CS 581 – Advanced Artificial Intelligence

Topic: Neural Networks

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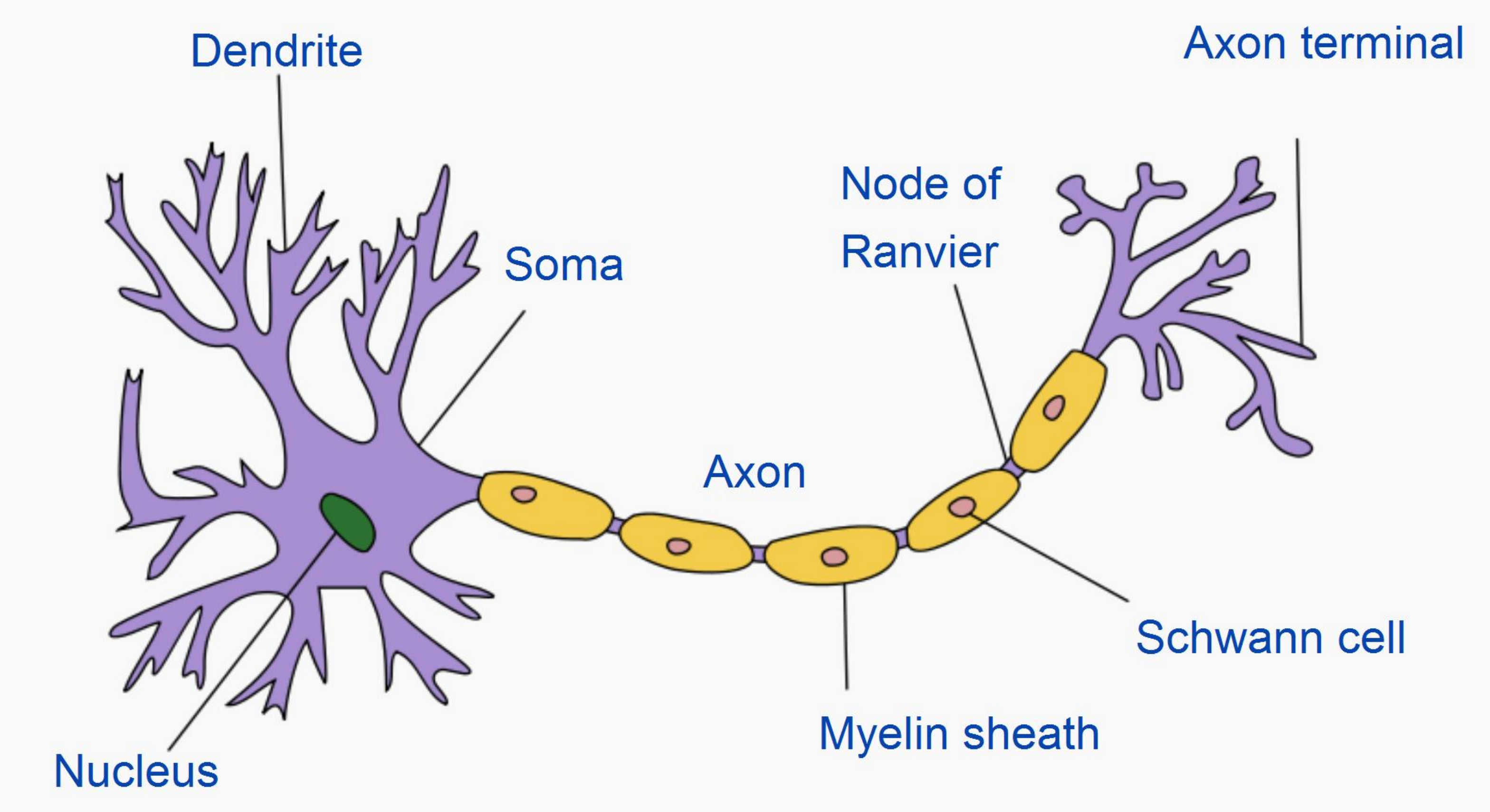
Neuron



Dendrite
Axon terminal
Node of
Ranvier
Soma
Axon
Schwann cell
Myelin sheath
Nucleus

