Topics:

- Convolutional Neural Networks

CS 4644-DL / 7643-A
ZSOLT KIRA

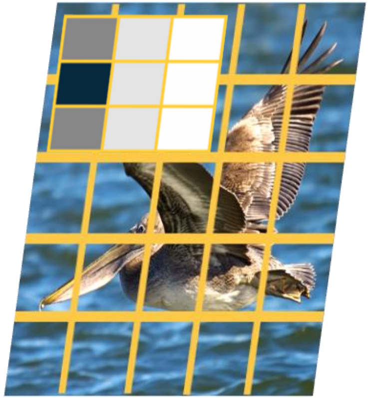
- **Assignment 2 – Due June 22nd**
  - Implement convolutional neural networks
  - Resources (in addition to lectures):
    - DL book: Convolutional Networks
    - CNN notes https://www.cc.gatech.edu/classes/AY2022/cs7643_spring/assets/L10_cnns_notes.pdf
    - Backprop notes https://www.cc.gatech.edu/classes/AY2023/cs7643_spring/assets/L10_cnns_backprop_notes.pdf
    - **HW2 Tutorial, Conv backward Coming Soon**
    - Slower OMSCS lectures on dropbox: Module 2 Lessons 5-6 (M2L5/M2L6) (https://www.dropbox.com/sh/iviro188gq0b4vs/AADdHxX_Uy1TkpF_yvIzX0nPa?dl=0)
- **Project**
  - Proposal planning session Wed.
  - Proposal due June 15th
- **Reminder:** Please do readings announced for discussions!

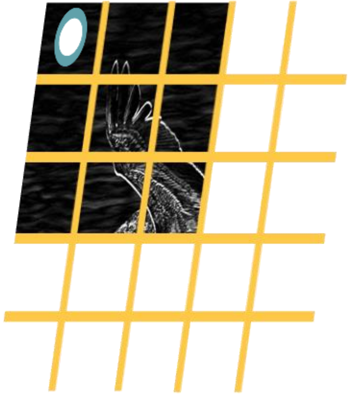
$$X(0:2,0:2) = \begin{bmatrix} 200 & 150 & 150 \\ 100 & 50 & 100 \\ 25 & 25 & 10 \end{bmatrix}$$

$$K' = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}$$

$$\Rightarrow \quad X(0{:}2,0{:}2) \cdot K' = 65 + \text{bias}$$

Dot product
(element-wise multiply and sum)



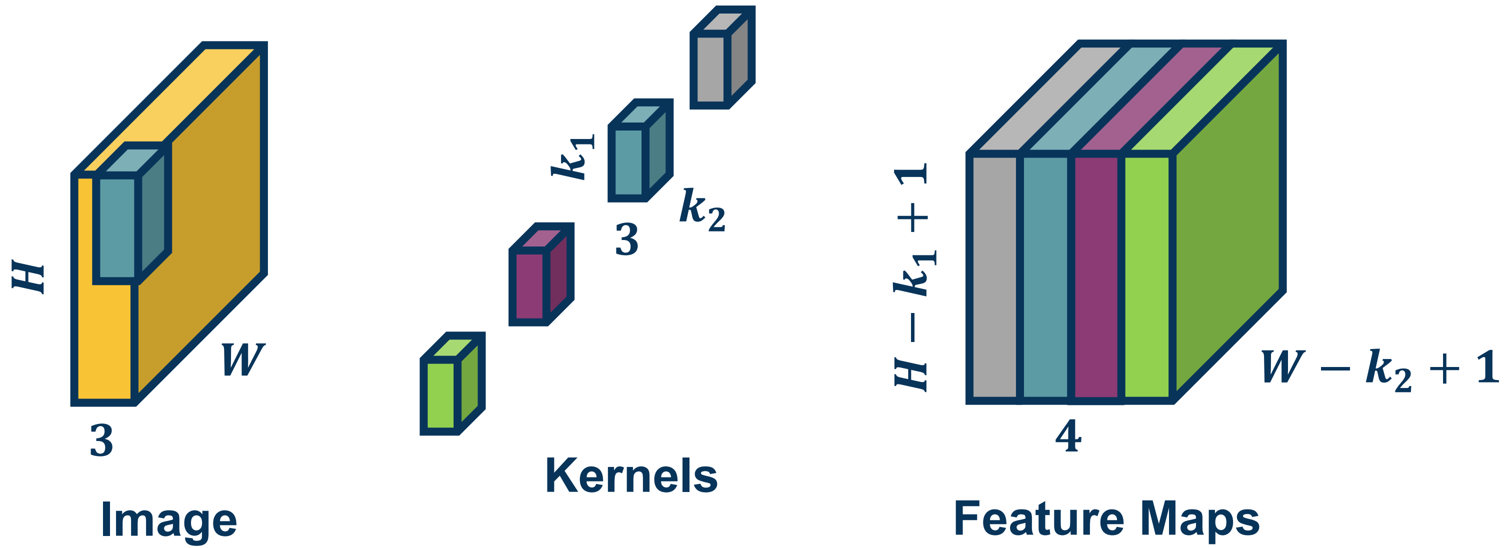


$$\boldsymbol{y(r,c) = (x * k)(r,c) = \sum_{a=0}^{k_1-1} \sum_{b=0}^{k_2-1} x(r+a, c+b)\, k(a,b)}$$

Cross-Correlation

Number of parameters with N filters is: $N * (k_1 * k_2 * 3 + 1)$

- Example:
  $k_1 = 3, k_2 = 3,\ N = 4\ input\ channels = 3$, then $(3 * 3 * 3 + 1) * 4 =$112



Chain Rule over all Output Pixels

Need to incorporate all upstream gradients:

$$\left\{\frac{\partial L}{\partial y(0,0)}, \frac{\partial L}{\partial y(0,1)}, \dots, \frac{\partial L}{\partial y(H,W)}\right\}$$

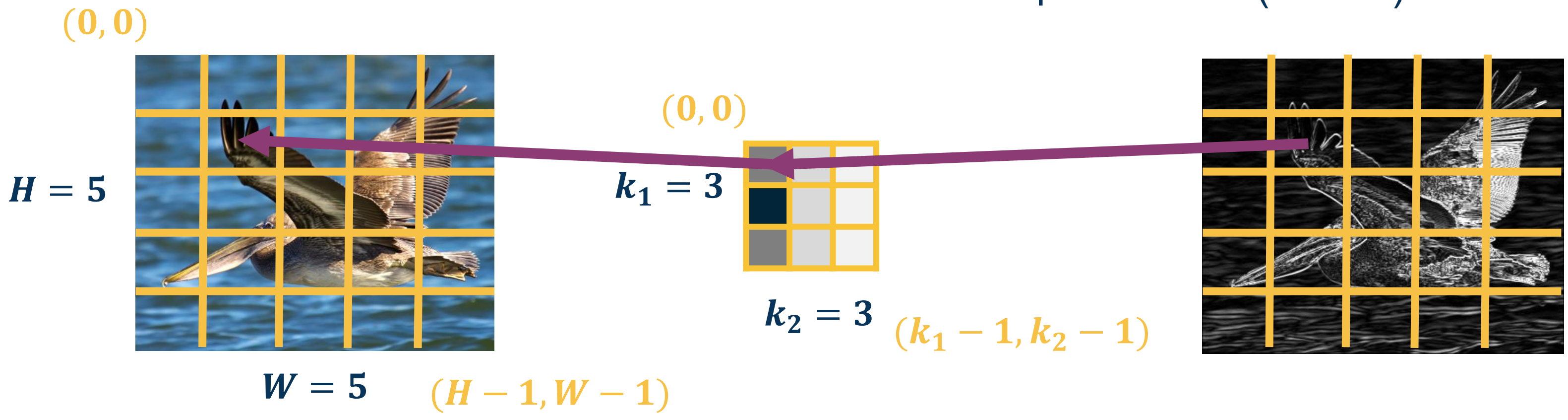
Chain Rule:

$$\frac{\partial L}{\partial k(a,b)} = \sum_{r=0}^{H-1} \sum_{c=0}^{W-1} \frac{\partial L}{\partial y(r,c)} \frac{\partial y(r,c)}{\partial k(a,b)}$$

Sum over all output pixels

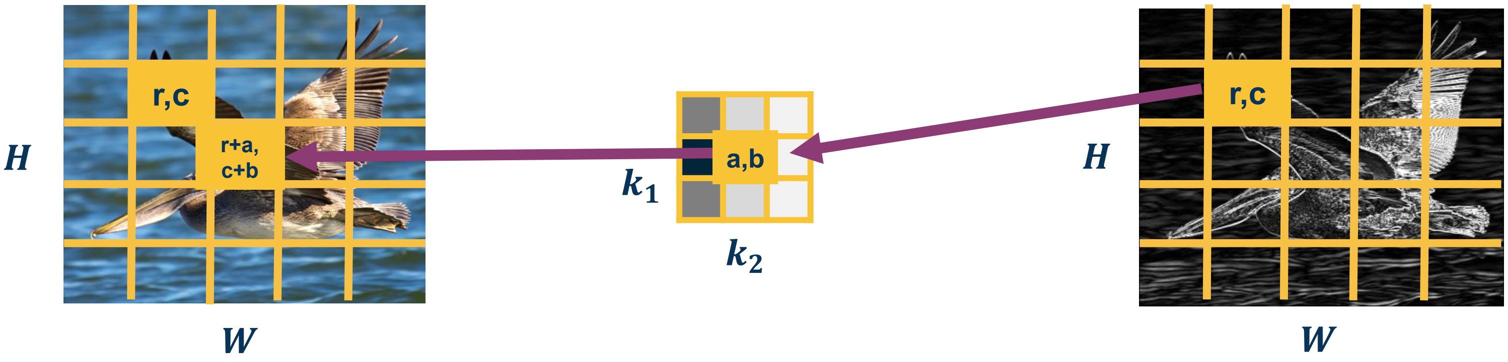
Upstream gradient (known)

We will compute



$$\frac{\partial y(r,c)}{\partial k(a,b)} = x(r+a, c+b)$$

$$\frac{\partial L}{\partial k(a,b)} = \sum_{r=0}^{H-1} \sum_{c=0}^{W-1} \frac{\partial L}{\partial y(r,c)} x(r+a, c+b)$$



Gradients and Cross-Correlation

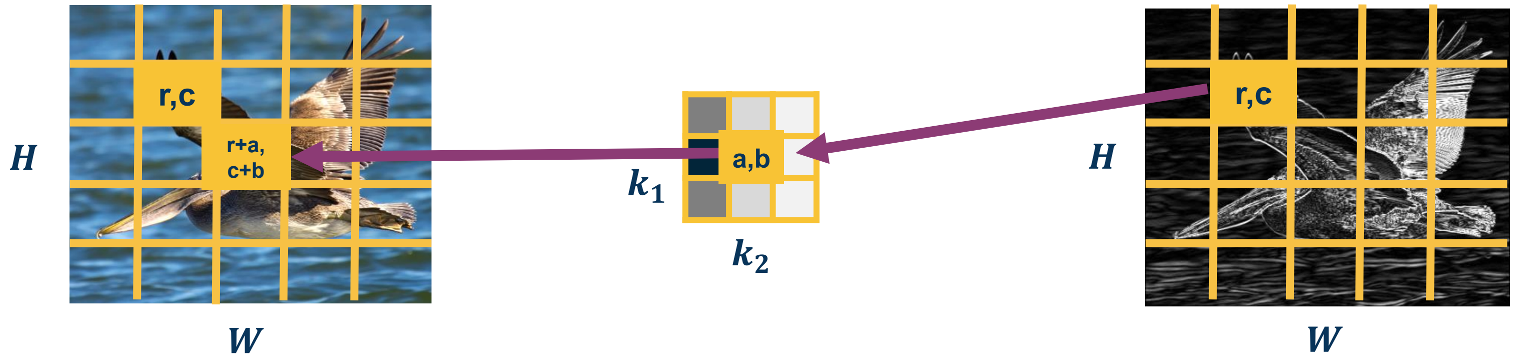
$$\frac{\partial y(r,c)}{\partial k(a,b)} = x(r+a, c+b)$$

$$\frac{\partial L}{\partial k(a,b)} = \sum_{r=0}^{H-1} \sum_{c=0}^{W-1} \frac{\partial L}{\partial y(r,c)} x(r+a, c+b)$$

Does this look familiar?

Cross-correlation between upstream gradient and input!

(until $k_1 \times k_2$ output)



$$\frac{\partial L}{\partial x} = \frac{\partial L}{\partial y} \frac{\partial y}{\partial x}$$

What does this input pixel affect at the output?

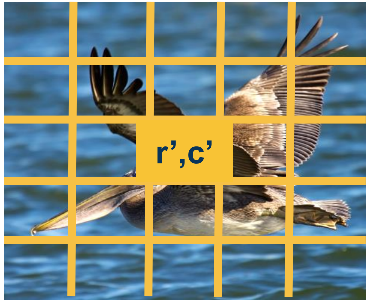
Gradient for input (to pass to prior layer)

Calculate one pixel at a time $\frac{\partial L}{\partial x(r', c')}$

Neighborhood around it (where part of the kernel touches it)

$(0, 0)$

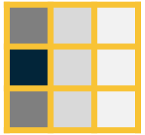
$H = 5$



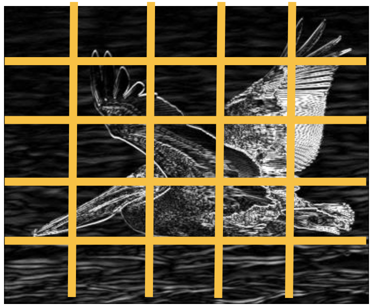
$W = 5$ $(H - 1, W - 1)$

$(0, 0)$

$k_1 = 3$



$k_2 = 3$ $(k_1 - 1, k_2 - 1)$



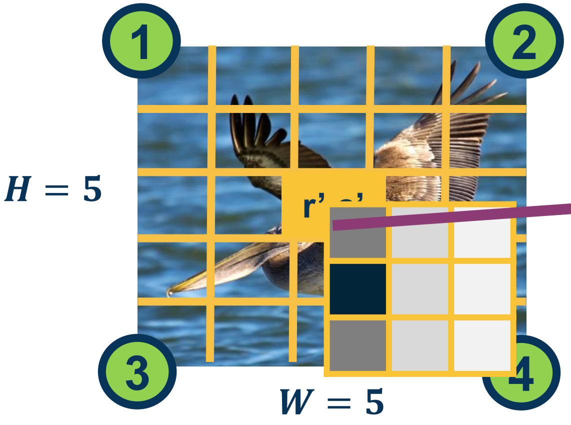
What an Input Pixel Affects at Output

Chain rule for affected pixels (sum gradients):

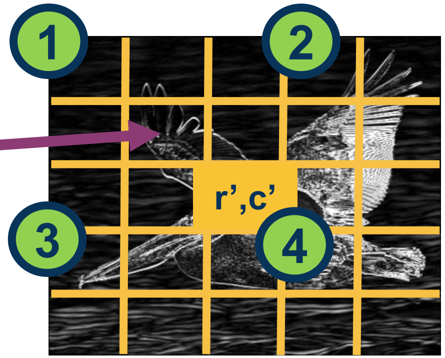
$$\frac{\partial L}{\partial x(r',c')} = \sum_{Pixels\ p} \frac{\partial L}{\partial y(p)} \frac{\partial y(p)}{\partial x(r',c')}$$

$x(r',c') * k(0,0) \Rightarrow y(r',c')$
$x(r',c') * k(1,1) \Rightarrow y(r'-1,c'-1)$
…
$x(r',c') * k(a,b) \Rightarrow y(r'-a,c'-b)$

$$\frac{\partial L}{\partial x(r',c')} = \sum_{a=0}^{k_1-1} \sum_{b=0}^{k_2-1} \frac{\partial L}{\partial y(?,?)} \frac{\partial y(?,?)}{\partial x(r',c')}$$



$(r'-k_1+1, c'-k_2+1)$

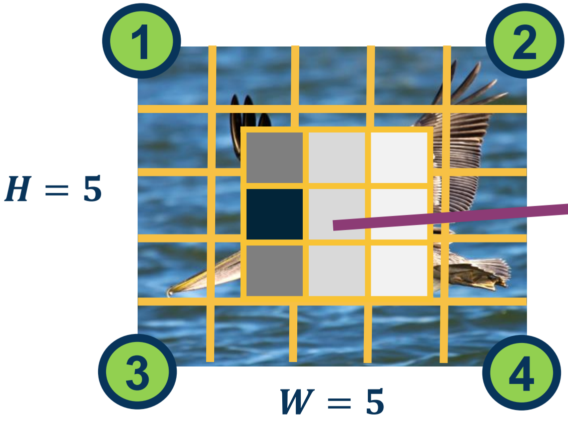


Chain rule for affected pixels (sum gradients):

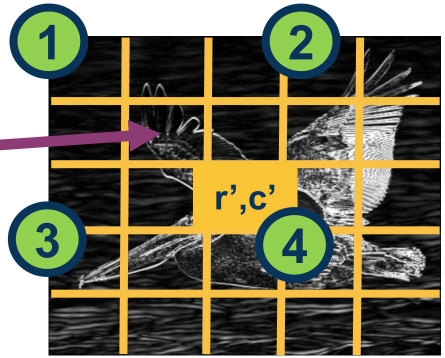
$$\frac{\partial L}{\partial x(r',c')} = \sum_{Pixels\ p} \frac{\partial L}{\partial y(p)} \frac{\partial y(p)}{\partial x(r',c')}$$

Let's derive it analytically this time (as opposed to visually)

$$\frac{\partial L}{\partial x(r',c')} = \sum_{a=0}^{k_1-1} \sum_{b=0}^{k_2-1} \frac{\partial L}{\partial y(r'-a,c'-b)} \frac{\partial y(r'-a,c'-b)}{\partial x(r',c')}$$



$(r'-k_1+1, c'-k_2+1)$



Summing Gradient Contributions

Plugging in to earlier equation:

$$\frac{\partial L}{\partial x(r',c')} = \sum_{a=0}^{k_1-1}\sum_{b=0}^{k_2-1} \frac{\partial L}{\partial y(r'-a,c'-b)} \frac{\partial y(r'-a,c'-b)}{\partial x(r',c')}$$

$$= \sum_{a=0}^{k_1-1}\sum_{b=0}^{k_2-1} \frac{\partial L}{\partial y(r'-a,c'-b)} k(a,b)$$

Does this look familiar?

Convolution between upstream gradient and kernel!

(can implement by flipping kernel and cross- correlation)

Again, all operations can be implemented via matrix multiplications (same as FC layer)!

- Convolutions are mathematical descriptions of striding linear operation

- In practice, we implement **cross-correlation neural networks!** (still called convolutional neural networks due to history)
  - Can connect to convolutions via duality (flipping kernel)
  - Convolution formulation has mathematical properties explored in ECE

- Duality for forwards and backwards:
  - **Forward**: Cross-correlation
  - **Backwards w.r.t. K**: Cross-correlation b/w upstream gradient and input
  - **Backwards w.r.t. X**: Convolution b/w upstream gradient and kernel
    - In practice implement via cross-correlation and flipped kernel

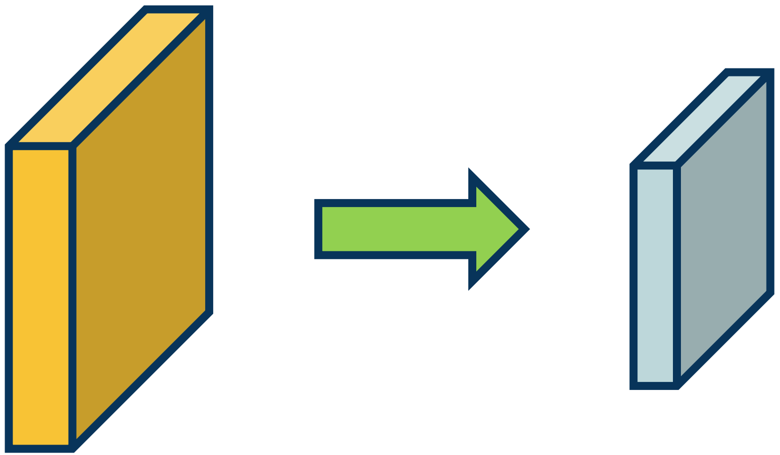
- All operations still implemented via **efficient linear algebra** (e.g. matrix-matrix multiplication)

Summary

Pooling Layers

Pooling Layers

- **Dimensionality reduction** is an important aspect of machine learning
- Can we make a layer to **explicitly down-sample** image or feature maps?



