Convolutional Neural Networks 5
State Of The Art (SOTA)

CS109B Data Science 2

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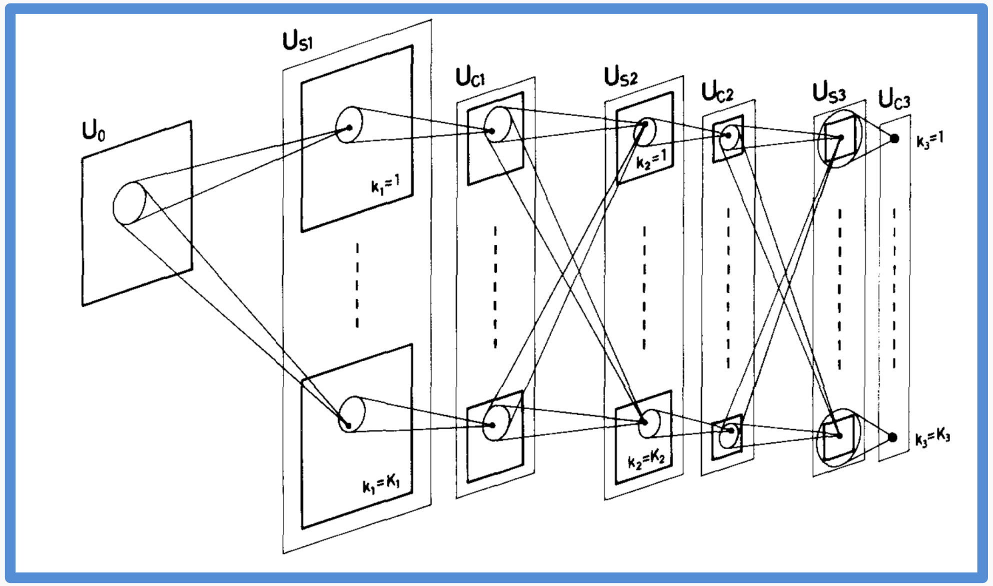
Initial ideas

- The first research proposing something similar to a Convolutional Neural Network was authored by Kunihiko Fukushima in **1980** and was called the **NeoCognitron**.
- Inspired by discoveries on visual cortex of mammals.
- Fukushima applied the NeoCognitron to hand-written character recognition.

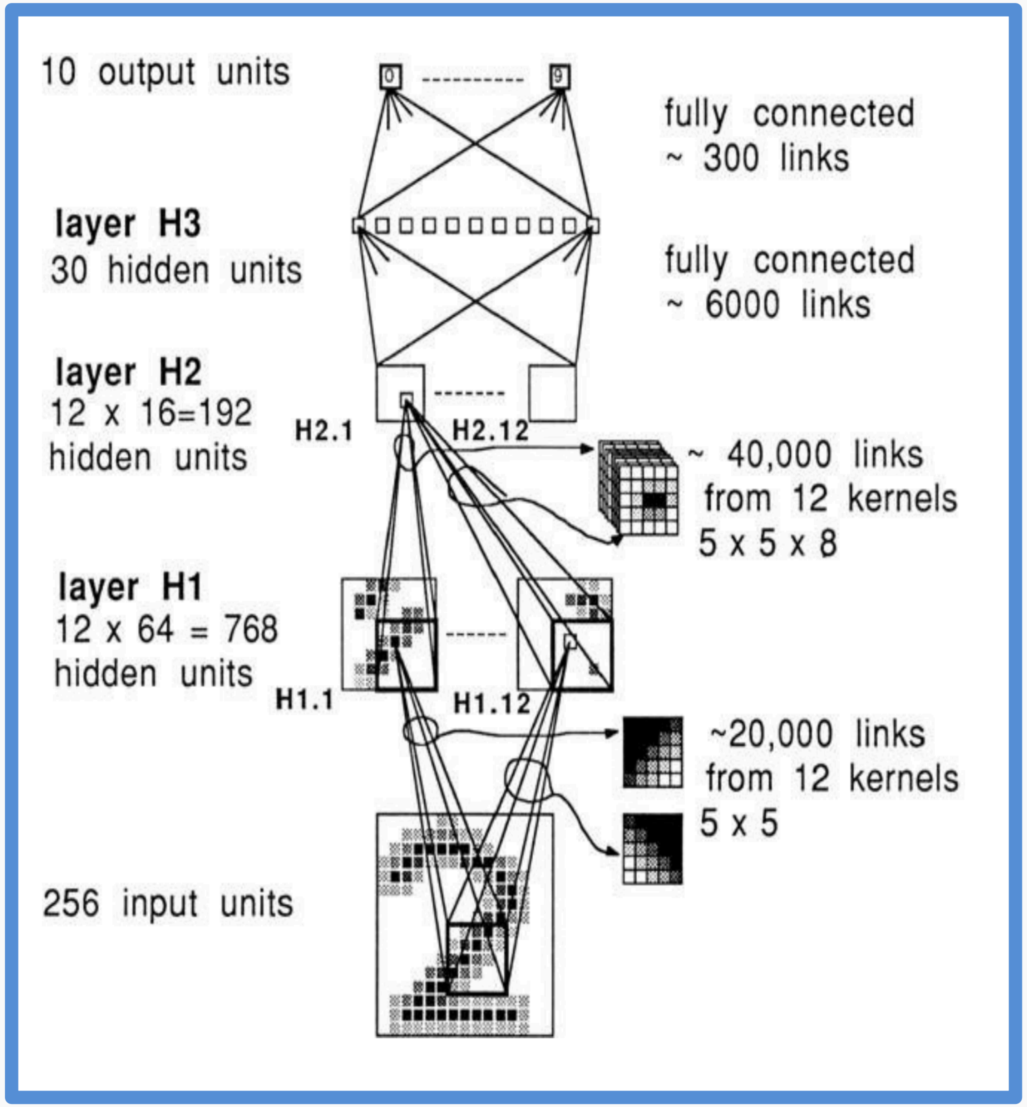


[1] K. Fukushima. Neocognitron: A self-organizing neural network model for a mechanism of pattern recognition unaffected by shift in position. Biological Cybernetics, 36(4): 93-202, 1980.

Initial ideas

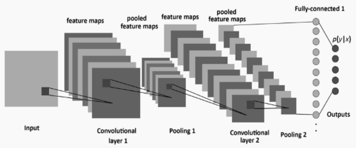
End of the 80's: several papers advanced the field

- **Backpropagation** published in French by Yann LeCun in 1985 (independently discovered by other researchers as well)
- TDNN by Waibel et al., 1989 - **Convolutional-like** network trained with backprop.
- Backpropagation applied to handwritten zip code recognition by LeCun et al., 1989

