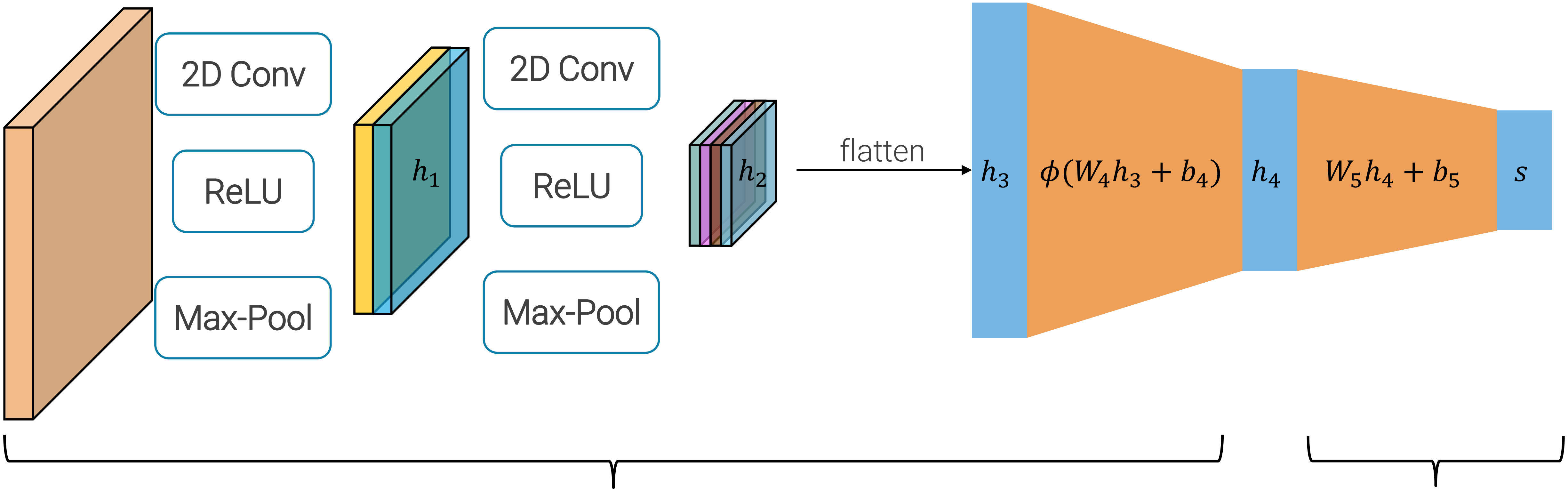
Lecture 5
Successful Architectures

IMAGE PROCESSING AND COMPUTER VISION – PART 2

SAMUELE SALTI

Convolutional Neural Networks



N convolutional+pooling layers followed by M fully connected layers
This is also called the feature extractor
(with max-pool, ReLU can be the last operation in a block)

The final fully connected layer is also called the classifier

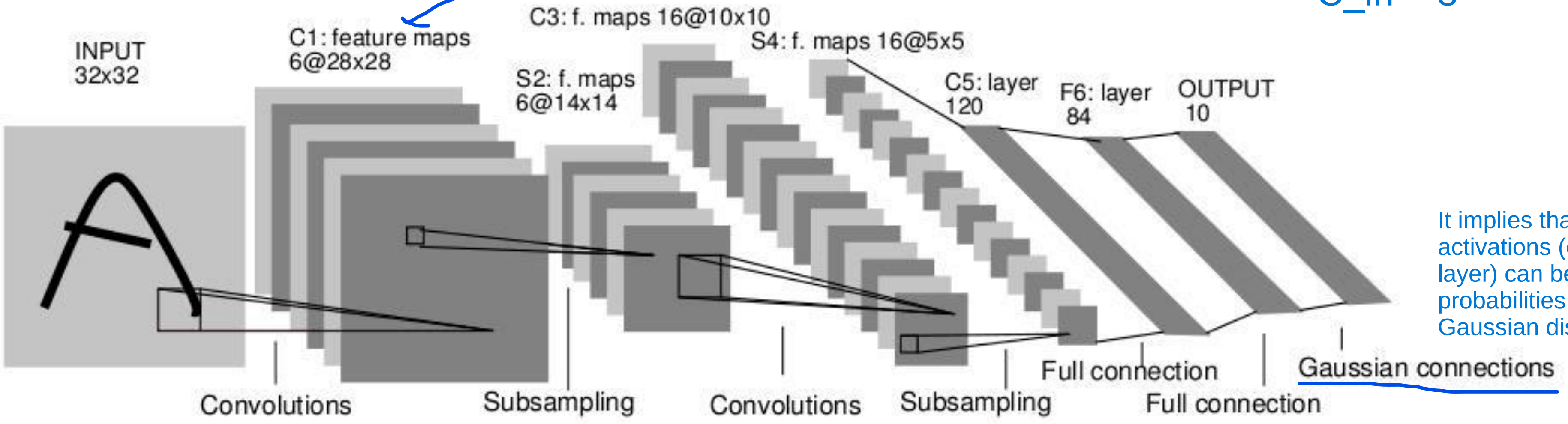
Example: LeNet5

H_out / W_out = 32 - 5 + 1
= 28

first
expansion

k = 5
stride = 1
padding = 0
C_out = depth = number of channels = 6
C_in = 3

Average pooling tends to have a smoothing effect on the feature maps. It averages out the values within the window, which can help in preserving general trends, capturing diverse aspects of the input, and reducing noise in the feature maps



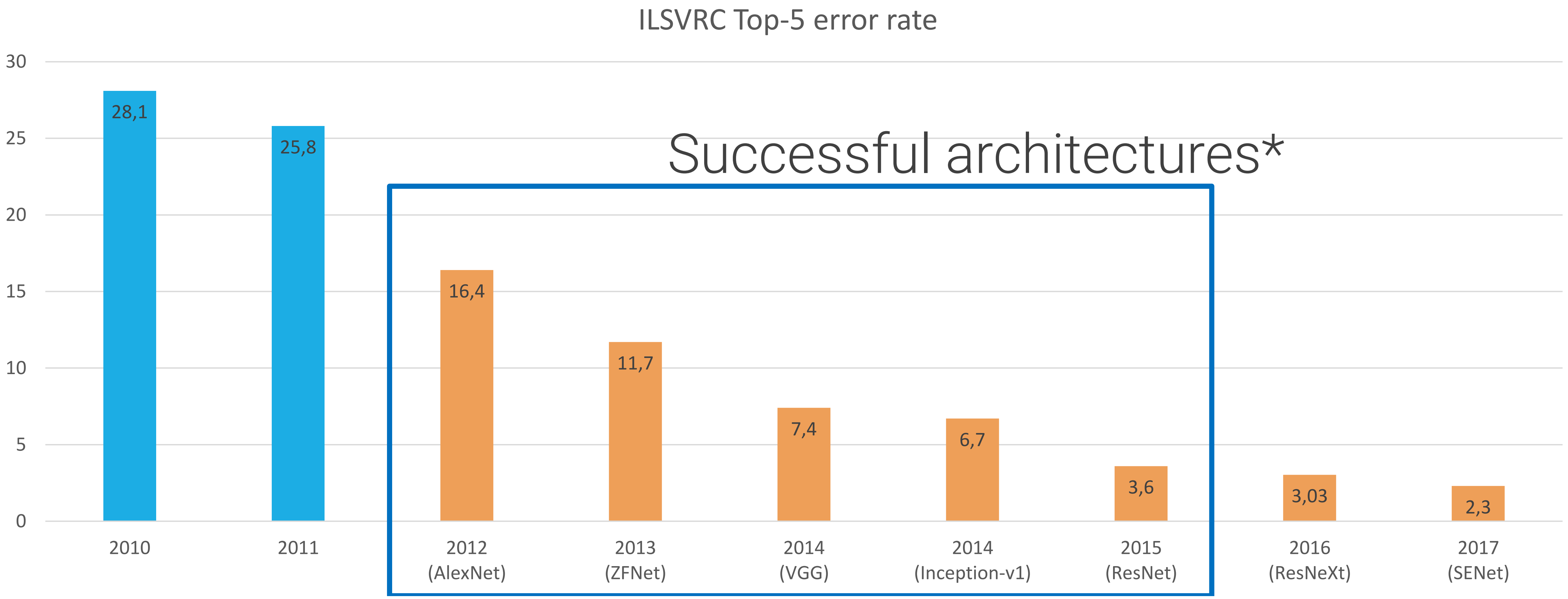
It implies that the output layer's activations (often a softmax layer) can be interpreted as probabilities derived from a Gaussian distribution.

- As depth increases, number of channels increase, and spatial dimension decreases
- Average pooling
- 5x5 convolutional kernels, no padding   6 convs
- Sigmoid or tanh non-linearities with carefully selected amplitudes
- Multiple fully connected layers + RBF classifier
- No residual connections
- No (batch) normalization

this is a good process because at the beginning we want to extract low level features, but the more we progress, we want to process higher level features and a higher number of features, combining the low level features

Lecun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. "Gradient-based learning applied to document recognition", Proceedings of the IEEE. 1998.

ILSVRC error rate evolution



*Results based on ensembles and, sometimes, heavy test-time augmentation

AlexNet

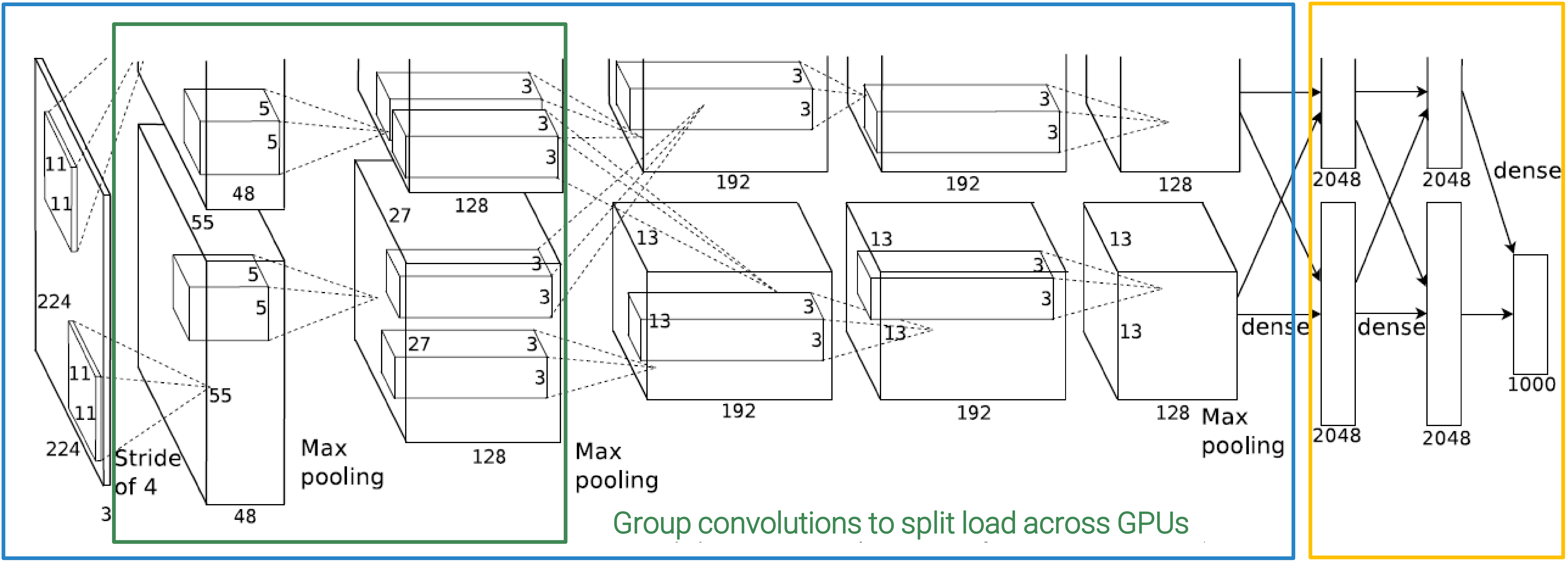
wrt LeNet does not change too much: it's deeper and ReLU is used instead

most of the numbers are magic numbers: decided by trial and error

model parallelism: upper convolutions are computed on a GPU and the lower ones on another GPU (this means that for ex. vertical edges feature computed on one GPU, horizontal on another one)

5 convolutional layers (conv+relu) optionally followed by max-pooling

3 fc layers



AlexNet

Won ILSVRC 2012.

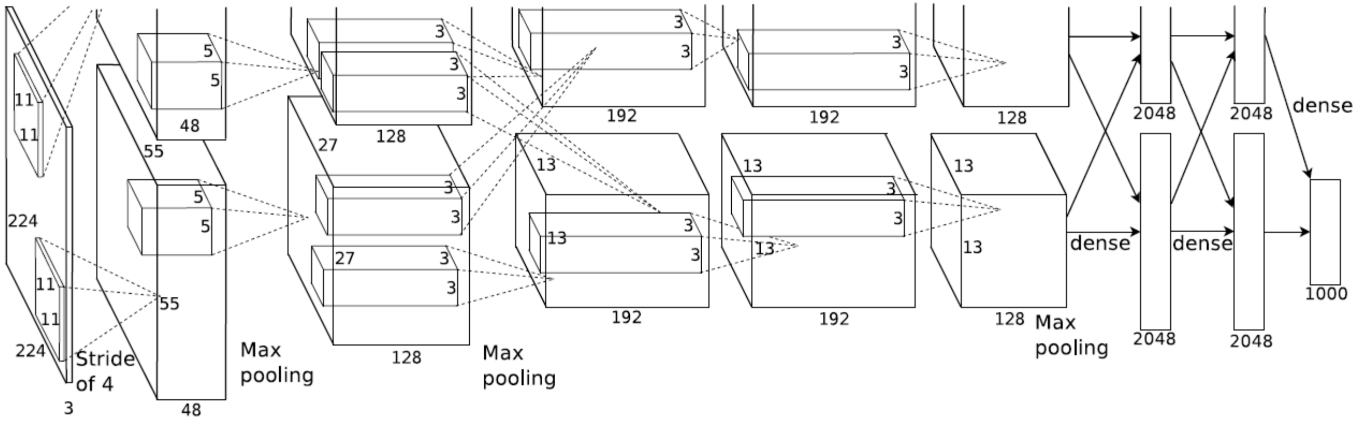
Was trained on two GTX580 GPUs.

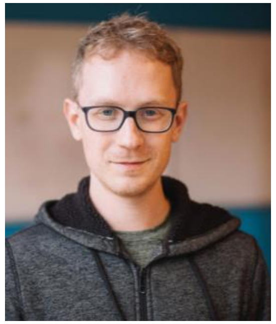
Used local response normalization (LRN) in some layers, not used in subsequent architectures.

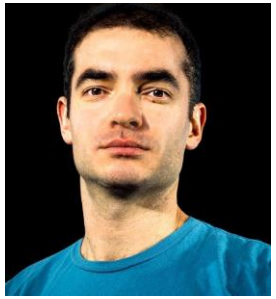
Took between five and six days to train

“All our experiments suggest that our results can be improved simply by waiting for faster GPUs and bigger datasets to become available.”

it's not all just about bigger datasets or more powerful GPUs

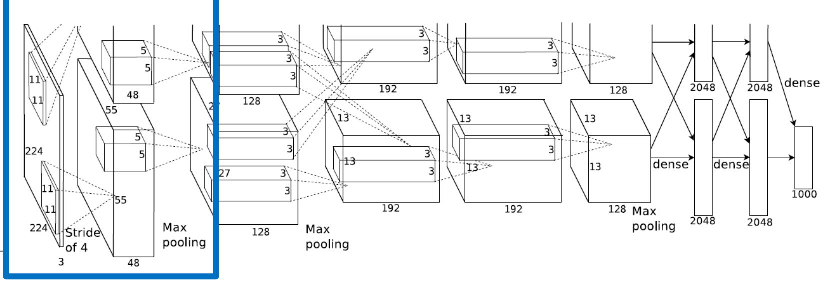






Alex Krizhevsky, Ilya Sutskever, Geoffrey E. Hinton, “ImageNet Classification with Deep Convolutional Neural Networks”, NeurIPS 2012

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0

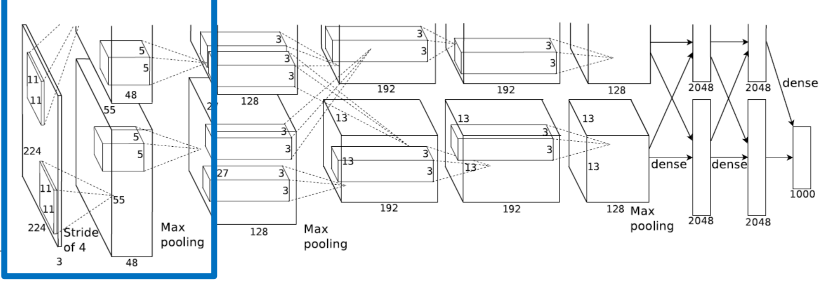
Input elements = $W_{in} \times H_{in} \times C_{in}$
=227*227*3
=154,587

AlexNet used mini-batch size 128,
activations are usually floating point number, i.e. 4 bytes for each element.

