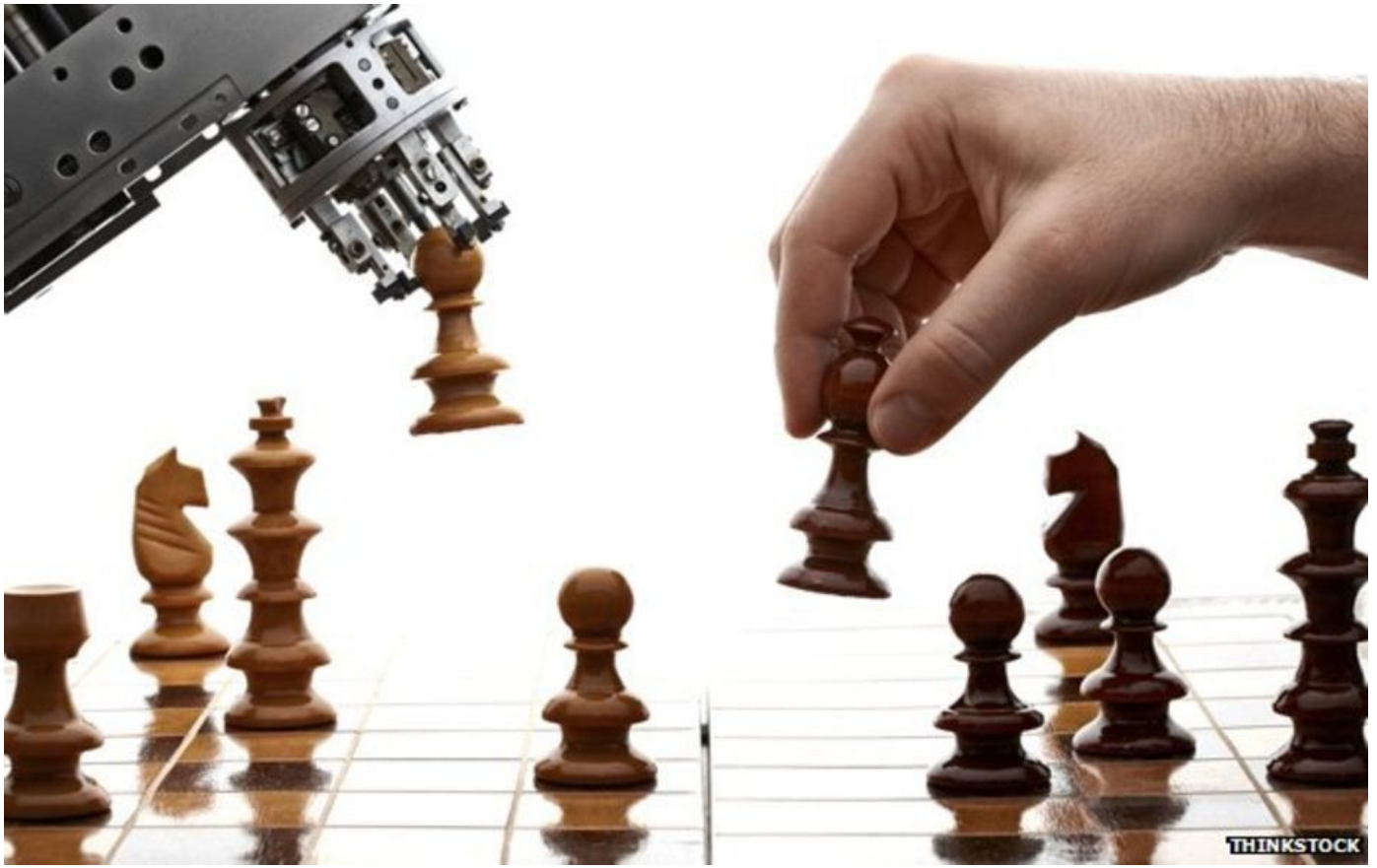


Introduction to Artificial Intelligence

COSC 4550 / COSC 5550

Professor Cheney

11/6/17

sample exam posted

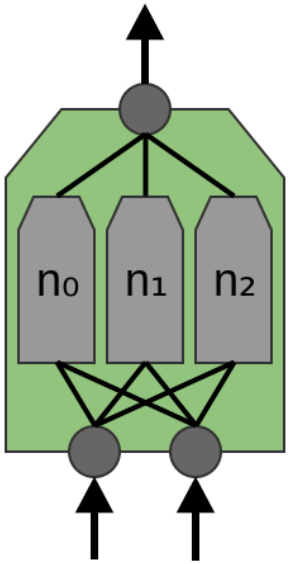
2 weeks until project half-way check-in

paper readings

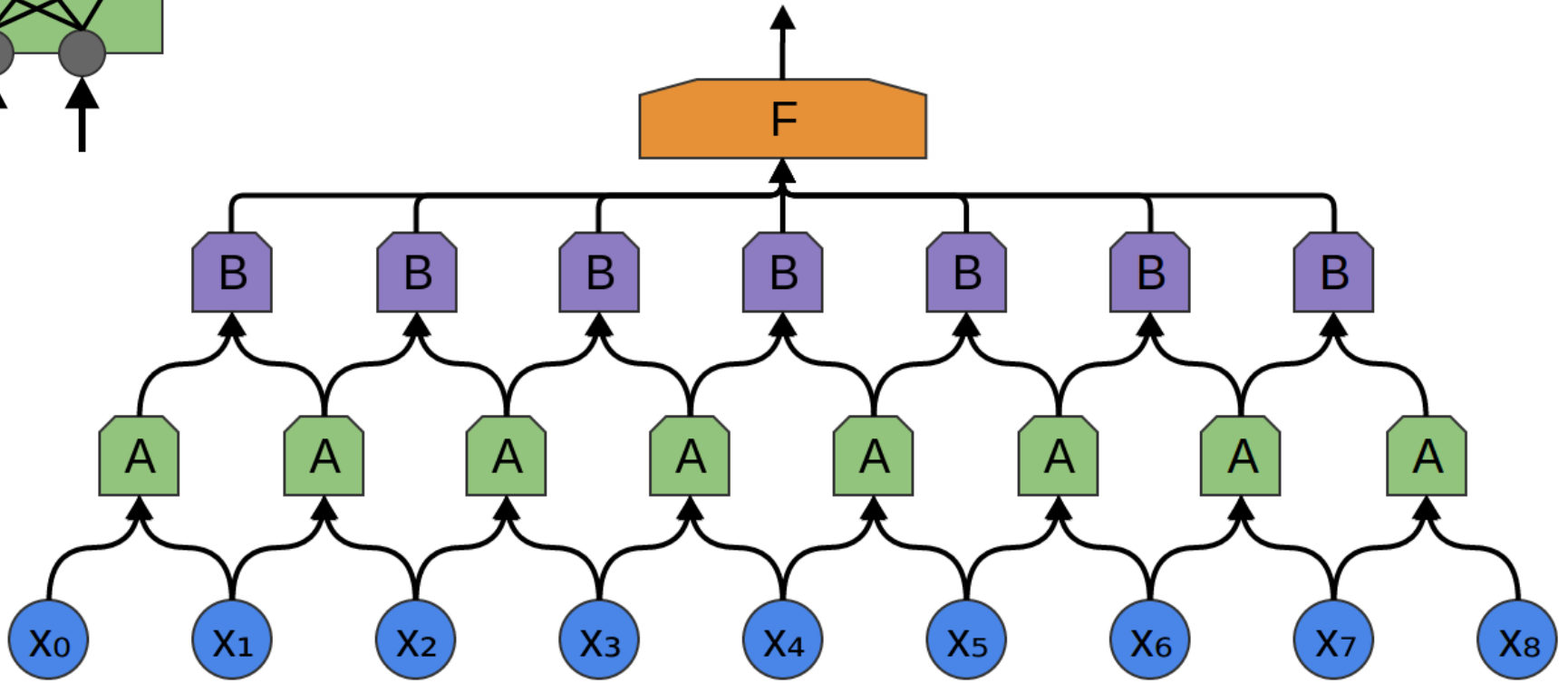
withdraw deadline this week!

many slides today borrowed
from Xavier Giro-i-Nieto

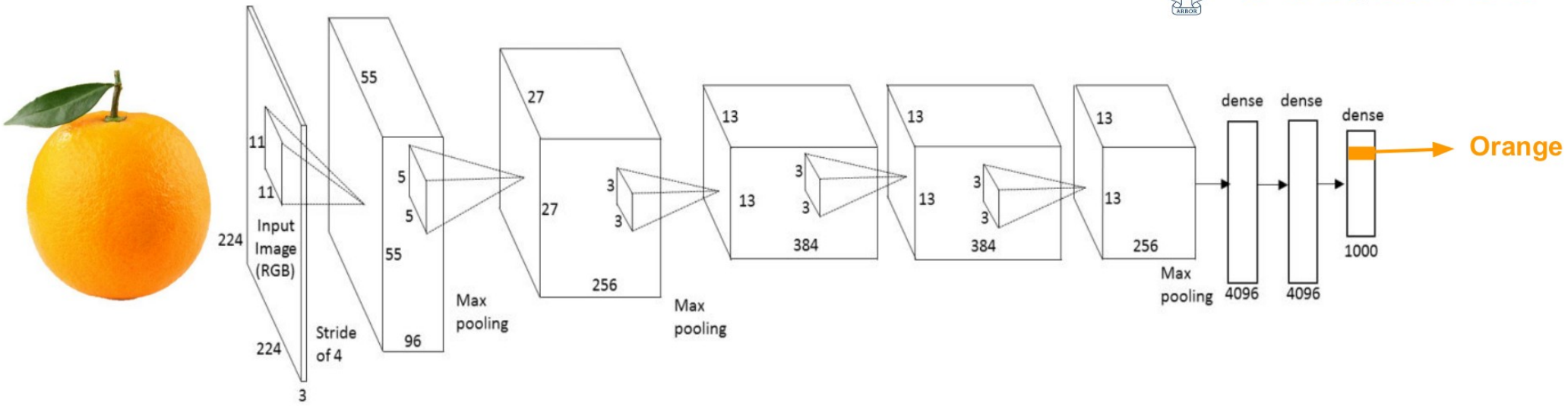
(sorry for lack of pixels…)



end-to-end differentiable!



