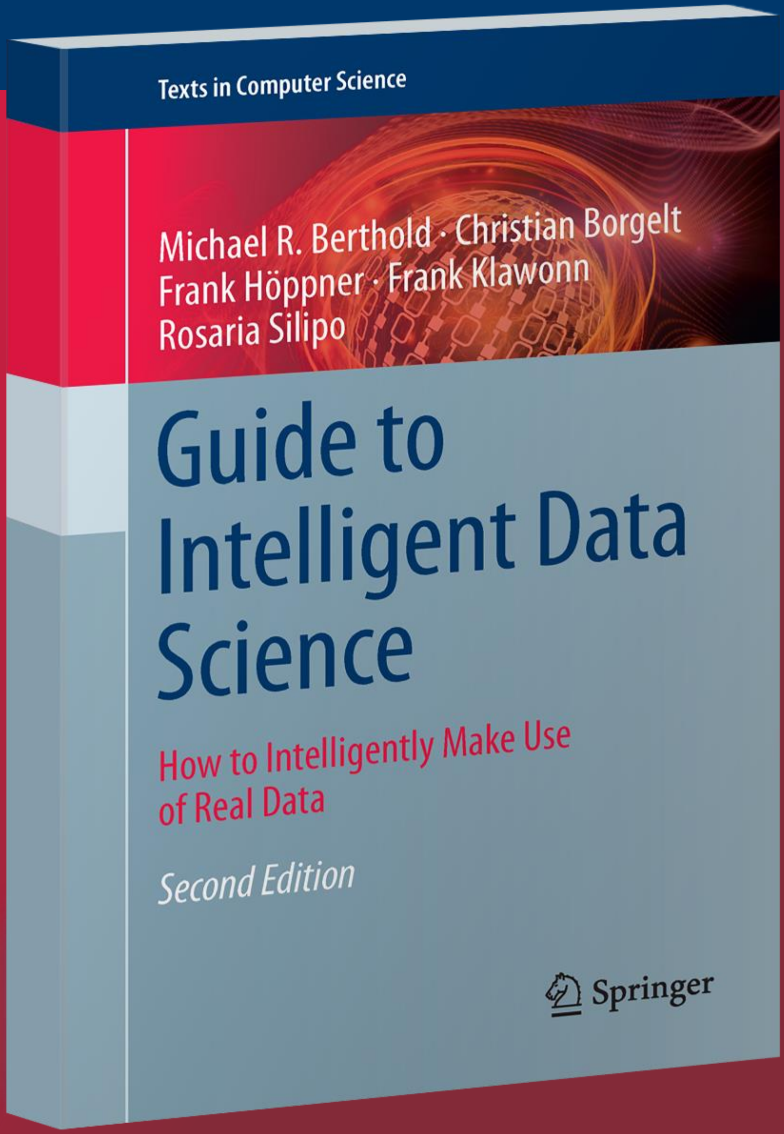
# Deep Learning




Caption

# 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*

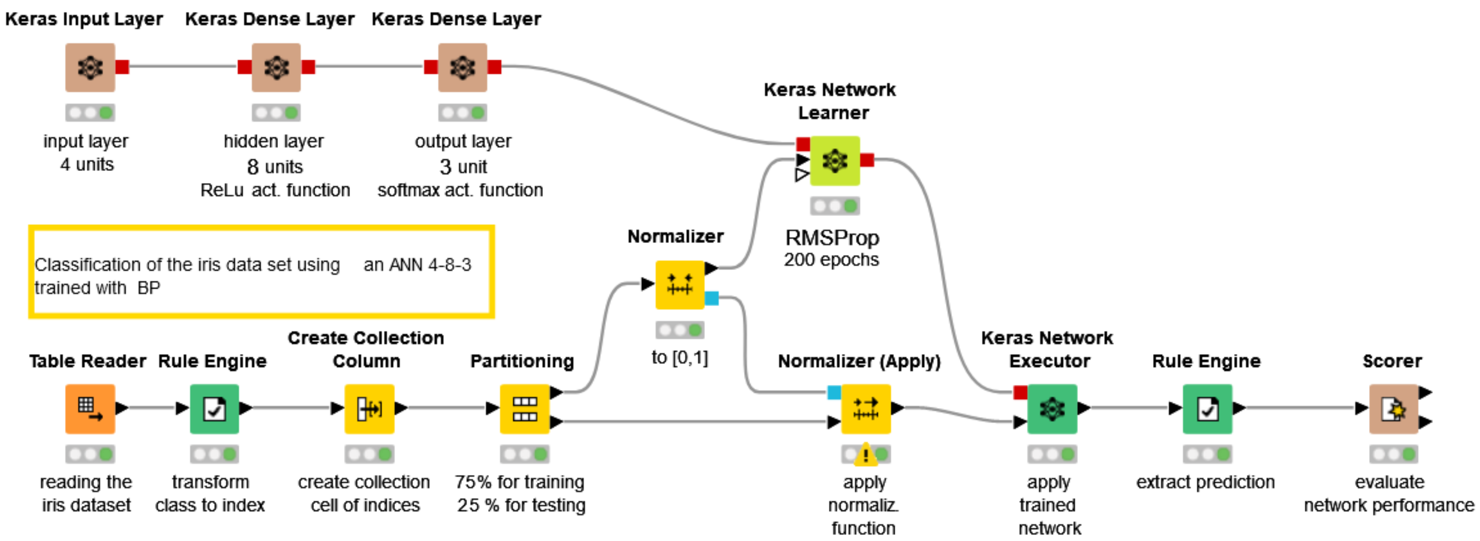
How deep can we dig in AI?

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

# Content of this Lesson

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

- Datasets used : iris dataset
- Example Workflows:
  - „Classifying the iris data set with ANN“ https://kni.me/w/ei3eX9Sj5-RFEUat
    - Keras layers
    - Multi-layer perceptrion
    - Back propagation



- 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?

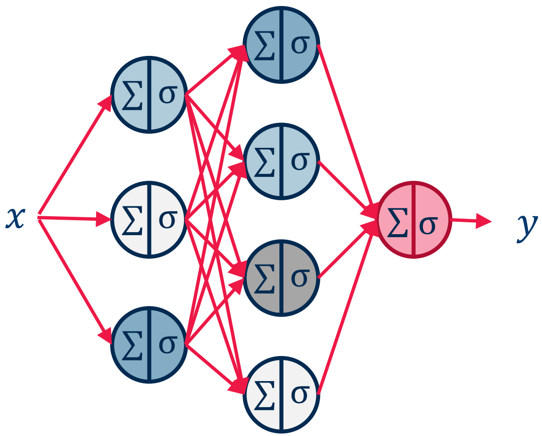
- **R**ecurrent **N**eural **N**etworks (RNNs) are a family of neural networks suitable for processing of sequential data
- RNNs include auto and backward connections

- 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
  - …

# Why do we need RNNs for Sequential Data?

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

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




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

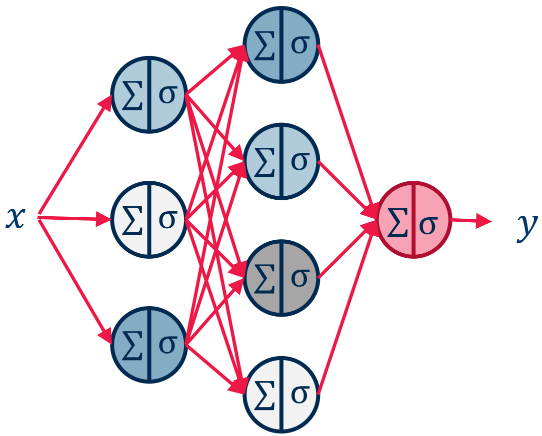
| Input x | Output y |
|---|---|
| Ich | I |
| mag | like |
| Schokolade | chocolate |

- But what happens with this question?

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

# Why do we need RNNs for Sequential Data?

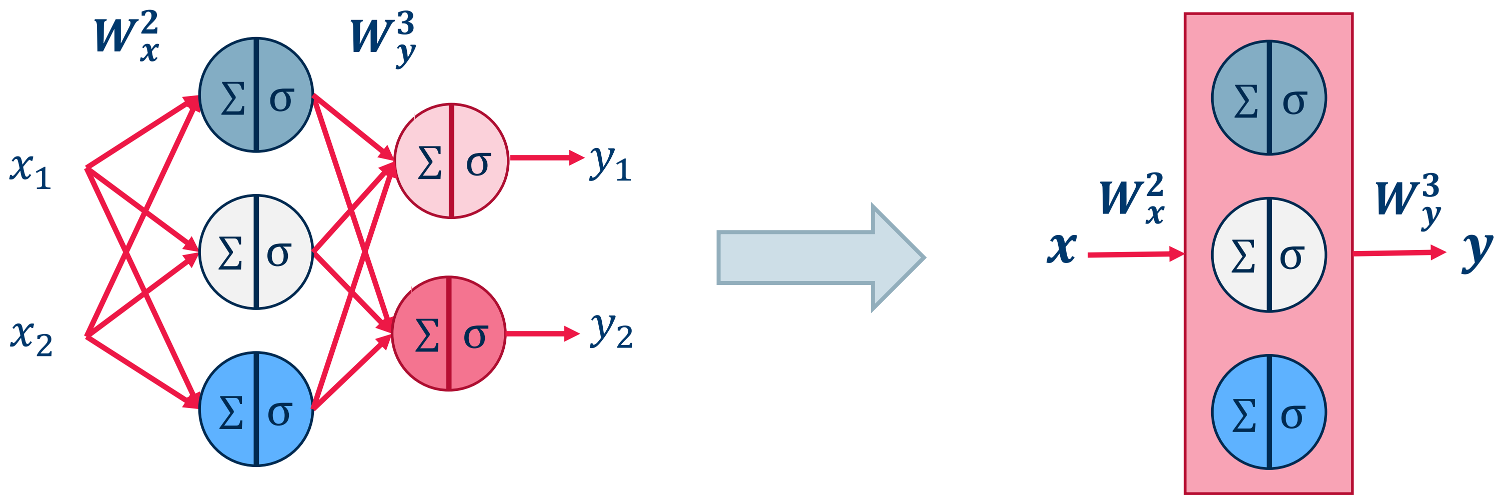
- Problems with FFNN:
  - Each time step is completely independent
  - For translations we need context
  - More general: we need a network that remembers inputs from the past



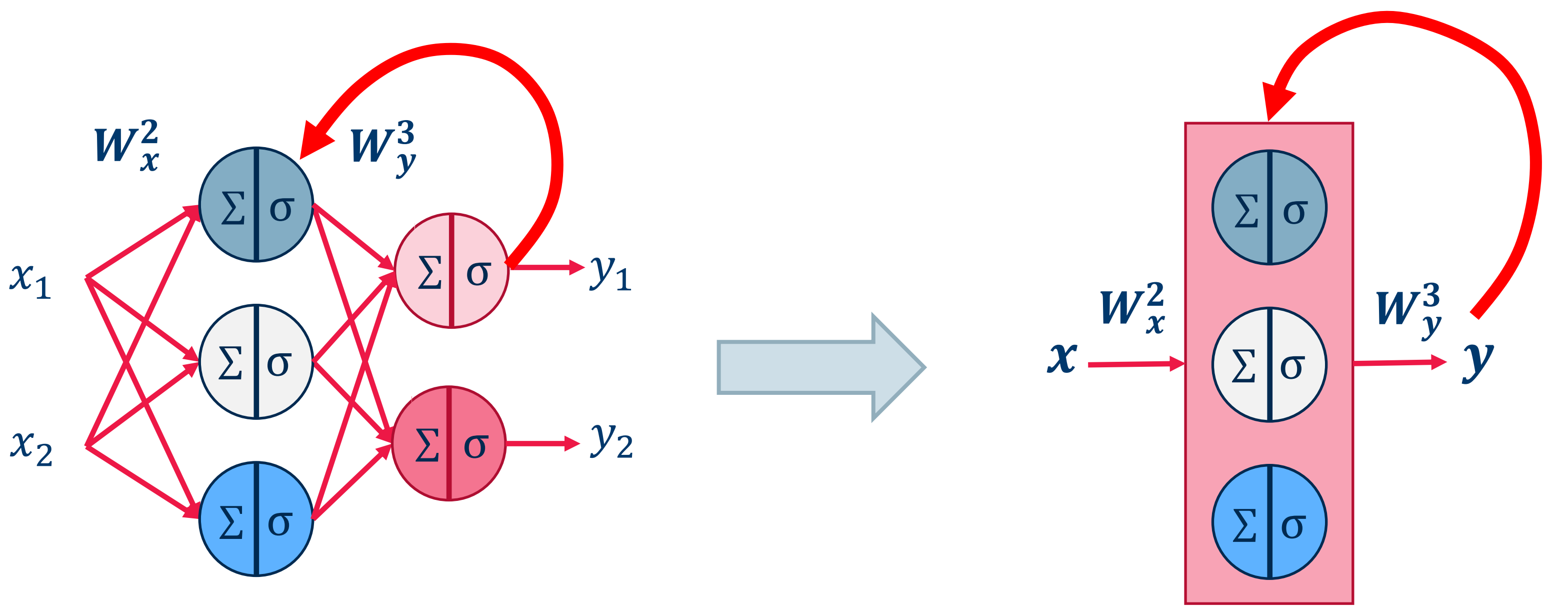

- **Solution**: Recurrent Neural Networks

| Input | Output y |
|---|---|
| Mag | Like |
| Ich | I |
| Schokolade | chocolate |

