Deep Learning

QCon London, March 9th

Today's Overview

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  - Short recap on machine learning
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  - Gradient Descent
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- 16:00 End of workshop

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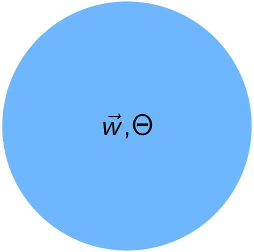
- It can often write better computational rules than we could
- It can check more cases than we could

Perceptron

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



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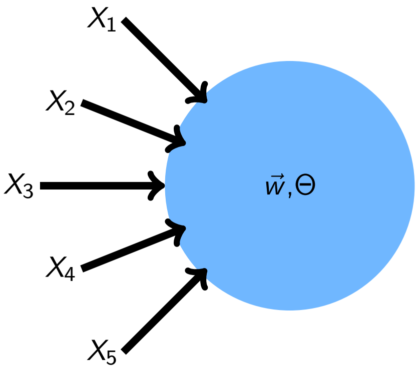

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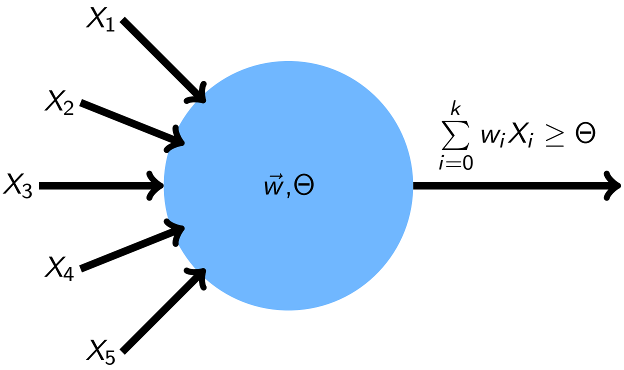
- Its output can be calculated as $\sum_{i=0}^{k} w_i X_i \geq \Theta$



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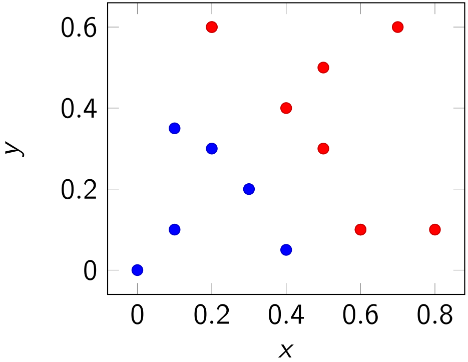
- Why didn't we wait for the final weights, but stop after one run over the dataset?

Linear Separability



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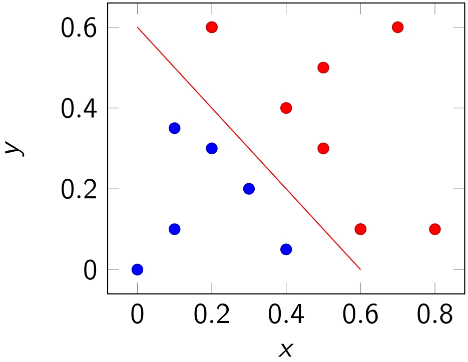

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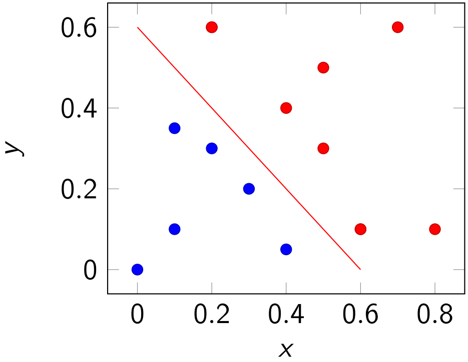

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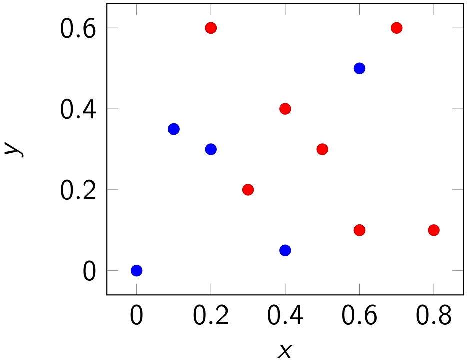

