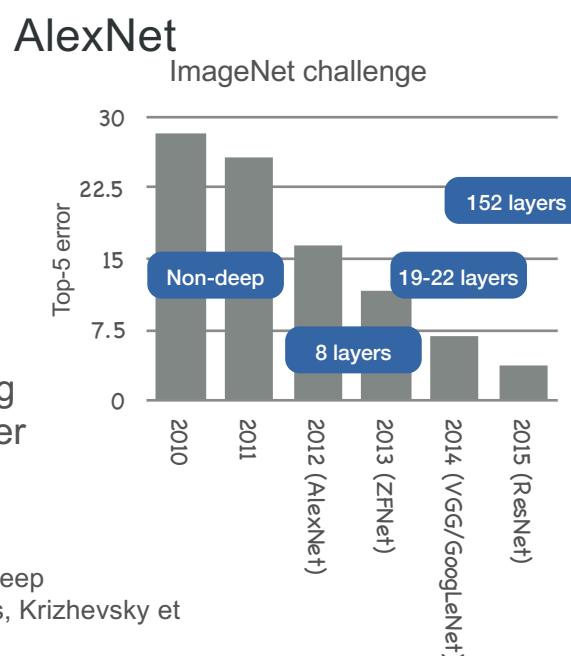


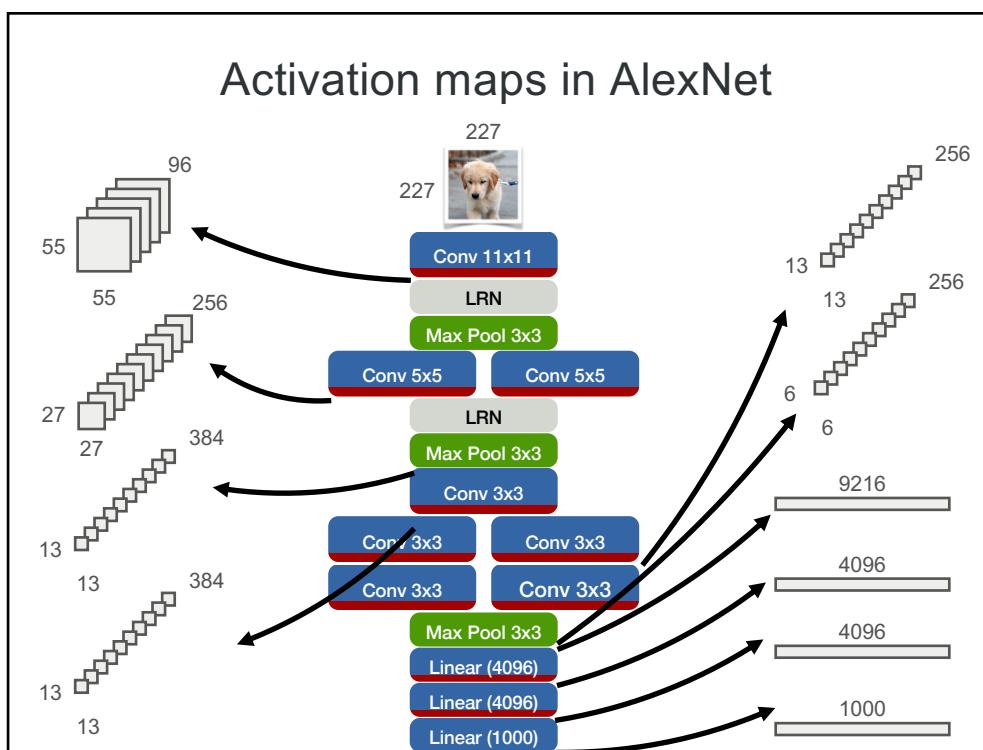
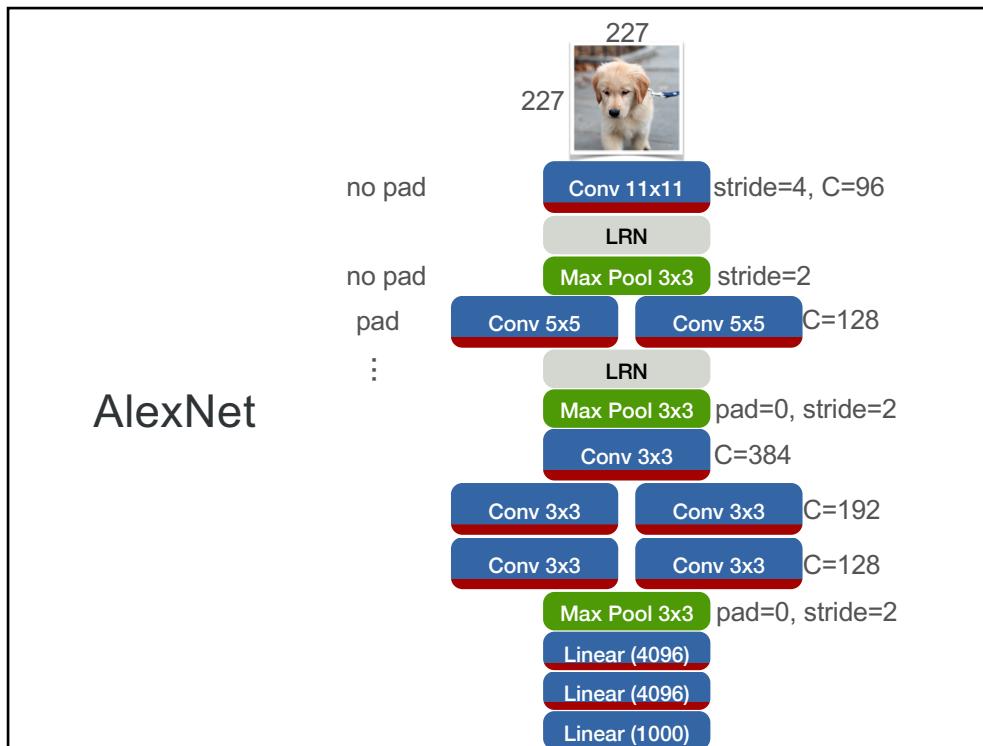
CNN architectures and visualization

