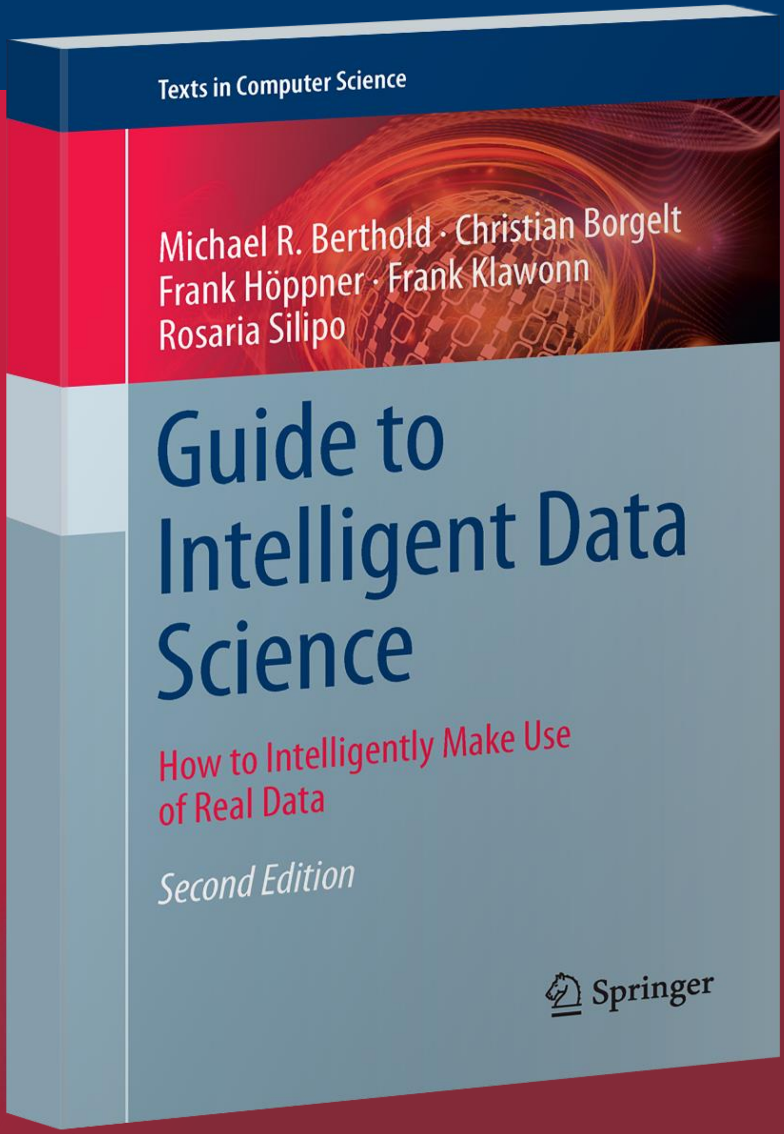
Deep Learning



Summary of this lesson

"What people call *AI* is no more than finding answers to questions we know to ask. Real *AI* is answering questions we haven't dreamed of yet"
-Tom Golway

How deep can we dig in AI?

***This lesson refers to chapter 9 of the GIDS book**

Content of this lesson

- Recurrent Neural Networks (RNNs)
- Long Short Term Memories (LSTMs)
- Convolutional Neural Networks (CNNs)
- Generative Adversarial Networks (GANs)

Datasets

- Datasets used:

Deep Learning

- Deep Learning is the recent evolution of Neural Networks
- It covers:
  - Feedforward networks with many hidden layers (deep ☺)
  - New paradigms, like LSTMs in Recurrent Neural Networks, suitable for time series analysis
  - New topological layers, like convolutional and pooling layers, mainly for image processing
  - New architectures as in Generative Adversarial Networks (GANs)
  - ...
- Improvements are mainly due to:
  - Increased computational power for faster calculations, like GPUs
  - Parallel Computation

Recurrent Neural Networks (RNNs)

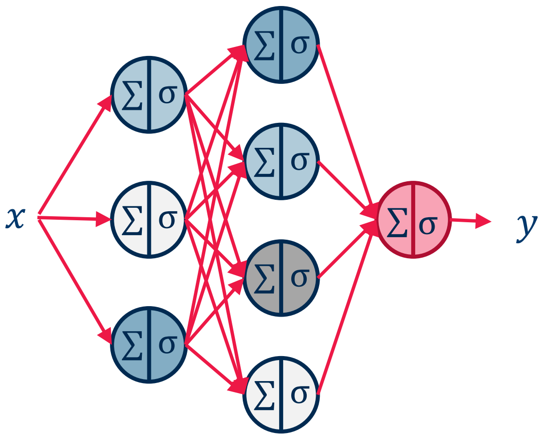
What are Recurrent Neural Networks?

- **R**ecurrent **N**eural **N**etworks (RNNs) are a family of neural networks suitable for processing of sequential data
- RNNs include auto and backward connections
- RNNs are used for all sorts of tasks:
  - Language modeling / Text generation
  - Text classification
  - Neural machine translation
  - Image captioning
  - Speech to text
  - Numerical time series data, e.g. sensor data
  - Time series analysis
  - …

- **Goal**: Translation from German to English

  "Ich mag Schokolade"
  => "I like chocolate"

- Option one: Use feed forward network to translate word by word



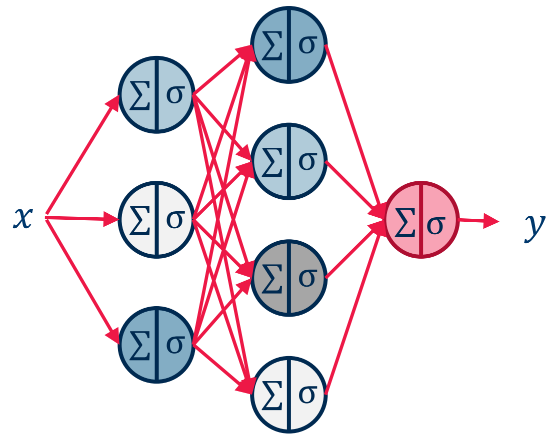
Input x	Output y
Ich	I
mag	like
Schokolade	chocolate

- But what happens with this question?

  "Mag ich Schokolade?"
  => "Do I like chocolate?"

- Problems with FFNN:
  - Each time step is completely independent
  - For translations we need context
    - More general: we need a network that remembers inputs from the past
  - Handle variable sequence length

- **Solution**: Recurrent Neural Networks



Input x	Output y
Mag	Like
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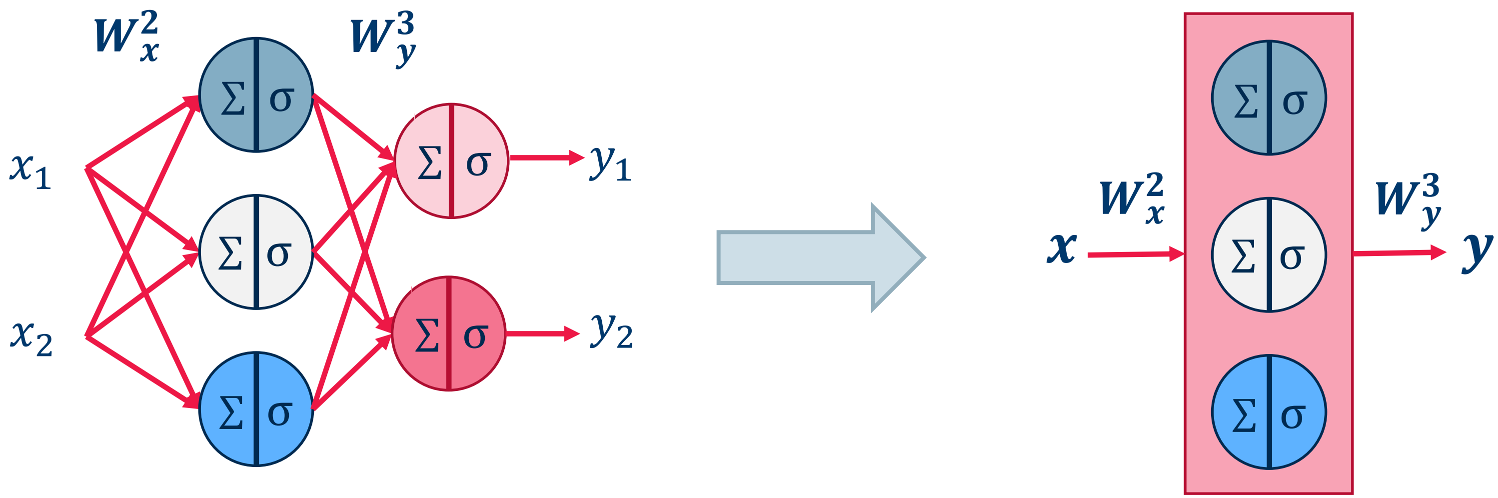
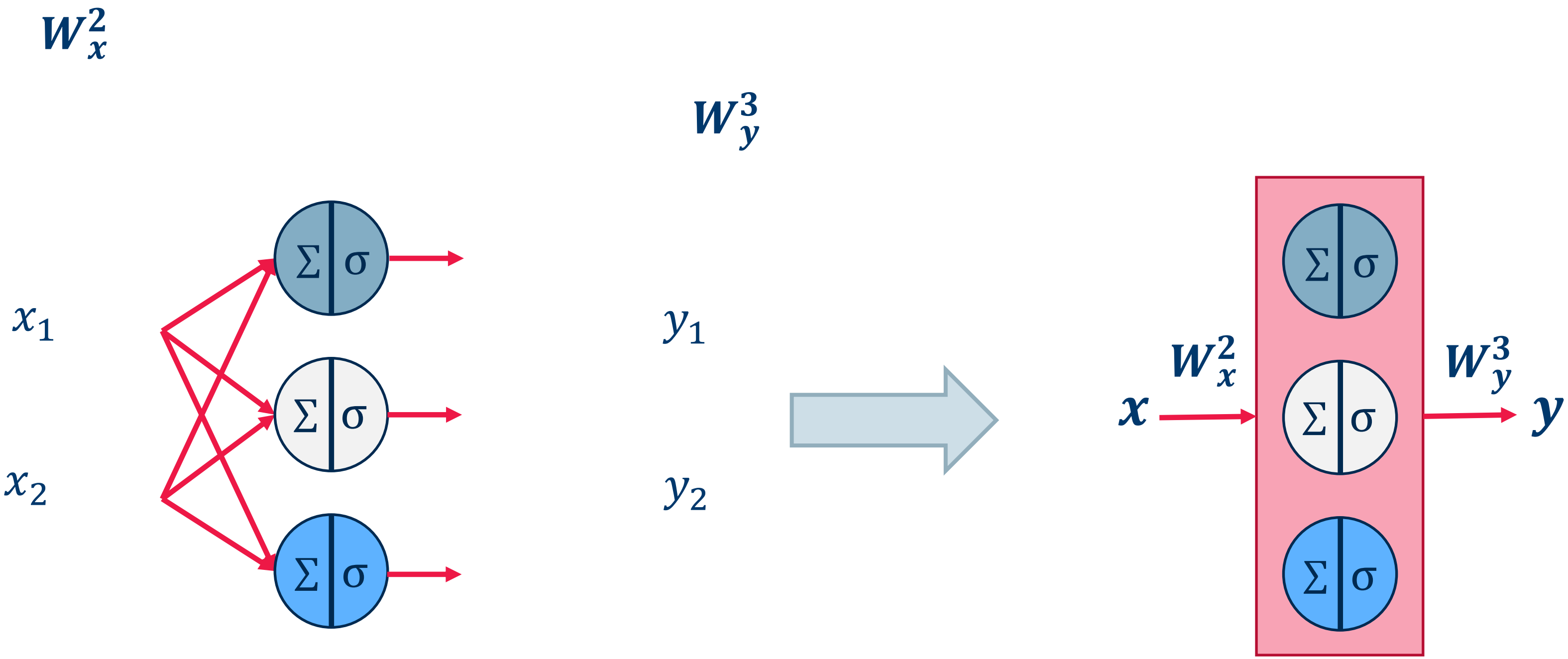
Schokolade	chocolate

From Feed Forward to Recurrent Neural Networks



From Feed Forward to Recurrent Neural Networks



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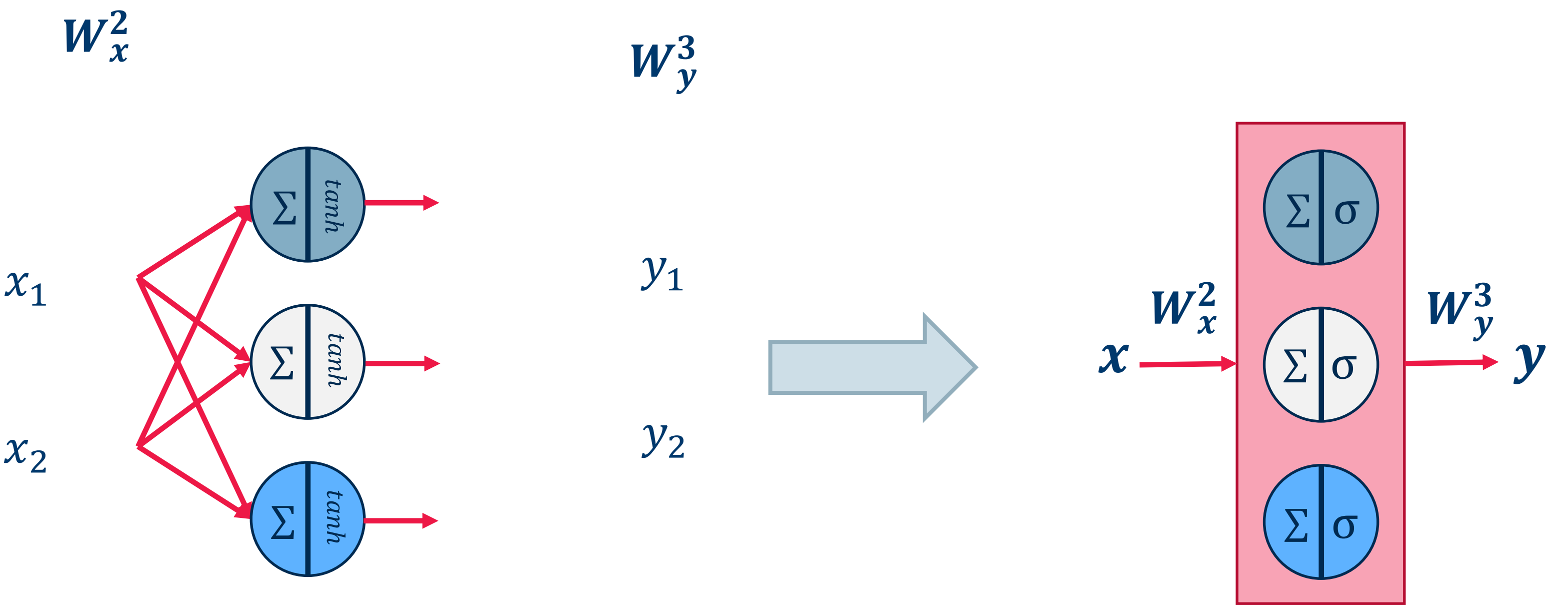
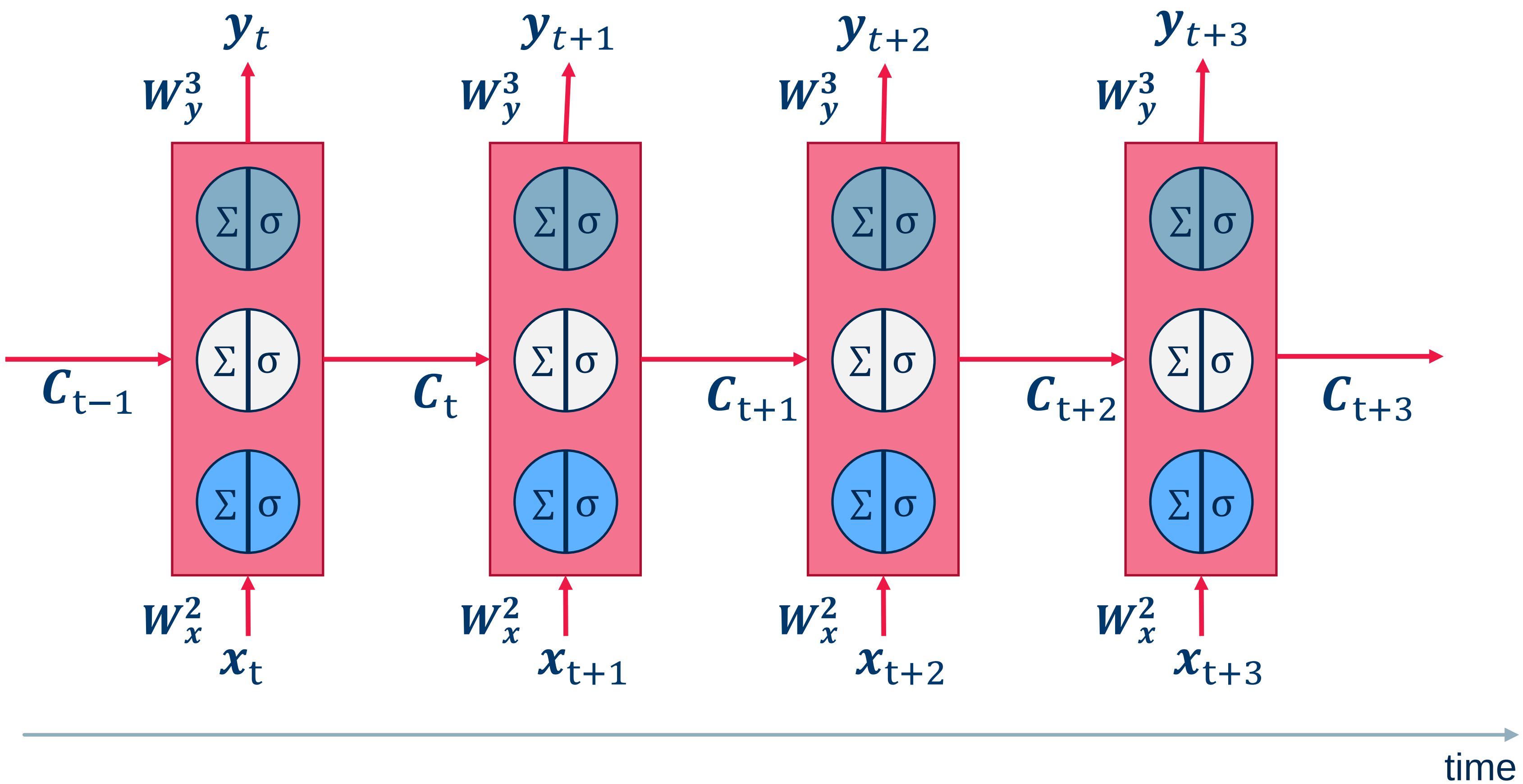
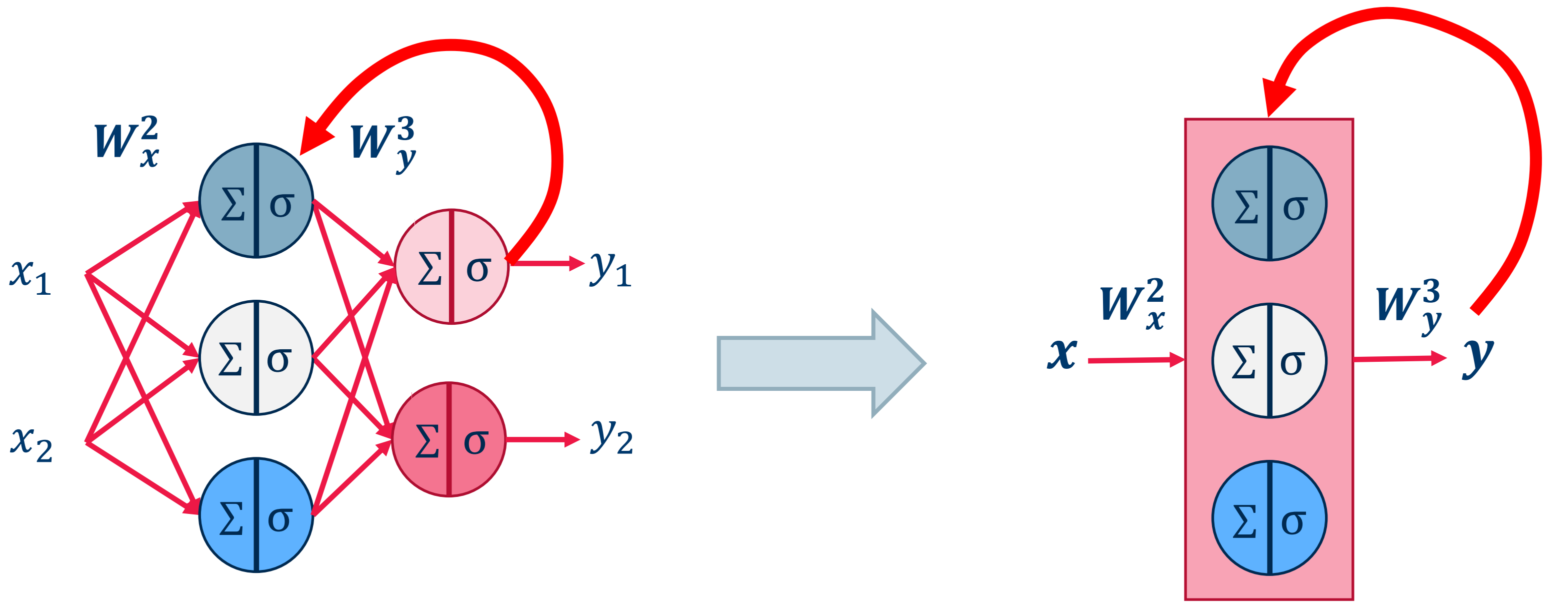


