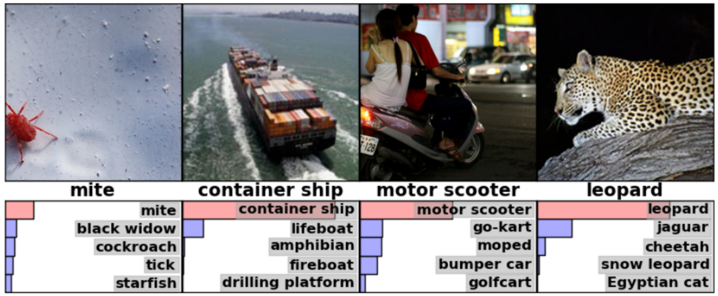
Convolutional Neural Networks

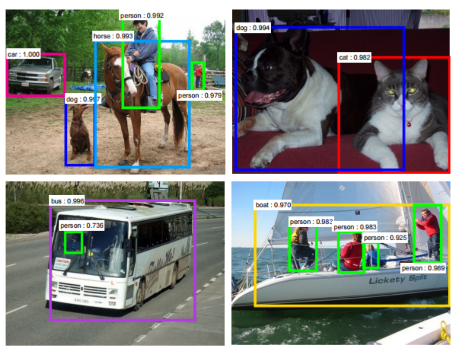
(from a course of Charles Ollion - Olivier Grisel)

Used everywhere for Vision



[Krizhevsky 2012]

[Ciresan et al. 2013]



[Faster R-CNN - Ren 2015]

[NVIDIA dev blog]

Many other applications

Speech recognition

Many other applications

Speech recognition

NLP

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NLP

Protein/DNA binding prediction

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Any problem with a spatial (or sequential) structure

ConvNets for image classification

CNN = Convolutional Neural Networks = ConvNet

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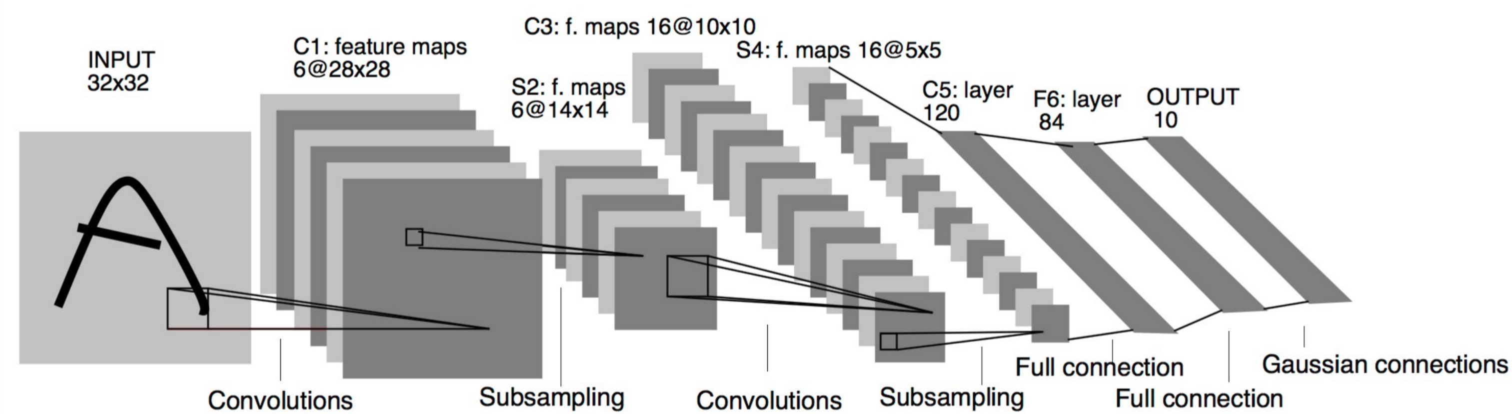

LeCun, Y., Bottou, L., Bengio, Y., and Haffner, P. (1998). Gradient-based learning applied to document recognition.

Outline

Convolutions

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Convolutions

CNNs for Image Classification

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CNNs for Image Classification

CNN Architectures

Convolutions

Motivations

Standard Dense Layer for an image input:

```
x = Input((640, 480, 3), dtype='float32')
# shape of x is: (None, 640, 480, 3)
x = Flatten()(x)
# shape of x is: (None, 640 x 480 x 3)
z = Dense(1000)(x)
```

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Motivations

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We never use Dense layers directly on large images. Most standard solution is **convolution** layers

Fully Connected Network: MLP

```
input_image = Input(shape=(28, 28, 1))
x = Flatten()(input_image)
x = Dense(256, activation='relu')(x)
x = Dense(10, activation='softmax')(x)
mlp = Model(inputs=input_image, outputs=x)
```

