Deep Learning

QCon London, March 9th

Machine Learning (Recap)

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- What is machine learning?

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$$X \longrightarrow \qquad\qquad \longrightarrow Y$$

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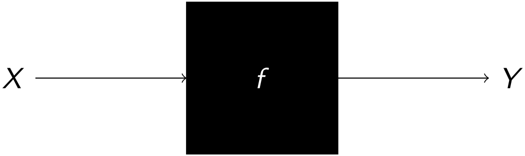

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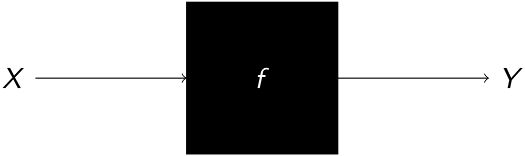

- By knowing a set of data and their targets we can tune f to output what we want.

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- It can check more cases than we could

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- 9:00 Introduction to Deep Learning
  - Short recap on machine learning
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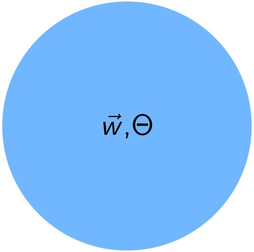
Perceptron

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



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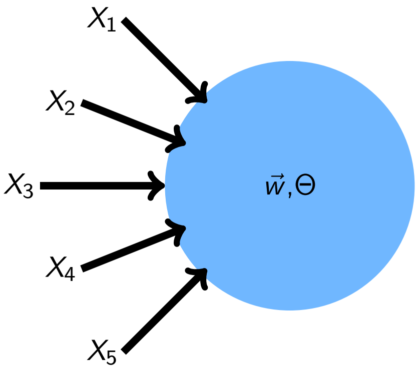

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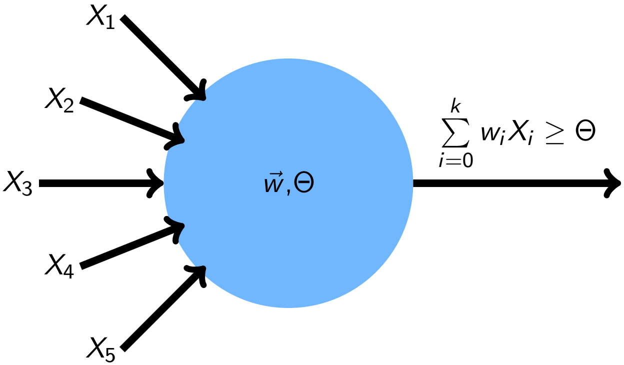
- Its output can be calculated as $\sum_{i=0}^{k} w_i X_i \geq \Theta$



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- Let us actually implement this in the first notebook (Perceptron)

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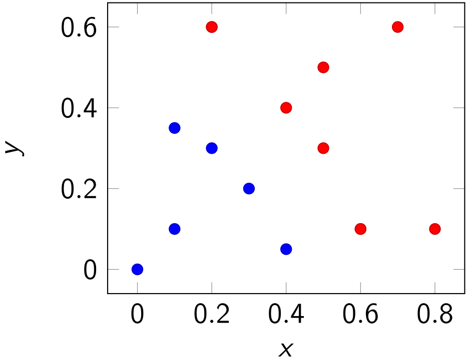
- Why didn't we wait for the final weights, but stop after one run over the dataset?

Linear Separability



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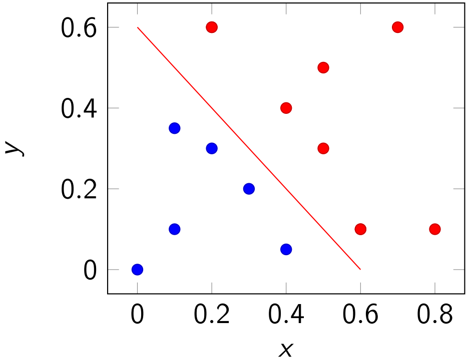

