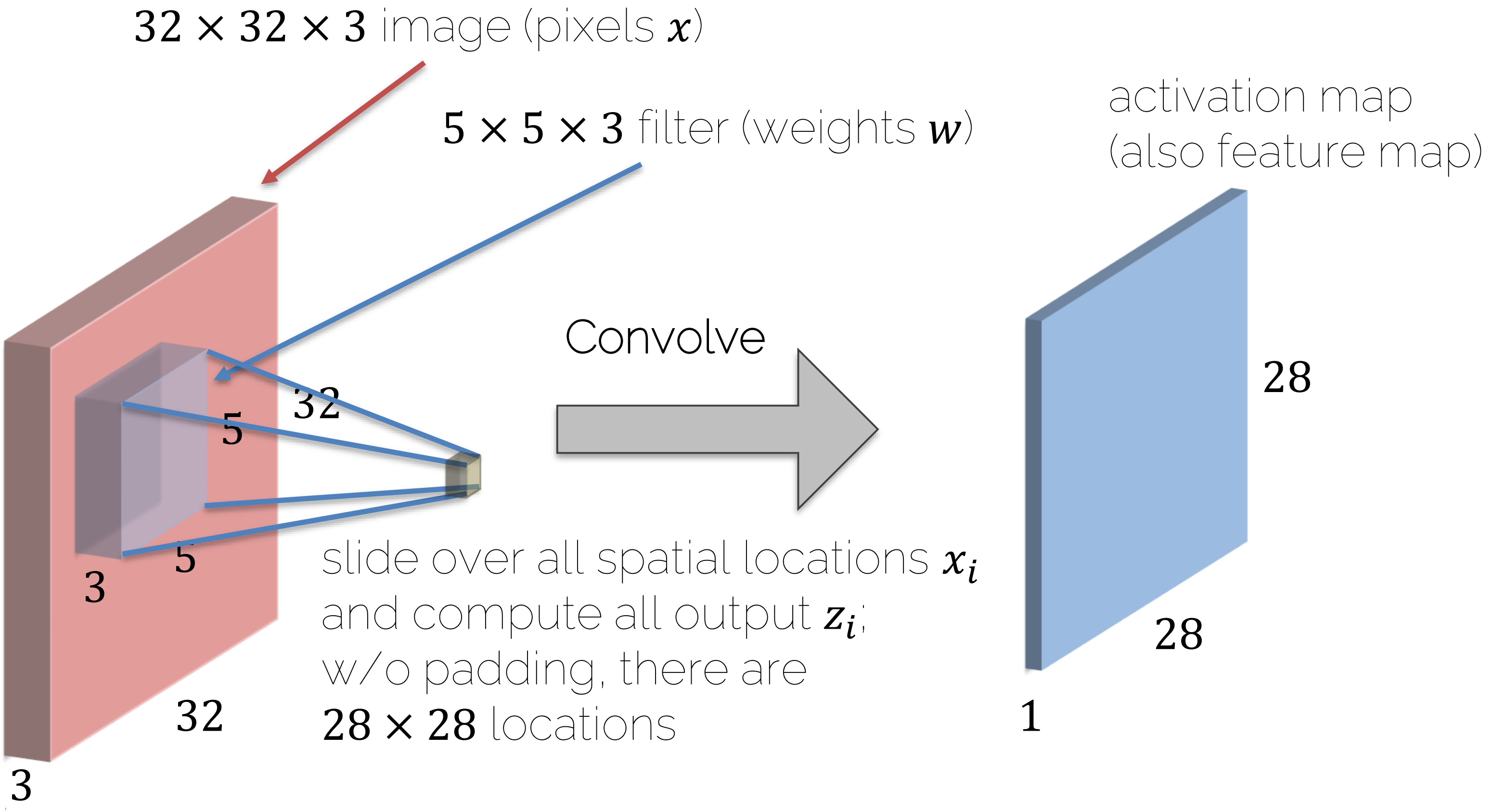
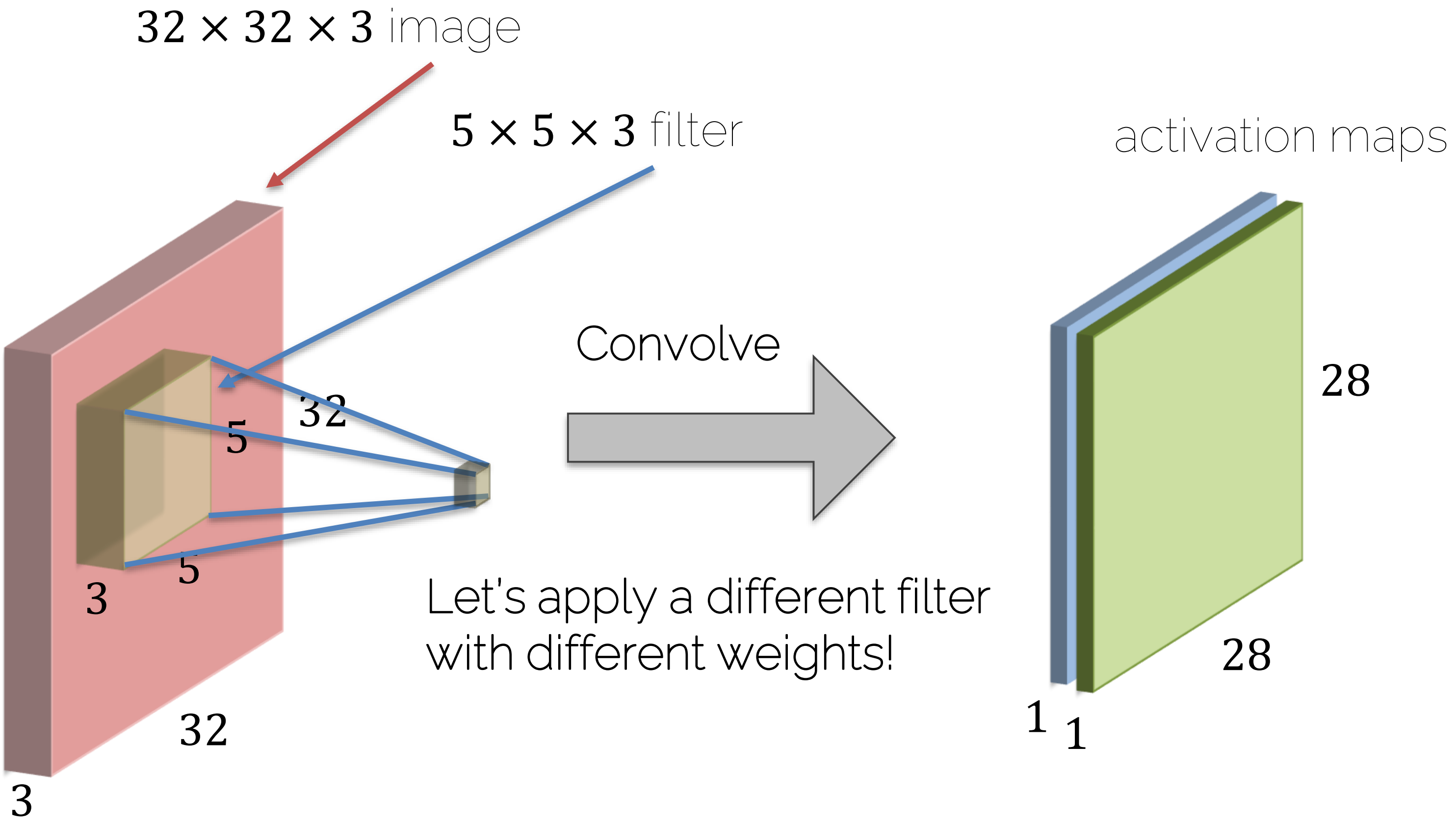
CNN Architectures

Convolutions on RGB Images



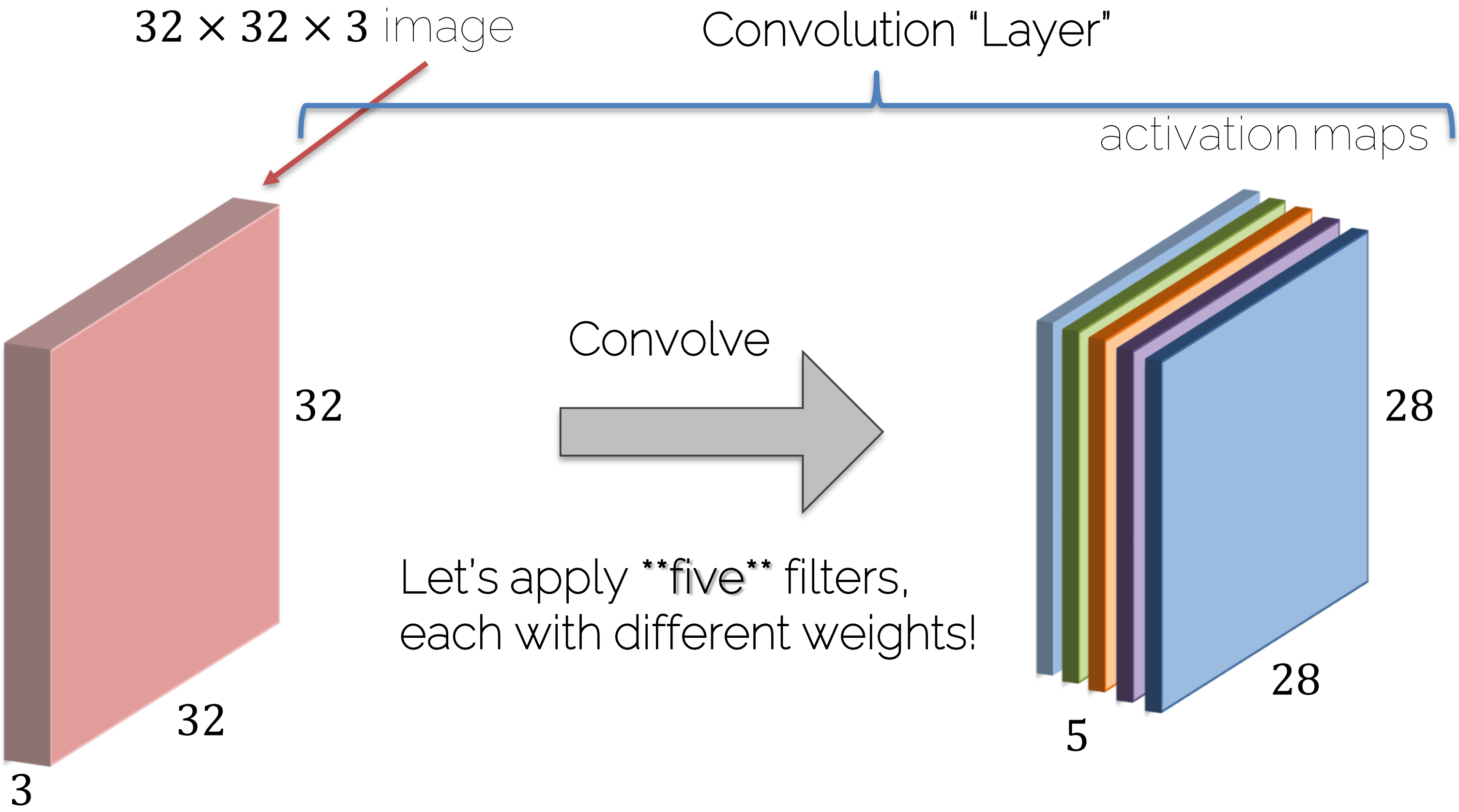
slide over all spatial locations $\boldsymbol{x}_i$ and compute all output $\boldsymbol{z}_i$;
w/o padding, there are 28×28 locations

Convolution Layer



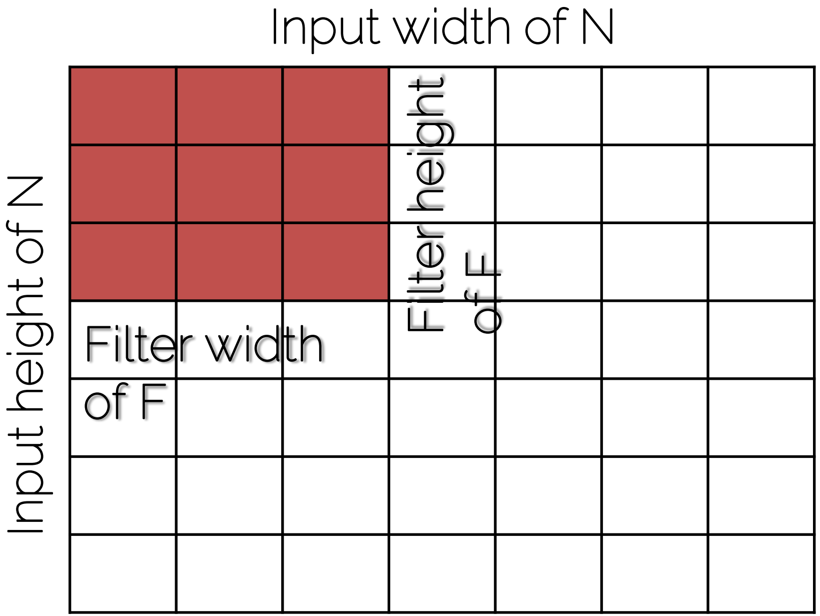
Let's apply a different filter with different weights!

Convolution Layer



Let's apply **five** filters,
each with different weights!

Convolution Layers: Dimensions



Input: $N \times N$
Filter: $F \times F$
Stride: S
Output: $\left(\frac{N-F}{S}+1\right) \times \left(\frac{N-F}{S}+1\right)$

$$N=7, F=3, S=1: \quad \frac{7-3}{1}+1=5$$

$$N=7, F=3, S=2: \quad \frac{7-3}{2}+1=3$$

$$N=7, F=3, S=3: \quad \frac{7-3}{3}+1=2.3333$$

Fractions are illegal

Convolution Layers: Padding

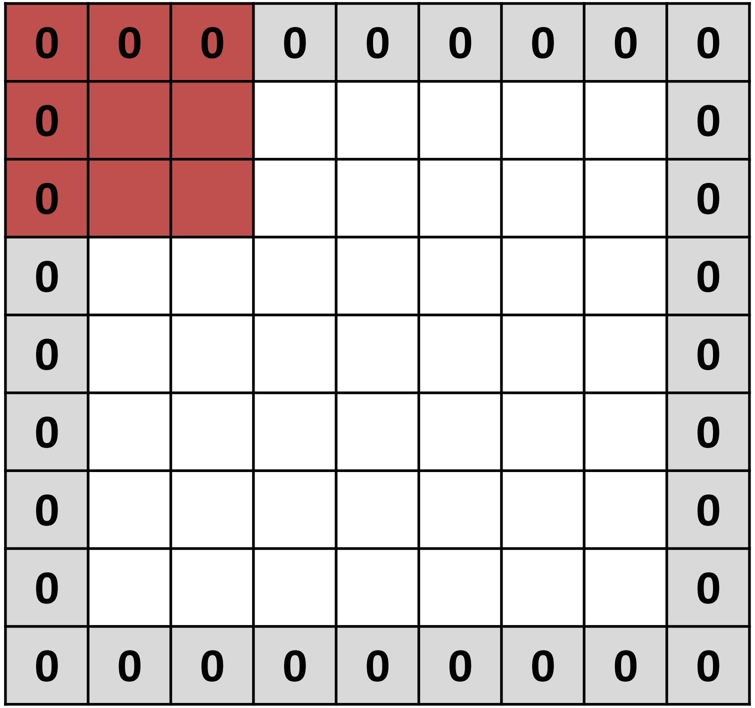


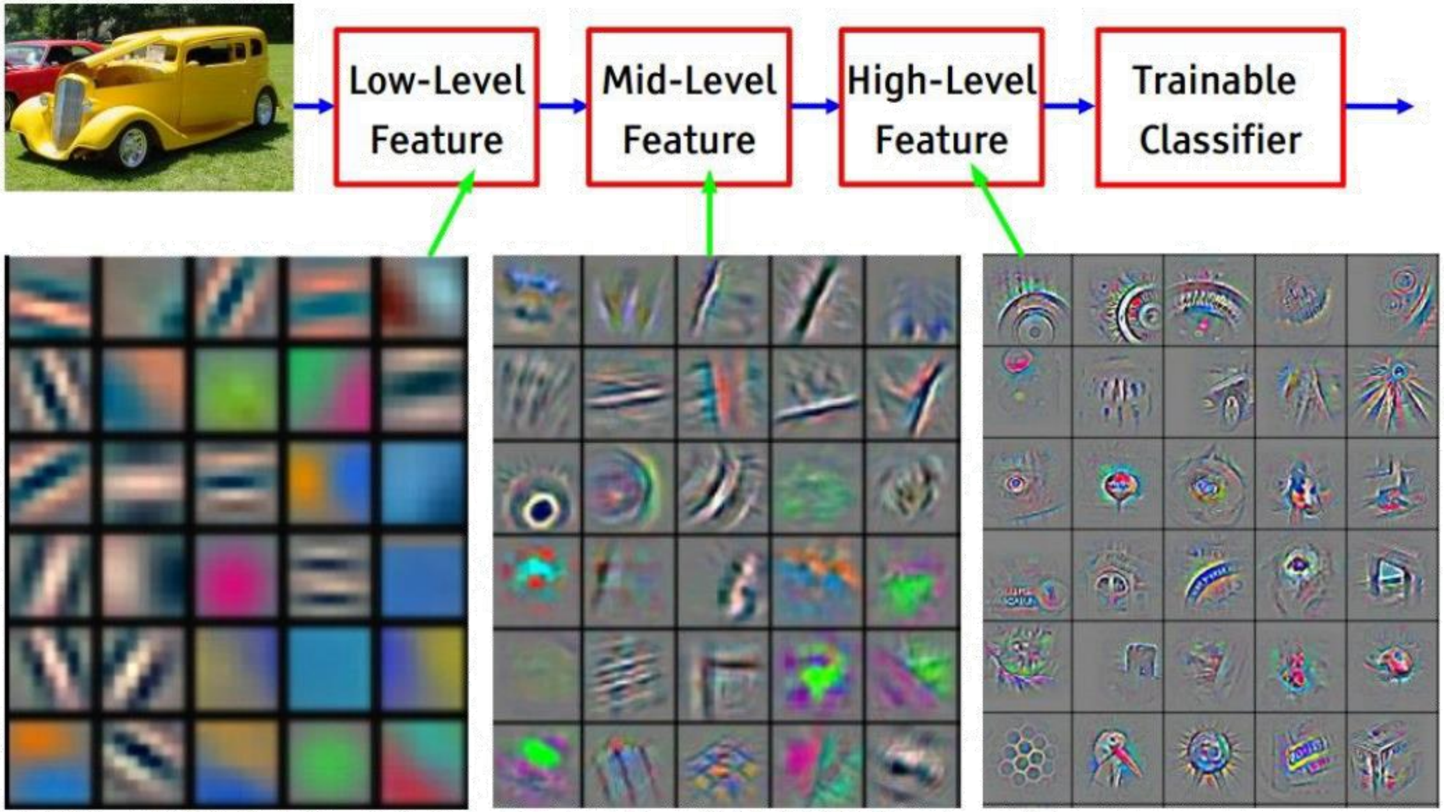
Image 7x7 + zero padding

Types of convolutions:

- **Valid** convolution: using no padding
- **Same** convolution: output=input size

