Deep Learning I: Convolutional and Recurrent Networks

COMP5318 Machine Learning and Data Mining

Semester 2, 2024, week 8

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Reference: Witten ch. 10.3 and 10.6, Geron: ch.14 and ch.15

Outline

- Convolutional neural networks
- Recurrent neural networks

Convolutional Neural Networks (CNN)

Convolutional neural networks

- Introduced by Yan LeCun et al. in 1989
  http://yann.lecun.org/exdb/publis/pdf/lecun-89e.pdf
- Gained popularity in 2012 when AlexNet (Alex Krizhevsky at al.) won the ImageNet competition reducing the error rate from 26% to 15%

  https://proceedings.neurips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf
- A special type of multilayer NN; trained with the backpropagation algorithm
- Designed to recognize visual patterns directly from pixel images with minimal pre-processing
- Can recognize patterns with high variability, e.g. handwritten characters; robust to distortions and geometric transformations such as shifting
- Used in image and speech recognition; have shown excellent performance in hand-written digit classification, face detection and image classification

CNN are designed for images

- CNNs are designed for images
  - (but can also be used with other types of data)
- Images are represented as matrices of pixel values
  - Black and white images: a value from 0 (black) to 255 (white) – 1 matrix
  - Color images: the same but for 3 channels: red, green and blue, so 3 matrices

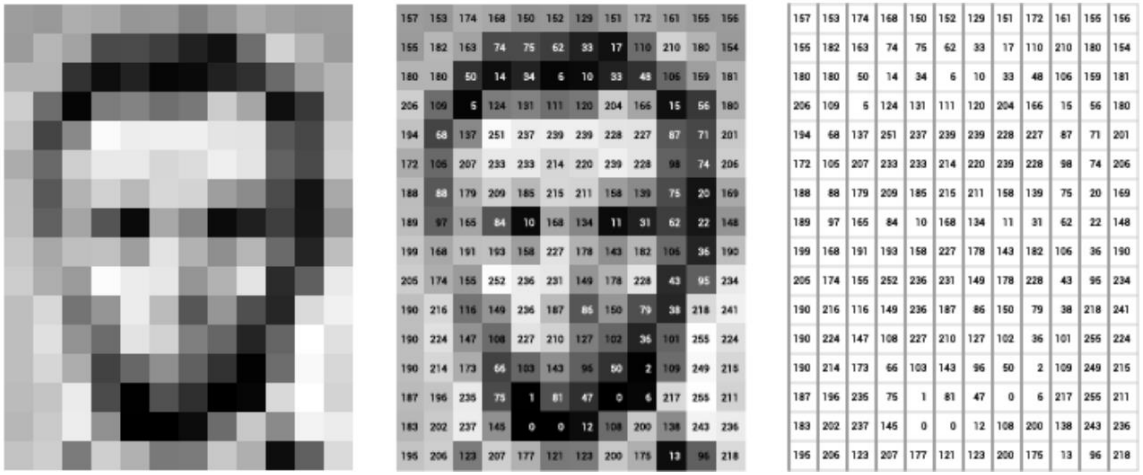
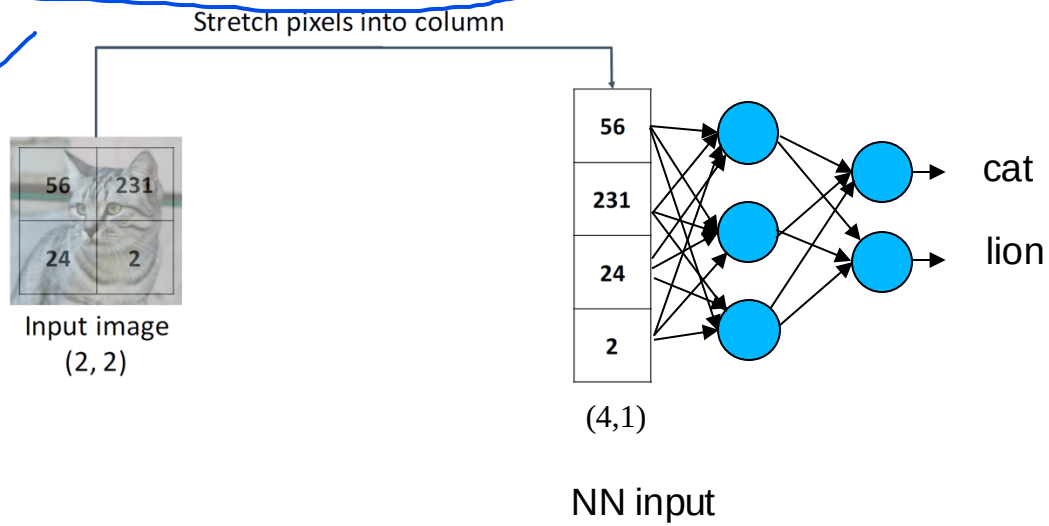


Image ref: https://ai.stanford.edu/~syyeung/cvweb/tutorial1.html

Classifying images with feedforward NNs

- Traditional NNs (multilayer feedforward networks) do not consider the spatial structure of the image

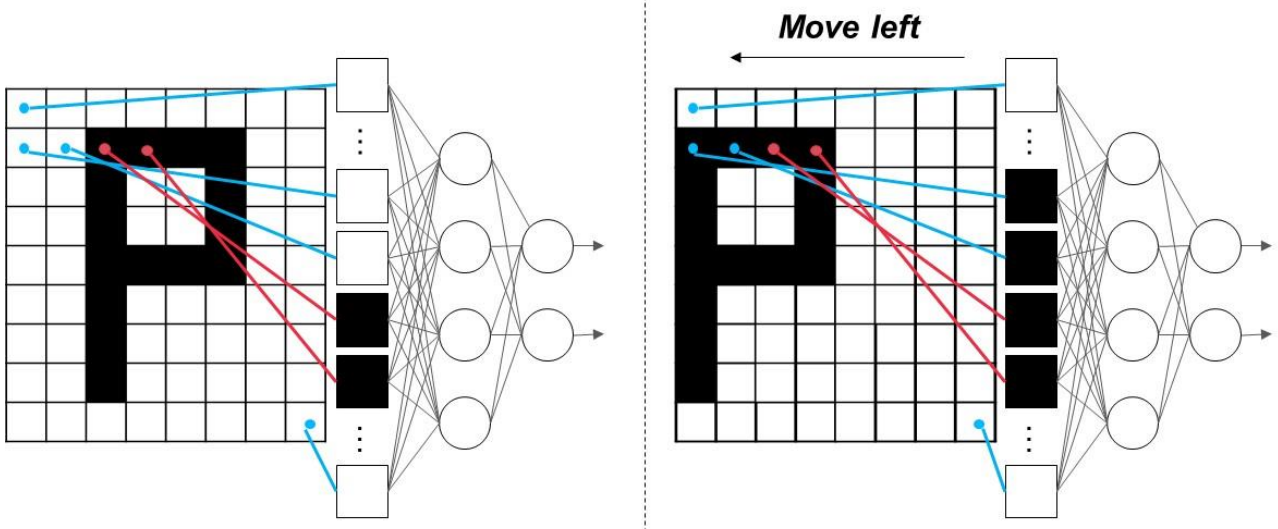


- CNNs do this by using new types of layers - convolutional and pooling

Adapted from http://cs231n.stanford.edu/

Classifying images with feedforward NNs (2)

- Traditional NNs (multilayer feedforward networks) are sensitive to the position of an object in the image; CNN are more robust to shifts/translation
- Robustness to translation is important for image and sound data as translation is one of the main sources of distortion



- Moving only 2 pixels but the input values will be very different and the already learned weights will not be very useful

CNN structure

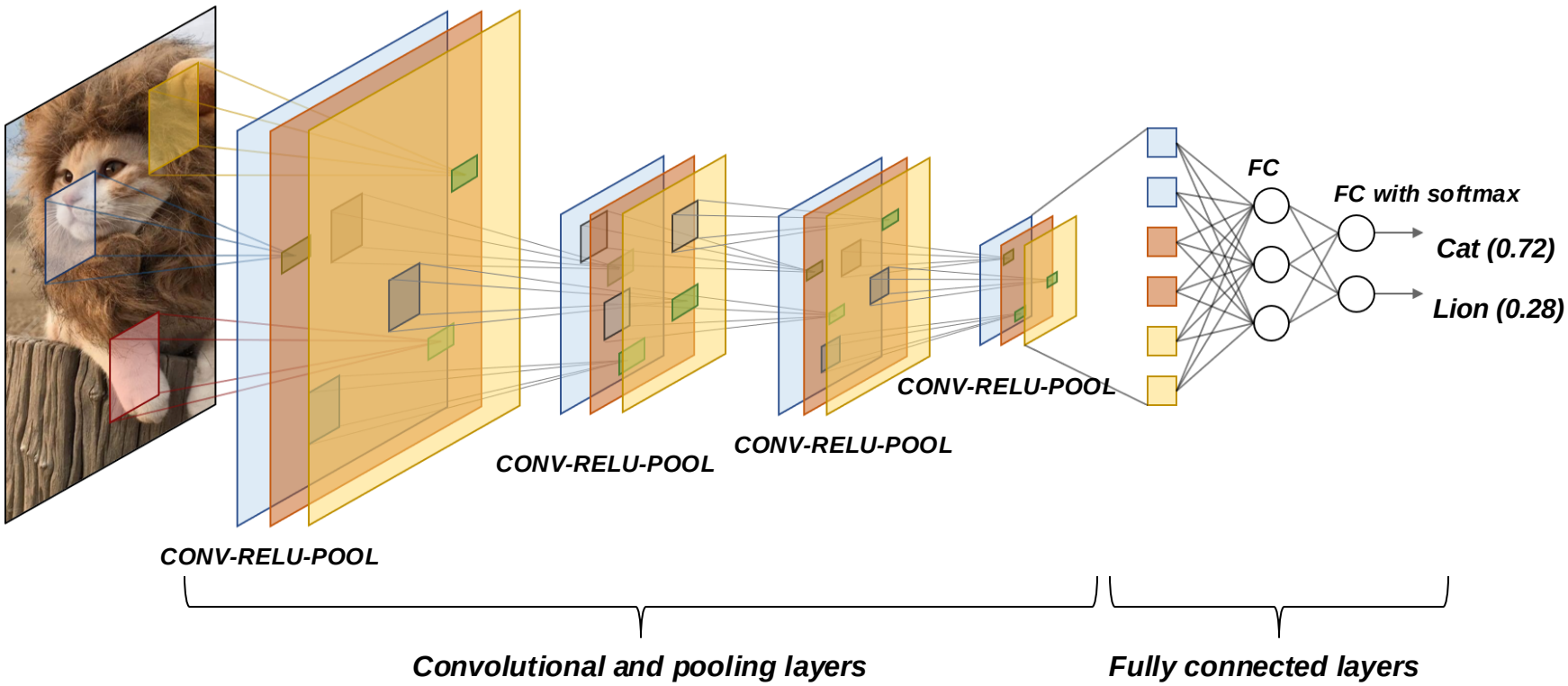
- Input layer for the image values - INPUT
- Convolutional layer - CONV
- ReLu or LReLu (or other non-linear activation function) - RELU
- Pooling layer - POOL
- Fully connected layer with softmax activation function at the output - FC

- INPUT–CONV–RELU-POOL-FC

- The CONV-RELU-POOL block can be repeated several times
- FC can contain one or more FC layers

CNN structure - example

Example: 3 blocks of CONV-RELU-POOL, 2 FC layers



CNN structure

- CNNs are similar to the fully connected NNs we studied last week
- They are made up of neurons that have learnable weights
- Each neuron receives some inputs (e.g. raw pixel values), performs a dot product and follows it with a non-linear activation function
- The network expresses a single differentiable function: from the raw image pixels to the class scores, and is trained with the backpropagation algorithm
- What we studied last week applies here too

Convolutional layer

- Convolution is like applying a sliding window to a matrix
  - The corresponding elements are multiplied and summed
  - Example: image of black and white values (e.g. 0 is black, 1 is white)
  - 3x3 sliding window (filter, kernel) with values (weights) shown in red
  - The filter is shifted from left to right and then down as shown
  - The resulting convolved features formed a feature map (or activation map)
  - The first convolved feature is 4 = 1*1+1*0+1*1+0*0+1*1+1*0+0*1+0*0+1*1

Image ref: http://deeplearning.stanford.edu/tutorial/supervised/FeatureExtractionUsingConvolution/

Filter

1	0	1
0	1	0
1	0	1

Image

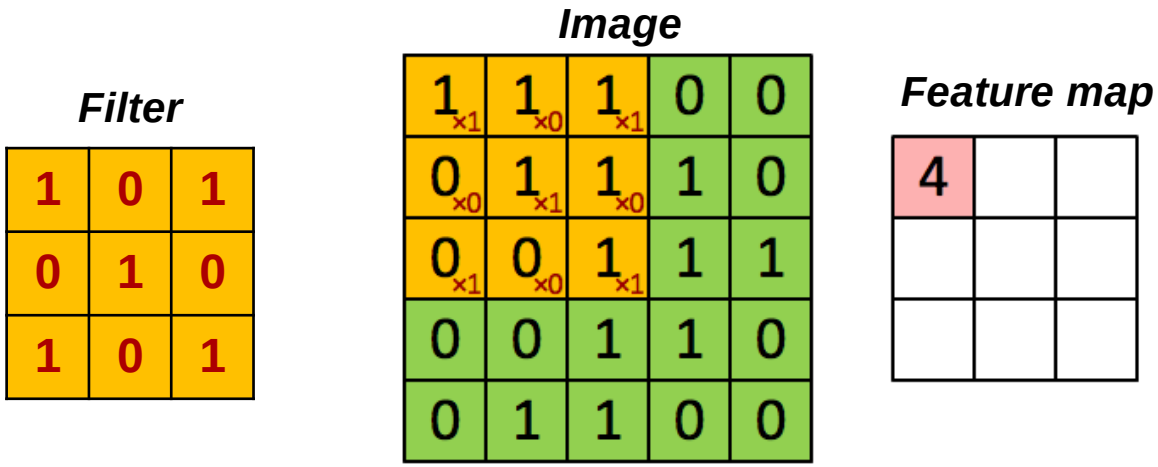
$1_{\times 1}$	$1_{\times 0}$	$1_{\times 1}$	0	0
$0_{\times 0}$	$1_{\times 1}$	$1_{\times 0}$	1	0
$0_{\times 1}$	$0_{\times 0}$	$1_{\times 1}$	1	1
0	0	1	1	0
0	1	1	0	0

Feature map

4		

Receptive field

- Receptive field of the filter – the image region that is currently being convolved with the filter

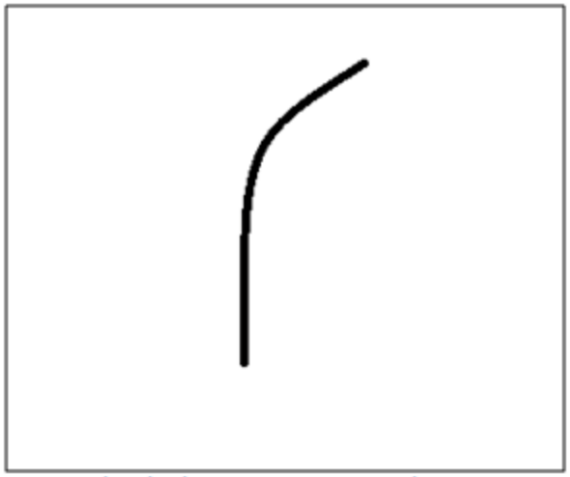


Understanding convolution

- Higher-level perspective – we can think about the filters as feature detectors
- Example: a filter for detecting a curve

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter



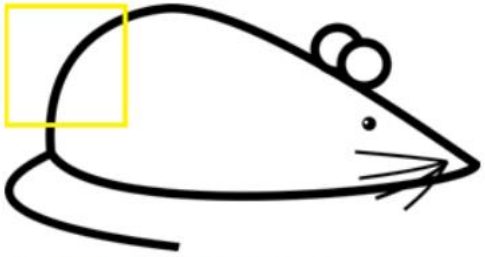
Visualization of a curve detector filter

Ref.: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Understanding convolution (2)

- Let's apply the filter to an image that we want to classify and put the filter at the top left corner

Original image



Visualization of the filter on the image

Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

*

Filter

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Feature map value:

Multiplication and Summation = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 (A large number!)

