MASTER OF SCIENCE
IN ENGINEERING

Deep Learning

TSM-DeLearn

8. Keras - Convolutional Neural Networks

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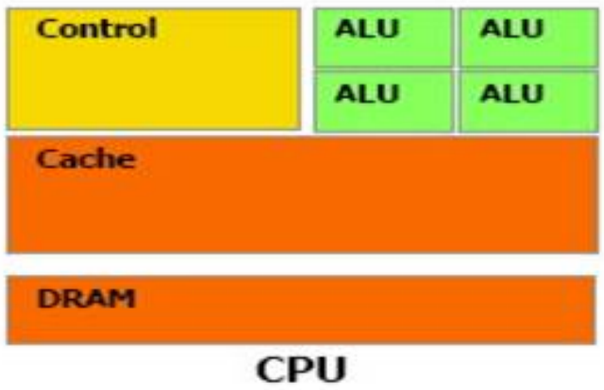
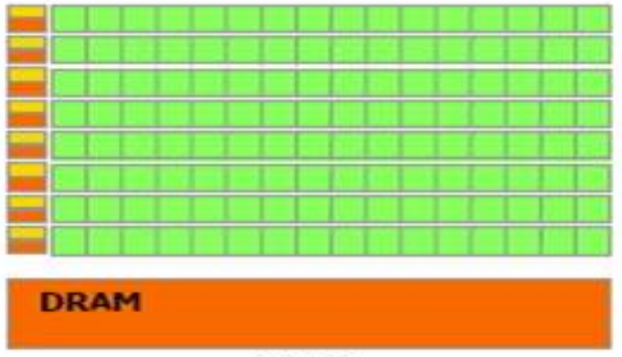
RECAP 1 - CPU vs GPU



CPU



GPU

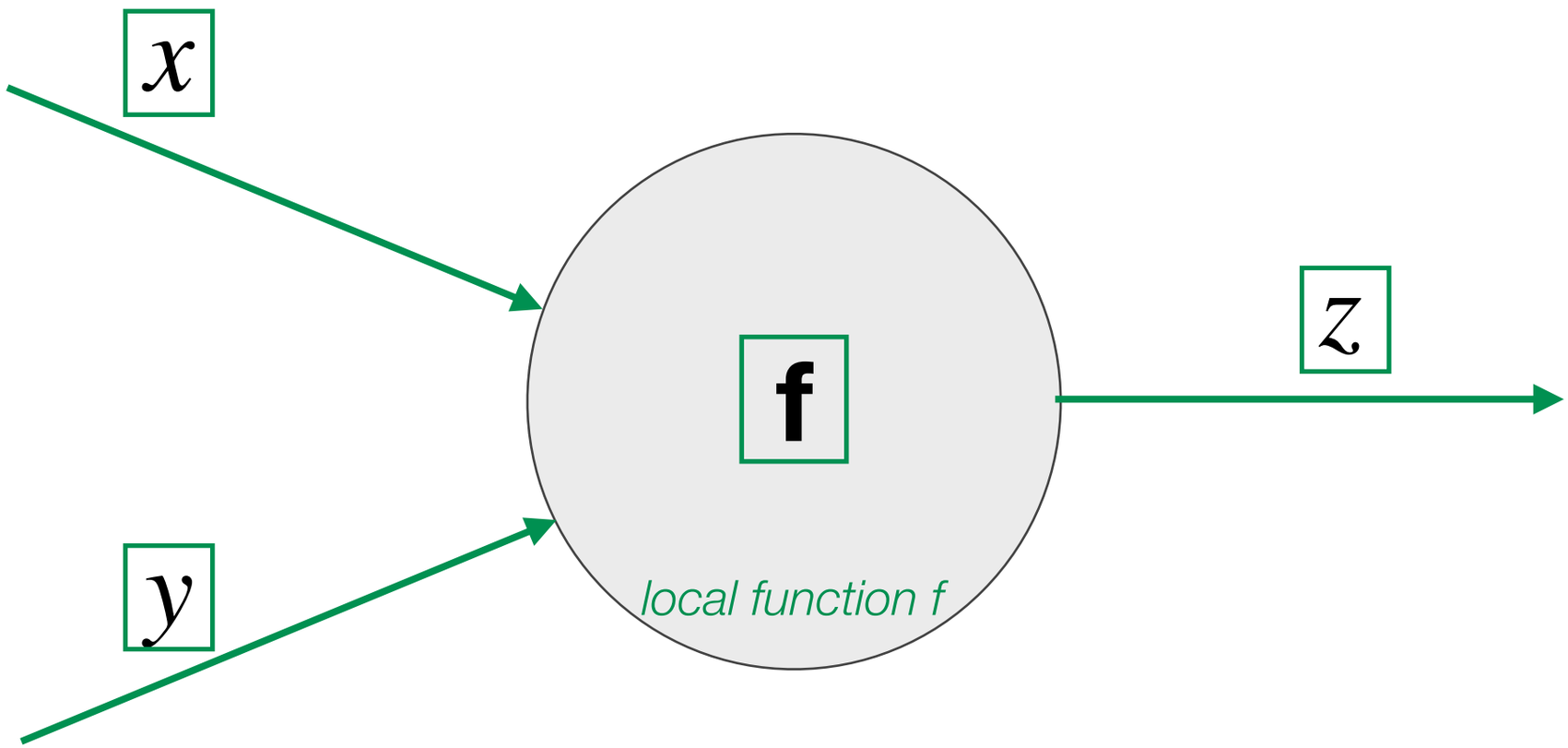
CPU - Central Processing Unit

- Few cores (~10), fast (~4 GHz), lots of cache, few parallel processes
- Great at sequential tasks
- Providers: Intel, AMD

GPU - Graphical Processing Unit

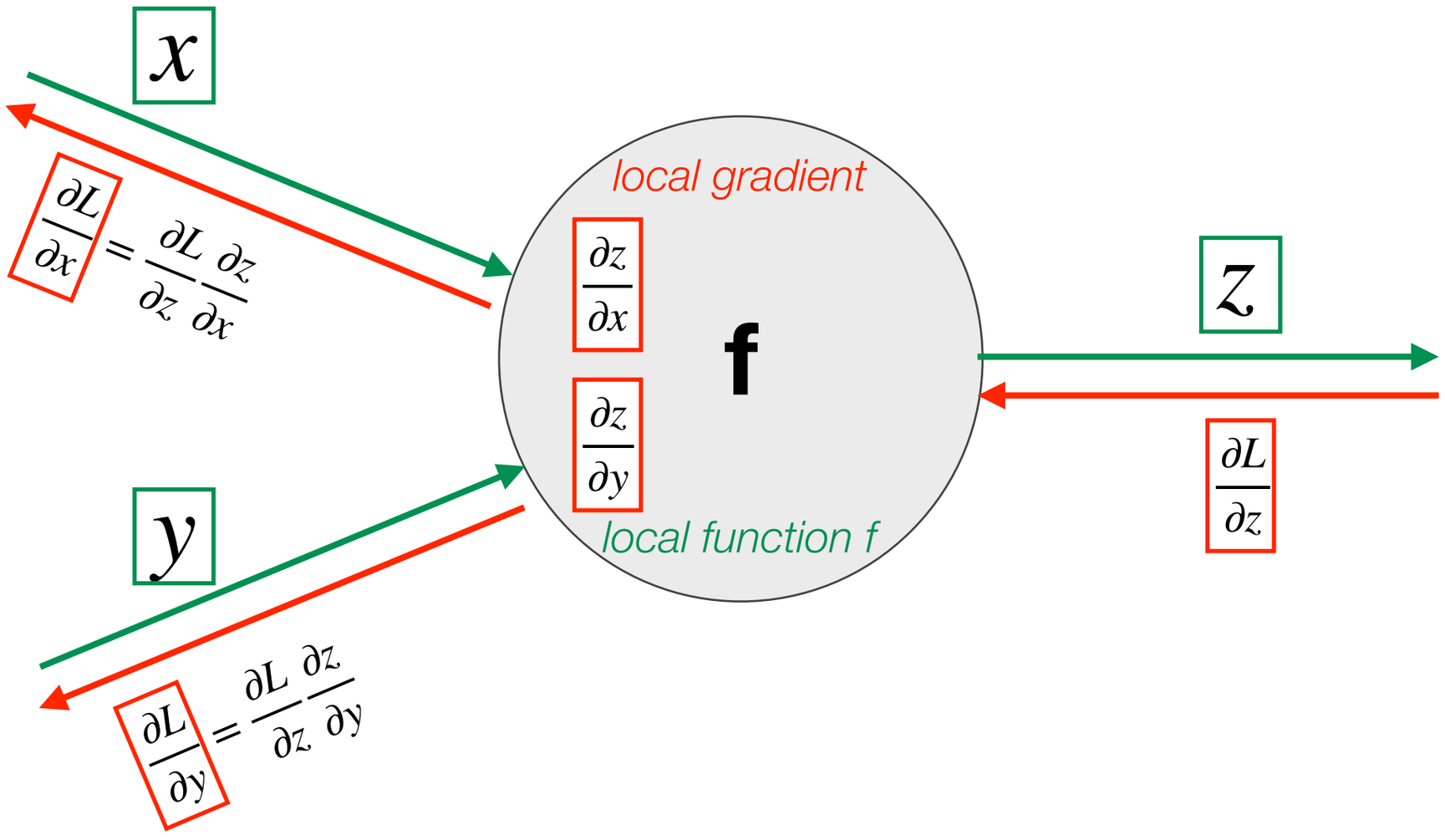
- Many cores (~1’000), slow (~1.5 GHz)), few cache, many parallel processes
- Great at parallel tasks
- Providers: **NVIDIA**, AMD

RECAP 2 - Computational Graphs
Node - forward / backward principles



Forward = propagate the signal in the graph

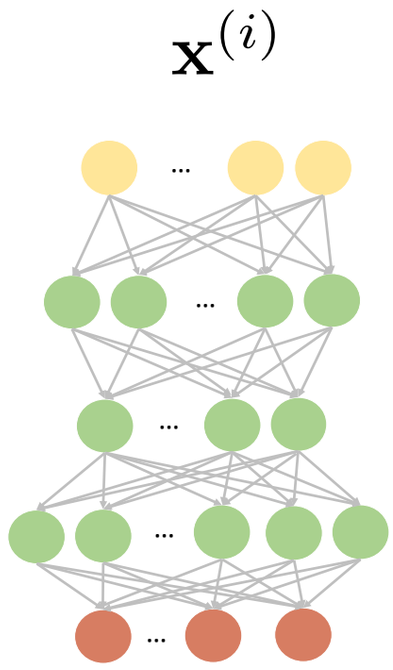
RECAP 2 - Computational Graphs
Node - forward / backward principles



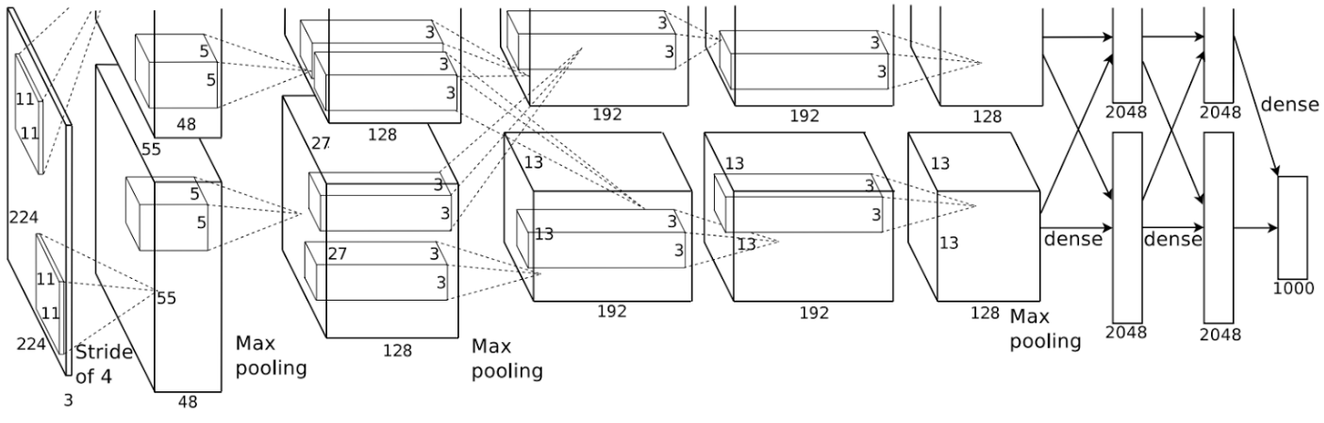
Backward = back-propagate the gradient in the graph with the chain rule

RECAP 3
4 main reasons to use DL frameworks

1. Easily build big computational graphs
2. Easily compute losses $L(\hat{\mathbf{y}}^{(i)}, \mathbf{y}^{(i)})$ and gradients in computational graphs for update rules $\text{param} \leftarrow \text{param} - \alpha \frac{\partial L}{\partial \text{param}}$
3. Have at hand all the state-of-the-art strategies for regularisations and optimisations
4. Switch easily from cpu to gpu when needed

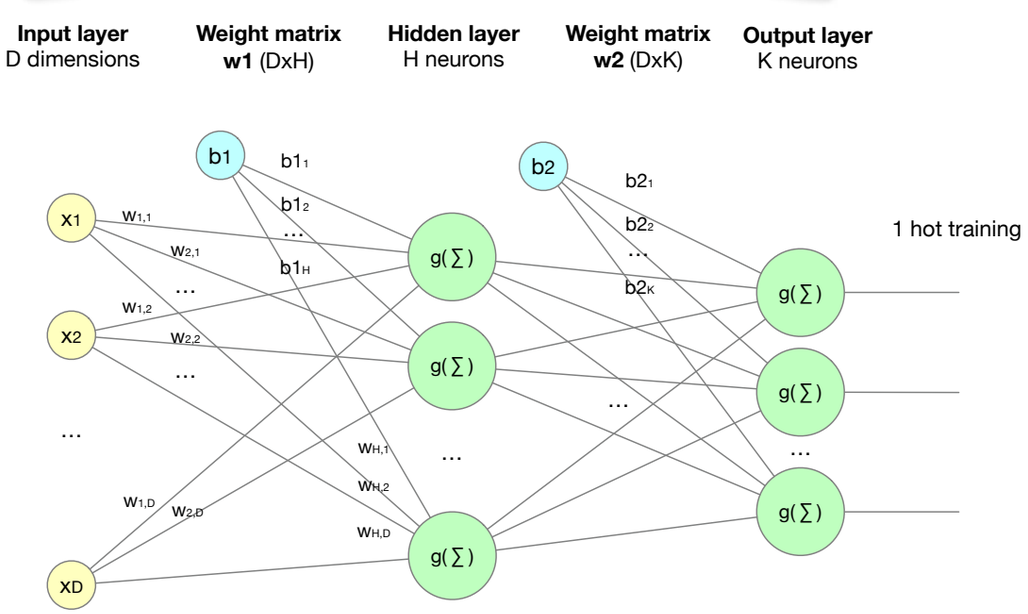


$$\hat{\mathbf{y}}^{(i)} = h_\theta(\mathbf{x}^{(i)})$$



RECAP 4 - TensorFlow - a more complex example

First define the computational graph.
No computation, just building the graph.




```
# Build the computational graph
x = tf.placeholder(tf.float32, shape=(B, D))
y = tf.placeholder(tf.float32, shape=(B, n_classes))
alpha = tf.placeholder(tf.float32, shape=())
w1 = tf.Variable(tf.truncated_normal((D, H), stddev = 0.1))
b1 = tf.Variable(tf.constant(0.0, shape=[H]))
w2 = tf.Variable(tf.truncated_normal((H, n_classes), stddev = 0.1))
b2 = tf.Variable(tf.constant(0.0, shape=[n_classes]))

h = tf.maximum(tf.matmul(x, w1) + b1, 0.0)
y_pred = tf.sigmoid(tf.matmul(h, w2) + b2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))
grad_w1, grad_b1, grad_w2, grad_b2 = tf.gradients(loss, [w1, b1, w2, b2])

new_w1 = w1.assign(w1 - alpha * grad_w1)
new_b1 = b1.assign(b1 - alpha * grad_b1)
new_w2 = w2.assign(w2 - alpha * grad_w2)
new_b2 = b2.assign(b2 - alpha * grad_b2)
updates = tf.group(new_w1, new_b1, new_w2, new_b2)
```

Then run the graph.

```
# Run the computational graph
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    J = []
    for epoch in range(E):
        J_epoch = 0.0
        for _ in range(int(N/B)): # number of batches to visit for 1 epoch
            x_train_batch, y_train_batch = next_batch(B, x_train, y_train)
            values = { x: x_train_batch, y: y_train_batch, alpha: A}
            loss_val = sess.run([loss, updates], feed_dict=values)
            J_epoch += loss_val[0]
        J.append(J_epoch)
        print("epoch", epoch, J_epoch)

    # now retrieve the weights and bias out of the computational graph
    w1_trained, b1_trained, w2_trained, b2_trained = sess.run([w1, b1, w2, b2])
```