AlexNet



A Krizhevsky, I Sutskever, GE Hinton "Imagenet classification with deep convolutional neural networks" Part of: Advances in Neural Information Processing Systems 25 (NIPS 2012)

neural networks have been around for decades – why now?

recent advances in deep learning are due to:

huge labeled datasets

deeper and deeper architectures

some simple, but clever, tricks to better train these networks

demo! …?

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

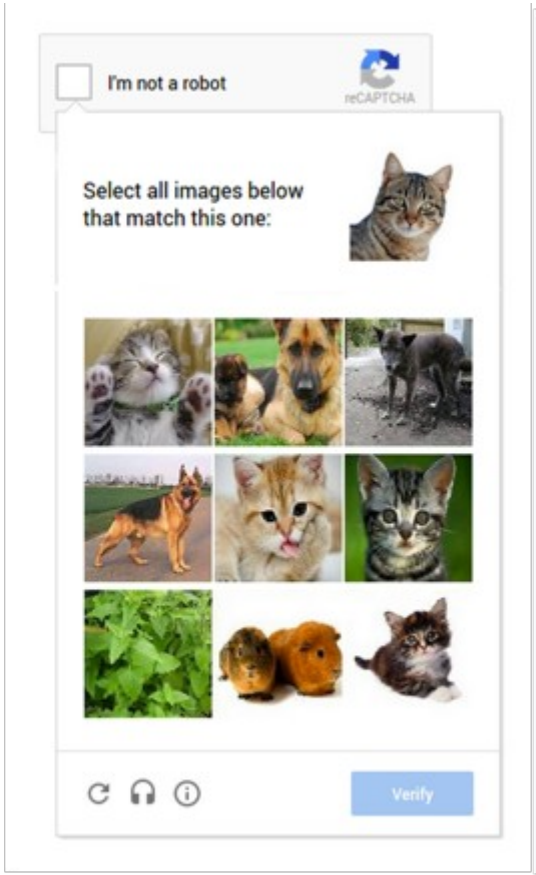
huge labeled datasets

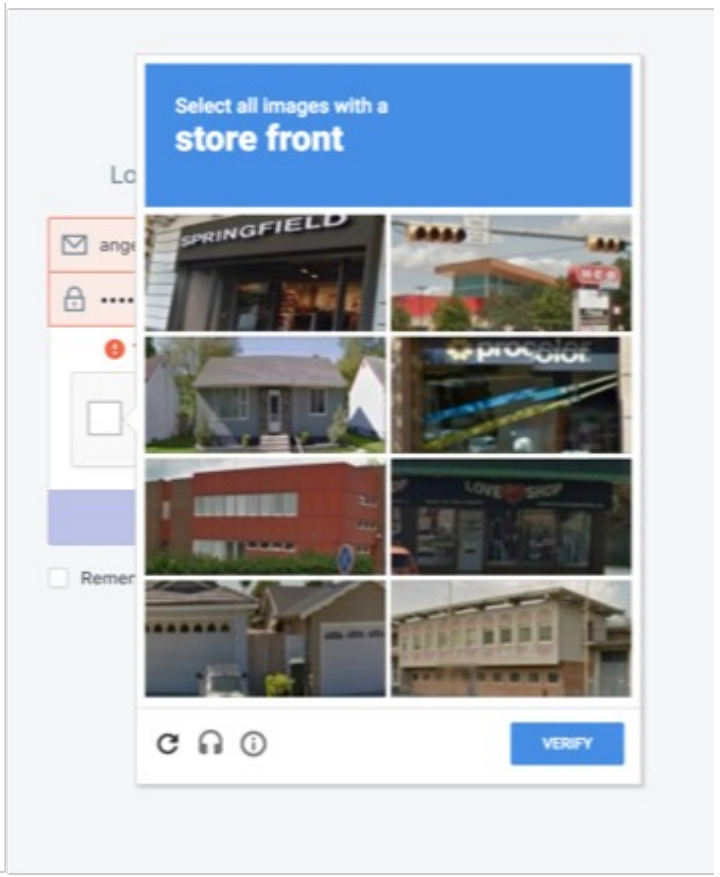
ImageNet Challenge

IMAGENET

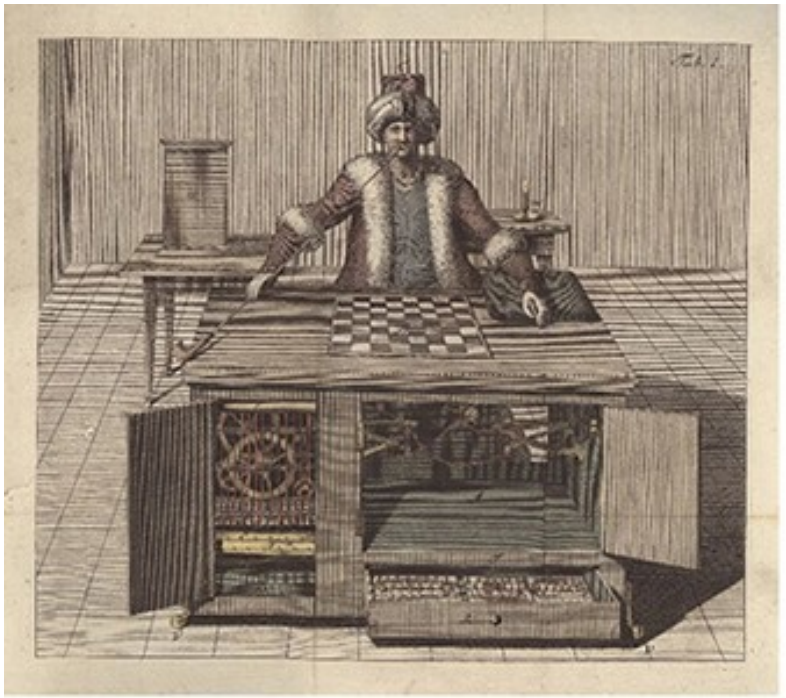
- 1,000 object classes (categories).
- Images:
  - 1.2 M train
  - 100k test.

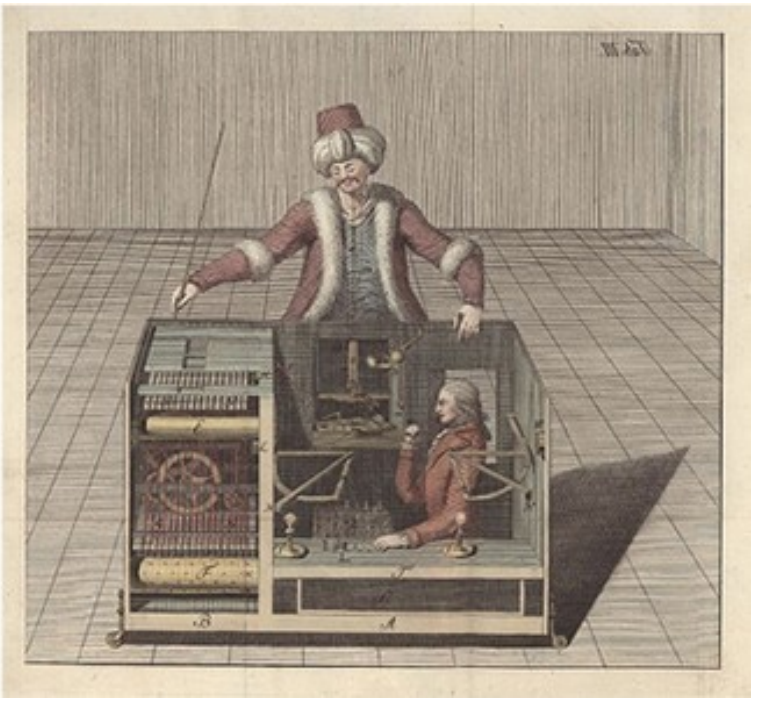
I'm not a robot
reCAPTCHA
Type the text
250
Verify