Total memory in MB for a mini-batch is
128* 154,587 *4/1024/1024
= 75.5

Minibatch:	128

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0							

First layer is a 96x3x11x11 convolutional layer, with stride 4.
We will see again this stem layer at the beginning of convnets, i.e. a conv layer that performs a fast reduction in the spatial size of the activations, mainly to reduce memory and computational cost, but also to rapidly increase the receptive field.

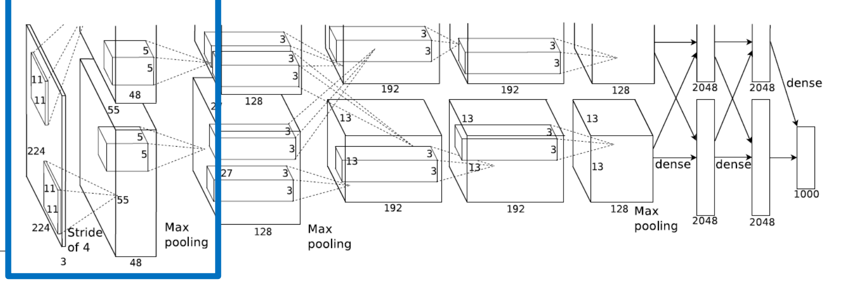
Output channel = # kernels = 96

$$\text{Activation H/W} = \left\lfloor \frac{(W_{in} - W_K + 2P)}{S} \right\rfloor + 1$$
$$= (227-11+0) / 4 + 1$$
$$=216/4+1=55$$

Convolutional layers are used as stem layers because they are more informative and effective in the initial stages of a convolutional neural network compared to pooling layers.

Minibatch:	128

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400				

$$\# \text{params} = (\boldsymbol{W_K} \times \boldsymbol{H_K} \times \boldsymbol{C_{in}} + \mathbf{1}) \times \boldsymbol{C_{out}}$$

=(11*11*3+1)*96

=34,944

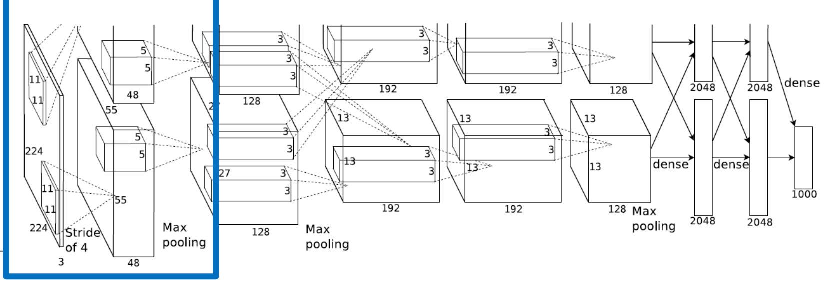
$$\text{flops} = \#\text{activations} \times (\boldsymbol{W_K} \times \boldsymbol{H_K} \times \boldsymbol{C_{in}}) \times \mathbf{2}$$

=290,400 * (11*11*3)*2 *128

=27 Gflops

Minibatch:	128

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3		

Given activation size and #parameters, how much memory will we need at training time?

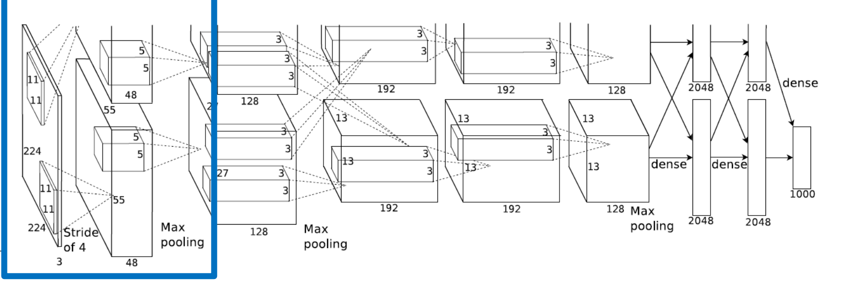
- We need to store all intermediate activations, in order to compute the gradient of the loss with respect to everyone of its entries, i.e. another tensor of the same size
- We will have as many activations (and gradients) as there are input images in our mini-batch

- For every parameter, we will need to store its value and the gradient of the loss with respect to it
- If we use advanced optimizers like momentum, we will have a velocity term for each parameter, if using Adam first and second order moments for each parameter, etc..

Hard to have a precise estimate of memory requirements, but we can get approximate values by considering twice the activation size and 3-4 times the #params. This is usually a lower bound on the actual requirements.

Minibatch:	128

Architecture breakdown



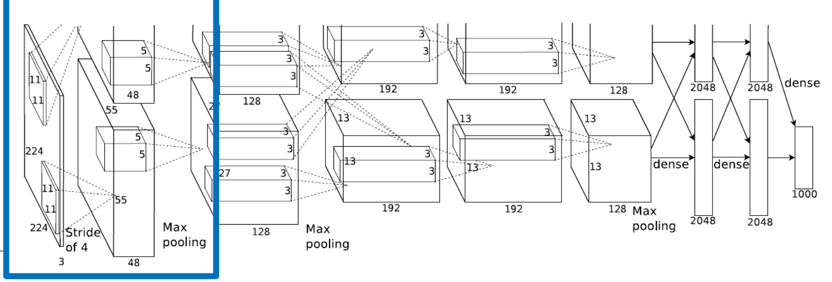
Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3		

Total memory for activations for conv1 is then
2 * 128 * #activations * 4 / 1024/1024=
283.6 MB

Total memory for parameters for conv1 is then
3*#params * 4 / 1024/1024=
0.4 MB

Minibatch:	128

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0							

All pooling layers are "overlapping" pooling layers: they have size 3x3, but stride 2. Reduces the top-1 and top-5 errors in their experiments compared to 2x2 with stride 2.

Here, the pooling window is 3x3, and the stride is 2. Since the window is larger than the stride, there is overlap between adjacent pooling regions (the current one and the previous one)

output channels = # input channels = 96

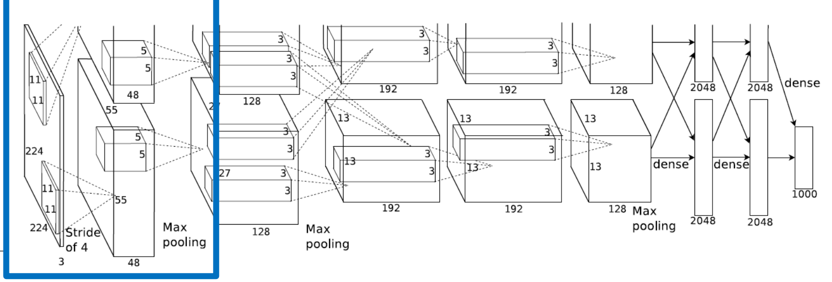
$$\text{Activation H/W} = \left\lfloor \frac{(W_{in} - W_K + 2P)}{S} \right\rfloor + 1$$

= (55-3+0) / 2 + 1

=52/2+1=27

Minibatch:	128

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984				

params = 0 -> size of params in memory = 0 MB

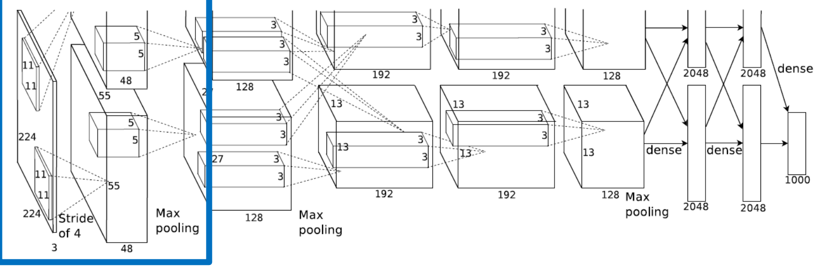
maxpooling: 0 params because it doesn't have to learn them

flops = #activations $\times (\boldsymbol{W_K} \times \boldsymbol{H_K})$
=69,984 * 3 * 3
= 629,856 = 0.6 Mflops

Size of activations for pool1 is then
2 * 128 * #activations * 4 / 1024/1024=
68.3 MB

Minibatch:	128

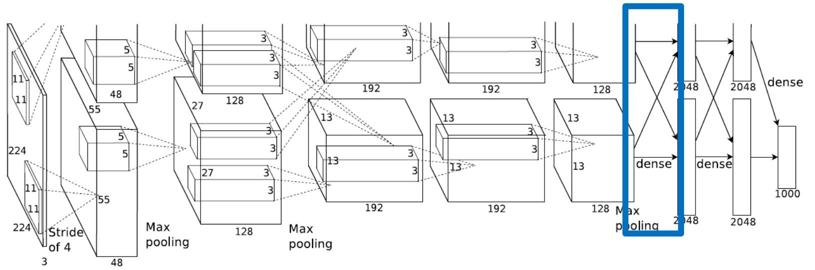
Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984	0	80,6	68,3	0,0

Minibatch:	128

Architecture breakdown

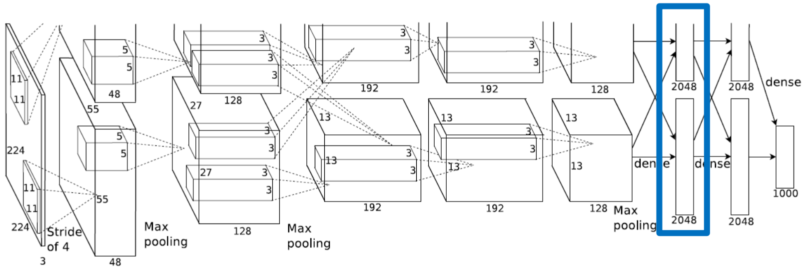


Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984	0	80,6	68,3	0,0
conv2	256	5	1	2	27	256	186624	615	114661,8	182,3	7,0
pool2	1	3	2	0	13	256	43264	0	49,8	42,3	0,0
conv3	384	3	1	1	13	384	64896	885	38277,2	63,4	10,1
conv4	384	3	1	1	13	384	64896	1327	57415,8	63,4	15,2
conv5	256	3	1	1	13	256	43264	885	38277,2	42,3	10,1
pool3	1	3	2	0	6	256	9216	0	10,6	9,0	0,0
flatten	0	0	0	0	1	9216	9216				

Flatten layer to throw away the spatial structure and prepare for FC layers. No computation, so no parameters. Not even memory consumption, it is just a view over the same area of memory which is interpreted as a $C_{out} \times 1$ vector, where $C_{out} = C_{in} \times W_{in} \times \mathrm{H}_{in}$

Minibatch:	128

Architecture breakdown



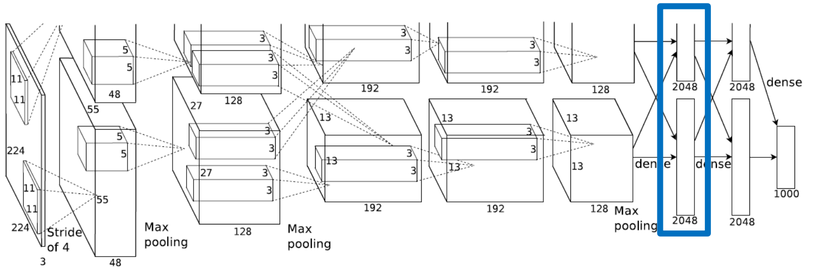
Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984	0	80,6	68,3	0,0
conv2	256	5	1	2	27	256	186624	615	114661,8	182,3	7,0
pool2	1	3	2	0	13	256	43264	0	49,8	42,3	0,0
conv3	384	3	1	1	13	384	64896	885	38277,2	63,4	10,1
conv4	384	3	1	1	13	384	64896	1327	57415,8	63,4	15,2
conv5	256	3	1	1	13	256	43264	885	38277,2	42,3	10,1
pool3	1	3	2	0	6	256	9216	0	10,6	9,0	0,0
flatten	0	0	0	0	1	9216	9216	0	0,0	0,0	0,0
fc6	4096	1	1	0							

output channels = # kernels = 4096 , no spatial dimensions -> memory of actvs = $2*128*4096*4/1024^2$= 4 MB

this is because in FC layers the kernel has the same dim of its previous layer

Minibatch:	128

Architecture breakdown

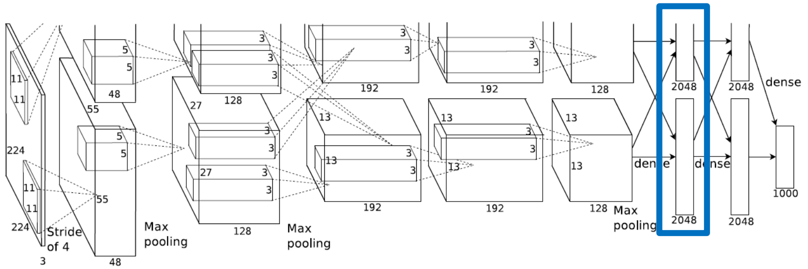


Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984	0	80,6	68,3	0,0
conv2	256	5	1	2	27	256	186624	615	114661,8	182,3	7,0
pool2	1	3	2	0	13	256	43264	0	49,8	42,3	0,0
conv3	384	3	1	1	13	384	64896	885	38277,2	63,4	10,1
conv4	384	3	1	1	13	384	64896	1327	57415,8	63,4	15,2
conv5	256	3	1	1	13	256	43264	885	38277,2	42,3	10,1
pool3	1	3	2	0	6	256	9216	0	10,6	9,0	0,0
flatten	0	0	0	0	1	9216	9216	0	0,0	0,0	0,0
fc6	4096	1	1	0	1	4096	4096			4,0	

params = $C_{out} \times C_{in} + C_{out}$ = 37,752,832 -> memory for params = 3 * #params *4 / 1024^2 = 432,1 MB

Minibatch:	128

Architecture breakdown

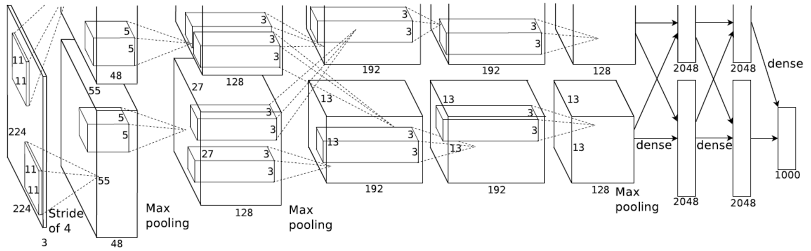


Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984	0	80,6	68,3	0,0
conv2	256	5	1	2	27	256	186624	615	114661,8	182,3	7,0
pool2	1	3	2	0	13	256	43264	0	49,8	42,3	0,0
conv3	384	3	1	1	13	384	64896	885	38277,2	63,4	10,1
conv4	384	3	1	1	13	384	64896	1327	57415,8	63,4	15,2
conv5	256	3	1	1	13	256	43264	885	38277,2	42,3	10,1
pool3	1	3	2	0	6	256	9216	0	10,6	9,0	0,0
flatten	0	0	0	0	1	9216	9216	0	0,0	0,0	0,0
fc6	4096	1	1	0	1	4096	4096	37758		4,0	432,0

flops = $\#minibatch \times 2 \times C_{in} \times \#\, activations$ = 128*2*9,126*4,096 = 9.569 Gflops

