CS489/698: Intro to ML

Lecture 13: CNNs

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Outline

- Review
- Pooling
- Architectures

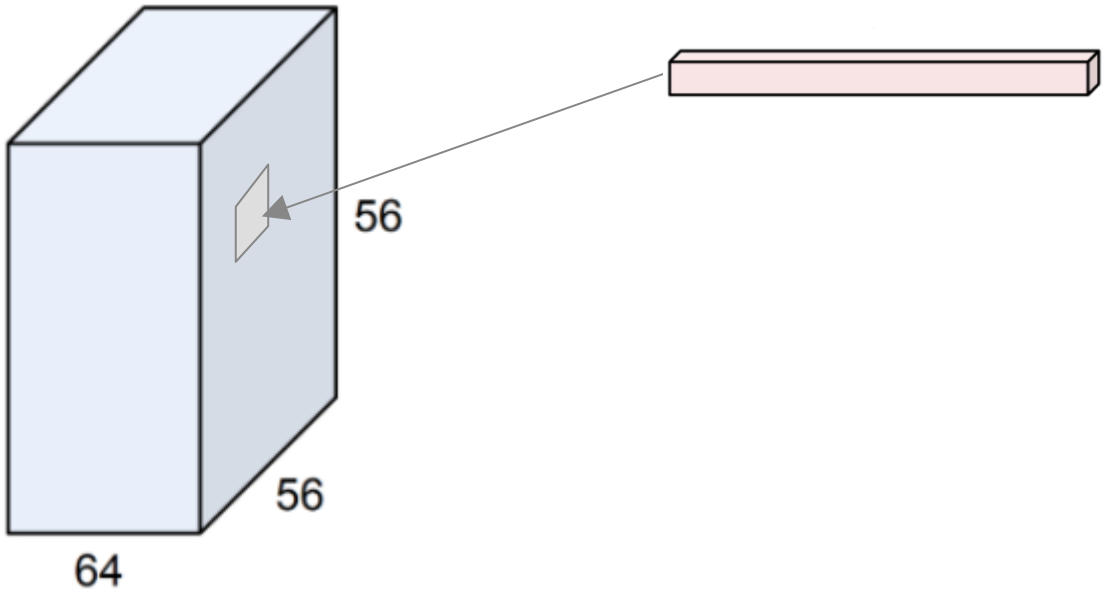
Convolutional Layer

Summary. To summarize, the Conv Layer:

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

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf

What is a conv feature?



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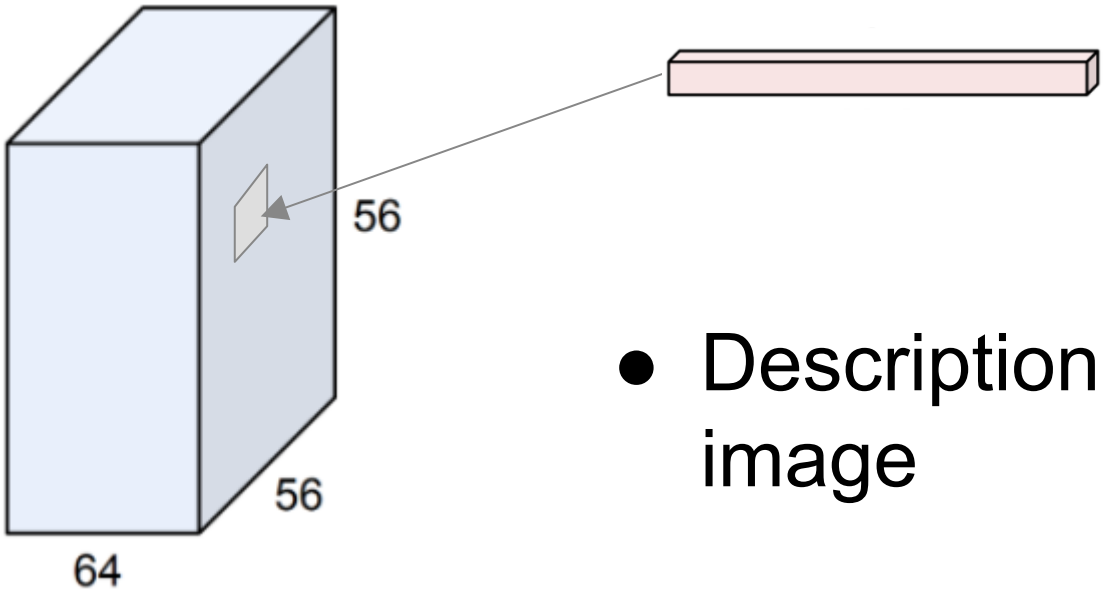
What is a conv feature?



- Description of region of image

Motivation

- We care more about knowing that a feature is present than exactly where it is
- i.e. We don't need the exact pixels of Obama's eyes and nose to know it is obama's face

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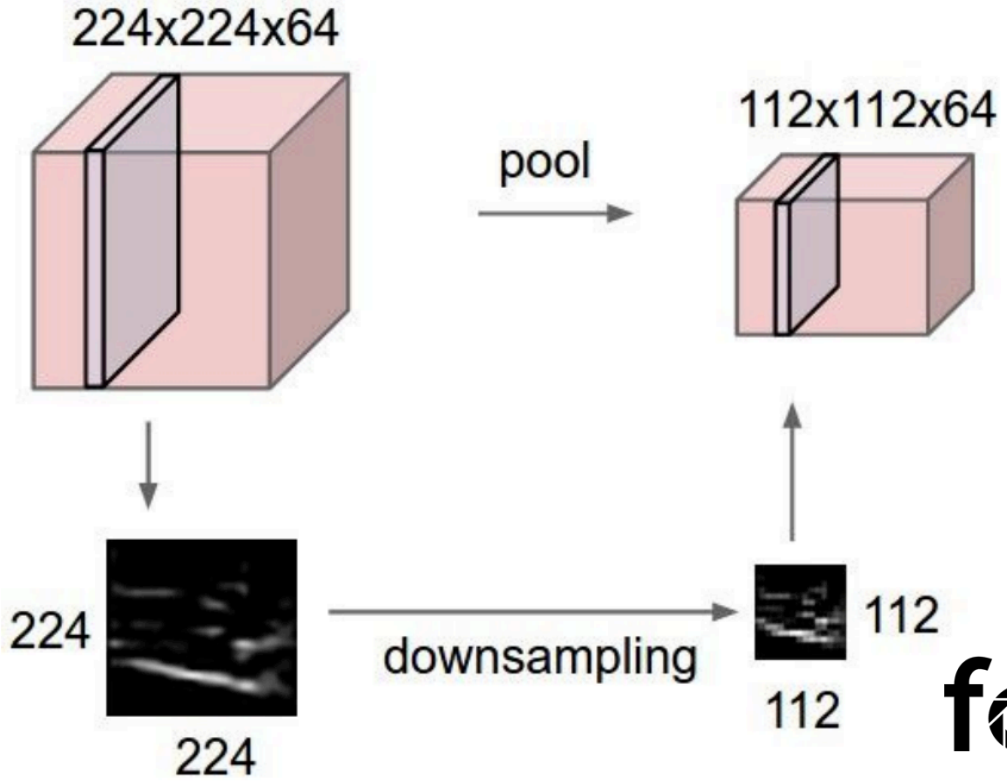
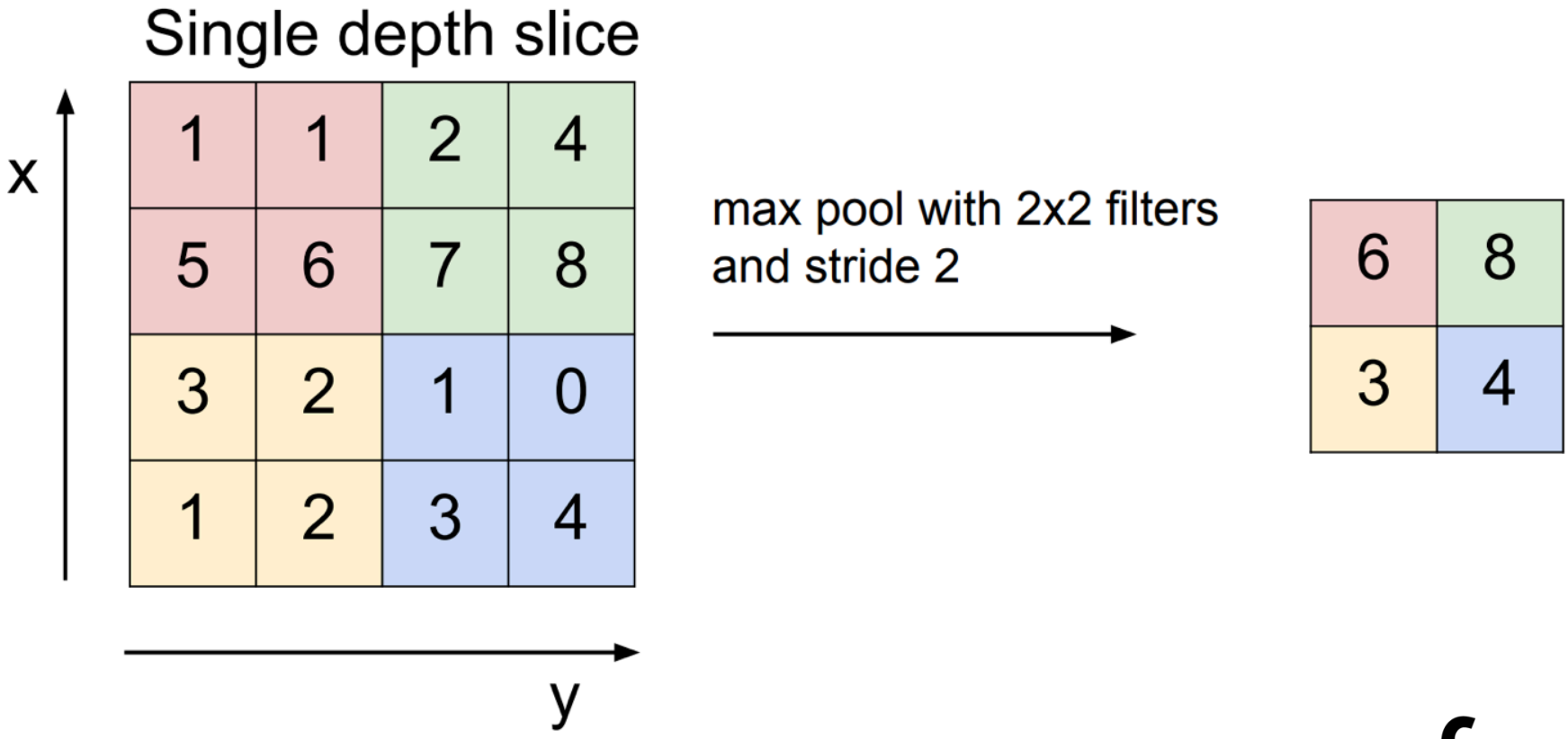
Solution: Pooling

