Convolutional Neural Networks

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References

CS231n: Convolutional Neural Networks for Visual Recognition

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Fast R-CNN

Ross Girshick
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Rich feature hierarchies for accurate object detection and semantic segmentation

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Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks

Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun

Spatial Pyramid Pooling in Deep Convolutional Networks for Visual Recognition

Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun

Selective Search for Object Recognition

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Technical Report 2012, submitted to IJCV

Fully Convolutional Networks for Semantic Segmentation

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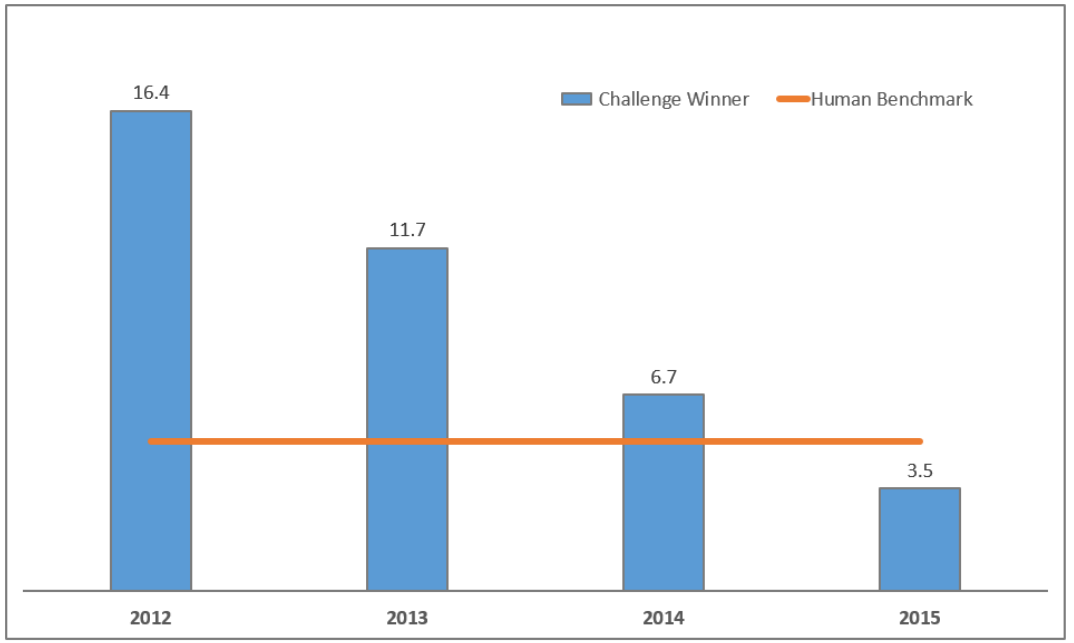
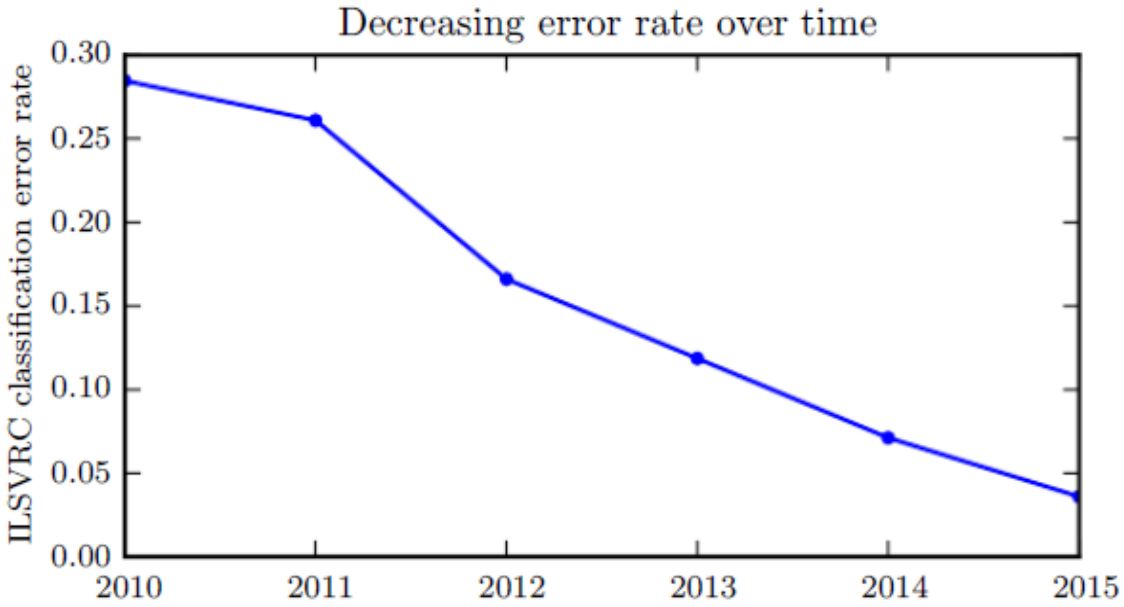
"**A dramatic moment in the meteoric rise of deep learning came when a convolutional network won this challenge for the first time and by a wide margin, bringing down the state-of-the-art top-5 error rate from 26.1% to 15.3%** (Krizhevsky *et al.*, 2012), meaning that the convolutional network produces a ranked list of possible categories for each image and the correct category appeared in the first five entries of this list for all but 15.3% of the test examples. **Since then, these competitions are consistently won by deep convolutional nets**, and as of this writing, advances in deep learning have brought the latest top-5 error rate in this contest down to 3.6%" – Ref: Deep Learning Book by Y Bengio et al

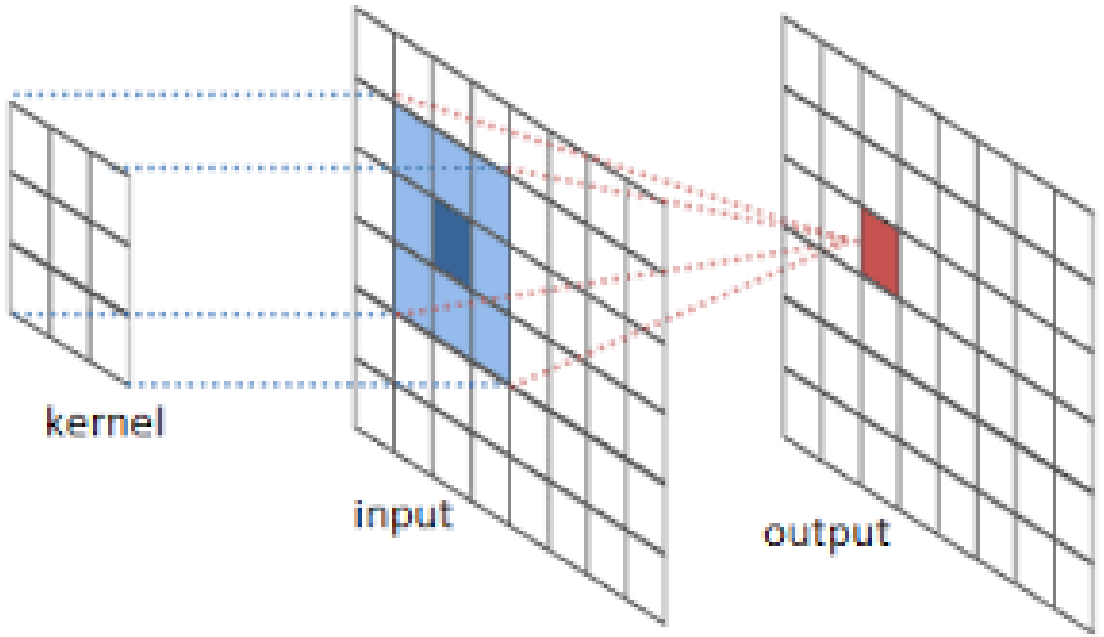




What is a convolutional neural network?

Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

- Convolution is a mathematical operation having a linear form



Types of inputs

- Inputs have a structure
  - Color images are three dimensional and so have a volume
  - Time domain speech signals are 1-d while the frequency domain representations (e.g. MFCC vectors) take a 2d form. They can also be looked at as a time sequence.
  - Medical images (such as CT/MR/etc) are multidimensional
  - Videos have the additional temporal dimension compared to stationary images
  - Speech signals can be modelled as 2 dimensional
  - Variable length sequences and time series data are again multidimensional

- Hence it makes sense to **model them as tensors** instead of vectors.

- The classifier then needs to accept a tensor as input and perform the necessary machine learning task. In the case of an image, this tensor represents a volume.

CNNs are everywhere

- Image retrieval
- Detection
- Self driving cars
- Semantic segmentation
- Face recognition (FB tagging)
- Pose estimation
- Detect diseases
- Speech Recognition
- Text processing
- Analysing satellite data

CNNs for applications that involve images

- Why CNNs are more suitable to process images?

- Pixels in an image correlate to each other. However, nearby pixels correlate stronger and distant pixels don’t influence much
  - Local features are important: Local Receptive Fields

- Affine transformations: The class of an image doesn’t change with translation. We can build a feature detector that can look for a particular feature (e.g. an edge) anywhere in the image plane by moving across. A convolutional layer may have several such filters constituting the depth dimension of the layer.

Fully connected layers

- Fully connected layers (such as the hidden layers of a traditional neural network) are agnostic to the structure of the input
  - They take inputs as vectors and generate an output vector
  - There is no requirement to share parameters unless forced upon in specific architectures. This blows up the number of parameters as the input and/or output dimensions increase.
- Suppose we are to perform classification on an image of 100x100x3 dimensions.
- If we implement using a feed forward neural network that has an input, hidden and an output layer, where: hidden units (nh) = 1000, output classes = 10 :
  - Input layer = 10k pixels * 3 = 30k, weight matrix for hidden to input layer = 1k * 30k = 30 M and output layer matrix size = 10 * 1000 = 10k
- We may handle this is by extracting the features using pre processing and presenting a lower dimensional input to the Neural Network. But this requires expert engineered features and hence domain knowledge

CNNs for applications that involve images

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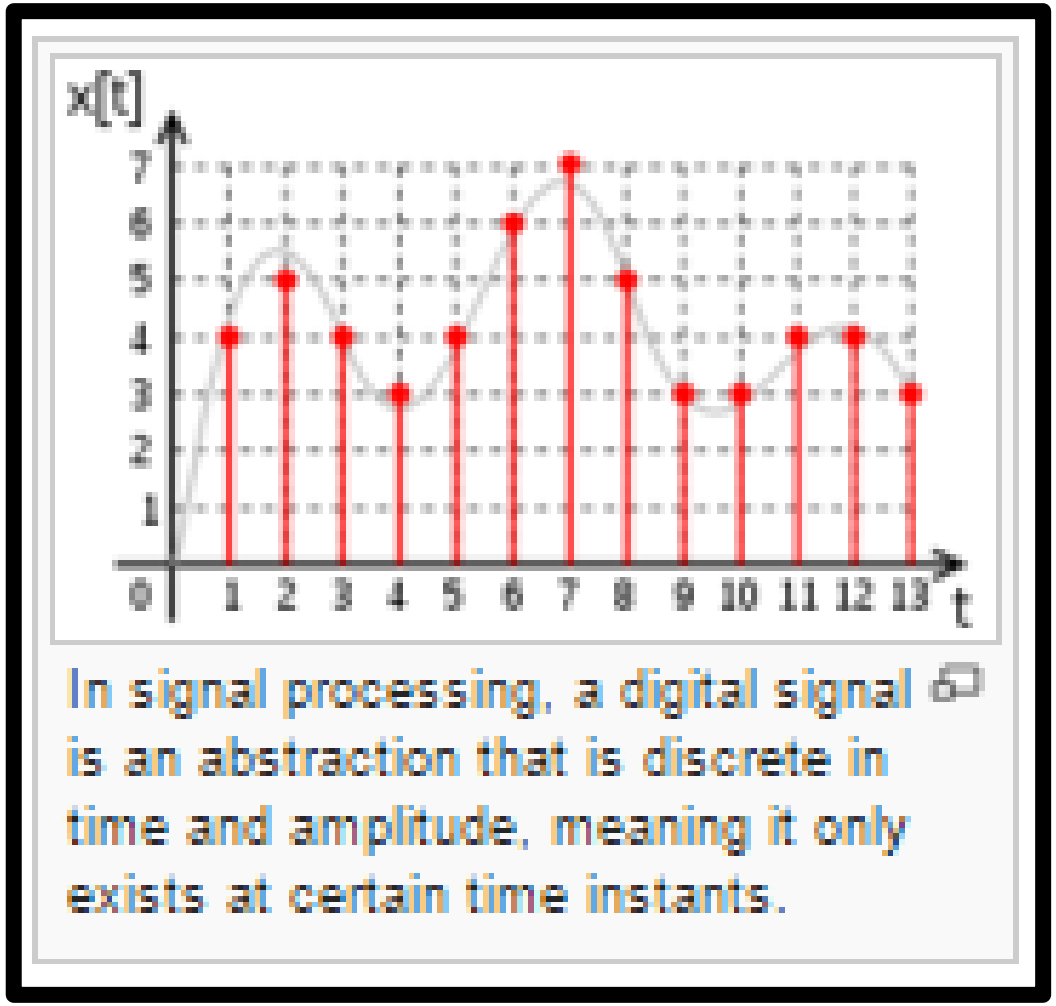
Convolution: From first principles

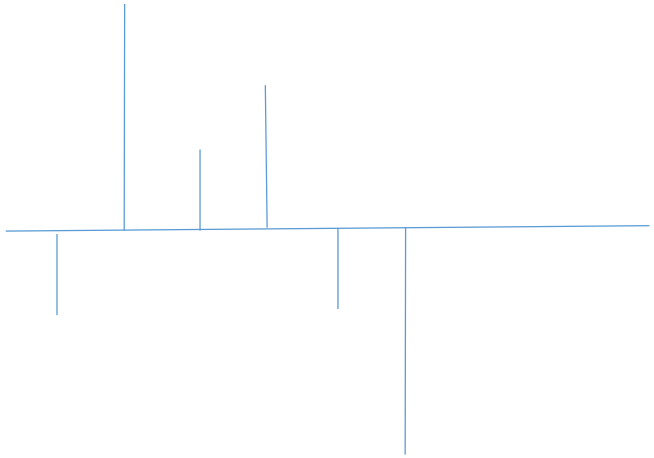
What is a digital signal?

- Refer books on DSP for formal definitions.
- We will use the following working definition: A digital signal is an entity in digital form that carries the information we want to process.
- Examples:
  - An image (gif file)
  - Audio file
  - Text file
  - Facebook posts
  - Tweets



What is a system?

- We consider the system as a function that transforms the input signal.
- A linear system satisfies the properties of:
  - Scaling
  - Superposition
- Shift Invariant Systems: If the input is shifted by a distance k, the output is also shifted exactly by the same distance.
- A linear shift invariant system is both linear and shift invariant.
- If a system is linear shift invariant, its output is fully characterized by its impulse response and is determined as the convolution of the input and the impulse response
- Important implications:
  - Impulse Response fully characterizes the system and so we can treat the system as a black box.
  - Inputs can be looked at as scaling factors to the impulse response and so don't play a role in modifying the nature of output except for scaling



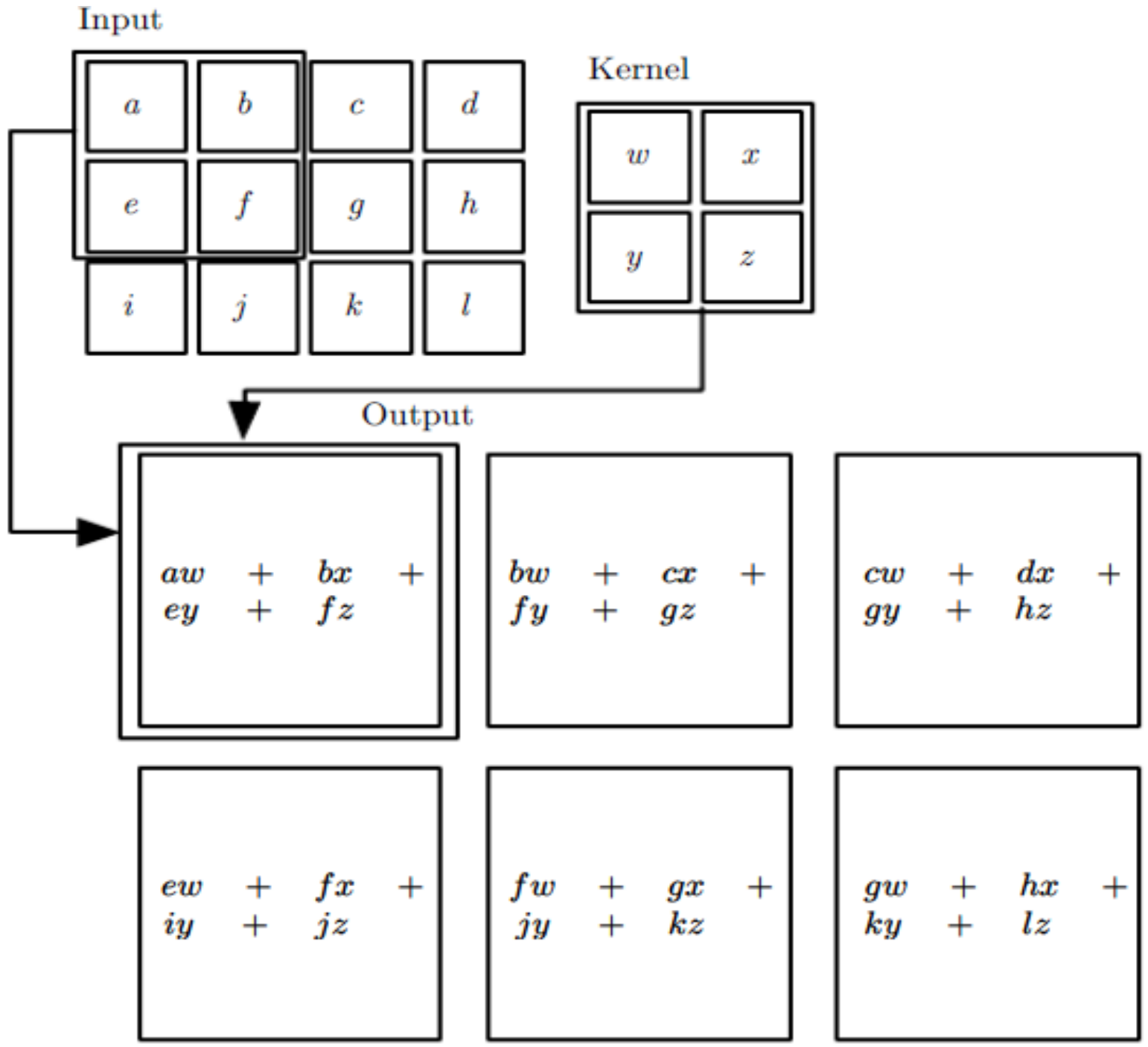
Convolution

$Convolution\ in\ 1\ Dimension$:

$$y[n] = \sum_{k=-\infty}^{k=\infty} x[k]h[n-k]$$

$Convolution\ in\ 2\ Dimensions$:

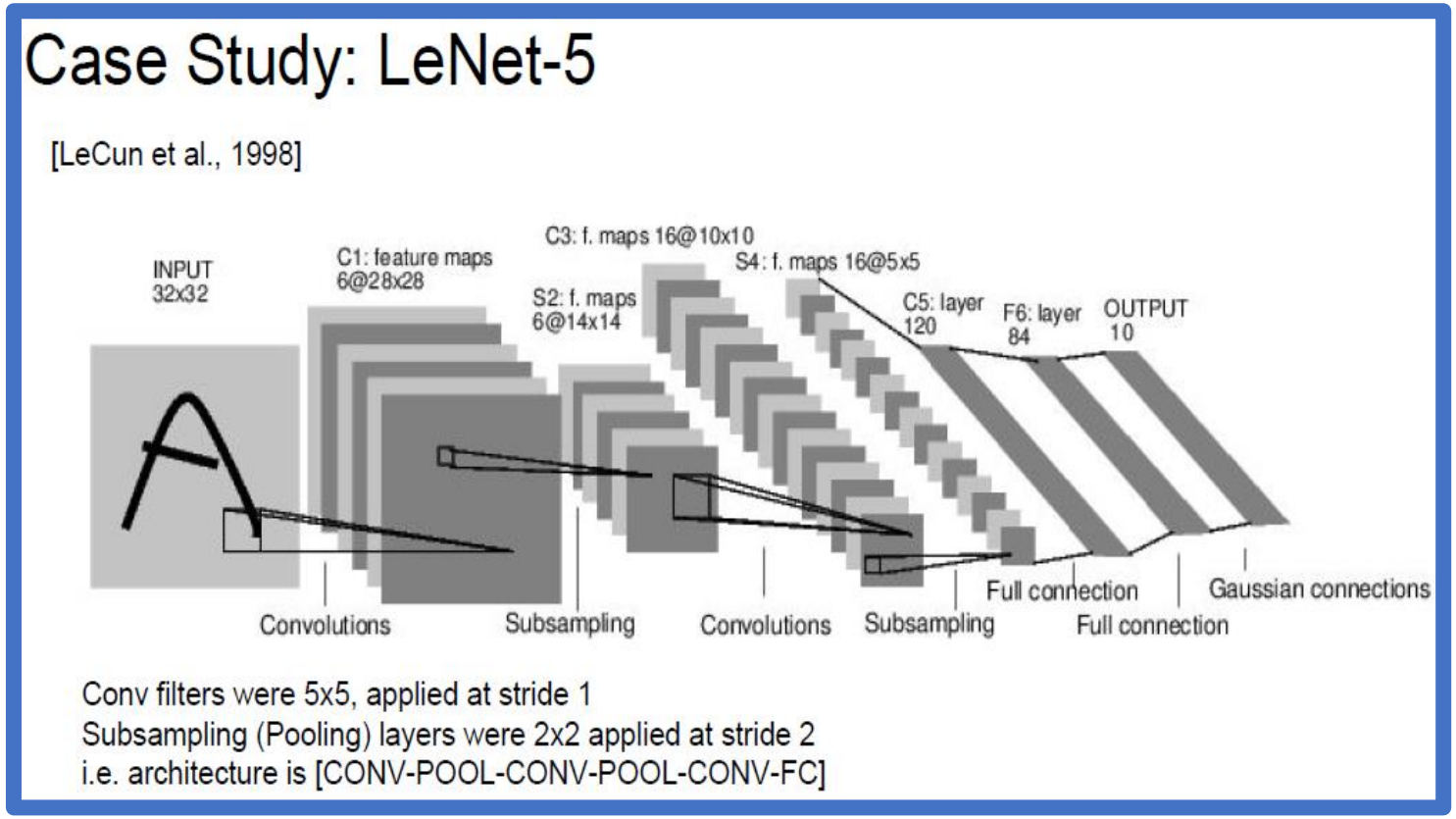
$$y[n_1, n_2] = \sum_{k1=-\infty}^{k1=\infty} \sum_{k2=-\infty}^{k2=\infty} x[k_1, k_2]h[(n_1 - k_1), (n_2 - k_2)]$$


Input
a b c d
e f g h
i j k l
Kernel
w x
y z
Output
aw + bx +
ey + fz
bw + cx +
fy + gz
cw + dx +
gy + hz
ew + fx +
iy + jz
fw + gx +
jy + kz
gw + hx +
ky + lz

CNNs

Types of layers in a CNN:

- Convolution Layer
- Pooling Layer
- Fully Connected Layer

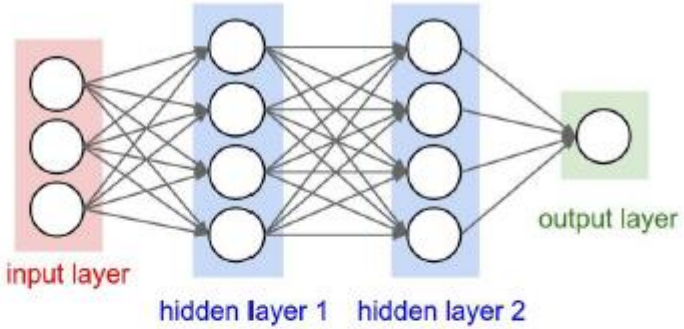


Convolution Layer

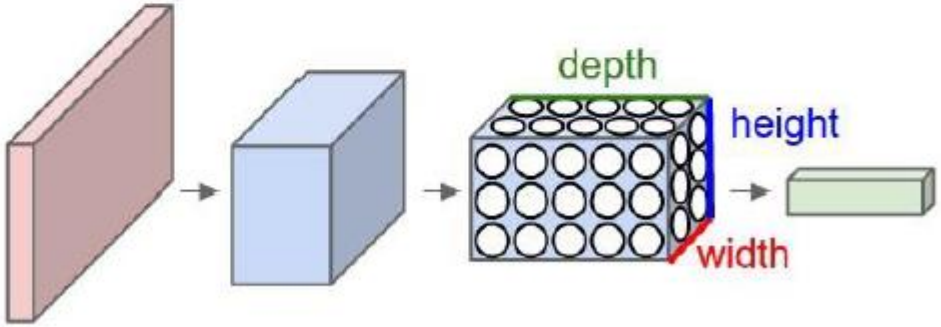
- A layer in a regular neural network take vector as input and output a vector.

