Deep Learning

QCon London, March 7th

Today's Overview

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- 15:00 TCN vs. RNN

Why Deep Learning?

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

Perceptron

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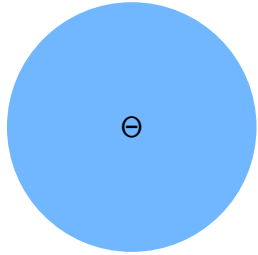

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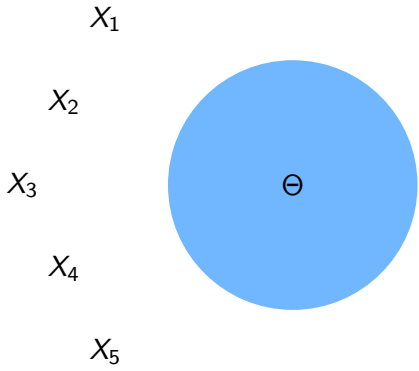

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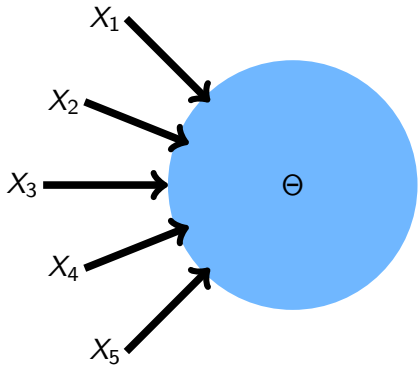

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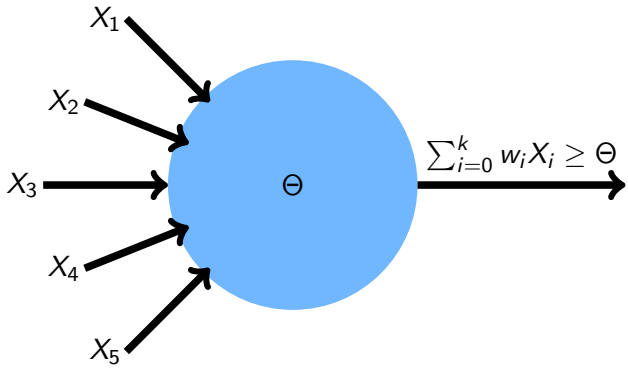

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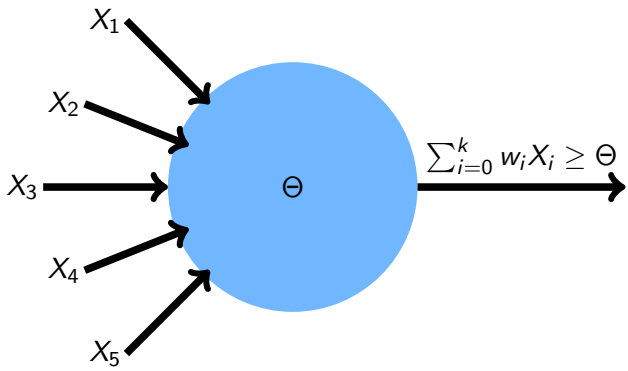

A perceptron can represent every arbitary! boolean function!

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

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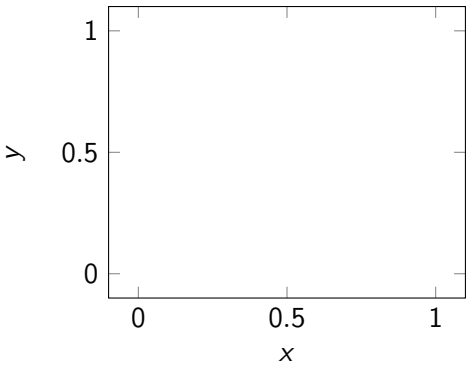
- Why didn't we wait for the final weights?