# From Feed Forward to Recurrent Neural Networks

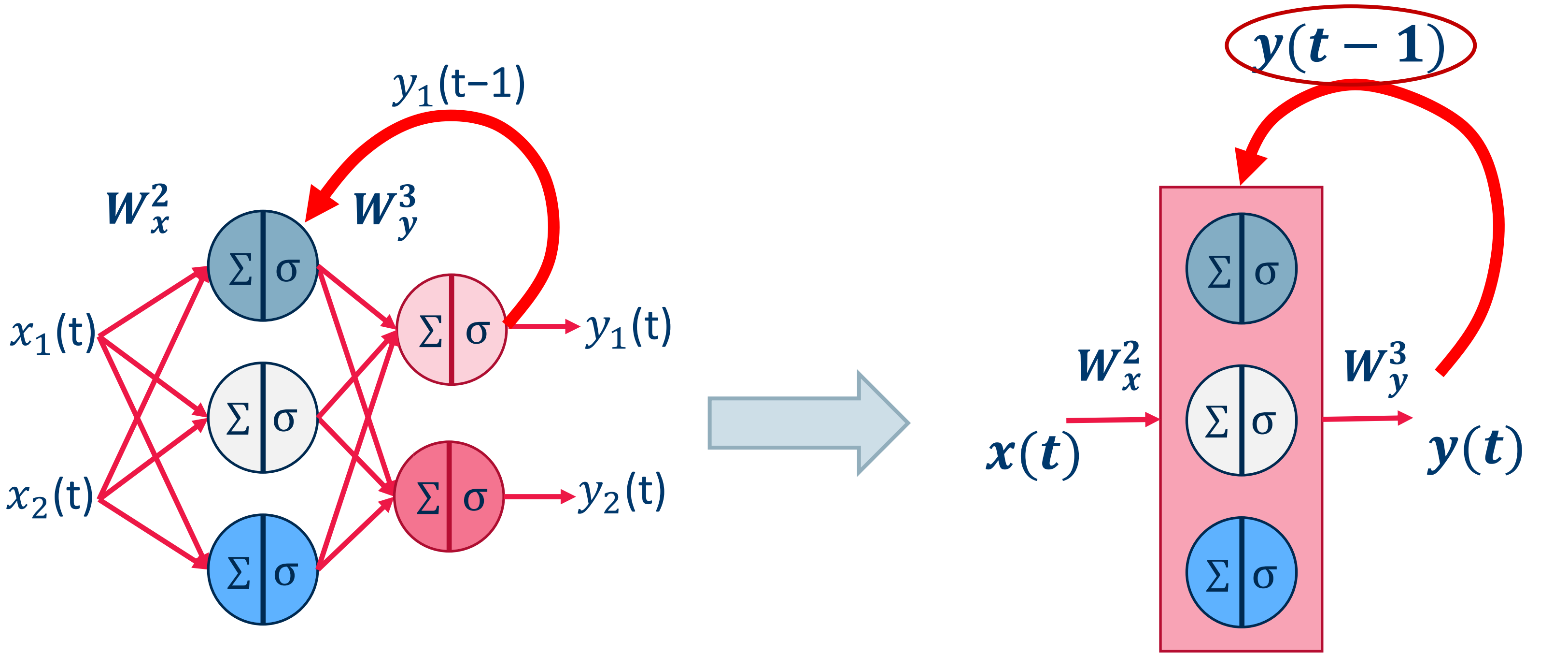


# From Feed Forward to Recurrent Neural Networks




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

# From Feed Forward to Recurrent Neural Networks

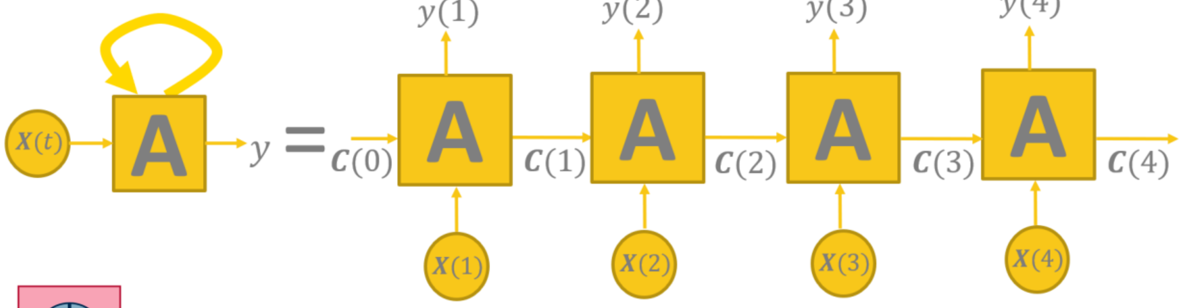


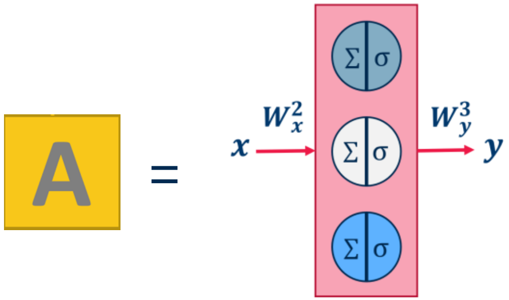

- A Recurrent Neural Network is a FFNN with auto and/or backward connections
- Recurrent connections introduce the concept of **time** in FFNNs

# How can we represent a RNN over time?

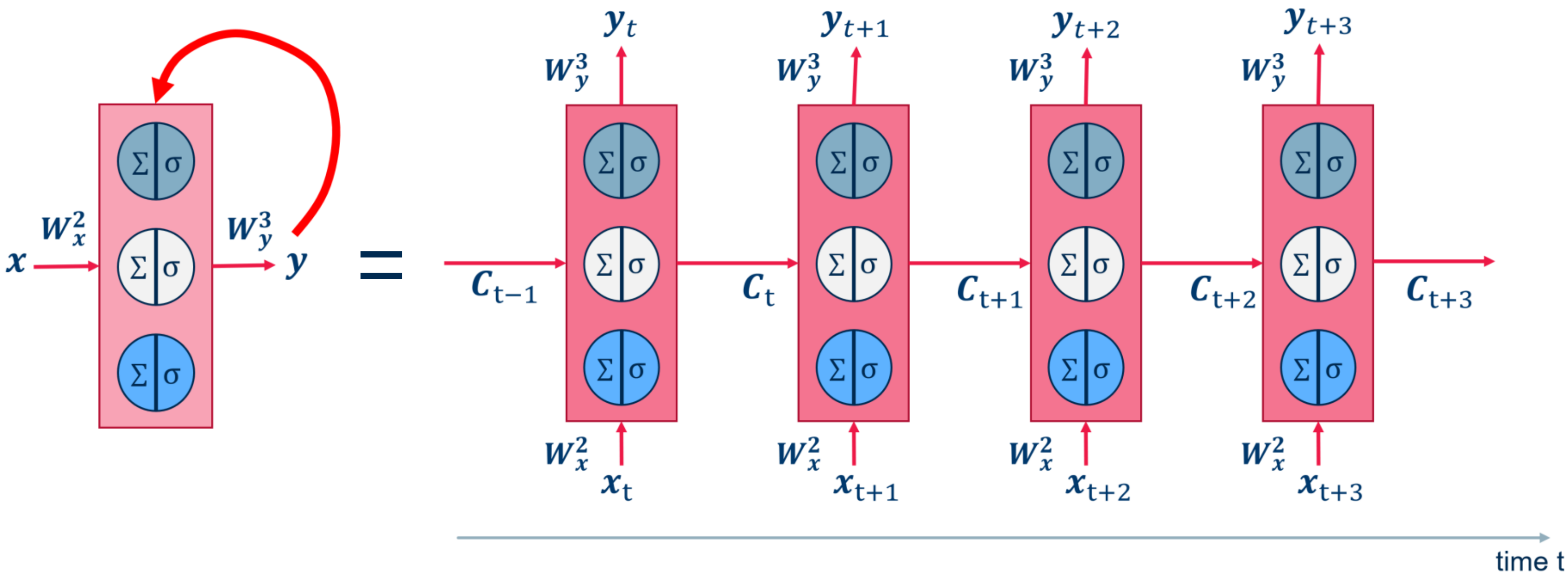
- At every time t, FFNN A has two inputs:
  - ***x**(t)*
  - some shape of ***y**(t-1)* -> state of network A: ***C**(t-1)*

- 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).**

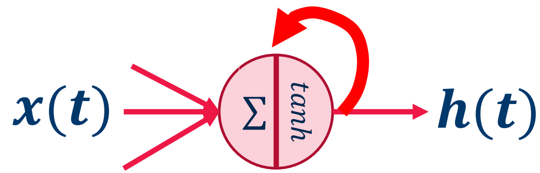


# Summarizing: RNNs and BPTT

- 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.
- Training set: {**X**(t), y(t) } for t=1, 2, … N.
- For each **X**(t), the recurrent connection requires *m* steps into the future to produce the final output.
- 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 the unrolled version in *m* intermediate steps of the original neural architecture: Back-Propagation Through Time (BPTT).

# Long Short Term Memory

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



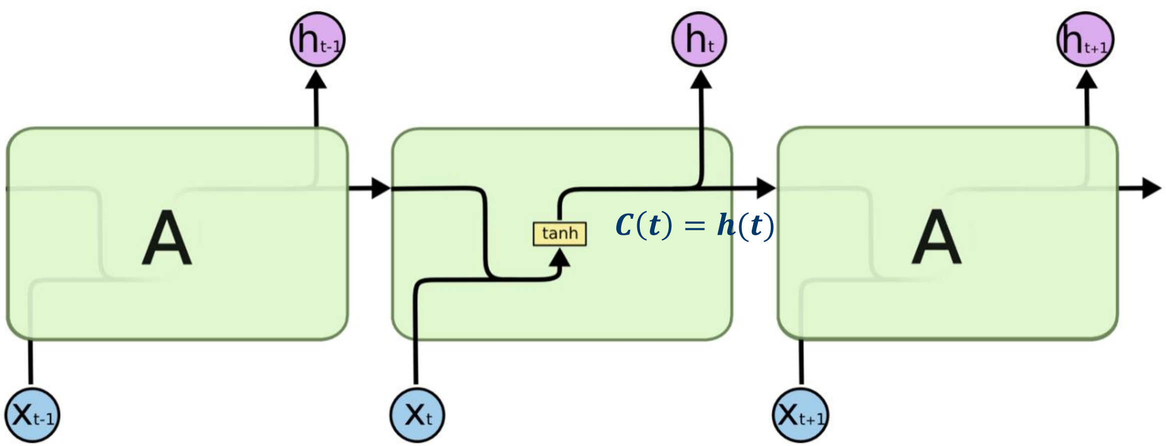




Image Source: Christopher Olah, https://colah.github.io/posts/2015-08-Understanding-LSTMs/

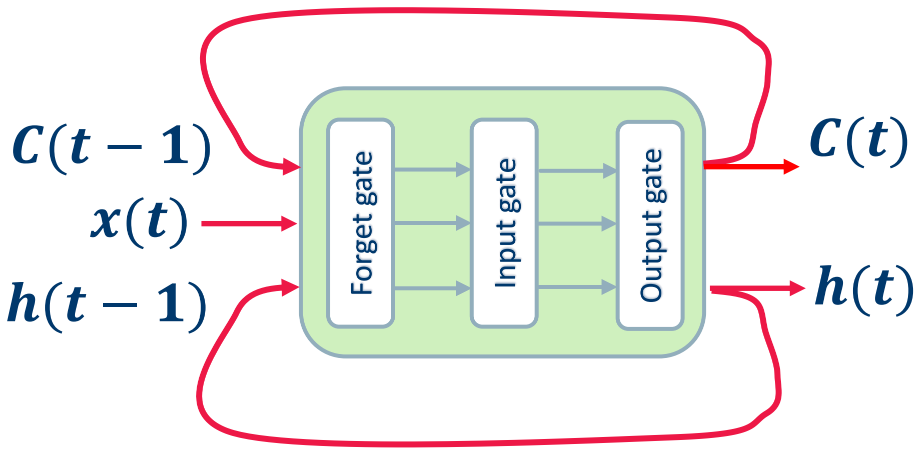
## Limitations of Layers with Simple Recurrent Units

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

This is an engineered type of unit with three gates:

- Forget gate
- Input gate
- Output gate



# LSTM = Forget Gate

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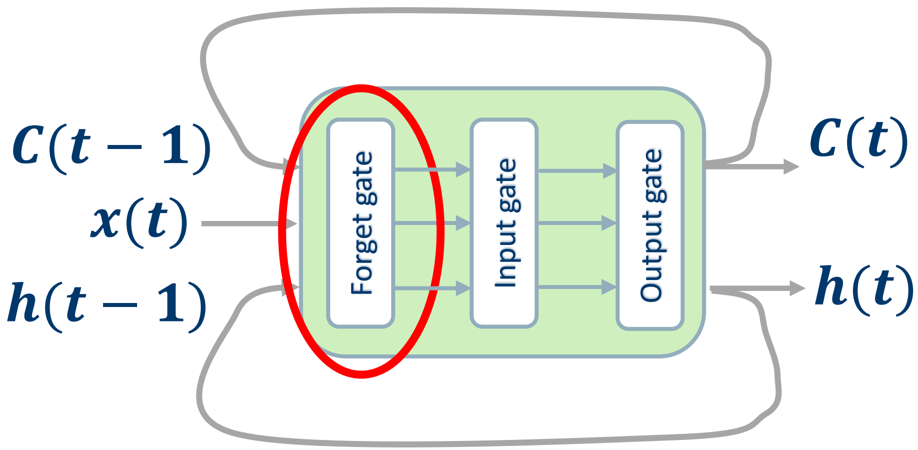
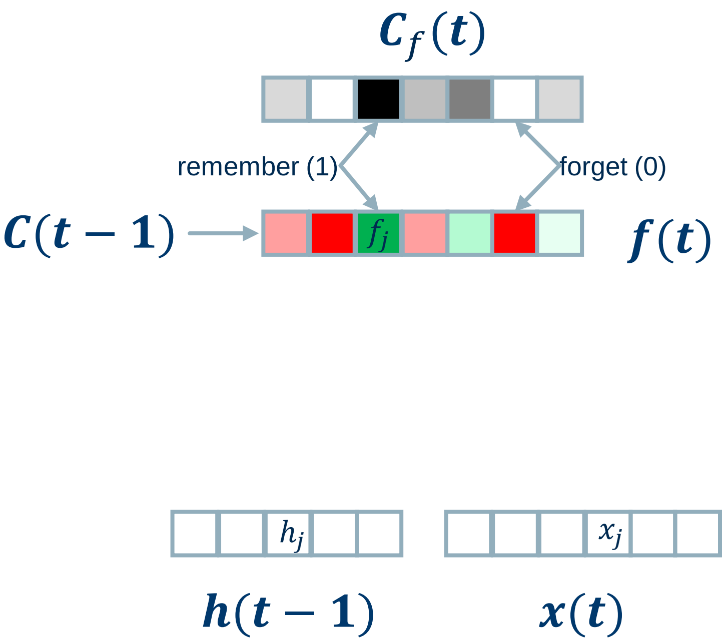


- ***Forget Gate*** is trained to forget the status.
- At time $t$, the forget gate decides which item of $\boldsymbol{C}(t-1)$ to keep (and how much of it) in $\boldsymbol{C}(t)$, given input vector $\boldsymbol{x}(t)$ and previous output $\boldsymbol{h}(t-1)$.



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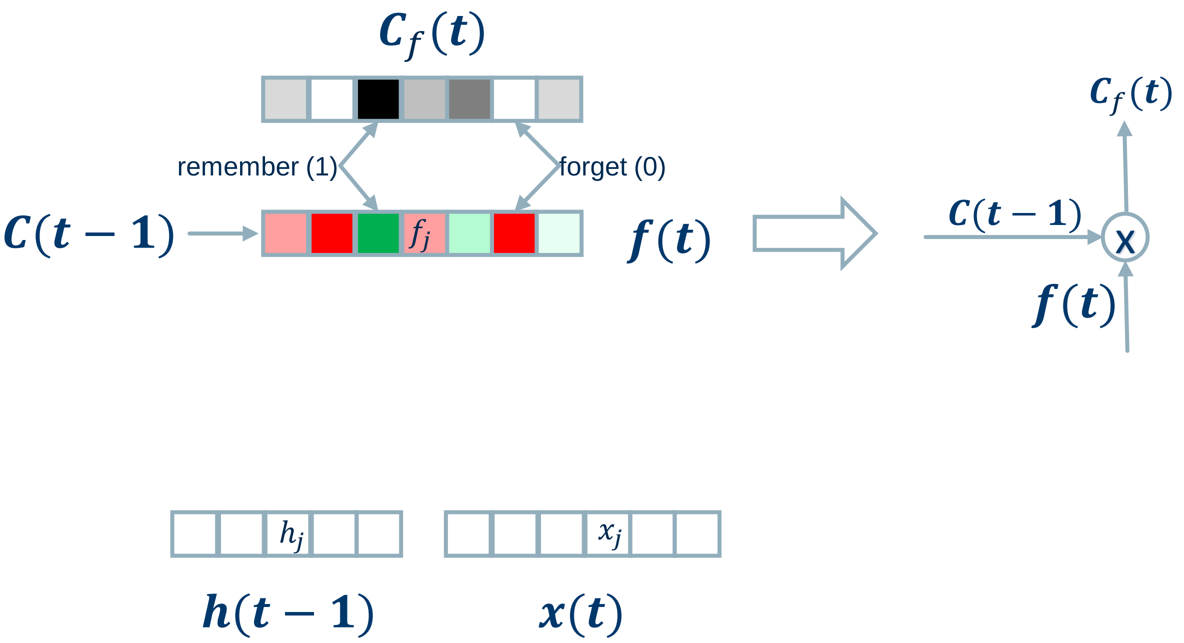

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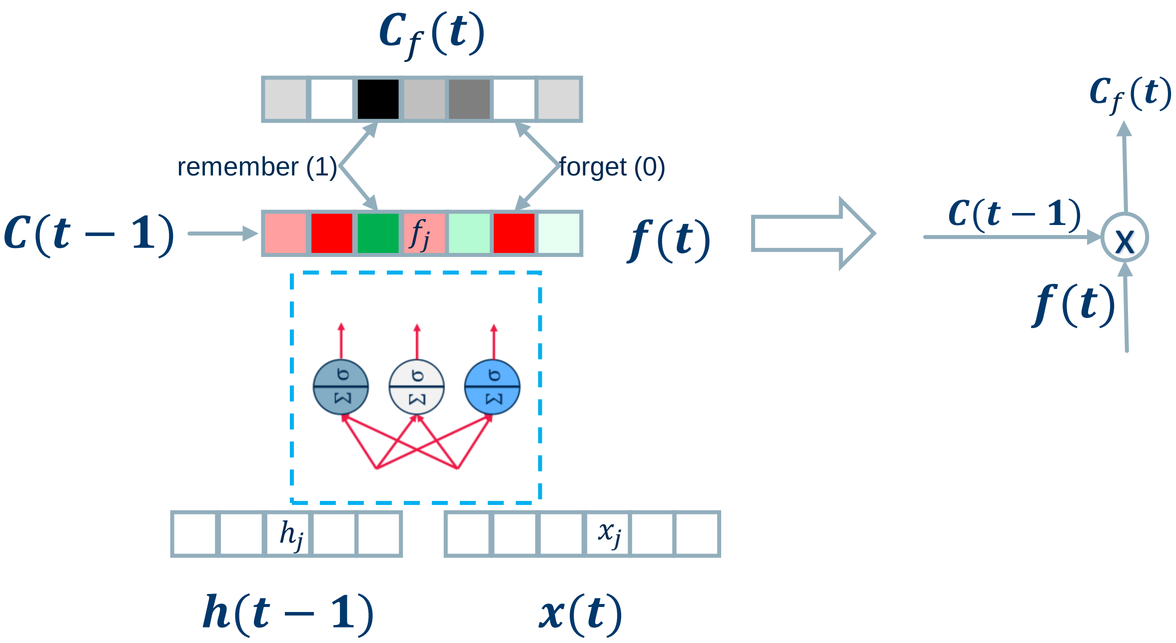

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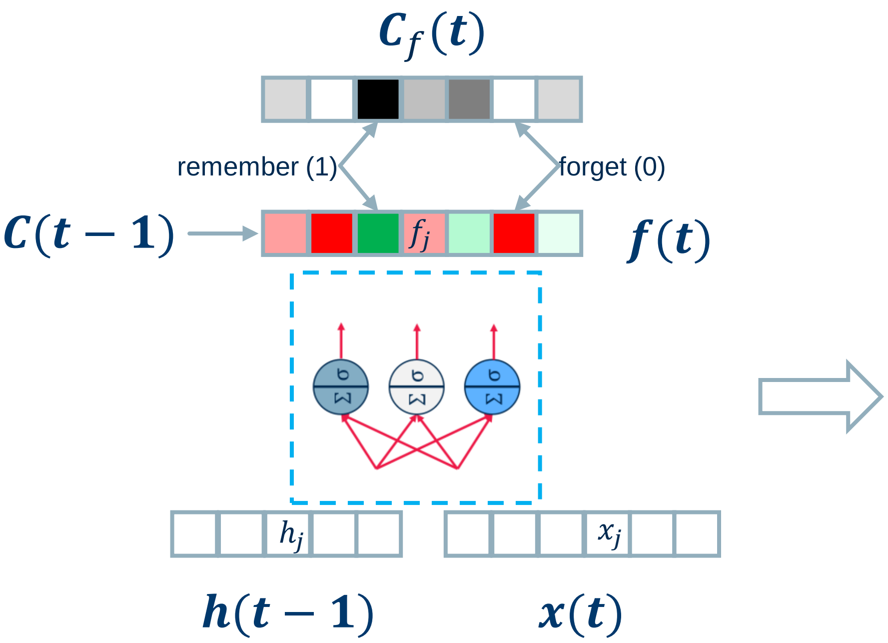


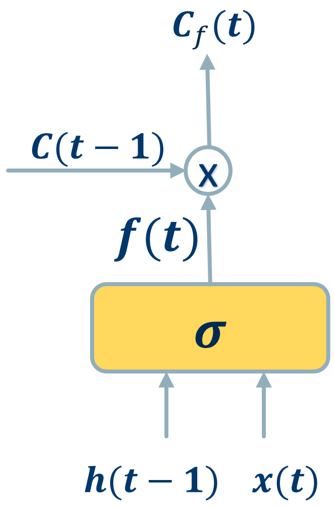

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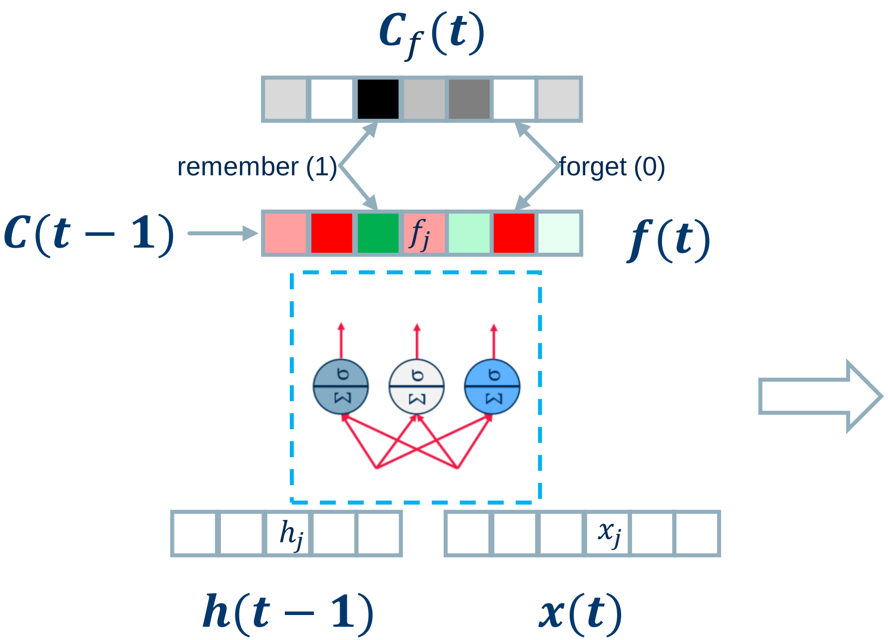