Plan

1. Keras
2. CNN - Convolutional Neural Networks
3. PW on CNN with Keras

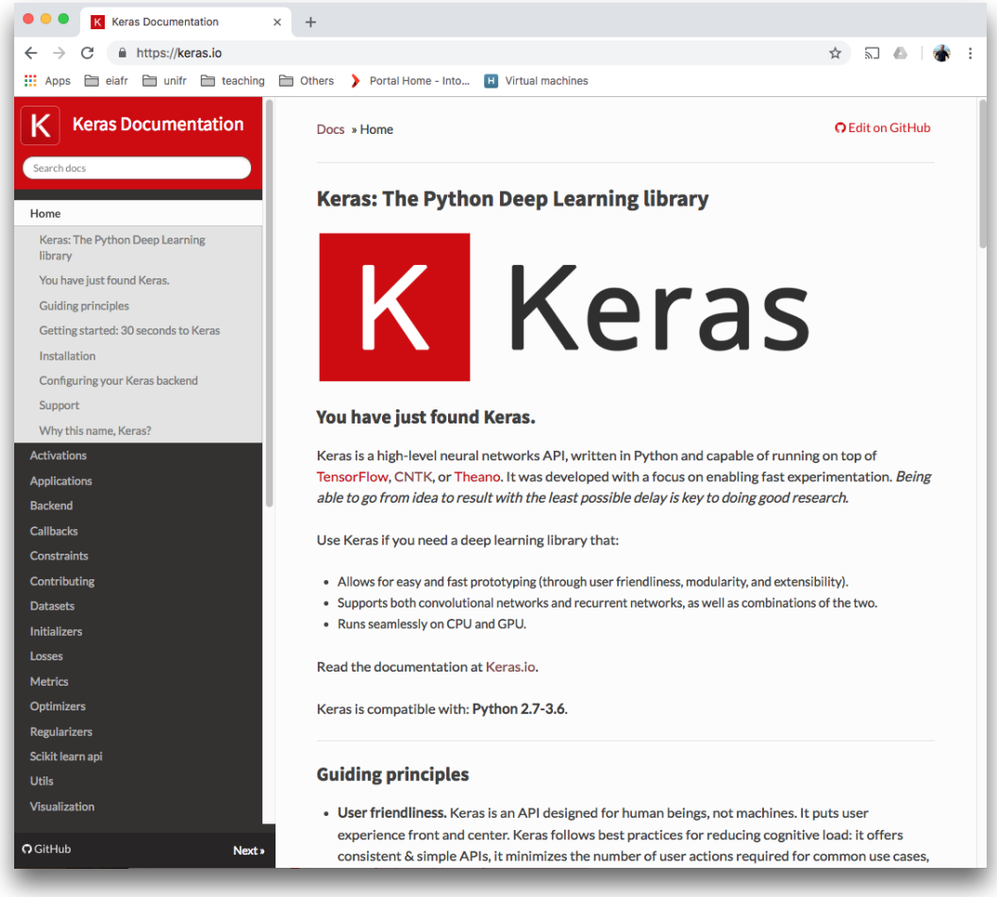
Keras

Overview
Cheat Sheet
Example

Keras - what is it?

Keras is a high-level open-source neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation.

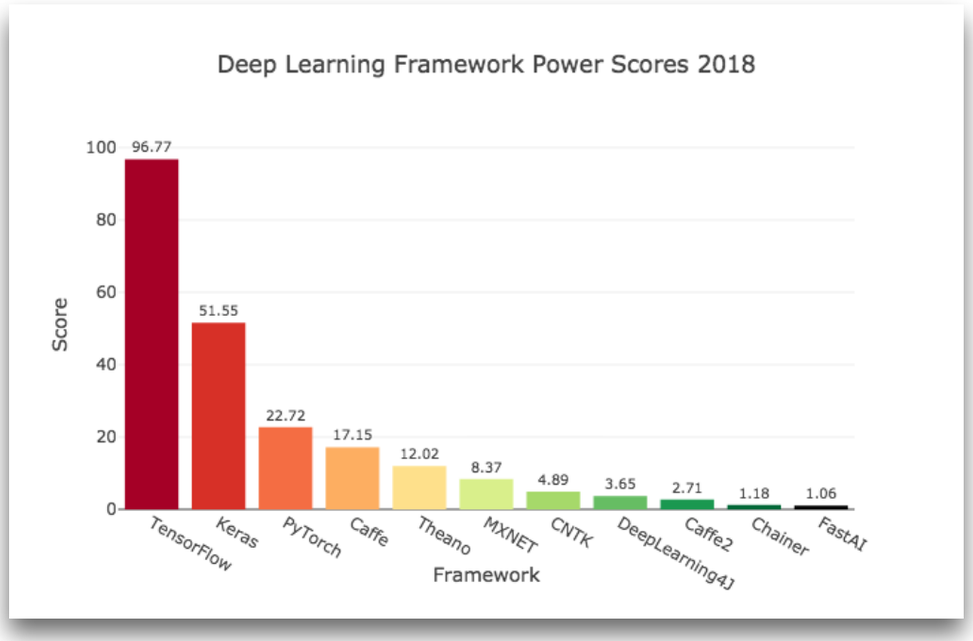
- Designed to be minimalistic & straight forward yet extensive
- “Deep” enough to build serious models
  - Support Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), combination of both.
- Wrapper on top of TF / CNTK / Theano backend
  - But not only a wrapper - see next slides

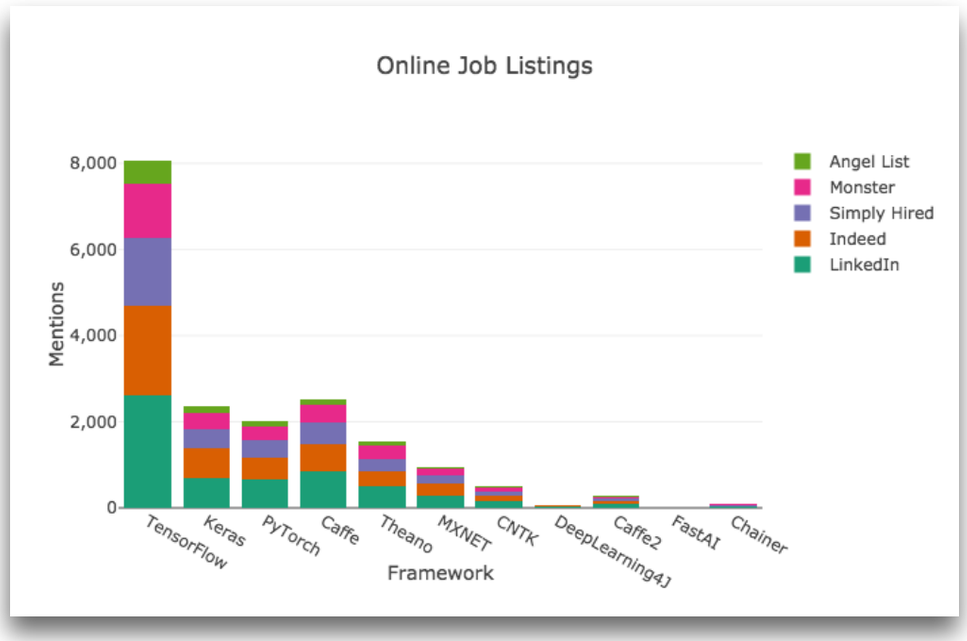


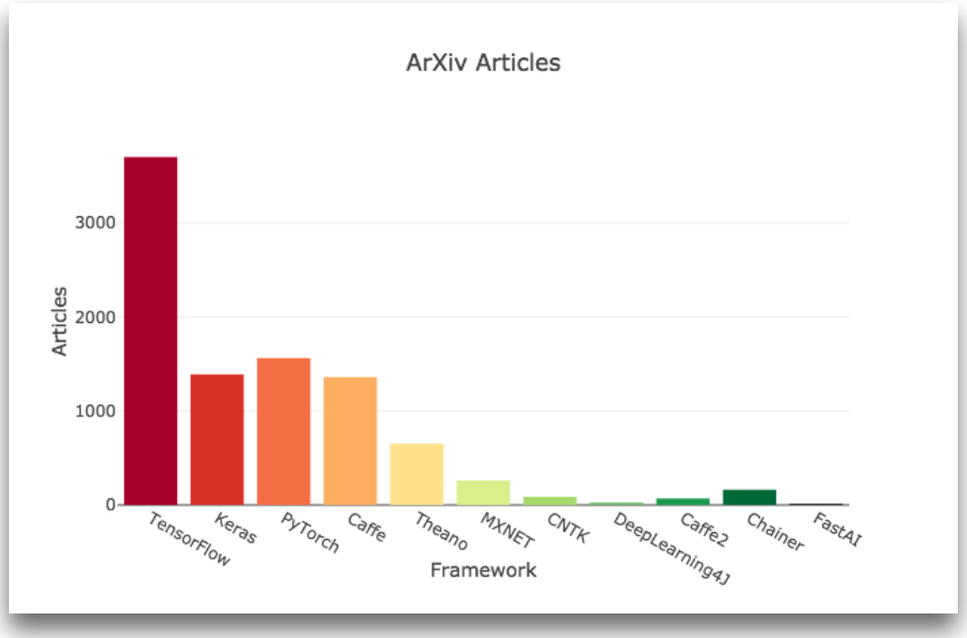
Source: https://keras.io

Keras - why using?

- Simple to use, well done documentation
- Not only wrapper, it “integrates” with TensorFlow
  - K can call low-level TF methods
  - TF can call high-level Keras methods
- Not only TF, also CNTK (from Microsoft) and Theano
  - Code and model portability
    - For ex train on TF and test on CNTK
  - MXNet coming soon (officially not supported yet)





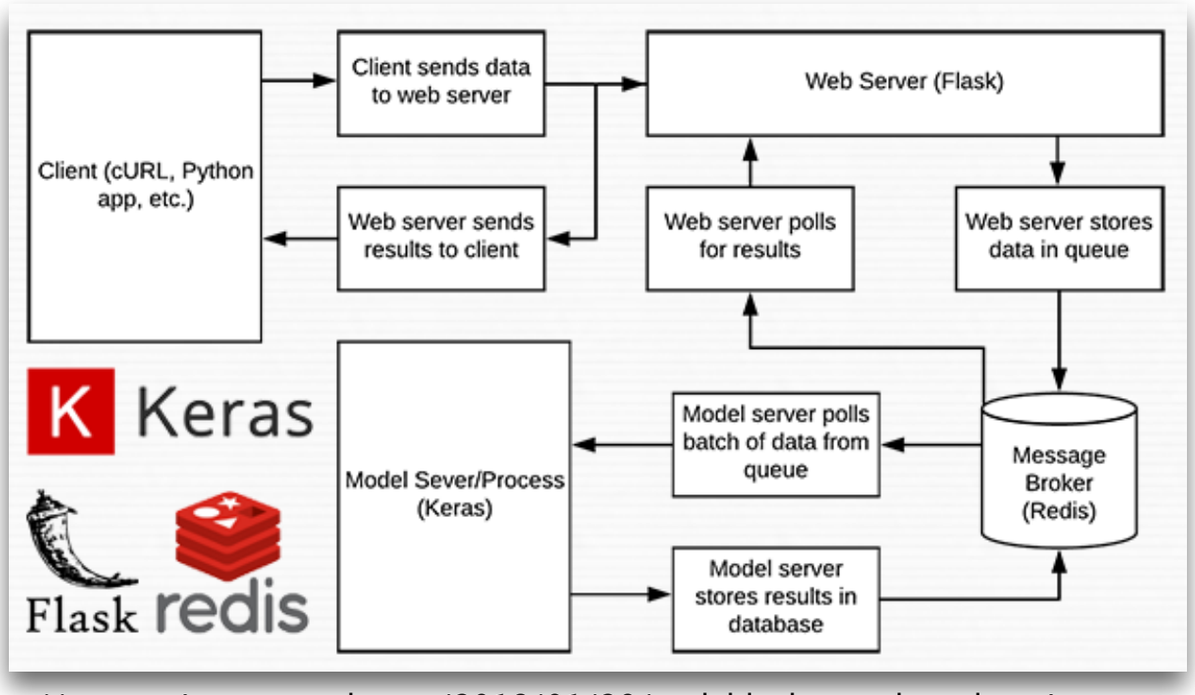


Source: https://towardsdatascience.com/deep-learning-framework-power-scores-2018-23607ddf297a

Keras - why using?

- Not only for research, in production at Netflix, Uber, Yelp, Instacart, Zocdoc, Square, and many others.
- Going into production:
  - On iOS, via Apple's CoreML
  - On Android, via TensorFlow Android runtime.
    - Example: Not Hotdog app. See the hilarious Silicon Valley episode https://youtu.be/mrk95jFVKqY
- In the browser, via GPU-accelerated JavaScript runtimes such as Keras.js and WebDNN
- On Google Cloud, via TensorFlow-Serving
- In an R or Python webapp backend (such as a Shiny or Flask app)

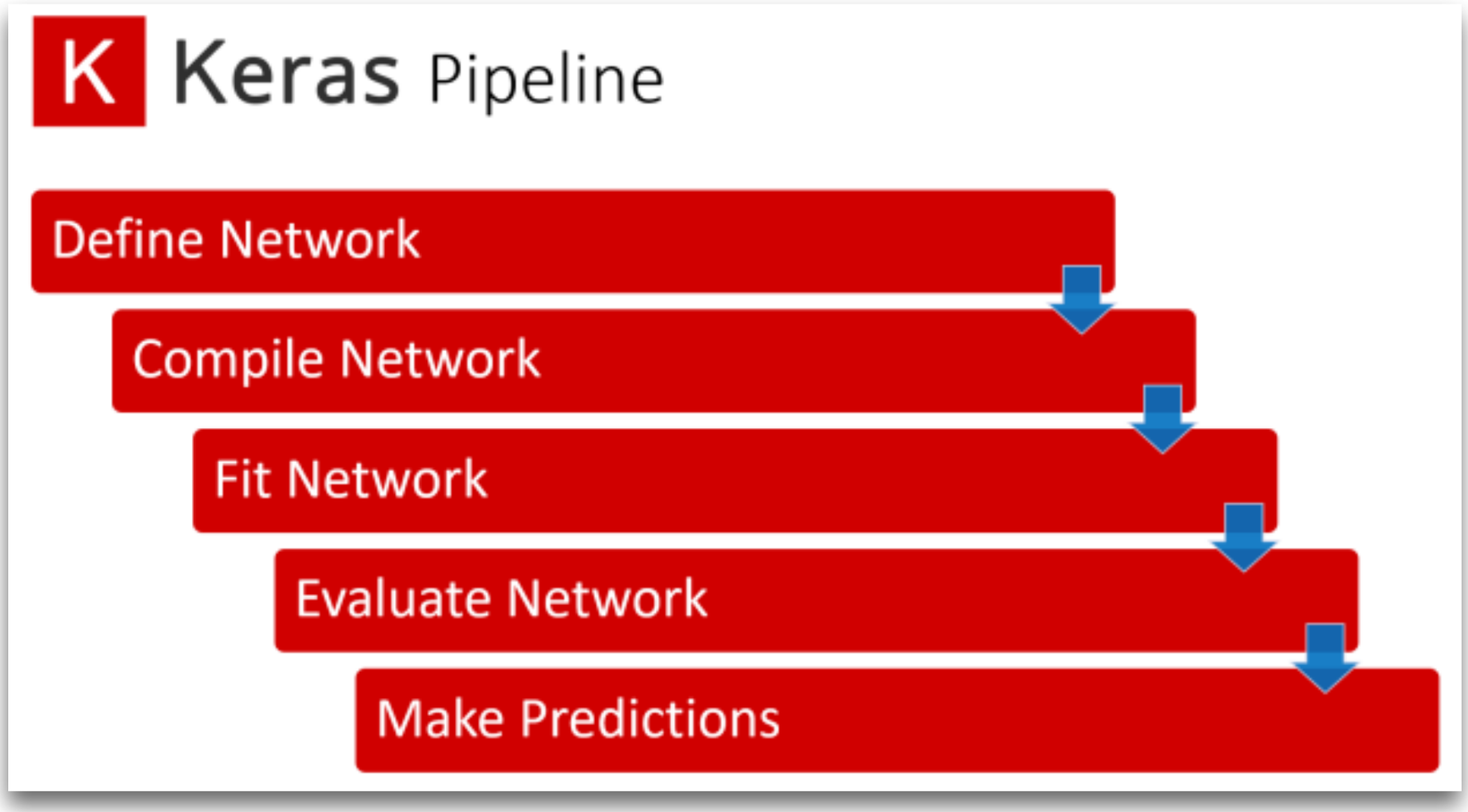
Source: https://keras.rstudio.com/articles/why_use_keras.html



https://www.pyimagesearch.com/2018/01/29/scalable-keras-deep-learning-rest-api/

Keras pipeline

- Simple unified neural network pipeline



Source: https://naadispeaks.wordpress.com/2018/06/26/keras-the-api-for-human-beings/

In-class exercise - MNIST-MLP with Keras

- Get the '`MNIST-MLP_from_raw_data-to-complete.ipynb`'
- Complete the missing parts to implement a simple MLP taking the pixel data as input.
- Use the cheatsheet as help.

Python For Data Science *Cheat Sheet*

Keras

Learn Python for data science **Interactively** at www.DataCamp.com

Keras

Keras is a powerful and easy-to-use deep learning library for Theano and TensorFlow that provides a high-level neural networks API to develop and evaluate deep learning models.