- Replaces activations with summary statistic of nearby activations



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf

Example: Max Pooling



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf

Benefits Of Pooling

- Some translation invariance
- No parameters
- Easy to backprop
- Less computations
- Increased receptive field

Where is pooling used?

- After series of convs
- Followed by double depth

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 imag)					
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					

The 6 different architecures of VGG Net. Configuration D produced the best results

Drawbacks of Pooling

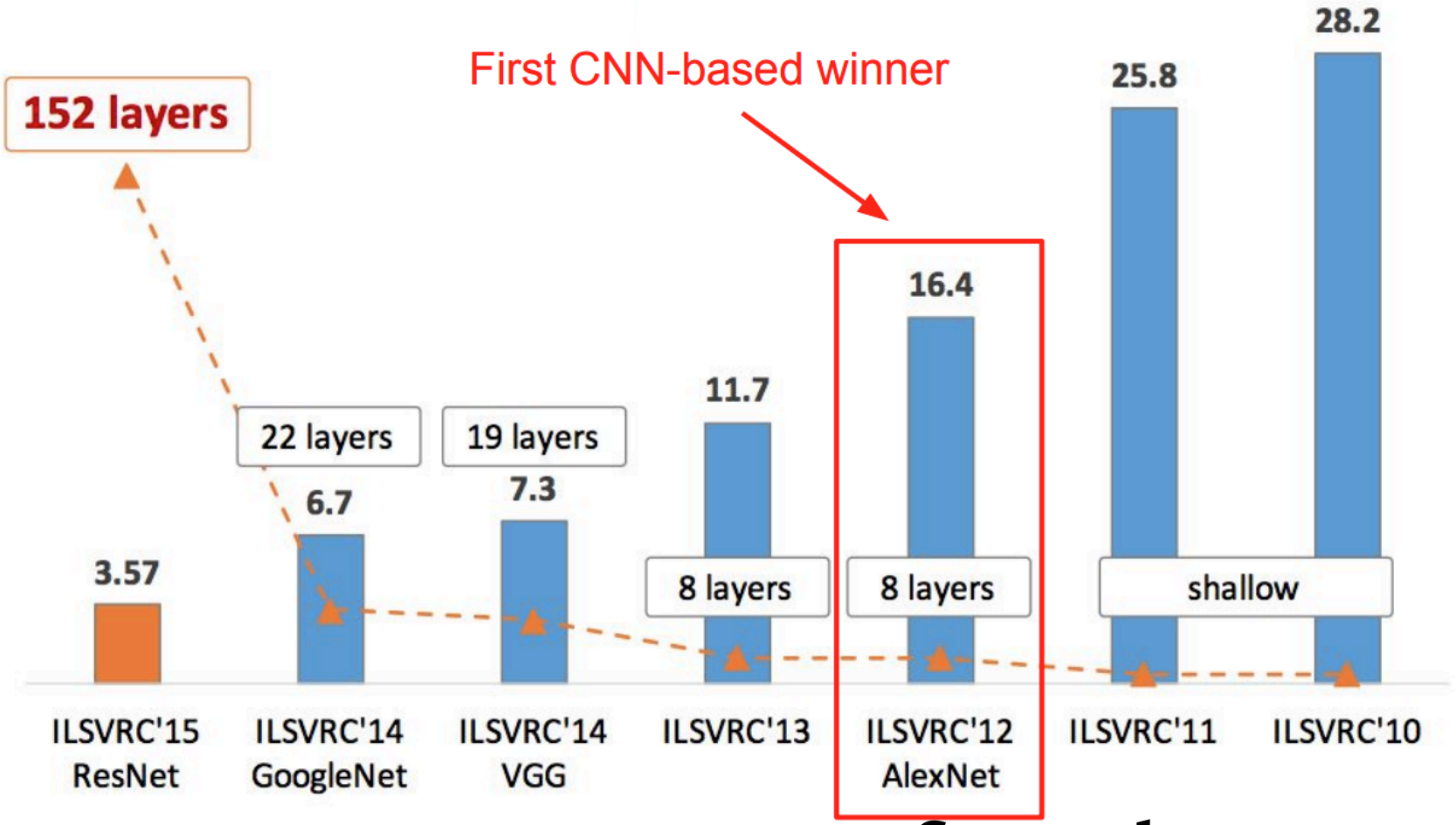
- Loss of information

Pooling Layer Summary

- Accepts a volume of size $W_1 \times H_1 \times D_1$
- Requires three hyperparameters:
  - their spatial extent F,
  - the stride S,
- Produces a volume of size $W_2 \times H_2 \times D_2$ where:
  - $W_2 = (W_1 - F)/S + 1$
  - $H_2 = (H_1 - F)/S + 1$
  - $D_2 = D_1$
- Introduces zero parameters since it computes a fixed function of the input
- Note that it is not common to use zero-padding for Pooling layers

