MSE | MASTER OF SCIENCE IN ENGINEERING

Deep Learning

TSM-DeLearn

9. Deep Architectures

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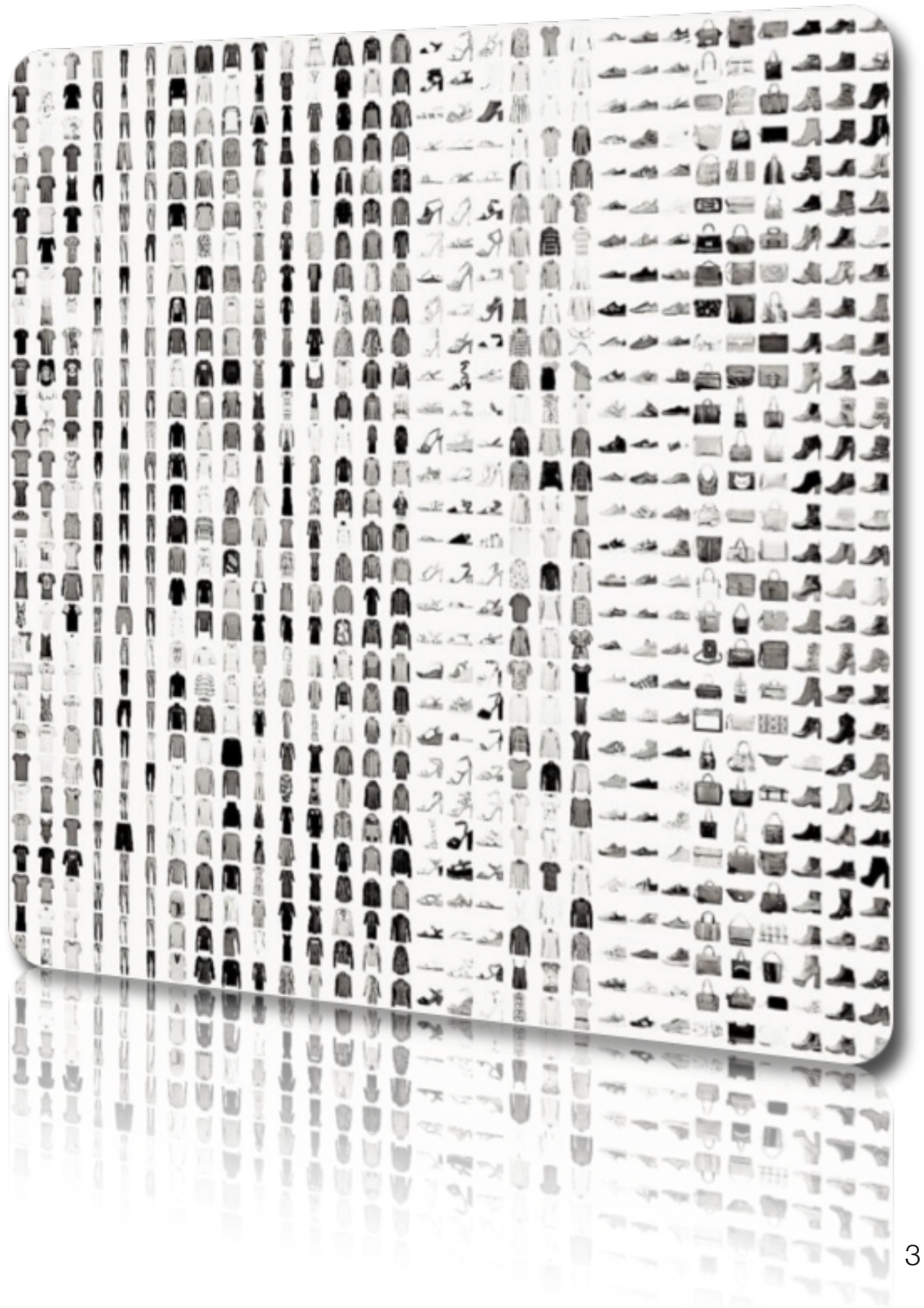
Plan

1. CNN recaps - example on Fashion MNIST
2. CNN - hierarchical features / visualisation inside network
3. Data augmentation
4. Overview of deep CNN Architectures
5. PW

CNN recaps



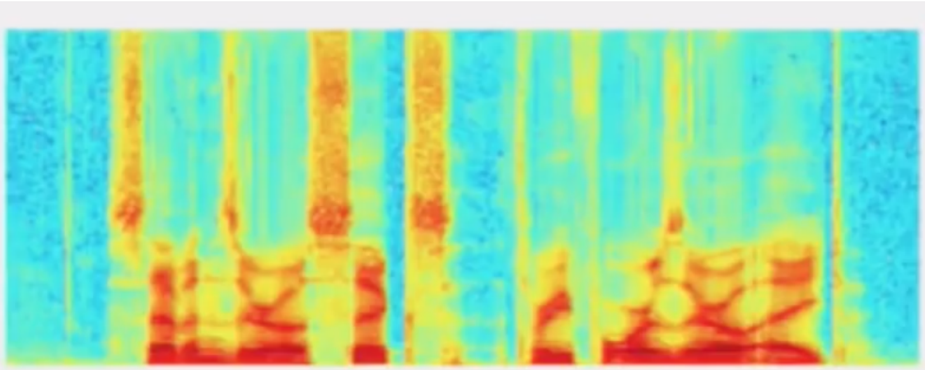
Recaps through FashionMNIST

CIFAR10 leaderboard

CIFAR10 online demo

RECAP 1 - Convolution and spatial structure

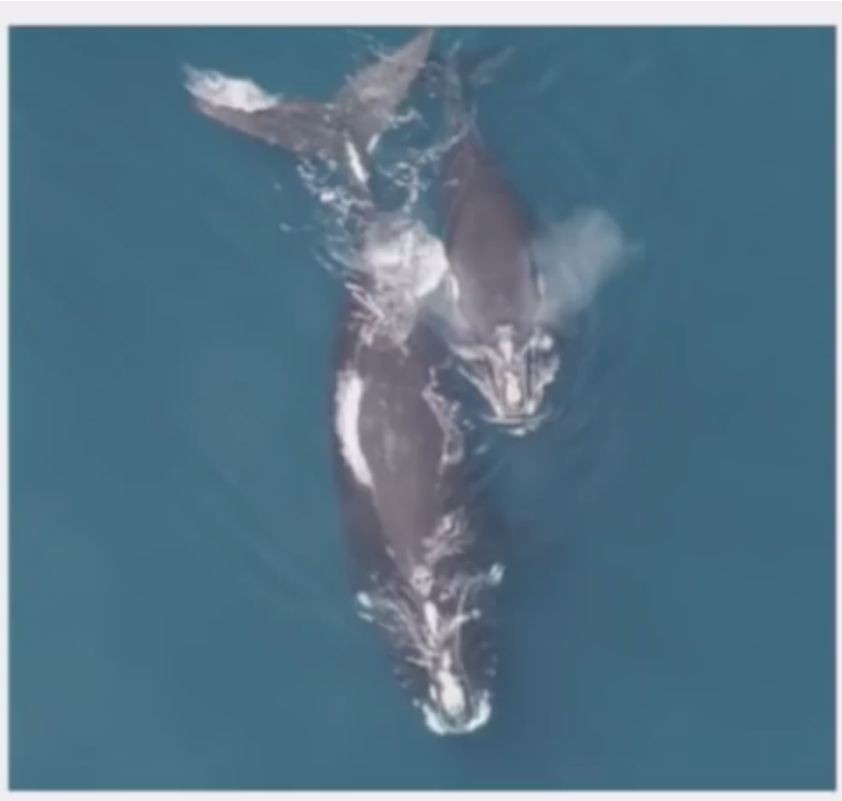
- In most real-world applications input vectors have a spatial **structure**, a “local connectivity” that you would like to model
- **Convolution layers** have the property to preserve the spatial structure and discover the local connectivity



Spectrograms

"Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum."

Text



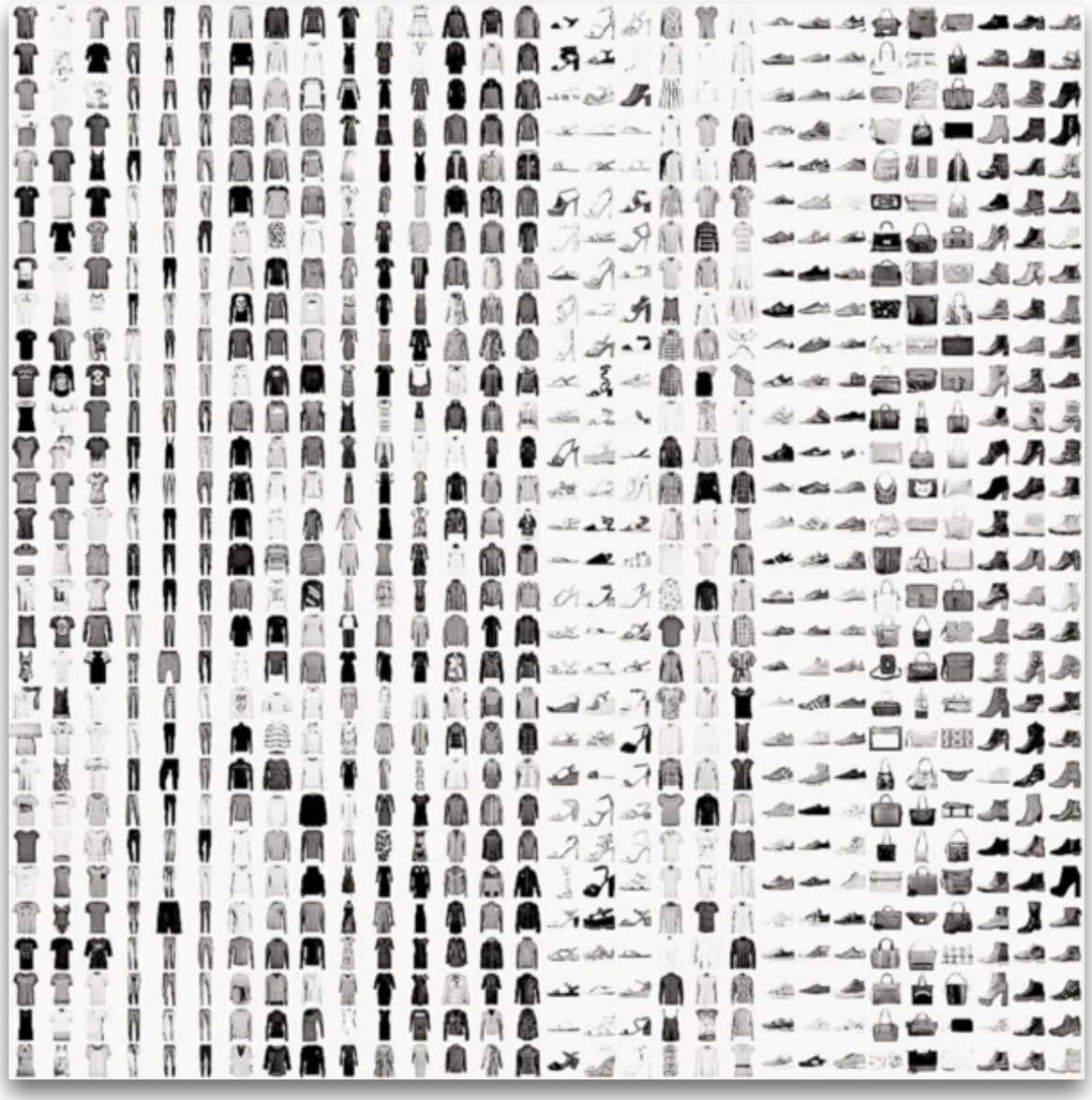
Images

Source image: Andrej Karpathy, OpenAI - Deep learning for computer vision

CNN for FashionMNIST

- https://github.com/zalandoresearch/fashion-mnist
- Alternative to MNIST
  - 60’000 train images
  - 10’000 test images
  - 28x28x1 grayscale
  - 10 classes
- A bit more challenging than MNIST

Label	Description
0	T-shirt/top
1	Trouser
2	Pullover
3	Dress
4	Coat
5	Sandal
6	Shirt
7	Sneaker
8	Bag
9	Ankle boot



CNN for FashionMNIST - data preparation

Load FashionMNIST

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras import utils
```

Transform into float32, normalise between 0 and 1.0, reshape in a (60000, 28, 28, 1) tensor.

```
(X_train, y_train), (X_test, y_test) = fashion_mnist.load_data()
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train /= 255.0
X_test /= 255.0
X_train = X_train.reshape(60000, 28, 28, 1)
X_test = X_test.reshape(10000, 28, 28, 1)
```

The y_train is an array with scalar values as in `[5 0 4 1 ...] The target values of the network are supposed to be 1-hot targets.

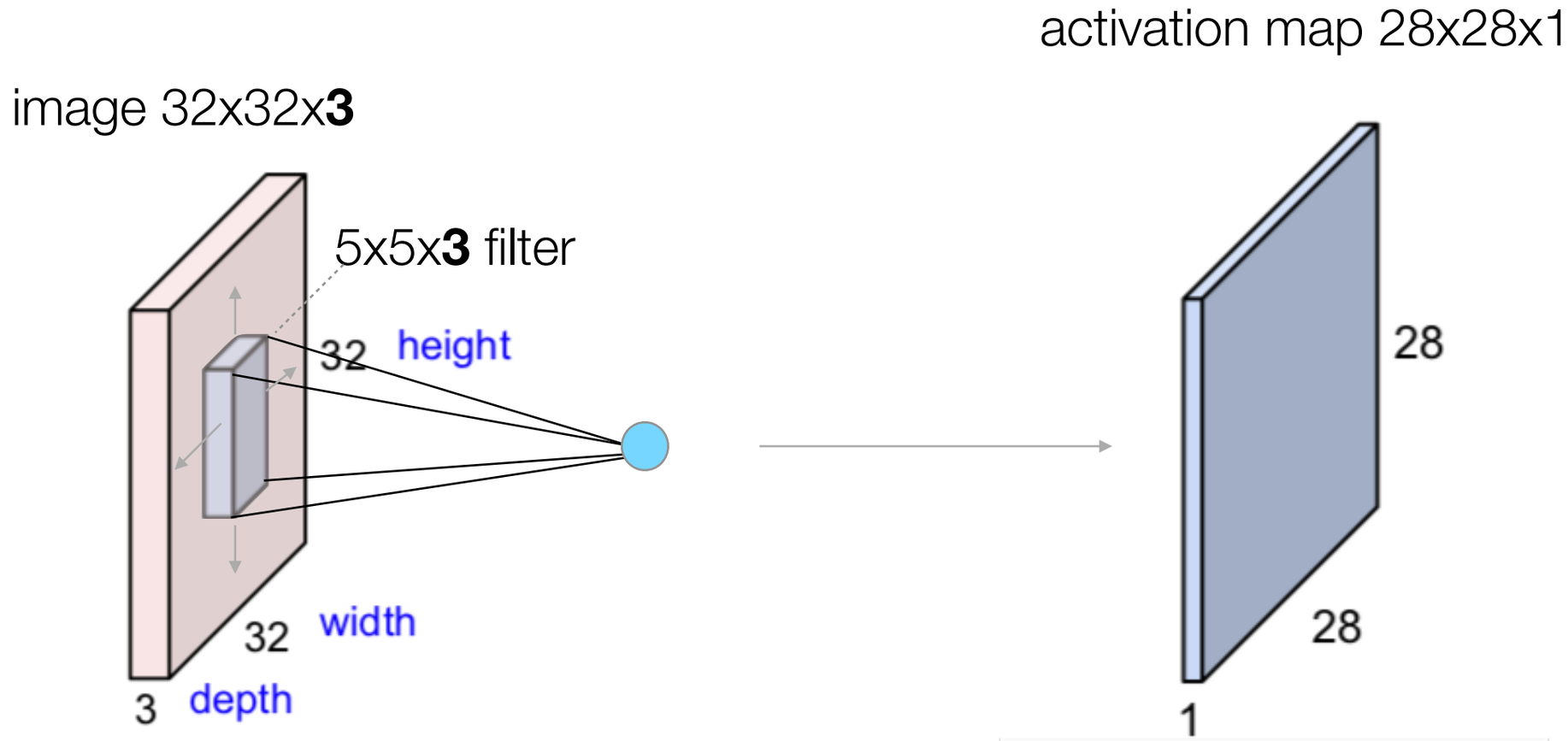
```
n_classes = 10
Y_train = utils.to_categorical(y_train, n_classes)
Y_test = utils.to_categorical(y_test, n_classes)
```

```
[9 0 0 3 0 2 7 2 5 5]
```

```
[[0. 0. 0. 0. 0. 0. 0. 0. 0. 1.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 1. 0. 0. 0. 0.]]
```

RECAP 2 - Convolution layer - 2D signals

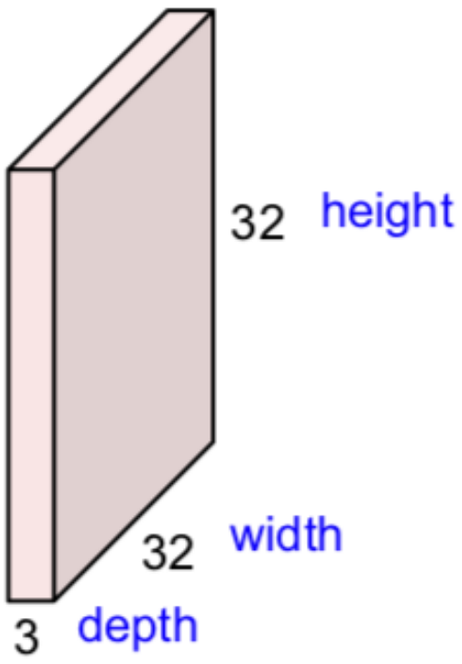
- Notion of **activation map** that is the result of the convolution of the filter, i.e. the sliding over all possible spatial locations of the image.
- This sliding of the filter gives us **translation invariance** regarding to what the filter is sensitive for.



RECAP 3 - Convolution layer - 2D signals

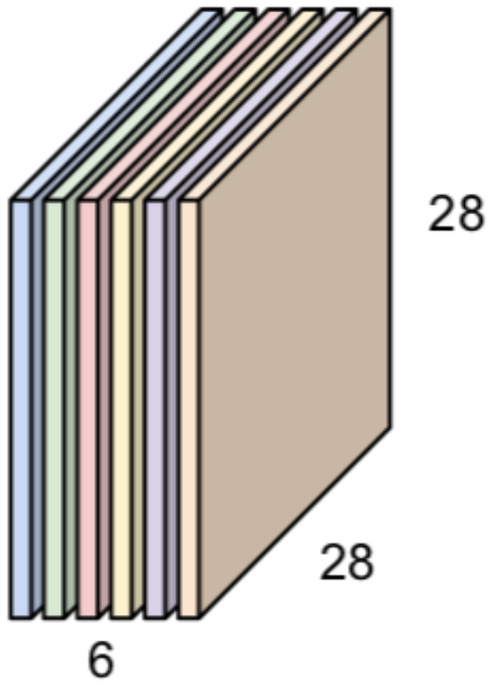
- Notion of **several filters** producing **several activation maps**
- Let’s say we have 6 5x5x3 filters, we’ll get 6 maps

image 32x32x3



convolution
layer 6 filters
of 5x5x3

activation maps 28x28x6



CNN for FashionMNIST - network definition

We use the Sequential() model from Keras that allow to **stack** layers to compose a CNN.

1st layer is a Conv2D layer for the **convolution** operation that extracts features from the input images by sliding a convolution filter over the input to produce a feature map. Here we choose filters with size 3 x 3. The first layer must also specify the size of the input with `input_shape=(28, 28, 1)`

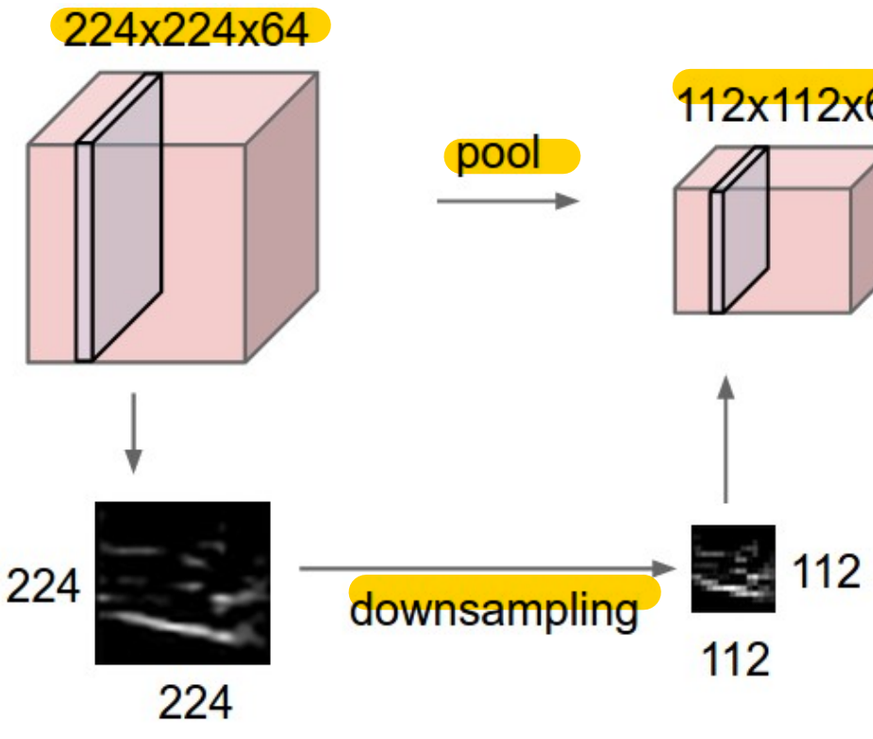
The next layer is a ReLU **activation** layer.

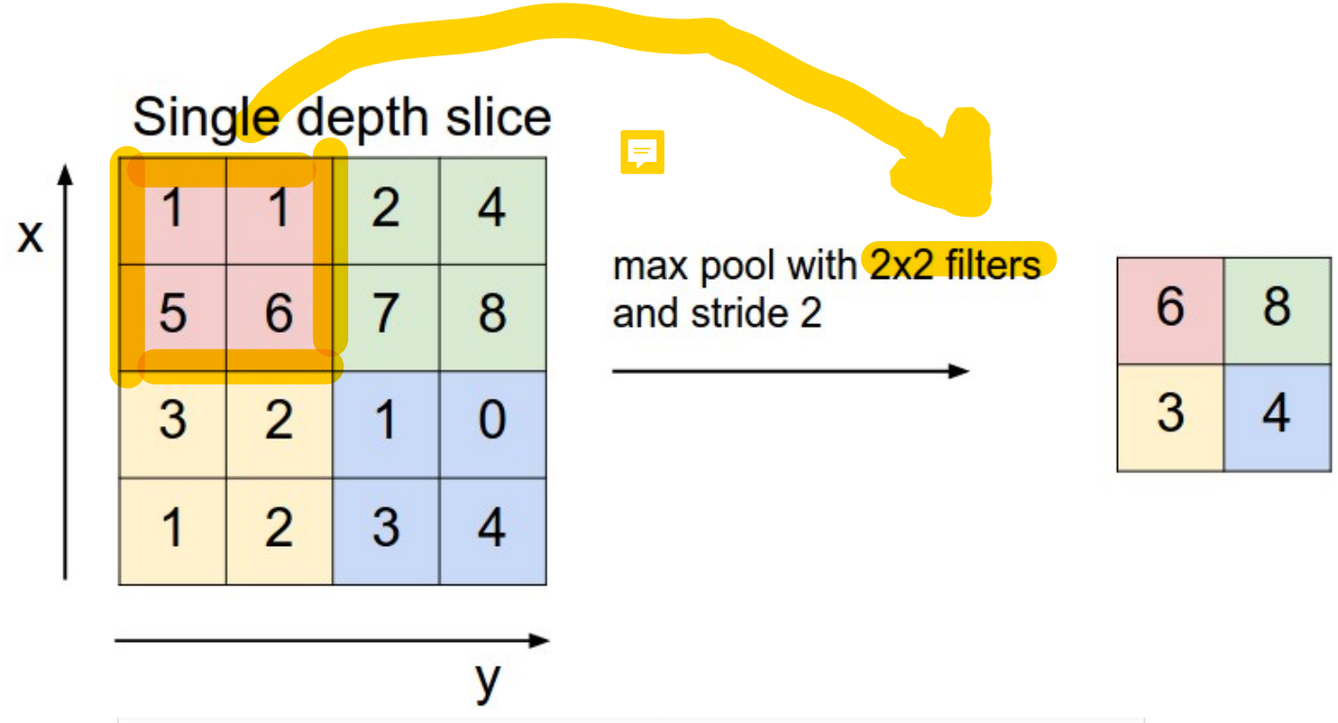
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.layers import Flatten, Activation
from tensorflow.keras.layers import Conv2D, MaxPooling2D

cnn1 = Sequential()

cnn1.add(Conv2D(32, kernel_size=(3, 3), padding='same',
                input_shape=(28, 28, 1)))
cnn1.add(Activation('relu'))
cnn1.add(MaxPooling2D(pool_size=(2, 2)))
cnn1.add(Dropout(0.2))

cnn1.add(Flatten())

cnn1.add(Dense(128, activation='relu'))
cnn1.add(Dense(10, activation='softmax'))

cnn1.summary()
```

