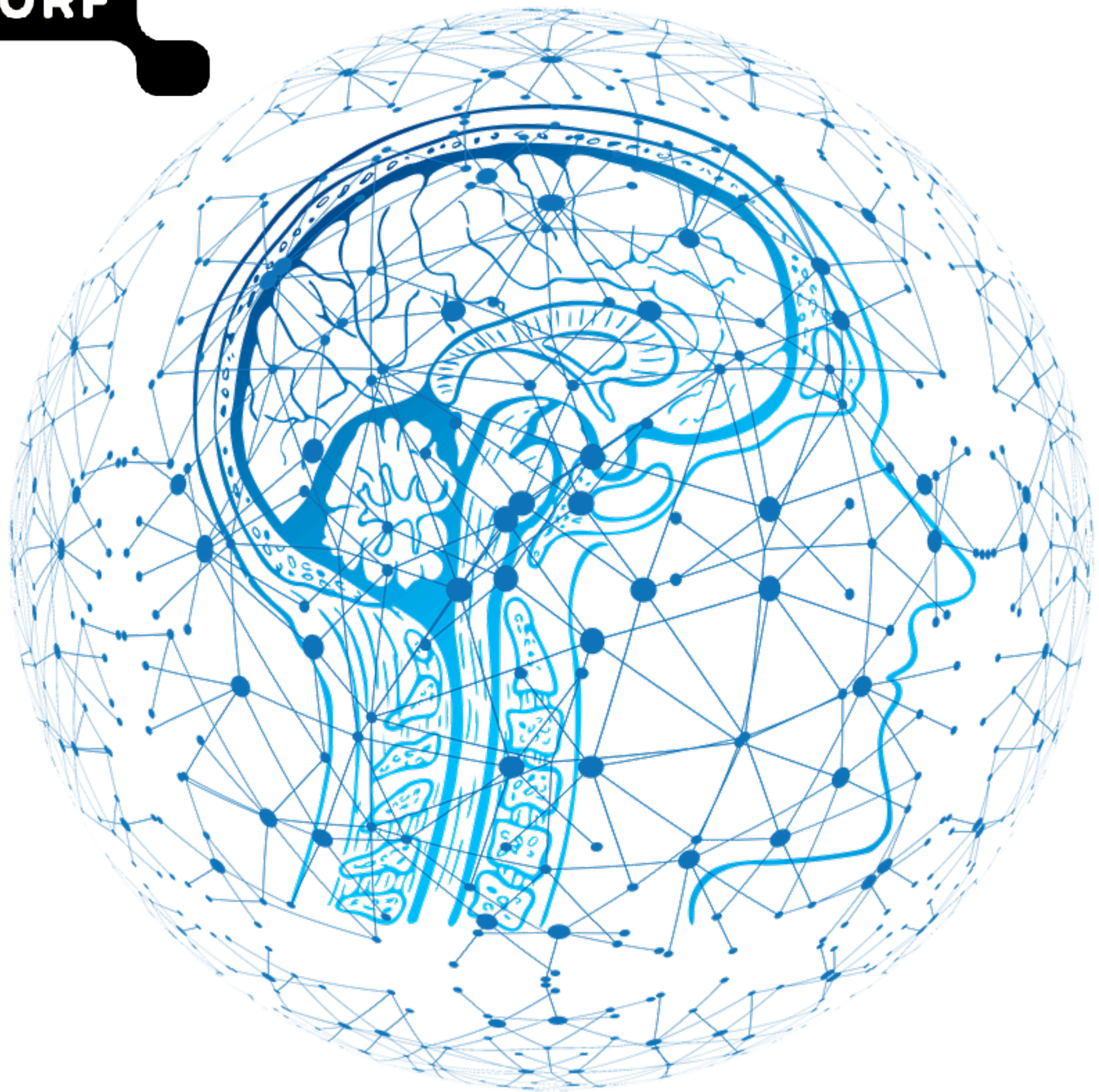


Introduction to Deep Learning

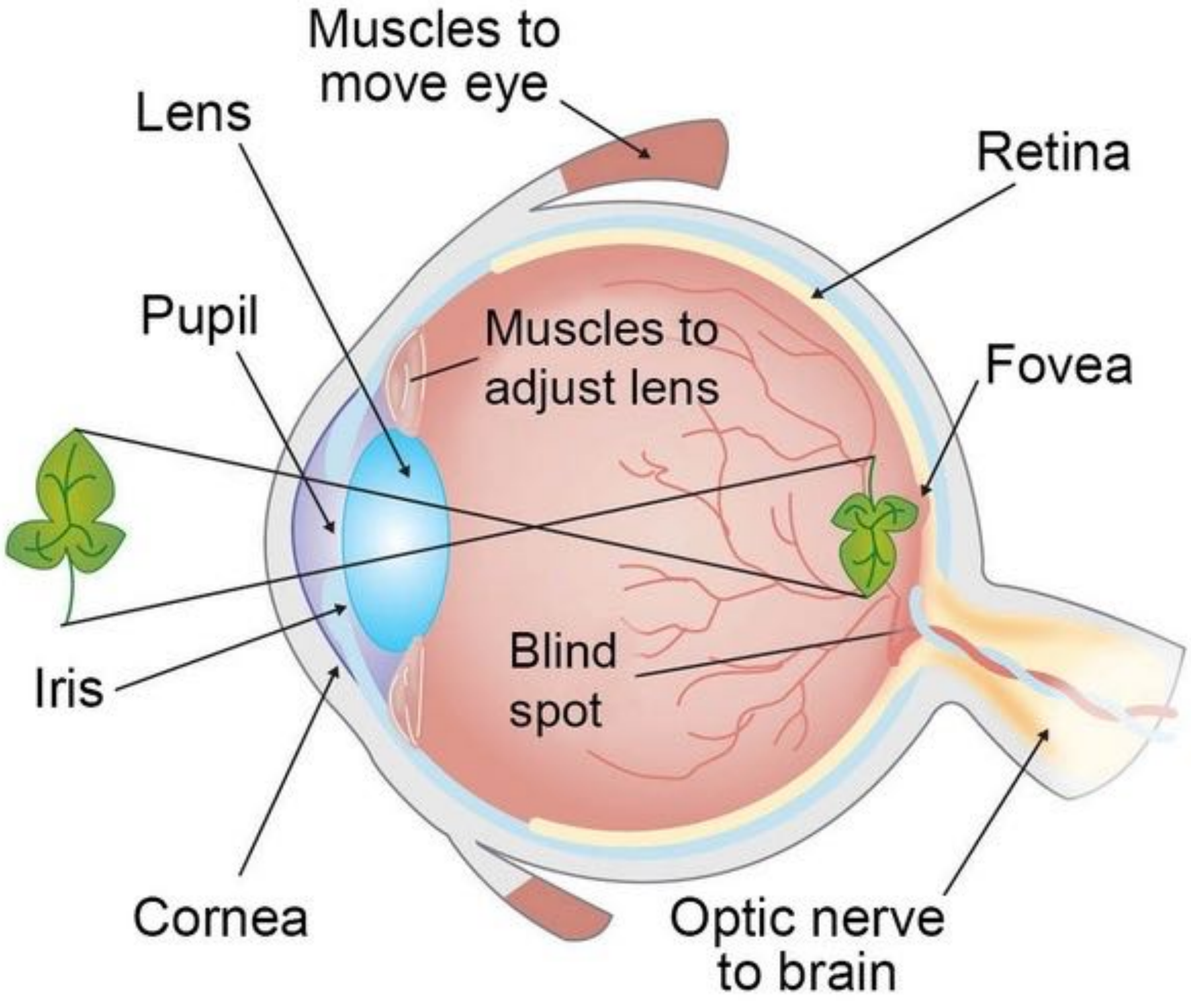
Maxwell Cai, Joris Mollinga
surf.nl

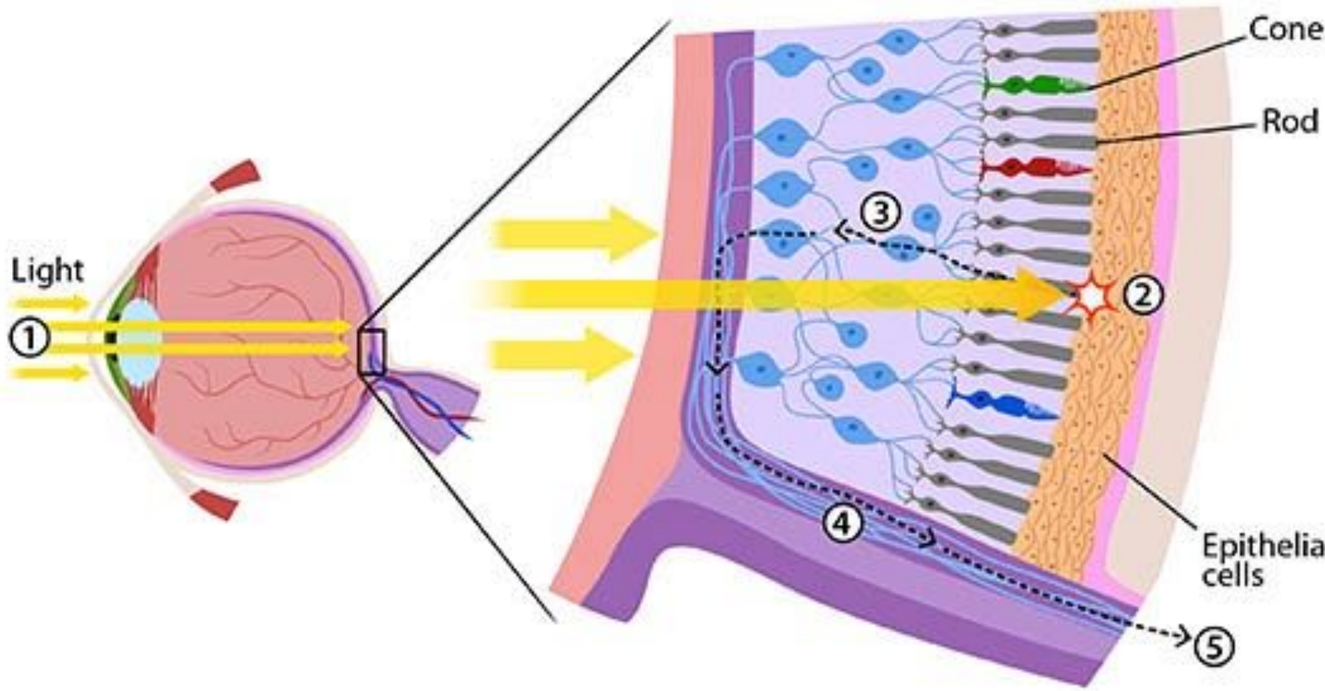
Welcome to the world of computer vision!

How do we let computers “see” something?

Ask ourselves first: How do we (humans) see something?

Human eyes

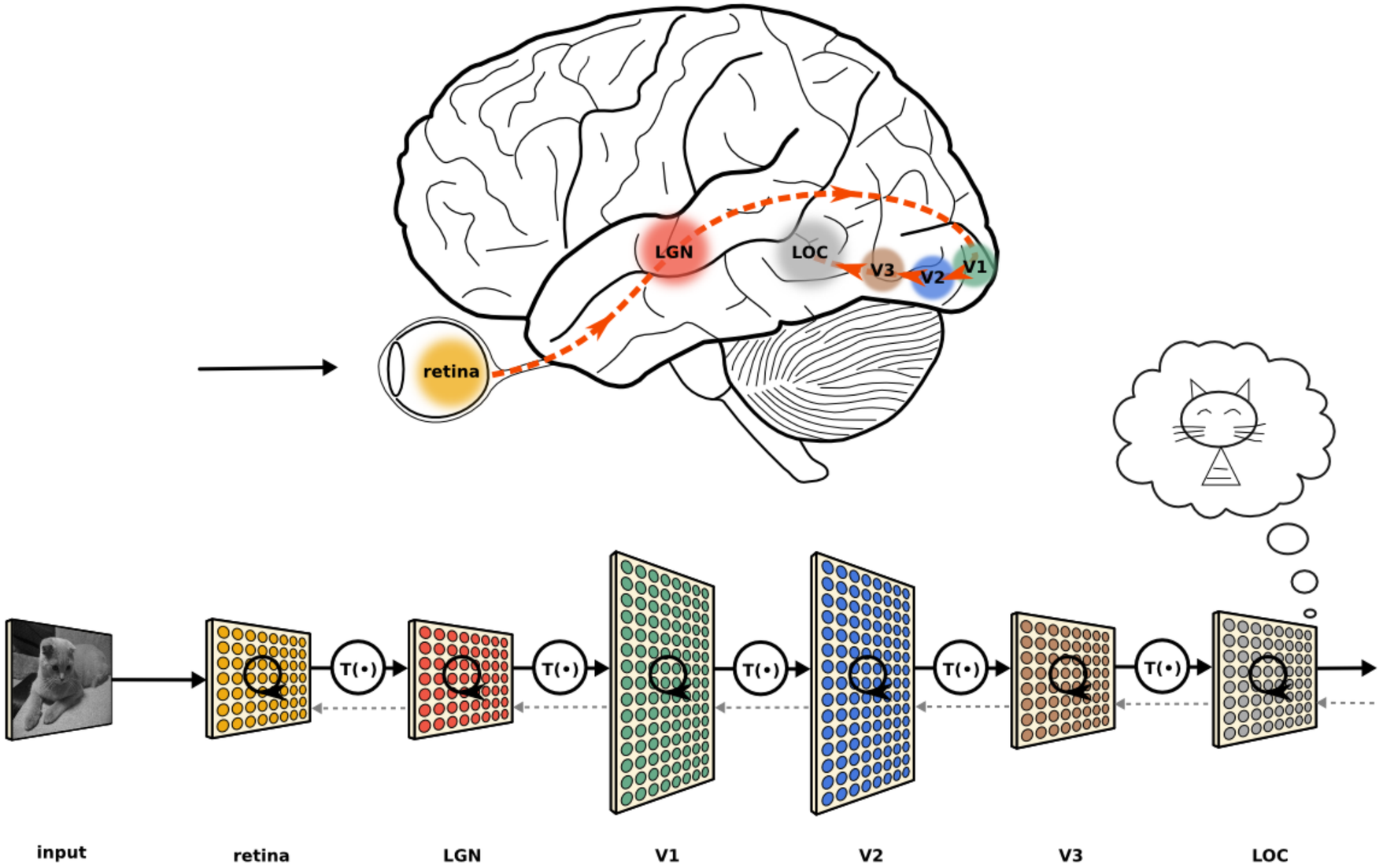




Source: Quora

Human brain: the (real) neural network

Source: arimaresearch.com



Representation of images in computers

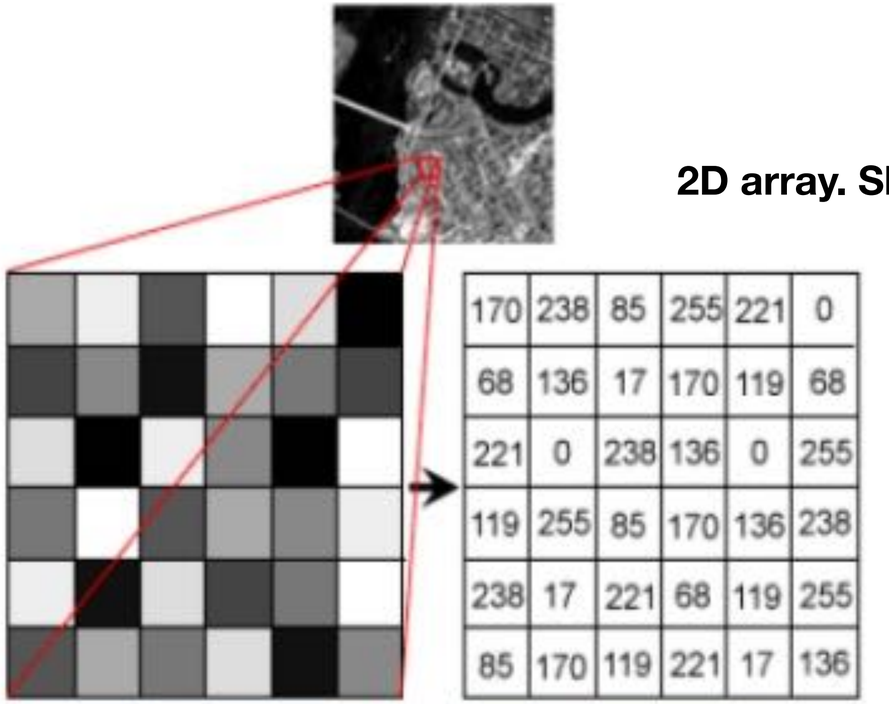
An image

… is a **matrix/array** of intensity values

… usually consists integers of [0, 255] or float points of [0, 1]