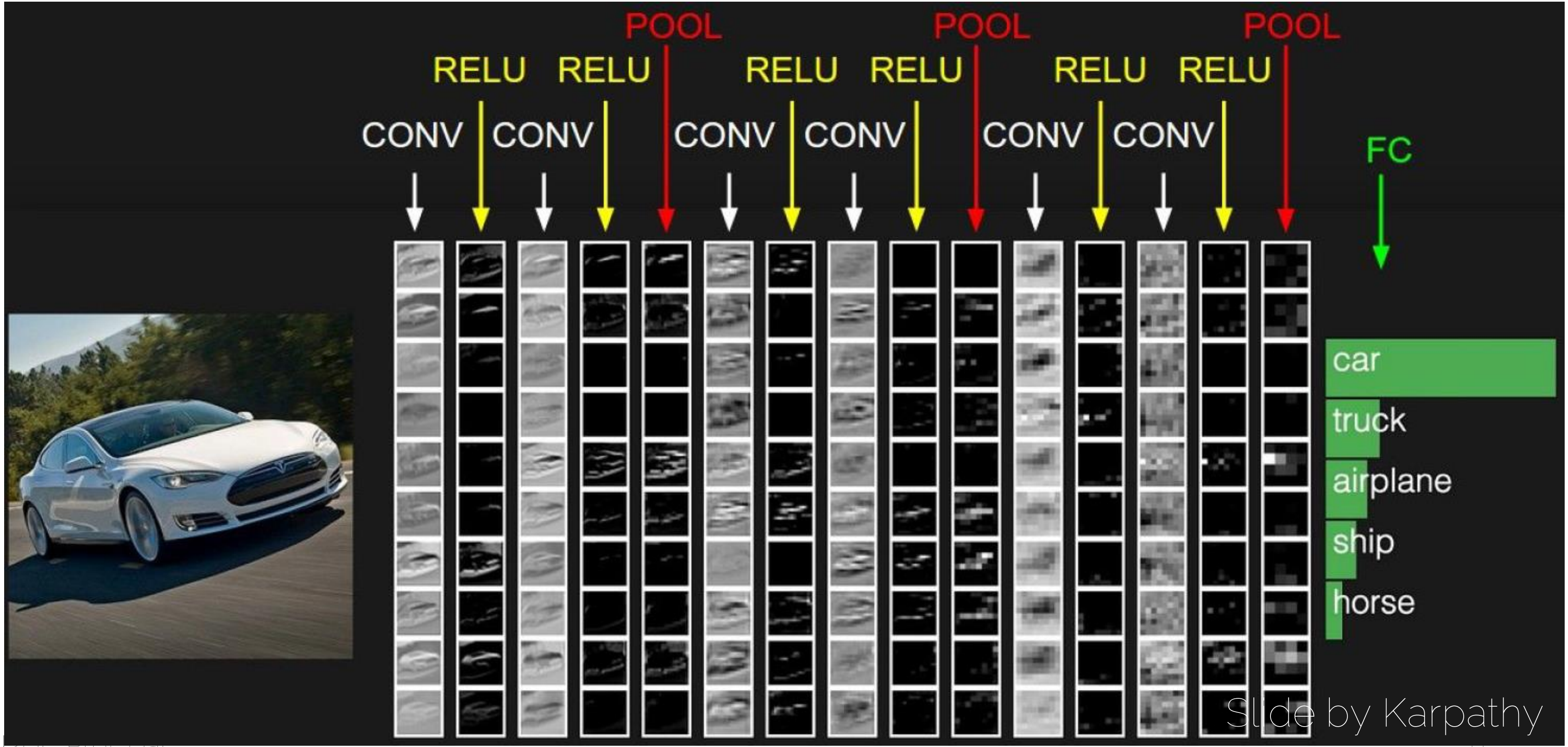
Set padding to $P = \frac{F-1}{2}$

CNN Learned Filters



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

CNN Prototype



Classic Architectures

LeNet

- Digit recognition: 10 classes

$32 \times 32 \times 1$

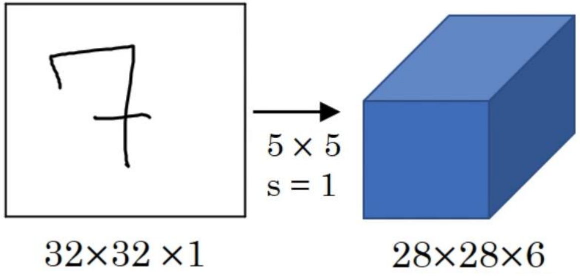
Input: 32×32 grayscale images

This one: Labeled as class "7"

[LeCun et al. '98] LeNet

LeNet

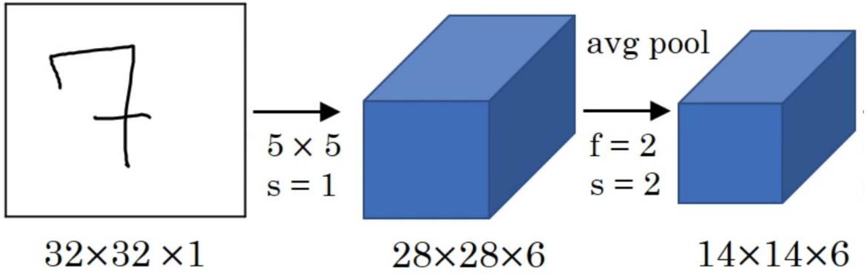
- Digit recognition: 10 classes



- Valid convolution: size shrinks
- How many conv filters are there in the first layer?

LeNet

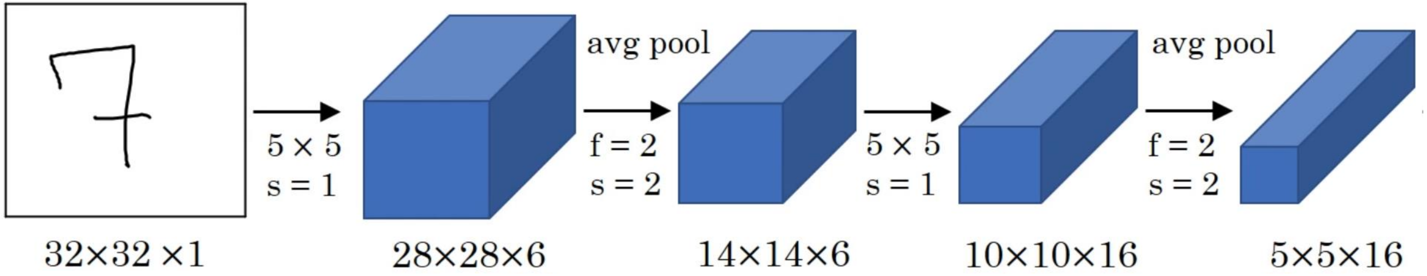
- Digit recognition: 10 classes



- At that time average pooling was used, now max pooling is much more common

LeNet

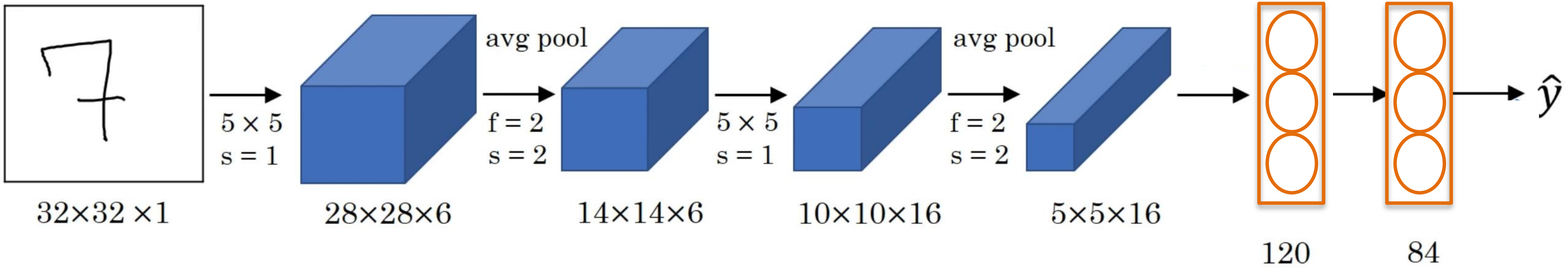
- Digit recognition: 10 classes



- Again valid convolutions, how many filters?

LeNet

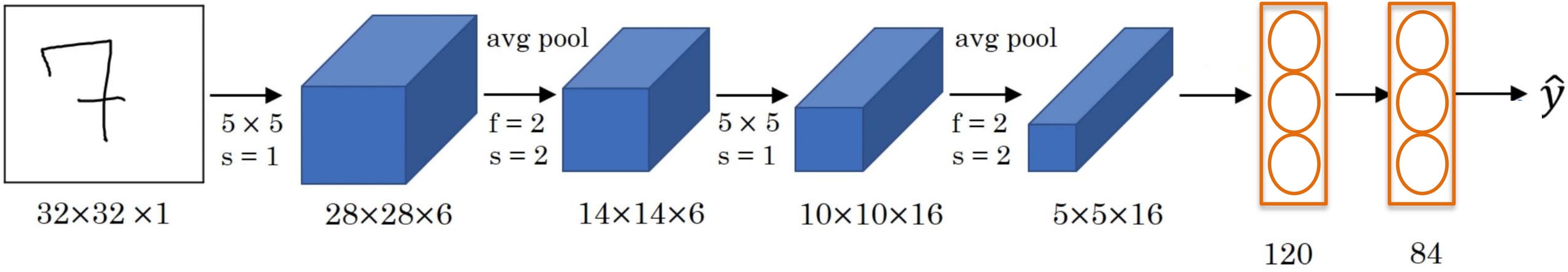
- Digit recognition: 10 classes



- Use of tanh/sigmoid activations → not common now!

LeNet

- Digit recognition: 10 classes

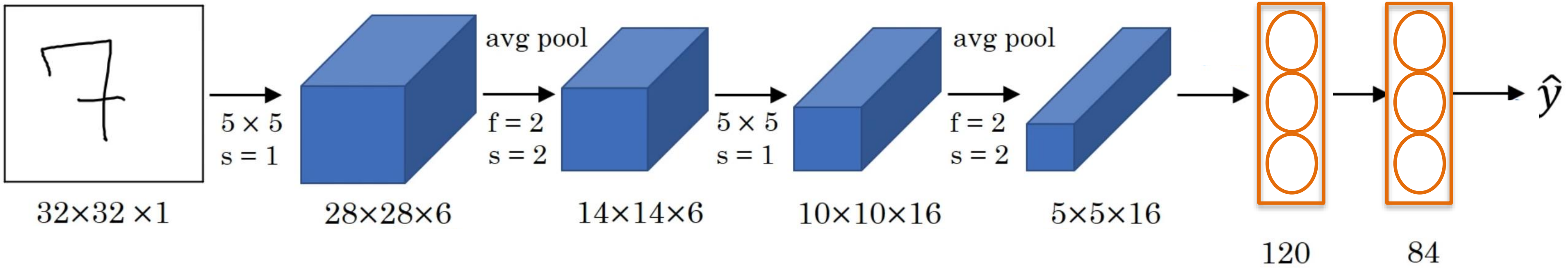


- Conv -> Pool -> Conv -> Pool -> Conv -> FC

LeNet

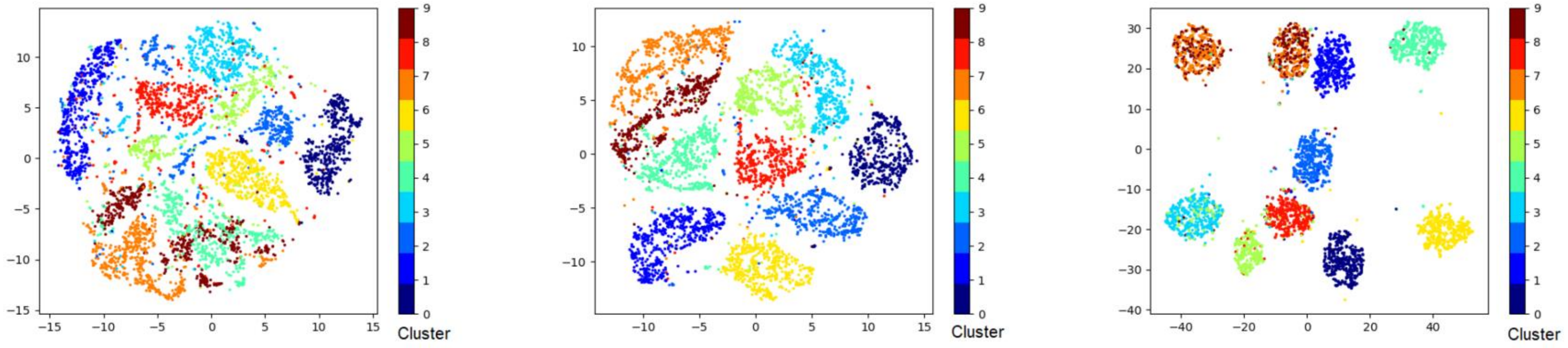
- Digit recognition: 10 classes

60k parameters



- Conv -> Pool -> Conv -> Pool -> Conv -> FC
- As we go deeper: Width, Height ↓ Number of Filters ↑

Deep Neural Clustering



(a) k-Means (b) Autoencoder + k-Means (c) Proposed

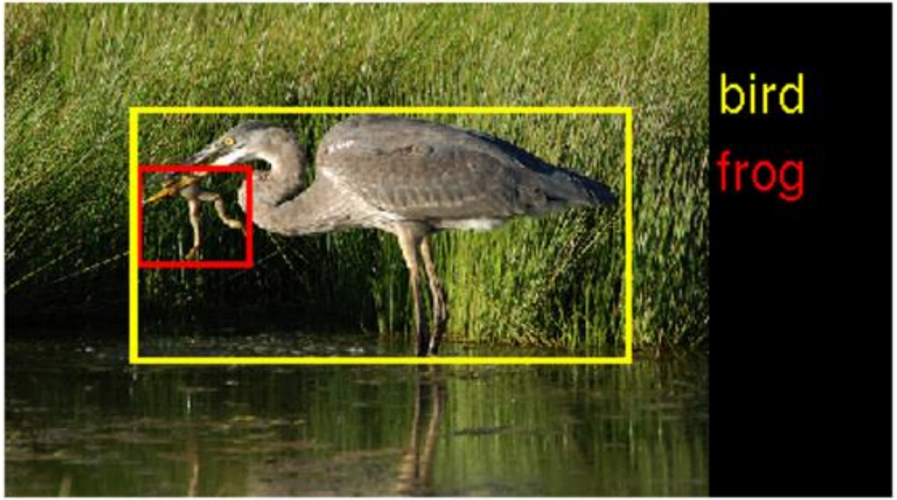
- Today MNIST is considered an easy classification problem.
- It can be solved (almost perfectly) without supervision as a clustering problem, where clustering is performed not in input space (a), but in the latent space of a deep network (b,c).

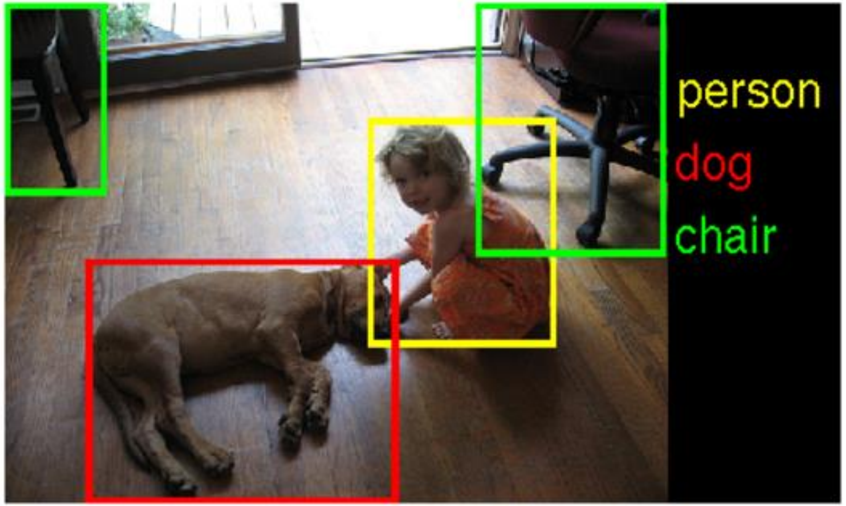
Aljalbout, Golkov, Siddiqui, Strobel, Cremers, "Clustering with Deep Learning: Taxonomy and New Methods", arxiv 2018.
Haeusser, Golkov, Aljalbout, Cremers, "Associative Deep Clustering: Training a Classification Network with no Labels", GCPR 2018.

Test Benchmarks

- ImageNet Dataset:

  ImageNet Large Scale Visual Recognition Competition (ILSVRC)





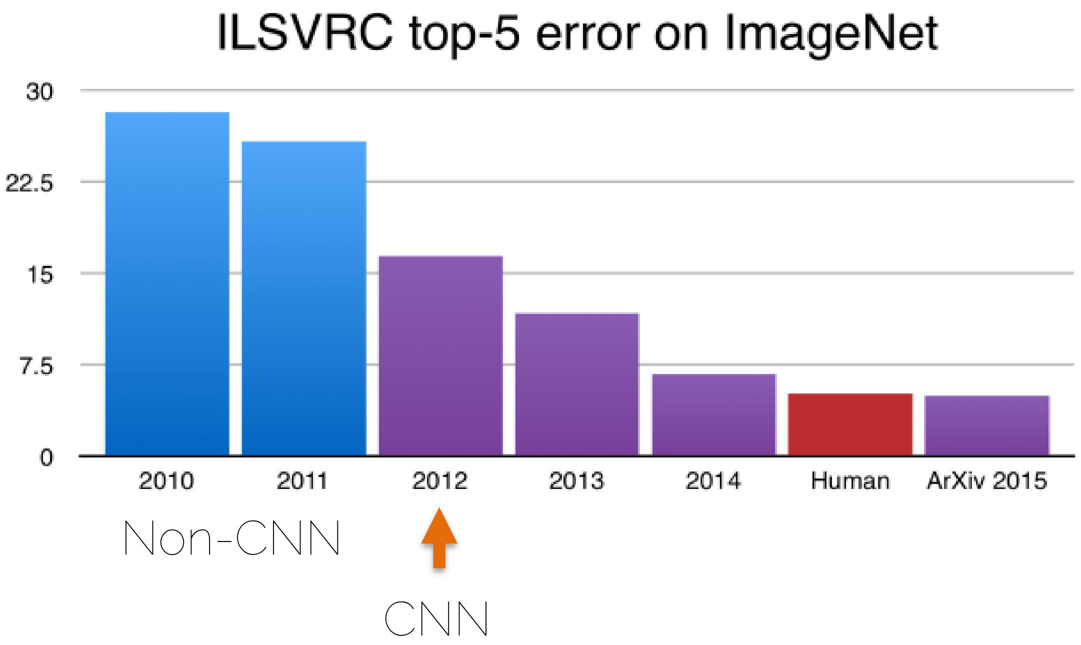
[Russakovsky et al., IJCV'15] "ImageNet Large Scale Visual Recognition Challenge."

