

Deep Learning

QCon.ai San Francisco, April 15h

Machine Learning (Recap)

- What is machine learning?

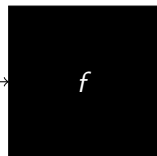
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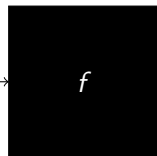
- What is machine learning?



dog

Machine Learning (Recap)

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- By knowing a set of data and their targets we can tune f to output what we want.

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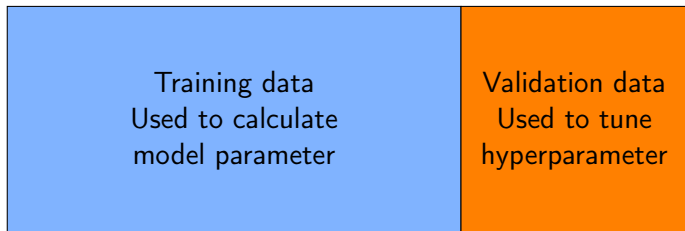
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- It can check more cases than we could

Validating Machine Learning (Recap)

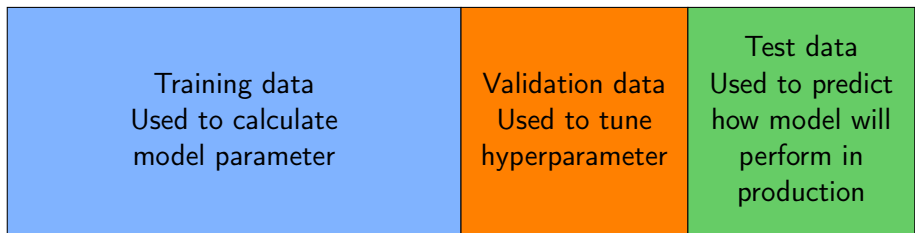
Validating Machine Learning (Recap)

Training data
Used to calculate
model parameter

Validating Machine Learning (Recap)



Validating Machine Learning (Recap)



Today's Overview

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- 9:00 Introduction to Deep Learning
 - Short recap on machine learning
 - Build and train a perceptron in numpy
 - Change the code to use PyTorch
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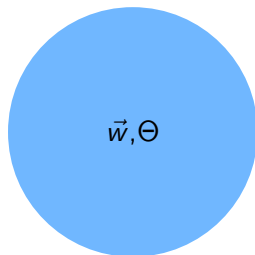
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- 16:00 End of workshop

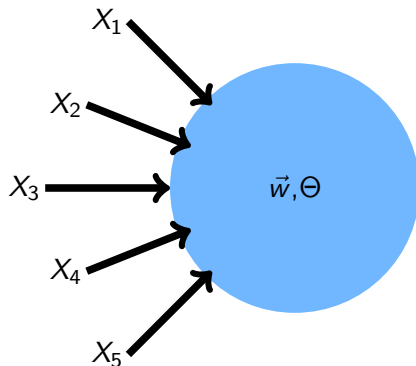
Perceptron

- The perceptron contains a weight (\vec{w}) for each input and a threshold (Θ)



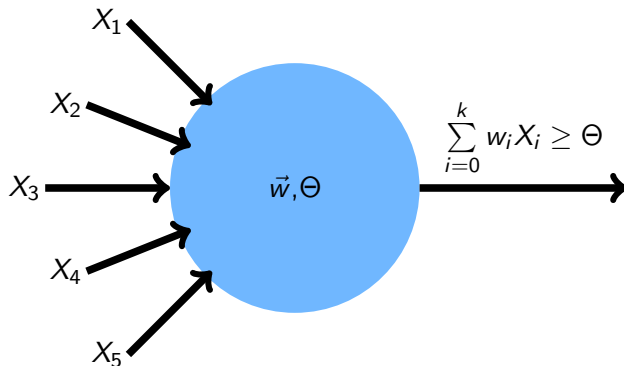
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- Its output can be calculated as $\sum_{i=0}^k w_i X_i \geq \Theta$



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- Restart the process until the solution is found
- Let us actually implement this in the first notebook (Perceptron)

Conclusions

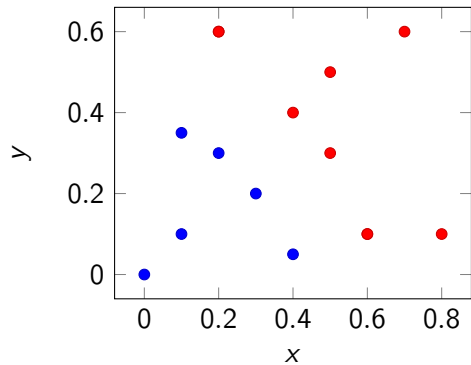
Conclusions

- Congratulations on training your first perceptron! You just taught a computer to learn!