What is the size of the activation feature maps?

RECAP 4 - Max pooling layer

- Reduce the spatial size of the representation
  - Applies independently to every depth, defined by a stride and size
  - Rationale:
    - most significant activations are kept, brings hierarchical approach
    - reduce the amount of computation and control overfitting





Other options: average pooling or L2-norm pooling.
Common settings: S=2, size=2 or S=2, size=3

Images from Fei Fei Li - Stanford University School of Engineering - CS231

CNN for FashionMNIST - network definition

The next layer is a MaxPooling2D layer for the **max-pooling** operation that reduces the dimensionality of each feature, which helps shorten training time and reduce number of parameters. Here we choose the pooling window with size 2 x 2.

To "fight" overfitting, we may add a **dropout** layer. It forces the model to learn multiple independent representations of the same data by randomly disabling neurons in the learning phase. We specify the quantity of neurons randomly disabled: 20%.

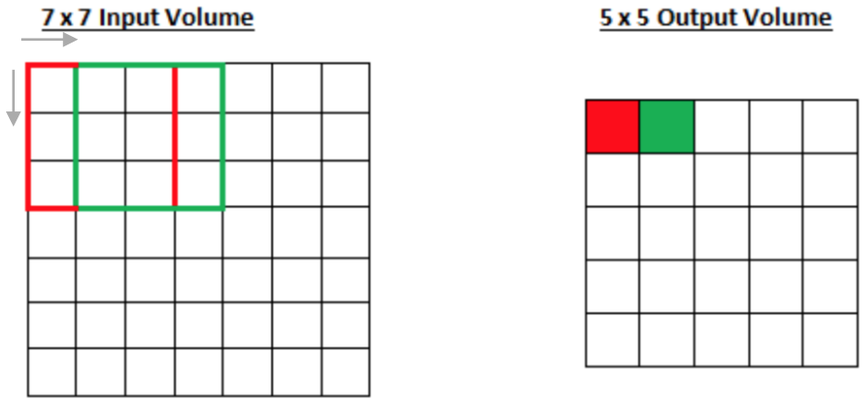
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.layers import Flatten, Activation
from tensorflow.keras.layers import Conv2D, MaxPooling2D

cnn1 = Sequential()

cnn1.add(Conv2D(32, kernel_size=(3, 3), padding='same',
                input_shape=(28, 28, 1)))
cnn1.add(Activation('relu'))
cnn1.add(MaxPooling2D(pool_size=(2, 2)))
cnn1.add(Dropout(0.2))

cnn1.add(Flatten())

cnn1.add(Dense(128, activation='relu'))
cnn1.add(Dense(10, activation='softmax'))

cnn1.summary()
```

What is the size of the max pooling outputs?

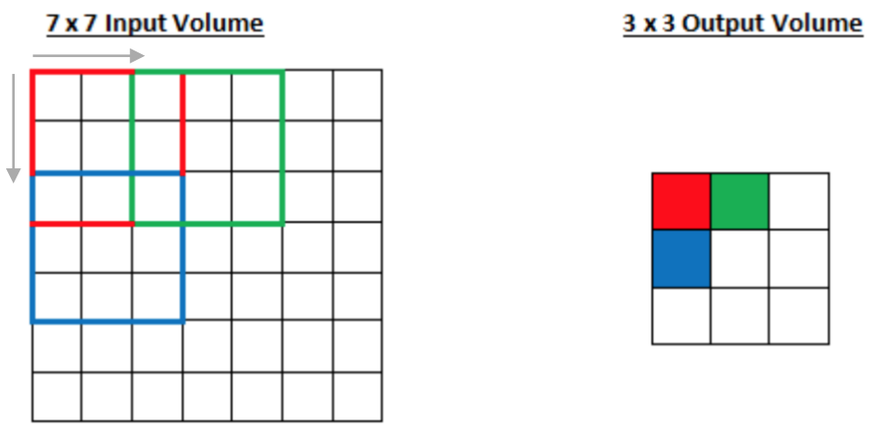
RECAP 5 - Convolution layer - stride & padding

- The **stride S** specifies a step size when moving the filter across the signal.
- The **padding P** specifies the size of a zeroed frame added around the input.

S = 1



S = 2



$P_H = 2$

$P_W = 2$

Image: Adit Deshpande, https://adeshpande3.github.io/adeshpande3.github.io/A-Beginner's-Guide-To-Understanding-Convolutional-Neural-Networks-Part-2/

CNN for FashionMNIST - network definition

The next step is to feed the last output tensor into one or several Dense, **fully-connected** layers.

These layers take as input vectors that are 1-D. In our case, the output of the conv-relu-pool-dropout layers is a 3-D tensor (14, 14, 32). Thus, we need to flatten the 3-D outputs to 1-D using a **Flatten** layer.

10 classes = 10 neurons
Softmax activation enables to estimate class posterior probabilities, i.e. winner class is the one with the highest value

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.layers import Flatten, Activation
from tensorflow.keras.layers import Conv2D, MaxPooling2D

cnn1 = Sequential()

cnn1.add(Conv2D(32, kernel_size=(3, 3), padding='same',
                input_shape=(28, 28, 1)))
cnn1.add(Activation('relu'))
cnn1.add(MaxPooling2D(pool_size=(2, 2)))
cnn1.add(Dropout(0.2))

cnn1.add(Flatten())

cnn1.add(Dense(128, activation='relu'))
cnn1.add(Dense(10, activation='softmax'))

cnn1.summary()
```

The `summary()` methods prints out the structure of the network created with the sequential model.

CNN for FashionMNIST - network definition

Output of the summary() method.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 28, 28, 32)        320
_________________________________________________________________
activation (Activation)      (None, 28, 28, 32)        0
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 14, 14, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 14, 14, 32)        0
_________________________________________________________________
flatten (Flatten)            (None, 6272)              0
_________________________________________________________________
dense (Dense)                (None, 128)               802944
_________________________________________________________________
dense_1 (Dense)              (None, 10)                1290
=================================================================
Total params: 804,554
Trainable params: 804,554
Non-trainable params: 0
```

CNN for FashionMNIST - compile & train

We choose here ‘categorical_crossentropy’ as loss function. This loss is relevant for multi-class, single-label classification problem.

We chose here the ‘adam’ optimizer. The Adam optimizer is an improvement over SGD (Stochastic Gradient Descent). The optimizer is defining the update rule for the weights of the neurons during back-propagation of the gradients.

```
cnn1.compile(loss='categorical_crossentropy',
             optimizer='adam', metrics=['accuracy'])
```

```
log = cnn1.fit(X_train, Y_train,
          batch_size=256,
          epochs=10,
          verbose=1,
          validation_data=(X_test, Y_test))
```

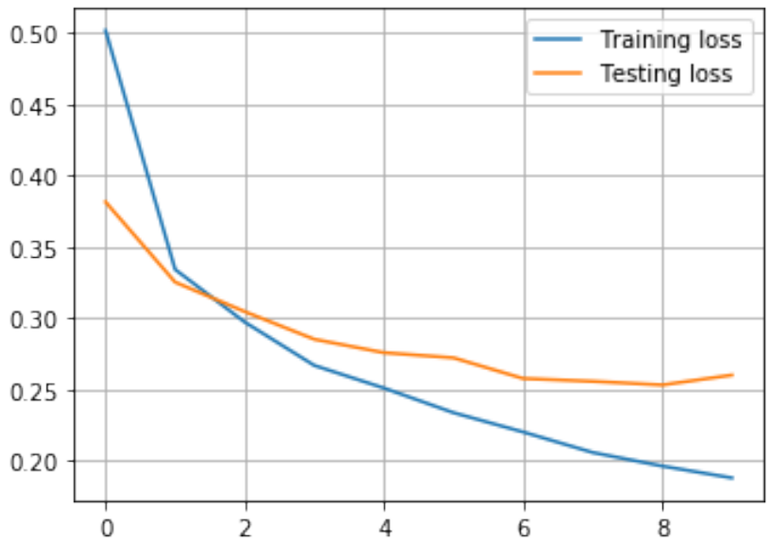
We can now train the model. We need to select the batch size and the number of epochs, in this case batches of 256 with 10 epochs. We also need to give as argument the training and validation data.

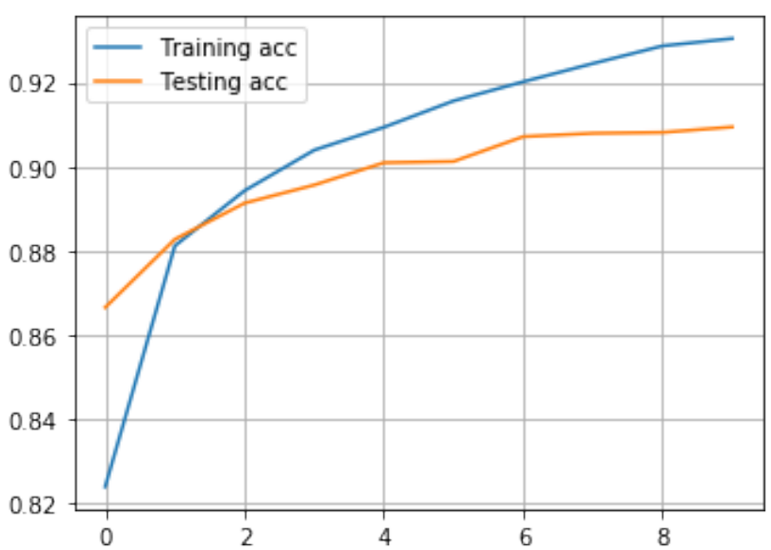
CNN for FashionMNIST - evaluate

We can then evaluate on the test set regarding loss and accuracy.

```
loss_test, metric_test = cnn1.evaluate(X_test, Y_test,
                                       verbose=0)
print('Test loss:', loss_test)
print('Test accuracy:', metric_test)
```

```
Test loss: 0.26002298431396487
Test accuracy: 0.9094
```



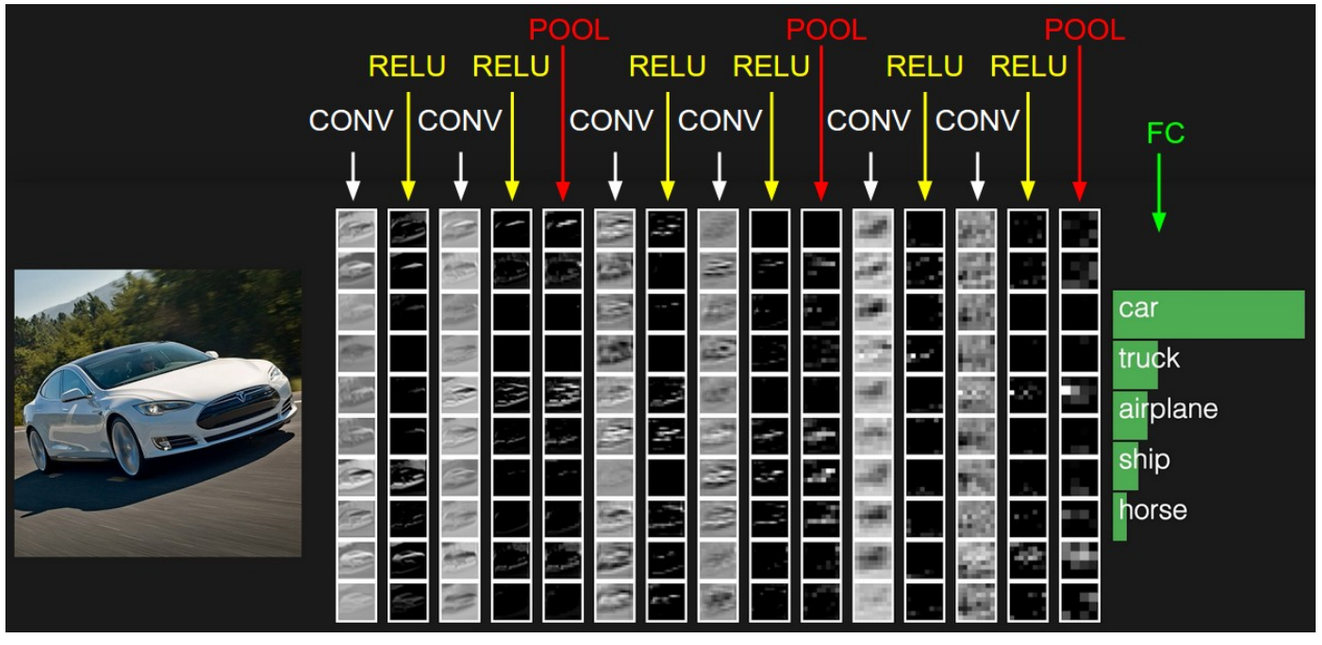



```
f = plt.figure(figsize=(12,4))
ax1 = f.add_subplot(121)
ax2 = f.add_subplot(122)
ax1.plot(log.history['loss'], label='Training loss')
ax1.plot(log.history['val_loss'], label='Testing loss')
ax1.legend()
ax1.grid()
ax2.plot(log.history['accuracy'], label='Training acc')
ax2.plot(log.history['val_accuracy'], label='Testing acc')
ax2.legend()
ax2.grid()
```

CNN for FashionMNIST - going deeper

As seen in the previous exercises, we may improve the model performances by stacking CONV-RELU-POOL layers and playing with the different hyper-parameters of the different layers: number of filters, kernel size, etc.

