Lecture Notes for

Machine Learning in Python

Professor Eric Larson

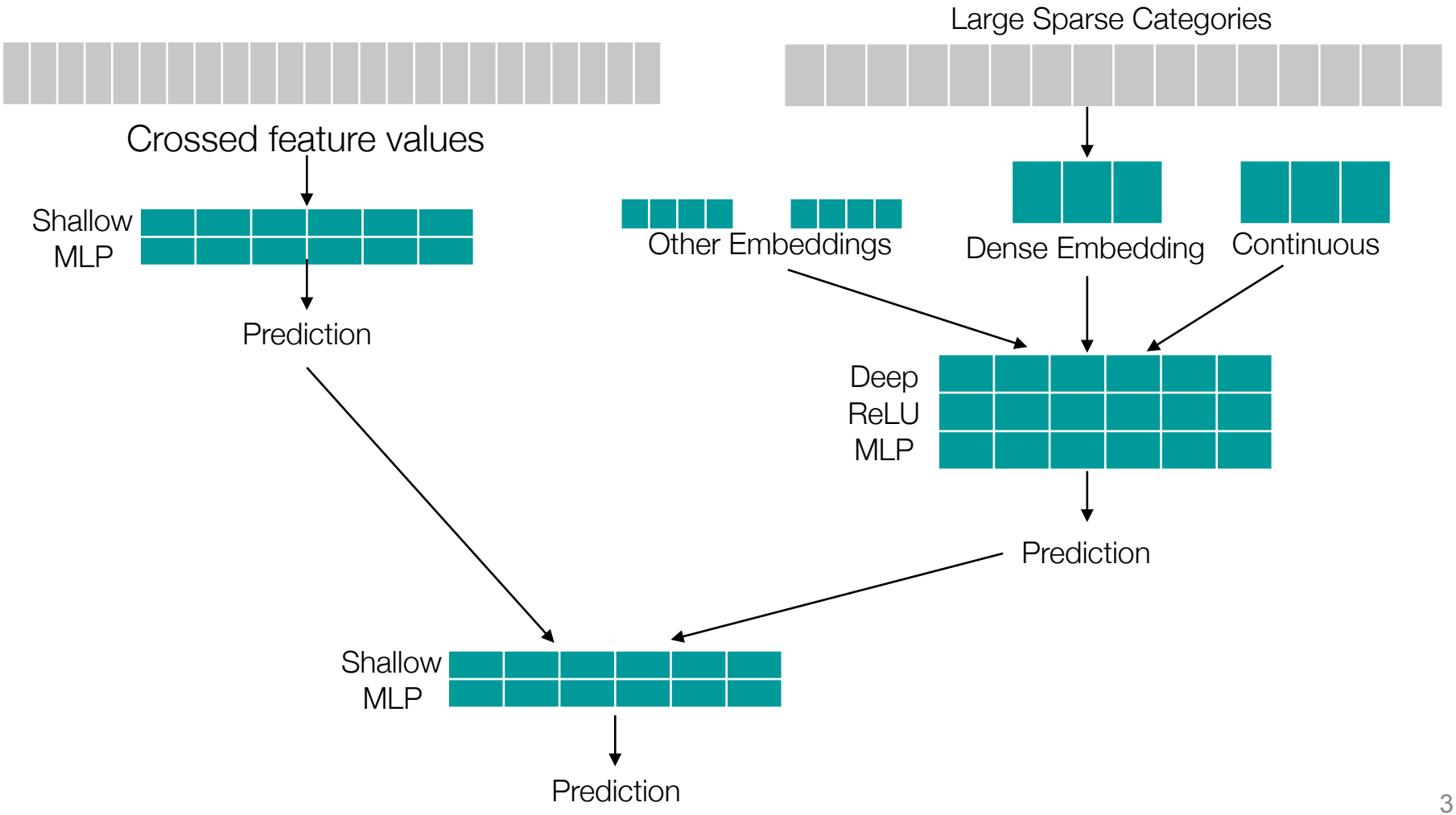
Basic Convolutional Neural Networks

Logistics and Agenda

- Logistics
  - Wide/Deep due date coming up!
- Agenda
  - Finish Town Hall
  - Basic CNN architectures and Demo

Last Time:

- Deep refers to increasingly smaller hidden layers
- Embed into sparse representations via ReLU



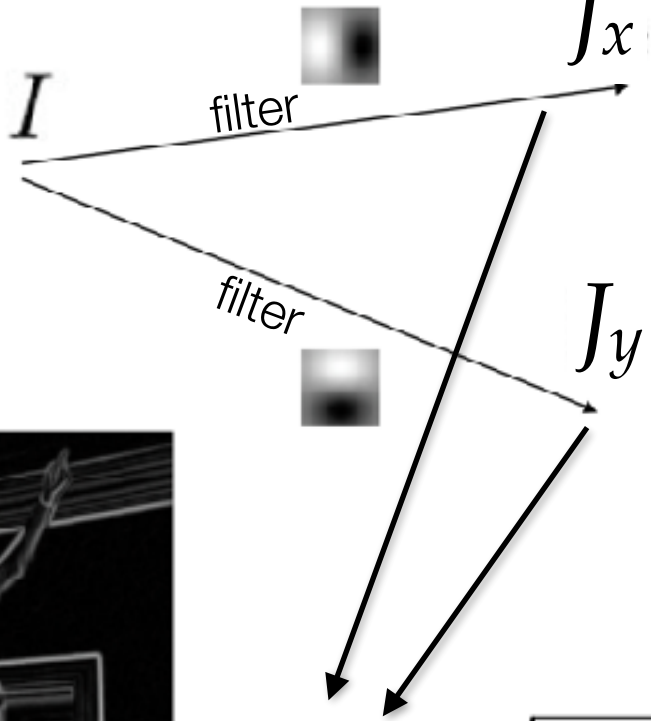
Town Hall, Wide and Deep

WHEN VISITING A NEW HOUSE, IT'S GOOD TO CHECK WHETHER THEY HAVE AN ALWAYS-ON DEVICE TRANSMITTING YOUR CONVERSATIONS SOMEWHERE.

Convolutional Neural Networks

What we did before

- the gradient (2D derivative)

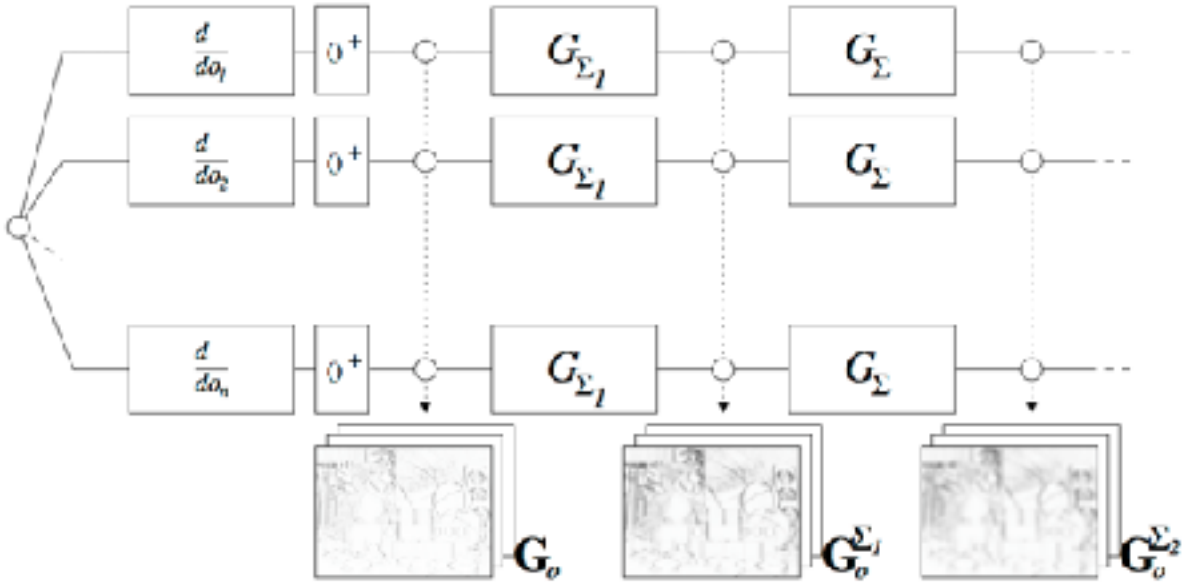


$$\|\nabla J\| = \sqrt{J_x^2 + J_y^2}$$

$$O = \tan^{-1}(Jx / Jy)$$

images: Jianbo Shi, Upenn

What we did before



take normalized histogram at point u,v

$$\widetilde{\mathbf{h}}_{\Sigma}(u,v) = \left\| \left[\mathbf{G}_1^{\Sigma}(u,v), \ldots, \mathbf{G}_H^{\Sigma}(u,v) \right]^{\top} \right\|$$

$$\mathcal{D}(u_0, v_0) =$$

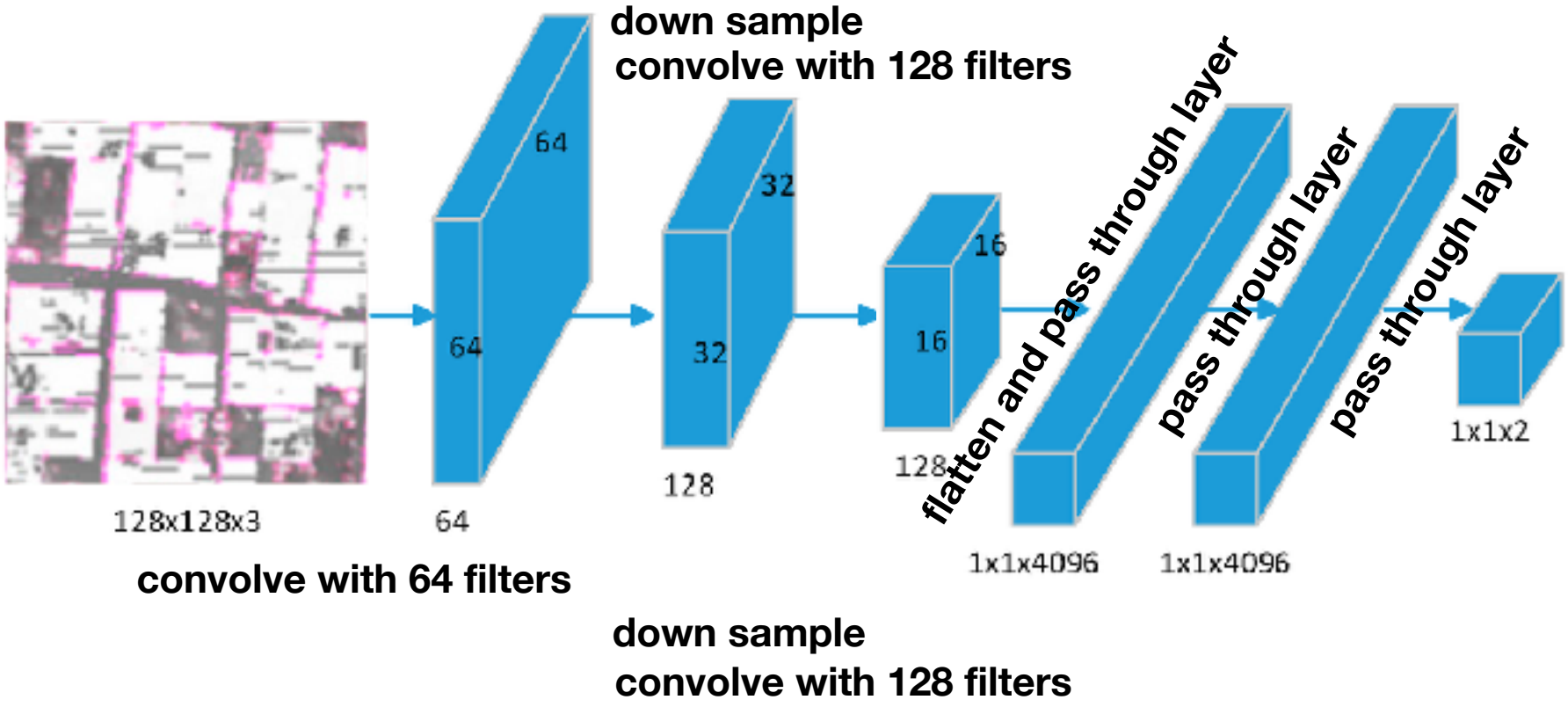
$$\Big[\; \widetilde{\mathbf{h}}_{\Sigma_1}^{\top}(u_0, v_0),$$

$$\widetilde{\mathbf{h}}_{\Sigma_1}^{\top}(\mathbf{l}_1(u_0, v_0, R_1)), \cdots, \widetilde{\mathbf{h}}_{\Sigma_1}^{\top}(\mathbf{l}_T(u_0, v_0, R_1)),$$

$$\widetilde{\mathbf{h}}_{\Sigma_2}^{\top}(\mathbf{l}_1(u_0, v_0, R_2)), \cdots, \widetilde{\mathbf{h}}_{\Sigma_2}^{\top}(\mathbf{l}_T(u_0, v_0, R_2)),$$

Tola et al. “Daisy: An efficient dense descriptor applied to wide-baseline stereo.” Pattern Analysis and Machine Intelligence, IEEE Transactions

