

# Recurrent Neural Network

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**Week 9**

ECEGR4750 - Introduction to Machine Learning  
Seattle University

November 20, 2023

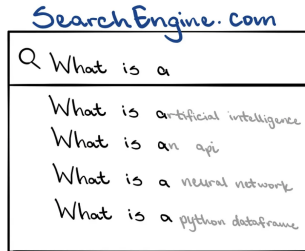
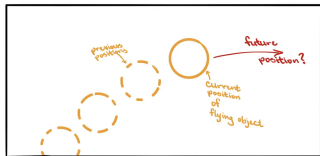
# Recap and Updates

- Lab Take Home Assignment due next Wednesday 11/22/23 at 11.59pm
- Office Hours: please email me your desired timeslot and to make appointments
- Final Homework 5 due: 12/1/23 at 11.59pm
- Final week of class: review + in class “exam” on 11/30/23 as bonus
- Final project due: 12/8/23 at 11.59pm
- Additional Reading:
  - ① Backpropagation Through Time: [link](#)
  - ② LSTM: [link](#)

- 1 Recurrent Neural Network
  - Architecture of an RNN
  - Backpropagation Through Time
  - Limitations
- 2 Long Short Term Memory (LSTM)

# Recurrent Neural Network (RNN)

- Deep learning approach for modeling sequential data (such as time series and language).
- Remembers “history”.
- More modern variants include the Long-Short Term Memory (LSTM) and attention-based models like transformers.



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# Architecture of an RNN

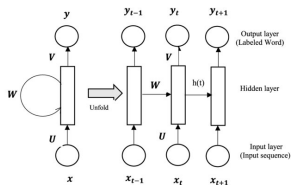
Think of the RNN as a set of singular feed-forward models, where each model is linked together by the internal state update.

Left:

- Simple RNN with input, hidden, and output nodes.
- Input  $x$  is sequential with  $t + 1$  elements.

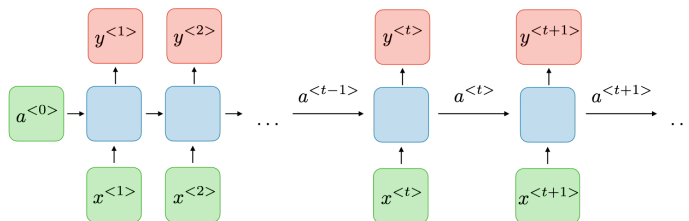
Right:

- “Unrolled” representation of the RNN.
- Each “layer” shares the same structure, weights, and activation functions.
- Working memory for each iteration is passed to the next.



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# Architecture of an RNN



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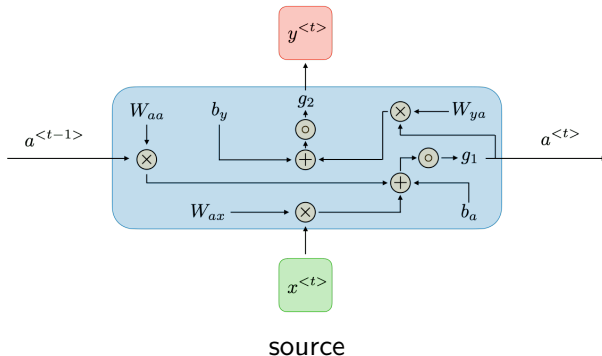
For each timestep  $t$ , the activation  $a^{<t>}$  and the output  $y^{<t>}$  are expressed as:

$$a^{<t>} = g_1(W_{aa}a^{<t-1>} + W_{ax}x^{<t>} + b_a)$$
$$y^{<t>} = g_2(W_{ya}a^{<t>} + b_y)$$

where  $W_{ax}$ ,  $W_{aa}$ ,  $W_{ya}$ ,  $b_a$ , and  $b_y$  are the weights and biases shared temporally; and  $g_1$  and  $g_2$  are the activation functions.

# Architecture of an RNN

Zooming in to one hidden node:



# Architecture of an RNN

Common activation functions used in RNN:

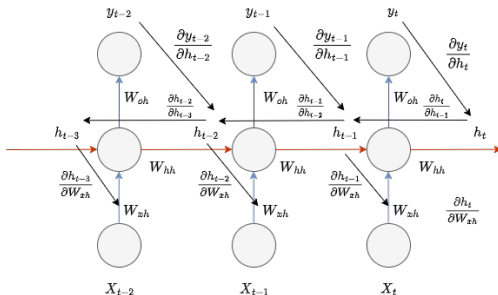
- 1 Sigmoid
- 2 Tanh
- 3 ReLU



# Backpropagation Through Time (BPTT)

- 1 BPTT works backwards through the chain, calculating the loss and loss gradients across each unrolled ANN in the chain
- 2 The network is rolled up and the weights are updated

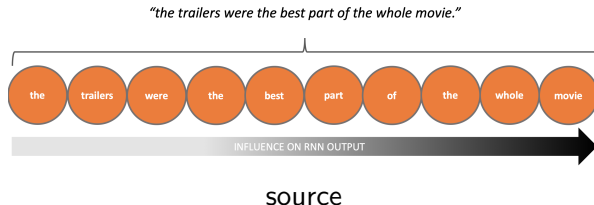
For further reading and derivation, check this out.



