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Advanced Machine Learning

Lecture 2: Supervised Deep Learning

Syllabus

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- Deep Sequential Modeling
  - RNN
    - LSTM
    - GRU
  - Bidirectional RNNs

- Convolutional NN (CNN)
  - What are they for?
  - Step 1: Convolution
  - Step 1(b) - ReLU
  - Step 2 - Pooling
  - Step 3 - Flattening
  - Step 4 - Full Connection

Deep Sequence modelling

Why do we need sequence modelling?

I Can assure, this ball is moving:

Can you predict the direction this ball is heading?

Why do we need sequence modelling?

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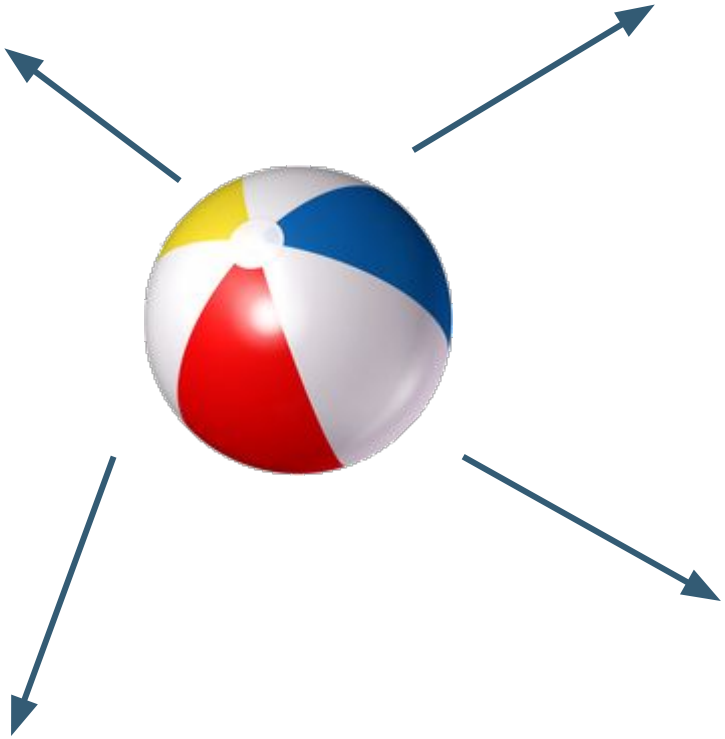
Can you predict the direction this ball is heading?

With no other information, it can be ANYWHERE



Why do we need sequence modelling?

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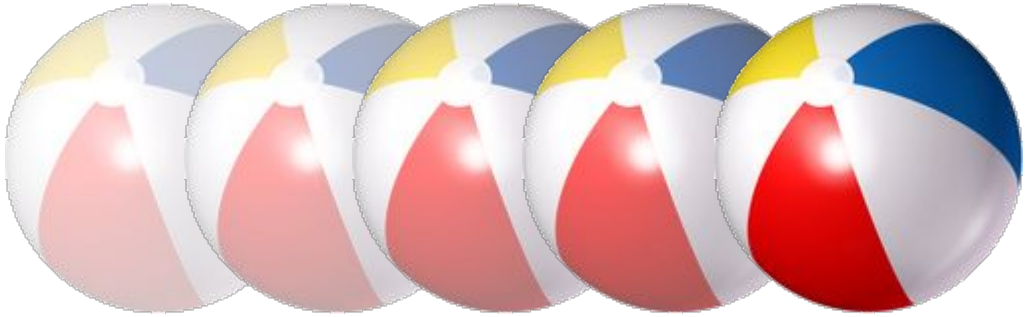
Can you predict the direction this ball is heading, if I tell you that its last movements were these ones?



Why do we need sequence modelling?

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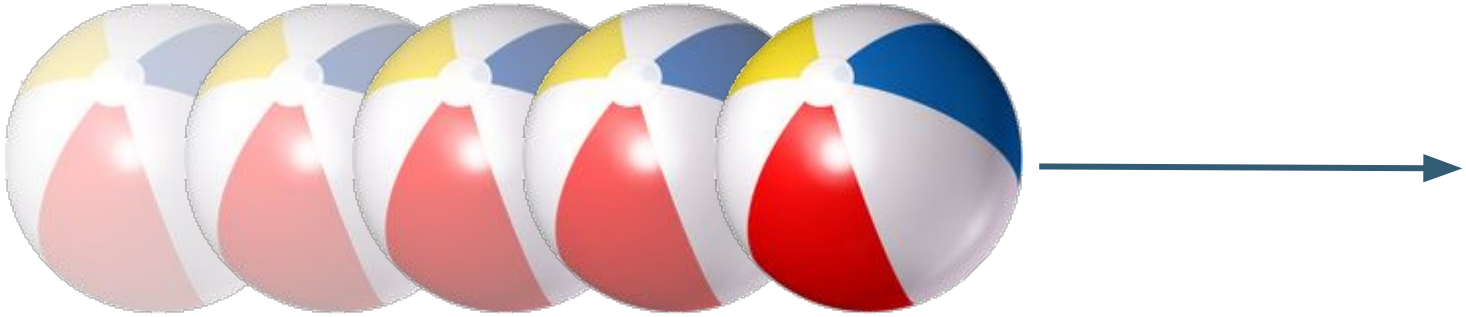
Can you predict the direction this ball is heading, if I tell you that its last movements were these ones?

It is easy…. it is heading East



Why do we need sequence modelling?

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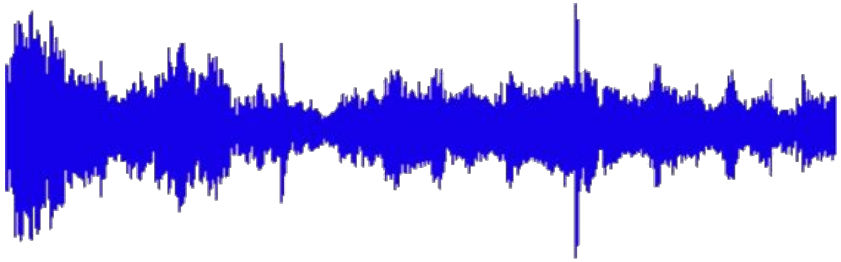
- Basically, in order to predict, sometimes, **past knowledge is needed**.
- Examples of Sequence data (or TimeSeries):
  - Audio or sensor data, is a sequence of values
  - Text can be seen as sequences of characters or words



Audio, Sensor data, ...

character sequence:
H E L L O M Y N A M E I S E K H I

Word sequence:
Hello My Name Is Ekhi

Text data

Can we predict Sequences using FFNN?

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"This morning I took my cat for a walk."

given these words — predict the next word

- Limitation:
  - Inputs in FFNN are fixed, so we would not be able to predict variable length sentences.

"This morning I took my cat for a walk."

given these two words — predict the next word

- OK, let us take only 2 words and try to predict the 3rd one
- Limitation:
  - We loose long time dependency:

I am **Basque**, right now I live in Guatemala, but I still speak fluent ____

- There are even more Limitations:
  - Order importance
  - No information Share across the sequence

The food was good, not bad at all.

vs.

The food was bad, not good at all.

Sequence Modelling: Design Criteria

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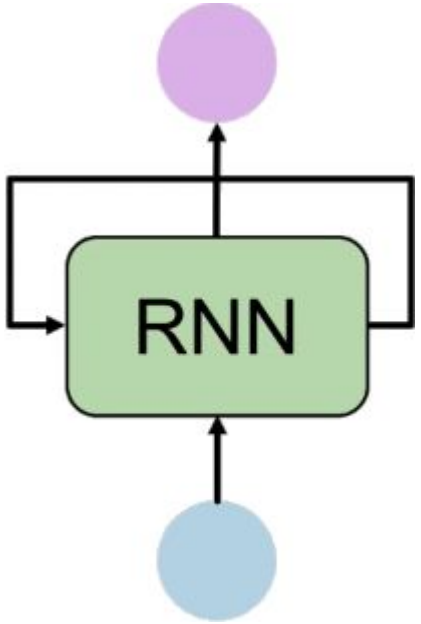
1. Handle Variable length Sequences
2. Track long-term dependencies
3. Maintain order information
4. Share parameters across the sequence



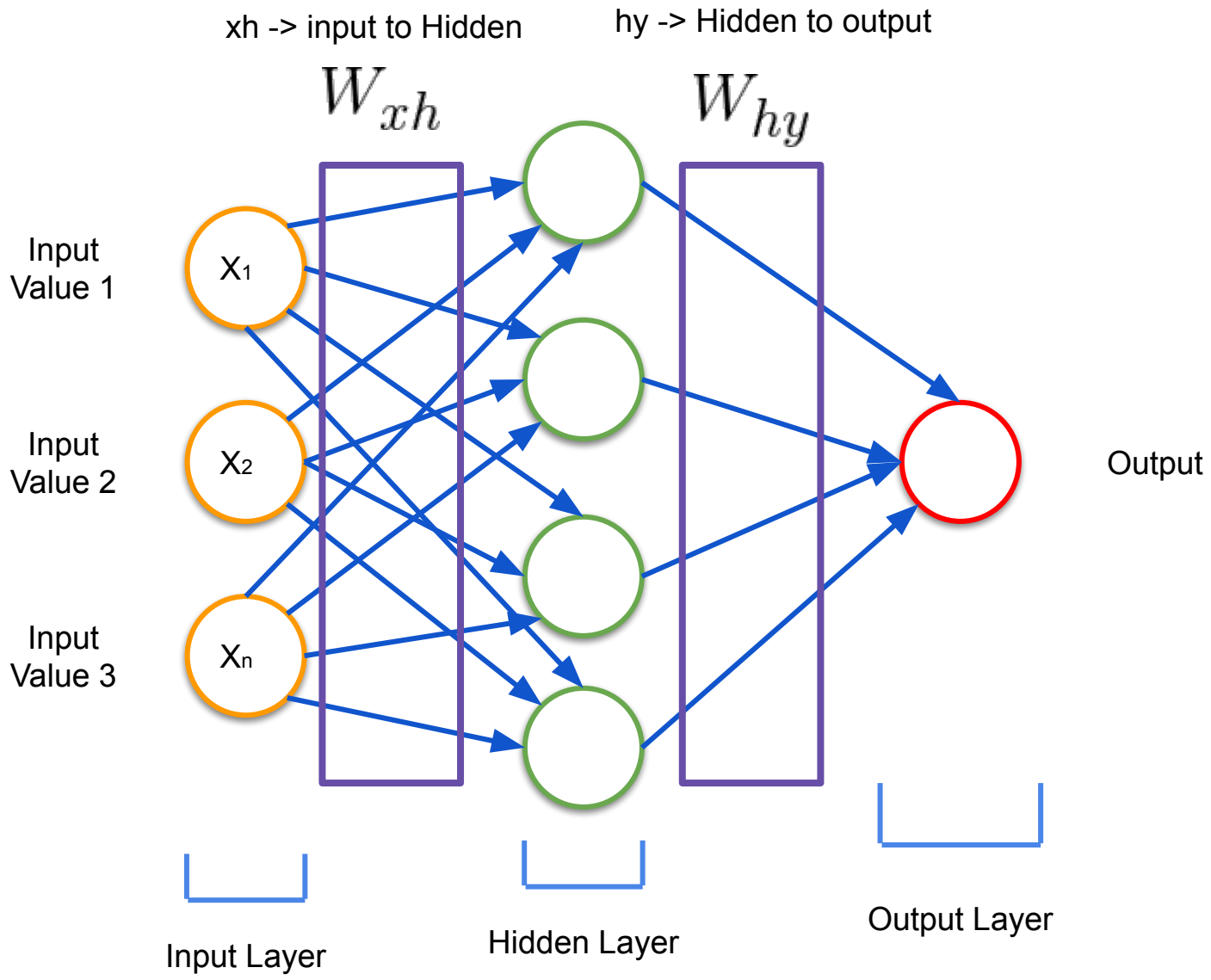
RNN in action - SunsPring

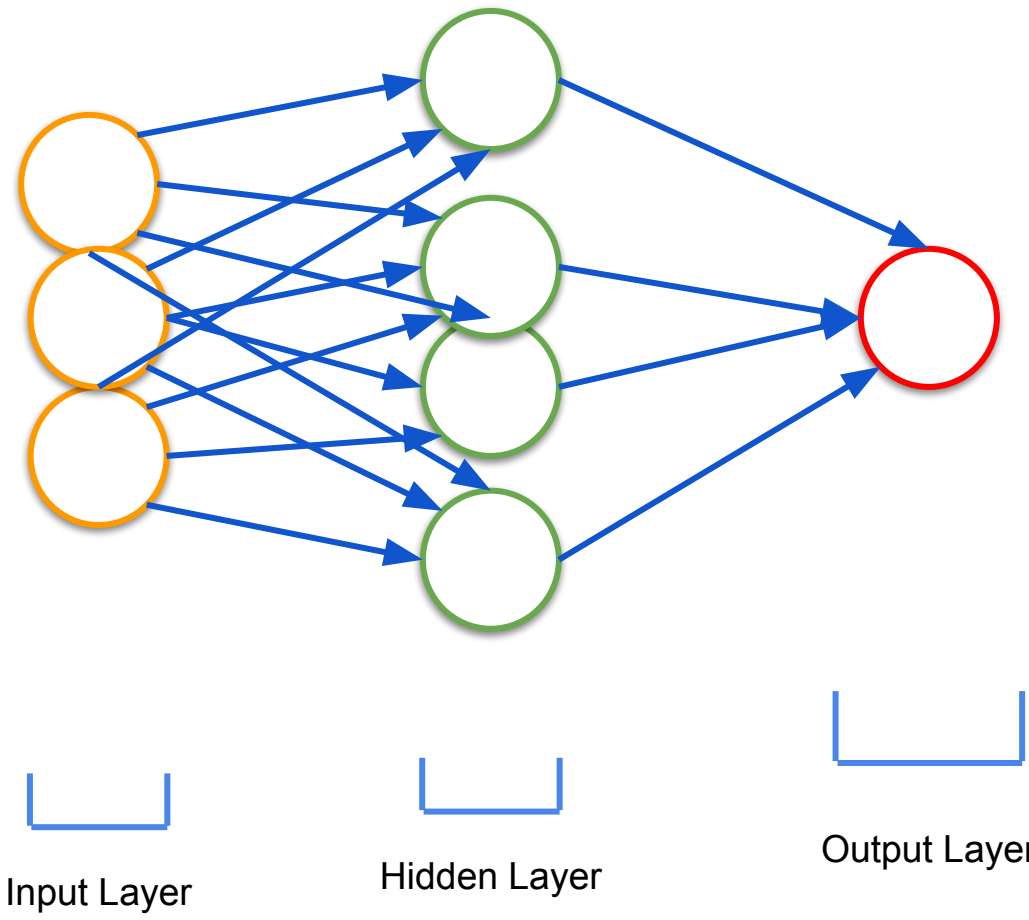
https://www.imdb.com/title/tt5794766/

Short movie written by an RNN (llamado Benjamin)

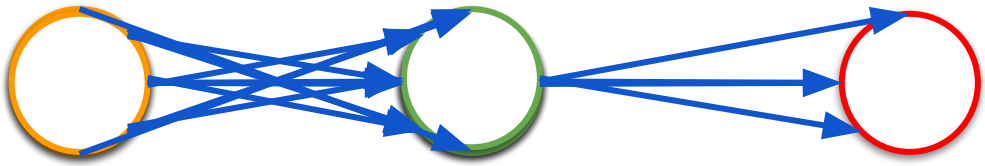
Learning: Hundreds of science fiction film plots
although each phrase has a meaning, there is a lack of a global vision

Recurrent Neural Networks (RNN)


xh -> input to Hidden
hy -> Hidden to output
W_{xh}
W_{hy}
Input Value 1
Input Value 2
Input Value 3
X_1
X_2
X_n
Output
Input Layer
Hidden Layer
Output Layer


Input Layer
Hidden Layer
Output Layer

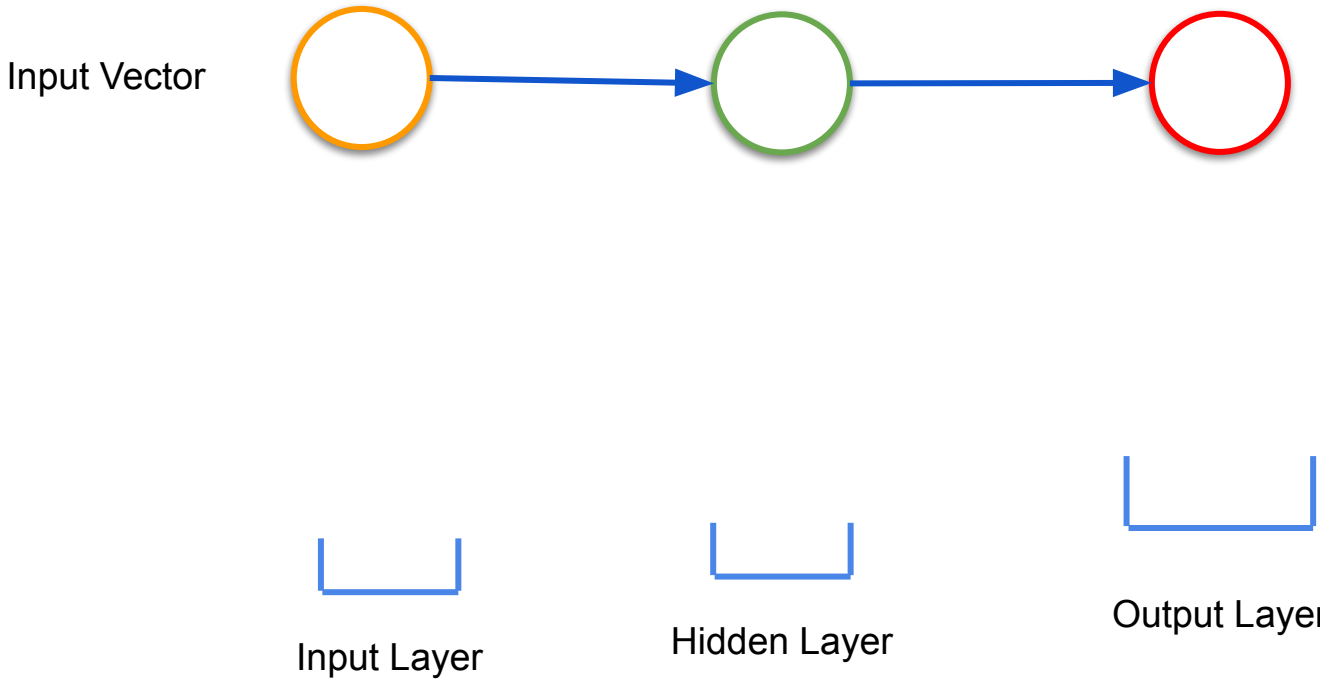
Input Vector

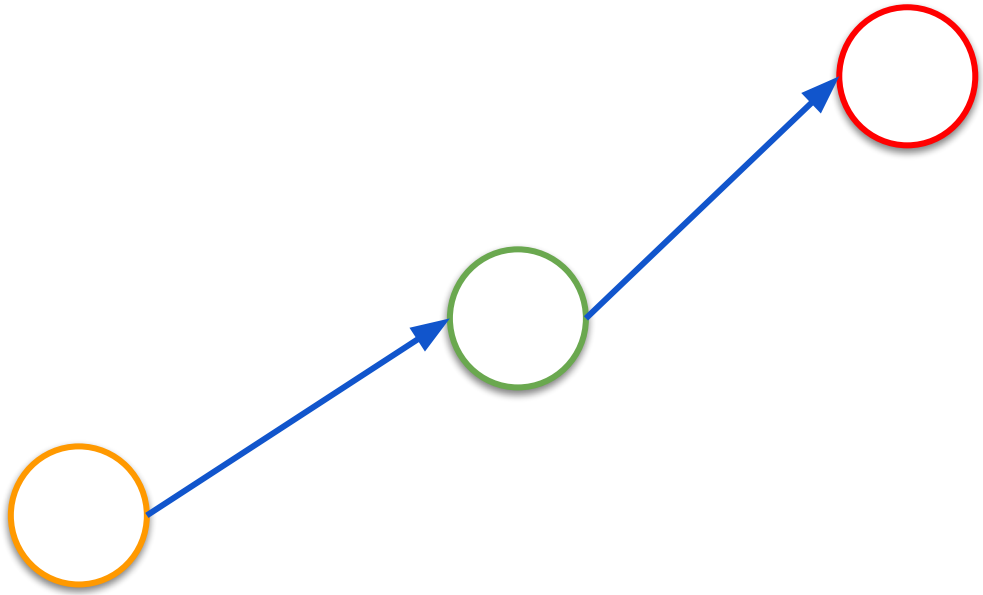


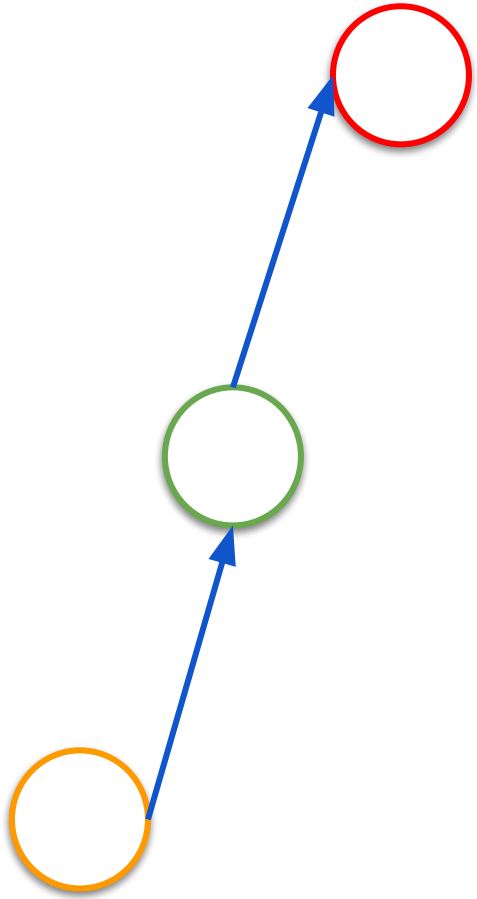
Input Layer

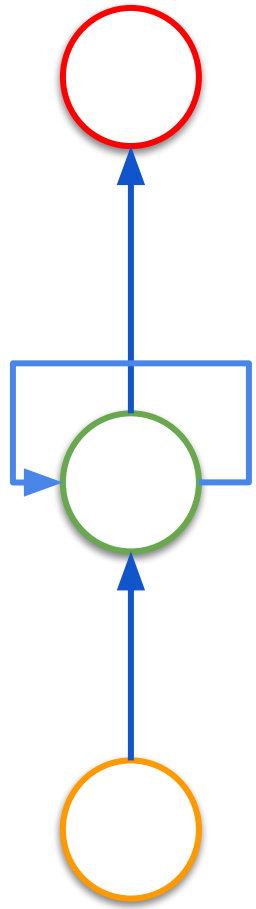
Hidden Layer

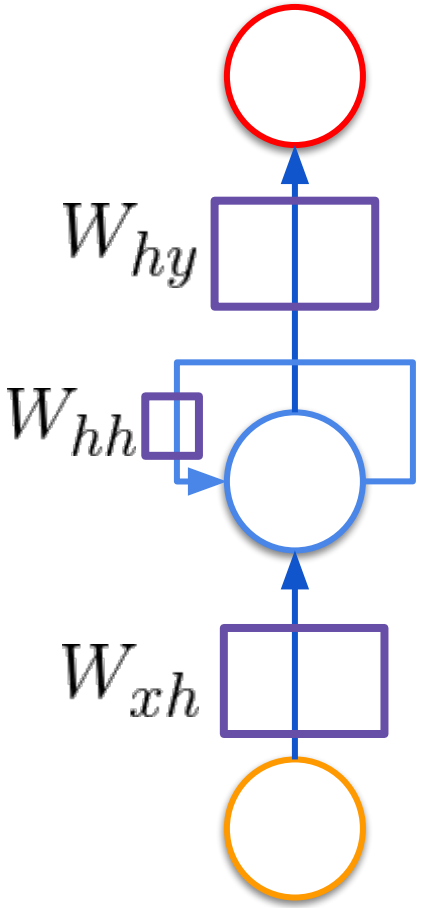
Output Layer

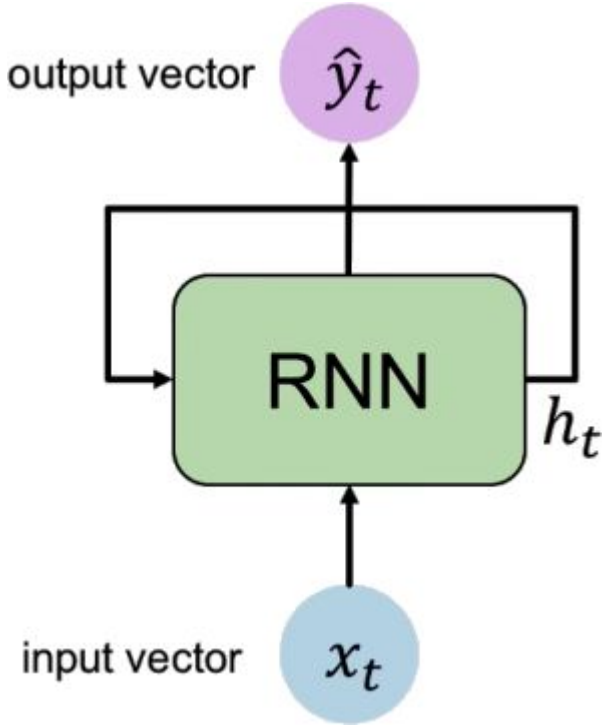

Input Vector
Input Layer
Hidden Layer
Output Layer



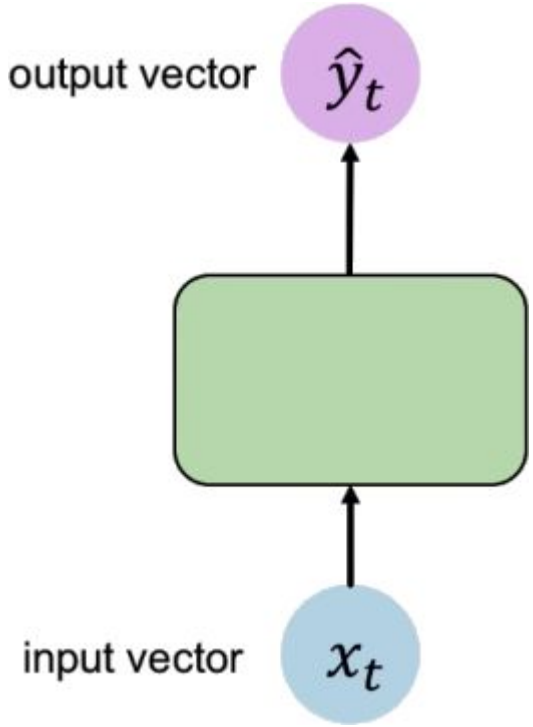


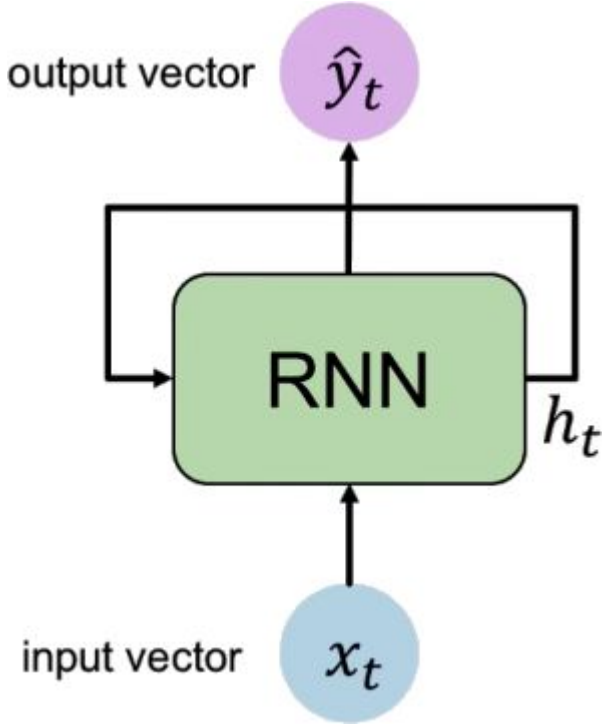



W_{hy}
W_{hh}
W_{xh}


output vector
$\hat{y}_t$
RNN
h_t
input vector
x_t

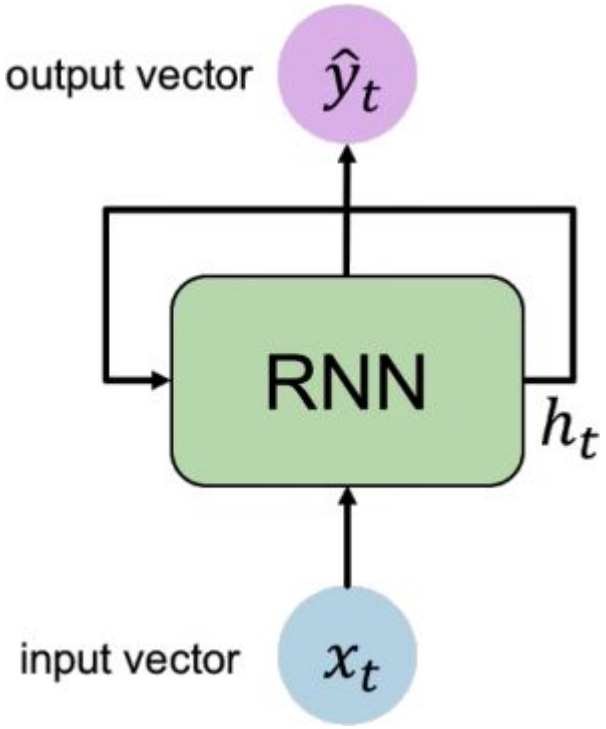
“Vanilla” FFNN vs RNN





RNN

- In each timeStamp, RNNs have as input:
  - Xt (current reading)
  - ht (internal state)
- and one output:
  - yt



Output Vector

$$\hat{y}_t = \boldsymbol{W}_{hy}^{T} h_t$$

Update Hidden State

$$h_t = \tanh(\boldsymbol{W}_{hh}^{T} h_{t-1} + \boldsymbol{W}_{xh}^{T} x_t)$$

Input Vector

$$x_t$$

Wxh -> input to hidden
Whh -> hidden to hidden
Why -> hidden to output

```
tf.keras.layers.SimpleRNN(rnn_units)
```

RNN Usages

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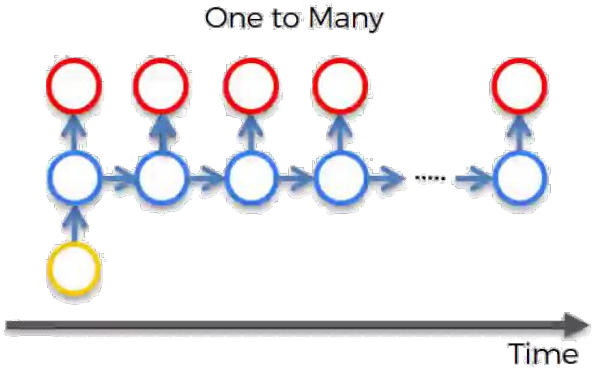
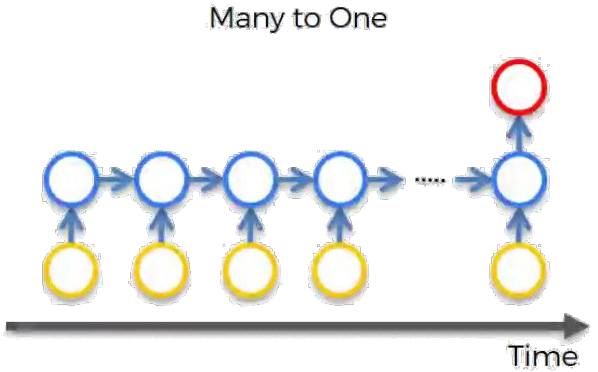
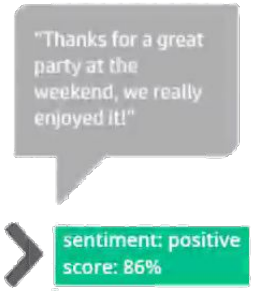
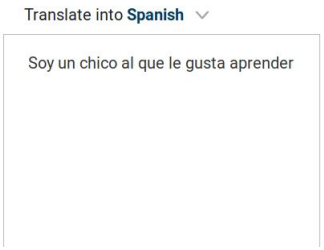
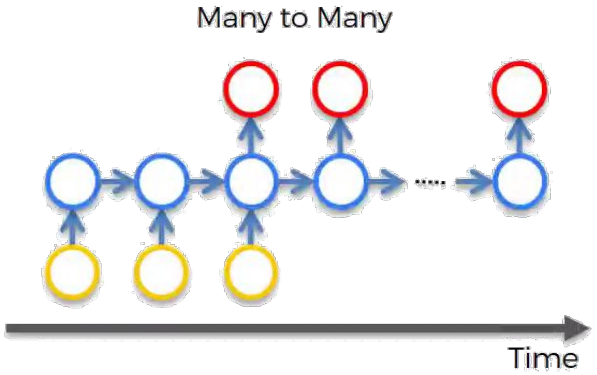
"black and white dog jumps over bar."

