Applications

Of Data Science

Convolutional Neural Networks

Applications of Data Science - Class 17

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2021-02-23

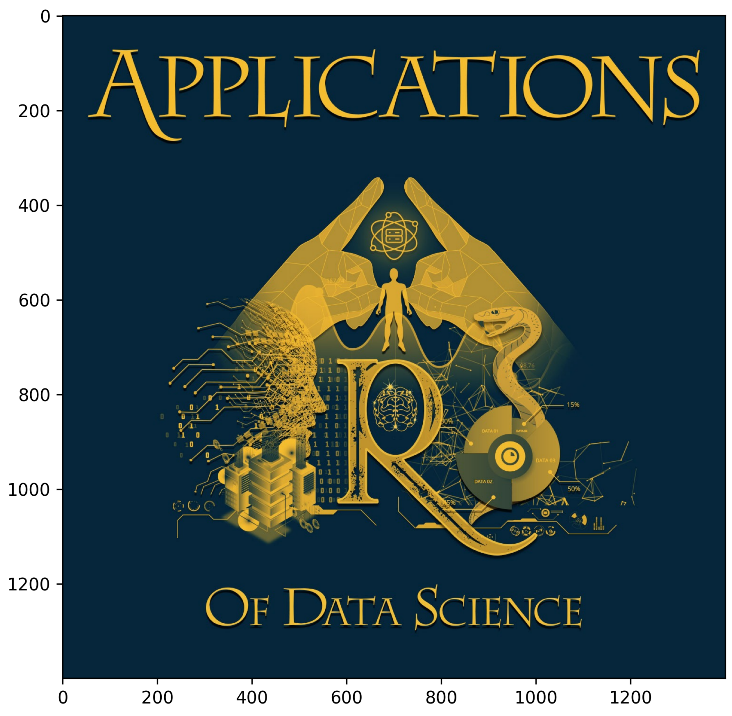
Applications of Data Science

Understanding Images

APPLICATIONS

OF DATA SCIENCE

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

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

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



```
print(type(logo))
```

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

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

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

```
print(logo[:4, :4, 0])
```

```
## [[6 6 6 6]
##  [6 6 6 6]
##  [6 6 6 6]
##  [6 6 6 6]]
```

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

```
## 0 255
```

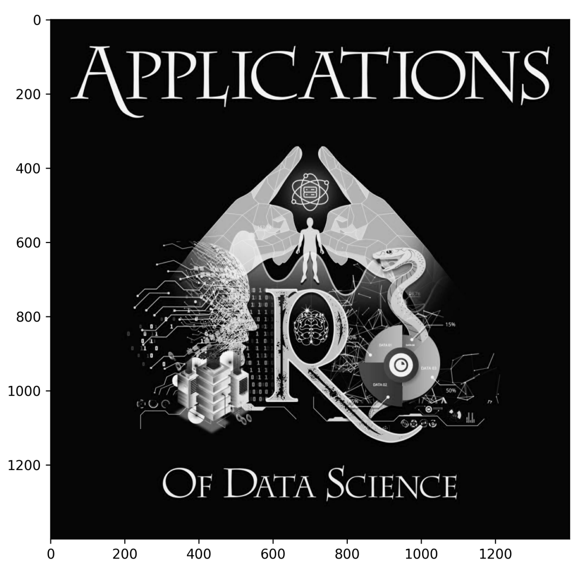
```
print(logo.dtype, logo.size * logo.itemsize)
```

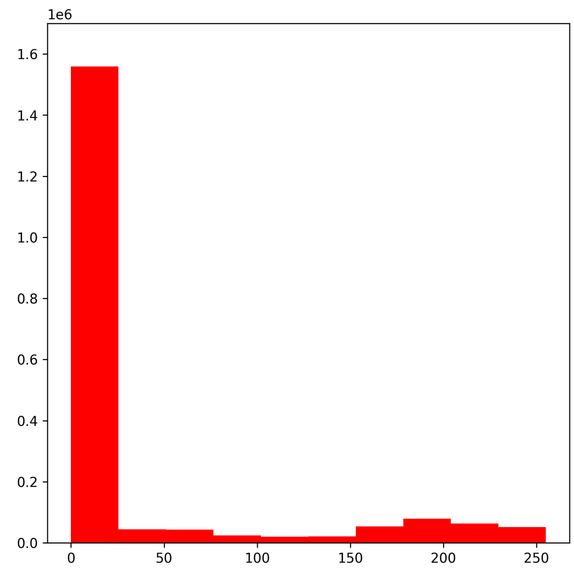
```
## uint8 5880000
```

Red channel

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

```
fig = plt.hist(red.flatten(),
  color = 'r')
fig = plt.ylim(0, 1700000)
plt.show()
```

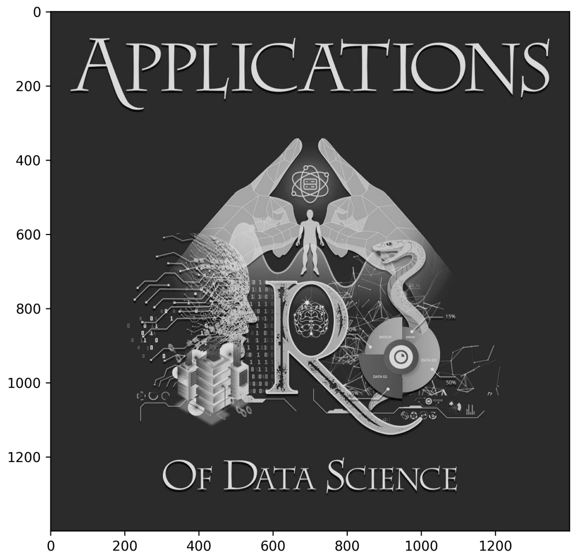


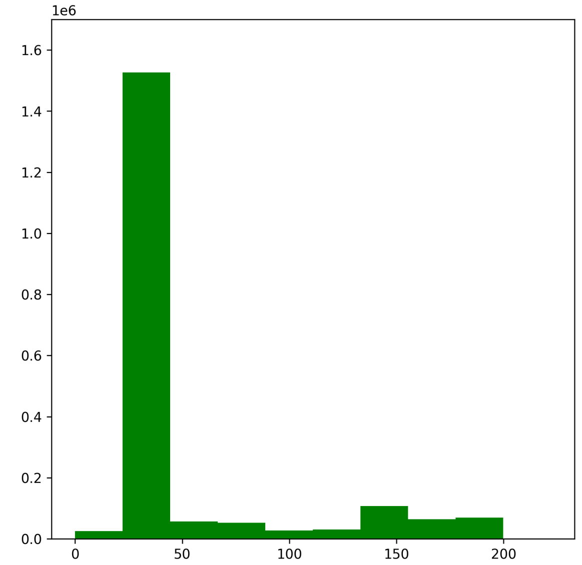


Green channel

```
green = logo[:, :, 1]
plt.imshow(green,
  cmap='gray')
plt.show()
```

```
fig = plt.hist(green.flatten(),
  color = 'g')
fig = plt.ylim(0, 1700000)
plt.show()
```

