Long Short-Term Memory

Joint Proseminar on Machine Learning and Image Processing

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Chair of Computer Science 13 (Computer Vision)
RWTH Aachen

Contents

Introduction - The importance of Sequence Data

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Recurrent Neural Networks: Pick up on patterns in sequences

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Recurrent Neural Networks: Pick up on patterns in sequences

In practice: Difficult to train

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Background – Neural Networks

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- A **perceptron** computes a weighted sum of inputs:

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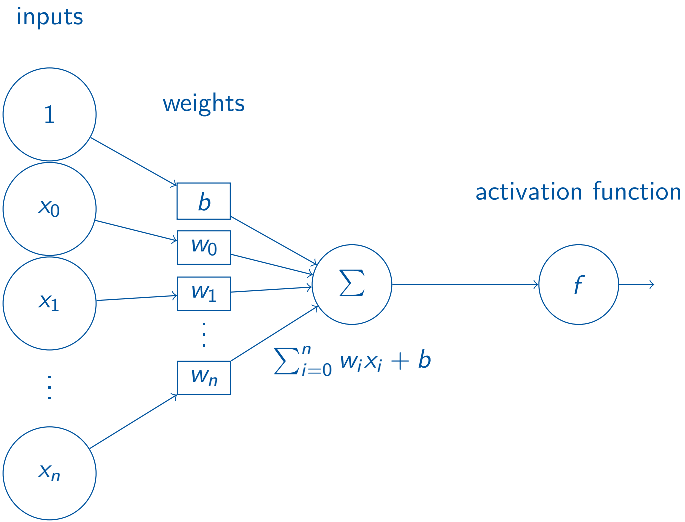
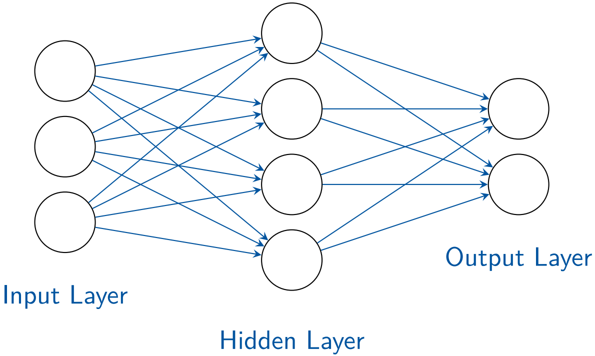
- Non-linearity introduced via activation function f

Background - Neural Networks



Perceptrons are combined into multi-layer neural networks (MLPs)



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- Use **stochastic gradient descent** (SGD):

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- Gradients are computed using **backpropagation**
- Works well for fixed-size input/output — not ideal for sequences

Source: LeCun et al. 1998

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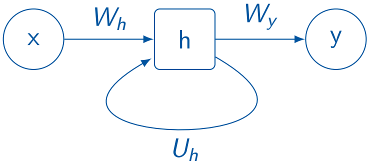

Source: Elman 1990

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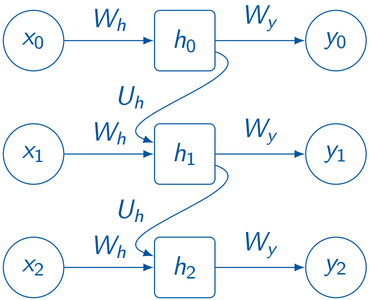
- Hidden state carries memory across time



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$$\frac{\partial \mathcal{L}_T}{\partial h_t} = \sum_{k=t}^{T} \left(\frac{\partial \mathcal{L}_T}{\partial h_k} \cdot \prod_{j=t+1}^{k} \frac{\partial h_j}{\partial h_{j-1}} \right)$$

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- Each $\frac{\partial h_j}{\partial h_{j-1}}$ is a Jacobian matrix

Source: Werbos 1990; Pascanu et al. 2013

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- When multiplying many Jacobians, gradients can:
  - **Shrink rapidly** $\Rightarrow$ vanish
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- **Gradient clipping** can limit explosion, but not vanishing
- $\rightarrow$ We need an **architectural solution**

Source: Hochreiter 1991; Pascanu et al. 2013

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Naive Solution - Constant Error Flow

Single Unit (j) Constant Error Carousel (CEC):

