Lecture Notes for
Machine Learning in Python

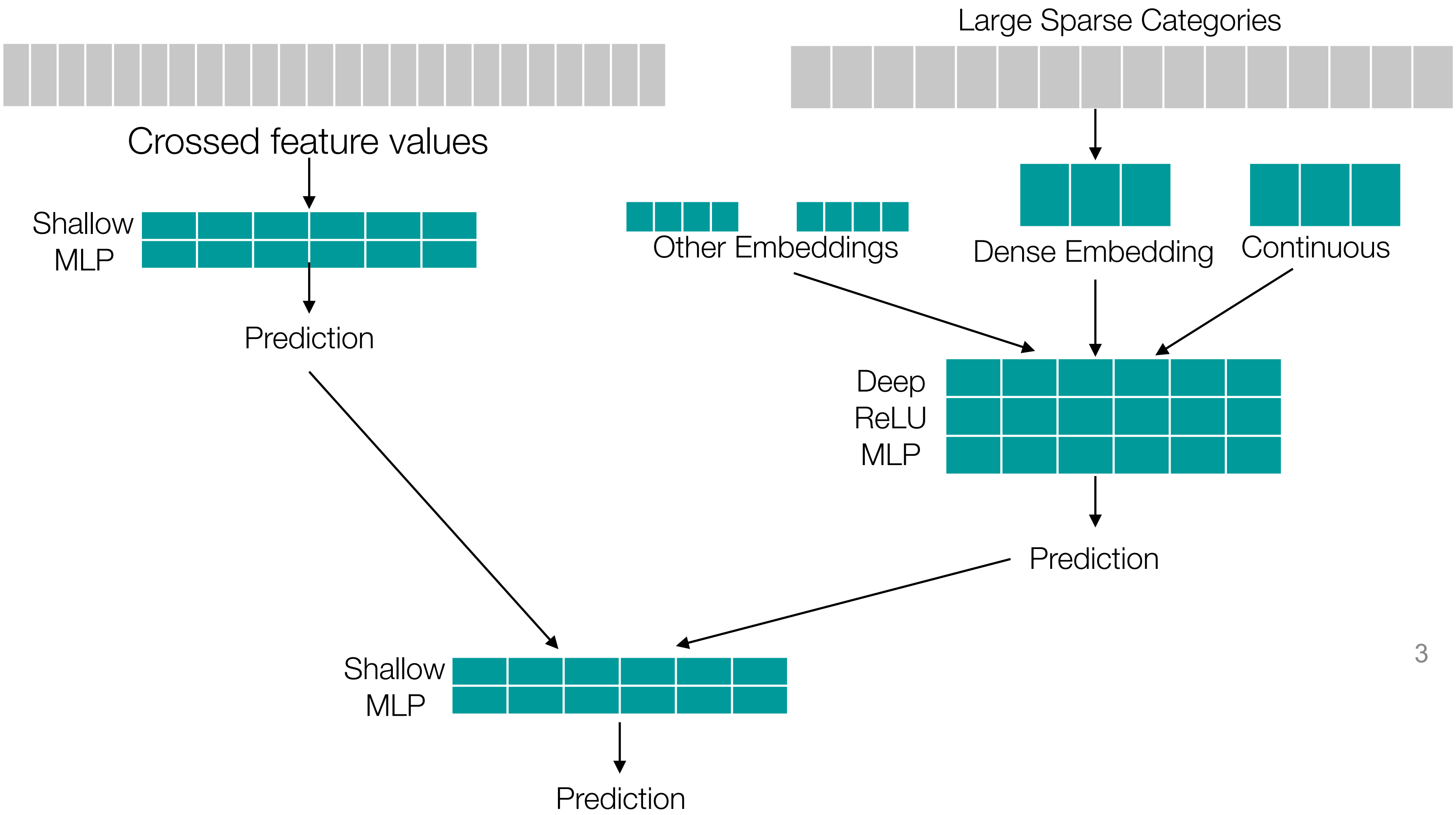
Professor Eric Larson

Basic Convolutional Neural Networks

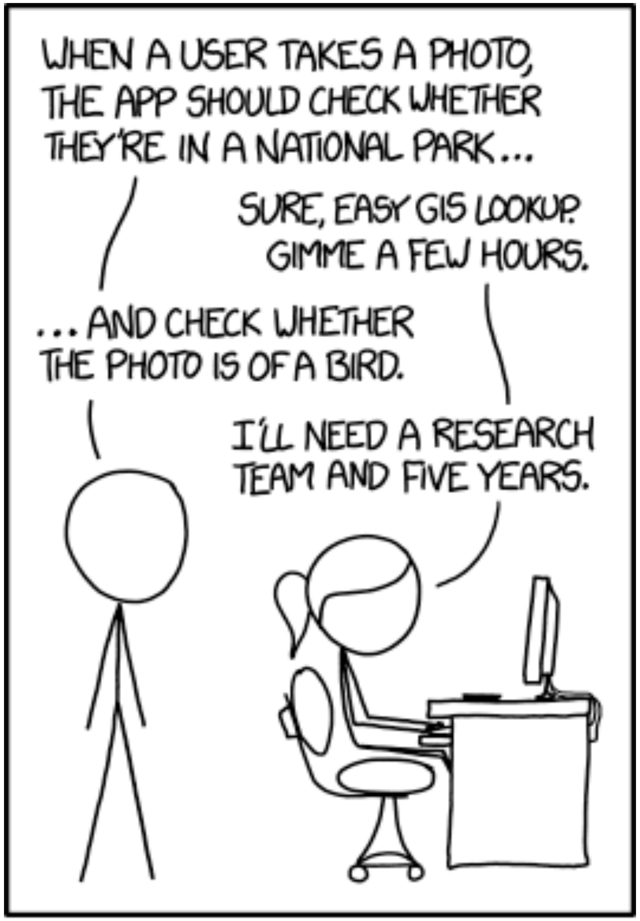
Logistics and Agenda

- Logistics
  - Wide/Deep due this week
- Agenda
  - Basic CNN architectures and Demo

Last Time:


Large Sparse Categories
Crossed feature values
Shallow MLP
Prediction
Other Embeddings
Dense Embedding
Continuous
Deep ReLU MLP
Prediction
Shallow MLP
Prediction

Convolutional Neural Networks



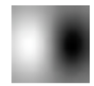
IN CS, IT CAN BE HARD TO EXPLAIN THE DIFFERENCE BETWEEN THE EASY AND THE VIRTUALLY IMPOSSIBLE.

What we did before

- the gradient (2D derivative)

I

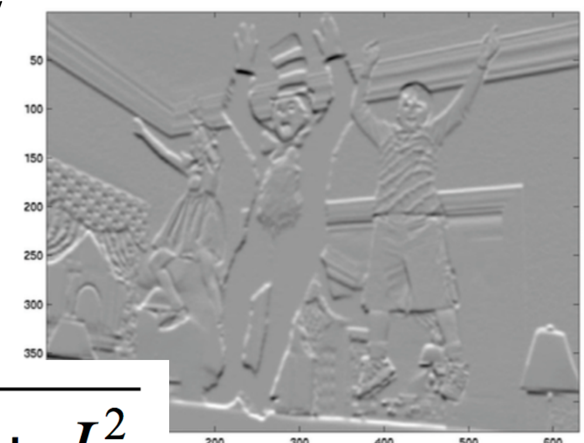
filter



J_x

filter

J_y

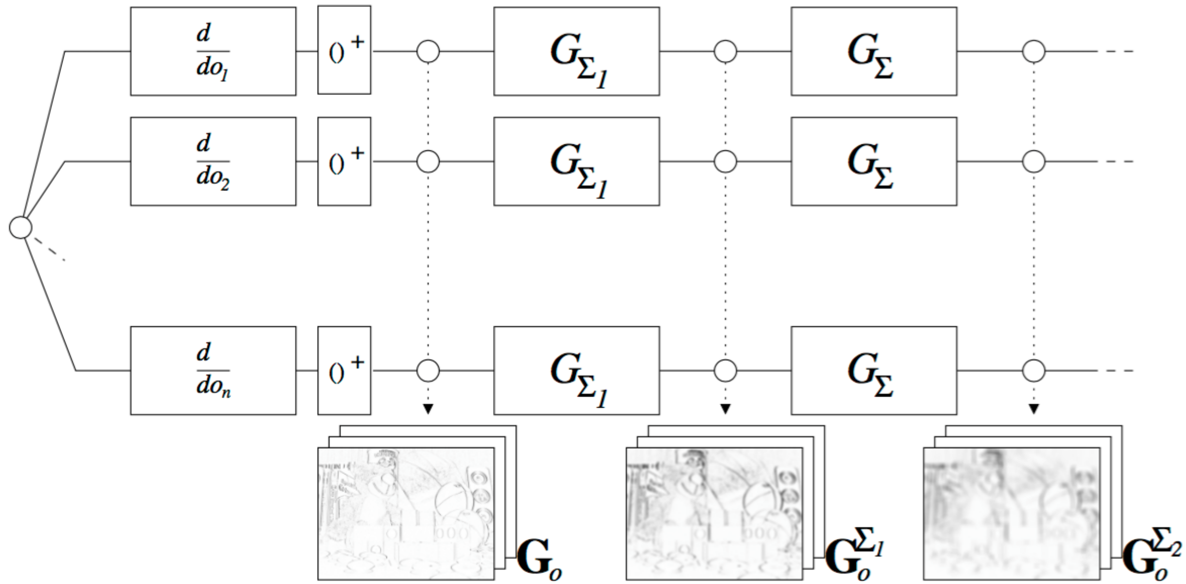


$$\left\|\nabla J\right\| = \sqrt{J_x^2 + J_y^2}$$

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

images: Jianbo Shi, Upenn

What we did before



take normalized histogram at point u,v

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

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

$$\begin{bmatrix} \widetilde{\mathbf{h}}^{\top}_{\Sigma_1}(u_0,v_0), \\ \widetilde{\mathbf{h}}^{\top}_{\Sigma_1}(\mathbf{l}_1(u_0,v_0,R_1)), \cdots, \widetilde{\mathbf{h}}^{\top}_{\Sigma_1}(\mathbf{l}_T(u_0,v_0,R_1)), \\ \widetilde{\mathbf{h}}^{\top}_{\Sigma_2}(\mathbf{l}_1(u_0,v_0,R_2)), \cdots, \widetilde{\mathbf{h}}^{\top}_{\Sigma_2}(\mathbf{l}_T(u_0,v_0,R_2)), \end{bmatrix}$$

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

CNN Overview

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

CNN Overview: Self Test

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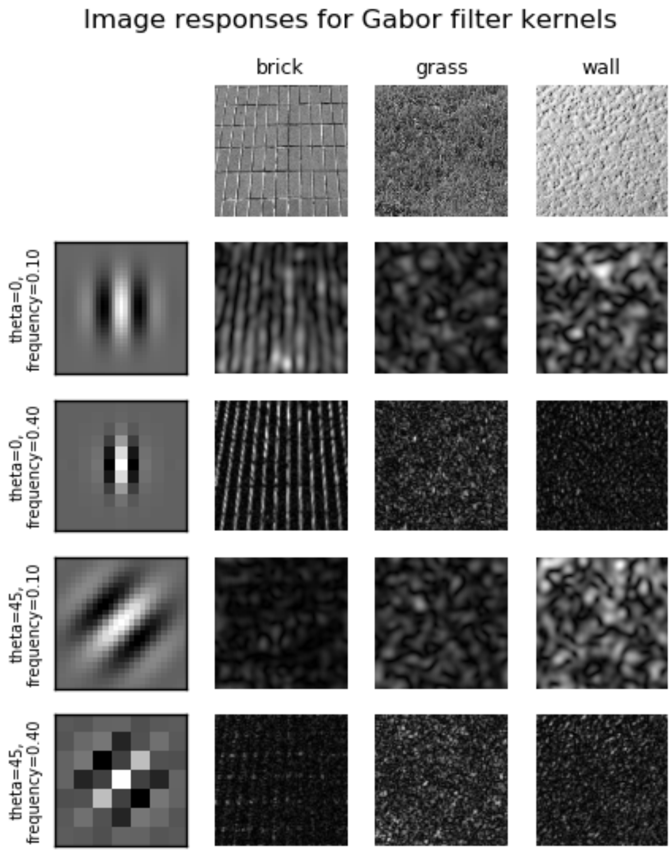
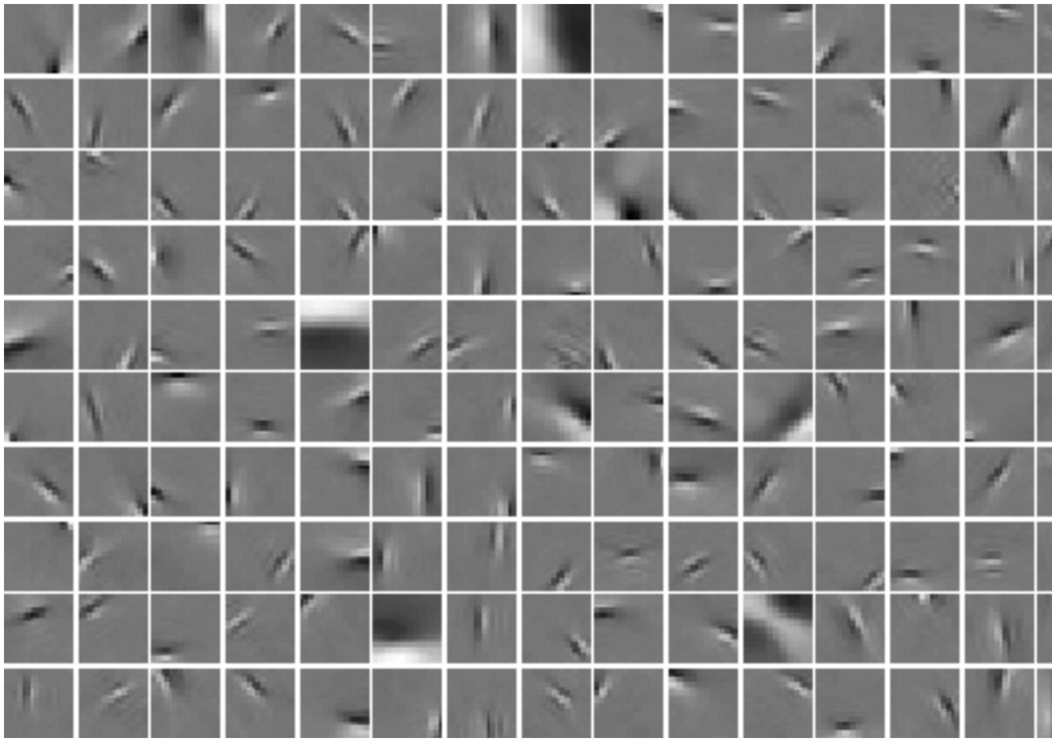
- Where are unstable gradients **most** problematic?
    - (A) During Convolution Layer(s) updates
    - (B) During Fully Connected Layer(s) updates
    - (C) Both A and B
    - (D) They are not a problem