- A convolution layer takes a tensor (3d volume for RGB images) as input and generates a tensor as output

Regular neural network (fully connected):



Convolutional neural network:

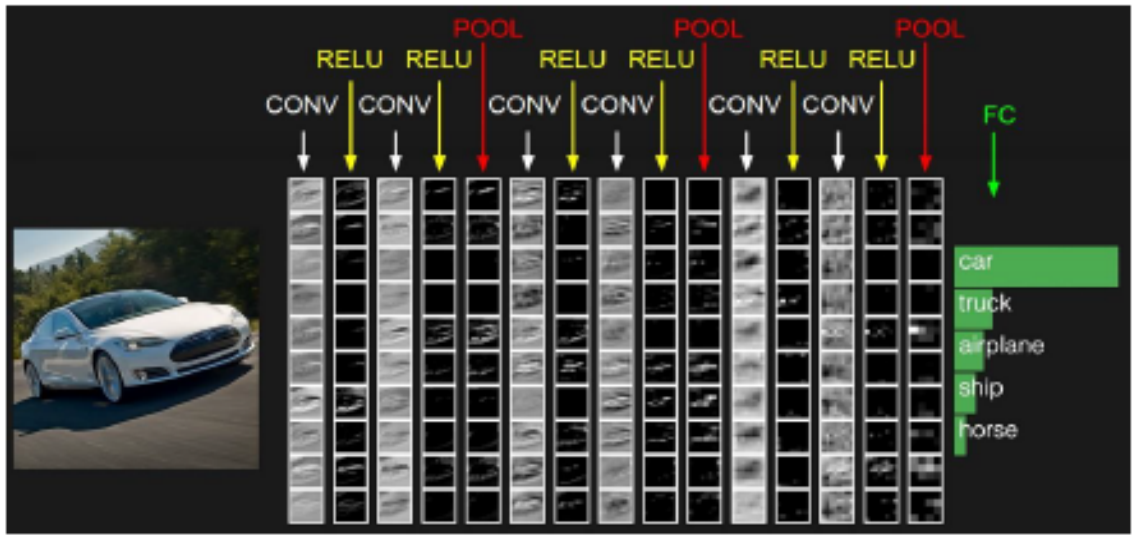


Each layer takes a 3d volume, produces 3d volume with some smooth function that may or may not have parameters.

Fig Credit: Lex Fridman, MIT, 6.S094

Convolutional Neural Networks: Layers

- **INPUT** [32x32x3] will hold the raw pixel values of the image, in this case an image of width 32, height 32, and with three color channels R,G,B.
- **CONV** layer will compute the output of neurons that are connected to local regions in the input, each computing a dot product between their weights and a small region they are connected to in the input volume. This may result in volume such as [32x32x12] if we decided to use 12 filters.
- **RELU** layer will apply an elementwise activation function, such as the *max(0,x)* thresholding at zero. This leaves the size of the volume unchanged ([32x32x12]).
- **POOL** layer will perform a downsampling operation along the spatial dimensions (width, height), resulting in volume such as [16x16x12].
- **FC** (i.e. fully-connected) layer will compute the class scores, resulting in volume of size [1x1x10], where each of the 10 numbers correspond to a class score, such as among the 10 categories of CIFAR-10. As with ordinary Neural Networks and as the name implies, each neuron in this layer will be connected to all the numbers in the previous volume.

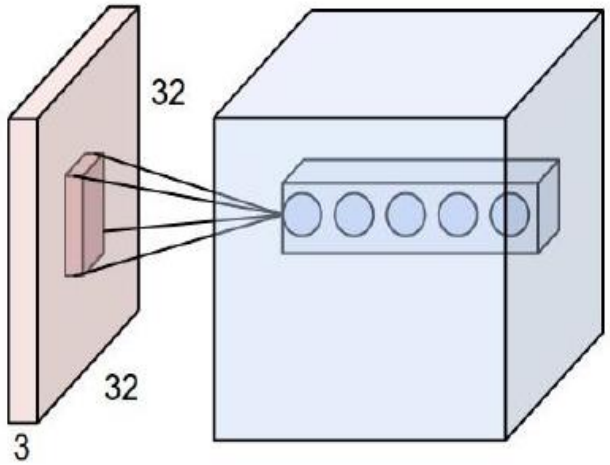


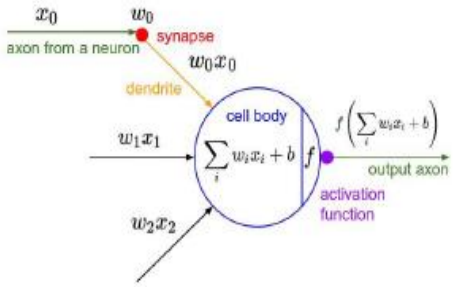
Slide Credit: Lex Fridman, MIT, 6.S094

Local Receptive Fields

- Filter (Kernel) is applied on the input image like a moving window along width and height
- The depth of a filter matches that of the input.
- For each position of the filter, the dot product of filter and the input are computed (Activation)
- The 2d arrangement of these activations is called an activation map.
- The number of such filters constitute the depth of the convolution layer

Dealing with Images: Local Connectivity





Same neuron. Just more focused (narrow "receptive field").

The parameters on a each filter are spatially "shared"

(if a feature is useful in one place, it's useful elsewhere)

Fig Credit: Lex Fridman, MIT, 6.S094

Convolution Operation between filter and image

- The convolution layer computes dot products between the filter and a piece of image as it slides along the image
- The step size of slide is called stride
- Without any padding, the convolution process decreases the spatial dimensions of the output

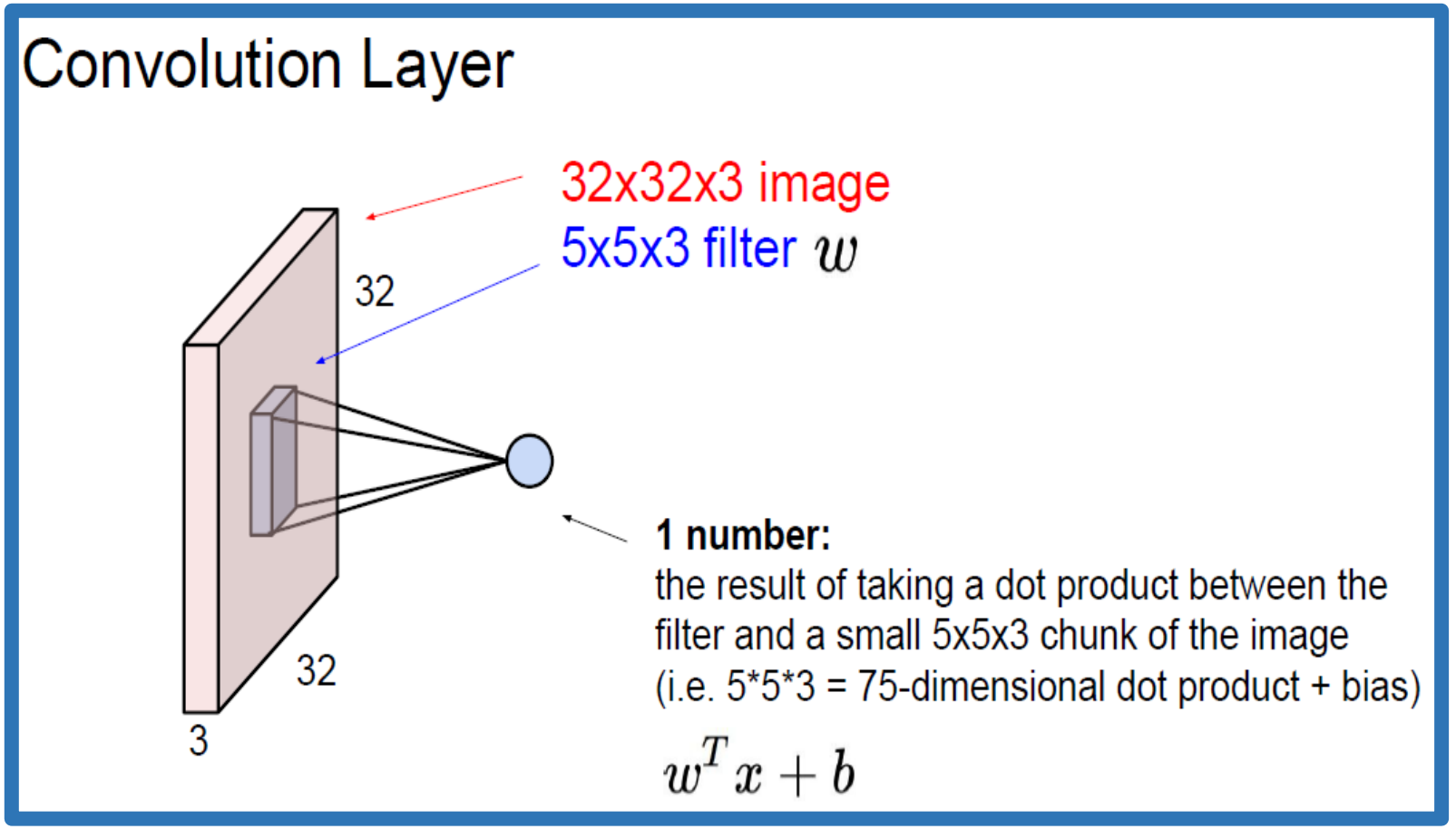


Fig Credit: A Karpathy, CS231n

Activation Maps

- Example:
  - Consider an image 32 x 32 x 3 and a 5 x 5 x 3 filter.
  - The convolution happens between a 5 x 5 x 3 chunk of the image with the filter: $w^T x + b$
  - In this example we get 75 dimensional vector and a bias term
  - In this example, with a stride of 1, we get 28 x 28 x 1 activation for 1 filter without padding
  - If we have 6 filters, we would get 28 x 28 x 6 without padding
- In the above example we have an activation map of 28 x 28 per filter.
- Activation maps are feature inputs to the subsequent layer of the network
- Without any padding, the 2D surface area of the activation map is smaller than the input surface area for a stride of >= 1

Stacking Convolution Layers

Preview: ConvNet is a sequence of Convolutional Layers, interspersed with activation functions

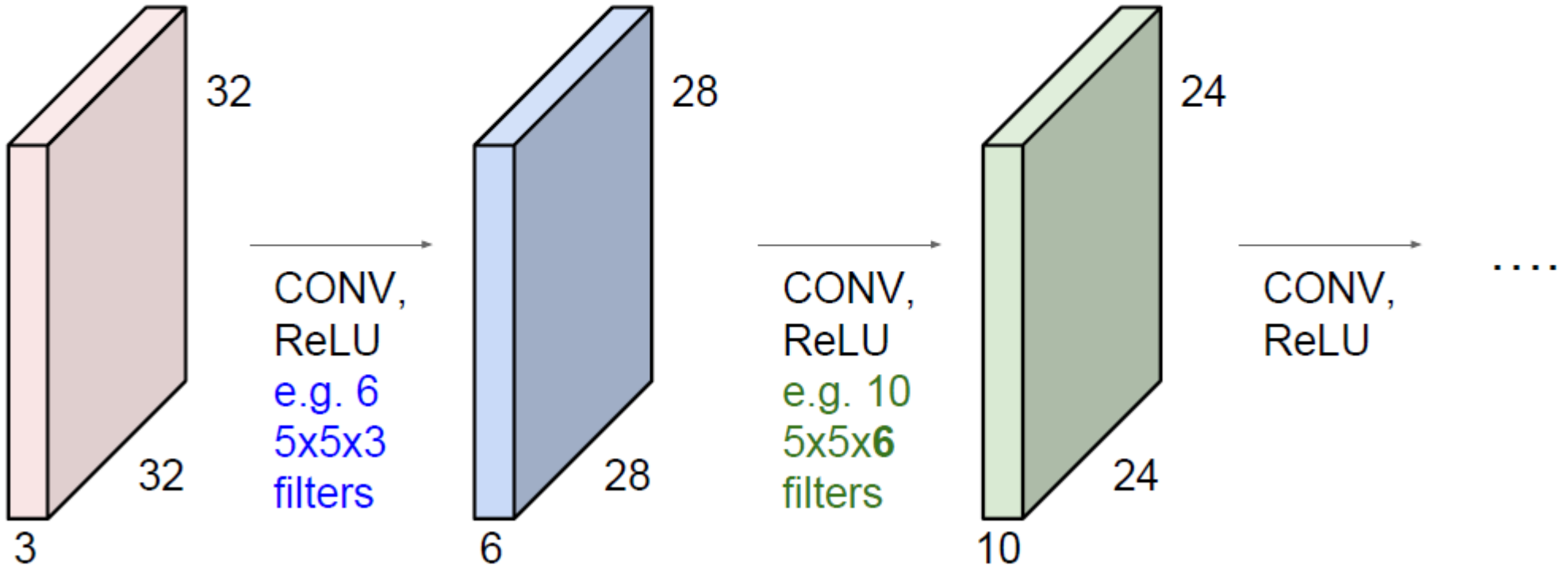
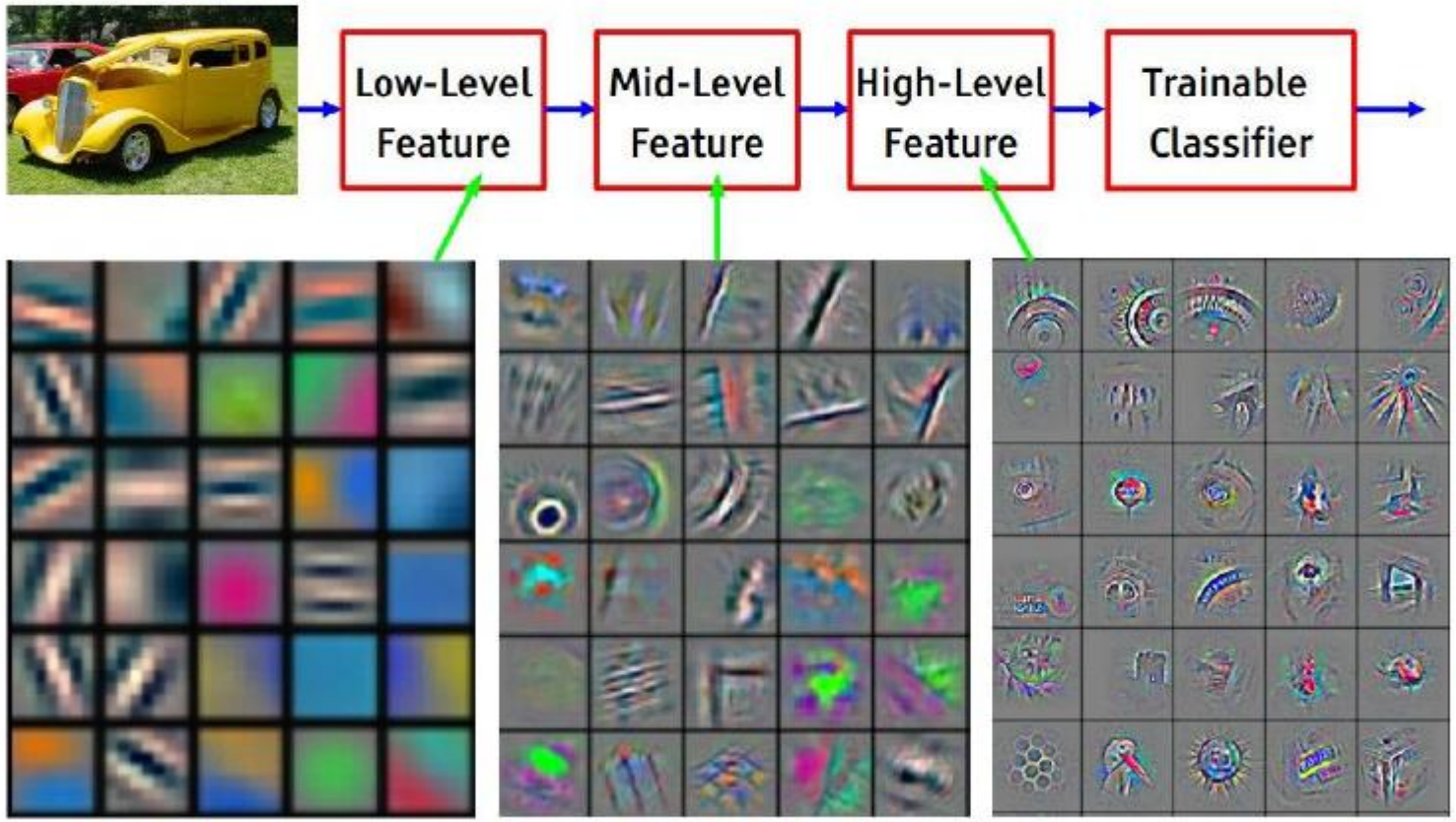


Fig Credit: A Karpathy, CS231n

Feature Representation as a hierarchy

[From recent Yann LeCun slides]



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

Padding

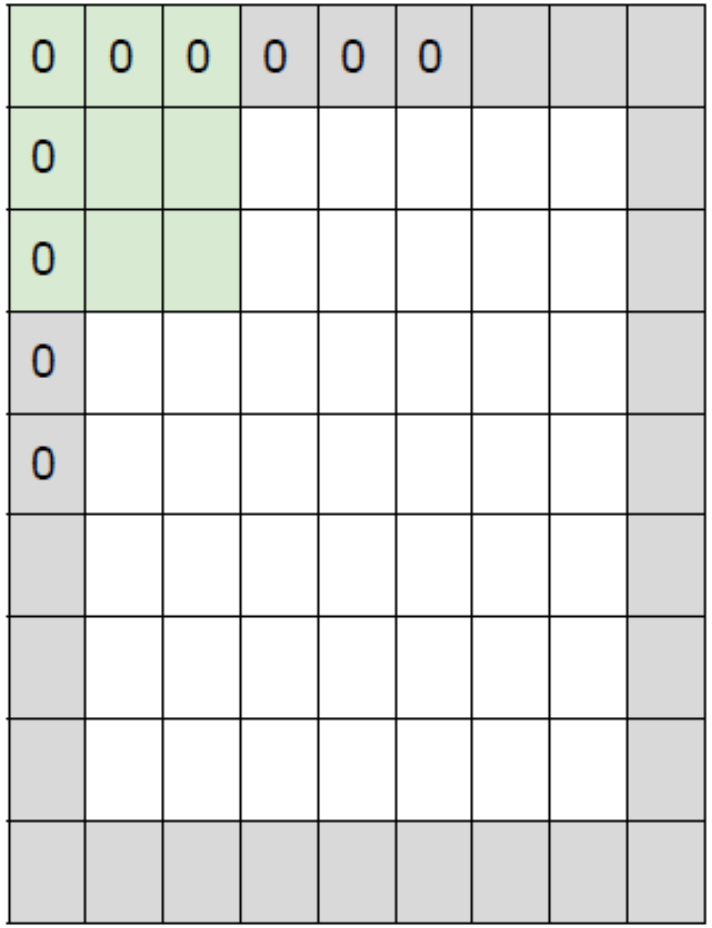
- The spatial (x, y) extent of the output produced by the convolutional layer is less than the respective dimensions of the input (except for the special case of 1 x 1 filter with a stride 1).

- As we add more layers and use larger strides, the output surface dimensions keep reducing and this may impact the accuracy.

- Often, we may want to preserve the spatial extent during the initial layers and downsample them at a later time.

- Padding the input with suitable values (padding with zero is common) helps to preserve the spatial size

Zero Padding the border



e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Fig Credit: A Karpathy, CS231n

Hyperparameters of the convolution layer

- Filter Size
- # Filters
- Stride
- Padding

Common settings:

K = (powers of 2, e.g. 32, 64, 128, 512)
- F = 3, S = 1, P = 1
- F = 5, S = 2, P = 2
- F = 5, S = 2, P = ? (whatever fits)
- F = 1, S = 1, P = 0

Summary. To summarize, the Conv Layer:

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires four hyperparameters:
  - Number of filters K,
  - their spatial extent F,
  - the stride S,
  - the amount of zero padding P.
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F + 2P)/S + 1$
  - $H_2 = (H_1 - F + 2P)/S + 1$ (i.e. width and height are computed equally by symmetry)
  - $D_2 = K$
- With parameter sharing, it introduces $F \cdot F \cdot D_1$ weights per filter, for a total of $(F \cdot F \cdot D_1) \cdot K$ weights and K biases.
- In the output volume, the d-th depth slice (of size $W_2 \times H_2$) is the result of performing a valid convolution of the d-th filter over the input volume with a stride of S, and then offset by d-th bias.