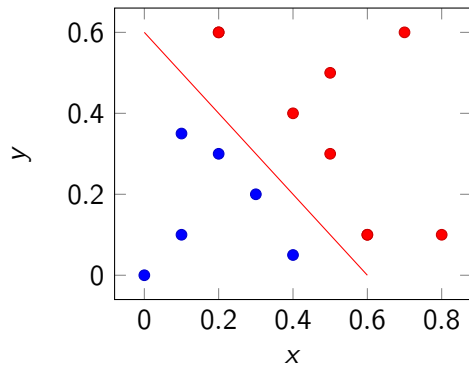
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- Congratulations on training your first perceptron! You just taught a computer to learn!
- Why didn't we wait for the final weights, but stop after one run over the dataset?

Linear Separability

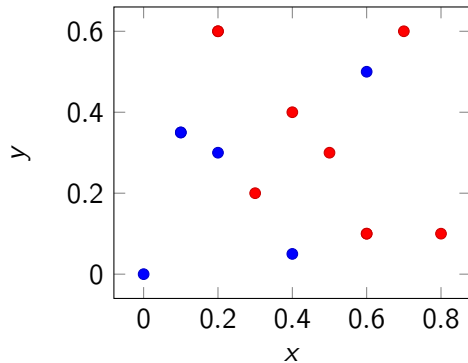
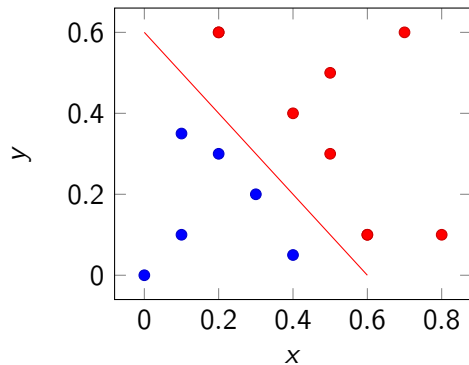


Linear Separability



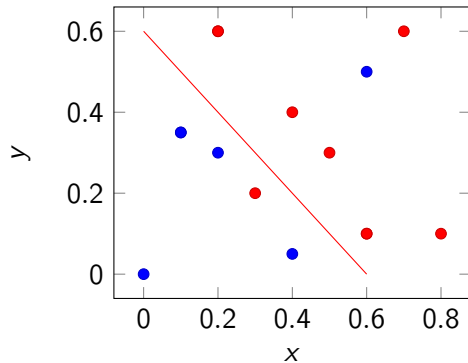
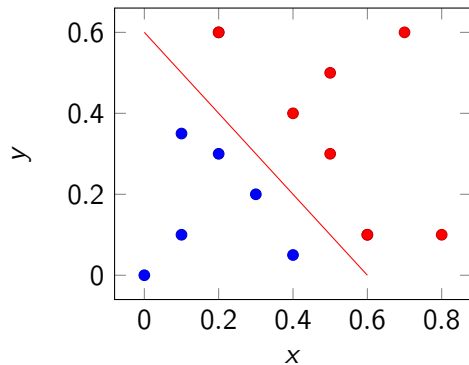
Data is linearly separable -> Can be divided by a plane