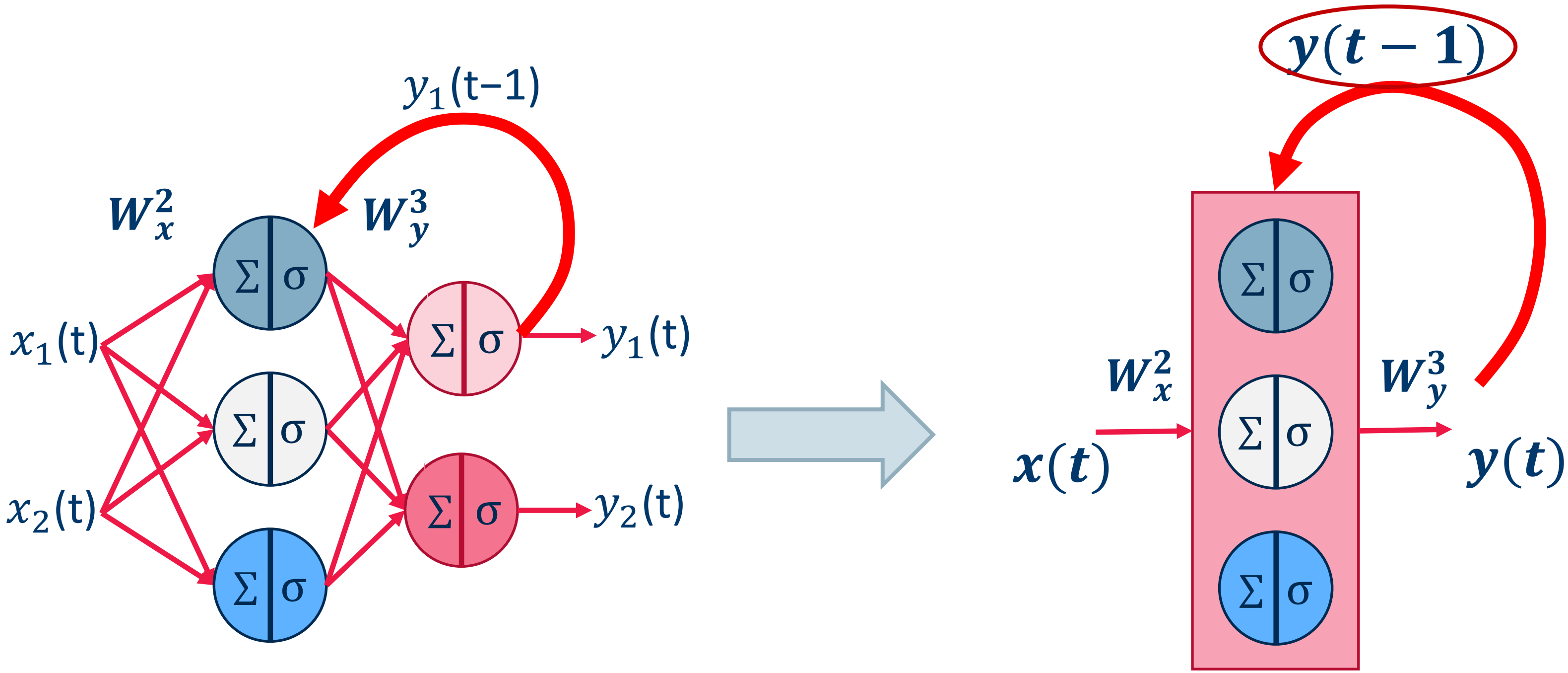
Unrolling of a RNN over time





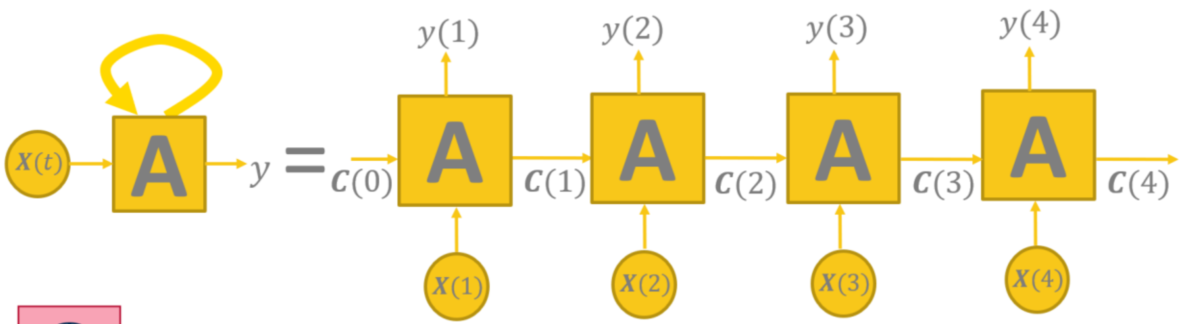
- A Recurrent Neural Network is a FFNN with auto and/or backward connections
- Recurrent connections introduce the concept of **time** in FFNNs

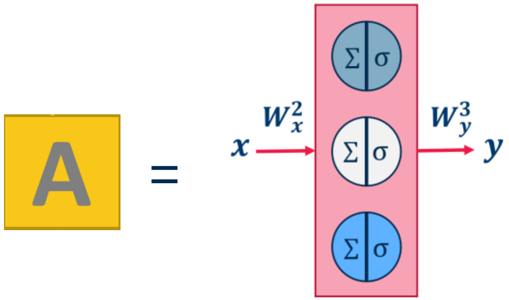
From Front Feed Forward to Recurrent Neural Networks



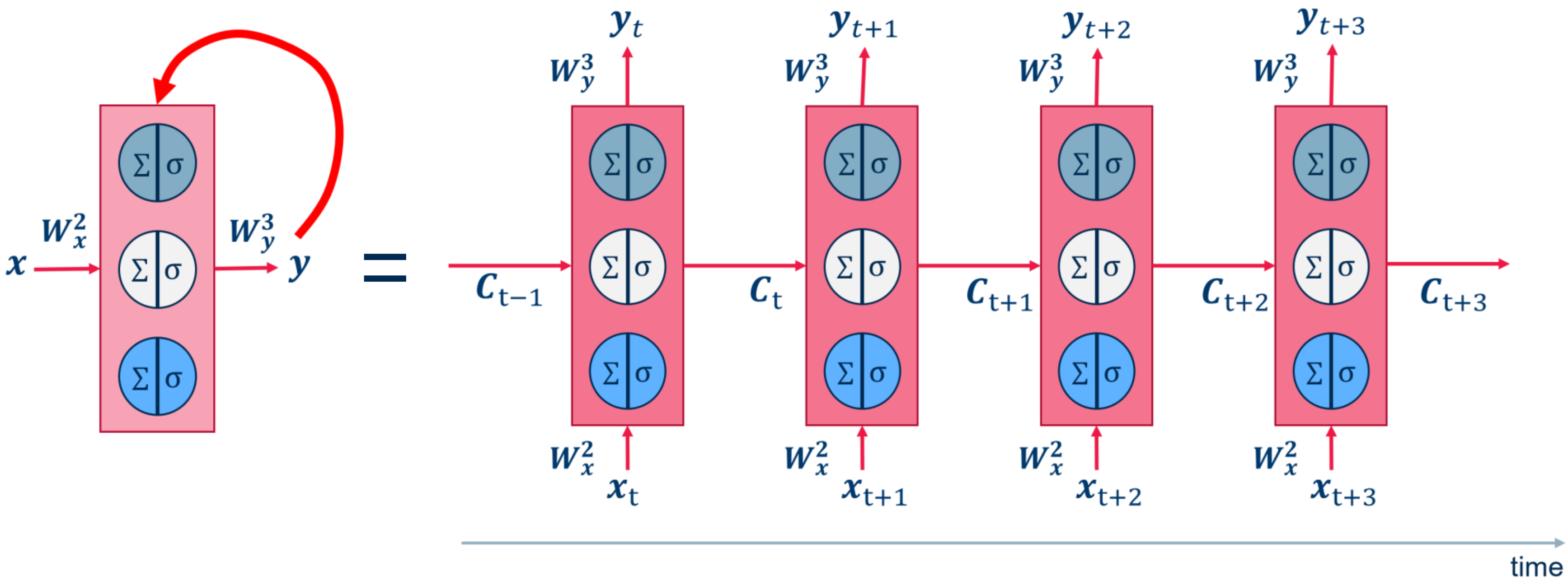
- A Recurrent Neural Network is a FFNN with auto and/or backward connections
- Recurrent connections introduce the concept of **time** in FFNNs

- At every time t, FFNN A has two inputs:
  - **x**(t)
  - some shape of ***y****(t-1)* -> state of network A: ***C****(t-1)*
- The recurrent network can then be **unrolled** over time around **A**





The unrolled version of the original network in *m* intermediate steps becomes a FFNN and can be trained with BackPropagation: **Back-Propagation Through Time (BPTT).**



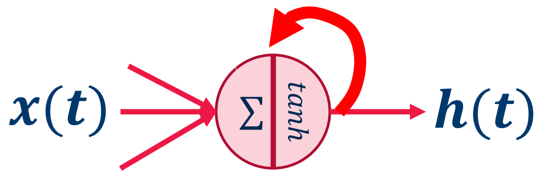
Summarizing: RNNs and BPTT

- Neural network architectures with recurring connections on some units are named Recurrent Neural Networks (RNNs).
- Adding a recurrent connection to one unit might store information about past inputs in the evolving status of the unit.
- An easy trick to represent the recurrent network is to unroll it into *m* copies of the feedforward internal block “A”, each with their set of static weight matrix **W.** Each copy of “A” receives inputs **X**(t) and **C**(t-1) and produces output **y**(t).
- A modified version of the Back-Propagation algorithm is used to train RNNs: Back-Propagation Through Time (BPTT).

Long Short Term Memory

Simple Recurrent Unit

The simplest possible recurrent unit is a single layer with an auto-connection.



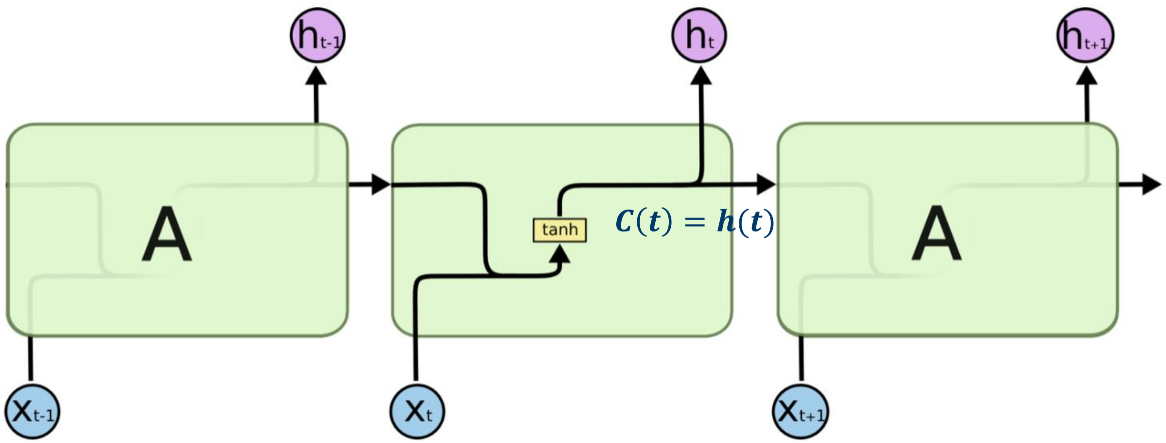


Image Source: Christopher Olah, https://colah.github.io/posts/2015-08-Understanding-LSTMs/

