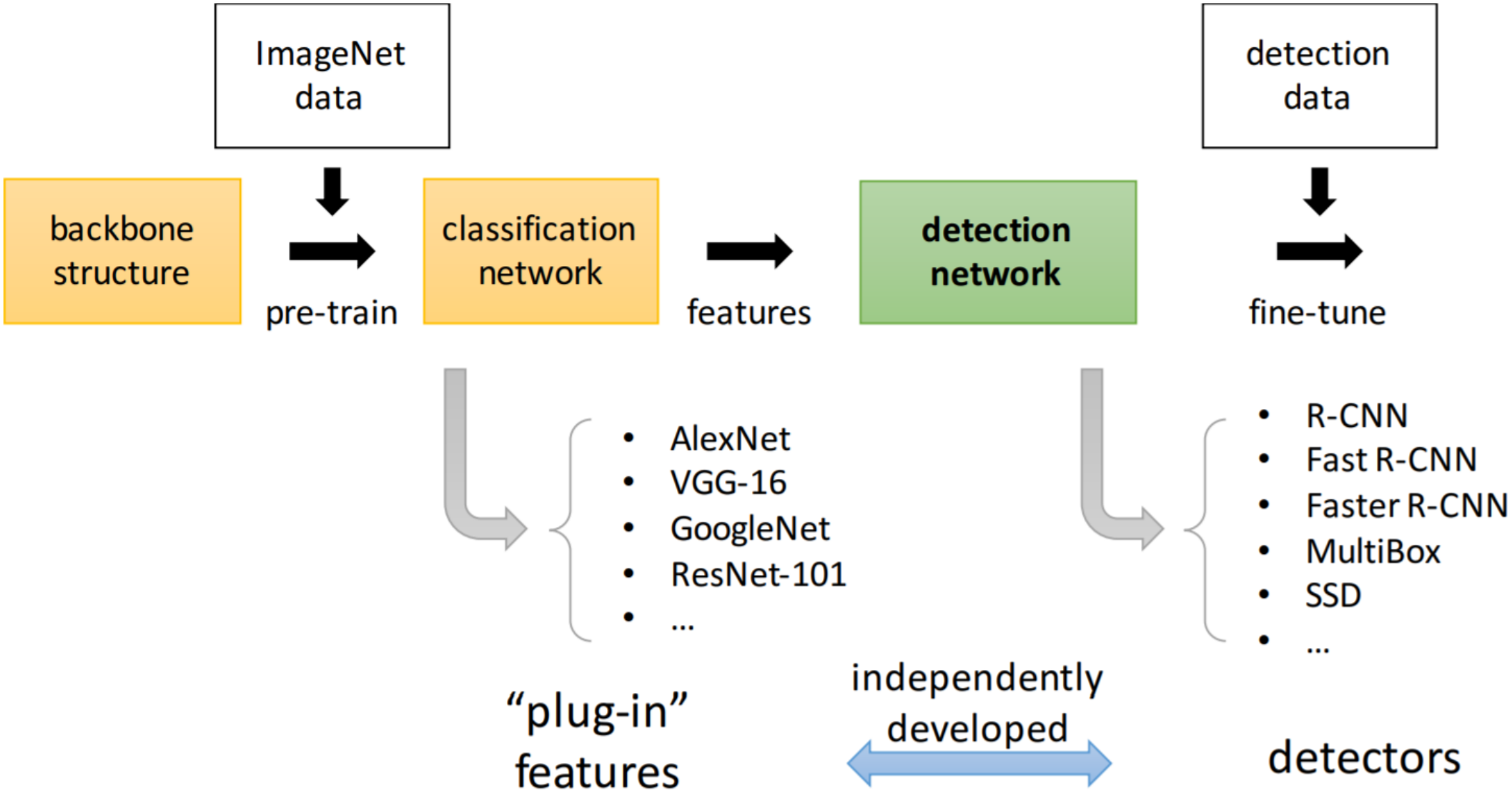


Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

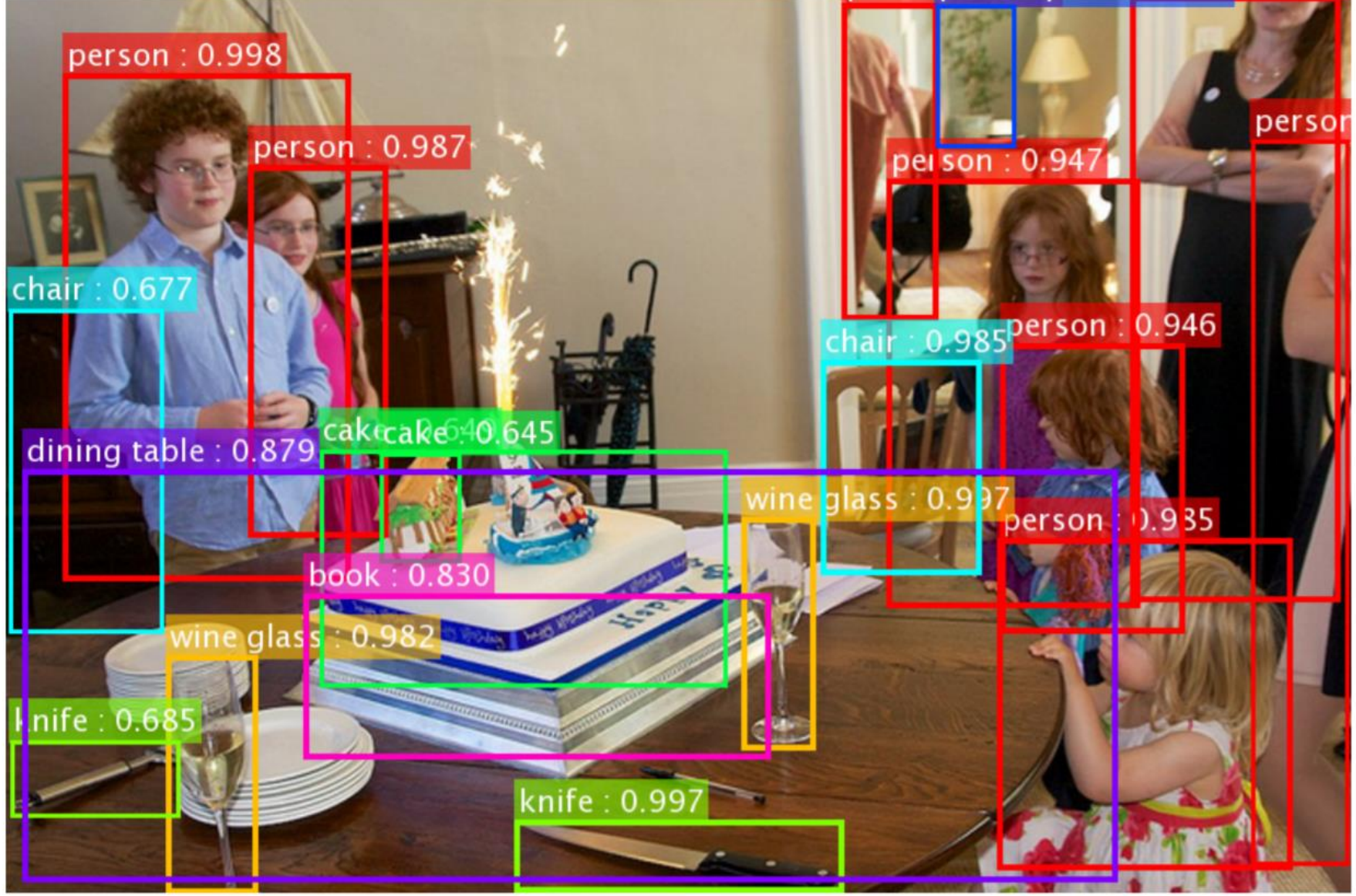
Faster R-CNN: Make CNN do proposals!



Object Detection



Source: http://icml.cc/2016/tutorials/icml2016_tutorial_deep_residual_networks_kaiminghe.pdf



ResNet's object detection result on COCO