Common Performance Metrics

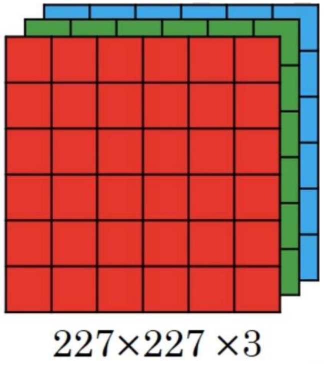
- Top-1 score: check if a sample's top class (i.e. the one with highest probability) is the same as its target label
- Top-5 score: check if your label is in your 5 first predictions (i.e. predictions with 5 highest probabilities)
- → Top-5 error: percentage of test samples for which the correct class was not in the top 5 predicted classes

AlexNet

- Cut ImageNet error down in half

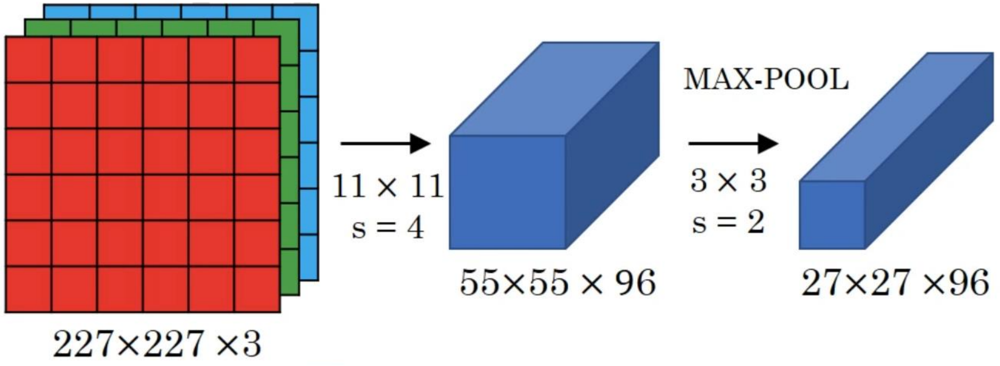


AlexNet



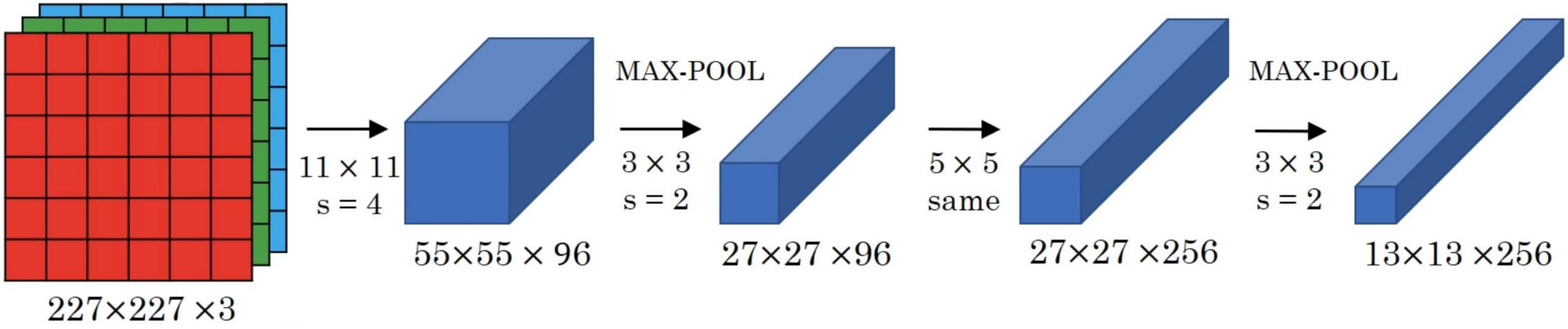
[Krizhevsky et al. NIPS'12] AlexNet

AlexNet



[Krizhevsky et al. NIPS'12] AlexNet

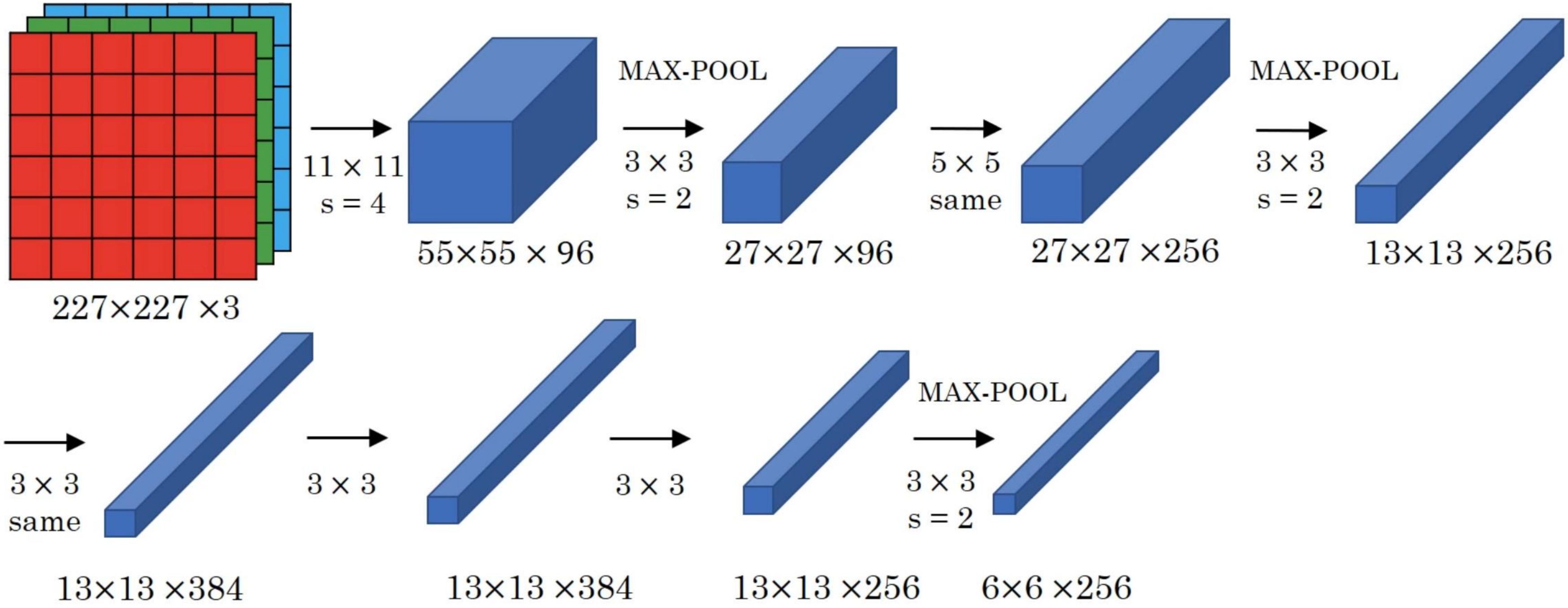
AlexNet



- Use of same convolutions
- As with LeNet: Width, Height ↓ Number of Filters ↑

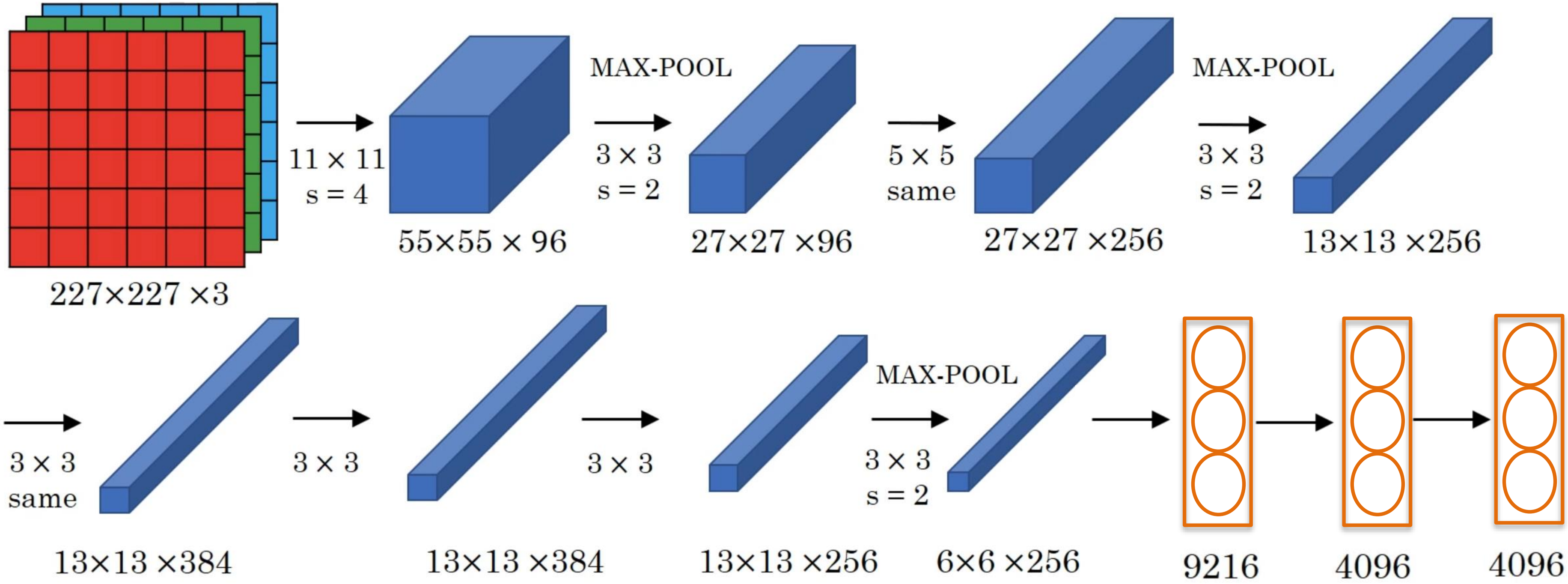
[Krizhevsky et al. NIPS'12] AlexNet

AlexNet



[Krizhevsky et al. NIPS'12] AlexNet

AlexNet



- Softmax for 1000 classes

[Krizhevsky et al. NIPS'12] AlexNet

AlexNet

- Similar to LeNet but much bigger (~1000 times)

- Use of ReLU instead of tanh/sigmoid

$\boxed{\text{60M parameters}}$

[Krizhevsky et al. NIPS'12] AlexNet

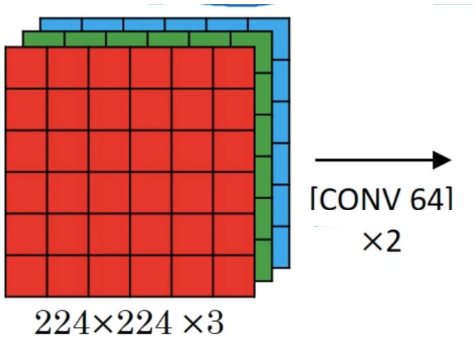
VGGNet

- Striving for simplicity
- CONV = 3x3 filters with stride 1, same convolutions
- MAXPOOL = 2x2 filters with stride 2

[Simonyan and Zisserman ICLR'15] VGGNet

VGGNet

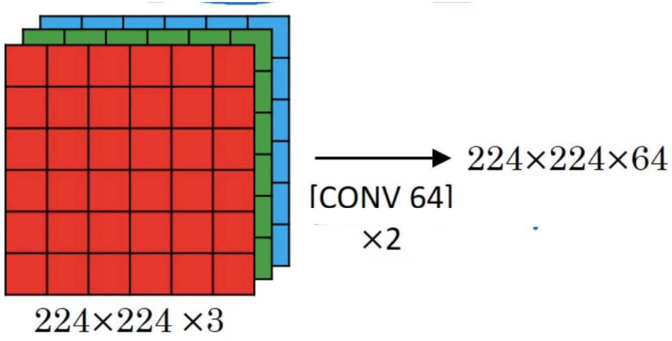
Conv=3x3,s=1,same
Maxpool=2x2,s=2



[Simonyan and Zisserman ICLR'15] VGGNet

VGGNet

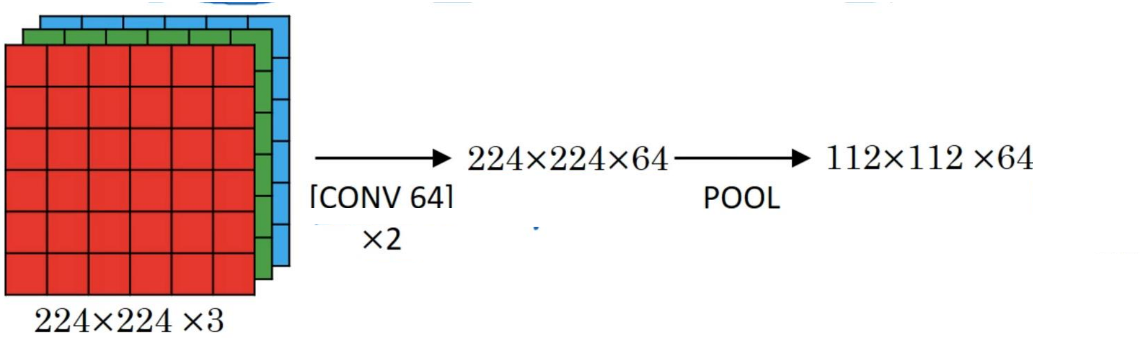
Conv=3x3,s=1,same
Maxpool=2x2,s=2



[Simonyan and Zisserman ICLR'15] VGGNet

VGGNet

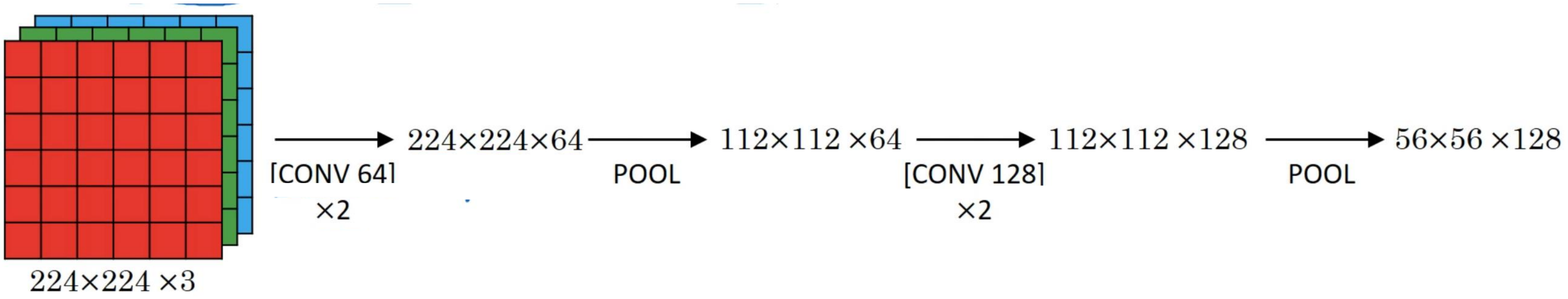
Conv=3x3,s=1,same
Maxpool=2x2,s=2



[Simonyan and Zisserman ICLR'15] VGGNet

VGGNet

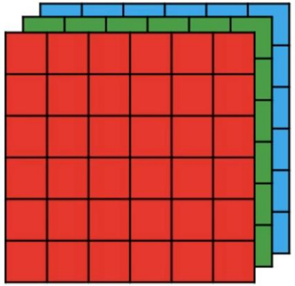
Conv=3x3,s=1,same
Maxpool=2x2,s=2



[Simonyan and Zisserman ICLR'15] VGGNet

VGGNet

Conv=3x3,s=1,same
Maxpool=2x2,s=2



224×224 ×3

→ [CONV 64] ×2 → 224×224×64 → POOL → 112×112 ×64 → [CONV 128] ×2 → 112×112 ×128 → POOL → 56×56 ×128

→ [CONV 256] ×3 → 56×56 ×256 → POOL → 28×28 ×256 → [CONV 512] × 3 → 28×28 ×512 → POOL → 14×14×512

→ [CONV 512] ×3 → 14×14 ×512 → POOL → 7×7×512 → FC 4096 → FC 4096 → Softmax 1000

[Simonyan and Zisserman ICLR'15] VGGNet

VGGNet

- Conv -> Pool -> Conv -> Pool -> Conv -> FC
- As we go deeper: Width, Height ↓ Number of Filters ↑

- Called VGG-16: 16 layers that have weights

138M parameters

- Large but simplicity makes it appealing

[Simonyan and Zisserman ICLR'15] VGGNet

VGGNet

- A lot of architectures were analyzed

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					

[Simonyan and Zisserman 2014]

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

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

Skip Connections

The Problem of Depth

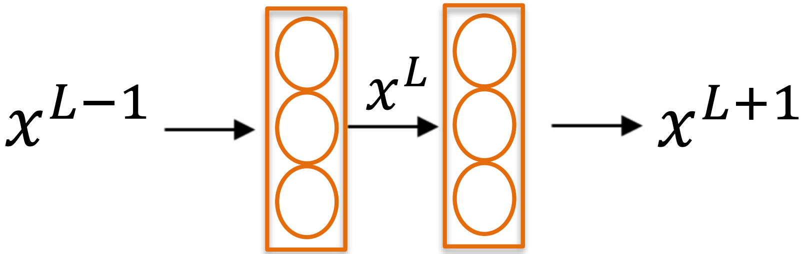
- As we add more and more layers, training becomes harder

- Vanishing and exploding gradients

- How can we train very deep nets?

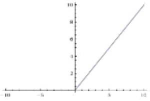
Residual Block

- Two layers



Input → $W^L x^{L-1} + b^L$ → $x^L = f(W^L x^{L-1} + b^L)$ →

Linear

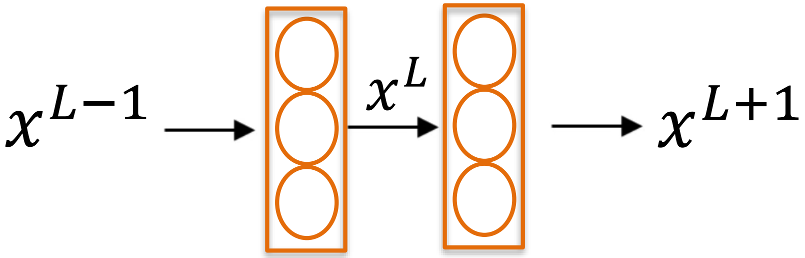


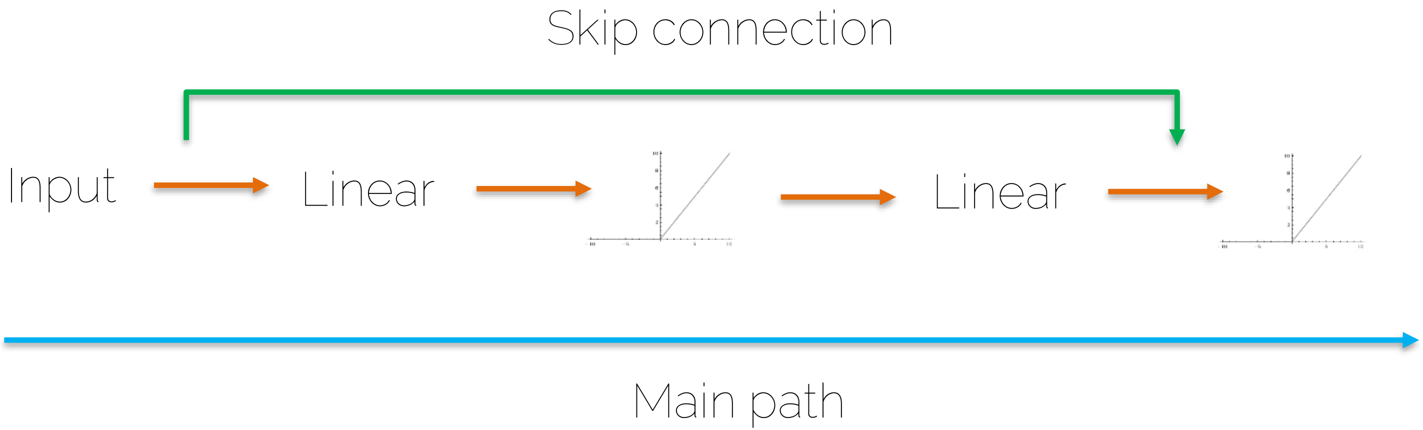
Non-linearity

→ $x^{L+1} = f(W^{L+1} x^L + b^{L+1})$

Residual Block

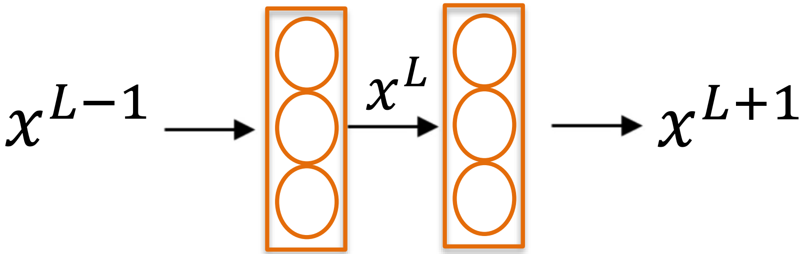
- Two layers



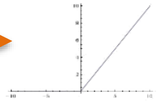
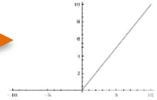


Residual Block

- Two layers



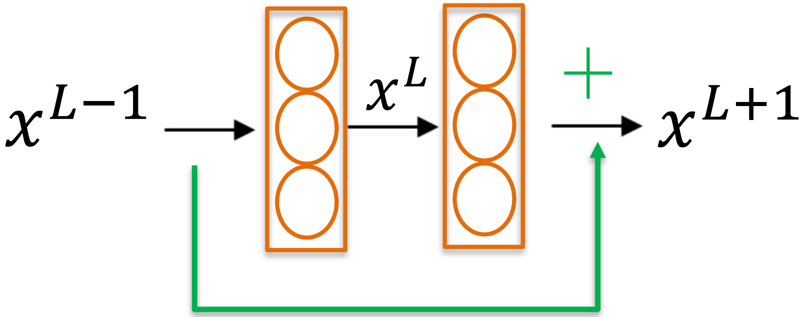
$$x^{L+1} = f(W^{L+1}x^{L} + b^{L+1} + x^{L-1})$$