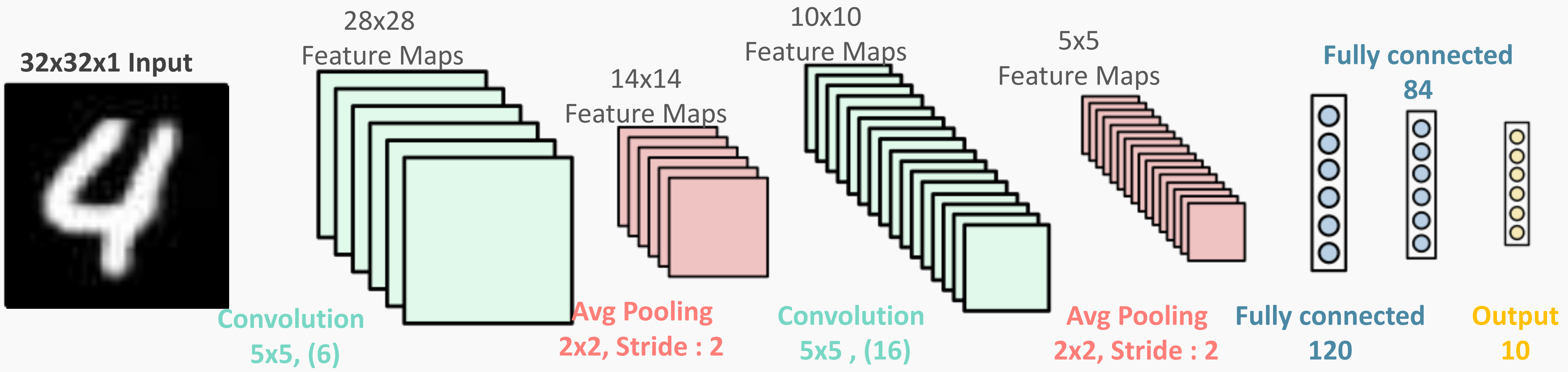


LeCun et al., 1989

LeNet



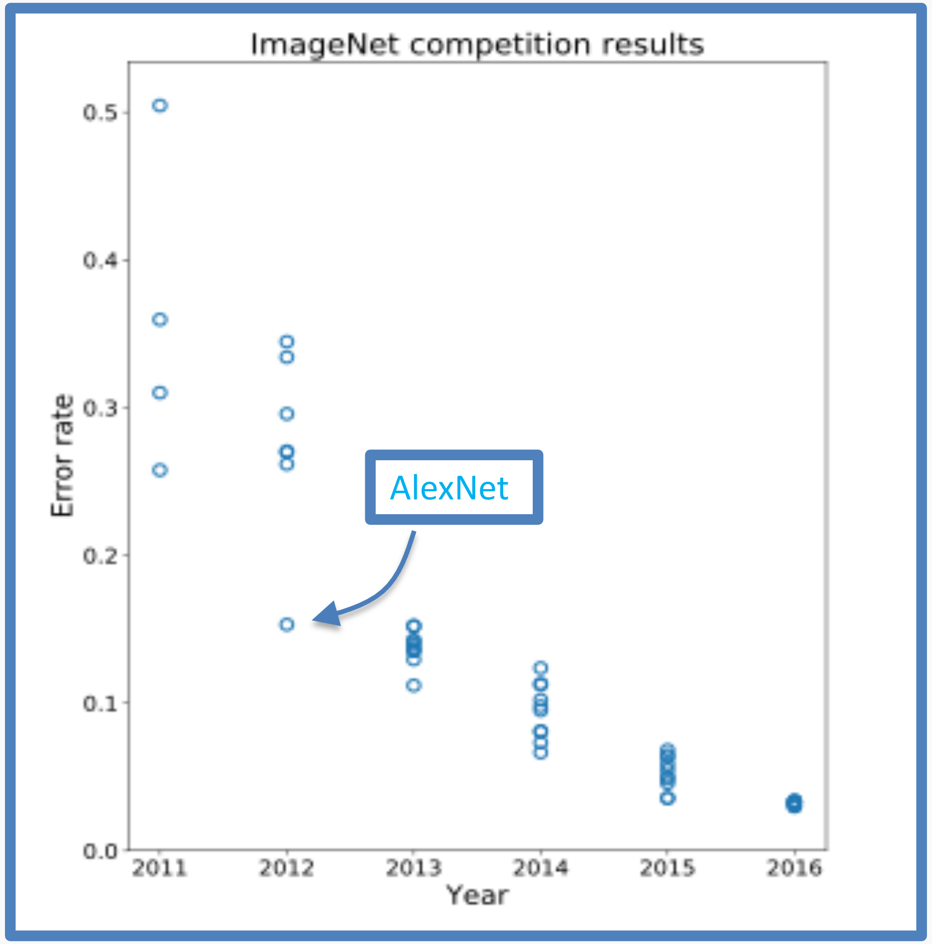
- November 1998: LeCun publishes one of his most recognized papers describing a “modern” CNN architecture for document recognition, called LeNet[1].
- Not his first iteration, this was in fact LeNet-5, but this paper is the commonly cited publication when talking about LeNet.



[1] LeCun, Yann, et al. "Gradient-based learning applied to document recognition." *Proceedings of the IEEE* 86.11 (1998): 2278-2324.

AlexNet

- Developed by Alex Krizhevsky, Ilya Sutskever and Geoffrey Hinton at Utoronto in 2012. More than 25000 citations.
- Destroyed the competition in the 2012 ImageNet Large Scale Visual Recognition Challenge. Showed benefits of CNNs and kickstarted AI revolution.
- top-5 error of 15.3%, more than 10.8 percentage points lower than runner-up.



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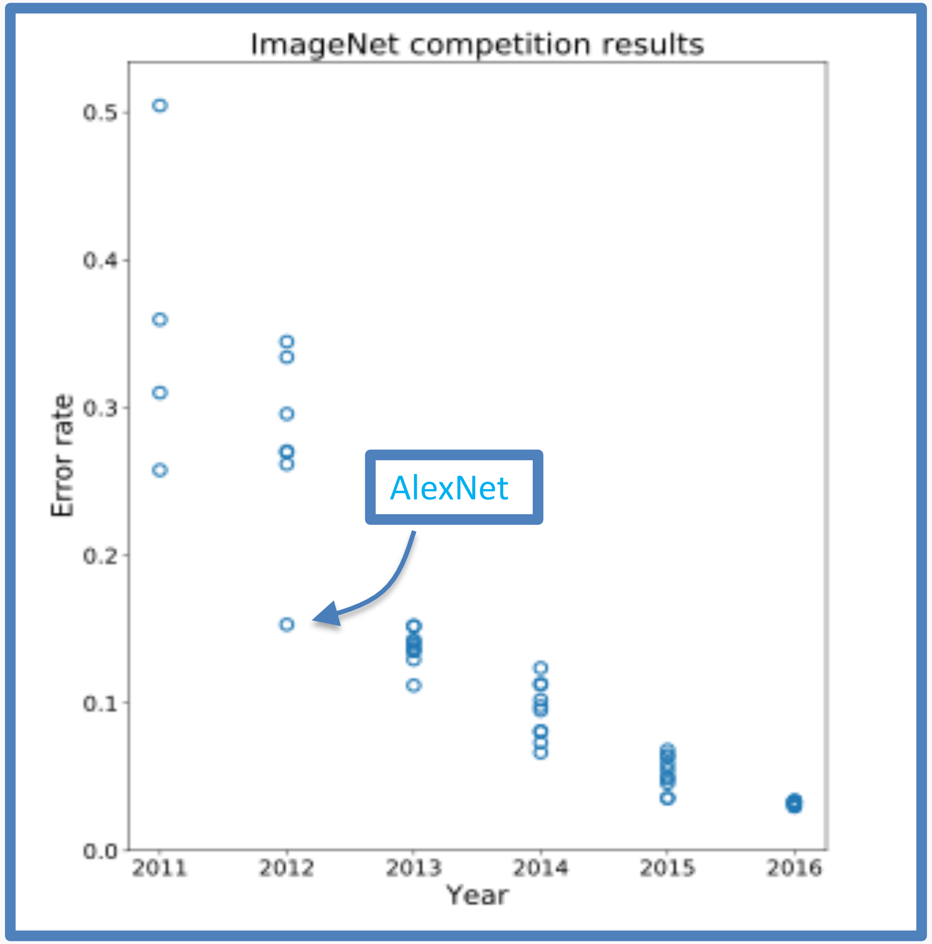
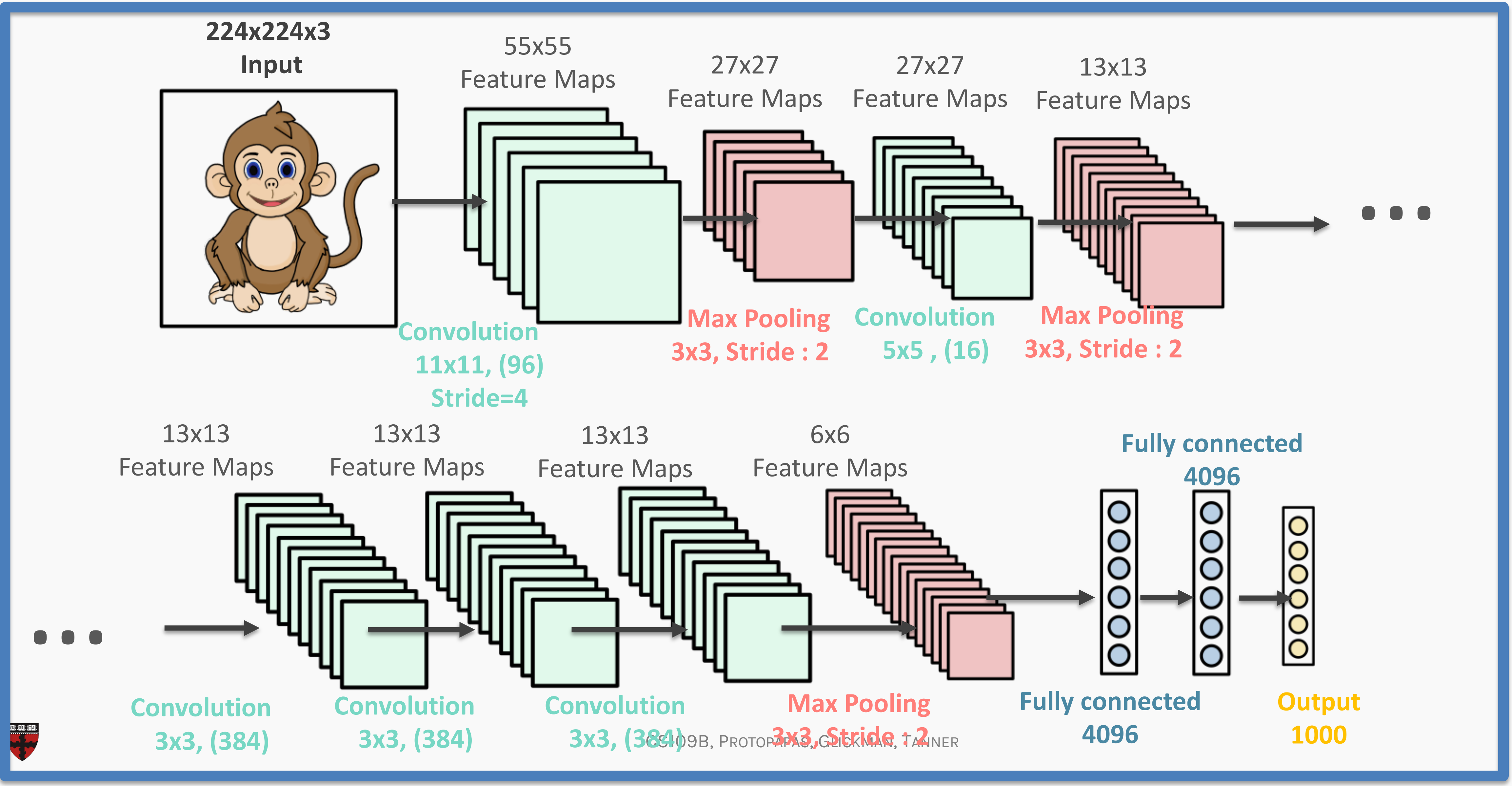
- Main contributions:
  - Trained on ImageNet with data augmentation.
  - Increased depth of model, GPU training (*six days*).
  - Smart optimizer and Dropout layers.
  - ReLU activation!



