Deep Learning

Akka Ecole Technology

Overview

Three Day Overview

- First Day

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- First Day
  - Learn and Understand the Basics of Deep Learning

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  - Introduction to TensorFlow

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- Third Day - Hackathon

Today's Goals

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- Knowledge about available Deep Learning Frameworks

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- 10:00 Motivation and Theoretical Introduction to Deep Learning

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- 17:00 Checking who survived :P

Introduction

Why Deep Learning?

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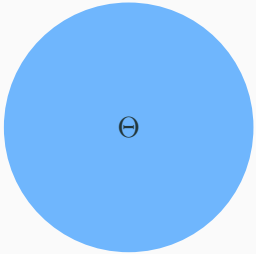
- It can often write better computational rules than we could
- It can check more cases than we could

Perceptron

Perceptron



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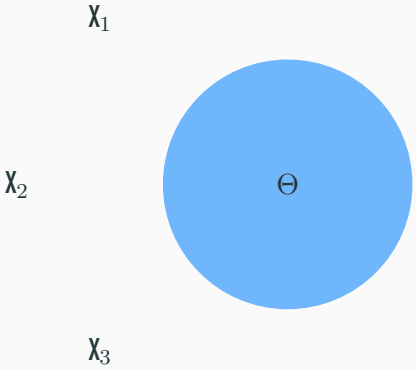

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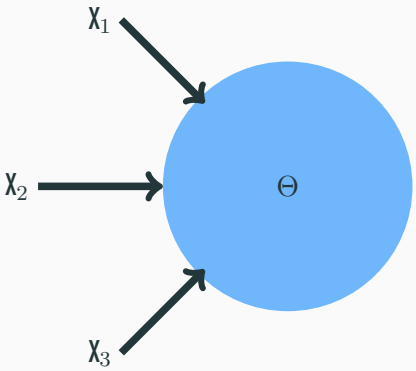

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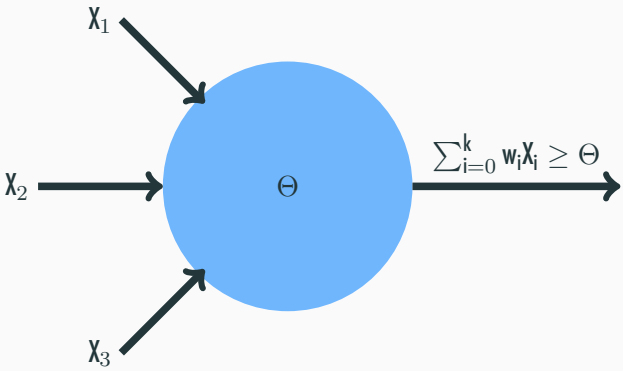

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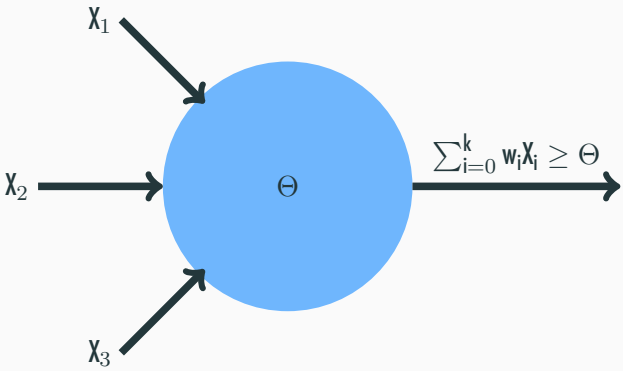

A perceptron can represent every arbitary! boolean function!

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- However, we can not be certain that the problem is linearly separable

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- From that we can then update the weights using: $w_i = w_i + \eta (y - a) X_i$

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- Perceptron Rule: $w_i = w_i + \eta(y - \hat{y})x_i$
  - Guaranteed to converge, if problem is seperable
  - Finite number of steps
- Gradient Descent: $w_i = w_i + \eta(y - a)x_i$
  - Robust due to the continuously differentiable functions
  - Only converges in the limit and only to local optima

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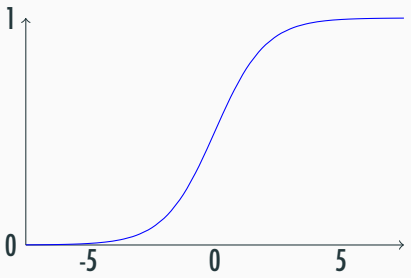

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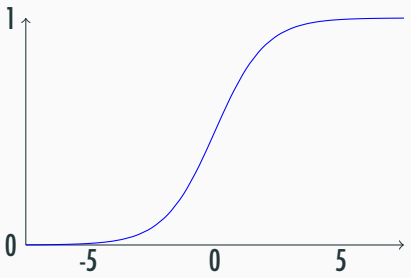

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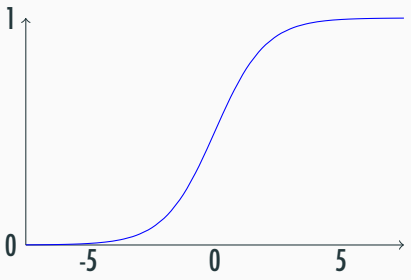