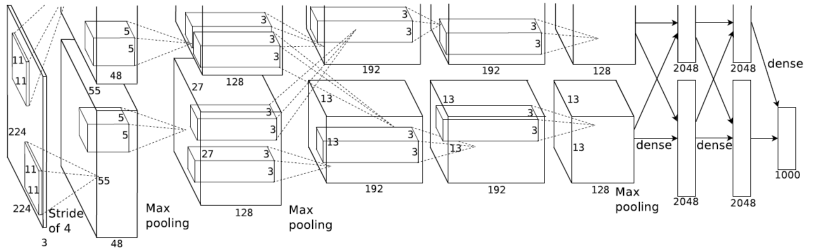
Minibatch:	128

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984	0	80,6	68,3	0,0
conv2	256	5	1	2	27	256	186624	615	114661,8	182,3	7,0
pool2	1	3	2	0	13	256	43264	0	49,8	42,3	0,0
conv3	384	3	1	1	13	384	64896	885	38277,2	63,4	10,1
conv4	384	3	1	1	13	384	64896	1327	57415,8	63,4	15,2
conv5	256	3	1	1	13	256	43264	885	38277,2	42,3	10,1
pool3	1	3	2	0	6	256	9216	0	10,6	9,0	0,0
flatten	0	0	0	0	1	9216	9216	0	0,0	0,0	0,0
fc6	4096	1	1	0	1	4096	4096	37758	9663,7	4,0	432,0
fc7	4096	1	1	0	1	4096	4096	16781	4295,0	4,0	192,0
fc8	1000	1	1	0	1	1000	1000	4097	1048,6	1,0	46,9
					Minibatch:	128	Totals:	62378	290851	1.406	714

Architecture breakdown



Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					227	3	154587	0	-	75,5	0,0
conv1	96	11	4	0	55	96	290400	35	26986,3	283,6	0,4
pool1	1	3	2	0	27	96	69984	0	80,6	68,3	0,0
conv2								615	114661,8	182,3	7,0
pool2								0	49,8	42,3	0,0
conv3								885	38277,2	63,4	10,1
conv4								1327	57415,8	63,4	15,2
conv5								885	38277,2	42,3	10,1
pool3								0	10,6	9,0	0,0
flatten								0	0,0	0,0	0,0
fc6								37758	9663,7	4,0	432,0
fc7								16781	4295,0	4,0	192,0
fc8	1000	1	1	0	1	1000	1000	4097	1048,6	1,0	46,9
					Minibatch:	128	Totals:	62378	290851	1.406	714

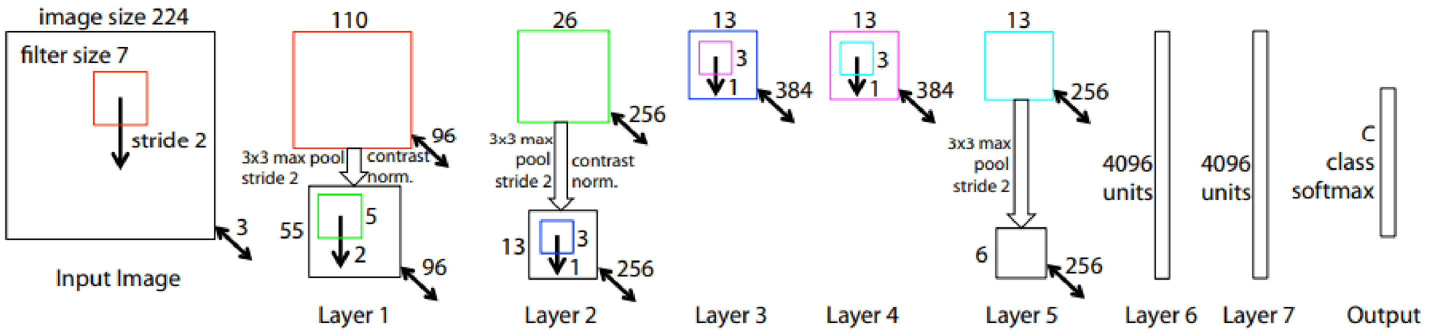
Trends to note:

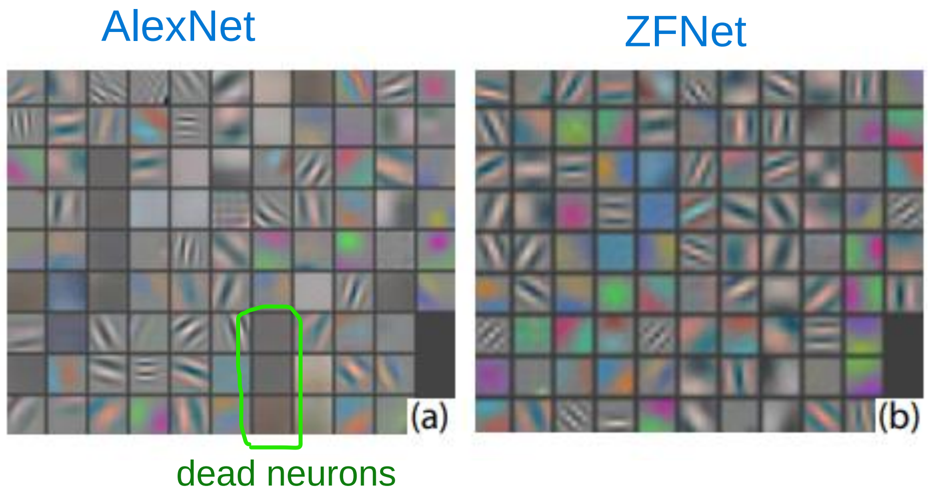
- Stem layer at the beginning of the network
- Nearly all parameters are in the fully connected layers
- Largest memory consumption from activations due to the first conv layers bigger images
- Largest number of flops required by the conv layers
- Activations and parameters have a similar memory footprint at training time
- More than 60 million parameters learned, more than 290 Gflops to process a mini-batch, 2.2 Gflops/image

ZFNet / Clarifai: a better AlexNet

* unlike AlexNet, which uses a big stem layer with a high stride, ZFNet uses more layers with less stride as stem layers

this is because of ablation studies





First author founded a company, Clarifai, which won ILSVRC 2013 with a modified version of this network.

Tries to reduce the “trail and error” approach to network design, by introducing powerful visualizations (via Deconvnets) for layers other than the first one.

Based on the visualizations and ablation studies, they found out that aggressive stride and large filter size in the first layer results in dead filters and missing frequencies in the first layer filters and aliasing artifacts in the second layer activations in the image a) which refers to AlexNet, we notice much more gray meaningless pixels, namely dead neurons

They propose to counteract these problems by using **7×7 convs with stride 2** in the first layer and **stride 2 also in the second 5×5 conv layer.**

wrt AlexNet differences lies in the first two layers: 7x7 conv and stride 2 instead of 11x11 with stride 4 in the first *

Matthew D. Zeiler and Rob Fergus, “Visualizing and Understanding Convolutional Networks”, ECCV 2014 only 11 layers

unlike AlexNet

VGG: Deep but regular

VGG-16 VGG-19

Second place in ILSVRC 2014, 7.5% top-5 error

Commit to explore the effectiveness of simple design choices, by allowing only the combination of :

- 3x3 convolutions, S=1, P=1 using this values we will never reduce the spatial dimension using convolutions
- 2x2 max-pooling, S=2, P=0 halving each spatial dimension
- #channels doubles after each pool

the overall n° of FLOPS of convolutions stay constant (spatial dimension halves, but the # of channels doubles)

Dropped local response normalization (LRN)

Batch norm not invented yet! Pre-initialization of deeper networks with weights from shallower architectures crucial to let training progress (unless smart initialization strategies are used).

very useful to capture STYLE of images

we will see that it is because more smaller convs are used, which capture a lot of details, and also because it doesn't have a stem layer

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 3x3 conv 64 output ch.	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128 64 x 2 channels	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					

same structure of AlexNet in the final part, the classifier

Karen Simonyan and Andrew Zisserman, "Very Deep Convolutional Networks for Large-scale Image Recognition", ICLR 2015

Stages

since a lot of big convs can be emulated by smaller convs

* this is good because stacking convs is more convenient: less parameters then less flops required

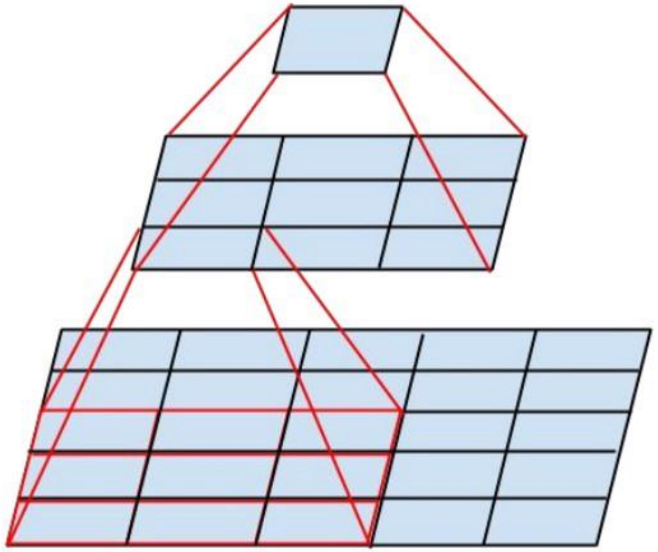
the main drawback is that much more memory is required (double)

VGG introduces the idea of designing a network as repetitions of **stages**, i.e. a fixed combination of layers that process activations **at the same spatial resolution**.

In VGG, stages are either:

- conv-conv-pool
- conv-conv-conv-pool
- conv-conv-conv-conv-pool

we pass in another stage when spatial resolution changes, and it does after the max pooling



One stage **has same receptive field of larger convolutions** but **requires less params and computation** and introduces more non-linearities. more ReLUs means more expressiveness

No free-lunch, though: **memory for activations doubles**

Conv layer	Params	Flops	ReLUs	#Activations
$C \times C \times 5 \times 5\ , S = 1, P = 2$	$25C^2 + C$	$50C^2 W_{in} H_{in}$	1	$C \times W_{in} \times H_{in}$
* 2 stacked $C \times C \times 3 \times 3, S = 1, P = 1$	$18C^2 + 2C$	$36C^2 W_{in} H_{in}$	2	$2 \times C \times W_{in} \times H_{in}$

VGG-16	VGG-19
D	E
16 weight layers	19 weight layers
conv3-64 conv3-64	conv3-64 conv3-64
conv3-128 conv3-128	conv3-128 conv3-128
conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool	maxpool
FC-4096	FC-4096
FC-4096	FC-4096
FC-1000	FC-1000
soft-max	soft-max

VGG-16 summary

by design it doesn't have a stem layer

a lot of resources to process the first layers

Bigger network than AlexNet

138 M params (2.3x AlexNet) again, mostly in fc layers

~4 Tflops (~ 14x), 31 Gflops/img, mainly due to convolutions

~16.5 GB of memory (~ 12x)
Memory mostly stores activations (of first conv layers), which are much larger than in AlexNet for the absence of stem layers)

Trained on 4 GPUs with data parallelism for 2-3 weeks

layer	Kernels	K_W/H	S	P	Actv H/W	Actv Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Params memory (MB)
input					224	3	150528	0	-	73,5	0,0
conv1	64	3	1	1	224	64	3211264	2	22196,3	3136,0	0,0
conv2	64	3	1	1	224	64	3211264	37	473520,1	3136,0	0,4
pool1	1	2	2	0	112	64	802816	0	411,0	784,0	0,0
conv3	128	3	1	1	112	128	1605632	74	236760,1	1568,0	0,8
conv4	128	3	1	1	112	128	1605632	148	473520,1	1568,0	1,7
pool2	1	2	2	0	56	128	401408	0	205,5	392,0	0,0
conv5	256	3	1	1	56	256	802816	295	236760,1	784,0	3,4
conv6	256	3	1	1	56	256	802816	590	473520,1	784,0	6,8
conv7	256	3	1	1	56	256	802816	590	473520,1	784,0	6,8
pool3	1	2	2	0	28	256	200704	0	102,8	196,0	0,0
conv8	512	3	1	1	28	512	401408	1180	236760,1	392,0	13,5
conv9	512	3	1	1	28	512	401408	2360	473520,1	392,0	27,0
conv10	512	3	1	1	28	512	401408	2360	473520,1	392,0	27,0
pool4	1	2	2	0	14	512	100352	0	51,4	98,0	0,0
conv11	512	3	1	1	14	512	100352	2360	118380,0	98,0	27,0
conv12	512	3	1	1	14	512	100352	2360	118380,0	98,0	27,0
conv13	512	3	1	1	14	512	100352	2360	118380,0	98,0	27,0
pool5	1	2	2	0	7	512	25088	0	12,8	24,5	0,0
flatten	1	1	1	0	1	25088	25088	0	0,0	0,0	0,0
fc14	4096	1	1	0	1	4096	4096	102786	26306,7	4,0	1176,3
fc15	4096	1	1	0	1	4096	4096	16781	4295,0	4,0	192,0
fc16	1000	1	1	0	1	1000	1000	4100	1048,6	1,0	46,9
					Minibatch:	128	Totals:	138.382	3.961.171	14.733	1.584

Inception v1 (GoogLeNet)

INCREASING WIDTH -> more channels within each conv layer:

CONS: more computational cost -> more parameters, more FLOPs, more memory usage

PROS: more diverse and complex features, parallelization stabilizes learning process -> less prone to van/exp gradient

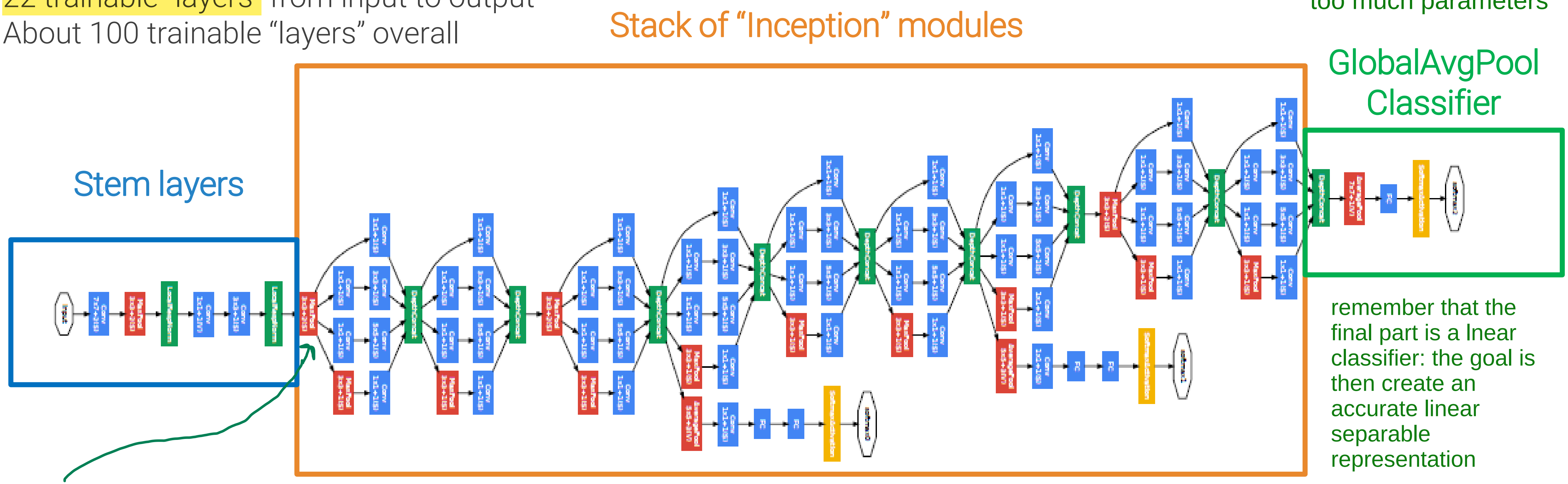
"The main hallmark of this architecture is the improved utilization of the computing resources inside the network. This was achieved by a carefully crafted design that allows for increasing the depth and width of the network while keeping the computational budget constant."