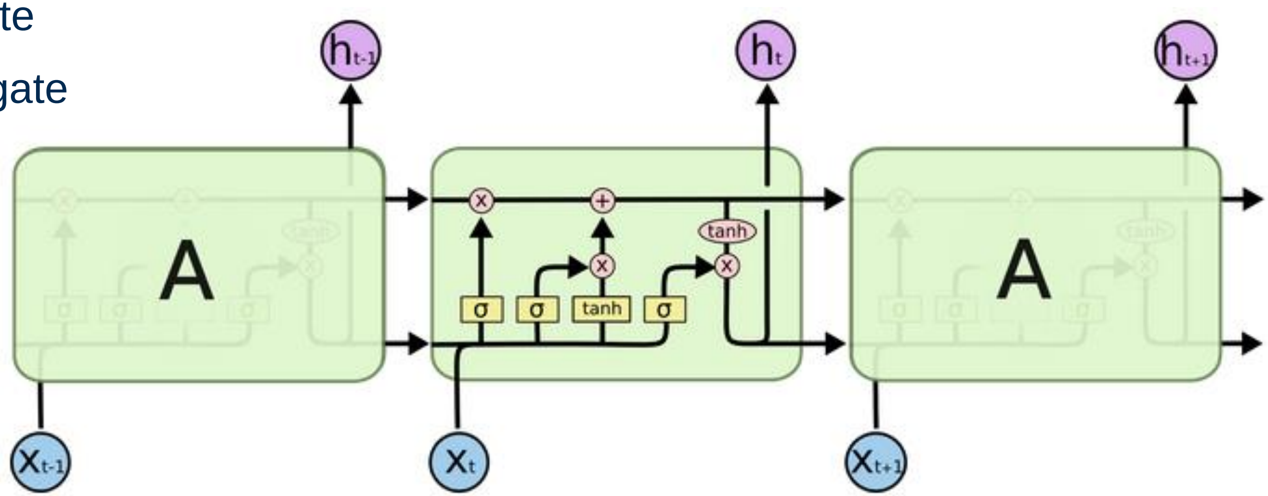
Limitations of Layers with Simple Recurrent Units

The “memory” of simple RNNs is sometimes too limited to be useful:

- *“Cars drive on the ____” (road)*
- *“I love the beach.*
  My favorite sound is the crashing of the ____“ (cars? glass? waves?)
- Sometimes we need to go back deeper in time

Special type of unit with three gates

- Forget gate
- Input gate
- Output gate



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This is an engineered type of unit with three gates:

- Forget gate
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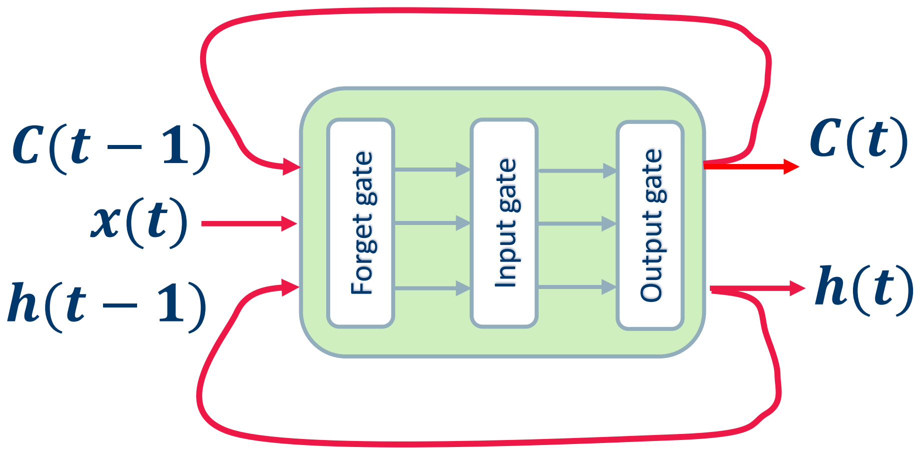

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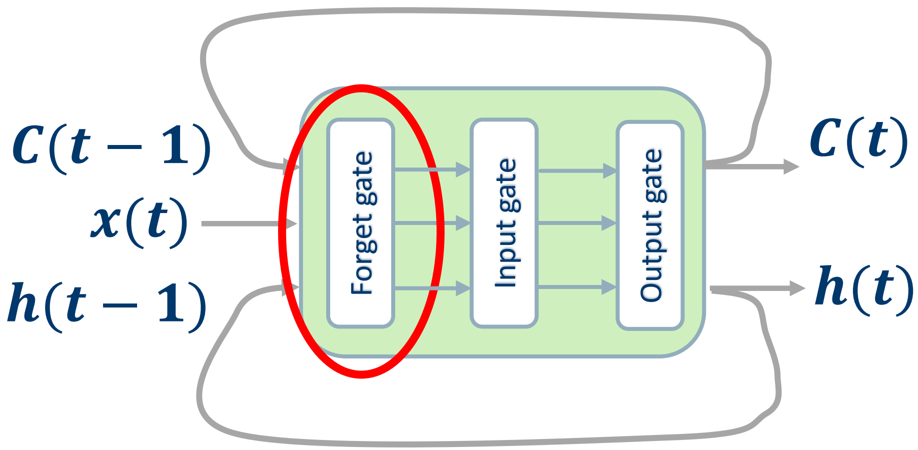
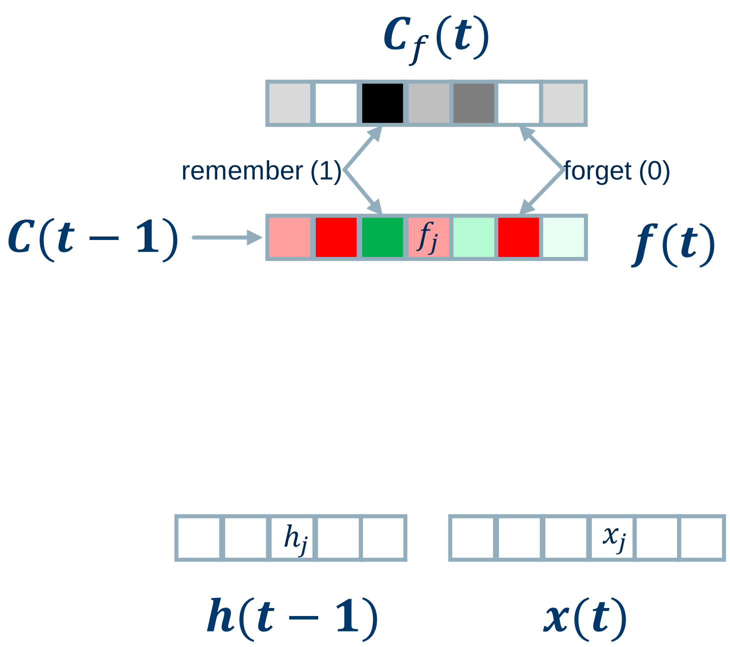


- ***Forget Gate*** is trained to forget parts of the cell state.
- At time t, the forget gate decides which item of $\boldsymbol{C}(t-1)$ to keep (and how much of it) in $\boldsymbol{C}(t)$, given input vector $\boldsymbol{x}(t)$ and previous output $\boldsymbol{h}(t-1)$.



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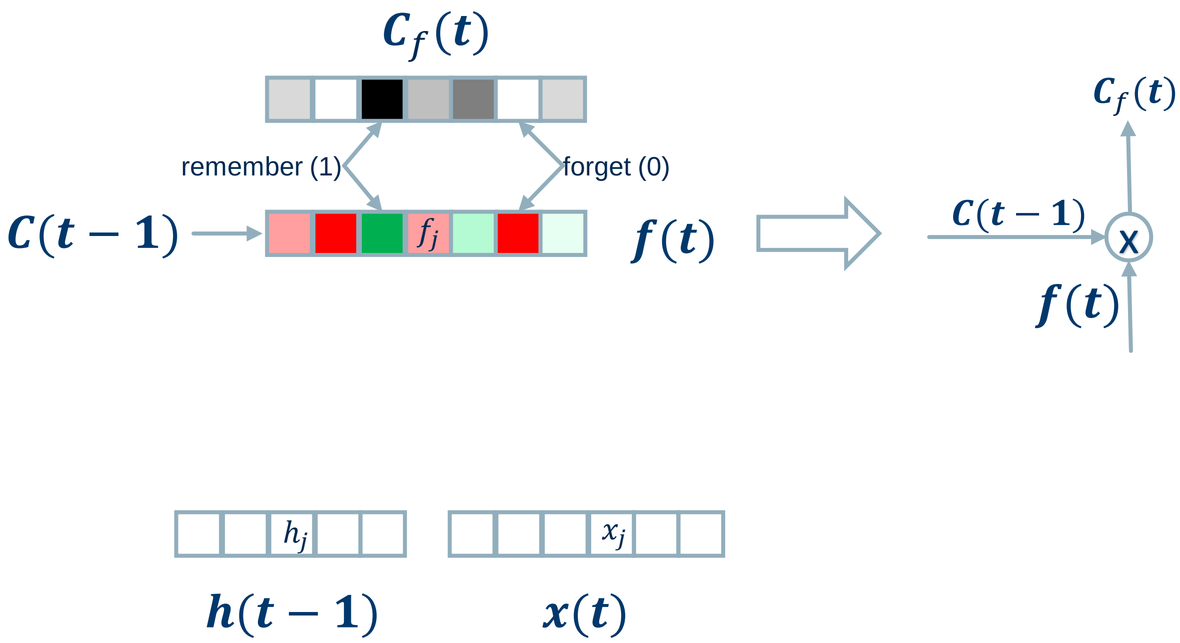

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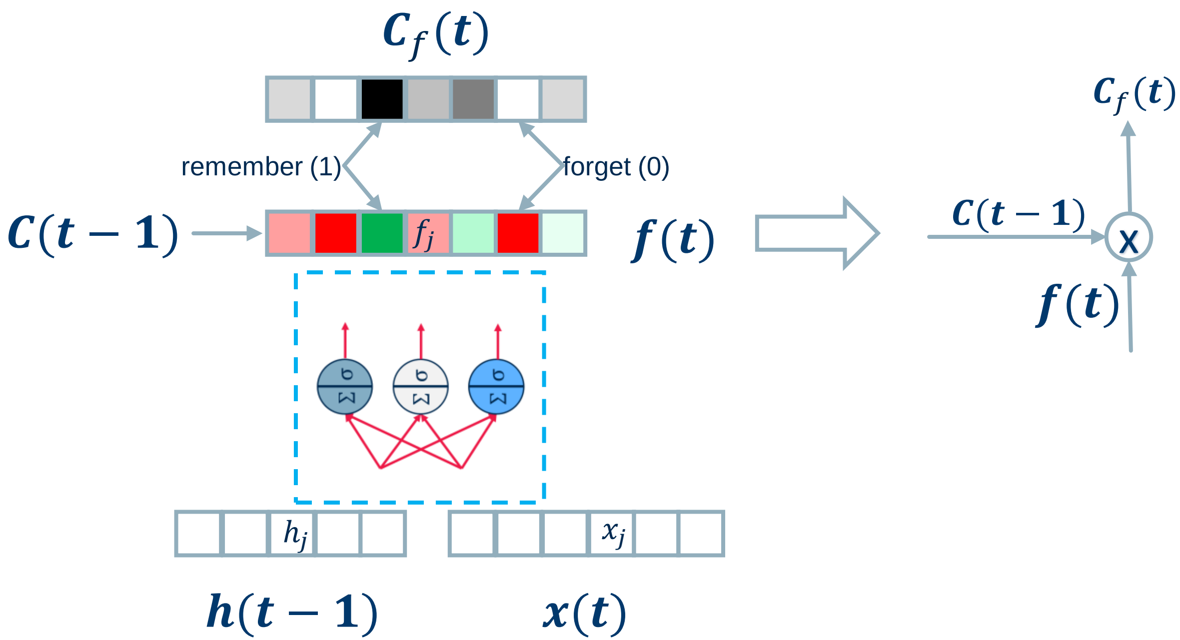

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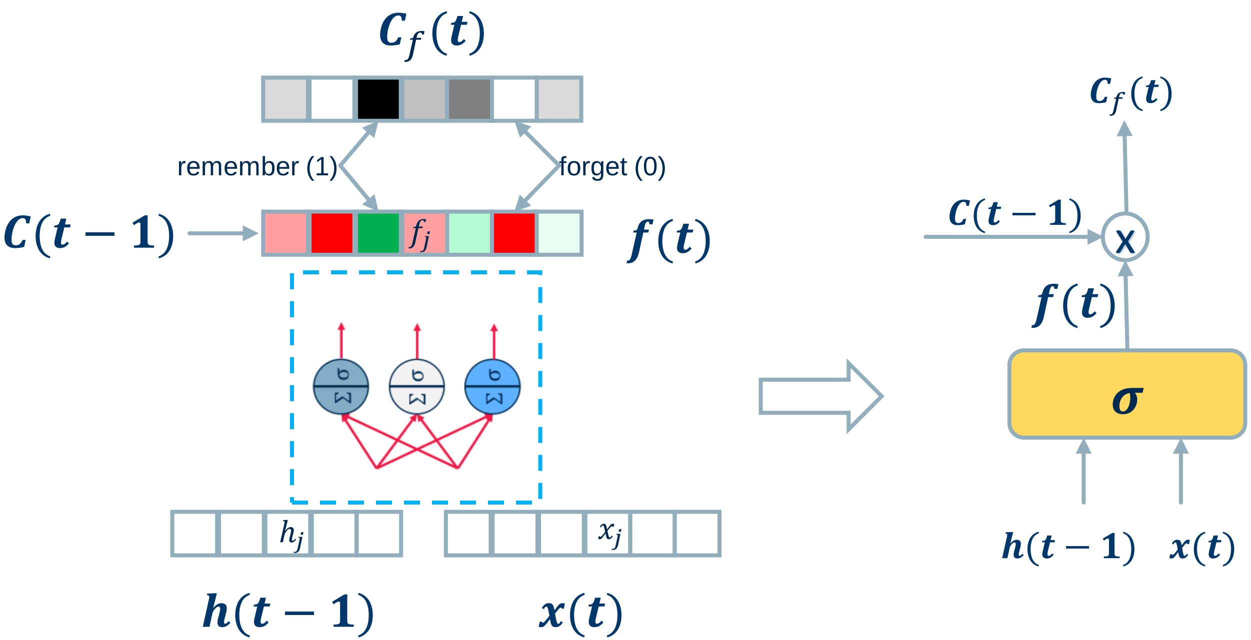

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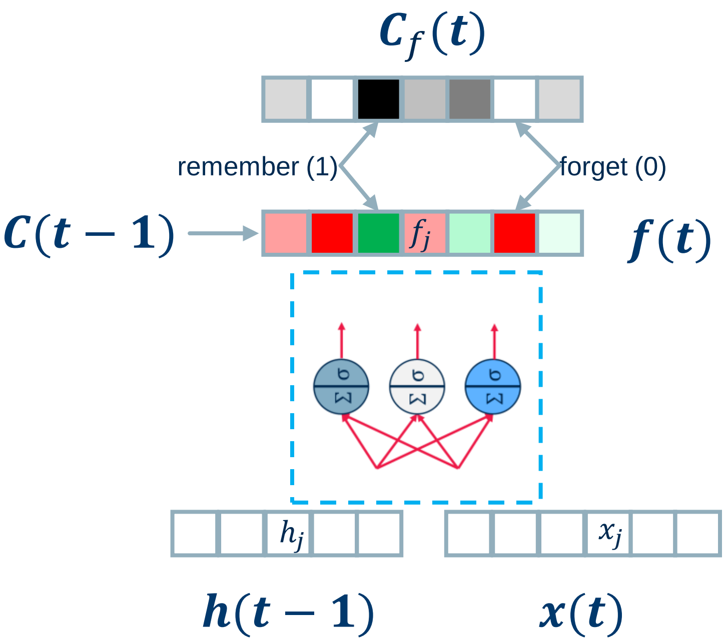

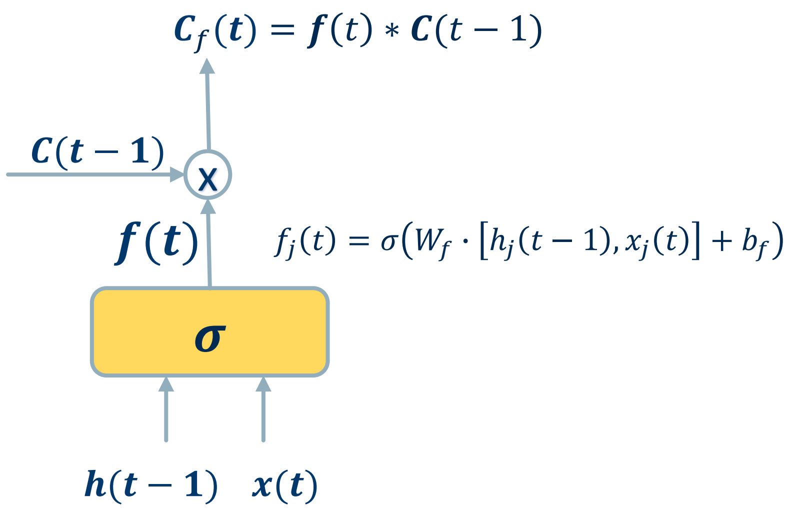

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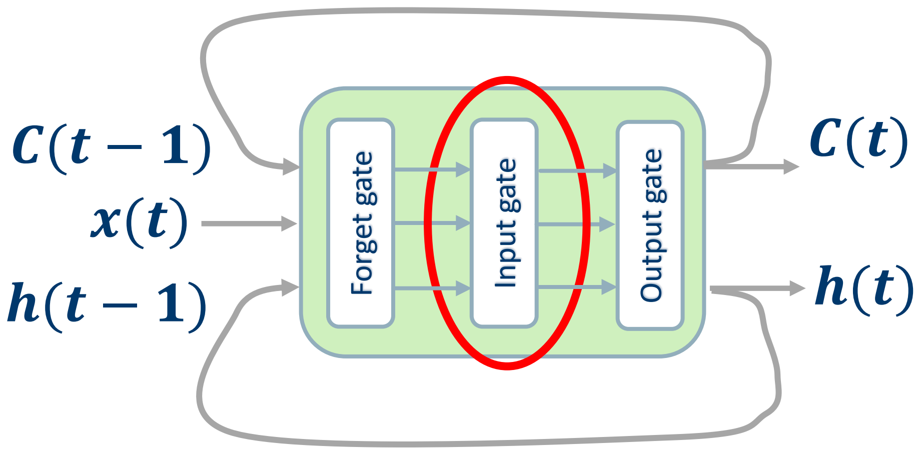

