CNNs Vision Applications

M. Soleymani

Sharif University of Technology

Spring 2024

Most slides have been adopted from Fei Fei Li and colleagues lectures, cs231n, Stanford 2022

and some from Bhiksha Raj, 11-785, CMU

Image classification

This image is CC0 public domain

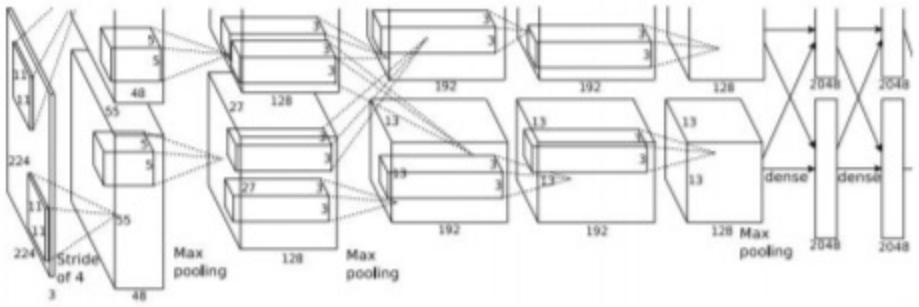


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

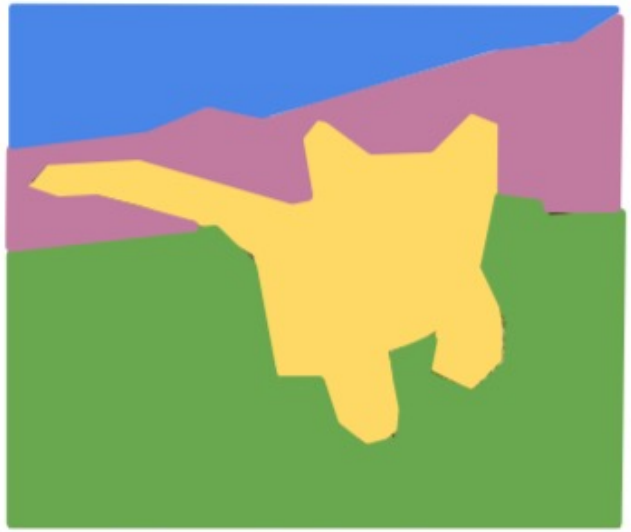
Vector:
4096

Fully-Connected:
4096 to 1000

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

Other Computer Vision Tasks

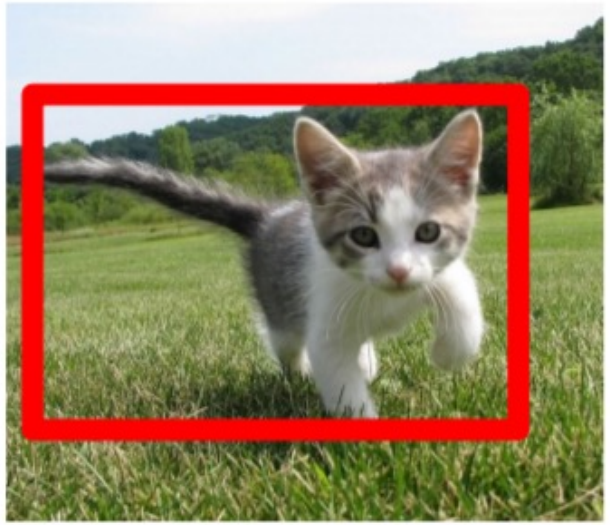
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Classification + Localization



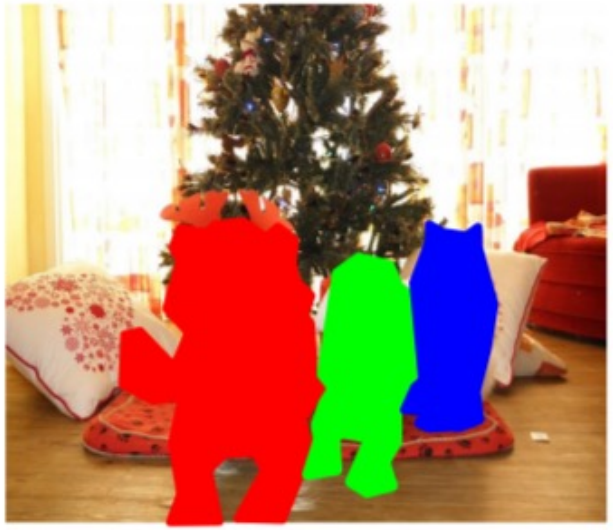
CAT

Single Object

Object Detection

DOG, DOG, CAT

Instance Segmentation



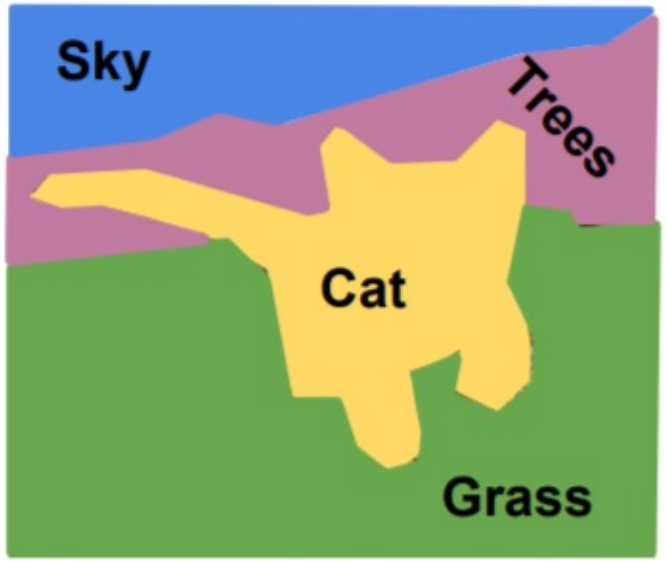
DOG, DOG, CAT

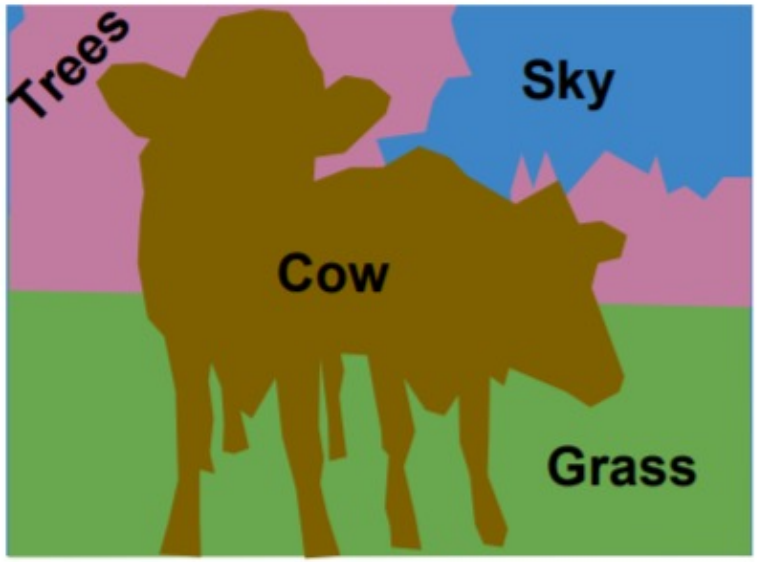
Multiple Object

Semantic Segmentation

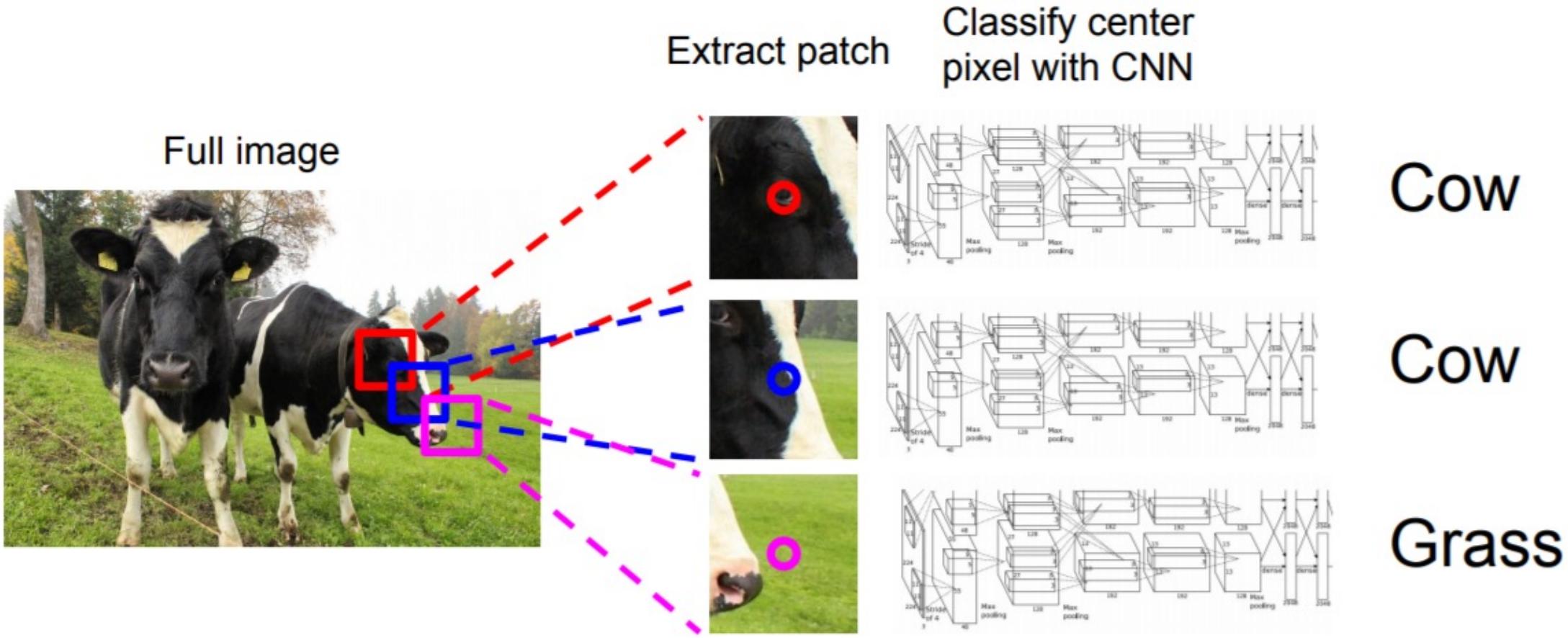
Label each pixel in the image with a category label

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: Convolution

- An intuitive idea: encode the entire image with conv net, and do semantic segmentation on top.

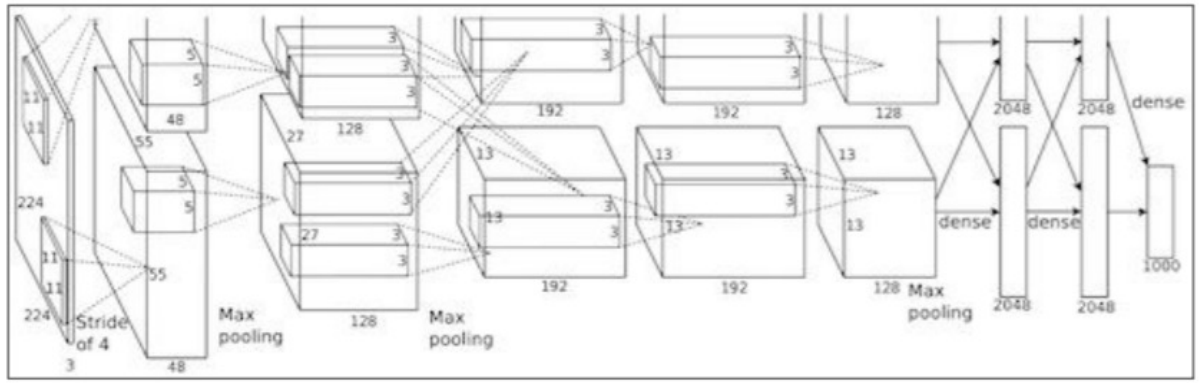


Figure copyright Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, 2012. Reproduced with permission.

Problem: classification architectures often reduce feature spatial sizes to go deeper, but semantic segmentation requires the output size to be the same as input size.

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

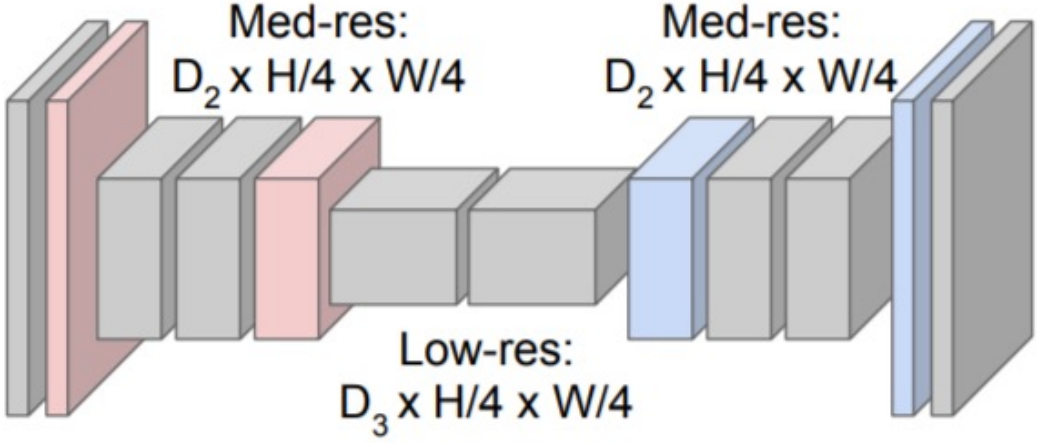
Predictions:
H x W

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

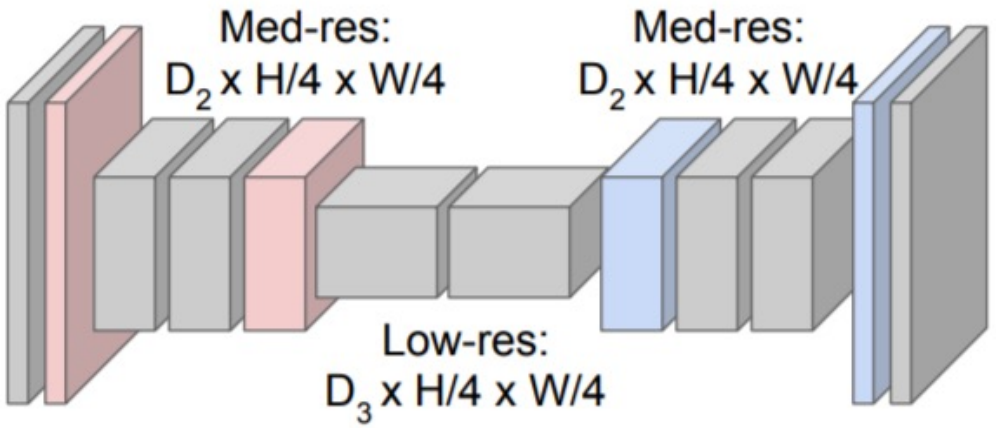
Semantic Segmentation Idea: Fully Convolutional

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

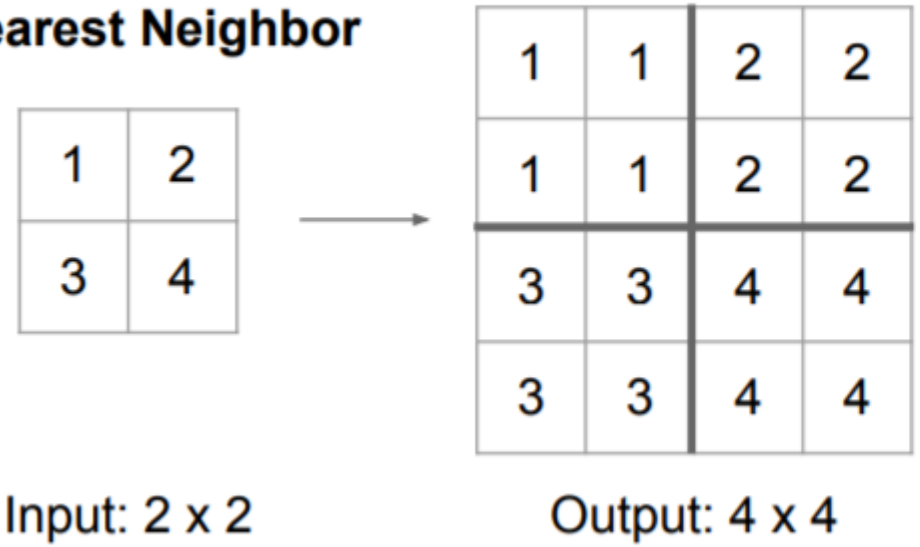
High-res:
D_1 x H/2 x W/2

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”

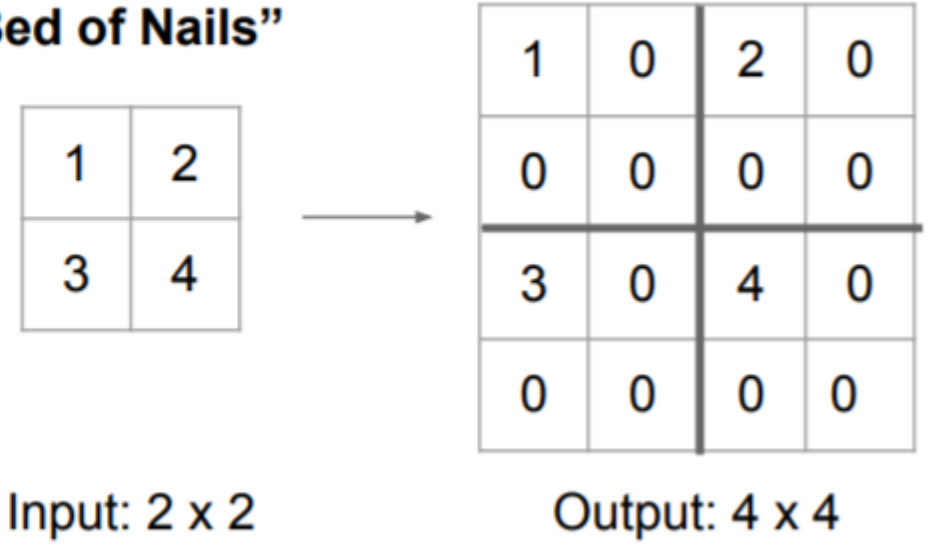
Nearest Neighbor



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

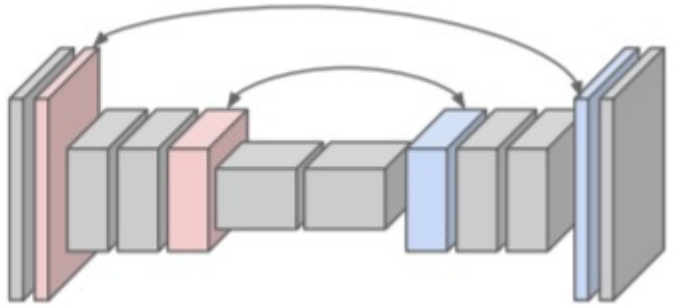
1	2
3	4

Input: 2 x 2

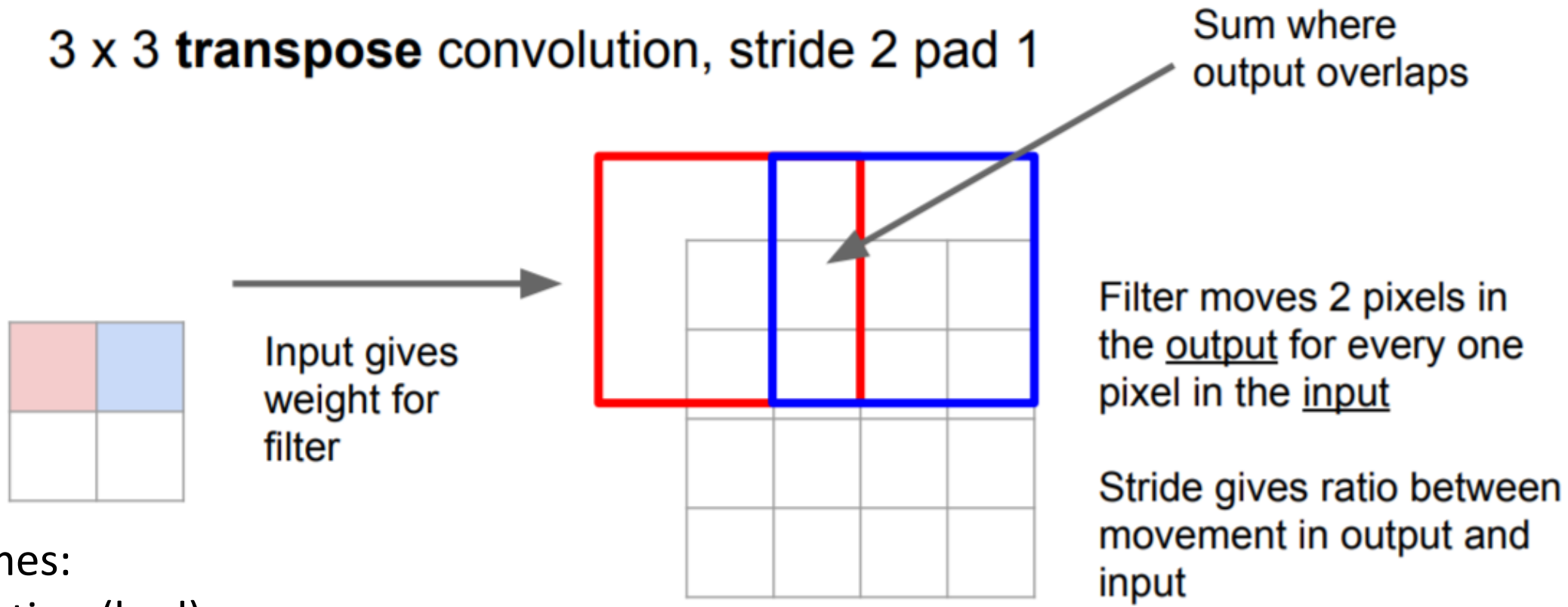
0	0	2	0
0	1	0	0
0	0	0	0
3	0	0	4

Output: 4 x 4

Corresponding pairs of downsampling and upsampling layers

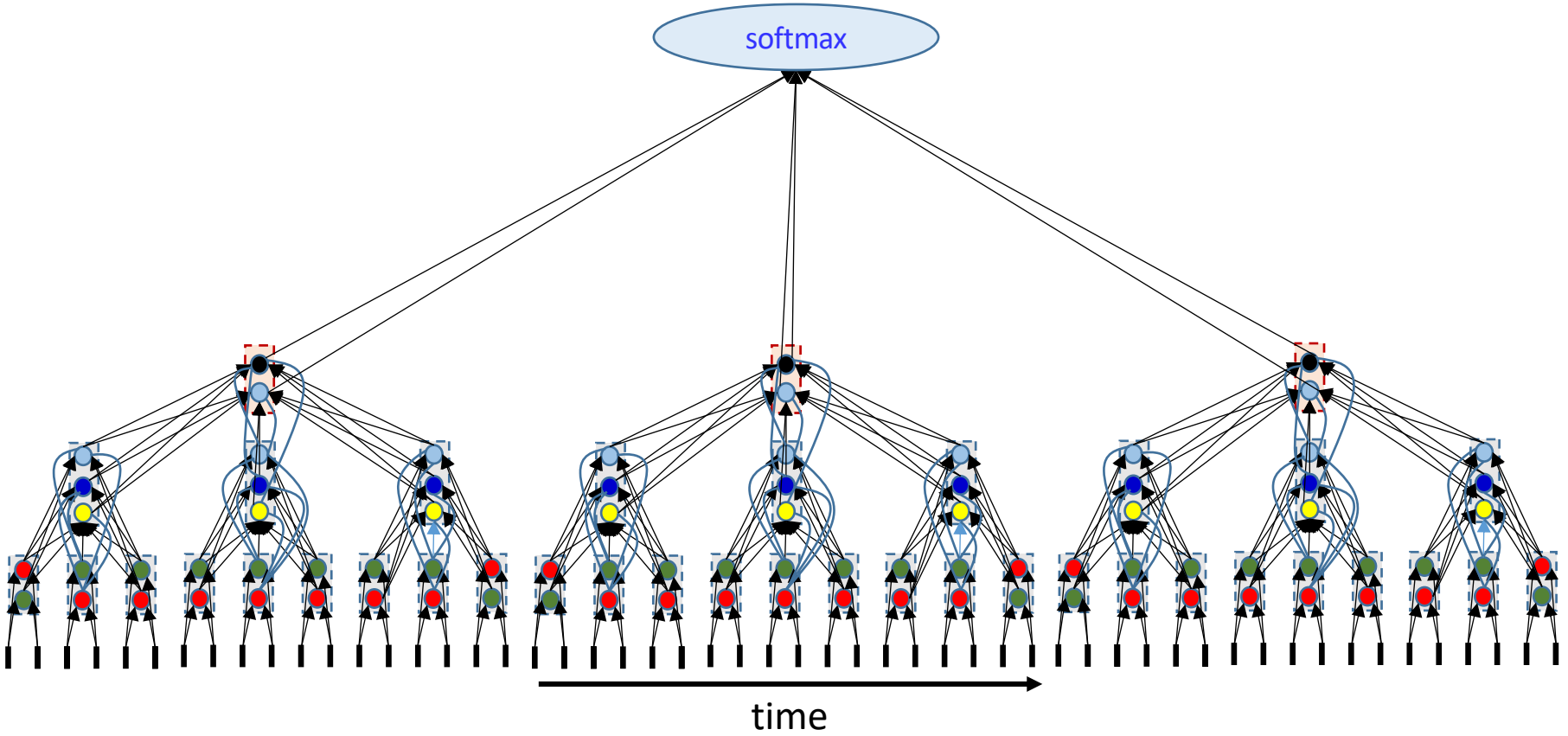


Learnable Upsampling: Transposed Convolution



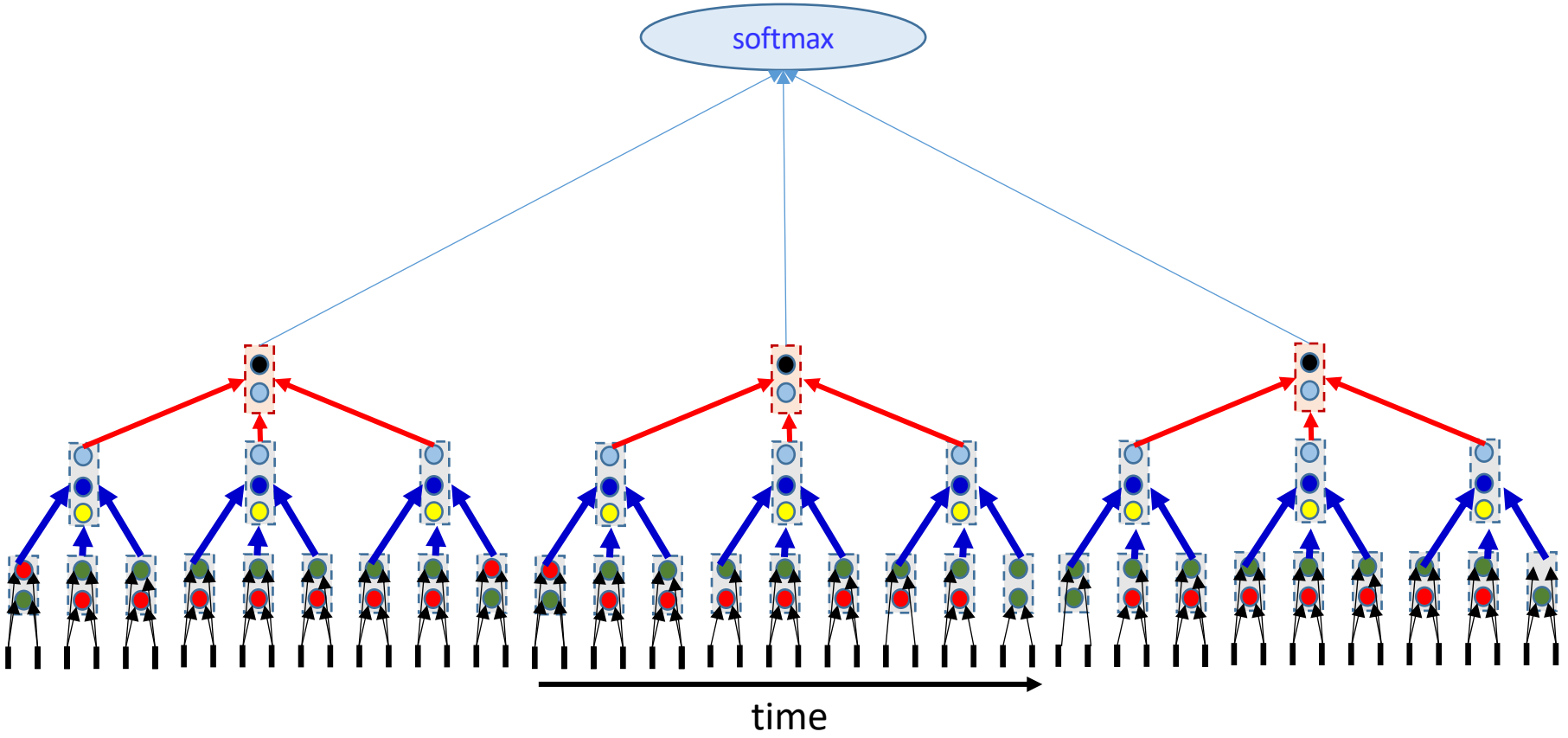
Other names:
Deconvolution (bad)
Upconvolution
Fractionally strided convolution
Backward strided convolution

1-D Conv



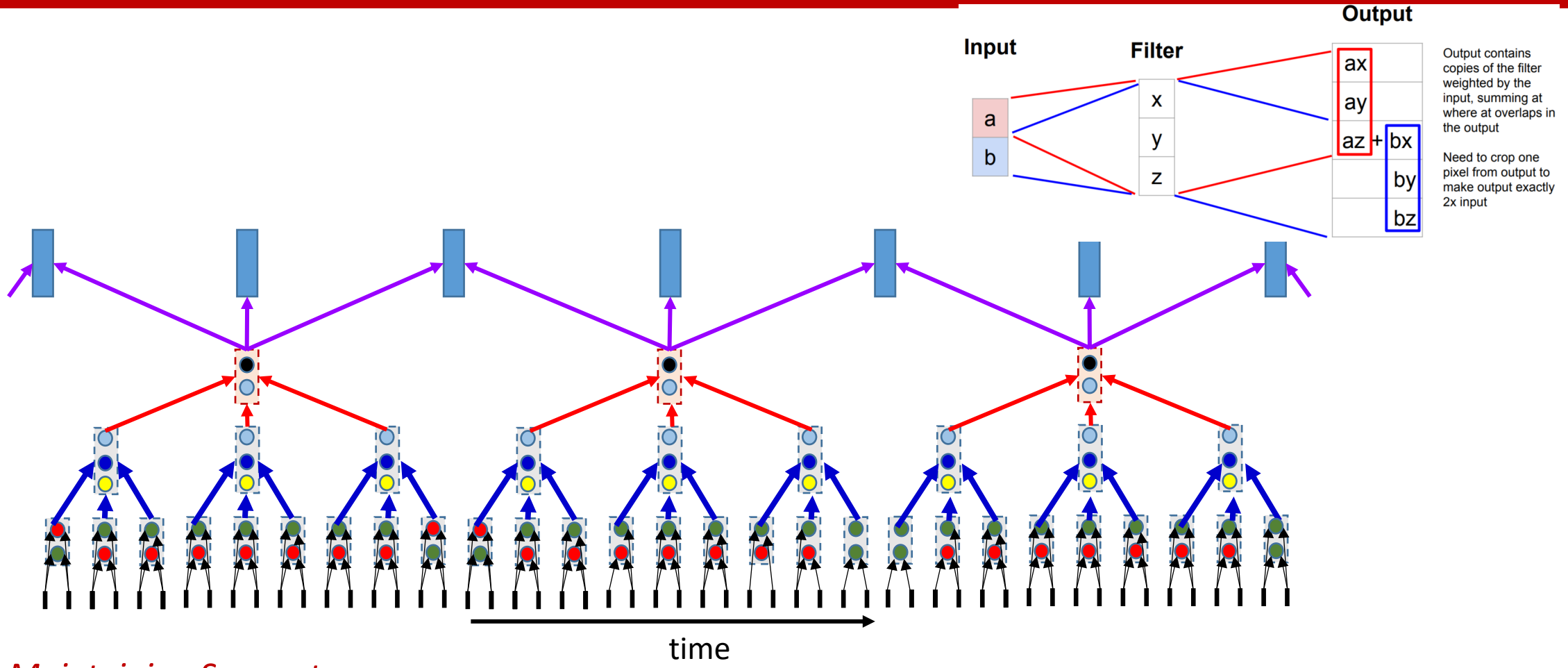
- We've seen this before.. where??

