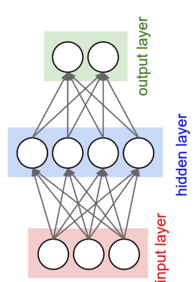
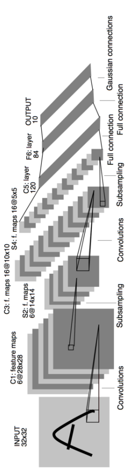
CSCI 497P/597P: Computer Vision

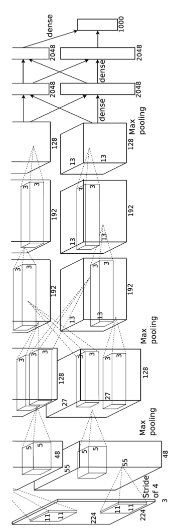
Convolutional Neural Networks

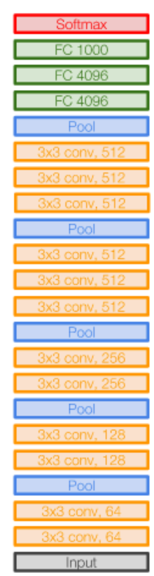
Architectures

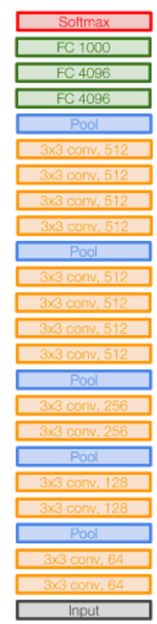
Application to other problems

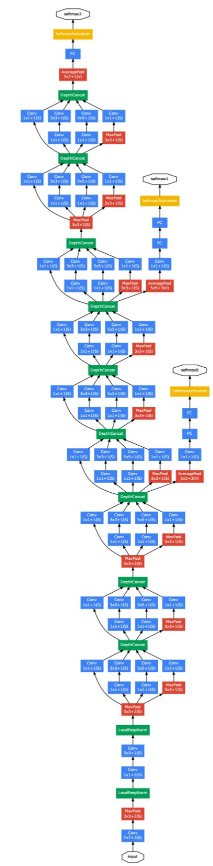


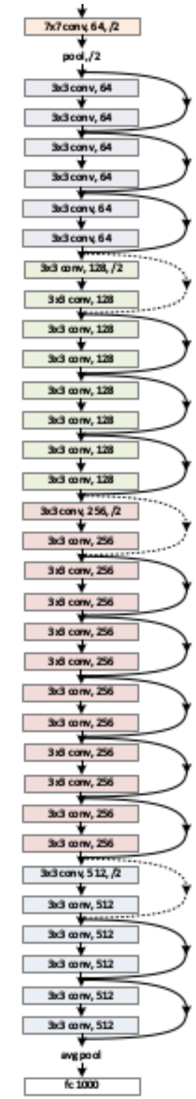








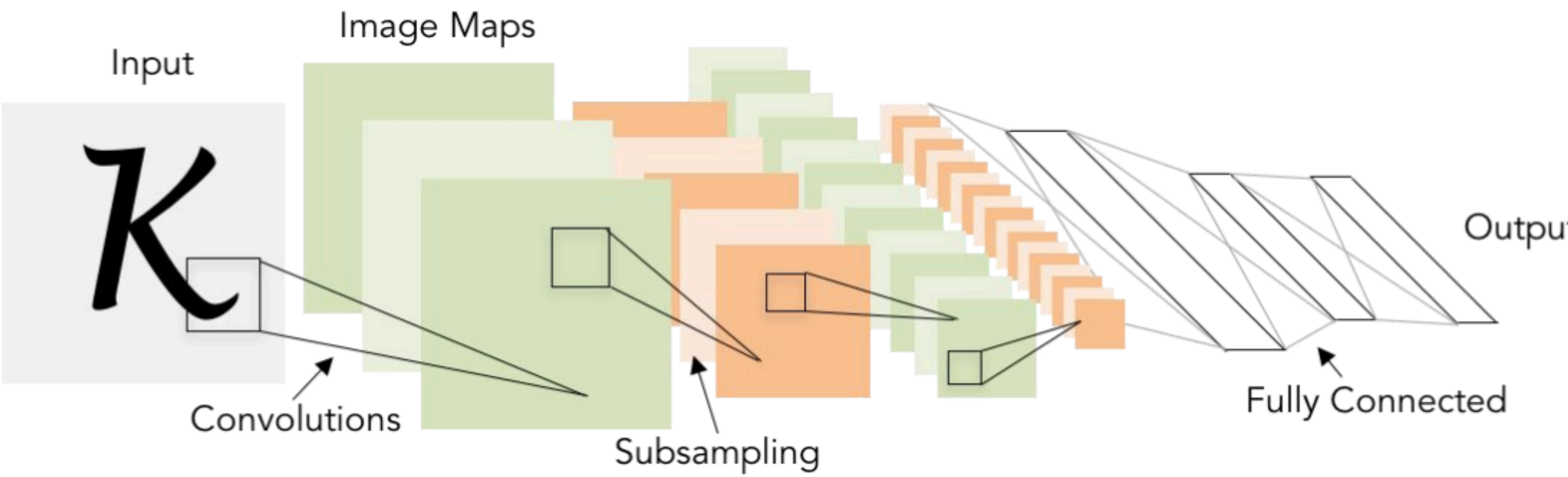




Announcements

Review: LeNet-5

[LeCun et al., 1998]



Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]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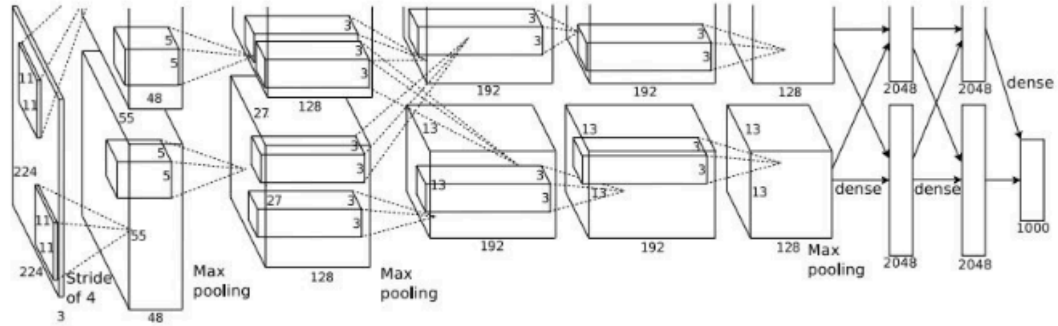
Case Study: AlexNet

[Krizhevsky et al. 2012]

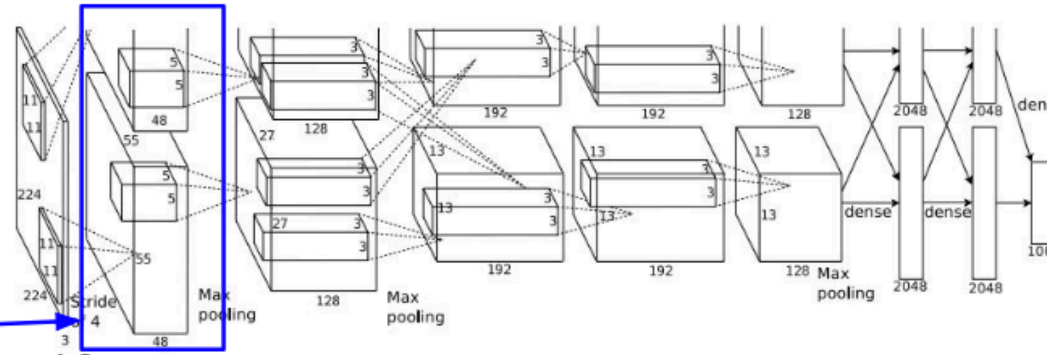


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] 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%

Case Study: AlexNet

[Krizhevsky et al. 2012]



[55x55x48] x 2

Full (simplified) AlexNet architecture:
[227x227x3] INPUT
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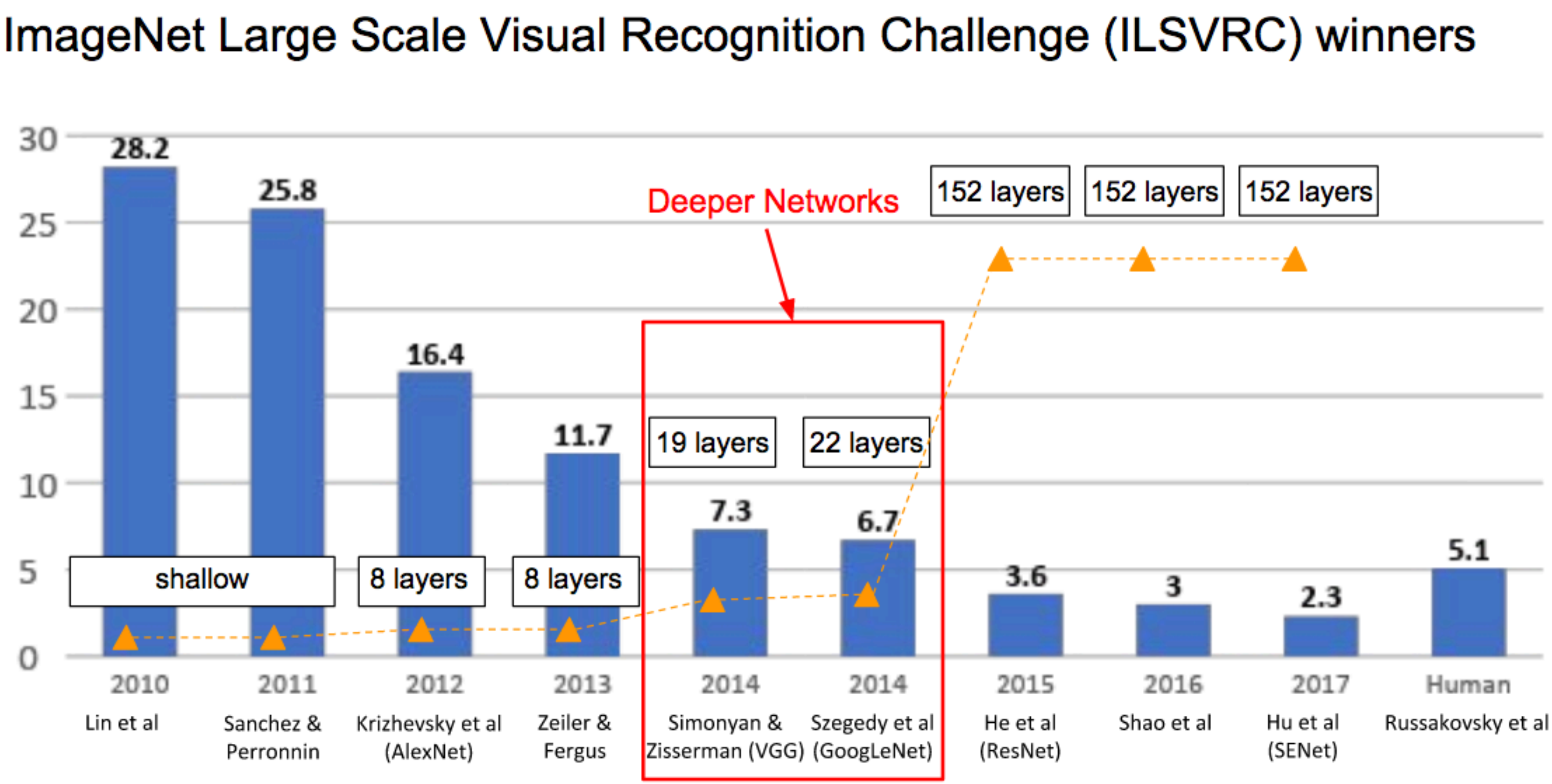
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Historical note: Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.



Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung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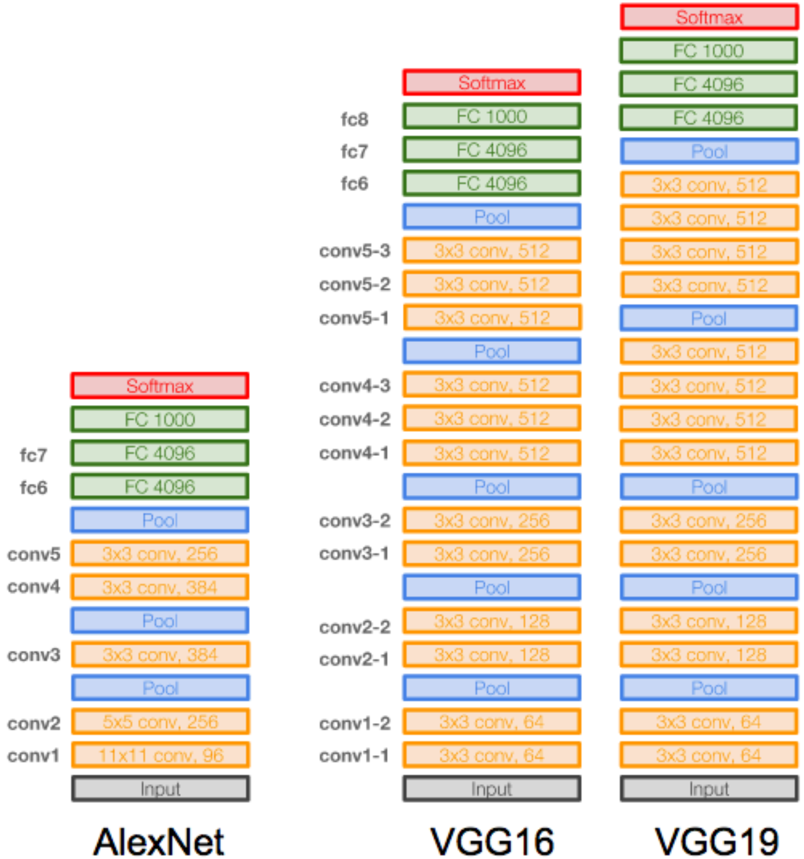
Case Study: VGGNet

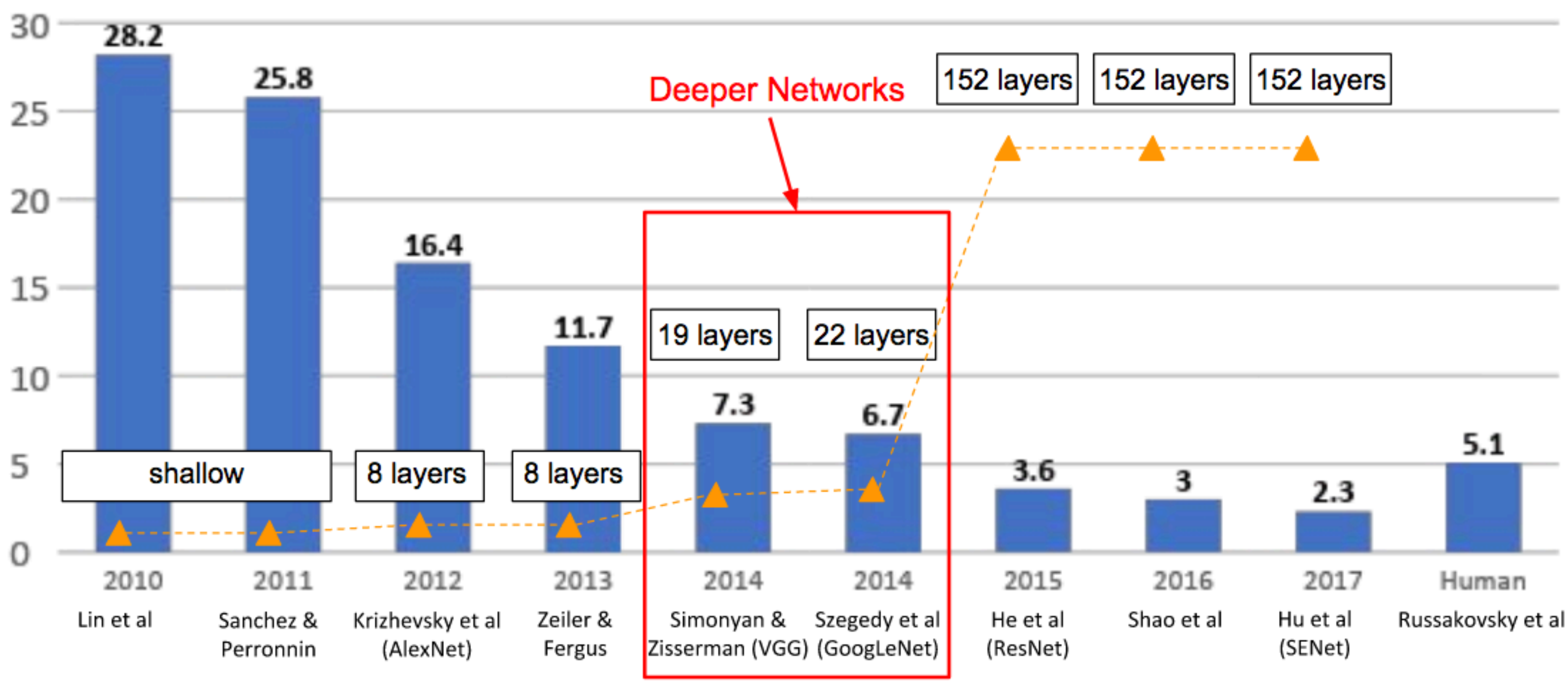
[Simonyan and Zisserman, 2014]

Details:

- ILSVRC'14 2nd in classification, 1st in localization
- Similar training procedure as Krizhevsky 2012
- No Local Response Normalisation (LRN)
- Use VGG16 or VGG19 (VGG19 only slightly better, more memory)
- Use ensembles for best results
- FC7 features generalize well to other tasks



ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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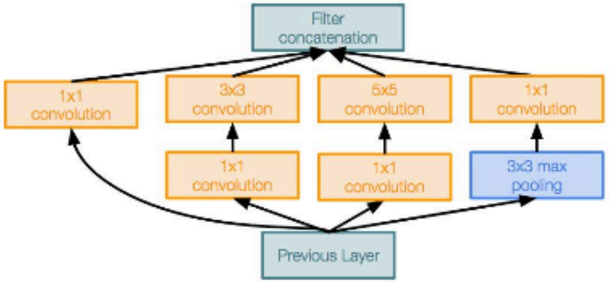
Case Study: GoogLeNet

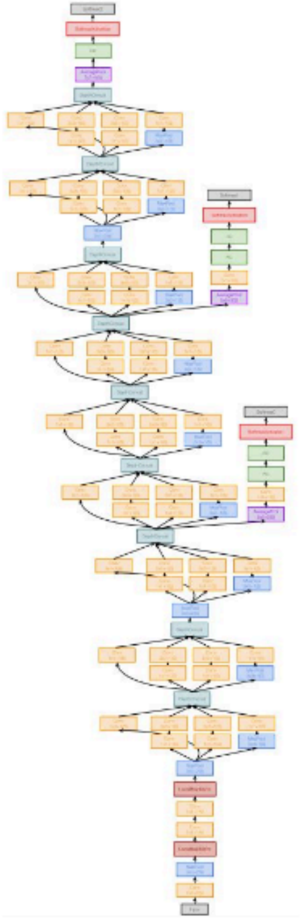
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient "Inception" module
- No FC layers
- Only 5 million parameters!
  12x less than AlexNet
- ILSVRC'14 classification winner
  (6.7% top 5 error)



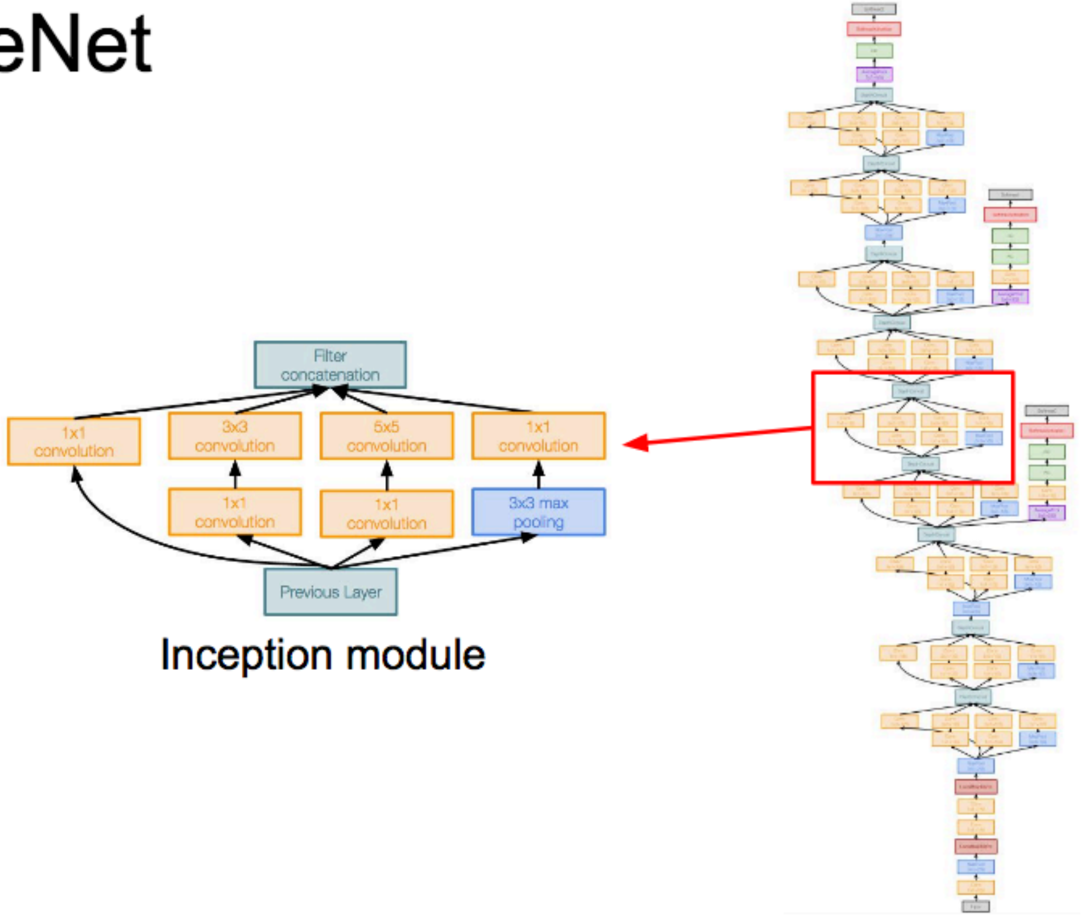
Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]

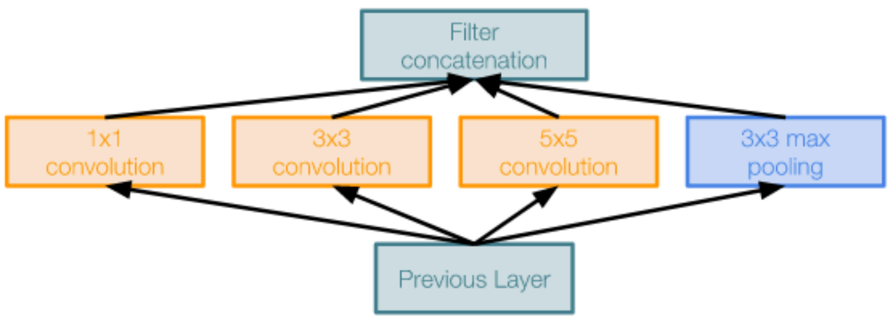
"Inception module": design a good local network topology (network within a network) and then stack these modules on top of each other



Inception module

Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

Apply parallel filter operations on the input from previous layer:

- Multiple receptive field sizes for convolution (1x1, 3x3, 5x5)
- Pooling operation (3x3)

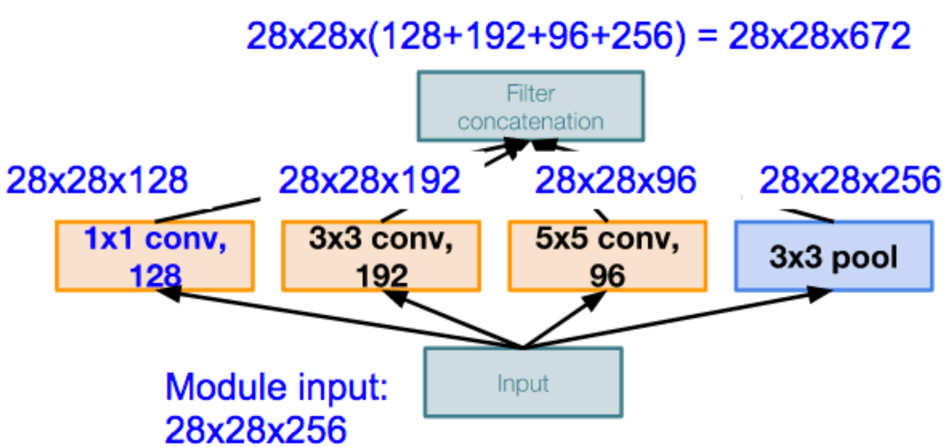
Concatenate all filter outputs together depth-wise

Case Study: GoogLeNet

[Szegedy et al., 2014]

Example:

Q3:What is output size after filter concatenation?