- **Yes!** We call one class of these operations **pooling** operations

Parameters

- **kernel_size** – the size of the window to take a max over
- **stride** – the stride of the window. Default value is `kernel_size`
- **padding** – implicit zero padding to be added on both sides

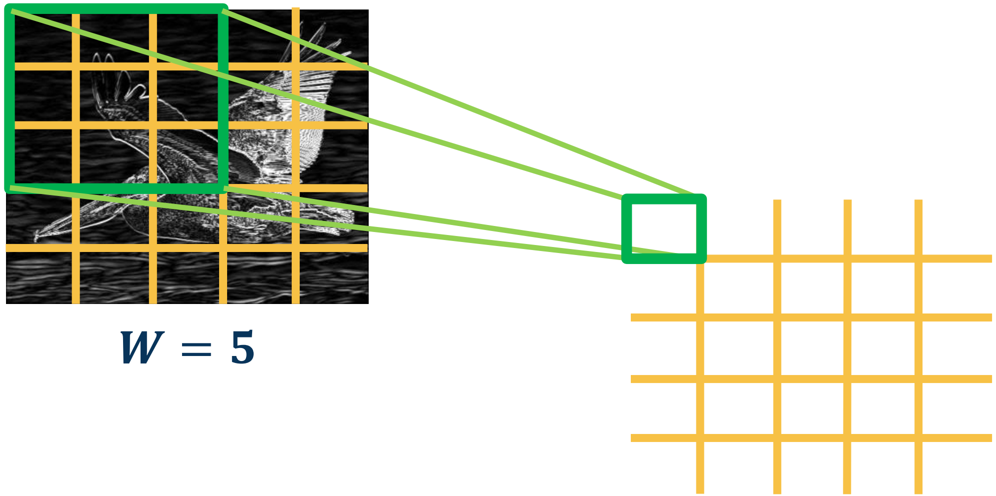
From: https://pytorch.org/docs/stable/generated/torch.nn.MaxPool2d.html#torch.nn.MaxPool2d

Example: Max pooling

- Stride window across image but perform per-patch **max operation**

$$X(0{:}2, 0{:}2) = \begin{bmatrix} 200 & 150 & 150 \\ 100 & 50 & 100 \\ 25 & 25 & 10 \end{bmatrix} \Rightarrow \max(0{:}2,0{:}2) = 200$$

$H = 5$

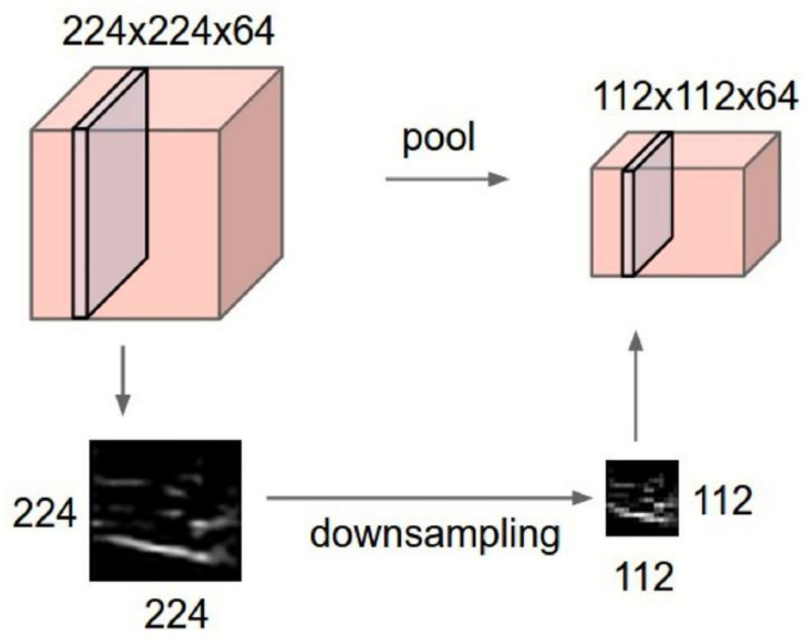


$W = 5$

How many learned parameters does this layer have?

None!

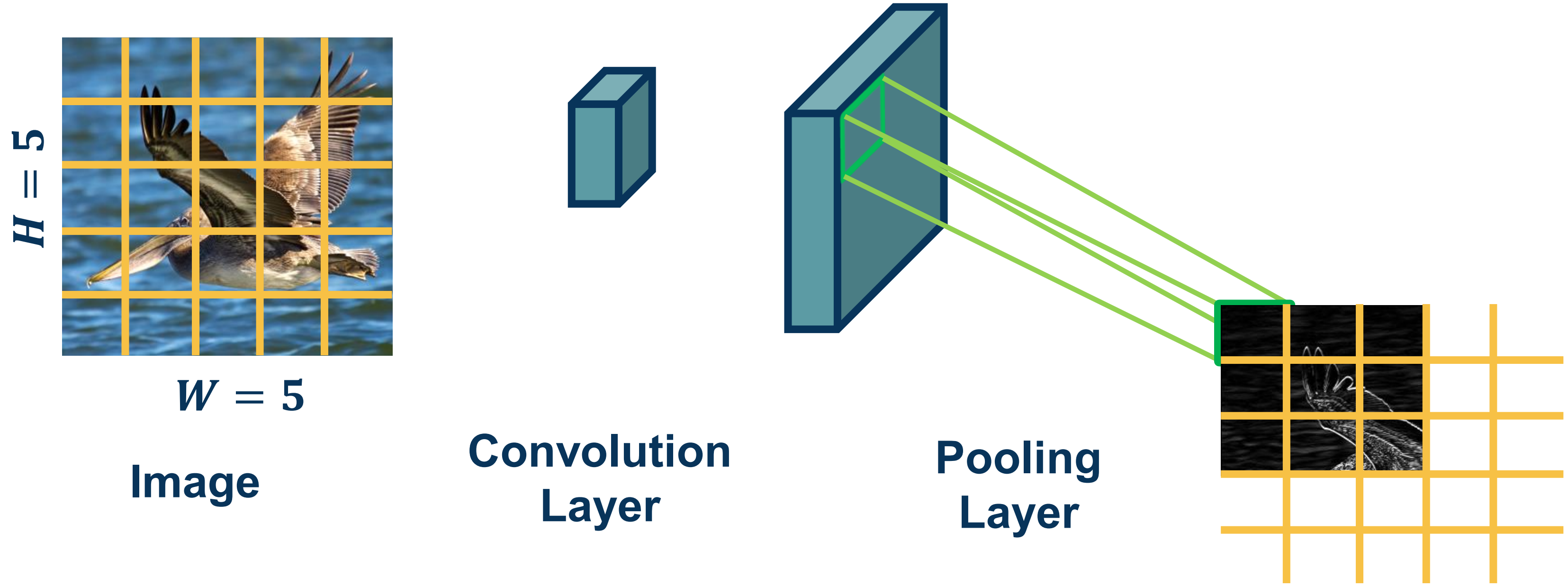
- makes the representations spatially smaller
- saves computation (GPU mem & speed), allows go deeper
- operates over each activation map independently:



From: Slides by CS 231n, Danfei Xu

Pooling with Tensors

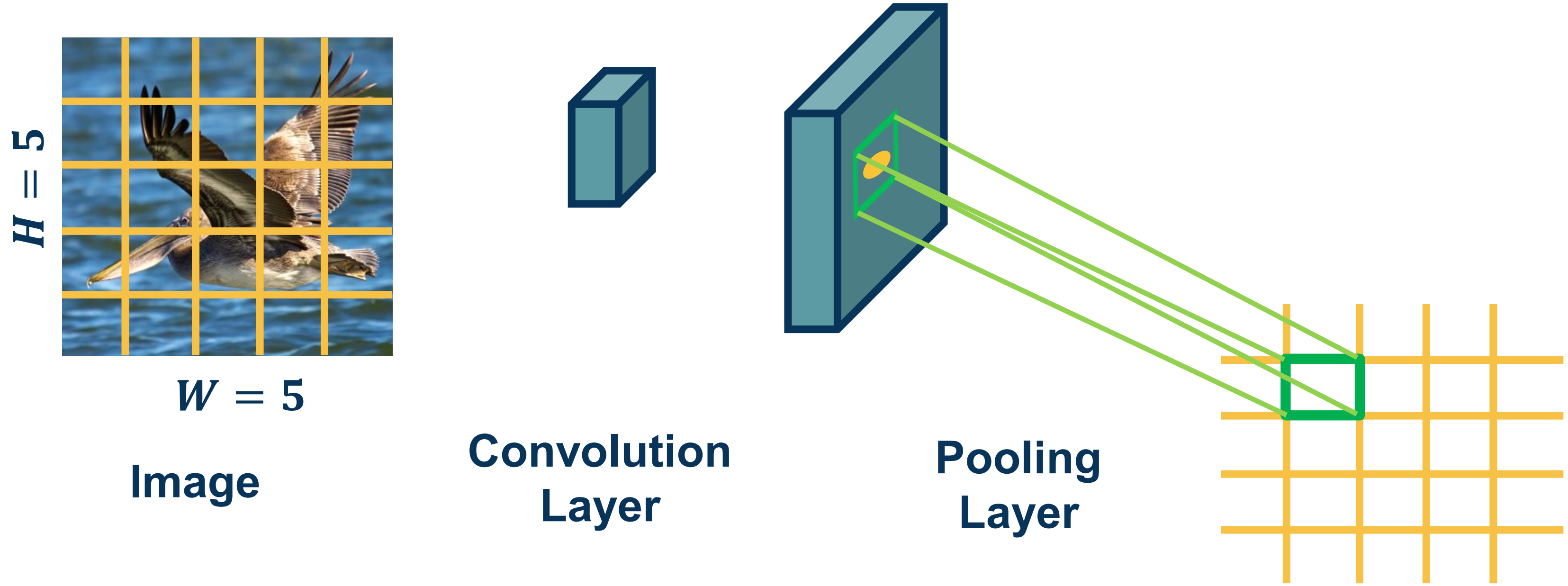
Since the **output** of convolution and pooling layers are **(multi-channel) images**, we can sequence them just as any other layer



Combining Convolution & Pooling Layers

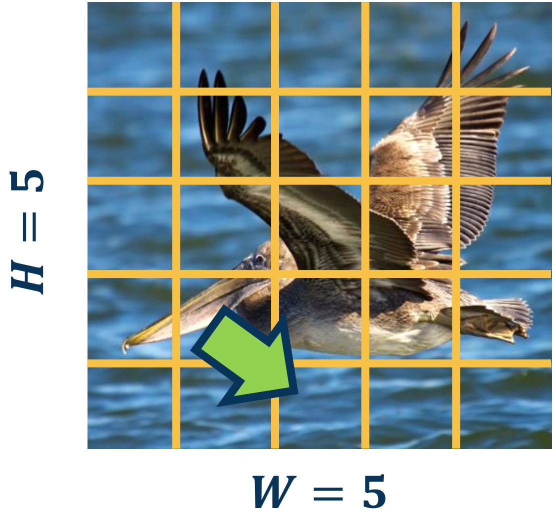
This combination adds some **invariance** to translation of the features

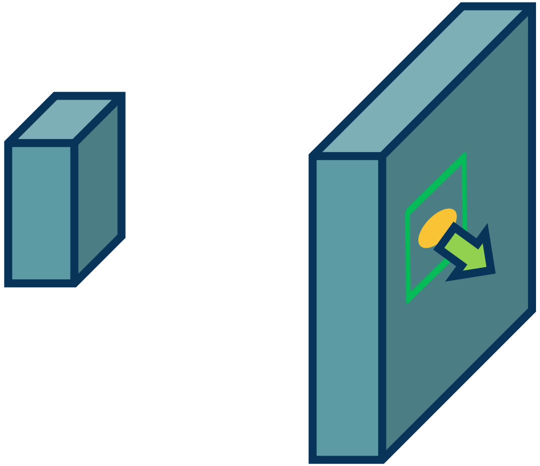
- If feature (such as beak) translated a little bit, output values still **remain the same**



Convolution by itself has the property of **equivariance**

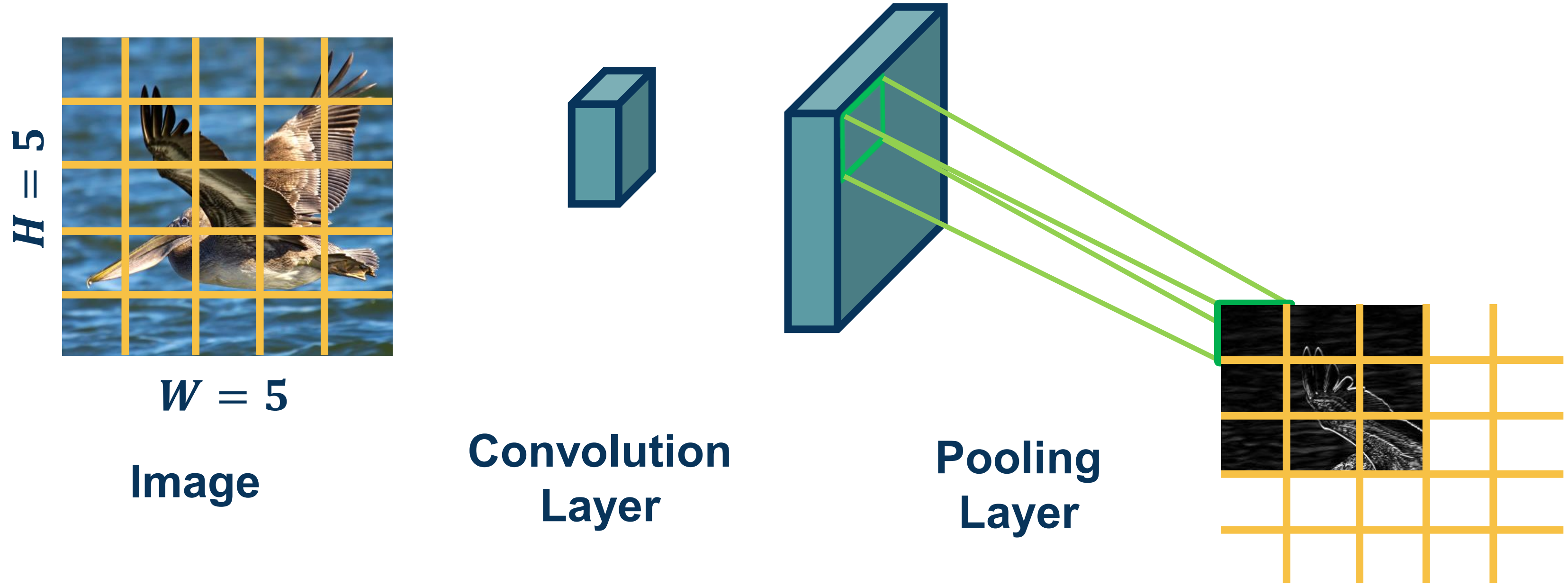
- If feature (such as beak) translated a little bit, output values **move by the same translation**