A Basic Example

```
>>> import numpy as np
>>> from keras.models import Sequential
>>> from keras.layers import Dense
>>> data = np.random.random((1000,100))
>>> labels = np.random.randint(2,size=(1000,1))
>>> model = Sequential()
>>> model.add(Dense(32,
                    activation='relu',
                    input_dim=100))
>>> model.add(Dense(1, activation='sigmoid'))
>>> model.compile(optimizer='rmsprop',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions = model.predict(data)
```

Data

Also see NumPy, Pandas & Scikit-Learn

Your data needs to be stored as NumPy arrays or as a list of NumPy arrays. Ideally, you split the data in training and test sets, for which you can also resort to the `train_test_split` module of `sklearn.cross_validation`.

Keras Data Sets

```
>>> from keras.datasets import boston_housing,
                               mnist,
                               cifar10,
                               imdb
>>> (x_train,y_train),(x_test,y_test) = mnist.load_data()
>>> (x_train2,y_train2),(x_test2,y_test2) = boston_housing.load_data()
>>> (x_train3,y_train3),(x_test3,y_test3) = cifar10.load_data()
>>> (x_train4,y_train4),(x_test4,y_test4) = imdb.load_data(num_words=20000)
>>> num_classes = 10
```

Other

```
>>> from urllib.request import urlopen
>>> data = np.loadtxt(urlopen("http://archive.ics.uci.edu/
ml/machine-learning-databases/pima-indians-diabetes/
pima-indians-diabetes.data"),delimiter=",")
>>> X = data[:,0:8]
>>> y = data [:,8]
```

Model Architecture

Sequential Model

```
>>> from keras.models import Sequential
>>> model = Sequential()
>>> model2 = Sequential()
>>> model3 = Sequential()
```

Multilayer Perceptron (MLP)

Binary Classification

```
>>> from keras.layers import Dense
>>> model.add(Dense(12,
                    input_dim=8,
                    kernel_initializer='uniform',
                    activation='relu'))
>>> model.add(Dense(8,kernel_initializer='uniform',activation='relu'))
>>> model.add(Dense(1,kernel_initializer='uniform',activation='sigmoid'))
```

Multi-Class Classification

```
>>> from keras.layers import Dropout
>>> model.add(Dense(512,activation='relu',input_shape=(784,)))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(512,activation='relu'))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(10,activation='softmax'))
```

Regression

```
>>> model.add(Dense(64,activation='relu',input_dim=train_data.shape[1]))
>>> model.add(Dense(1))
```

Convolutional Neural Network (CNN)

```
>>> from keras.layers import Activation,Conv2D,MaxPooling2D,Flatten
>>> model2.add(Conv2D(32,(3,3),padding='same',input_shape=x_train.shape[1:]))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(32,(3,3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))

>>> model2.add(Conv2D(64,(3,3), padding='same'))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv2D(64,(3, 3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D(pool_size=(2,2)))
>>> model2.add(Dropout(0.25))

>>> model2.add(Flatten())
>>> model2.add(Dense(512))
>>> model2.add(Activation('relu'))
>>> model2.add(Dropout(0.5))
>>> model2.add(Dense(num_classes))
>>> model2.add(Activation('softmax'))
```

Recurrent Neural Network (RNN)

```
>>> from keras.klayers import Embedding,LSTM
>>> model3.add(Embedding(20000,128))
>>> model3.add(LSTM(128,dropout=0.2,recurrent_dropout=0.2))
>>> model3.add(Dense(1,activation='sigmoid'))
```

Inspect Model

`>>> model.output_shape`	Model output shape
`>>> model.summary()`	Model summary representation
`>>> model.get_config()`	Model configuration
`>>> model.get_weights()`	List all weight tensors in the model

Compile Model

MLP: Binary Classification

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

MLP: Multi-Class Classification

```
>>> model.compile(optimizer='rmsprop',
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
```

MLP: Regression

```
>>> model.compile(optimizer='rmsprop',
                  loss='mse',
                  metrics=['mae'])
```

Recurrent Neural Network

```
>>> model3.compile(loss='binary_crossentropy',
                   optimizer='adam',
                   metrics=['accuracy'])
```

Model Training

```
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               verbose=1,
               validation_data=(x_test4,y_test4))
```

Evaluate Your Model's Performance

```
>>> score = model3.evaluate(x_test,
                            y_test,
                            batch_size=32)
```

Prediction

```
>>> model3.predict(x_test4, batch_size=32)
>>> model3.predict_classes(x_test4,batch_size=32)
```

Save/ Reload Models

```
>>> from keras.models import load_model
>>> model3.save('model_file.h5')
>>> my_model = load_model('my_model.h5')
```

Model Fine-tuning

Optimization Parameters

```
>>> from keras.optimizers import RMSprop
>>> opt = RMSprop(lr=0.0001, decay=1e-6)
>>> model2.compile(loss='categorical_crossentropy',
                   optimizer=opt,
                   metrics=['accuracy'])
```

Early Stopping

```
>>> from keras.callbacks import EarlyStopping
>>> early_stopping_monitor = EarlyStopping(patience=2)
>>> model3.fit(x_train4,
               y_train4,
               batch_size=32,
               epochs=15,
               validation_data=(x_test4,y_test4),
               callbacks=[early_stopping_monitor])
```

Preprocessing

Also see NumPy & Scikit-Learn

Sequence Padding

```
>>> from keras.preprocessing import sequence
>>> x_train4 = sequence.pad_sequences(x_train4,maxlen=80)
>>> x_test4 = sequence.pad_sequences(x_test4,maxlen=80)
```

One-Hot Encoding

```
>>> from keras.utils import to_categorical
>>> Y_train = to_categorical(y_train, num_classes)
>>> Y_test = to_categorical(y_test, num_classes)
>>> Y_train3 = to_categorical(y_train3, num_classes)
>>> Y_test3 = to_categorical(y_test3, num_classes)
```

Train and Test Sets

```
>>> from sklearn.model_selection import train_test_split
>>> X_train5,X_test5,y_train5,y_test5 = train_test_split(X,
                                                         y,
                                                         test_size=0.33,
                                                         random_state=42)
```