http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture5.pdf

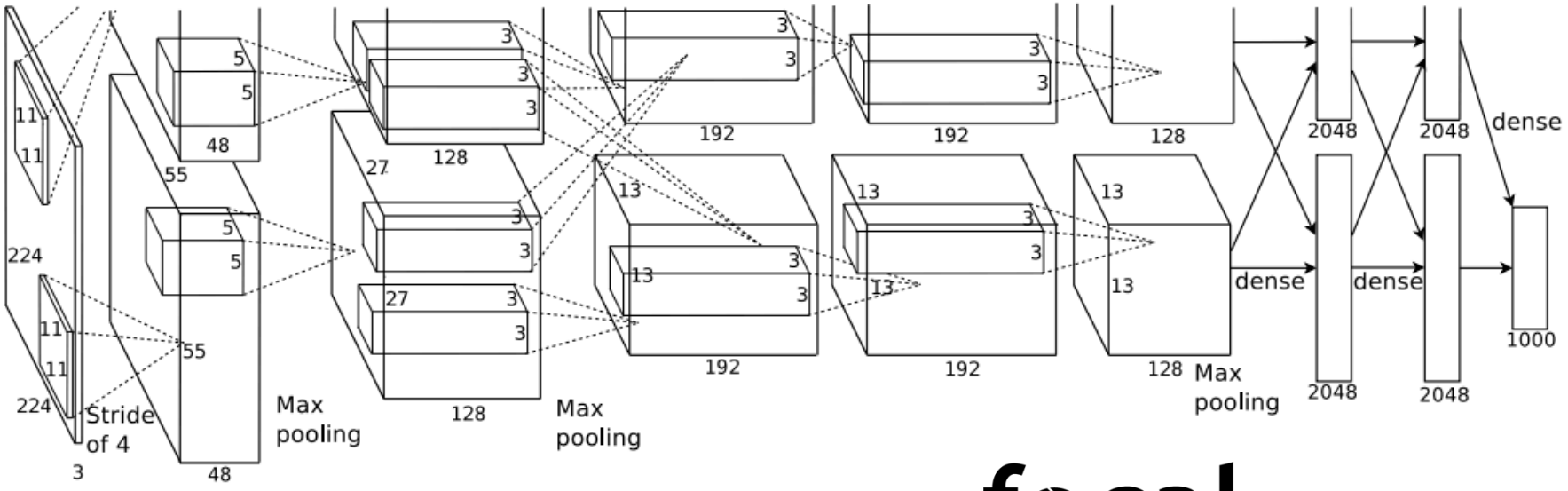
Architectures for ImageNet



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

AlexNet - 2012

- Input Image 227x227x3



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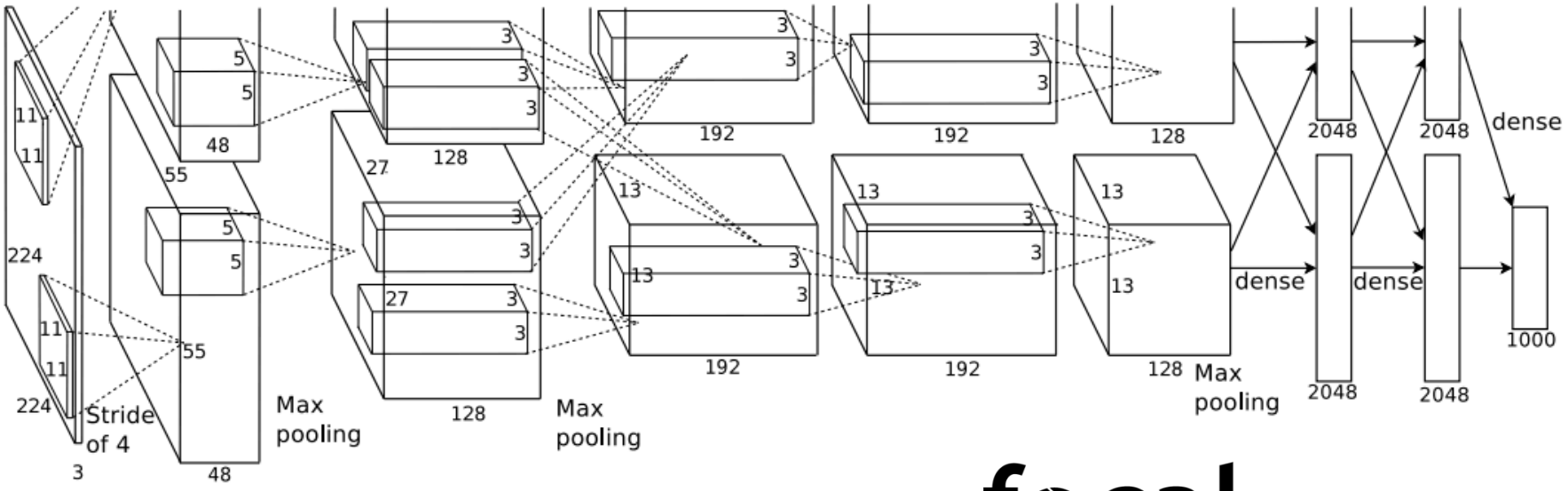
AlexNet - 2012

- Input Image 227x227x3
- First Layer: 96 11x11 Conv filters stride 4 pad 0
- What is output size?



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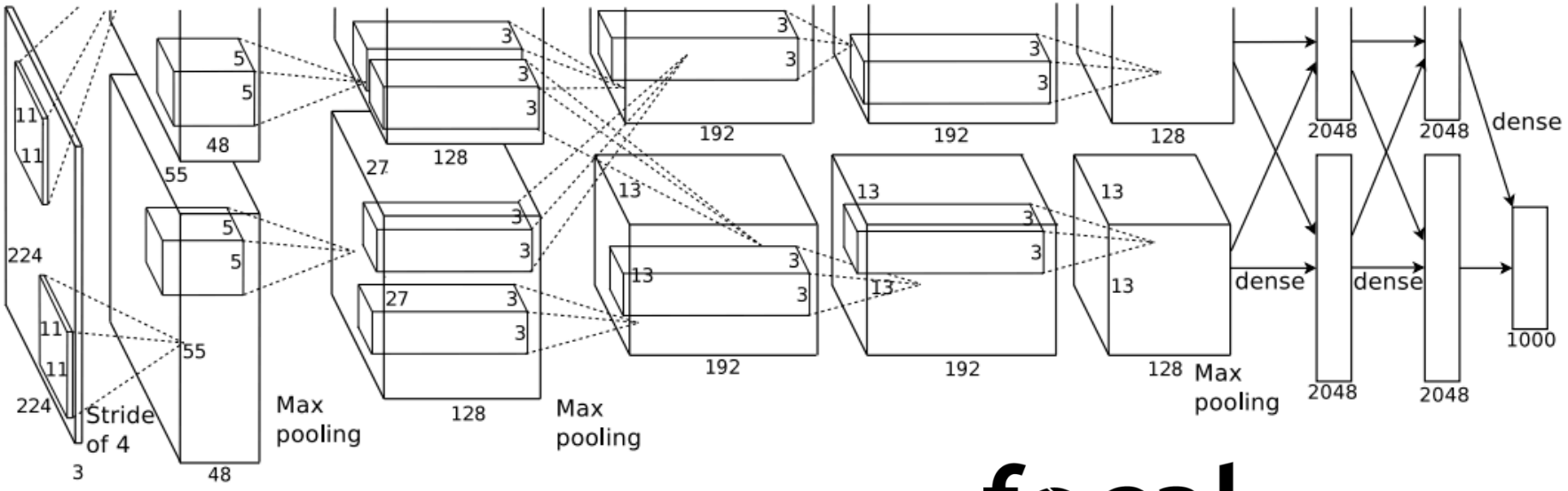
AlexNet - 2012

- Input Image 227x227x3
- First Layer: 96 11x11 Conv filters stride 4 pad 0
- What is output size? 55x55x96