Linear Separability



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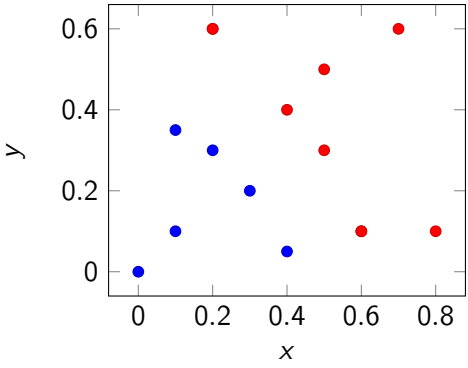

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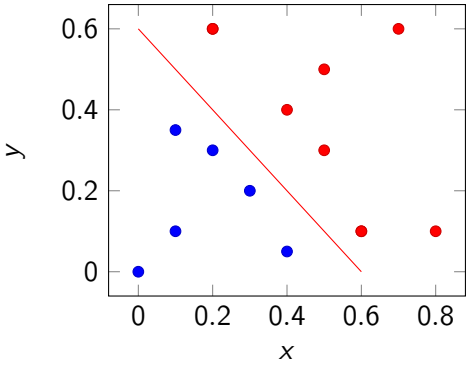

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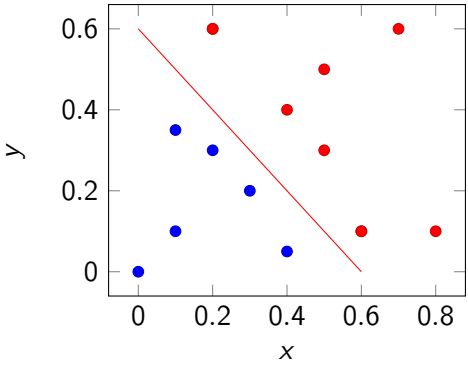

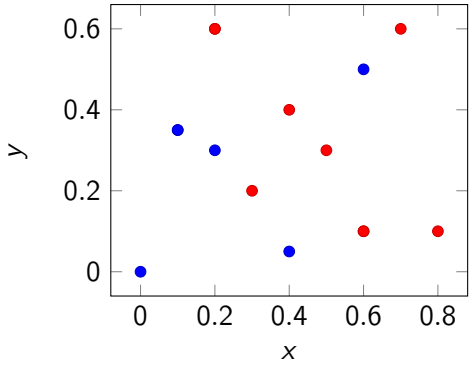

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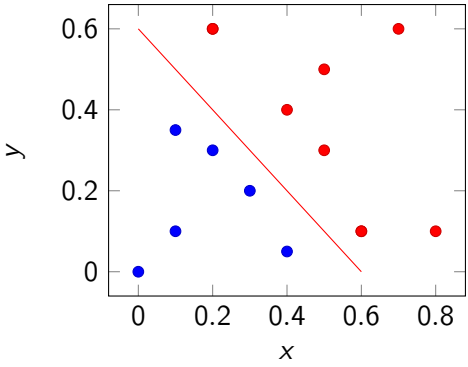

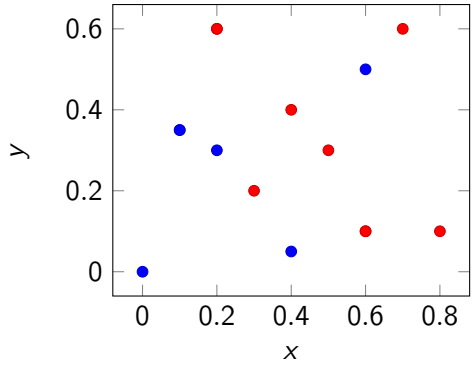

The algorithm only converges, if the problem is linearly separable.