Fig Credit: A Karpathy, CS231n

Pooling Layer

- Pooling is a downsampling operation
- The rationale is that the “meaning” embedded in a piece of image can be captured using a small subset of “important” pixels
- Max pooling and average pooling are the two most common operations
- Pooling layer doesn’t have any trainable parameters

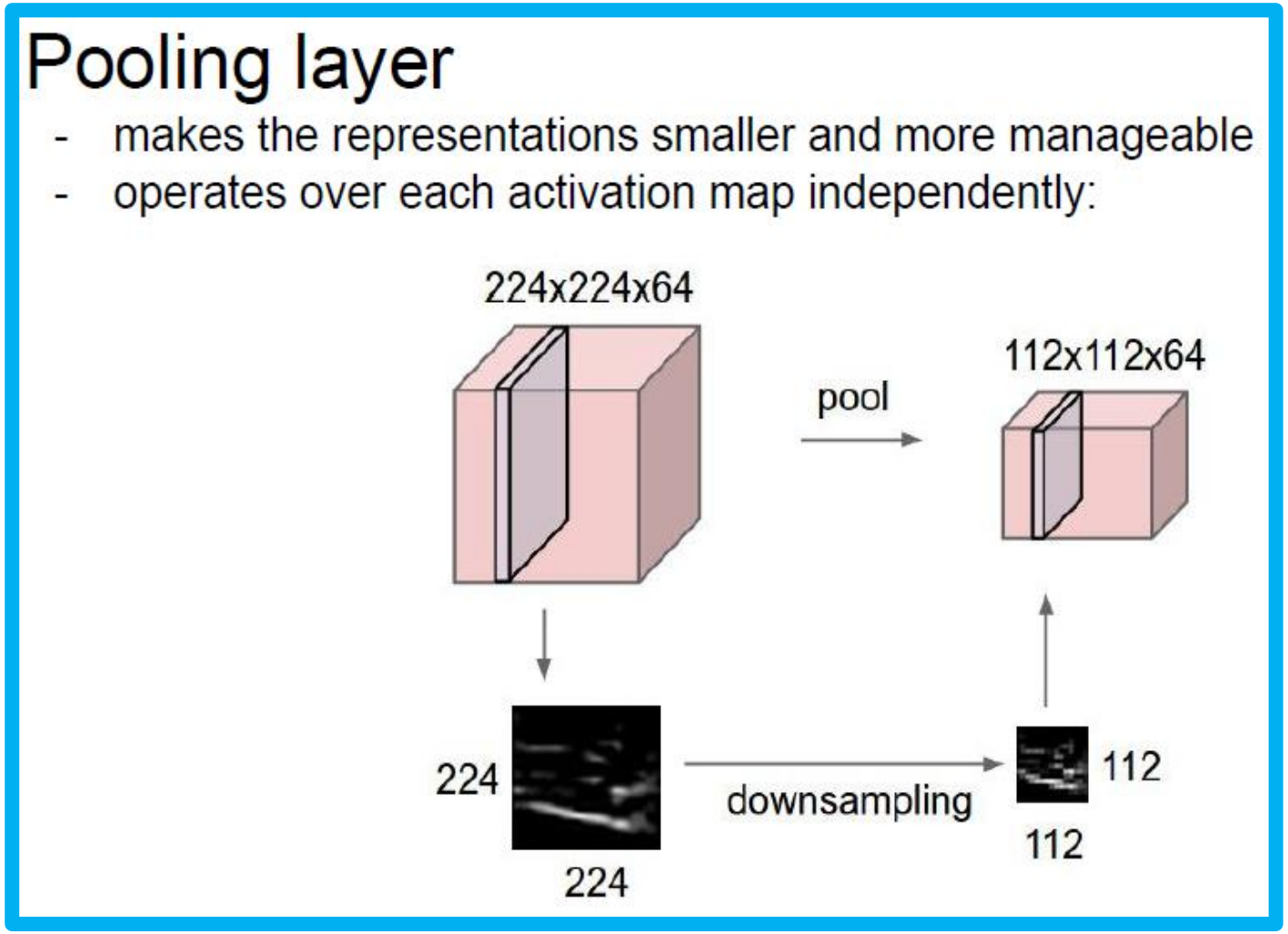
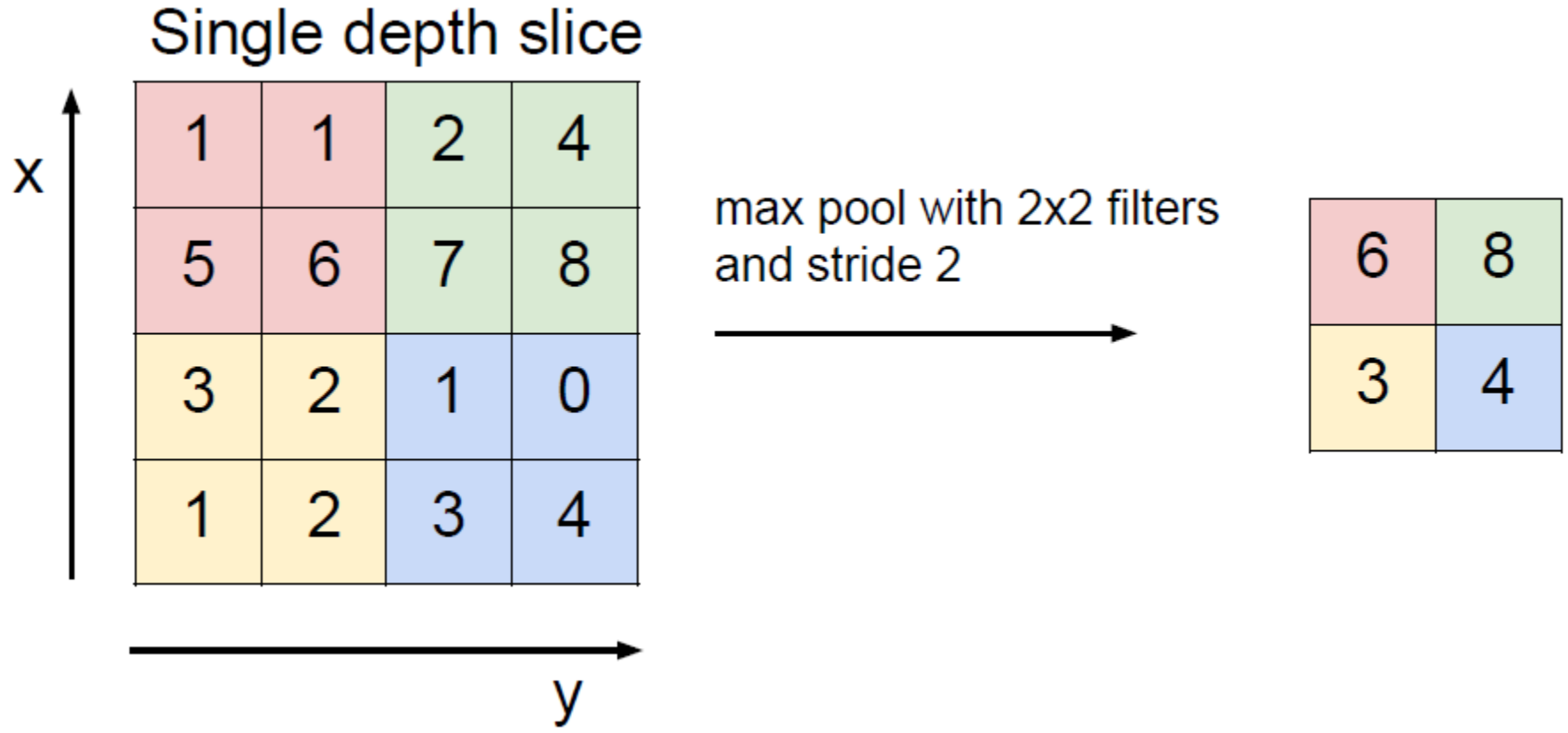


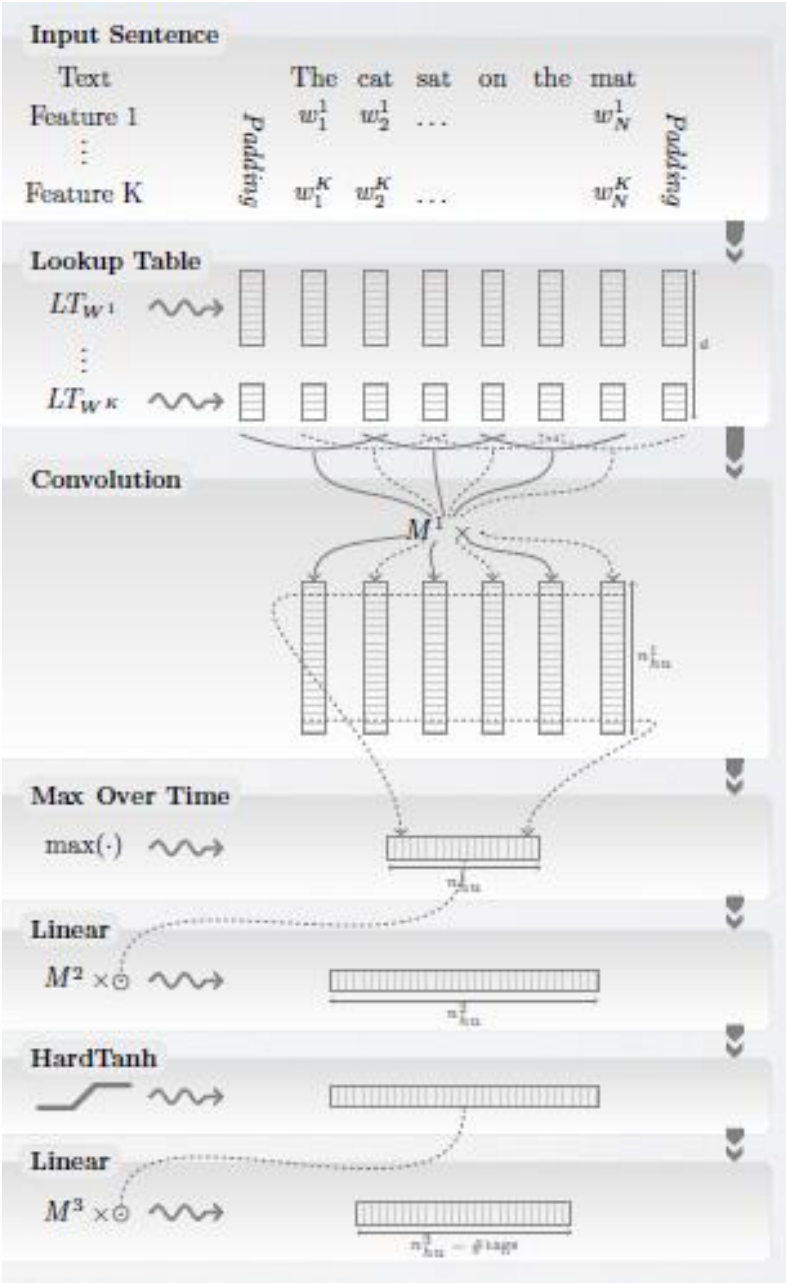
Fig Credit: A Karpathy, CS231n

Max Pooling Illustration



CNNs for NLP (Collabert and Weston)

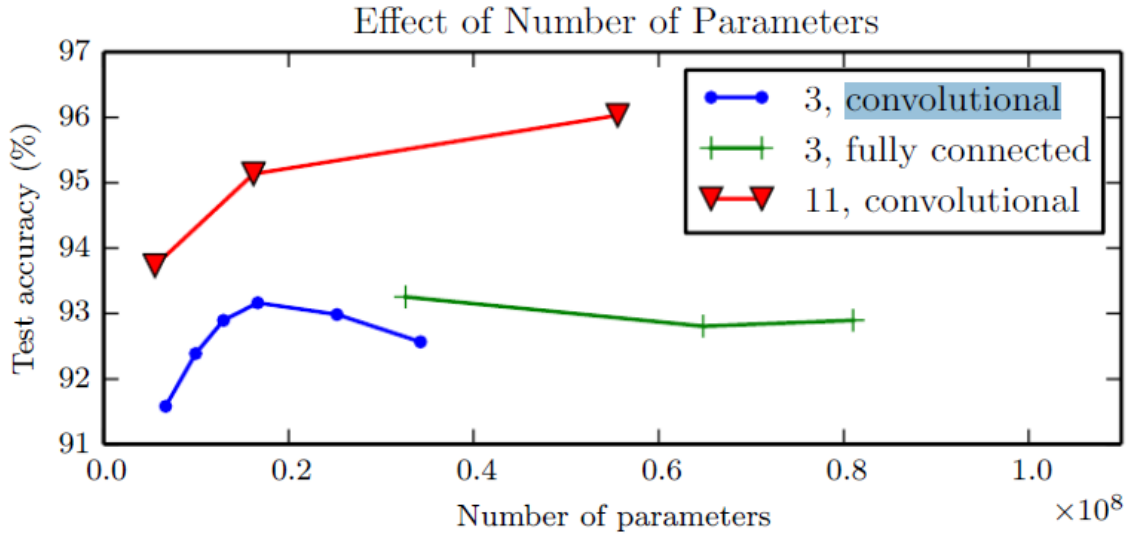
- Features are obtained from a combination of feature functions and word vector representation
- Each word can have one or more features
- Look up tables are used to covert the features in to vectors
- Features include an encoding of current word we are tagging
- For semantic role labelling (SRL) we also encode the relative position with respect to a verb
- Look up table, convolution and max pooling
- Outputs are used with a sequence model (CRF)



Popular Network Architectures

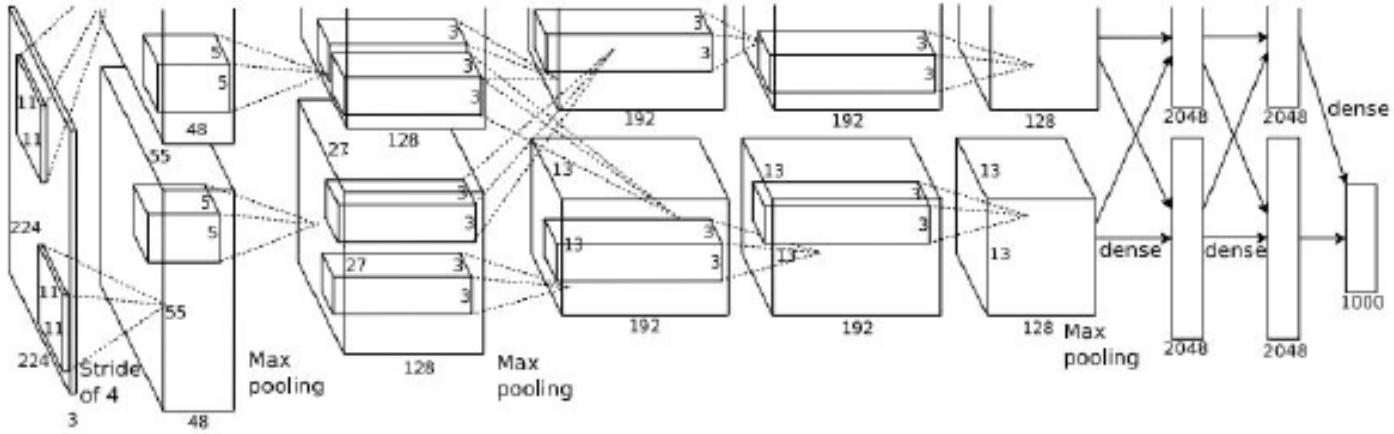
Current trend: Deeper Models

- CNNs consistently outperform other approaches for the core tasks of CV
- Deeper models work better
- Increasing the number of parameters in layers of CNN without increasing their depth is not effective at increasing test set performance.
- Shallow models overfit at around 20 million parameters while deep ones can benefit from having over 60 million.
- Key insight: Model performs better when it is architected to reflect composition of simpler functions than a single complex function. This may also be explained off viewing the computation as a chain of dependencies



Case Study: AlexNet

[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

VGG Net

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

ConvNet Configuration			
B	C	D	
13 weight layers	16 weight layers	16 weight layers	
put (224 × 224 RGB image)			
conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	
maxpool			
conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	
maxpool			
conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	
maxpool			
conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	
maxpool			
FC-4096			
FC-4096			
FC-1000			
soft-max			

VGG net

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: **224*224*64=3.2M** params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = **102,760,448**
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

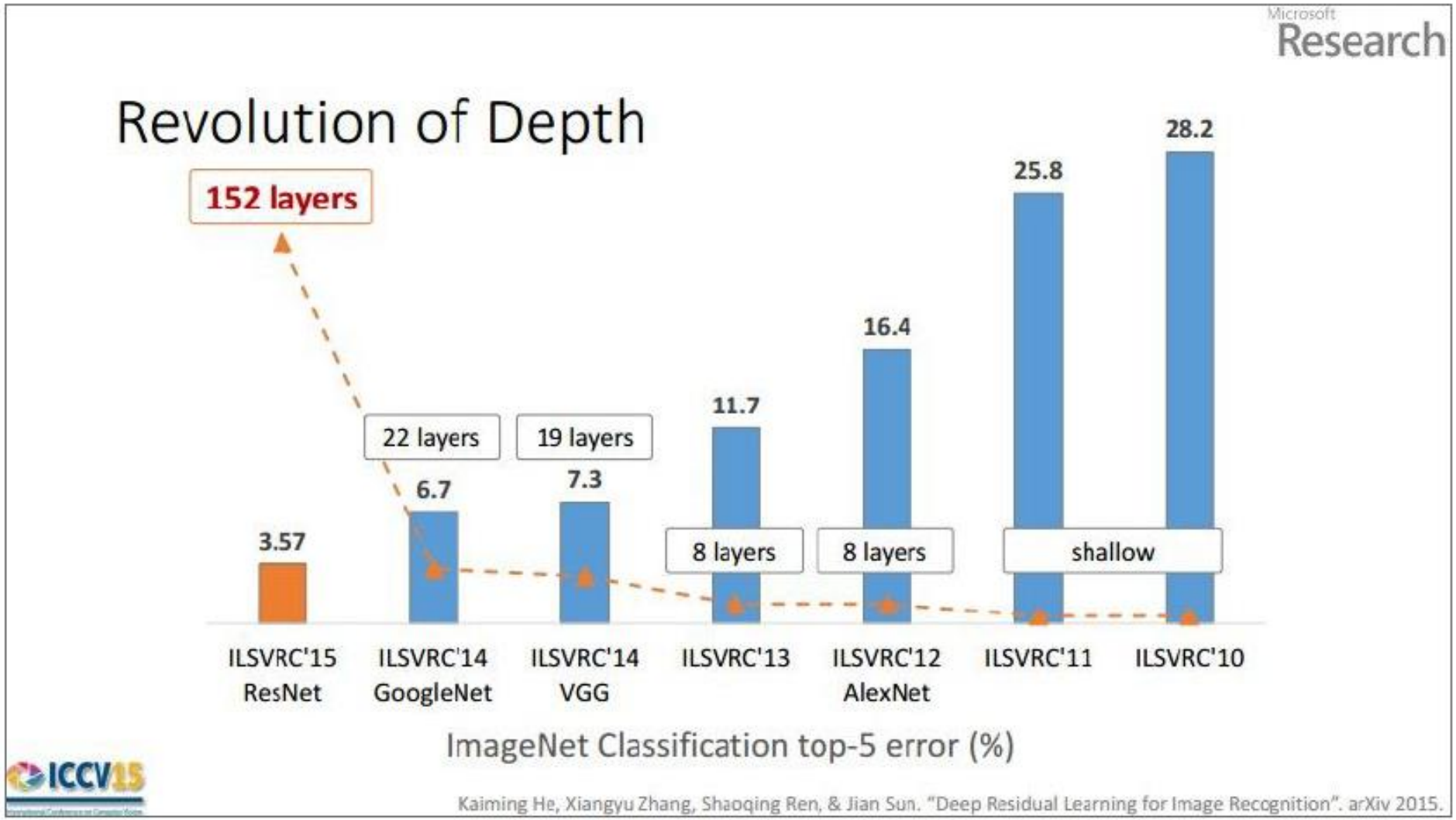
Note:

Most memory is in early CONV

Most params are in late FC

TOTAL memory: 24M * 4 bytes ~= 93MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

ResNet



(slide from Kaiming He's recent presentation)

Resnet Motivation

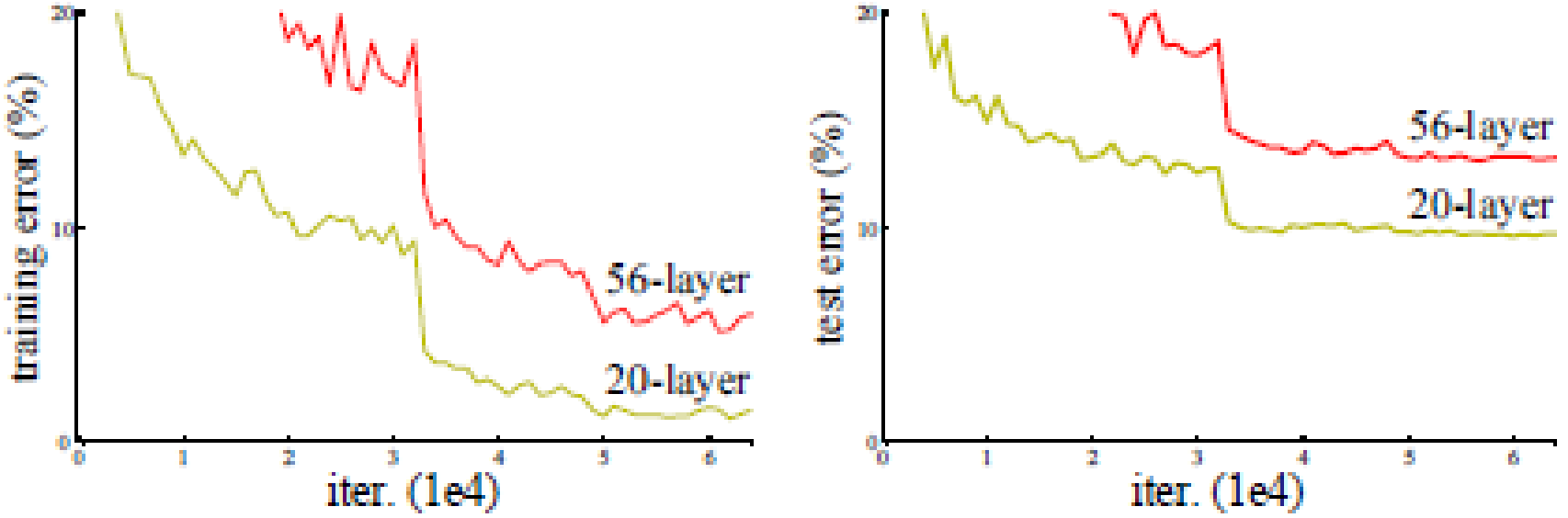
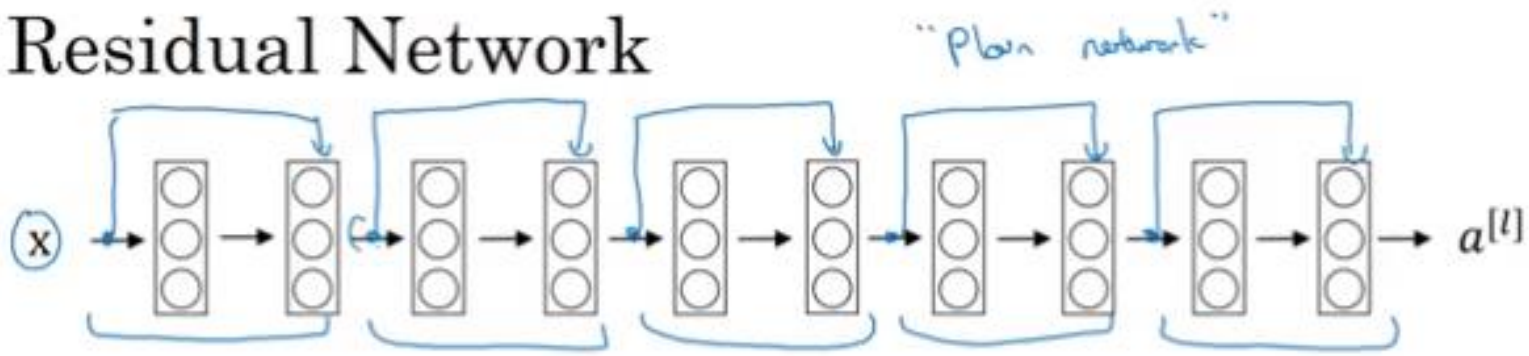
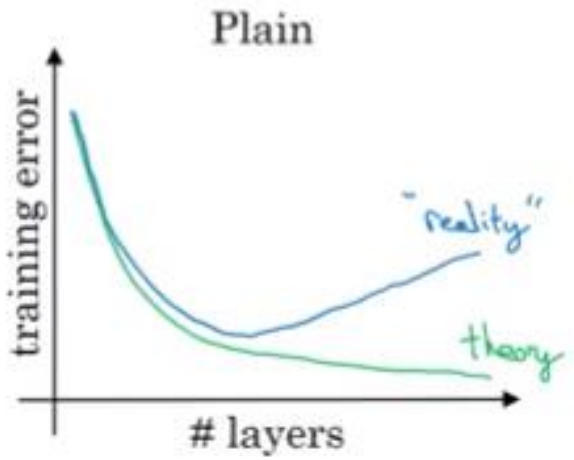
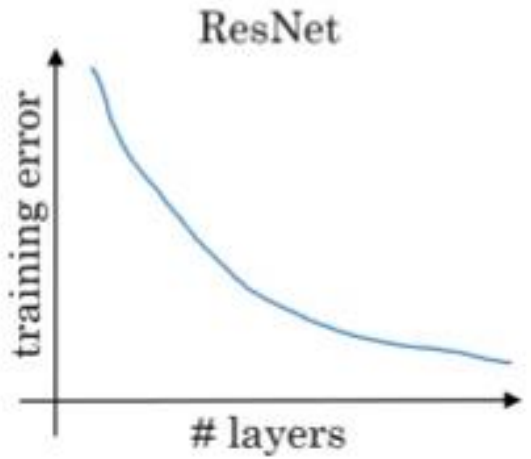


Figure 1. Training error (left) and test error (right) on CIFAR-10 with 20-layer and 56-layer "plain" networks. The deeper network has higher training error, and thus test error. Similar phenomena on ImageNet is presented in Fig. 4.