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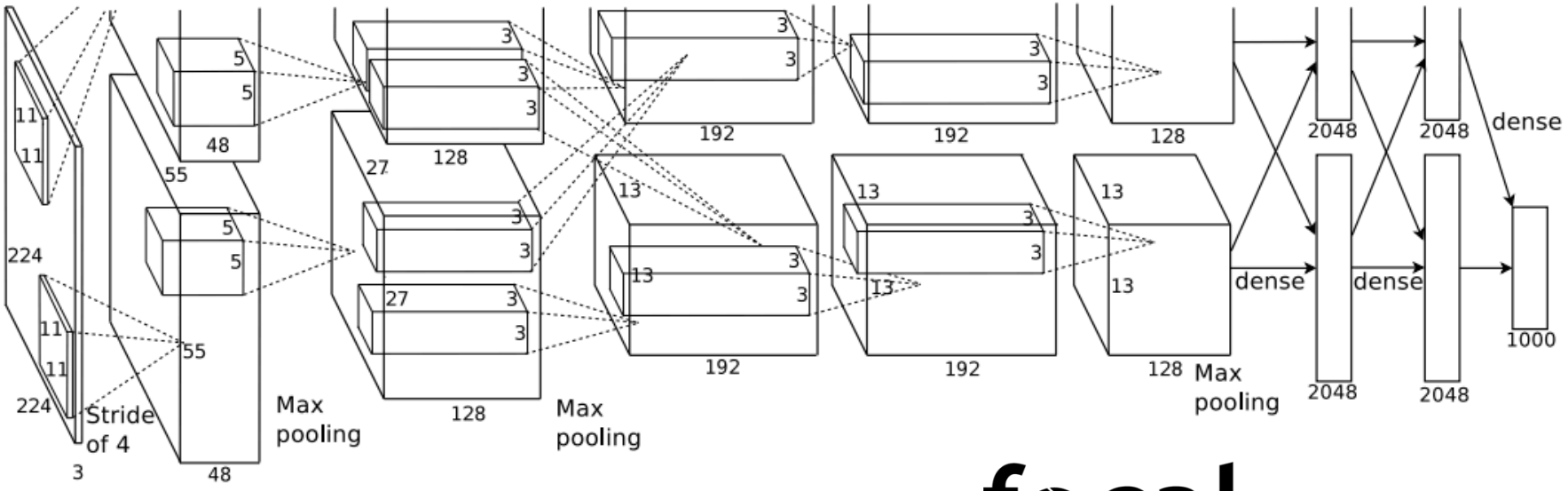
AlexNet - 2012

- Input Image 227x227x3
- First Layer: 96 11x11 Conv filters stride 4 pad 0
- How Many Parameters?



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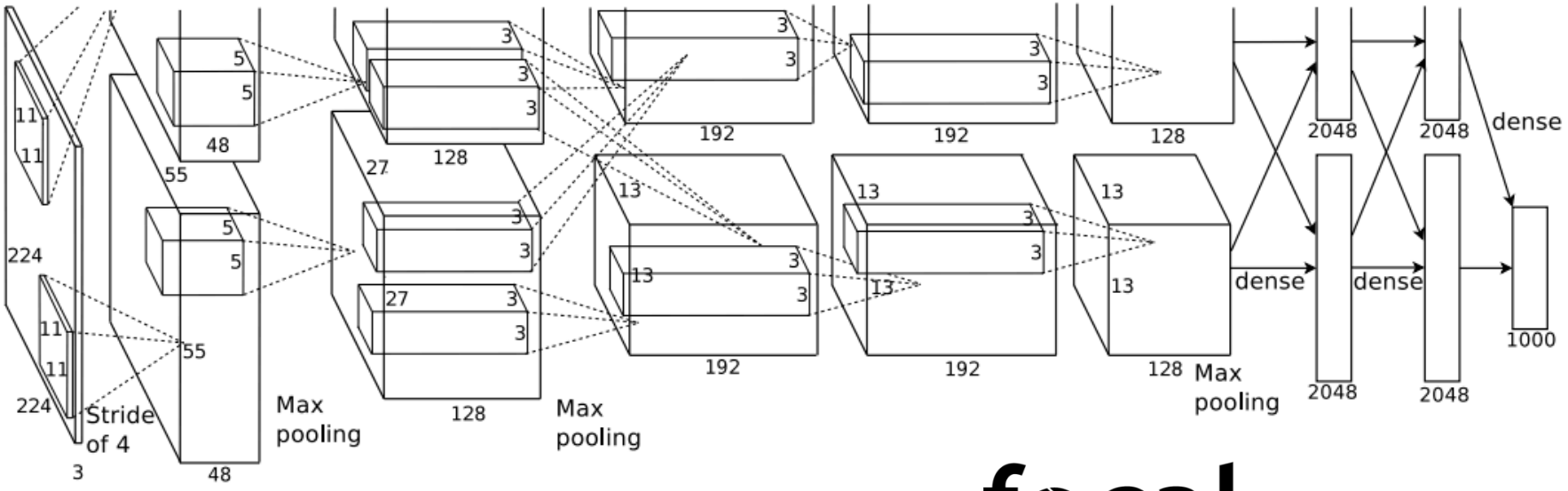
AlexNet - 2012

- Input Image 227x227x3
- First Layer: 96 11x11 Conv filters stride 4 pad 0
- How Many Parameters? 11x11x3x96 = 34,848



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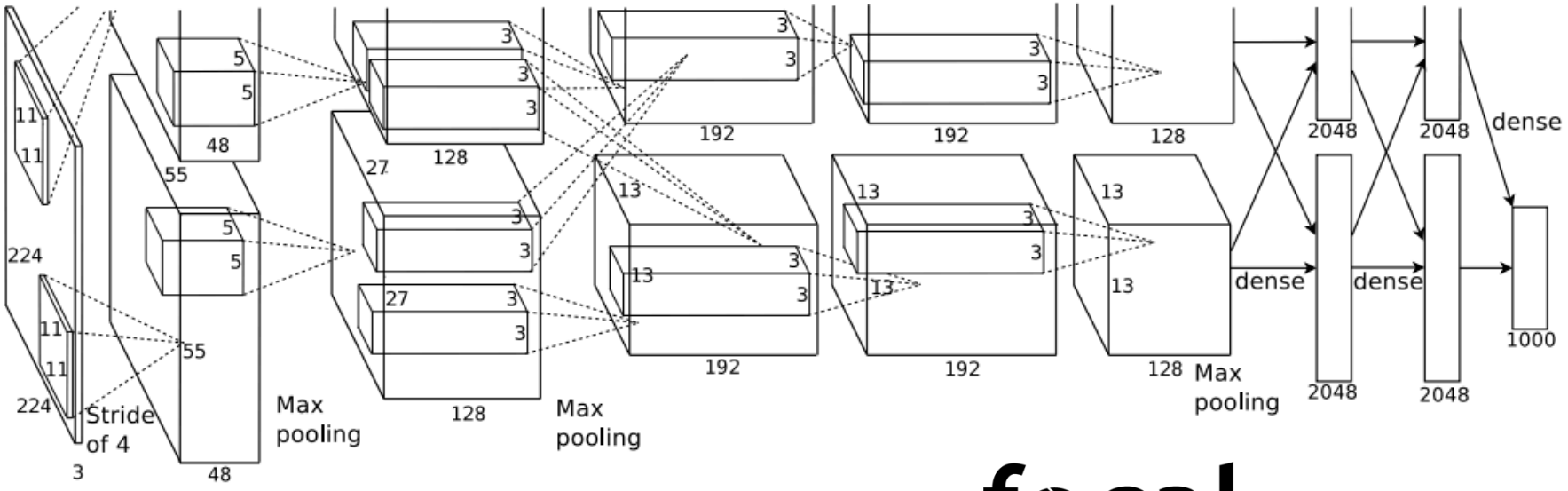
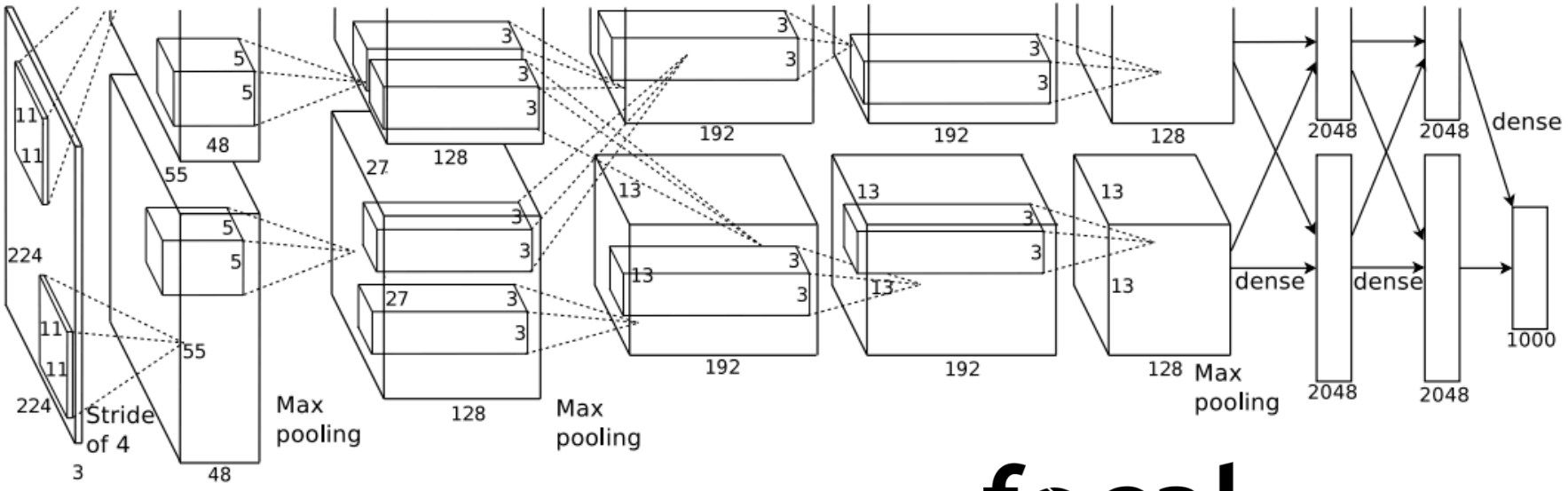
AlexNet - 2012