- 1.2 million high-resolution (227x227x3) images in the ImageNet 2010 contest
- 1000 different classes, NN with 60 million parameters to optimize (~ 255 MB)
- Uses ReLu activation functions; GPUs for training, 12 layers

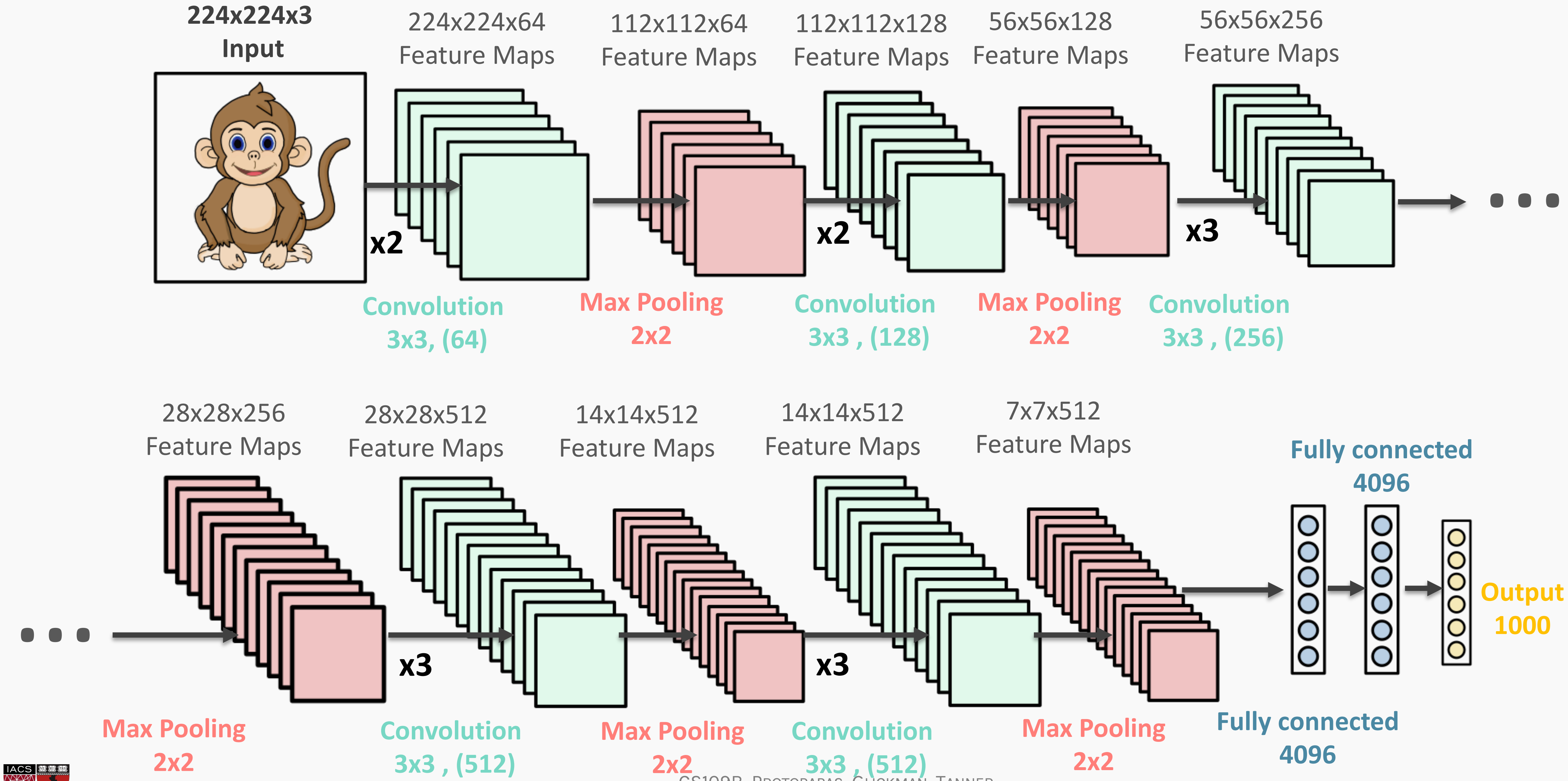


VGG

- Introduced by Simonyan and Zisserman (Oxford) in 2014.
- Simplicity and depth as main points. Used **3x3 filters exclusively** and 2x2 MaxPool layers with stride 2.
- Showed that two 3x3 filters have an effective receptive field of 5x5.
- As spatial size decreases, depth increases.
- Convolutional layers use ‘same’ padding and stride s=1.
- Max-pooling layers use a window size 2 and stride s=2.

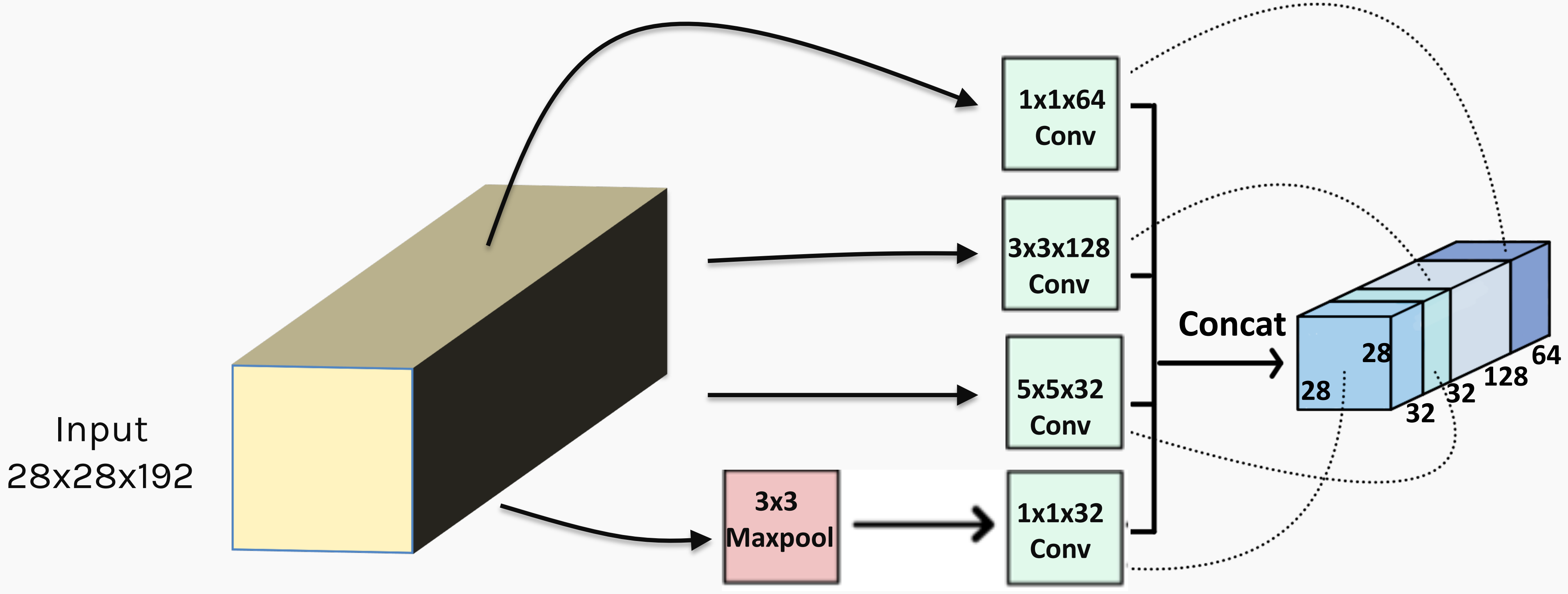
- ImageNet Challenge 2014; 16 or 19 layers; 138 million parameters.
- Trained for two to three weeks.
- Still used as of today.

VGG


224x224x3
Input
224x224x64
Feature Maps
112x112x64
Feature Maps
112x112x128
Feature Maps
56x56x128
Feature Maps
56x56x256
Feature Maps
x2
x2
x3
Convolution
3x3, (64)
Max Pooling
2x2
Convolution
3x3 , (128)
Max Pooling
2x2
Convolution
3x3 , (256)
28x28x256
Feature Maps
28x28x512
Feature Maps
14x14x512
Feature Maps
14x14x512
Feature Maps
7x7x512
Feature Maps
Fully connected
4096
x3
x3
Output
1000
Max Pooling
2x2
Convolution
3x3 , (512)
Max Pooling
2x2
Convolution
3x3 , (512)
Max Pooling
2x2
Fully connected
4096

SOTA Deep Models: Inception (GoogLeNet)

- The motivation behind inception networks is to use more than a singe type of convolution layer at each layer.
- Use `1x1,3x3,5x5` convolutional layers, and max-pooling layers in parallel.
- All modules use `same` convolution.