Resnet : ref Andrew Ng Coursera







[He et al., 2015. Deep residual networks for image recognition]

Andrew Ng

Core Tasks of Computer Vision

Core CV Task	Task Description	Output	Metrics
Classification	Given an image, assign a label	Class Label	Accuracy
Localization	Determine the bounding box containing the object in the given image	Box given by (x1, y1, x2, y2)	Ratio of intersection to the union (Overlap) between the ground truth and bounding box
Object Detection	Given an image, detect all the objects and their locations in the image	For each object: (Label, Box)	Mean Avg Best Overlap (MABO,) mean Average Precision (mAP)
Semantic Segmentation	Given an image, assign each pixel to a class label, so that we can look at the image as a set of labelled segments	A set of image segments	Classification metrics, Intersection by Union overlap
Instance Segmentation	Same as semantic segmentation, but each instance of a segment class is determined uniquely	A set of image segments	

Object Localization

- Given an image containing an object of interest, determine the bounding box for the object

- Classify the object

Classification + Localization: Task

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

→ CAT

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

→ (x, y, w, h)

Classification + Localization: Do both

Slide Credit: A Karpathy, CS231n

Classification + Localization: ImageNet

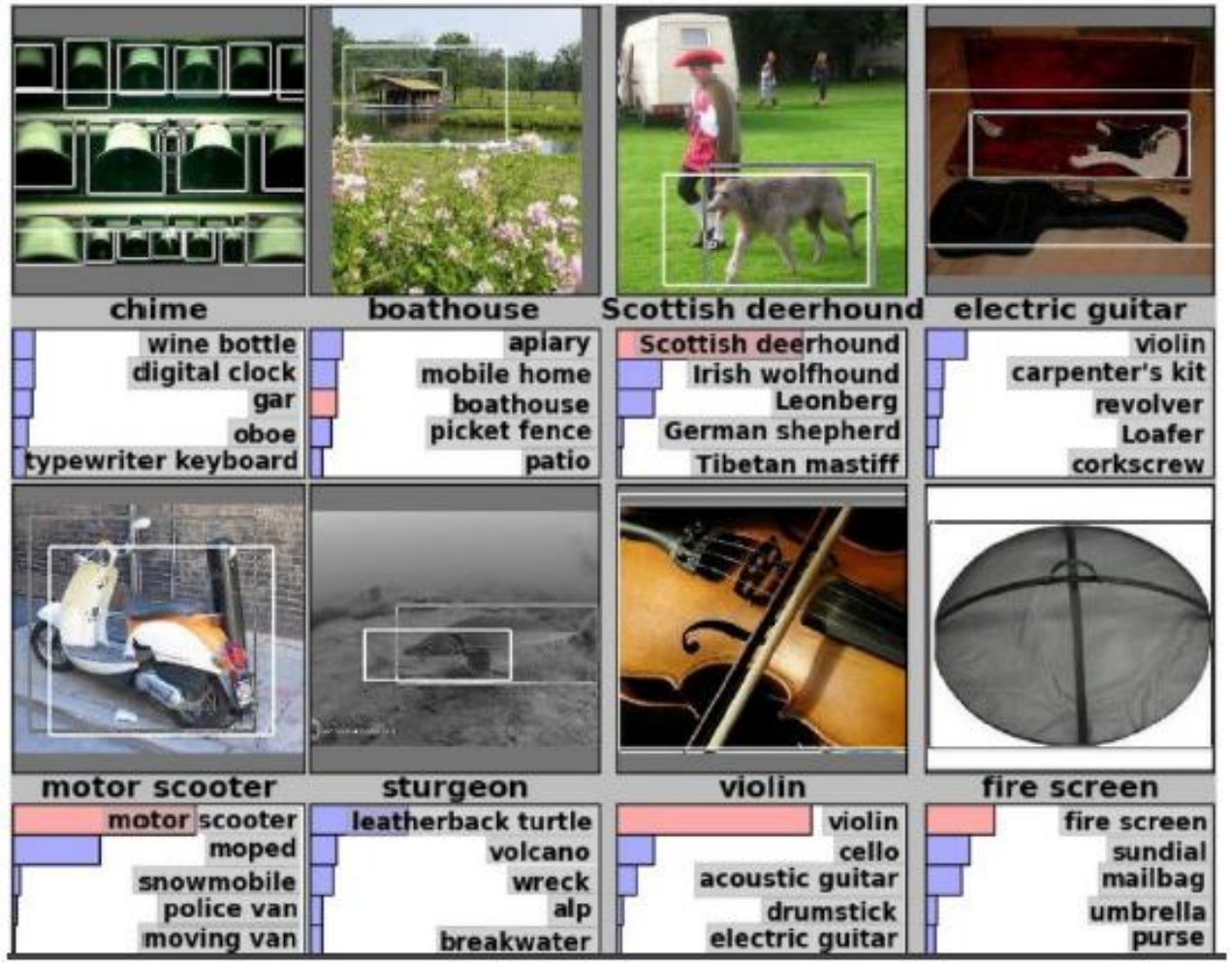
1000 classes (same as classification)

Each image has 1 class, at least one bounding box

~800 training images per class

Algorithm produces 5 (class, box) guesses

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



Krizhevsky et. al. 2012

Idea #1: Localization as Regression

Input: image

Only one object,
simpler than detection

Neural Net

Output:
Box coordinates
(4 numbers)

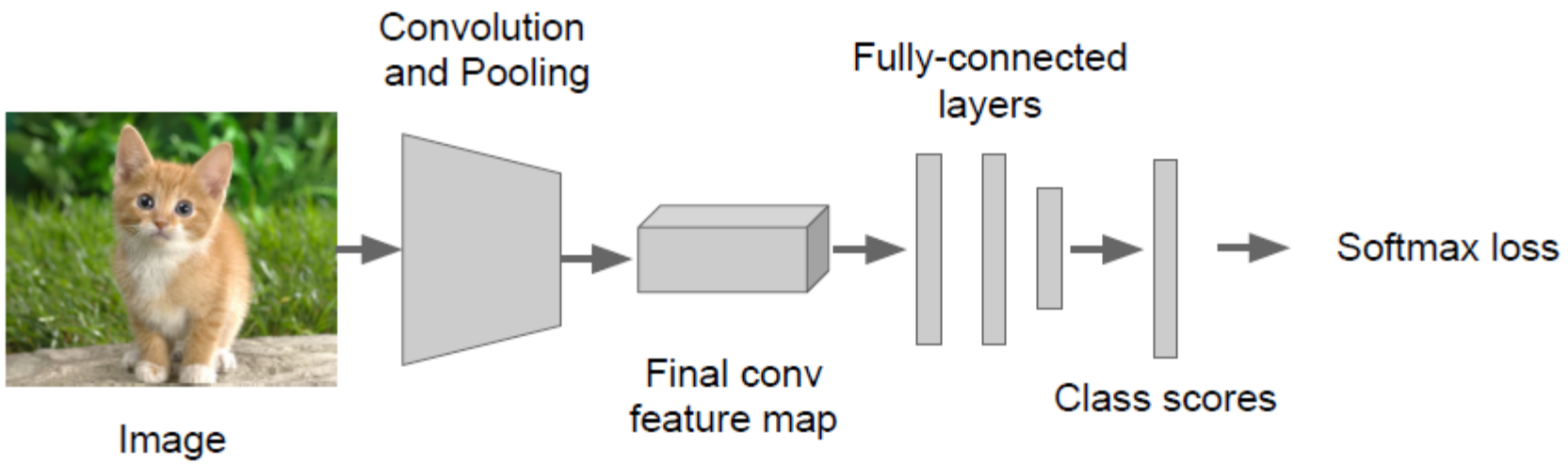
Correct output:
box coordinates
(4 numbers)

Loss:
L2 distance

Slide Credit: A Karpathy, CS231n

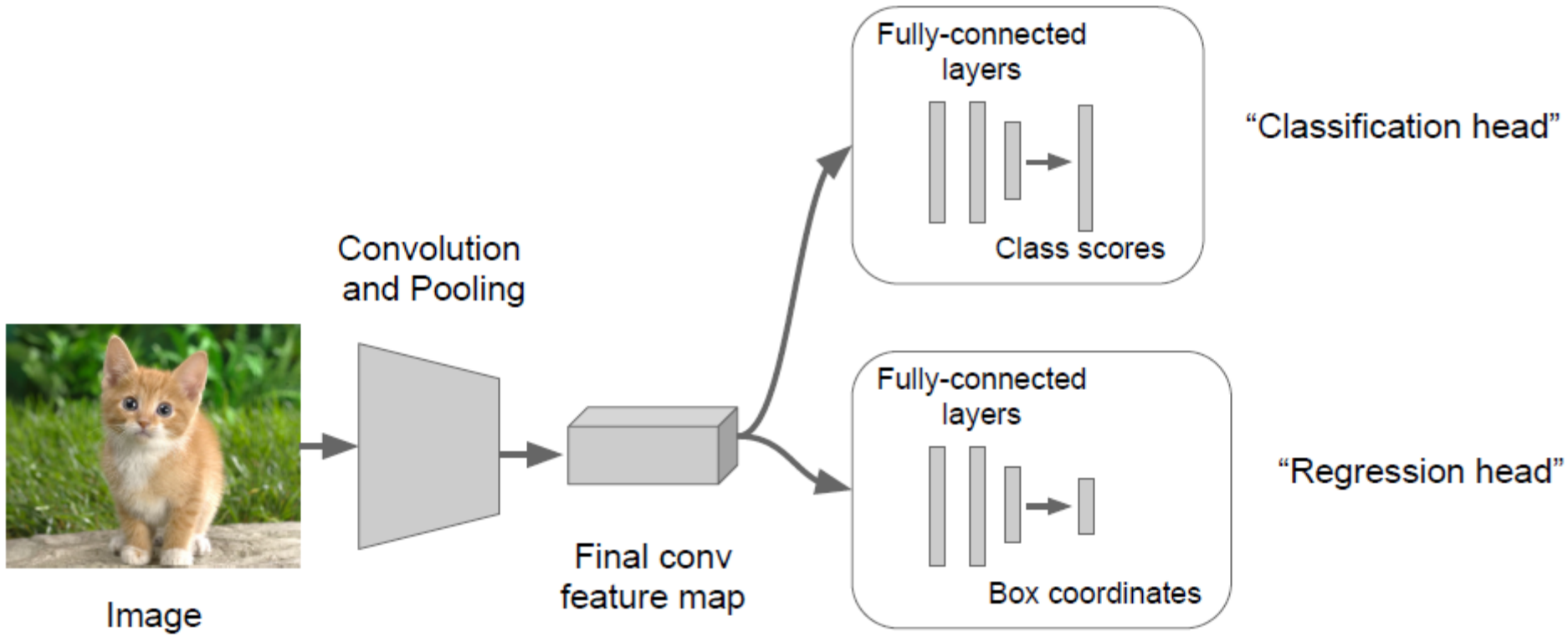
Simple Recipe for Classification + Localization

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



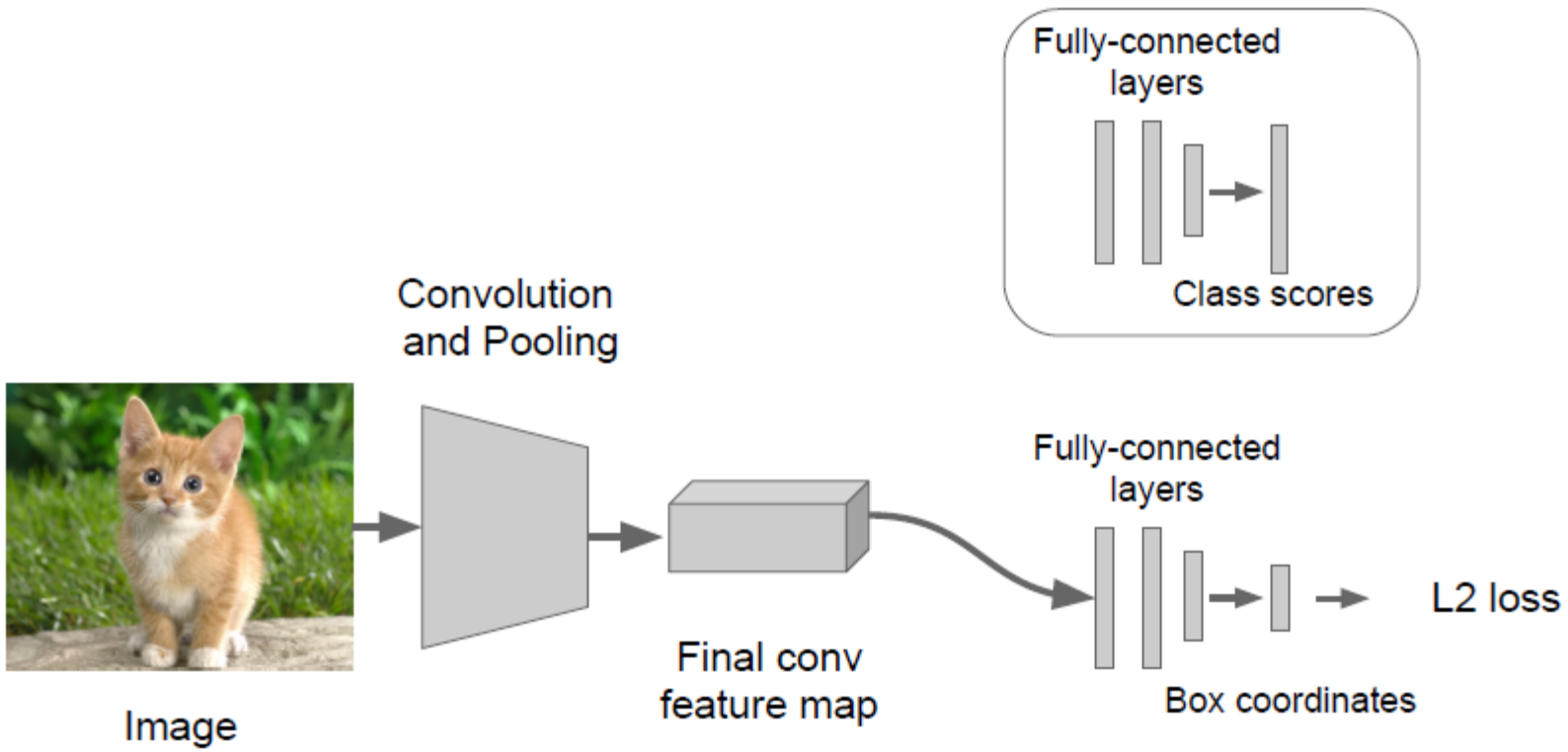
Simple Recipe for Classification + Localization

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



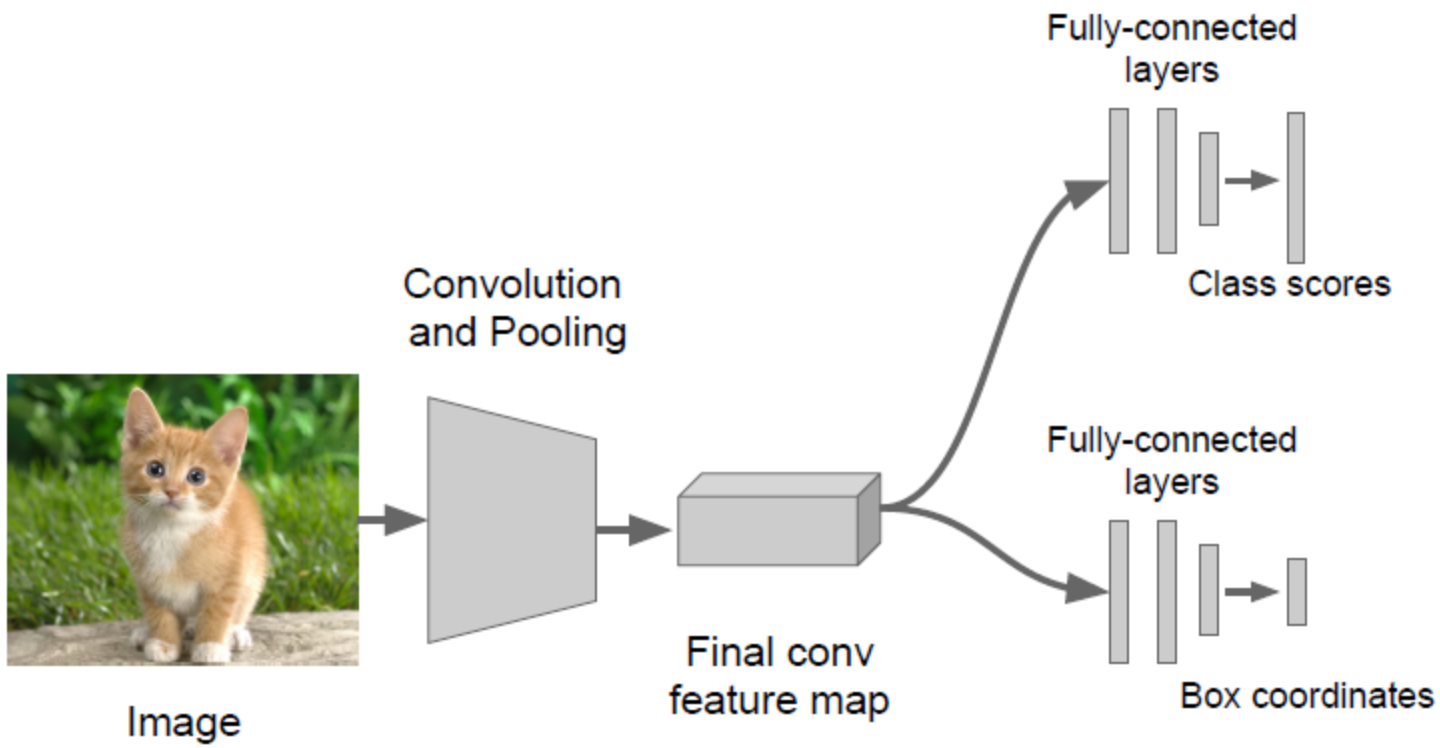
Simple Recipe for Classification + Localization

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



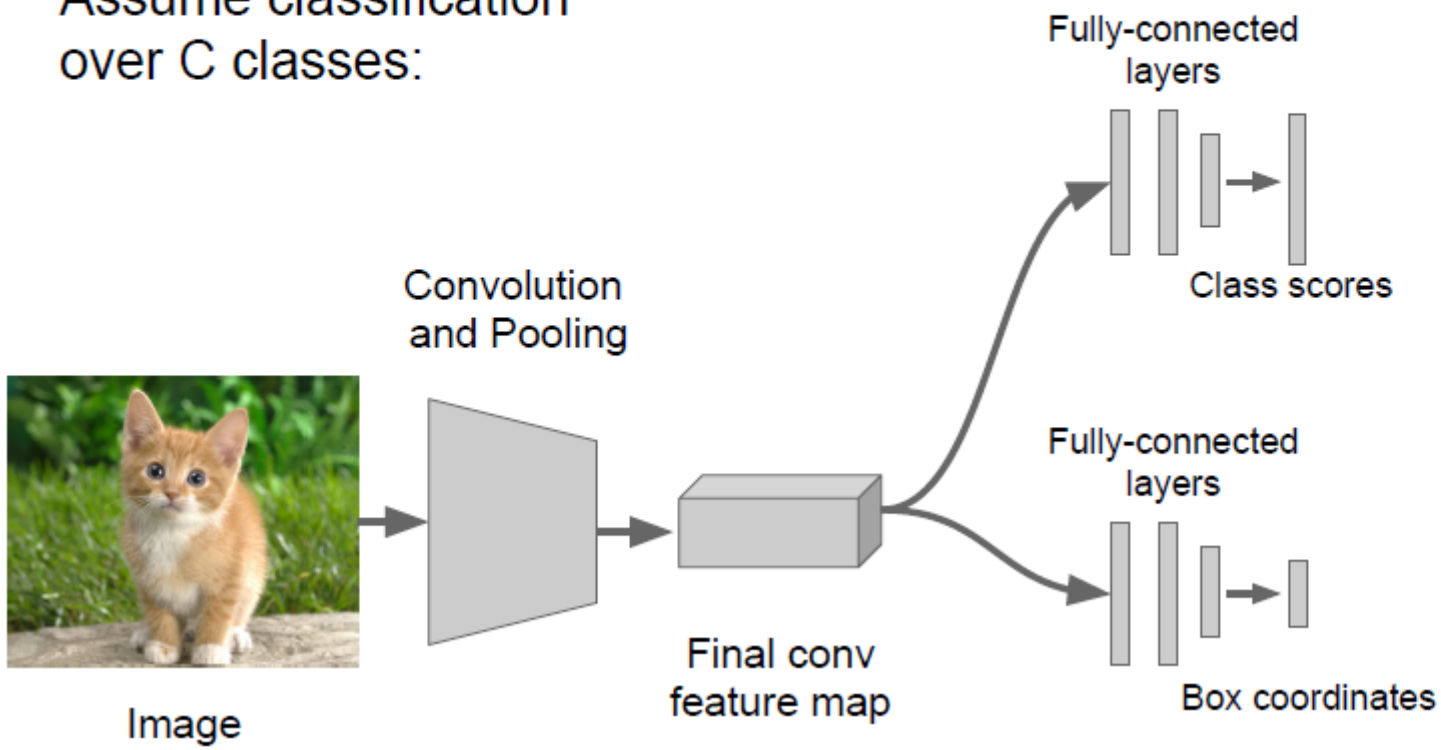
Simple Recipe for Classification + Localization

Step 4: At test time use both heads



Per-class vs class agnostic regression

Assume classification over C classes:

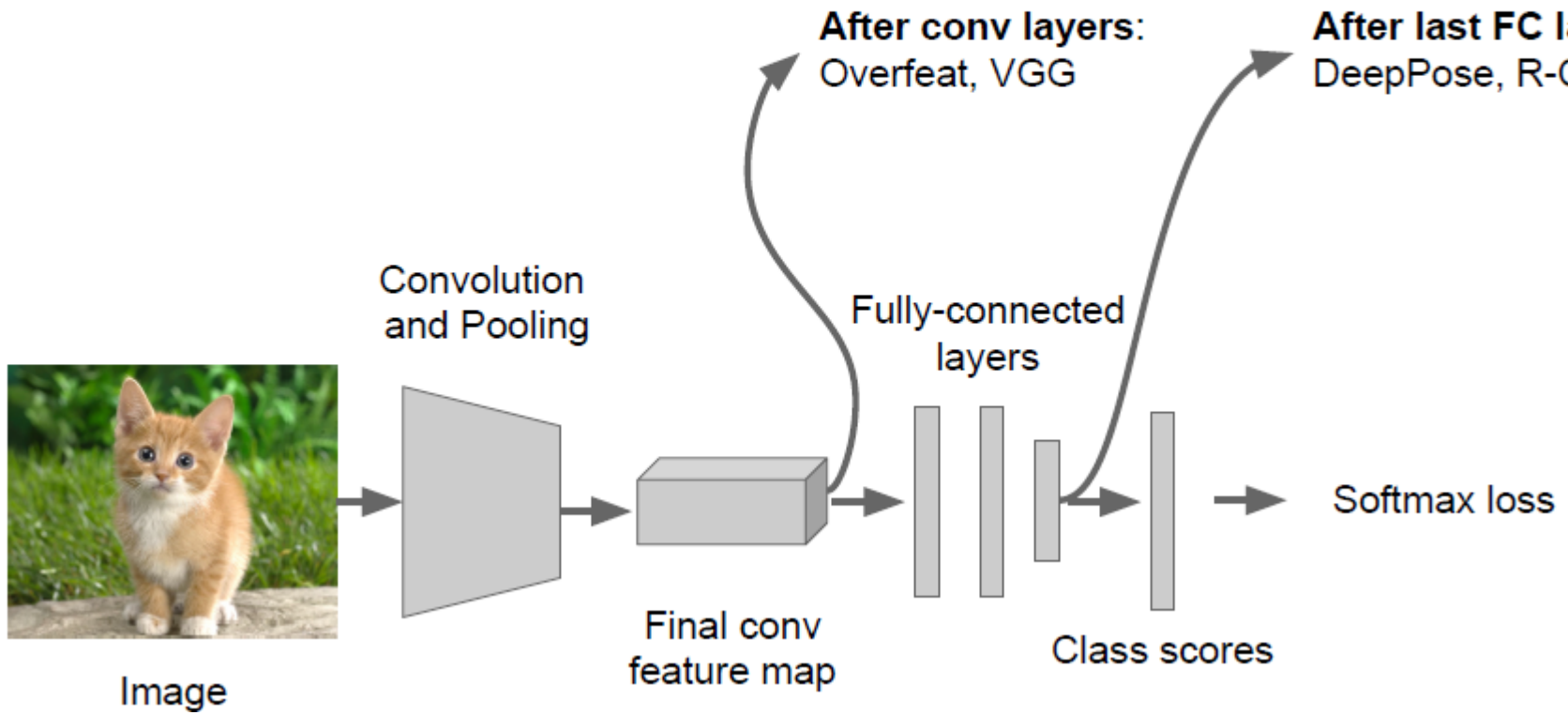


Classification head:
C numbers
(one per class)

Class agnostic:
4 numbers
(one box)

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

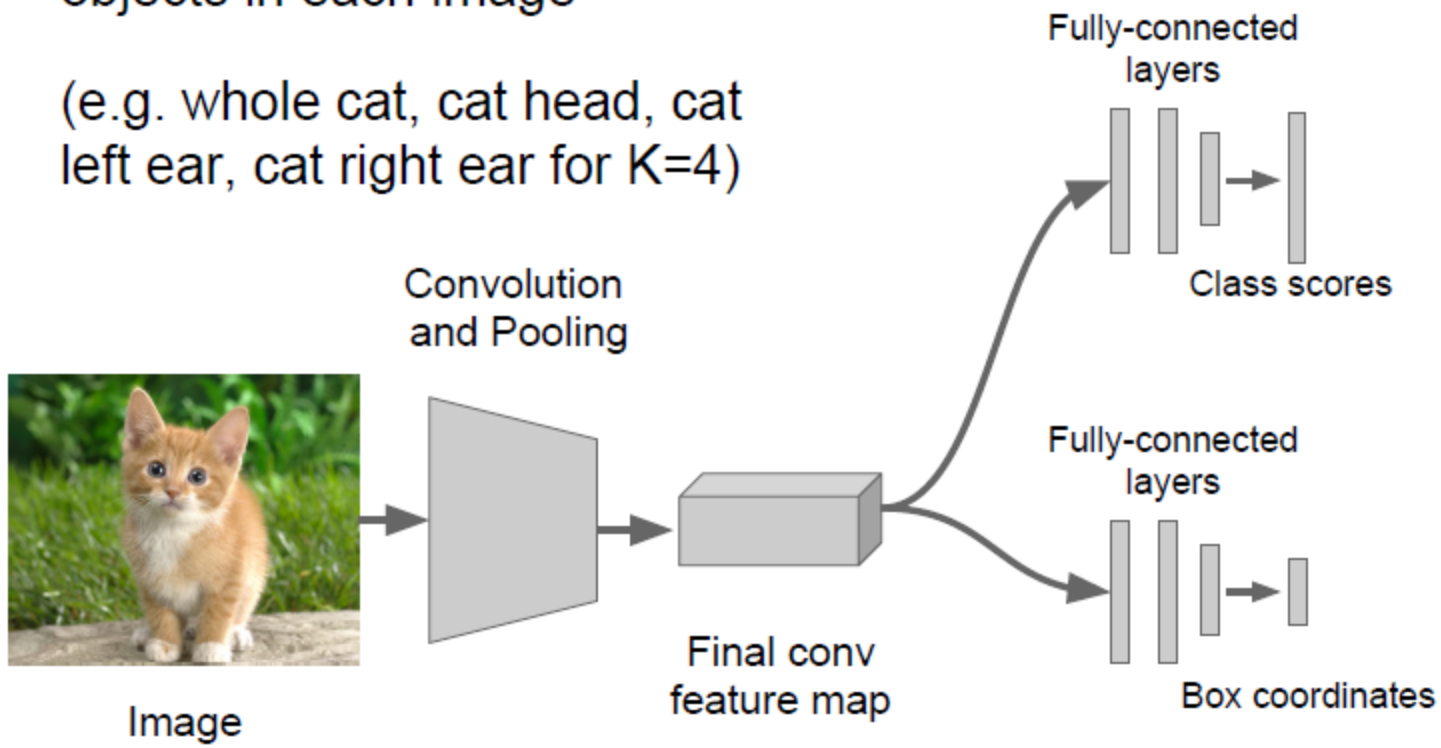
Where to attach the regression head?