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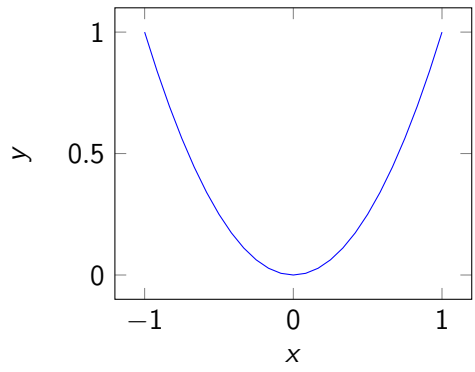

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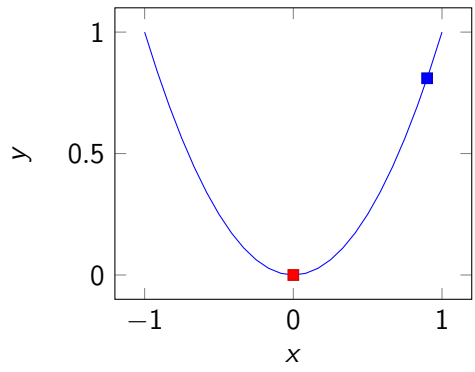

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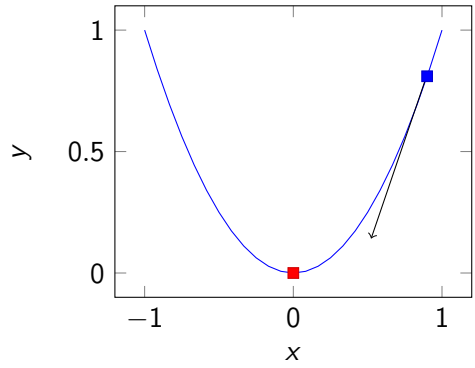

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- This brings us back to regression with an error: $E(w) = \frac{1}{2} \sum_{(x,y) \in D} (y - a)^2$
- If we want to decrease $E(w)$ by changing w we need to calculate the gradient of w
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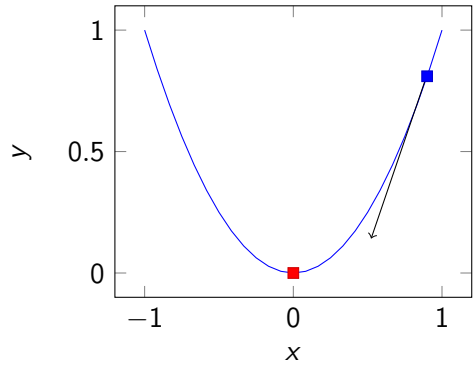

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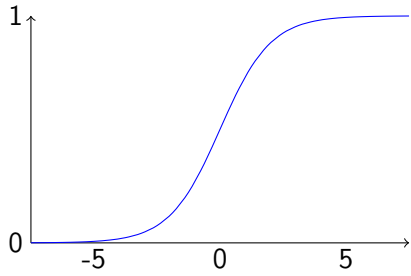

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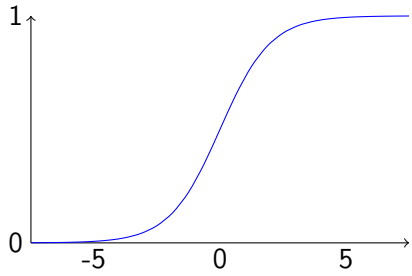
- The sigmoid allows us to convert the strict classification into a regression over the probability to classify the points



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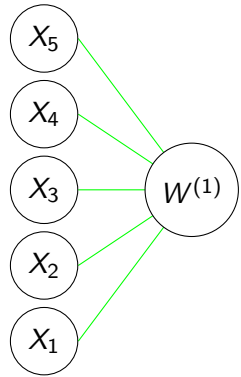

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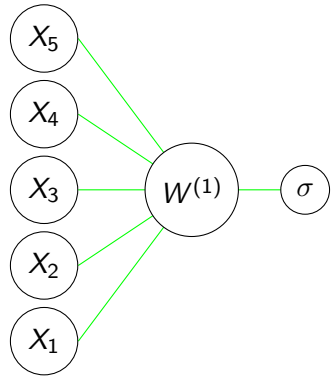