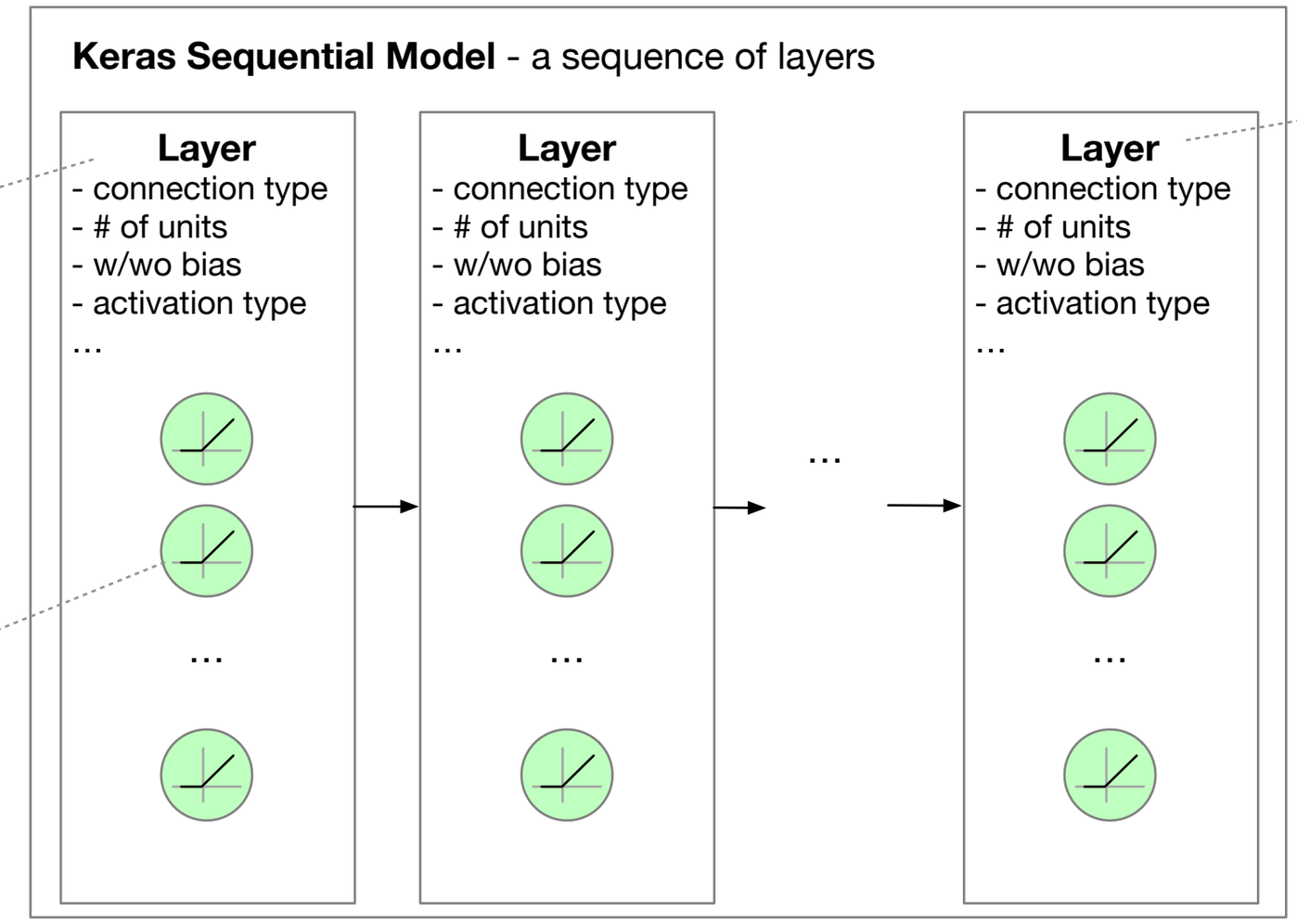
Standardization/Normalization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler = StandardScaler().fit(x_train2)
>>> standardized_X = scaler.transform(x_train2)
>>> standardized_X_test = scaler.transform(x_test2)
```

DataCamp
Learn Python for Data Science Interactively

Keras Models

- A **model** in Keras is the way to organise the layers of neurons: sequential or graph
- The **sequential** model corresponds to a regular stack of layers
  - 1 layer = 1 object that feeds to the next



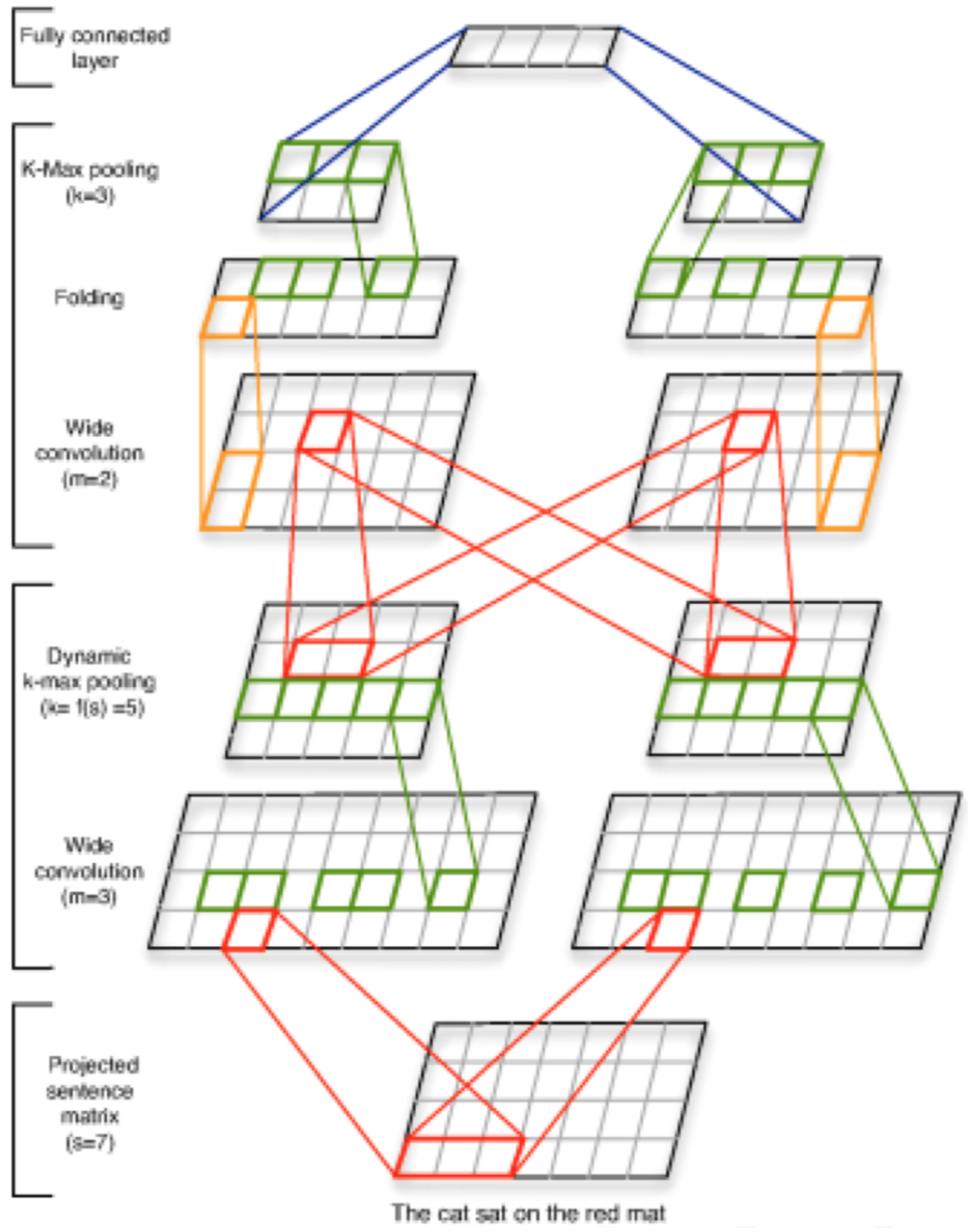
Once the model initialised, we "add()" layers

The term "unit" is used to represent a neuron

A layer is defined by the type of connections to the previous layer, e.g. Dense, by the number of neurons, by the activation type, e.g. ReLu, sigmoid, … by the use or not of bias terms, etc

Keras Models

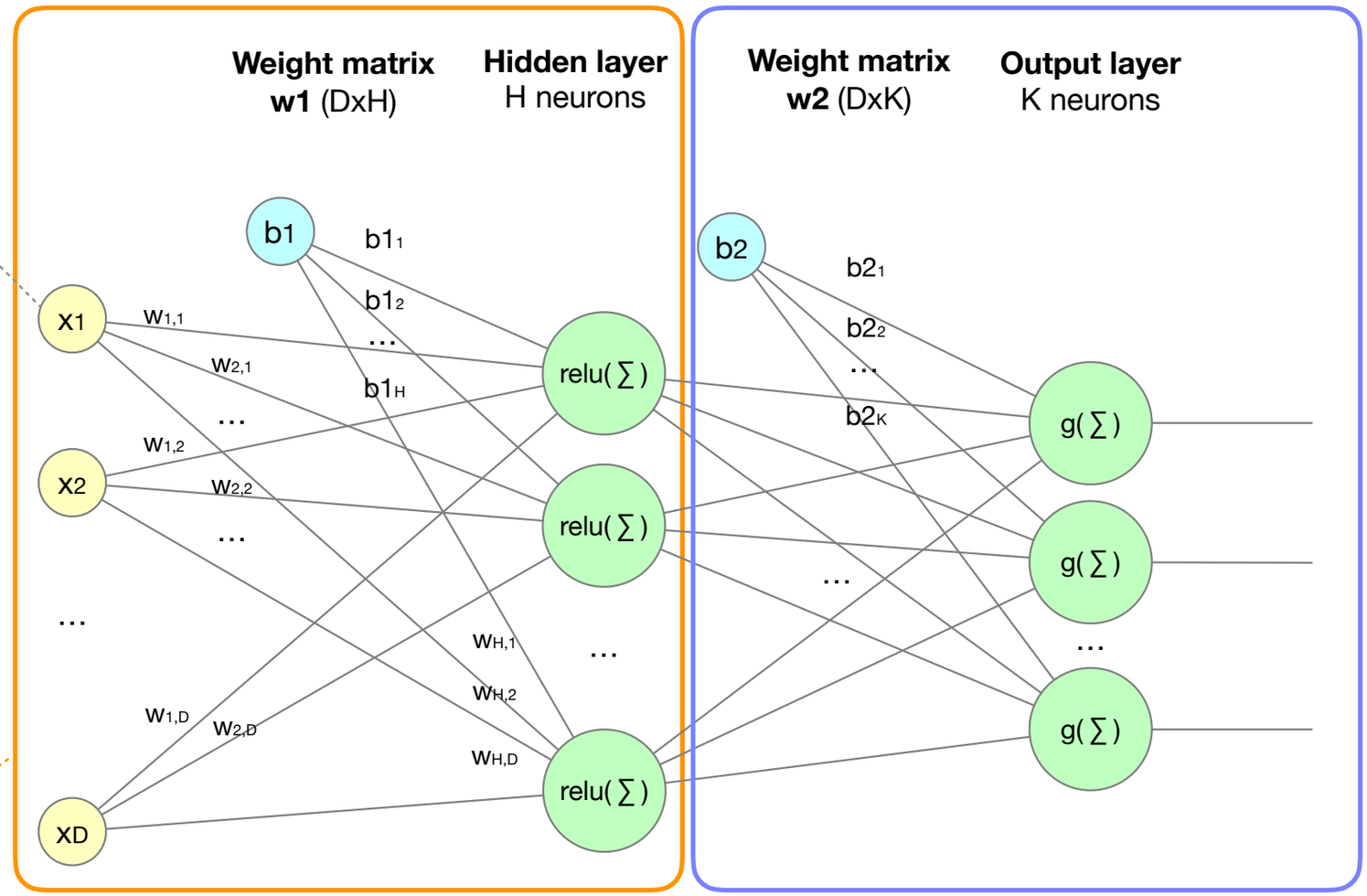
- The **graph** model is used for non sequential architectures
  - Typically allowing for independent networks to diverge or merge



Layers in Keras - Dense

- Dense layers represent fully connected layers of neurons

Note: the "input layer" usually defined in books is actually not a really a layer.



model.add(Dense(H, input_shape=(D,), activation='relu'))

model.add(Dense(n_classes, activation='sigmoid'))

Convolutional Neural Networks - CNN

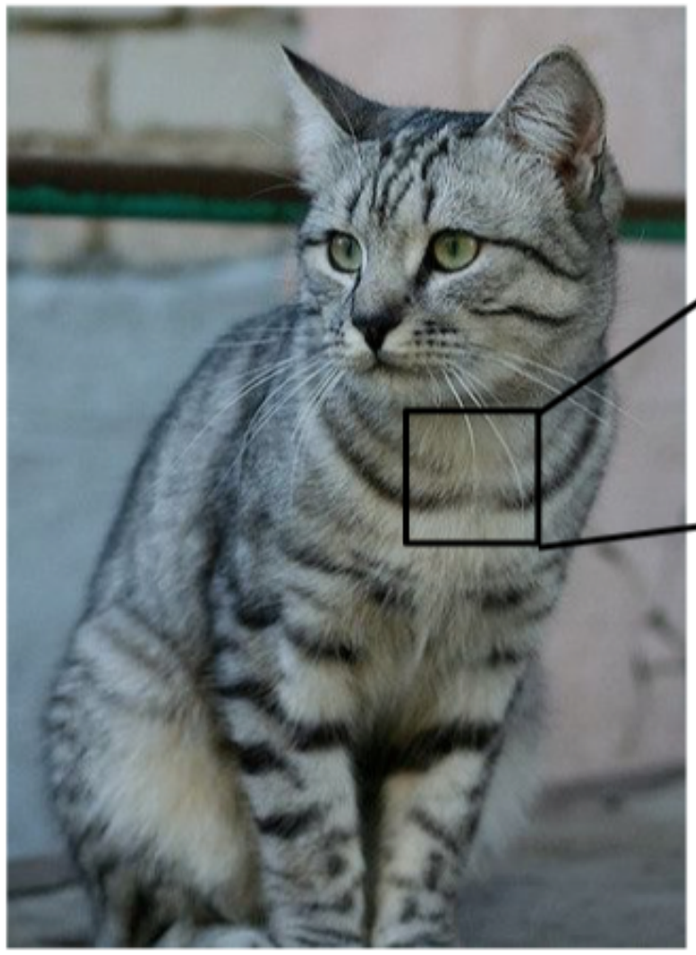
Motivations - image classification

Intuition behind a one-layer classifier

CNN Motivations

- Initially motivated to face the challenges of object recognition in images
  - viewpoint, zoom
  - illumination variability
  - object deformation
  - object occlusion
  - background noise
  - intra-class variability
- General idea: let's define new type of layers and connections that will bring
  - preservation of the spatial structure
  - hierarchical feature detection - objects are composed of features that are themselves composed of other features
  - robustness to object variabilities such as viewpoint, occlusion, etc

Image representation



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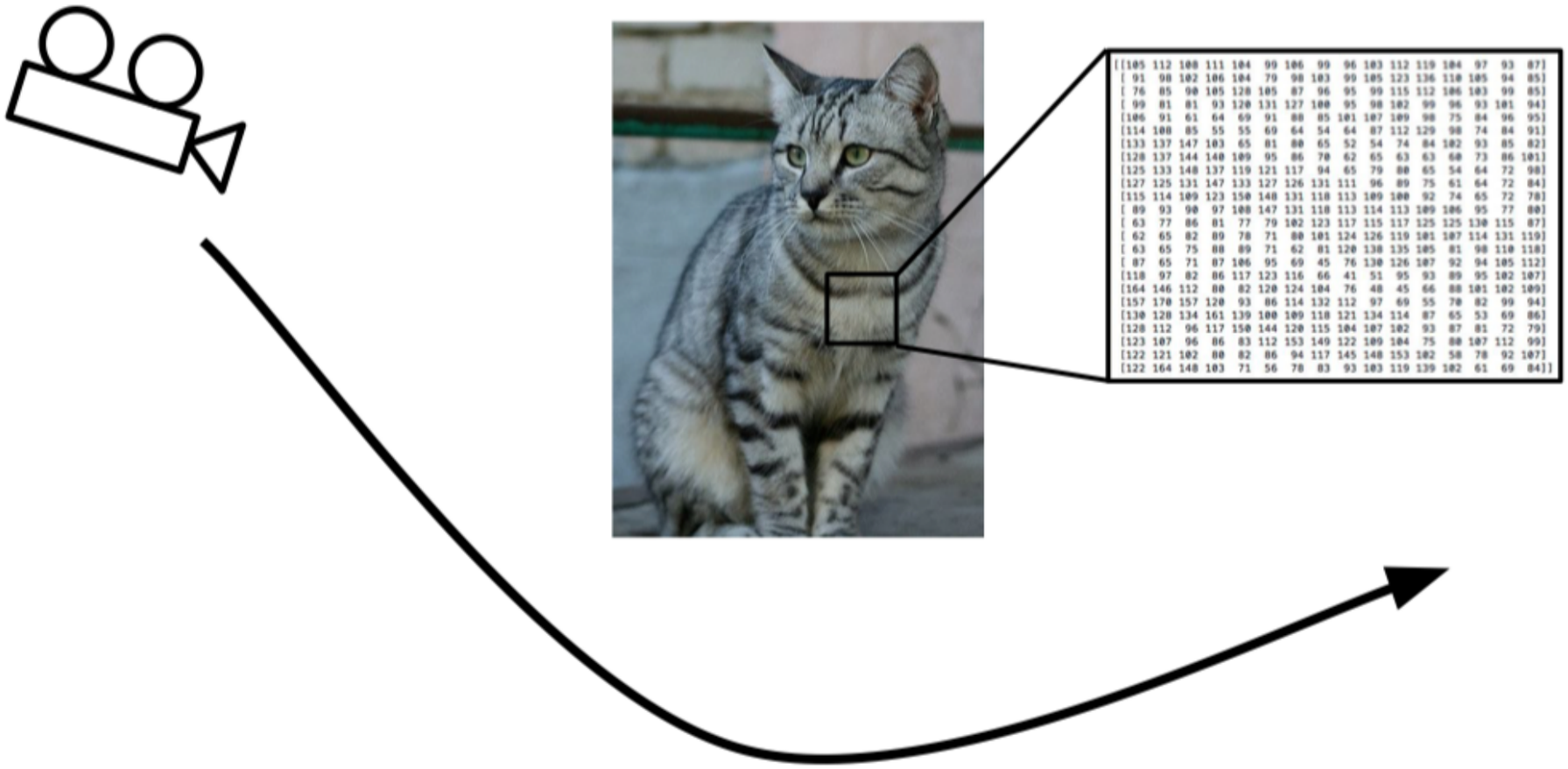
```
[[105 112 108 111 104  99 106  99  96 103 112 119 104  97  93  87]
 [ 91  98 102 106 104  79  98 103  99 105 123 136 110 105  94  85]
 [ 76  85  90 105 128 105  87  96  95  99 115 112 106 103  99  85]
 [ 99  81  81  93 120 131 127 100  95  98 102  99  96  93 101  94]
 [106  91  61  64  69  91  88  85 101 107 109  98  75  84  96  95]
 [114 108  85  55  55  69  64  54  64  87 112 129  98  74  84  91]
 [133 137 147 103  65  81  80  65  52  54  74  84 102  93  85  82]
 [128 137 144 140 109  95  86  70  62  65  63  63  60  73  86 101]
 [125 133 148 137 119 121 117  94  65  79  80  65  54  64  72  98]
 [127 125 131 147 133 127 126 131 111  96  89  75  61  64  72  84]
 [115 114 109 123 150 148 131 118 113 109 100  92  74  65  72  78]
 [ 89  93  90  97 108 147 131 118 113 114 113 109 106  95  77  80]
 [ 63  77  86  81  77  79 102 123 117 115 117 125 125 130 115  87]
 [ 62  65  82  89  78  71  80 101 124 126 119 101 107 114 131 119]