Aside: Localizing multiple objects

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

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



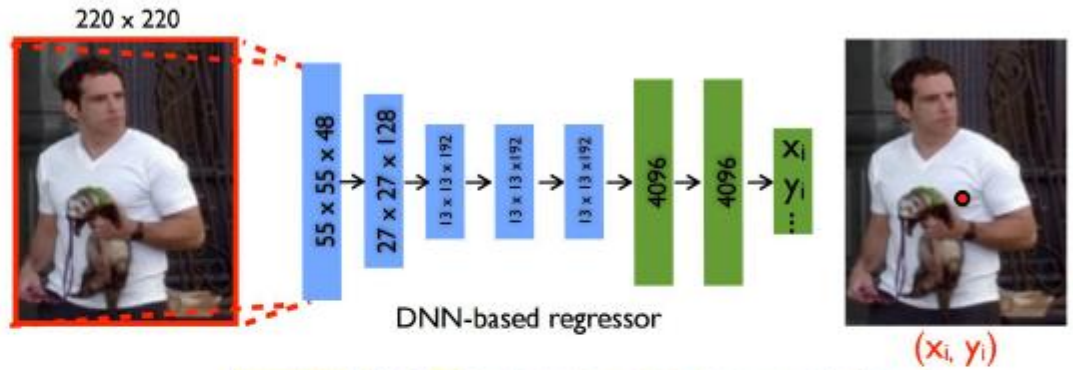
K x 4 numbers
(one box per object)

Aside: Human Pose Estimation

Represent a person by K joints

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

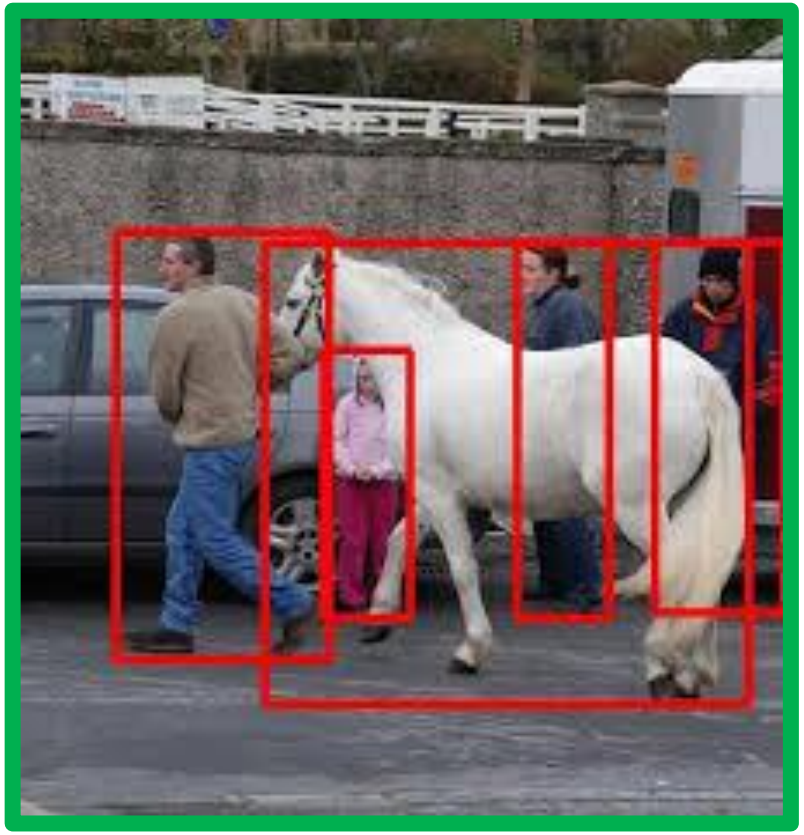
(Details: Normalized coordinates, iterative refinement)



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

Object Detection

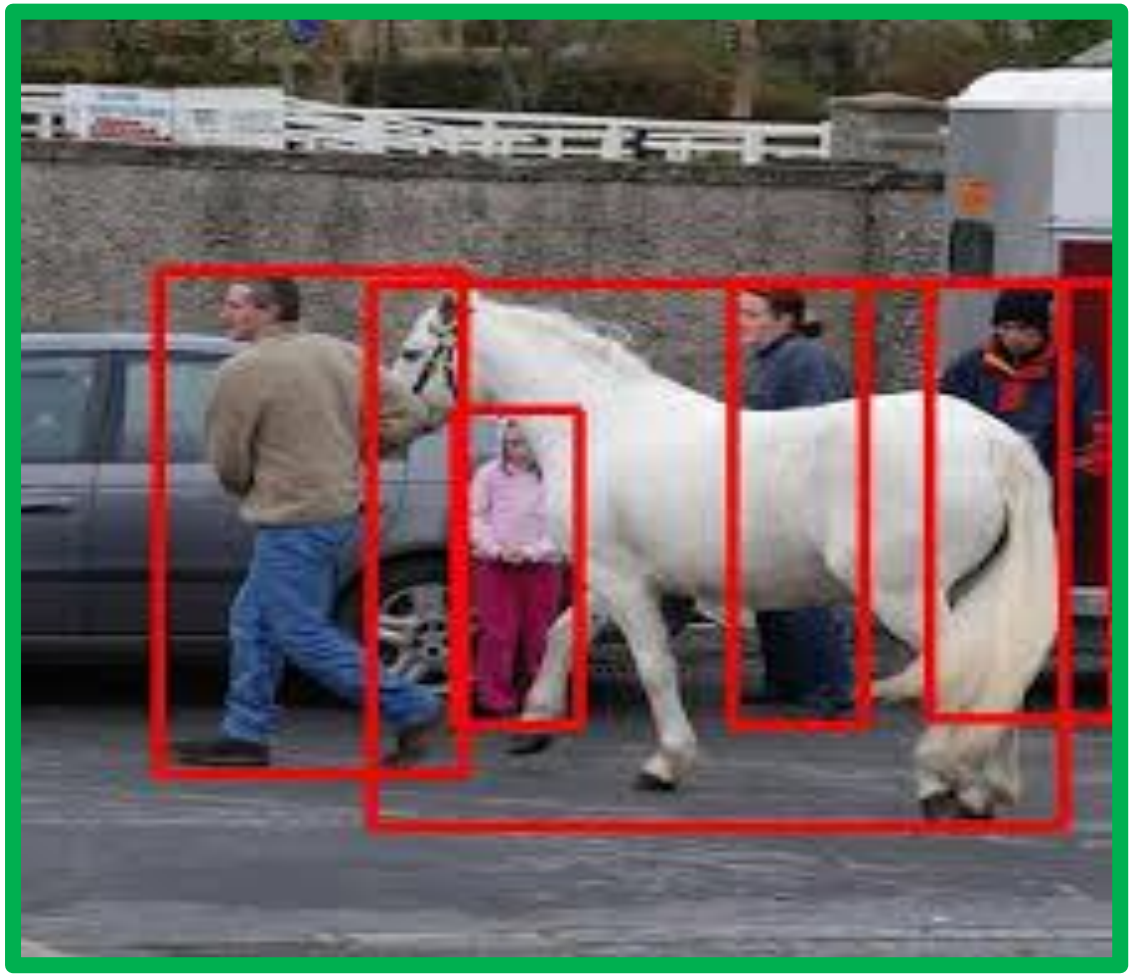
- Given an image, detect all the objects and their locations in the image



- Challenges
  - An arbitrary number of objects
  - Different scales
  - Objects may be occluded
  - Images may contain objects that are hierarchical

Object Detection: Approaches

- Can we formulate object detection as a regression problem?
  - This is a logical extension of the classification + localization algorithm
  - But the issue is there could be arbitrary number of objects at different locations.
  - Needs variable number of outputs: HORSE (x_1, y_1, x_2, y_2), GIRL CAT (x_3, y_3, x_4, y_4),…
- Can we treat this as a classification problem?
  - Need to test multiple locations and scales



Object Detection – A brute force approach

- Form a predefined set of window sizes for different scales
- Extract patches from the given image at various locations as per these window sizes
- Warp these patches to fixed dimensions
- Use these as inputs to a fast classifier and perform classification
- Define the necessary procedures to merge any overlaps between the patches in order to accurately classify.

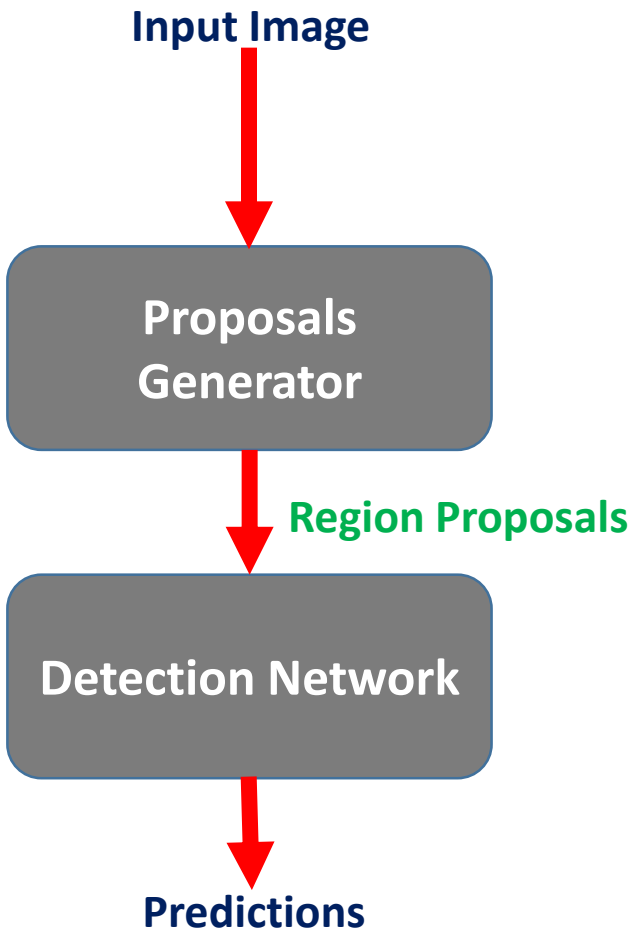
Use this method if you classifier is fast enough and/or your problem can be solved with a small number of fixed sized windows

Object Detection – improved approach

- Problem: Need to test for multiple positions and scales using a deep network (like a CNN). This approach is intractable.

- Solution: Don't attempt to do an exhaustive test. Apply the expensive classifier only to a smaller set of windows that are likely to contain the object

Key Idea: **Region Proposals**



Object Detection

- The architecture has a 2 stage pipeline that consists of a Proposal Generator and the Detection network
  - Proposals generator can be realized through a number of algorithms – class agnostic and fast
  - Detection network can be a shallow or a deep network like CNN

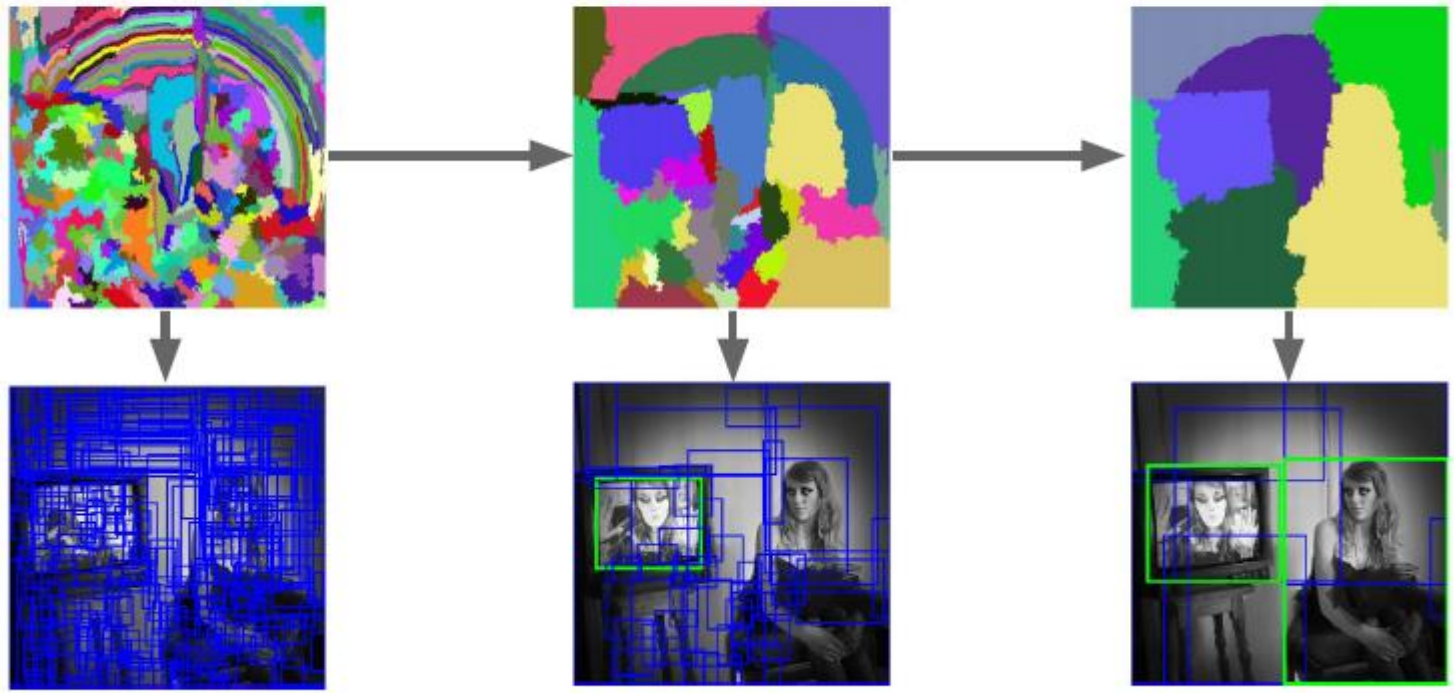
- This modular structure allows the flexibility to design sub systems independent of each other

- Modern approaches (e.g: Faster RCNN) merge these 2 stages in to a large CNN network as they strive to achieve real time performance (> 9 fps)

Region Proposals: Selective Search

Bottom-up segmentation, merging regions at multiple scales

Convert regions to boxes



Uijlings et al, "Selective Search for Object Recognition", IJCV 2013

Detecting regions

Look for blobs where a blob of nearby pixels share some property: e.g: color, texture and so on.

- The petals of the flower shown in the figure share the property of same yellow colour and similar texture while the background is sky blue. The leaves are green and distinct from the flower.

- We can use these information to discriminate between different objects.

Selective Search

Design Considerations

- Capture all scales

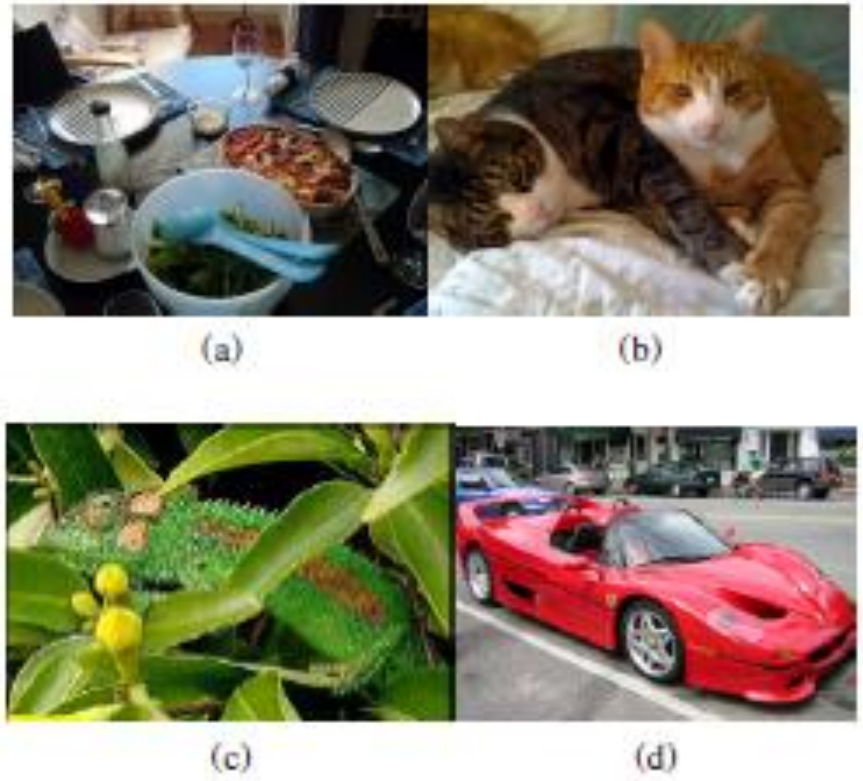


Figure 1: There is a high variety of reasons that an image region forms an object. In (b) the cats can be distinguished by colour, not texture. In (c) the chameleon can be distinguished from the surrounding leaves by texture, not colour. In (d) the wheels can be part of the car because they are enclosed, not because they are similar in texture or colour. Therefore, to find objects in a structured way it is necessary to use a variety of diverse strategies. Furthermore, an image is intrinsically hierarchical as there is no single scale for which the complete table, salad bowl, and salad spoon can be found in (a).

- Diversification

- Fast to compute

Algorithm 1: Hierarchical Grouping Algorithm

Input: (colour) image

Output: Set of object location hypotheses L

Obtain initial regions $R = \{r_1, \cdots, r_n\}$ using [13]
Initialise similarity set $S = \emptyset$
foreach *Neighbouring region pair* (r_i, r_j) **do**
    Calculate similarity $s(r_i, r_j)$
    $S = S \cup s(r_i, r_j)$

while $S \neq \emptyset$ **do**
    Get highest similarity $s(r_i, r_j) = \max(S)$
    Merge corresponding regions $r_t = r_i \cup r_j$
    Remove similarities regarding $r_i : S = S \setminus s(r_i, r_*)$
    Remove similarities regarding $r_j : S = S \setminus s(r_*, r_j)$
    Calculate similarity set S_t between r_t and its neighbours
    $S = S \cup S_t$
    $R = R \cup r_t$

Extract object location boxes L from all regions in R

Complementary Similarity Measures

- Four complementary similarity measures:
  - Color, Texture, Size, Fill

- The final similarity measure $s(r_i, r_j)$ is computed as a sum of these complementary measures

$$s(r_i, r_j) = a_1 s_{colour}(r_i, r_j) + a_2 s_{texture}(r_i, r_j) + a_3 s_{size}(r_i, r_j) + a_4 s_{fill}(r_i, r_j),$$

Evaluation Measure

- Average Best Overlap (ABO) measures the best overlap between each ground truth annotation $g_i^c \in G^c$ and the object hypotheses L generated for the corresponding image and average:

$$\text{ABO} = \frac{1}{|G^c|} \sum_{g_i^c \in G^c} \max_{l_j \in L} \text{Overlap}(g_i^c, l_j).$$

$$\text{Overlap}(g_i^c, l_j) = \frac{\text{area}(g_i^c) \cap \text{area}(\text{l}_\text{j})}{\text{area}(g_i^c) \cup \text{area}(\text{l}_\text{j})}.$$

- Mean ABO is defined as the mean over all classes

Other choices

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

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

Object Detection: Evaluation

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

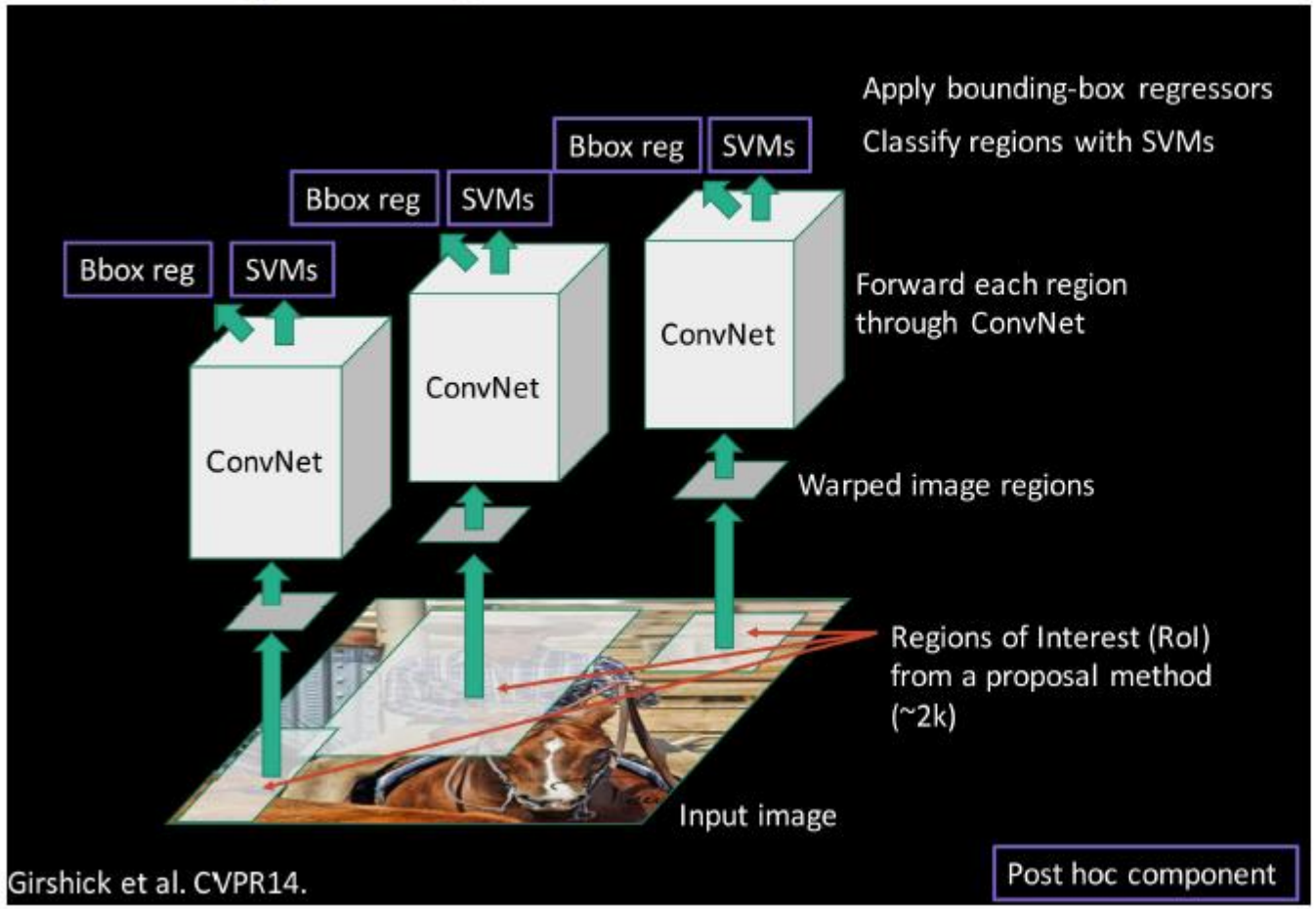
Compute average precision (AP) separately for each class, then average over classes