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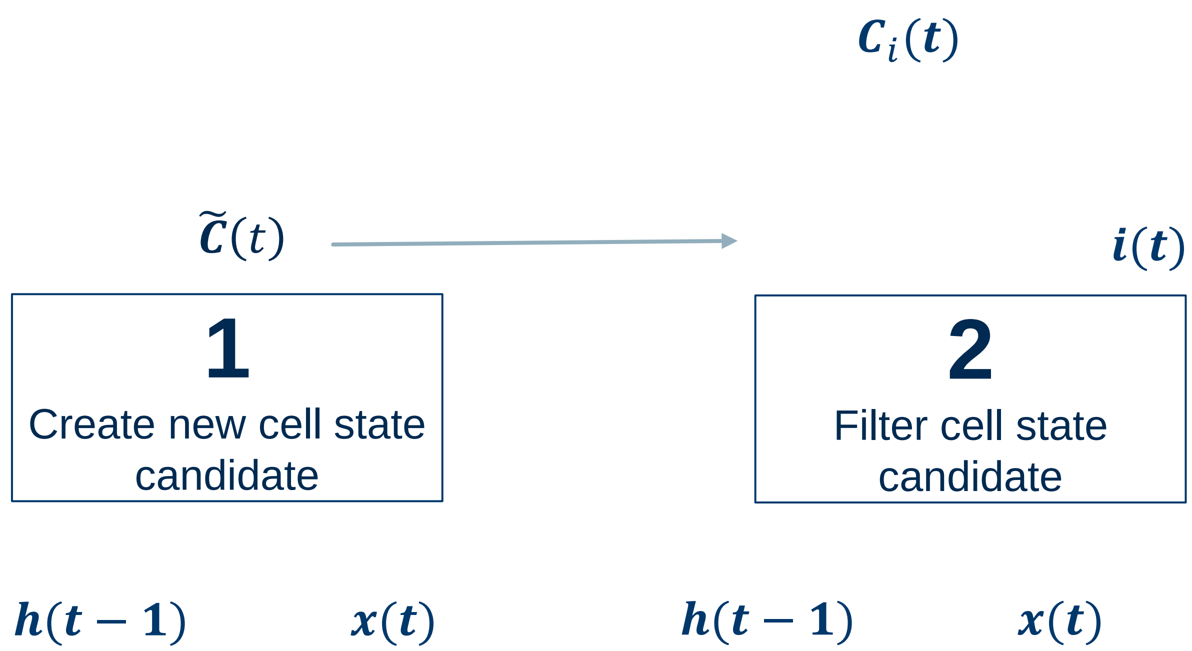

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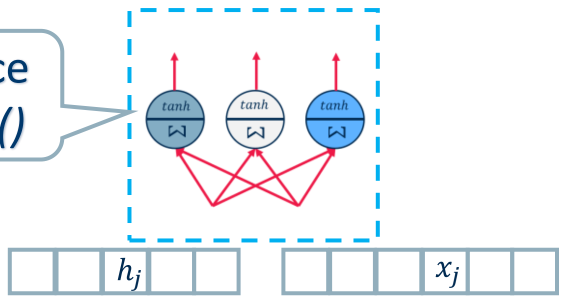
$\boldsymbol{C}_i(\boldsymbol{t})$

$\widetilde{\boldsymbol{C}}(t)$ → $\boldsymbol{i}(\boldsymbol{t})$

Notice *tanh()*



2

Filter cell state candidate

$\boldsymbol{h}(\boldsymbol{t}-\mathbf{1})$ $\boldsymbol{x}(\boldsymbol{t})$ $\boldsymbol{h}(\boldsymbol{t}-\mathbf{1})$ $\boldsymbol{x}(\boldsymbol{t})$

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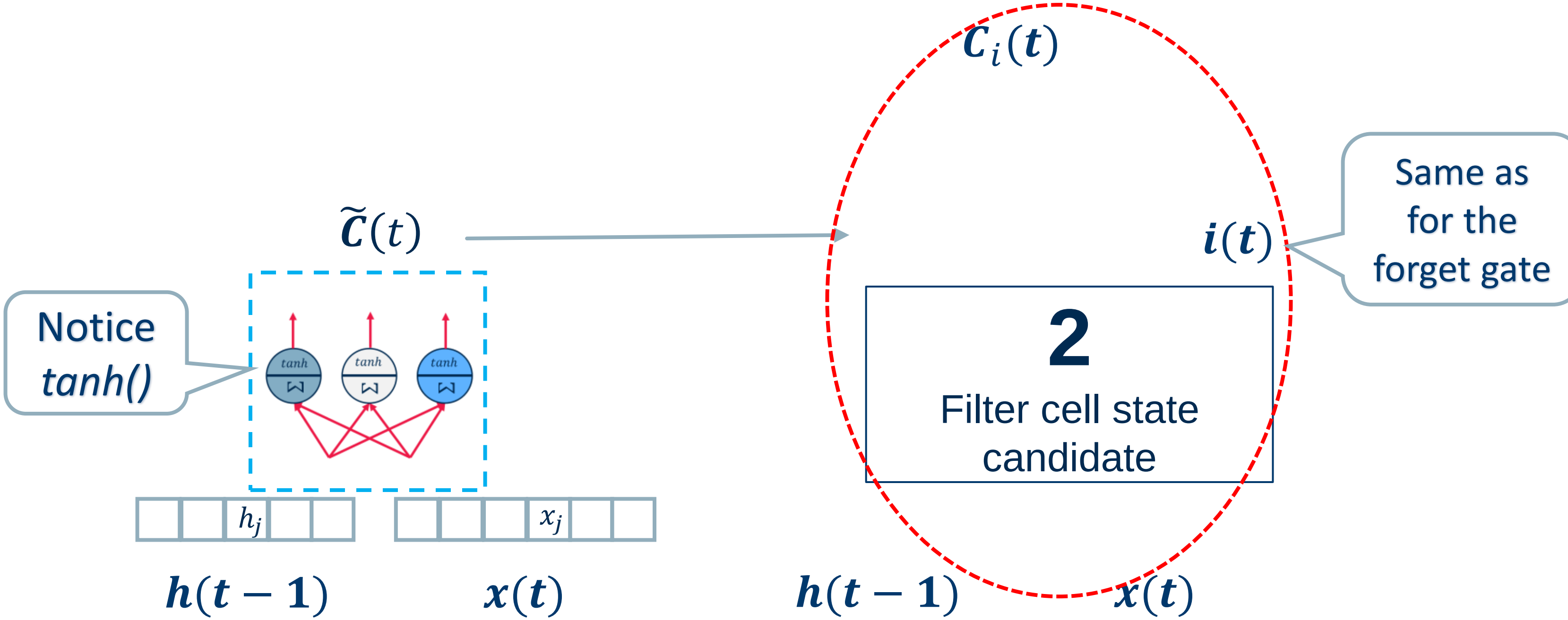

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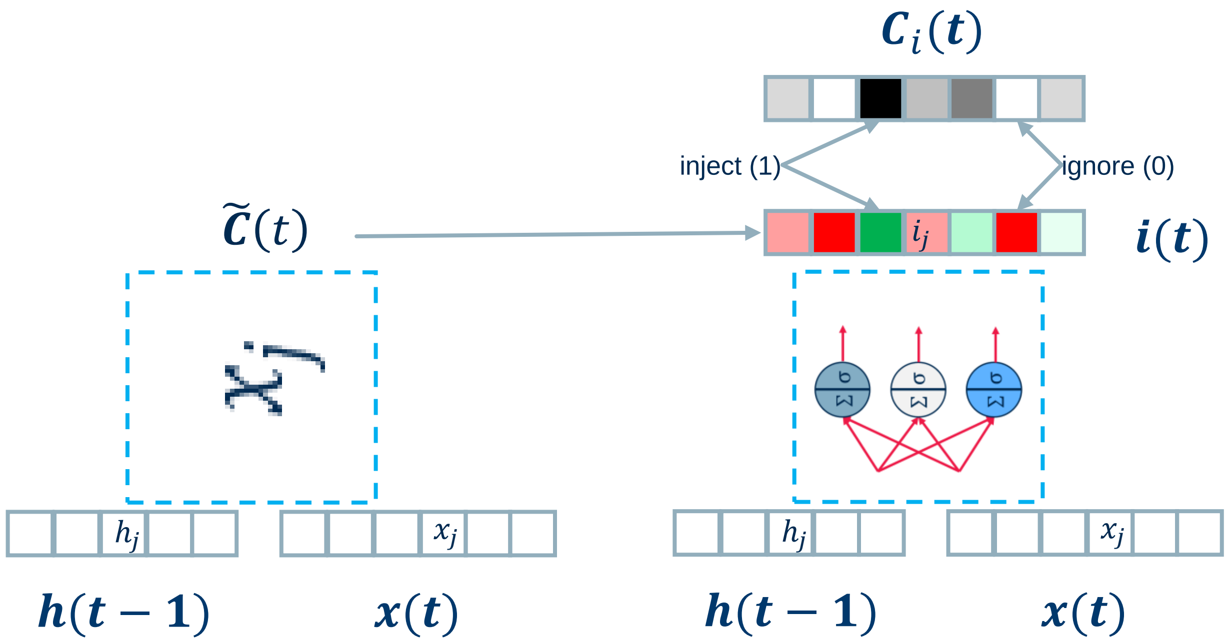

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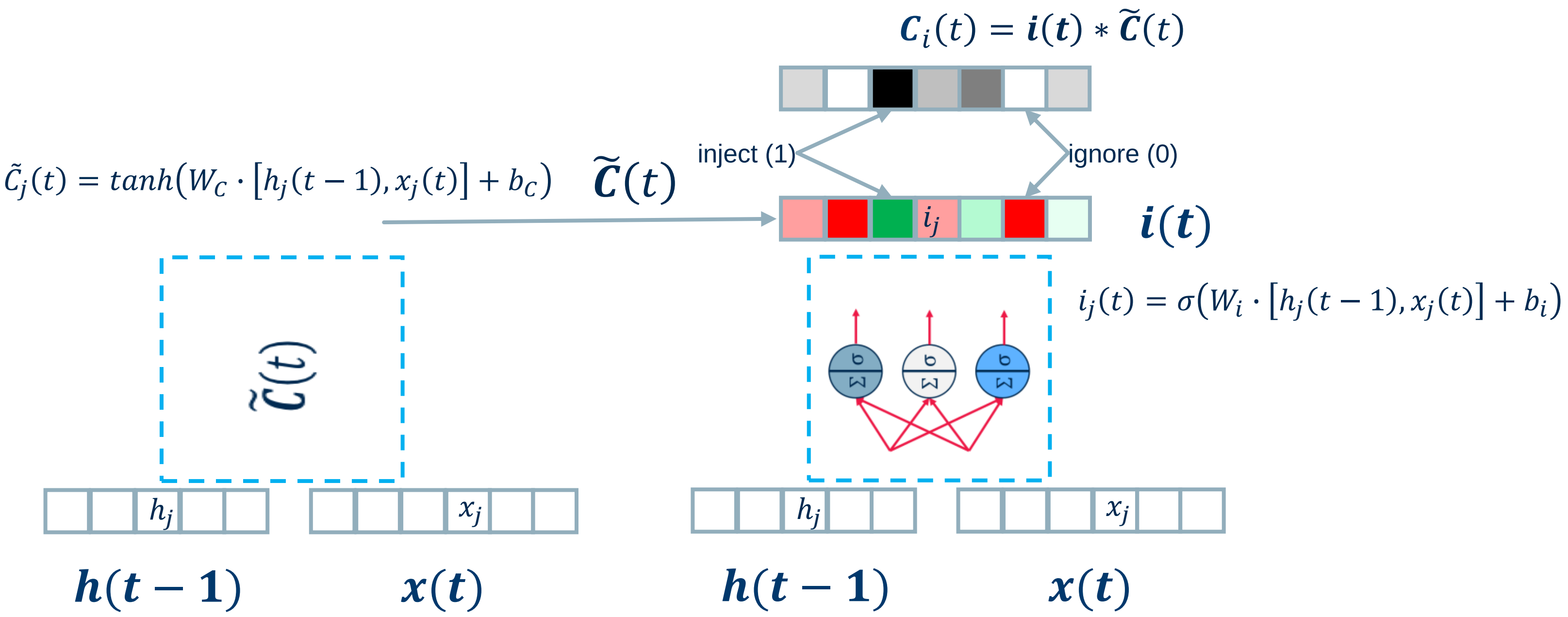

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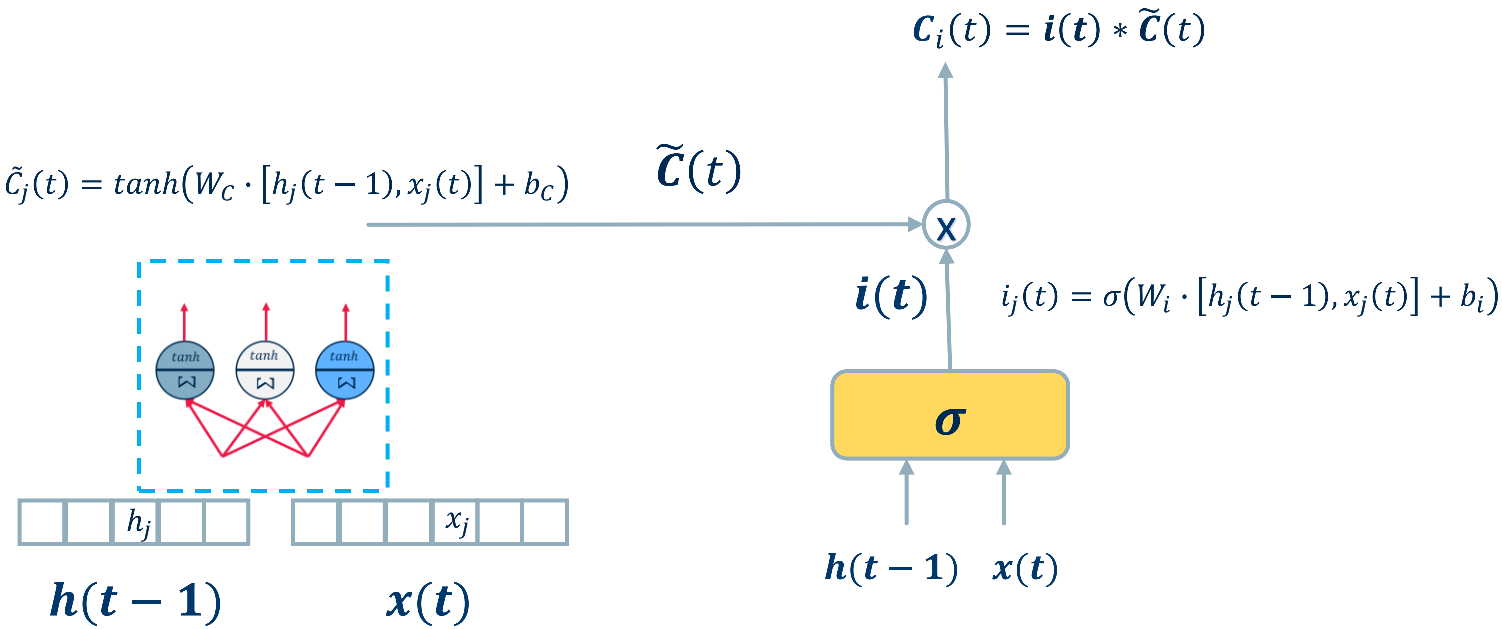