… each element of this matrix is called a **pixel**

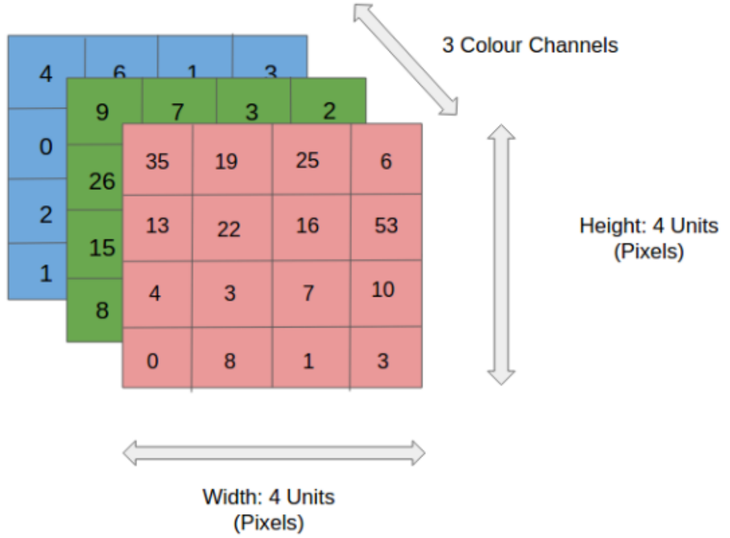
… can have 1 (greyscale) or multiple (color) **channels**



170	238	85	255	221	0
68	136	17	170	119	68
221	0	238	136	0	255
119	255	85	170	136	238
238	17	221	68	119	255
85	170	119	221	17	136

2D array. Shape: [width, height]

3D array. Shape: [width, height, channel]

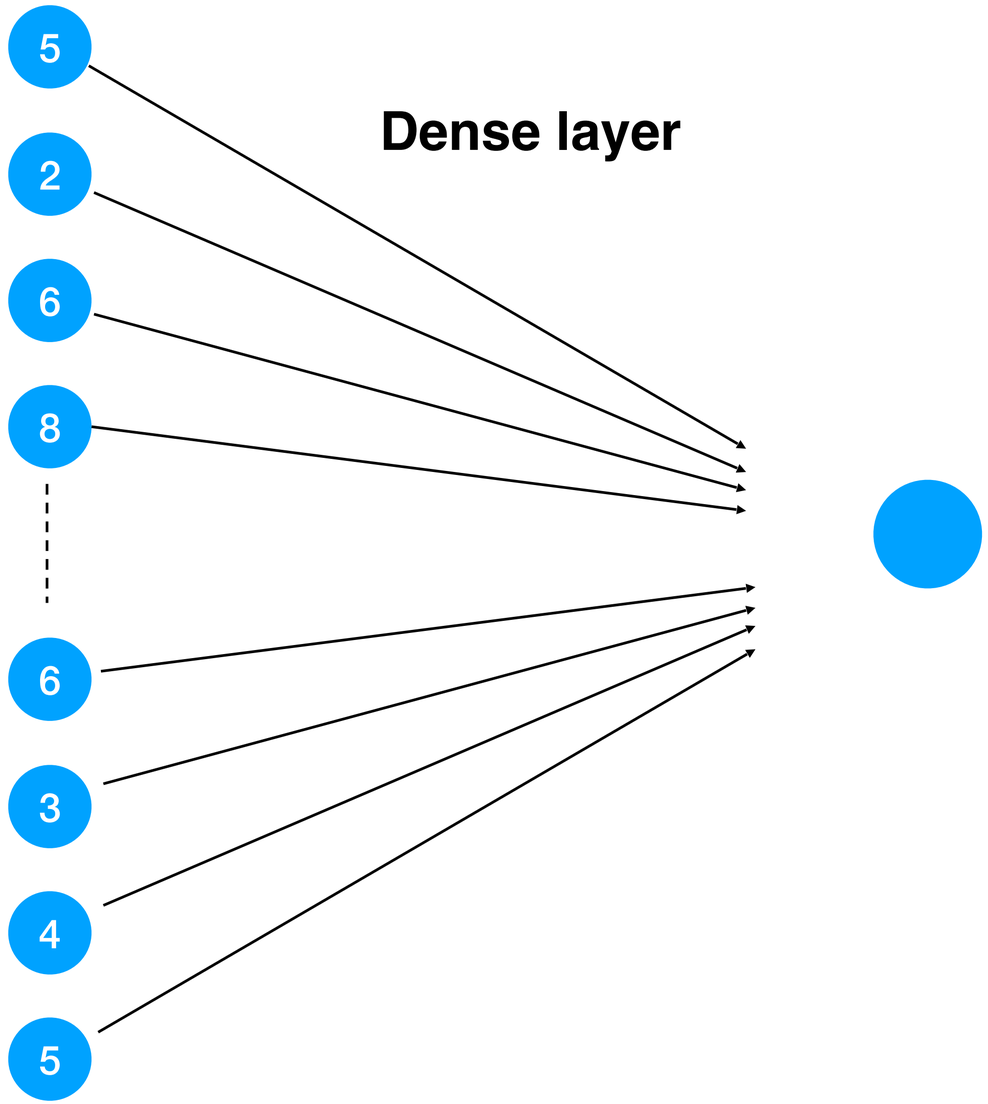


Dense network classifier (MLP)

So far, we have used multi-layer perceptions (MLP) to carry out some computer vision tasks (e.g., recognizing hand-written digits)…

5	2	6	8	2	0	1	2
4	3	4	5	1	9	6	3
3	9	2	4	7	7	6	9
1	3	4	6	8	2	2	1
8	4	6	2	3	1	8	8
5	8	9	0	1	0	2	3
9	2	6	6	3	6	2	1
9	8	8	2	6	3	4	5

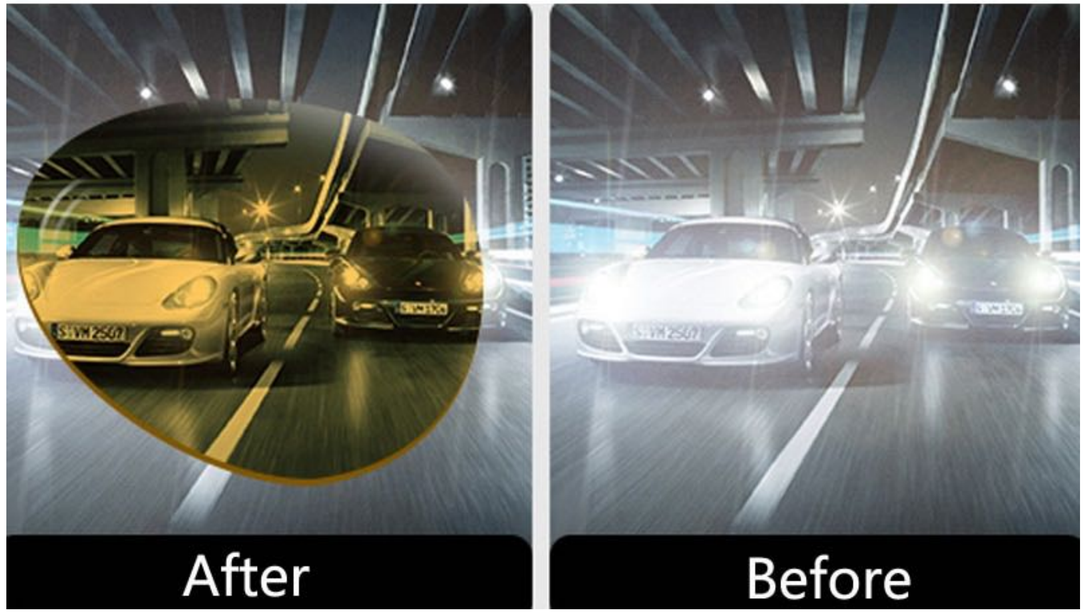
Flatten layer



Problem:

- The resulting encoding is pixel location dependent.
- Spatial relationship is not preserved after flattening.

Filters in our daily lives



Forget about the commercial advertisements themselves…
Just think about the mathematical principles behind them…

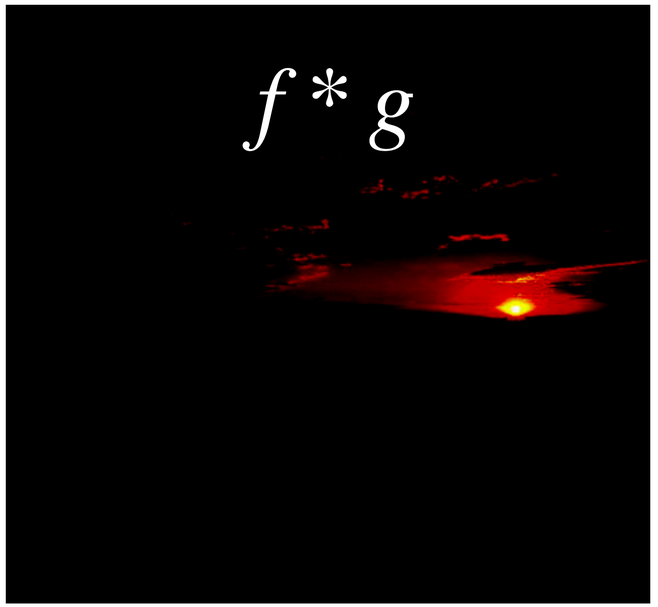
Filter in image processing

f

+

Filter
g

=



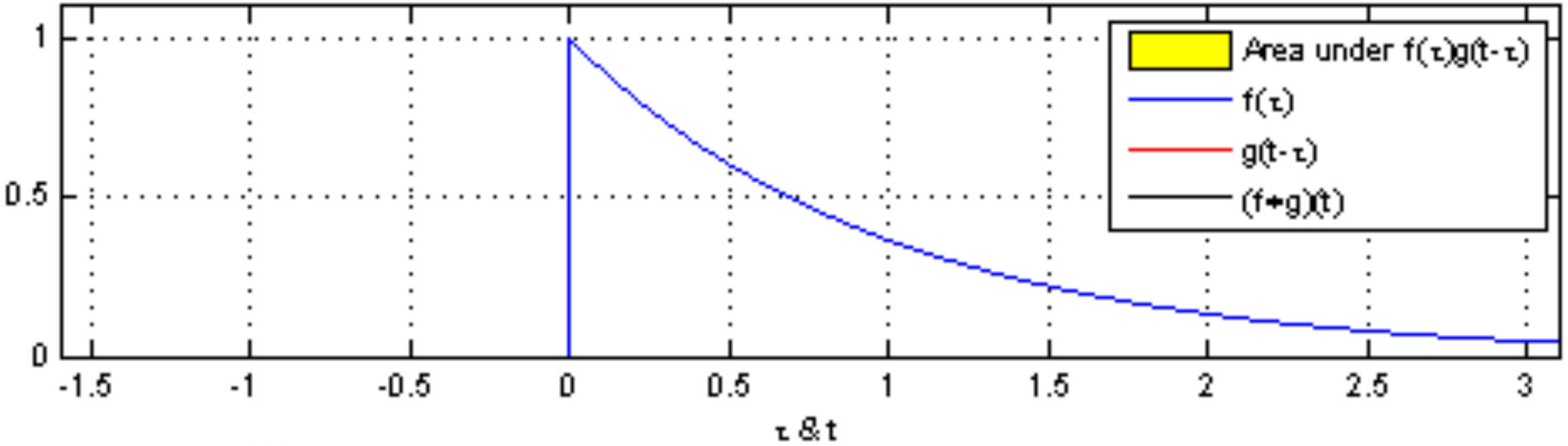
Filter
h

=

Using **different filters**, we can see the **same signal** in **different perspectives**.

Convolution

Typically, a filter applies a **convolution** operation upon the original signal.



