Deep Learning

QCon London, March 9th

Today's Overview

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  - Short recap on machine learning
  - Build and train a perceptron in numpy
  - Gradient Descent
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- 16:00 End of workshop

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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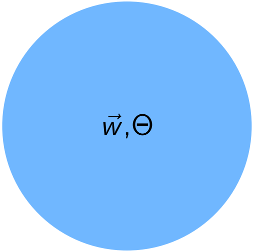
- It can check more cases than we could

Perceptron

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



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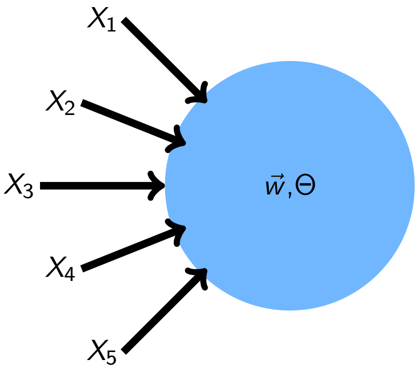

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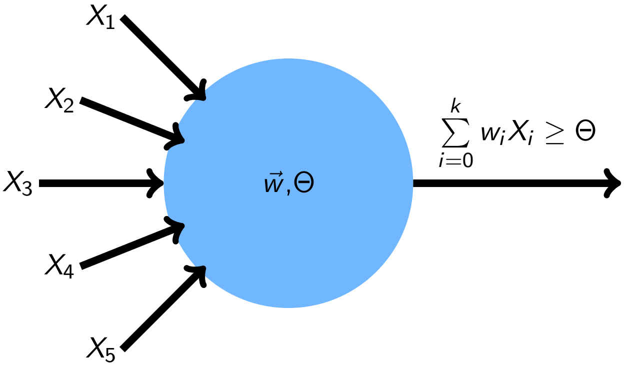
- Its output can be calculated as $\sum_{i=0}^{k} w_i X_i \geq \Theta$



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

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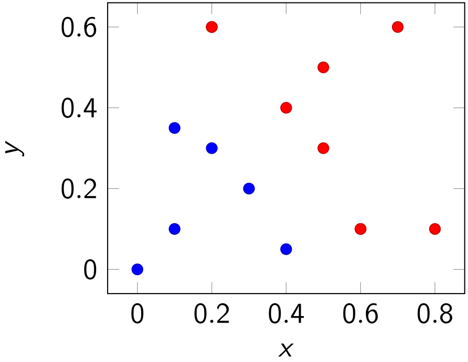
- Why didn't we wait for the final weights, but stop after one run over the dataset?

Linear Separability



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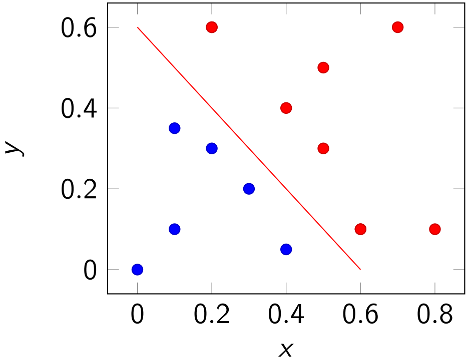

Data are linearly separable -> Can be divided by a plane

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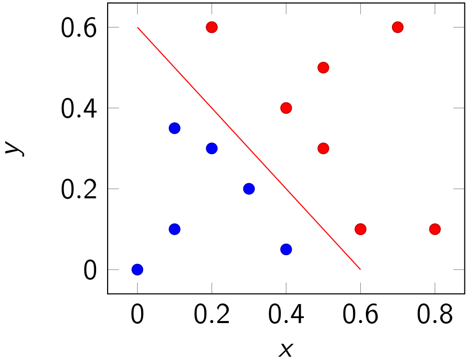

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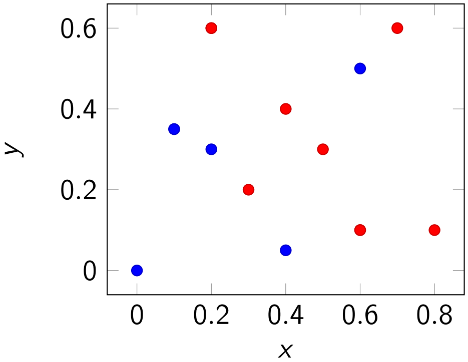

