Recurrent Neural Networks

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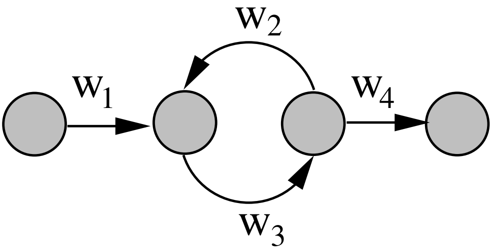
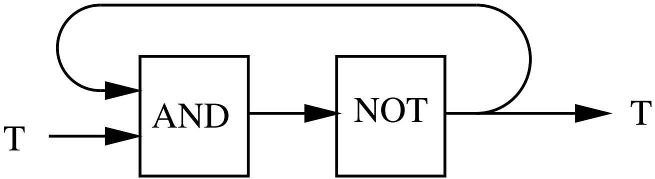
A recurrent network is simply a network with cycles.



In presence of backward connections, hidden states depend on the past history of the net.

Instability

Cycles in logical circuits are a potential source of instability:



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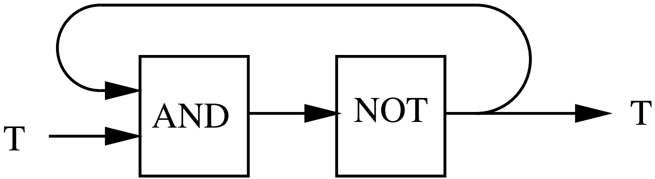

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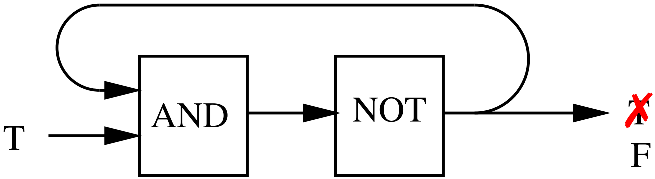

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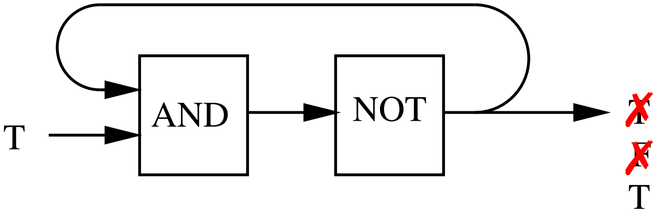
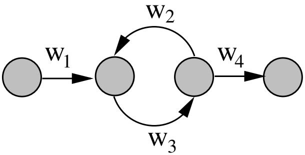
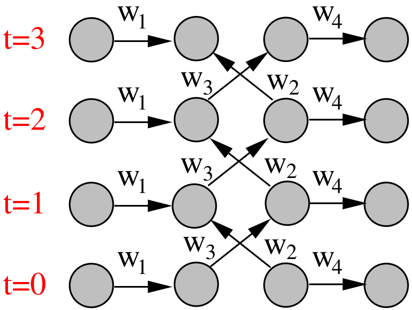


Temporal unfolding





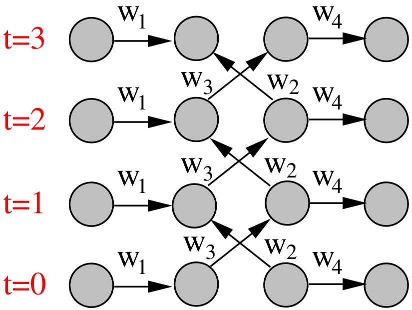
Activations are updated at precise times steps

The recurrent net is just a layered net that keeps reusing the same weights

Input/output sequences

Due to the temporal unfolding, you expect an input and produce an output at **each timestep**

This is why recurrent networks are naturally suited to **process sequences**.



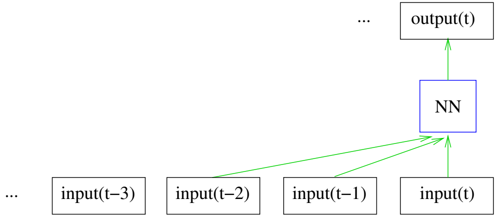
Modelling sequences

Typical problems:

- **turn an input sequence into an output sequence** (possibly in a different domain):
  - - translation between different languages
  - - speech/sound recognition
  - - ...
- **predict the next term in a sequence**
  The target output sequence is the input sequence with an advance of 1 step. Blurs the distinction between supervised and unsupervised learning.
- **predict a result from a temporal sequence of states**
  Typical of Reinforcement learning, and robotics.

Memoryless approach

Compute the output as a result of a fixed number of elements in the input sequence



Used e.g. in

- \- Bengio's (first) predictive natural language model
- \- Qlearning for Atari Games

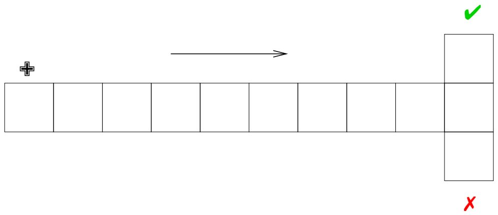
Difficult to deal with very long-term dependencies.