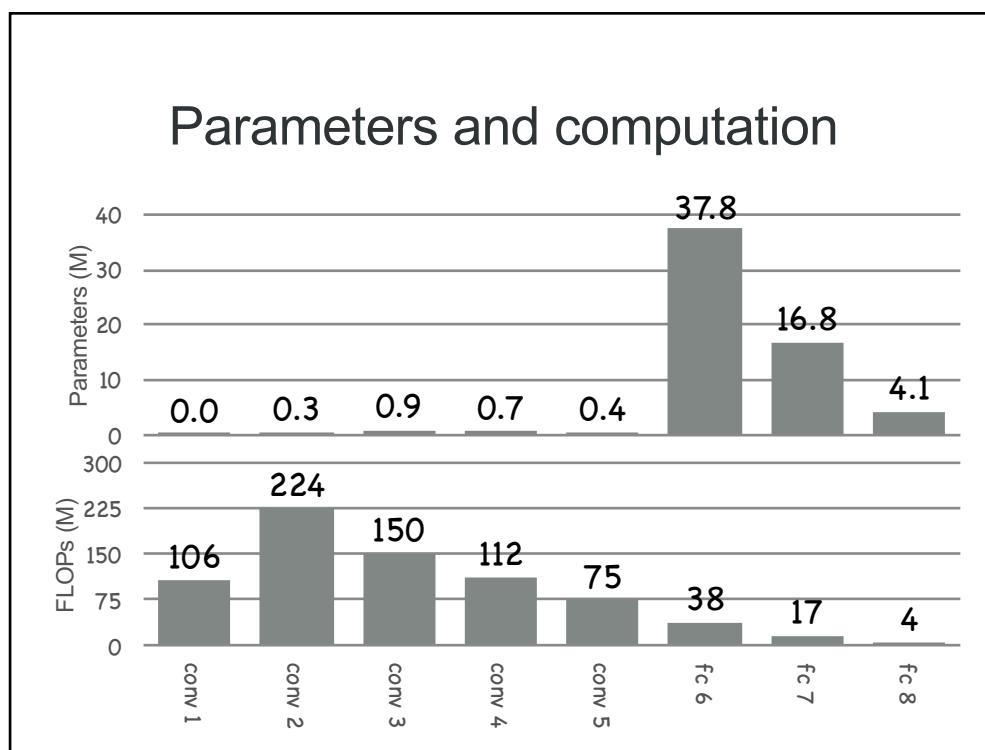
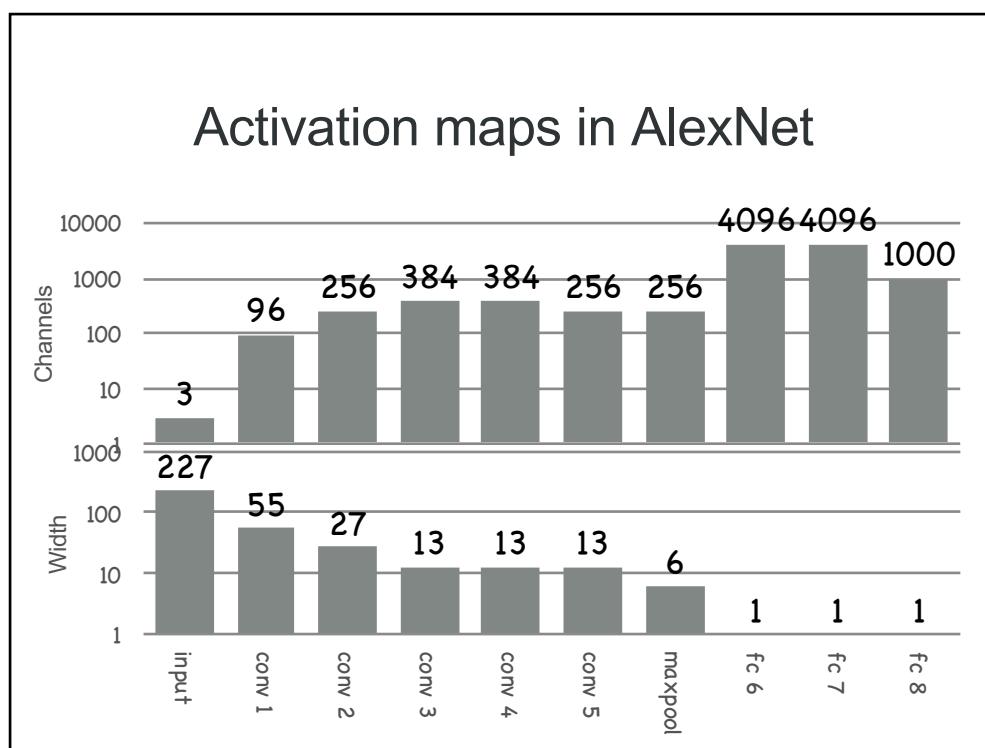
Adopted from: © 2019 Philipp Krähenbühl and Chao-Yuan Wu