22 trainable "layers" from input to output

About 100 trainable "layers" overall

no more 3 FC layers in the classifier

too much parameters



remember that the final part is a lnear classifier: the goal is then create an accurate linear separable representation

everything from here on reasons on images of 28x28, after the reduction of stem layers

Christian Szegedy et al., "Going deeper with convolutions", CVPR 2015

INCREASING DEPTH -> more layers and larger receptive field:

CONS: more computational cost -> more parameters, more FLOPs, more GD iterations, more probability of vanishing/exploding GD, more memory usage

PROS: increasing the ability of the network to learn complex features and relationships between data, improving generalization, more powerfulness and expressiveness

Stem layers

	inception 1x1				inception 3x3			Inception 5x5			Maxpool		Activations					Acts	Params
Layer	Ks	H/W	S	P	C_out	1x1	H/W	C_out	1x1	H/W	1x1	H/W	H/W	Channels	#Activations	#params (K)	flops (M)	memory (MB)	memory (MB)
input													224	3	150528	0	-	73,5	0,0
conv1	64	7	2	3									112	64	802816	9	30211,6	784,0	0,1
pool1	1	3	2	1									56	64	200704	0	231,2	196,0	0,0
conv2	64	1	1	0									56	64	200704	4	3288,3	196,0	0,0
conv3	192	3	1	1									56	192	602112	111	88785,0	588,0	1,3
pool2	1	3	2	1									28	192	150528	0	173,4	147,0	0,0

Stem layers aggressively downsamples inputs: from 224 to 28 width/height in 5 layers, which require about 130 G glops, 124 K parameters, and 2 GB of memory

layered stemming

Yet, it brings it down a bit more gently than AlexNet, as per ZFNet lesson

- only uses strides of 2
- largest conv is 7x7

huge spatial reduction, but within 5 steps: from 224x224 to 28x28

Compare with VGG: to reach 28x28, it uses 10 layers, with more than half of the total flops (2.4 Tflops), more than 1.7 M parameters, and 13 GB of memory.

all of these branches are computed in parallel, unlike the previous architectures...

not very good because it increase a lot the number of channels -> it becomes very slow

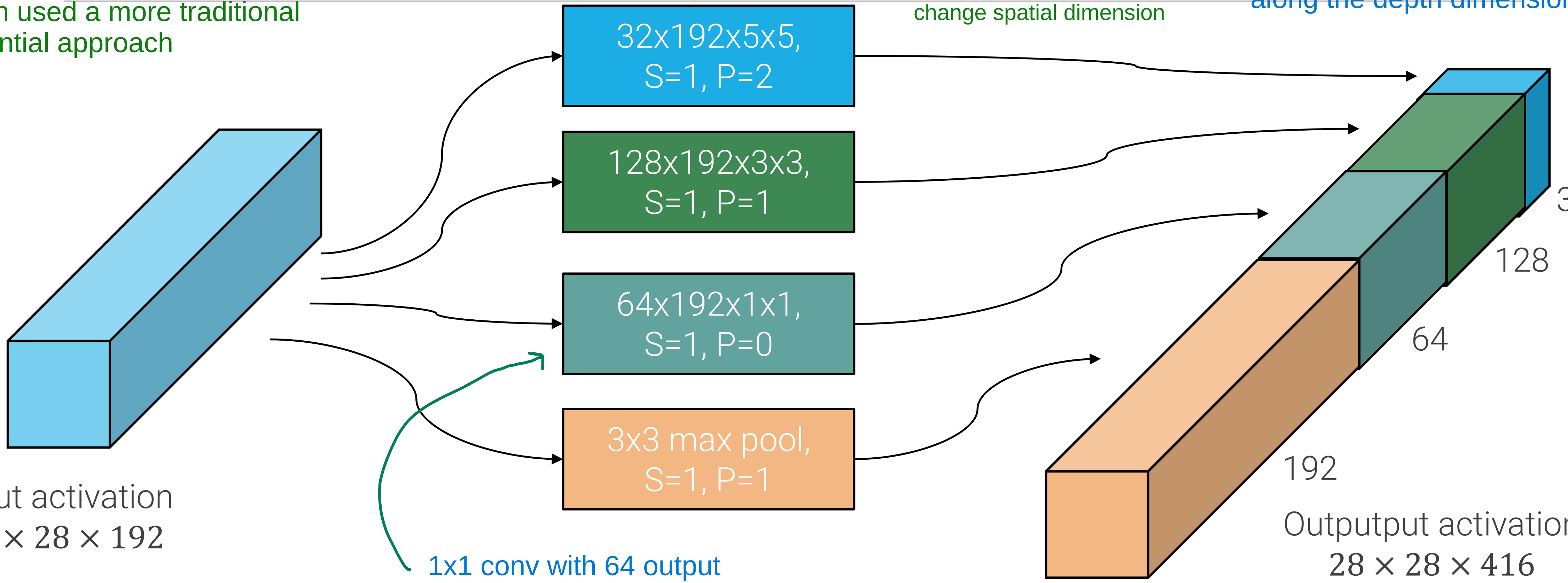
Naïve Inception module

...which used a more traditional sequential approach

all in parallel!!

these convolution does not change spatial dimension

after each branch computes its output, time to concatenate along the depth dimension



1x1 conv with 64 output channels (kernels)

Two main problems:

- Due to max-pool, #channels grows very fast when inception modules are stacked on top of each other
- 5x5 and 3x3 convs on many channels become prohibitively expensive if we stack a lot of them, e.g. here conv 5x5 = 2x28x28x32x192x5x5=240 Mflops, conv 3x3 = 2x28x28x128x192x3x3=350 Mflops

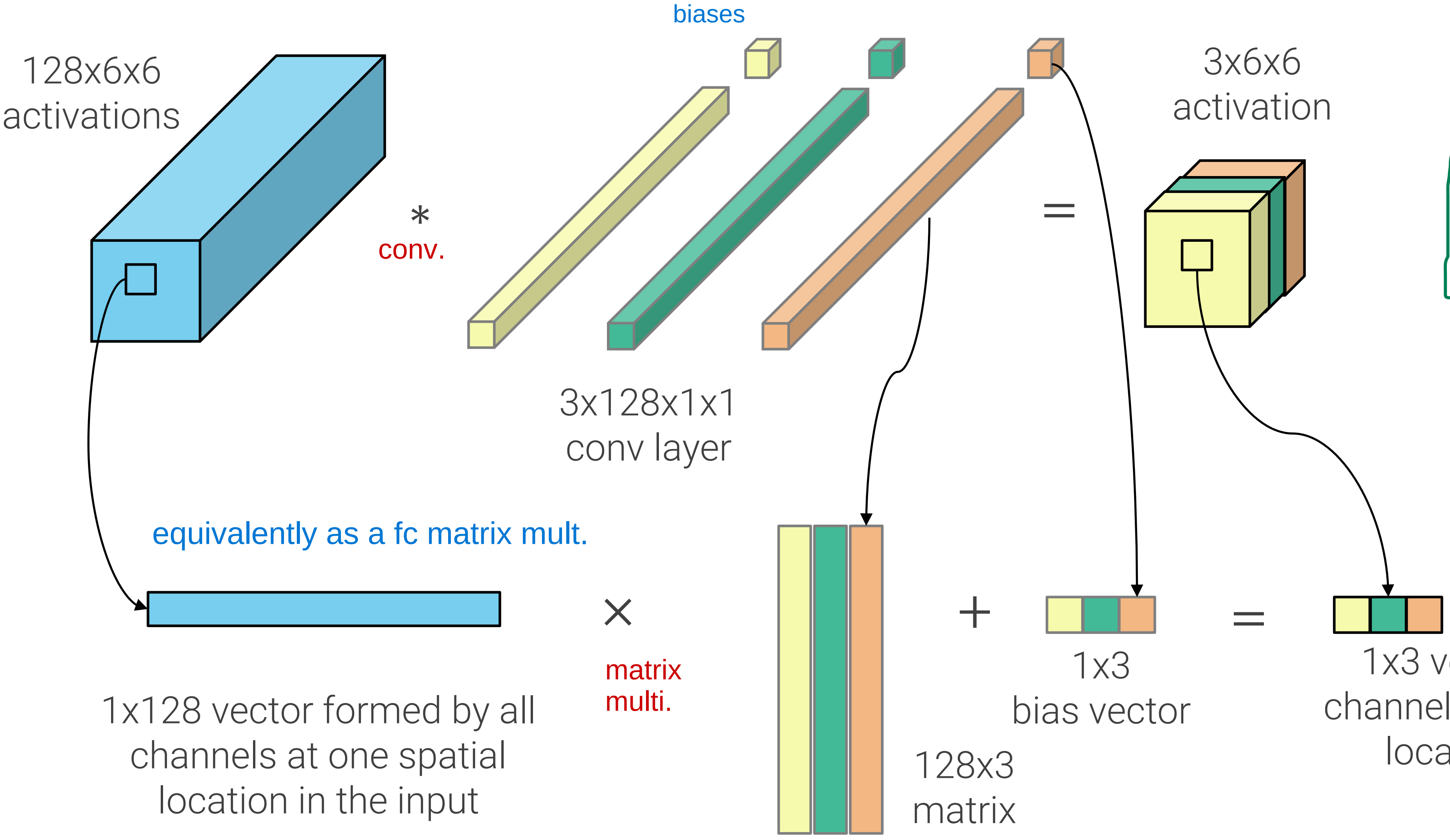
also regular convs can preserve spatial dims,
but 1x1 always do that

1 x 1 convolutions

Yann LeCun
April 6, 2015 ·

The 1×1 convolutional layer can be thought of as applying a fully connected layer independently at each spatial location of the input feature map, where the input channels behaves as input neurons for a FC, doing the classical linear combination

In Convolutional Nets, there is no such thing as "fully-connected layers". There are only convolution layers with 1x1 convolution kernels and a full connection table.



1 x 1 convolutions behaves like all other convolutions.

They allows us to **change the depth** of the activations while preserving the spatial size.

We can also interpret them as **applying a linear FC layer at each spatial location.**

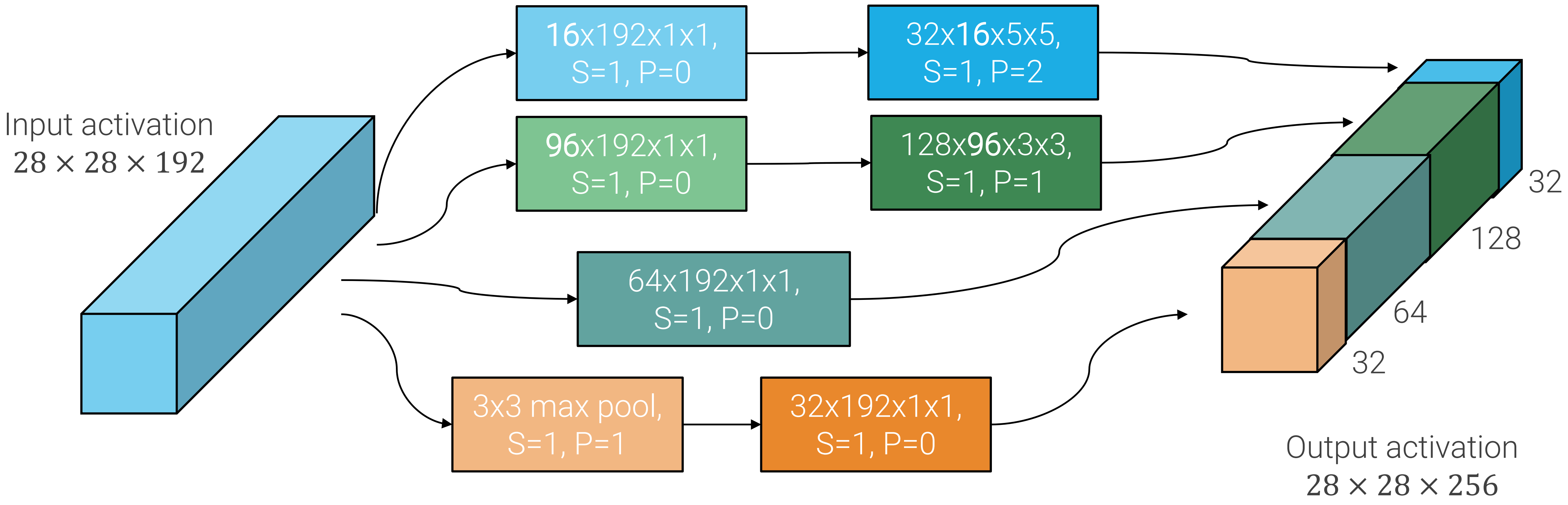
If we stack several of them we are actually **applying an MLP at each location.**

multi layer perceptron can learn any function -> two 1x1 convs form a MLP

Lin et al., "Network in network", ICLR 2014

Inception module

in order to make it feasible to run inception modules onto machines, add 1x1 convolution before larger convs and after max pool



By adding 1x1 convolutions before larger convs and after max pool we can
- Control the number of output channels by reducing the depth of the max pool output
- Control the time complexity of the larger convolutions by reducing the channel dimension, e.g. now flops are

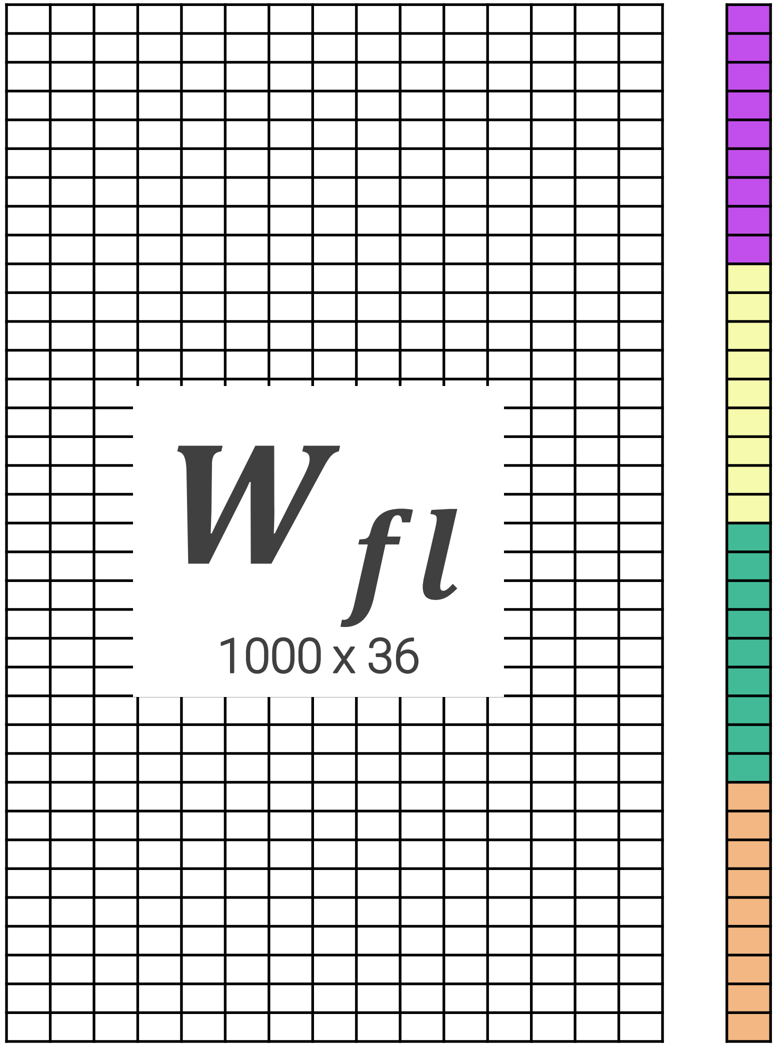
Conv 5x5 = 28x28x16x192x2 + 28x28x32x16x5x5x2≅5M+10M=**25M flops (was 240M)**

Conv 3x3=28x28x96x192x2 + 28x28x128x96x3x3x2 ≅29M+173M=**202M flops (was 350M)** millions of params: 1000 classes and 36 is the dim of the input vector