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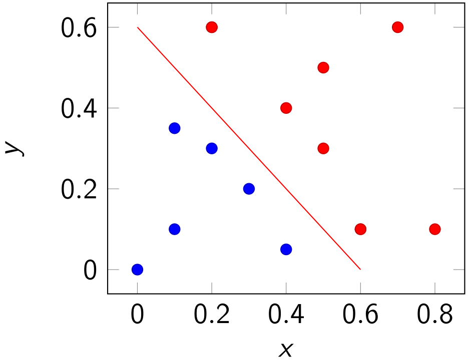

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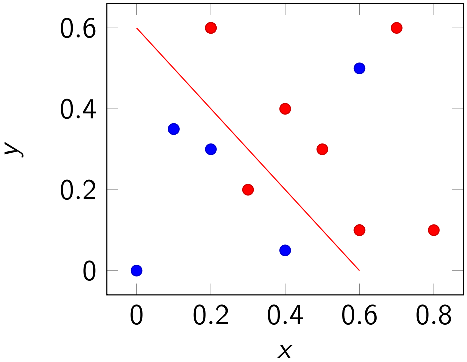

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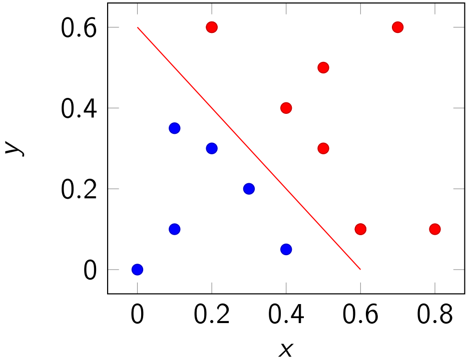

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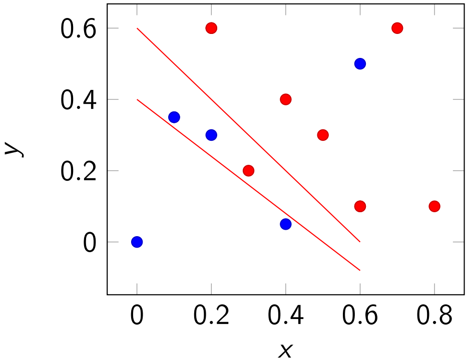

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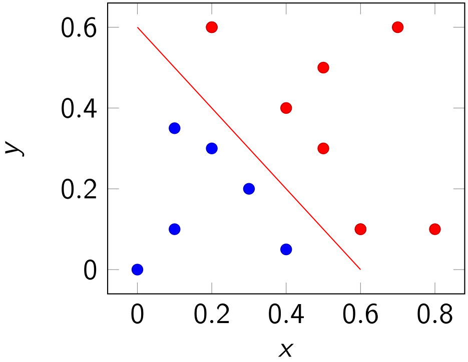

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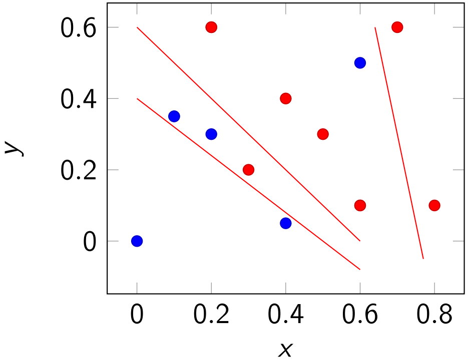

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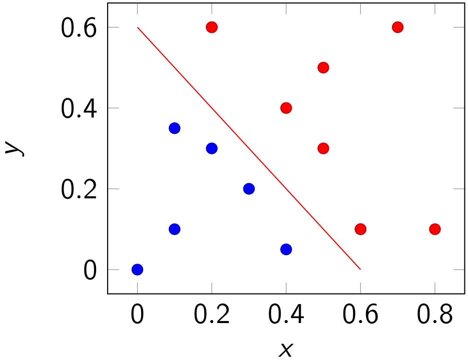

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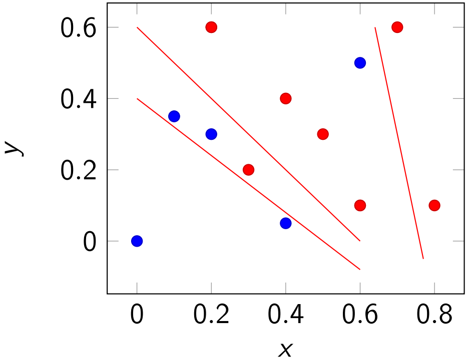

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The algorithm only converges, if the problem is linearly separable.