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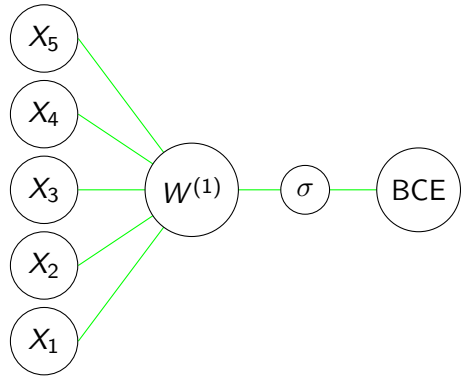

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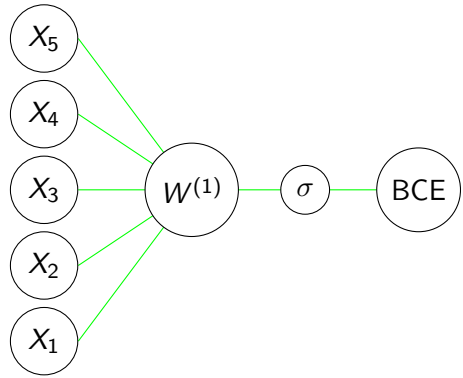

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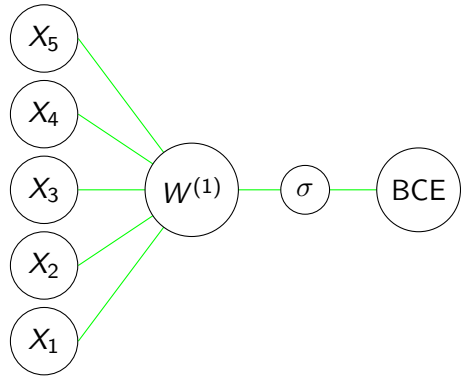
- This allows a framework to compute gradients for every node, given that the gradient for each step is known.



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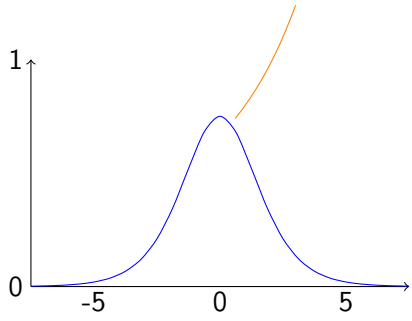

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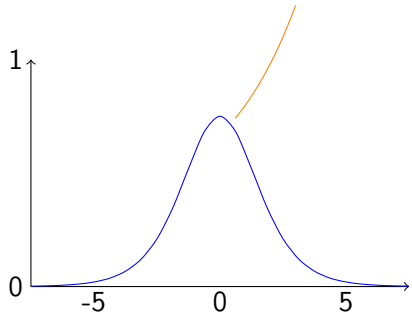

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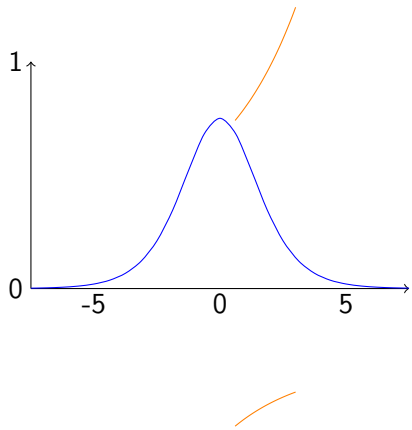

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- Cross- Entropy $E = -\frac{1}{n} \sum_{i=1}^{n} \sum_{k=1}^{m} y_{i,k} \ln p_{i,k}$

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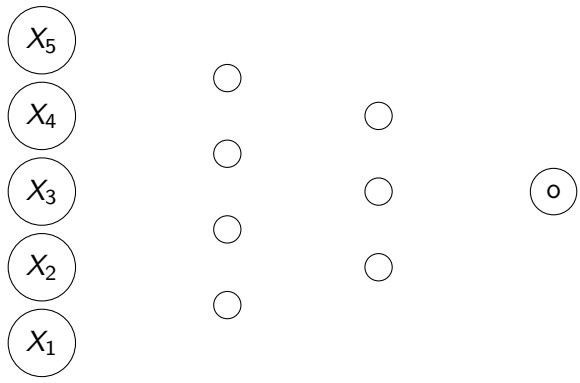