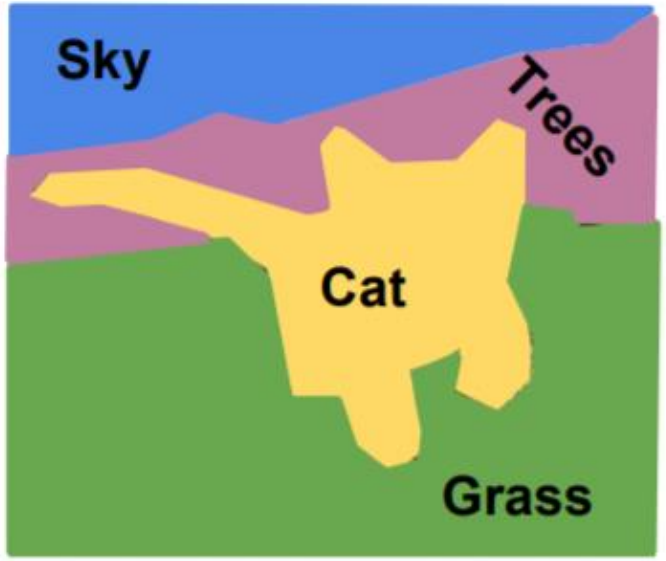
*the original image is from the COCO dataset

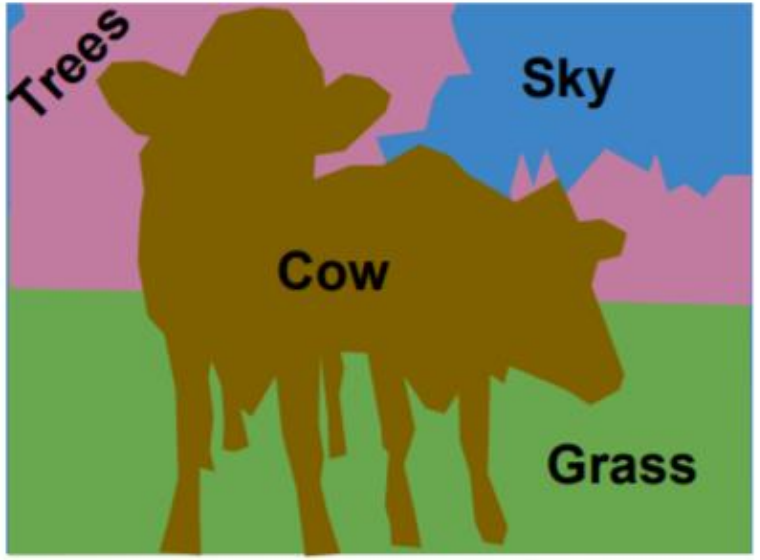
Kaiming He, Xiangyu Zhang, Shaoqing Ren, & Jian Sun. "Deep Residual Learning for Image Recognition". arXiv 2015.
Shaoqing Ren, Kaiming He, Ross Girshick, & Jian Sun. "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks". NIPS 2015.