1-D Conv



- Simplified diagram

1D Transposed Conv



- *Maintaining Symmetry:*
  - Vertical bars in the 4th layer are regularly arranged w.r.t. bars of layer 3
  - The pattern of values of upward weights for each of the three pink (3rd layer) bars is identical

1D Transposed Conv

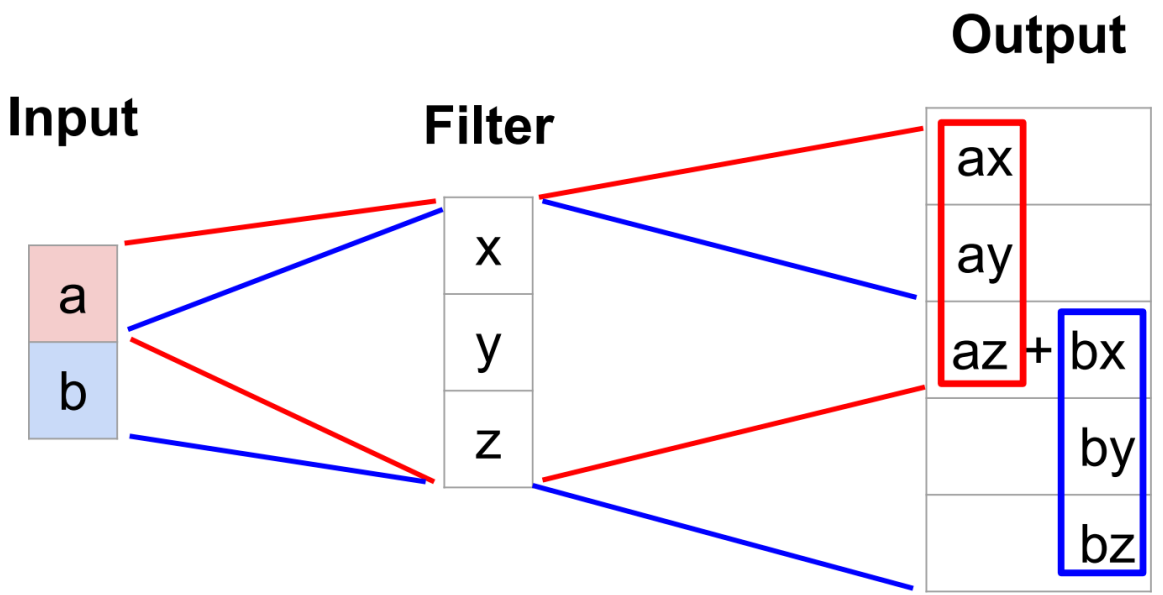
- Connection rules are transposed for expanding layers
  - In shrinking layers, the pattern of *incoming weights* is identical for each bar
  - In expanding layers, the pattern of *outgoing (upward) weights* is identical for each bar

- When thought of as an MLP, can write

$$Z_l = W_l Y_{l-1}$$

- W_l is broader than tall for a shrinking layer
- W_l is taller than broad for an expanding layer
  - Sometimes viewed as the transpose of a broad matrix
- Leading to terminology “transpose convolution”

Learnable Upsampling: 1D Example



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

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 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

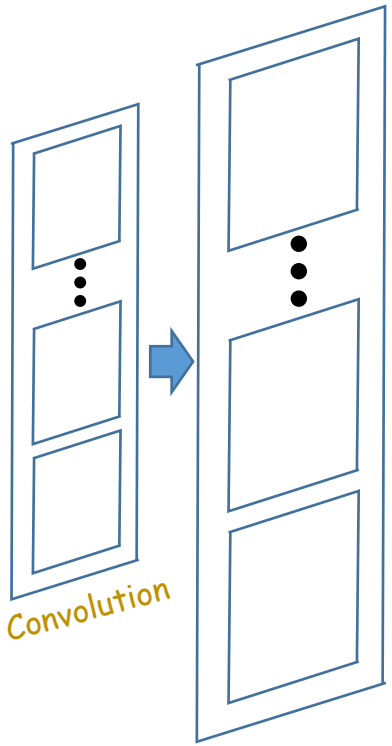
Transposed convolution multiplies by the transpose of the same matrix:

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

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

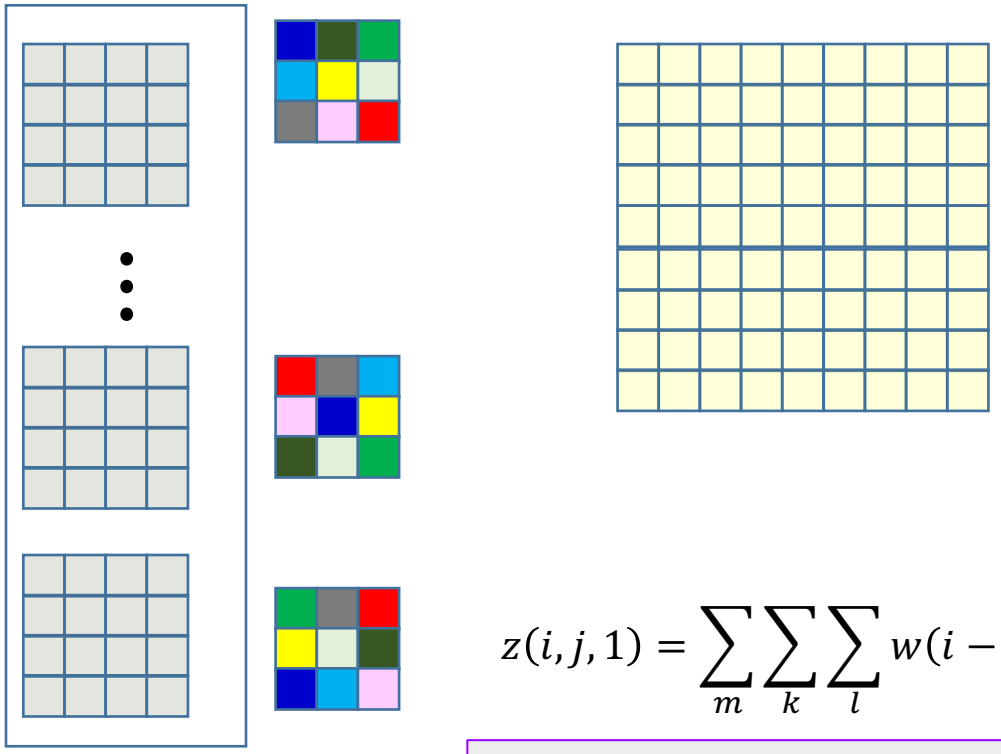
Example: 1D transposed conv, kernel size=3, stride=2, padding=0

In 2-D



- Similar computation

2D expanding convolution

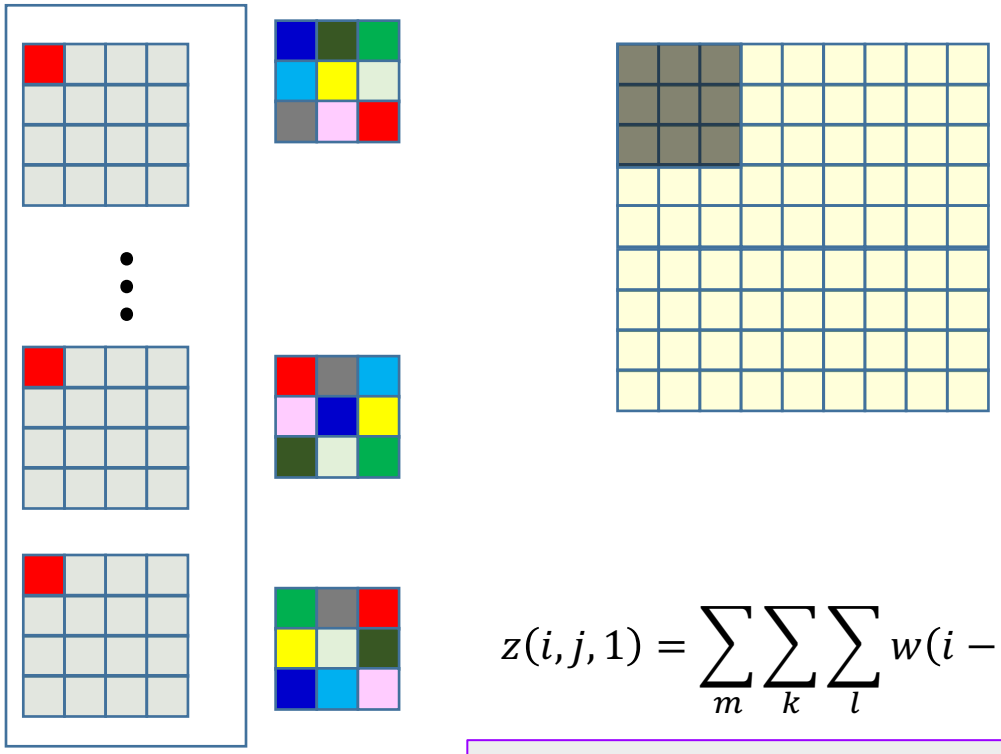


$$z(i,j,1) = \sum_m \sum_k \sum_l w(i - kb, j - lb, m, 1) I(k,l,m)$$

b is the "stride"
(scaling factor between the sizes of Z and Y)

- Output size is typically an integer multiple of input
  - +1 if filter width is odd
  - Easier to determine assignment of output to input

2D expanding convolution

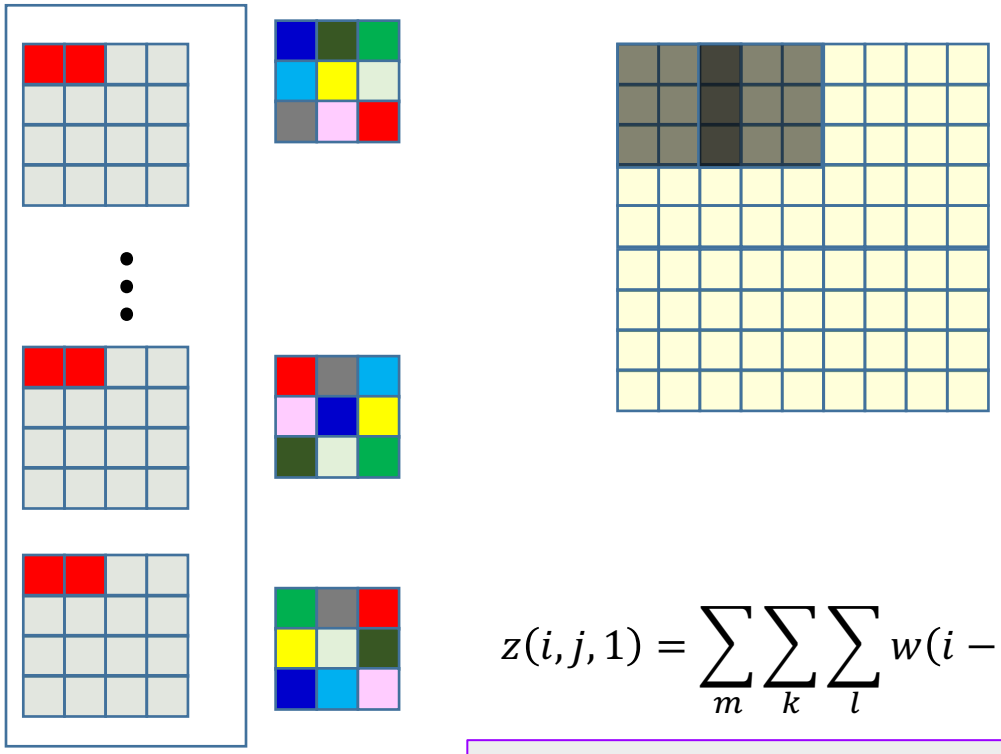


$$z(i,j,1) = \sum_m \sum_k \sum_l w(i - kb, j - lb, m, 1) I(k,l,m)$$

b is the "stride"
(scaling factor between the sizes of Z and Y)

- Output size is typically an integer multiple of input
  - +1 if filter width is odd
  - Easier to determine assignment of output to input

2D expanding convolution

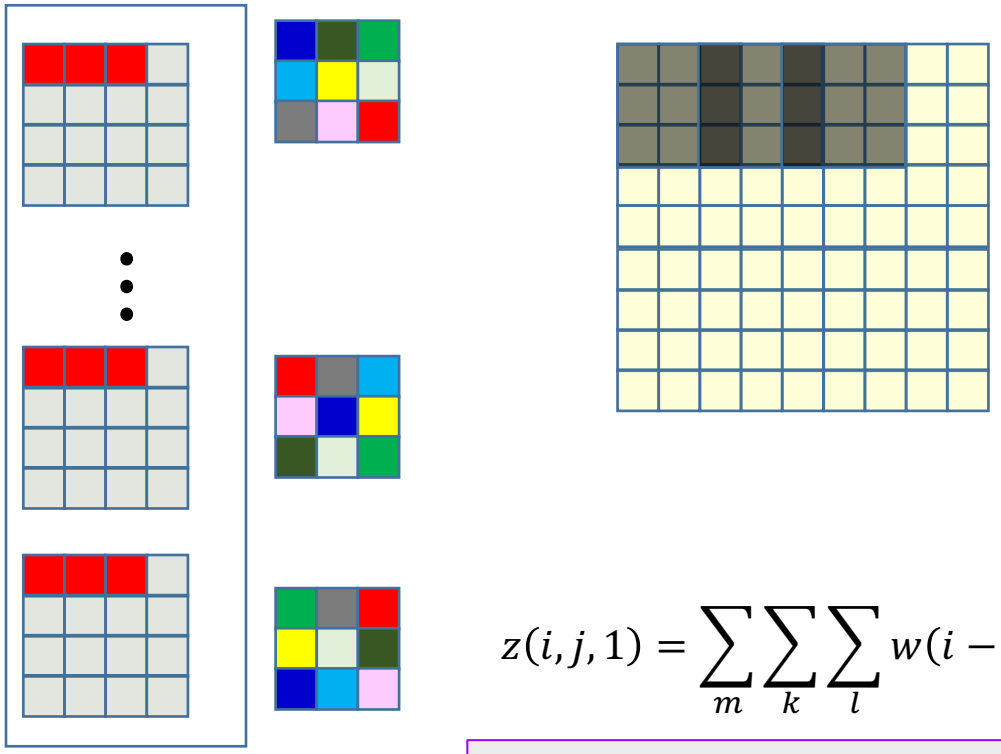


$$z(i,j,1) = \sum_m \sum_k \sum_l w(i-kb, j-lb, m, 1) I(k,l,m)$$

b is the "stride"
(scaling factor between the sizes of Z and Y)

- Output size is typically an integer multiple of input
  - +1 if filter width is odd
  - Easier to determine assignment of output to input

2D expanding convolution

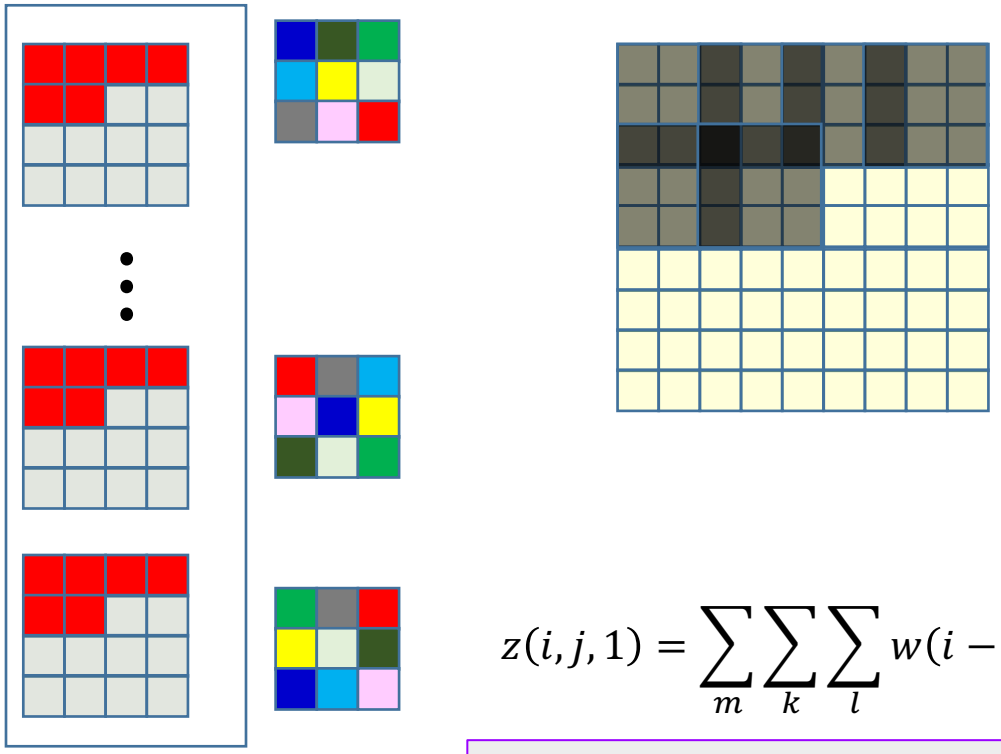


$$z(i,j,1) = \sum_m \sum_k \sum_l w(i - kb, j - lb, m, 1) I(k,l,m)$$

b is the "stride"
(scaling factor between the sizes of Z and Y)

- Output size is typically an integer multiple of input
  - +1 if filter width is odd
  - Easier to determine assignment of output to input

2D expanding convolution



$$z(i,j,1) = \sum_m \sum_k \sum_l w(i - kb, j - lb, m, 1) I(k,l,m)$$

b is the "stride"
(scaling factor between the sizes of Z and Y)

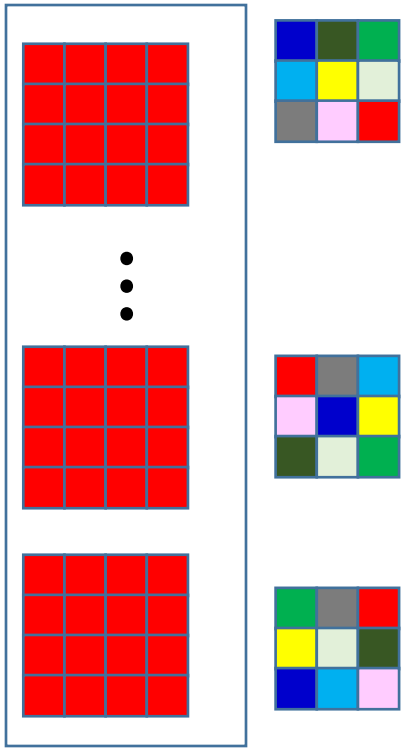
- Output size is typically an integer multiple of input
  - +1 if filter width is odd
  - Easier to determine assignment of output to input

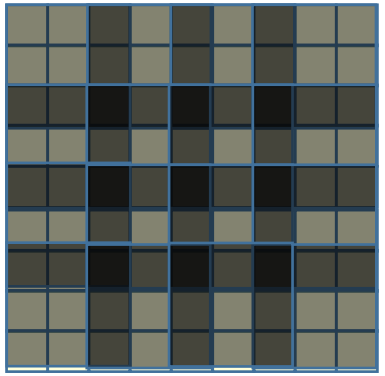
CNN: Expanding convolution layer l

```
Z(l) = zeros(Dl x (Wb+K_l) x (Hb+K_l)) # b = stride
for j = 1:D_l
  for x = 1:W
    for y = 1:H
      for i = 1:D_l-1
        for x' = 1:K_l
          for y' = 1:K_l
            z(l,j,(x-1)b+x',(y-1)b+y') +=
                    w(l,j,i,x',y')y(l-1,i,x,y)
```

We leave the rather trivial issue of how to modify this code to compute the derivatives w.r.t `w` and `y` to you

2D expanding convolution





$$z(1,i,j) = \sum_m \sum_k \sum_l w(1,m,i-kb,j-lb) I(m,k,l)$$

b is the "stride"
(scaling factor between the sizes of Z and Y)

- Also called *transpose convolution*
  - If you recast the CNN as a shared-parameter MLP, expanding layers have weight matrices that are taller than wide
- Also called "deconvolution"
  - Strictly speaking, abuse of terminology

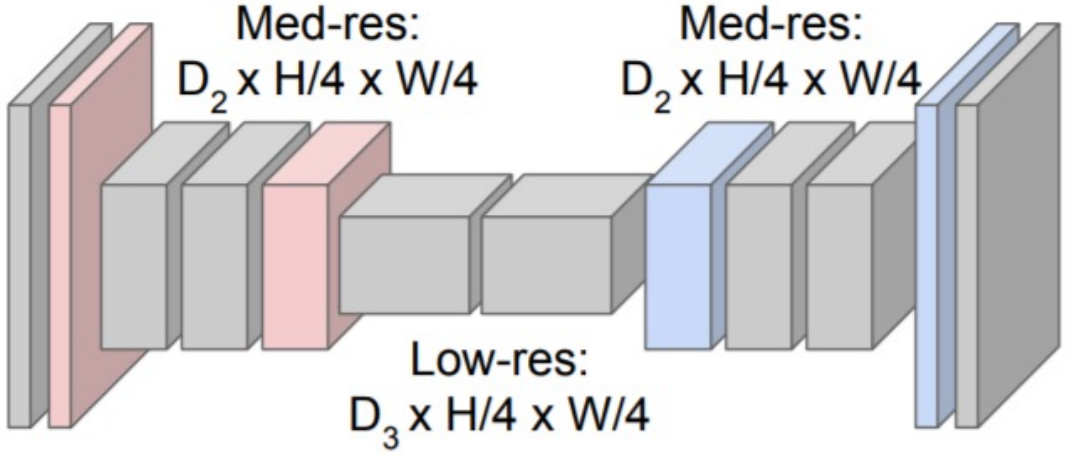
Semantic Segmentation Idea: Fully Convolutional

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



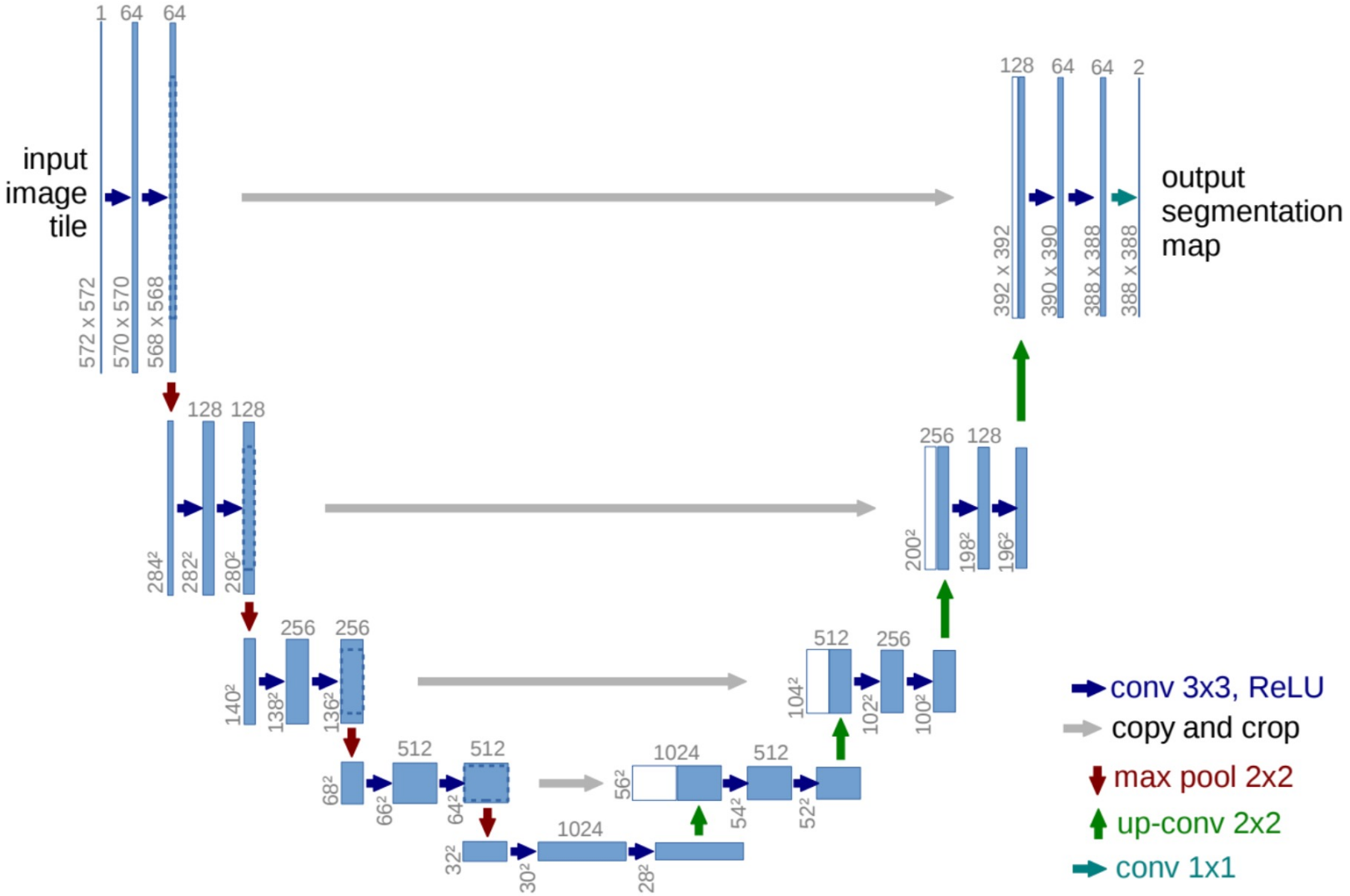
High-res:
D_1 x H/2 x W/2

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

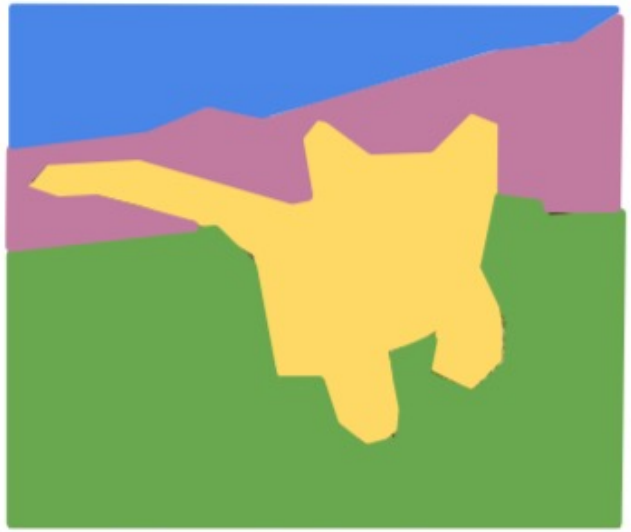
U-Net Architecture



Ronneberger et al., U-Net: Convolutional Networks for Biomedical Image Segmentation, MICCAI 2015

Computer Vision Tasks

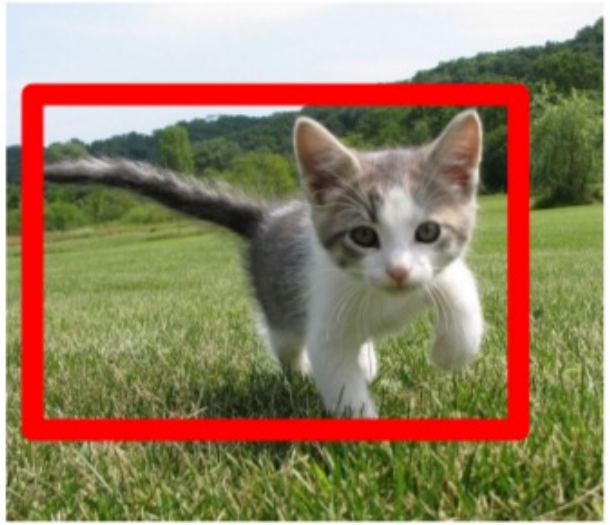
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Classification + Localization