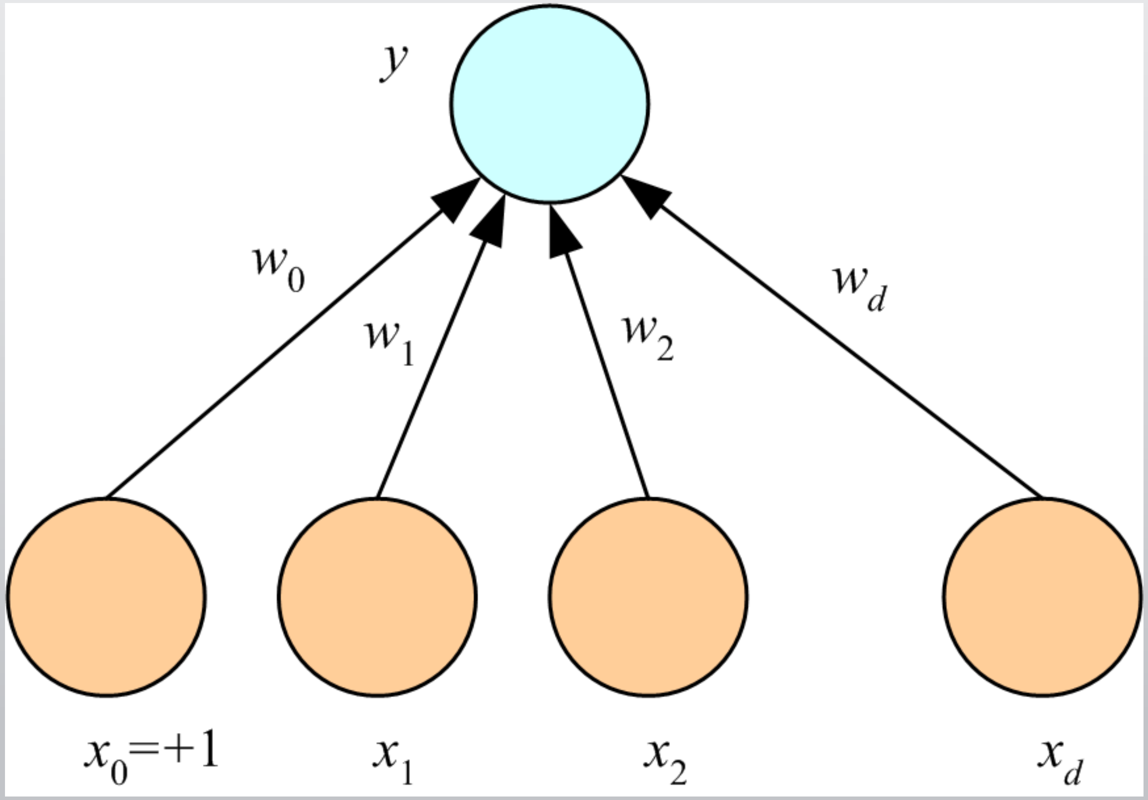
NEURON

- Neurons can have multiple dendrites and at most one axon
- Typical connections are from an axon of a neuron to dendrites of other neurons
- Synaptic signals are received through dendrites and somas; signals are transmitted through axons
- Signals can excite or inhibit the receiving neuron
- A neuron fires when the excitement is above a threshold

ARTIFICIAL NEURAL NETWORKS

- Artificial neural networks are inspired by real neurons
- 1943 – One of the first neural computational models was proposed by McCulloch and Pits
- 1958 – Rosenblatt proposed perceptron
- 1969 – A paper by Minsky and Papert almost killed the entire field
  - Perceptrons are incapable of representing XOR
  - Computational resources are too great
- 1975 – Backpropagation algorithm renewed interest in neural networks
- 1980s – parallel architectures were popular
- Late 1990s and 2000s – other methods, such as support vector machines, became more popular
- 2010s – neural networks of several hidden layers are back with the new name “deep learning”

Perceptron



$$y = sign(w_0 + \sum w_i x_i)$$

What an Artificial Neuron Does

- Takes a weighted sum of its inputs
  - $w_0 + \sum_{i=1}^{k} w_i x_i$
  - Assume that there is always a constant input 1, that is, $x_0 = 1$. Then,
  - $\sum_{i=0}^{k} w_i x_i$
- Passes this sum through its activation function
  - $f\left(\sum_{i=0}^{k} w_i x_i\right)$