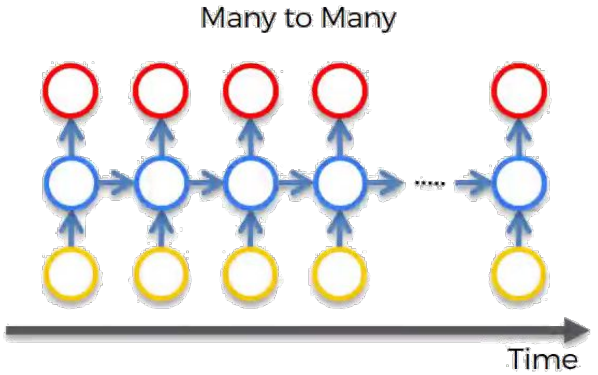


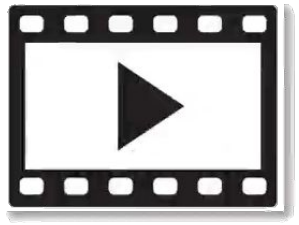












RNN, Forward pass and Loss calculation

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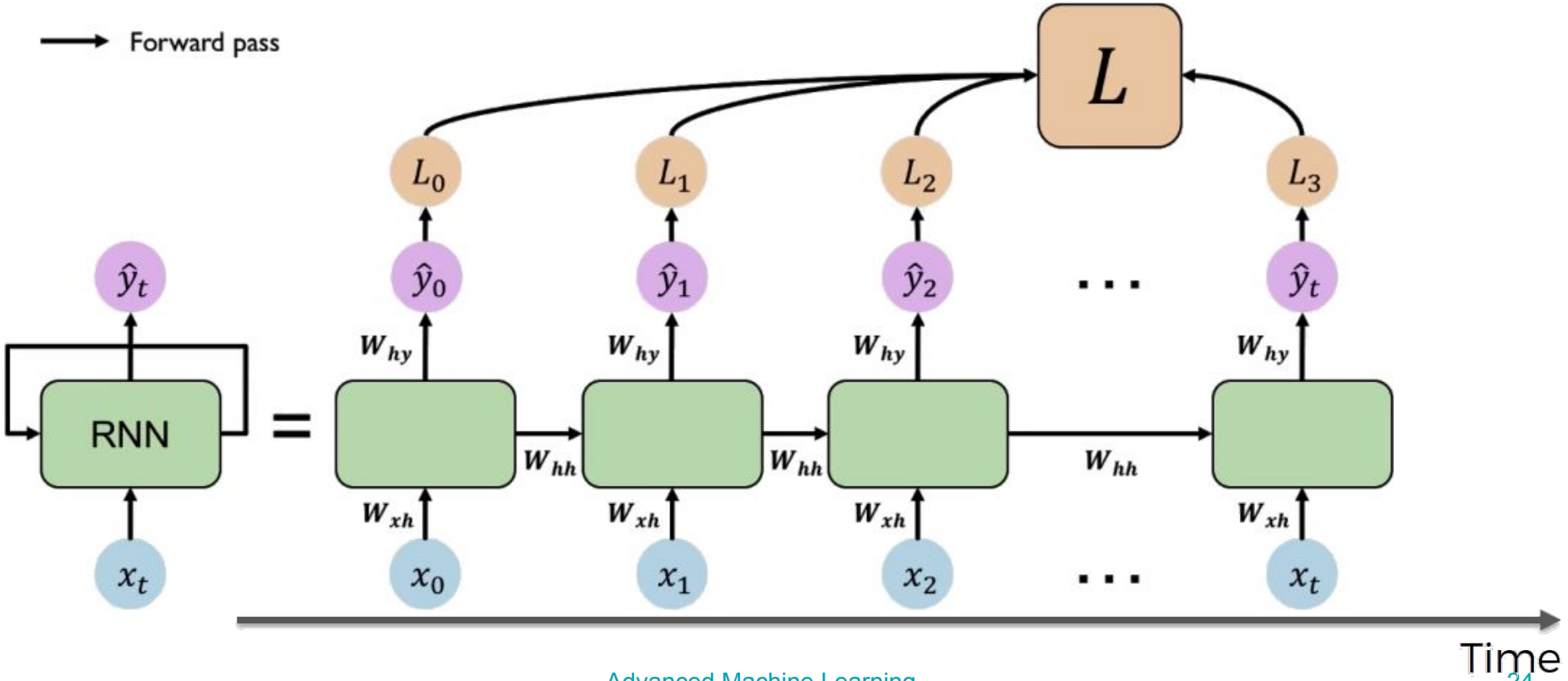
- We can depict RNNs as:
  - Multiple copies of themselves, that pass down a message through time (ht)
  - REMEMBER: we reuse the same Weight matrices at each time step
  - In the forward pass:
    - We can compute a loss for each time step, and the global loss will be the sum of all the losses



RNN-> Backpropagation Through Time

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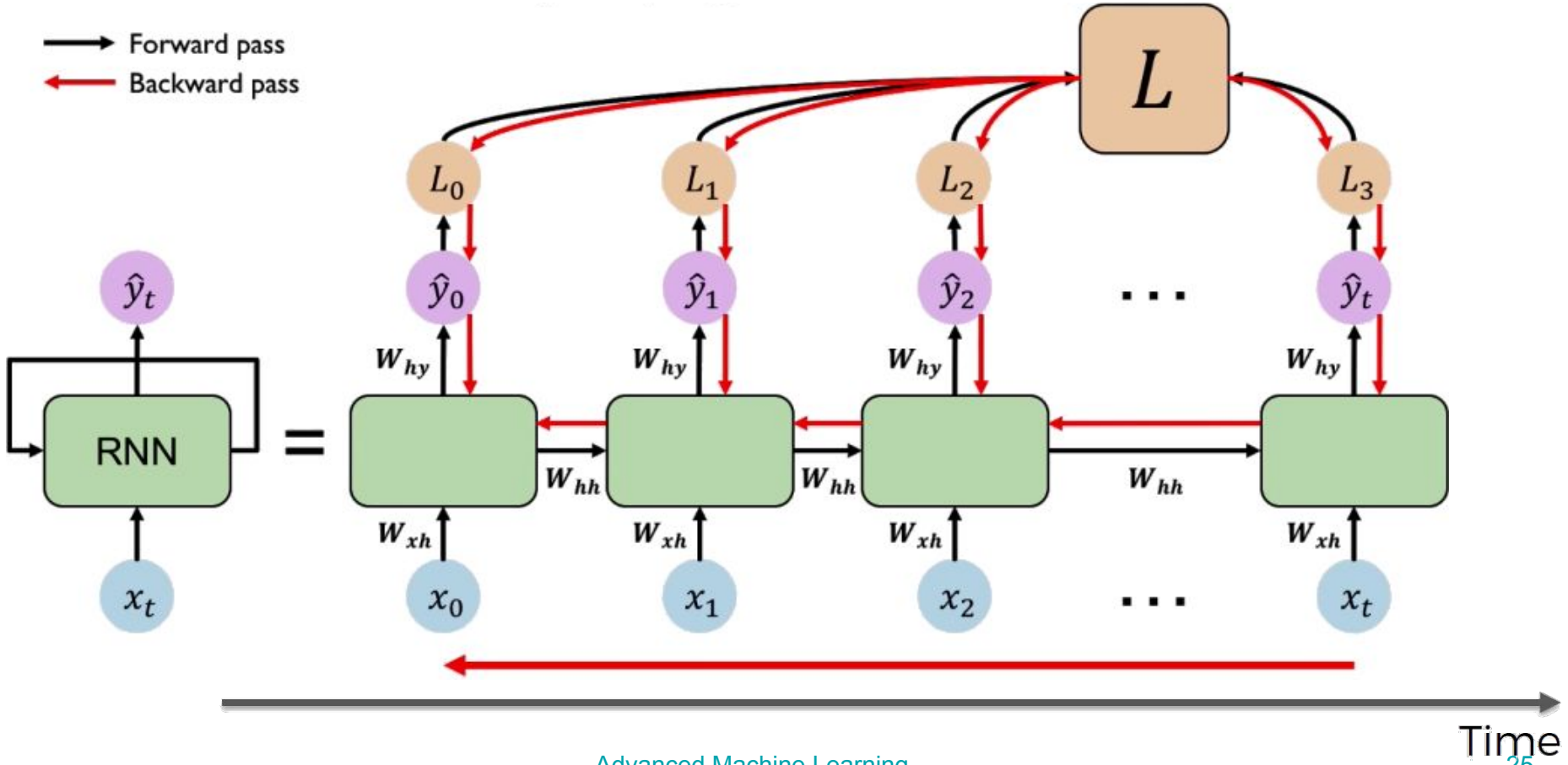
- BPTT
  - Error is Back Propagated
    - First though each state
    - Finally through Hidden states



Problems with RNNs

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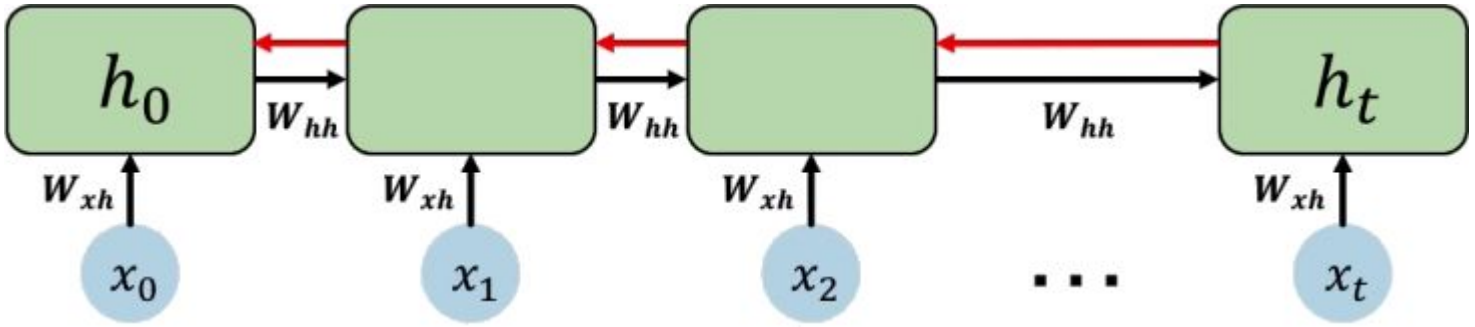
- The RNN : “Vanishing / Exploding Gradient”
- Computing the gradient of h0:
  - involves many “factors” (multiplications) of Whh and activation function derivatives



Razvan Pascanu et al. (2013)

Many values > 1:
exploding gradients

Gradient clipping to scale big gradients

Many values < 1:
vanishing gradients

1. Activation function
2. Weight initialization
3. Network architecture

Tackling Vanishing Gradient Problem

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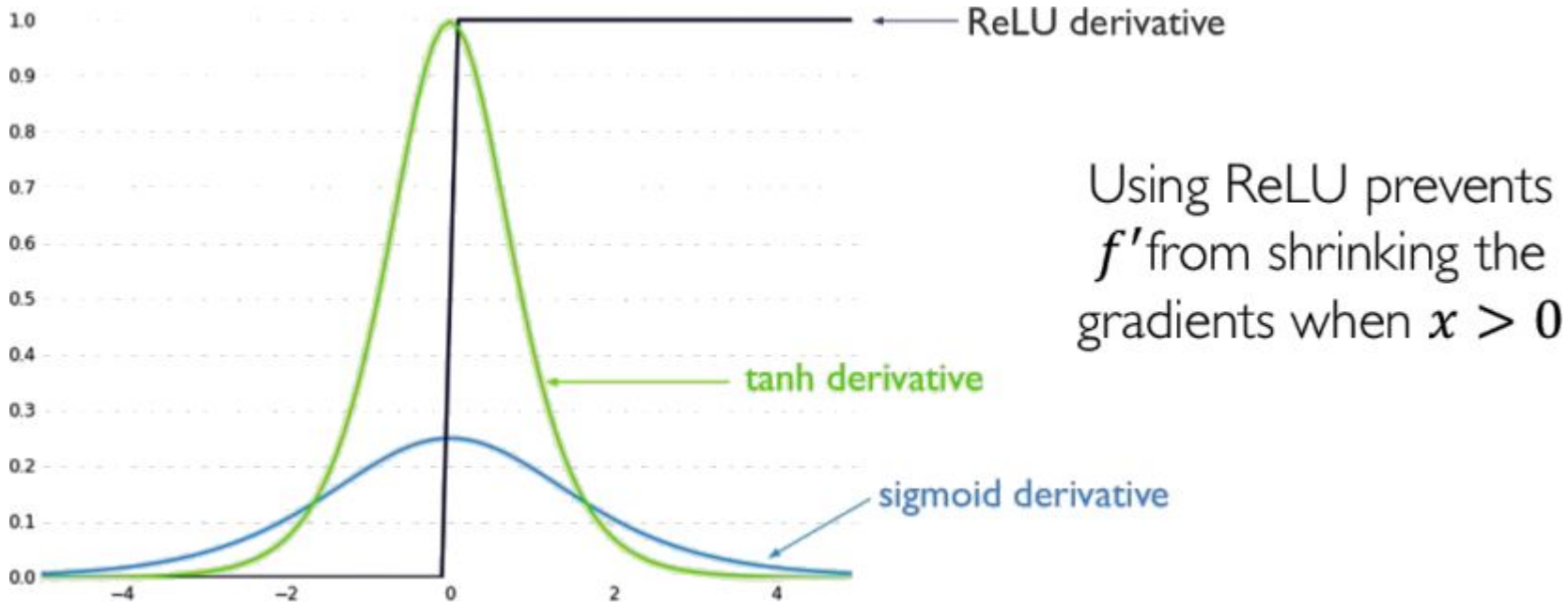
- Strategy 1: **Choose activation function whose derivative is = 1**



Tackling Vanishing Gradient Problem

- Strategy 2: **Initialise the weights to identity matrix**
  - Usually, Weights are initialized to a number close to 0
  - Initialising them to identity matrix, helps from shrinking too quickly

$$I_n = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{pmatrix}$$

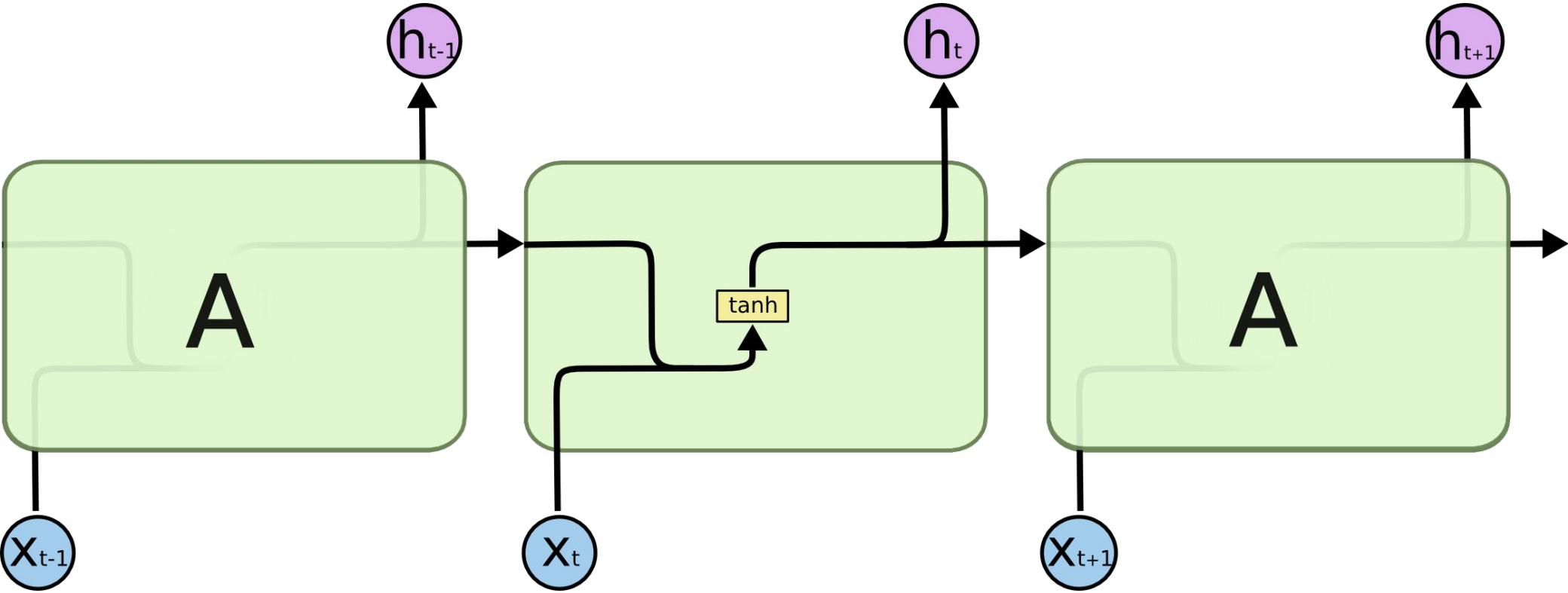
Tackling Vanishing Gradient Problem

- Strategy 3: **Using complex recurrent units with gates**
  - Instead of using vanilla RNN
  - These help control the information that is passing to the future

Long Short-Time Memory Networks (LSTM)