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Convolutional Network

```
input_image = Input(shape=(28, 28, 1))
x = Conv2D(32, 5, activation='relu')(input_image)
x = MaxPool2D(2, strides=2)(x)
x = Conv2D(64, 3, activation='relu')(x)
x = MaxPool2D(2, strides=2)(x)
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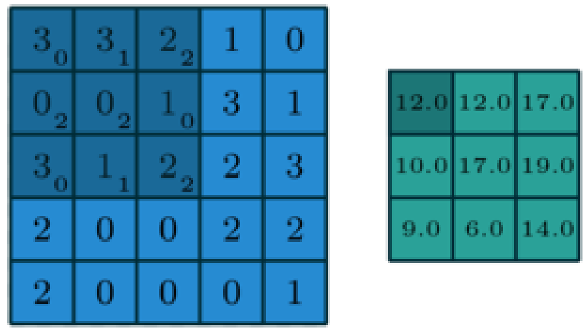
2D spatial organization of features preserved untill `Flatten`.

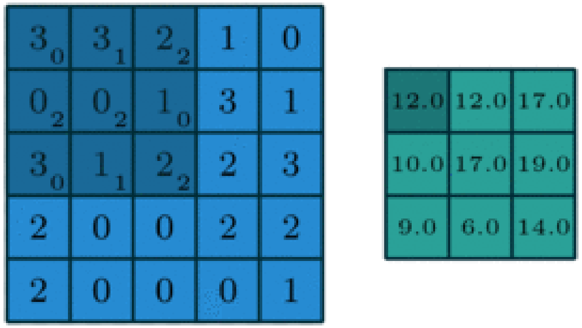
Convolution in a neural network



- x is a 3×3 chunk (dark area) of the image *(blue array)*
- Each output neuron is parametrized with the 3×3 weight matrix $\mathbf{w}$ *(small numbers)*

These slides extensively use convolution visualisation by V. Dumoulin available at
https://github.com/vdumoulin/conv_arithmetic

Convolution in a neural network



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The activation obtained by sliding the 3×3 window and computing:

$$z(x) = relu(\mathbf{w}^T x + b)$$

Motivations

Local connectivity

- A neuron depends only on a few local input neurons
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- Make use of spatial structure: **strong prior** for vision!

Animal Vision Analogy

Hubel & Wiesel, RECEPTIVE FIELDS OF SINGLE NEURONES IN THE CAT'S STRIATE CORTEX (1959)

Why Convolution

Discrete convolution (actually cross-correlation) between two functions f and g:

$$(f \star g)(x) = \sum_{a+b=x} f(a).\, g(b) = \sum_{a} f(a).\, g(x+a)$$

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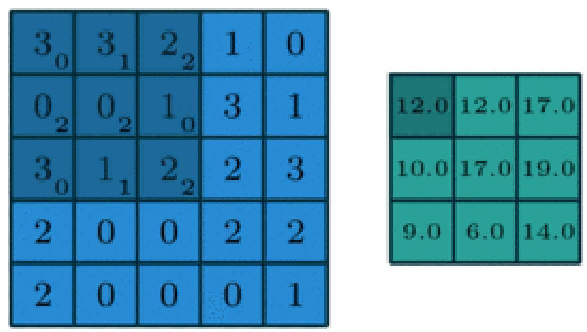
f is a convolution **kernel** or **filter** applied to the 2-d map g (our image)

Example: convolution image

- Image: im of dimensions 5×5
- Kernel: k of dimensions 3×3

$$(k \star im)(x, y) = \sum_{n=0}^{2} \sum_{m=0}^{2} k(n, m).\, im(x + n - 1, y + m - 1)$$



Channels

Colored image = tensor of shape `(height, width, channels)`

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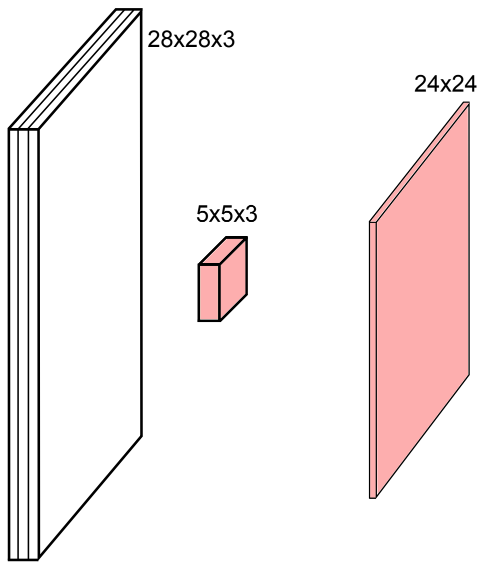
Convolutions are usually computed for each channel and summed:



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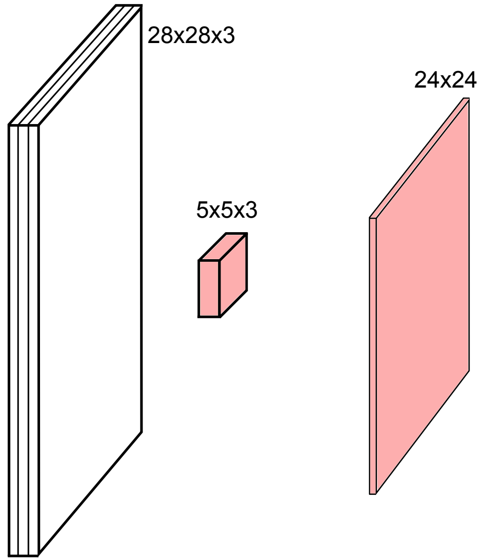
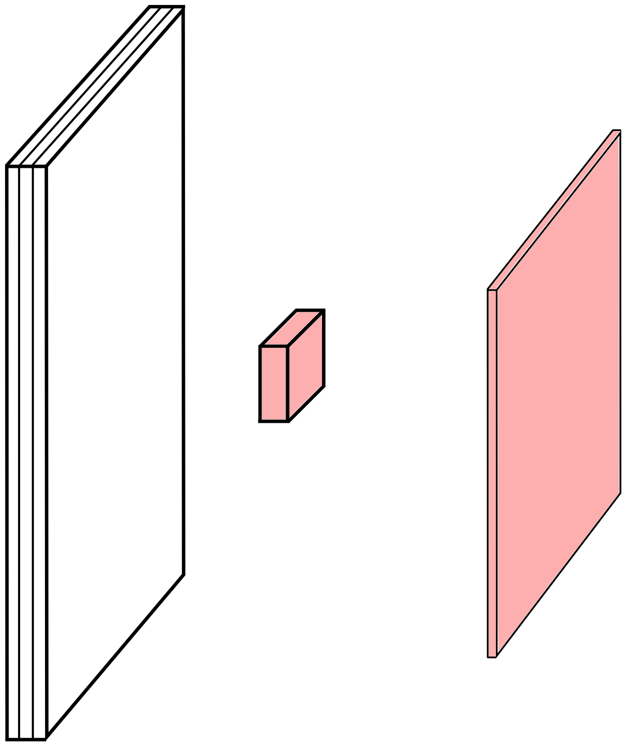


$$(k \star im^{color}) = \sum_{c=0}^{2} k^c \star im^c$$

Multiple convolutions



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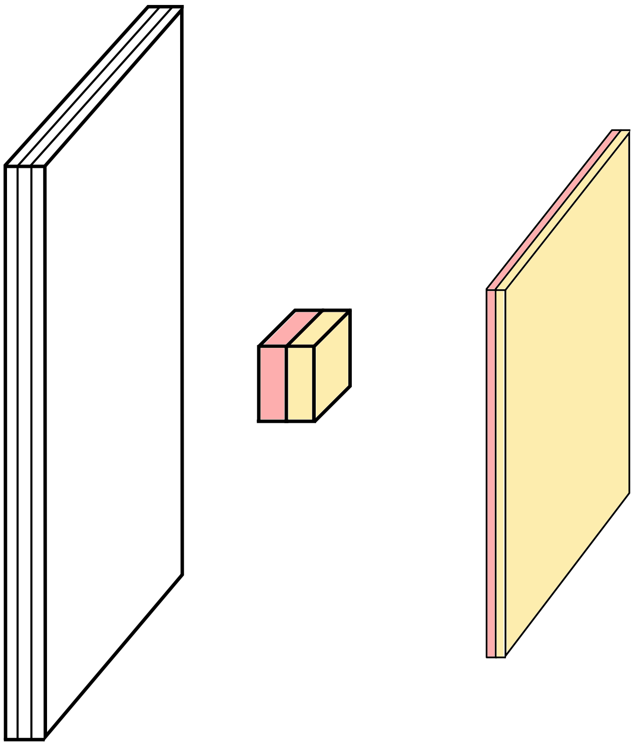

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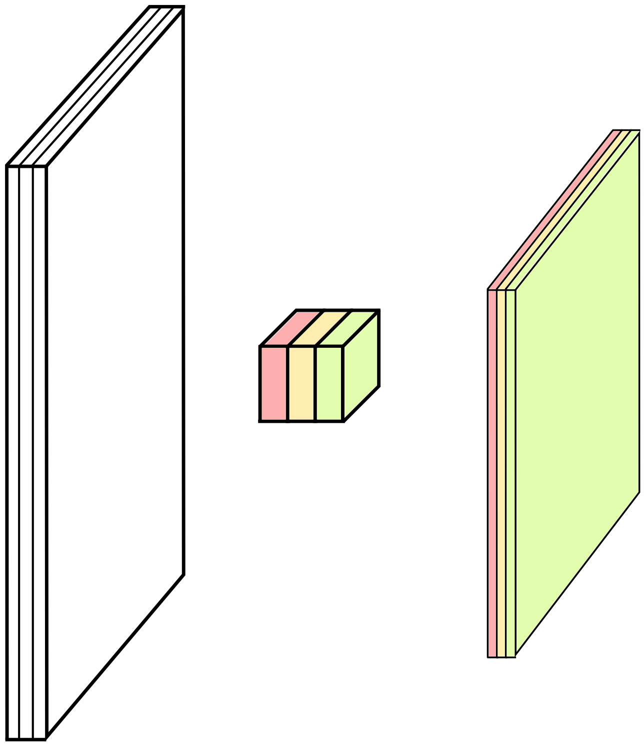

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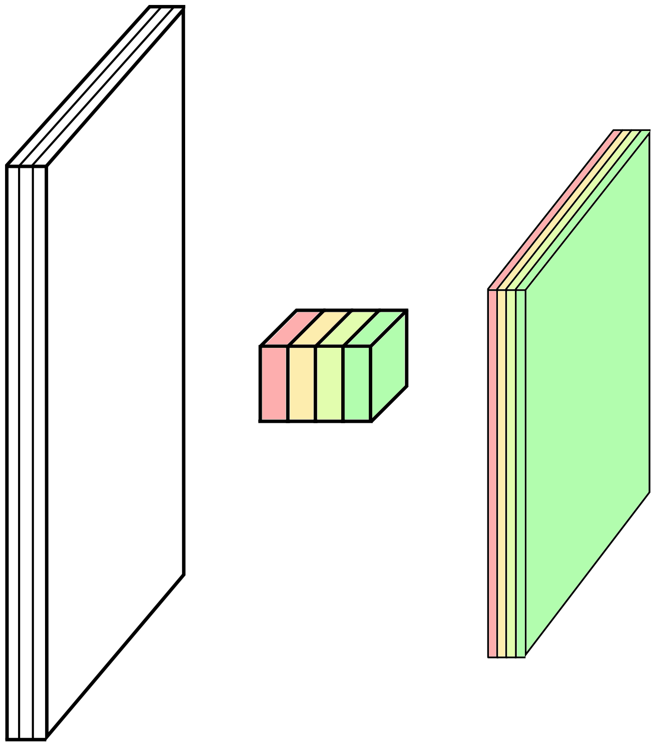

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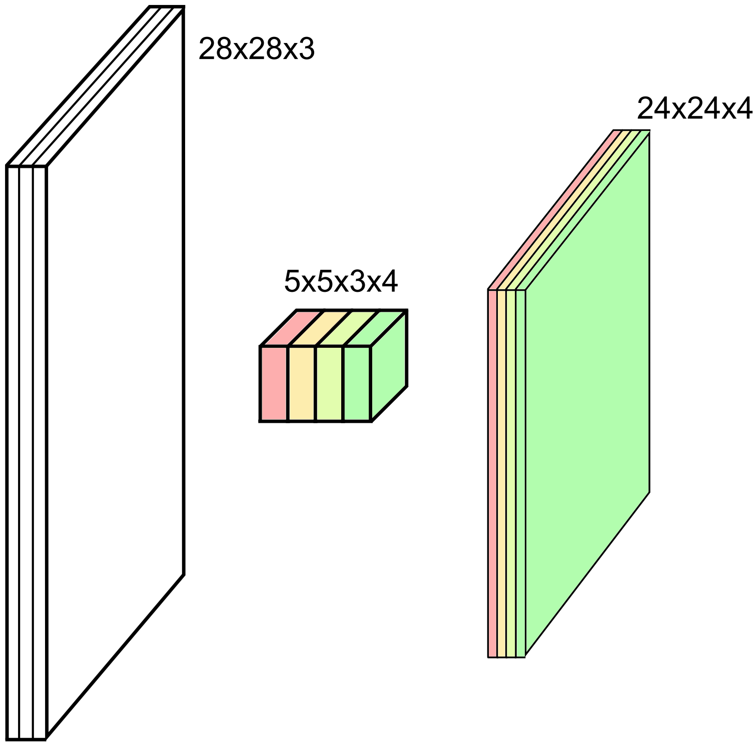

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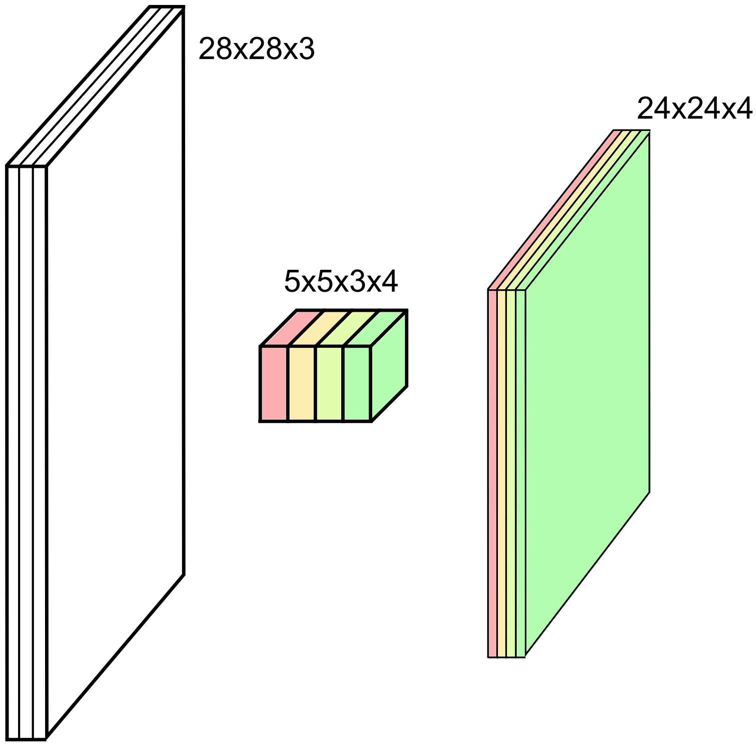
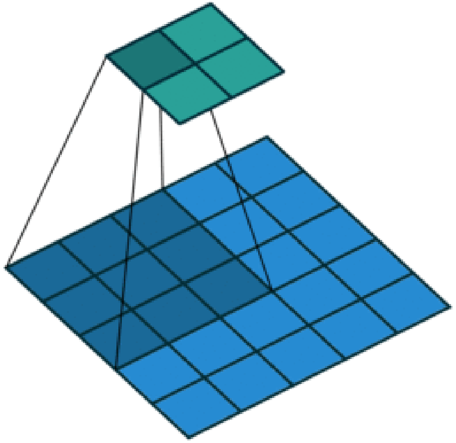


