Lecture Notes for

Machine Learning in Python

[👨‍🏫, 👨‍💻, 🐍, 👨‍🔬]

Professor Eric Larson

Practical Introductory CNNs

Class logistics and Agenda

- Wide/Deep Lab (late turn in)
- Agenda:
  - CNN Demo
  - CNN Town Hall
  - History of CNNs
    - with Modern CNN Architectures
    - However far we make it…
- Next Time:
  - Transformers

Class Overview, by topic

Table Data Visualization

Numpy, Pandas, Seaborn

Overviews with some in-depth discussion

Dimension Reduction and Image Processing

Scikit-learn, Scikit Image,

Intuition only, Some mathematics

Linear and Logistic Regression

Numpy, Recreate API for Scikit-learn

Detailed mathematics for simple optimization
intuition for advanced optimization

Neural Networks and Back Prop.

Numpy

Detailed mathematics for NN operations

Wide and Deep Networks

Convolutional Networks

Recurrent Networks

Keras, Tensorflow

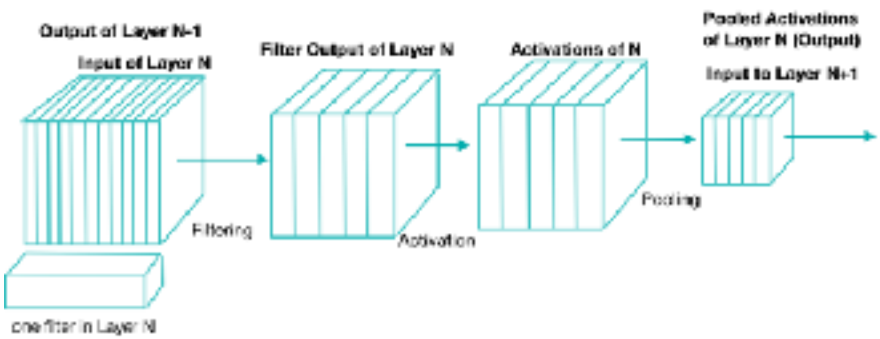
Intuition, Detailed implement.

Ethics in Language Models

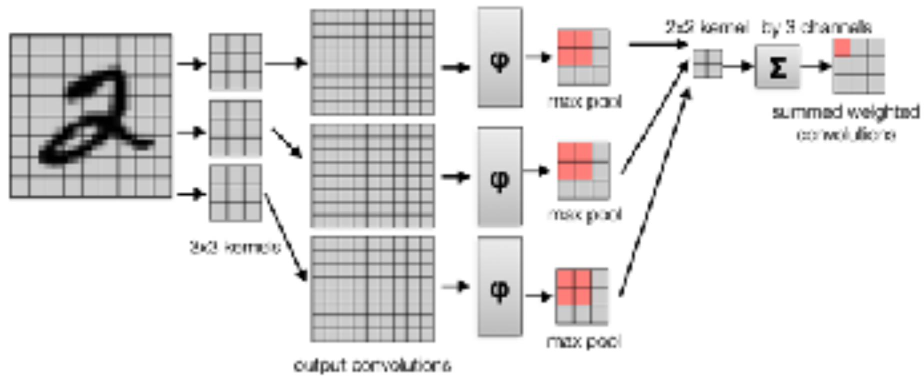
ConceptNet

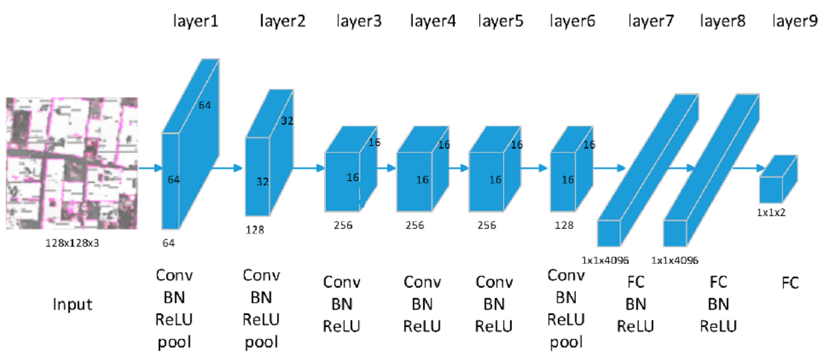
Case studies

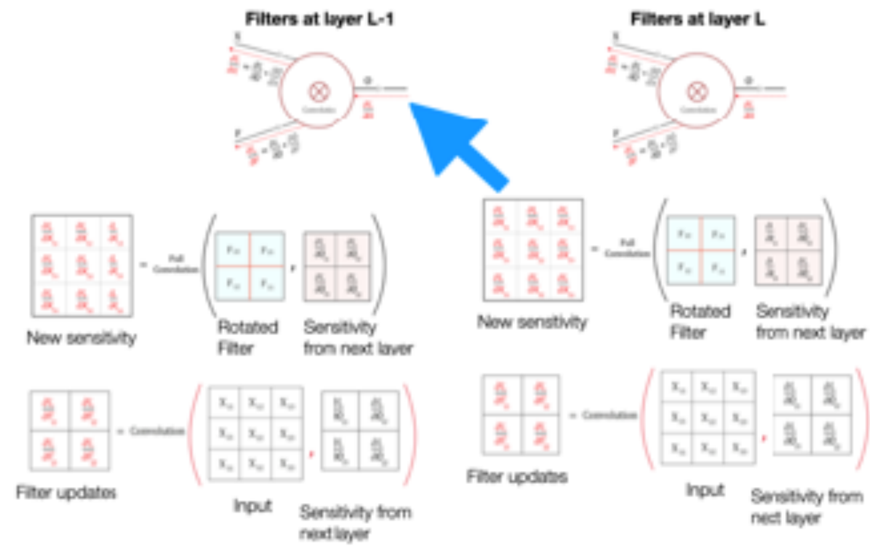
Last Time:



Structure of Each Tensor: Channels x Rows x Columns







TensorFlow and Basic CNNs

Last Time!

If needed:

Finish Demo

Convolutional Neural Networks
in TensorFlow
with Keras

with Sequential API!

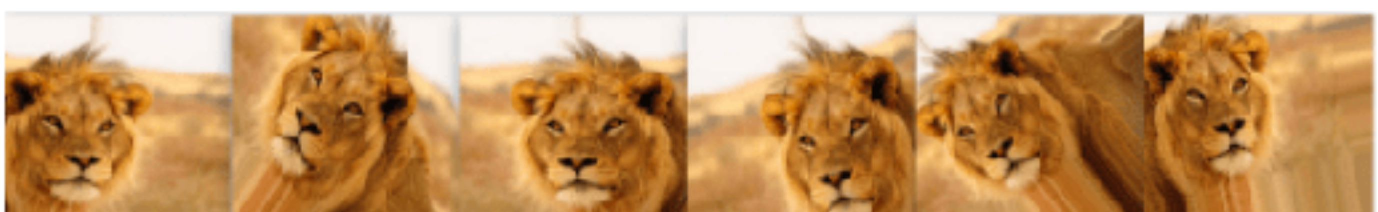
`11. Convolutional Neural Networks.ipynb`

Image Data Augmentation

```
cnn = Sequential()
```

```
# add in augmentations directly
cnn.add( RandomFlip("horizontal") ) # flip horizontally
cnn.add( RandomRotation(0.05) ) # rotate by 5%
cnn.add( RandomTranslation(height_factor=0.1, width_factor=0.1) )
cnn.add( RandomBrightness(factor=0.1, value_range=(0.0, 1.0)) ) #
cnn.add( RandomContrast(0.1) ) # add or decrease contrast
```

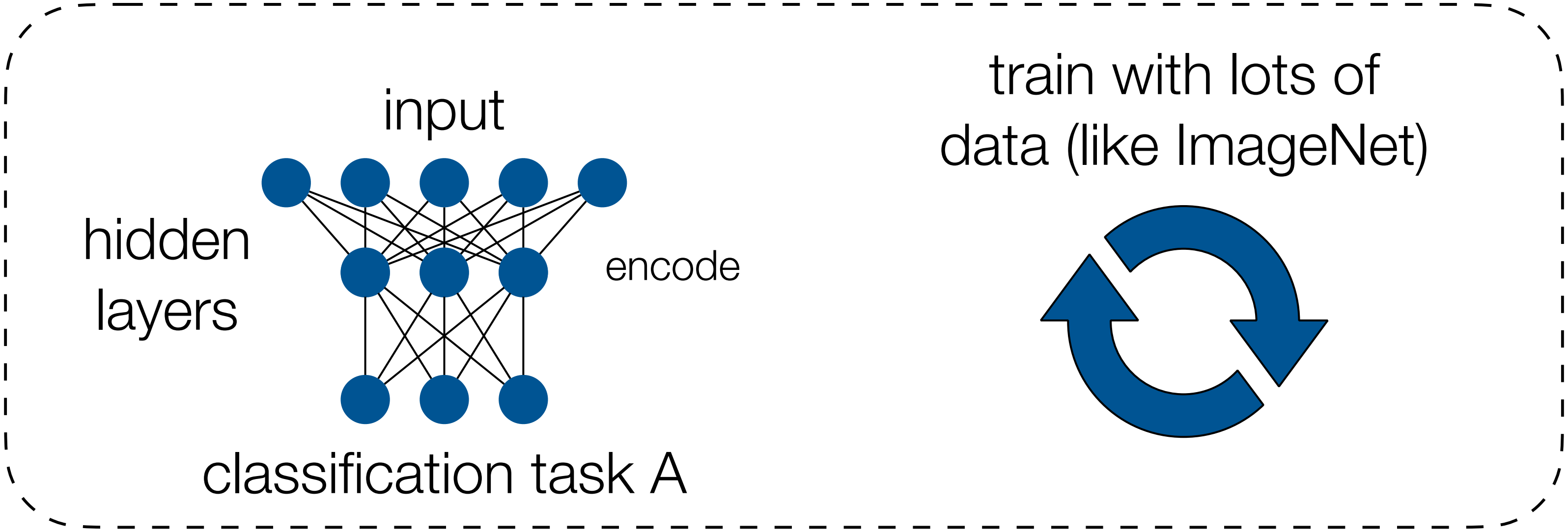
RandomRotation( )