Function: $f(t)$

Kernel: $g(t)$

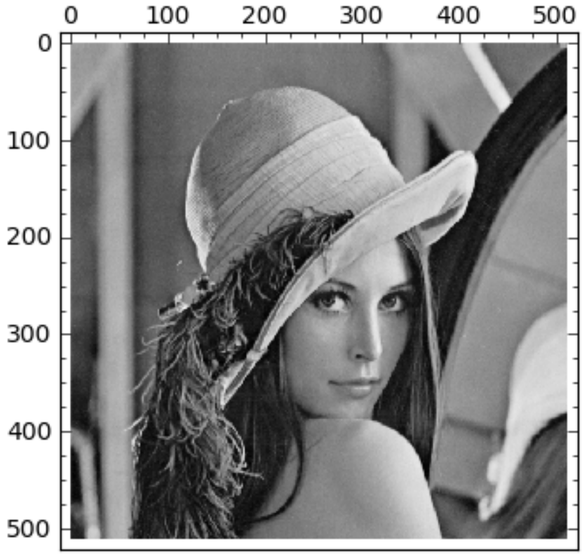
Convolution: $(f * g)(t)$

No signal → no response

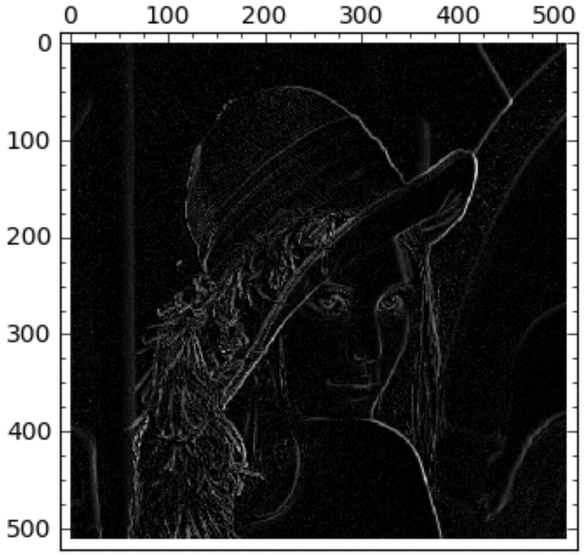
Strong signal → strong response

Filtering: a signal processing technique

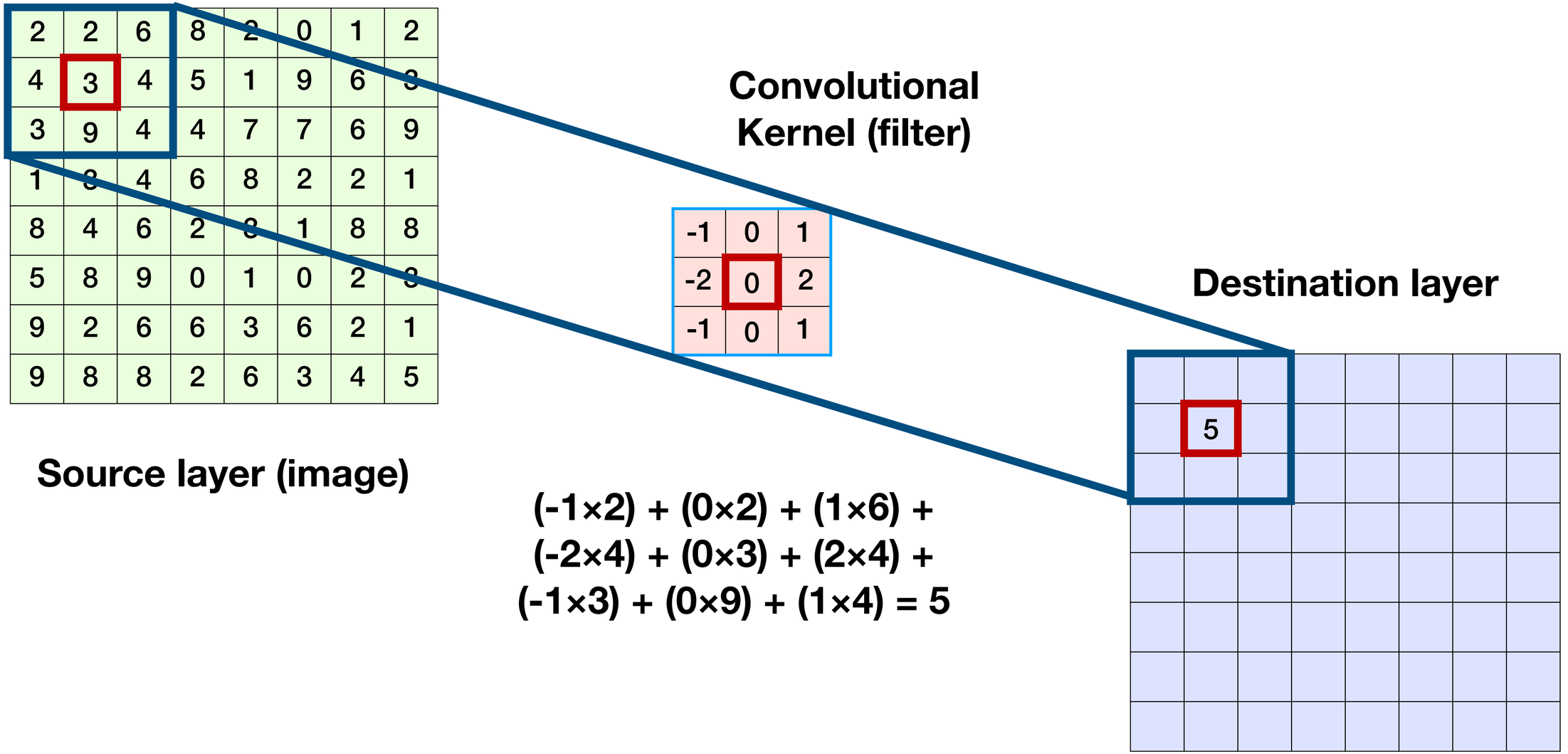
Convolution



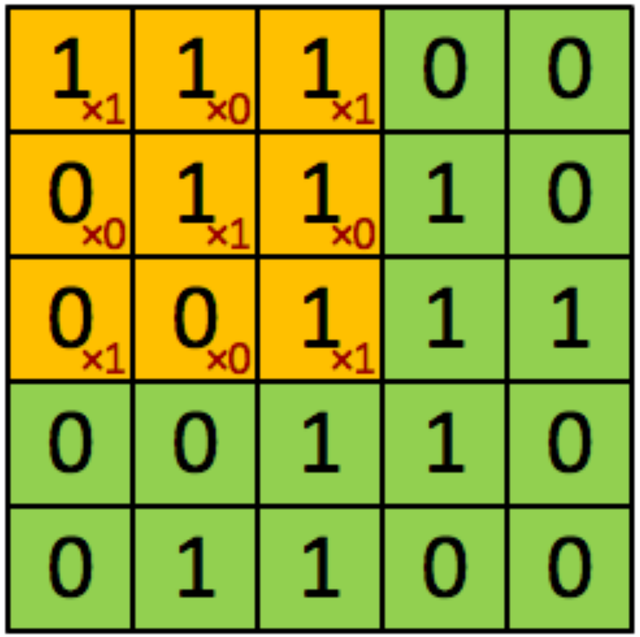
Convolution

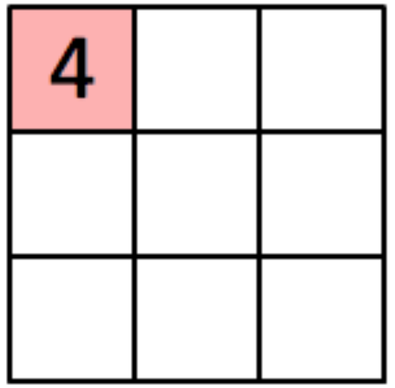


Convolution

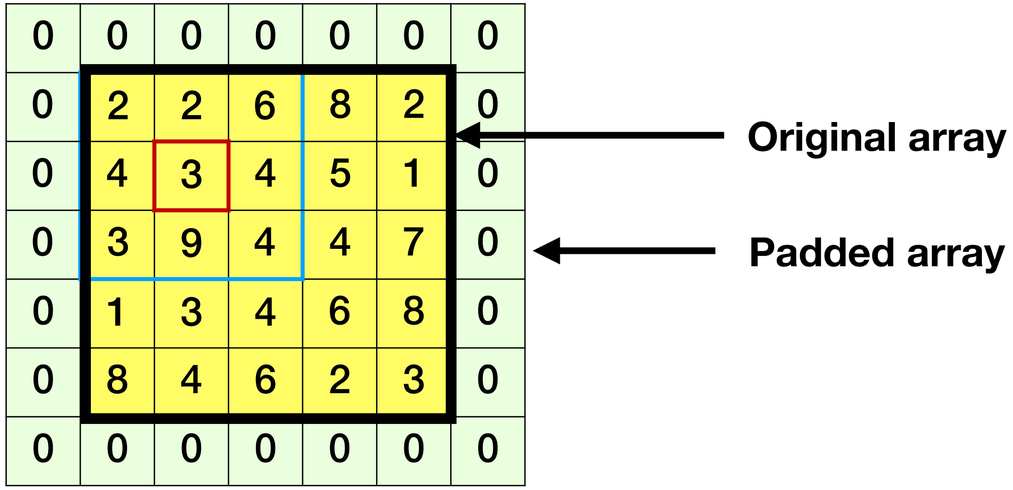


Convolution



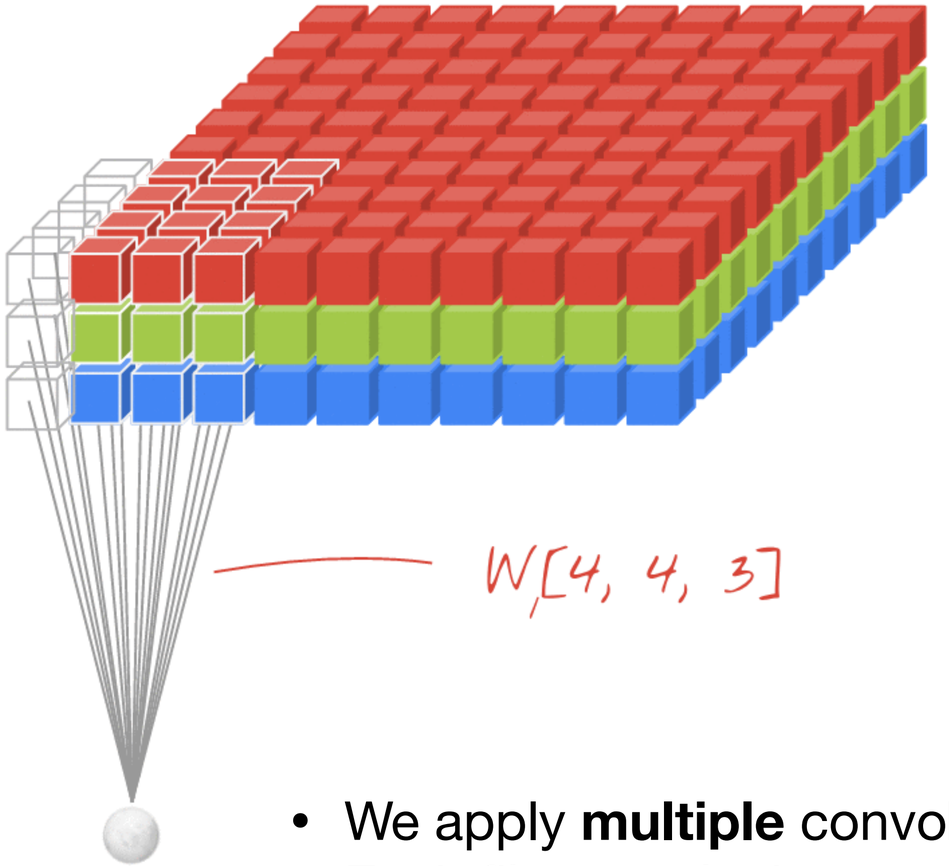


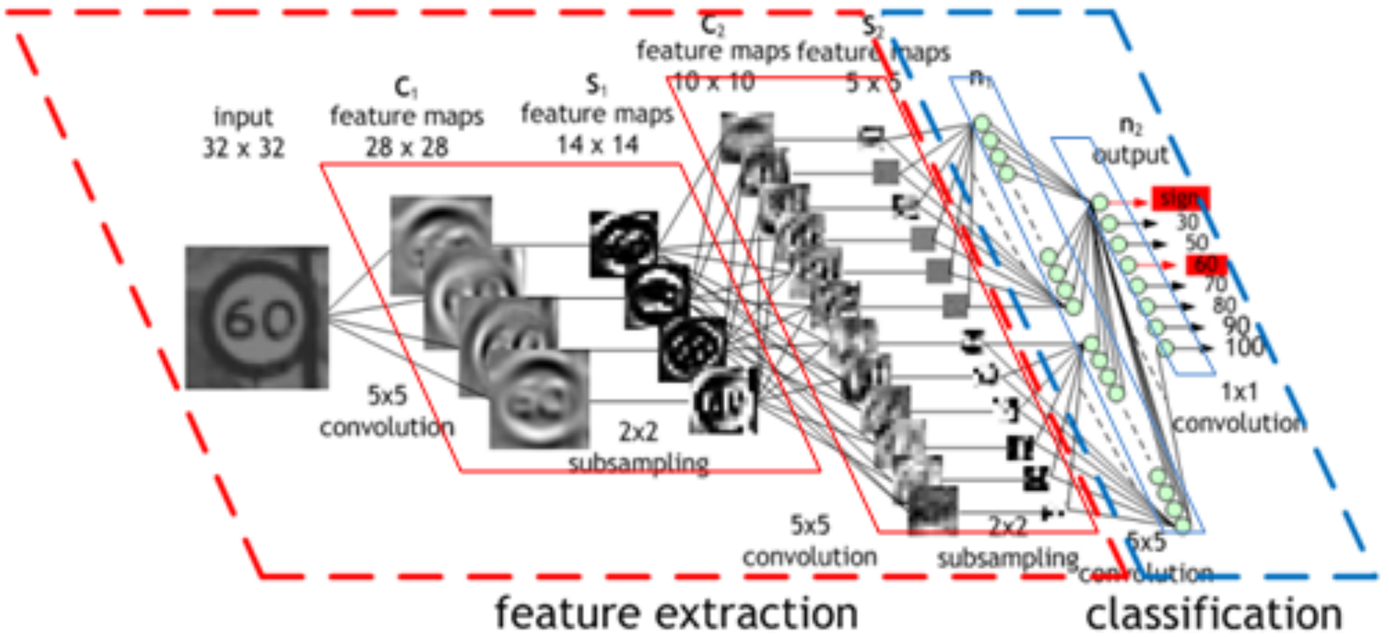
- The kernel is **shifted** over the image with a step size, and computes the output for each position.
- The step size is called **stride**.
- Output has **smaller** dimension than input:
  $\dim(\text{output}) = \dim(\text{input}) - (\dim(\text{kernel}) - 1)$
- **Padding** is used to solve this problem, which artificially make the image “bigger” by adding synthesis data (typically 0-padding)



Animation: Sumit Saha/Towards Data Science

Multiple convolutional channels





- We apply **multiple** convolutional **filters/kernels** to the **same** image.
- Each filter results in one convolutional **channel**.
- By learning the same image from different channels, one can detect complex patterns.