Input → Linear →  → Linear → 

$$x^{L+1} = f(W^{L+1}x^{L} + b^{L+1})$$

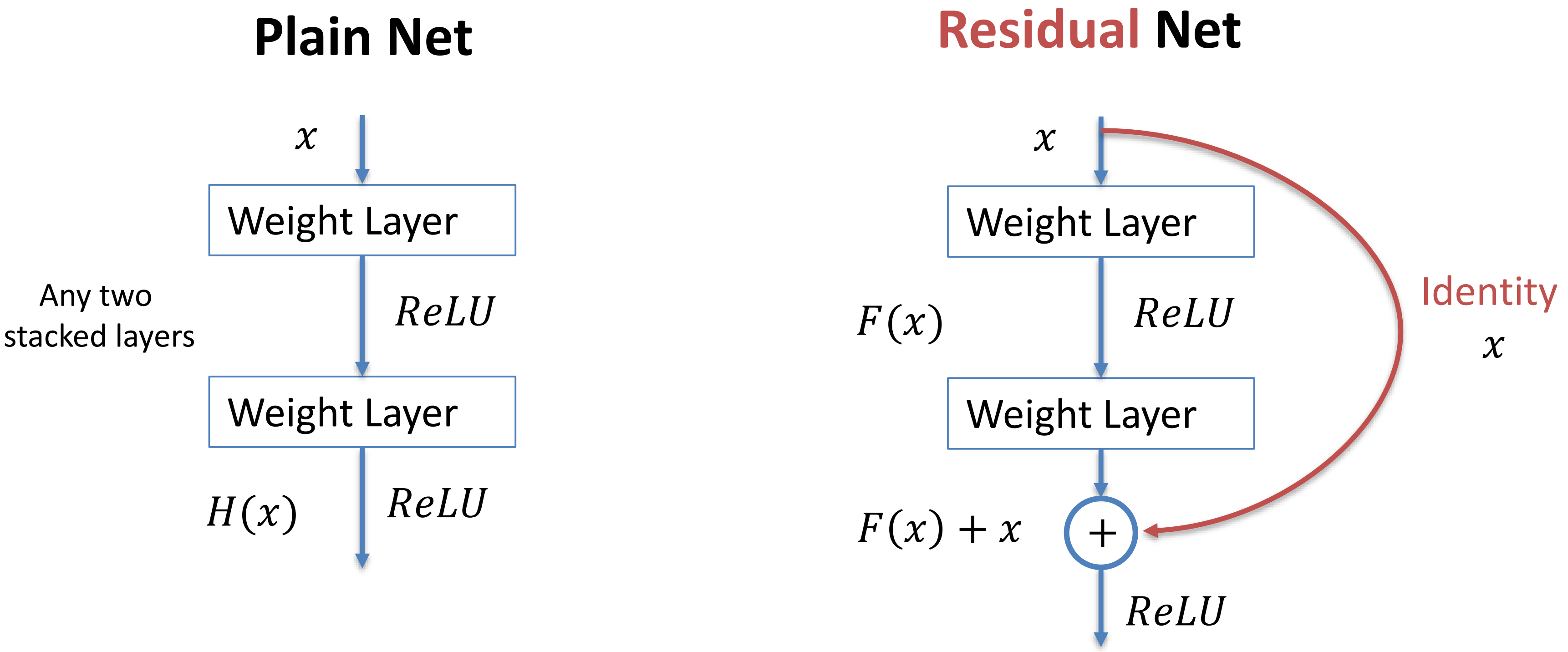
Residual Block

- Two layers



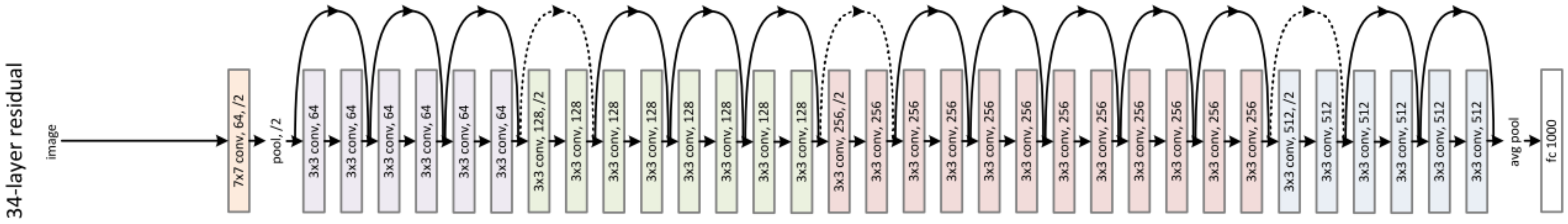
- Usually use a same convolution since we need same dimensions
- Otherwise we need to convert the dimensions with a matrix of learned weights or zero padding

ResNet Block



[He et al. CVPR'16] ResNet

ResNet



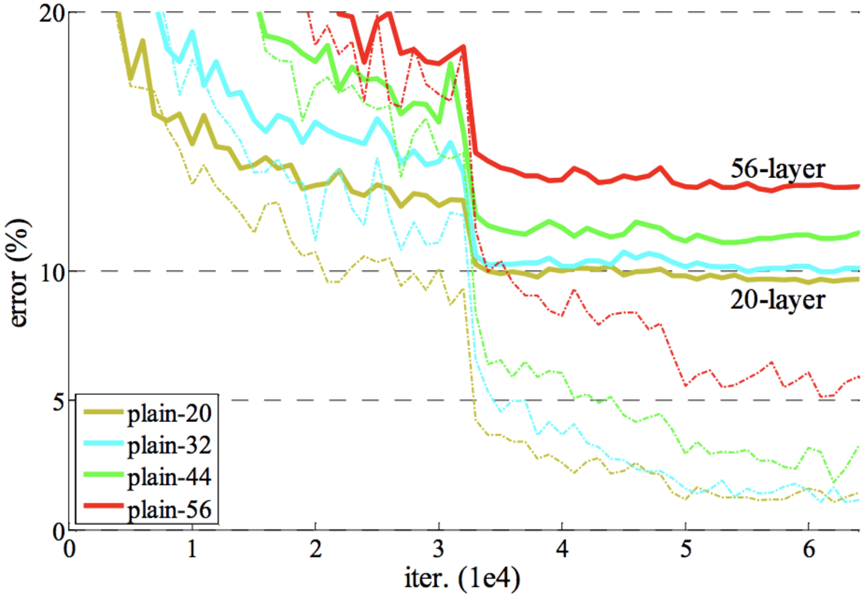
- Xavier/2 initialization
- SGD + Momentum (0.9)
- Learning rate 0.1, divided by 10 when plateau
- Mini-batch size 256
- Weight decay of 1e-5
- No dropout

ResNet-152:
60M parameters

[He et al. CVPR'16] ResNet

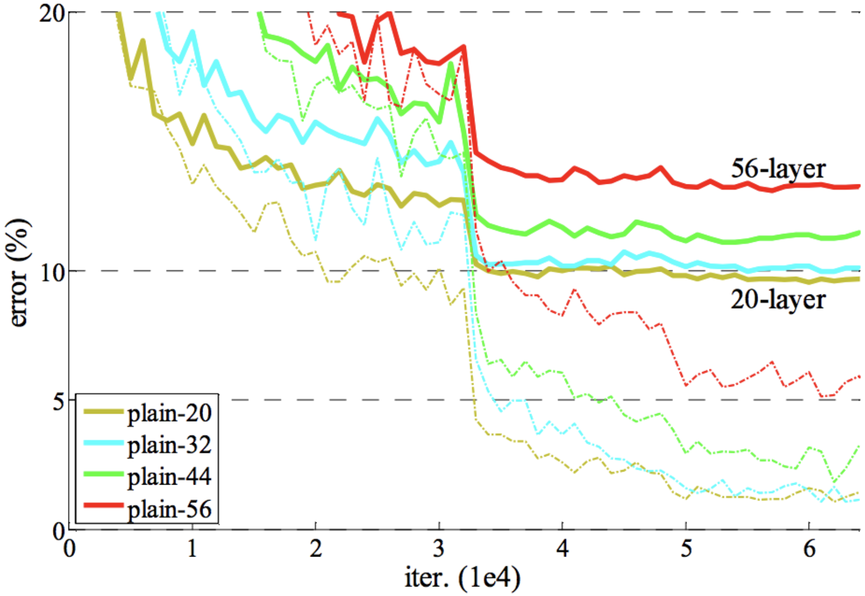
ResNet

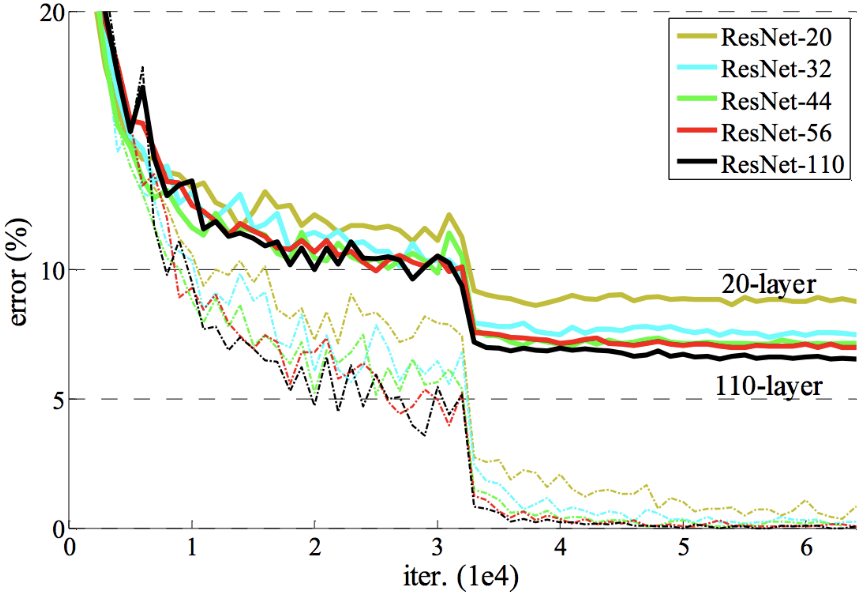
- Without ResNet, if we make the network deeper, at some point performance starts to degrade:



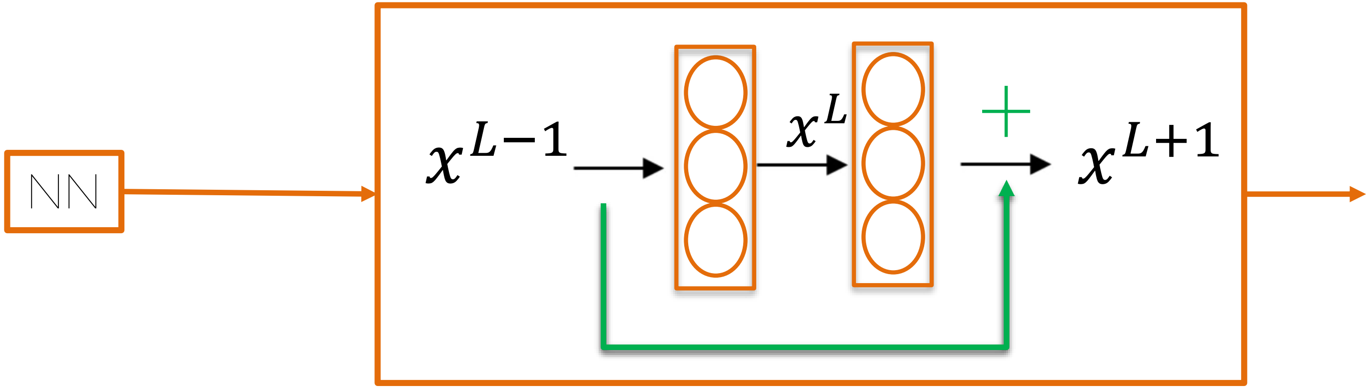
ResNet

- With Residual Blocks, performance gets better with deeper network:



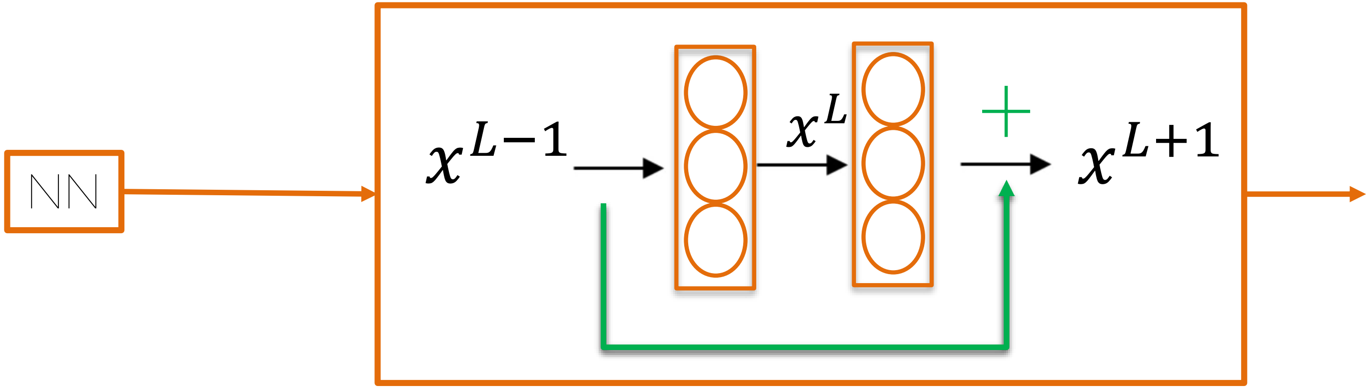


Why do ResNets Work?



- How is this block really affecting me?

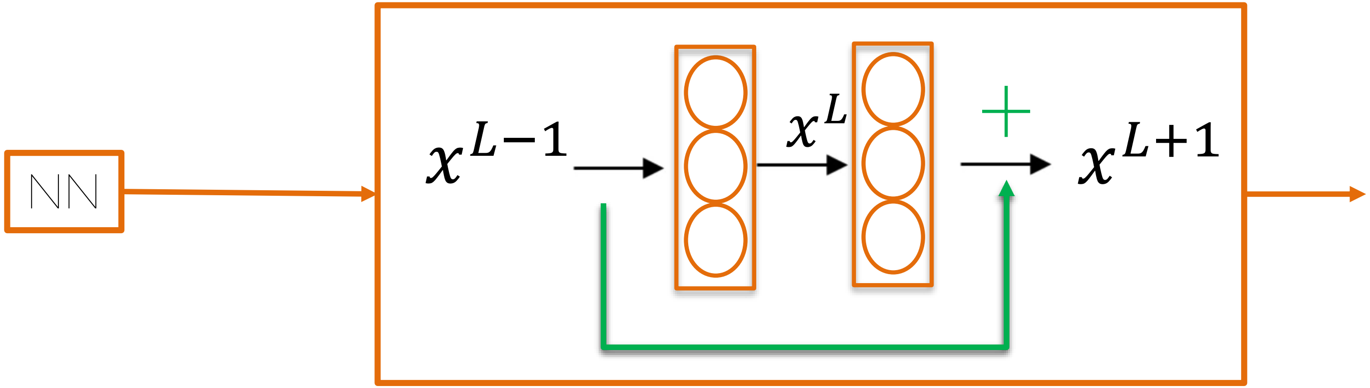
Why do ResNets Work?



$$x^{L+1} = f(\underbrace{W^{L+1}}_{\sim\text{zero}} x^L + \underbrace{b^{L+1}}_{\sim\text{zero}} + x^{L-1})$$

$$x^{L+1} = f(x^{L-1})$$

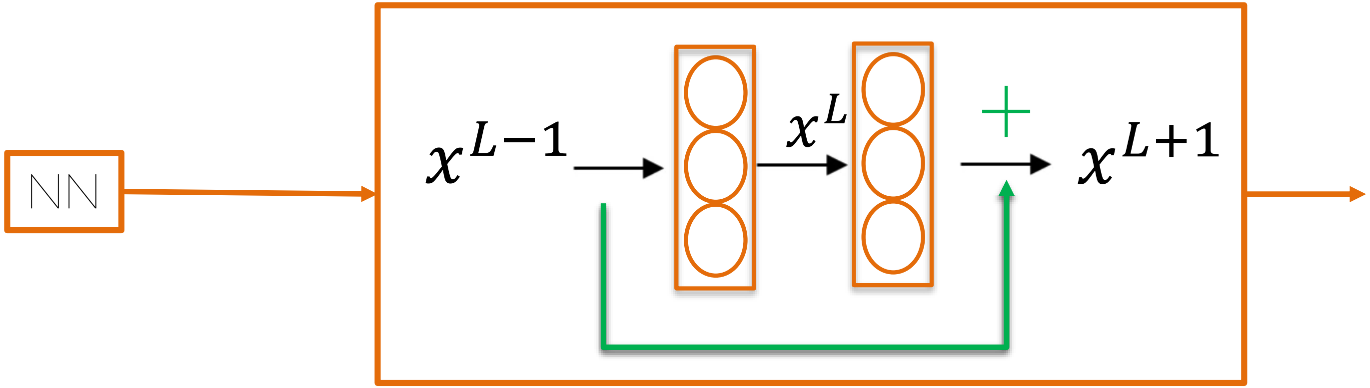
Why do ResNets Work?



- We kept the same values and added a non-linearity

$$x^{L+1} = f(x^{L-1})$$

Why do ResNets Work?



- The identity is easy for the residual block to learn
- Guaranteed it will not hurt performance, can only improve

1x1 Convolutions

Recall: Convolutions on Images

Image 5x5

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

Kernel 3x3

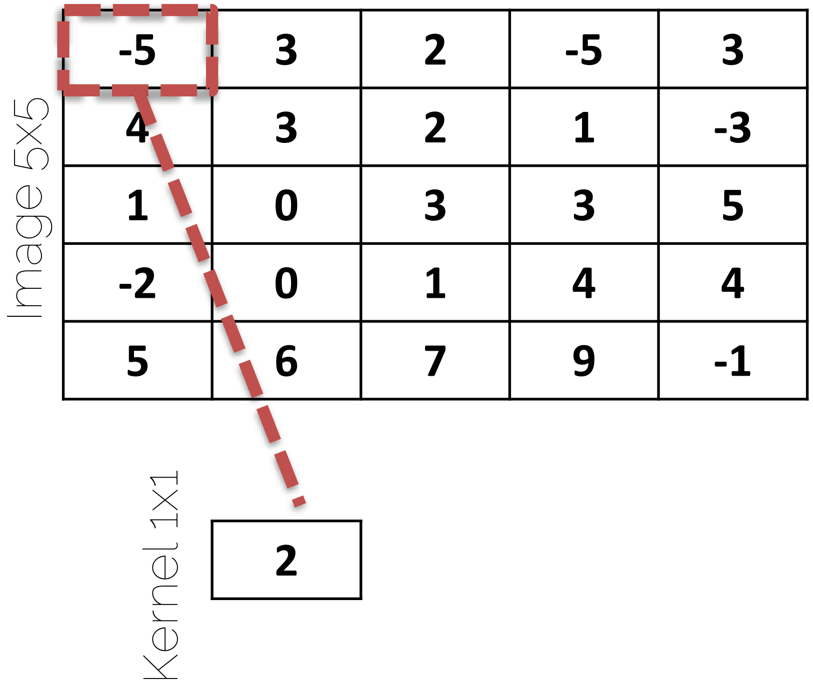
0	-1	0
-1	5	-1
0	-1	0

Output 3x3

6		

$$5 \cdot 3 + (-1) \cdot 3 + (-1) \cdot 2 + (-1) \cdot 0 + (-1) \cdot 4 =$$
$$15 - 9 = 6$$

1x1 Convolution



What is the output size?