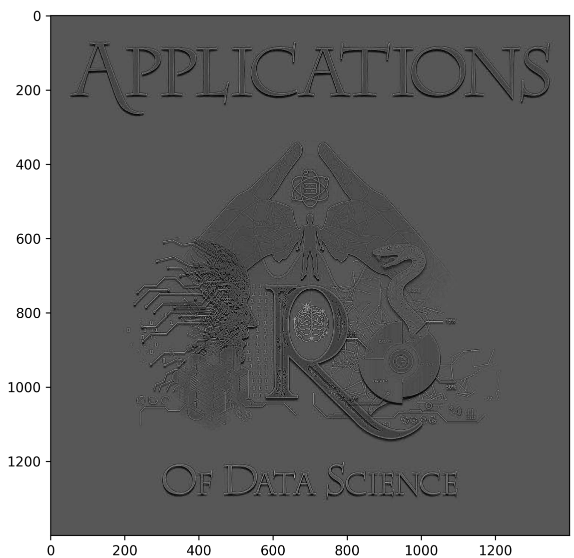


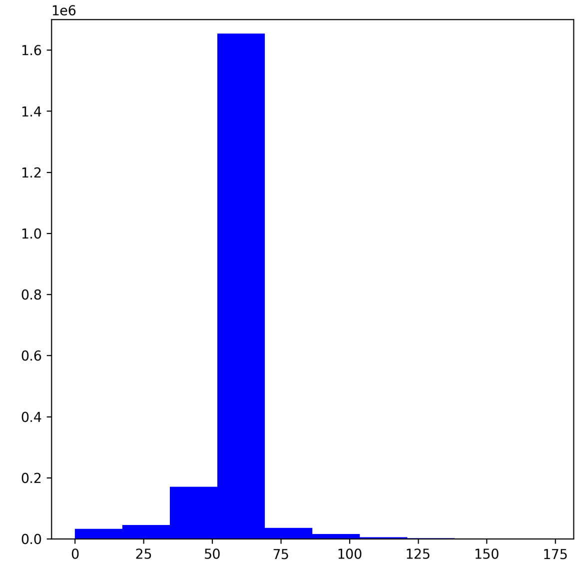


Blue channel

```
blue = logo[:, :, 2]
plt.imshow(blue,
  cmap='gray')
plt.show()
```

```
fig = plt.hist(blue.flatten(),
  color = 'b')
fig = plt.ylim(0, 1700000)
plt.show()
```





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)

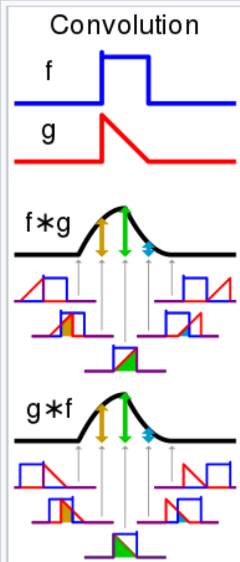
What is Convolution?

Convolution

From Wikipedia, the free encyclopedia

For the usage in formal language theory, see Convolution (computer science). For other uses, see Convolute.

In mathematics (in particular, functional analysis) **convolution** is a mathematical operation on two functions (f and g) that produces a third function expressing how the shape of one is modified by the other. The term *convolution* refers to both the result function and to the process of computing it. It is defined as the integral of the product of the two functions after one is reversed and shifted. And the integral is evaluated for all values of shift, producing the convolution function.

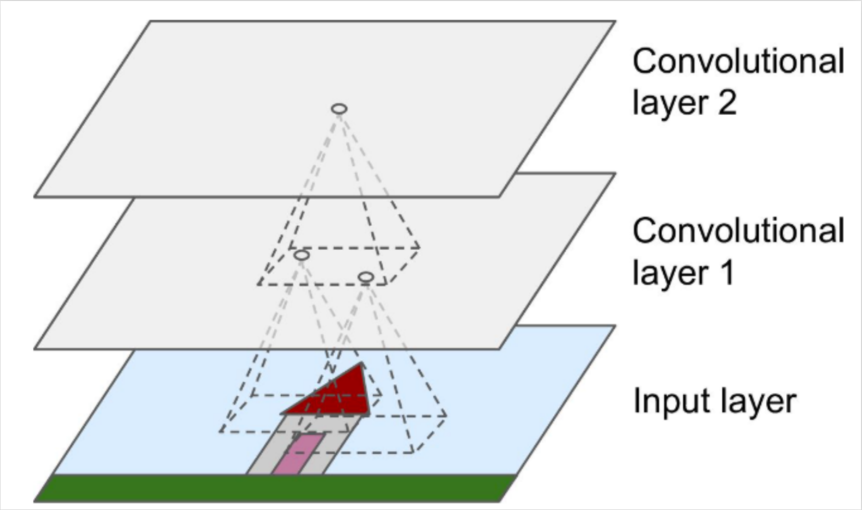


Some features of convolution are similar to cross-correlation: for real-valued functions, of a continuous or discrete variable, it differs from cross-correlation only in that either $f(x)$ or $g(x)$ is reflected about the y-axis; thus it is a cross-correlation of $f(x)$ and $g(-x)$, or $f(-x)$ and $g(x)$.[A] For continuous functions, the cross-correlation operator is the adjoint of the convolution operator.

Convolution has applications that include probability, statistics, computer vision, natural language processing, image and signal processing, engineering, and differential equations.[*citation needed*]

The convolution can be defined for functions on Euclidean space, and other groups.[*citation needed*] For example, periodic functions, such as the discrete-time Fourier transform, can be defined on a

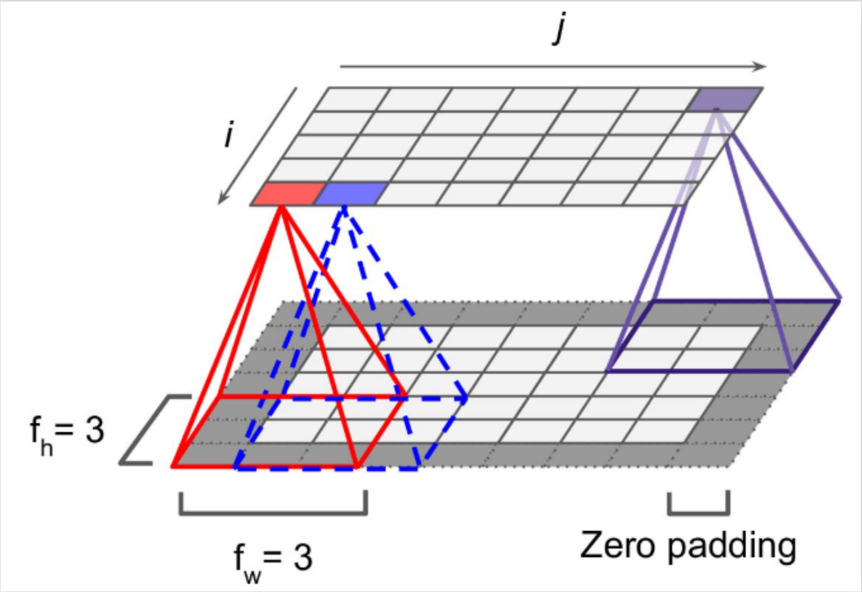
The Convolutional Layer



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

- The $[i, j]$ neuron looks at the rectangle at rows i to $i + f_h - 1$, columns j to $j + f_w - 1$
- Zero Padding: adds 0s around the image to make the next layer the same dimensions

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}:

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

Good God, Excel?