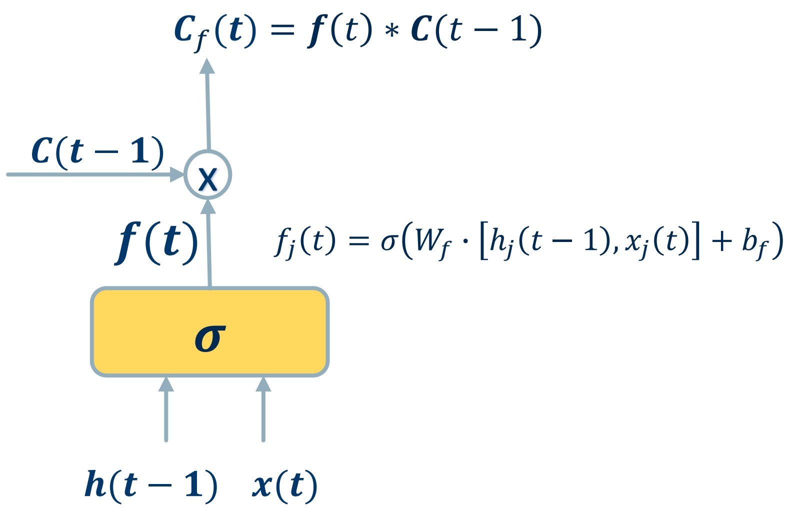

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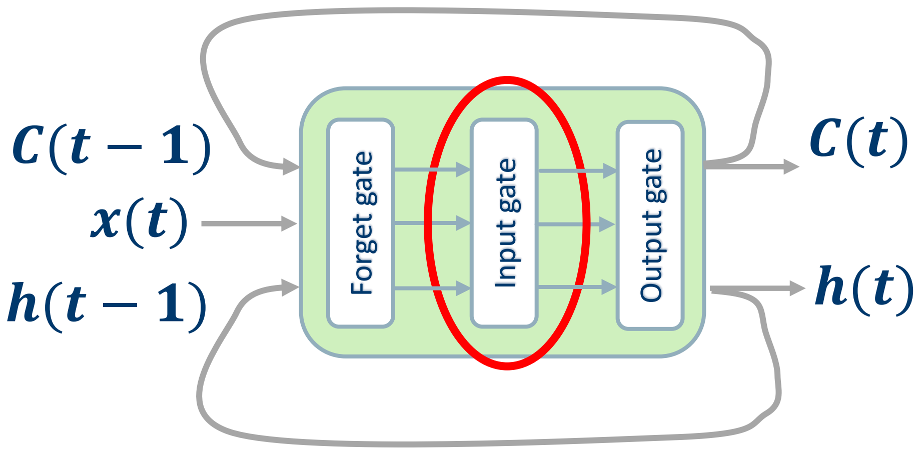

- ***Input Gate*** is trained to inject significant parts of the current input into the status.
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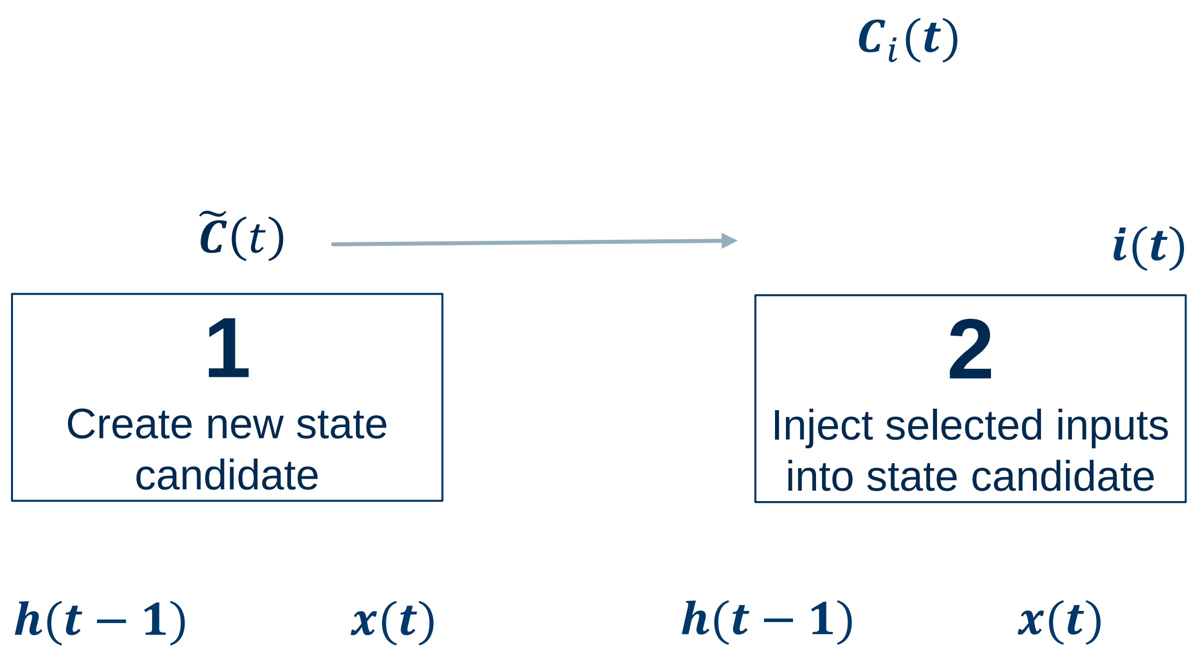

# LSTM: Input Gate – create new state candidate

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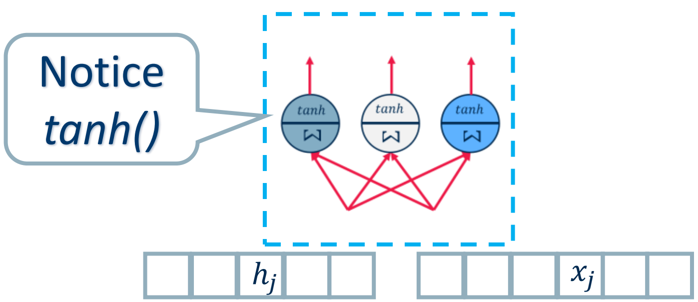
$\boldsymbol{C}_i(\boldsymbol{t})$

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




**2**

Inject selected inputs into 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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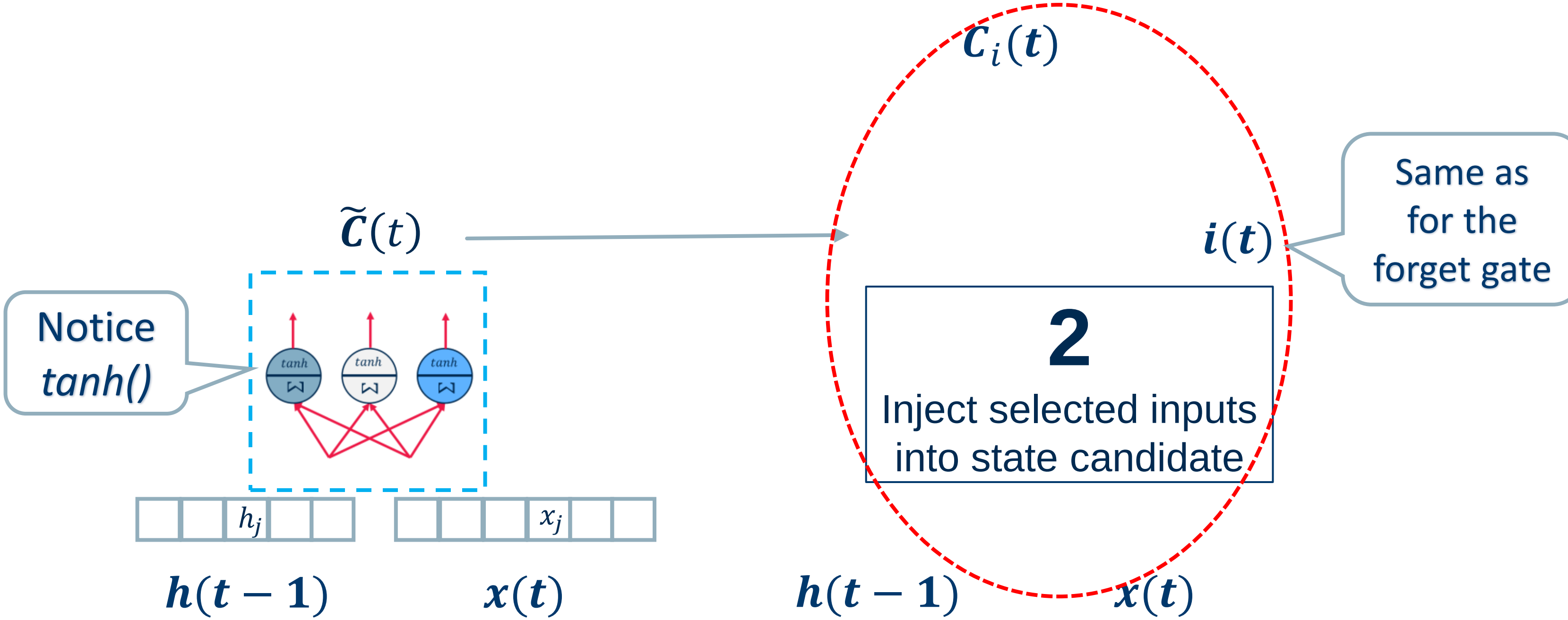

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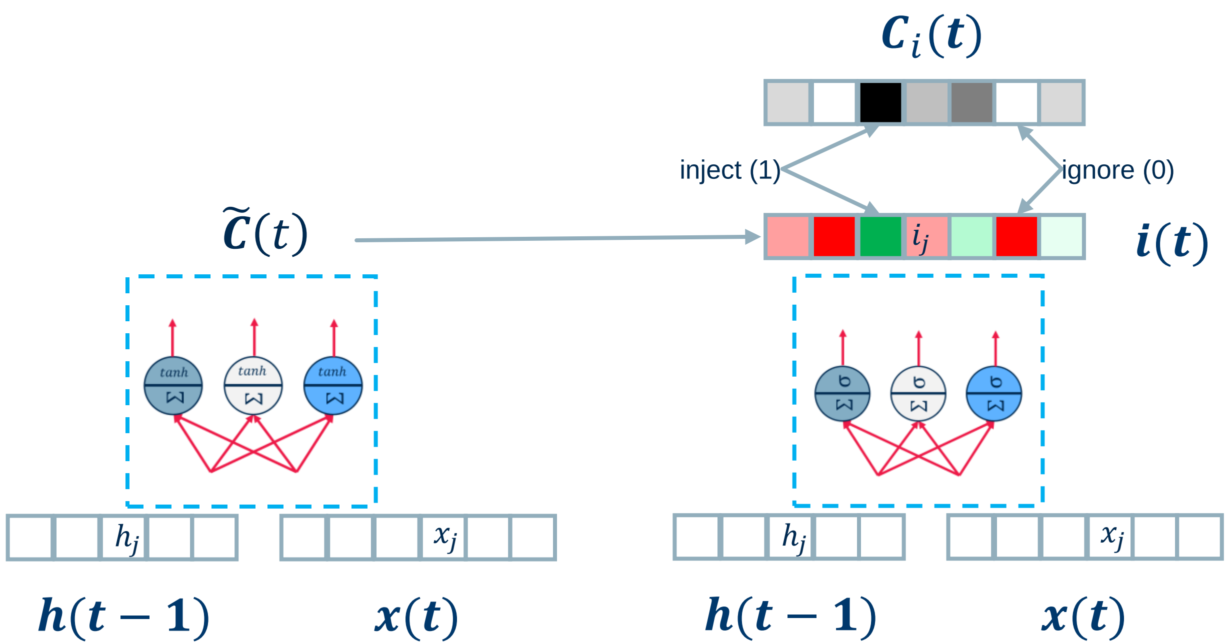

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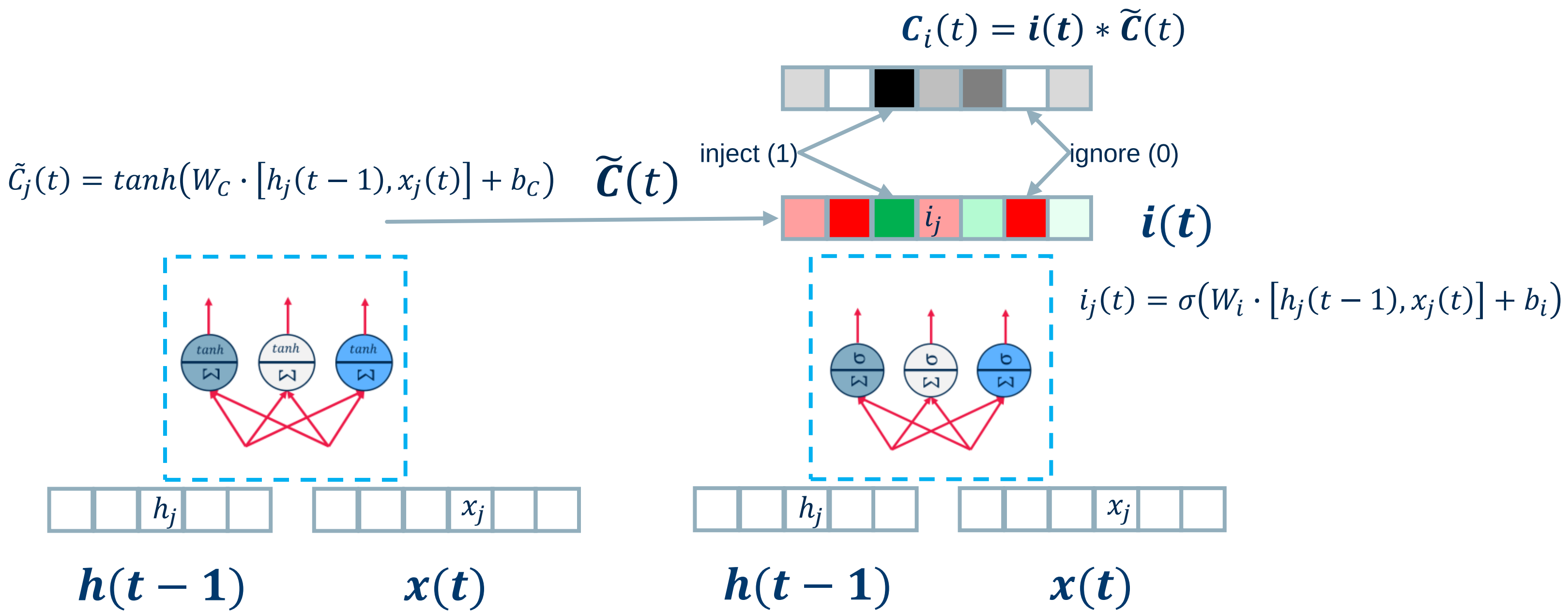