Animation: Martin Görner

Image: Maurice Peemen

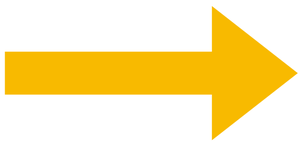
Automatic Kernel Determination

Source layer (image)

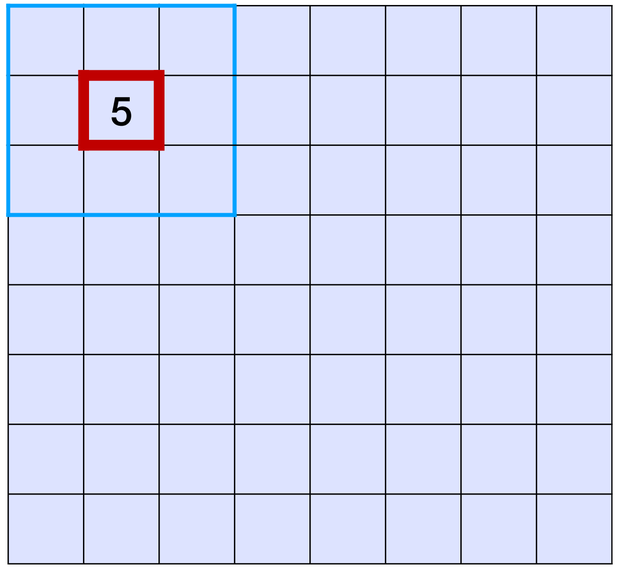
2	2	6	8	2	0	1	2
4	3	4	5	1	9	6	3
3	9	4	4	7	7	6	9
1	3	4	6	8	2	2	1
8	4	6	2	3	1	8	8
5	8	9	0	1	0	2	3
9	2	6	6	3	6	2	1
9	8	8	2	6	3	4	5

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

Kernel (filter)



Feature map (activation map)

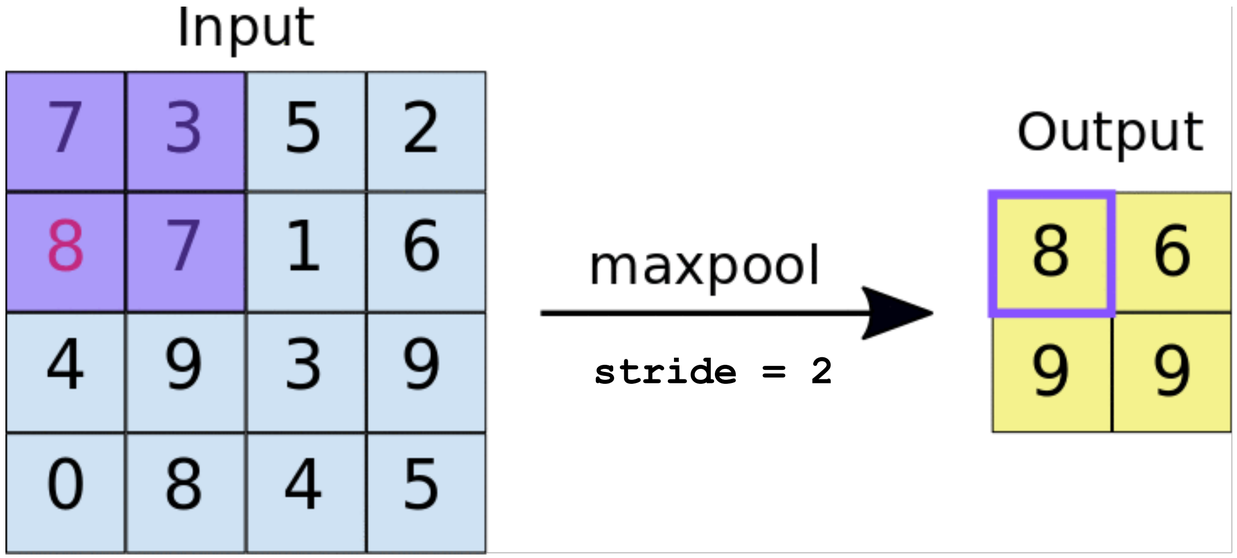


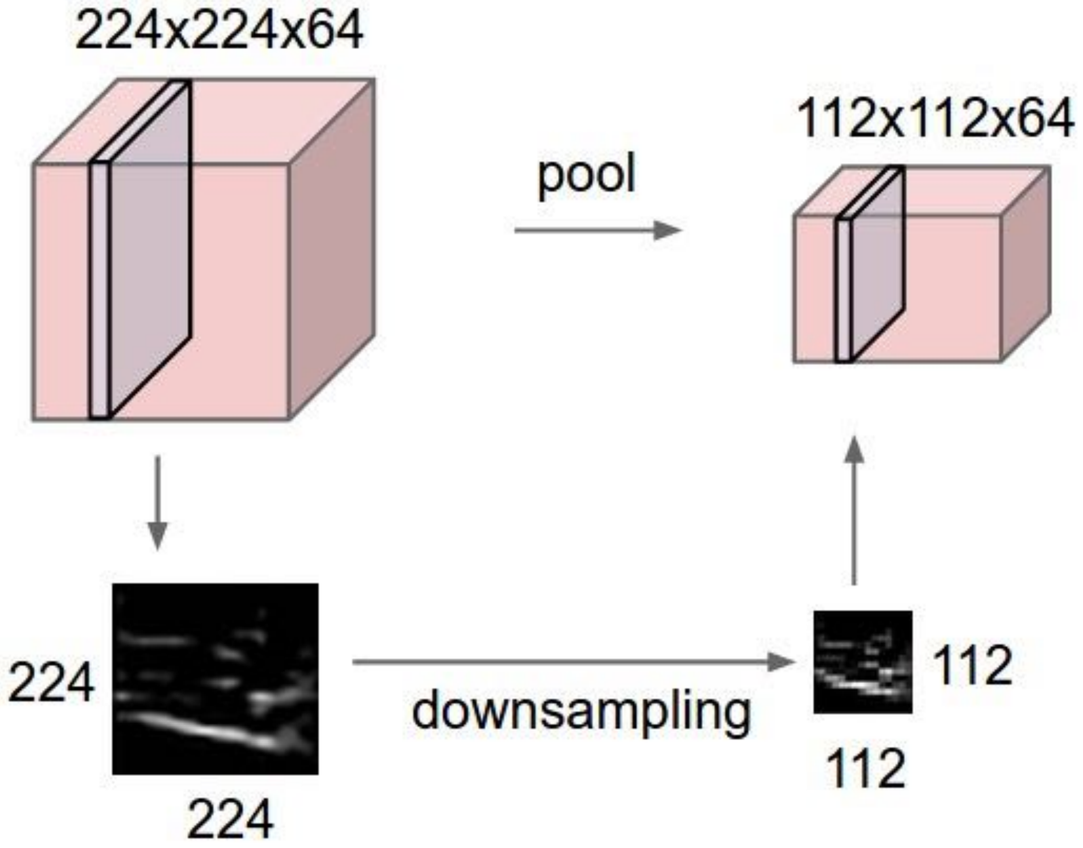
How do we know which kernels to use?

- In **traditional** signal processing, a filter is designed by human experts.
- In **deep learning**, data are too complex and too many different kernels are needed.
- Therefore, kernels are no longer fixed. They are initialized **randomly**.
- Kernels are updated through **backward propagation**, in the way that it **learns** which features to detect.
- **Gradient descent** algorithms are used.

Pooling (downsampling)

We need to **discard** information **gradually**.
Pooling is a way of information **abstraction**.
Pooling is usually applied **after** convolutions.

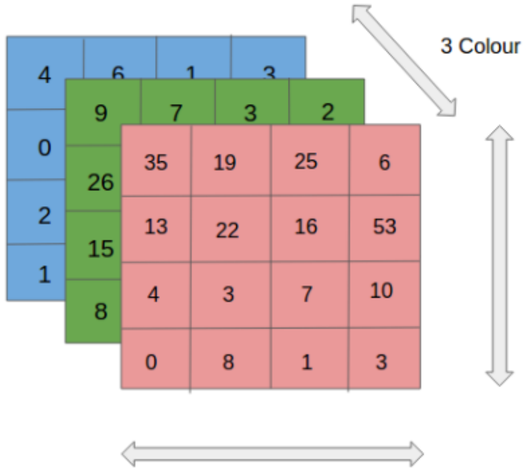


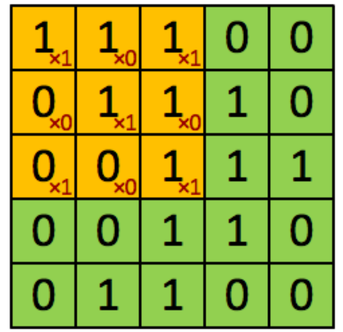


Max pooling: keep the **strongest** signal
Average pooling: use the **local average** as the signal

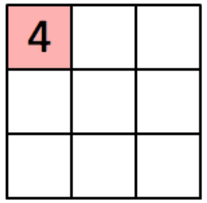
Animation: Google Developers

CNN Architecture

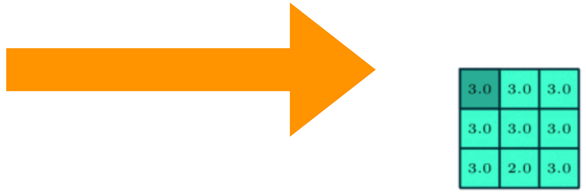


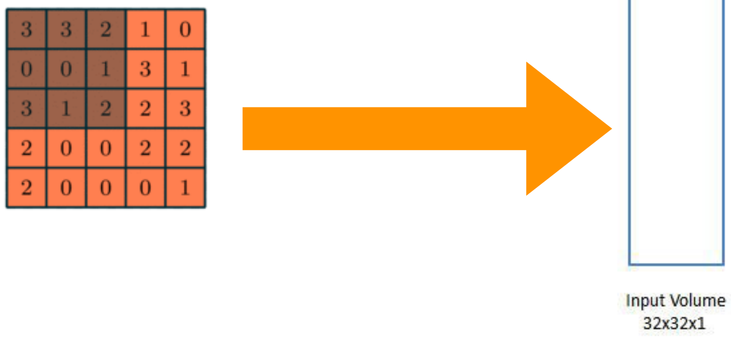


Image



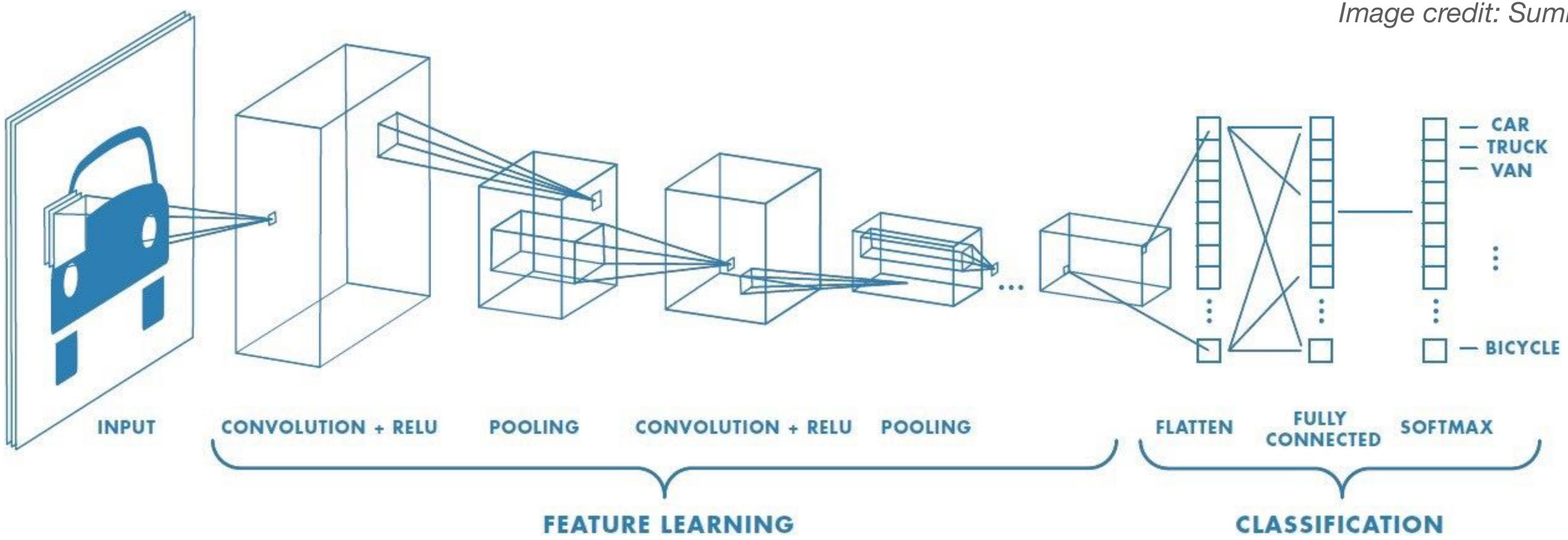
Convolved Feature





Convolution Neural Network (CNN)

Image credit: Sumit Saha



- Typically, **images** become increasingly **smaller** as they go to the **deeper** layers;
- Typically, the number of **filters increases** in the **deeper** layers;
  - Low-level features are limited, thus requires few filters;
  - High-level features are rich, thus requires many filters;
- The **decision making** (i.e., classification) is made in the **last layers**, typically with **dense** layers and the `softmax` activation function.

Go to https://jupyter.lisa.surfsara.nl/jhlsrf003

Select “SURF jupyterhub - course hours” profile

Notebook: notebook_2_mnist_cnn.ipynb

Hacking until 12:30

Wouldn’t it be easier to handle sequences (1D) than images (2D)?

Yes and no…

Sequence Modeling

Language translation

Speech recognition

Music generation

Sentiment classification

Video captioning

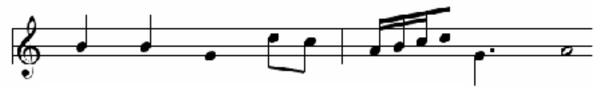
Chatbot

Text summary

...

“Hoi, hoe gaat het?” → “Hi, how are you?”

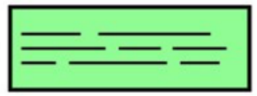
 → “Hi, how are you?”