Simple problems requiring memory

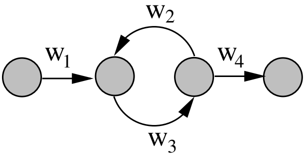
arithmetical sum

$$
\begin{array}{cccccccc}
 & & & \longleftarrow & & & & \\
\dots & 1 & 1 & 0 & 1 & 1 & 1 & 1 \\
\dots & 0 & 1 & 1 & 1 & 0 & 1 & 0 \\
\hline
\dots & 0 & 1 & 0 & 1 & 0 & 0 & 1
\end{array}
$$

the T-maze



Back to Recurrent Networks



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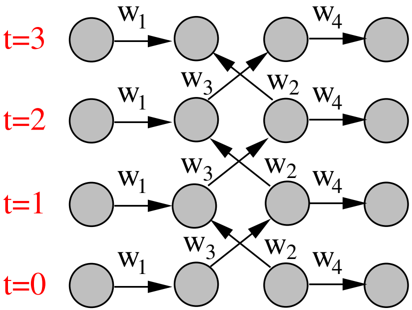


Sharing weights through time

It is easy to modify the backprop algorithm to incorporate equality constraints between weights.

We compute the gradients as usual, and then average gradients so that they induce a same update.

If the initial weights started satisfied the constraints, they will continue to do.

To constrain $w_1 = w_2$
we need $\Delta w_1 = \Delta w_2$

compute $\frac{\partial E}{\partial w_1}$ and $\frac{\partial E}{\partial w_2}$

and use $\frac{\partial E}{\partial w_1} + \frac{\partial E}{\partial w_2}$

to update both w_1 and w_2

Hidden state initialization

We need to specify the initial activity state of all the hidden and output units.

The best approach is to treat them as parameters, learning them in the same way as we learn the weights:

- start off with an initial random guess for the initial states
- at the end of each training sequence, backpropagate through time all the way to the initial states to get the gradient of the error function with respect to each initial state
- adjust the initial states by following the negative gradient

Long-Short Term Memory (LSTM)

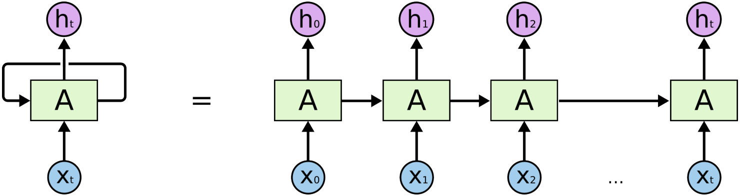
Largely based on Colah's blog

The goal

Find a **basic** component (NN-layer):

- simple
- flexible
- effective
- modular

Unrolling recurrent nets

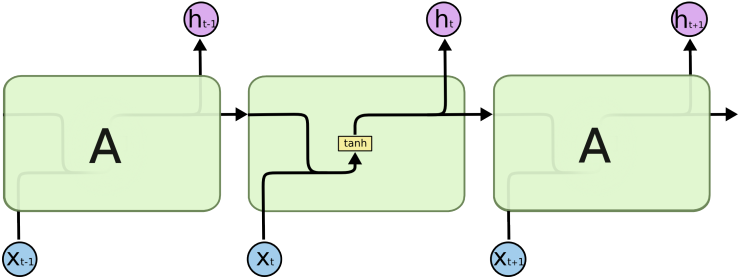


In the following, we shall mostly depict RNN in unrolled form.

A forward link between two units muts be understood as a looping connection.

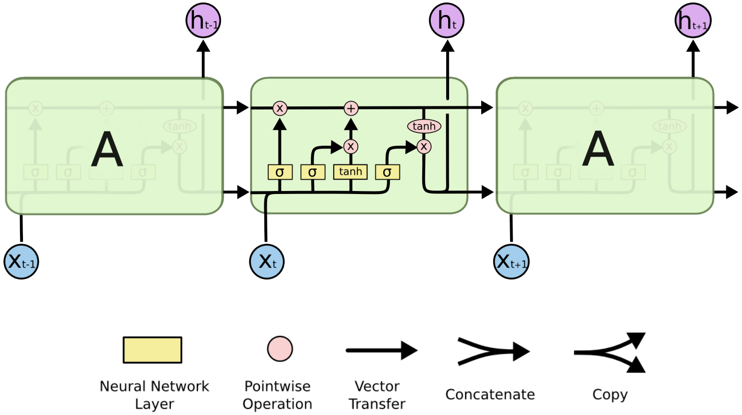
A simple, basic RNN

The content of the memory cell C_t, and the input x_t are combined through a simple neural net to produce the output h_t that coincides with the new content of the cell C_{t+1}.



Why $C_{t+1} = h_t$? Better trying to preserve the memory cell, letting the neural net learn how and when to update it.