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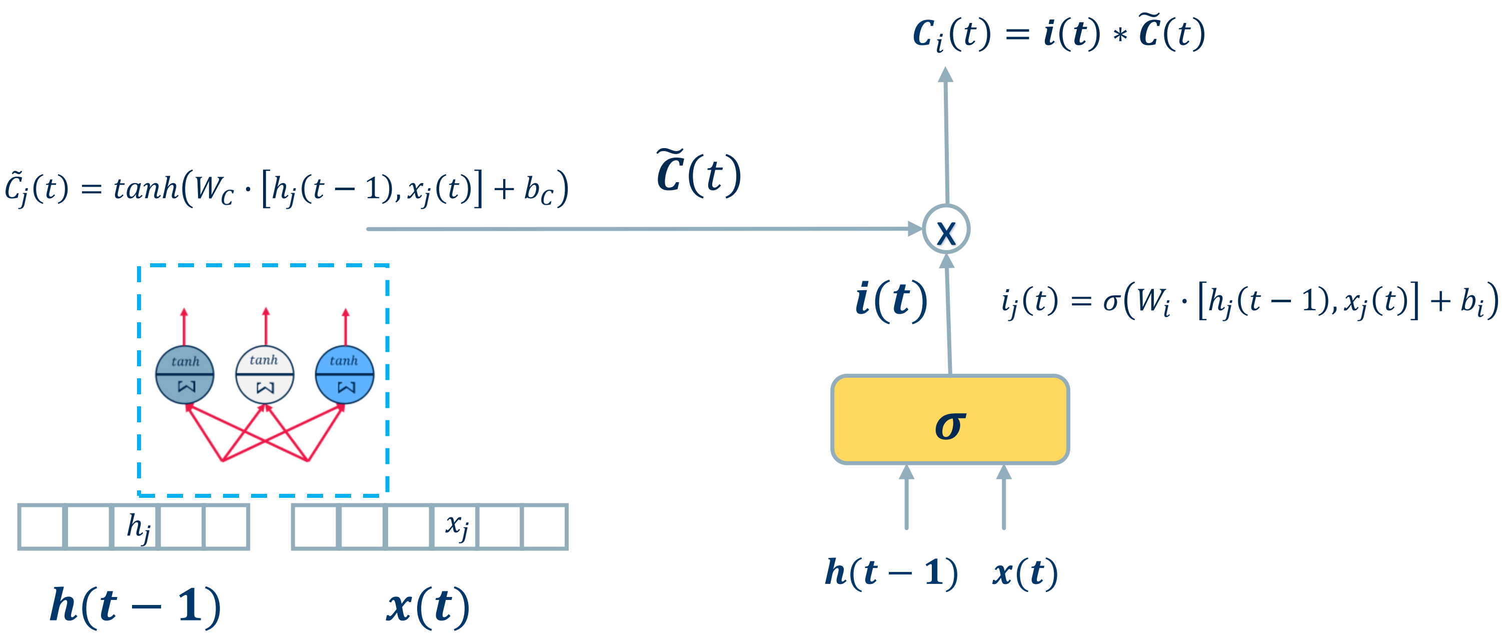

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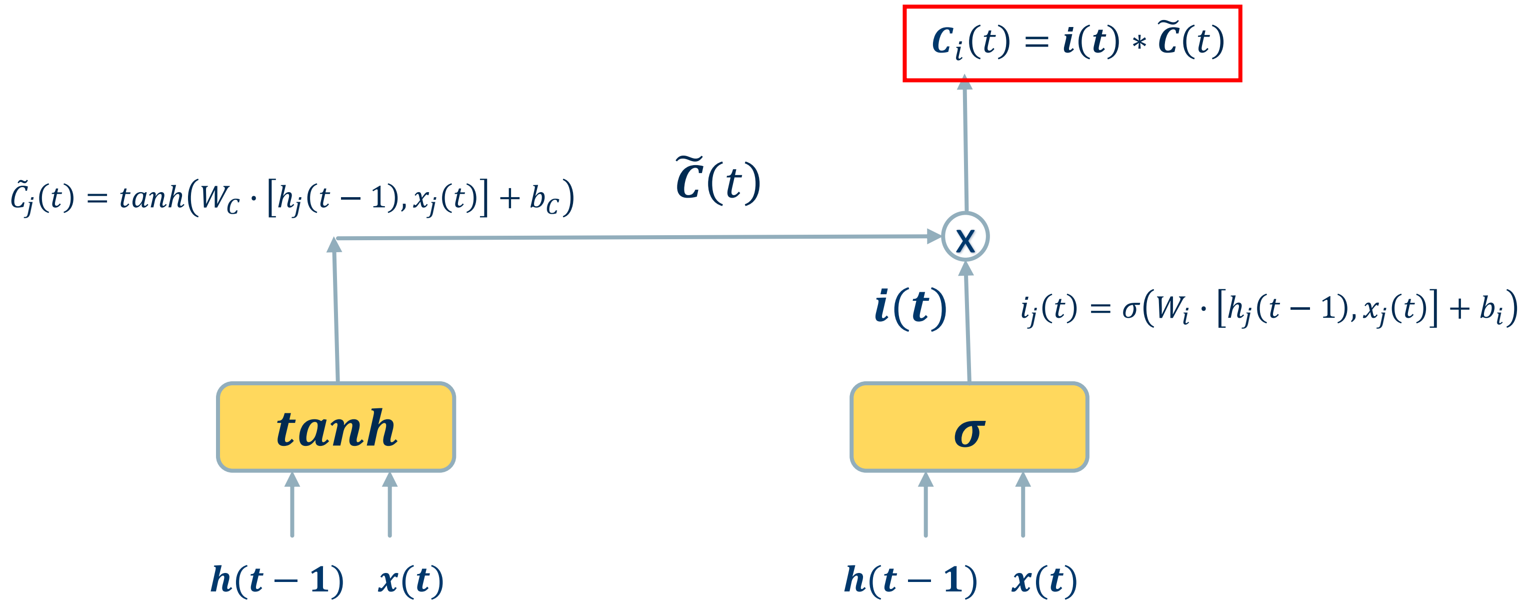

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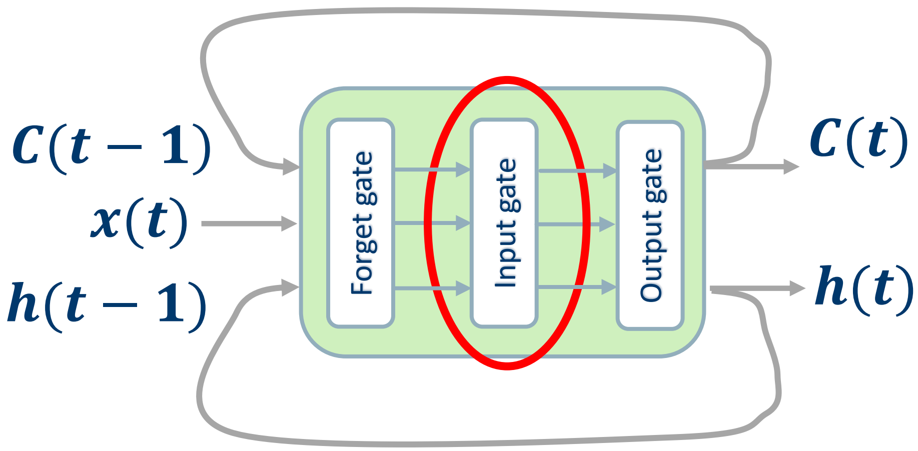


$$\boxed{C(t) = C_f(t) + C_i(t) = f(t) * C(t-1) + i(t) * \widetilde{C}(t)}$$

# LSTM = Output Gate

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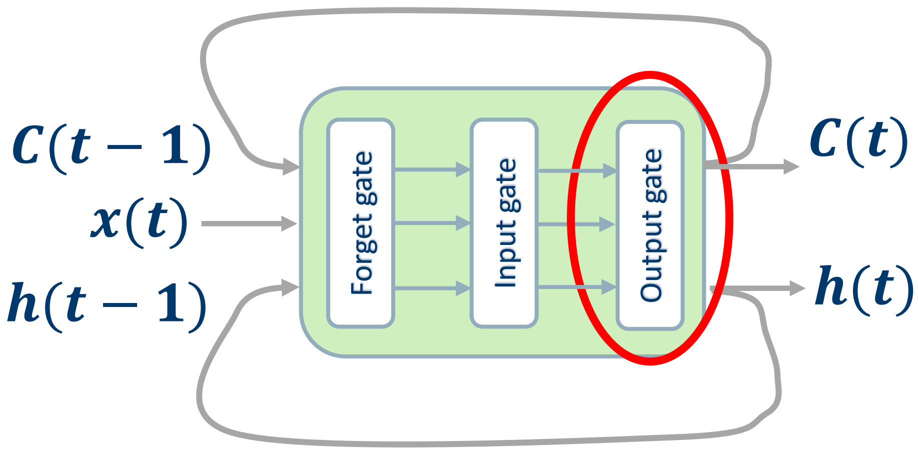
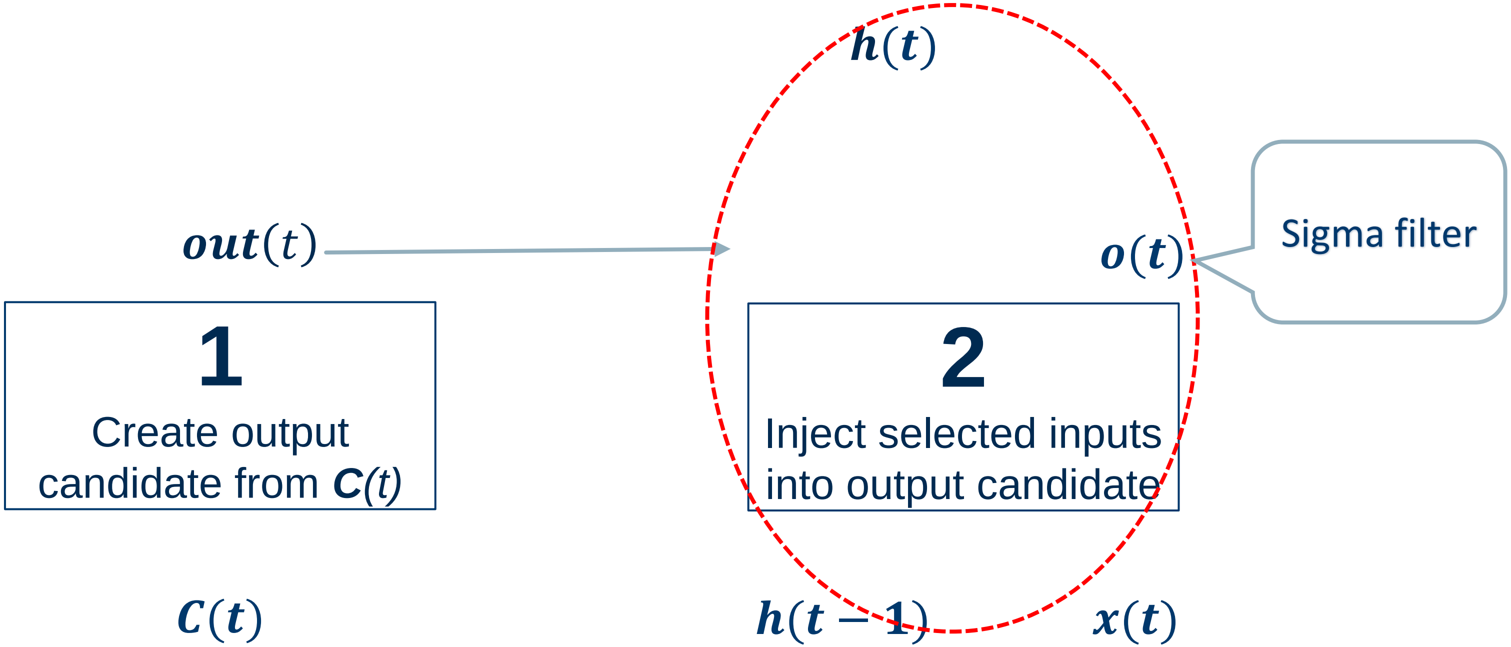


- ***Output Gate*** is trained to output a reasonable result.
- At time $t$, output gate decides which parts of status $\boldsymbol{C}(t)$ (and how much of it) will be output, given input vector $\boldsymbol{x}(t)$ and previous output $\boldsymbol{h}(t-1)$.