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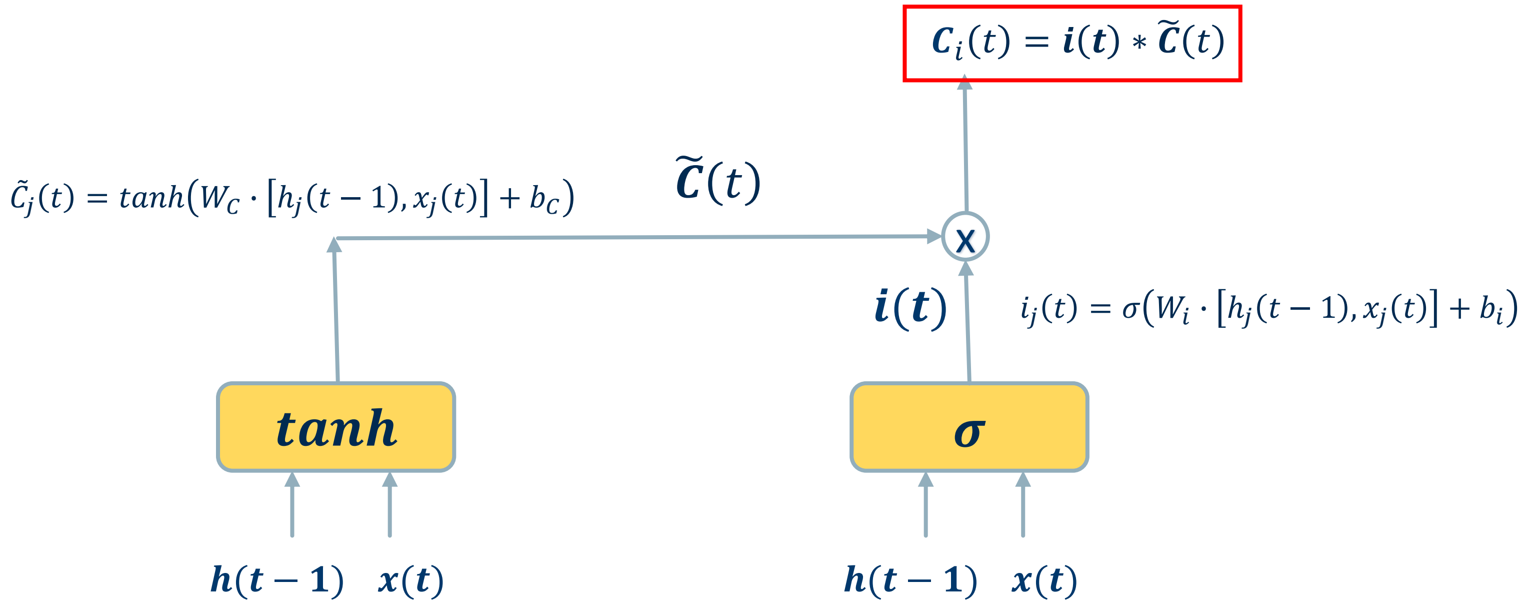

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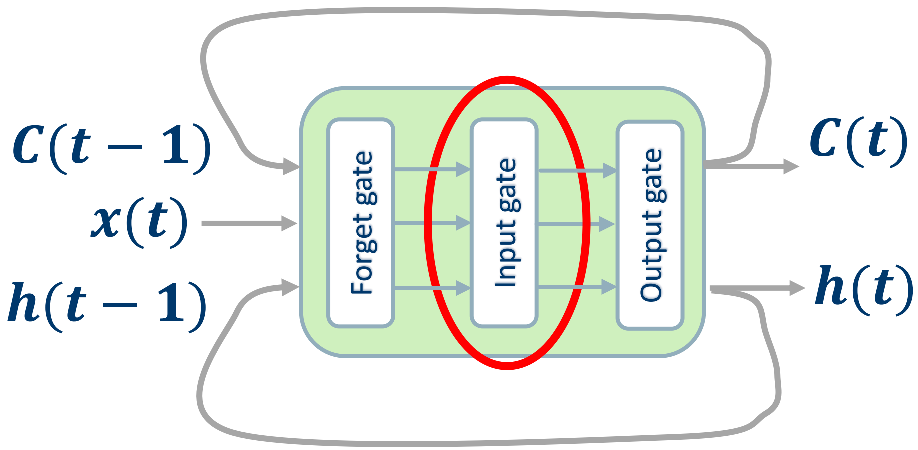

$$\boxed{C(t) = C_f(t) + C_i(t) = f(t) * C(t-1) + i(t) * \tilde{C}(t)}$$

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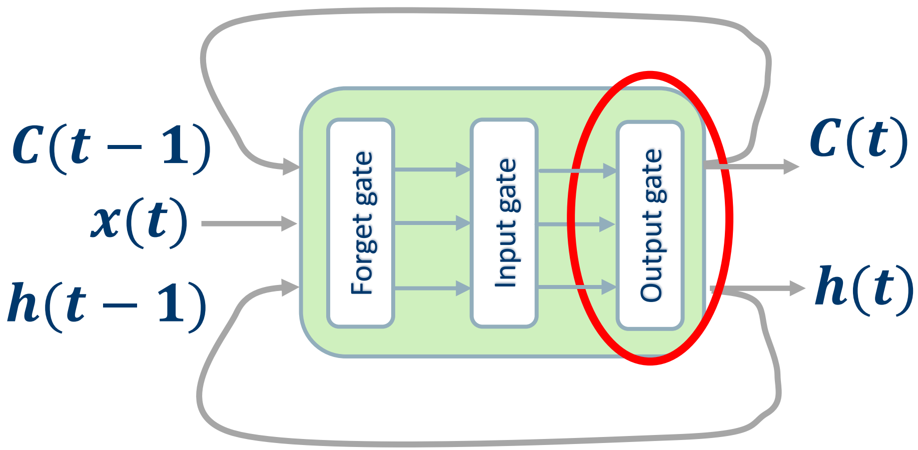

- ***Output Gate*** is trained to output a reasonable result.
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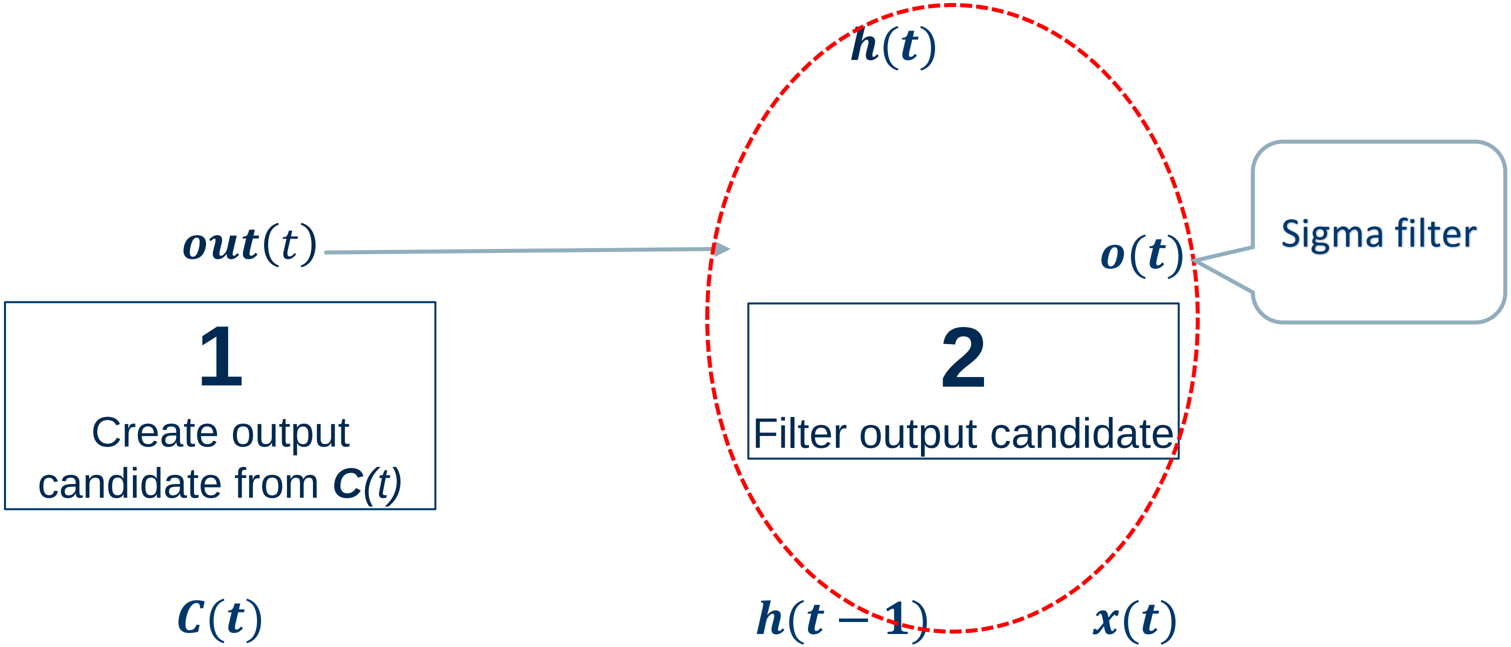

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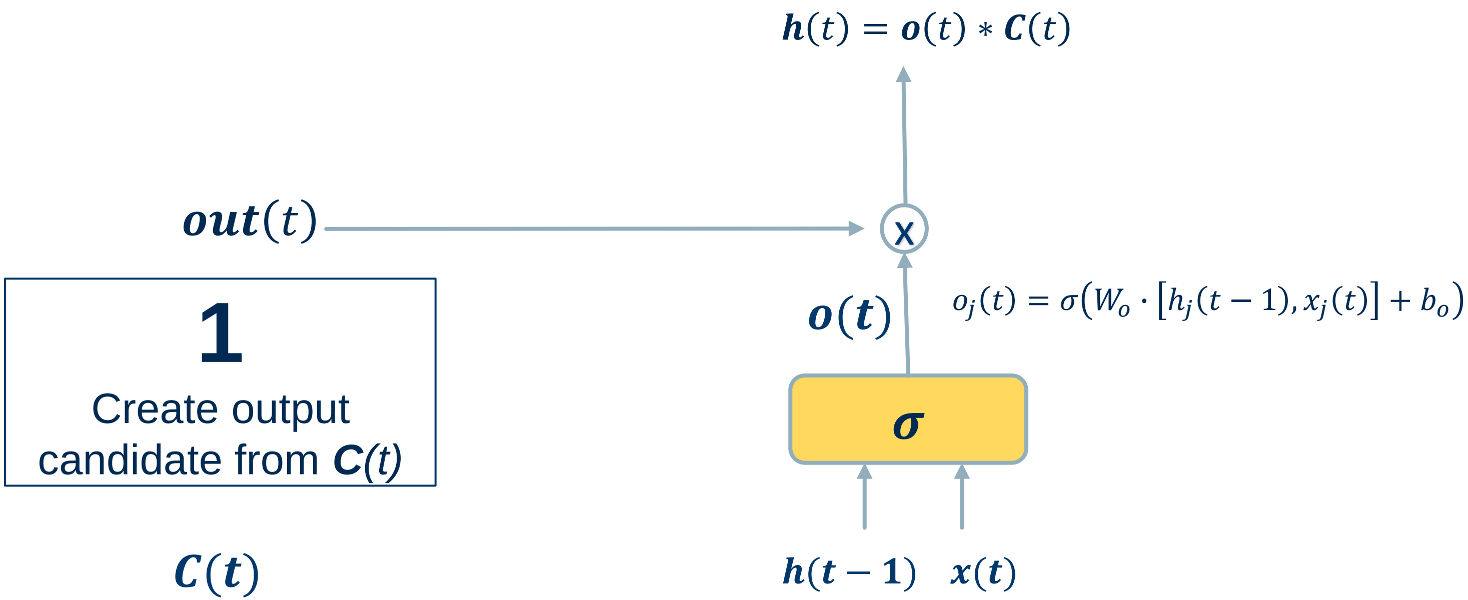

LSTM: Input Gate – prepare output candidate

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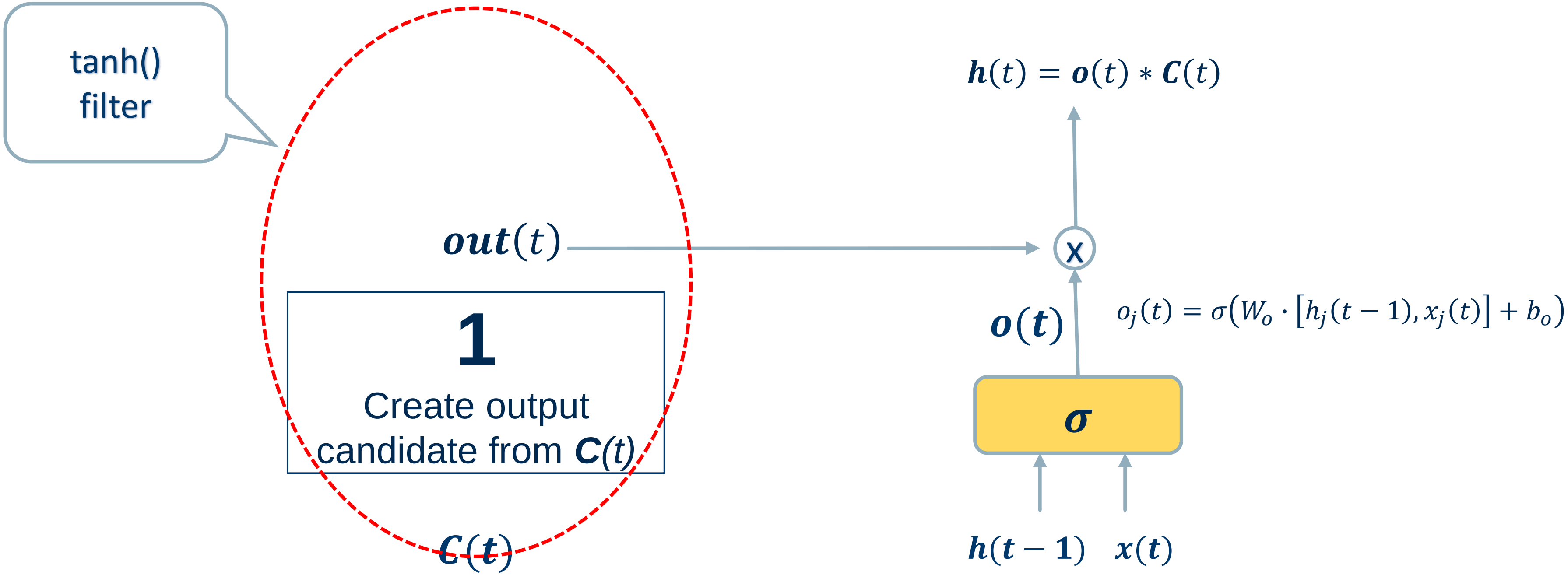

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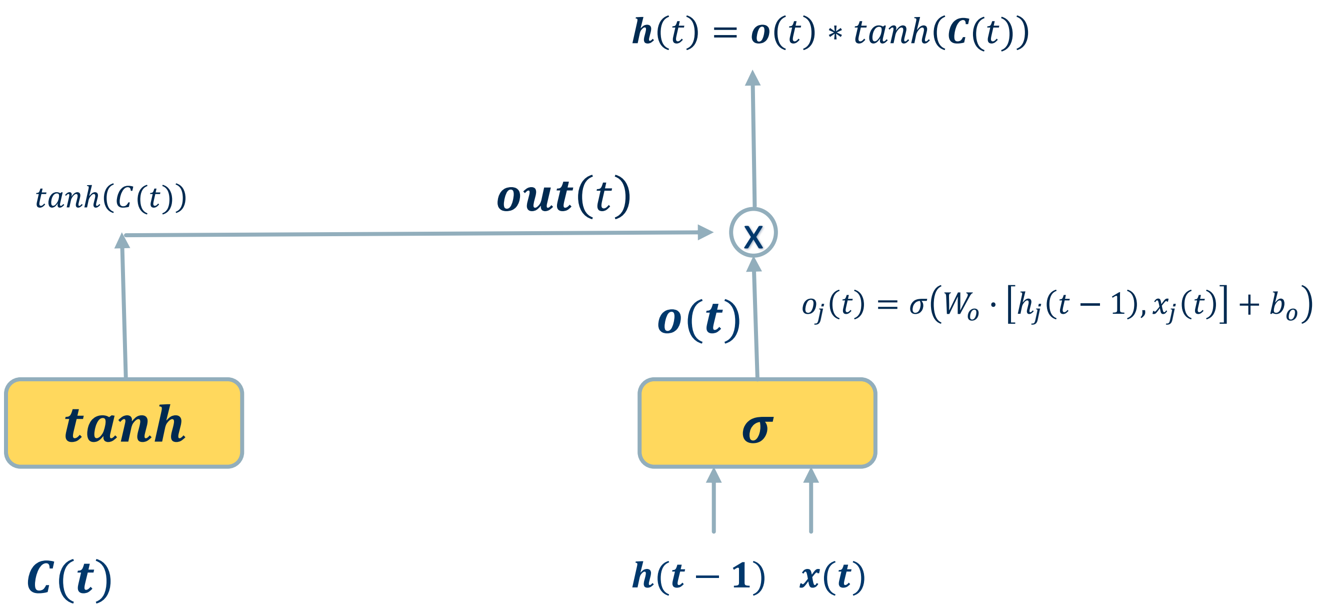
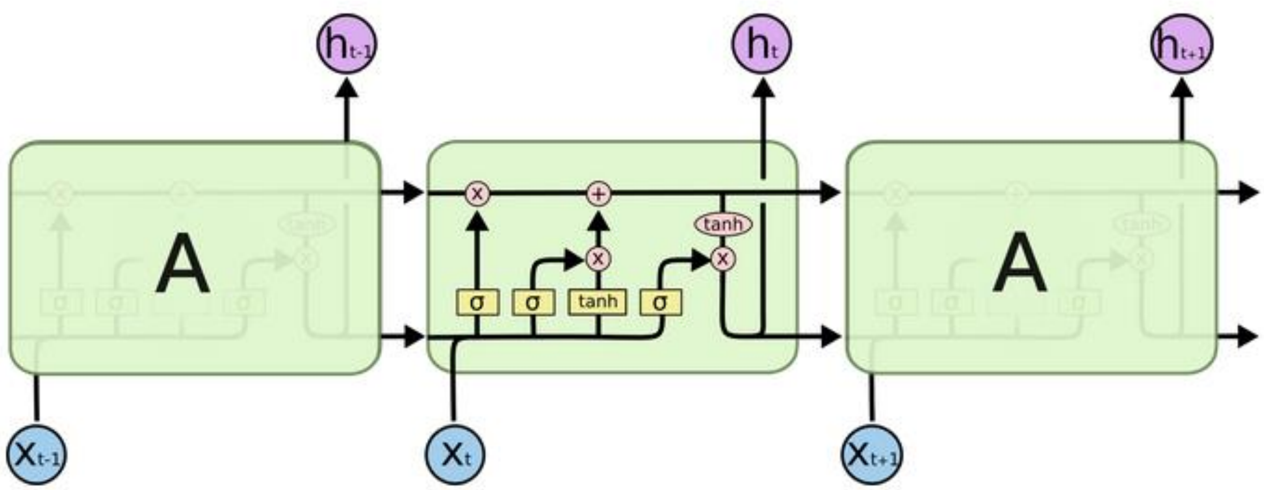