1x1 Convolution

Image 5x5

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

-10				

Kernel 1x1

2

$$-5 * 2 = -10$$

1x1 Convolution

Image 5x5

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

-10	6	4	-10	6
8	6	4	2	-6
2	0	6	6	10
-4	0	2	8	8
10	12	14	18	-2

Kernel 1x1

2

$$-1 * 2 = -2$$

1x1 Convolution

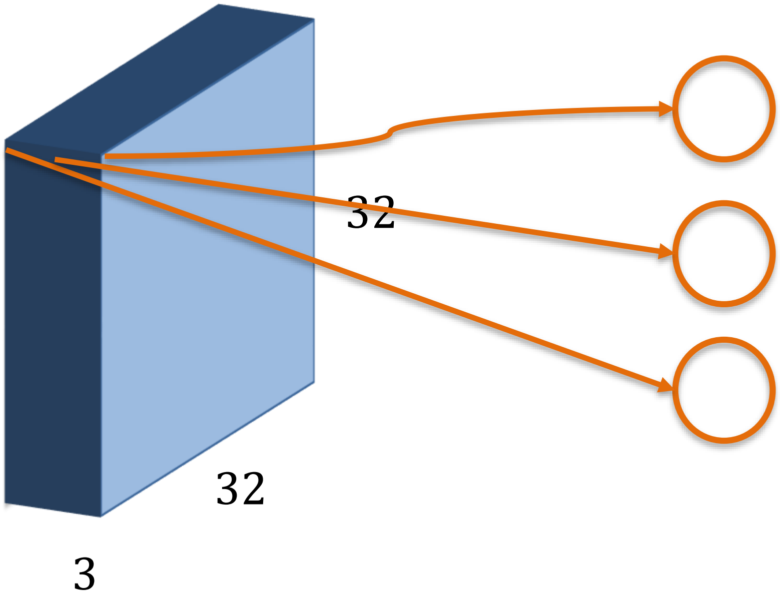
Image 5x5

-5	3	2	-5	3
4	3	2	1	-3
1	0	3	3	5
-2	0	1	4	4
5	6	7	9	-1

-10	6	4	-10	6
8	6	4	2	-6
2	0	6	6	10
-4	0	2	8	8
10	12	14	18	-2

- 1x1 kernel: keeps the dimensions and scales input

1x1 Convolution

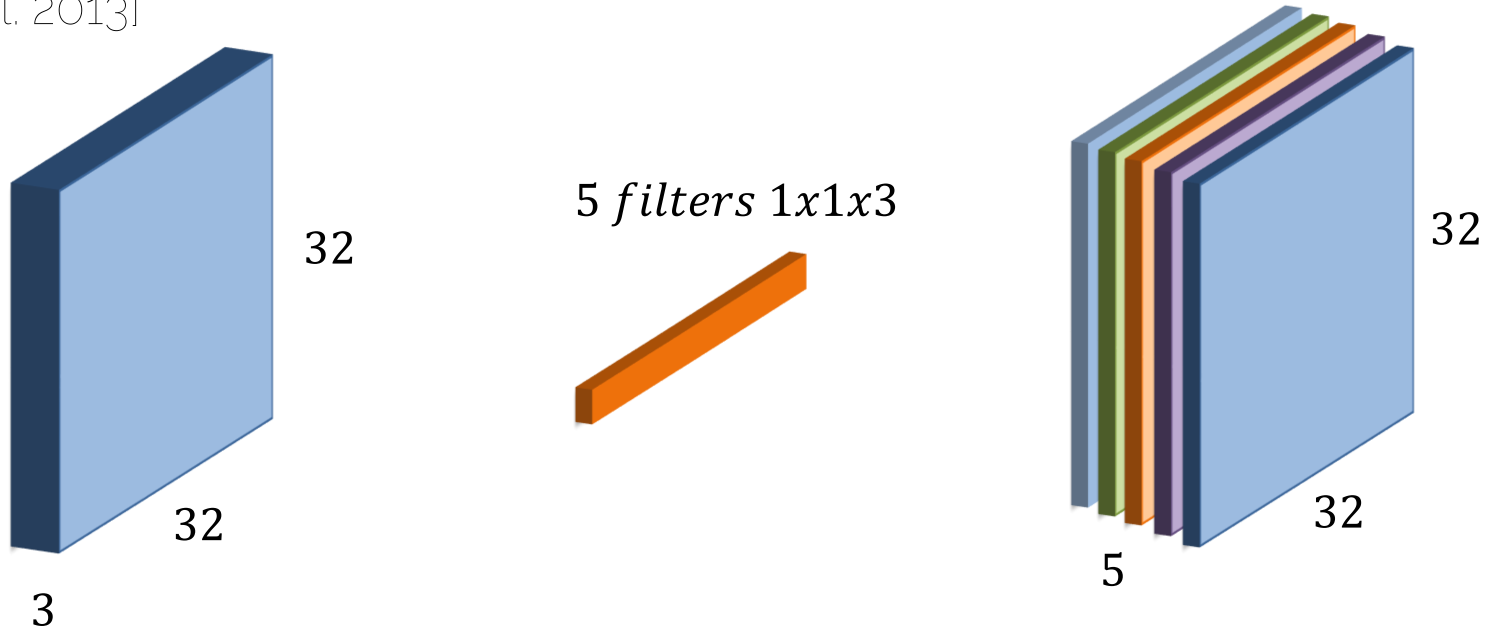


1 output

- Same as having a 3 neuron fully connected layer

1x1 Convolution

[Li et al. 2013]



- As always we use more convolutional filters

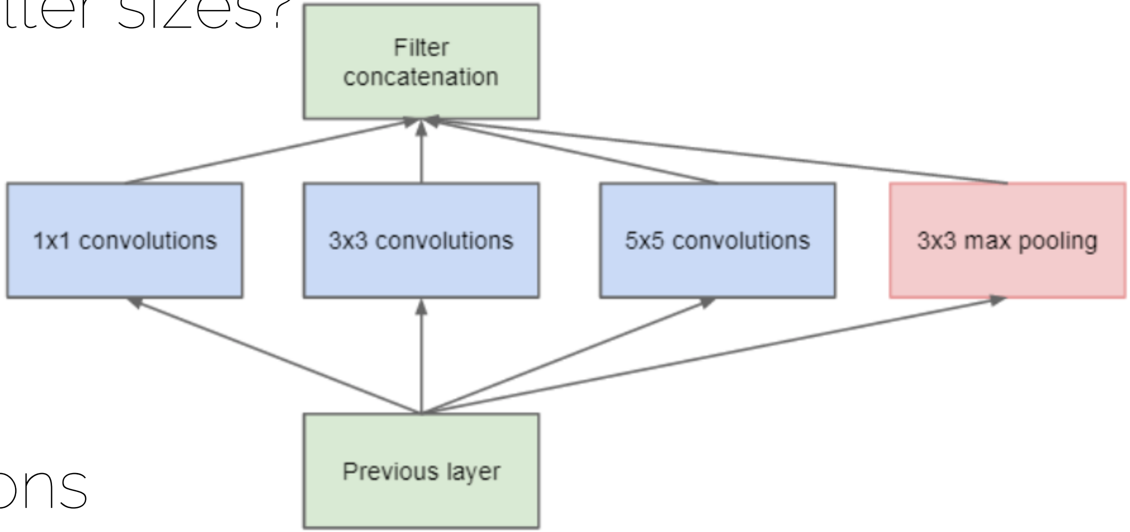
Using 1x1 Convolutions

- Use it to shrink the number of channels
- Further adds a non-linearity → one can learn more complex functions

Inception Layer

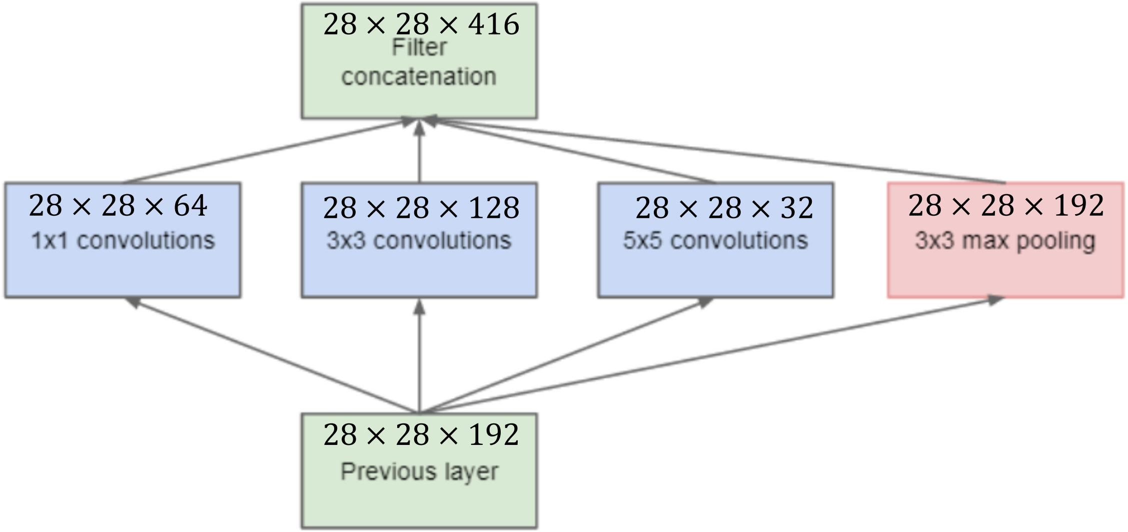
Inception Layer

- Tired of choosing filter sizes?
- Use them all!
- All same convolutions
- 3x3 max pooling is with stride 1



Inception Layer

- Possible size of the output



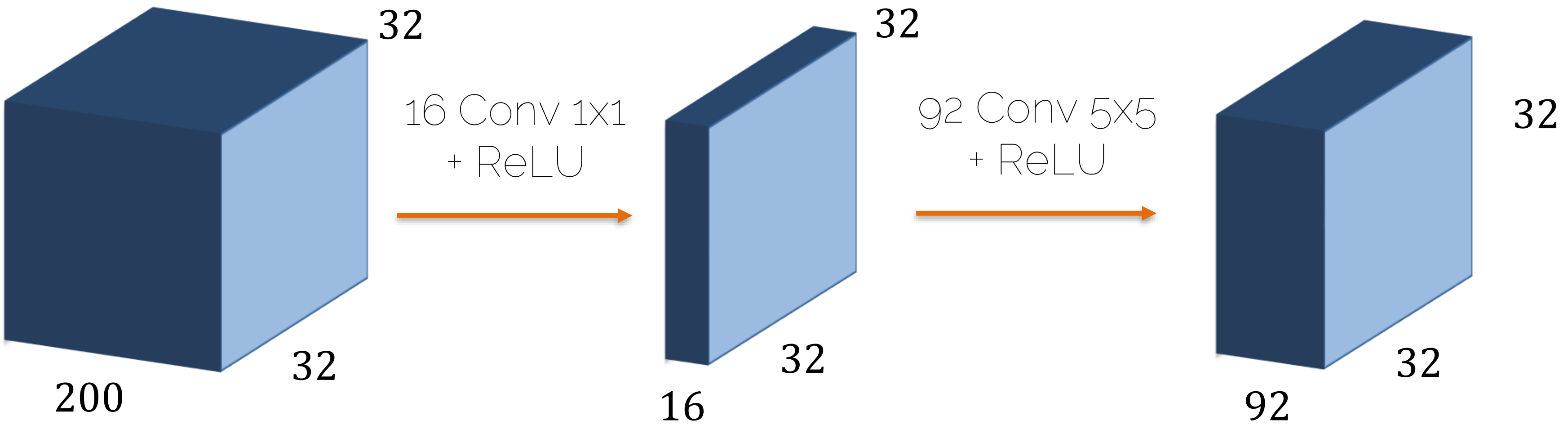
- Not sustainable!

Inception Layer: Computational Cost

Multiplications: 5x5x200 x 32x32x92 ~ 470 million

1 value of the output volume

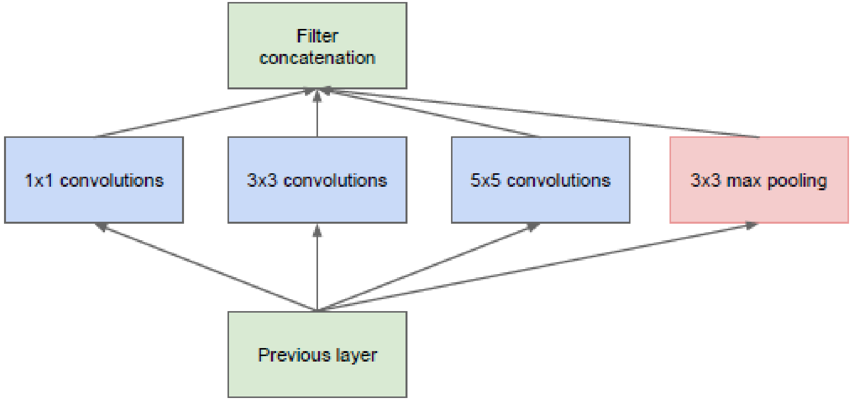
Inception Layer: Computational Cost



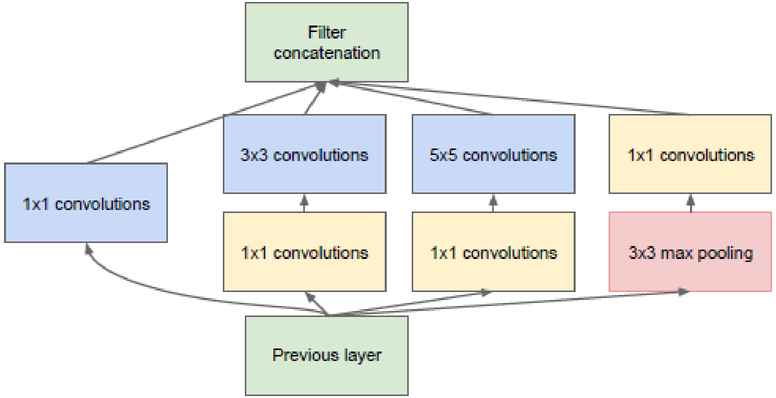
Multiplications: 1x1x200x32x32x16 5x5x16x32x32x92 ~ 40 million

Reduction of multiplications by 1/10

Inception Layer



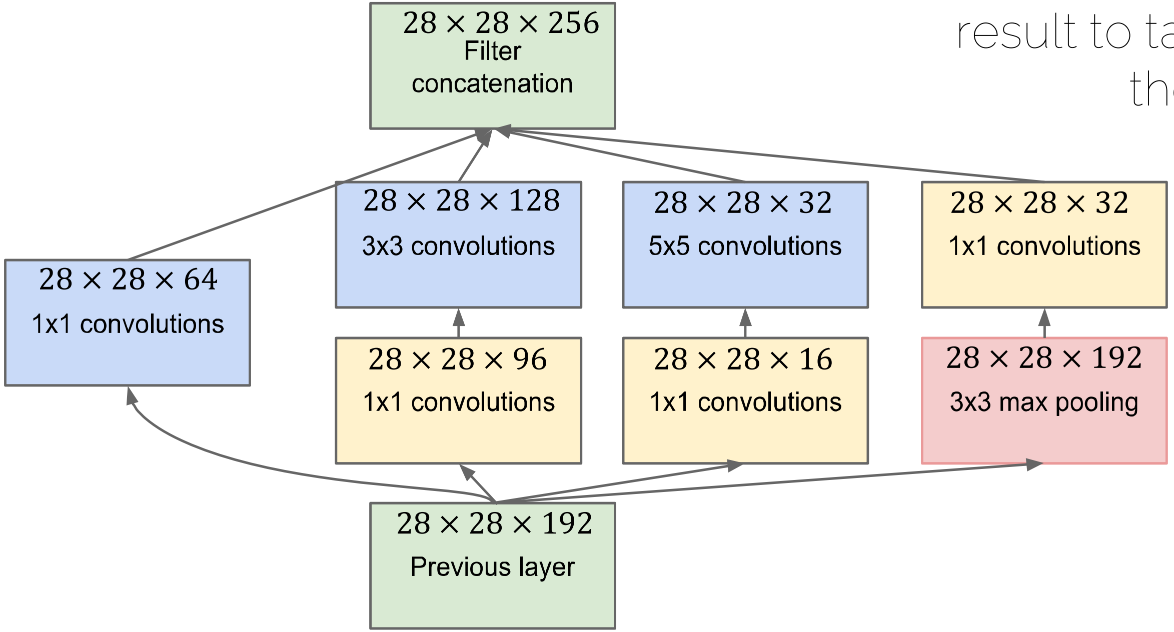
(a) Inception module, naïve version



(b) Inception module with dimensionality reduction

[Szegedy et al CVPR'15] GoogLeNet

Inception Layer: Dimensions

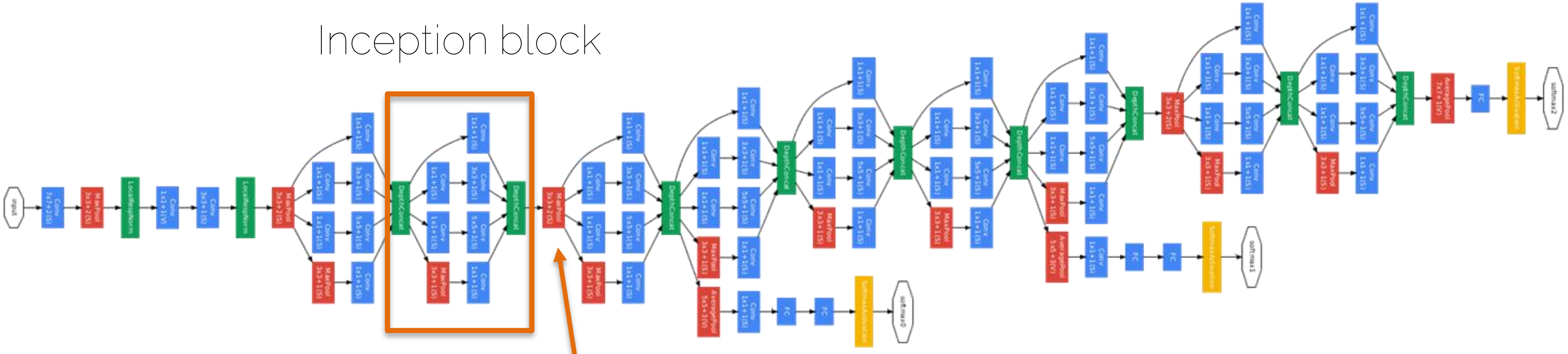


We do not want max pool result to take up almost all the output

[Szegedy et al CVPR'15] GoogLeNet

GoogLeNet: Using the Inception Layer

Inception block



Extra max pool layers to
reduce dimensionality

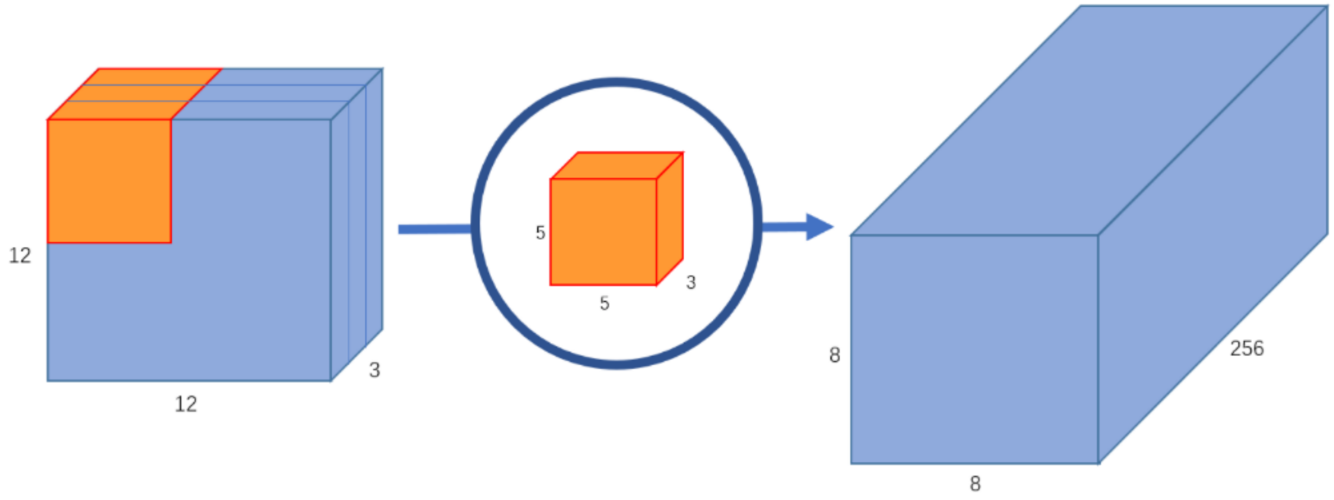
[Szegedy et al CVPR'15] GoogLeNet

Xception Net

- "Extreme version of Inception": applying (modified) Depthwise Separable Convolutions instead of normal convolutions
- 36 conv layers, structured into several modules with skip connections
- outperforms Inception Net V3

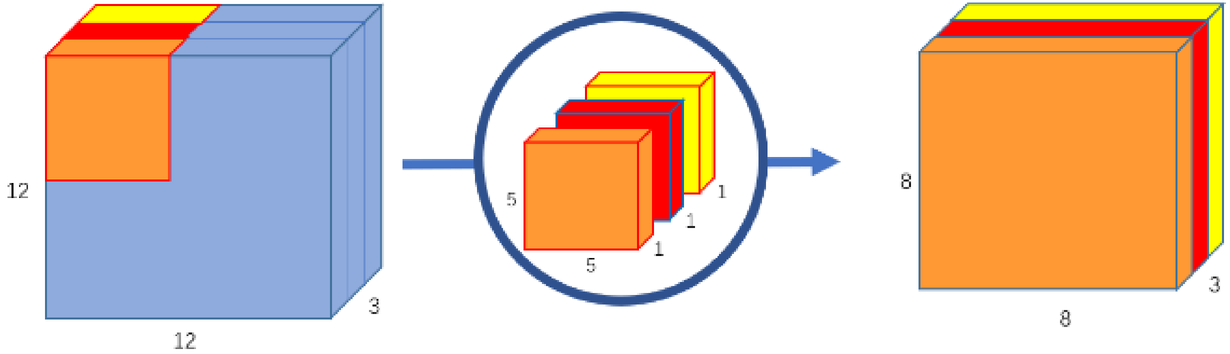
[Chollet CVPR'17] Xception

Depth-wise separable convolutions



Normal convolutions act on all channels.

