Deep Learning

QCon.ai San Francisco, April 15h

Machine Learning (Recap)

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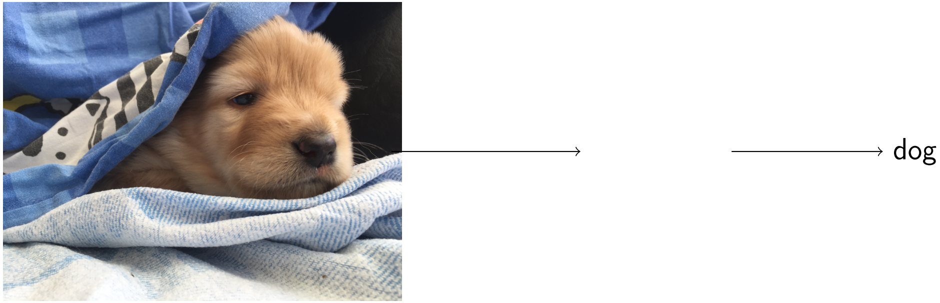

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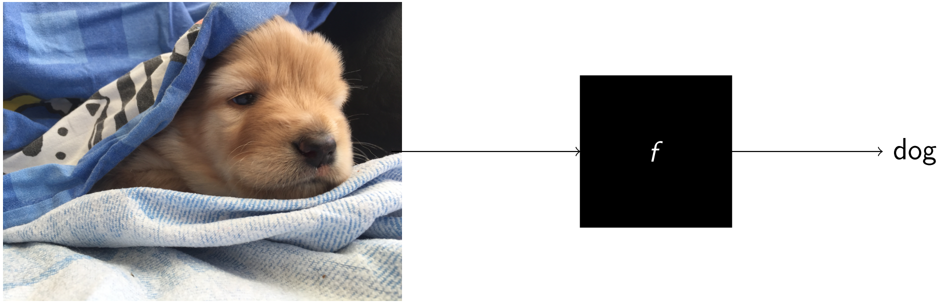

Machine Learning (Recap)

- What is machine learning?

$$\begin{tikzcd} \arrow[r] & \boxed{f} \arrow[r] & \text{dog} \end{tikzcd}$$

- 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

Validating Machine Learning (Recap)

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Training data
Used to calculate
model parameter

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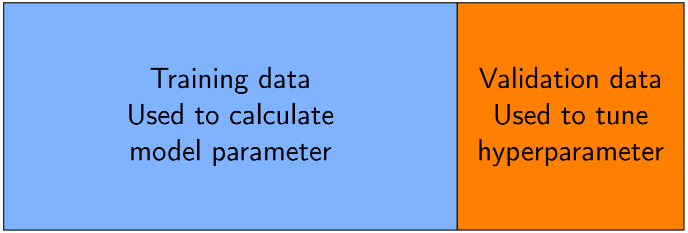

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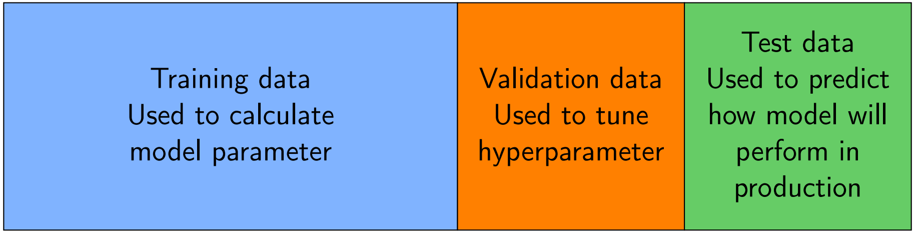
Training data
Used to calculate model parameter
Validation data
Used to tune hyperparameter
Test data
Used to predict how model will perform in production

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  - Short recap on machine learning
  - Build and train a perceptron in numpy
  - Change the code to use PyTorch
  - Gradient Descent

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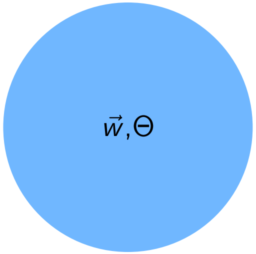
- 16:00 End of workshop

Perceptron

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



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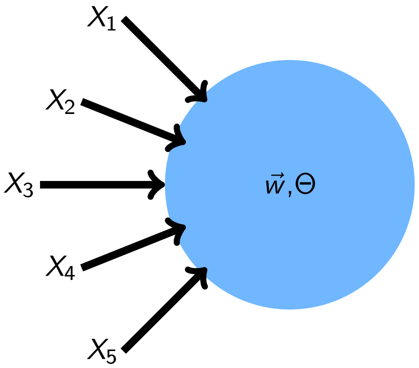