Examples

- Logical AND
- Logical OR
- Logical XOR
- See OneNote and Notebook

Simple Multilayer Network for XOR

- $XOR(A, B) = (A \land \neg B) \lor (\neg A \land B)$
- One perceptron for $(A \land \neg B)$
- One perceptron for $(\neg A \land B)$
- One perceptron for combining the outputs, through OR, of the two previous perceptrons
- See Notebook

Various Activation Functions

- Identity function
- Bipolar step function
- Binary sigmoid
- Bipolar sigmoid
- Hyperbolic tangent

IDENTITY FUNCTION

- $f\left(\sum_{i=0}^{k} w_i x_i\right) = \sum_{i=0}^{k} w_i x_i$
- Typically used for the output neurons, when the task is regression
- The identity function should not be used in the hidden layers
  - Linear combination of linear functions is another linear function, and hence using the identity function in the hidden layers do not increase representative power of the neural network

Bipolar Step Function

- $f\left(\sum_{i=0}^{k} w_i x_i\right) = sign\left(\sum_{i=0}^{k} w_i x_i\right)$
- Returns either +1 or -1 (except right on the decision boundary)
- Useful for both hidden layers and output layer
- However, its discontinuous and it is problematic for learning algorithms that require taking its derivative

Binary Sigmoid

- $f\left(\sum_{i=0}^{k} w_i x_i\right) = \frac{1}{1+e^{-\sum_{i=0}^{k} w_i x_i}}$
- This is the logistic function that we used
  - Except, notice the minus sign in front of the sum
    - This is only a convention and does not change much
- The output of the binary sigmoid is between 0 and 1
  - Useful for output layer when the task is classification
  - The output can be interpreted as a probability

Bipolar Sigmoid

- $f\left(\sum_{i=0}^{k} w_i x_i\right) = \frac{2}{1+e^{-\sum_{i=0}^{k} w_i x_i}} - 1$
- This is a rescaled version of the binary sigmoid
- The output of the bipolar sigmoid is between -1 and +1
  - Useful for output layer when the task is classification
  - Useful for both hidden and output layers