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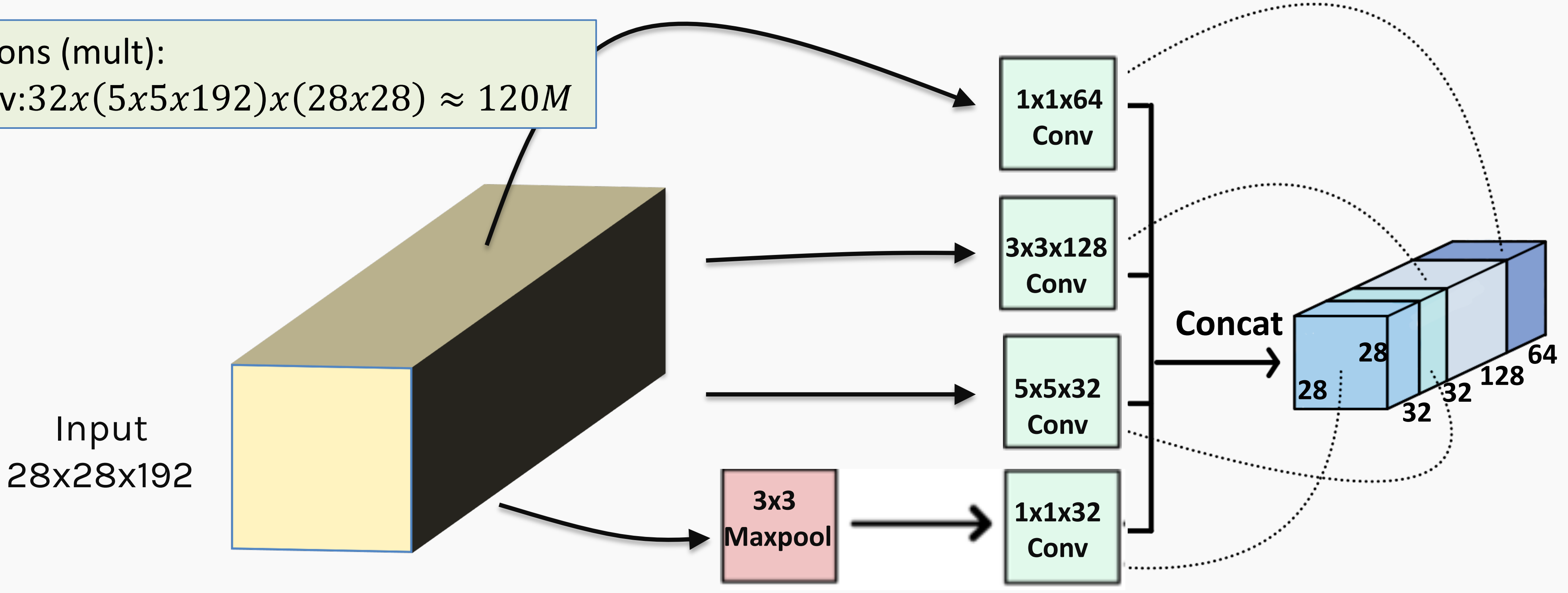
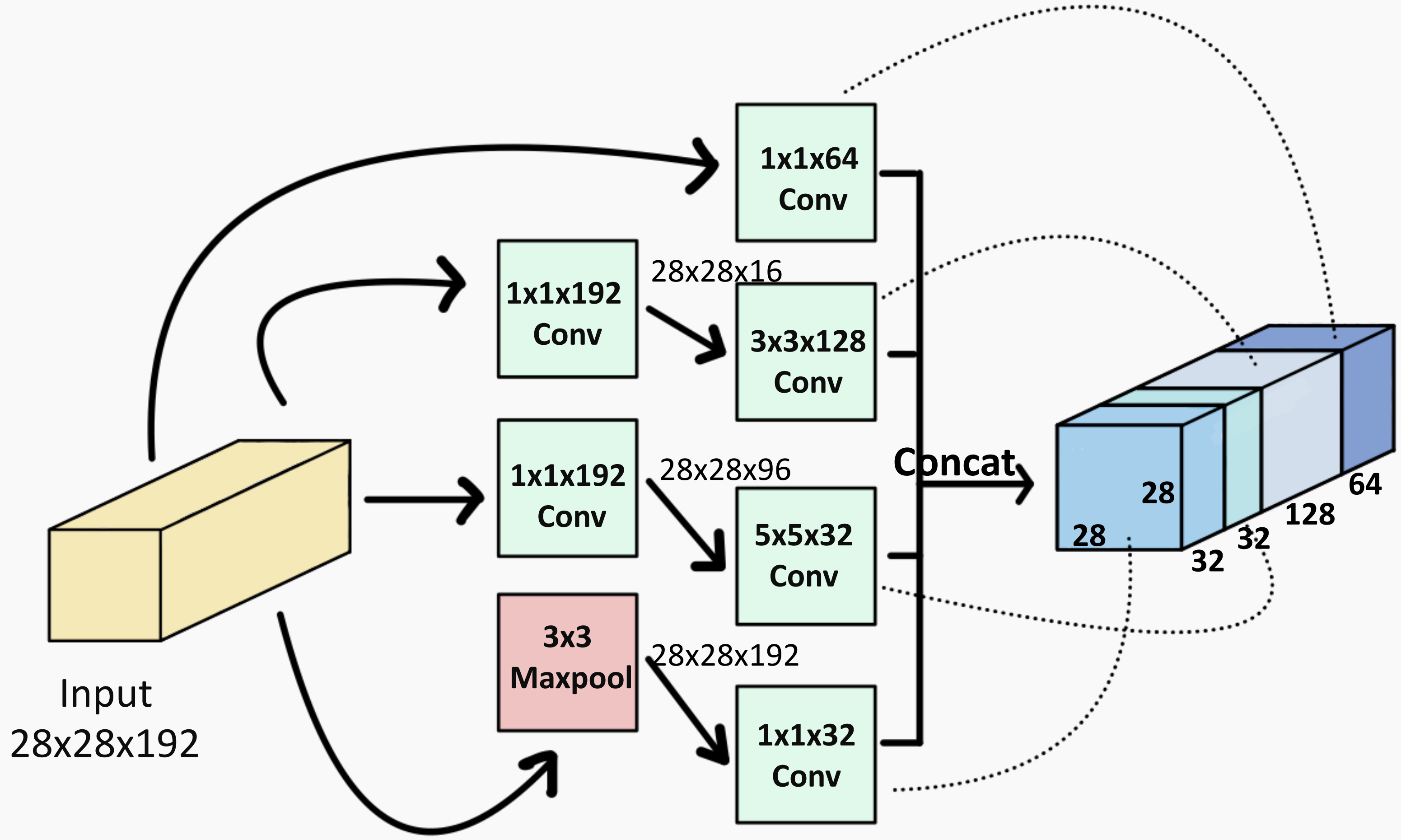
Operations (mult):
5x5 conv: $32x(5x5x192)x(28x28) \approx 120M$



SOTA Deep Models: Inception (GoogLeNet)

- Use 1 x 1 convolutions that reduce the size of the channel dimension.
  - The number of channels can vary from the input to the output.



SOTA Deep Models: Inception (GoogLeNet)

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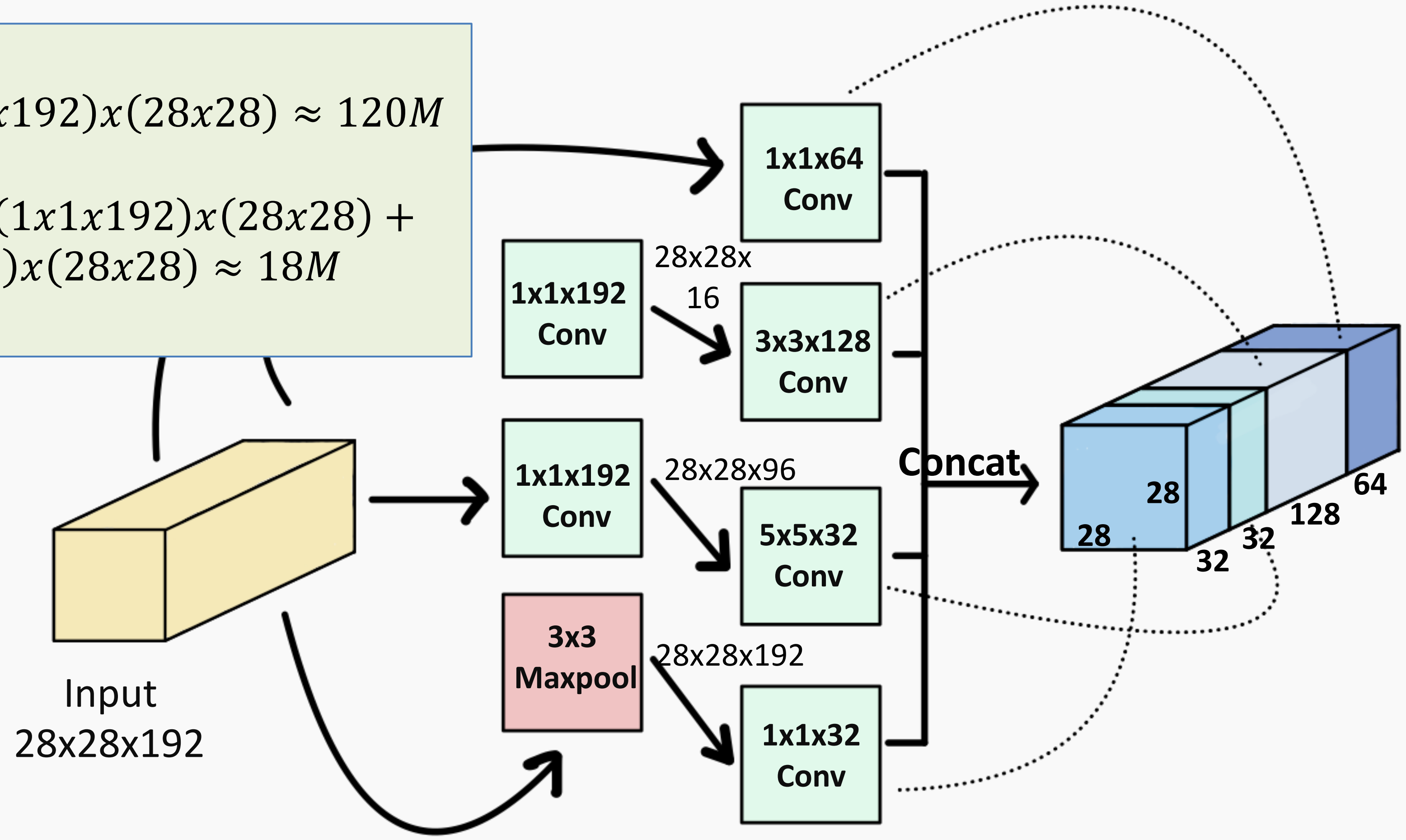
Operations (mult):