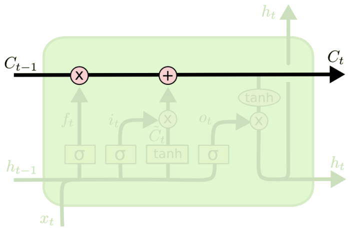
The overall structure of a LSTM



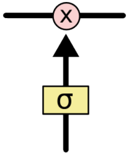
C-line and gates

The LSTM has the ability to remove or add information to the cell state, in a way regulated by suitable gates.

Gates are a way to optionally let information through: the product with a sigmoid neural net layer simulates a boolean mask.

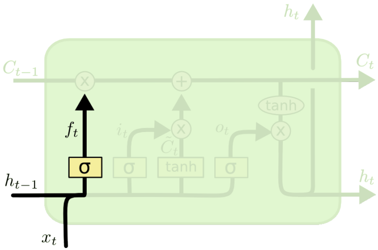


the C-line



a gate

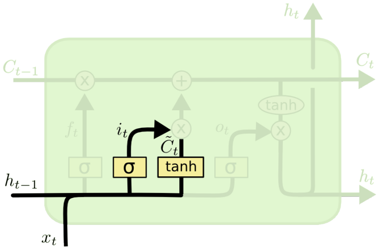
The forget gate



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

The forget gate decides what part of the memory cell to preserve

The update gate



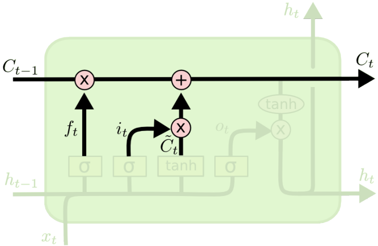
$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

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

The input gate decides what part of the input to preserve.

The tanh layer creates a vector of new candidate values $\tilde{C}_t$ to be added to the state.

Cell updating



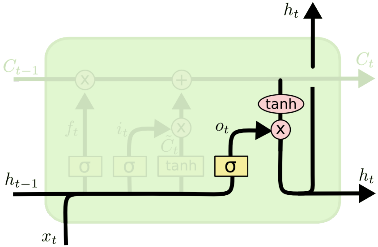
$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

We multiply the old state by the boolean mask f_t.

Then we add $i_t * \tilde{C}_t$.

output gate

The output h_t is a filtered version of the content of the cell.



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

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

The output gate decides what parts of the cell state to output.

The tanh function is used to renormalize values in the interval $[-1, 1]$.

Many variants

Essential bibliography

- S.Hochreiter, J. Schmidhuber. "Long short-term memory". Neural Computation. 9 (8): pp.1735-1780. 1997
- F.A.Gers, Jürgen Schmidhuber, F.Cummins. "Learning to Forget: Continual Prediction with LSTM". Neural Computation. 12 (10), pp.2451-2471. 2000.
- F.A.Gers, E.Schmidhuber. "LSTM recurrent networks learn simple context-free and context-sensitive languages". IEEE Transactions on Neural Networks. 12 (6): pp. 1333-1340. 2001.
- Y.Chung, C.Gulcehre, K.Cho, Y.Bengio. "Empirical Evaluation of Gated Recurrent Neural Networks on Sequence Modeling". arXiv:1412.3555. 2014

The lstm layer in Keras

From a practical point of view, the LSTM layer is very similar to a traditional layer.

When you **define** the layer, you specify the number of **units**, that is the dimension of the memory cell, equal to the dimension of the hidden state and the output.

When you **apply** the layer, you pass as **input** an array of dimension

$$[batch, timesteps, features]$$

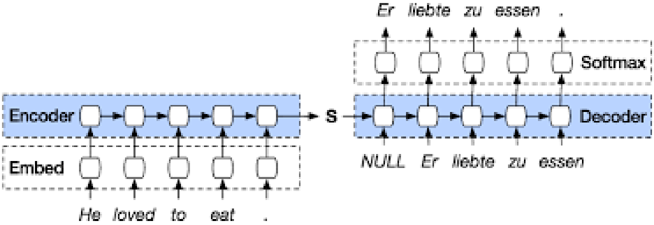
You get as output an array of dimension

$$[batch, units]$$

(unless you ask to return sequences)

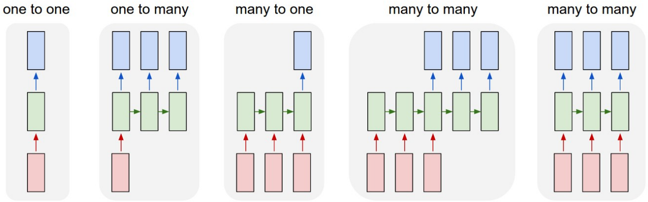
A simple application

A ten-minute introduction to sequence-to-sequence learning in Keras



An old but wondrous blog

The Unreasonable Effectiveness of Recurrent Neural Networks



- one to one: no recurrrence
- one to many: e.g. caption generation
- many to one: e.g. sentiment ananlysis
- many to many (async): e.g. language translation
- many to many (sync): per frame video processing