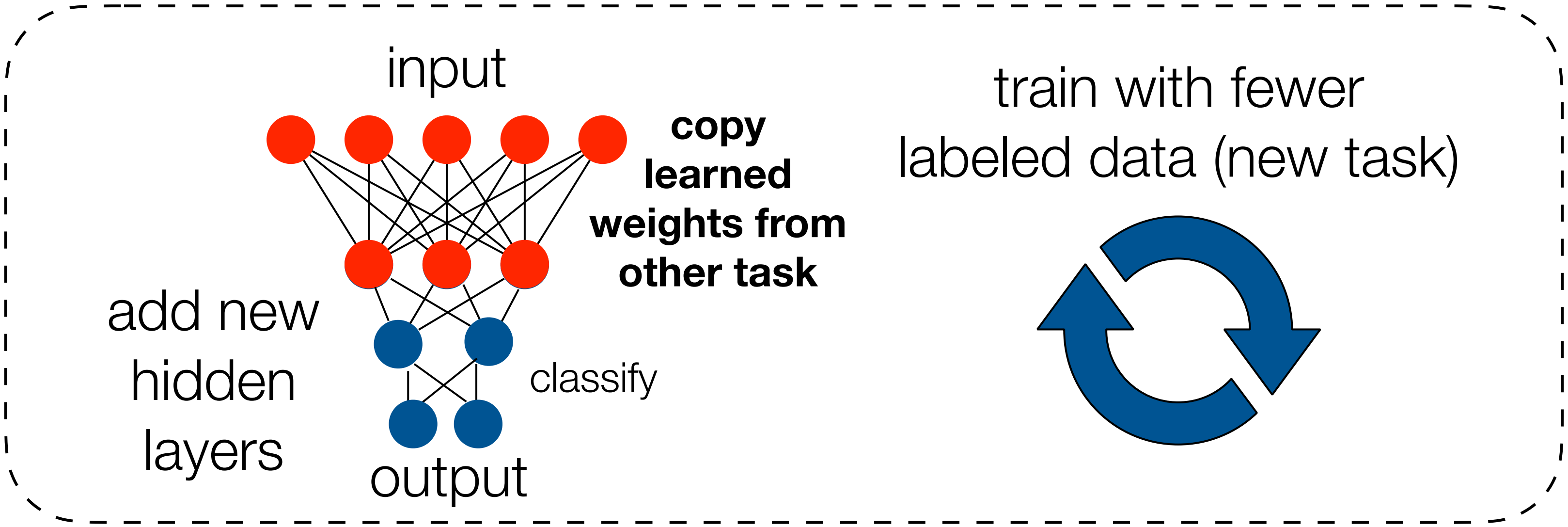


https://machinelearningmastery.com/how-to-configure-image-data-augmentation-when-training-deep-learning-neural-networks/

Transfer Learning

- transfer learning: a basic primer





Many Pre-trained Models to choose from!

AlexNet

A landmark in computer vision, this 2012 winner of ImageNet has over 50,000 citations.

AlexNet (Places)

The same architecture as the classic AlexNet model, but trained on the Places365 dataset.

Inception v1

Also known as GoogLeNet, this network set the state of the art in ImageNet classification in 2014

Inception v1 (Places)

The same architecture as the classic Inception v1 model, but trained on the Places365 dataset.

VGG 19

Introduced in 2014, this network is simpler than Inception variants, using only 3x3 convolutions and no branches

Inception v3

Released in 2015, this iteration of the Inception architecture improved performance and efficiency

Inception v4

Released in 2016, this is the fourth iteration of the inception architecture, focusing on uniformity.

ResNet v2 50

ResNets use skip connections to enable stronger gradients in much deeper networks. This variant has 50 layers

CNN Town Hall

Thanks to
Machine Learning the
robot apocalypse was
short lived!