CNN Filtering

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





CNN Filtering

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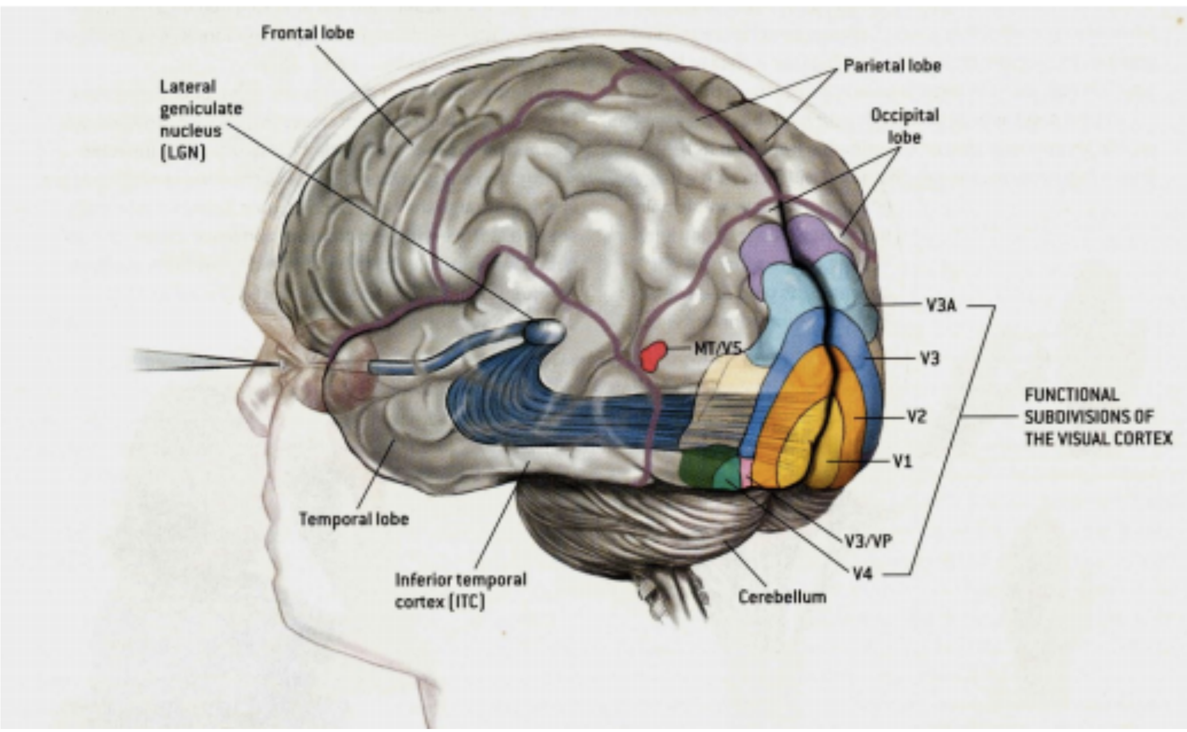
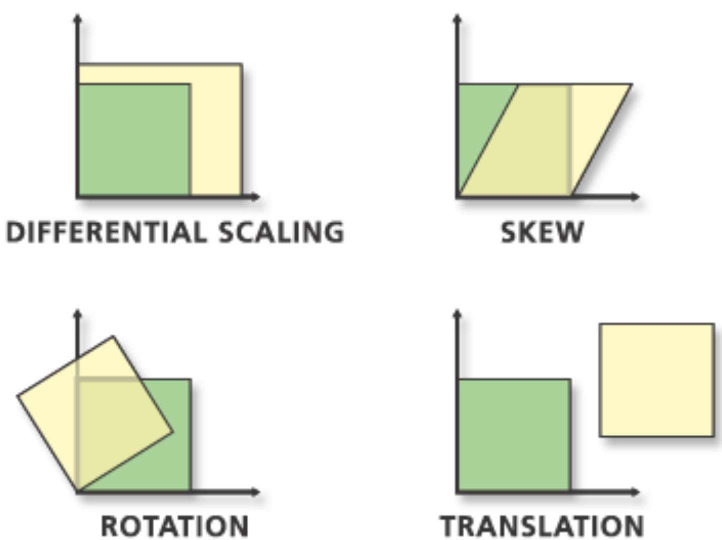
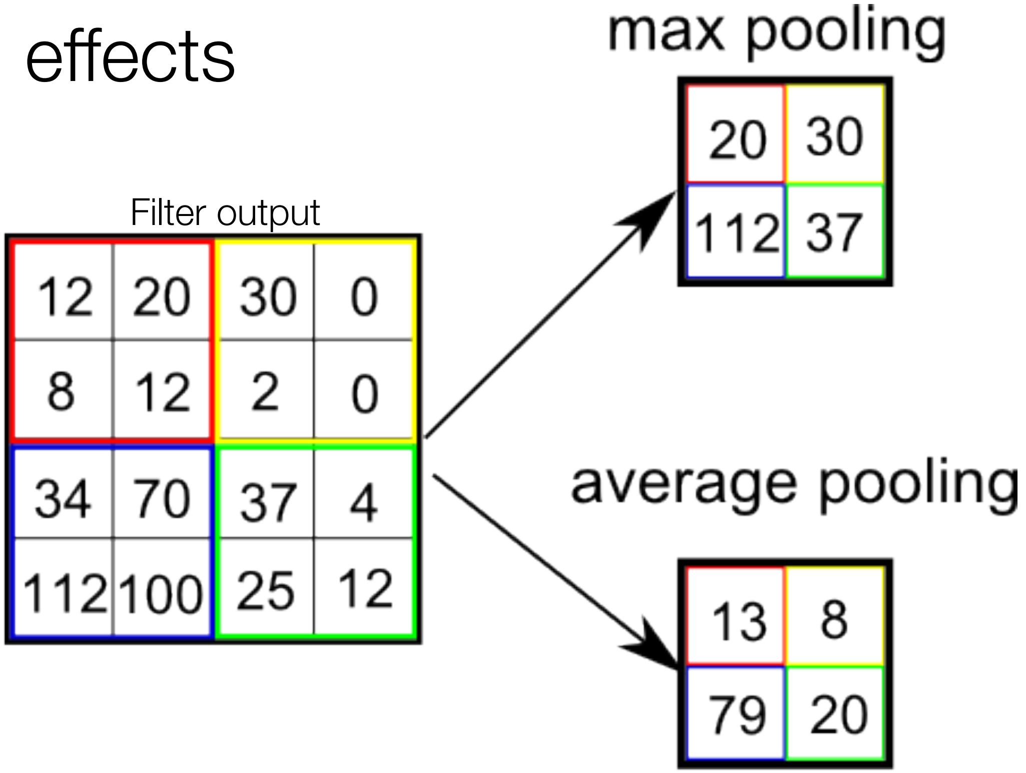


V1	Motion
V2	Stereo
V3	Color
V3a	Texture segregation
V3b	Segmentation, grouping
V4	Recognition
V7	Face recognition
MT	Attention
MST	Working memory/mental imagery