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

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

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

RCNN

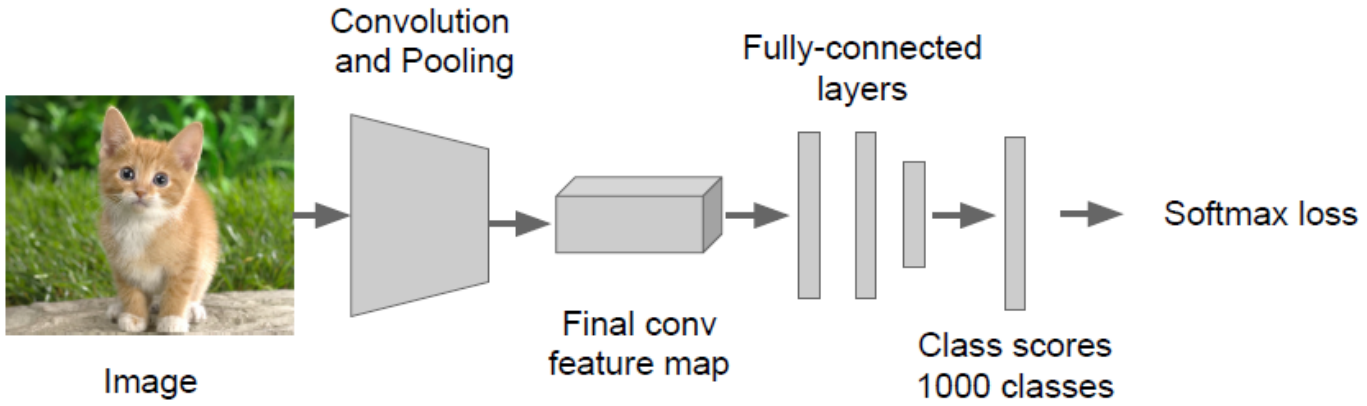


Girschick et al, "Rich feature hierarchies for accurate object detection and semantic segmentation", CVPR 2014

Slide credit: Ross Girschick

RCNN Training Process

- Train or download a classifier for Imagenet (AlexNet)



- Finetune the model for detection
  - Replace the output layer of AlexNet with a custom layer of 21 classes and finetune

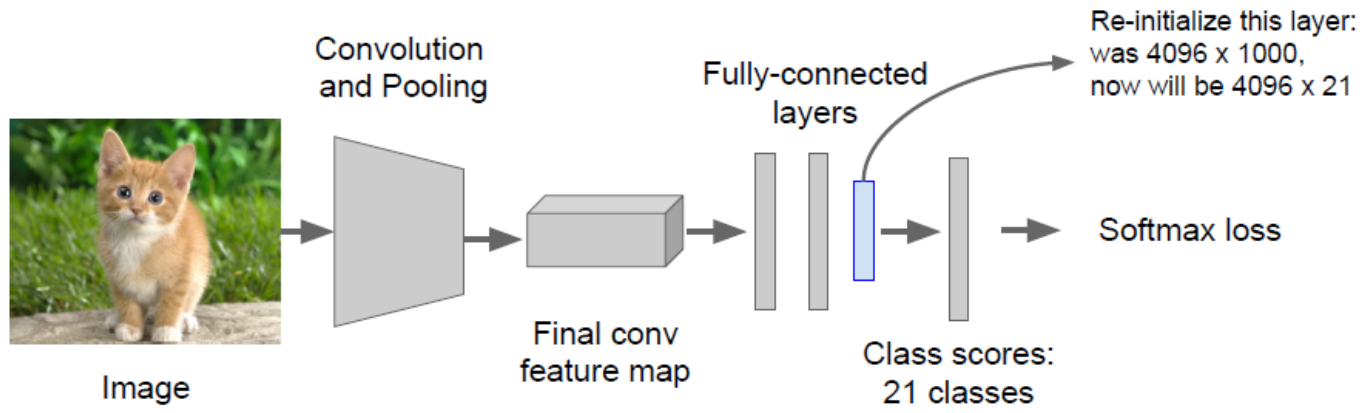


Fig Credit: A Karpathy, CS231n

RCNN Training Process

- **Extract features**
  - Get the region proposals (Selective Search) and warp the region to fit to AlexNet input format
  - Forward pass through CNN till pool5 layer
  - Save features to disk (200 GB! For PASCAL 2010 dataset)

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

Fig Credit: A Karpathy, CS231n

RCNN Training Process

- Perform bounding box regression
  - For each class, train a regression model that maps the cached features to bounding box co ordinates from ground truth box

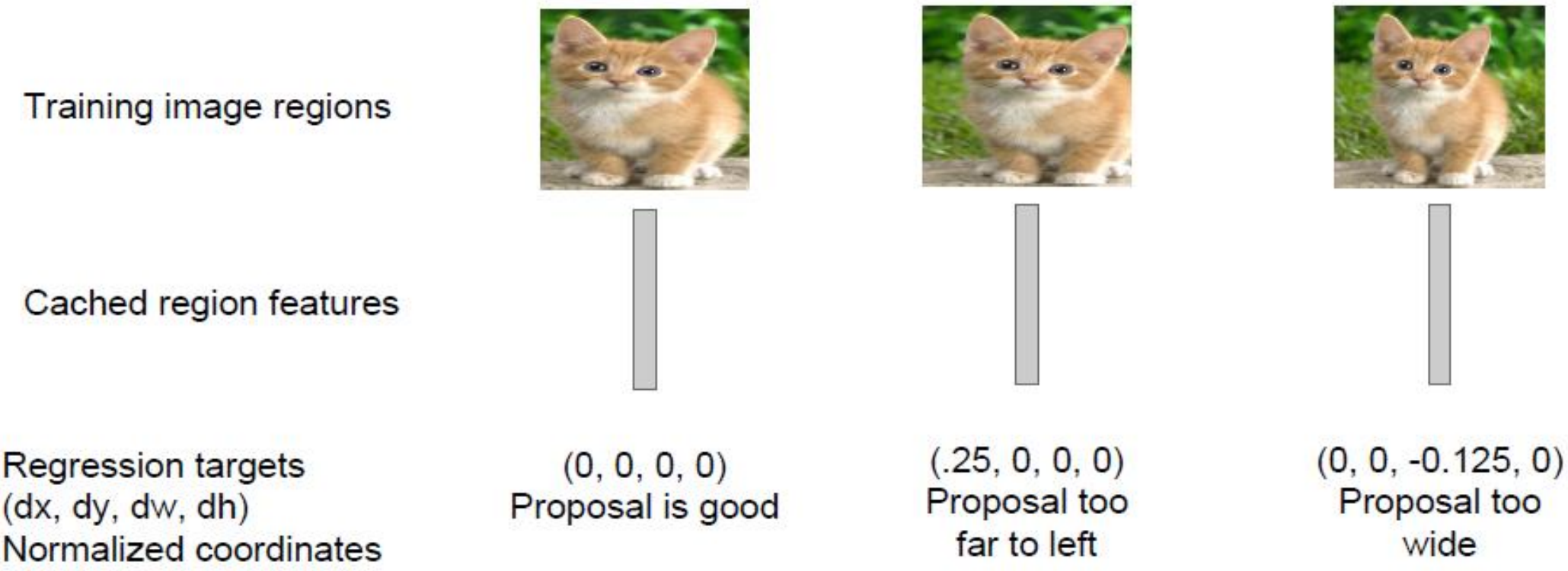


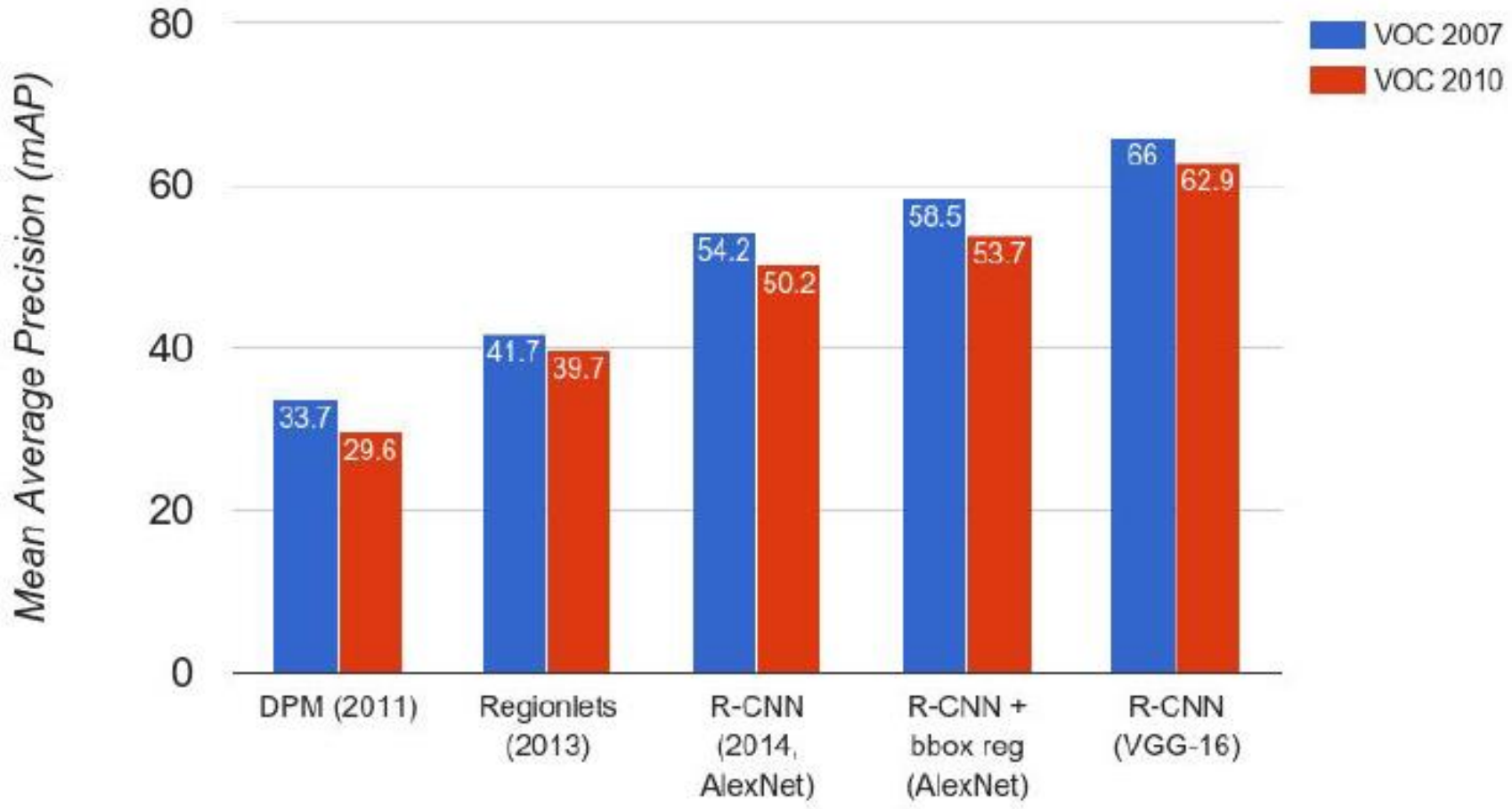
Fig Credit: A Karpathy, CS231n

Datasets for evaluation

- Imagenet challenges provide a platform for researchers to benchmark their novel algorithms
- PASCAL VOC 2010 is great for small scale experiments. About 1.3 GB download size.
- MS COCO datasets are available for tasks like Image Captioning. Download size is huge but selective download is possible.

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

Performance of RCNN



Wang et al, "Regionlets for Generic Object Detection", ICCV 2013

Problems with RCNN

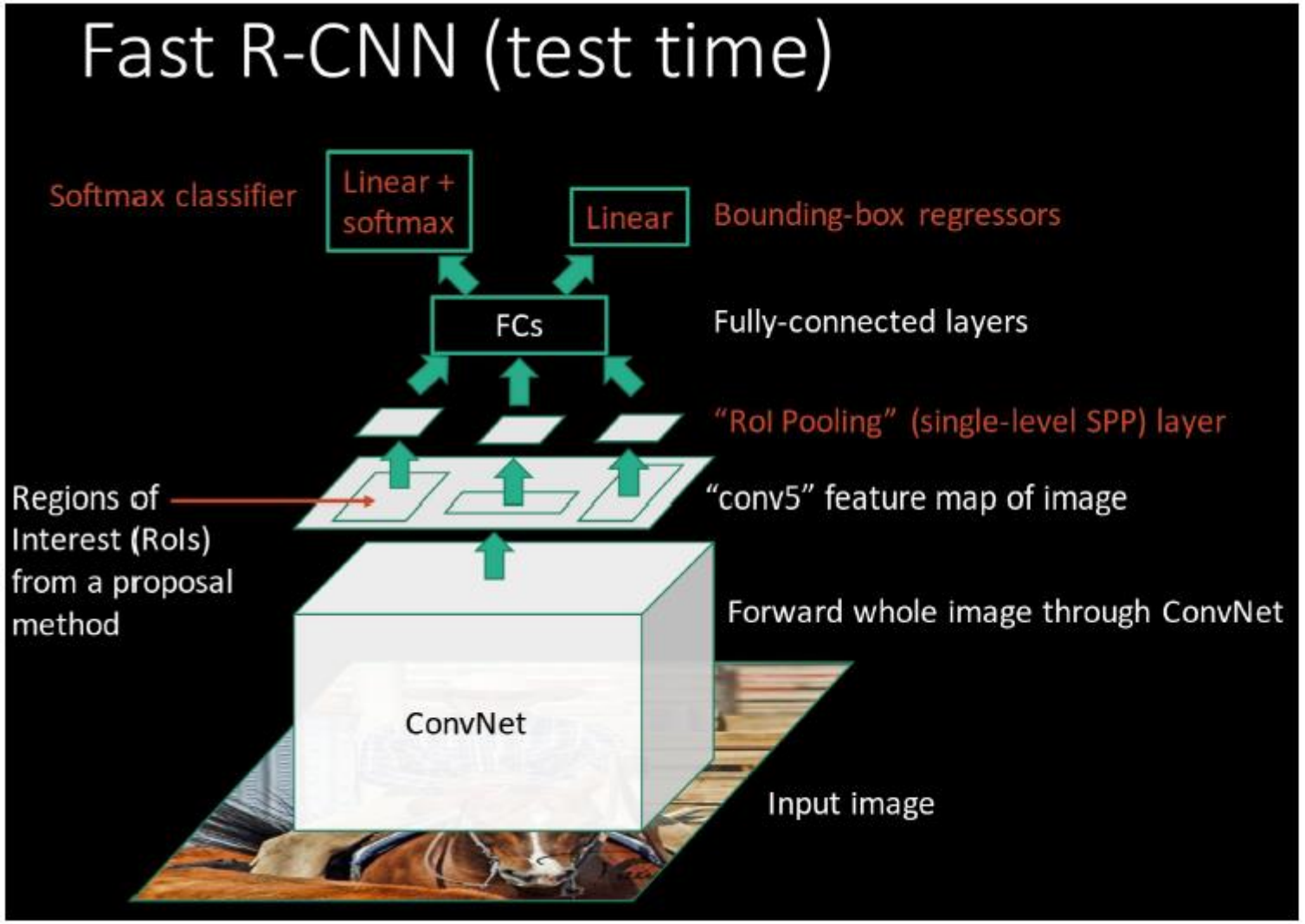
- Each region proposal is passed through the deep CNN in order to generate features.
  - Suppose there are about 2000 regions per image and 10K training images, we end up passing 20 M regions through the deep network
- Training process involves multiple steps
  - Finetuning with custom classes, training SVM and the regressors
- As a result, the training time as well as the prediction time is high

Fast RCNN

- Challenges with RCNN: Object detection performance is good but is quite slow. Not suitable for a real time application

- Solution: Fast RCNN that optimizes both the training and testing time

Fast RCNN

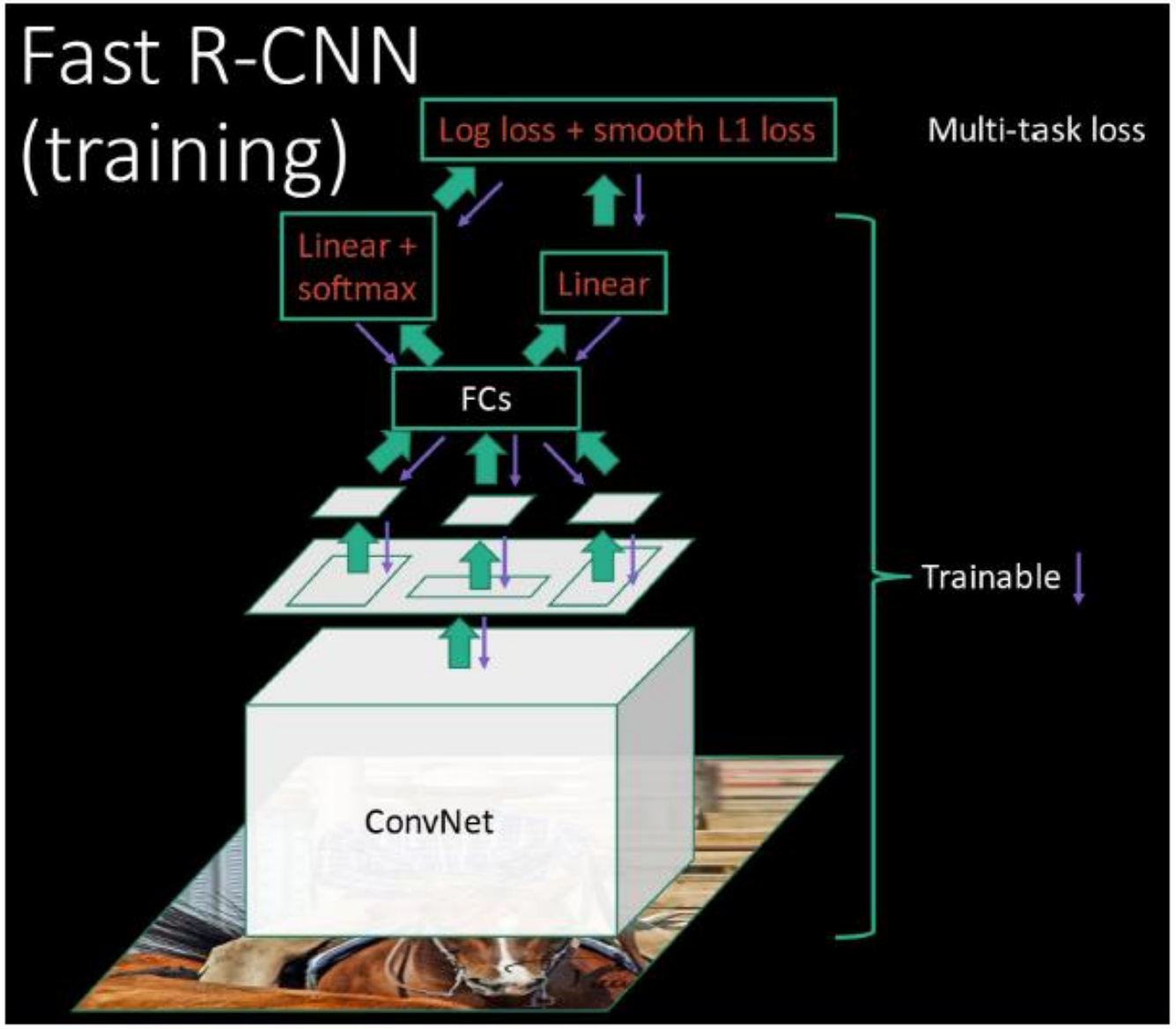


R-CNN Problem #1:
Slow at test-time due to independent forward passes of the CNN

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

Fig Credit: A Karpathy, CS231n

Fast RCNN



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

R-CNN Problem #3:
Complex training pipeline

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

Slide credit: Ross Girschick

Fast RCNN Training Procedure

- Given a hi-res image with the region proposals, perform convolution over the entire image and obtain the full image feature map
- Project the region proposal on to the conv feature map
- Divide the projected region to h x w grid
- Pass them through fully connected layers as before
- Can backpropagate through the entire network

Fast R-CNN Results

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

Using VGG-16 CNN on Pascal VOC 2007 dataset

Fast R-CNN Problem:

Test-time speeds don't include region proposals

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

Fast RCNN

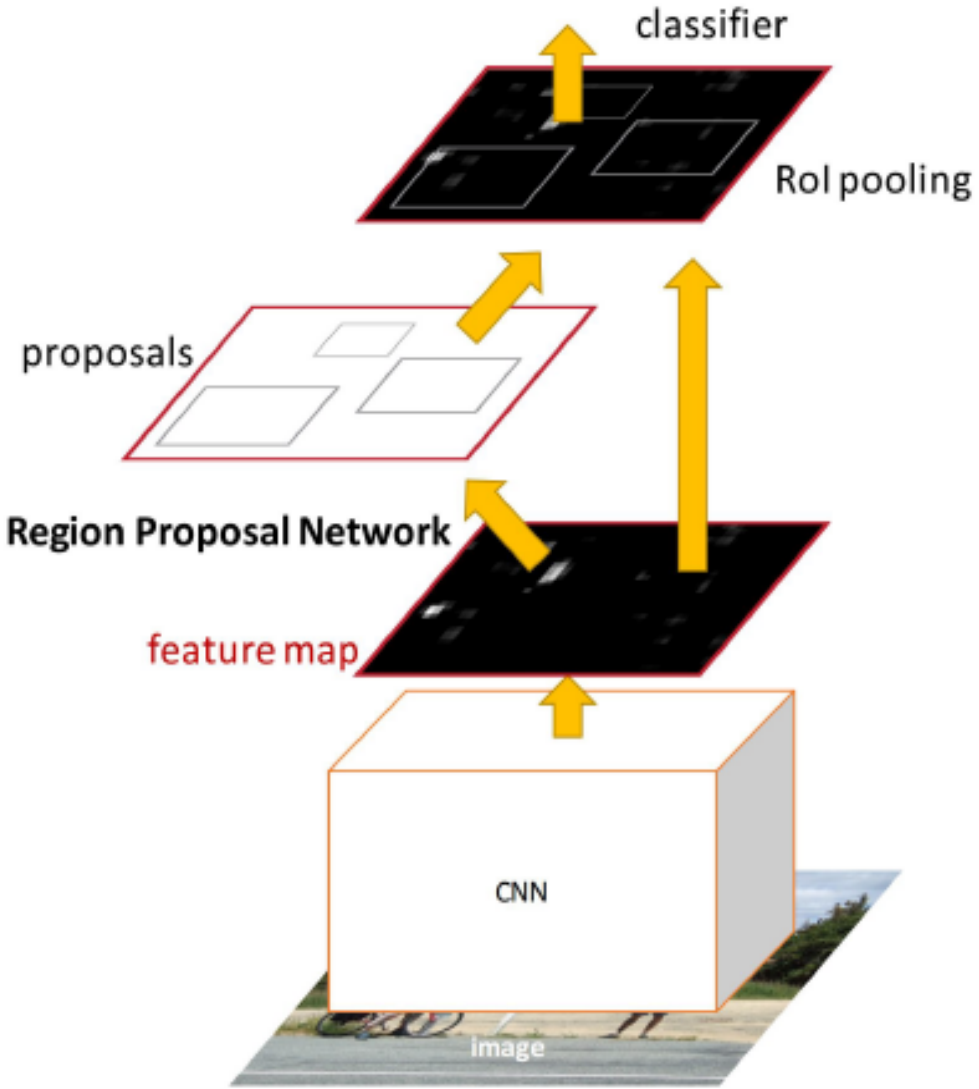
- Performs much faster compared to RCNN in terms of classification speed