History of Convolutional Neural Networks

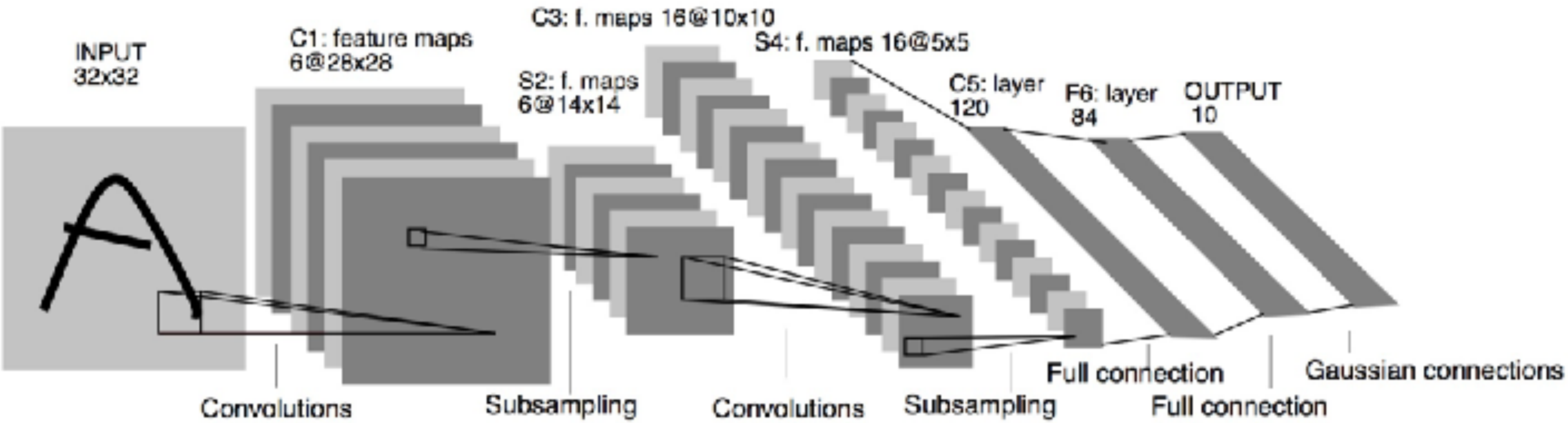
Machine Learning 101

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

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

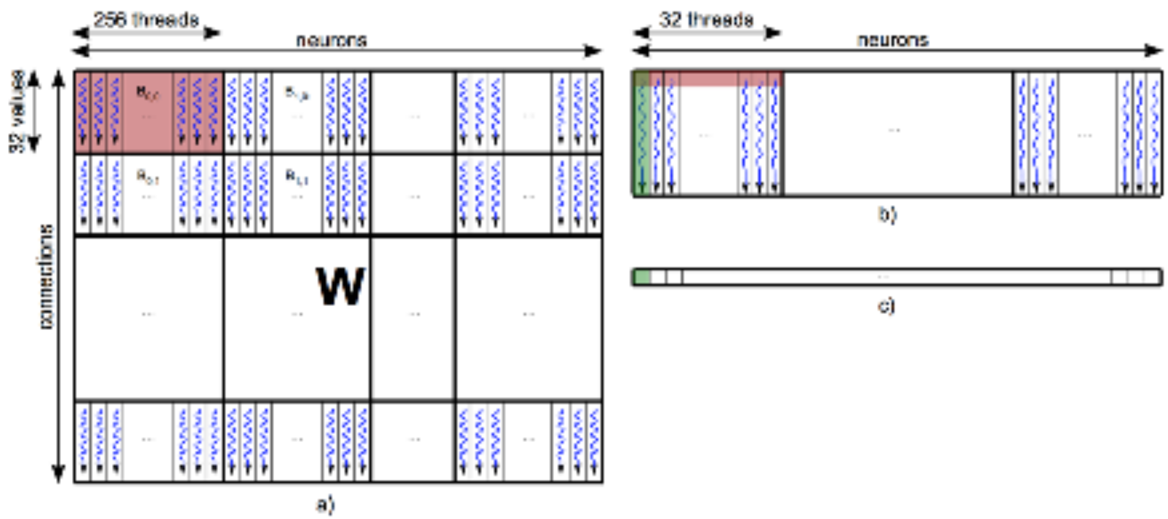
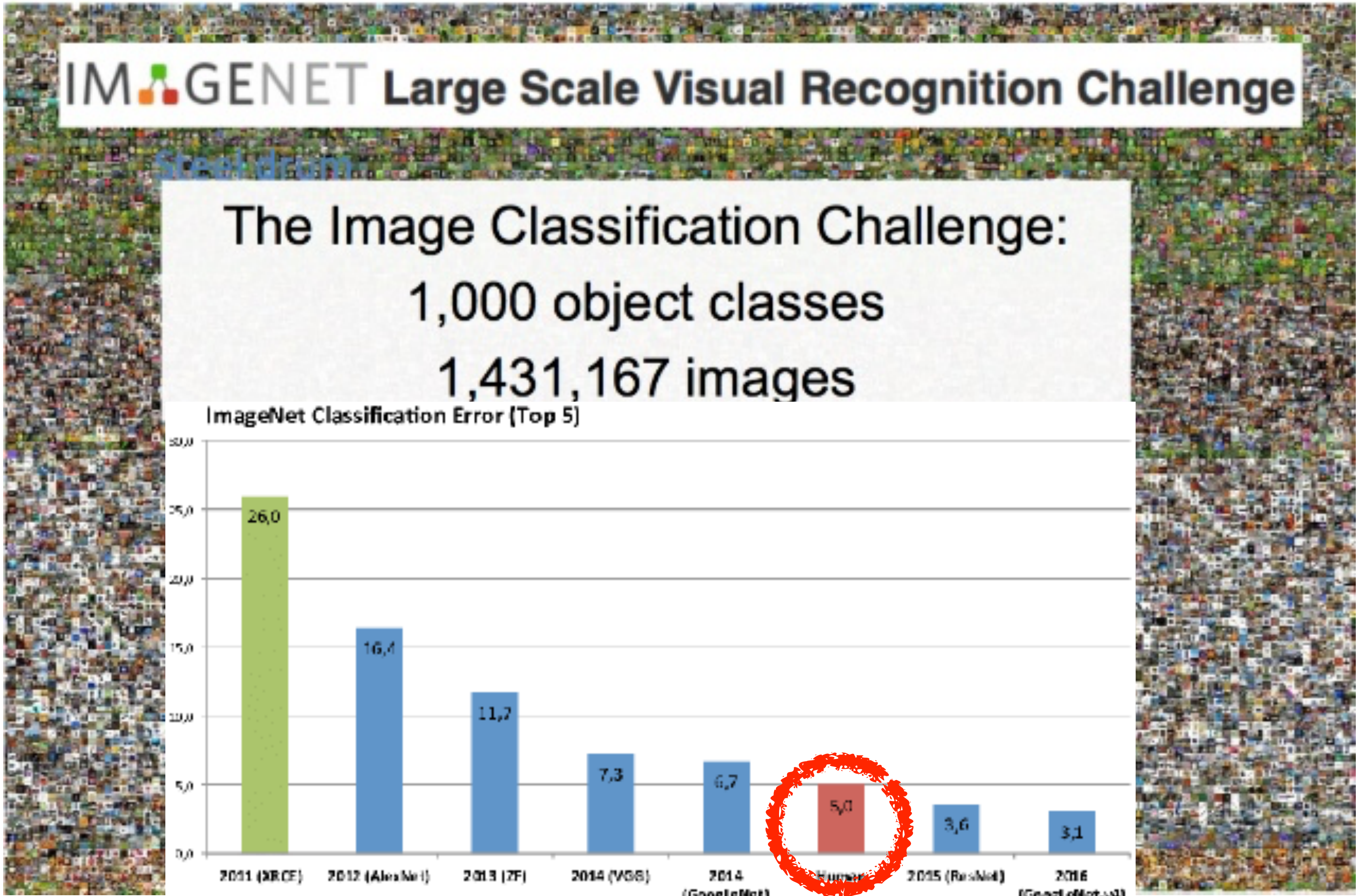


Figure 2: Forward propagation: a) mapping of kernel 1 grid onto the padded weight matrix; b) mapping the kernel 2 grid onto the partial dot products matrix; c) output of forward propagation.

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

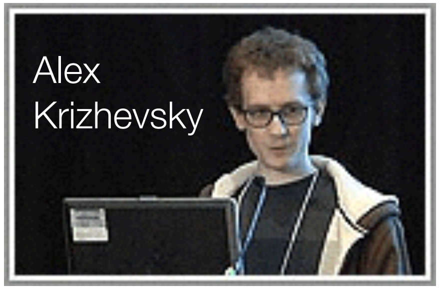
ImageNet Competition (2010-2016)



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

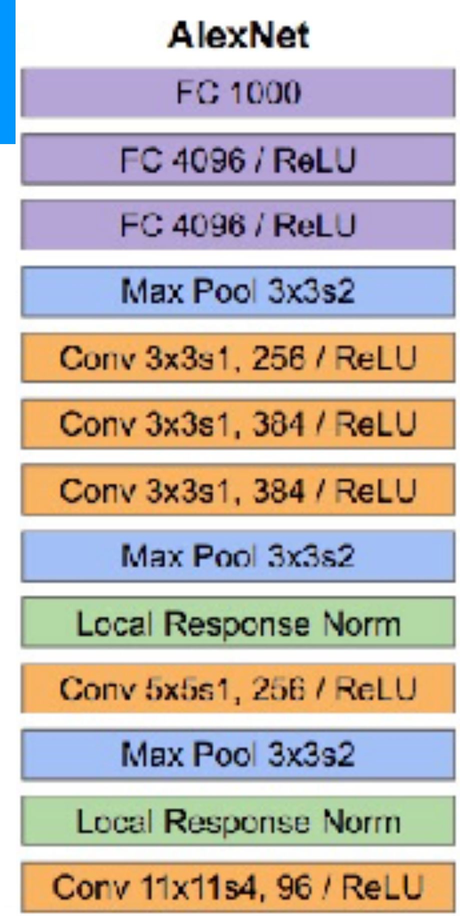
https://www.slideshare.net/nmhkahn/case-study-of-convolutional-neural-network-61556303

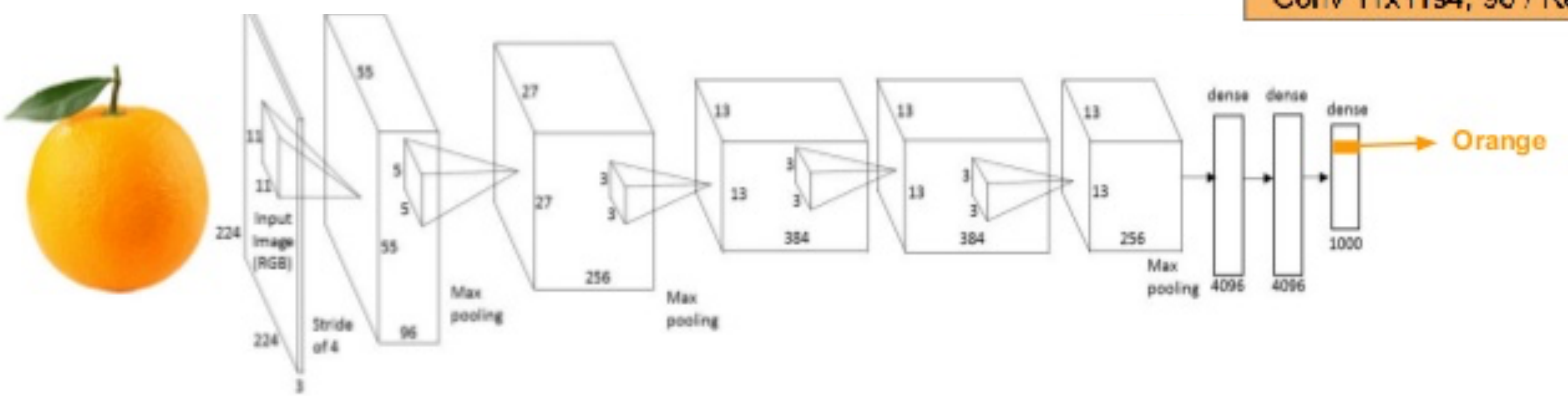
Types of CNN, 2012



Google

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



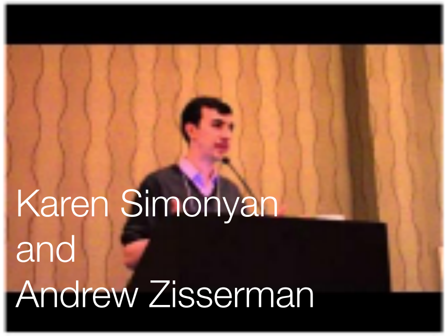


https://culurciello.github.io/tech/2016/06/04/nets.html

Warning

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

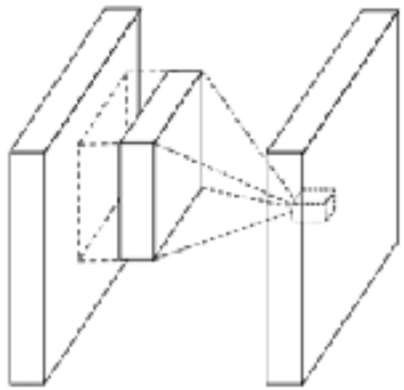
http://www.robots.ox.ac.uk/~vgg/practicals/cnn/