Semantic Segmentation

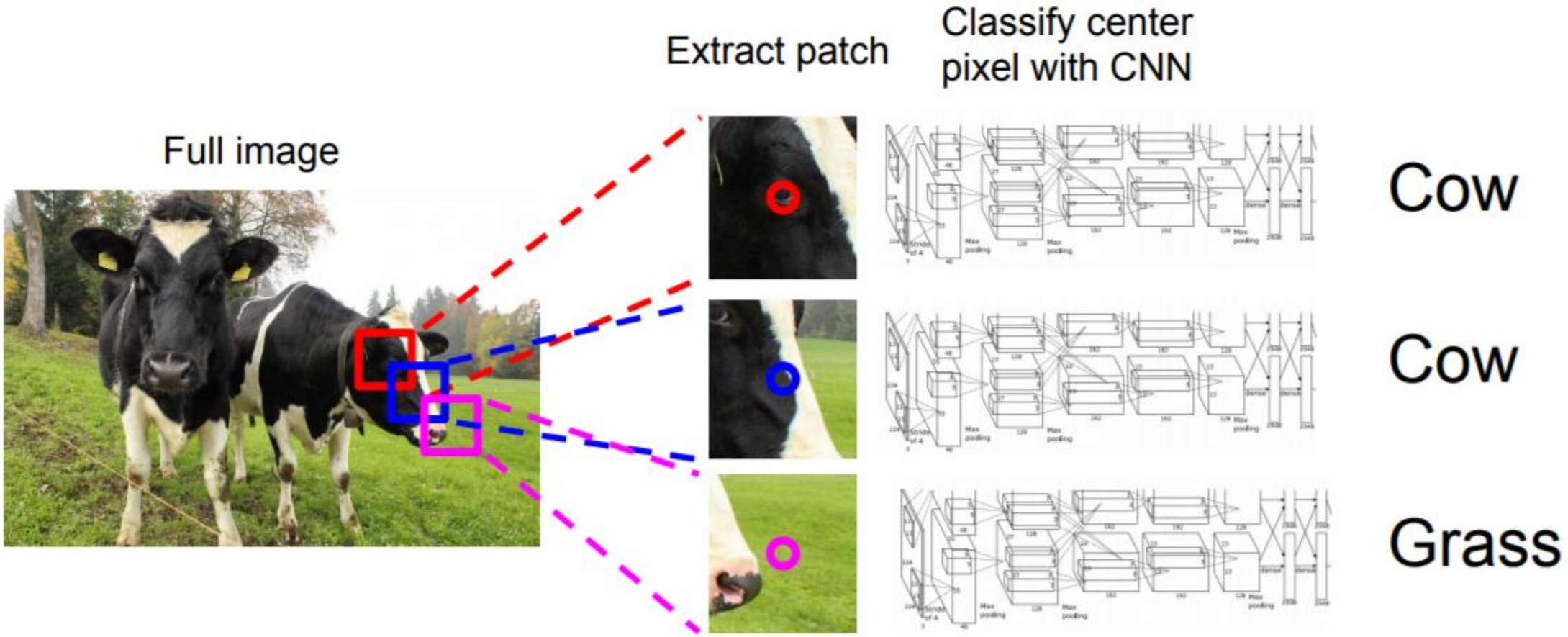
Label each pixel in the image with a category label

Don’t differentiate instances, only care about pixels





Semantic Segmentation Idea: Sliding Window



Problem: Very inefficient!
Not reusing shared features between overlapping patches

Farabet et al, "Learning Hierarchical Features for Scene Labeling," TPAMI 2013
Pinheiro and Collobert, "Recurrent Convolutional Neural Networks for Scene Labeling", ICML 2014

Semantic Segmentation Idea: Fully Convolutional

Design a network as a bunch of convolutional layers to make predictions for pixels all at once!

Input:
3 x H x W

Conv → Conv → Conv → Conv → argmax

Convolutions:
D x H x W

Scores:
C x H x W

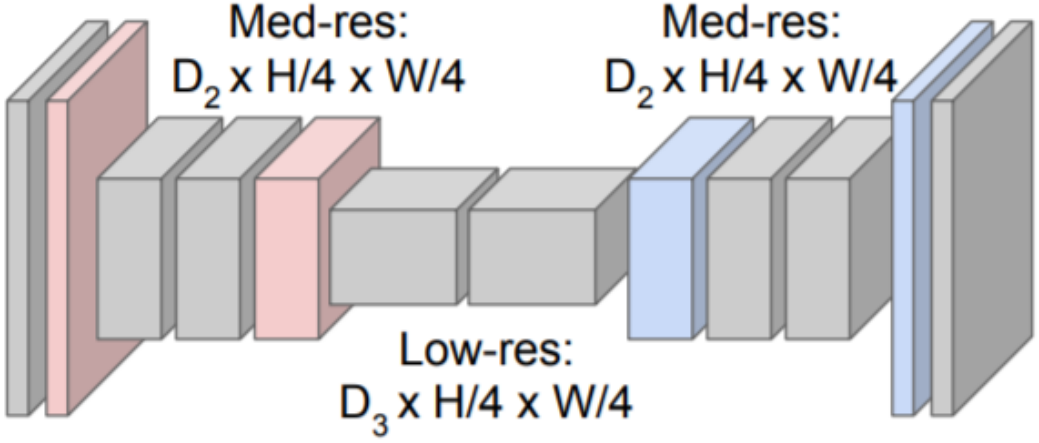
Predictions:
H x W

Problem: convolutions at original image resolution will be very expensive ...