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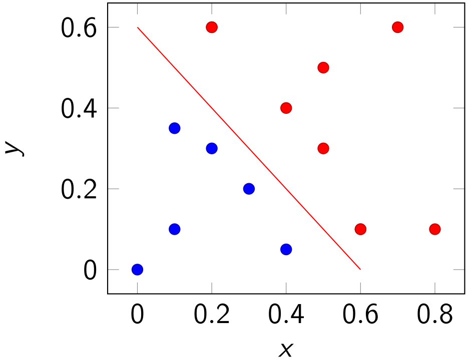

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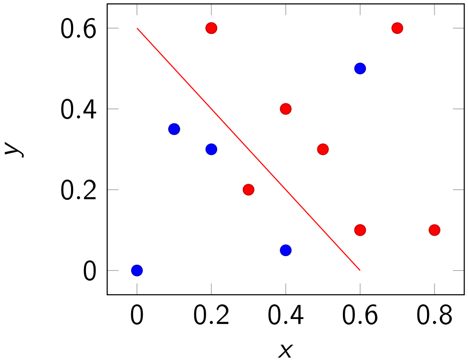

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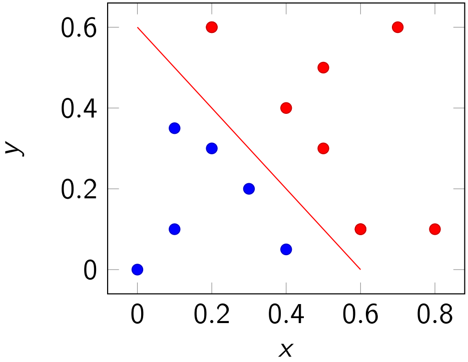

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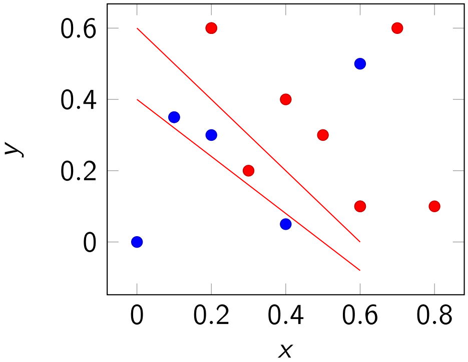

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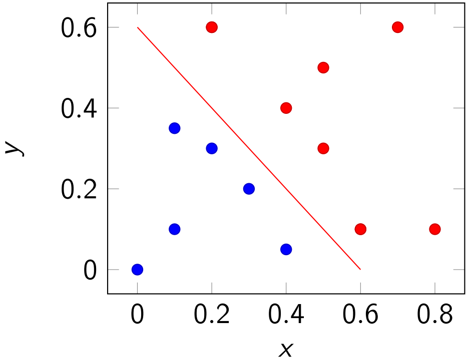

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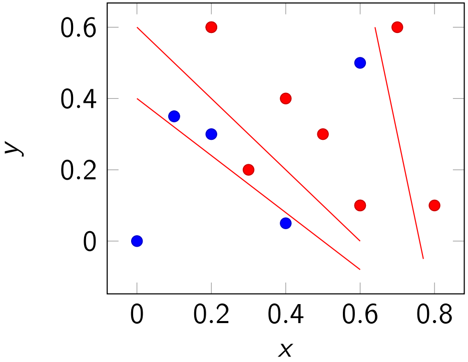

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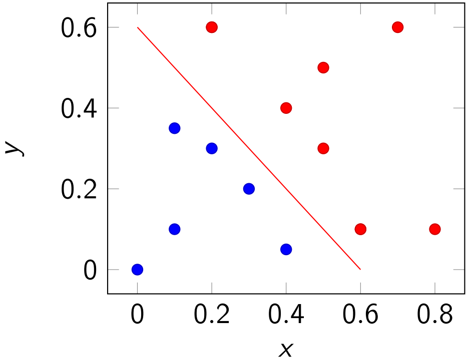

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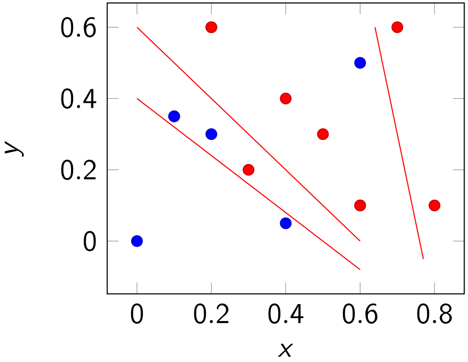

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The algorithm only converges, if the problem is linearly separable.