The curve is detected!

Ref.: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Understanding convolution (3)

- Move the filter to another part of the image
- The value is much lower (0) – the curve is not detected
- There wasn't anything in the image region that responded to the curve detector filter

Visualization of the filter on the image

0	0	0	0	0	0	0
0	40	0	0	0	0	0
40	0	40	0	0	0	0
40	20	0	0	0	0	0
0	50	0	0	0	0	0
0	0	50	0	0	0	0
25	25	0	50	0	0	0

Pixel representation of receptive field

*

0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = 0

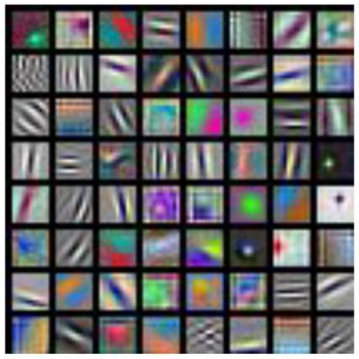
The curve is not detected!

Ref.: https://adeshpande3.github.io/A-Beginner%27s-Guide-To-Understanding-Convolutional-Neural-Networks/

Understanding convolution (4)

- The feature map will show the image regions in which there are curves (specific features)
  - High values: there is some curve which activated the filter
  - Low values: there is no curve
- We can use more than one filter – we will detect different features
- The filters convolve with the image parts and “activate” (have high values) when a specific feature is detected

First-layer conv filters: local image templates
(Often learns oriented edges, opposing colors)



AlexNet: 64 filters, each 3x11x11

Image ref.: http://cs231n.stanford.edu/

More on convolution

- In CNNs, the filters are not pre-designed to detect a particular type of feature, their values are learned during training with the backpropagation algorithm
- A typical convolutional layer includes many filters, each detecting a different feature
  - => Many feature maps: feature map 1 created by filter 1, feature map 2 created by filter 2 etc.

Strides

- In our example, we moved the filter along the image 1 pixel at a time;
- When we reached the end of the image, the filter returned to the left but 1 pixel lower
- We say that the horizontal and vertical strides were both 1: $s_h=1$, $s_v=1$
- Different strides can be used – illustration of $s_h=2$, $s_v=2$:

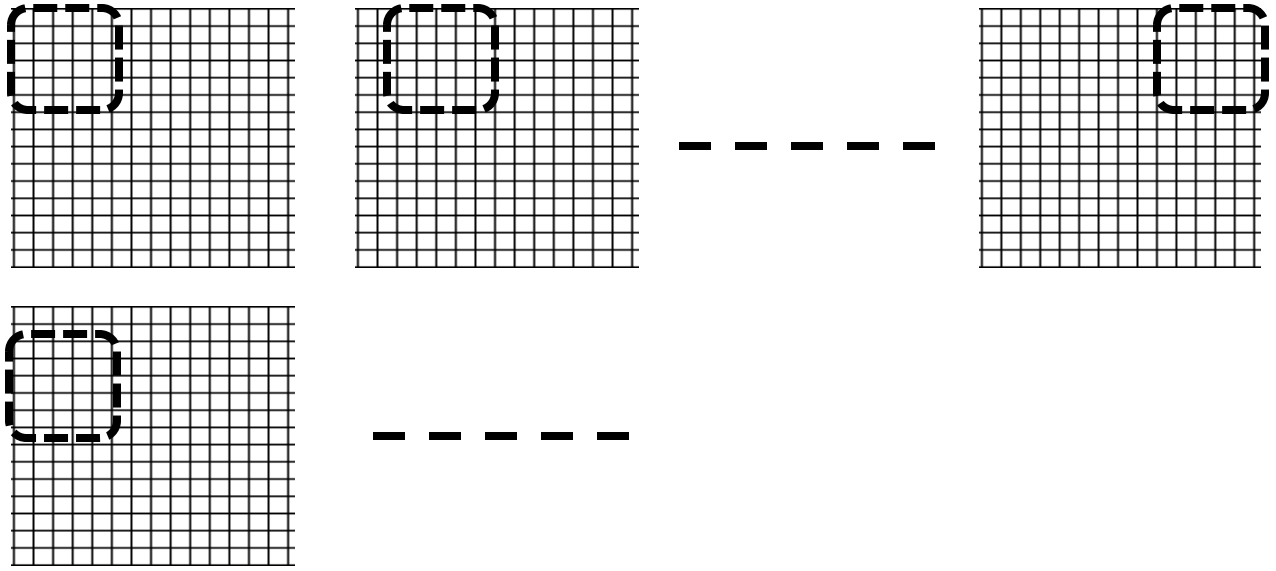


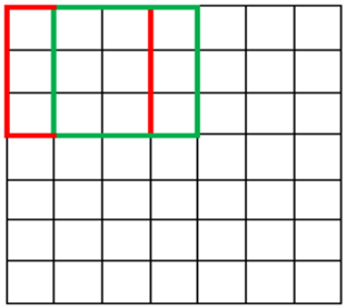
Image ref.: M. Kubat, Introduction to ML, Springer

Strides – another example

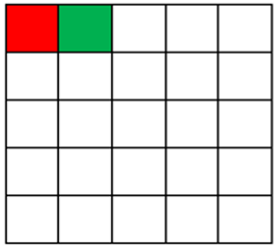
- Bigger strides produce smaller feature maps

Stride = 1 (filer = 3 x 3)

7 x 7 image

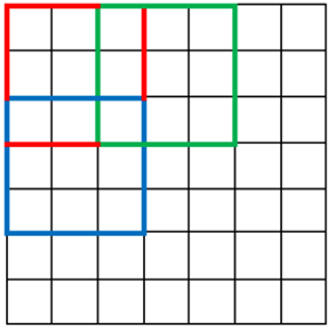


5 x 5 feature map

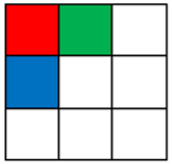


Stride = 2 (filter = 3 x 3)

7 x 7 image



3 x 3 feature map

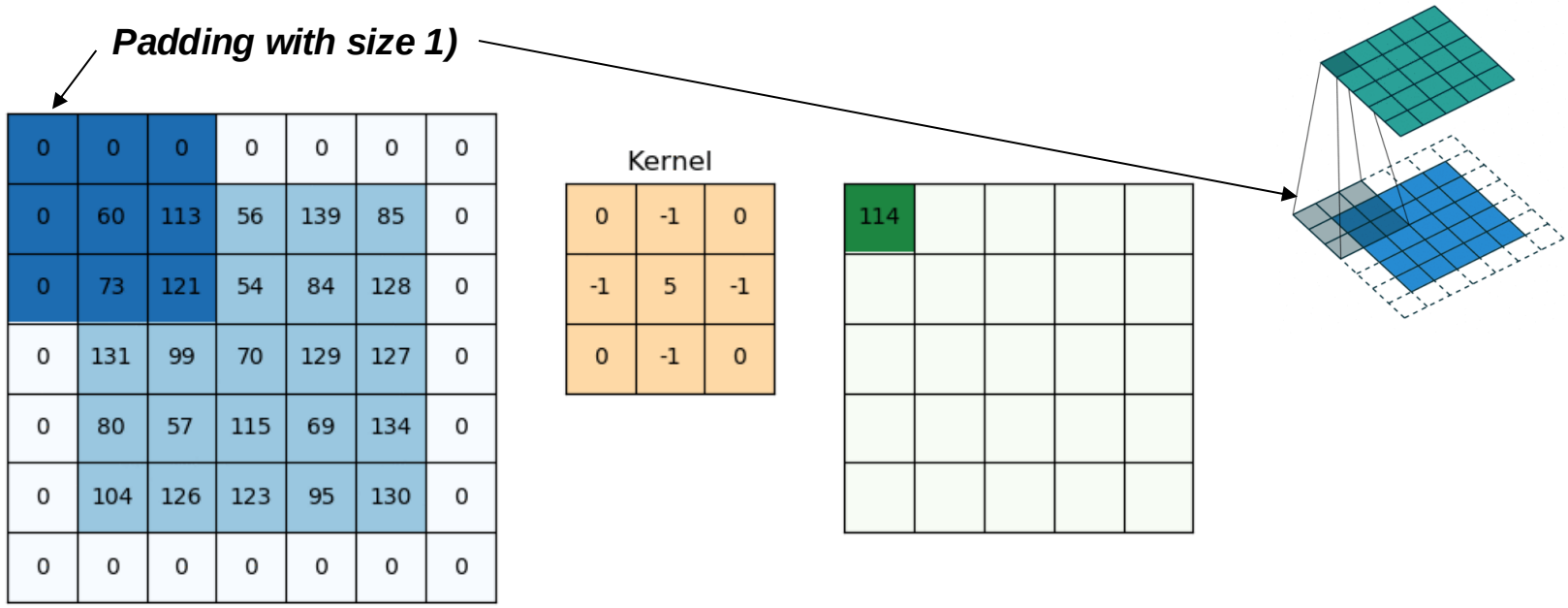


Padding

- Motivation: at the end of the row (or column), the filter may “reach beyond” the original image
- If the next stride would make the filter reach beyond the image, fill the fields outside the image with zeros
  - This means adding zeros around the border
  - The size of the padding is a hyperparameter
- Padding allows for better coverage of the image around the image and feature extraction

Padding - example

- An example of padding with size 1

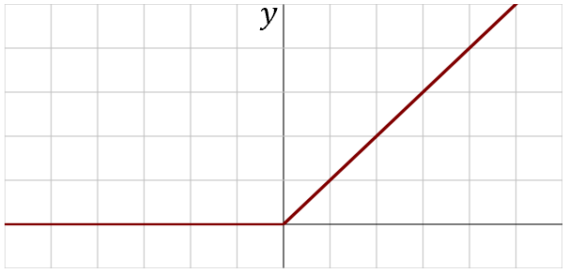


ReLu activation function

- We apply an activation function to the feature maps, typically ReLU
- ReLu is simpler than sigmoid or tanh => faster computation
- Simplifies the gradient-descent calculation
- No upper bound, no saturation of the output, less vanishing gradient

ReLU

$$y = max(0, x)$$



Pooling

- The exact location of a feature is not so important; we just want to know where approximately it is and how it relates to other features
- We can use a pooling layer (also called sub-sampling layer)
  - "Summarizes" the input from the previous layer
  - Reduces the number of parameters (by 75% in the example below) and helps prevent overfitting
  - Improves robustness to shifts in the receptive field

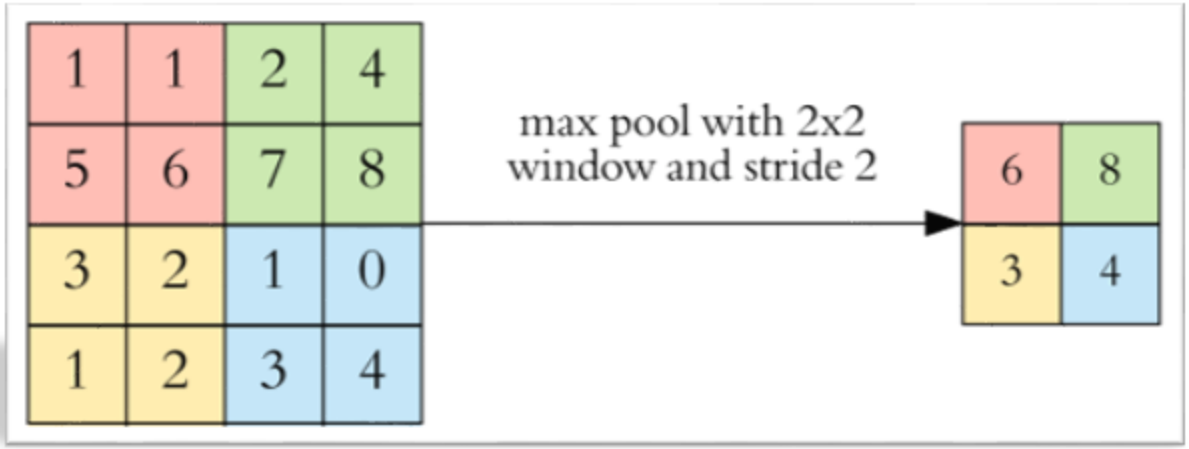
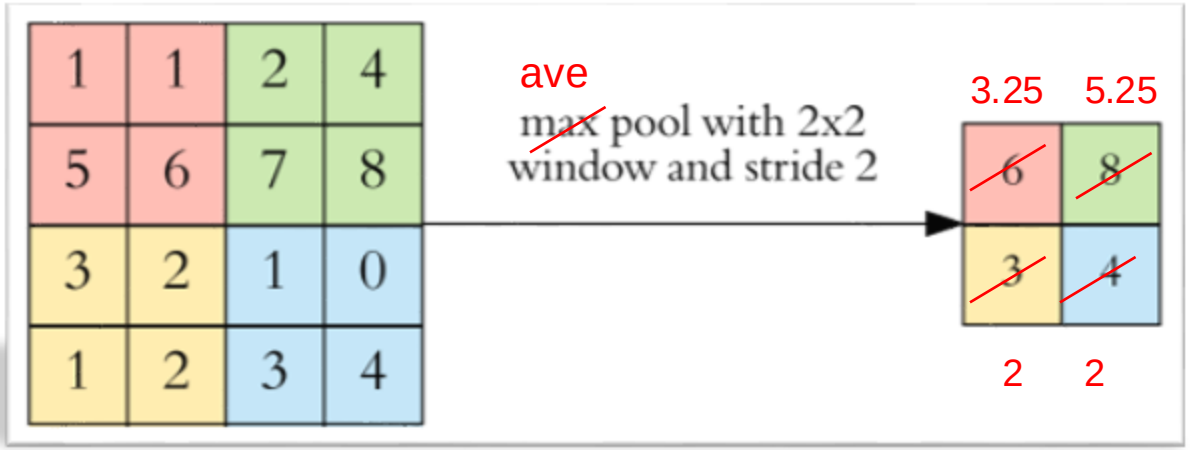


Image ref.: M. Kubat, Introduction to ML, Springer

Two versions of pooling

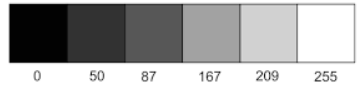
- Max pooling (max pool) – take the maximum value of the region
- Average pooling (ave pool) – take the average value of the image region