Depth-wise separable convolutions

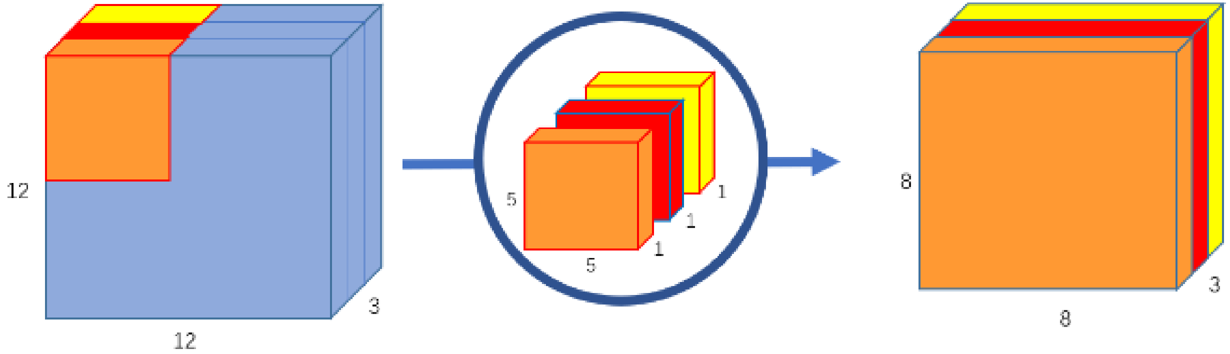


Filters are applied only at certain depths of the features. Normal convolutions have groups set to 1, the convolutions used in this image have groups set to 3.

class **`torch.nn.Conv2d`**(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, *groups=3*)

class **`torch.nn.ConvTranspose2d`**(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, *groups=3*)

Depth-wise separable convolutions

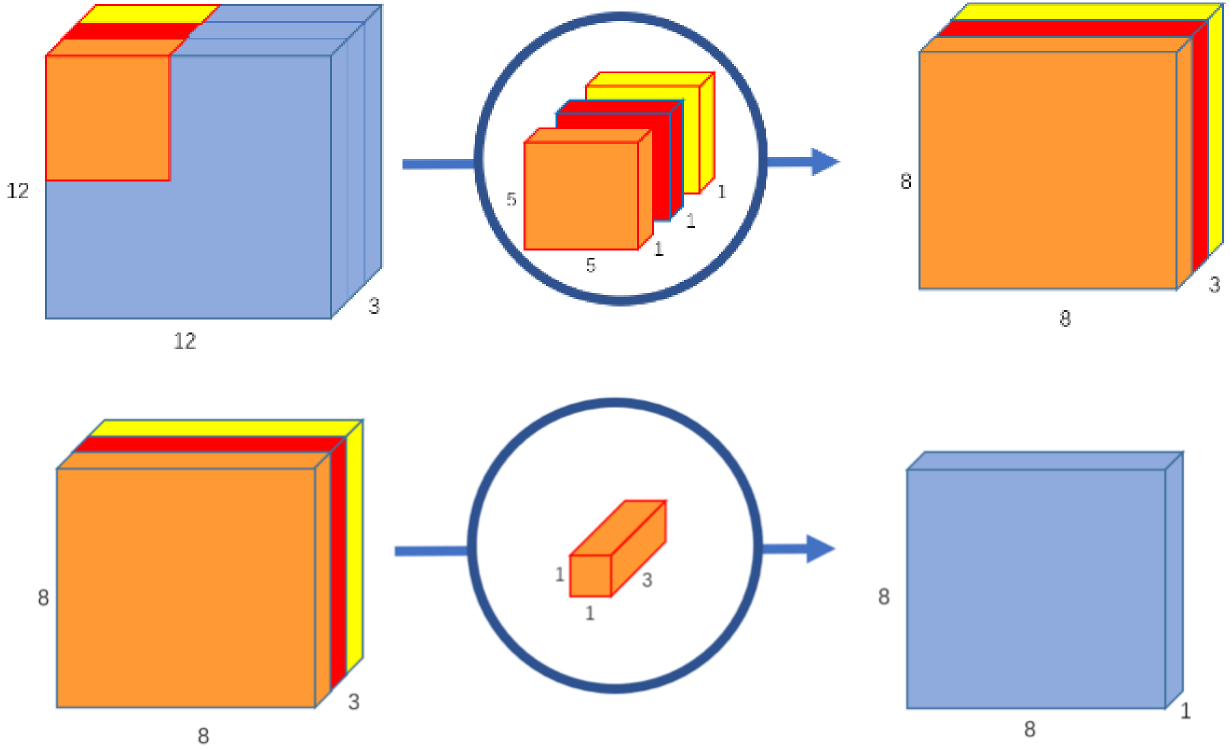


But the depth size is always the same!

class **torch.nn.Conv2d**(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, ***groups=3***)

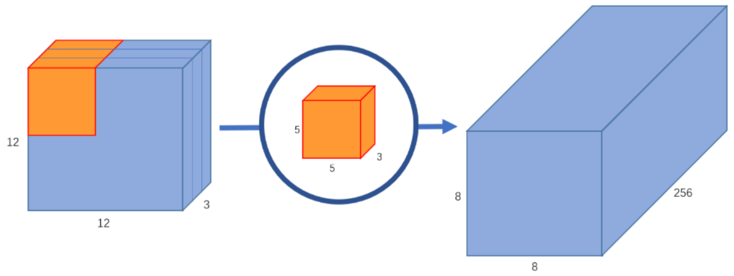
class **torch.nn.ConvTranspose2d**(*in_channels*, *out_channels*, *kernel_size*, *stride=1*, *padding=0*, ***groups=3***)

Depth-wise separable convolutions



Solution:
1x1 convs!

But why?



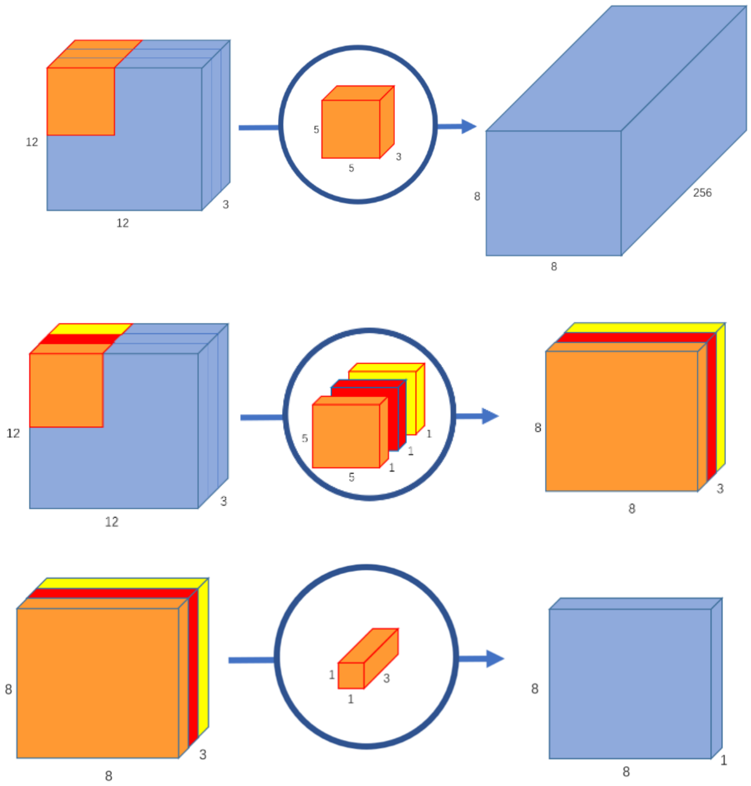
Original convolution

256 kernels of size 5x5x3

Multiplications:

256x5x5x3 x (8x8 locations) = 1.228.800

But why?



Original convolution
256 kernels of size 5x5x3

Multiplications:
256x5x5x3 x (8x8 locations) = 1.228.800

Depth-wise convolution
3 kernels of size 5x5x1

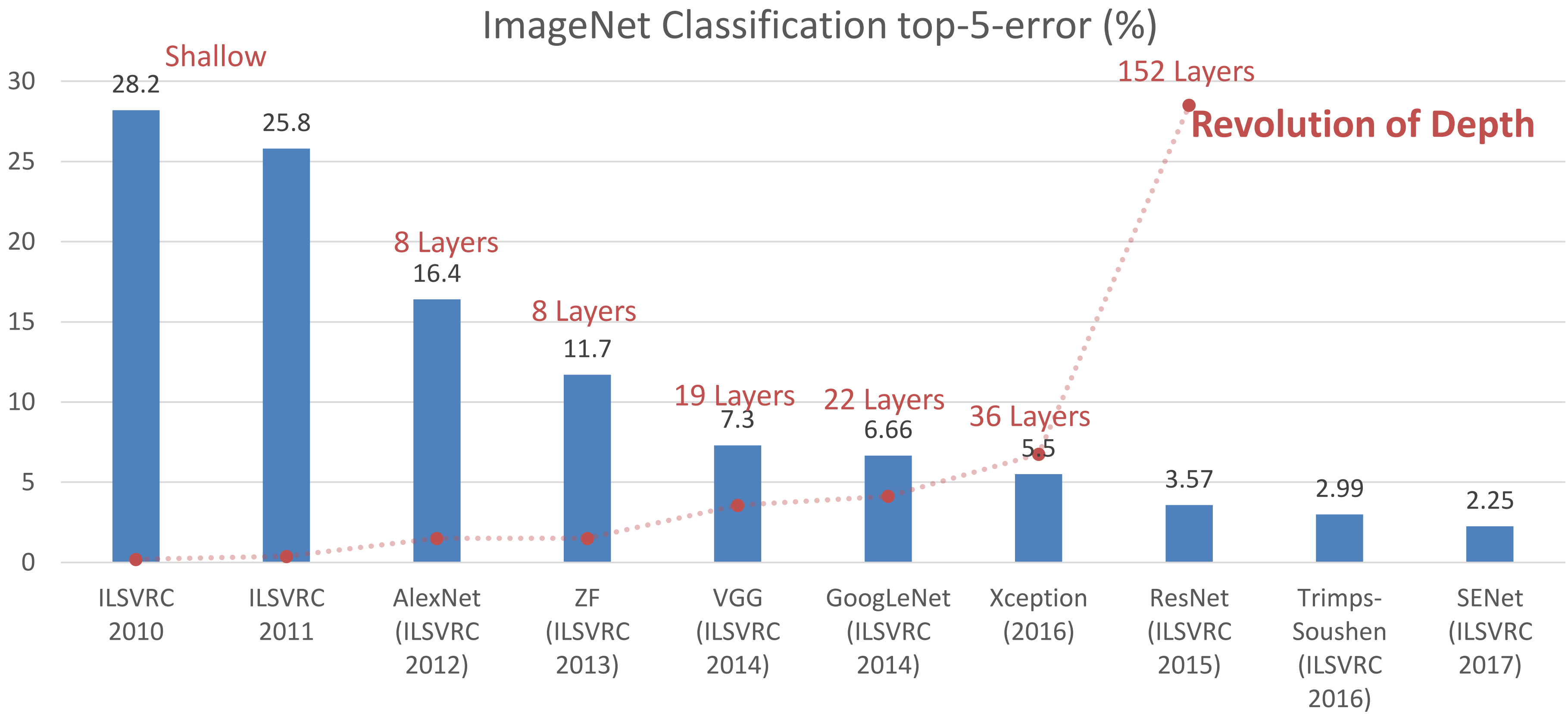
Multiplications:
5x5x3 x (8x8 locations) = 4800

1x1 convolution
256 kernels of size 1x1x3

Multiplications:
256x1x1x3x (8x8 locations) = 49152

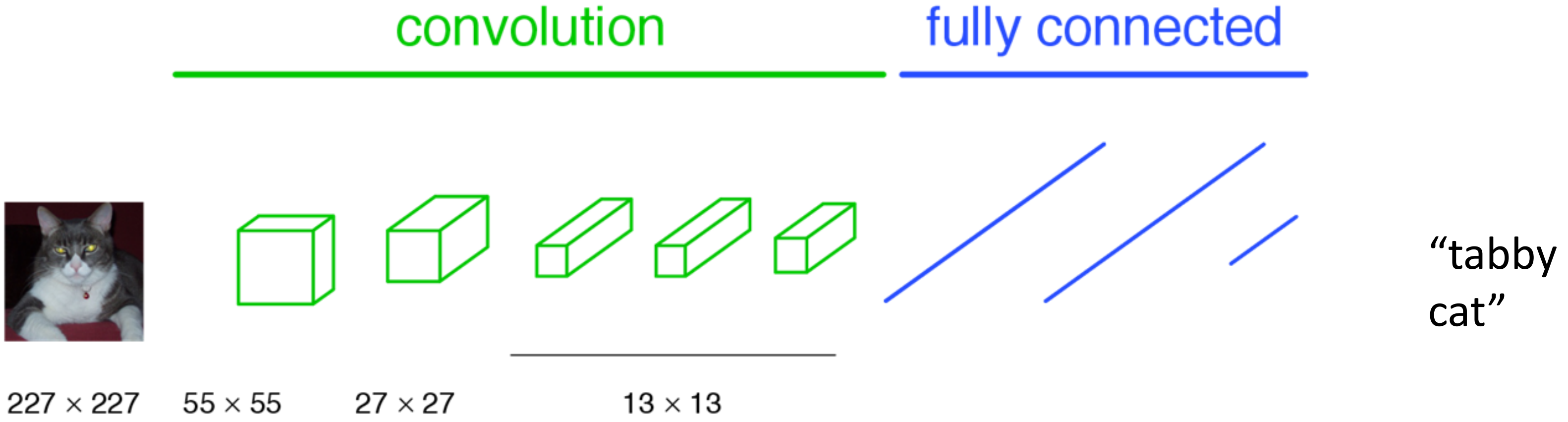
Less computation!

ImageNet Benchmark

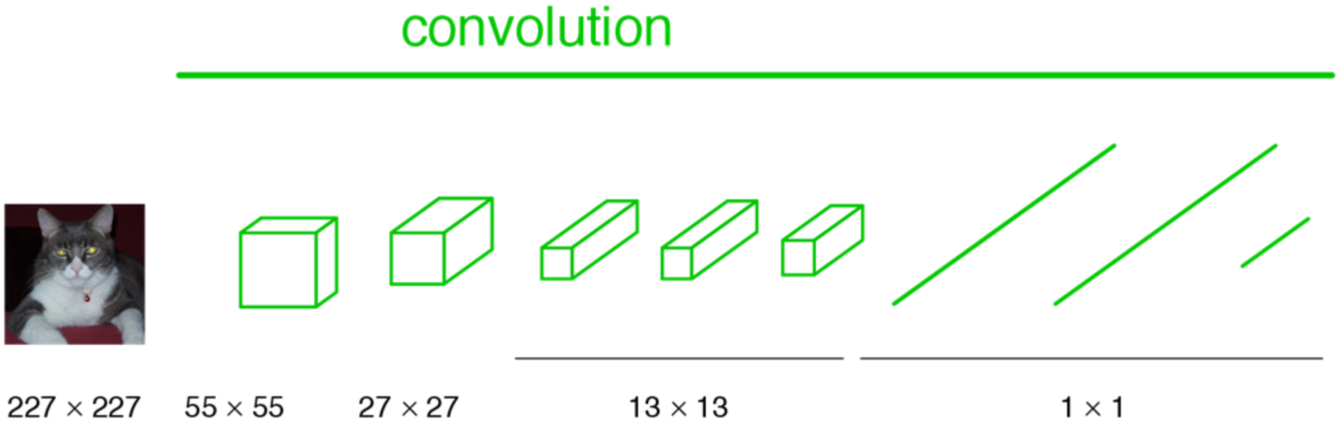


Fully Convolutional Network

Classification Network

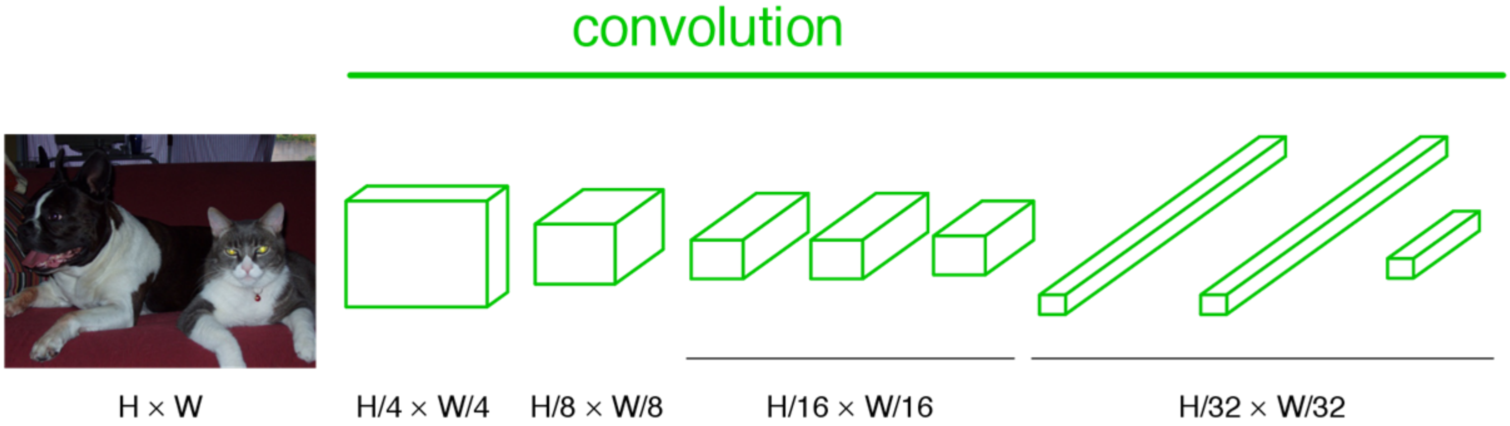


FCN: Becoming Fully Convolutional

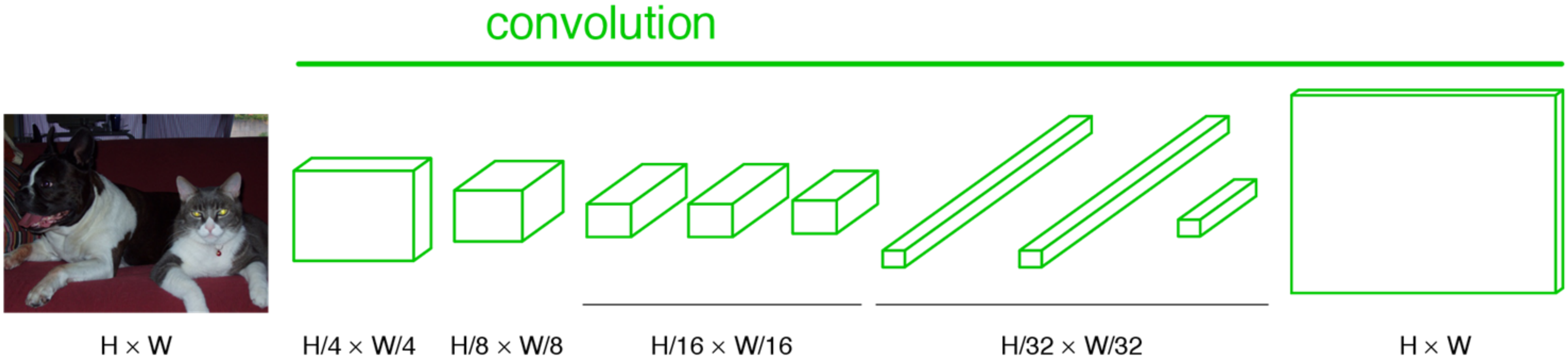


Convert fully connected layers to convolutional layers!