```
# add blocks such as these one below to increase the depth
cnn1.add(Conv2D(32, kernel_size=(3, 3), input_shape=input_shape))
cnn1.add(Activation('relu'))
cnn1.add(MaxPooling2D(pool_size=(2, 2)))
cnn1.add(Dropout(0.2))
```

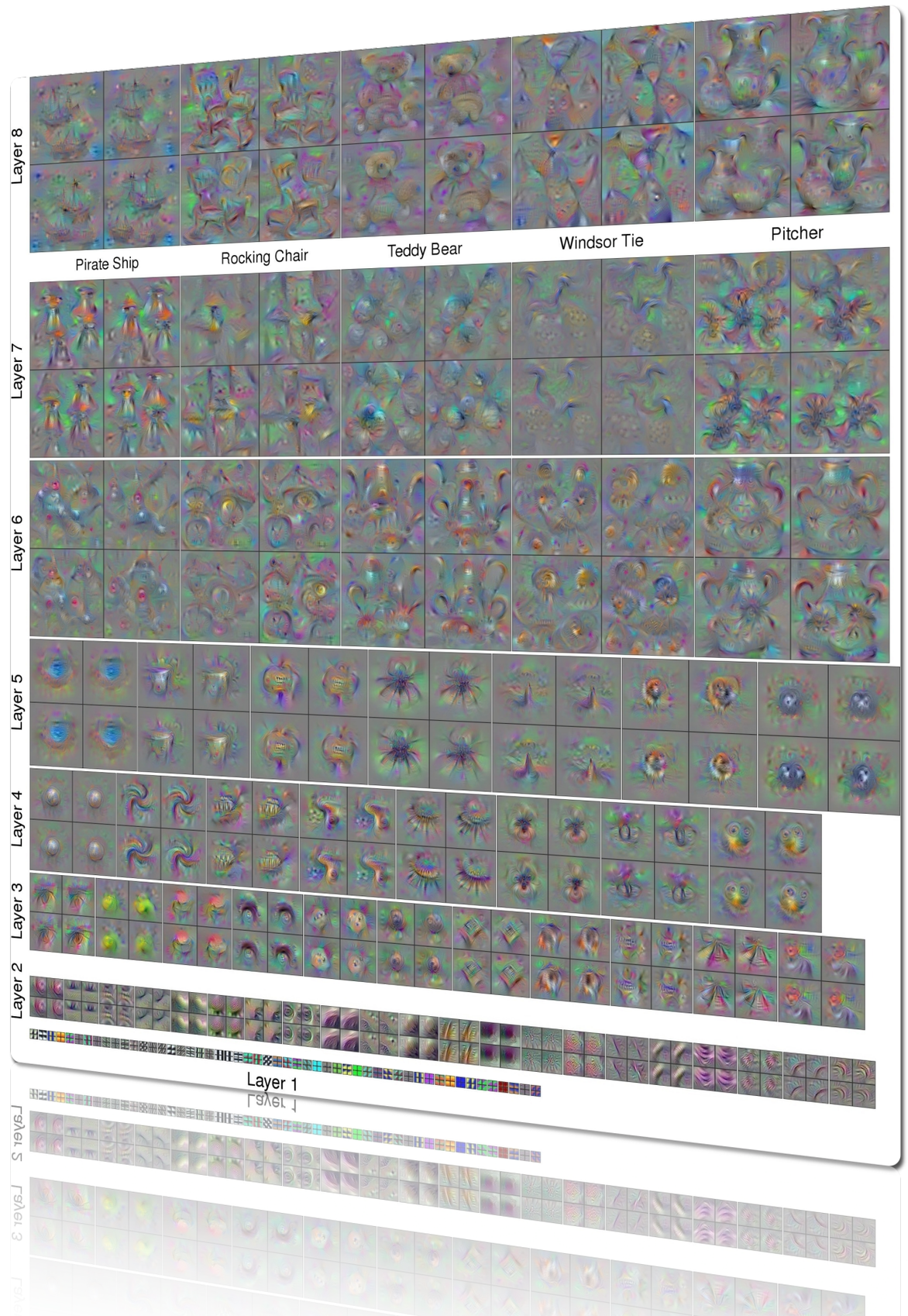


CIFAR10 - online demo

- https://cs.stanford.edu/people/karpathy/convnetjs/demo/cifar10.html

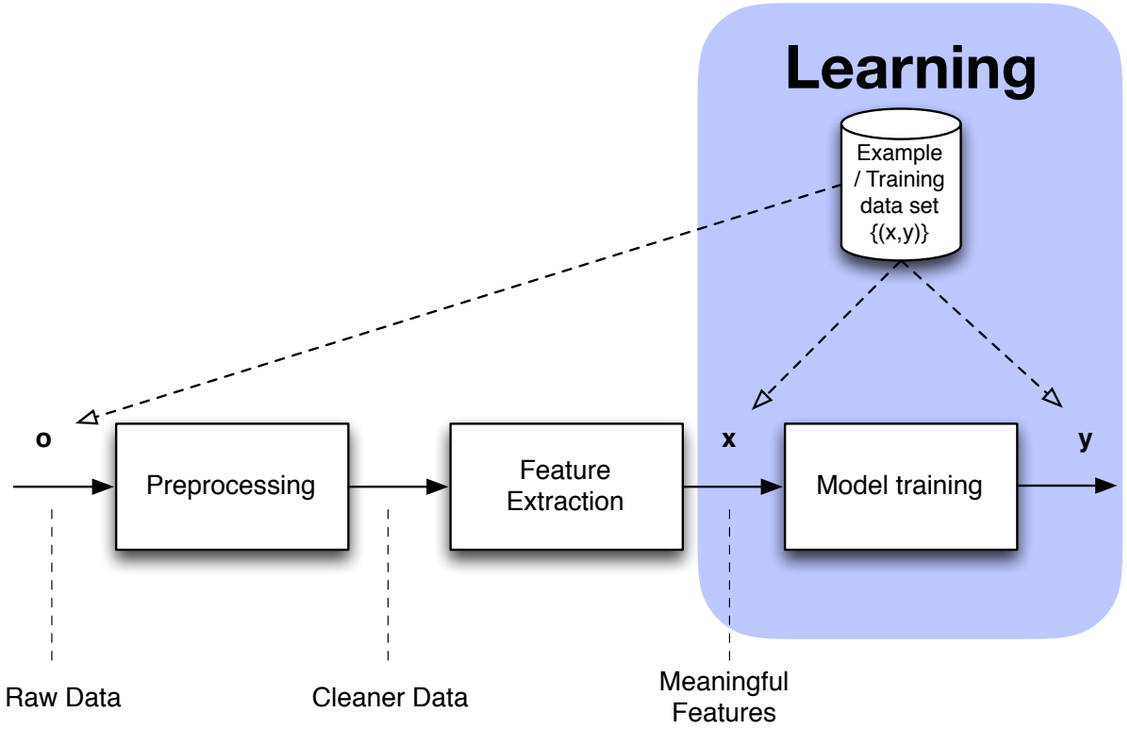
CNN and hierarchical features

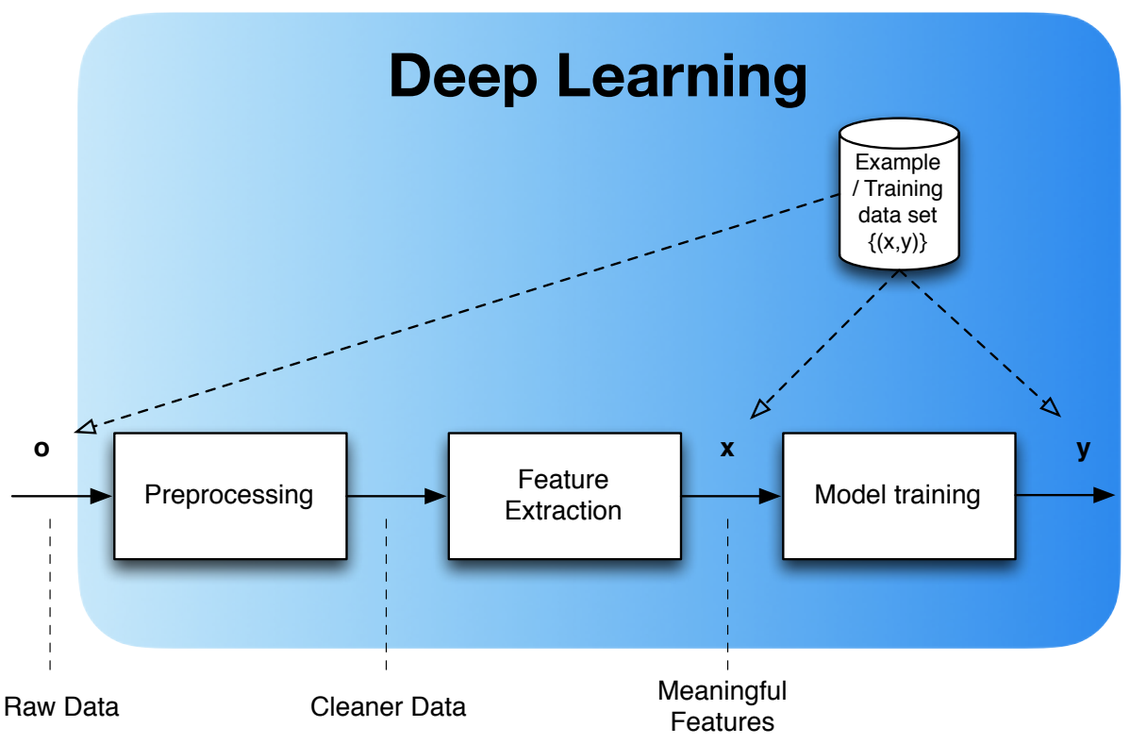
- Feature extraction
- Hierarchy of features
- Visualisation
  - Activation maps
  - Inputs with max outputs

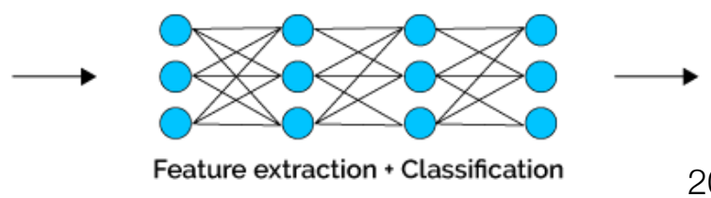


Convolution layers are extracting features

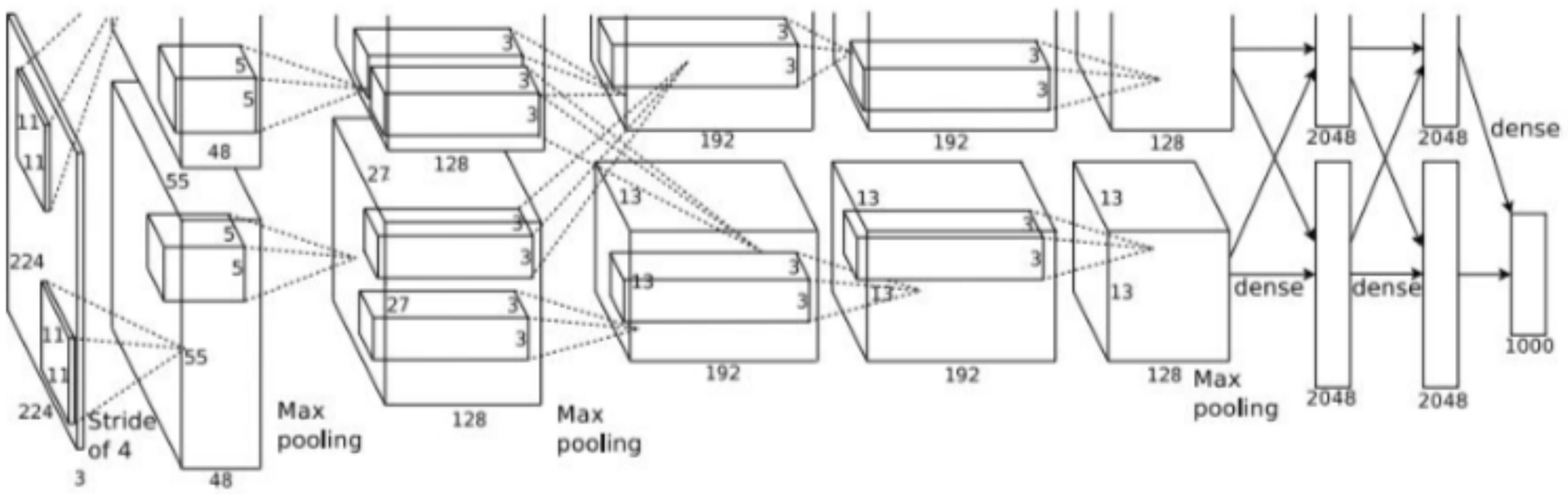
- The filter parameters are **learnt** through the training process. The whole system is learning not only to classify but also to extract features.







A hierarchy of features

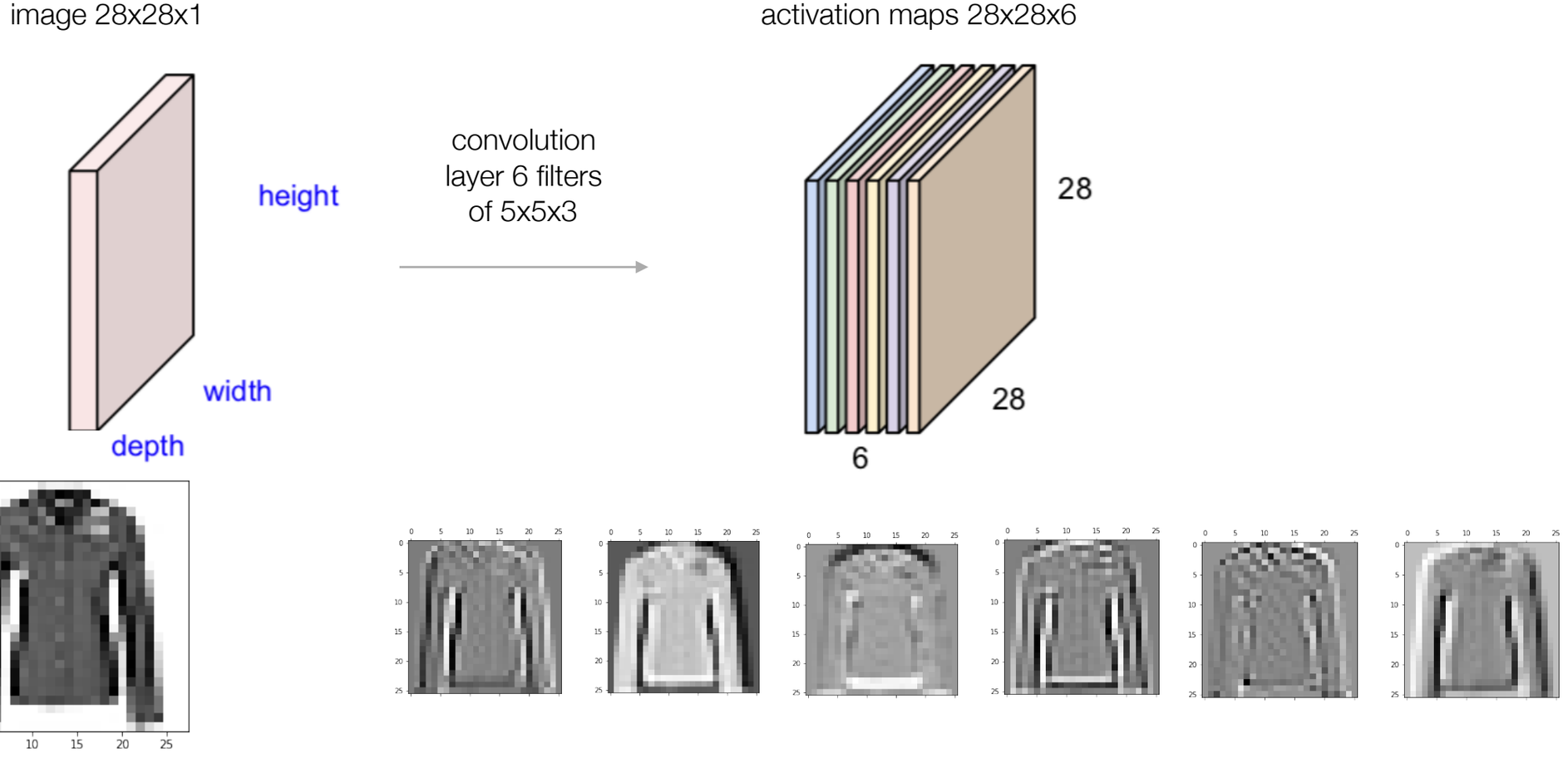


- Above is the AlexNet architecture [2012]
- The deeper the network:
  - The bigger are the number of filters in the conv layers
  - The smaller are the activation maps due to max pooling
- Intuitively:
  - Early layers will extract lower-level features
  - Late layers will extract higher-level features

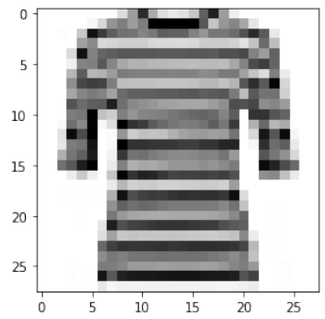
How can we visualise what has learnt the network?

Visualisation - activation maps

- First strategy: **visualise the activation maps**
  - For a given conv layer, consider each filter independent and visualise the corresponding activation map



Visualisation - activation maps



Extract the output of the 1st layer from the CNN model.

Rebuild a new Keras Model with the input layer and the output of the first layer.

The network expects a batch of images so we need to reshape the input image into a batch of 1.

Do the forward pass and plot the activations for 6 of the filters.

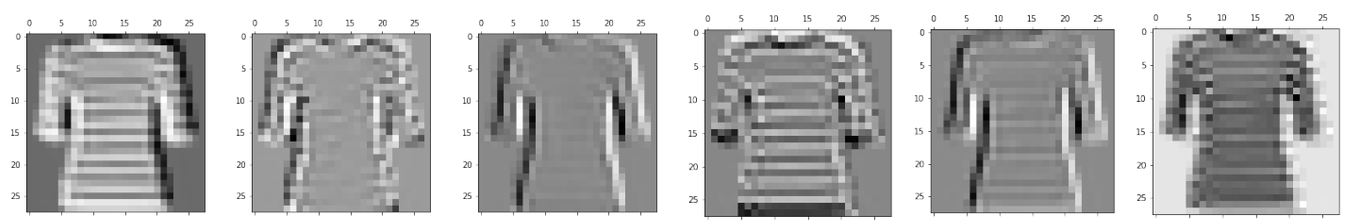
```
test_im1 = X_train[26]
plt.imshow(test_im1.reshape(28,28), cmap='Greys',
           interpolation='none')
plt.show()
```

```
from tensorflow.keras import models
# extracts the output of the first layer
layer_1st_conv = cnn1.layers[0].output
```

```
# creates a model able to return these outputs, given an input
activation_model = models.Model(inputs=cnn1.input,
                                outputs=layer_1st_conv)
```

```
# we need to reshape the image (28,28,1) into (1,28,28,1)
# as the network expect a batch of images as input
test_im1 = test_im1.reshape(1,28,28,1)
```

```
# returns the first layer activation
first_layer_activation = activation_model.predict(test_im1)

# display 6 of the activations of the 1st conv layer
plt.matshow(first_layer_activation[0, :, :, 0], cmap='Greys')
plt.matshow(first_layer_activation[0, :, :, 1], cmap='Greys')
plt.matshow(first_layer_activation[0, :, :, 2], cmap='Greys')
plt.matshow(first_layer_activation[0, :, :, 3], cmap='Greys')
plt.matshow(first_layer_activation[0, :, :, 4], cmap='Greys')
plt.matshow(first_layer_activation[0, :, :, 5], cmap='Greys')
```

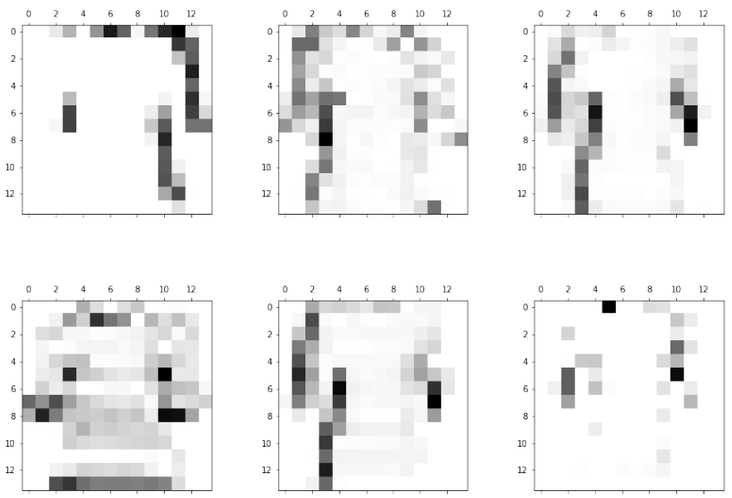


Visualisation - activation maps

- The same principle applies to all layers.
  - Below example for the first max pooling layer

Extract the output of the 3rd layer from the CNN model = max pool

Rebuild a new Keras Model with the input layer and the output of the first max pooling layer.



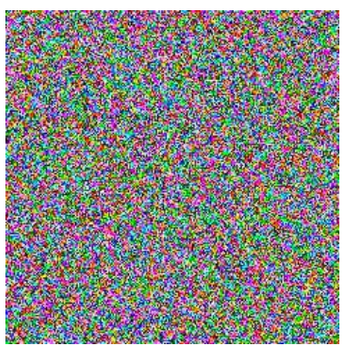
```
from tensorflow.keras import models
# extracts the output of the first layer
layer_1st_maxpool = cnn1.layers[2].output

# creates a model able to return these outputs, given an input
activation_model = models.Model(inputs=cnn1.input,
                                outputs=layer_1st_maxpool)

# we need to reshape the image (28,28,1) into (1,28,28,1)
# as the network expects a batch of images as input
test_im1 = test_im1.reshape(1,28,28,1)

# returns the first layer activation
first_maxpool_activation = activation_model.predict(test_im1)

# display 6 of the activations of the 1st conv layer
plt.matshow(first_maxpool_activation[0, :, :, 0], cmap='Greys')
plt.matshow(first_maxpool_activation[0, :, :, 1], cmap='Greys')
plt.matshow(first_maxpool_activation[0, :, :, 2], cmap='Greys')
plt.matshow(first_maxpool_activation[0, :, :, 3], cmap='Greys')
plt.matshow(first_maxpool_activation[0, :, :, 4], cmap='Greys')
plt.matshow(first_maxpool_activation[0, :, :, 5], cmap='Greys')
```

Visualisation - inputs with max activations

- Second strategy: find **input images that maximise the activation** of a given neuron
  1. Start with a random image $\mathbf{x}$
  2. Forward: compute the activation of a given neuron $a_{i,j}(\mathbf{x})$
  3. Backward: perform the backprob of the gradient of $a_{i,j}(\mathbf{x})$ up to the pixel values: $\frac{\partial a_{i,j}(\mathbf{x})}{\partial \mathbf{x}}$
  5. This gradient tells us how to change the pixel values to increase the activation of the neuron. We can then apply an update rule in the form of a gradient ascent:

$$x \leftarrow x + \alpha \frac{\partial a_{i,j}(\mathbf{x})}{\partial \mathbf{x}} + \text{Regularisation Term}$$

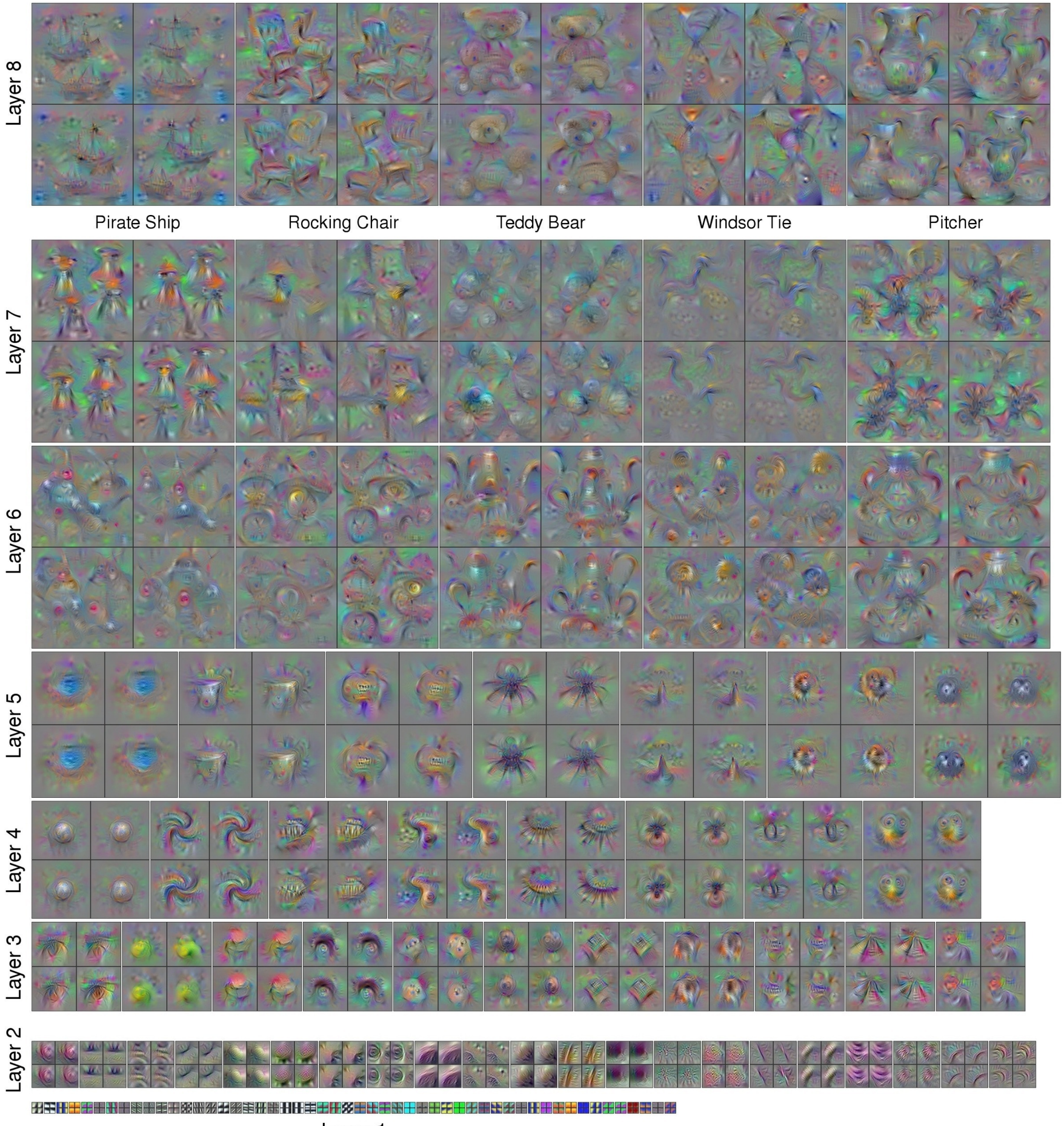
  6. Iterate in 2 until convergence



goose

The **regularisation** term impeach pixels to be at extreme values. It kind of pressure to converge to natural looking images.
See e.g. http://yosinski.com/deepvis

Source: http://yosinski.com/deepvis



Deep Visualization Toolbox

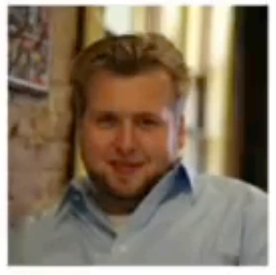
yosinski.com/deepvis

#deepvis

Jason Yosinski

Jeff Clune

Anh Nguyen



Thomas Fuchs

Hod Lipson

Cornell University

University of Wyoming

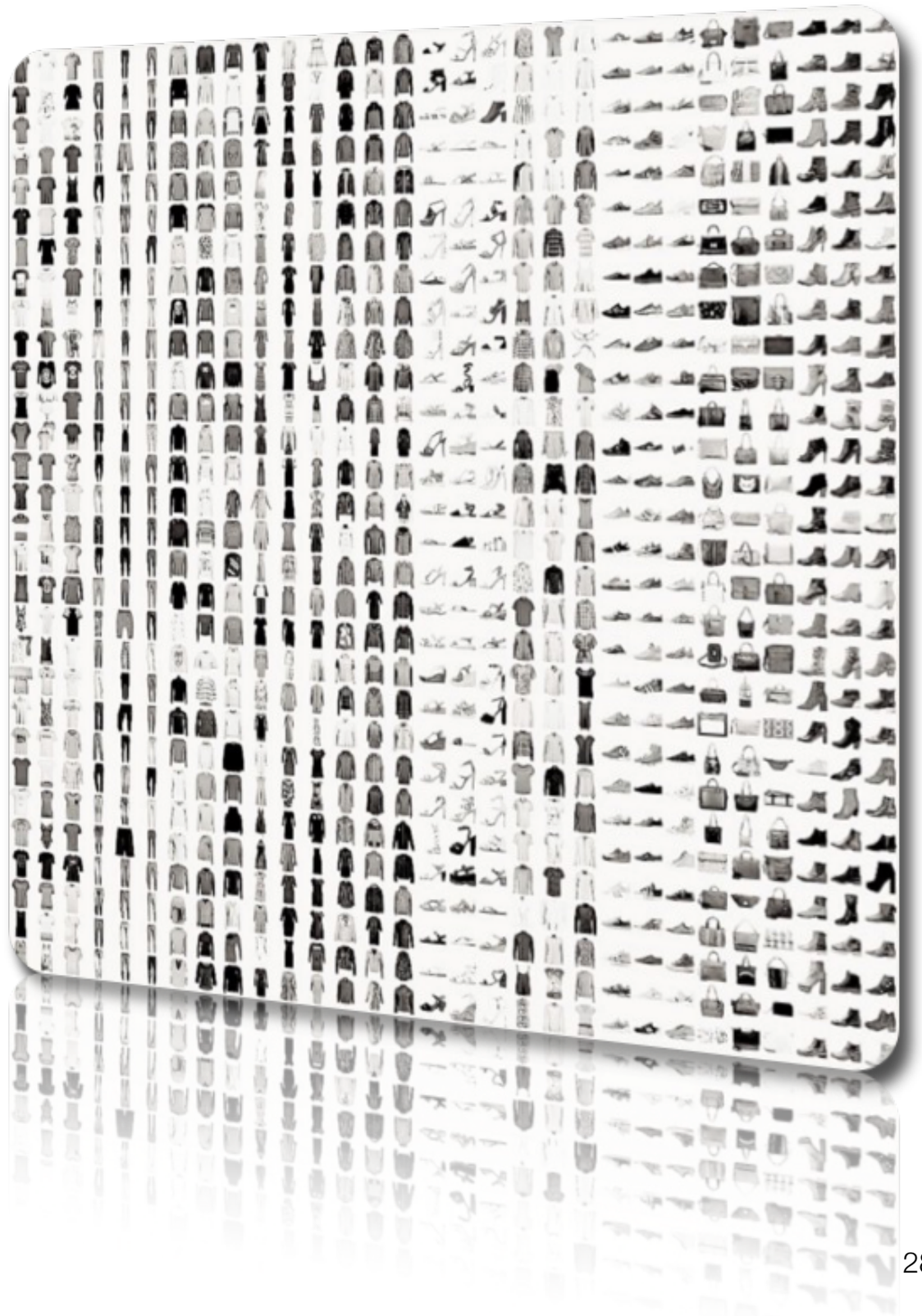
Jet Propulsion Laboratory
California Institute of Technology

http://yosinski.com/deepvis
https://youtu.be/AgkfIQ4IGaM

Data Augmentation

Principles

Example on FashionMNIST



Principles of data augmentation

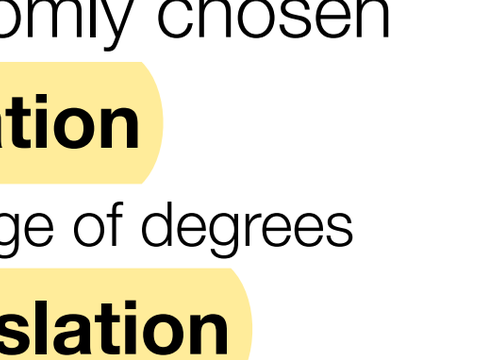
- Overfitting can be caused by having networks with too many parameters that are trained on too few samples. Through training, the model learns *by hart* and generalises poorly.

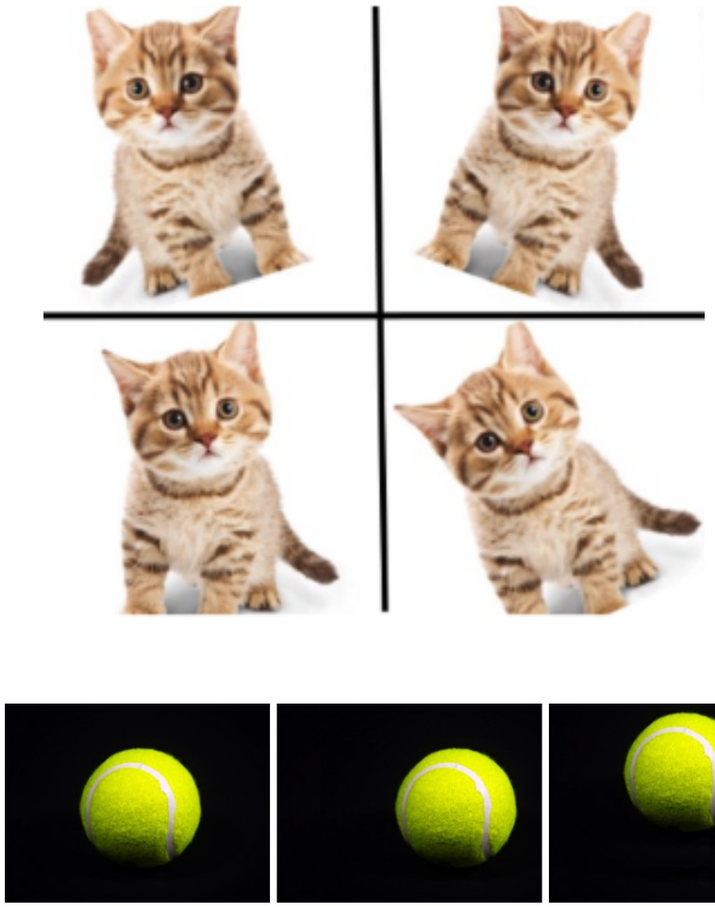
- **Data augmentation** takes the approach of generating artificially more training data from existing training samples.

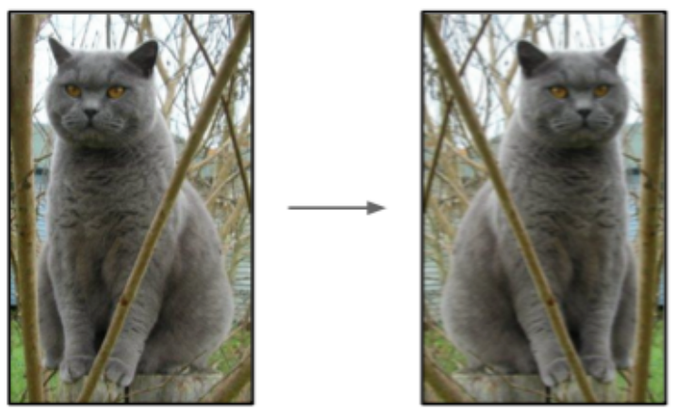
- For images, data augmentation is performed via a number of random transformations that yield believable-looking images.
- The goal is that at training time, the model will not see the exact same picture twice. This helps expose the model to more aspects of the data and generalise better.

2D data augmentation

- Quantity of “perturbations” are randomly chosen
- **Rotation**
  - range of degrees
- **Translation**
  - percentage of shift in a range
    - for width and height
- **Flip**
  - may not be applicable to all types of images
    - e.g. images with text

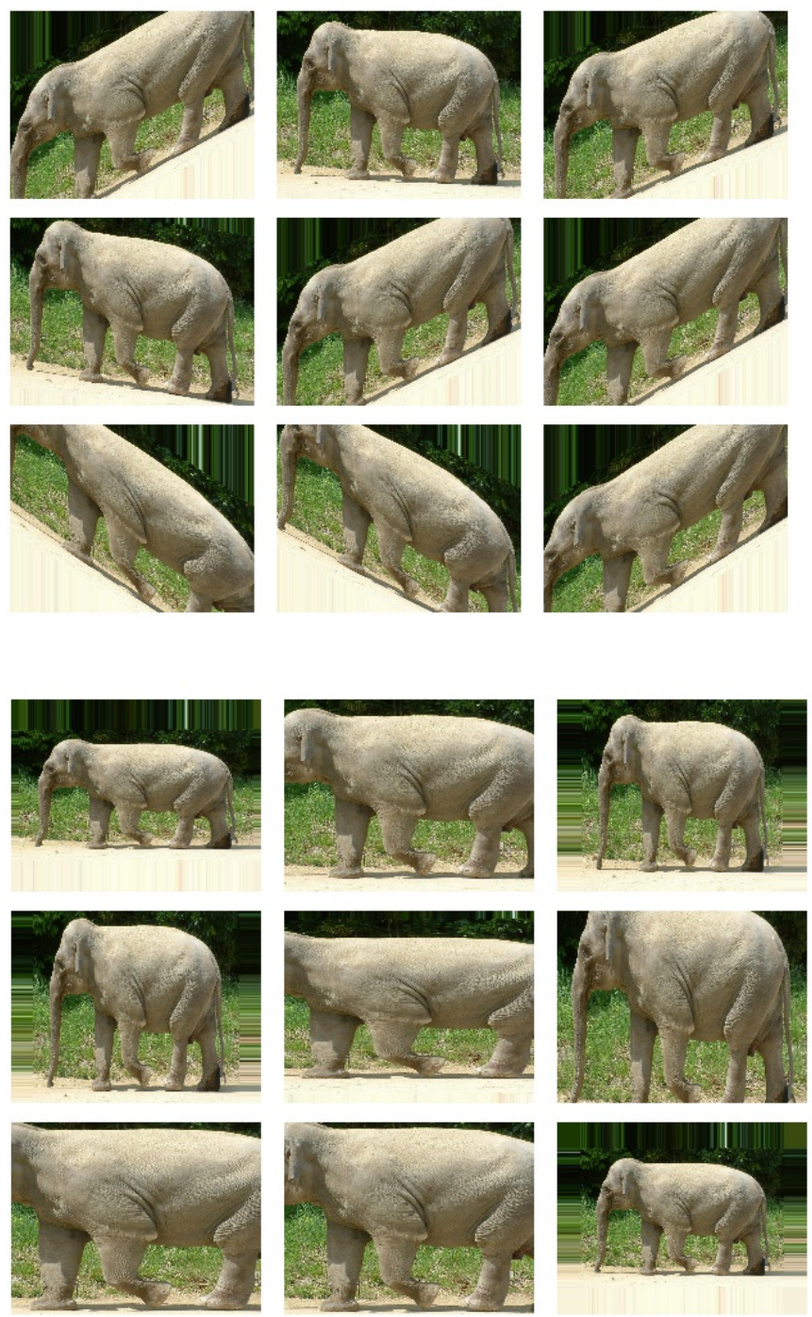






2D data augmentation

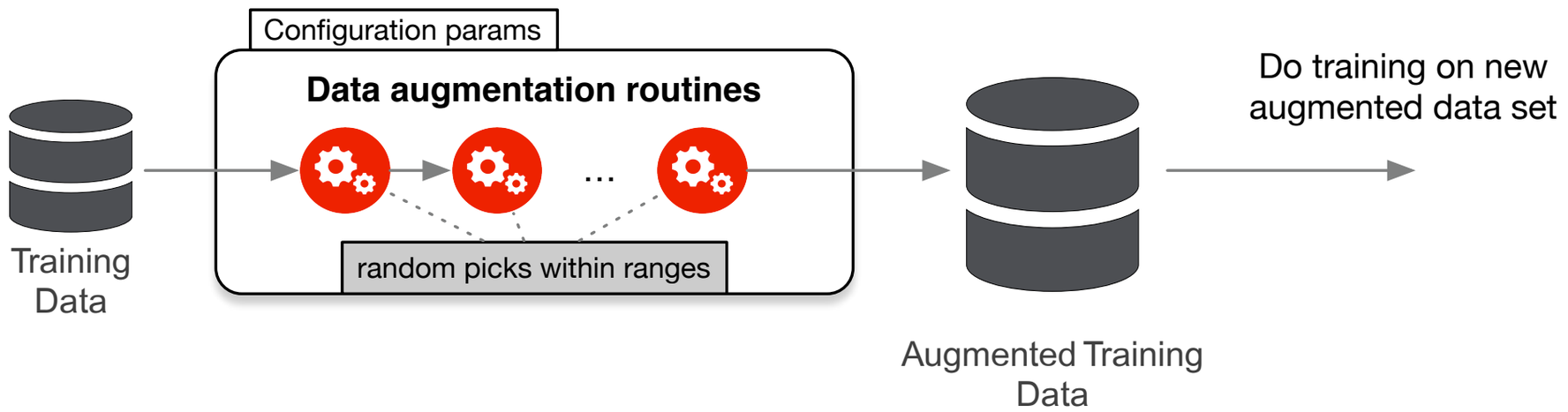
- **Shear**
- **Zoom**
- **Color**
  - shifting
  - illumination
  - …



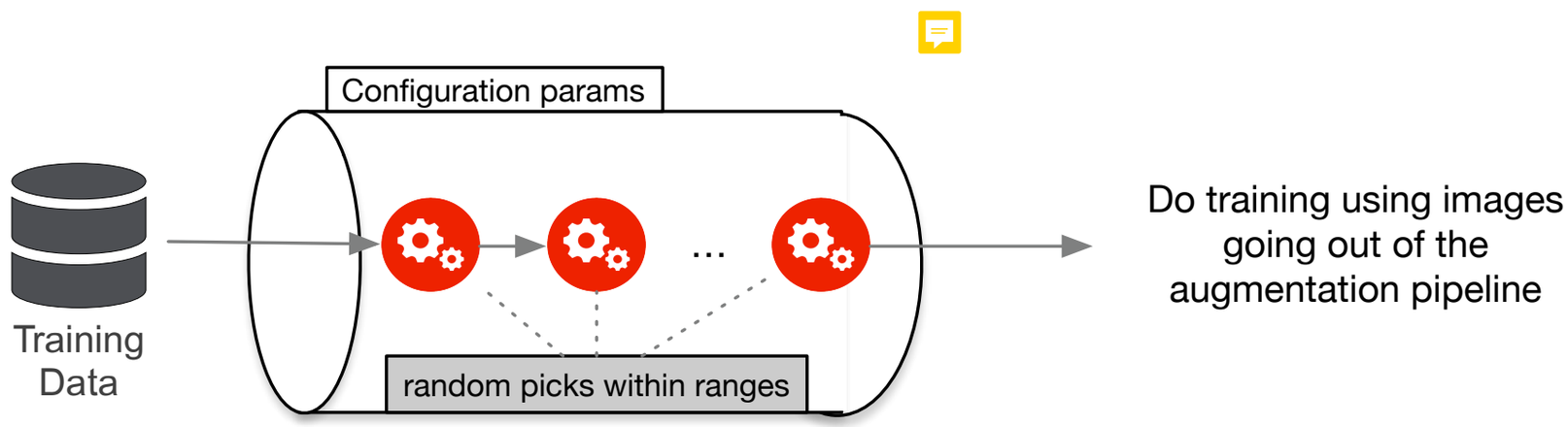

STOP

Data augmentation - implementation strategies

Data augmentation - pre-augmentation

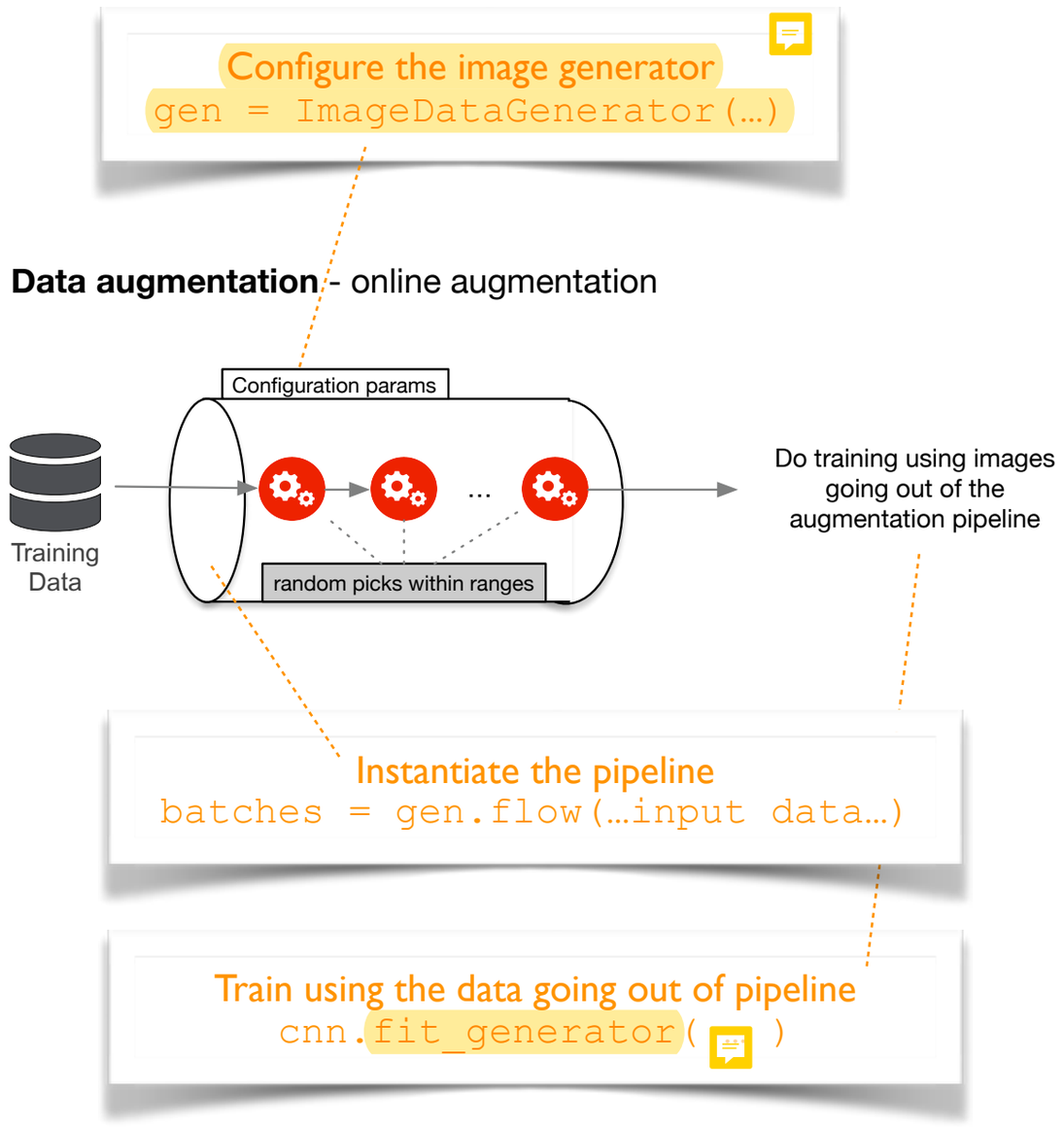


Data augmentation - online augmentation



Data augmentation - Keras implementation

- Principle: online augmentation strategy
- Steps:
  - Configure the image data generator
    - Which augmentation to apply
    - In which ranges
  - Instantiate a pipeline on the input data set
  - Tell the training method that you use a pipeline



CNN for FashionMNIST - data augmentation

In Keras, the ImageDataGenerator() can be configured with many different options for rotation, shift, shear, zoom , etc.

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator
gen = ImageDataGenerator(rotation_range=8,
                         width_shift_range=0.08,
                         shear_range=0.3,
                         height_shift_range=0.08,
                         zoom_range=0.08)
```

Flow pipelines can then be declared, here fed by training and validation images

```
batches = gen.flow(X_train, Y_train, batch_size=256)
val_batches = gen.flow(X_test, Y_test, batch_size=256)
```

Training can be done calling the fit_generator() method that will take the outputs of the data augmentation pipelines

```
log = cnn1.fit_generator(batches,
                         steps_per_epoch=60000//256,
                         epochs=50,
                         validation_data=val_batches,
                         validation_steps=10000//256,
                         use_multiprocessing=True)
```

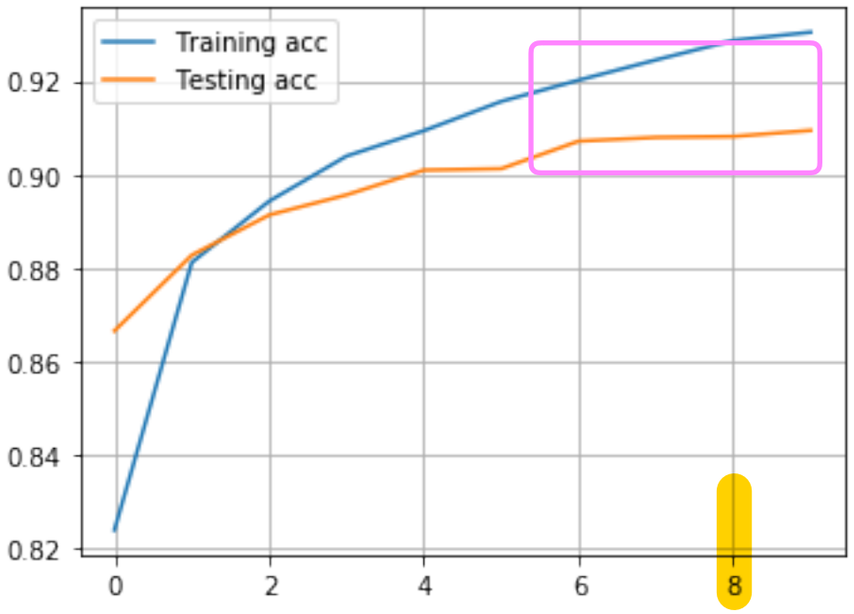
We can evaluate as usual

```
score1 = cnn1.evaluate(X_test, Y_test, verbose=0)
print('Test loss:', score1[0])
print('Test accuracy:', score1[1])
```

```
Test loss: 0.255321241492033
Test accuracy: 0.9123
```

CNN for FashionMNIST - data augmentation

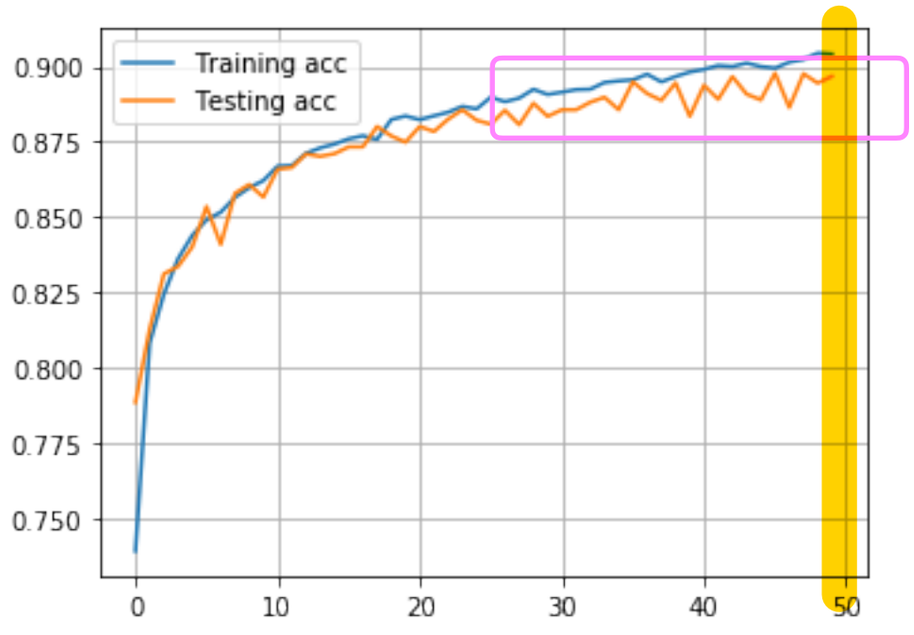
Without data augmentation




```
loss_test, metric_test = cnn1.evaluate(X_test, Y_test, verbose=0)
print('Test loss:', loss_test)
print('Test accuracy:', metric_test)
```

```
Test loss: 0.26002298431396487
Test accuracy: 0.9094
```

With data augmentation




```
lost_test, metric_test = cnn1.evaluate(X_test, Y_test, verbose=0)
print('Test loss:', loss_test)
print('Test accuracy:', metric_test)
```

```
Test loss: 0.255321241492033
Test accuracy: 0.9123
```

- We may observe that with data augmentation:
  - Training shows less difference between training set and validation set - less prone to overfitting
  - Overall improvement is not so high in this case.
    - This is probably due to the “stability” of the images of FashionMNIST

Deep CNN Architectures

- Convolutional pattern
- LeNet-5
- AlexNet
- VGGNet
- GoogLeNet
- ResNet

Convolutional layer patterns

- Common forms of conv. network stack layers as follows:

```
INPUT -> [[CONV -> RELU]*N -> POOL?]*M -> [FC -> RELU]*K -> FC
```

  - Where * indicates repetition, POOL? indicates optional pooling layer with: N >= 0 (usually <=3), M >= 0, K >= 0 (usually K<3)

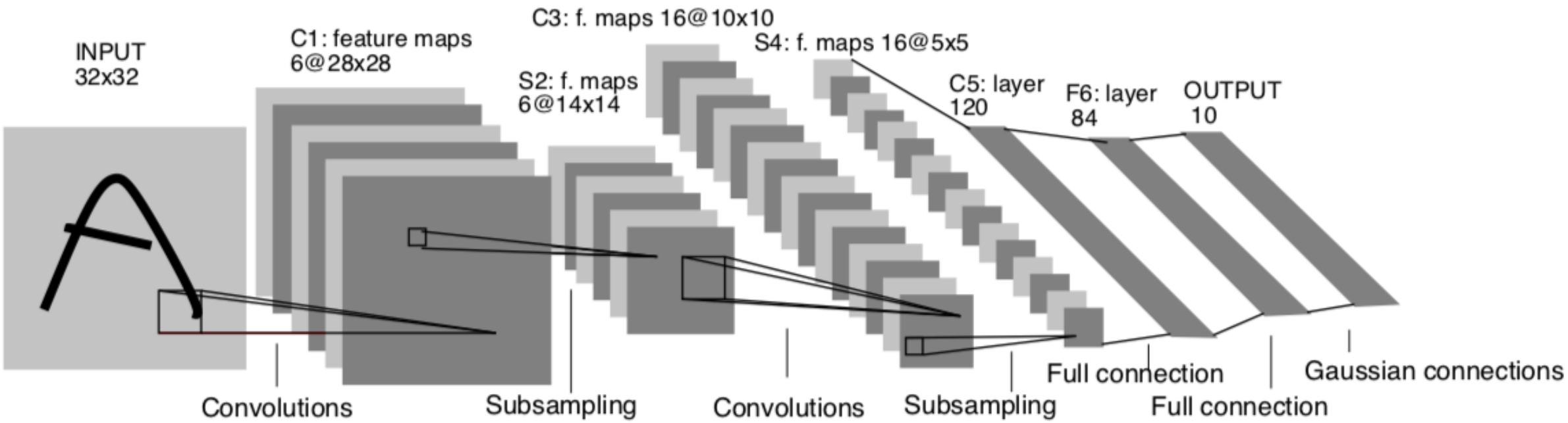
- For example:

```
INPUT -> CONV -> RELU -> FC
```

`INPUT -> [CONV -> RELU -> POOL]*2 -> FC -> RELU -> FC`. Here we see that there is a single CONV layer between every POOL layer.

`INPUT -> [CONV -> RELU -> CONV -> RELU -> POOL]*3 -> [FC -> RELU]*2 -> FC` Here we see two CONV layers stacked before every POOL layer. This is generally a good idea for larger and deeper networks, because multiple stacked CONV layers can develop more complex features of the input volume before the “destructive” pooling operation.

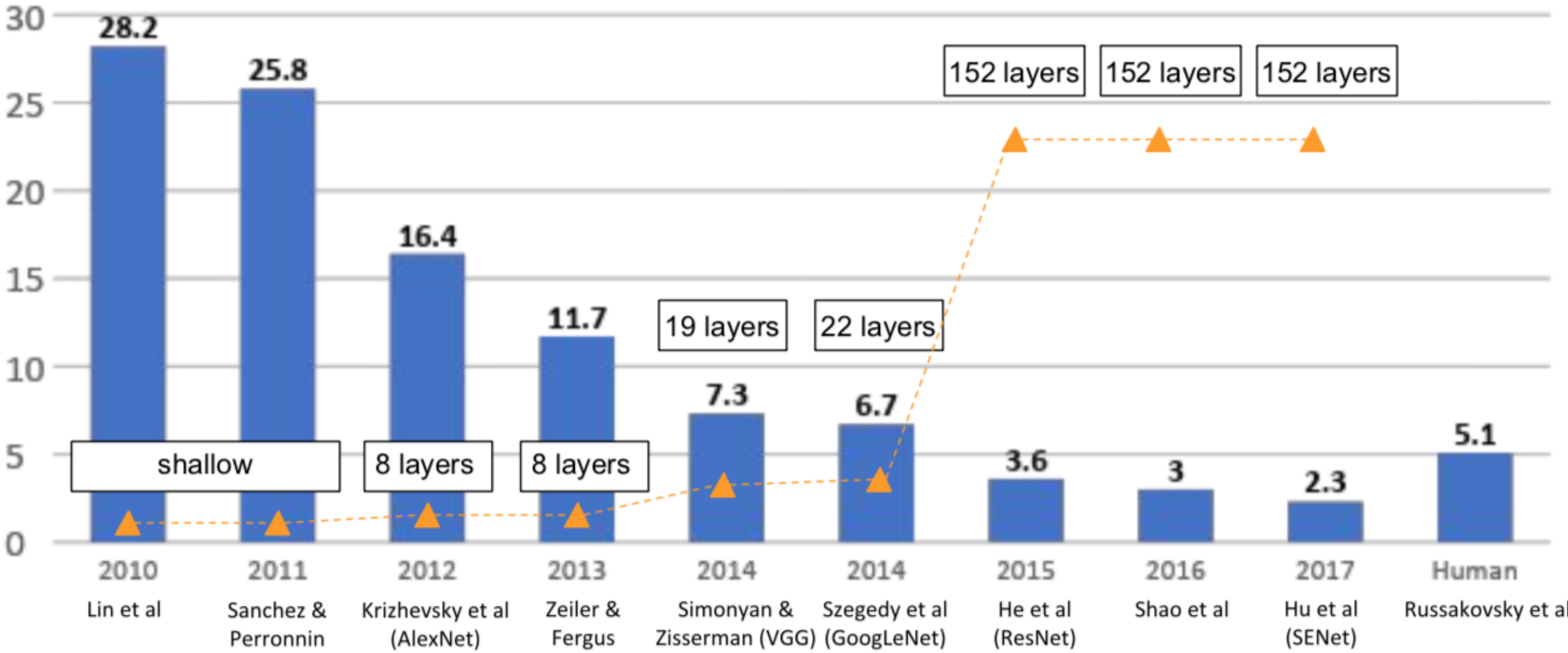
LeNet-5 [1998]



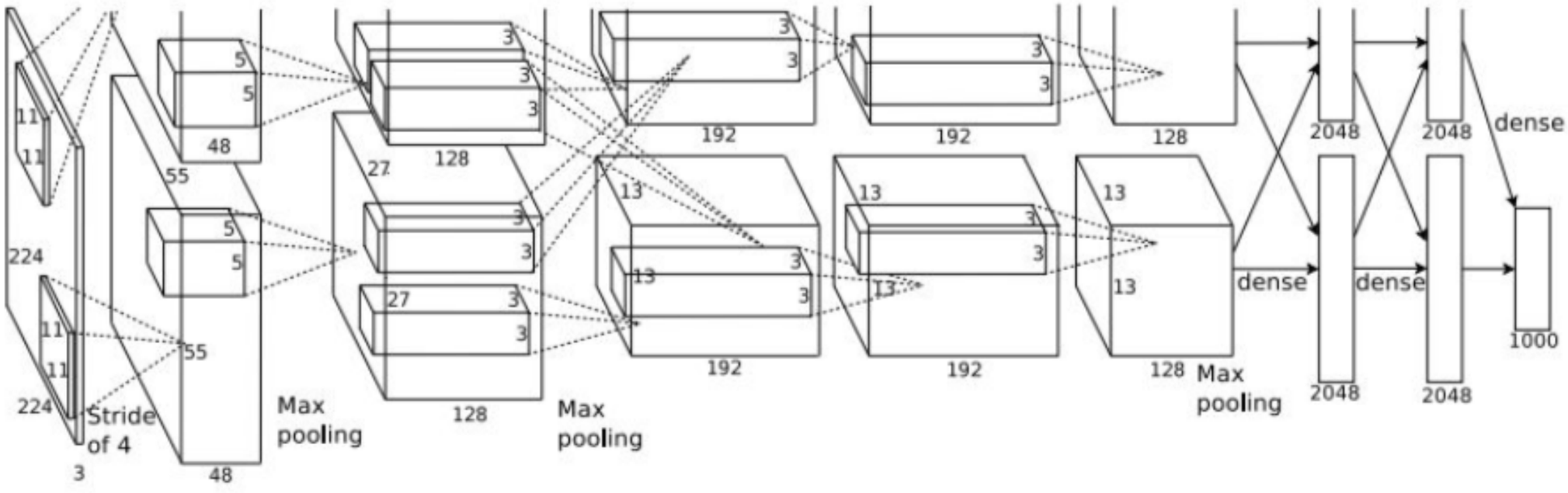
Conv filters were 5x5, applied at stride 1
Subsampling (Pooling) layers were 2x2 applied at stride 2
i.e. architecture is [CONV-POOL-CONV-POOL-FC-FC]

- LeNet. The first successful applications of Convolutional Networks were developed by **Yann LeCun** in 1990's. Of these, the best known is the LeNet architecture that was used to read zip codes, digits, etc.
- http://yann.lecun.com/exdb/publis/pdf/lecun-98.pdf

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) - winners



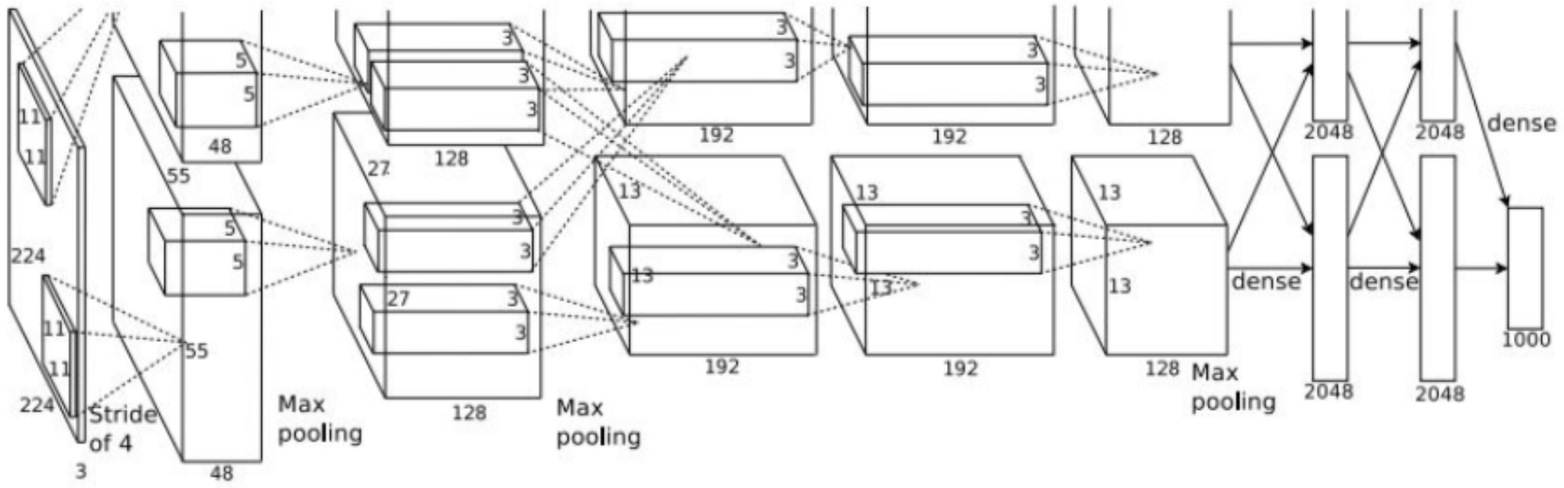
AlexNet [2012]



Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8

- The first work that popularized Convolutional Networks in Computer Vision was the AlexNet, developed by **Alex Krizhevsky**, Ilya Sutskever and Geoff Hinton.
- The AlexNet was submitted to the ImageNet ILSVRC challenge in 2012 and significantly outperformed the second runner-up (top 5 error of 16% compared to runner-up with 26% error).
- The Network had a very similar architecture to LeNet, but was deeper, bigger, and featured Convolutional Layers stacked on top of each other (previously it was common to only have a single CONV layer always immediately followed by a POOL layer).
- http://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks

AlexNet [2012]



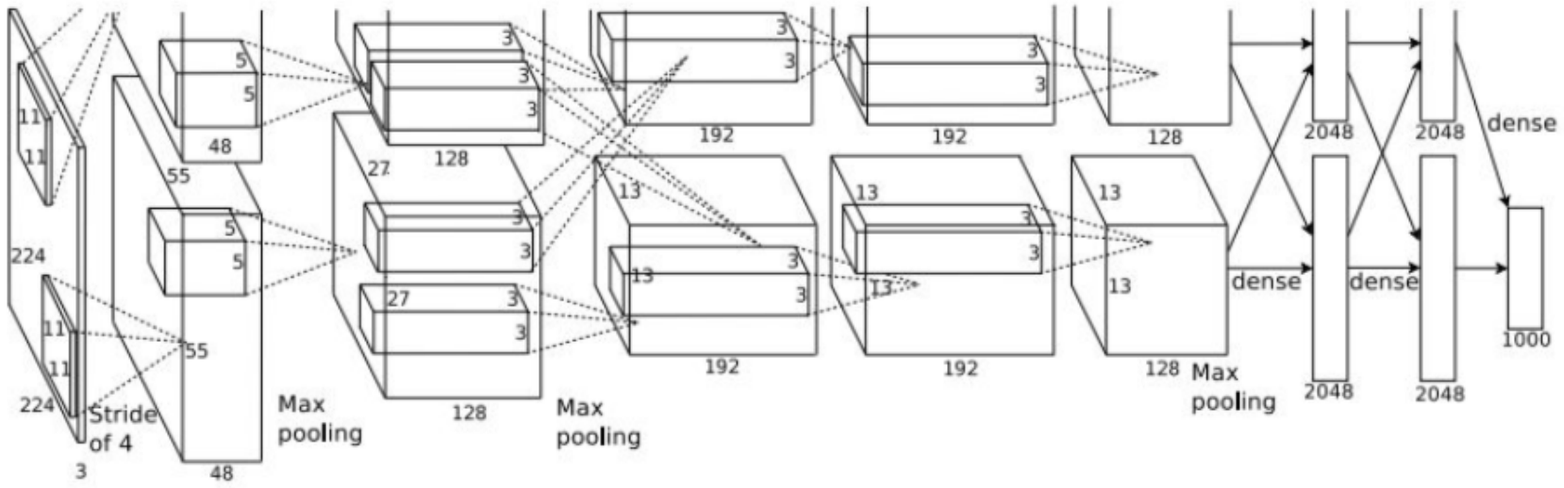
Input : 227x227x3 images

First layer (CONV1): 96 filters
11x11, S = 4

Q1: what is the output volume size of CONV1?

Q2: how many parameters for CONV1?

AlexNet [2012]



Input : 227x227x3 images

First layer (CONV1): 96 11x11 filters, S = 4

Q1: what is the output volume size of CONV1?

Q2: how many parameters for CONV1?

Q1:

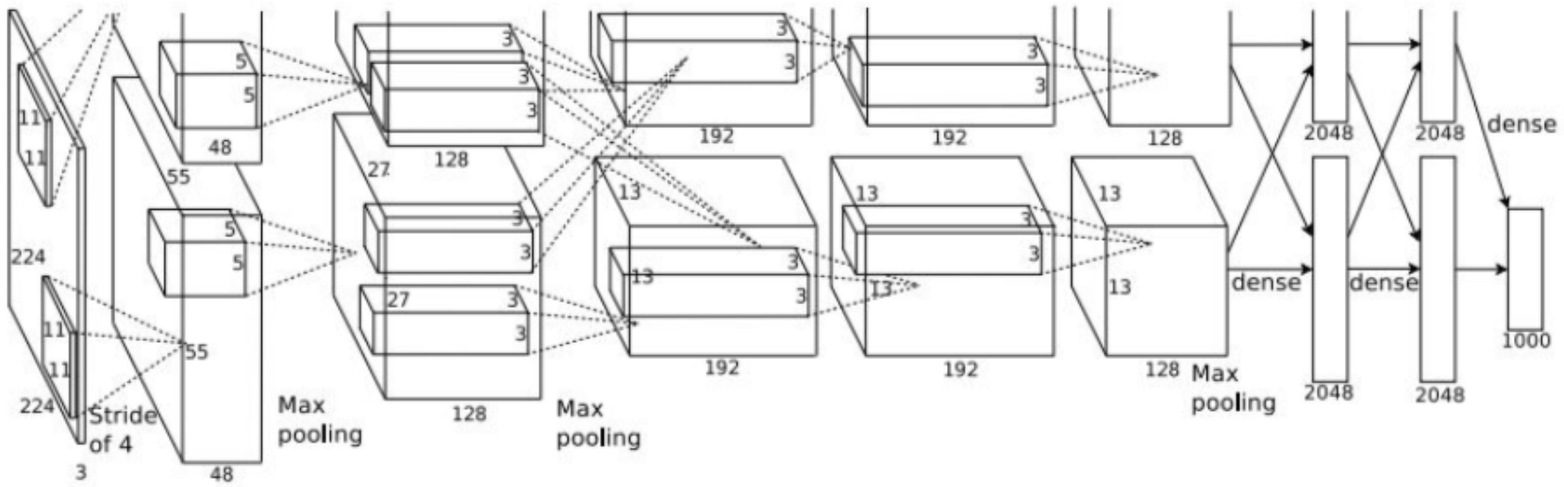
activation map size = (227-11)/4 + 1 = 55x55

output volume = (55x55x96)

Q2:

96x(11x11x3) + 96 = 34'944 ~ 35K

AlexNet [2012]



Input : 227x227x3 images

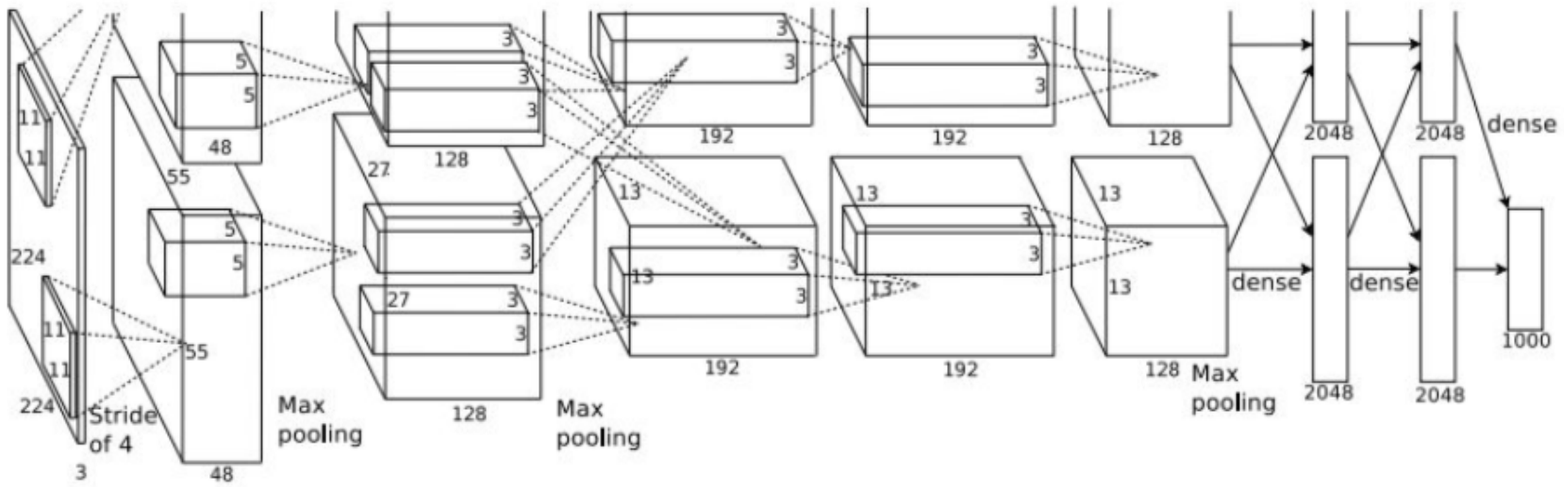
After CONV1: 55x55x96

Second layer (POOL1): 3x3, S = 2

Q3: what is the output volume size of POOL1?

Q4: how many parameters for POOL1?

AlexNet [2012]



Input : 227x227x3 images

After CONV1: 55x55x96

Second layer (POOL1): 3x3, S = 2

Q3: what is the output volume size of POOL1?

Q4: how many parameters for POOL1?

Q3:

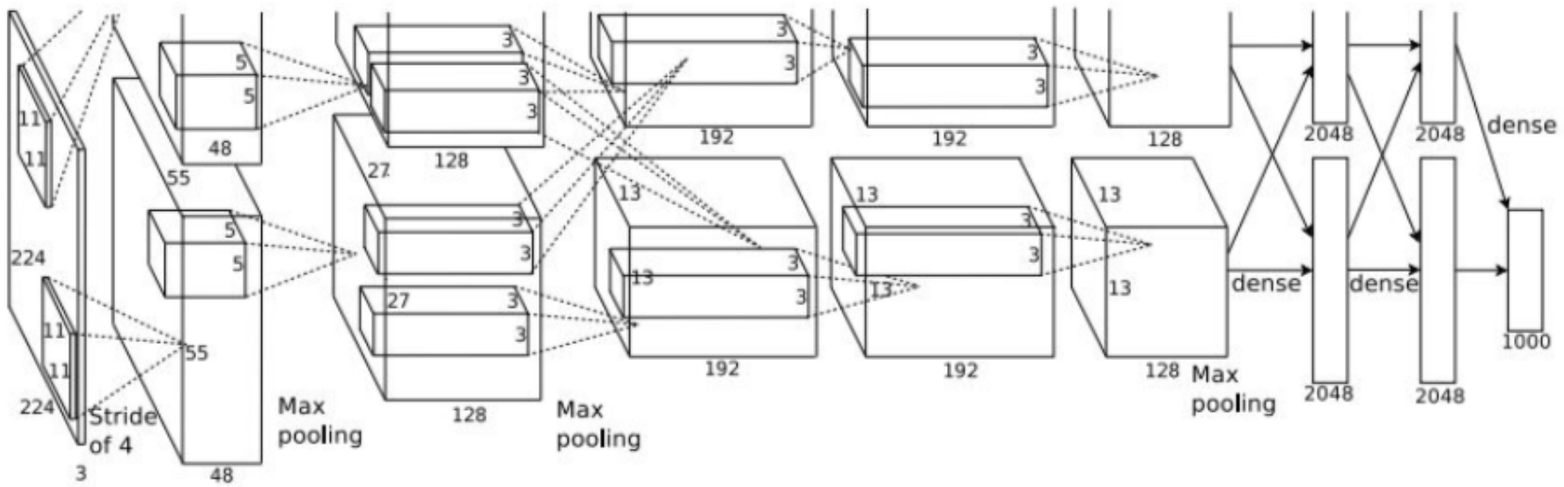
activation map size = (55-3)/2 + 1 = 27x27

output volume = 27x27x96

Q4:

0

AlexNet [2012]



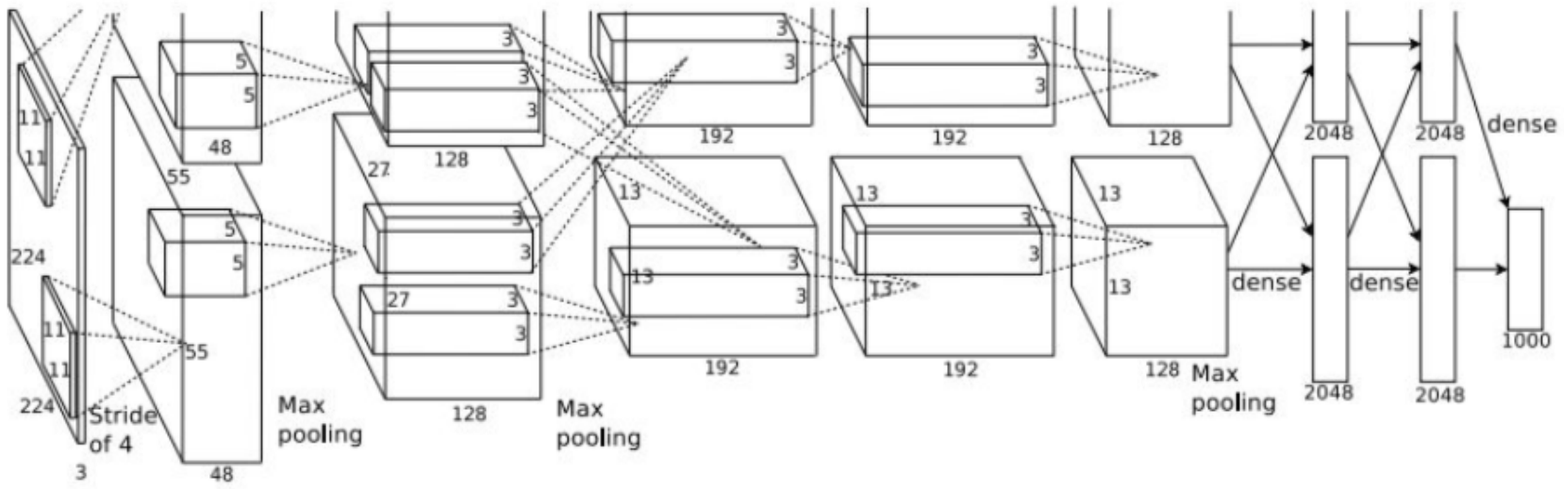
Input : 227x227x3 images

After CONV1: 55x55x96

After POOL1: 27x27x96

…

AlexNet [2012]

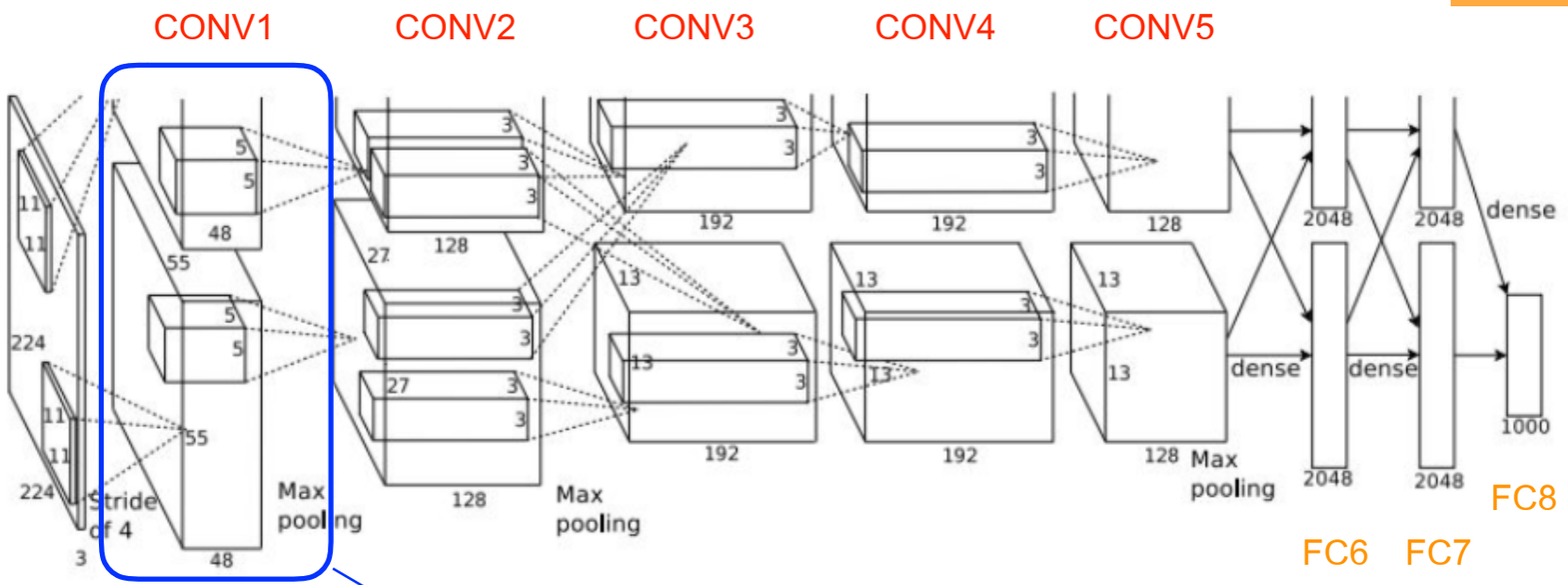


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:

- first use of ReLU
- used Norm layers (not common anymore) - heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- CNN ensemble: 18.2% -> 15.4%

AlexNet [2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

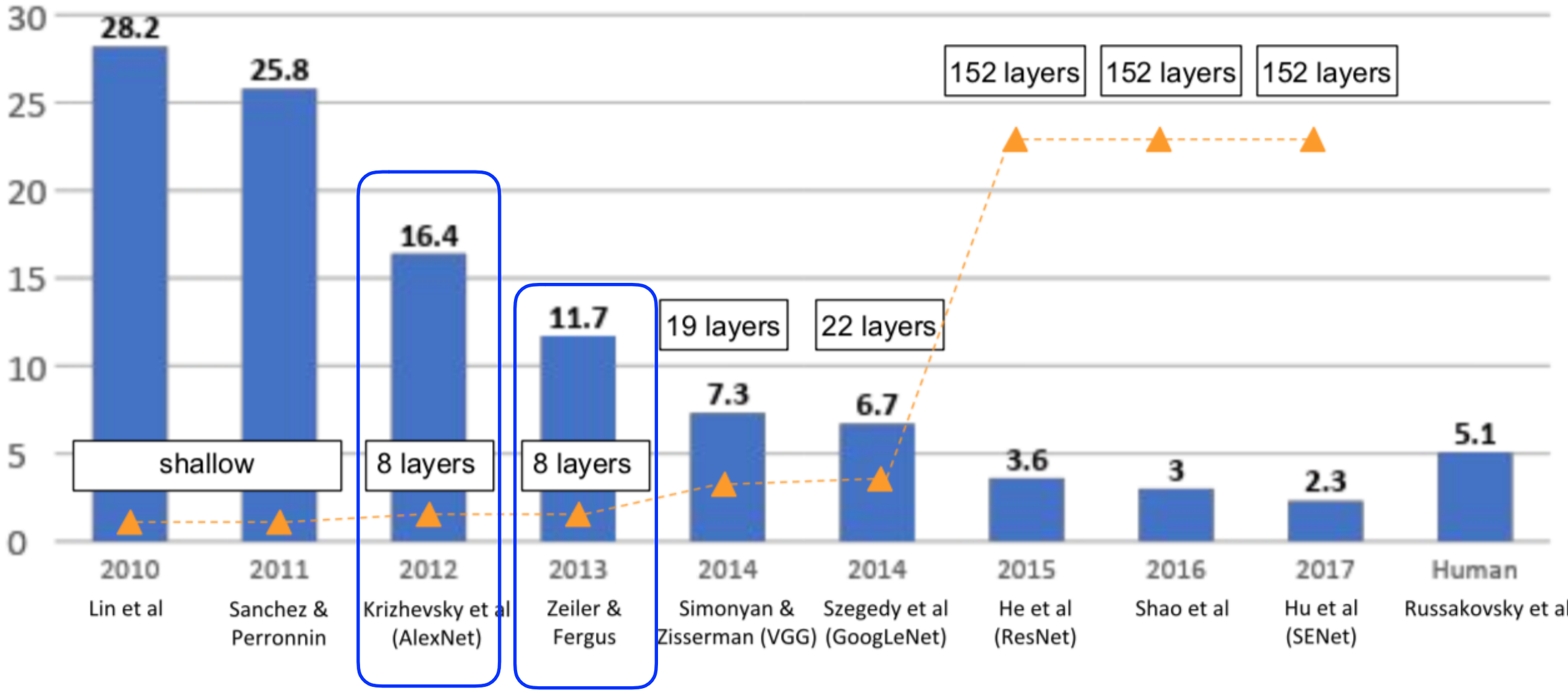
Historical note**:** Trained on GTX 580 GPU with only 3 GB of memory. Network spread across 2 GPUs, half the neurons (feature maps) on each GPU.

CONV1, CONV2, CONV4, CONV5: Connections only with feature maps on same GPU

CONV3, FC6, FC7, FC8: Connections with all feature maps in preceding layer, communication across GPUs

Total of 60M parameters !

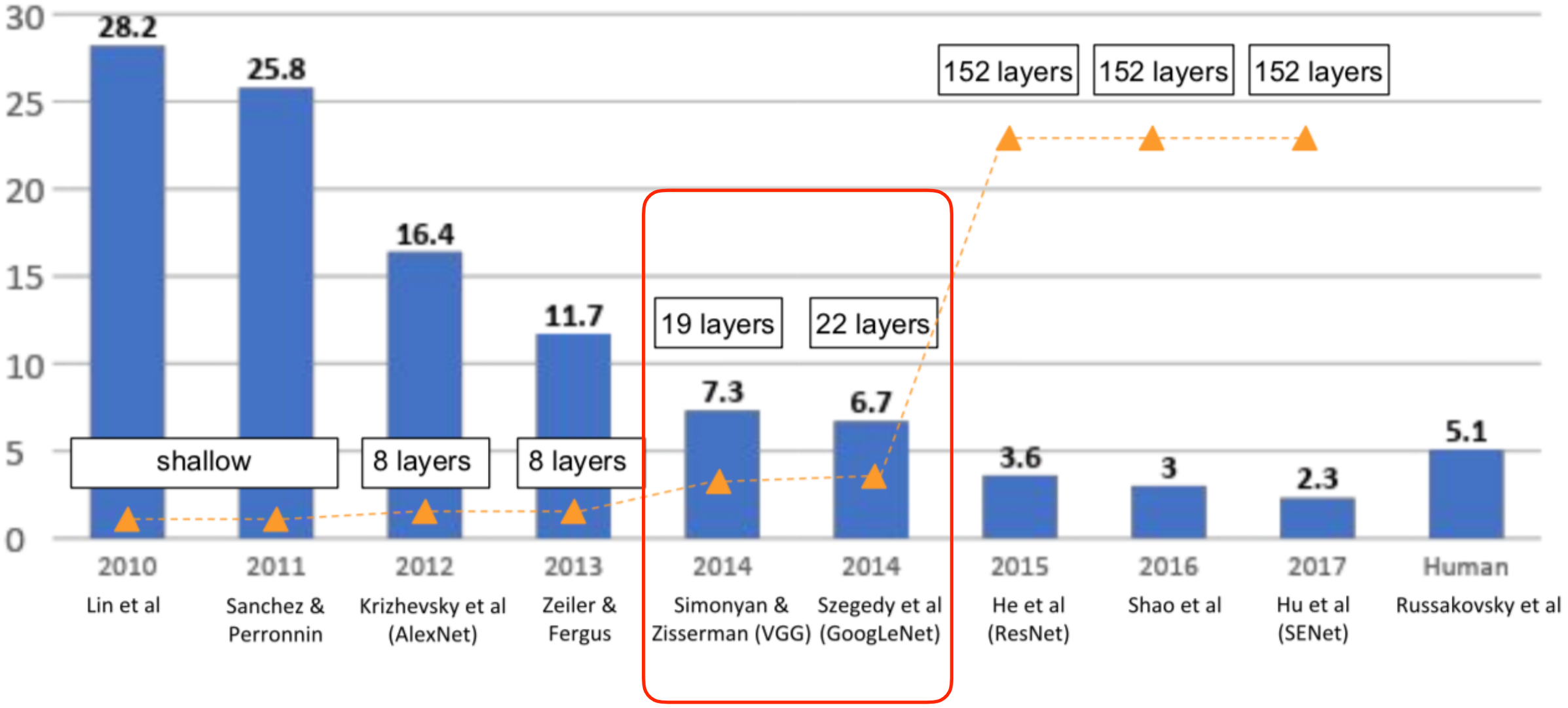
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) - winners



AlexNet : First deep learning based approach winner of the competition.

ZFNet : similar to AlexNet but with hyper-parameter tuning.

ImageNet Large Scale Visual Recognition Challenge (ILSVRC) - winners



Deeper networks

VGGNet [2014]

Stack of three 3x3 conv (stride 1) layers has same effective receptive field as one 7x7 conv layer.