- Kernel size aka receptive field (usually 1, 3, 5, 7, 11)
- Output dimension: `length - kernel_size + 1`

Strides

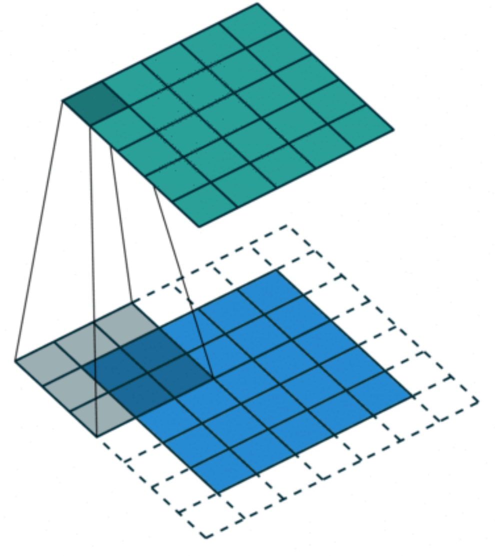
- Strides: increment step size for the convolution operator
- Reduces the size of the ouput map



Example with kernel size 3×3 and a stride of 2 (image in blue)

Padding

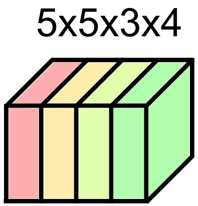
- Padding: artificially fill borders of image
- Useful to keep spatial dimension constant across filters
- Useful with strides and large receptive fields
- Usually: fill with 0s



Dealing with shapes

Kernel or **Filter** shape (F, F, C^i, C^o)

- $F \times F$ kernel size,
- C^i input channels
- C^o output channels



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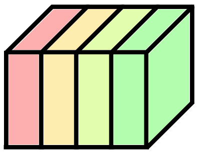

Number of parameters: $(F \times F \times C^i + 1) \times C^o$

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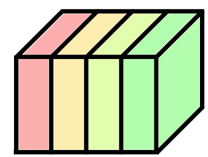

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Activations or **Feature maps** shape:

- Input (W^i, H^i, C^i)
- Output (W^o, H^o, C^o)

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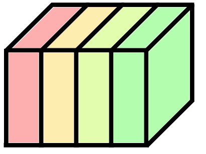

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- Input (W^i, H^i, C^i)
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$$W^o = (W^i - F + 2P)/S + 1$$

Pooling

- Spatial dimension reduction
- Local invariance
- No parameters: max or average of 2x2 units

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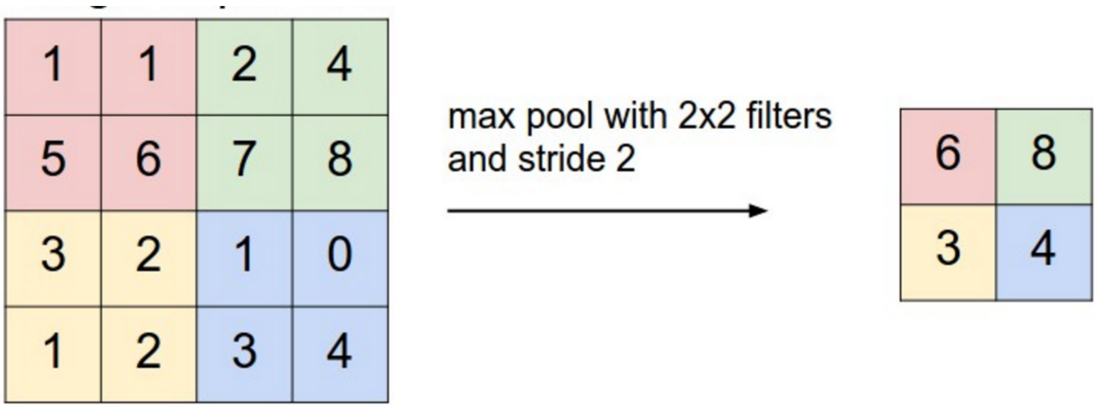

Schematic from Stanford http://cs231n.github.io/convolutional-networks

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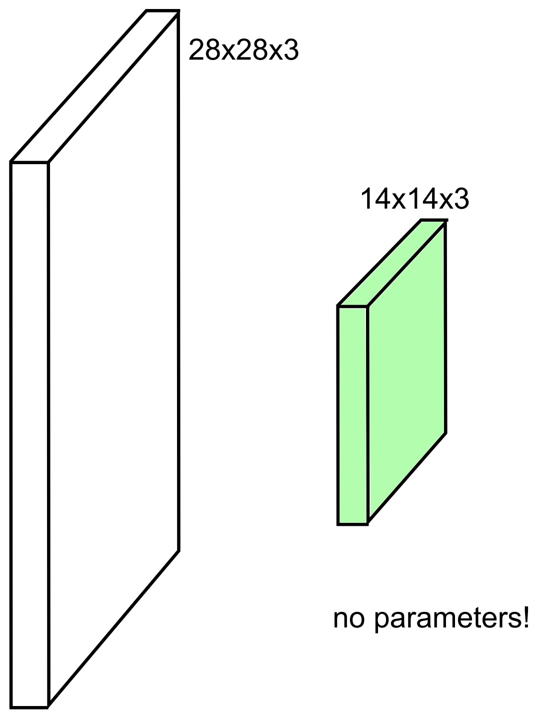

Architectures

Classic ConvNet Architecture

Input

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Input

Conv blocks

- Convolution + activation (relu)
- Convolution + activation (relu)
- ...
- Maxpooling 2x2

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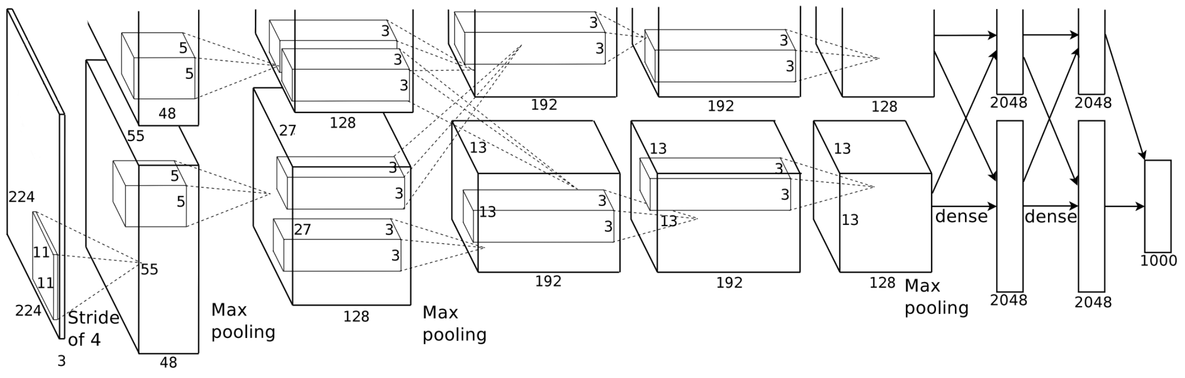
Output

- Fully connected layers
- Softmax

AlexNet



Simplified version of Krizhevsky, Alex, Sutskever, and Hinton. "Imagenet classification with deep convolutional neural networks." NIPS 2012

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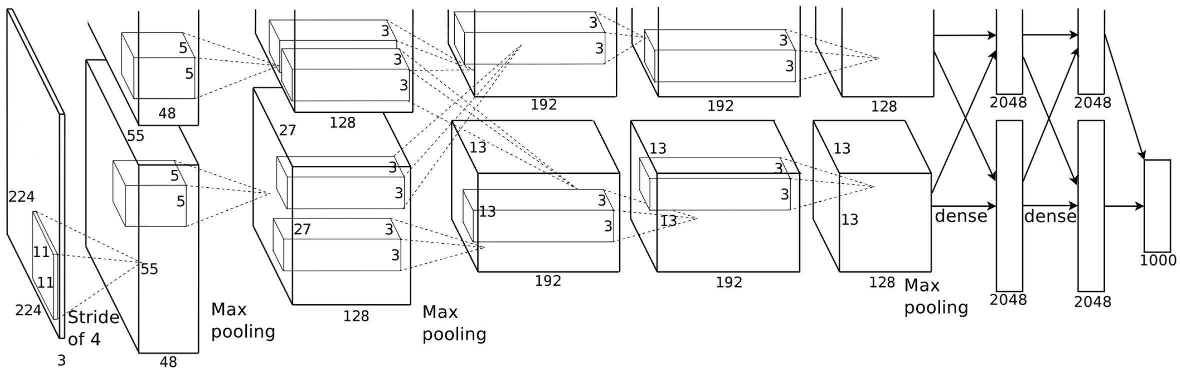

First conv layer: kernel 11x11x3x96 stride 4

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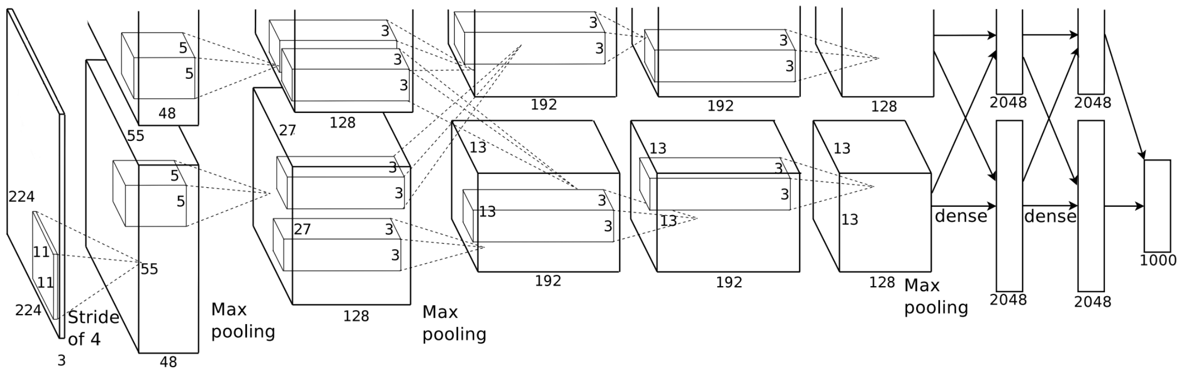

First conv layer: kernel 11x11x3x96 stride 4

- Kernel shape: `(11,11,3,96)`
- Output shape: `(55,55,96)`
- Number of parameters: `34,944`
- Equivalent MLP parameters: `43.7 x 1e9`

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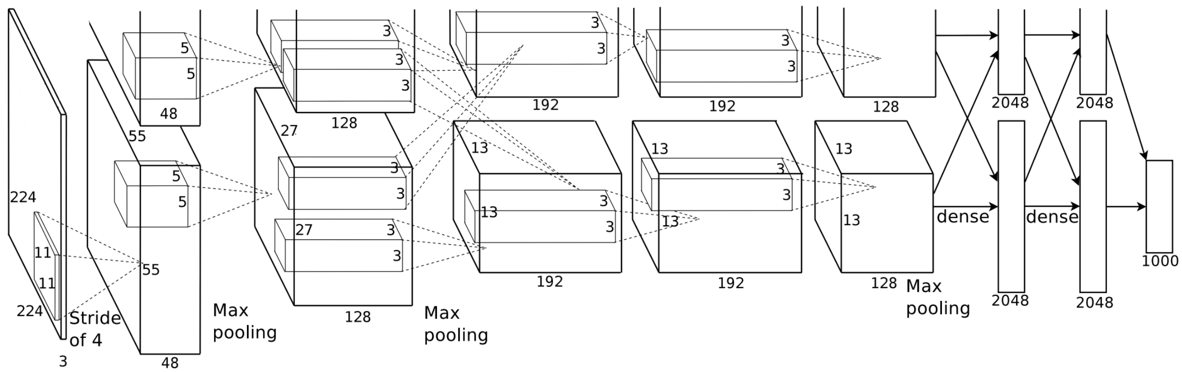
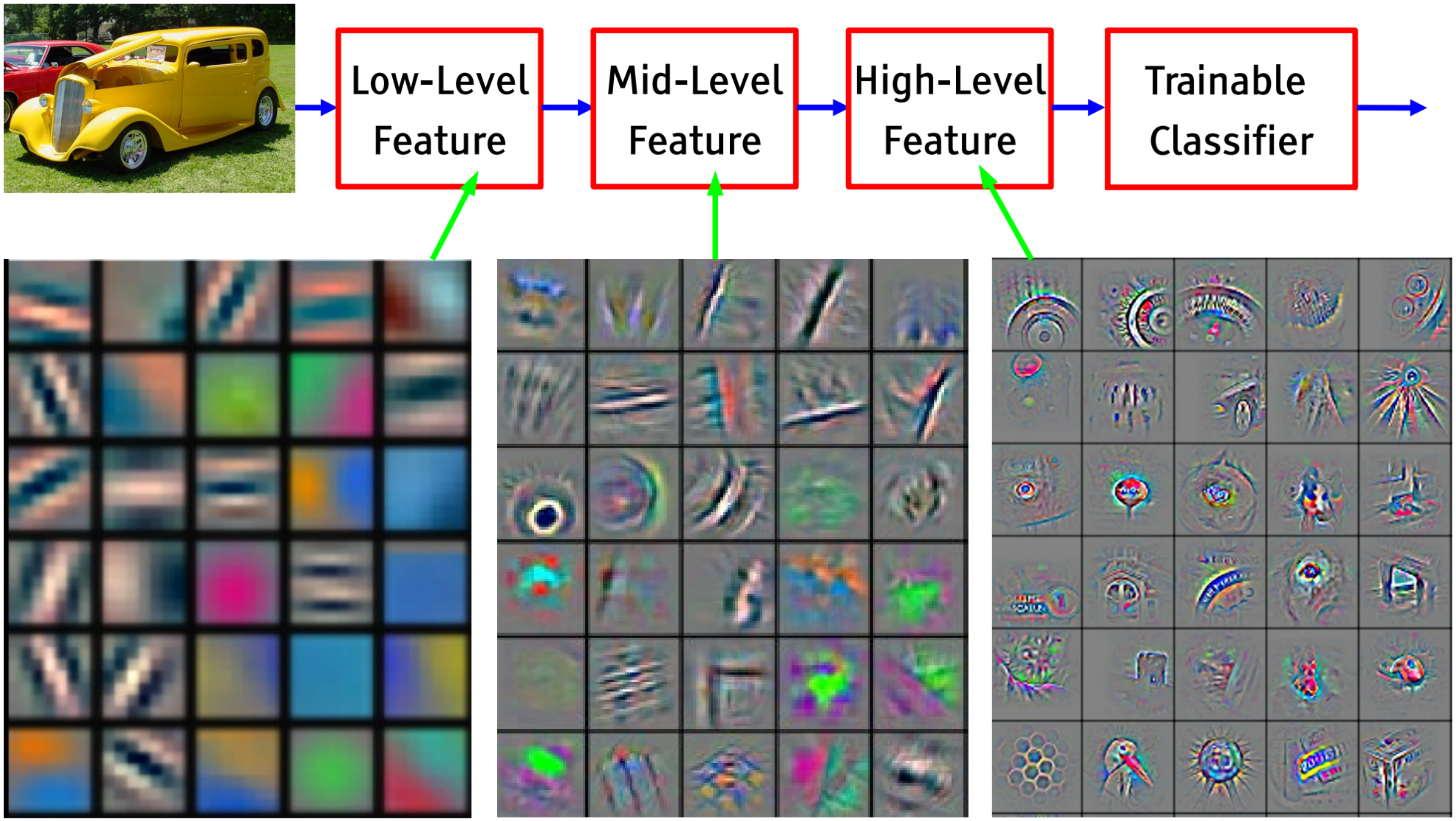


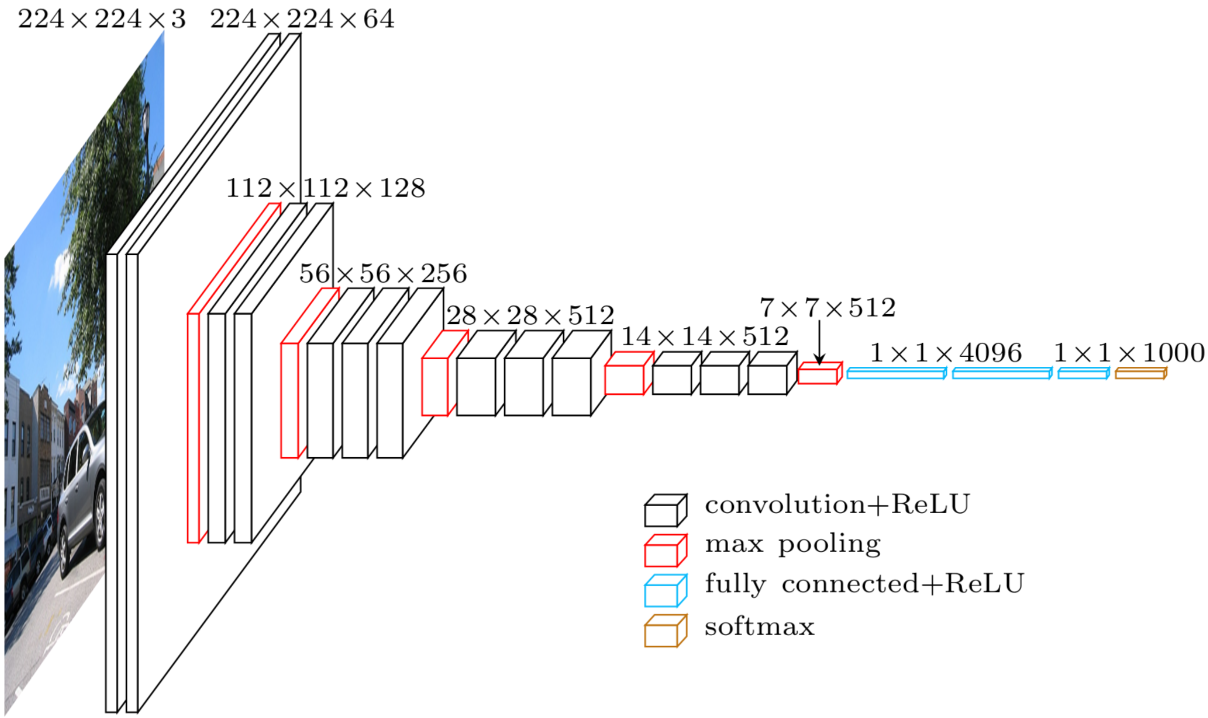