Types of CNN, 2014

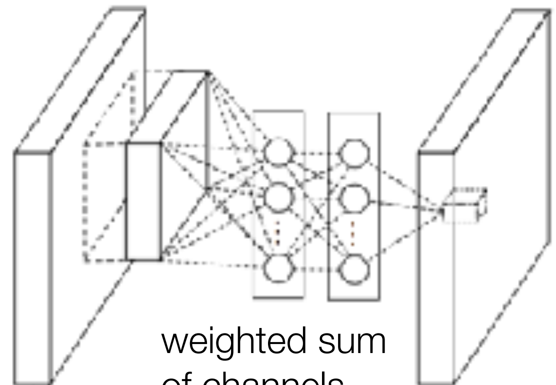
Network In Network

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

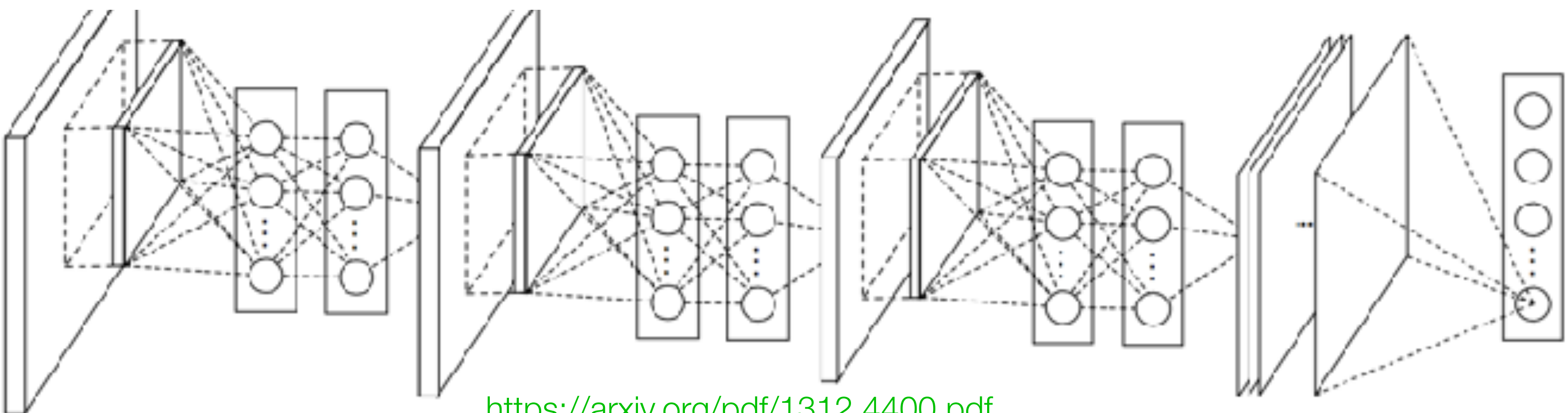
- Network in Network **NiN**
  - or MLPConv



(a) Linear convolution layer



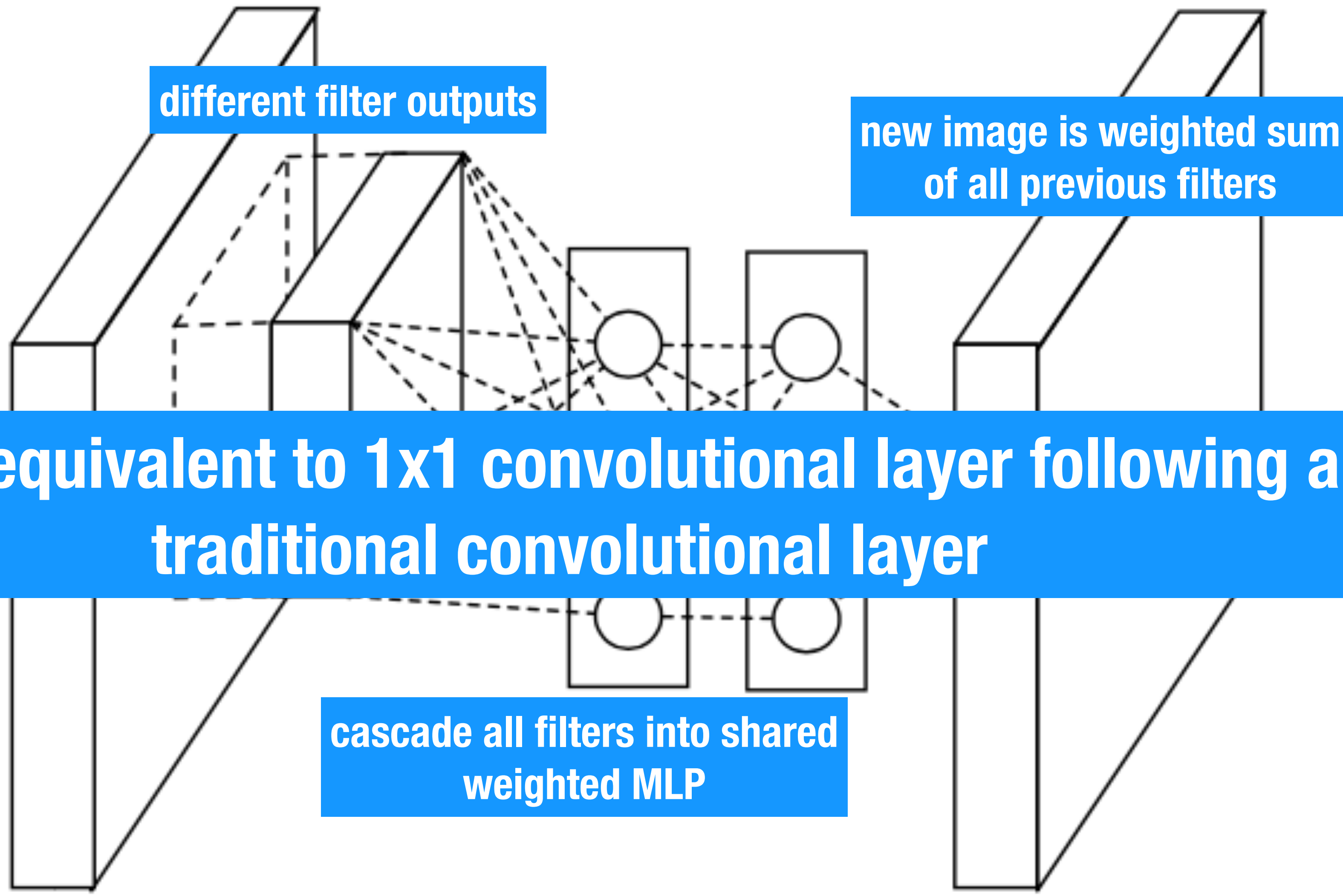
(b) Mlpconv layer



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

Types of CNN, 2014

- Network in Network



this is equivalent to 1x1 convolutional layer following a traditional convolutional layer

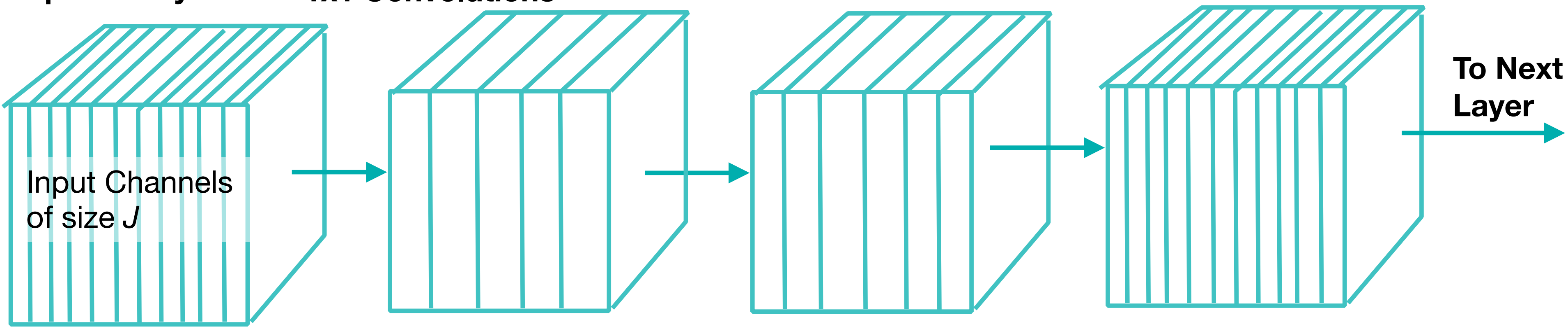
https://arxiv.org/pdf/1312.4400.pdf

NiN, expanded view

J and ***M*** >> ***K*** and ***L***

Common Choice: ***J***==***M*** and ***K***==***L***

Input of Layer N **1x1 Convolutions** **k x k Convolution** **1x1 Convolutions**

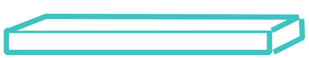


Convolve with *K* filters
1x1 filters

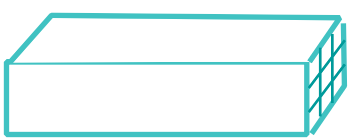
Convolve with *L* filters
k x k filters

Convolve with *M*, 1x1 Filters
Optional Output Bottleneck

Convolve with *K*, 1x1 Filters
Equivalently: each new channel
is weighted sum of convolutions
complete control of channels size