LSTM = Long Short Term Memory

Special type of unit with three gates:

Forget gate | Input gate | Output gate



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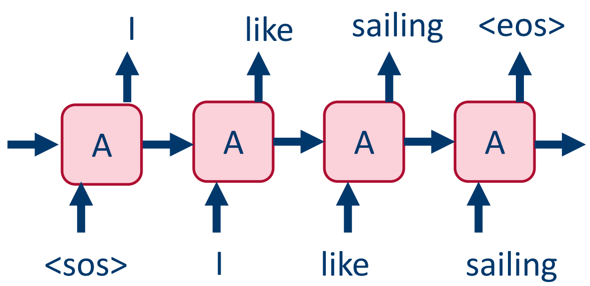
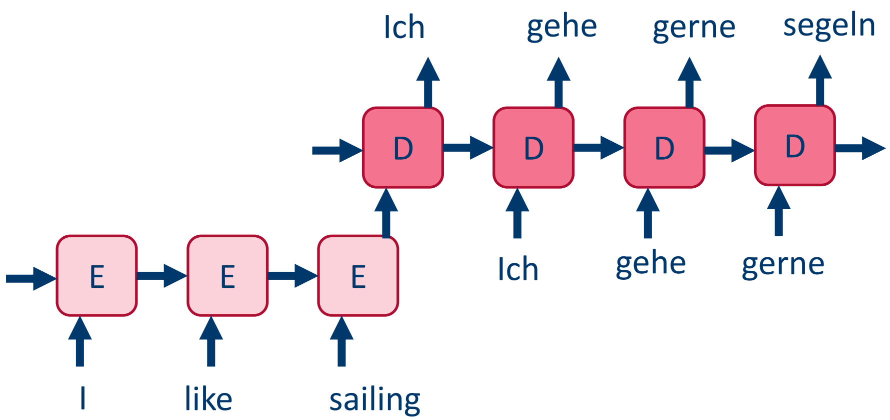
Many to Many



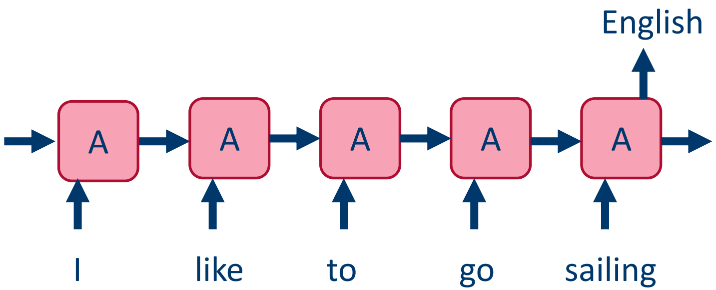


Language model

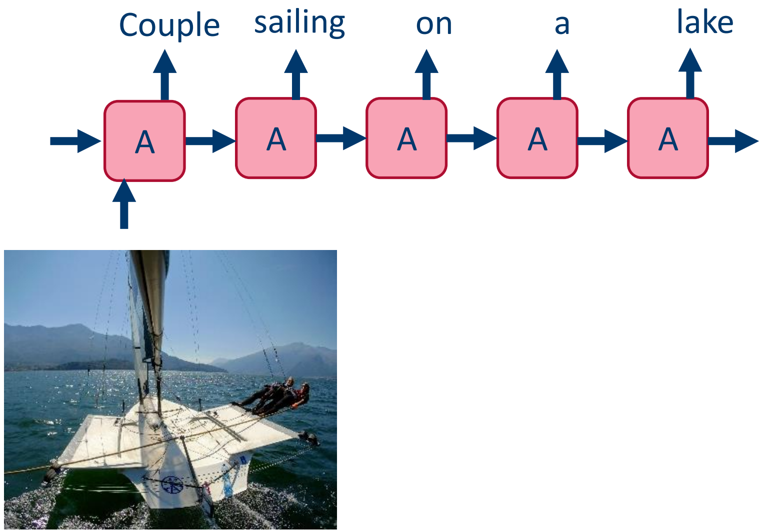
Neural machine translation

Different Network-Structures and Applications

Many to one



One to many

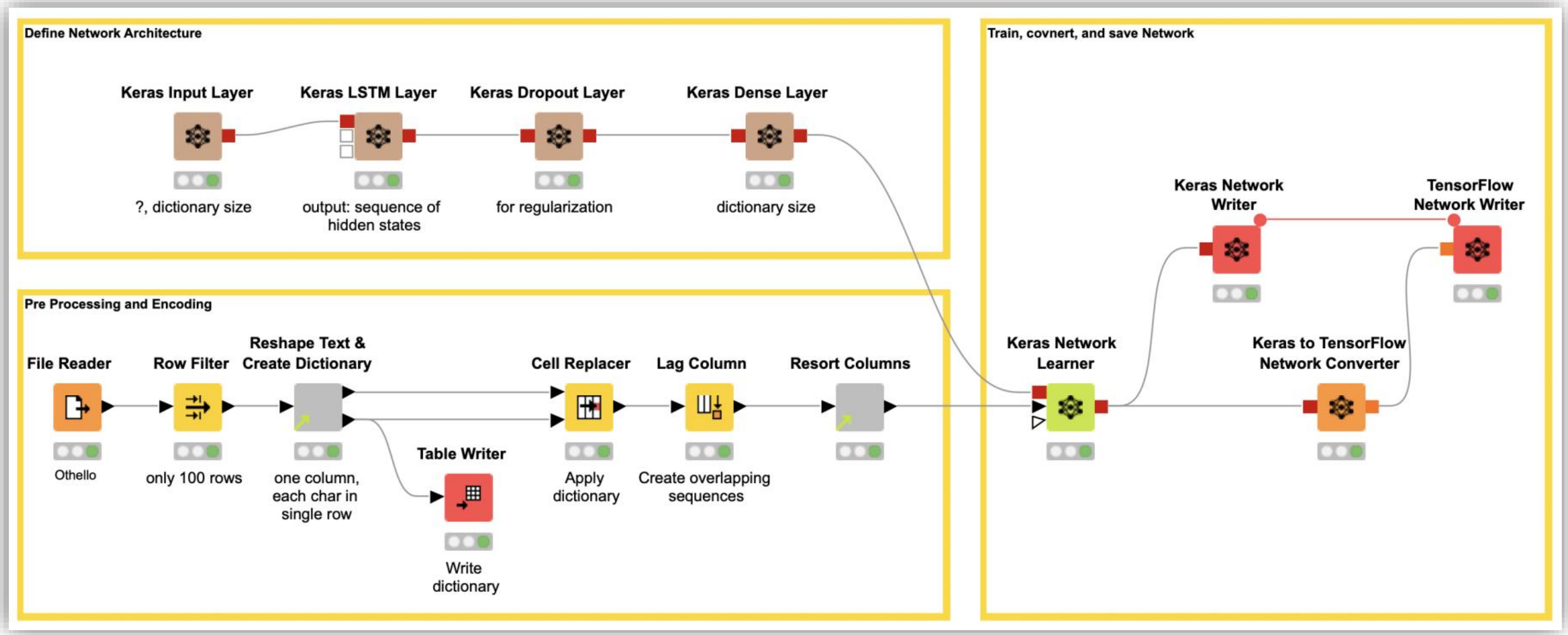


Language classification

Text classification

Image captioning

Neural Network: Code-free Example



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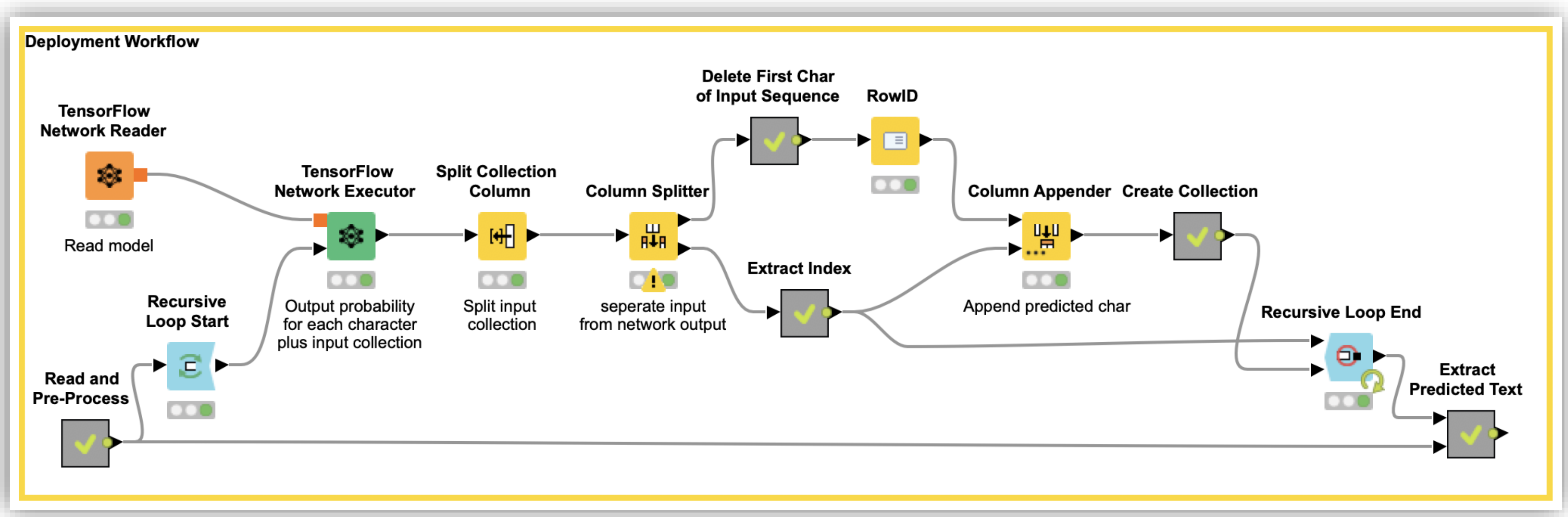
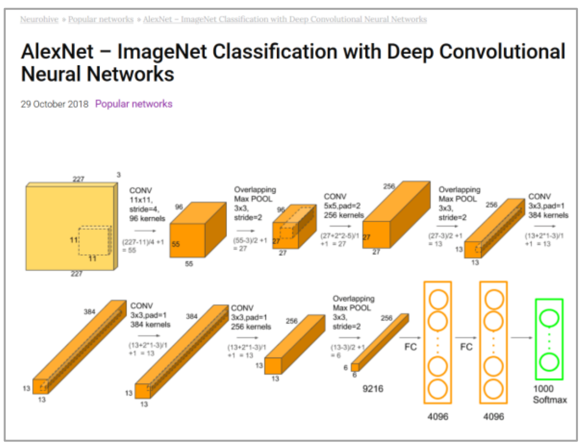


Convolutional Neural Networks (CNNs)

- The big breakthrough in deep learning happened in 2012 with deep convolutional neural networks
- Here deep learning based AlexNet network won the ImageNet challenge with an unprecedented margin.
- The top-five error rate of AlexNet was 15 percent, while the next best competitor ended up with 26 percent.
- This victory kicked off the surge in deep learning networks.



https://neurohive.io/en/popular-networks/alexnet-imagenet-classification-with-deep-convolutional-neural-networks/

- Inspired by the organization of the visual cortex in the human brain, convolutional layers simulate the concept of a receptive field.
- Individual neurons in the convolutional layer respond only when a specific area of the image (the visual field) is active.
- An array of such neurons covers the entire image by responding to slightly overlapping separated areas of the input image.

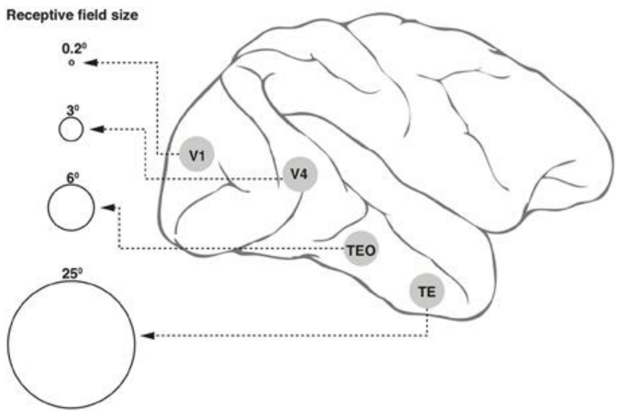
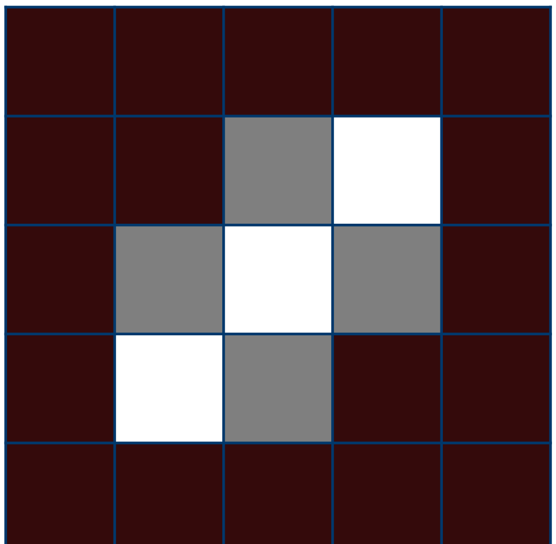


Image from: Wikimedia commons – https://commons.wikimedia.org/wiki/File:Receptive_field_sizes_along_the_ventral_cortical_stream_in_the_primate.jpg

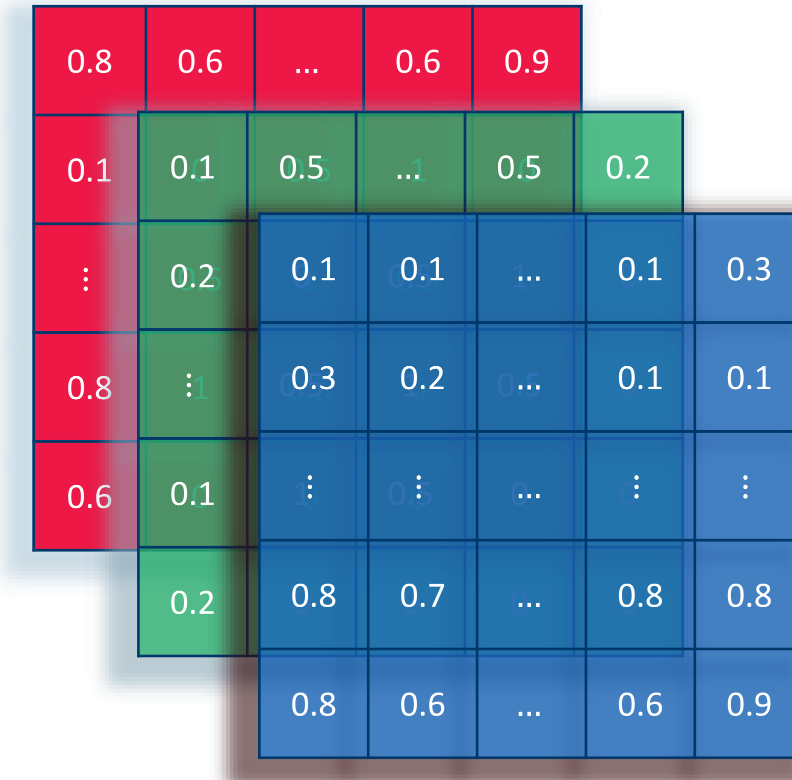
Numerical Representation of a Black and White Image



