
# WORKSHOP
# INTRODUCTION TO DEEP LEARNING

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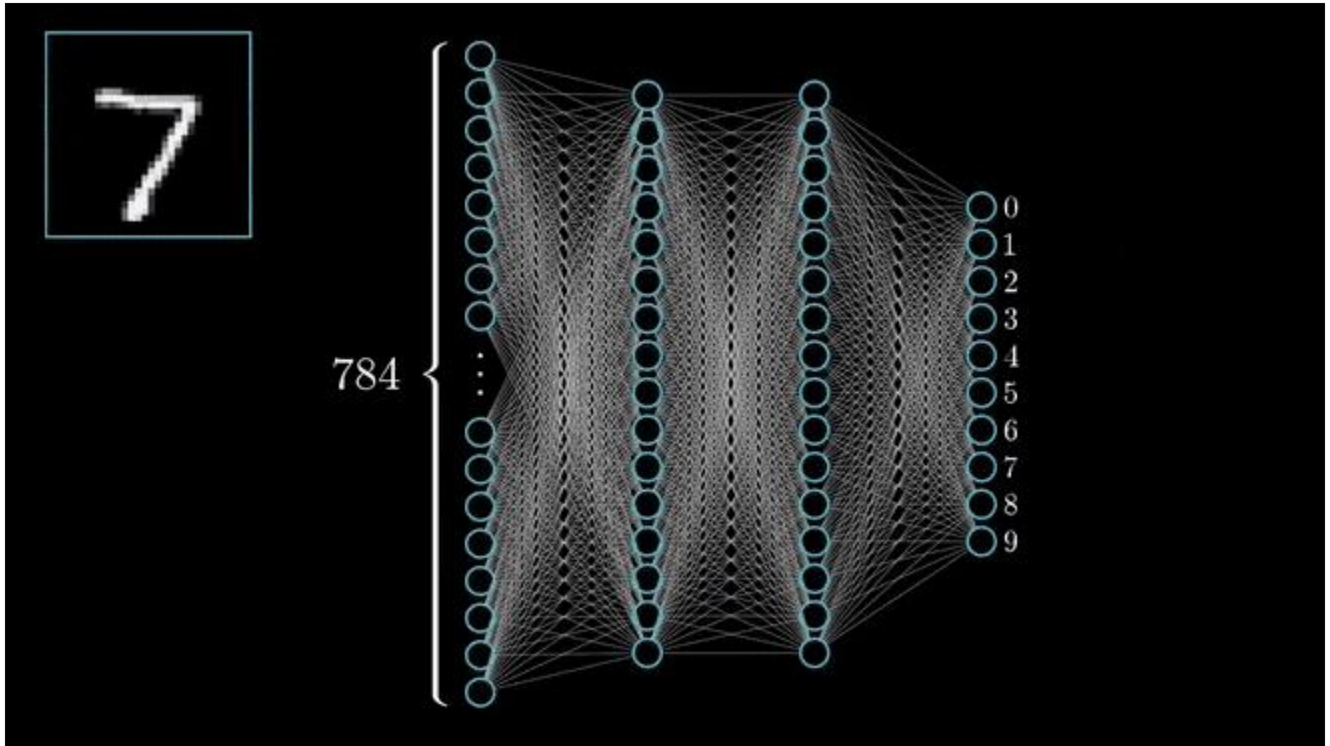
# Outline

1. Convolution Neural Network
2. Recurrent Neural Network
3. Long-Short Term Memory



# 1. Convolution Neural Network

- CNNs are one type of ANN which utilize the neuron, kernel, activation function.
- Inputs must be in images (or assumed to be images in 2D format)
- Using Forward & Backpropagation technique with certain property to process it faster
- CNNs best for object detection, image classification, computer vision

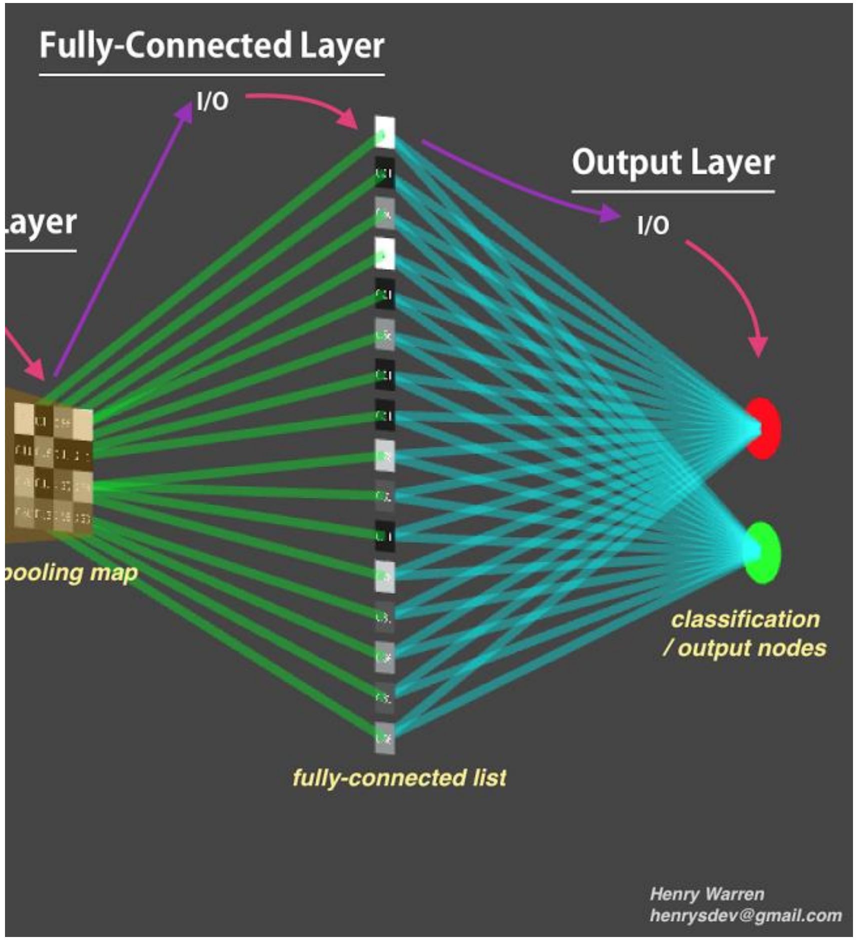


# 1. Convolution Neural Network

## Architecture of MLPs

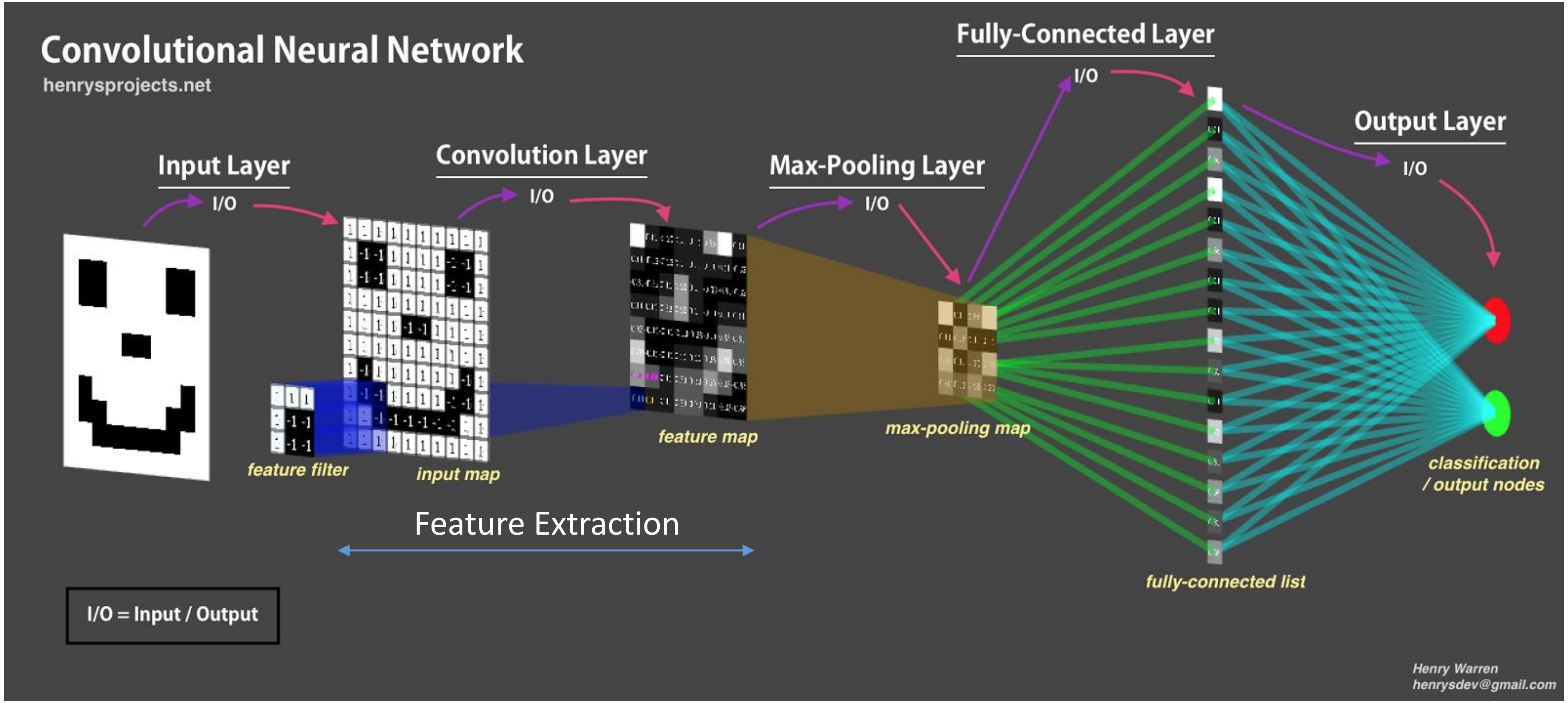
- Previous examples (MNIST, Fashion MNIST) use fully connected MLP NN to predict the images
- The accuracy/loss are ok but not so great

***Fully connected (Dense) Layer***



# 1. Convolution Neural Network

## Architecture of CNNs



# 1. Convolution Neural Network

## Architecture of CNNs

- Convolutional Layers
- Pooling Layers
- Flatten Layer

# 1. Convolution Neural Network

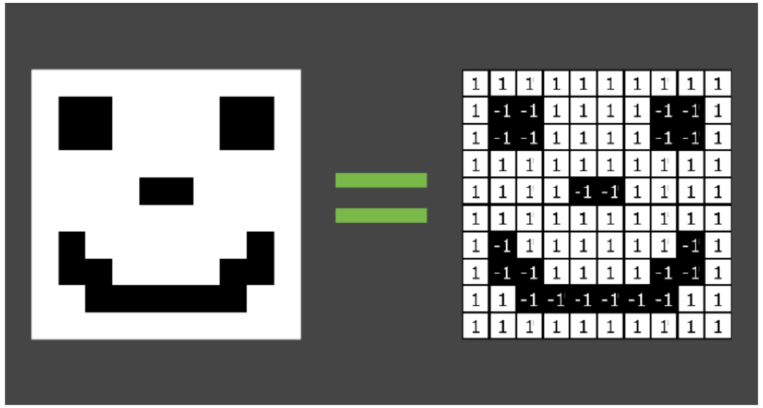
Parameters of Convolutional Layers (Conv2D):

