

Coen's AI Notes and Links

diverse

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Table of contents

1	Introduction	1
2	AI Overview	3
2.1	AI, Machine Learning, Deep Learning, Generative AI	3
I	GenAI	5
3	GenAI	7
3.1	What is GenAI?	7
3.2	GPT - Generative Pre-Trained Transformer	7
3.3	Prompting	7
3.4	Hallucinating	7
3.5	RAG - Retrieval Augmented Generation	8
3.6	Active Inference	8
3.7	Running LLM's locally	8
3.8	Coding with GenAI	8
3.9	MCP - Model Context Protocol	8
3.10	GenAI	8
3.11	Some more sites, nice to play around with	8
4	AI versus education	9
4.1	Media & Opinions	9
4.2	Tools, Best Practices & lesson material	9
5	Jobs and AI	11
6	Resources and References GenAI	13
6.1	Blogs and articles	13
6.2	Online Platforms	13
6.3	(Short) Courses	14
6.4	Code Repositories	14
6.5	Community Resources	14
6.6	Academic Papers: Modern Breakthroughs	14

7 No-Code / Low Code	15
II AI Act Europe	17
8 AI Act Resources and References	19
III Train, Fine Tune, RAG	21
9 Train, Fine Tune, RAG	23
10 RAG: Retrieval Augmented Generation	25
11 Finetune	27
12 Training	29
IV Data	31
13 Finding and Preparing Data	33
13.1 The Importance of Data	33
13.2 Popular Data Sources	33
V Related subjects	35
14 Agents	37
14.1 Agent Development Kit	37
14.2 Open Agent Platform	37
15 MCP - Model Context Protocol	39
16 Journalism and AI	41
VI Neuron & Network	43
17 Understanding the Perceptron	45
17.1 The Biological Inspiration: From Brain Neurons to Artificial In- telligence	45
17.2 From Biology to Machine: Implementing a Perceptron	46
17.3 Network	48
17.4 First Implementation of Perceptron algorithm	48
17.5 Reference	48

18 The Learning Perceptron	51
18.1 The Learning Algorithm	51
18.1.1 Mathematical Foundation	51
18.1.2 Training Process	52
18.2 Visualizing the Learning Process	52
18.3 Practical Considerations	52
19 Understanding Perceptron Limitations	53
19.1 The XOR Problem: A Classic Challenge	53
19.1.1 What is XOR?	53
19.1.2 Why Can't a Single Perceptron Solve XOR?	54
19.2 The Solution: Multiple Layers	55
19.3 Key Takeaways	57
20 Introduction to Neural Networks	59
20.1 Beyond Single Perceptrons: Building Neural Networks	59
20.2 Understanding Network Architecture	60
20.2.1 Key Components	60
20.3 How Information Flows	60
20.4 Creating a Simple Network	61
21 Practical Example: Classifying Iris Flowers	63
21.1 A Real-World Machine Learning Challenge	63
21.2 The Dataset	64
21.3 Key Learning Points	64
22 The Mathematics Behind Neural Networks	65
22.1 Understanding the Magic	65
22.2 The Building Blocks	65
22.2.1 1. Neurons and Weights	65
22.2.2 2. Activation Functions	65
22.3 The Learning Process	66
22.3.1 1. Forward Propagation	66
22.3.2 2. Loss Calculation	66
23 Exploring Neural Network Architectures	67
23.1 The Rich Landscape of Neural Networks	67
23.2 Feedforward Neural Networks (FNN)	67
23.3 Convolutional Neural Networks (CNN)	67
23.4 Recurrent Neural Networks (RNN)	67
23.5 Long Short-Term Memory (LSTM)	68
23.6 Autoencoders	68
23.7 Generative Adversarial Networks (GAN)	68
23.8 Choosing the Right Architecture	68
23.9 Future Directions	68
24 Resources and References AI	71