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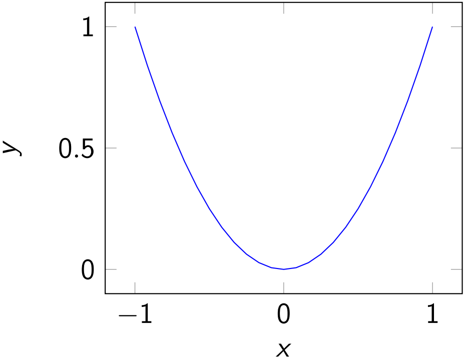
- This brings us back to regression with an error: $E(w) = \frac{1}{2} \sum_{(x,y) \in D} (y - a)^2$



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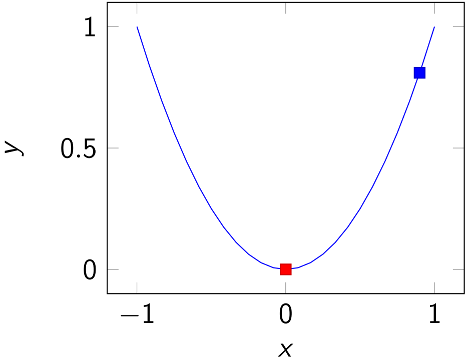

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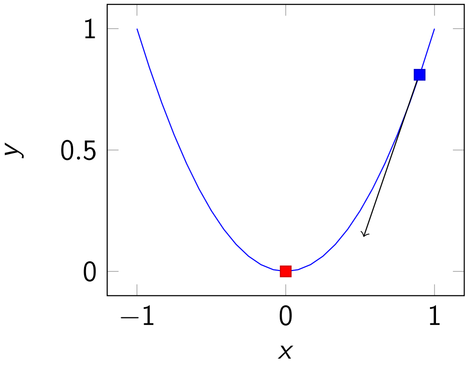

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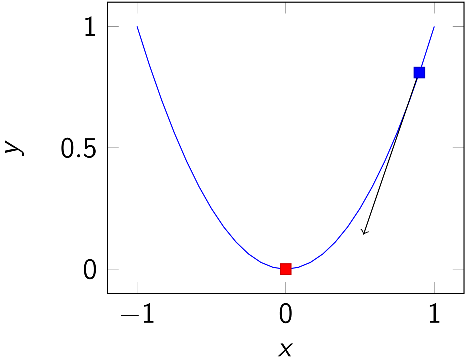
- Every deep learning framework can calculate those weights using the chain rule and backpropagation.



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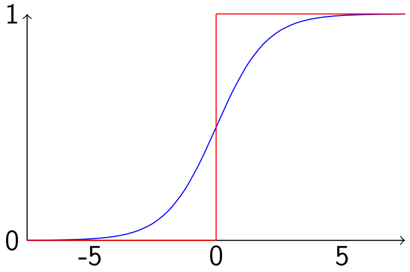

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- Even though the perceptron is great for boolean functions it is not differentiable and has no continuous error function, consequently the gradient cannot be calculated
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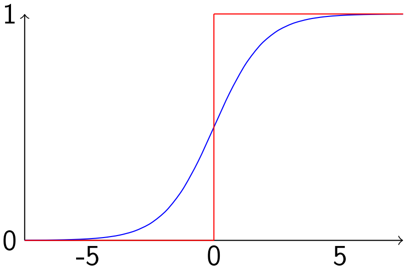
- The sigmoid allows us to convert the strict classification into a regression over the probability for each point to belong to a certain class



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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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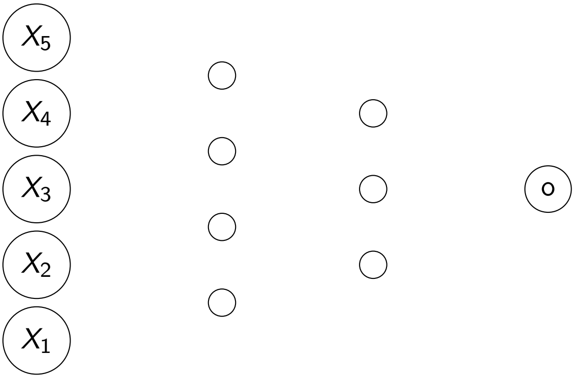