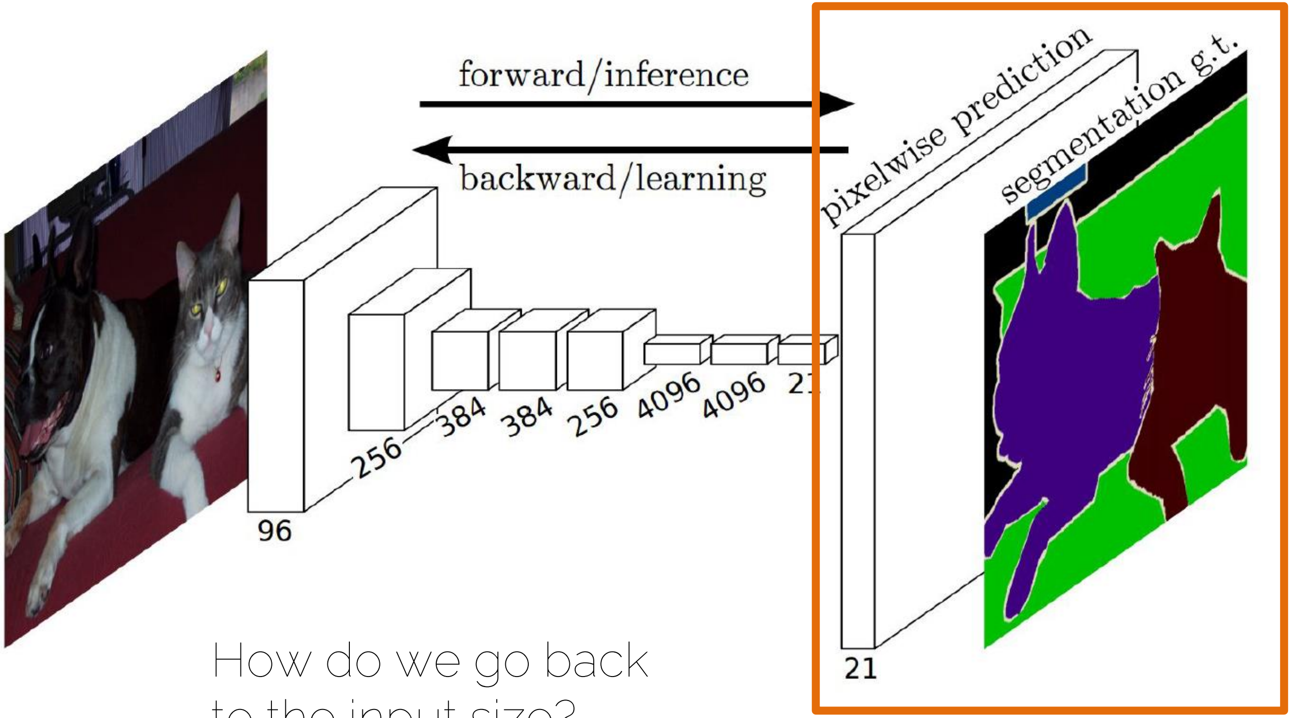
FCN: Becoming Fully Convolutional



FCN: Upsampling Output



Semantic Segmentation (FCN)

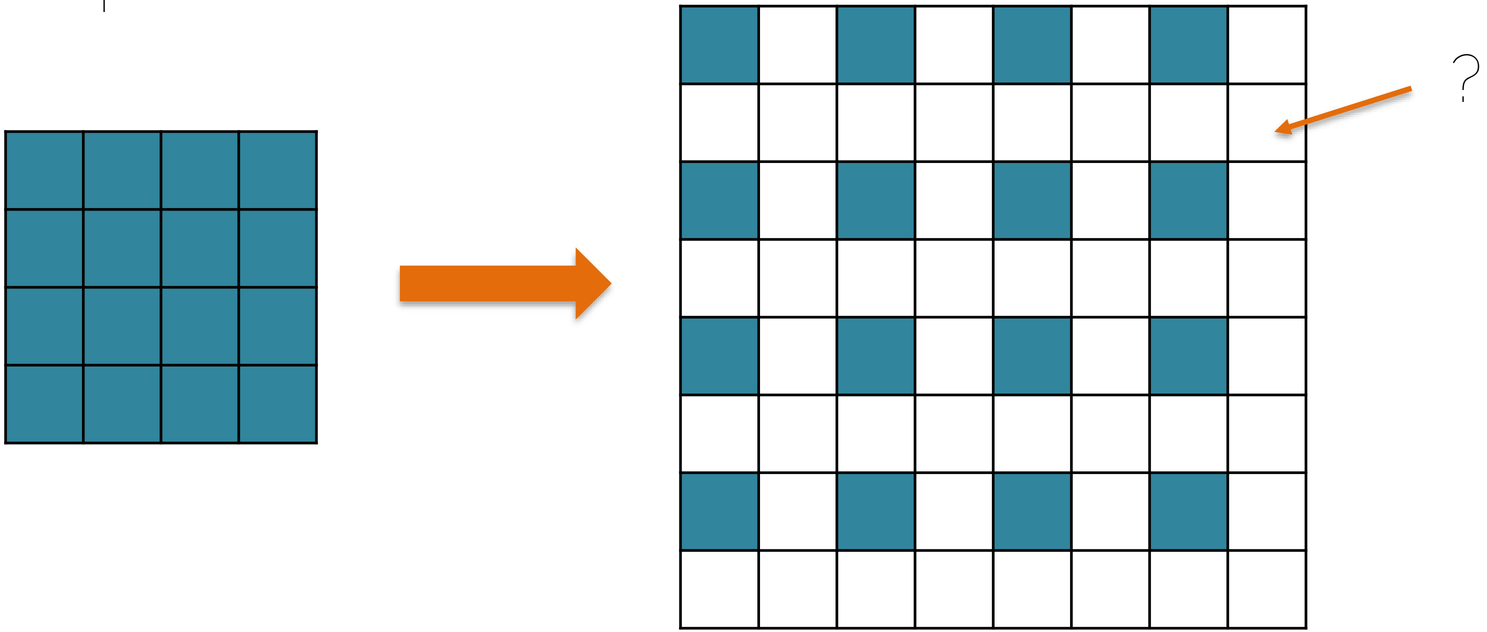


How do we go back
to the input size?

[Long and Shelhamer, 15] FCN

Types of Upsampling

- 1. Interpolation



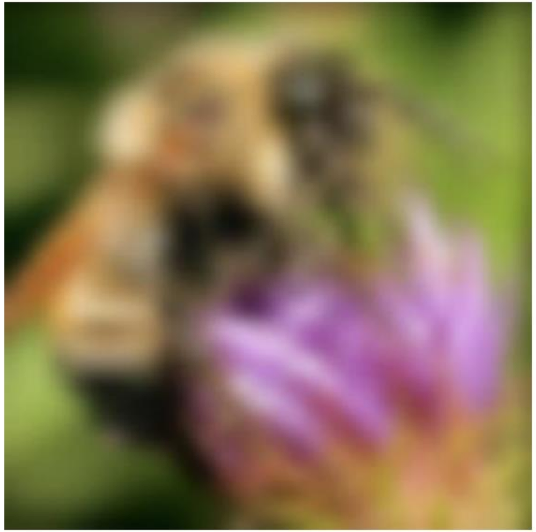
Types of Upsampling

- 1. Interpolation

Original image  x 10

Nearest neighbor interpolation

Bilinear interpolation



Bicubic interpolation

Image: Michael Guerzhoy

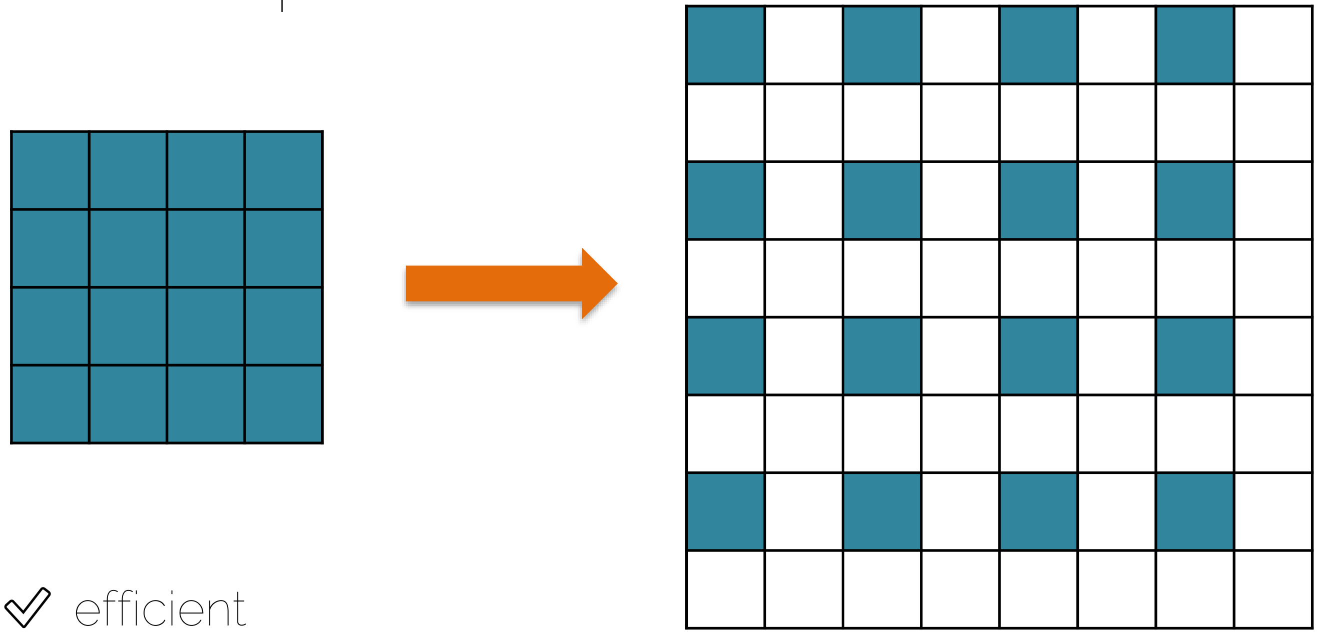
Types of Upsampling

- 1. Interpolation

  ✓ Few artifacts

Types of Upsampling

- 2. Transposed conv



\+ CONVS

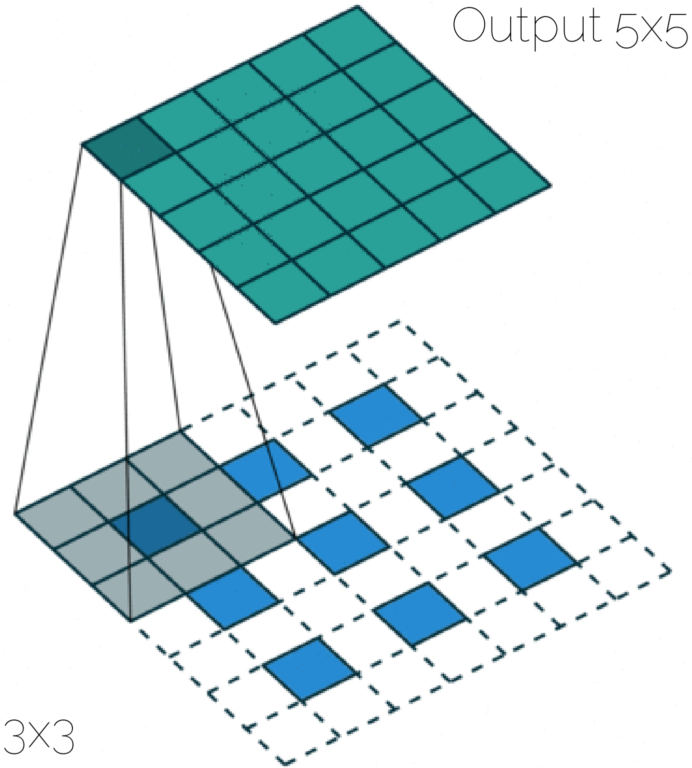
✓ efficient

[Dosovitskiy, Springenberg, Brox, "Learning to Generate Chairs with Convolutional Networks", CVPR 2015]

Types of Upsampling

- 2. Transposed convolution
  - Unpooling
  - Convolution filter (learned)

  - Also called up-convolution (**never** deconvolution)

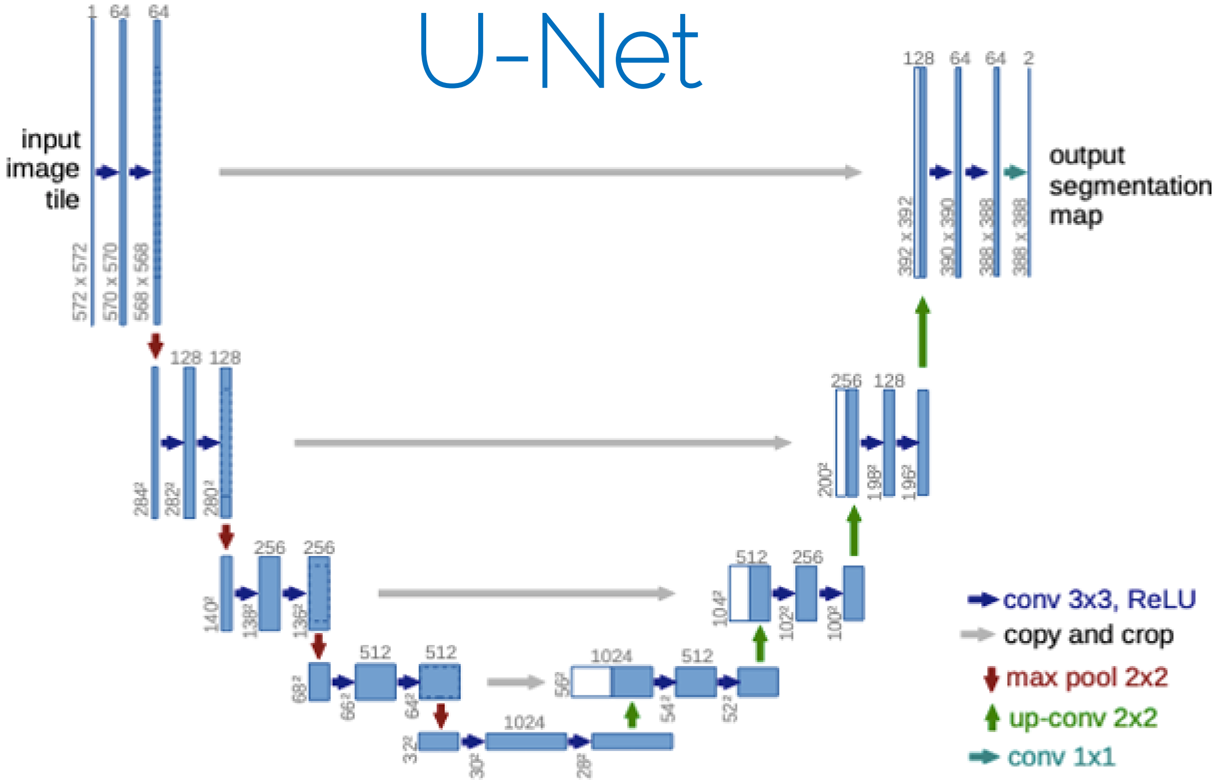


Refined Outputs

- If one does a cascade of unpooling + conv operations, we get to the encoder-decoder architecture

- Even more refined: Autoencoders with skip connections (aka U-Net)

U-Net



U-Net architecture: Each blue box is a multichannel feature map. Number of channels denoted at the top of the box, dimensions at the top. White boxes are copied feature maps.

[Ronneberger, Fischer, Brox, "U-net: Convolutional networks for biomedical image segmentation", MICCAI'15]

U-Net: Encoder

Left side: **Contraction Path** (Encoder)

- Captures context of the image
- Follows typical architecture of a CNN:
  - Repeated application of 2 unpadded 3x3 convolutions
  - Each followed by ReLU activation
  - 2x2 maxpooling operation with stride 2 for downsampling
  - At each downsampling step, # of channels is doubled

→ as before: Height, Width ↓, Depth: ↑

[Ronneberger, Fischer, Brox, "U-net: Convolutional networks for biomedical image segmentation", MICCAI'15]

U-Net: Decoder

Right Side: **Expansion Path** (Decoder):

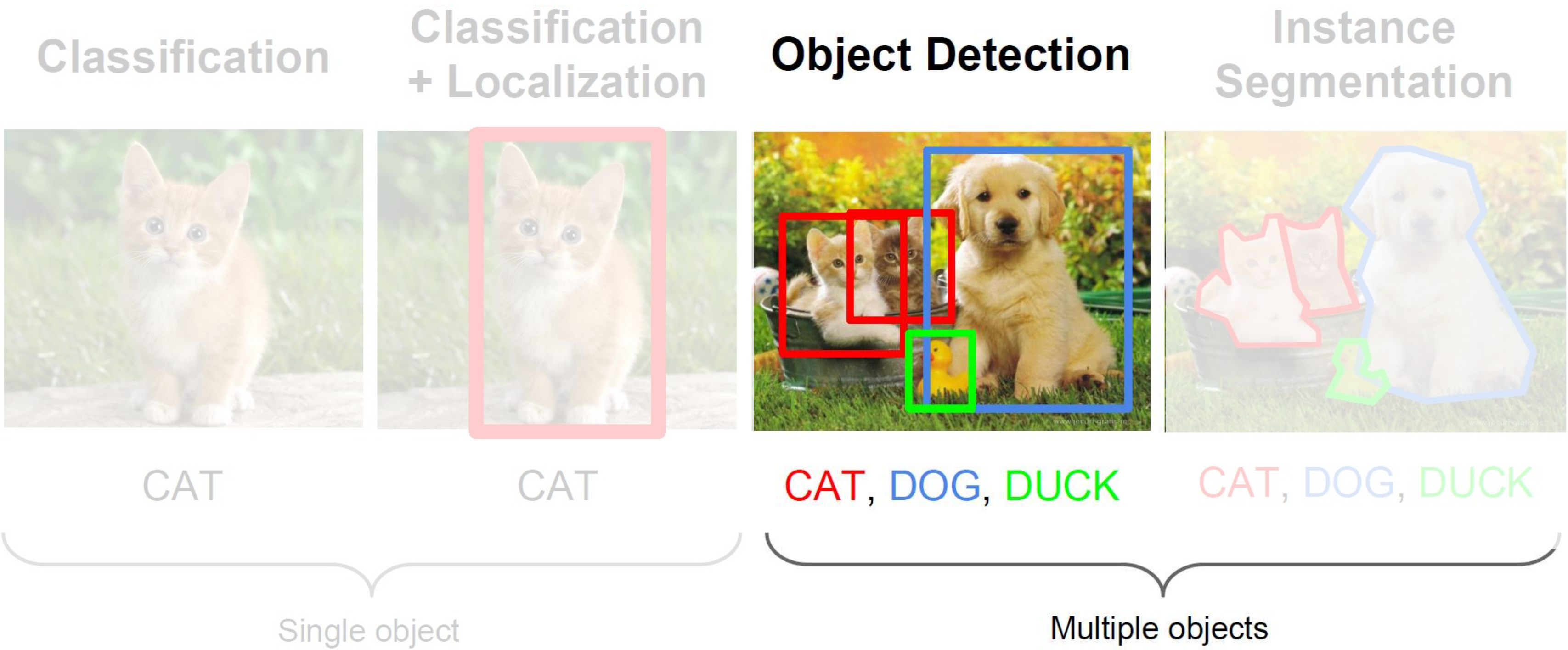
- Upsampling to recover spatial locations for assigning class labels to each pixel
  - 2x2 up-convolution that halves number of input channels
  - **Skip Connections**: outputs of up-convolutions are concatenated with feature maps from encoder
  - Followed by 2 ordinary 3x3 convs
  - final layer: 1x1 conv to map 64 channels to # classes

- Height, Width: ↑ , Depth: ↓

[Ronneberger, Fischer, Brox, "U-net: Convolutional networks for biomedical image segmentation", MICCAI'15]

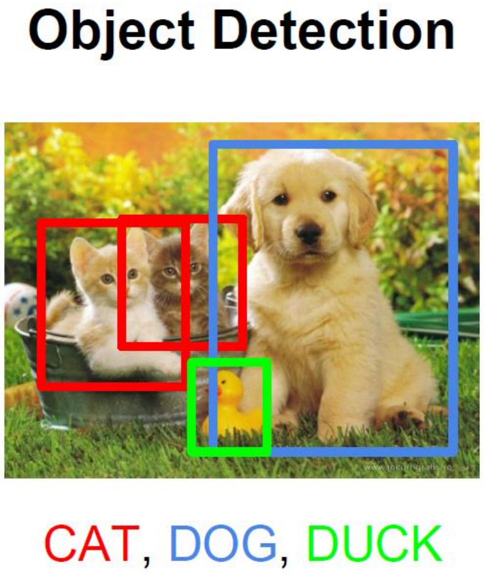
Object Detection

What is Object Detection?