Style / nothing → 

“Hoi, hoe gaat het?” → ★★★★★

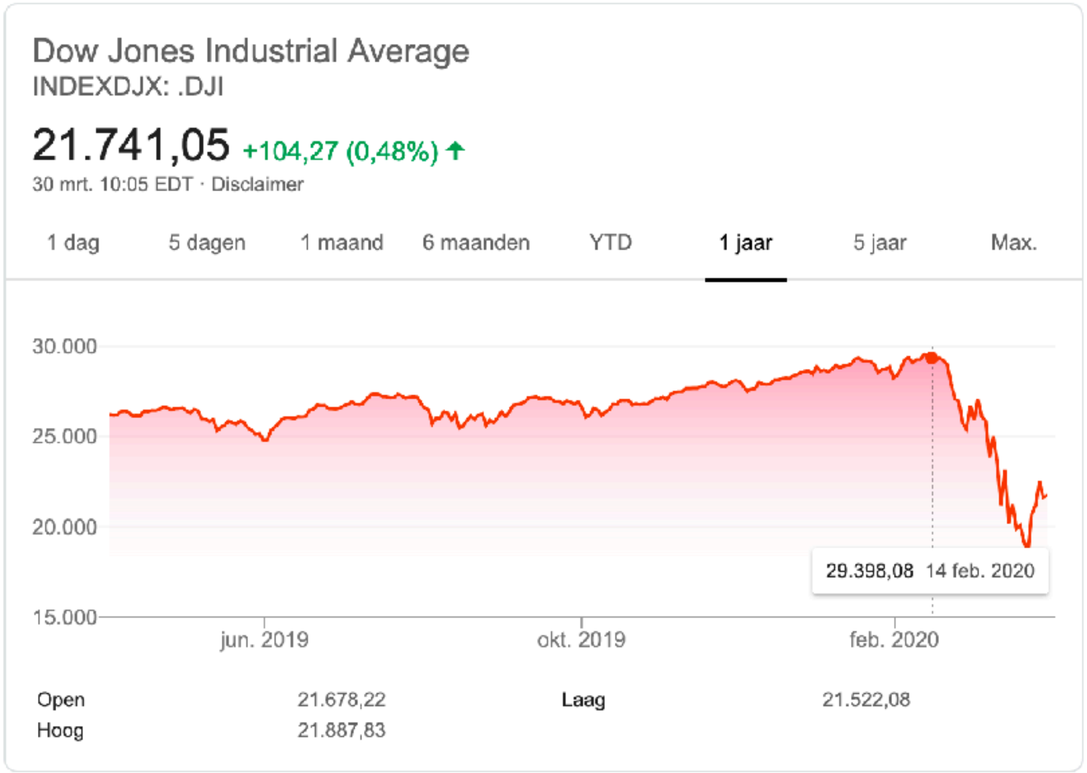
 → A person is running

“Tell me my day” → You have two appointments.

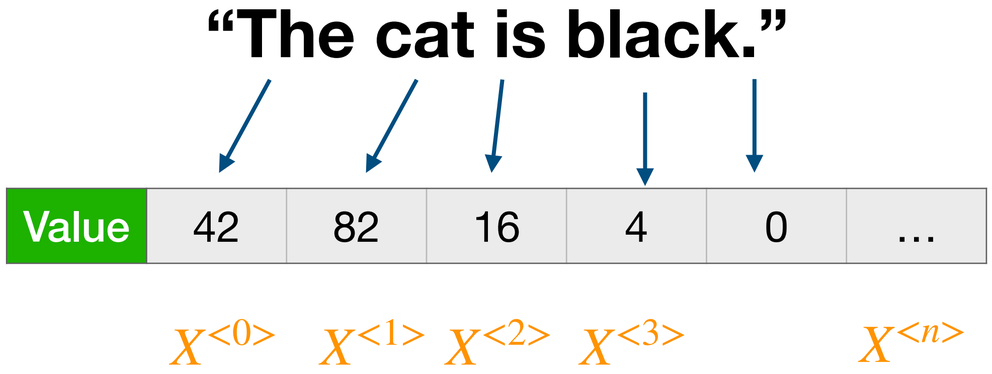
 → 

Sequential Data

Sequential data are represented with **1D or 2D arrays**.



Time	24/3	25/3	26/3	27/3	28/3	…
Value	19,722	21,050	21,188	22,532	21,678	…

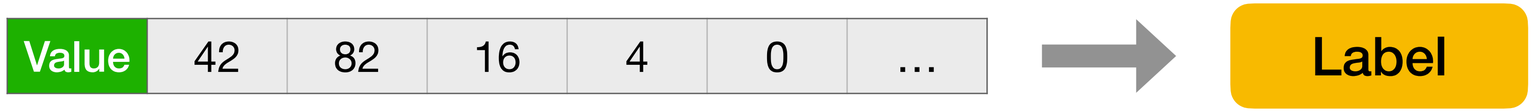


In **natural language processing** (NLP),

- Each **word** is converted into a **token**;
- A token is typically represented as a **numerical** value;
- A **sentence** is a **sequence** of tokens;
- A sequence can have **arbitrary length**;
- Tokens may be **logically related** to each other.

Sequential Data Modeling

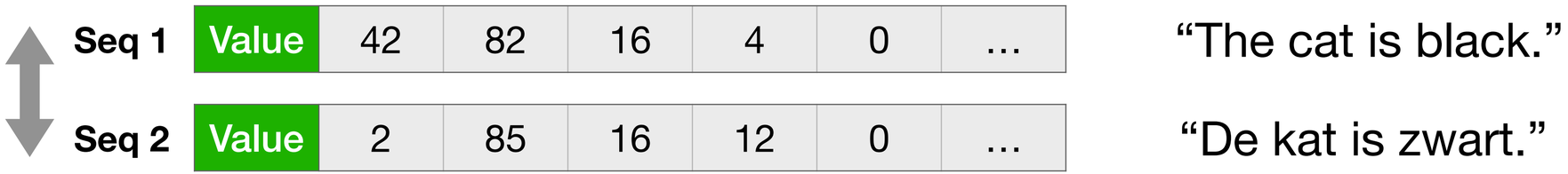
Classification



Generation

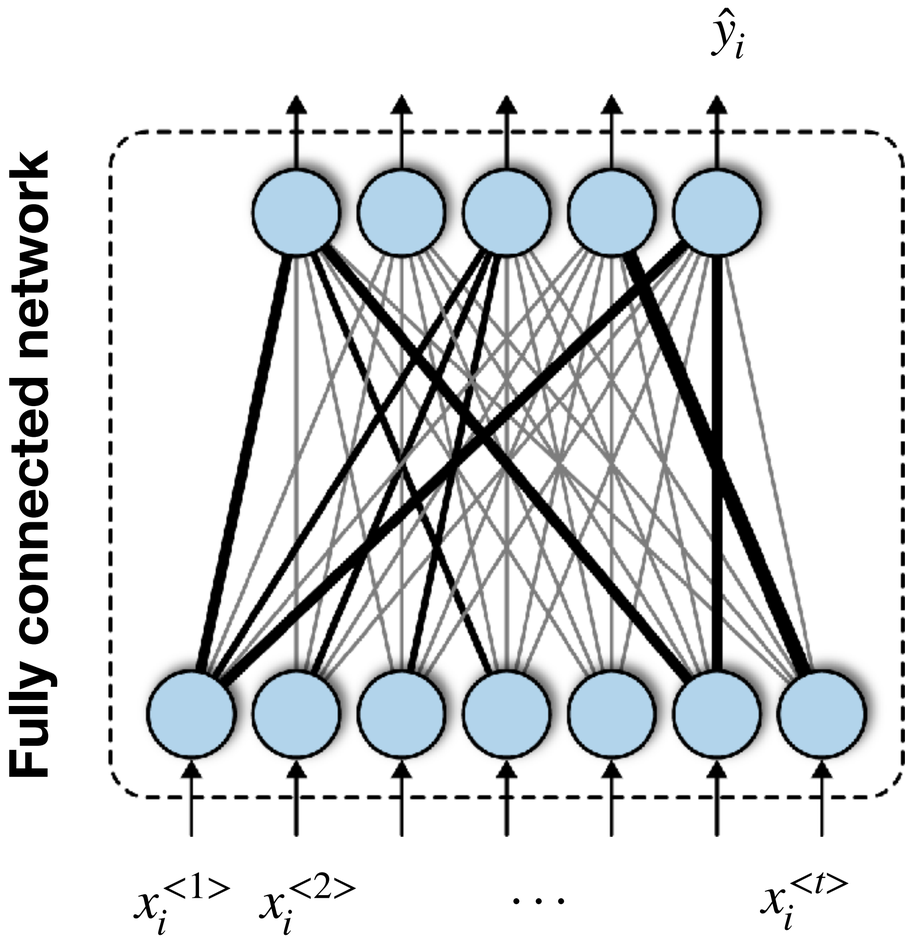
Regression

Sequence to Sequence (e.g., Translation)



The fundamental problem in sequence model is to understand the **relations between tokens**/elements.

Naive Approaches



Modeling the **full sentence** using a fully connected network requires a **huge number of parameters**!

A FC network needs to model the pairwise relation between each word, thus the network scales as $\mathcal{O}(k^n)$, where k is size of the vocabulary and n is the length of the sequence.

For example, consider that in the English language, there are $k = 2000$ words. To model a sentence of $n = 100$ words, one single FC layer requires 2000^{100} parameters!!

Sequence modeling with 1D convolution

CNNs works because they can take into account the relation between **nearby** tokens.

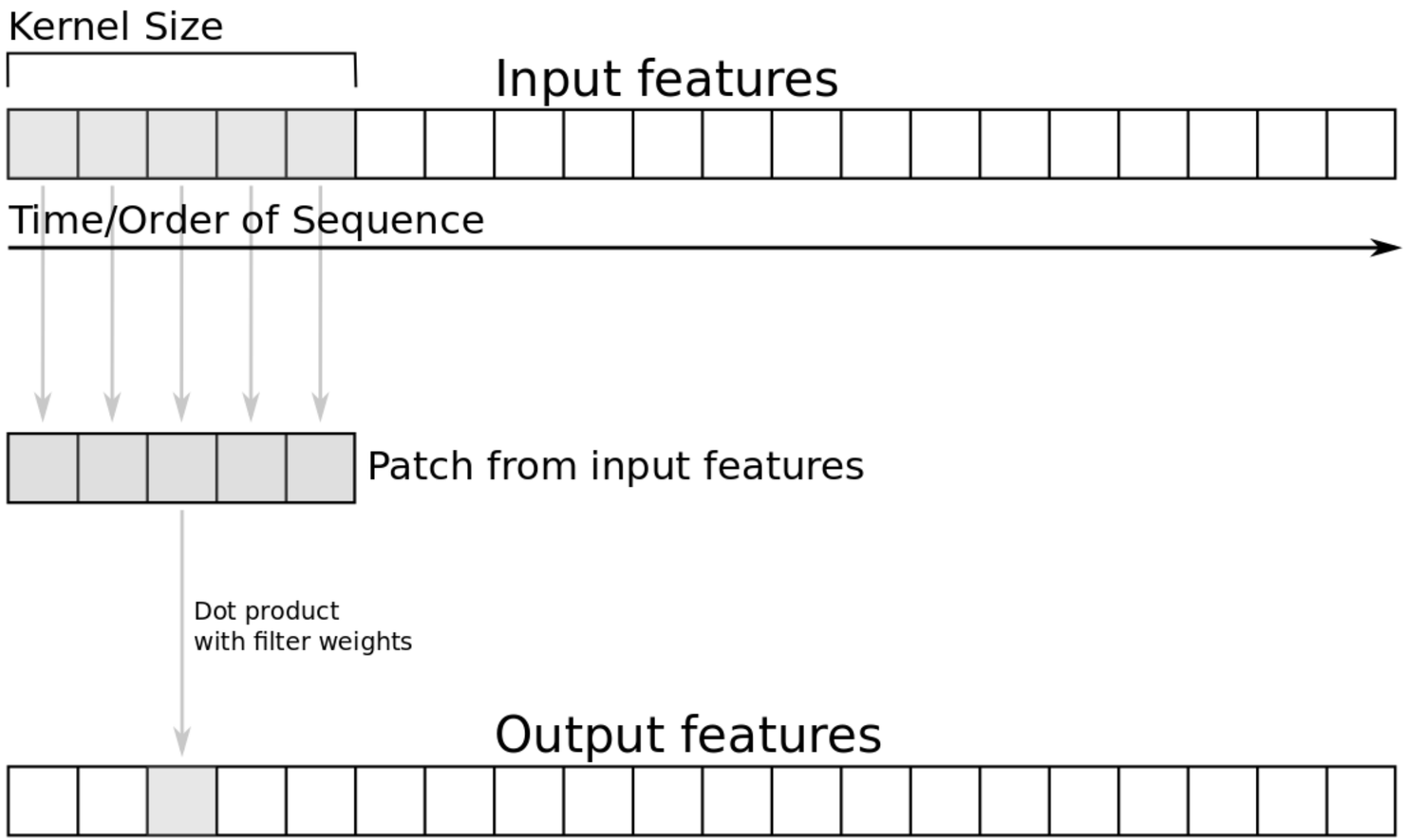
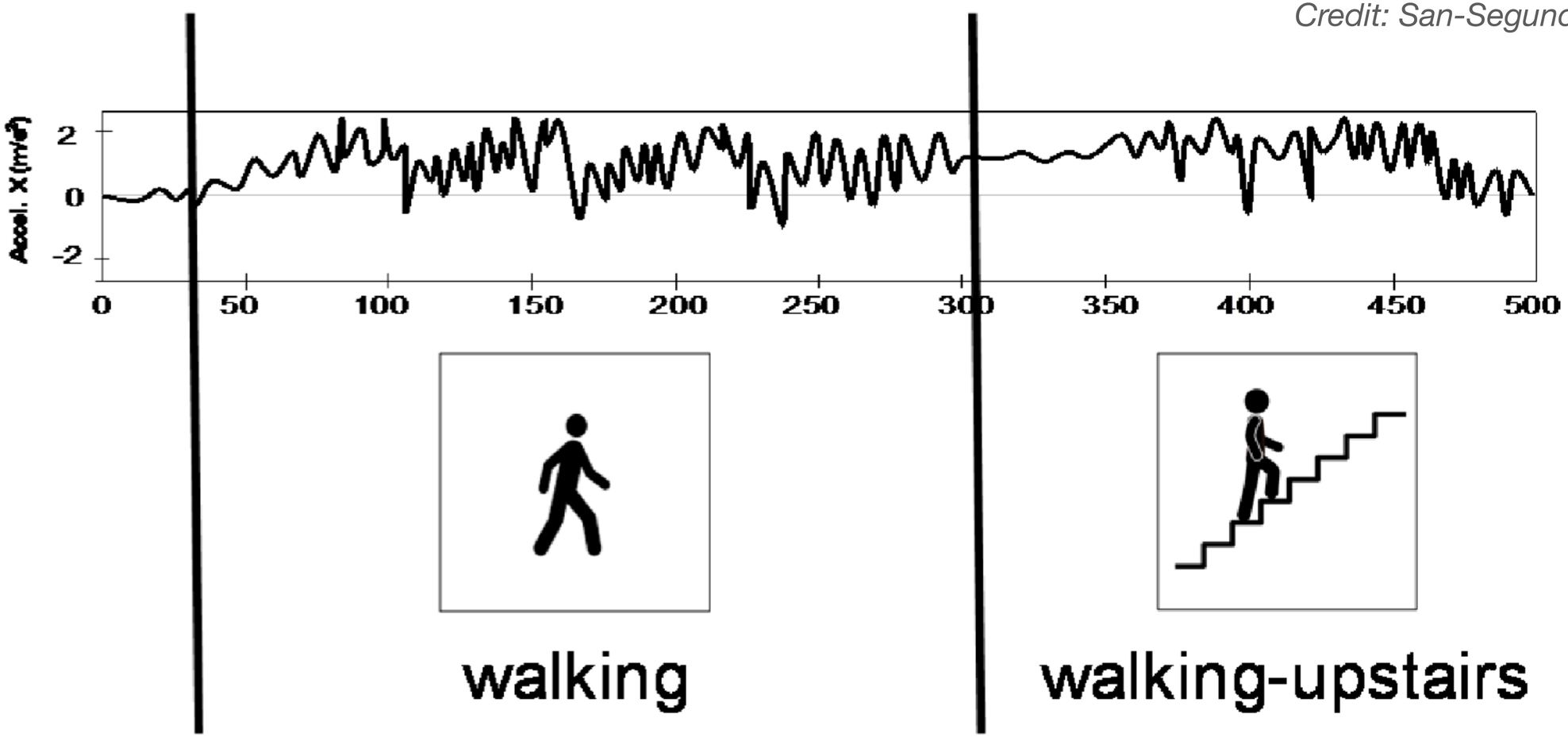