- Won the ImageNet competition 2012
- Start of deep learning revolution in computer vision

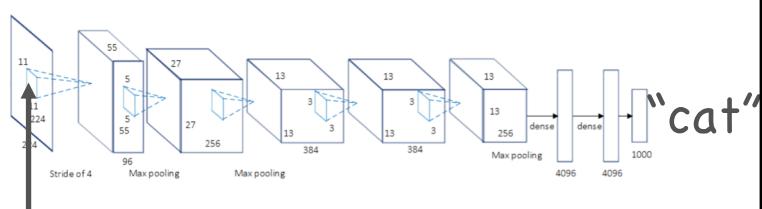
ImageNet Classification with Deep Convolutional Neural Networks, Krizhevsky et al., NIPS 2012



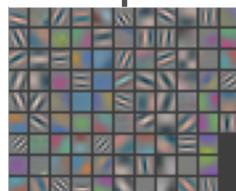




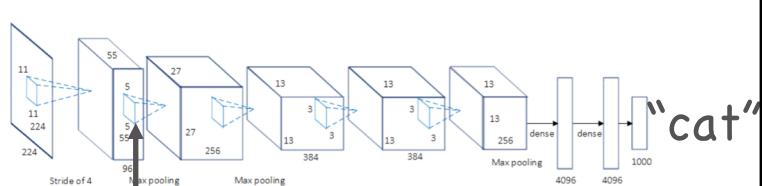
What's happening inside the black box?



Visualize first-layer weights directly



What's happening inside the black box?

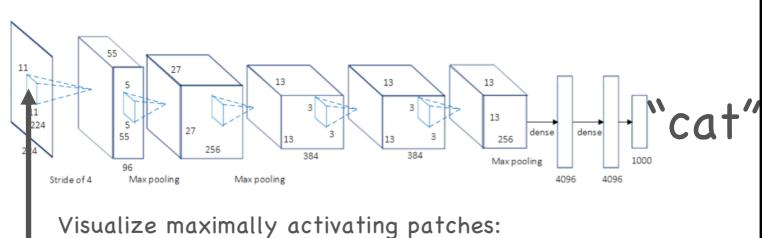


Not too helpful for subsequent layers

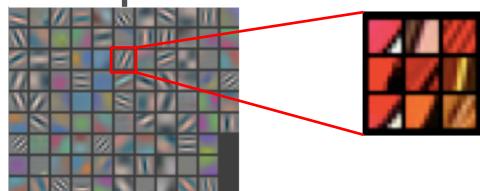


Features from a CIFAR10 network, via [Stanford CS231n](#)

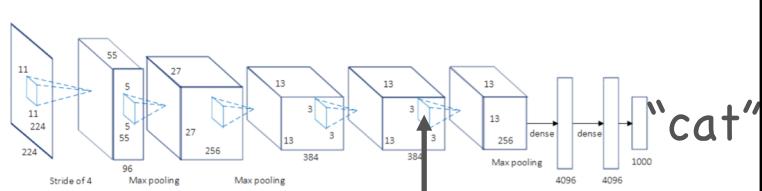
What's happening inside the black box?