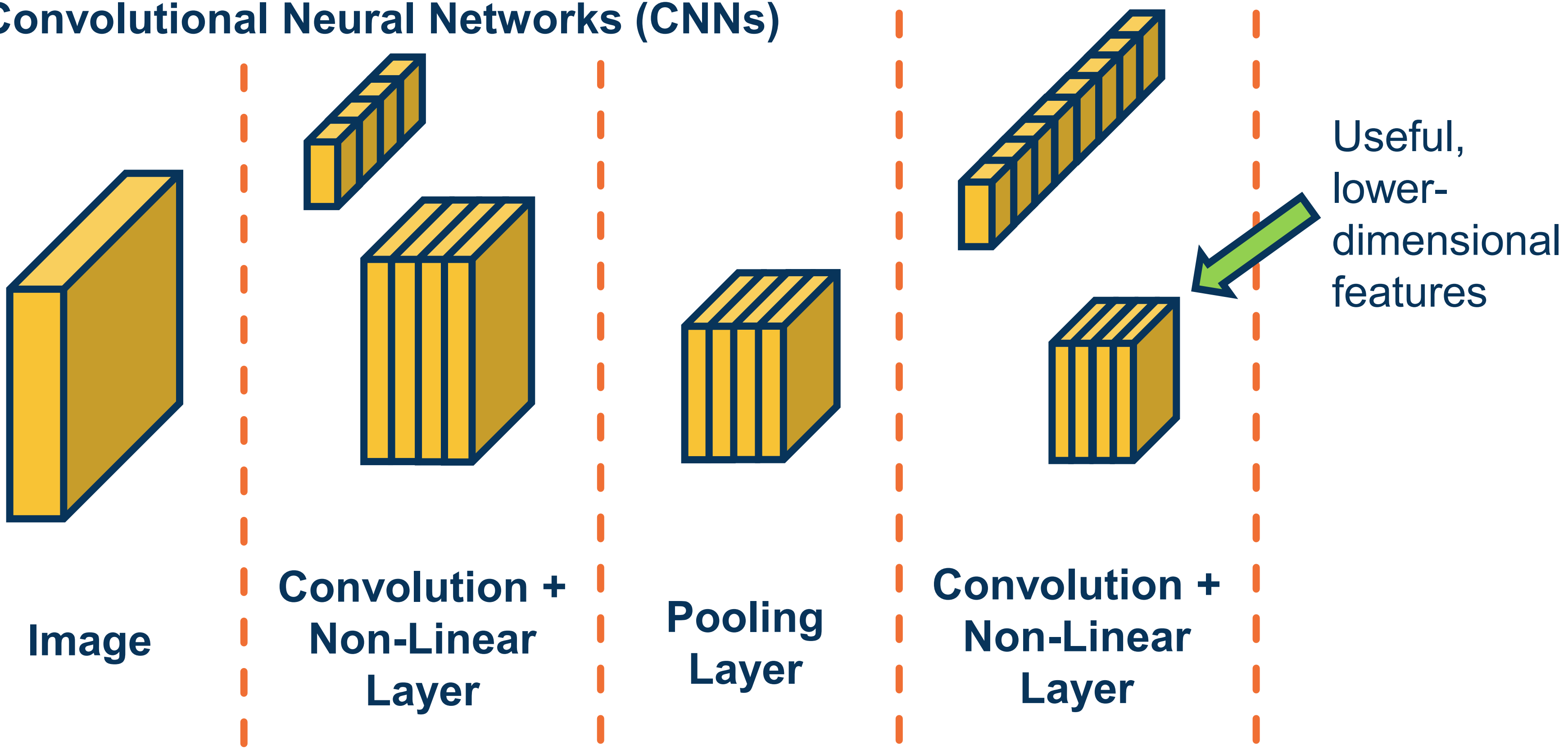


Simple Convolutional Neural Networks

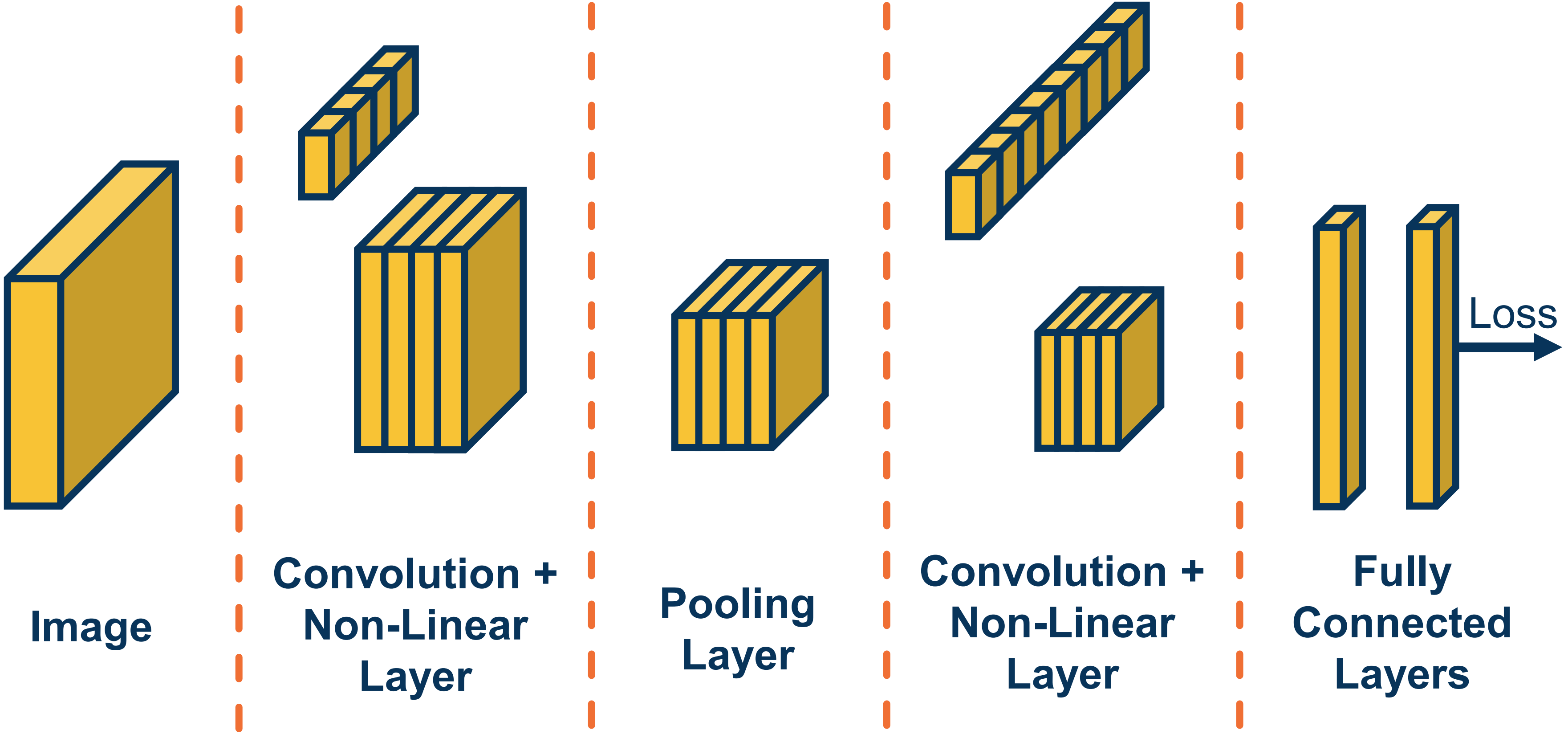
Since the **output** of convolution and pooling layers are **(multi-channel) images**, we can sequence them just as any other layer



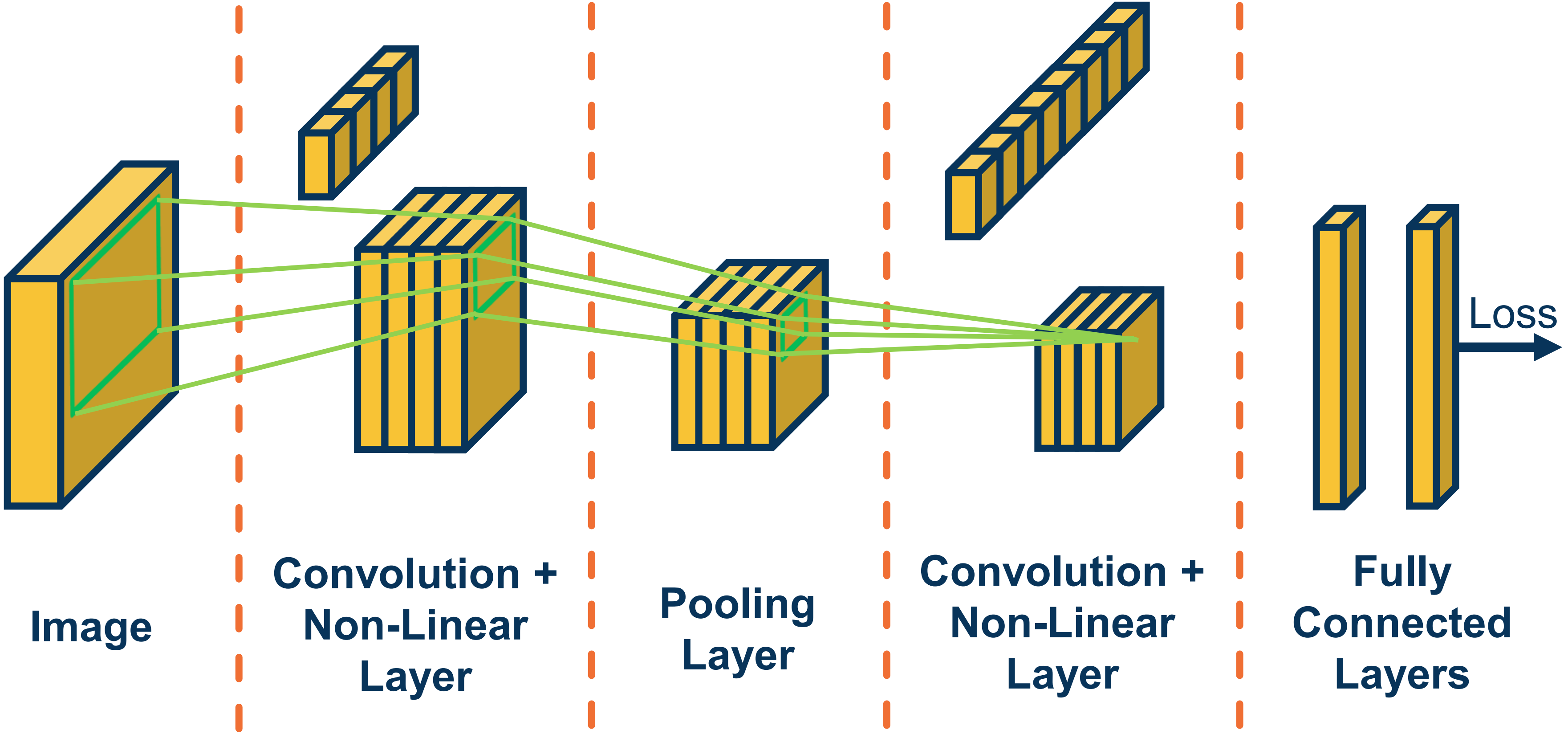
Convolutional Neural Networks (CNNs)



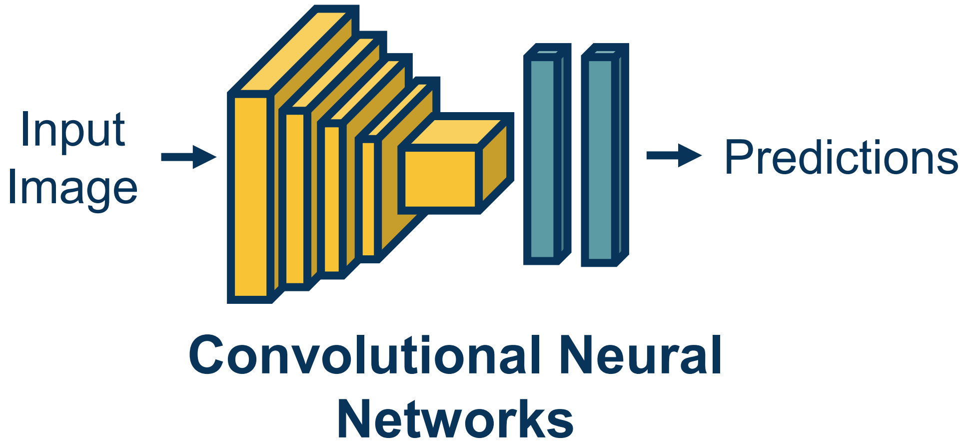
Alternating Convolution and Pooling

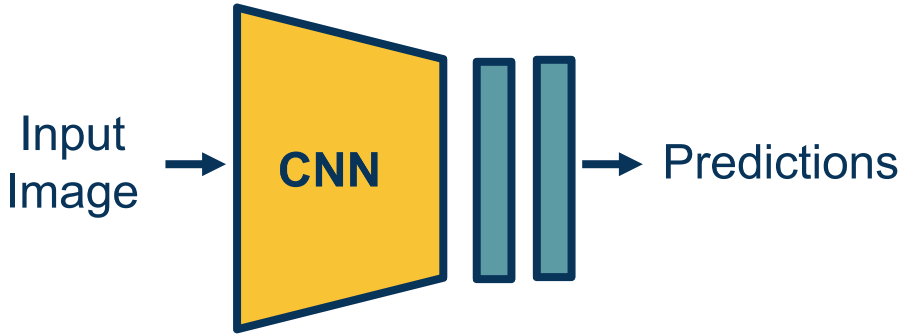


Adding a Fully Connected Layer



Receptive Fields





Typical Depiction of CNNs

These architectures have existed **since 1980s**

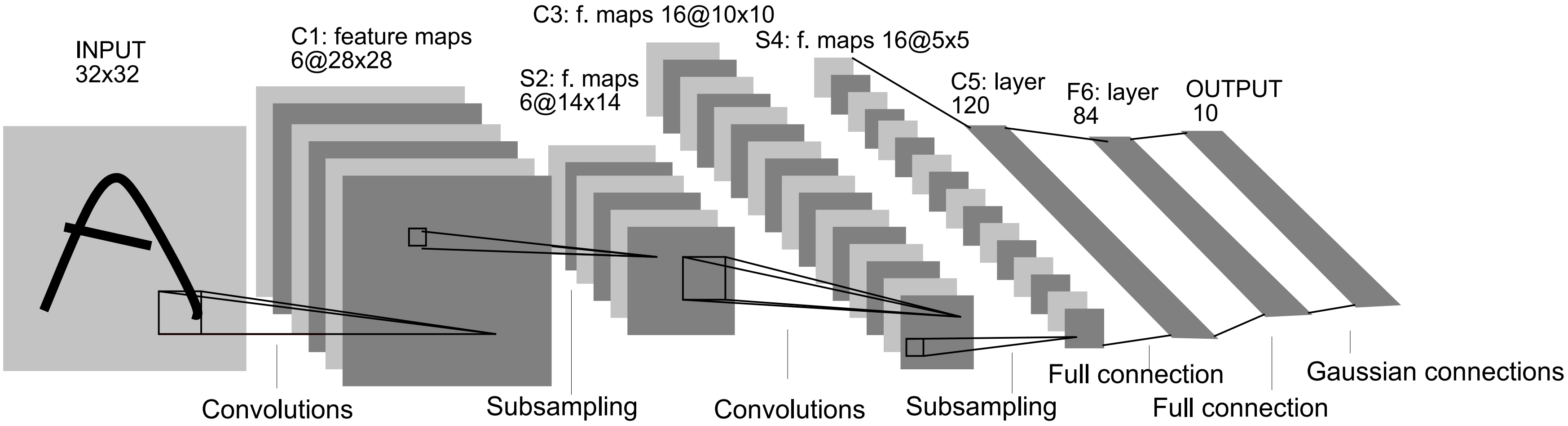


Image Credit: Yann LeCun, Kevin Murphy

Handwriting Recognition

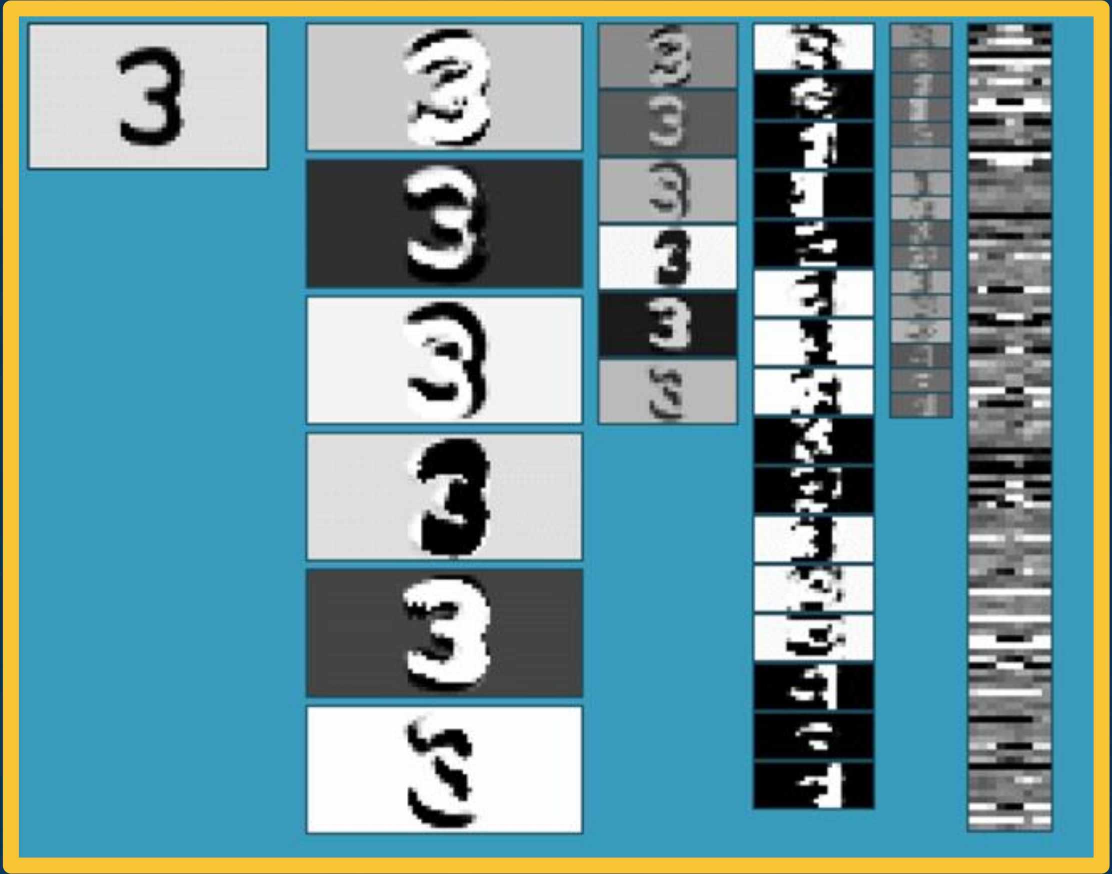


Image Credit: Yann LeCun

Translation Equivariance (Conv Layers) & Invariance (Output)

Image Credit: Yann LeCun

(Some) Rotation Invariance

Image Credit: Yann LeCun

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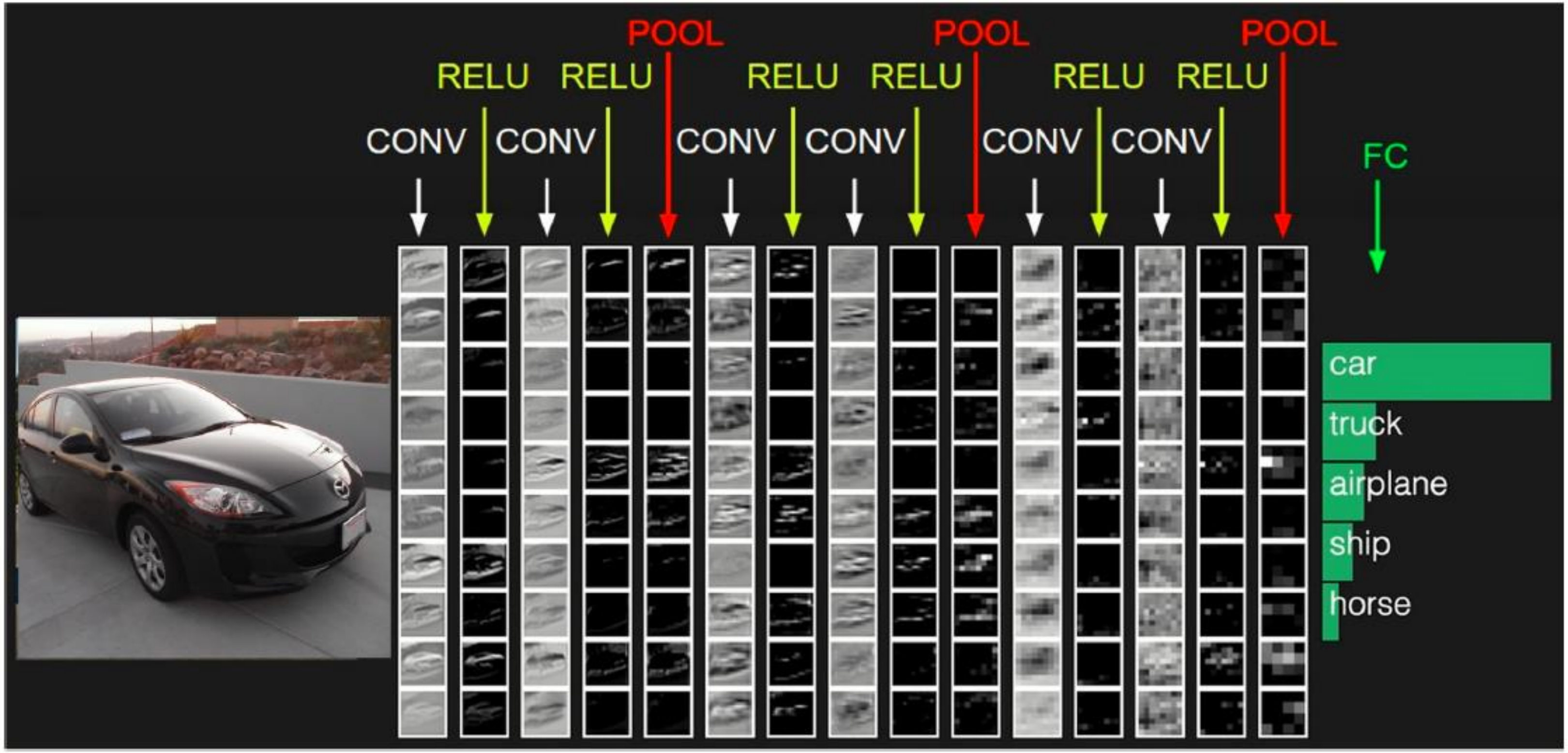
(Some) Scale Invariance

Image Credit: Yann LeCun

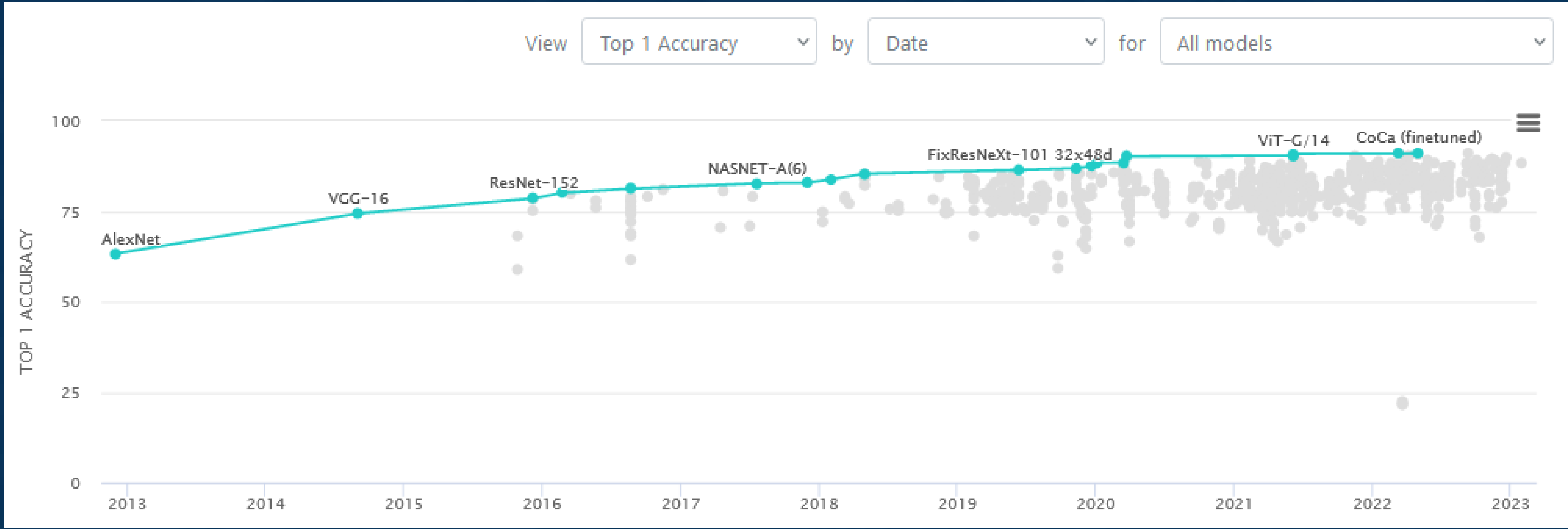


A More Modern Canonical CNN

Advanced Convolutional Networks

The **ImageNet** dataset contains 14,197,122 annotated images according to the WordNet hierarchy. ImageNet Large Scale Visual Recognition Challenge (ILSVRC) is a benchmark for image classification and object detection based on the dataset.