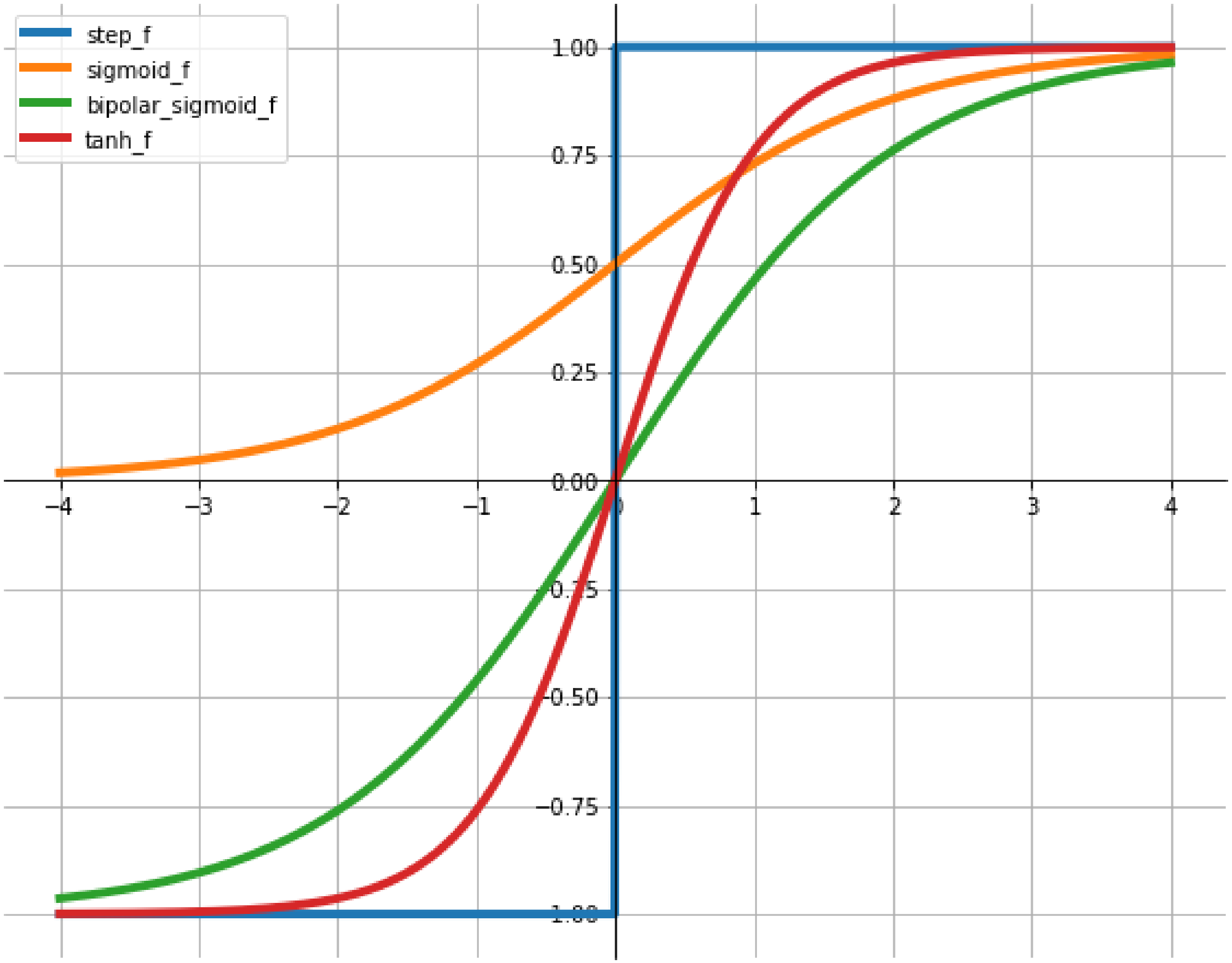
Hyperbolic Tangent

- $f\left(\sum_{i=0}^{k} w_i x_i\right) = \frac{e^{\sum_{i=0}^{k} w_i x_i} - e^{-\sum_{i=0}^{k} w_i x_i}}{e^{\sum_{i=0}^{k} w_i x_i} + e^{-\sum_{i=0}^{k} w_i x_i}}$
- The output of tanh is between -1 and +1
  - Useful for output layer when the task is classification
  - Useful for both hidden and output layers

Relu

- $f\left(\sum_{i=0}^{k} w_i x_i\right) = \sum_{i=0}^{k} w_i x_i$ if $\sum_{i=0}^{k} w_i x_i > 0$; 0 otherwise
- Typically used for hidden layers, especially for computer vision tasks

Activation Function Plots



Learning the Weights

- Define an error (loss) function
- Take its derivative with respect to the weights
- Perform gradient descent

Some Error/Loss Functions

- Classification: log-loss, cross entropy, negative CLL
  - $-(1-t) \times ln(1-y) - t \times ln(y)$
  - t: the true target value (0/1)
  - y: probability of class 1
- Regression: squared error
  - $\frac{1}{2}(t-y)^2$
  - t: the true target value
  - y: the predicted value

Derivatives of the Activation Functions

- f is the activation function, h is the weighted sum of the incoming signals
- $f(h(x)) \equiv$ binary sigmoid
  - $\frac{\partial f(h(x))}{\partial x} = f(h(x)) \times \left(1 - f(h(x))\right) \times \frac{\partial h(x)}{\partial x}$
- $f(h(x)) \equiv$ tanh
  - $\frac{\partial f(h(x))}{\partial x} = \left(1 + f(h(x))\right) \times \left(1 - f(h(x))\right) \times \frac{\partial h(x)}{\partial x}$
- See OneNote

Backpropagation Algorithm

- See OneNote

Example Network Architectures

- Convolutional neural networks (CNN)
- Recurrent neural networks (RNN)
- Long Short-Term Memory networks (LSTM)