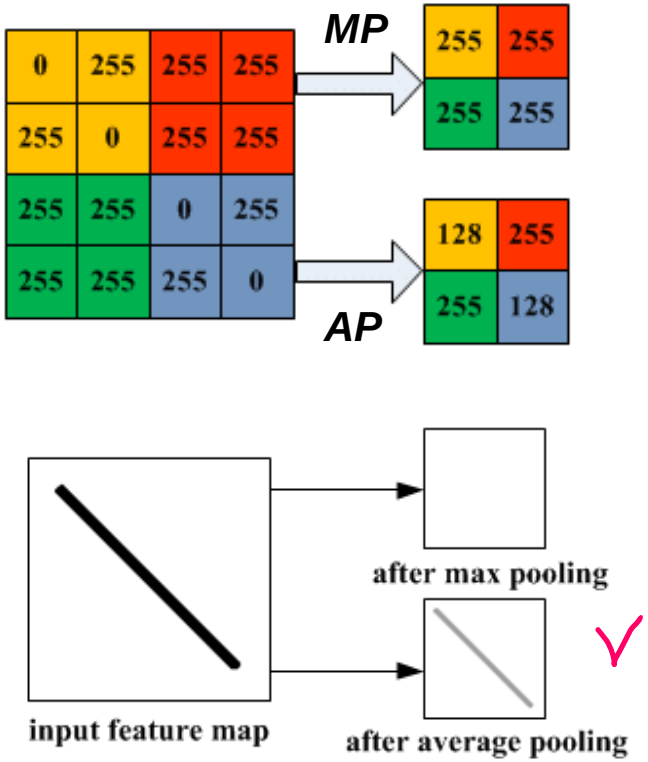


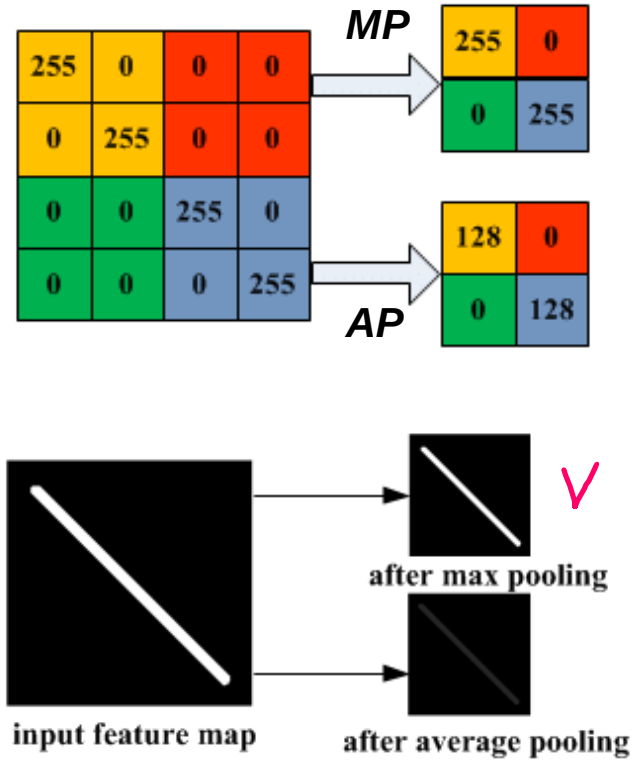
Which type of pooling will be better?

Max Pooling (MP)

Average Pooling (AP)

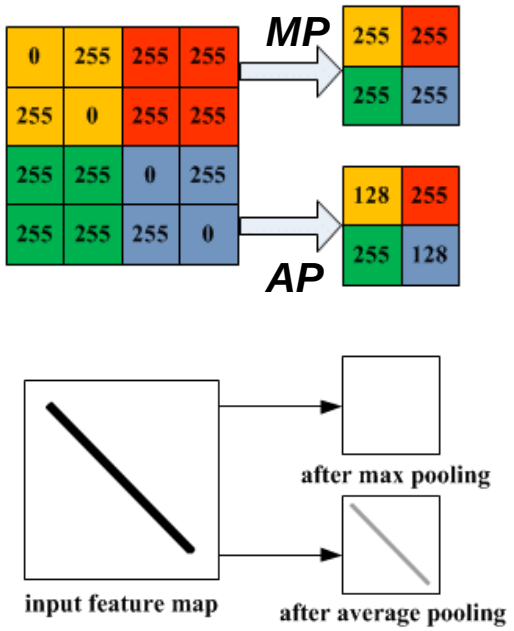


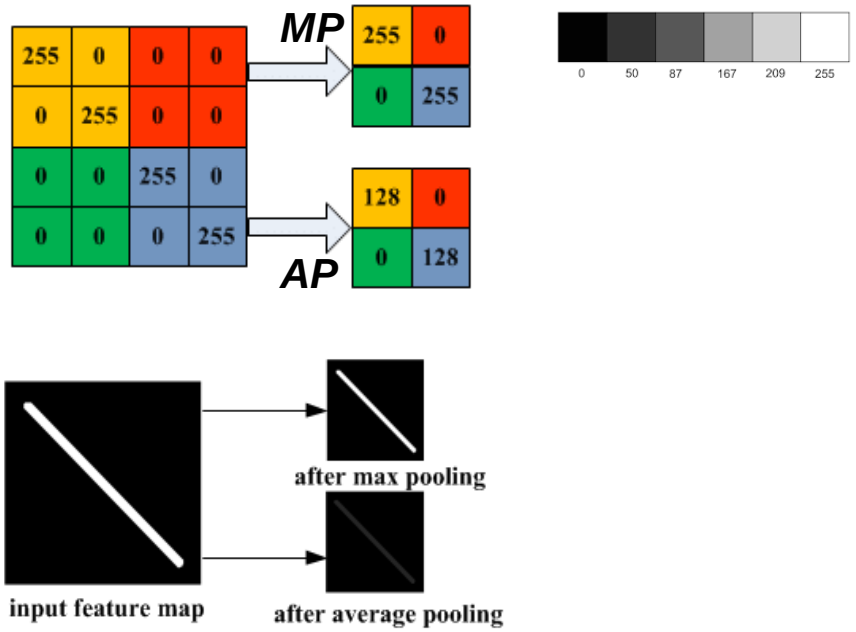




Which type of pooling will be better? (2)

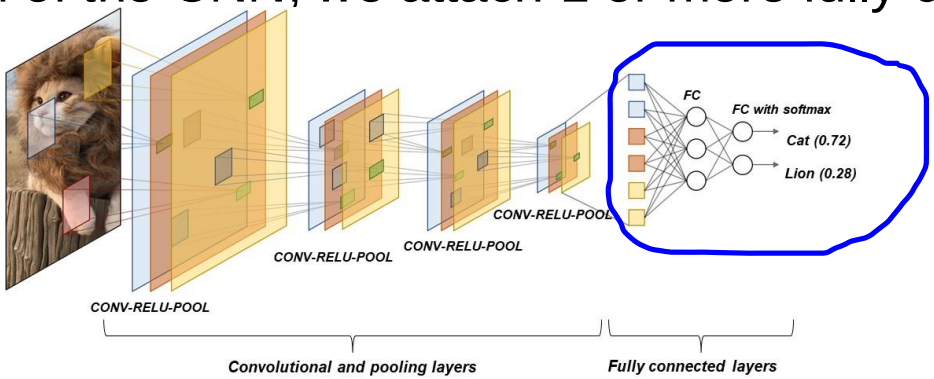
- MP or AP - it depends on the task
- MP selects the max value (brightest pixel) -> useful for images with dark background, when we are interested in the lighter pixels, e.g. MNIST dataset – white digits on a dark background
- AP smooths the image





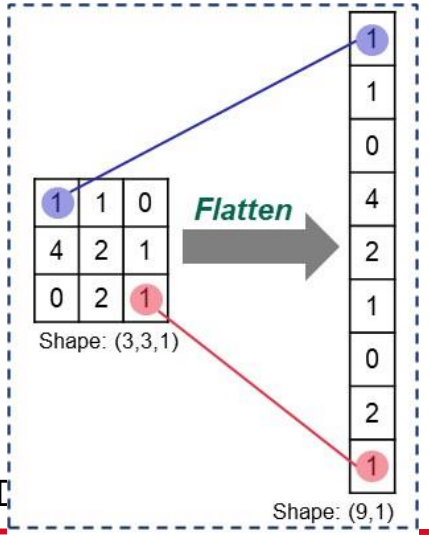
Fully connected layer

- At the end of the CNN, we attach 1 or more fully connected (FC) layers



- The first FC layer takes the output of the last layer which is either convolutional or pooling (conv are not always followed by pool)

- The first thing to do is to “flatten” the output -
- transform the multi-dimensional matrix of features into a vector that can be fed in the FC layer



Fully connected layer (2)

- The last FC layer outputs a n-dimensional vector where n is the number of classes. It typically uses a softmax function to output probabilities for each class.
  - E.g. if the task is digit classification and the resulting output is

  [0.1, 0, 0, 0.1, 0, 0, 0.6, 0, 0, 0.2], this means 10% probability that the image is "1", 10% that it is "3", 60% that it is "6" and 20% that it is '9'
  - The probabilities sum up to 1

- Essentially, the FC layers looks at the features extracted by the convolutional layers, combine them and output the probabilities for each class

Extending CNNs to multi-channel input

- Color images have 3 channels: Red, Green and Blue

Input
[32 x 32 x 3]

=

Red
32 x 32

+

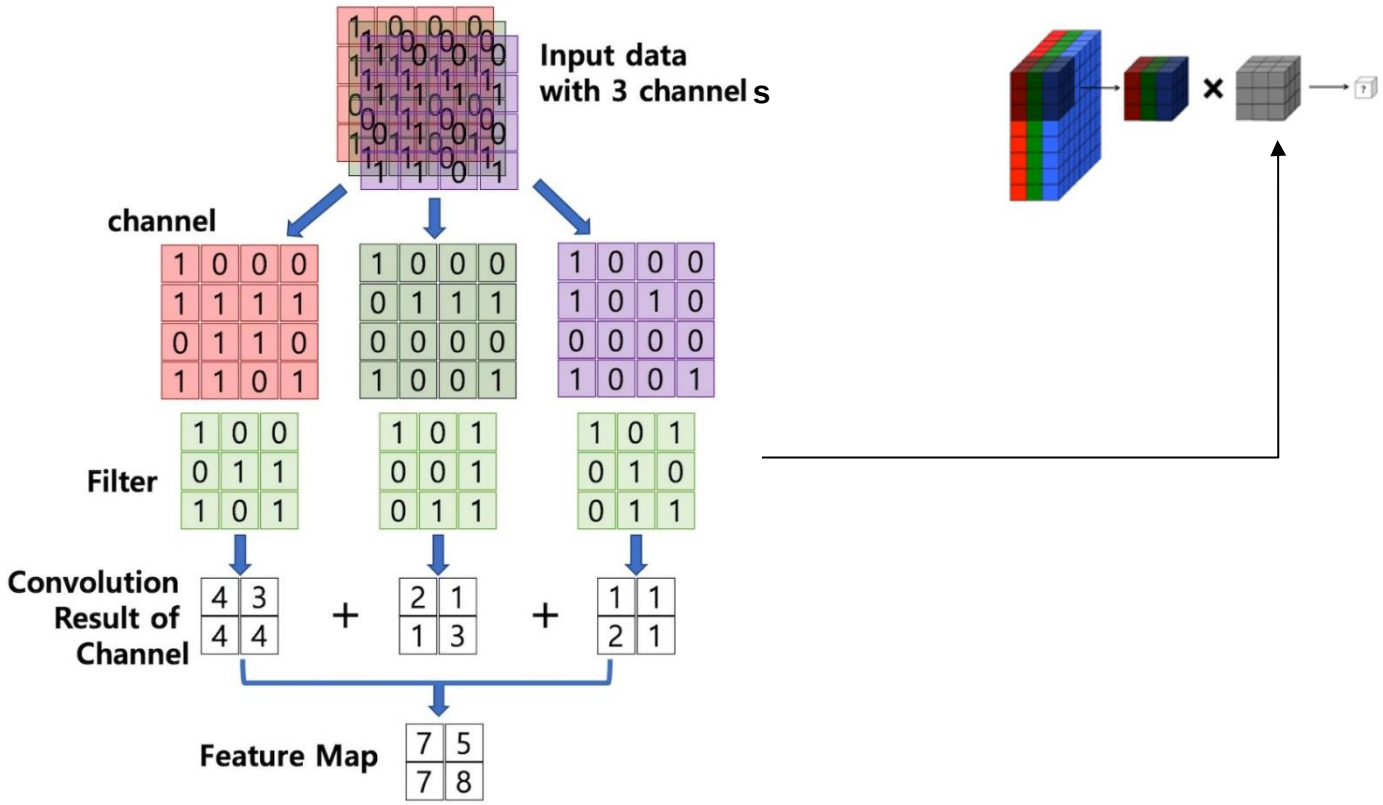
Green
32 x 32

+

Blue
32 x 32

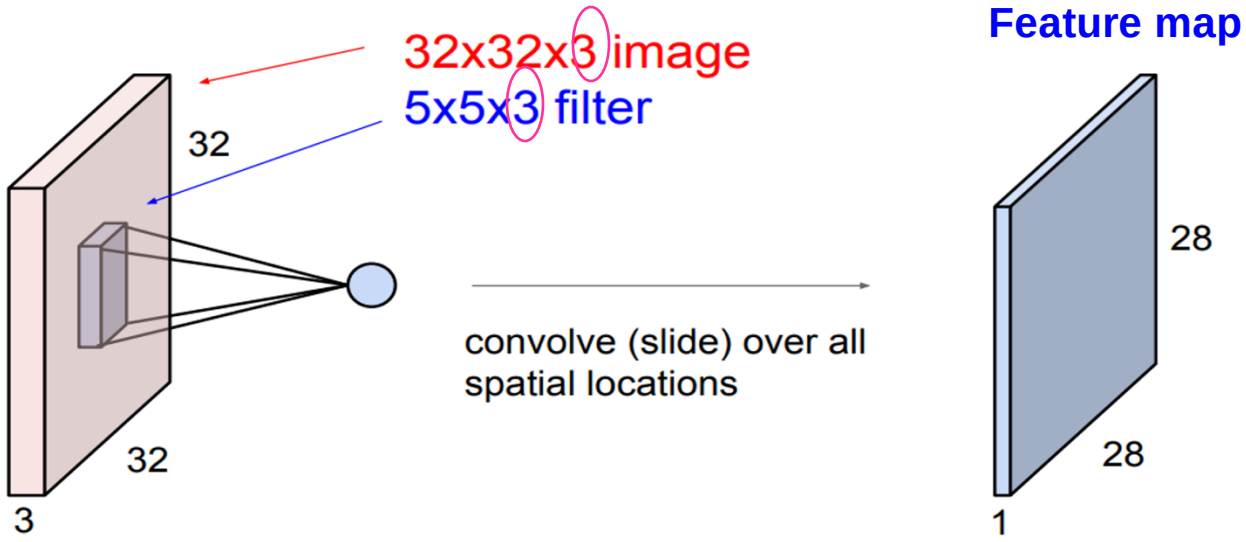
Extending CNNs to multi-channel input (2)