- Depth
- Filter/kernel
- Stride
- Padding

# 1. Convolution Neural Network

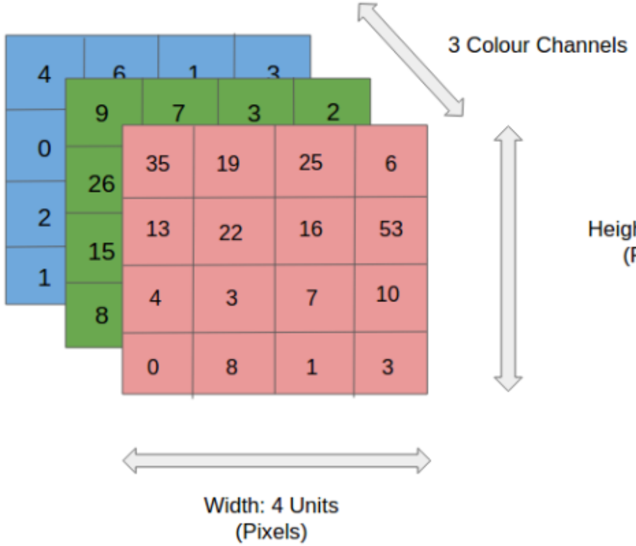
## Parameters of Conv2D: depth

**Depth = 1**




MNIST
Fashion MNIST

**Depth = 3**
**(RGB)**




Regular
images

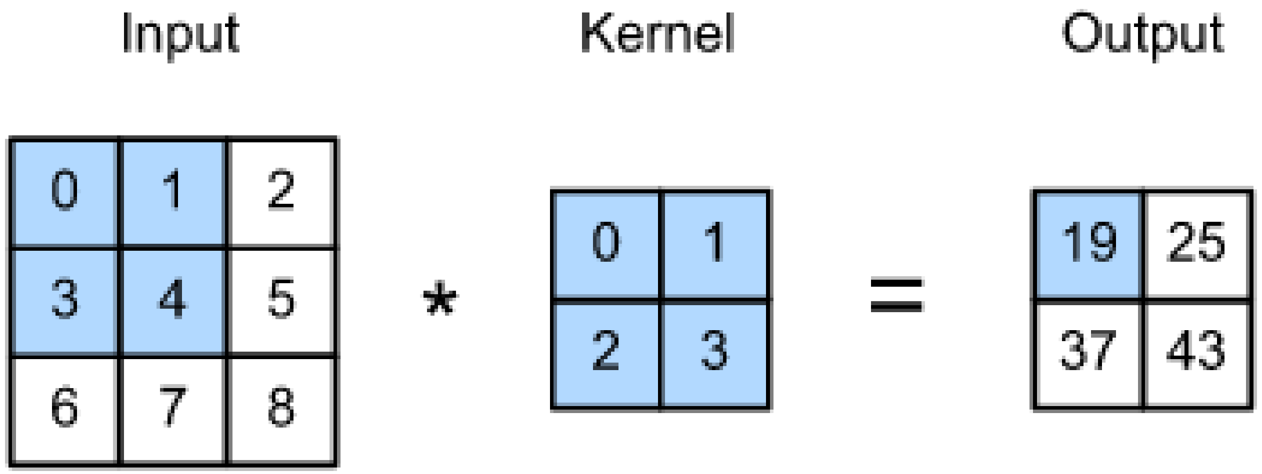
# 1. Convolution Neural Network

## Parameters of Conv2D: filter & kernel

# 1. Convolution Neural Network

## Parameters of Conv2D: filter & kernel

- dot product



# 1. Convolution Neural Network

## Parameters of Conv2D : filter & kernel

Kernel size (3,3)

| | | |
|---|---|---|
| 1/9 | 1/9 | 1/9 |
| 1/9 | 1/9 | 1/9 |
| 1/9 | 1/9 | 1/9 |

Blur filter

# 1. Convolution Neural Network

## Parameters of Conv2D : filter & kernel

Kernel size (3,3)

| | | |
|---|---|---|
| 0 | -1 | 0 |
| -1 | 5 | -1 |
| 0 | -1 | 0 |

Sharp filter

# 1. Convolution Neural Network

## Parameters of Conv2D : filter & kernel

Kernel size (3,3)

| | | |
|---|---|---|
| -1 | -2 | -1 |
| 0 | 0 | 0 |
| 1 | 2 | 1 |

Horizontal

| | | |
|---|---|---|
| -1 | 0 | 1 |
| -2 | 0 | 2 |
| -1 | 0 | 1 |

Vertical

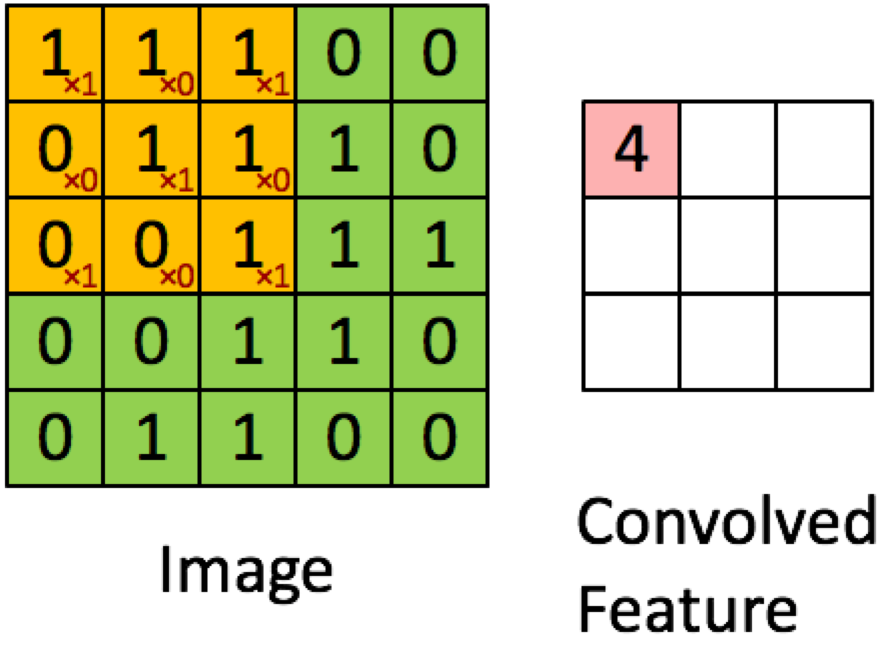
Edge detection

# 1. Convolution Neural Network

## Parameters of Conv2D : filter & kernel

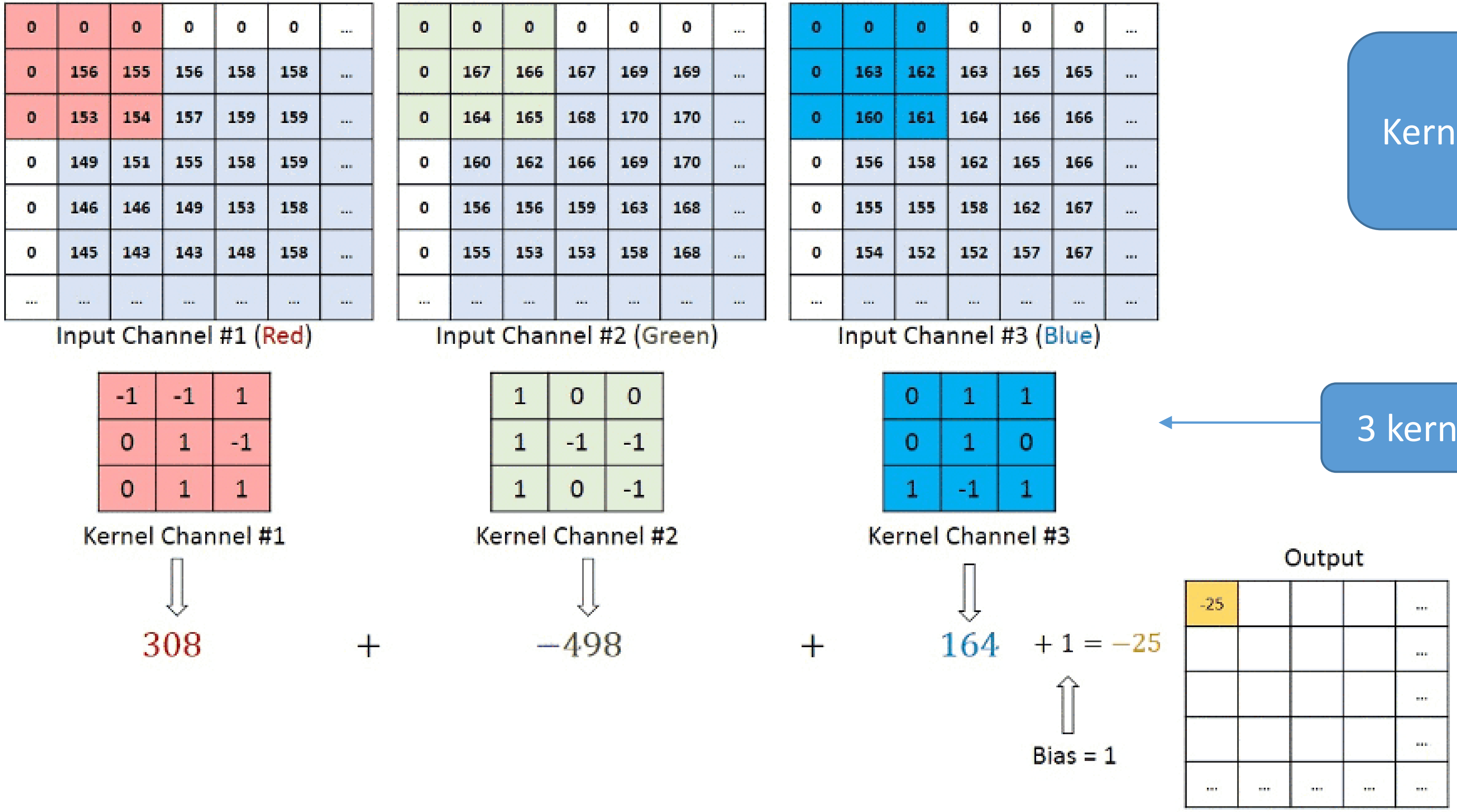
### Convolved Feature with filter

- CNN uses the Convolved Feature to reduce the image size by dot product with given kernel (filter)
- The image reduction without losing features and easier to process for good prediction
- In CNNs, filters are not defined. The value of each filter is learned during the training process.