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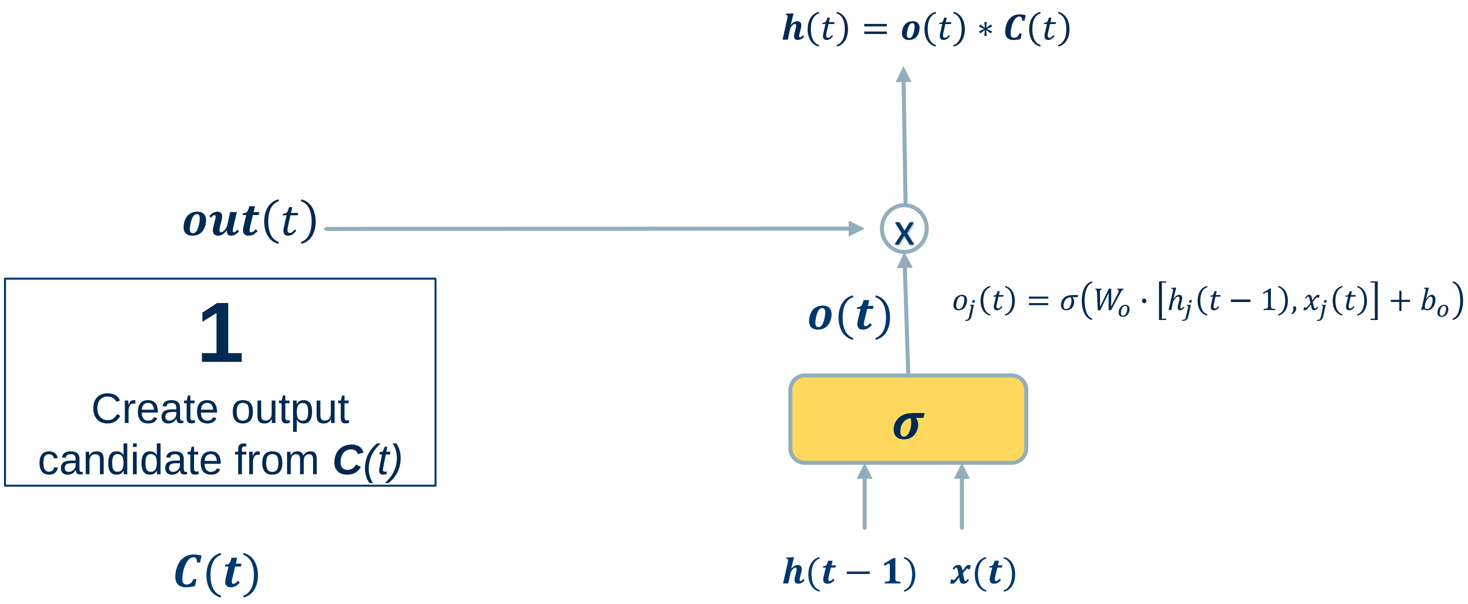

# LSTM: Input Gate – prepare output candidate

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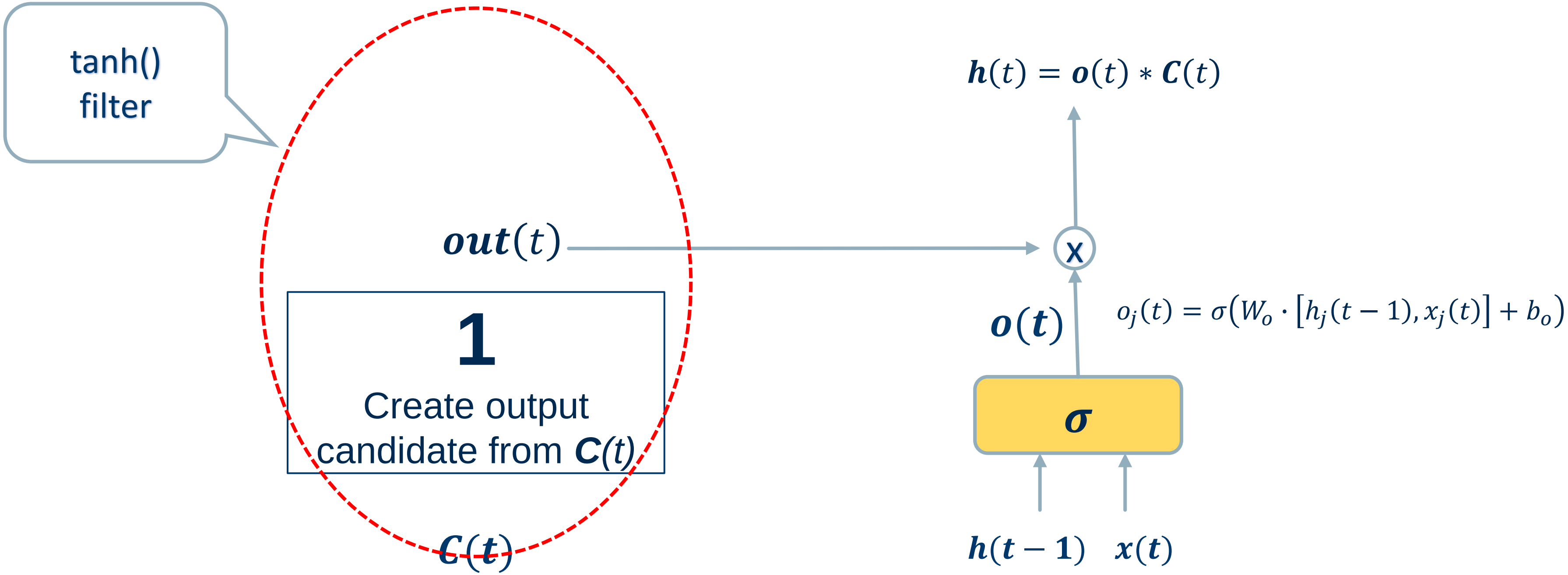

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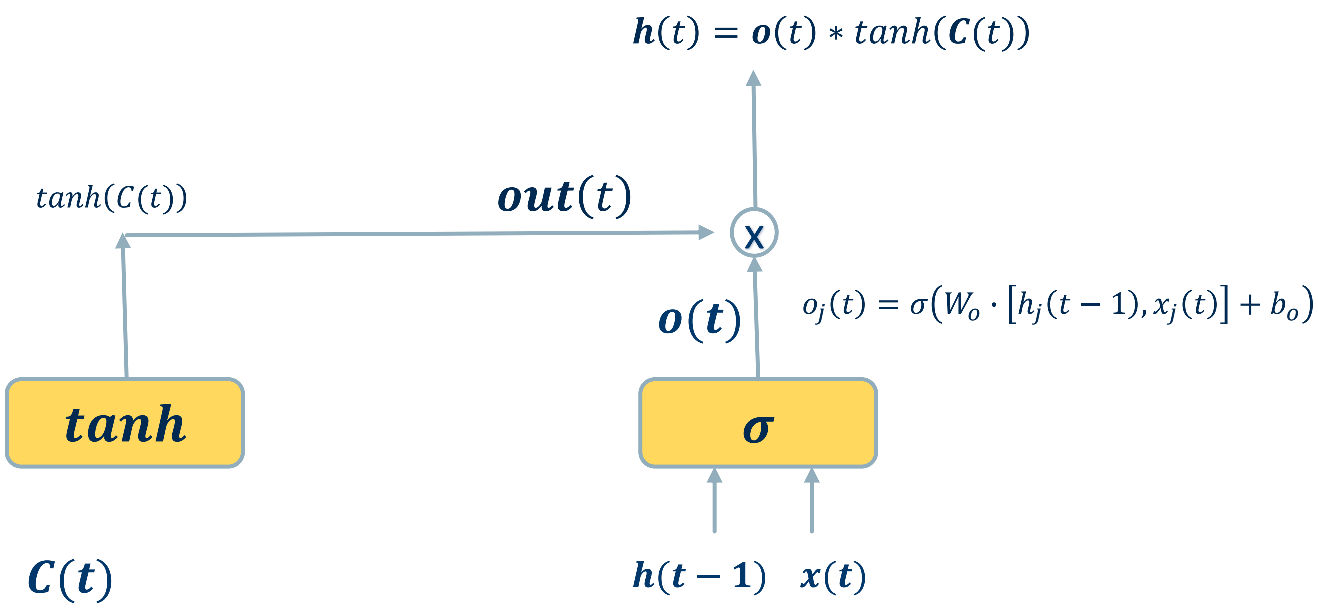


# LSTM = Long Short Term Memory

## Special type of unit with three gates

- Forget gate
- Input gate
- Output gate

Forget gate

Input gate

Output gate

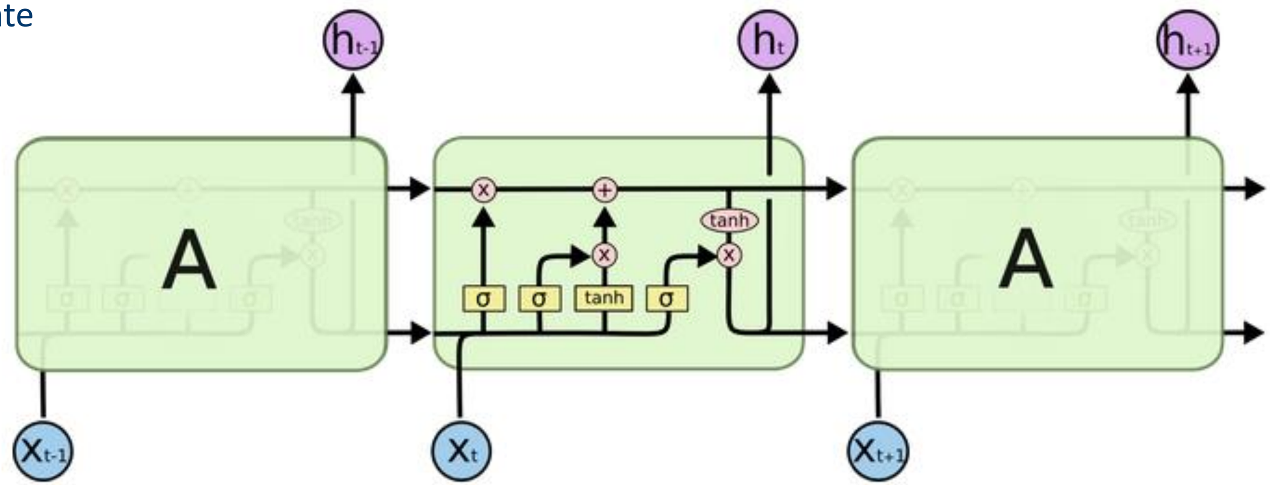
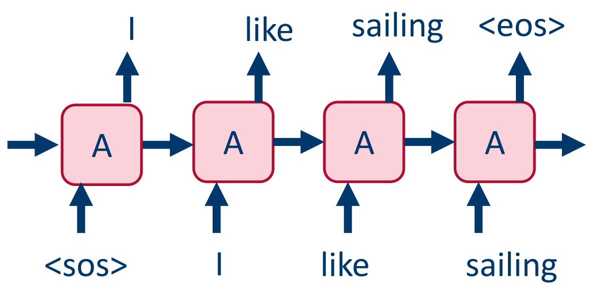
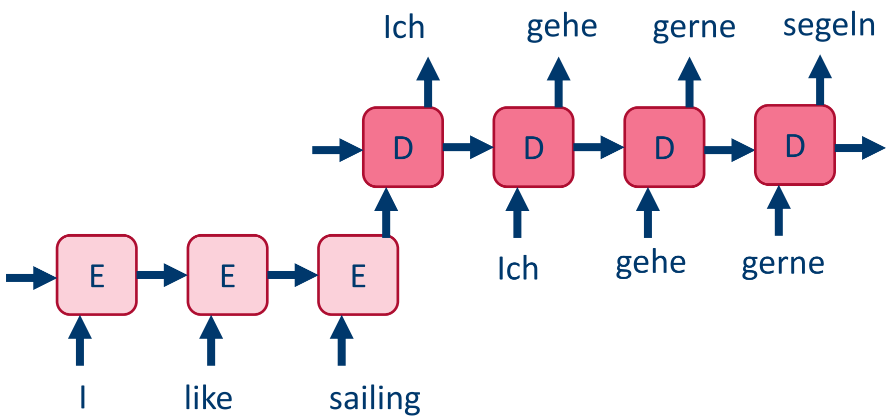