- We can modify the CNN architecture to work with multiple channels



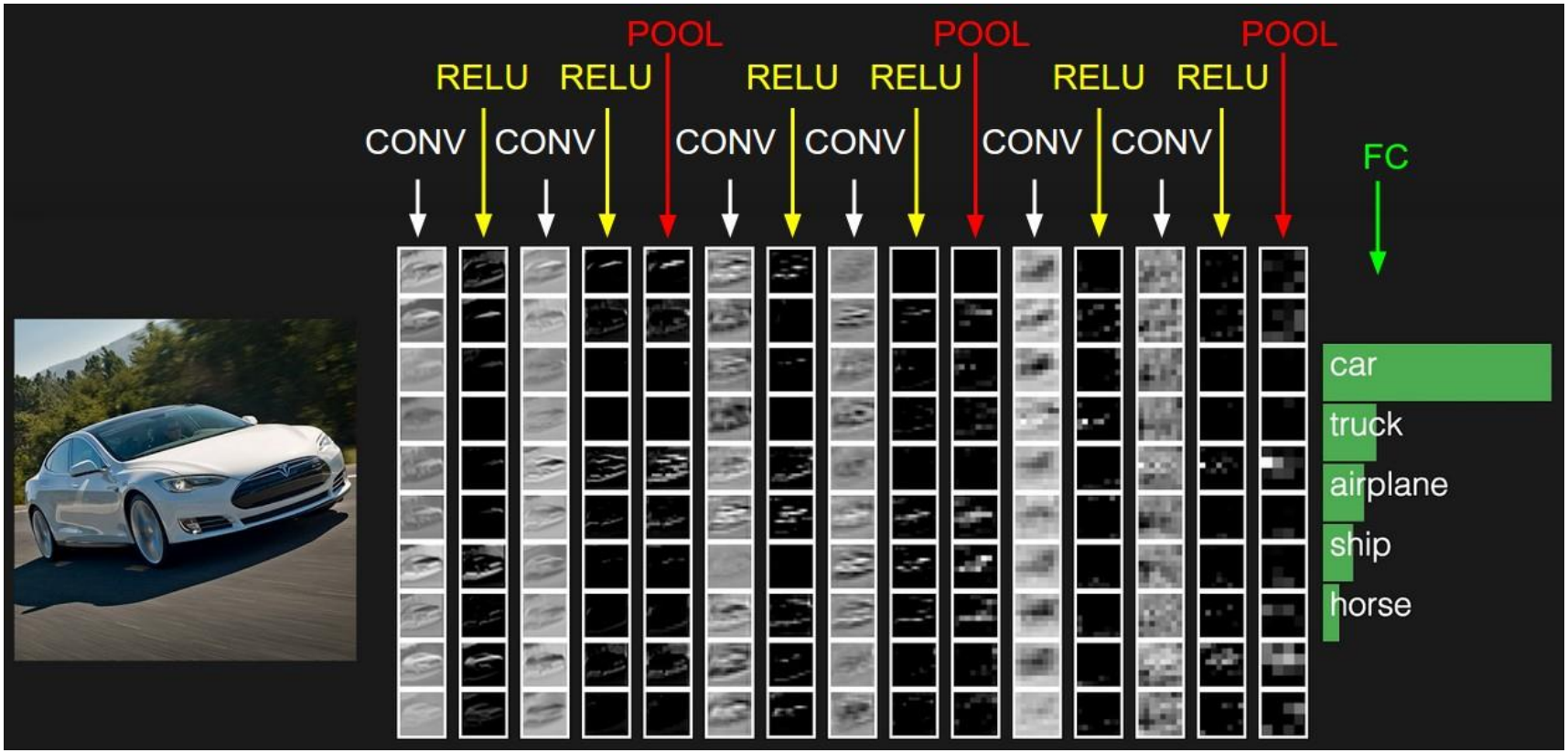
Extending CNNs to multi-channel input (3)

- Using multi-channel data increases the dimension of the filters too - the third dimension should be the same
- Example: 3-dim data (3 color channels) -> 3-dim filter; the third dimension should be the same – 3 in this case



CNN architecture - example

INPUT – CONV – RELU – POOL - FC



Web-based demo: http://cs231n.stanford.edu/

CNN architectural issues

- What is the right way to combine the CNN components?
- How many convolution layers?
- How many filters in each of these layers?
- What should be the size of these filters (e.g., 3-by-3 or 5-by-5)?
- How frequent should be the pooling layers? After each convolution layer? Or less frequent?
- What should be the size of the pooling layers? 2-by-2 or 3-by-3? Other dimensions? Should they perform max-pooling or ave-pooling?

CNN architectures

LeNet-5

- Task: Handwritten digit recognition
  - LeCun, L. Bottou, Y. Bengio and P. Haffner (1998), Gradient-based learning applied to document recognition, Proceedings of the IEEE.
  - http://yann.lecun.com/exdb/publis/pdf/lecun-01a.pdf
- Architecture: 2 convolution, 2 max-pooling, 3 fully connected

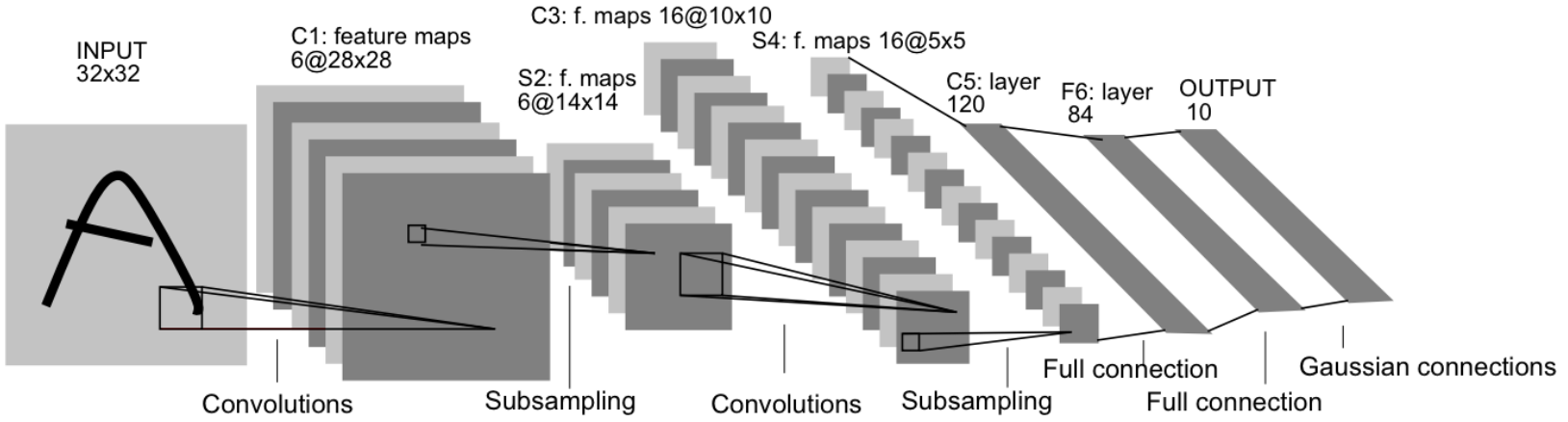


Fig. 2. Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

LeNet-5 (2)

Image from http://yann.lecun.com/exdb/lenet/multiples.html

AlexNet

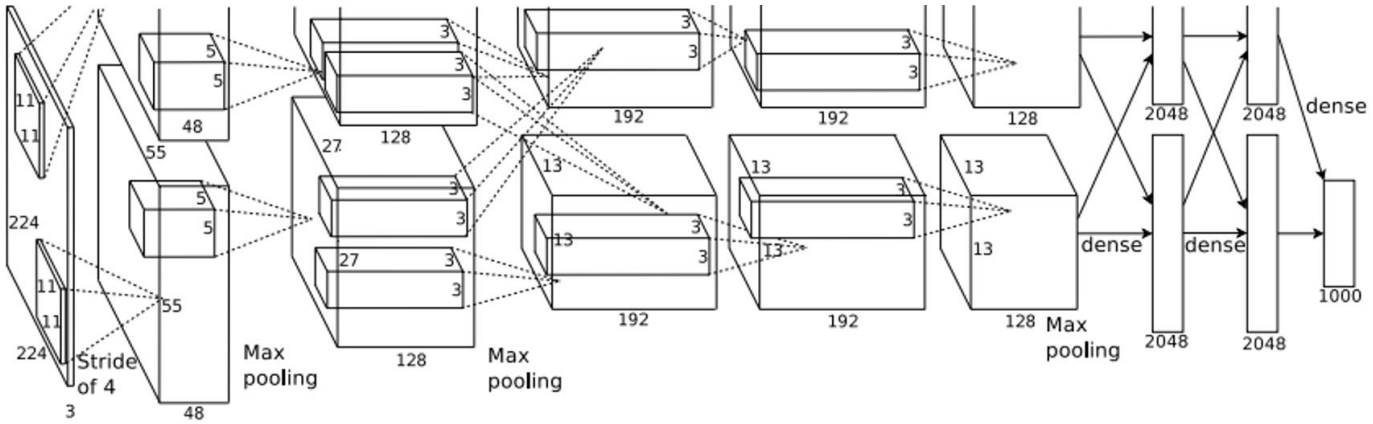
- Task: Classification of images into different categories
- ImageNet and ImageNet Large Scale Visual Recognition Challenge - facilitated important advances in computer vision
  - A. Krizhevsky, I. Sutskever, G. Hinton (2012), ImageNet classification with deep convolutional neural networks, Proceedings of NIPS
  - https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf
- Training data: 1.2 million images from ImageNet dataset labelled in 1000 classes

Image from http://vision.stanford.edu/resources_links.html

AlexNet (2)

- Input: 227 x 227 images
- 5 convolutional layers, 3 max pooling layers, 3 fully-connected layers

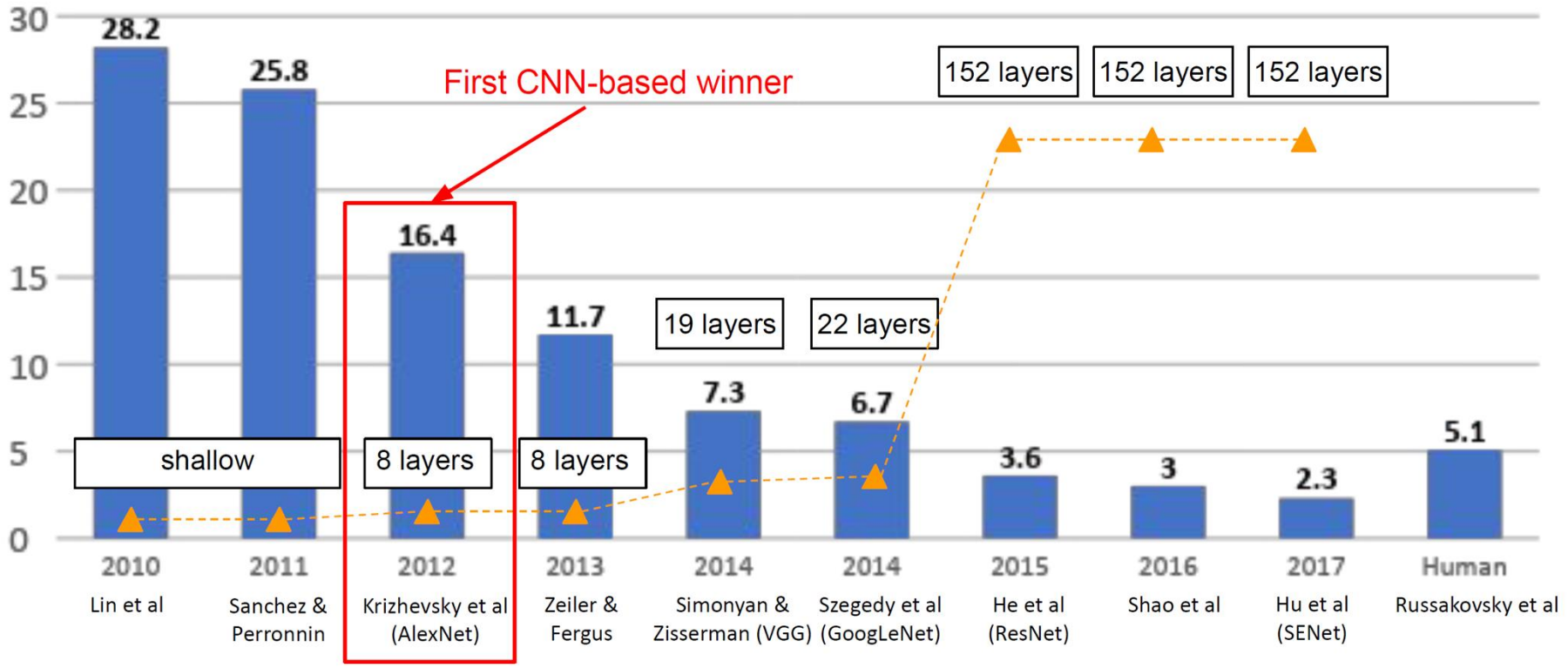
Architecture:
CONV1
MAX POOL1
NORM1
CONV2
MAX POOL2
NORM2
CONV3
CONV4
CONV5
Max POOL3
FC6
FC7
FC8



http://cs231n.stanford.edu/

AlexNet (2)

- ImageNet Large Scale Visual Recognition Challenge (ILSVRC) winners



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VGG

- Simonyan and Zisserman, 2014; https://arxiv.org/abs/1409.1556
- An improved version of AlexNet
- Deeper network, simpler design

- Convolutions: 3x3 filters, stride=1, padding=1
- Max pooling: 2x2, stride=2

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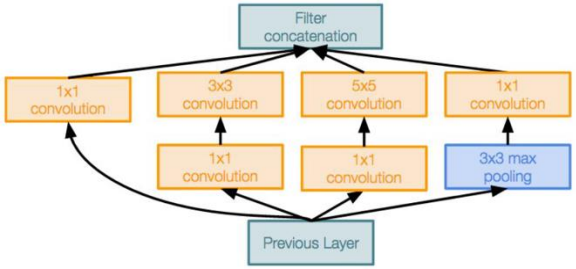
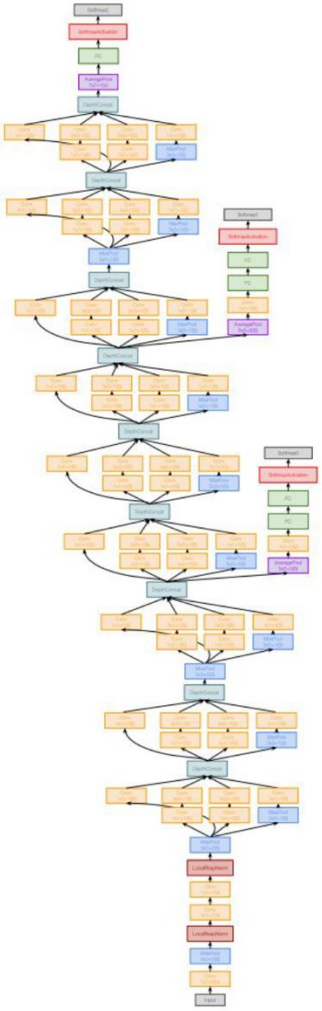
GoogLeNet

- Szegedy et al., 2014; https://arxiv.org/abs/1409.4842
- Deeper networks, with computational efficiency
- - ILSVRC'14 classification winner - 6.7% error

- 22 layers
- Only 5 million parameters!
  - 12x less than AlexNet and 27x less than VGG-16
- Efficient "Inception" module
- No FC layers



Inception module



http://cs231n.stanford.edu/

CNN - summary

- CNNs are designed for image data but can be applied to other data types
- Key elements: convolution, pooling and fully connected layer
- The convolutional layers extract features
- The pooling layers summarize the information from the convolutional layers, reduce the number of parameters to prevent overfitting and improve the robustness to shifts in the data
- The fully connected layer combines the extracted features and outputs the probabilities for each class
- CNNs have been very successful in image processing and computer vision tasks

Recurrent Neural Networks

Introduction

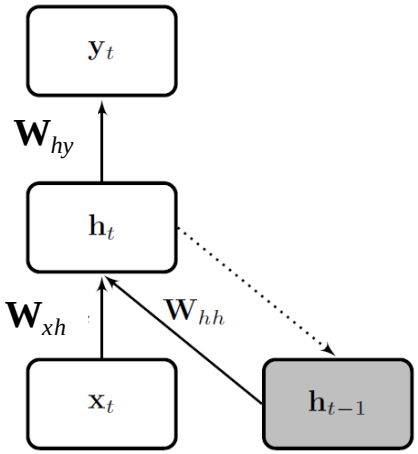
- Recurrent Neural Networks (RNN) are used for sequential data
- Text (natural language) data is an example of sequential data
  - Sentences are sequences of words – 1 word follows the other
  - Each sentence may have a different number of words (varying length)
  - Each sentence may contain long-distance dependencies between the words
    - The dog in that house is aggressive
    - The dogs in that house are aggressive
- Processing this type of data requires a model that can remember relevant information from the earlier in the sequence (needs memory)
- RNNs can do this