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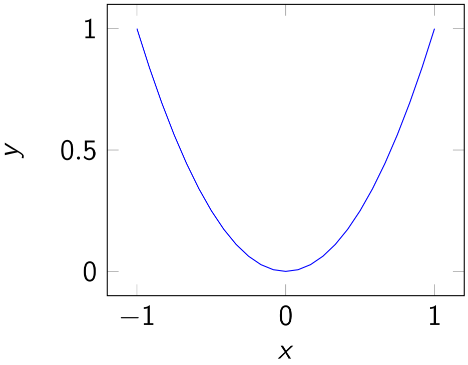
- This brings us back to regression with an error: $E(w) = \frac{1}{2} \sum_{(x,y) \in D} (y - a)^2$



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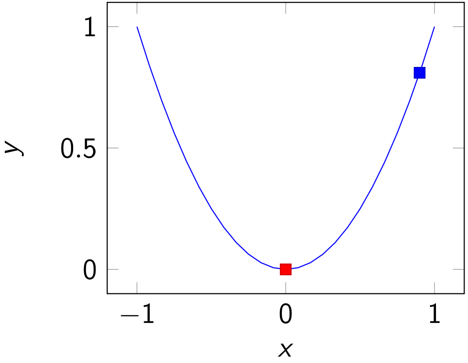

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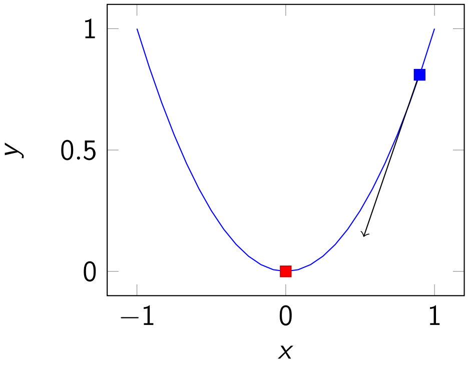

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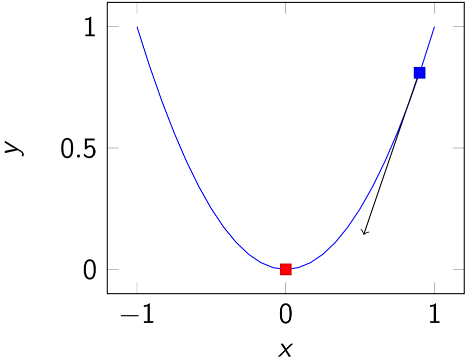
- Every deep learning framework can calculate those weights using the chain rule and backpropagation.



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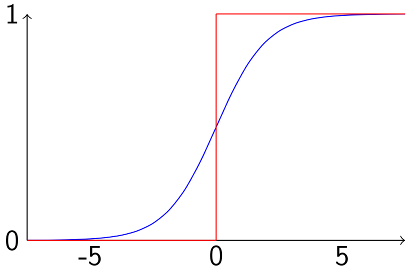

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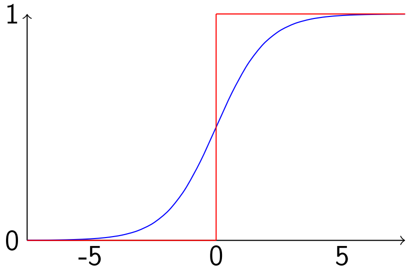
- The sigmoid allows us to convert the strict classification into a regression over the probability for each point to belong to a certain class



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- Cross-Entropy $E = -\frac{1}{n} \sum_{i=1}^{n} \sum_{k=1}^{m} y_{i,k} \ln p_{i,k}$

  $y_{i,k}$ 1, if $i = k$ else 0
  $p_{i,k}$ probability for point i belonging to class k

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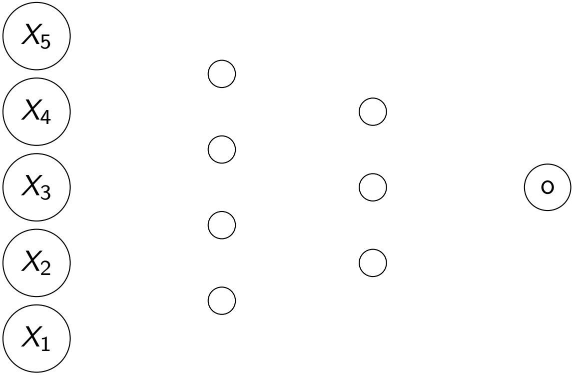