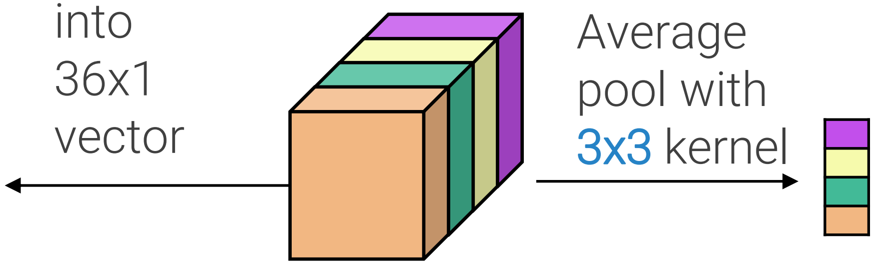
global view of the content of the image, a very high level one

Fully-connected classifier vs global average pooling

instead of having one huge flattened vector, we do a pooling along depth dimension



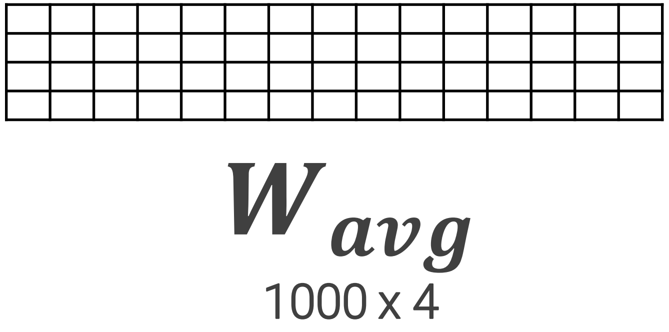
Flatten into 36x1 vector



Average pool with 3x3 kernel

throws away spatial dim

4x3x3
Last activation before classifier



why avg pooling and not a conv? no explicit reason

To reduce the number of parameters needed at the interface between convolutional features and fully connected layers, NiN proposed to get rid of spatial dimensions by averaging them out

Lin et al., "Network in network", ICLR 2014

GoogLeNet: Global Average Pooling

what is important is the BLUEPRINT (the template), the global structure of an architecture, not the specific details

	inception 1x1				inception 3x3			Inception 5x5			Maxpool		Activations						
Layer	Ks	H/W	S	P	C_out	1x1	H/W	C_out	1x1	H/W	1x1	H/W	H/W	Channels	#Activations	#params (K)	flops (M)	Acts memory (MB)	Params memory (MB)
incep8	384	1	1	0	384	192	3	128	48	5	128	3	7	1024	50176	1443	16689,7	49,0	16,5
avgpool	1	7	1	0									1	1024	1024	0	6,4	1,0	0,0
fc1	1000	1	1	0									1	1000	1000	1025	262,1	1,0	11,7

GoogLeNet uses global average pooling to remove spatial dimensions and one FC layer to produce class scores.

- It results in 1 million parameters and negligible numbers of flops

VGG has 124 millions parameters in the final 3 fc layers, which requires 31 Gflops to compute.

- If the kernel size of pooling covering the full input activation is computed by the layer instead of being specified by the user, i.e. `AdaptiveAvgPool2d` layer instead of `AvgPool2d` in PyTorch , this makes the network able (at least as far as tensor dimensions are concerned) to work on any input image size.

CLASS `torch.nn.AdaptiveAvgPool2d(output_size: Union[T, Tuple[T, ...]])` [SOURCE]

Applies a 2D adaptive average pooling over an input signal composed of several input planes.

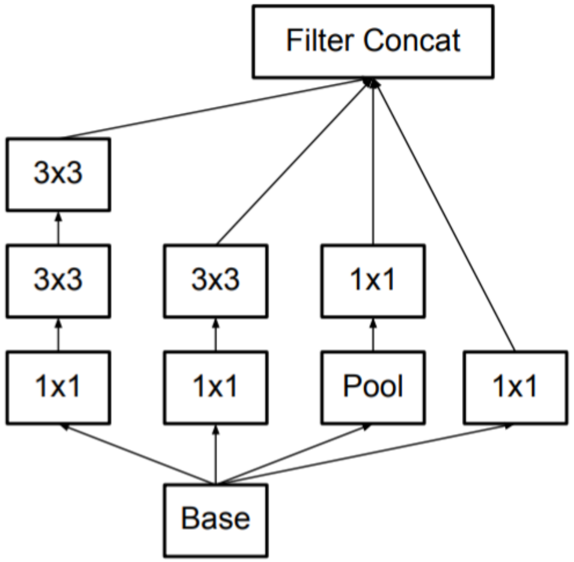
GoogLeNet summary

	inception 1x1				inception 3x3			Inception 5x5			Maxpool		Activations						
Layer	Ks	H/W	S	P	C_out	1x1	H/W	C_out	1x1	H/W	1x1	H/W	H/W	Channels	#Activations	#params (K)	flops (M)	Acts memory (MB)	Params memory (MB)
input													224	3	150528	0	-	73,5	0,0
conv1	64	7	2	3									112	64	802816	9	30211,6	784,0	0,1
pool1	1	3	2	1									56	64	200704	0	231,2	196,0	0,0
conv2	64	1	1	0									56	64	200704	4	3288,3	196,0	0,0
conv3	192	3	1	1									56	192	602112	111	88785,0	588,0	1,3
pool2	1	3	2	1									28	192	150528	0	173,4	147,0	0,0
incep1	64	1	1	0	128	96	3	32	16	5	32	3	28	256	200704	163	31380,5	196,0	1,9
incep2	128	1	1	0	192	128	3	96	32	5	64	3	28	480	376320	388	75683,1	367,5	4,4
pool3	1	3	2	1									14	480	94080	0	108,4	91,9	0,0
incep3	192	1	1	0	208	96	3	48	16	5	64	3	14	512	100352	376	17403,4	98,0	4,3
incep4	160	1	1	0	224	112	3	64	24	5	64	3	14	512	100352	449	20577,8	98,0	5,1
incep5	128	1	1	0	256	128	3	64	24	5	64	3	14	512	100352	509	23609,2	98,0	5,8
incep5	112	1	1	0	288	144	3	64	32	5	64	3	14	528	103488	605	28233,4	101,1	6,9
incep6	256	1	1	0	320	160	3	128	32	5	128	3	14	832	163072	867	41445,4	159,3	9,9
pool4	1	3	2	1									7	832	40768	0	47,0	39,8	0,0
incep7	256	1	1	0	320	160	3	128	32	5	128	3	7	832	40768	1042	11860,0	39,8	11,9
incep8	384	1	1	0	384	192	3	128	48	5	128	3	7	1024	50176	1443	16689,7	49,0	16,5
avgpool	1	1	1	0									1	1024	1024	0	6,4	1,0	0,0
fc1	1000	1	1	0									1	1000	1000	1025	262,1	1,0	11,7
											Minibatch:			128	Totals:	6.992	389.996	3.251	80

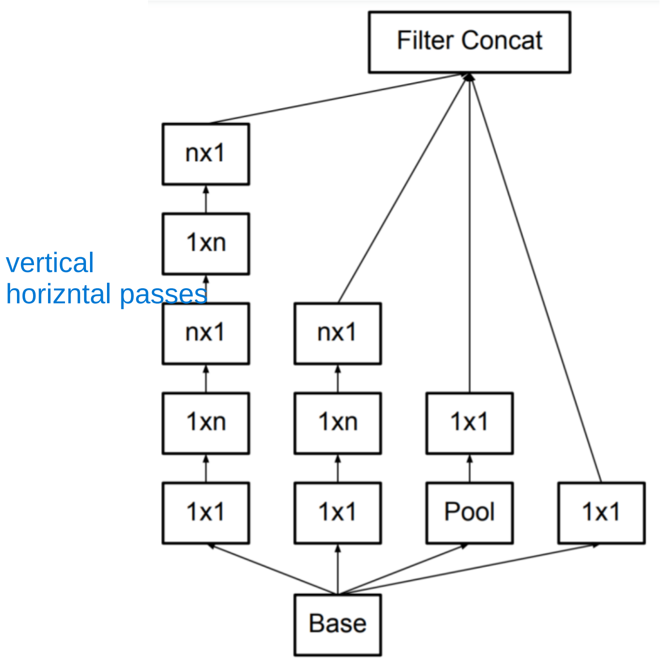
Only 7 millions parameters, 390 Gflops (3 Gflops/img), and 3.3 GB of memory. 10.07% error rate on ILSVRC 14 validation set with one model and one test crop, 7.89 with one model and aggressive cropping (144 crops)

Inception v3

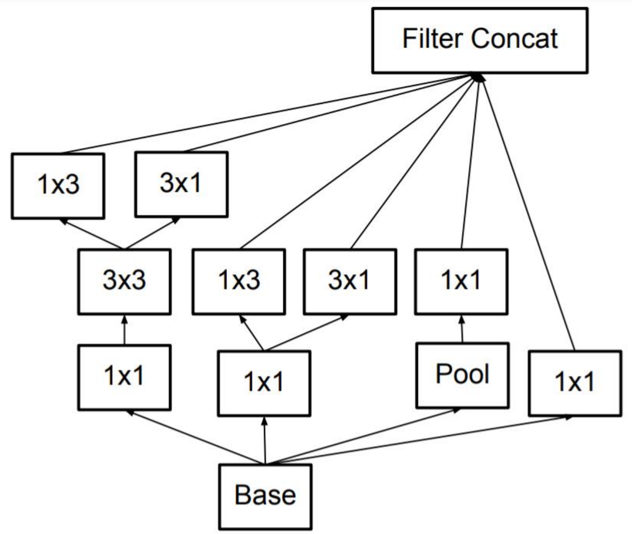
It leverages convolution factorizations to increase computational efficiency and to reduce the number of parameters. Less parameters should be more disentangled and therefore easier to train. Achieved 4.48% top-5 error on ILSVRC12 with 12 crops.



Factorization A, used for fine-scale activations (35x35)



Factorization B, used for mid-scale activations (17x17)



Factorization C, used for coarse-scale activations (8x8)

C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. "Rethinking the inception architecture for computer vision", CVPR 2016

Residual Networks

* Adding identity layers demonstrates that the network's depth alone is not the problem, but rather the optimization process. If it were possible to train very deep networks effectively, adding these identity layers should not degrade performance

VGG lesson: growing depth improves performance. Yet, stacking more layers doesn't automatically improve performance.

increasing depth means also more params and flops, more GD iters, higher prob of van/expl gradient

Too many parameters increase overfitting and hurts generalization? We also observe higher training errors, so overfitting it's not the only reason, there is also a training problem, even when using Batch Norm.

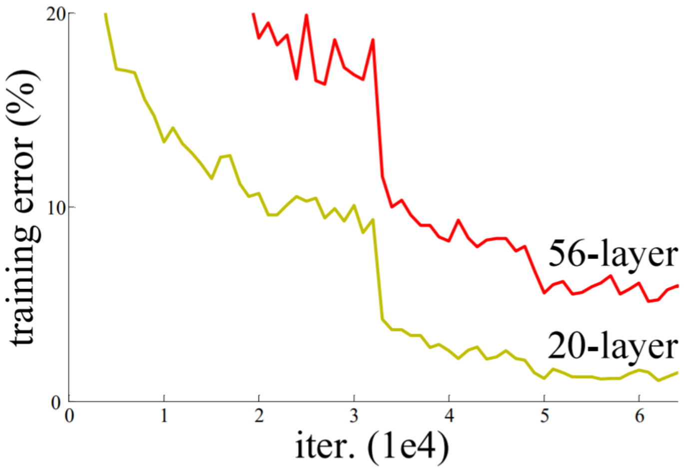
training error increases due to various factors, not just overfitting: also vanishing/exploding can be a possible reason

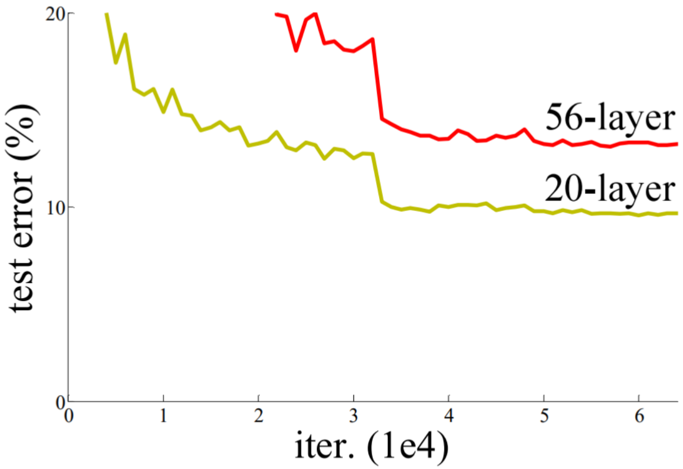
* Yet, a solution exists by construction: if a network with 20 layers achieves performance X, then we can stack 36 more identity layers and we should keep performance at X.

An identity layer is one where the output is the same as the input, essentially y = x

SGD is not able to find this solution with the parameterization we use for layers: optimizing very deep networks is hard.

this is due to vanishing/exploding gradient





ResNet doesn't prove that depth isn't the problem and adding it always beneficial: it proves that deep architecture can be trained effectively with the right structure, the skip connections. They prove indeed that in the worst case the model learns the identity function, meaning that additional identity layer won't hurt performances.

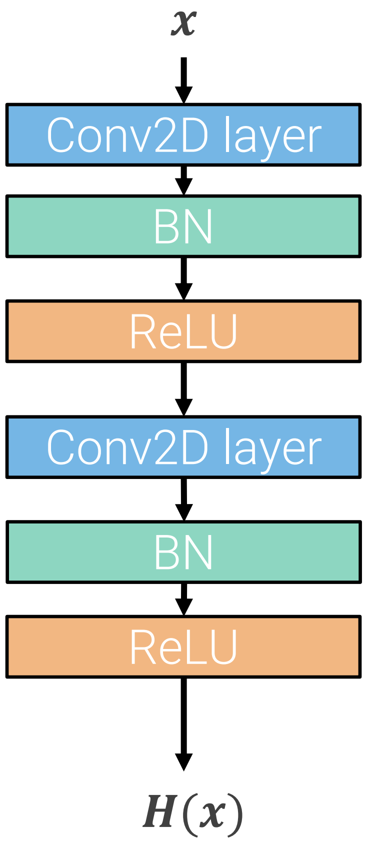
Kaiming He et al., "Deep Residual learning for image recognition", CVPR 2016 the innovation was heavy use of BN and these skip connections

Residual block

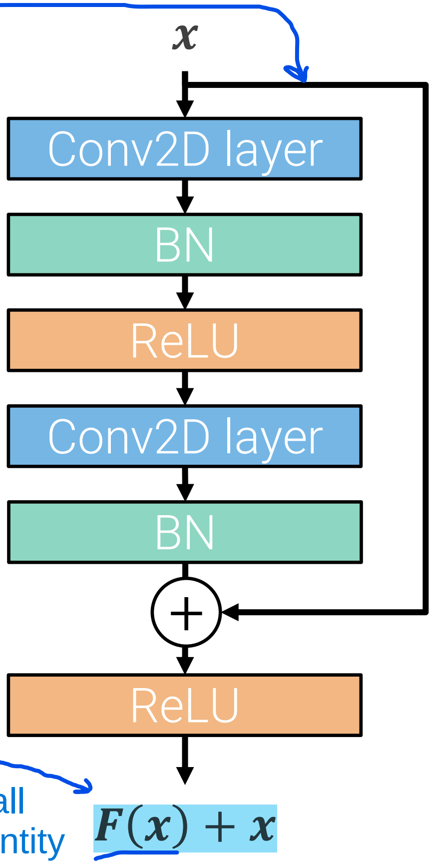
- residual blocks allow the network to learn residual functions with reference to the layer inputs, instead of learning unreferenced functions.
- using skip connections helps preserve information and ensures that gradients can flow more easily during backpropagation
- instead of hoping that optimization algorithms like SGD can find the right parameterization, the network architecture itself ensures that learning deep representations is feasible.

The proposed solution is to change the network so that learning identity functions is easy by introducing residual blocks. Implemented by adding skip connections skipping two convolutional layers.