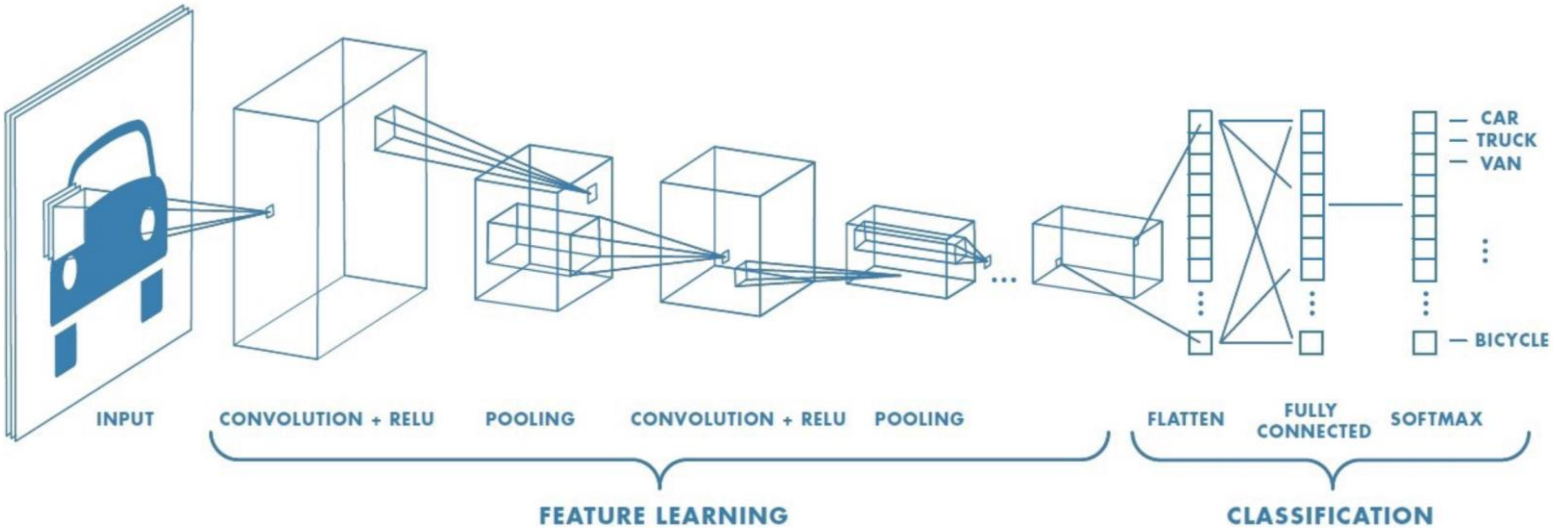
0	0	0	0	0
0	0	0.5	1	0
0	0.5	1	0.5	0
0	1	0.5	0	0
0	0	0	0	0

Numerical Representation of a Color Image

=

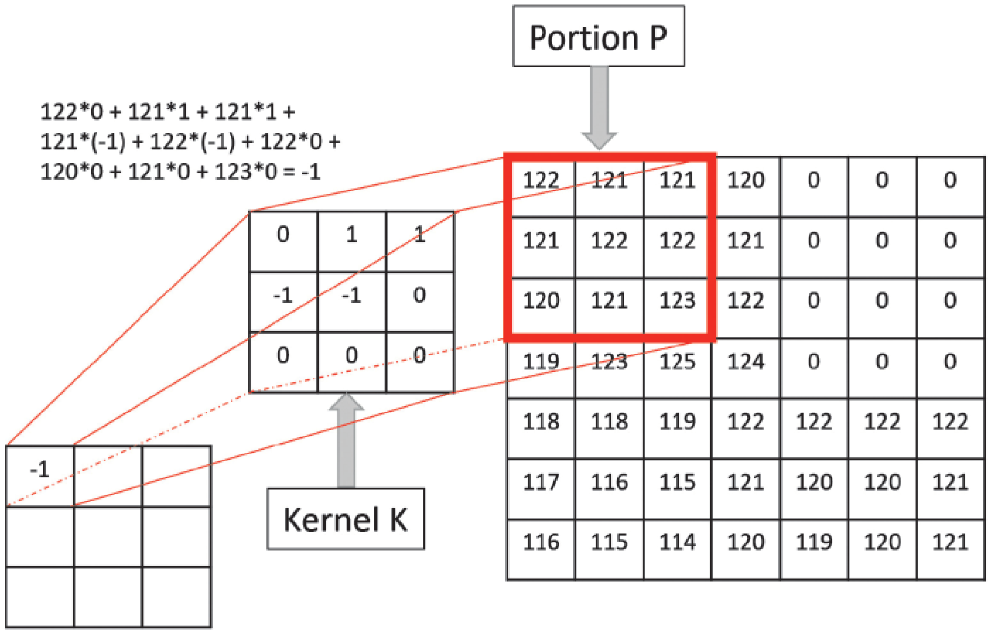


Convolutional Neural Networks



- The idea of convolution relies on a kernel *K*, a mask to overlap onto a portion *P* of the image pixels for the convolution operation.
- From the product of the kernel *K* and the pixels in portion *P* we get a number, which will be the output of the first neuron in the convolutional layer.
- Then the kernel *K* moves *n* steps on the right and goes to cover another portion *P* of the image possibly slightly overlapping with the previous one; the output for the second unit of the convolutional layer is generated.
- And so on till the whole image has been covered by the kernel *K* and convoluted into output values.
- The distance in number of pixels *n* between two adjacent portions *P* is called *stride*.

Convolutional Neurons: Example



- Zero padding
  - Artificially increases the input at the boundary
  - Helps with preserving the spatial resolution and alignment

- Stride
  - The *jump* the kernel makes when moving over the input
  - Reduces the spatial resolution

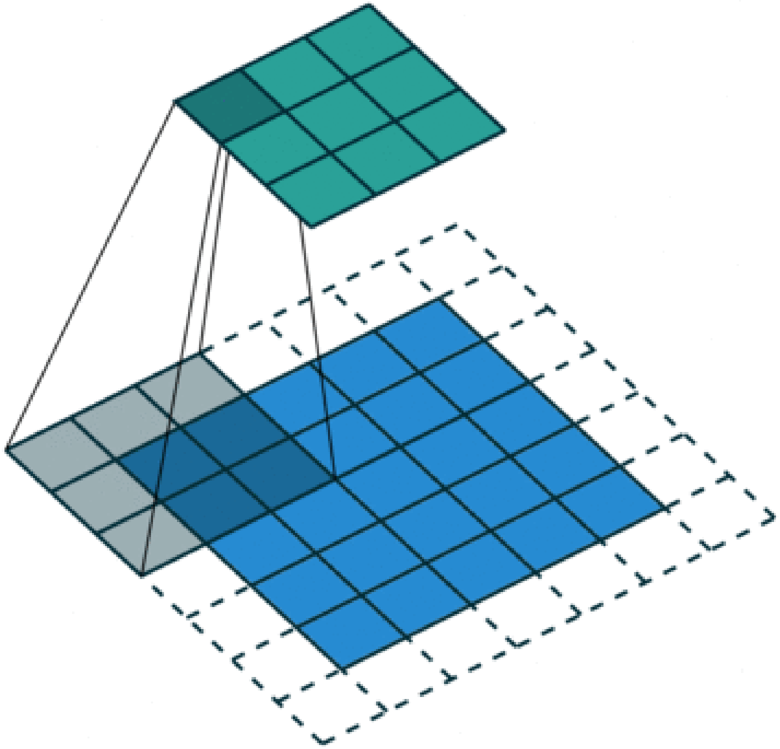
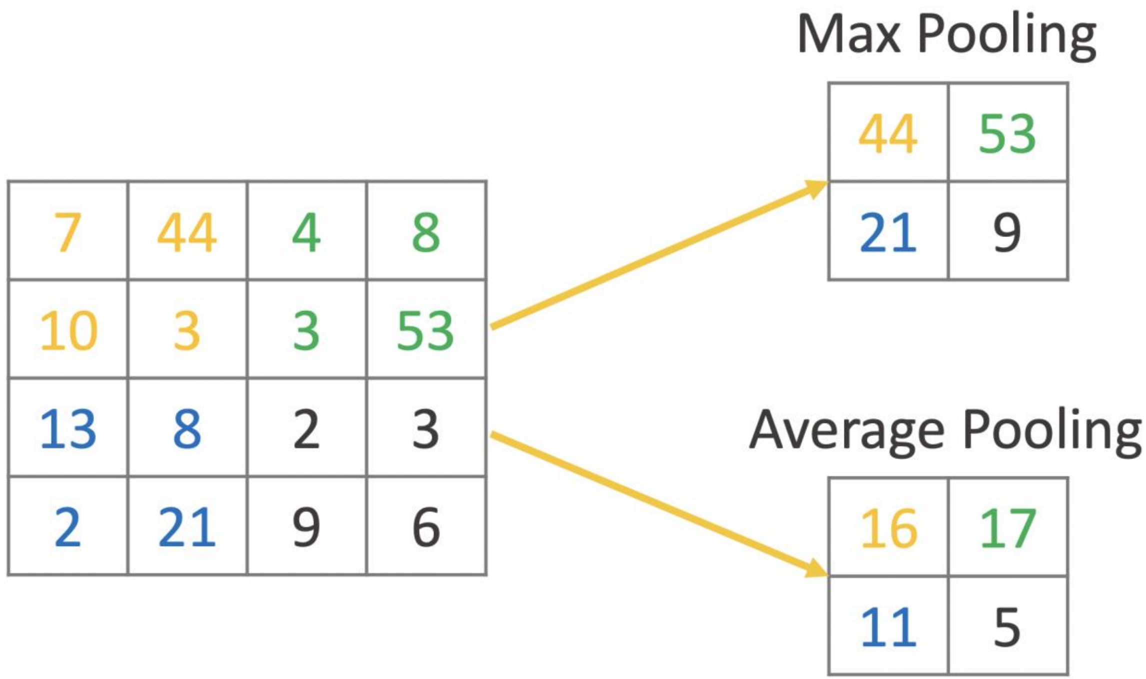


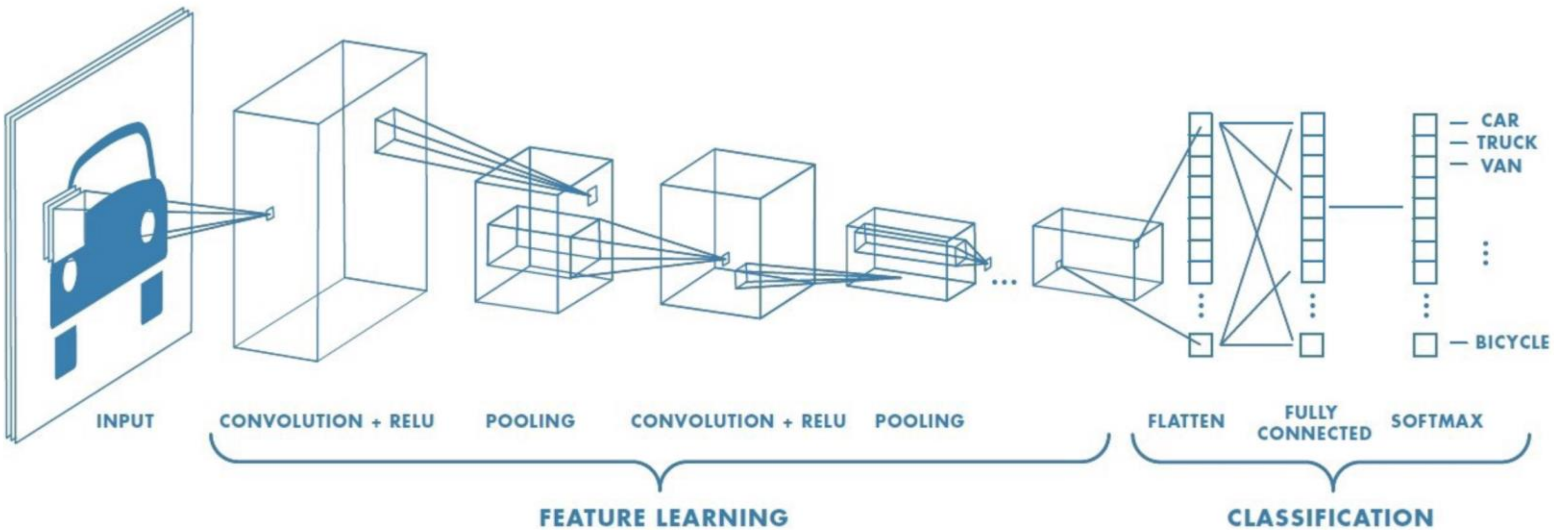
Image from: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

- Usually a number of convolutional layers are used.
- Each layer provides one further step in the process of extracting high-level features from the input image (colors, edges, entities, …).
- *Pooling layers* are often used to reduce the spatial resolution in between convolutional layers to
  - Increase the *receptive field* of the following layers
  - Reduce computational complexity
- Two types of Pooling
  - **Max Pooling** returns the **maximum value** from the portion of the image covered by the Kernel.
  - **Average Pooling** returns the **average of all values** from the portion of the image covered by the Kernel.

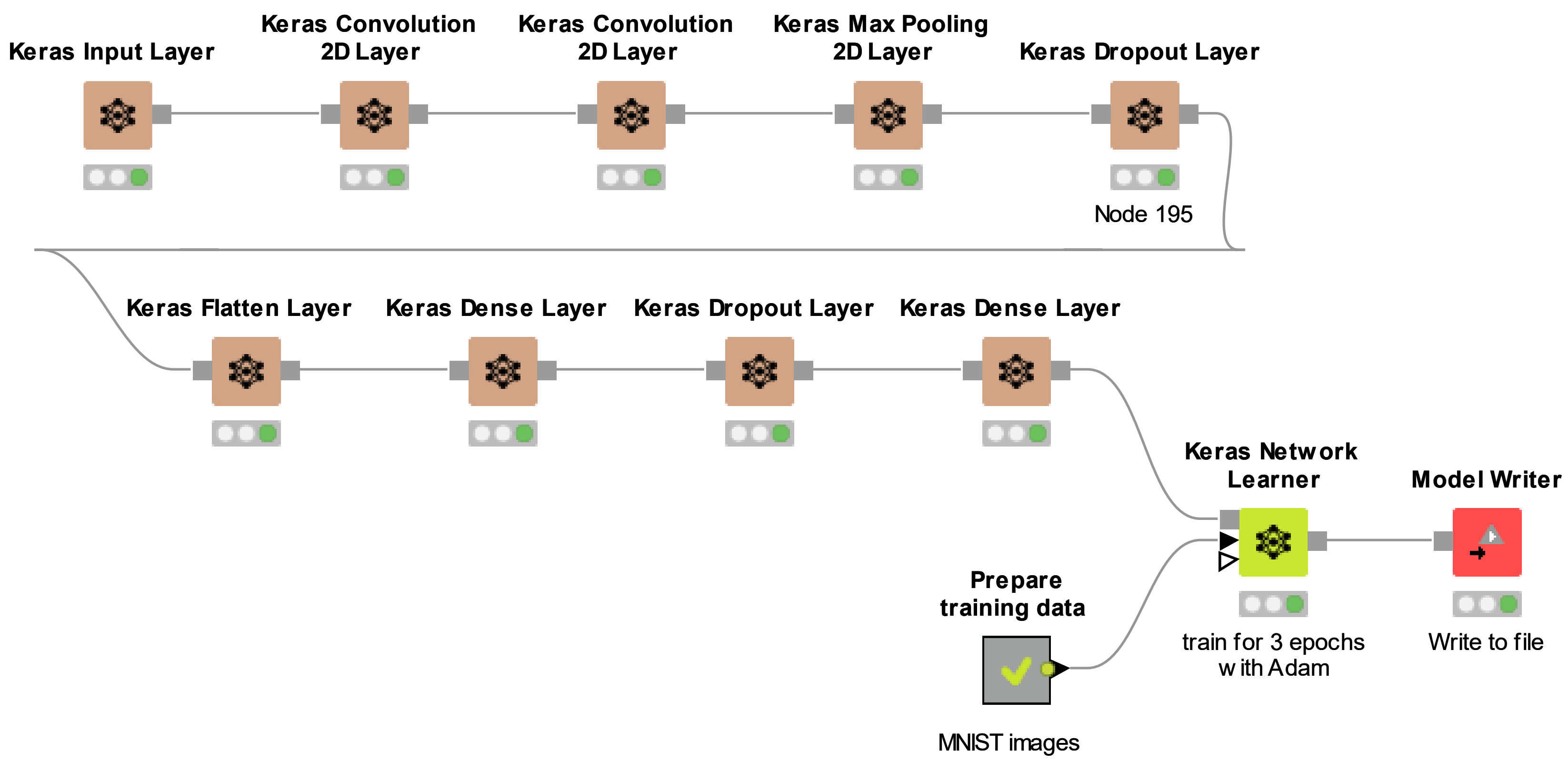
Example Pooling



- After the sequence of convolutional + pooling layers, a classic feedforward multilayer Perceptron network is applied to carry out the classification process.
- Successful examples of CNNs for image recognition : LeNet, AlexNet, VGGNet, GoogLeNet, ResNet, ZFNet.



- Training such networks is a long and complex process, requiring very powerful machines.
- Instead of retraining a new network completely from scratch, we could recycle existing networks, already built and trained by others on **similar** data.
- This technique is called ***Transfer Learning***.
- In Transfer Learning a model developed for a task is reused as the starting point for another model on a second task.
- On top of a previously trained network we add one or more neural layers
- We freeze all or some of the previously trained layers
- And we retrain only the remaining part of the whole network on our new task


Keras Input Layer
Keras Convolution 2D Layer
Keras Convolution 2D Layer
Keras Max Pooling 2D Layer
Keras Dropout Layer
Node 195
Keras Flatten Layer
Keras Dense Layer
Keras Dropout Layer
Keras Dense Layer
Keras Network Learner
Model Writer
Prepare training data
train for 3 epochs w ith Adam
Write to file
MNIST images

Generative-Adversarial Networks (GANs)

- So far: RNNs and CNNs
- Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) represent probably the biggest contribution of deep learning to the field of neural networks.
- However, deep learning is responsible for other innovations, such as for example Generative Adversarial Networks (GANs).