 [ 63  65  75  88  89  71  62  81 120 138 135 105  81  98 110 118]
 [ 87  65  71  87 106  95  69  45  76 130 126 107  92  94 105 112]
 [118  97  82  86 117 123 116  66  41  51  95  93  89  95 102 107]
 [164 146 112  80  82 120 124 104  76  48  45  66  88 101 102 109]
 [157 170 157 120  93  86 114 132 112  97  69  55  70  82  99  94]
 [130 128 134 161 139 100 109 118 121 134 114  87  65  53  69  86]
 [128 112  96 117 150 144 120 115 104 107 102  93  87  81  72  79]
 [123 107  96  86  83 112 153 149 122 109 104  75  80 107 112  99]
 [122 121 102  80  82  86  94 117 145 148 153 102  58  78  92 107]
 [122 164 148 103  71  56  78  83  93 103 119 139 102  61  69  84]]
```

What the computer sees

An image is just a big grid of numbers between [0, 255]:

e.g. 800 x 600 x 3
(3 channels RGB)

Challenges: viewpoint



From Fei Fei Li - Stanford University School of Engineering - Class #2 on Image Classification

Challenges: illumination / deformations

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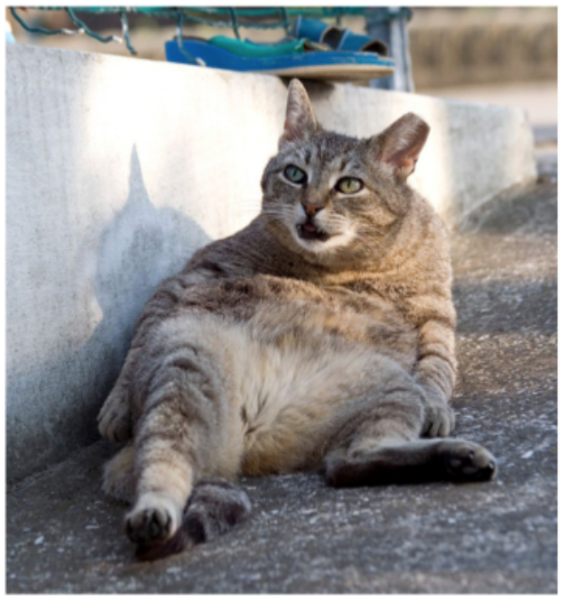

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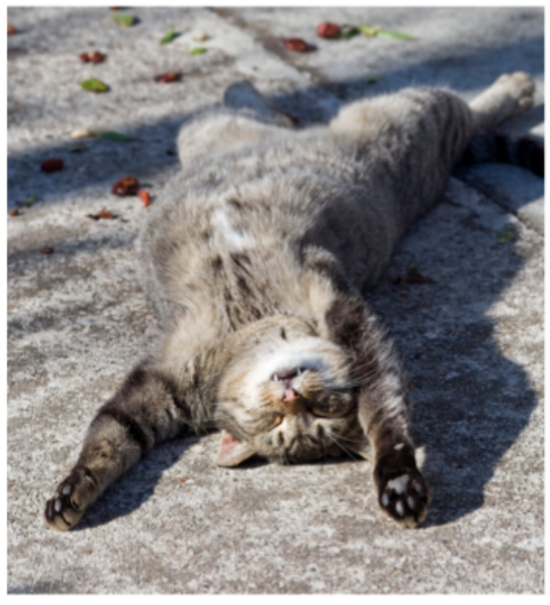

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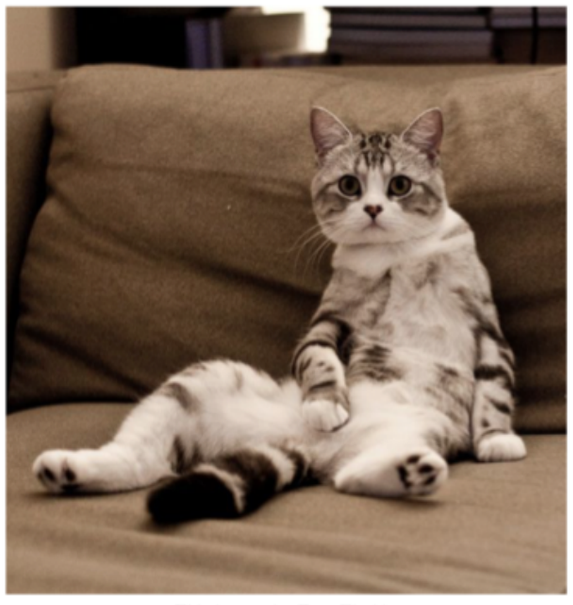

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Challenges: occlusions / background

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Challenges: intra-class variabilities

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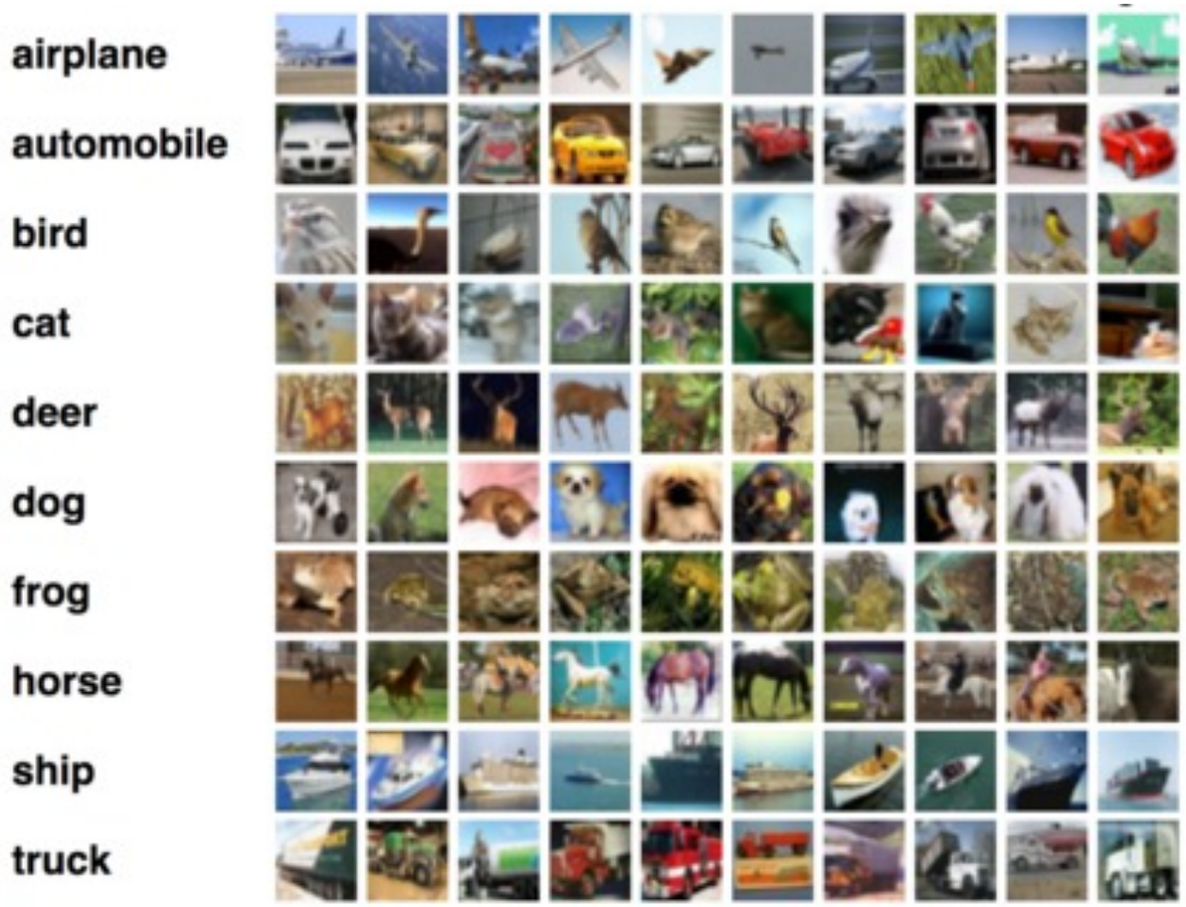
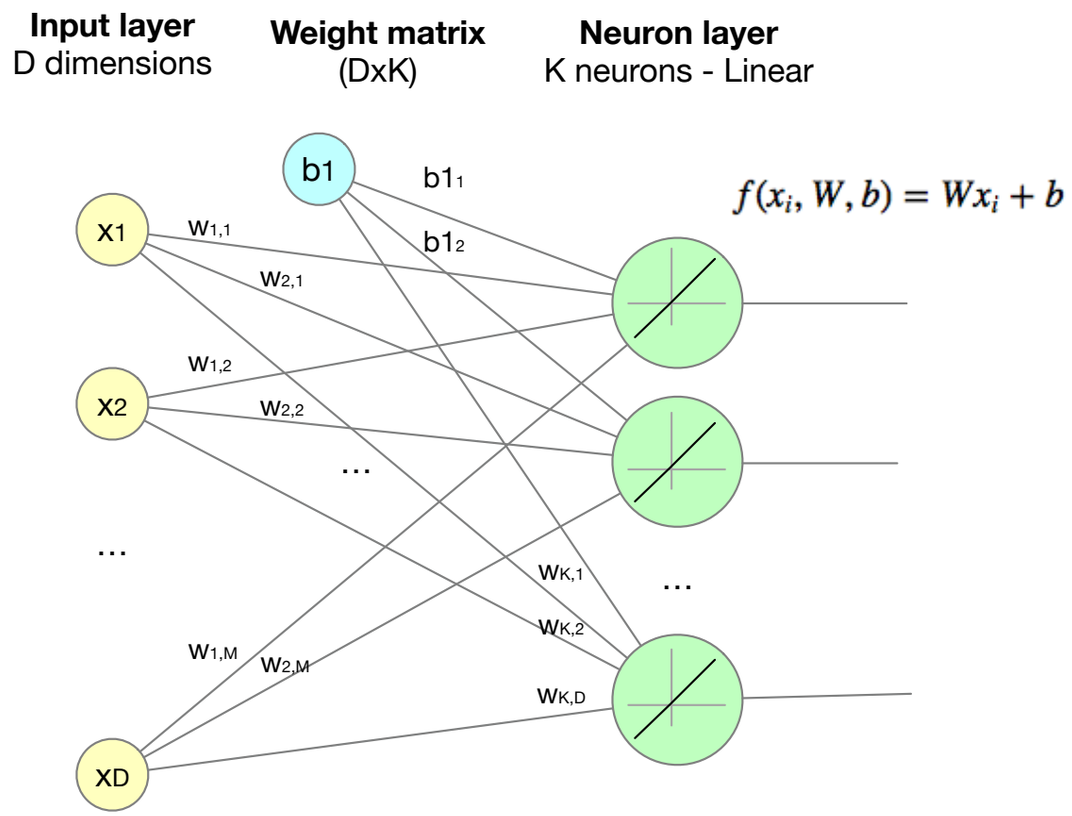
From Fei Fei Li - Stanford University School of Engineering - Class #2 on Image Classification

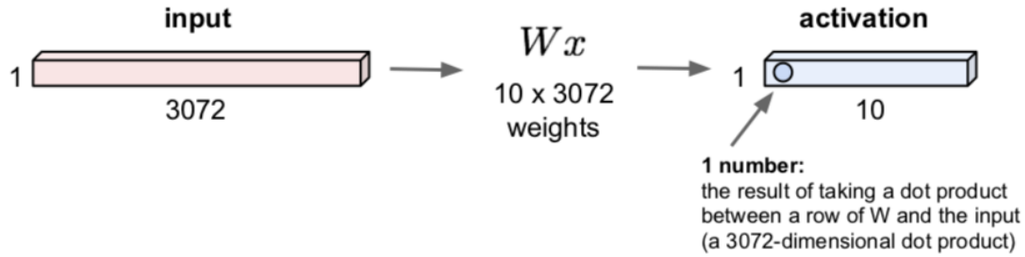
Example on CIFAR10 - let's assume a one-layer classifier

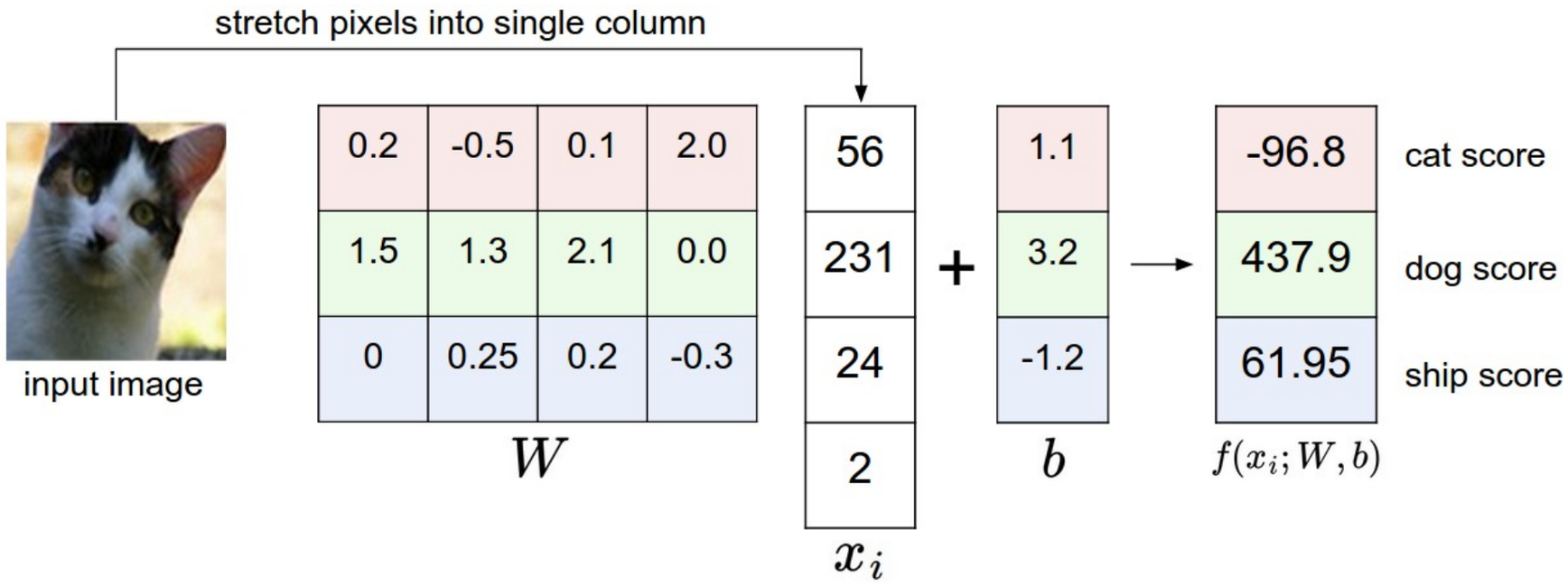
- 60'000 images : 10 classes X 6'000 images
- input dim = 32 X 32 X 3
- 50'000 for training and 10'000 for test





Example on CIFAR10 - let's assume a one-layer classifier



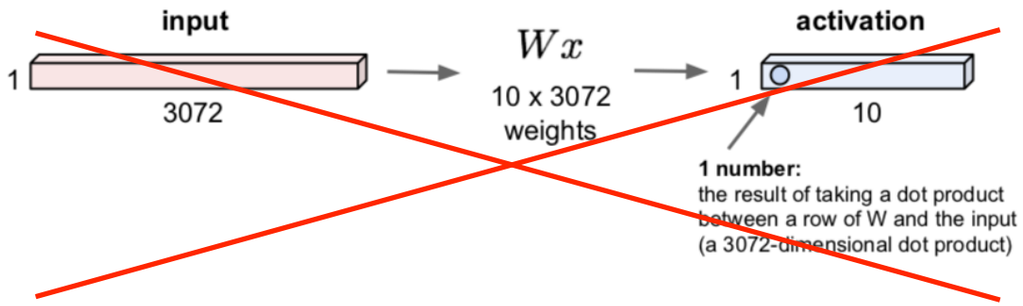


- The weights on a given row are connected to a given output neuron and then contributes to a given class "score"
- Intuitively, we can feel that if the weights are "aligned" to the pixel values, then the score for the given class will be high
- For this reason, the weights for a given class can be interpreted as "templates" or "filters" for that class
- As these weights have the same dimension as the input image, they can actually be associated to the pixel positions and compose images (after re-scaling)

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

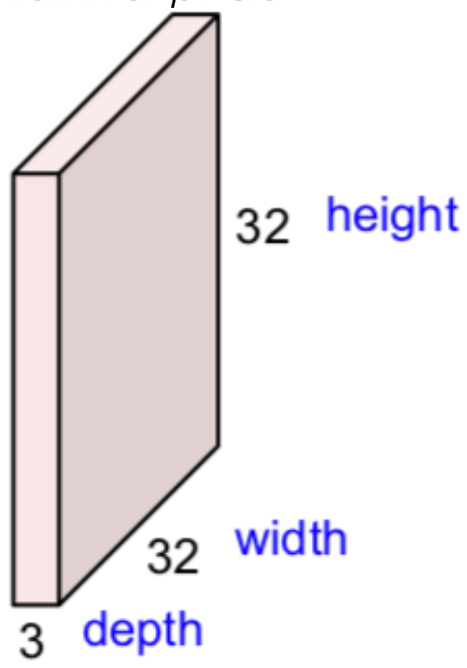
Convolution layer - 2D signals

- The first idea is to **preserve the spatial structure**

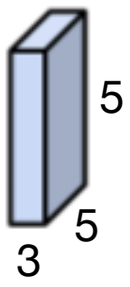


In dense layers, we completely loose the information on the spatial structure as the output neurons are fully connected. E.g. we could shuffle the pixels randomly (but equally for all images) and the network would perform the same.

image 32x32x**3**
"3D matrix of pixels"



filter 5x5x**3**
"3D matrix of weights"



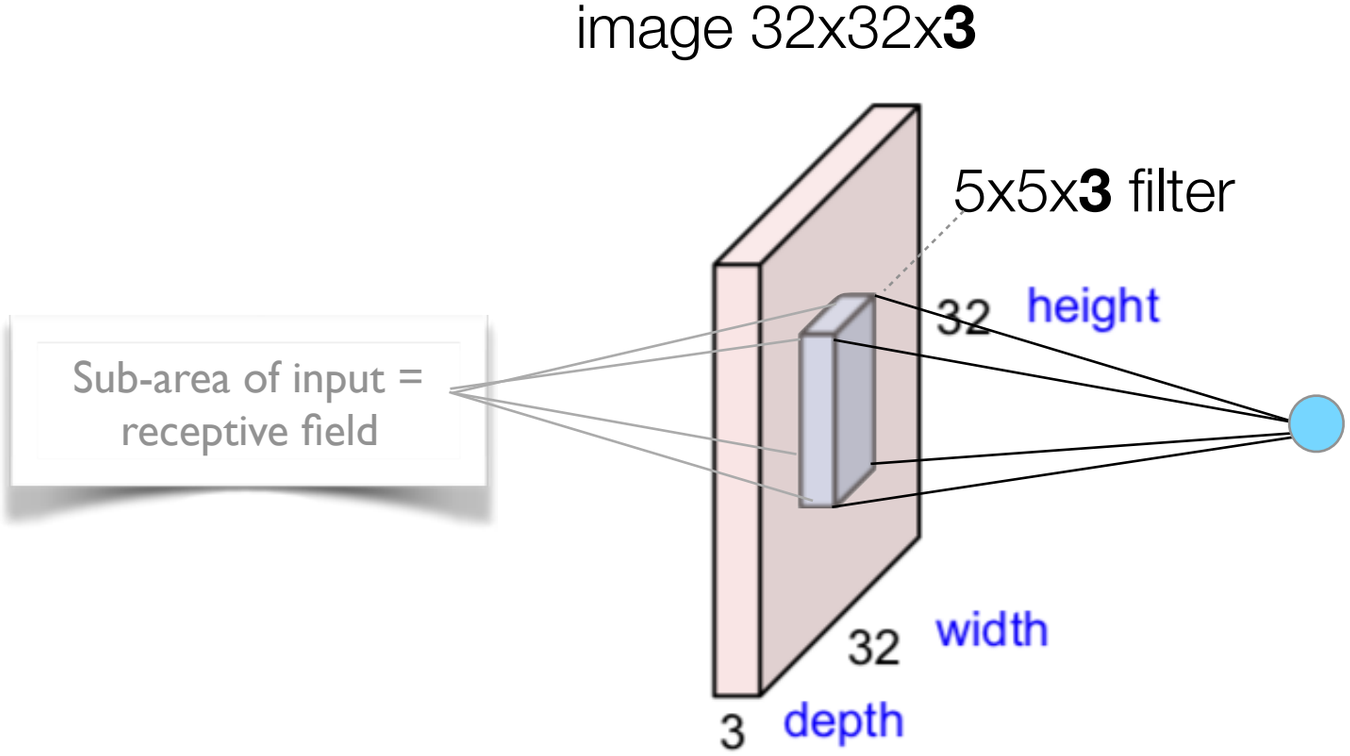