M1 | =A1*I1+B1*J1+C1*K1+A2*I2+B2*J2+C2*K2+A3*I3+B3*J3+C3*K3

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
1	0	0	0	0	0	0	0		0	1	0		0	2	0	2	0
2	0	0	1	0	1	0	0		0	1	0		0	2	0	2	0
3	0	0	1	0	1	0	0		0	1	0		1	1	0	1	1
4	0	0	0	0	0	0	0						1	1	1	1	1
5	0	1	0	0	0	1	0						1	1	1	1	1
6	0	0	1	1	1	0	0										
7	0	0	0	0	0	0	0										
8																	
9			X							W					Z		
10																	

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

Another filter

O4

=C4*I1+D4*J1+E4*K1+C5*I2+D5*J2+E5*K2+C6*I3+D6*J3+E6*K3

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1	0	0	0	0	0	0	0		0	0	0		1	1	2	1	1				
2	0	0	1	0	1	0	0		0	0	0		0	0	0	0	0				
3	0	0	1	0	1	0	0		1	1	1		1	1	0	1	1				
4	0	0	0	0	0	0	0						1	2	3	2	1				
5	0	1	0	0	0	1	0						0	0	0	0	0				
6	0	0	1	1	1	0	0														
7	0	0	0	0	0	0	0														
8																					
9			X							W					Z						
10																					

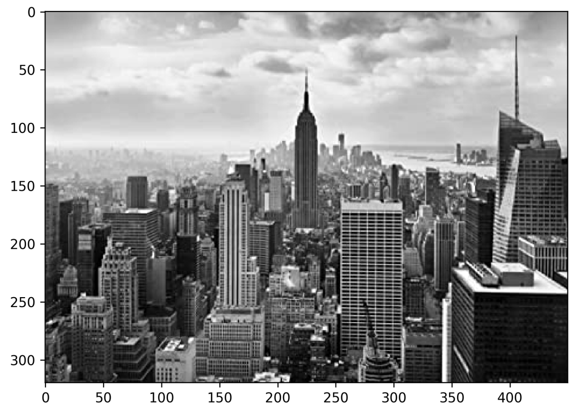
What low-level feature did this layer learn to look for? What pattern will make its neurons most positive (i.e. will "turn them on")?

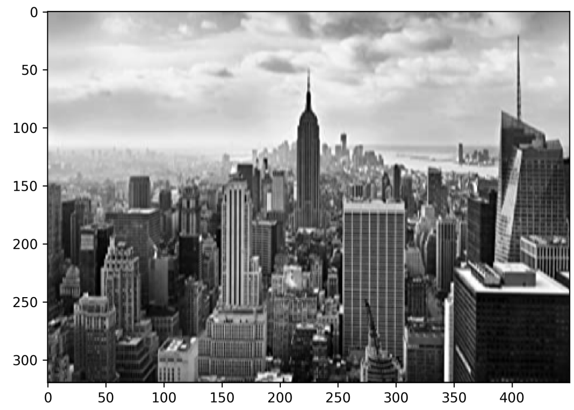
Convolving with Tensorflow

```
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')
```

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

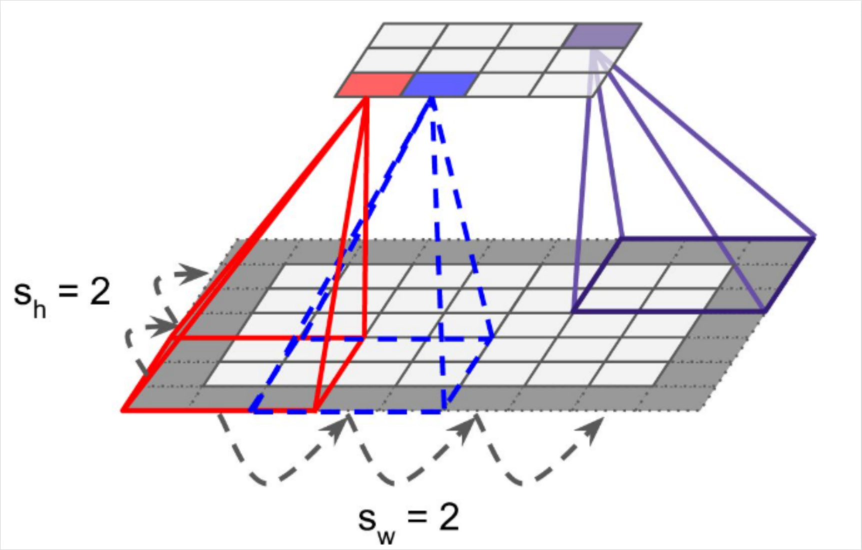
```python
plt.imshow(
  ny_convolved[0, :, :, 0],
  cmap = 'gray')
plt.show()
```





Strides

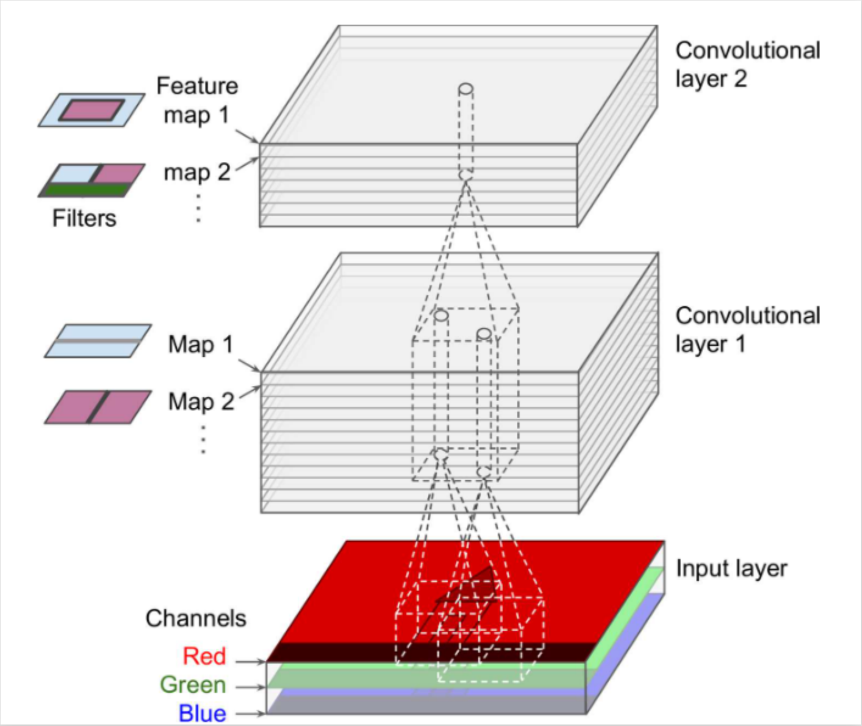
In many CNN architechtures layers tend to get smaller and smaller using *strides*:



- The $[i, j]$ neuron looks at the rectangle at rows $i \cdot s_h$ to $i \cdot s_h + f_h - 1$, columns $j \cdot s_w$ to $j \cdot s_w + f_w - 1$

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 *cube*!)
- 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

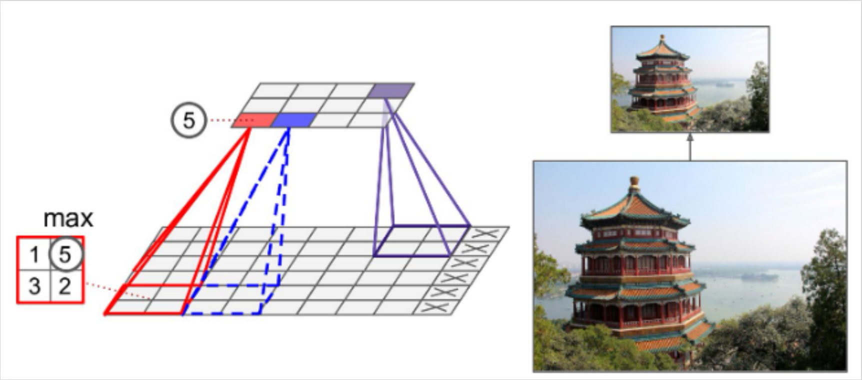
That's still quite a lot.

- 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`):

S1 | =MAX(M1:N2)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	0	0	0	0	0	0	0		0	0	0		1	1	2	1	1		1	2
2	0	0	1	0	1	0	0		0	0	0		0	0	0	0	0		2	3
3	0	0	1	0	1	0	0		1	1	1		1	1	0	1	1			
4	0	0	0	0	0	0	0						1	2	3	2	1			
5	0	1	0	0	0	1	0						0	0	0	0	0			
6	0	0	1	1	1	0	0													
7	0	0	0	0	0	0	0													
8																				
9			X							W					Z					

Clearly we're losing info.

> 💡 A 2x2 max pooling layer would reduce the size of the previous layer by how many percents?

But maybe sometimes it's a *good* thing to ignore some neurons? Where did we get this crazy idea from?

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 ImageDataGenerato

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
- Hardware/Software advancements enable processing of huge amounts of images

Back to Malaria!

```
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.flo
  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_si

print(X_train.shape)
```

```
## (2000, 100, 100, 3)
```

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

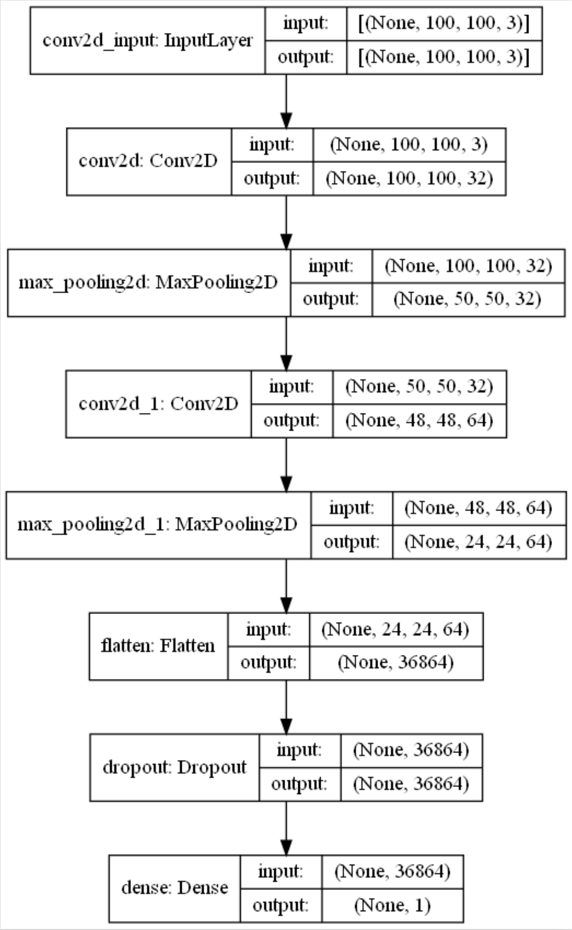
```
## (500, 100, 100, 3)
```

```
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Conv2D, MaxPooling2D, F
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()
```