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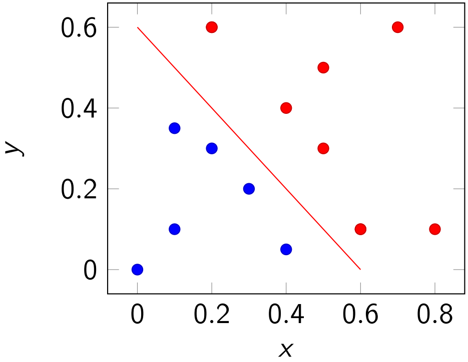

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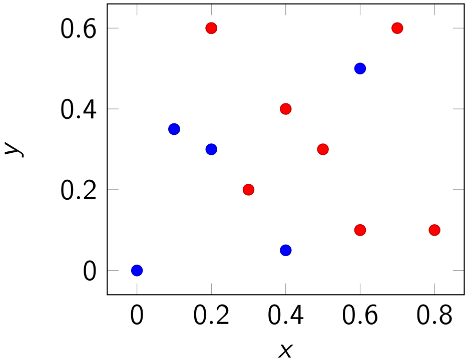

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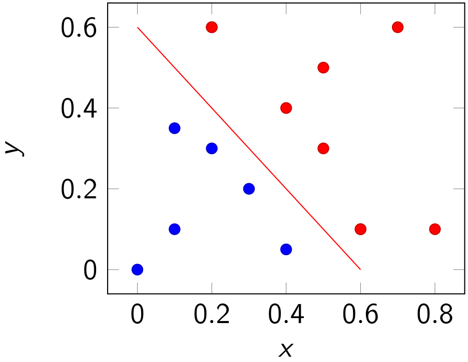

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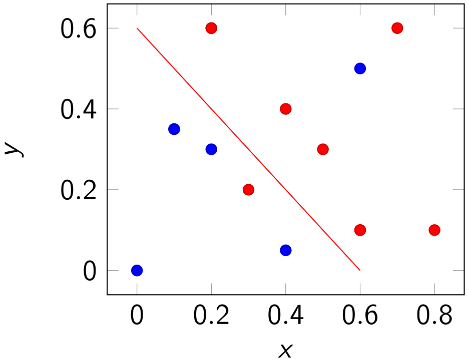

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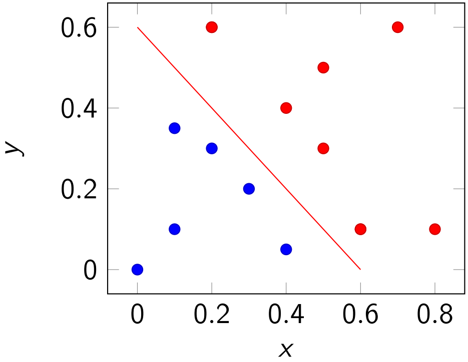

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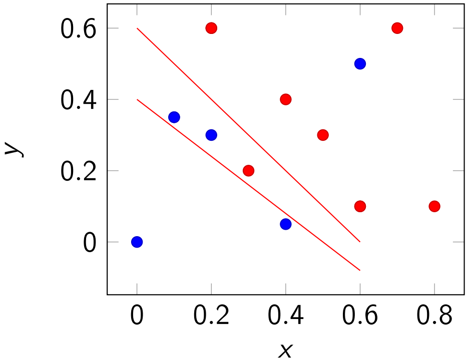

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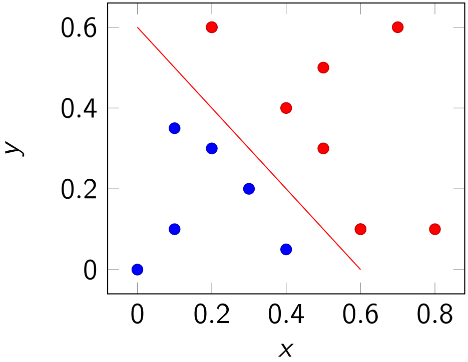

