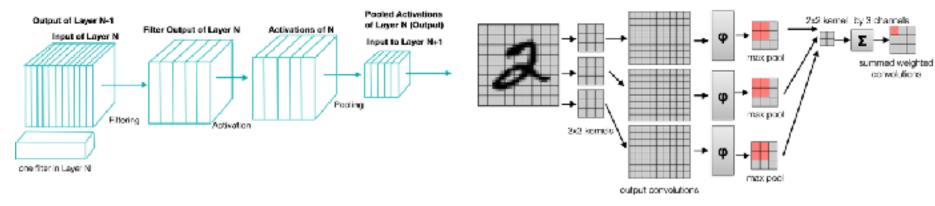
Lecture Notes for **Machine Learning in Python**

Professor Eric Larson More Convolutional Networks

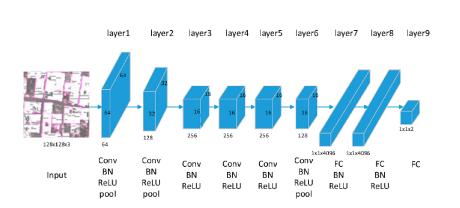
Class logistics and Agenda

- Wide/Deep Lab due soon!
- Agenda:
 - CNN Demo
 - History of CNNs
 - with Modern CNN Architectures
- Next Time:
 - More Advanced CNN Demo

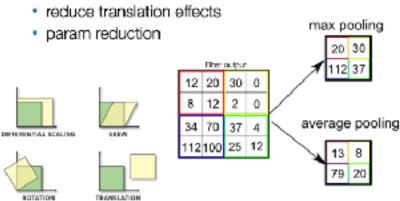
Last Time:



Structure of Each Tensor: Channels x Rows x Columns



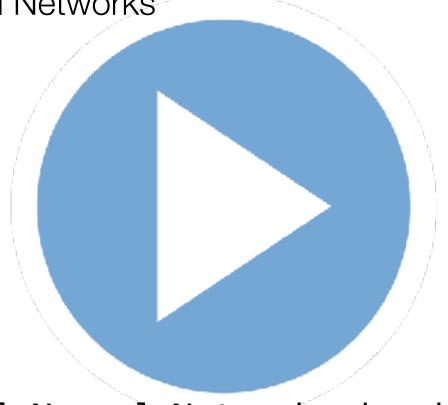
- · Why perform pooling?
- Why max pooling?



TensorFlow and Basic CNNs

Demo

Convolutional Neural Networks in TensorFlow with Keras



11. Convolutional Neural Networks.ipynb

History of Convolutional Neural THAT WAS SURPRISINGLY IF YOU LOOK TO NETWORKS ROBOTIC UPRISING USED HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IF YOU LOOK TO HISTORICAL DATA, SPEAZS AND POCKS NEW YORK OF THE HISTORICAL DATA, SPEAZS AND POCKS NEW YORK OF THE HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IF YOU LOOK TO HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IF YOU LOOK TO HISTORICAL DATA, SPEAZS AND POCKS NEW YORK OF THE HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IF YOU LOOK TO HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IN THE HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IN THE HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IN THE HISTORICAL DATA, SPEAZS AND POCKS THAT WAS SURPRISINGLY IN THE HISTORICAL DATA, SPEAZS AND POCKS THE YOU LOOK TO HISTORICAL DATA AND THE



Thanks to machine-learning algorithms, the robot apccalypse was short-lived.

Types of CNN, 1988-1998



Heads Facebook Al Team

- **LeNet-1** (1988)
 - ~2600 params, not many layers
- **LeNet-5** (1998)
 - 7 layers, gets excellent MNIST performance

tanh or sigmoid

Major contribution, general structure:

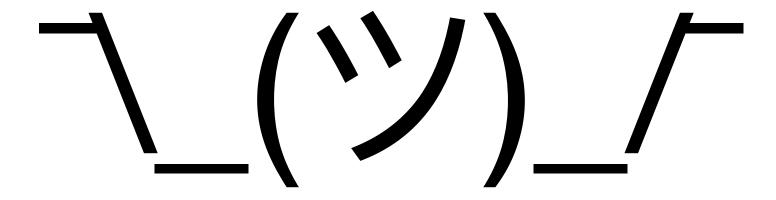
avg

conv=>pool=>non-linearity=> ...=>MLP

C3: f. maps 16@10x10 C1: feature maps \$4: f. maps 16@5x5 INPUT 6@28x28 32x32 S2: f. maps C5: layer F6: layer OUTPUT 6@14x14 Full connection Gaussian connections Subsampling Subsampling Full connection Convalutions Convolutions