Anatomy of a convolution

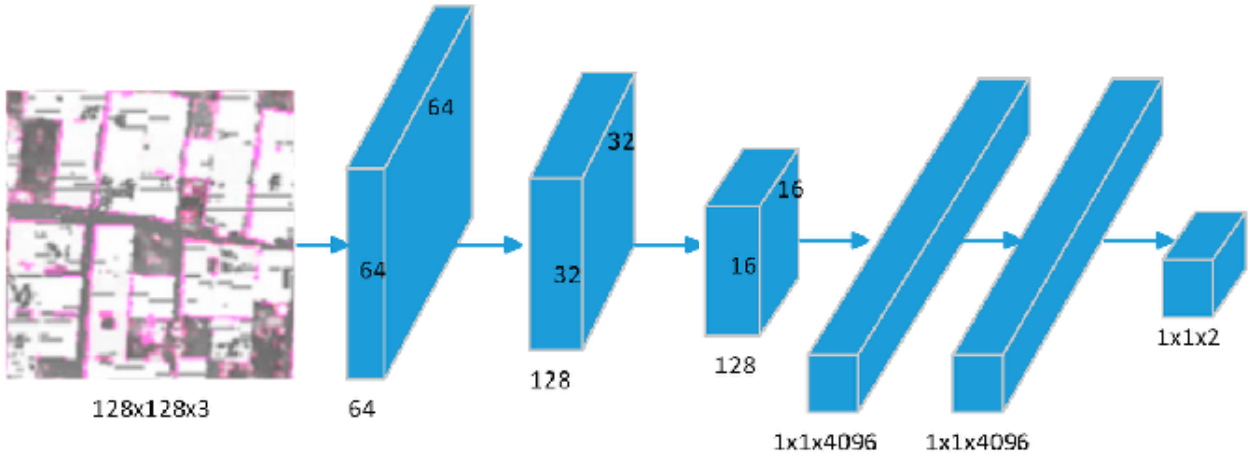


Blue Tensors: Outputs of Each Layer

Learned Params: Weights in Each Filter and Fully Connected Layer

CNN Overview

- First layer(s):
  - convolution
  - nonlinearity
  - pooling
  - Each pooling layer *can* make the input image "smaller"
    - allows for "Information Distilation"
    - less dependence on exact pixels
- Final layers are densely connected
  - typically multi-layer perceptrons



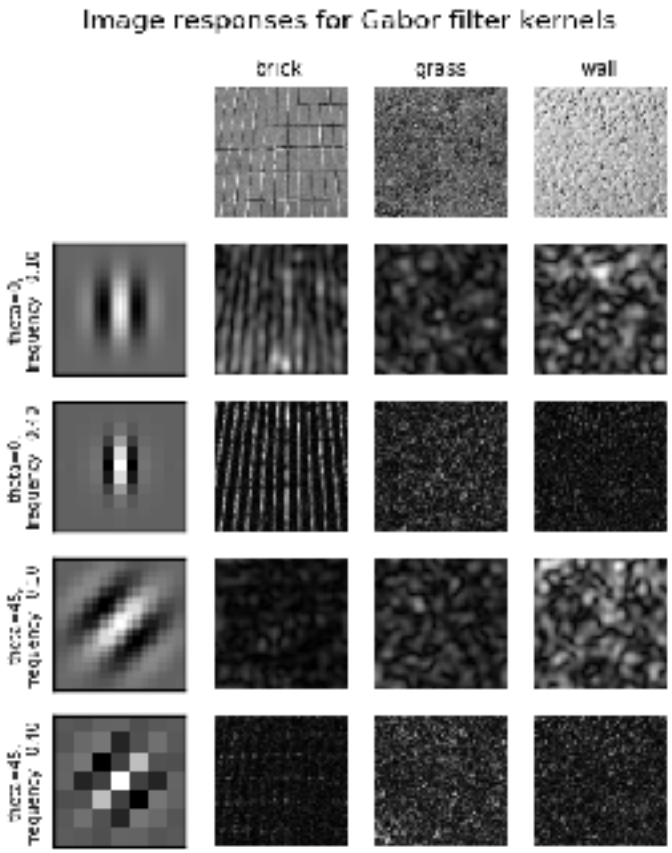
CNN Overview: Self Test

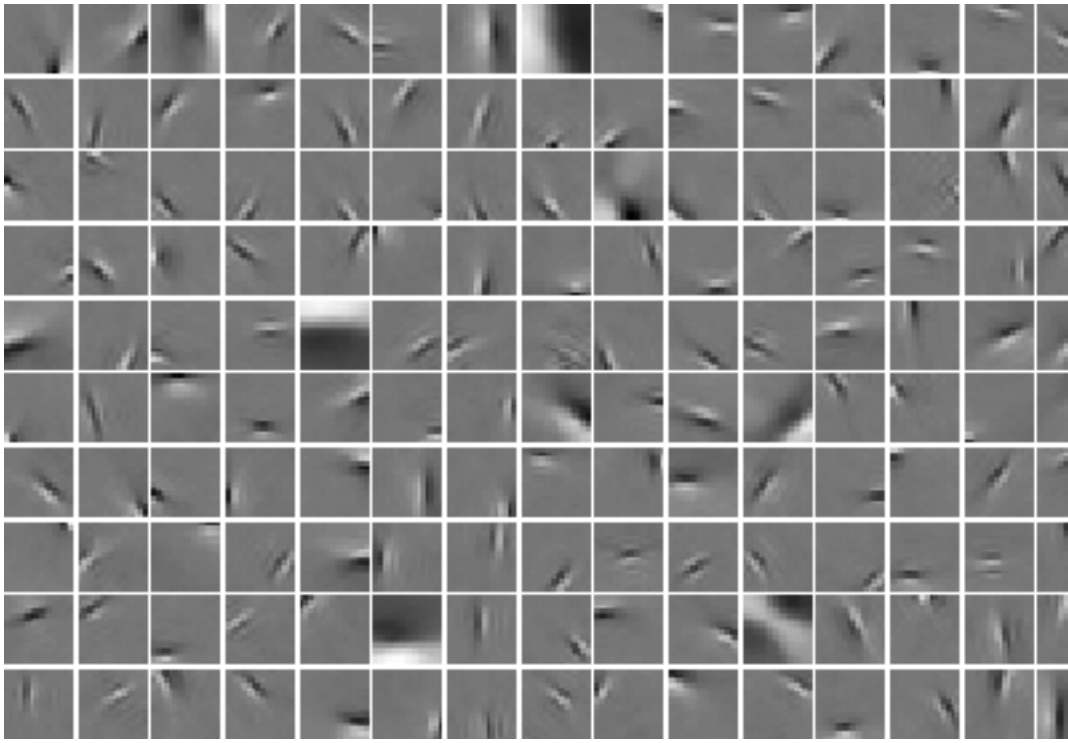
- First layer(s):
  - convolution
  - nonlinearity
  - pooling
  - Each pooling layer *can* make the input image "smaller"
    - allows for "Information Distilation"
    - less dependence on exact pixels
- Final layers are densely connected
  - typically multi-layer perceptrons

- Where are unstable gradients **most** problematic?
  - (A) During Convolution Layer(s) updates
  - (B) During Fully Connected Layer(s) updates
  - (C) Both A and B
  - (D) They are not a problem

CNN Filtering

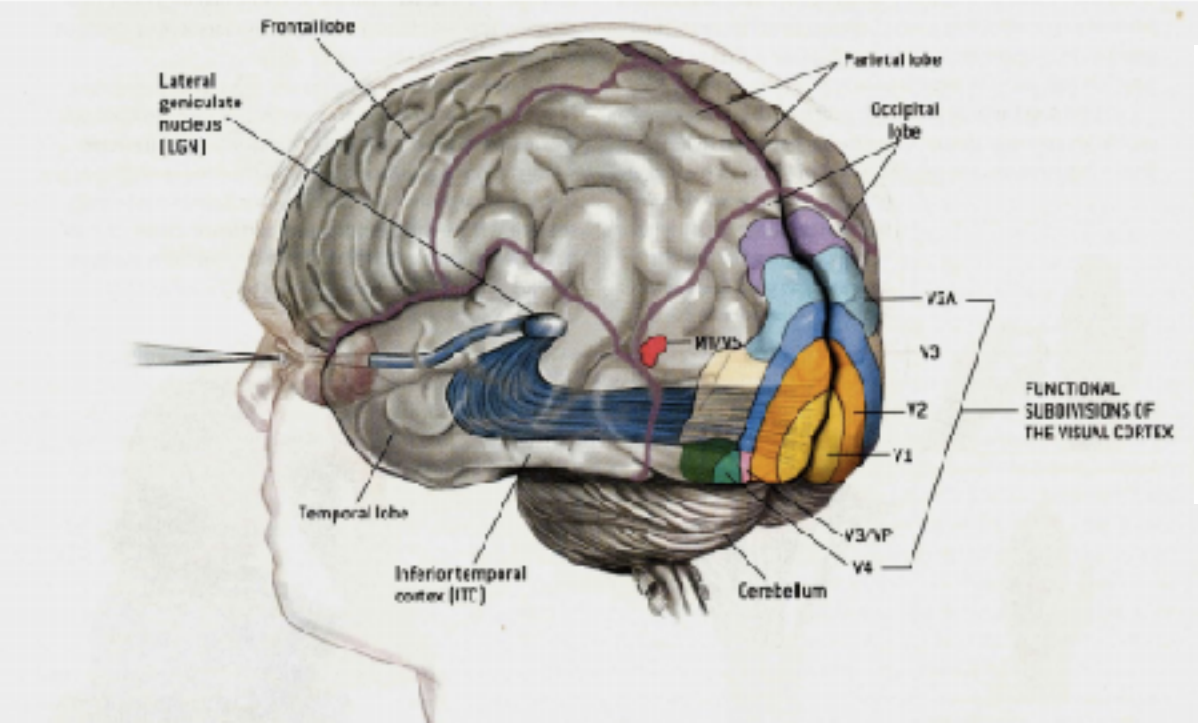
- Why perform lots of filtering?
  - recall gabor filtering?





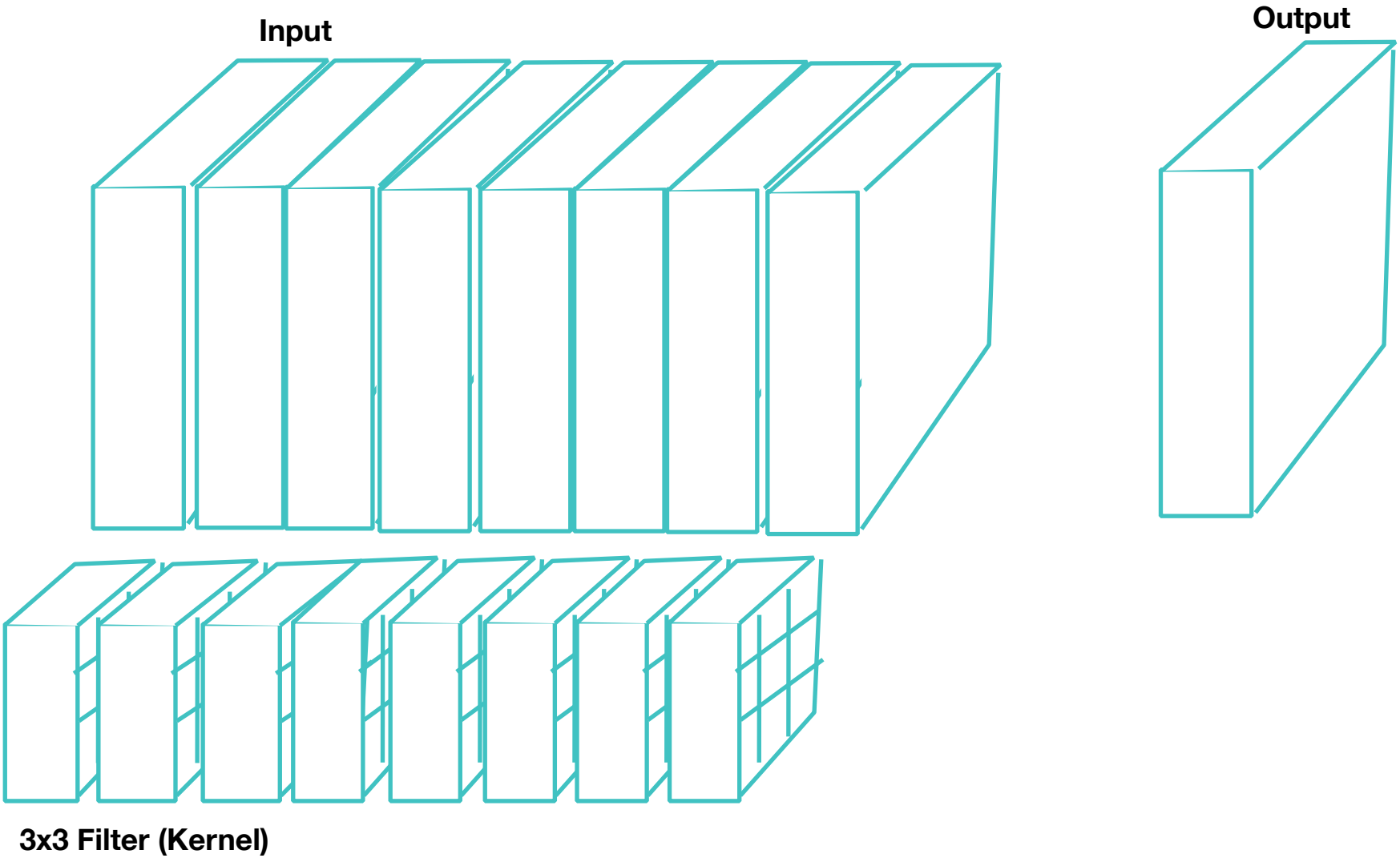
CNN Filtering

- Why perform lots of filtering?
  - recall gabor filtering?