Naive Inception module

Q: What is the problem with this?
[Hint: Computational complexity]

Conv Ops:

[1x1 conv, 128] 28x28x128x1x1x256

[3x3 conv, 192] 28x28x192x3x3x256

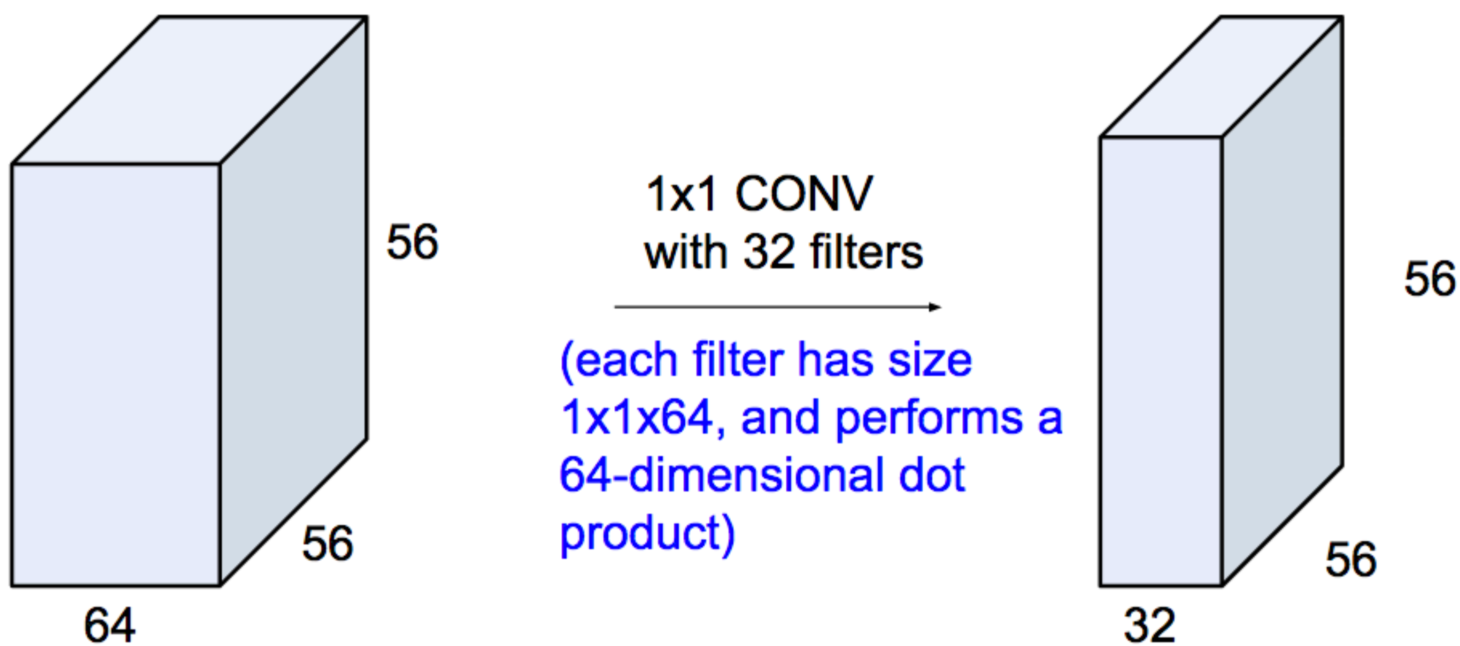
[5x5 conv, 96] 28x28x96x5x5x256

Total: 854M ops

Very expensive compute

Pooling layer also preserves feature depth, which means total depth after concatenation can only grow at every layer!

Reminder: 1x1 convolutions



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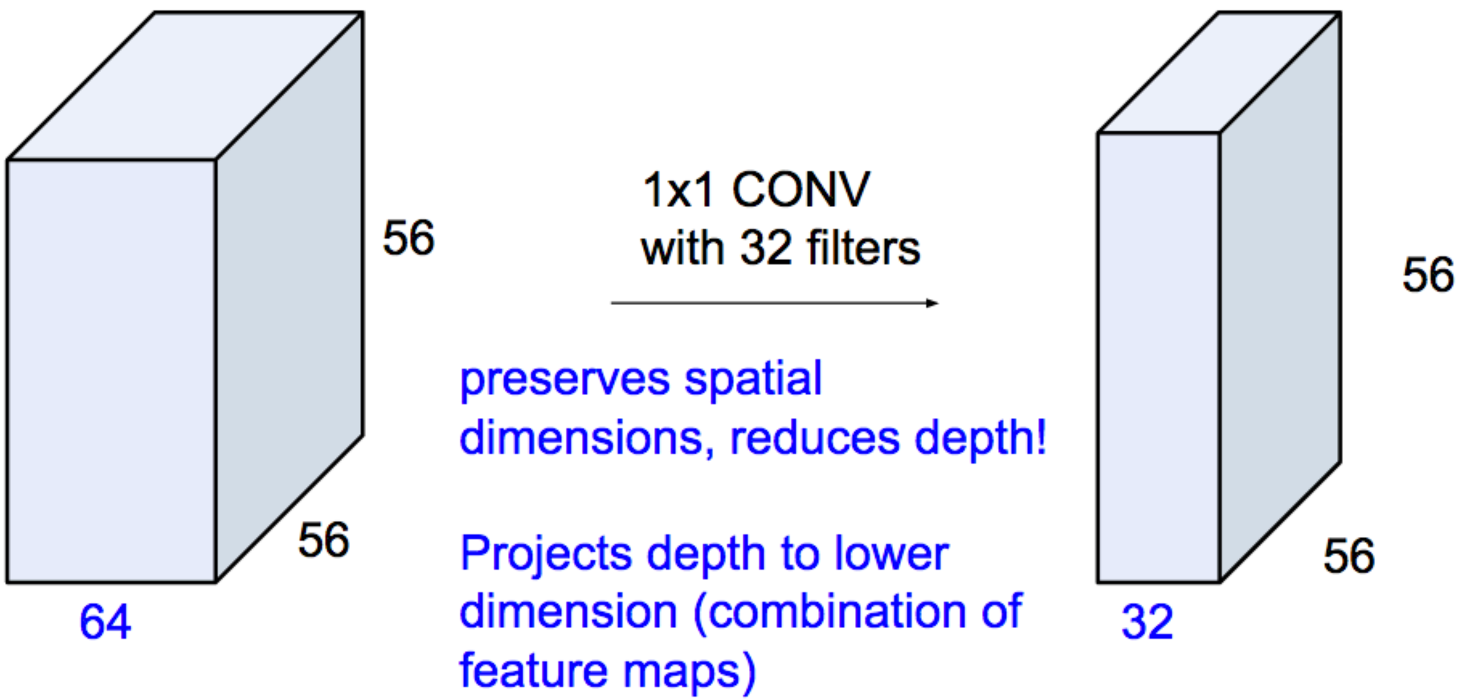
Reminder: 1x1 convolutions



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Case Study: GoogLeNet

[Szegedy et al., 2014]

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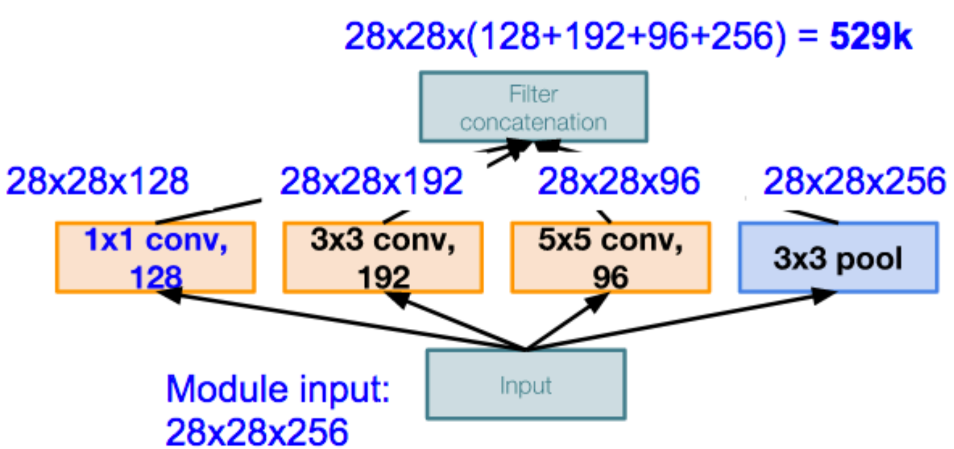
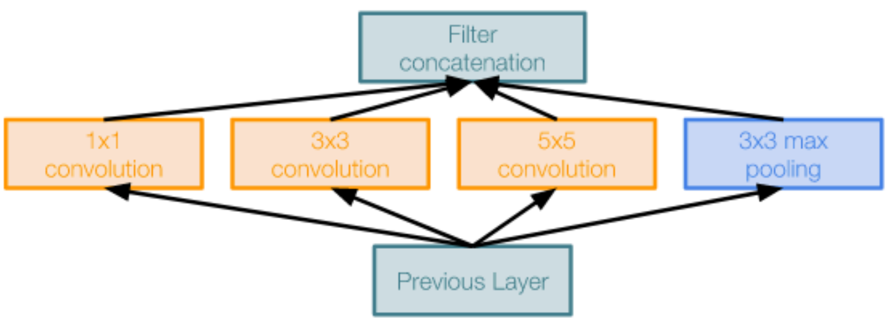


Naive Inception module

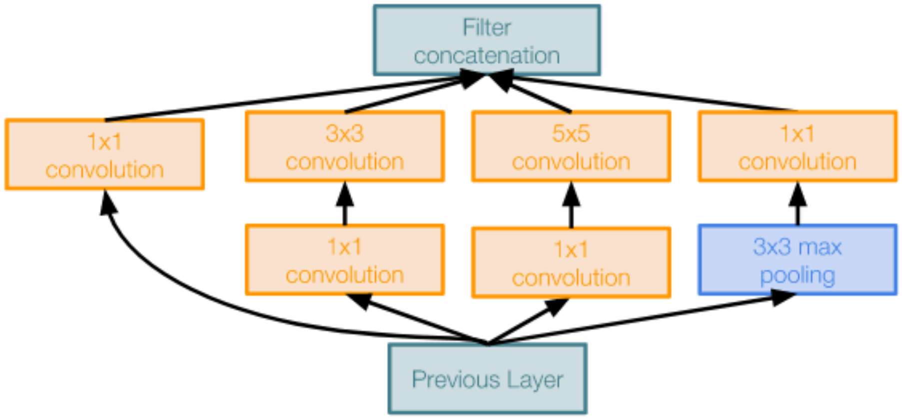
Solution: "bottleneck" layers that use 1x1 convolutions to reduce feature depth

Case Study: GoogLeNet

[Szegedy et al., 2014]



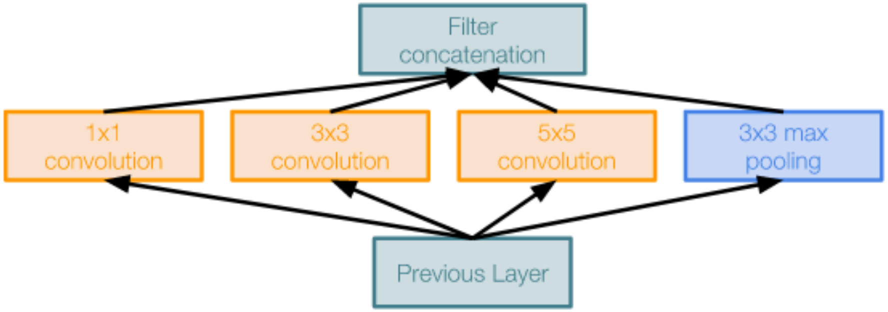
Naive Inception module



Inception module with dimension reduction

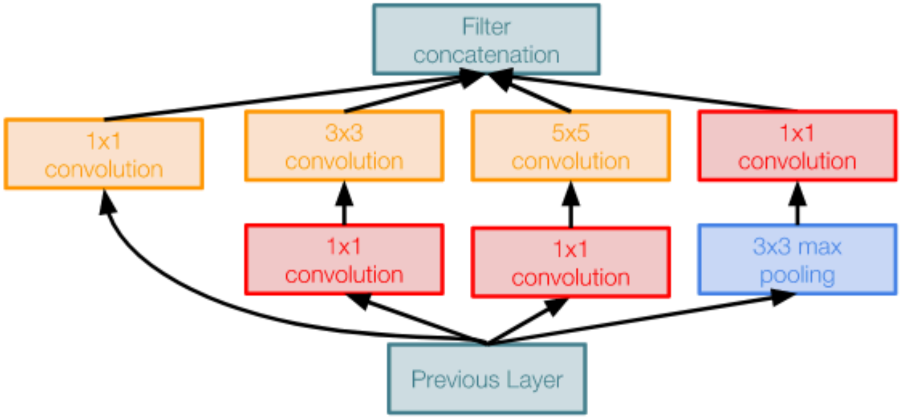
Case Study: GoogLeNet

[Szegedy et al., 2014]



Naive Inception module

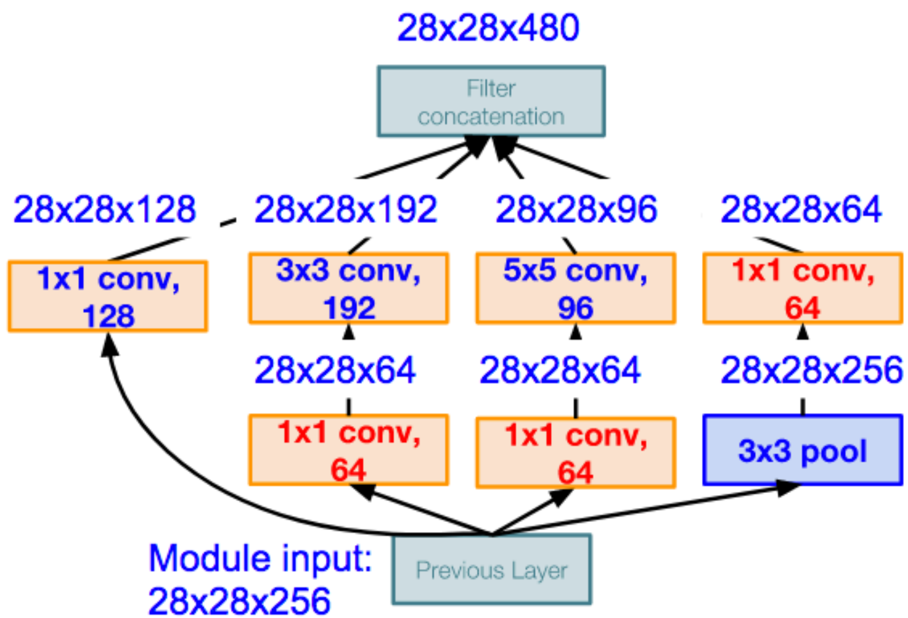
1x1 conv "bottleneck" layers



Inception module with dimension reduction

Case Study: GoogLeNet

[Szegedy et al., 2014]



Inception module with dimension reduction

Using same parallel layers as naive example, and adding "1x1 conv, 64 filter" bottlenecks:

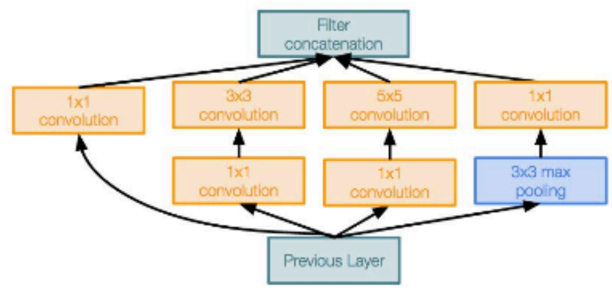
Conv Ops:
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 64] 28x28x64x1x1x256
[1x1 conv, 128] 28x28x128x1x1x256
[3x3 conv, 192] 28x28x192x3x3x64
[5x5 conv, 96] 28x28x96x5x5x64
[1x1 conv, 64] 28x28x64x1x1x256
Total: 358M ops

Compared to 854M ops for naive version
Bottleneck can also reduce depth after pooling layer

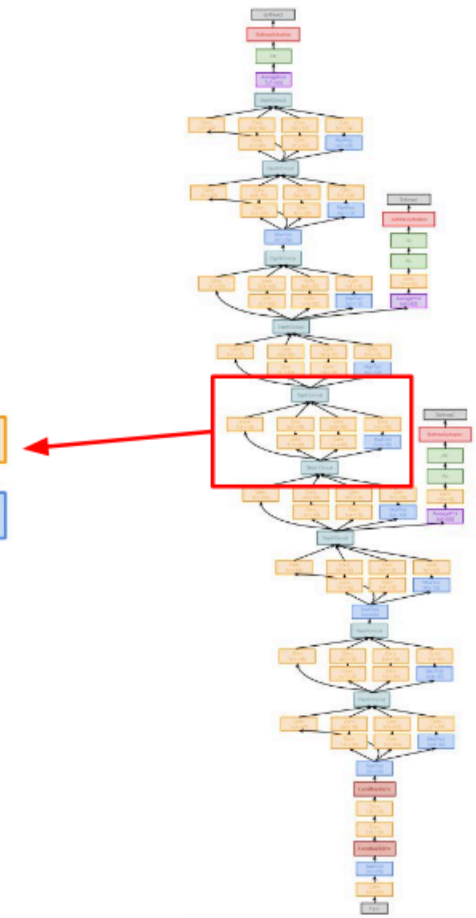
Case Study: GoogLeNet

[Szegedy et al., 2014]

Stack Inception modules with dimension reduction on top of each other



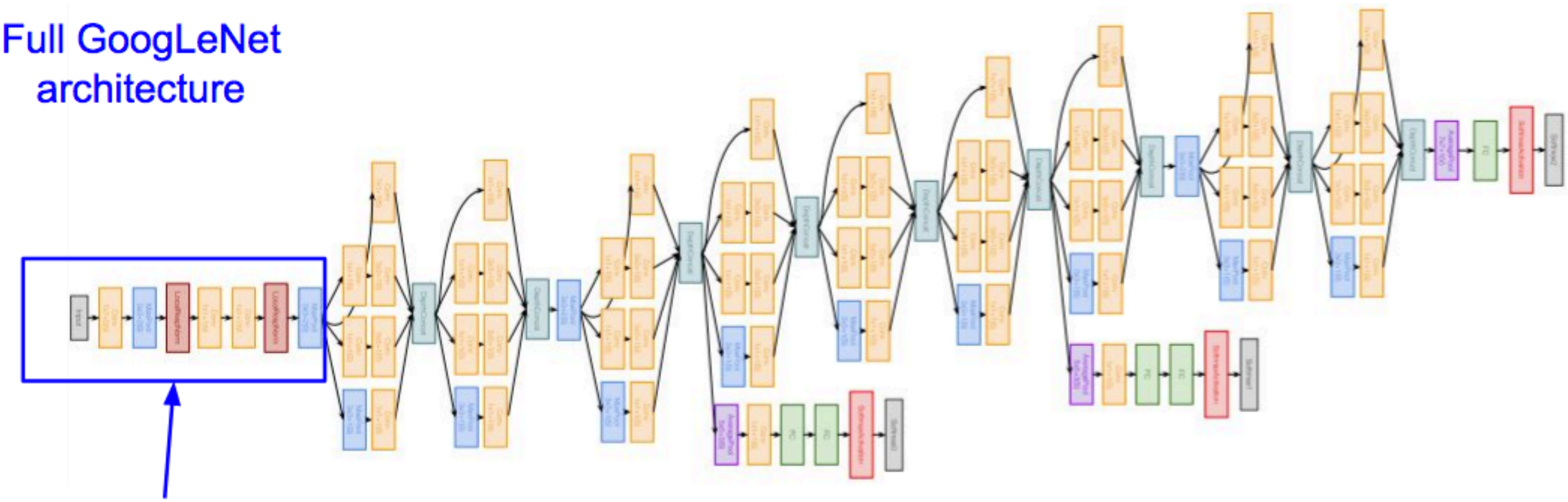
Inception module



Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



Stem Network:
Conv-Pool-
2x Conv-Pool

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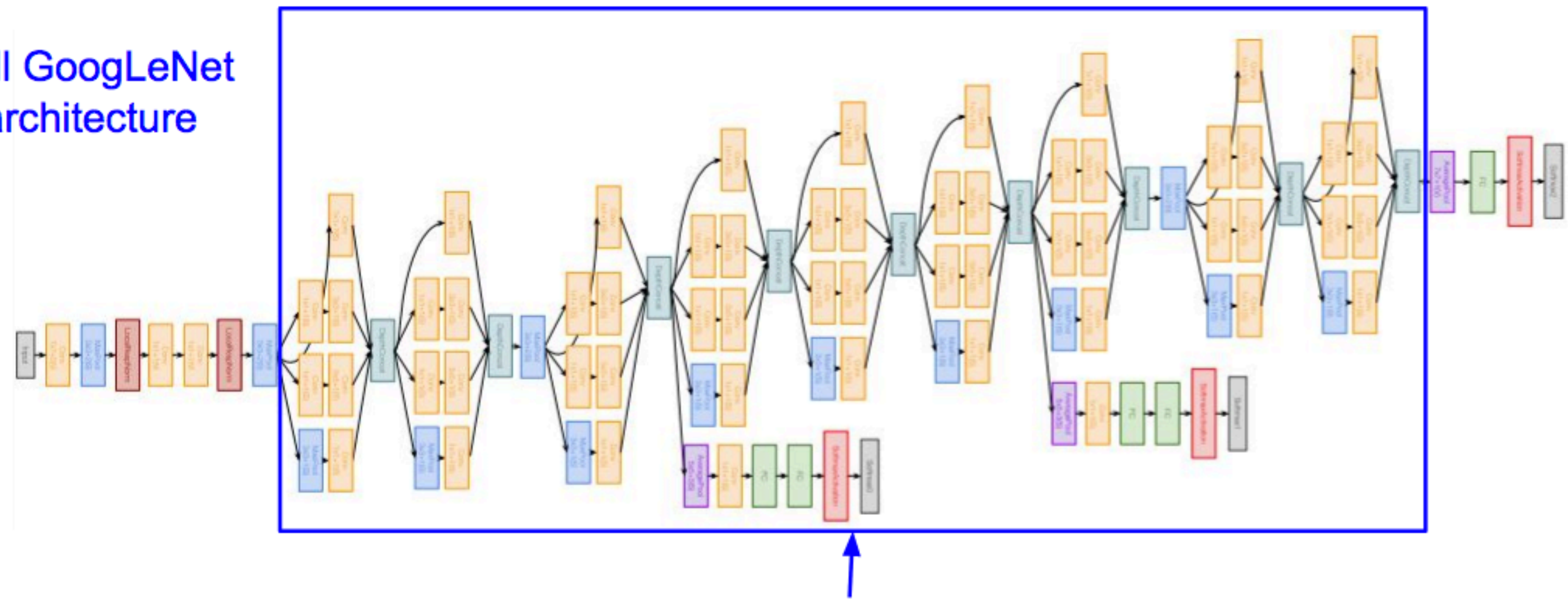
Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