CNN History

 List of major breakthroughs from 1998 through 2010 in convolutional networks:



2010





Al Researcher IDSA, Switzerland

Ciresan Net

- Publishes code for running CNN via GPU
 - Subsequently wins 5 international competitions
 - from stop signs => cancer detection
- Major contribution: NVIDIA parallelized training algorithms

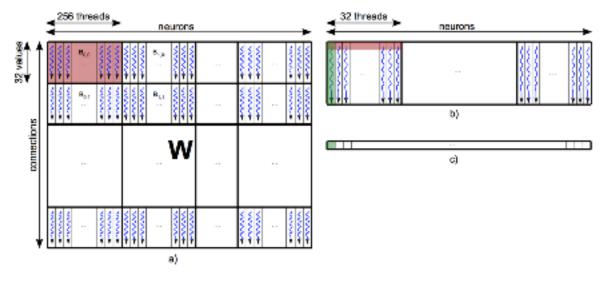
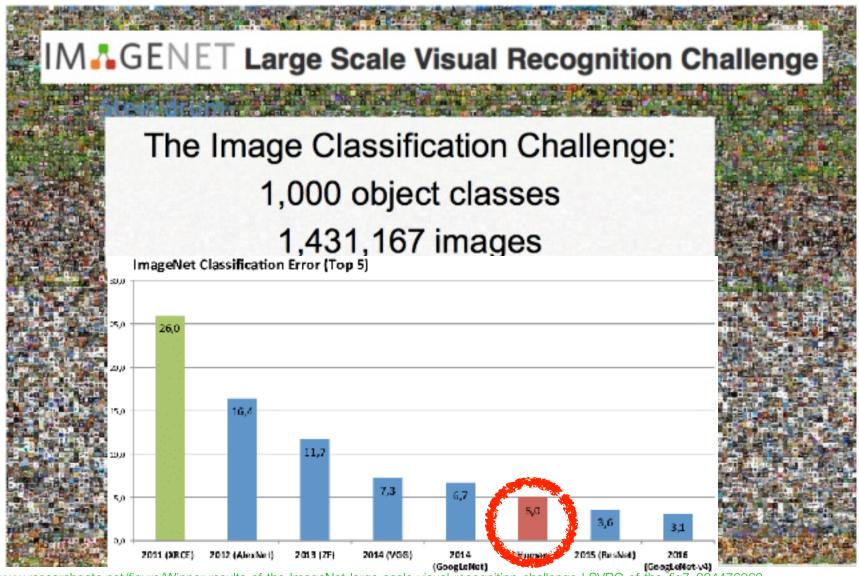


Figure 2: Forward propagation: a) mapping of kernel 1 grid onto the padded weight matrix; b) mapping the kernel 2 grid onto the partial dot products matrix; c) output of forward propagation.

ImageNet Competition (2010-2016)



https://www.researchgate.net/figure/Winner-results-of-the-ImageNet-large-scale-visual-recognition-challenge-LSVRC-of-the_fig7_324476862

https://www.slideshare.net/nmhkahn/case-study-of-convolutional-neural-network-61556303



Google

- AlexNet, Hinton is mentor
 - wins ImageNet competition
- Major contributions:
 - dropout for regularization
 - systematic use of ReLU
 - data expansion
 - overlapping max pool



FC 1000

FC 4096 / ReLU

FC 4096 / ReLU

Max Pool 3x3s2

Conv 3x3s1, 256 / ReLU

Conv 3x3s1, 384 / ReLU

Conv 3x3s1, 384 / ReLU

Max Pool 3x3s2

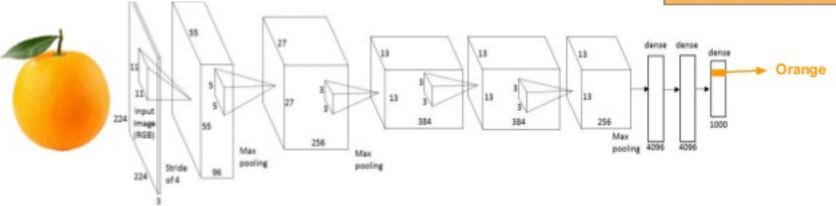
Local Response Norm

Conv 5x5s1, 256 / ReLU

Max Pool 3x3s2

Local Response Norm

Conv 11x11s4, 96 / ReLU



Warning









- Oxford VGG Net (Visual Geometry Group)
- Major contributions:
 - small cascaded kernels
 - way more layers (19 versus ~7)
 - "emulates" biology "better"
 - trained on NVIDIA GPUs for 2-3 weeks