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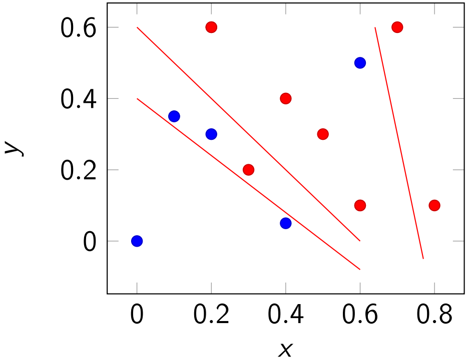

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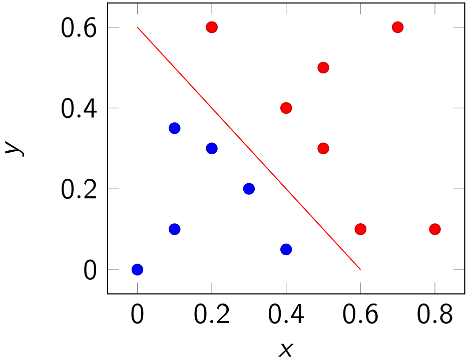

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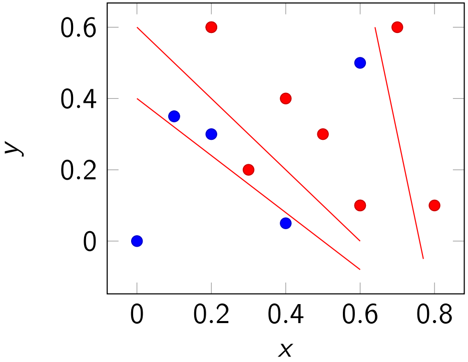

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The algorithm only converges, if the problem is linearly separable.

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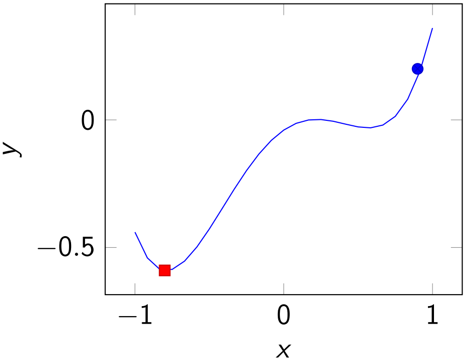

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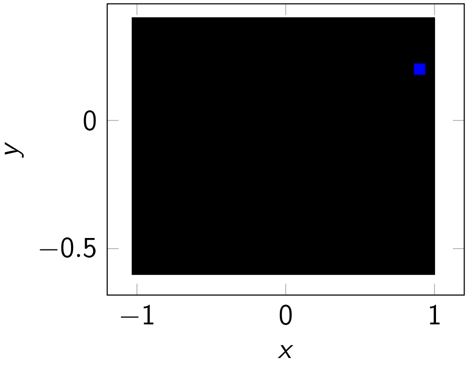

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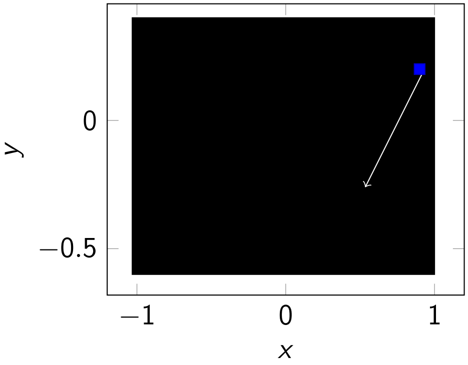

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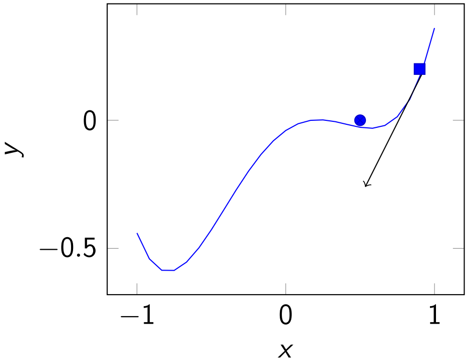
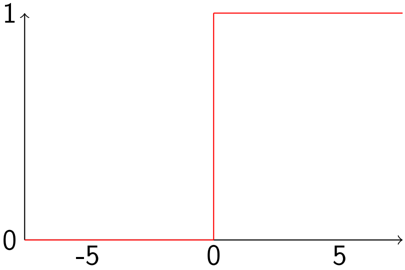
- Every deep learning framework can calculate those gradients using the chain rule and backpropagation.