Image source: “Deep Learning With Python” (Francois Chollet)

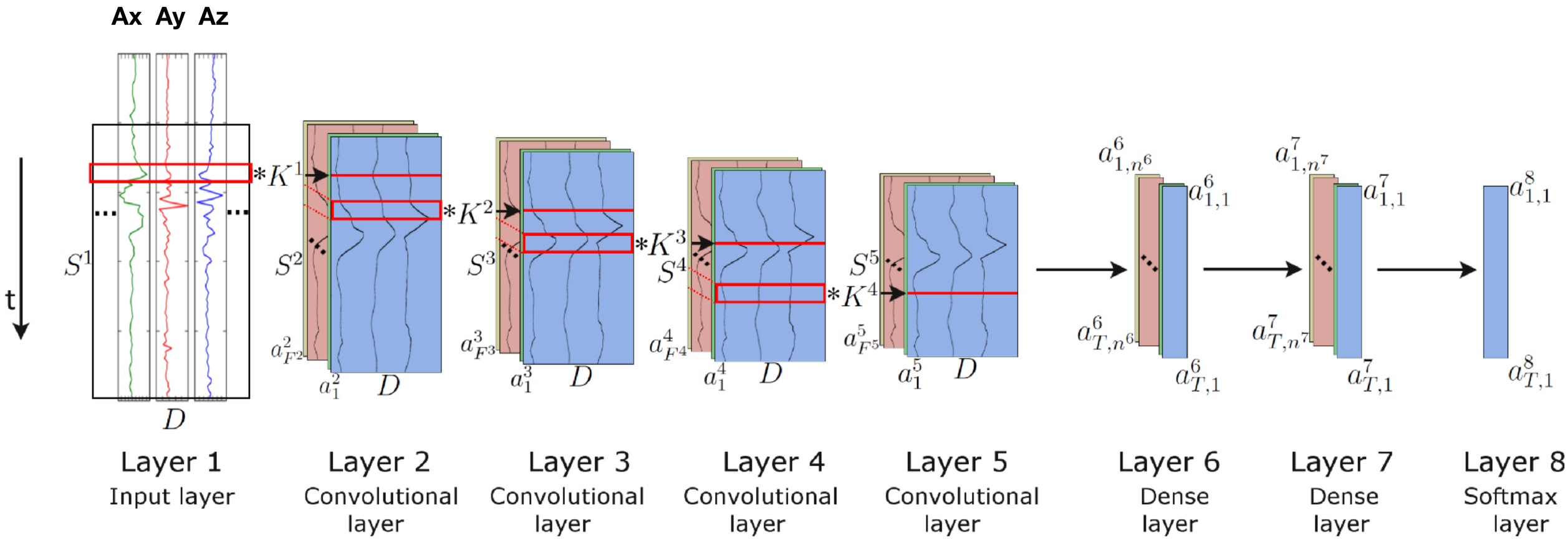
Example: human activity recognition

Credit: San-Segundo et al. (2016)



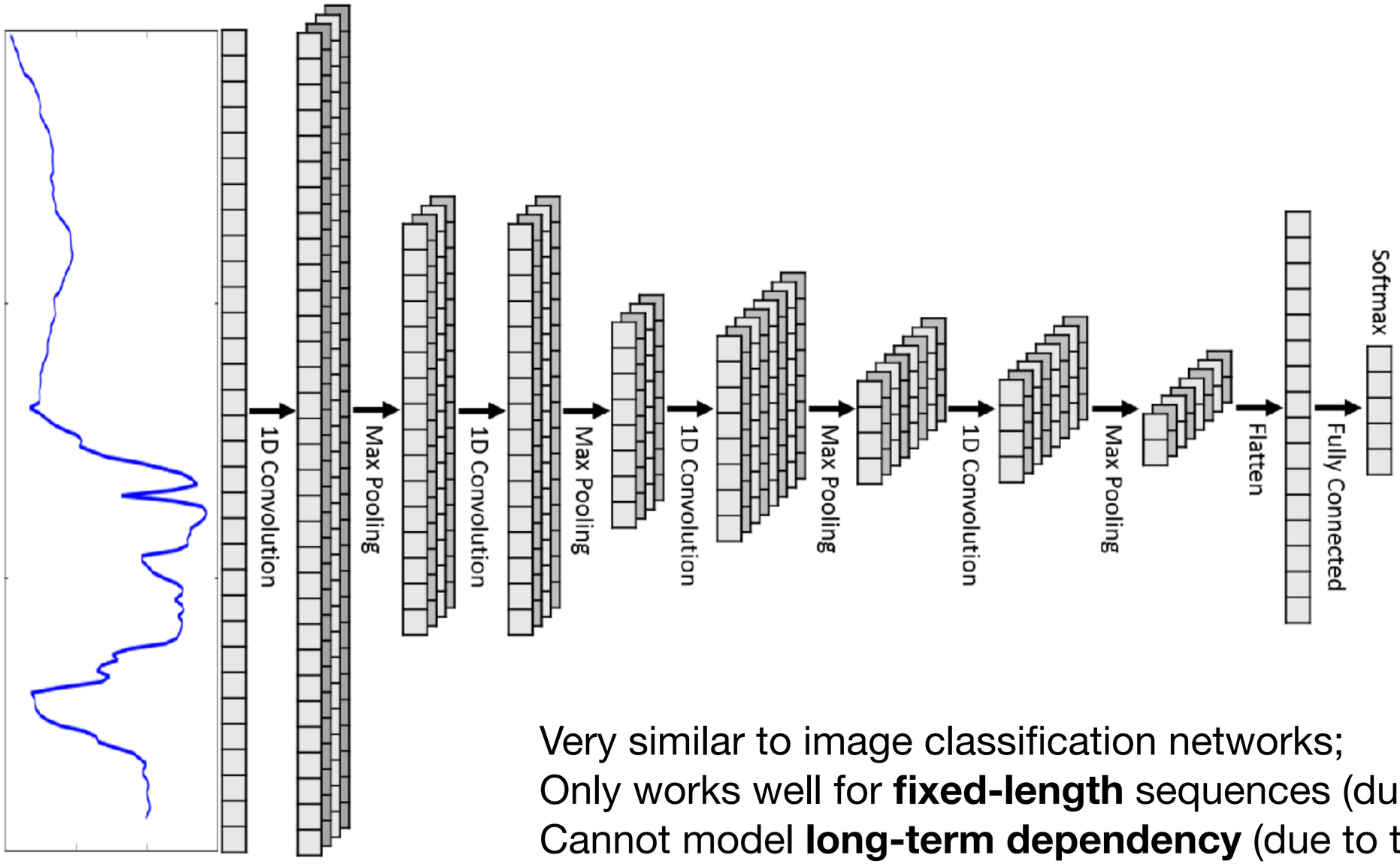
The DNN can be trained with **existing** open datasets!
e.g., https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones

Human activity recognition with 1D Convolution



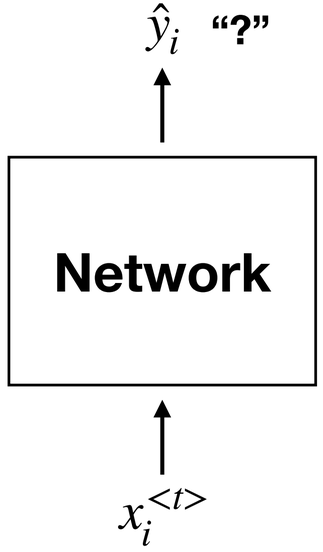
Ordóñez et al. (2016)

Sequence modeling with 1D convolution



Very similar to image classification networks;
Only works well for **fixed-length** sequences (due to the FC layer);
Cannot model **long-term dependency** (due to the limited kernel size).

Naive Approaches v2



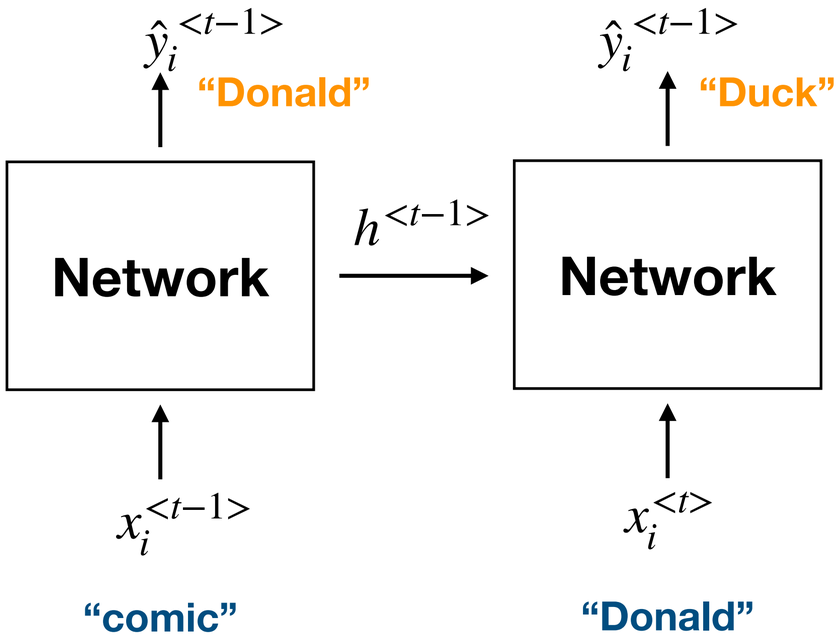
How about modeling just the next word?

The formal president of the United States is Donald Trump.
Wherever Donald Trump went, security was tight.

The comic Donald Duck is very famous.

Context matters to the prediction!

Context Propagation



The meaning of the sentence depends on the **context**.

The context at $x_i^{<t-1>}$ is propagated to the next time step via the **hidden state** $h_i^{<t-1>}$.

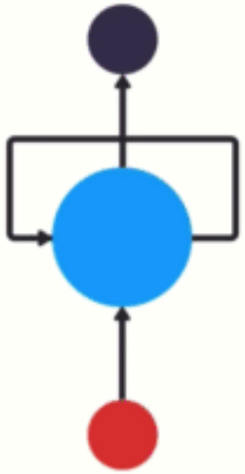
The next prediction is then modeled with both $x_i^{<t>}$ and $h_i^{<t-1>}$.

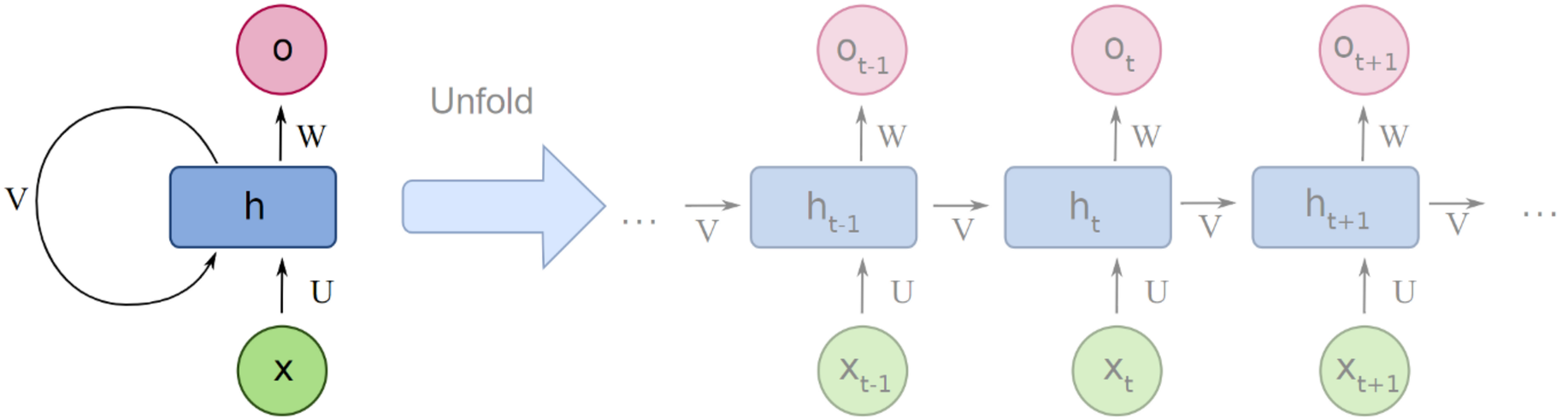
The introduction of the hidden state h_i allows the network to have **memory**.

"The comic Donald Duck is very famous."

Recurrent Neural Networks

In recurrent neural networks (RNNs), weights are **reused** across multiple time steps.