```
INPUT:     [227x227x3]
CONV1:     [55x55x96]   96 11x11 filters at stride 4, pad 0
MAX POOL1: [27x27x96]      3x3   filters at stride 2
CONV2:     [27x27x256] 256 5x5   filters at stride 1, pad 2
MAX POOL2: [13x13x256]     3x3   filters at stride 2
CONV3:     [13x13x384] 384 3x3   filters at stride 1, pad 1
CONV4:     [13x13x384] 384 3x3   filters at stride 1, pad 1
CONV5:     [13x13x256] 256 3x3   filters at stride 1, pad 1
MAX POOL3: [6x6x256]       3x3   filters at stride 2
FC6:       [4096]      4096 neurons
FC7:       [4096]      4096 neurons
FC8:       [1000]      1000 neurons (softmax logits)
```

Hierarchical representation



Feature visualization of convolutional net trained on ImageNet from [Zeiler & Fergus 2013]

VGG-16



Simonyan, Karen, and Zisserman. "Very deep convolutional networks for large-scale image recognition." (2014)

VGG in Keras

```
model.add(Convolution2D(64, 3, 3, activation='relu',input_shape=(3,224,224)))
model.add(Convolution2D(64, 3, 3, activation='relu'))
model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Convolution2D(128, 3, 3, activation='relu'))
model.add(Convolution2D(128, 3, 3, activation='relu'))
model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Convolution2D(256, 3, 3, activation='relu'))
model.add(Convolution2D(256, 3, 3, activation='relu'))
model.add(Convolution2D(256, 3, 3, activation='relu'))
model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Convolution2D(512, 3, 3, activation='relu'))
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model.add(Convolution2D(512, 3, 3, activation='relu'))
model.add(MaxPooling2D((2,2), strides=(2,2)))

