Deep Learning

Übung WS 23/24

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11-01-2024

Evaluation der Veranstaltung

Zugänglich bis 17.01.2024 23:59:00 Uhr!

`https://uzk-evaluation.uni-koeln.de/evasys/online.php?pswd=6K8QK`

Semesterende-Party

Hoch die Hände, Semesterende!

Kommt und feiert mit uns das Ende der Vorlesungszeit 2023/24!
Wann: Do., 01.02.2024 ab 18 Uhr
Wo: IDH, Universitätsstr. 22, 1.OG

Für Bier und ein paar Snacks ist gesorgt.

A group of students and professors having a party to celebrate the end of the semester, pop art

Today

Sequential Data

Recurrent Neural Networks

Long Short-Term Memory (LSTM)

Exercise

Section 1

Sequential Data

Introduction

- So far: ›bag of words‹
- We count the number of times a word appears in a text

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- This is not how language works
  - Example
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  - Both sentences have the same feature vector, but different meanings
- Convolution: Take multi-word structures into account

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        - After the good predecessor, this movie was very bad.
    - Both sentences have the same feature vector, but different meanings
- Convolution: Take multi-word structures into account
- CNNs mostly used for image recognition

Intuition

- Moving window over the input
- For each window, we apply logistic regression
- And continue with a slightly shorter vector

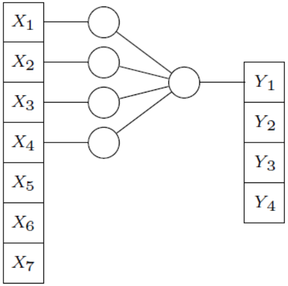

Figure: A 1D convolutional layer of size 4 (strides = 1)

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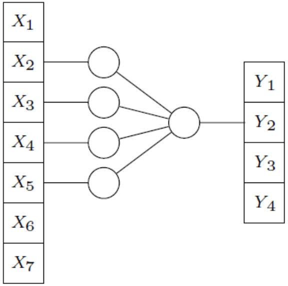

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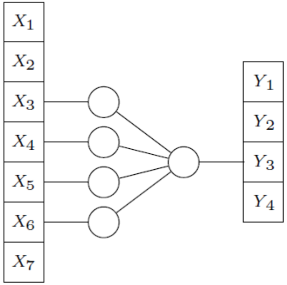

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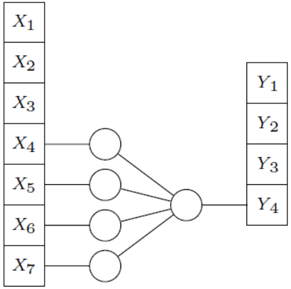

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1D Convolution

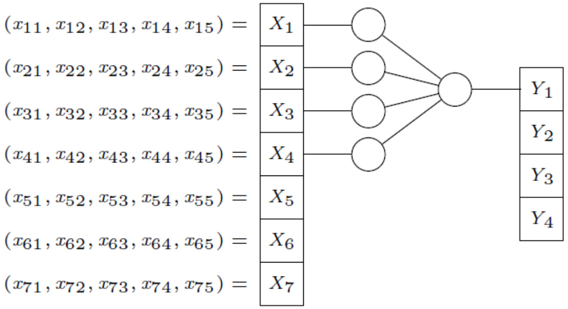
$(x_{11}, x_{12}, x_{13}, x_{14}, x_{15}) =$
$(x_{21}, x_{22}, x_{23}, x_{24}, x_{25}) =$
$(x_{31}, x_{32}, x_{33}, x_{34}, x_{35}) =$
$(x_{41}, x_{42}, x_{43}, x_{44}, x_{45}) =$
$(x_{51}, x_{52}, x_{53}, x_{54}, x_{55}) =$
$(x_{61}, x_{62}, x_{63}, x_{64}, x_{65}) =$
$(x_{71}, x_{72}, x_{73}, x_{74}, x_{75}) =$
X_1
X_2
X_3
X_4
X_5
X_6
X_7
Y_1
Y_2
Y_3
Y_4

Figure: A 1D convolutional layer of size 4 (strides = 1)

- » Requires a 2D input shape – because of embeddings!
  - (if you're not using embeddings, each token can be coded as a vector of length 1)

Convolution in Two Dimensions (e.g., images)