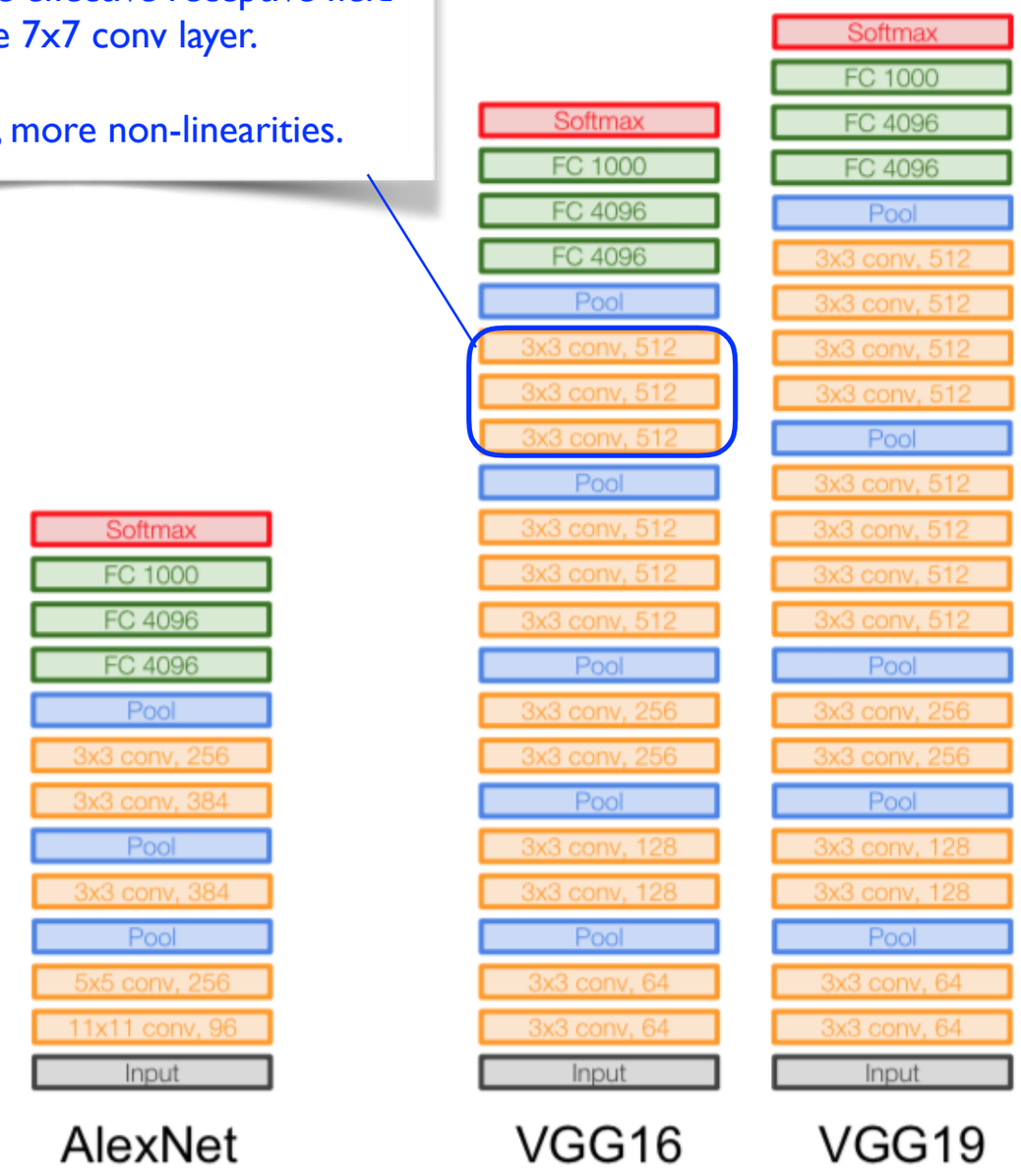
But deeper, more non-linearities.

Small filters, Deeper networks

From 8 layers (AlexNet) to 16 - 19 layers (VGGNet)

Only 3x3 CONV S=1, P=1 and 2x2 MAX POOL S=2

7.3% top 5 error in ILSVRC'14



- Simonyan and Zisserman, 2014

VGGNet [2014]

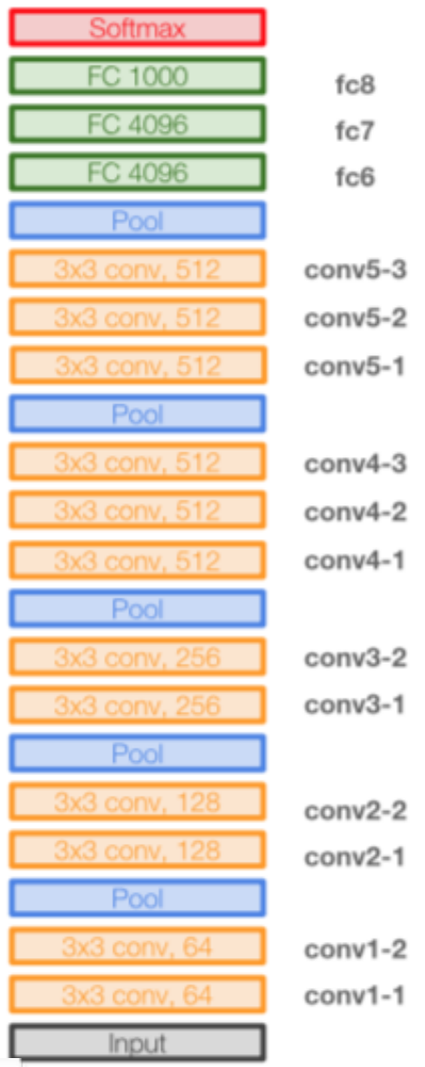
Most memory usage in CONV layers

(not counting biases)

INPUT: [224x224x3] memory: 224*224*3=150K params: 0
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

Most parameters in FC layers

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters



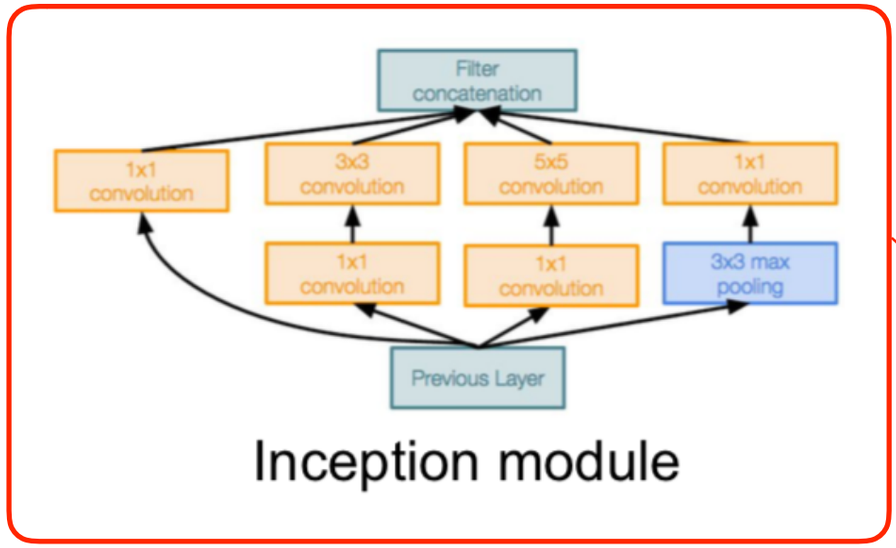
VGG16

Common names

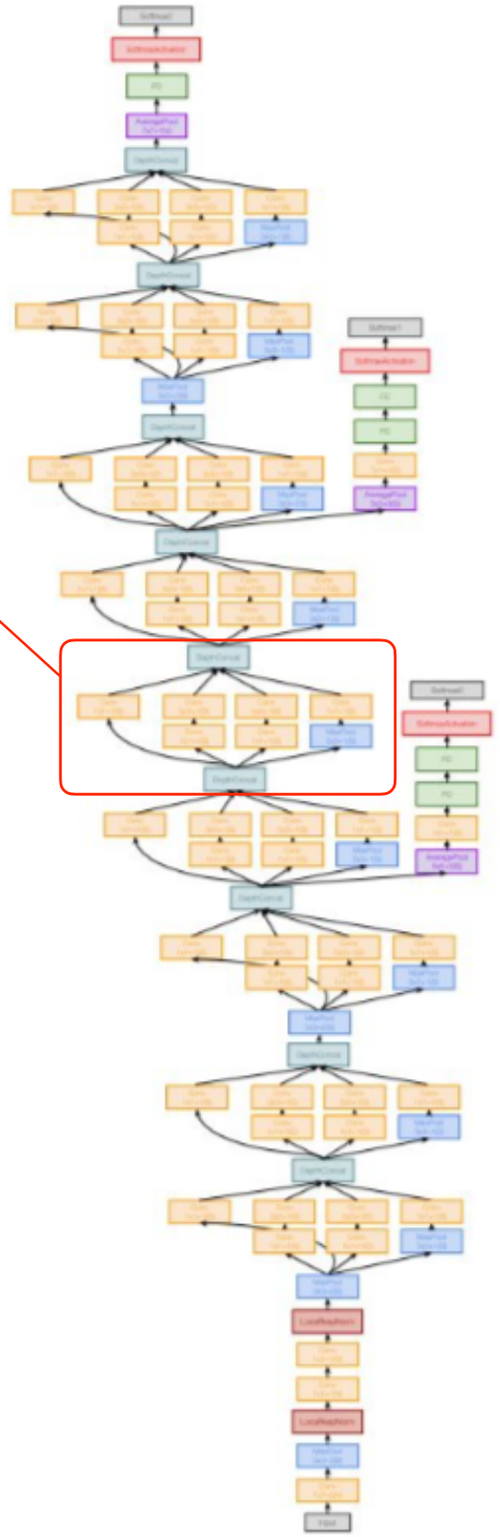
GoogLeNet [2014]

Deeper networks, with computational efficiency

- 22 layers
- ”Network in the network” efficient “**Inception**” module
- No FC layers
- Only 5 million parameters!
  12x less than AlexNet
- ILSVRC’14 classification winner
  (6.7% top 5 error)

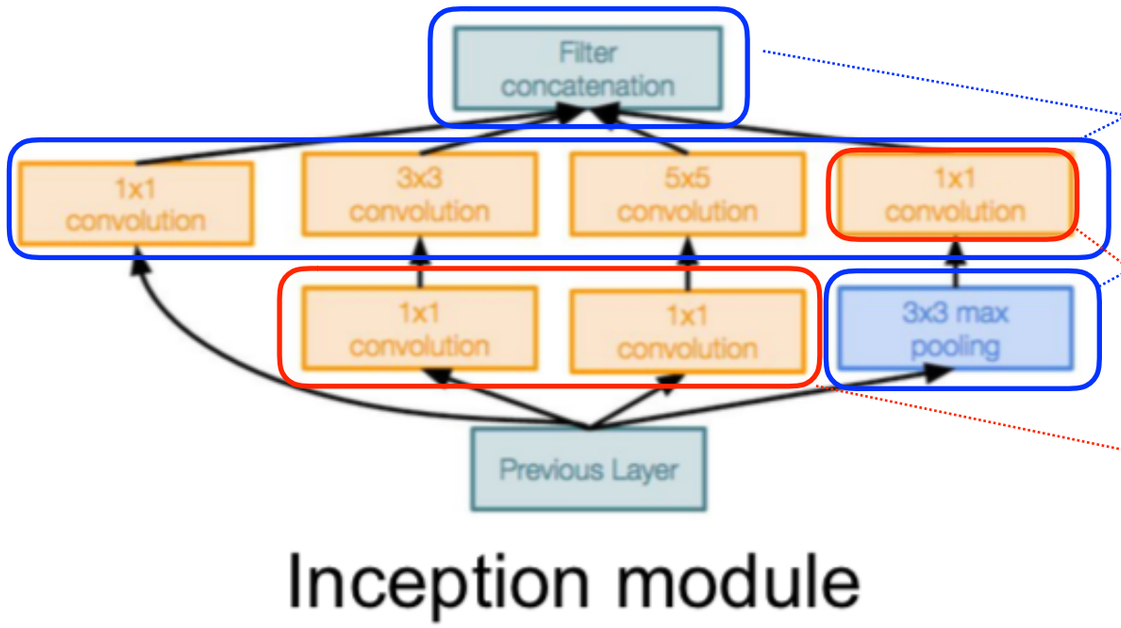


Inception module



- Szegedy et al., 2014

GoogLeNet [2014]



Inception module

Intuition: mix filter size to allow looking for more or less details from the previous layer, i.e. related to the receptive field size. We don't know in advance what is the best size, e.g. close or far object.

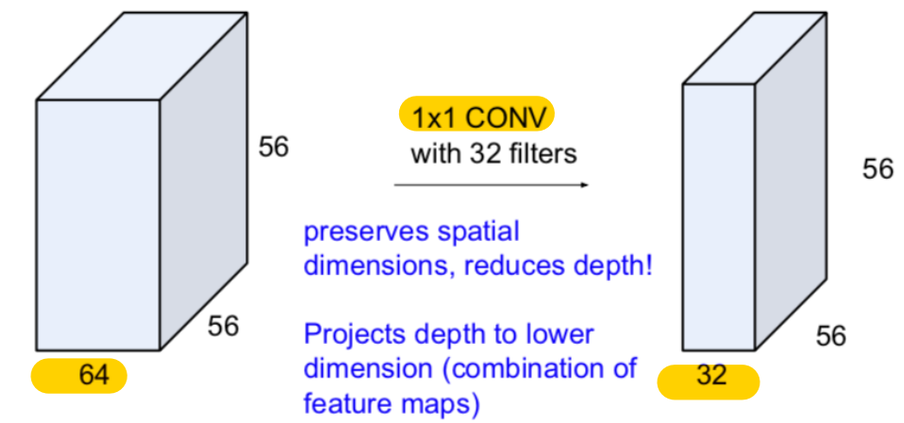
So let's use **in parallel** different filter size, (1x1, 3x3, 5x5).

Ultimately no filter but pooling operation (3x3).

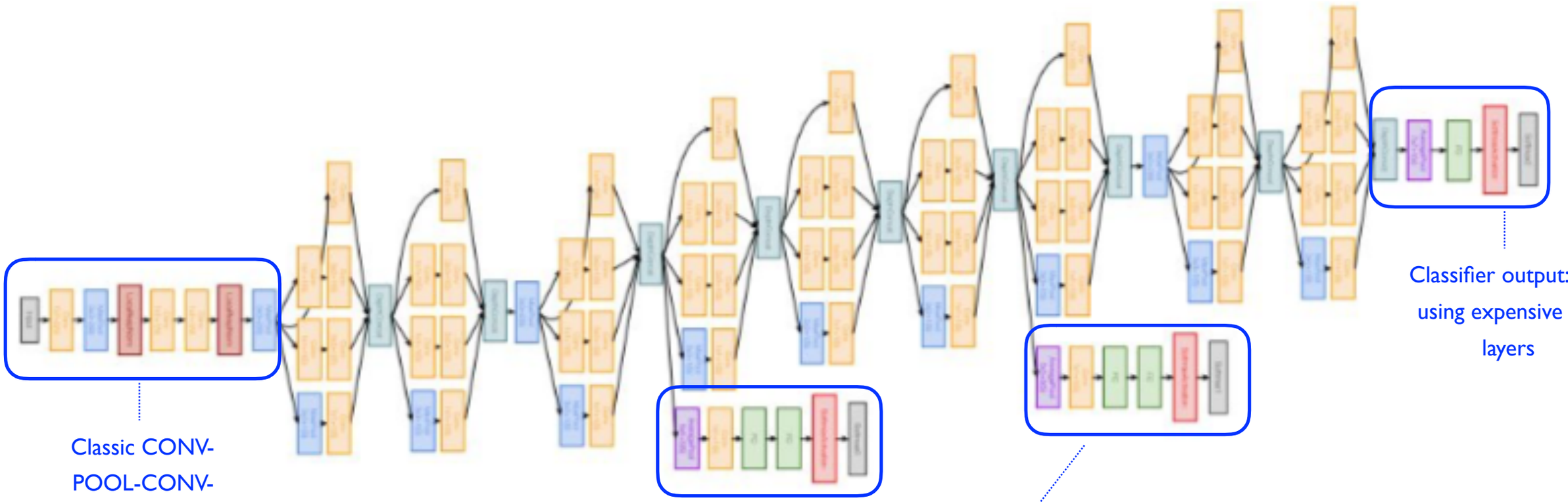
Then concatenate all filter outputs together depth-wise.

To reduce the number of operation, 1x1 conv are used. So-called **bottleneck layers**.

Reminder: 1x1 convolutions

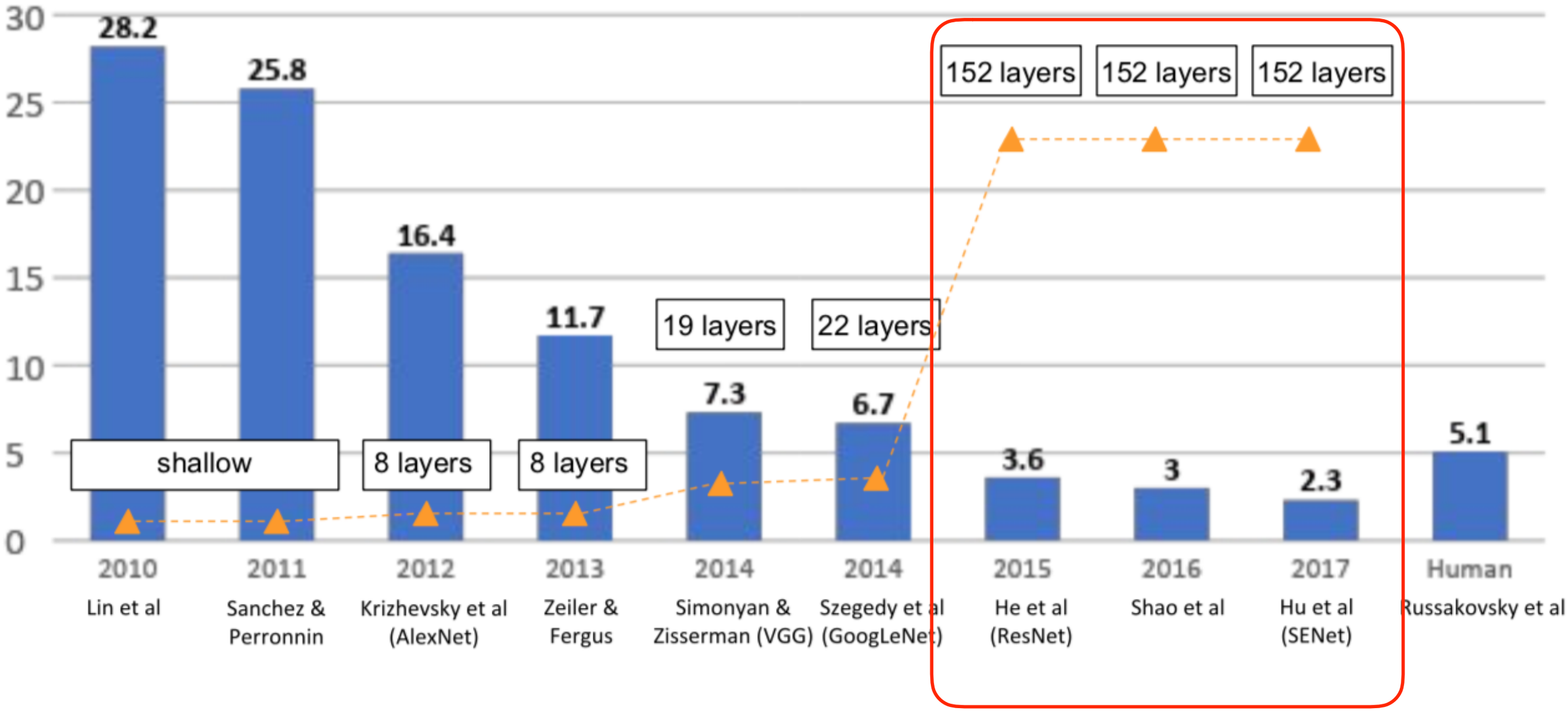


GoogLeNet [2014]



The architecture becomes non-sequential and complex !