24.1 Books	71
24.2 Video Courses and Tutorials	71
24.2.1 1. Foundational Series	71
24.2.2 2. Programming Tutorials	72
24.2.3 3. Advanced Topics	72
24.3 Online Platforms	72
24.3.1 1. Interactive Learning	72
24.3.2 2. Research Papers	72
24.3.3 3. Code Repositories	72
24.4 Community Resources	73
24.4.1 1. Forums and Discussion	73
24.4.2 2. Blogs and Newsletters	73
24.4.3 3. Tools and Libraries	73
24.5 Academic Papers	73
24.5.1 Foundational Papers	73
 VII Experiments	 75
25 Experiments	77
26 MCP hands-on	79
27 to look at still:	81
28 MCP Client	83

Chapter 1

Introduction

Welcome! This is a Work-in-Progress, a collection of notes on AI I am collecting and which I use in my workshops about AI and GenAI. The newest version of this pdf can be downloaded from [here](#)

It is not complete nor self-describing, but when you attended one of my workshops you will probably find familiar stuff in one or more chapters.

Our world is changing rapidly through AI and GenAI. One can ignore it or decide to not use it, but that does not stop it... One can also decide to dive in and help ‘invent’ the future, or at least learn about all the new stuff.

These notes started out as visualizations of Perceptrons and Neural Networks in the Glamorous Toolkit, which helped me give students insights in Neural Networks.

I advise to get hands-on with the tools around.

When using online AI tools, please keep the privacy in mind when using personal data! One way to make sure private data will stay private is using local AI's.

Please also keep the Societal impact in mind! We can use AI to help us all, but there is of course also a dark side:
People getting fired, it's easier to create fake news, a few people getting rich at the expense of others,
some nice activities (I like programming for example) will never be the same.
Please use it wisely...



Figure 1.1: art and laundry

Chapter 2

AI Overview

2.1 AI, Machine Learning, Deep Learning, Generative AI

The video “AI, Machine Learning, Deep Learning and Generative AI Explained” provides an excellent 10-minute overview:

[AI, Machine Learning, Deep Learning and Generative AI Explained](#)

Part I

GenAI

Chapter 3

GenAI

Recent:

- [Amy Webb SxSW 2025 - Emerging Tech Trend](#)

3.1 What is GenAI?

- Why not ask [perplexity.ai](#) ?

3.2 GPT - Generative Pre-Trained Transformer

- [Generative AI & the Transformer \(Financial Times, interactive site\)](#)
- [History of ChatGPT \(30 min\)](#)
- [But what is a GPT? \(3Blue1Brown, 30 min\)](#)

3.3 Prompting

- [Prompting basics](#)
- [Prompting ChatGPT4.1](#)
- Look for course with 'Prompting' in name: <https://www.deeplearning.ai/short-courses/>

3.4 Hallucinating

- 'Which day do I have to put the garbage can out on the street?'
- 'Can you help me find my lost keys?'
- 'Can you create an image of a watch that says it is 3 o' clock?'

3.5 RAG - Retrieval Augmented Generation

- [IBM, Marina Danilevsky \(7 min\)](#)
- <https://www.deeplearning.ai/short-courses>: Great resource for courses!

3.6 Active Inference

- [Andy Clark about Active Interference: How the Brains shapes reality \(60 min\)](#)

3.7 Running LLM's locally

On your laptop/desktop or on a company server:

- [ollama](#)
- [LM-studio](#)
- [Open Web AI](#)

3.8 Coding with GenAI

- [vs code with co-pilot \(free plan\)](#)
- [Cursor.com \(20 euro p/m\)](#)
- [AIDER.chat \(free\)](#)
- [Open Devin: Create any Application with Open Source AI Engineer](#)
- [Avante \(AI in neovim, free\)](#)

3.9 MCP - Model Context Protocol

A way (AI) systems can communicate to each other. This way it helps building modular (AI) systems.