Visualize maximally activating patches:
pick a unit; run many images through the
network; visualize patches that produce
the highest output values

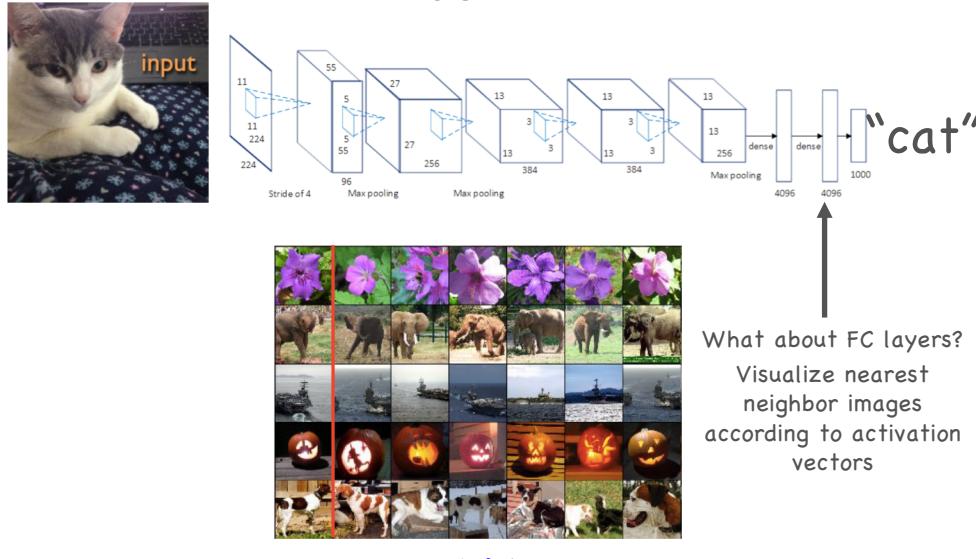


What's happening inside the black box?

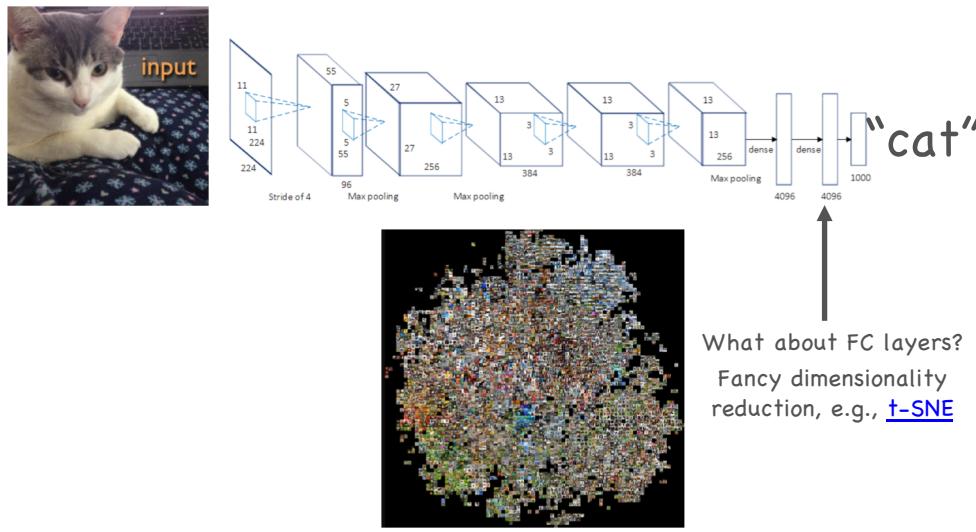


Visualize maximally activating patches

What's happening inside the black box?



What's happening inside the black box?



What's happening inside the black box?

input

11 11 224
224

Stride of 4

55 5 96 Max pooling

27 256

Max pooling

13 13 384

13 13 384

13 13 384

Max pooling

256 4096

dense 4096

dense 4096

“cat”

selected channel

Visualize activations for a particular image

[Source](#)

What's happening inside the black box?

input

11 11 224
224

Stride of 4

55 5 96 Max pooling

27 256

Max pooling

13 13 384

13 13 384

13 13 384

Max pooling

256 4096

dense 4096

dense 4096

“cat”

deconv

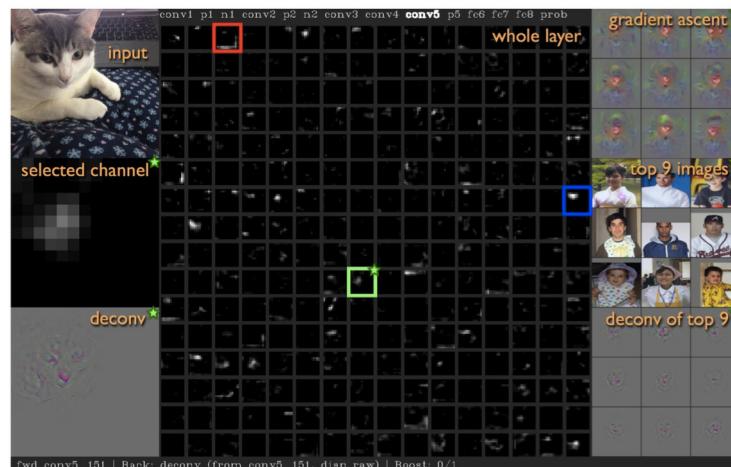
Visualize activations for a particular image