RNN

$$h_t = \sigma(Ux_t + Vh_{t-1} + b_h)$$

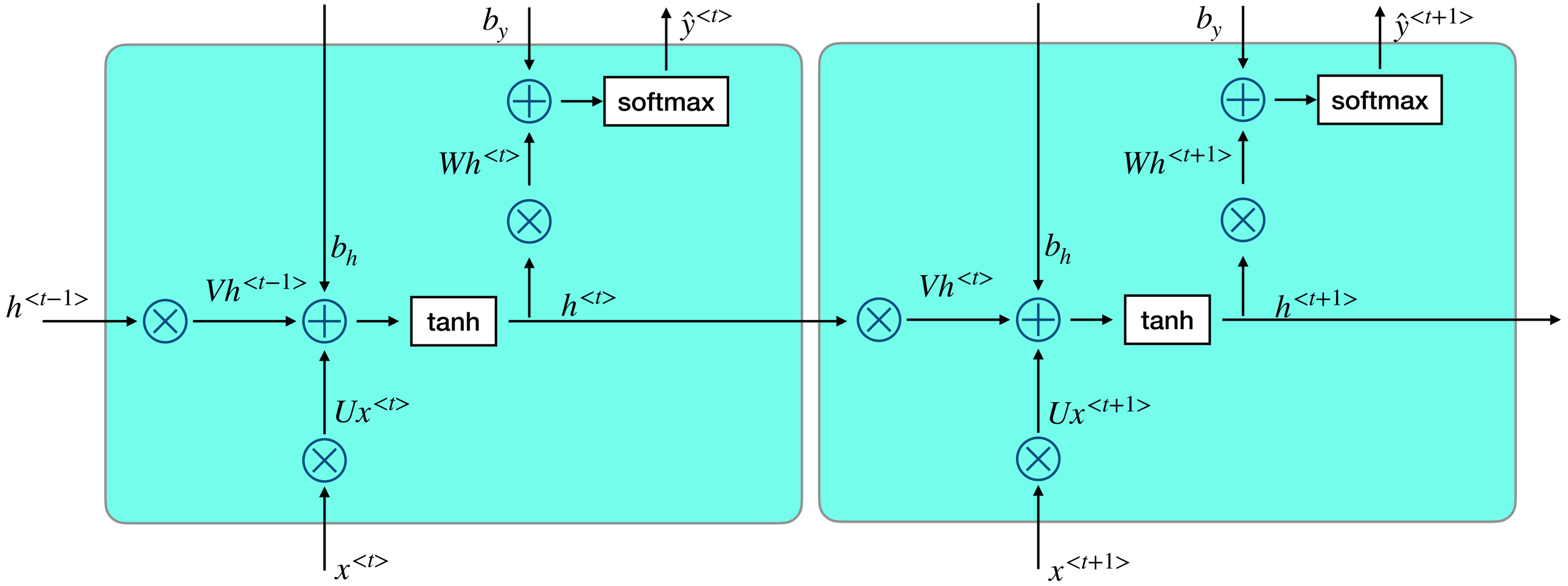
$$O_t = \sigma(Wh_t + b_o)$$

Back propagation through **time**

Non-RNN $O_t = \sigma(Wx_t + b)$

Back propagation through **layers**

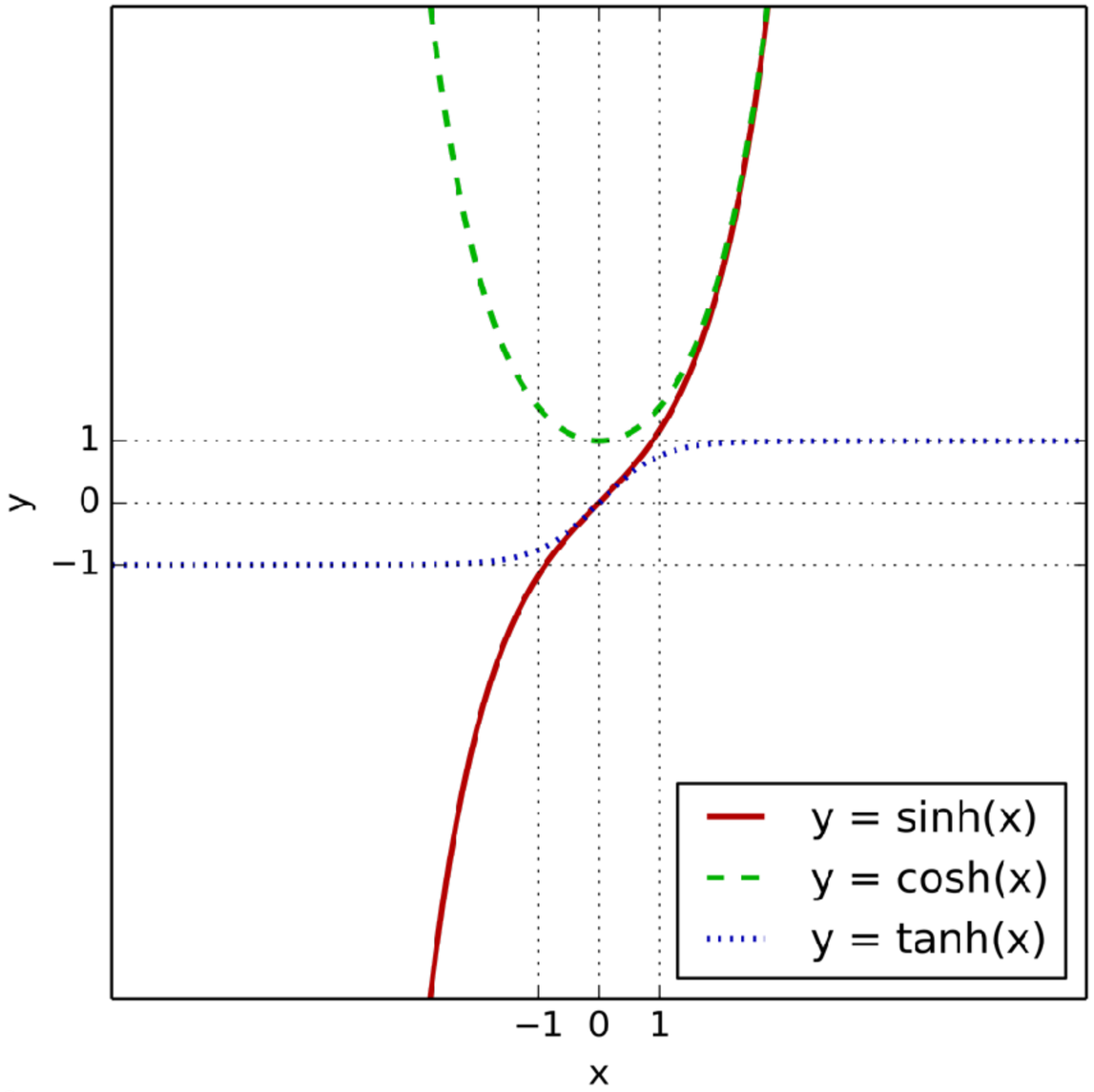
Anatomy of an RNN Cell



$$h^{<t>} = \tanh(Ux^{<t>} + Vh^{<t-1>} + b_h)$$

$$\hat{y}^{<t>} = \text{softmax}(Wh^{<t>} + b_y)$$

Hyperbolic Tangent as an Activation Function



$$\tanh(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

Between **[-1, 1]**, the function behaves **linearly** (more or less).

As long as the input range is within [-1,1], the derivative in this range is approximately 1.

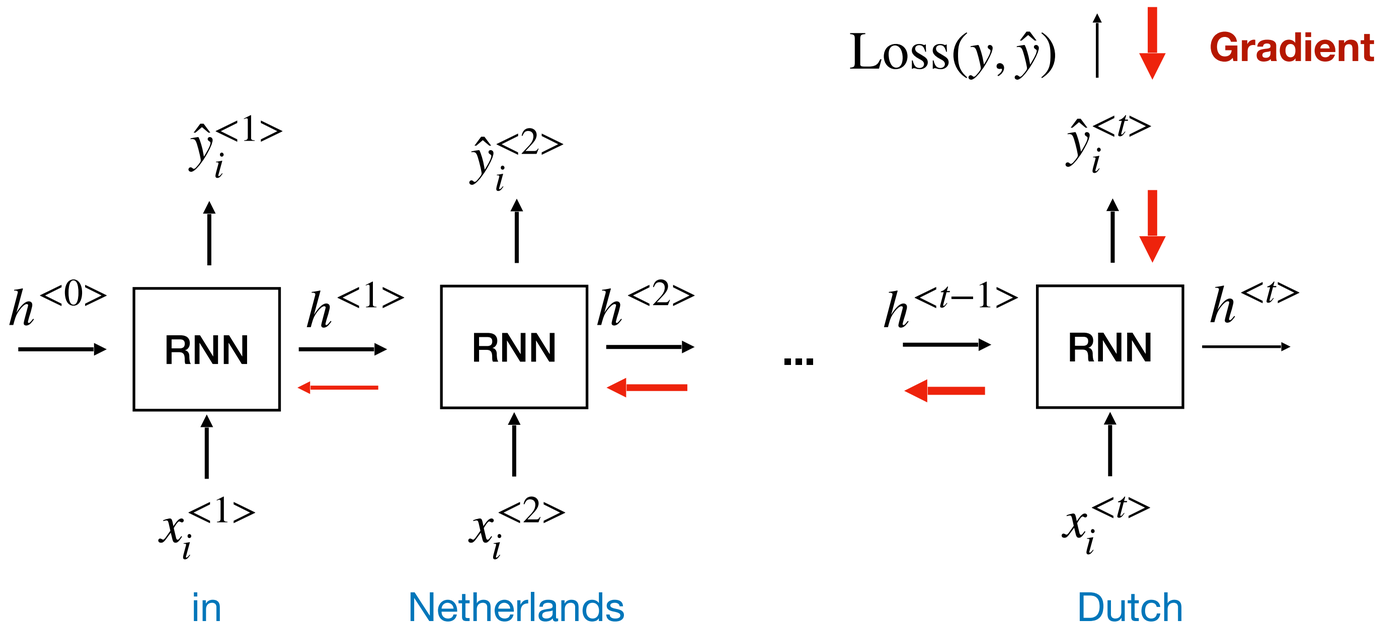
The function always scales the input to the well-controlled range of [-1,1].

Long-term Dependency

Sometimes, the contexts are far away.

The clouds are in the *sky*.

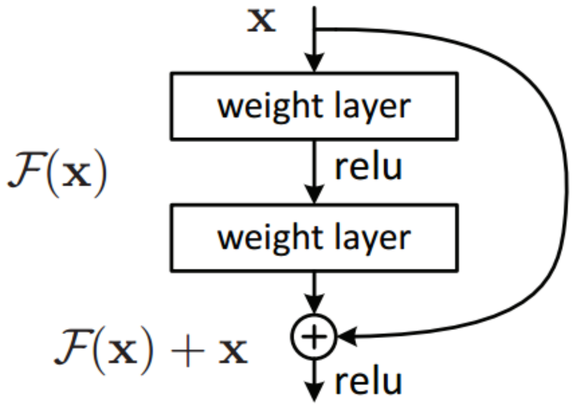
I grew up in the Netherlands… I speak fluent *Dutch*.



Contexts can be **forgotten**; the **gradients** are **vanishing** during back propagation.

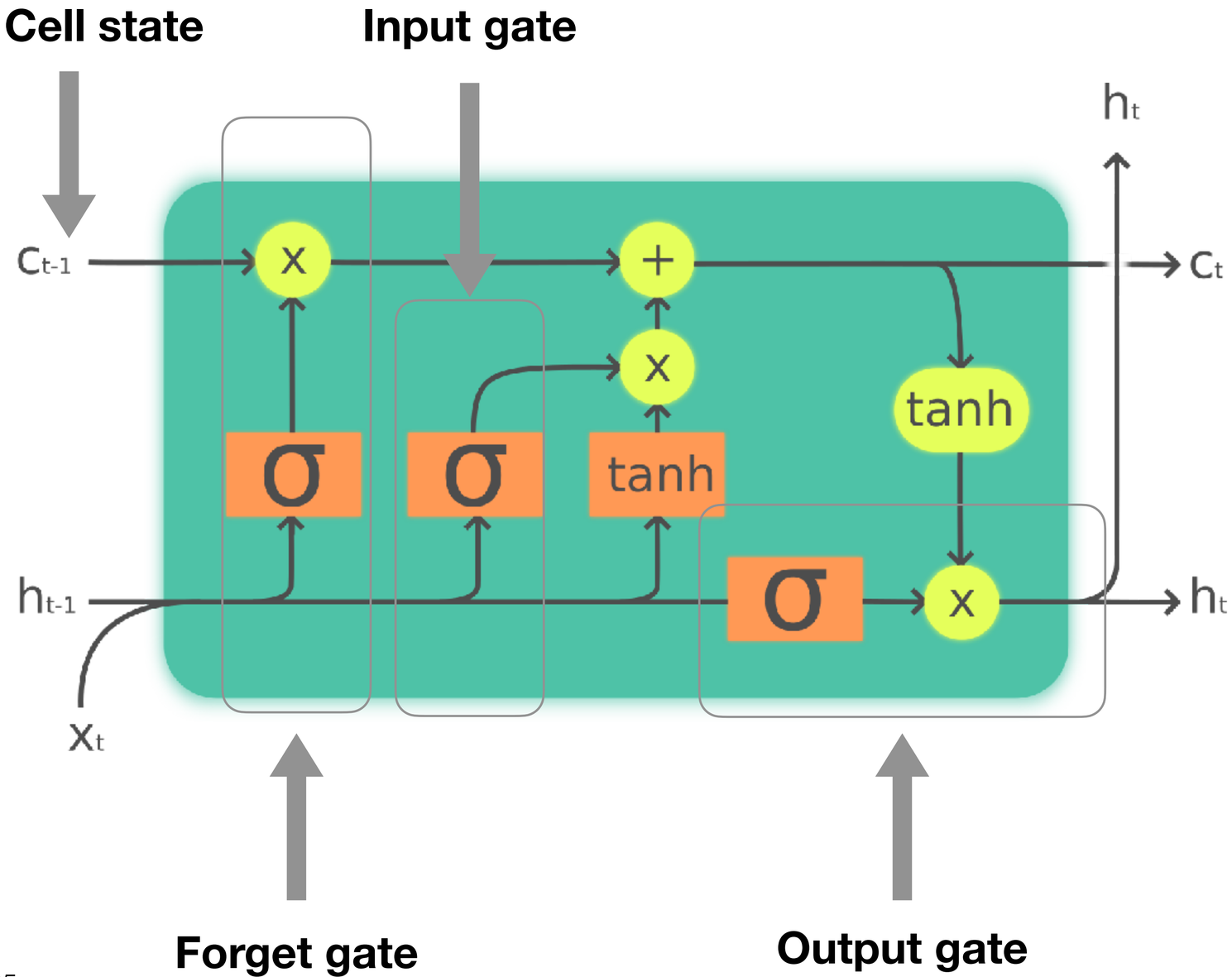
Vanishing Gradient Problem in RNNs

Residual connection is a general solution to the vanishing gradient problem.



However, for very long dependency (which is common in RNNs), this solution is not sufficient.
We should instead regulate which information to **keep** and which to **forget**.

