CNN Architectures

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ILSVRC

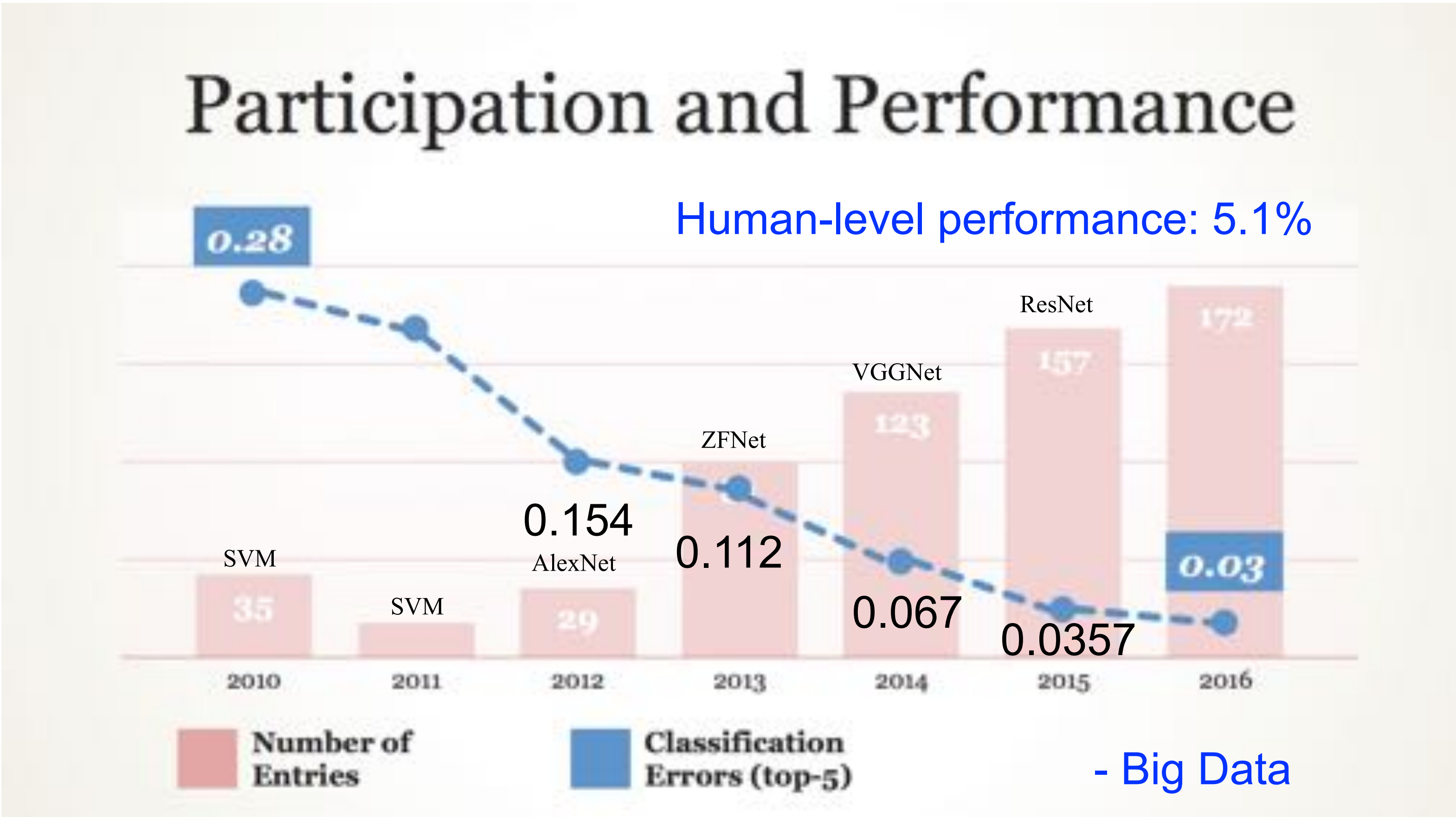
- **Image Classification**
  - one of the core problems in computer vision
  - many other tasks (such as object detection, segmentation) can be reduced to image classification

- **ImageNet Large Scale Visual Recognition Challenge**
  - 2010 - 2017
  - main tasks: classification and detection
  - a large-scale benchmark for image classification methods
    - 1000 classes
    - 1.2 million training images
    - 50 thousand verification images
    - 150 thousand test images

** Some slides are borrowed from cs231n.stanford.edu*

ILSVRC

ILSVRC



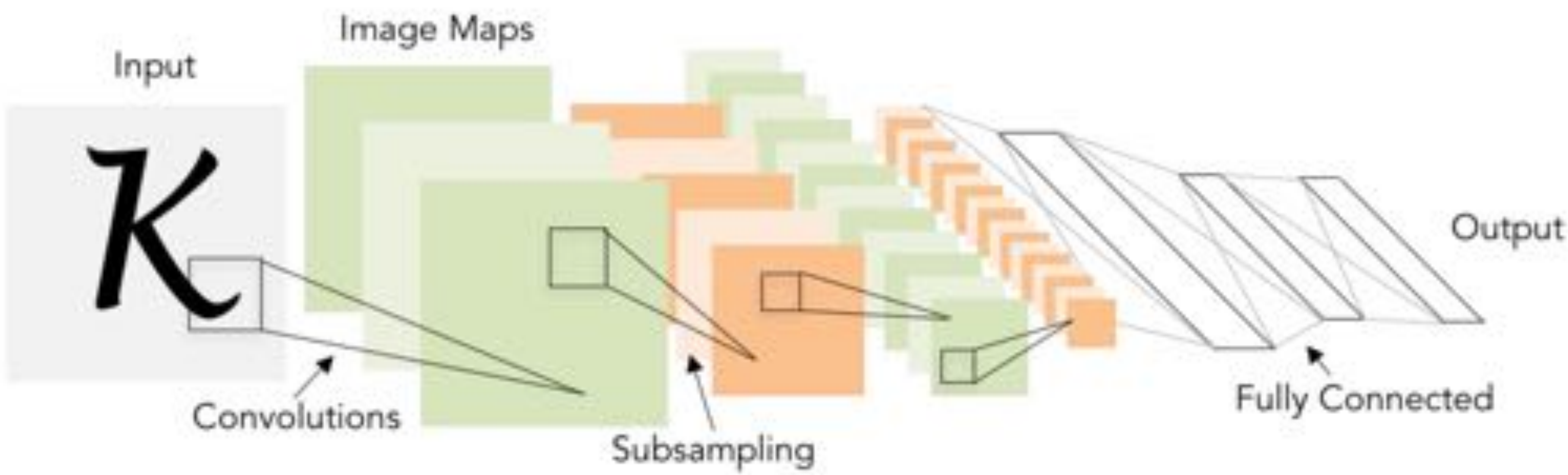
- Big Data
- GPU
- Algorithm improvement

Winning CNN Architectures

Model	AlexNet	ZF Net	GoogLeNet	Resnet
Year	2012	2013	2014	2015
#Layer	8	8	22	152
Top 5 Acc	15.4%	11.2%	6.7%	3.57%
Data augmentation	√	√	√	√
Dropout	√	√		
Batch normalization				√

CNN Architecture: Part I

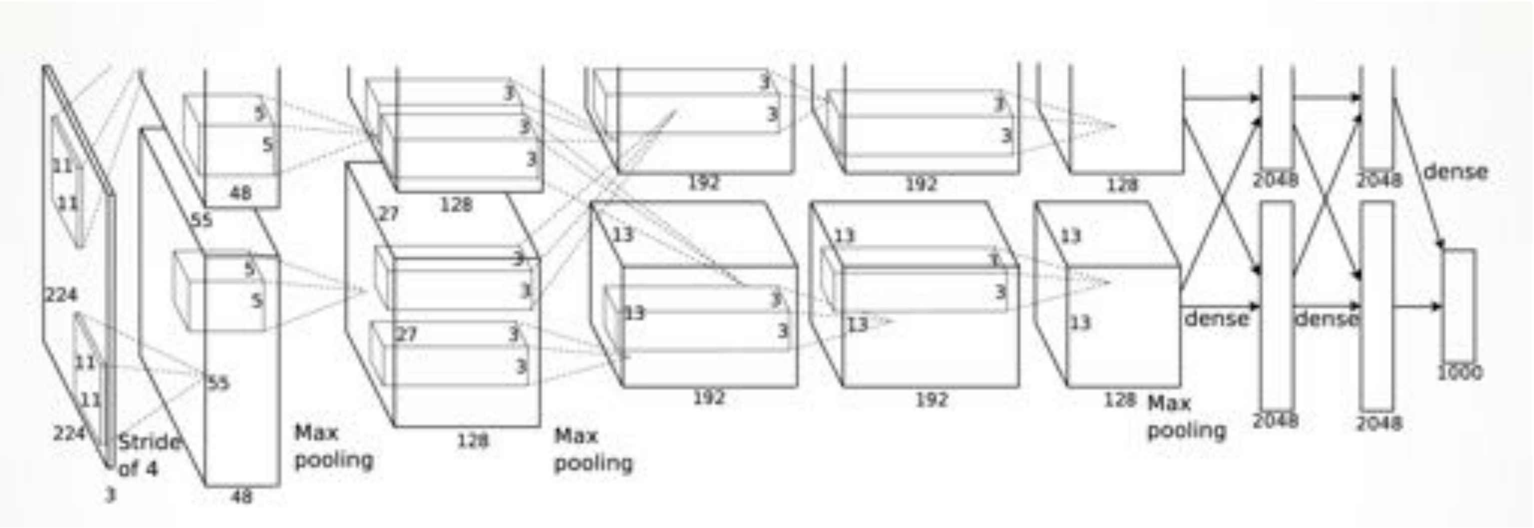
❑ **LeNet** [LeCun et al., 1998]



- Architecture is [CONV-POOL-CONV-POOL-FC-FC]
- CONV: 5x5 filter, stride=1
- POOL: 2x2 filter, stride=2

CNN Architecture: Part I

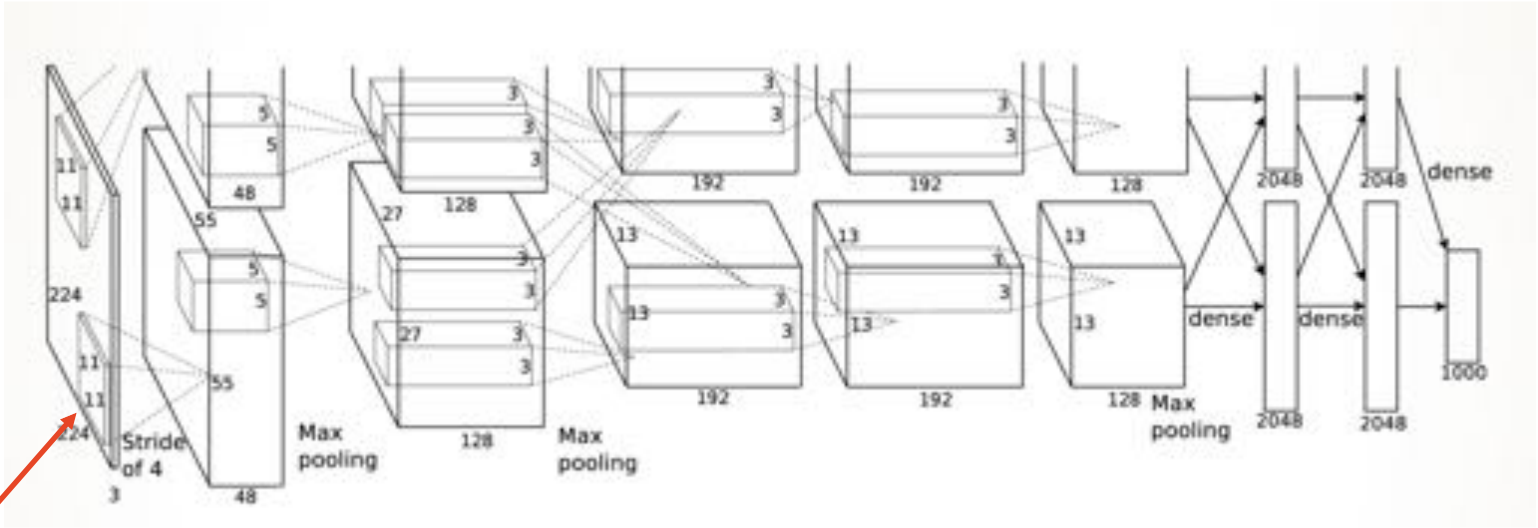
- **AlexNet** [Krizhevsky et al. 2012]



ILSVRC2010: 28.2%
ILSVRC2011: 25.8%
ILSVRC2012: 16.4% (second winner 26.2%)

CNN Architecture: Part I

❑ **AlexNet** [Krizhevsky et al. 2012] -5 conv layers, 3 fully connected layers.



11x11 filters

- Activation function: ReLU
- Data Augmentation
- Dropout (drop rate=0.5)
- Local Response Normalization
- Overlapping Pooling

CNN Architecture: Part I

❑ **AlexNet** [Krizhevsky et al. 2012] -5 conv layers, 3 fully connected layers.

- Activation function: ReLU
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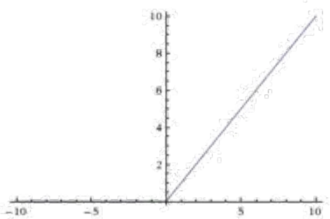


$$f(x) = \begin{cases} 0 & \text{for } x < 0 \\ x & \text{for } x \ge 0 \end{cases}$$

$$f'(x) = \begin{cases} 0 & \text{for } x < 0 \\ 1 & \text{for } x \ge 0 \end{cases}$$

Pros:

- Easy to feed forward
- Easy to back propagate
- Help prevent saturation
- Sparse

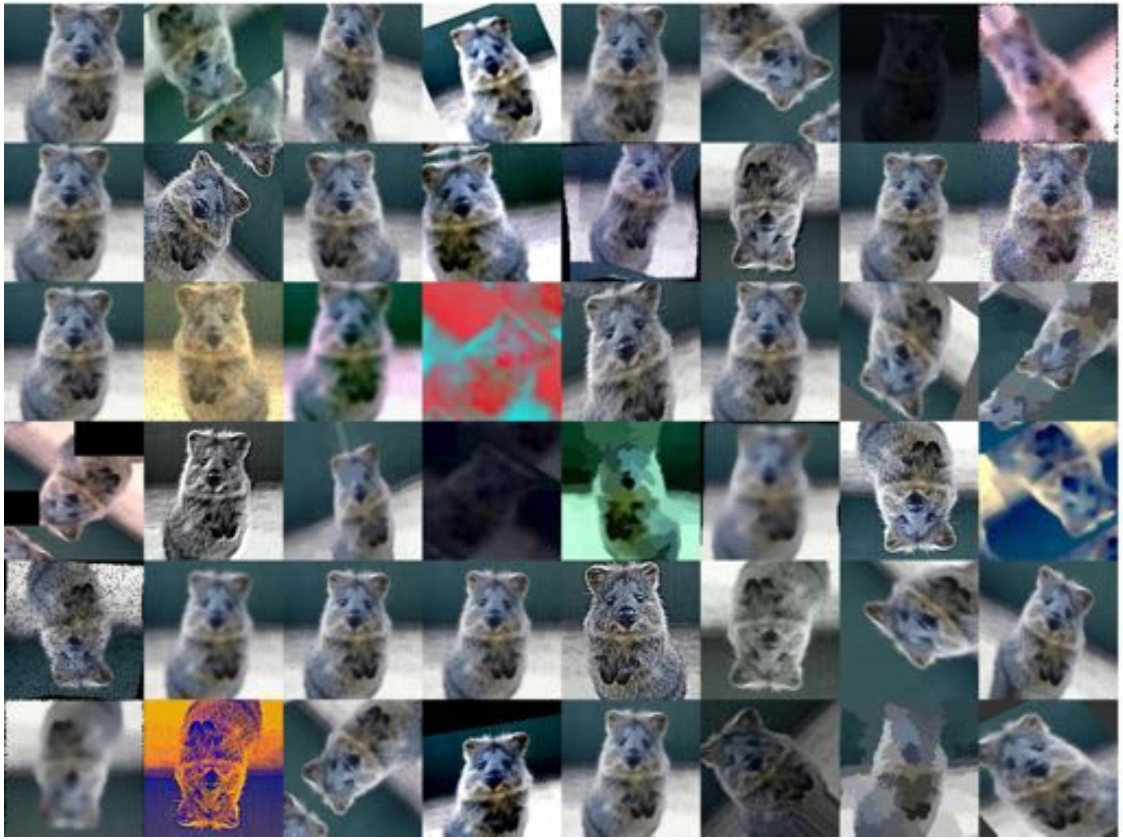
Cons:

- Dead ReLU

CNN Architecture: Part I

❑ AlexNet [Krizhevsky et al. 2012]

- Activation function: ReLU
- Data Augmentation
- Dropout
- Local Response Normalization
- Overlapping Pooling

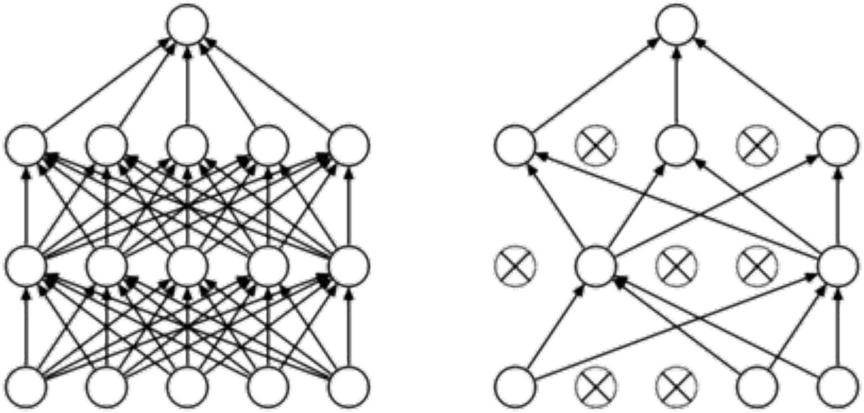


- Randomly Rotate Images
- Flip Images
- Shift Images
- Contrast Stretching
- Adaptive Equalization
- etc.