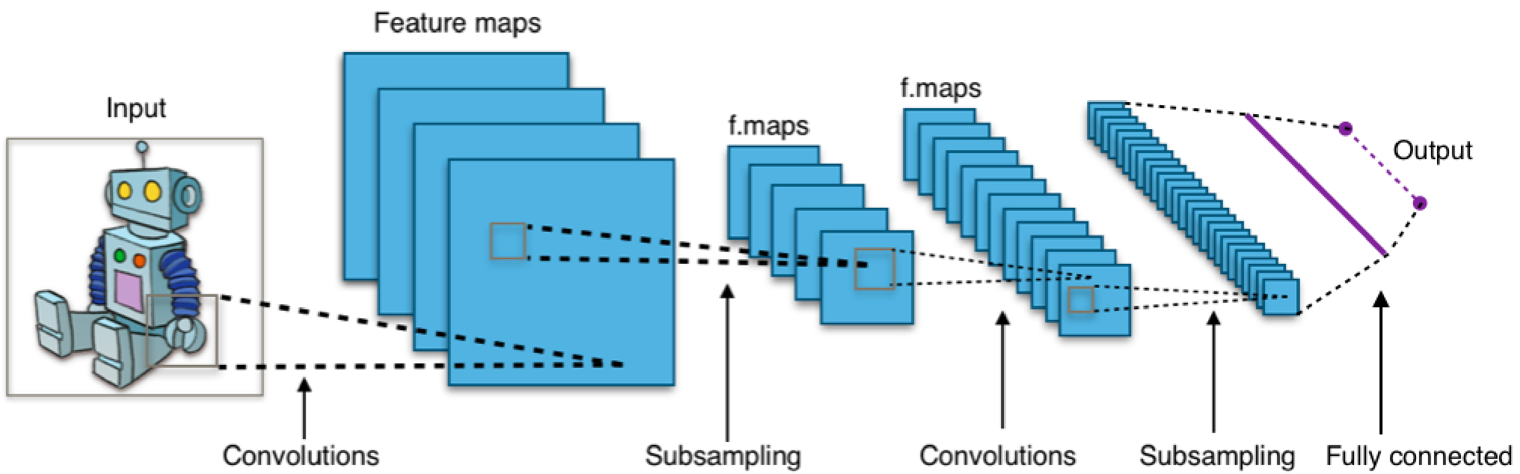
Overfitting

- Neural networks are powerful tools
- Even with a single hidden layer, they are "universal approximators", i.e., they can approximate arbitrary functions arbitrarily close
- Therefore, it is very easy to overfit them
- To prevent overfitting, utilize
  - Domain knowledge
  - Shared parameters
  - Validation data
  - Regularization

Deep Learning

- Several hidden layers
  - Millions of parameters
- Big data, big computation
- Strongly-recommended reading
  - "Why and When Can Deep -- but Not Shallow -- Networks Avoid the Curse of Dimensionality: a Review" https://arxiv.org/abs/1611.00740