Sigmoid $\rightarrow$ Differentiable Threshold



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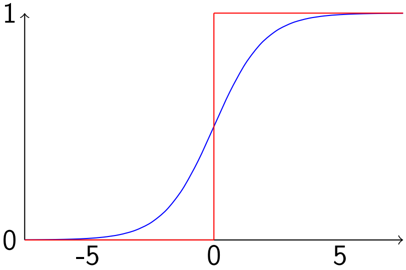

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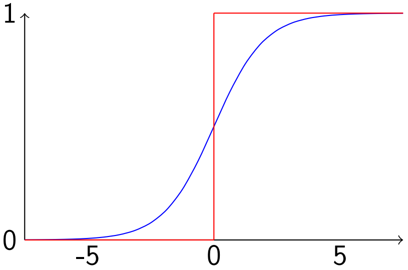

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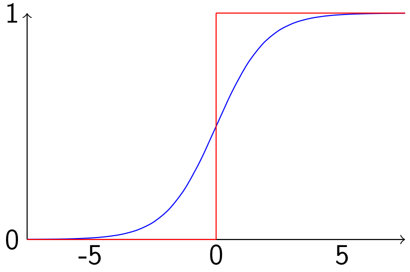

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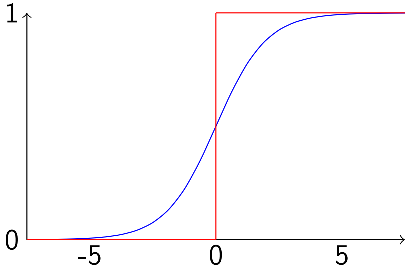
- Let us use this new knowledge to implement gradient descent in the next notebook.



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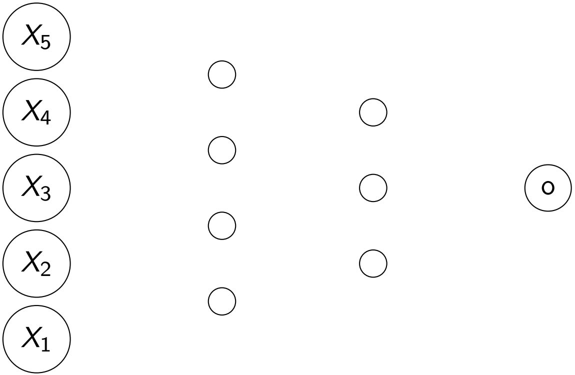

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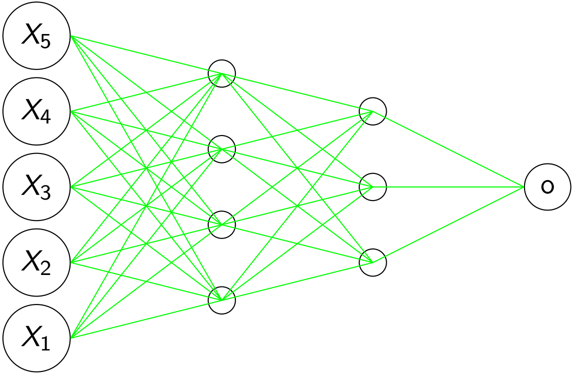

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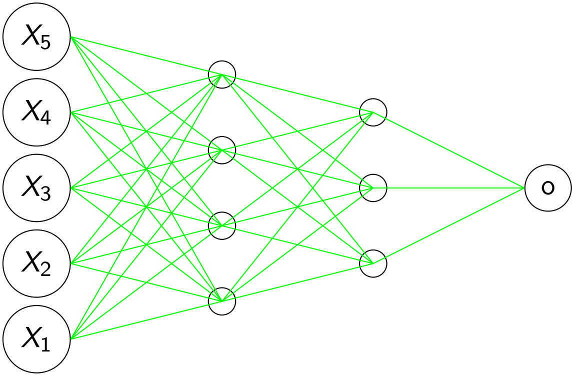
- Since every unit is differentiable, the whole network is differentiable $\rightarrow$ We can use backpropagation to minimize the error as we can calculate the gradients