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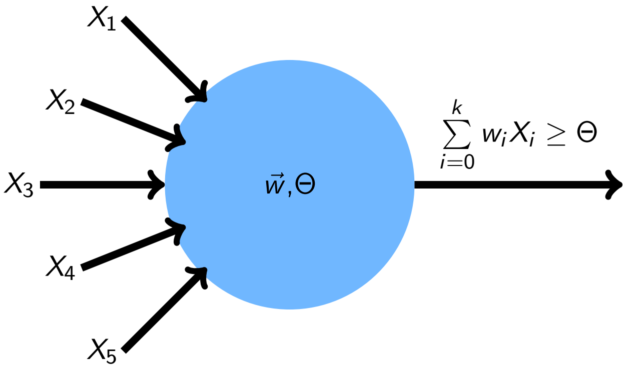
- Its output can be calculated as $\sum_{i=0}^{k} w_i X_i \geq \Theta$



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

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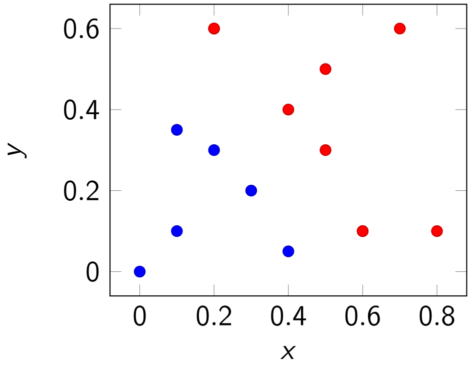
- Why didn't we wait for the final weights, but stop after one run over the dataset?

Linear Separability



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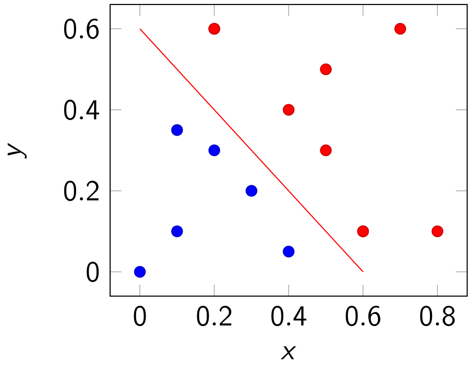

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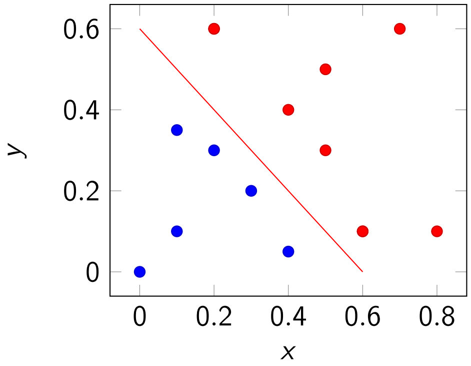

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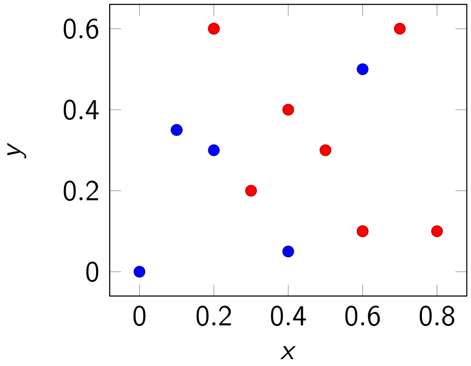

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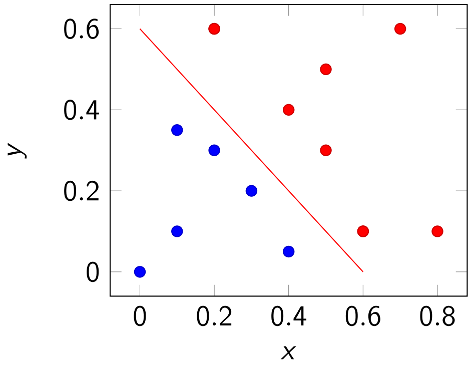