Adding identity layers (or residual connections) helps demonstrate that the architecture's depth isn't the problem; it's the optimization process. By incorporating identity mappings, ResNets ensure that even very deep networks can be trained effectively. This approach leverages the idea that if a shallower network performs well, a deeper network with identity layers can maintain that performance while potentially learning more complex features. This insight addresses both the challenge of overfitting and the difficulty of optimizing very deep networks.



SGD is not able to find a solution for this VGG like block



residual function

the output is a small variation of the identity

Weights usually initialized to be very small (or 0 for biases). Network starts with the identity function and learns an "optimal" perturbation of it.

It makes heavy use of batch-norm

why relu outside? identity can be also negative, and with relu i obtain only positive values, so otherwise i will keep increasing, having no flexibility no maxpooling like in VGG

Residual Networks

same rules of VGG:
- halves the spatial dimension
- doubles n° of channels

therefore also here the # of flops remains constant

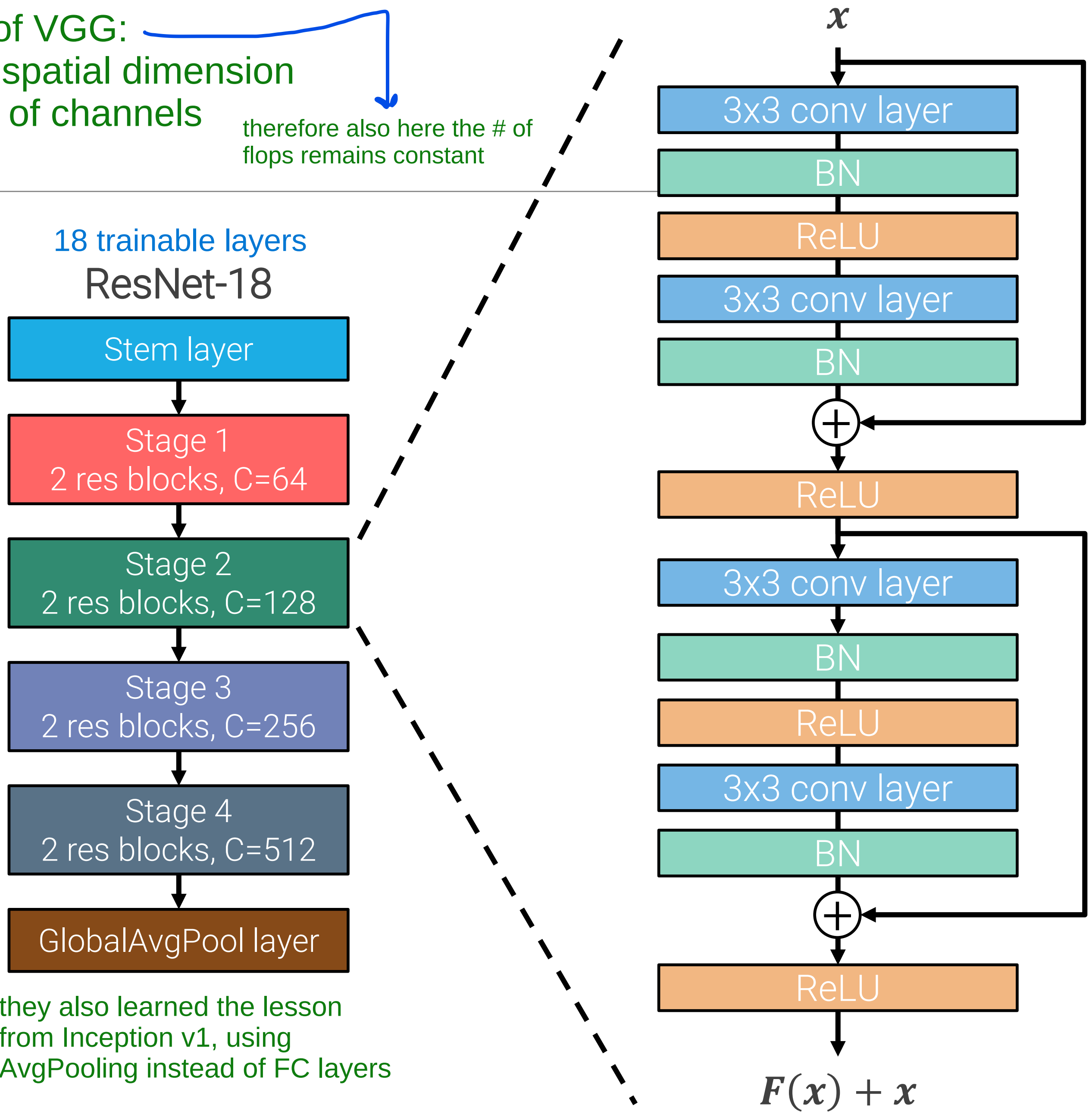
Inspired by VGG regular design. Network is a stack of stages with fixed design rules:

- Stages are a stack of residual blocks
- Each residual block is a stack of two 3x3 convolutions with batch-norm
- the first block of each stage halves the spatial resolution (with stride-2 convs) and doubles the number of channels

It uses stem layer and global average pooling as GoogLeNet

Naming conventions follow VGG, as well: ResNet-*X*, where *X* is the number of layers with learnable parameters

18 trainable layers



they also learned the lesson from Inception v1, using AvgPooling instead of FC layers

Stem layer and global average pooling

just three

First layers are stem layers, as in GoogLeNet. However, it only uses one conv+pool layer, and reduces only to 56×56, probably because residual blocks are lightweight compared to Inception modules.

they tend to be a good compromise: not too expensive, not to aggressive in the downsampling in the stem layer

Layer	Kernels	Kernel H/W	S	P	Activations H/W	Activations Channels	#Activations	#params (K)	flops (M)	Activations memory (MB)	Parameters memory (MB)
input					224	3	150528	0	-	73,5	0,0
conv1	64	7	2	3	112	64	802816	9	30211,6	784,0	0,1
pool1	1	3	2	1	56	64	200704	0	231,2	196,0	0,0
...											
conv.s4.b3.2	512	3	1	1	7	512	25088	2360	29595,0	24,5	27,0
avgpool	1	7	1	0	1	512	512	0	3,2	0,5	0,0
fc1	1000	1	1	0	1	1000	1000	513	131,1	1,0	5,9

It also uses the same average pooling + linear layer at the end.

Skip conn dimensions

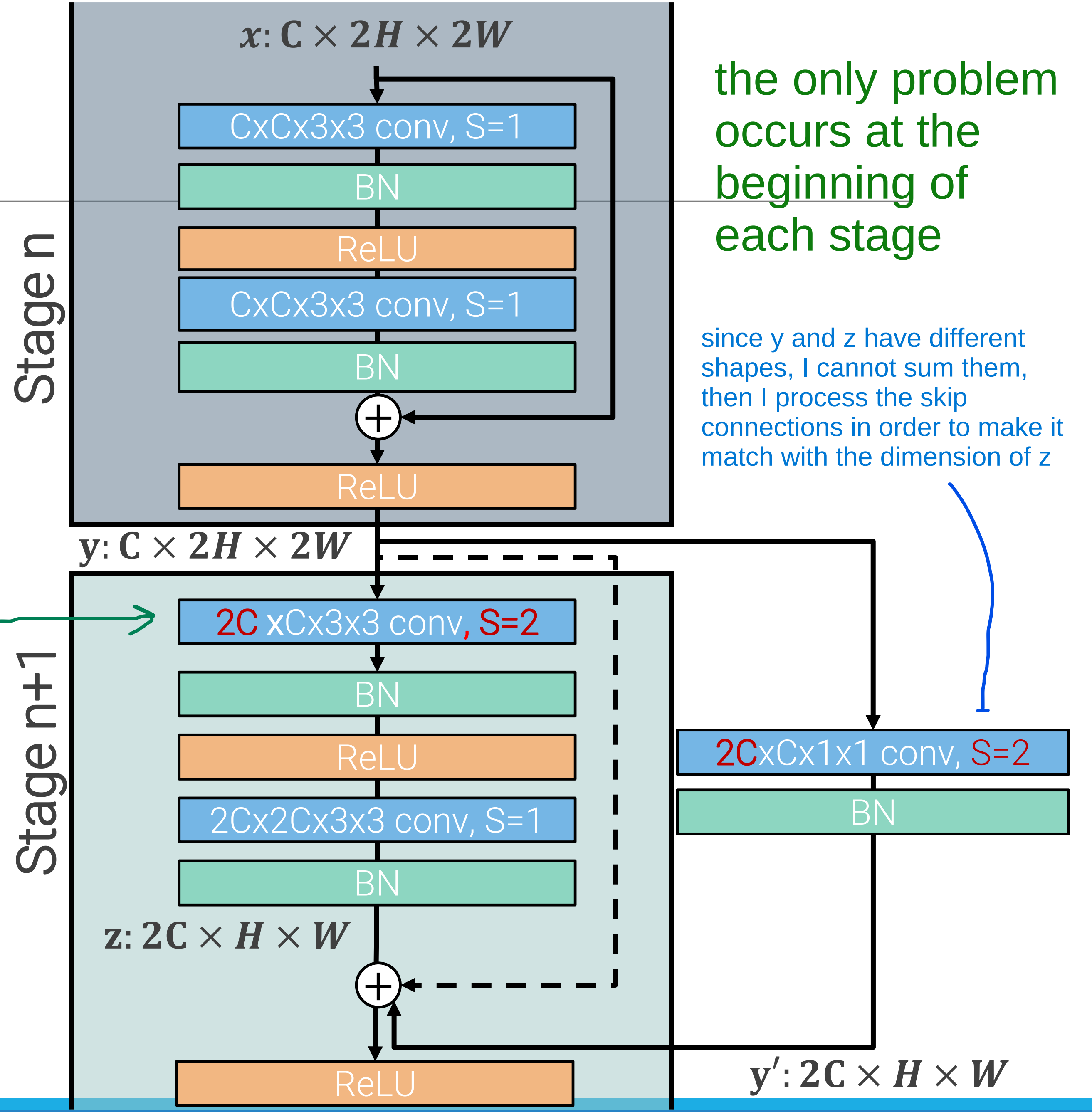
The residual blocks described so far **cannot be used as the first block of a new stage**, because the number of channels and the spatial dimensions do not match along the residual connection (dashed arrow)

The authors tried two solutions:

- apply stride 2 to y and zero pad the missing channels (no extra parameters)
- **1x1 conv with stride 2 and 2C output channels** (solid arrow)

and verified the second one to perform slightly better

the only problem occurs at the beginning of each stage



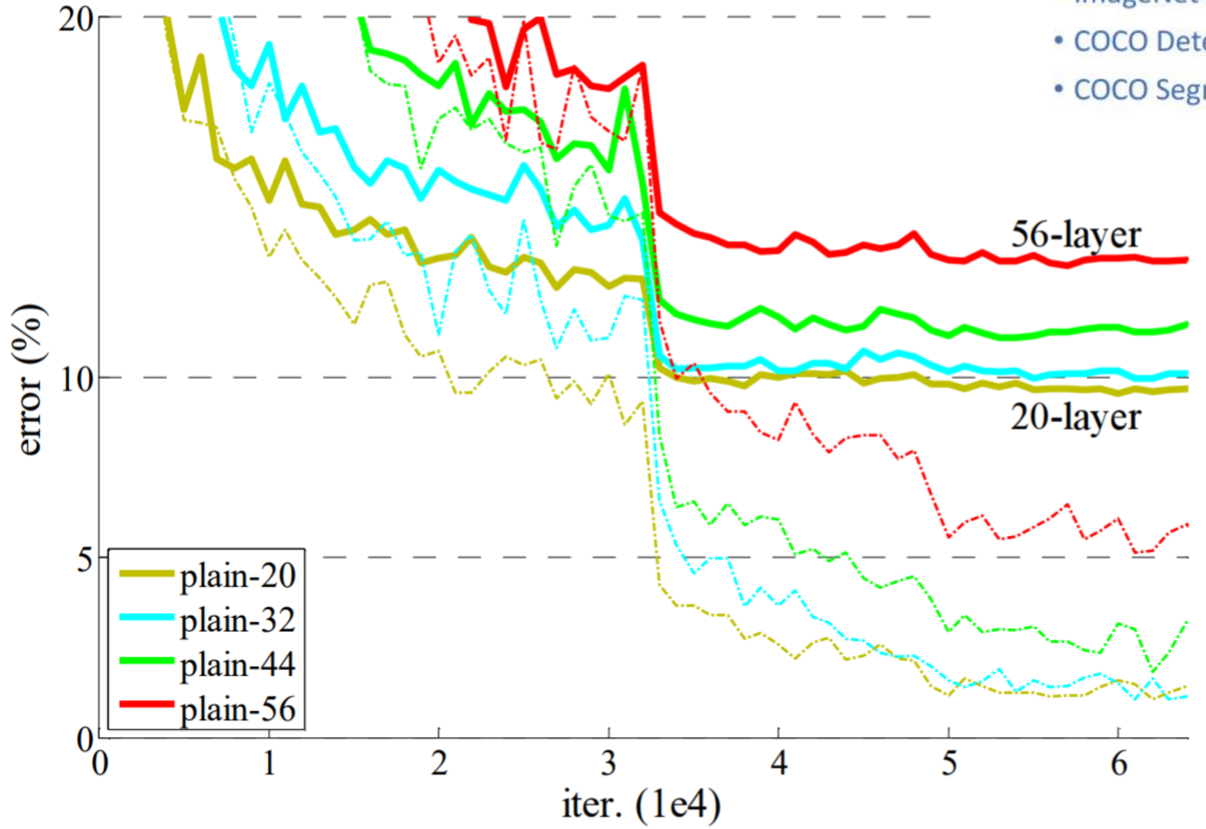
since y and z have different shapes, I cannot sum them, then I process the skip connections in order to make it match with the dimension of z

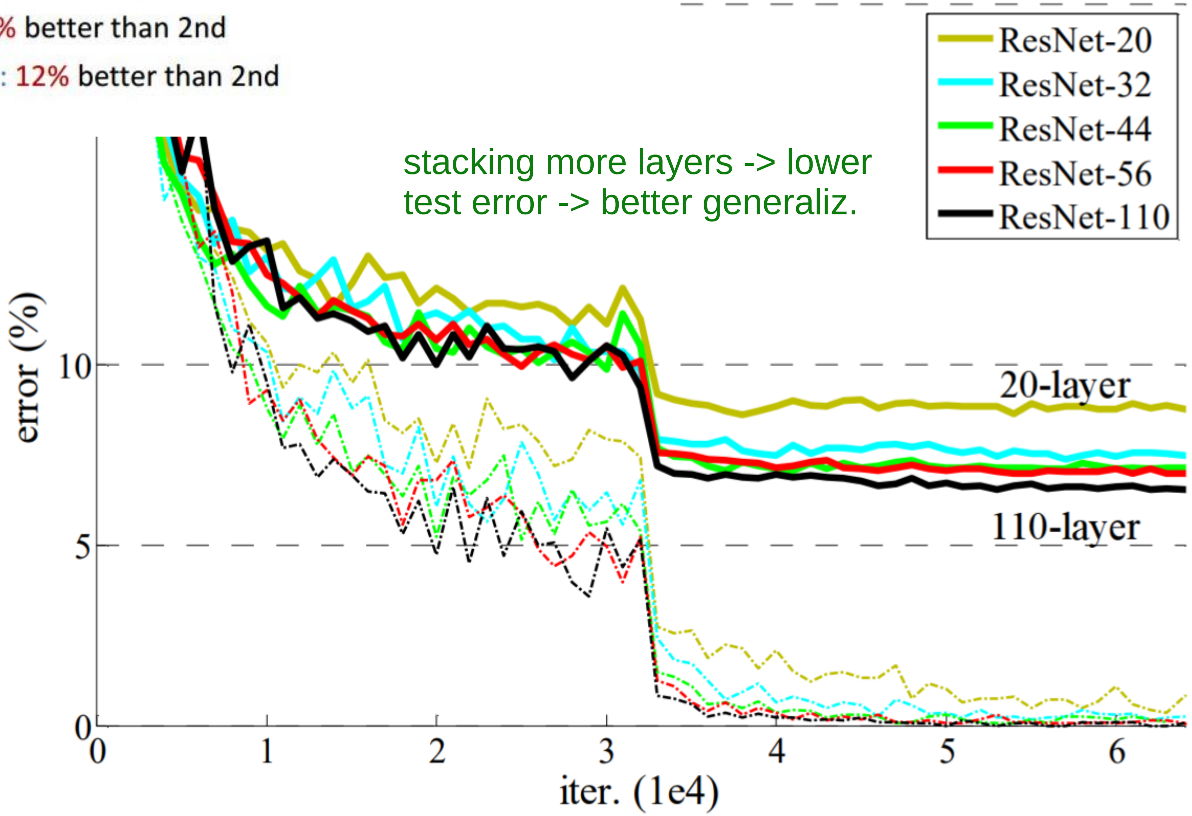
the first conv halves the spatial dim with stride = 2 and doubles n° of channels, 2C

Results updated

MSRA @ ILSVRC & COCO 2015 Competitions

- **1st places in all five main tracks**
  - ImageNet Classification: *"Ultra-deep"* (quote Yann) 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





stacking more layers -> lower test error -> better generaliz.