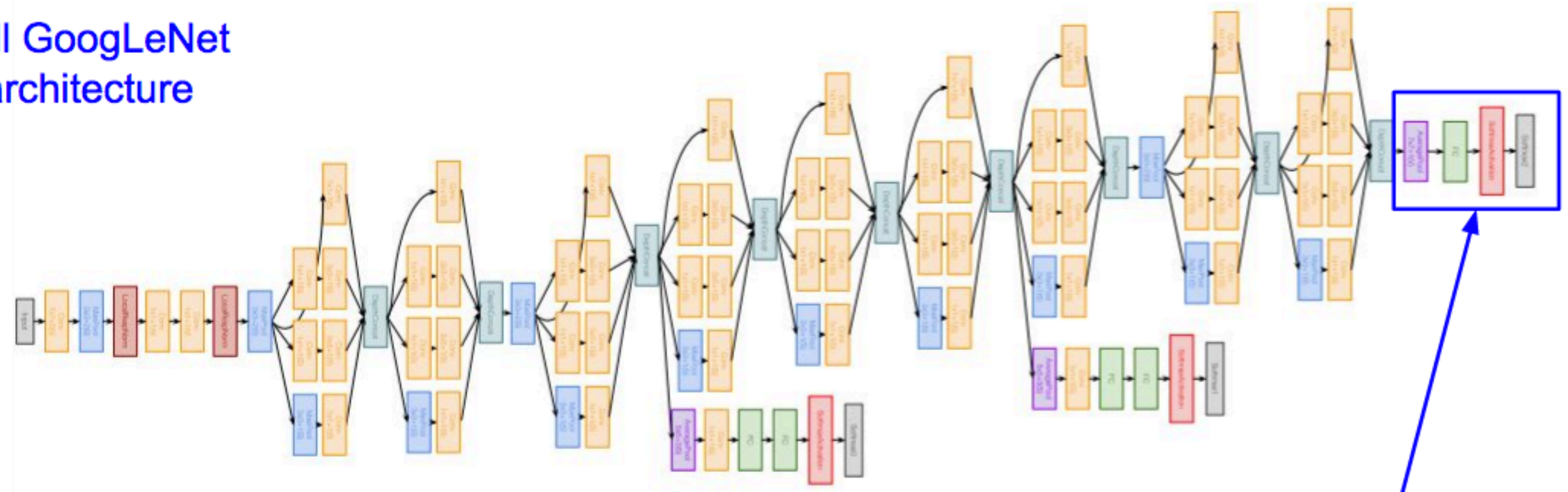


Stacked Inception Modules

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

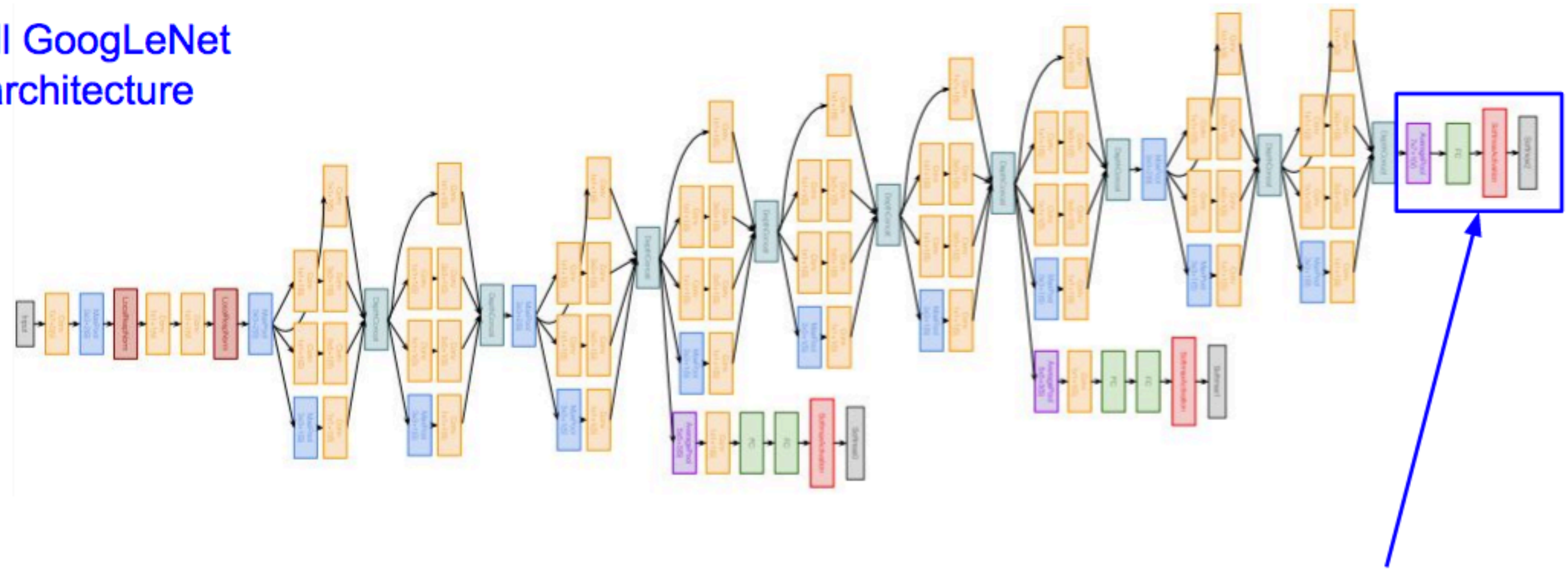


Classifier output

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

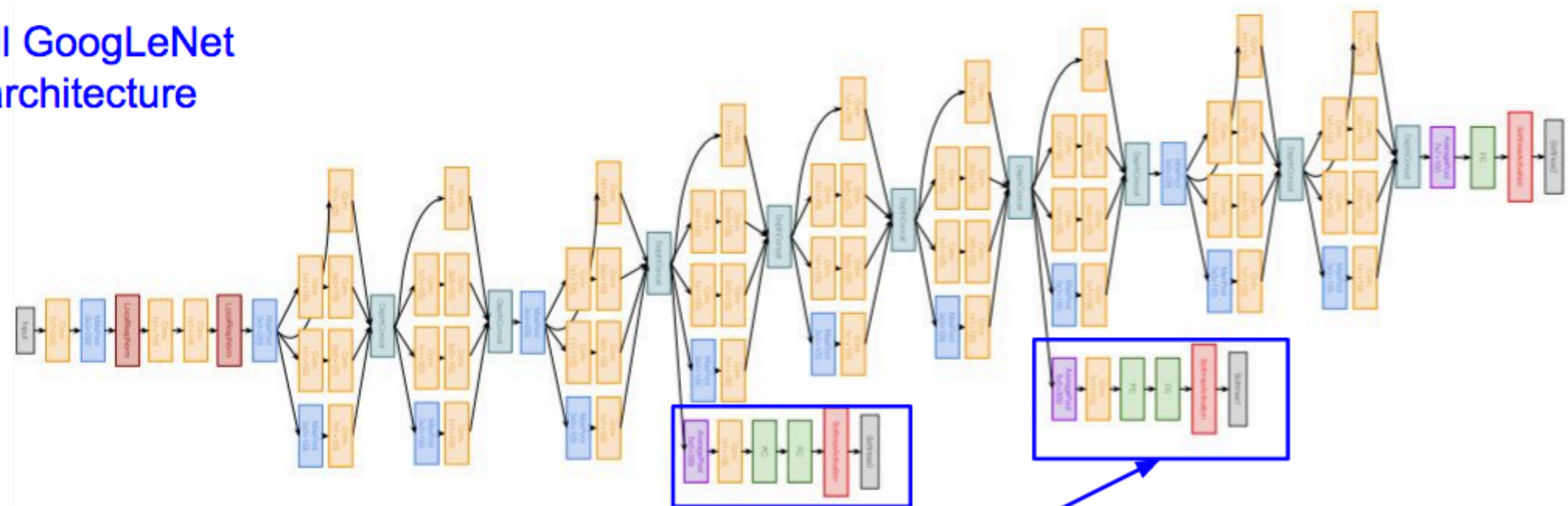


Classifier output
(removed expensive FC layers!)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture

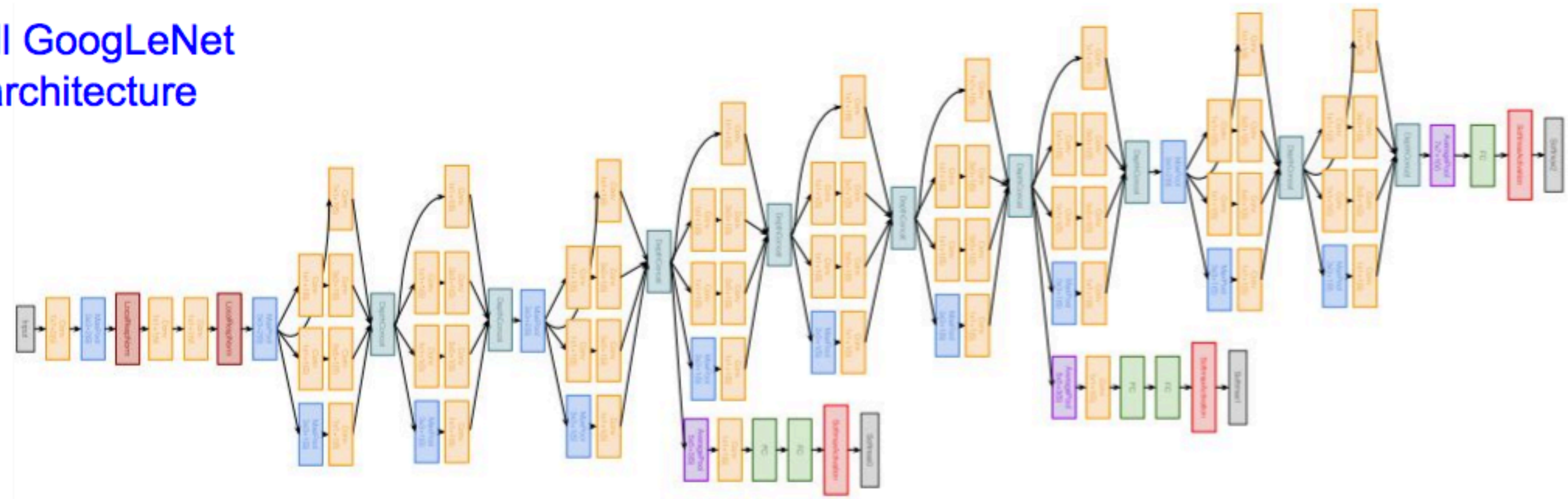


Auxiliary classification outputs to inject additional gradient at lower layers
(AvgPool-1x1Conv-FC-FC-Softmax)

Case Study: GoogLeNet

[Szegedy et al., 2014]

Full GoogLeNet architecture



22 total layers with weights

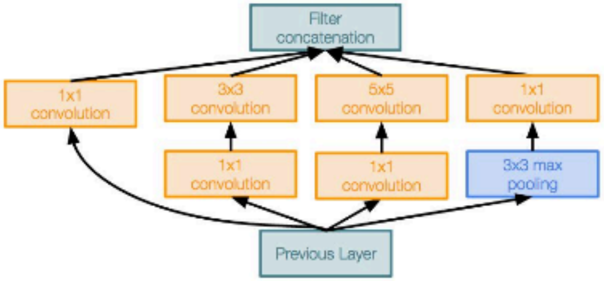
(parallel layers count as 1 layer => 2 layers per Inception module. Don't count auxiliary output layers)

Case Study: GoogLeNet

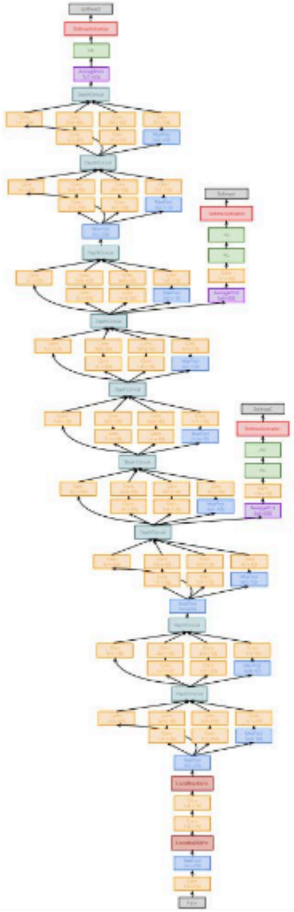
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient “Inception” module
- No FC layers
- 12x less params than AlexNet
- ILSVRC’14 classification winner (6.7% top 5 error)



Inception module

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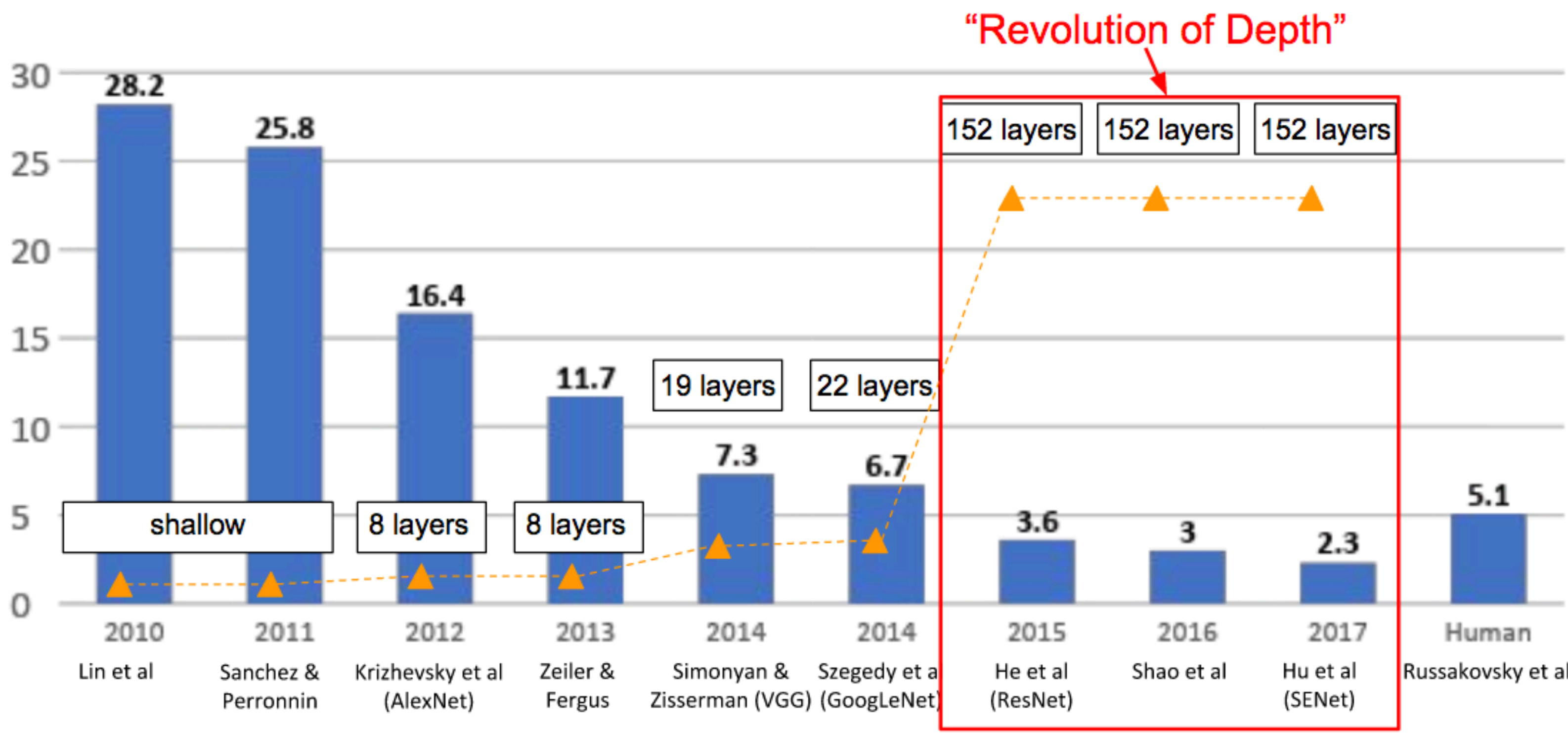
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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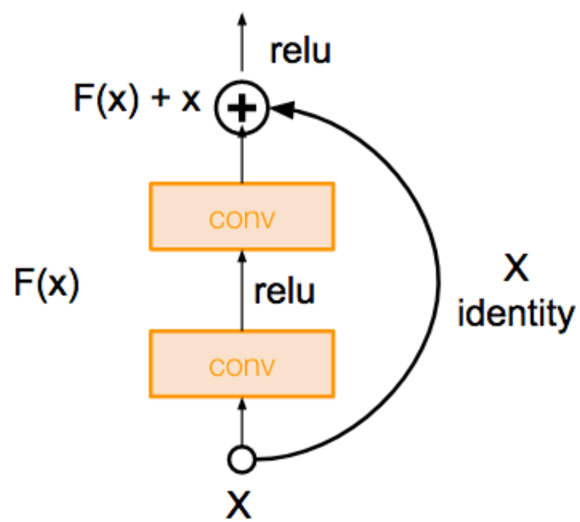
Case Study: ResNet

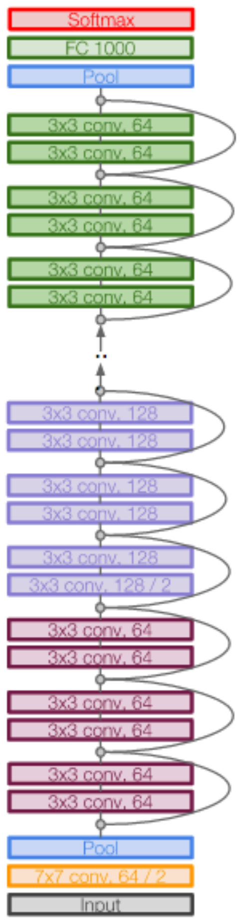
[He et al., 2015]

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!



Residual block



Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Case Study: ResNet

[He et al., 2015]

What happens when we continue stacking deeper layers on a “plain” convolutional neural network?

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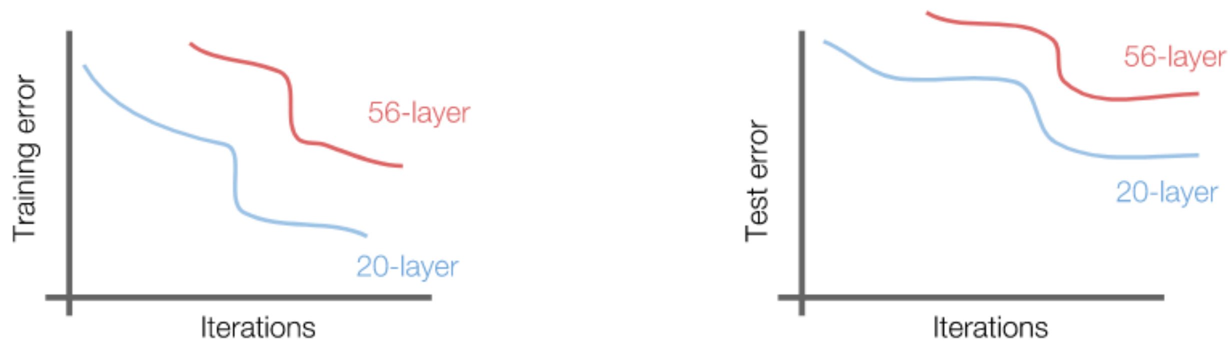


Q: What's strange about these training and test curves?
[Hint: look at the order of the curves]

56-layer model performs worse on both training and test error-> The deeper model performs worse, but it's not caused by overfitting!

Case Study: ResNet

[He et al., 2015]

Hypothesis: the problem is an *optimization* problem, deeper models are harder to optimize

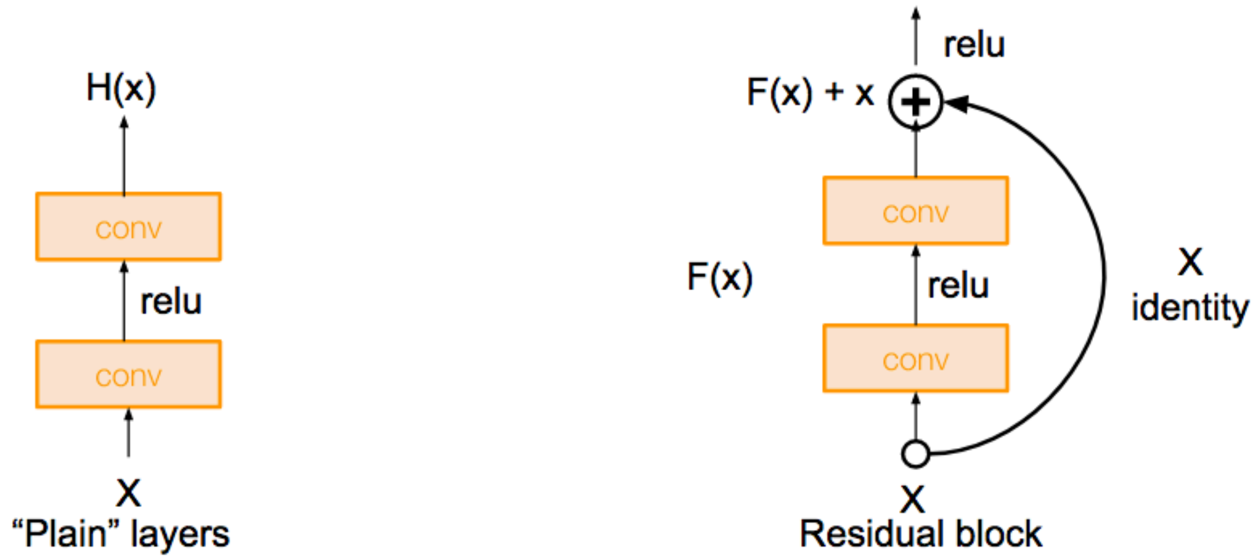
The deeper model should be able to perform at least as well as the shallower model.

A solution by construction is copying the learned layers from the shallower model and setting additional layers to identity mapping.