Linear Separability



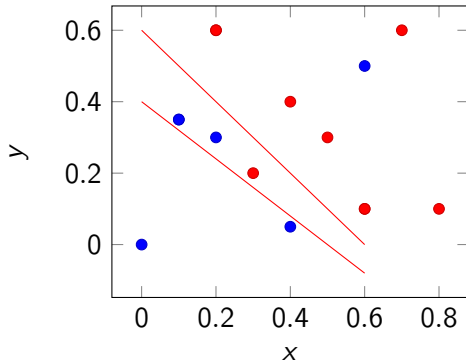
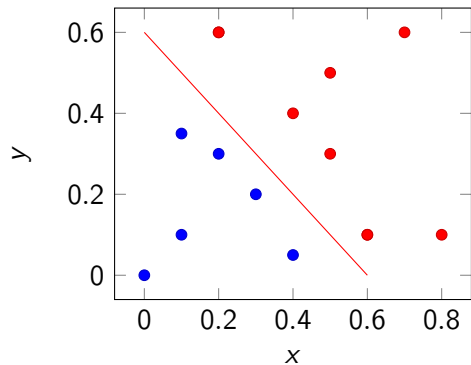
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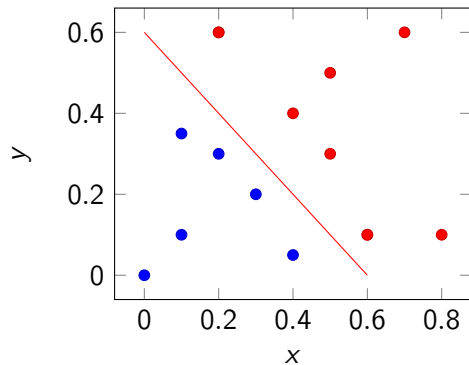
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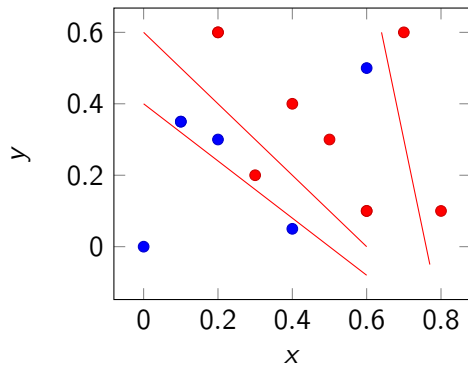


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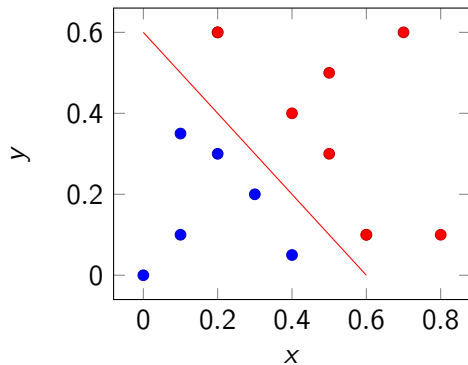


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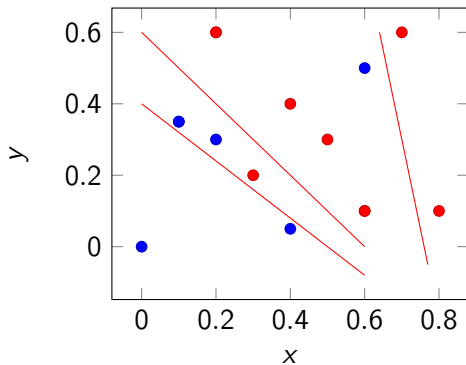


Data is not linearly separable -> Can not be divided by a plane

Linear Separability



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The algorithm only converges, if the problem is linearly separable.

Gradient Descent

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- What we calculated is an activation