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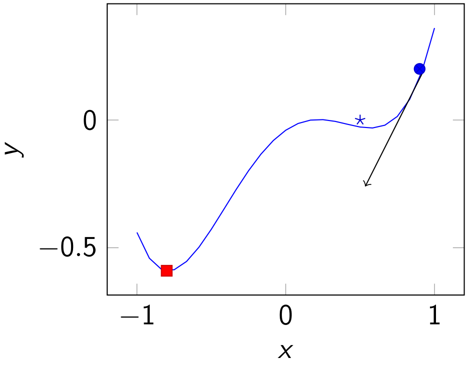

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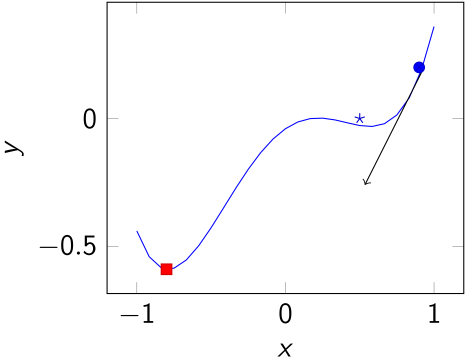

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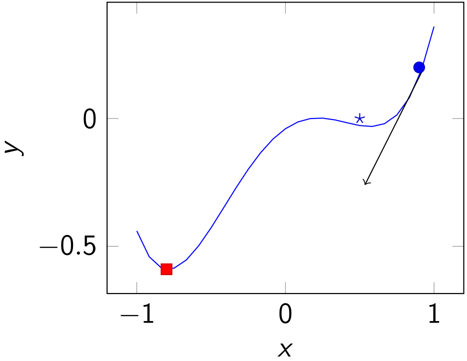

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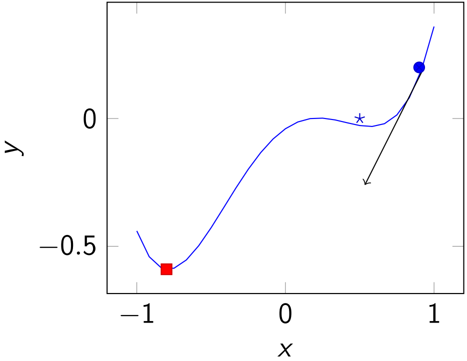

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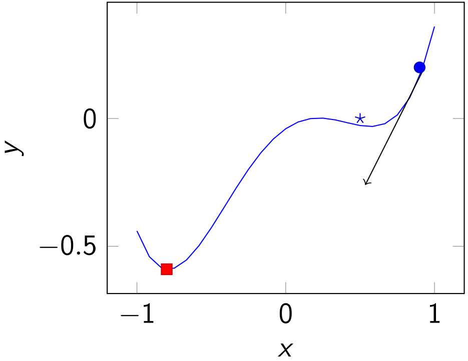
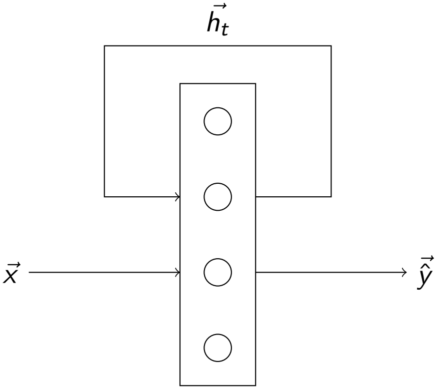
  - Penalty for Complexity