# 1. Convolution Neural Network

## Parameters of Conv2D : filter & kernel




Kernel size (3,3)

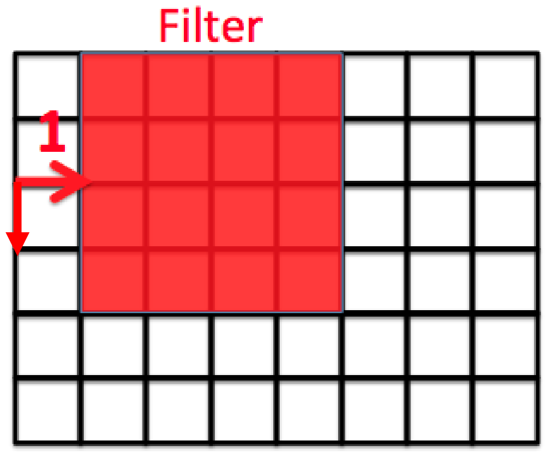
3 kernels = 3 filters

# 1. Convolution Neural Network

## Parameters of Conv2D : stride

- Stride tuned for the compression of images and video data

Stride = (1,1)



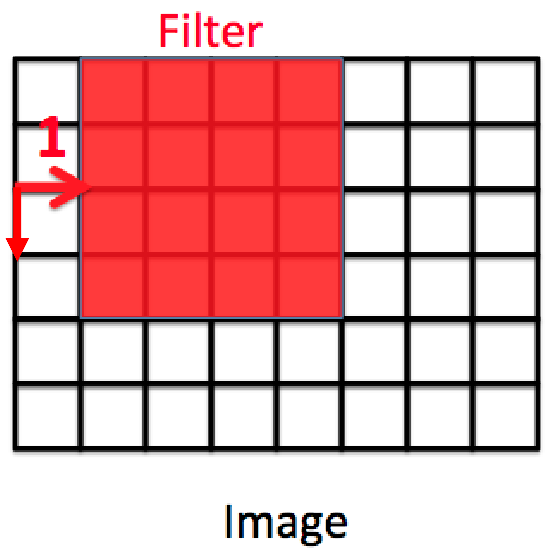

Image

# 1. Convolution Neural Network

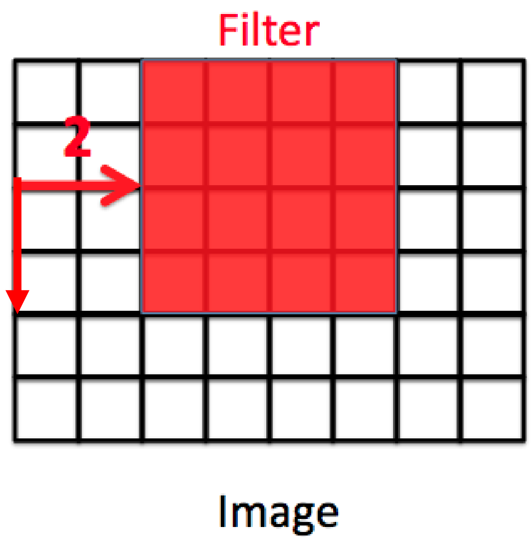
## Parameters of Conv2D : stride

- Stride tuned for the compression of images and video data

Stride = (1,1)




Stride = (2,2)

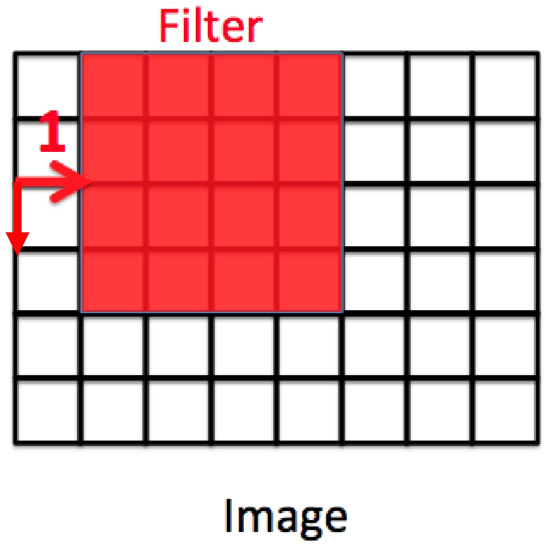


# 1. Convolution Neural Network

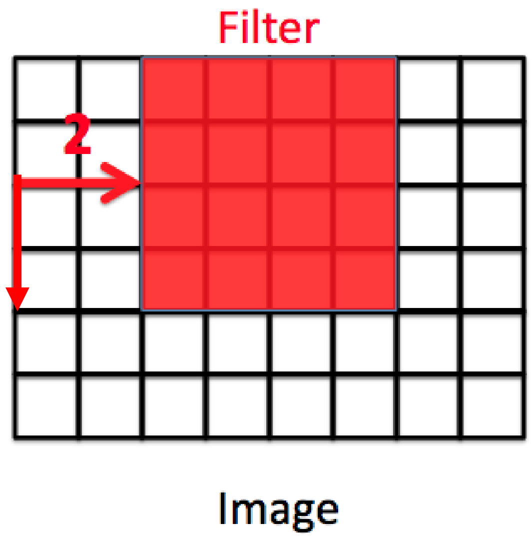
## Parameters of Conv2D : stride

- Stride tuned for the compression of images and video data

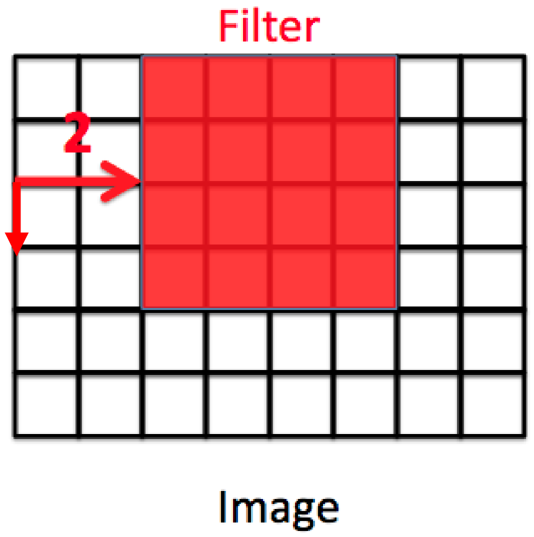
Stride = (1,1)




Stride = (2,2)



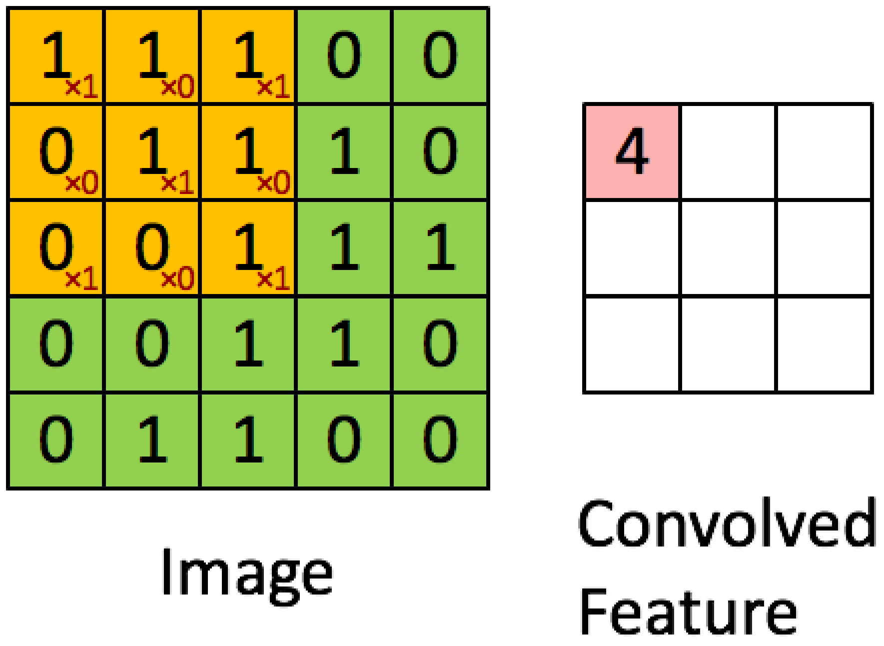

Stride = (2,1) or (1,2)?
Yes but not common



# 1. Convolution Neural Network

## Parameters of Conv2D : padding

- The pixels located on the corners and the edges are used much less than those in the middle => the information on borders and edges are note preserved



# 1. Convolution Neural Network

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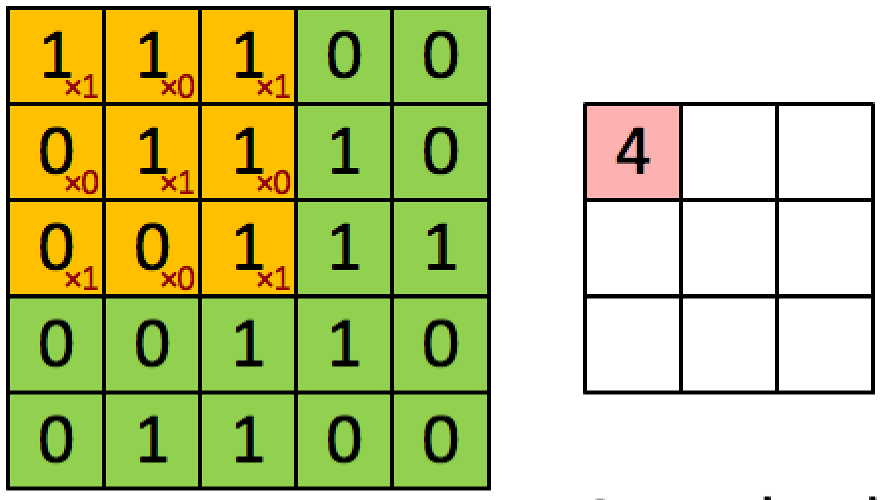



Image

Convolved Feature

**Solution?**

# 1. Convolution Neural Network

## Parameters of Conv2D : padding

- The pixels located on the corners and the edges are used much less than those in the middle => the information on borders and edges are not preserved

| | | | | |
|---|---|---|---|---|
| 3 | 5 | 9 | 1 | 10 |
| 13 | 2 | 4 | 6 | 11 |
| 16 | 24 | 9 | 13 | 1 |
| 7 | 1 | 6 | 8 | 3 |
| 8 | 4 | 9 | 1 | 9 |

(W, H)

padding

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 3 | 5 | 9 | 1 | 10 | 0 | 0 |
| 0 | 0 | 13 | 2 | 4 | 6 | 11 | 0 | 0 |
| 0 | 0 | 16 | 24 | 9 | 13 | 1 | 0 | 0 |
| 0 | 0 | 7 | 1 | 6 | 8 | 3 | 0 | 0 |
| 0 | 0 | 8 | 4 | 9 | 1 | 9 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