Can You Tell Real from Fake?

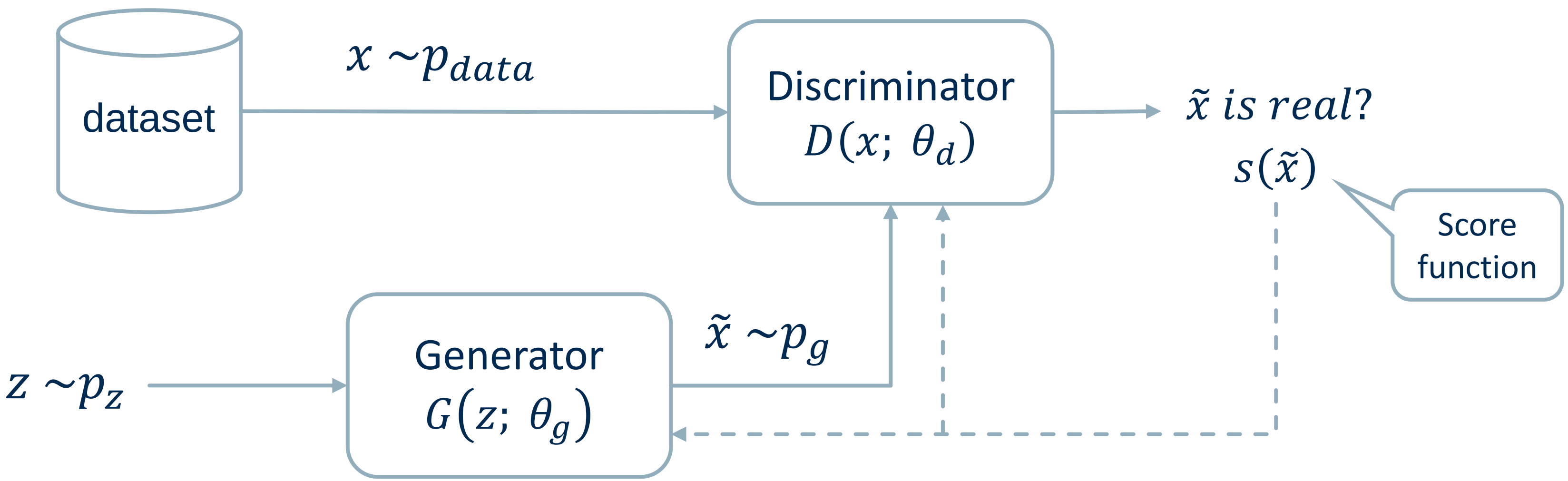
Source: https://thispersondoesnotexist.com

GAN: Generator

- GANs include two neural networks competing with each other: the generator and the discriminator.
- A **generator *G*** is a transformation that transforms the input noise z into a tensor – usually an image – x ($x=G(z)$). The generated image x is then fed into the discriminator network D.
- The **discriminator network D** compares the real images in the training set and the image generated by the generator network and produces an output D(x), which is the probability that image x is real.

GAN: Training

- Both generator and discriminator are trained using the backpropagation and gradient descent.
- Both networks are trained in alternating steps, competing with each other to improve themselves.
  - The objective of the generator is to fool the discriminator i.e. $D\big(G(z)\big) = 1$
  - The objective of the discriminator is to output $D\big(G(z)\big) = 0$ and $D(x_{real}) = 1$
- The GAN model eventually converges and produces images that look real.
- Given a training set, this technique learns to generate new data under the same statistics as the training set.


dataset
$x \sim p_{data}$
Discriminator
$D(x;\ \theta_d)$
$\tilde{x}\ is\ real?$
$s(\tilde{x})$
Score function
$z \sim p_z$
Generator
$G(z;\ \theta_g)$
$\tilde{x} \sim p_g$

- For example, a GAN trained on photographs can generate new photographs that look at least superficially authentic to human observers, having many realistic characteristics.

- GANs have been successfully applied to image tensors to create anime, human figures, and even van Gogh-like masterpieces.

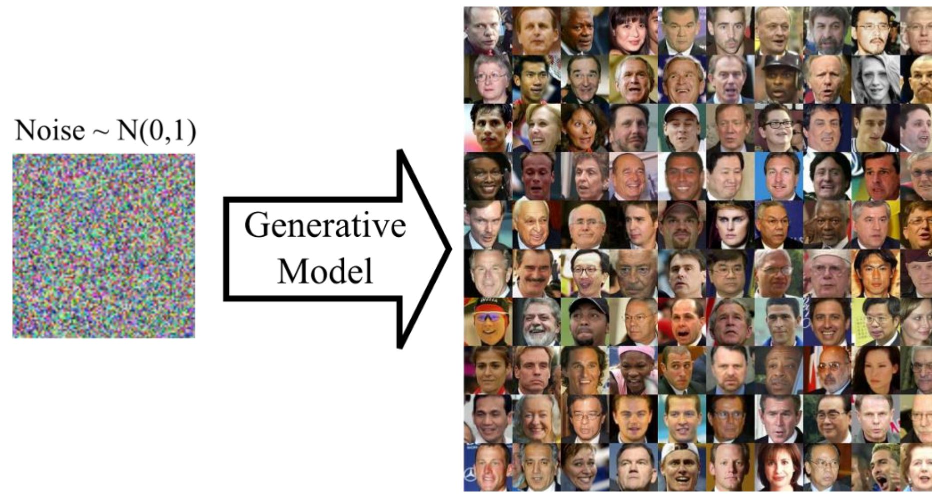


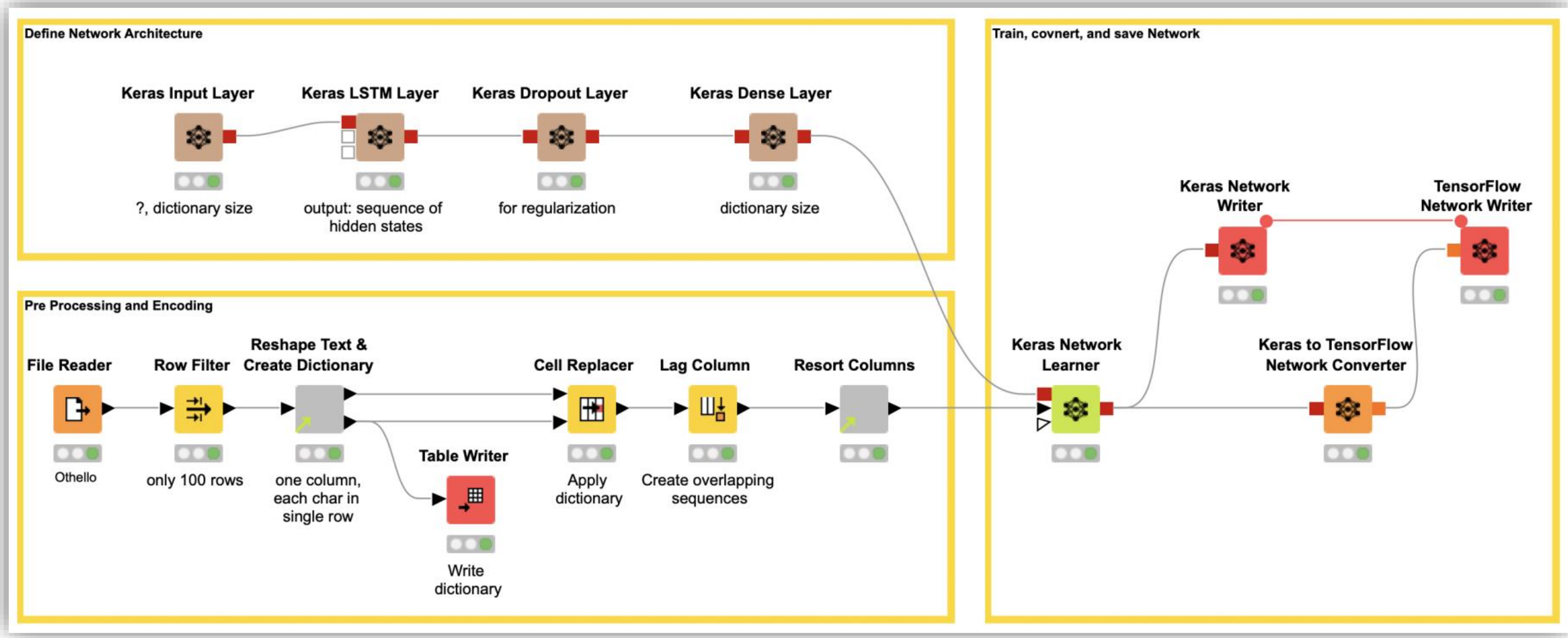
Image from: Pankaj Kishore, Towards data Science
https://towardsdatascience.com/art-of-generative-adversarial-networks-gan-62e96a21bc35

Summary

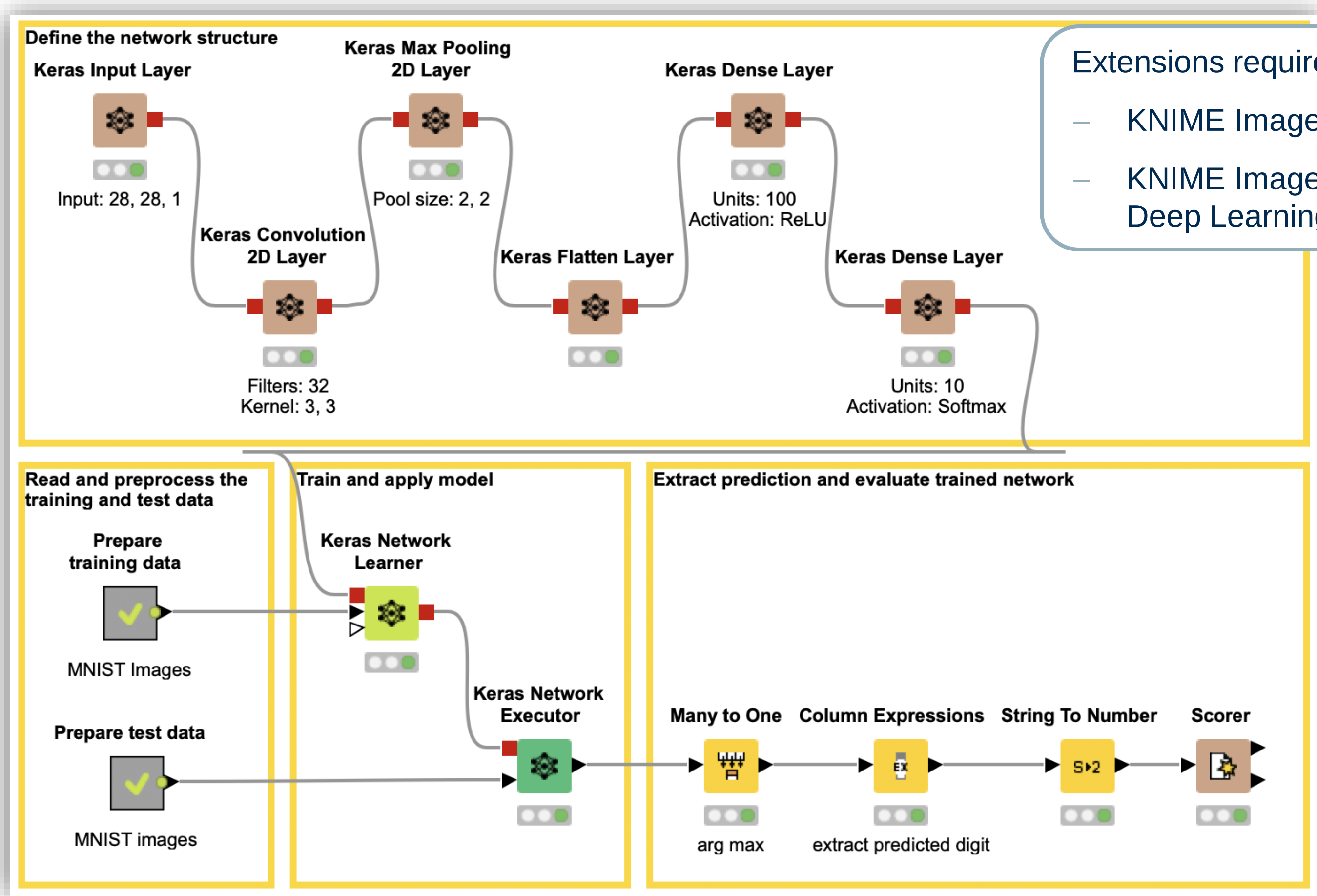
- Recurrent Neural Networks (RNNs)
- Long Short Term Memories (LSTMs)
- Convolutional Neural Networks (CNNs)
- Generative Adversarial Networks (GANs)

Practical Examples with KNIME Analytics Platform

RNN Workflow: Text Generation



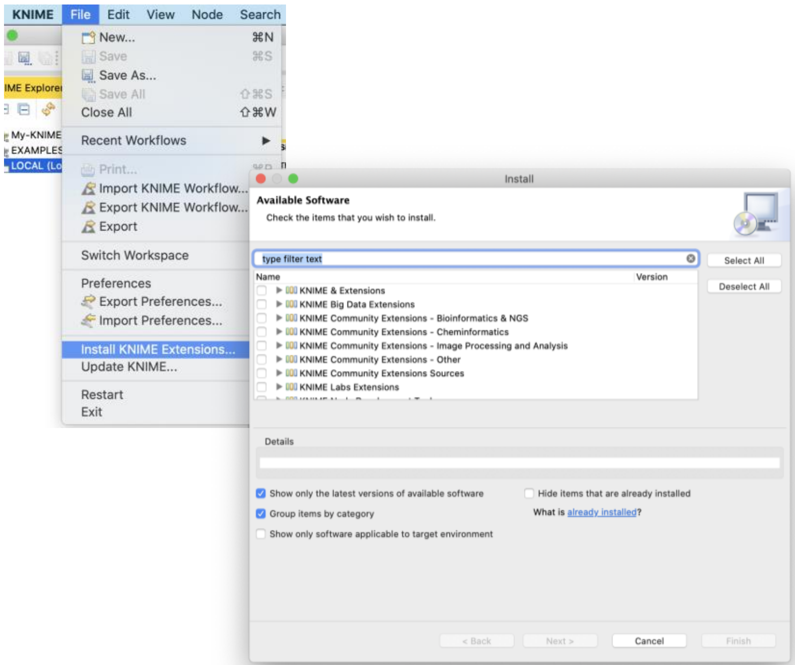
CNN Workflow: Image Classification using MNIST

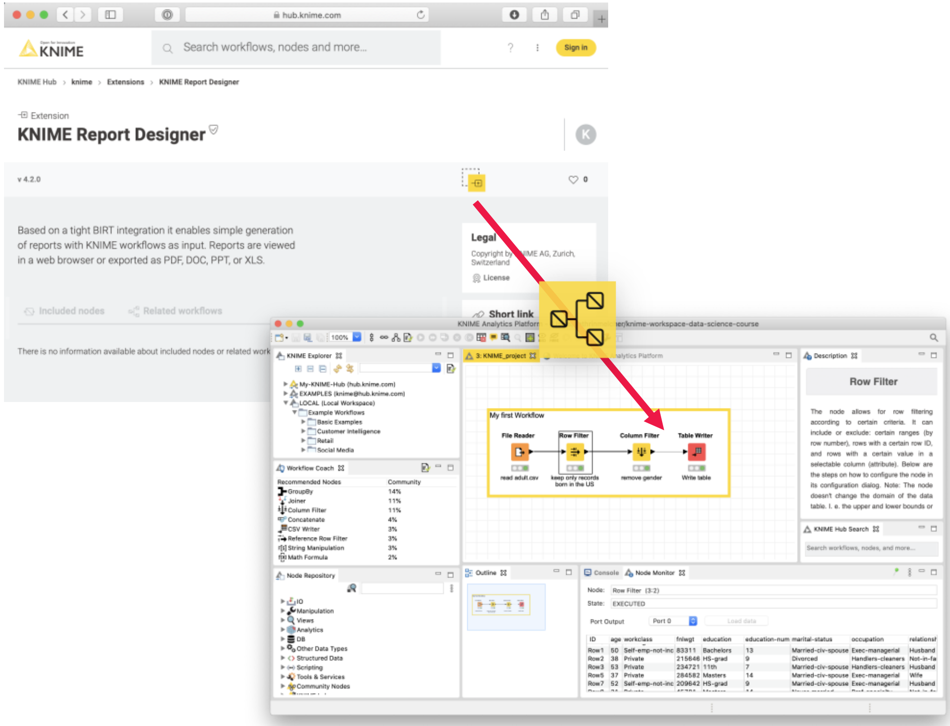


Extensions required:

- KNIME Image Processing
- KNIME Image Processing – Deep Learning Extension

– Install extension by going to File -> Install KNIME Extension or via Drag & Drop from the KNIME Community Hub





Thank you