Recurrent Neural Networks



Recurrent Neural Networks

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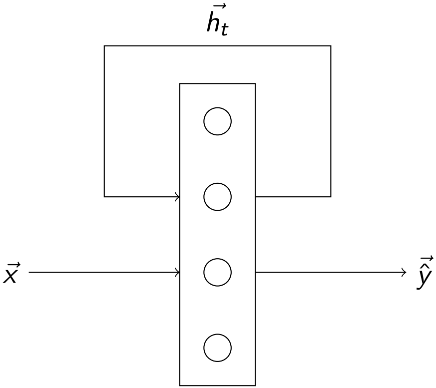

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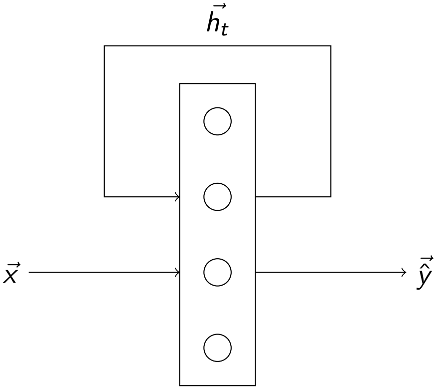

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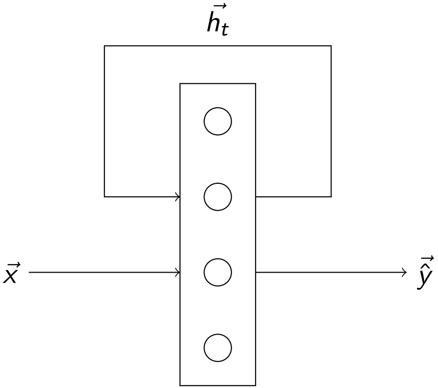

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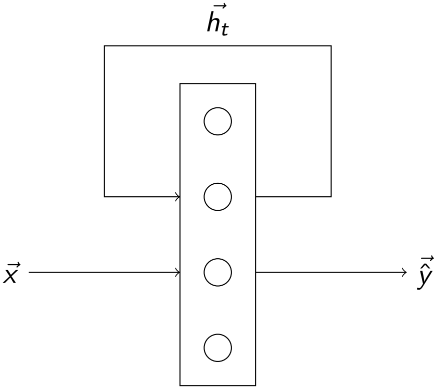
- These networks cannot represent long-term dependencies as U_h is always multiplied by itself.



LSTM

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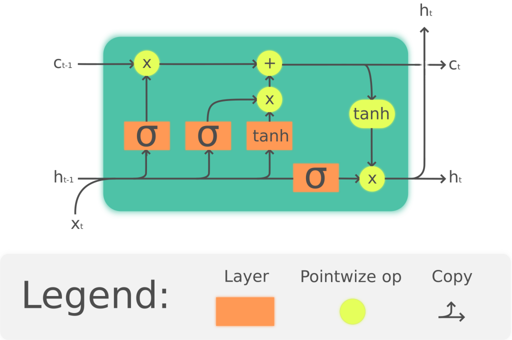

Figure: Courtesy of wikipedia

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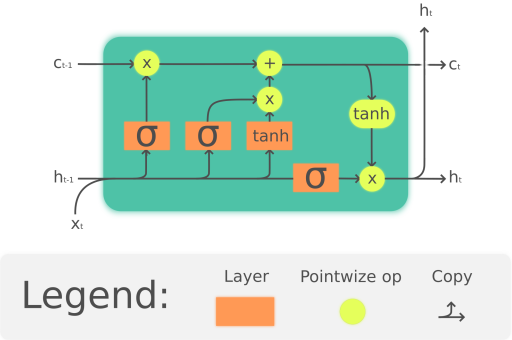

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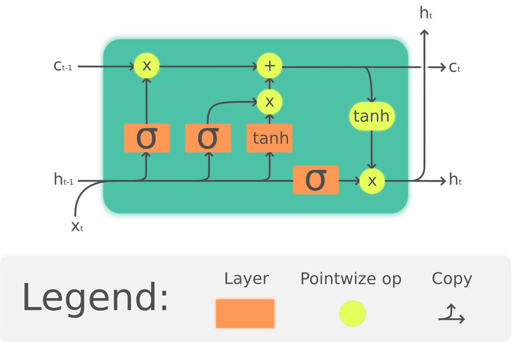