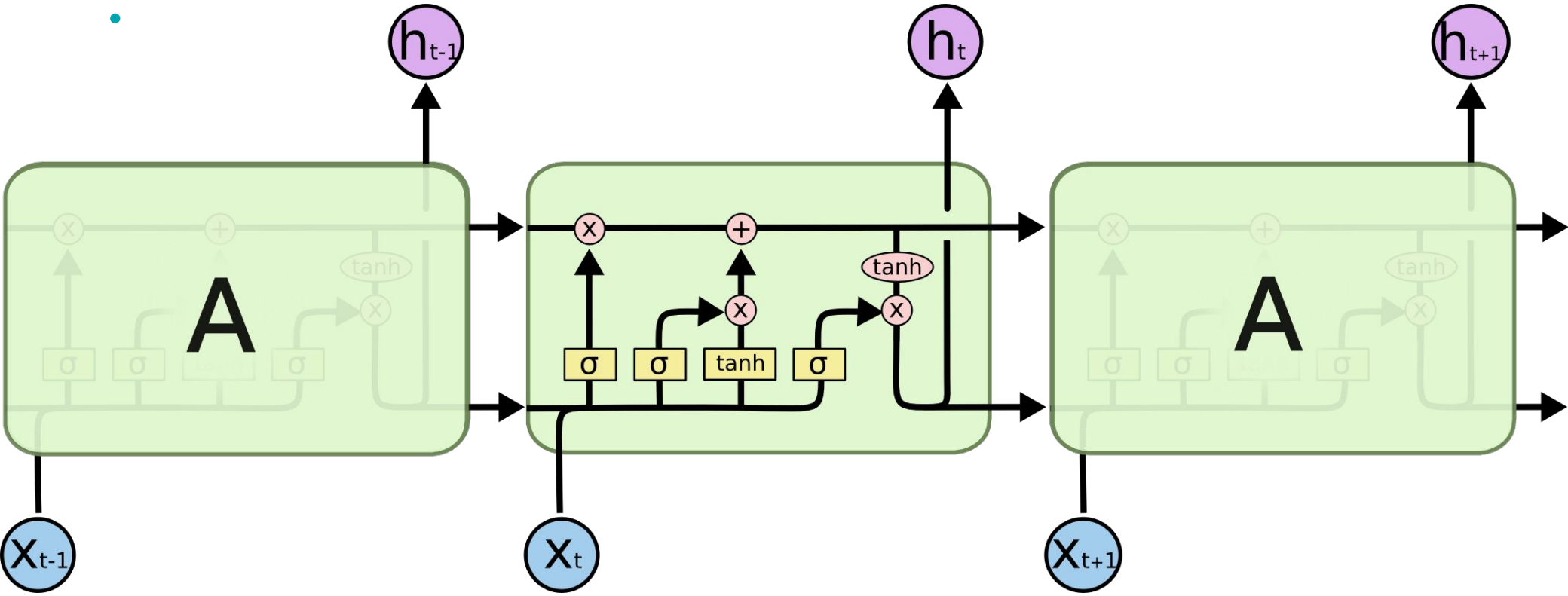
```
tf.keras.layers.LSTM(units)
```

Normal RNN



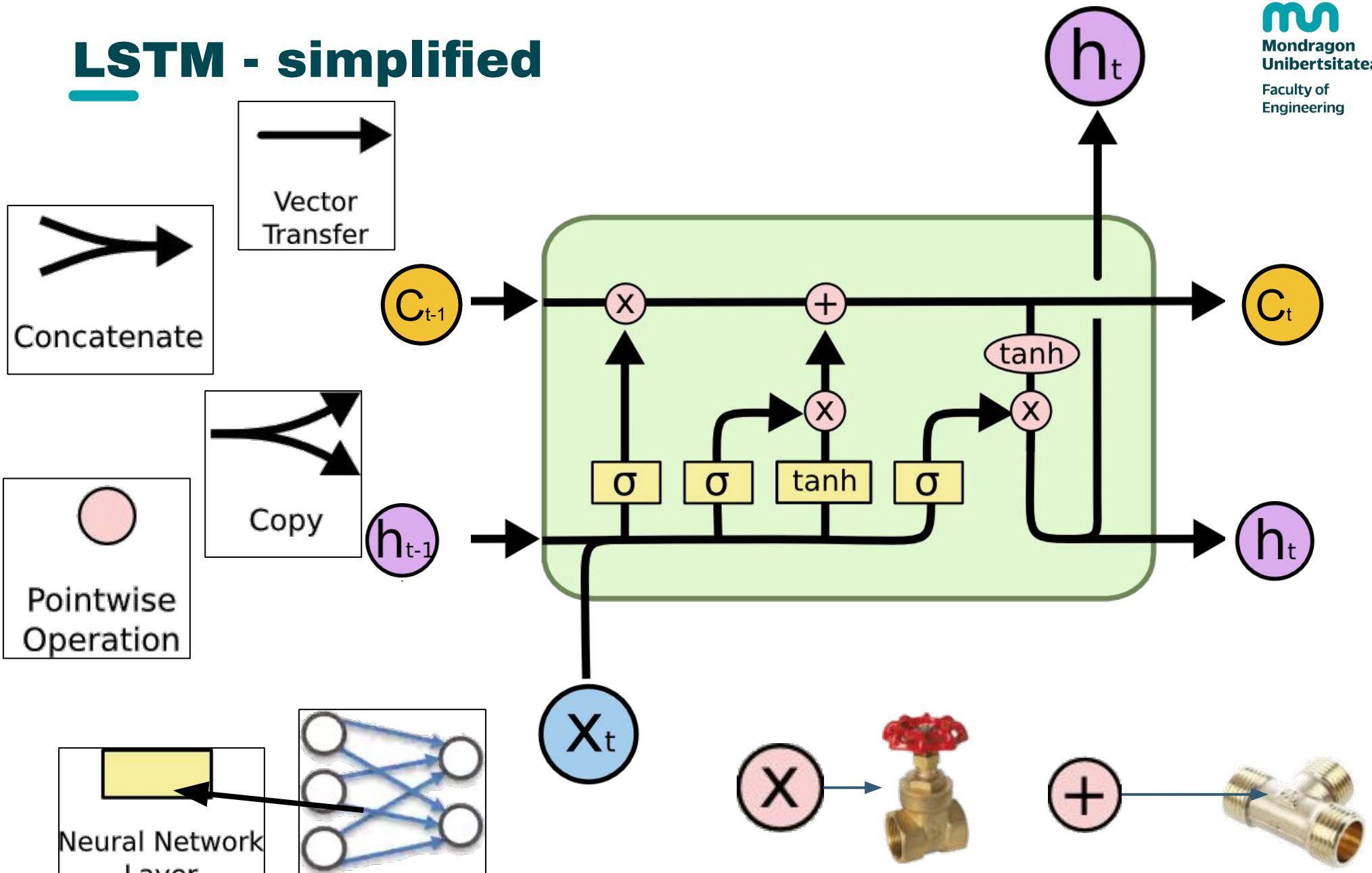
source: Christopher Olah blog

LSTM - simplified



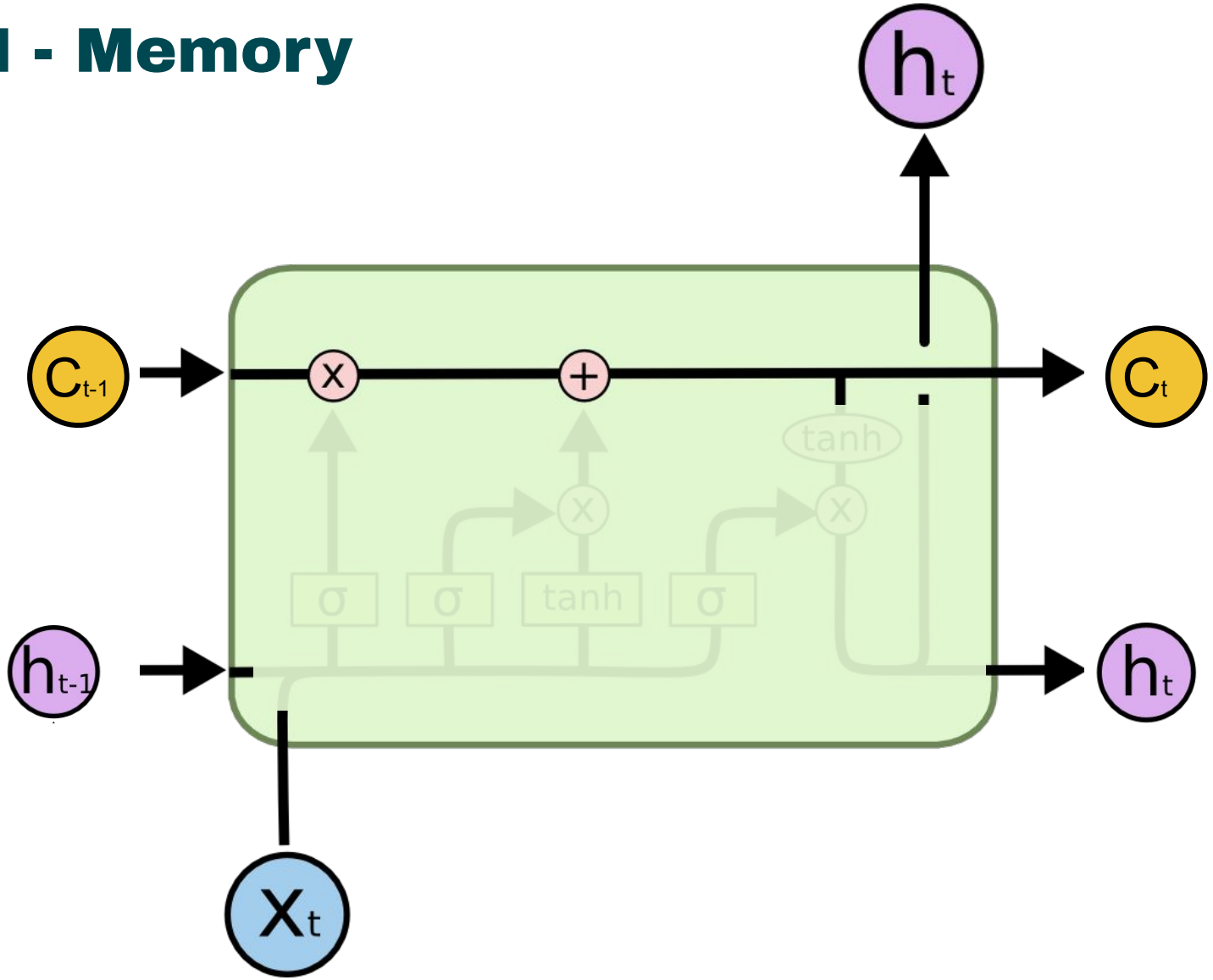
source: Christopher Olah blog

LSTM - simplified



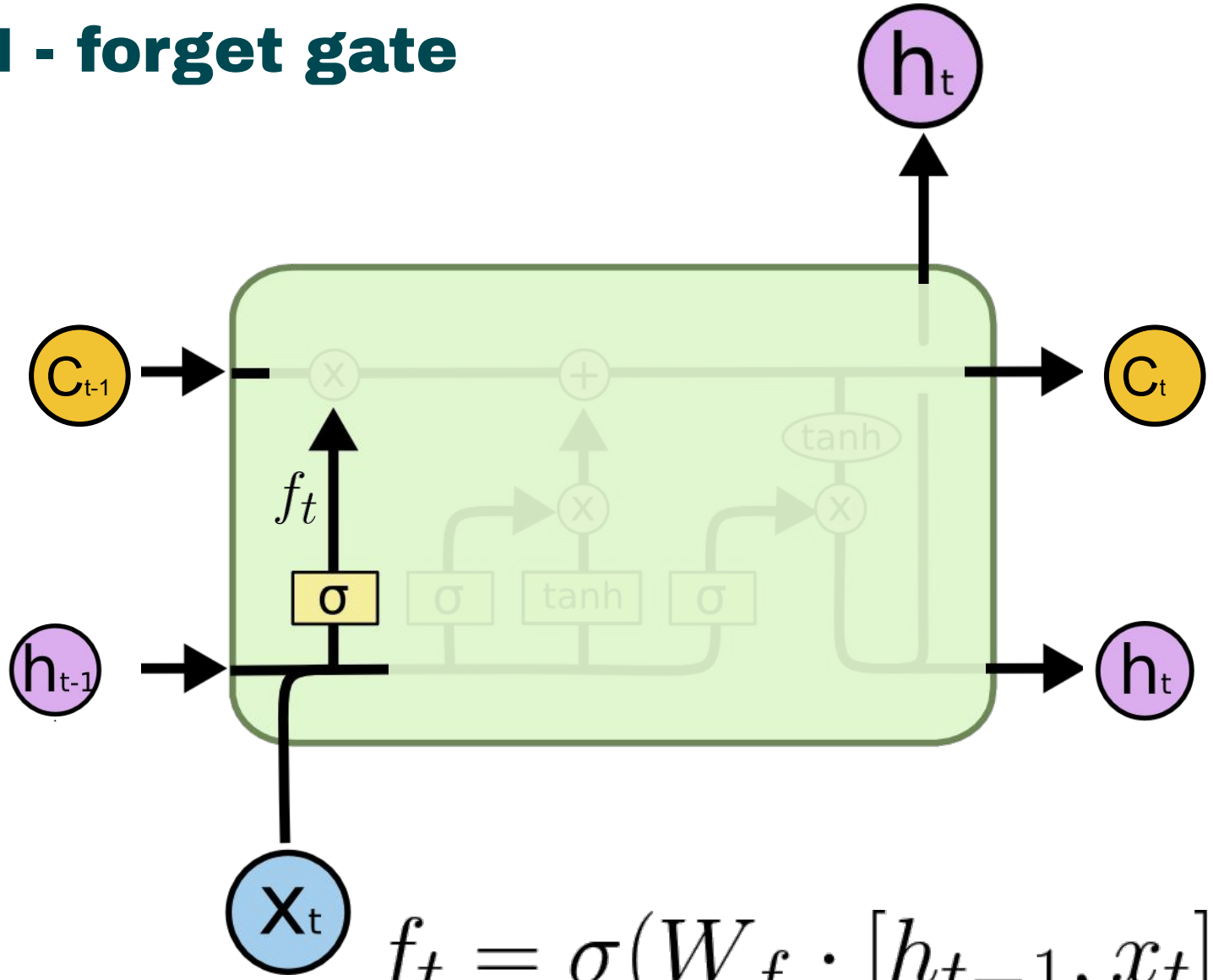
source: Christopher Olah blog

LSTM - Memory



source: Christopher Olah blog

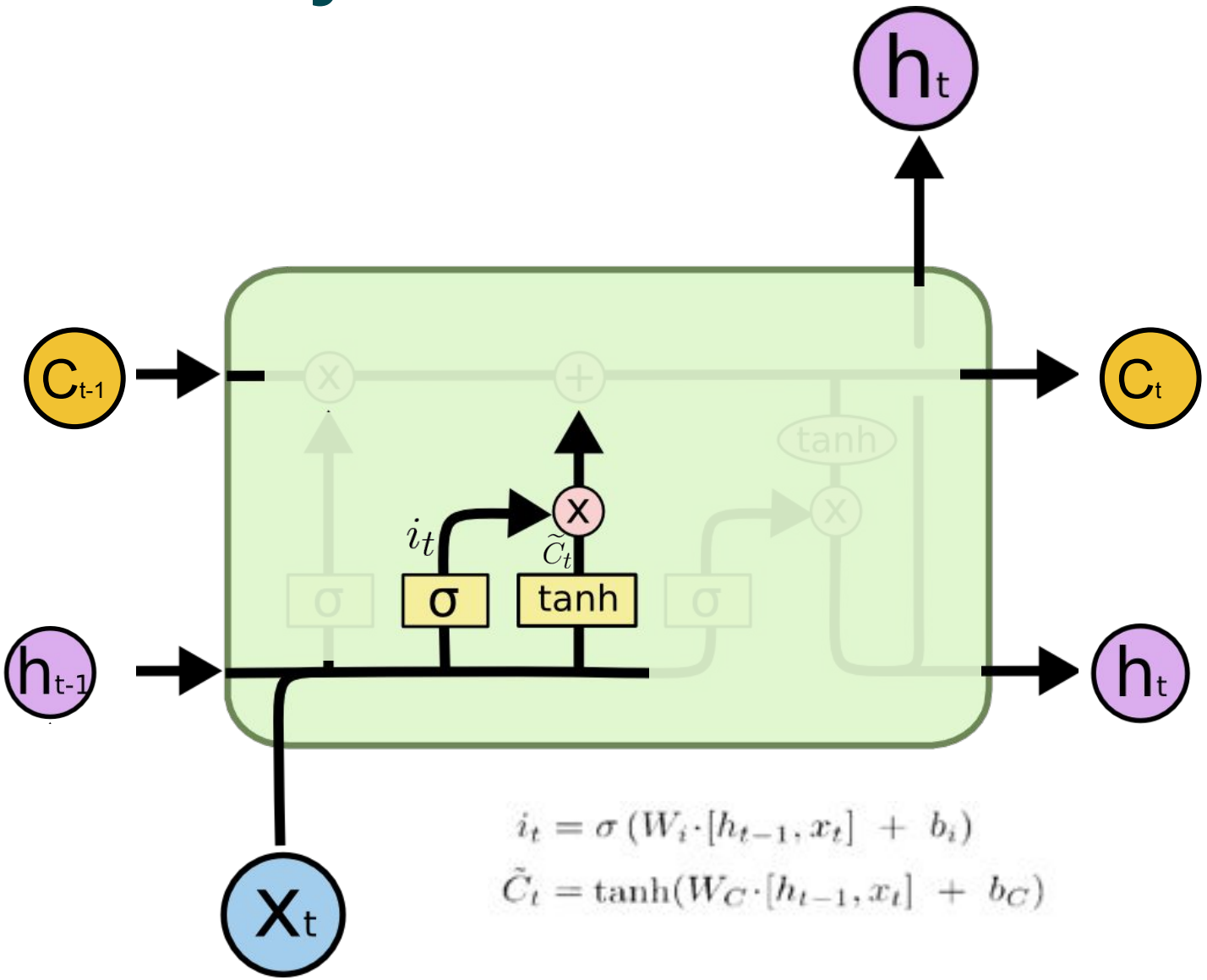
LSTM - forget gate



$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

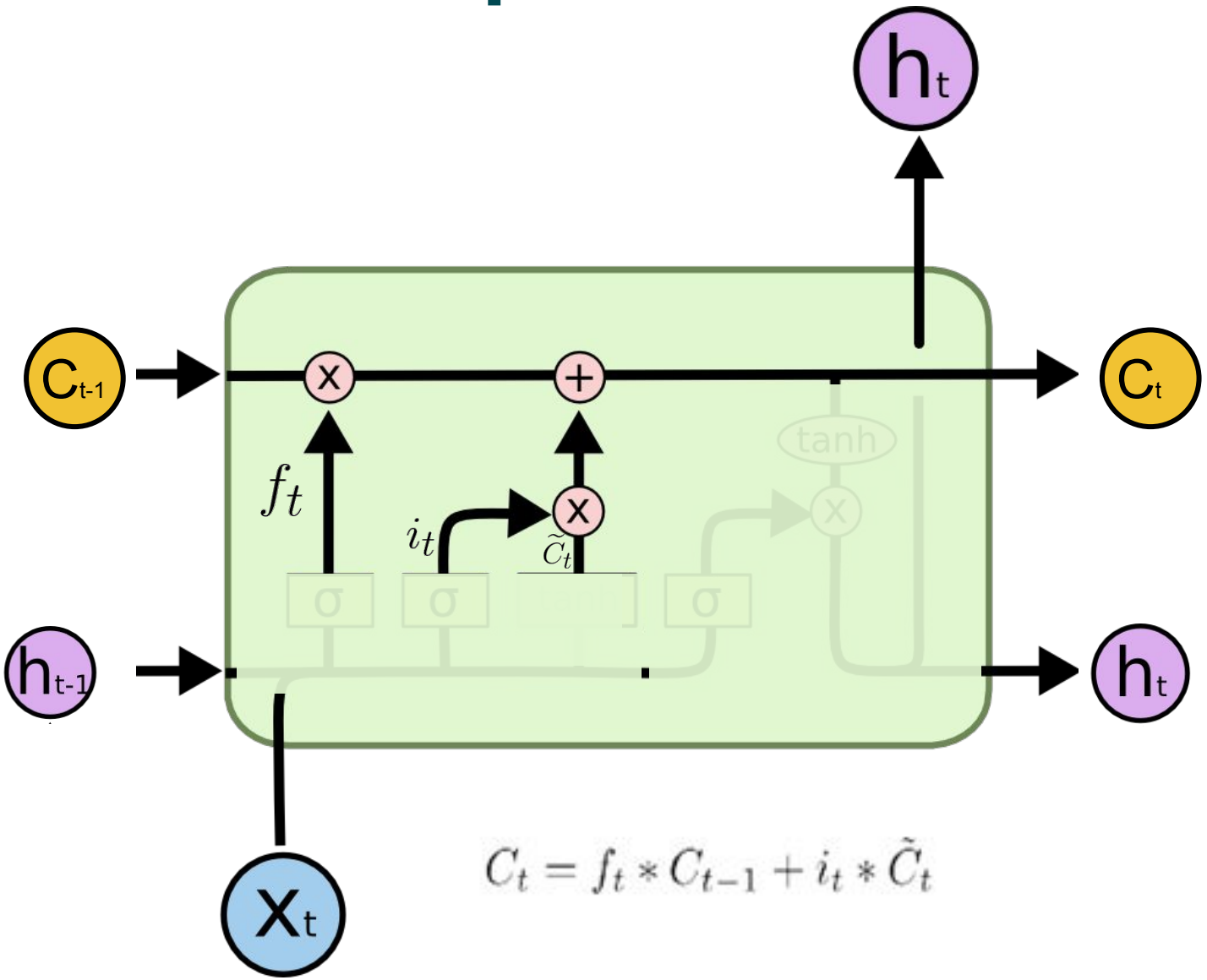
source: Christopher Olah blog

LSTM - Memory Gate



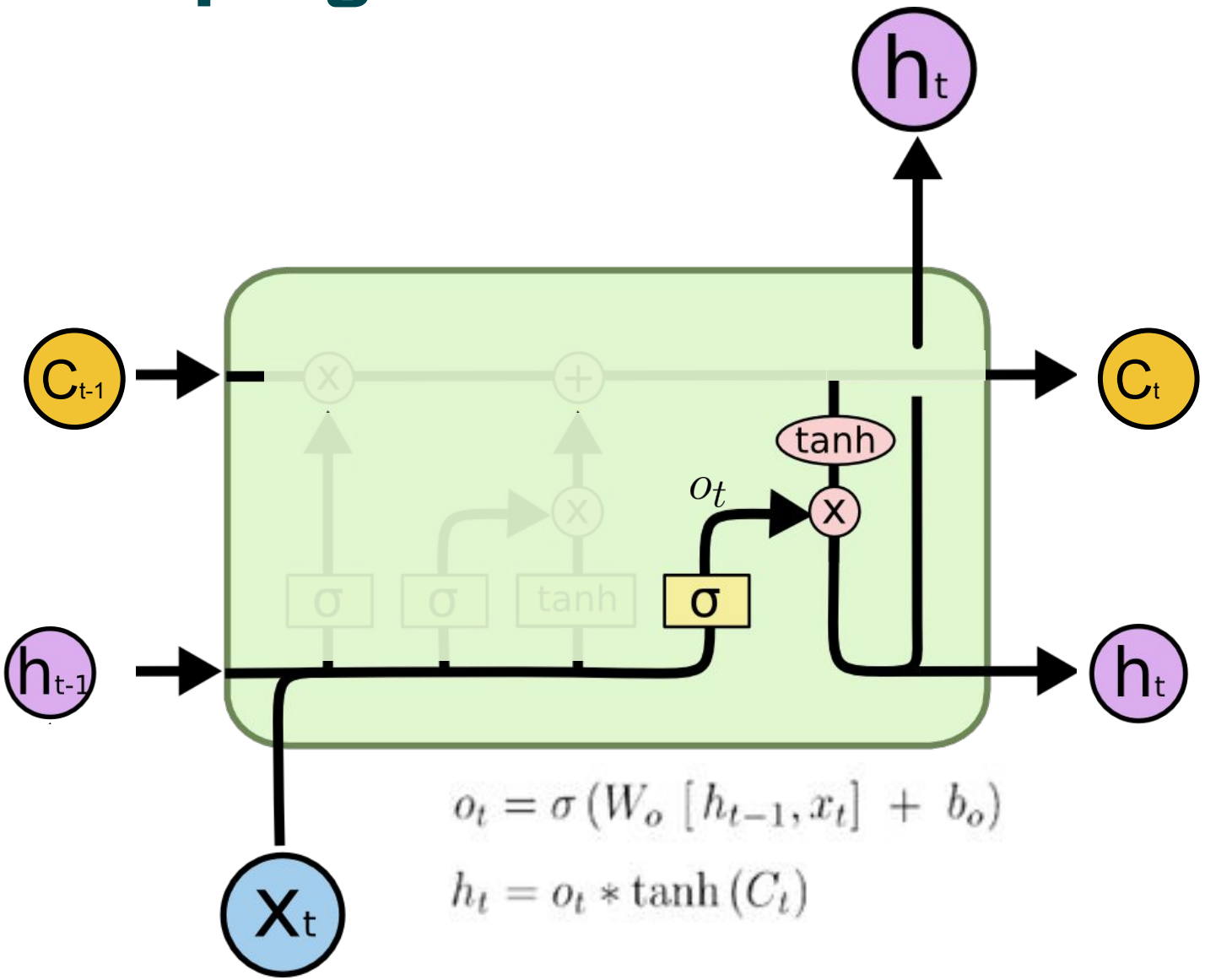
source: Christopher Olah blog

LSTM - Cell State Update



source: Christopher Olah blog

LSTM - Output gate



source: Christopher Olah blog

LSTM - Cosas a tener en cuenta

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- El número de variables a optimizar es muy grande por cada LSTM:
  - pesos y bias del forget gate
  - pesos y bias del memory gate X2
  - Pesos y bias del output gate
- Todo eso, por cada neurona LSTM!

Son muy potentes, pero, el tiempo de aprendizaje es alto, hay que diseñarlos con cabeza, si no, perdemos mucho tiempo.

Gated Recurrent Unit (GRU)

```
tf.keras.layers.GRU(units)
```

RNN - GRU

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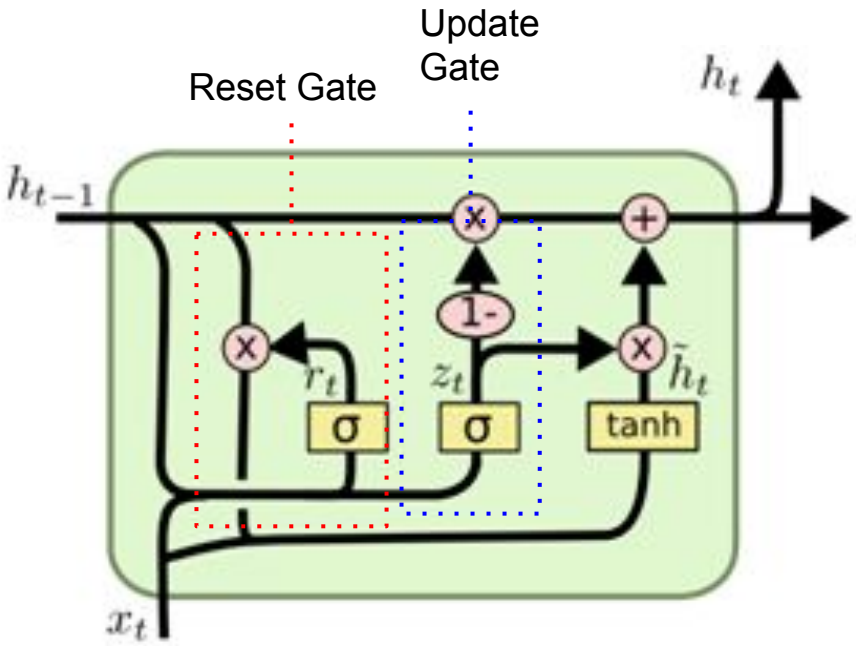
- Similar to LSTM
  - They combine the forget and input gate into only one gate, called the update gate
  - They also merge the Cell state and the hidden state into one

RNN - Gated Recurrent Unit



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

RNN - GRU

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- The main advantage of GRU is **the reduced number of parameters** as compared to LSTM's without any compromise whatsoever which has resulted in **faster convergence** and a **more generalized** model.

Advanced use of RNNs

RNN - Recurrent Dropout

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- RNNs also tend to Overfit.
- But applying dropout is not trivial for RNN
- The same pattern of dropped units should be applied every time step
  - Otherwise instead of helping learn you achieve the contrary *(Yarin Gal 2015)*
- Keras has 2 dropouts for RNNs
  - Dropout-> specifies dropout rate for input units of the layer
  - Recurrent_dropout-> specifies dropout rate for RNN units

```
model.add(layers.GRU(64, activation='relu',
                     dropout=0.1,
                     recurrent_dropout=0.5))
```

RNN - Stacking Recurrent Layers

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- We can stack several recurrent layers one after another
  - For example, in 2018 7 huge LSTM layers powered google translate
- In order to be able to do this, we need all intermediate layers to return their full sequence of outputs (a 3D tensor)
- This is done the next way:

```
model.add(layers.GRU(32,
                     dropout=0.1,
                     recurrent_dropout=0.5,
                     return_sequences=True,
                     input_shape=(None, float_data.shape[-1])))
```

RNN - Bidirectional RNNs

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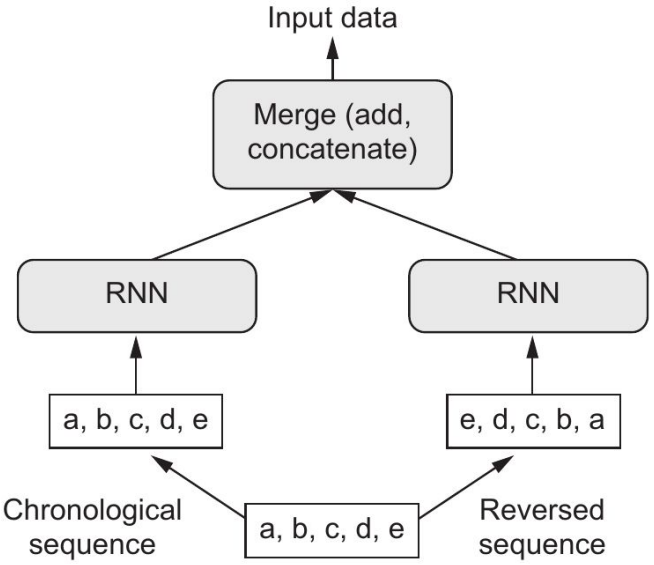
- The basic idea behind the bidirectional RNNs is to have 2 RNNs
  - One looking at the data in the given order (chronologically)
  - The other having the data reversed (anti-chronologically)
- Later, the both representations are merged
  - Helps to catch patterns that may have been overlooked




```
model = Sequential()
model.add(layers.Bidirectional(
    layers.GRU(32), input_shape=(None, float_data.shape[-1])))
```

RNN - Bidirectional RNNs

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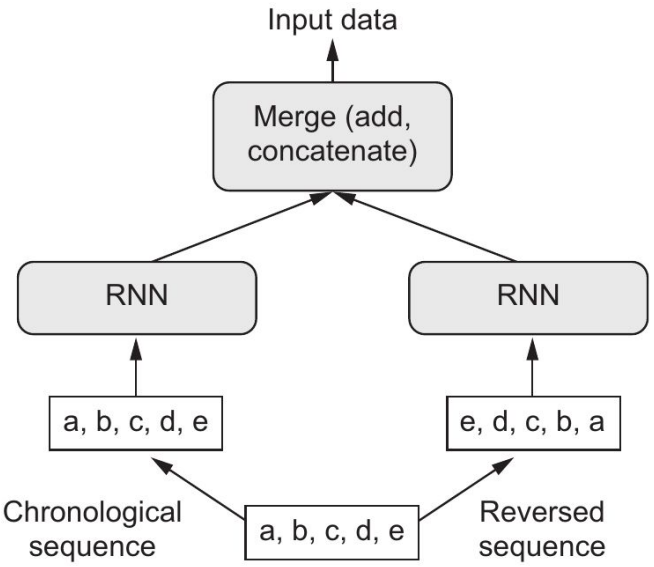


```
model = Sequential()
model.add(layers.Bidirectional(
    layers.GRU(32), input_shape=(None, float_data.shape[-1])))
```

Exercises

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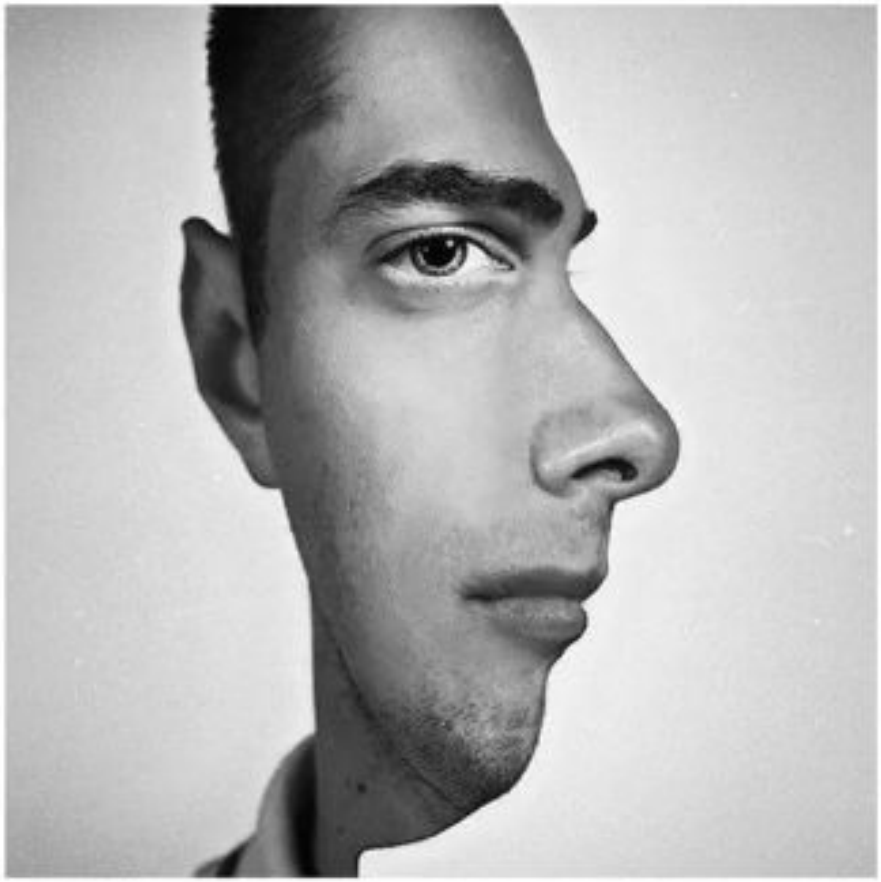
- 2 rnn examples
- exercise 1
  - google stock prediction
- exercise 2
  - text generation with rnn, moby dick

Convolutional Neural Networks

Features from images



Features from images

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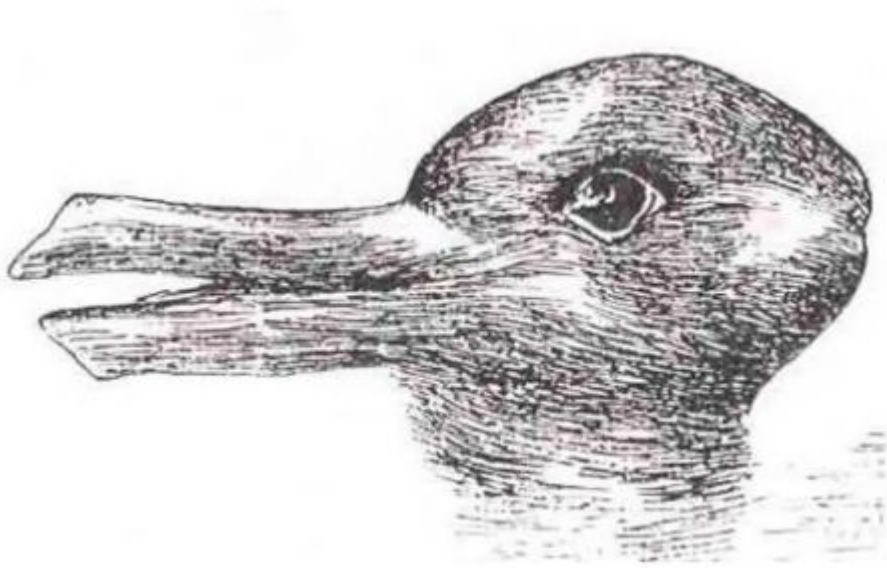

Examples from the test set
(with the network's guesses)

source: Geoffrey Hinton (charla)

CNNs

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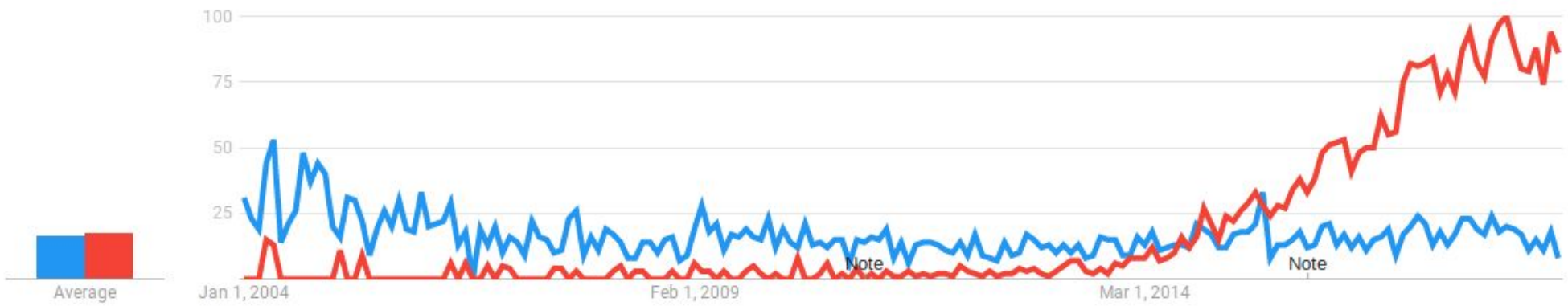
artificial neural network
Search term