$$a = \sum_i w_i X_i$$

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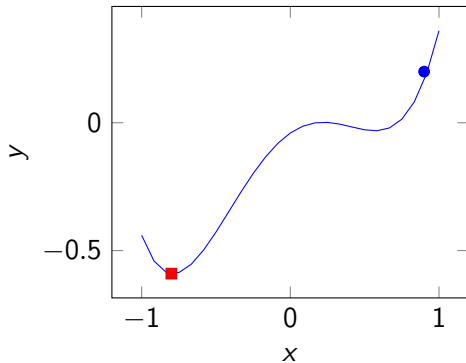
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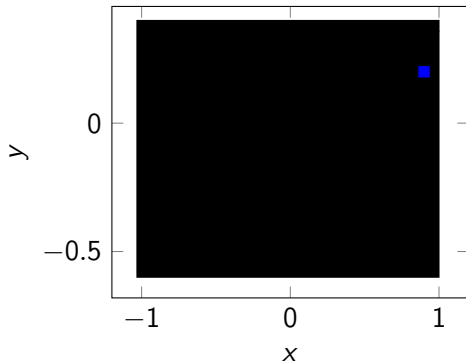
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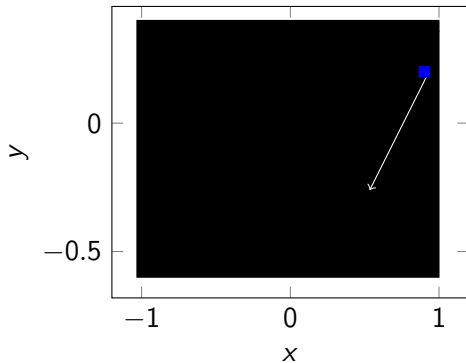
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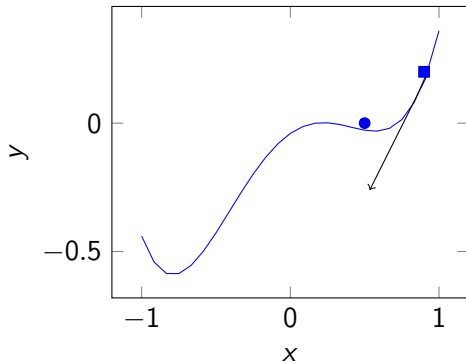
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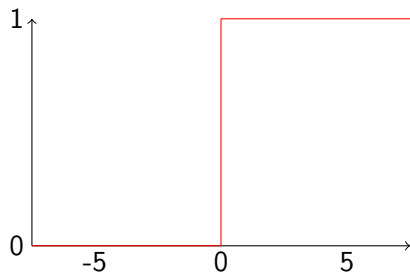


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- Every deep learning framework can calculate those gradients using the chain rule and backpropagation.

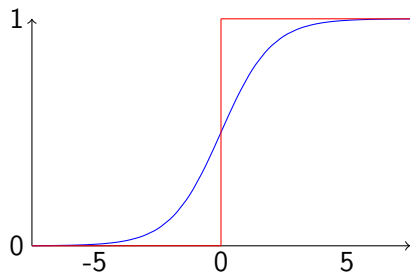


Sigmoid \rightarrow Differentiable Threshold



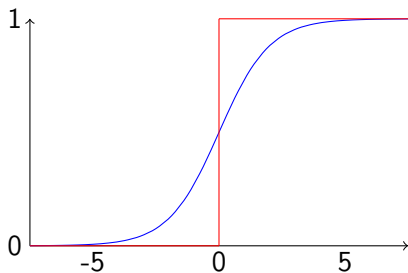
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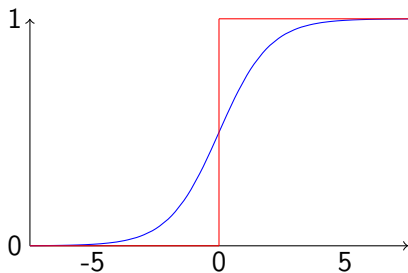
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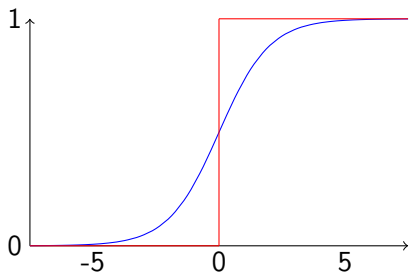
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- Let us use this new knowledge to implement gradient descent in the next notebook.