Long Short-term Memory



Hochreiter & Schmidhuber (1997)

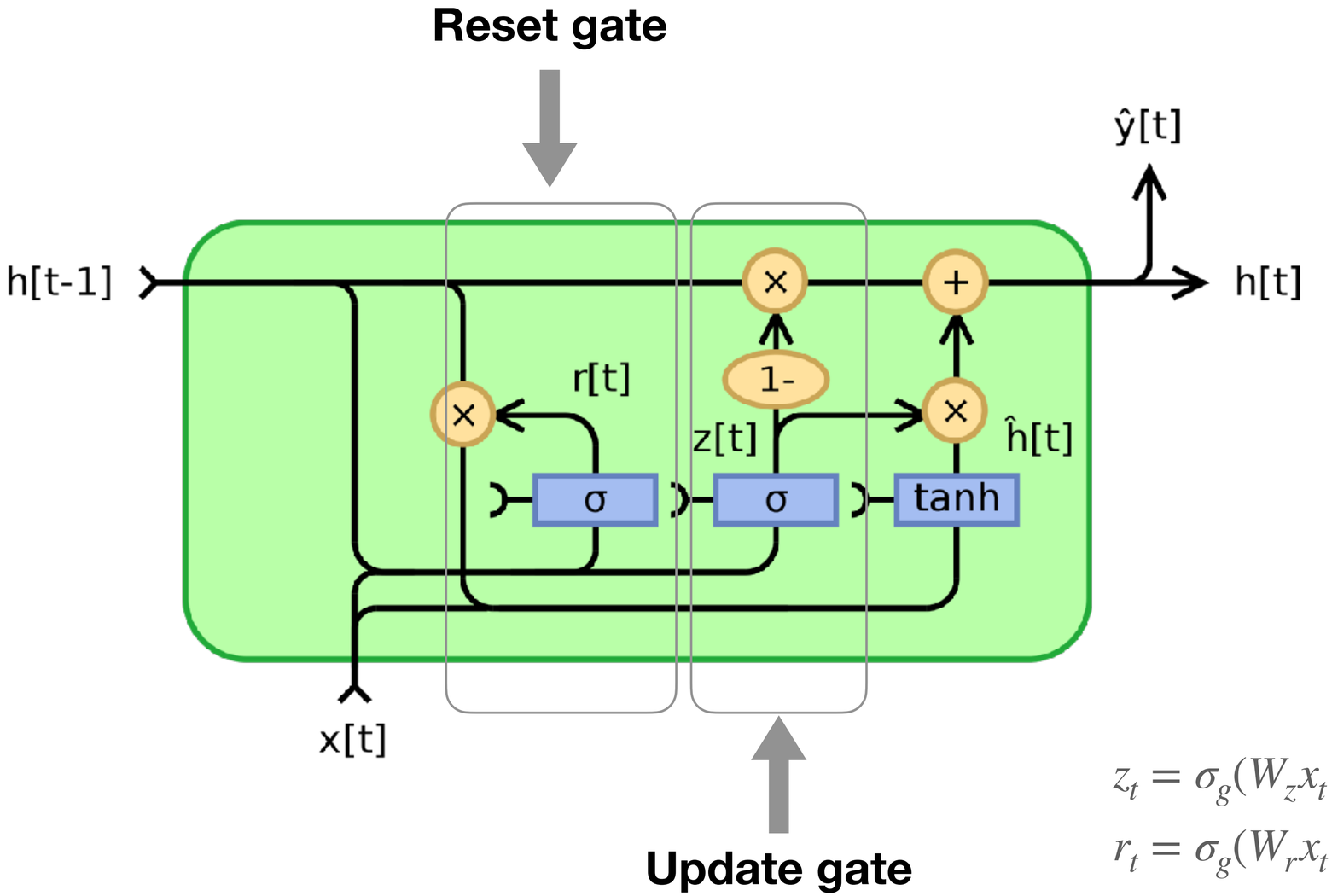
LSTM regulates the flow of information through gates.

- **Input gate**: controls the extent to which a new value flows into the cell;
- **Forget gate**: controls the extent a value remains in the cell;
- **Output gate**: controls the extent to which the value in the cell is used to calculate the output activation.

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f)$$
$$i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i)$$
$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o)$$
$$\tilde{c}_t = \sigma_h(W_c x_t + U_c h_{t-1} + b_c)$$
$$c_t = f_t \circ c_{t-1} + i_t \circ \tilde{c}_t$$
$$h_t = o_t \circ \sigma_h(c_t)$$

Image source: Wikipedia

Gated Recurrent Unit



Cho et al. 2014 (arXiv:1406.1078)

GRU regulates the flow of information through gates:

- **Reset gate**: controls how much past information to forget;
- **Update gate**: controls what information to discard and what to keep (similar to the LSTM's input gate and forget gate combined)

$$z_t = \sigma_g(W_z x_t + U_z h_{t-1} + b_z)$$
$$r_t = \sigma_g(W_r x_t + U_r h_{t-1} + b_r)$$
$$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot \phi_h(W_h x_t + U_h(r_t \odot h_{t-1}) + b_h)$$

Generating Input Sequences

To apply a long sequence to a RNN, we need to define the training data x and the labels y:

(1, ...) (2, ...) (3, ...) (4, ...) (5, ...) (6, ...) (7, ...) (8, ...) (9, ...) (10, ...) (11, ...) (12, ...) (13, ...) (14, ...)

We could either **reshape** it:

x (1, ...) (2, ...) (3, ...) (4, ...) (5, ...) (6, ...) (7, ...)

y (8, ...) (9, ...) (10, ...) (11, ...) (12, ...) (13, ...) (14, ...)

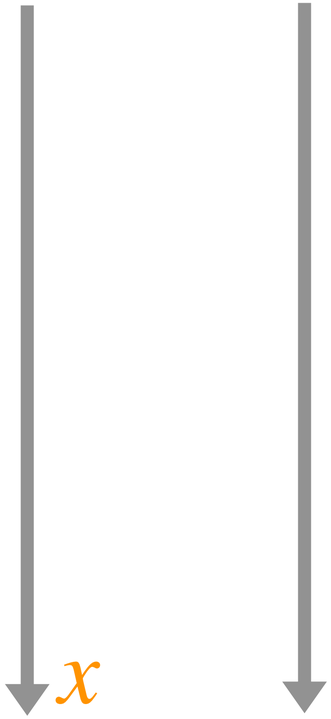
Or truncate it using a **rolling window**:

(1, ...) (2, ...) (3, ...) (4, ...) (5, ...) (6, ...) (7, ...)

(3, ...) (4, ...) (5, ...) (6, ...) (7, ...) (8, ...) (9, ...)

(5, ...) (6, ...) (7, ...) (8, ...) (9, ...) (10, ...) (11, ...)

(7, ...) (8, ...) (9, ...) (10, ...) (11, ...) (12, ...) (13, ...)



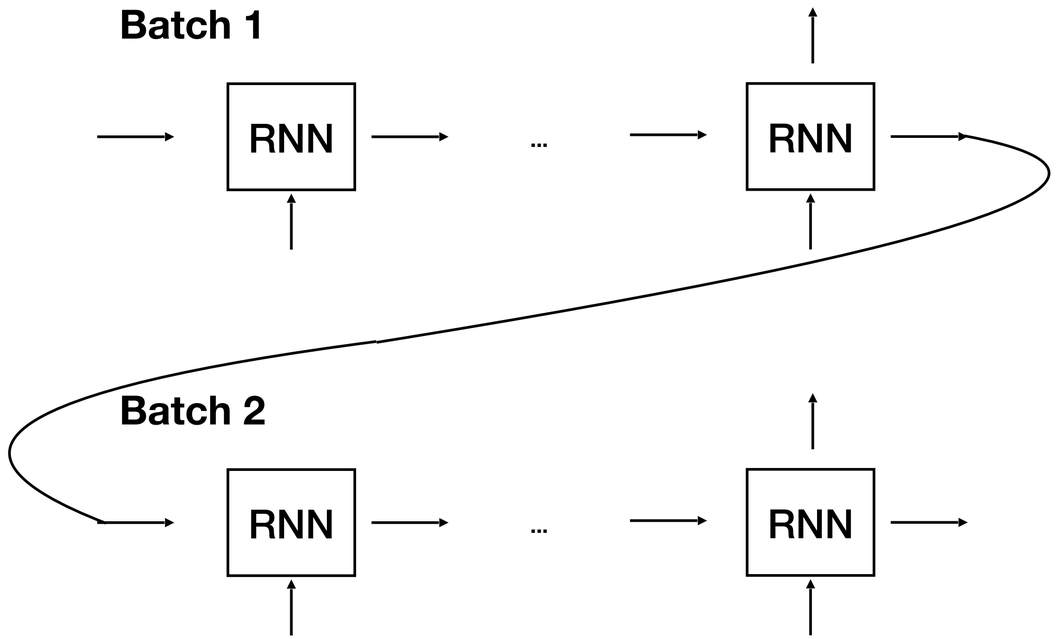
(13, ...)

Stateful RNNs

A stateful RNN passes the **last state** of the **previous batch** as the **initial state** of the **next batch**.

This is useful if there is some connections between batches. This feature essentially allows long sequences to be **folded** into batches.

A non-stateful RNN initialises state of each batch to zero.



Batch 1	(1, ...) (2, ...) (3, ...) (4, ...) (5, ...) (6, ...) (7, ...)
Batch 2	(8, ...) (9, ...) (10, ...) (11, ...) (12, ...) (13, ...) (14, ...)

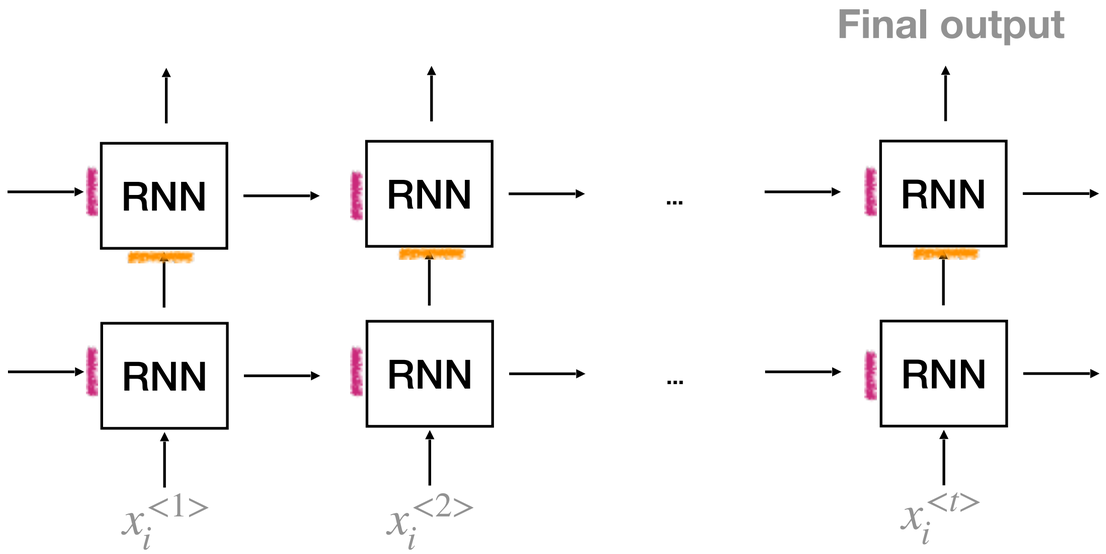
Implementation in TensorFlow/Keras

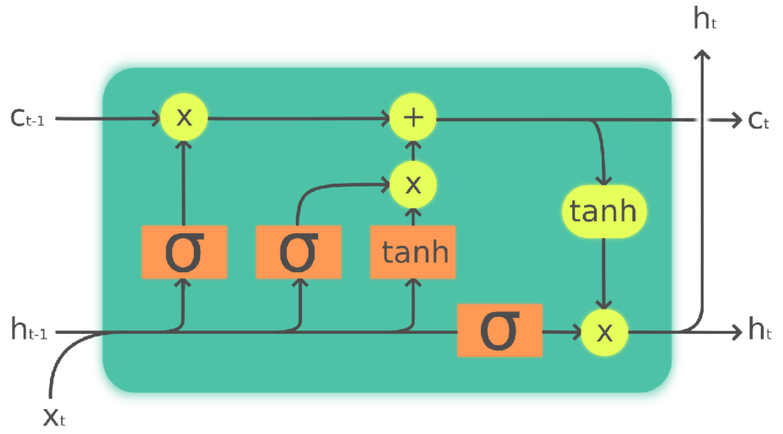
The complexity of LSTM/GRU is hidden by TensorFlow.

```
layer_lstm(units=10)
layer_gru(units=10)
```

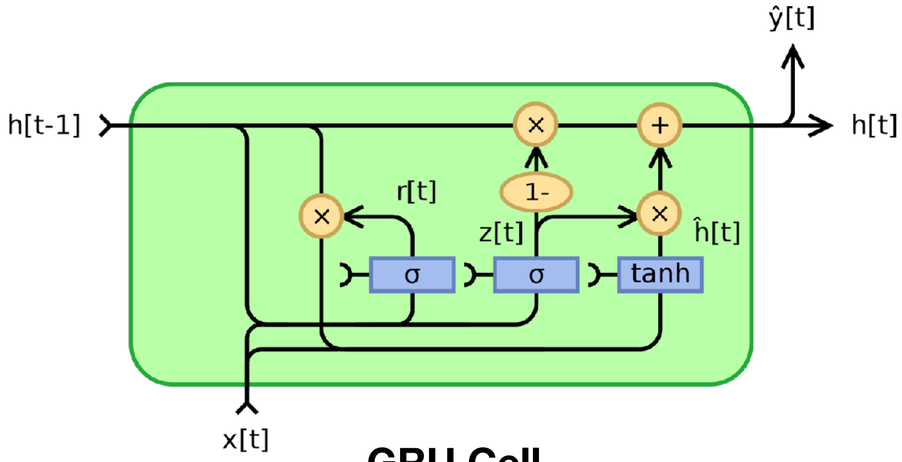
Building a multi-layer RNN is therefore very straightforward:

```
layer_gru(units = 10, return_sequences = TRUE) %>%
layers_gru(units = 10)
```





LSTM Cell

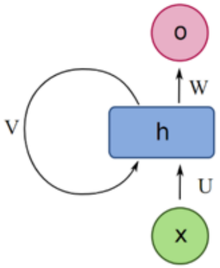


GRU Cell

Take Home Messages

Sequence modelling

… is a task that aims to solve the **dependency** between **tokens** in a sequence;
… requires passing information along the flow of the sequence;
… can be categorised into classification, regression, generation, and translation.



Recurrent neural networks (RNNs)

… are NN architectures that allow weights and states to be shared across multiple time steps;
… backward propagate through **time**;
… are usually slow to train because the time step dependency cannot be parallelised.

Miscellaneous

- Long short-term memory (LSTM) and gated recurrent units (GRU) are RNNs that designed to mitigate the **vanishing gradient problem**.
- LSTM and GRU use **gates** to regulate the flow of information.
- The **encoder-decoder** architecture is particular useful in RNNs for sequence to sequence translation.

Go to https://jupyter.lisa.surfsara.nl/jhlsrf003

Select “SURF jupyterhub - course hours” profile

Notebook: notebook_3_time_series.ipynb

Hacking until 15:15