- First Layer Output 55x55x96
- Second Layer: 2x2 Max Pooling stride 2
- What is the output size?



AlexNet - 2012

- First Layer Output 55x55x96
- Second Layer: 2x2 Max Pooling stride 2
- What is the output size? 27x27x96



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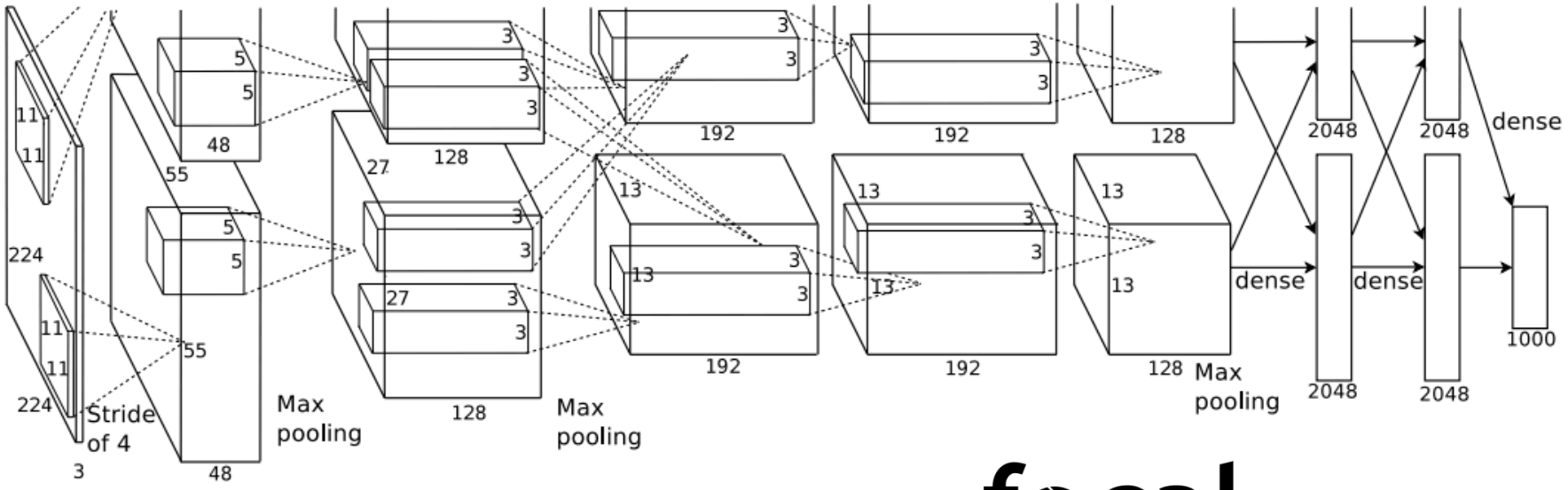
AlexNet - 2012

- First Layer Output 55x55x96
- Second Layer: 2x2 Max Pooling stride 2
- What is the number of params?



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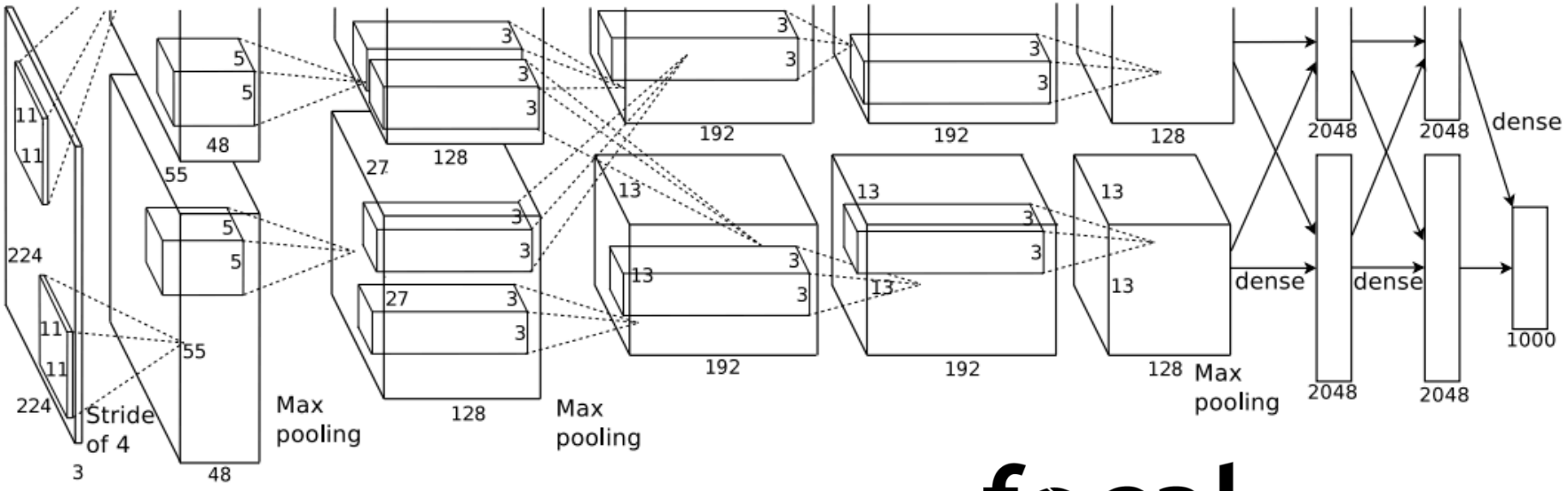
AlexNet - 2012

- First Layer Output 55x55x96
- Second Layer: 2x2 Max Pooling stride 2
- What is the number of params? 0