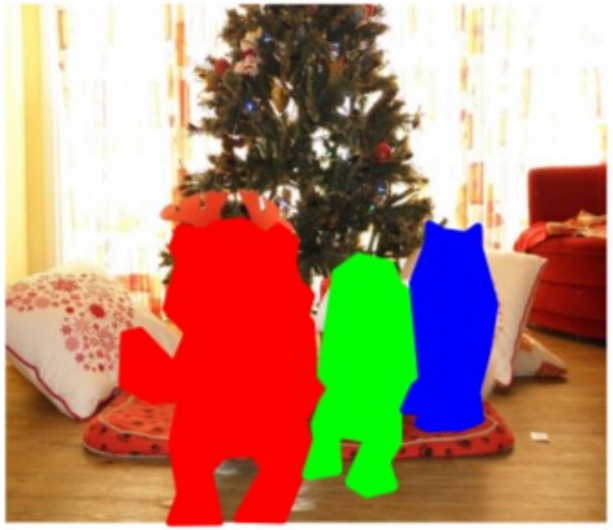
CAT

Single Object

Object Detection

DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

Classification + Localization

Classification: C classes

Input: Image

Output: Class label

Evaluation metric: Accuracy

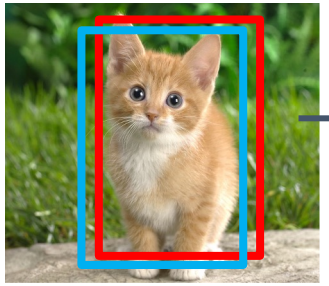
CAT

Localization:

Input: Image

Output: Box in the image (x, y, w, h)

Evaluation metric: Intersection over Union

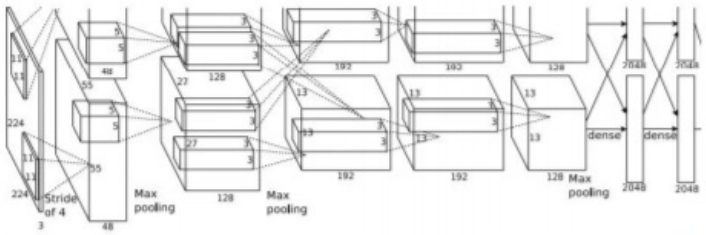


(x, y, w, h)

Classification + Localization: Do both

Classification + Localization

This image is CC0 public domain



Often pretrained on ImageNet (Transfer learning)

Vector: 4096

Fully Connected: 4096 to 1000

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

Softmax Loss

Correct label:
Cat

Fully Connected: 4096 to 4

Box Coordinates
(x, y, w, h)

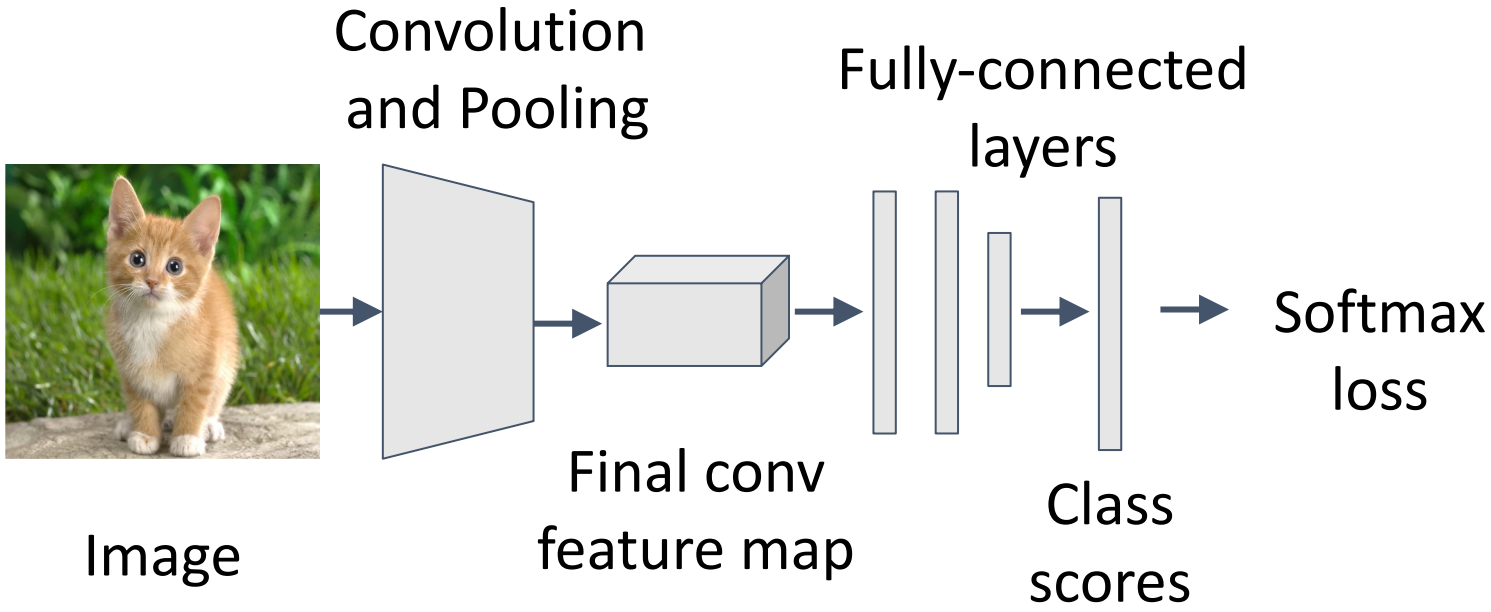
L2 Loss

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

+ → **Loss**

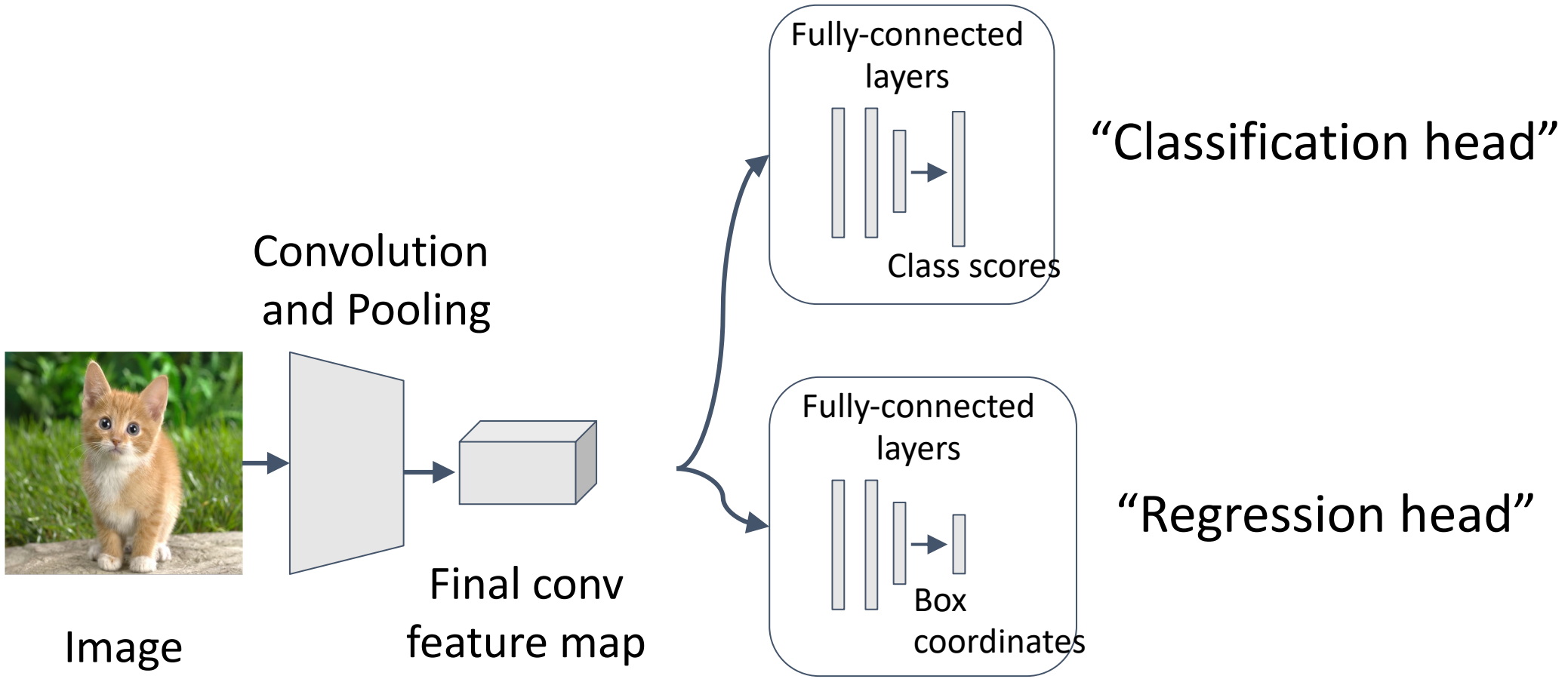
Simple Recipe for Classification + Localization

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



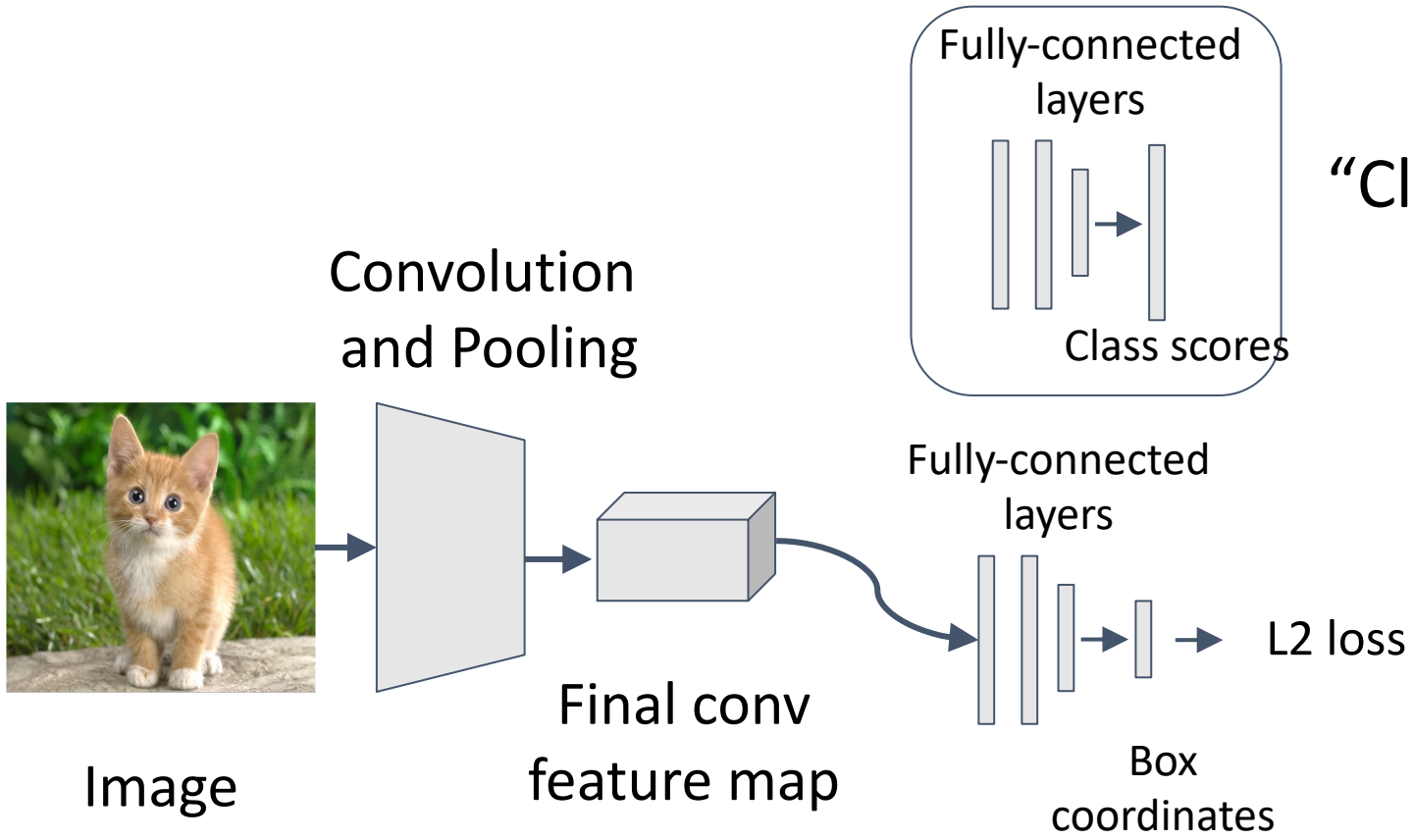
Simple Recipe for Classification + Localization

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



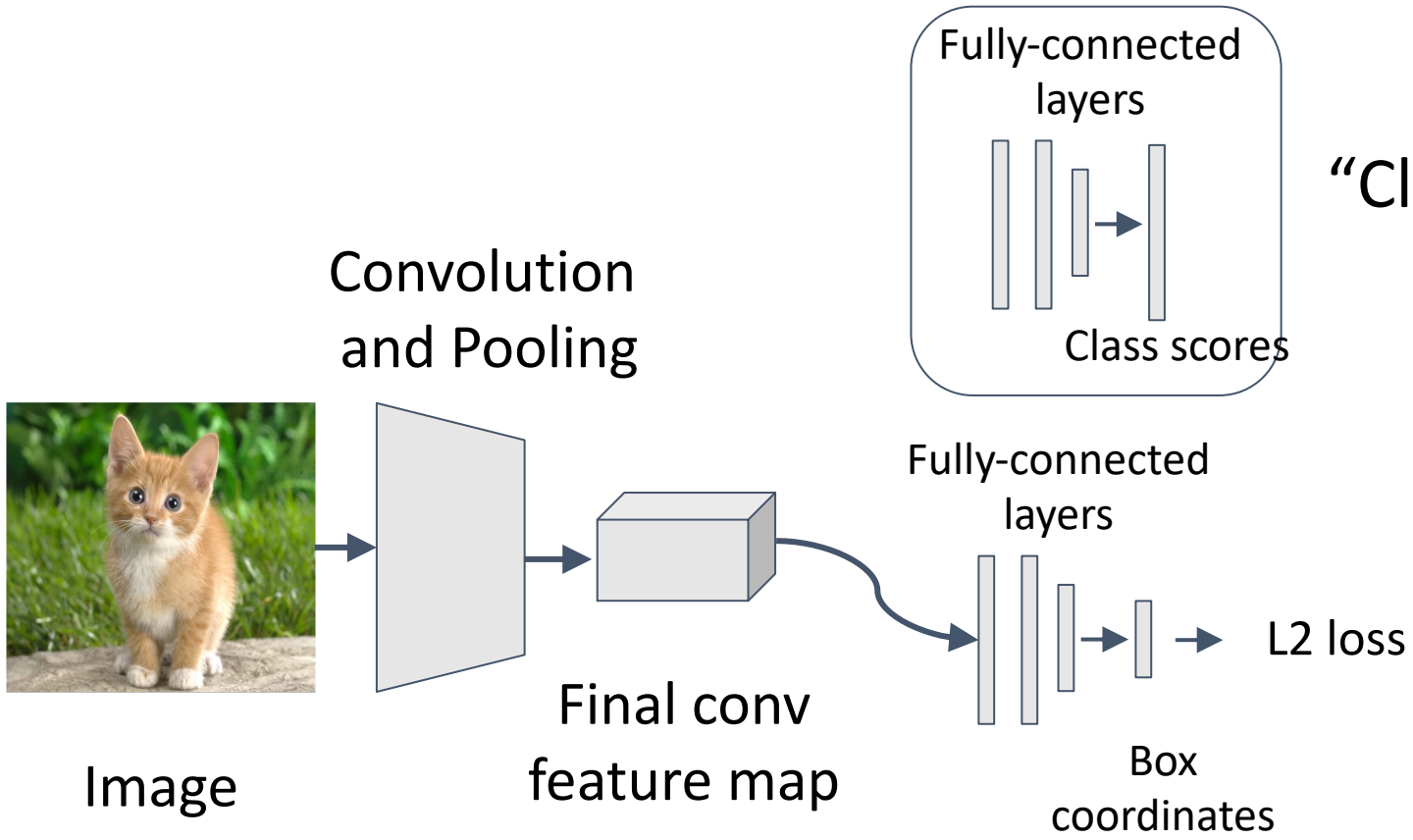
Simple Recipe for Classification + Localization

- **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



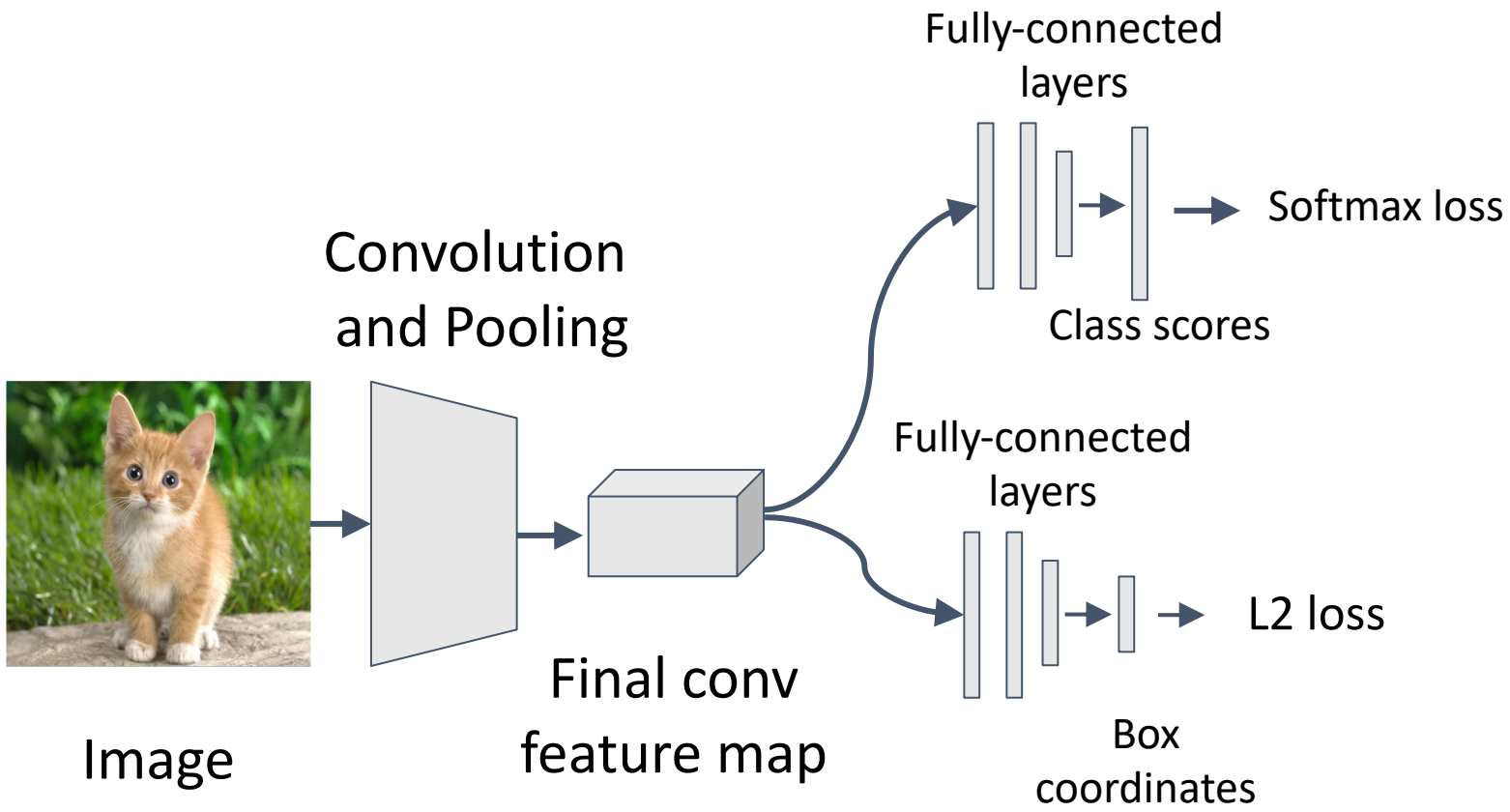
Simple Recipe for Classification + Localization

- **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

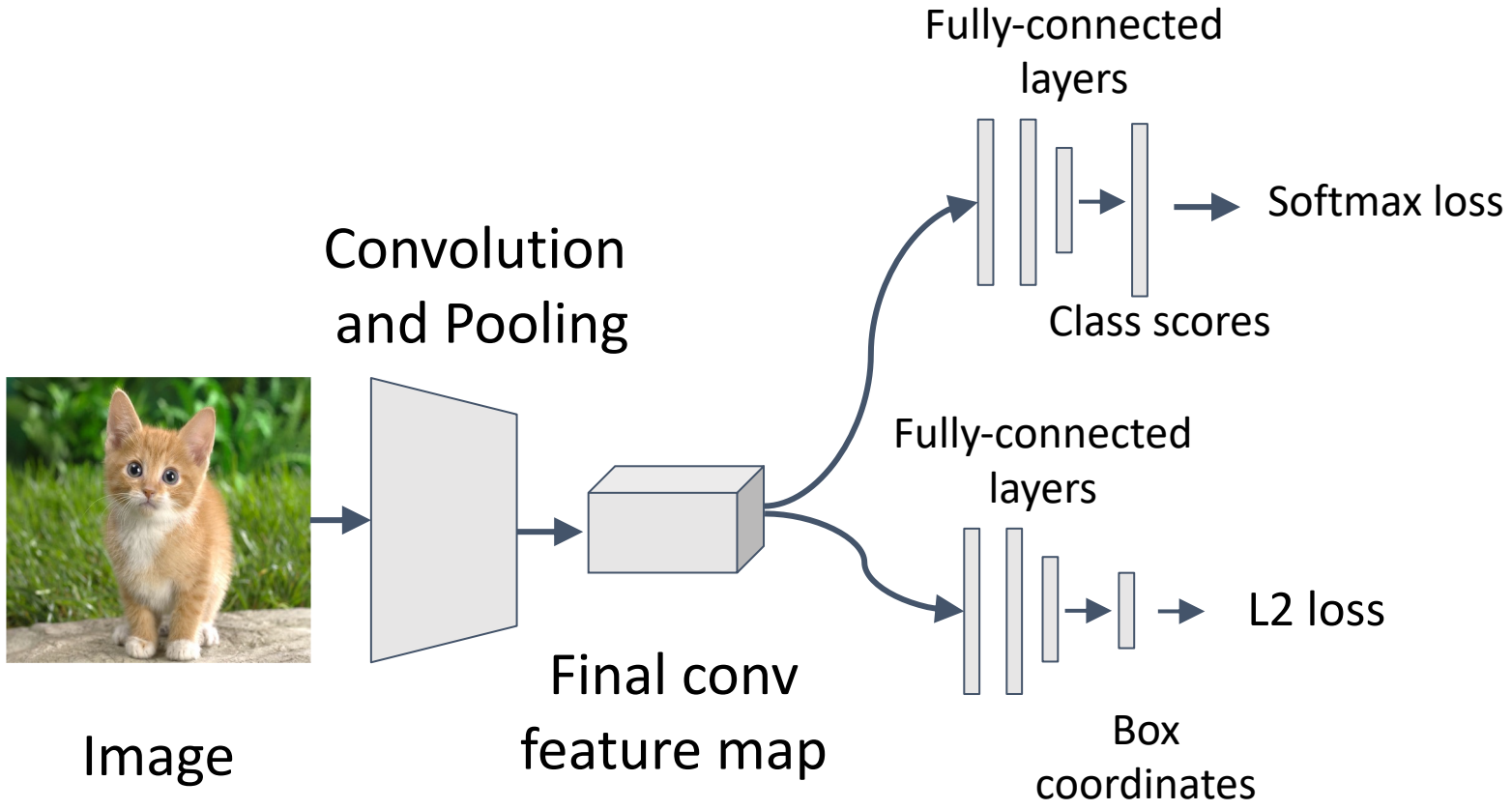


Simple Recipe for Classification + Localization

- **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



Classification + Localization

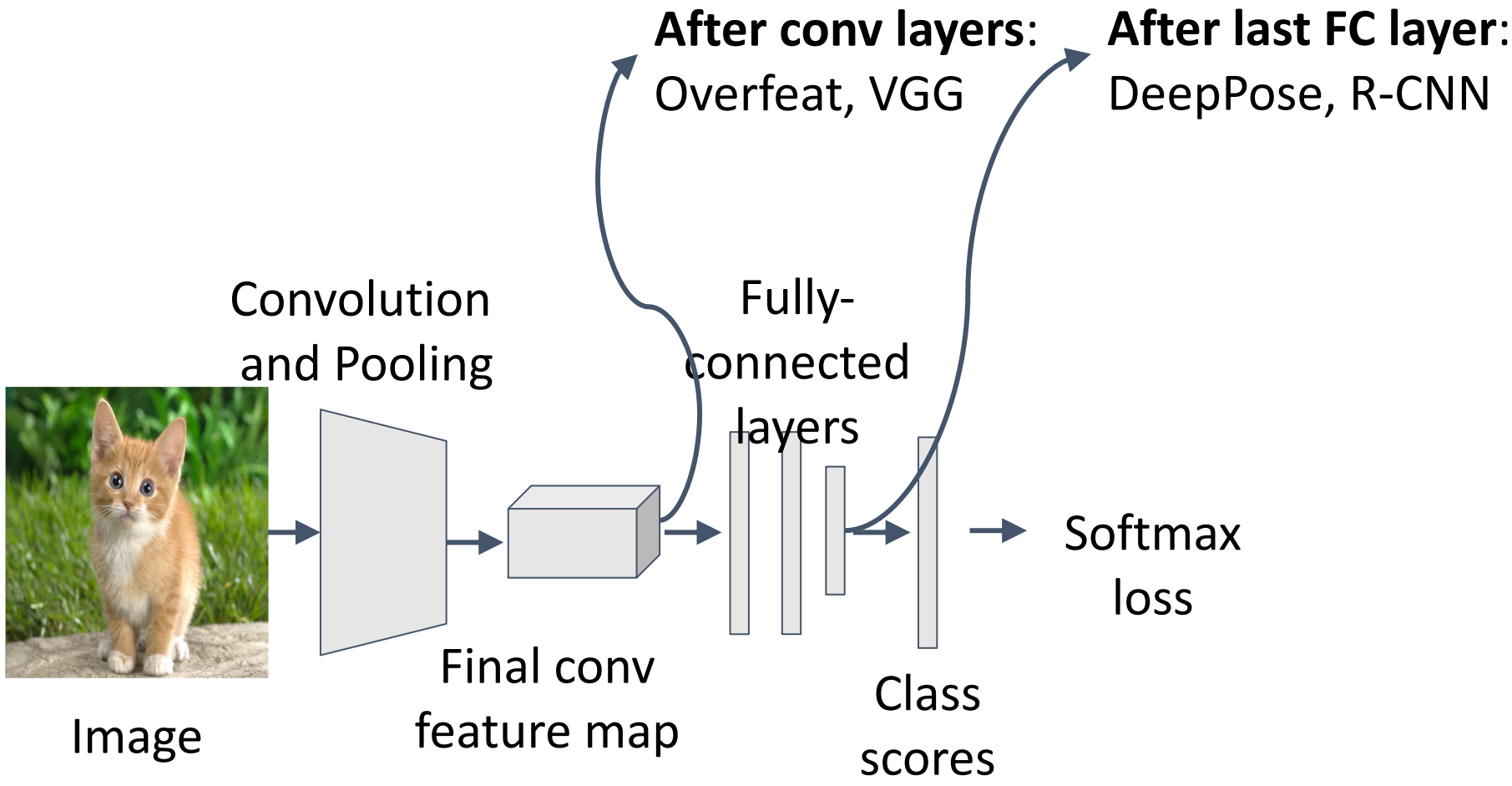


Classification head:
C numbers
(one per class)

Class agnostic:
4 numbers
(one box)

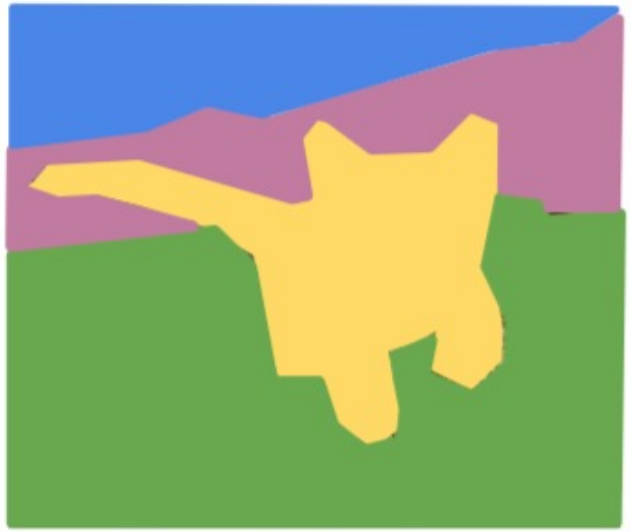
Class specific:
C x 4 numbers
(one box per class)

Where to attach the regression head?