- Bottleneck arises from region proposal sub system

- Solution: Build a Faster RCNN ☺

    - Eliminate the separate sub system that does region proposal generation, merge it with the CNN so that the CNN can generate region proposals too

Faster R-CNN:



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

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

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

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

Slide credit: Ross Girschick

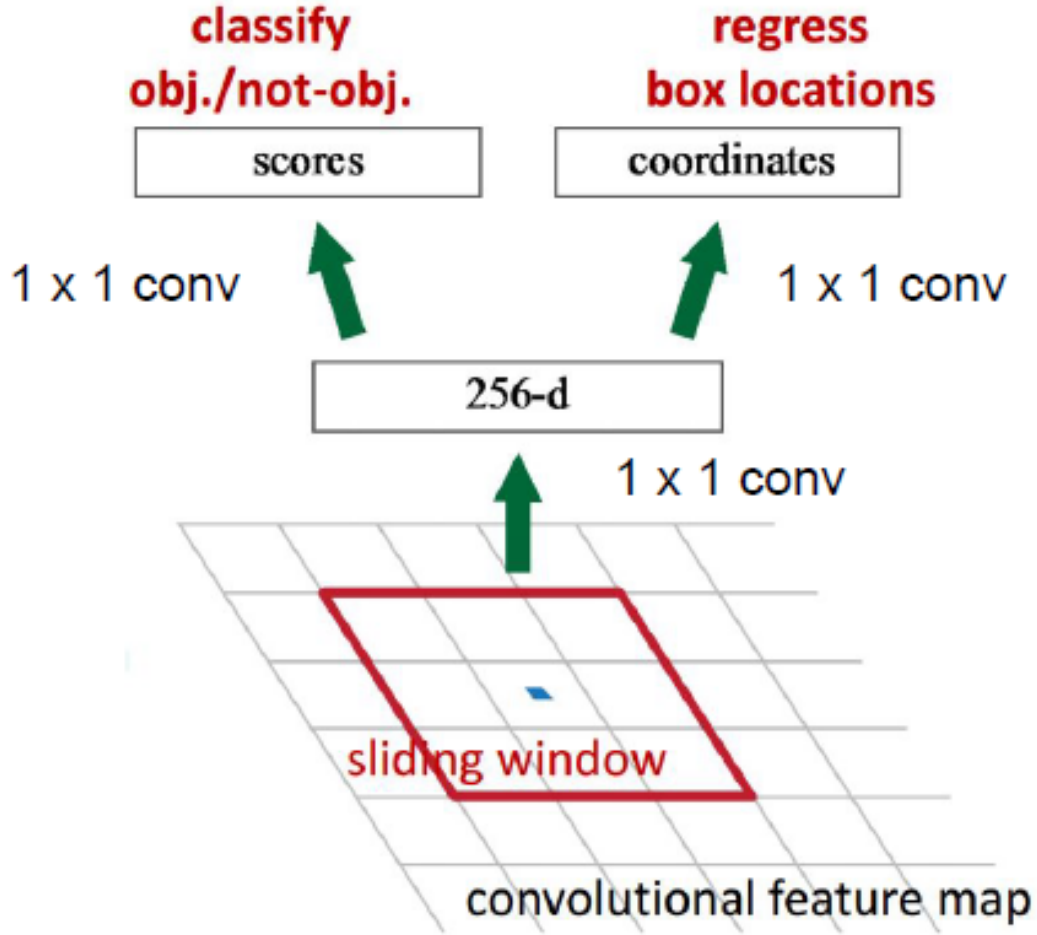
Faster R-CNN: Region Proposal Network

Slide a small window on the feature map

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

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

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



Slide credit: Kaiming He

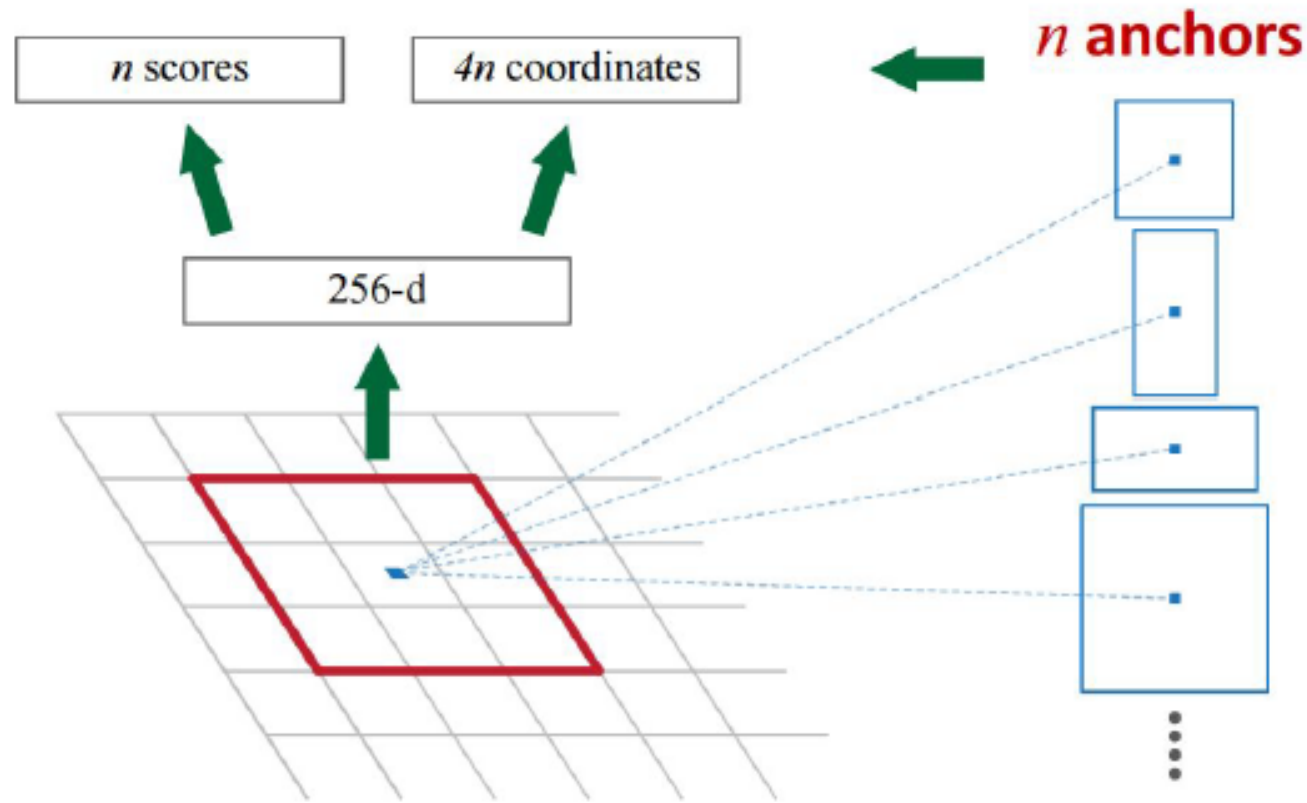
Faster R-CNN: Region Proposal Network

Use **N anchor boxes** at each location

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

Regression gives offsets from anchor boxes

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



Faster R-CNN: Training

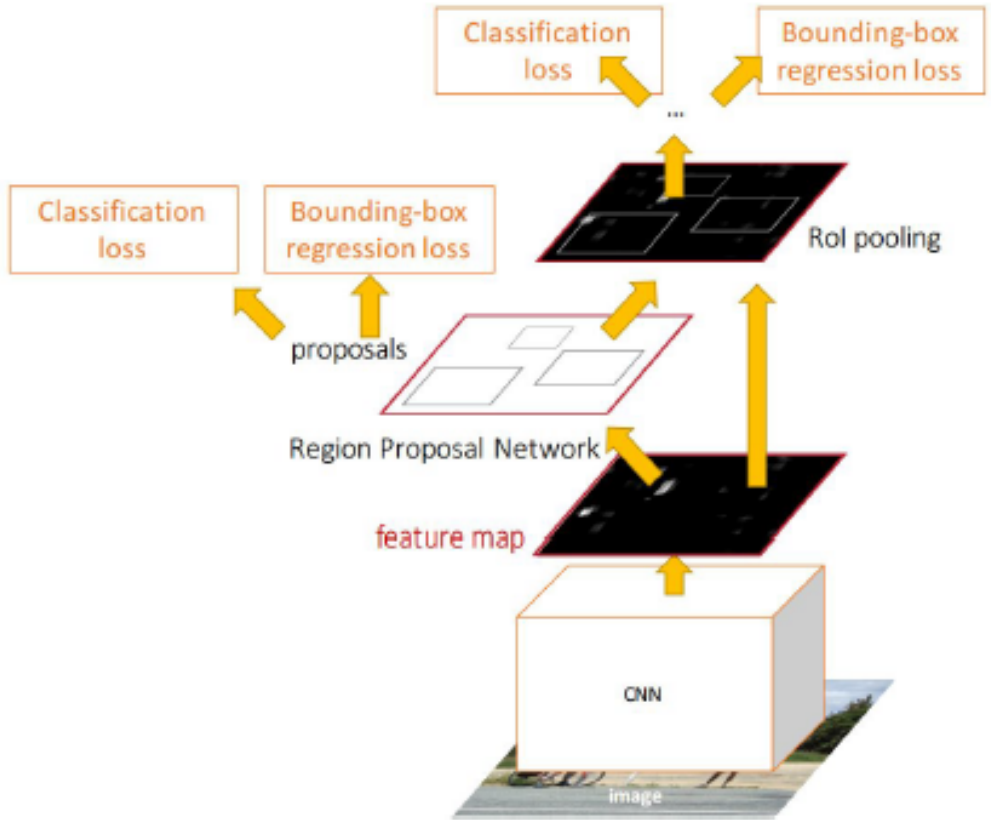
In the paper: Ugly pipeline

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

Since publication: Joint training!

One network, four losses

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

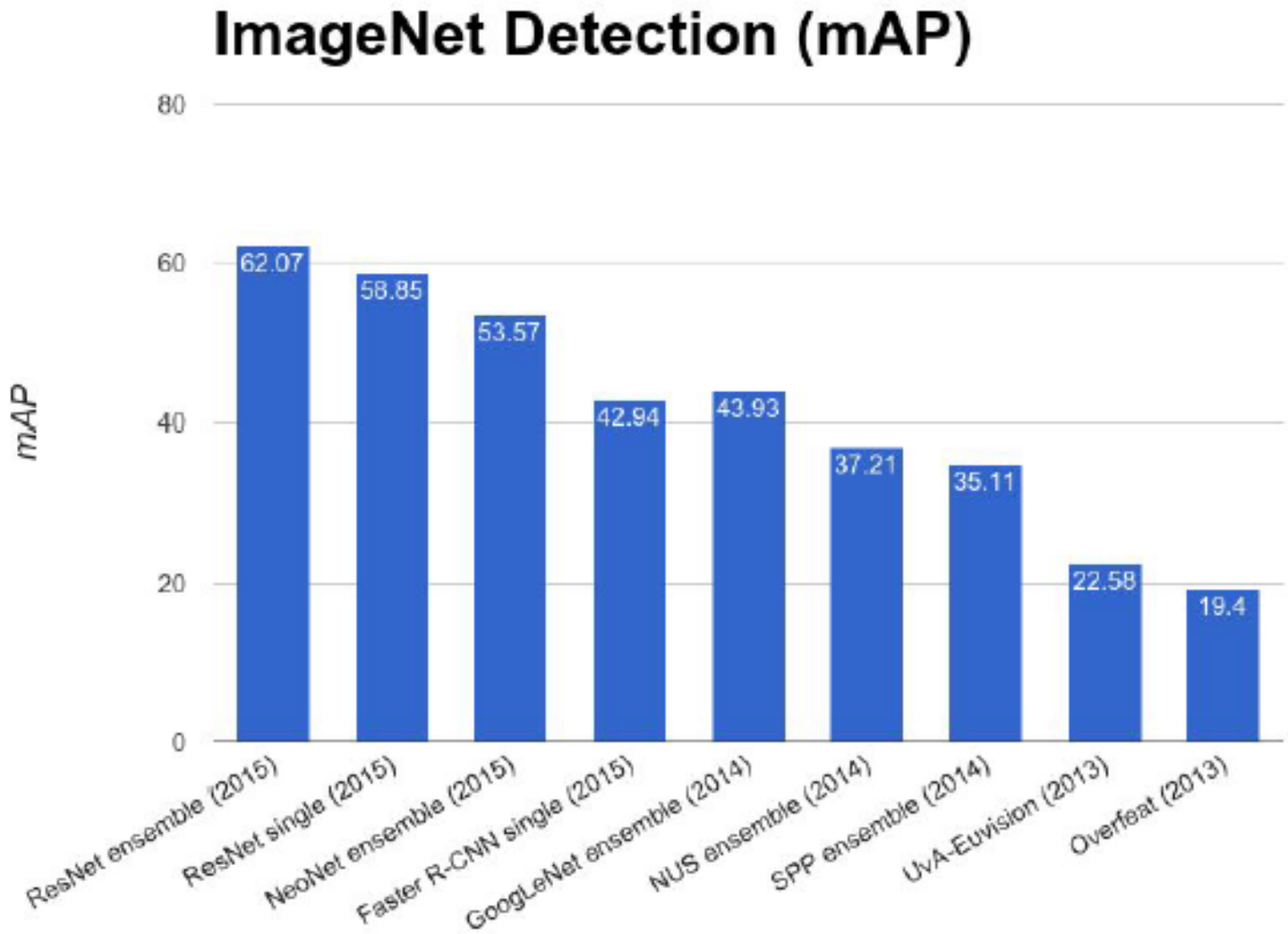


Slide credit: Ross Girschick

Faster R-CNN: Results

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

ImageNet Detection 2013 - 2015



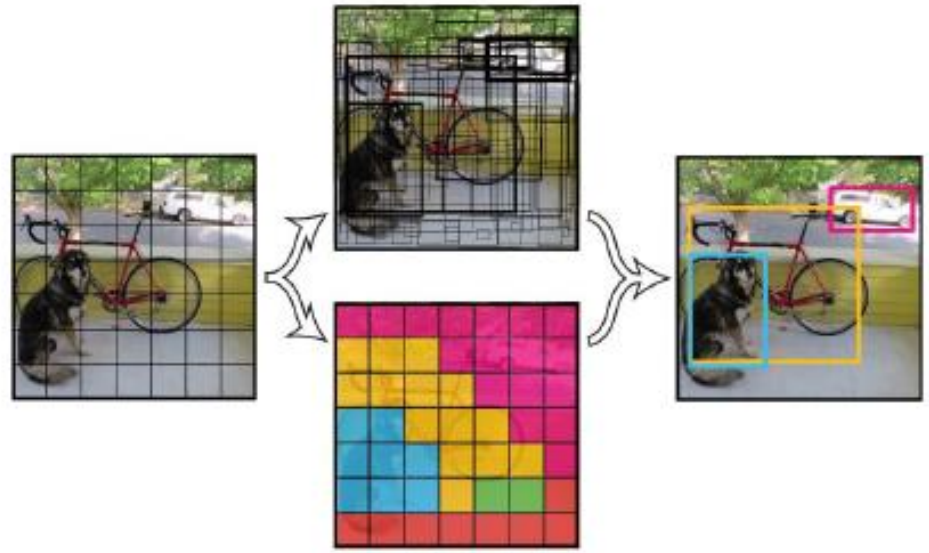
YOLO: You Only Look Once
Detection as Regression

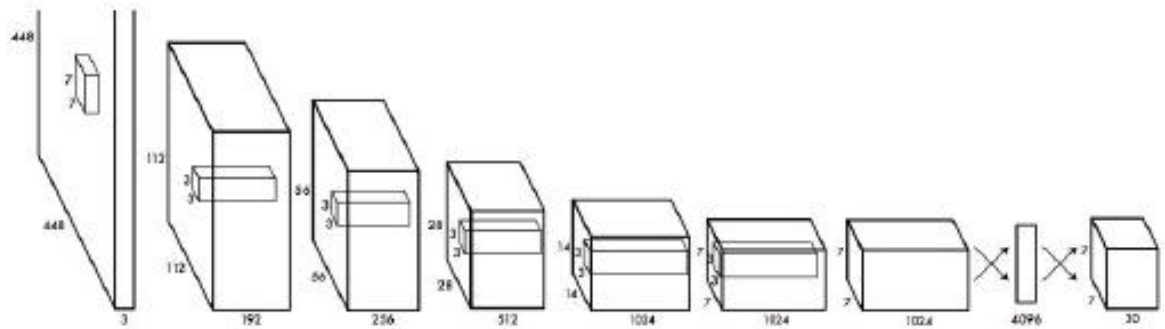
Divide image into S x S grid

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

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

Direct prediction using a CNN





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

YOLO: You Only Look Once
Detection as Regression

Faster than Faster R-CNN, but not as good

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

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

Face Recognition

- Face recognition involves addressing a series of problems

- We can implement this as a pipeline

Face Recognition Pipeline

- Given an image, localize the human face
- Do any preprocessing (if needed) such as adjusting the direction of the face (e.g: making it frontal)
- Pick out features that are critical to recognition
- Compare unique features across all classes and classify

Segmentation

Segmentation Tasks

- Coarse to fine: Image Classification predicts a class label for the whole image, while segmentation predicts a label for each pixel

- **Semantic segmentation** assigns a class label to each pixel but doesn't distinguish between instances
  - Many of these concepts are known in the traditional Computer Vision field

- **Instance segmentation** assigns the class labels to each pixel and also identifies the instances
  - More recent concept and the progress is rapid in the last 2 years

Fig Credit: MIT 6.S094

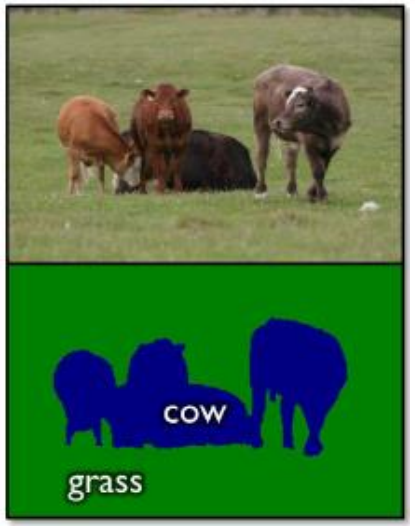


Fig Credit: A Karpathy, CS231n

Semantic Segmentation – Naïve approach

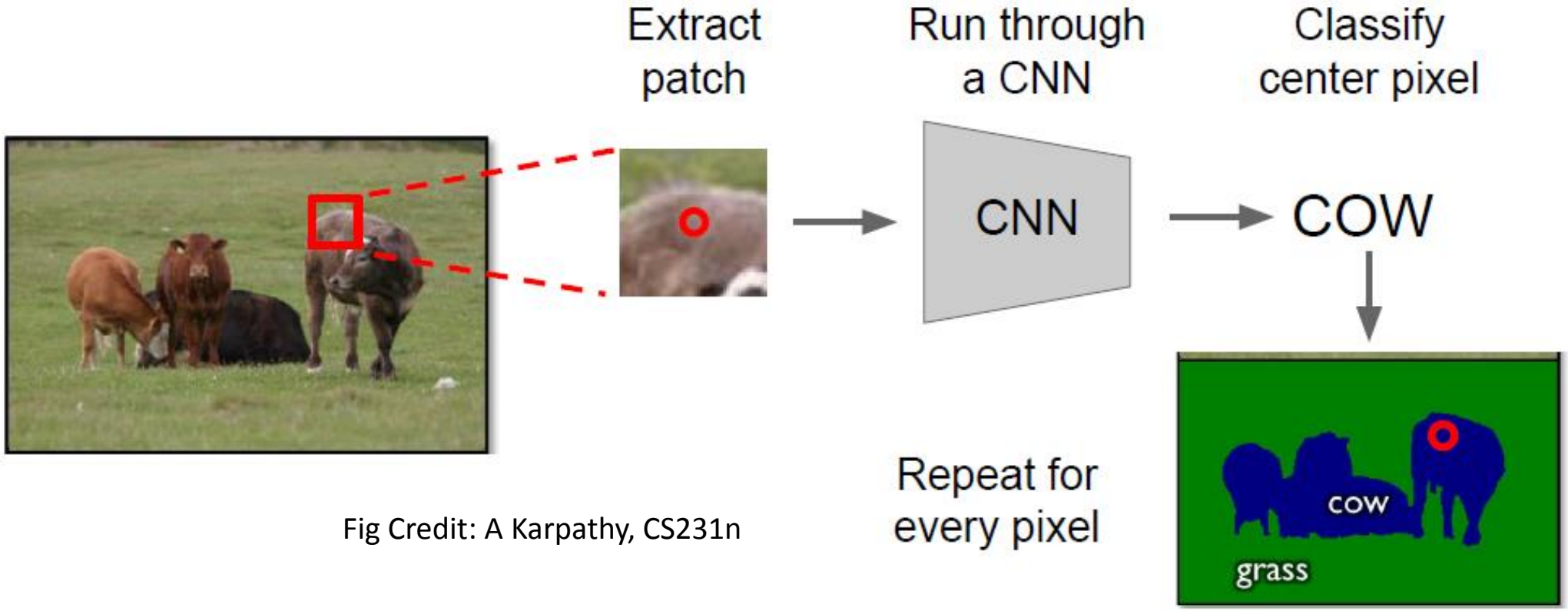
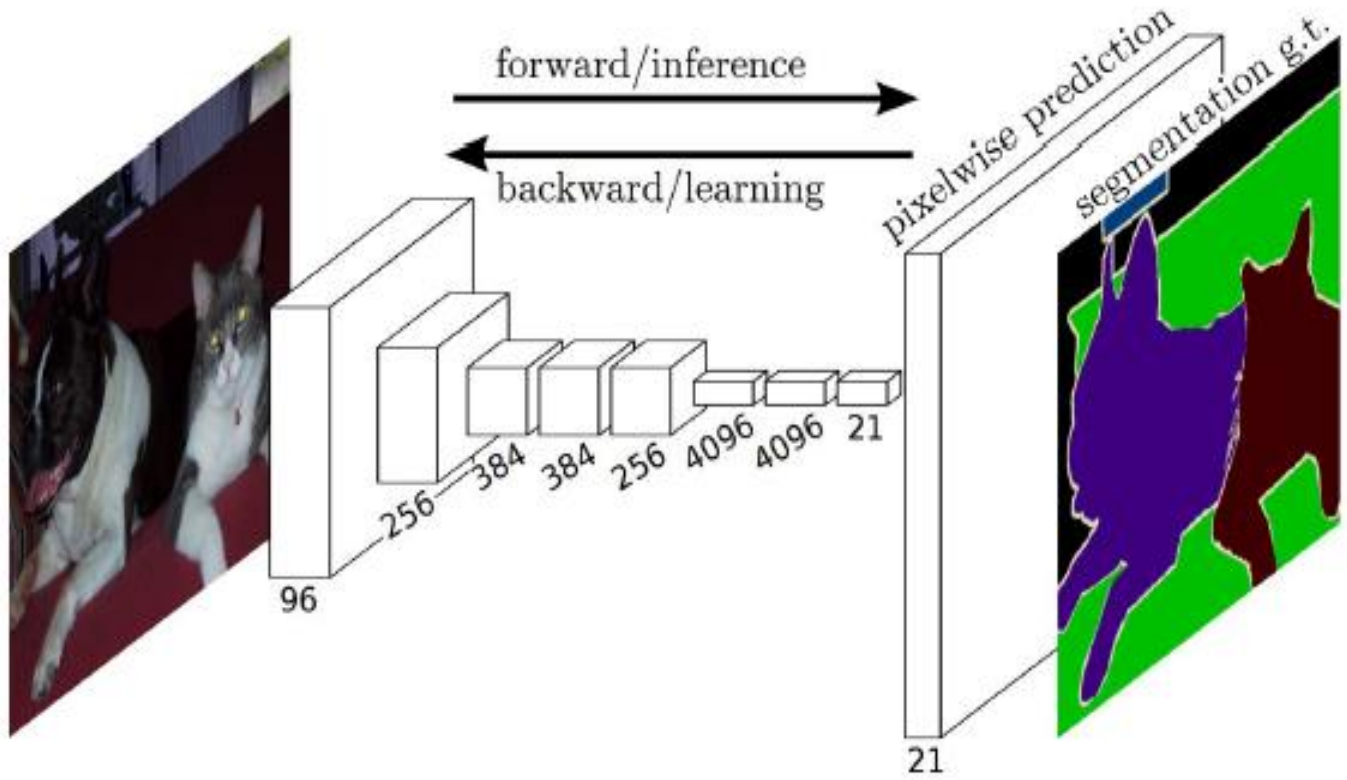


Fig Credit: A Karpathy, CS231n

- This approach is computationally expensive
- Another key criterion is the size of context patch to produce an accurate label

Semantic Segmentation: Upsampling

- Convolution and pooling layers progressively decrease the surface area of the image without suitable padding
- This is a downsampling process
- One way of getting back the original resolution is by upsampling



Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

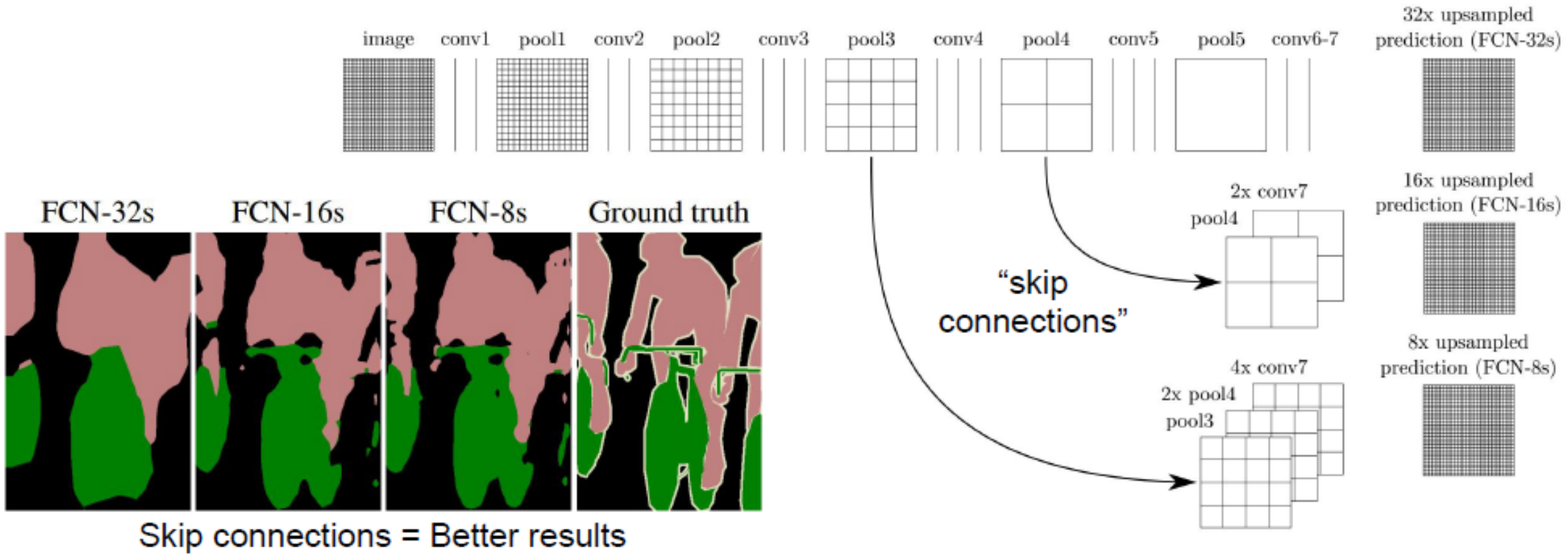
Fully Convolutional Networks

- Fully convolutional networks proposed by J Long et al perform upsampling using the so called deconvolution process.