Convolutional Neural Networks



https://commons.wikimedia.org/wiki/File:Typical_cnn.png

Convolution

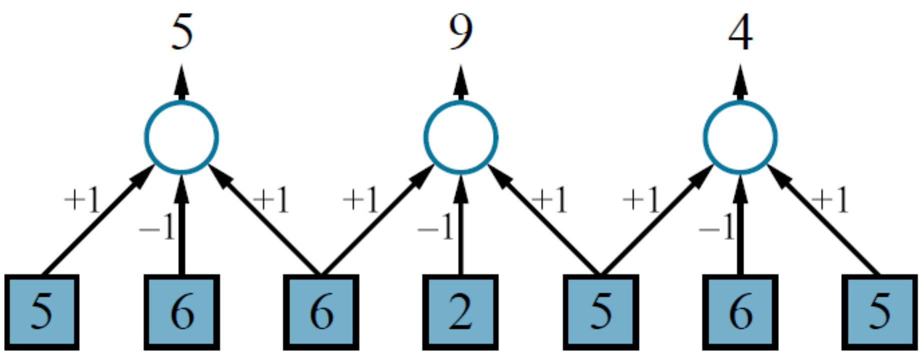


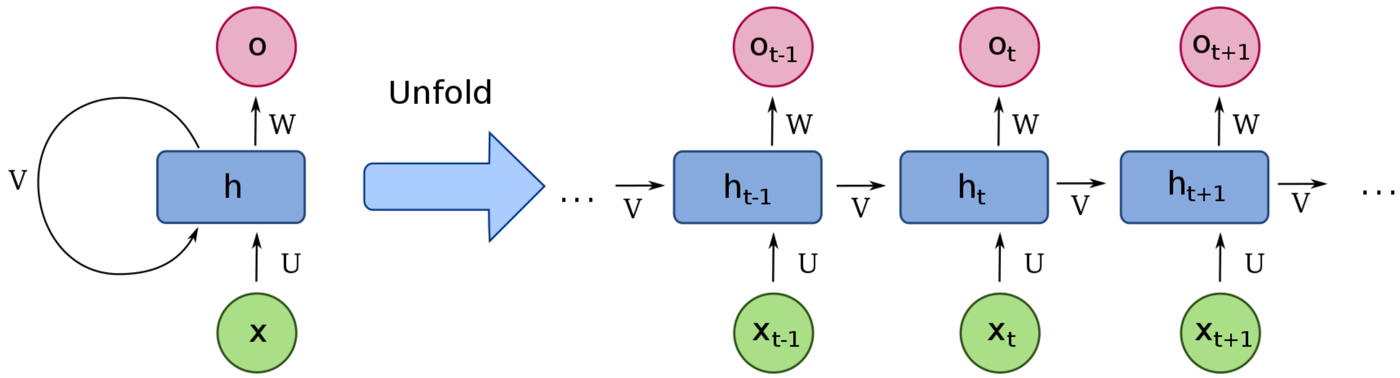
Figure 21.4 An example of a one-dimensional convolution operation with a kernel of size $l = 3$ and a stride $s = 2$. The peak response is centered on the darker (lower intensity) input pixel. The results would usually be fed through a nonlinear activation function (not shown) before going to the next hidden layer.

Figure from http://aima.cs.berkeley.edu/figures.pdf

Pooling

- Aggregates a set of adjacent units
- Like convolution, has a kernel size and a stride size
- Unlike convolution, weights are fixed (not learned)
- Examples
  - Average pooling
  - Max pooling

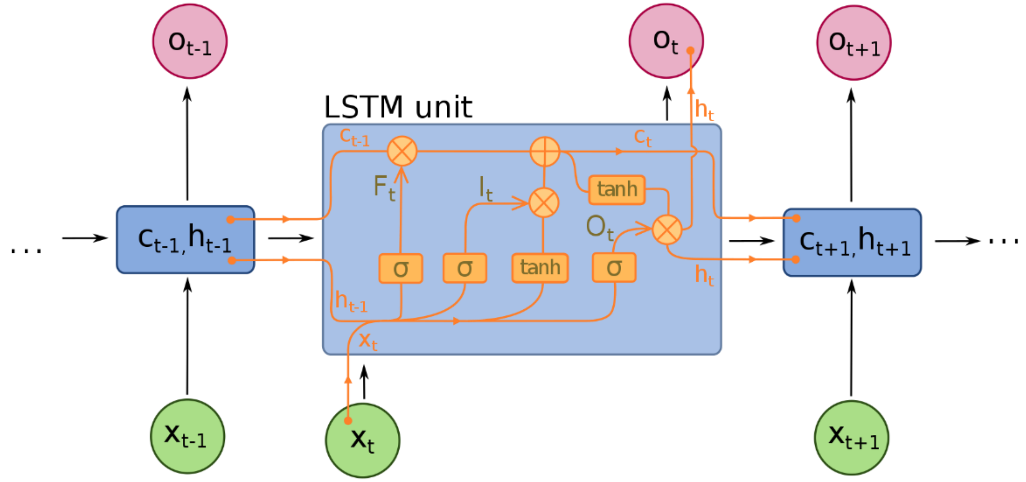
Recurrent Neural Networks



https://commons.wikimedia.org/wiki/File:Recurrent_neural_network_unfold.svg

Long Short-Term Memory (LSTM)

- A specialized RNN
- Works better than vanilla RNN for "remembering" long sequences
- Has additional units
  - Cell, forget gate, input gate, output gate



https://commons.wikimedia.org/wiki/File:Long_Short-Term_Memory.svg

Other Networks/Concepts

- Autoencoder
  - Input and output are the same
- Deep autoregressive model
  - Predict an element of the data using the other elements
- Generative adversarial networks (GAN)
  - A pair of generator and discriminator networks

LIBRARIES

- Scikit-learn
  - https://scikit-learn.org/stable/modules/neural_networks_supervised.html
- Keras
  - https://keras.io/
- Tensorflow
  - https://github.com/tensorflow/tensorflow
- PyTorch
  - https://github.com/pytorch/pytorch
- Fast.ai
  - https://docs.fast.ai/
- Others
  - Use your favorite search engine ☺