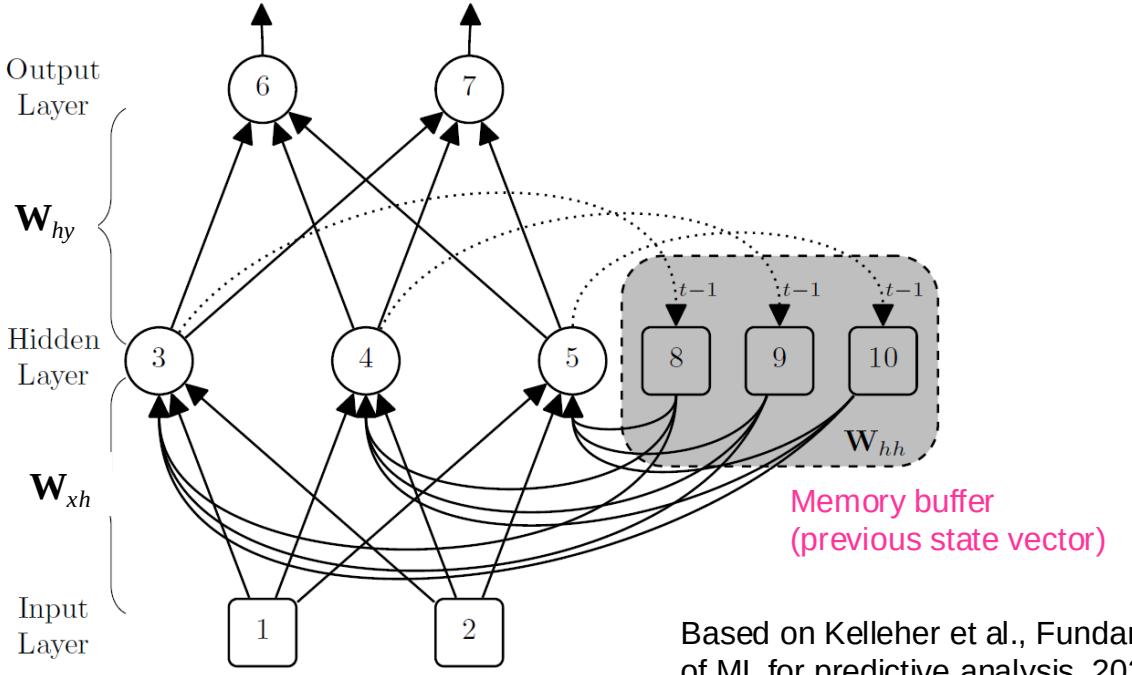
One element at a time

- When processing the sequence, a RNN takes 1 element from the sequence at each time point, e.g. 1 word:
  - The dog in the house is aggressive
  - at time t: the, t+1: dog, t+2: in, t+3: the, t+4: house, t+5: is, t+6: aggressive
- It is called recurrent because it contains feedback connections (e.g. from the hidden layer to the input layer)
  - => feedforward NN is a directed acyclic graph; RNN is a directed cyclic graph
- Specifically, the output of a neuron at one time point is fed back into the same neuron at the next time point (or another time point)
- Consequence: RNN has a memory over past activations (and hence past inputs which contributed to these activations)
- => RNN can capture long-distance dependences => useful for sequences
- There are different architectures; we will cover:
  - Simple RNN (also called Elman network)
  - Long Short-Term Memory (LSTM) network

Simple RNN

- A feedforward architecture with 1 hidden layer
- The hidden layer is extended with a memory buffer which stores the previous state of the hidden layer (from the previous time-step)
- At each time-step, the information from the memory is concatenated with the next input to each neuron

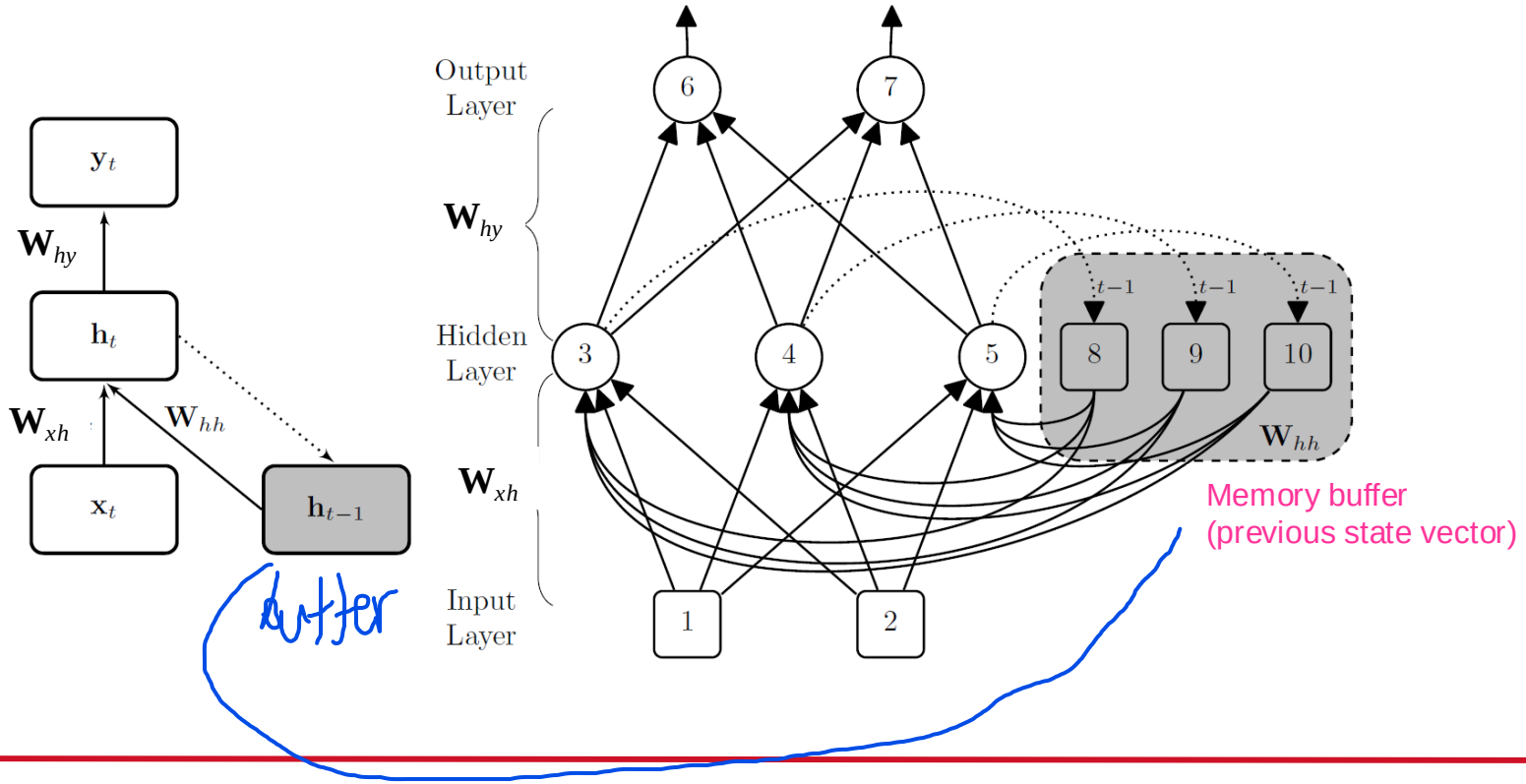




Based on Kelleher et al., Fundamentals of ML for predictive analysis, 2020, MIT.

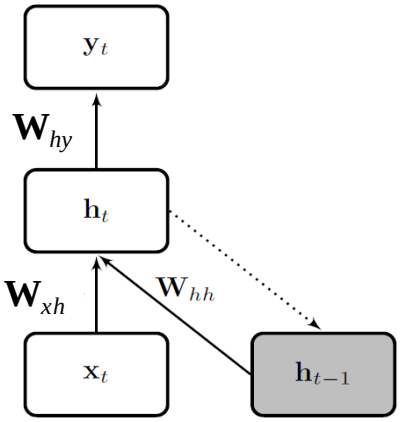
Input, hidden and output layers

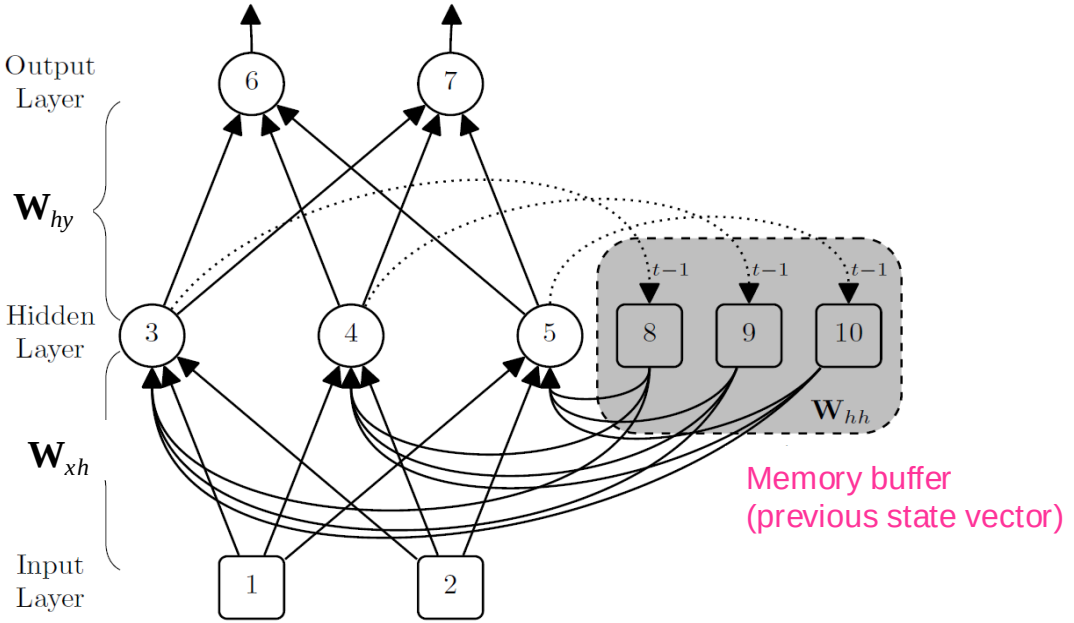
- x_t – input vector at time t
- h_t - hidden layer activations at time t
- y_t – output vector at time t
- E.g. given word at t (x_t), predict the next word – the word at t+1 (y_t)



Weight matrices

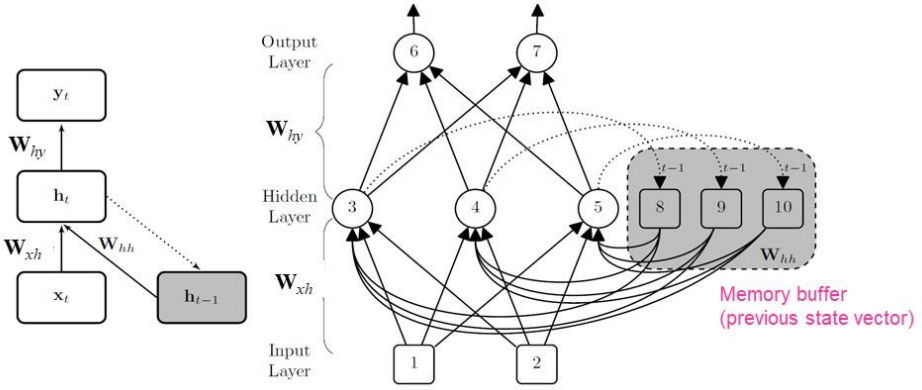
- 3 weight matrices:
  - W_{xh} - weights between the input and hidden layer
  - W_{hy} - weights between the hidden and output layer
  - W_{hh} - weights between the memory buffer and the hidden layer (*hh* because these are weights of the recurrent connections from the hidden layer back to the hidden layer)





Specific example

- Let's consider a specific example:
  - 2 neurons in the input layer, 3 in the hidden and 2 in the output layer
- At each time-step a new input vector is presented
- Each hidden neuron
  - 1) Receives both the input vector and the previous state information from the memory buffer
  - 2) Processes this information and generates activations that are passed to the output layer and also written to the memory buffer
- At the next time-step, the information from the memory buffer is fed back to the hidden neurons, together with the new input

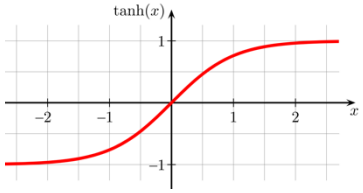


Forward pass - calculating output

New state | Old state | Input vector

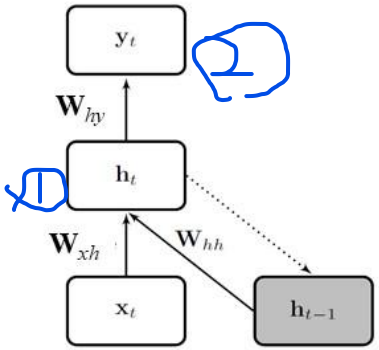
$$h_t = f_W(h_{t-1}, x_t)$$

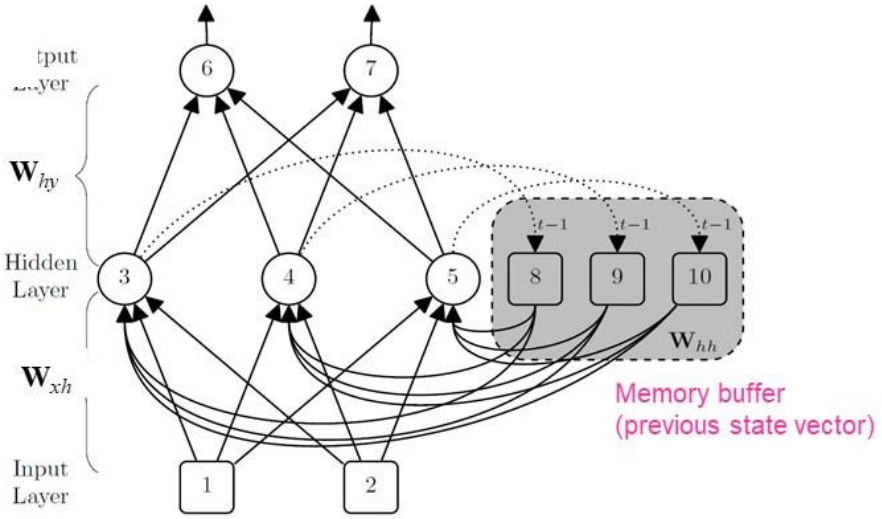
f_W – function with parameters W; tanh is typically used: output between 1 and -1