1. Unpool
2. Rectify
3. Deconvolve

Visualize pixel values responsible for the activation

[Source](#)

Deep visualization toolbox



[YouTube video](#)

J. Yosinski, J. Clune, A. Nguyen, T. Fuchs, and H. Lipson, [Understanding neural networks through deep visualization](#), ICML DL workshop, 2015

Additional visualization techniques

K. Simonyan, A. Vedaldi, and A. Zisserman, [Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps](#), ICLR 2014

J. Springenberg, A. Dosovitskiy, T. Brox, M. Riedmiller, [Striving for simplicity: The all convolutional net](#), ICLR workshop, 2015

A. Nguyen, J. Yosinski, J. Clune, [Multifaceted Feature Visualization: Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks](#), ICML workshop, 2016

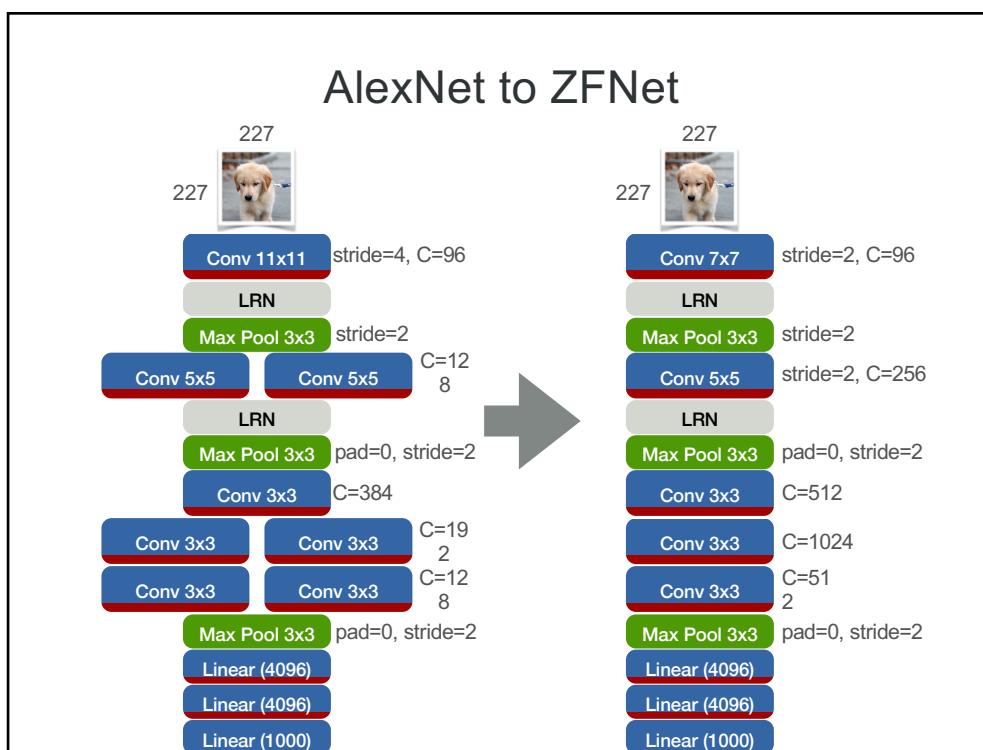
ZFNet

ImageNet challenge

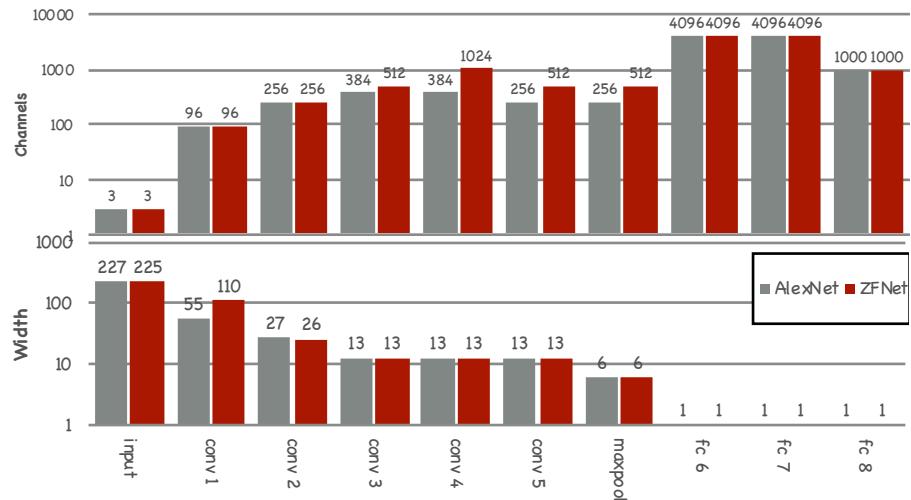
Year	Model Type	Top-5 error (%)
2010	Non-deep	~29
2011	Non-deep	~27
2012	8 layers	~15
2013	19-22 layers	~13
2014	19-22 layers	~7.5
2015 (ResNet)	152 layers	~3