5x5 conv:$32x(5x5x192)x(28x28) \approx 120M$

1x1+5x5 conv: $96x(1x1x192)x(28x28) +$
$32x(5x5x96)x(28x28) \approx 18M$



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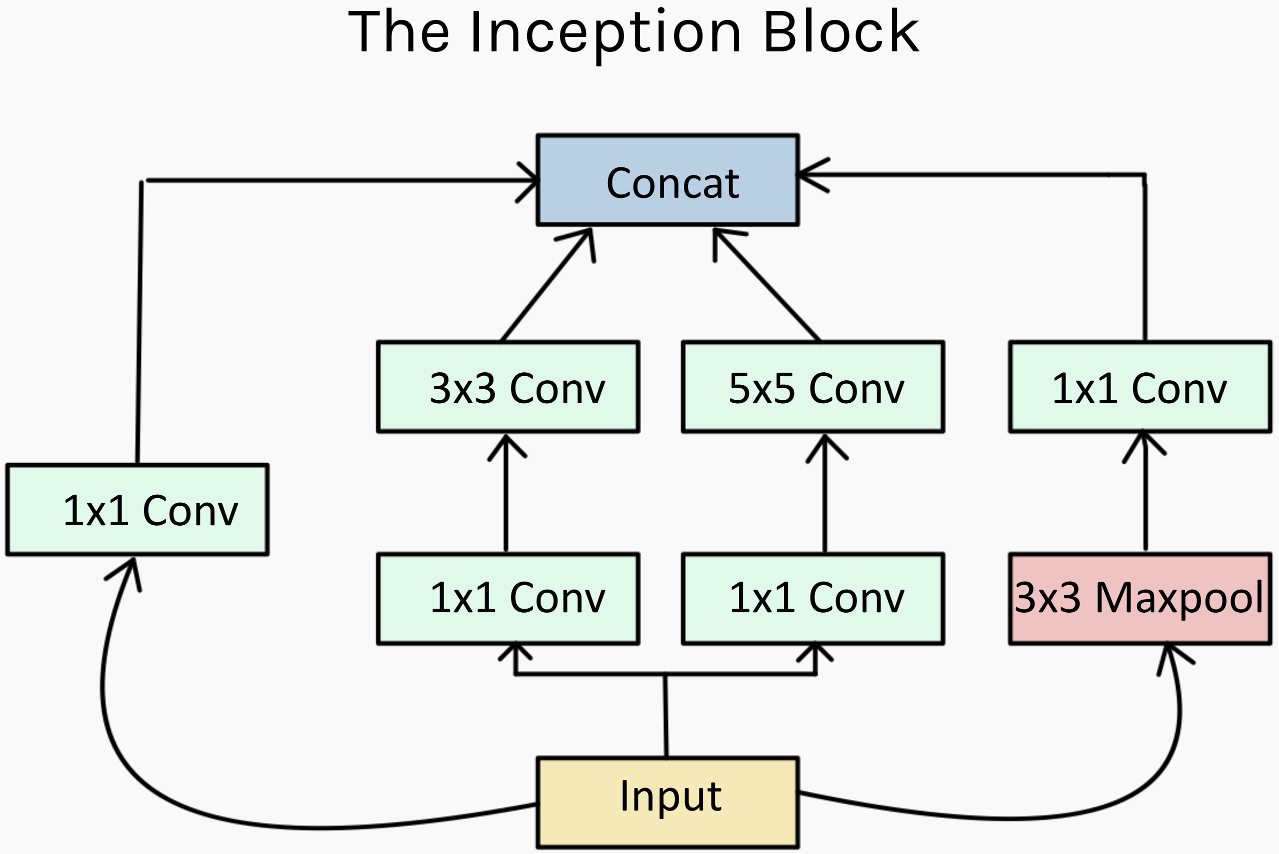
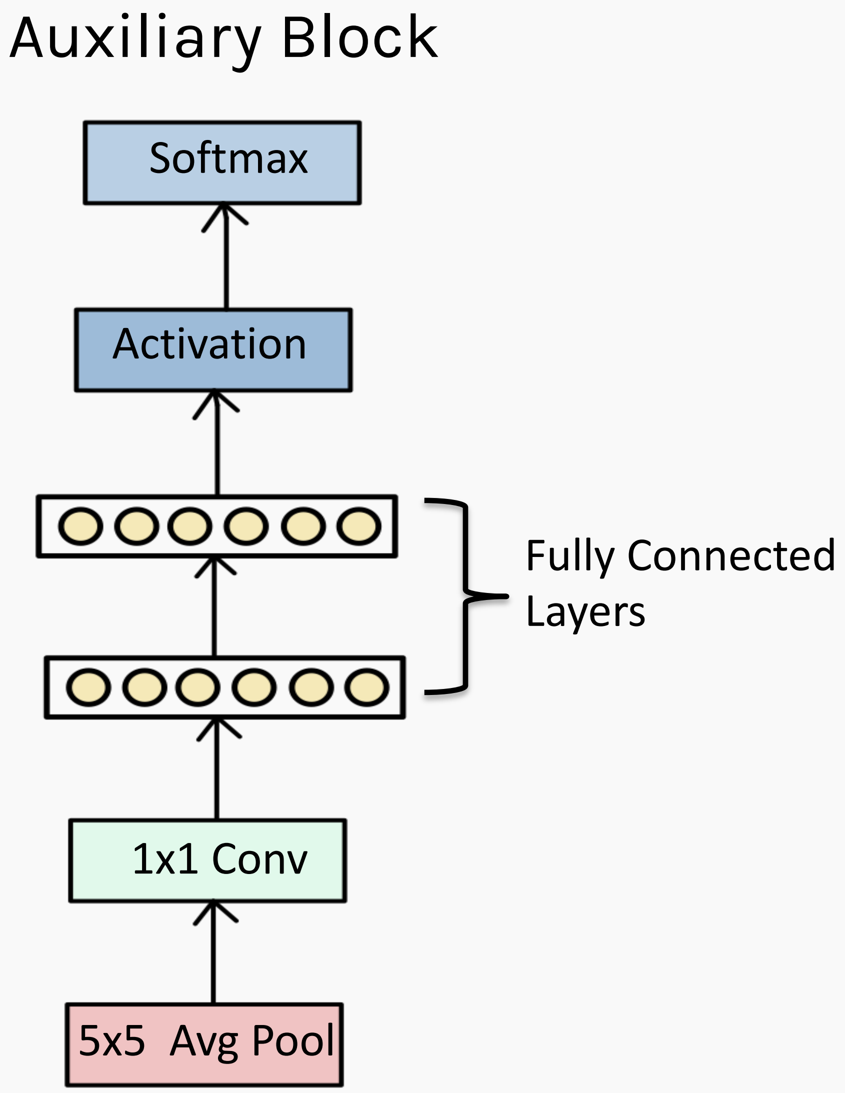
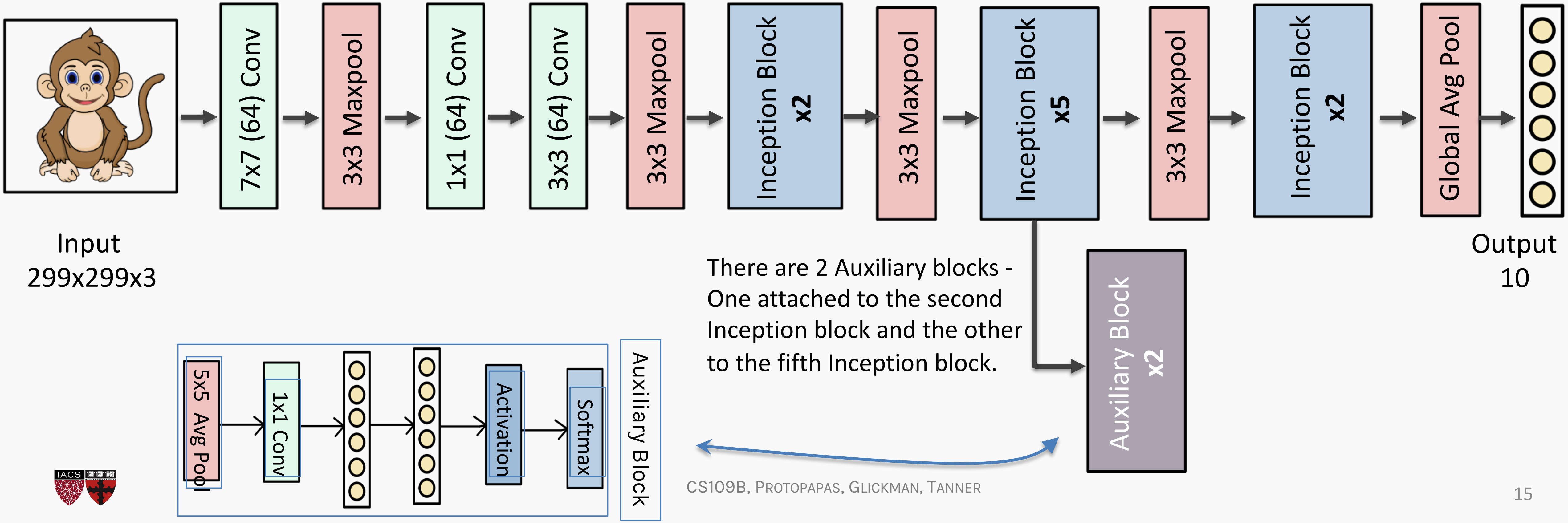




SOTA Deep Models: Inception (GoogLeNet)

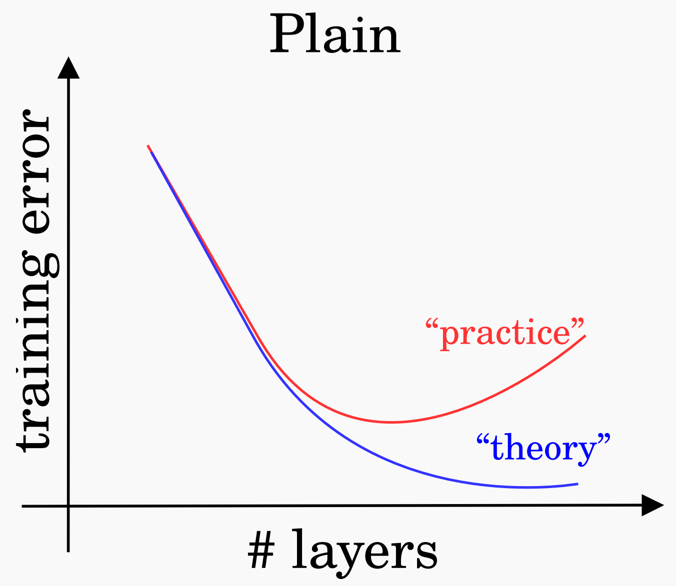
- The inception network is formed by concatenating other inception modules.
- It includes several softmax output units to enforce regularization.