$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$

$$y_t = W_{hy}h_t + b_y$$





Hidden state update

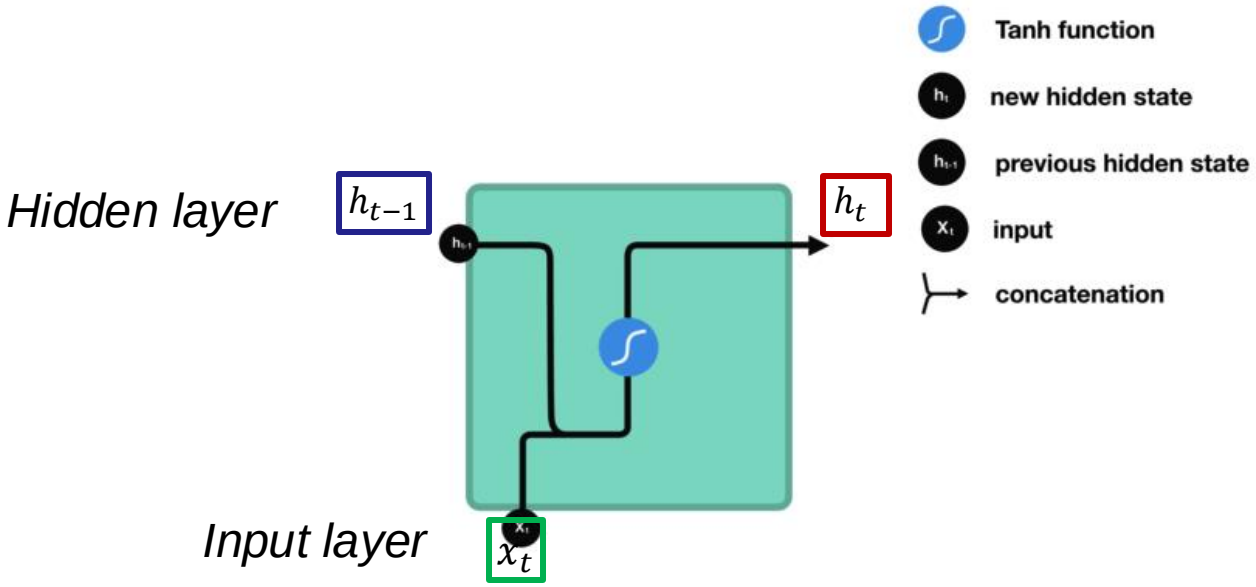
- Animation :-)

New state

Old state

Input vector

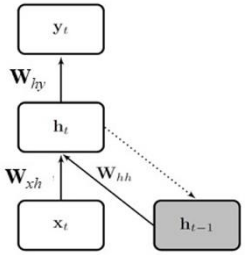
$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$



https://towardsdatascience.com/illustrated-guide-to-recurrent-neural-networks-79e5eb8049c9

Unrolling RNNs

- As we saw, RNNs have cyclic connections - the output of the hidden neuron at time *t*-1 is fed back as input to the hidden neuron at time *t*

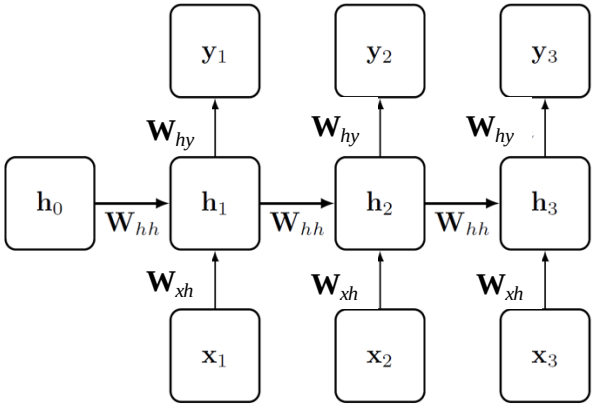


New state — Old state — Input vector

$$h_t = f_W(h_{t-1}, x_t)$$

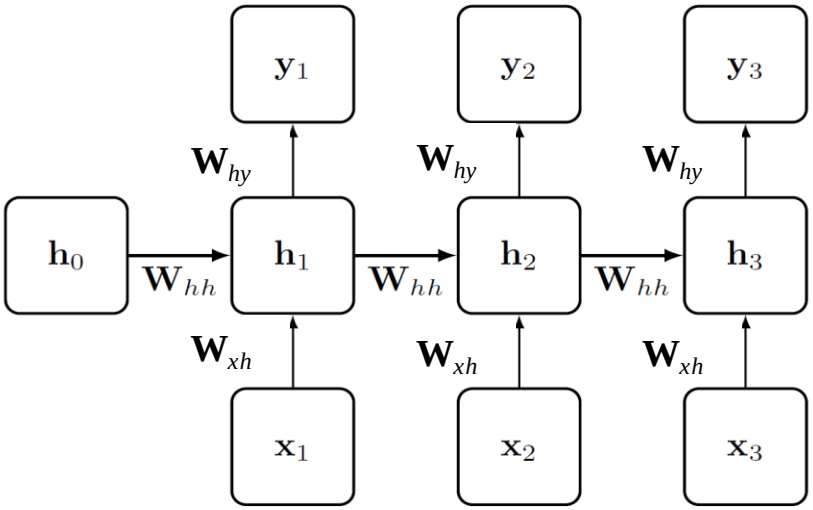
- These cycles make it difficult to understand the information flow in RNN over many time steps

- Instead, we can visualize the information flow in another way – by "unrolling" (or "unfolding") the RNN along the time steps
  - There will be no cycles in the graph
  - Important: the RNN is the same between the unfolded time steps – the weights do not change



The unrolled network

- Suppose there are 3 time-steps – we can “unroll” the RNN through these 3 steps to calculate the output:



- h_0 is the initial state of the memory buffer when RNN is initialized
- Note: RNN has only 3 weight matrices, not 3x3=9 (3x3 time steps)
- Again, “unroll over time” means following the sequence of steps that are performed

Training RNN: backpropagation through time

- We can see that a RNN is an augmented feedforward NN (feedforward NN + memory). It has an additional matrix: W_{hh} .
- It can be trained with a variant of the backpropagation algorithm, called backpropagation through time
- The error at time *t* is backpropagated to all parameters that contributed to it, this means it is propagated through the previous states of the network. Hence the name - we are "going back in time"

Algorithm 3 The Backpropagation Through Time Algorithm

Require: h_0 initialized hidden state
Require: $\mathbf{x}$ a sequence of inputs
Require: $\mathbf{y}$ a sequence of target outputs
Require: n length of the input sequence
Require: Initialized weight matrices (with associated biases)
Require: $\Delta\mathbf{w}$ a data structure to accumulate the summed weight updates for each weight across time-steps

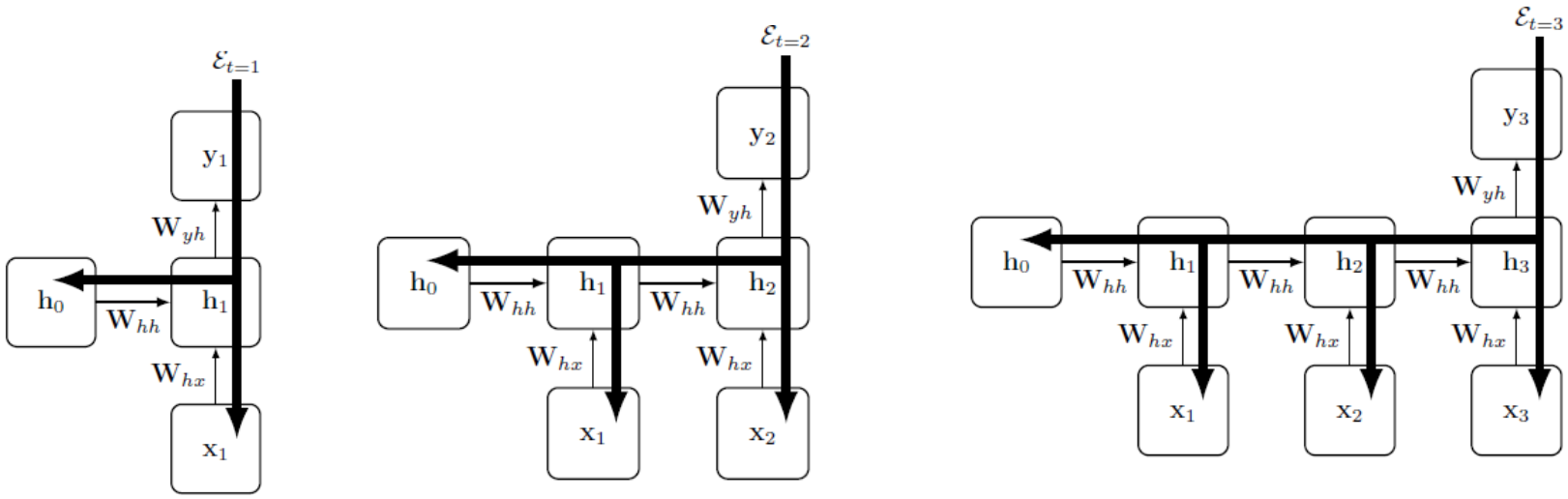
for $t = 1$ to n **do**
  $Inputs = [x_0, \ldots, x_t]$
  $h_{tmp} = h_0$
  for $i = 0$ to t **do** ▷ Unroll the network through t steps
    $h_{tmp} = ForwardPropagate(Inputs[i], h_{tmp})$
  end for
  $\hat{y}_t = OutputLayer(h_{tmp})$ ▷ Generate the output for time-step t
  $\mathcal{E}_t = \mathbf{y}[t] - \hat{y}_t$ ▷ Calculate the error at time-step t
  $Backpropagate(\mathcal{E}_t)$ ▷ Backpropagate $\mathcal{E}_t$ through t steps
  For each weight, sum the weight updates across the unrolled network and update $\Delta\mathbf{w}$
end for
Update the network weights using $\Delta\mathbf{w}$

Kelleher et al., Fundamentals of ML for predictive analysis, 2020, MIT.

Backward pass

- The error at time *t* is backpropagated to all parameters that contributed to it

- Propagating the error for outputs y_1, y_2 and y_3:



Ref.: Kelleher et al., Fundamentals of ML for predictive analysis, 2020, MIT.

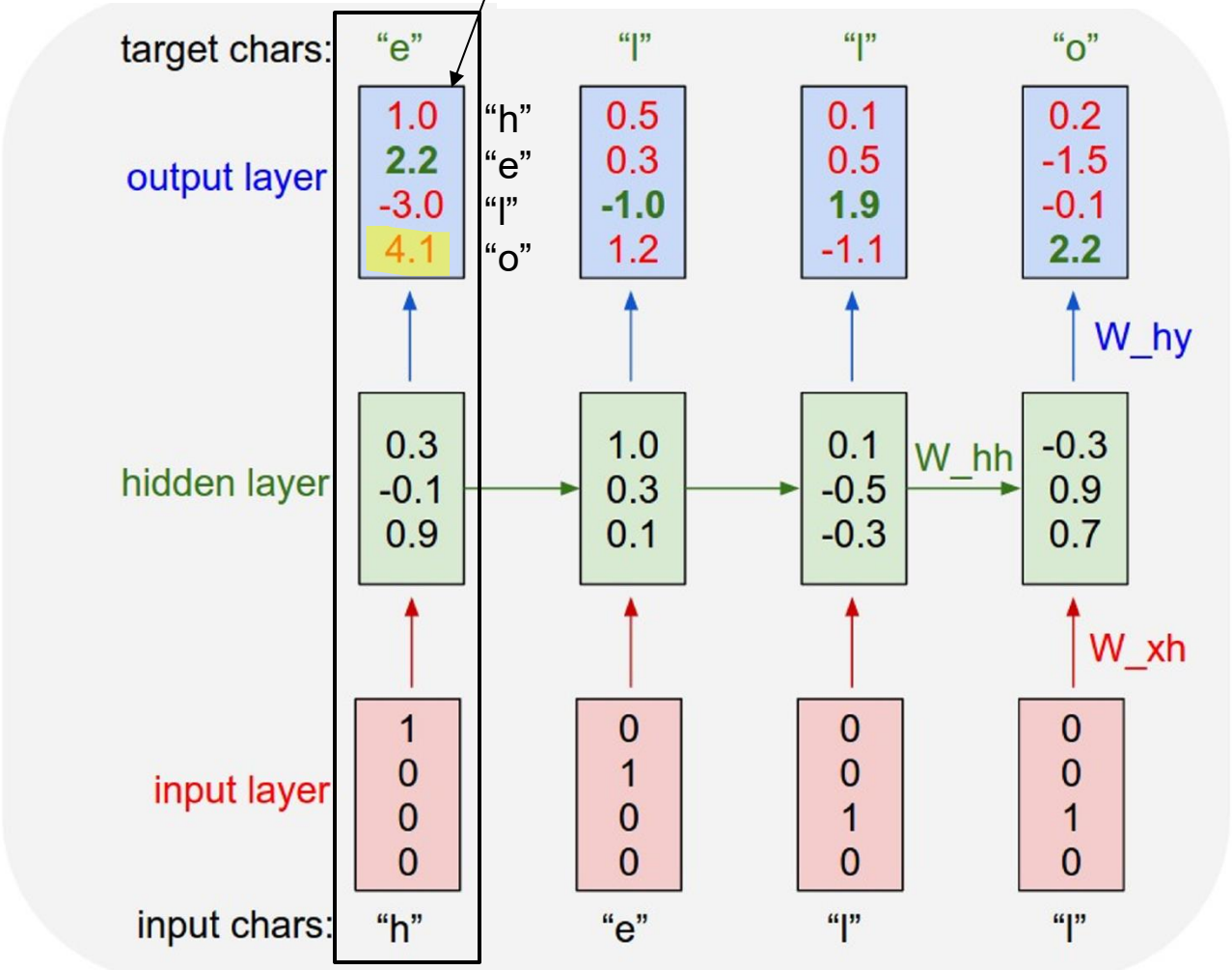
RNN example: predicting the next character

- Given a sequence of previous characters, predict the next one, i.e. given a sequence of characters at times 1, 2, .., t-1, predict the character at time t
- Application: generating new text, 1 character at a time
- Simple example: assume vocabulary of 4 letters only = {h, e, l, o}
- Let's train RNN on the sequence "hello"!
- This means 4 training examples:
  - given "h", predict "e", given "he", predict "l"
  - given "hel", predict l, given "hell", predict "o"
- Encode each character using 1-hot encoding, e.g. "h" is 1000, "e" is 0100
- =>Input vector is 4-dim
- Output vector is 4-dim – 1 value for "h", 1 for "e", 1 for "l" and 1 for "o"; the highest activation determines the predicted letter
- Let's use 3 hidden neurons
- We feed the characters 1 at a time

Example and images from:
http://karpathy.github.io/2015/05/21/rnn-effectiveness/
http://cs231n.stanford.edu/

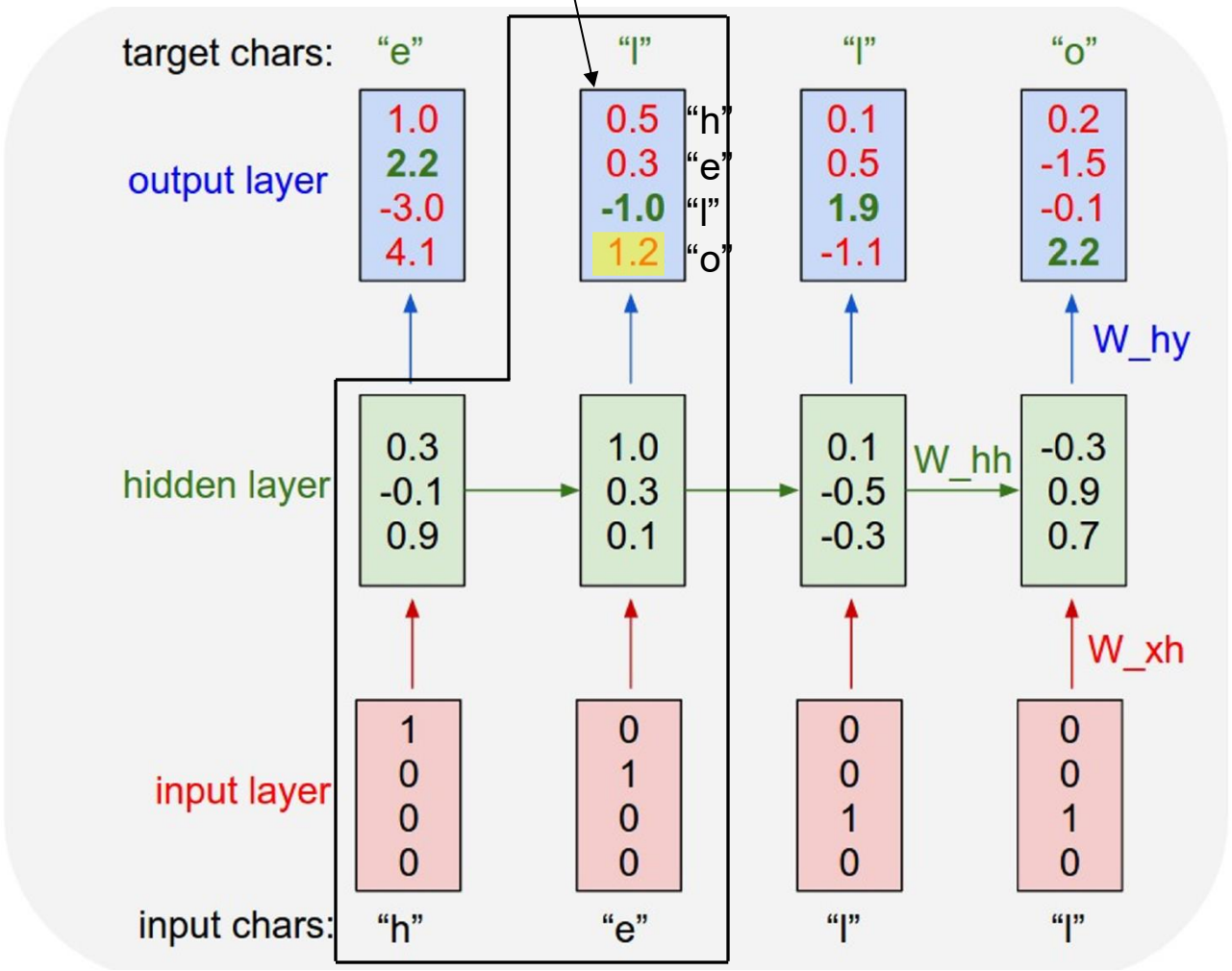
First time step

- Given “h”, predict “e”