- [MCP Quickstart](#)
- [Short deeplearning.ai course MCP](#)

3.10 GenAI

- [awesome GenAI guide](#)
- [huggingface](#)

3.11 Some more sites, nice to play around with

- <https://skyreels.ai/>
- <https://civitai.com/>

Chapter 4

AI versus education

4.1 Media & Opinions

- bron.fontys.nl/nieuw-fraudebeleid-met-focus-op-preventie
- [How AI is changing education](#)
- [column-mark-de-graaf-ga-ict-studeren](#)
- [bron.fontys: een-eigen-ai-tool-voor-fontys](#)

4.2 Tools, Best Practices & lesson material

- [How to cite ChatGPT? Use AI Archive](#)
- aiarchives.org
- [You did it together with AI? Make a statement!](#)
- [hbo-i-outcomes-example-generator chatbot](#)
- <https://roadmap.sh/ai>

Chapter 5

Jobs and AI

- [pabo-wint-aan-populariteit-ict-en-fysio-juist-niet](#)

Chapter 6

Resources and References GenAI

6.1 Blogs and articles

Perplexity is often a great start for finding things (with references): perplexity.ai

- [Jessy: Het belang van duidelijke AI-prompts](#)
- [Journalists on Hugging Face](#)
- [How polite should we be when prompting LLMs?](#)
- [Information literacy and chatbots as search](#)

To understand about Transformers this is a very nice start: <https://ig.ft.com/generative-ai/> ‘Our own’ page about (Gen)AI: <https://stasemsoft.github.io/FontysICT-sem1/docs/artificial-intelligence/ai.html> To dive further into how Transformers works: <https://www.deeplearning.ai/short-courses/how-transformer-llms-work/> and also to other short courses on [deeplearning.ai](https://www.deeplearning.ai) The development I showed was <https://www.cursor.com/> you have like only 500 requests for free... after that you could choose to pay 20 euro a Month (yes, that can be a lot for students, I know), or look for alternatives, 2 of which I tried a bit (you can use local LLM’s with them, which basically makes them free): AIDER: <https://aider.chat/>.

Avante: <https://github.com/yetone/avante.nvim> (but then you need to learn about ‘vi’: <https://neovim.io/> which is a hurdle).

6.2 Online Platforms

- spacy.io : NLP

6.3 (Short) Courses

- [Short courses at Deeplearning.ai](#)
 - Implementations of papers
 - Benchmarks
 - State-of-the-art tracking

6.4 Code Repositories

- [Papers With Code](#)
 - Implementations of papers
 - Benchmarks
 - State-of-the-art tracking

6.5 Community Resources

- [Distill.pub](#)
 - Interactive explanations
 - Visual learning
 - Deep insights

6.6 Academic Papers: Modern Breakthroughs

- “Deep Residual Learning for Image Recognition” (He et al., 2015)
- “Attention Is All You Need” (Vaswani et al., 2017)
- “Language Models are Few-Shot Learners” (Brown et al., 2020)

Chapter 7

No-Code / Low Code

Worth looking at:

- docs.oap.langchain.com
- n8n.io
- flowai.cc

Part II

AI Act Europe

Chapter 8

AI Act Resources and References

- [youtube 4min: How is Europe becoming a leader in AI?](#)
- [SURF startdocument AI Act](#)

Part III

Train, Fine Tune, RAG

Chapter 9

Train, Fine Tune, RAG

Several ways to ‘teach’ the AI about the knowledge it needs to perform the task you need it for. The most easy of these is building a RAG system: Retrieval Augmented Generation.

Chapter 10

RAG: Retrieval Augmented Generation

Chapter 11

Finetune

Chapter 12

Training

Training a model from scratch is a complex and resource-intensive process. It involves collecting a large dataset, preprocessing the data, and training the model using powerful hardware. This is typically done by large organizations with significant resources.

short course: [fine tuning](#)

Part IV

Data

Chapter 13

Finding and Preparing Data

13.1 The Importance of Data

Data is the foundation of most machine learning projects. The quality and quantity of your data often matter more than the sophistication of your model.

13.2 Popular Data Sources

- [Kaggle](#)
 - Competitions and datasets
 - Active community
 - Detailed documentation
- [Eindhoven open data](#)
 - lots of data about Eindhoven

Part V

Related subjects

Chapter 14

Agents

14.1 Agent Development Kit

- <https://google.github.io/adk-docs/><https://google.github.io/adk-docs/>

14.2 Open Agent Platform

- docs.oap.langchain.com

Chapter 15

MCP - Model Context Protocol

MCP is a standardization of the way to how LLM's connect to other tools.