one 1x1 filter input filter

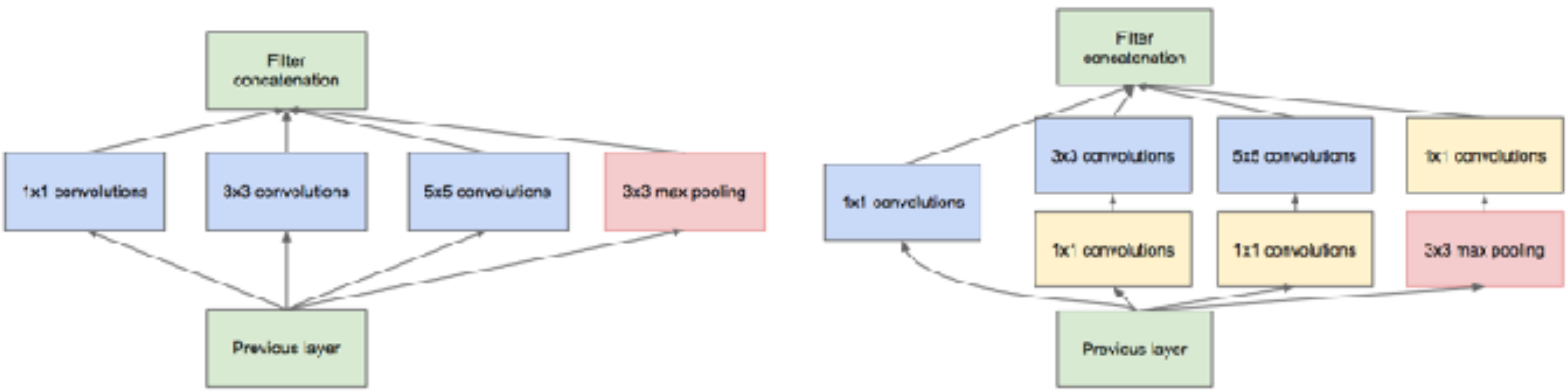


one full filter, *k* x *k*

optional one 1x1 filters
to control output size

Structure of Each Tensor: Channels x Rows x Columns

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

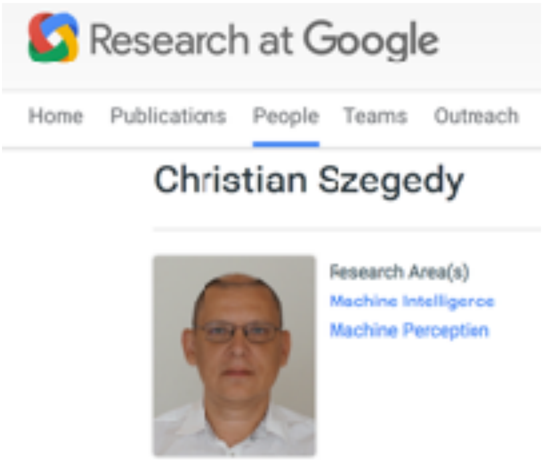


(a) Inception module, naïve version (b) Inception module with dimension reductions