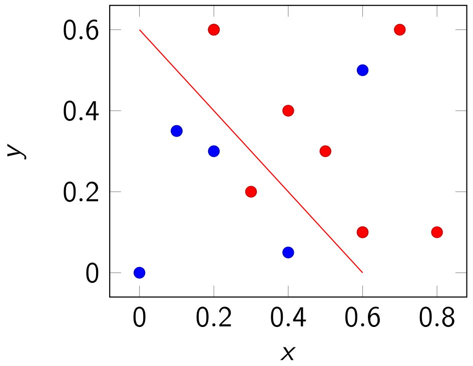

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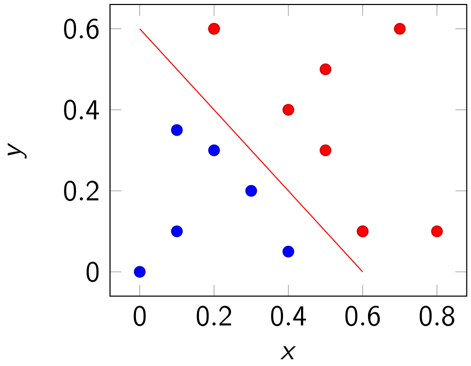

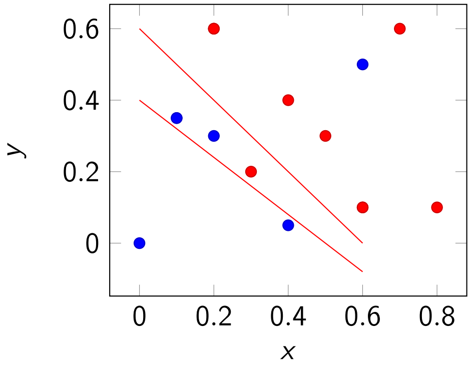

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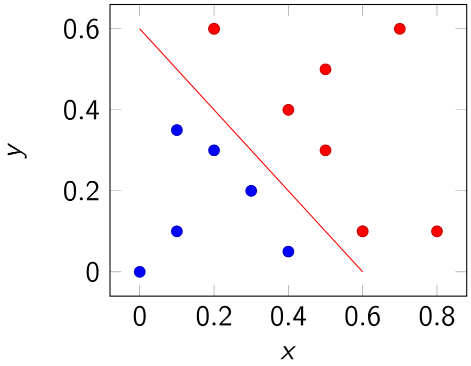

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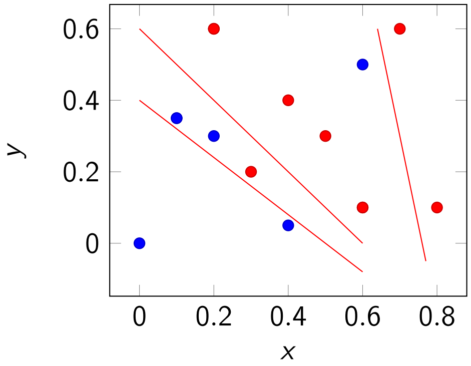

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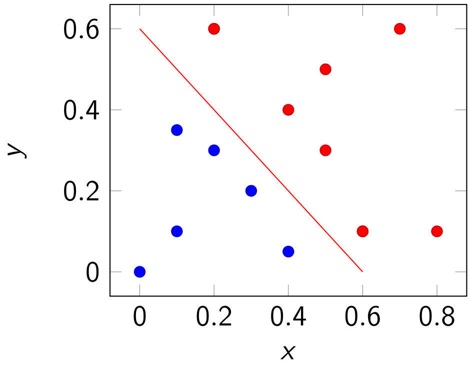

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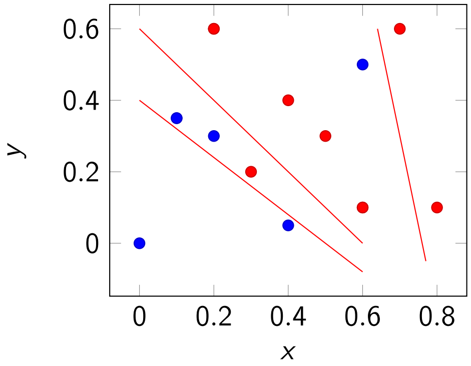

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The algorithm only converges, if the problem is linearly separable.