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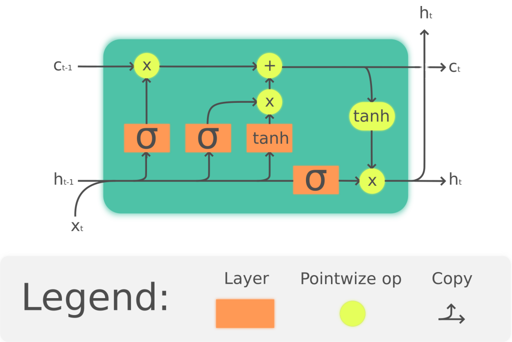

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Word2Vec

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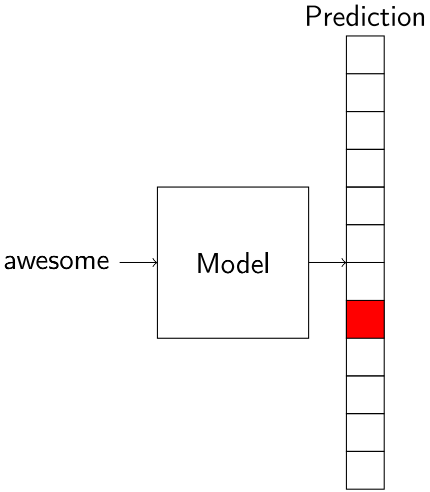

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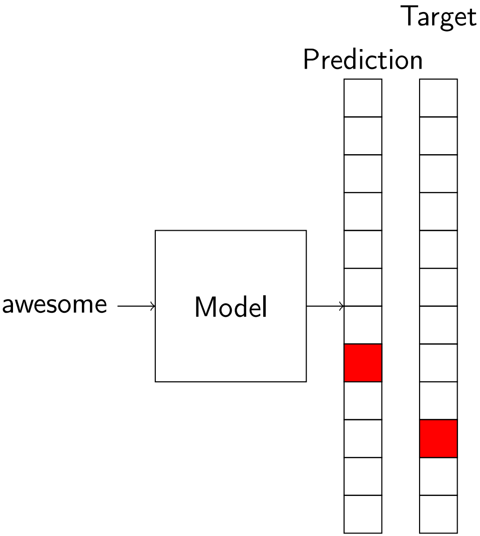

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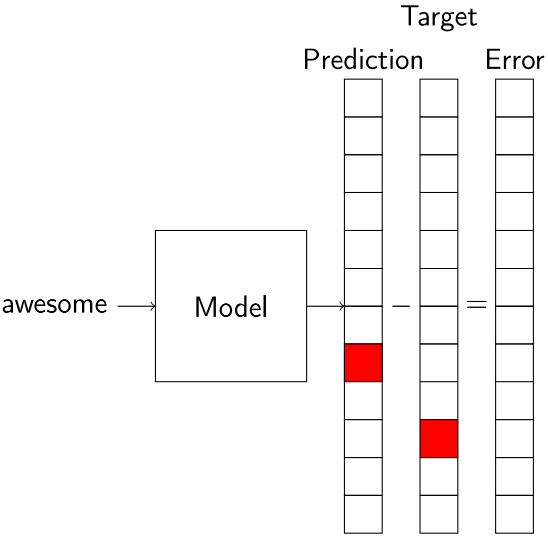

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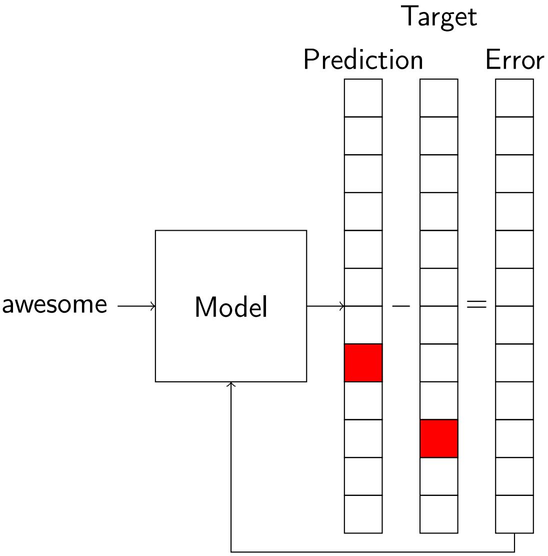