- Won the ImageNet competition 2013
- Nice analysis and visualization of AlexNet
 - Introduced up-conv

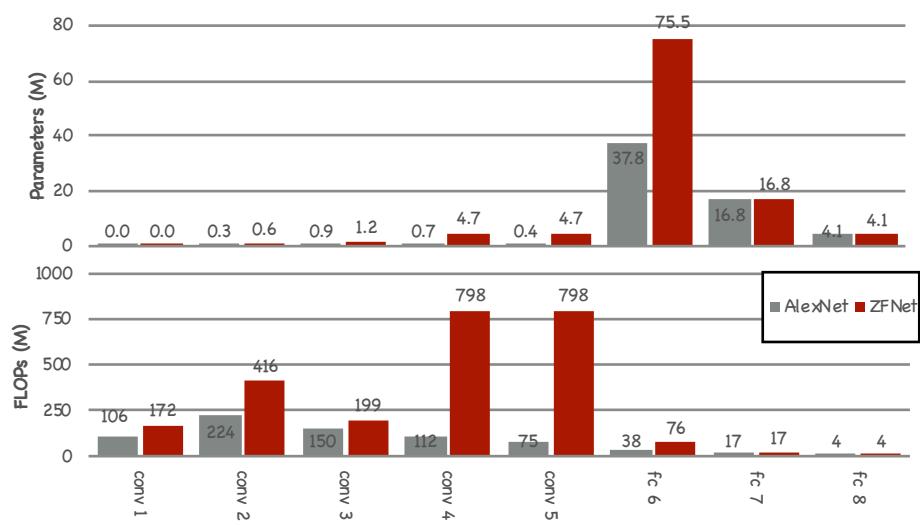
Visualizing and Understanding Convolutional Networks, Zeiler & Fergus, ECCV 2014

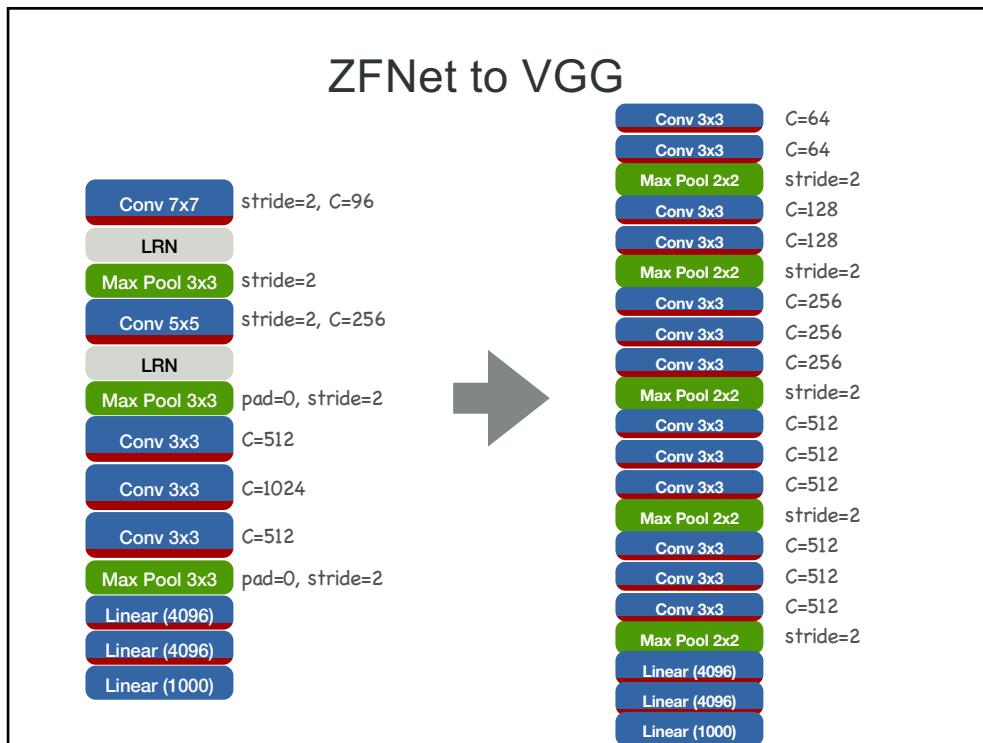
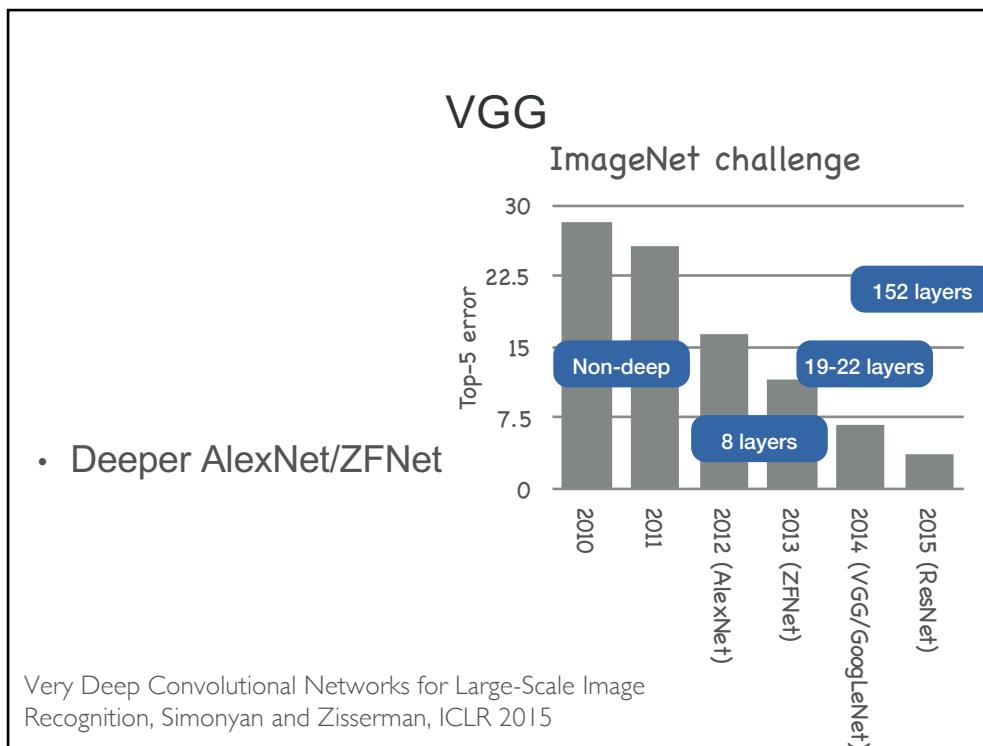