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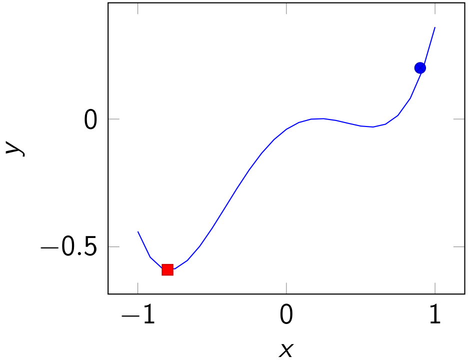
- This brings us back to regression with an error: $E(w) = \frac{1}{2} \sum_{(x,y)\in D} (y - a)^2$



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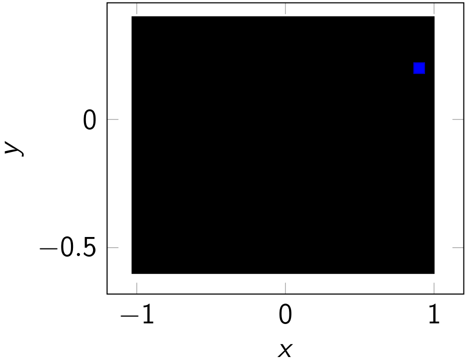

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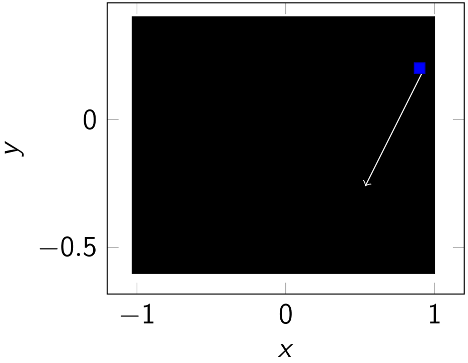

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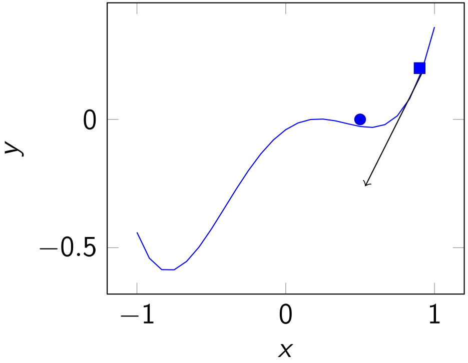
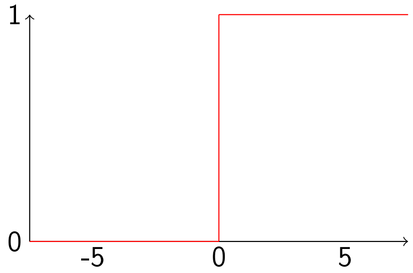
- Every deep learning framework can calculate those gradients using the chain rule and backpropagation.



Sigmoid $\rightarrow$ Differentiable Threshold



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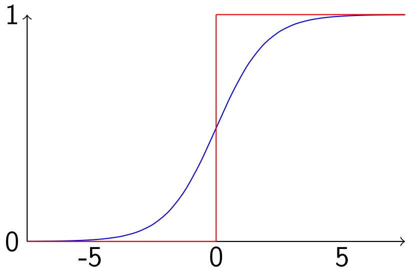

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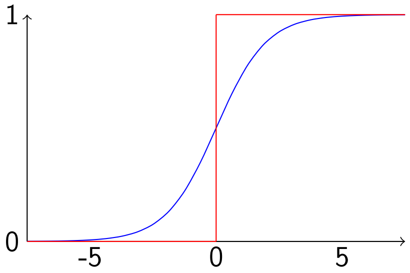

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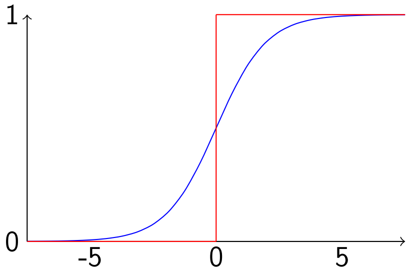

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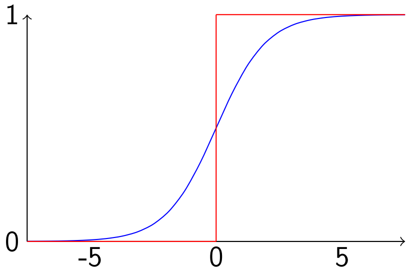
- Let us use this new knowledge to implement gradient descent in the next notebook.