convolutional neural
Search term

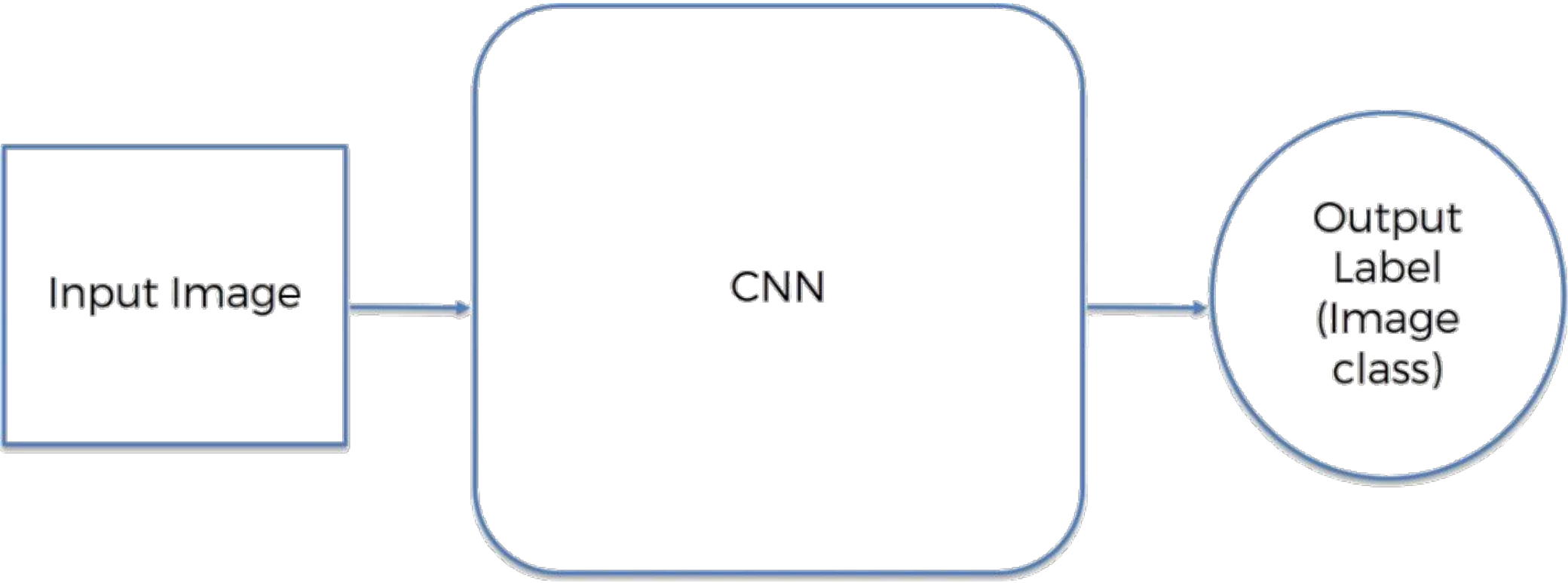
Interest over time

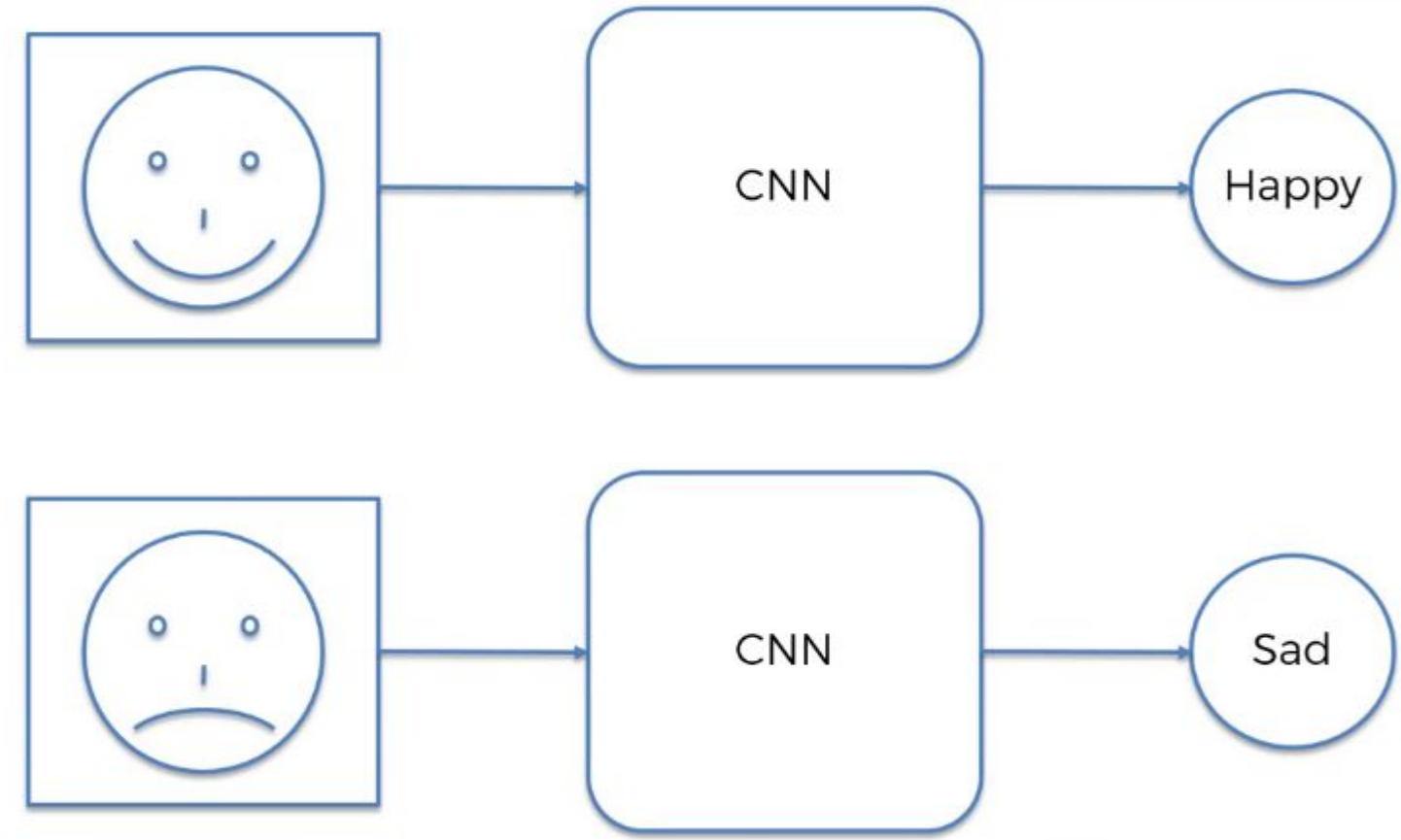


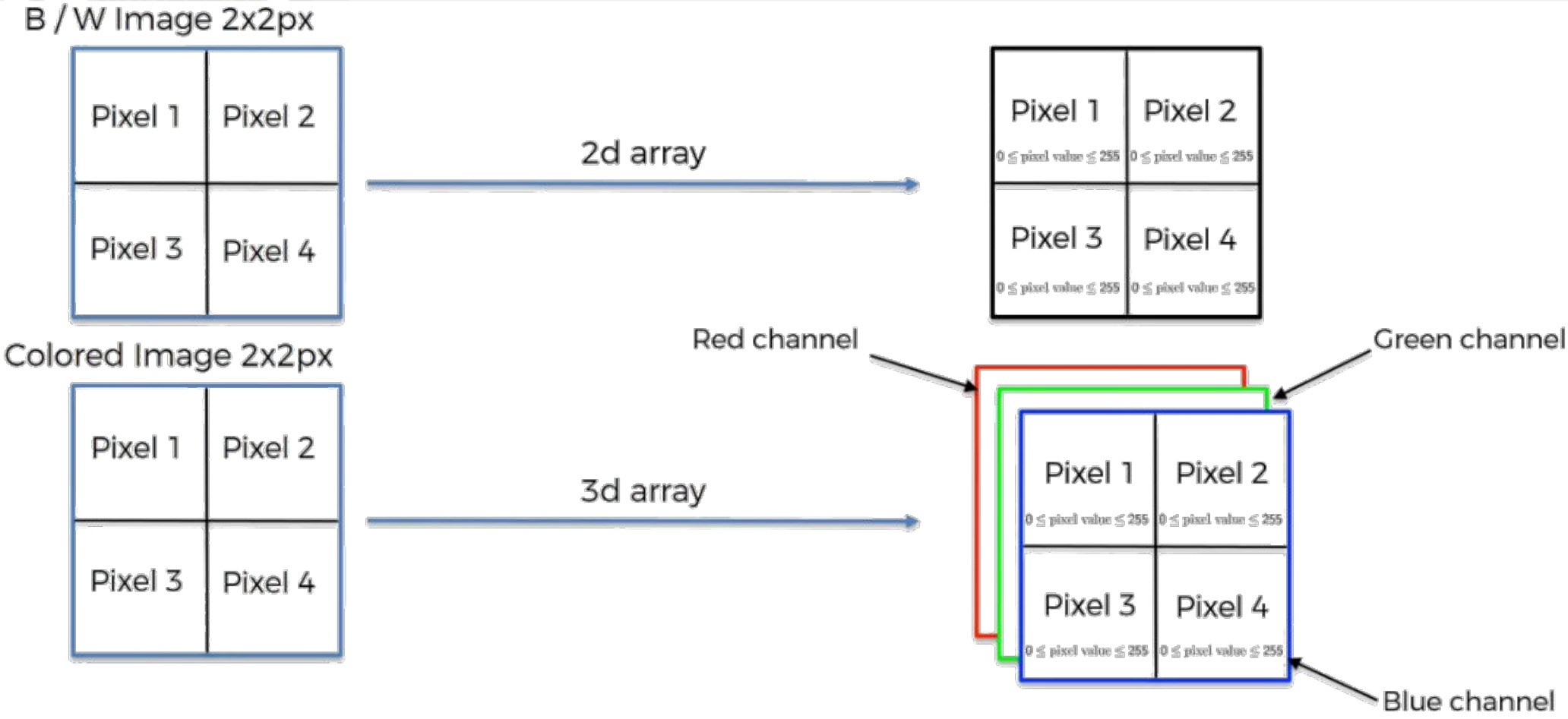
source: Google Trends

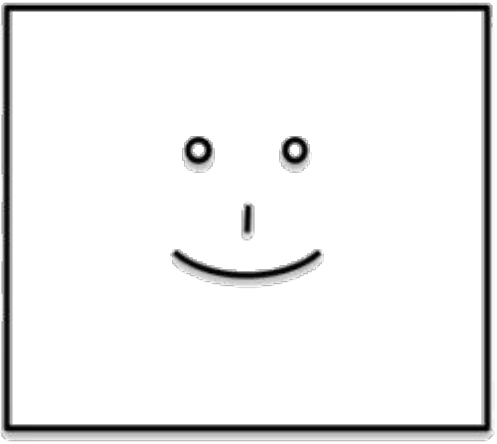
Yann Lecun

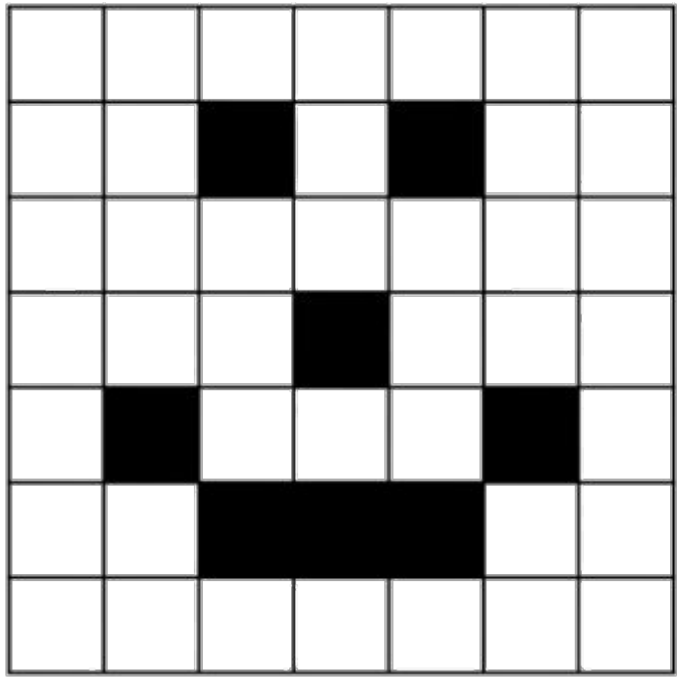
Google Facebook


Input Image
CNN
Output Label (Image class)


CNN
Happy
CNN
Sad


B / W Image 2x2px
Pixel 1
Pixel 2
Pixel 3
Pixel 4
2d array
Pixel 1
0 ≤ pixel value ≤ 255
Pixel 2
0 ≤ pixel value ≤ 255
Pixel 3
0 ≤ pixel value ≤ 255
Pixel 4
0 ≤ pixel value ≤ 255
Colored Image 2x2px
Pixel 1
Pixel 2
Pixel 3
Pixel 4
3d array
Red channel
Green channel
Blue channel
Pixel 1
0 ≤ pixel value ≤ 255
Pixel 2
0 ≤ pixel value ≤ 255
Pixel 3
0 ≤ pixel value ≤ 255
Pixel 4
0 ≤ pixel value ≤ 255





0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

Steps of a CNN

1. Convolution
2. Max Pooling
3. Flattening
4. Full Connection

Step 1
Convolution

CNN Step 1: Convolution

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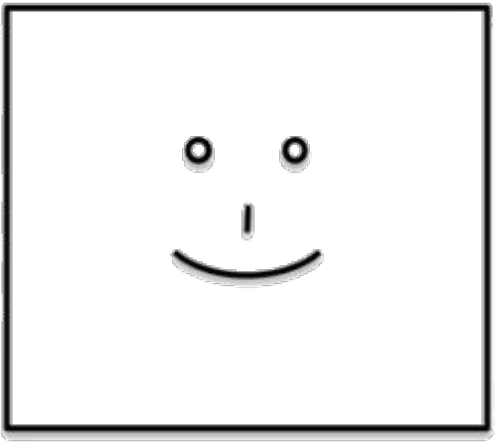
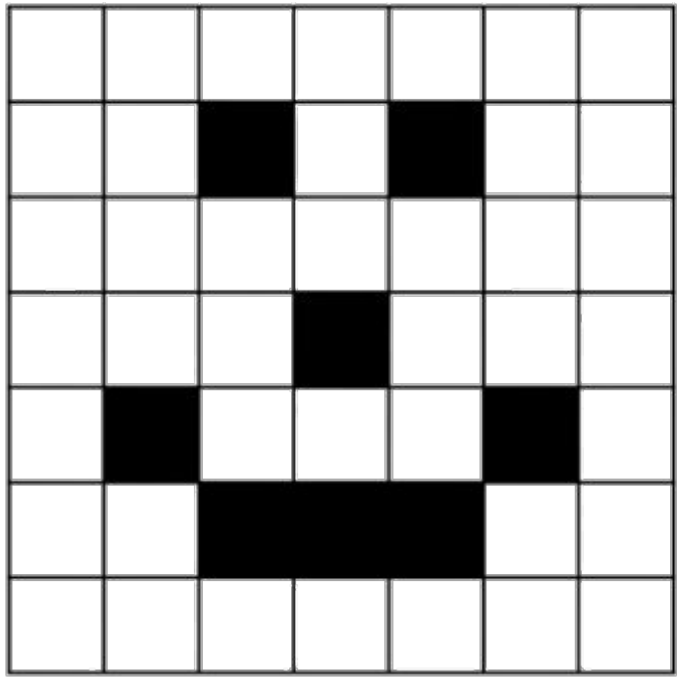
$$(f * g)(t) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f(\tau)\, g(t-\tau)\, d\tau$$

CNN Step 1: Convolution





0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

CNN Step 1: Convolution

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0	0	0	0	0	0	0
0	1	0	0	0	1	0
0	0	0	0	0	0	0
0	0	0	1	0	0	0
0	1	0	0	0	1	0
0	0	1	1	1	0	0
0	0	0	0	0	0	0