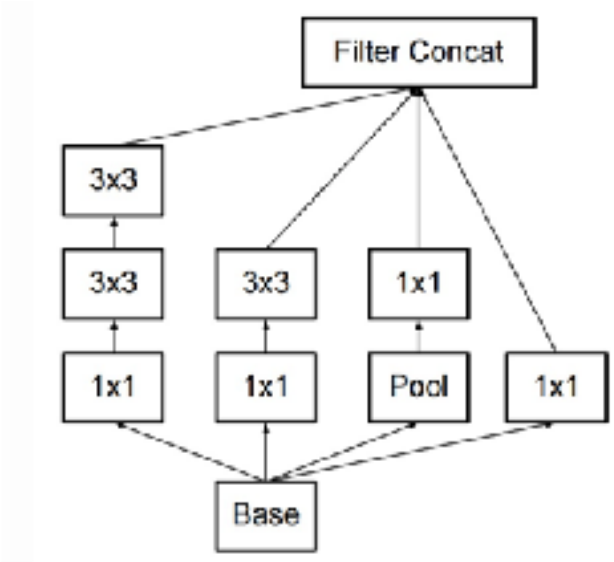
Figure 2: Inception module

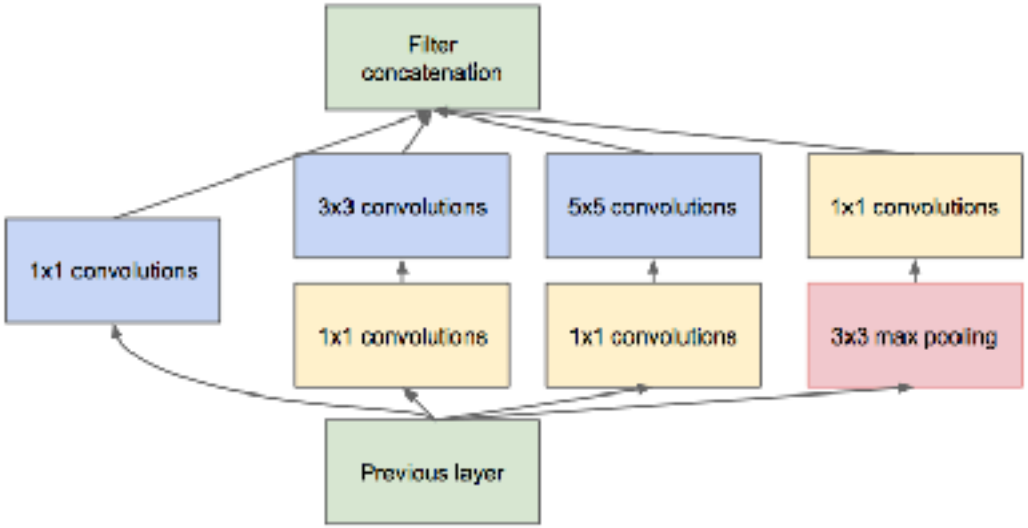
https://arxiv.org/pdf/1409.4842.pdf

Types of CNN, 2015 February and December



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



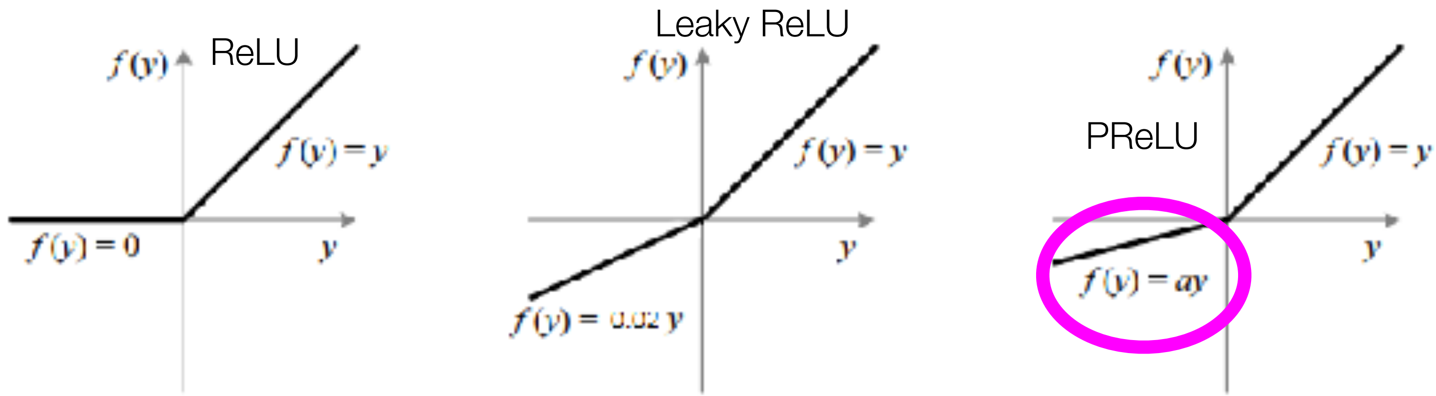


https://arxiv.org/pdf/1512.00567.pdf

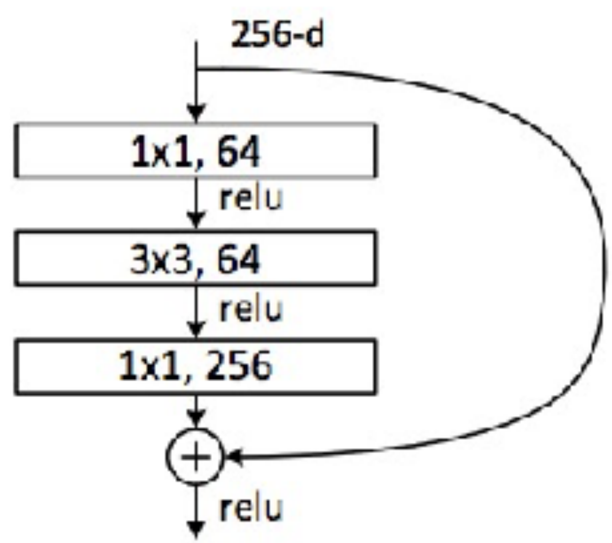
Types of CNN, 2015 December

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

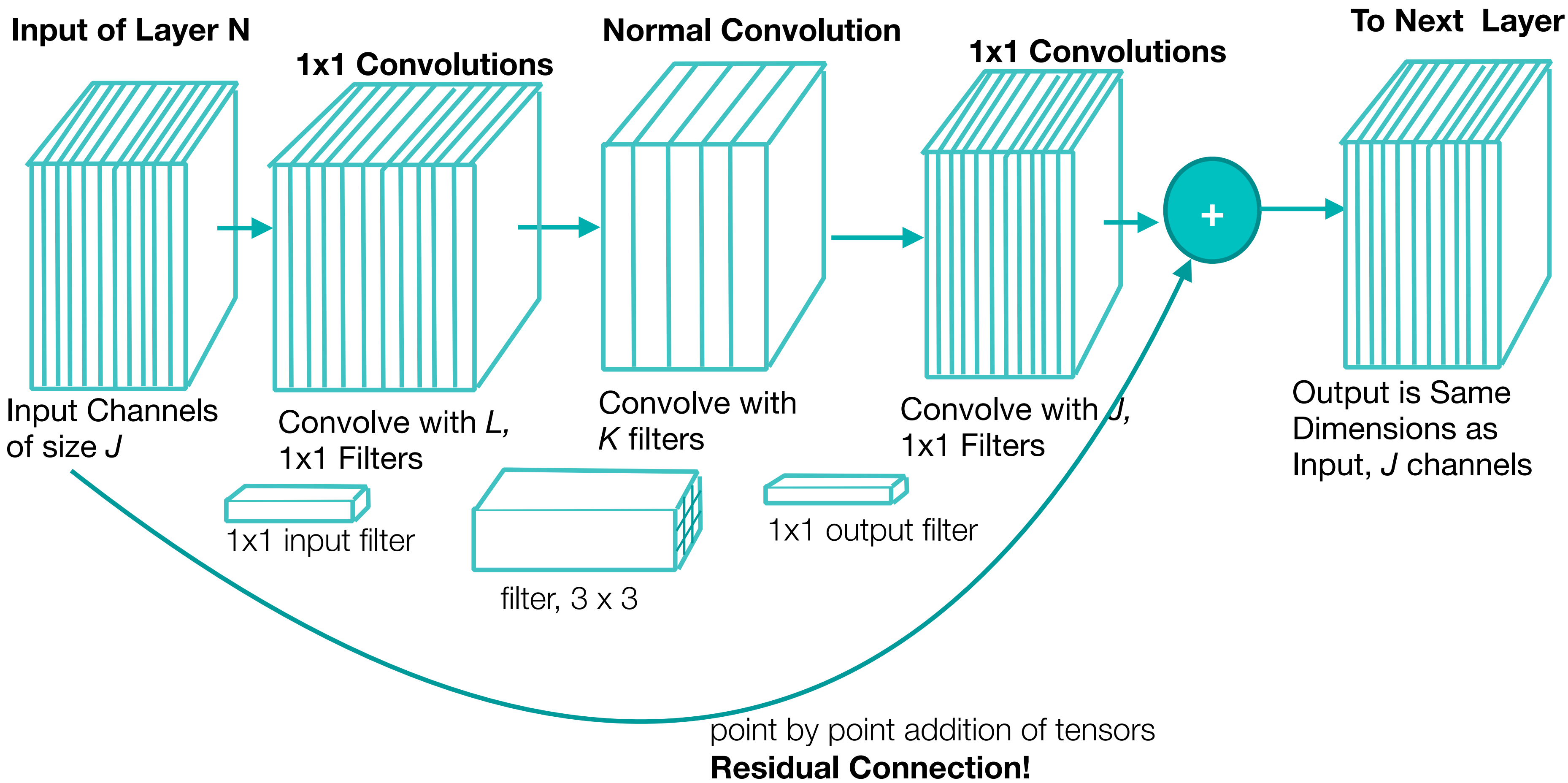
- **ResNet**
  - Parametric ReLU
    PReLU: adaptive trained slope



- NiN: triple bypass layer
  - similar to bottelneck



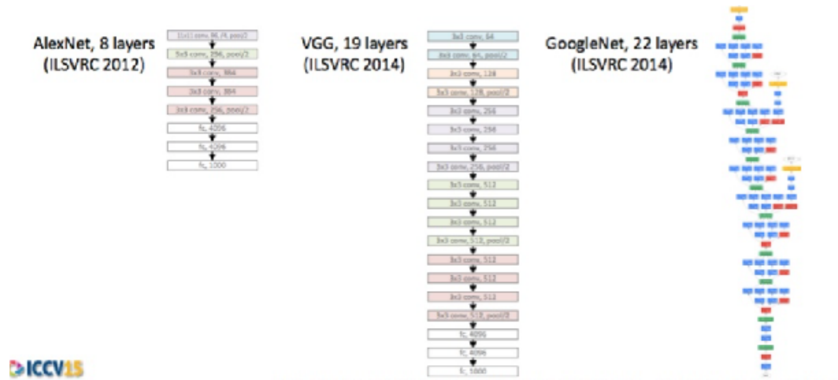
Residual Connection, expanded view

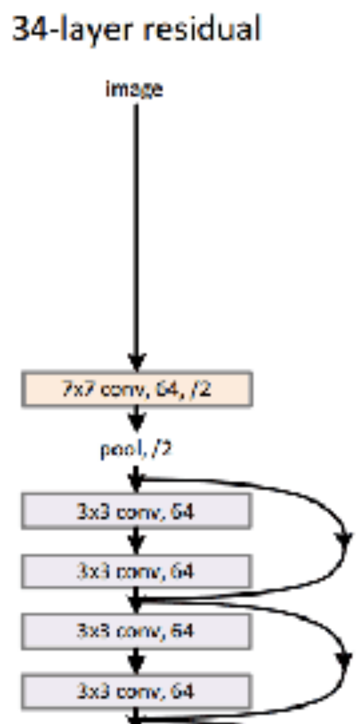


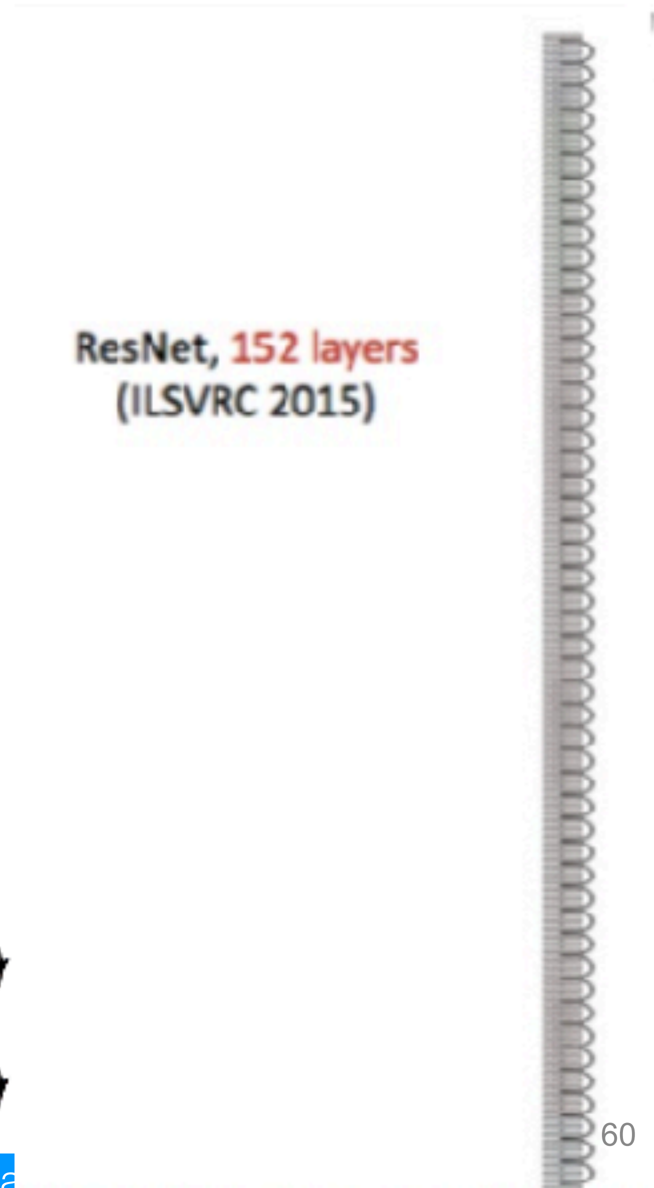
Back Propagation: Two paths, including one without ANY operations that cause the gradient to vanish…

How big are these networks?

How big are these networks?