I'm not a robot
reCAPTCHA
Select all images below
that match this one:
Verify

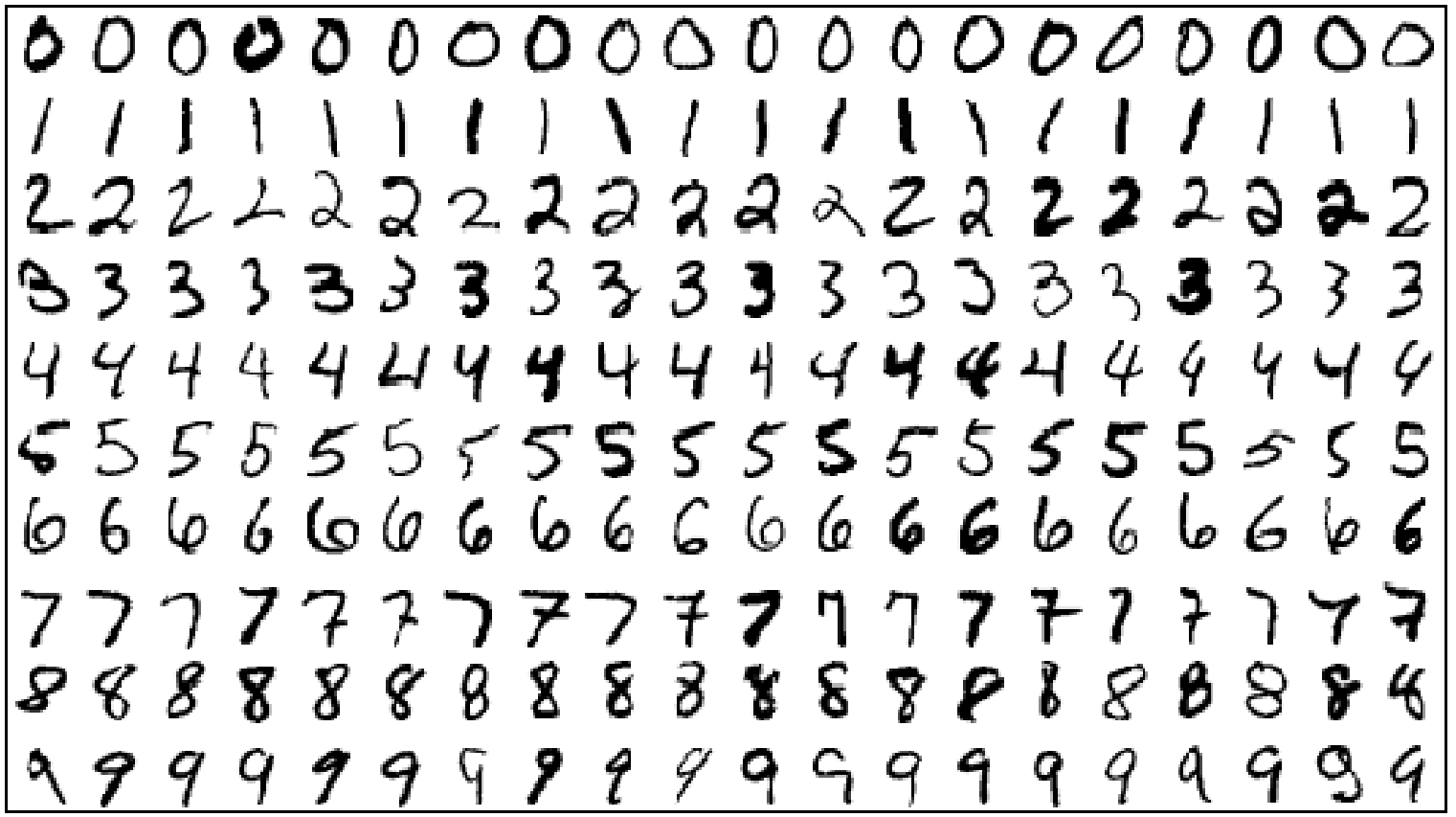

Select all images with a
store front
SPRINGFIELD
VERIFY

amazon mechanical turk





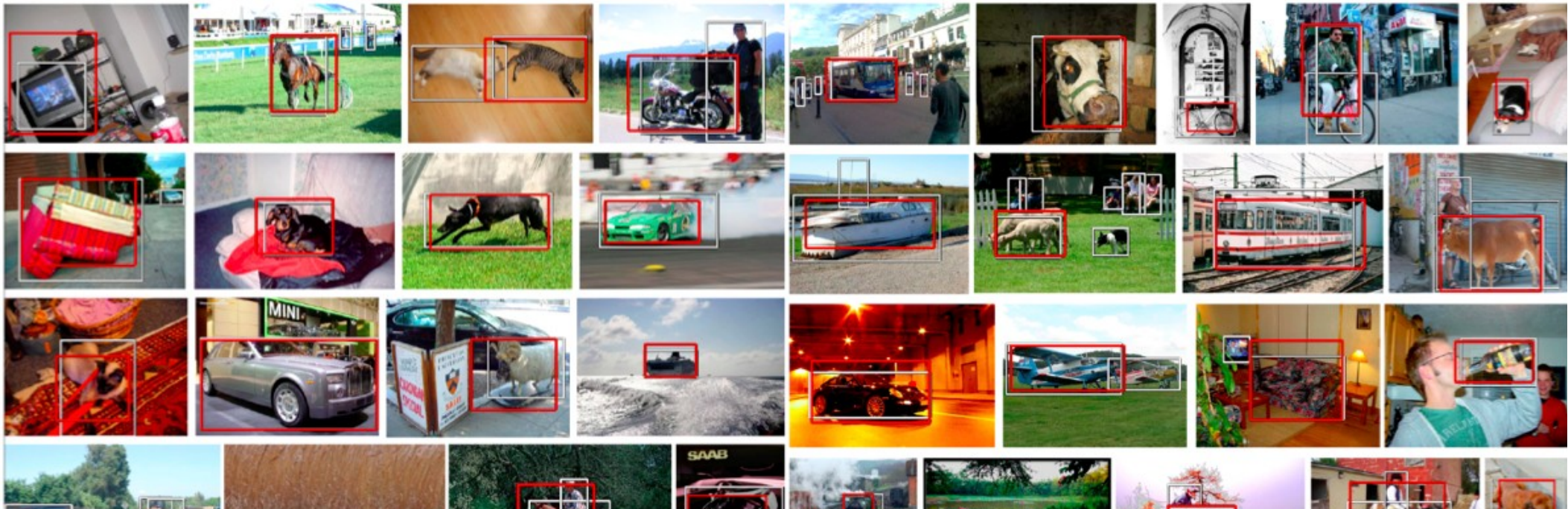
MNIST
(Modified National Institute of Standards and Technology)
60,000 training, 10,000 testing



Visual Object Classes Challenge 2009 (VOC2009)

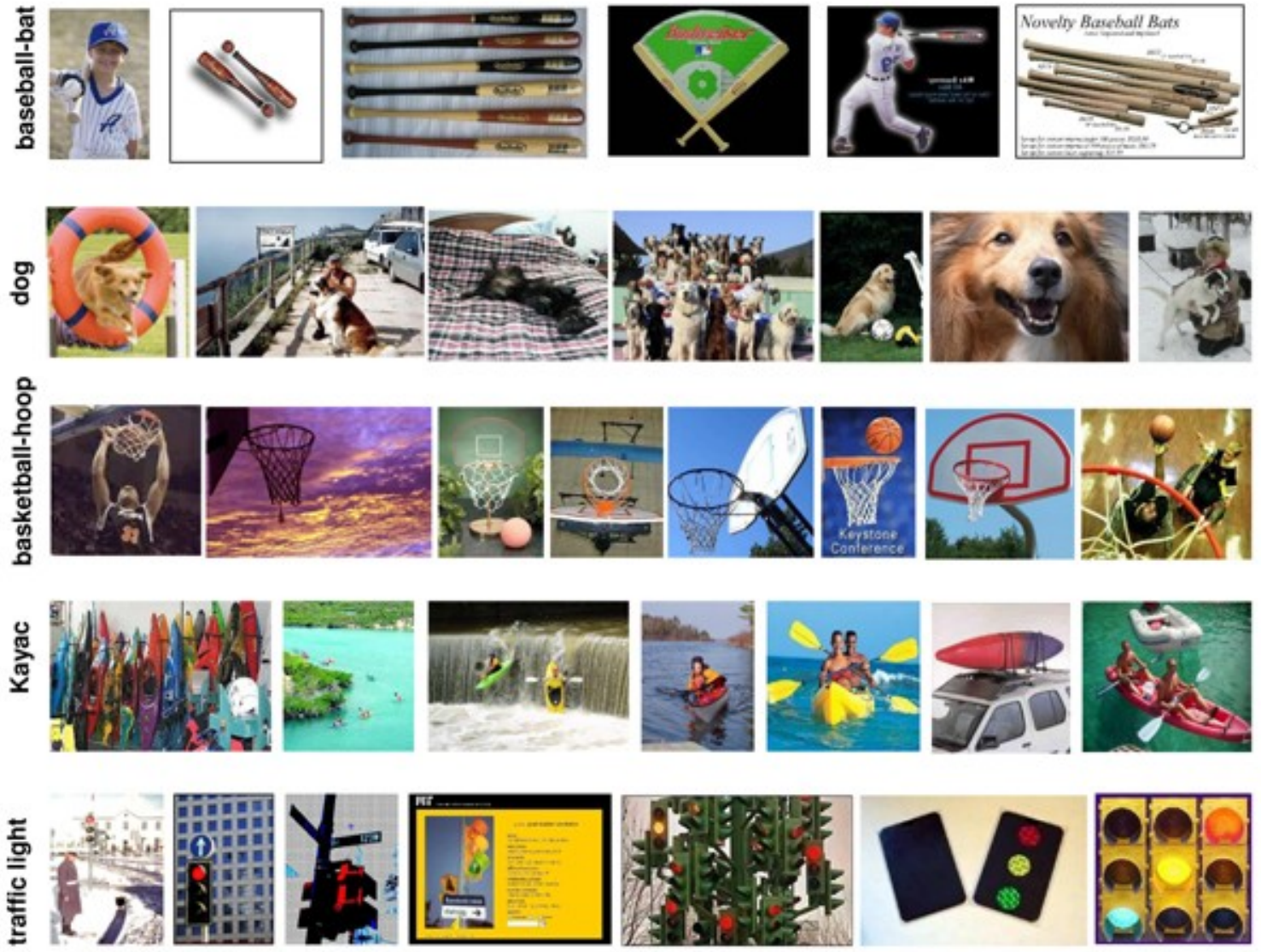
PASCAL2
Pattern Analysis, Statistical Modelling and Computational Learning