Residual blocks allow us to train deep networks. When properly trained, deep networks outperform shallower network as expected

Won all 2015 competitions by a large margin, still the standard baseline/backbone for most tasks today.

in order to train deeper networks, a variance was proposed

Bottleneck residual block

this variance allow us to grow faster wrt number of channels without paying the price for it

- use 1x1 conv to reduce #channels and then FLOPs
- apply 3x3 conv
- apply 1x1 restoring #channels

bottleneck because we start with 4*C channels, go to C channels to perform 3x3 conv and then go back to 4C

$2 \times 3 \times 3 \times C \times C \times H \times W$

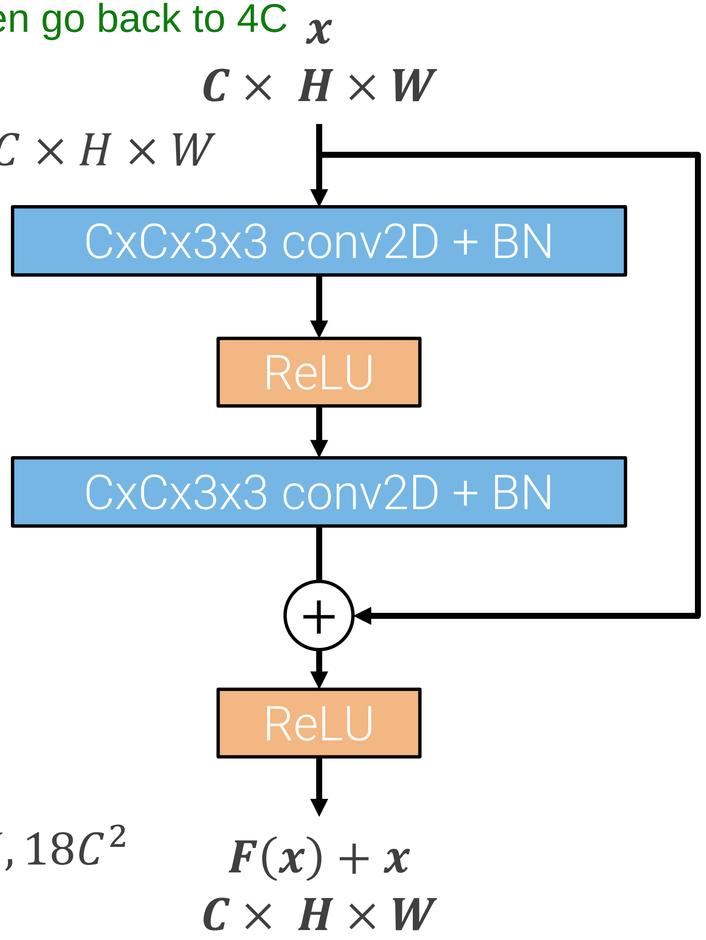
Flops: $18C^2HW$

Params $\cong 9C^2$

Flops: $18C^2HW$

Params $\cong 9C^2$

Total: $36C^2HW, 18C^2$



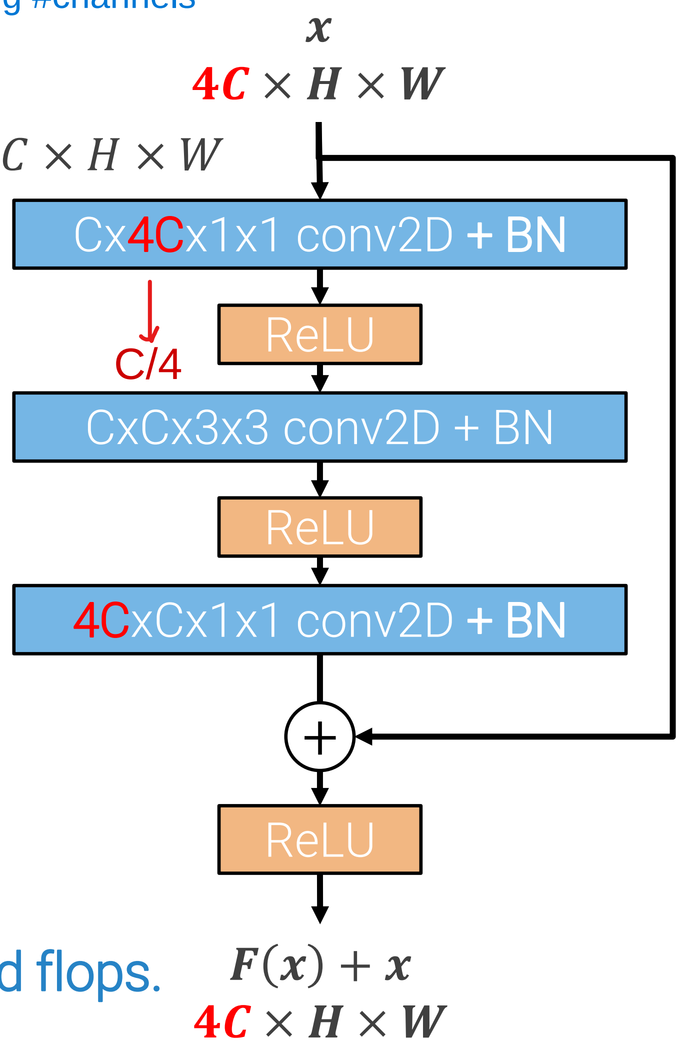
$2 \times 1 \times 1 \times C \times 4C \times H \times W$

Flops: $8C^2HW$
Params $\cong 4C^2$

Flops: $18C^2HW$
Params $\cong 9C^2$

Flops: $8C^2HW$
Params $\cong 4C^2$

Total: $34C^2HW, 17C^2$
#Flops approx the same



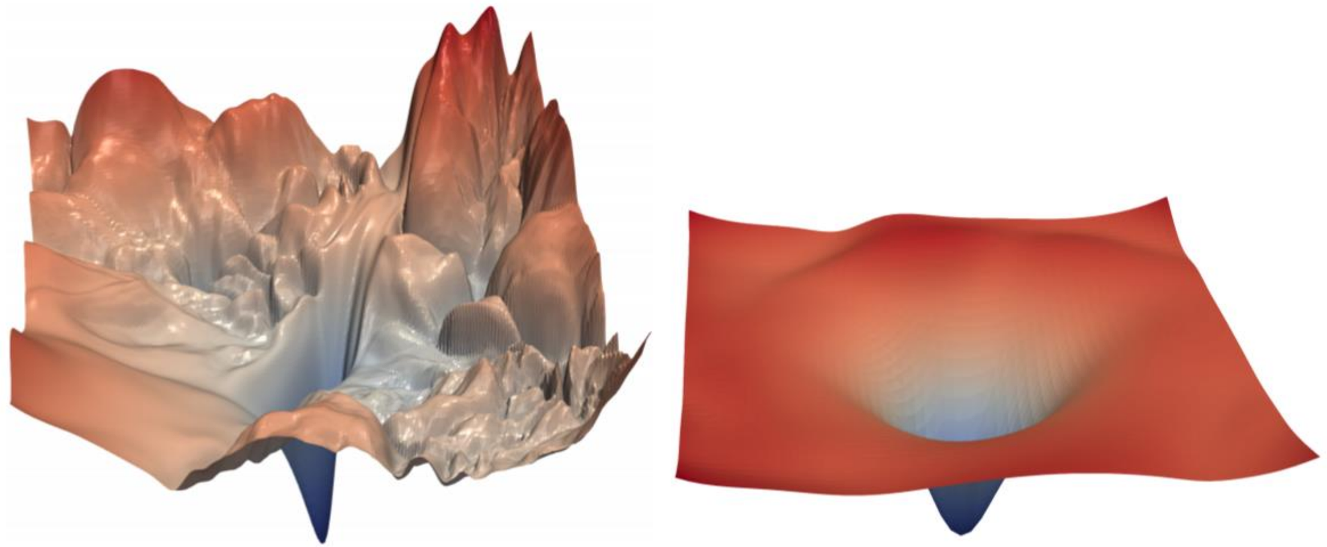
Used with very deep resnets: more layers with approx same parameters and flops.
It enables faster increases in depth without altering computational budget

Effects of residual learning

we know why resnet are so successful and well-working, unlike other architectures

LOSS LANDSCAPES

evey point on this chart is the value of the loss for some configuration of the parameters



(a) without skip connections (b) with skip connections

Figure 1: The loss surfaces of ResNet-56 with/without skip connections. The proposed filter normalization scheme is used to enable comparisons of sharpness/flatness between the two figures.

this landscape approximates the leftmost one, creating a SMOOTHER landscape because it focuses just on what we care about, the minimum

Hao Li et al., "Visualizing the Loss Landscape of Neural Nets", NeurIPS 2018

When we interpret ResNets as having multiple paths, we mean that the output can be viewed as a combination of transformations of varying depths. This interpretation helps explain why gradients can flow more easily through the network.

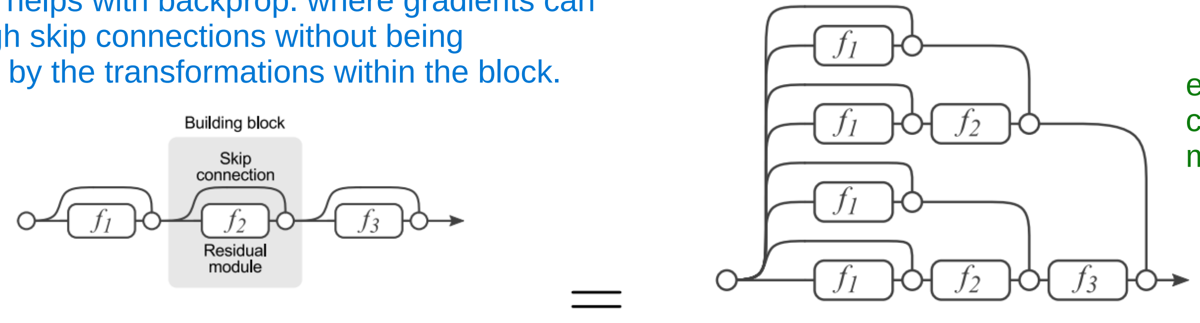
the main reason why resnets allow to train deeper networks

Resnets as ensembles of relatively shallow networks

this mainly helps with backprop. where gradients can flow through skip connections without being diminished by the transformations within the block.

avoiding or at least minimizing the problem of vanishing gradient!!

at the beginning, as if I can decide going throug the skip connection or through the block

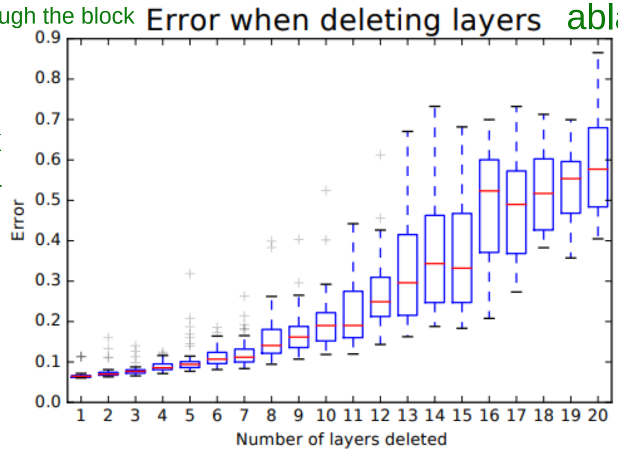


(a) Conventional 3-block residual network

(b) Unraveled view of (a)

each residual block can be viewed as a mini-network

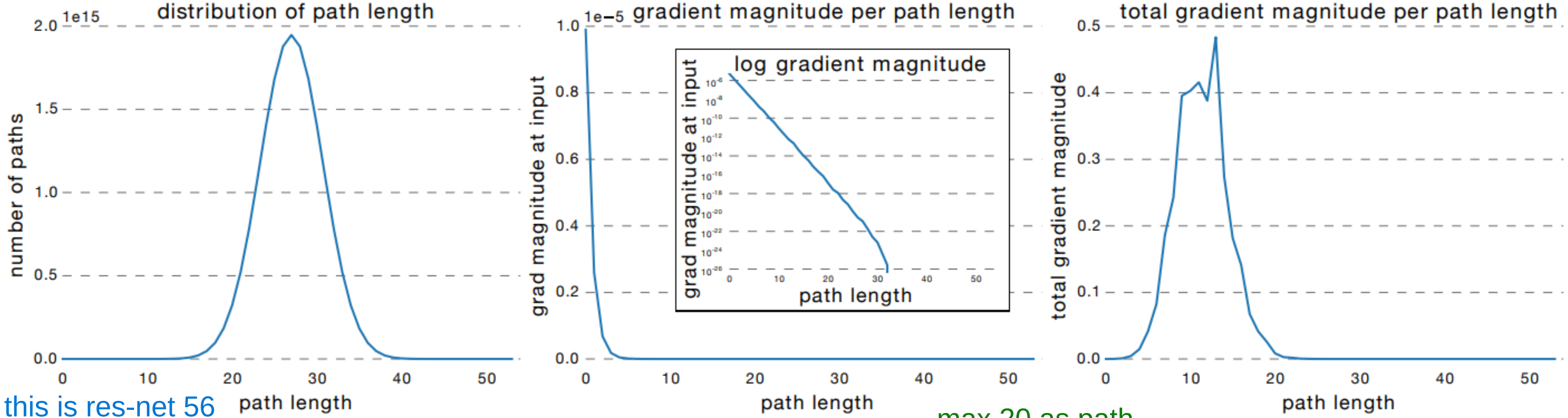
ablation studies



the error gets higher when layers are deleted, but always in a not too much aggersive way, just like ensemble models

Since the skip connections enable the network to bypass certain layers when needed, the entire ResNet can be interpreted as a combination of different " paths" of varying lengths, where each path represents a shallower network.