- modelcontextprotocol.info/
- [Example Clients](#)
- [Servers](#)
- [Greg Isenberg/Ras Mic explaining MCP](#)
- [short course MCP at deeplearning.ai](#)

Chapter 16

Journalism and AI

- [Hey Aftonbladet \(chatbot\): What do YOU want to know?](#)

Part VI

Neuron & Network

Chapter 17

Understanding the Perceptron

17.1 The Biological Inspiration: From Brain Neurons to Artificial Intelligence

The Perceptron represents one of the most fundamental concepts in artificial intelligence, drawing its inspiration directly from the human brain's neural structure. This groundbreaking idea was first introduced in 1943 by Warren S. McCulloch and Walter Pitts in their seminal paper 'A Logical Calculus of the Ideas Immanent in Nervous Activity', where they proposed a mathematical model of biological neurons.

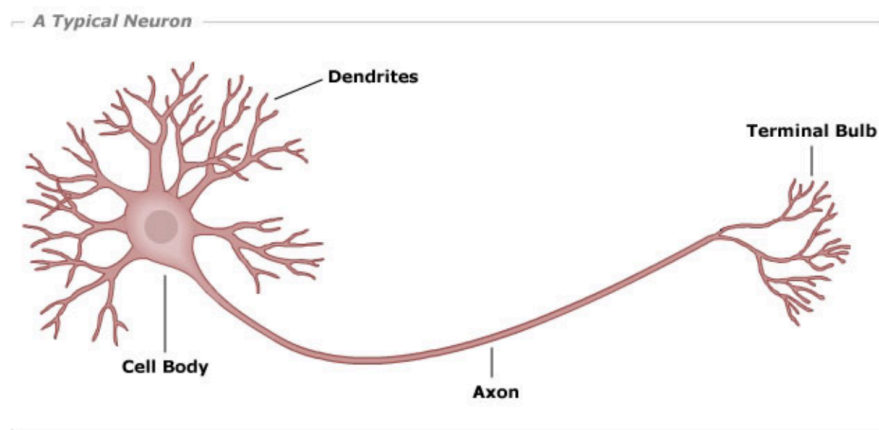


Figure 17.1: A typical biological neuron structure

17.2 From Biology to Machine: Implementing a Perceptron

A Perceptron's architecture mirrors its biological counterpart through three key components: **inputs**, **weights**, and a **bias**. Each input connection has an associated weight that determines its relative importance, while the bias helps adjust the Perceptron's overall sensitivity to activation.

Let's look at a simple yet useful perceptron with 2 inputs.

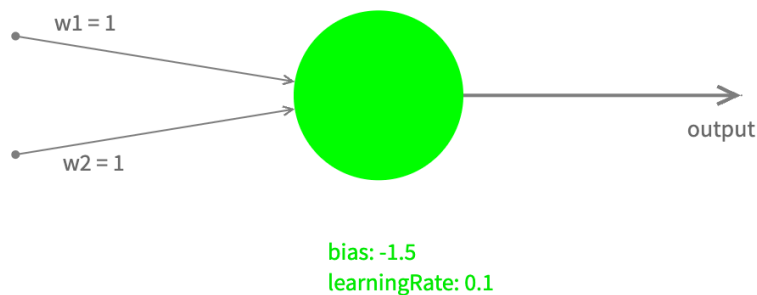


Figure 17.2: Perceptron's architectural diagram

We'll call our input values $x1$, $x2$ with their corresponding weights $w1$, $w2$. The Perceptron processes these inputs in two steps:

1. First, it calculates a **weighted sum** and adds the bias: $z := w1*x1 + w2*x2 + \text{bias}$
2. Then, it applies what we call an **activation function** to produce the final output: let's use a very simple activation function, called a Step function:

17.2. FROM BIOLOGY TO MACHINE: IMPLEMENTING A PERCEPTRON⁴⁷

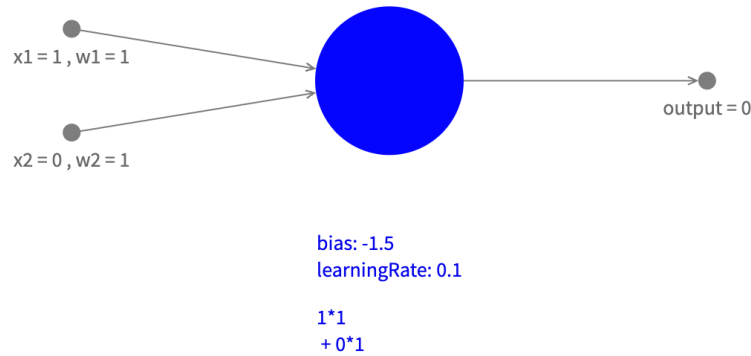


Figure 17.3: Perceptron's architectural diagram

$$\begin{cases} \text{Output is 1 if } z > 0 \\ \text{Output is 0 if } z \leq 0 \end{cases}$$

which determines the final output.

Let's restrict ourselves for now to possible input values 0 and 1: If we look at all possibilities combinations of input and the corresponding output we can create a table:

Input 1	Input 2	Output
0	0	0
0	1	0
1	0	0
1	1	1

A close look will tell us that the output is only 1 when inputs are 1, and 0 in all other cases, which you could recognize as a logical AND. So with these weights and bias this Perceptron can be used to act as a logical AND.

For different values it will behave like a logical OR (and more). Can you come up with those values?

17.3 Network

By combining several Perceptrons (sending the output of a perceptron to the input of another one) you can probably imagine that it is possible to create Networks of Perceptrons. By changing the values of weights and biases of the connected Perceptrons it is possible to build complex electronic circuits.

When we generalize this concept to other values, not only 0 and 1, and different activation functions, the Perceptron becomes an incredibly versatile tool. This generalization opens up possibilities for pattern recognition, classification tasks, regression problems, and complex decision-making systems. This is where the true power of neural networks begins to emerge, as they can learn to handle continuous data and make sophisticated decisions based on multiple inputs.

Up until now we didn't look at how a perceptron can learn and become smarter. That will be subject of next chapter chapters. The concept of a Perceptron was generalized to what we now call an (artificial) Neuron.

Search terms: Perceptron, Artificial Neuron, Multi Layered Perceptron (MLP), (Artificial) Neural Network (ANN).

17.4 First Implementation of Perceptron algorithm

According to Wikipedia:

The artificial neuron network was invented in 1943 by Warren McCulloch and Walter Pitts in 'A logical calculus of the ideas immanent in nervous activity'. the Perceptron Machine was first implemented in hardware in the Mark I, which was demonstrated in 1960.

It was connected to a camera with 20×20 cadmium sulfide photocells to make a 400-pixel image. The main visible feature is the sensory-to-association plugboard, which sets different combinations of input features. To the right are arrays of potentiometers that implemented the adaptive weights.

17.5 Reference

- [wikipedia: perceptron](#)