- The upsampling is done as a learnable process where the parameters are obtained through supervised training

- The technique also uses skip connections between the convolution layers
  - Lower layers closer to the input layer represent higher resolution compared to upper layers
  - Making skip connections allow the classifier to make use of finer resolution features

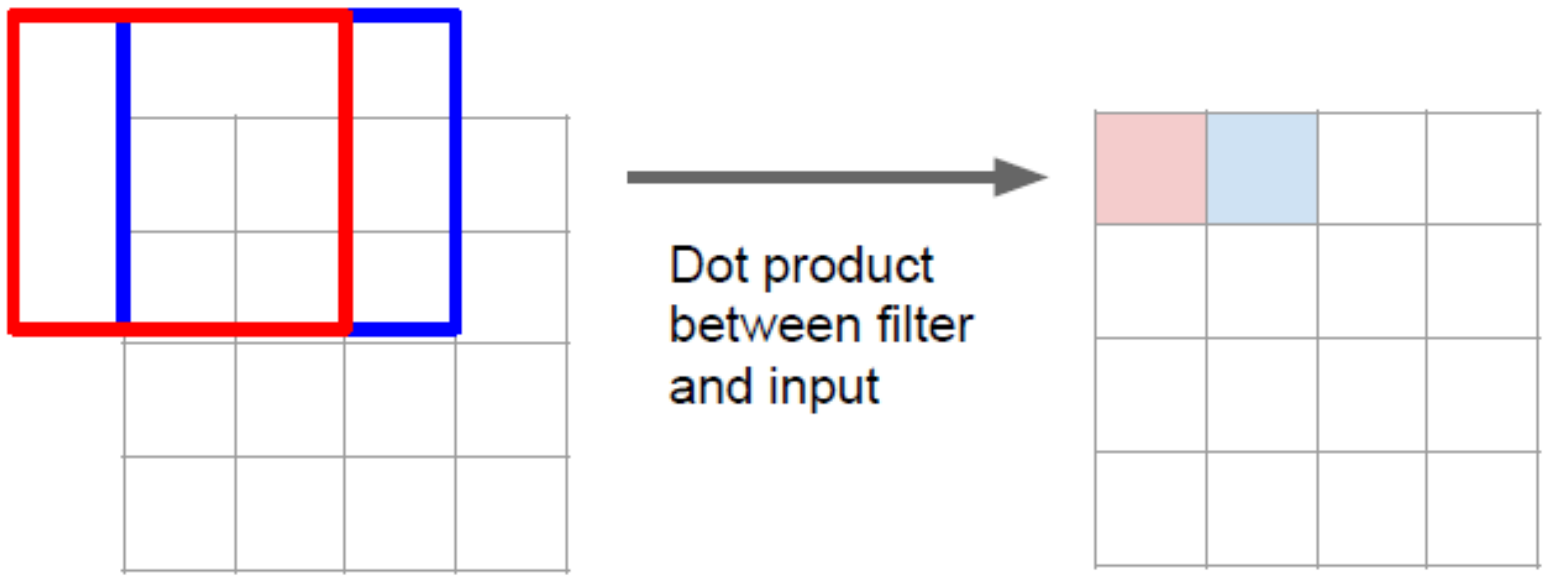
Semantic Segmentation: Upsampling



Long, Shelhamer, and Darrell, "Fully Convolutional Networks for Semantic Segmentation", CVPR 2015

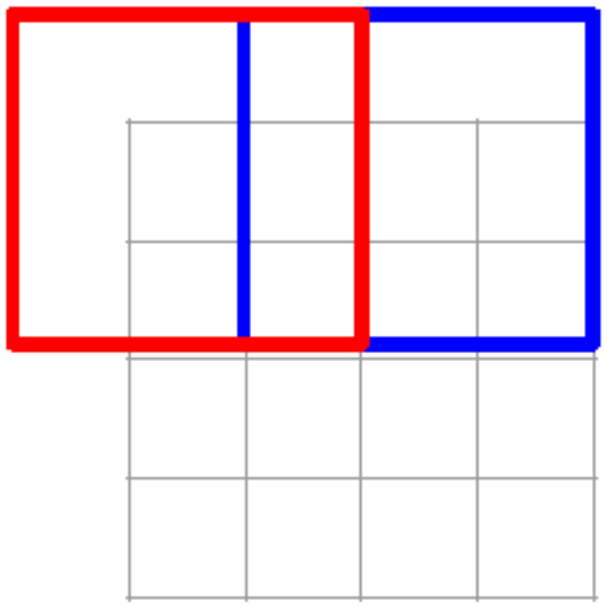
Learnable Upsampling: “Deconvolution”

Typical 3 x 3 convolution, stride 1 pad 1



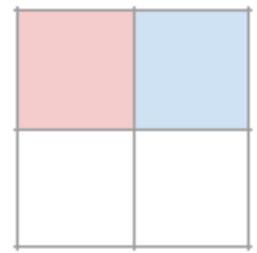
Learnable Upsampling: “Deconvolution”

Typical 3 x 3 convolution, stride 2 pad 1



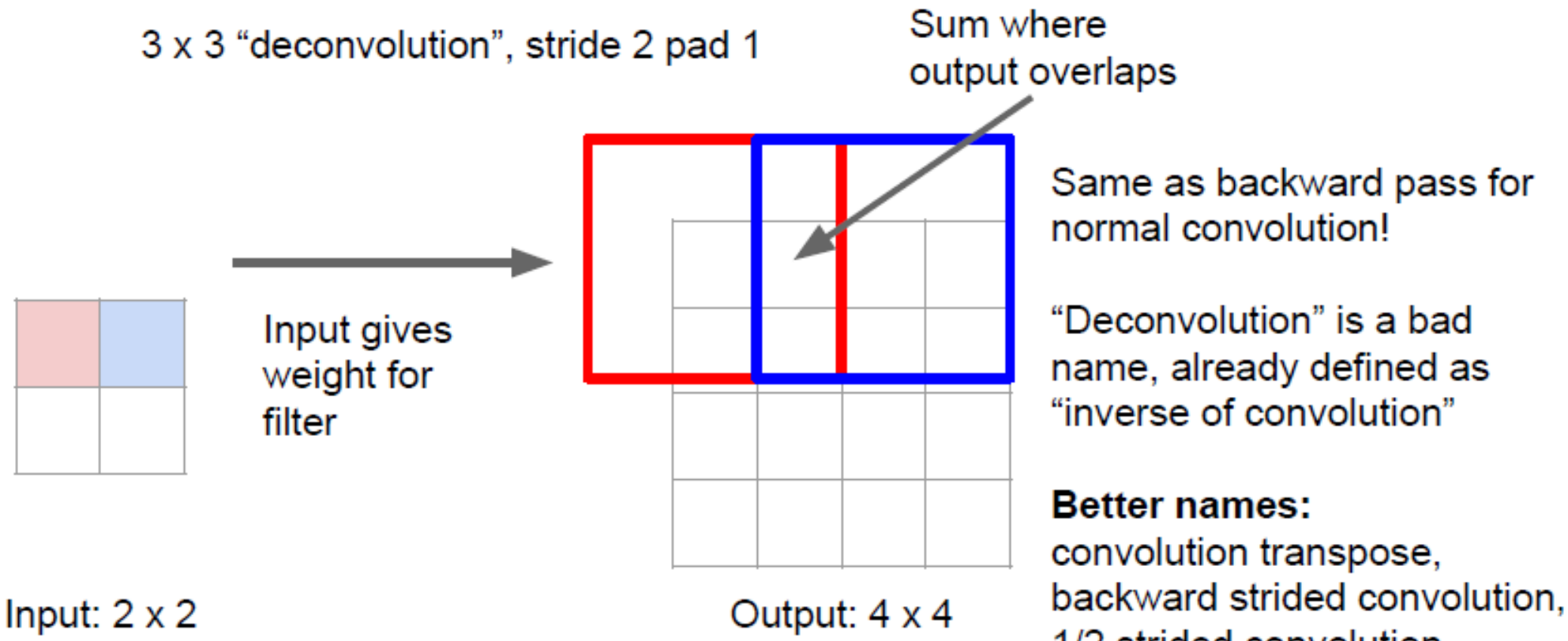
Input: 4 x 4

Dot product between filter and input



Output: 2 x 2

Learnable Upsampling: “Deconvolution”



Same as backward pass for normal convolution!

“Deconvolution” is a bad name, already defined as “inverse of convolution”

Better names:
convolution transpose, backward strided convolution, 1/2 strided convolution, upconvolution

Learnable Upsampling: “Deconvolution”

[1]It is more proper to say “convolutional transpose operation” rather than “deconvolutional” operation. Hence, we will be using the term “convolutional transpose” from now.

Im et al, “Generating images with recurrent adversarial networks”, arXiv 2016

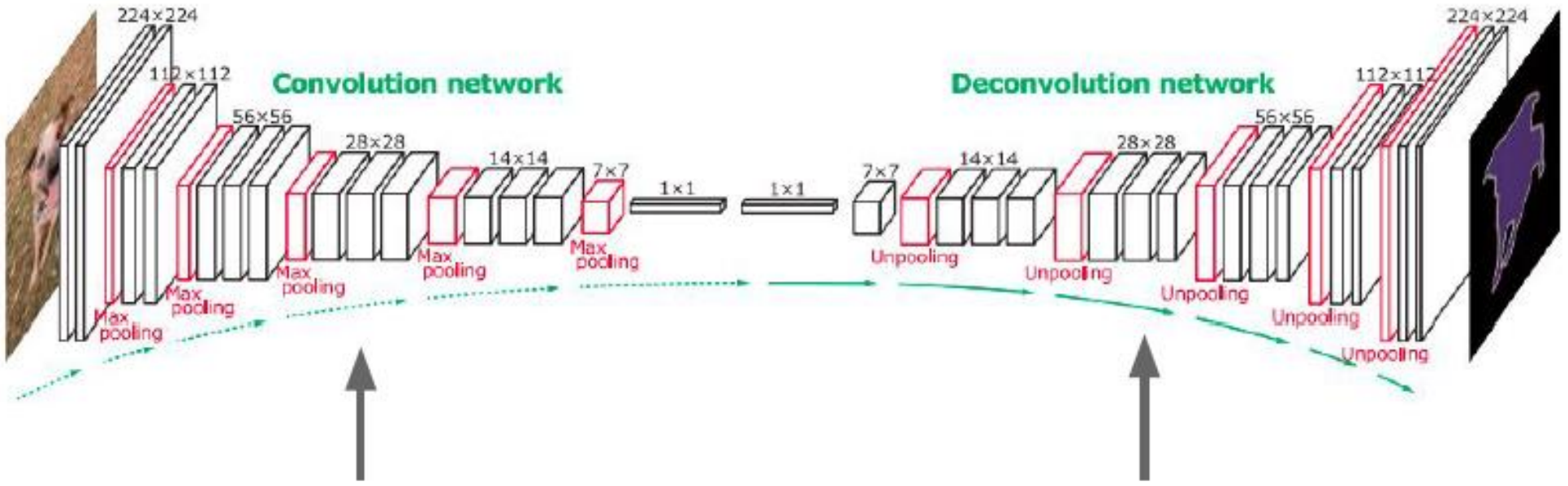
A series of four fractionally-strided convolutions (in some recent papers, these are wrongly called deconvolutions)

Radford et al, “Unsupervised Representation Learning with Deep Convolutional Generative Adversarial Networks”, ICLR 2016

“Deconvolution” is a bad name, already defined as “inverse of convolution”

Better names:
convolution transpose,
backward strided convolution,
1/2 strided convolution,
upconvolution

Semantic Segmentation: Upsampling

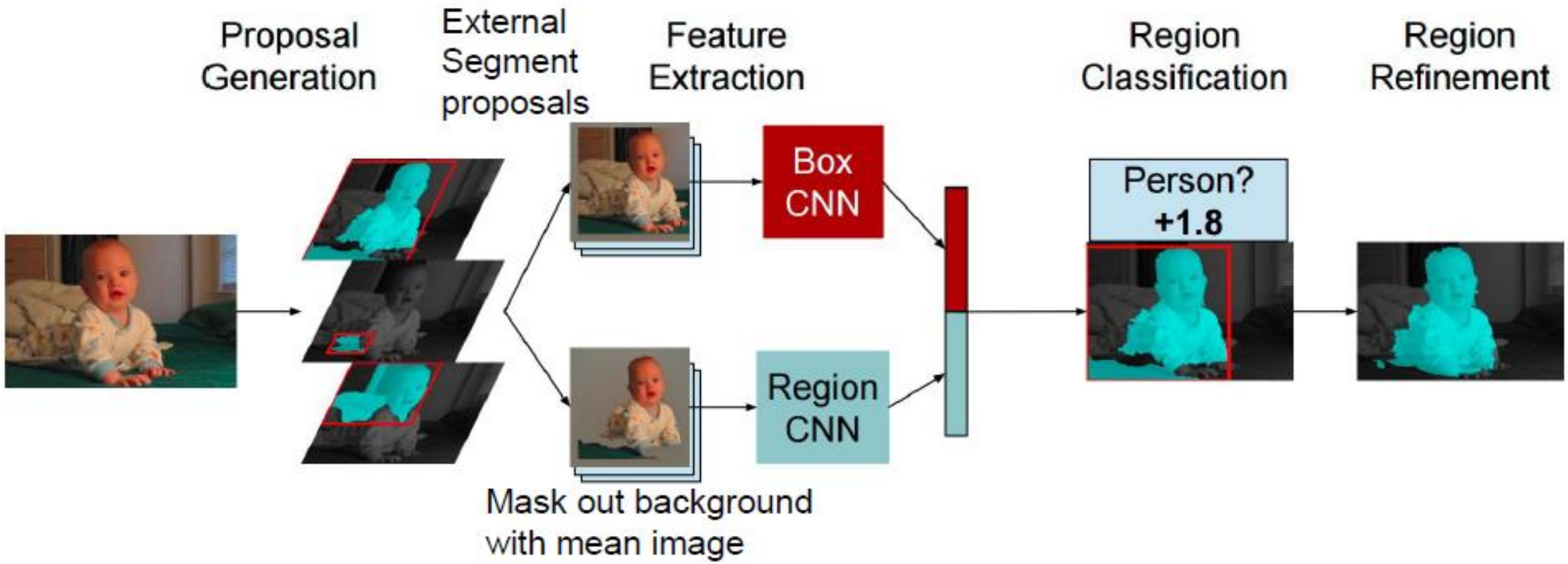


Noh et al, "Learning Deconvolution Network for Semantic Segmentation", ICCV 2015

6 days of training on Titan X…

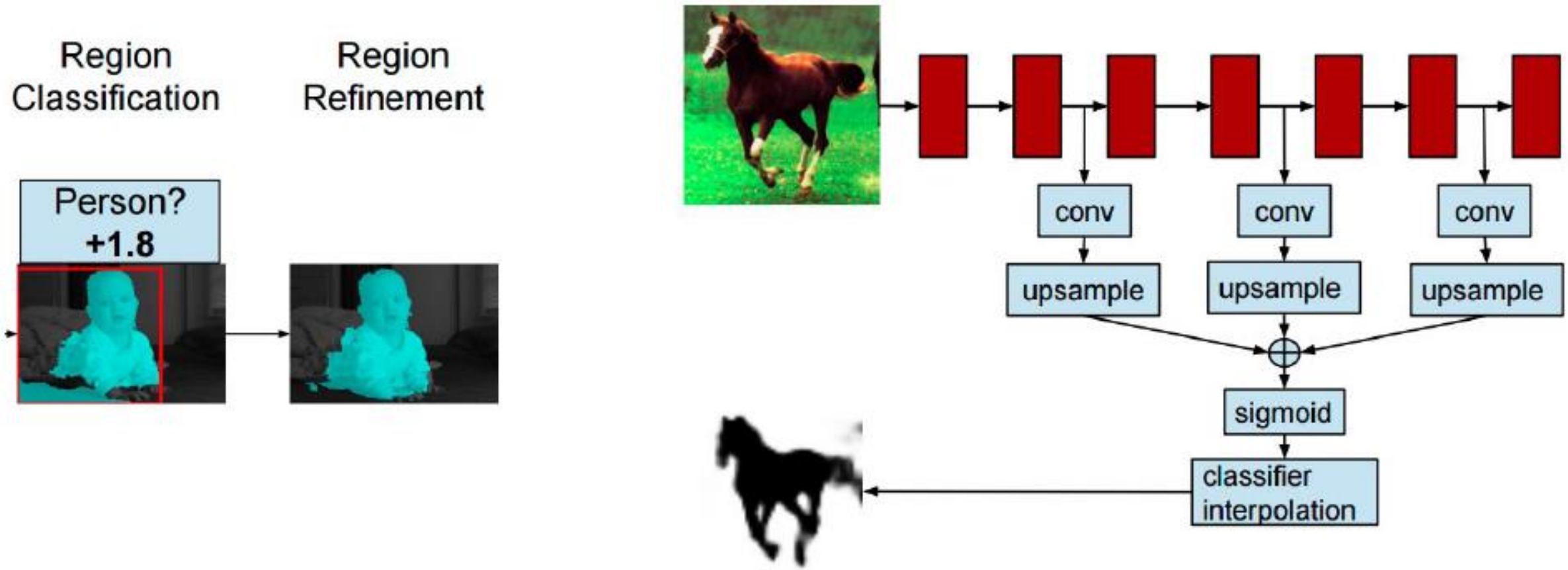
Instance Segmentation

Similar to R-CNN, but with segments



Hariharan et al, "Simultaneous Detection and Segmentation", ECCV 2014

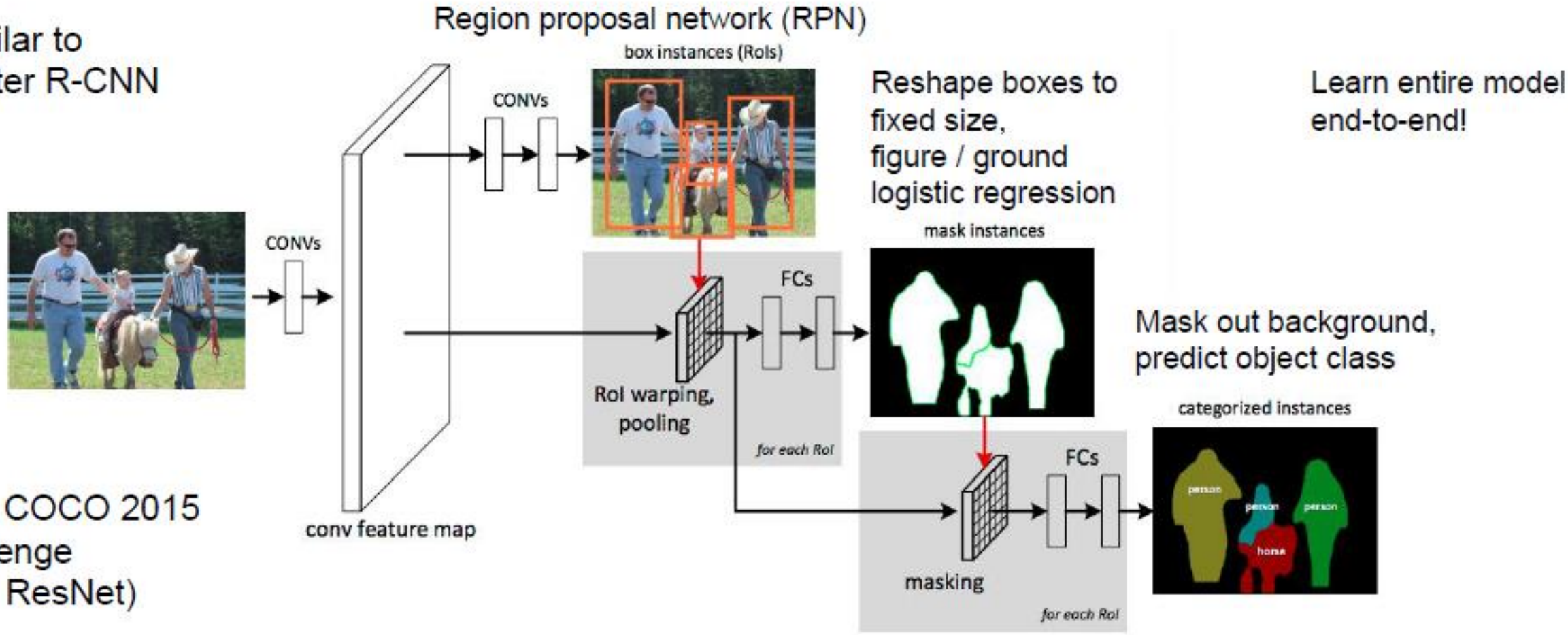
Instance Segmentation: Hypercolumns



Hariharan et al, "Hypercolumns for Object Segmentation and Fine-grained Localization", CVPR 2015

Instance Segmentation: Cascades

Similar to
Faster R-CNN



Learn entire model
end-to-end!

Won COCO 2015
challenge
(with ResNet)

Dai et al, "Instance-aware Semantic Segmentation via Multi-task Network Cascades", arXiv 2015