(W + 2P, H + 2P)

**Solution?**

- Add rows and columns of 0 to the input images
- The image on left was added with padding parameter P=2

# 1. Convolution Neural Network

## Parameters of Conv2D : padding

- The pixels located on the corners and the edges are used much less than those in the middle => the information on borders and edges are not preserved

| | | | | |
|---|---|---|---|---|
| 3 | 5 | 9 | 1 | 10 |
| 13 | 2 | 4 | 6 | 11 |
| 16 | 24 | 9 | 13 | 1 |
| 7 | 1 | 6 | 8 | 3 |
| 8 | 4 | 9 | 1 | 9 |

(W, H)

padding

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 3 | 5 | 9 | 1 | 10 | 0 | 0 |
| 0 | 0 | 13 | 2 | 4 | 6 | 11 | 0 | 0 |
| 0 | 0 | 16 | 24 | 9 | 13 | 1 | 0 | 0 |
| 0 | 0 | 7 | 1 | 6 | 8 | 3 | 0 | 0 |
| 0 | 0 | 8 | 4 | 9 | 1 | 9 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

(W + 2P, H + 2P)

**In Keras**

- padding = “valid”: no padding
- padding = “same”: padding with 0 evenly left/right, up/down
- padding = “same” with strides = (1,1): output has same size as input

# 1. Convolution Neural Network

## Parameters of Conv2D :

- Depth (L): 3 or 1
- Number of Filter: F
- kernel: (K, K): (3,3) or (5,5)
- Stride (S, S): (1,1) or (2,2)
- Padding (P)

W

H

| | | | | | | |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | ... |
| 0 | 156 | 155 | 156 | 158 | 158 | ... |
| 0 | 153 | 154 | 157 | 159 | 159 | ... |
| 0 | 149 | 151 | 155 | 158 | 159 | ... |
| 0 | 146 | 146 | 149 | 153 | 158 | ... |
| 0 | 145 | 143 | 143 | 148 | 158 | ... |
| ... | ... | ... | ... | ... | ... | ... |

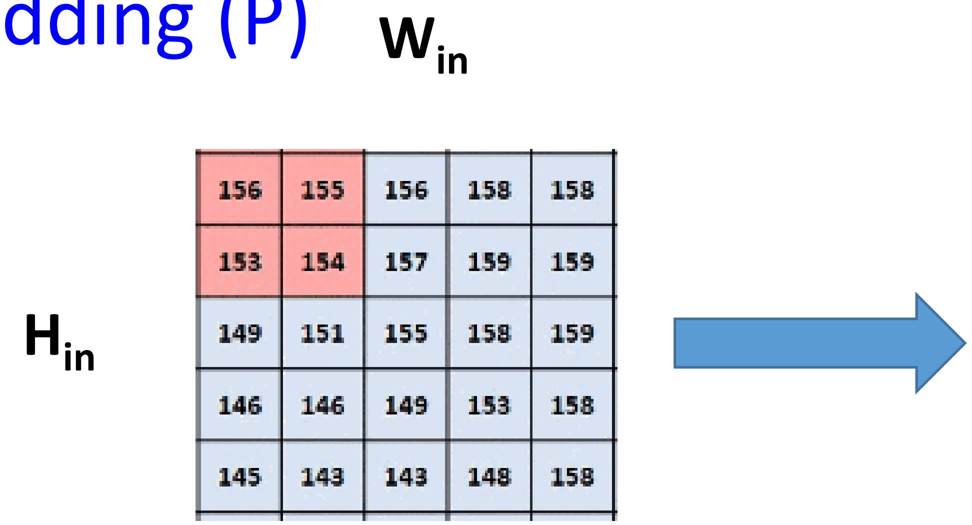
Formulation to compute the output size of a convolutional layer from an image with size (W, H)?

# 1. Convolution Neural Network

## Parameters of Conv2D :

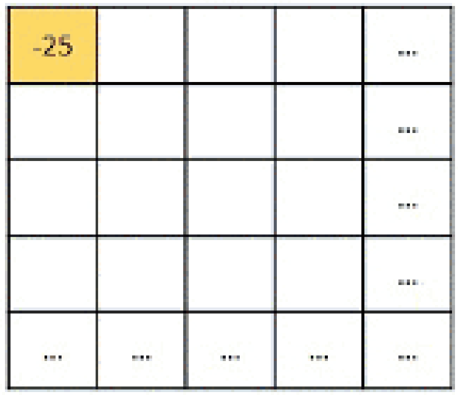
- Depth (L): 3 or 1
- Number of Filter: F
- kernel: (K, K): (3,3) or (5,5)
- Stride (S, S): (1,1) or (2,2)
- Padding (P)

Formulation to compute the output size of a convolutional layer from an image with size (W, H)?




$$W_{out} = \frac{W_{in} - K + 2P}{S} + 1$$

$$H_{out} = \frac{H_{in} - K + 2P}{S} + 1$$

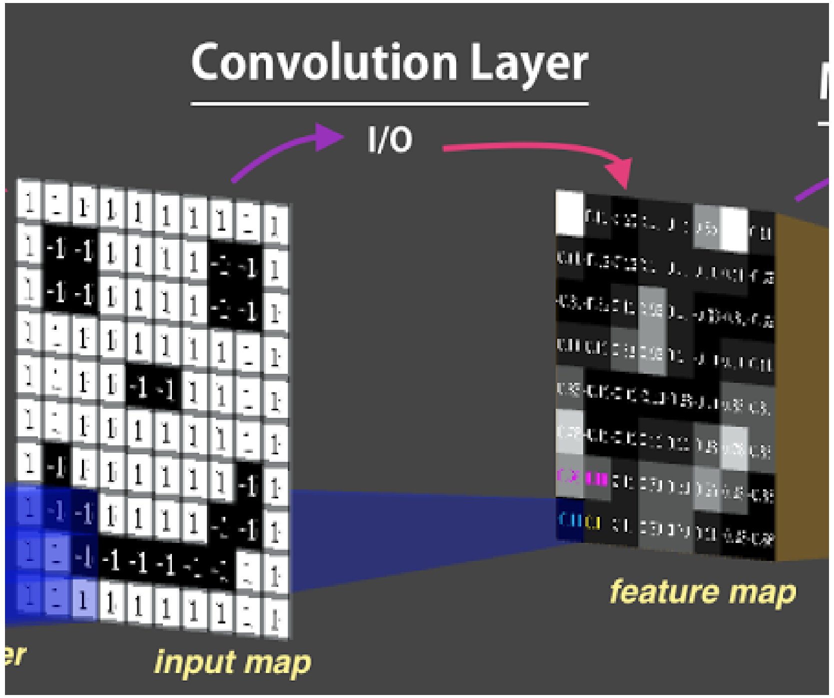



Convoluted features

# 1. Convolution Neural Network

## How to add Conv2D in keras?

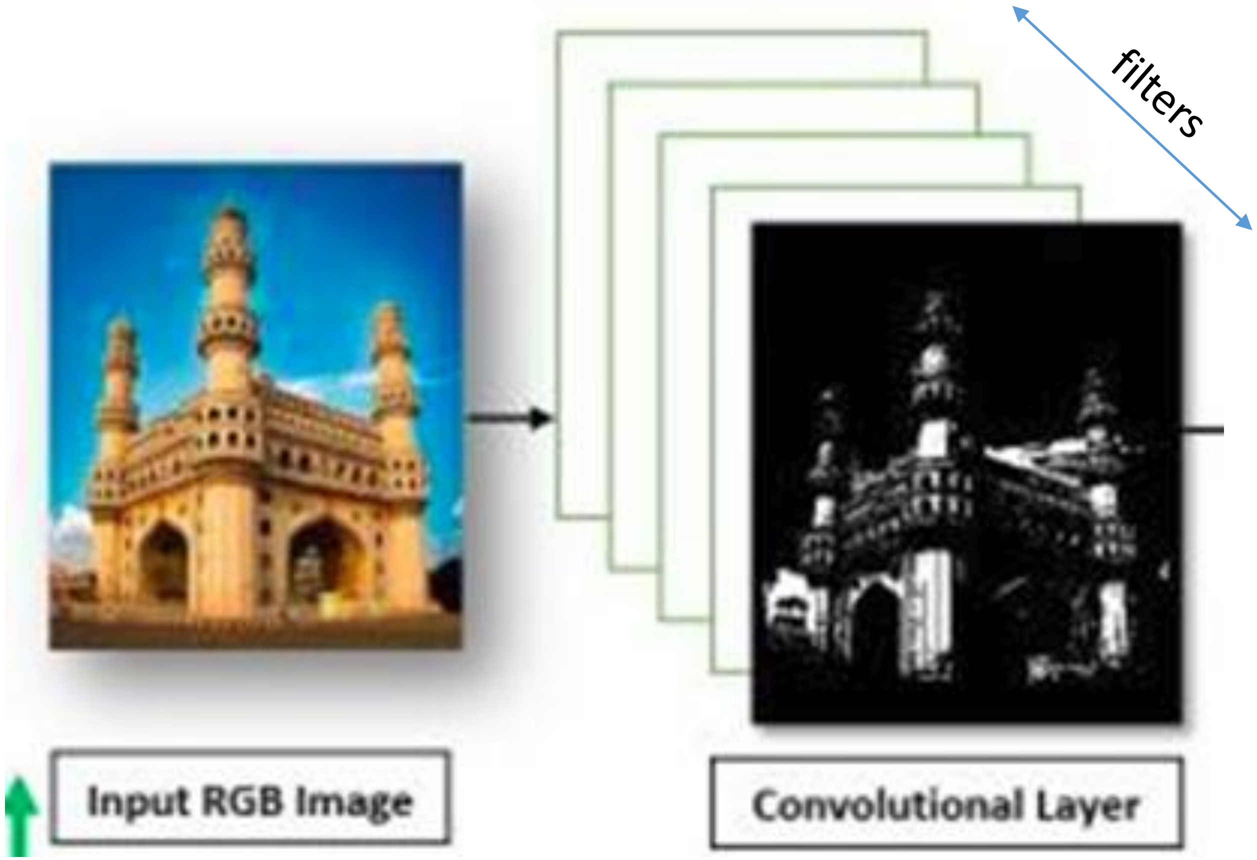
```
model = Sequential()
model.add(Conv2D(F, (K, K), strides=(S, S), activation='relu', padding="same", input_shape=(32, 32, L)))
```



# 1. Convolution Neural Network

## Convolutional Layer (CNN or ConvNet):

- The CNN will reduce the original RGB images to its Convolutional Layer
- Multiple layers can be applied