CNN Architecture: Part I

❑ **AlexNet** [Krizhevsky et al. 2012]

- Activation function: ReLU
- Data Augmentation
- Dropout
- Local Response Normalization
- Overlapping Pooling



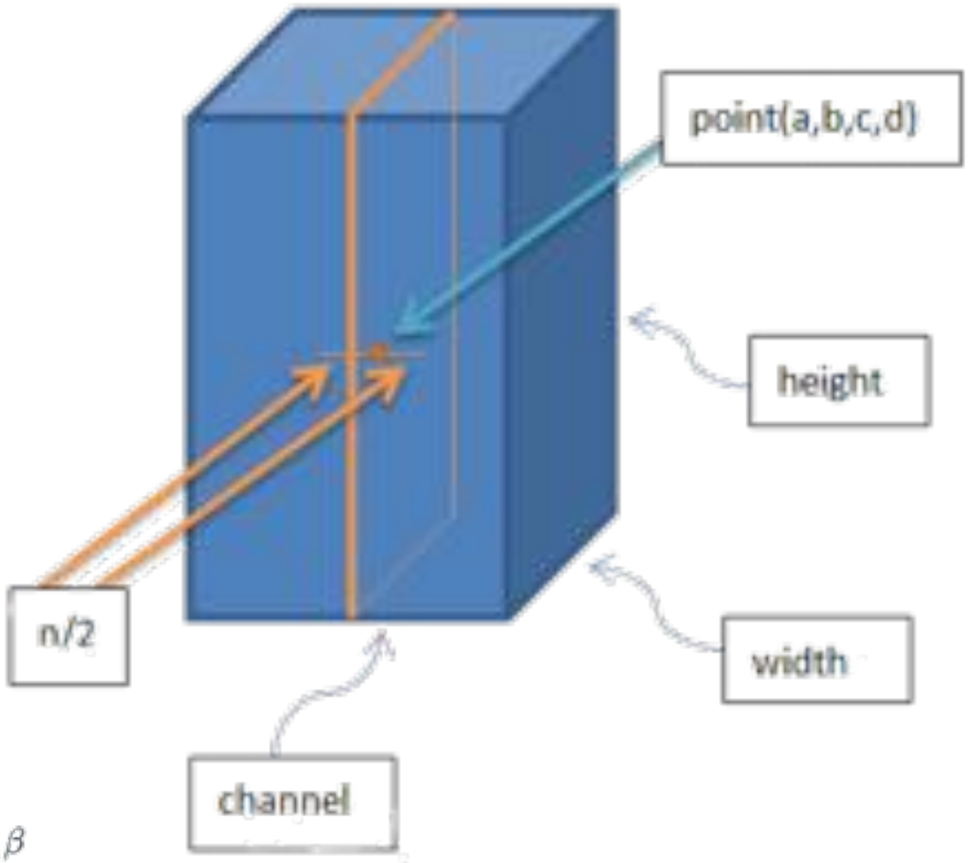
In practice, dropout trains 2^n networks (n – number of units).

Drop is a technique which deal with overfitting by combining the predictions of many different large neural nets at test time.

CNN Architecture: Part I

❑ **AlexNet** [Krizhevsky et al. 2012]

- Activation function: ReLU
- Data Augmentation
- Dropout
- Local Response Normalization
- Overlapping Pooling

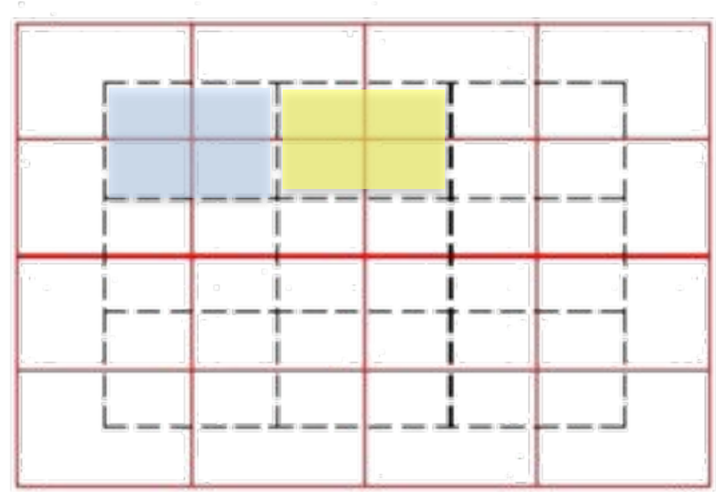


$$b^i_{x,y} = a^i_{x,y} / (k + \alpha \sum_{j=max(0,i-n/2)}^{min(N-1,i+n/2)} (a^i_{x,y})^2)^\beta$$

CNN Architecture: Part I

❑ AlexNet [Krizhevsky et al. 2012]

- Activation function: ReLU
- Data Augmentation
- Dropout
- Local Response Normalization
- Overlapping Pooling



Pooling stride < Pooling kernel size

Overlapping Pooling

-1	4	1	2
0	1	3	-2
1	5	-2	6
3	-1	-2	-2

Feature map

4	3
5	6

Max pooling

1	1
2	0

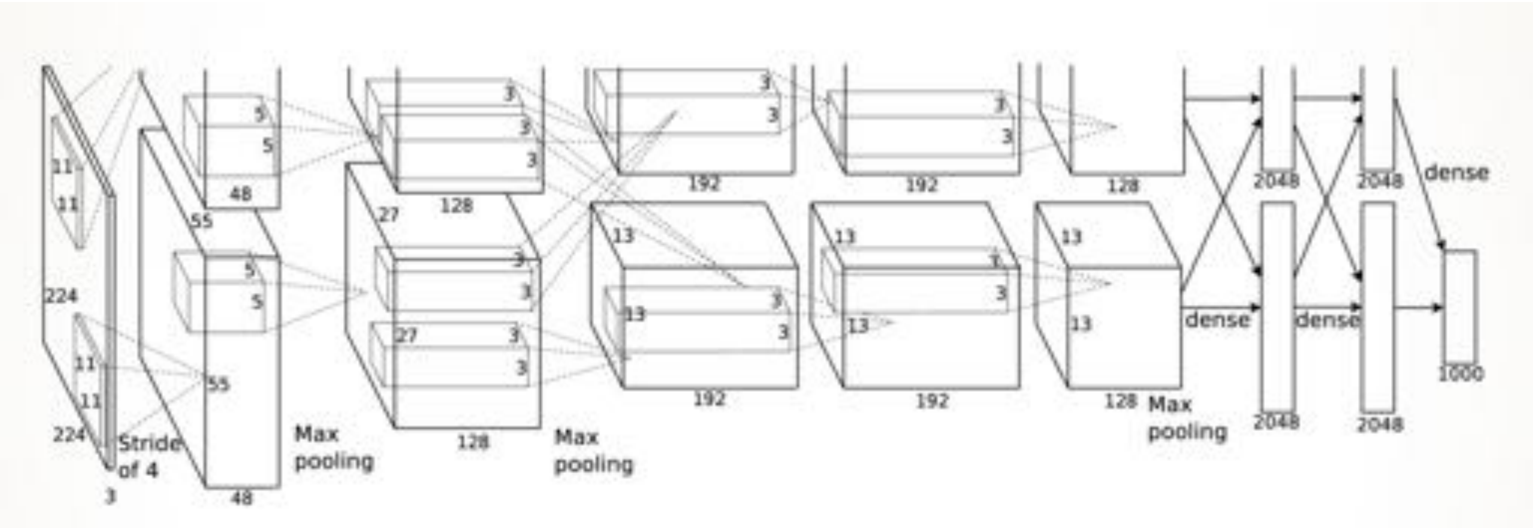
Average pooling

Standard Pooling

Pooling stride = Pooling kernel size

CNN Architecture: Part I

- **AlexNet** [Krizhevsky et al. 2012]

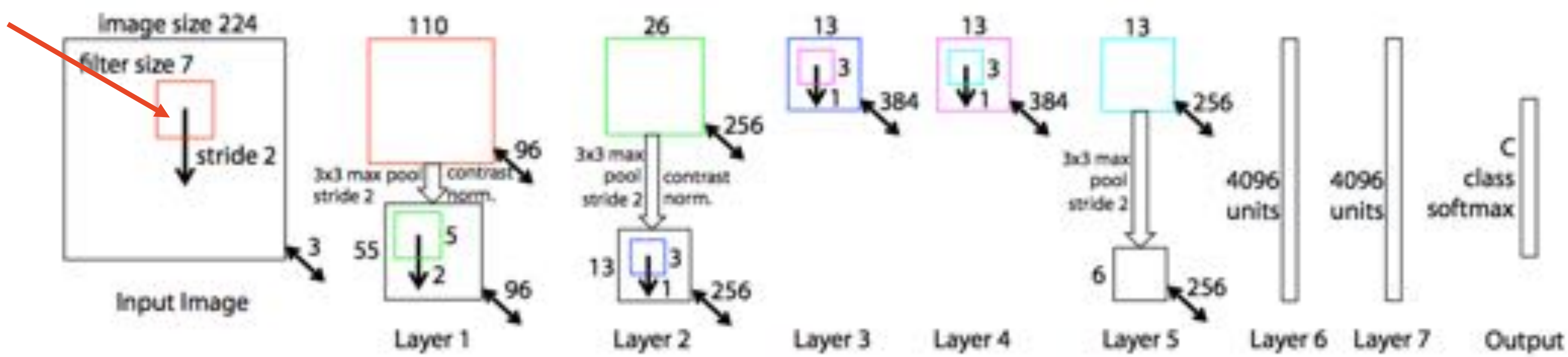


The problem set is divided into 2 parts, half executing on GPU 1 & another half on GPU 2.

CNN Architecture: Part I

❑ ZFNet [Zeiler and Fergus, 2013]

7x7 filters



- An improved version of AlexNet: top-5 error from 16.4% to 11.7%
- First convolutional layer: 11x11 filter, stride=4 -> 7x7 filter, stride=2
- The number of filters increase as we go deeper.

CNN Architecture: Part I

❑ VGGNet [Simonyan and Zisserman, 2014]

Small filters:
- 3x3 convolutional layers (stride 1, pad 1)
- 2x2 max-pooling, stride 2

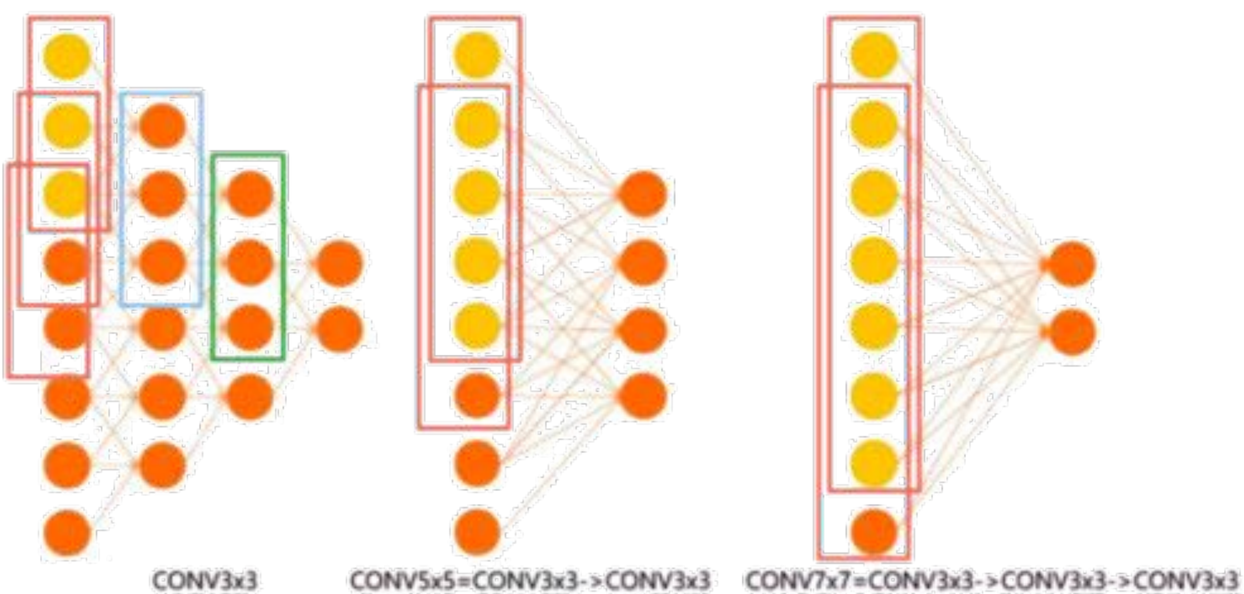
Deeper networks:
- AlexNet: 8 layers
- VGGNet: 16 or 19 layers

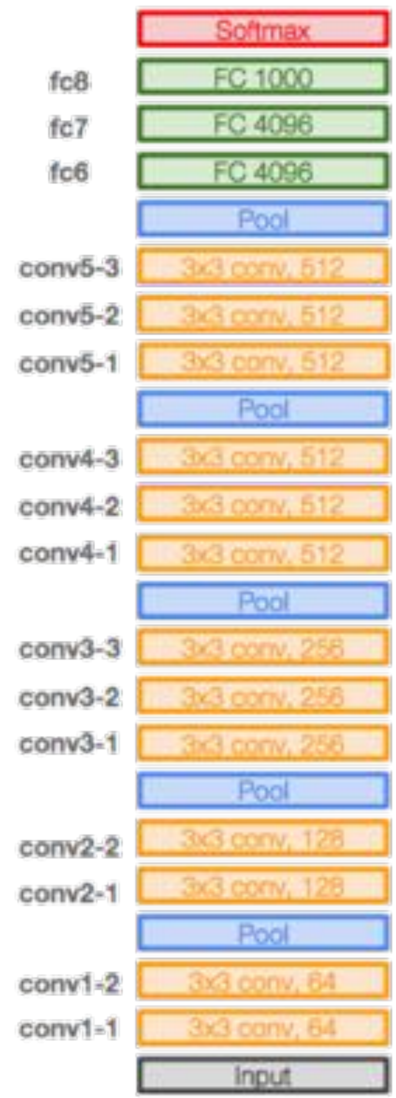
CNN Architecture: Part I

Why small filters?

- Two 3x3 layer = 5x5 layer
  Three 3x3 layer = 7x7 layer
- Deeper, more non-linearity
- Less parameters

Receptive Field (RF): the region in the input space that a particular CNN's feature is looking at (i.e. be affected by).





VGG16

Image credit to mc.ai

CNN Architecture: Part I

Why small filters?

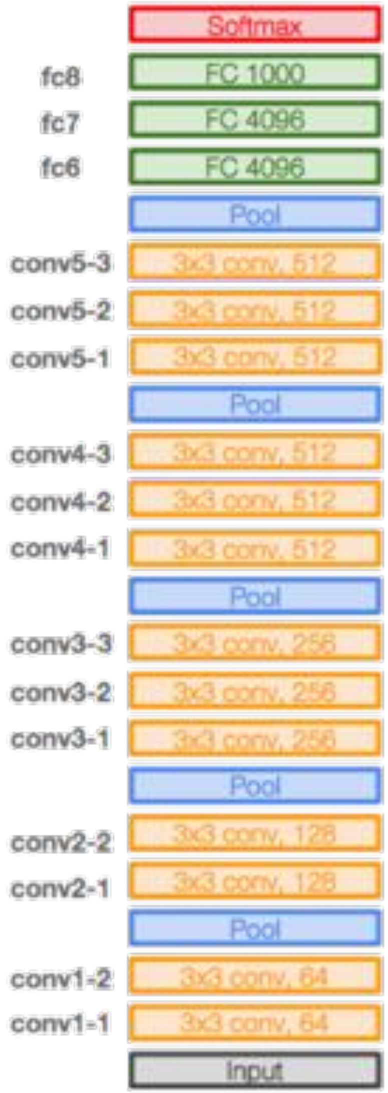
- Two 3x3 layer = 5x5 layer
  Three 3x3 layer = 7x7 layer
- Deeper, more non-linearity
- Less parameters

Why popular?