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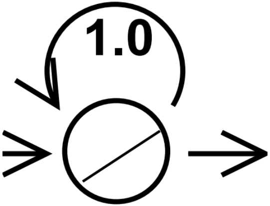

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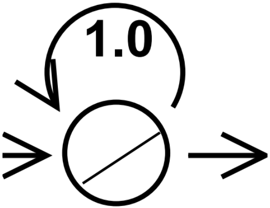

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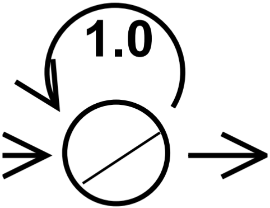

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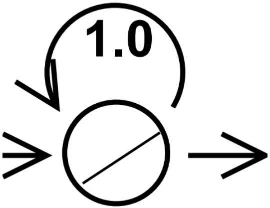

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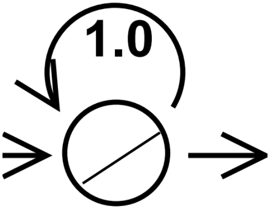

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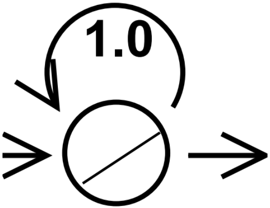

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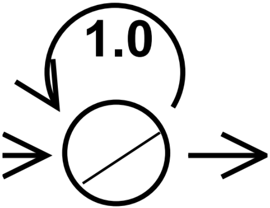

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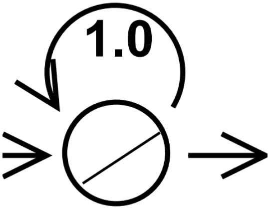

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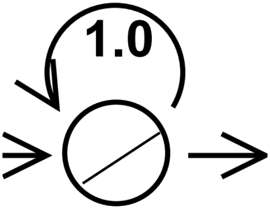

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Conflicting weight update signals for w_{ji} & $w_{kj} \implies$ Mechanism for storage and retrieval

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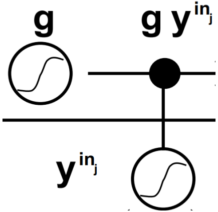

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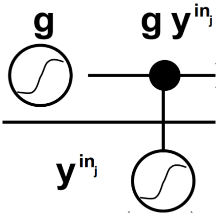

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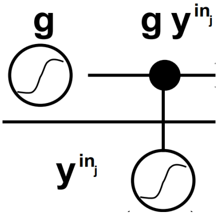

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Input gets scaled by number computed from context

Source: Hochreiter et al. 1997

LSTM Architecture - Memory Cell

Memory Cell: CEC unit with input and output gate units

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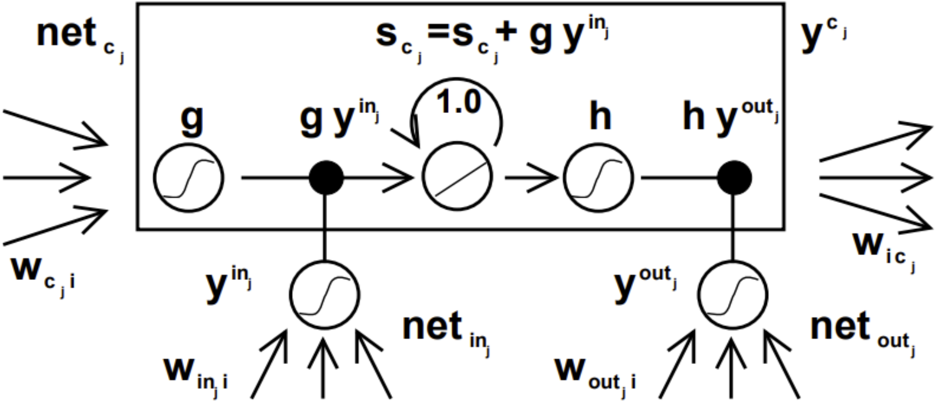

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- Better performance on sequences that include random data
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- Can solve tasks RNNs previously could not (sequences with no local regularities)

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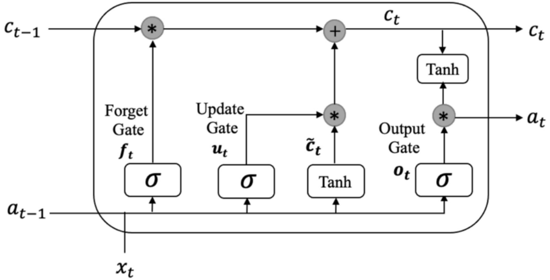