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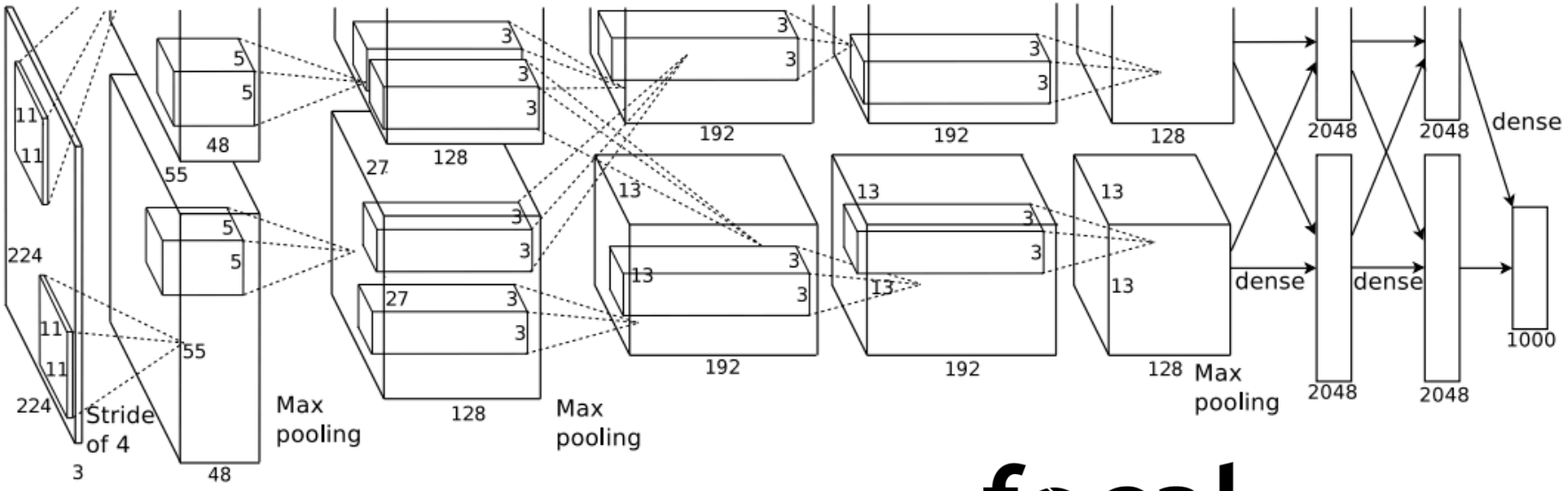
AlexNet - 2012

- First use of dropout, relu
- Heavy data augmentation
- SGD + Momentum, lr=1e-2, momentum=0.9, l2=5e-4



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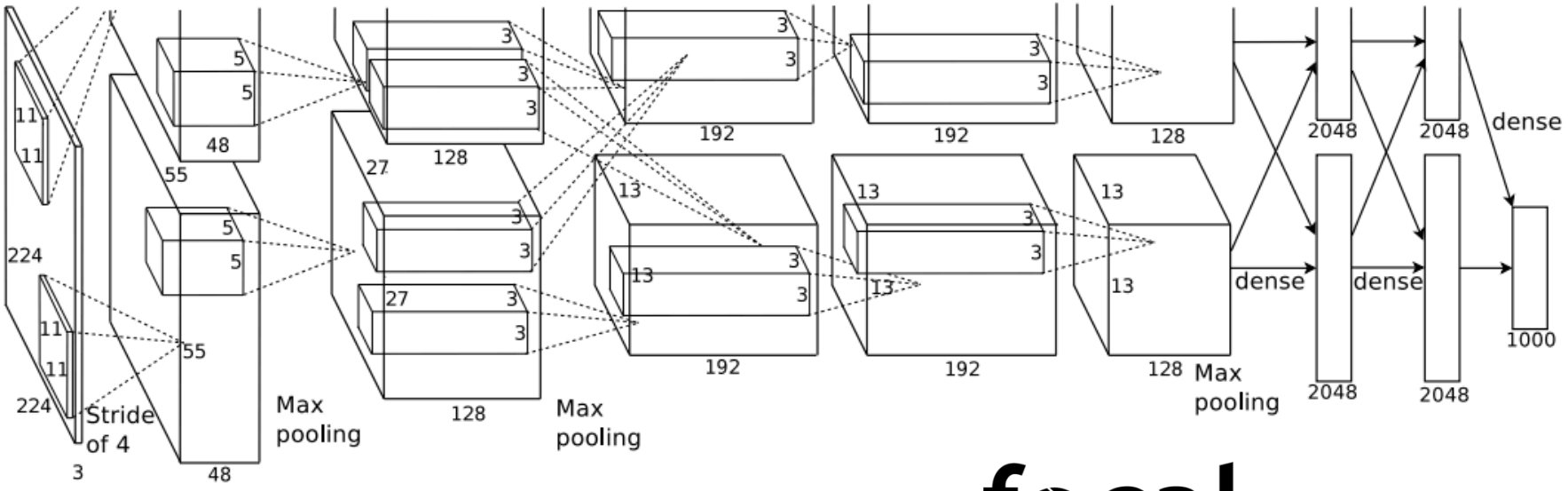
AlexNet - 2012

- GPUs too small, so they had half the network on different GPUs



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VGGNet 2014

- First simple widely used net
- Smaller and Deeper

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VGGNet 2014

- First simple widely used net
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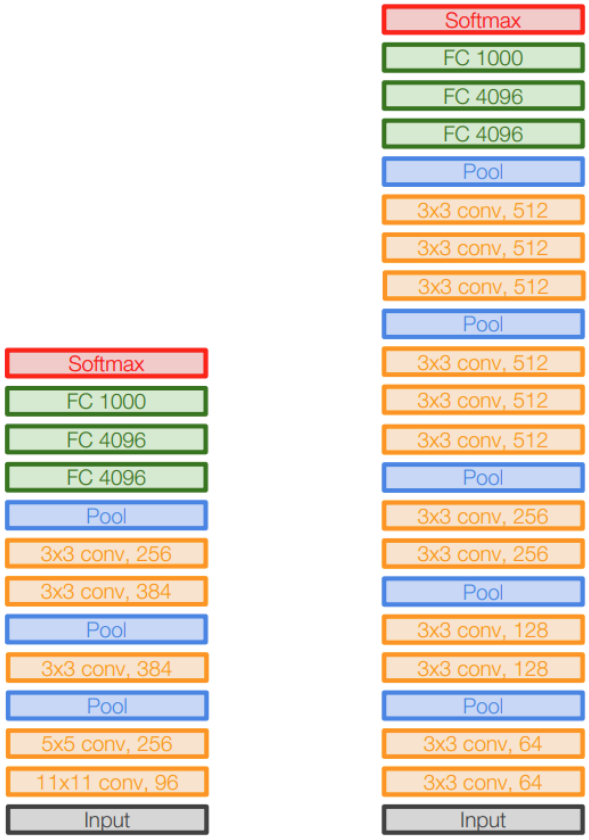
What is receptive field of 7x7 conv layer?