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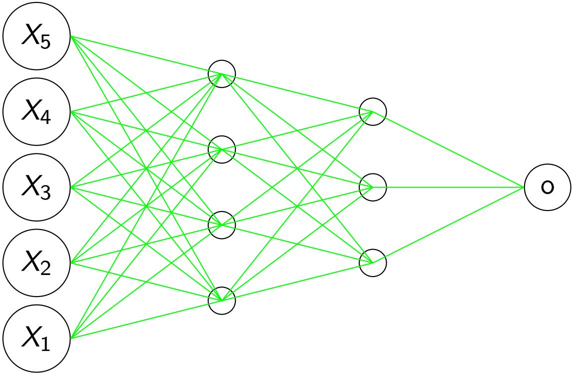

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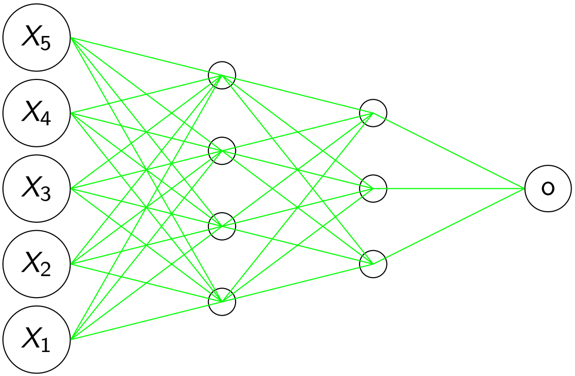
- Since every unit is differentiable, the whole network is differentiable $\rightarrow$ We can use backpropagation to minimise the error as we can calculate the gradients



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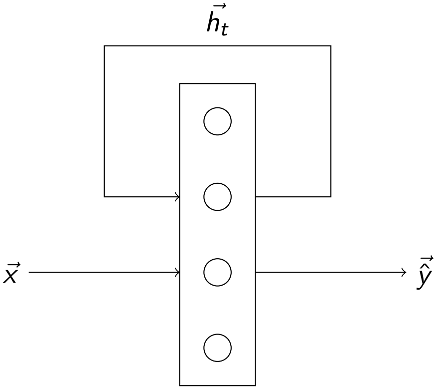
- What do we do if we want to store information about previous examples in the network

Recurrent Neural Networks



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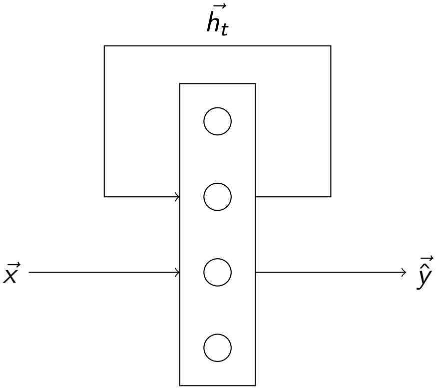

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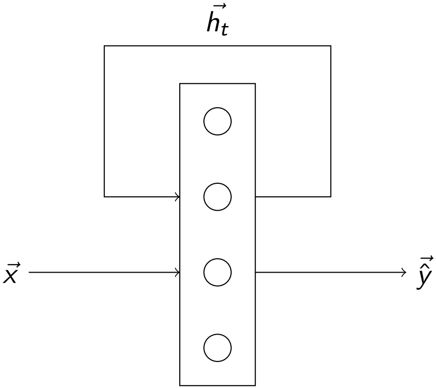

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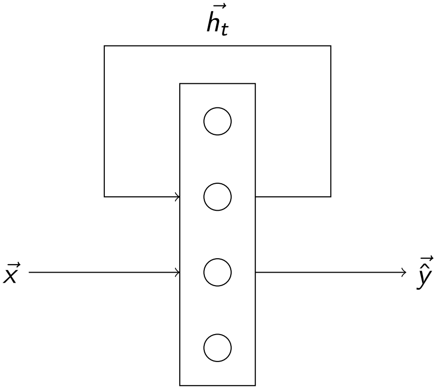
- From this hidden state the current output is calculated as $y_t = \sigma_y(W_y h_t + b_y)$
- These networks cannot represent long-term dependencies as U_h is always multiplied by itself.



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- The output gate decides how much of the cell state is output to the hidden state.

Word2Vec

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- How can we turn text into numbers?

Chatbot

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- Let's chat