Source: Nguyen et al. 2022

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- Can use **past and future** context $\rightarrow$ better performance in many NLP tasks

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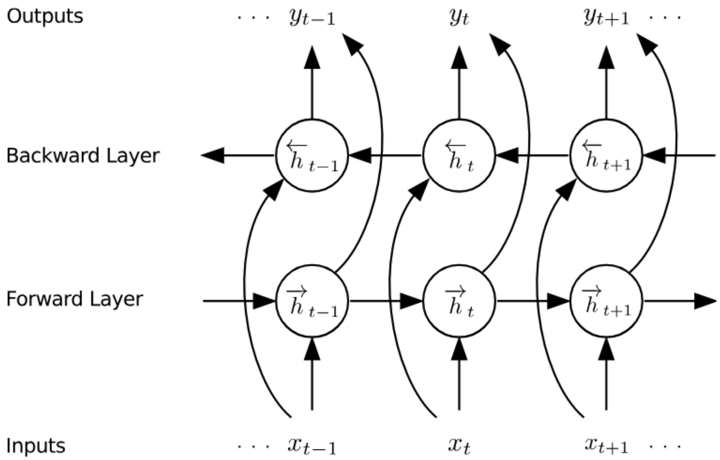

Source: Graves & Schmidhuber 2005

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- Often performs well with:
  - less data
  - shorter sequences
  - faster training needs

Source: Cho et al. 2014

GRU vs. LSTM

- **LSTM**
  - Uses a separate memory cell c_t
  - Has input and output gates (forget gate was added later)
  - Two internal states: h_t and c_t

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  - Two internal states: h_t and c_t
- **GRU**
  - Merges cell and hidden state into a single h_t
  - Uses update and reset gates
  - Simpler architecture, faster training

GRU simplifies LSTM by merging its memory and control into fewer components.

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- In recent years, **Transformers** have become the dominant model in NLP and beyond
- Transformers offer a different approach: no recurrence, full attention

Source: Vaswani et al. 2017

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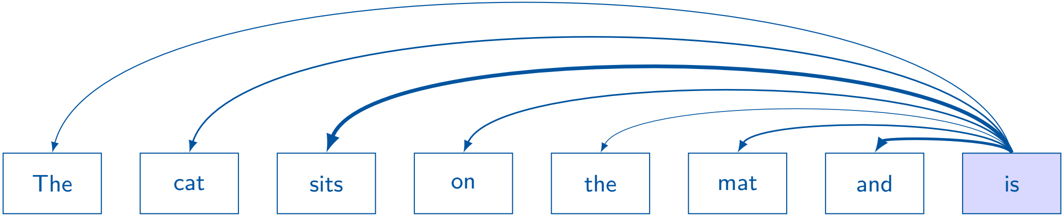

Source: Vaswani et al. 2017

LSTM vs. Transformer – Comparison

LSTM

- Recurrence-based
- Hidden state carries memory
- Sequential processing
- Better on smaller data
- Fewer resources needed

Transformer

- Attention-based
- Global context at each step
- Fully parallelizable
- Excels with large datasets
- High compute demand

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- LSTMs can learn how current sounds depend on earlier ones:
  - e.g. understanding that ”s” at the end of “cats” depends on earlier phonemes
- Bidirectional LSTMs are especially useful:
  - They consider both past and future context in a sentence
  - This helps distinguish similar sounds in different contexts

Application – Speech Recognition

- Spoken language is a sequence of sounds that unfolds over time
- LSTMs can learn how current sounds depend on earlier ones:
  - e.g. understanding that "s" at the end of "cats" depends on earlier phonemes
- Bidirectional LSTMs are especially useful:
  - They consider both past and future context in a sentence
  - This helps distinguish similar sounds in different contexts
- LSTMs reduce the need for manual feature extraction

Applications - Time Series Forecasting

LSTMs perform better on:

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2002: LSTM Architecture used to compose music

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Discussion - the Future of LSTMs

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Source: Zhao et al. 2025

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- Inspired many Variants and RNN Architectures

Currently:

- Replaced by transformers in many Applications
- Development of new LSTM based architectures
- Remain useful in some cases

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