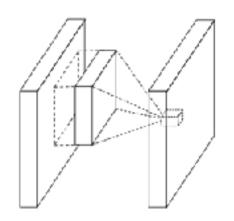
ConvNet Configuration										
A	A-LRN	В	C	D	D I E					
11 weight	11 weight	13 weight	16 weight	16 weight	19 weight					
lavers	layers	layers	layers	layers	layers					
input (224 × 224 RGB image)										
conv3-64	conv3-64	conv3-64	conv3-64	conv3-64	conv3-64					
	LRN	conv3-64	conv3-64	conv3-64	conv3-64					
maxpool										
conv3-128	conv3-128	comv3-128	comv3-128	comv3-128	conv3-128					
		conv3-128	conv3-128	conv3-128	conv3-128					
maxpool										
conv3-256	comv3-256	comv3-256	comv3-256	comv3-256	conv3-256					
conv3-256	conv3-256	com/3-256	conv3-256	comv3-256	conv3-256					
			conv1-256	conv3-256	conv3-256					
					conv3-256					
			pool							
conv3-512	conv3-512	comv3-512	conv3-512	conv3-512	conv3-512					
conv3-512	conv3-512	conv3-512	comv3-512	conv3-512	conv3-512					
			conv1-512	conv3-512	conv3-512					
					conv3-512					
			peol							
conv3-512	conv3-512	comv3-512	conv3-512	comv3-512	conv3-512					
conv3-512	conv3-512	comv3-512	comv3-512	conv3-512	conv3-512					
			conv1-512	conv3-512	conv3-512					
			<u> </u>		conv3-512					
			pool							
	FC-4096									
FC-4096										
FC-1000										
		soft-	-max							

Table 2: Number of parameters (in millions).