Case Study: ResNet

[He et al., 2015]

Solution: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



Case Study: ResNet

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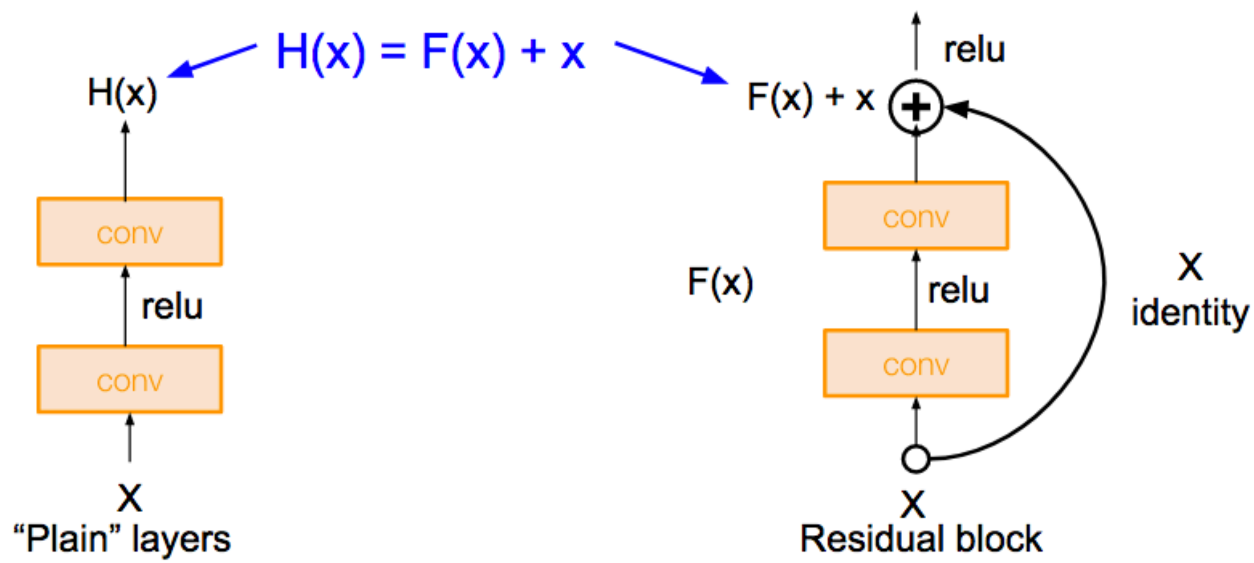

Use layers to fit residual $F(x) = H(x) - x$ instead of $H(x)$ directly

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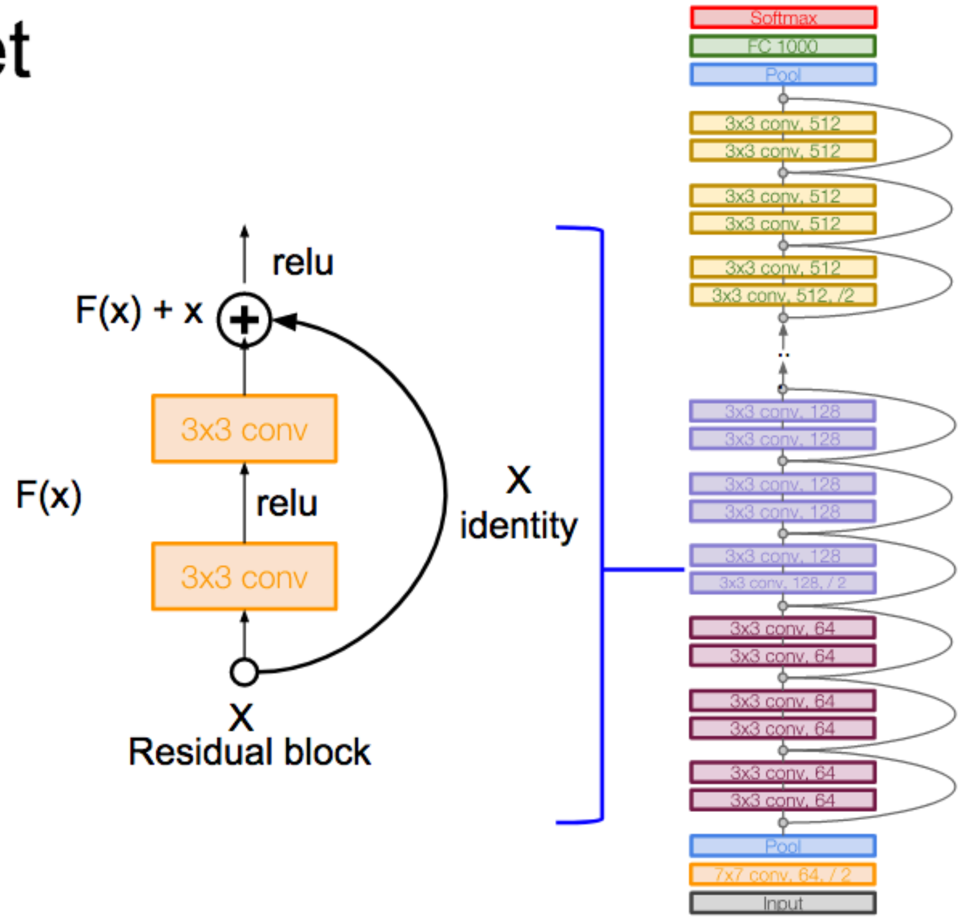
Case Study: ResNet

[He et al., 2015]

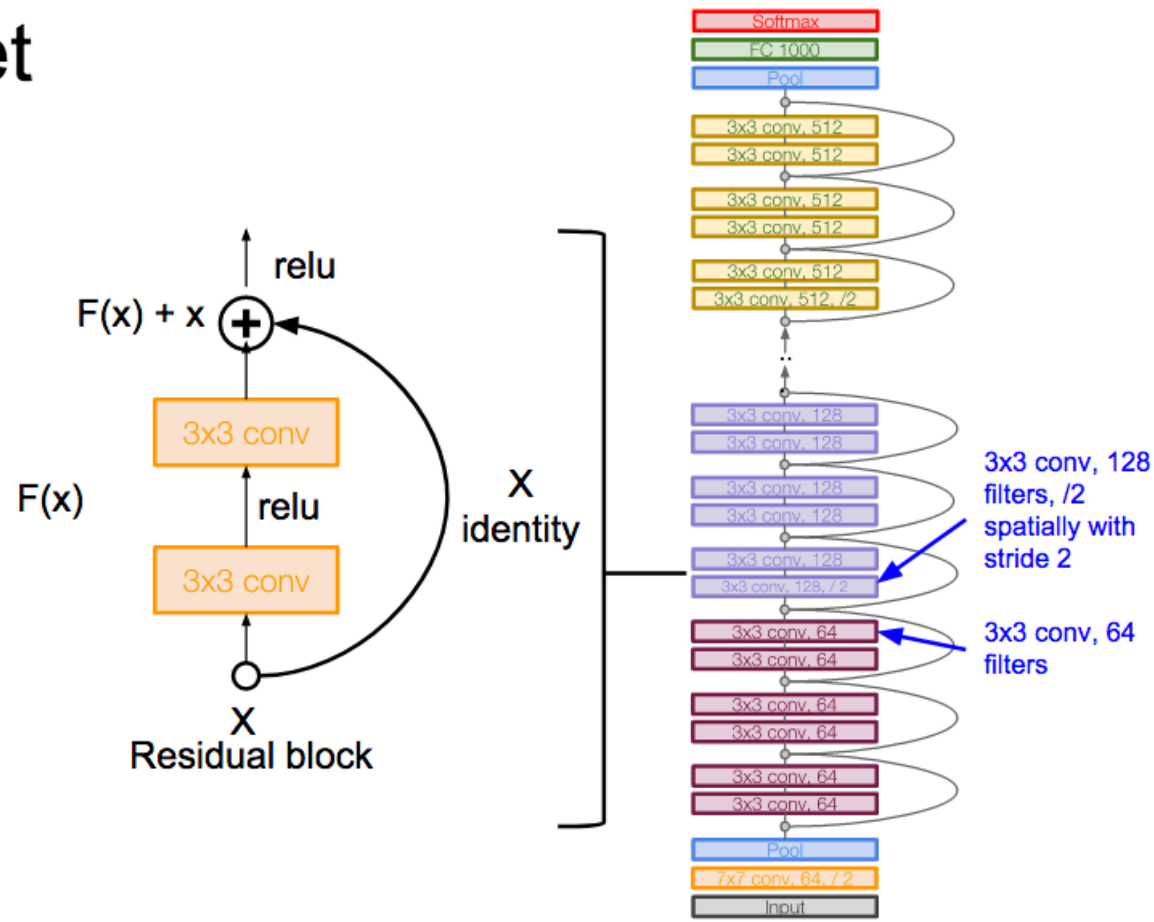
Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers



Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)



Case Study: ResNet

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Full ResNet architecture:
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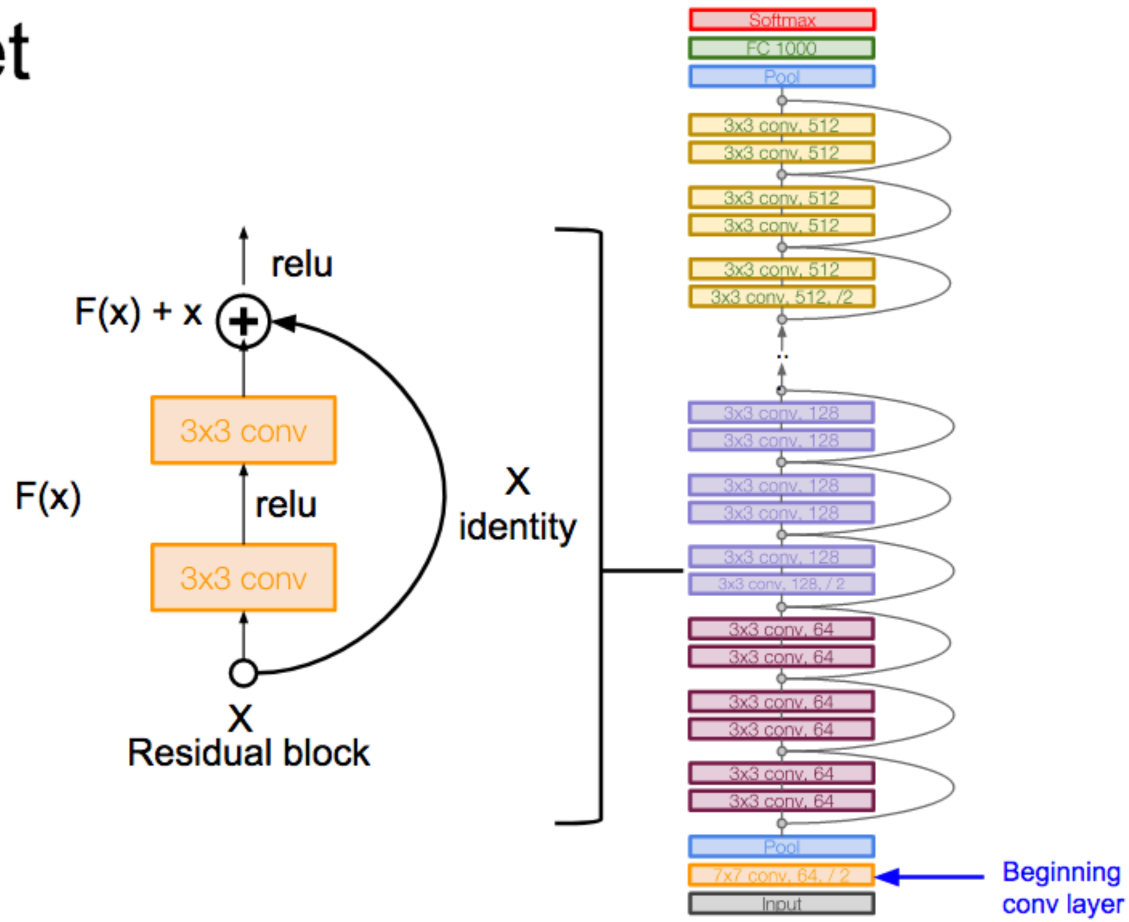
- Additional conv layer at the beginning



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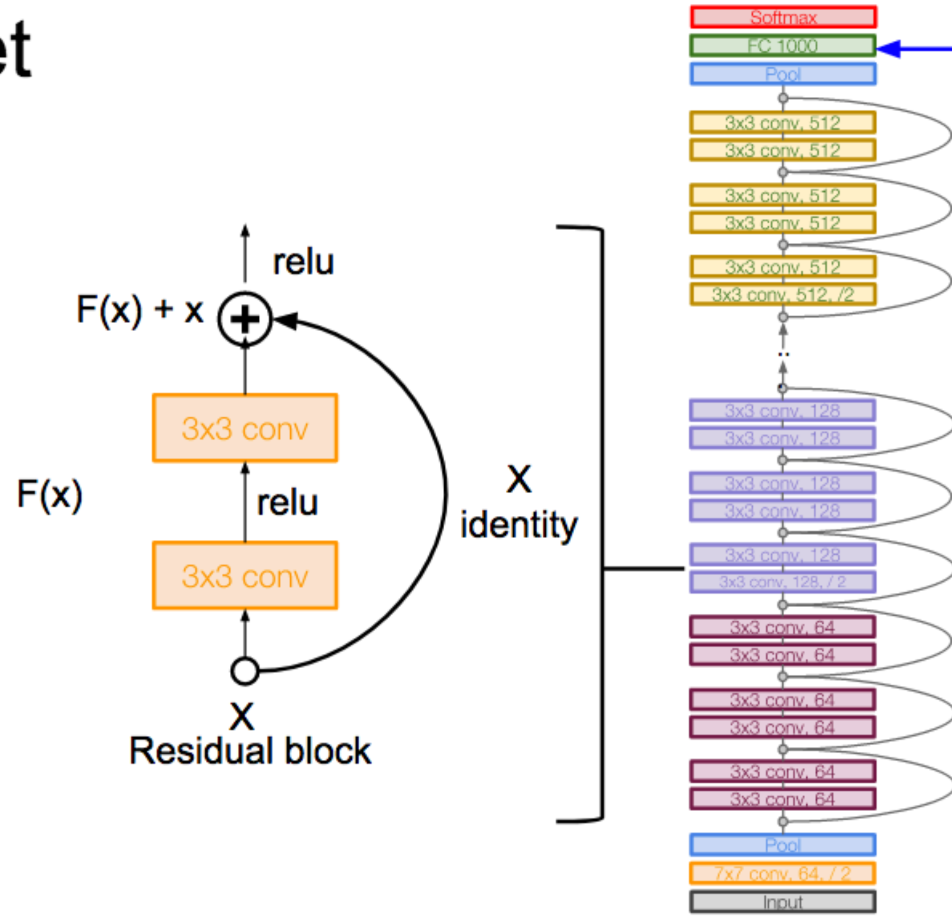
Case Study: ResNet

[He et al., 2015]

Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers
- Periodically, double # of filters and downsample spatially using stride 2 (/2 in each dimension)
- Additional conv layer at the beginning
- No FC layers at the end (only FC 1000 to output classes)



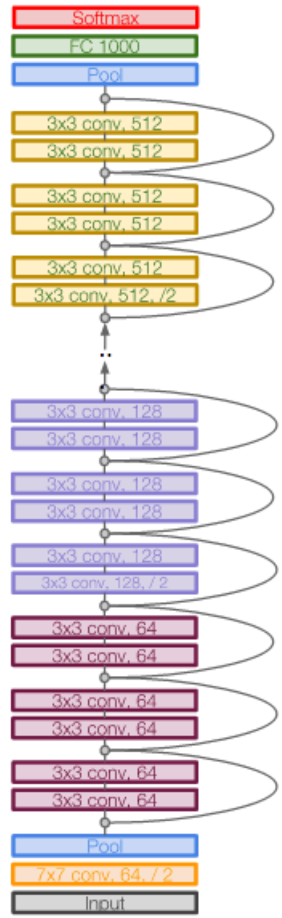
No FC layers besides FC 1000 to output classes

Global average pooling layer after last conv layer

Case Study: ResNet

[He et al., 2015]

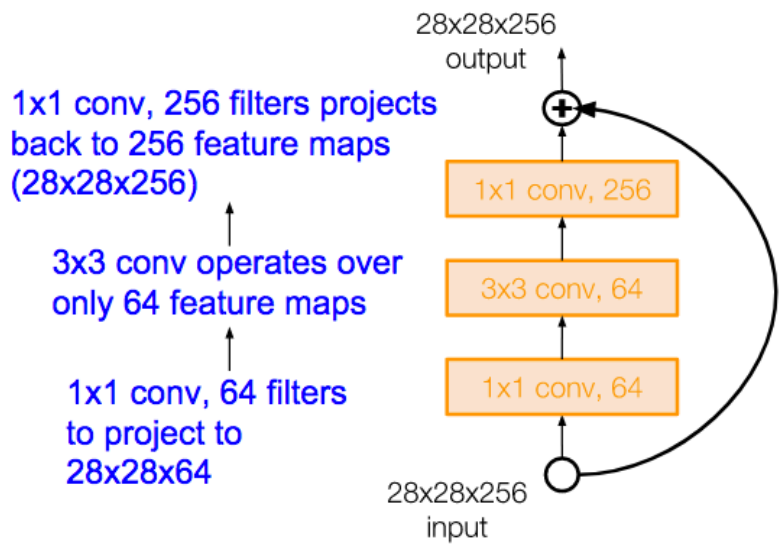
Total depths of 34, 50, 101, or 152 layers for ImageNet



Case Study: ResNet

[He et al., 2015]

For deeper networks (ResNet-50+), use "bottleneck" layer to improve efficiency (similar to GoogLeNet)



Case Study: ResNet

[He et al., 2015]

Experimental Results

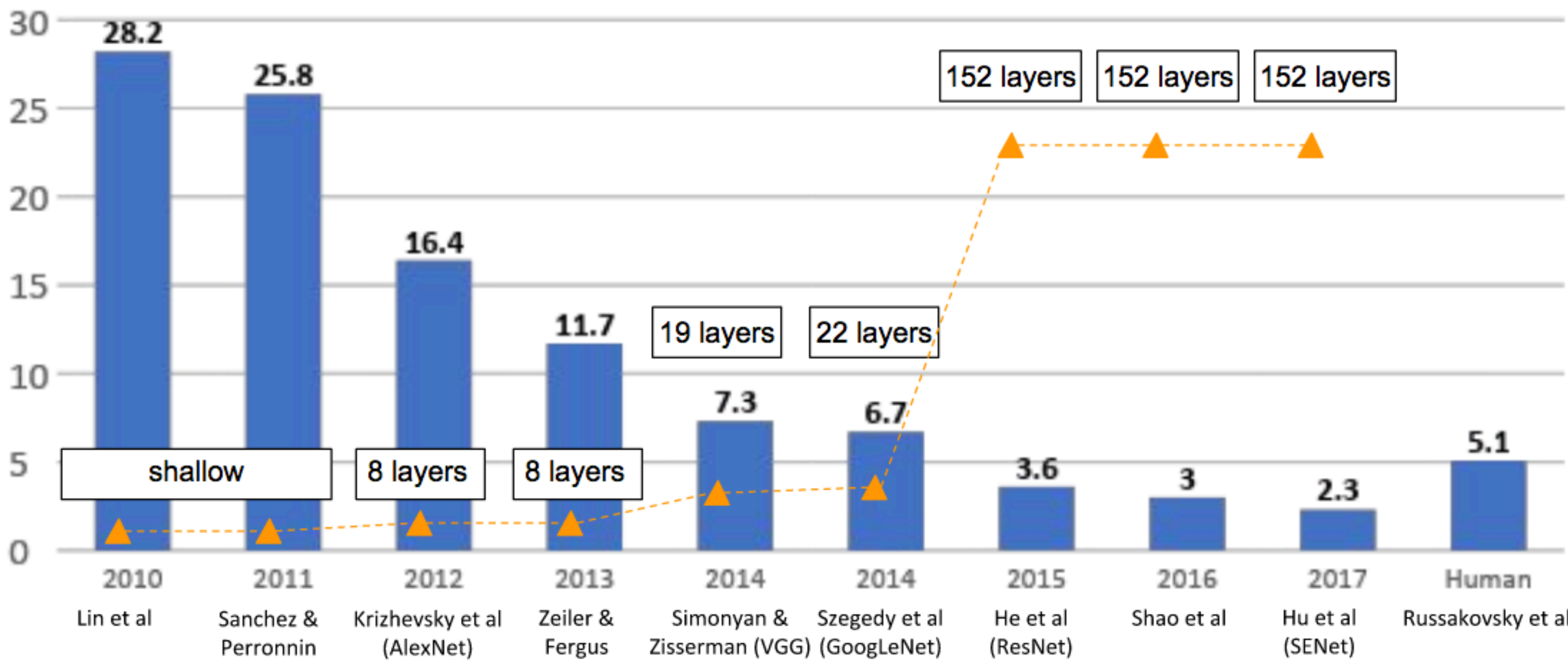
- Able to train very deep networks without degrading (152 layers on ImageNet, 1202 on Cifar)
- Deeper networks now achieve lowing training error as expected
- Swept 1st place in all ILSVRC and COCO 2015 competitions

MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

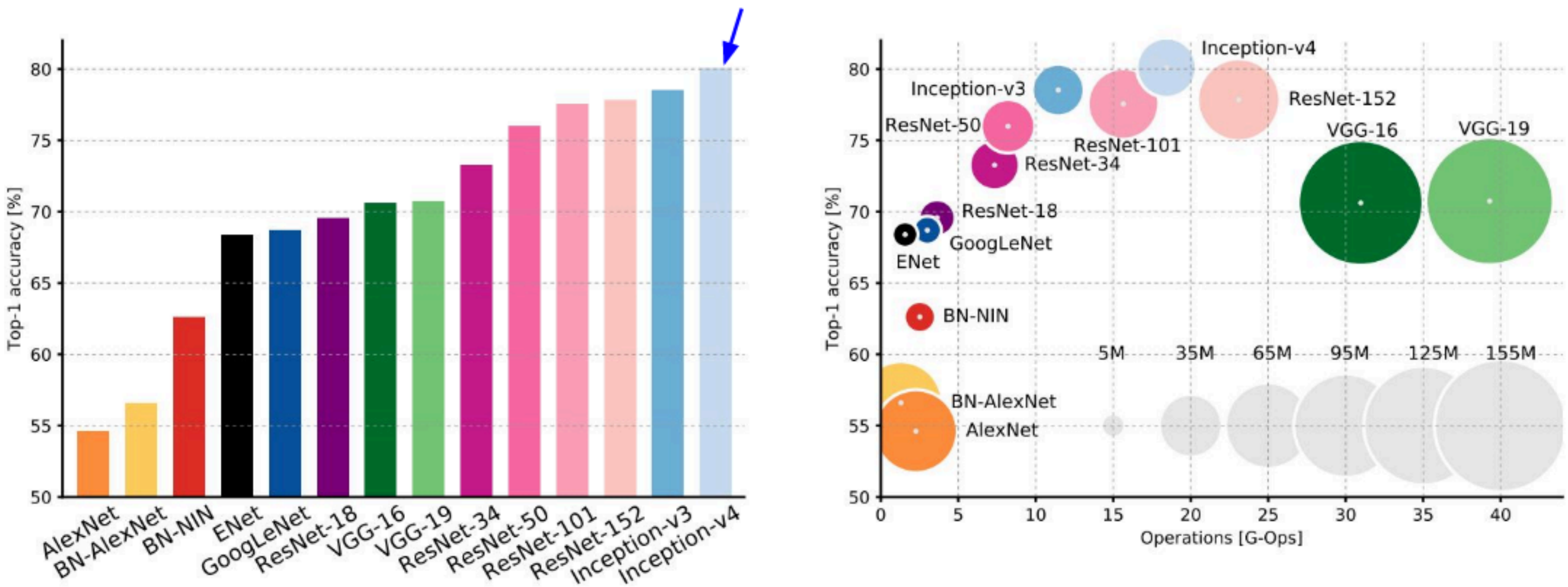
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

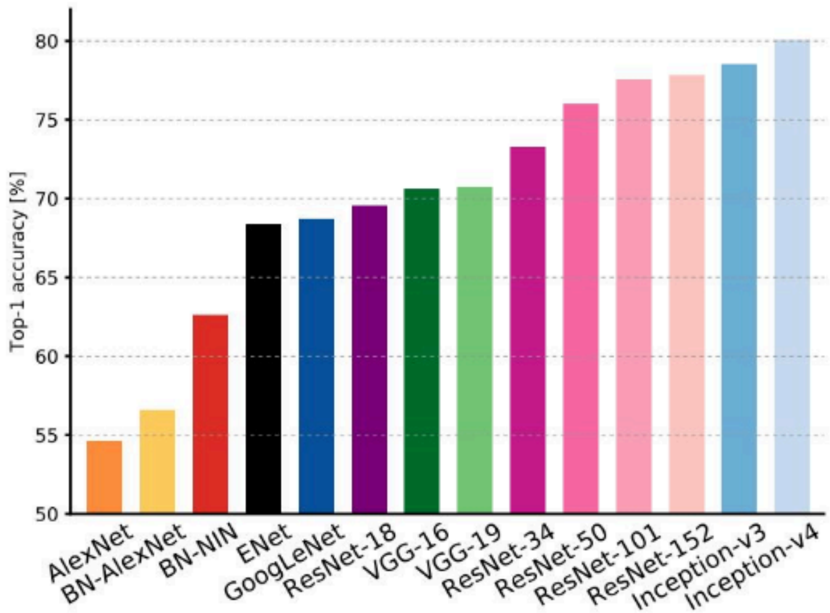
Comparing complexity...