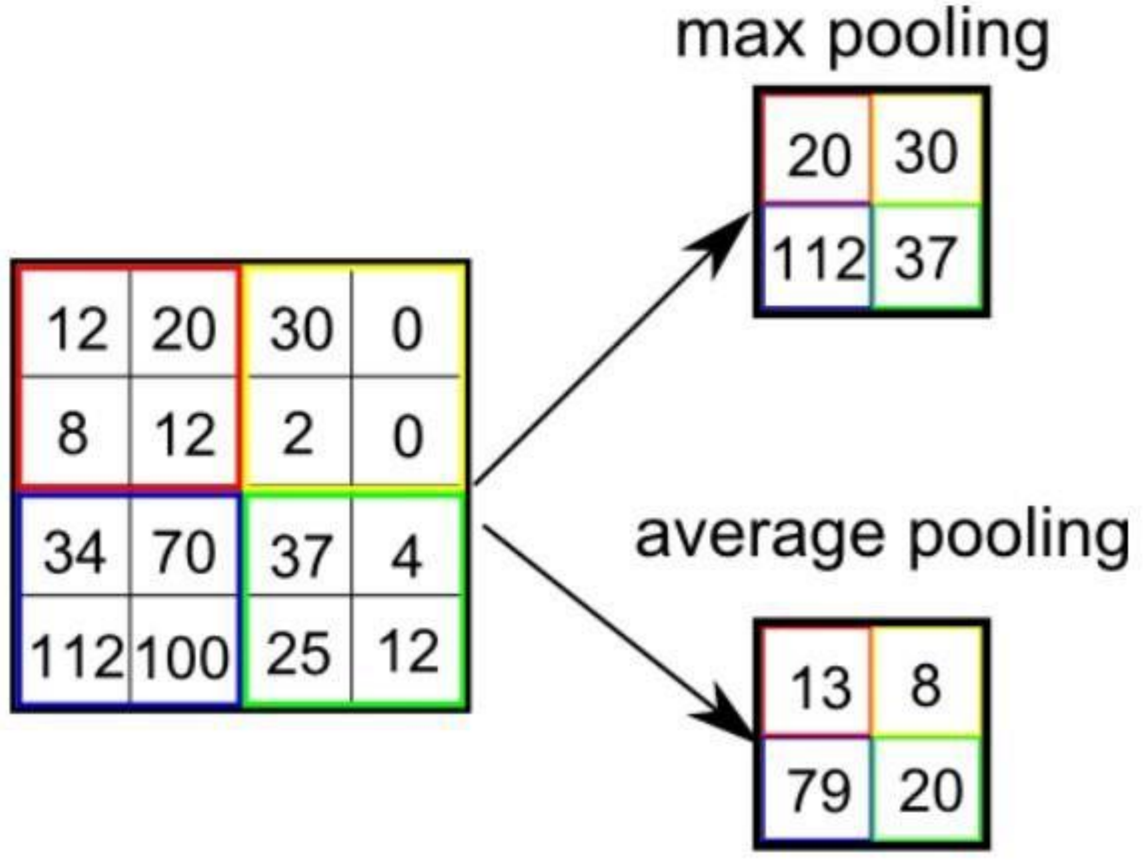
# 1. Convolution Neural Network

## Pooling Layer

- Pooling Layer should follow Convolutional Layer
- Similar to the Convolutional Layer, the Pooling layer is responsible for reducing the spatial size of the Convolved Feature.
- This is to decrease the computational power required to process the data through dimensionality reduction
- Two types of Pooling: Max Pooling & Average Pooling.

# 1. Convolution Neural Network

## Pooling Layer

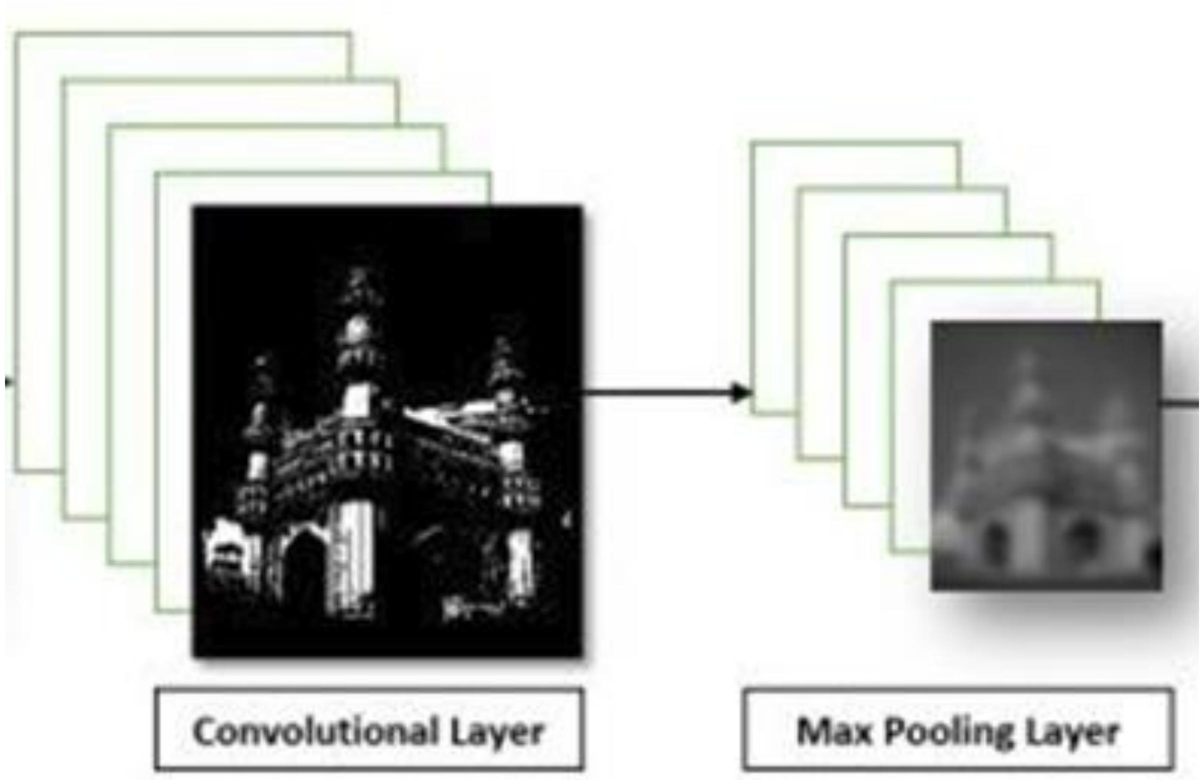



In which Max Pooling performs a lot better than Average Pooling.

# 1. Convolution Neural Network

## Pooling Layer

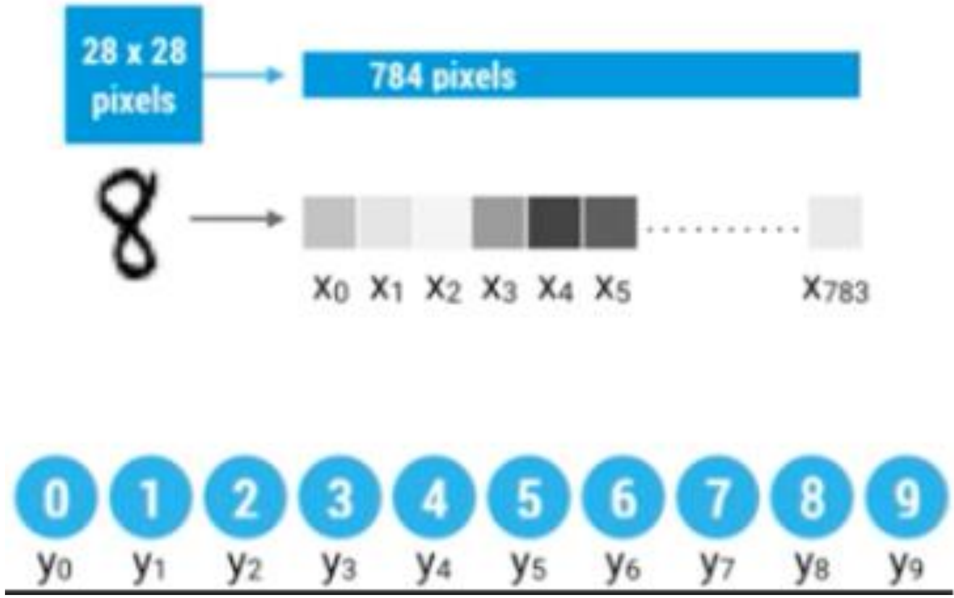
•The image after Max Pooling layer would look like:



# 1. Convolution Neural Network

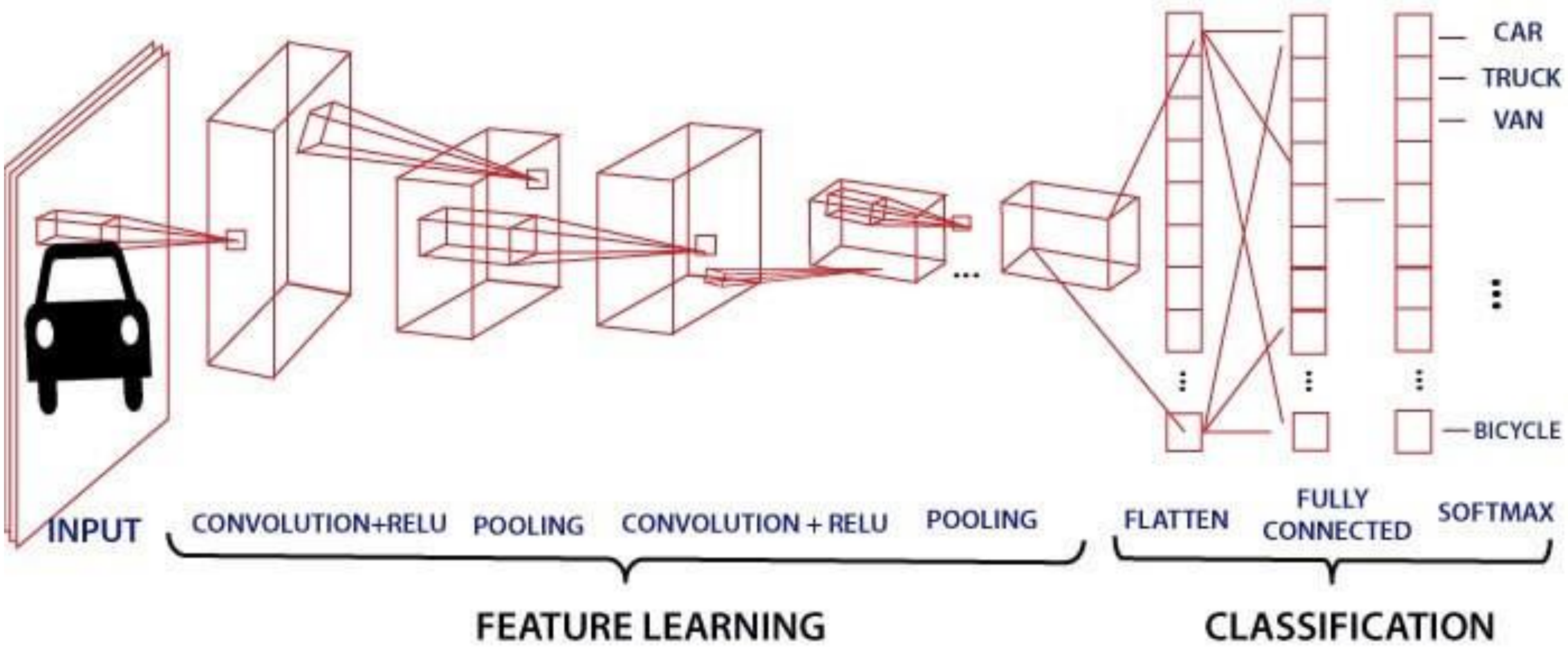
## Flatten Layer

- Once the images have passed through Convolution Layer and Pooling Layer, its size has been reduced greatly and ready for MLP training (or to another Convolution steps).
- The image is then flatten to a column vector and passed through feed-forward NN and BackPropagation applied to every iteration.
- Softmax activation function is applied to classified the multi-output/multi-labels