model.add(Flatten())
model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(4096, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(1000, activation='softmax'))
```

Memory and Parameters

```
            Activation maps          Parameters
INPUT:     [224x224x3]   = 150K     0
CONV3-64:  [224x224x64]  = 3.2M     (3x3x3)x64    =       1,728
CONV3-64:  [224x224x64]  = 3.2M     (3x3x64)x64   =      36,864
POOL2:     [112x112x64]  = 800K     0
CONV3-128: [112x112x128] = 1.6M     (3x3x64)x128  =      73,728
CONV3-128: [112x112x128] = 1.6M     (3x3x128)x128 =     147,456
POOL2:     [56x56x128]   = 400K     0
CONV3-256: [56x56x256]   = 800K     (3x3x128)x256 =     294,912
CONV3-256: [56x56x256]   = 800K     (3x3x256)x256 =     589,824
CONV3-256: [56x56x256]   = 800K     (3x3x256)x256 =     589,824
POOL2:     [28x28x256]   = 200K     0
CONV3-512: [28x28x512]   = 400K     (3x3x256)x512 =   1,179,648
CONV3-512: [28x28x512]   = 400K     (3x3x512)x512 =   2,359,296
CONV3-512: [28x28x512]   = 400K     (3x3x512)x512 =   2,359,296
POOL2:     [14x14x512]   = 100K     0
CONV3-512: [14x14x512]   = 100K     (3x3x512)x512 =   2,359,296
CONV3-512: [14x14x512]   = 100K     (3x3x512)x512 =   2,359,296
CONV3-512: [14x14x512]   = 100K     (3x3x512)x512 =   2,359,296
POOL2:     [7x7x512]     =  25K     0
FC:        [1x1x4096]    = 4096     7x7x512x4096  = 102,760,448
FC:        [1x1x4096]    = 4096     4096x4096     =  16,777,216
FC:        [1x1x1000]    = 1000     4096x1000     =   4,096,000

TOTAL activations: 24M x 4 bytes ~=  93MB / image (x2 for backward)
TOTAL parameters: 138M x 4 bytes ~= 552MB (x2 for plain SGD, x4 for Adam)
```

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CONV3-256: [56x56x256]   = 800K     (3x3x128)x256 =     294,912
CONV3-256: [56x56x256]   = 800K     (3x3x256)x256 =     589,824
CONV3-256: [56x56x256]   = 800K     (3x3x256)x256 =     589,824
POOL2:     [28x28x256]   = 200K     0
CONV3-512: [28x28x512]   = 400K     (3x3x256)x512 =   1,179,648
CONV3-512: [28x28x512]   = 400K     (3x3x512)x512 =   2,359,296
CONV3-512: [28x28x512]   = 400K     (3x3x512)x512 =   2,359,296
POOL2:     [14x14x512]   = 100K     0
CONV3-512: [14x14x512]   = 100K     (3x3x512)x512 =   2,359,296
CONV3-512: [14x14x512]   = 100K     (3x3x512)x512 =   2,359,296
CONV3-512: [14x14x512]   = 100K     (3x3x512)x512 =   2,359,296
POOL2:     [7x7x512]     =  25K     0
FC:        [1x1x4096]    = 4096     7x7x512x4096   = 102,760,448
FC:        [1x1x4096]    = 4096     4096x4096      =  16,777,216
FC:        [1x1x1000]    = 1000     4096x1000      =   4,096,000

TOTAL activations: 24M x 4 bytes ~=  93MB / image (x2 for backward)
TOTAL parameters: 138M x 4 bytes ~= 552MB (x2 for plain SGD, x4 for Adam)
```
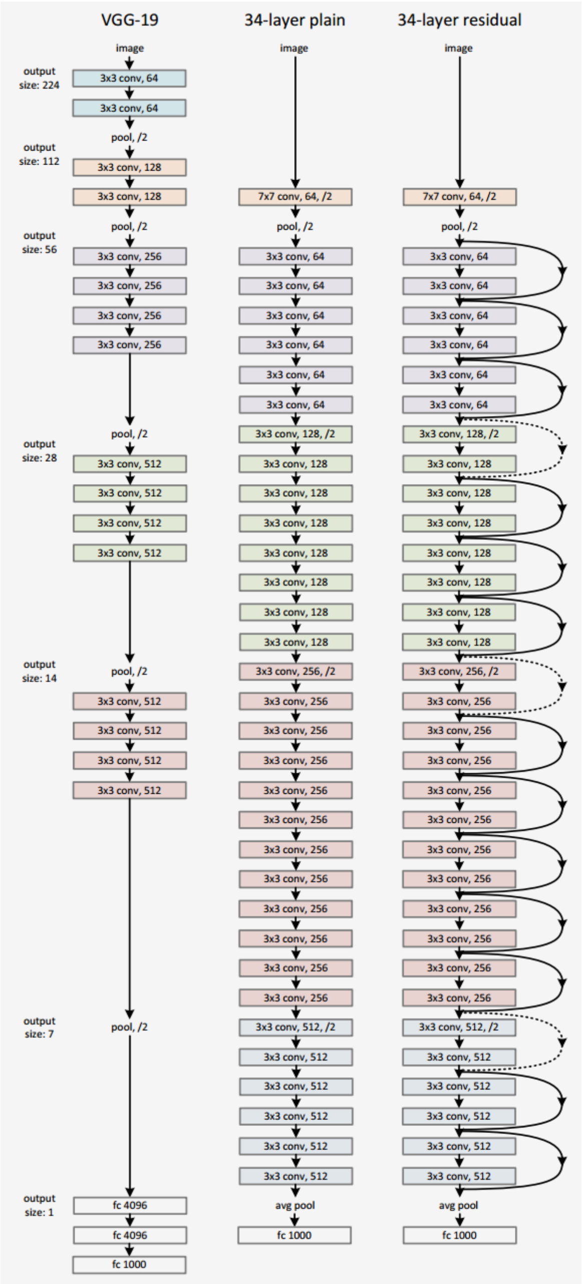

ResNet

Even deeper models:

34, 50, 101, 152 layers



He, Kaiming, et al. "Deep residual learning for image recognition." CVPR. 2016.

ResNet

A block learns the residual w.r.t. identity

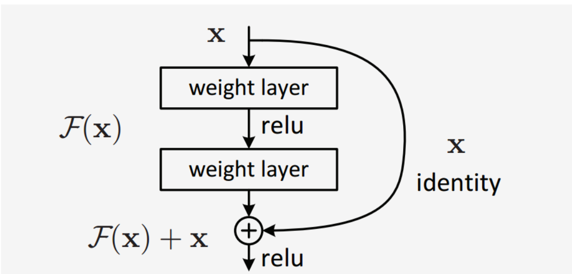
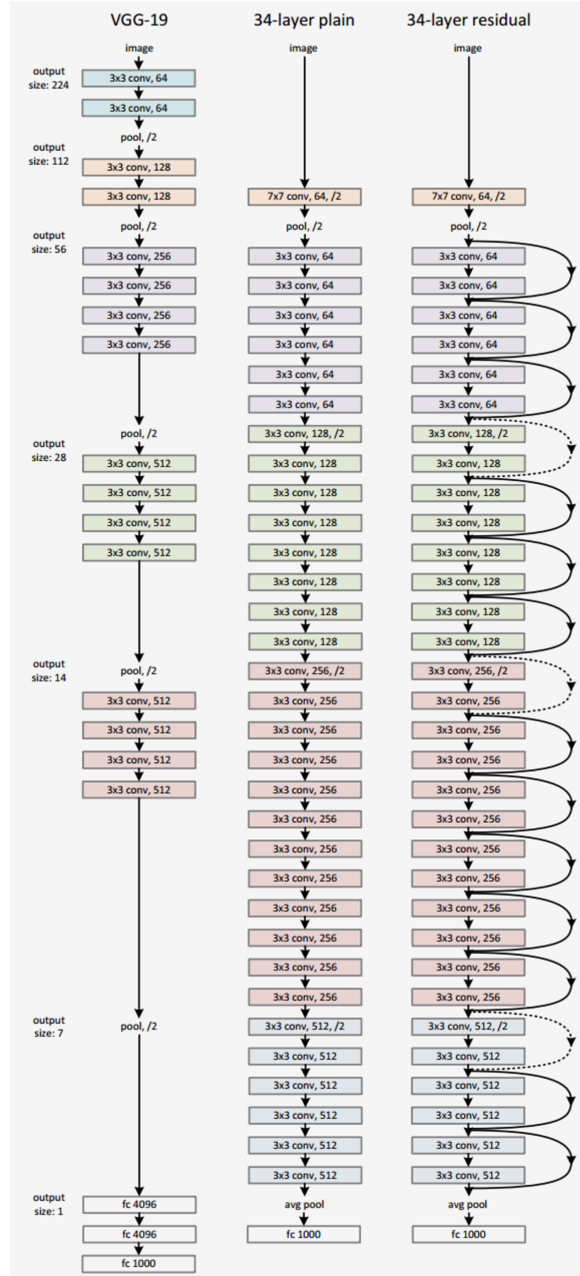


Figure 2. Residual learning: a building block.