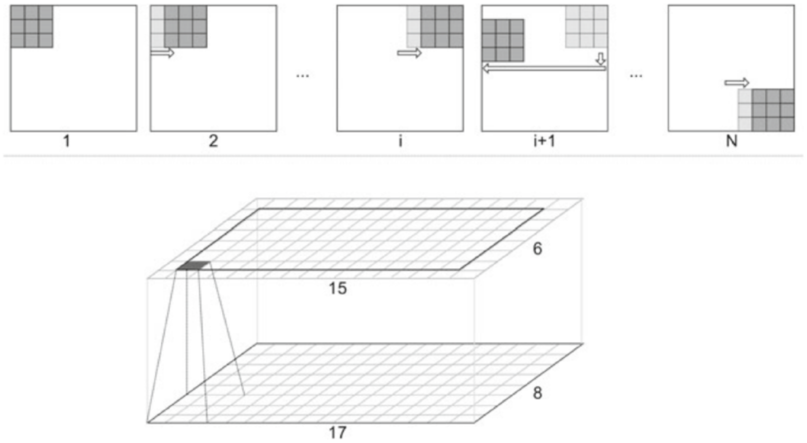

Figure: 2D convolutional layer (Skansi, 2018, p. 124)

Sequential Text Data

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  - Word meaning depends on context

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- Both are conceptually not adequate for natural language
- Length of influencing context varies
- Recurrent neural networks are one solution to this problem

Section 2

Recurrent Neural Networks

Sequence Labeling

- So far: Classification
- Sequence labeling
  - Special case of classification
  - Instances are organized sequentially and dependent of each other
    - I.e.: The prediction for one class influences the next

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Examples

- Part of speech tagging
  - »the dog barks« → »DET NN VBZ«
- Named entity recognition, mention detection
  - »John Bercow says he has changed allegiances to join Labour«
    → »B-PER I-PER O O O O O O O B-ORG«

BIO Scheme

- Named entity recognition is complicated
  - Not every token is part of a named entity (NE)
  - Many named entities span multiple tokens
  - We distinguish NEs based on the ontological type of the referent
    - PERson, ORGanization, LOCation, . . .

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- BIO scheme
  - How to represent NE annotations token-wise
  - Each token gets a label
    - B: Beginning of a NE
    - I: Inside of a NE
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    - B: Beginning of a NE
    - I: Inside of a NE
    - O: Outside of a NE (the majority of tokens)
- Why B: Marking the beginning allows to recognize multiple multi-word NEs in direct sequence
  - ». . . hat Peter Schneider Maria Müller geküsst« $\rightarrow$ »O B-PER I-PER B-PER I-PER O«

Towards Recurrent Neural Networks

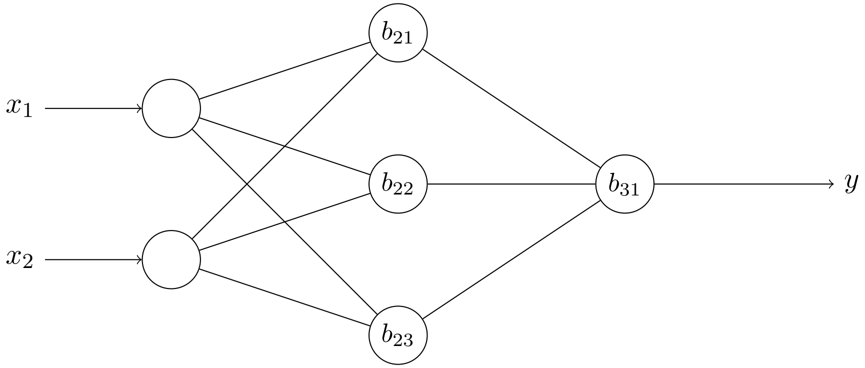


Figure: A feedforward neural network with 1 hidden layer (same picture as in Session 2)