- FC7 features generalize well to other tasks
- Plain network structure

The rule for network design

- Prefer a stack of small filters to a large filter



VGG16

Image credit to: http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture9.pdf

CNN Architecture: Part I

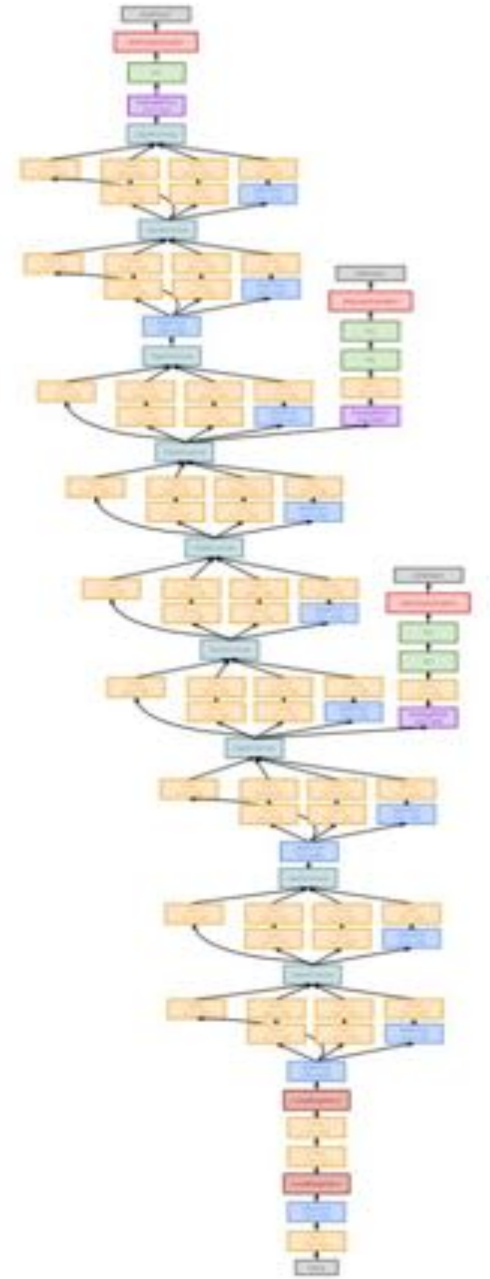
❑ **GoogLeNet** [Szegedy et al., 2014]

Deeper networks

- 22 layers.
- Auxiliary loss

Computational efficiency

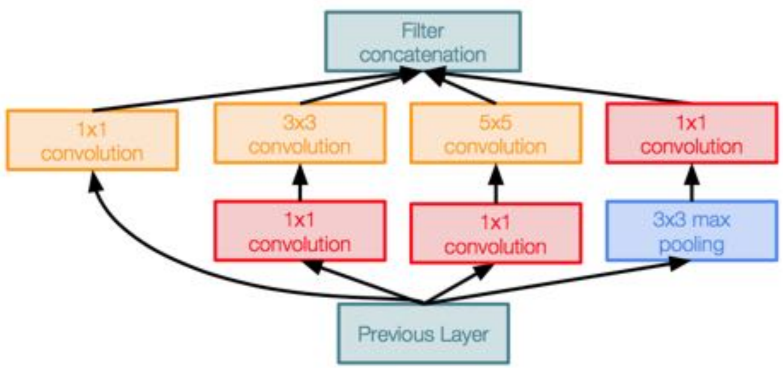
- Inception module
- Remove FC layer, use global average pooling
- 12x less parameters than AlexNet



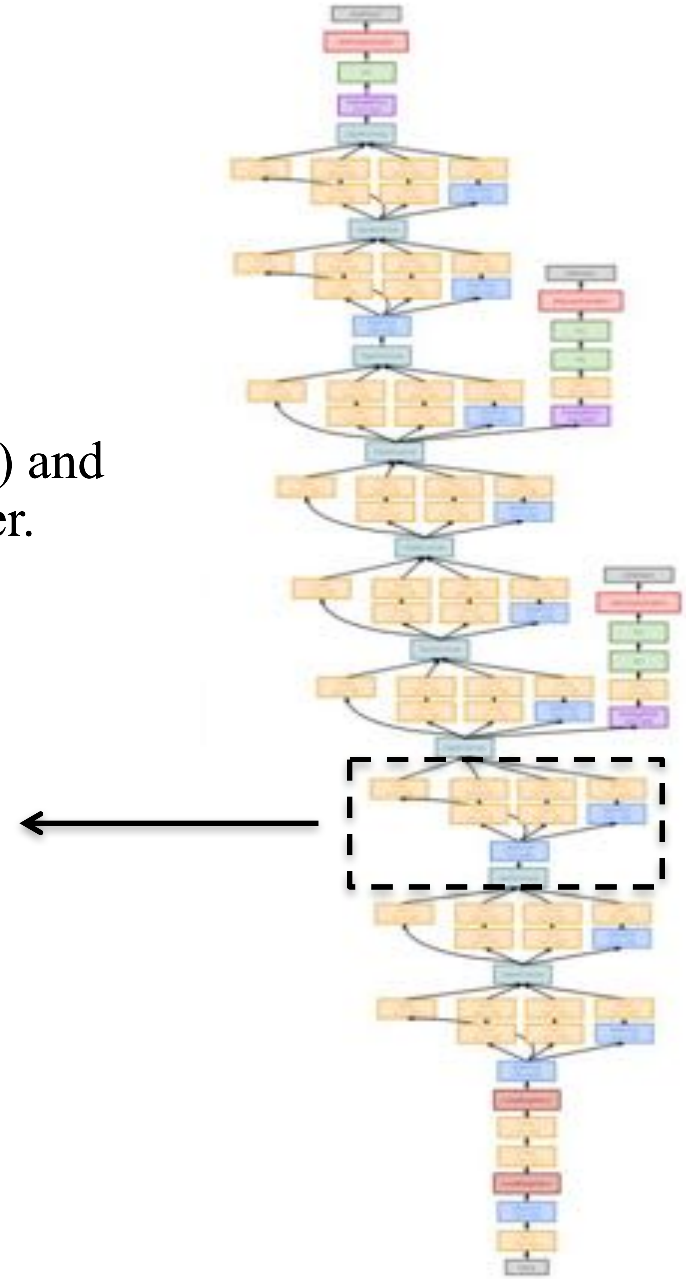
CNN Architecture: Part I

- ❑ **GoogLeNet** [Szegedy et al., 2014]

Design a good local network topology (NIN) and then stack these modules on top of each other.



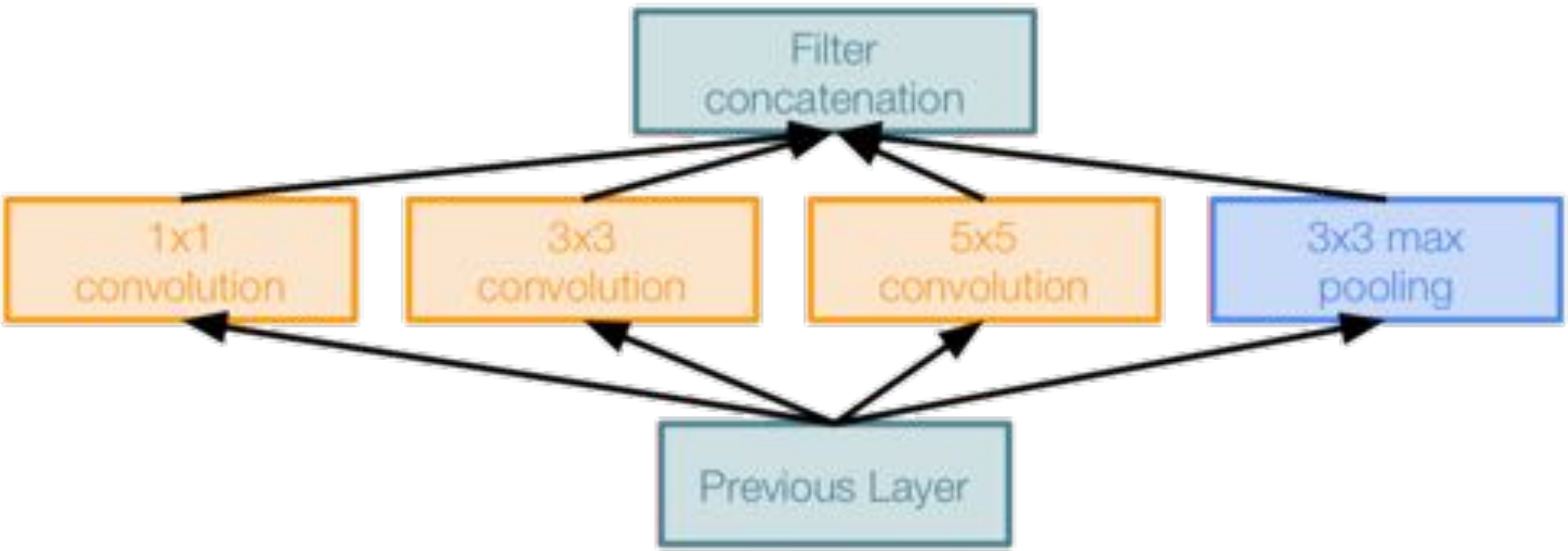
Inception module



CNN Architecture: Part I

❑ **GoogLeNet** [Szegedy et al., 2014]

- Different receptive fields
- The same feature dimension
- The effectives of pooling

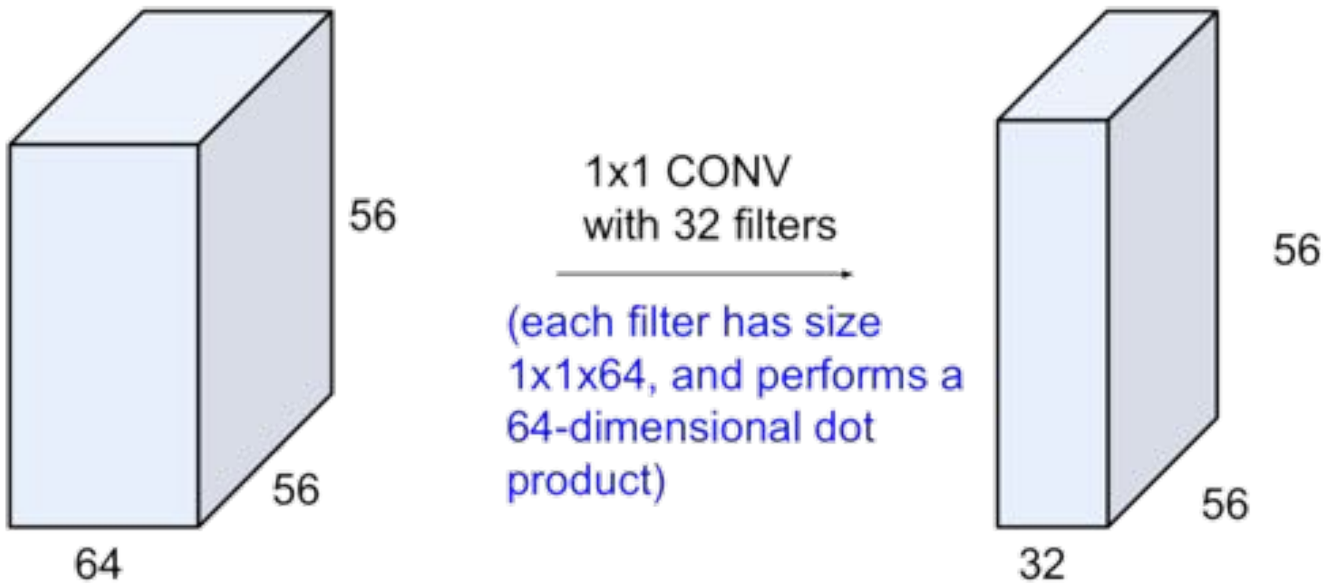


Naive Inception module

$$\text{Output Size} = \frac{N+2P-K}{S} + 1$$

CNN Architecture: Part I

- ❑ **GoogLeNet** [Szegedy et al., 2014]



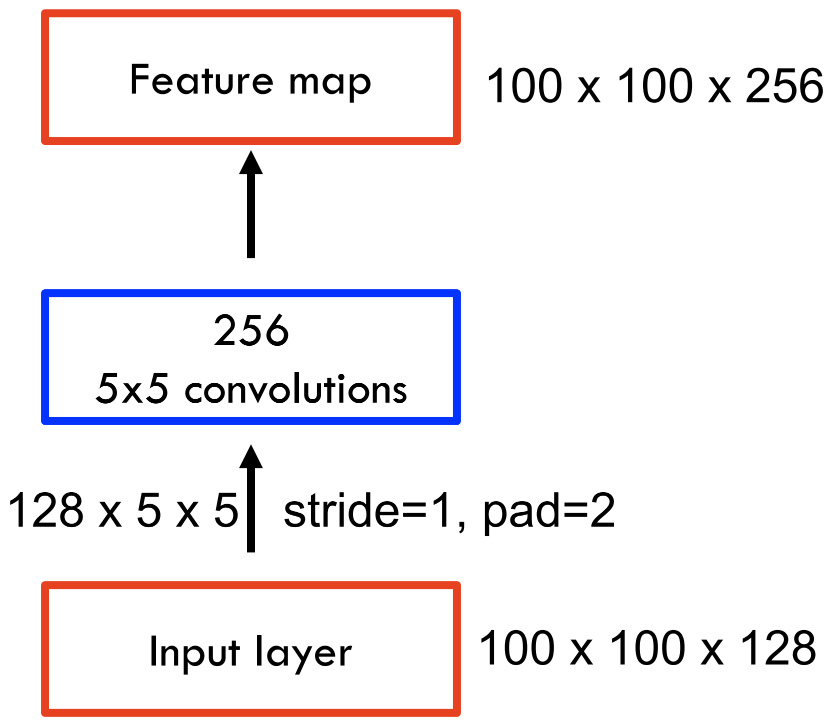
1x1 convolutional layer

- preserve spatial dimensions (56x56)
- reduces depth (64 -> 32)

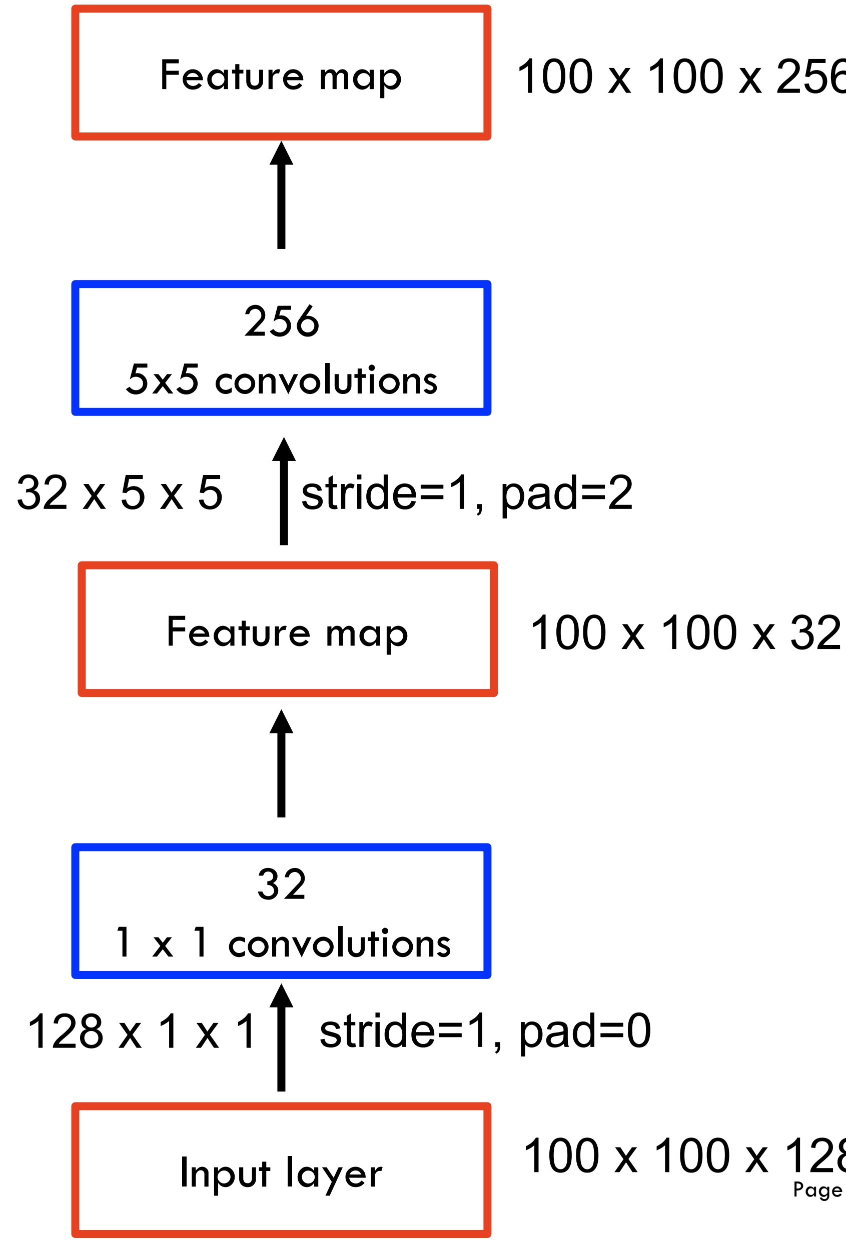
CNN Architecture: Part I

- ❑ **GoogLeNet** [Szegedy et al., 2014]