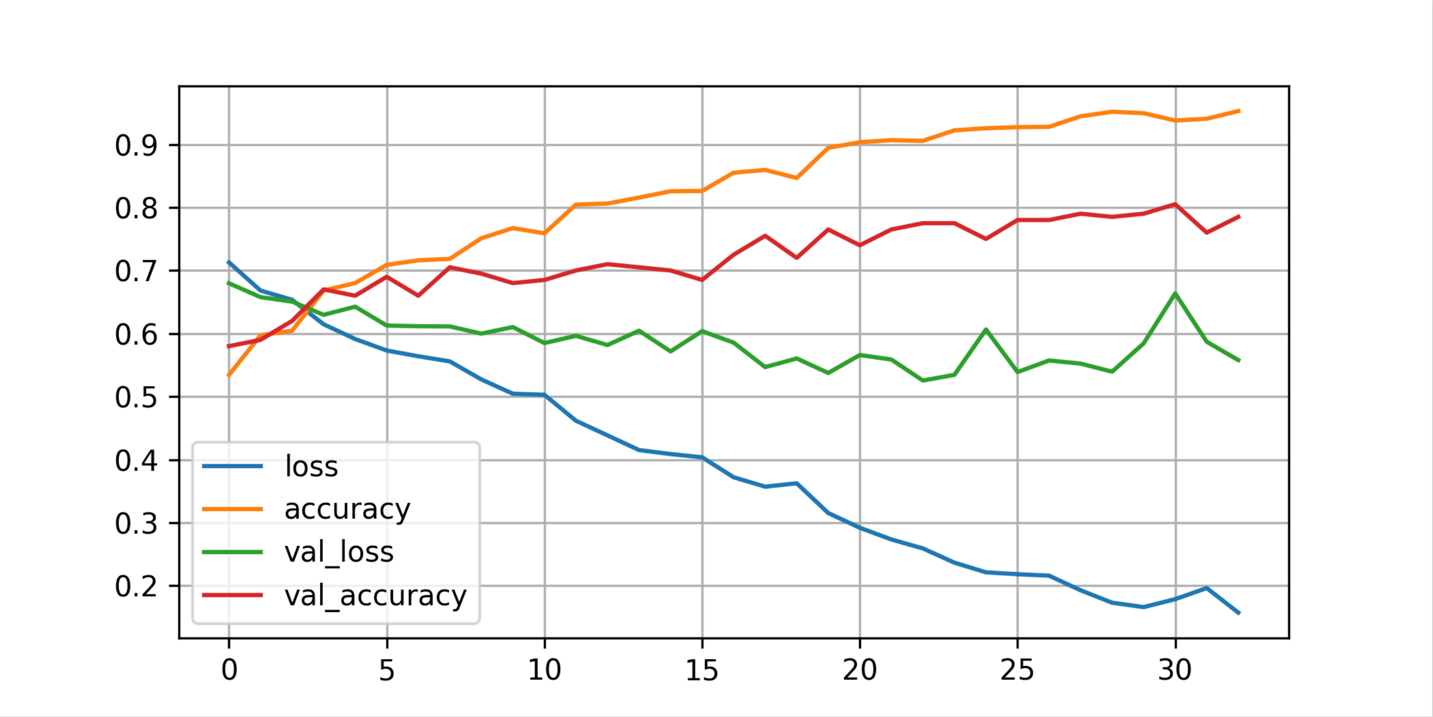
```
## Model: "sequential"
## ________________________________________________________________________________
## Layer (type)                       Output Shape                  Param #
## ================================================================================
## conv2d (Conv2D)                    (None, 100, 100, 32)          896
## ________________________________________________________________________________
## max_pooling2d (MaxPooling2D)       (None, 50, 50, 32)            0
## ________________________________________________________________________________
## conv2d_1 (Conv2D)                  (None, 48, 48, 64)            18496
## ________________________________________________________________________________
## max_pooling2d_1 (MaxPooling2       (None, 24, 24, 64)            0
## ________________________________________________________________________________
## flatten (Flatten)                  (None, 36864)                 0
## ________________________________________________________________________________
## dropout (Dropout)                  (None, 36864)                 0
## ________________________________________________________________________________
## dense (Dense)                      (None, 1)                     36865
## ================================================================================
## Total params: 56,257
## Trainable params: 56,257
## Non-trainable params: 0
## ________________________________________________________________________________
```

```
from tensorflow.keras import utils

utils.plot_model(model, 'images/malaria_cnn.png', show_shapes=True
```



```
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)

# Epoch 1/50
#
#  1/18 [>.............................] - ETA: 0s - loss: 0.6919
#  2/18 [==>...........................] - ETA: 8s - loss: 0.6895
#  3/18 [====>.........................] - ETA: 11s - loss: 0.7002
#  4/18 [=====>........................] - ETA: 11s - loss: 0.7009
#  5/18 [=======>......................] - ETA: 11s - loss: 0.6954
#  6/18 [=========>....................] - ETA: 10s - loss: 0.6925
#  7/18 [===========>..................] - ETA: 9s - loss: 0.6882
```

```
import pandas as pd

pd.read_csv(history.history).plot()
plt.grid(True)
plt.show()
```



Last time we got to 66% accuracy after tuning...

```
from sklearn.metrics import confusion_matrix

y_pred = (model.predict(X_test) > 0.5).astype(int).reshape(y_test.
```

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

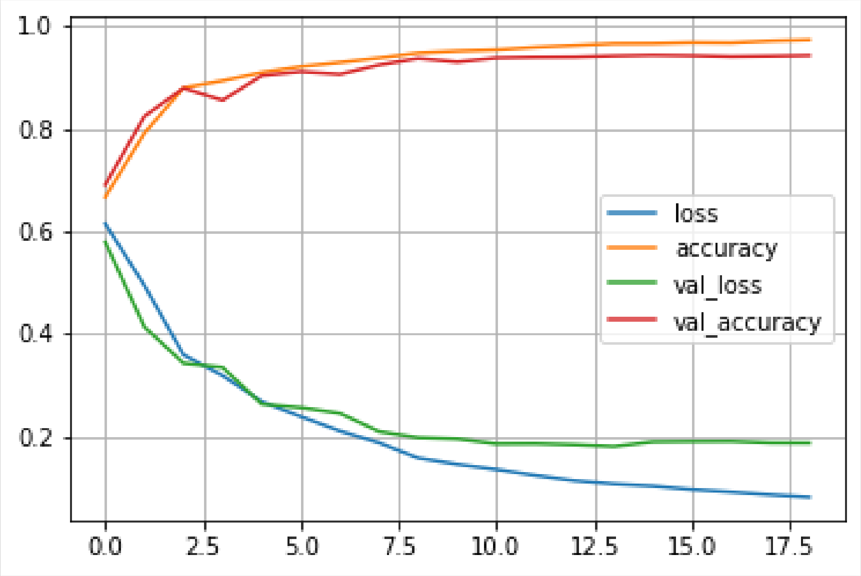
```
## 0.766
```

```
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 filters/kernels/features/weights

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

```
W.shape
```

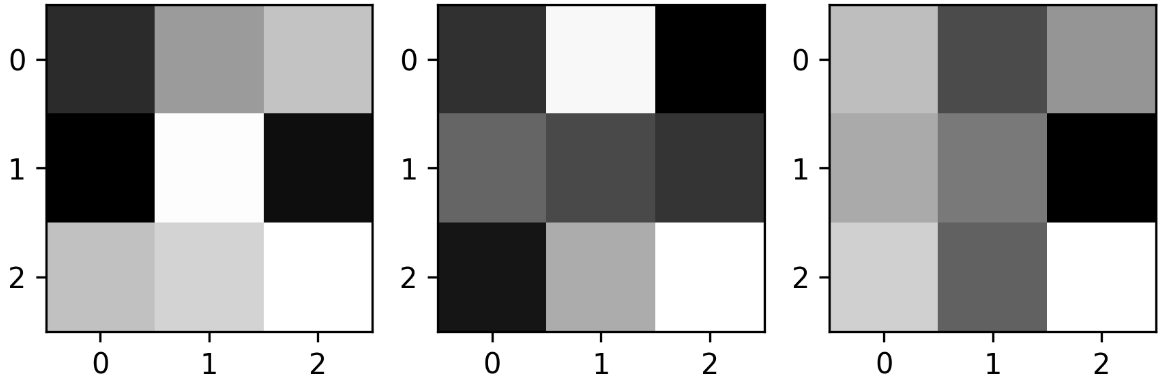
```
## (3, 3, 3, 32)
```