Image Source: Christopher Olah, https://colah.github.io/posts/2015-08-Understanding-LSTMs/

# Many to Many



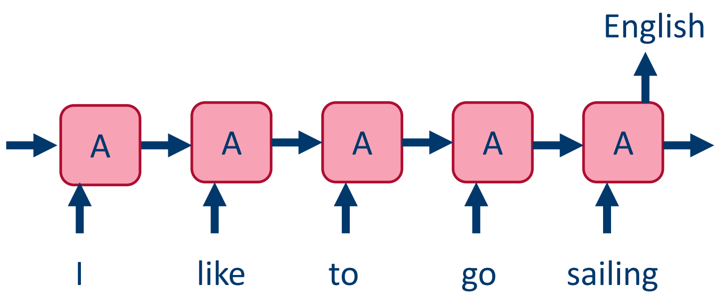

Language model




Neural machine translation

# Different Network-Structures and Applications

## Many to one




Language classification

Text classification

## One to many

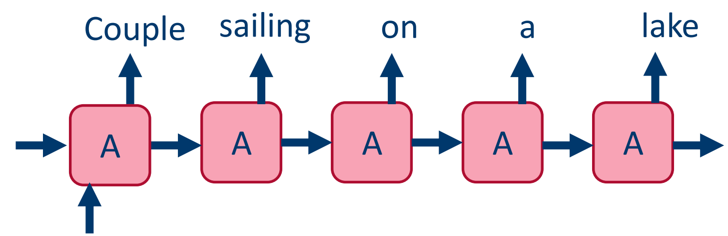
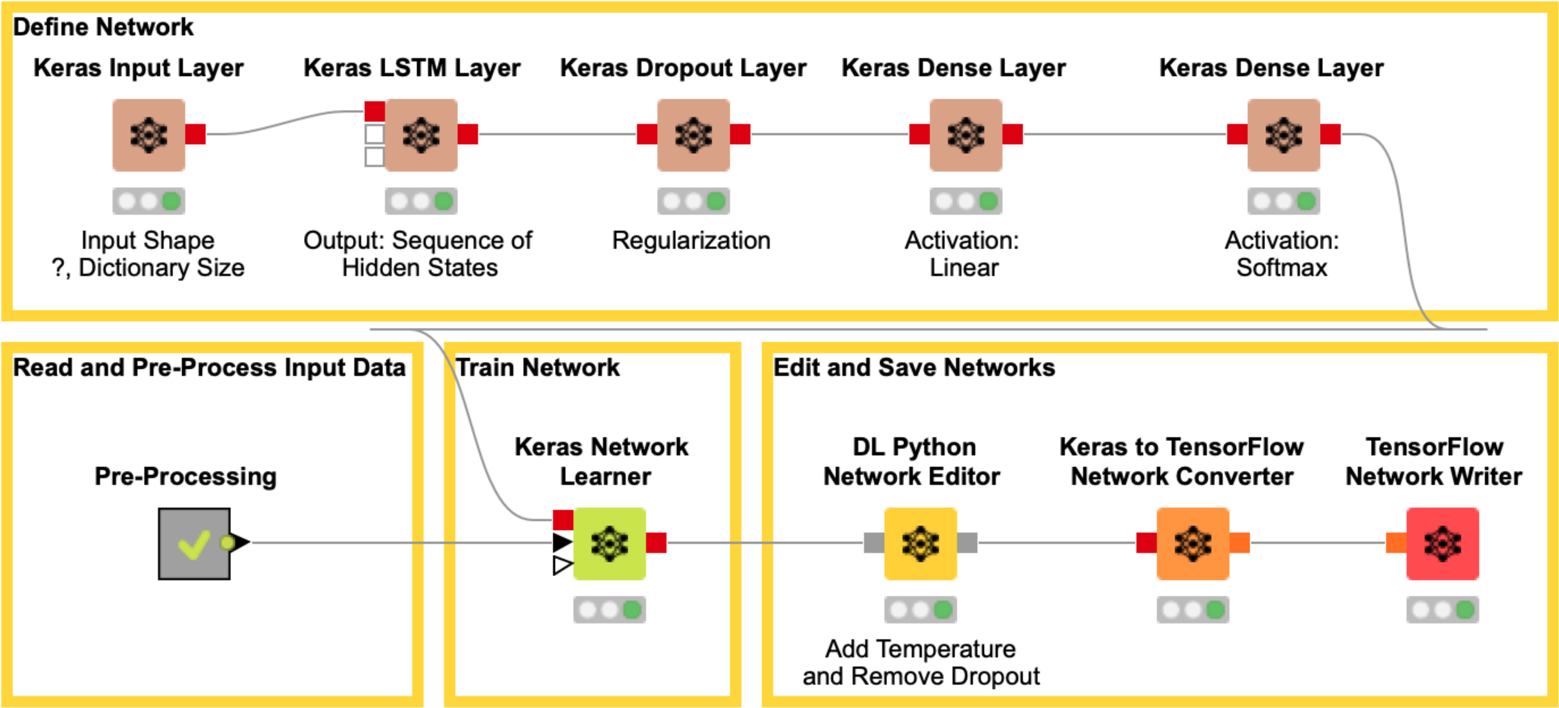



Image captioning

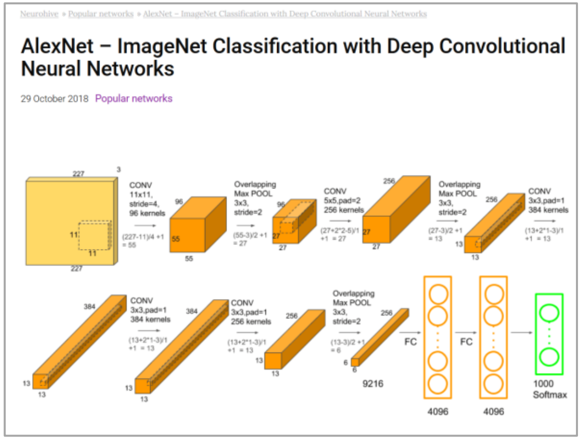
# Neural Network: Code-free Example



# Convolutional Neural Networks (CNNs)

# AlexNet & friends

- 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.

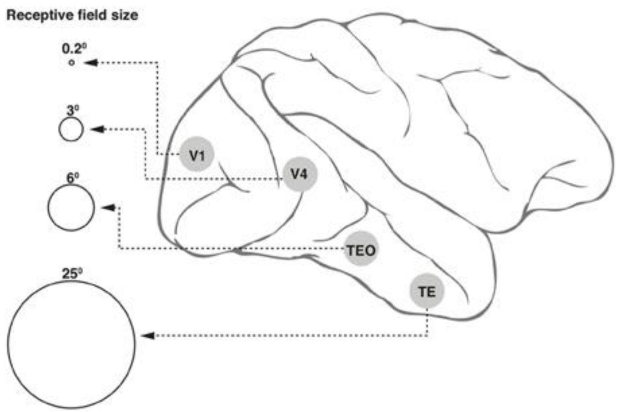
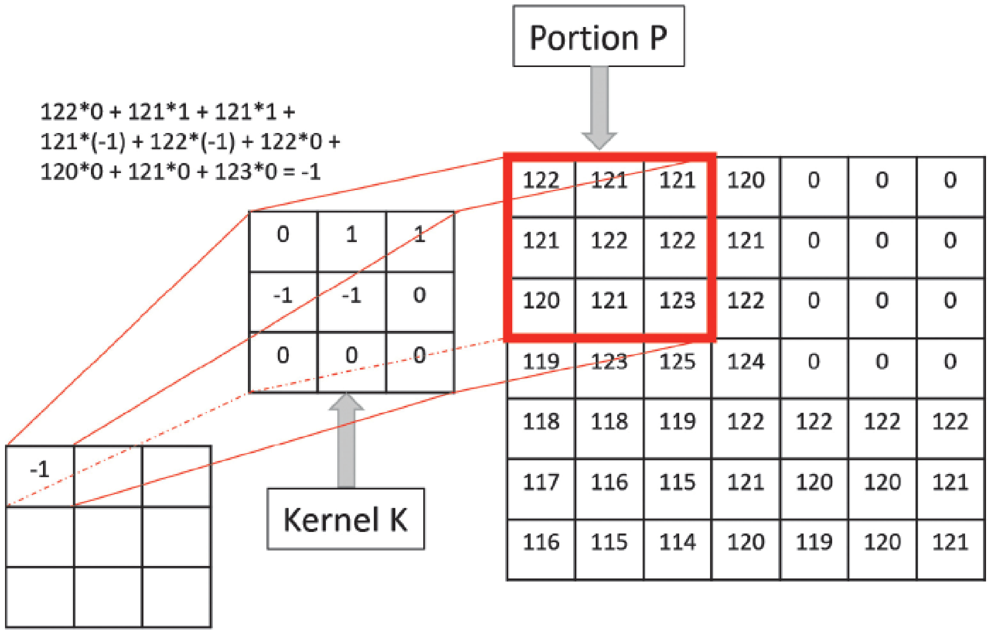



Image from: Wikimedia commons – https://commons.wikimedia.org/wiki/File:Receptive_field_sizes_along_the_ventral_cortical_stream_in_the_primate.jpg

- 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



- Used when data has spatial relationships, e.g. images
- Instead of connecting every neuron to the new layer a sliding window is used
- Some convolutions may detect edges or corners, while others may detect cats, dogs, or street signs inside an image

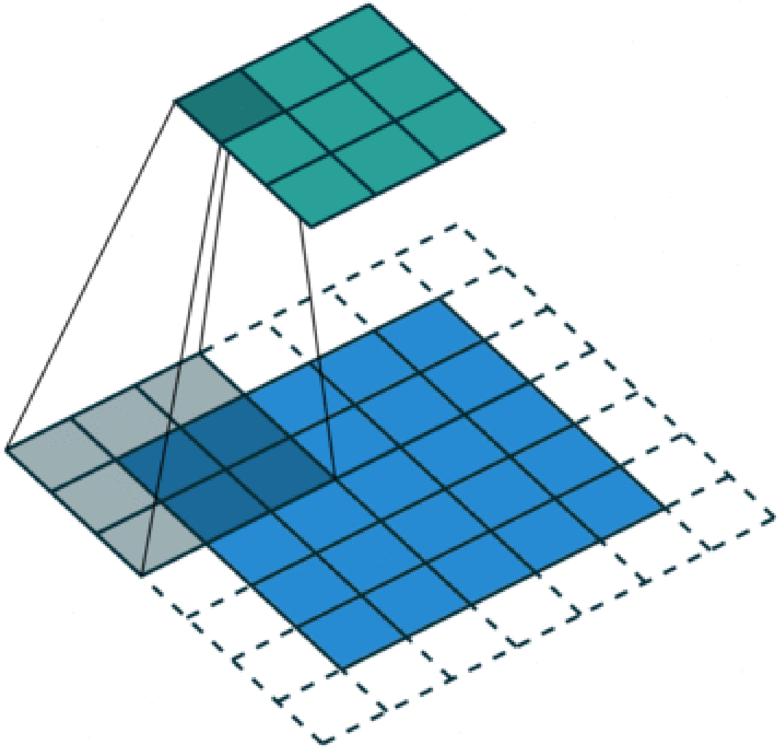


Image from: https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

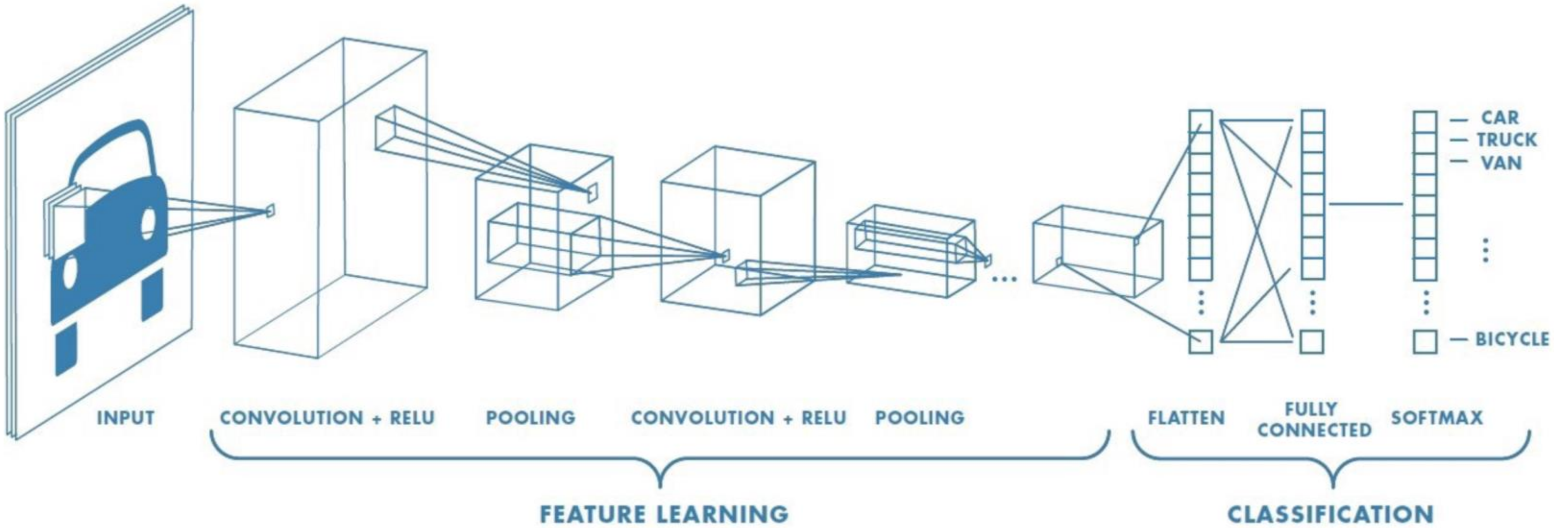
# Pooling Layers

- 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, …).
- After each convolutional layer, a *pooling layer* is often applied to reduce even further the data dimensionality.
- 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.