#parameter: 128x5x5x256

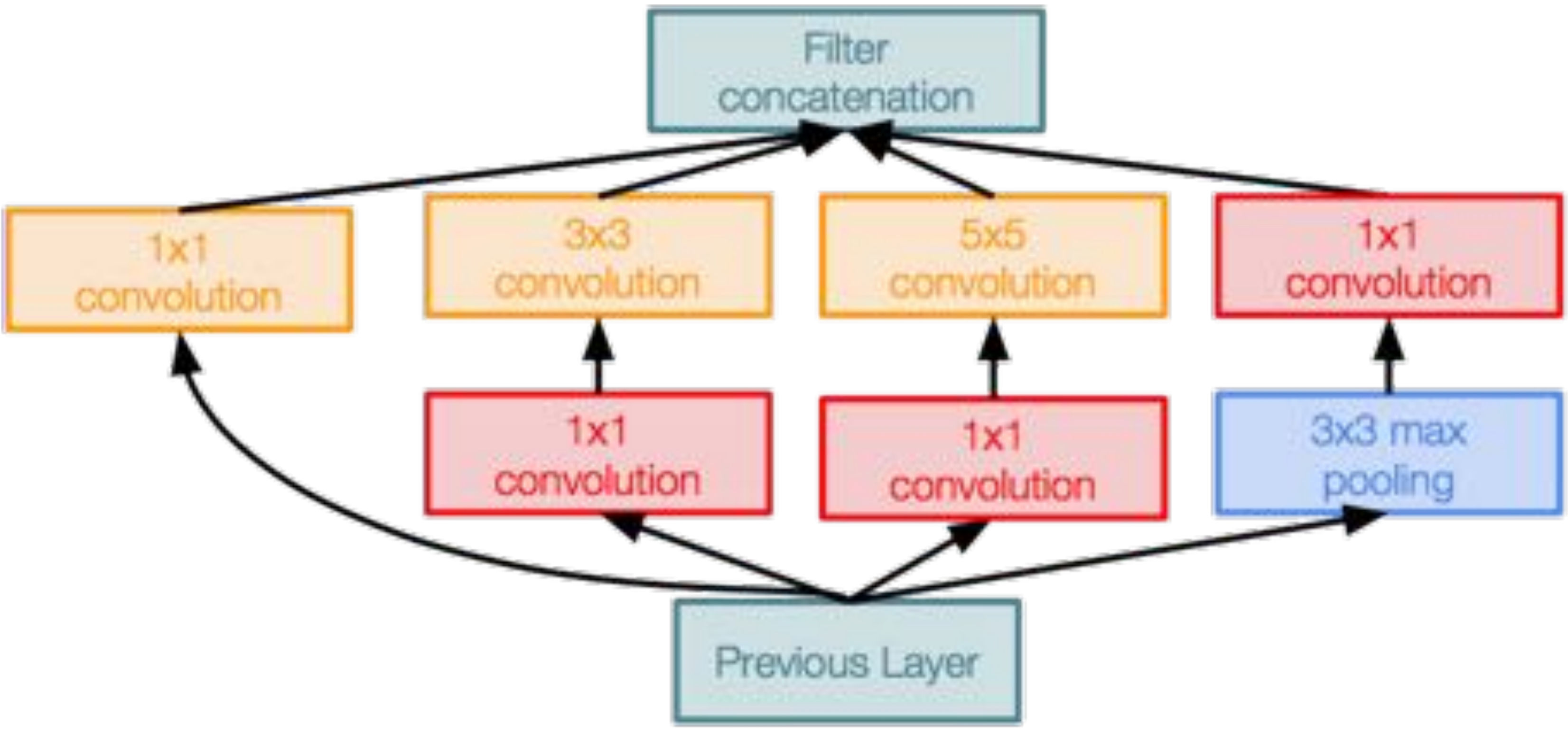


#parameter: 128x1x1x32 + 32x5x5x256



CNN Architecture: Part I

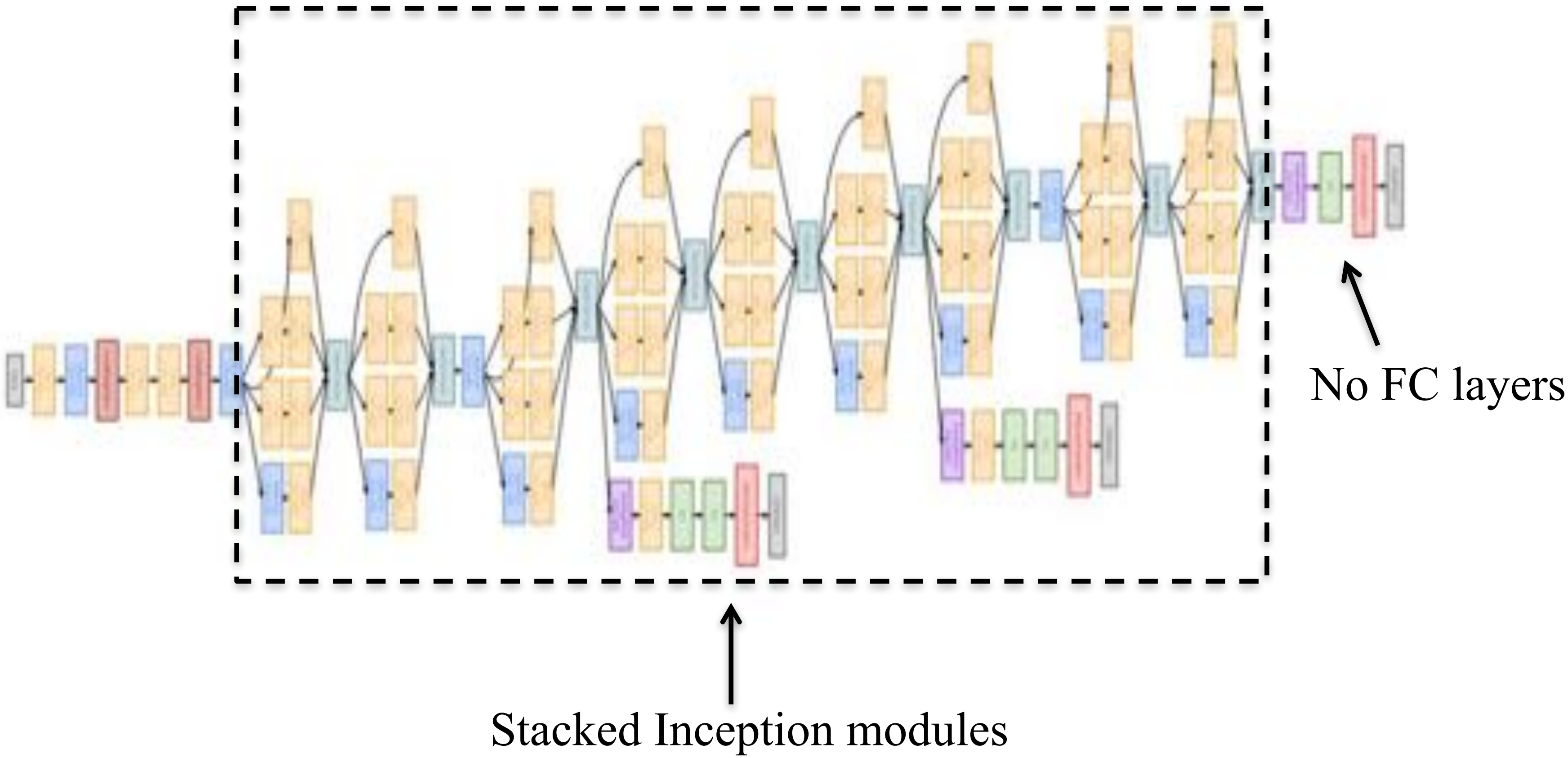
- ❑ **GoogLeNet** [Szegedy et al., 2014]



Inception module

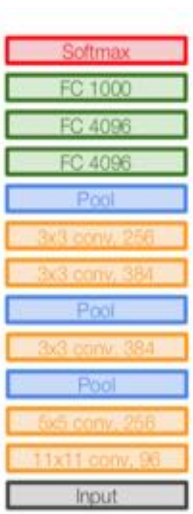
CNN Architecture: Part I

❑ GoogLeNet [Szegedy et al., 2014]

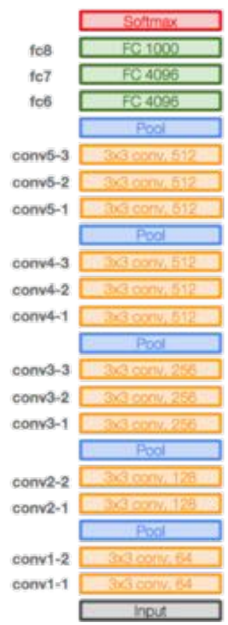


CNN Architecture: Part I

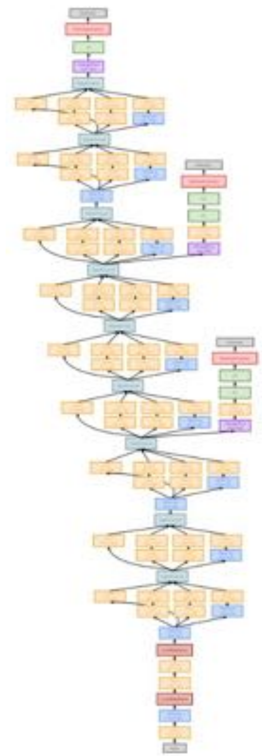
The deeper model should be able to perform at least as well as the shallower model.



AlexNet (9 layers)



VGG16 (16 layers)



GoogLeNet (22 layers)

CNN Architecture: Part I

❑ **ResNet** [He et al., 2015]

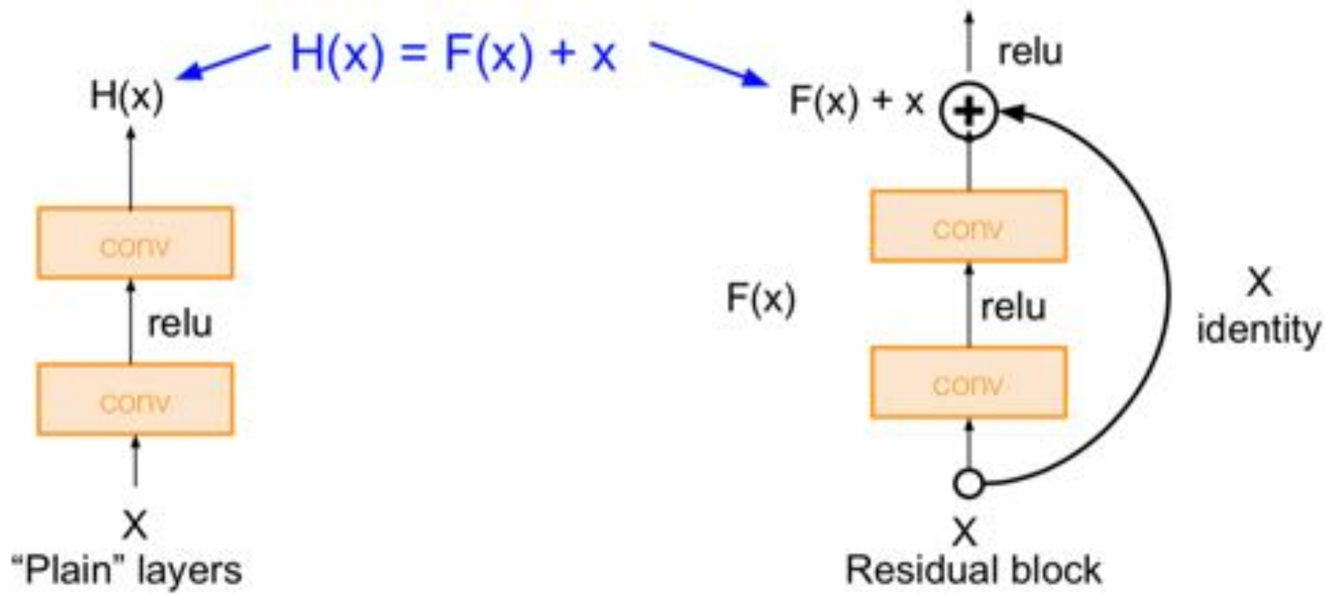
Stacking deeper layers on a "plain" convolutional neural network
=> the deeper model performs worse, but not overfitting.

Hypothesis: deeper models are harder to optimize.

CNN Architecture: Part I

❑ ResNet [He et al., 2015]

Solution: use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping



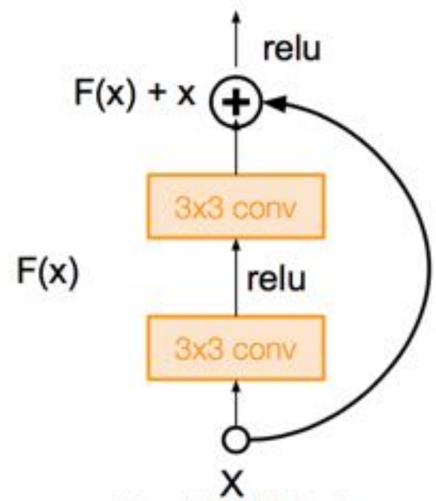
CNN Architecture: Part I

❑ ResNet [He et al., 2015]

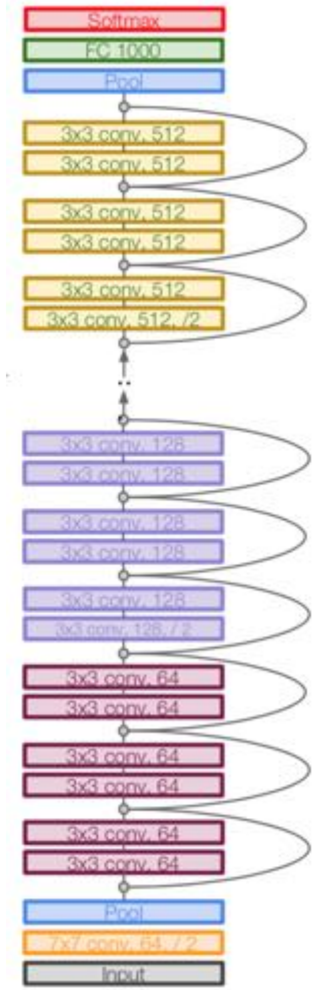
Very deep networks using residual connections

Basic design:

- all 3x3 conv (almost)
- spatial size /2 => #filter x2
- just deep
- average pooling (remove FC)
- no dropout



Residual block

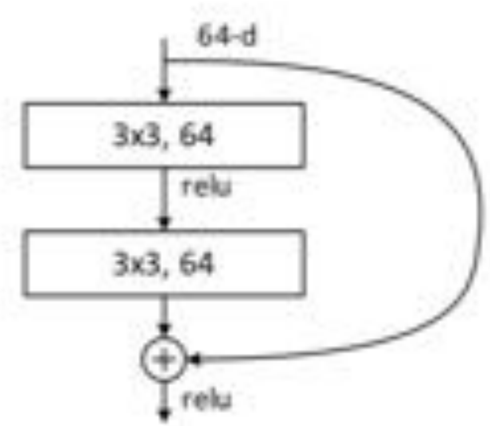


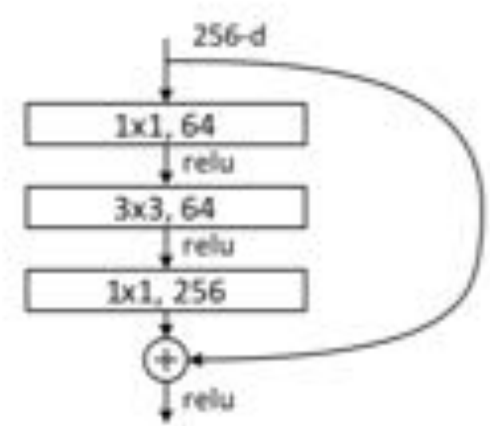
ResNet

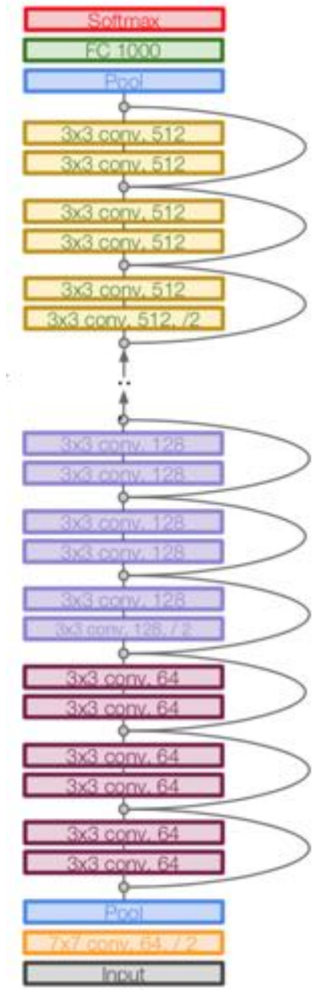
CNN Architecture: Part I

❑ **ResNet** [He et al., 2015]

Use "**bottleneck**" layer to improve efficiency (similar to GoogLeNet).