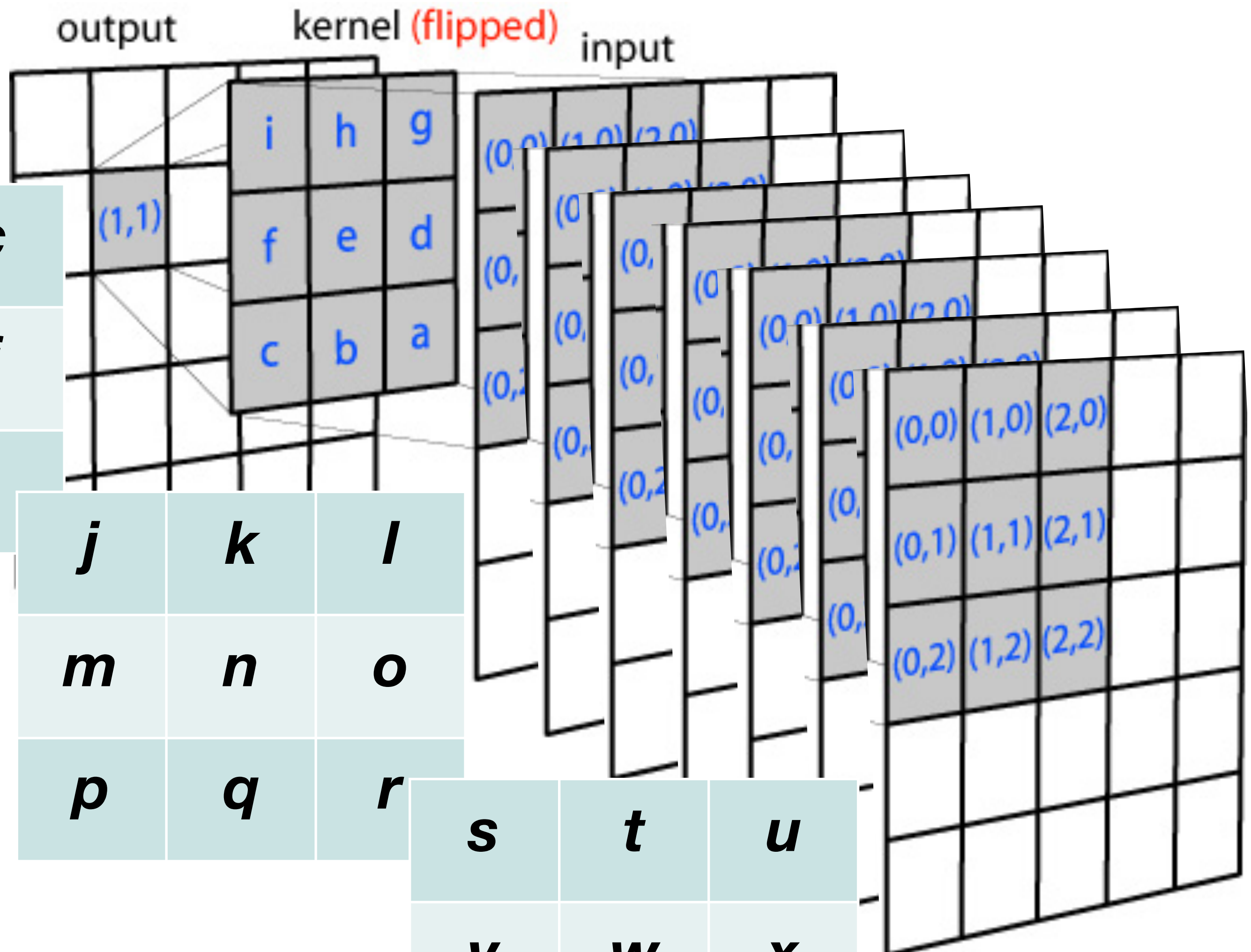
CNN Pooling

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





Convolution in a CNN

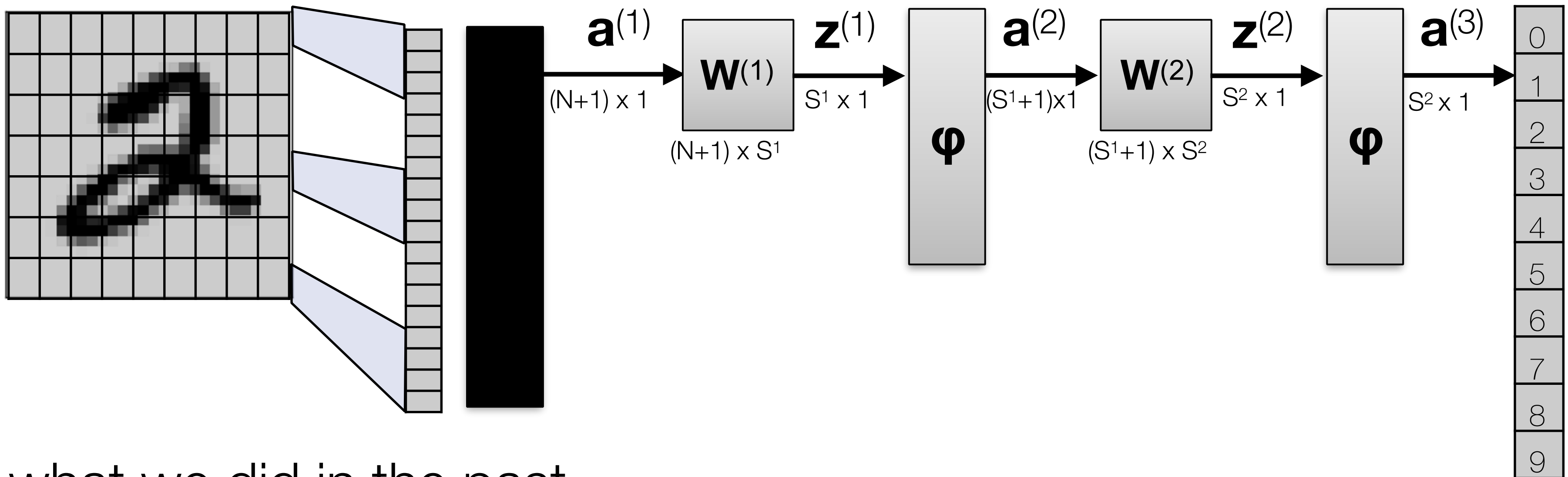


a	*b*	*c*
d	*e*	*f*
g	*h*	*i*

j	*k*	*l*
m	*n*	*o*
p	*q*	*r*

s	*t*	*u*
v	*w*	*x*
y	*z*	*η*

From Fully Connected to CNN



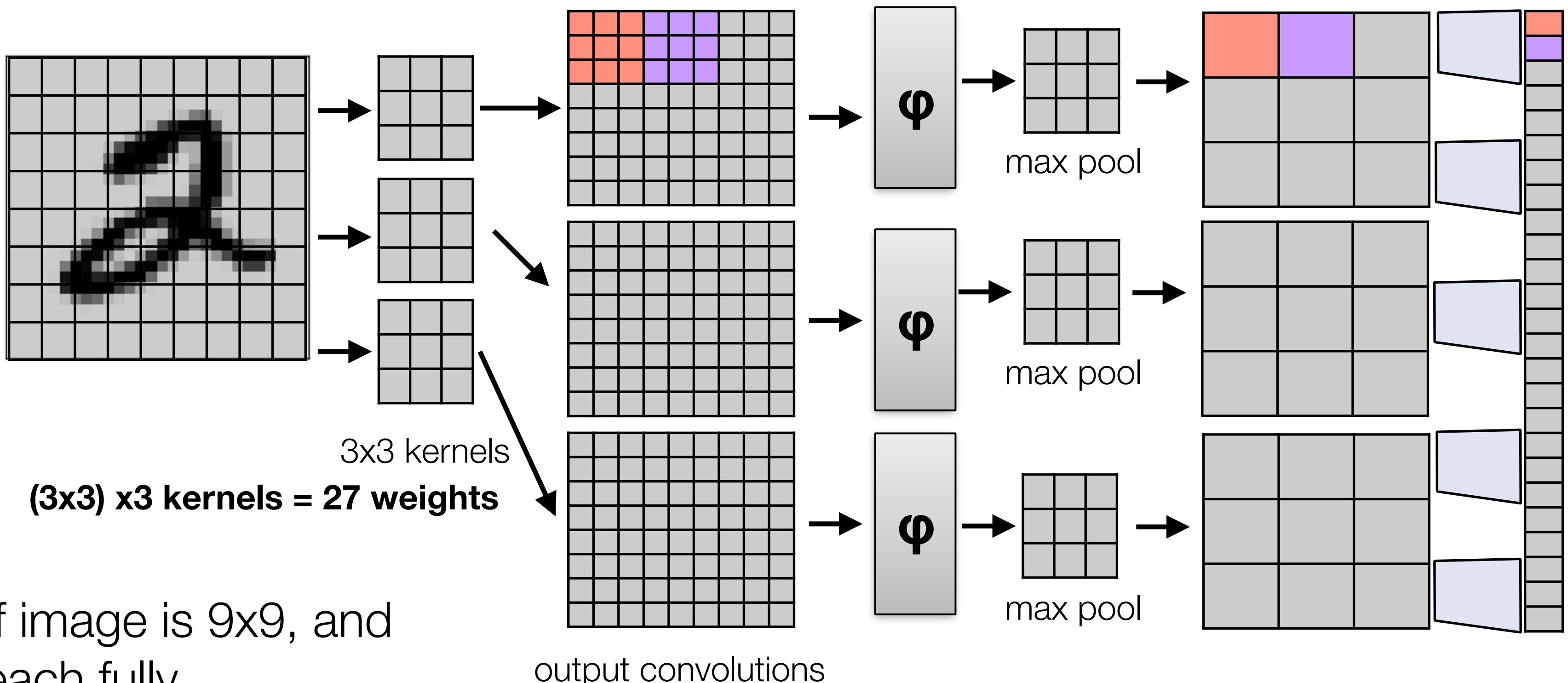
what we did in the past

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

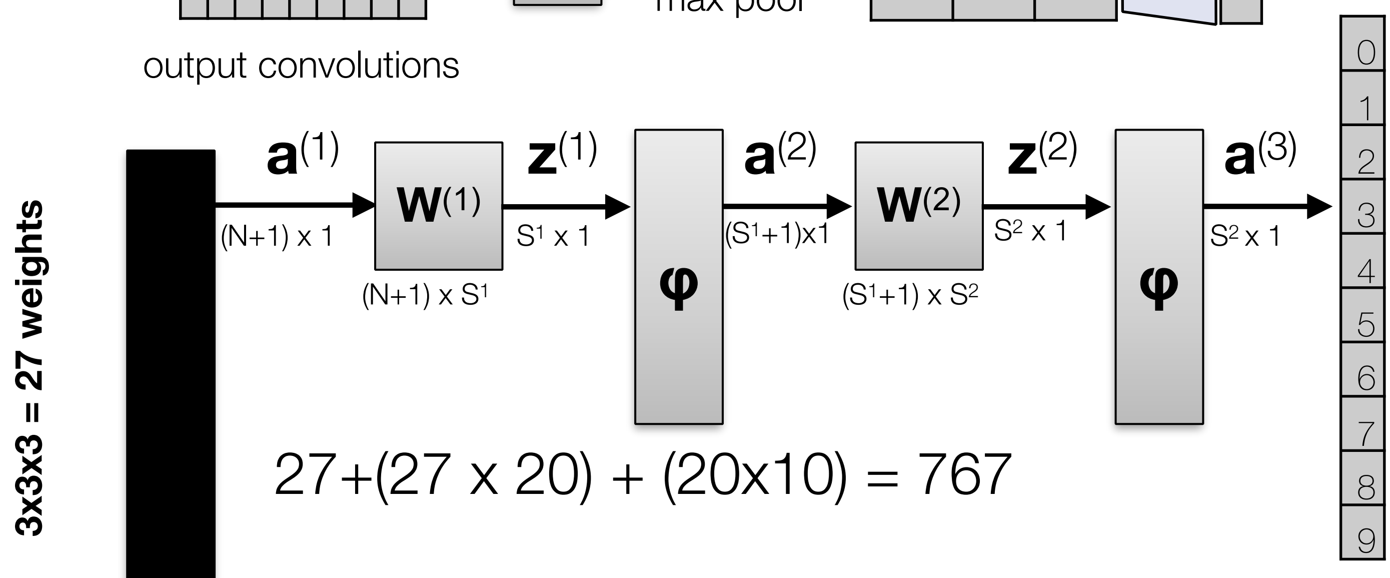
$(K^2 \times 20) + (20 \times 10) = 200 + 20\,K^2$

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

From Fully Connected to CNN

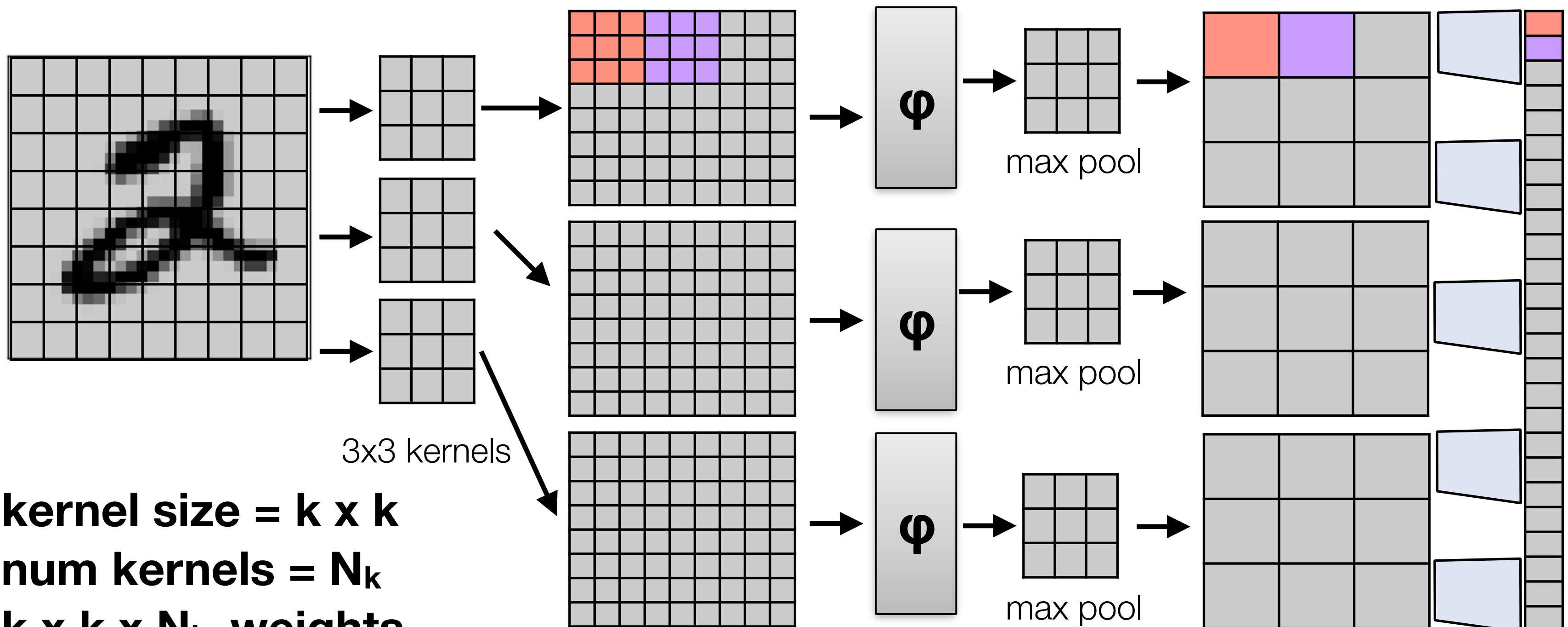


If image is 9x9, and each fully connected layer is 20 hidden neurons wide, how many parameters are in this NN (ignore bias)?