# Classification Layers

– After the sequence of convolutional + pooling layers, a classic feedforward multilayer Perceptron network is applied to carry out the classification process.

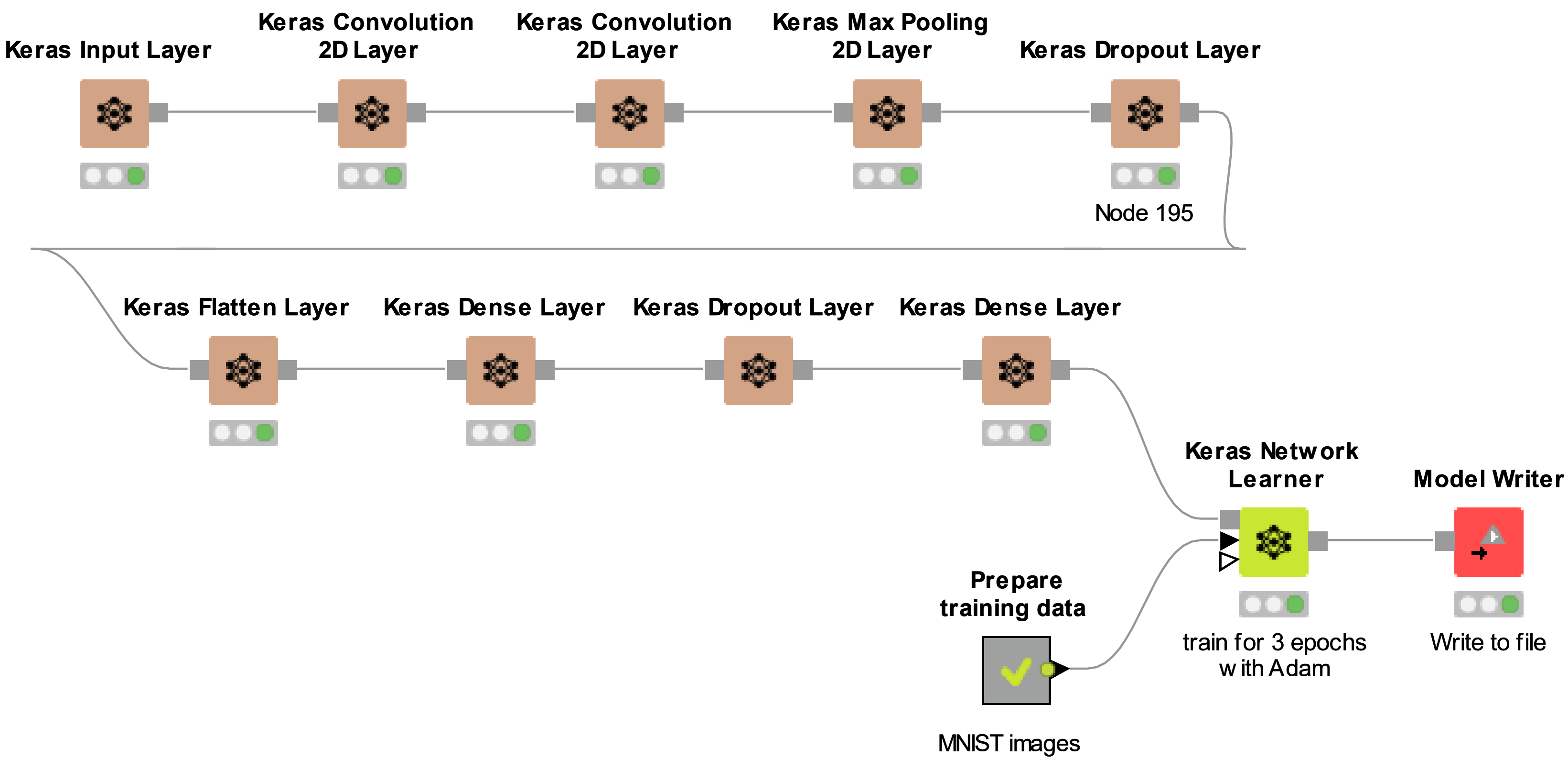
– Successful examples of CNNs for image recognition : LeNet, AlexNet, VGGNet, GoogLeNet, ResNet, ZFNet.



# CNN: Transfer Learning

- 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

# Building CNNs with KNIME



# Generative-Adversarial Networks (GANs)

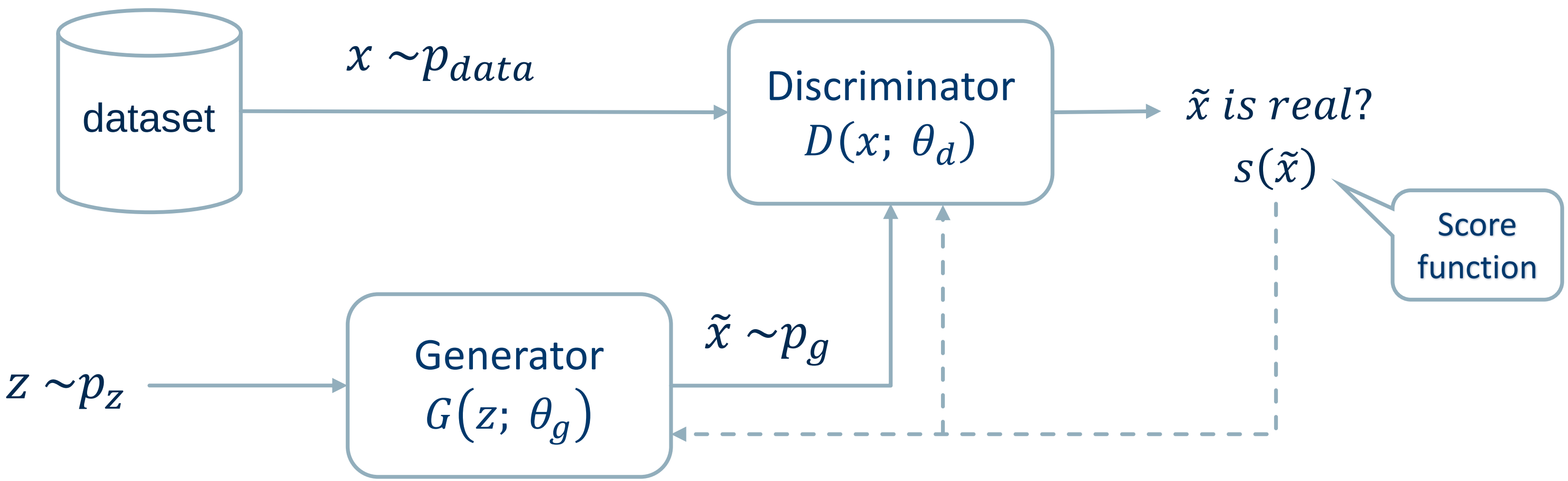
- So far: RNNs and CNNs
- Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) represent probably the biggest contribution of deep learning to the field of neural networks.
- However, deep learning is responsible for other innovations, such as for example Generative Adversarial Networks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

- 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 algorithm to produce $D(x)=1$ for the generated images $x$.
- Both networks are trained in alternating steps, competing with each other to improve themselves.
- 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.

# GAN: Architecture



## GANs

- 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.

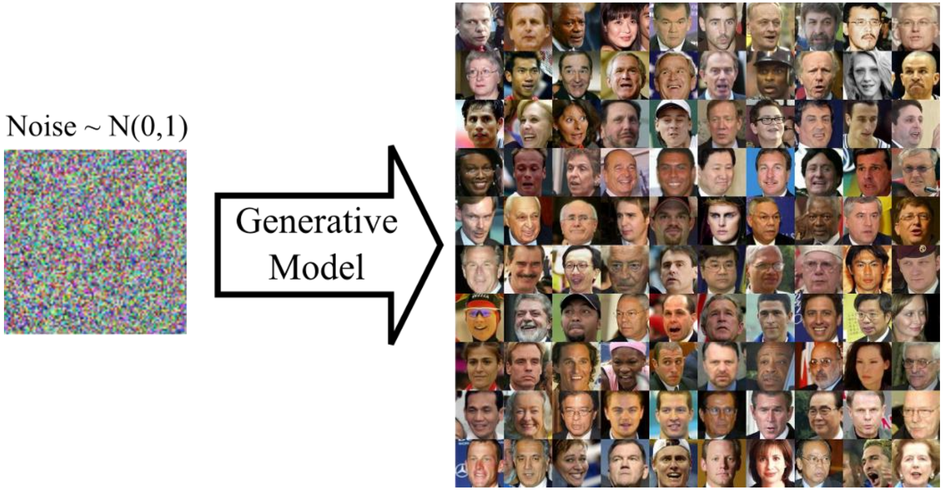
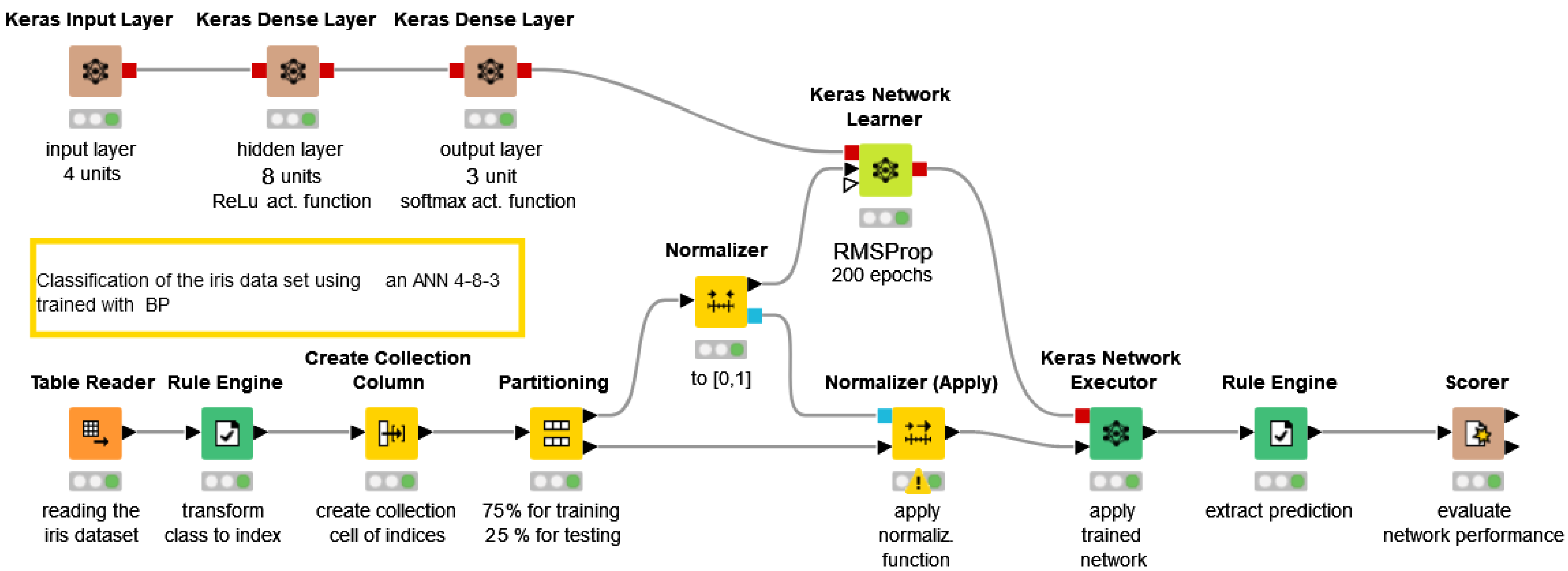



Image from: Pankaj Kishore, Towards data Science
https://towardsdatascience.com/art-of-generative-adversarial-networks-gan-62e96a21bc35

# Practical Example

– A multilayer perceptron with layers (4–8–3) is trained to classify the iris data set using the backpropagation algorithm, as set in the Keras Network Learner node



For any questions please contact: email@email.com