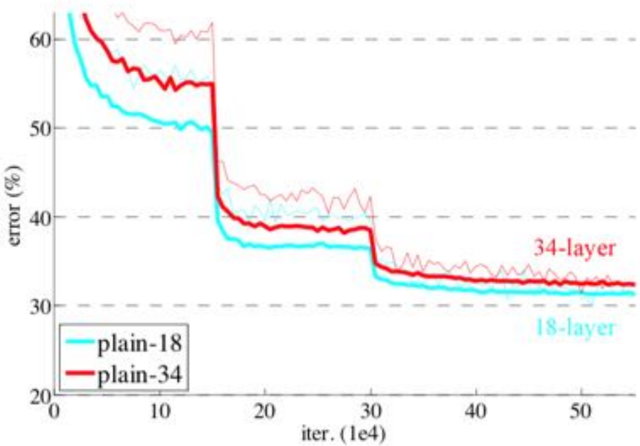


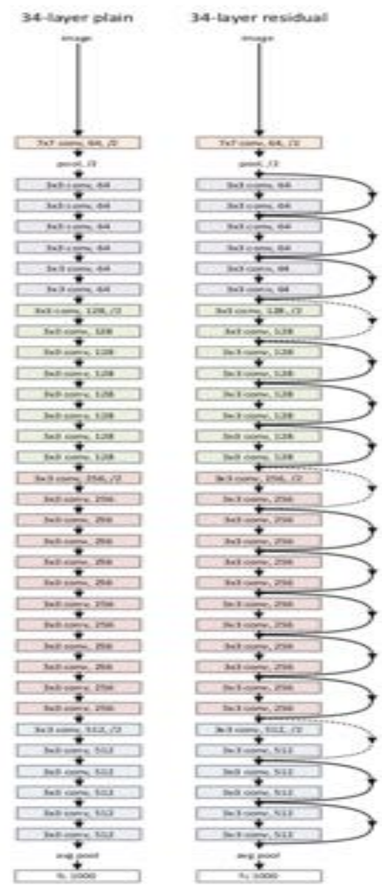


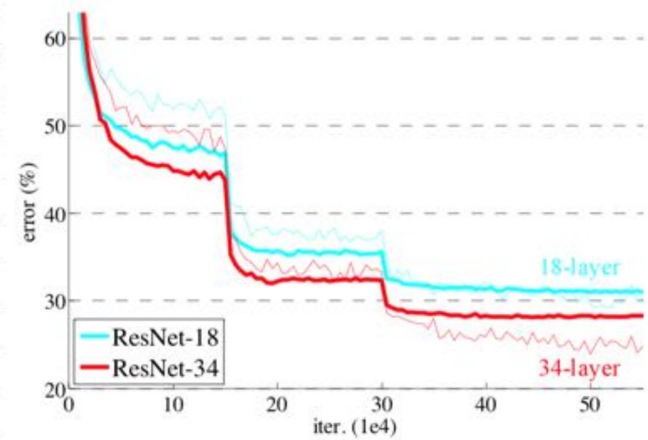
ResNet

CNN Architecture: Part I

- **ResNet** [He et al., 2015]







CNN Architecture: Part I

❑ ResNet [He et al., 2015]

- 1st places in all five main tracks
  - ImageNet Classification: *"Ultra-deep"* 152-layer nets
  - ImageNet Detection: 16% better than 2nd
  - ImageNet Localization: 27% better than 2nd
  - COCO Detection: 11% better than 2nd
  - COCO Segmentation: 12% better than 2nd

Features matter: deeper features are well transferrable

CNN Architecture: Part II

CNN Architecture: Part II

Inception: Inception v1,v2,v3,v4

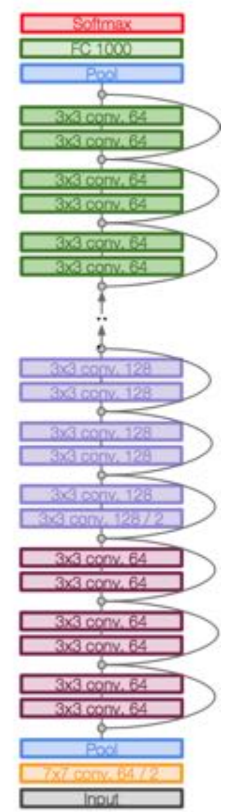
Inception-res-v1,v2

Xception

ResNet: Wide-ResNet

ResNeXt

DenseNet



CNN Architecture: Part II

❑ Inception v2

- batch normalization
- remove LRN and dropout
- small kernels (inspired by VGG)

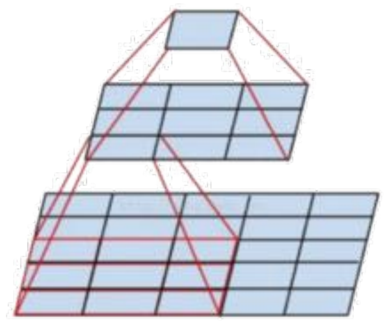
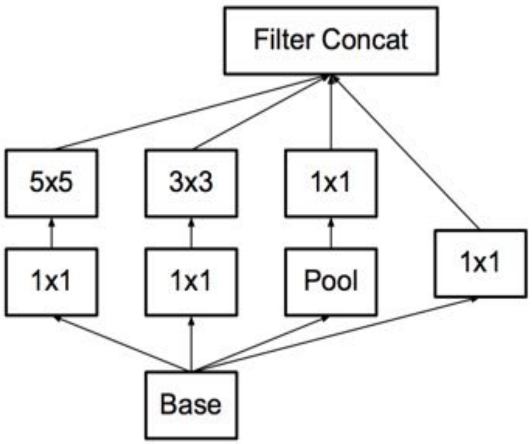
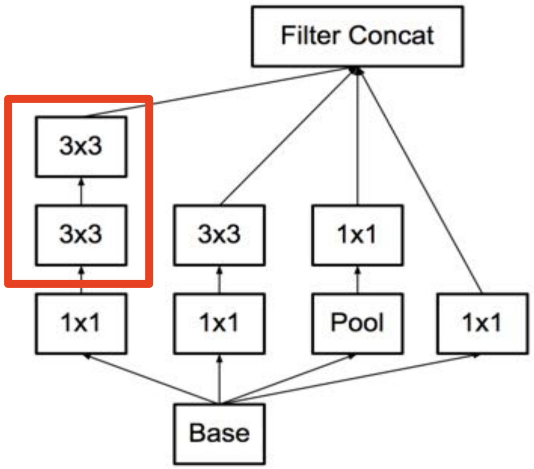
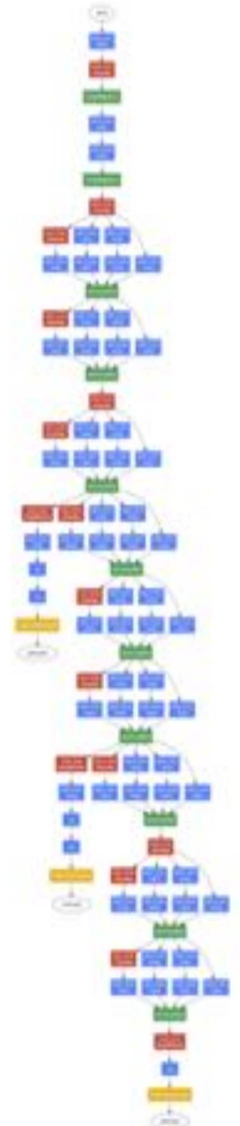


Figure 1. Mini-network replacing the 5 × 5 convolutions.



Inception module v1
(In GoogLeNet)





CNN Architecture: Part II

❑ Inception v2

Factorization

- 7x7 filter -> 7x1 and 1x7 filters
- 3x3 filter -> 3x1 and 1x3 filters

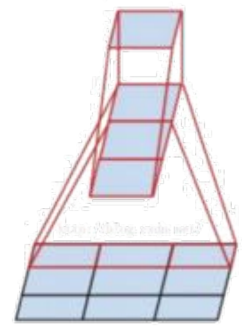
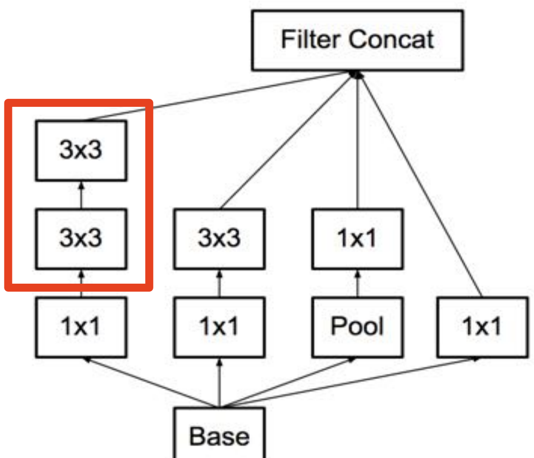
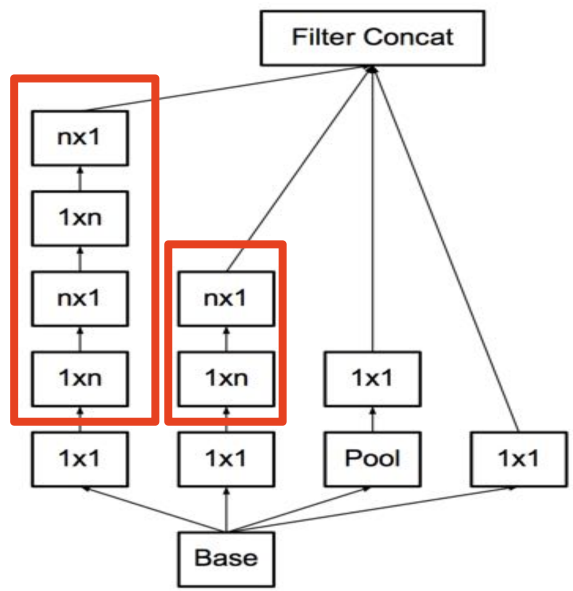


Figure 3. Mini-network replacing the 3 × 3 convolutions. The lower layer of this network consists of a 3 × 1 convolution with 3 output units.





CNN Architecture: Part II

❑ Inception v3

Label Smoothing

For a training example with ground-truth label y, we replace the label distribution with

$$q'(k|x) = (1-\epsilon)q(k|x) + \epsilon u(k)$$

Network	Top-1 Error	Top-5 Error	Cost Bn Ops
GoogLeNet [20]	29%	9.2%	1.5
BN-GoogLeNet	26.8%	-	**1.5**
BN-Inception [7]	25.2%	7.8	2.0
Inception-v2	23.4%	-	3.8
Inception-v2 RMSProp	23.1%	6.3	3.8
Inception-v2 Label Smoothing	22.8%	6.1	3.8
Inception-v2 Factorized 7×7	21.6%	5.8	4.8
Inception-v2 BN-auxiliary	**21.2%**	**5.6%**	4.8

CNN Architecture: Part II

❑ Inception v4

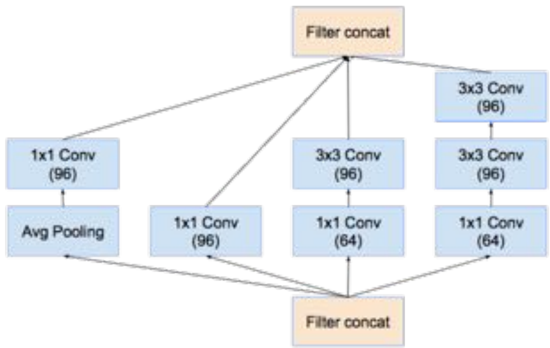


Figure 4. The schema for 35 × 35 grid modules of the pure Inception-v4 network. This is the Inception-A block of Figure 9.

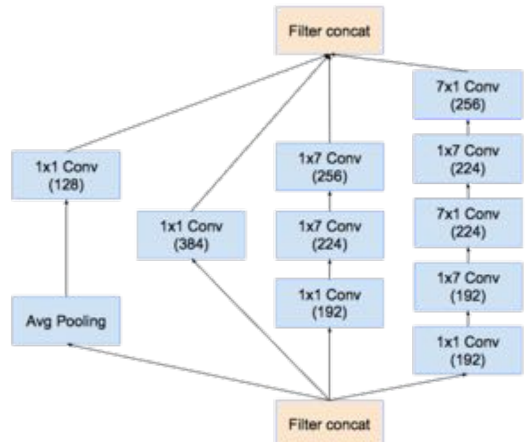


Figure 5. The schema for 17 × 17 grid modules of the pure Inception-v4 network. This is the Inception-B block of Figure 9.

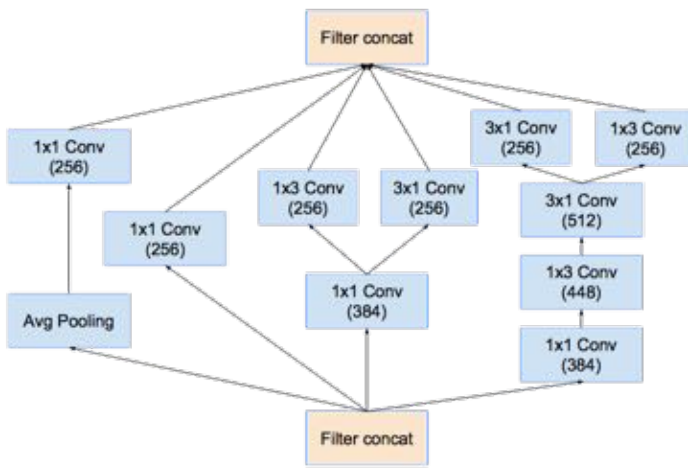
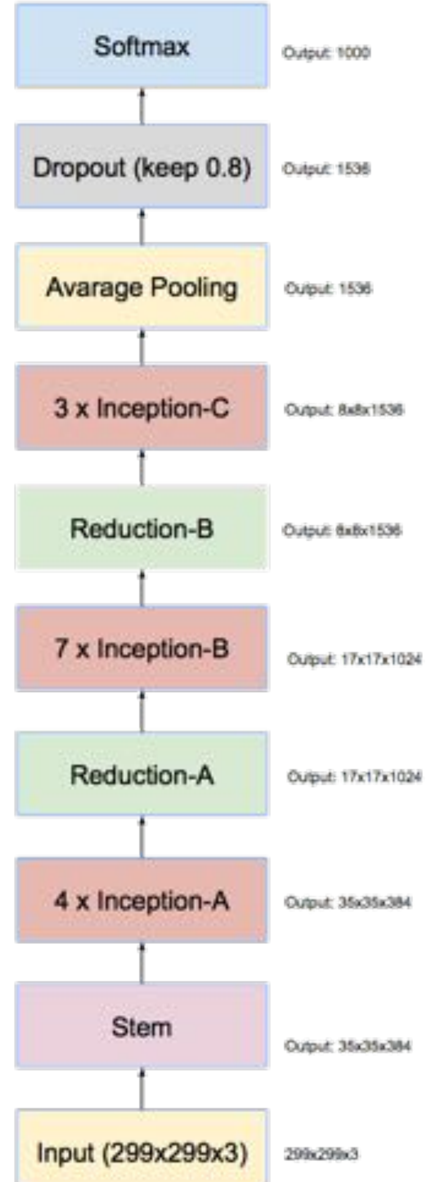


Figure 6. The schema for 8 × 8 grid modules of the pure Inception-v4 network. This is the Inception-C block of Figure 9.



CNN Architecture: Part II

❑ Inception-ResNet v1, v2

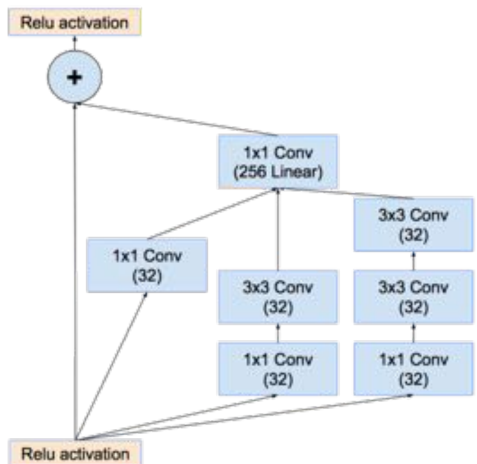


Figure 10. The schema for 35 × 35 grid (Inception-ResNet-A) module of Inception-ResNet-v1 network.

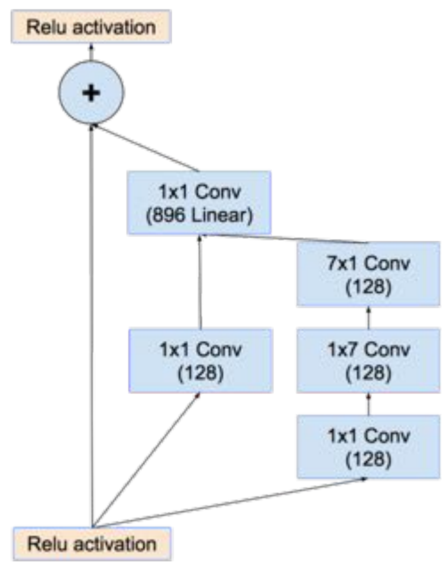


Figure 11. The schema for 17 × 17 grid (Inception-ResNet-B) module of Inception-ResNet-v1 network.