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

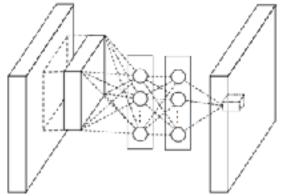
Network In Network

- Network in Network NiN
 - · or MLPConv

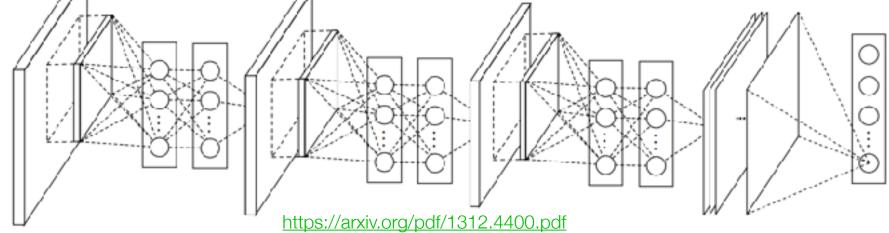


(a) Linear convolution layer

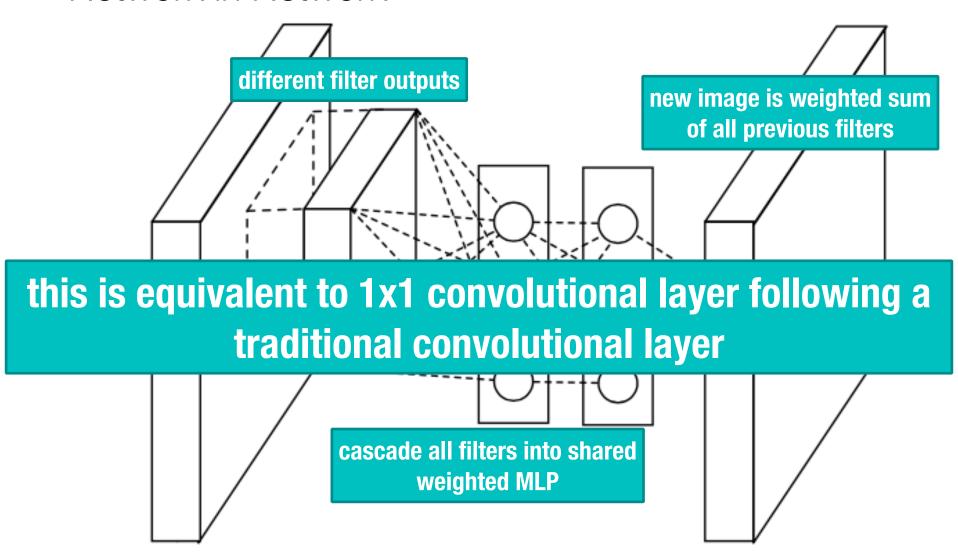




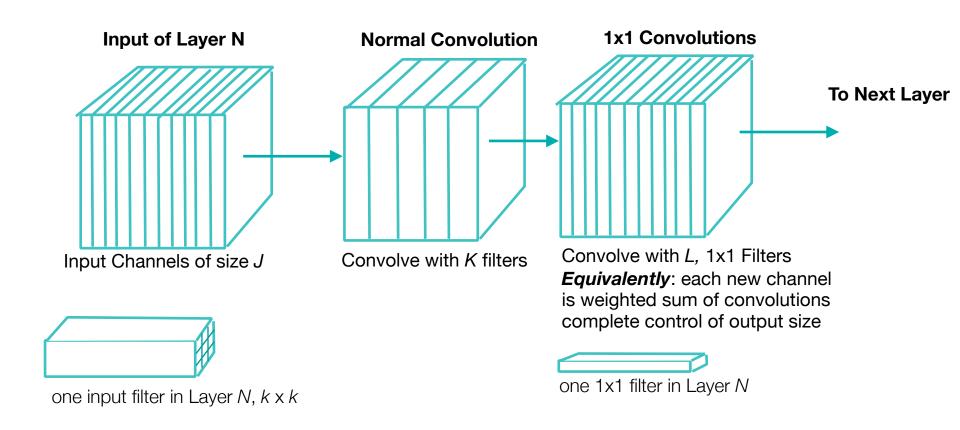
(b) Mlpconv layer



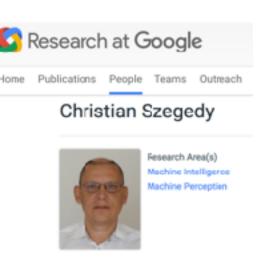
Network in Network



NiN, expanded view

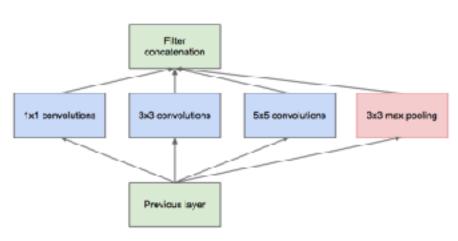


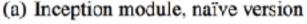
Structure of Each Tensor: Channels x Rows x Columns

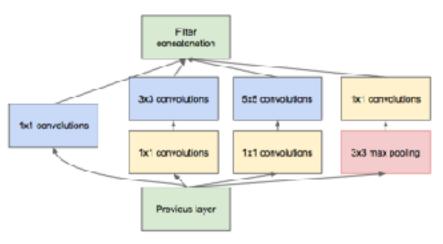


- GoogLeNet
 - or Inception V1
- Major contribution:
 - bottleneck layering
 - · parallel NiN









(b) Inception module with dimension reductions

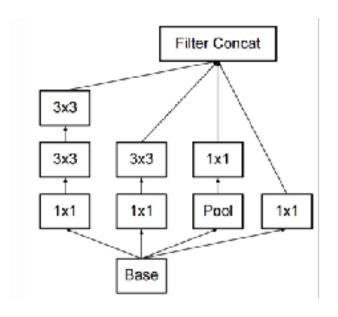
Figure 2: Inception module

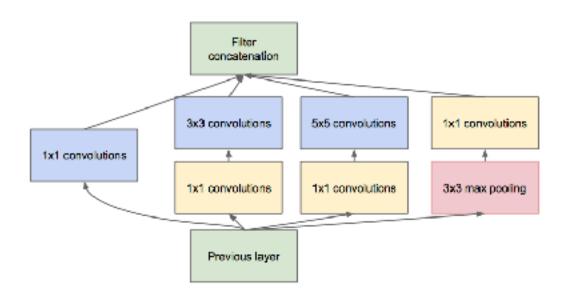
https://arxiv.org/pdf/1409.4842.pdf

Types of CNN, 2015 February and December



- Inception V2, Inception V1 with batch normalization
- Inception V3:
 - replace 5x5 with multiple 3x3