Neural Network

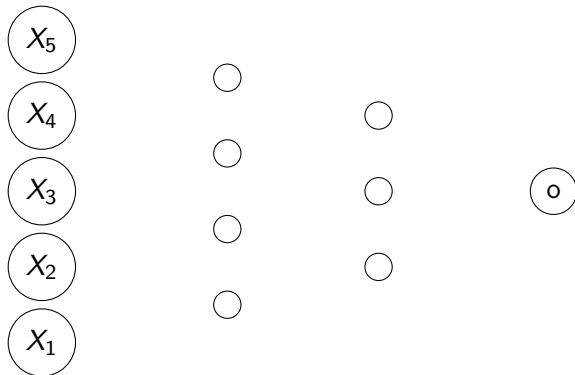
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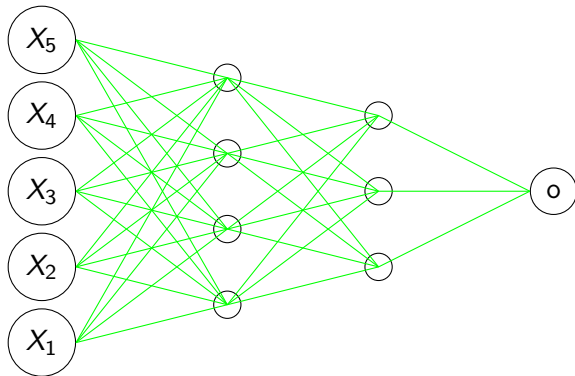
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- However, instead of going from start to end directly we now add hidden units
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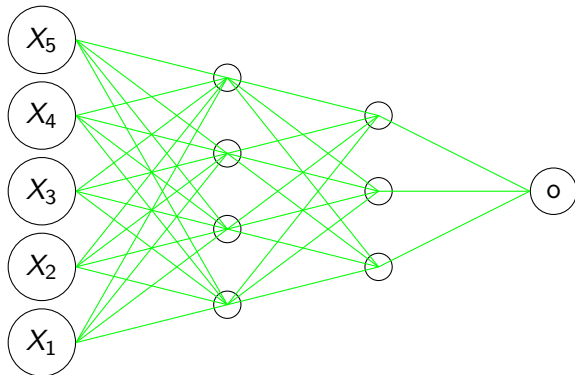
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- For each of the units we now apply the sigmoid function
- Since every unit is differentiable, the whole network is differentiable
→ We can use backpropagation to minimize the error as we can calculate the gradients



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 - Weight Decay

Optimizing Weights

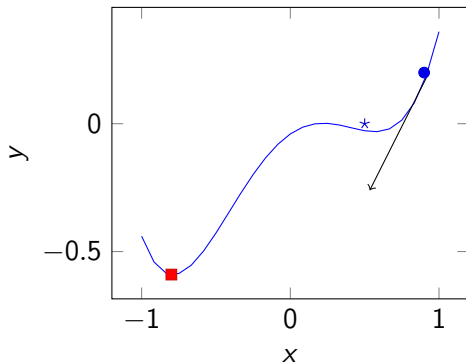
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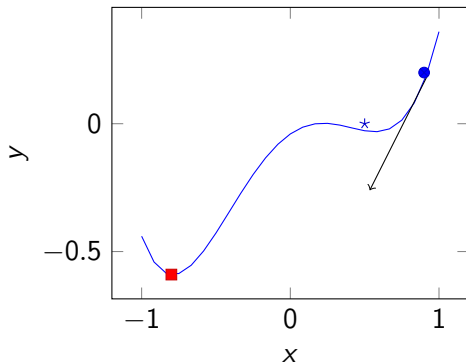
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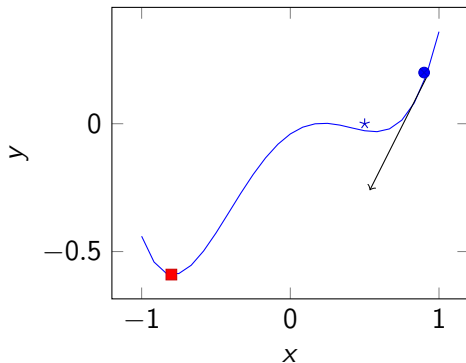
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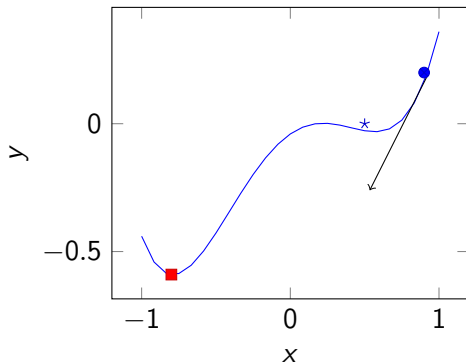
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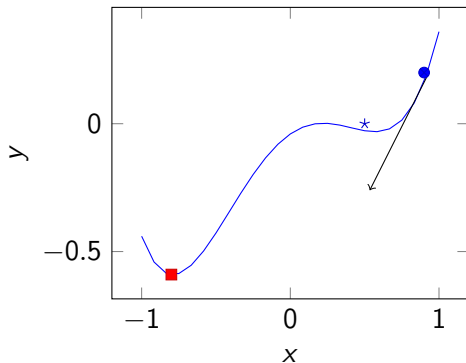
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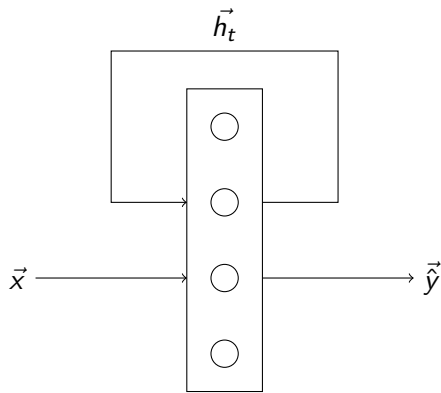