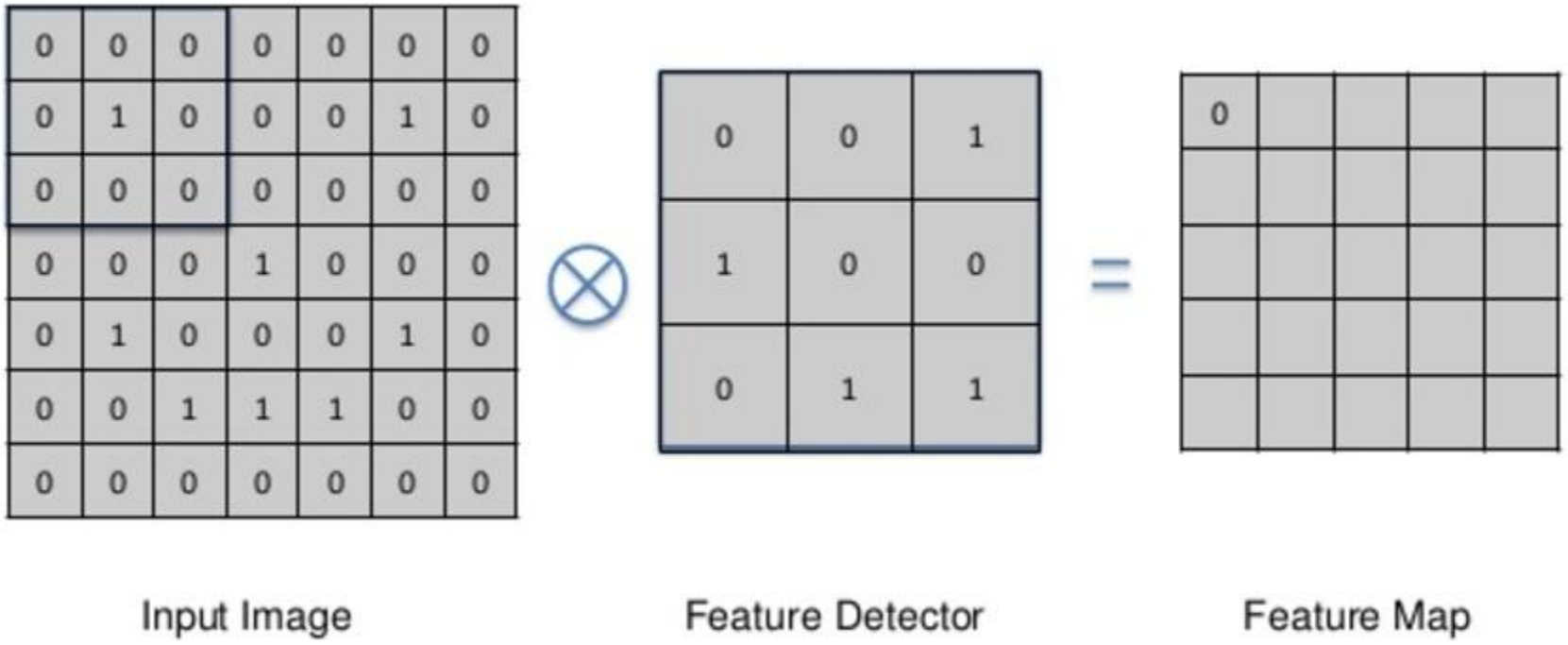
Input Image

0	0	1
1	0	0
0	1	1

Feature Detector

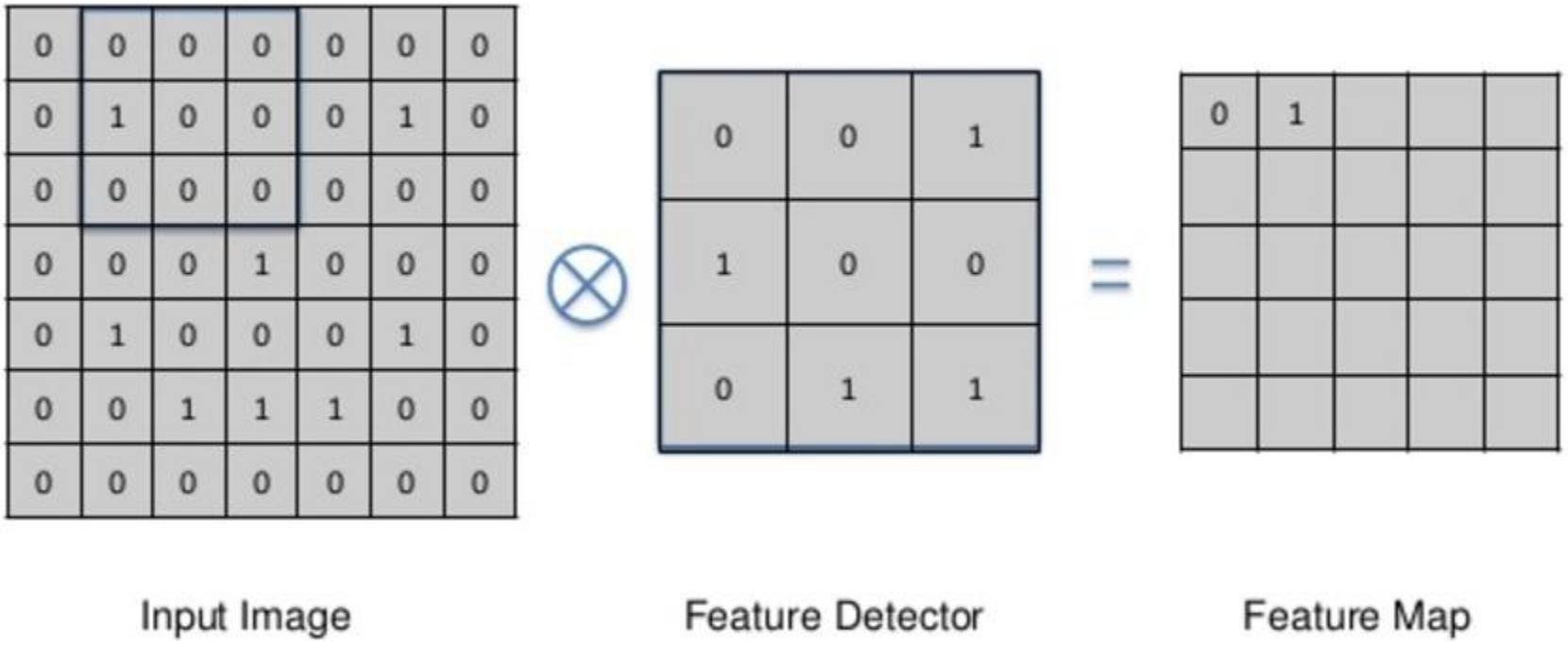
source: superdatascience

CNN Step 1: Convolution



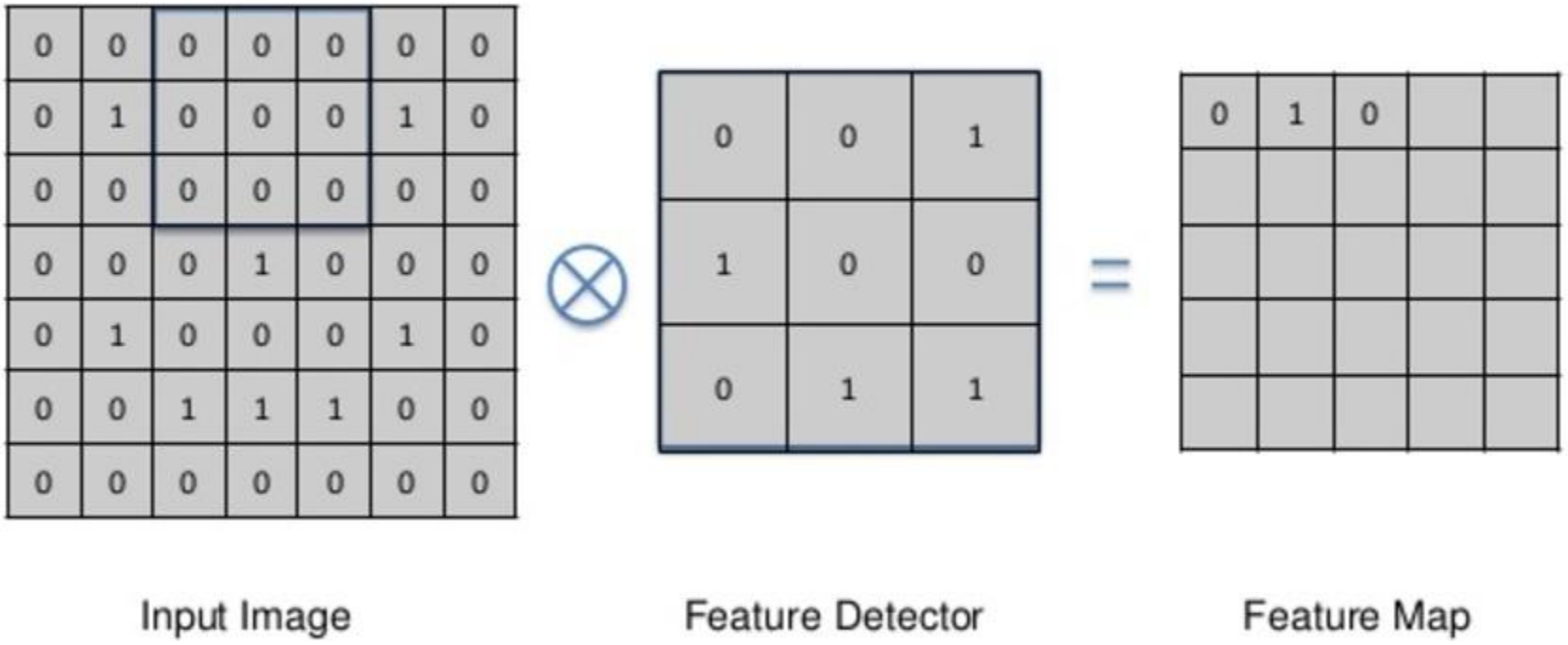
source: superdatascience

CNN Step 1: Convolution



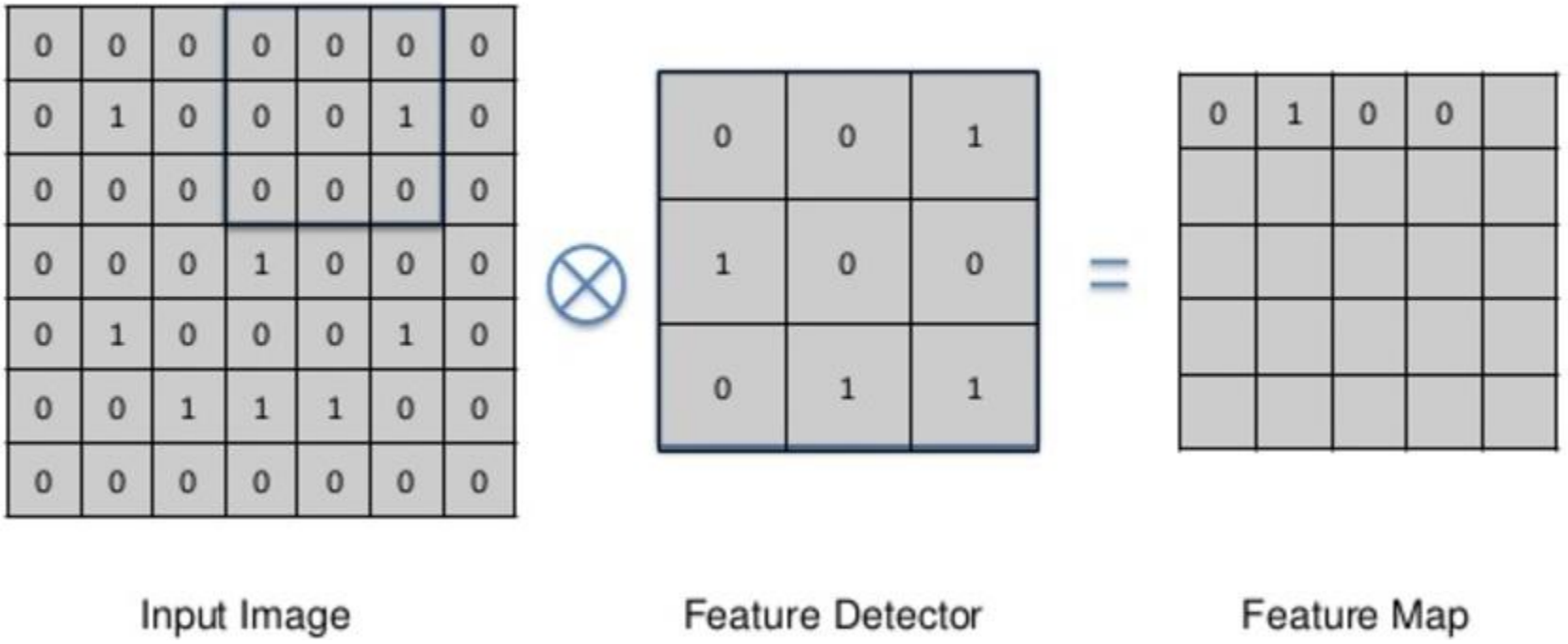
source: superdatascience

CNN Step 1: Convolution



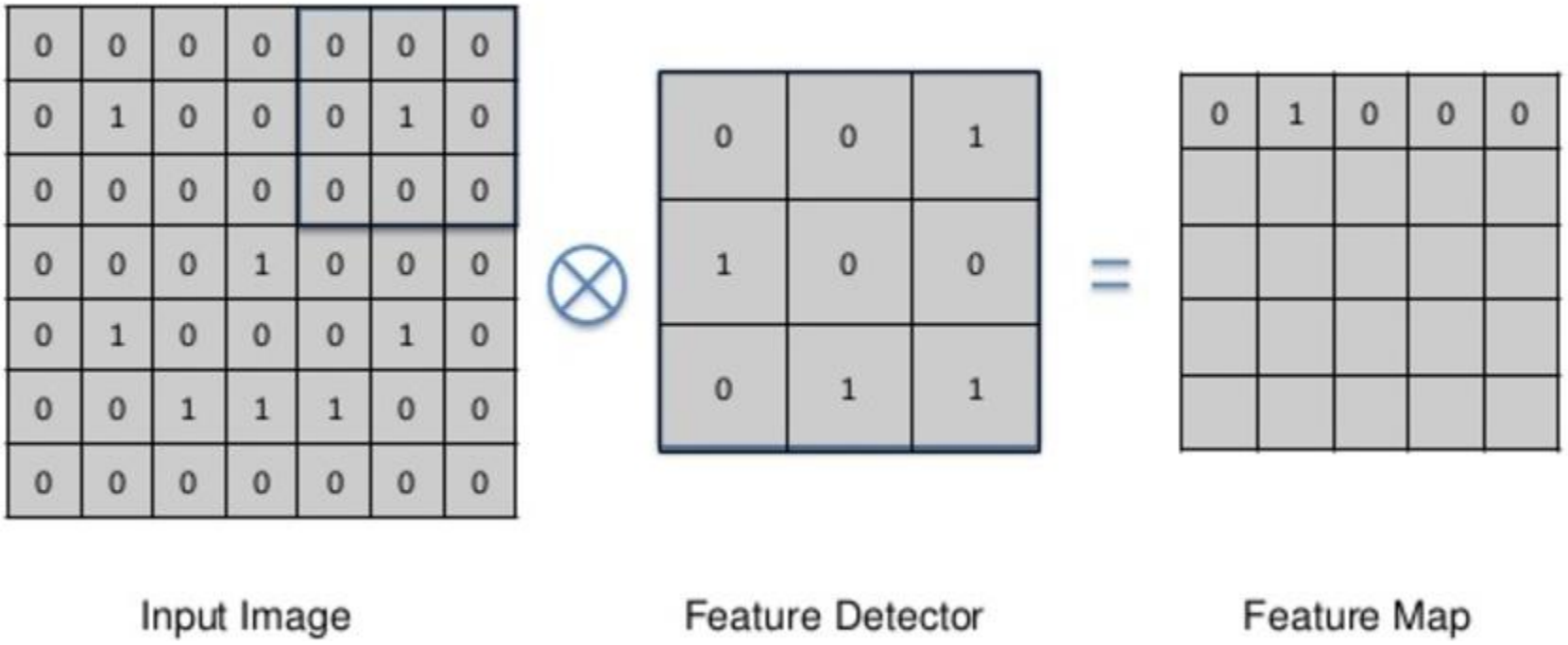
source: superdatascience

CNN Step 1: Convolution



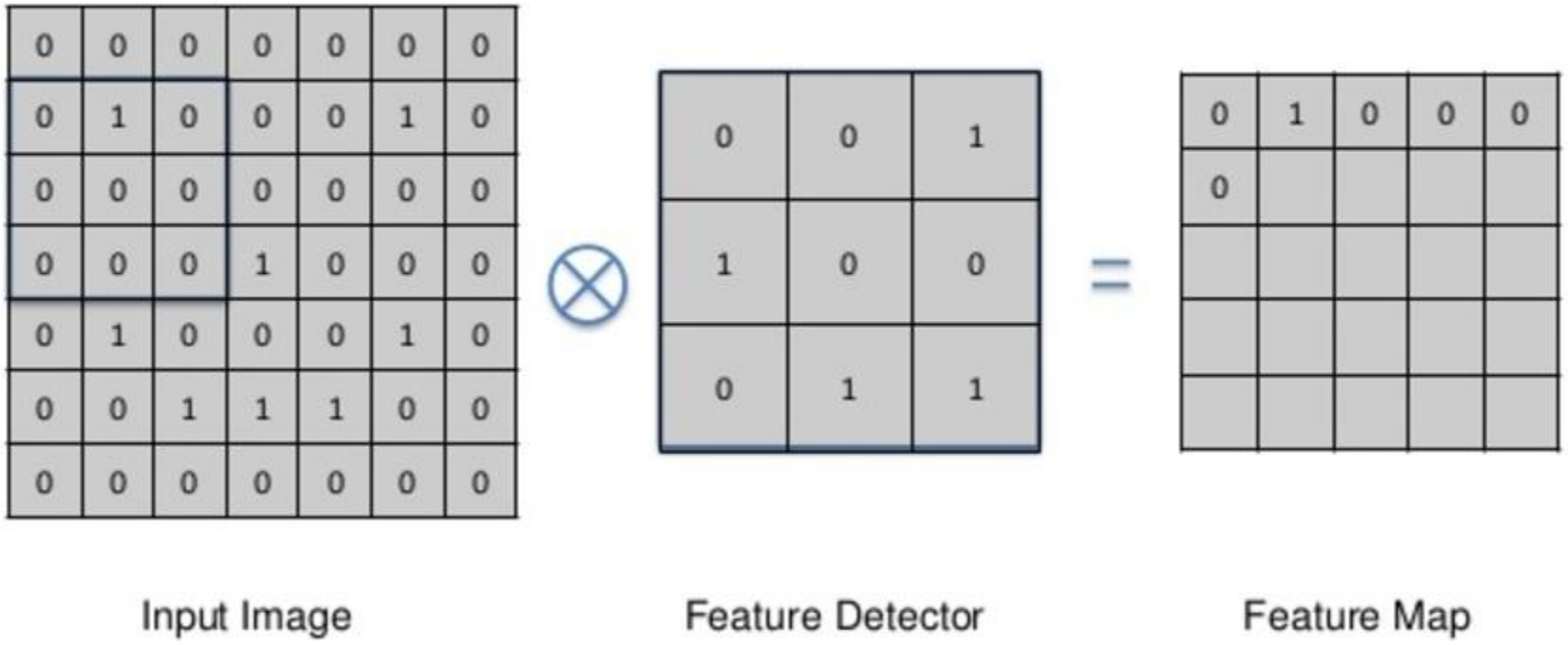
source: superdatascience

Convolution



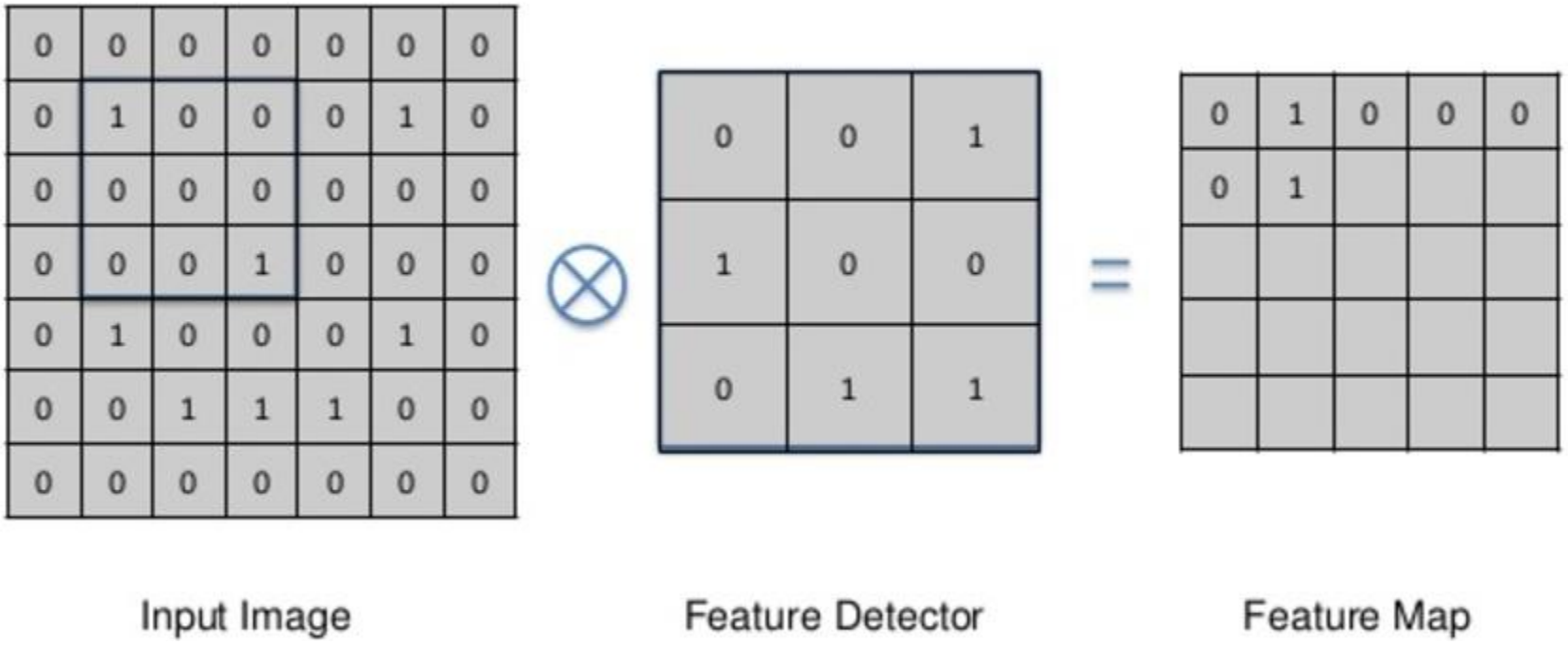
source: superdatascience

CNN Step 1: Convolution



source: superdatascience

CNN Step 1: Convolution



source: superdatascience

CNN Step 1: Convolution

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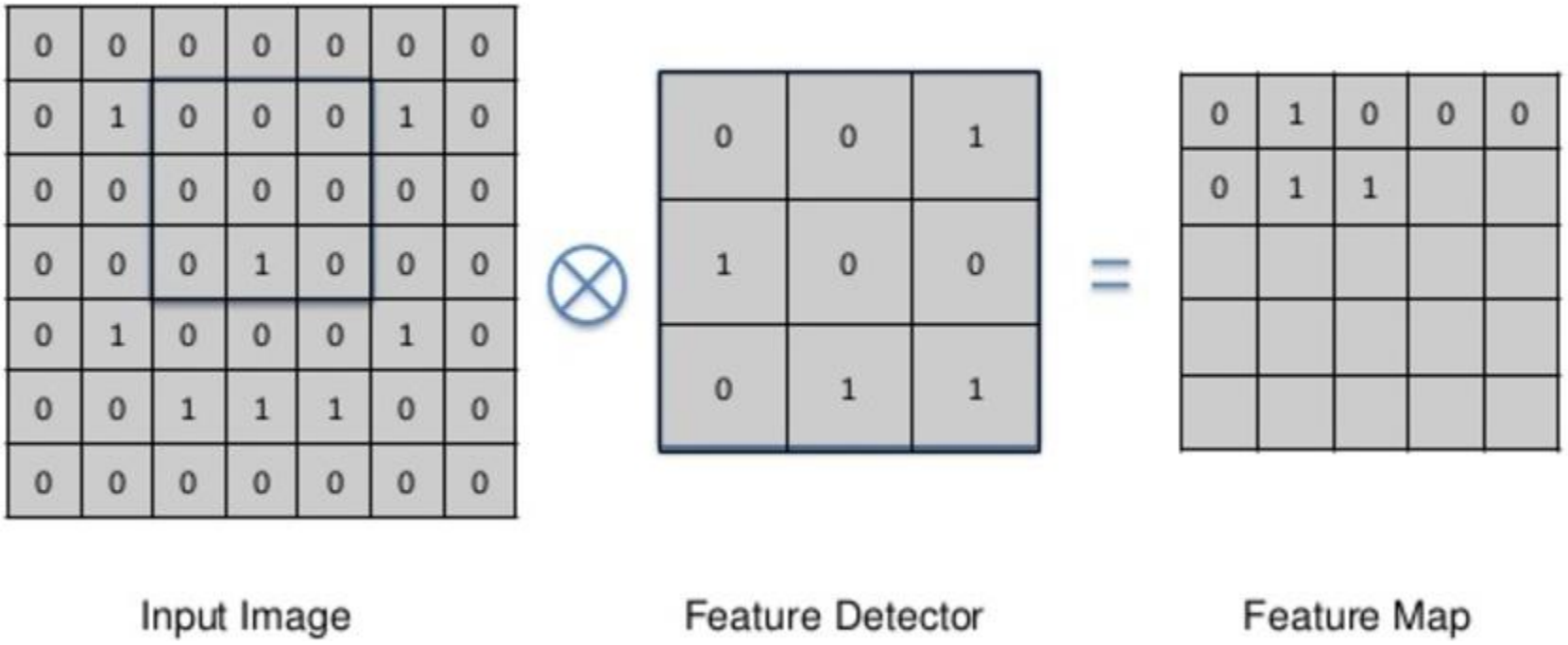
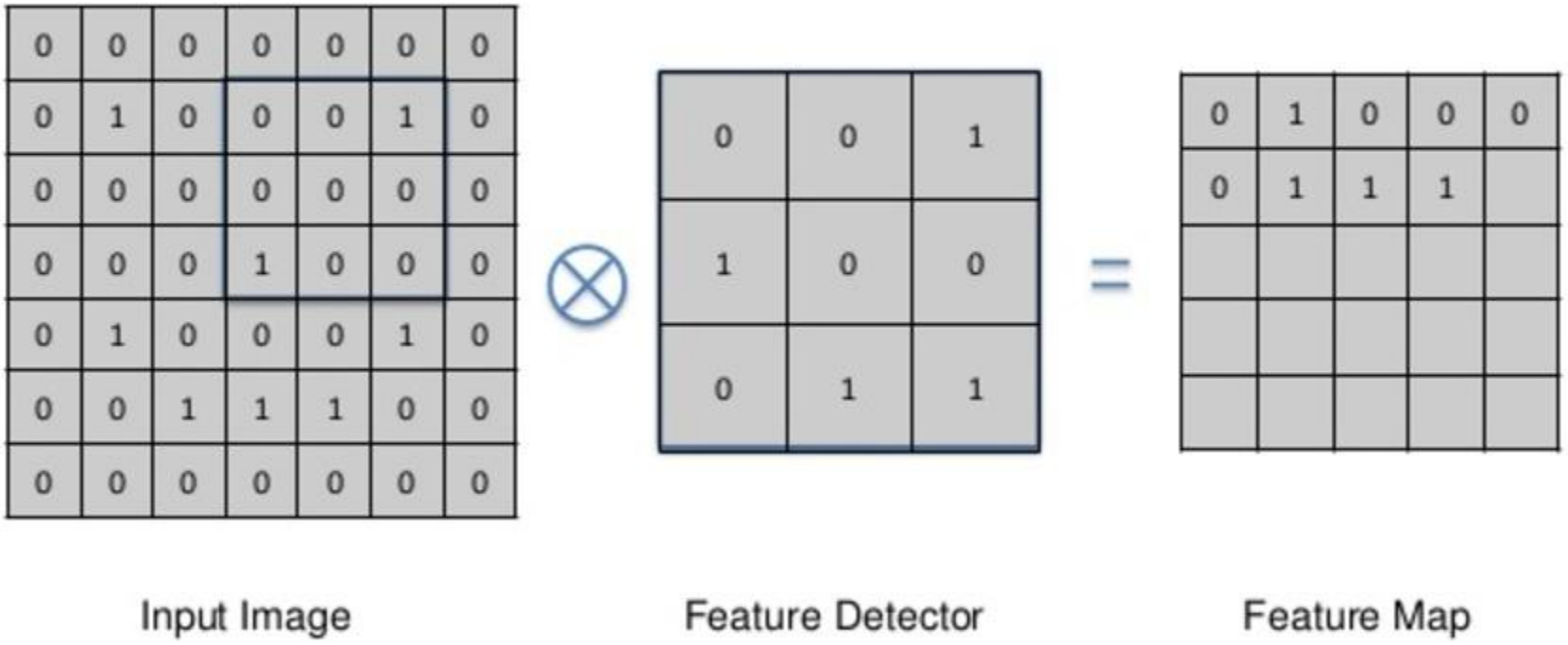