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VGGNet 2014

- First simple widely used net
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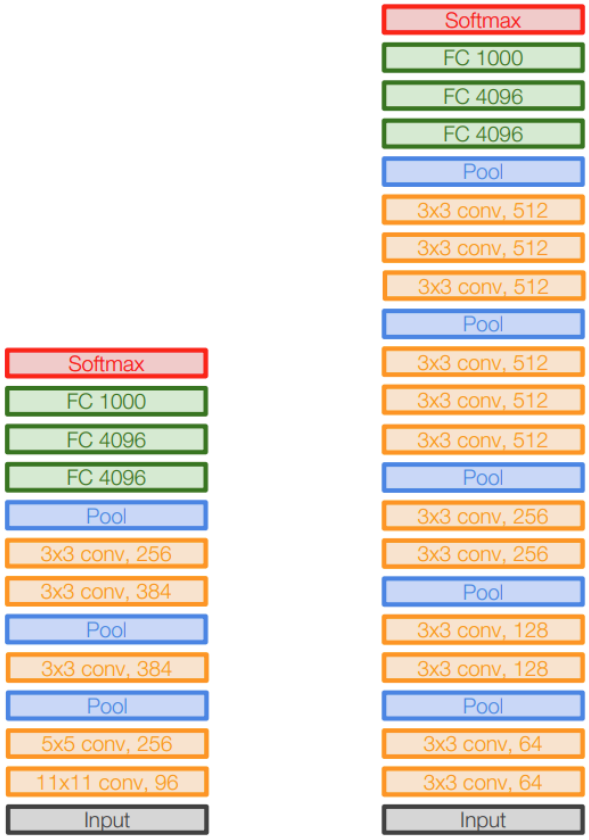
What is receptive field of 7x7 conv layer?
7x7



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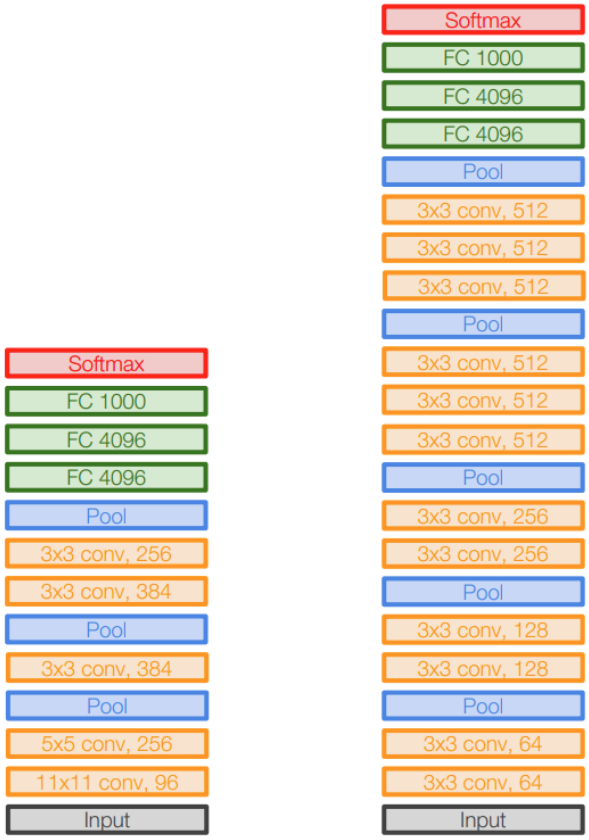
VGGNet 2014

- First simple widely used net
- Smaller and Deeper

What is receptive field of three 3x3 conv layers?



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VGGNet 2014

- First simple widely used net
- Smaller and Deeper

What is receptive field of three 3x3 conv layers?
Also 7x7

3 x 3 -> 5 x 5 -> 7 x7

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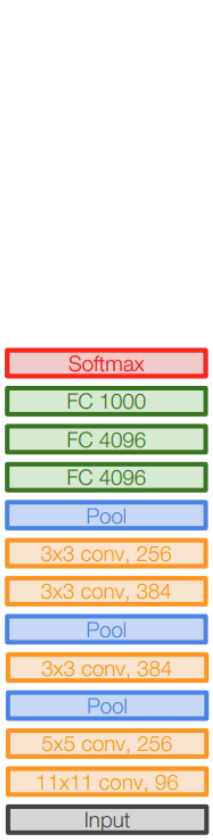
VGGNet 2014

- First simple widely used net
- Smaller and Deeper

How many params does a 7x7 layer with depth D have vs three 3x3 filters of depth D?



AlexNet

VGG16

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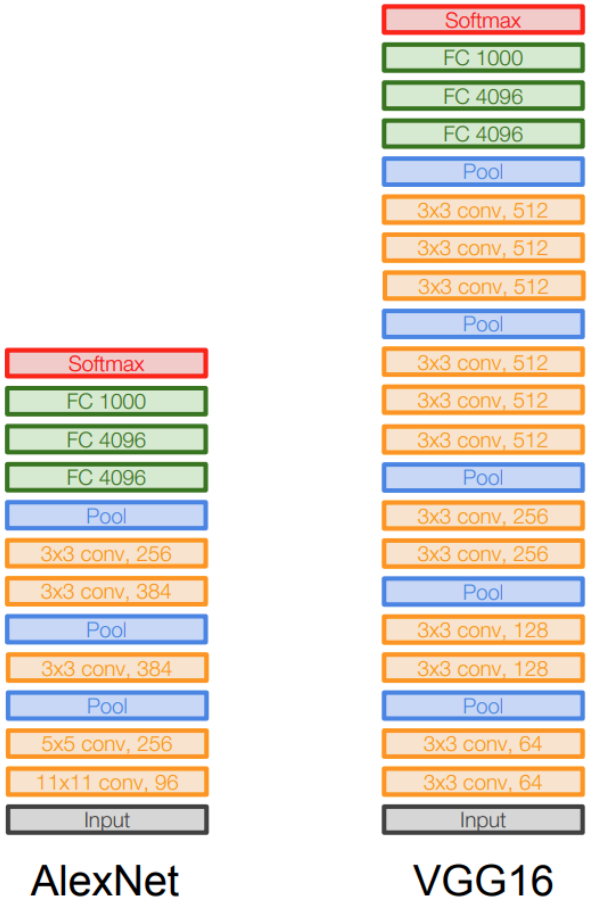
VGGNet 2014

- First simple widely used net
- Smaller and Deeper

How many params does a 7x7 layer with depth D have vs three 3x3 filters of depth D?
7*7*D*D = 49D^2
3*(3*3*D*D) = 27D^2



VGGNet 2014

- First simple widely used net
- Smaller and Deeper

How many non-linearities in a 7x7 filter vs three 3x3 filters?

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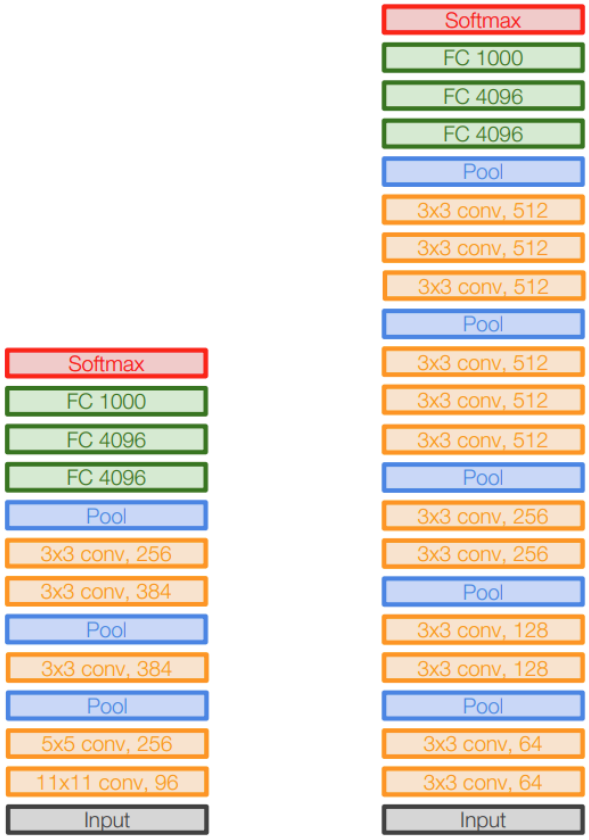
VGGNet 2014

- First simple widely used net
- Smaller and Deeper

How many non-linearities in a 7x7 filter vs three 3x3 filters?
1 vs 3



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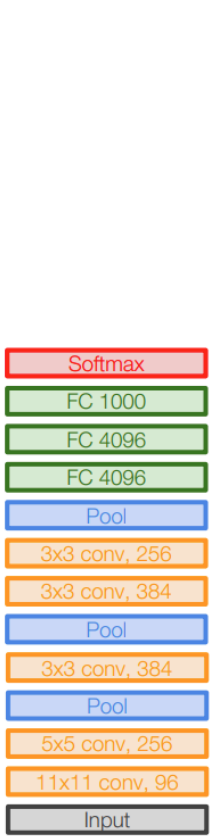
VGGNet 2014

- Similar training procedure
- Good out of box model + weights
- Downsamples input by 32 and then does fully connected layer