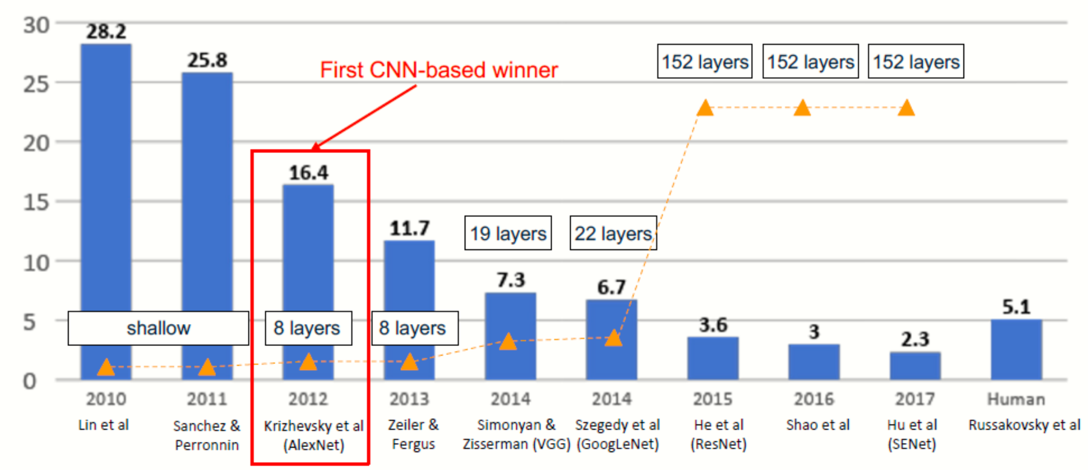
The Importance of Benchmarks



From: https://paperswithcode.com

Case Studies

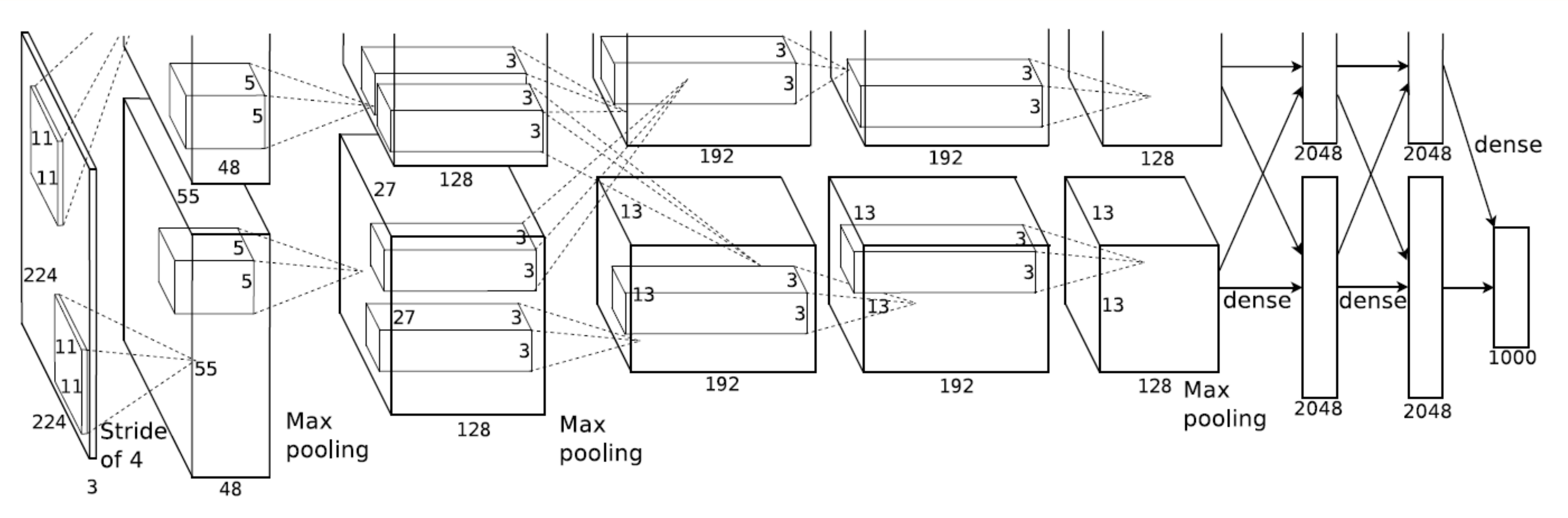
- AlexNet
- VGG
- GoogLeNet
- ResNet



Also....

- SENet
- Wide ResNet
- ResNeXT
- DenseNet
- MobileNets
- NASNet
- EfficientNet
- ConvNeXt v1/v2

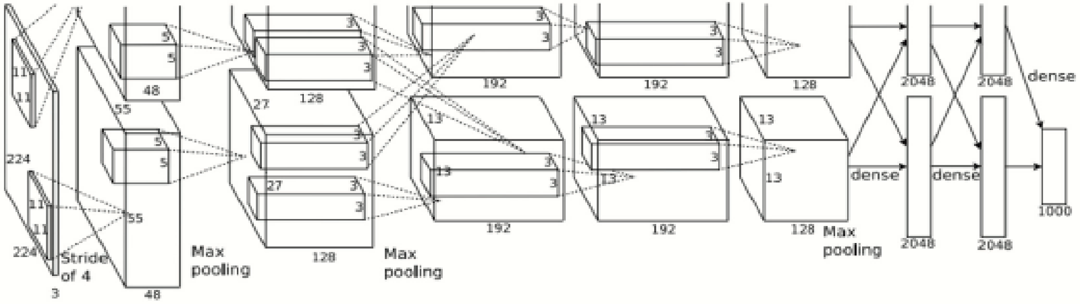
AlexNet - Architecture



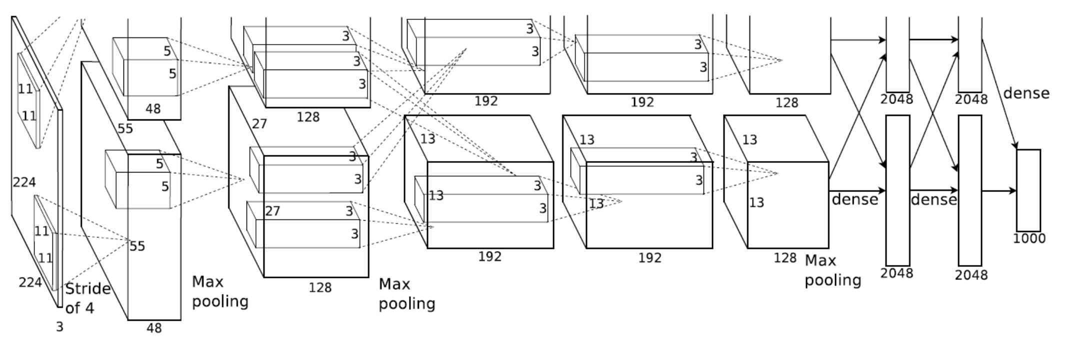
From: Krizhevsky et al., ImageNet Classification with Deep ConvolutionalNeural Networks, 2012.

Case Study: AlexNet

[Krizhevsky et al. 2012]



Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4

=>

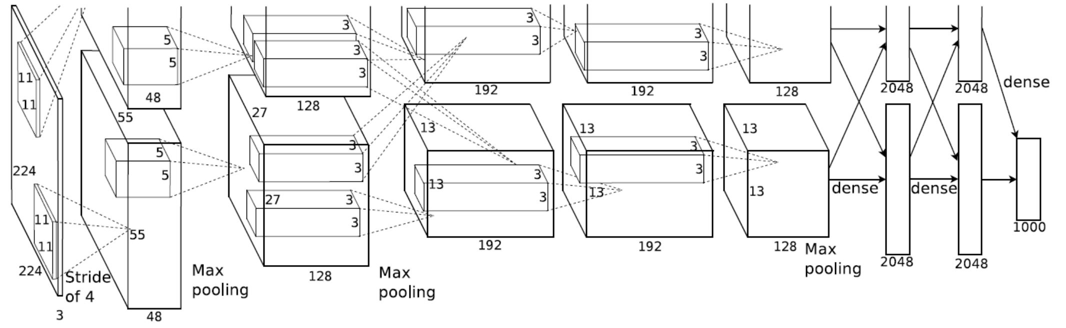
Q: what is the output volume size? Hint: (227-11)/4+1 = 55

W' = (W - F + 2P) / S + 1

From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

AlexNet – Layers and Key Aspects

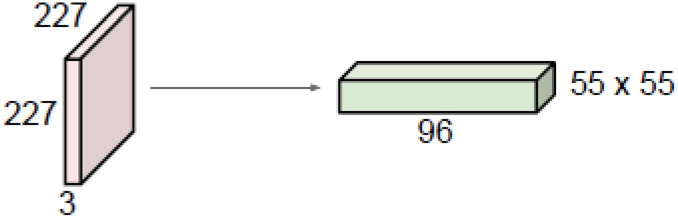
Georgia Tech



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

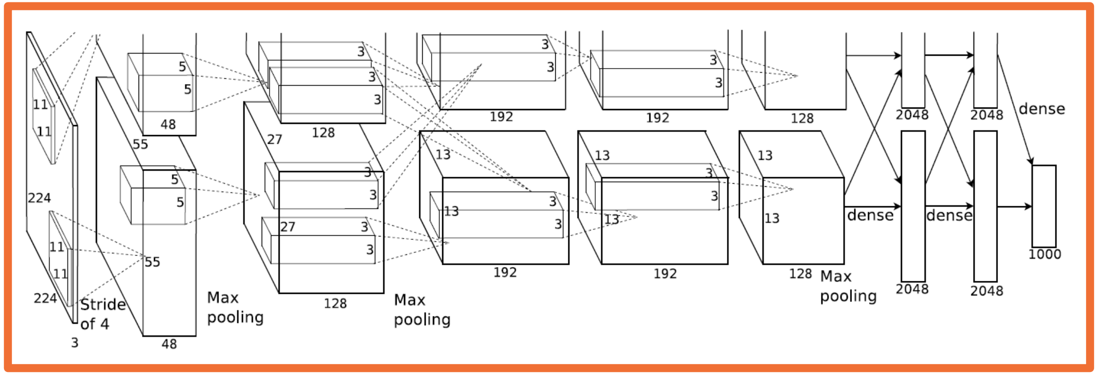
W' = (W - F + 2P) / S + 1



From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

AlexNet – Layers and Key Aspects

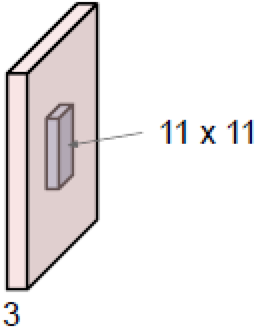
Georgia Tech



Input: 227x227x3 images

First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**

Q: What is the total number of parameters in this layer?



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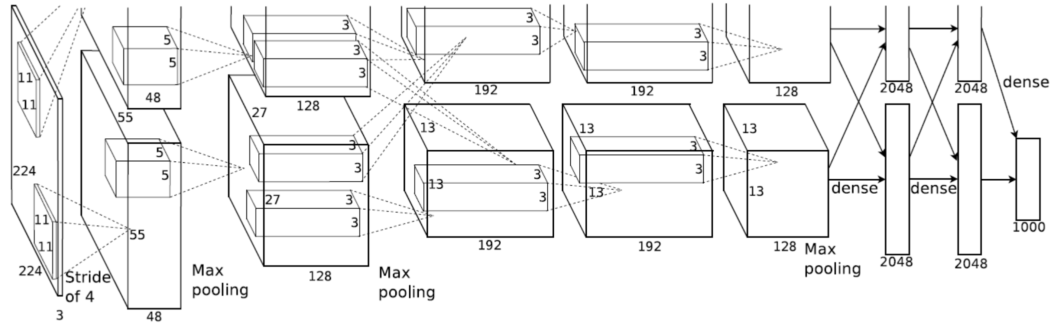
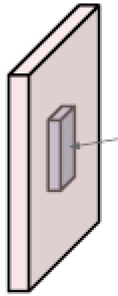
AlexNet – Layers and Key Aspects



Input: 227x227x3 images

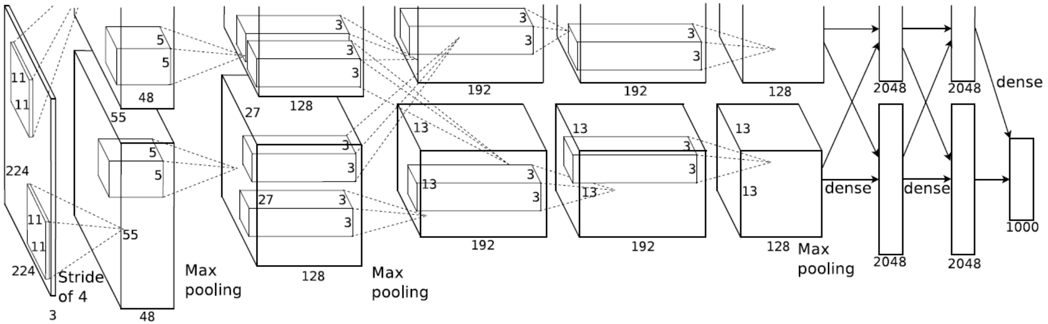
First layer (CONV1): 96 11x11 filters applied at stride 4
=>
Output volume **[55x55x96]**
Parameters: (11*11*3 + 1)*96 = **35K**



From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

AlexNet – Layers and Key Aspects

Full (simplified) AlexNet architecture:
[224x224x3] 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)



Key aspects:

- ReLU instead of sigmoid or tanh
- Specialized normalization layers
- PCA-based data augmentation
- Dropout
- Ensembling

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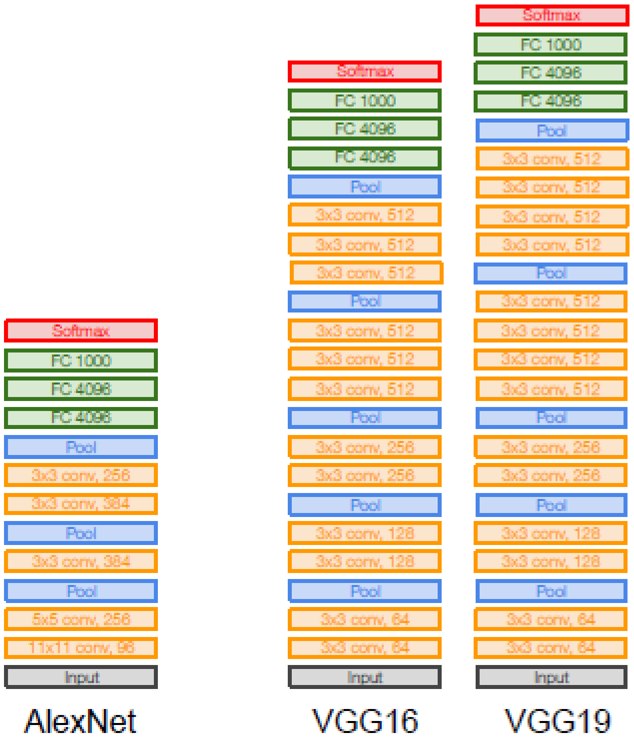
AlexNet – Layers and Key Aspects

Small filters, Deeper networks

8 layers (AlexNet)
-> 16 - 19 layers (VGG16Net)

Only 3x3 CONV stride 1, pad 1
and 2x2 MAX POOL stride 2

11.7% top 5 error in ILSVRC’13 (ZFNet)
-> 7.3% top 5 error in ILSVRC’14



From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

VGGNet

Q: Why use smaller filters? (3x3 conv)

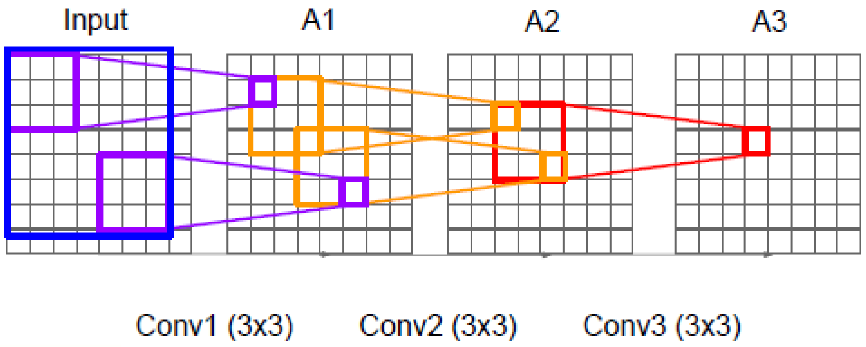
Stack of three 3x3 conv (stride 1) layers has same **effective receptive field** as one 7x7 conv layer

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?

From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

VGGNet

Q: What is the effective receptive field of three 3x3 conv (stride 1) layers?