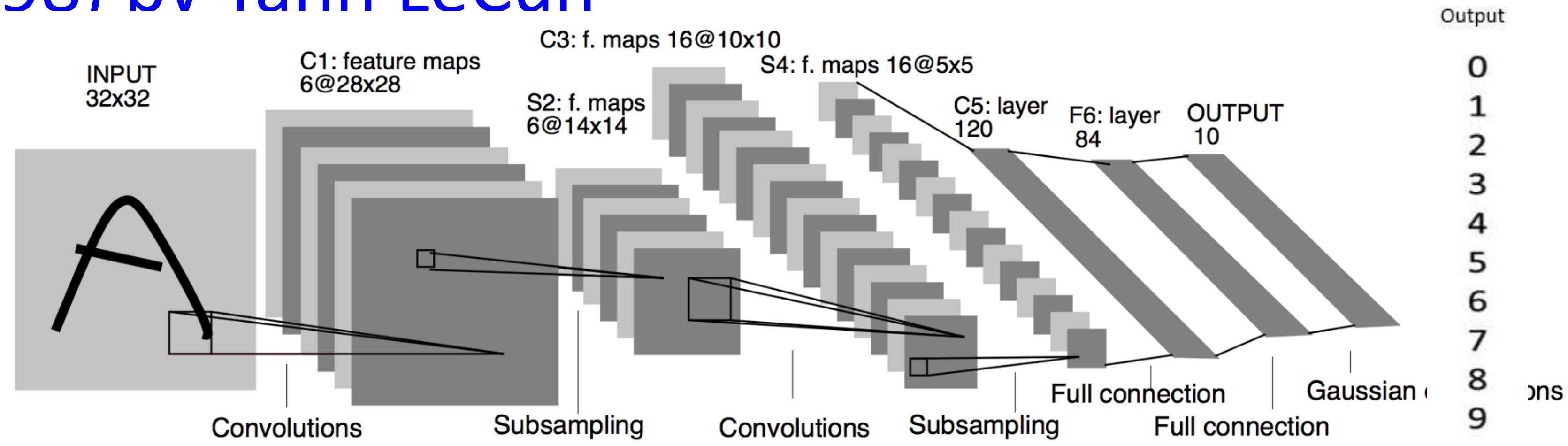
# 1. Convolution Neural Network

## A Sample of CNN:



# 1. Convolution Neural Network

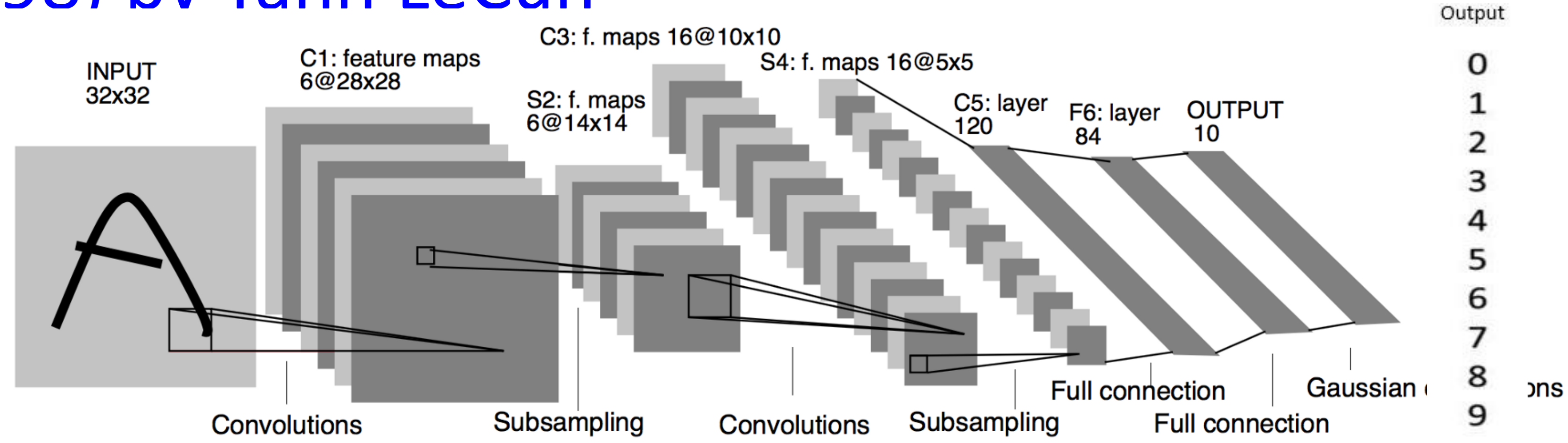
## Lenet-5 (1998) bv Yann LeCun




- LeNet-5 is designed for handwritten and machine-printed character recognition
- Input of 32x32x1
- Total parameters: 60k
- Activation function: tanh

# 1. Convolution Neural Network

## Lenet-5 (1998) bv Yann LeCun

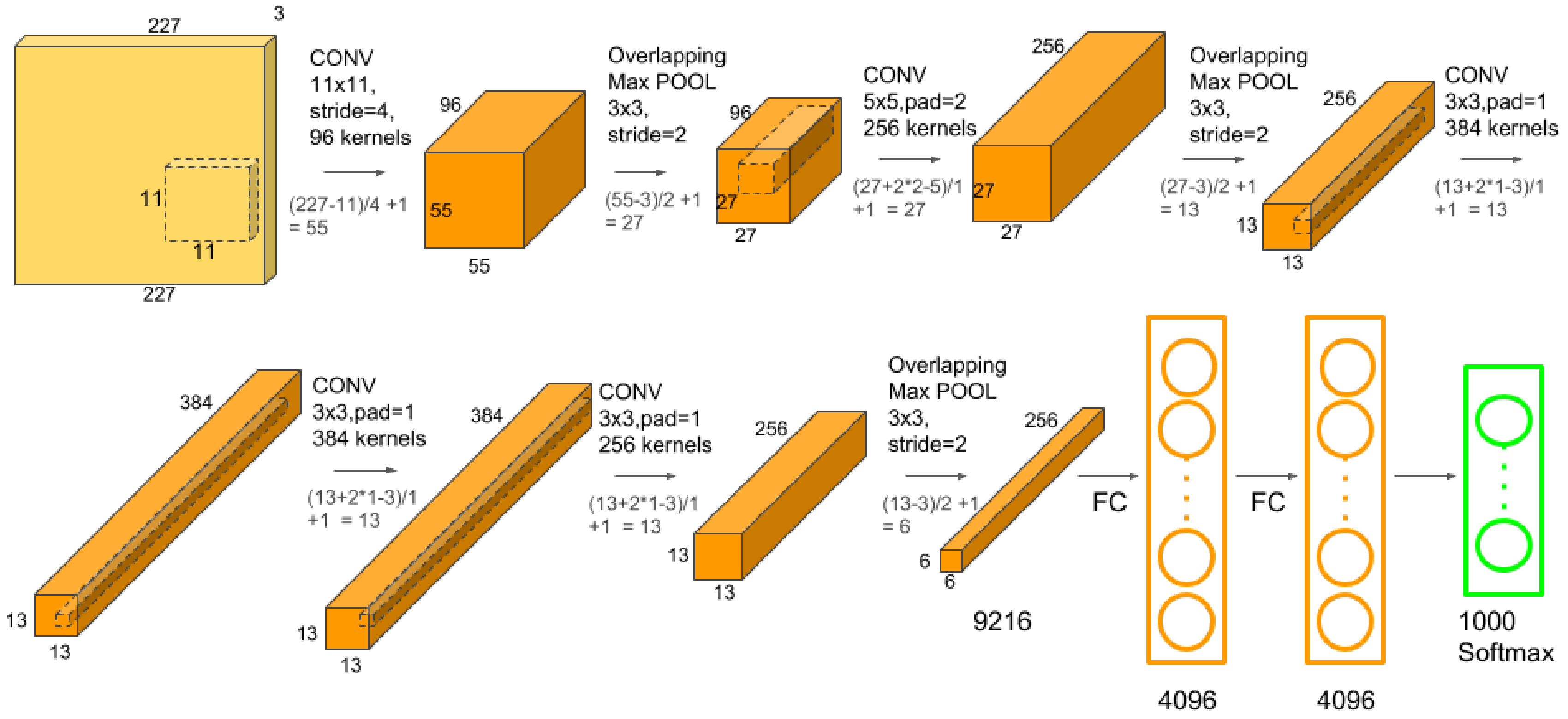



```
model = Sequential()
model.add(Conv2D(6, (5, 5), strides=(1, 1), activation='tanh', padding="valid", input_shape=(32, 32, 1)))
model.add(AveragePooling2D(pool_size=(2,2),strides=(2,2)))
model.add(Conv2D(16, (5, 5), strides=(1, 1), activation='tanh', padding="valid"))
model.add(AveragePooling2D(pool_size=(2,2),strides=(2,2)
model.add(Conv2D(120, (5, 5), strides=(1, 1), activation='tanh', padding="valid"))
model.add(Flatten())
model.add(Dense(84,activation='tanh'))
model.add(Dense(10,activation='softmax'))
```