$$27+(27 \times 20) + (20\times10) = 767$$

From Fully Connected to CNN

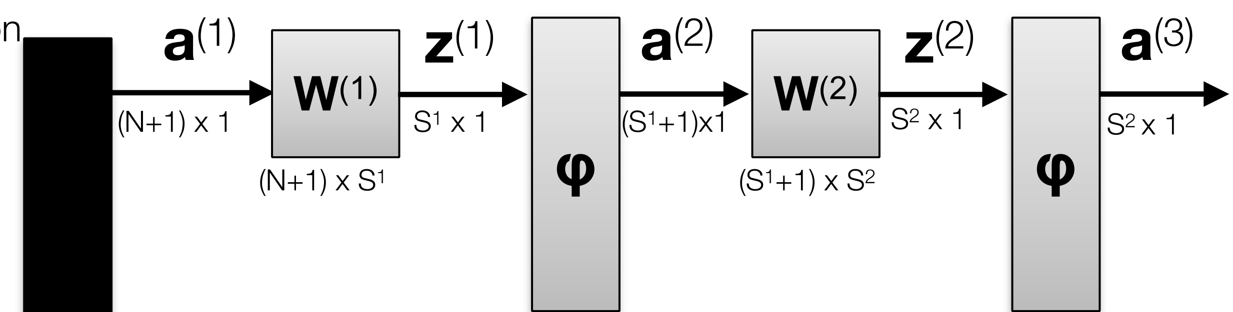


kernel size = k x k
num kernels = N_k
$k \times k \times N_k$ weights

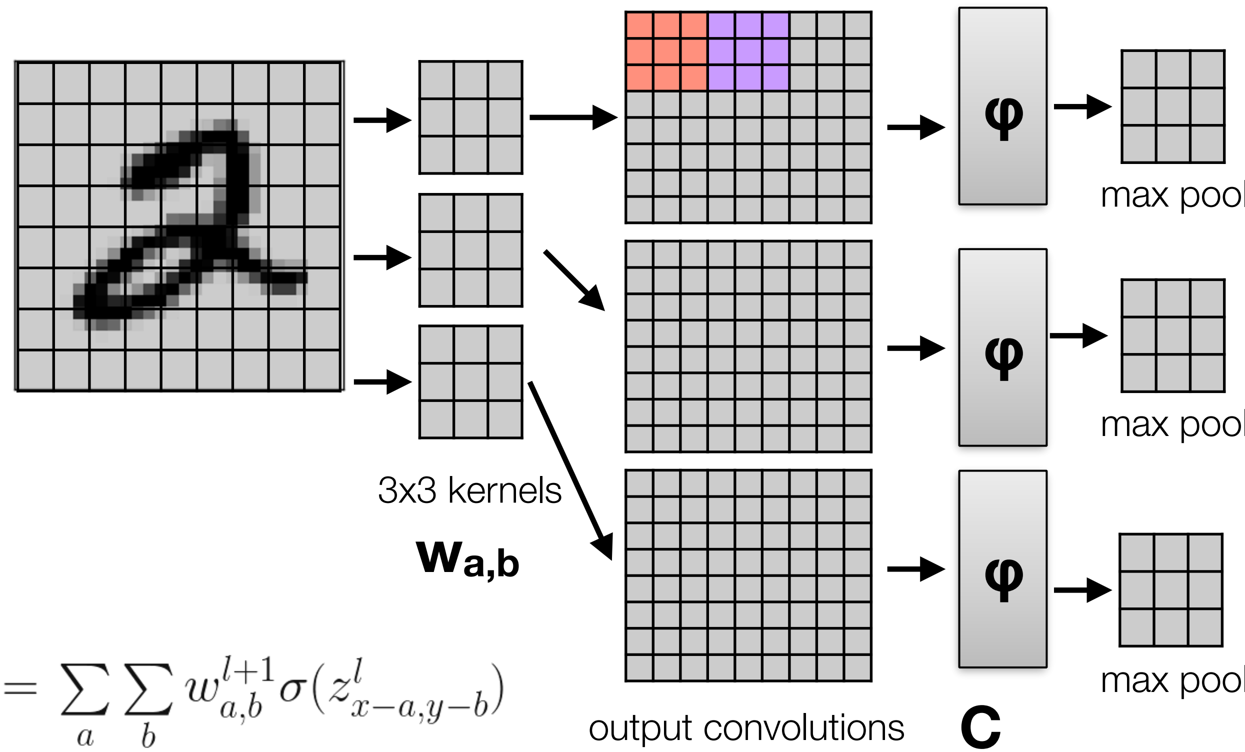
pooling outputs
if stride = k
$(K/k) \times (K/k) \times N_k$

total inputs
$N_k \times (k^2 + K^2/k^2)$

num filters
filter dimension
image dimension



CNN gradient



$$= \sum_a \sum_b w^{l+1}_{a,b} \sigma(z^l_{x-a,y-b})$$

Derivative of max pool is easy:

for each input x_i

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

Derivative of convolution is more involved:

$$\frac{\partial C}{\partial w^l_{a,b}} = \sum_x \sum_y \frac{\partial C}{\partial z^l_{x,y}} \frac{\partial z^l_{x,y}}{\partial w^l_{a,b}} = \sum_x \sum_y \delta^l_{x,y} \frac{\partial(\sum_{a'} \sum_{b'} w^l_{a',b'} \sigma(z^l_{x-a',y-b'}) + b^l_{x,y})}{\partial w^l_{a,b}} =$$

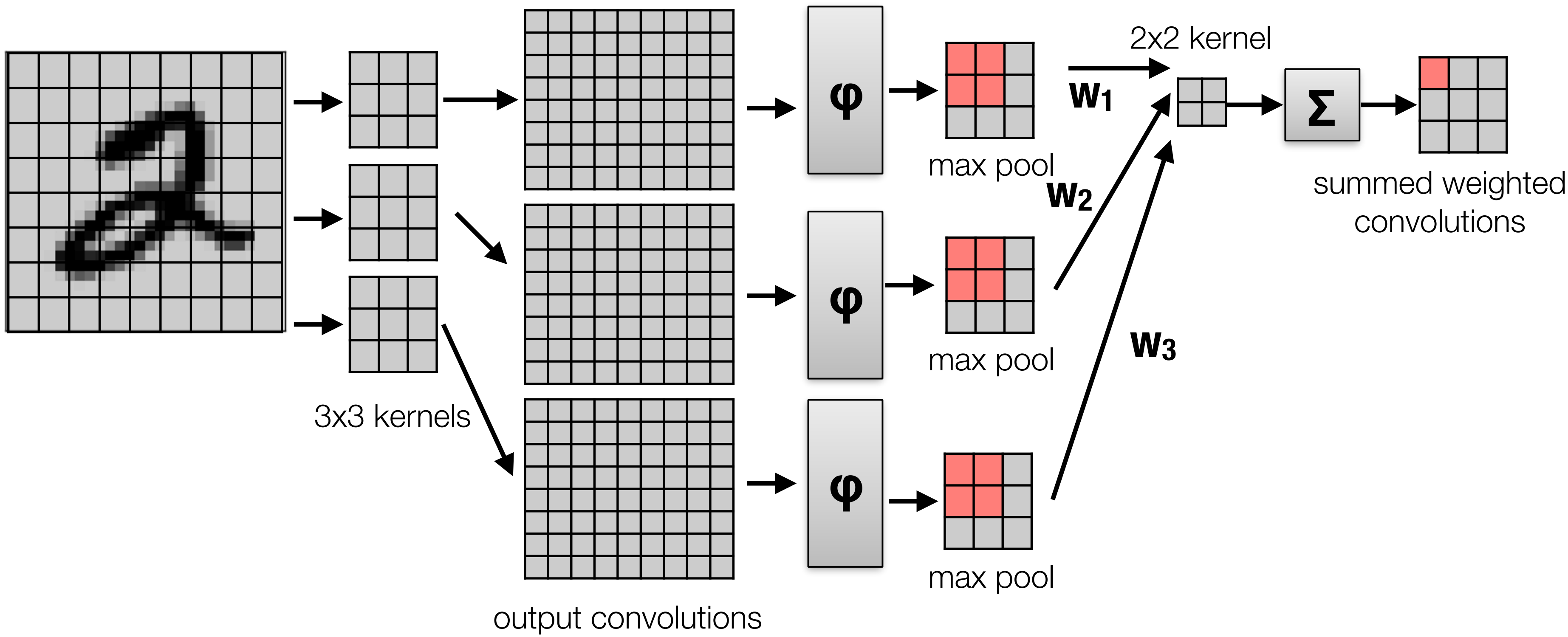
$$\sum_x \sum_y \delta^l_{x,y} \sigma(z^{l-1}_{x-a,y-b}) = \delta^l_{a,b} * \sigma(z^{l-1}_{-a,-b}) = \delta^l_{a,b} * \sigma(ROT180(z^{l-1}_{a,b}))$$

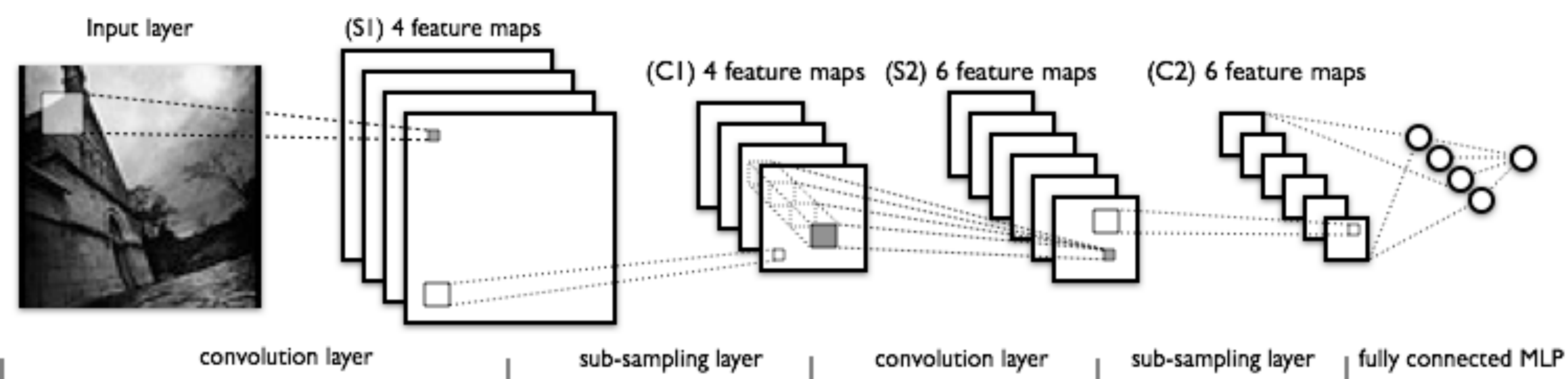
https://grzegorzgwardys.wordpress.com/2016/04/22/8/

CNN gradient

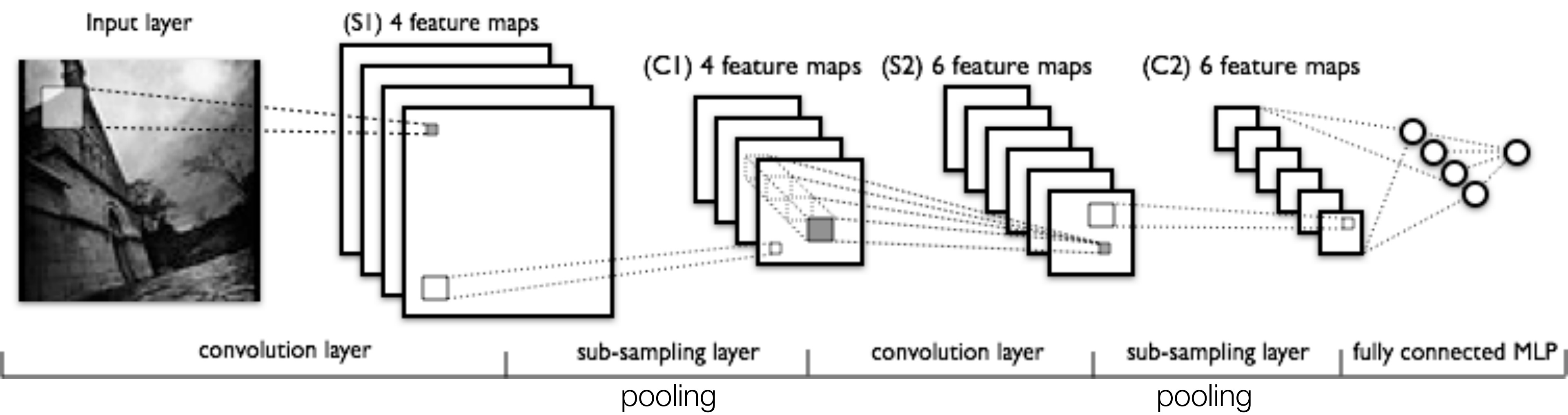
- But we really want to understand the process!
- These are great guides:
  - https://grzegorzgwardys.wordpress.com/2016/04/22/8/
  - http://andrew.gibiansky.com/blog/machine-learning/convolutional-neural-networks/

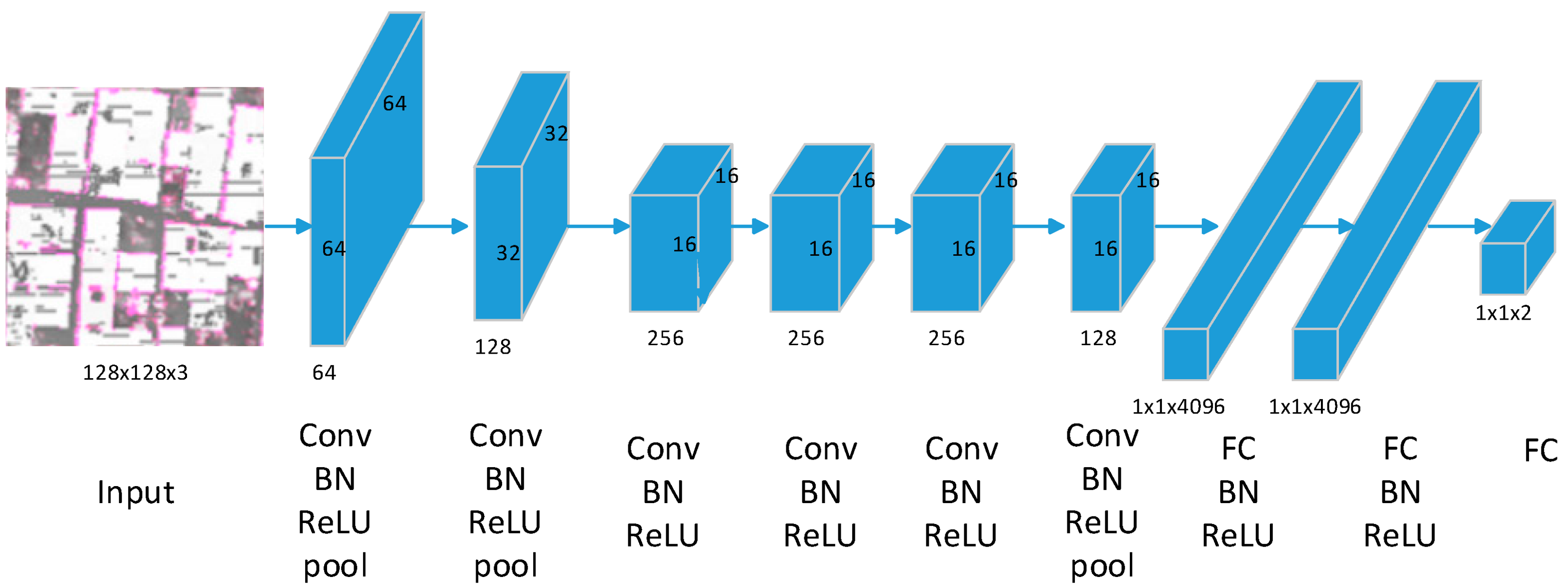
CNN adding more convolutional layers





Some Example CNN Architectures





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

Jet Propulsion Laboratory
California Institute of Technology

```
11. Convolutional Neural Networks.ipynb
```