But deeper, more non-linearities

And fewer parameters: $3 * (3^2C^2)$ vs. 7^2C^2 for C channels per layer

From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

VGGNet

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
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

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	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	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: **Number of parameters** (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

From: Simonyan & Zimmerman, Very Deep Convolutional Networks for Large-Scale Image Recognition
From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

VGG

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
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POOL2: [14x14x512] memory: 14*14*512=100K params: 0
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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

Most memory usage in convolution layers

Most parameters in FC layers

From: Simonyan & Zimmerman, Very Deep Convolutional Networks for Large-Scale Image Recognition
From: Slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

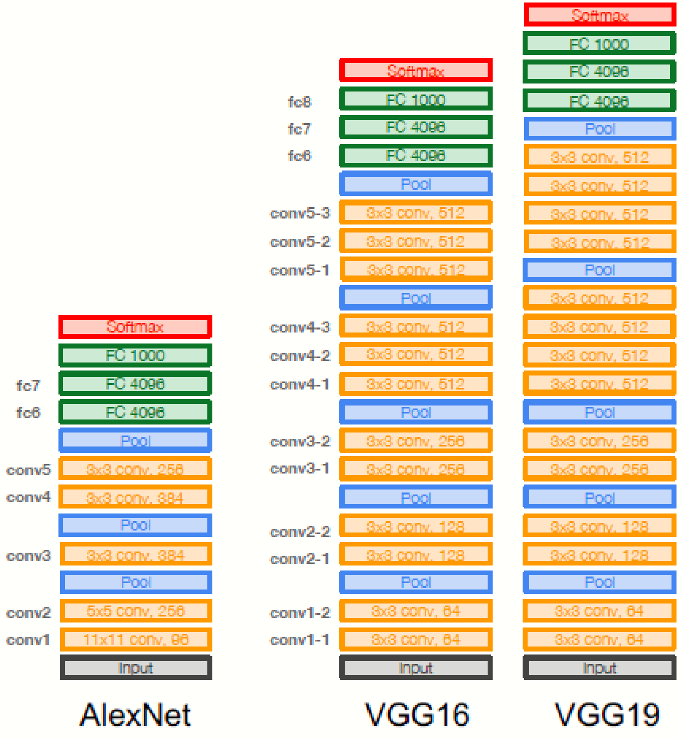
Parameters and Memory

Case Study: VGGNet

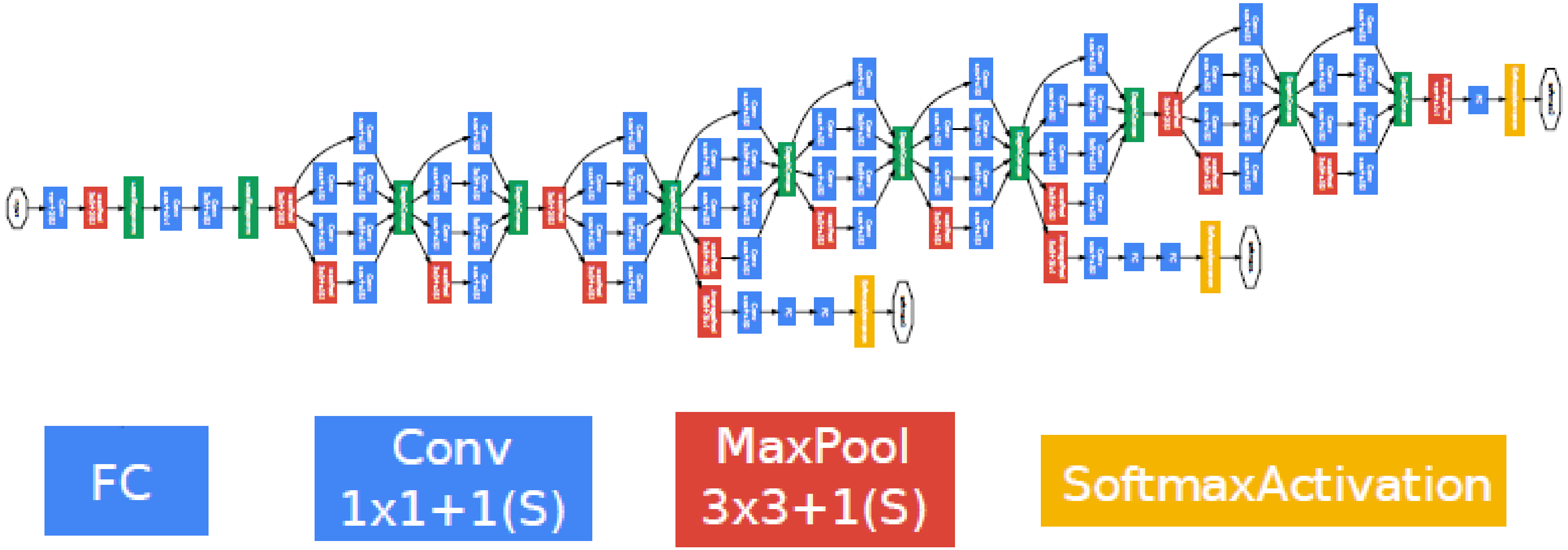
[Simonyan and Zisserman, 2014]

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

Still very expensive!
TOTAL memory: 24M * 4 bytes ~= 96MB / image
(only forward! ~*2 for bwd)
TOTAL params: 138M parameters



But have become **deeper and more complex**



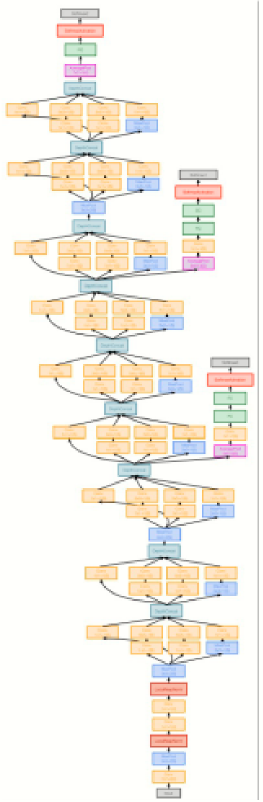
From: Szegedy et al. Going deeper with convolutions

Case Study: GoogLeNet

[Szegedy et al., 2014]

Deeper networks, focus on computational efficiency

- ILSVRC'14 classification winner (6.7% top 5 error)
- 22 layers
- Only 5 million parameters!
  12x less than AlexNet
  27x less than VGG-16
- Efficient "Inception" module
- No FC layers



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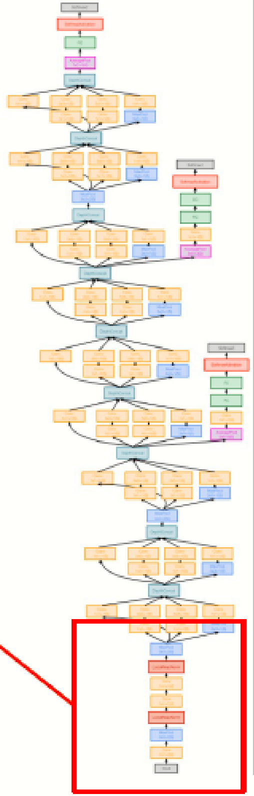
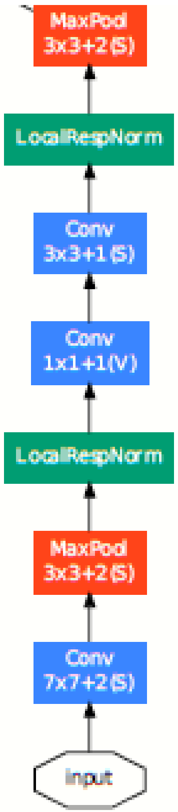
- No FC layers

Stem Network: aggressively reduce the input feature volume
- Conv 7 x 7 x 64 with stride 2
- MaxPool
- Conv 1 x 1 x 64
- Conv 3 x 3 x 192
- MaxPool

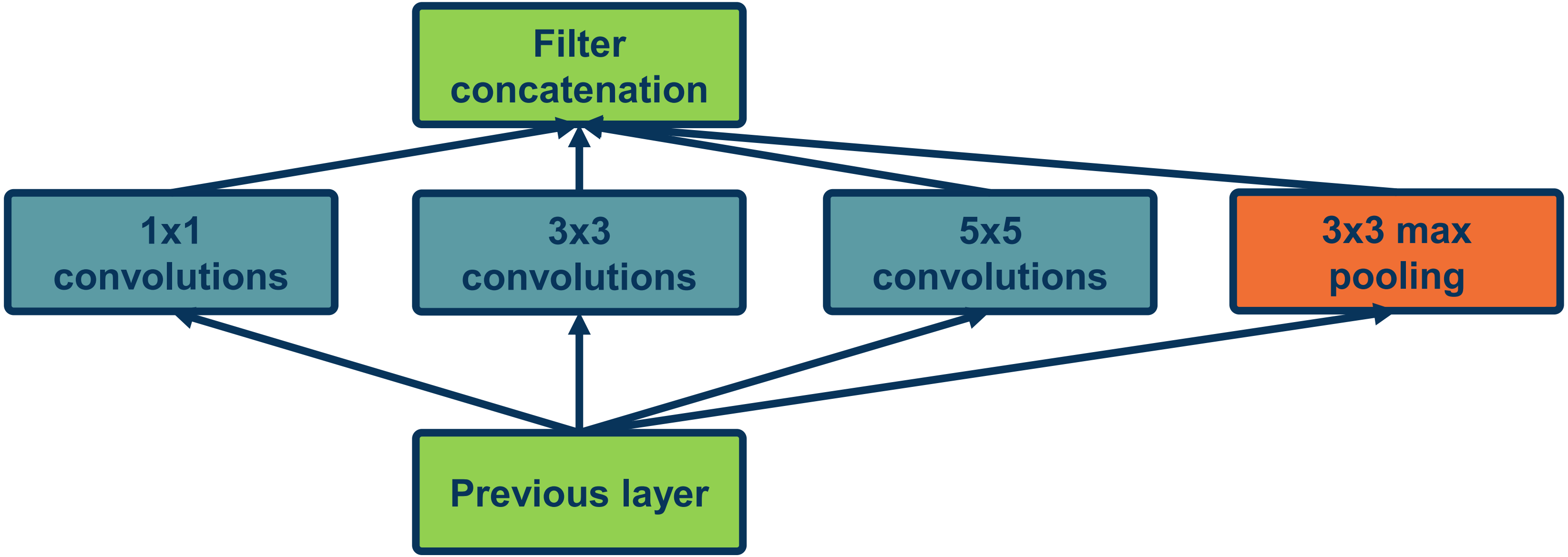
Reduce 224 x 224 spatial solution to 28 x 28 with just 418 MFLOP! (Comparing to 7485 MFLOP of VGG)





From: Szegedy et al. Going deeper with convolutions

Key idea: Repeated blocks and multi-scale features



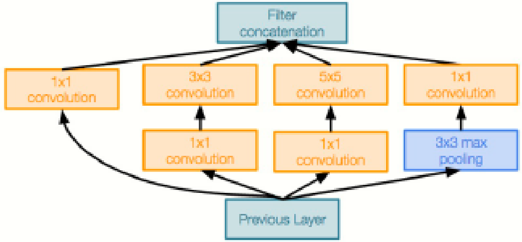
From: Szegedy et al. Going deeper with convolutions

Case Study: GoogLeNet

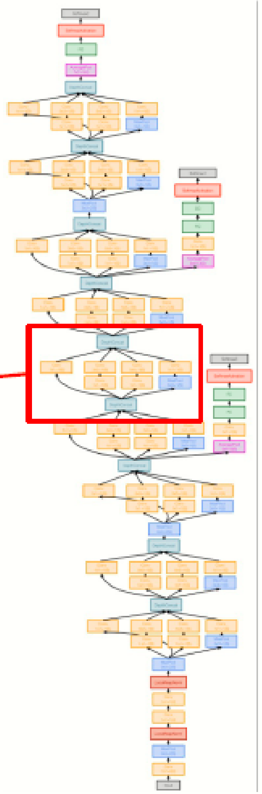
[Szegedy et al., 2014]

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

Multiple conv filter size diversifies learned features



Inception module

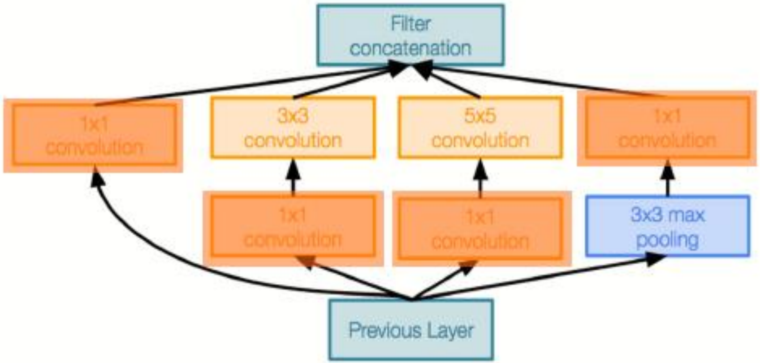


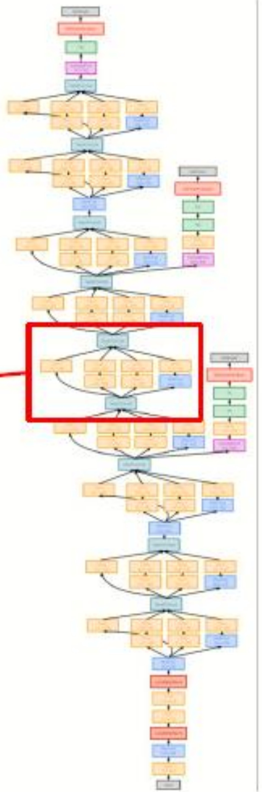
From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Case Study: GoogLeNet

[Szegedy et al., 2014]

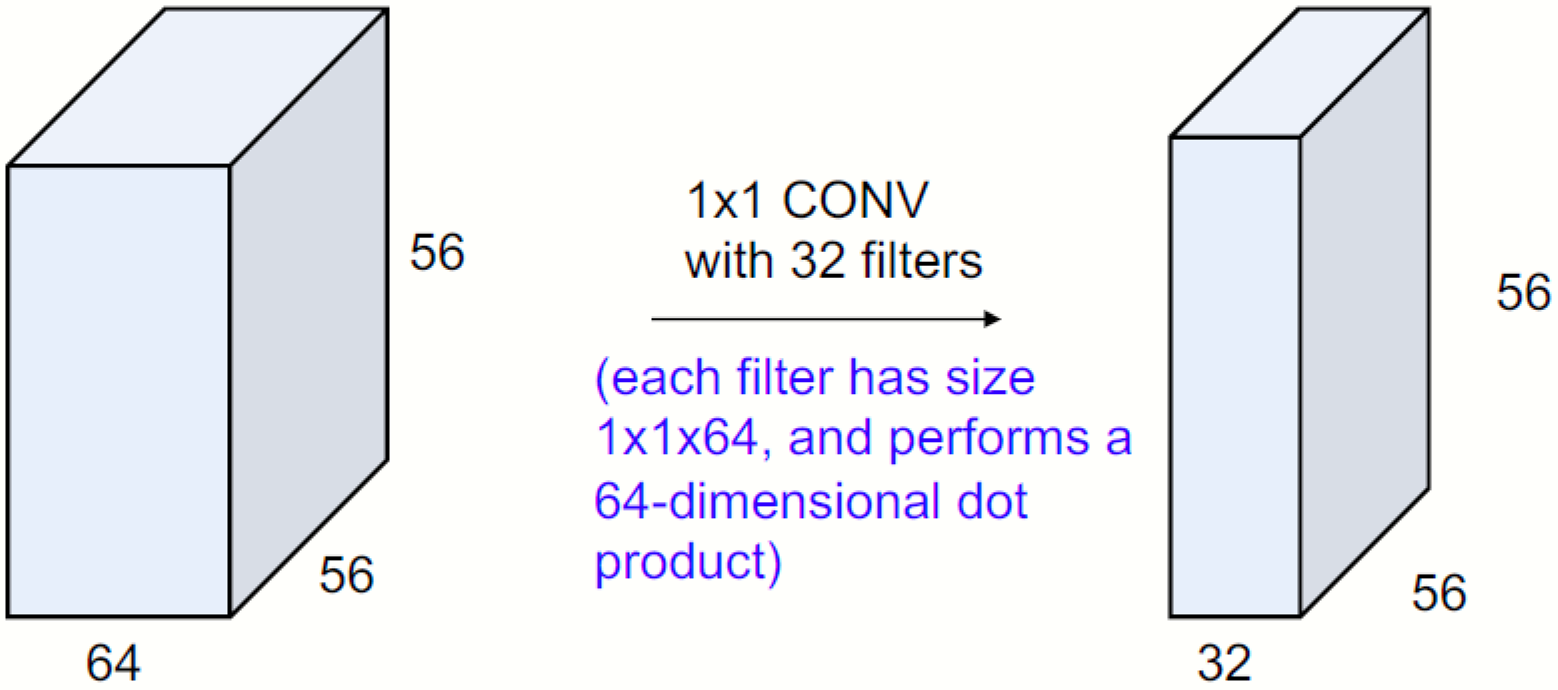
Inception module





Uses 1x1 “Bottleneck” layers to reduce channel dimension before expensive conv (we will revisit this with ResNet!)

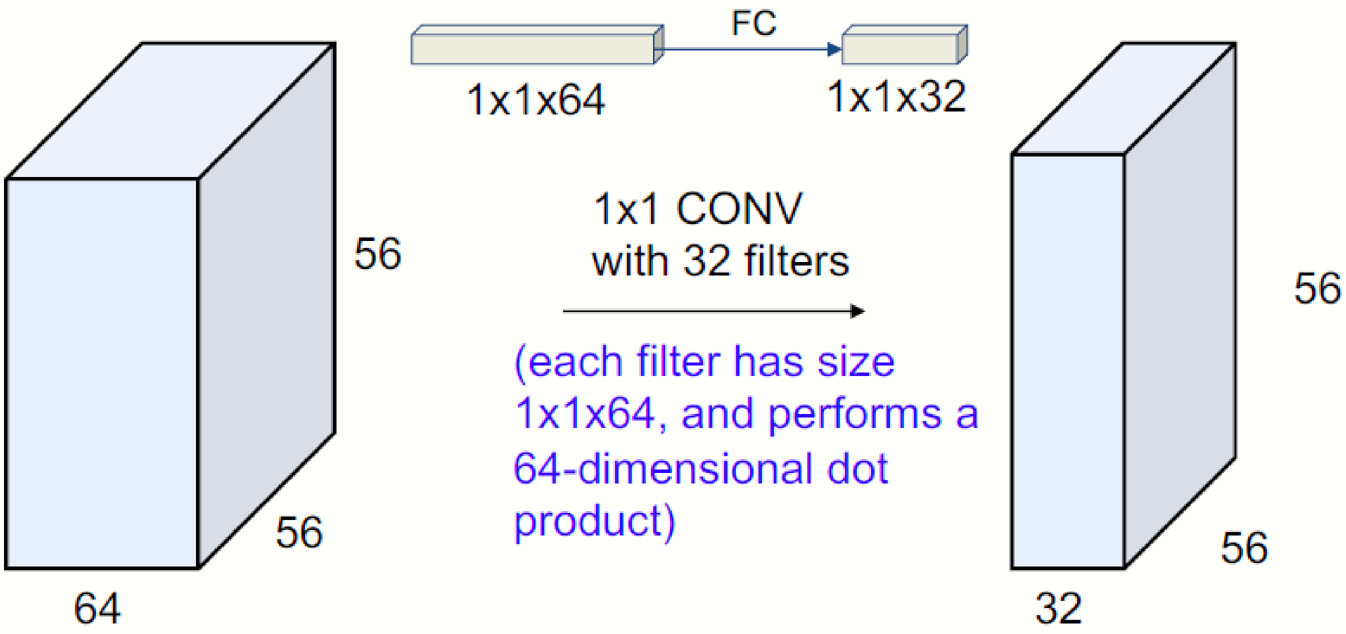
From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n



From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

1x1 Convolutions

Alternatively, interpret it as applying the same FC layer on each input pixel

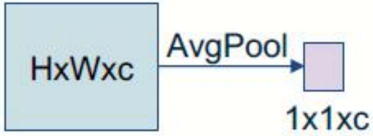


From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

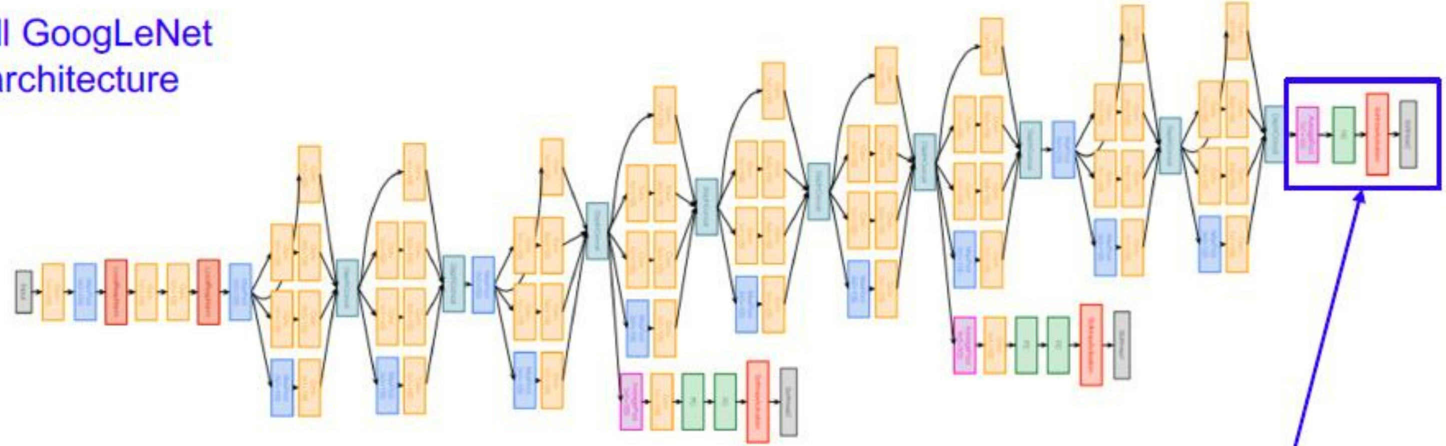
1x1 Convolutions

Case Study: GoogLeNet

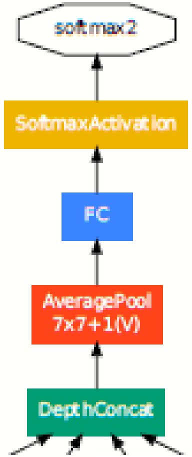
[Szegedy et al., 2014]