Semantic Segmentation Idea: Fully Convolutional

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

High-res:
D_1 x H/2 x W/2

Predictions:
H x W

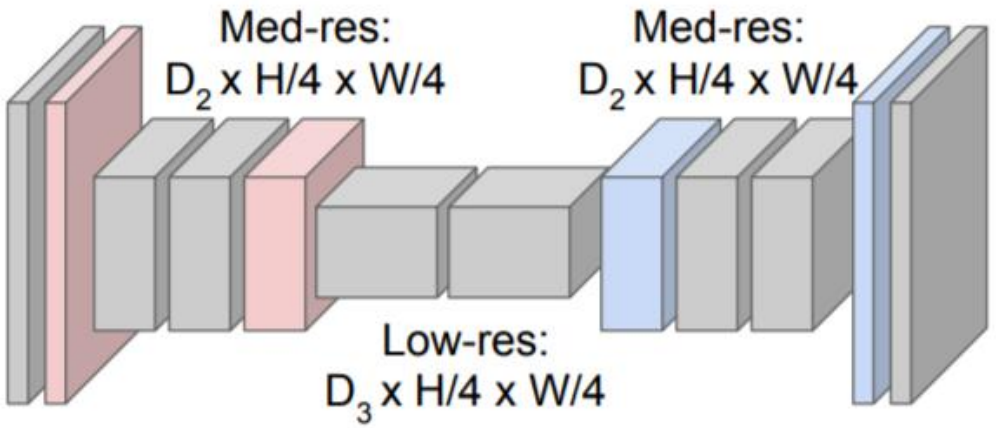
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling:
???

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

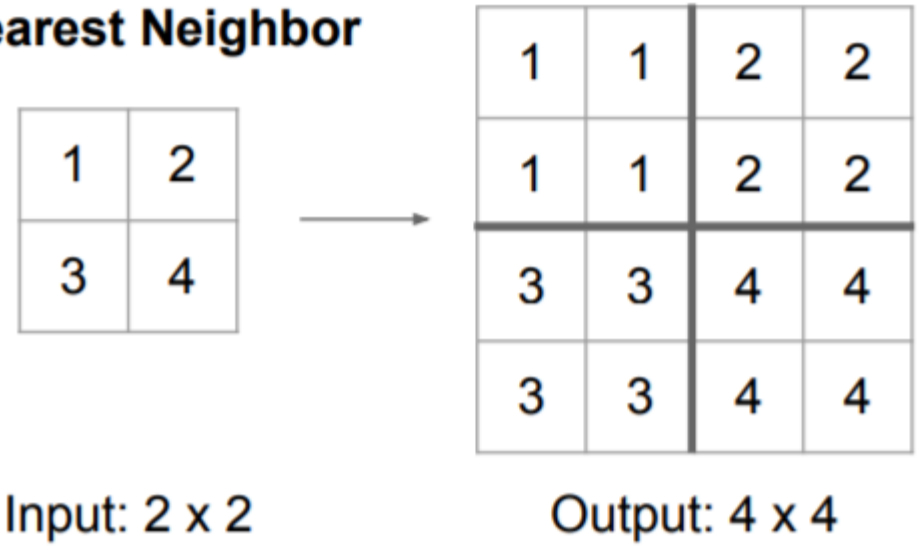
High-res:
D_1 x H/2 x W/2

Predictions:
H x W

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

In-Network upsampling: “Unpooling”

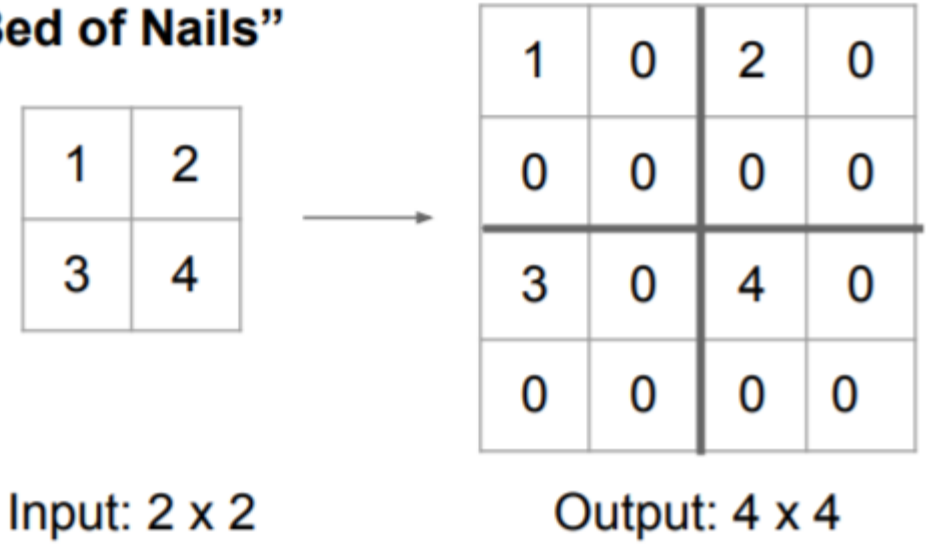
Nearest Neighbor



Input: 2 x 2

Output: 4 x 4

“Bed of Nails”



Input: 2 x 2

Output: 4 x 4

In-Network upsampling: “Max Unpooling”

Max Pooling
Remember which element was max!