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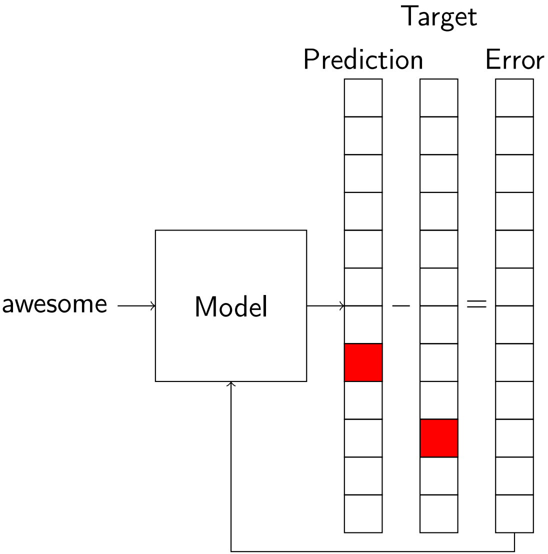
- As classical training would update all the weights for each target example (where vocabularies can be million of words), the weights will only be updated for the right targets and a random selection of false targets



Chatbot

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

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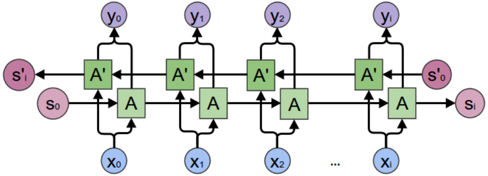

Figure: Image from `https://colah.github.io/posts/2015-09-NN-Types-FP/`

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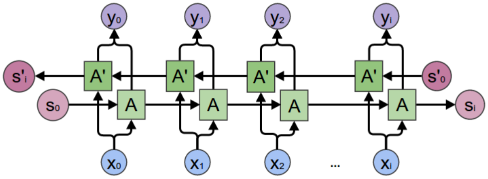

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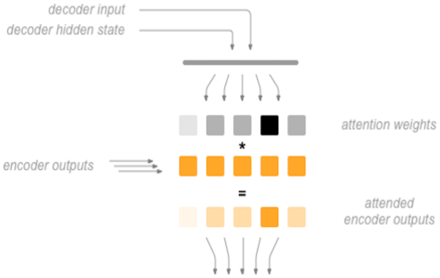

Figure: Courtesy of Sean Robertson

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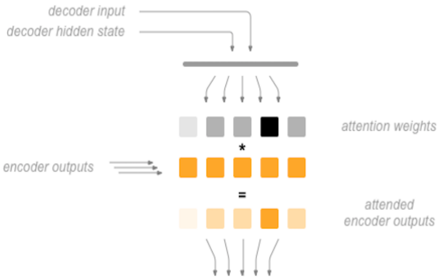

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- It will then merge the weighted encoder vectors with the current decoder output

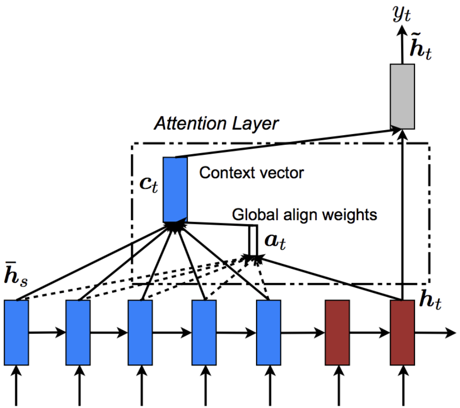

Figure: From arxiv 1508.04025