Towards Recurrent Neural Networks

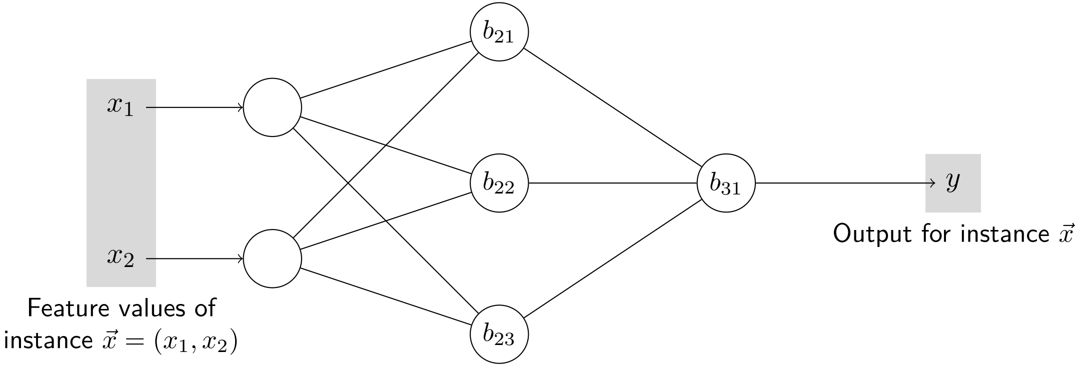

x_1
x_2
Feature values of instance $\vec{x} = (x_1, x_2)$
b_{21}
b_{22}
b_{23}
b_{31}
y
Output for instance $\vec{x}$

Figure: A feedforward neural network with 1 hidden layer (same picture as in Session 2)

Towards Recurrent Neural Networks

» To work with sequences, we need to include the sequence into the model

Notation

$X = (X_1, X_2, \dots)$	The input data set with instances
$X_i = (x_1, x_2, \dots)$	One instance with feature values
Y_i	Output for instance X_i

Towards Recurrent Neural Networks

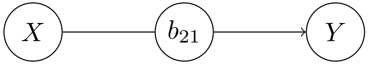


Figure: A simple neural network with 1 hidden layer

Recurrent Neural Networks

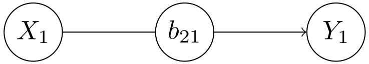
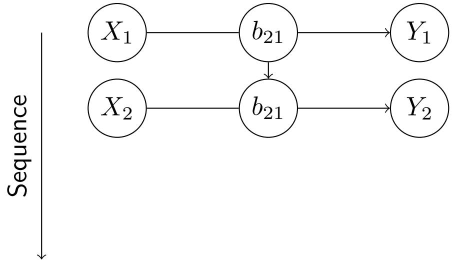


Figure: Recurrent Neural Network (unfolded)

Recurrent Neural Networks



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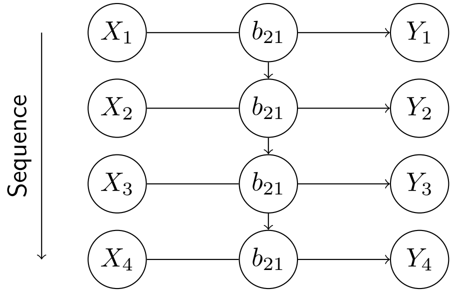

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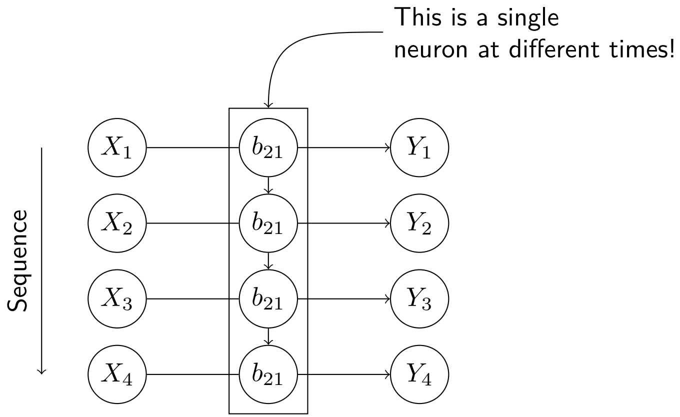

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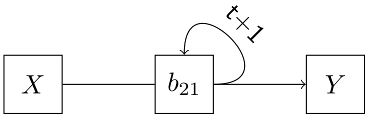
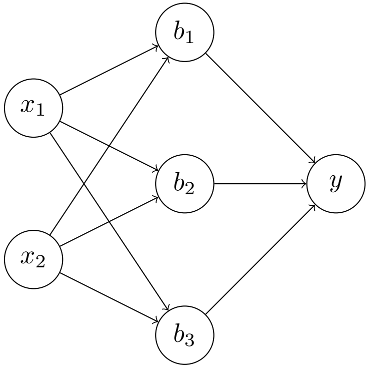


Figure: A recurrent neural network with 1 hidden layer (folded). Squares represent sequentially used neurons.