Transition Period in Convolutional Networks

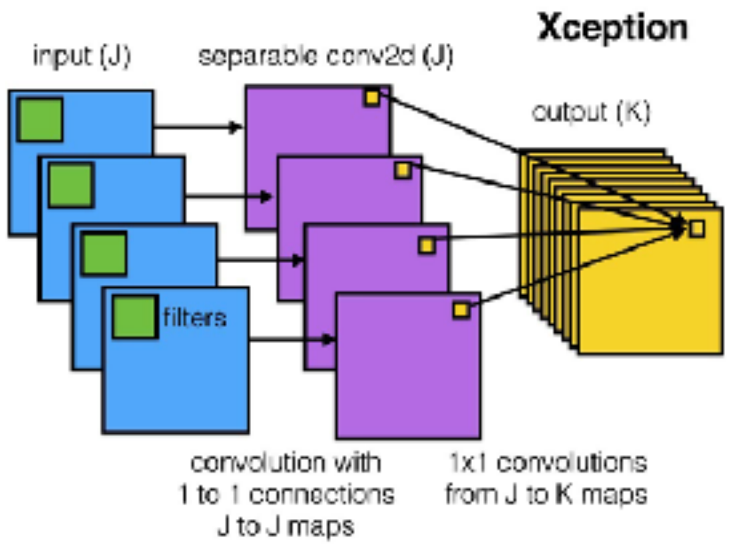
- 2012 - 2017:
    - Add more layers! 🤪
    - How can we train it even deeper? 🤓
    - Can we run out of memory? Let's try! 🫣
- 2017-present:
    - How can we get similar performance with reduced parameters? 🧐
    - How should the number of parameters scale for competing resource? Is there an optimum scaling for a given set of resources? 📉

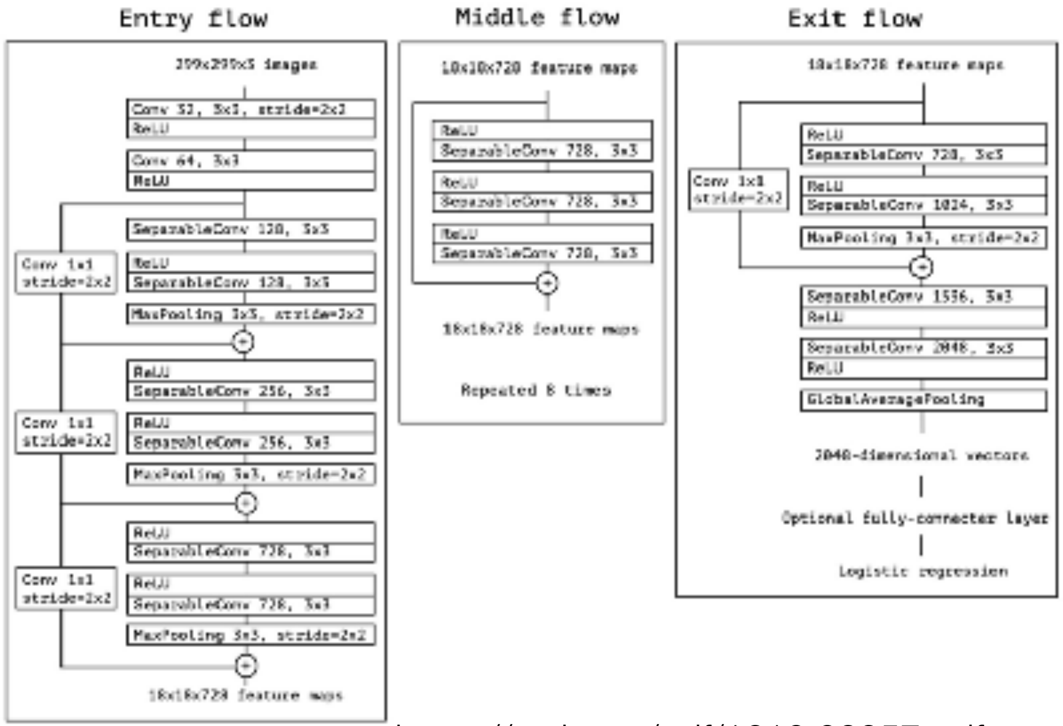
Types of CNN, 2017

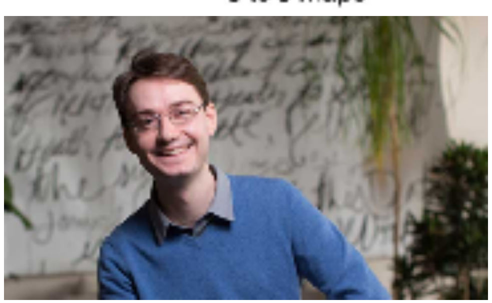
Xception · Major Contributions:

- combining branching / residual blocks
- separable convolutions (fewer trainable params)

Francois Chollet
Google

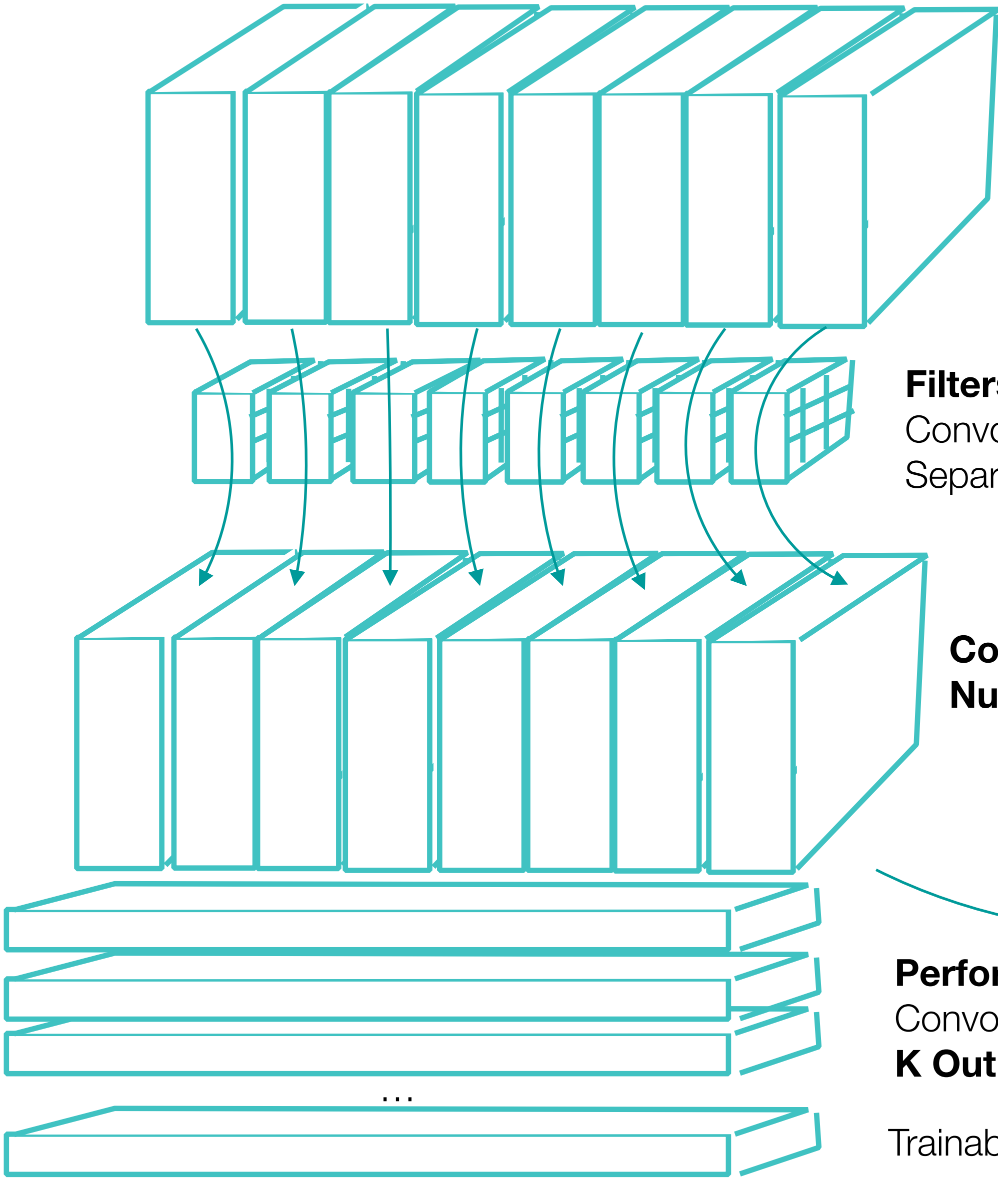






https://arxiv.org/pdf/1610.02357.pdf

Separable Convolution Explanation



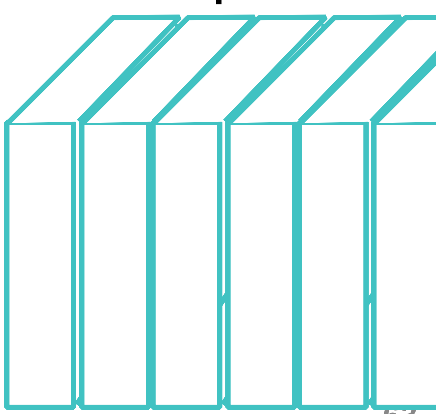
Inputs, From Layer N-1
Num Channels = J

Filters, Layer N
Convolve Each Channel Separately

Trainable params:
Same as one filter in traditional convolution!