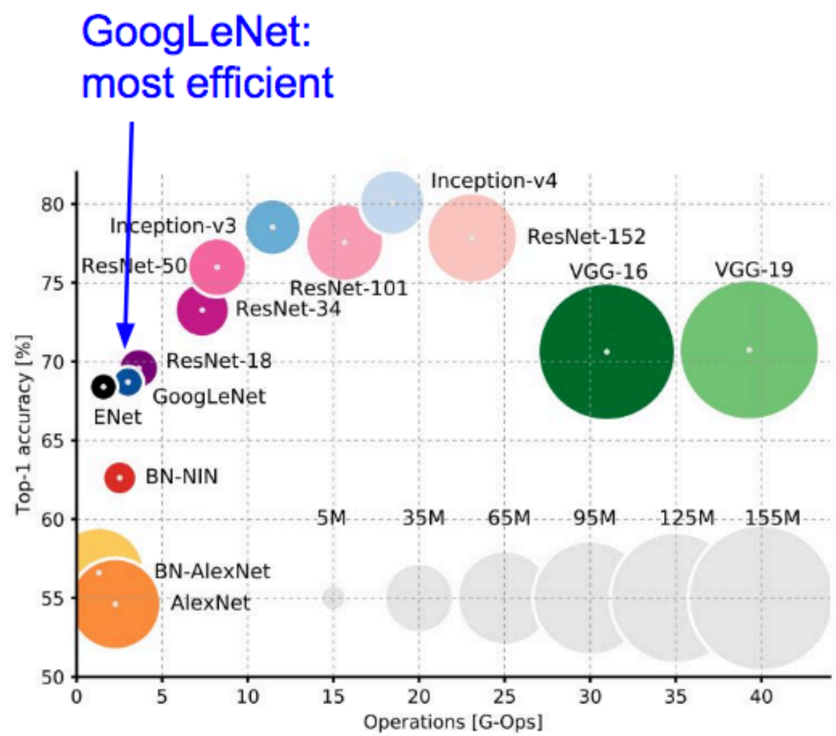
Inception-v4: Resnet + Inception!



An Analysis of Deep Neural Network Models for Practical Applications, 2017.

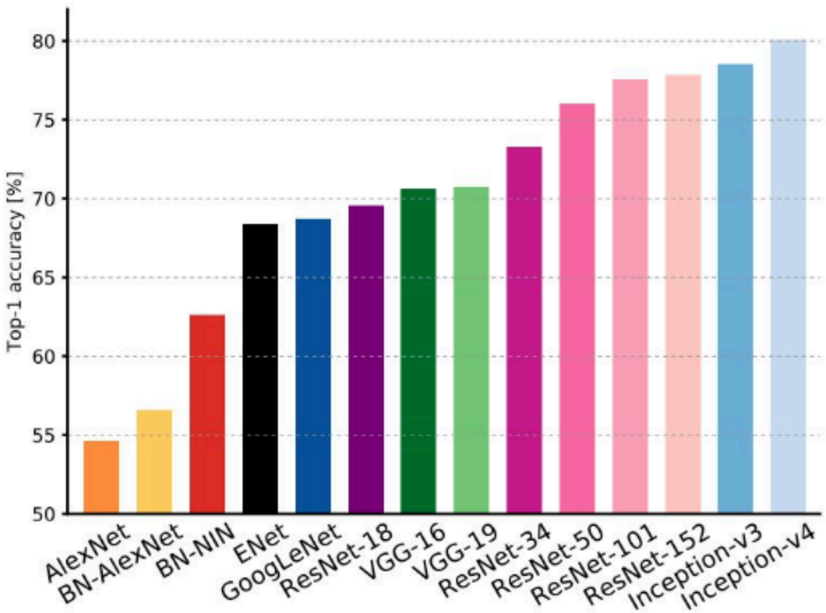
Comparing complexity...



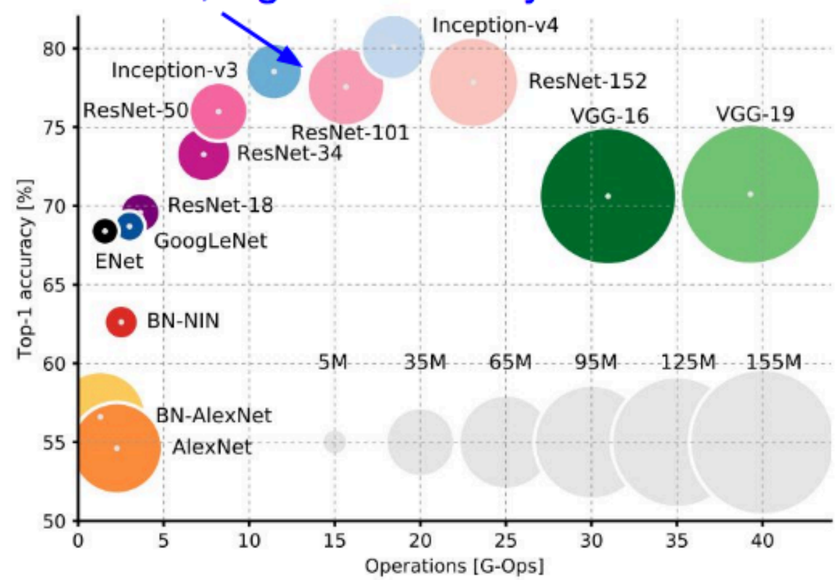


An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Comparing complexity...



ResNet:
Moderate efficiency depending on model, highest accuracy



An Analysis of Deep Neural Network Models for Practical Applications, 2017.

And so on and so forth…

- Dizzying number of papers since then proposing more architecture tricks and hacks.
- A couple notable examples:
  - FractalNet
  - DenseNet

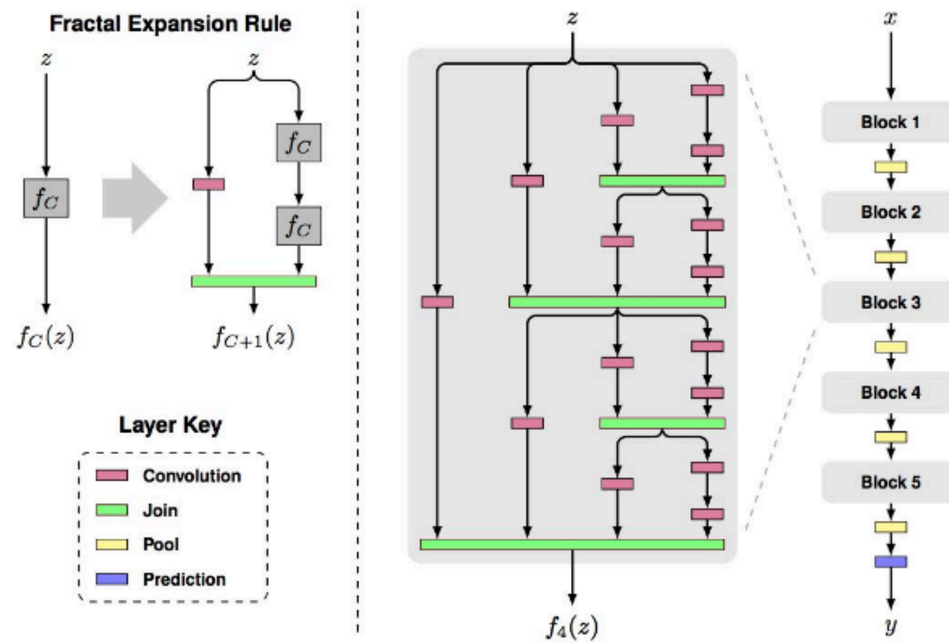
Do we though?
(open question)

Beyond ResNets...

FractalNet: Ultra-Deep Neural Networks without Residuals

[Larsson et al. 2017]

- Argues that key is transitioning effectively from shallow to deep and residual representations are not necessary
- Fractal architecture with both shallow and deep paths to output
- Trained with dropping out sub-paths
- Full network at test time

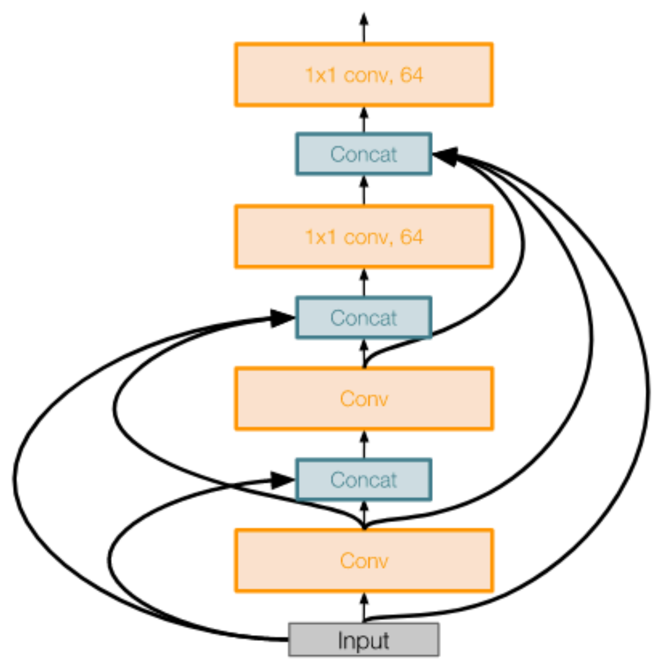


Beyond ResNets...

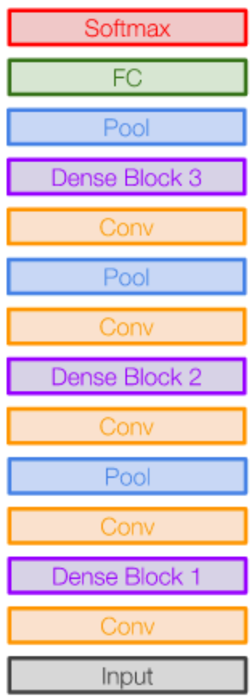
Densely Connected Convolutional Networks

[Huang et al. 2017]

- Dense blocks where each layer is connected to every other layer in feedforward fashion
- Alleviates vanishing gradient, strengthens feature propagation, encourages feature reuse



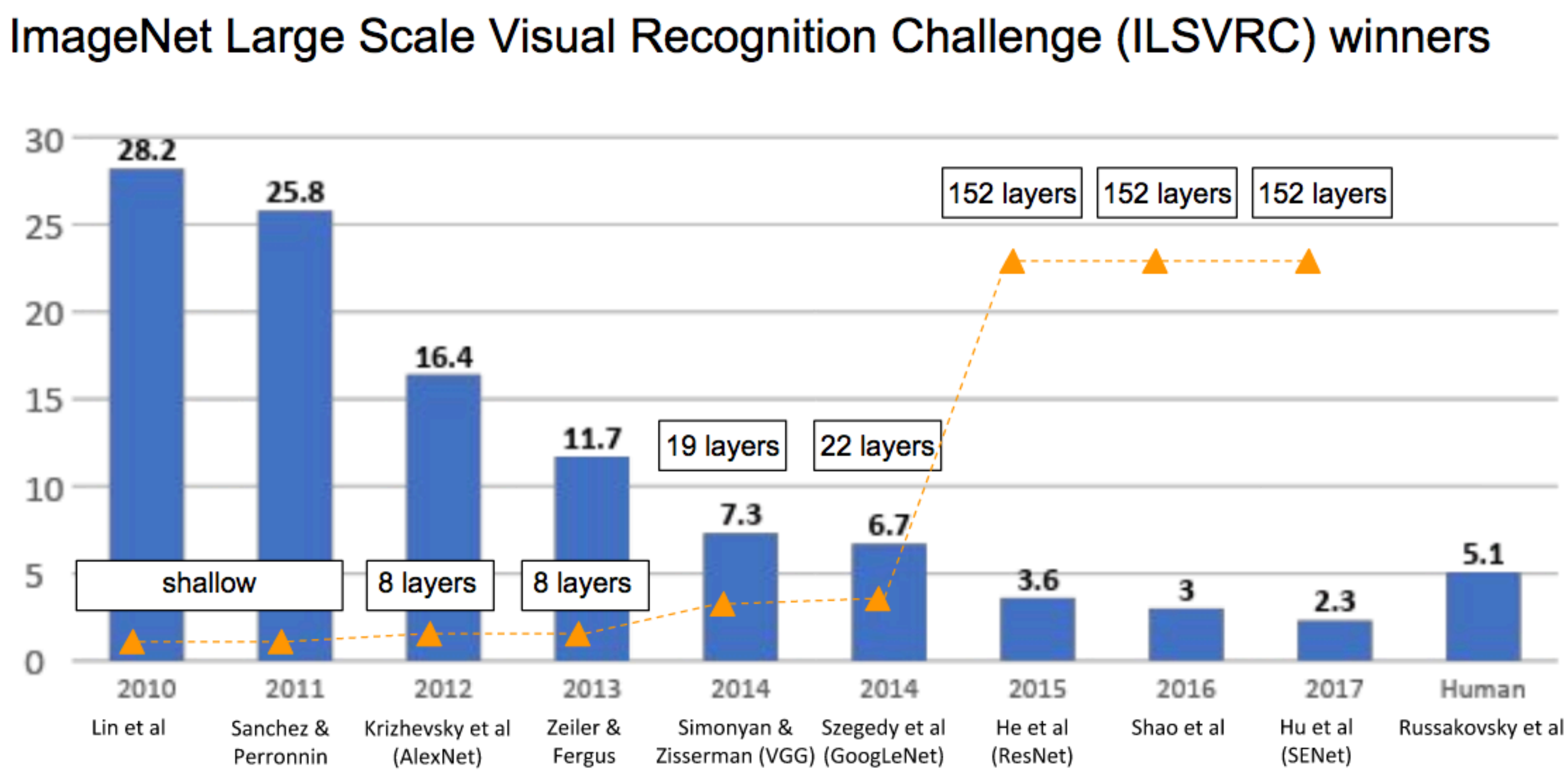
Dense Block



Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

And so on and so forth…

- So we’ve beat the crap out of ImageNet… what now?



And so on and so forth…

- So we’ve beat the crap out of ImageNet… what now?
  - Can we do image classification on other datasets?
  - Can we do things other than image classification?

And so on and so forth…

- So we've beat the crap out of ImageNet… what now?
  - **Can we do image classification on other datasets?**
  - Can we do things other than image classification?

Transfer Learning

"You need a lot of a data if you want to train/use CNNs"

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Transfer Learning

"You need a lot of a data if you want to train/use CNNs"

BUSTED

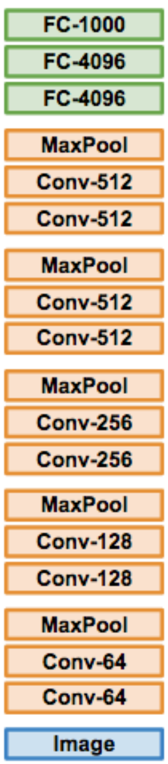
well… sort of

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

Transfer Learning with CNNs

1. Train on Imagenet



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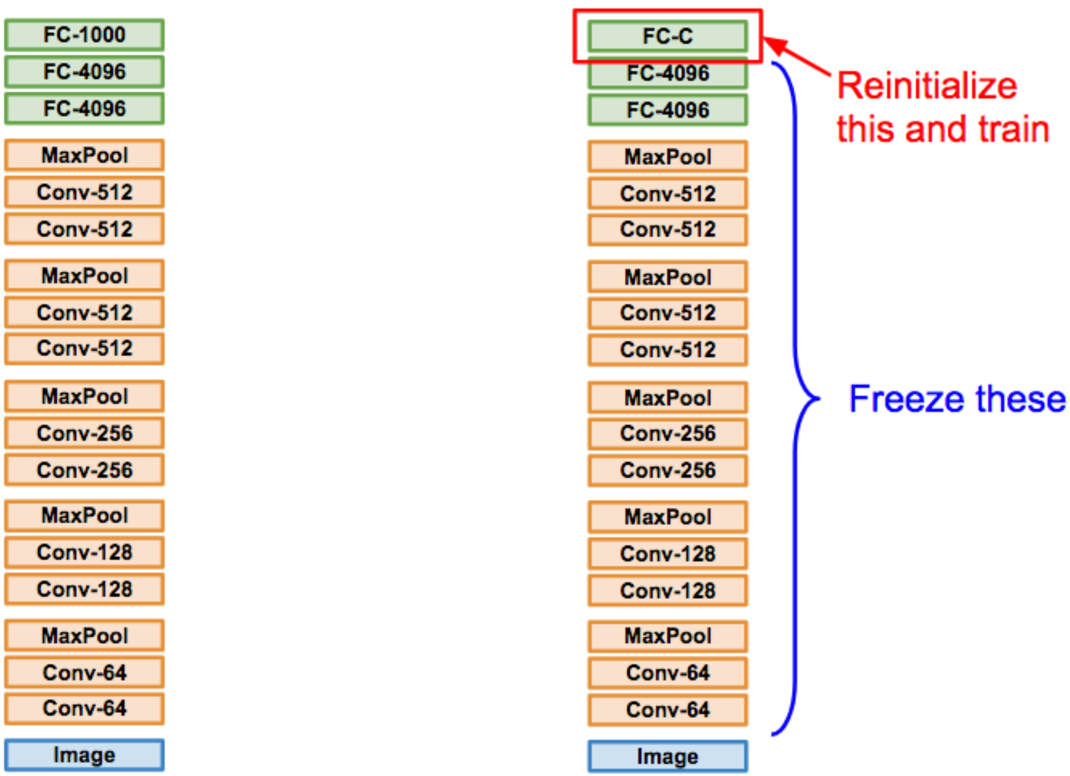
Transfer Learning with CNNs

Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

1. Train on Imagenet

2. Small Dataset (C classes)



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Transfer Learning with CNNs

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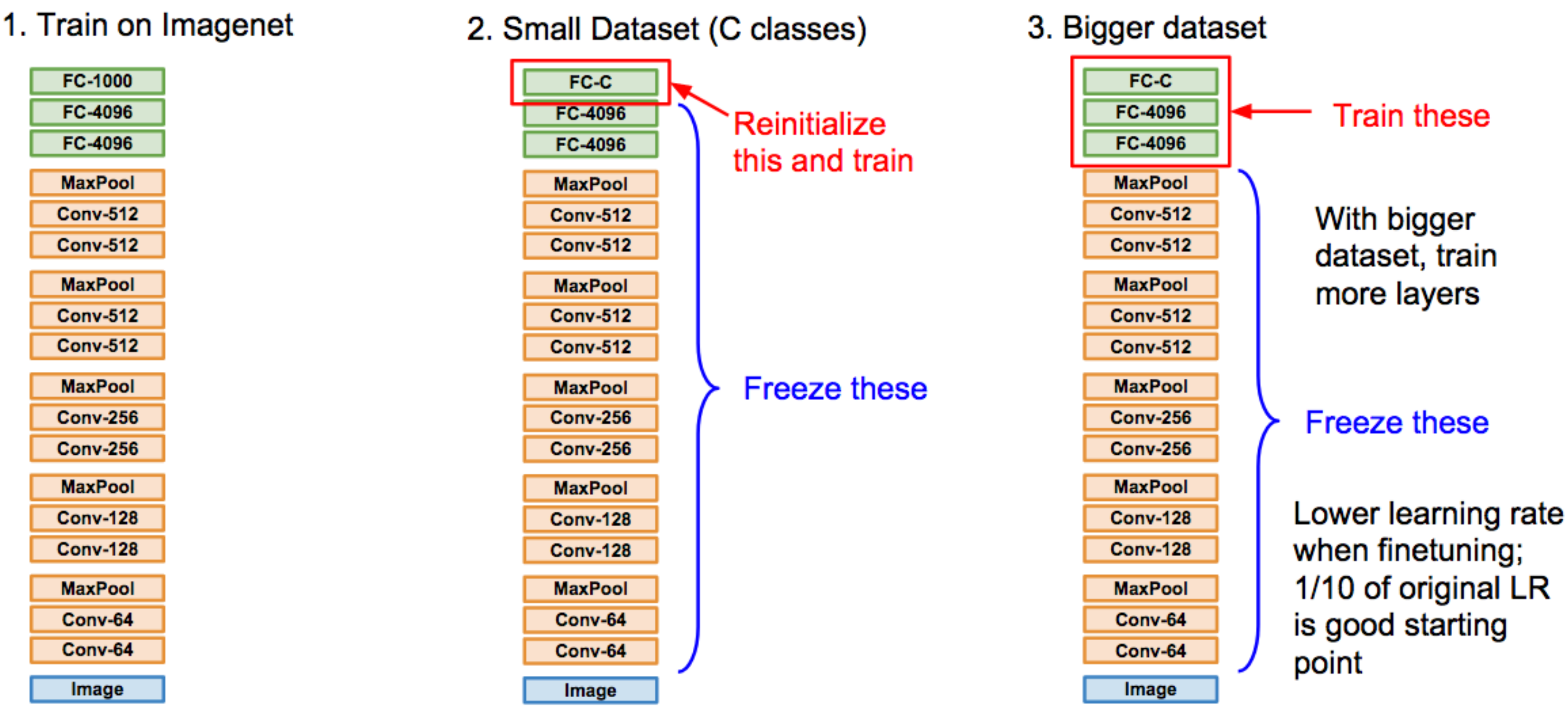


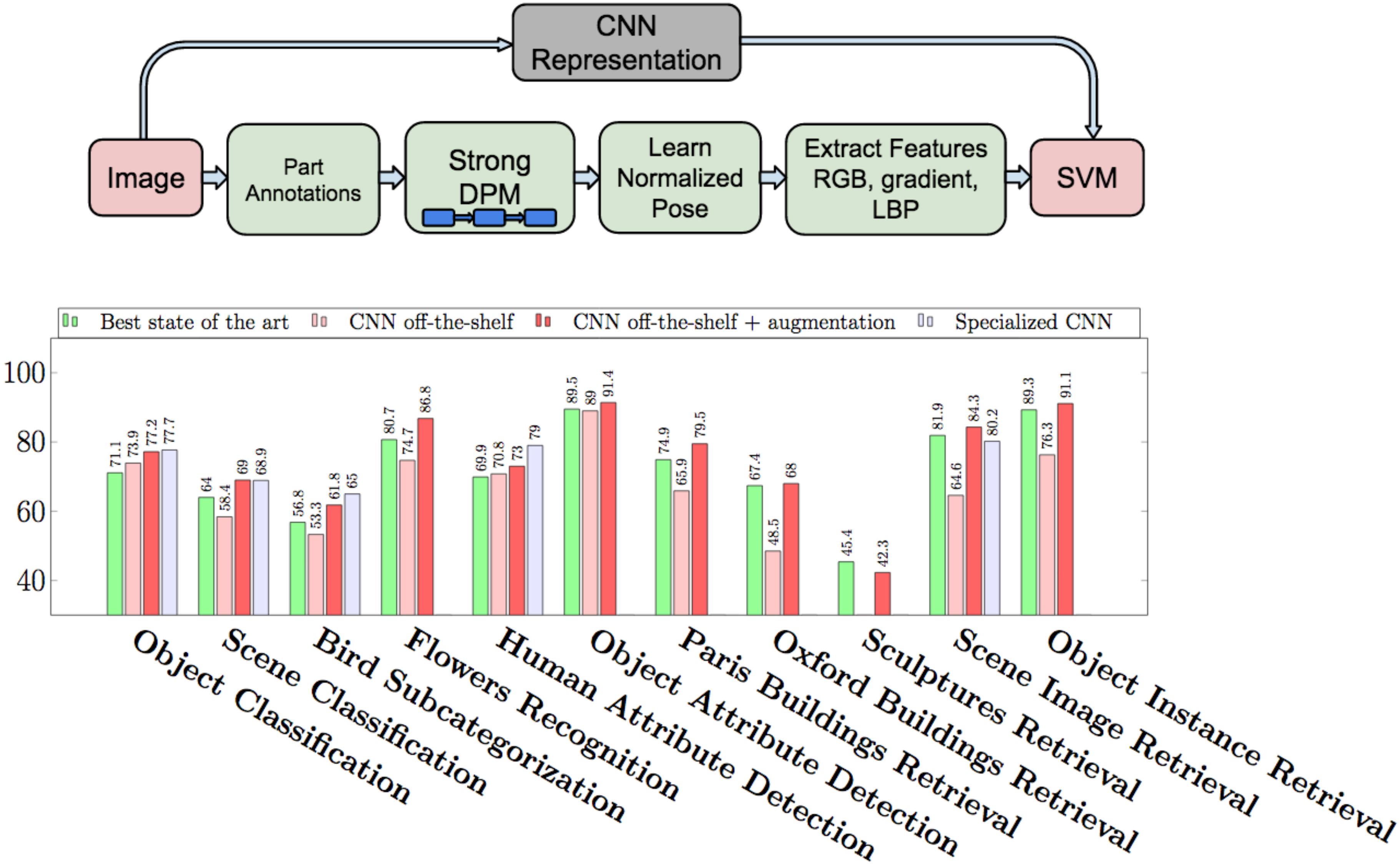


Figure: Razavian et al.: CNN Features off-the-shelf: an Astounding Baseline for Recognition
https://arxiv.org/pdf/1403.6382.pdf