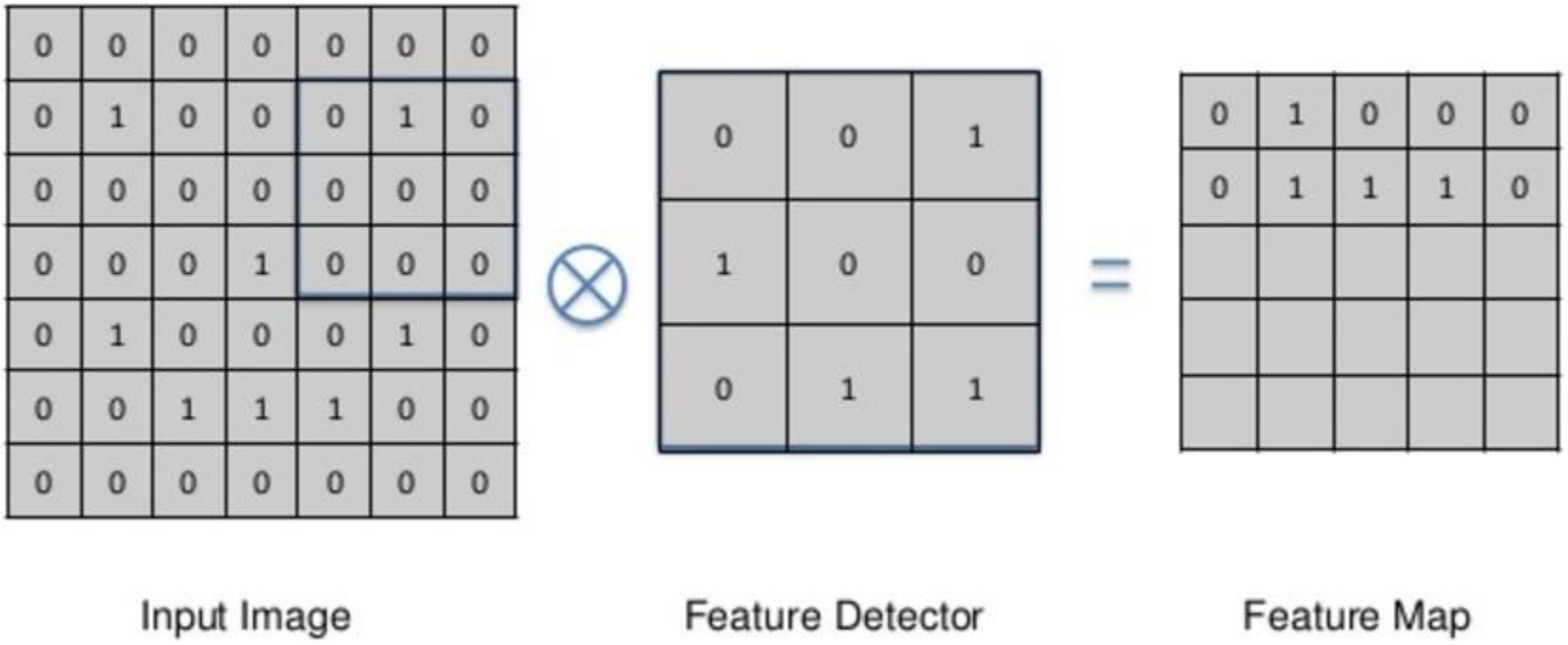
source: superdatascience

CNN Step 1: Convolution



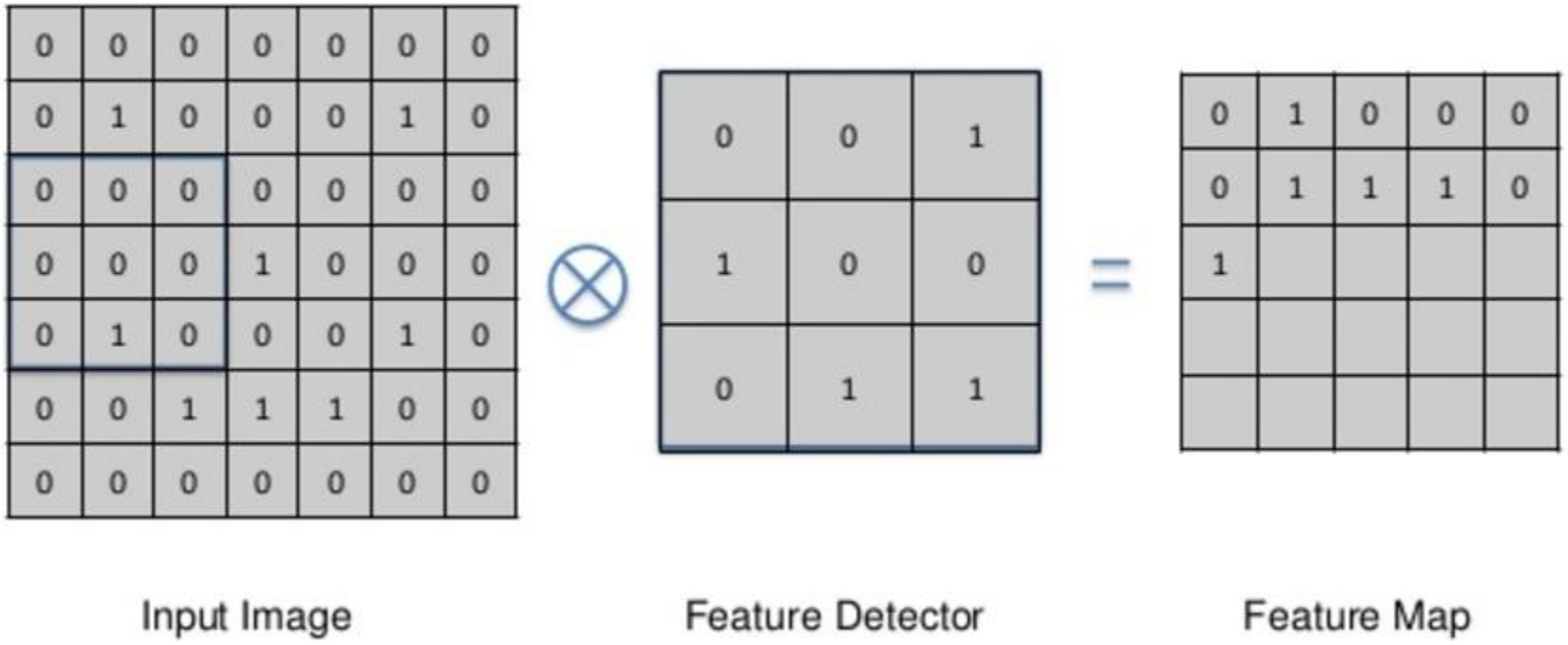
source: superdatascience

CNN Step 1: Convolution



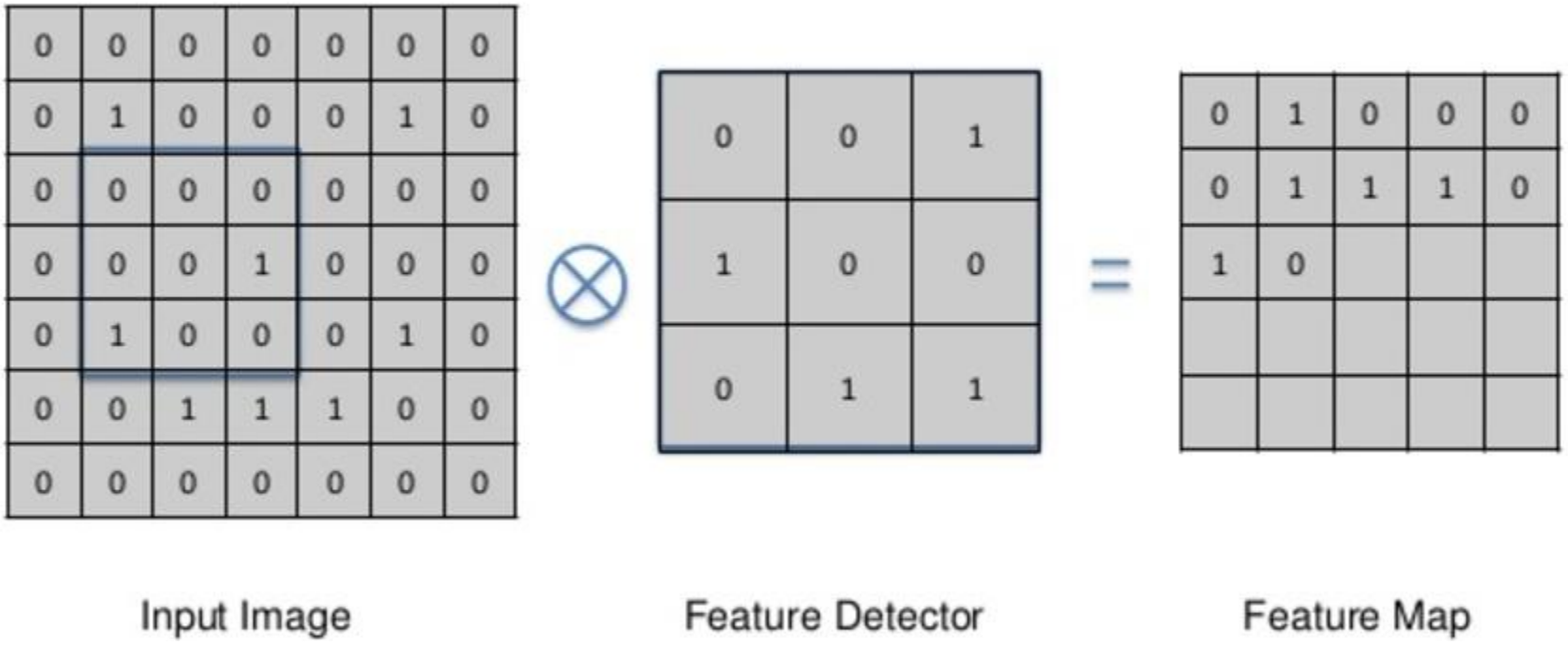
source: superdatascience

CNN Step 1: Convolution



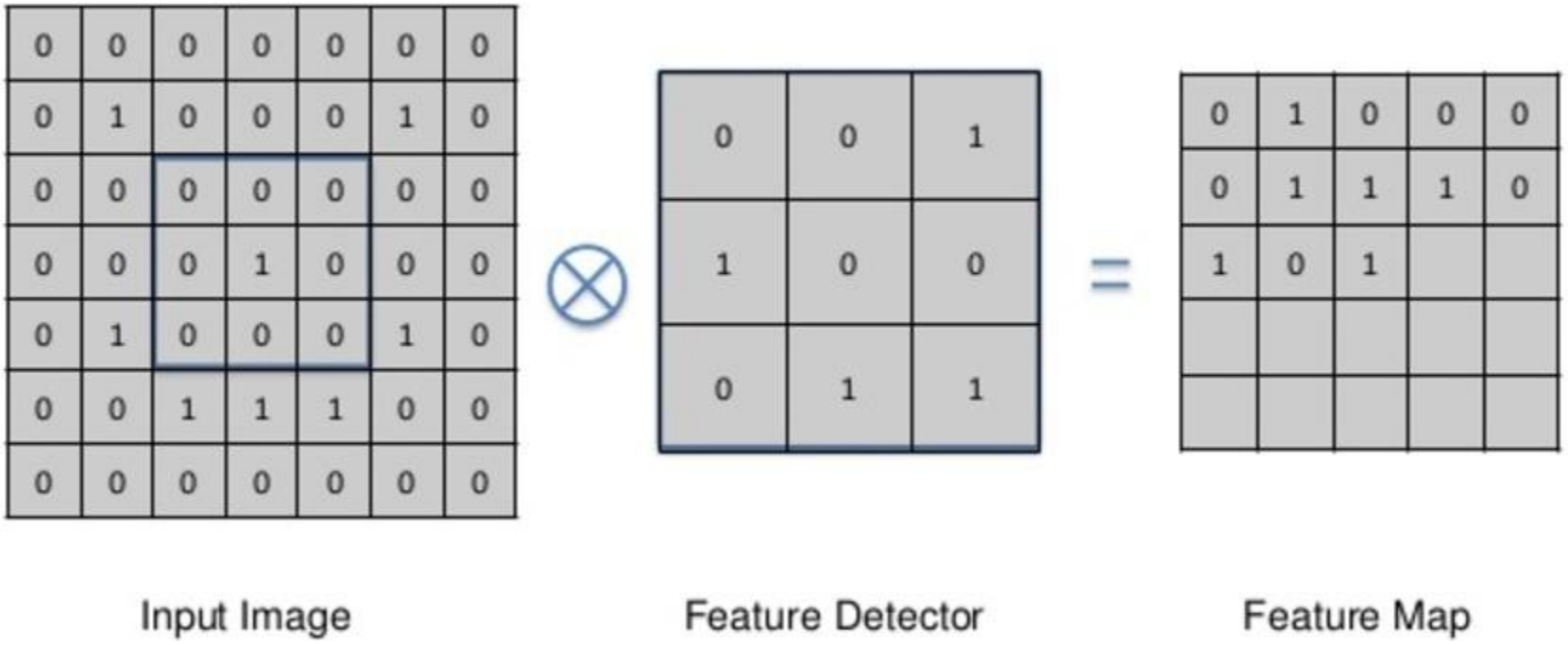
source: superdatascience

CNN Step 1: Convolution



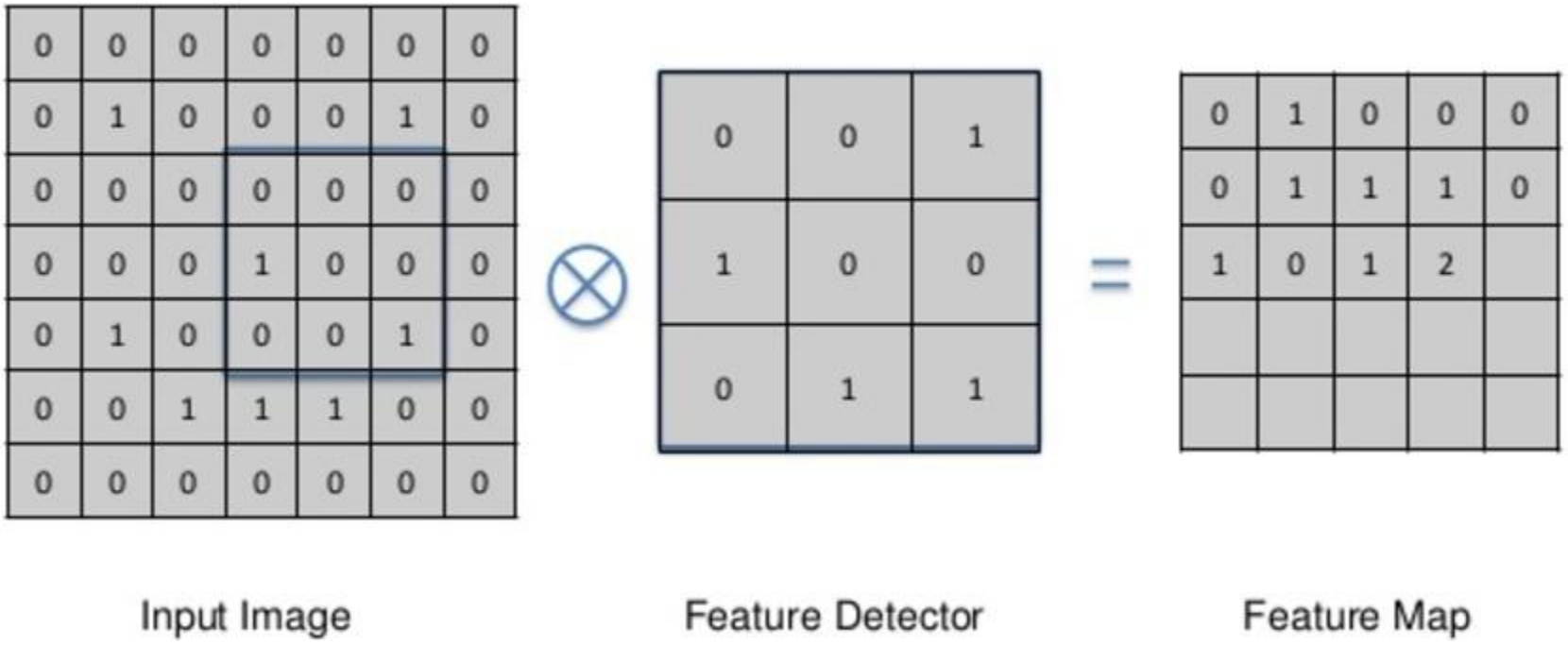
source: superdatascience

CNN Step 1: Convolution



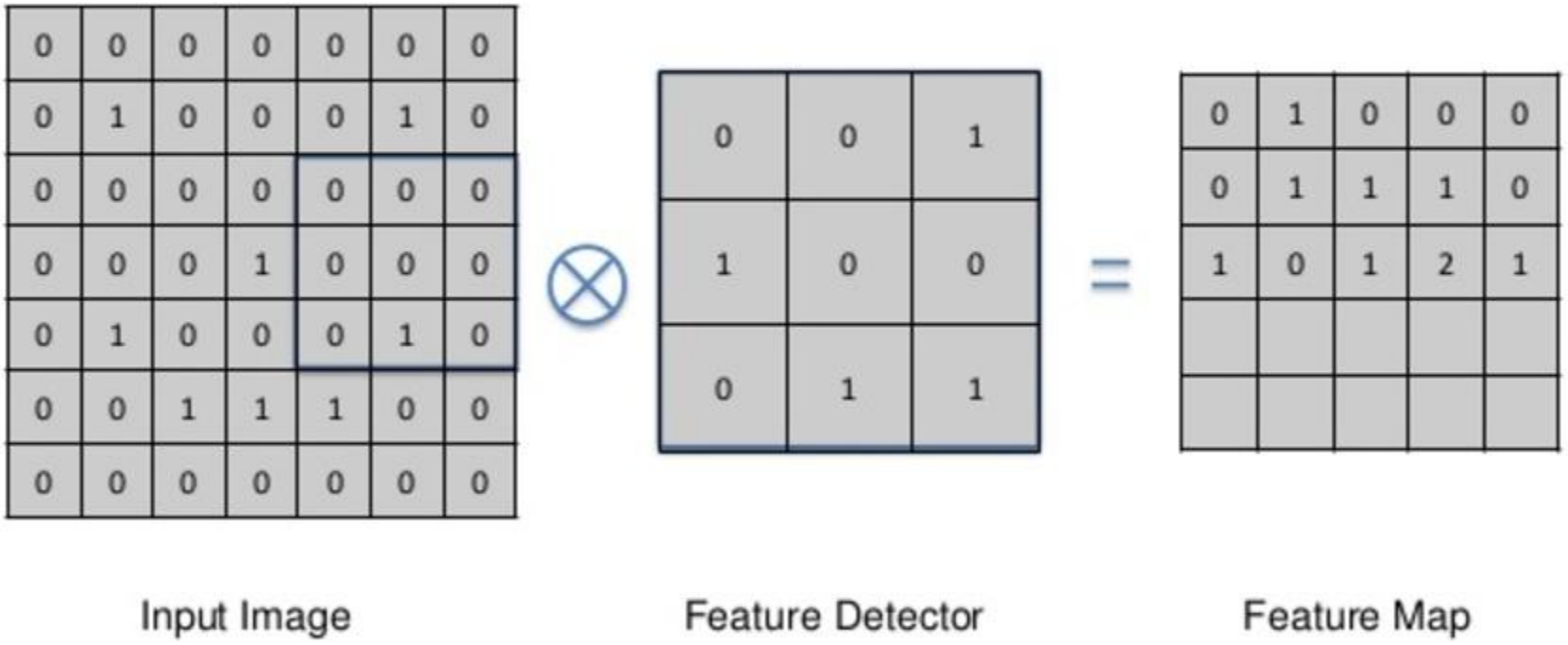
source: superdatascience

CNN Step 1: Convolution



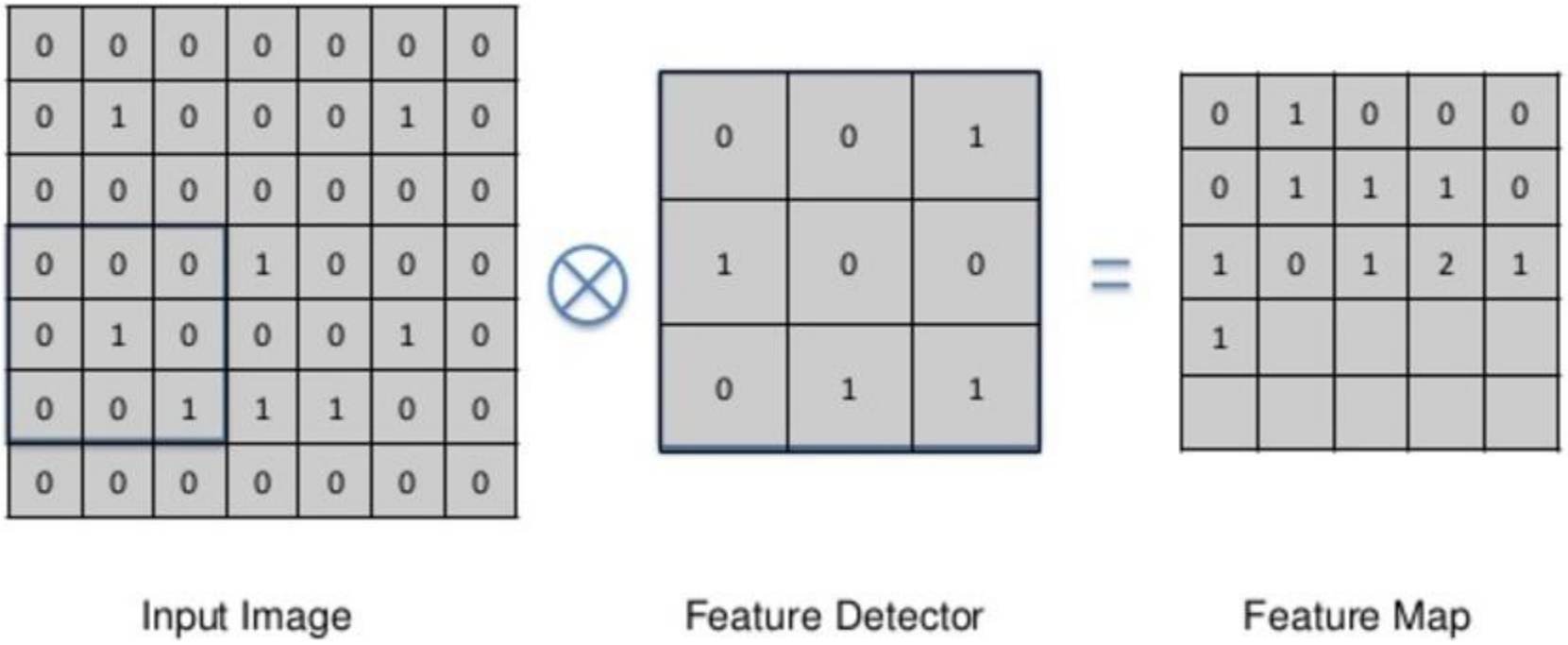
source: superdatascience

CNN Step 1: Convolution



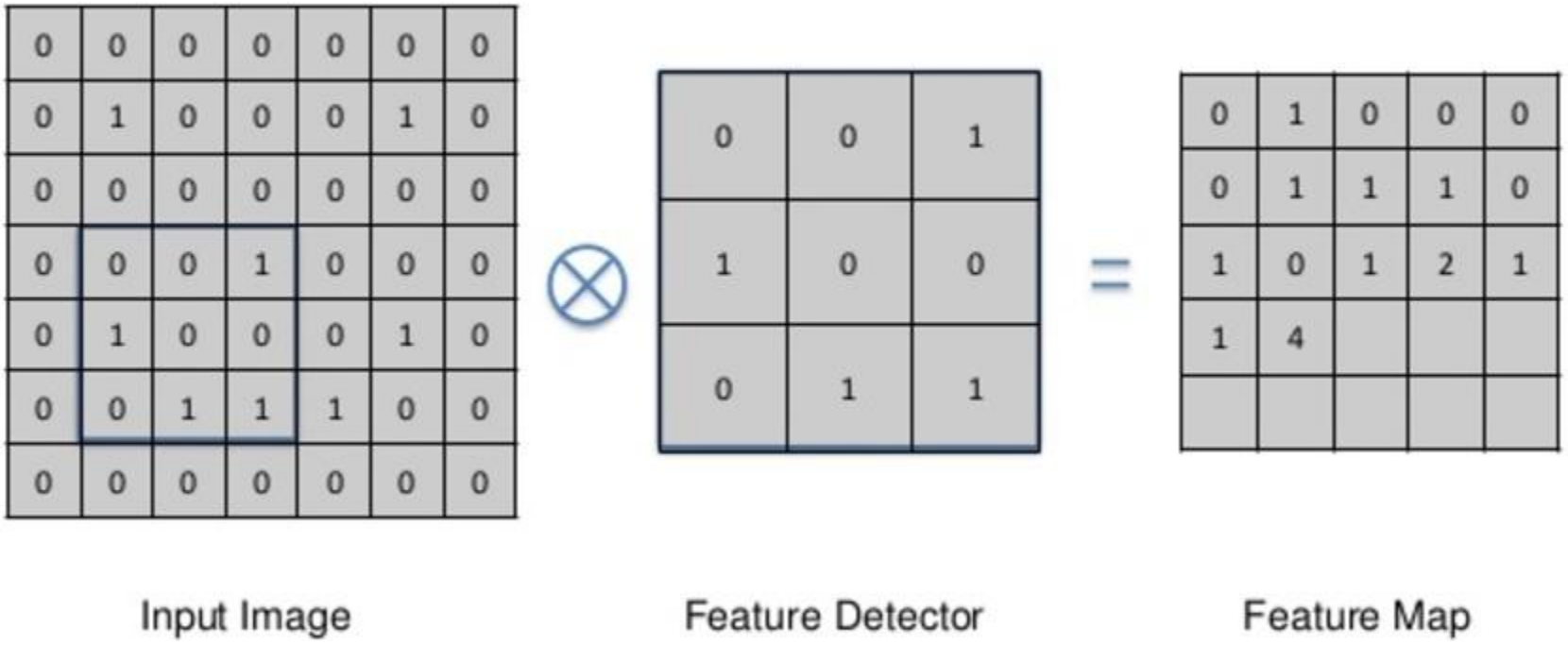
source: superdatascience

Convolution



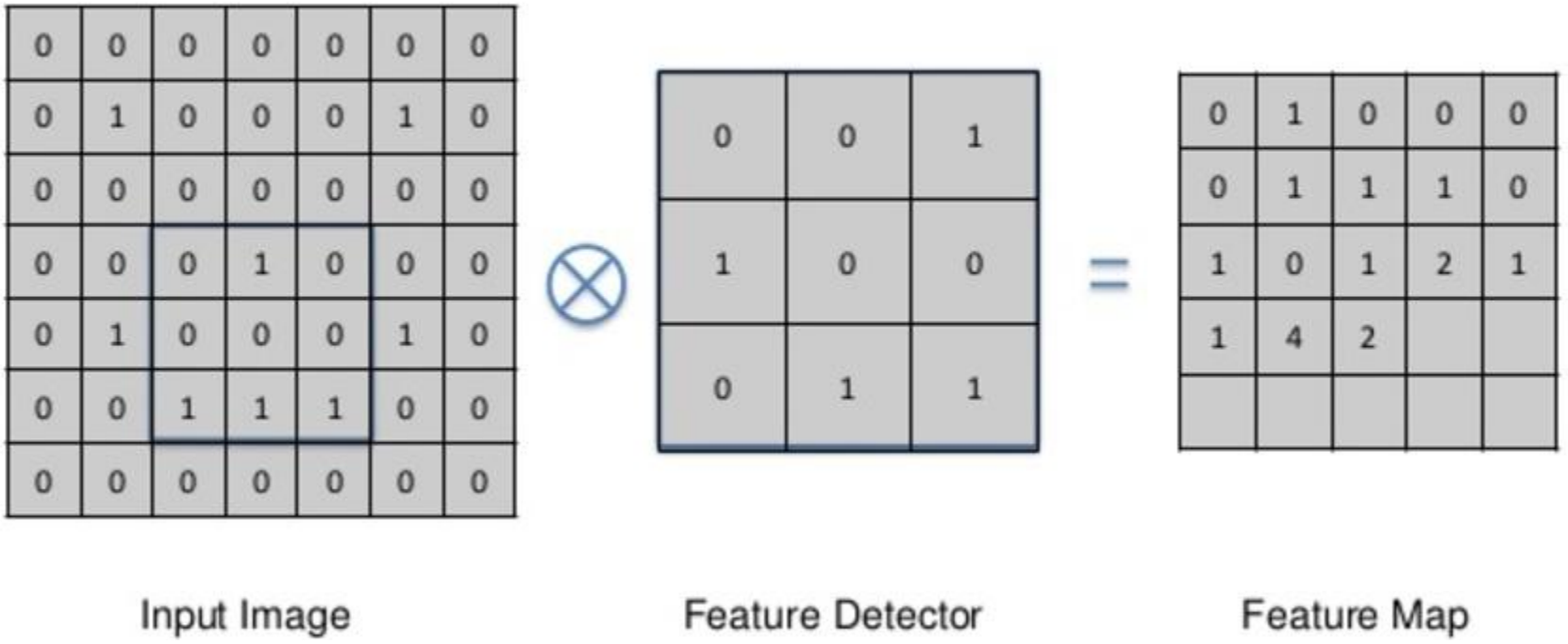
source: superdatascience

CNN Step 1: Convolution



source: superdatascience

CNN Step 1: Convolution



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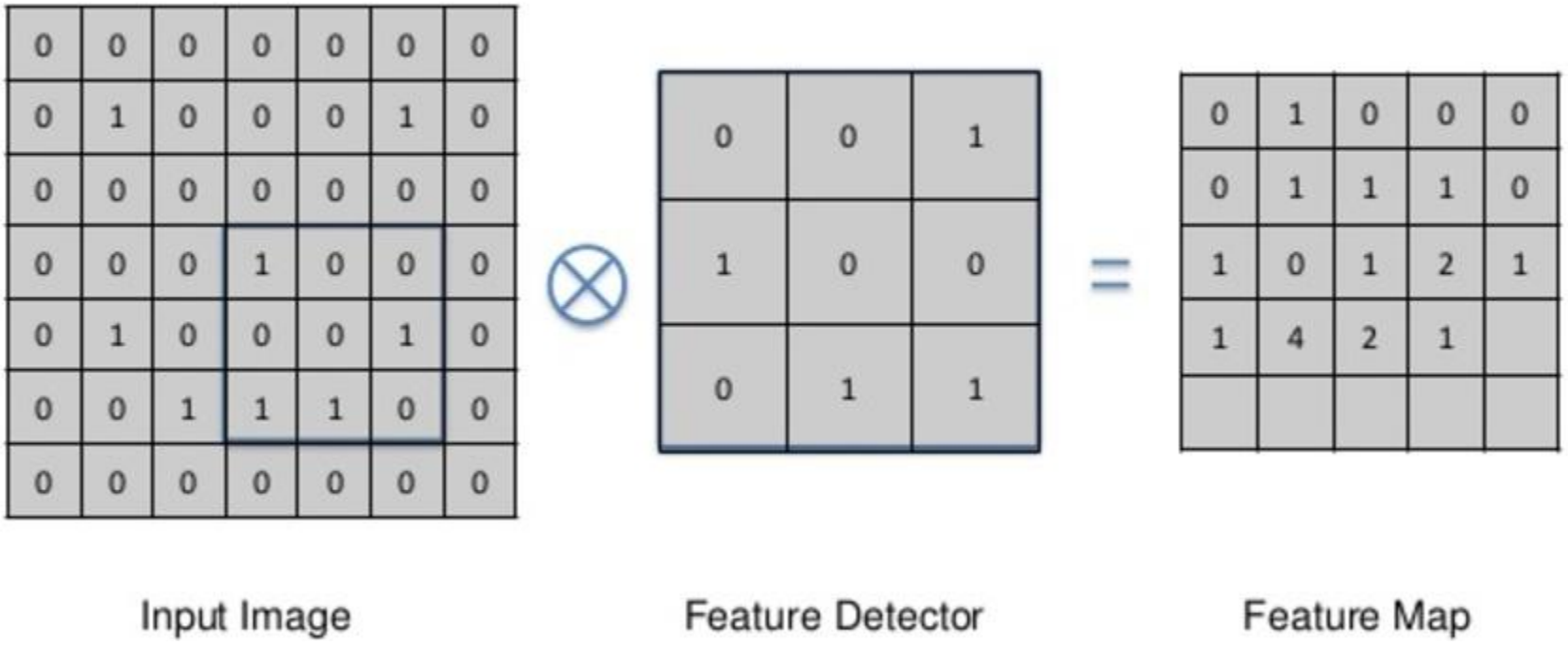
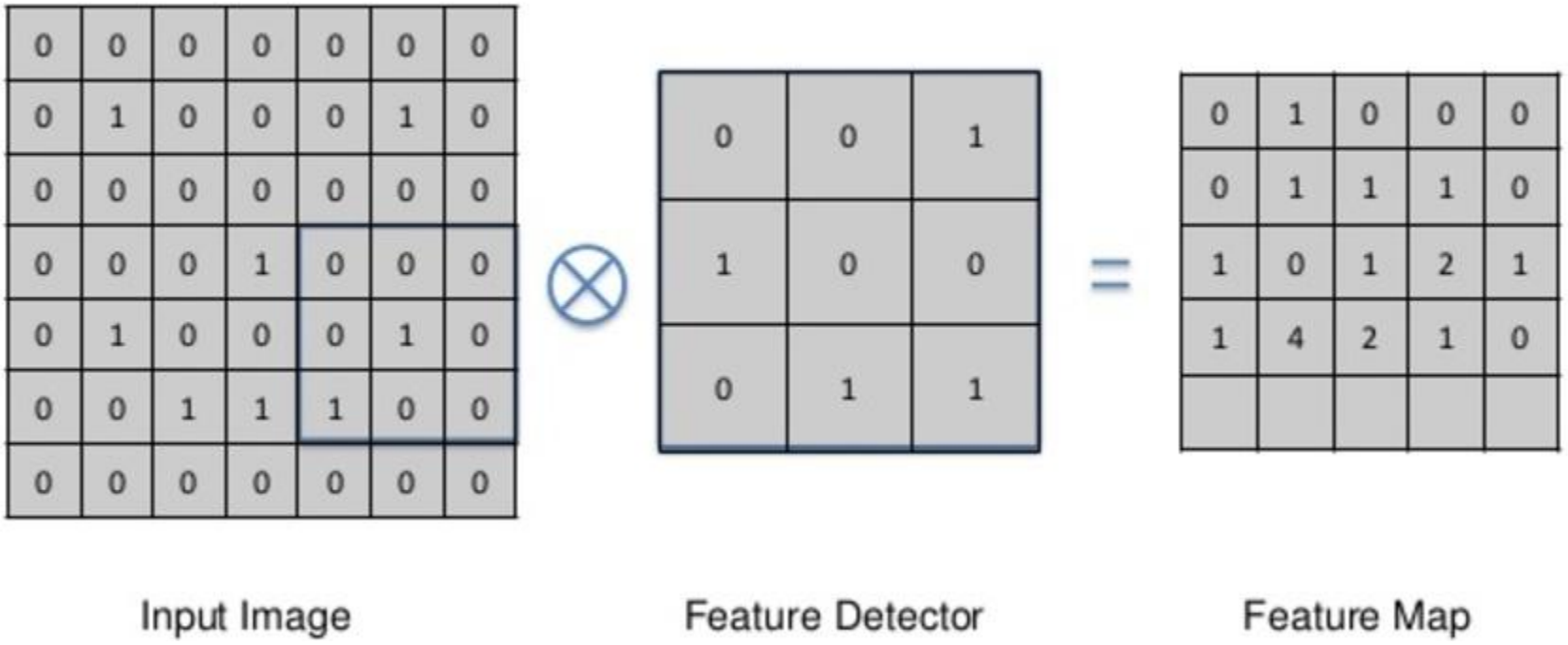
CNN Step 1: Convolution



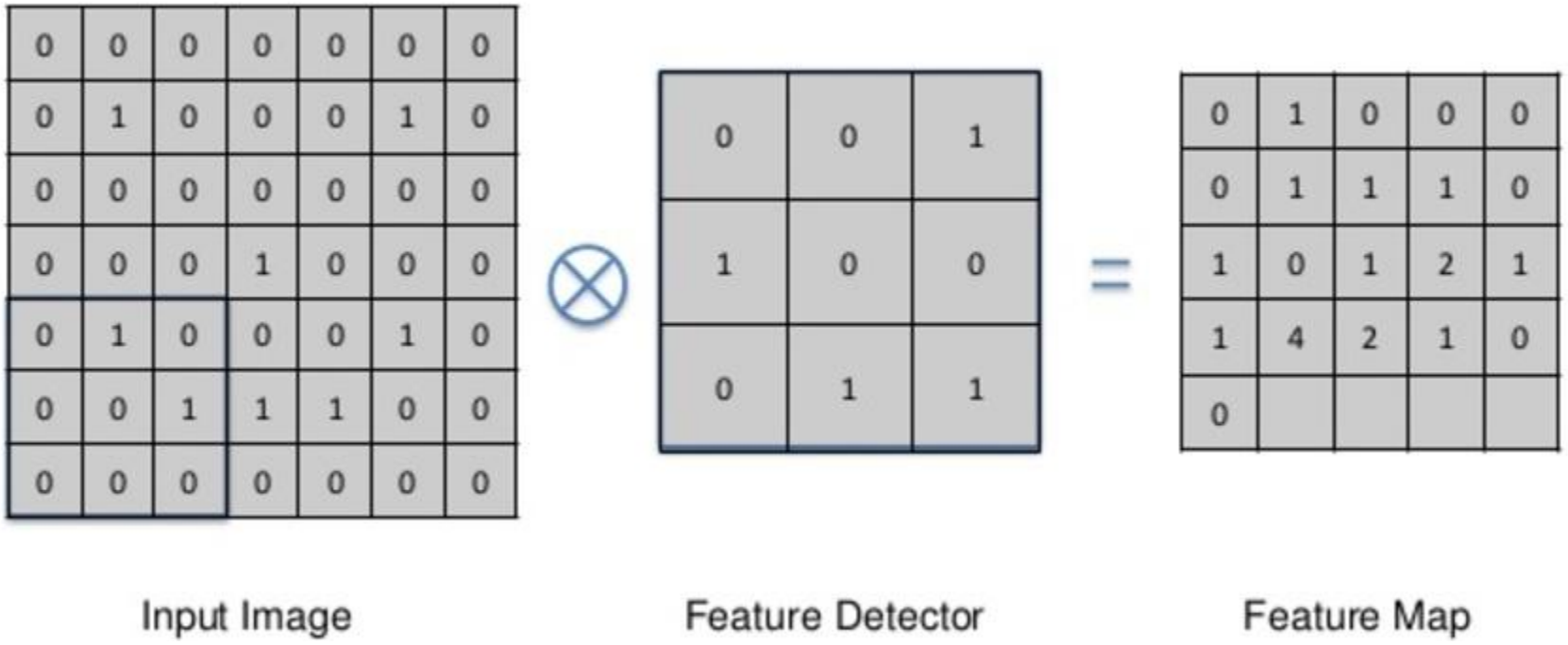
source: superdatascience

CNN Step 1: Convolution



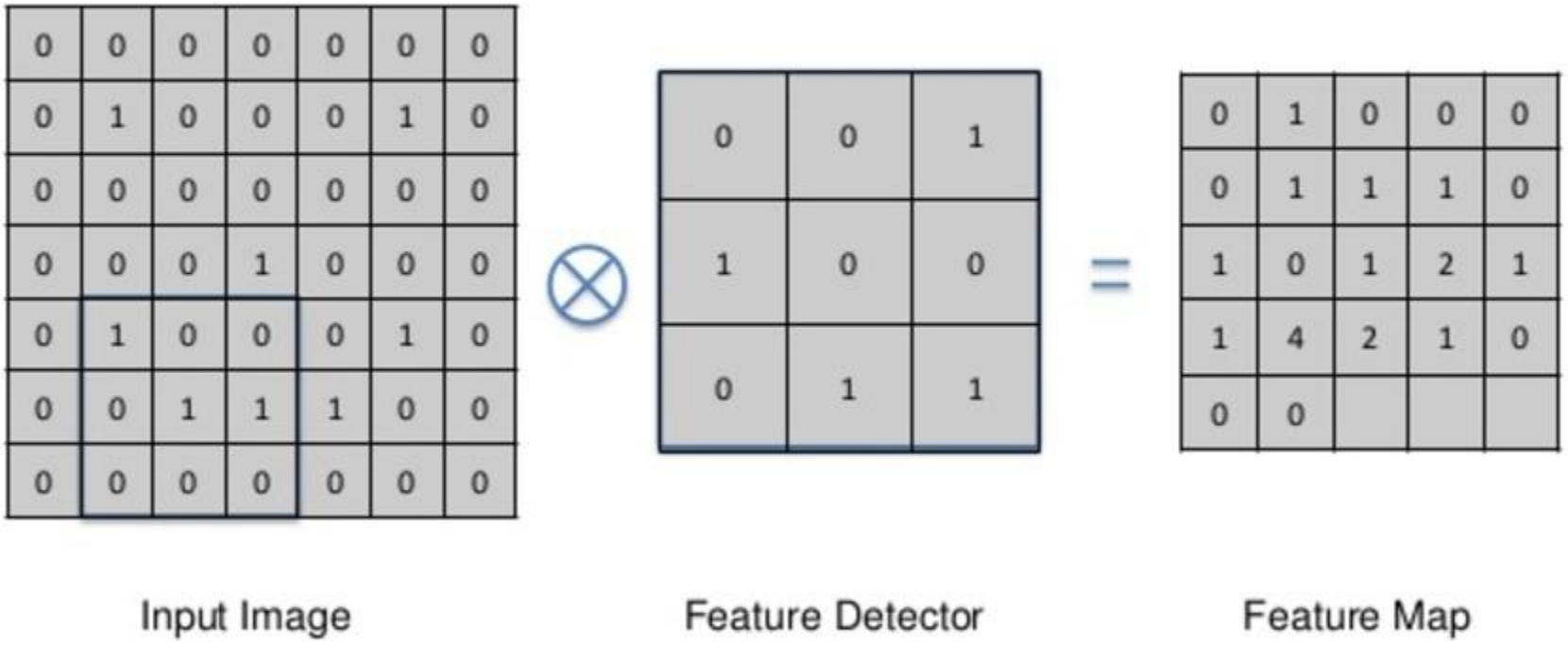
source: superdatascience

CNN Step 1: Convolution



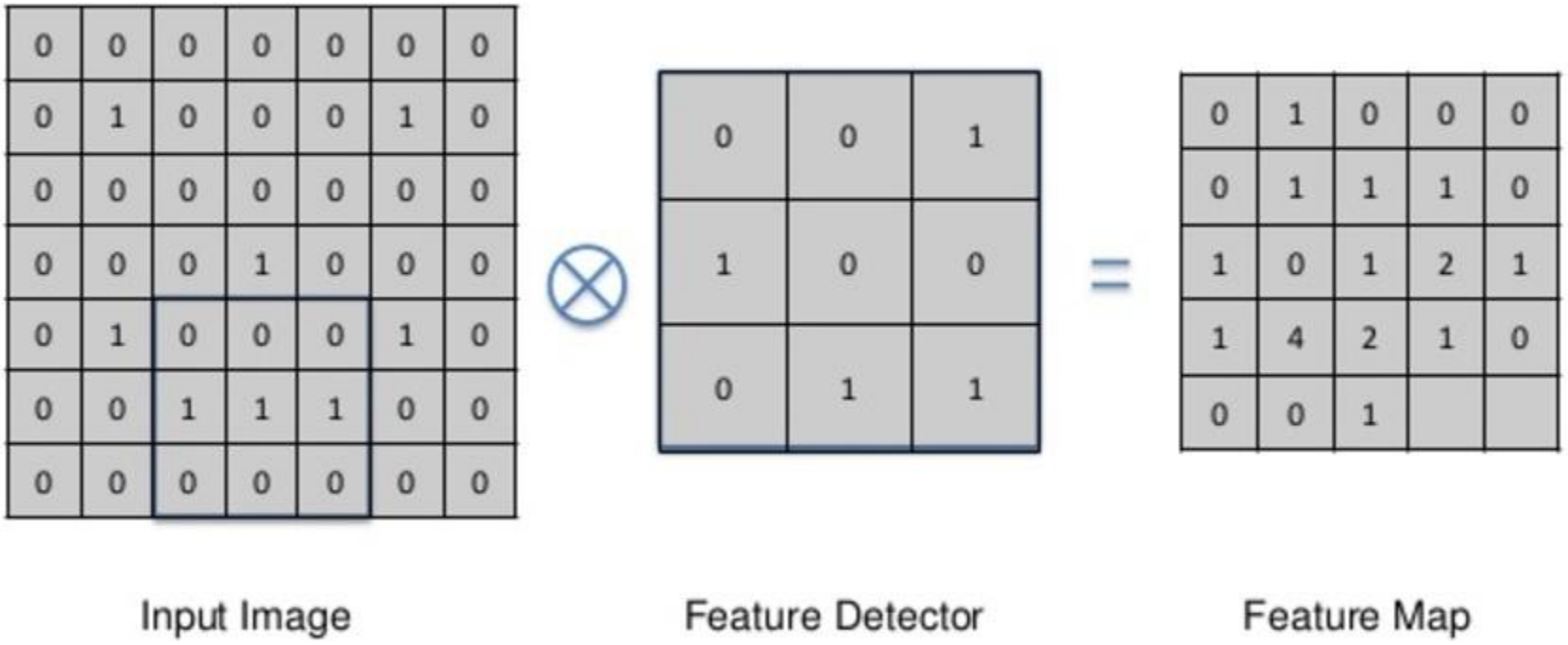
source: superdatascience

CNN Step 1: Convolution



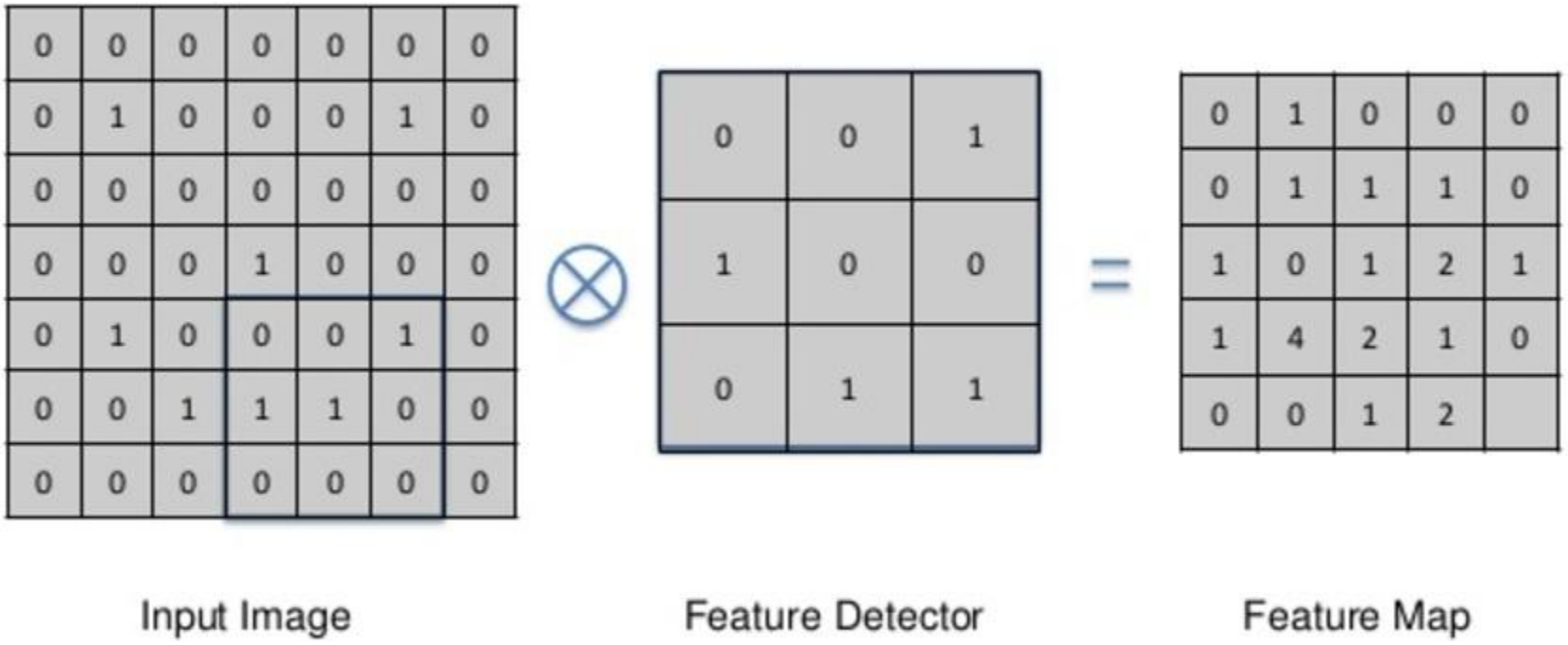
source: superdatascience

CNN Step 1: Convolution



source: superdatascience

CNN Step 1: Convolution



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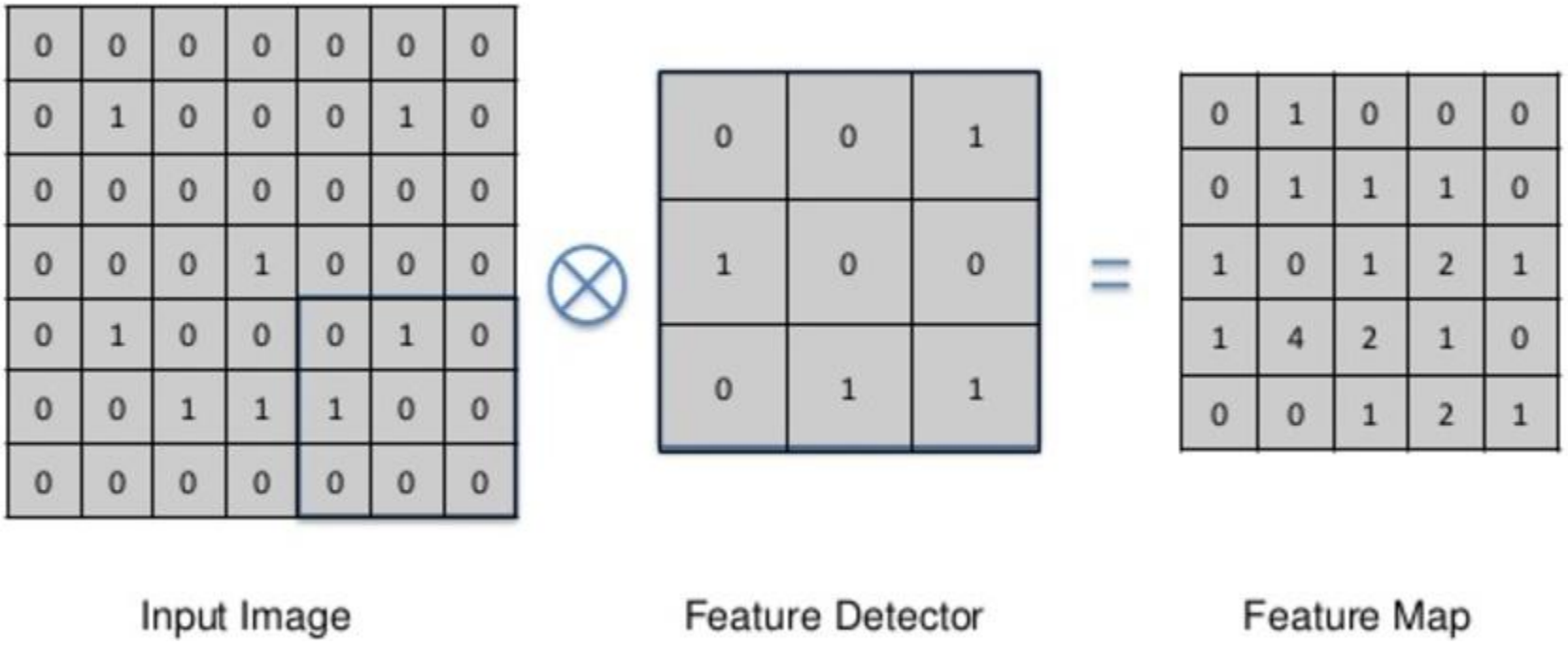
CNN Step 1: Convolution



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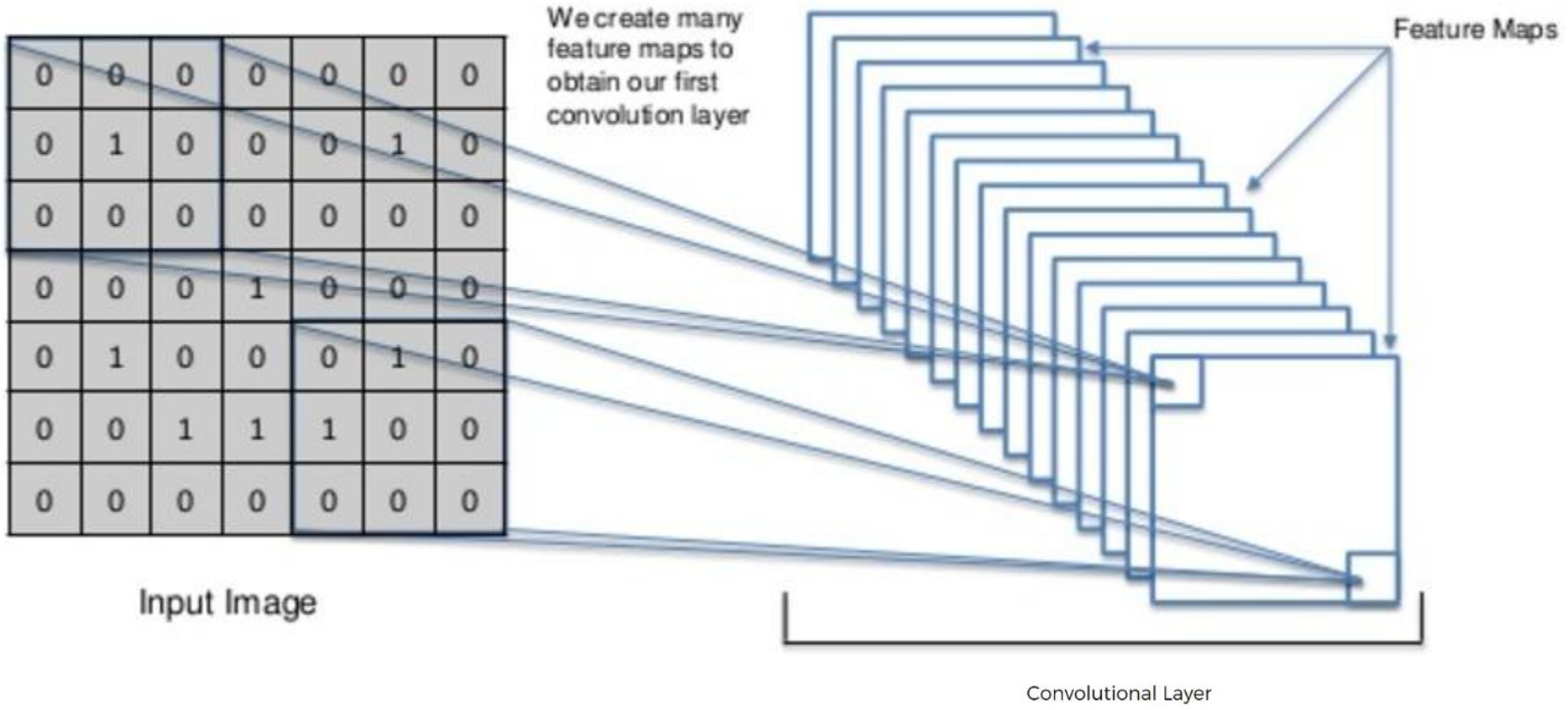
CNN Step 1: Convolution



source: superdatascience

Convolution result examples

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Sharpen

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

source: GIMP documentation

Convolution result examples

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Blur

0	0	0	0	0
0	1	1	1	0
0	1	1	1	0
0	1	1	1	0
0	0	0	0	0

source: GIMP documentation

Convolution result examples

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Edge Detect

	0	1	0	
	1	-4	1	
	0	1	0	

source: GIMP documentation

Convolution result examples

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Emboss

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

source: GIMP documentation

color images convolution

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	...
...	...	...	...	...	...	...

Input Channel #1 (Red)

0	0	0	0	0	0	...
0	167	166	167	169	169	...
0	164	165	168	170	170	...
0	160	162	166	169	170	...
0	156	156	159	163	168	...
0	155	153	153	158	168	...
...	...	...	...	...	...	...

Input Channel #2 (Green)

0	0	0	0	0	0	...
0	163	162	163	165	165	...
0	160	161	164	166	166	...
0	156	158	162	165	166	...
0	155	155	158	162	167	...
0	154	152	152	157	167	...
...	...	...	...	...	...	...