Object detection

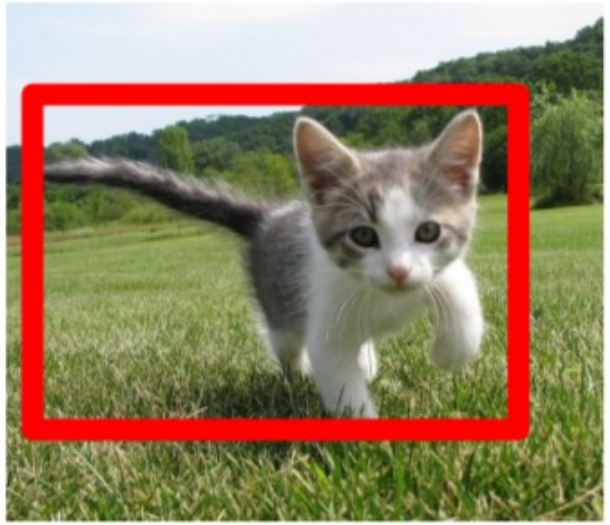
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Classification + Localization



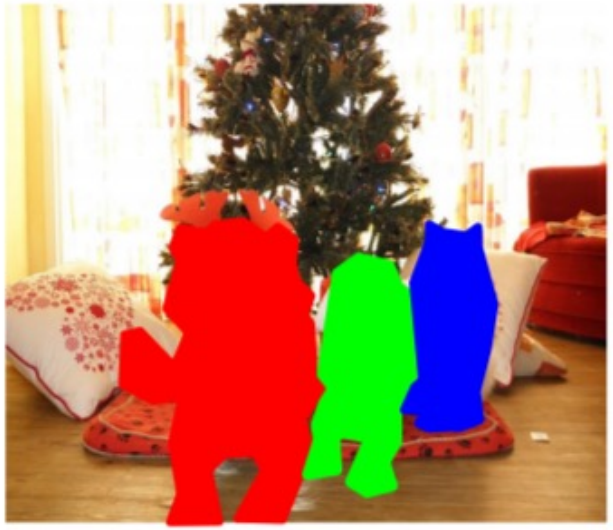
CAT

Single Object

Object Detection

DOG, DOG, CAT

Instance Segmentation

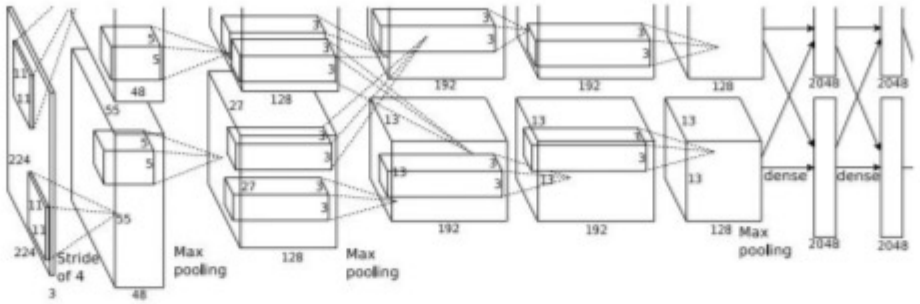


DOG, DOG, CAT

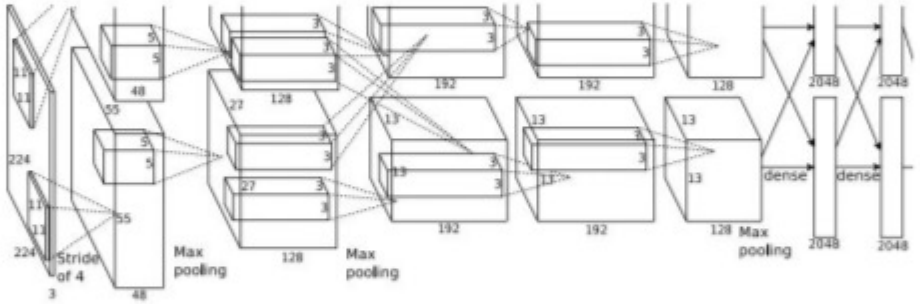
Multiple Object

Object Detection as Regression?

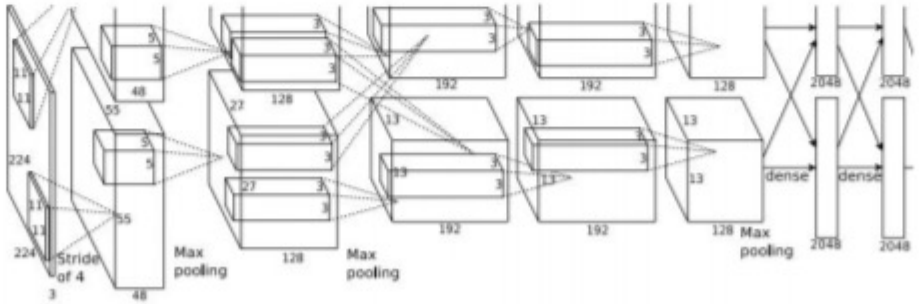
Each image needs a different number of outputs!



CAT: (x, y, w, h)



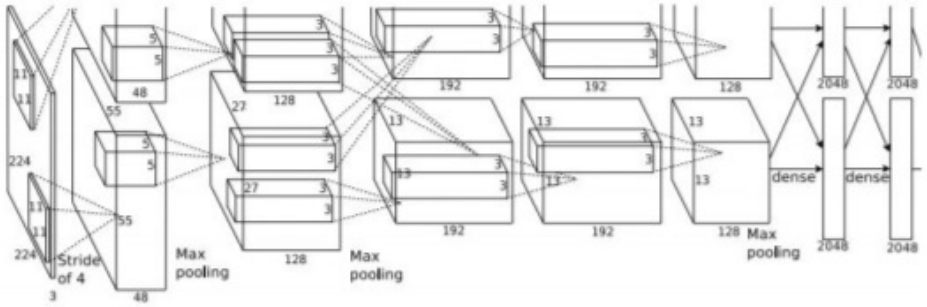
DOG: (x, y, w, h)
DOG: (x, y, w, h)
CAT: (x, y, w, h)



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

Object Detection as Classification: Sliding Window

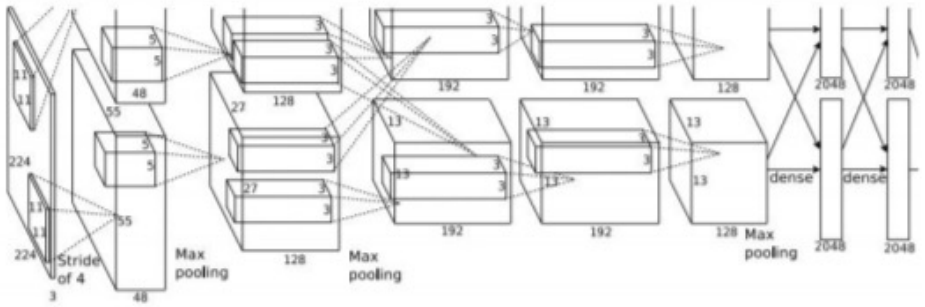
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? NO
Background? YES

Object Detection as Classification: Sliding Window

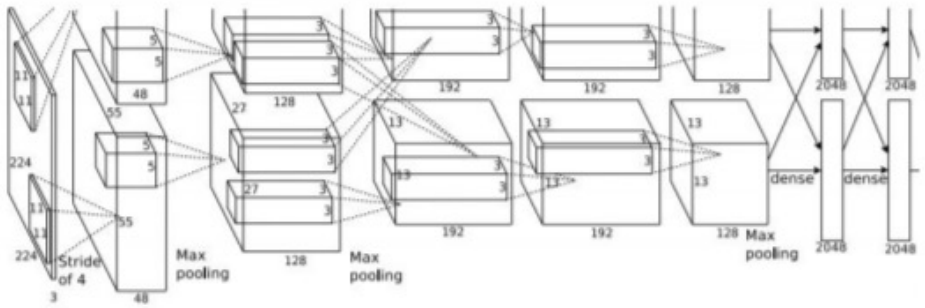
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? YES
Cat? NO
Background? NO

Object Detection as Classification: Sliding Window

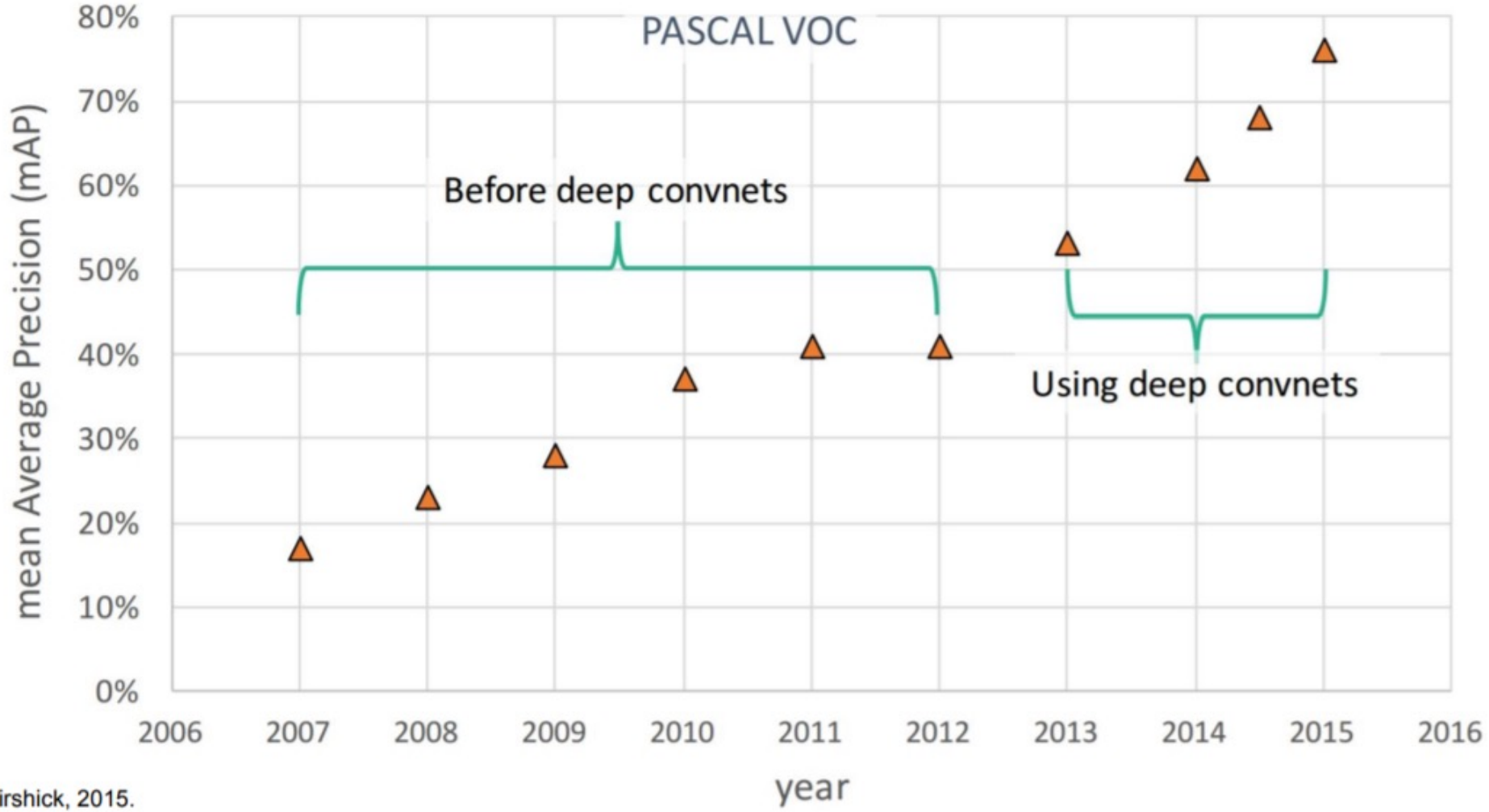
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



Dog? NO
Cat? YES
Background? NO

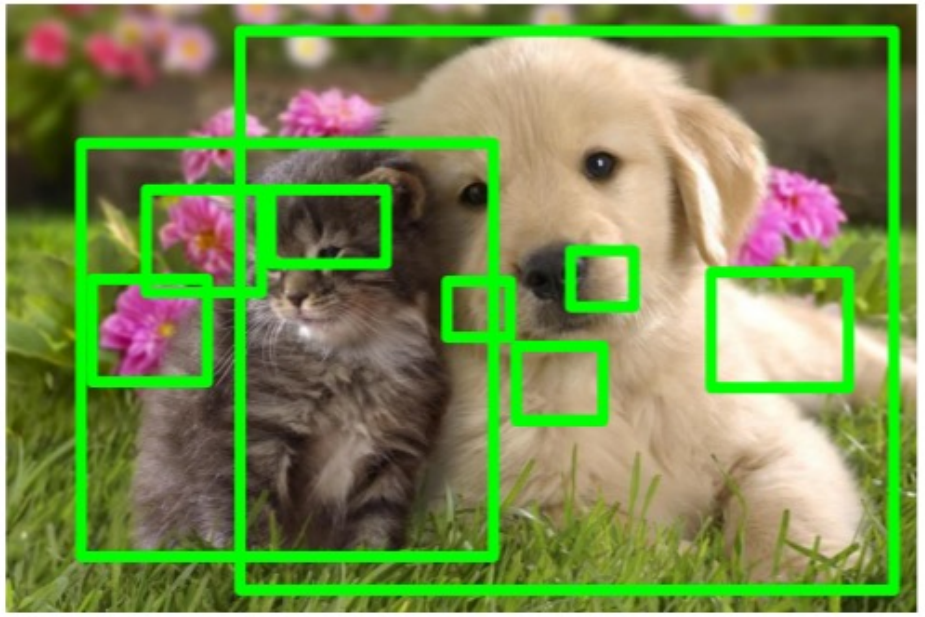
Problem: Need to apply CNN to huge number of locations and scales, very computationally expensive!

Object Detection: Impact of Deep Learning



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



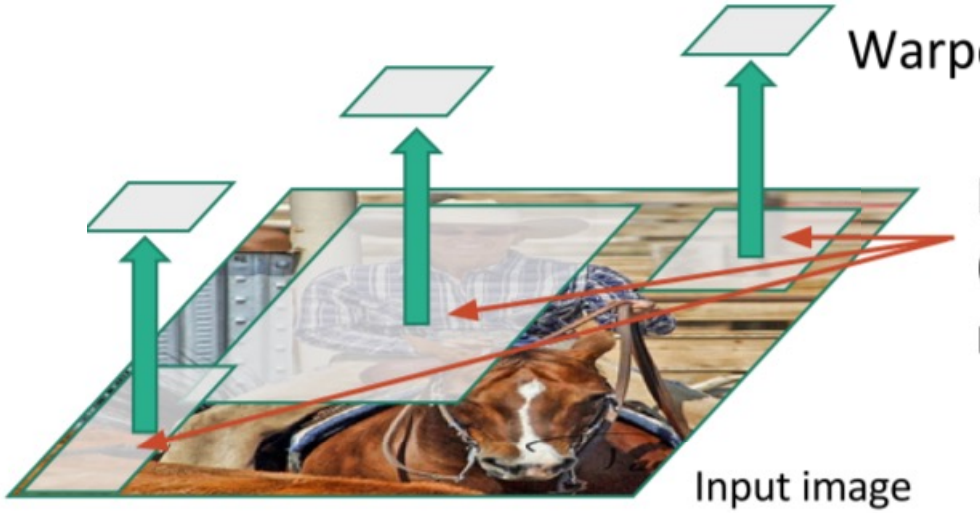
Alexe et al, “Measuring the objectness of image windows”, TPAMI 2012
Uijlings et al, “Selective Search for Object Recognition”, IJCV 2013
Cheng et al, “BING: Binarized normed gradients for objectness estimation at 300fps”, CVPR 2014
Zitnick and Dollar, “Edge boxes: Locating object proposals from edges”,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

R-CNN

Input image

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

R-CNN



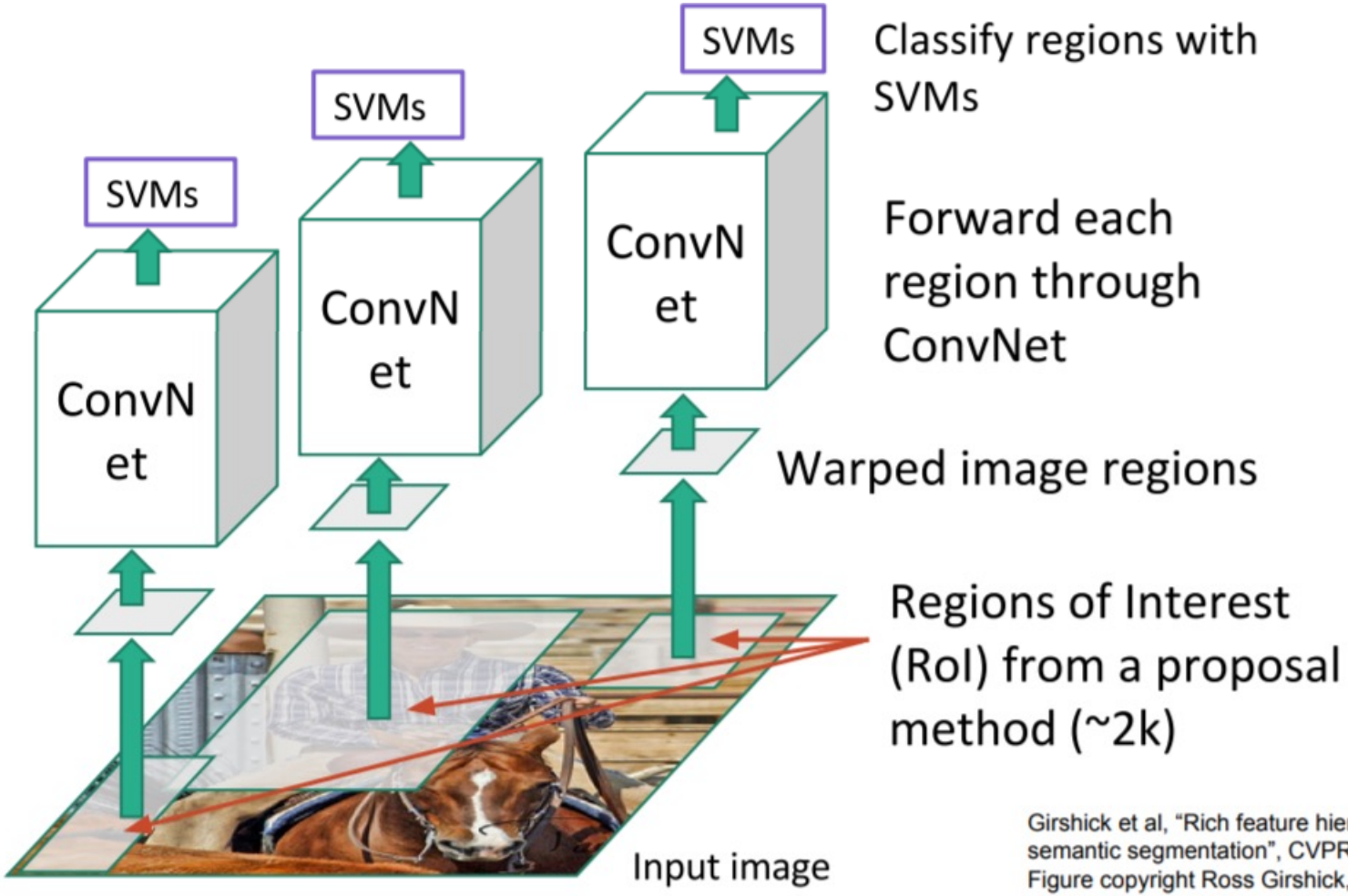
Warped image regions

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

Input image

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

R-CNN

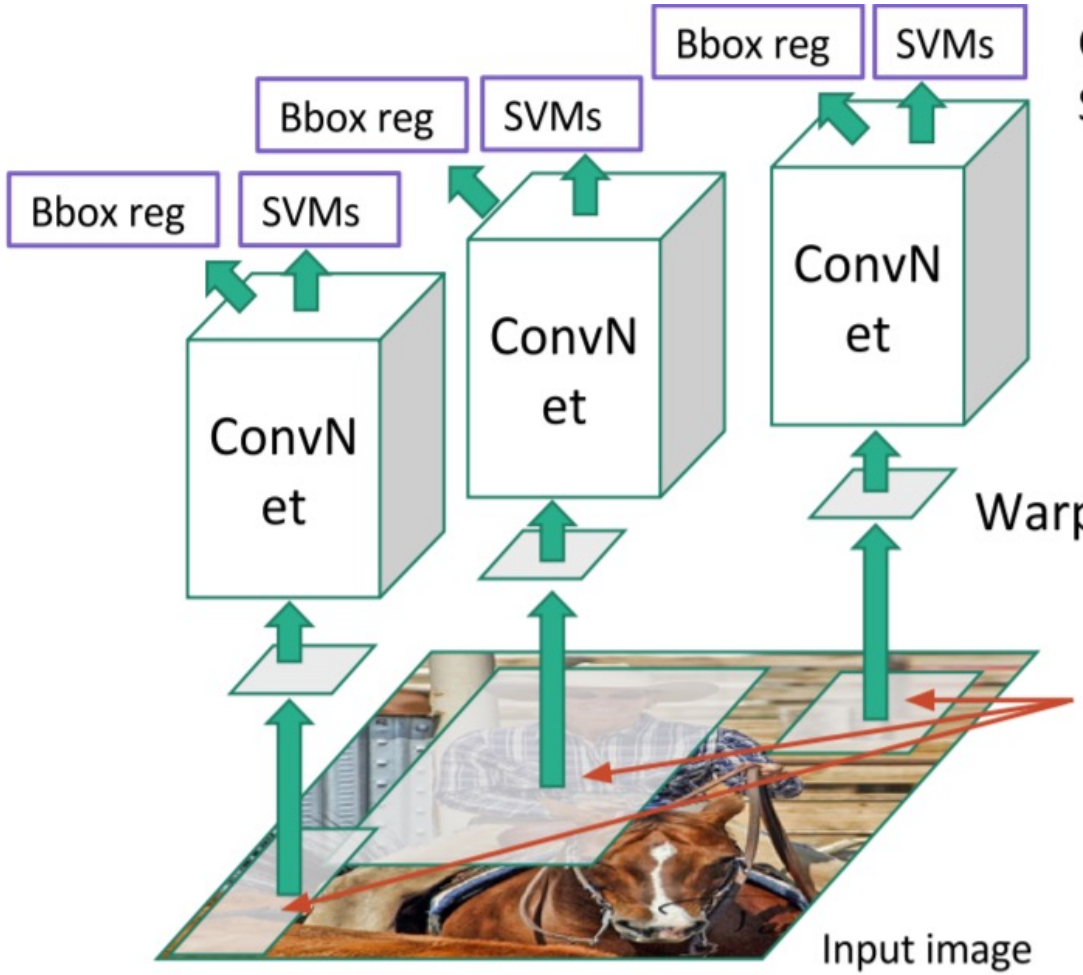


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

R-CNN

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)

Linear Regression for bounding box



Classify regions with SVMs

Forward each region through ConvNet

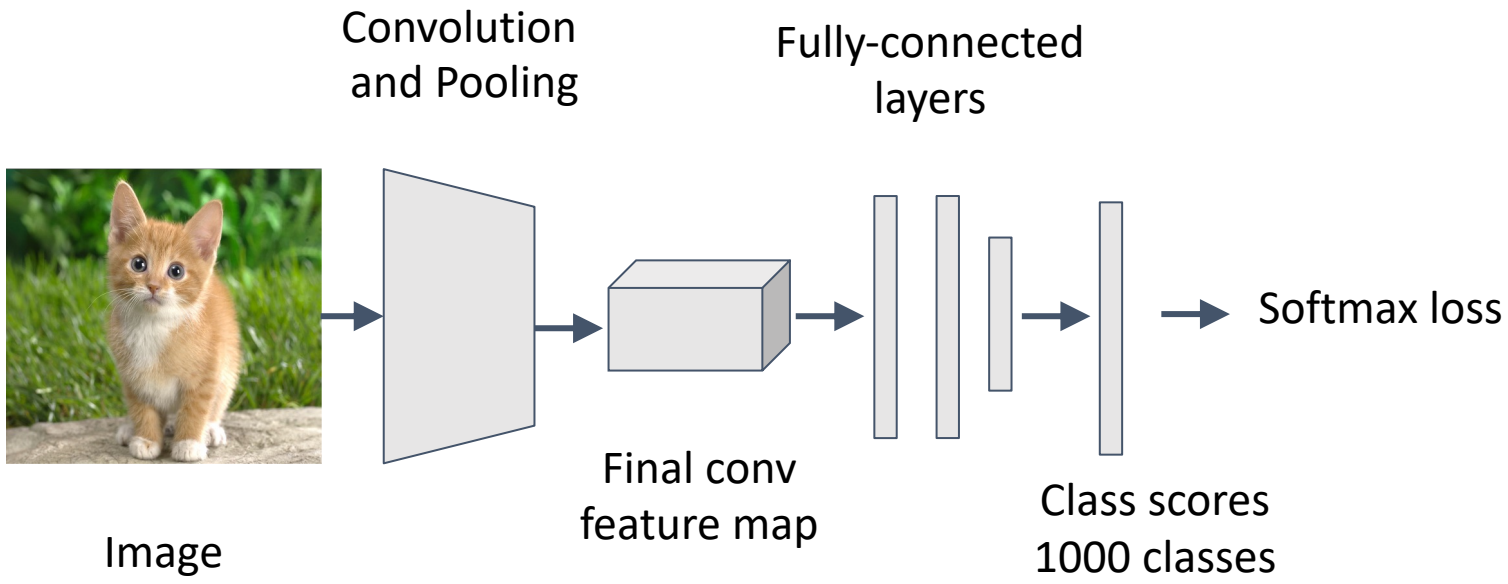
Warped image regions

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

Girshick et al, “Rich feature hierarchies for accurate object detection and semantic segmentation”, CVPR 2014.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

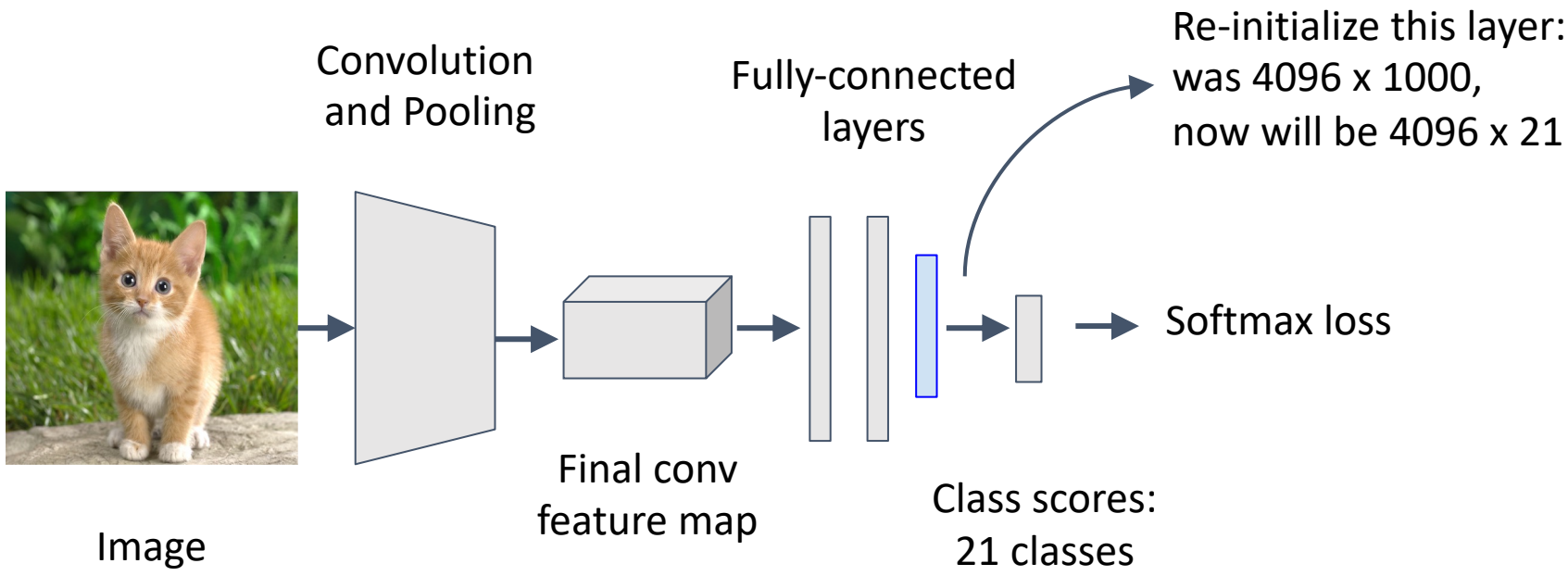
R-CNN Training

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



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

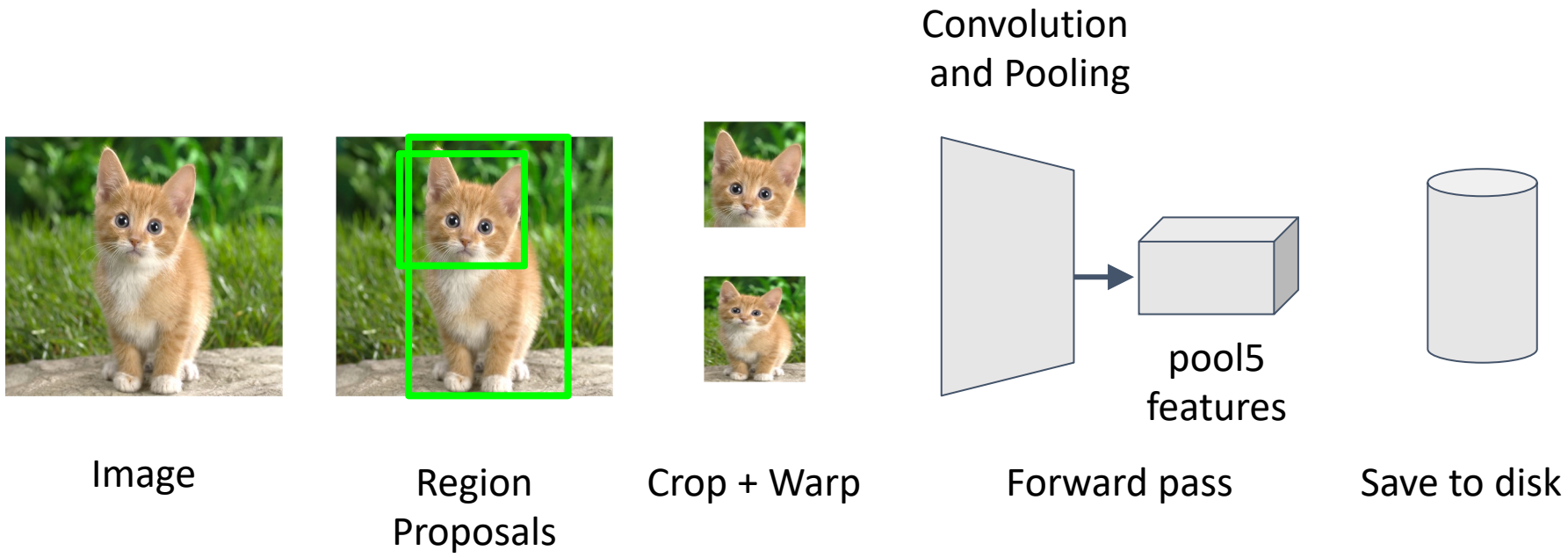


region proposals with IoU overlap ≥ 0.5 with a ground-truth box are considered as a sample for that box's class and the rest as background