20 classes. The train/val data has 11,530 images containing 27,450 ROI annotated objects and 6,929 segmentations.



Caltech 256

(256 object categories, 30607 images)



and many more…

including industrial datasets

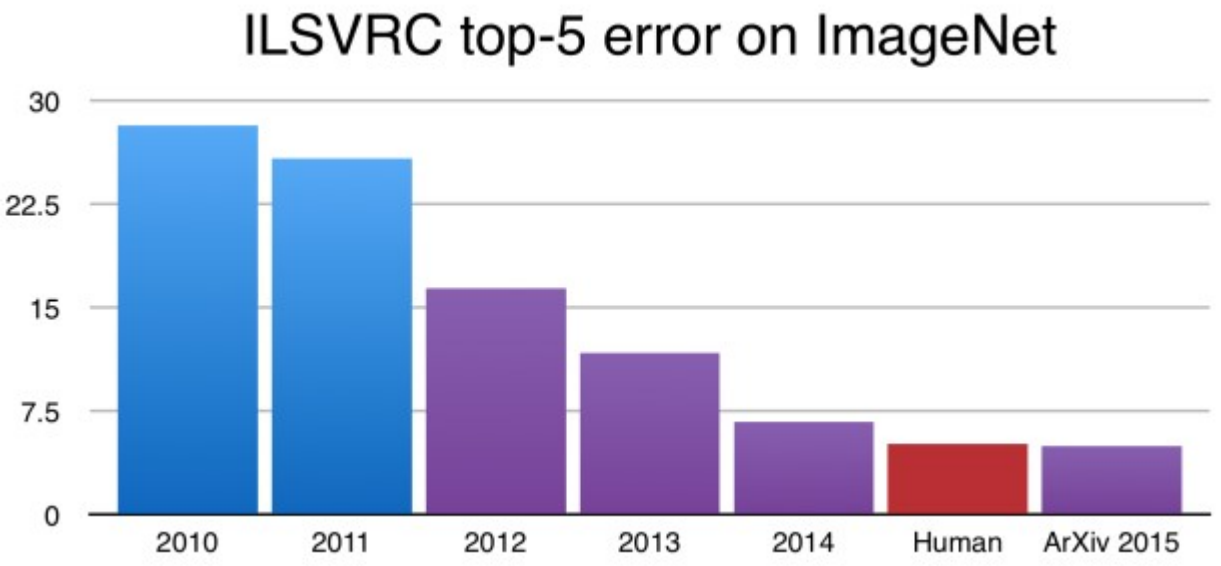
(e.g. Netflix Prize – $1,000,000 prize to create rating prediction algorithm better than Netflix's current best)

Kaggle.com

Data.gov

...

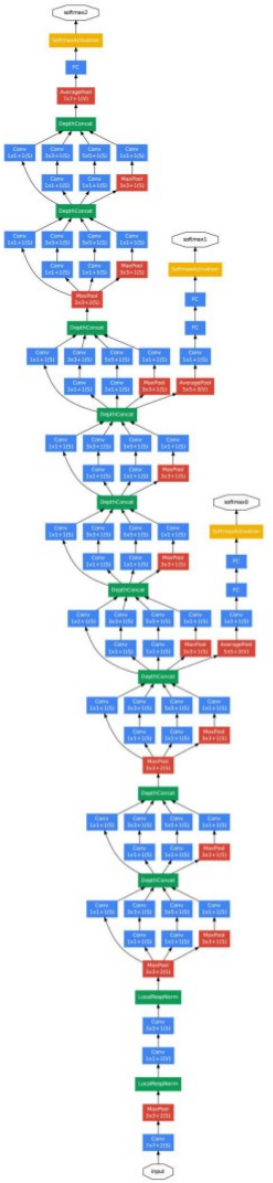
deeper and deeper architectures


ILSVRC top-5 error on ImageNet
30
22.5
15
7.5
0
2010
2011
2012
2013
2014
Human
ArXiv 2015

ImageNet Challenge: 2014

AlexNet

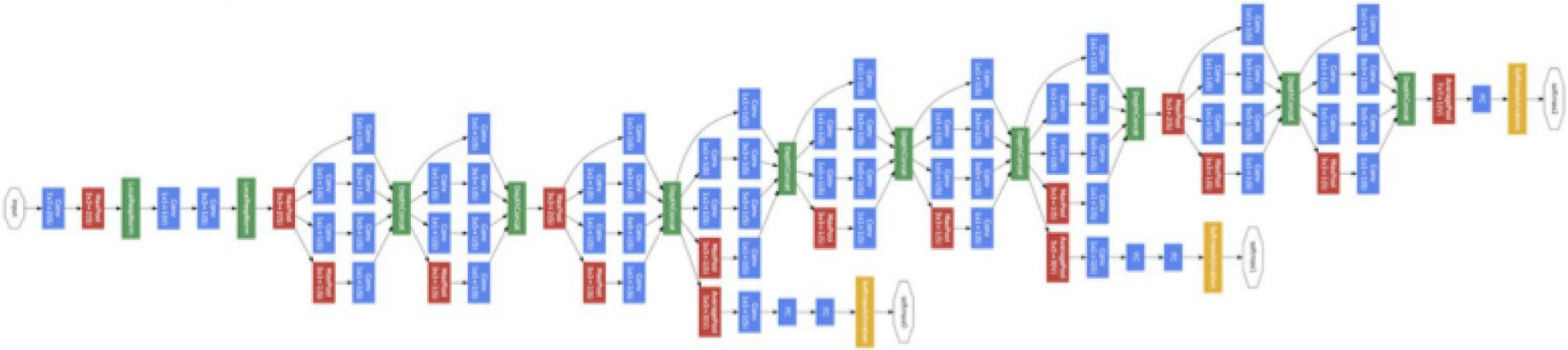
- image
- conv-64
- conv-192
- conv-384
- conv-256
- conv-256
- FC-4096
- FC-4096
- FC-1000



- image
- conv-64
- conv-64
- maxpool
- conv-128
- conv-128
- maxpool
- conv-256
- conv-256
- conv-256
- conv-256
- maxpool
- conv-512
- conv-512
- conv-512
- conv-512
- maxpool
- conv-512
- conv-512
- conv-512
- conv-512
- maxpool
- FC-4096
- FC-4096
- FC-1000
- softmax

GoogLeNet (Inception)