Demo

TensorFlow and Basic CNNs

Convolutional Neural Networks
in TensorFlow
with Keras

Next Lecture

- More CNN architectures and CNN history

Lecture Notes for
Machine Learning in Python

Professor Eric Larson

An Ongoing History of Convolutional Networks

Wanted:
Participants for a Research Study in Biometrics and Privacy

- SMU Researchers are seeking participants for an upcoming research study.
- We will be gathering data about your biometrics as you do a series of everyday tasks on a mobile phone and laptop.
- We ask for about **1.5-2 hours** of your time! For completing the session, you will receive a $10 Amazon gift card.
- Please contact **eesharp@smu.edu**

IRB Approved: 02/23/2018 SL
Expires: 02/23/2019
Study ID: H18-020-LARE

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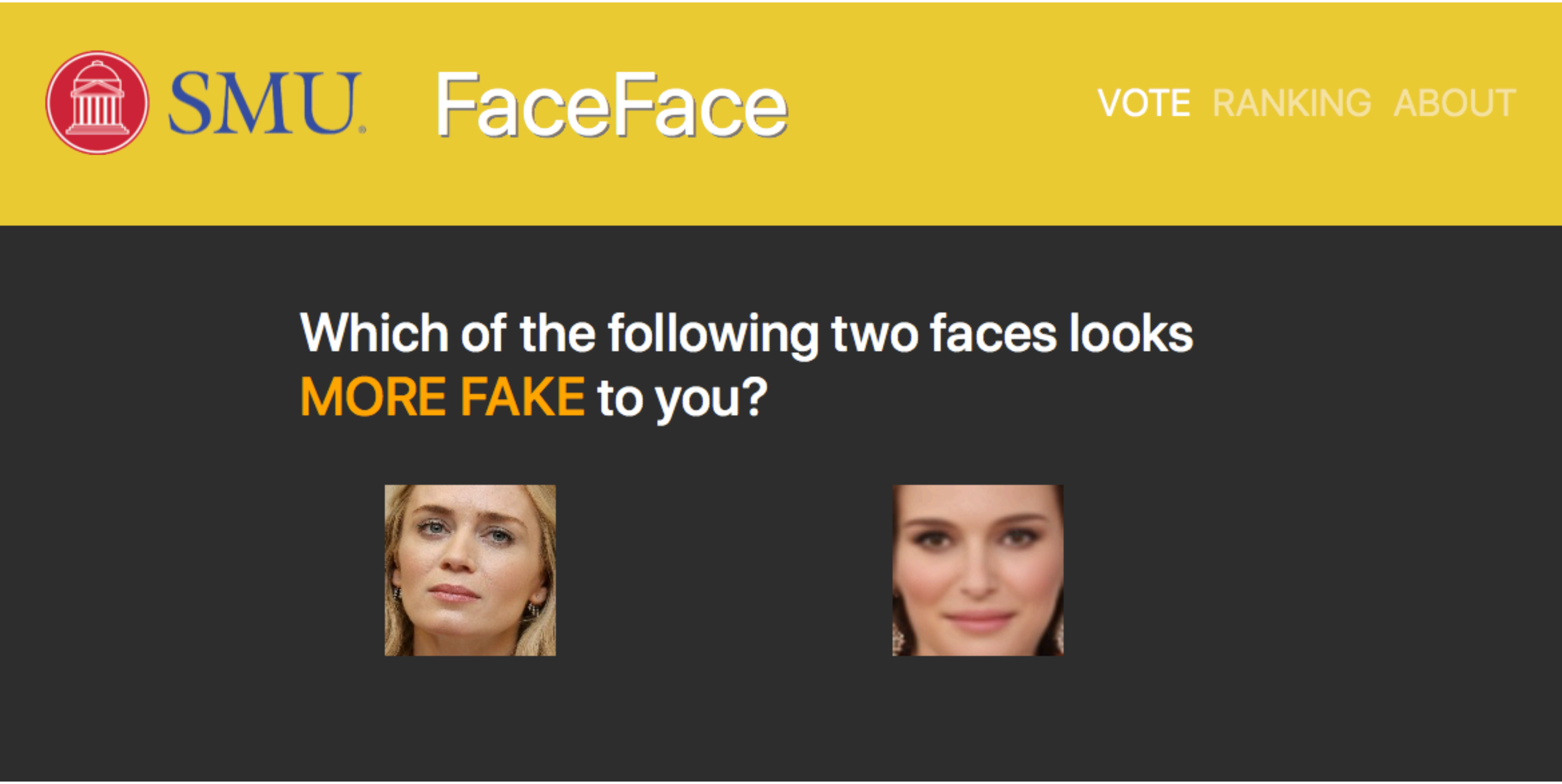
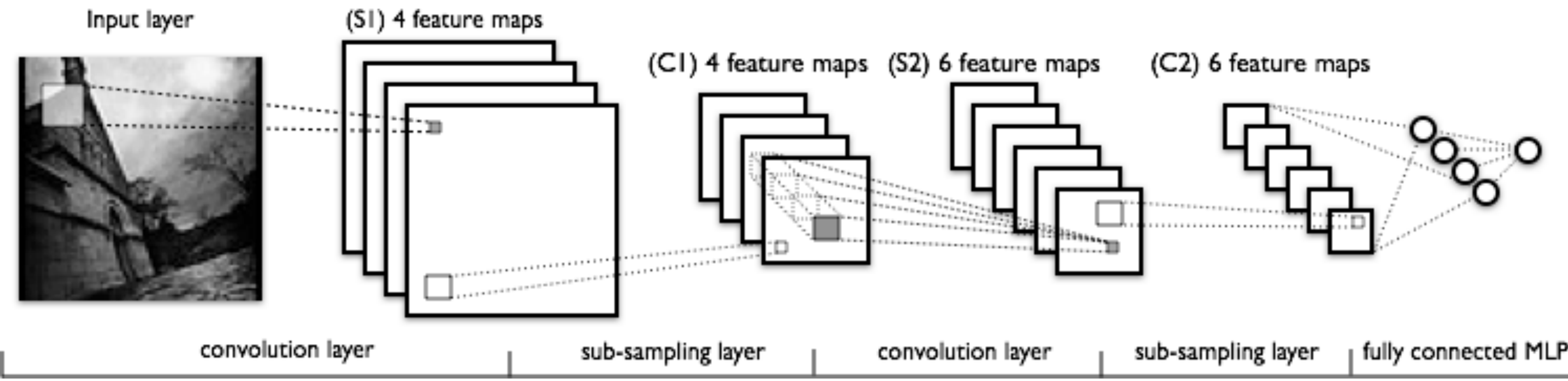
http://faceface.lyle.smu.edu/



Class logistics and Agenda

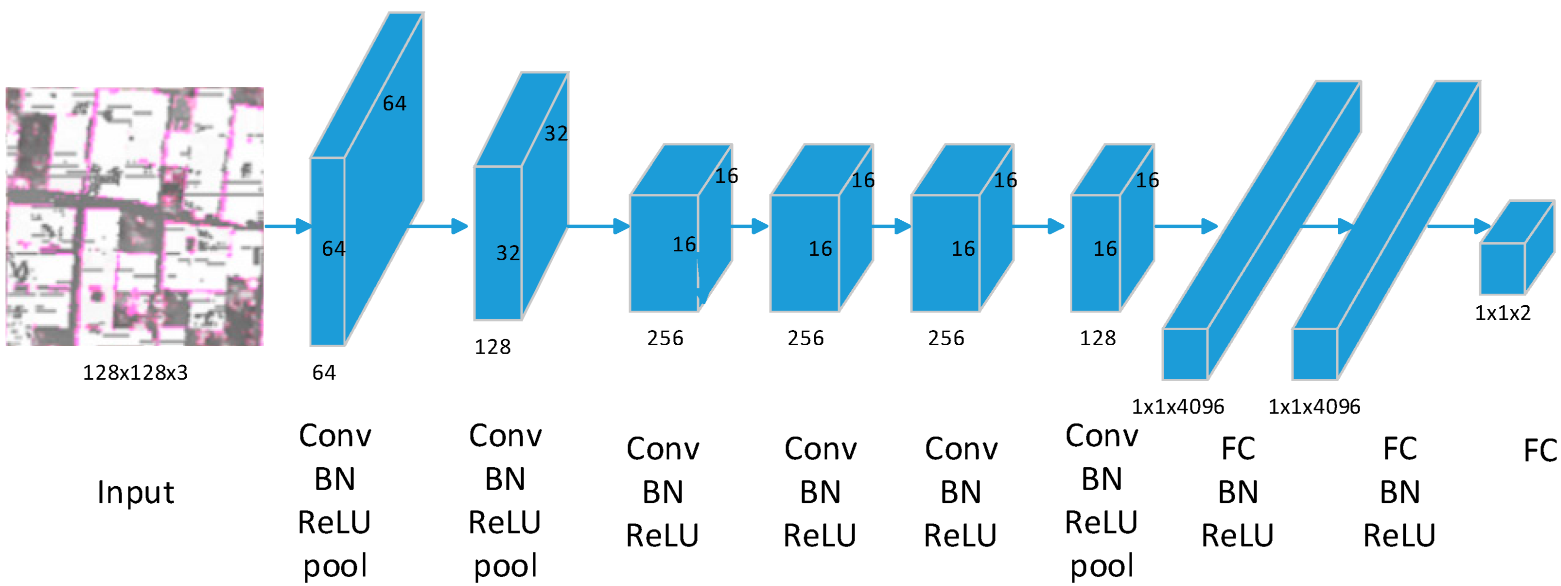
- Wide/Deep Lab due this week
- Agenda:
  - Finish CNN Demo
  - History of CNNs
  - with Modern CNN Architectures
- Next Time:
  - More Advanced CNN Demo

Last Time:



pooling pooling

layer1 layer2 layer3 layer4 layer5 layer6 layer7 layer8 layer9



TensorFlow and Basic CNNs

Finish Demo

Convolutional Neural Networks
in TensorFlow
with Keras

with Sequential API!

History of Convolutional Neural Networks

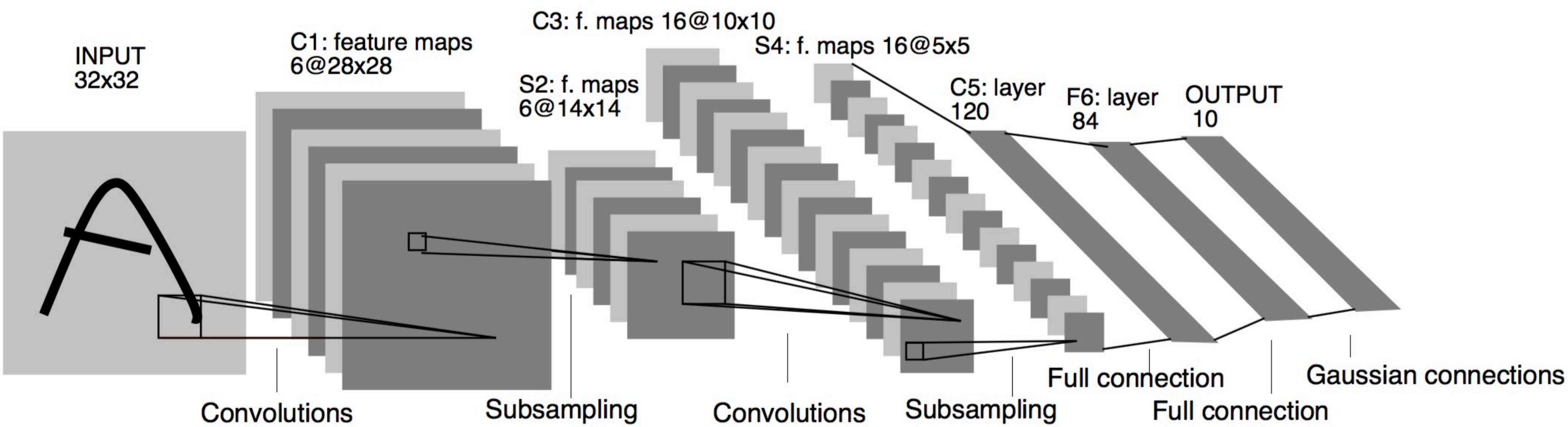
Thanks to machine-learning algorithms,
the robot apocalypse was short-lived.