Transfer learning with CNNs is pervasive…
(it’s the norm, not an exception)

Object Detection (Fast R-CNN)

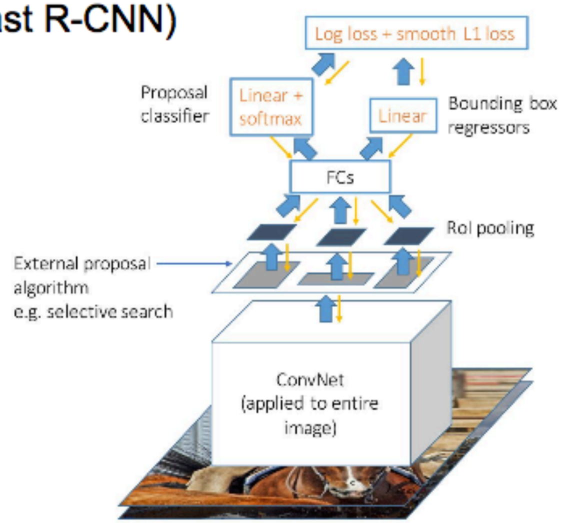
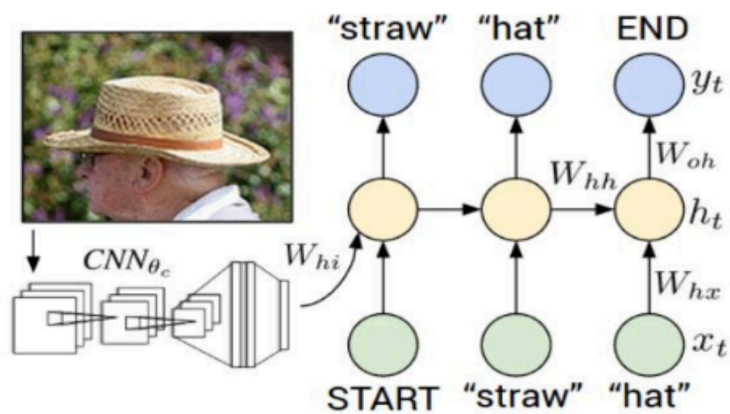


Image Captioning: CNN + RNN



Girshick, “Fast R-CNN”, ICCV 2015

Karpathy and Fei-Fei, “Deep Visual-Semantic Alignments for Generating Image Descriptions”, CVPR 2015

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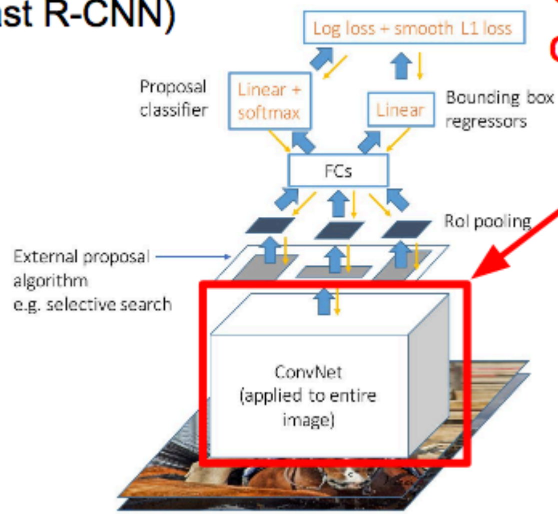
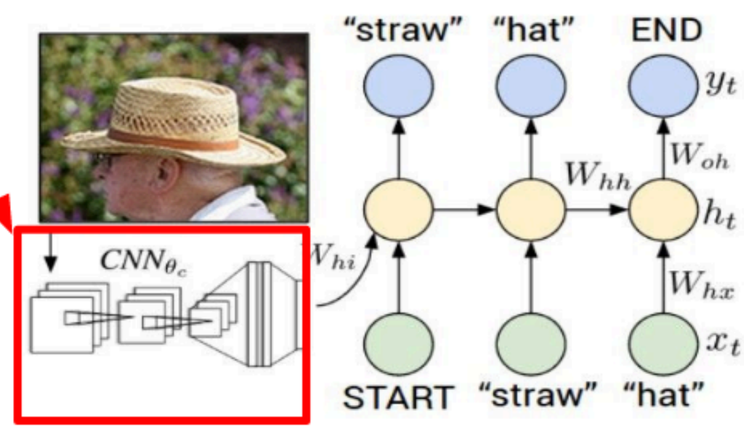


CNN pretrained on ImageNet

Image Captioning: CNN + RNN



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And so on and so forth…

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  - Can we do image classification on other datasets?
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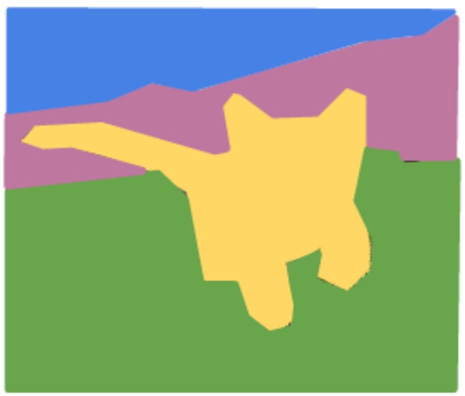
Other Computer Vision Tasks

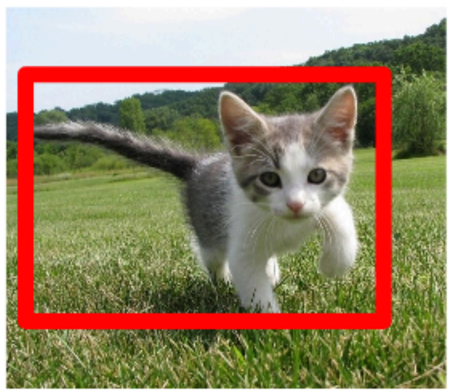
Semantic Segmentation



GRASS, CAT, TREE, SKY

No objects, just pixels

Classification + Localization



CAT

Single Object

Object Detection

DOG, DOG, CAT

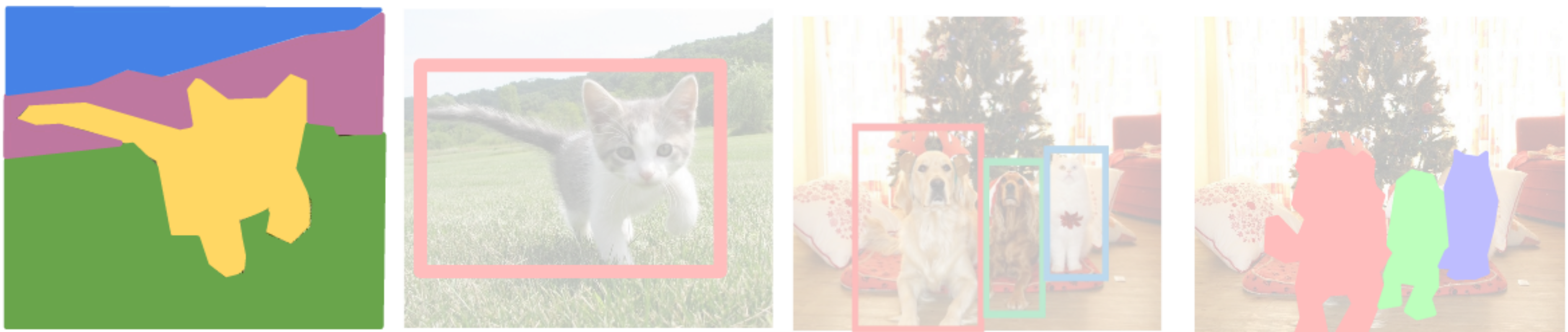
Instance Segmentation

DOG, DOG, CAT

Multiple Object

Other Computer Vision Tasks

Semantic Segmentation	Classification + Localization	Object Detection	Instance Segmentation



GRASS, CAT, TREE, SKY	CAT	DOG, DOG, CAT	DOG, DOG, CAT

No objects, just pixels

Single Object

Multiple Object

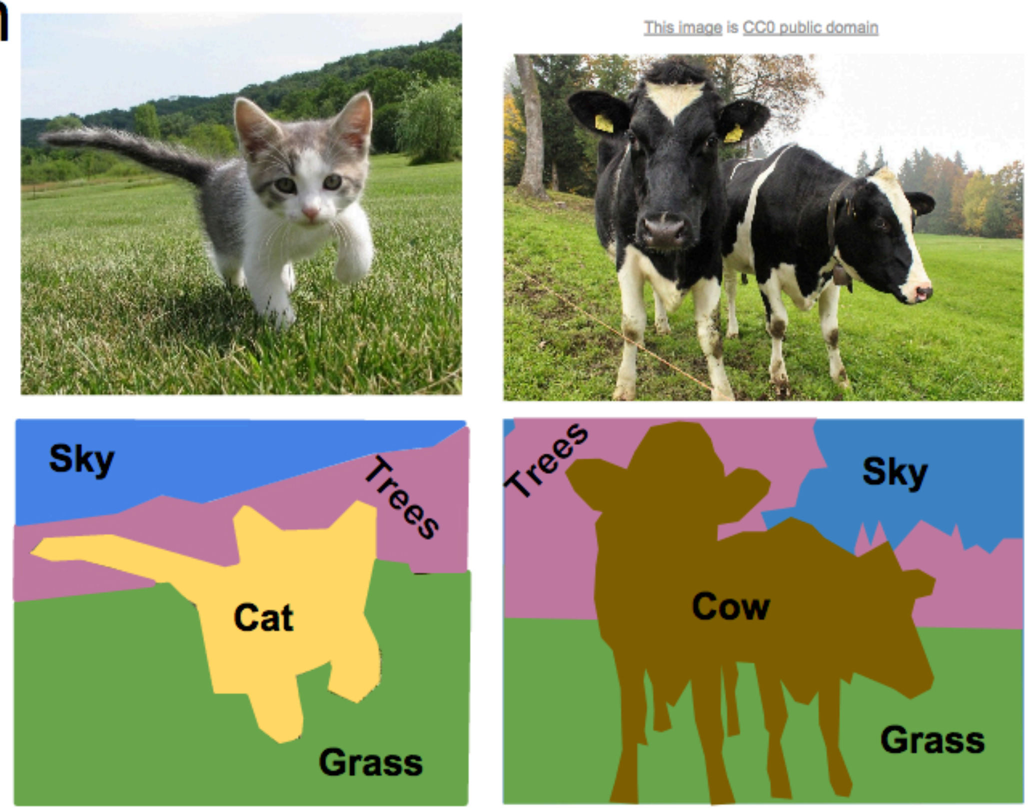
Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Semantic Segmentation

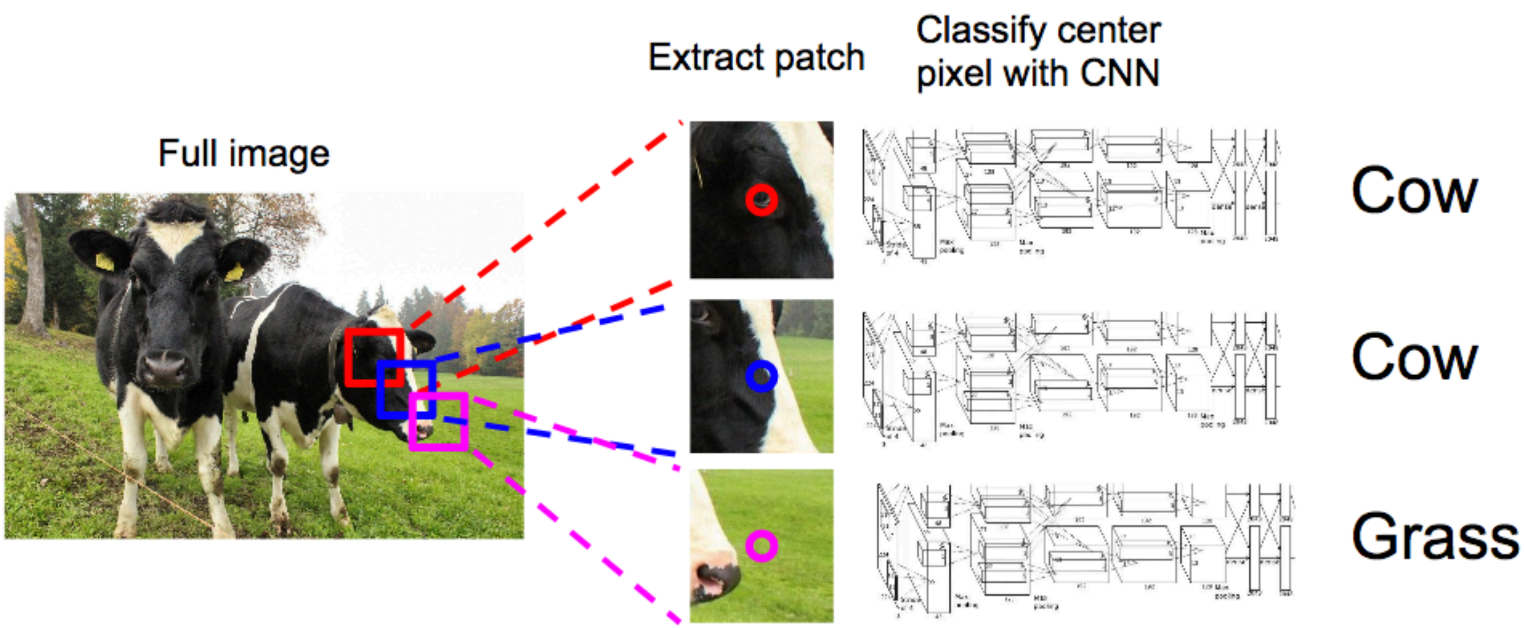
Label each pixel in the image with a category label

Don't differentiate instances, only care about pixels

This image is CC0 public domain

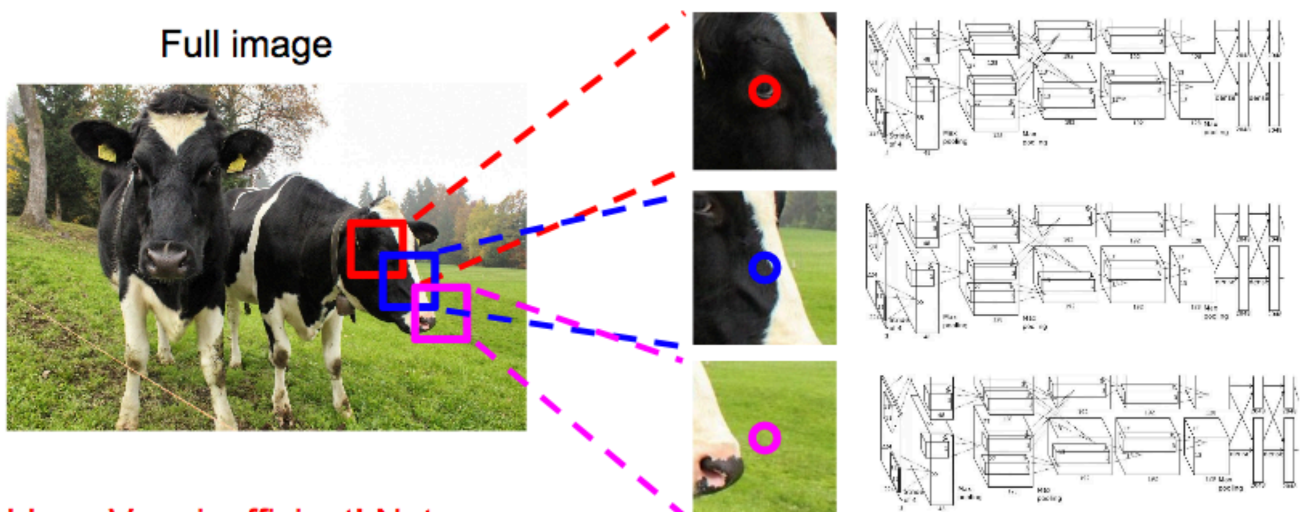


Semantic Segmentation Idea: Sliding Window



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: Sliding Window

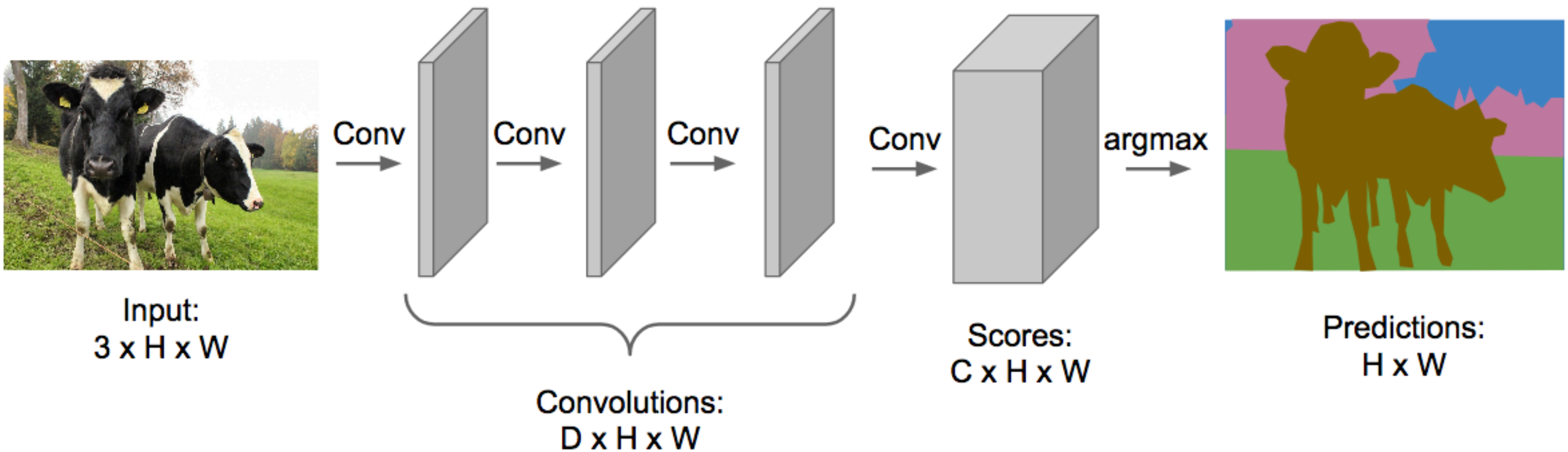


Problem: Very inefficient! Not reusing shared features between overlapping patches

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

Semantic Segmentation Idea: Fully Convolutional

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



Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

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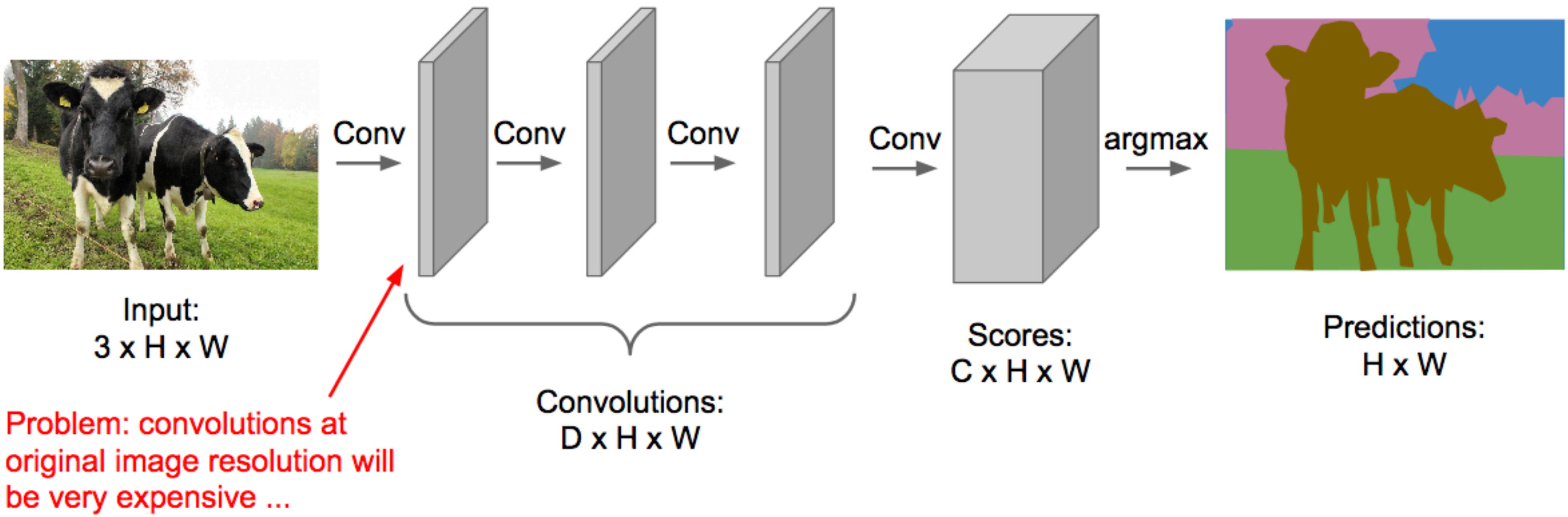

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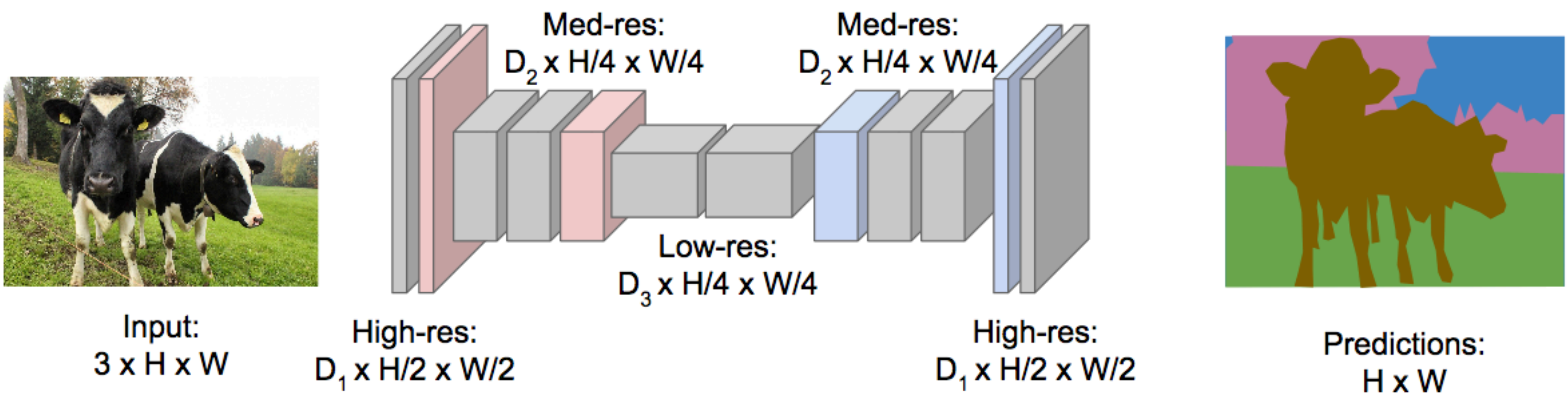
Semantic Segmentation Idea: Fully Convolutional

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



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

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

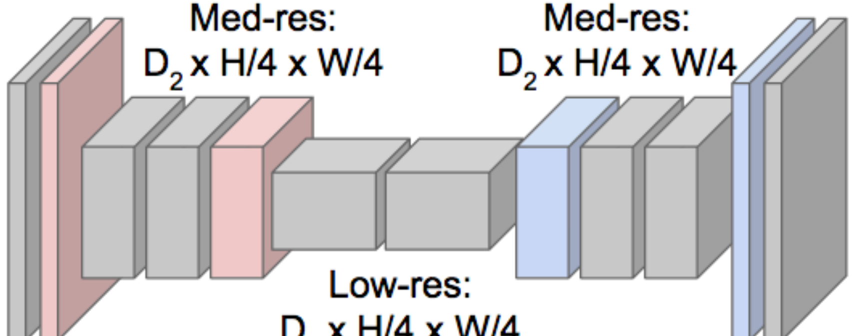
Semantic Segmentation Idea: Fully Convolutional

Downsampling: Pooling, strided convolution

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

Upsampling: ???