Full GoogLeNet architecture



Classifier output



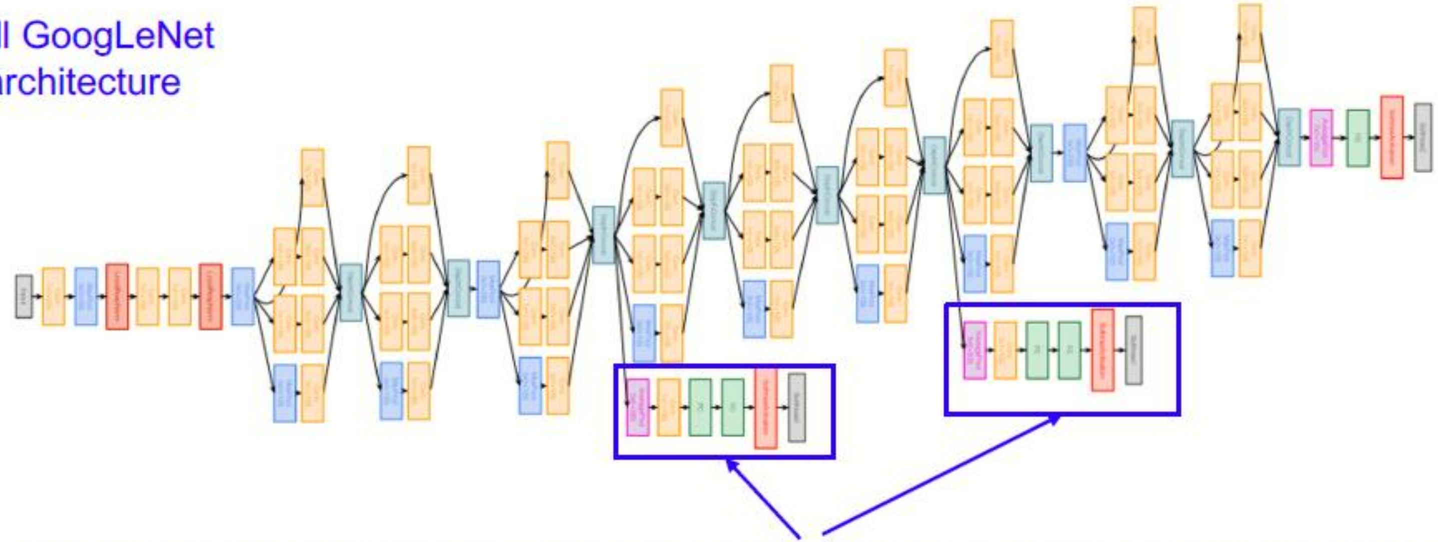
Note: after the last convolutional layer, a global average pooling layer is used that **spatially** averages across each feature map, before final FC layer. No longer multiple expensive FC layers!
(Also used in ResNet)

From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

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)

Why?

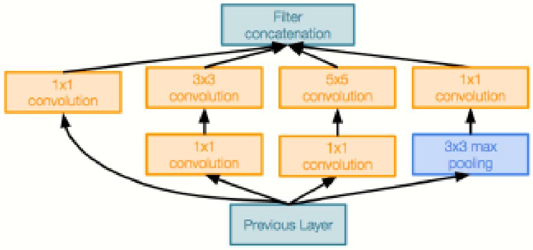
From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

Case Study: GoogLeNet

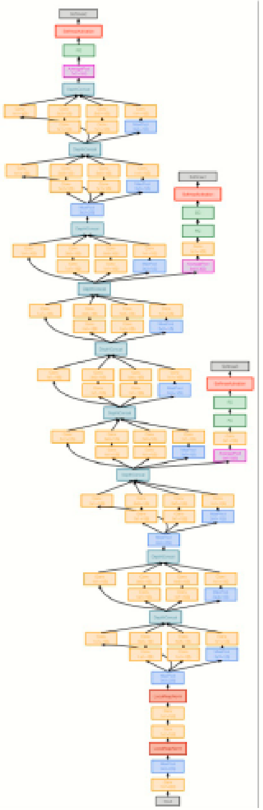
[Szegedy et al., 2014]

Deeper networks, with computational efficiency

- 22 layers
- Efficient "Inception" module
- Avoids expensive FC layers
- 12x less params than AlexNet
- 27x less params than VGG-16
- ILSVRC'14 classification winner (6.7% top 5 error)



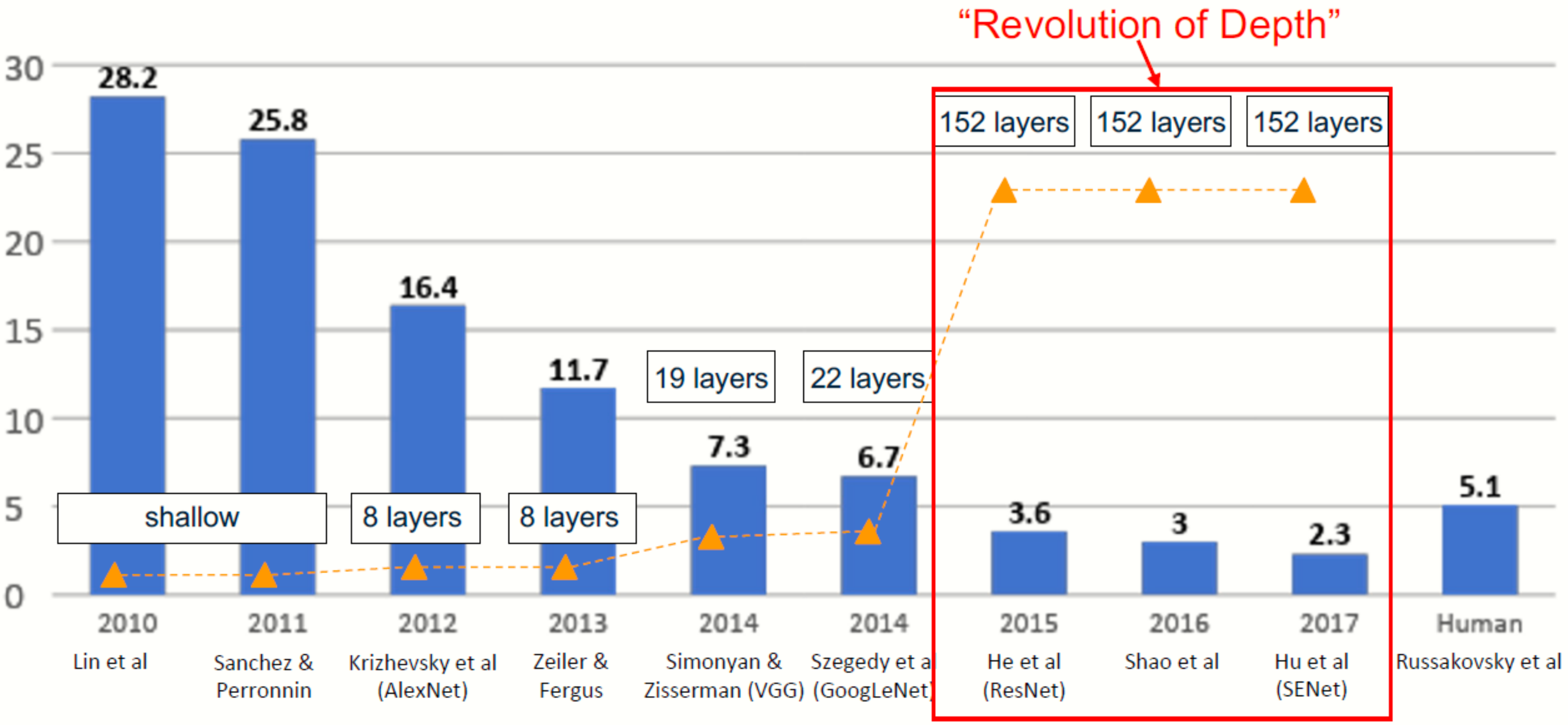
Inception module



From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

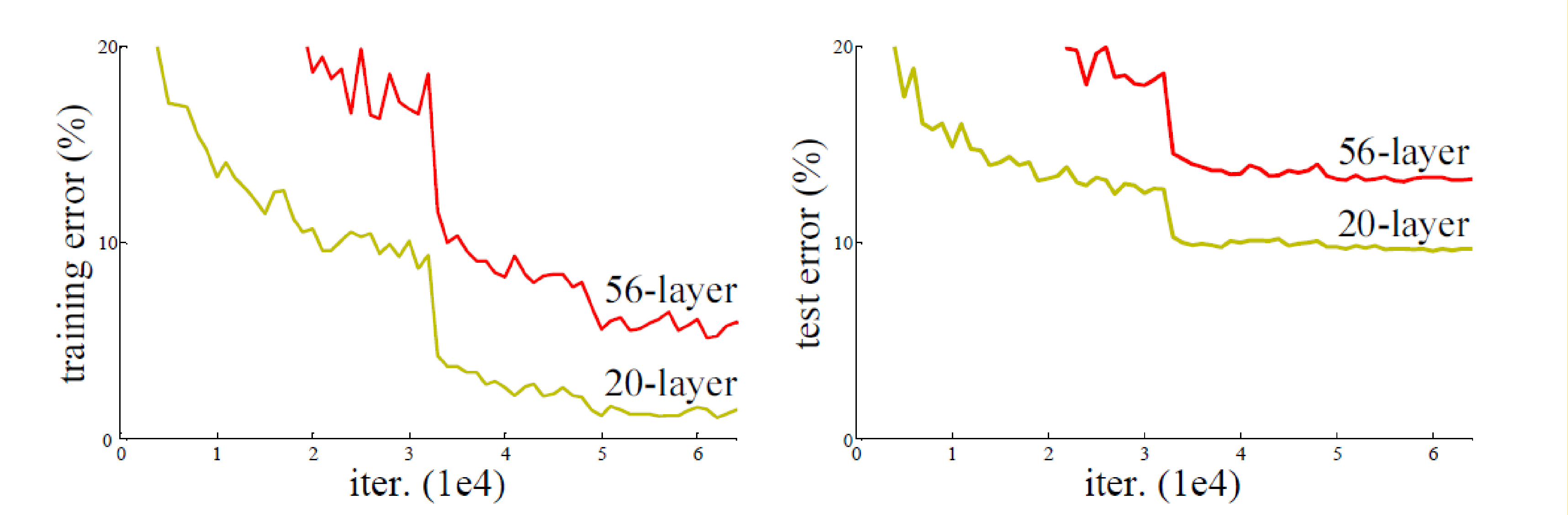
1x1 Convolutions

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



Revolution of Depth

The Challenge of Depth



From: He et al., Deep Residual Learning for Image Recognition

Optimizing very deep networks is challenging!

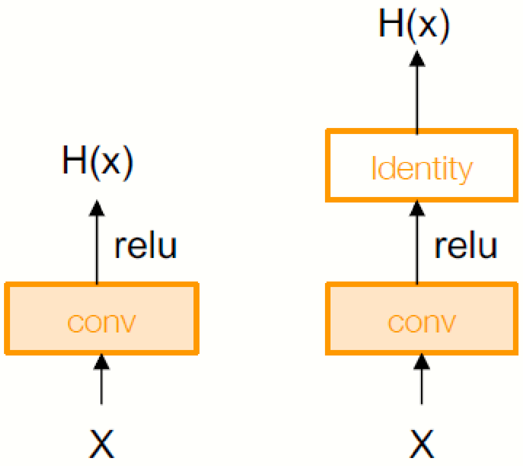
[He et al., 2015]

A deeper model can **emulate** a shallower model: copy layers from shallower model, set extra layers to identity

Thus deeper models should do at least as good as shallow models

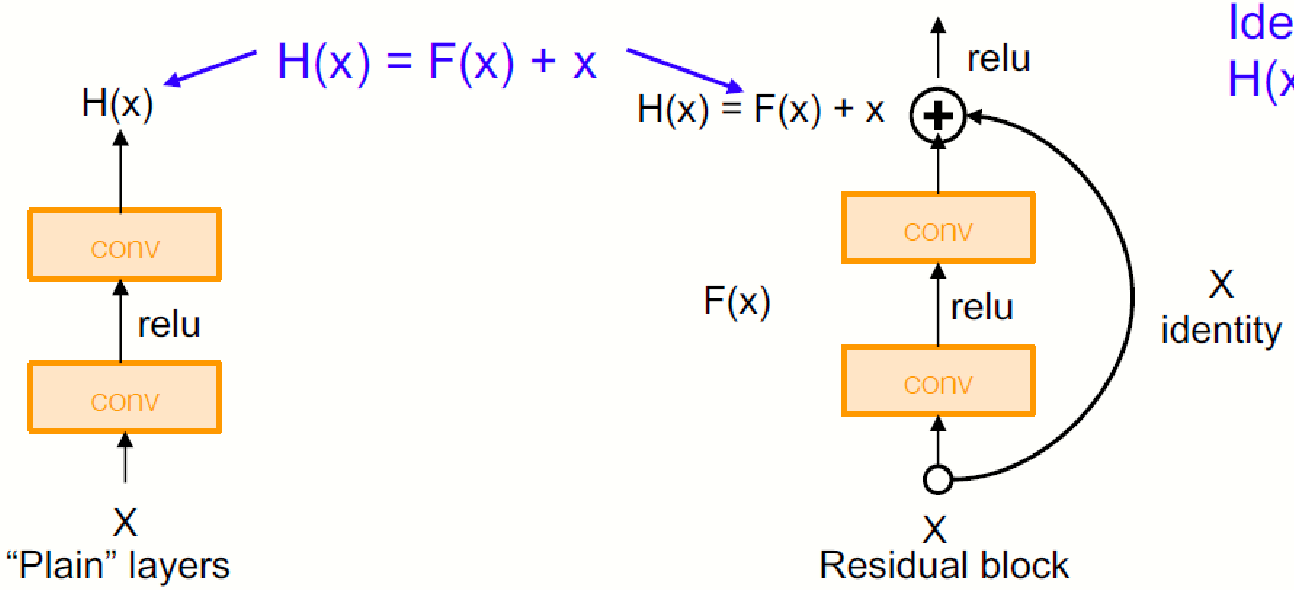
Deeper models are harder to optimize. They don't learn identity functions (no-op) to emulate shallow models

Solution: Change the network so learning identity functions (no-op) as extra layers is easy



[He et al., 2015]

Solution: Change the network so learning identity functions as extra layers is easy



Identity mapping:
$H(x) = x$ if $F(x) = 0$

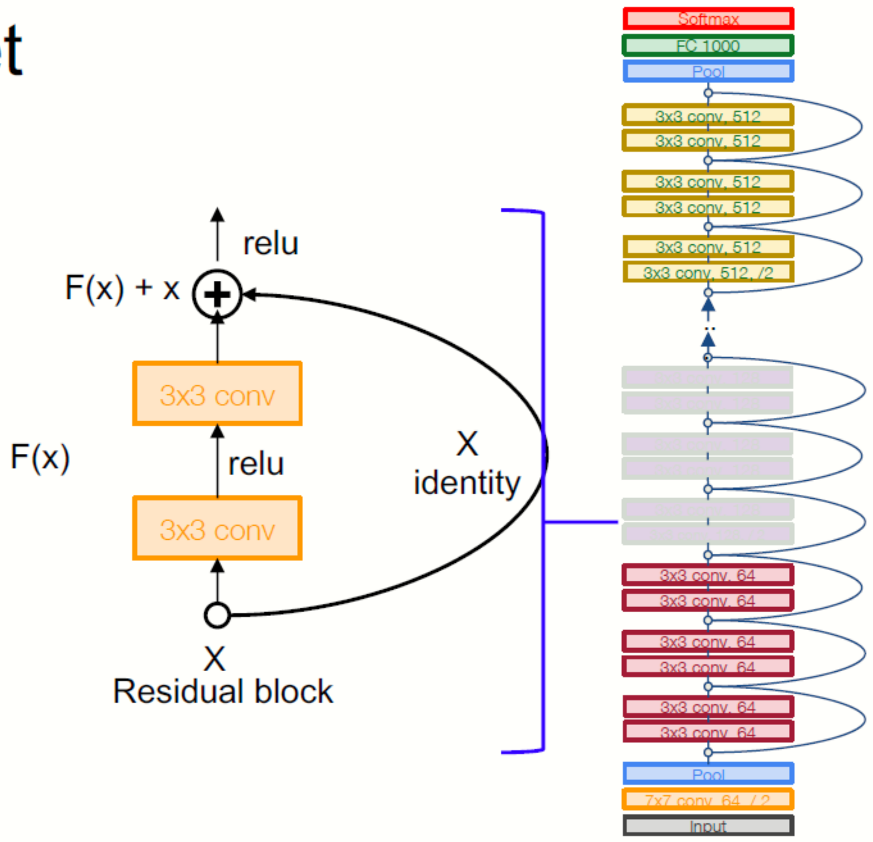
Use layers to fit **residual**
$F(x) = H(x) - x$
instead of
$H(x)$ directly

Skip Connections

Case Study: ResNet

[He et al., 2015]

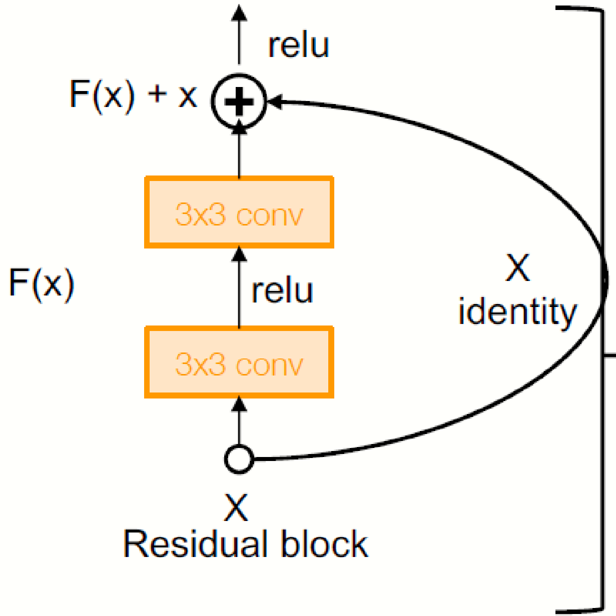
Full ResNet architecture:
- Stack residual blocks
- Every residual block has two 3x3 conv layers

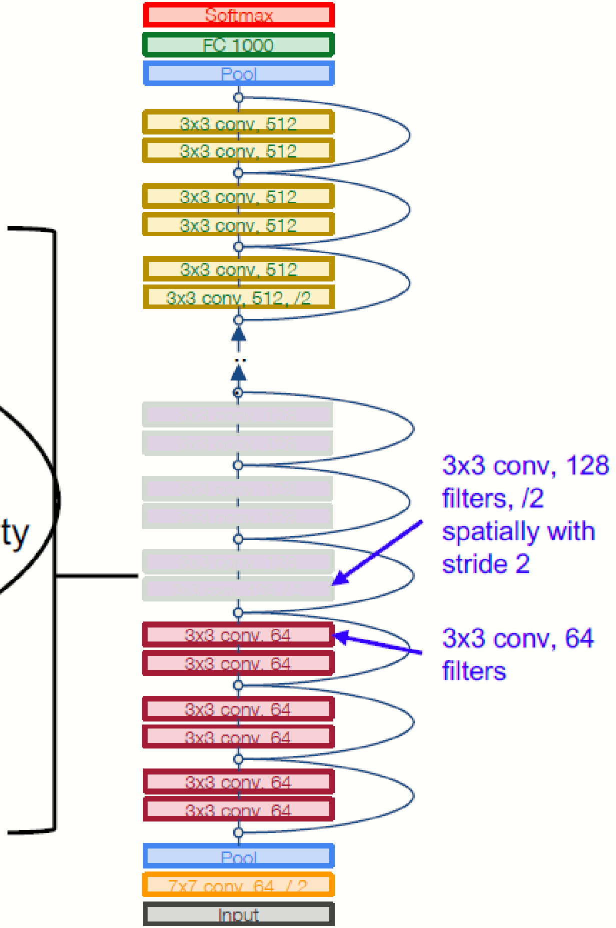


Case Study: ResNet

[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) Reduce the activation volume by half.