R-CNN Training

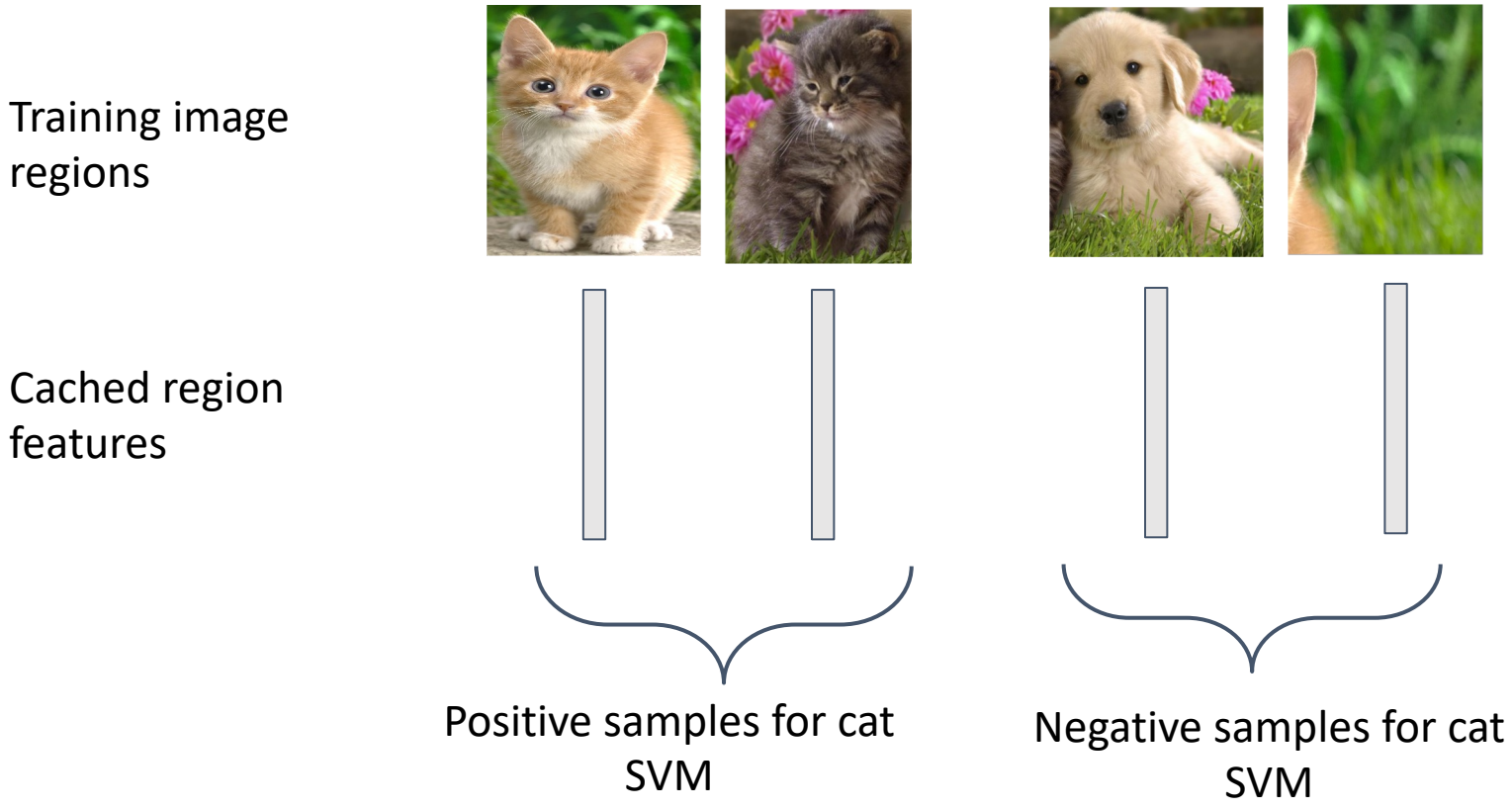
Step 3: Extract features

- 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

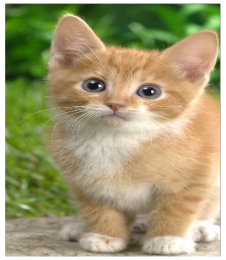
- **Step 4**: Train one binary SVM per class to classify region features

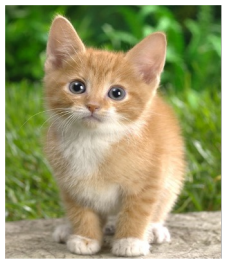


R-CNN Training

- **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

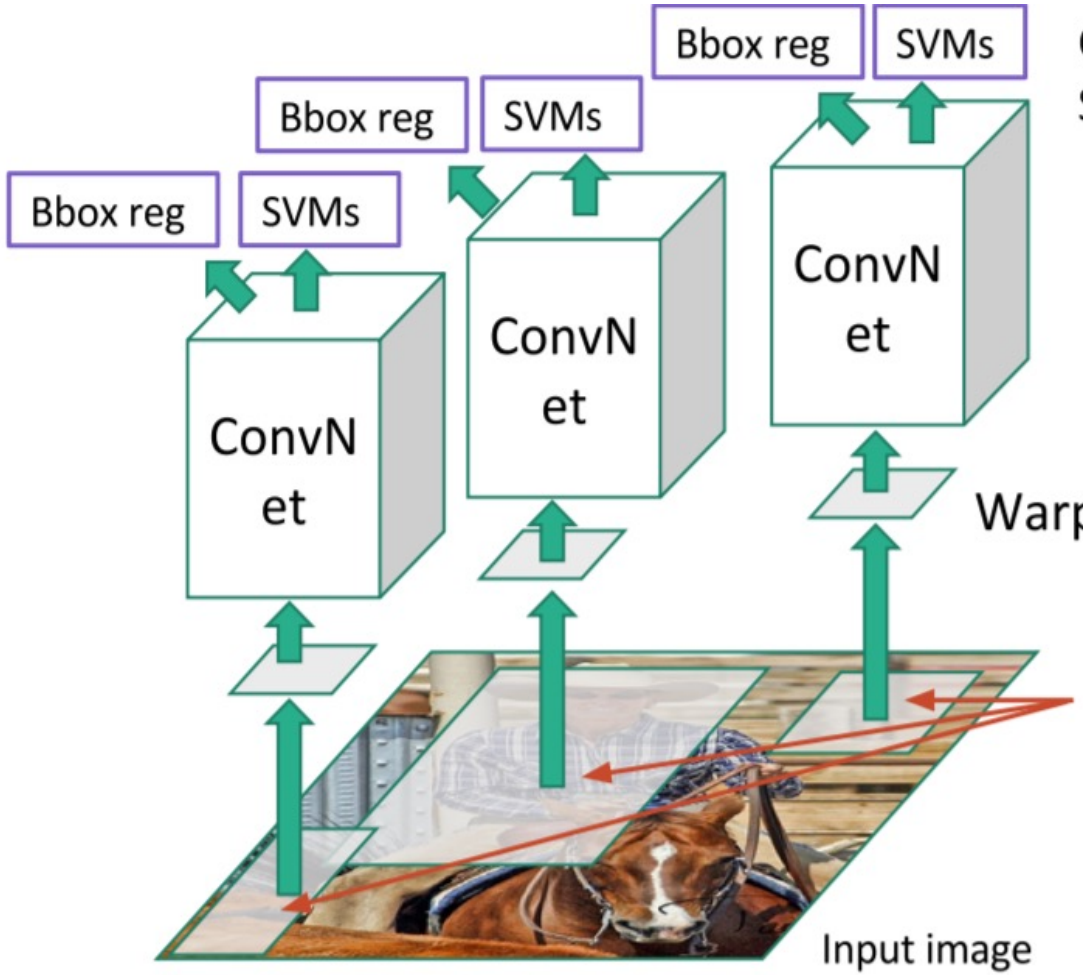
R-CNN: Problems

- 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]

R-CNN

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)

Linear Regression for bounding box



Classify regions with SVMs

Forward each region through ConvNet

Warped image regions

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

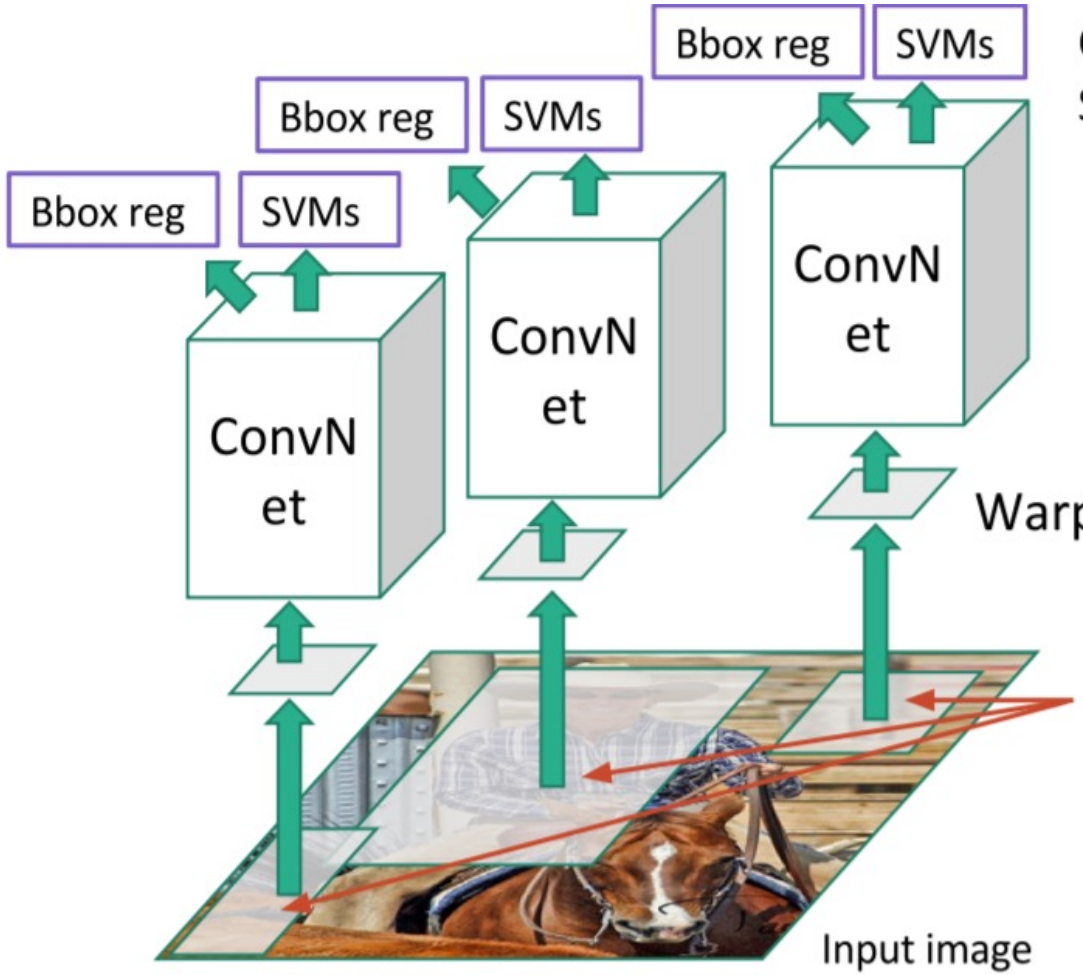
Problem: Very slow! Need to do ~2k independent forward passes for each image!

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

R-CNN

Predict “corrections” to the RoI: 4 numbers: (dx, dy, dw, dh)

Linear Regression for bounding box



Classify regions with SVMs

Forward each region through ConvNet

Warped image regions

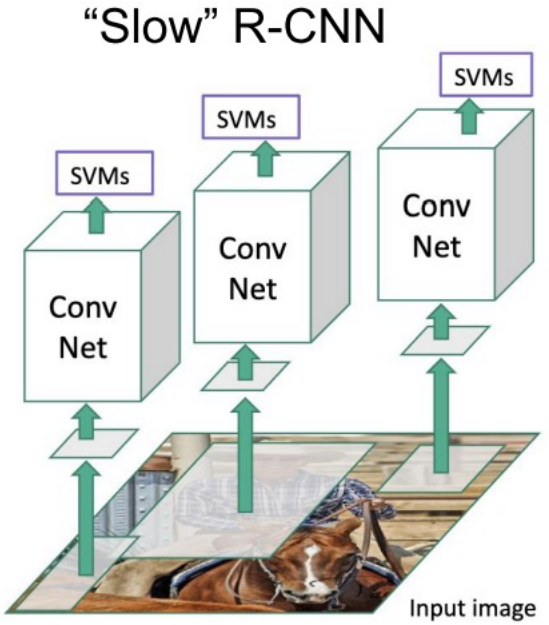
Regions of Interest (RoI) from a proposal method (~2k)

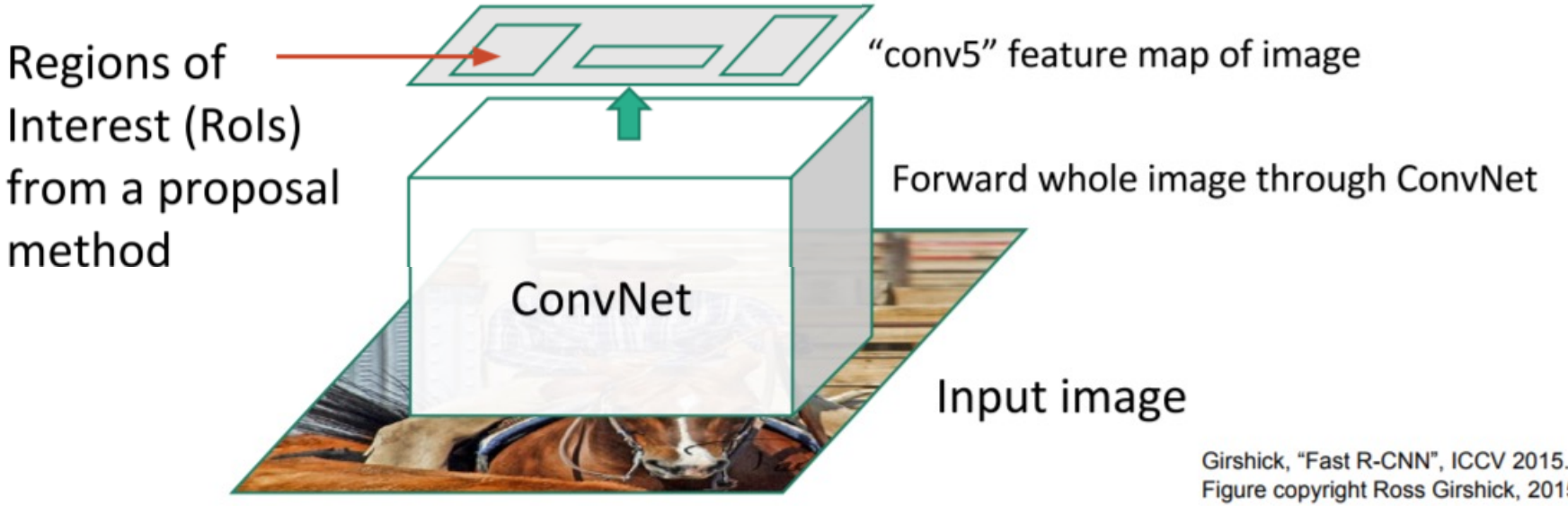
Problem: Very slow! Need to do ~2k independent forward passes for each image!

Idea: Pass the image through convnet before cropping! Crop the conv feature instead!

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

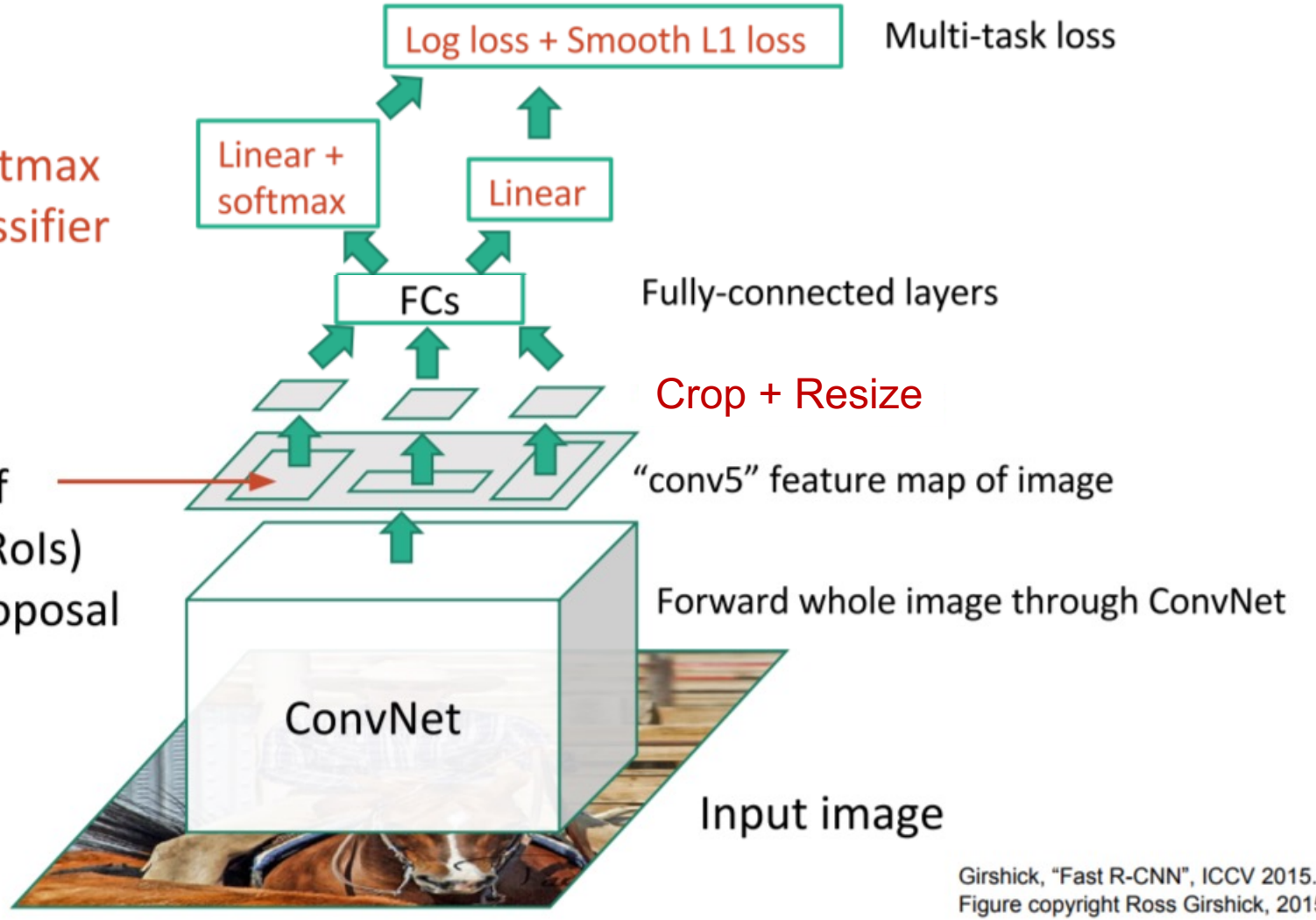
Fast R-CNN

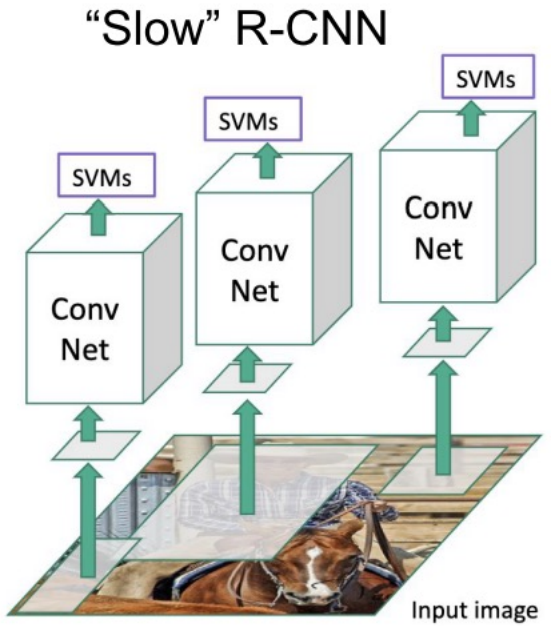




Girshick, "Fast R-CNN", ICCV 2015.
Figure copyright Ross Girshick, 2015; source. Reproduced with permission.

Fast R-CNN

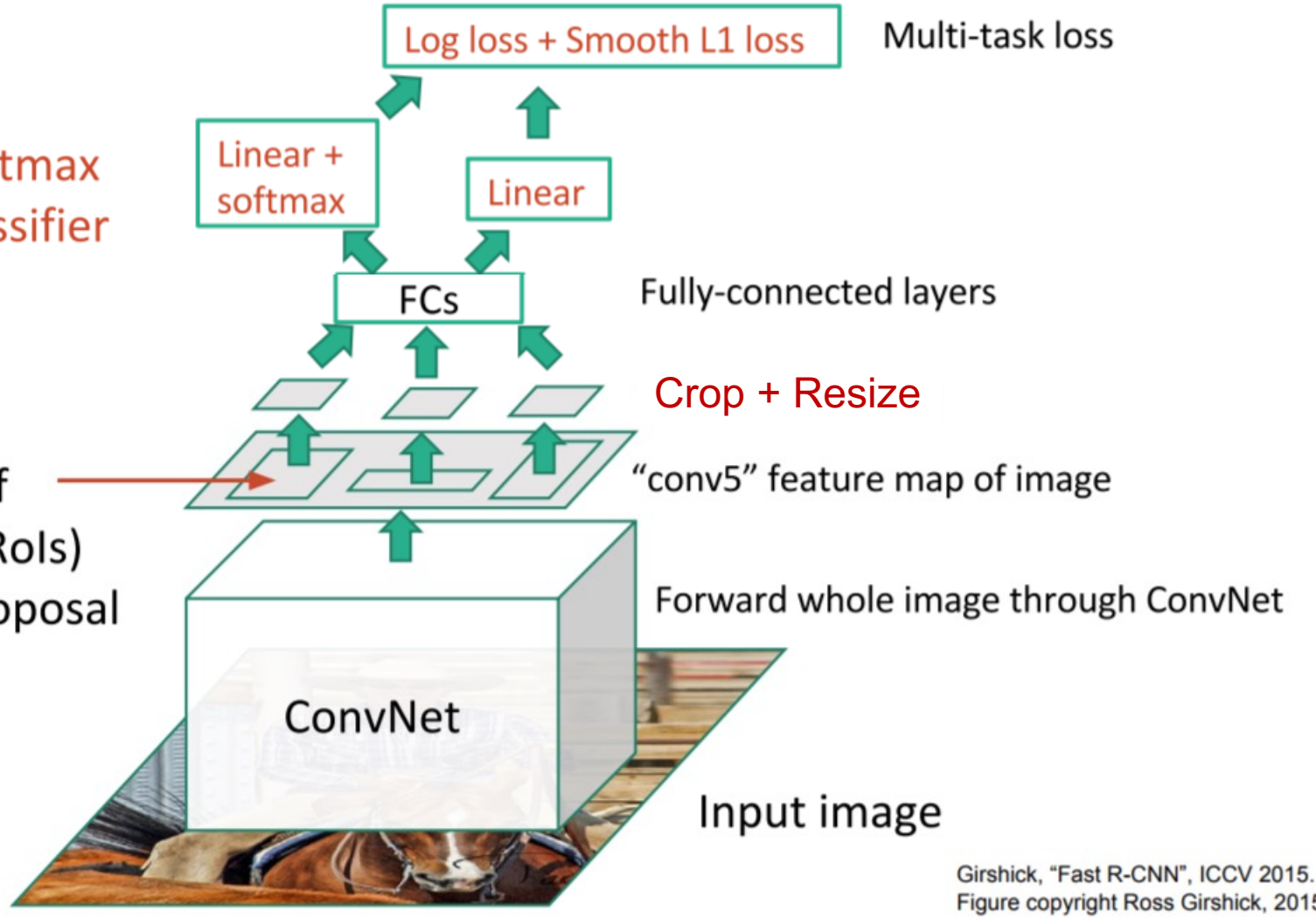




Share computation of convolutional layers between proposals for an image

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

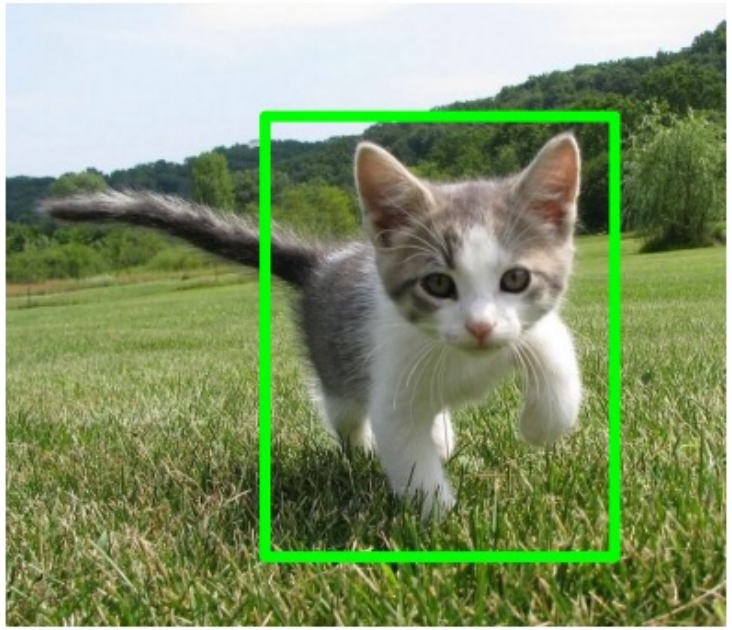
Fast R-CNN



Share computation of convolutional layers between proposals for an image

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

Cropping Features: RoI Pool



Input Image
(e.g. 3 x 640 x 480)

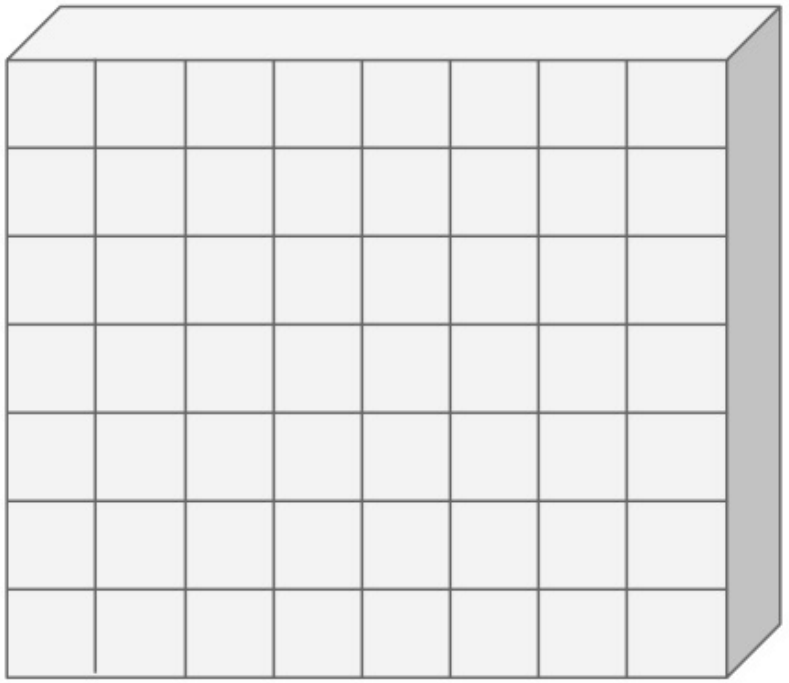
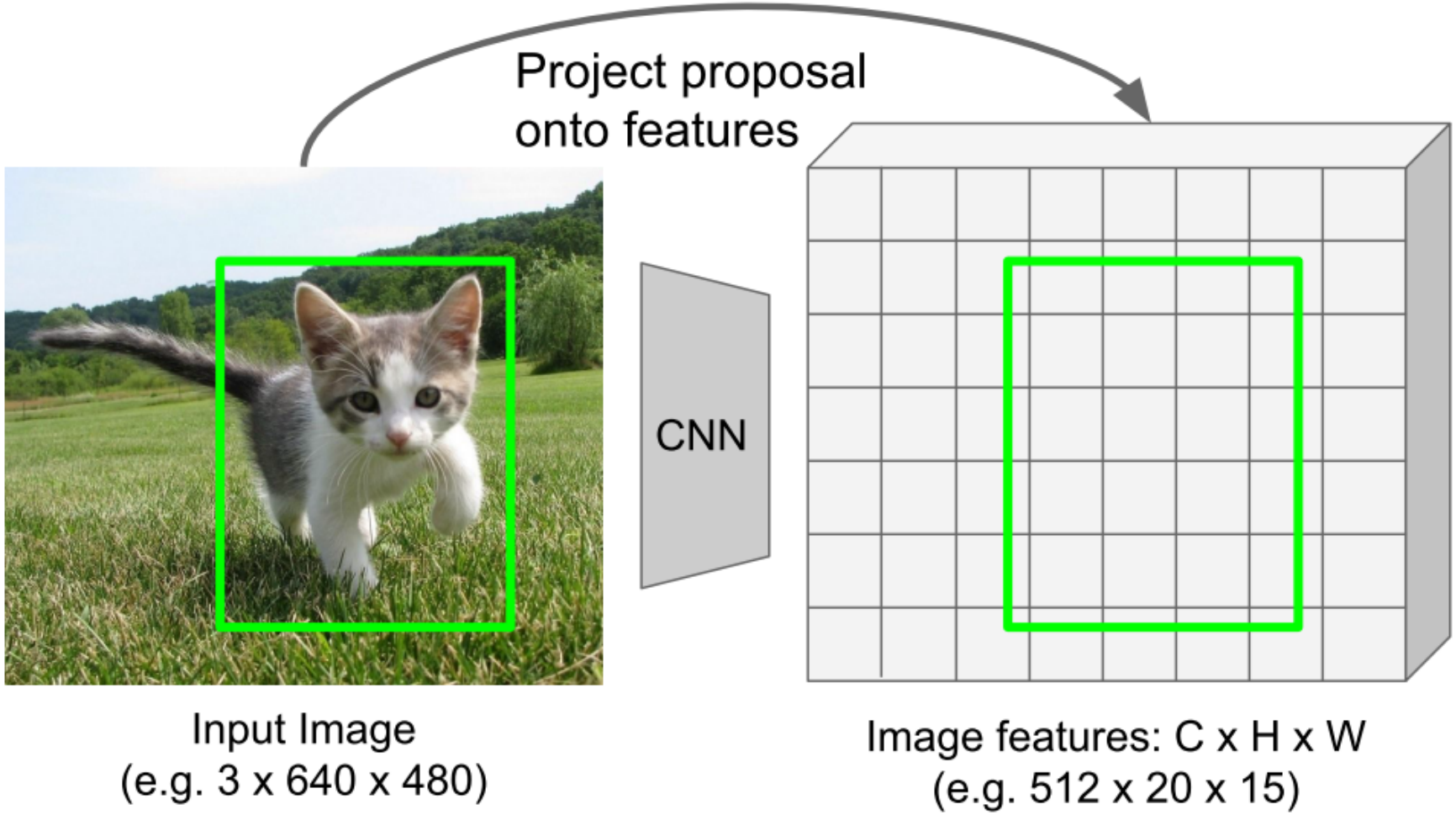