Neural Network

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X_5
X_4
X_3
X_2
X_1
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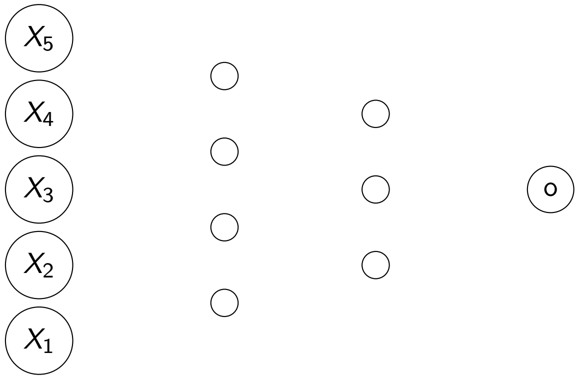

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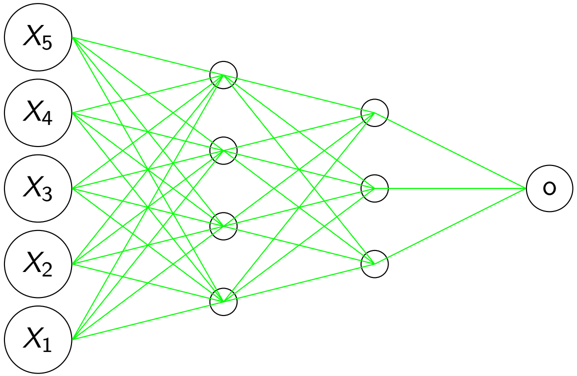

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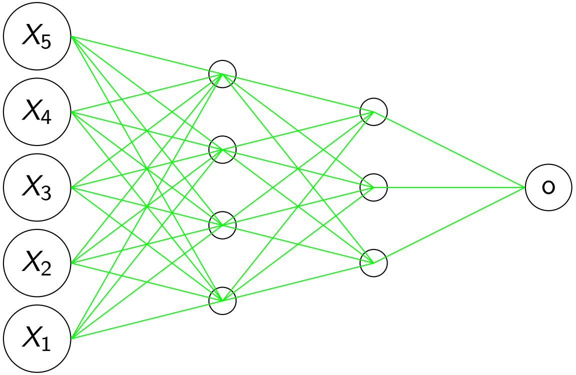
- Since every unit is differentiable, the whole network is differentiable $\rightarrow$ We can use backpropagation to minimize the error as we can calculate the gradients



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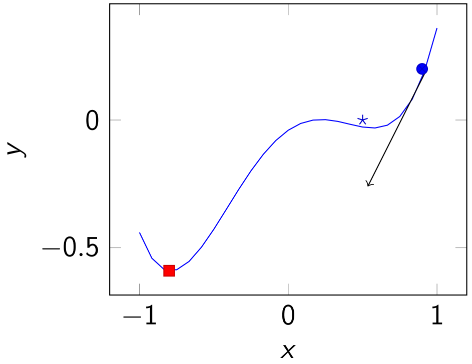

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- "Simple" Gradient Descent
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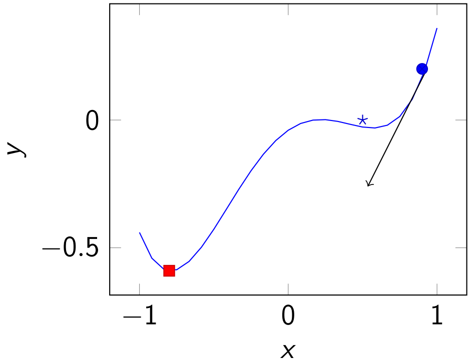

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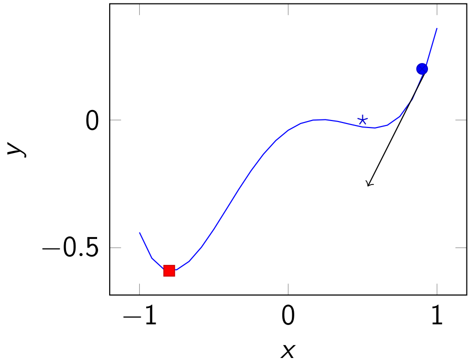
- "Simple" Gradient Descent
- Advanced Methods
    - Momentum
    - Higher Order Derivatives



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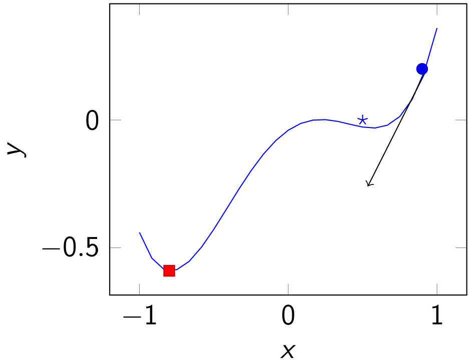