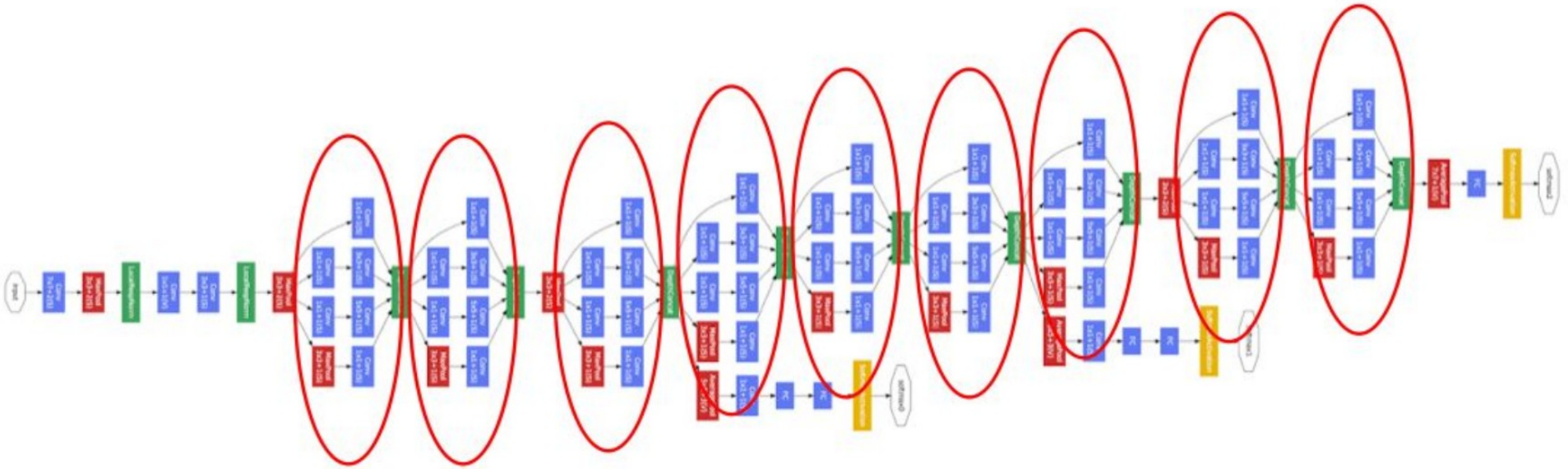
- 22 layers, but 12 times fewer parameters than AlexNet.



Convolution
Pooling
Softmax
Other

Szegedy, Christian, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. "Going deeper with convolutions."

GoogLeNet (Inception)

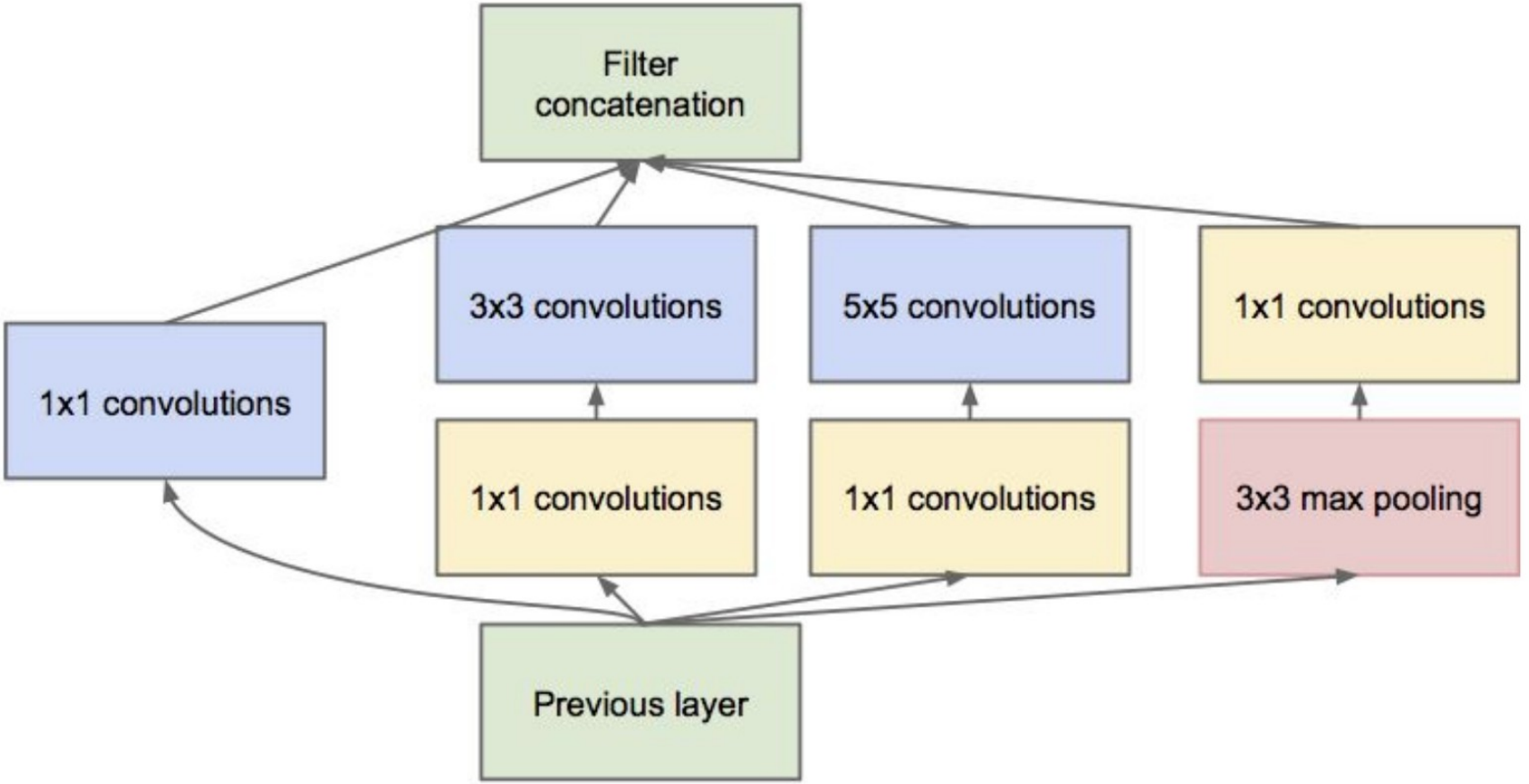


9 **Inception** modules

Network in a network in a network...

Convolution
Pooling
Softmax
Other

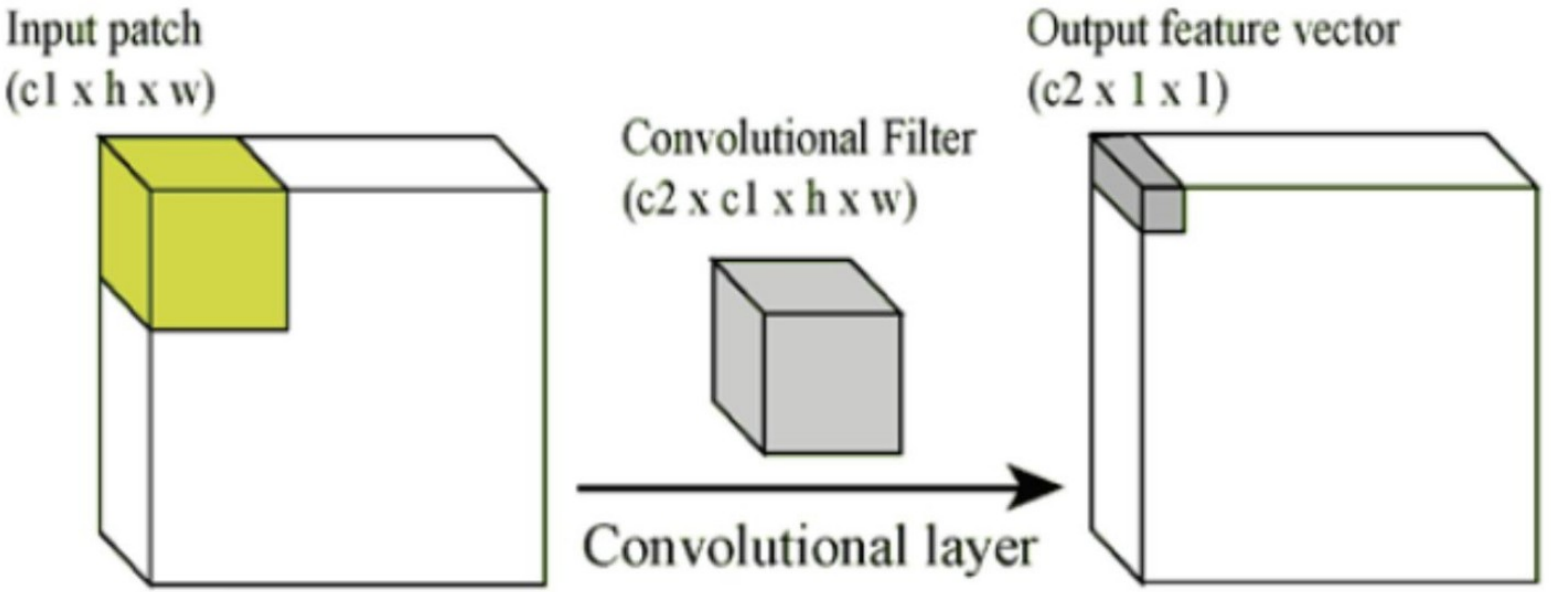
GoogLeNet (Inception)



Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014.*

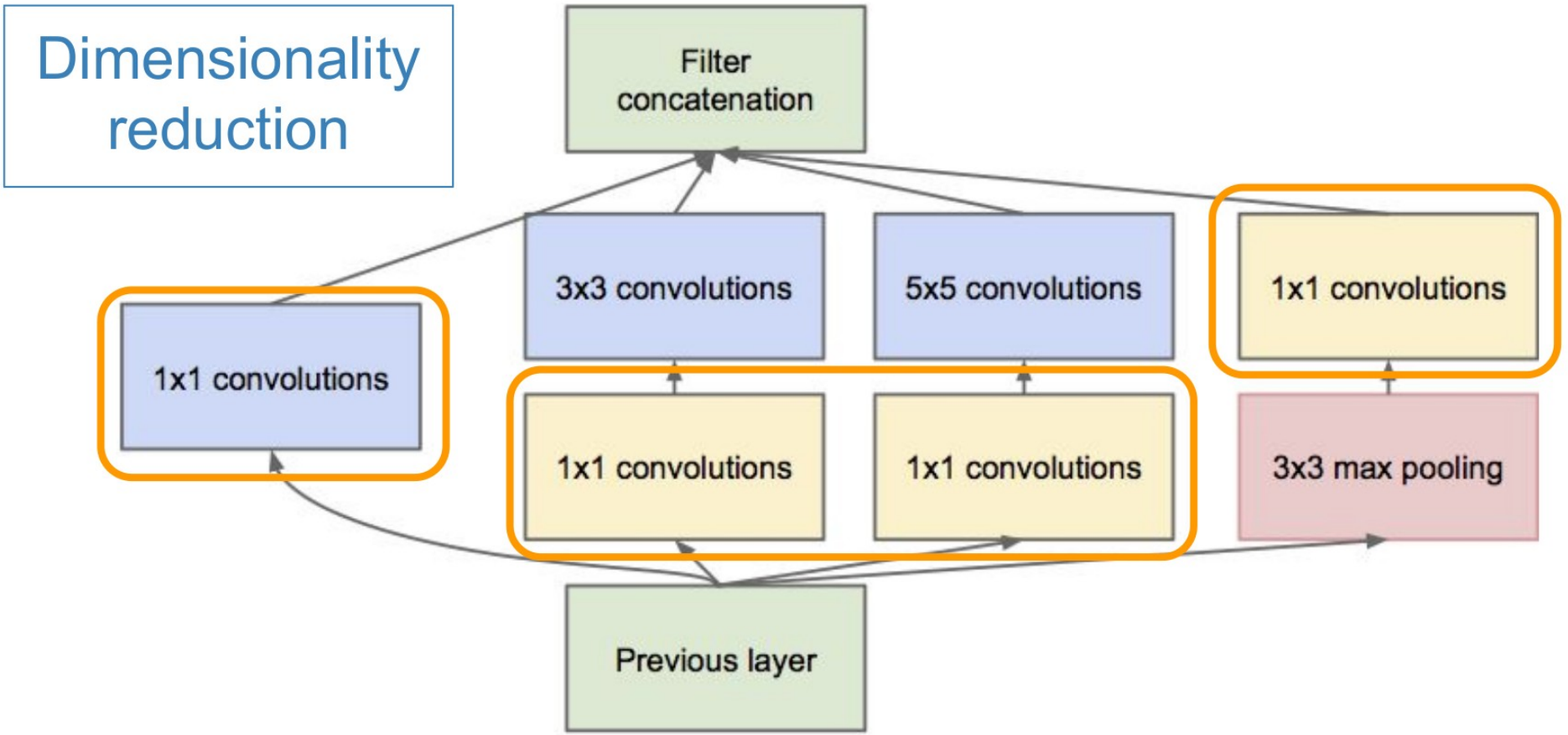
GoogLeNet (NiN)

3x3 and 5x5 convolutions deal with different scales.



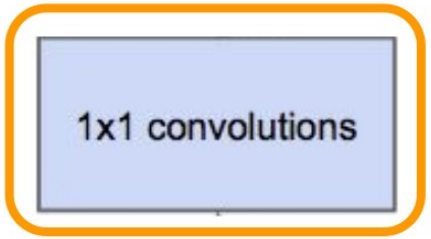
Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014.* *[Slides]*

GoogLeNet (Inception)

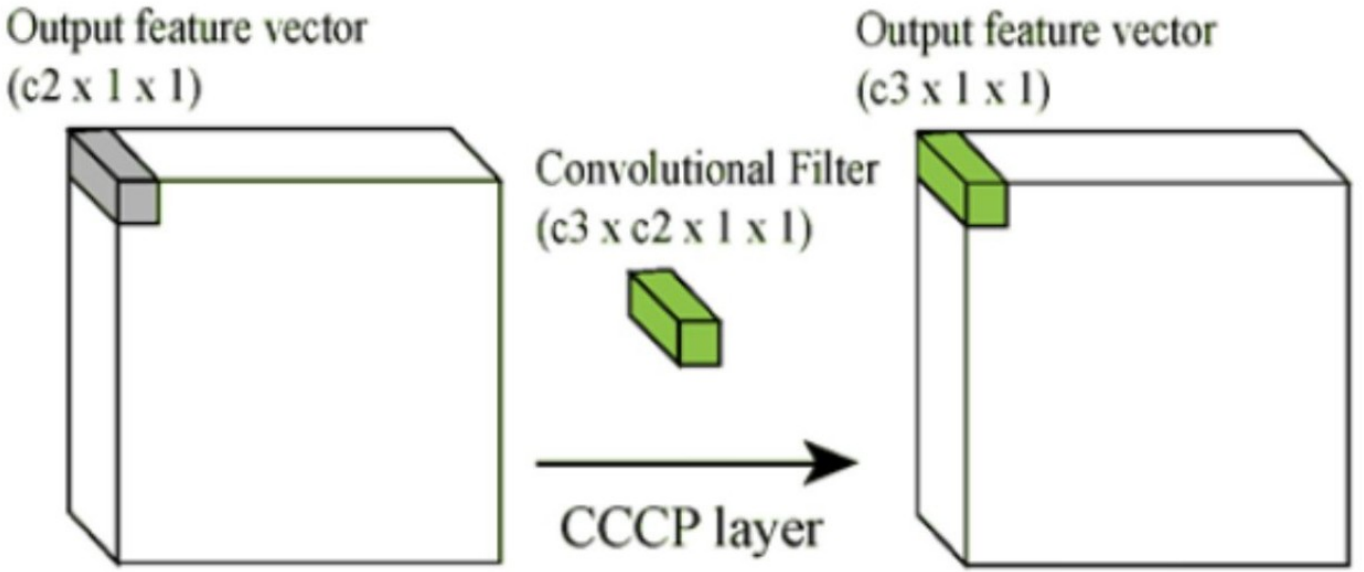


Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014.*

GoogLeNet (Inception)



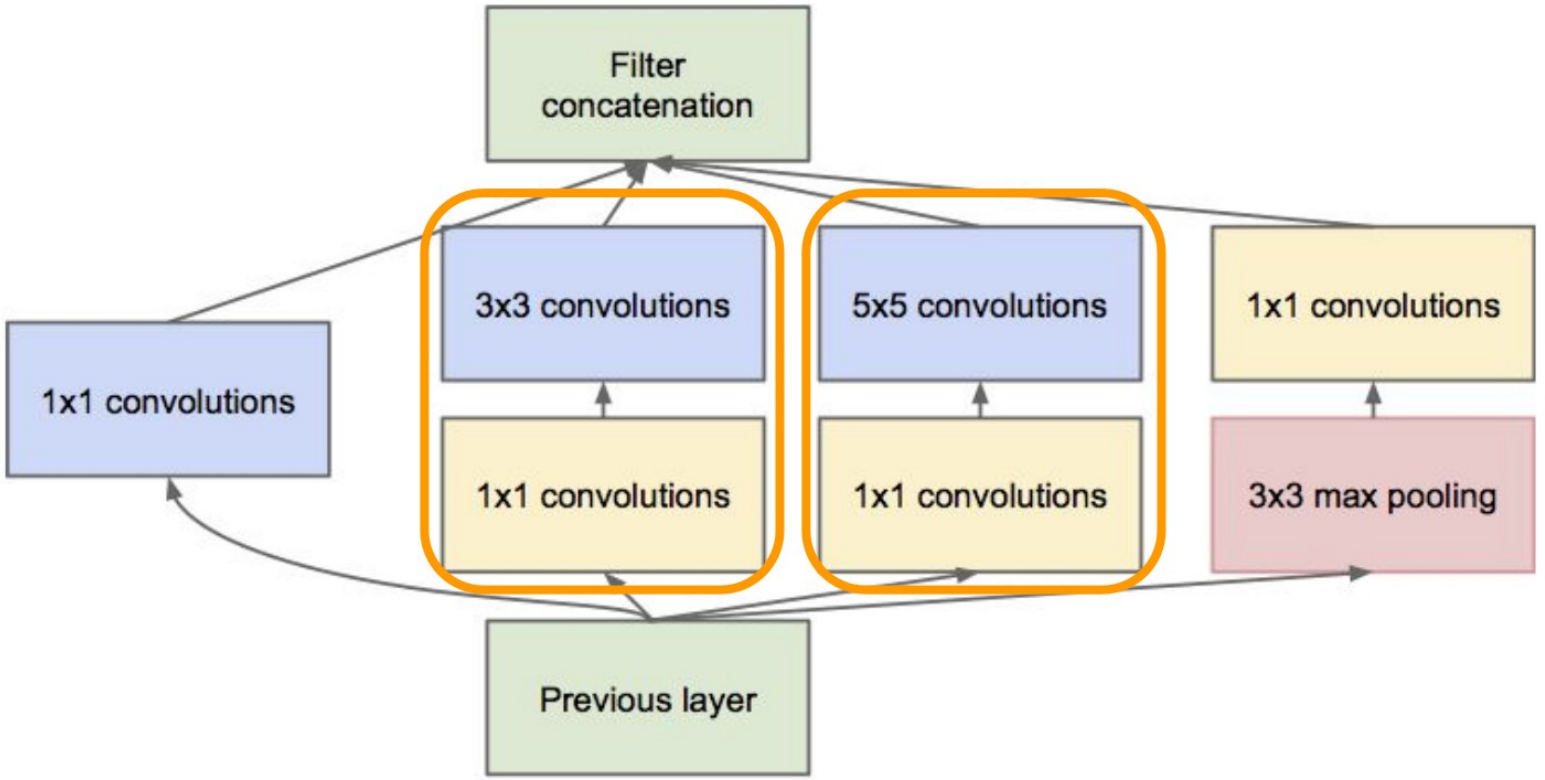
1x1 convolutions does dimensionality reduction (c3<c2) and accounts for rectified linear units (ReLU).