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

    avg **tanh or sigmoid**



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

CNN History

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

¯_(ツ)_/¯

- 2010

Types of CNN, 2010

AI Researcher
IDSA, Switzerland

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

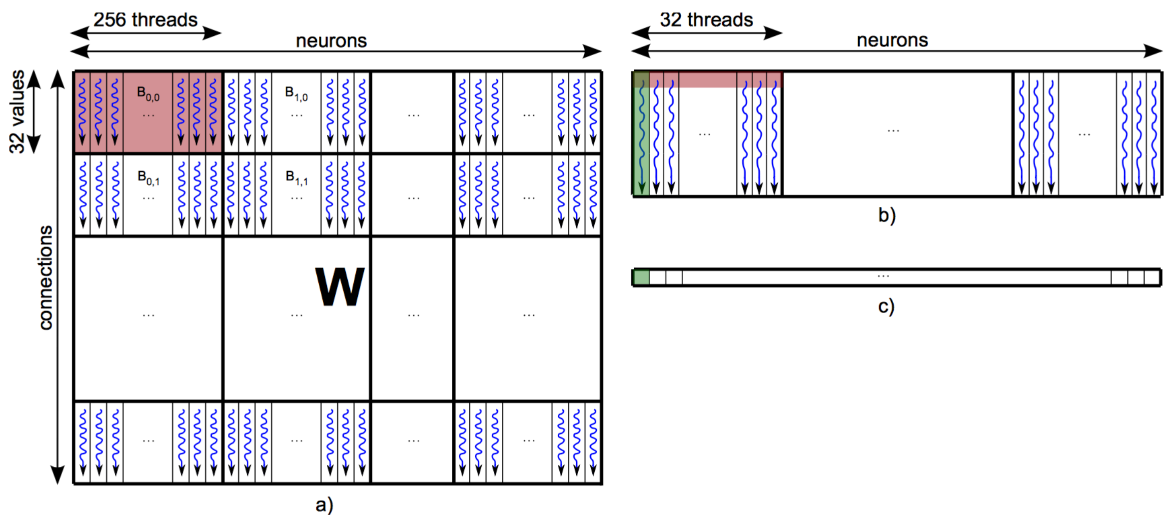
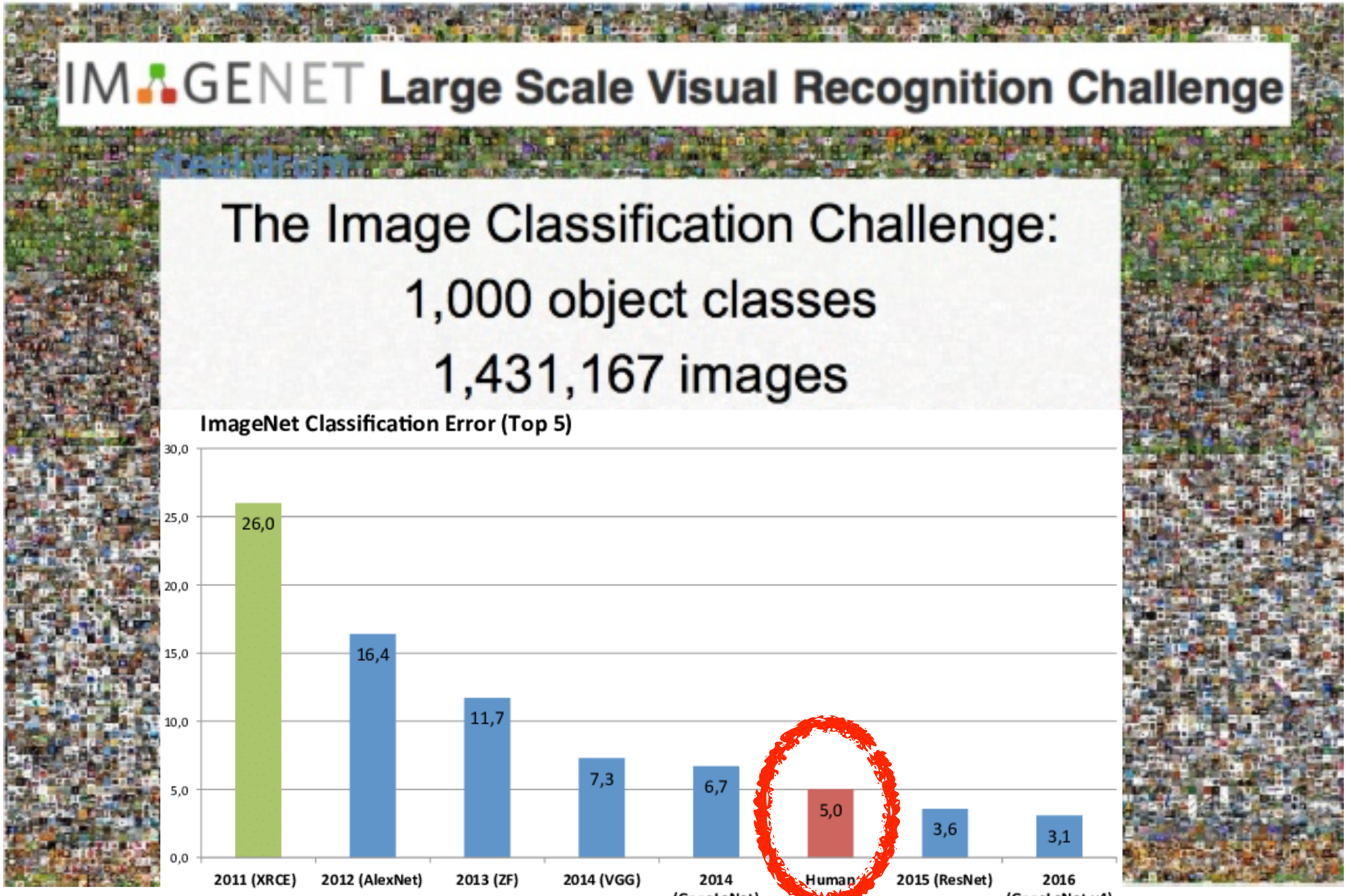


Figure 2: Forward propagation: a) mapping of kernel 1 grid onto the padded weight matrix; b) mapping the kernel 2 grid onto the partial dot products matrix; c) output of forward propagation.

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

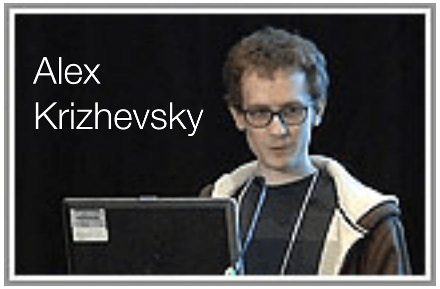
ImageNet Competition (2010-2016)



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

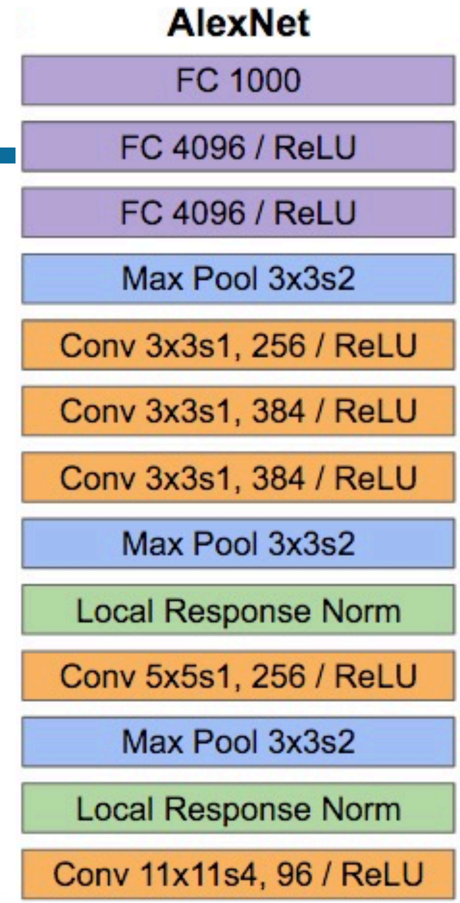
https://www.slideshare.net/nmhkahn/case-study-of-convolutional-neural-network-61556303

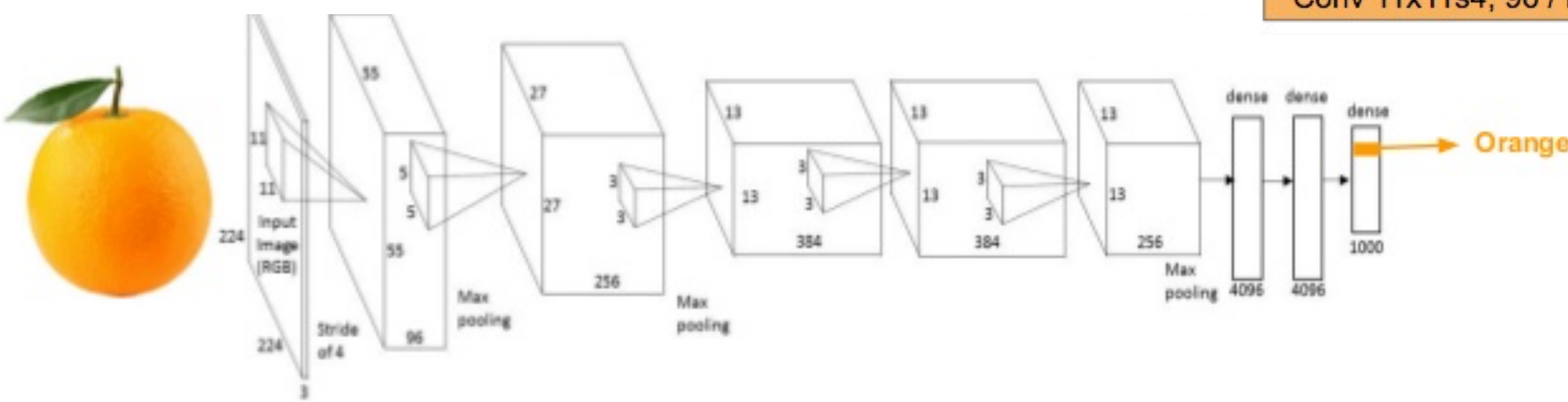
Types of CNN, 2012



Google

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



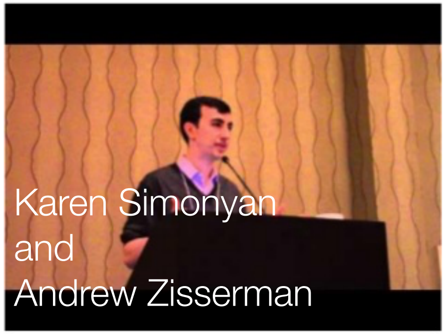


https://culurciello.github.io/tech/2016/06/04/nets.html

Warning


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

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

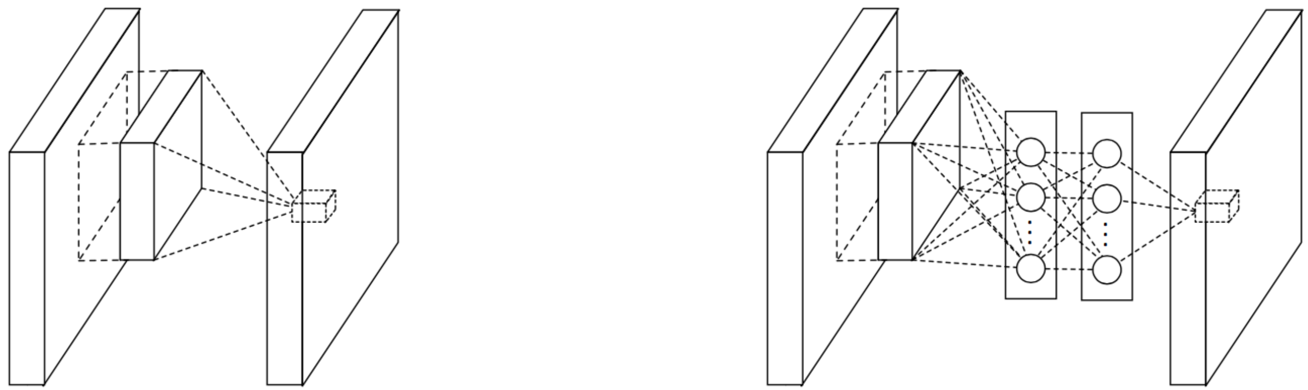
http://www.robots.ox.ac.uk/~vgg/practicals/cnn/

Types of CNN, 2014

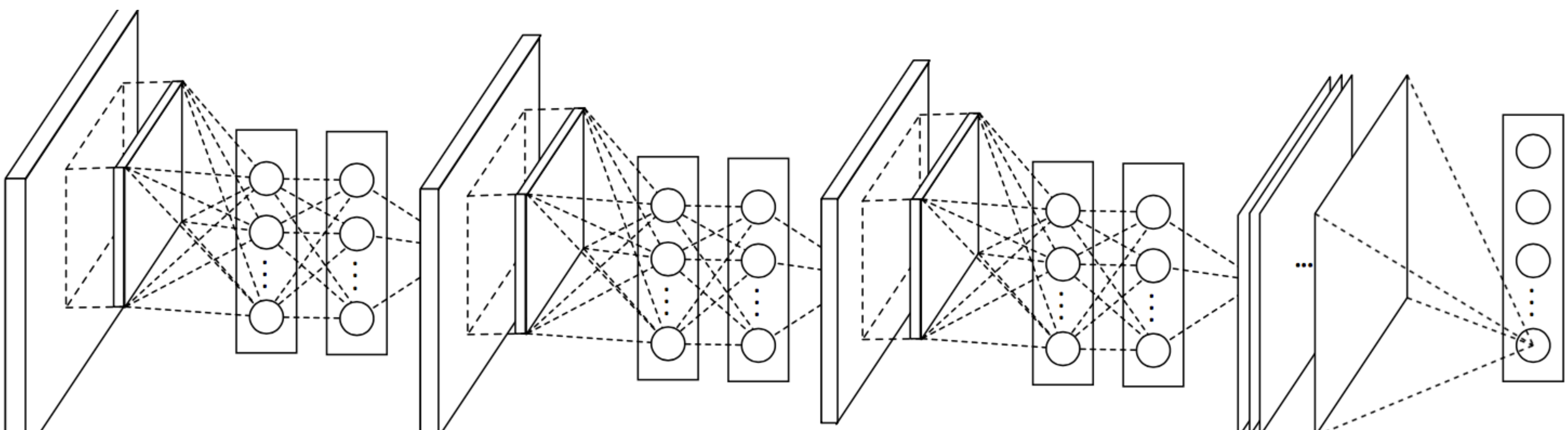
- Network in Network **NiN**
  - or MLPConv