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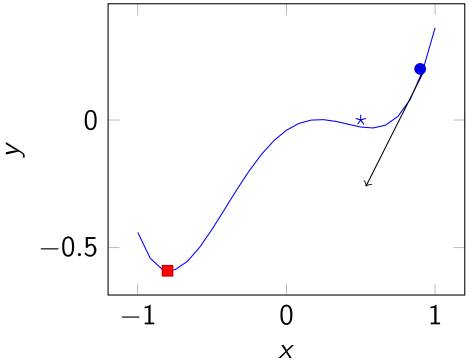
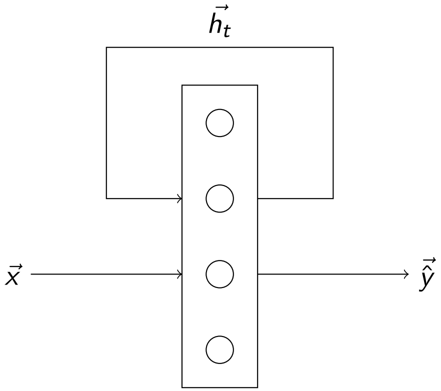
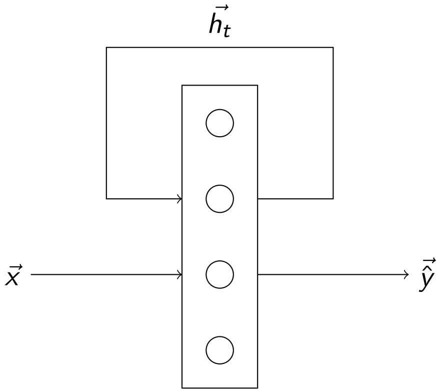


Recurrent Neural Networks



Recurrent Neural Networks

- Recurrent Neural Networks allow one to propagate states through time



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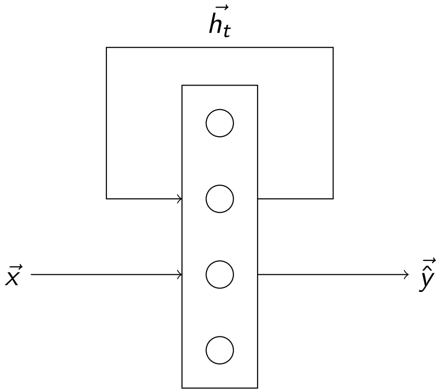

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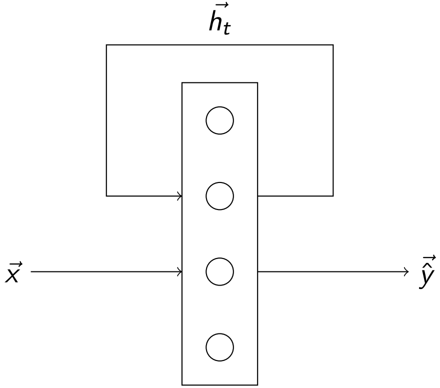

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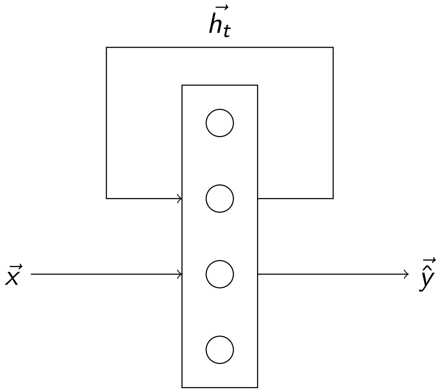
- These networks cannot represent long-term dependencies as U_h is always multiplied by itself.



LSTM

LSTM

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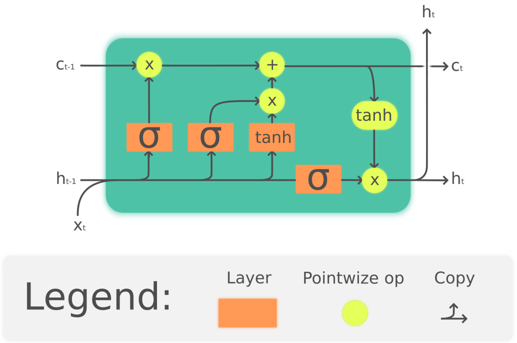