Image features: C x H x W
(e.g. 512 x 20 x 15)

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

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

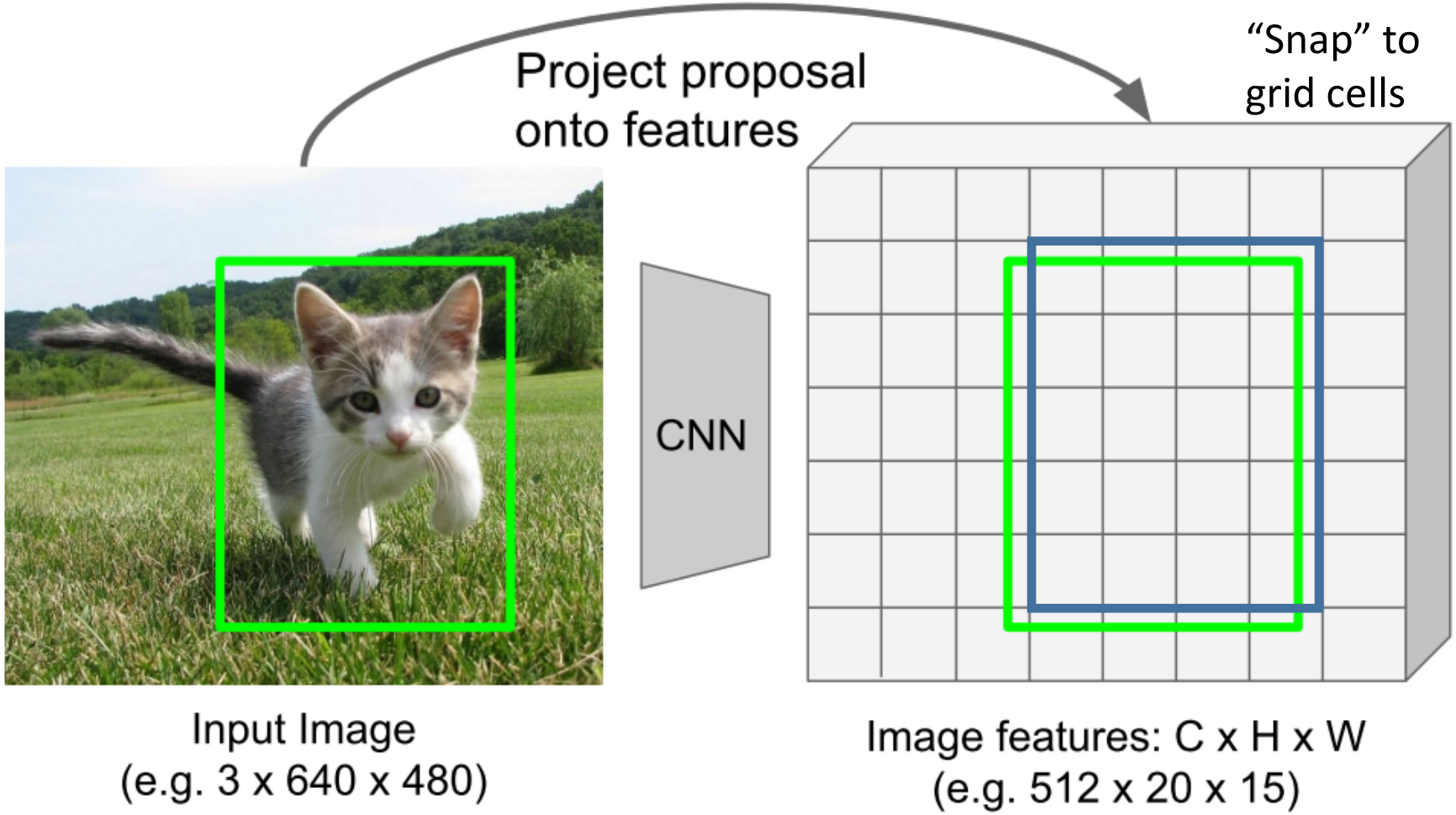
Cropping Features: RoI Pool



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

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

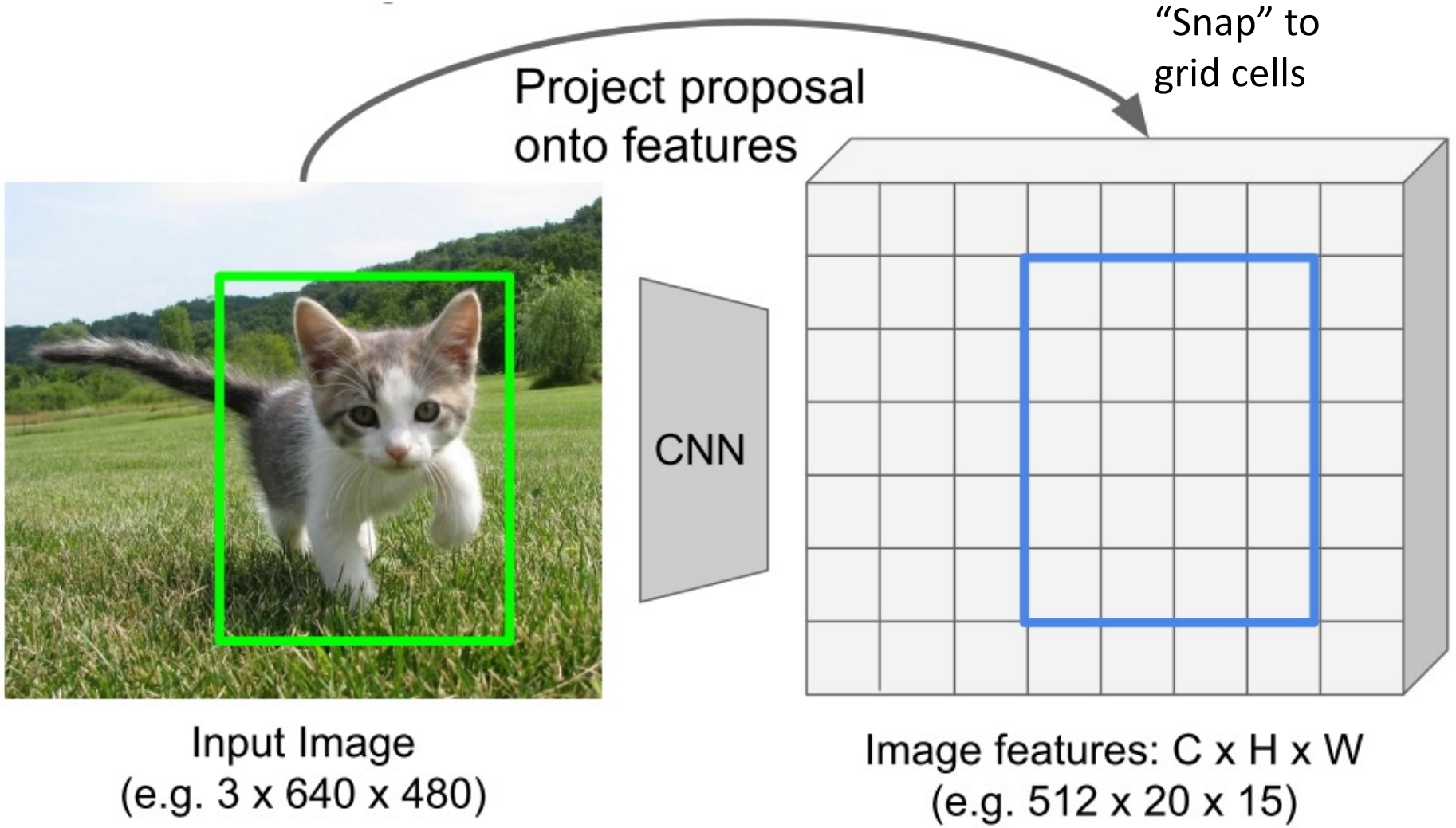
Cropping Features: RoI Pool



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

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

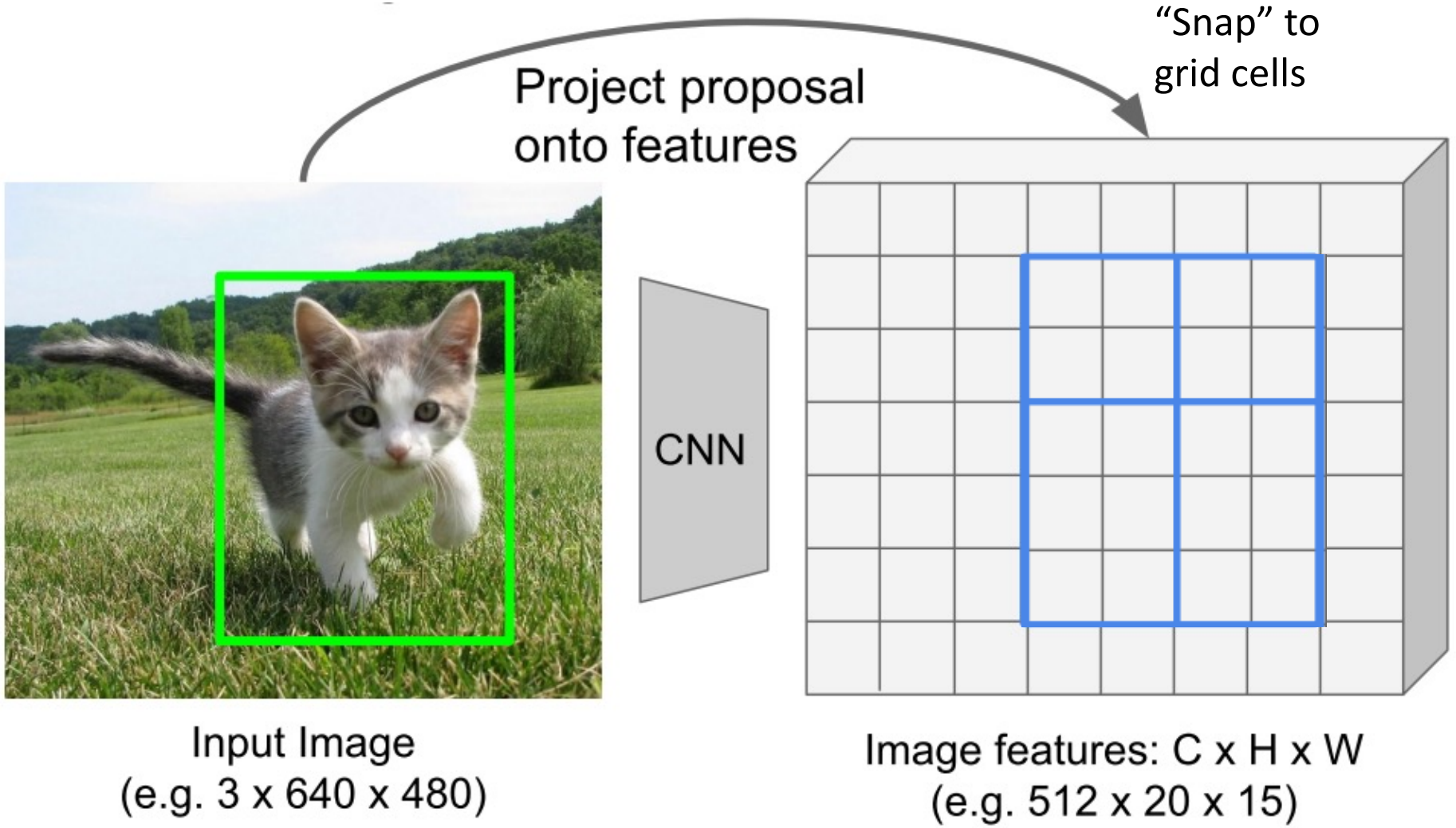
Cropping Features: RoI Pool



Q: how do we resize the 512 x 5 x 4 region to, e.g., a 512 x 2 x 2 tensor?

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

Cropping Features: RoI Pool

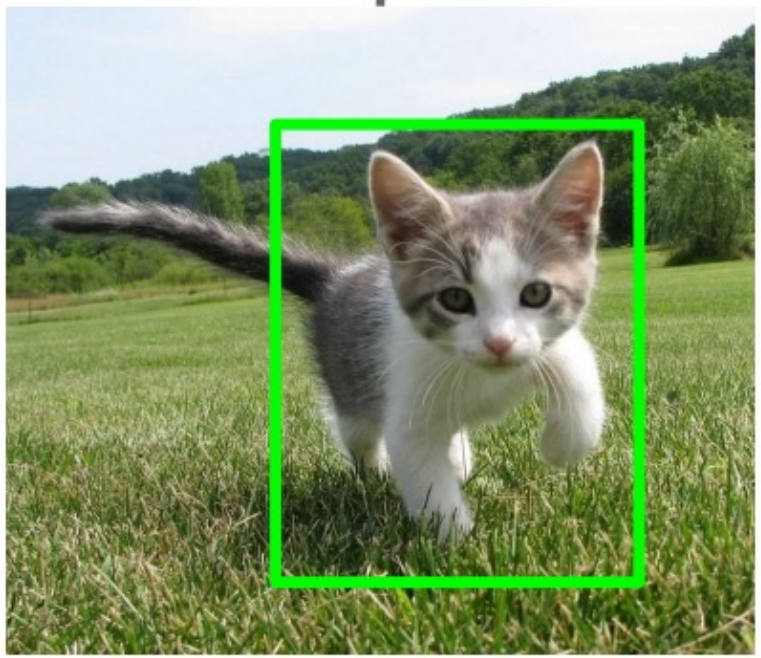


Divide into 2x2 grid of (roughly) equal subregions

Q: how do we resize the 512 x 5 x 4 region to, e.g., a 512 x 2 x 2 tensor?

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

Cropping Features: RoI Pool



Input Image
(e.g. 3 x 640 x 480)

Project proposal onto features

CNN

"Snap" to grid cells

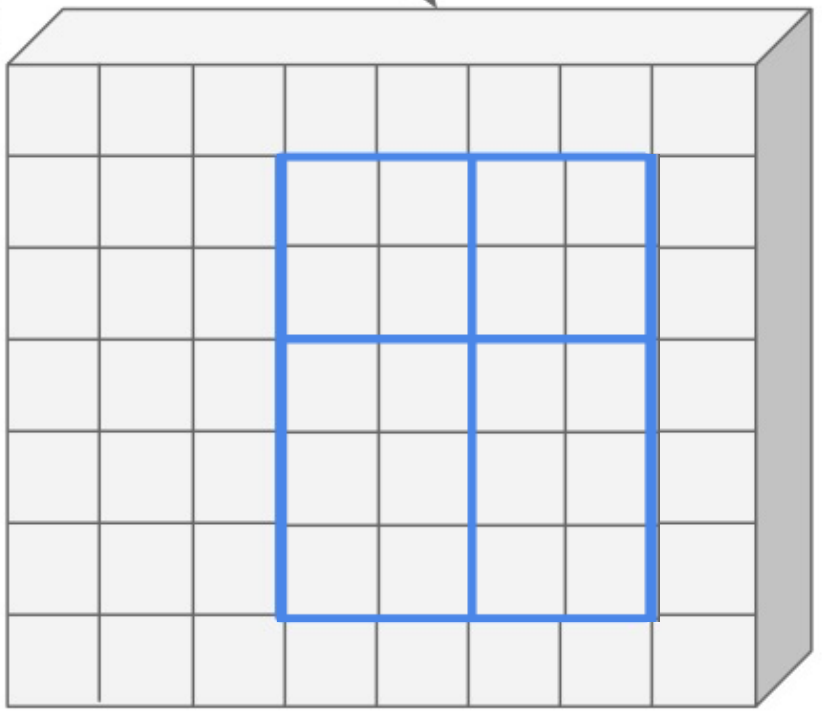
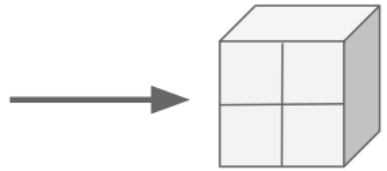


Image features: C x H x W
(e.g. 512 x 20 x 15)

Divide into 2x2 grid of (roughly) equal subregions

Max-pool within each subregion



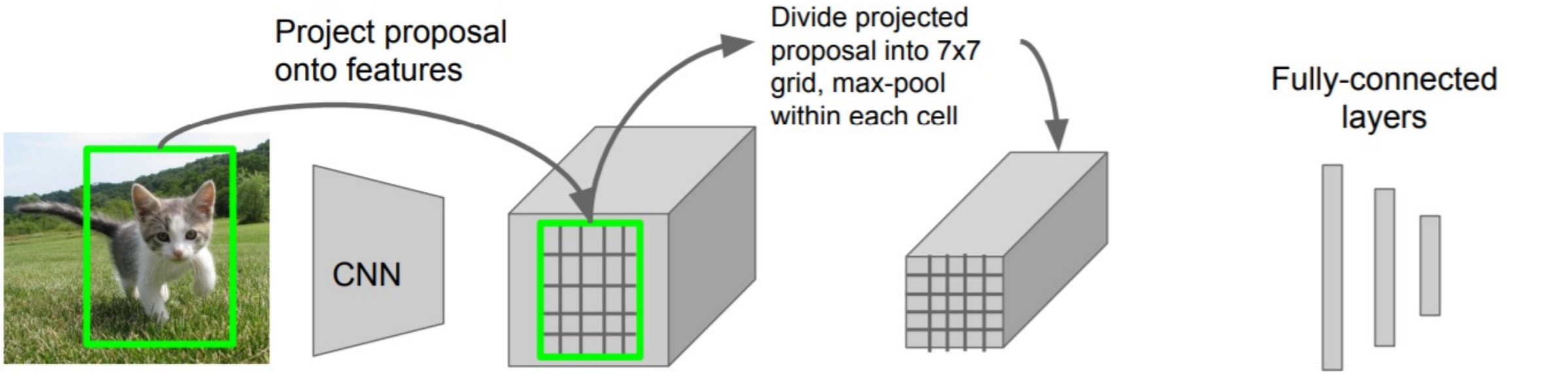
Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

Region features always the same size even if input regions have different sizes!

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

Problem: Region features slightly misaligned

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;

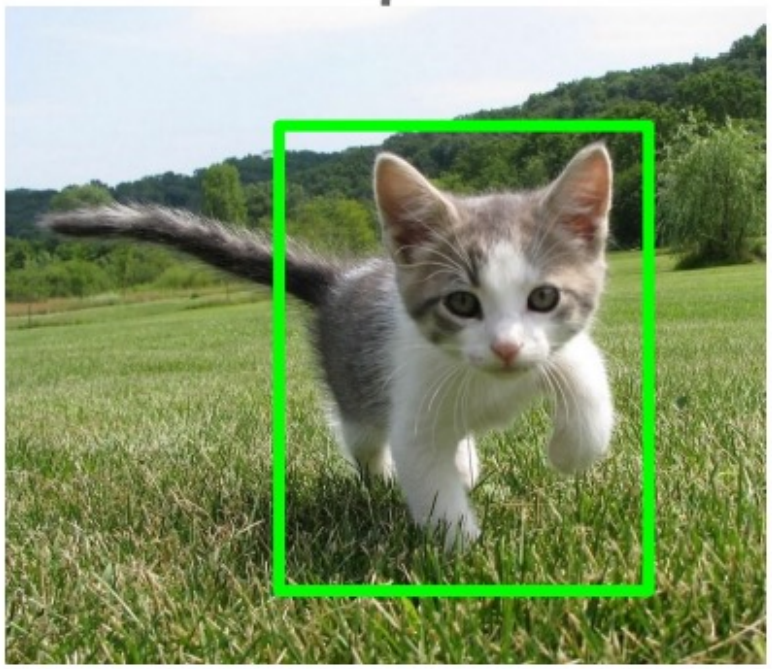
Projected region proposal is e.g.
512 x 18 x 8
(varies per proposal)

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.

Cropping Features: RoI Align



Input Image
(e.g. 3 x 640 x 480)

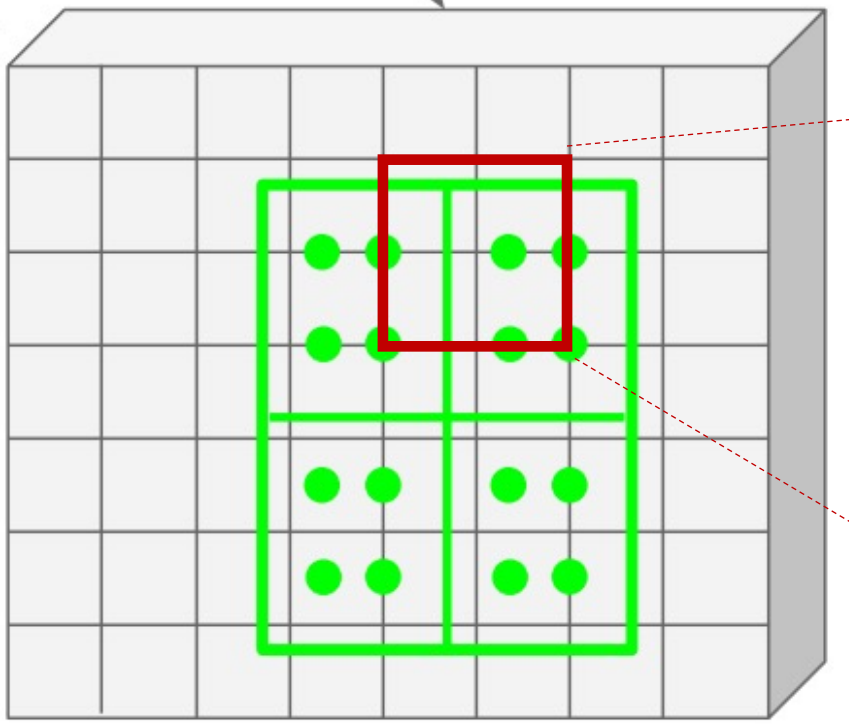
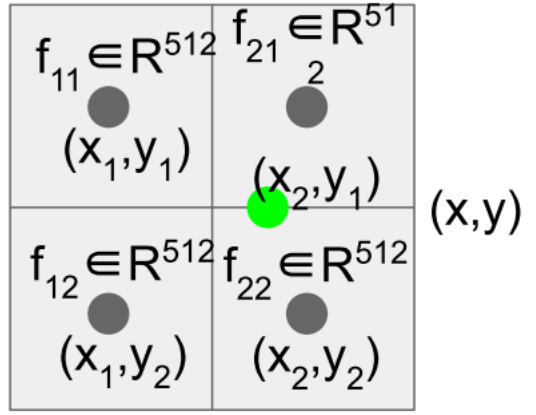


Image features: C x H x W
(e.g. 512 x 20 x 15)

Sample at regular points in each subregion using bilinear interpolation

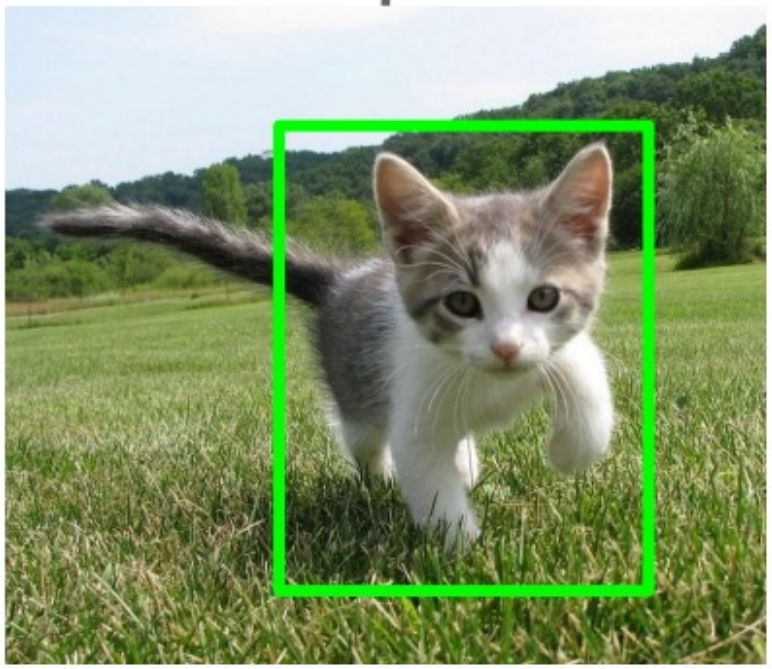


Feature f_{xy} for point (x, y) is a linear combination of features at its four neighboring grid cells:

$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

He et al, “Mask R-CNN”, ICCV 2017

Cropping Features: RoI Align



Input Image
(e.g. 3 x 640 x 480)

CNN

Project proposal onto features

No “snapping”!

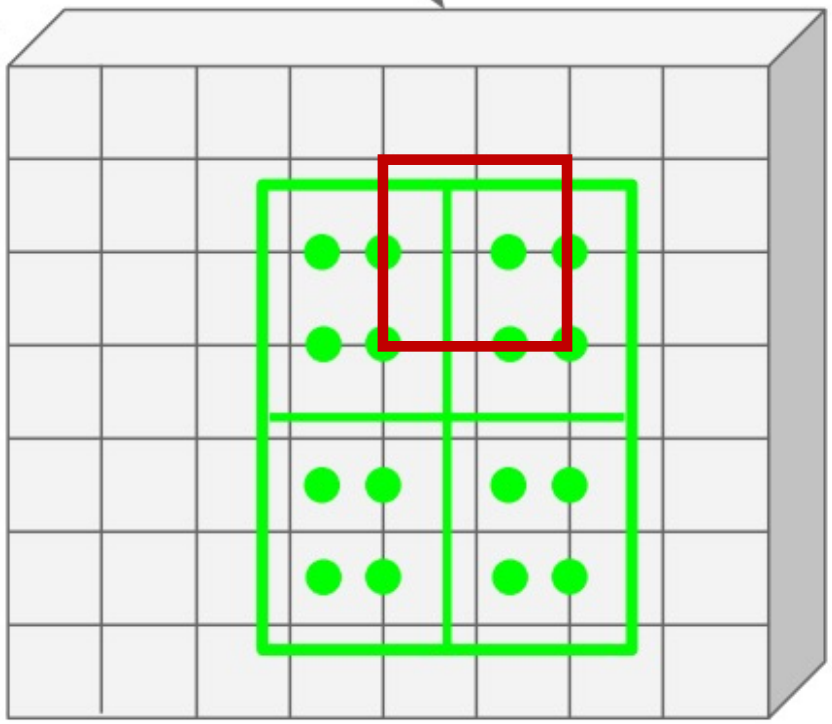
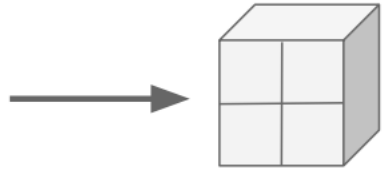


Image features: C x H x W
(e.g. 512 x 20 x 15)

Max-pool within each subregion

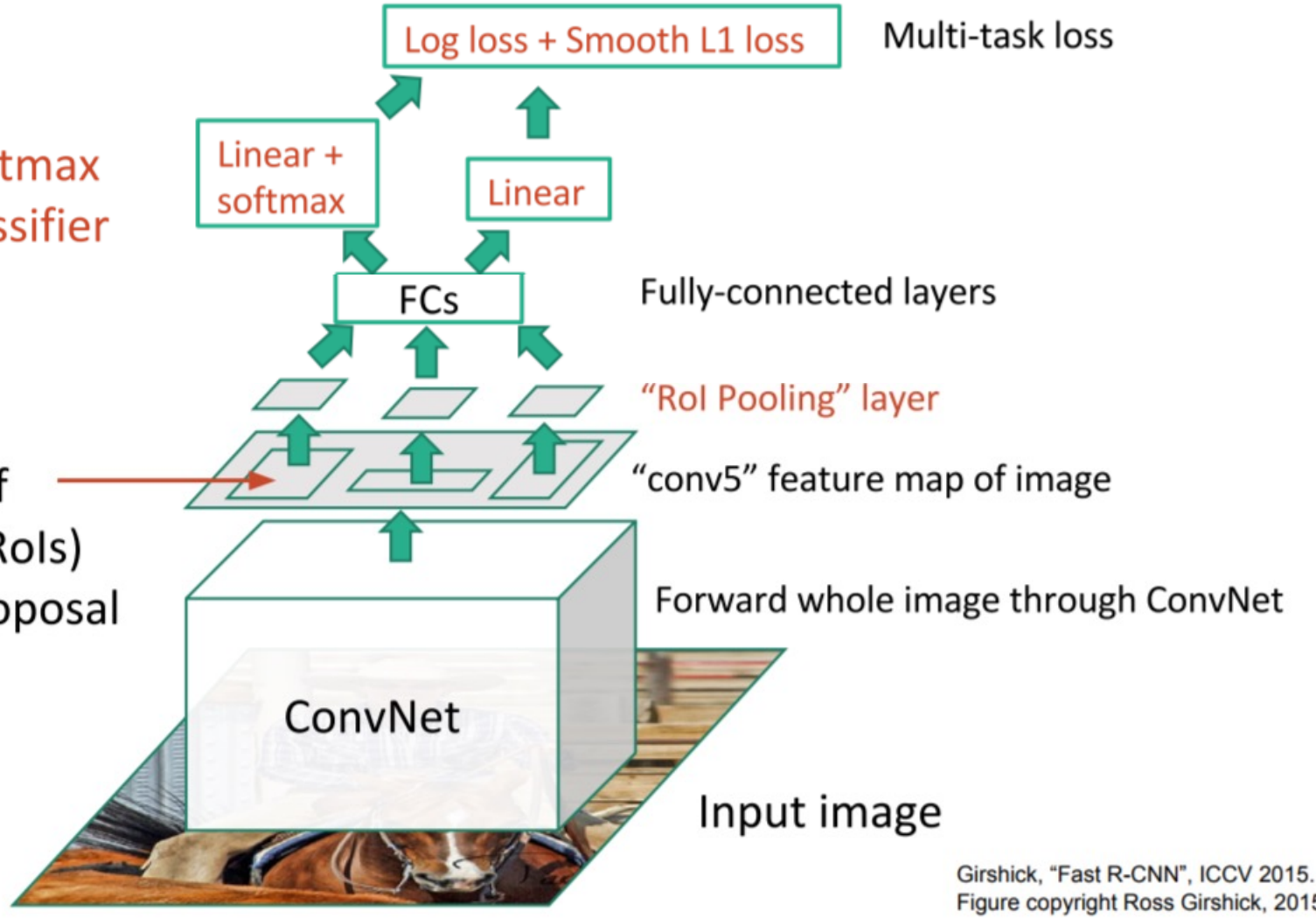


Region features
(here 512 x 2 x 2;
In practice e.g 512 x 7 x 7)