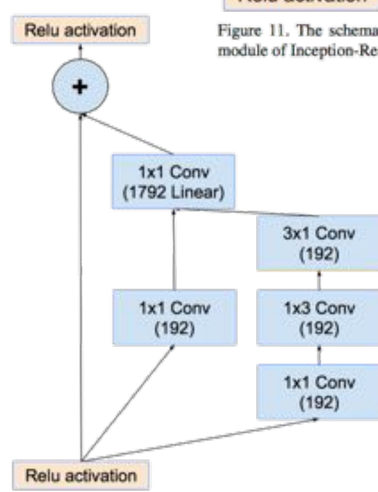
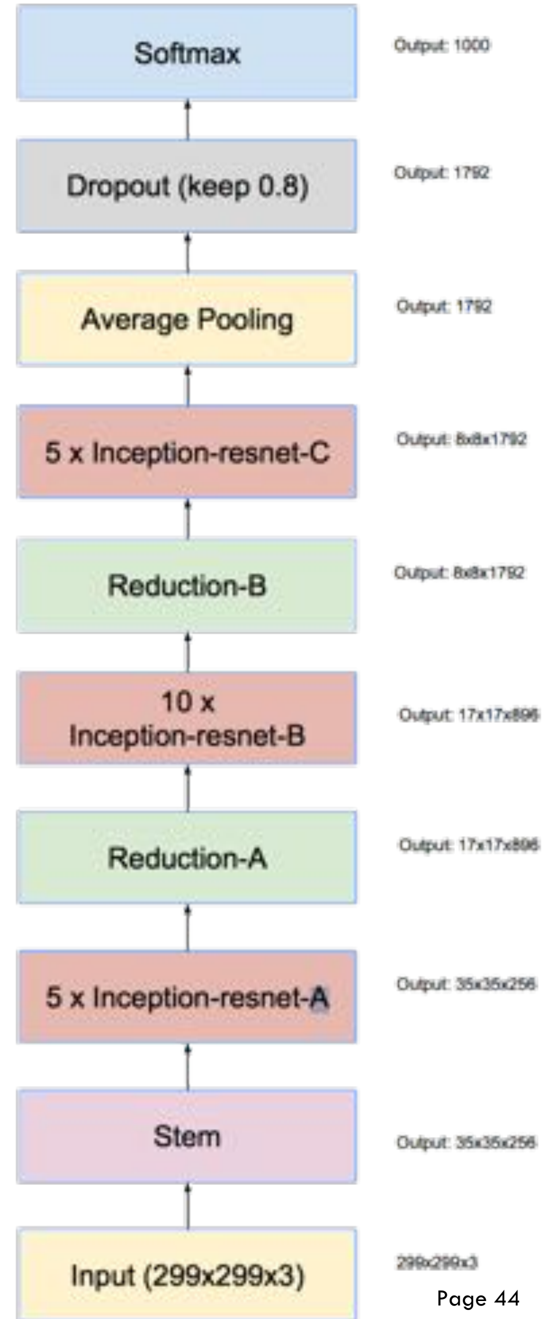


Figure 13. The schema for 8×8 grid (Inception-ResNet-C) module of Inception-ResNet-v1 network.



CNN Architecture: Part II

❑ Error on ImageNet-1000 classification

Network	Top-1 Error	Top-5 Error
BN-Inception [6]	25.2%	7.8%
Inception-v3 [15]	21.2%	5.6%
Inception-ResNet-v1	21.3%	5.5%
Inception-v4	20.0%	5.0%
Inception-ResNet-v2	19.9%	4.9%

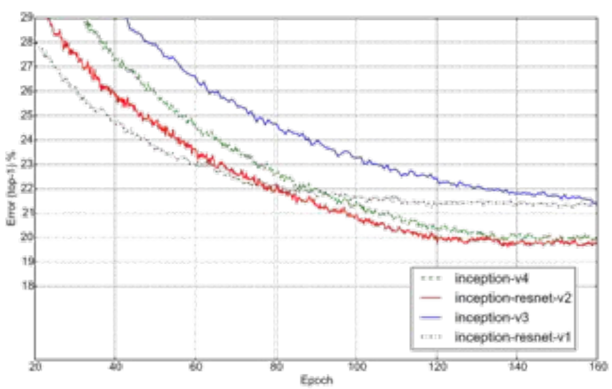


Figure 26. Top-1 error evolution of all four models (single model, single crop). This paints a similar picture as the top-5 evaluation.

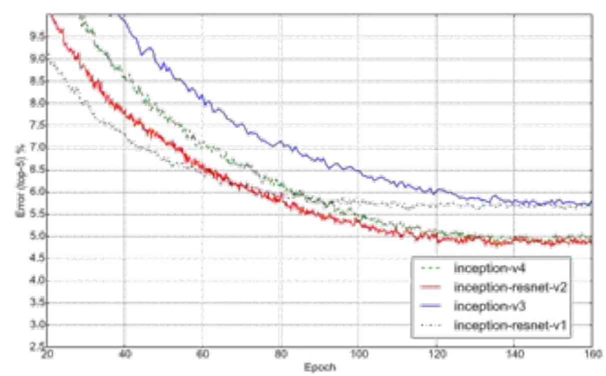


Figure 25. Top-5 error evolution of all four models (single model, single crop). Showing the improvement due to larger model size. Although the residual version converges faster, the final accuracy seems to mainly depend on the model size.

CNN Architecture: Part II

- **Xception** [Franc ̧ois Chollet ,2017]

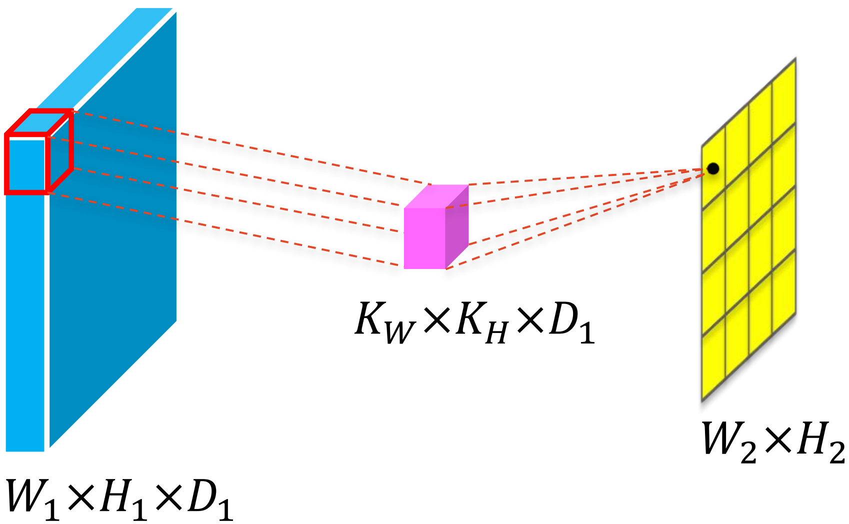


Figure 1. A canonical Inception module (Inception V3).

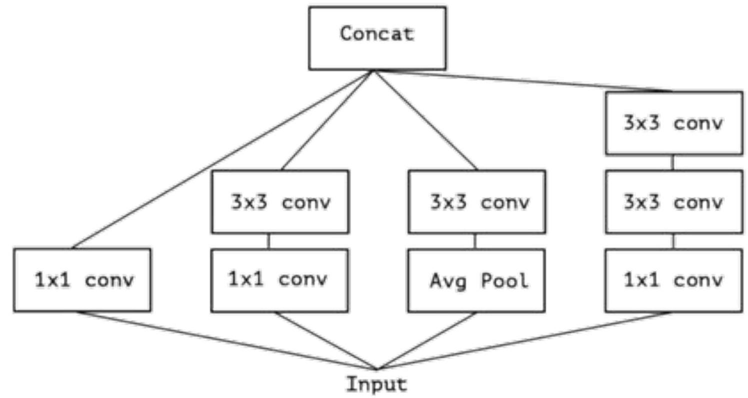
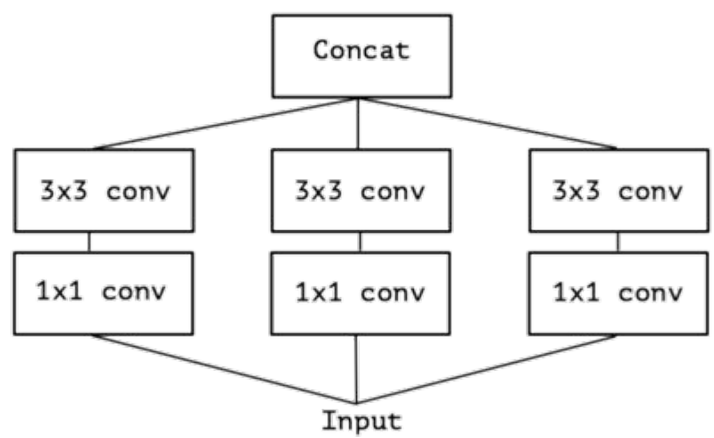


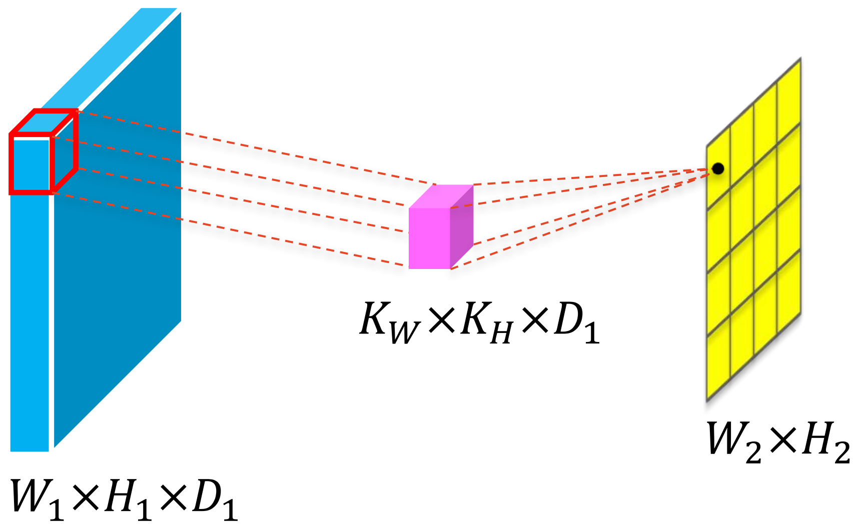
Figure 2. A simplified Inception module.



Inception module is to explicitly factorize it into a series of operations that would independently look at cross-channel correlations and at spatial correlations.

CNN Architecture: Part II

❑ Xception [Franc ̧ois Chollet ,2017]



Assume that cross-channel correlations and spatial correlations can be mapped completely separately.

Figure 4. An “extreme” version of our Inception module, with one spatial convolution per output channel of the 1x1 convolution.

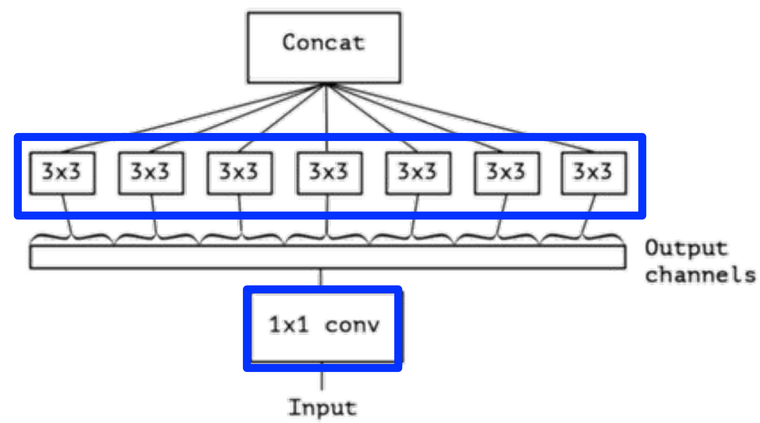
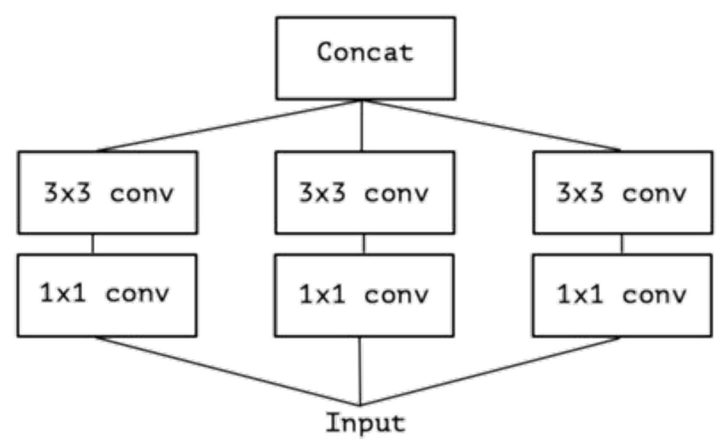


Figure 2. A simplified Inception module.



Inception module is to explicitly factorize it into a series of operations that would independently look at cross-channel correlations and at spatial correlations.

CNN Architecture: Part II

❑ Wide ResNet (WRNs) [Zagoruyko et al. 2016]

A percent of improved accuracy costs nearly doubling the number of layers.

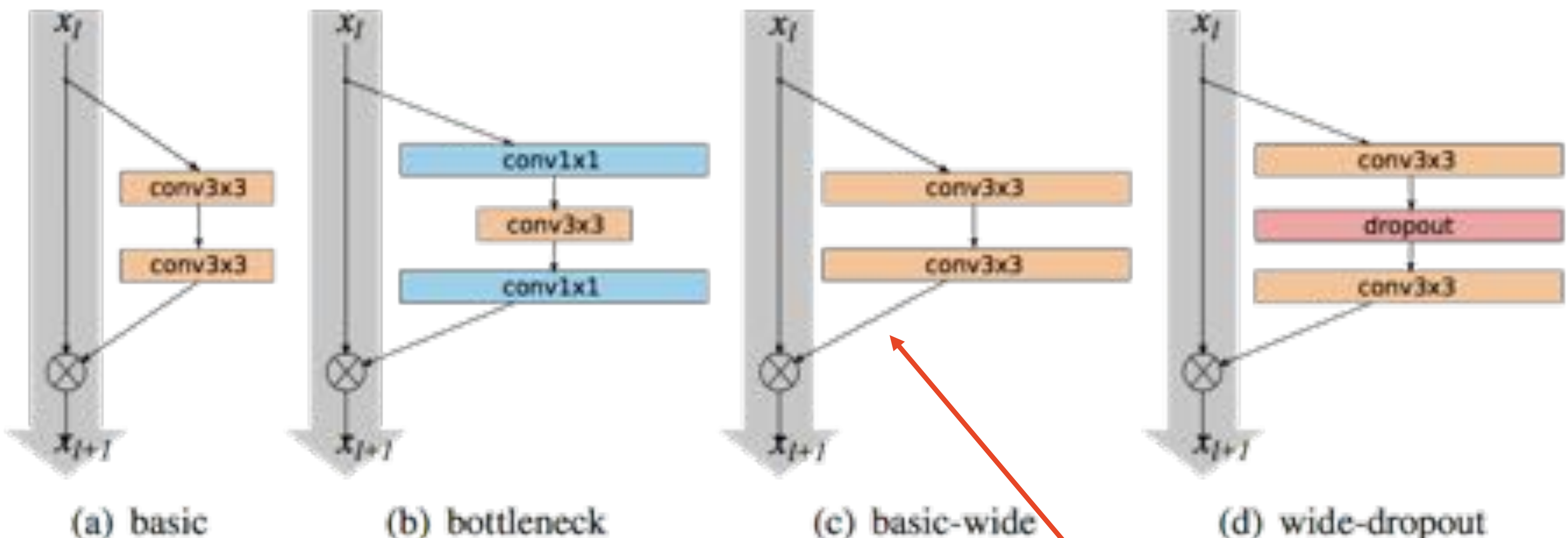
model	top-1	top-5
ResNet-50	22.9%	6.7%
ResNet-101	21.8%	6.1%
ResNet-152	21.4%	5.7%

trade-off: decrease depth and increase width of residual networks

CNN Architecture: Part II

❑ Wide ResNet (WRNs) [Zagoruyko et al. 2016]

- Residuals are important, not depth
- Increasing width instead of depth more computationally efficient



- more convolutional layers per block
- more feature planes

CNN Architecture: Part II

- **Wide ResNet (WRNs)** [Zagoruyko et al. 2016]

Model	top-1 err, %	top-5 err, %	#params	time/batch 16
ResNet-50	24.01	7.02	25.6M	49
ResNet-101	22.44	6.21	44.5M	82
ResNet-152	22.16	6.16	60.2M	115
WRN-50-2-bottleneck	21.9	6.03	68.9M	93

50-layer wide ResNet outperforms 152-layer original ResNet

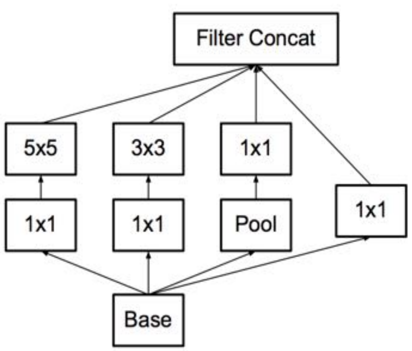
CNN Architecture: Part II

❑ ResNeXt [Xie et al. 2016]

Repeating a building block that aggregates a set of transformations with the same topology.

- Stack building blocks of the same shape, e.g. VGG and ResNets.

- Split-transform-merge strategy. In an Inception module, the input is split into a few lower-dimensional embeddings (by 1×1 convolutions), transformed by a set of specialized filters (3×3, 5×5, etc.), and merged by concatenation.