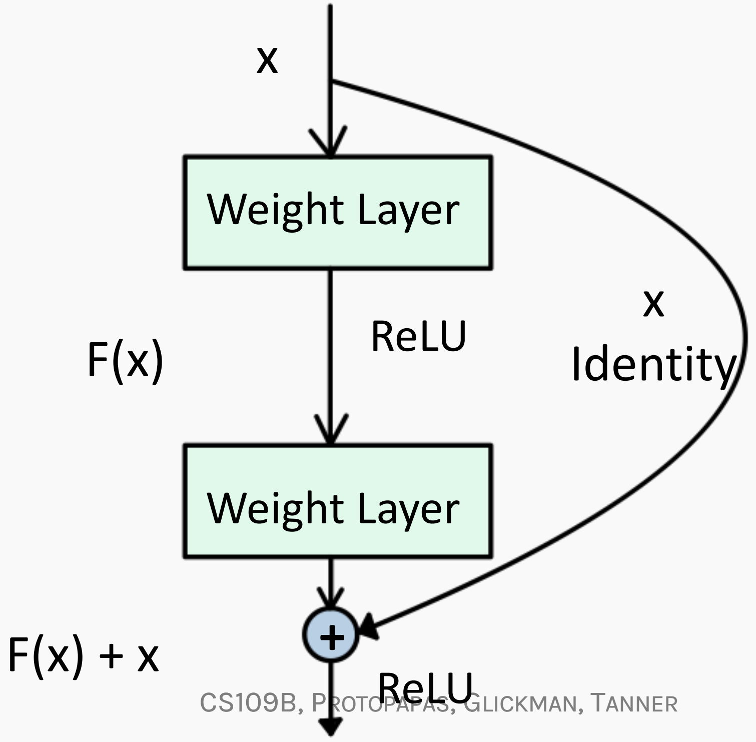


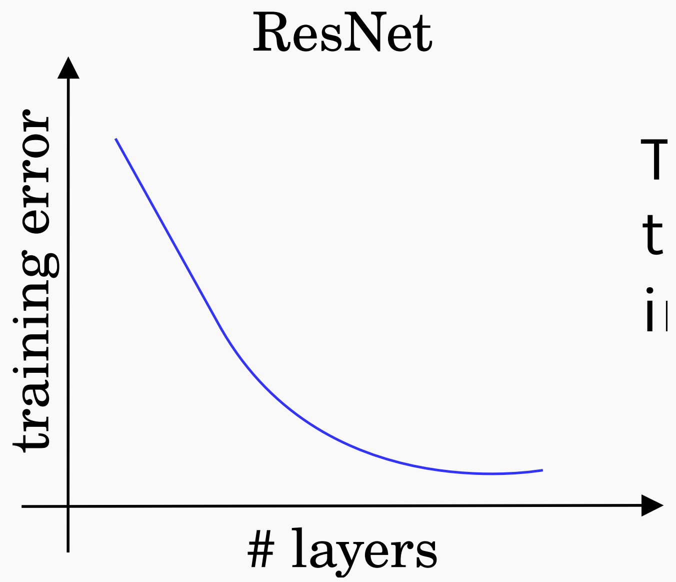
Mandatory Meme

ResNet

- Presented by He et al. (Microsoft), 2015. Won ILSVRC 2015 in multiple categories. Very similar to Highway Networks Srivastava et al. 2015 introduced the same time.
- Main idea: Residual block. Allows for extremely deep networks.
- Authors believe that it is easier to optimize the residual mapping than the original one. Furthermore, residual block can decide to “shut itself down” if needed.

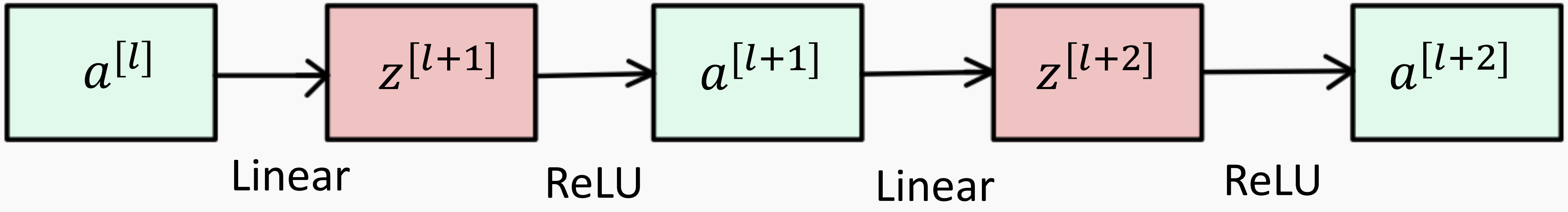




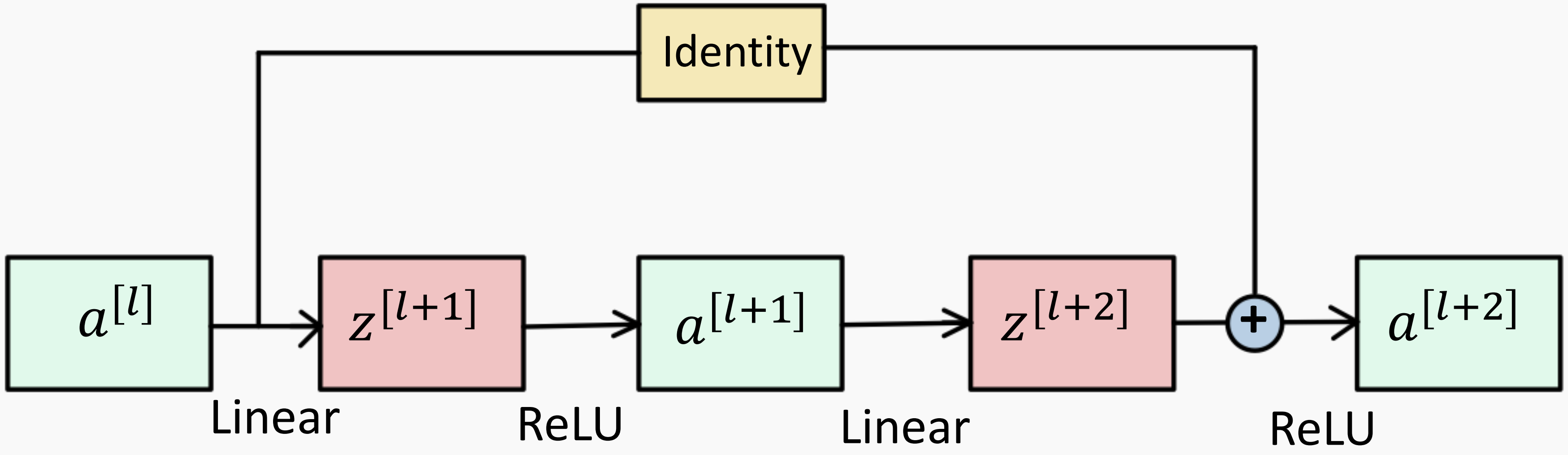


ResNet: Skip Connections

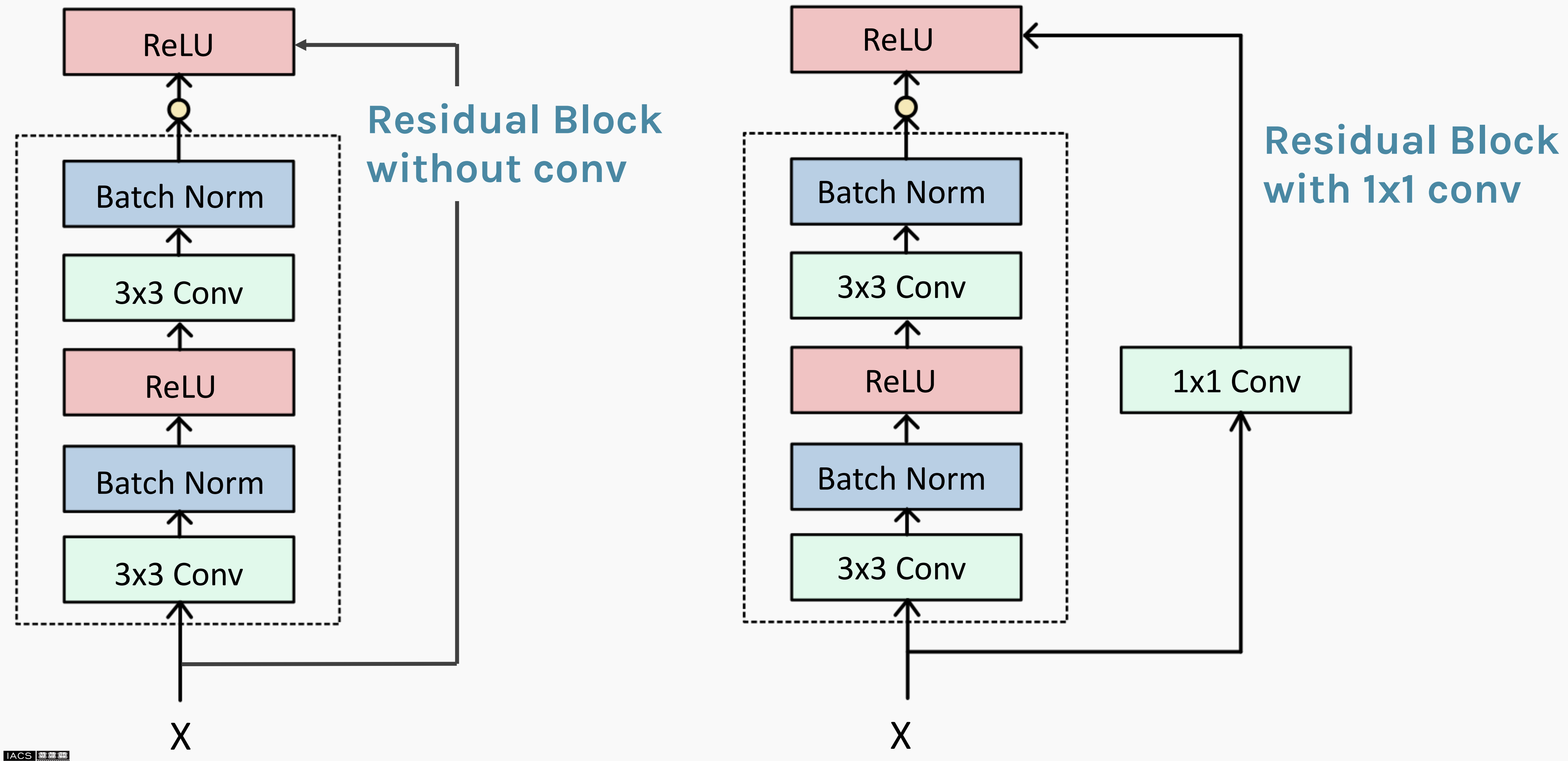
- Residual nets appeared in 2016 to train very deep NN (100 or more layers).
- Their architecture uses ‘residual blocks’.
- Plain network structure:



- **Residual network block**

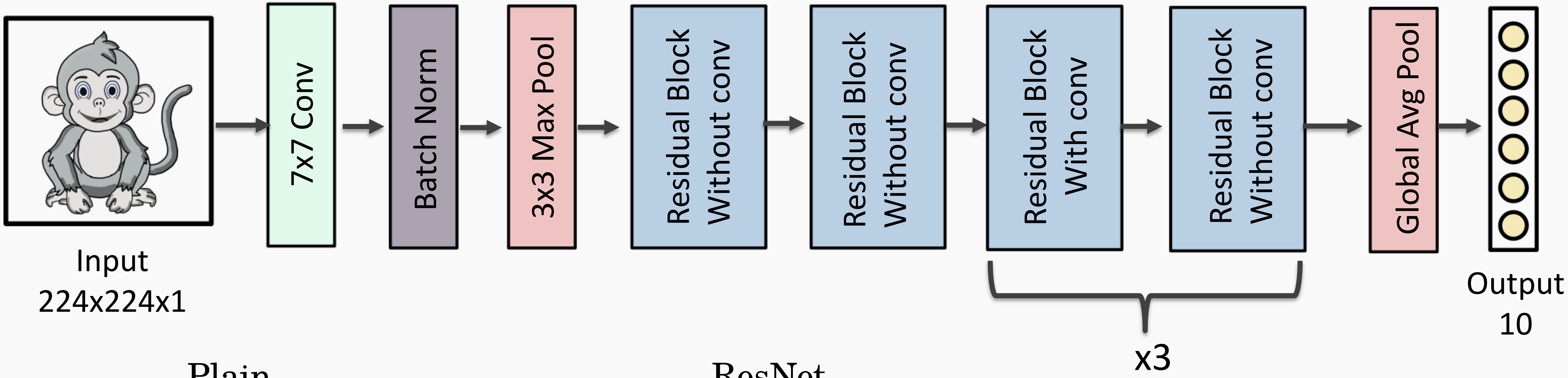


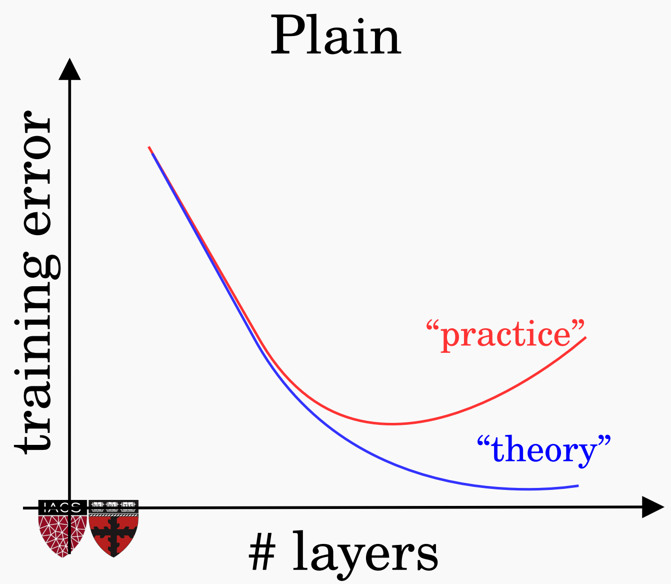
ResNet: Basic Units

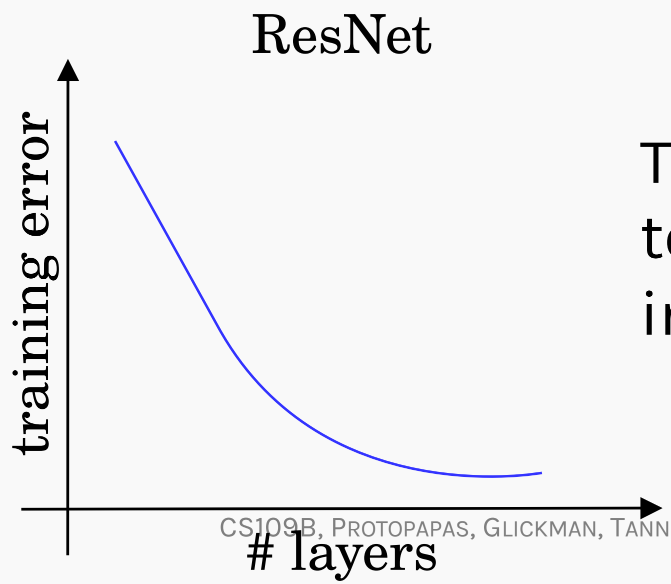


ResNet

The residual network stacks blocks sequentially





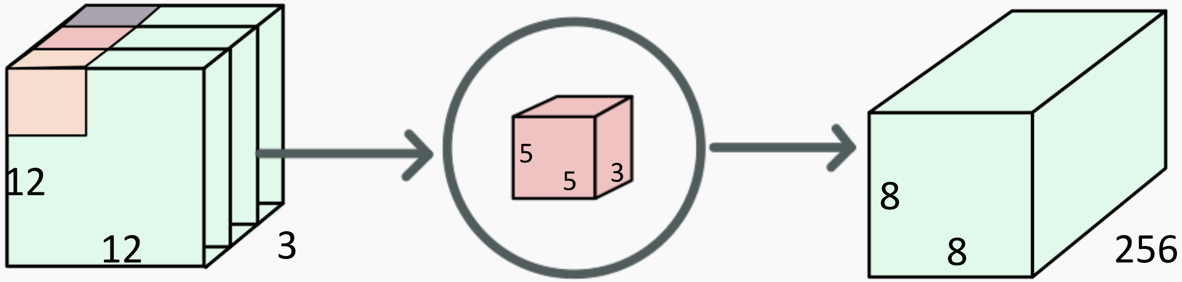


The idea is to allow the network to become deeper without increasing the training time

SOTA Deep Models: MobileNet

Standard Convolution

Filters and combines inputs into a new set of outputs in one step



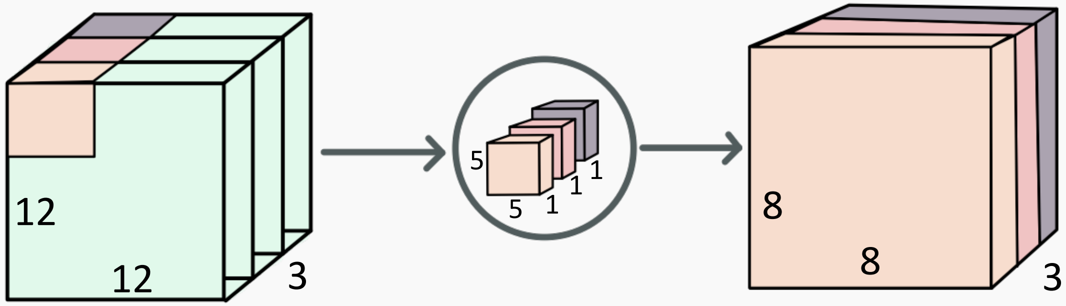
Input: 12x12x3
Filter: 5x5x3x256

Output: 8x8x256
(no padding)

MACs: (5x5)x3x256x(12x12) ~ **2.8M**
Parameters: (5x5x3)x256 + 256 ~ **20K**

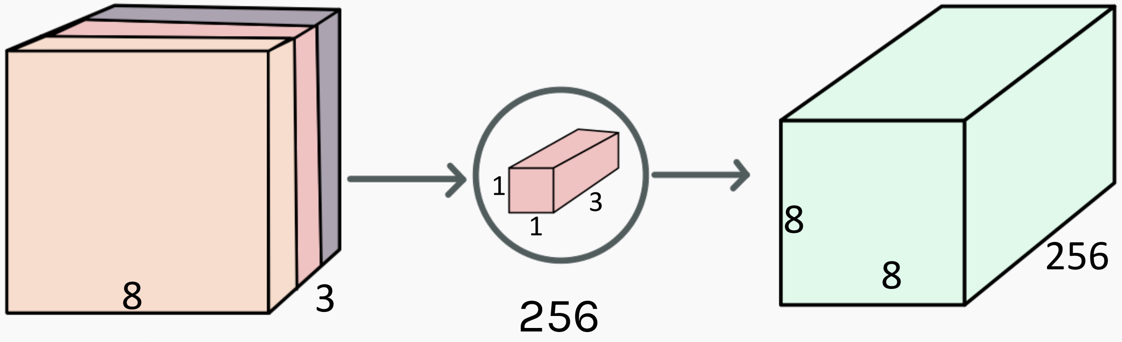
Depth-Wise Separable Convolution (DW)

It combines a depth wise convolution and a pointwise convolution



Input: 12x12x3
Filter: 3x(5x5)

Output: 8x8x3
(no padding)