He et al, “Mask R-CNN”, ICCV 2017

$$f_{xy} = \sum_{i,j=1}^{2} f_{i,j} \max(0, 1 - |x - x_i|) \max(0, 1 - |y - y_j|)$$

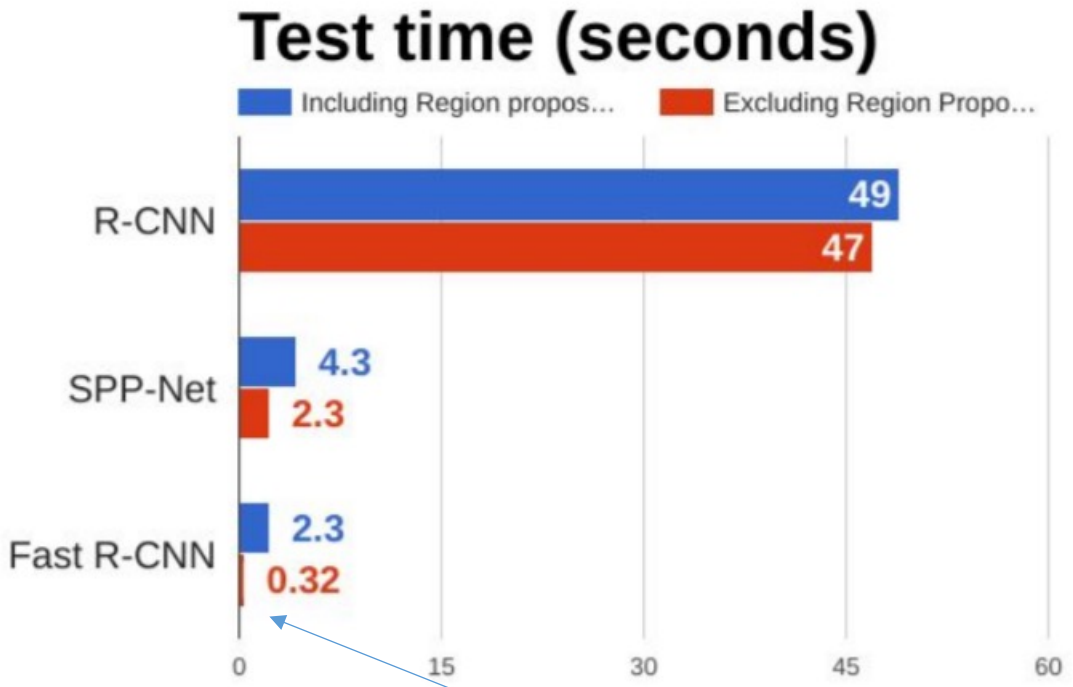
Fast R-CNN



Share computation of convolutional layers between proposals for an image

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

R-CNN vs SPP vs Fast R-CNN

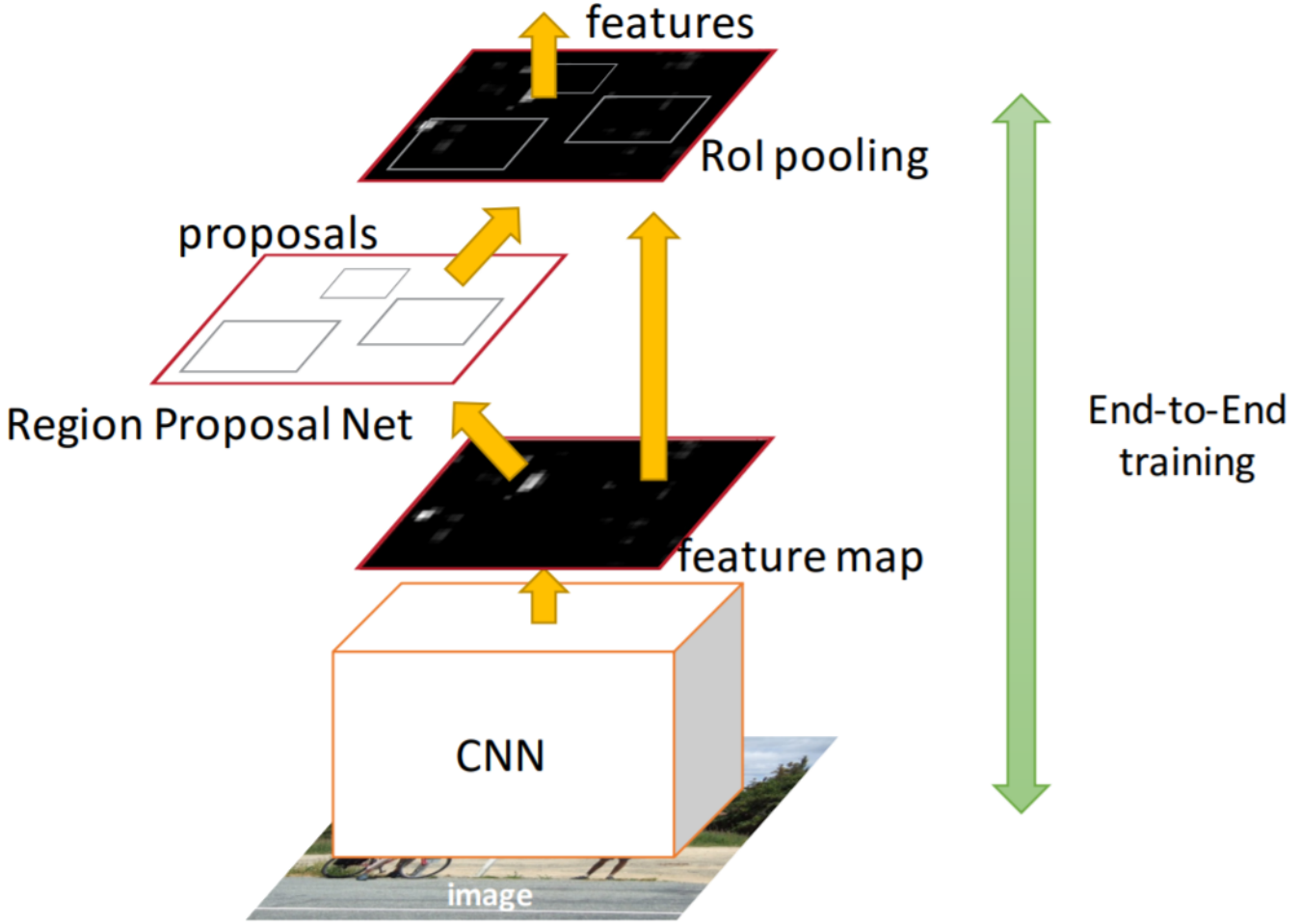


Girshick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014.
He et al, "Spatial pyramid pooling in deep convolutional networks for visual recognition", ECCV 2014
Girshick, "Fast R-CNN", ICCV 2015

Problem: Runtime dominated by region proposals!

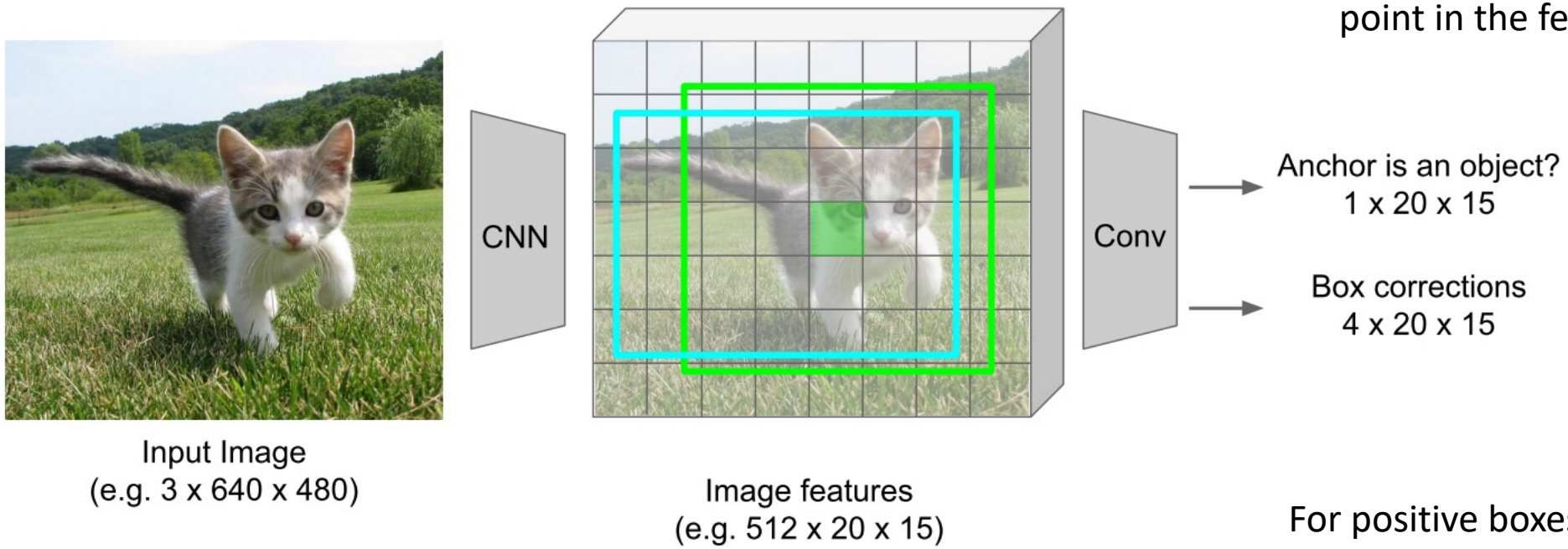
Faster R-CNN

- 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

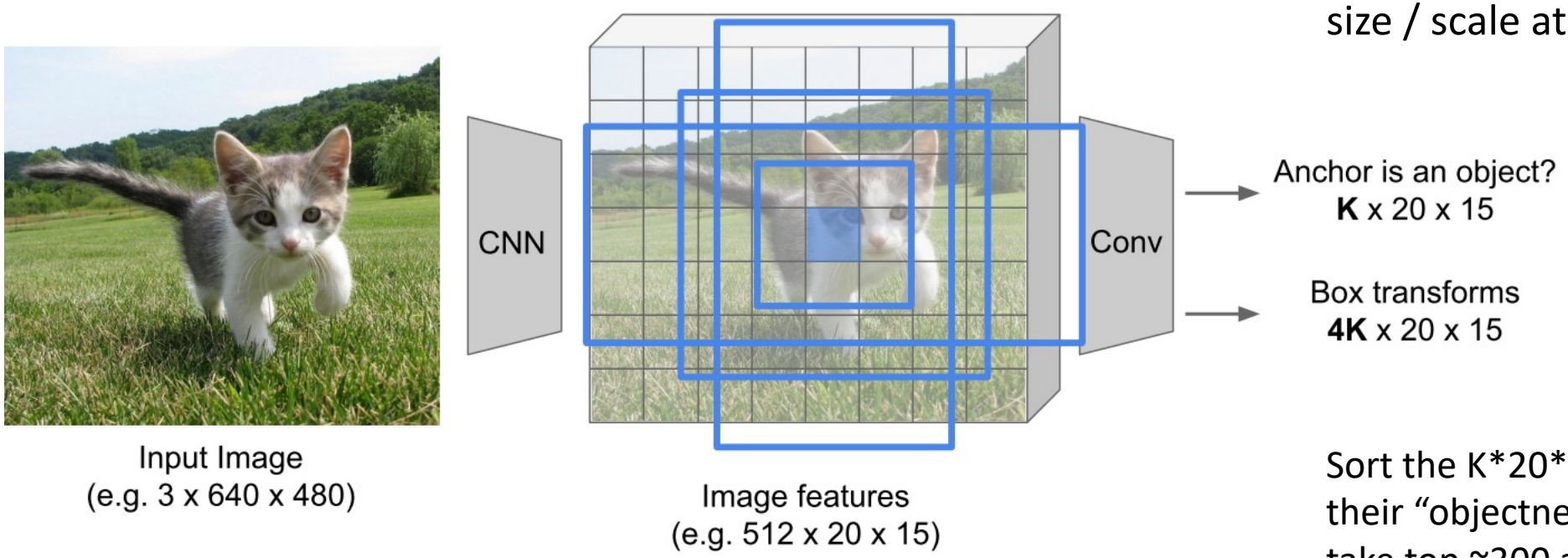
Region Proposal Network



Imagine an anchor box of fixed size at each point in the feature map

For positive boxes, also predict a corrections from the anchor to the ground-truth box (regress 4 numbers per pixel)

Region Proposal Network

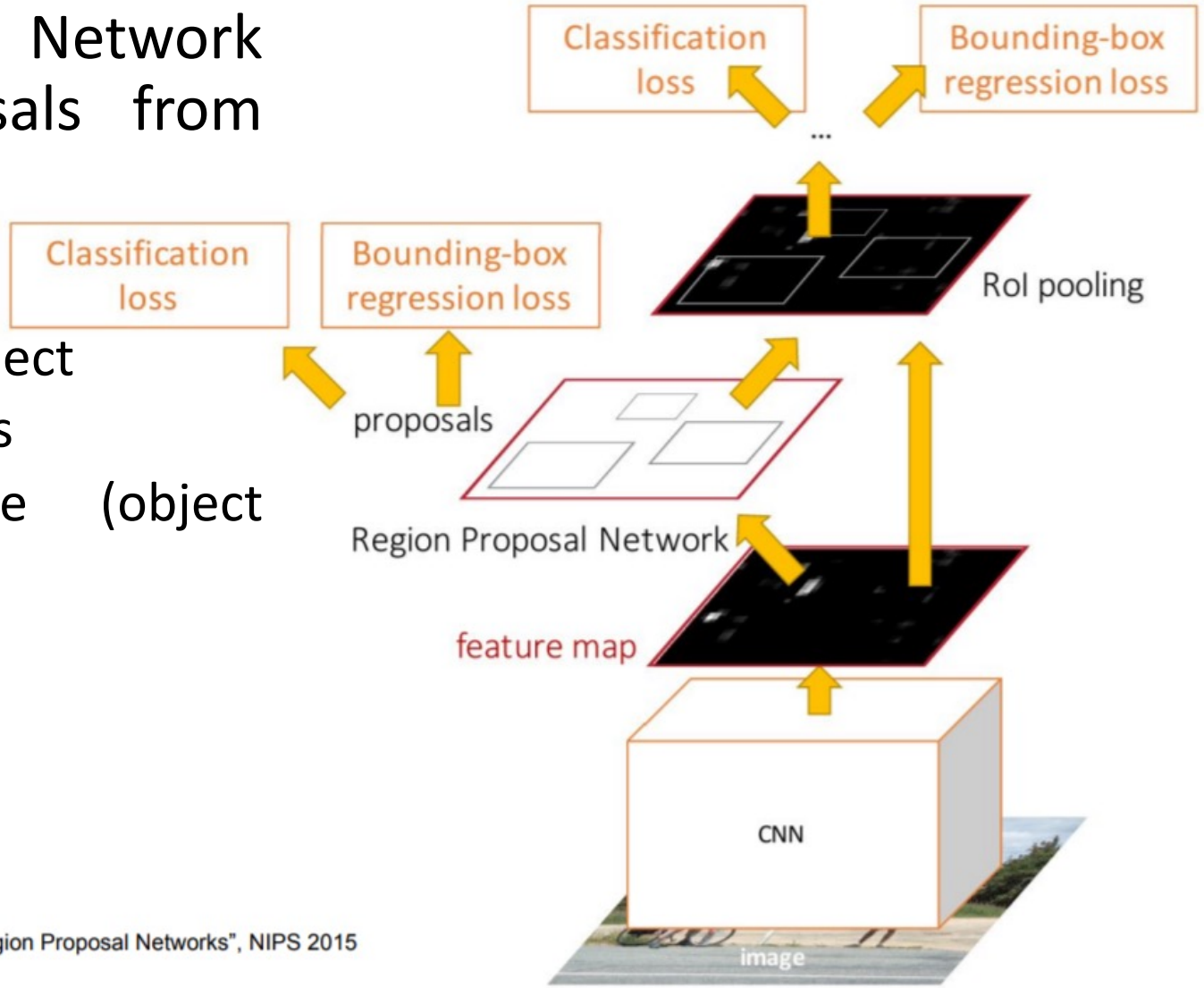


In practice use K different anchor boxes of different size / scale at each point

Sort the K*20*15 boxes by their “objectness” score, take top ~300 as our proposals

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

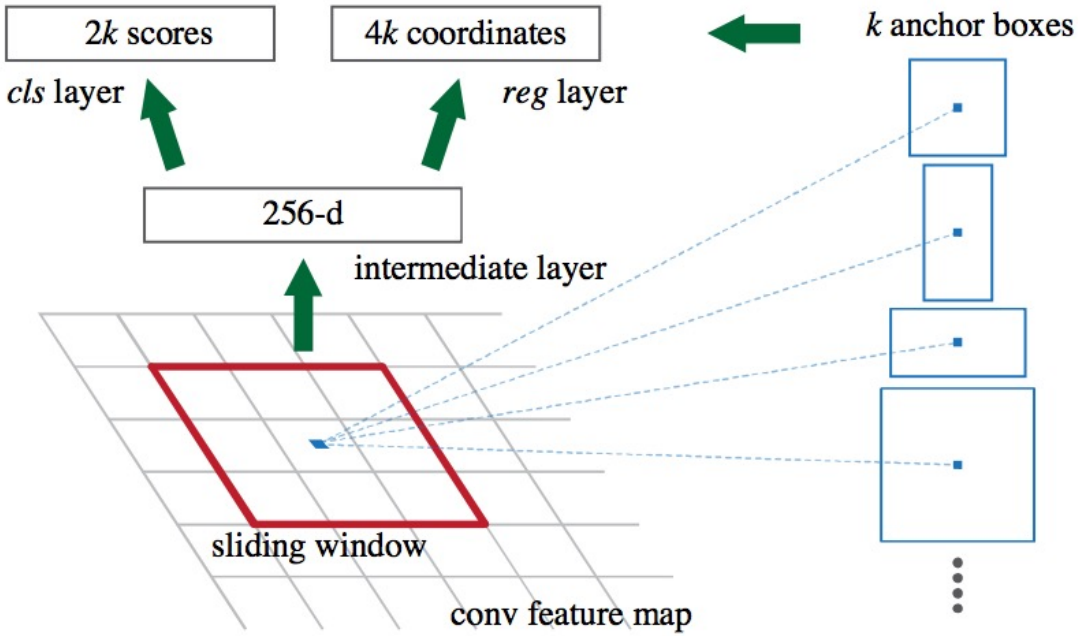
Faster R-CNN: Region Proposal Network

Use **K anchor boxes** at each location (e.g. K=3*3 showing boxes of 3 different sizes and 3 different aspect ratio at that location)

Mini-network operates in a sliding-window fashion (shared across all spatial locations)

Regression gives offsets from anchor boxes

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



Slide credit: Kaiming He

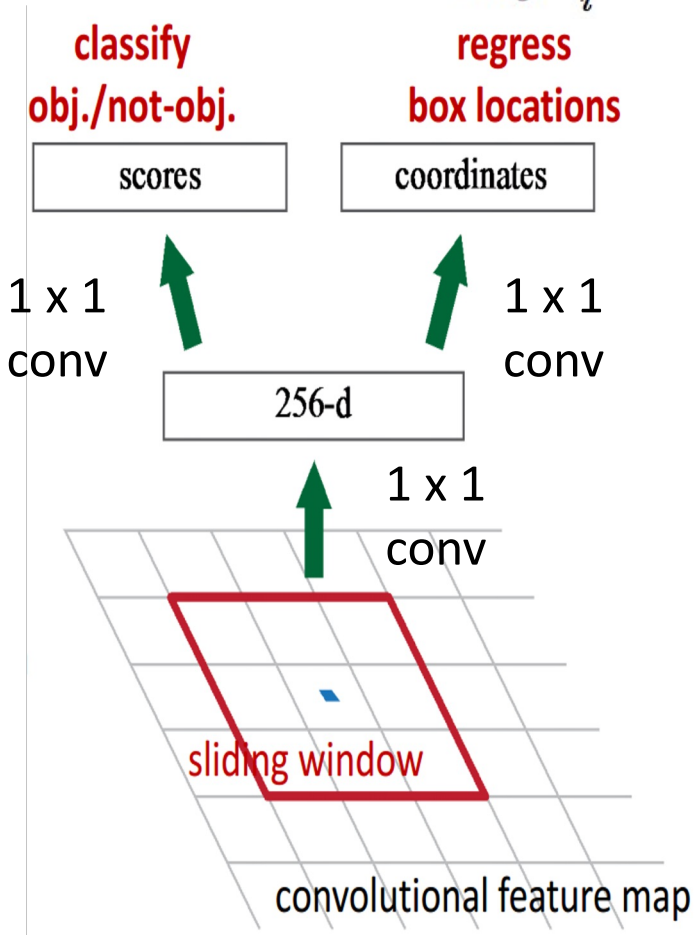
Faster R-CNN: Region Proposal Network

Slide a small window on the feature map

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

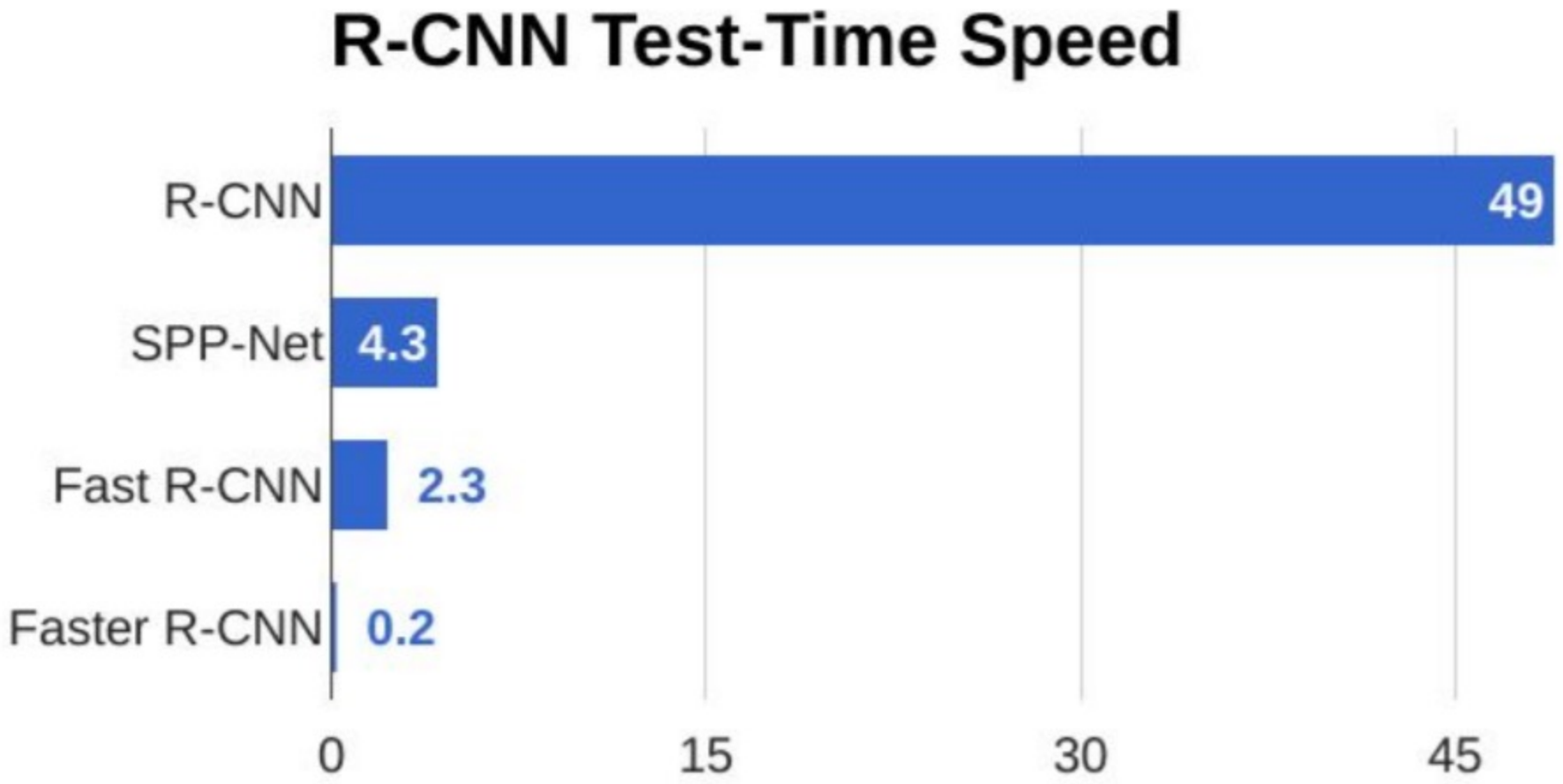
Box regression provides finer localization information with reference to the sliding window

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p_i^*) + \lambda\frac{1}{N_{reg}}\sum_i p_i^* L_{reg}(t_i, t_i^*).$$



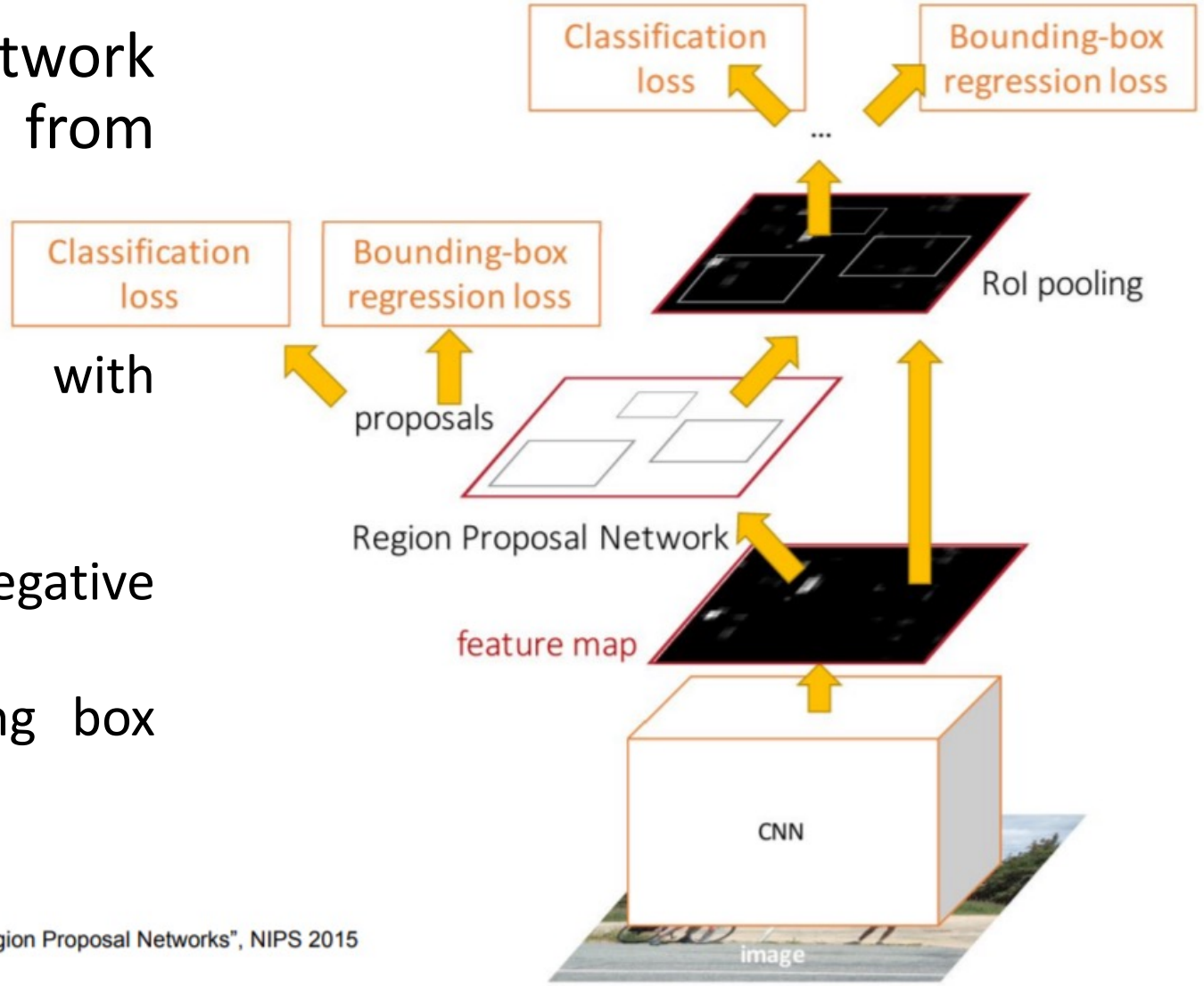
Slide credit: Kaiming He

Faster R-CNN: Make CNN do proposals!



Faster R-CNN

- Insert Region Proposal Network (RPN) to predict proposals from features Jointly
- Glossing over many details:
  - Ignore overlapping proposals with non-max suppression
  - How are anchors determined?
  - How do we sample positive / negative samples for training the RPN?
  - How to parameterize bounding box regression?