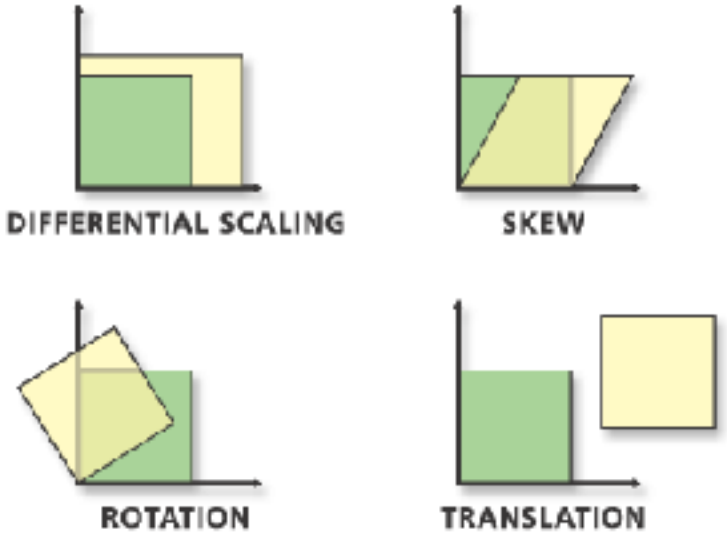
V1	Motion
V2	Stereo
V3	Color
V3a	Texture segregation
V3b	Segmentation, grouping
V4	Recognition
V7	Face recognition
MT	Attention
MST	Working memory/mental imagery

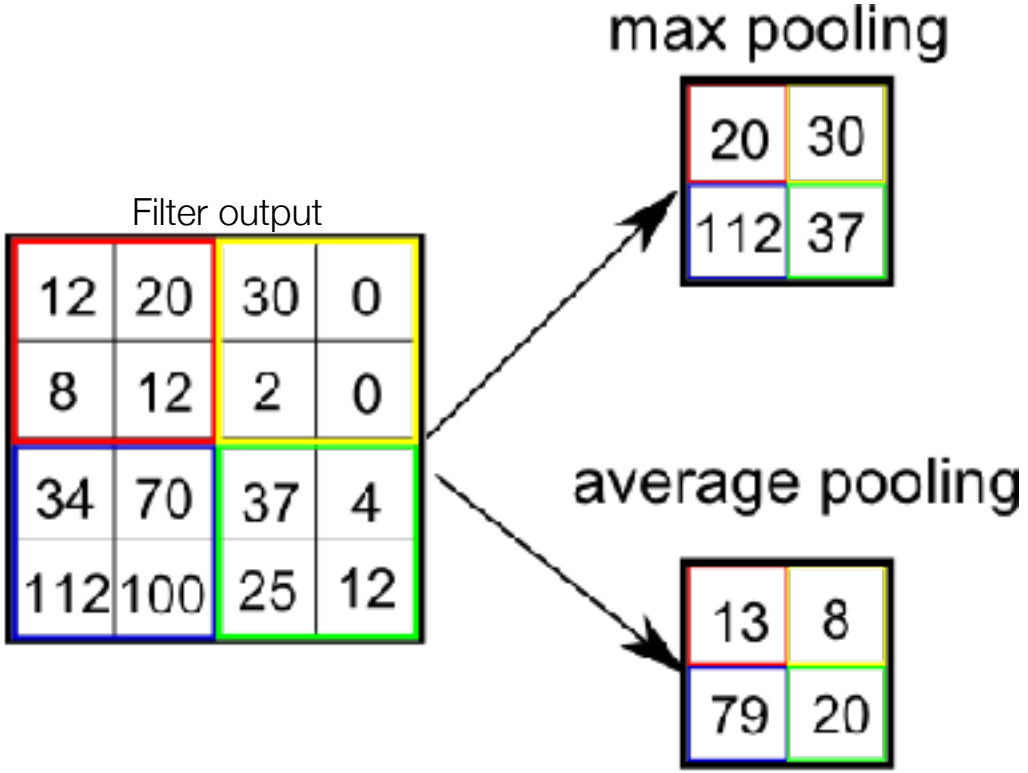
Convolution in a CNN



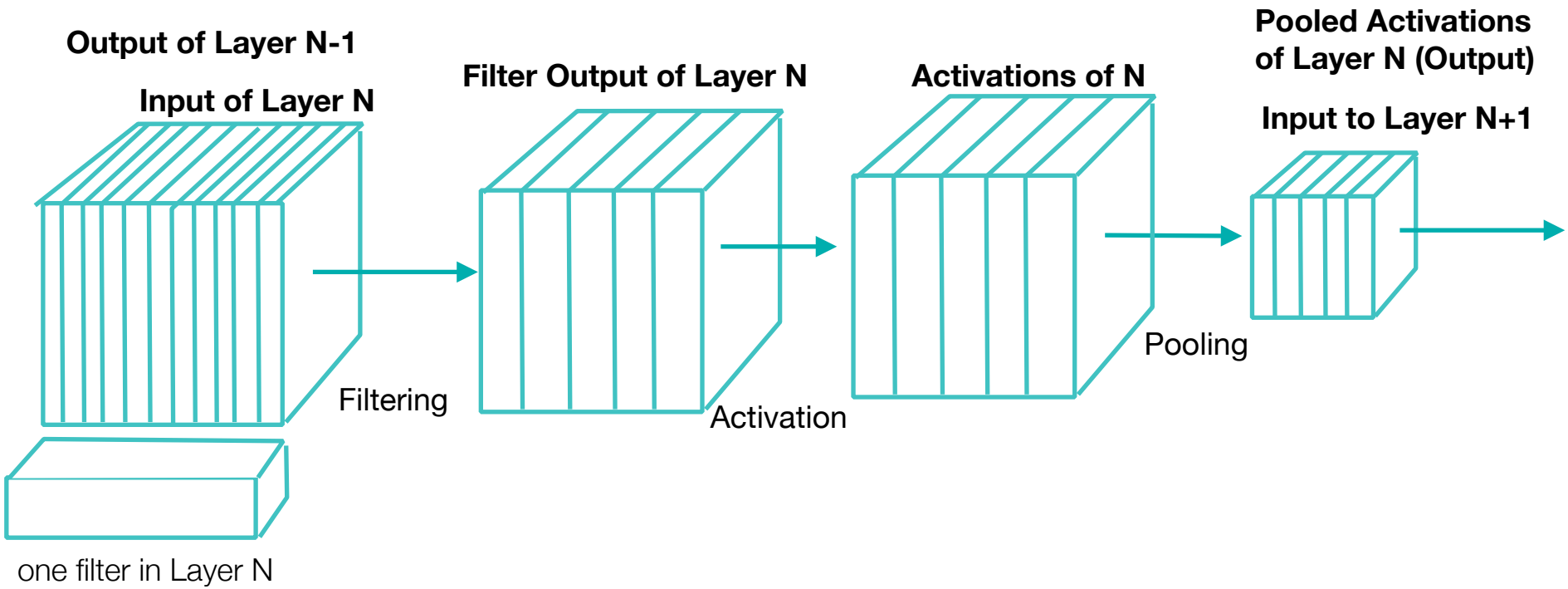
CNN Pooling

- Why perform pooling?
- Why max pooling?
  - reduce translation effects
  - param reduction



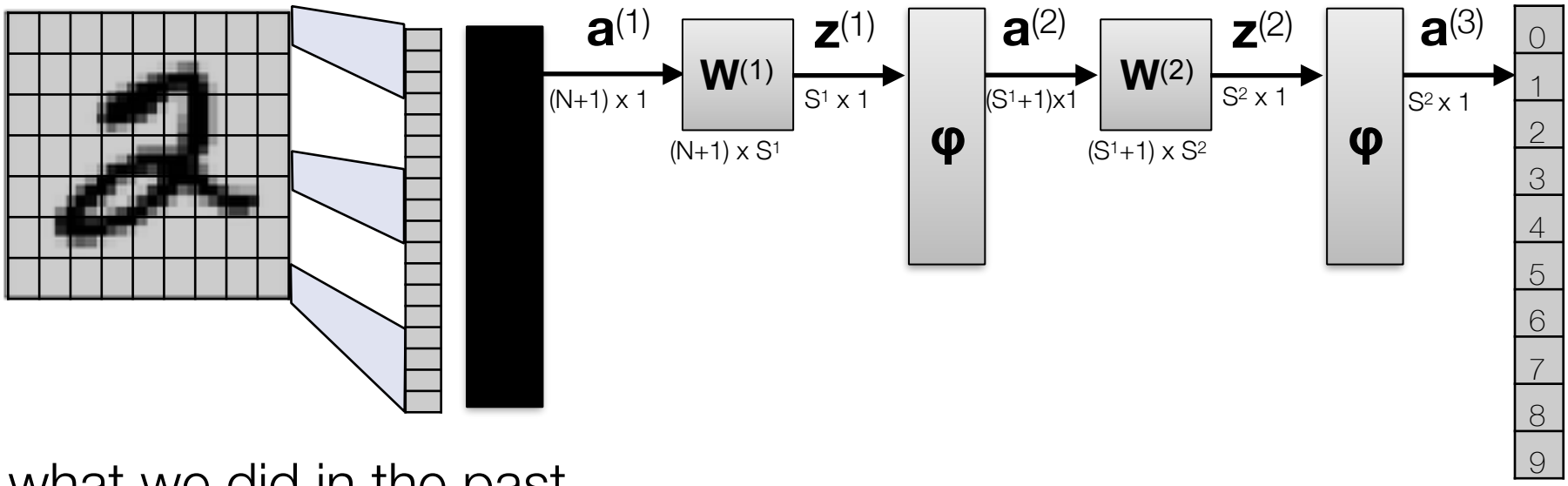


CNNs: Putting it together



Structure of Each Tensor: Channels x Rows x Columns

Simple Example: From Fully Connected to CNN



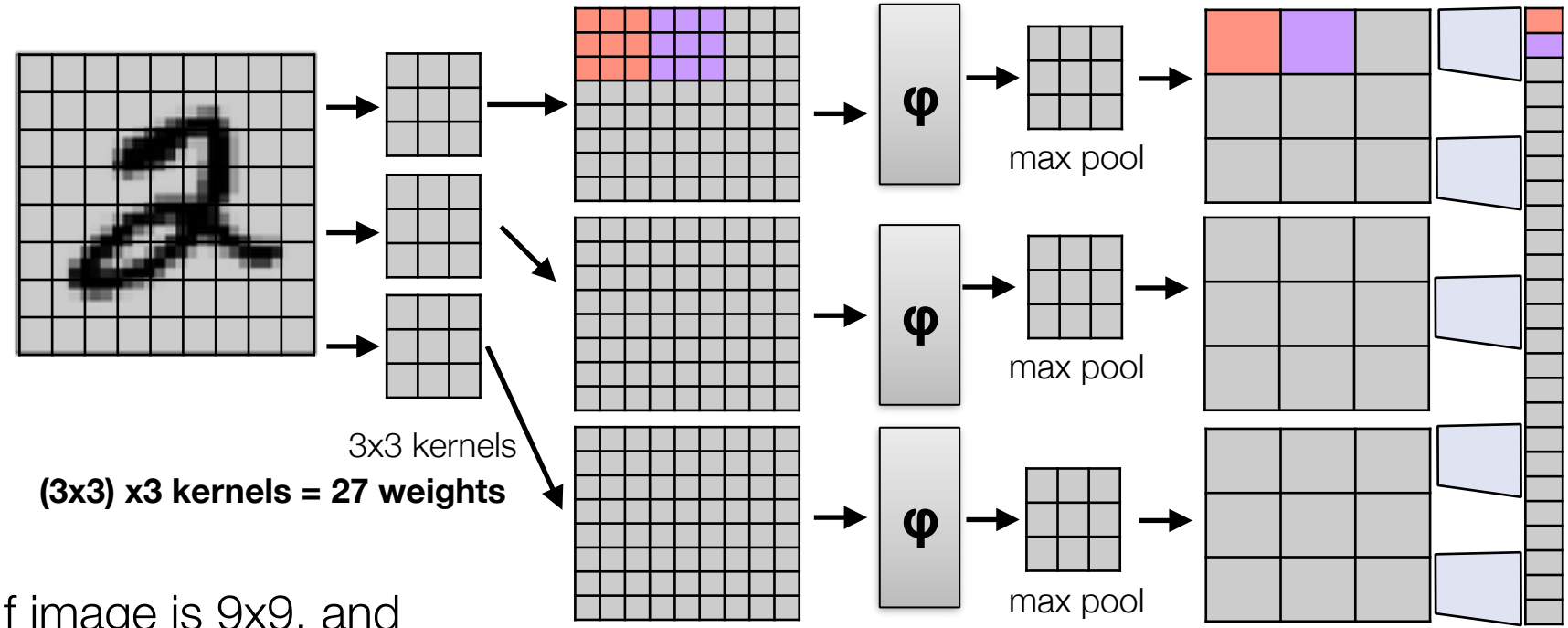
what we did in the past

If image is 9x9, and each fully connected layer is 20 hidden neurons wide, how many parameters are in this NN (ignore bias)?

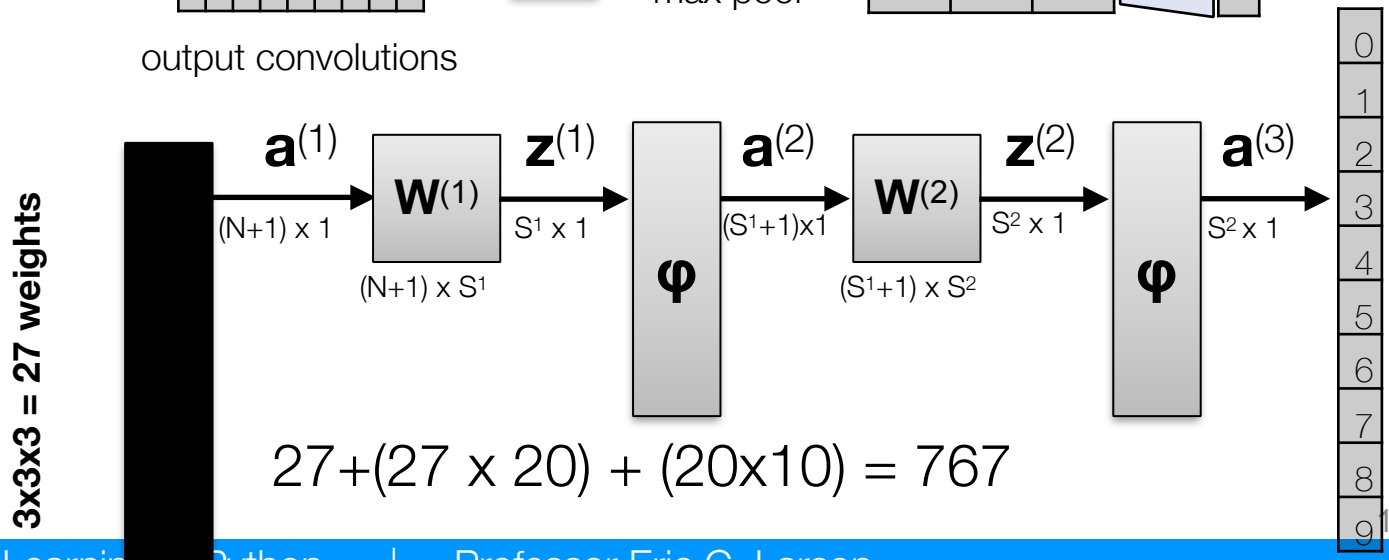
$(K^2 \times 20) + (20 \times 10) = 200 + 20\ K^2$

for 9x9 = $200 + 20 \times 9^2 =$ 1,820 parameters

Simple Example: From Fully Connected to CNN

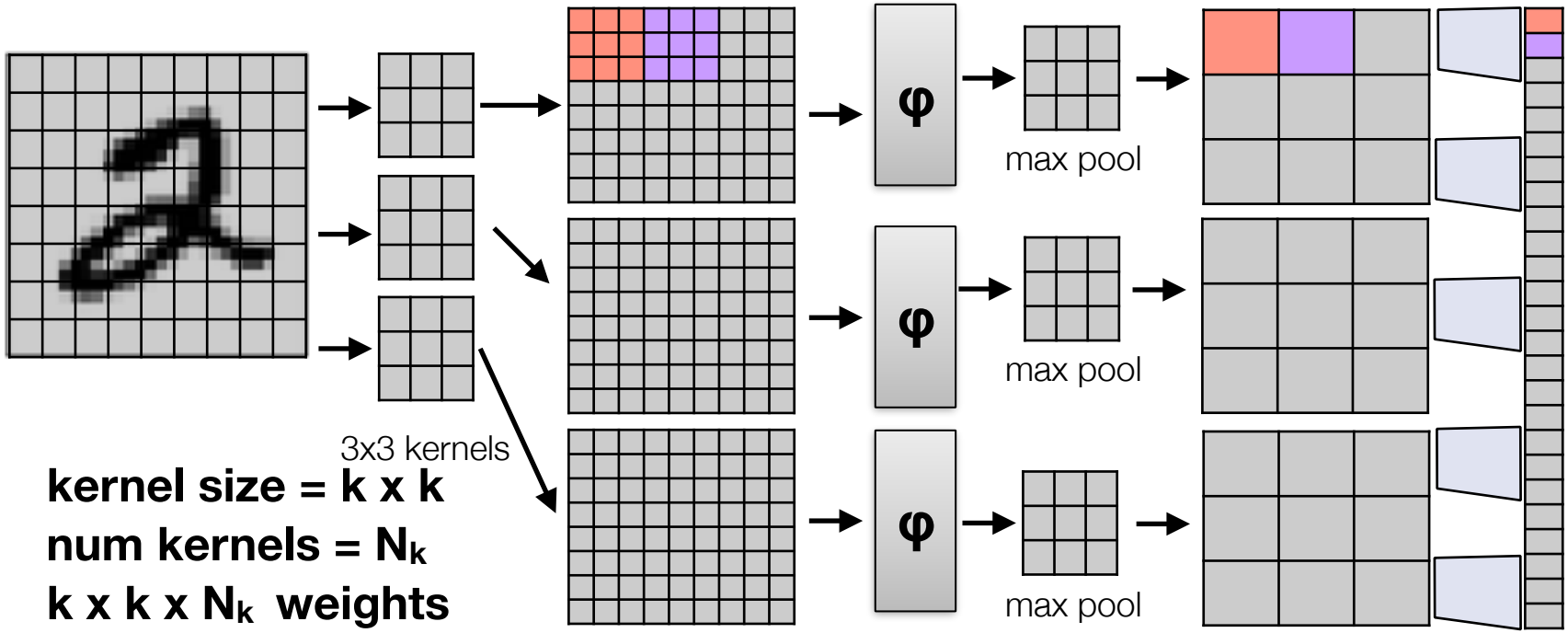


If image is 9x9, and each fully connected layer is 20 hidden neurons wide, how many parameters are in this NN (ignore bias)?



27+(27 x 20) + (20x10) = 767

Simple Example: From Fully Connected to CNN

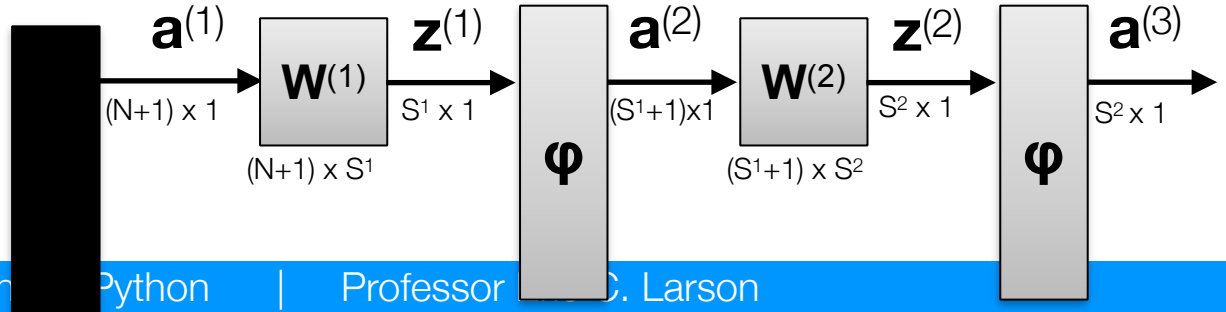


kernel size = k x k
num kernels = N_k
k x k x N_k weights

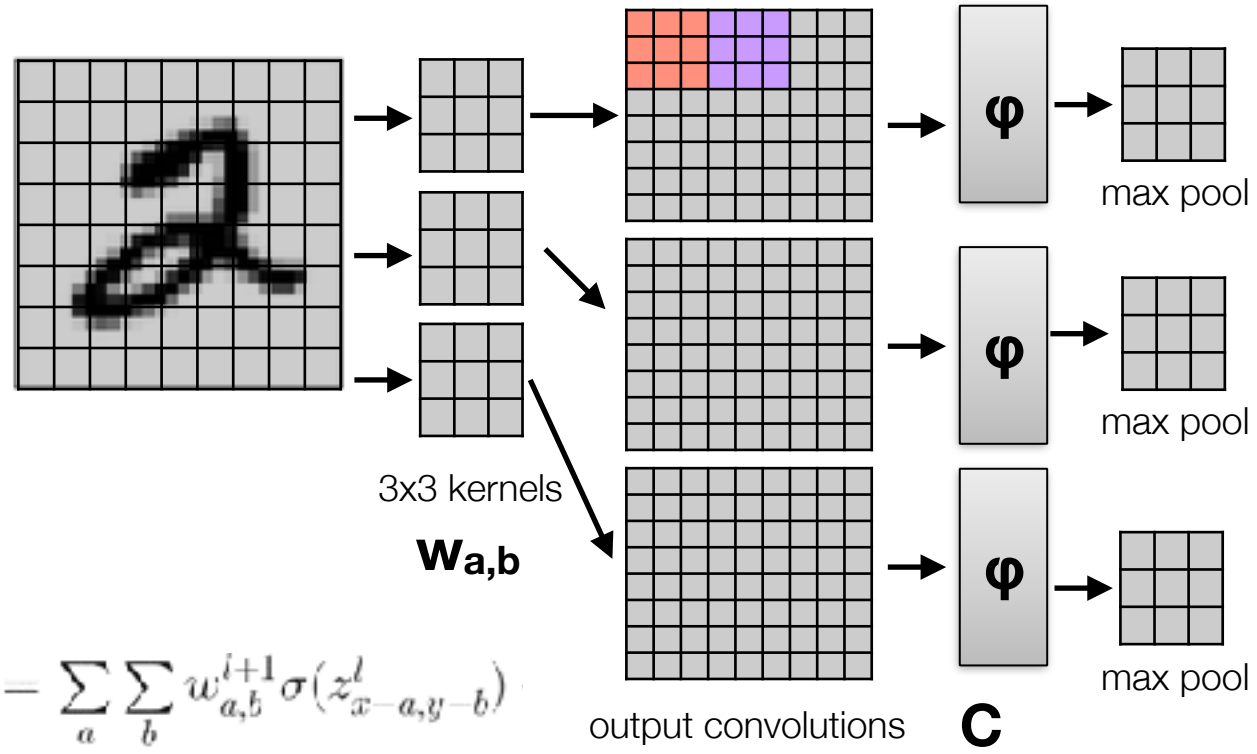
convolutional params
N_k x k^2 ← filter dimension
num filters

pooling outputs
if stride = k
(K/k) x (K/k) x N_k

Input to MLP
N_k x (K^2/k^2)
image dimension



CNN gradient



Derivative of max pool is easy:

for each input x_i

$f'(x_i) = 1$ if x_i is max

0 else

$$-\sum_a \sum_b w_{a,b}^{l+1} \sigma(z_{x-a,y-b}^l)$$

Derivative of convolution is more involved:

$$\frac{\partial C}{\partial w_{a,b}^l} = \sum_x \sum_y \frac{\partial C}{\partial z_{x,y}^l} \frac{\partial z_{x,y}^l}{\partial w_{a,b}^l} = \sum_x \sum_y \delta_{x,y}^l \frac{\partial (\sum_{a'} \sum_{b'} w_{a',b'}^l \sigma(z_{x-a',y-b'}^l) + b_{x,y}^l)}{\partial w_{a,b}^l} =$$

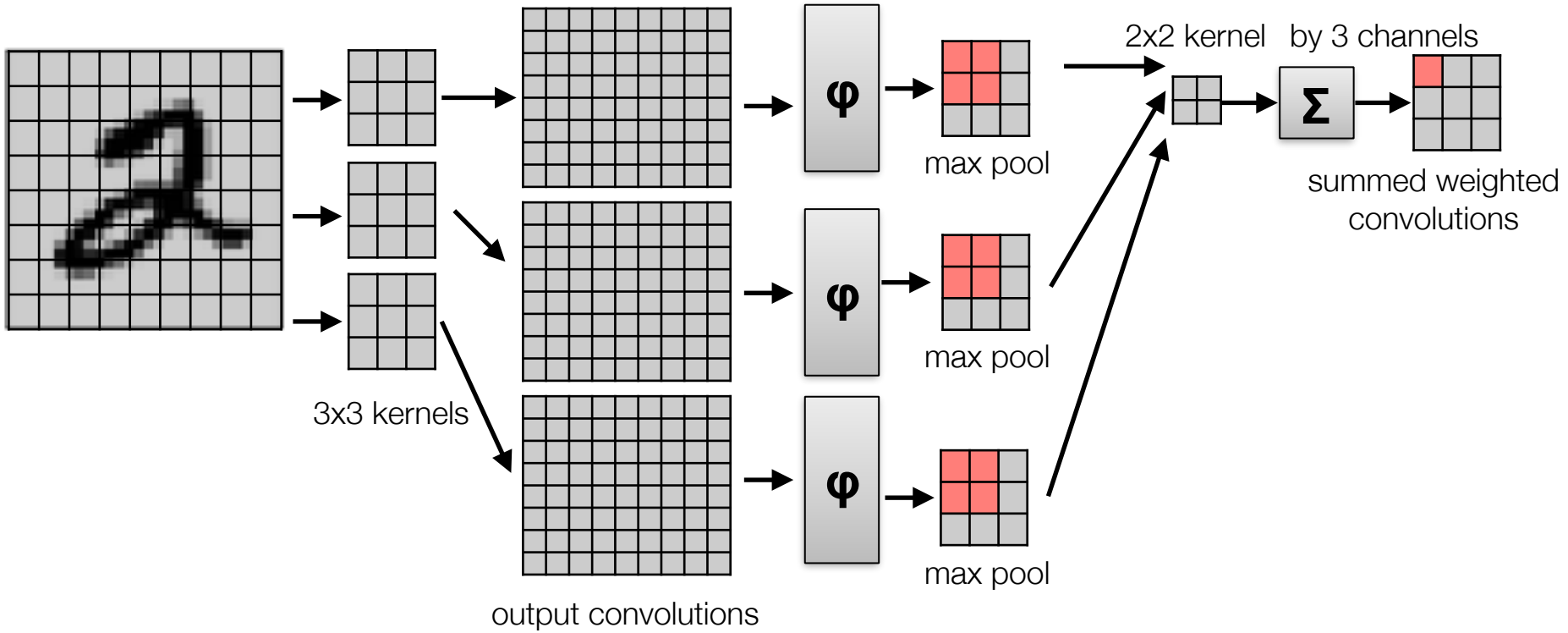
$$\sum_x \sum_y \delta_{x,y}^l \sigma(z_{x-a,y-b}^{l-1}) = \delta_{a,b}^l * \sigma(z_{-a,-b}^{l-1}) = \delta_{a,b}^l * \sigma(ROT180(z_{a,b}^{l-1}))$$