# 1. Convolution Neural Network

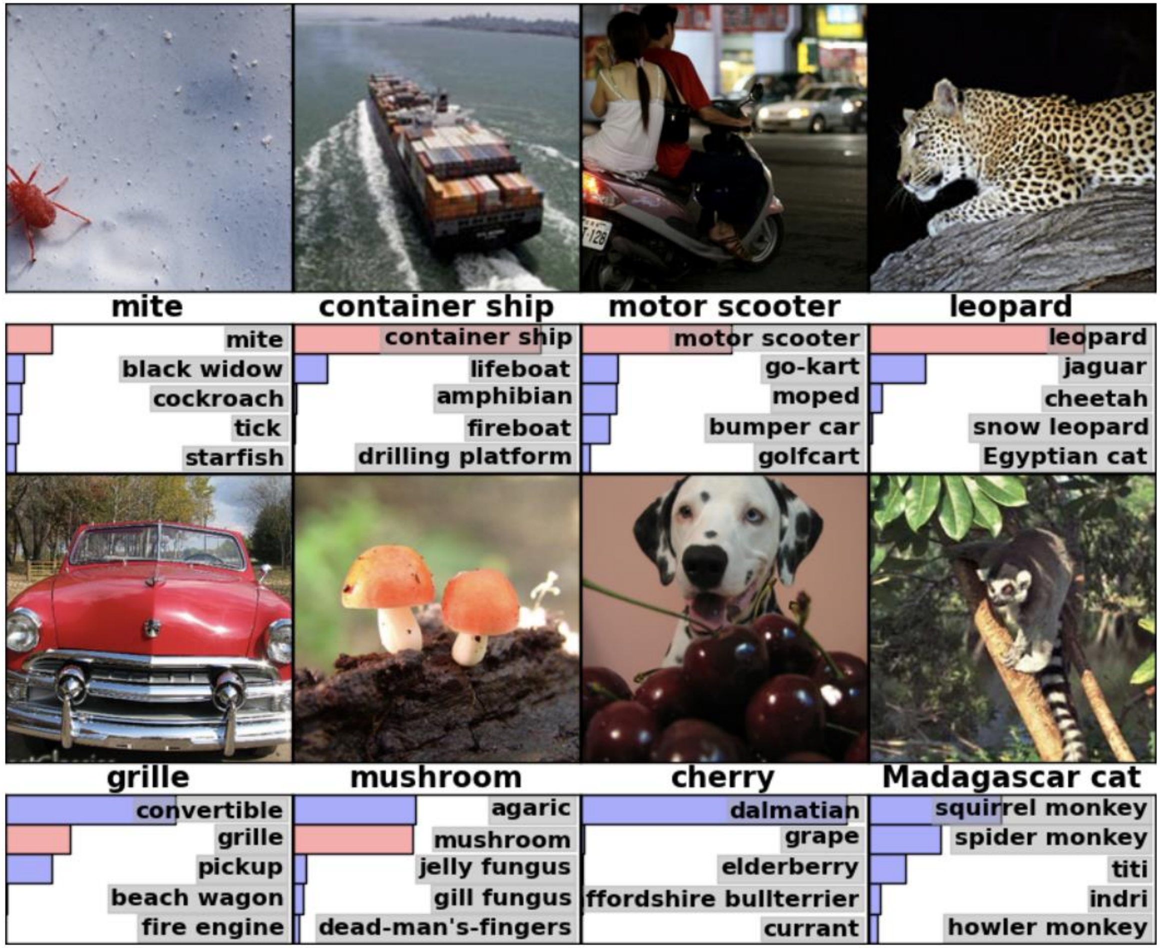
## AlexNet (2012) by Hinton Alex Krizhevsky

- AlexNet won the 2012 ImageNet challenge
- Input of 227x227x3
- Total parameters: 60M
- Activation: ReLU



# 1. Convolution Neural Network

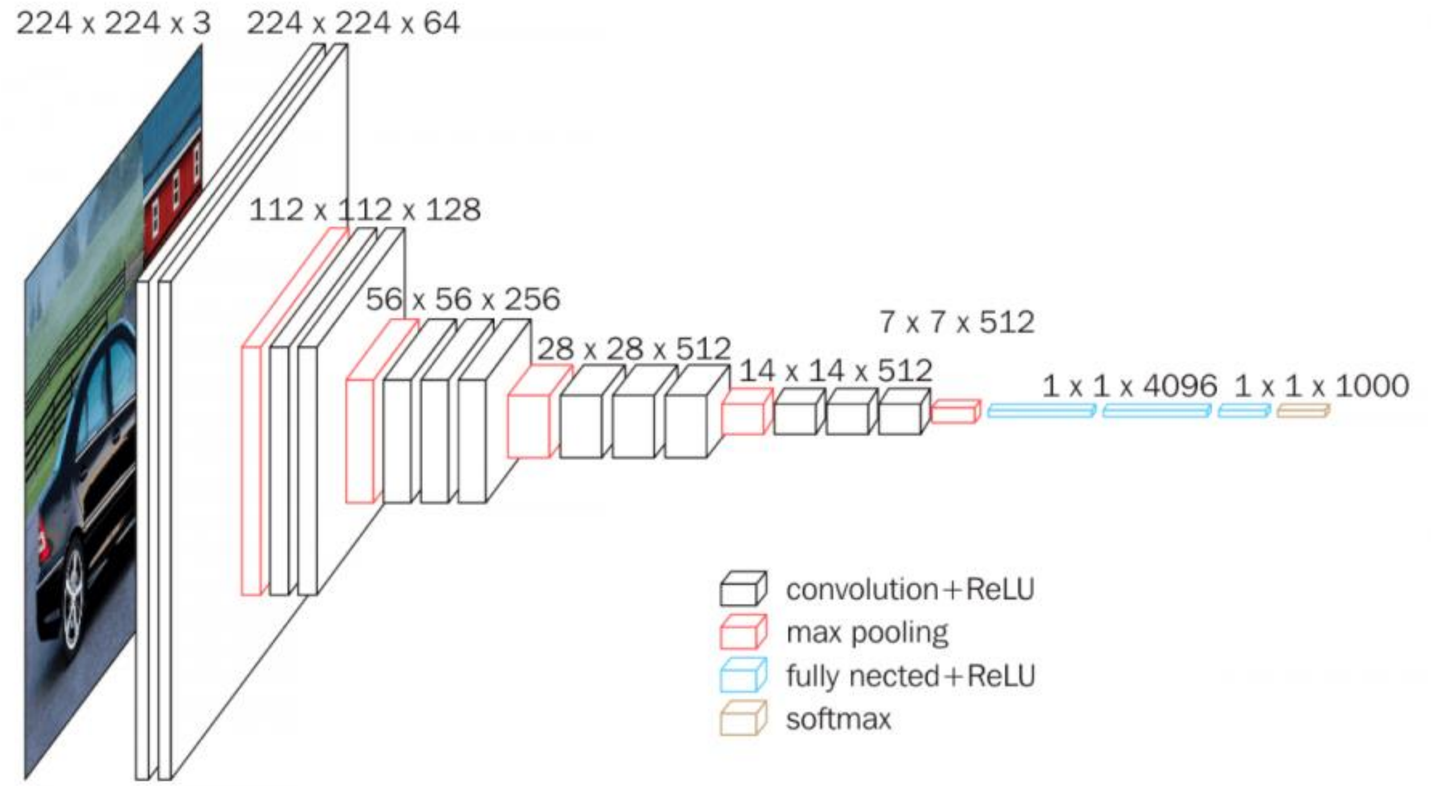
AlexNet (2012) by Hinton Alex Krizhevsky



# 1. Convolution Neural Network

## VGG16 (2014) - Visual Geometry Group

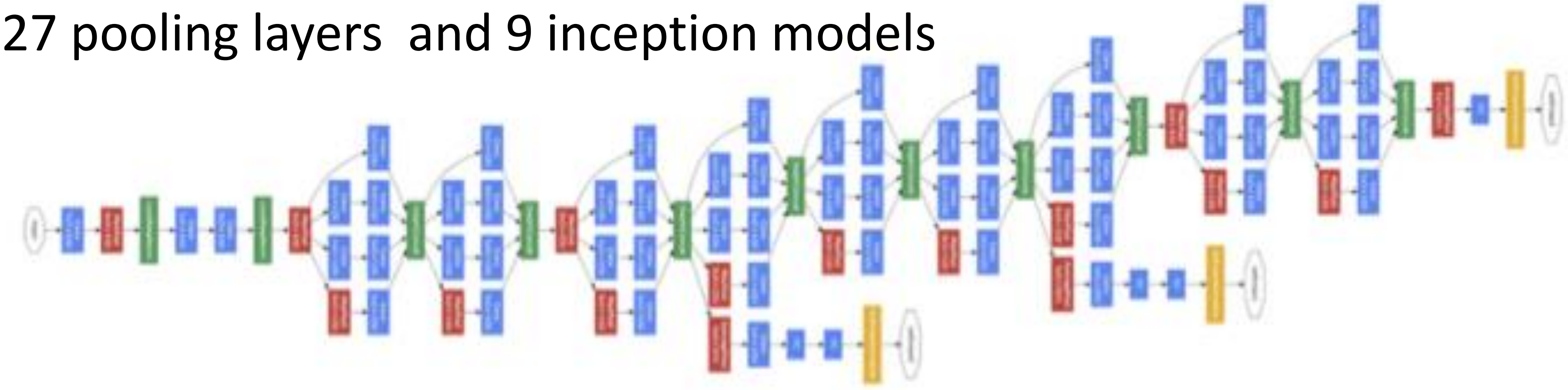
- VGG16 runner up of 2014 ImageNet challenge
- 16 layers: 13 ConvNet, 3 Fully Connected
- Total Parameters: 130M



# 1. Convolution Neural Network

## GoogleNet (2014)

- GoogleNet won the 2014 ImageNet challenge
- Introduced Inception Network
- 22 layers deep with 27 pooling layers  and 9 inception models

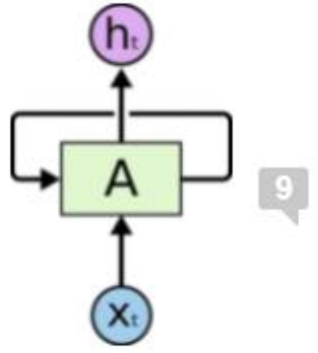


# 2. Recurrent Neural Network

# 2. Recurrent Neural Network

**Introduction**

- RNNs are type of Deep Learning models with built-in feedback mechanism.
- The output of a particular layer can be **re-fed** as the input in order to predict the output.
- This is different from traditional ML where output/predictand cannot be used as input

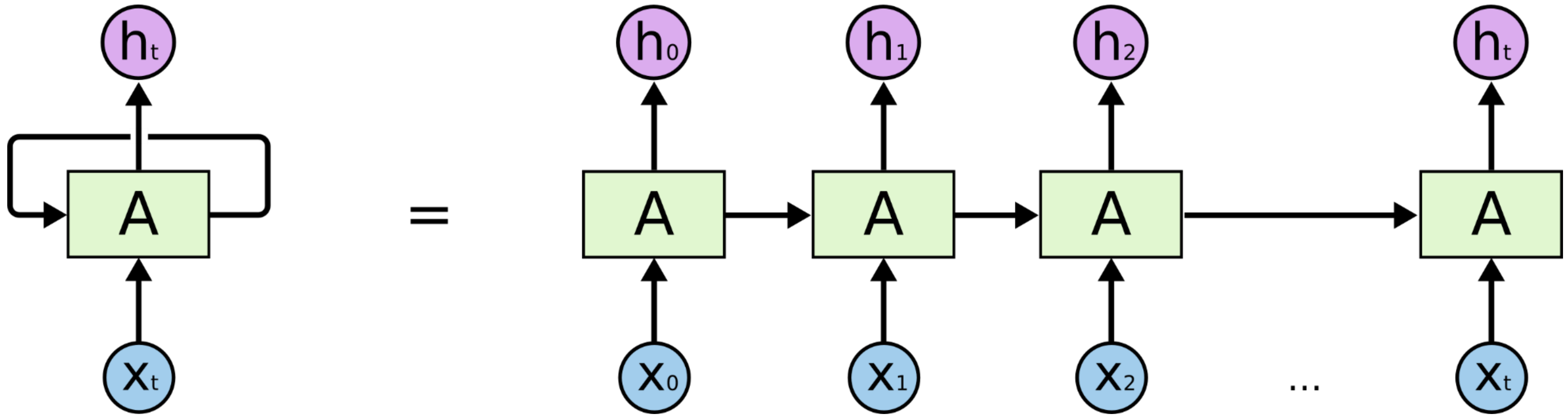



Recurrent Neural Networks have loops.