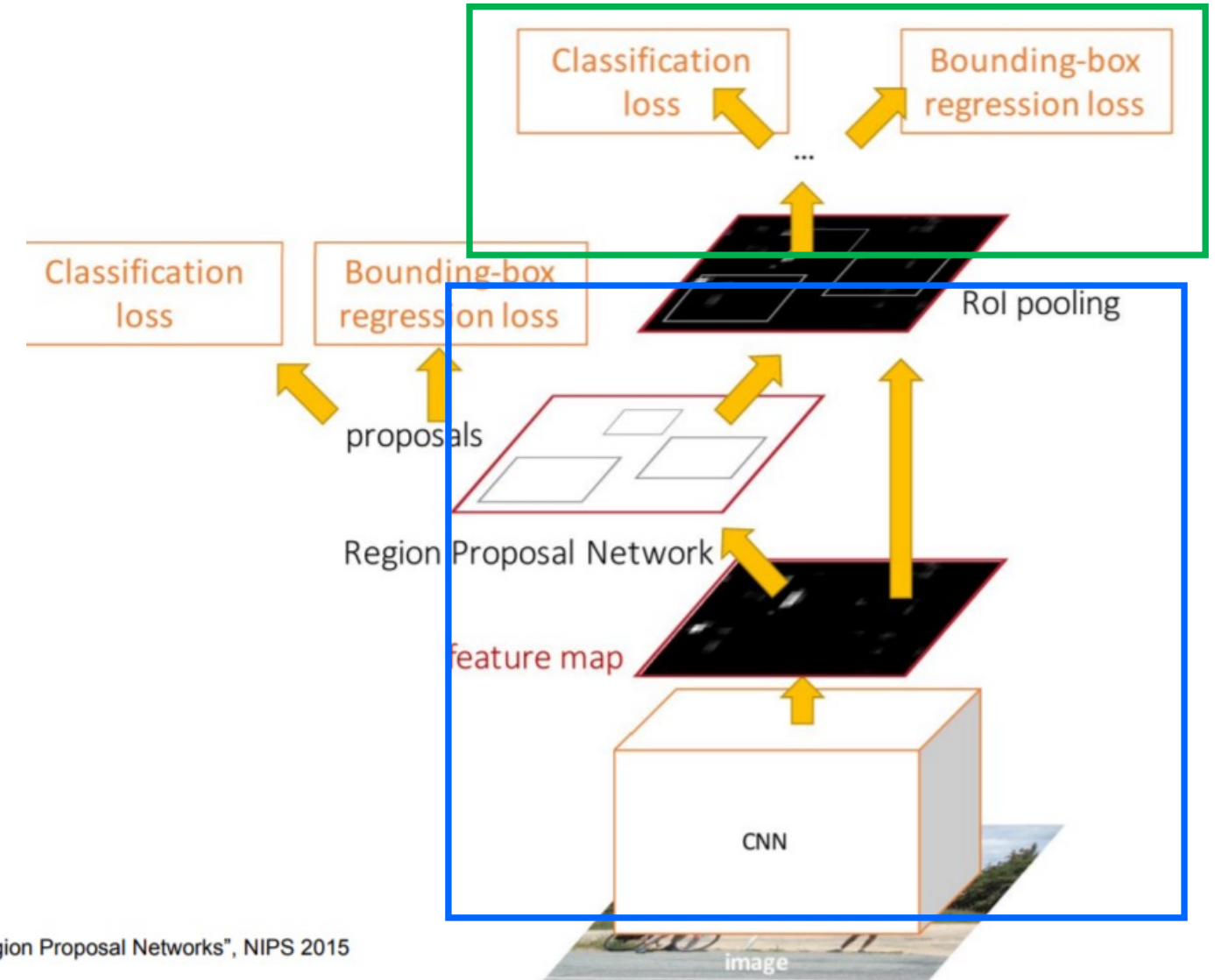
Ren et al, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks", NIPS 2015
Figure copyright 2015, Ross Girshick; reproduced with permission

Faster R-CNN

Faster R-CNN is a
Two-stage object detector

First stage: Run once per image
- Backbone network
- Region proposal network

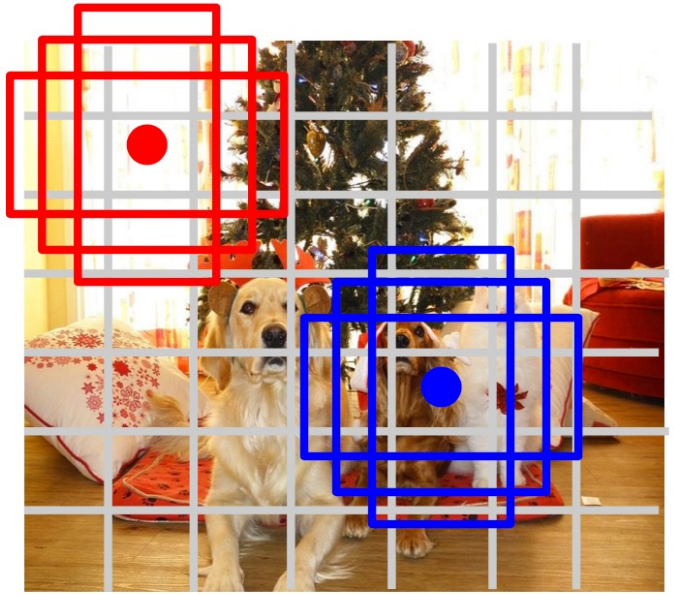
Second stage: Run once per region
- Crop features: RoI pool / align
- Predict object class
- Prediction bbox offset



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

Detection without Proposals: YOLO/SSD

Input image
3 x H x W



Divide image into grid
7 x 7

Image a set of **base boxes** centered at each grid cell
Here B = 3

Within each grid cell:

- Regress from each of the B base boxes to a final box with 5 numbers: (dx, dy, dh, dw, confidence)
- Predict scores for each of C classes (including background as a class)

Output:
7 x 7 x (5 * B + C)

Redmon et al, "You Only Look Once: Unified, Real-Time Object Detection", CVPR 2016
Liu et al, "SSD: Single-Shot MultiBox Detector", ECCV 2016

Object Detection: Lots of Variables …

Base Network
VGG16
ResNet-101
Inception V2
Inception V3
Inception
ResNet
MobileNet

Object Detection architecture
Faster R-CNN
R-FCN
SSD

Image Size
 # Region Proposals
…

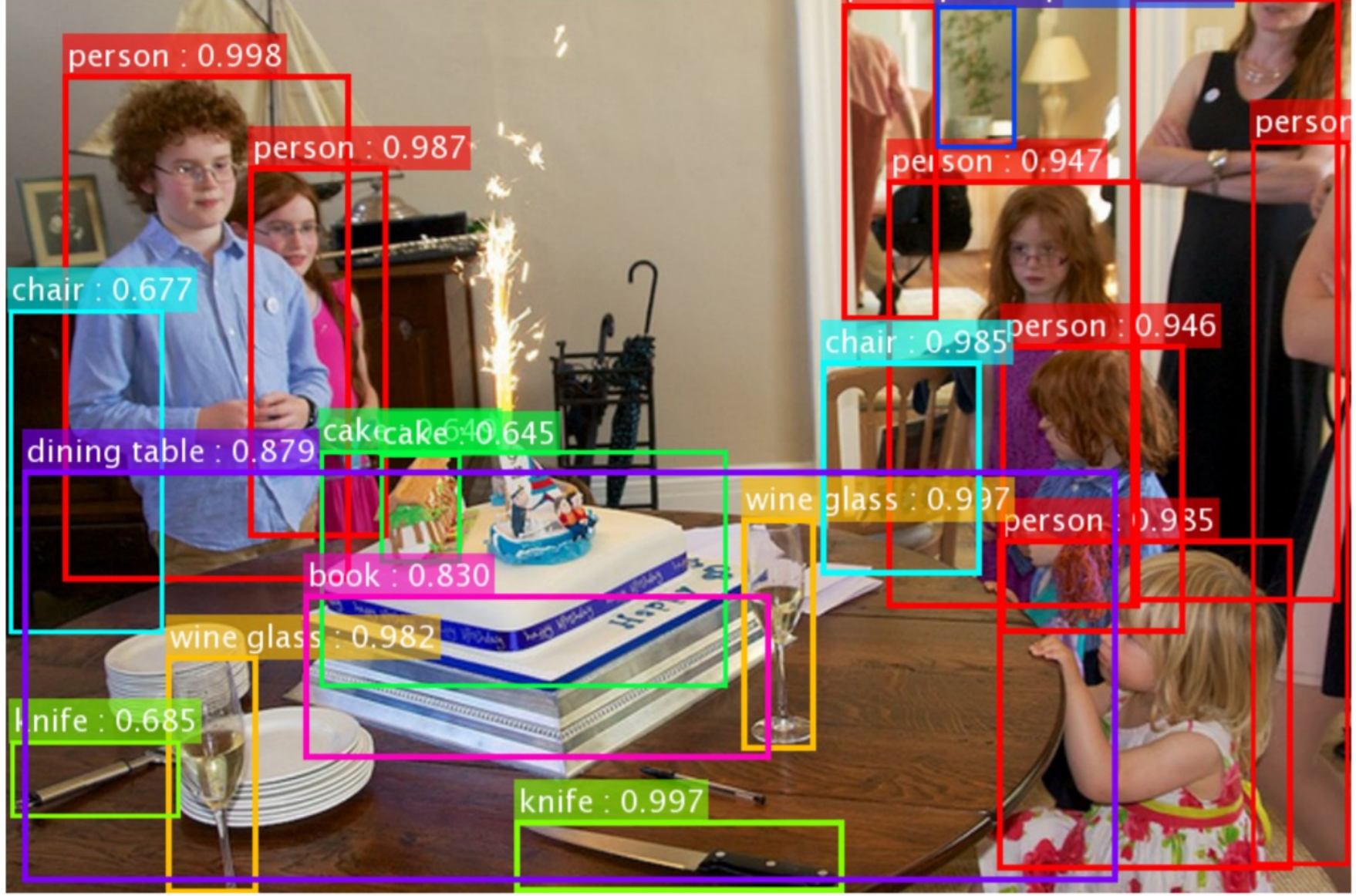
Takeaways
Faster R-CNN is slower but more accurate

SSD is much faster but not as accurate

Zou et al, "Object Detection in 20 Years: A Survey", arXiv 2019

Huang et al, "Speed/accuracy trade-offs for modern convolutional object detectors", CVPR 2017

R-FCN: Dai et al, "R-FCN: Object Detection via Region-based Fully Convolutional Networks", NIPS 2016
Inception-V2: Ioffe and Szegedy, "Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift", ICML 2015
Inception V3: Szegedy et al, "Rethinking the Inception Architecture for Computer Vision", arXiv 2016
Inception ResNet: Szegedy et al, "Inception-V4, Inception-ResNet and the Impact of Residual Connections on Learning", arXiv 2016

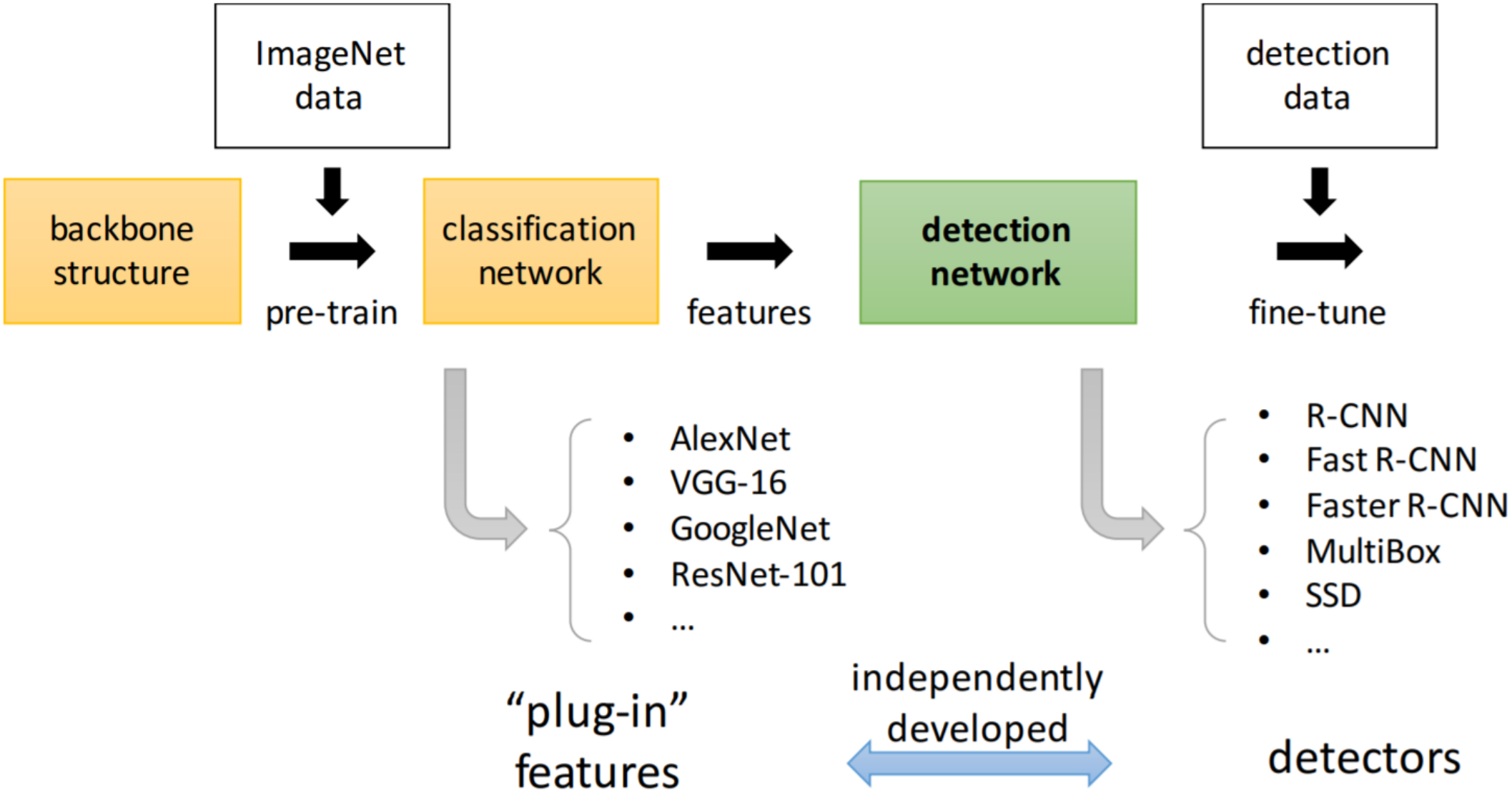


ResNet's object detection result on COCO

*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.

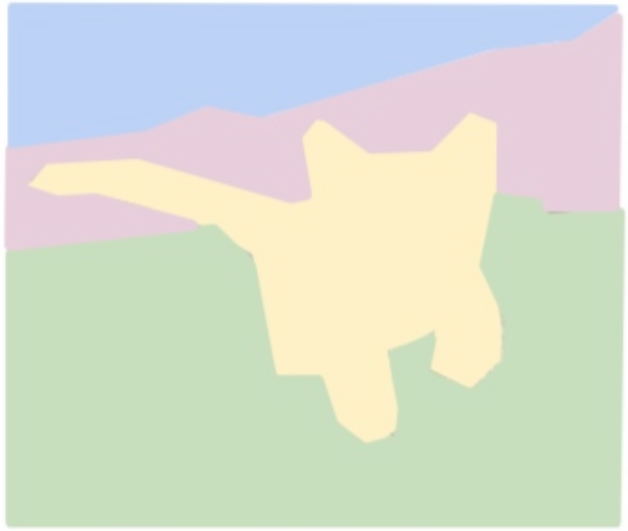
Object Detection



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

Instance Segmentation

Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Classification + Localization

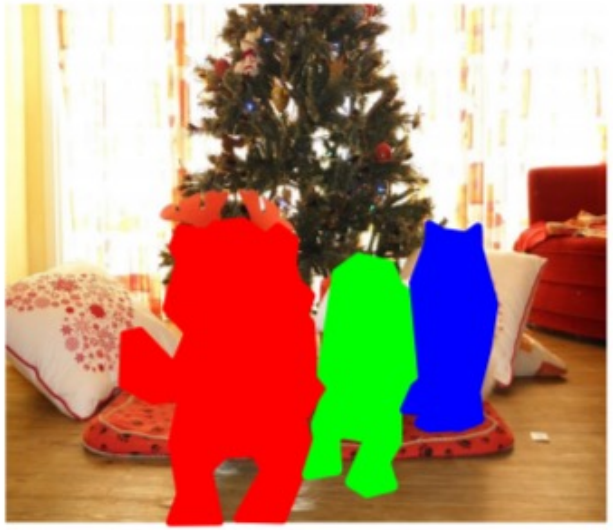
CAT

Single Object

Object Detection

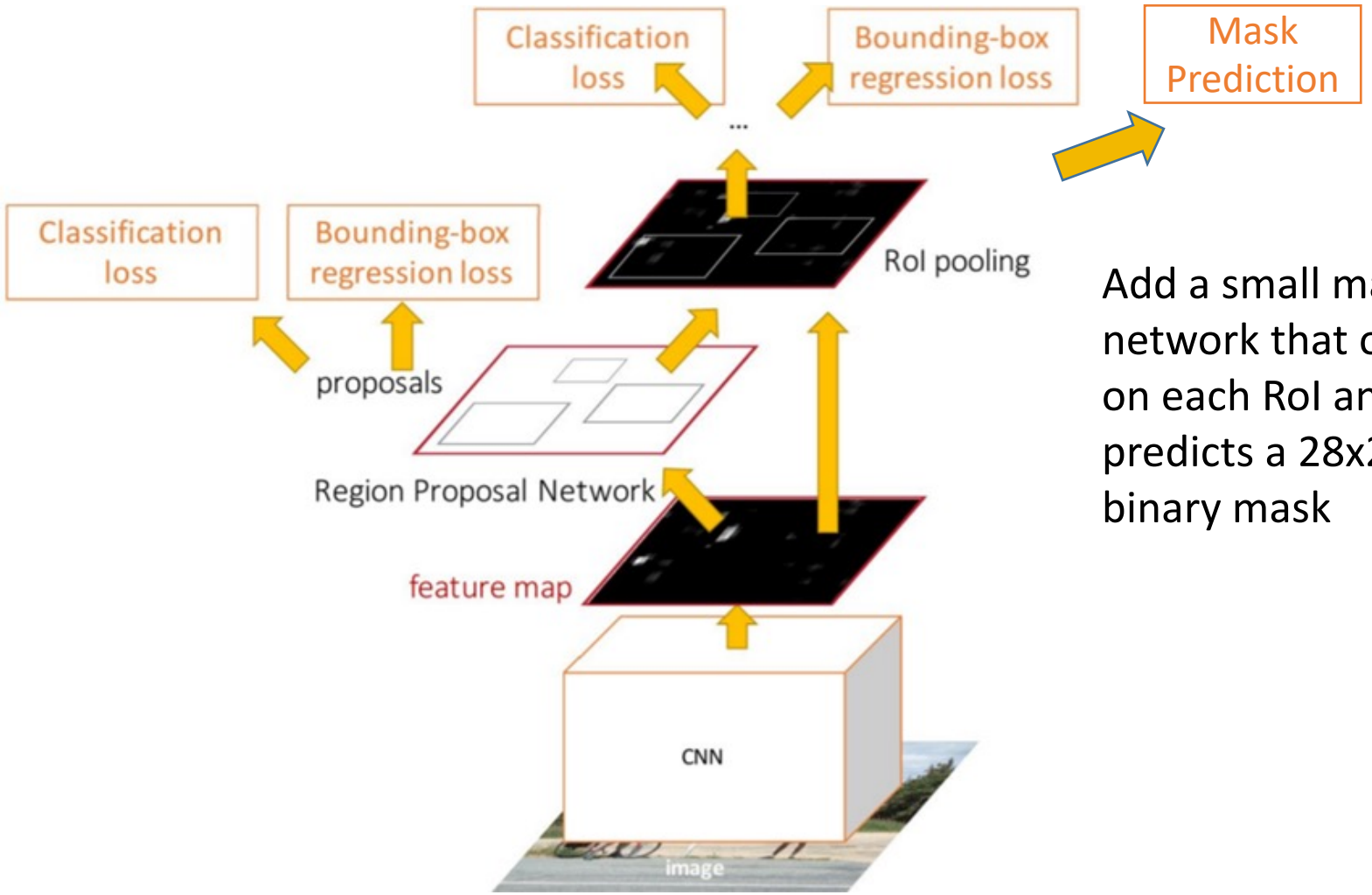
DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

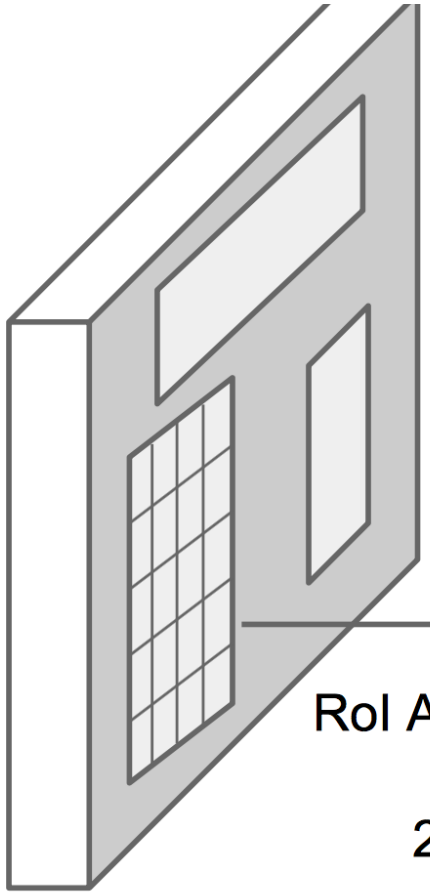
Multiple Object



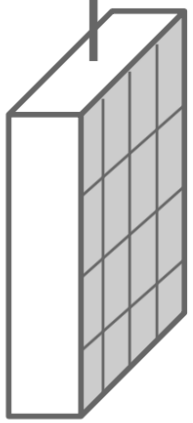
Add a small mask network that operates on each RoI and predicts a 28x28 binary mask

Mask R-CNN

CNN

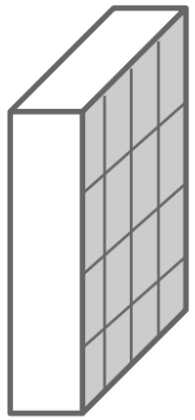


RoI Align



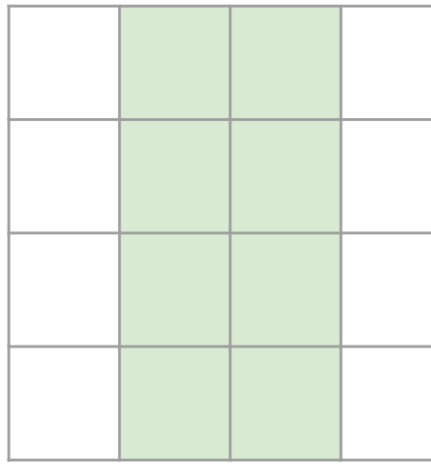
256 x 14 x 14

Conv



256 x 14 x 14

Conv



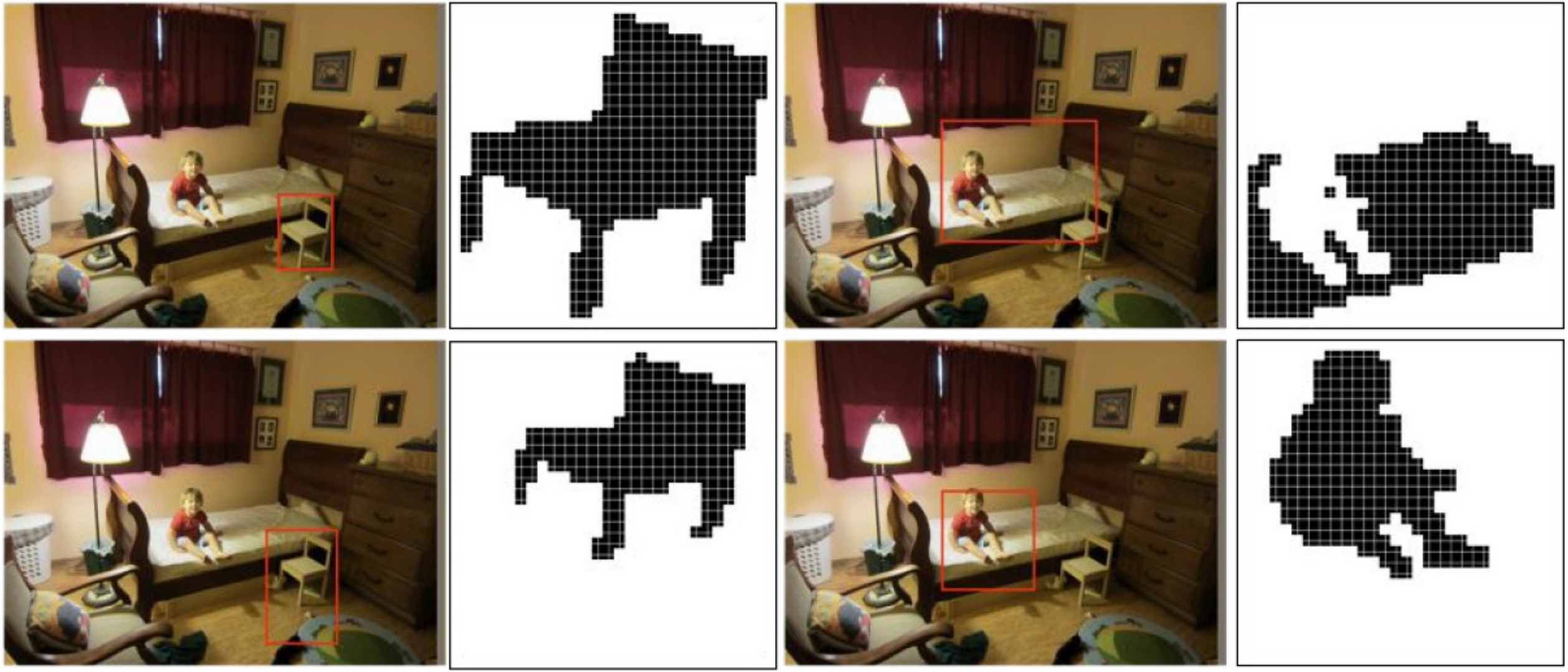
Predict a mask for each of C classes

C x 14 x 14

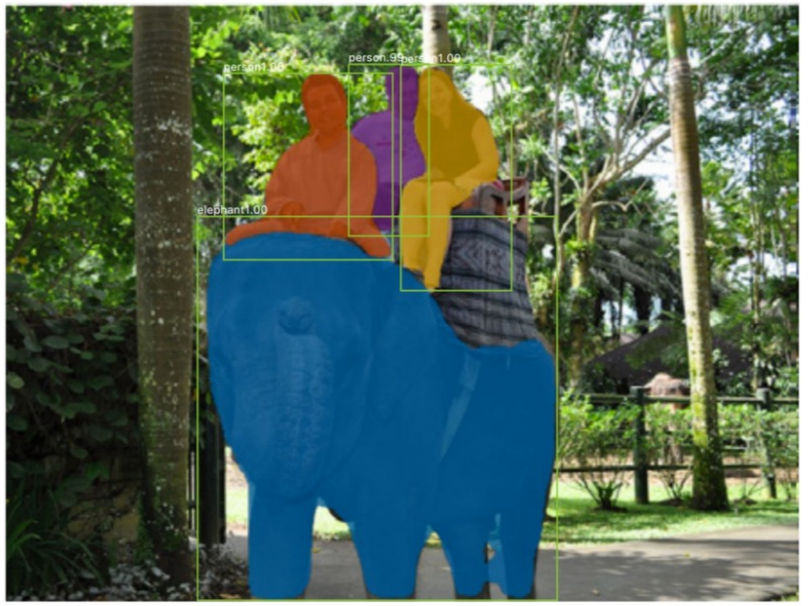
Classification Scores: C
Box coordinates (per class): 4 * C

He et al, “Mask R-CNN”, arXiv 2017

Mask R-CNN: Example Mask Training Targets



Mask R-CNN: Very Good Results!



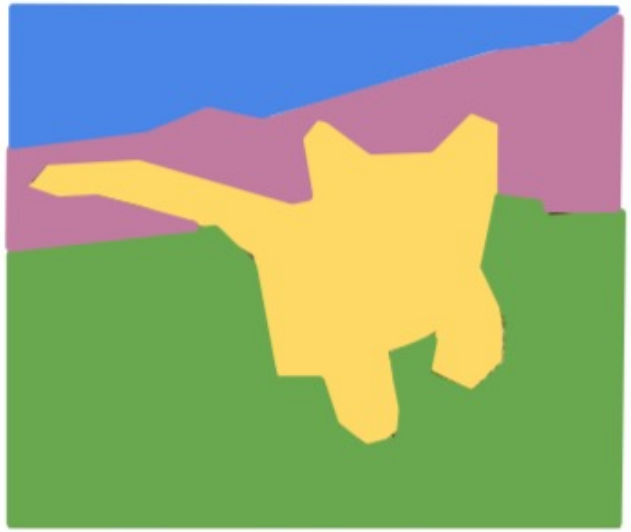
He et al, “Mask R-CNN”, arXiv 2017

Mask R-CNN: Also does pose

He et al, “Mask R-CNN”, arXiv 2017

Summary

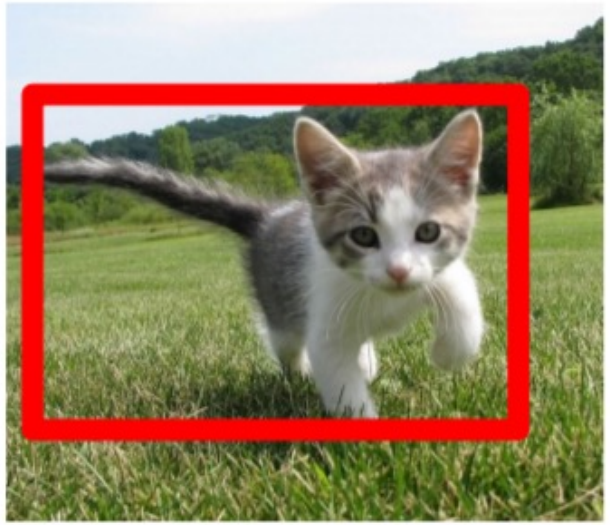
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Classification + Localization



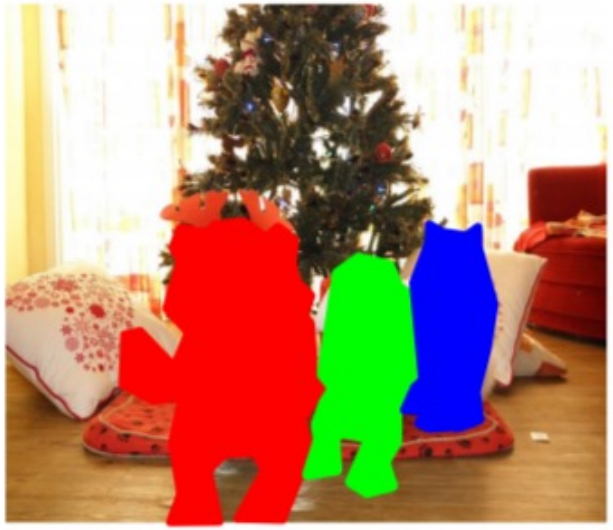
CAT

Single Object

Object Detection

DOG, DOG, CAT

Instance Segmentation



DOG, DOG, CAT

Multiple Object

Open Source Frameworks

- Lots of good implementations on GitHub!
- TensorFlow Detection API:
  - https://github.com/tensorflow/models/tree/master/research/object_detection
  - Faster RCNN, SSD, RFCN, Mask R-CNN
- Caffe2 Detection:
  - https://github.com/facebookresearch/Detectron
  - Mask R-CNN, RetinaNet, Faster R-CNN, RPN, Fast R-CNN, R-FCN

- Finetune on your own dataset with pre-trained models