He, Kaiming, et al. "Deep residual learning for image recognition." CVPR. 2016.



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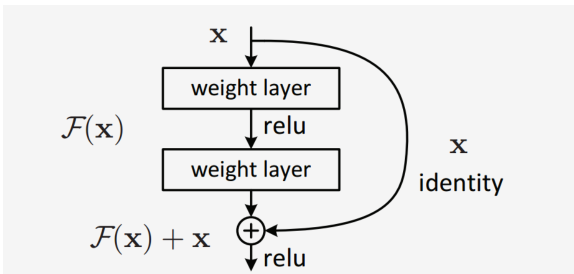
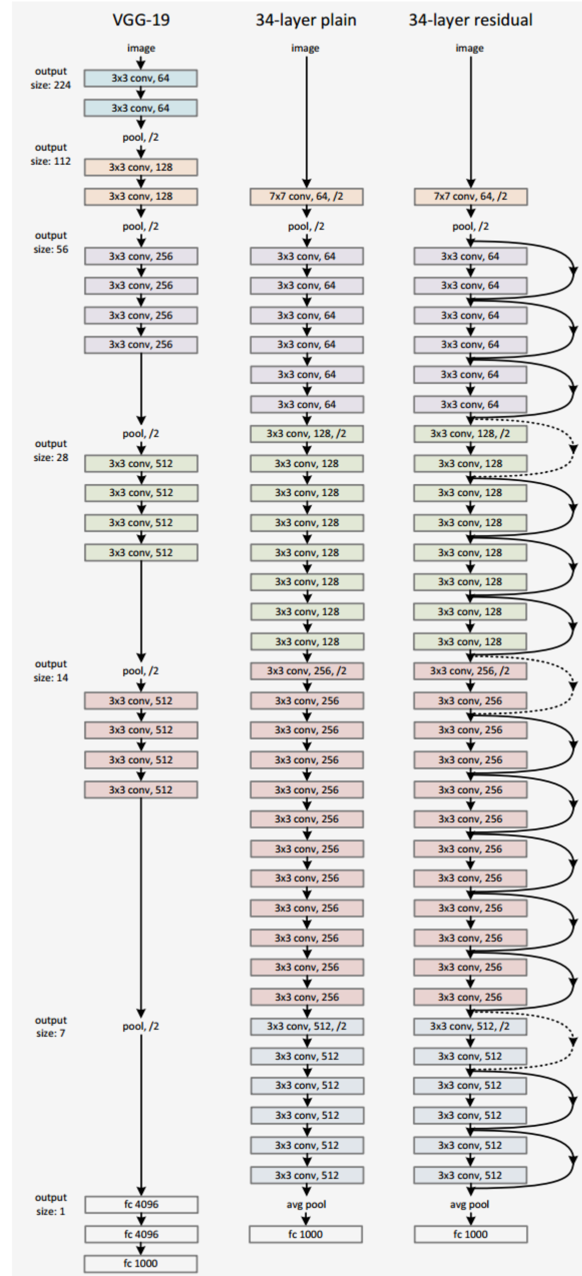


Figure 2. Residual learning: a building block.

- Good optimization properties

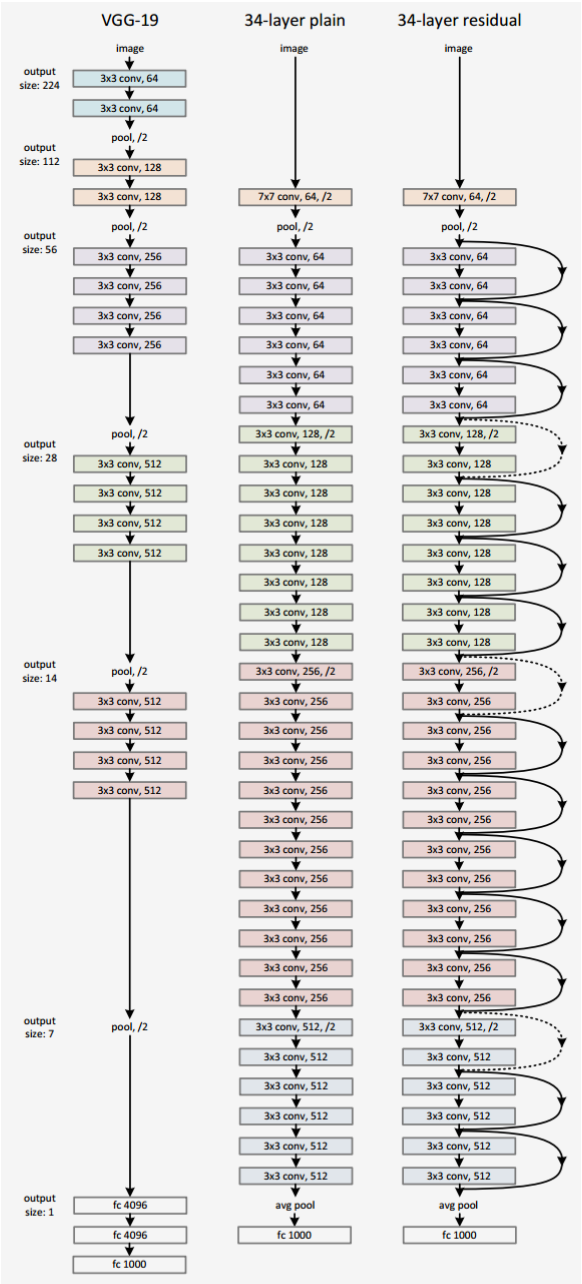
He, Kaiming, et al. "Deep residual learning for image recognition." CVPR. 2016.



ResNet

ResNet50 Compared to VGG:

Superior accuracy in all vision tasks
5.25% top-5 error vs 7.1%



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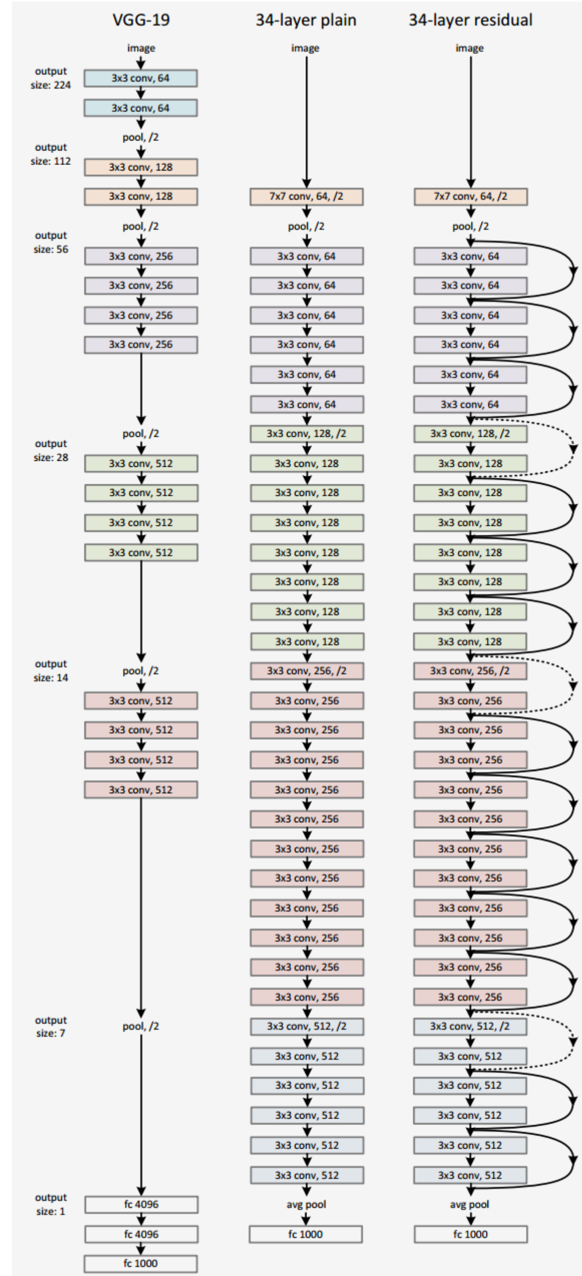
25M vs 138M



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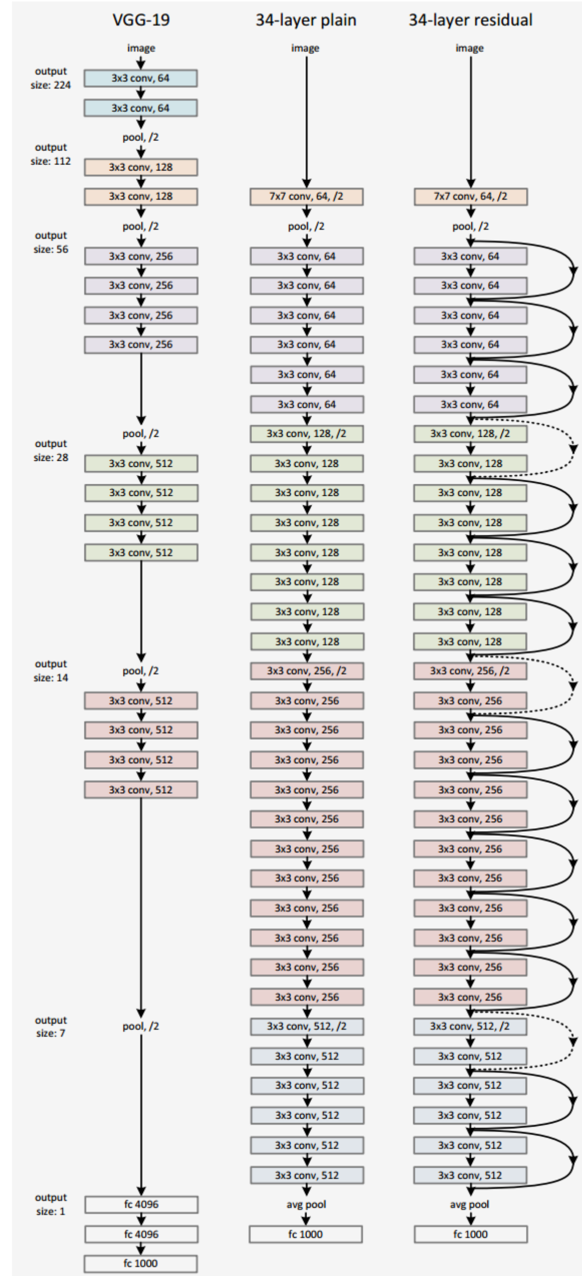