Concat Outputs
Num Channels = J

K Outputs

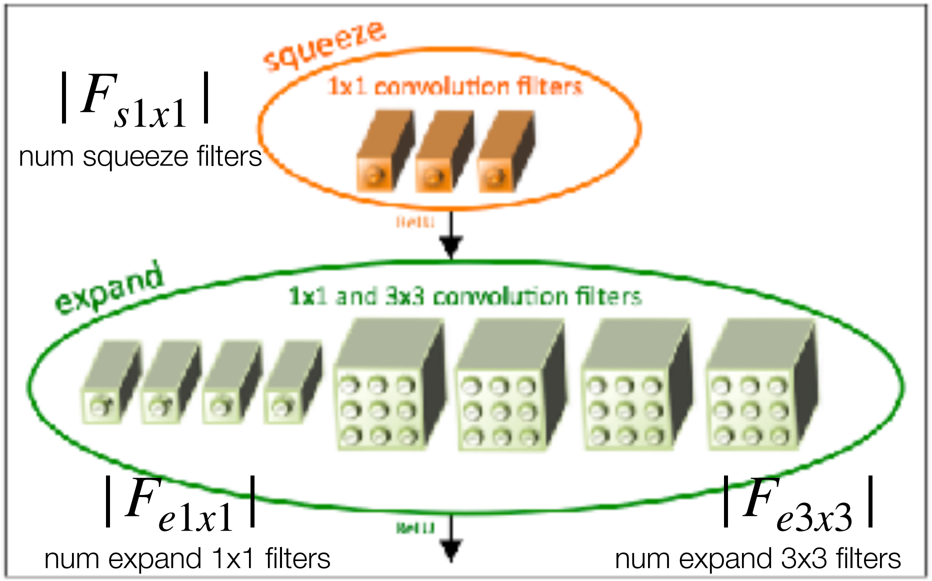


Perform K, 1x1 Traditional Convolutions
K Outputs

Trainable params: **K** x **J**

SqueezeNet (2018)

- Idea: squeeze and expand in each layer
  - Use mostly 1x1 filters
  - downsample later in network



$$SR = \frac{|F_{s1x1}|}{|F_{e1x1}| + |F_{e3x3}|}$$

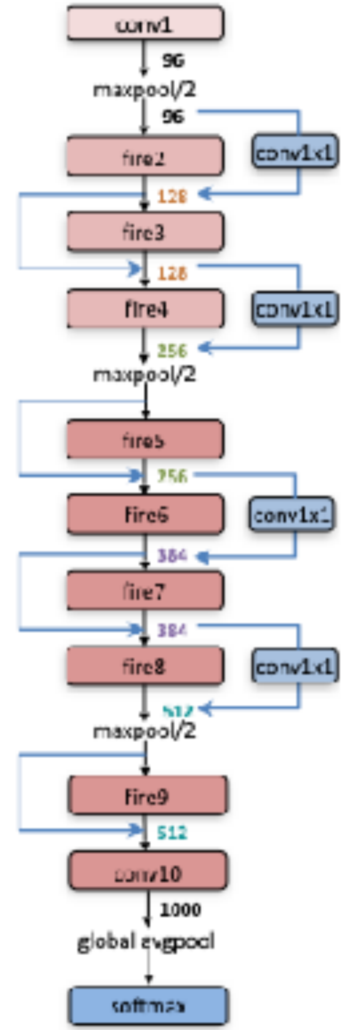
$$PCT_{3x3} = \frac{|F_{e3x3}|}{|F_{e1x1}| + |F_{e3x3}|}$$

SQUEEZENET: ALEXNET-LEVEL ACCURACY WITH 50X FEWER PARAMETERS AND <0.5MB MODEL SIZE

Forrest N. Iandola[1], Song Han[2], Matthew W. Moskewicz[1], Khalid Ashraf[1], William J. Dally[2], Kurt Keutzer[1]
[1]DeepScale* & UC Berkeley [2]Stanford University
{forresti, moskewcz, kashraf, keutzer}@eecs.berkeley.edu
{songhan, dally}@stanford.edu

In paper:

- Good SR = 12.5% up to 100%
- Good PCT_{3x3} from 25% up to 100%



Efficient Net (2019)

Start with so

Observation 1 – Scaling up any
width, depth, or resolution improve
racy gain diminishes for bigger mo

Observation 2 – In order to purs
efficiency, it is critical to balance al
width, depth, and resolution during

Filtering

Depth Scalin

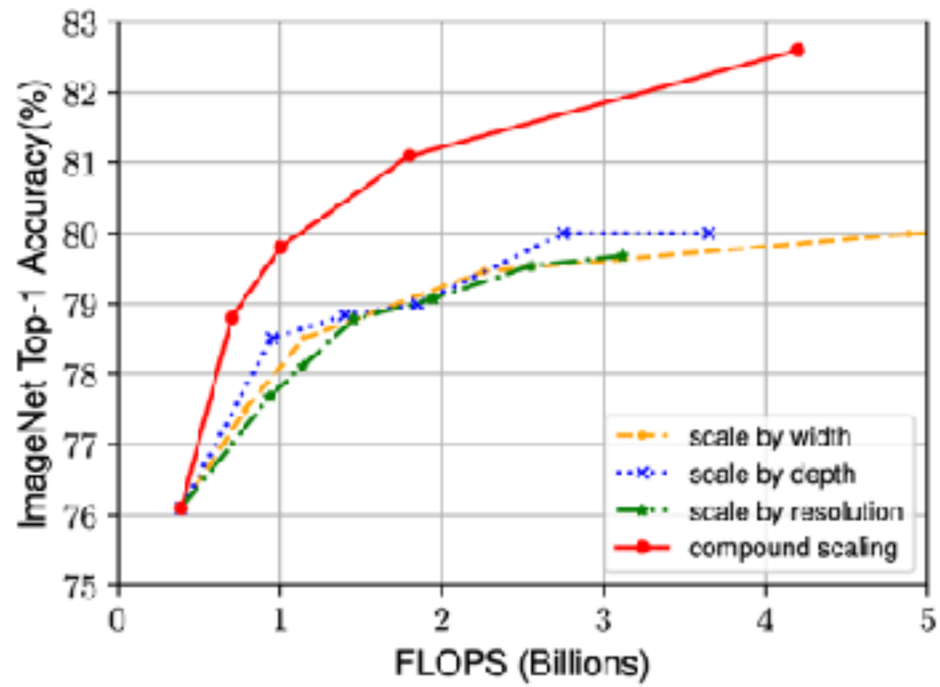


Figure 8. **Scaling Up EfficientNet-B0 with Different Methods.**

Resolution Scaling: If we use larger resolu

depth: $d = \alpha^{\phi}$

width: $w = \beta^{\phi}$

res.: $r = \gamma^{\phi}$

s.t. $\alpha \cdot \beta^2 \cdot \gamma^2 \approx 2$

$\alpha, \beta, \gamma \geq 1$

ϕ user specified scaling coefficient

$$\boxed{\begin{aligned}\alpha &= 1.2\\ \beta &= 1.1\\ \gamma &= 1.15\end{aligned}}$$

optimal values found in paper!

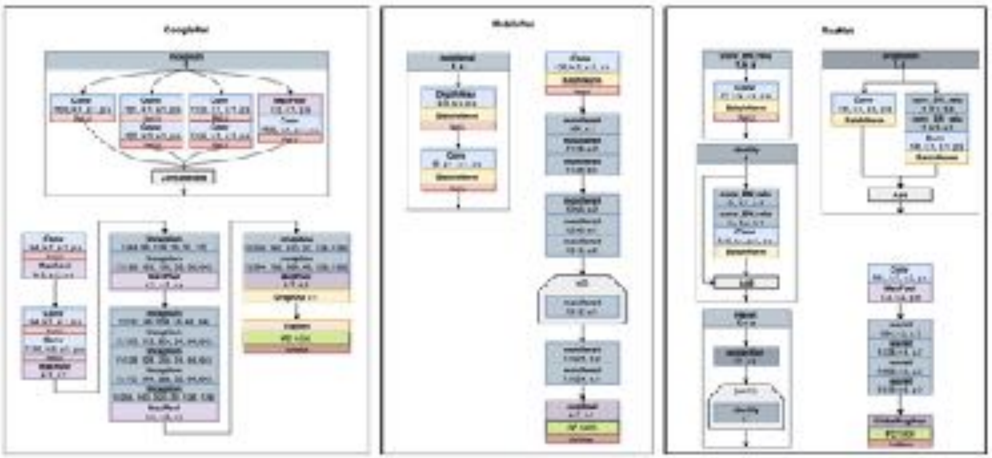
where α, β, γ are constants that can be determined by a small grid search. Intuitively, ϕ is a user-specified coefficient that controls how many more resources are available for model scaling, while α, β, γ specify how to assign these extra resources to network width, depth, and resolution re-

https://arxiv.org/pdf/1905.11946v5.pdf

More Modern CNN Architectures

Even more Convolutional Neural Networks
…in TensorFlow
…with Keras

Self Guided Demo



12. More Advanced CNN Techniques as TFData.ipynb

Next Time:

- Intro to Sequential Neural Network Architectures
  - Word Embeddings, 1D CNNs, Transformers
  - Ethics by Case Study