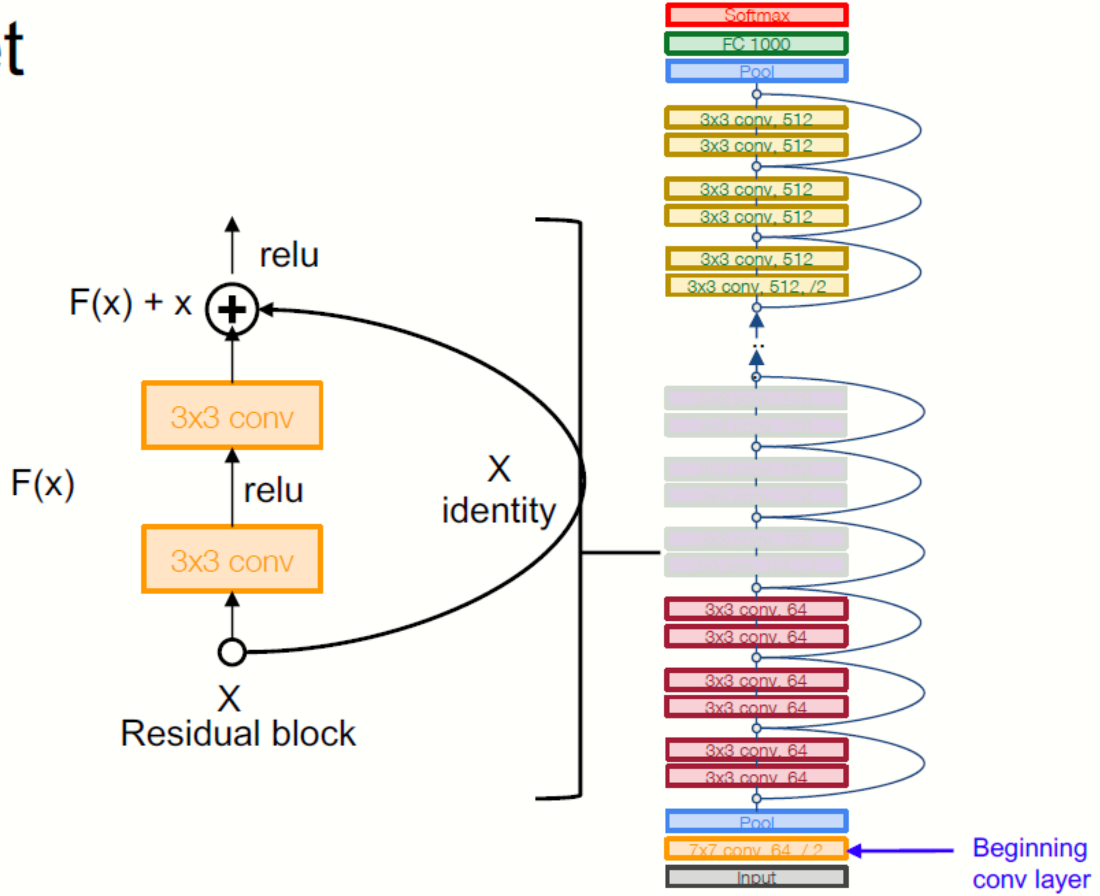


Case Study: ResNet

[He et al., 2015]

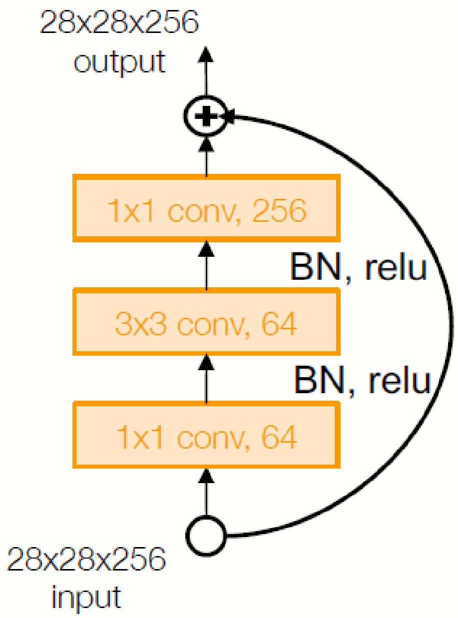
Full ResNet architecture:

- 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) Reduce the activation volume by half.
- Additional conv layer at the beginning (stem)



[He et al., 2015]

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



Bottleneck Layers

layer name	output size	18-layer	34-layer			
conv1	112×112					
conv2_x	56×56	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times3$			
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times4$			
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times6$			
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times3$			
	1×1	ave				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

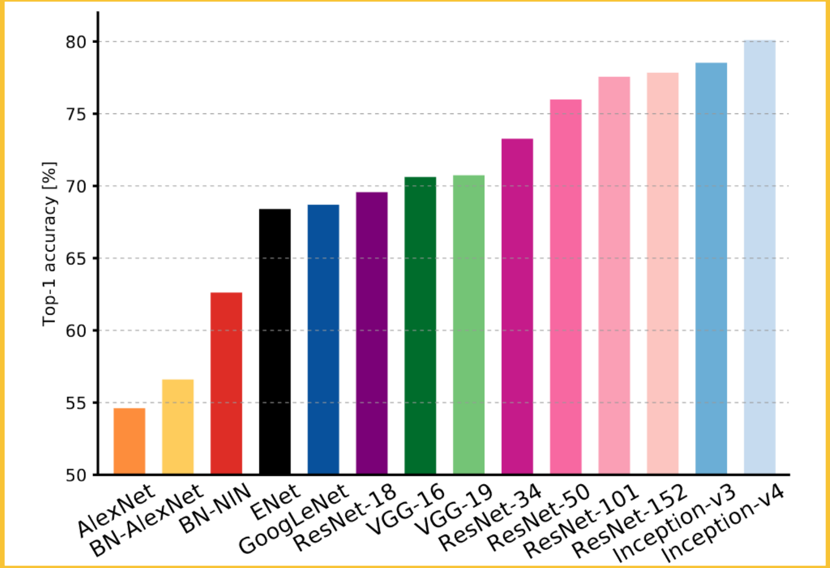
```
>>> import torch
>>> from torchvision.models import resnet18
>>> model = resnet18()
>>> summary(model2, (3, 224, 224), device='cpu')
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 64, 112, 112]           9,408
       BatchNorm2d-2         [-1, 64, 112, 112]             128
              ReLU-3         [-1, 64, 112, 112]               0
         MaxPool2d-4           [-1, 64, 56, 56]               0
            Conv2d-5           [-1, 64, 56, 56]          36,864
       BatchNorm2d-6           [-1, 64, 56, 56]             128
              ReLU-7           [-1, 64, 56, 56]               0
            Conv2d-8           [-1, 64, 56, 56]          36,864
       BatchNorm2d-9           [-1, 64, 56, 56]             128
             ReLU-10           [-1, 64, 56, 56]               0
       BasicBlock-11           [-1, 64, 56, 56]               0
           Conv2d-12           [-1, 64, 56, 56]          36,864
      BatchNorm2d-13           [-1, 64, 56, 56]             128
             ReLU-14           [-1, 64, 56, 56]               0
           Conv2d-15           [-1, 64, 56, 56]          36,864
      BatchNorm2d-16           [-1, 64, 56, 56]             128
             ReLU-17           [-1, 64, 56, 56]               0
       BasicBlock-18           [-1, 64, 56, 56]               0
           Conv2d-19          [-1, 128, 28, 28]          73,728
      BatchNorm2d-20          [-1, 128, 28, 28]             256
             ReLU-21          [-1, 128, 28, 28]               0
           Conv2d-22          [-1, 128, 28, 28]         147,456
```

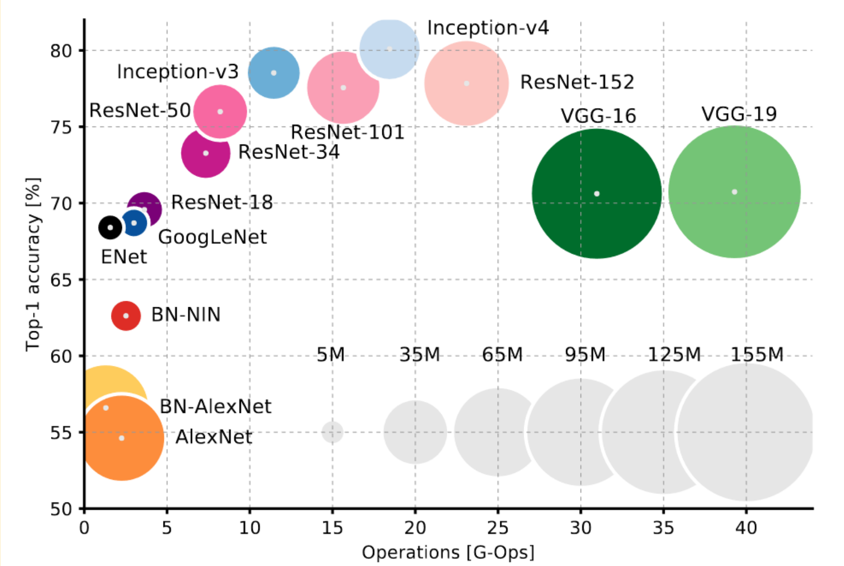
ResNet Details

Training ResNet in practice:

- Batch Normalization after every CONV layer
- Xavier initialization from He et al.
- SGD + Momentum
- Learning rate: 0.1, divided by 10 when validation error plateaus
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout used

Computational Complexity





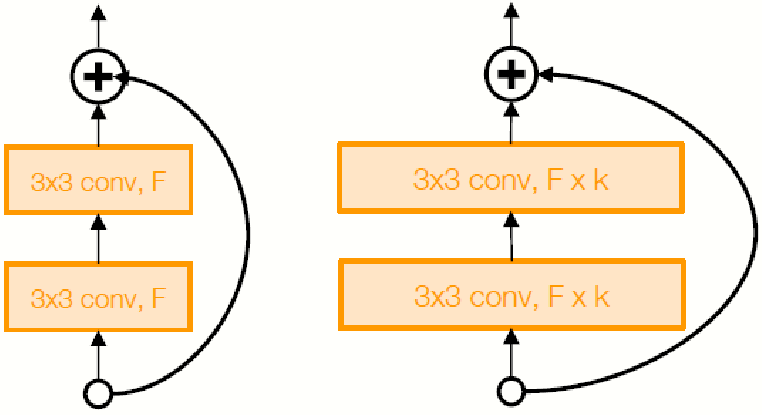
From: An Analysis Of Deep Neural Network Models For Practical Applications

Georgia Tech

Wide Residual Networks

[Zagoruyko et al. 2016]

- Argues that residuals are the important factor, not depth
- Use wider residual blocks (F x k filters instead of F filters in each layer)
- 50-layer wide ResNet outperforms 152-layer original ResNet
- Increasing width instead of depth more computationally efficient (parallelizable)

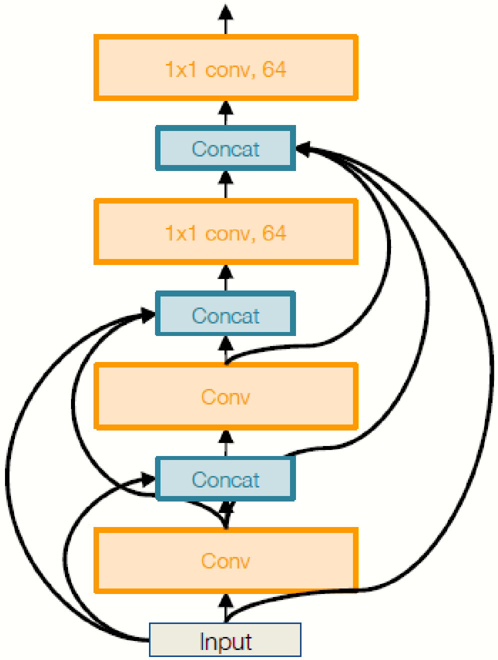


Basic residual block   Wide residual block

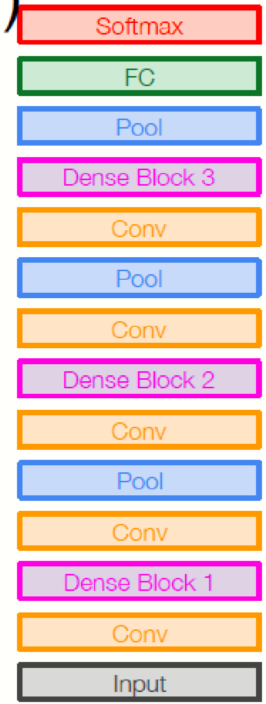
Densely Connected Convolutional Networks (DenseNet)

[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
- Showed that shallow 50-layer network can outperform deeper 152 layer ResNet



Dense Block

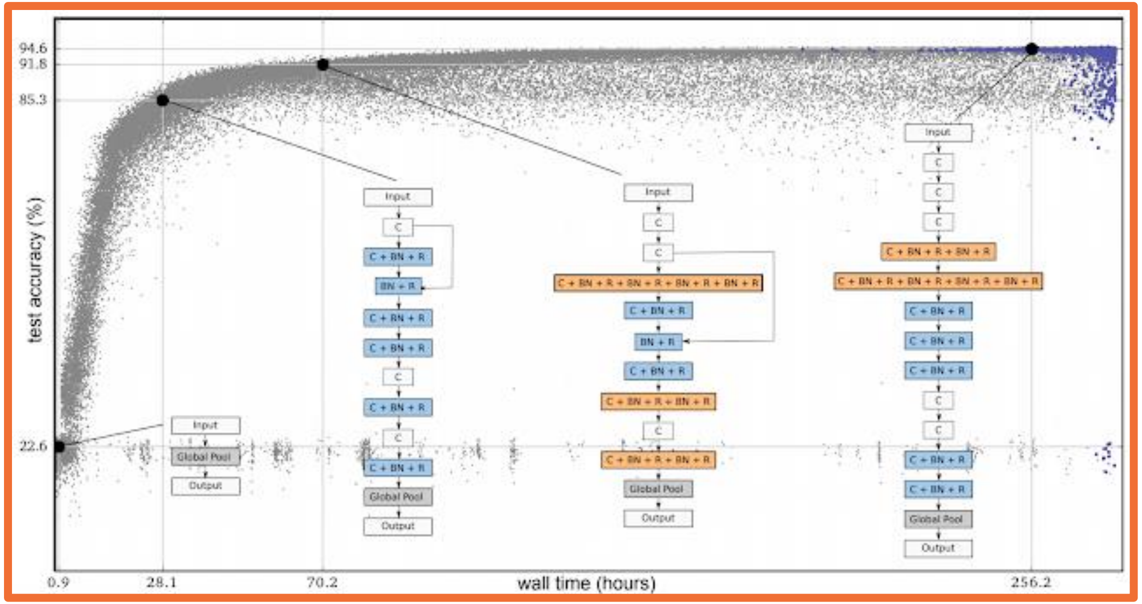


ConvNeXt (2022)

- ***Do the reading for discussion!***

Several ways to *learn* architectures:

- Evolutionary learning and reinforcement learning
- Prune over-parameterized networks
- Learning of **repeated blocks** typical

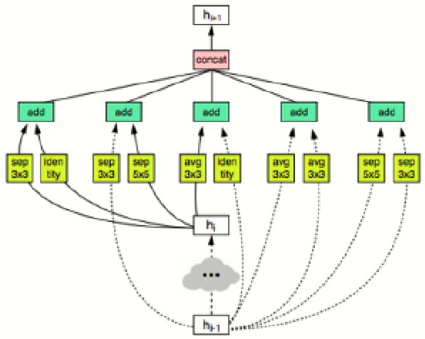


From: https://ai.googleblog.com/2018/03/using-evolutionary-automl-to-discover.html

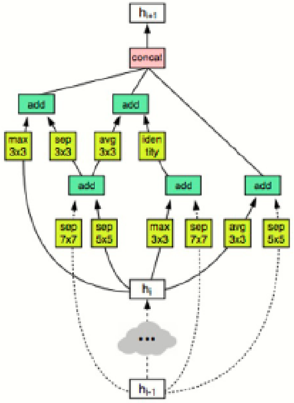
Learning Transferable Architectures for Scalable Image Recognition

[Zoph et al. 2017]

- Applying neural architecture search (NAS) to a large dataset like ImageNet is expensive
- Design a search space of building blocks ("cells") that can be flexibly stacked
- NASNet: Use NAS to find best cell structure on smaller CIFAR-10 dataset, then transfer architecture to ImageNet

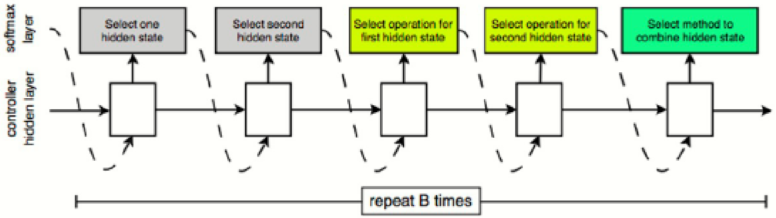


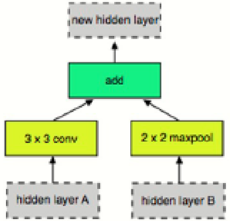
Normal Cell



Reduction Cell

- Many follow-up works in this space e.g. AmoebaNet (Real et al. 2019) and ENAS (Pham, Guan et al. 2018)