Input: 8x8x3
Filter: 1x1x3x256

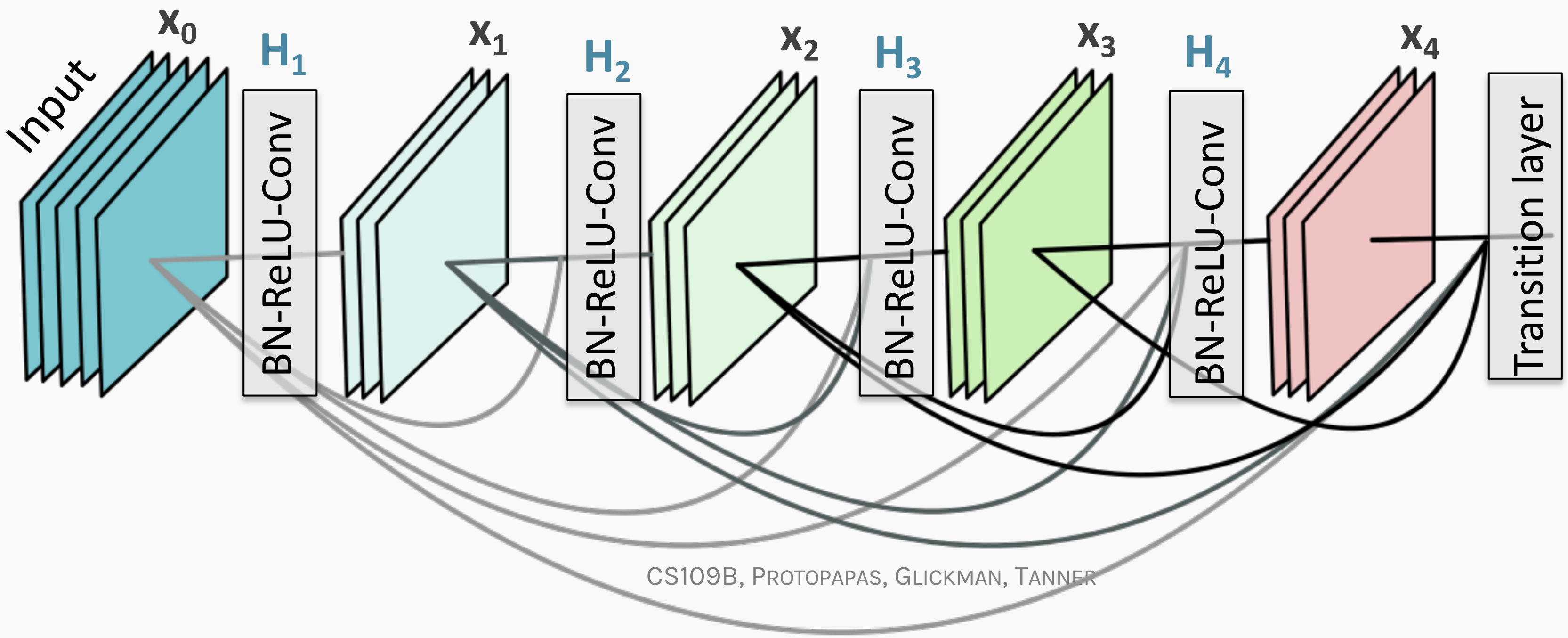
Output: 8x8x256
(no padding)

MACs: (5x5)x3x(12x12) + 3x256x(8x8) ~ **60K**
Parameters: (5x5x3 + 3) + (1x1x3x256+256) ~ **1K**

SOTA Deep Models: DenseNets

- **Goal**: allow maximum information (and gradient) flow → connect every layer directly with each other.
- DenseNets exploit the potential of the network through feature reuse → no need to learn redundant feature maps.
- DenseNets layers are very narrow (e.g. 12 filters), and they just add a small set of new feature-maps.

DENSE BLOCK



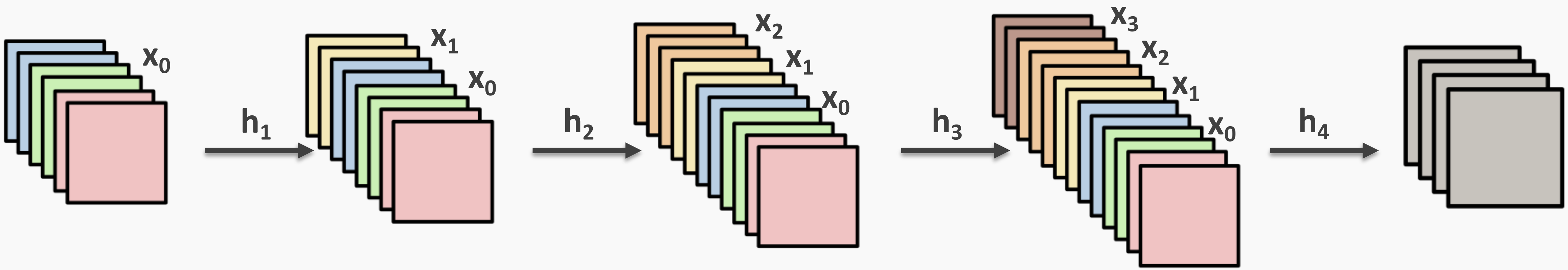
SOTA Deep Models: DenseNets

- DenseNets do not sum the output feature maps of the layer with the incoming feature maps but concatenate them:

$$a^{[l]} = g\left(\left[a^{[0]}, a^{[1]}, \dots, a^{[l-1]}\right]\right)$$

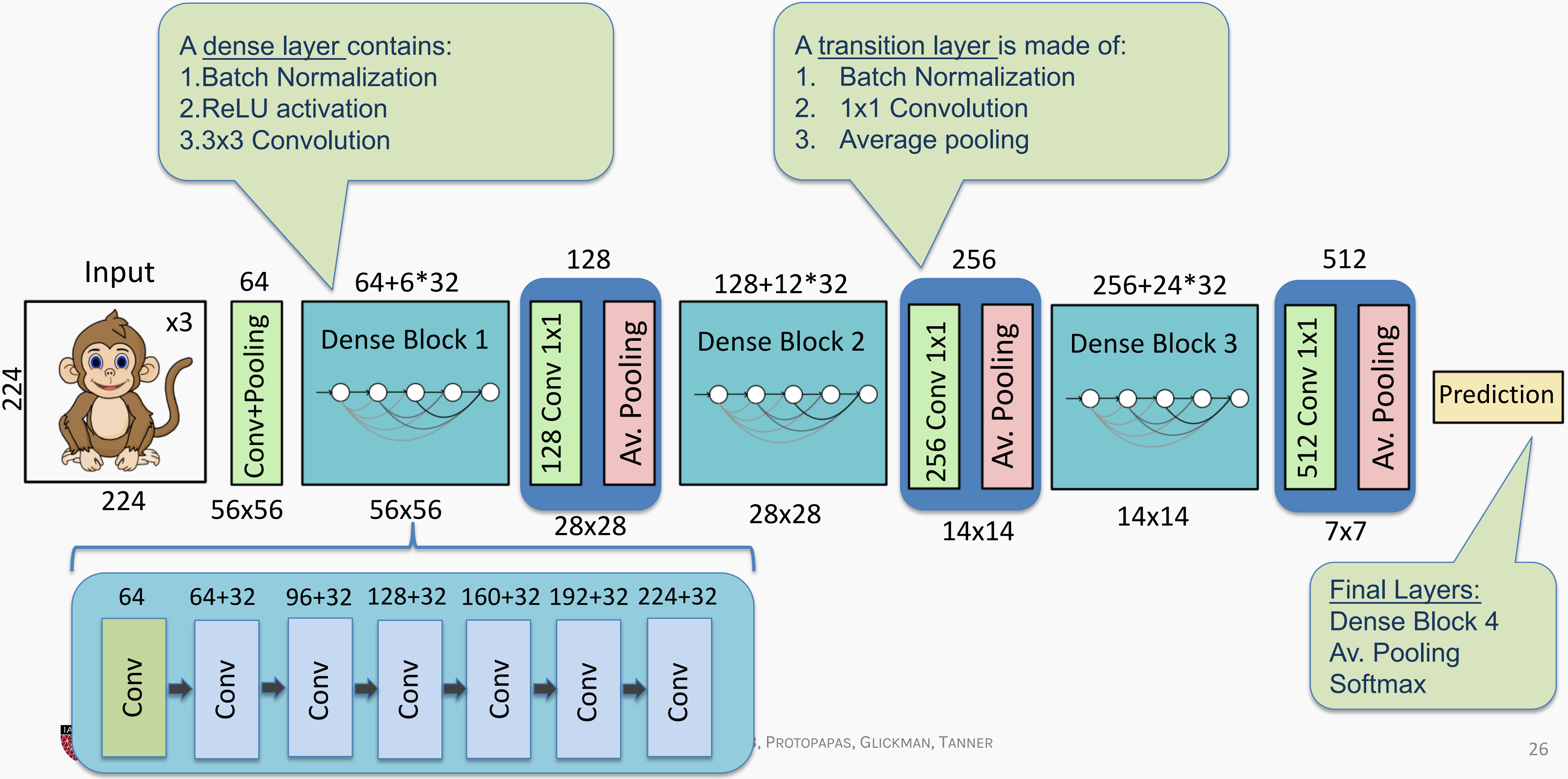
- Dimensions of the feature maps remains constant within a block, but the number of filters changes between them → **growth rate**:

$$k^{[l]} = k^{[0]} + k(l-1)$$



Concatenation during forward propagation

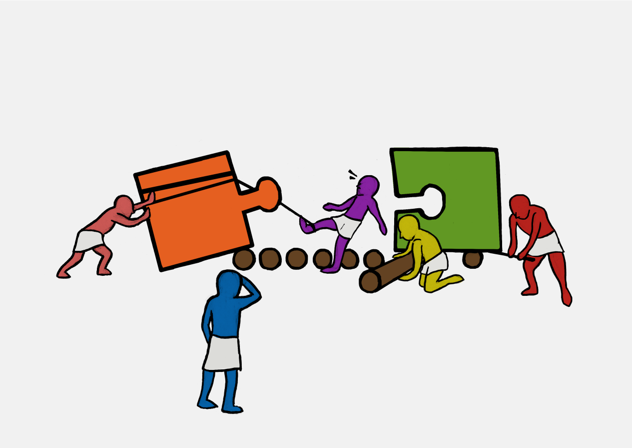
SOTA Deep Models: DenseNets



Beyond

- MobileNetV2 (https://arxiv.org/abs/1801.04381)
- Inception-Resnet, v1 and v2 (https://arxiv.org/abs/1602.07261)
- Wide-Resnet (https://arxiv.org/abs/1605.07146)
- Xception (https://arxiv.org/abs/1610.02357)
- ResNeXt (https://arxiv.org/pdf/1611.05431)
- ShuffleNet, v1 and v2 (https://arxiv.org/abs/1707.01083)
- Squeeze and Excitation Nets (https://arxiv.org/abs/1709.01507)

Exercise: Performance comparison of different SOTAs



The goal of this exercise is to compare different architectures on speed, size and performance.
There is very little coding to do in this exercise but familiarize yourself with colab and become comfortable using any of the SOTAs we have presented in this lecture.
WARNING: **DO NOT USE GPU for this exercises!**

Your final plot may **resemble** this one: