INTRODUCTION

To Data Science

Introduction to Data Science

Convolutional Neural Networks - Class 13

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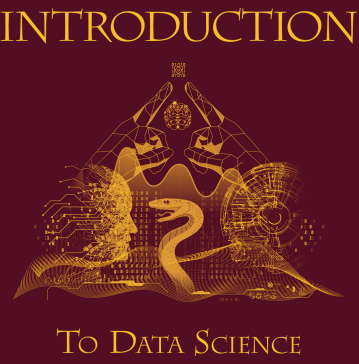


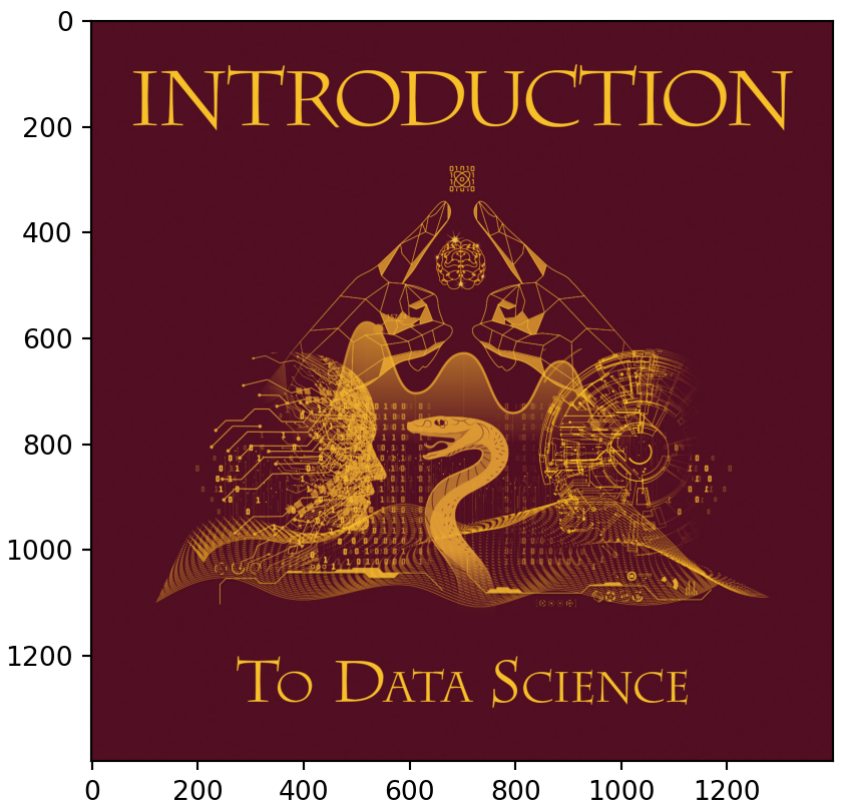
Before CNN

INTRODUCTION

To Data Science

Reminder: What is an image?

```
import matplotlib.pyplot as plt
from matplotlib.image import imread

logo = imread('../Intro2DS_logo.jpg')

plt.imshow(logo)
plt.show()
```



```
import numpy as np

print(type(logo))
```

```
<class 'numpy.ndarray'>
```

```
print(logo.shape)
```

```
(1400, 1400, 3)
```

```
print(logo[1000:1005, 1000:1005, 0])
```

```
[[ 82  83  86  80  83]
 [ 83  95 211 210 139]
 [ 82  83  80  93 109]
 [ 82  84  82  85  82]
 [ 81  81  81  82  83]]
```

```
print(logo.min(), logo.max())
```

```
8 255
```

```
print(logo.dtype, logo.size * logo.itemsize)
```

```
uint8 5880000
```

Until Convolutional Networks

So how many features is that?

- In 1998 LeCun et. al. published LeNet-5 for digit recognition
- But it wasn't until 2012 when Alex Krizhevsky, Ilya Sutskever and Geoffrey Hinton published AlexNet when the Deep Learning mania really took off.

Until then:

1. Treat it as a regular high-dimensional ML problem
2. Image feature engineering

Convolutional Layer (2D)

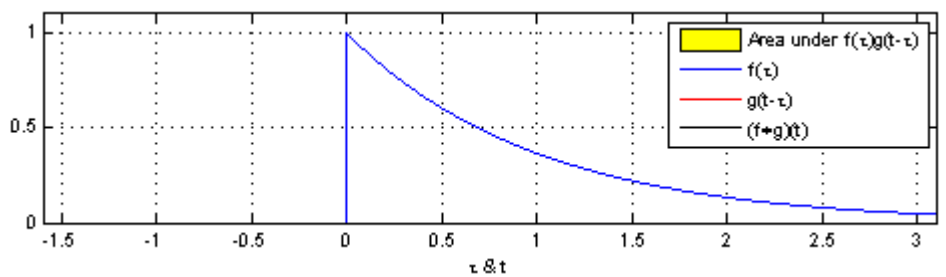
INTRODUCTION

TO DATA SCIENCE

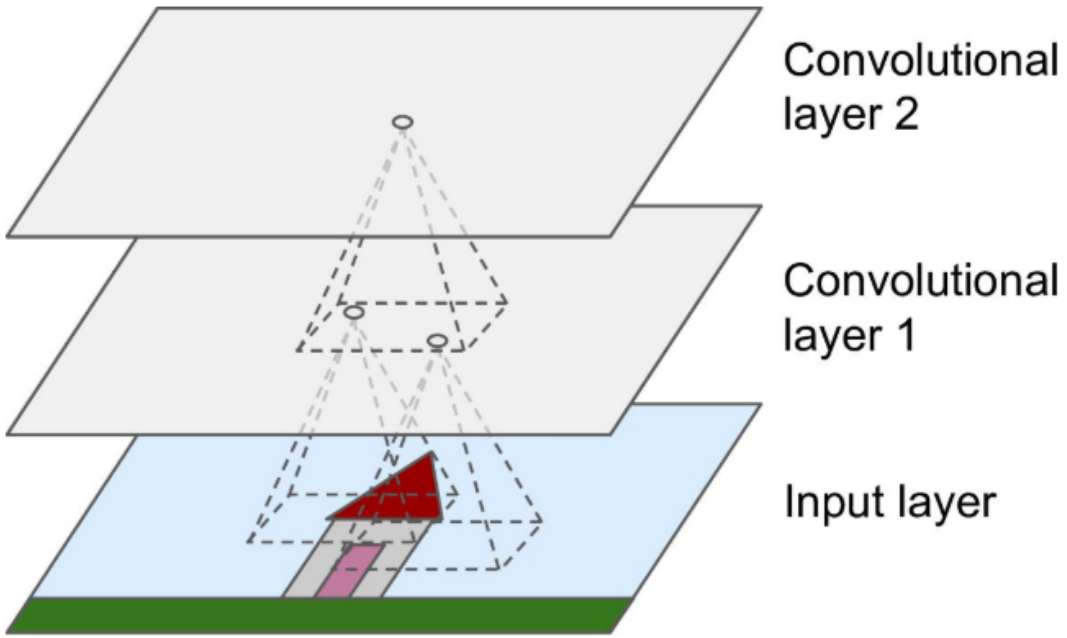
What is Convolution?

“the integral of the product of the two functions after one is reflected about the y-axis and shifted”

$$(f * g)(t) = \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau$$



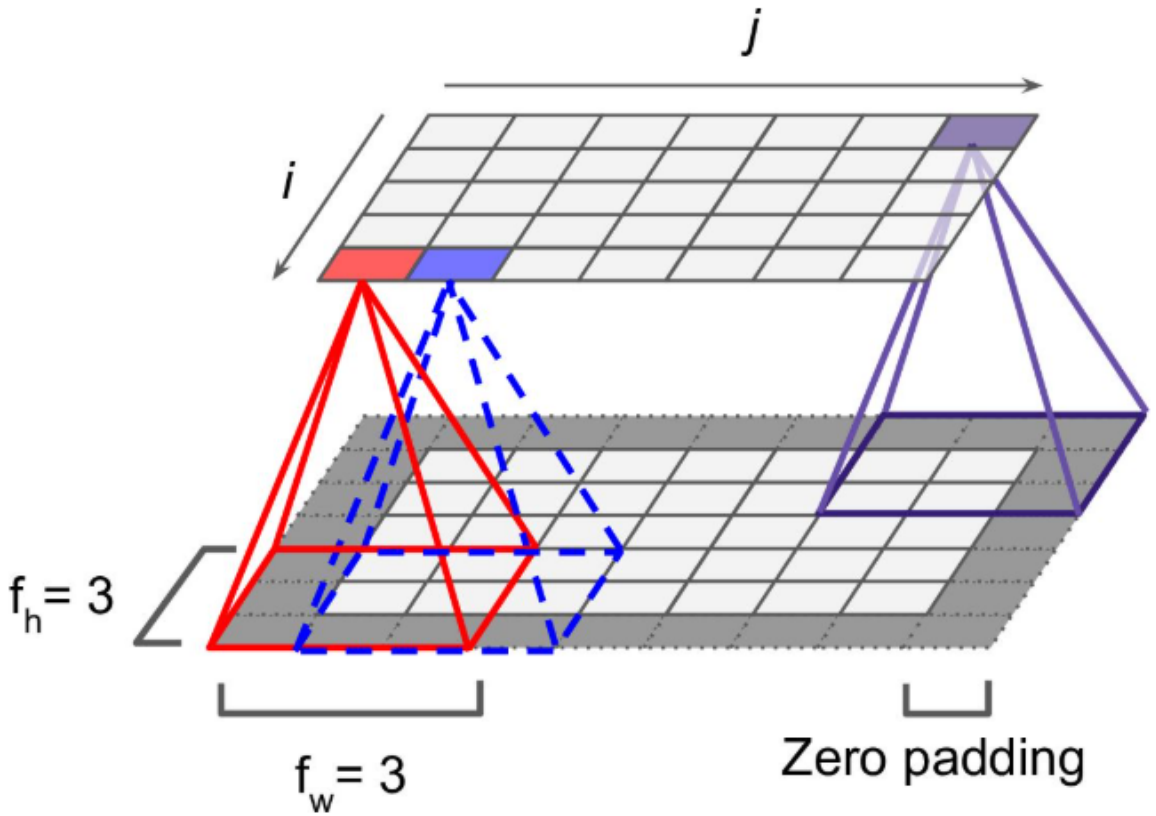
The Convolutional Layer



Source: Geron 2019

- First layer: every neuron has a “receptive field”, it is focused on a specific rectangle of the image, usually 2x2, 3x3
- Second layer: every neuron has a receptive field in the first layer
- Etc.

More specifically



Source: Geron 2019

Filters/Features/Kernels

But what does the neuron actually *do*?

All neurons in a layer learn a single *filter* the size of their receptive field, the f_h, f_w rectangle.

Suppose $f_h = f_w = 3$ and the first layer learned the W_{3x3} filter:

```
W = np.array(
   [
      [0, 1, 0],
      [0, 1, 0],
      [0, 1, 0]
   ]
)
```

X is the 5x5 image, suppose it has a single color channel (i.e. grayscale), sort of a smiley:

```
X = np.array(
  [
    [0,   1,  0,  1,  0],
    [0,   1,  0,  1,  0],
    [0,   0,  0,  0,  0],
    [1,   0,  0,  0,  1],
    [0,   1,  1,  1,  0]
  ]
)
```

Each nuron in the new layer Z would be the sum of elementwise multiplication of all 3x3 pixels/neurons in its receptive field with W_{3x3}:

$$Z_{i,j} = b + \sum_{u=0}^{f_h-1} \sum_{v=0}^{f_w-1} X_{i+u,j+v} W_{u,v}$$

What turns on this filter?

```
X = np.array(
  [
    [0,   1,  0,  1,  0]
    [0,   1,  0,  1,  0]
    [0,   0,  0,  0,  0]
    [1,   0,  0,  0,  1]
    [0,   1,  1,  1,  0]
  ]
)
```

```
W = np.array(
  [
    [0, 1, 0],
    [0, 1, 0],
    [0, 1, 0]
  ]
)
```

```
Z = np.array(
  [
    [0,   2,  0,  2,  0]
    [0,   2,  0,  2,  0]
    [1,   1,  0,  1,  1]
    [1,   1,  1,  1,  1]
    [1,   1,  1,  1,  1]
  ]
)
```

What low-level feature did this layer learn to look for? What pattern will make its neurons most positive (i.e. will “turn it on”)?

Another filter

```
X = np.array(
  [
    [0,   1,  0,  1,  0]
    [0,   1,  0,  1,  0]
    [0,   0,  0,  0,  0]
    [1,   0,  0,  0,  1]
    [0,   1,  1,  1,  0]
  ]
)
```

```
W = np.array(
  [
    [0, 0, 0],
    [0, 0, 0],
    [1, 1, 1]
  ]
)
```

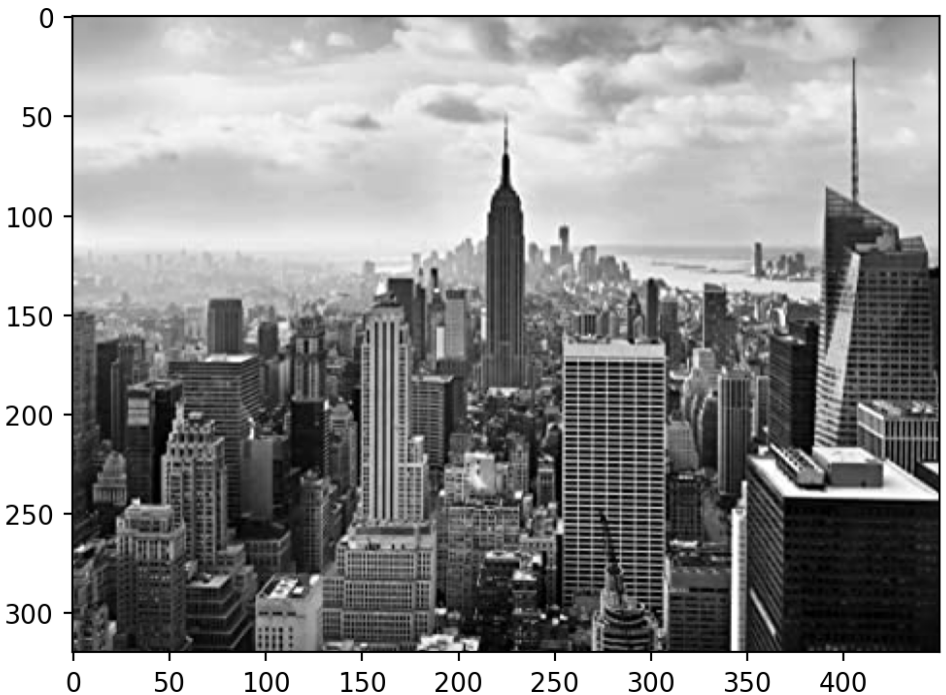
```
Z = np.array(
  [
    [1,   1,  2,  1,  1]
    [0,   0,  0,  0,  0]
    [1,   1,  0,  1,  1]
    [1,   2,  3,  2,  1]
    [0,   0,  0,  0,  0]
  ]
)
```

What low-level feature did this layer learn to look for? What pattern will make its neurons most positive (i.e. will “turn it on”)?

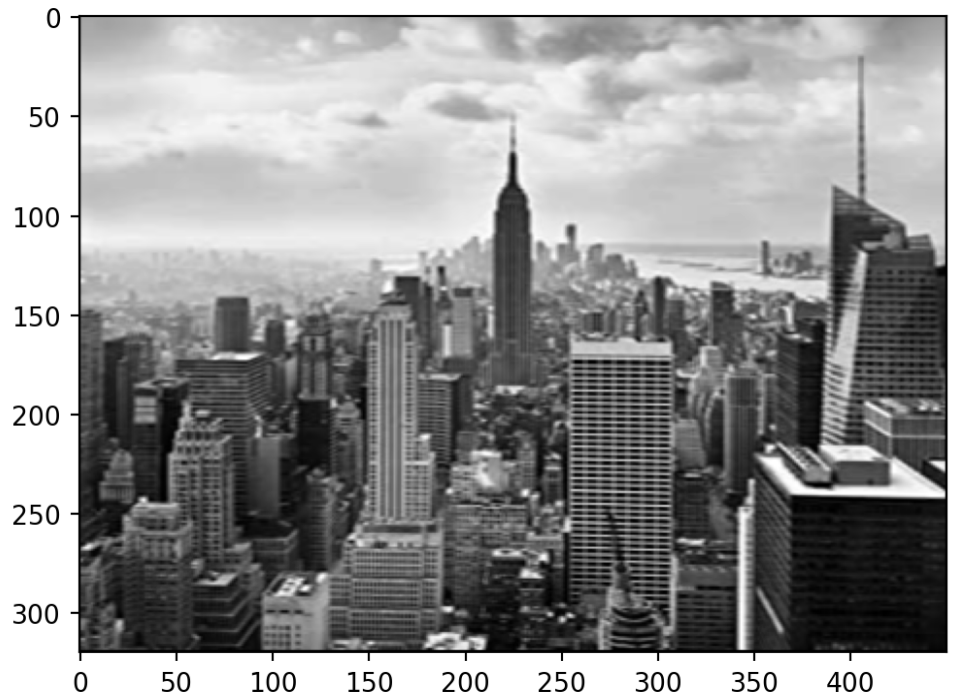
Convolving with Tensorflow

```
import tensorflow as tf

ny = imread('images/new_york.jpg').mean(axis=2)
ny4D = np.array([ny.reshape(ny.shape[0], ny.shape[1], 1)])
W4d = W.reshape(W.shape[0], W.shape[0], 1, 1)

ny_convolved = tf.nn.conv2d(ny4D, W4d, strides=1, padding='SAME')
```

```
plt.imshow(
  ny,
  cmap = 'gray')
plt.show()
```




```
plt.imshow(
  ny_convolved[0, :, :, 0],
  cmap = 'gray')
plt.show()
```



Making CNN Work

INTRODUCTION

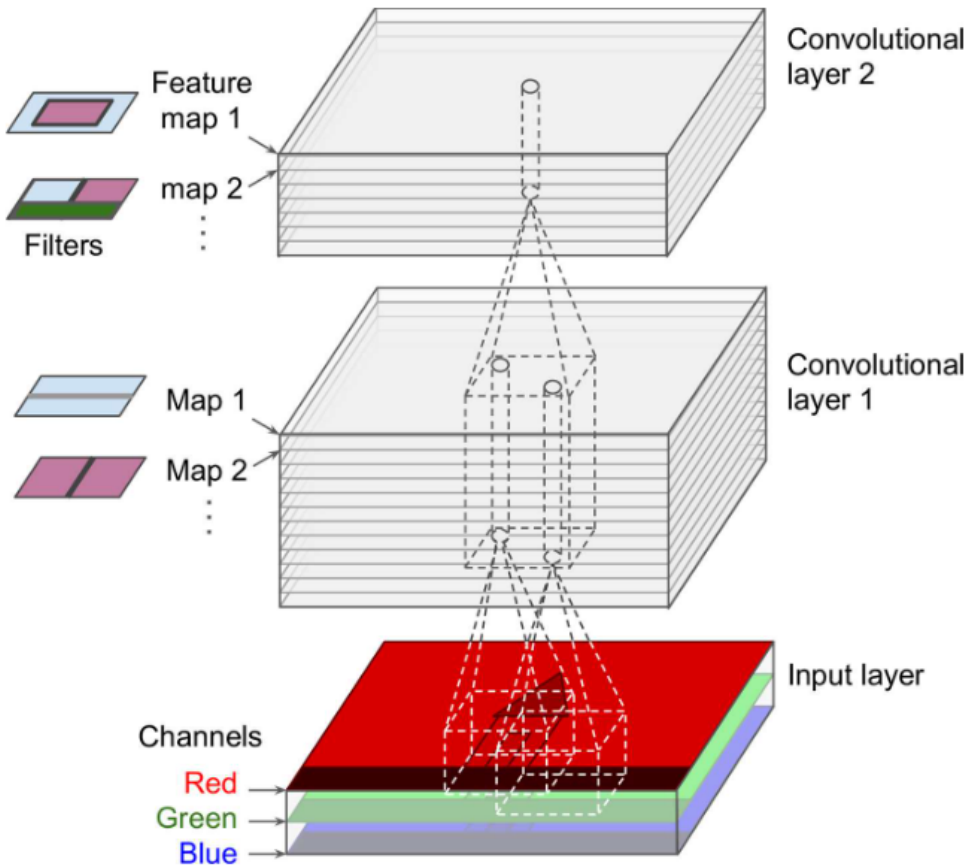
To Data Science

Strides

In many CNN architectures layers tend to get smaller and smaller using *strides*:

Stacking Feature Maps

A convolutional layer is actually a 3D stack of a few of the 2D layers we described (a.k.a *Feature Maps*), each learns a single filter.



Source: Geron 2019

- Feature map 1 learns horizontal lines
- Feature map 2 learns vertical lines
- Feature map 3 learns diagonal lines
- Etc.

And each such feature map takes as inputs all feature maps (or color channels) in the previous layer, and sums:

$$Z_{i,j,k} = b_k + \sum_{u=0}^{f_h-1} \sum_{v=0}^{f_w-1} \sum_{k'=0}^{f_n-1} X_{i \cdot s_h + u, j \cdot s_w + v, k'} \cdot W_{u,v,k',k}$$

Where f_n is the number of feature maps (or color channels) in the previous layer.

- Feature map 1 with $f_h \cdot f_w$ filter $\cdot f_n$ color channels + 1 bias term (it's a filter *cuboid*!)
- Feature map 2 with $f_h \cdot f_w$ filter $\cdot f_n$ color channels + 1 bias term
- Etc.

And how does the network *learn* these filters?

Too early to rejoice

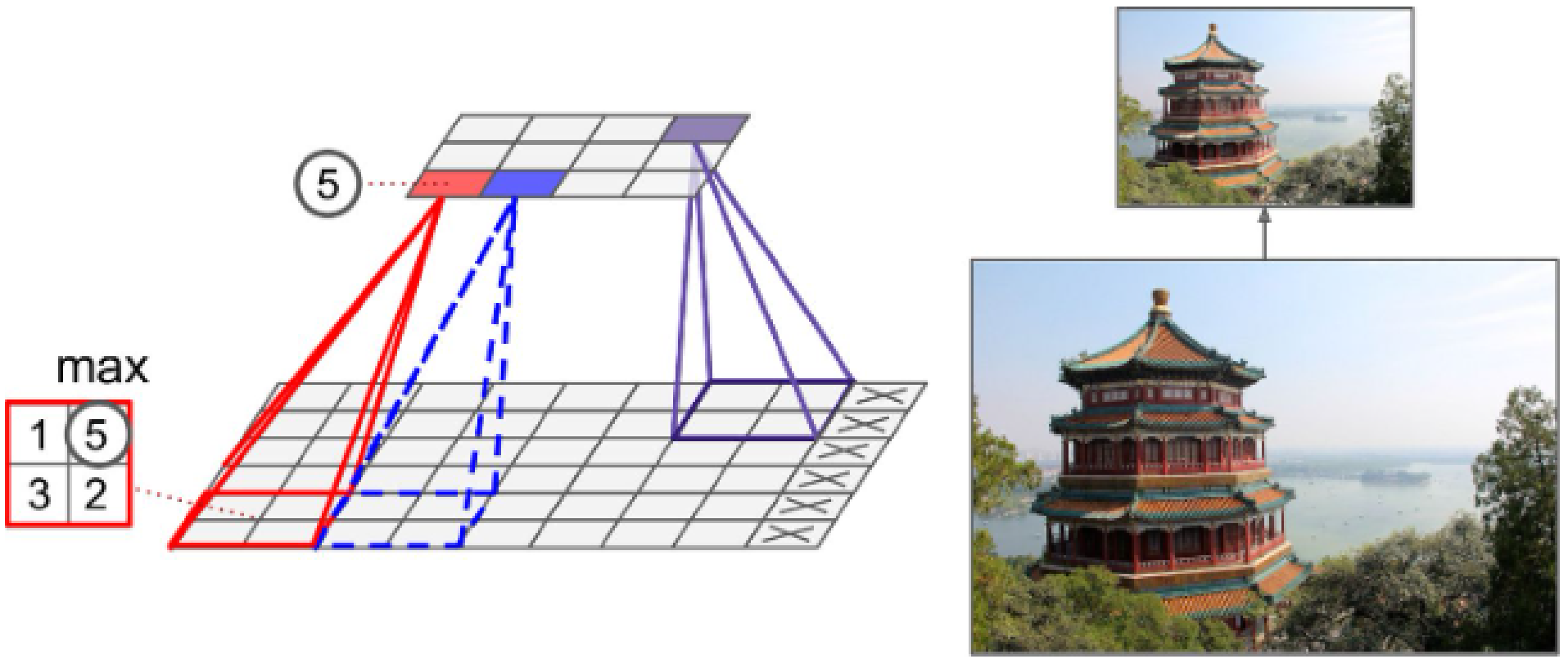
That's still quite a lot.

- 100 x 100 RGB image
- 100 feature maps in first layer of filter 3x3
- (3 x 3 x 3 + 1) x 100 = 2800 params, not too bad
- But 100 x 100 numbers in each feature map (x 100) = 1M numbers, each say takes 4B, that's 4MB for 1 image for 1 layer
- Each number is a weighted sum of 3 x 3 x 3 = 27 numbers, so that's 1M x 27 = 27M multiplications for 1 layer…

Pooling Layers

A pooling layer “sums up” a convolutional layer, by taking the max or mean of the receptive field.

No params!



Source: Geron 2019

Usually with strides $s_w = s_h = f_w = f_h$ and no padding (a.k.a VALID):

```
X = np.array(
  [
    [0,   1,  0,  1,  0]
    [0,   1,  0,  1,  0]
    [0,   0,  0,  0,  0]
    [1,   0,  0,  0,  1]
    [0,   1,  1,  1,  0]
  ]
)
```

```
W = np.array(
  [
    [0, 0, 0],
    [0, 0, 0],
    [1, 1, 1]
  ]
)
```

```
Z = np.array(
  [
    [1,   1,  2,  1,  1]
    [0,   0,  0,  0,  0]
    [1,   1,  0,  1,  1]
    [1,   2,  3,  2,  1]
    [0,   0,  0,  0,  0]
  ]
)
```

```
Z2 = np.array(
  [
    [1, 2],
    [2, 3]
  ]
)
```

Clearly we're losing info.

- A 2x2 max pooling layer with stride 2 would reduce the size of the previous layer by how many percents?
- But maybe sometimes it's a *good* thing to ignore some neurons?

Is CNN a linear operator?

Typical CNN

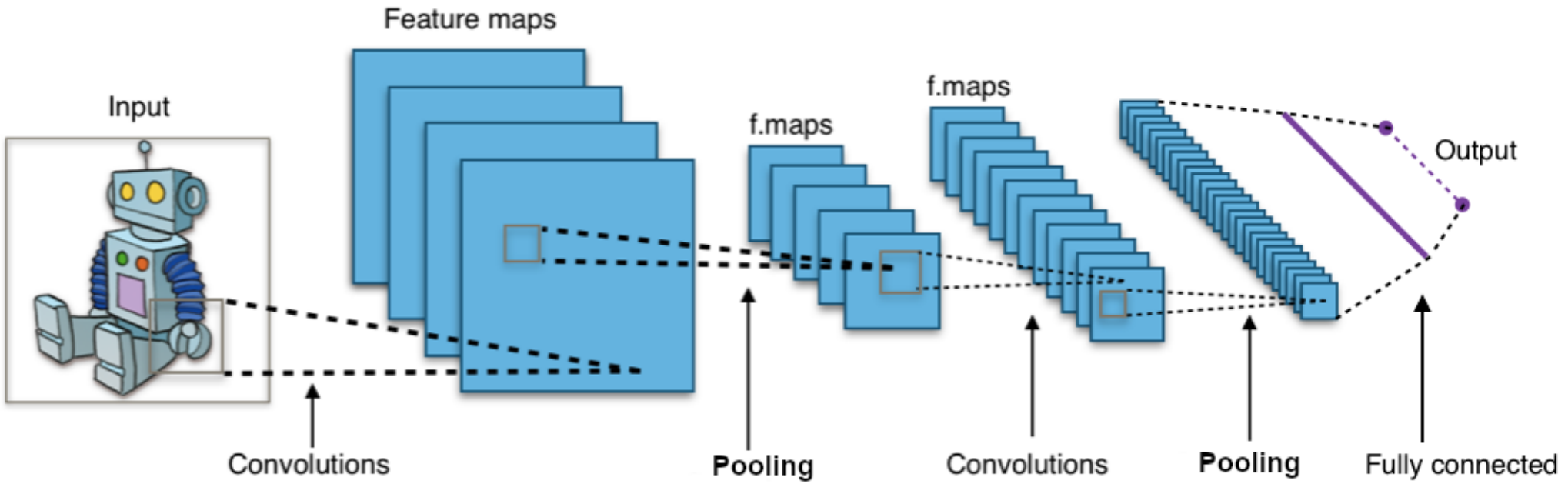

Feature maps
Input
f.maps
f.maps
Output
Convolutions
Pooling
Convolutions
Pooling
Fully connected

Image Data Augmentation

It's very hard to "augment" data about people, products, clicks.

Images are different.

- Translation
- Rotation
- Rescaling
- Flipping
- Stretching

Are there some images or applications you wouldn't want augmentations or at least should go about it very carefully?

In Keras you can augment “on the fly” as you train your model, here I’m just showing you this works:

```
from tensorflow.keras.preprocessing.image import ImageDataGenerator

idg = ImageDataGenerator(
    rotation_range=30,
    zoom_range=0.15,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.15,
    horizontal_flip=True,
    fill_mode='nearest'
)

ny_generator = idg.flow(ny4D, batch_size=1)

nys = [ny_generator.next() for i in range(10)]
```

See the ImageDataGenerator for more.









Why do CNN work?

- No longer a long 1D column of neurons, but 2D, taking into account spatial relations between pixels/neurons
- First layer learns very low-level features, second layer learns higher level features, etc.
- Shared weights –> learn feature in one area of the image, generalize it to the entire image
- Less weights –> smaller size, more feasible model, less prone to overfitting
- Less overfitting by Pooling
- Invariance by Max Pooling
- Image augmentation
- Hardware/Software advancements enable processing of huge amounts of images

Back to Malaria!

INTRODUCTION

TO DATA SCIENCE

Reminder

```
import tensorflow_datasets as tfds
from skimage.transform import resize
from sklearn.model_selection import train_test_split

malaria, info = tfds.load('malaria', split='train', with_info=True)

images = []
labels = []
for example in tfds.as_numpy(malaria):
  images.append(resize(example['image'], (100, 100)).astype(np.float32))
  labels.append(example['label'])
  if len(images) == 2500:
    break

X = np.array(images)
y = np.array(labels)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=

print(X_train.shape)
print(X_test.shape)
```

```
(2000, 100, 100, 3)
(500, 100, 100, 3)
```

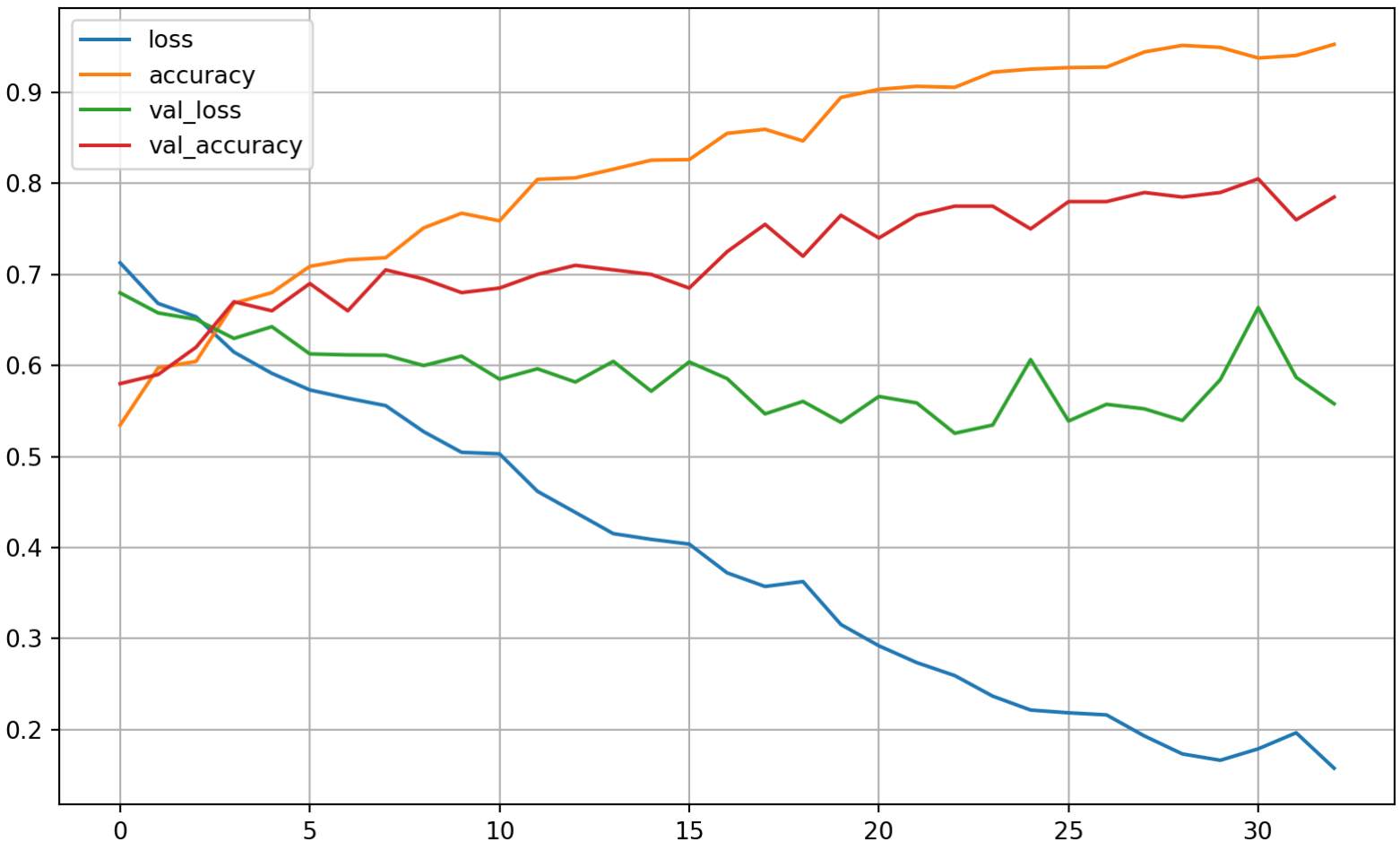
```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, Flatten, Dropout
from tensorflow.keras.callbacks import EarlyStopping

model = Sequential()
model.add(Conv2D(filters=32, input_shape=(X_train.shape[1:]),
  kernel_size=(3, 3), padding='same', activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Flatten())
model.add(Dropout(0.5))
model.add(Dense(1, activation='sigmoid'))
model.compile(loss='binary_crossentropy',
  optimizer='adam', metrics=['accuracy'])
```

```
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 100, 100, 32)      896

 max_pooling2d (MaxPooling2D  (None, 50, 50, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 48, 48, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 24, 24, 64)       0
 2D)

 flatten (Flatten)           (None, 36864)             0

 dropout (Dropout)           (None, 36864)             0

 dense (Dense)               (None, 1)                 36865

=================================================================
Total params: 56,257
```

```
callbacks = [EarlyStopping(monitor='val_loss', patience=5)]
history = model.fit(X_train, y_train, batch_size=100, epochs=50,
  validation_split=0.1, callbacks=callbacks)
```

```
import pandas as pd

pd.read_csv(history.history).plot(figsize=(10, 6))
plt.grid(True)
plt.show()
```



Last time we got to 69% accuracy after tuning...

```
from sklearn.metrics import confusion_matrix

y_pred = (model.predict(X_test, verbose=0) > 0.5).astype(int).reshape(y_test.shape)
```

```
np.mean(y_pred == y_test)
```

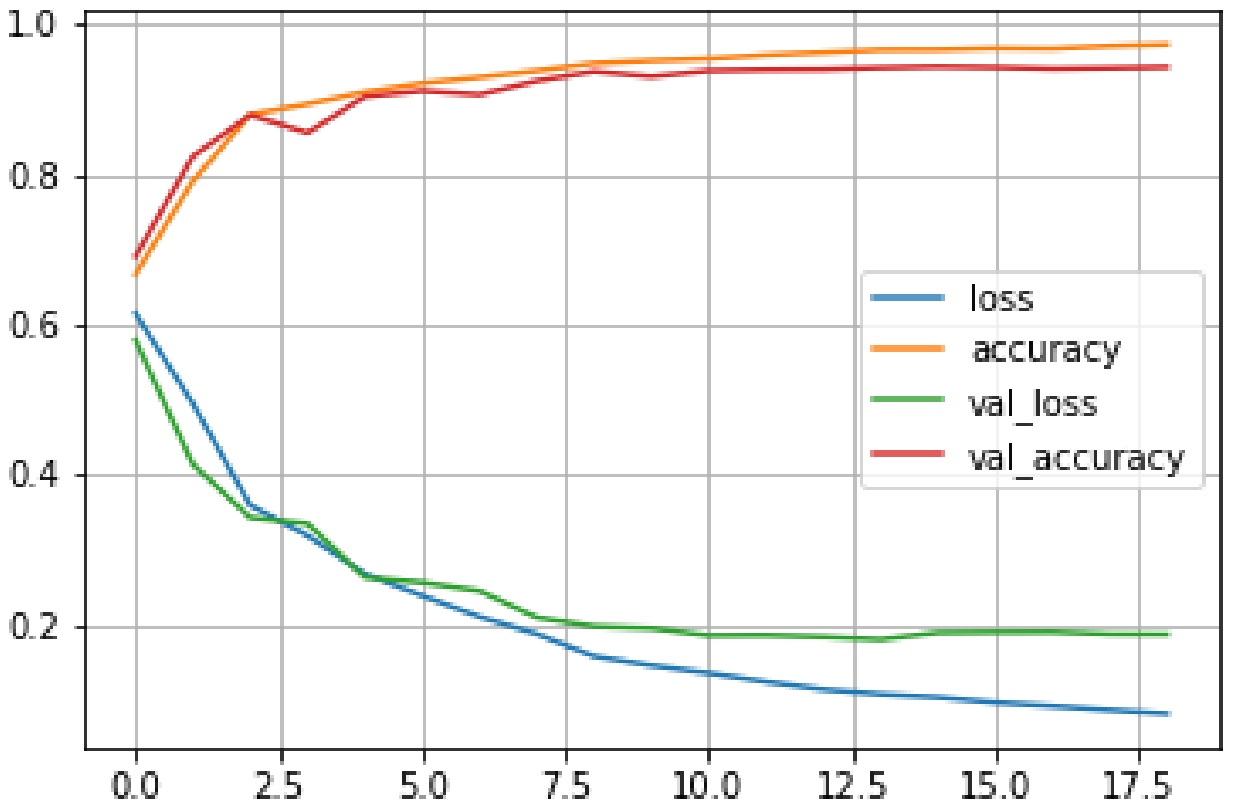
```
0.766
```

```
pd.DataFrame(
  confusion_matrix(y_test, y_pred),
  index=['true:yes', 'true:no'],
  columns=['pred:yes', 'pred:no']
)
```

	pred:yes	pred:no
true:yes	191	71
true:no	46	192

And this is just 10% of the data.

Watch me reach ~94% accuracy with 100% of the data in Google Colab.



Think about the researchers seeing this for the first time in 2012…

Visualizing CNN

INTRODUCTION

To Data Science

Visualizing filters/kernels/features/weights

```
W, b = model.get_layer('conv2d').get_weights()
```

```
W.shape
```

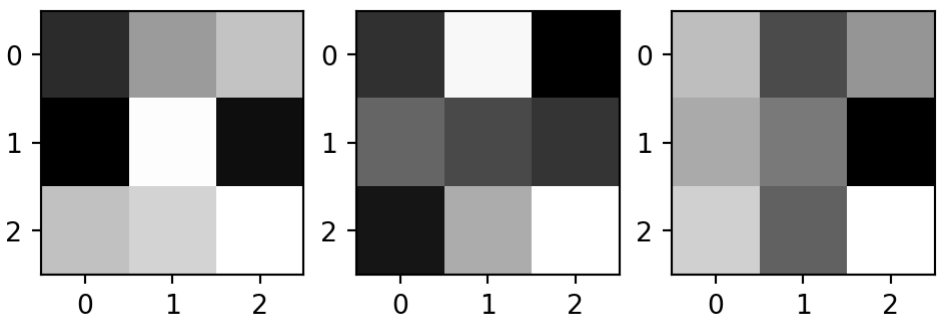
```
(3, 3, 3, 32)
```

```
W[:, :, 0, 0]
```

```
array([[-0.05327014,  0.05076471,  0.0883847 ],
       [-0.0933094 ,  0.14134812, -0.08010183],
       [ 0.08545554,  0.10305361,  0.14380825]], dtype=float32)
```

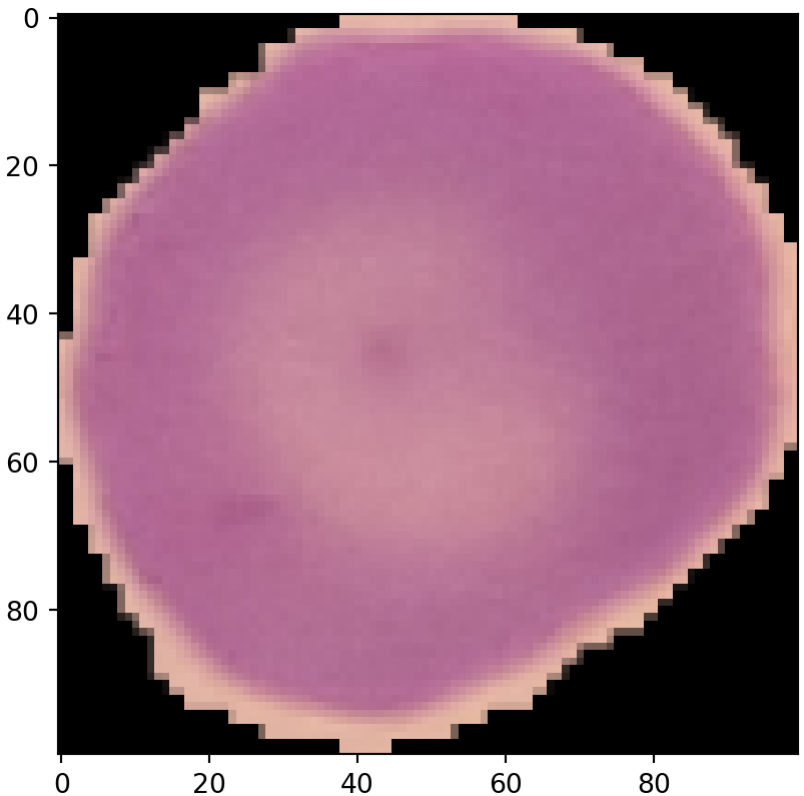
First filter of 32:

```
plt.subplot(1,3,1)
plt.imshow(W[:, :, 0, 0], cmap='gray')
plt.subplot(1,3,2)
plt.imshow(W[:, :, 1, 0], cmap='gray')
plt.subplot(1,3,3)
plt.imshow(W[:, :, 2, 0], cmap='gray')
plt.show()
```



Visualizing Feature Maps

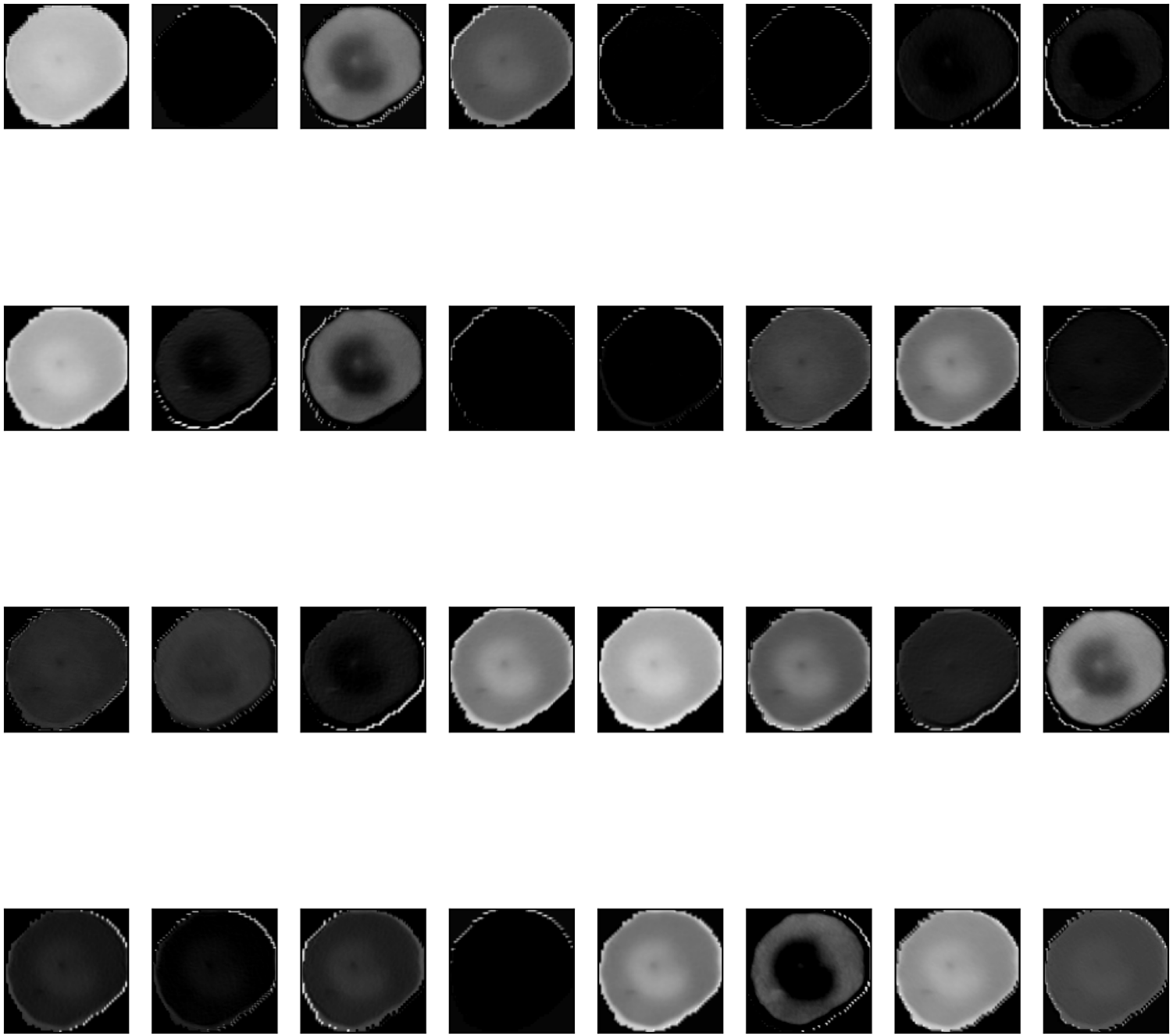
```
cell = X_test[0, :, :, :].reshape(1, 100, 100, 3)

plt.imshow(cell[0])
plt.show()
```



```
from tensorflow.keras import Model

model_1layer = Model(inputs=model.inputs,
  outputs=model.layers[0].output)

feature_maps = model_1layer.predict(cell)

feature_maps.shape
```

```
(1, 100, 100, 32)
```

```
width = 8
height = 4
ix = 1
_ = plt.figure(figsize = (10, 10))
for _ in range(height):
    for _ in range(width):
        ax = plt.subplot(height, width, ix)
        _ = ax.set_xticks([])
        _ = ax.set_yticks([])
        _ = plt.imshow(feature_maps[0, :, :, ix-1], cmap='gray')
        ix += 1
plt.show()
```

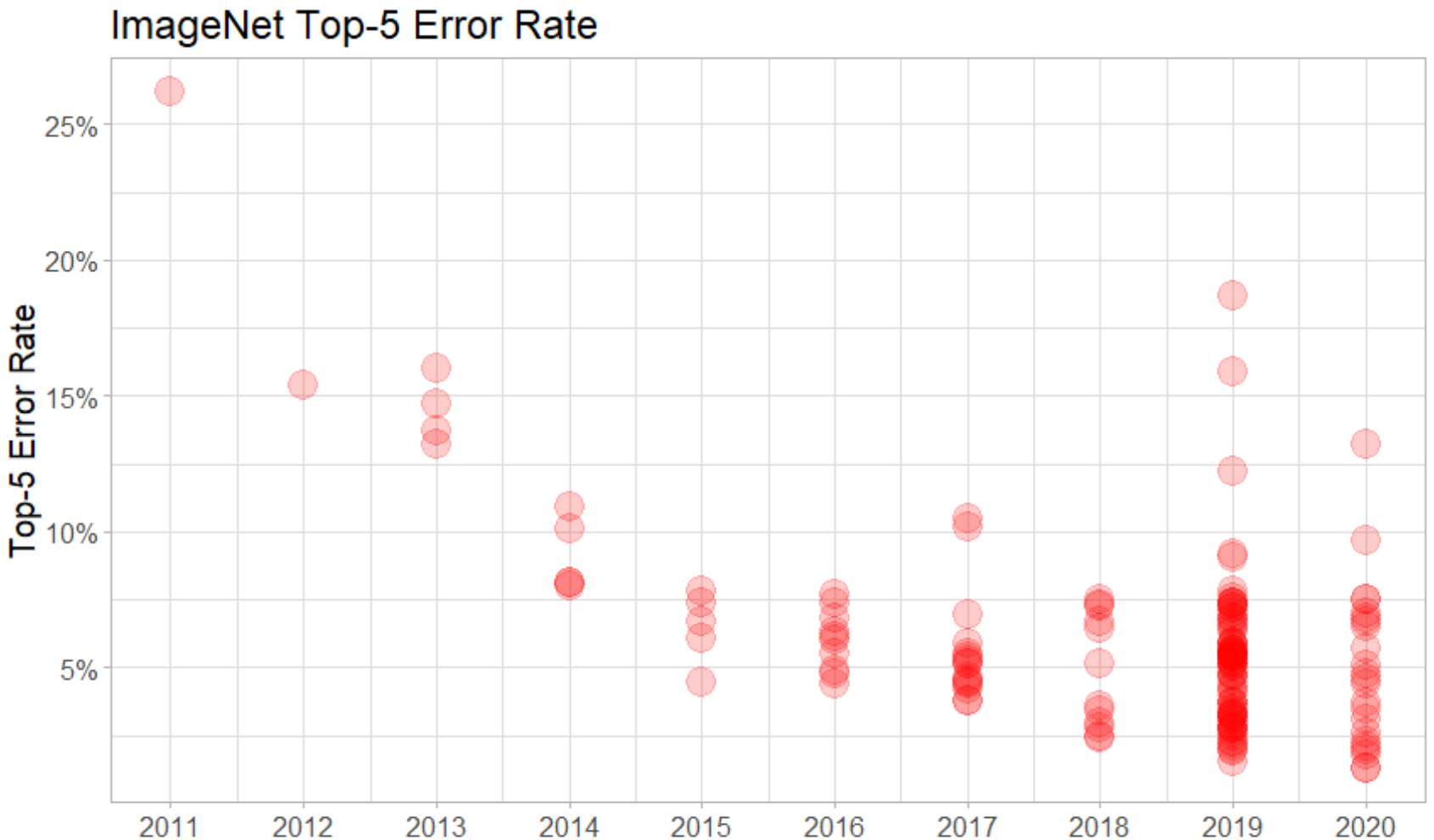


CNN Architectures

INTRODUCTION

To Data Science

ImageNet



Source: paperswithcode.com

LeNet-5 (1998)

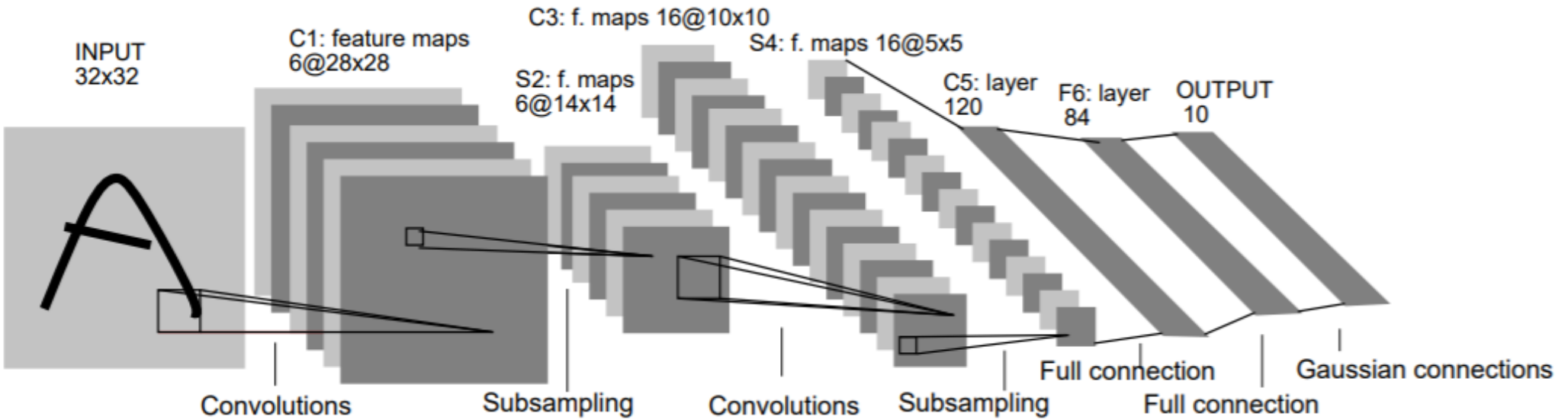


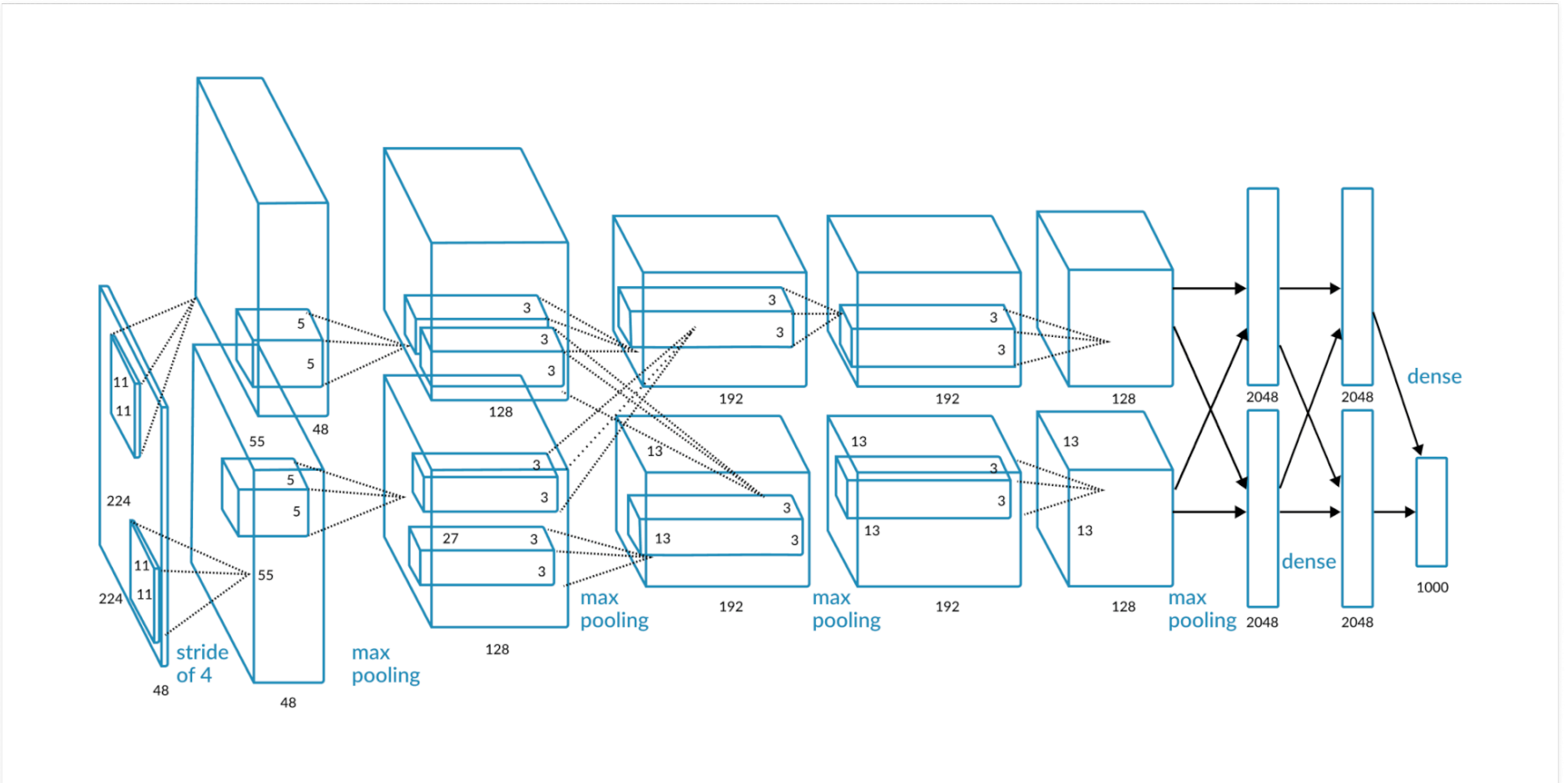
Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Source: LeCun et. al. 1998

You know you can implement this in just a few lines of Keras…

```
from tensorflow.keras.layers import Conv2D, AveragePooling2D,
  Flatten, Dense
from tensorflow.keras import Sequential

model = keras.Sequential()

model.add(Conv2D(filters=6, kernel_size=(3, 3),
  activation='relu', input_shape=(32,32,1)))
model.add(AveragePooling2D())
model.add(Conv2D(16, kernel_size=(3, 3), activation='relu'))
model.add(AveragePooling2D())
model.add(Flatten())
model.add(Dense(120, activation='relu'))
model.add(Dense(84, activation='relu'))
model.add(Dense(10, activation = 'softmax'))
```

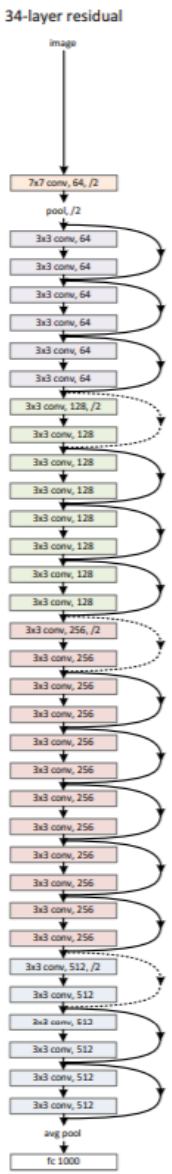
AlexNet (2012)



Source: Krizhevsky et. al. 2012

See a Keras implementation e.g. here

ResNet (2015)



- Source: He et. al.
- This is ResNet-34 (34 layers)
- ResNet-152 (152 layers!) achieved 4.5% Top-5 error rate with single model

Intro to Data Science

Residual Learning

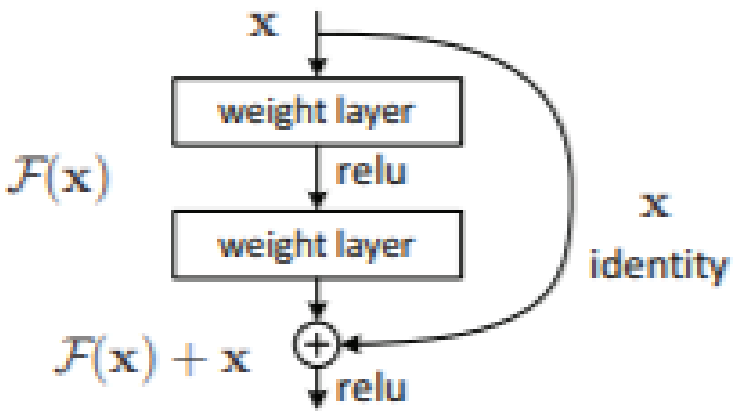


Figure 2. Residual learning: a building block.

- "Is learning better networks as easy as stacking more layers?" Yes, but:
- the vanishing/exploding gradients problem
- With *Residual Learning* the activation from a previous layer is being added to the activation of a deeper layer in the network
- The signal is allowed to propagate through the layers
- The model learning $H(X)$ will be forced to learn $H(X) - X$, hence *residual* learning.

Using Pre-trained Models

INTRODUCTION

TO DATA SCIENCE

What *is* a trained CNN?

Keras Applications

Keras Applications are deep learning models that are made available alongside pre-trained weights. These models can be used for prediction, feature extraction, and fine-tuning.

Weights are downloaded automatically when instantiating a model. They are stored at `~/.keras/models/`.

Upon instantiation, the models will be built according to the image data format set in your Keras configuration file at `~/.keras/keras.json`. For instance, if you have set `image_data_format=channels_last`, then any model loaded from this repository will get built according to the TensorFlow data format convention, "Height-Width-Depth".

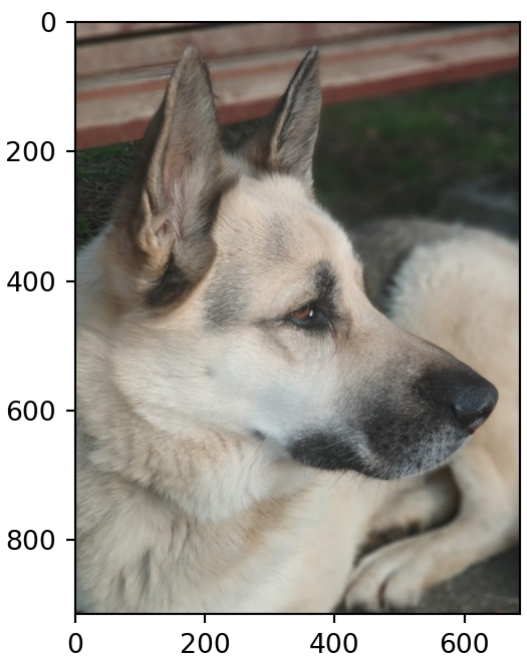
Available models

Model	Size (MB)	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth	Time (ms) per inference step (CPU)	Time (ms) per inference step (GPU)
Xception	88	79.0%	94.5%	22.9M	81	109.4	8.1
VGG16	528	71.3%	90.1%	138.4M	16	69.5	4.2
VGG19	549	71.3%	90.0%	143.7M	19	84.8	4.4
ResNet50	98	74.9%	92.1%	25.6M	107	58.2	4.6
ResNet50V2	98	76.0%	93.0%	25.6M	103	45.6	4.4
ResNet101	171	76.4%	92.8%	44.7M	209	89.6	5.2
ResNet101V2	171	77.2%	93.8%	44.7M	205	72.7	5.4

Look up keras.io/api/applications/

ResNet on your local machine

```
from tensorflow.keras.applications.resnet50 import ResNet50, preprocess_input, decode_p
from skimage.transform import resize

model = ResNet50(weights='imagenet')

johann = imread('images/johann.jpg')

fig, ax = plt.subplots(figsize=(7, 4))
_ = ax.imshow(johann)
```



```
johann = resize(johann, (224, 224))
johann = johann.reshape(1, 224, 224, 3) * 255
johann = preprocess_input(johann)

johann_pred = model.predict(johann, verbose=0)

print(johann_pred.shape)
```

```
(1, 1000)
```

```
johann_breed = decode_predictions(johann_pred, top=5)

for _, breed, score in johann_breed[0]:
  print('%s: %.2f' % (breed, score))
```

```
Norwegian_elkhound: 0.30
Eskimo_dog: 0.27
Siberian_husky: 0.17
German_shepherd: 0.15
malamute: 0.06
```

Look mom, no training!

What's Next?

INTRODUCTION

To Data Science

What's Next?

This was simple image classification. Furthermore you'd see:

- Transfer Learning
- Object Detection
- Segmentation
- Captioning
- 3D Reconstruction
- Restoration
- Pose Estimation
- Generative models (e.g. GANs)
- Doing it all on Video
- And doing it all in real time, on your phone or in your car 😀

Intro to Data Science