Filters have the same depth as the input "volume"

Filters are also called "kernels"

Images in colour have 3 "channels", Red-Green-Blue RGB

Convolution layer - 2D signals

- The second idea is to **convolve the filter with the image**, in our case “slide over the image spatially, computing dot products of the weights of the filter with the window of pixels where we slide the filter.
- The sub-area of an input that influences a component of the output is sometimes called the **receptive field** of the latter.



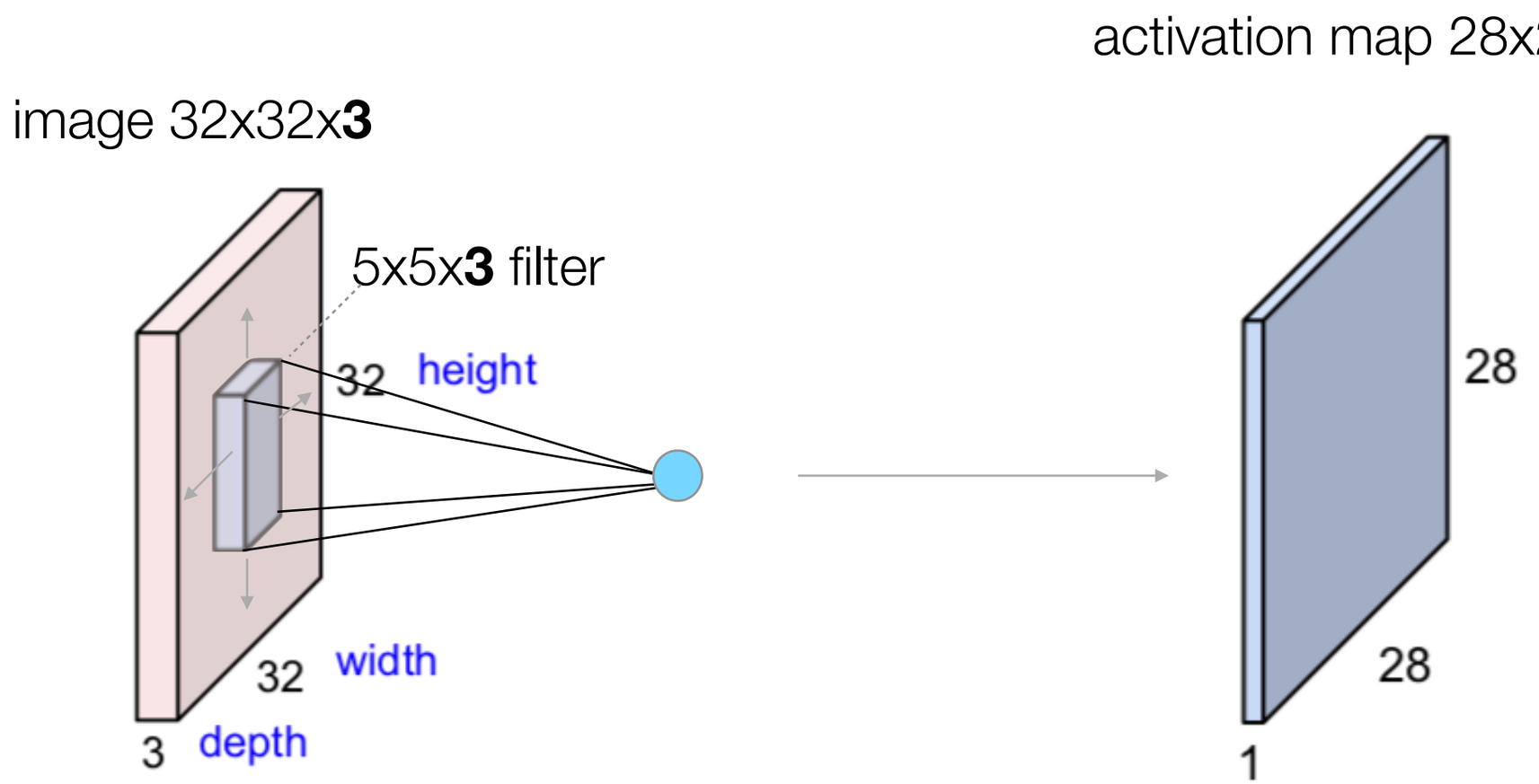
= 1 number

= the results of computing the dot product between the weights of the filters and a small 5x5x3 chunk of the image $w^T x + b$

= 5*5*3 multiplication + bias

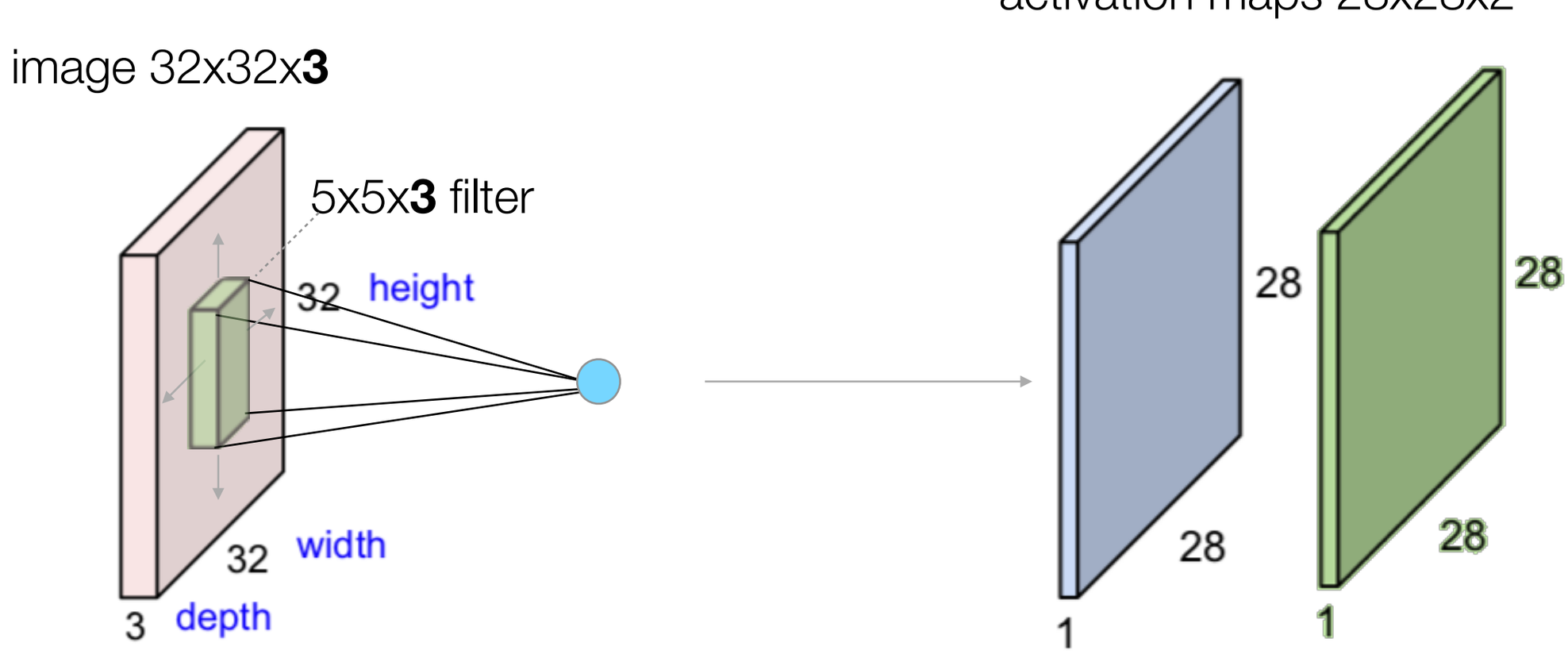
Convolution layer - 2D signals

- 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



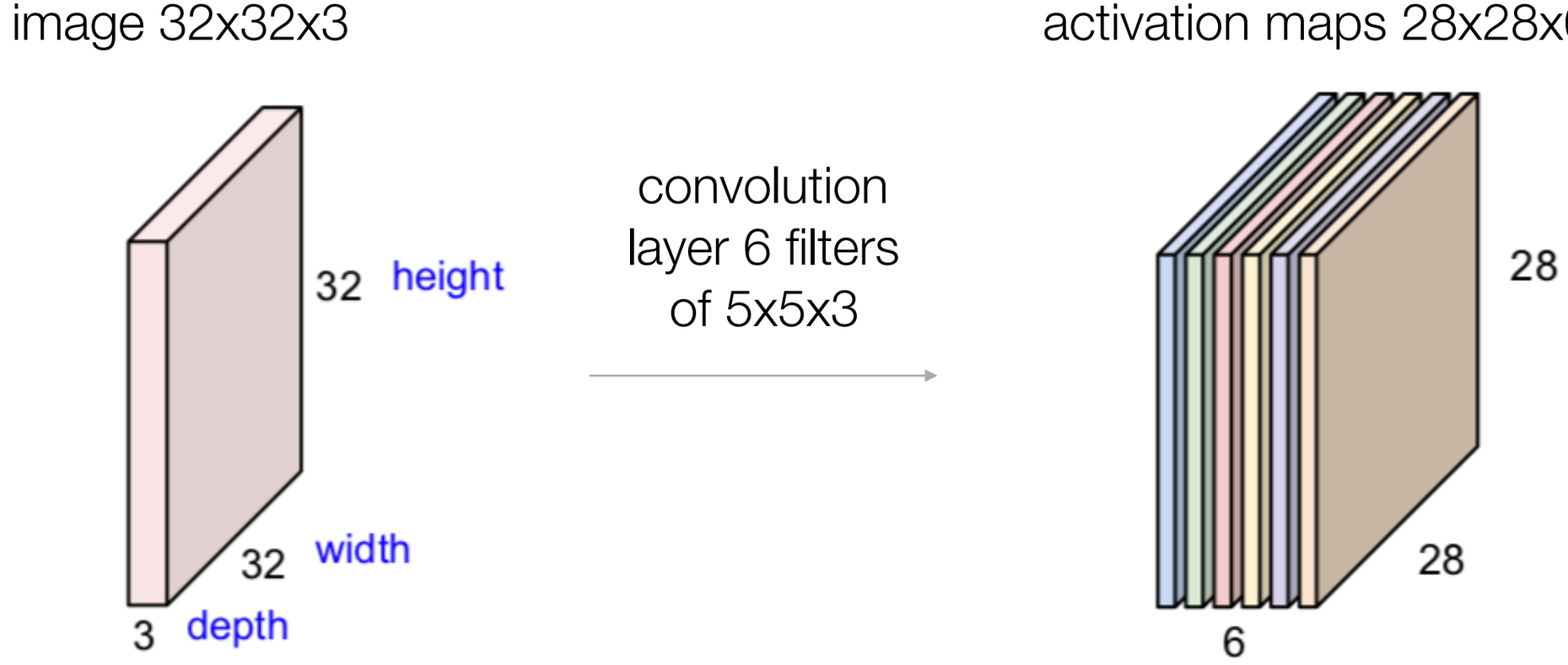
Convolution layer - 2D signals

- Notion of **several filters** producing **several activation maps**
- Now with another filter



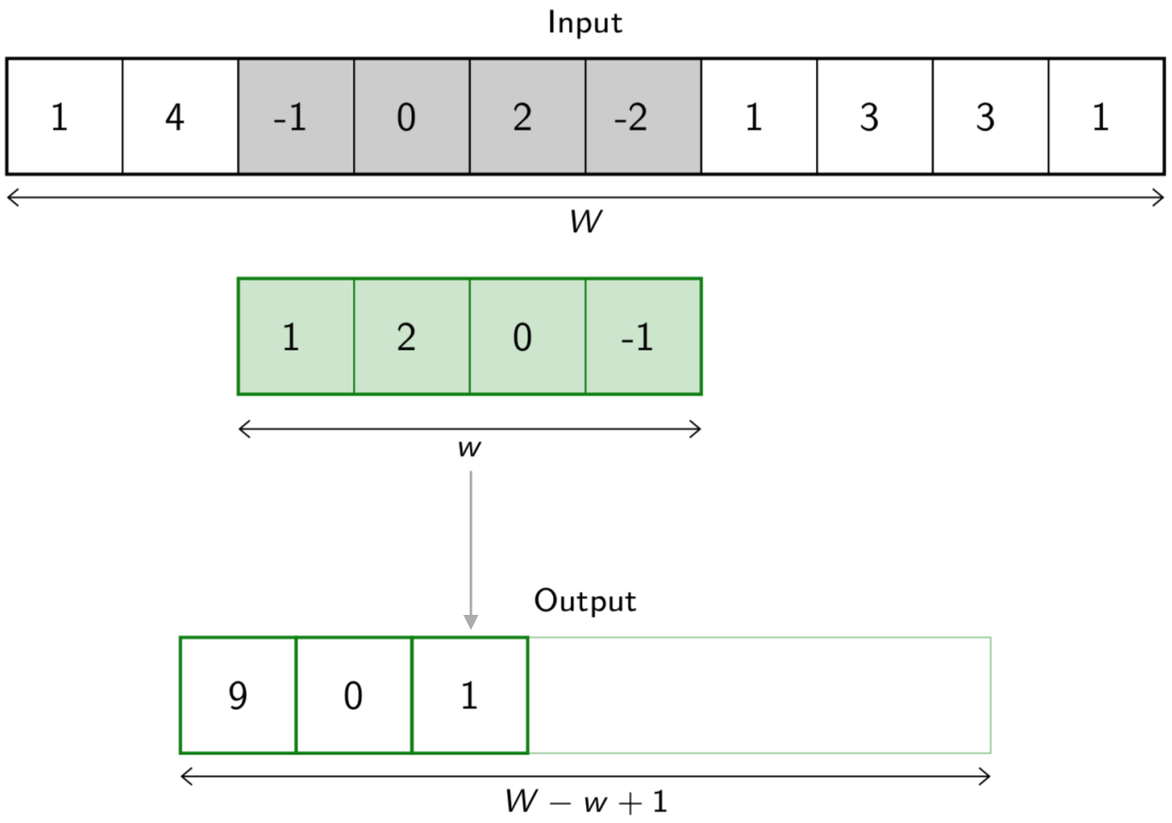
Convolution layer - 2D signals

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



Convolution layer - 1D signals

- The same principle holds for 1D signals such as time series.



Source: François Fleuret , CAS Deep Learning, Idiap 2018

Formally, in 1d, given

$$x = (x_1, \ldots, x_W)$$

and a "convolution kernel" (or "filter") of width w

$$u = (u_1, \ldots, u_w)$$

the convolution $x \circledast u$ is a vector of size $W - w + 1$, with

$$(x \circledast u)_i = \sum_{j=1}^{w} x_{i-1+j}\, u_j$$
$$= (x_i, \ldots, x_{i+w-1}) \cdot u$$

for instance

$$(1, 2, 3, 4) \circledast (3, 2) = (3 + 4, 6 + 6, 9 + 8) = (7, 12, 17).$$

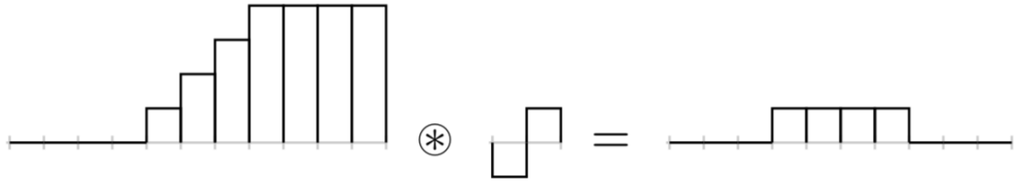
The convolution here is a bit different to the "classical" convolution as indices of filter weights and signal are visited in increasing order

Convolution layer - 1D signals

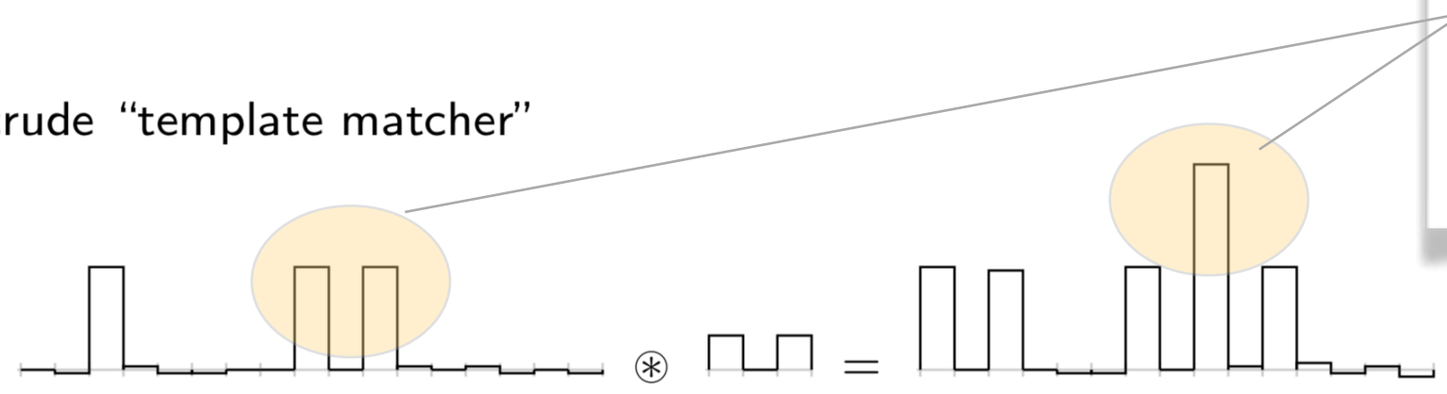
- What are doing such filters?

Convolution can implement a differential operator

$$(0,0,0,0,1,2,3,4,4,4,4) \circledast (-1,1) = (0,0,0,1,1,1,1,0,0,0).$$



or a crude "template matcher"



The sub-area of the input that "matches" the shape of the filter produces the highest output.

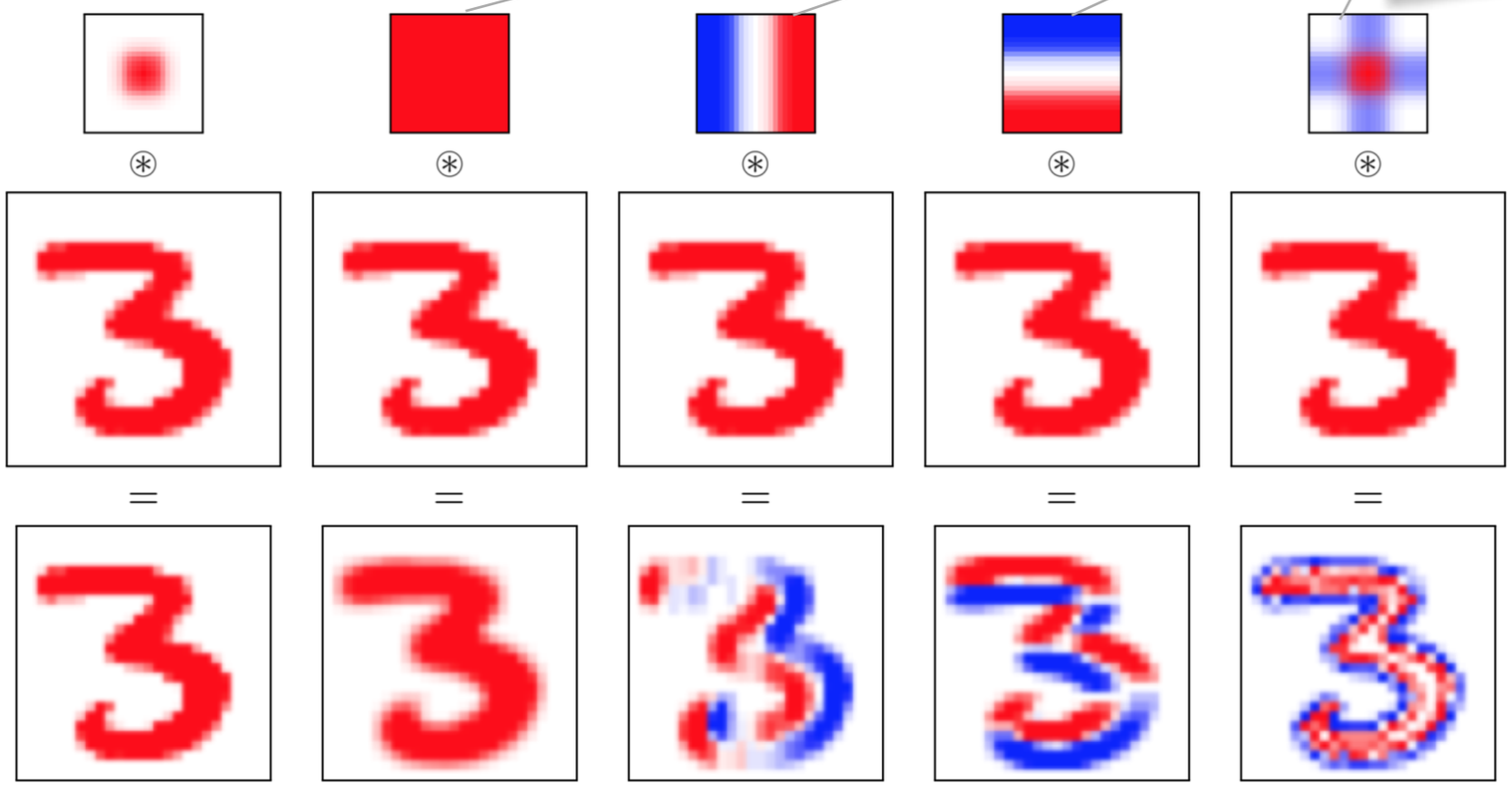
We can here really observe the **invariance in translation** and the fact that we preserve **spatial structure**, i.e. the output is also a 1D signal

Image: François Fleuret , CAS Deep Learning, Idiap 2018

Convolution layer - 2D signals

- What are doing such filters?

"Smoothing" low-pass filter
Filter sensitive to vertical strokes
Filter sensitive to horizontal strokes
Edge detection filter



For a given problem, the "best" filters will be discovered through the training process, i.e. weights of the filters will be learnt

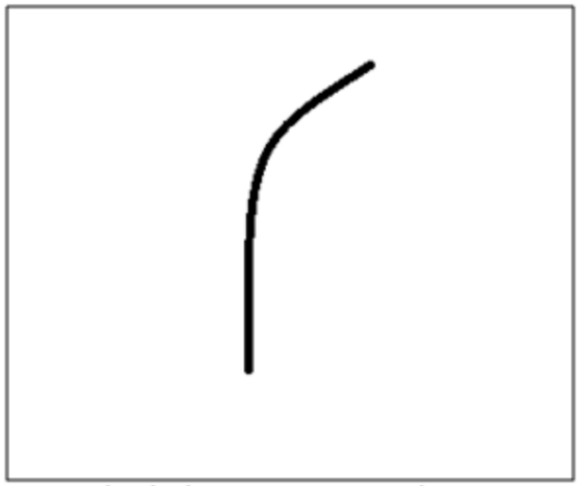
Image: François Fleuret , CAS Deep Learning, Idiap 2018

Convolution layer - 2D signals

- What are doing such filters?

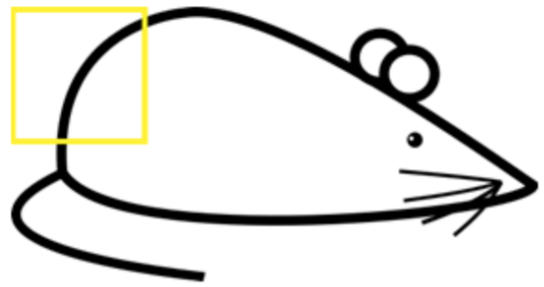
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter

Original image



Visualization of the filter on the image

Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 (A large number!)

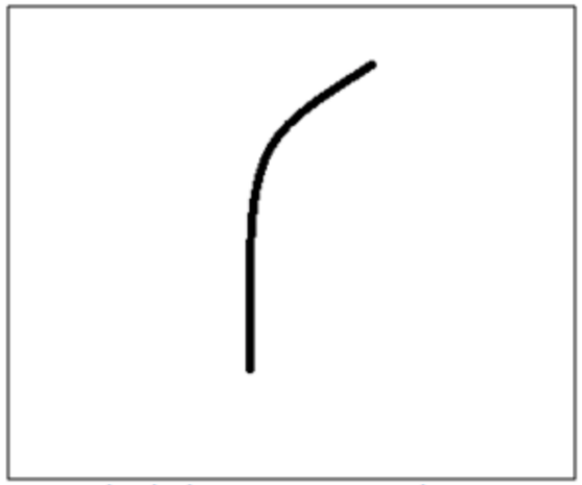
Image: Adit Deshpande, https://adeshpande3.github.io/adeshpande3.github.io/A-Beginner's-Guide-To-Understanding-Convolutional-Neural-Networks-Part-2/

Convolution layer - 2D signals

- What are doing such filters?

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



Visualization of a curve detector filter

Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

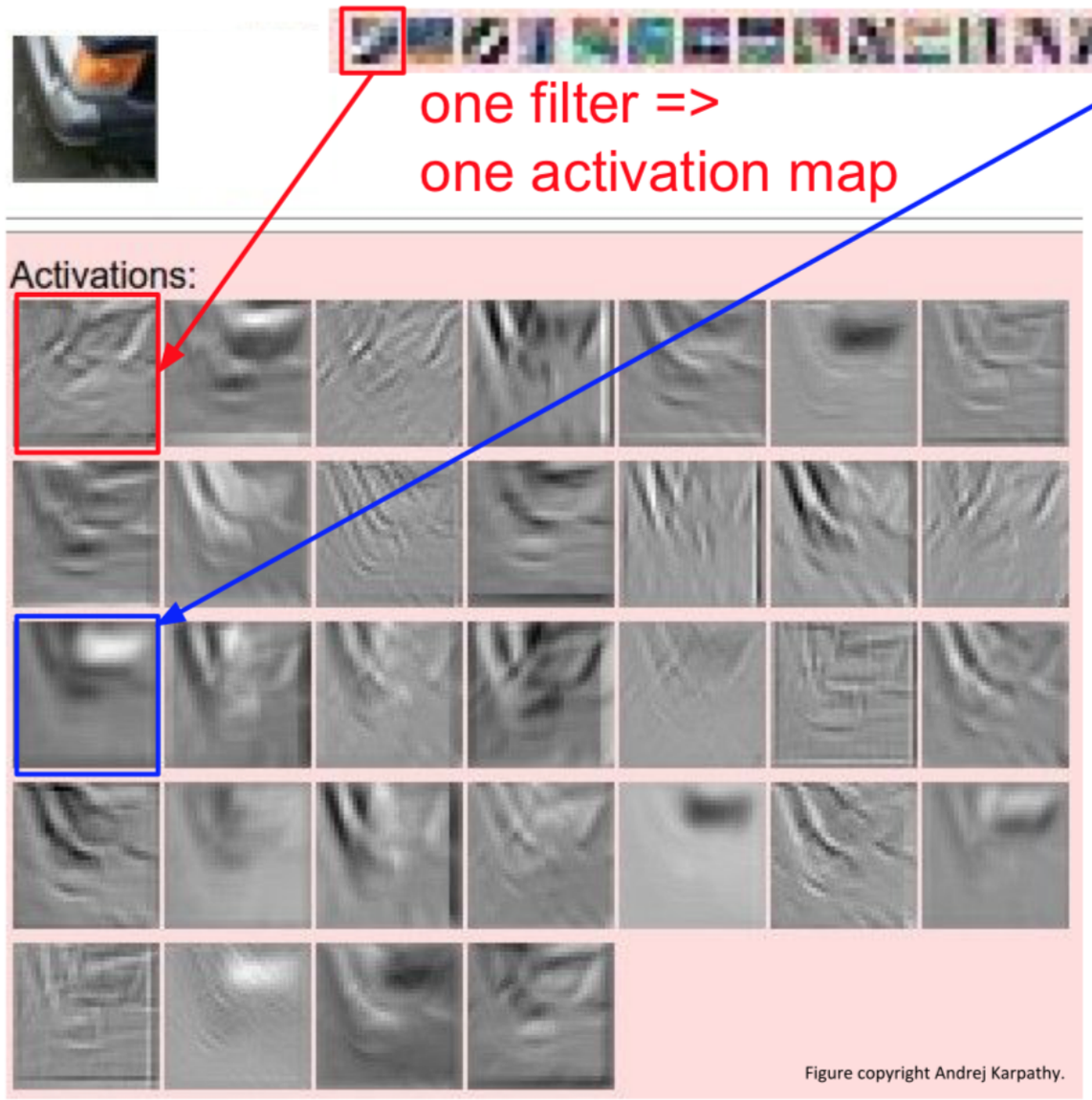
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = 0

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

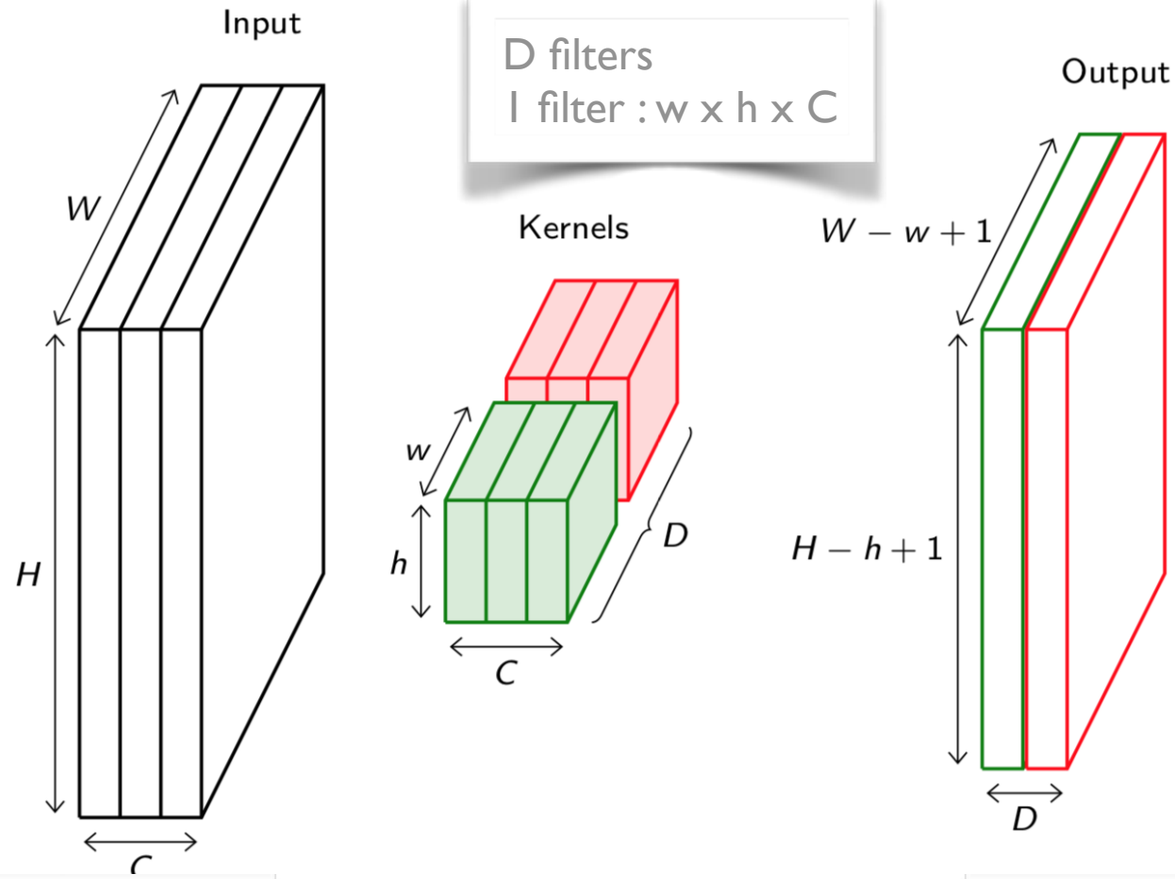
Convolution layer - 2D signals - CIFAR10



- The activation map for the red filter shows an activation that is more or less “flat”
- The one for the blue filter seems to have found patterns in the input that have “matched” with the input image.

Convolution layer - 2D signals - channels

- The input images have usually 3 channels, e.g. RGB
- The filters have then the same depth as the input “volume”
- The activation maps have a depth equal to the number of filters



C channels
I image :W x H x C

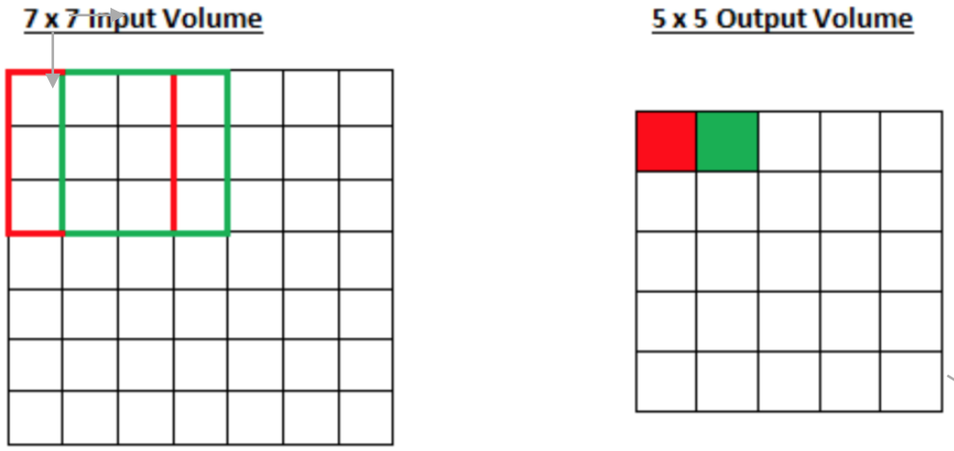
D activation maps = **depth**
I map : (W-w+1) x (H-h+1) x D

Image: François Fleuret , CAS Deep Learning, Idiap 2018

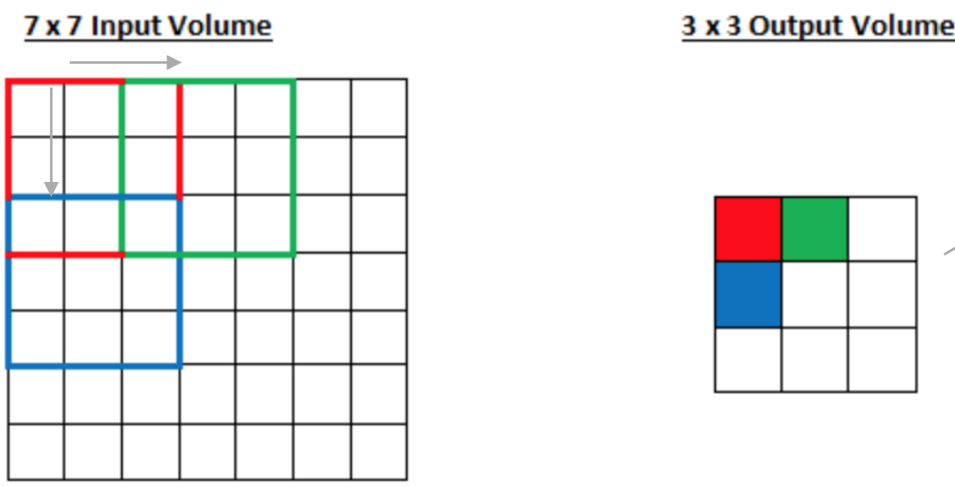
Convolution layer - stride

- The **stride S** specifies a step size when moving the filter across the signal.
- Rationale: reduce computation, reduce output size, no need of strong overlap

S = 1



S = 2



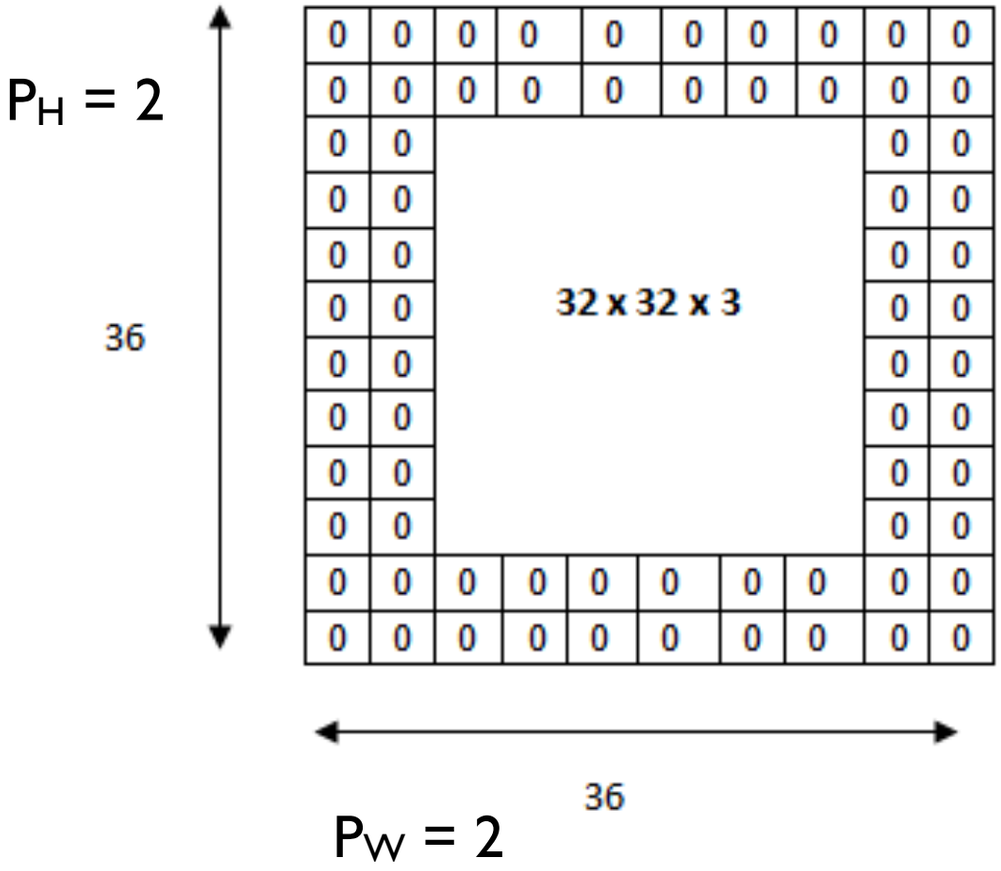
Larger stride S means less overlap and reduction of the output volume.

Some stride values are incompatible with the input size, e.g. a stride of 3 in this case. Frameworks may trigger errors in case of incompatible stride values.

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

Convolution layer - padding

- The **padding P** specifies the size of a zeroed frame added around the input.
- Rationale:
  - Apply filter at the border of the input
  - Avoid reducing the dimension from conv layer to conv layer



The input volume is 32 x 32 x 3. If we imagine two borders of zeros around the volume, this gives us a 36 x 36 x 3 volume. Then, when we apply our conv layer with our three 5 x 5 x 3 filters and a stride of 1, then we will also get a 32 x 32 x3 output volume.

Condition to obtain an output size equal to the input size:

$$P_W = \frac{w-1}{2}$$

$$P_H = \frac{h-1}{2}$$

w = width of filter
h = height of filter

Common settings: K=32, 64, 128, 512
h=w=3, S=1, P=1 h=w=5, S=1, P=2
h=w=1, S=1, P=0

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

Convolution layer - 1x1 convolution

- 1x1 convolutions are sometimes used
  - filters apply along the depth of the input

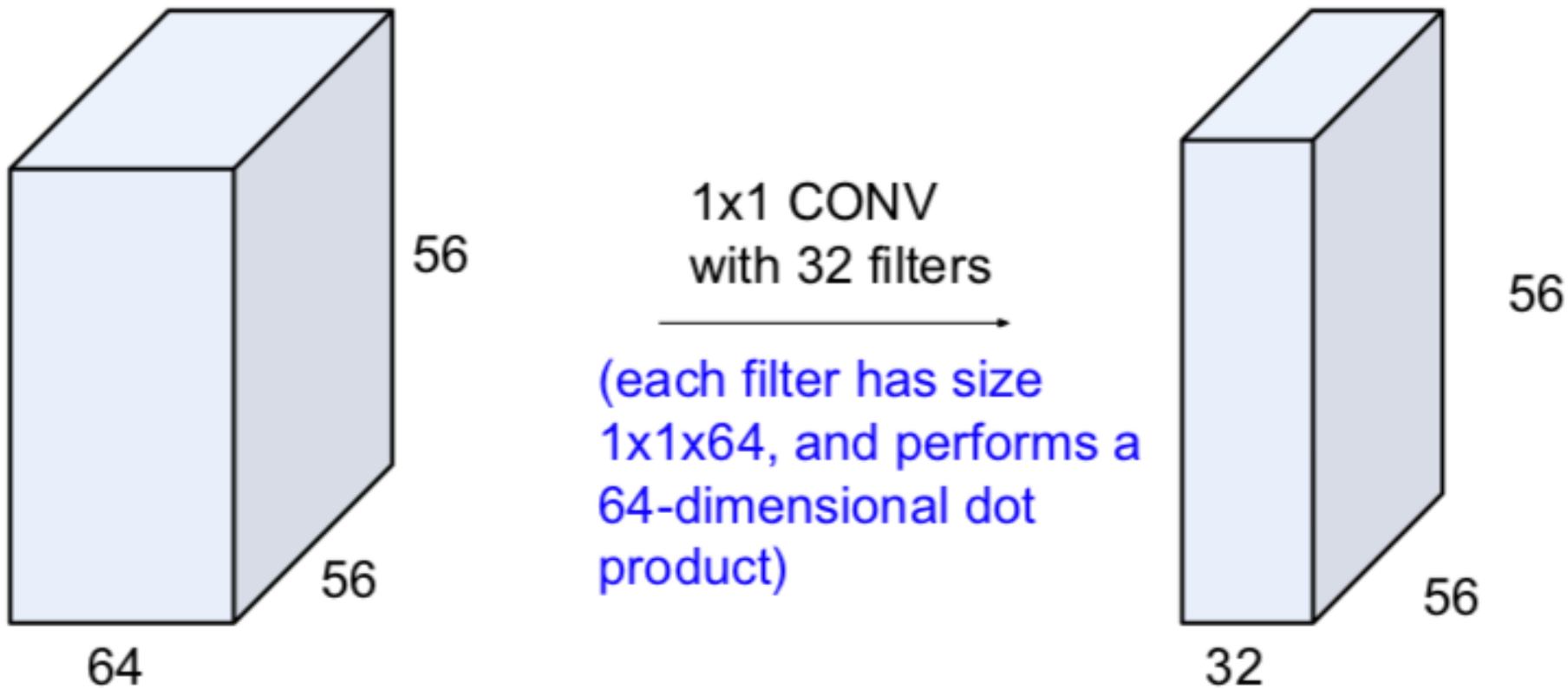


Image from Fei Fei Li - Stanford University School of Engineering - CS231

Convolution layer - output size / # params

- The output size can be computed with :

$$O_W = \frac{W - w + 2P_W}{S_w} + 1 \qquad O_H = \frac{H - h + 2P_H}{S_h} + 1$$