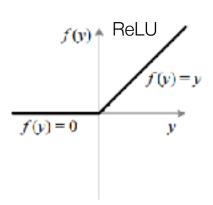
Types of CNN, 2015 December

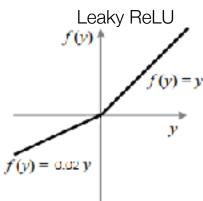
Research

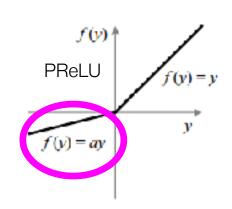
- Major Contributions:
 - "ensembles" not strictly sequential
 - "bio-plausible" with feedback

ResNet

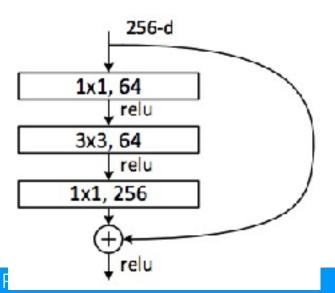
Parametric ReLU PReLU: adaptive trained slope



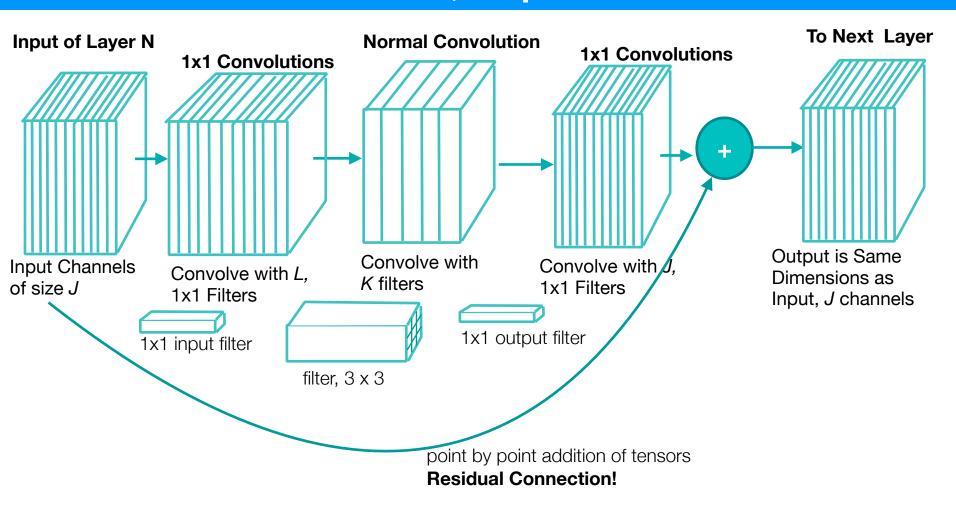




NiN: triple bypass layer similar to bottelneck



Residual Connection, expanded view



Back Propagation: Two paths, including one without ANY operations that cause the gradient to vanish...

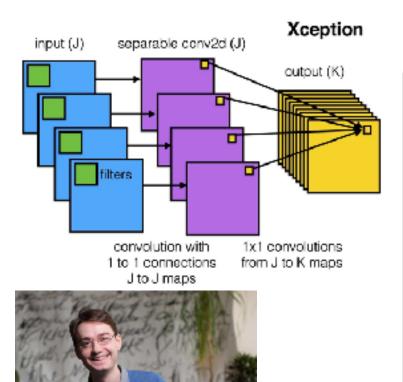
Types of CNN, 2017 April

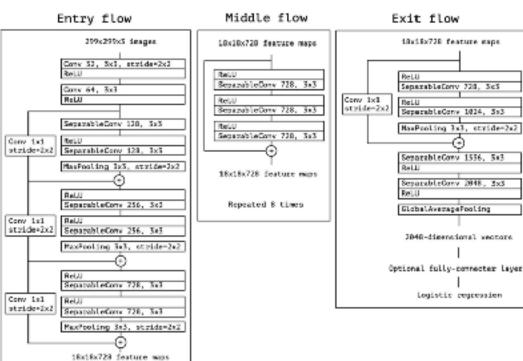
Xception

- Major Contributions:
 - combining branching / residual blocks
 - separable convolutions