Network In Network

Min Lin[1,2], Qiang Chen[2], Shuicheng Yan[2]
[1]Graduate School for Integrative Sciences and Engineering
[2]Department of Electronic & Computer Engineering
National University of Singapore, Singapore
{linmin,chenqiang,eleyans}@nus.edu.sg

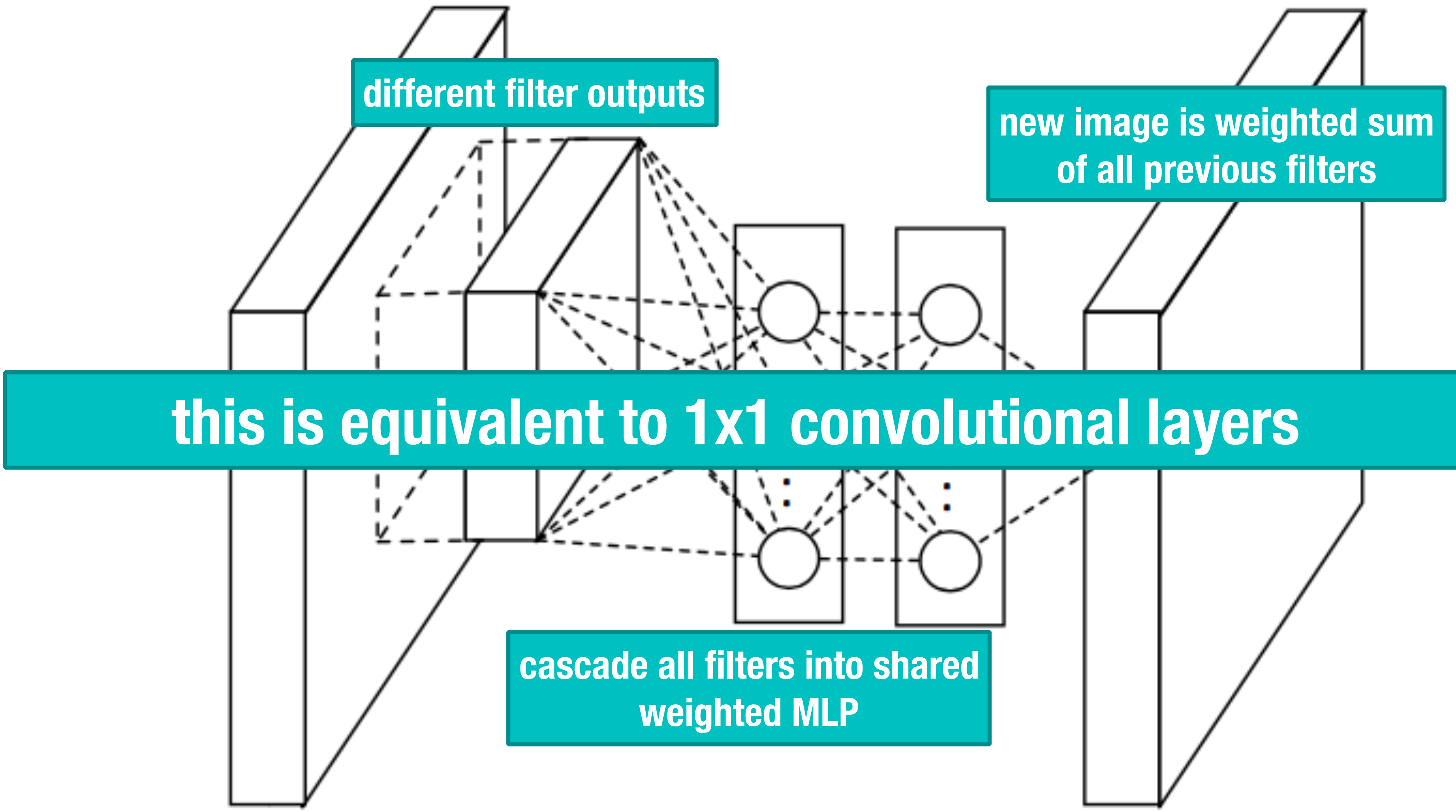


(a) Linear convolution layer (b) Mlpconv layer



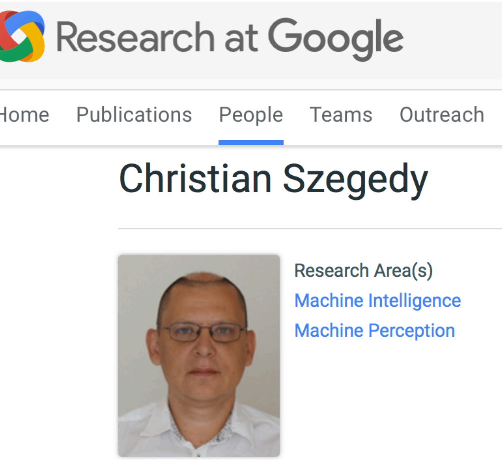
https://arxiv.org/pdf/1312.4400.pdf

Types of CNN, 2014

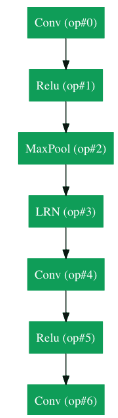


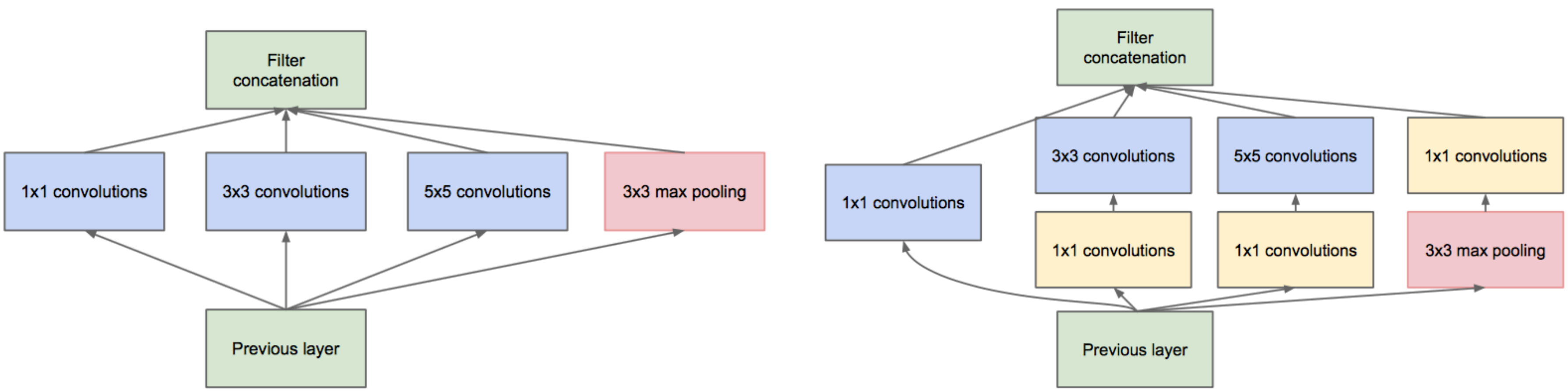
https://arxiv.org/pdf/1312.4400.pdf

Types of CNN, 2014



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





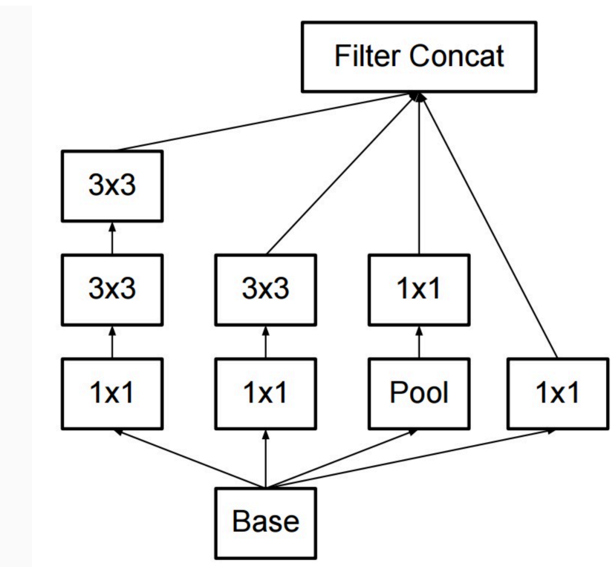
(a) Inception module, naïve version (b) Inception module with dimension reductions

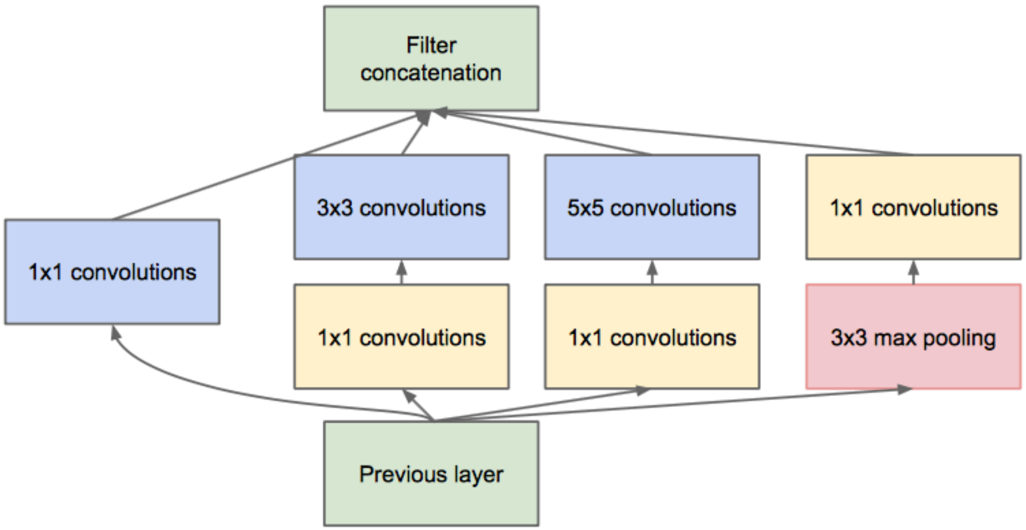
Figure 2: Inception module

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



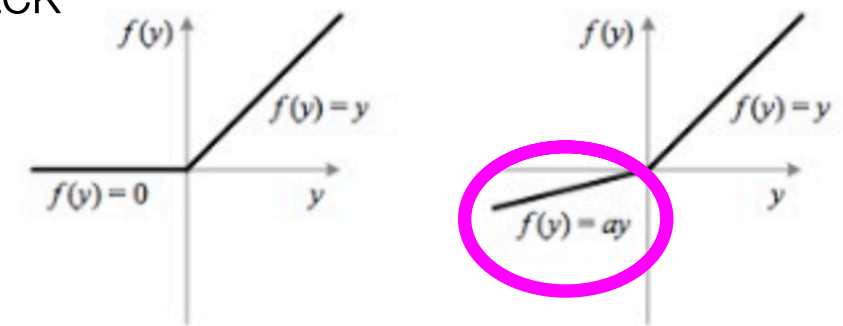


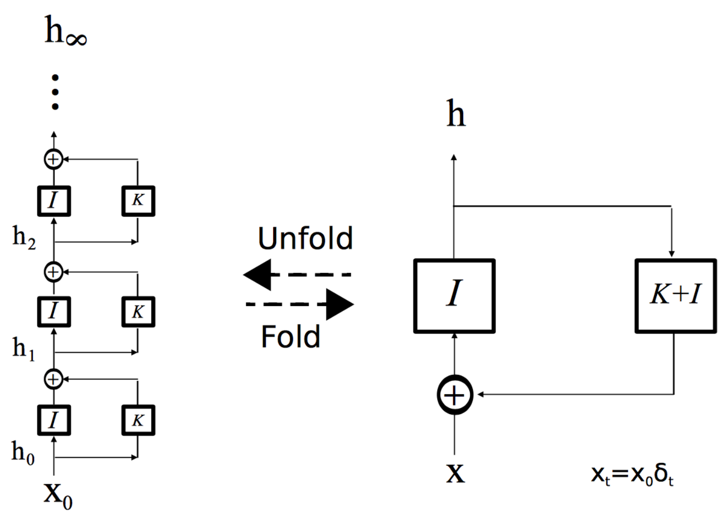
https://arxiv.org/pdf/1512.00567.pdf

Types of CNN, 2015 December

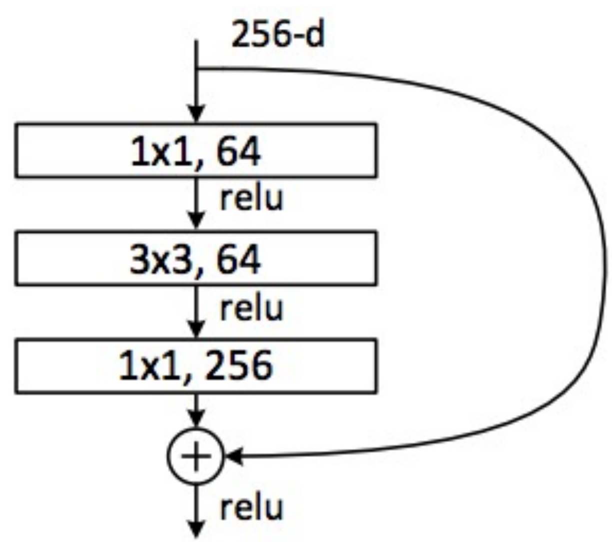
- Major Contributions:
  - ensembles, not strictly sequential
  - bio-plausible with feedback