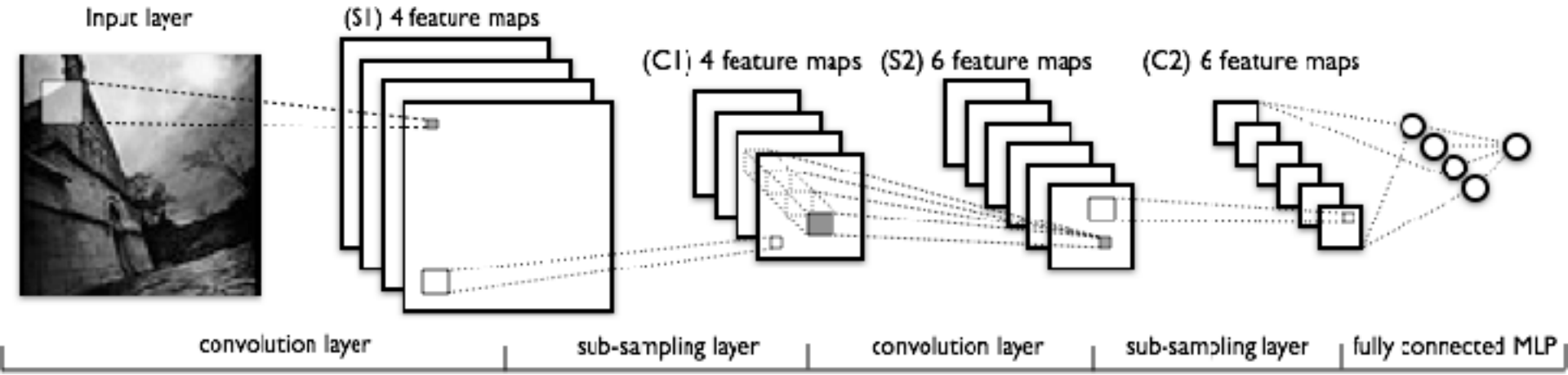
https://grzegorzgwardys.wordpress.com/2016/04/22/8/

CNN gradient

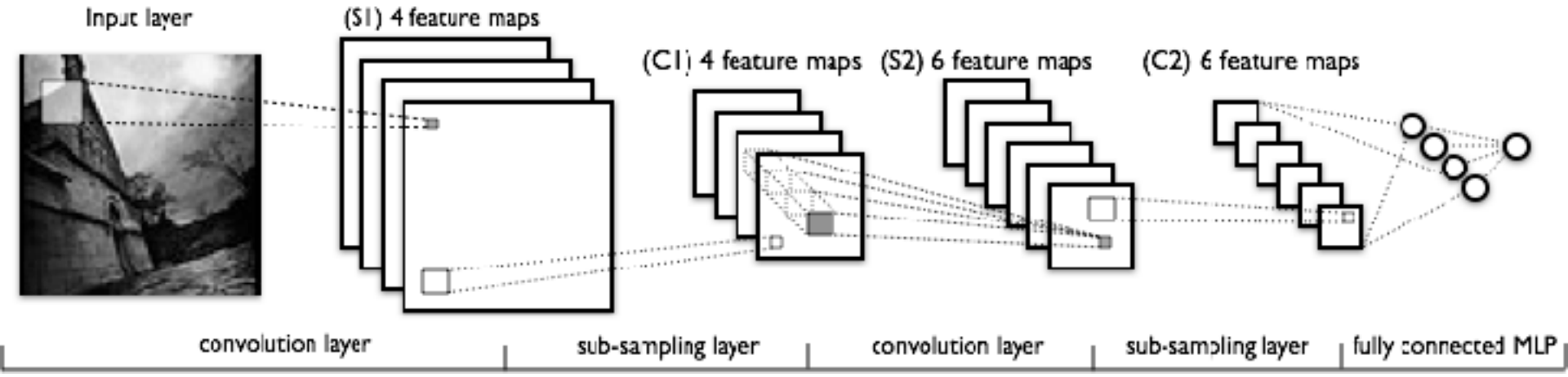
- But we really want to understand the process!
- These are great guides:
  - https://grzegorzgwardys.wordpress.com/2016/04/22/8/
  - http://andrew.gibiansky.com/blog/machine-learning/convolutional-neural-networks/

CNN adding more convolutional layers

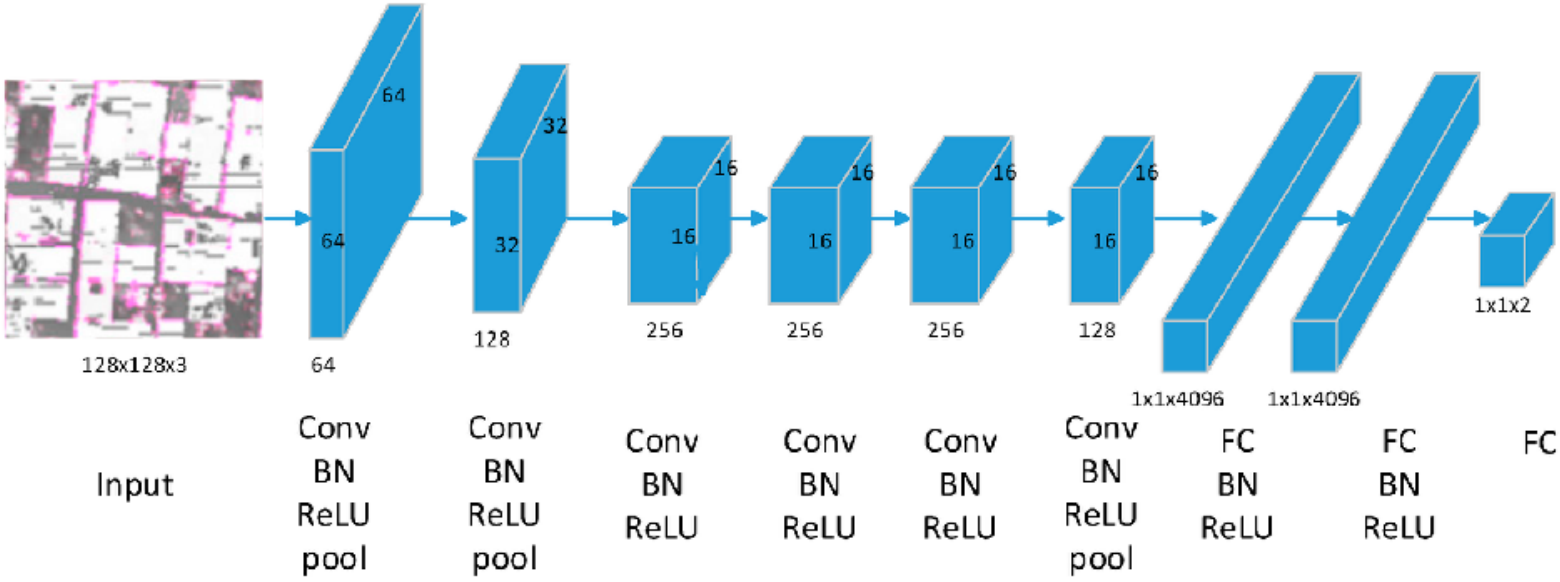




Some Example CNN Architectures



pooling pooling



CNN: What does it all mean?

Deep Visualization Toolbox

yosinski.com/deepvis

#deepvis


Jason Yosinski


Jeff Clune


Anh Nguyen


Thomas Fuchs


Hod Lipson

Cornell University

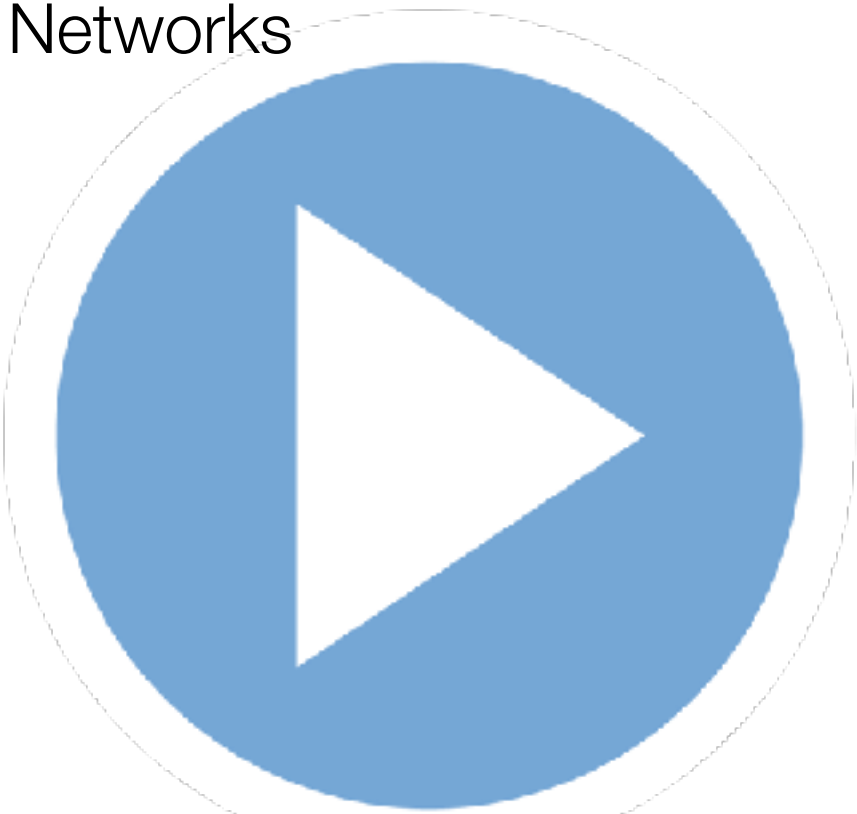
University of Wyoming

NASA Jet Propulsion Laboratory
California Institute of Technology

https://github.com/yosinski/deep-visualization-toolbox

Demo

Convolutional Neural Networks
in TensorFlow
with Keras



`11. Convolutional Neural Networks.ipynb`

Next Lecture

- More CNN architectures and CNN history

Lecture Notes for

Machine Learning in Python

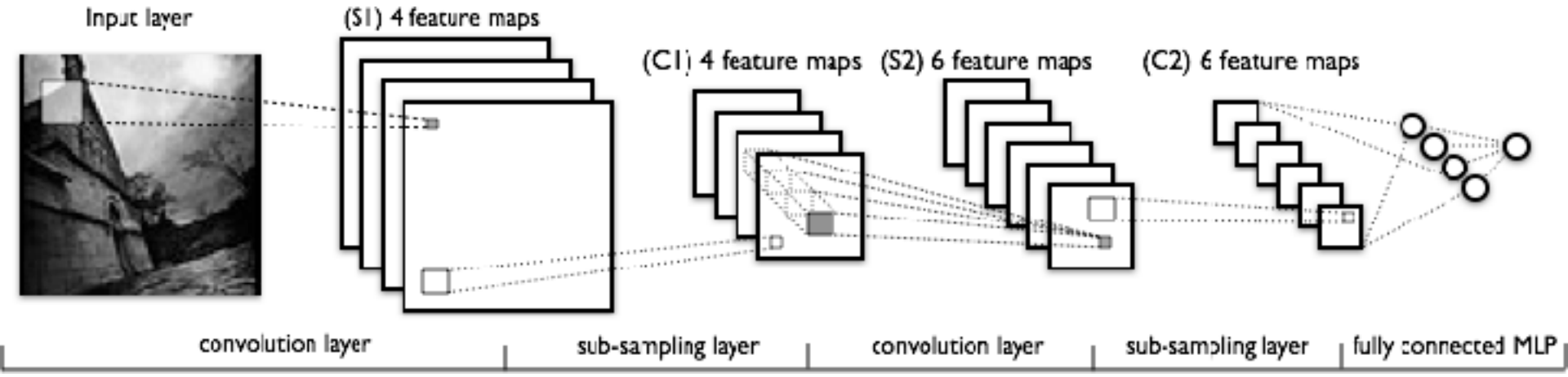
Professor Eric Larson

An Ongoing History of Convolutional Networks

Class logistics and Agenda

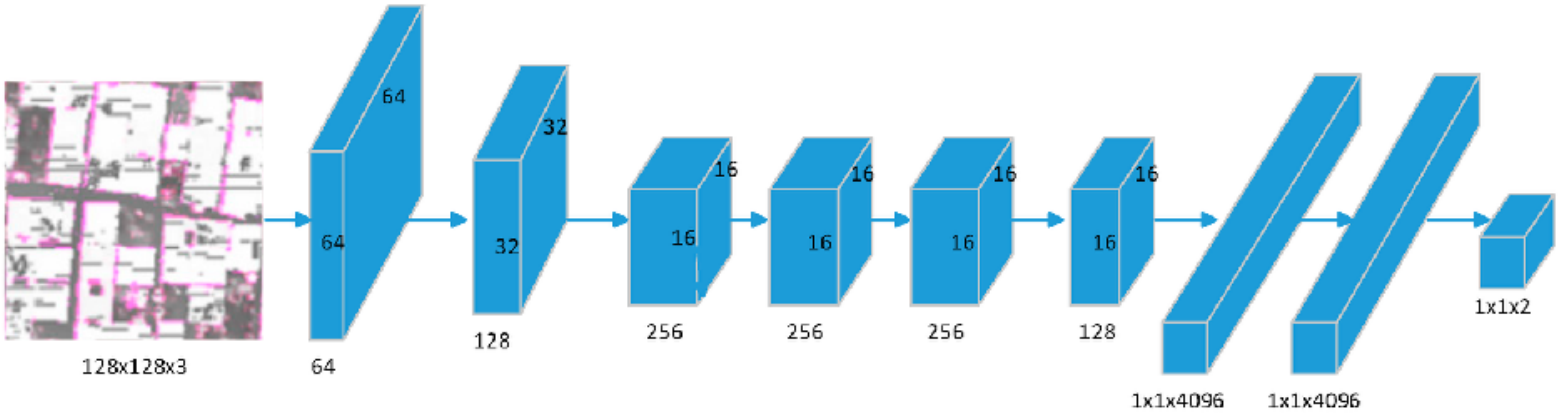
- Wide/Deep Lab due!
- Agenda:
  - Finish CNN Demo
  - History of CNNs
    - with Modern CNN Architectures
- Next Time:
  - More Advanced CNN Demo