Activation maps in ZFNet



Parameters and computation





Insights in VGG

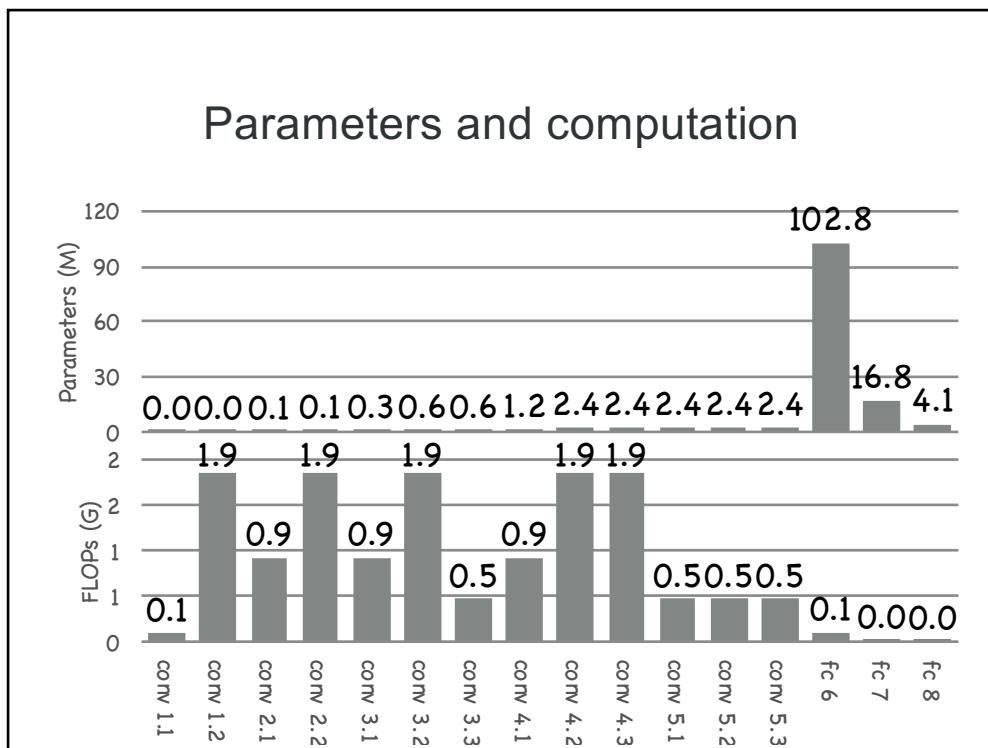
- Why use smaller filters?
 - Factorization



Training VGG

- Vanishing gradients

Conv 3x3	C=64
Conv 3x3	C=64
Max Pool 2x2	stride=2
Conv 3x3	C=128
Conv 3x3	C=128
Max Pool 2x2	stride=2
Conv 3x3	C=256
Conv 3x3	C=256
Conv 3x3	C=256
Max Pool 2x2	stride=2
Conv 3x3	C=512
Conv 3x3	C=512
Conv 3x3	C=512
Max Pool 2x2	stride=2
Conv 3x3	C=512
Conv 3x3	C=512
Conv 3x3	C=512
Max Pool 2x2	stride=2
Linear (4096)	
Linear (4096)	
Linear (1000)	



1x1 convolutions and factorization

- Convolutions are linear operators
 - Can we make them non-linear?