there are hence multiple paths of varying length for data to flow into the network



this is res-net 56

(a) (b) (c)

max 20 as path lenght, empirically

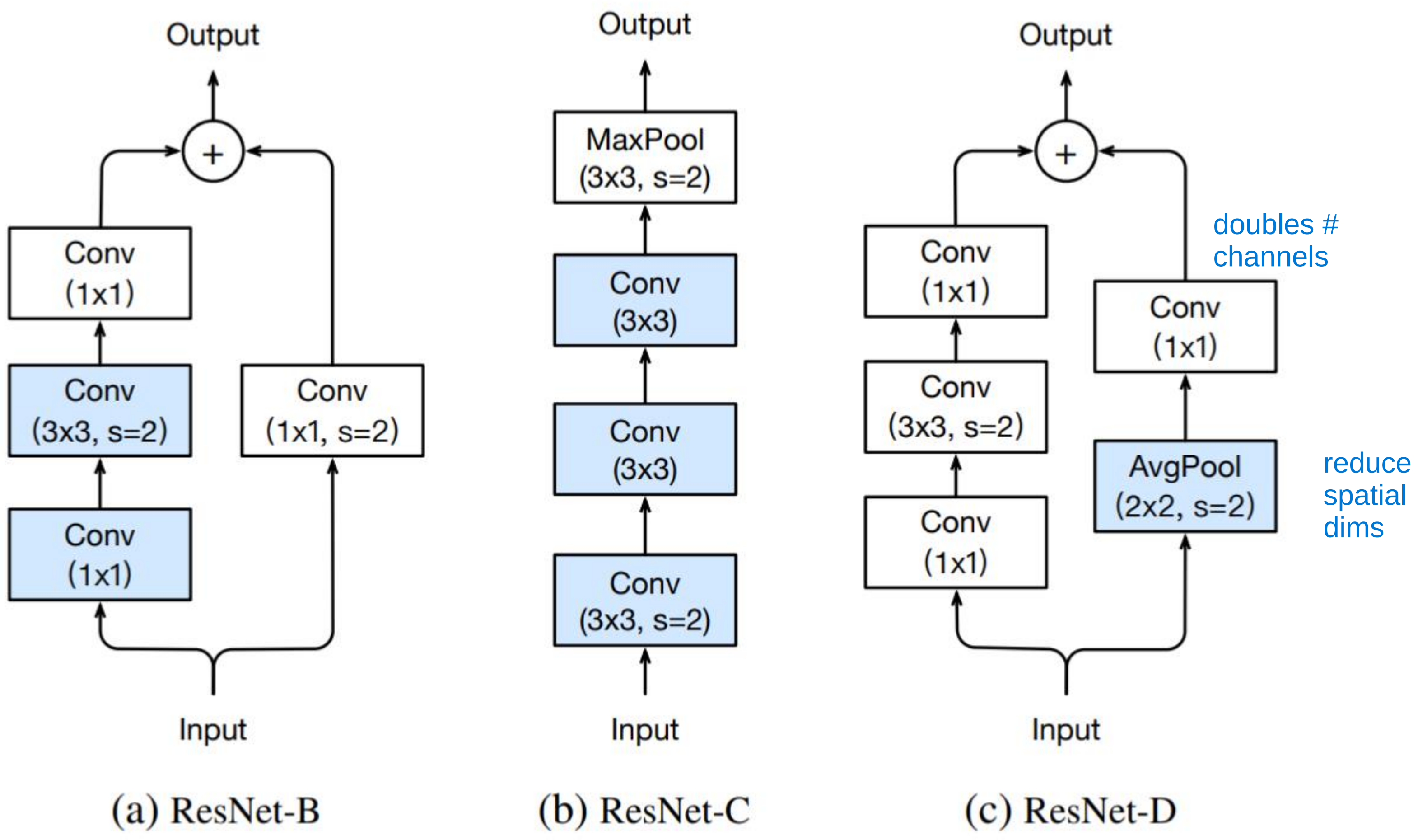
resnet receives infleuecn from all the possible paths

The skip connections reduce the need for the network to depend on all layers for each piece of information. As a result, the gradients and signals can travel through shorter paths (with fewer layers), allowing the model to learn as if it were an ensemble of shallower networks, despite its actual depth.

Andreas Veit, Michael Wilber, Serge Belongie. "Residual Networks Behave Like Ensembles of Relatively Shallow Networks", NeurIPS 2016

Further model tweaks – "ResNet v2"

- ResNet-B: 1x1 convolution at the beginning of bottleneck residual blocks ignore ¾ of the input activation. If we move stride 2 into the 3x3, all input is used.
- ResNet-C: replace 7x7 stride 2 conv in stem layers with 3 3x3 convs, the first one with stride 2
- ResNet-D: the 1x1 stride 2 conv used to match dimensions in the first block of each stage uses only ¾ of the input activation. Performing 2x2 stride 2 AvgPool before it fixes the problem.



Tong He et al., "Bag of Tricks for Image Classification with Convolutional Neural Networks", CVPR 19

Common variants on ImageNet

ResNet-18	ResNet-34	ResNet-50	ResNet-101	ResNet-152
Stem layer	Stem layer	Stem layer	Stem layer	Stem layer
Stage 1 2 res blocks, C=64	Stage 1 3 res blocks, C=64	Bottleneck Stage 1 3 res blocks, C=256	Bottleneck Stage 1 3 res blocks, C=256	Bottleneck Stage 1 3 res blocks, C=256
Stage 2 2 res blocks, C=128	Stage 2 4 res blocks, C=128	Bottleneck Stage 2 4 res blocks, C=512	Bottleneck Stage 2 4 res blocks, C=512	Bottleneck Stage 2 8 res blocks, C=512
Stage 3 2 res blocks, C=256	Stage 3 6 res blocks, C=256	Bottleneck Stage 3 6 res blocks, C=1024	Bottleneck Stage 3 23 res blocks, C=1024	Bottleneck Stage 3 36 res blocks, C=1024
Stage 4 2 res blocks, C=512	Stage 4 3 res blocks, C=512	Bottleneck Stage 4 3 res blocks, C=2048	Bottleneck Stage 4 3 res blocks, C=2048	Bottleneck Stage 4 3 res blocks, C=2048
GlobalAvgPool+FC	GlobalAvgPool+FC	GlobalAvgPool+FC	GlobalAvgPool+FC	GlobalAvgPool+FC

Use standard blocks

Use bottleneck blocks, 4 times #channels

Common variants on ImageNet

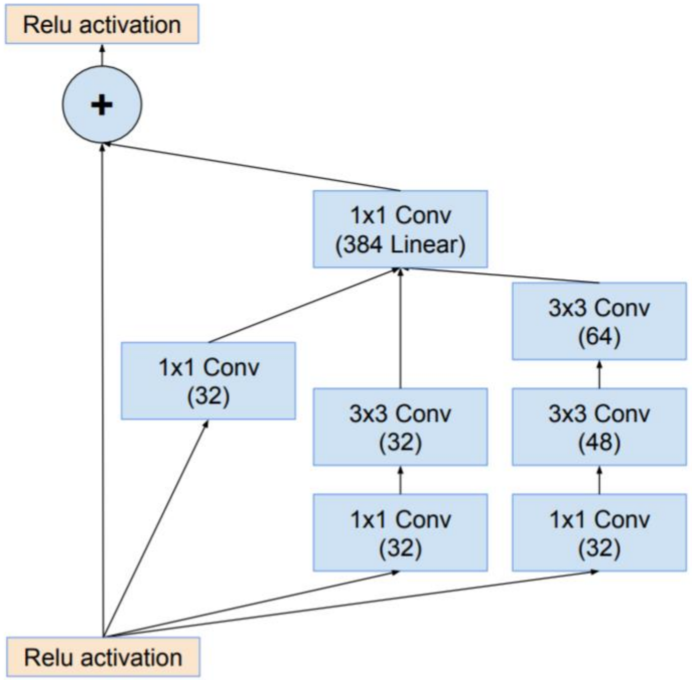
Good default choice

ResNet-18	ResNet-34	ResNet-50	ResNet-101	ResNet-152
Stem layer	Stem layer	Stem layer	Stem layer	Stem layer
Stage 1 2 res blocks, C=64	Stage 1 3 res blocks, C=64	Bottleneck Stage 1 3 res blocks, C=256	Bottleneck Stage 1 3 res blocks, C=256	Bottleneck Stage 1 3 res blocks, C=256
Stage 2 2 res blocks, C=128	Stage 2 4 res blocks, C=128	Bottleneck Stage 2 4 res blocks, C=512	Bottleneck Stage 2 4 res blocks, C=512	Bottleneck Stage 2 8 res blocks, C=512
Stage 3 2 res blocks, C=256	Stage 3 6 res blocks, C=256	Bottleneck Stage 3 6 res blocks, C=1024	Bottleneck Stage 3 23 res blocks, C=1024	Bottleneck Stage 3 36 res blocks, C=1024
Stage 4 2 res blocks, C=512	Stage 4 3 res blocks, C=512	Bottleneck Stage 4 3 res blocks, C=2048	Bottleneck Stage 4 3 res blocks, C=2048	Bottleneck Stage 4 3 res blocks, C=2048
GlobalAvgPool+FC	GlobalAvgPool+FC	GlobalAvgPool+FC	GlobalAvgPool+FC	GlobalAvgPool+FC
Errors are on the validation set with 10 crops	~7.3 Gflops/img ~22M params 7.46 top-5 error	~7.7 Gflops/img ~25M params 6.71 top-5 error	~15.1 Gflops/img ~44M params 6.05 top-5 error	~23.4 Gflops/img ~62M params 5.71 top-5 error

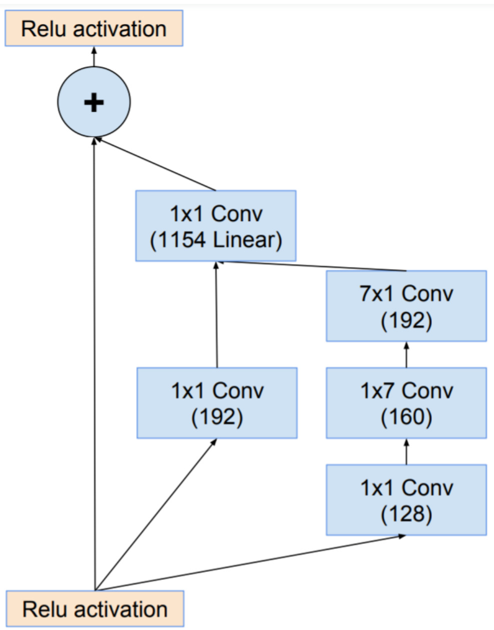
Inception-v4 and Inception-ResNet-v2

Inception-v4 is basically a larger Inception-v3 with a more complicated stem.

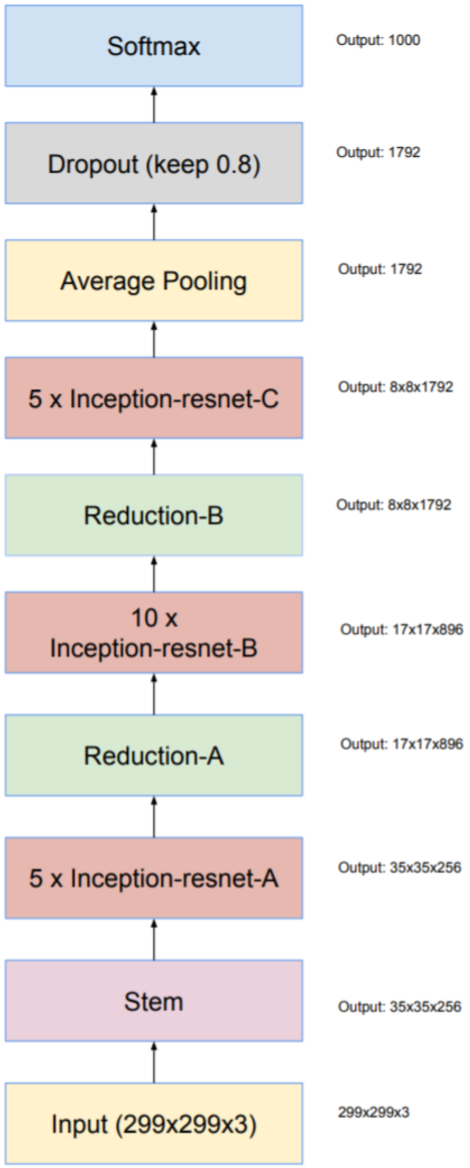
The authors also tried the residual connections idea around the Inception module.



Inception-resnet A, used for fine-scale activations (35x35)



Inception-resnet B, used for mid-scale activations (17x17)

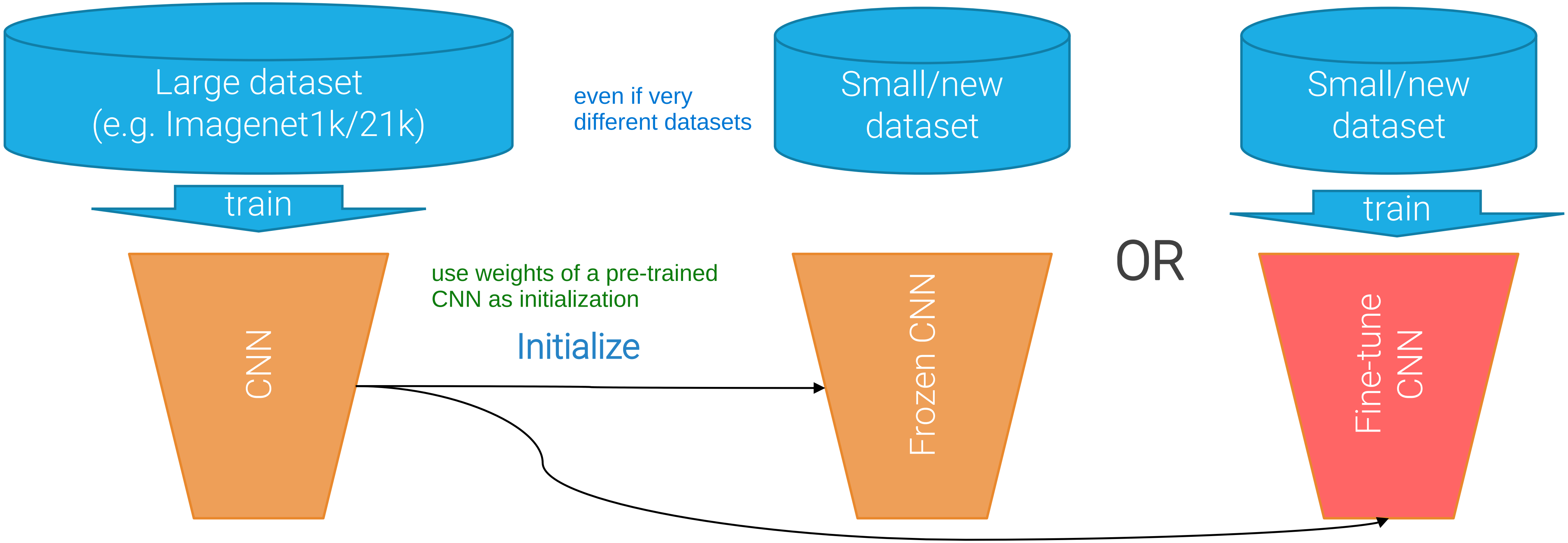


Christian Szegedy et al., “Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning”, AAAI 2017

Transfer Learning

We normally want to run CNNs on new classification datasets, not on ImageNet.

One of the most important features, from a practical point of view, of learned representations is that they can be effectively transferred to new datasets. Transfer learning is the process of using and adapting a pre-trained NN to new datasets. Usually, we pre-train on large datasets, and then we use it as frozen feature extractor or fine-tune it on the new dataset.



better than randomly intitalizing and training the whole set of parameters of each layer

Transfer learning

fine-tuning is just training the network again but using pre-learned weights as initialization

1. Trained on Imagenet (find parameters online)

ResNet-50

- Stem layer
- Bottleneck Stage 1
  3 res blocks, C=256
- Bottleneck Stage 2
  4 res blocks, C=512
- Bottleneck Stage 3
  6 res blocks, C=1024
- Bottleneck Stage 4
  3 res blocks, C=2048
- GlobalAvgPool + FC

2a. Use as pre-trained feature extractor

ResNet-50

- Stem layer
- Bottleneck Stage 1
  3 res blocks, C= 256
- Bottleneck Stage 2
  4 res blocks, C= 512
- Bottleneck Stage 3
  6 res blocks, C=1024
- Bottleneck Stage 4
  3 res blocks, C=2048

Freeze

- GlobalAvgPool + new FC

Train

OR

2b. Fine-tuning: train new head and feature extractor

ResNet-50

- Stem layer
- Bottleneck Stage 1
  3 res blocks, C= 256
- Bottleneck Stage 2
  4 res blocks, C= 512
- Bottleneck Stage 3
  6 res blocks, C=1024
- Bottleneck Stage 4
  3 res blocks, C=2048

Train

- GlobalAvgPool + new FC

Train

When fine-tuning:

1. Start with frozen feature extractor
2. Use smaller LR than the one used to train original architecture
3. Progressive LRs: use smaller learning rates when training extractor, and even freeze lower layers