Optimizing Weights

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 - Penalty for Complexity

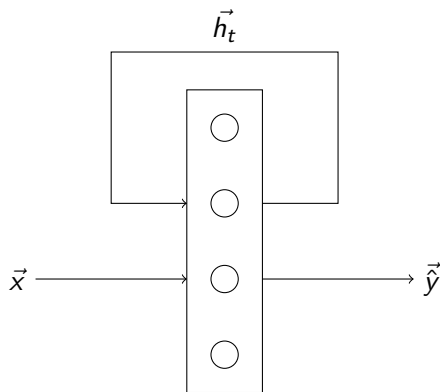


Recurrent Neural Networks



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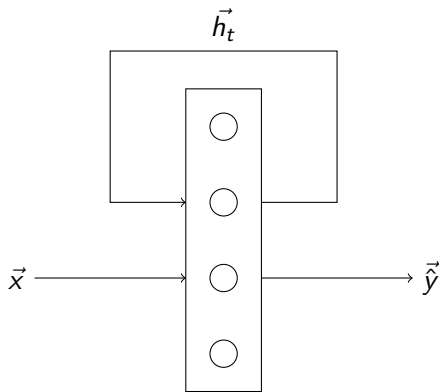
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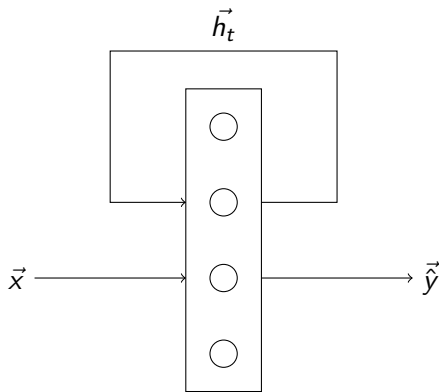
- Recurrent Neural Networks allow one to propagate states through time
- They calculate a hidden state \vec{h}_t which is kept for the next time step, as

$$h_t = \sigma_h(W_h x_t + U_h h_{t-1} + b_h)$$



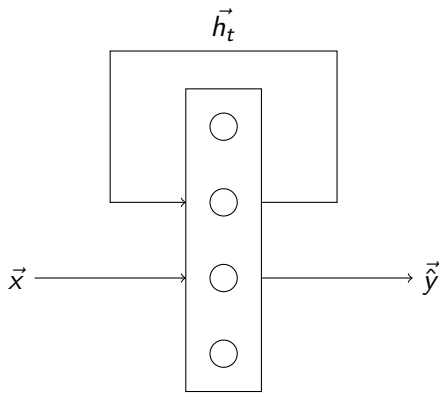
Recurrent Neural Networks

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Recurrent Neural Networks

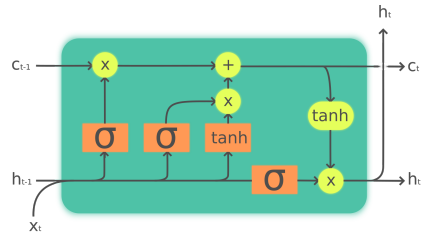
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- These networks cannot represent long-term dependencies as U_h is always multiplied by itself.



LSTM

LSTM

- LSTM (Long-Short-Term Memory) can store long term dependencies by adding a cell state and utilizing an input, forget and output gates.