Input:
$3 \times H \times W$



Med-res:
$D_2 \times H/4 \times W/4$

Med-res:
$D_2 \times H/4 \times W/4$

Low-res:
$D_3 \times H/4 \times W/4$

High-res:
$D_1 \times H/2 \times W/2$

High-res:
$D_1 \times H/2 \times W/2$

Predictions:
$H \times W$

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

$$\begin{bmatrix}1 & 2\\3 & 4\end{bmatrix} \rightarrow \begin{bmatrix}1 & 1 & 2 & 2\\1 & 1 & 2 & 2\\3 & 3 & 4 & 4\\3 & 3 & 4 & 4\end{bmatrix}$$

Input: 2 x 2

Output: 4 x 4

“Bed of Nails”

$$\begin{bmatrix}1 & 2\\3 & 4\end{bmatrix} \rightarrow \begin{bmatrix}1 & 0 & 2 & 0\\0 & 0 & 0 & 0\\3 & 0 & 4 & 0\\0 & 0 & 0 & 0\end{bmatrix}$$

Input: 2 x 2

Output: 4 x 4

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

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

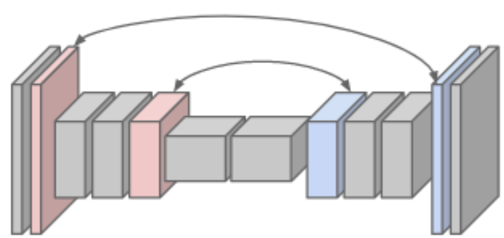
Input: 2 x 2

→

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

Output: 4 x 4

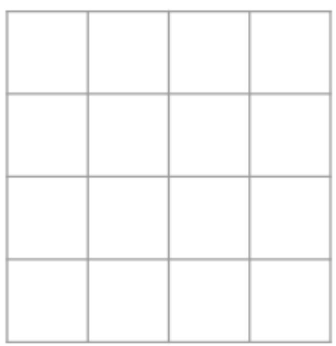
Corresponding pairs of downsampling and upsampling layers



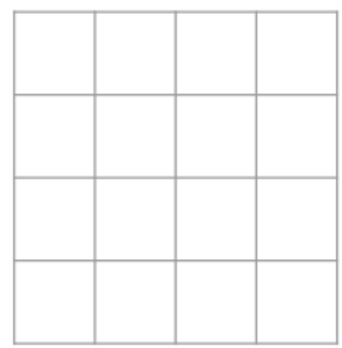
Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Learnable Upsampling: Transpose Convolution

Recall: Typical 3 x 3 convolution, stride 1 pad 1



Input: 4 x 4

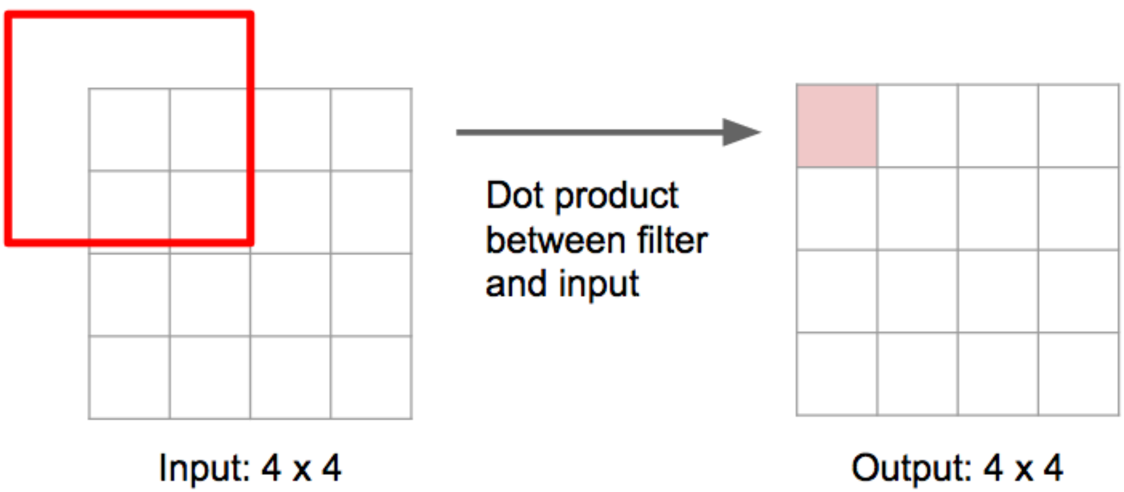


Output: 4 x 4

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 1 pad 1



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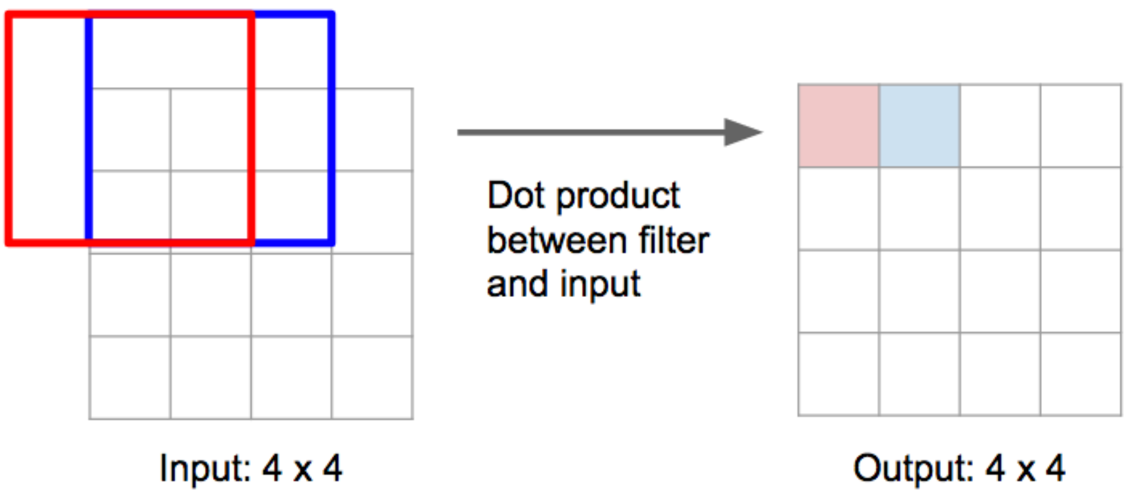
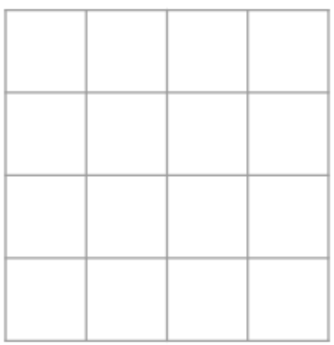


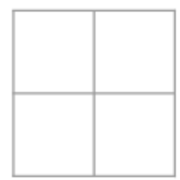
Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



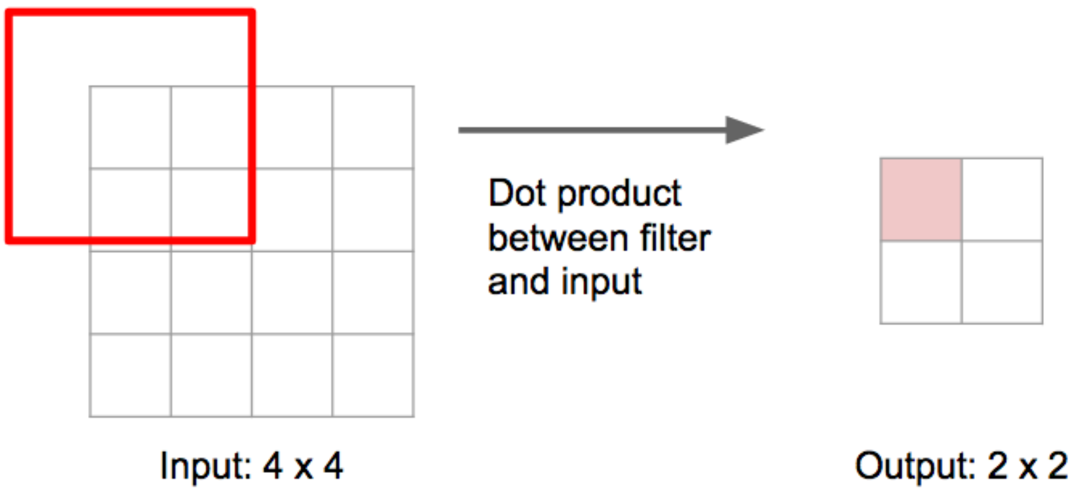
Input: 4 x 4



Output: 2 x 2

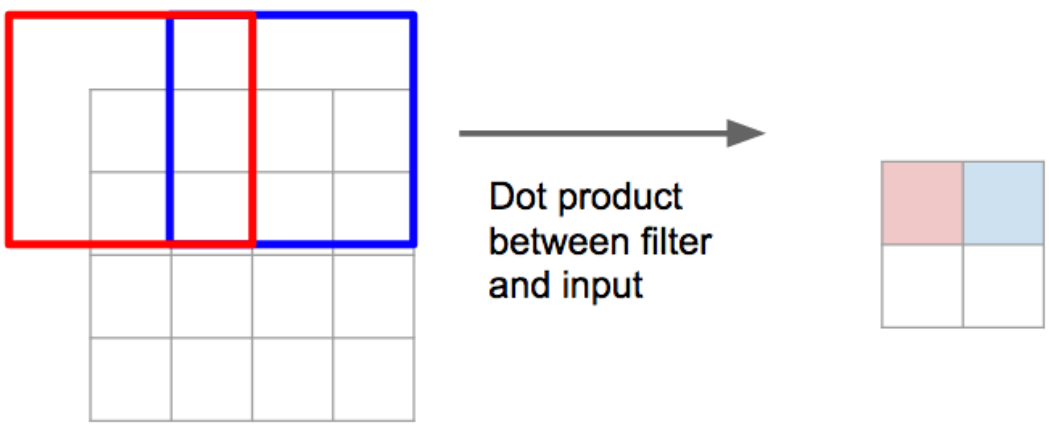
Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, stride 2 pad 1



Learnable Upsampling: Transpose Convolution

Recall: Normal 3 x 3 convolution, <u>stride 2</u> pad 1



Input: 4 x 4

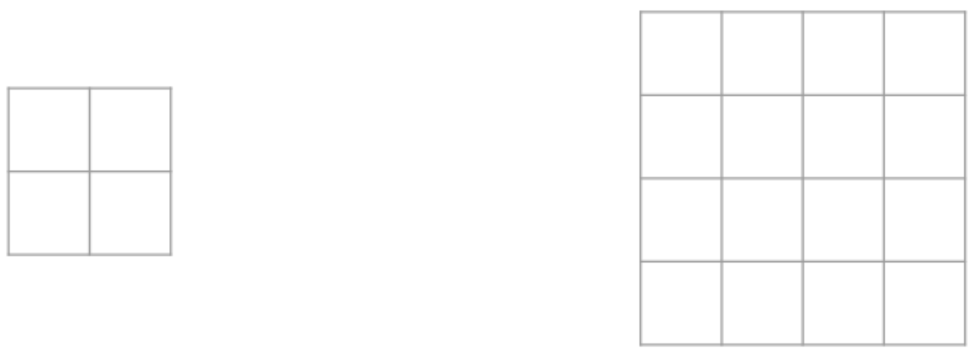
Output: 2 x 2

Filter moves 2 pixels in the input for every one pixel in the output

Stride gives ratio between movement in input and output

Learnable Upsampling: Transpose Convolution

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



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Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Learnable Upsampling: Transpose Convolution

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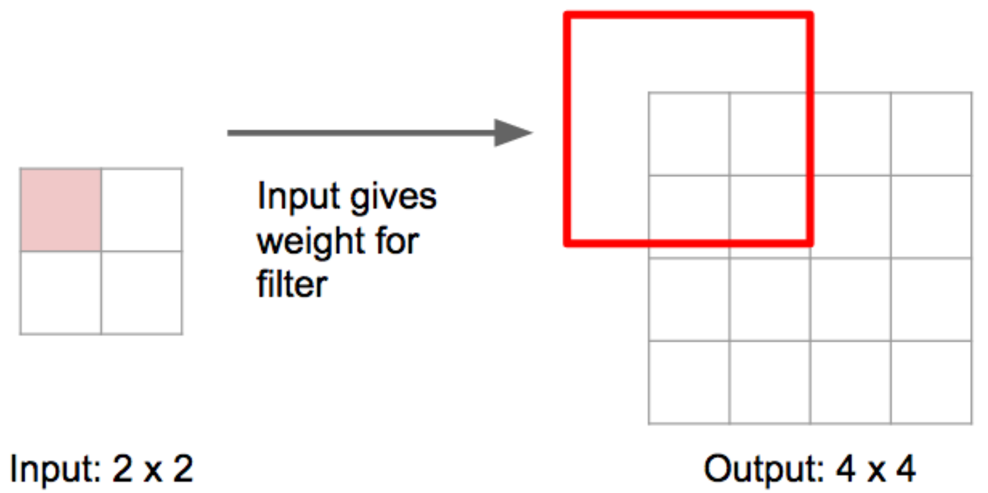
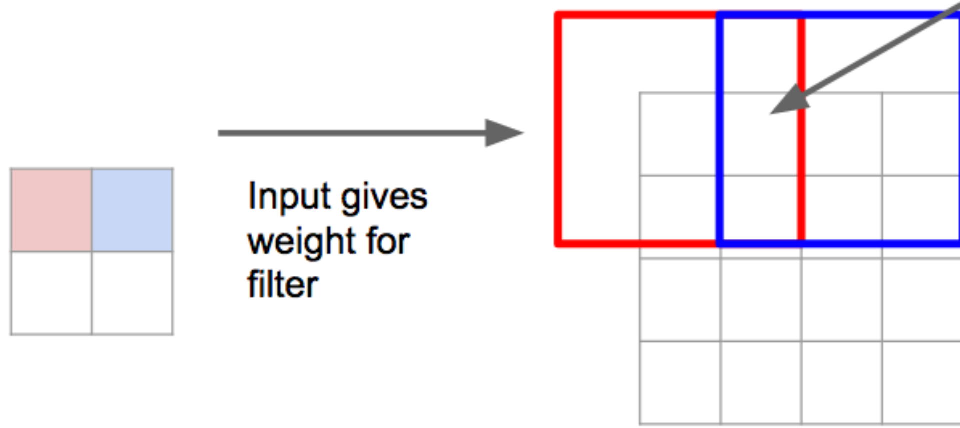


Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Learnable Upsampling: Transpose Convolution

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

Sum where output overlaps



Input: 2 x 2

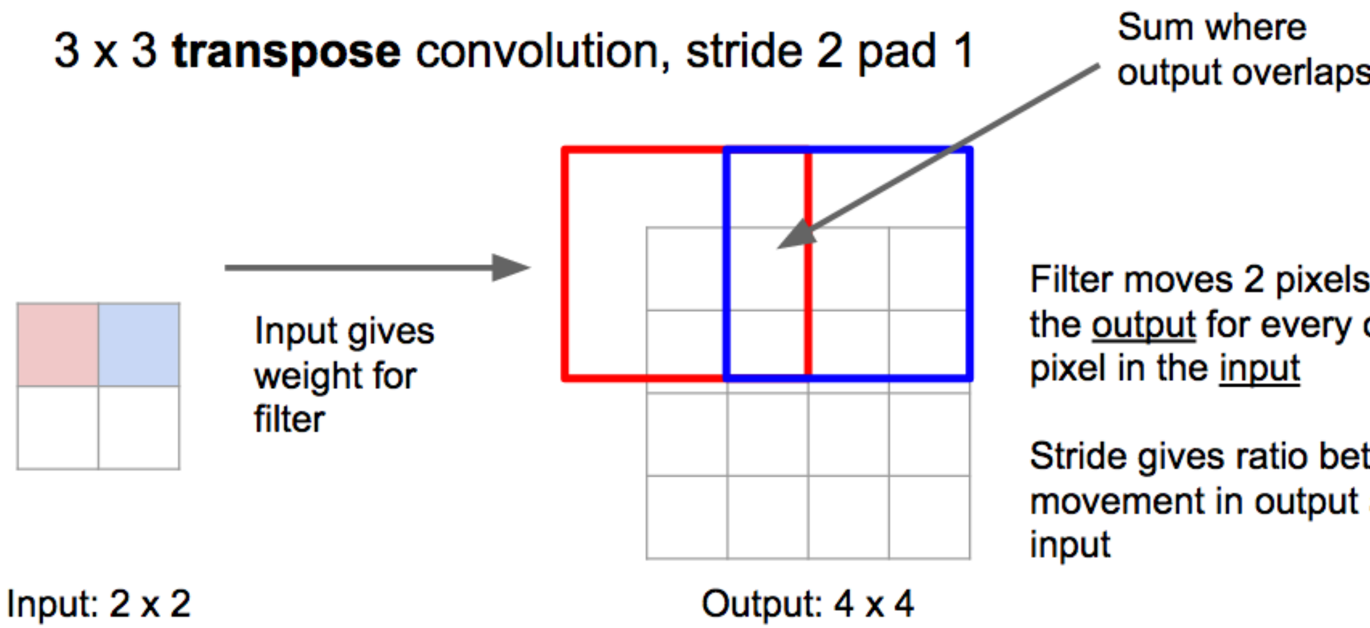
Output: 4 x 4

Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

Learnable Upsampling: Transpose Convolution

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



Filter moves 2 pixels in the output for every one pixel in the input

Stride gives ratio between movement in output and input

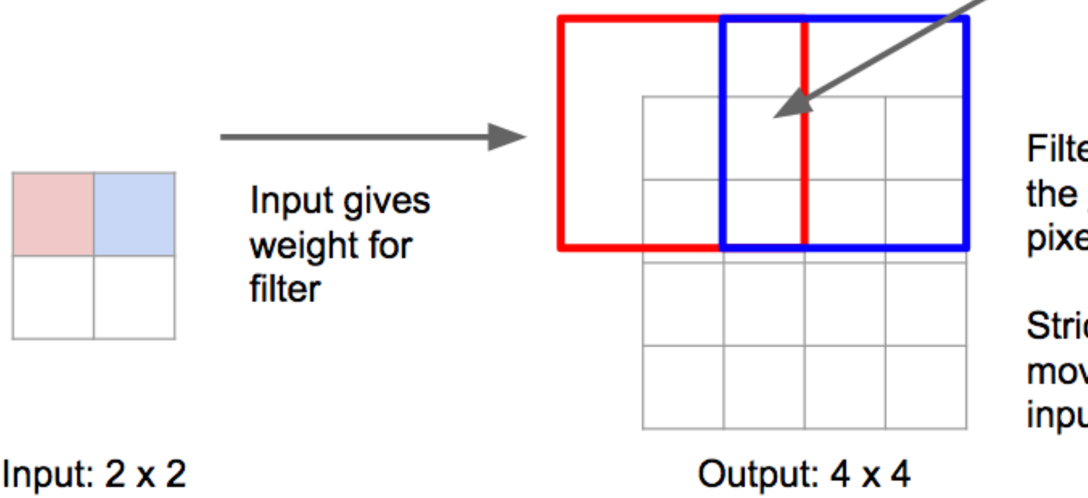
Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Learnable Upsampling: Transpose Convolution

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

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

Sum where output overlaps

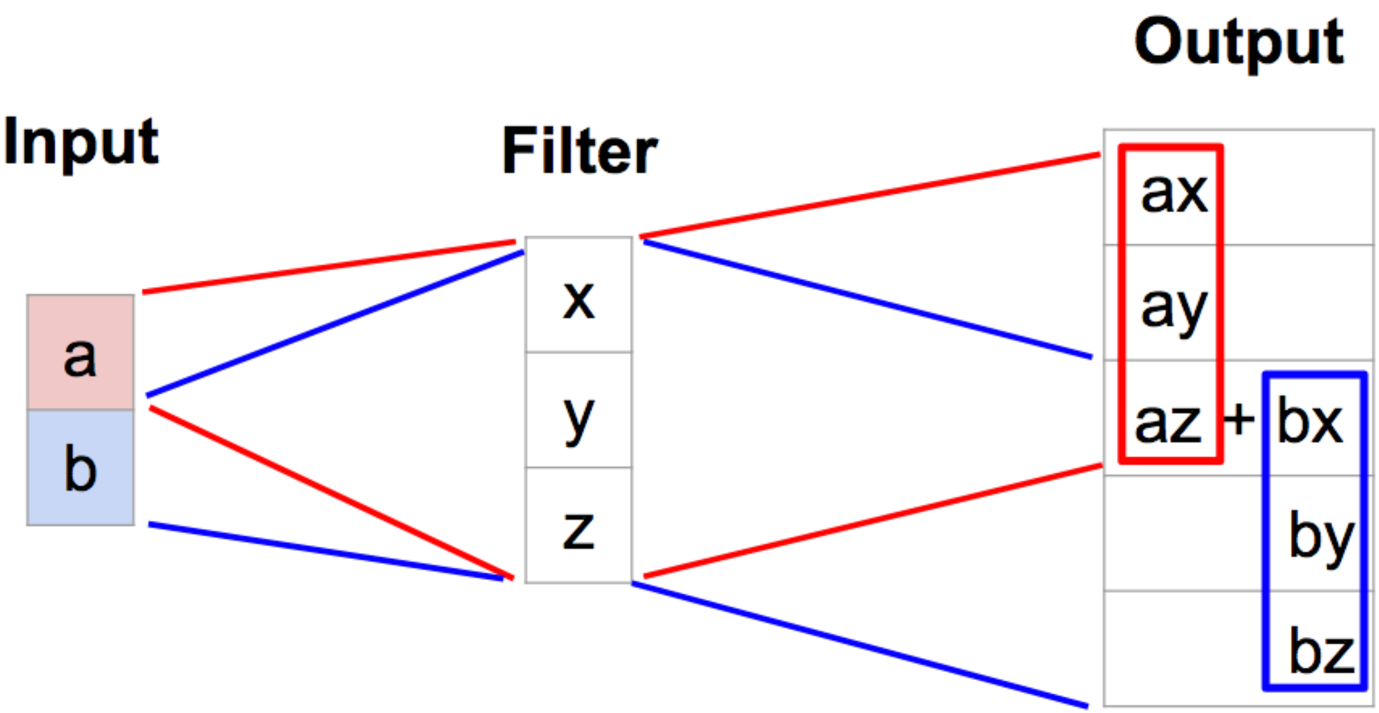


Filter moves 2 pixels in the <u>output</u> for every one pixel in the <u>input</u>

Stride gives ratio between movement in output and input

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Learnable Upsampling: 1D Example



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

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

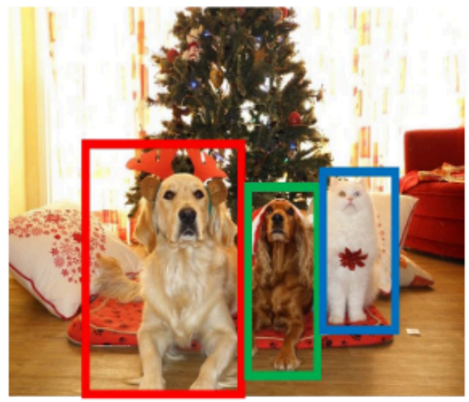
2D Object Detection

Semantic Segmentation

GRASS, CAT, TREE, SKY

No objects, just pixels

2D Object Detection



DOG, DOG, CAT

Object categories + 2D bounding boxes

3D Object Detection

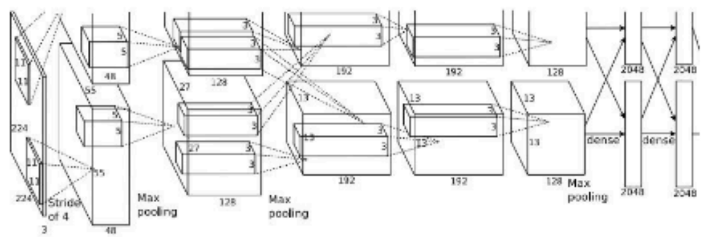
Car

Object categories + 3D bounding boxes

Slide: Fei-Fei Li, Justin Johnson, & Serena Yeung

Object Detection as Classification: Sliding Window

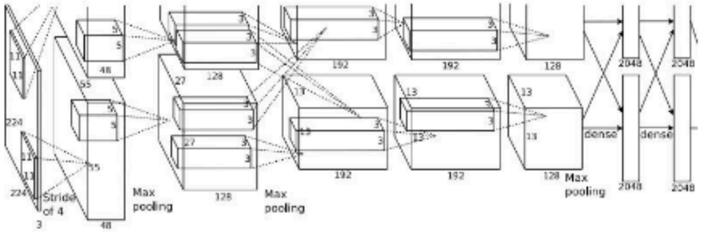
Apply a CNN to many different crops of the image, CNN classifies each crop as object or background