Lin, Min, Qiang Chen, and Shuicheng Yan. "Network in network." *ICLR 2014.* *[Slides]*

GoogLeNet (Inception)

In GoogLeNet, **the Cascaded 1x1 Convolutions** compute reductions before the expensive 3x3 and 5x5 convolutions.



GoogLeNet (Inception)

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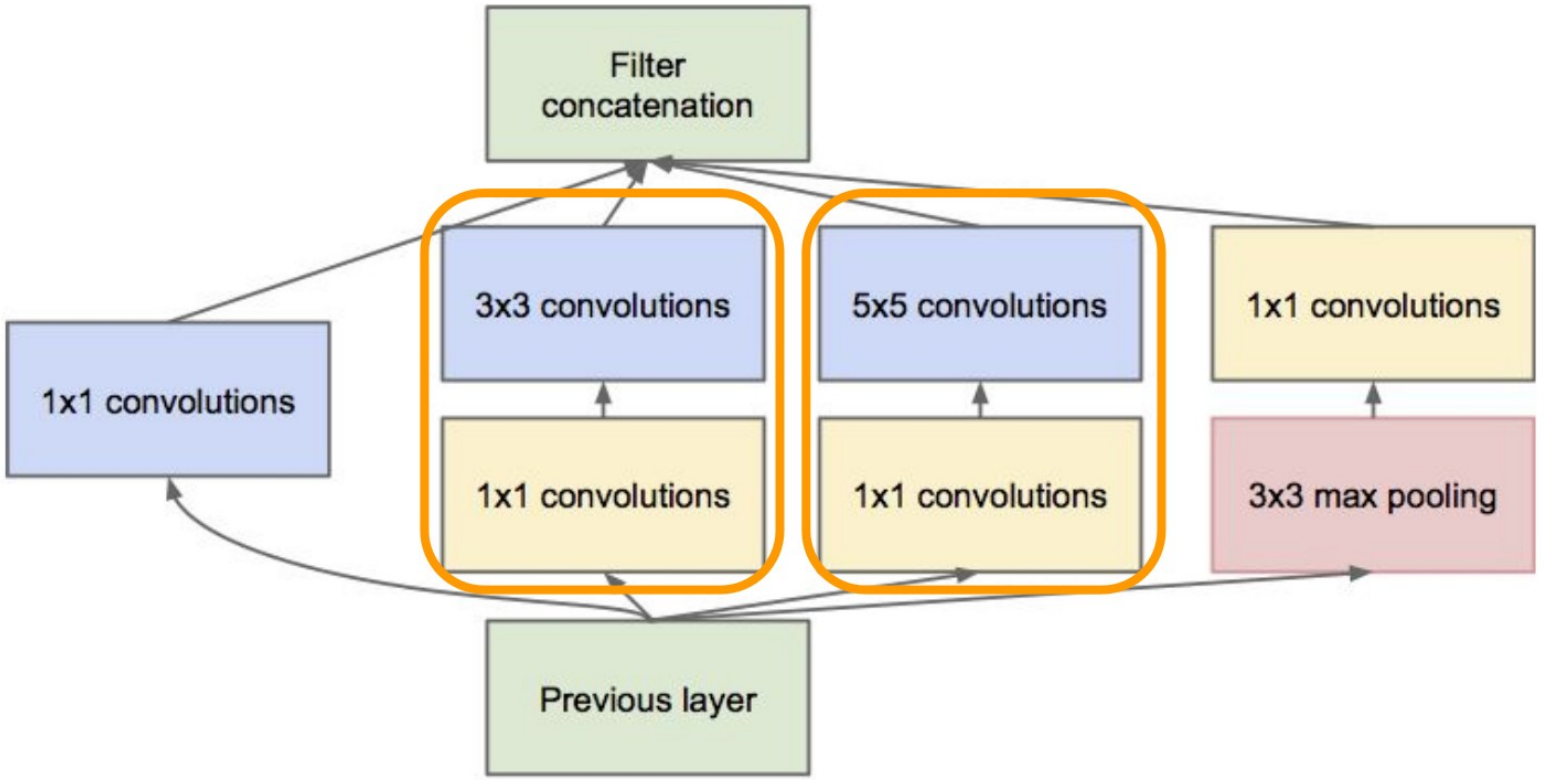
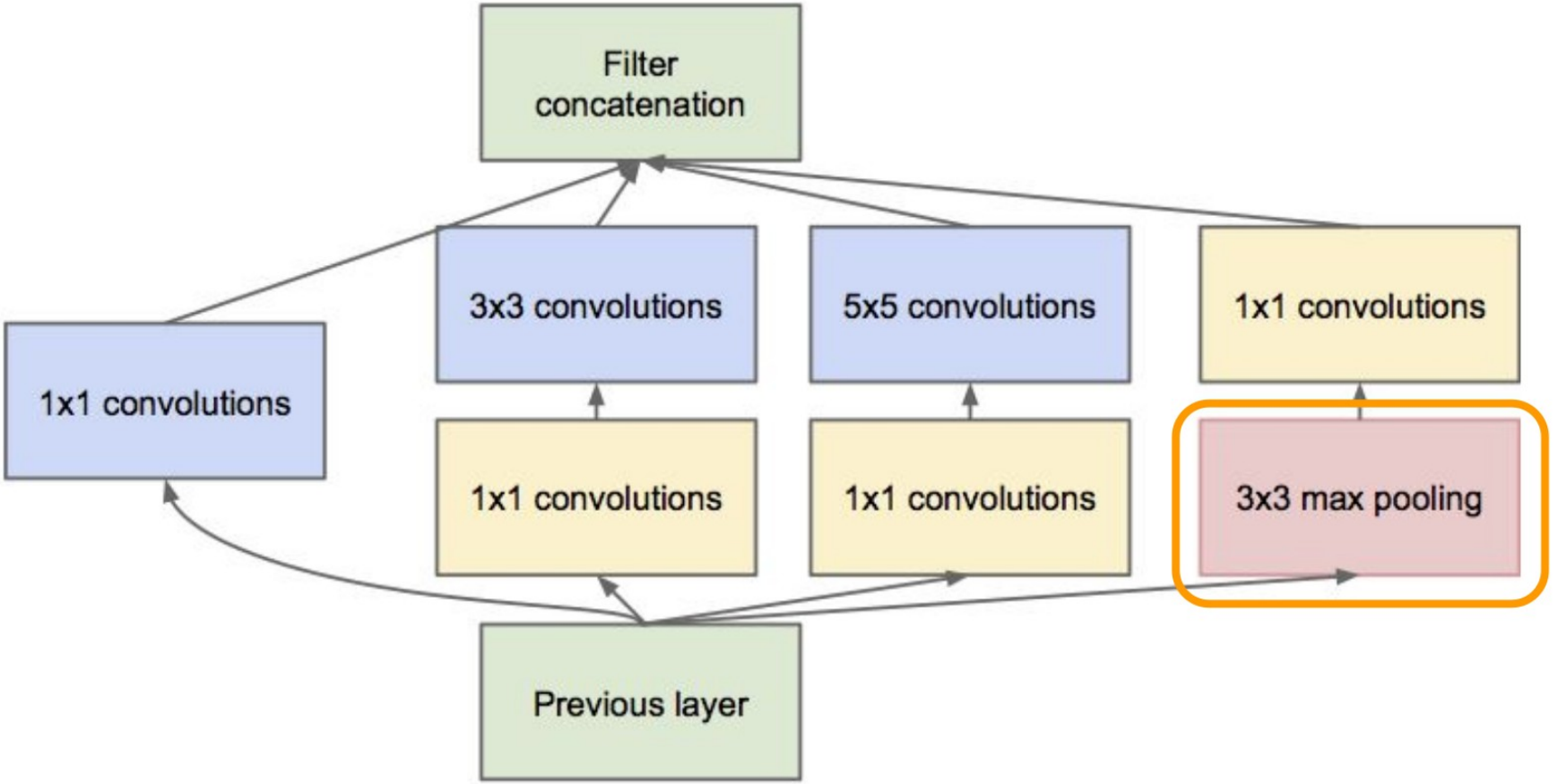