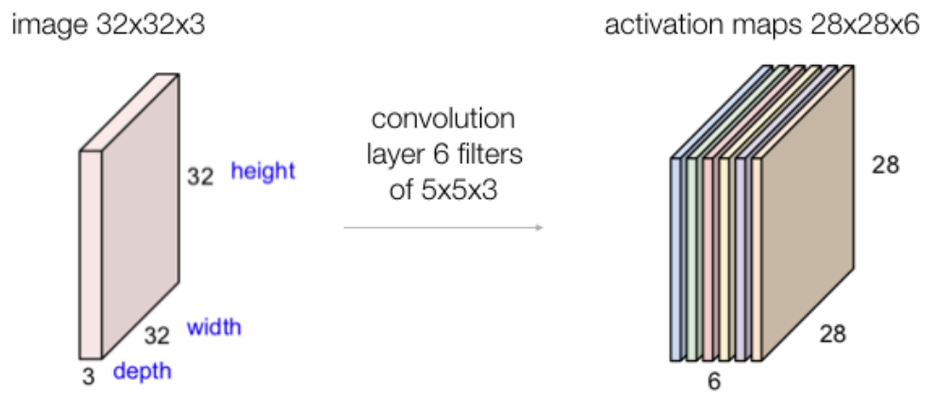
(W, H) = width and height of input
(w, h) = width and height of filter
P = padding, S = stride

- The number of parameters can be computed with:

$$N_{param} = whCD + D$$

weights bias

C = number of channels
D = number of filters



5*5*3*6 + 6 =
456 parameters

Red

Green

Blue

Input Volume (+pad 1) (7x7x3)

x[:,:,0]

0	0	0	0	0	0	0
0	2	1	0	2	2	0
0	2	0	1	2	1	0
0	0	2	1	2	0	0
0	0	0	1	0	2	0
0	1	2	0	1	0	0
0	0	0	0	0	0	0

x[:,:,1]

0	0	0	0	0	0	0
0	0	2	2	1	0	0
0	0	2	2	1	1	0
0	2	0	2	0	1	0
0	1	1	0	2	0	0
0	0	0	1	2	0	0
0	0	0	0	0	0	0

x[:,:,2]

0	0	0	0	0	0	0
0	0	2	0	0	1	0
0	2	1	1	1	1	0
0	2	0	0	2	1	0
0	0	2	0	2	2	0
0	2	2	1	2	1	0
0	0	0	0	0	0	0

Filter W0 (3x3x3)

w0[:,:,0]

1	1	0
0	0	-1
1	1	-1

w0[:,:,1]

0	-1	1
0	-1	1
0	0	1

w0[:,:,2]

0	0	-1
0	0	-1
0	0	-1

Bias b0 (1x1x1)

b0[:,:,0]

1

Filter W1 (3x3x3)

w1[:,:,0]

1	0	1
1	1	1
0	1	-1

w1[:,:,1]

0	-1	1
0	1	0
-1	1	0

w1[:,:,2]

0	1	1
-1	1	1
1	1	1

Bias b1 (1x1x1)

b1[:,:,0]

0

Output Volume (3x3x2)

o[:,:,0]

3	-3	4
-1	-5	4
-5	0	3

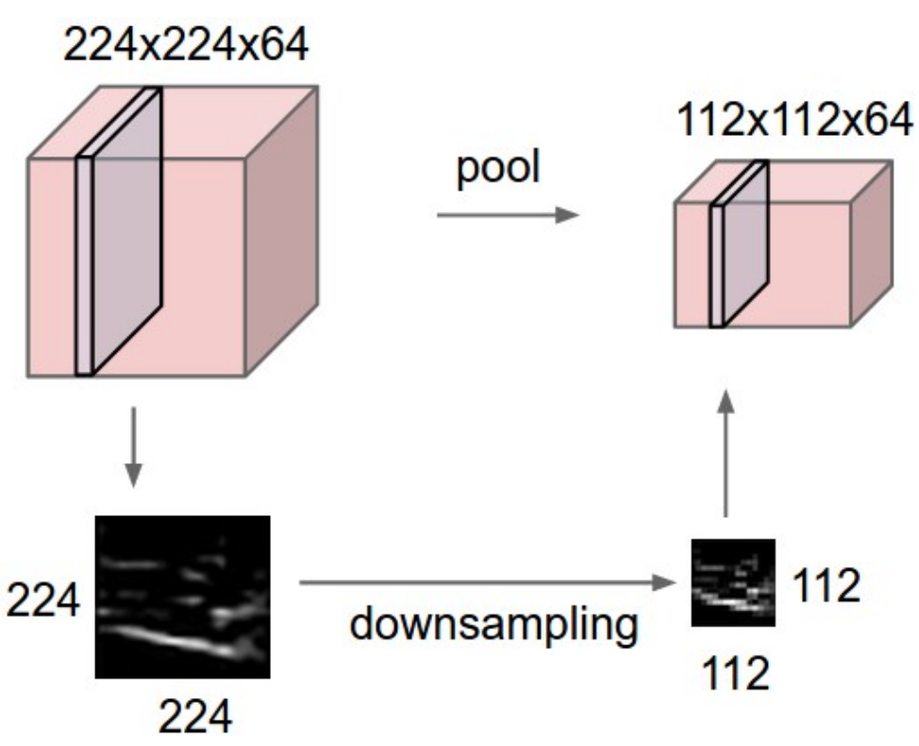
o[:,:,1]

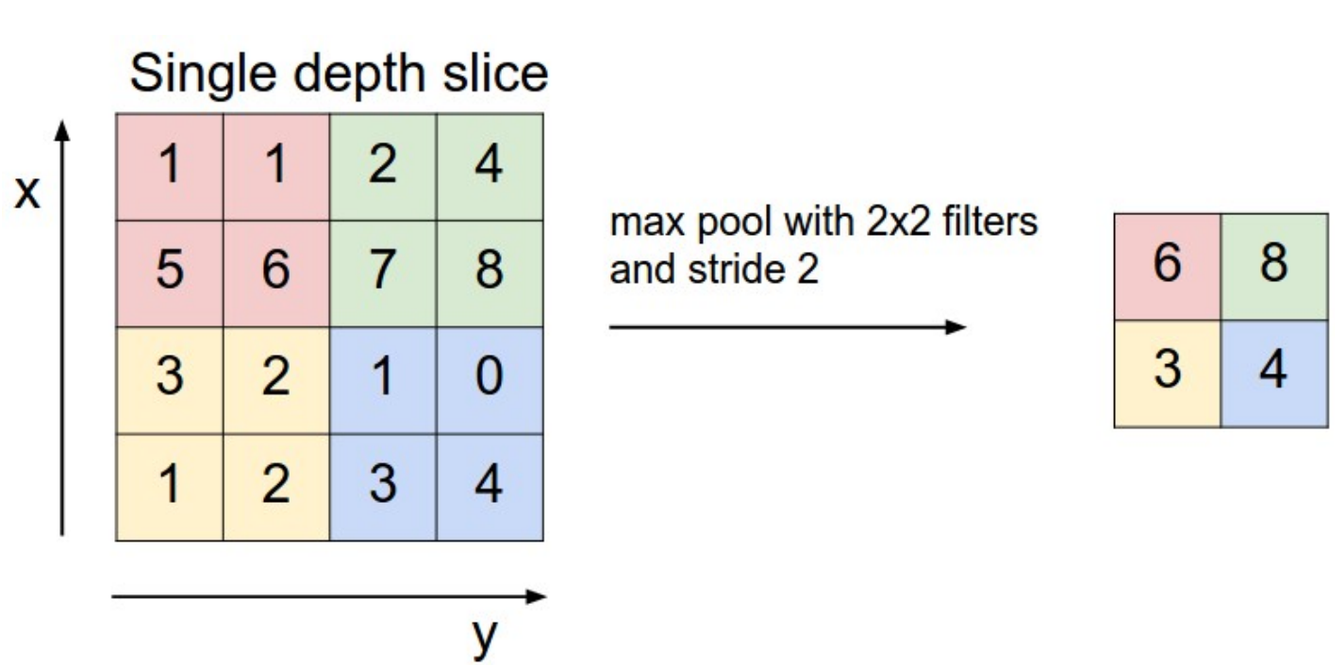
10	5	8
14	16	8
9	9	2

toggle movement

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

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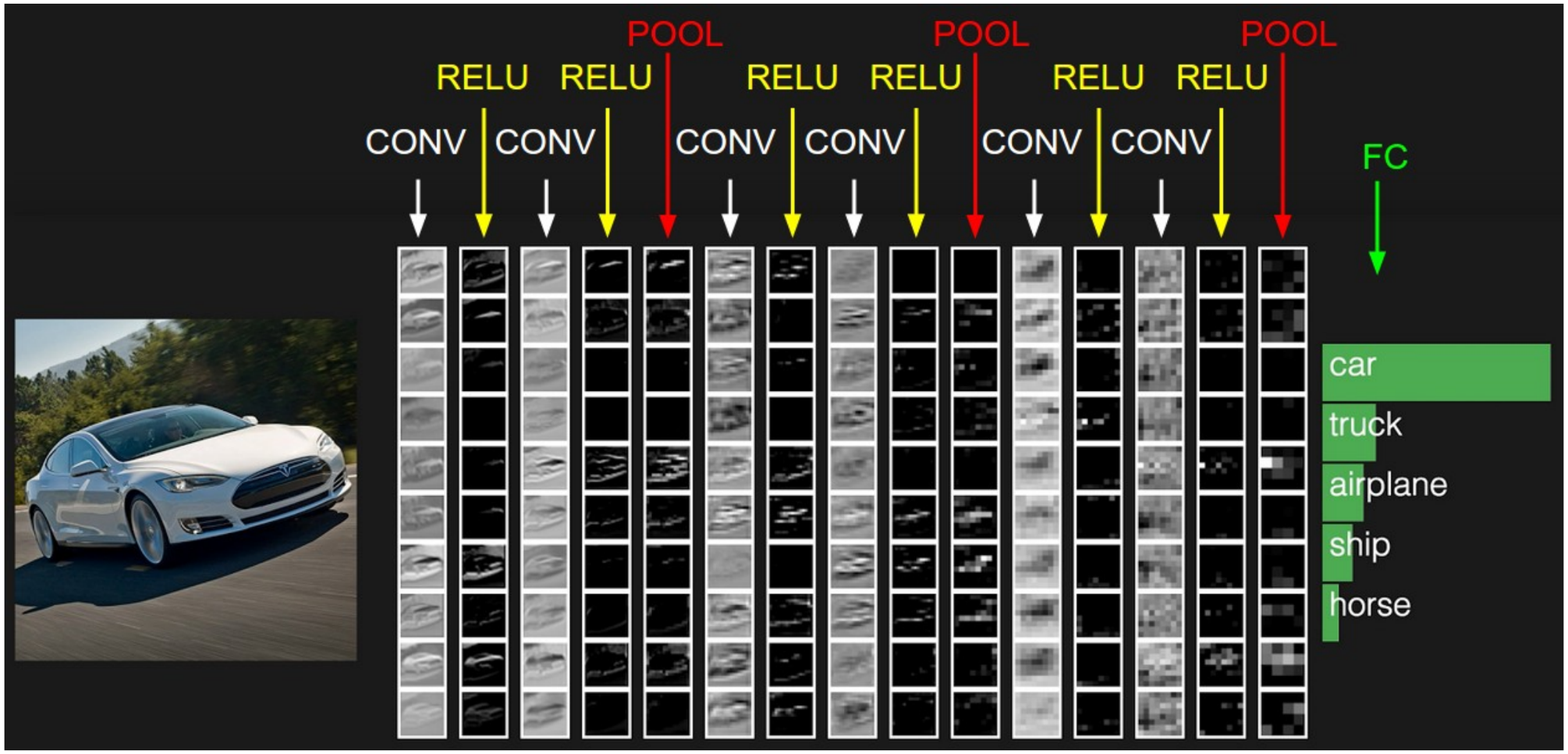
Other layers

- Dropout layer
  - The layer drops out a random set of activations by setting them to zero
  - Rationale:
    - makes the network more robust, redundant
    - avoids overfitting
- Dense - fully connected layer
  - Can be viewed as a convolution layer with K filters spanning the full input space
  - Usually used at the output of the CNN architecture to “use” all the features provided by the previous layer in order to take a decision about a class label.

Full architecture for image recognition



- Typical configuration:
  - stack sequences of CONV-RELU-POOL or CONV-RELU-CONV-RELU-POOL
  - end with a fully connected “dense” layer to perform classification

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Wrap-up

- **Keras** is a high-level open-source neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano.
  - Large community in both research and industry
  - Simple unified neural network pipeline: **define**, **compile**, **fit**, **evaluate**, **use**
  - Concept of **sequential model** corresponding to a sequence of layers, one feeding the next
- **Convolutional neural networks - CNN** are deep neural network architectures composed of:
  - **Convolution layers**: principle is to convolve filters on the image with the effect to provide spatial preservation and translation invariance. A given filter is translated on **receptive fields** of the input and produces as output an **activation map**. The output of the layer is usually a "**volume**" corresponding to several activation maps.
  - **Max pooling layers**: layers that are applied to the activation maps of a previous layer in order to reduce its spatial dimension.
  - **Dense layers**: regular fully connected layers usually used as the last layers in the architecture to take classification decisions