1	2	6	3
3	5	2	1
1	2	2	1
7	3	4	8

Input: 4 x 4

5	6
7	8

Output: 2 x 2

Rest of the network

Max Unpooling
Use positions from pooling layer

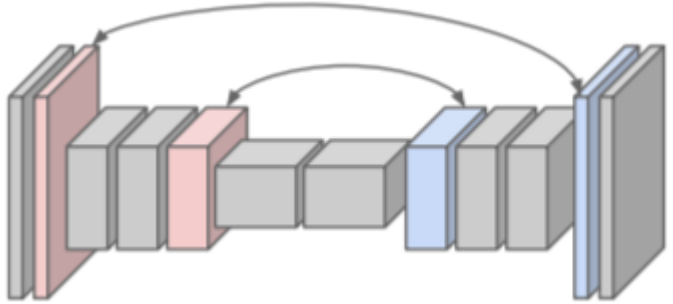
1	2
3	4

Input: 2 x 2

0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

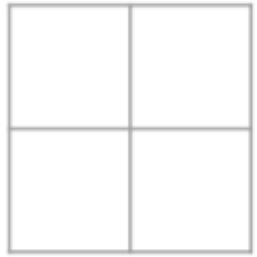
Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

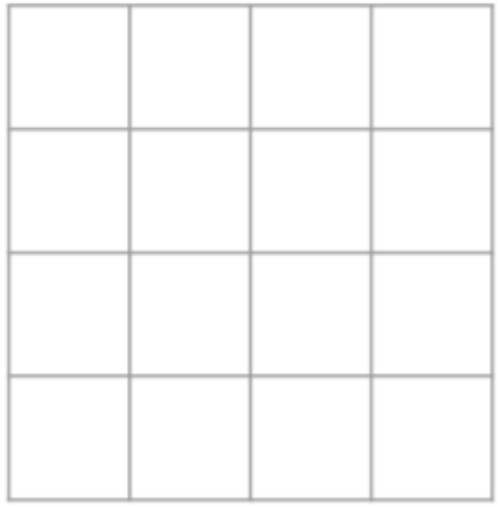


Learnable Upsampling: Transpose Convolution

3 x 3 **transpose** convolution, stride 2 pad 1

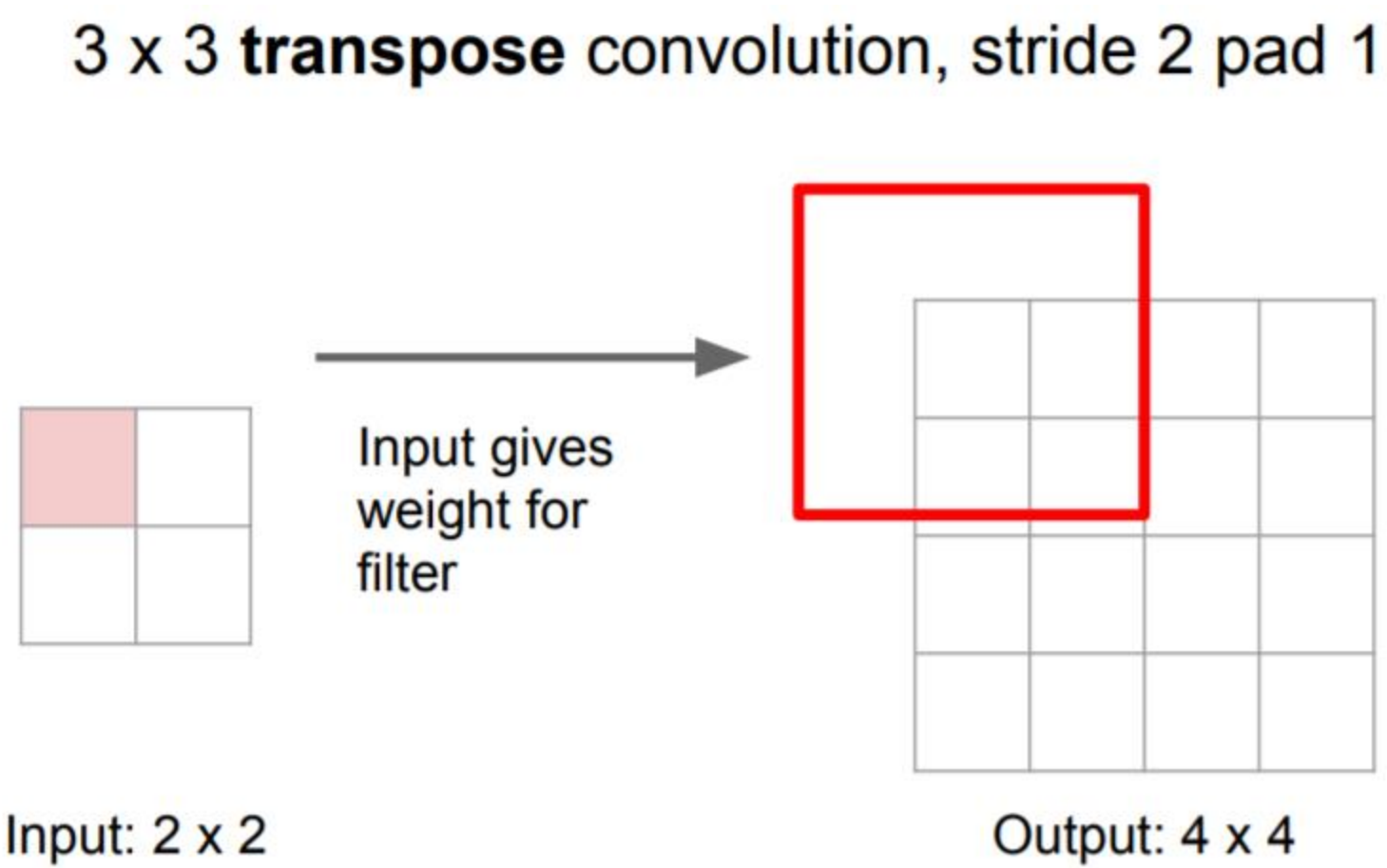


Input: 2 x 2

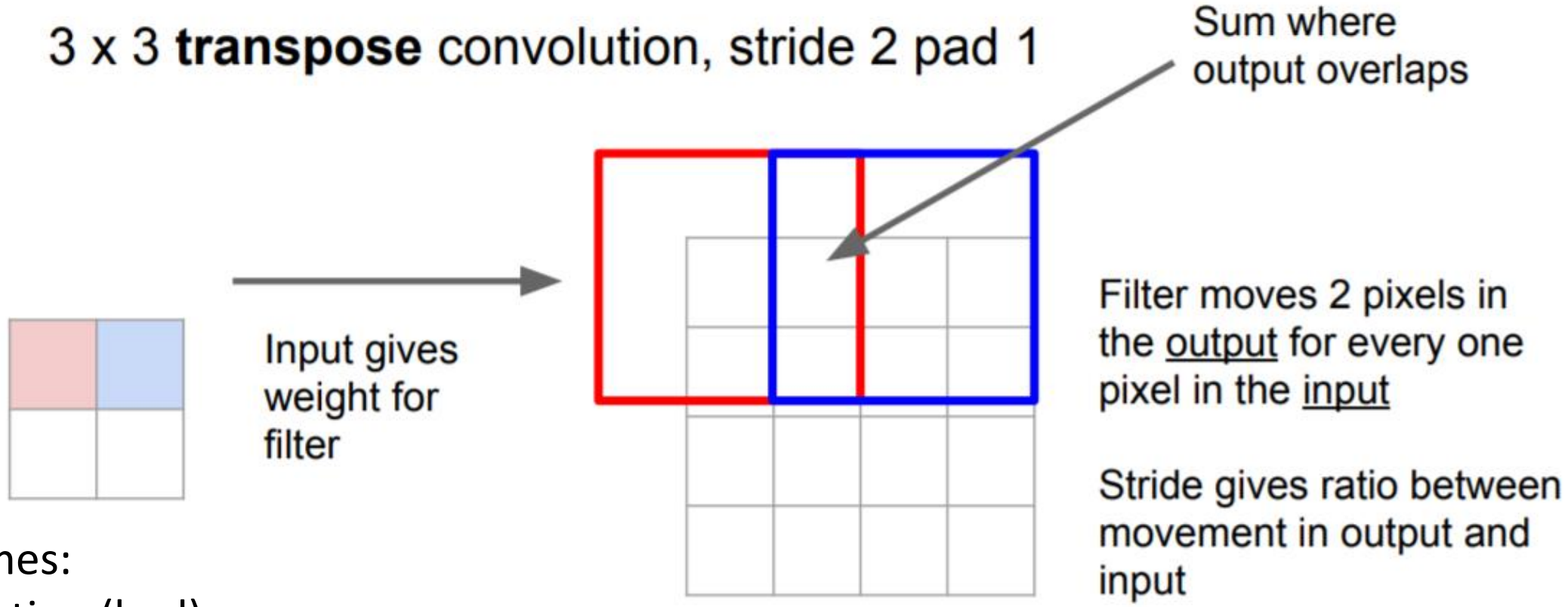


Output: 4 x 4

Learnable Upsampling: Transpose Convolution

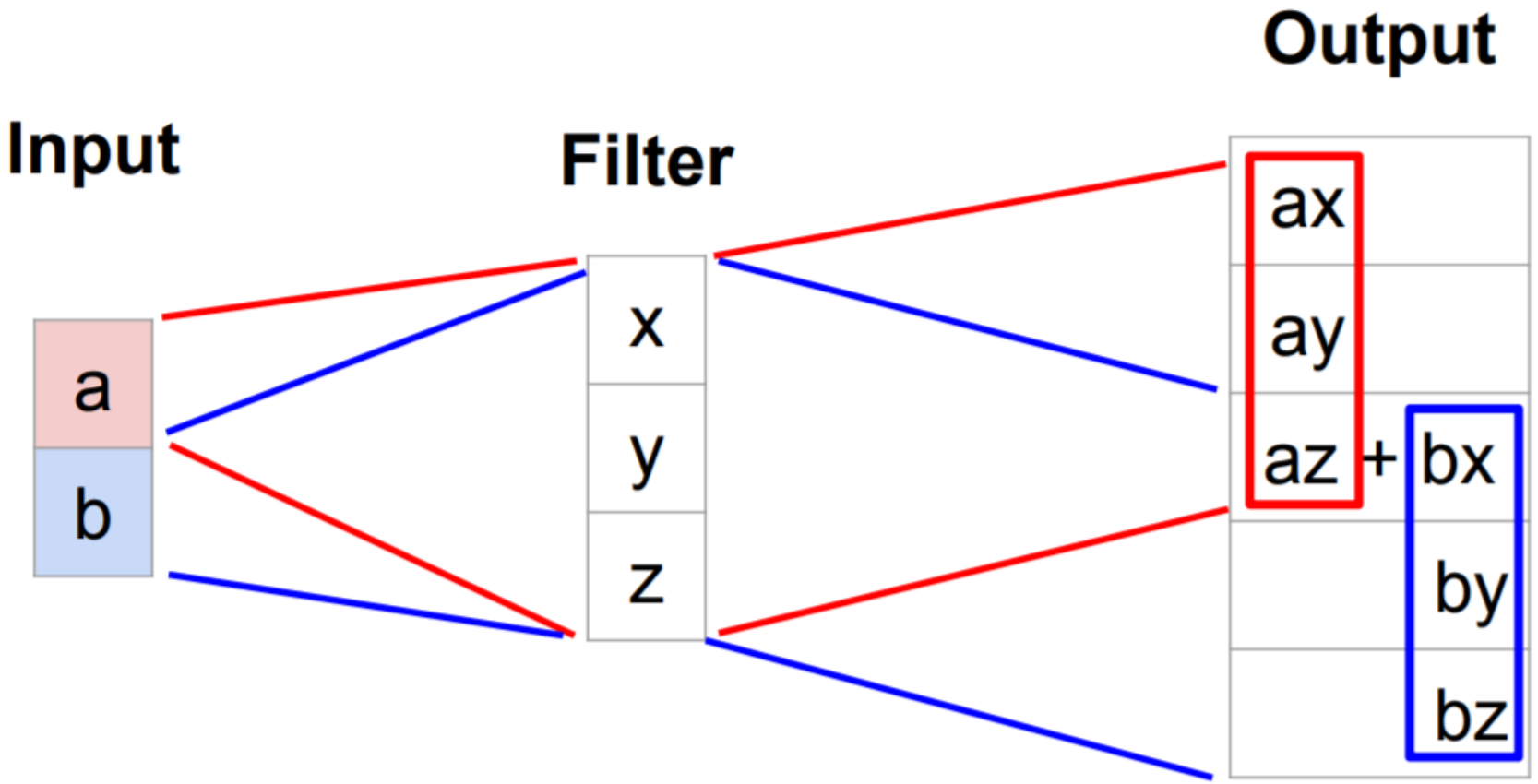


Learnable Upsampling: Transpose Convolution



Other names:
Deconvolution (bad)
Upconvolution
Fractionally strided convolution
Backward strided convolution