GoogLeNet (Inception)



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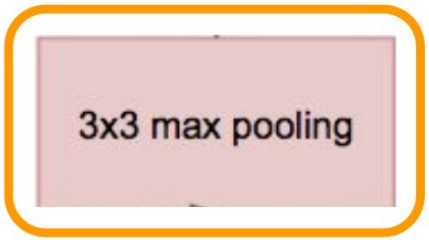
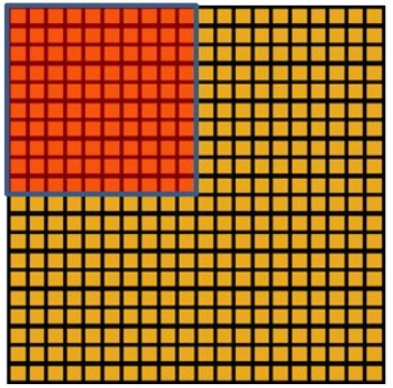
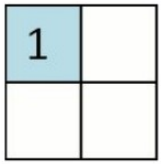
GoogLeNet (Inception)



They somewhat spatial invariance, and has proven a benefitial effect by adding an alternative parallel path.

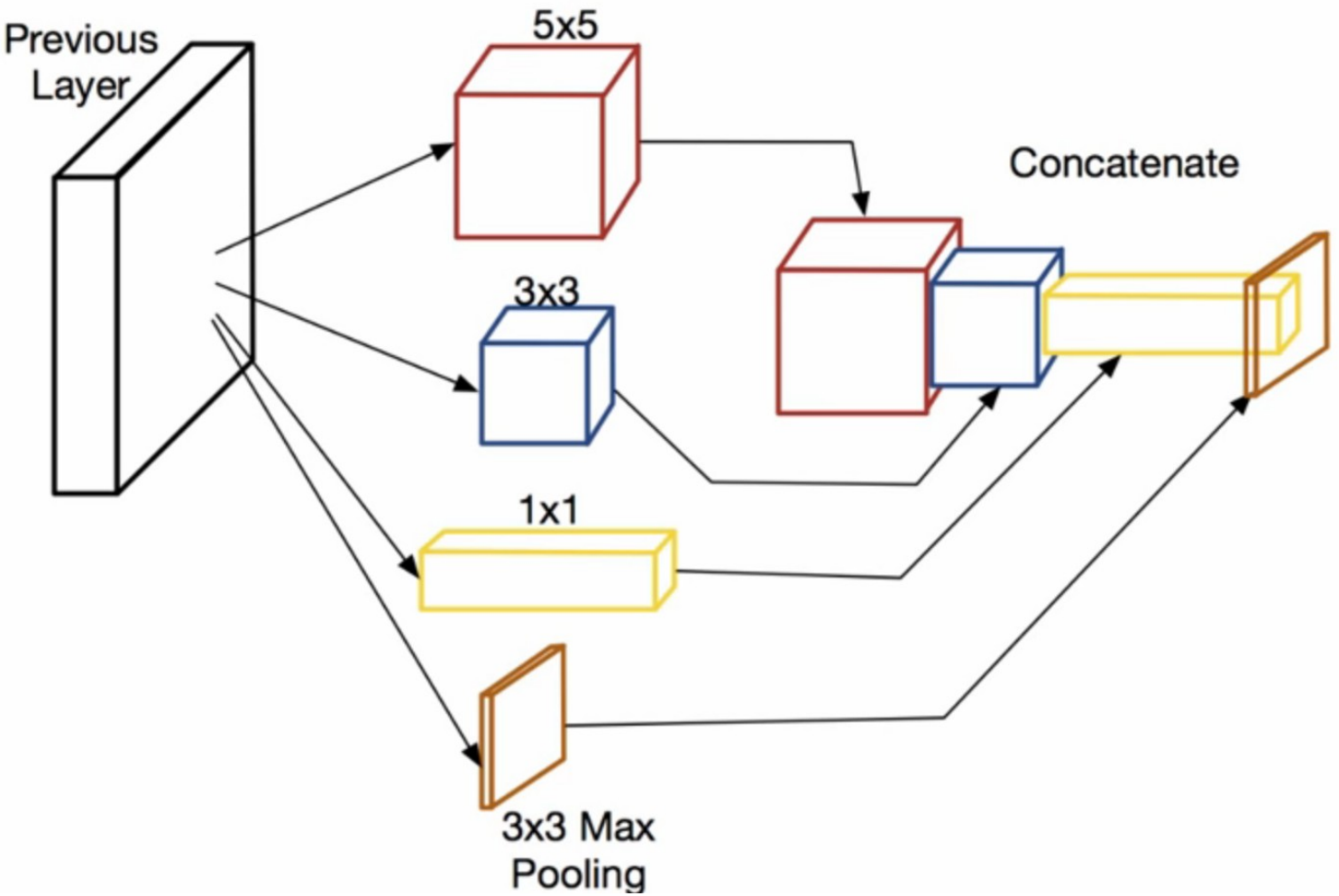




Convolved feature

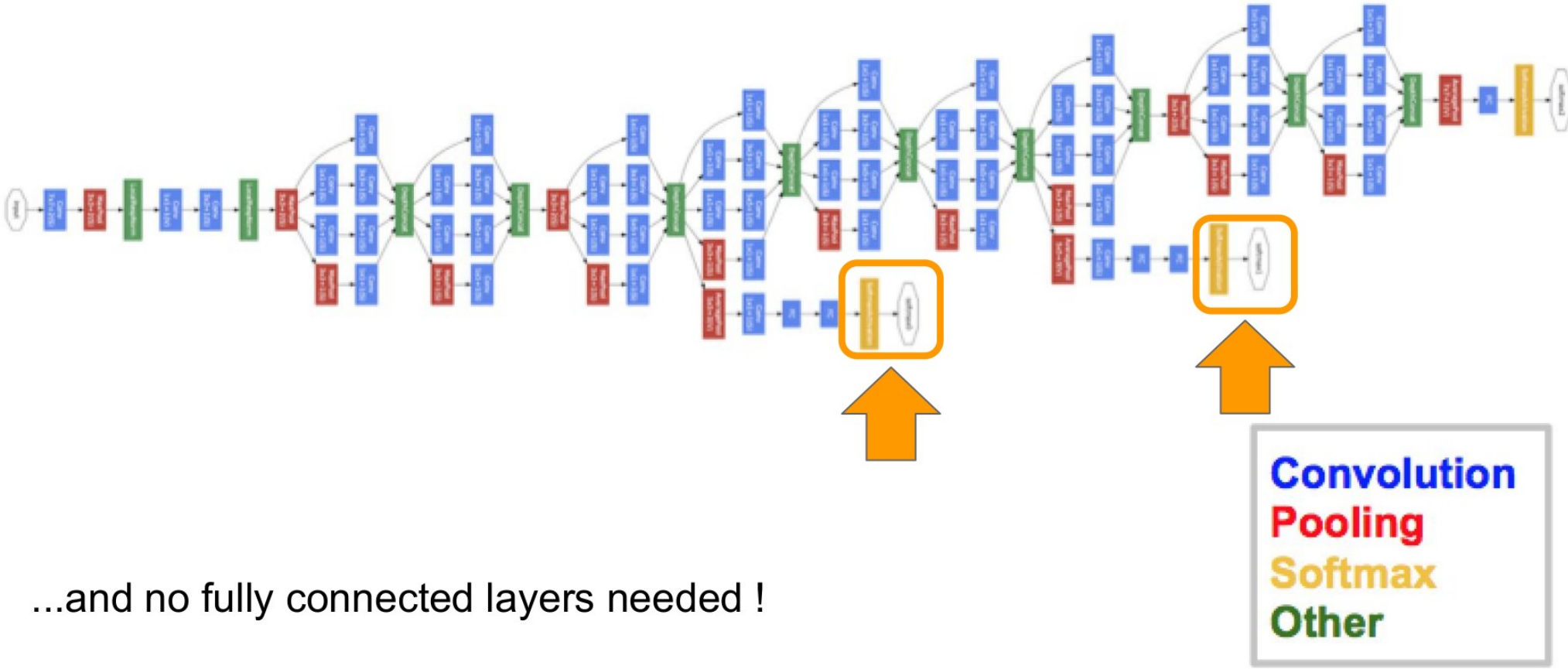
Pooled feature

Conceiving the Inception Module



GoogLeNet (Inception)

Two Softmax Classifiers at intermediate layers combat the vanishing gradient while providing regularization at training time.



...and no fully connected layers needed !