Figure: Courtesy of wikipedia

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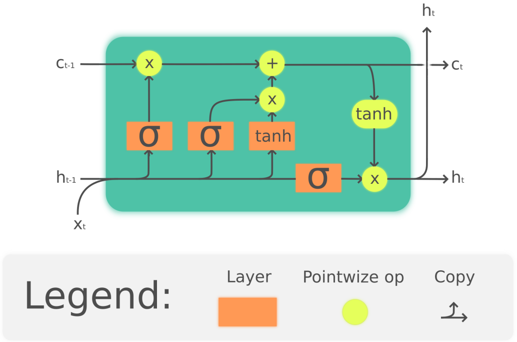

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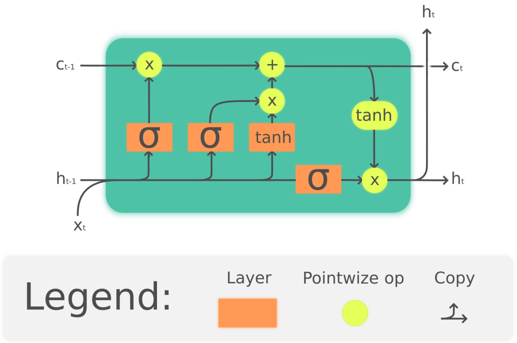

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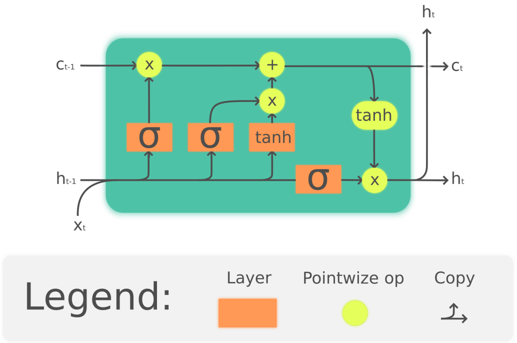

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Word2Vec

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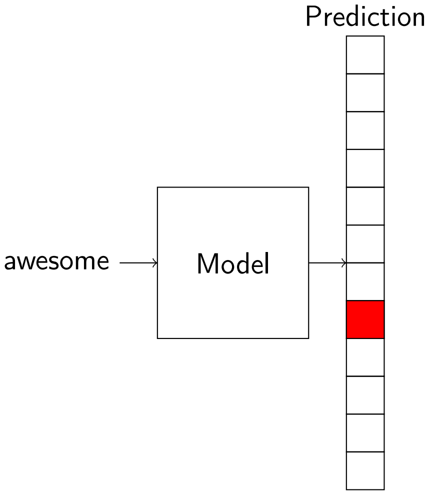

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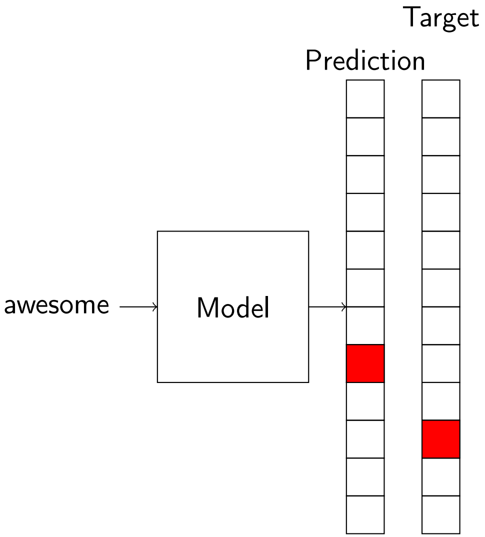

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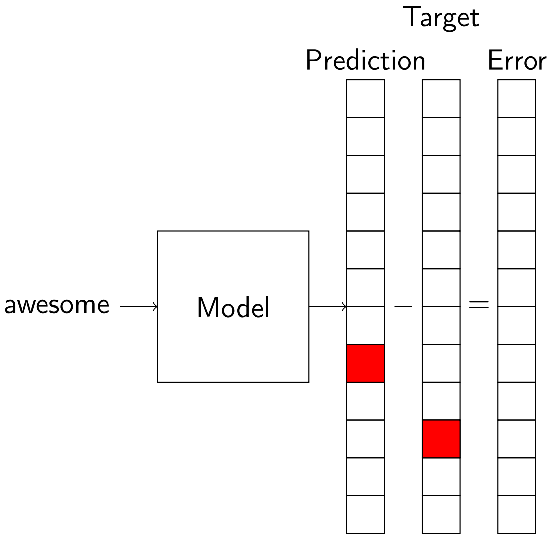