Inception model

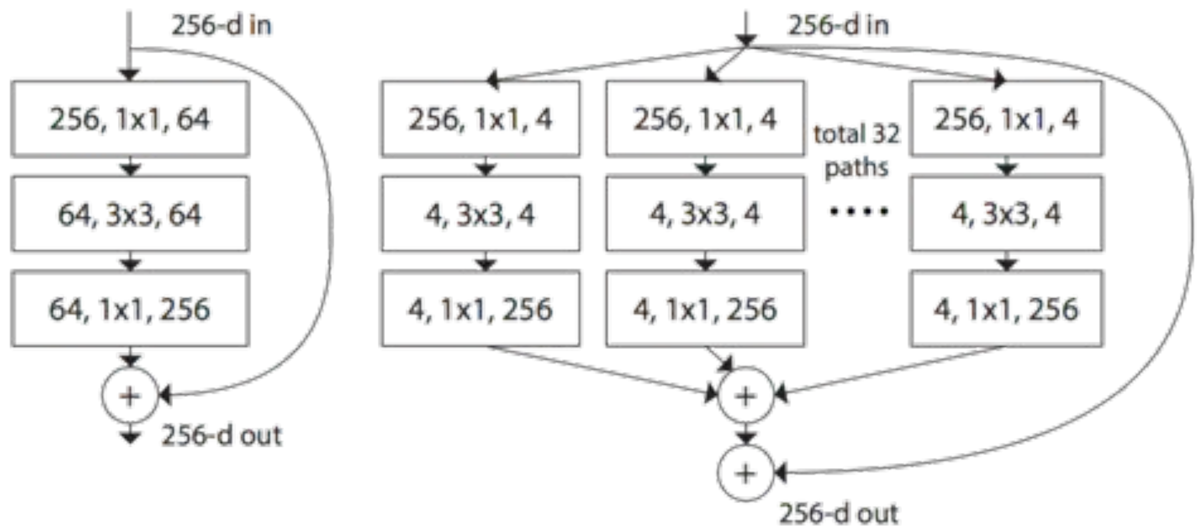


Figure 1. **Left**: A block of ResNet [14]. **Right**: A block of ResNeXt with cardinality = 32, with roughly the same complexity. A layer is shown as (# in channels, filter size, # out channels).

CNN Architecture: Part II

- ❑ ResNeXt [Xie et al. 2016]

stage	output	ResNet-50	ResNeXt-50 (32×4d)
conv1	112×112	7×7, 64, stride 2	7×7, 64, stride 2
conv2	56×56	3×3 max pool, stride 2	3×3 max pool, stride 2
		$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128, C{=}32 \\ 1\times1, 256 \end{bmatrix} \times 3$
conv3	28×28	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256, C{=}32 \\ 1\times1, 512 \end{bmatrix} \times 4$
conv4	14×14	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512, C{=}32 \\ 1\times1, 1024 \end{bmatrix} \times 6$
conv5	7×7	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times1, 1024 \\ 3\times3, 1024, C{=}32 \\ 1\times1, 2048 \end{bmatrix} \times 3$
	1×1	global average pool 1000-d fc, softmax	global average pool 1000-d fc, softmax
# params.		**25.5**$\times10^6$	**25.0**$\times10^6$
FLOPs		**4.1**$\times10^9$	**4.2**$\times10^9$

Similar complexity

ResNet = ResNeXt

CNN Architecture: Part II

- ResNeXt [Xie et al. 2016]

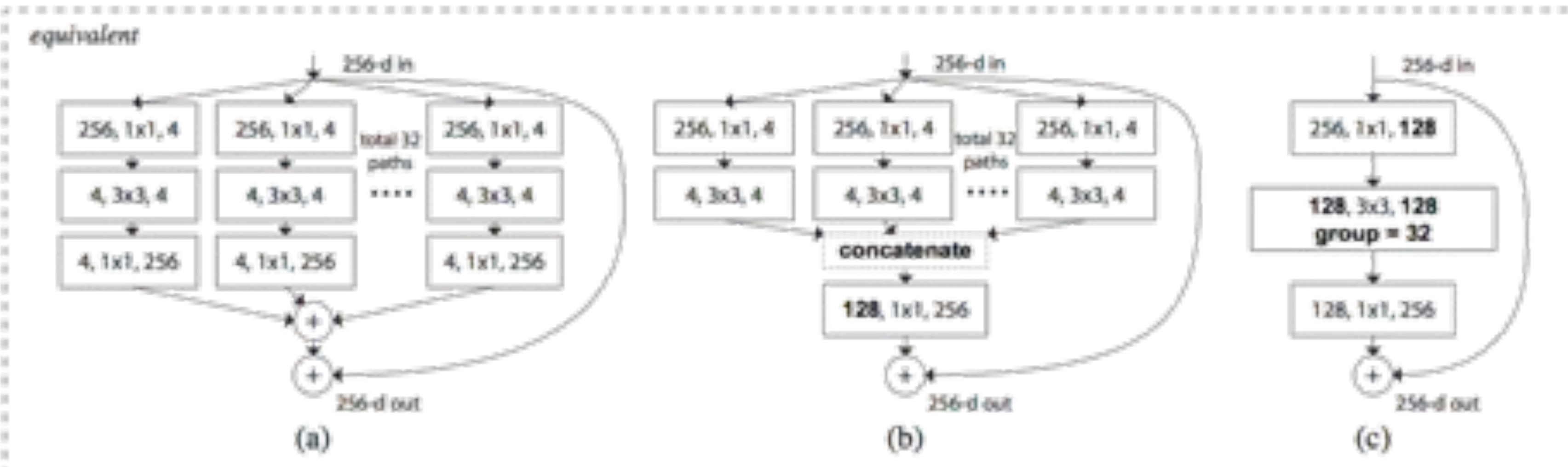
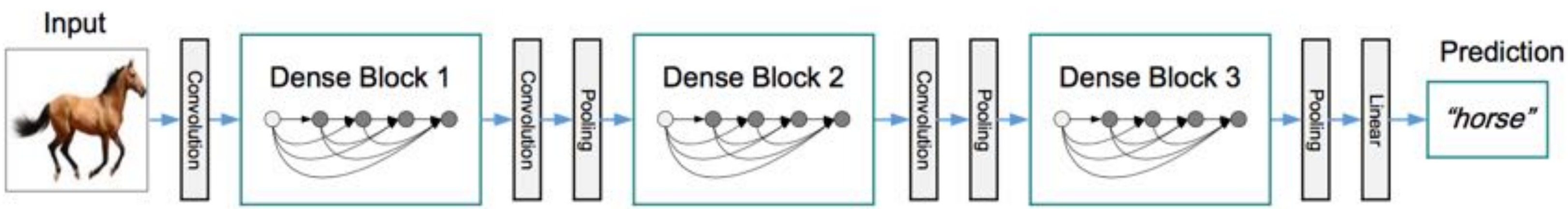


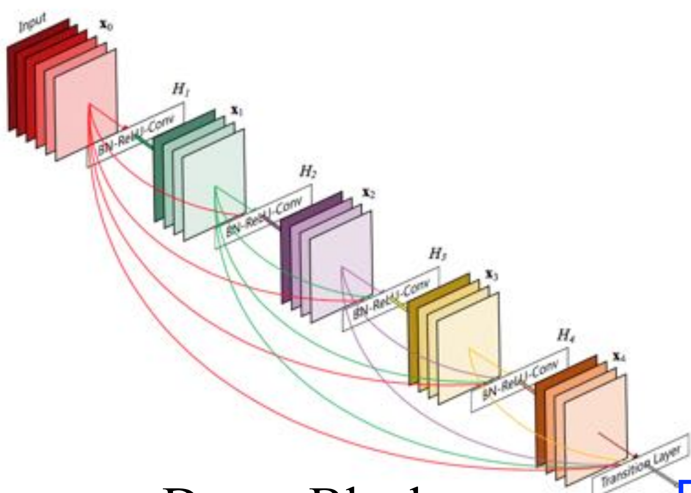
Figure 3. Equivalent building blocks of ResNeXt. (**a**): Aggregated residual transformations, the same as Fig. 1 right. (**b**): A block equivalent to (a), implemented as early concatenation. (**c**): A block equivalent to (a,b), implemented as grouped convolutions [24]. Notations in **bold** text highlight the reformulation changes. A layer is denoted as (# input channels, filter size, # output channels).

CNN Architecture: Part II

❑ DenseNet [Huang et al. 2017]

Each layer has direct access to the gradients from the loss function and the original input signal, leading to an implicit deep supervision.





Dense Block

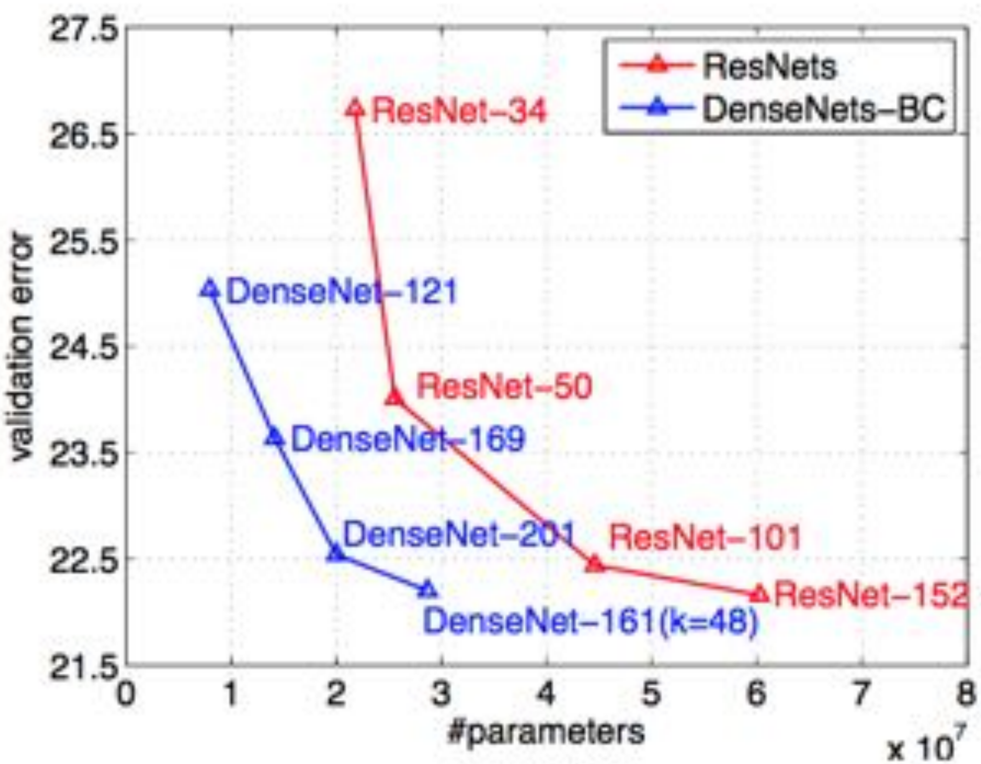
- alleviate the vanishing-gradient problem
- strengthen feature propagation
- encourage feature reuse
- reduce the number of parameters

ResNets: $\mathbf{x}_\ell = H_\ell(\mathbf{x}_{\ell-1}) + \mathbf{x}_{\ell-1}$

DenseNets: $\mathbf{x}_\ell = H_\ell([\mathbf{x}_0, \mathbf{x}_1, \ldots, \mathbf{x}_{\ell-1}])$

CNN Architecture: Part II

❑ **DenseNet** [Huang et al. 2017]



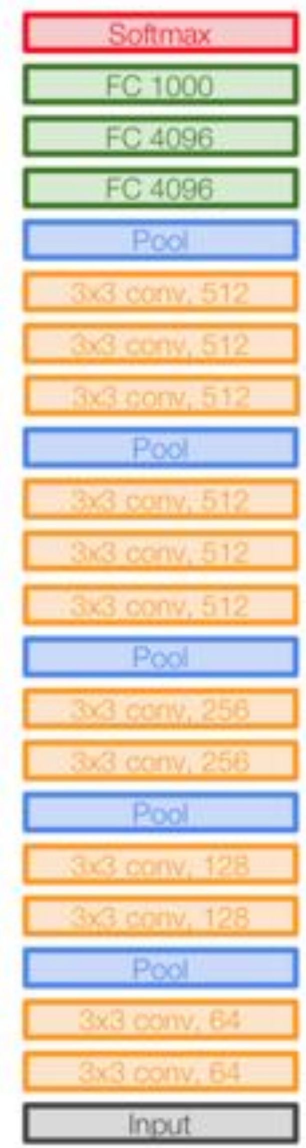
Comparison of the DenseNet and ResNet on model size

CNN Architecture: Part III

(Efficient Convolutional Neural Networks)

CNN Architecture: Part III

- ❑ **Efficient**
  - ❑ **less parameter** (most parameters in late FC)
    - ❑ more efficient distributed training
    - ❑ exporting new models to clients
    - ❑ …
  - ❑ **less memory cost** (most memory is in early conv)
    - ❑ embedded deployment (e.g., FPGAs often have less than 10MB memory)
    - ❑ **…**
  - ❑ **less computation**

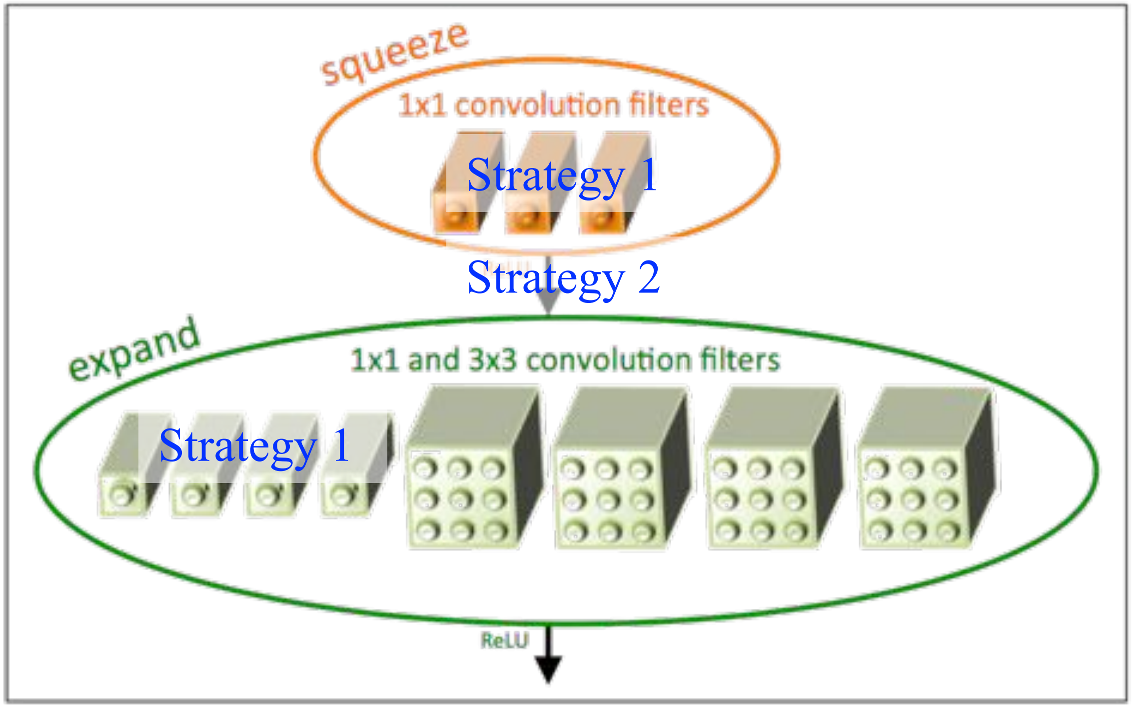


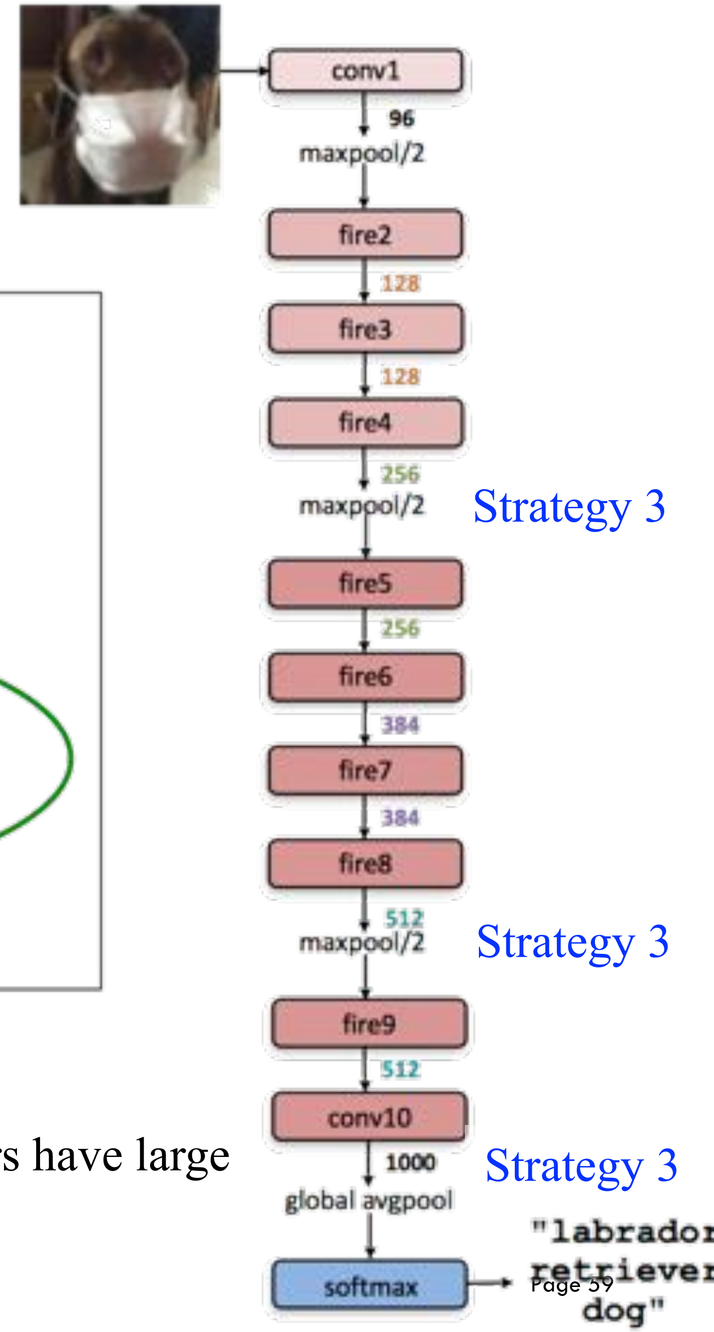
CNN Architecture: Part III

- **SqueezeNet** [Iandola et al. 2017]
- **MobileNet** [Howard et al. 2017]
- **ShuffleNet** [Zhang et al. 2017]

CNN Architecture: Part III

❑ **SqueezeNet** [Iandola et al. 2017]





- Replace 3x3 filters with 1x1 filters
- Decrease the number of input channels to 3x3 filters
- Downsample late in the network so that convolution layers have large activation maps

CNN Architecture: Part III

❑ SqueezeNet [Iandola et al. 2017]

AlexNet level accuracy on ImageNet with 50x fewer parameters

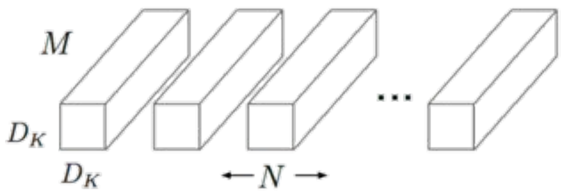
Table 2: Comparing SqueezeNet to model compression approaches. By *model size*, we mean the number of bytes required to store all of the parameters in the trained model.