```
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])
```

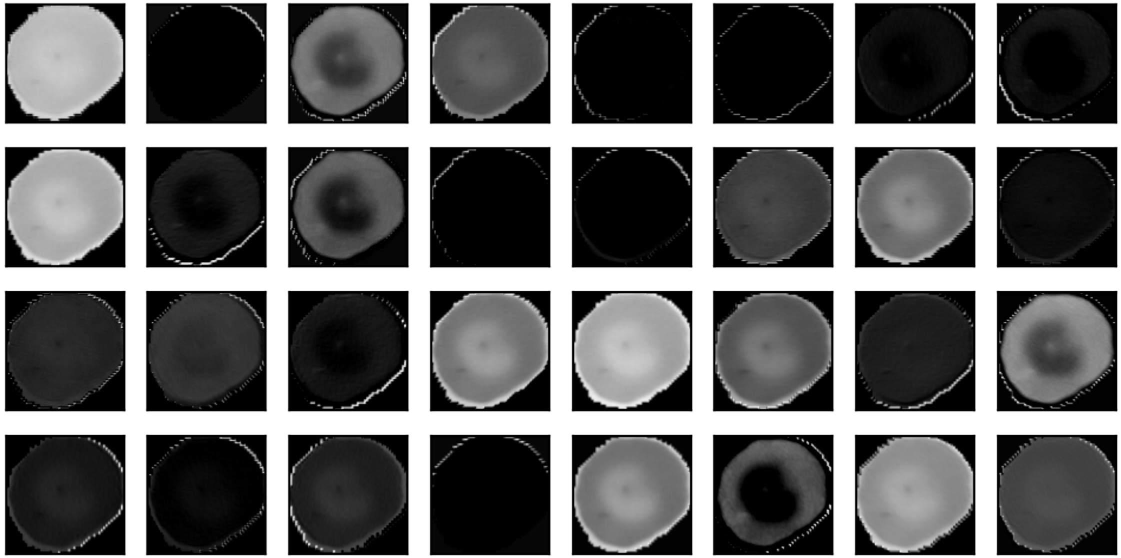
```
## <matplotlib.image.AxesImage object at 0x00000002A68DDB80>
```

```
plt.show()
```

```python
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
```

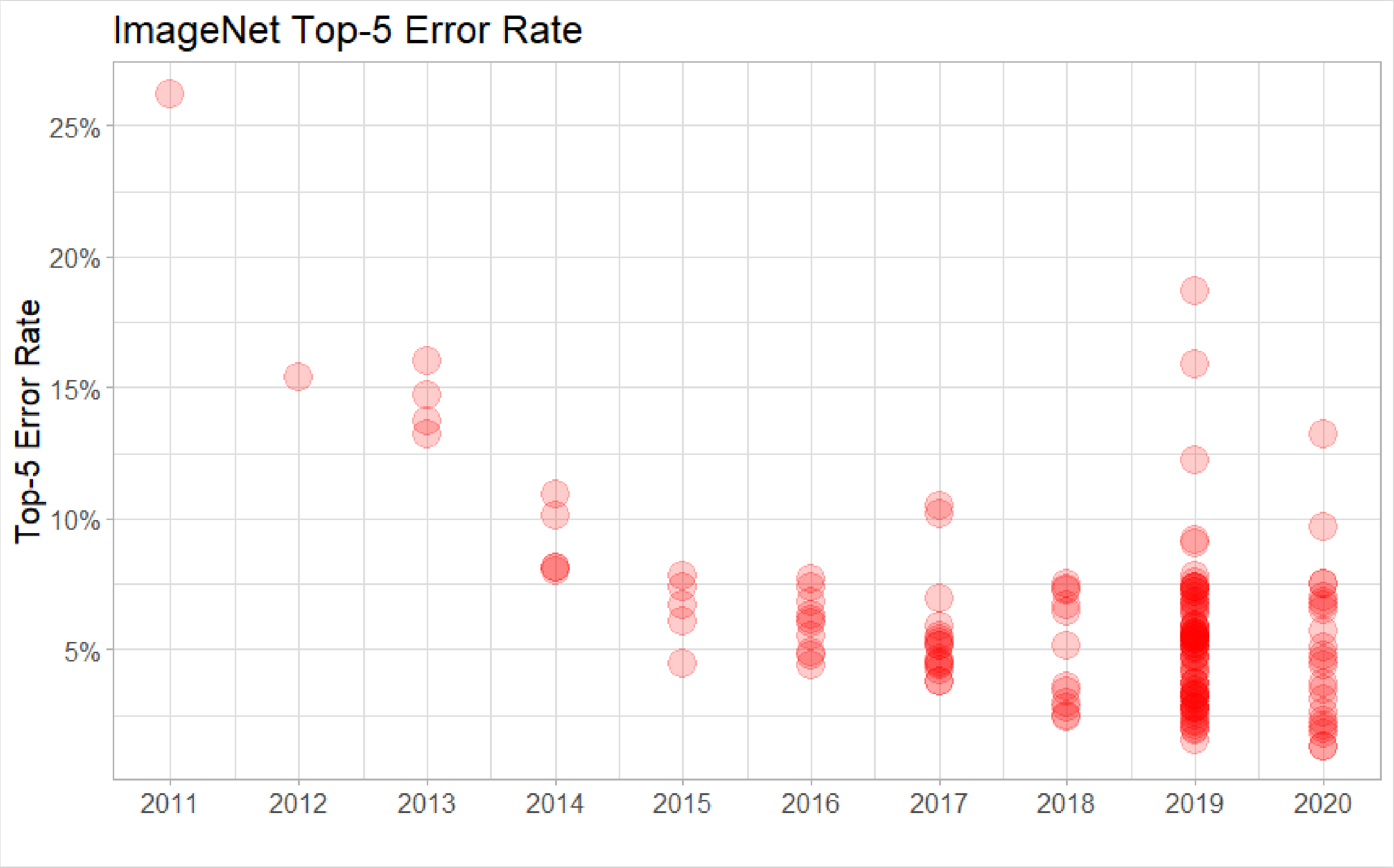
```
## (1, 100, 100, 32)
```

```python
# source: https://machinelearningmastery.com/how-to-visualize-filt
width = 8
height = 4
ix = 1
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

ImageNet



Source: paperswithcode.com

LeNet-5 (1998)