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

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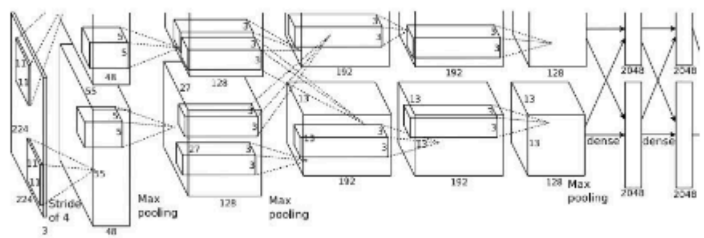

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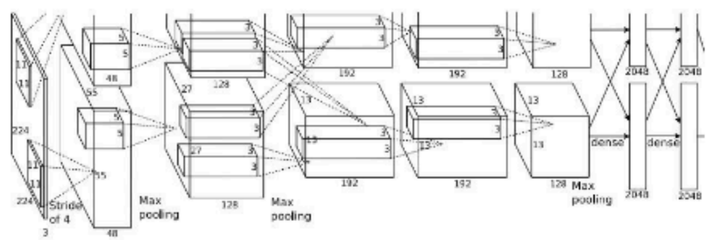

Dog? NO
Cat? YES
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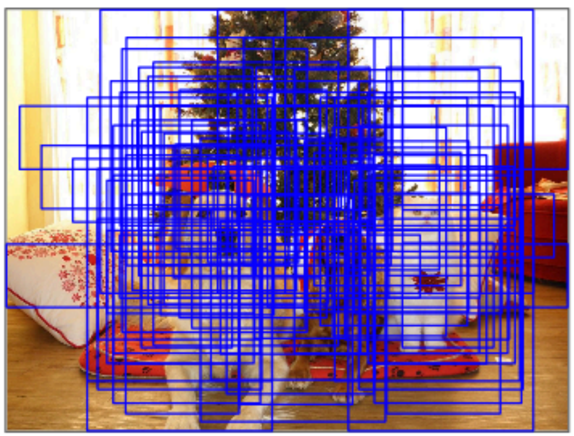
Object Detection as Classification: Sliding Window



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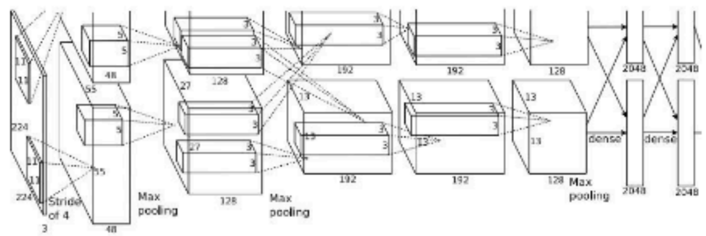

Dog? NO
Cat? YES
Background? NO

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

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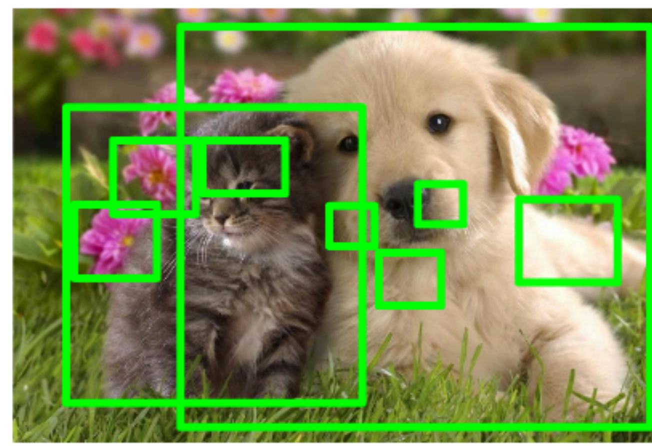
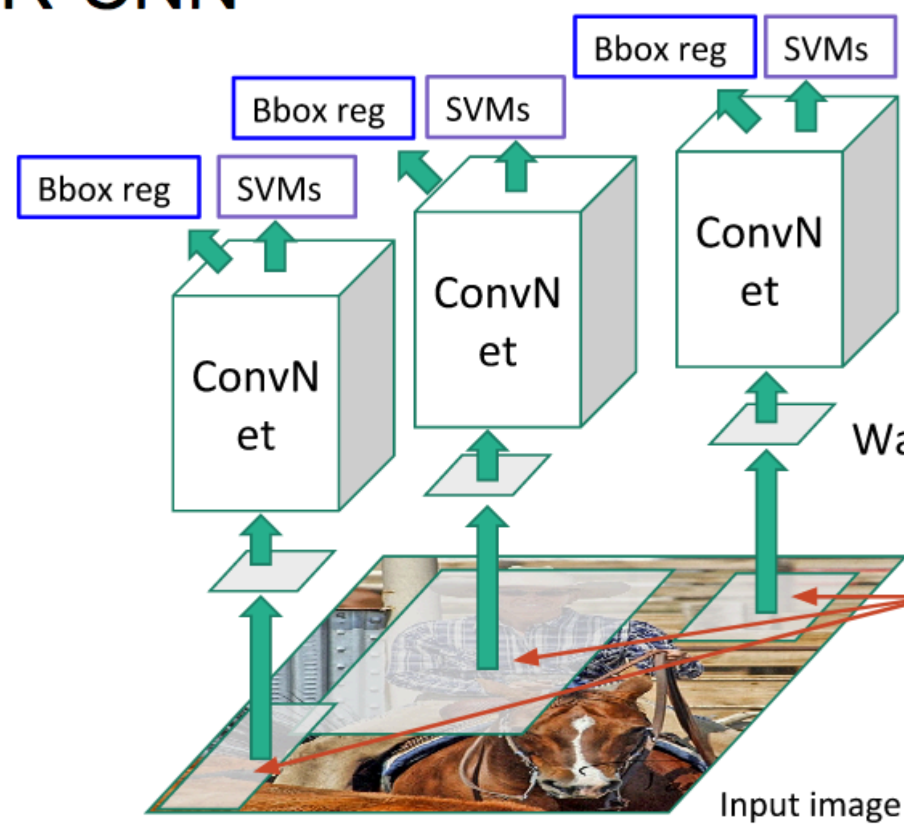
Region Proposals / Selective Search

- Find "blobby" image regions that are likely to contain objects
- Relatively fast to run; e.g. Selective Search gives 2000 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



Linear Regression for bounding box offsets

Classify regions with SVMs

Forward each region through ConvNet

Warped image regions

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

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

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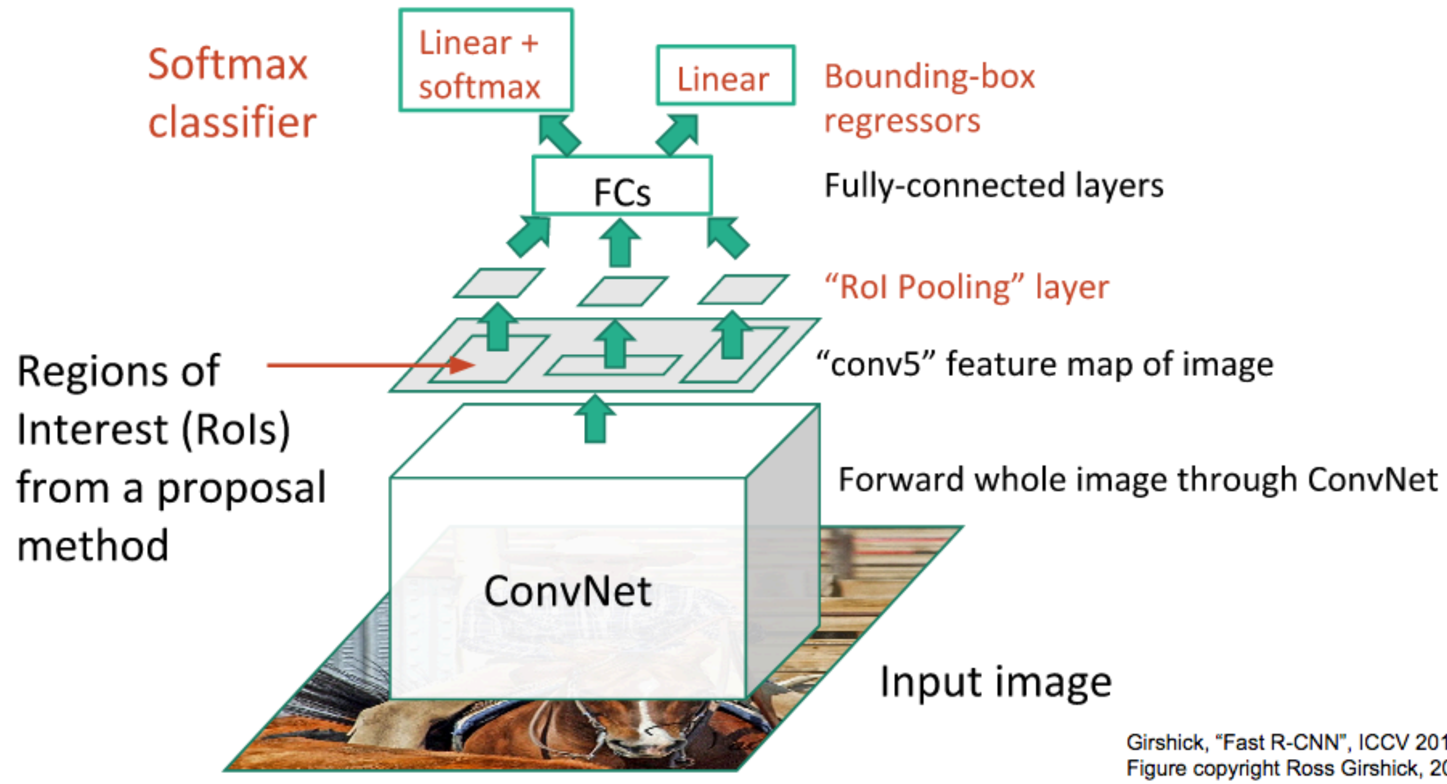
Fast R-CNN



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

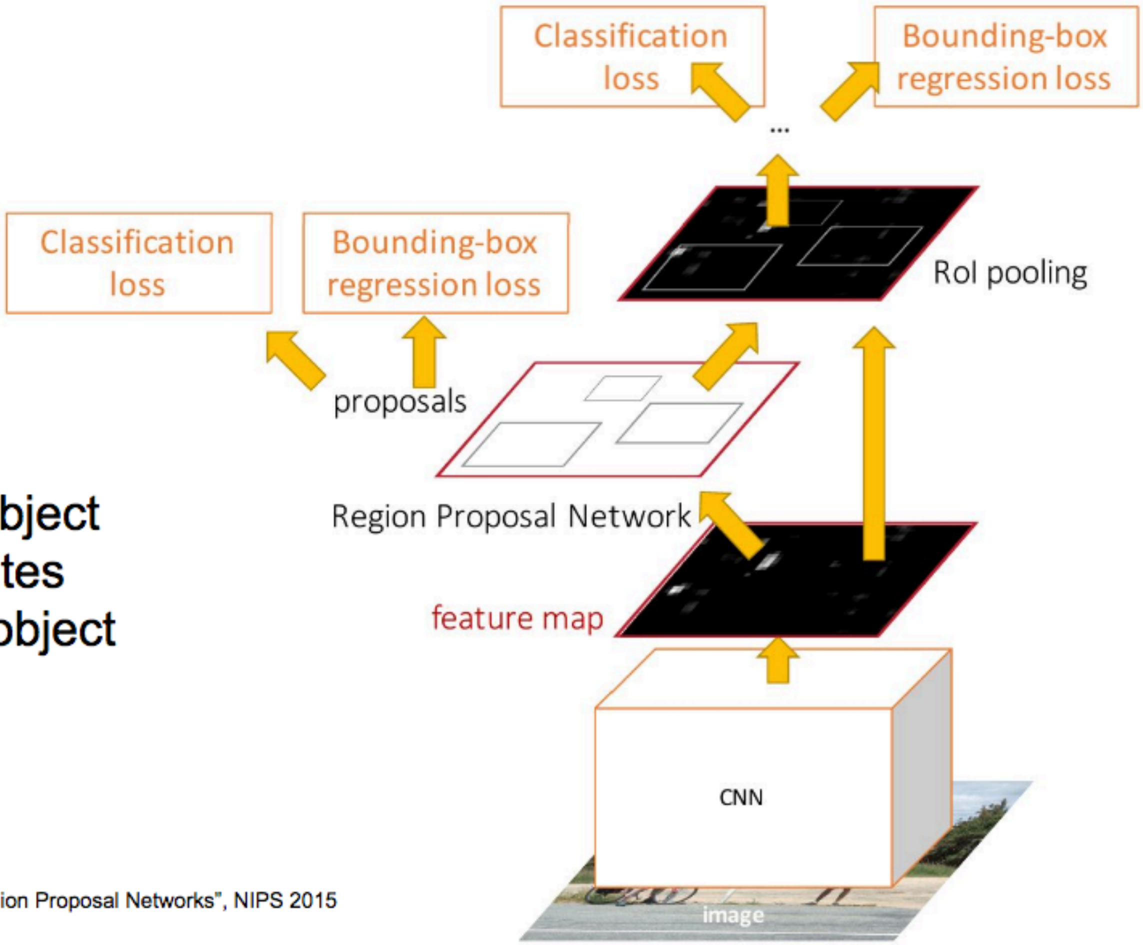
Faster R-CNN:

Make CNN do proposals!

Insert **Region Proposal Network (RPN)** to predict proposals from features

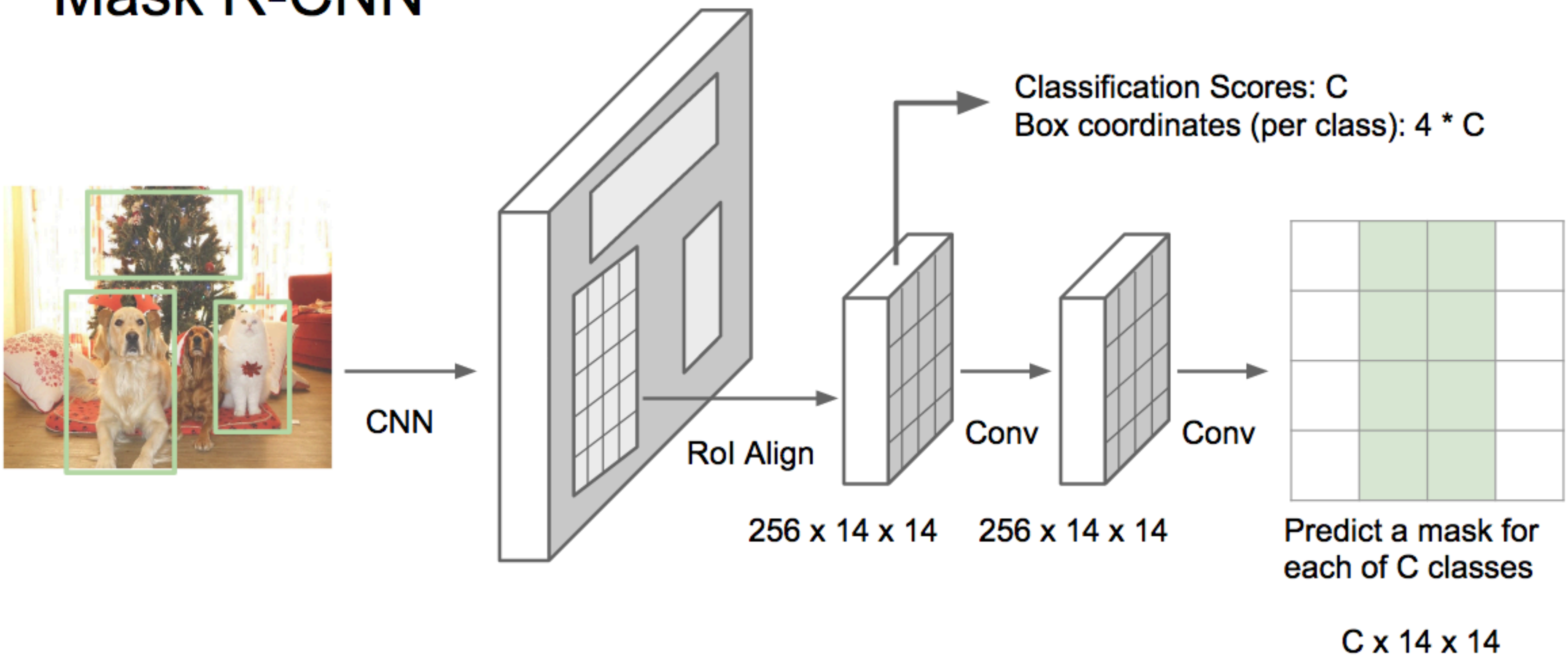
Jointly train with 4 losses:

1. RPN classify object / not object
2. RPN regress box coordinates
3. Final classification score (object classes)
4. Final box coordinates



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

Mask R-CNN



He et al, "Mask R-CNN", arXiv 2017

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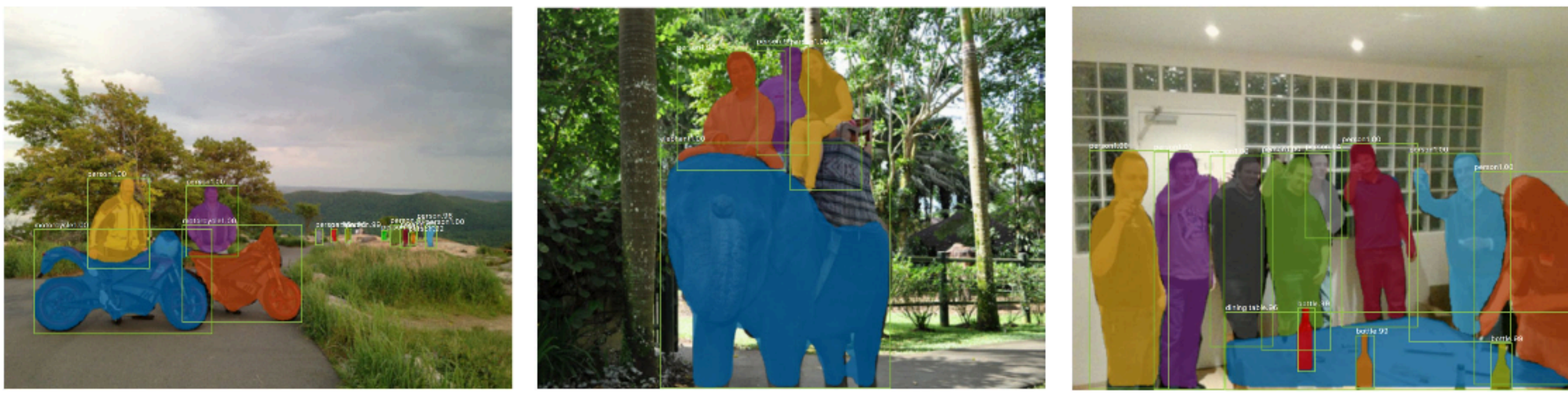
Mask R-CNN: Very Good Results!

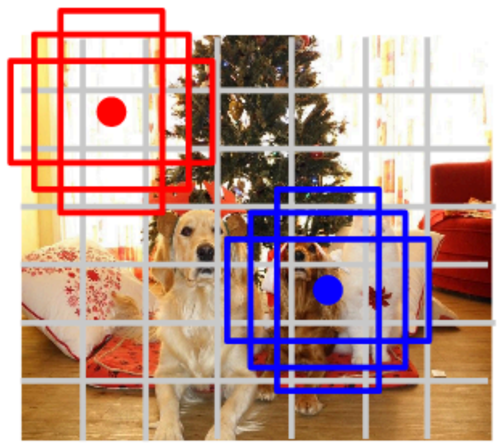


He et al, "Mask R-CNN", arXiv 2017

Detection without Proposals: YOLO / SSD

Go from input image to tensor of scores with one big convolutional network!

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

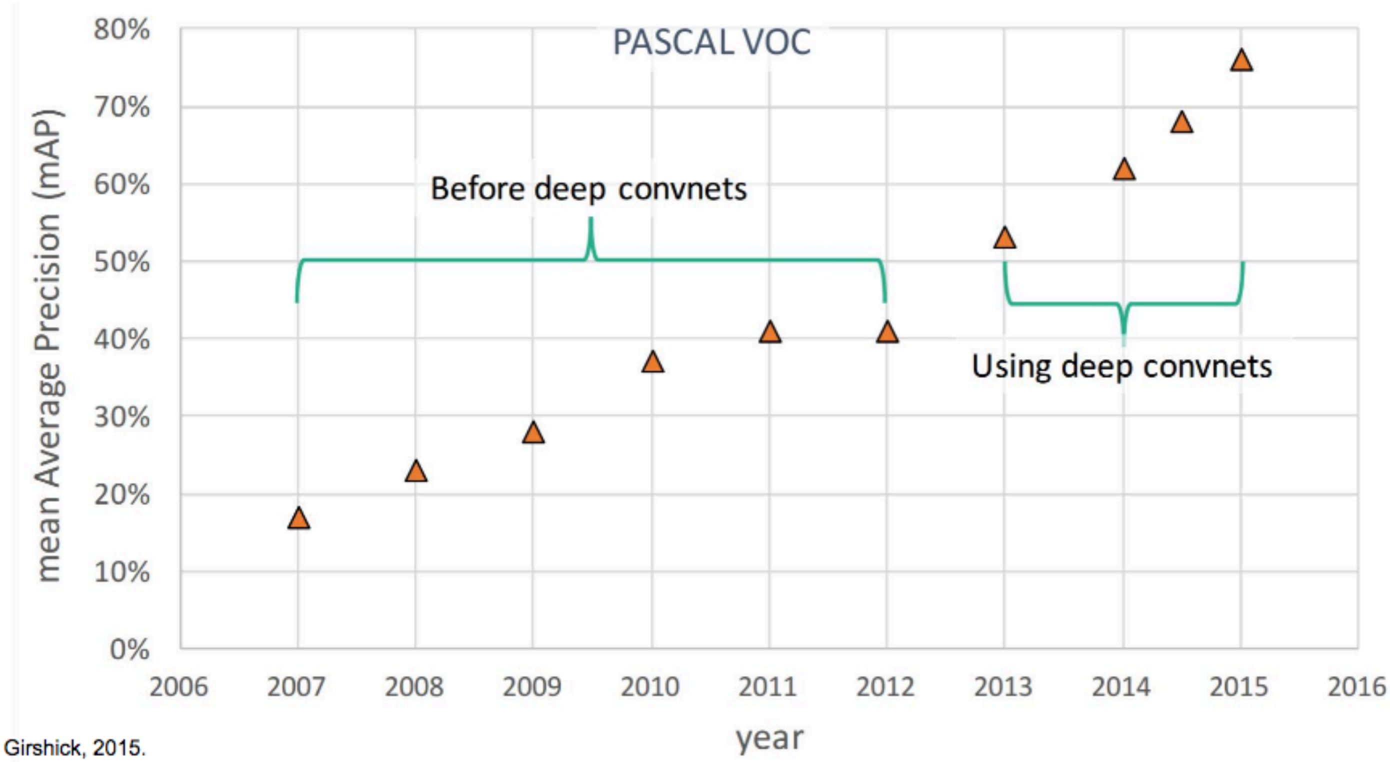
Within each grid cell:

- 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: Impact of Deep Learning



Other Problems

- Fine-grained recognition (e.g., dog/bird species)
- Instance segmentation
- Face detection and recognition
- Motion estimation
- Feature detection and description
- Depth estimation
- Novel view synthesis
- ...and many others