Last Time:



pooling pooling

layer1 layer2 layer3 layer4 layer5 layer6 layer7 layer8 layer9



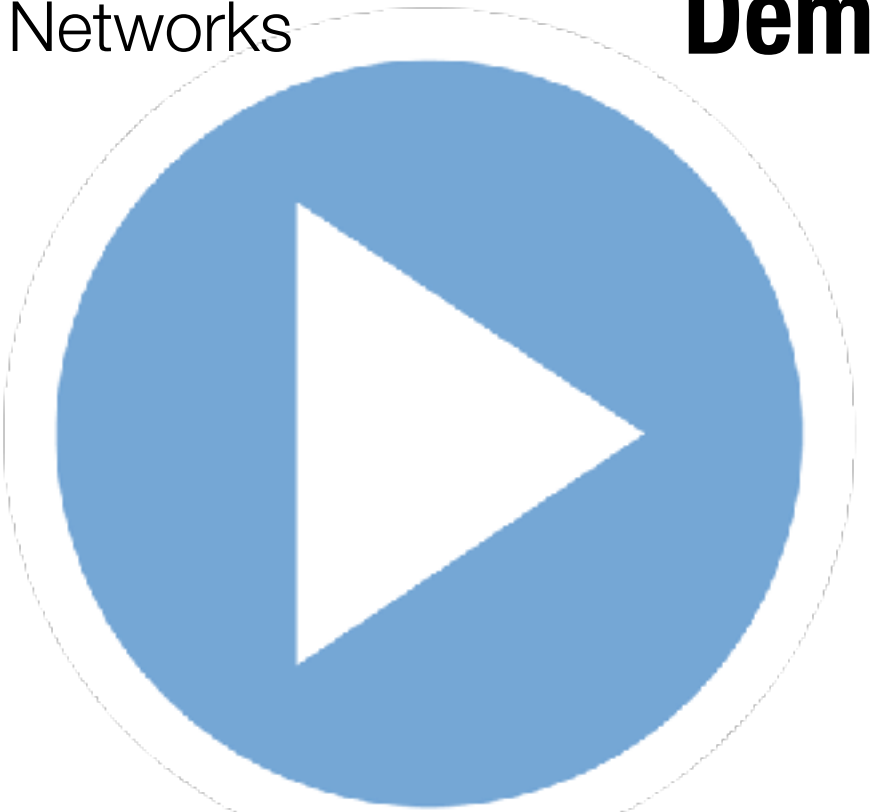
Input | Conv BN ReLU pool | Conv BN ReLU pool | Conv BN ReLU | Conv BN ReLU | Conv BN ReLU | Conv BN ReLU pool | FC BN ReLU | FC BN ReLU | FC

TensorFlow and Basic CNNs

Finish Demo

Convolutional Neural Networks
in TensorFlow
with Keras

with Sequential API!



`11. Convolutional Neural Networks.ipynb`

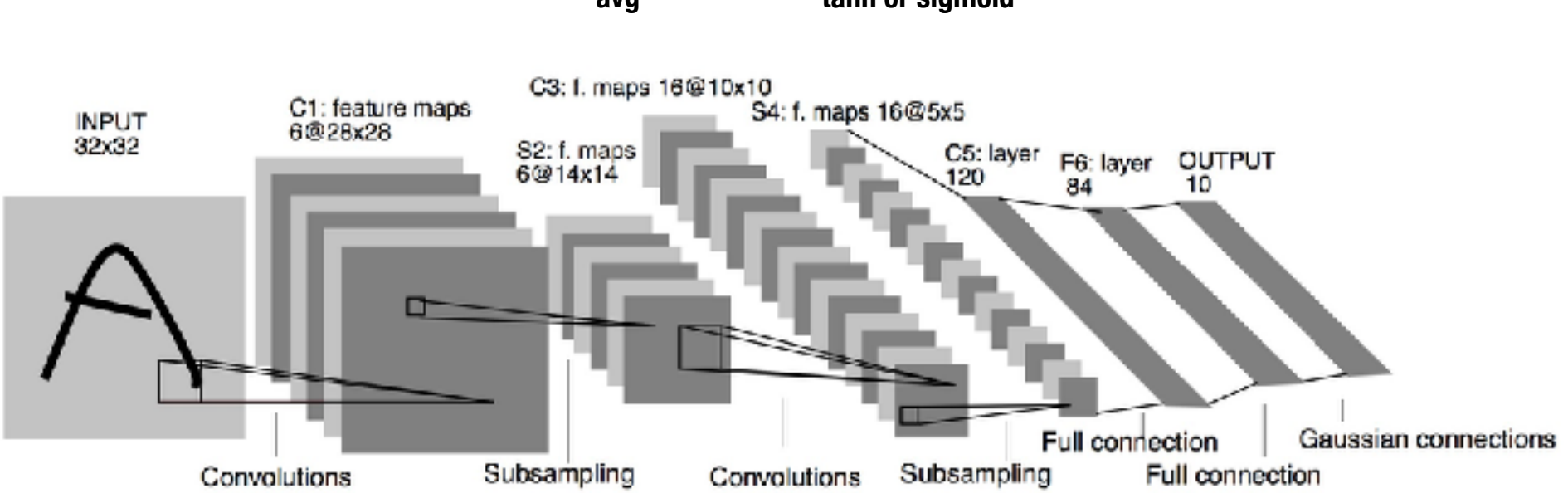
History of Convolutional Neural Networks

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

Types of CNN, 1988-1998

Heads Facebook AI Team

- **LeNet-1** (1988)
  - ~2600 params, not many layers
- **LeNet-5** (1998)
  - 7 layers, gets excellent MNIST performance
- Major contribution, general structure:
  - conv=>pool=>non-linearity=> …=>MLP



CNN History

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

¯_(ツ)_/¯

- 2010

Types of CNN, 2010

AI 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

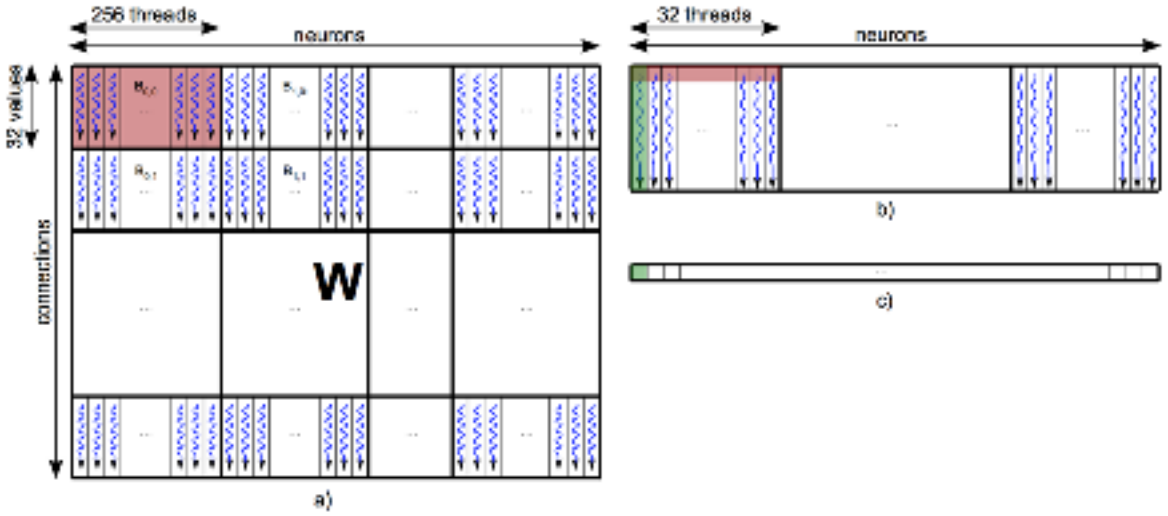
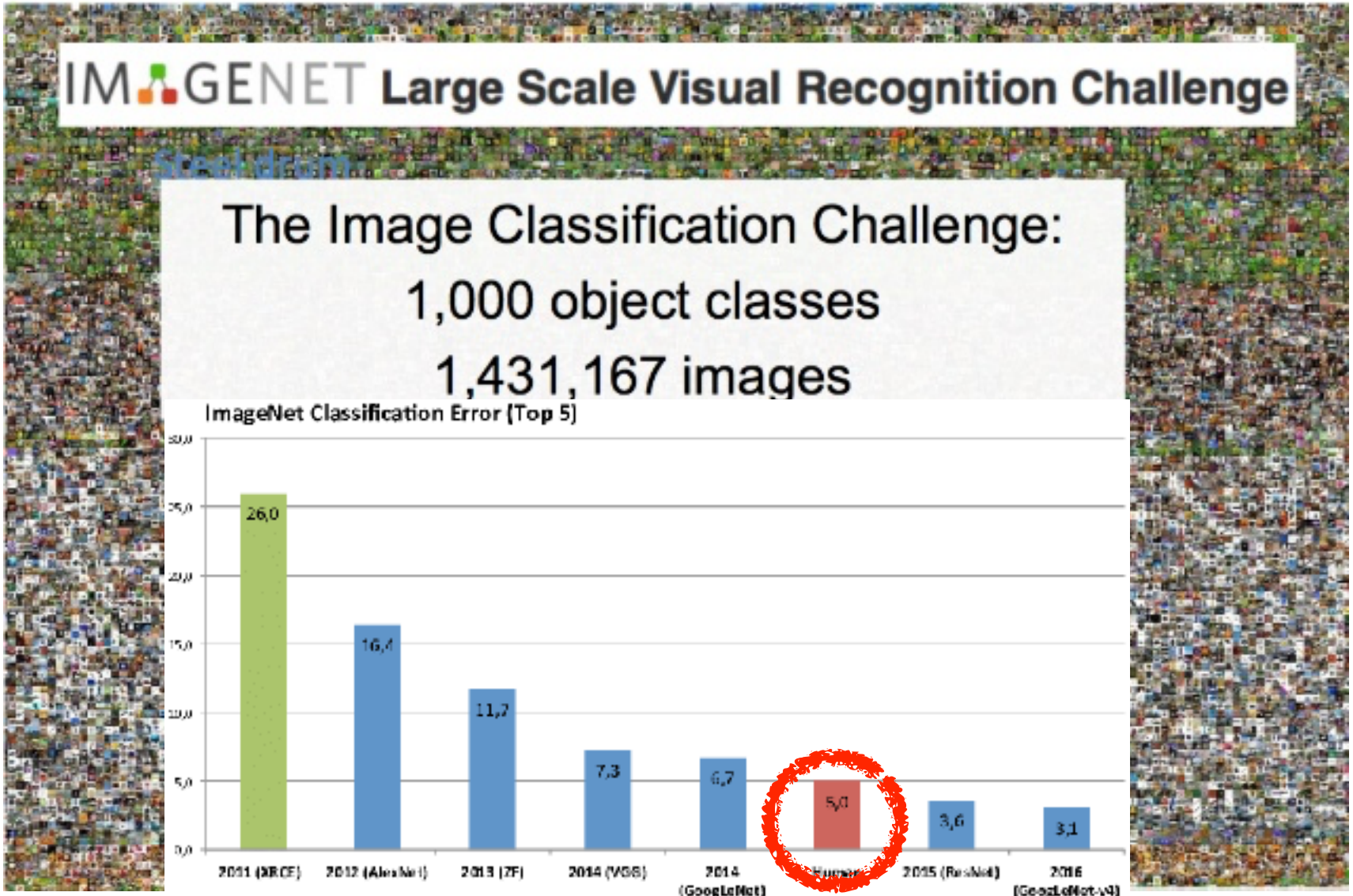


Figure 2: Forward propagation: a) mapping of kernel 1 grid onto the padded weight matrix; b) mapping the kernel 2 grid onto the partial dot products matrix; c) output of forward propagation.

https://arxiv.org/pdf/1003.0358.pdf

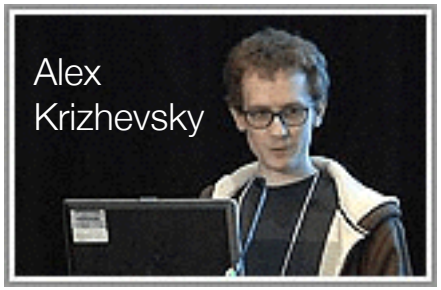
ImageNet Competition (2010-2016)



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

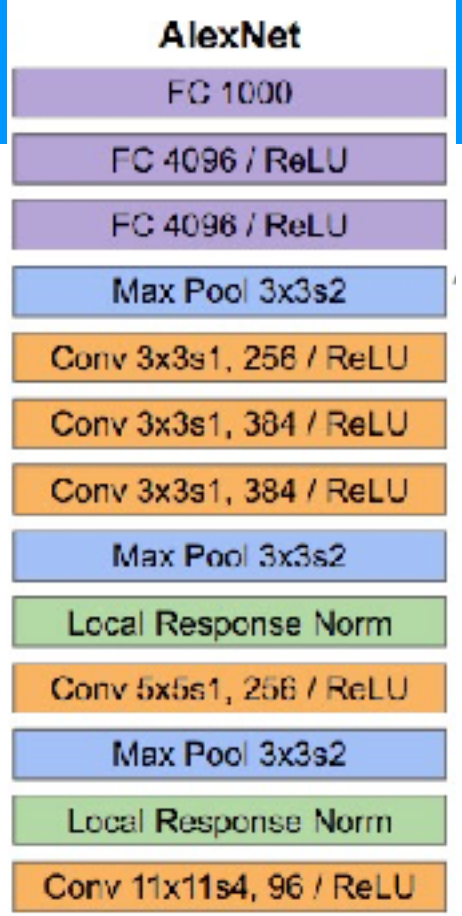
https://www.slideshare.net/nmhkahn/case-study-of-convolutional-neural-network-61556303