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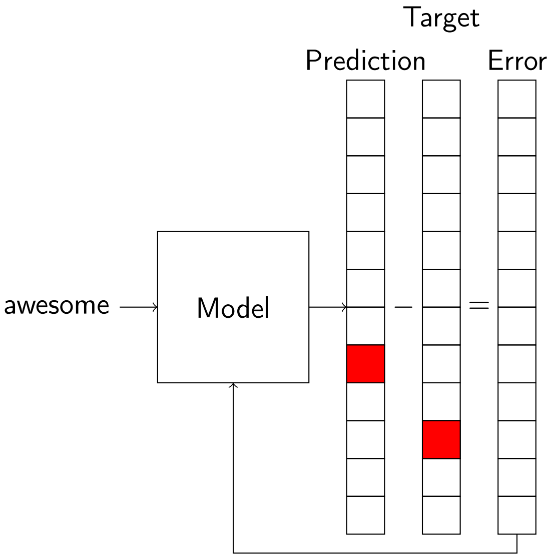

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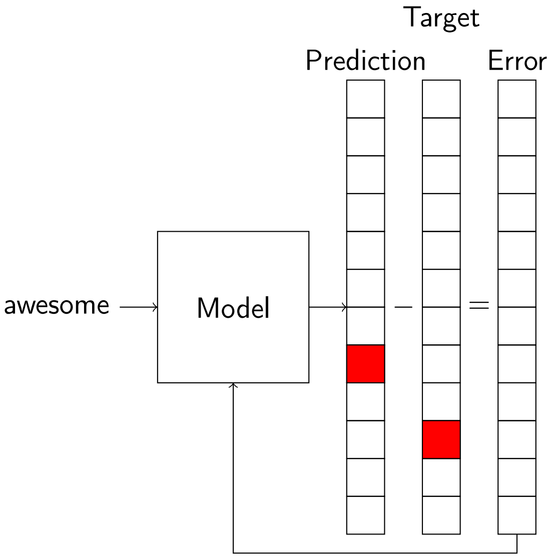
- As classical training would update all the weights for each target example (where vocabularies can be million of words), the weights will only be updated for the right targets and a random selection of false targets



Chatbot

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- Let's chat

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

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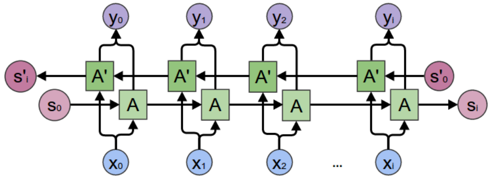

Figure: Image from `https://colah.github.io/posts/2015-09-NN-Types-FP/`

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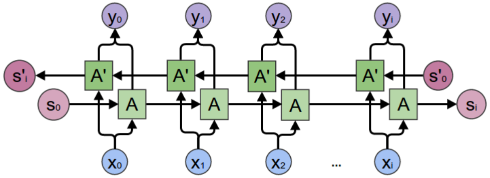

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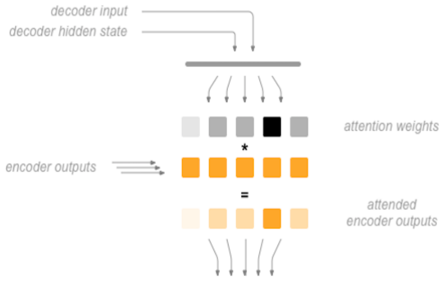

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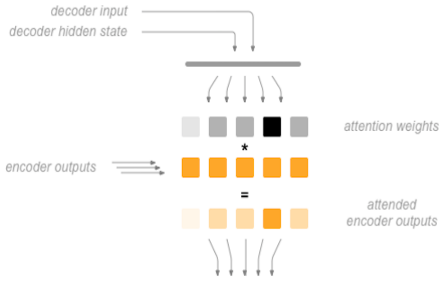

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- It will then merge the weighted encoder vectors with the current decoder output

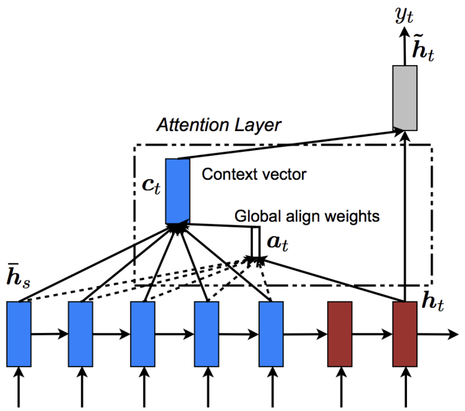

Figure: From arxiv 1508.04025