Input Channel #3 (Blue)

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

Kernel Channel #1

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

Kernel Channel #2

0	1	1
0	1	0
1	-1	1

Kernel Channel #3

$308 + (-498) + 164 + 1 = -25$

Bias = 1

Output

-25				...
				...
				...
				...
...	...	...	...	...

source: stack Overflow

CNN Step 1: Convolution

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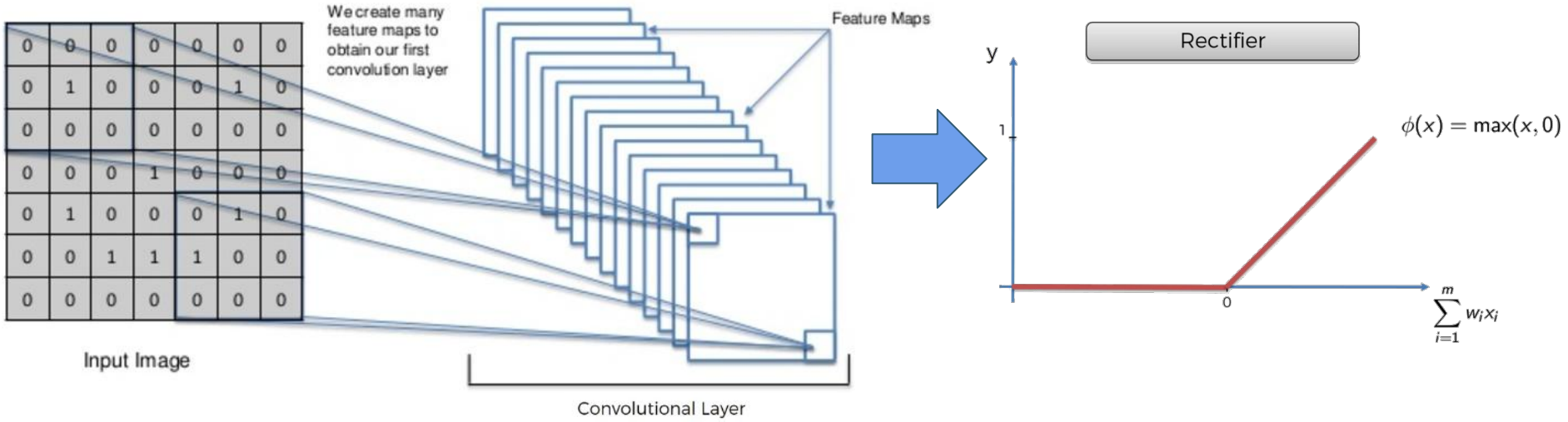
Searching for features in the images, using a feature detector, and putting them on a feature map that still preserves the spatial relationships between pixels.

Many times, we won't know what these characteristics mean, but they work.

source: superdatascience

Step 1(b)
ReLU Activation

Step 1b: ReLU layer



We add NonLinearity to the output

source: superdatascience

Step 2
Max Pooling

Step 2: Pooling

Step 2: Pooling

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Step 2: MAX Pooling

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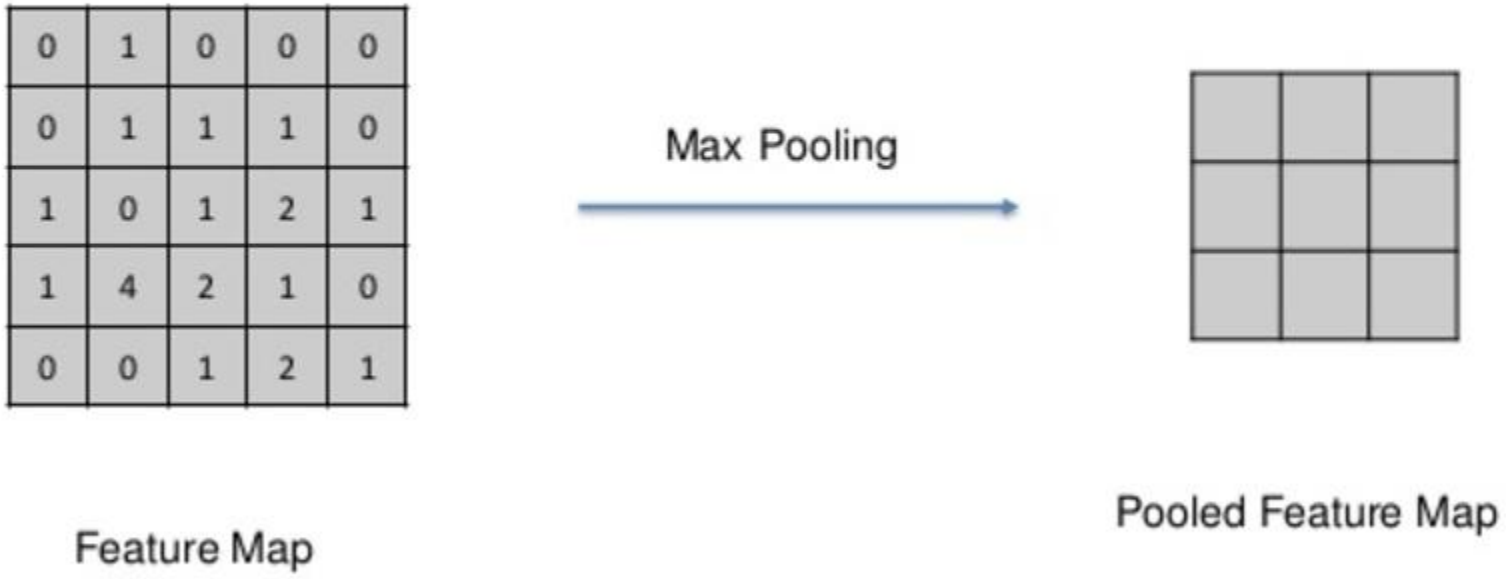
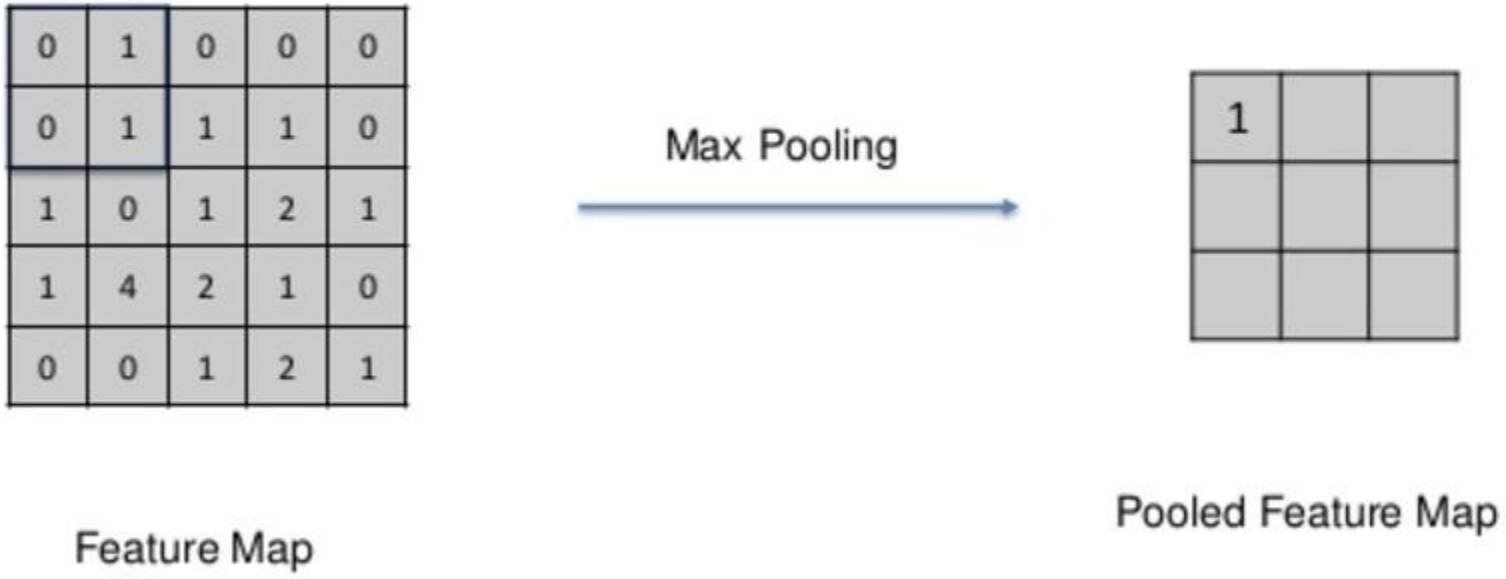
0	1	0	0	0
0	1	1	1	0
1	0	1	2	1
1	4	2	1	0
0	0	1	2	1

Feature Map

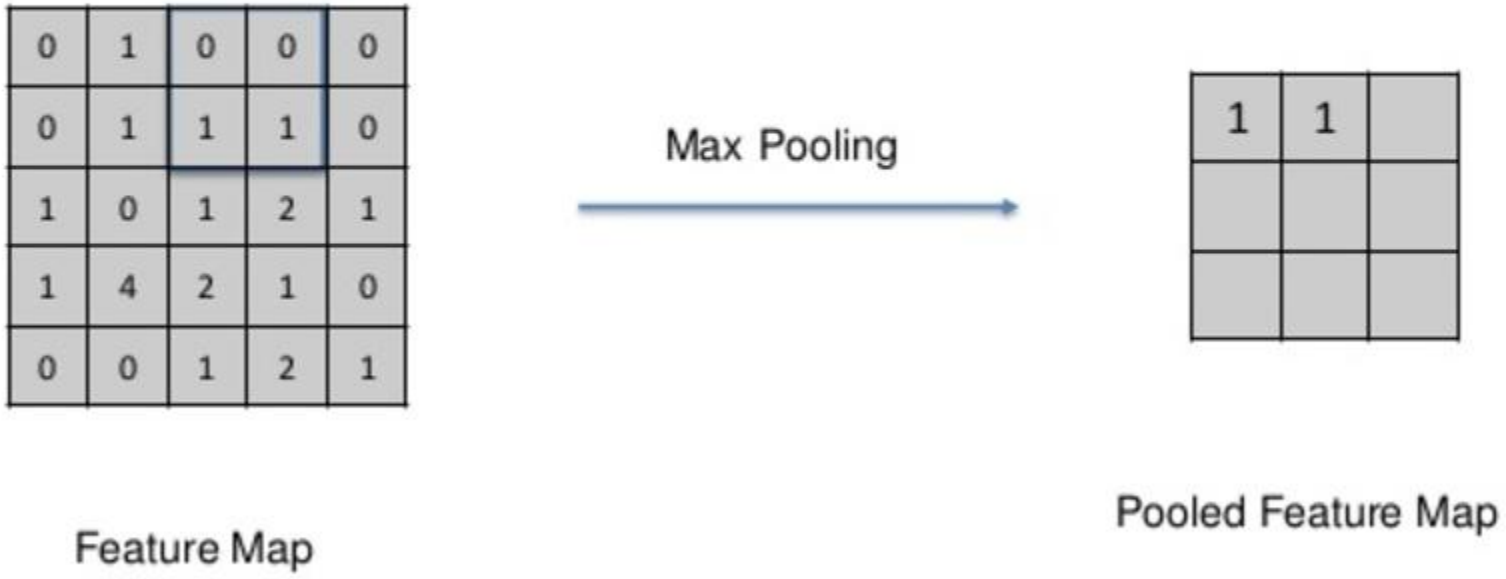
Step 2: MAX Pooling



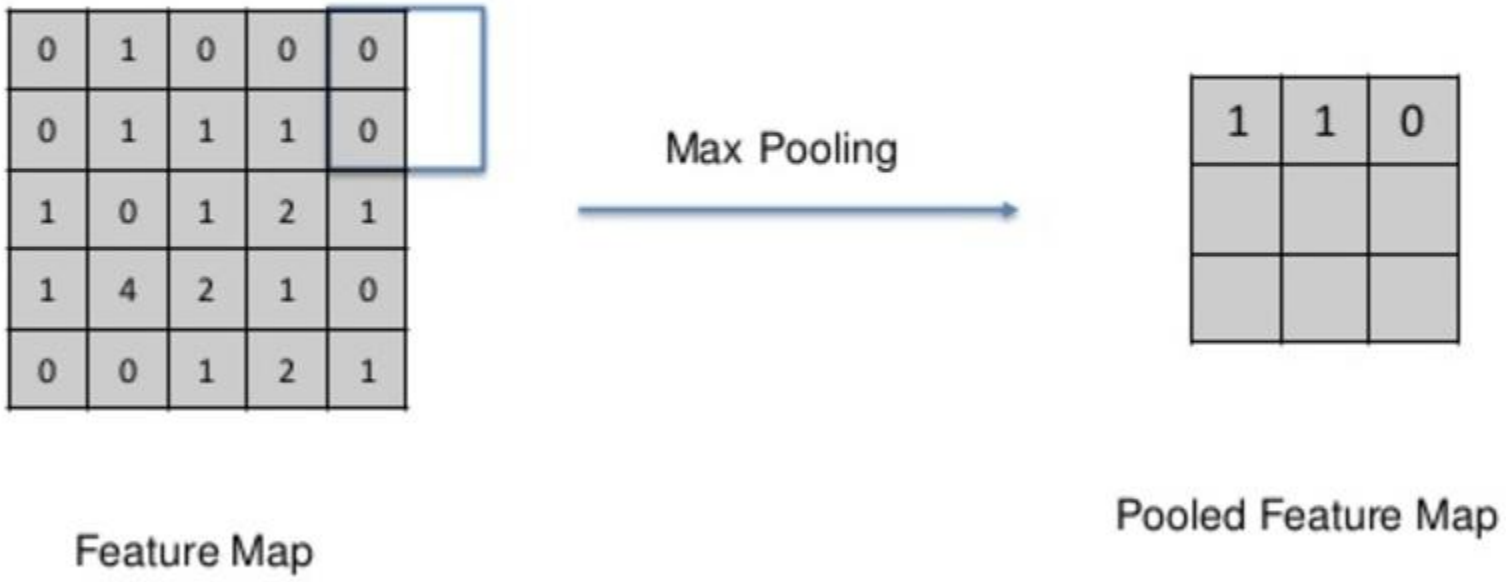
Step 2: MAX Pooling



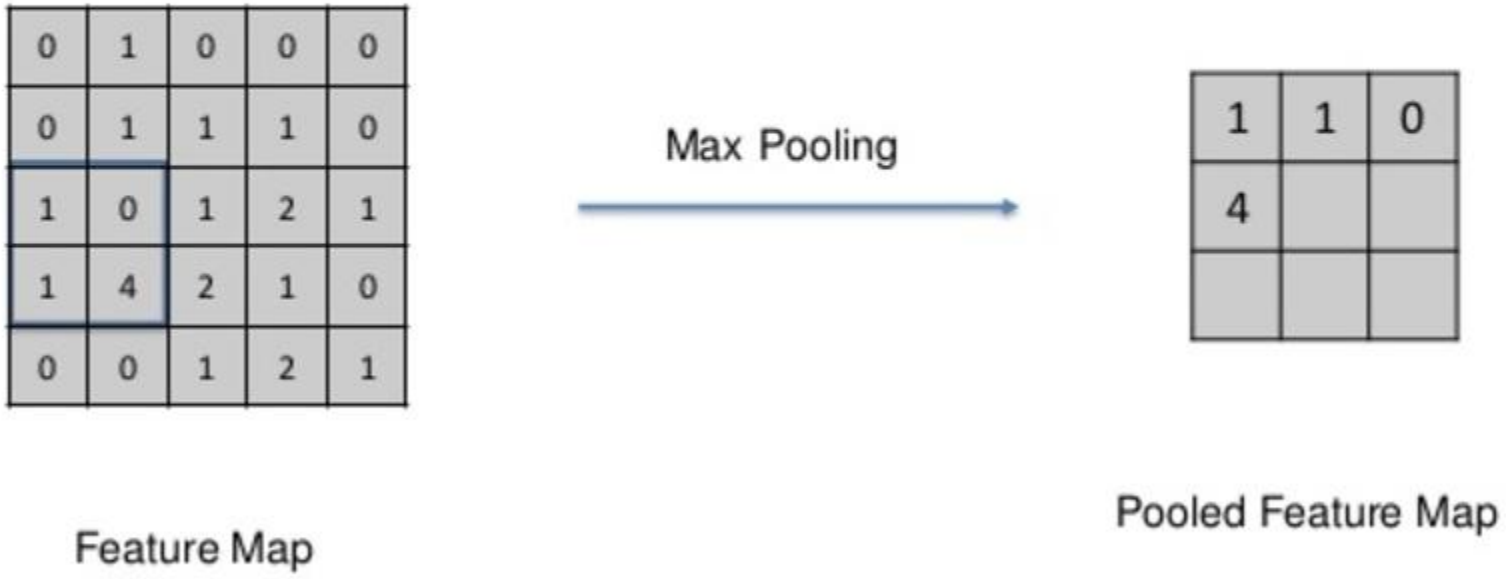
Step 2: MAX Pooling



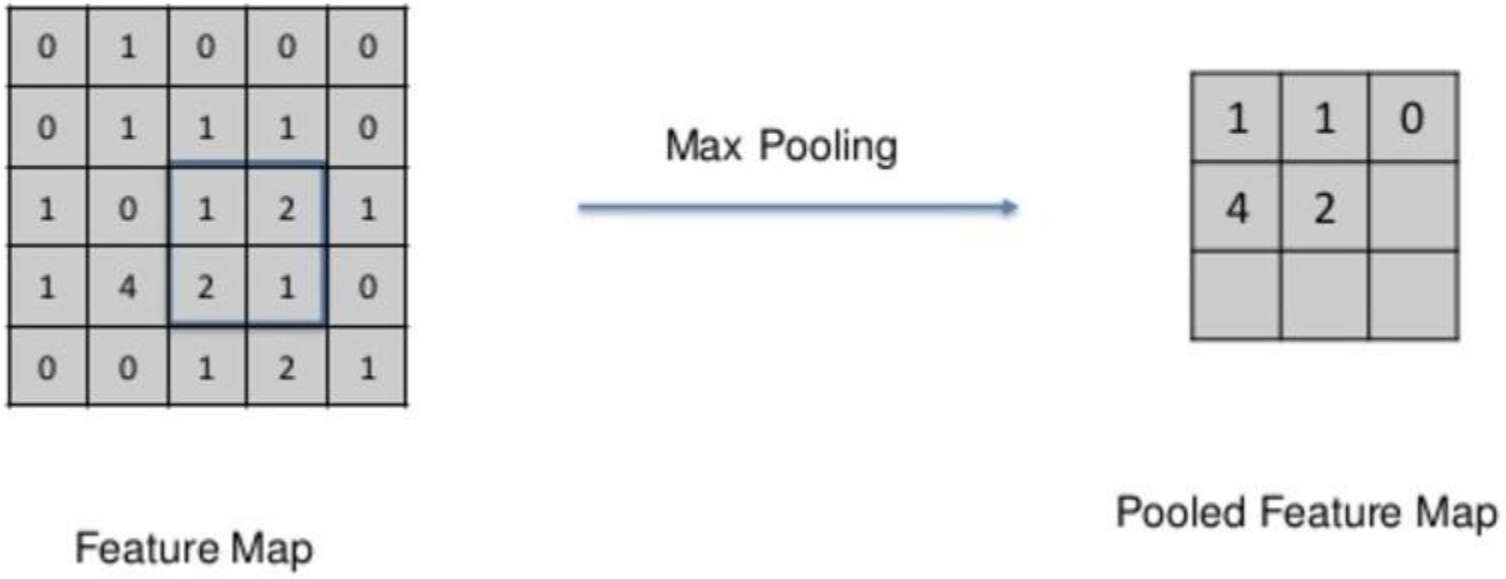
Step 2: MAX Pooling



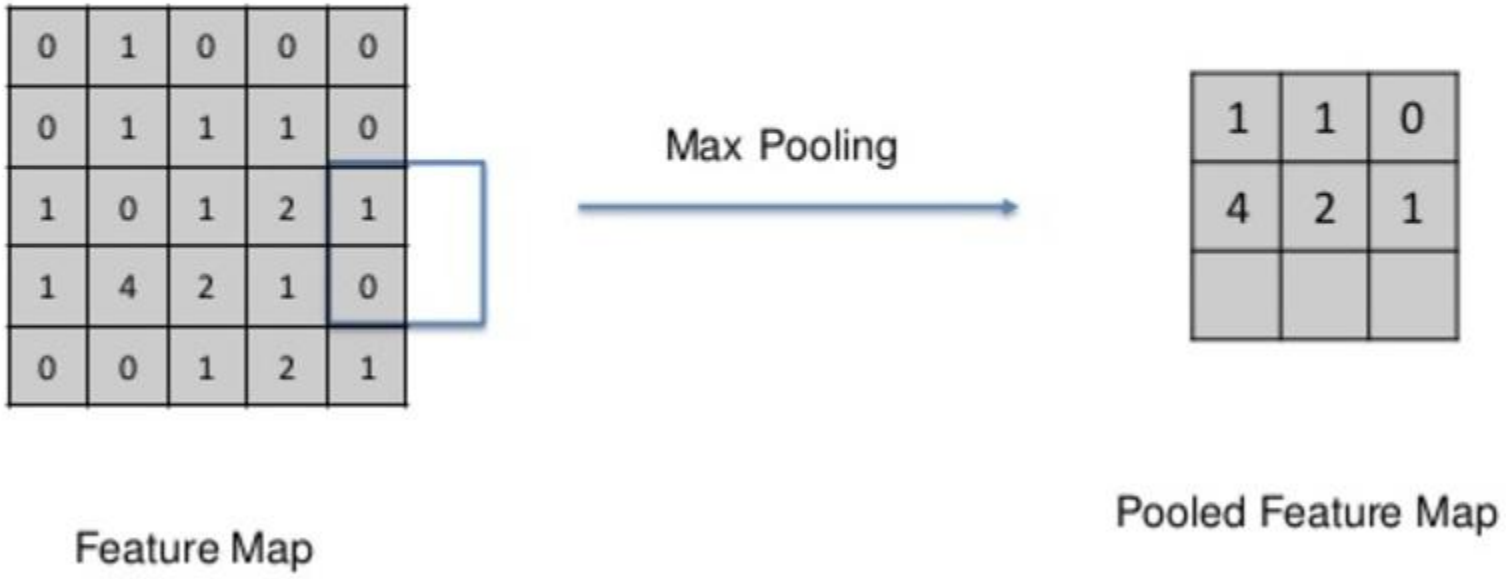
Step 2: MAX Pooling



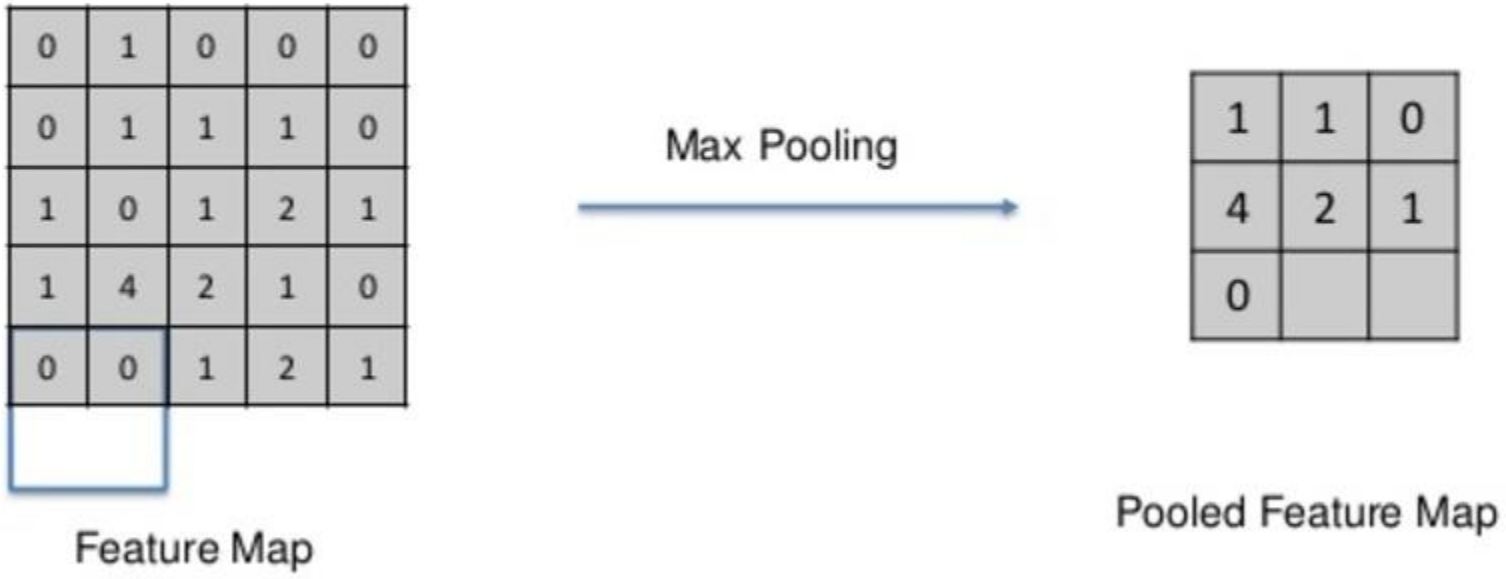
Step 2: MAX Pooling



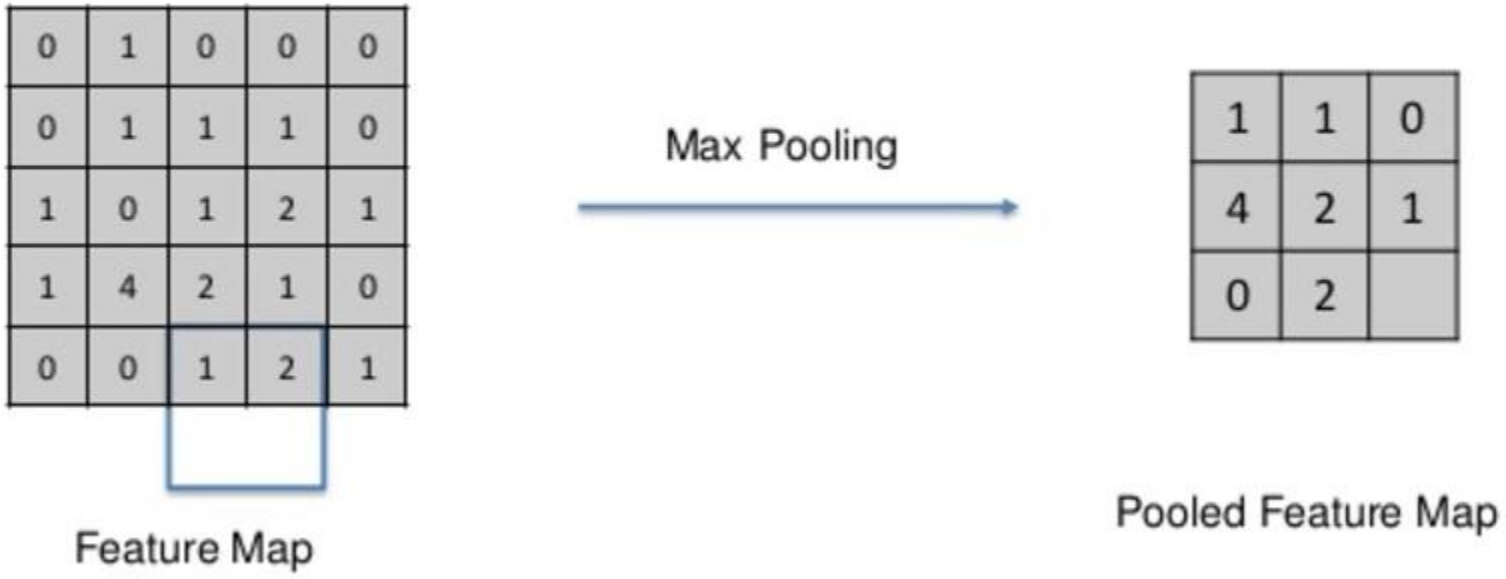
Step 2: MAX Pooling



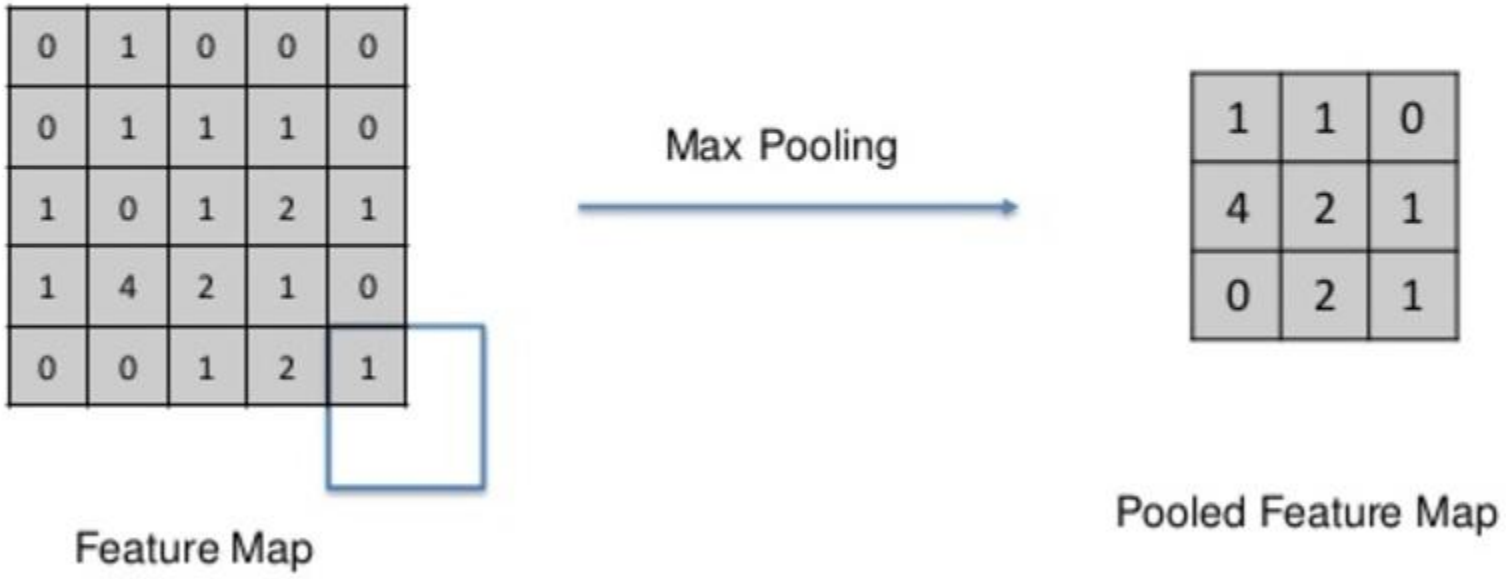
Step 2: MAX Pooling



MAX Pooling


0 1 0 0 0
0 1 1 1 0
1 0 1 2 1
1 4 2 1 0
0 0 1 2 1
Feature Map
Max Pooling
1 1 0
4 2 1
0 2
Pooled Feature Map