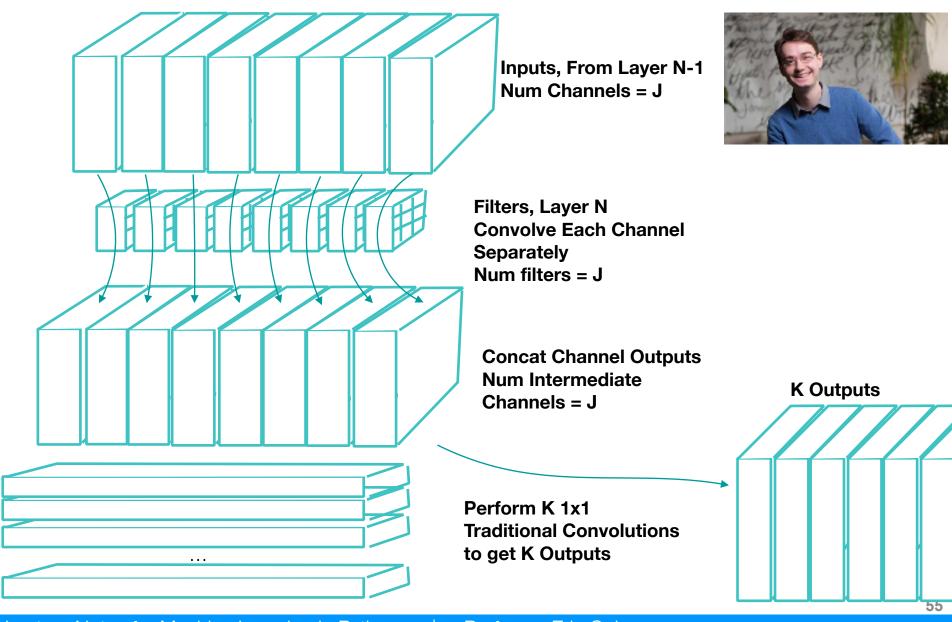


Francois Chollet **Google**



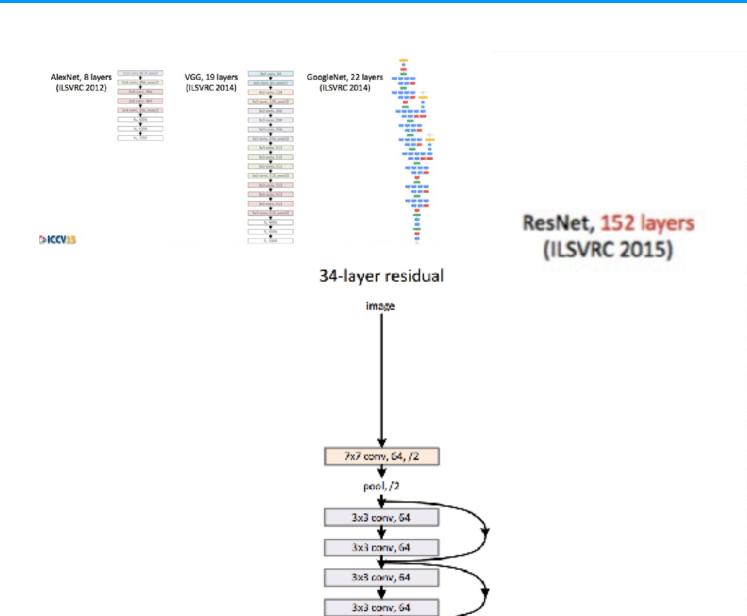


Separable Convolution Primer



How big are these networks?

How big are these networks?



Professor Eric C.

Self Test

- We have seen a lot of different networks.
- The most important concept to understand in using convolutional neural networks is:
 - A. Use proper initialization of layers
 - B. Have plenty of data or use expansion
 - C. Set aside time for training
 - D. Use batch normalization

Next Time:

- CNN Lab Discussion (Town Hall)
- Intro to Recurrent Neural Network Architectures
 - RNNs, GRUs, LSTMs
 - Training for characters