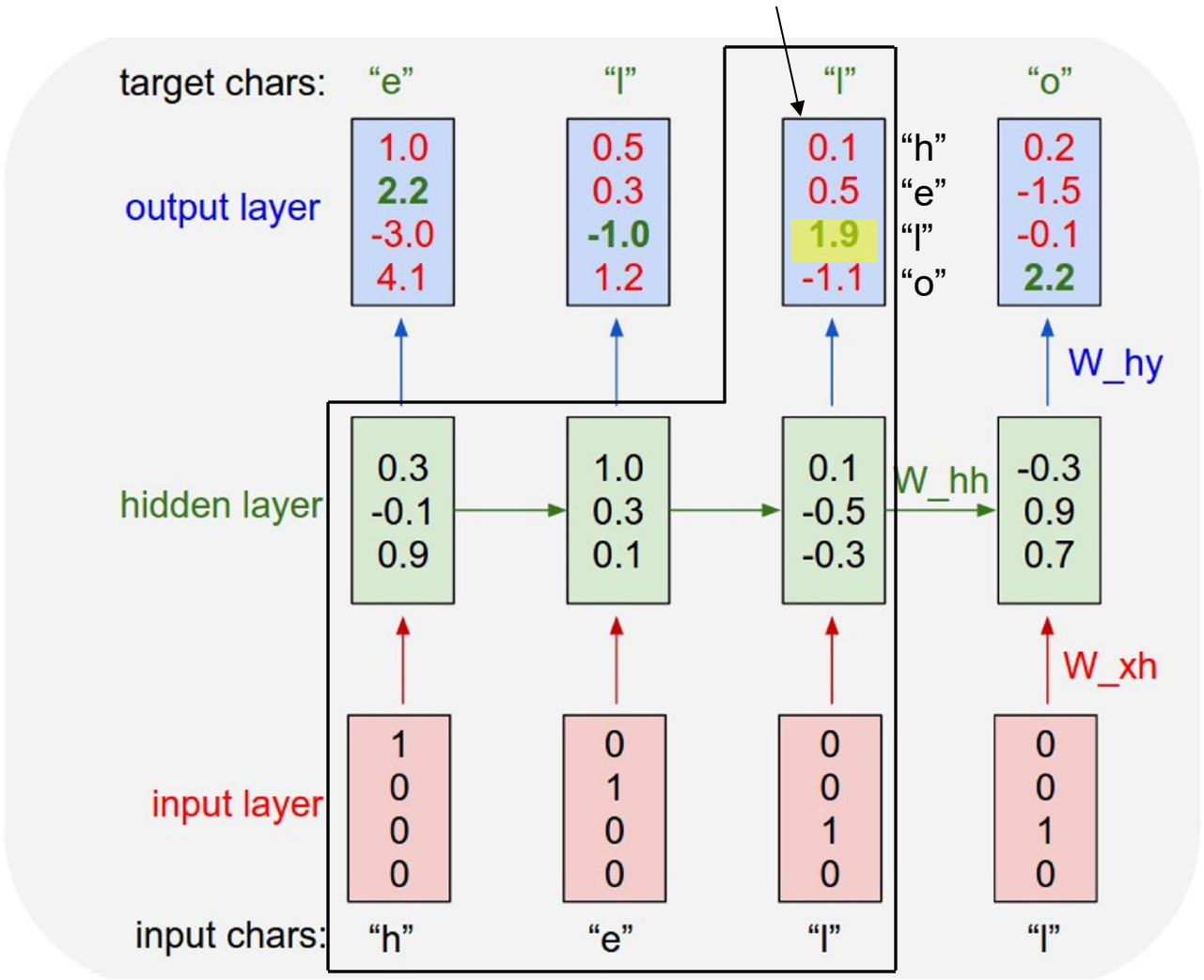
Second time step

- Given “he”, predict “l”



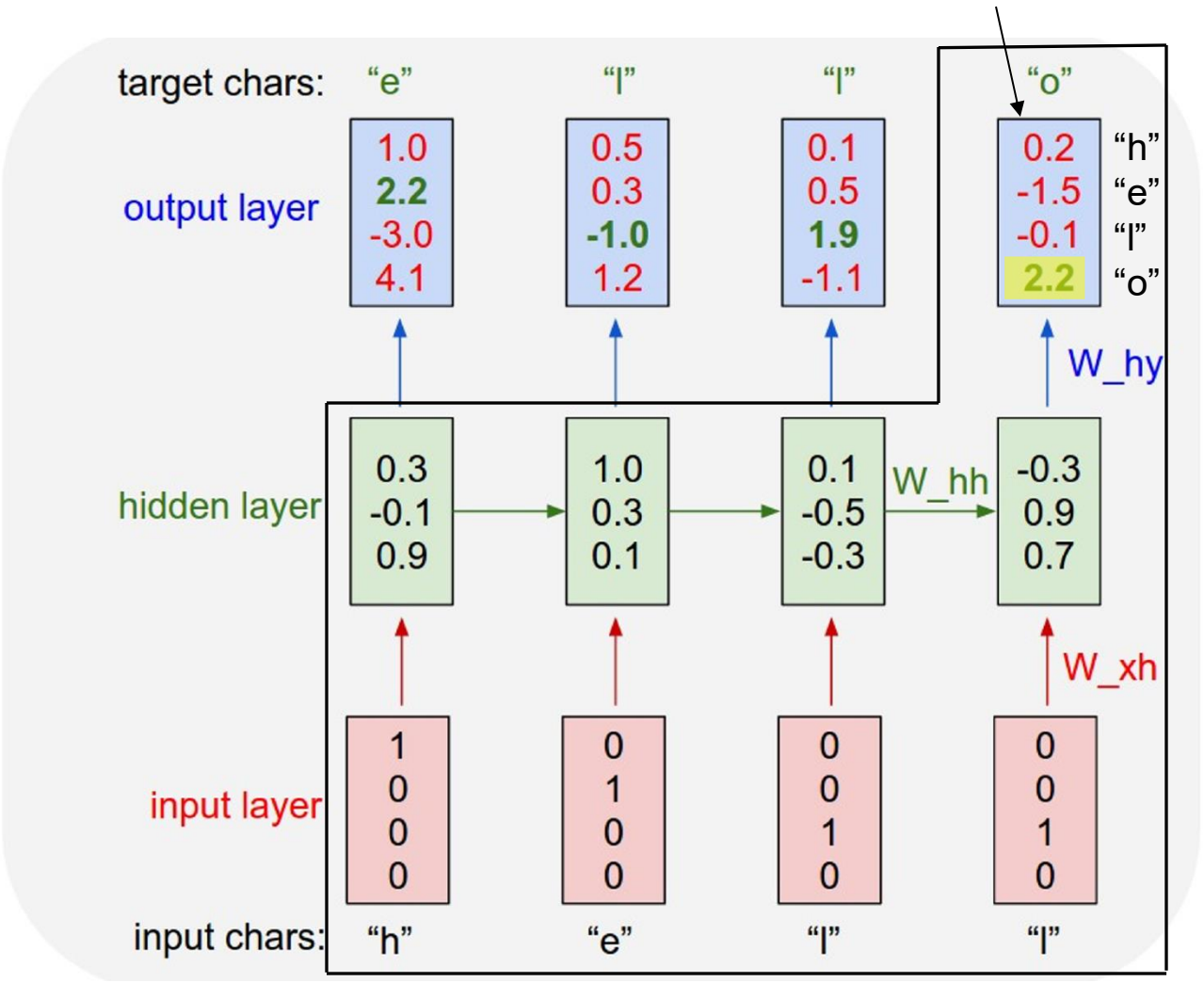
Third time step

- Given “hel”, predict “l”



Fourth time step

- Given “hell”, predict “o”

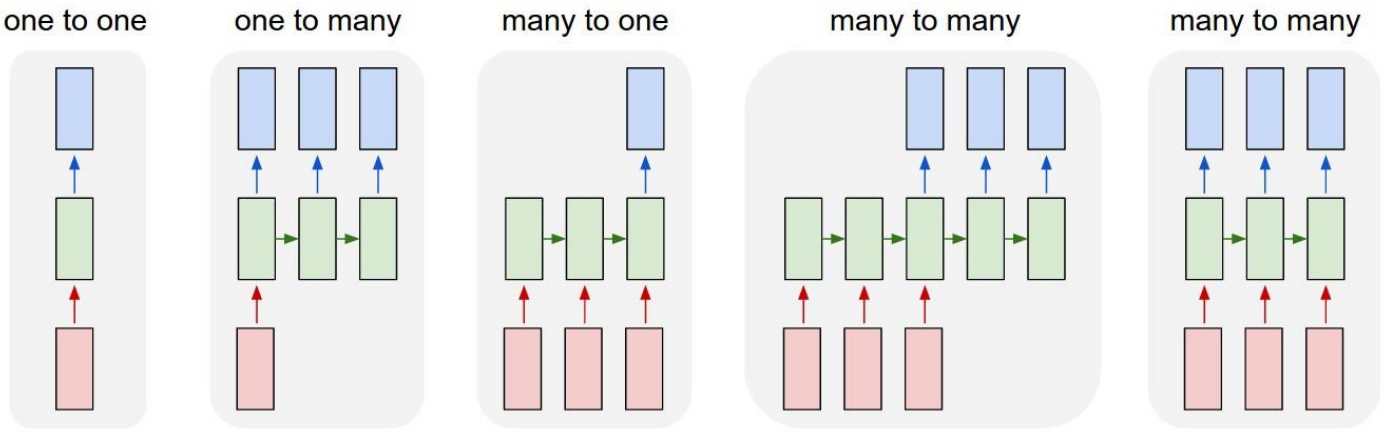


Backward pass

- Backward pass – weight update:
  - After each character (element of the sequence) is applied, a weight update is calculated for each location of the network that was used
  - At the end of the epoch, the weigh updates for the same locations are summed and the whole network is updated using the summed weight update
- The backpropgation algorithm is applied many times, until convergence, e.g. until all characters are classified correctly
- After the training is completed, we can use the RNN to generate text, character after character (words, paragraphs, etc.)
- Feed a character to RNN and predict the next one
- Feed the predicted character and predict the next one
- …

RNN are flexible

- RNN can be deployed in different scenarios



No RNN, no sequence
Ex: image classification
Input: image
Output: image class

Sequence output
Ex: image captioning
Input: image
Output: sequence of words

Sequence input
Ex: sentiment analysis
Input: text document
Output: positive or negative sentiment

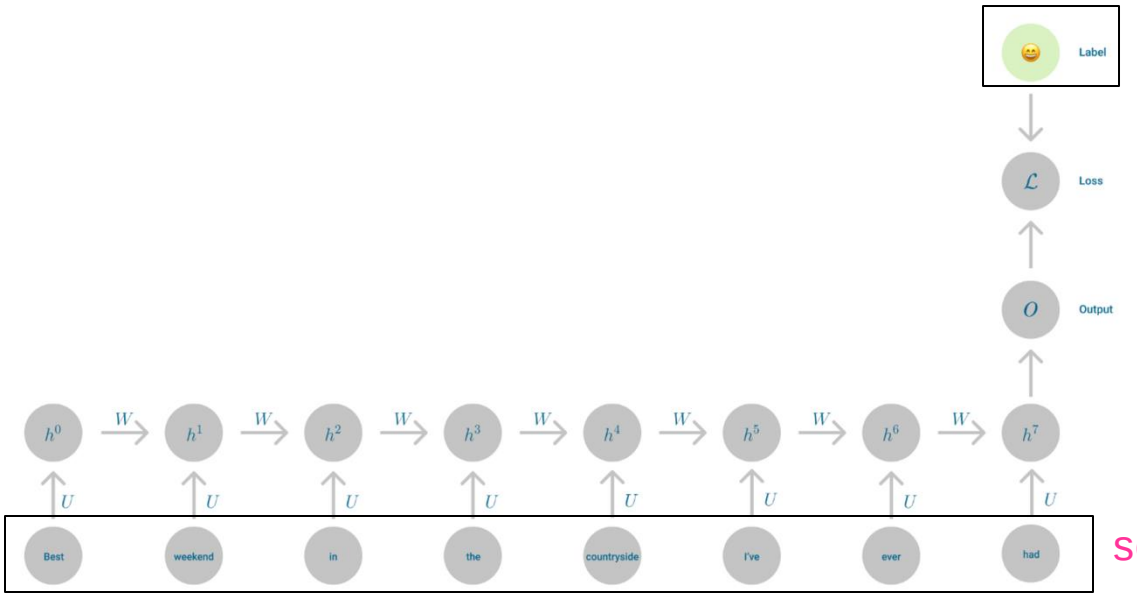
Sequence input and sequence output
Ex: machine translation:
Input: a sentence in English, output: a sentence in Italian

Synced sequence input and sequence output
Ex: video classification where we want to label each video frame with a class

http://karpathy.github.io/2015/05/21/rnn-effectiveness/

RNN are flexible (2)

- They don't need to generate an output after each element (e.g. after each word) as in our example
- In some tasks, e.g. sentiment analysis, RNN outputs a single value (positive or negative sentiment) after the whole sentence is processed
- We have a sentiment analysis exercise at the tutorial



class: positive or negative sentiment

sentence, word by word

Image ref: https://towardsdatascience.com/recurrent-neural-networks-explained-with-a-real-life-example-and-python-code-e8403a45f5de