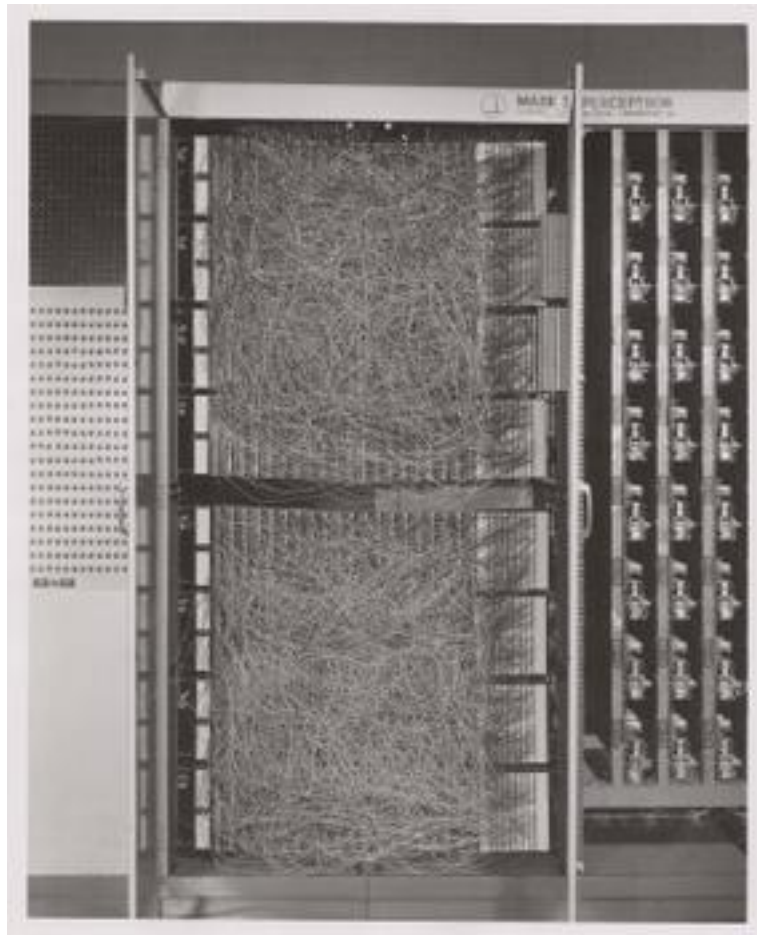


Figure 17.4: The Mark I Perceptron machine, the first implementation of the perceptron algorithm (source: wikipedia)

Chapter 18

The Learning Perceptron

One of the most fascinating aspects of Perceptrons is their ability to learn from examples. Instead of manually setting weights and bias, we can train a Perceptron to discover the optimal parameters through a process called supervised learning.

18.1 The Learning Algorithm

The learning process follows these key steps:

1. Start with random weights and bias
2. Present a training example
3. Compare the Perceptron's output with the desired output
4. Adjust the weights and bias based on the error
5. Repeat with more examples until performance is satisfactory

18.1.1 Mathematical Foundation

The weight update rule is elegantly simple:

`new_weight := current_weight + learning_rate * error * input`

Where:

- `learning_rate` is a small number (like 0.1) that controls how big each adjustment is
- `error` is the difference between desired and actual output (1 or -1)
- `input` is the input value for that weight

18.1.2 Training Process

To train the Perceptron, we have to have **labeled data** (ie. input data combined with the desired output for those values)

So for training AND gate behavior we have to list all combinations of 2 bits that are possible as input, and also the desired output value:

Input	Desired Output
(0, 0)	0
(0, 1)	0
(1, 0)	0
(1, 1)	1

and training (1 epoc) means calling the train function with each of these examples:

```
foreach dataItem in trainingData do:
    inputs := dataItem[0]
    desiredOutput := dataItem[1]
    learningPerceptron train(inputs, desiredOutput)
```

18.2 Visualizing the Learning Process

As the Perceptron learns, its decision boundary gradually moves to the correct position. You can monitor this progress by:

1. Tracking the error rate over time
2. Visualizing the decision boundary's movement
3. Testing the Perceptron with new examples

18.3 Practical Considerations

For successful learning: - Ensure your training data is representative - Consider using multiple training epochs (complete passes through the data) - Monitor for convergence (when the weights stabilize) - Be aware that not all problems are linearly separable

In the next chapter, we'll explore the limitations of what a single Perceptron can learn, which will lead us naturally to the need for more complex neural networks.

Chapter 19

Understanding Perceptron Limitations

19.1 The XOR Problem: A Classic Challenge

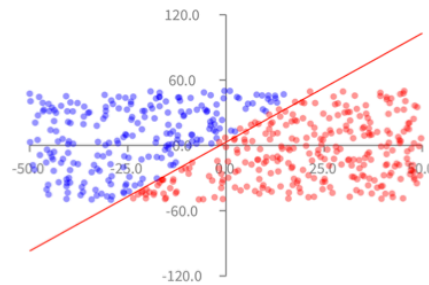
While Perceptrons are powerful tools for many classification tasks, they face a fundamental limitation: they can only solve linearly separable problems. The classic example of this limitation is the XOR (exclusive OR) function.