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# Limitations of RNN

## The Vanishing and Exploding Gradient Problems

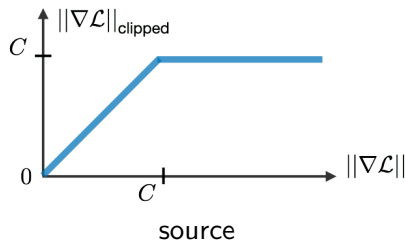


- When the “working memory” of an RNN struggles to retain long term dependencies.
- As the number of hidden layers increases, or as the width of the unrolled RNN increases, BPTT is performed over multiple (long) time steps. Error gradients get amplified or diminished making gradient descent and weight update tricky.

# Limitations of RNN

## Solving the Exploding Gradient Problem

The exploding gradient problem can be solved by **gradient clipping**. The maximum value of the gradient is capped so that it doesn't grow uncontrollably.



# Limitations of RNN

## Solving the Vanishing Gradient Problem

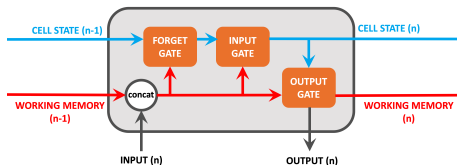
To solve the vanishing gradient problems, variants of the RNN were created: **Gated Recurrent Unit (GRU)** and **Long Short Term Memory (LSTM)**.

LSTM is a generalized version of GRU and is a fairly popular solution for time series and early language related machine learning tasks.

# Architecture of an LSTM

LSTM introduce new types of mechanisms that help regulate the vanishing gradient problem:

- 1 **Cell state.** Cell state persists (long-term) information over all iterations of the node. It can be amended to remove or keep information. such that important info from early iterations will not be lost over long sequences.
- 2 **Forget gate.** Decides information to be removed from the cell state.
- 3 **Input gate.** Decides information to be added to the cell state.
- 4 **Output gate.** Decides the working memory this node will output.



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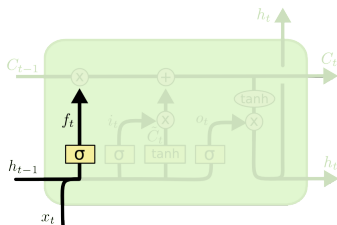
# Architecture of an LSTM

## Forget Gate

What information to throw away from the cell state.

Input:  $h_{t-1}$  (hidden state from the previous time step),  $x_t$  (input at current time step).

Output: a number between 0 and 1 for each number in the cell state  $C_{t-1}$ .



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

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Example: Predicting next word based on a previous ones. If the cell state includes the gender of the current subject to use the correct pronouns, we want to forget the previous gender once a new subject is seen.

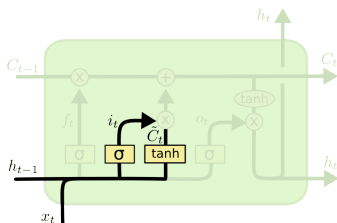
# Architecture of an LSTM

## Input Gate

What new information to store in the cell state.

“Input Gate Layer”  $i_t$  returns 0 or 1 to decide which values to update.

Tanh Layer creates a vector of new candidate values  $\hat{C}_t$  to add to the cell state.



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

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

Example: Deciding to add the gender of the new subject to the cell state.

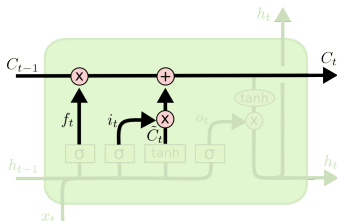
# Architecture of an LSTM

## Update Gate

Update the old cell state  $C_{t-1}$  into the new one  $C_t$ .

Multiply the old state  $C_{t-1}$  by  $f_t$ , forgetting things decided early on.

Add scaled new candidate values decided by the input gate layer  $i_t \times \hat{C}_t$ .



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

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Example: Where we actually drop the info about the old subject's gender and add the new subject's gender.



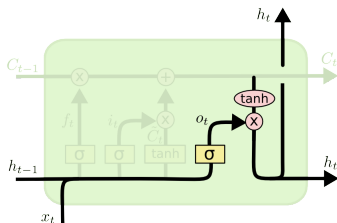
# Architecture of an LSTM

## Output Gate

Output based on a filtered version of the current cell state.

$o_t$  returns 0 or 1 to decide which parts of the cell state to output.

Tanh layer to push the values of the current cell state between -1 and 1, and multiply it by the output of the sigmoid layer.



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

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

Example: Since it just saw a subject, output information relevant to a verb, such as if the subject is singular or plural so we know what form the verb should be.

# References



Mark West

Explaining Recurrent Neural Networks

*Bouvet*



Afshine Amidi and Shervine Amidi

Recurrent Neural Network Cheatsheet

*Stanford University*



Christopher Olah (2015)

Understanding LSTM Networks