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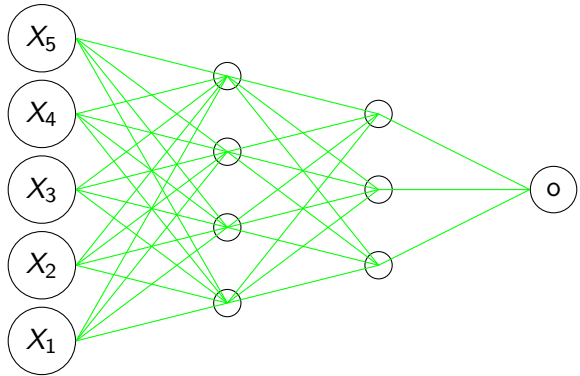

Neural Network

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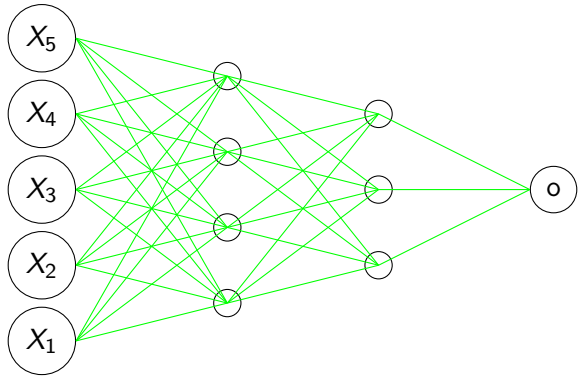
- However, instead of going from start to end directly we now add hidden units
- For each of the units we now apply the sigmoid function
- Since every unit is differentiable, the whole network is differentiable $\rightarrow$ We can use backpropagation to minimise the error as we can calculate the gradients



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- What can we represent with a network?
  - Boolean Functions: Yes, because we have a network of threshold-like units

Restriction Bias

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- Sigmoids $\rightarrow$ non-linear function
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- What can we represent with a network?
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  - Arbitrary Functions: Yes, with two (infinitly wide) hidden layers

Available Deep Learning Frameworks

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- TensorFlow

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Advantages, Disadvantages

Framework	Advantages	Disadva

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Tensorflow Tutorials

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- Let us have a look at some TensorFlow examples

Tensorflow Tutorials

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- Use the terminal to navigate to TensorFlow-Examples/notebooks and run 'jupyter notebook'

Small Test: Traffic Sign Classifier

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- Let's see what you learned.

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- Try solving the given problem with a network of your choice

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- Just assigning an image to class is not sufficent in lots of situations
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  - Akka Hamburg?
- We clearly need another approach, if we want to have a car driving

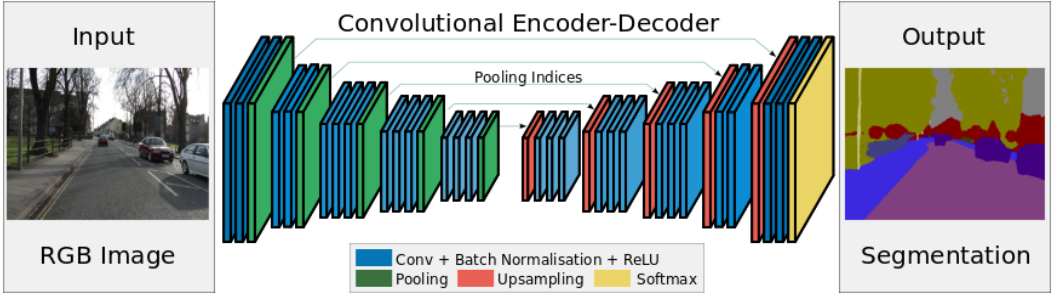
Bounding Boxes

Bounding Boxes

Semantic Segmentation

Semantic Segmentation

Network Structure



Implementation

- Let's investigate how to programm a SegNet

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- We probably cannot run it as it takes 6+ GB of VRAM