AlexNet

VGG16

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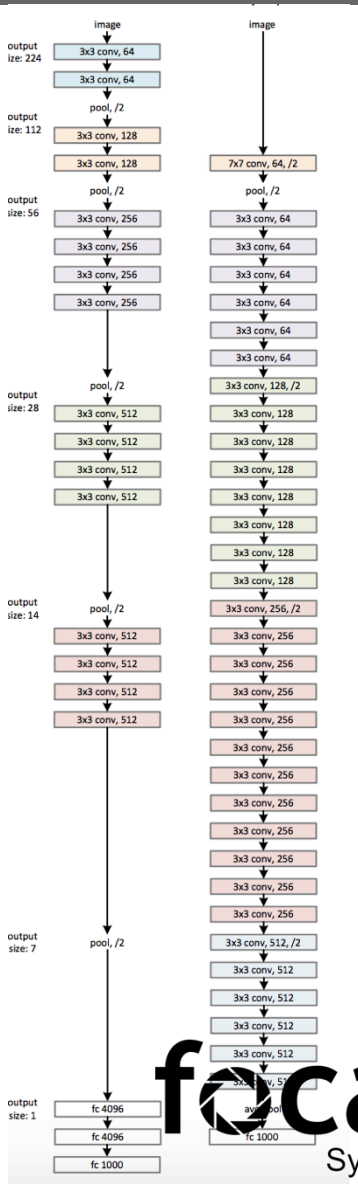
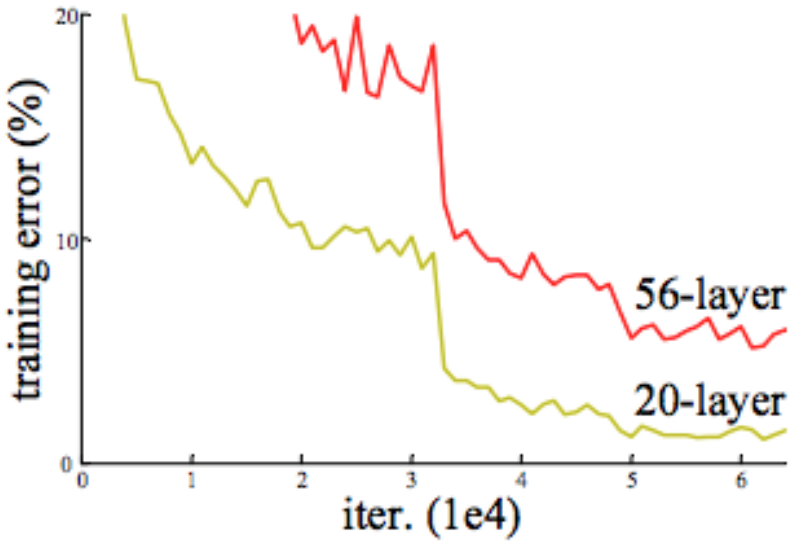
ResNet 2015

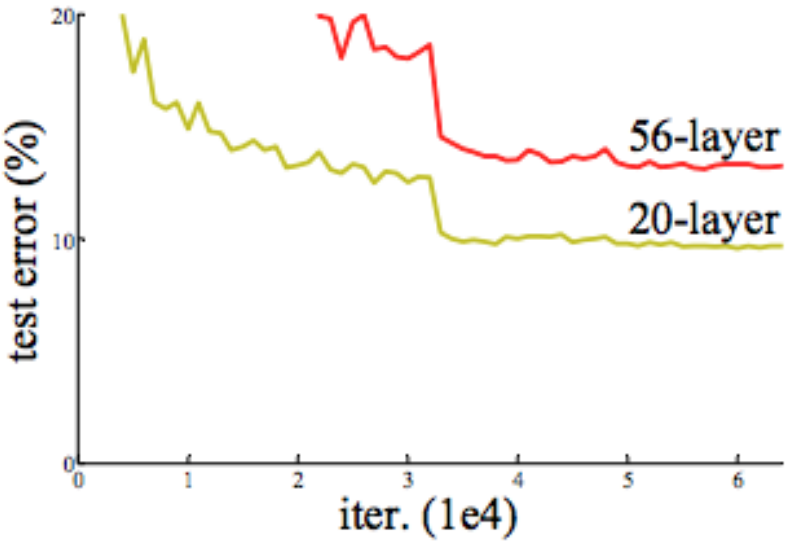
- Lets go much deeper!
- Why not just add many convs?



ResNet 2015

- Training curves for plain models





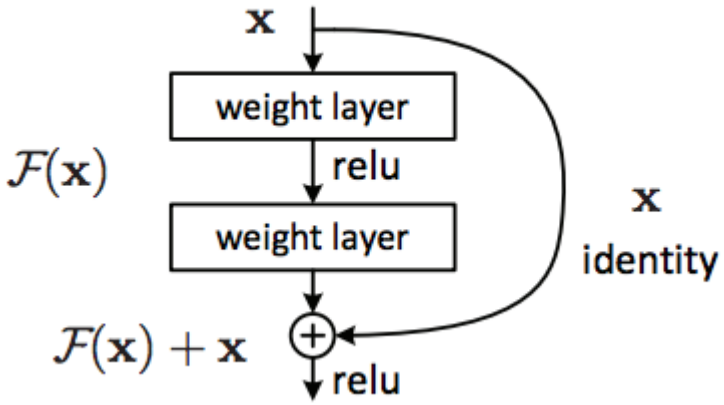
ResNet 2015

- Training deep networks is a hard optimization problem

ResNet 2015

- Solution: Identity Mappings

$$\mathcal{F}(\mathbf{x}) := \mathcal{H}(\mathbf{x}) - \mathbf{x}$$



ResNet 2015

- Normal Networks: $y = f(g(h(x)))$
- Residual Networks: $y = f(g(h(x) + x) + h(x) + x) + g(h(x) + x) + h(x) + x$
- There is always direct gradient flow to x

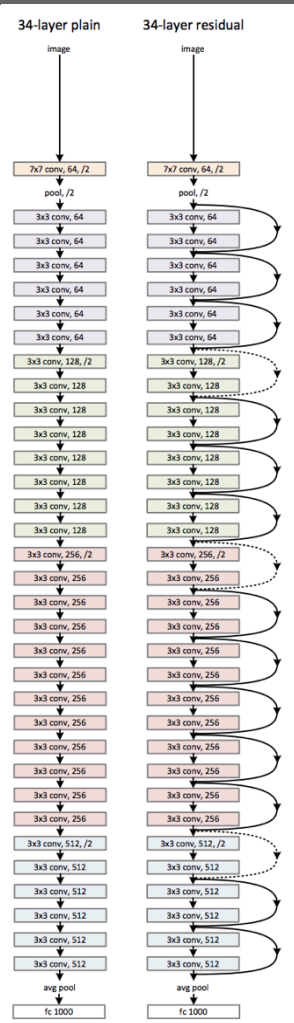
ResNet 2015

- Showed continual improvement with increased depth

model	top-1 err.	top-5 err.
VGG-16 [41]	28.07	9.33
GoogLeNet [44]	-	9.15
PReLU-net [13]	24.27	7.38
plain-34	28.54	10.02
ResNet-34 A	25.03	7.76
ResNet-34 B	24.52	7.46
ResNet-34 C	24.19	7.40
ResNet-50	22.85	6.71
ResNet-101	21.75	6.05
ResNet-152	**21.43**	**5.71**

ResNet 2015

- Great default
- final layer does global average pooling
- start with 7x7x64 conv followed by 3x3 max pool stride 2. <= standard input processing
- Uses Conv - Batch Norm - Relu
- No Dropout, No other pooling
- Uses 1x1 Convs to downsize, and then 3x3s



Architectures Summary

- Deeper is better
- Focus on gradient flow
- Conv - Batch Norm - ReLu
- Compositions of small filters are key: 3x3, 1x1
- Pretrained ImageNet weights are very good
- Keras: https://github.com/fchollet/keras/tree/master/keras/applications

Deep Learning for Retail