19.1.1 What is XOR?

The XOR function outputs 1 only when exactly one of its inputs is 1: - Input (0,0) → Output: 0 - Input (0,1) → Output: 1 - Input (1,0) → Output: 1 - Input (1,1) → Output: 0

What we have seen so far

We have seen that the perceptron can (more or less accurately) guess the side on which a point is located



34

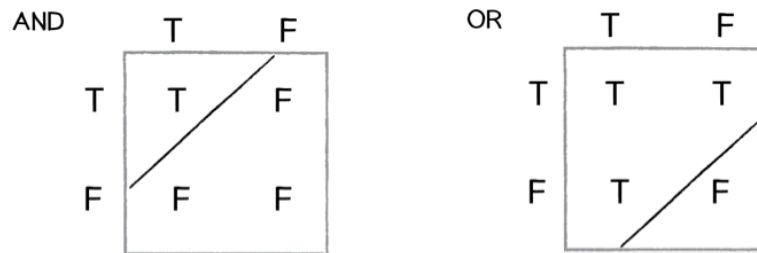
Figure 19.1: Visual representation of XOR problem

19.1.2 Why Can't a Single Perceptron Solve XOR?

A Perceptron creates a single straight line (or hyperplane in higher dimensions) to separate its outputs. However, the XOR problem requires two separate lines to correctly classify all points.

What we have seen so far

We can easily make our perceptron to represent the AND, OR logical operations



38

Figure 19.2: Attempted linear separation of XOR

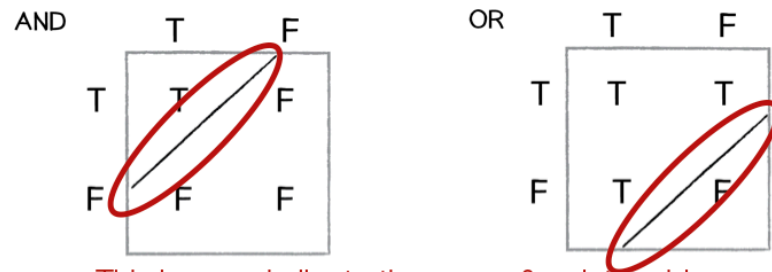
As you can see, no single straight line can separate the points where output should be 1 (blue) from points where output should be 0 (red).

19.2 The Solution: Multiple Layers

To solve the XOR problem, we need to combine multiple Perceptrons in layers. This is our first glimpse at why we need neural networks!

What we have seen so far

We can easily make our perceptron to represent the AND, OR logical operations



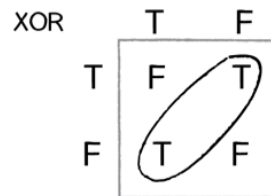
This is very similar to the space & point problem.
It is all about having a line as a limit

39

Figure 19.3: Multi-layer solution

By using multiple Perceptrons, we can: 1. First create separate regions with individual Perceptrons 2. Then combine these regions to form more complex decision boundaries

Limitation of a perceptron



With the XOR operation, you cannot have one unique line that limit the range of true and false

40

Figure 19.4: Complete neural network solution

19.3 Key Takeaways

1. Single Perceptrons can only solve linearly separable problems
2. Many real-world problems (like XOR) are not linearly separable
3. Combining Perceptrons into networks overcomes this limitation
4. This limitation led to the development of multi-layer neural networks

In the next section, we'll explore how to build and train these more powerful multi-layer networks.

Chapter 20

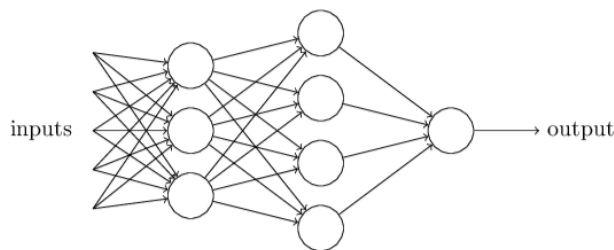
Introduction to Neural Networks

20.1 Beyond Single Perceptrons: Building Neural Networks

Having seen the limitations of single Perceptrons, we now venture into the fascinating world of neural networks. These powerful structures combine multiple Perceptrons in layers to solve complex problems that single Perceptrons cannot handle.