Legend:

Layer



Pointwise op



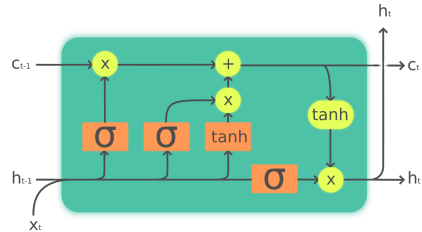
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Figure: Courtesy of wikipedia

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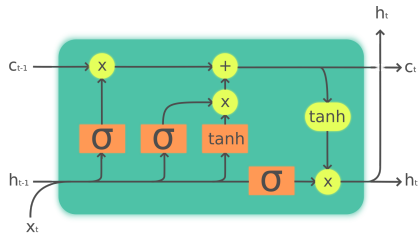
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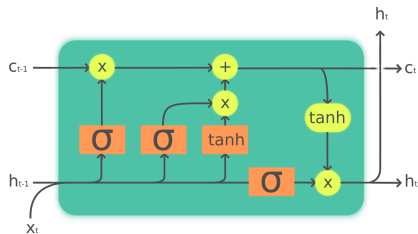
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Word2Vec

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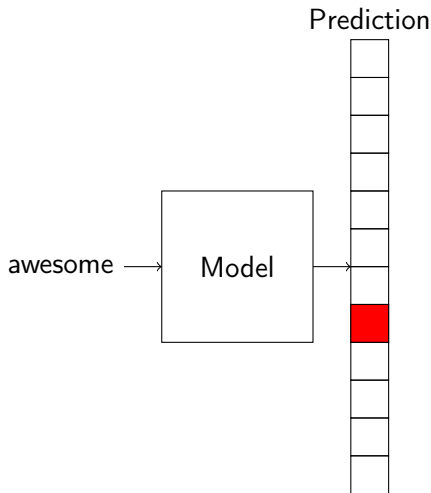
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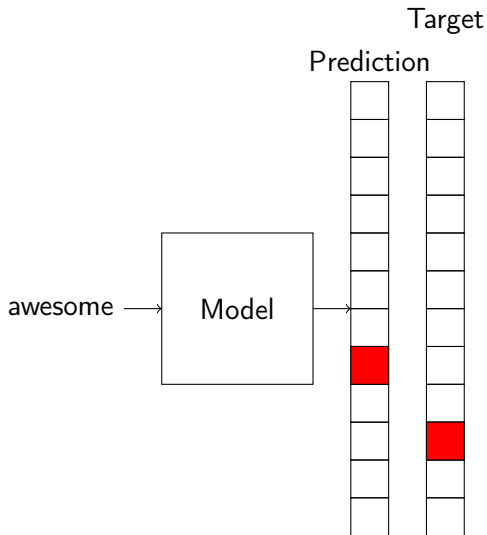
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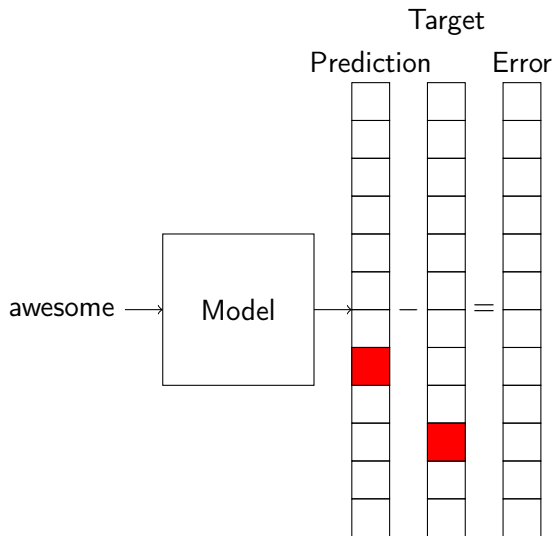
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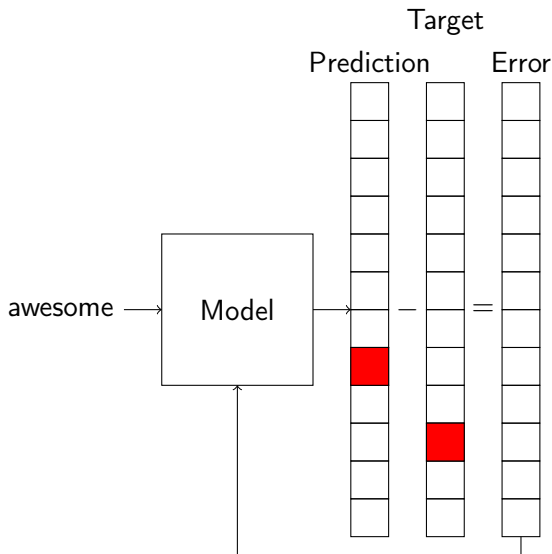
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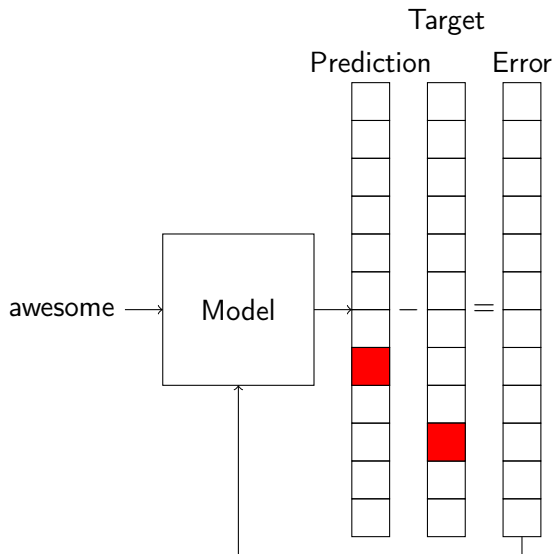
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- As classical training would update all the weights for each target example (where vocabularies can be million of words), the weights will only be updated for the right targets and a random selection of false targets