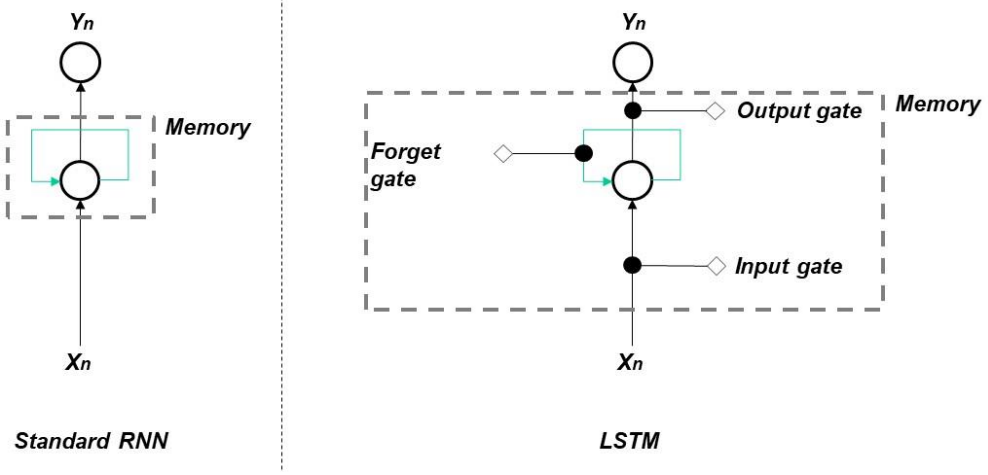
Shortcomings of RNN

- RNN are susceptible to the vanishing gradient problem
- Reason: during the backward pass, the error gradients will be multiplied by the W_{hh} matrix multiple times - once for each time-step
- This repeated multiplication may cause the gradient to vanish if the weights are too small
- =>Although in principle RNNs have the ability to learn long-term dependencies, in practice this is limited
- Long-term dependencies – dependencies over long distances in a sequence
- Ex.: predicting the next word based on the previous; predicting the last word:
  - The clouds are in the sky
  - Given the previous words, it is obvious that the next word will be “sky” – the gap between the relevant information and the point where it is needed is small (short distance)
  - I grew up in Italy…I speak fluent Italian
  - Recent information suggests we need the name of a language but which one? We need the context of Italy, from further back (long distance)
  - Another example: Translating a long sentence; by the time you have finished it, you have forgotten how it started ☺

LSTM networks

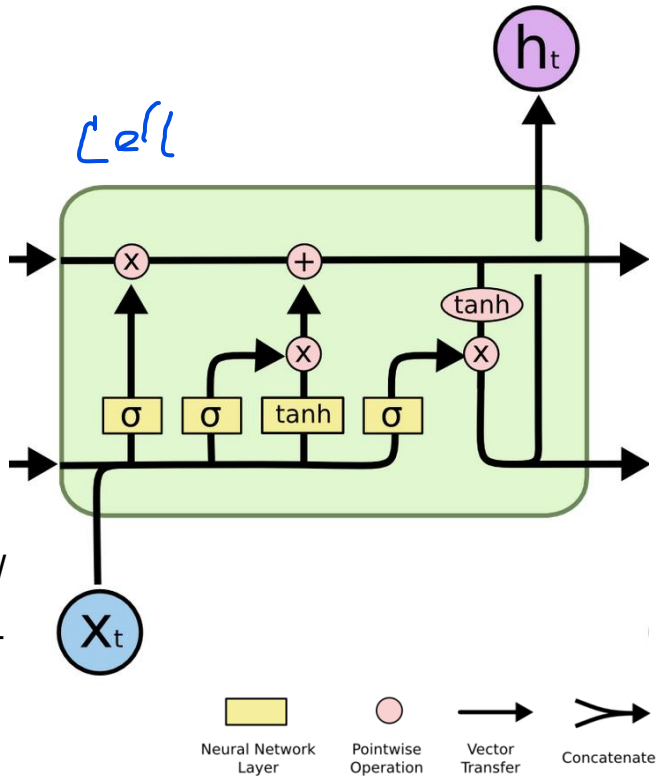
- Long Short Term Memory (LSTM) networks are a type RNN, specifically designed to improve the ability of RNN to model long dependencies
- Introduced by Hochreiter and Schmidhuber in 1997

  https://doi.org/10.1162/neco.1997.9.8.1735
- The key idea is the network can learn what to store, what to throw away and what to read from
- An LSTM cell includes 3 gates: forget, input and output



LSTM cell

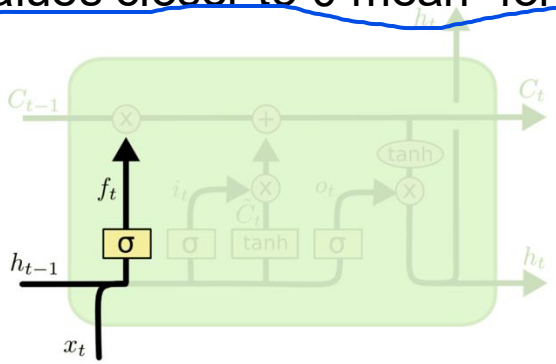
- The current input vector x_t and the previous short-term state h_{t-1} are fed to 4 different fully connected layers (not 1 as in the simple RNN)
- The 3 new layers have sigmoid activation function denoted with σ => their outputs range from 0 to 1
- Then, their outputs are fed to element-wise multiplication ⊗
  - If they output 0, they "close" the gate
  - If they output 1s, they "open" the gate



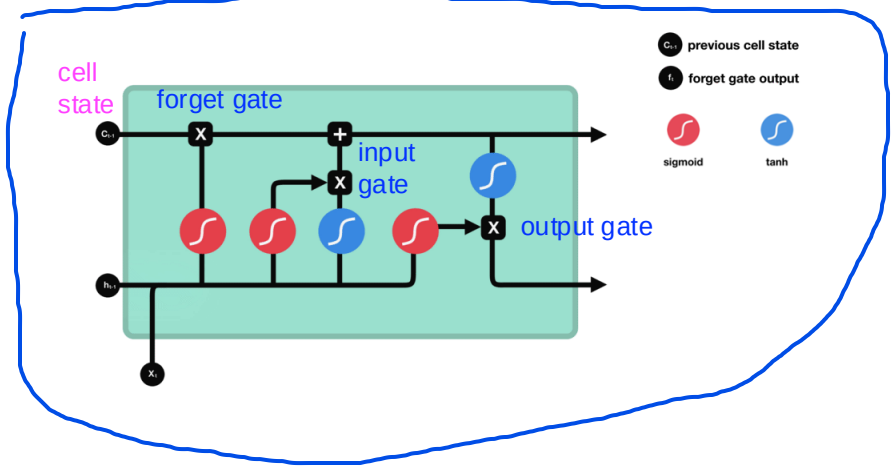
- These and next slides are based on https://colah.github.io/posts/2015-08-Understanding-LSTMs/
- Animations: https://towardsdatascience.com/illustrated-guide-to-lstms-and-gru-s-a-step-by-step-explanation-44e9eb85bf21

Forget gate layer

- Decides what information from the long-term state C_{i-1} should be thrown away or kept
- Uses information from the previous hidden state h_{t-1} and information from the current input x_t , passed through a sigmoid function, which outputs values between 0 and 1 for each number in the cell state C_{i-1}
- Values closer to 0 mean “forget” this and closer to 1 mean “keep this”



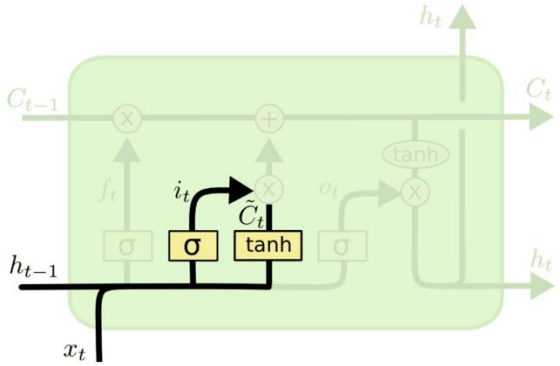
$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

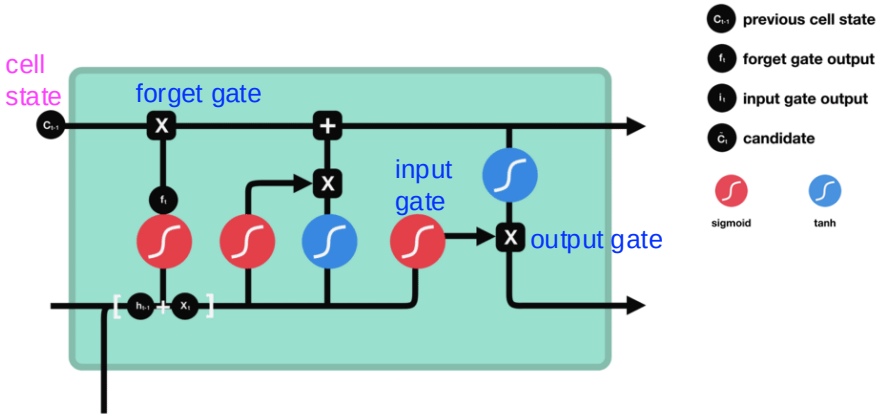


- For our example (predicting the next word based on the previous): the cell state may include the gender of the present subject, so that the correct pronoun (he/she) can be used. When we see a new subject, we want to forget the gender of the old subject.

Input gate layer

- Decides what new information should be stored in the cell state
- 1) A sigmoid layer (input gate layer) decides which values to update
- 2) A tanh layer (as in the simple RNN) creates a vector of new candidate state values $\tilde{C}_t$ that could be added to the state
- 3) Combine them using point-wise multiplication





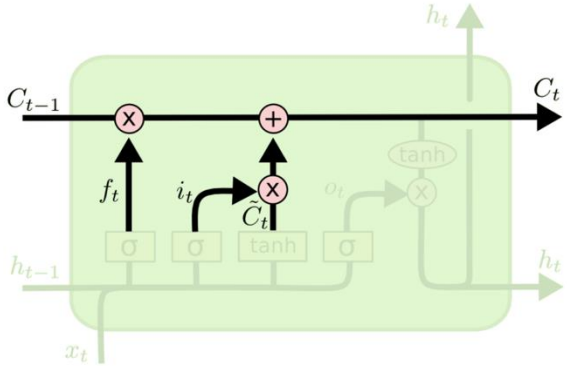
$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C)$$

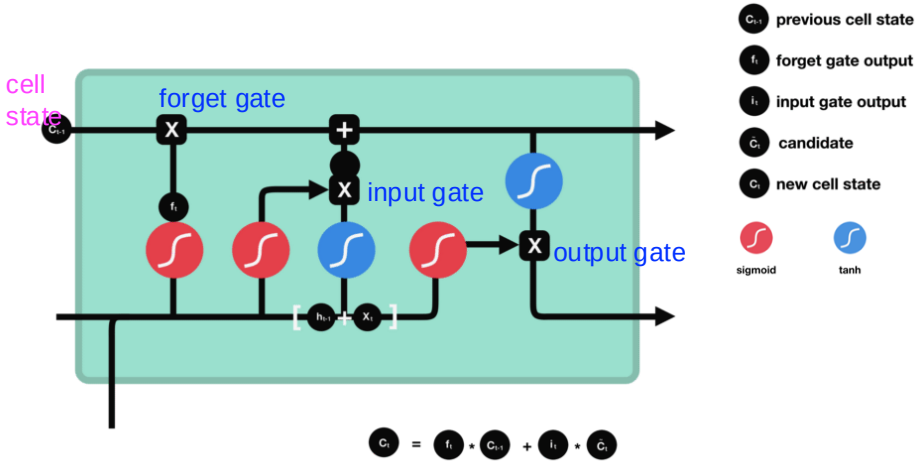
- For our example: add the gender of the new subject to the cell state, to replace the old one we are forgetting

Update the cell state

- Update the old cell state C_{t-1} to produce the new state C_t by combining the previous 2 results (the values of the forget and input layers):
- 1) Multiply the old state C_{t-1} by f_t = forgetting the things we decided to forget earlier
- 2) Add $i_t * \tilde{C}_t$ - the new candidate cell values, scaled by how much we decided to update each of them



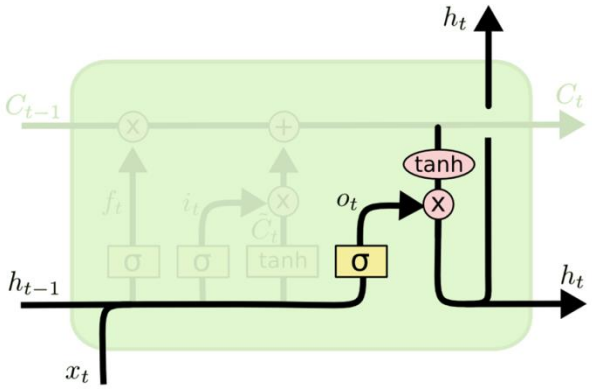
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

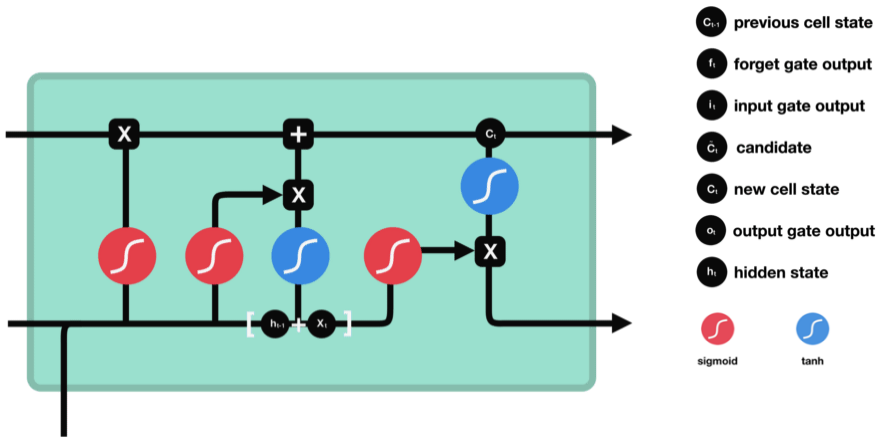


- For our example: drop the information about the old subject's gender and add the new information, as decided in the previous steps

Output gate layer

- Decides what exactly to output - the output will be based on the cell state, but it will be a filtered version
- 1) A sigmoid layer computes o_t which determines the parts of the cell state we will output
- 2) The previously computed cell state C_t goes through tanh (to push the values to −1 and 1) and is then multiplied by o_t, so that we only output the parts we decided to





$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t * \tanh(C_t)$$

- For our example: the network just saw a subject, we can output information about the verb, in case that is what is coming next – e.g. if the subject is singular or plural, so that we know what form of the verb should be used next

Other RNN architectures

- Many other RNN architectures have been proposed, e.g.:

- Gated Recurrent Unit (GRU)

  Cho et al. (2014), *Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation*

  https://arxiv.org/abs/1406.1078

- IRNN

  Le et al. (2015), *A Simple Way to Initialize Recurrent Networks of Rectified Linear Units*

  https://arxiv.org/abs/1504.00941

RNN and LSTM - summary

- RNNs have cyclic connections (e.g. from the hidden layer output back to the hidden layer as input)
- They have memory which stores the previous state of the hidden layer – the past activations and the inputs which contributed to these activations
- They are used on sequential data, where each element of the sequence is applied one-by-one
- RNNs have flexible architecture and can be applied for various types of tasks: one-to-many, many-to-one, etc.
- We studied 2 types of RNNs: simple RNN and LSTM
- Simple RNNs work well with sequences which include dependent features that are short distances apart. They don't work well for long distances because of the vanishing gradient problem.

RNN and LSTM – summary (2)

- LSTM are specifically designed to model dependencies between features that are long distances apart in the input sequence
- They have a complex internal structure which includes 4 fully connected layers and 3 gates which control the information flow: forget, input and output
- An LSTM cell can recognize an important input (via the input gate), store it in the long-term state and keep it as long as needed (via the forget gate) and extract it when needed (vis the output gate)
- As RNN, LSTMs are trained with the “backpropagation through time” algorithm
- However, there is no repeated multiplication by W_{hh} as we backpropagate the error – no vanishing gradient problem
- LSTMs have a complex architecture but have produced state-of-the-art results for many tasks, e.g. machine translation, speech recognition, handwriting recognition, speech synthesis and video analysis