PROC. OF THE IEEE, NOVEMBER 1998 7

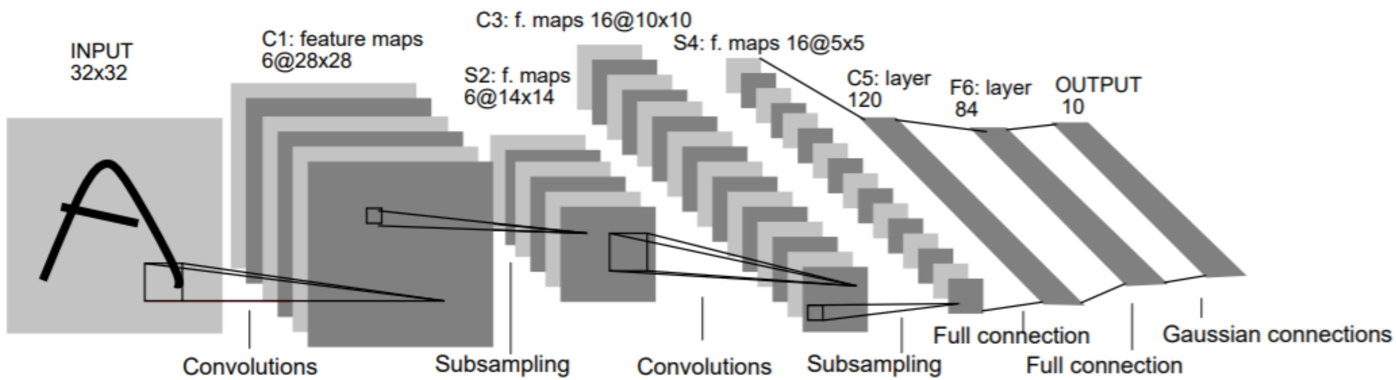


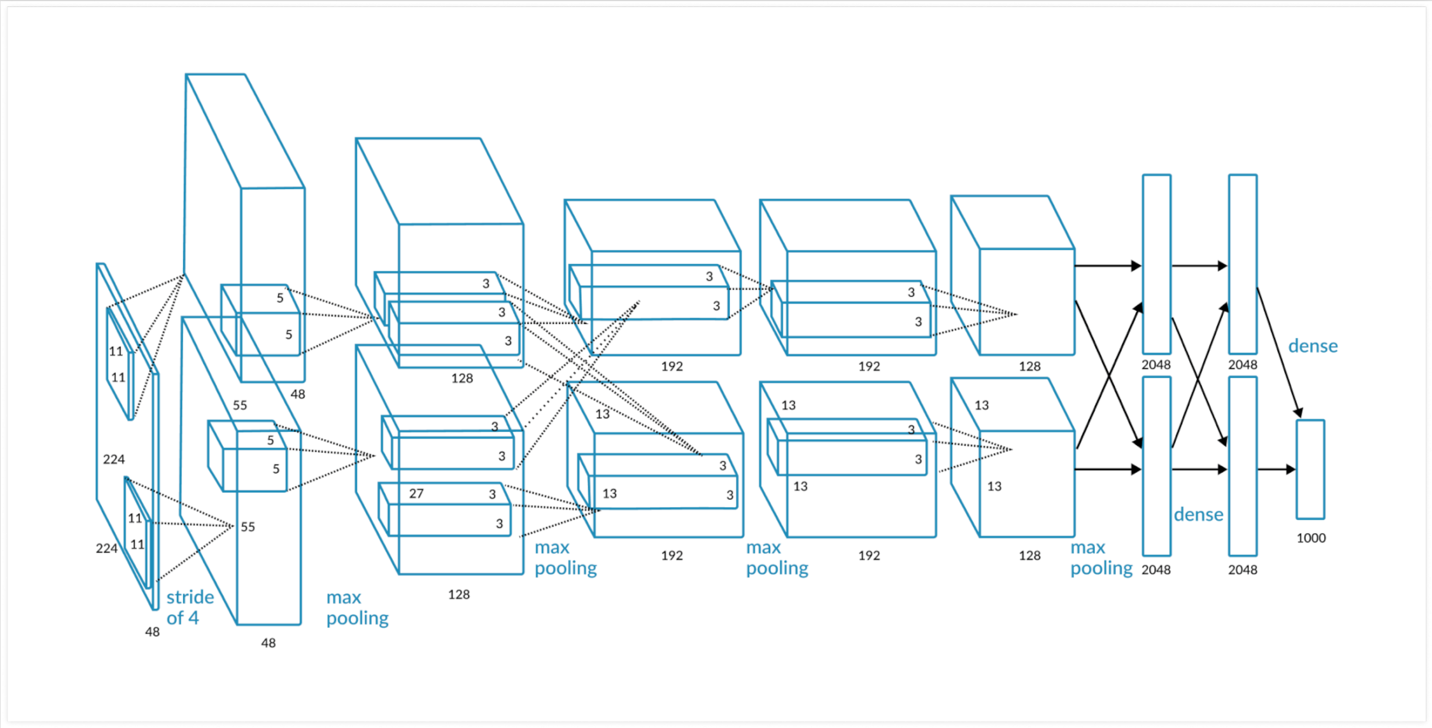
Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

Source: [LeCun et. al. 1998]

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

```python
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'))
```

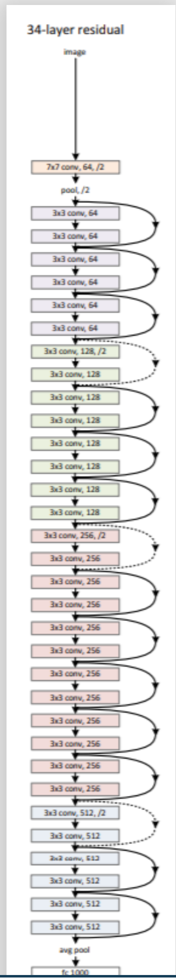
AlexNet (2012)



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% To-5 error rate with single model

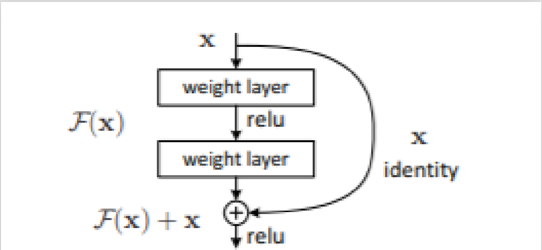


Figure 2. Residual learning: a building block.

Residual Learning

- "Is learning better networks as easy as stacking more layers?" Yes, but:
- "When deeper networks are able to start converging, a degradation problem has been exposed: with the network depth increasing, accuracy gets saturated... and then degrades rapidly. Unexpectedly, such degradation is not caused by overfitting, and adding more layers to a suitably deep model leads to higher training error" (a.k.a 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

APPLICATIONS

OF DATA SCIENCE

Why are we working so hard?

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/`.

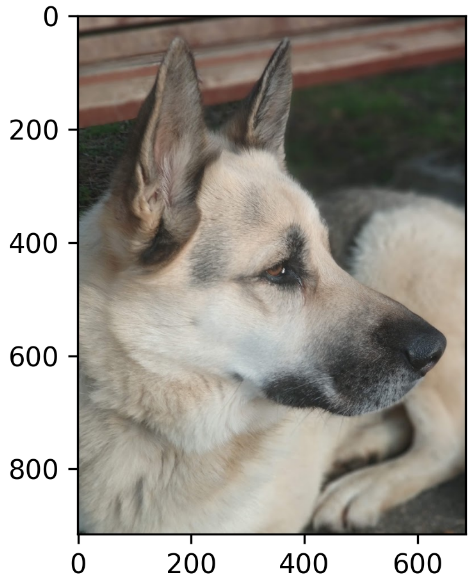
Upon instantiation, the models will be built according to the image data format set in your Keras configuration file at `~/.keras/keras.json`. For instance, if you have set `image_data_format=channels_last`, then any model loaded from this repository will get built according to the TensorFlow data format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