Chatbot

Chatbot

- Let's chat

Chatbot

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- The notebook we will use is inspired by the PyTorch chatbot tutorial, but it utilizes AllenNLP.

Encoder

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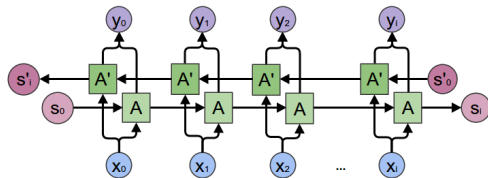


Figure: Image from <https://colah.github.io/posts/2015-09-NN-Types-FP/>

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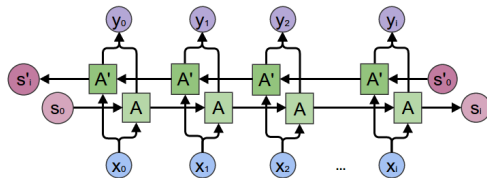


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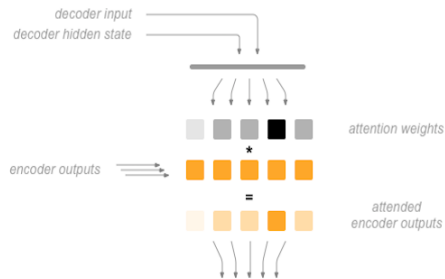


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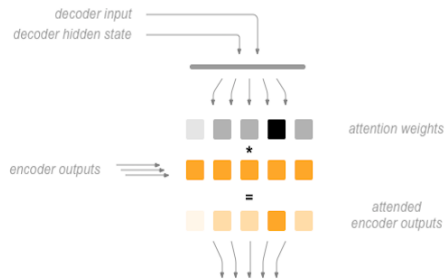


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- It will then merge the weighted encoder vectors with the current decoder output

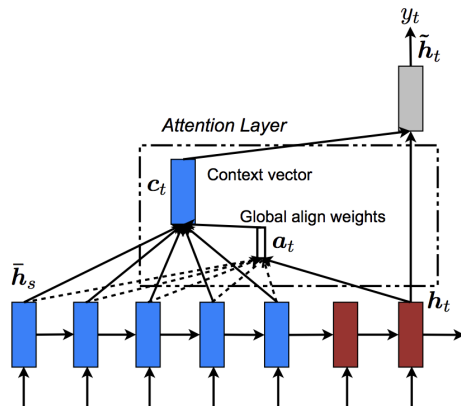


Figure: From arxiv 1508.04025