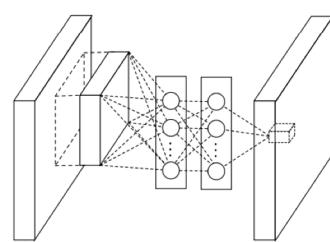
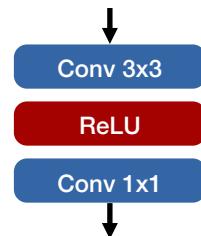


Figure source: "Network-in-Network", ICLR 2014 paper

Network-in-Network, Lin et al., ICLR 2014

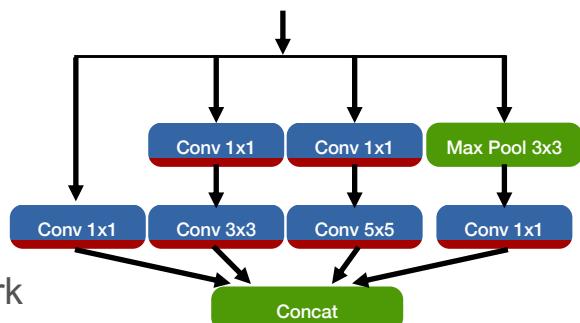
Factorized convolution

- Implements “non-linear” convolution
- Less computation, fewer parameters



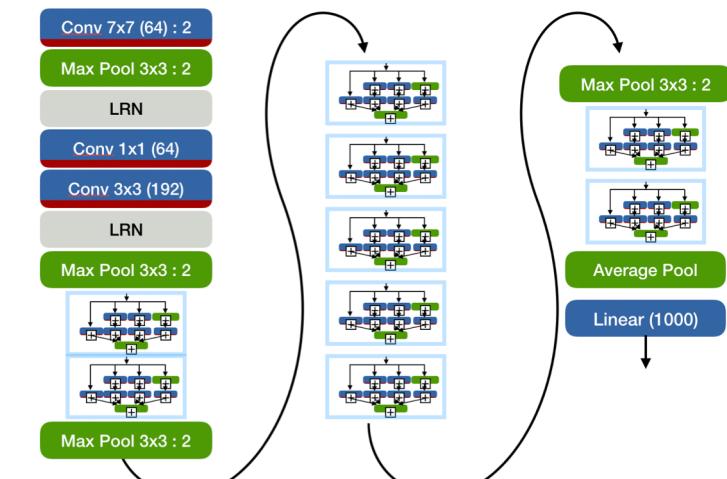
Inception architecture

- GoogLeNet
 - Evolution of Network-in-Network



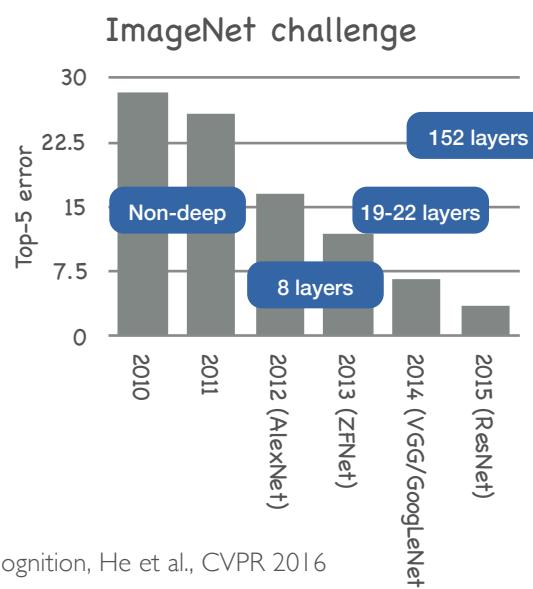
Going deeper with convolutions, Szegedy et al. CVPR 2015.

Inception architecture



Residual Networks

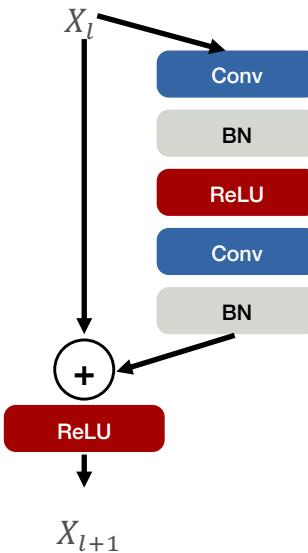
- Uses residual connections to build deeper networks
 - Activation maps are additive



Deep Residual Learning for Image Recognition, He et al., CVPR 2016

Residual blocks

- Add shortcut connections for gradients
 - Identity
 - Strided 1x1 convolution



ResNet

- Multiple variants
 - ResNet-18, ResNet-34, ResNet-50, ResNet-101, ResNet-152, ResNet-1001

ResNet-152