Available models

Model	Size	Top-1 Accuracy	Top-5 Accuracy	Parameters	Depth
Xception	88 MB	0.790	0.945	22,910,480	126
VGG16	528 MB	0.713	0.901	138,357,544	23
VGG19	549 MB	0.713	0.900	143,667,240	26
ResNet50	98 MB	0.749	0.921	25,636,712	-
ResNet101	171 MB	0.764	0.928	44,707,176	-
ResNet152	232 MB	0.766	0.931	60,419,944	-
ResNet50V2	98 MB	0.760	0.930	25,613,800	-
ResNet101V2	171 MB	0.772	0.938	44,675,560	-
ResNet152V2	232 MB	0.780	0.942	60,380,648	-
InceptionV3	92 MB	0.779	0.937	23,851,784	159
InceptionResNetV2	215 MB	0.803	0.953	55,873,736	572

Look up keras.io/api/applications/

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

model = ResNet50(weights='imagenet')

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

fig = plt.imshow(johann)
plt.show()
```



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

johann_pred = model.predict(johann)

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: 0.28
## Siberian_husky: 0.17
## German_shepherd: 0.14
## malamute: 0.06
```

Transfer Learning

Applications

Of Data Science

Got Data?

- I want a model that would be able to tell a barking dog vs. a non-barking dog.
- I have only 100 images of barking dogs and 100 images of non-barking dogs, I lazily saved from Google Images.
- I use `ImageDataGenerator` to augment my training set and build my go-to CNN.

```python
from tensorflow.keras.preprocessing.image import ImageDataGenerato

train_datagen = 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'
)

valid_datagen = ImageDataGenerator()
test_datagen = ImageDataGenerator()
```

```python
train_generator = train_datagen.flow_from_directory(
  'dogs/train/',
  target_size = (224,224),
  color_mode = 'rgb',
  batch_size = 10,
  class_mode = 'binary',
  shuffle = True,
  seed = 42
)
```

```
## Found 120 images belonging to 2 classes.
```

```
valid_generator = valid_datagen.flow_from_directory(
  'dogs/valid/',
  target_size = (224,224),
  color_mode = 'rgb',
  batch_size = 10,
  class_mode = 'binary',
  shuffle = False,
  seed = 42
)
```

```
## Found 40 images belonging to 2 classes.
```

```
test_generator = test_datagen.flow_from_directory(
  'dogs/test/',
  target_size = (224,224),
  color_mode = 'rgb',
  batch_size = 10,
  class_mode = 'binary',
  shuffle = False,
  seed = 42
)
```

```
## Found 40 images belonging to 2 classes.
```

```
model = Sequential()
model.add(Conv2D(filters=32, input_shape=(224, 224, 3),
  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'])

step_size_train = train_generator.n // train_generator.batch_size
step_size_valid = valid_generator.n // valid_generator.batch_size
step_size_test = test_generator.n // test_generator.batch_size

callbacks = [EarlyStopping(monitor='val_loss', patience=5,
  restore_best_weights=True)]

history = model.fit(train_generator, steps_per_epoch = step_size_t
  epochs = 50, callbacks = callbacks, validation_data = valid_gene
  validation_steps = step_size_valid, verbose = 0)
```

```python
y_true = test_generator.classes
y_pred = model.predict(test_generator, steps = step_size_test)
y_pred = (y_pred > 0.5).astype(int).reshape(y_true.shape)

print(np.mean(y_true == y_pred))
```

```
## 0.625
```

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

```
##           pred:yes  pred:no
## true:yes        14        6
## true:no          9       11
```

For my next trick I shall need someone else's hard work.

```
from tensorflow.keras.applications.mobilenet import MobileNet, pre
from tensorflow.keras.layers import GlobalAveragePooling2D
from tensorflow.keras import Model

base_model = MobileNet(weights='imagenet', include_top=False,
  input_shape = (224, 224, 3))
```

```python
l = base_model.output
l = GlobalAveragePooling2D()(l)
out = Dense(1, activation='sigmoid')(l)

model = Model(inputs = base_model.input, outputs = out)

for layer in model.layers[:20]:
    layer.trainable = False
for layer in model.layers[20:]:
    layer.trainable = True

model.compile(loss='binary_crossentropy',
  optimizer='adam', metrics=['accuracy'])
```

```
train_datagen = ImageDataGenerator(
  preprocessing_function = preprocess_input,
  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'
)

valid_datagen = ImageDataGenerator(
  preprocessing_function = preprocess_input
)

test_datagen = ImageDataGenerator(
  preprocessing_function = preprocess_input
)
```

```
train_generator = train_datagen.flow_from_directory(
  'dogs/train/',
  target_size = (224,224),
  color_mode = 'rgb',
  batch_size = 10,
  class_mode = 'binary',
  shuffle = True,
  seed = 42
)
```

```
## Found 120 images belonging to 2 classes.
```

```
valid_generator = valid_datagen.flow_from_directory(
  'dogs/valid/',
  target_size = (224,224),
  color_mode = 'rgb',
  batch_size = 10,
  class_mode = 'binary',
  shuffle = False,
  seed = 42
)
```

```
## Found 40 images belonging to 2 classes.
```

```
test_generator = test_datagen.flow_from_directory(
  'dogs/test/',
  target_size = (224,224),
  color_mode = 'rgb',
  batch_size = 10,
  class_mode = 'binary',
  shuffle = False,
  seed = 42
)
```

```
## Found 40 images belonging to 2 classes.
```

```
step_size_train = train_generator.n // train_generator.batch_size
step_size_valid = valid_generator.n // valid_generator.batch_size
step_size_test = test_generator.n // test_generator.batch_size

callbacks = [EarlyStopping(monitor='val_loss', patience=5,
  restore_best_weights=True)]

history = model.fit(train_generator, steps_per_epoch = step_size_t
  epochs = 50, callbacks = callbacks, validation_data = valid_gene
  validation_steps = step_size_valid, verbose = 0)
```

```
y_true = test_generator.classes
y_pred = model.predict(test_generator, steps = step_size_test)
y_pred = (y_pred > 0.5).astype(int).reshape(y_true.shape)

print(np.mean(y_true == y_pred))

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

```
## 0.85
```

```
##           pred:yes  pred:no
## true:yes        17        3
## true:no          3       17
```

⚠ Bug in `ImageDataGenerator`?

What just happened?

- The ImageNet networks have learned to differentiate between 120 dog breeds!
- Clearly there's some knowledge about dogs gained in the low-level layers (features)
- Freezing those layers and harnessing that output for our purpose makes sense
- Think of it as a "warm start"
- After a few epochs try to unfreeze the low layers then use a very small learning rate for a few additional epochs, to gain some more predictive power

Other Computer Vision Tasks

What's Next?

- Localization
- Object Detection
- Segmentation
- Captioning
- 3D Reconstruction
- Restoration
- Pose Estimation
- GANs GANs GANs
- Doing it all on Video
- And doing it all in real time, on your phone or in your car