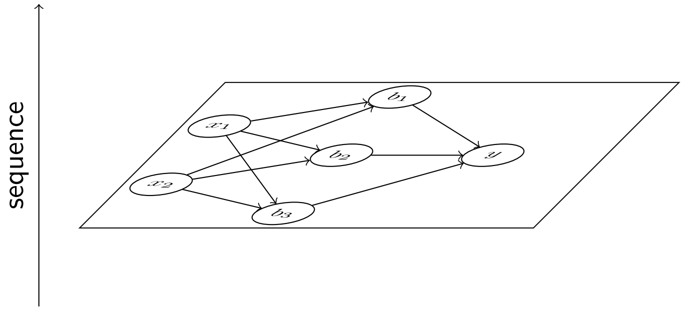
Recurrent Neural Networks

Example with multiple features per instance



Recurrent Neural Networks

Example with multiple features per instance



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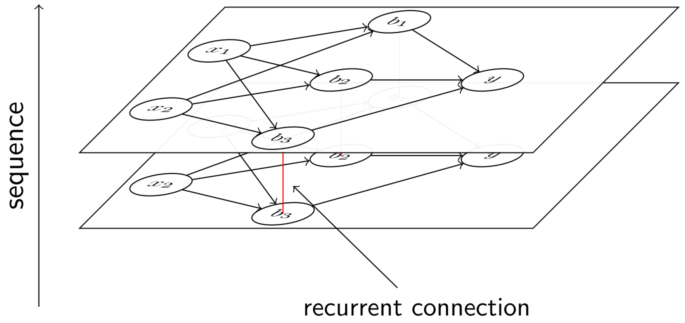

Recurrent Neural Networks

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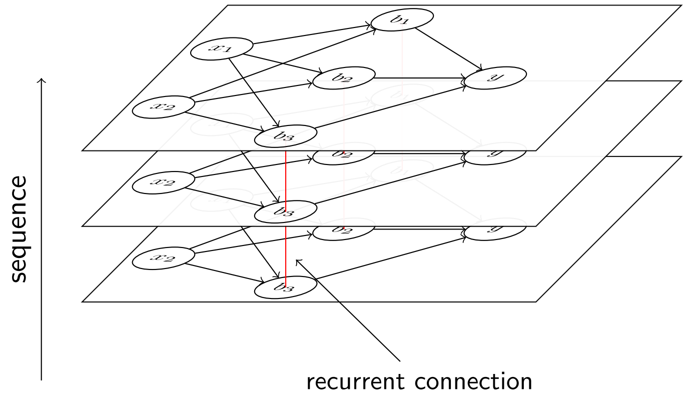

Recurrent Neural Networks

- FFNN, CNN: Weights between neurons
- RNN
  - Weights between neurons
  - Weight(s) for recurrent connections

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Input shape

RNN layers need 2D input:

- Length of input sequences (if needed, padded)
- Number of features (dimensions)
  - (this is where embeddings would go)

Implementation in keras

- `tf.keras.layers.SimpleRNN`
  - Documentation: `https://keras.io/api/layers/recurrent_layers/simple_rnn/`
    Selected parameters:
  - `recurrent_dropout=0.0` Dropout for recurrent links
  - `return_sequences=False` Wether to return the entire sequence or just the last element

```
model.add(layers.SimpleRNN(...))
```

Section 3

Long Short-Term Memory (LSTM)

Issues with RNNs

- Single neuron that transmits information along the sequence
- Long-distance information gets lost, because short-distance information is more prominent
- Slow because of the increased complexity
- Problem of vanishing and exploding gradients
- But: First architecture to process sequences as sequences

Long Short-Term Memory (LSTM)

- Most often used architecture for sequence labeling tasks
- Sub type of a recurrent layer
- Recurrent layer
  - Simple neuron, one connection along the sequence
- LSTM
  - Hochreiter and Schmidhuber (1997)
  - A neuron with more internal structure (often called »cell« or »unit«)
  - Two connections along the sequence