Transpose Convolution: 1D Example



Output contains copies of the filter weighted by the input, summing at where at overlaps in the output

Need to crop one pixel from output to make output exactly 2x input

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & x & y & z & 0 & 0 \\ 0 & 0 & x & y & z & 0 \\ 0 & 0 & 0 & x & y & z \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ ax + by + cz \\ bx + cy + dz \\ cx + dy \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=1, padding=1

Convolution transpose multiplies by the transpose of the same matrix:

$$\vec{x} *^T \vec{a} = X^T\vec{a}$$

$$\begin{bmatrix} x & 0 & 0 & 0 \\ y & x & 0 & 0 \\ z & y & x & 0 \\ 0 & z & y & x \\ 0 & 0 & z & y \\ 0 & 0 & 0 & z \end{bmatrix} \begin{bmatrix} a \\ b \\ c \\ d \end{bmatrix} = \begin{bmatrix} ax \\ ay + bx \\ az + by + cx \\ bz + cy + dx \\ cz + dy \\ dz \end{bmatrix}$$

When stride=1, convolution transpose is just a regular convolution (with different padding rules)

Convolution as Matrix Multiplication (1D Example)

We can express convolution in terms of a matrix multiplication

$$\vec{x} * \vec{a} = X\vec{a}$$

$$\begin{bmatrix} x & y & z & 0 & 0 & 0 \\ 0 & 0 & x & y & z & 0 \end{bmatrix} \begin{bmatrix} 0 \\ a \\ b \\ c \\ d \\ 0 \end{bmatrix} = \begin{bmatrix} ay + bz \\ bx + cy + dz \end{bmatrix}$$

Example: 1D conv, kernel size=3, stride=2, padding=1

Convolution transpose multiplies by the transpose of the same matrix:

$$\vec{x} *^T \vec{a} = X^T \vec{a}$$

$$\begin{bmatrix} x & 0 \\ y & 0 \\ z & x \\ 0 & y \\ 0 & z \\ 0 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} ax \\ ay \\ az + bx \\ by \\ bz \\ 0 \end{bmatrix}$$

When stride>1, convolution transpose is no longer a normal convolution!