CNN architecture	Compression Approach	Data Type	Original → Compressed Model Size	Reduction in Model Size vs. AlexNet	Top-1 ImageNet Accuracy	Top-5 ImageNet Accuracy
AlexNet	None (baseline)	32 bit	240MB	1x	57.2%	80.3%
AlexNet	SVD (Denton et al., 2014)	32 bit	240MB → 48MB	5x	56.0%	79.4%
AlexNet	Network Pruning (Han et al., 2015b)	32 bit	240MB → 27MB	9x	57.2%	80.3%
AlexNet	Deep Compression (Han et al., 2015a)	5-8 bit	240MB → 6.9MB	35x	57.2%	80.3%
SqueezeNet (ours)	None	32 bit	4.8MB	**50x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	8 bit	4.8MB → 0.66MB	**363x**	57.5%	80.3%
SqueezeNet (ours)	Deep Compression	6 bit	4.8MB → 0.47MB	**510x**	57.5%	80.3%

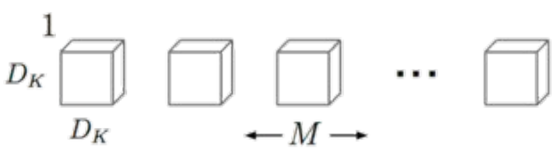
CNN Architecture: Part III

❑ MobileNet [Howard et al. 2017]

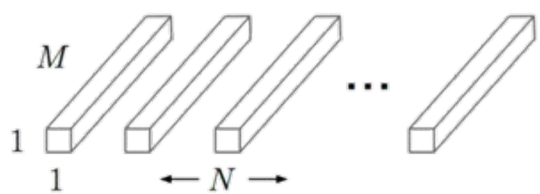
- Depthwise separable convolution
- Less channels



(a) Standard Convolution Filters



(b) Depthwise Convolutional Filters



(c) 1×1 Convolutional Filters called Pointwise Convolution in the context of Depthwise Separable Convolution

Standard convolutions have the computational cost of:

$$D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F$$

Depthwise separable convolutions cost:

$$D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F$$

A reduction in computation of

$$\frac{D_K \cdot D_K \cdot M \cdot D_F \cdot D_F + M \cdot N \cdot D_F \cdot D_F}{D_K \cdot D_K \cdot M \cdot N \cdot D_F \cdot D_F} = \frac{1}{N} + \frac{1}{D_K^2}$$

CNN Architecture: Part III

❑ MobileNet [Howard et al. 2017]

Table 8. MobileNet Comparison to Popular Models

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
1.0 MobileNet-224	70.6%	569	4.2
GoogleNet	69.8%	1550	6.8
VGG 16	71.5%	15300	138

Table 9. Smaller MobileNet Comparison to Popular Models

Model	ImageNet Accuracy	Million Mult-Adds	Million Parameters
0.50 MobileNet-160	60.2%	76	1.32
Squeezenet	57.5%	1700	1.25
AlexNet	57.2%	720	60

- less parameters
- less computation

CNN Architecture: Part III

❑ **ShuffleNet** [Zhang et al. 2017]

help the information flowing across feature channels

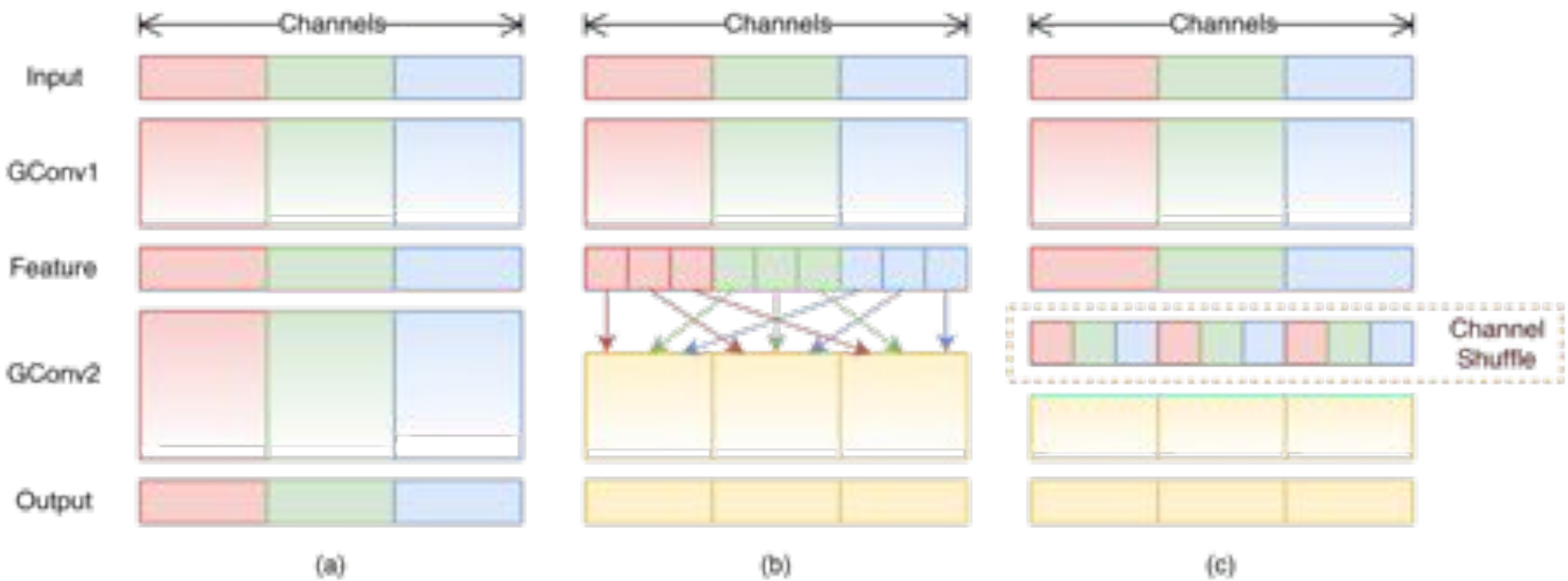


Figure 1. Channel shuffle with two stacked group convolutions. GConv stands for group convolution. a) two stacked convolution layers with the same number of groups. Each output channel only relates to the input channels within the group. No cross talk; b) input and output channels are fully related when GConv2 takes data from different groups after GConv1; c) an equivalent implementation to b) using channel shuffle.

CNN Architecture: Part III

❑ ShuffleNet [Zhang et al. 2017]

Table 5: ShuffleNet vs. MobileNet [12] on ImageNet Classification

Model	Complexity (MFLOPs)	Cls err. (%)	Δ err. (%)
1.0 MobileNet-224	569	29.4	-
ShuffleNet 2× ($g = 3$)	524	**29.1**	0.3
0.75 MobileNet-224	325	31.6	-
ShuffleNet 1.5× ($g = 3$)	292	**31.0**	0.6
0.5 MobileNet-224	149	36.3	-
ShuffleNet 1× ($g = 3$)	140	**34.1**	2.2
0.25 MobileNet-224	41	49.4	-
ShuffleNet 0.5× (arch2, $g = 8$)	40	**42.7**	6.7
ShuffleNet 0.5× (shallow, $g = 3$)	40	45.2	4.2

LegoNet: Efficient Convolutional Neural Networks with Lego Filters [ICML2019]

Motivation

A set of network design principles have been developed in network engineering.

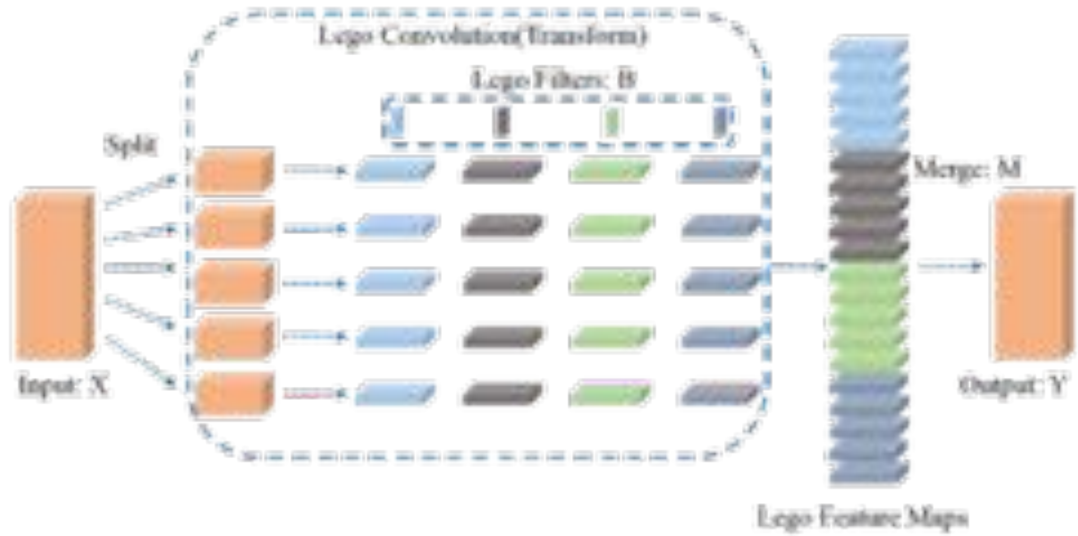
VGGNets and ResNets stack building blocks of the same shape, which reduces the free choices of hyper-parameters.

Another important strategy is *split-transform-merge* in Inception models, where the input is split into a few embeddings of lower dimensionalities, trans- formed by a set of specialized filters, and merged by concatenation.

As **filter is the basic unit** in constructing deep neural networks, we must ask whether these network design principles are applicable for re-designing filters in deep learning.

Lego Filters

(a) conv filters (b) Lego filters (c) stacked filters

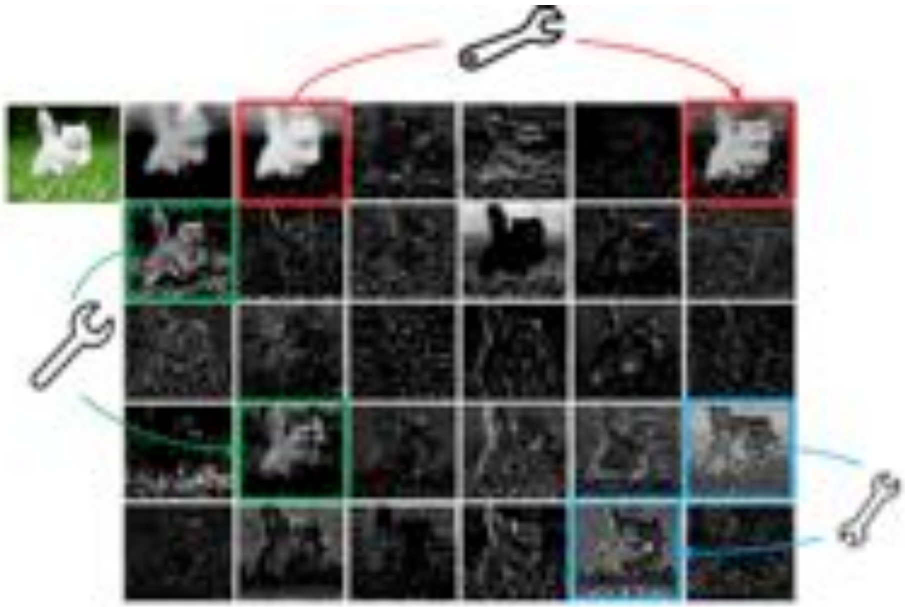


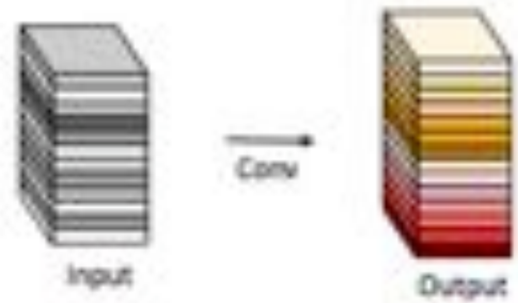
A set of lower-dimensional filters are discovered and taken as Lego bricks to be stacked for more complex filters

Instead of manually stacking these Lego filters, we develop a method to learn the optimal permutation of Lego filters for a filter module.

We adapt the split-transform-merge strategy to accelerate their convolutions.

GhostNet: More Features from Cheap Operations [CVPR2020]





(a) The convolutional layer.

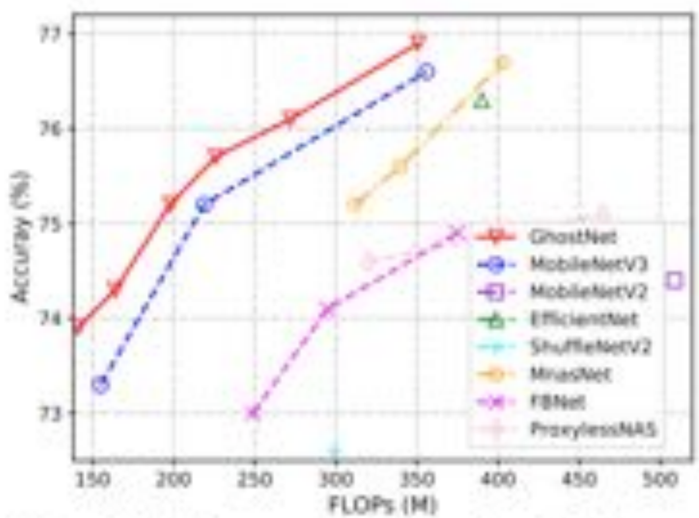
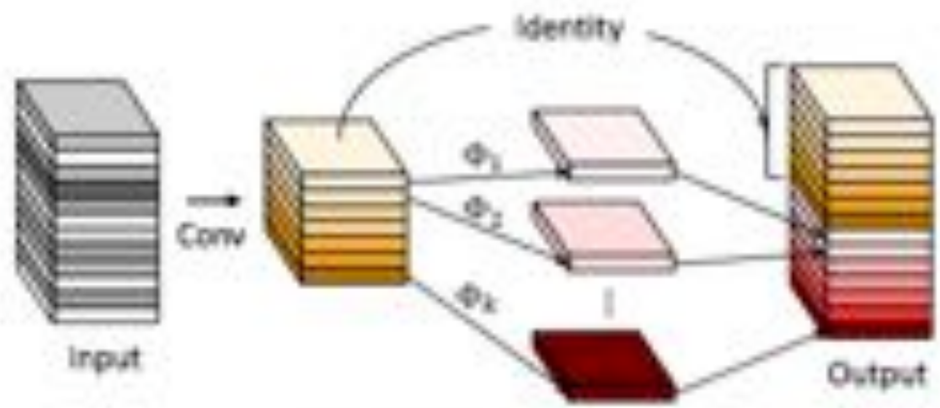


Figure 6. Top-1 accuracy v.s. FLOPs on ImageNet dataset.



(b) The Ghost module.