Recurrent Layer

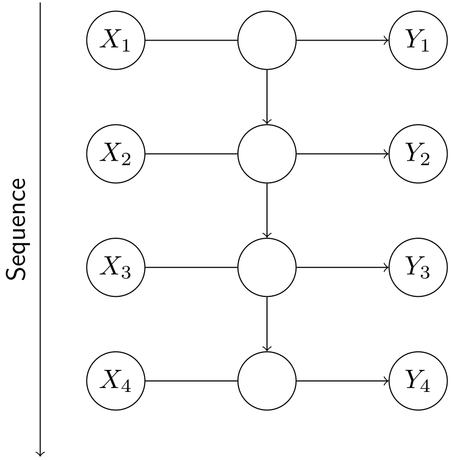


Figure: Recurrent Neural Network

LSTM Layers

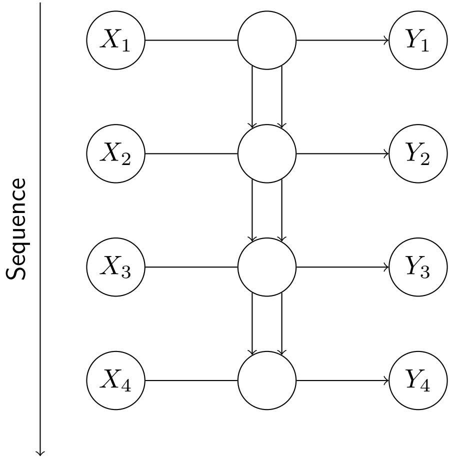


Figure: Neural Network with an LSTM Layer

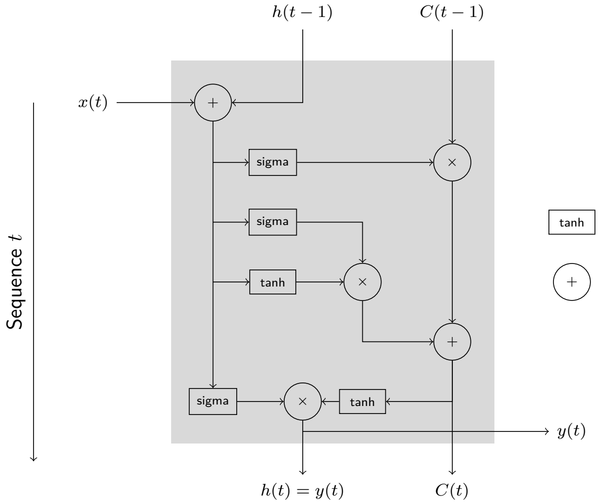
LSTM Cells

- Two connections along the sequence
  - h: The regular history of outcomes
    - I.e., the outcome of a neuron is passed into the neuron for the next sequence element
  - C: A state for the cell
    - Allows long-term storage

LSTM Cells

- Two connections along the sequence
  - h: The regular history of outcomes
    - I.e., the outcome of a neuron is passed into the neuron for the next sequence element
  - C: A state for the cell
    - Allows long-term storage
- Cell state is controlled within the cell
  - Forget: Previous state is removed
  - Input: Current input is (partially) stored in the cell state
  - Output: How much of the cell state is added to the cell output
- All ›gates‹ are controlled by weights, learned during training

An LSTM Cell

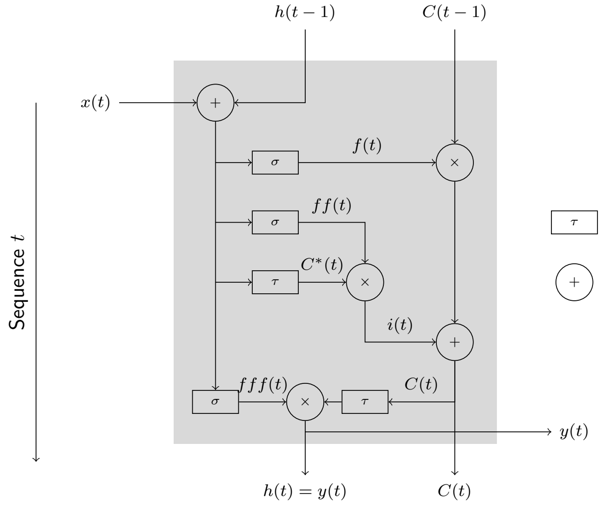


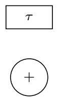
activation function
sigmoid: $[0;1]$
tanh: $[-1;1]$

arithmetical operator

An LSTM Cell

with labeled connections





activation function
$\sigma : [0;1]$
$\tau : [-1;1]$

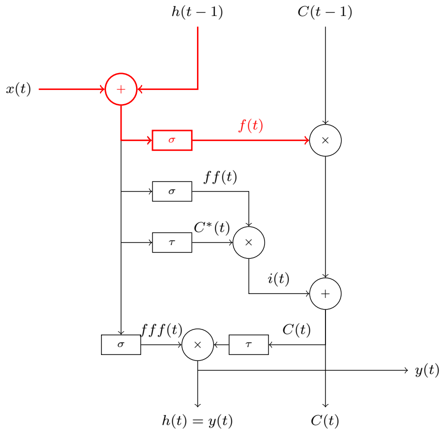
arithmetical operator

An LSTM Cell

Forget Gate

$$f(t) = \sigma\left(\vec{w}_f \times (x_t + h(t-1))\right)$$

- How much of the cell state do we forget?
- If $f(t) = 0$, cell state is emptied
- $\vec{w}_f$: Trainable weights for this gate