Step 2: MAX Pooling



Step 1 and 2: Conv + pooling

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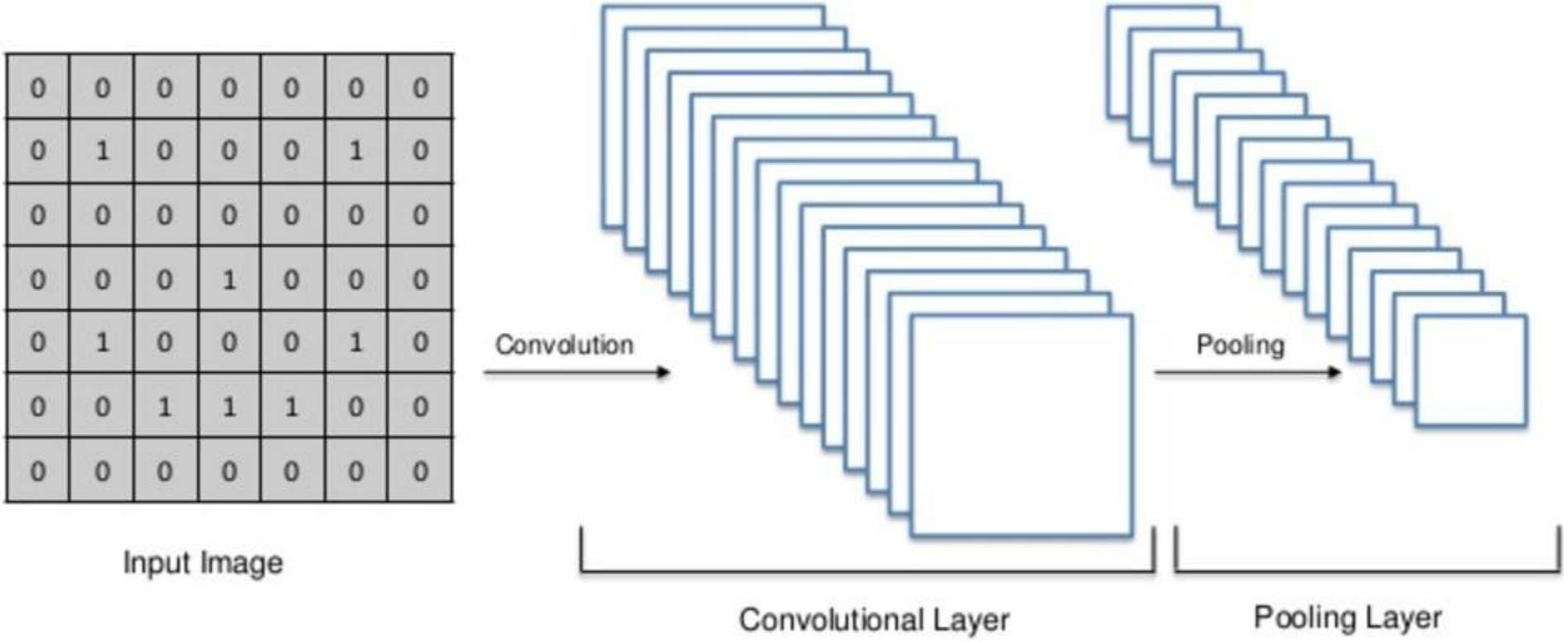

Step 1 and 2: Conv + pooling

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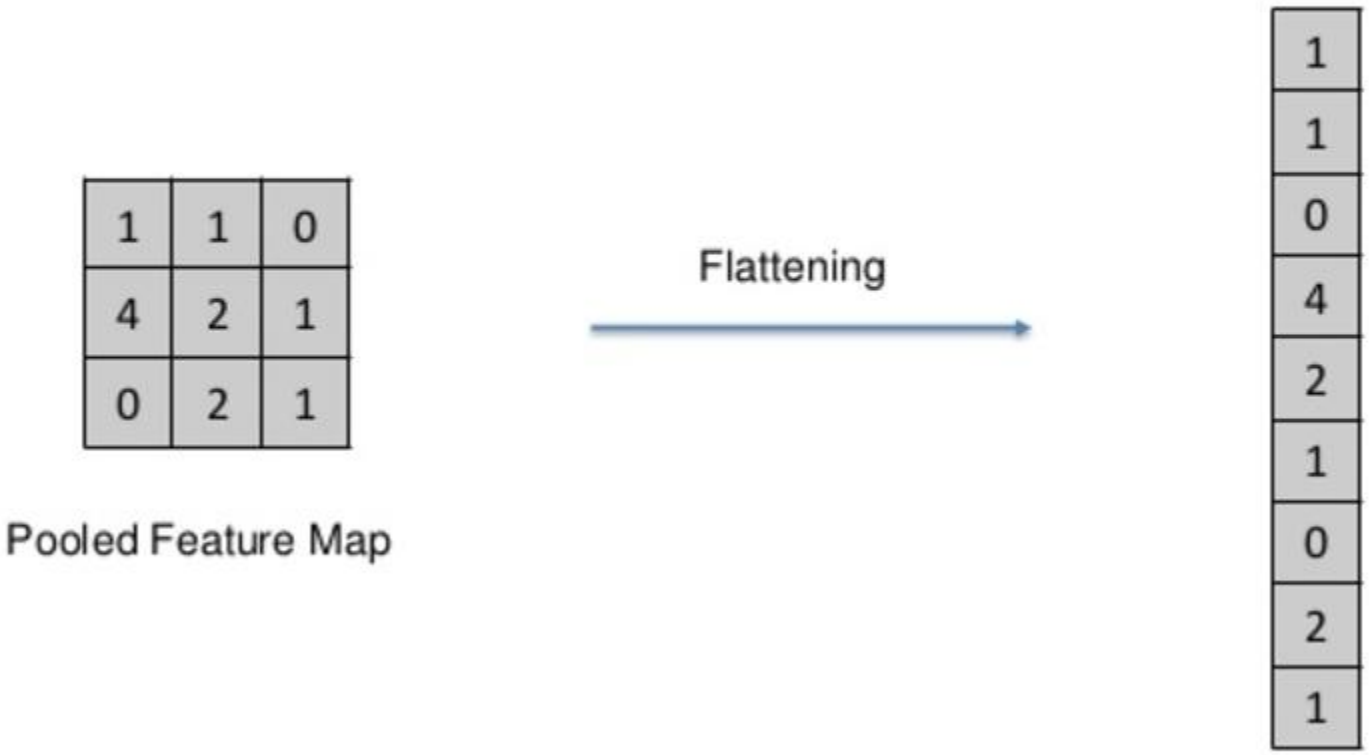
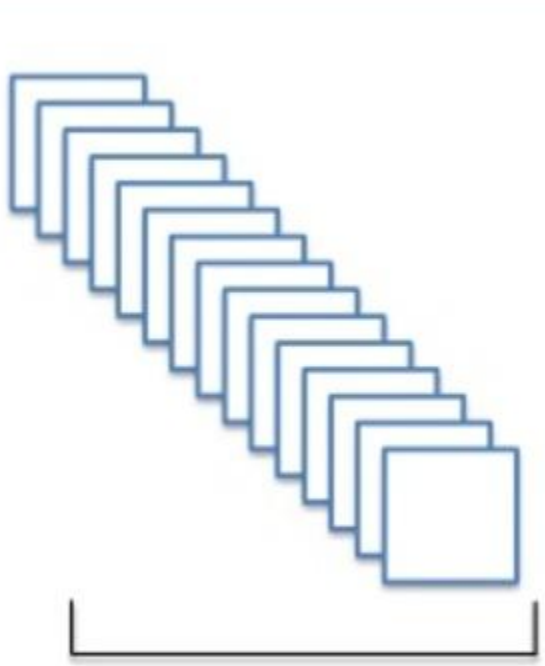
- Interesting paper about poolings: http://www.ais.uni-bonn.de/papers/icann2010_maxpool.pdf
- Convolution and pooling live! example: http://scs.ryerson.ca/~aharley/vis/conv/flat.html
-

Step 3
Flattening

Step 3: Flattening

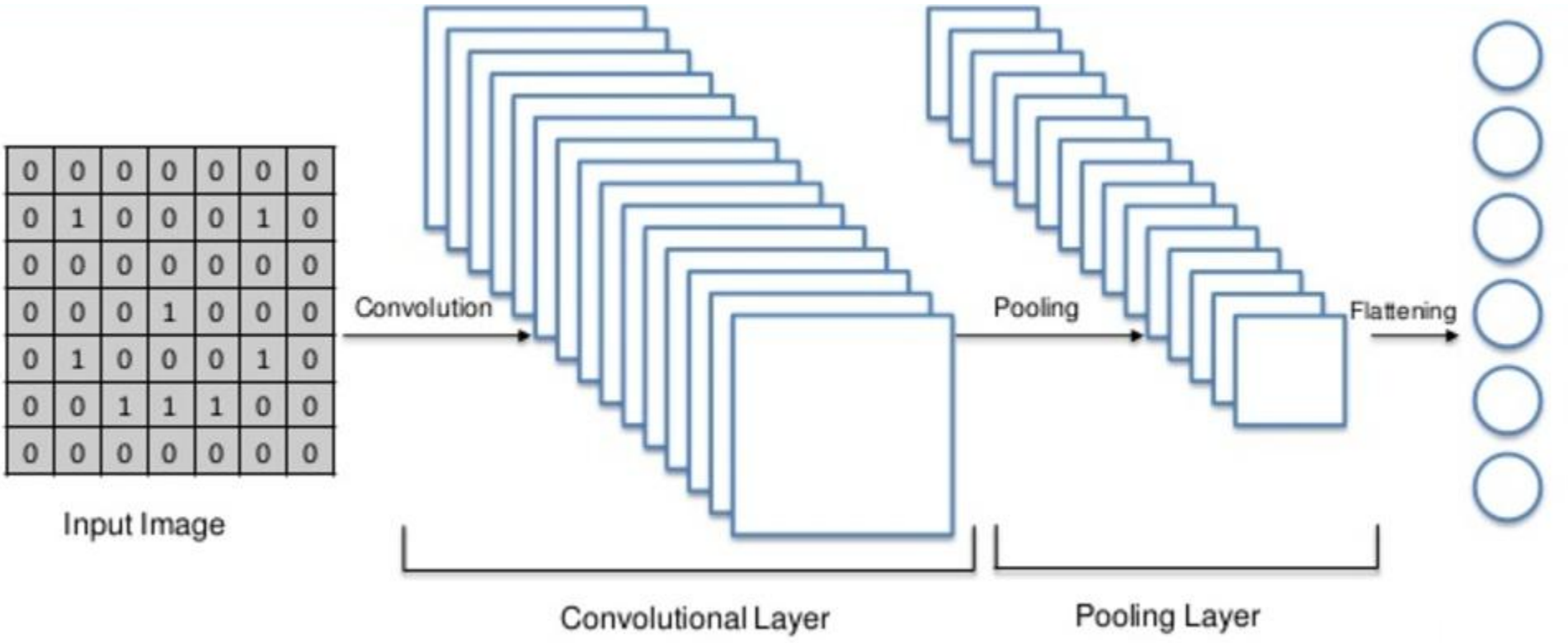


Step 3: Flattening



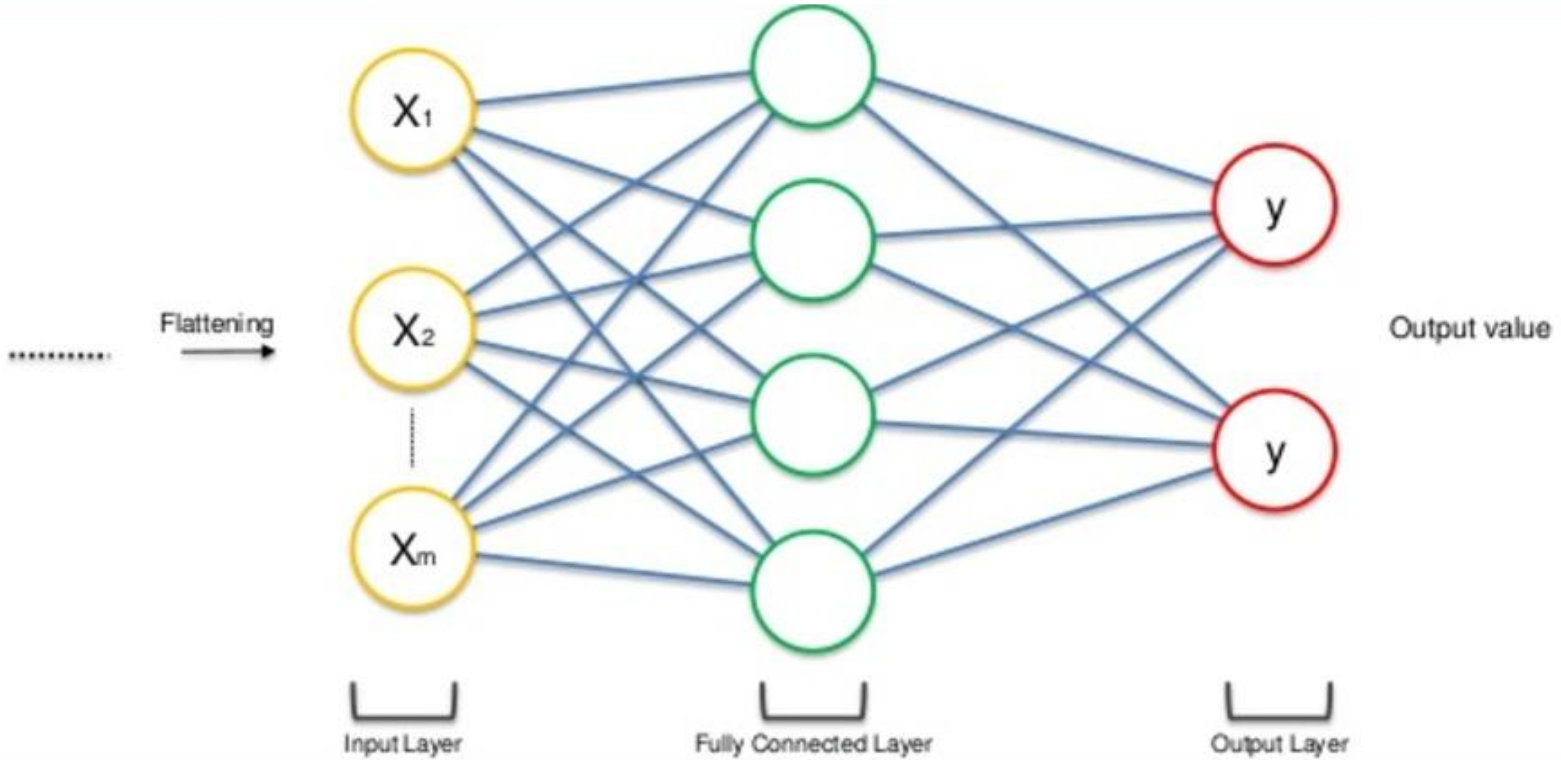
Entrada a un ANN

steps 1+2+3: conv.+pool.+flat.

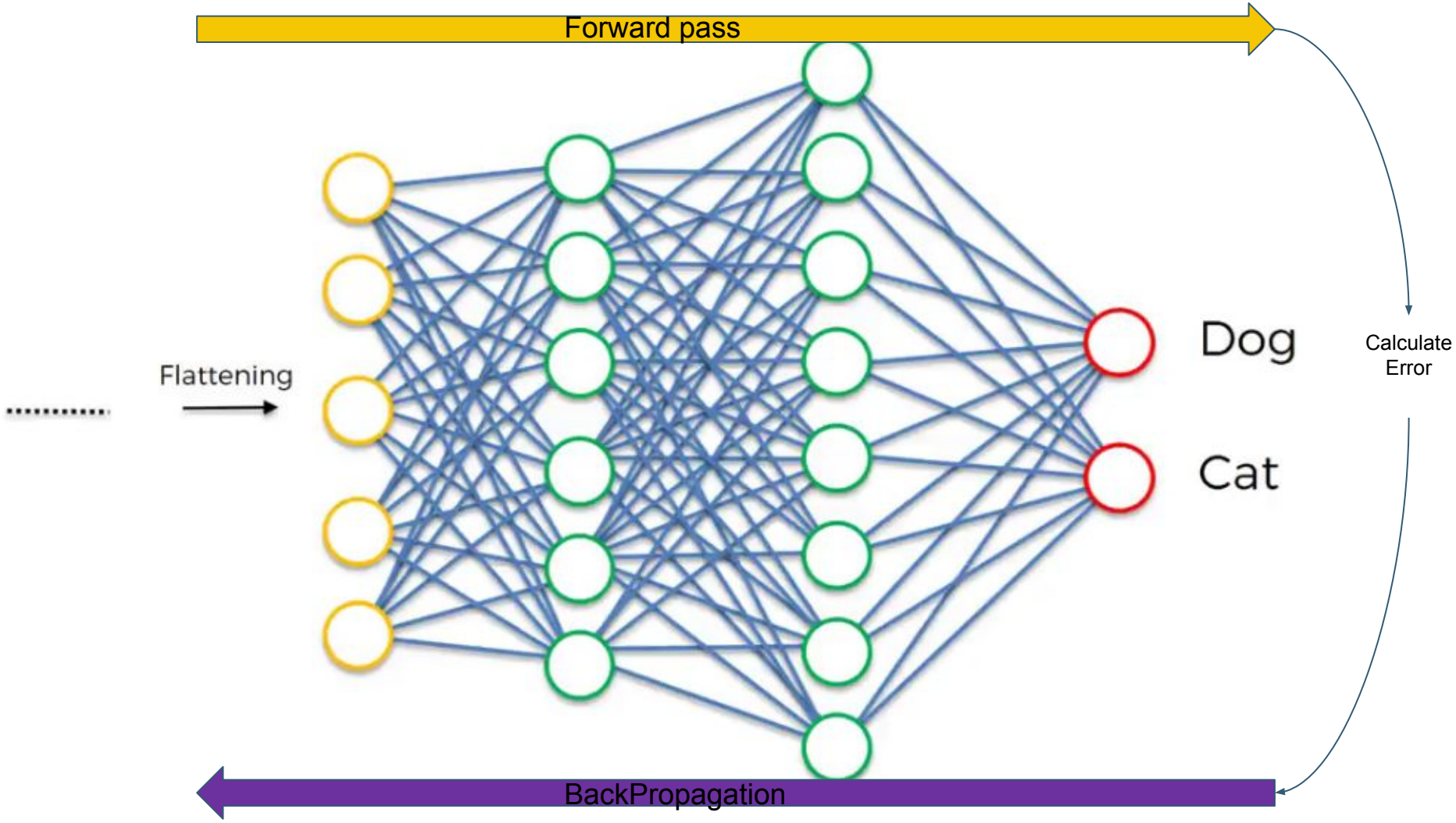


Step 4
Full Connection

Step 4: Fully connected ANN

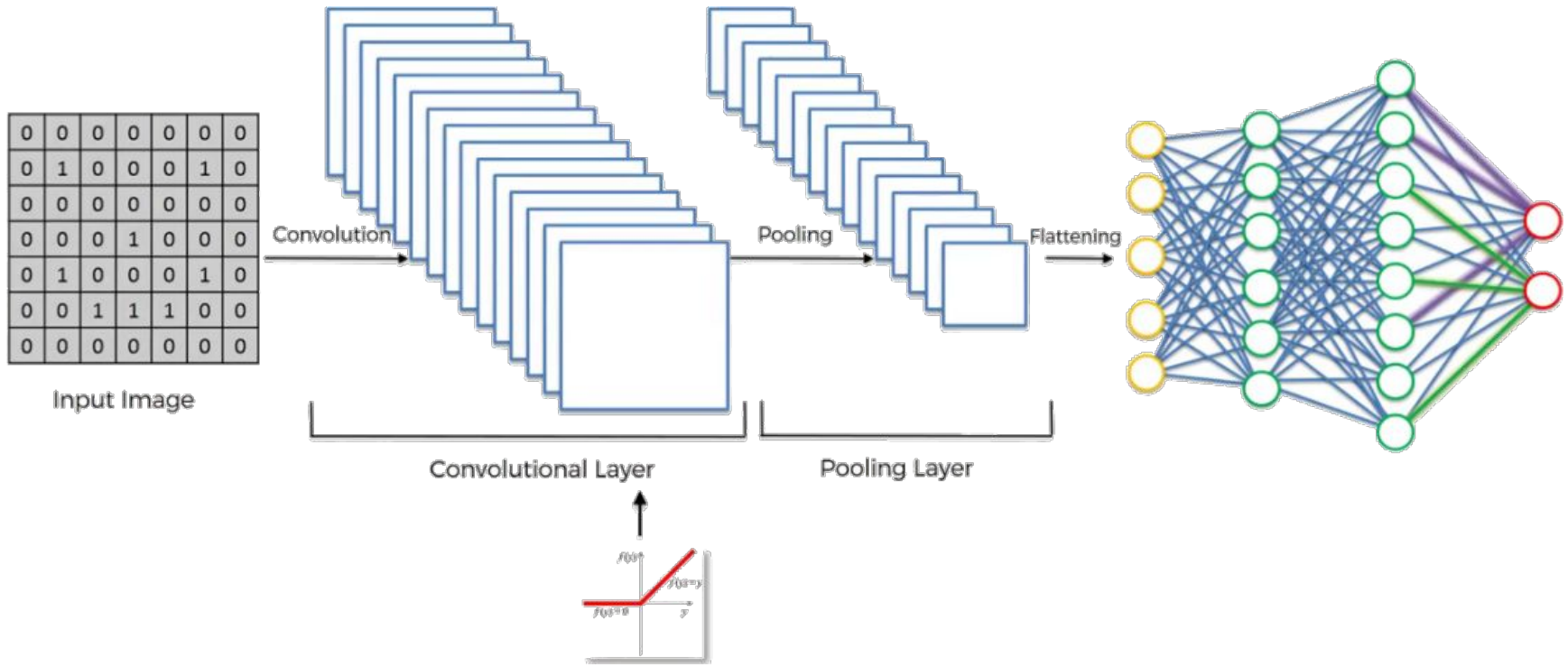


Step 4: Fully connected ANN



Summary

Summary


0 0 0 0 0 0 0
0 1 0 0 0 1 0
0 0 0 0 0 0 0
0 0 0 1 0 0 0
0 1 0 0 0 1 0
0 0 1 1 1 0 0
0 0 0 0 0 0 0
Input Image
Convolution
Pooling
Flattening
Convolutional Layer
Pooling Layer

CNN Tensorflow utils

Image preprocessing with TF

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- Preprocessing steps:
  - Read the picture files
  - decode JPEG content to RGB pixels
  - Convert these into floating-point tensors
  - Rescale the pixels to be between [0,1]

- Image Agumentation
  - rotate
  - width/height shift
  - shear
  - zoom
  - horizontal/vertical flip
- Luckily, Keras has a ImageDataGenerator that makes
- This generator can also

Image preprocessing with TF


```
train_datagen = ImageDataGenerator(
    rescale=1./255,
    rotation_range=40,
    width_shift_range=0.2,
    height_shift_range=0.2,
    shear_range=0.2,
    zoom_range=0.2,
    horizontal_flip=True,)

test_datagen = ImageDataGenerator(rescale=1./255)

train_generator = train_datagen.flow_from_directory(
        train_dir,
        target_size=(150, 150),
        batch_size=32,
        class_mode='binary')

validation_generator = test_datagen.flow_from_directory(
        validation_dir,
        target_size=(150, 150),
        batch_size=32,
        class_mode='binary')
```

Note that the validation data shouldn't be augmented!

Target directory

Resizes all images to 150 × 150

Because you use binary_crossentropy loss, you need binary labels.

Using a pretrained covnet

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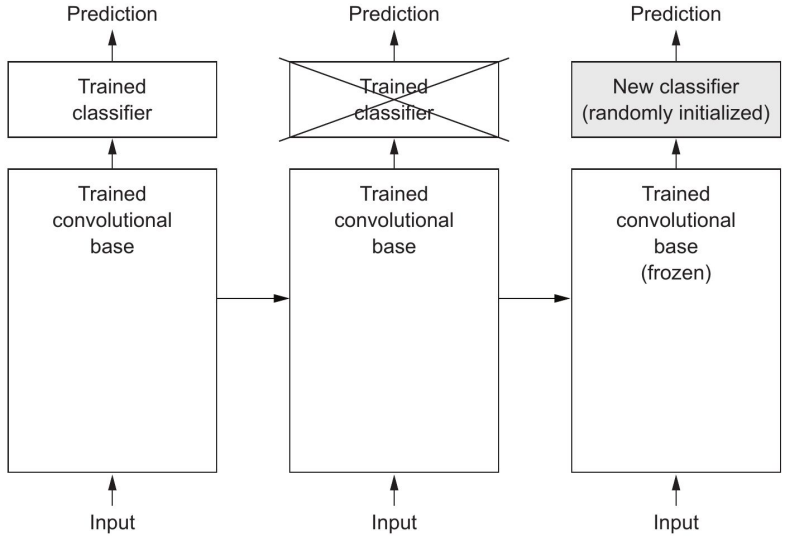
- It is common to use a pretrained network to extract characteristics from images
  - A pretrained network is a network that was trained previously on a huge dataset
- Usually, the features learned by a pretrained network are general enough to use them in many different vision problems
- Usually, we change the “fully connected” layer and “freeze” the convolutional part
- There are several pretrained networks
  - VGG16
  - MobileNet
  - ResNet
  - ...

```
from keras.applications import VGG16

conv_base = VGG16(weights='imagenet',
                  include_top=False,
                  input_shape=(150, 150, 3))
```



Exercises

exercises

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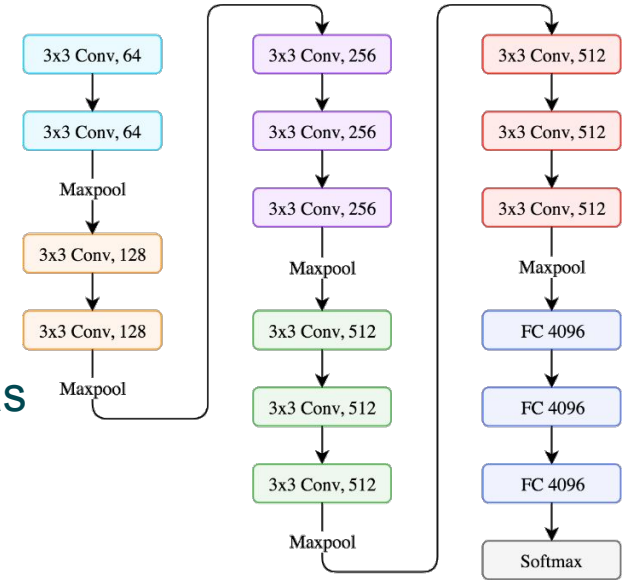
1. Crear y entrenar una red neuronal que diferencie perros de gatos con Keras y CNN
   1.1. Aprenderemos a crear todo lo explicado con las CNN
      1.1.1. Capa Convolucional + ReLU
      1.1.2. Max Pooling
      1.1.3. Flattening
      1.1.4. Red fully connected

2. Utilizar redes neuronales preentrenadas (VGG16)
   2.1. Aprenderemos a utilizar redes ya creadas y entrenadas
      2.1.1. VGG16

3. perros y gatos con resnet



Apendix 1

Embedding Layer

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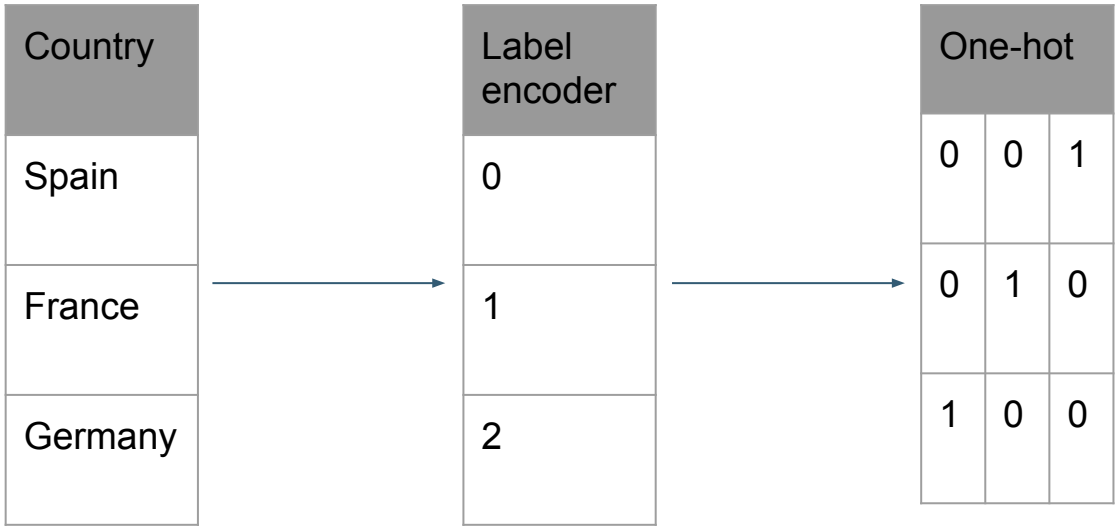
- Se utiliza cuando hay datos categóricos



Embedding Layer

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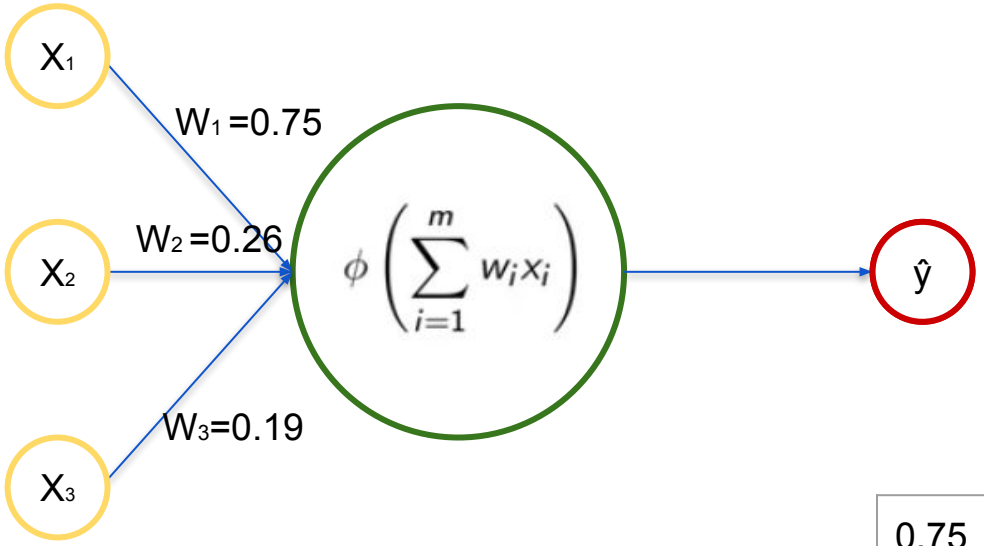
One-hot		
0	0	1
0	1	0
1	0	0



1	0	0	X	0.75 0.26 0.19	=	0.75		
0	0	1	X	0.75 0.26 0.19	=	0.19	0 1 0	X 0.75 0.26 0.19 = 0.26

Embedding Layer

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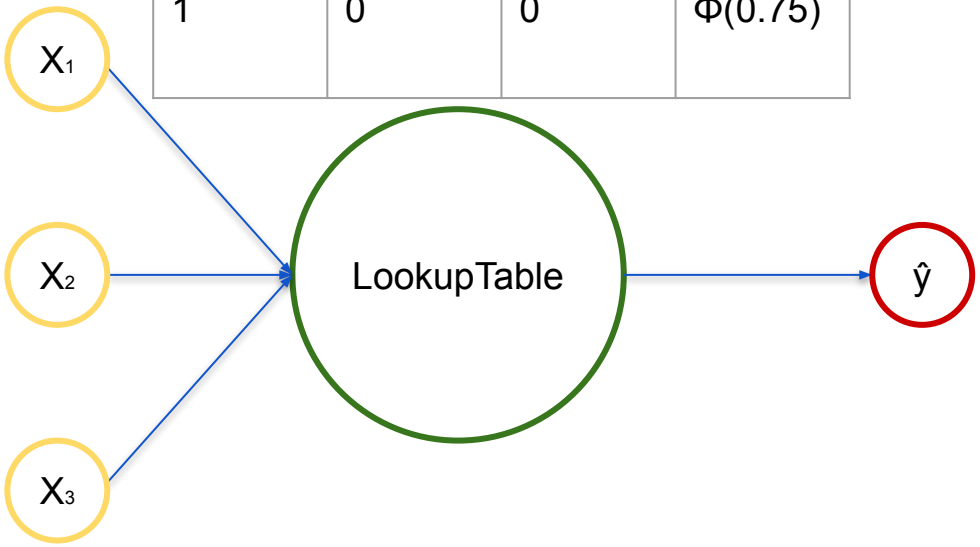
- No es más que un “lookup table” para datos categóricos
- así ahorra computación

Input			output
0	0	1	Φ(0.19)
0	1	0	Φ(0.26)
1	0	0	Φ(0.75)



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Eskerrik asko

Muchas gracias

Thank you

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