# 2. Recurrent Neural Network

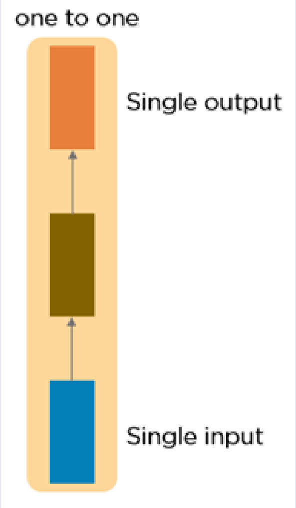
## Introduction

- Unroll the RNN loop



# 2. Recurrent Neural Network

## Type of RNNs

<table>
<tr><th>One to One</th><th>One to Many</th><th>Many to One</th><th>Many to Many</th></tr>
<tr>
<td>
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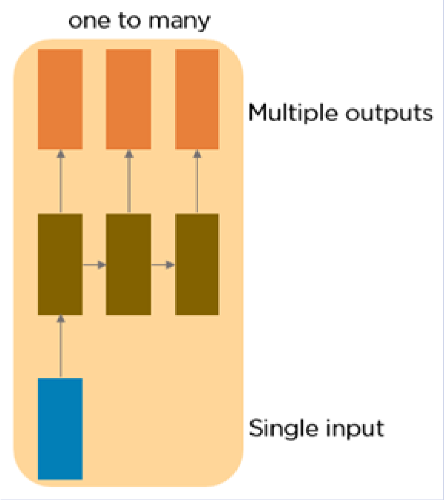
<td>
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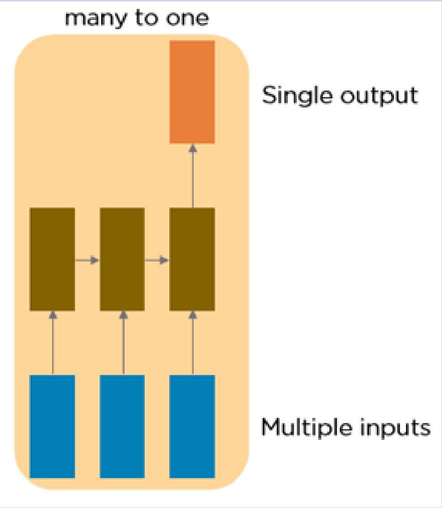
<td>
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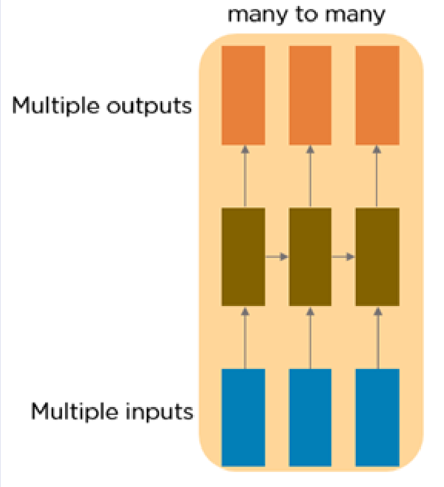
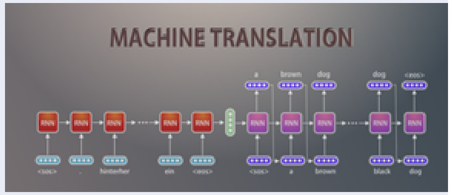
<td>
</td>
</tr>
<tr>
<td>So called Vanilla NN.<br>Similar to Backpropagation for general ML problem</td>
<td>Image captioning<br>
</td>
<td>Sentiment analysis<br>
</td>
<td>Machine translation<br>
</td>
</tr>
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# 2. Recurrent Neural Network

## Applications

It is specifically designed for Sequential problem **Weather forecast, Stock forecast, Image captioning, Natural Language Processing, Speech/Voice Recognition**

# 2. Recurrent Neural Network

## Some Disadvantages of RNN:

- Computationally Expensive and large memory requested
- RNN is sensitive to changes in parameters and having gradient problem such as **Exploding Gradient** or **Vanishing Gradient**
- In order to resolve the **gradient problem** of RNN, a method Long-Short Term Memory (LSTM) is proposed.

In this limited workshop, we only cover LSTM for timeseries forecast problem (stock forecast and weather forecast)

# 2. Recurrent Neural Network

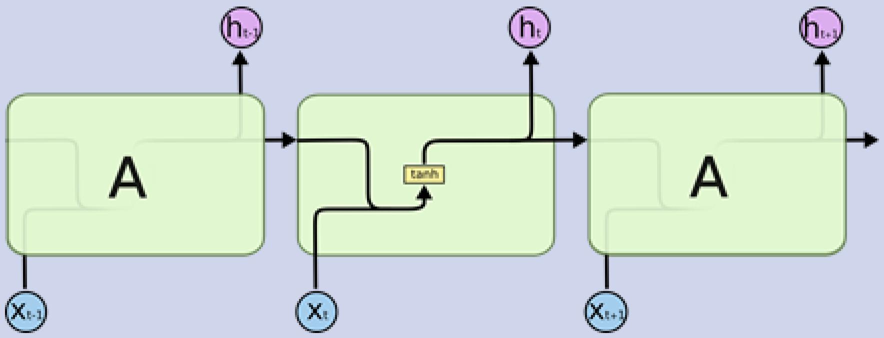
## Long-Short Term Memory model - LSTM

- LSTMs are a special kind of RNN — capable of learning long-term dependencies by remembering information for long periods is the default behavior.
- They were introduced by Hochreiter & Schmidhuber (1997) and were refined and popularized by many people
- LSTMs are explicitly designed to avoid the long-term dependency problem.

# 2. Recurrent Neural Network

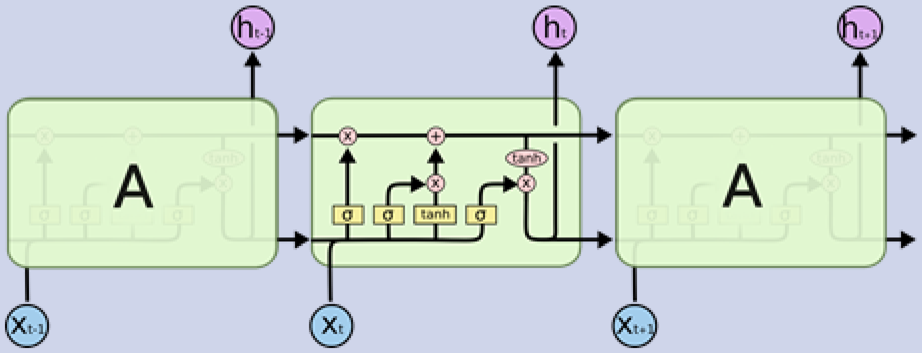
## Comparison between traditional RNN and LSTM

**Standard RNN structure**




The repeating module in a standard RNN contains a single layer.

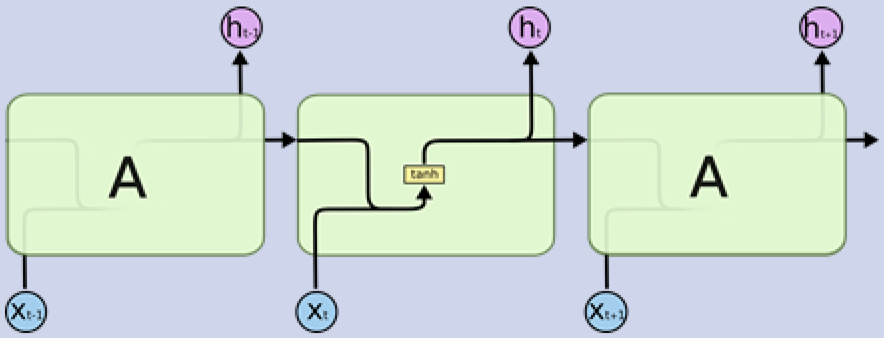
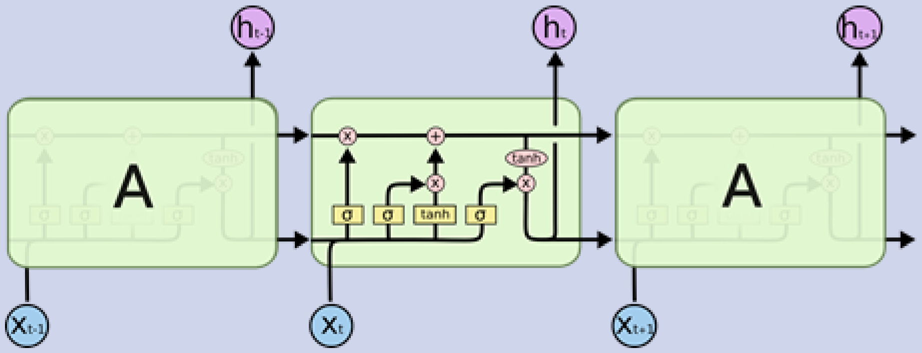
**LSTM structure**




The repeating module in an LSTM contains four interacting layers.

# 2. Recurrent Neural Network

## Comparison between traditional RNN and LSTM

| Standard RNN structure | LSTM structure |
|---|---|
|   The repeating module in a standard RNN contains a single layer. |   The repeating module in an LSTM contains four interacting layers. |


```
model = Sequential()
model.add(LSTM(128, return_sequences=True, input_shape= (x_train.shape[1], 1)))
model.add(LSTM(64, return_sequences=False))
```

# 2. Recurrent Neural Network

**Hands-on section**