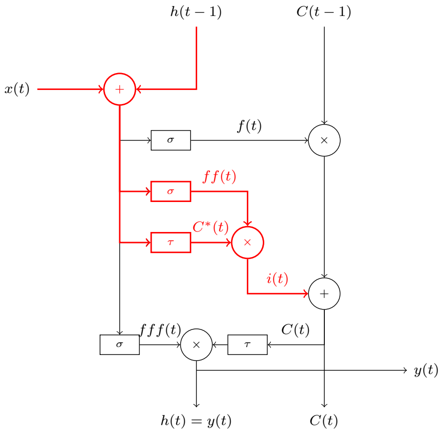
An LSTM Cell

Input Gate

How much of the current value is put into the cell state?

$$
\begin{aligned}
ff(t) &= \sigma\left(\vec{w}_{ff} \times (x_t + h(t-1))\right) \\
C^*(t) &= \tau\left(\vec{w}_C \times (x_t + h(t-1))\right) \\
i(t) &= ff(t) \times C^*(t)
\end{aligned}
$$

» $\vec{w}$: trainable weights



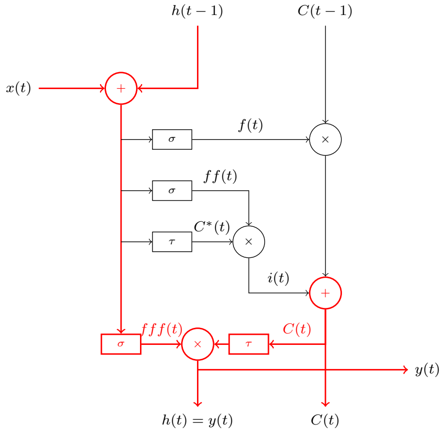
An LSTM Cell

Output Gate

How do we calculate the output(s) of the cell?

- Three outputs:
  - $y(t)$: regular output for the next layer
  - $h(t)$: passed on to the next sequence element
  - $C(t)$: new cell state

$$\begin{aligned} C(t) &= f(t) \times C(t-1) + i(t) \\ fff(t) &= \sigma\left(\vec{w}_{fff} \times (x_t + h(t-1))\right) \\ y(t) &= fff(t) \times \tau(C(t)) \end{aligned}$$



An LSTM Unit

Cell state $C(t)$

- A LSTM unit has a cell state (used for the long-term memory)
- Three gates control the state of the cell – each with its own weight
  - Forget gate $f(t)$: How much of the previous state is kept
    - $f(t) = \sigma(\vec{w}_f \times (x(t) + h(t\breve{}1)))$

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  - Input gate $ff(t)$, $C^*(t)$, $i(t)$: How much of the current state is stored
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  - Output gate $fff(t)$: What do we push to the next unit and what do we give out
    - $fff(t) = \sigma(\vec{w}_{fff}(x(t) + h(t\breve{}1)))$
    - $C(t) = f(t) \times C(t\breve{}1) + i(t)$
    - $h(t) = fff(t) \times \tau(C(t))$

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    - $fff(t) = \sigma(\vec{w}_{fff}(x(t) + h(t\breve{\ }1)))$
    - $C(t) = f(t) \times C(t\breve{\ }1) + i(t)$
    - $h(t) = fff(t) \times \tau(C(t))$
- Weights to be learned: $\vec{w}_f$, $\vec{w}_{ff}$, $\vec{w}_{fff}$, $\vec{w}_C$

LSTM in Keras

`layers.LSTM`

- Docs: `https://keras.io/api/layers/recurrent_layers/lstm/`
- `units` – Number of LSTM units to create
  - corresponds to `timesteps` for RNNs

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- `units` – Number of LSTM units to create
  - corresponds to `timesteps` for RNNs
- Bi-LSTM
  - Best performance for many tasks
  - `model.add(layers.Bidirectional(layers.LSTM(...)))`

Section 4

Exercise

Exercise 09

`https://github.com/IDH-Cologne-Deep-Learning-Uebung/exercise-09`