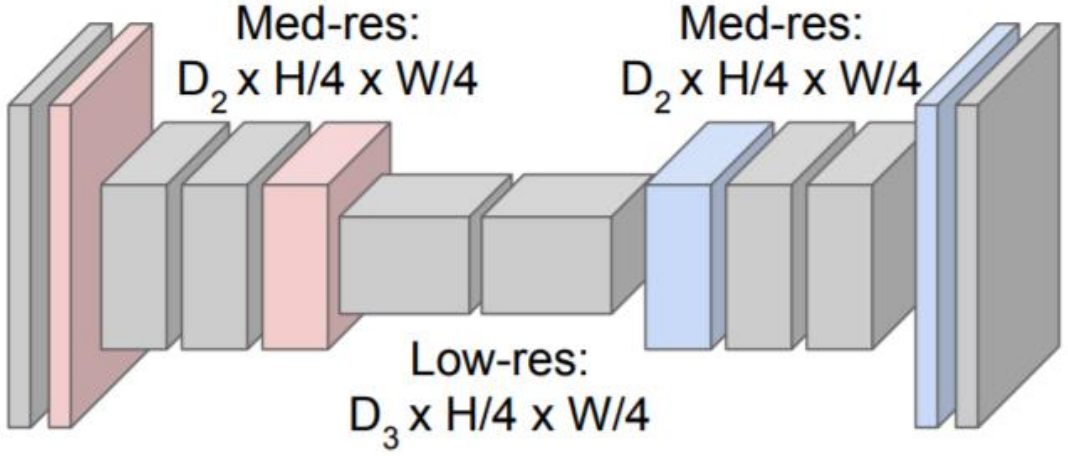
Semantic Segmentation Idea: Fully Convolutional

Downsampling:
Pooling, strided convolution

Design network as a bunch of convolutional layers, with **downsampling** and **upsampling** inside the network!

Upsampling:
Unpooling or strided transpose convolution

Input:
3 x H x W



High-res:
D_1 x H/2 x W/2

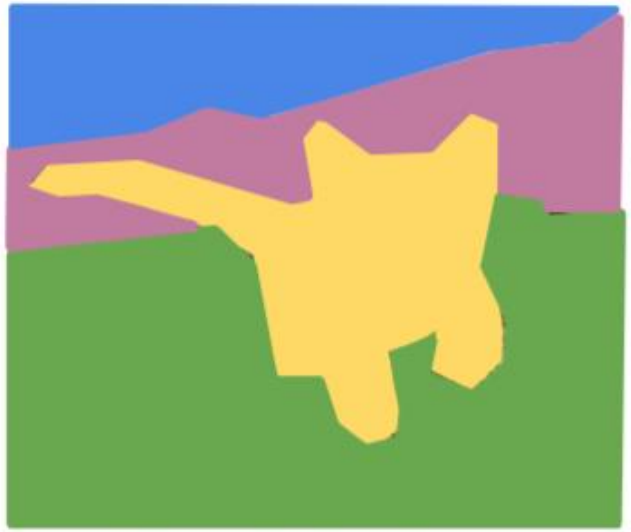
High-res:
D_1 x H/2 x W/2

Predictions:
H x W

Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015
Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

Computer Vision Tasks

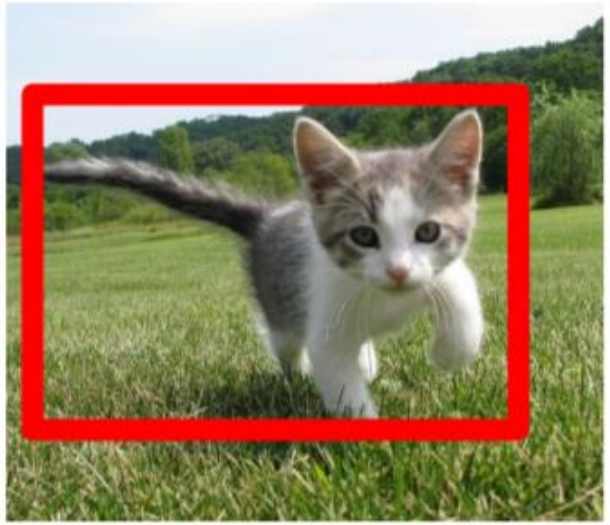
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

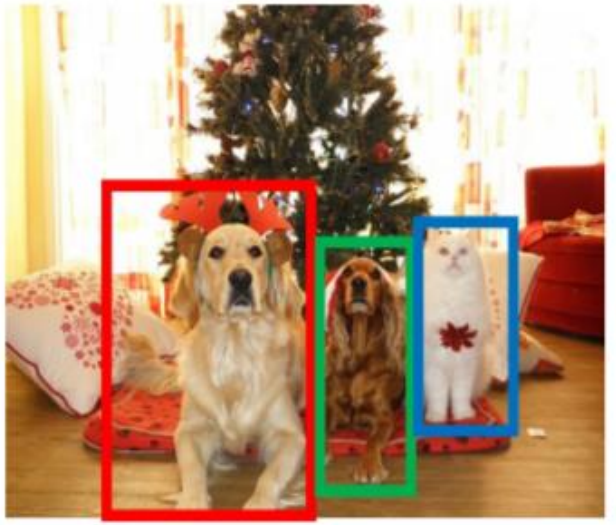
Classification + Localization



CAT

Single Object

Object Detection



DOG, DOG, CAT

Instance Segmentation

DOG, DOG, CAT

Multiple Object