- **ResNet**
  - PReLU: adaptive trained slope





(A) ResNet with shared weights (B) ResNet in recurrent form



- NiN: triple bypass layer
  - similar to bottleneck

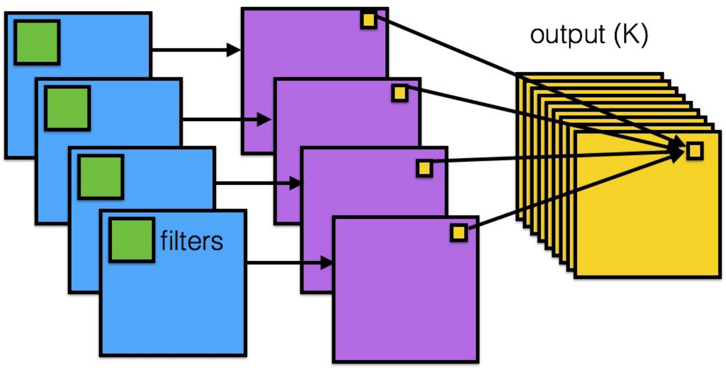
Types of CNN, 2017 April

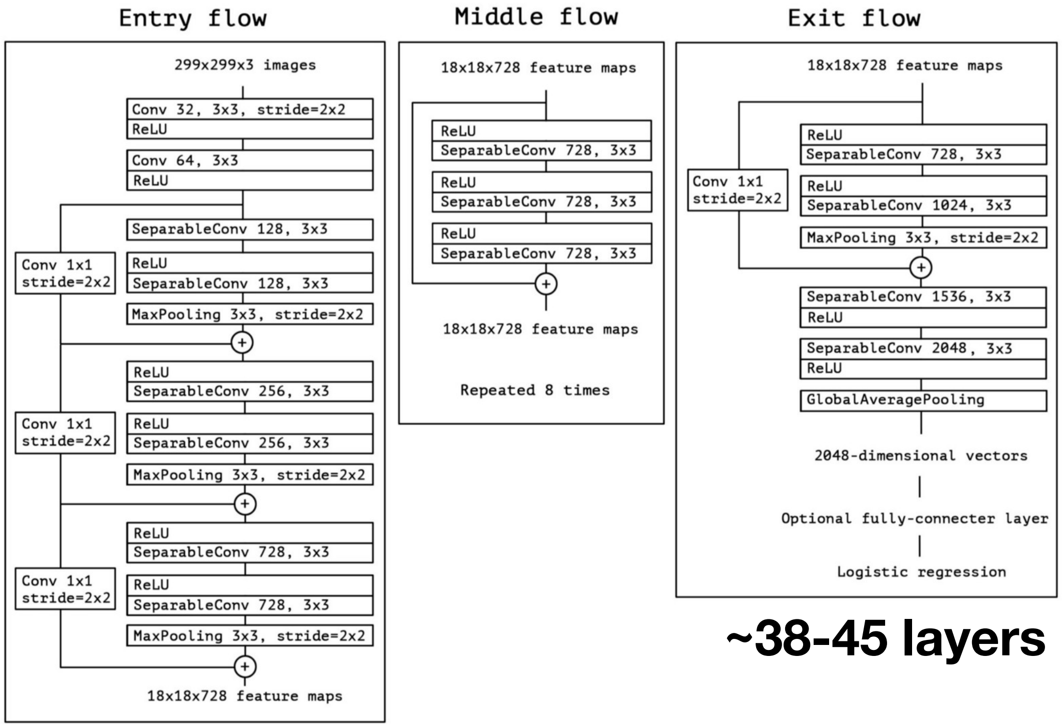
- Major Contributions:
  - combining branching / residual blocks
  - separable convolutions

Xception

Francois Chollet
Google

Xception



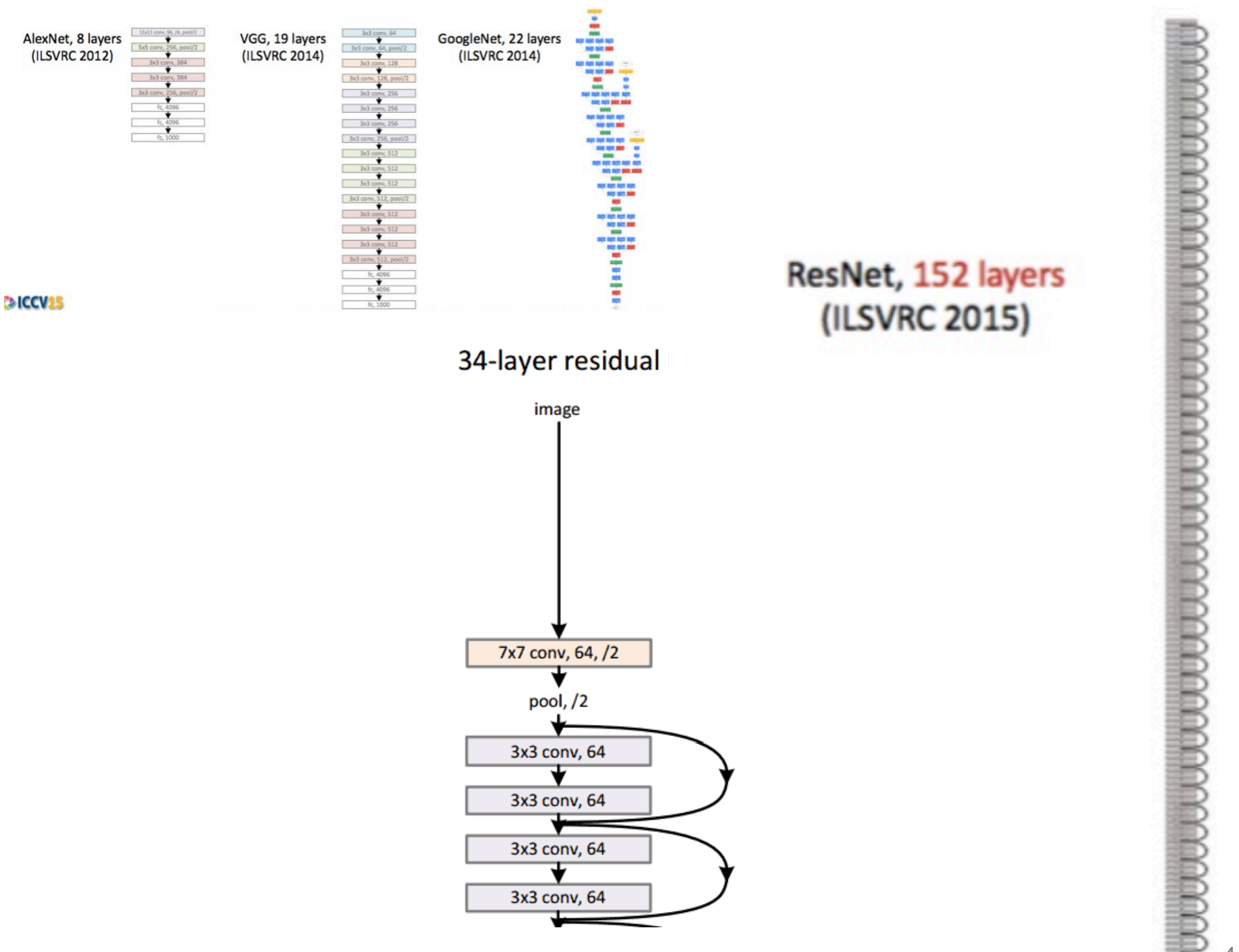


~38-45 layers

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

How big are these networks?

How big are these networks?



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

`12. More Advanced CNN Techniques.ipynb`

More Modern CNN Architectures

Demo

Even more Convolutional Neural Networks

…in TensorFlow

…with Keras

Next Time:

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

Lecture Notes for
Machine Learning in Python

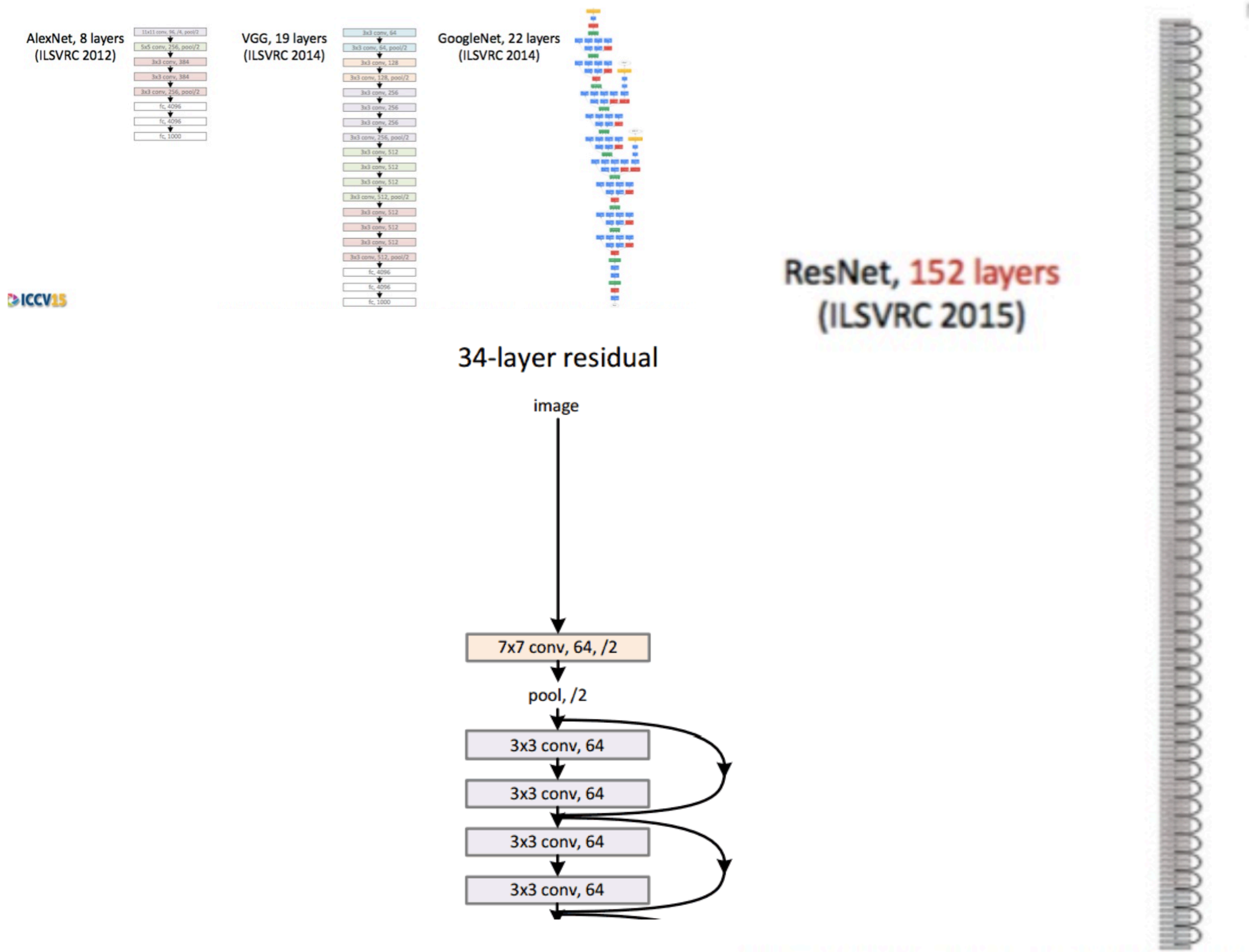
Professor Eric Larson

Demonstration of More Advanced
Convolutional Neural Networks

Class logistics and Agenda

- CNNs due next week
- Agenda:
    - More Advanced CNN Demo
- Next Time:
    - CNN Town Hall
    - Introduction to RNNs

Last Time:


AlexNet, 8 layers
(ILSVRC 2012)
VGG, 19 layers
(ILSVRC 2014)
GoogleNet, 22 layers
(ILSVRC 2014)
ICCV15
ResNet, 152 layers
(ILSVRC 2015)
34-layer residual
image
7x7 conv, 64, /2
pool, /2
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64
3x3 conv, 64

12. More Advanced CNN Techniques.ipynb

More Modern CNN Architectures

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