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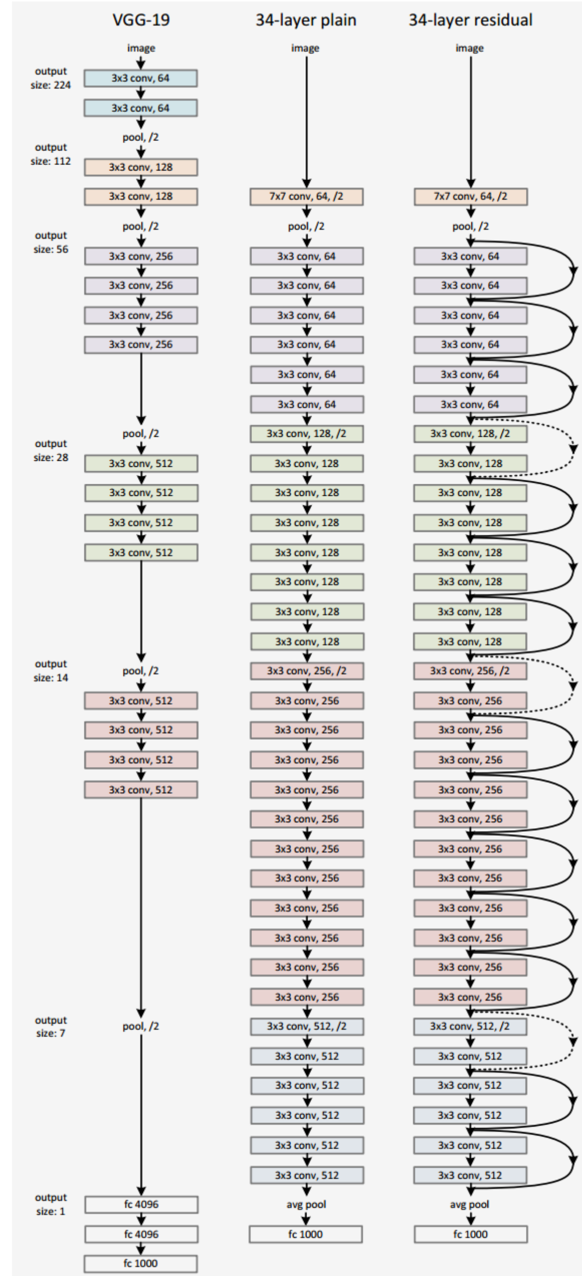
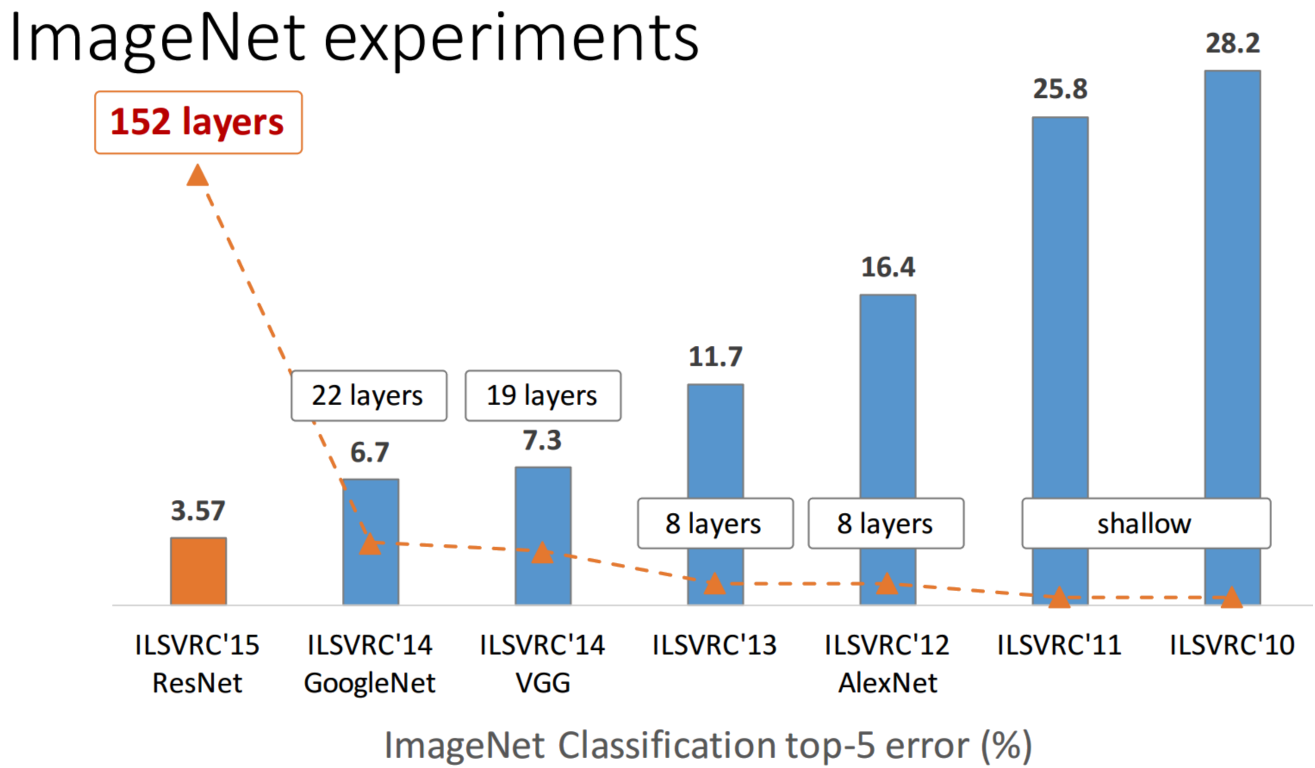
Fully Convolutional until the last layer

He, Kaiming, et al. "Deep residual learning for image recognition." CVPR. 2016.



Deeper is better



from Kaiming He slides "Deep residual learning for image recognition." ICML. 2016.

State of the art

- Finding right architectures: Active area or research

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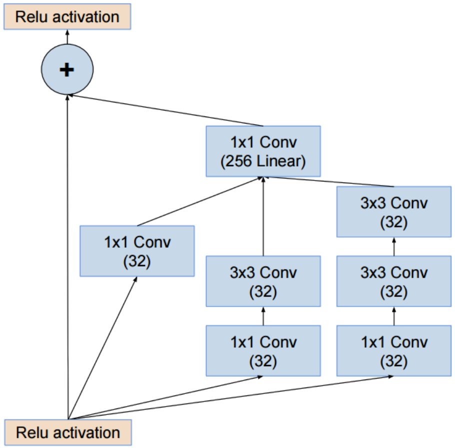
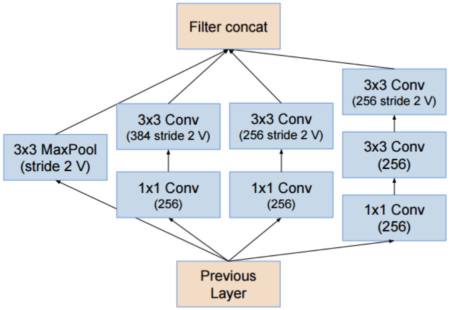
Model	Params	$\times+$	1/5-Acc (%)
Inception V3	23.8M	5.72B	78.0 / 93.9
Xception	22.8M	8.37B	79.0 / 94.5
Inception ResNet V2	55.8M	13.2B	80.4 / 95.3
ResNeXt-101 (64x4d)	83.6M	31.5B	80.9 / 95.6
PolyNet	92.0M	34.7B	81.3 / 95.8
Dual-Path-Net-131	79.5M	32.0B	81.5 / 95.8
Squeeze-Excite-Net	145.8M	42.3B	82.7 / **96.2**
GeNet-2	156M	–	72.1 / 90.4
Block-QNN-B, N=3	–	–	75.7 / 92.6
Hierarchical (2, 64)	64M	–	79.7 / 94.8
PNASNet-5 (4, 216)	86.1M	25.0B	**82.9** / 96.1
NASNet-A (6, 168)	88.9M	23.8B	82.7 / **96.2**
AmoebaNet-B (6, 190)	84.0M	22.3B	82.3 / 96.1
AmoebaNet-C (6, 168)	85.5M	22.5B	82.7 / 96.1
AmoebaNet-A (6, 190)	86.7M	23.1B	82.8 / 96.1
AmoebaNet-A (6, 204)	99.6M	26.2B	82.8 / **96.2**

Esteban Real, et al. Regularized Evolution for Image Classifier Architecture Search (Feb 2018)

State of the art

- Finding right architectures: Active area or research



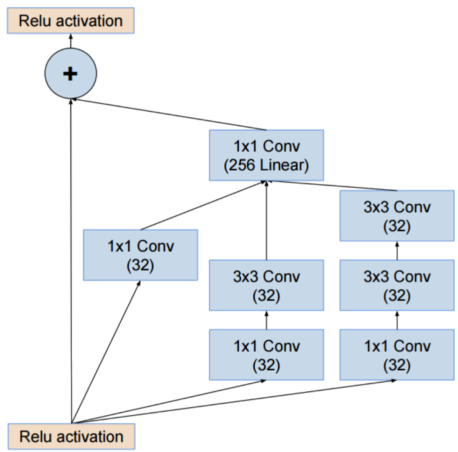


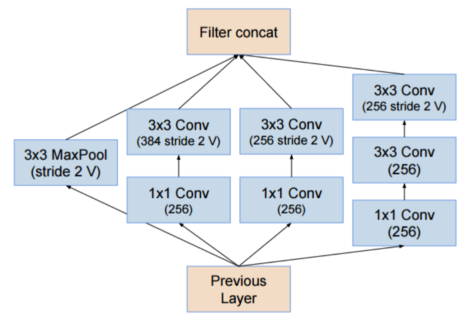
Modular building blocks engineering

from He slides "Deep residual learning for image recognition." ICML. 2016.