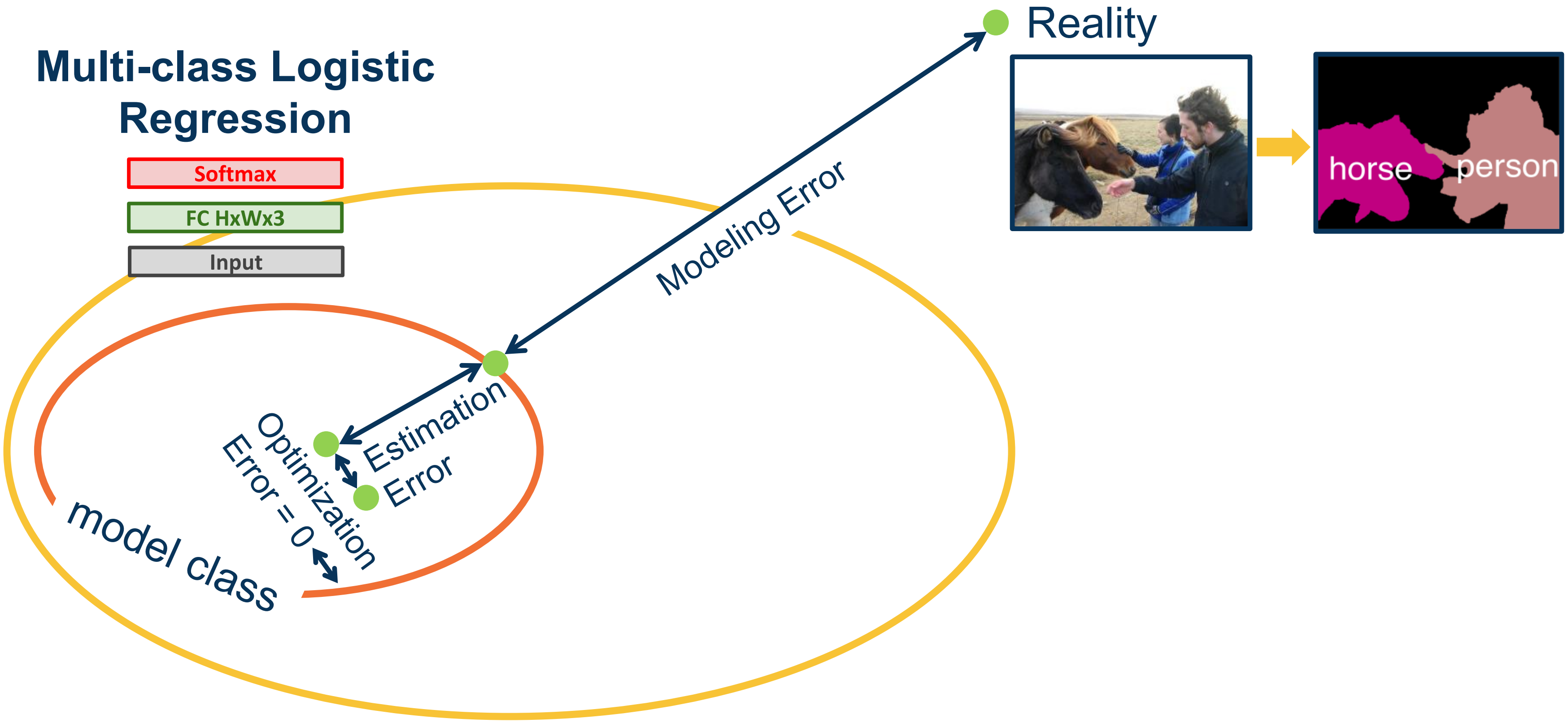


- Convolutional neural networks (CNNs) stack pooling, convolution, non-linearities, and fully connected (FC) layers

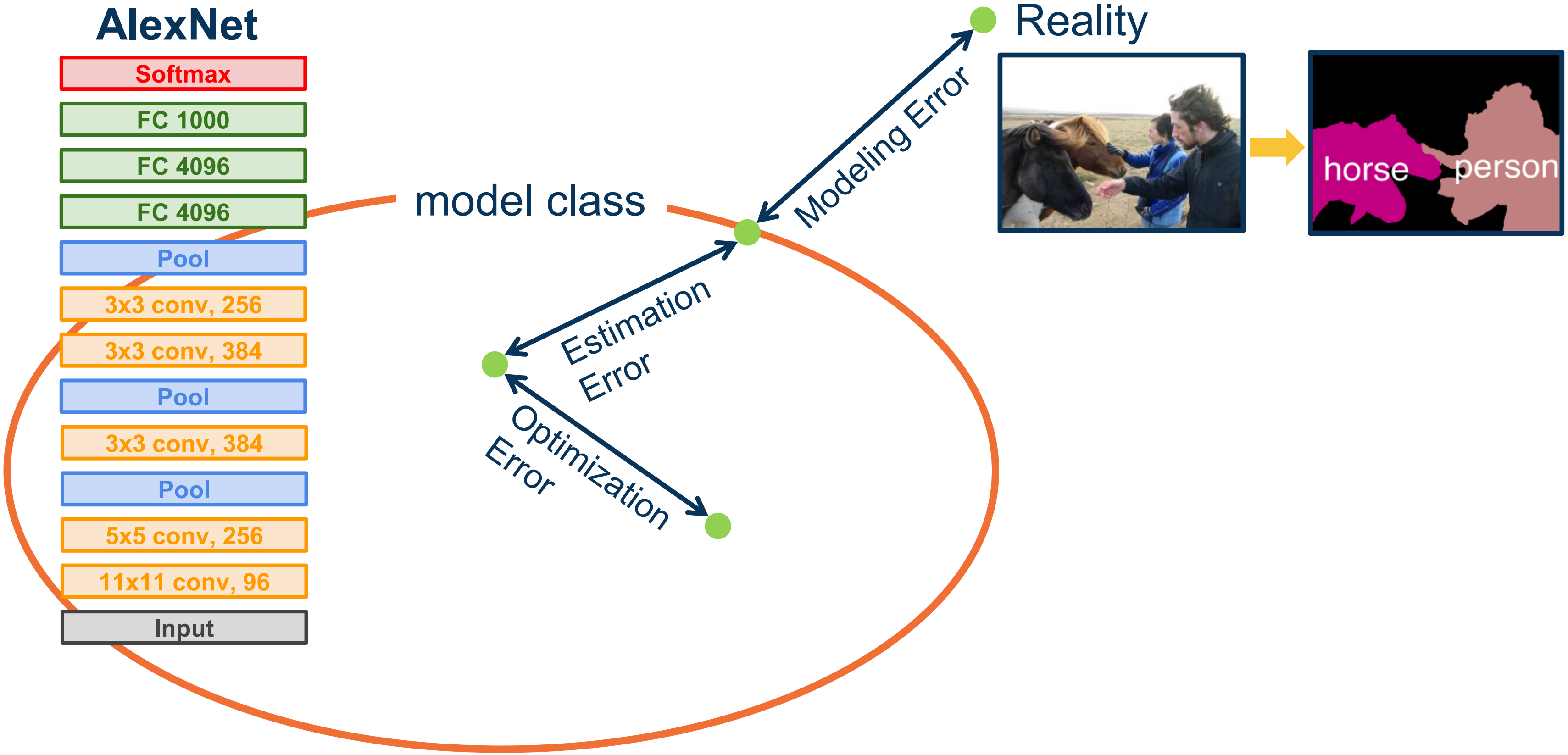
- Feature engineering => architecture engineering!
  - Tons of small details and tips/tricks
  - Considerations: Memory, compute/FLO, dimensionality reduction, diversity of features, number of parameters/capacity, etc.

Summary

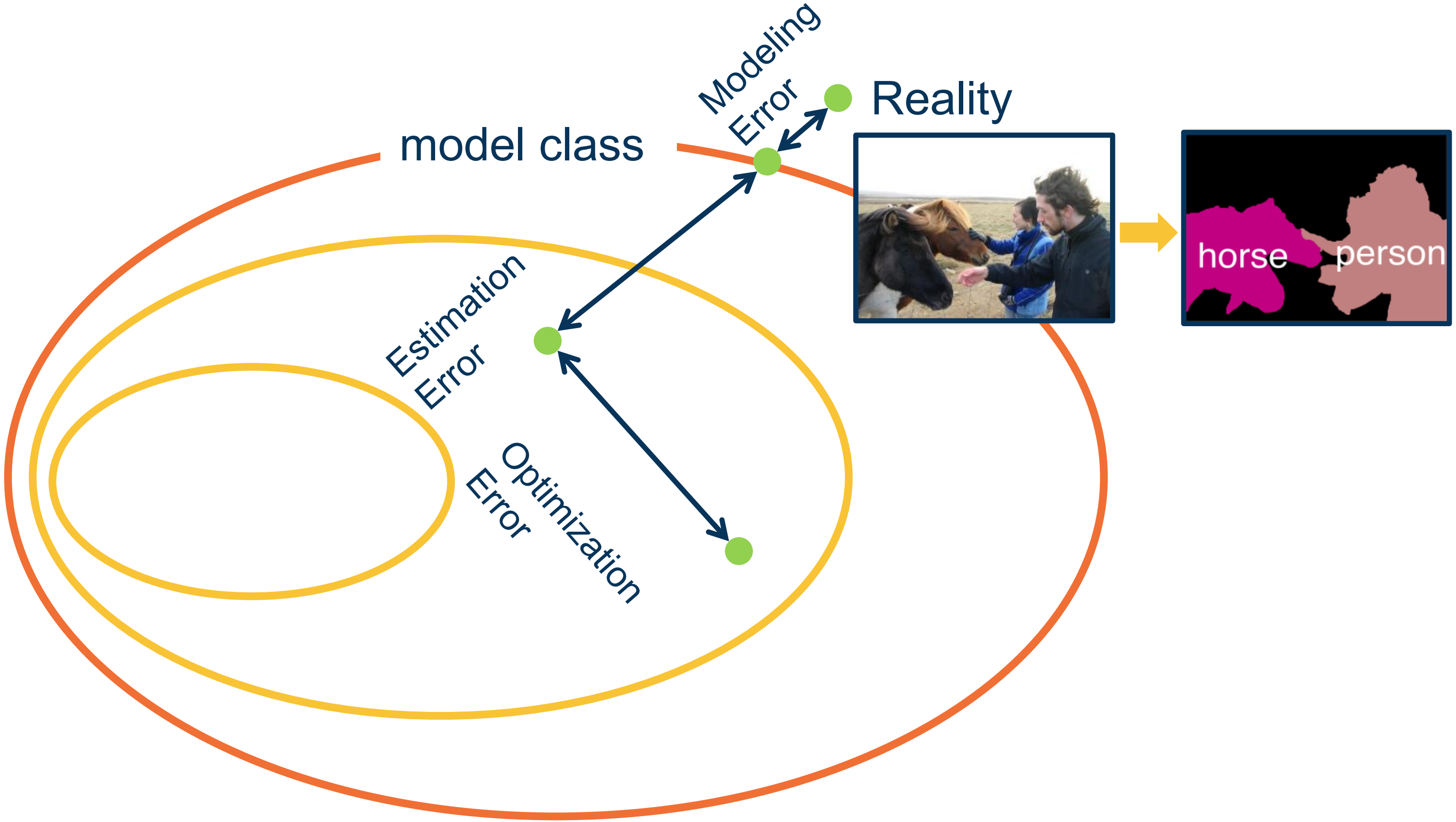
Transfer Learning & Generalization



From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n



From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

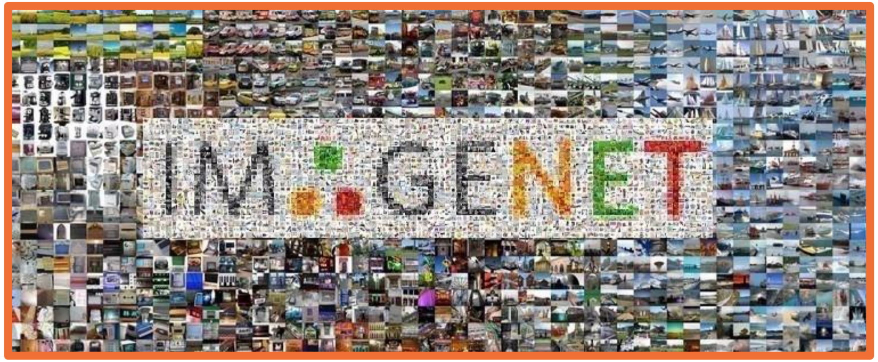


From: slides by Fei-Fei Li, Justin Johnson, Serena Yeung, CS 231n

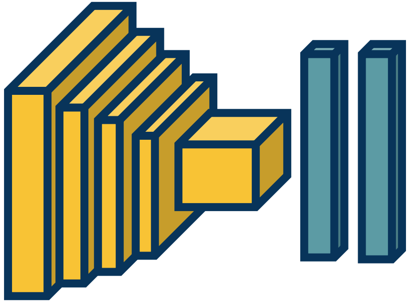
Generalization

What if we don't have enough data?

Step 1: Train on large-scale dataset



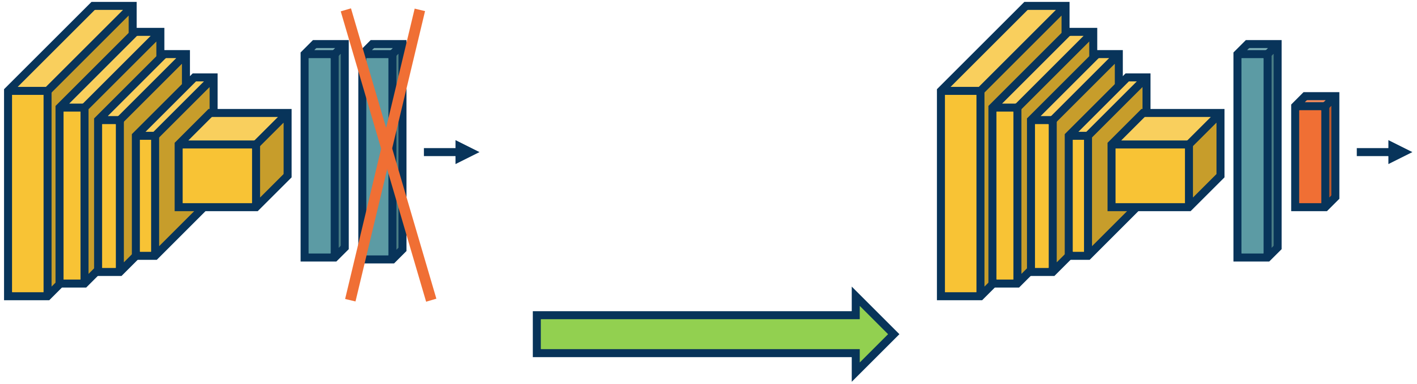
Input Image



→ Predictions

Convolutional Neural Networks

Step 2: Take your custom data and **initialize** the network with weights trained in Step 1



Replace last layer with new fully-connected for output nodes per new category

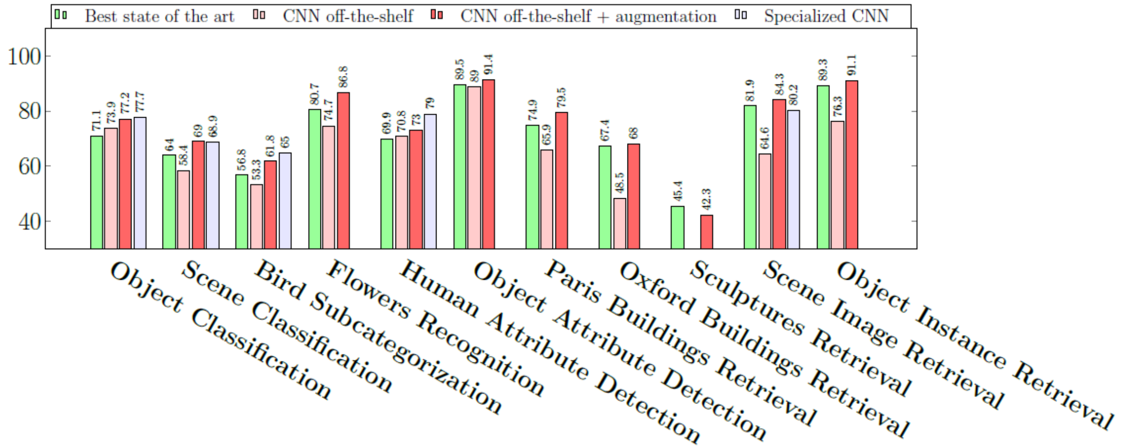
Step 3: (Continue to) train on new dataset

- **Finetune:** Update all parameters
- **Freeze** feature layer: Update only last layer weights (used when not enough data)

Replace last layer with new fully-connected for output nodes per new category

This works extremely well! It was surprising upon discovery.

- Features learned for 1000 object categories will work well for 1001st!
- Generalizes even across tasks (classification to object detection)



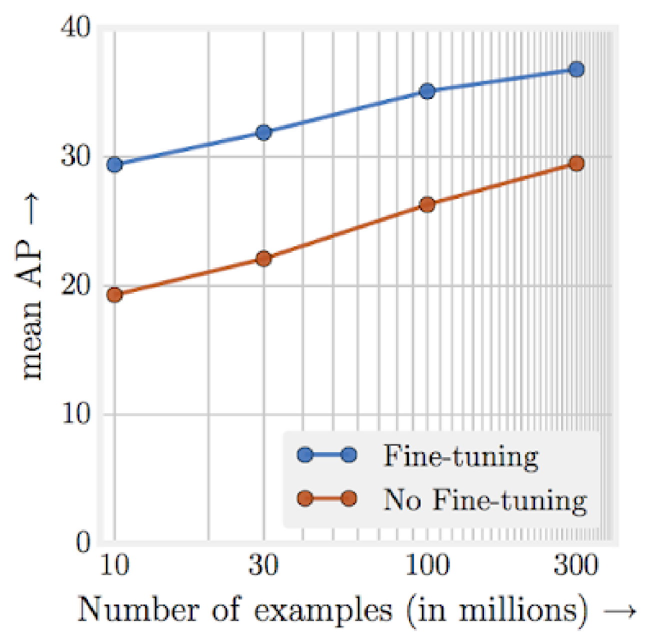
From: Razavian et al., CNN Features off-the-shelf: an Astounding Baseline for Recognition

Learning with Less Labels

But it doesn't always work that well!

- If the **source** dataset you train on is very different from the **target** dataset, transfer learning is not as effective
- If you have enough data for the target domain, it just results in faster convergence
  - See He et al., "Rethinking ImageNet Pre-training"

Effectiveness of More Data



From: Revisiting the Unreasonable Effectiveness of Data https://ai.googleblog.com/2017/07/revisiting-unreasonable-effectiveness.html

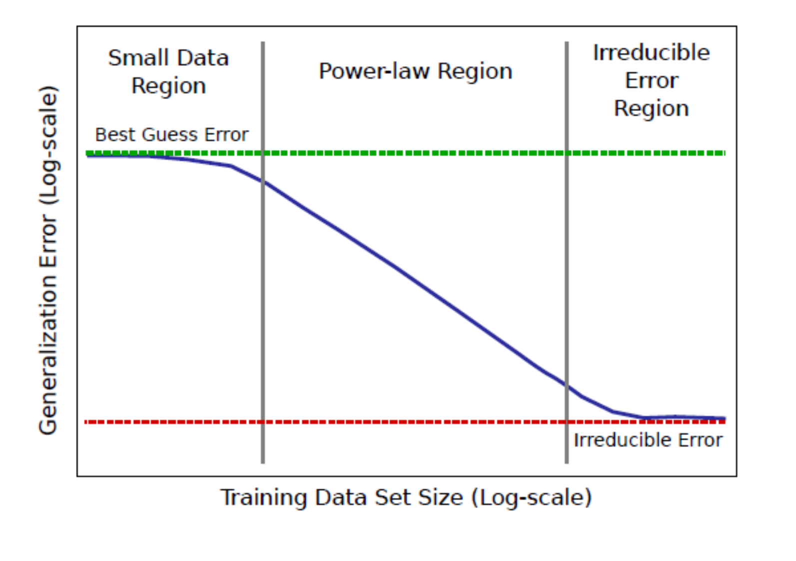


Figure 6: Sketch of power-law learning curves

From: Hestness et al., Deep Learning Scaling Is Predictable

There is a large number of different low-labeled settings in DL research

Setting	Source	Target	Shift Type
Semi-supervised	Single labeled	Single unlabeled	None
Domain Adaptation	Single labeled	Single unlabeled	Non-semantic
Domain Generalization	Multiple labeled	Unknown	Non-semantic
Cross-Task Transfer	Single labeled	Single unlabeled	Semantic
Few-Shot Learning	Single labeled	Single few-labeled	Semantic
Un/Self-Supervised	Single unlabeled	Many labeled	Both/Task

Non-Semantic Shift

Semantic Shift