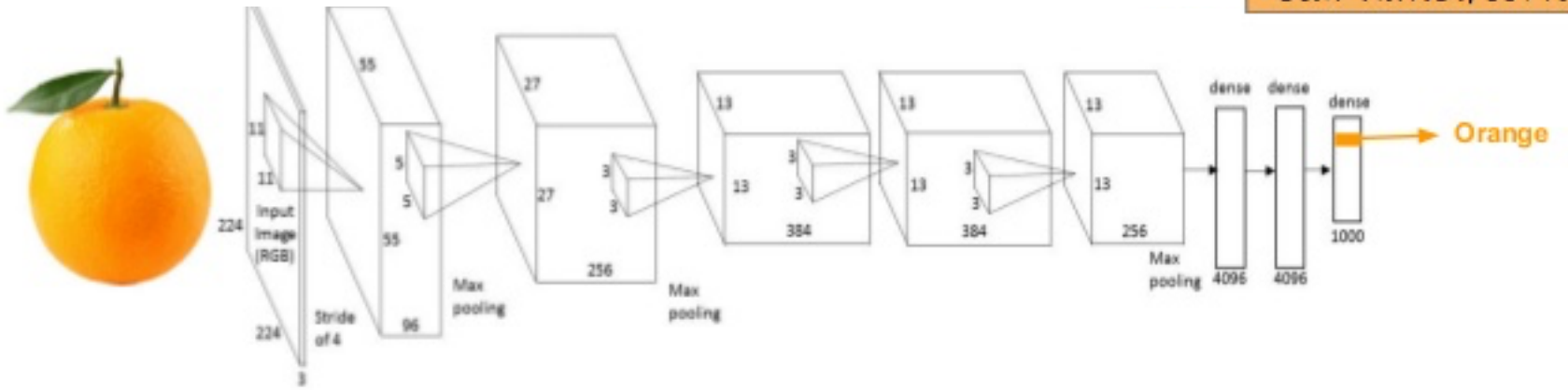
Types of CNN, 2012



Google

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



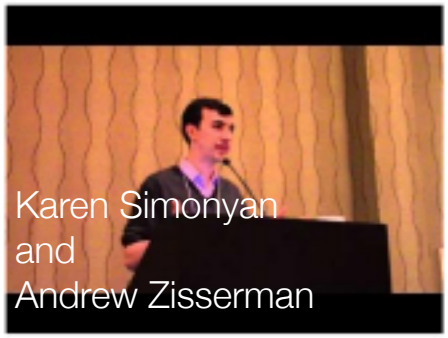


https://culurciello.github.io/tech/2016/06/04/nets.html

Warning


DON'T TRY WHAT YOU'RE ABOUT TO SEE AT HOME
WE'RE WHAT YOU CALL EXPERTS
WeKnowMemes

Types of CNN, 2013



UNIVERSITY OF OXFORD

Google DeepMind

- 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	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					

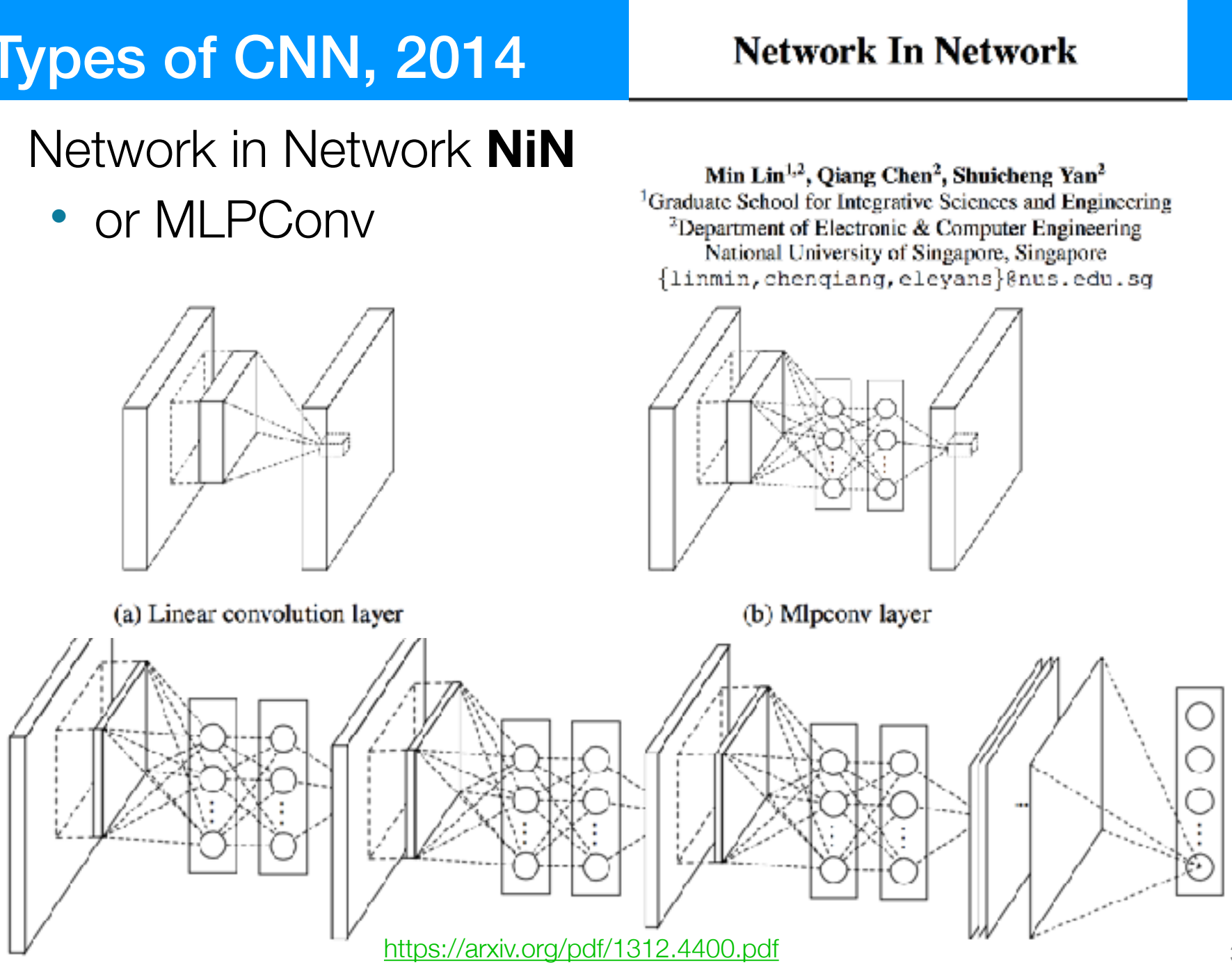
Table 2: **Number of parameters** (in millions).

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

http://www.robots.ox.ac.uk/~vgg/practicals/cnn/

Types of CNN, 2014

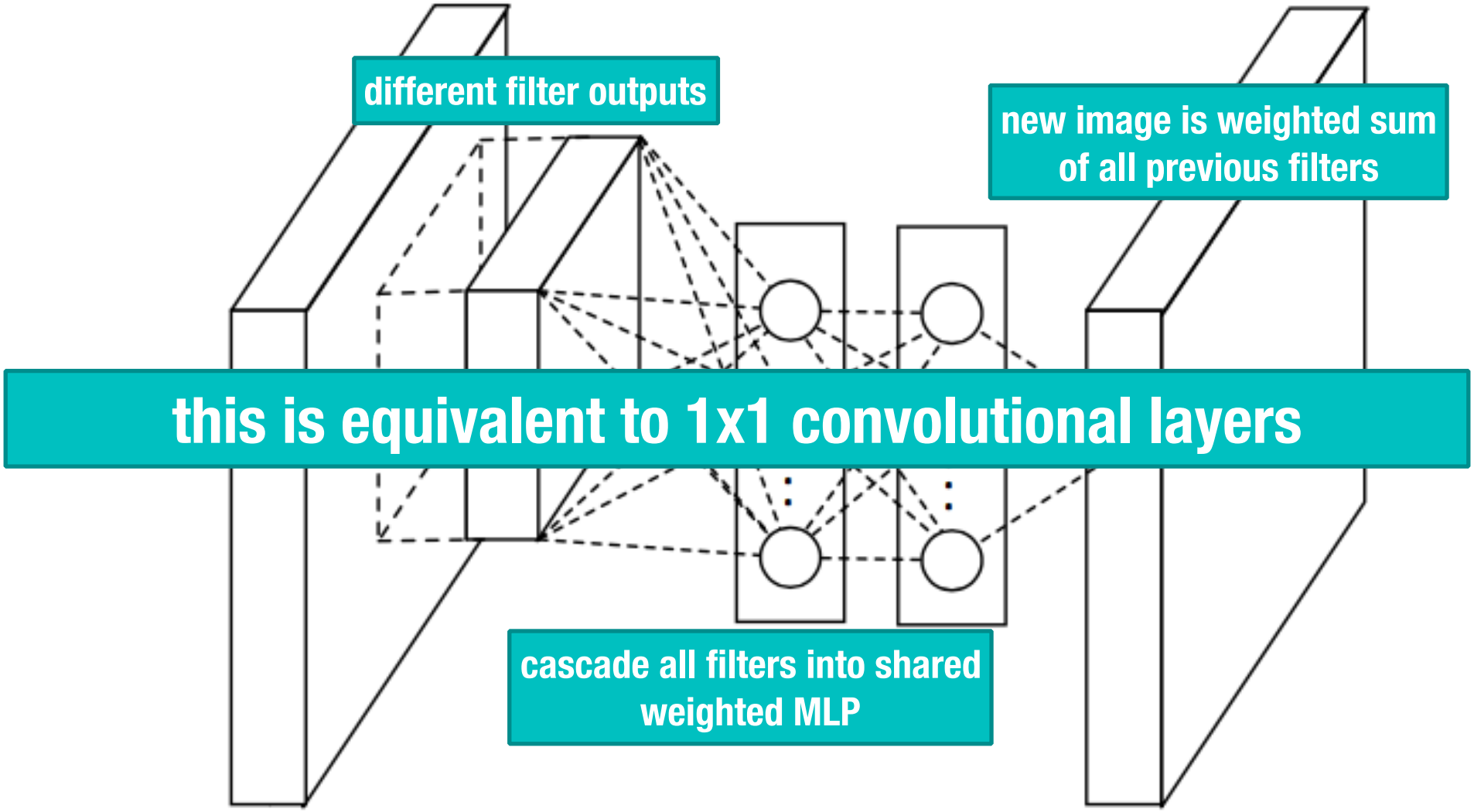
- Network in Network **NiN**
  - or MLPConv