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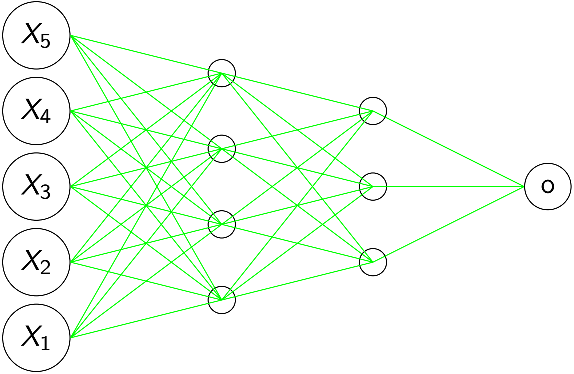

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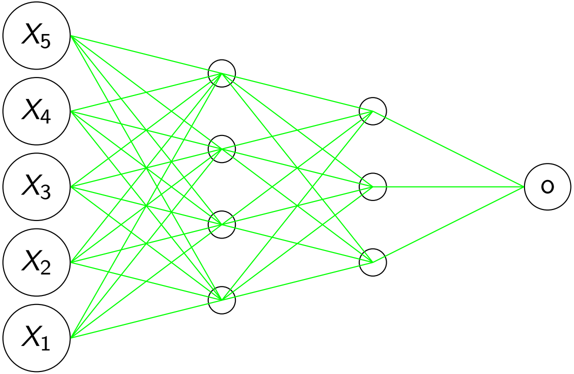
- Since every unit is differentiable, the whole network is differentiable $\rightarrow$ We can use backpropagation to minimize the error as we can calculate the gradients



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How do we make sure that we do not learn the arbitrary noise in the dataset?

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- All of these can be perfectly tested using a validation set

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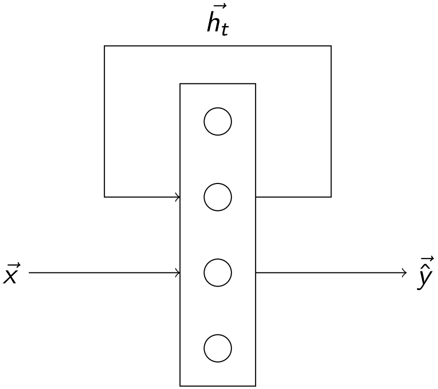

Recurrent Neural Networks

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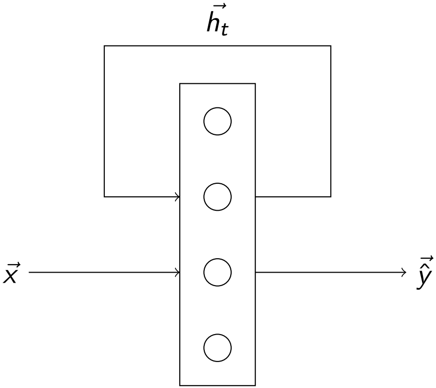

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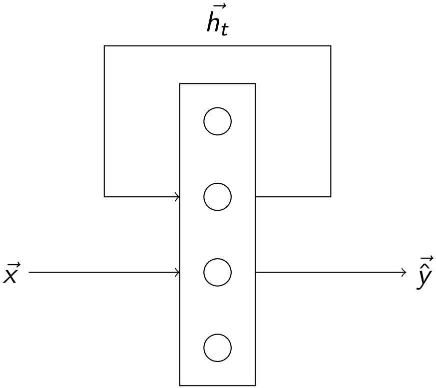

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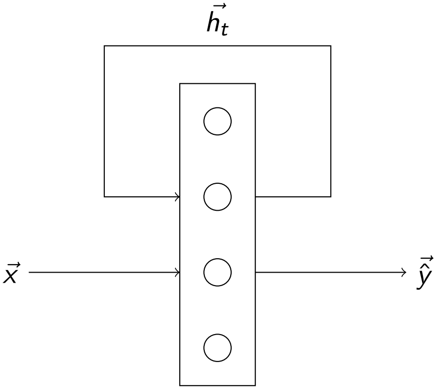
- From this hidden state the current output is calculated as $y_t = \sigma_y(W_y h_t + b_y)$
- These networks cannot represent long-term dependencies as U_h is always multiplied by itself.



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Word2Vec

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- How can we turn text into numbers?

Chatbot

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- Let's chat