State of the art

- Finding right architectures: Active area or research





Modular building blocks engineering

see also DenseNets, Wide ResNets, Fractal ResNets, ResNeXts, Pyramidal ResNets

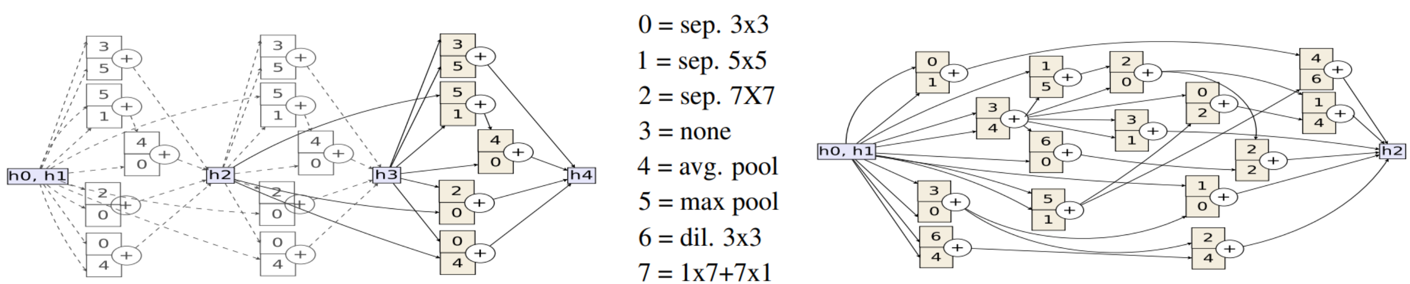
from He slides "Deep residual learning for image recognition." ICML. 2016.

State of the art

- Finding right architectures: Active area or research

Automated Architecture search:

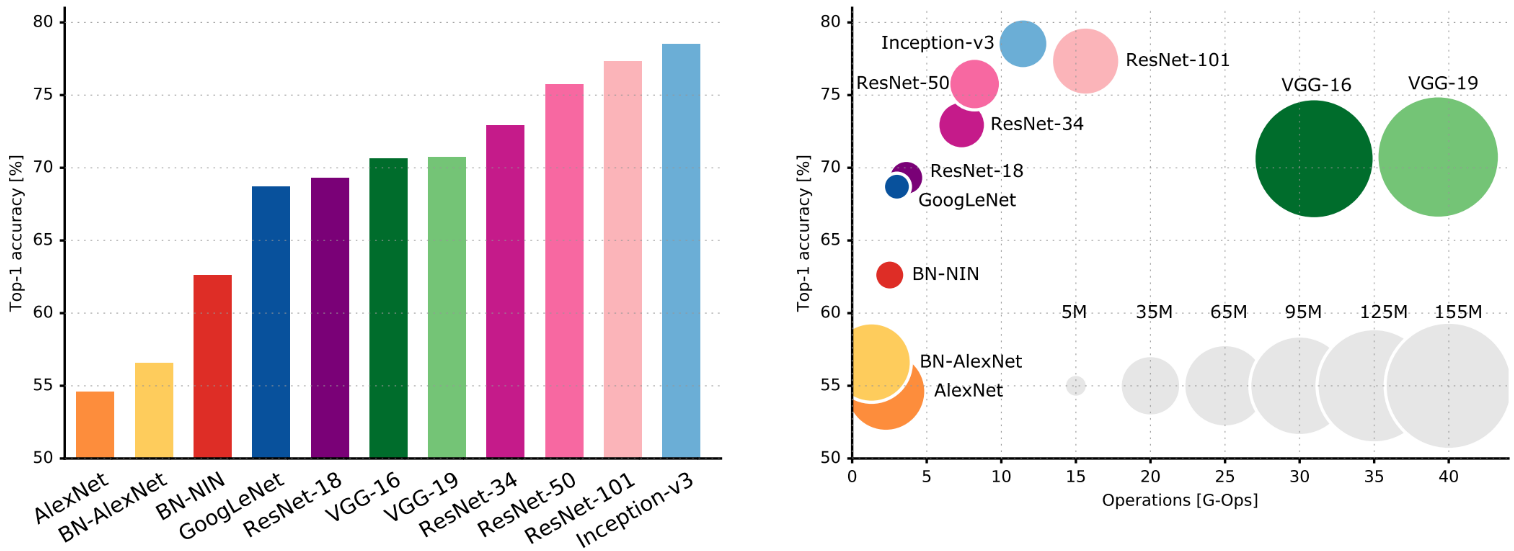
- reinforcement learning
- evolutionary algorithms



Esteban Real, et al. Regularized Evolution for Image Classifier Architecture Search (Feb 2018)

Comparison of models

Top 1-accuracy, performance and size on ImageNet



Canziani, Paszke, and Culurciello. "An Analysis of Deep Neural Network Models for Practical Applications." (May 2016).

Pre-trained models

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Many models trained on ImageNet and their weights are publicly available!

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Transfer learning

- Use pre-trained weights, remove last layers to compute representations of images
- Train a classification model from these features on a new classification task
- The network is used as a generic feature extractor
- Better than handcrafted feature extraction on natural images

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Fine-tuning

Retraining the (some) parameters of the network (given enough data)

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Retraining the (some) parameters of the network (given enough data)

- Truncate the last layer(s) of the pre-trained network
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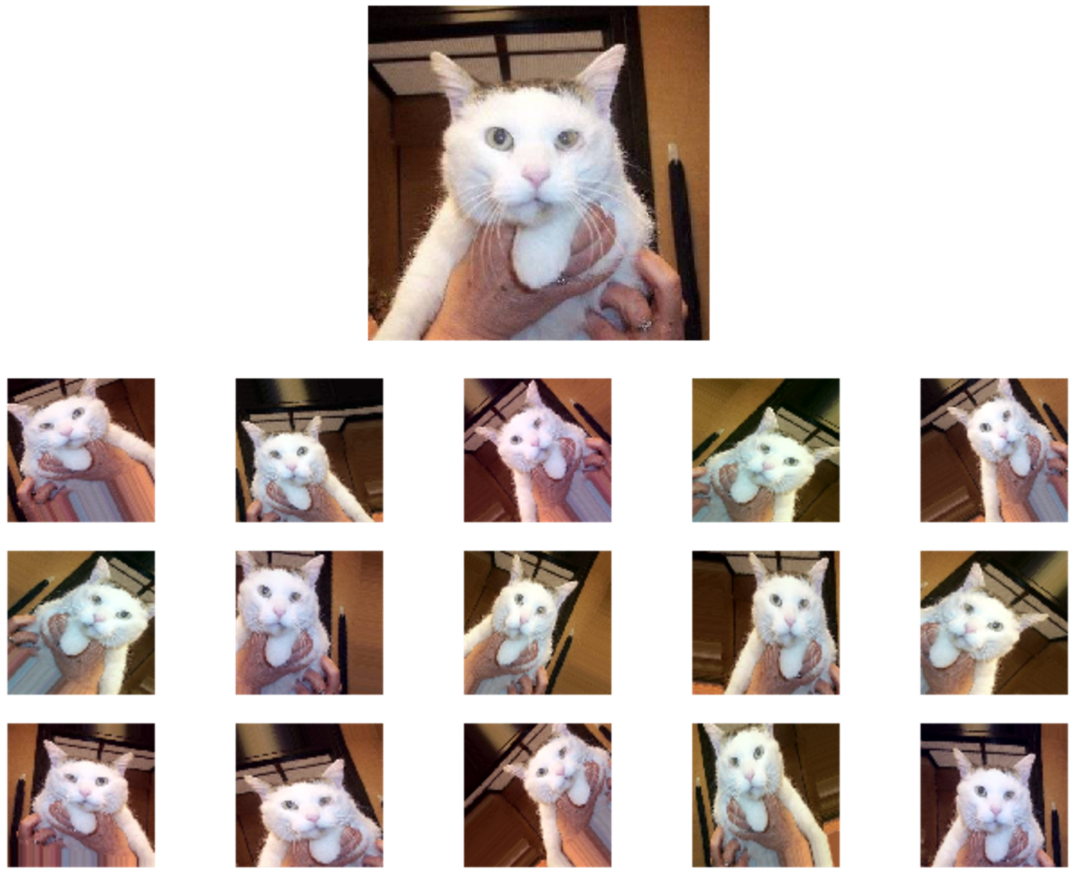
- Add a (linear) classifier on top and train it for a few epochs
- Then fine-tune the whole network or the few deepest layers
- Use a smaller learning rate when fine tuning

Data Augmentation

Data Augmentation



Data Augmentation

With Keras:

```
from keras.preprocessing.image import ImageDataGenerator

image_gen = ImageDataGenerator(
    rescale=1. / 255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,
    channel_shift_range=9,
    fill_mode='nearest'
)

train_flow = image_gen.flow_from_directory(train_folder)
model.fit_generator(train_flow, train_flow.n)
```