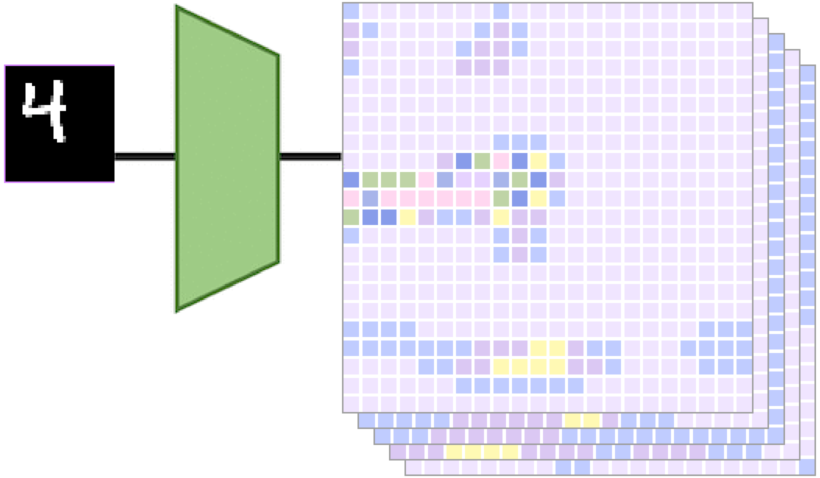
What is object detection?

- Goal: localize + classify objects in an image
- Input: image
- Output: list of bounding boxes, class labels (+ confidences)



Challenges in Detection

- Convolutions are translationally equivariant
  - Convolutions share weights: same filters slide across all positions
  - Shifting input image -> output feature maps will shift by same amount



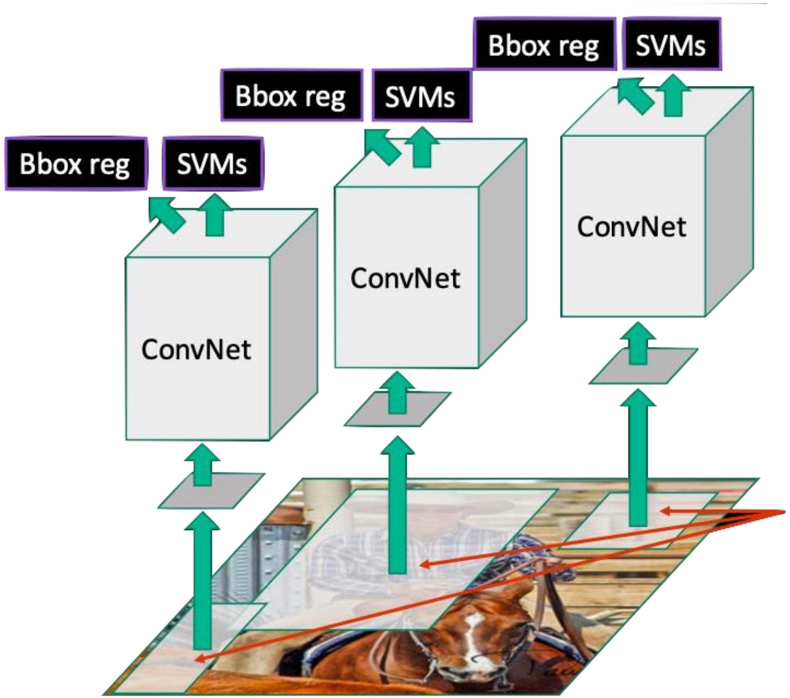
https://chriswolfvision.medium.com/what-is-translation-equivariance-and-why-do-we-use-convolutions-to-get-it-6f18139d4c59

Challenges in Detection

- Convolutions are translationally equivariant
- Good for identifying "what" (e.g., classification), makes "where" challenging

- Detection: need to detect multiple objects, likely different sizes/places

Region-Based CNNs (R-CNNs)

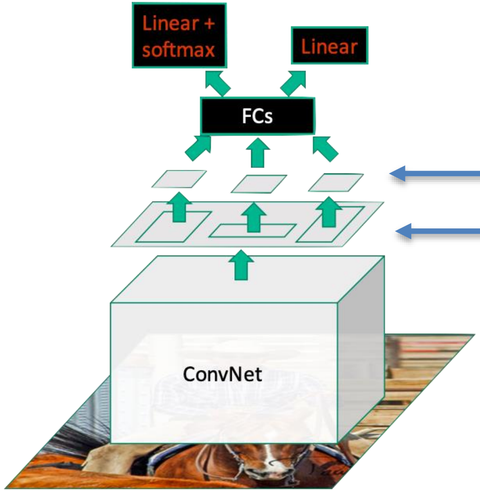


- Use selective search to generate candidate regions
- Warp/rescale each region to fixed image size, pass through a CNN
- CNN extracts features for predicting class + box offsets
- Slow: runs CNN separately for each region

[**Girshick et al.** CVPR'14] R-CNN

Fast R-CNN

- Instead of running CNN once per region, run CNN once for the entire image
- Use region of interest (ROI) pooling to extract fixed-size feature maps for each region



ROI-Pooling
Regions of Interest (ROIs)

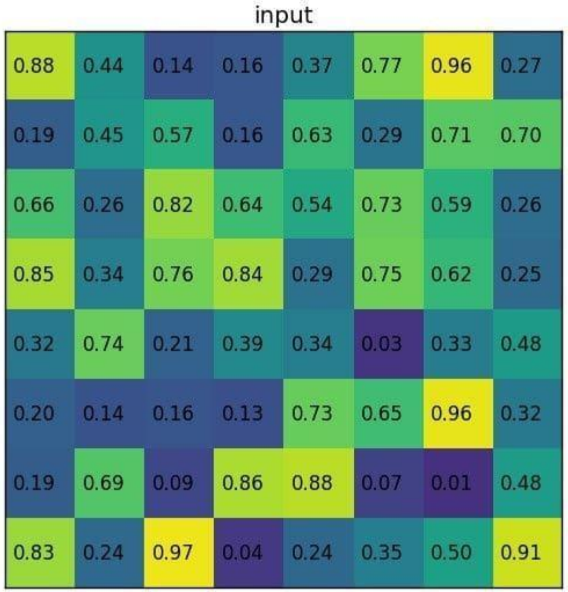
Region of Interest Pooling

- Used to handle variable-sized object proposals efficiently
- Proposed regions have different sizes and aspect ratios
- Fully-connected layers expect fixed-size inputs

➢ Convert each variable-sized region of interest (ROI) from the feature map and rescale it into a fixed-sized output using max pooling

Region of Interest Pooling

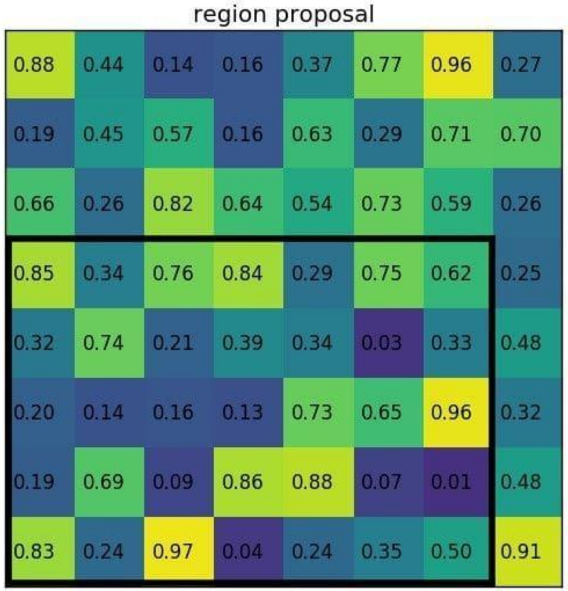
- Input: 8x8 feature map
- Output size: 2x2



Source: https://deepsense.ai/region-of-interest-pooling-explained/

Region of Interest Pooling

- Input: 8x8 feature map
- Output size: 2x2



Source: https://deepsense.ai/region-of-interest-pooling-explained/

Region of Interest Pooling

- Input: 8x8 feature map
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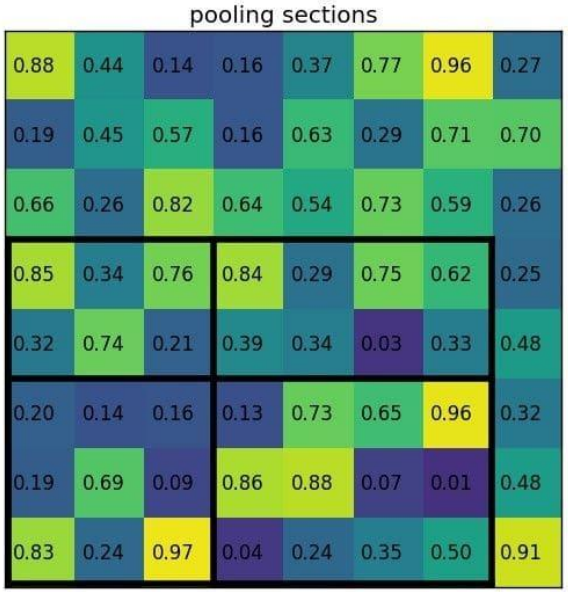
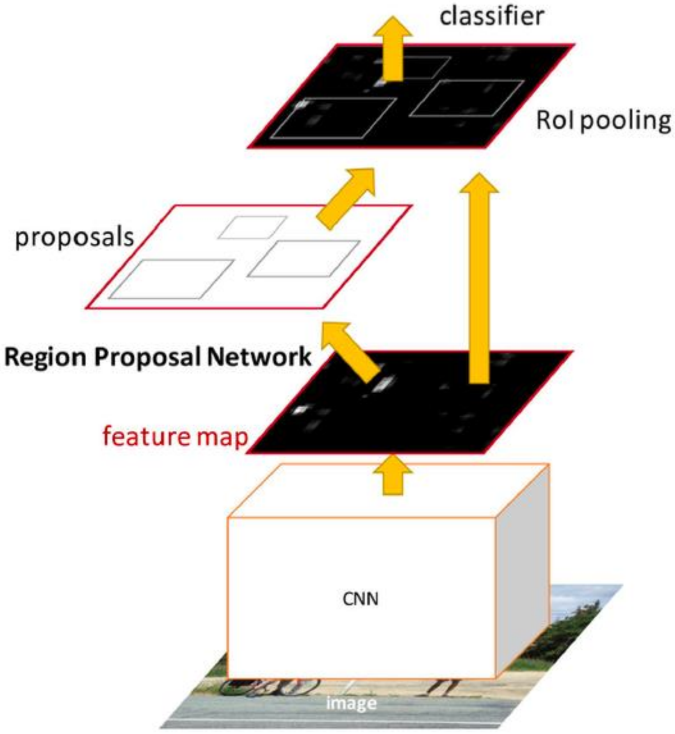


Source: https://deepsense.ai/region-of-interest-pooling-explained/

Faster R-CNN

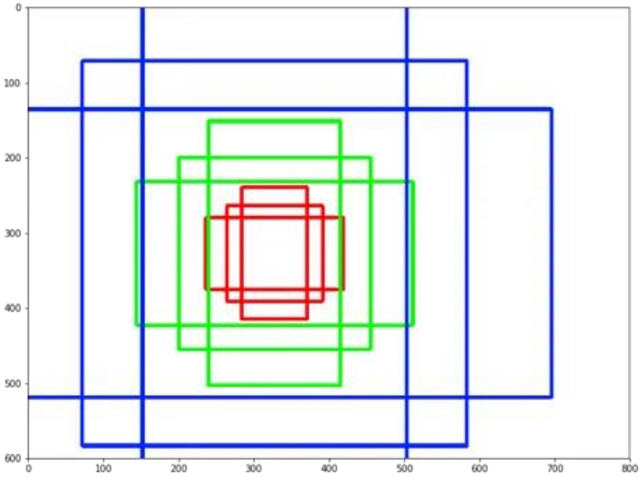
- Use convolutions to get sliding window effect
- Replace selective search with a region proposal network (RPN)
  – Small CNN that slides over feature map
  – Produces region proposals based on anchors

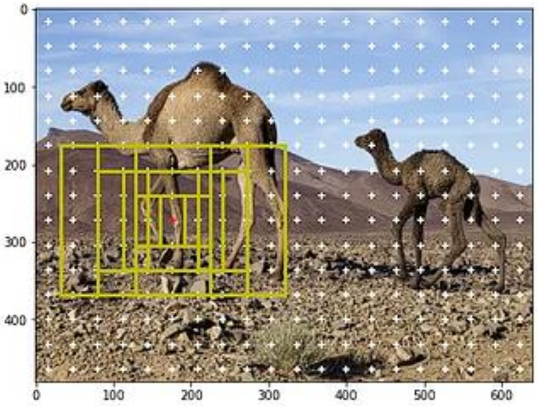


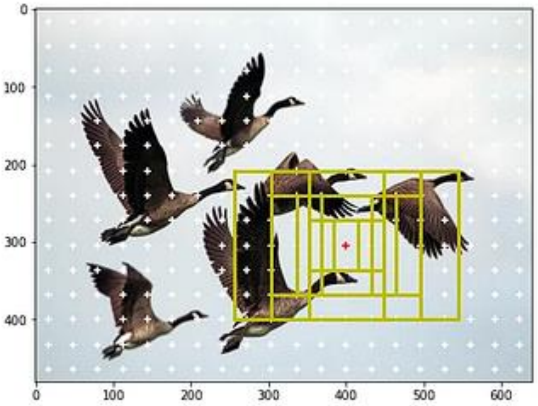
[Ren et al. NeurIPS'15] Faster R-CNN

Anchors

- Potential bounding box candidates where an object can be detected



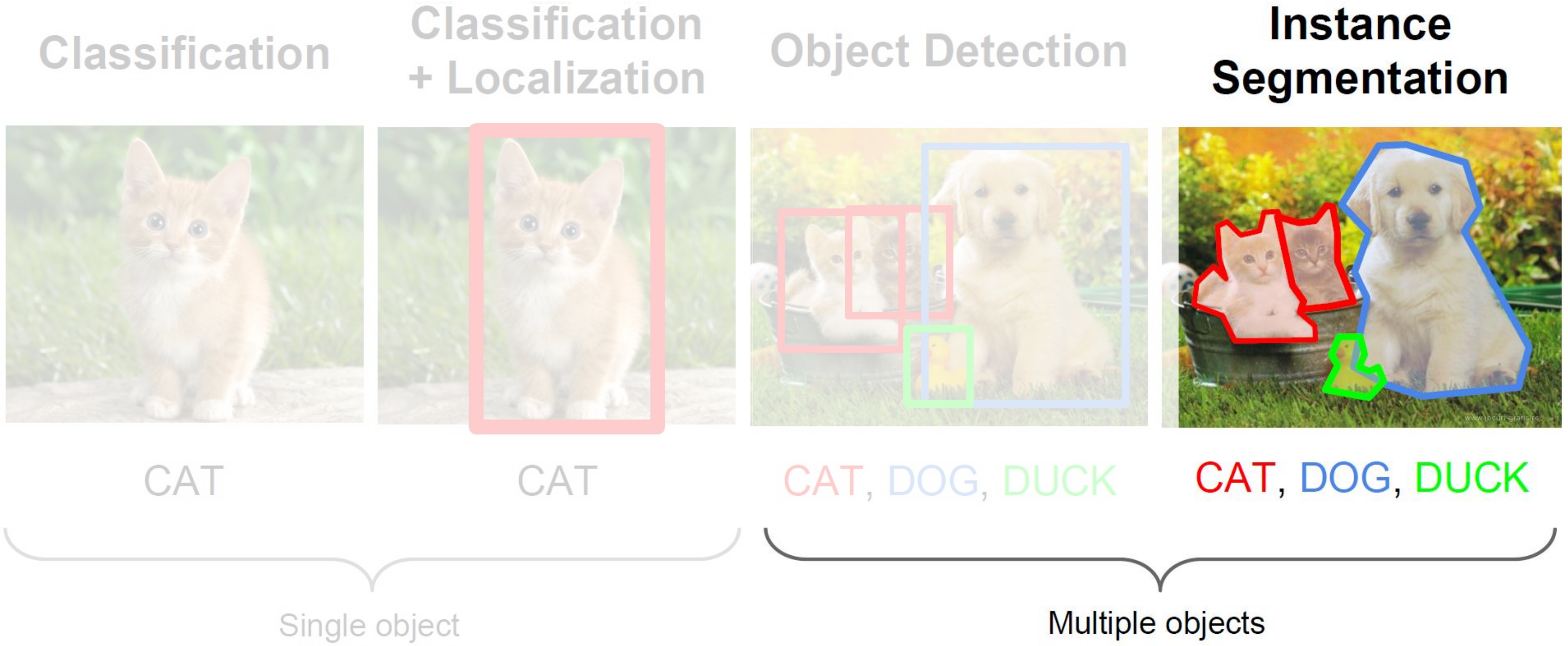




https://medium.com/thedeephub/faster-r-cnn-object-detection-5dfe77104e31

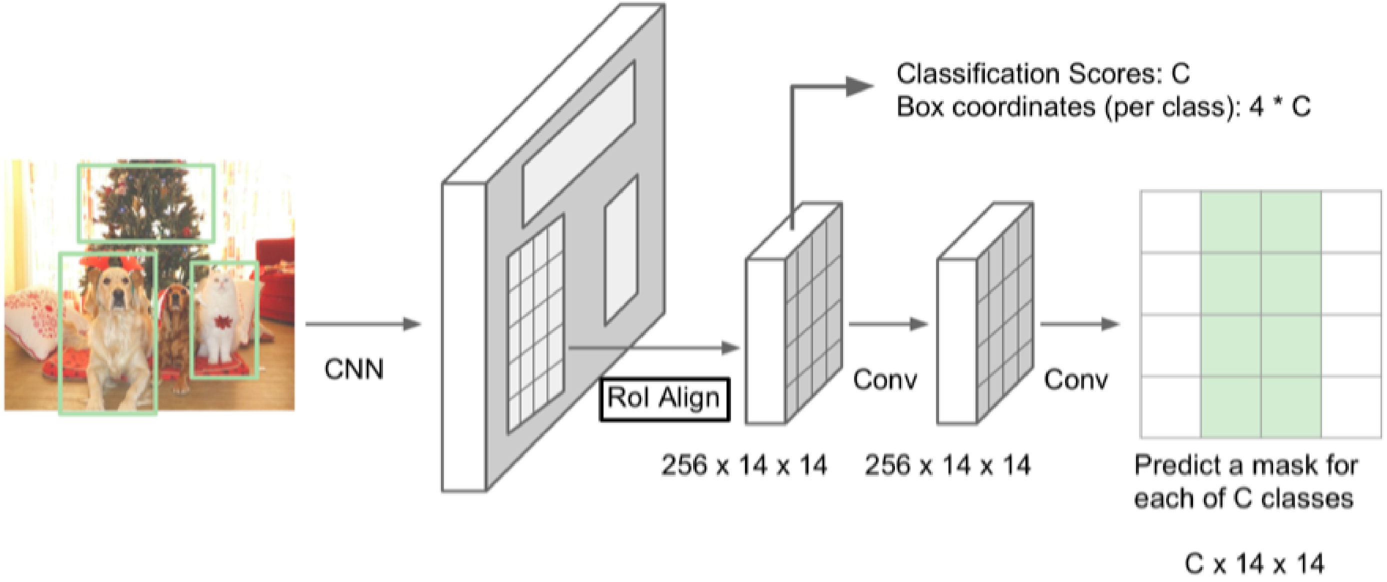
Instance Segmentation

- Predict list of object bounding boxes, classes, and pixel-wise masks



Mask R-CNN

- Extend Faster R-CNN to also predict pixel-wise mask for each object



[**He et al.** ICCV'17] Mask R-CNN

R-CNNs for Detection + Segmentation

- R-CNN, Fast R-CNN, Faster R-CNN, Mask-RCNN: two-stage detectors
- First generate region proposals, then refine boxes + predict class labels (+ masks)

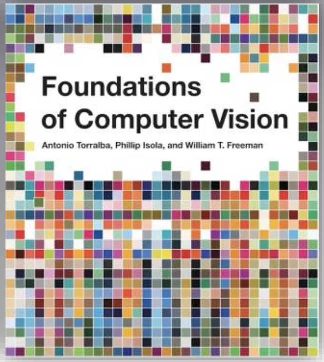
- Today: end-to-end, unified approach with transformers

Next Time: Guest Lecture

- July 14: Guest Lecture!
  - In person, regular lecture slot (recording released later)

Phillip Isola, MIT

- Leader in vision and generative models
- Created Pix2Pix, CycleGAN, representation learning
- Foundations of Computer Vision textbook
- Live Q&A – ask questions directly!



See you next time!

References

We highly recommend to read through these papers!

- AlexNet [Krizhevsky et al. 2012]
- VGGNet [Simonyan & Zisserman 2014]
- ResNet [He et al. 2015]
- GoogLeNet [Szegedy et al. 2014]
- Xception [Chollet 2016]
- Fast R-CNN [Girshick 2015]
- U-Net [Ronneberger et al. 2015]
- EfficientNet [Tan & Le 2019]