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- Softmax: $p = \frac{e^{o_i}}{\sum_i e^{o_i}}$
- With this we can as well define the general loss
- Cross- Entropy $E = -\frac{1}{n} \sum_{i=1}^{n} \sum_{k=1}^{m} y_{i,k} \ln p_{i,k}$

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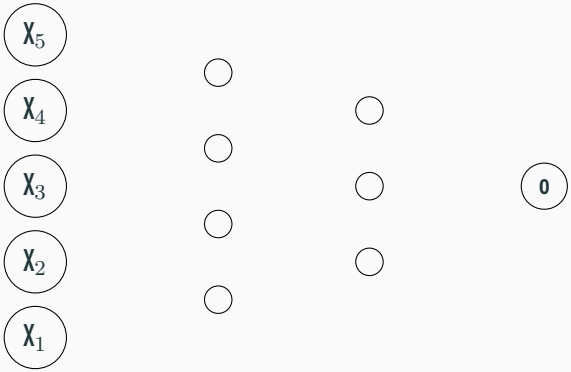

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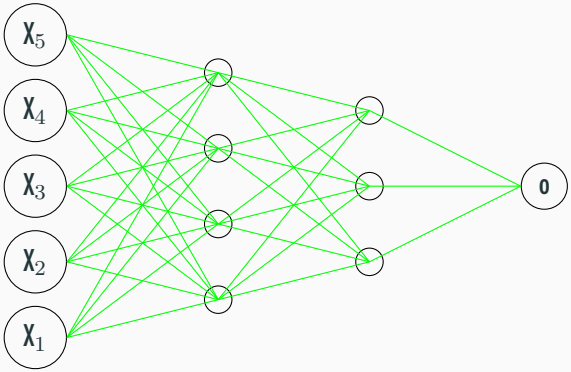

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- However, instead of going from start to end directly we now add hidden units
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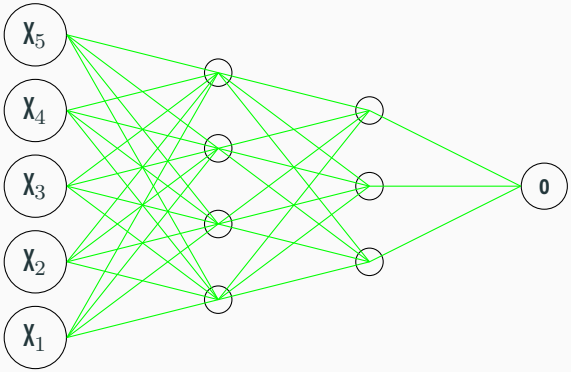
- Since every unit is differentiable, the whole network is differentiable $\rightarrow$ We can use backpropagation to minimise the error as we can calculate the gradients



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- One can see, that we can start calculating the gradient at the end and continue to the input

Optimising Weights

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- Gradient Descent

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- Advanced Methods

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    - Momentum

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  - Arbitrary Functions: Yes, with two (infinitly wide) hidden layers

Frameworks

Available Deep Learning Frameworks

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- Caffe

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PyTorch	Perfect integration into Python Objects Graph can be dynamically changed without rebuilding it Will probably be integrated into TensorRT	

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Tensorflow Tutorials

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- Let us have a look at some TensorFlow examples

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- Let us have a look at some TensorFlow examples
- 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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- Use the terminal to navigate to TrafficSignClassifier and run 'jupyter notebook'
- Try solving the given problem with a network of your choice

SegNet

Motivation

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Motivation

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  - Image from Car?
  - Street?
  - Traffic Lights?
  - Akka Hamburg?
- We clearly need another approach, if we want to have a car driving

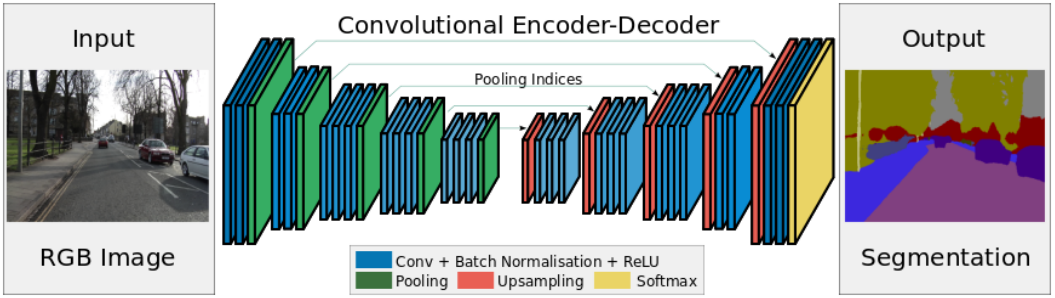
Bounding Boxes

Bounding Boxes

Semantic Segmentation

Semantic Segmentation

Network Structure



Implementation

- Let's investigate how to programm a SegNet

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- Use the terminal to navigate to SegNet and run 'jupyter notebook'

Implementation

- Let's investigate how to programm a SegNet
- Use the terminal to navigate to SegNet and run 'jupyter notebook'
- We probably cannot run it as it takes 6+ GB of VRAM