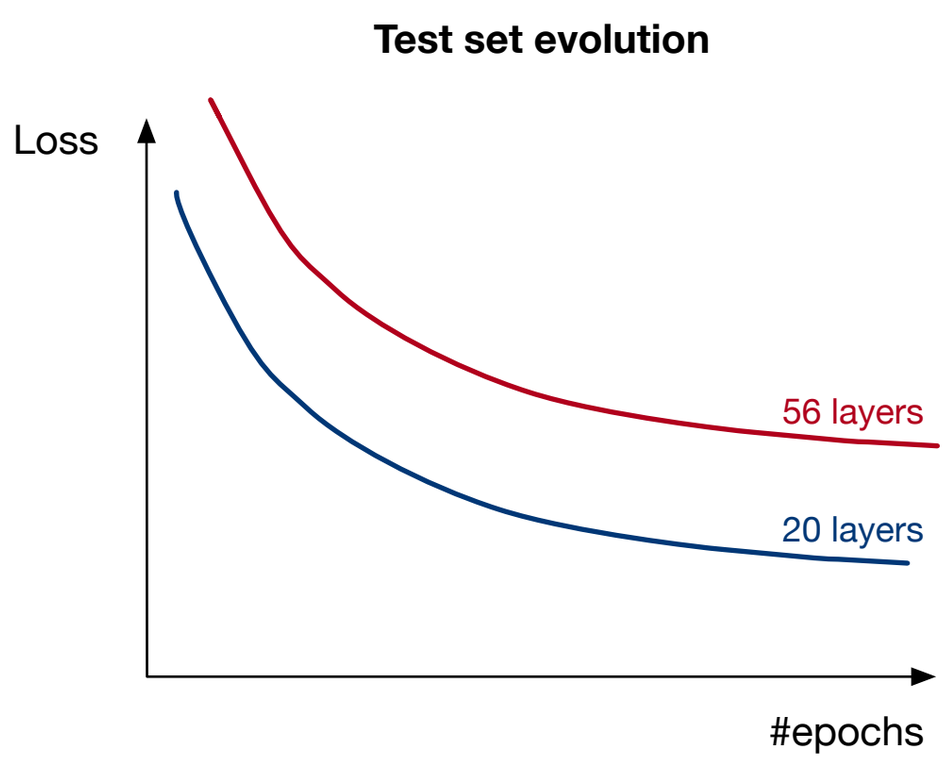
ImageNet Large Scale Visual Recognition Challenge (ILSVRC) - winners

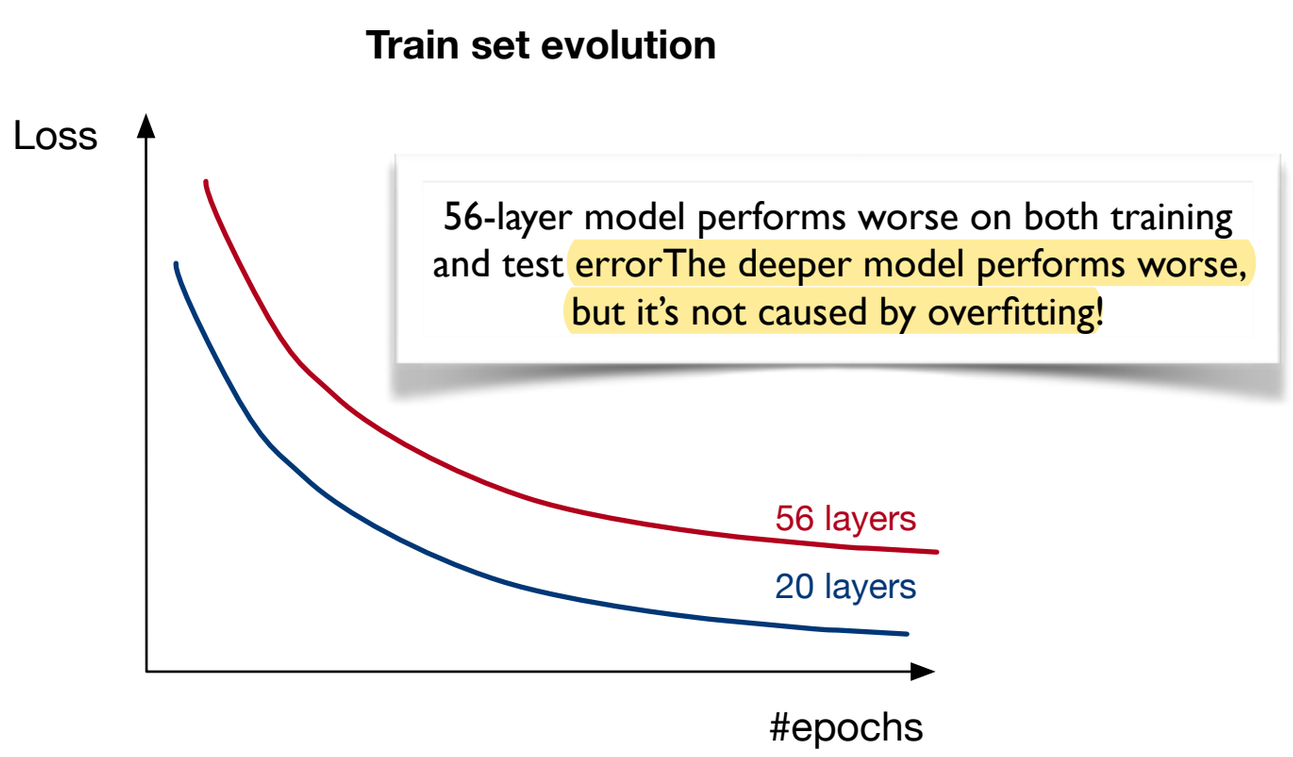


Revolution of depth !

ResNet [2015]

- He et al., 2015
- Observation they did: from AlexNet and VGGNet, increasing the number of layers did not succeed. They observed something like this:

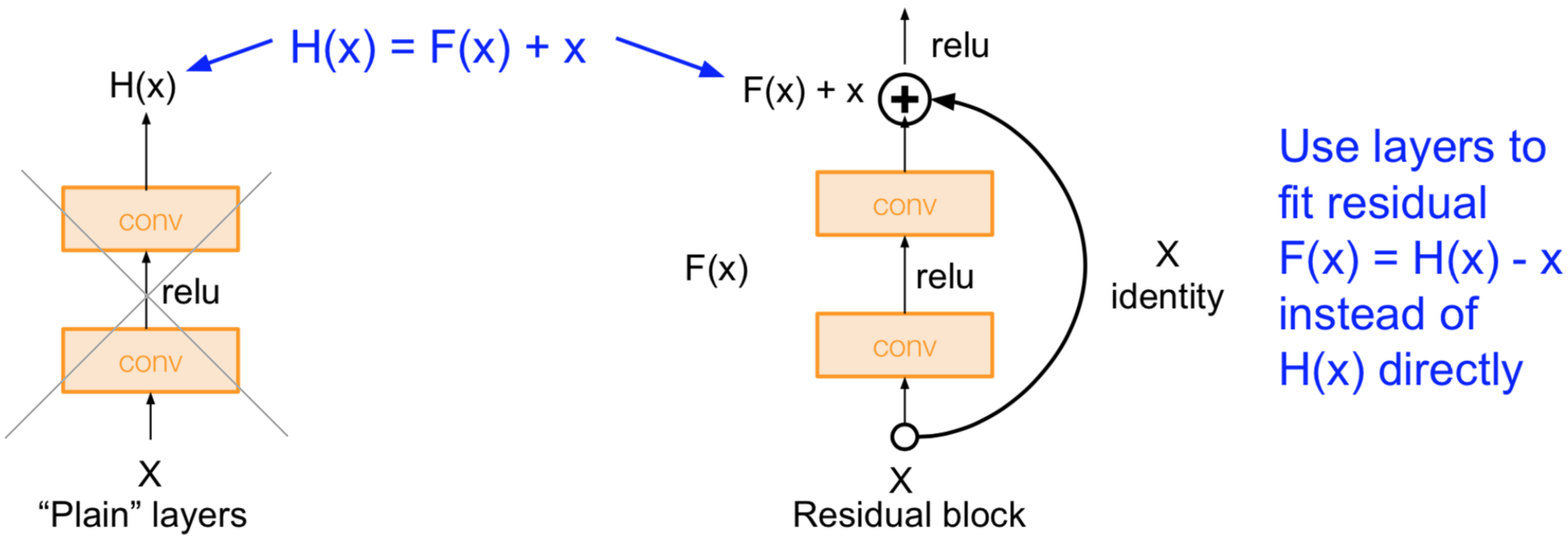




Overfitting?

ResNet [2015]

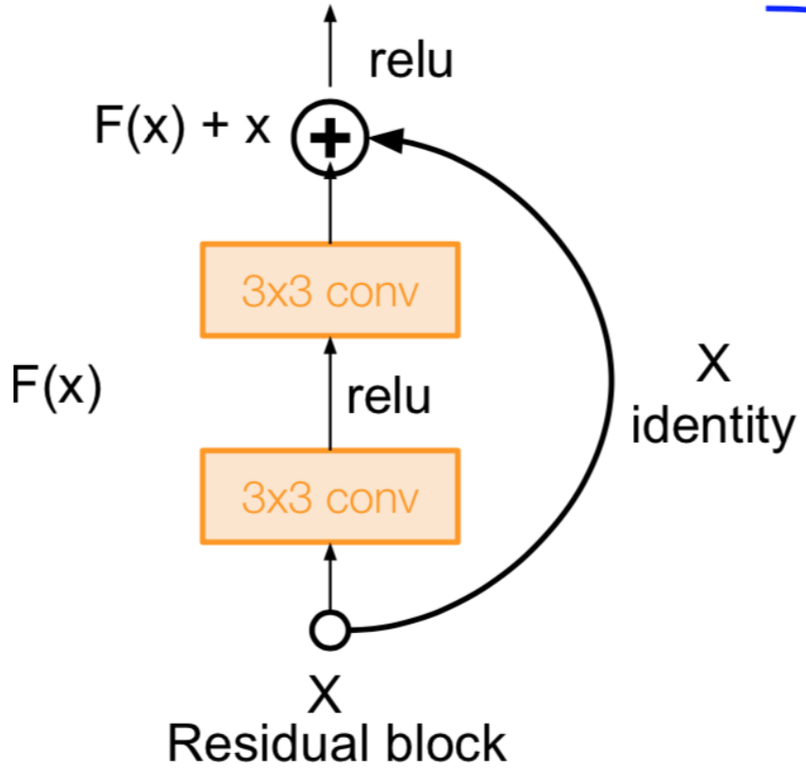
- **Hypothesis**: the problem is an optimization problem, deeper models are more difficult to optimize
- **Ideas**:
  - Deeper layers should be able to "fall back" to identity mapping if difficulties to converge
  - Easier to model a "delta" from one layer to the other than a full feature
- **Solution**: Use network layers to fit a residual mapping instead of directly trying to fit a desired underlying mapping

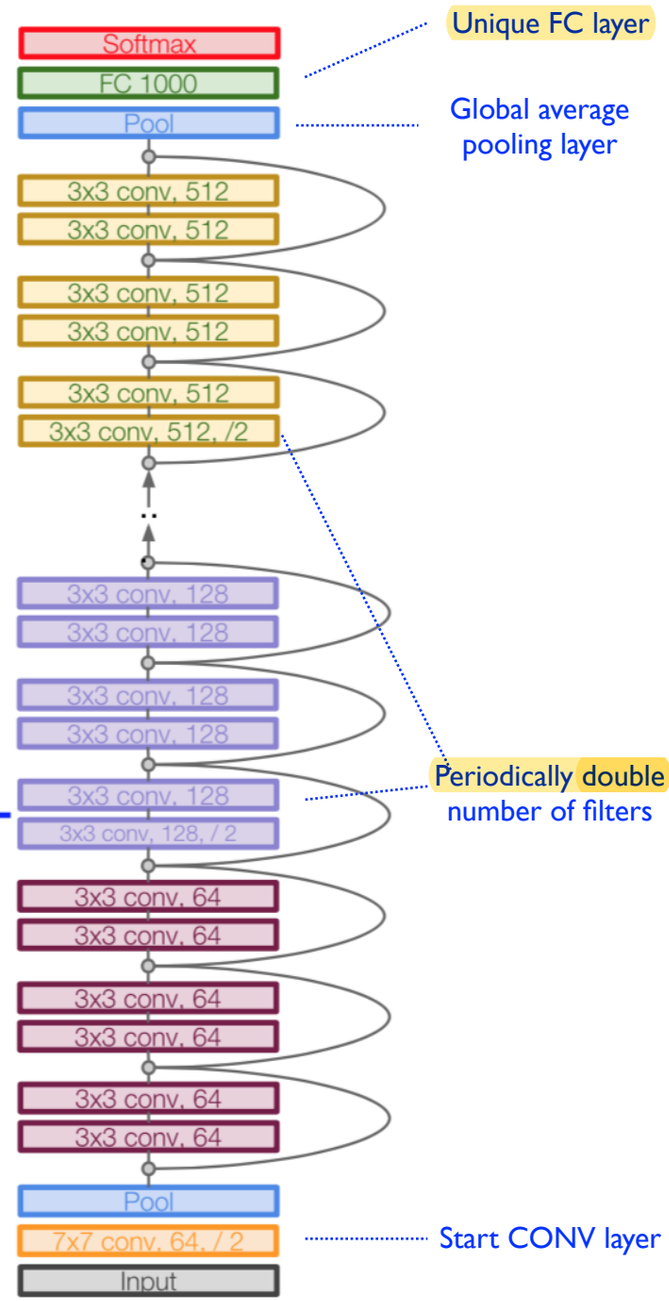


ResNet [2015]

Very deep networks using residual connections

- 152-layer model for ImageNet
- ILSVRC'15 classification winner (3.57% top 5 error)
- Swept all classification and detection competitions in ILSVRC'15 and COCO'15!

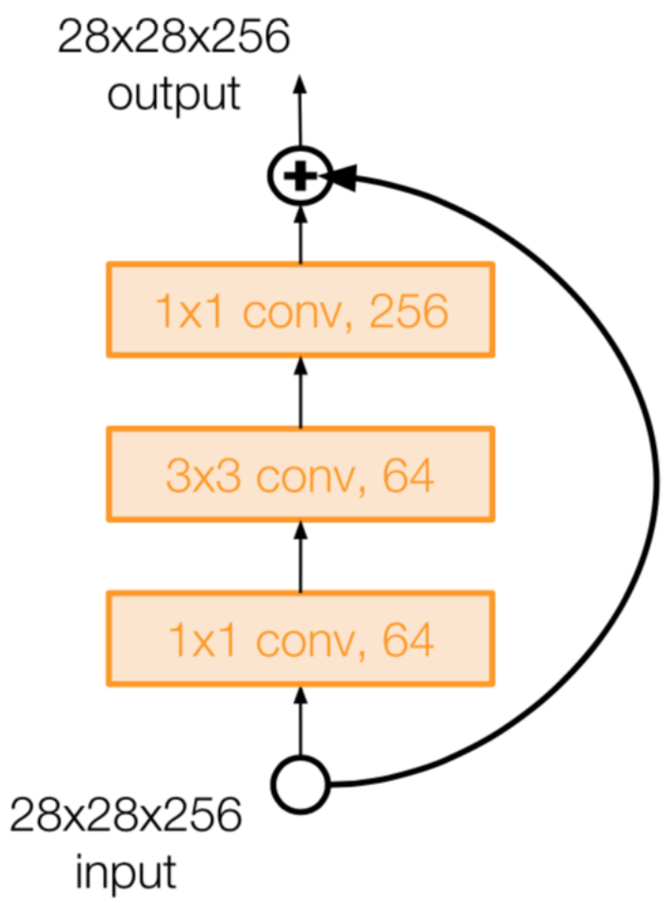


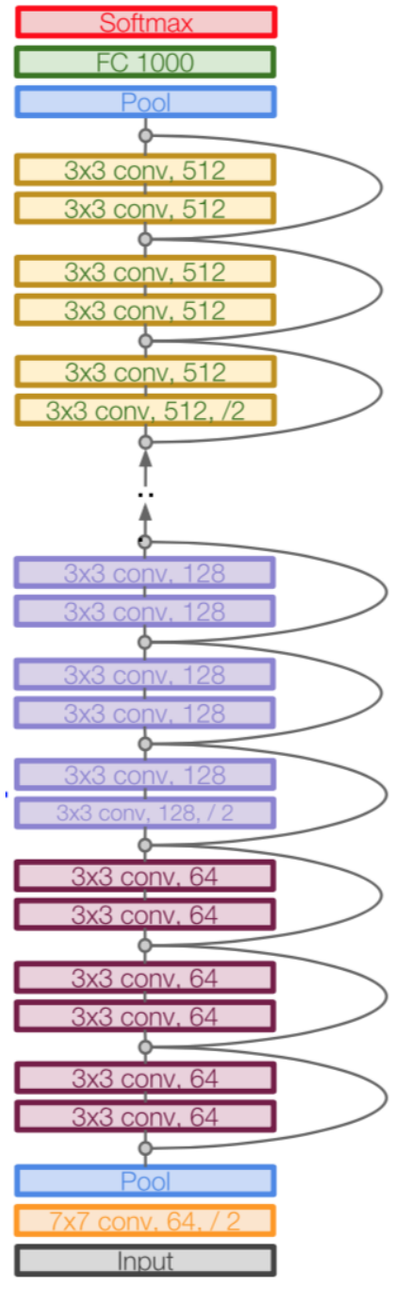


ResNet [2015]

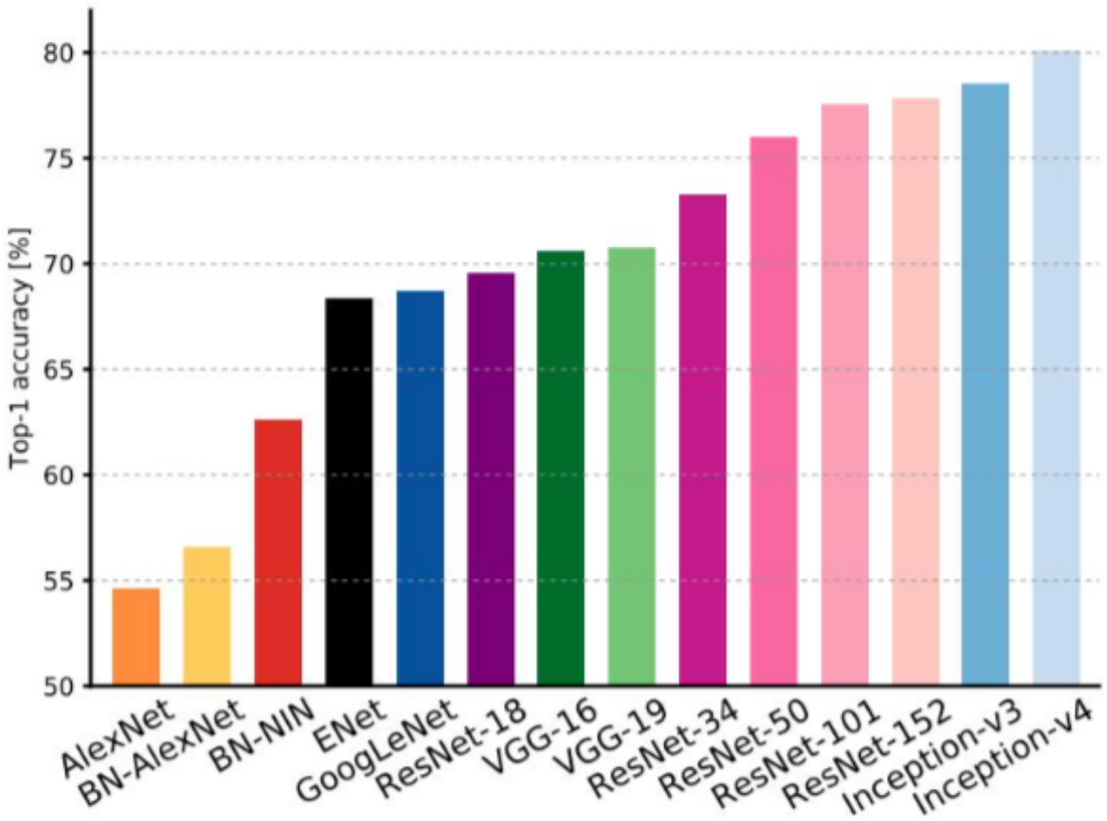
Total depth = 152 layers for imageNet competition !

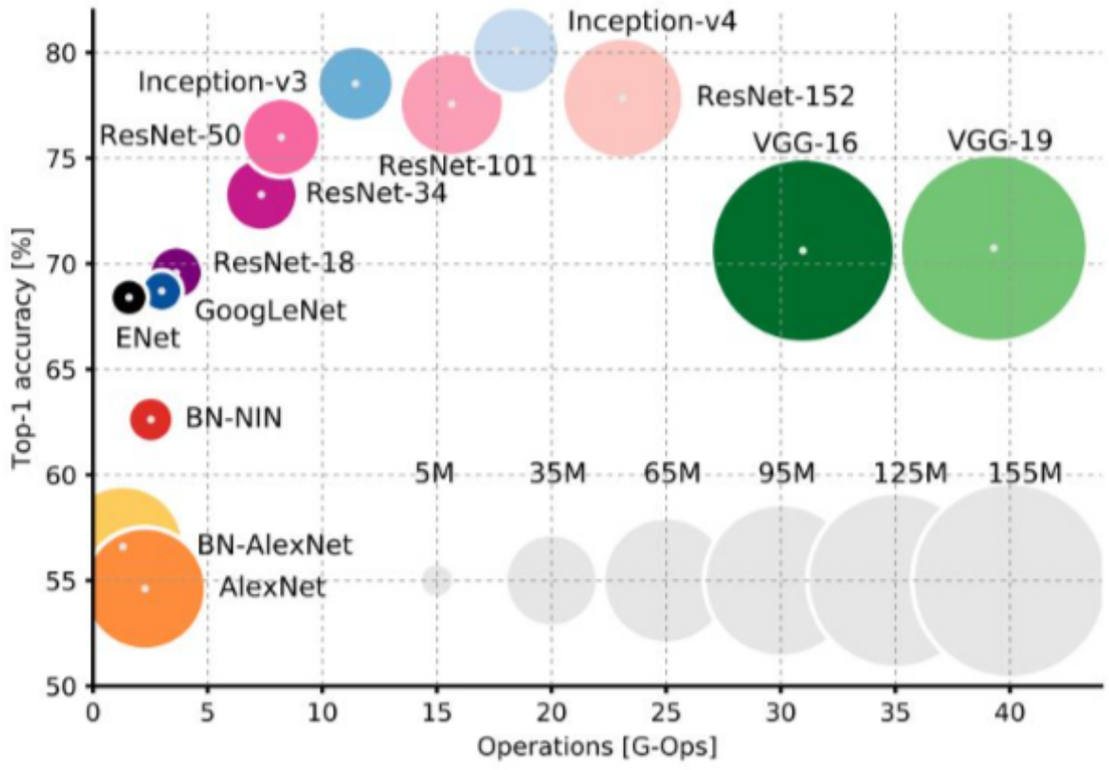
- **Trick to go deeper than 50 layers:**
  - Use bottleneck layers 1x1x64 to reduce the number of operations and parameters
- **Other training strategies:**
  - Batch Normalization after every CONV layer
  - Xavier 2/ initialization from He et al.
  - SGD + Momentum (0.9)
  - Learning rate: 0.1, divided by 10 when validation error plateaus
  - Mini-batch size 256
  - Weight decay of 1e-5
  - No dropout used





Comparing complexity





An Analysis of Deep Neural Network Models for Practical Applications, 2017.

Wrap-up

- CNNs are learning the **feature extraction**
  - Notion of hierarchical features going deeper in the network
- Visualisation strategies:
  - **Plot of activation maps** at each layer
  - Finding **images** that are **maximising the activation** of a given neuron
- Data augmentation is a good strategy to **fight overfitting**
  - 2 implementation strategies: off-line and on-line
- **Deep CNN architectures**
  - Big fights were going on in the ImageNet competitions to discover the best architectures
  - AlexNet: the “boot” of deep architectures
  - VGGNet: going deeper with simpler filter
  - GoogLeNet: inception module = network in network to get features at different resolutions in a given layer, injection of gradient at early stages
  - ResNet: going way deeper using modules that model residual information from layer to layer.