https://arxiv.org/pdf/1312.4400.pdf

Types of CNN, 2014

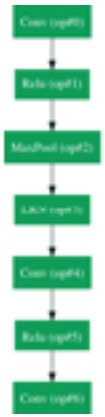
- Network in Network

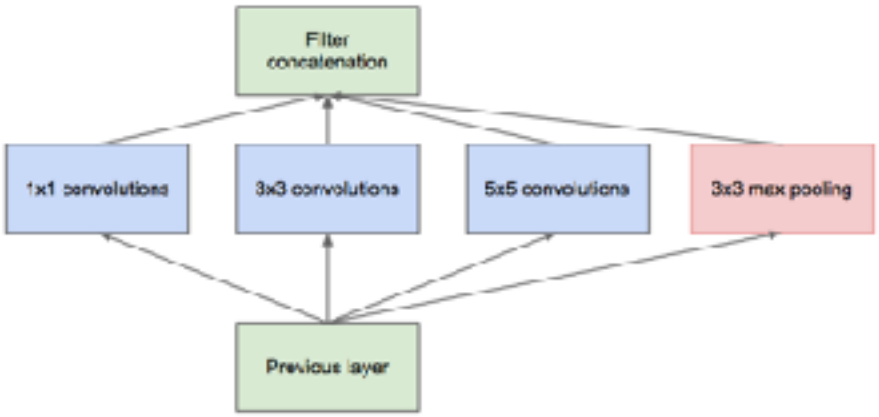


https://arxiv.org/pdf/1312.4400.pdf

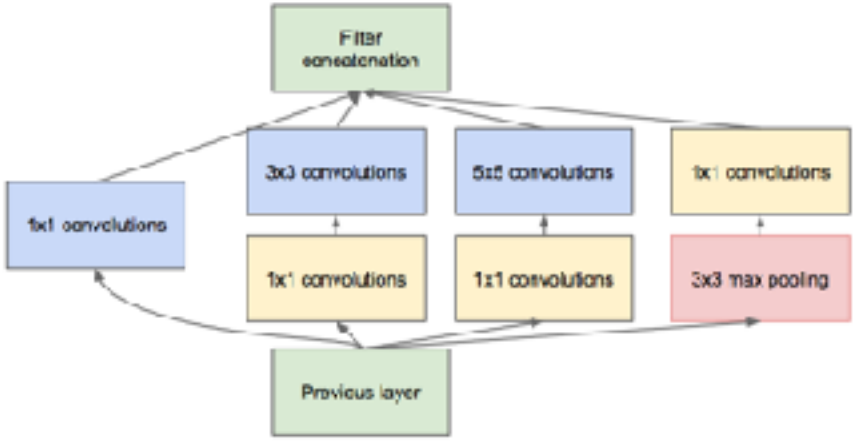
Types of CNN, 2014

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





(a) Inception module, naïve version

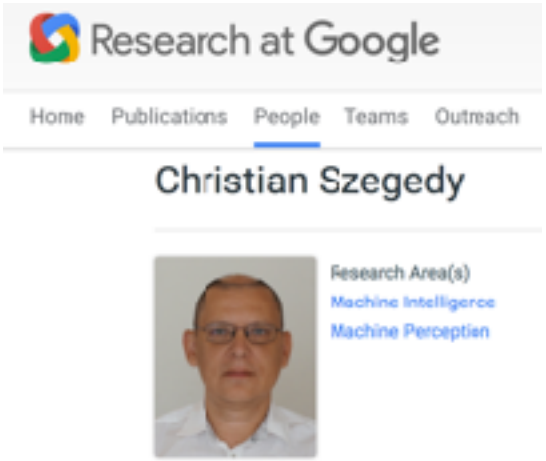


(b) Inception module with dimension reductions

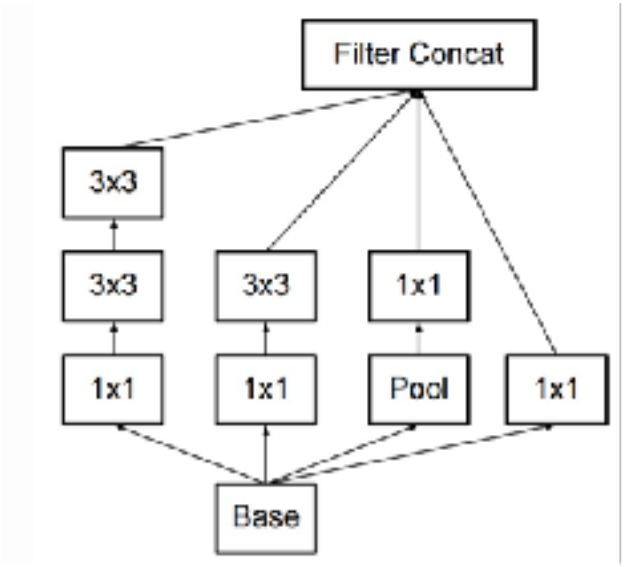
Figure 2: Inception module

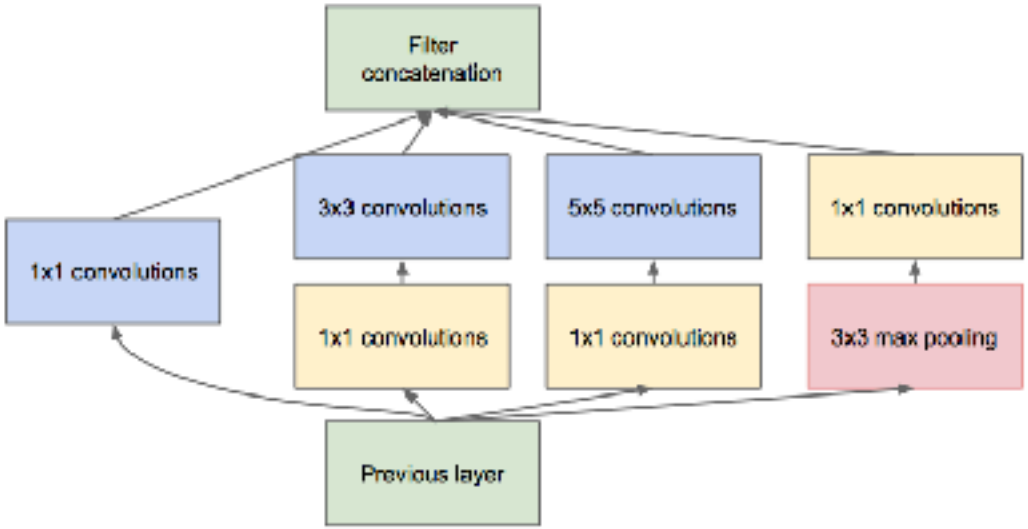
https://arxiv.org/pdf/1409.4842.pdf

Types of CNN, 2015 February and December



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



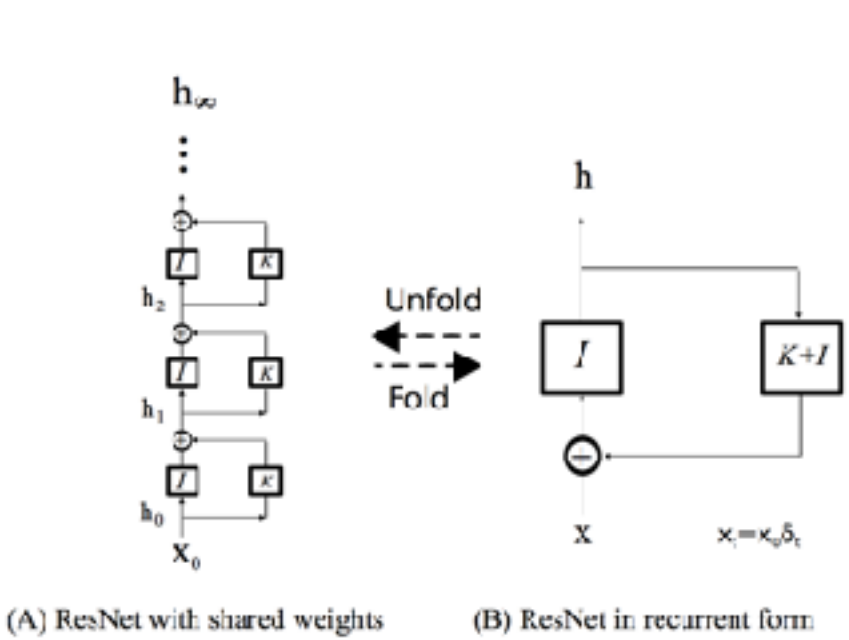


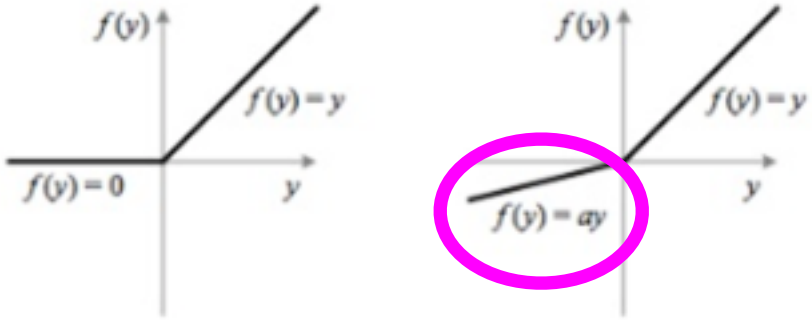
https://arxiv.org/pdf/1512.00567.pdf

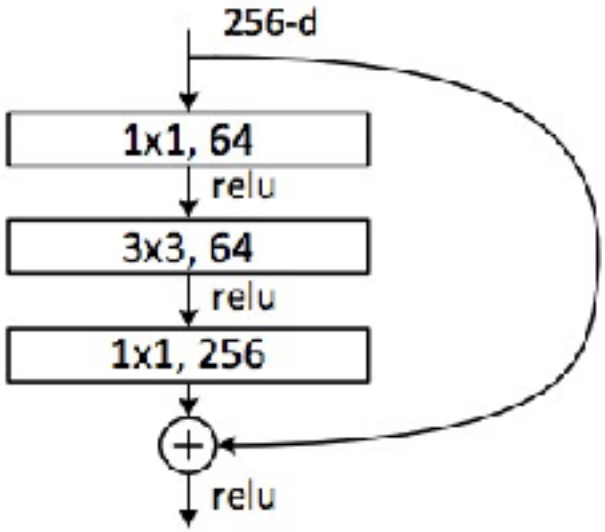
Types of CNN, 2015 December

Microsoft Research

- Major Contributions:
  - ensembles, not strictly sequential
  - bio-plausible with feedback
- **ResNet**
  - PReLU: adaptive trained slope







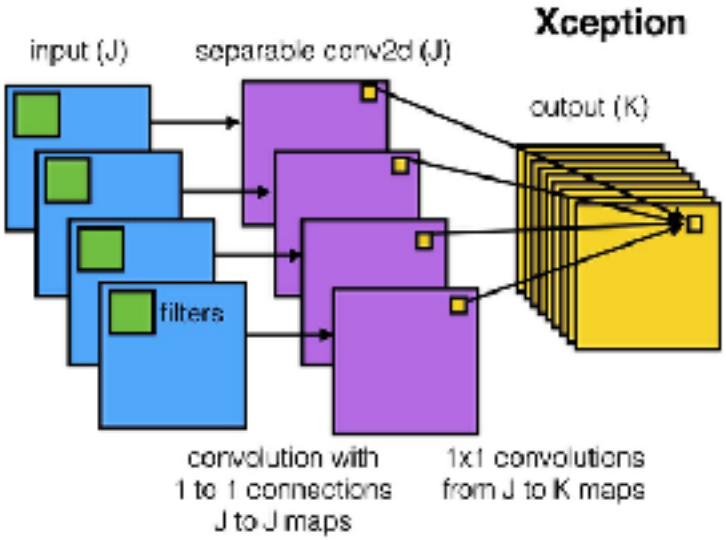
- NiN: triple bypass layer
  - similar to bottelneck

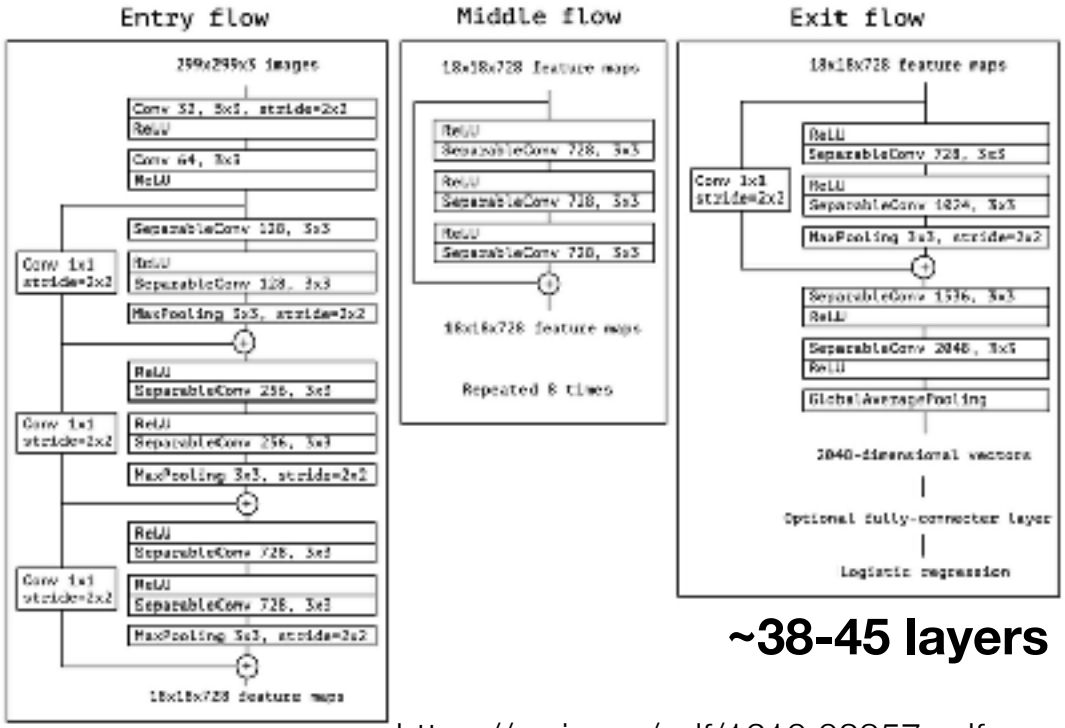
Types of CNN, 2017 April

Xception

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

Francois Chollet
Google



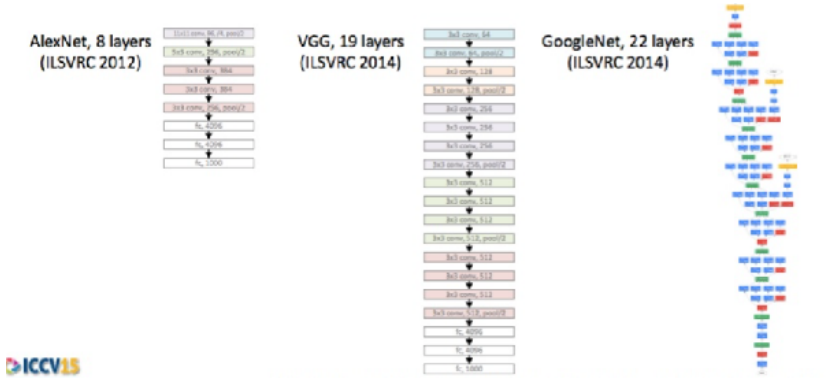


~38-45 layers

https://arxiv.org/pdf/1610.02357.pdf

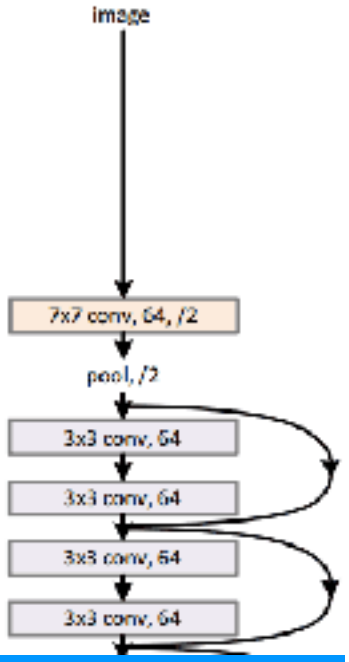
How big are these networks?

How big are these networks?



ResNet, 152 layers
(ILSVRC 2015)

34-layer residual



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

Demo

Even more Convolutional Neural Networks

…in TensorFlow

…with Keras

`12. More Advanced CNN Techniques.ipynb`

Next Time:

- CNN Lab Discussion (Town Hall)

- Intro to Recurrent Neural Network Architectures
  - RNNs, GRUs, LSTMs
  - Training for characters