Network of neurons

A network has the following structure



41

Figure 20.1: Basic neural network architecture

20.2 Understanding Network Architecture

A typical neural network consists of three main components:

1. **Input Layer:** Receives the raw data
2. **Hidden Layer(s):** Processes the information through multiple Perceptrons
3. **Output Layer:** Produces the final result

20.2.1 Key Components

Each connection in the network has:

- A weight that determines its strength
- A direction of information flow (forward only)
- An associated neuron that processes the incoming signals

20.3 How Information Flows

The network processes information in these steps:

1. Input values are presented to the input layer
2. Each neuron in subsequent layers:

- Receives weighted inputs from the previous layer
 - Applies its activation function
 - Passes the result to the next layer
3. The output layer produces the final result

20.4 Creating a Simple Network

You probably have seen a picture of a neural network before.

Neural Networks can

1. solve problems that are more difficult.
2. Handle complex pattern recognition
3. Learn hierarchical features automatically
4. Scale well to large problems

In the next sections, we'll explore practical applications and see how to train networks on real-world data.

Chapter 21

Practical Example: Classifying Iris Flowers

21.1 A Real-World Machine Learning Challenge

The Iris flower classification problem is a classic example in machine learning. It involves predicting the species of an Iris flower based on measurements of its physical characteristics. This problem perfectly illustrates how neural networks can solve real-world classification tasks.



Figure 21.1: Different types of Iris flowers

21.2 The Dataset

The Iris dataset includes measurements of three different Iris species: - Iris Setosa - Iris Versicolor - Iris Virginica

For each flower, we have four measurements: 1. Sepal length 2. Sepal width 3. Petal length 4. Petal width

Building a network that can do this is really outside of the scope of these notes, but a lot of info can be found on the internet on [Iris Classification](#).

21.3 Key Learning Points

1. Neural networks can handle multi-class classification
2. Real-world data often needs preprocessing
3. We can measure success with accuracy metrics
4. The same principles apply to many similar problems

This practical example demonstrates how neural networks can solve real classification problems. In the next section, we'll explore the mathematics behind how these networks learn.

Chapter 22

The Mathematics Behind Neural Networks

22.1 Understanding the Magic

While neural networks might seem magical, they're built on solid mathematical foundations. Let's demystify (a bit of) how they actually work under the hood.

22.2 The Building Blocks

22.2.1 1. Neurons and Weights

To be formally correct we should say **artificial neuron** to distinguish them from **biological neurons** like we have in our brain. A neuron normally has inputs: 1, or 2, or ...

Each neuron performs two key operations: 1. Weighted sum of inputs. 2. Activation function: $a = f(z)$

22.2.2 2. Activation Functions

Common activation functions include:

1. Sigmoid: $f(x) = \frac{1}{1+e^{-x}}$
 - Outputs between 0 and 1
 - Useful for probability predictions
2. ReLU (Rectified Linear Unit): $f(x) = \max(0, x)$
 - Simple and efficient
 - Helps prevent vanishing gradients
3. Tanh: $f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

- Outputs between -1 and 1
- Often better than sigmoid for hidden layers

22.3 The Learning Process

22.3.1 1. Forward Propagation

Information flows through the network.

22.3.2 2. Loss Calculation

Measure the network's Error and Backpropagation

- What is the output?
- What would be my desired output?

The smaller the difference between the output I got and the output I desired, the better the output of my model is. This difference is calculated with a so-called Loss function. Backpropagation is an algorithm that helps make that difference small. When backpropagation is performed we call that Training the AI model.

Chapter 23

Exploring Neural Network Architectures

23.1 The Rich Landscape of Neural Networks

Neural networks come in many shapes and sizes, each designed to excel at specific types of tasks. Let's explore some of the most important architectures and their applications.

23.2 Feedforward Neural Networks (FNN)

The classic architecture: Information flows in one direction:

- Input layer \rightarrow Hidden layer(s) \rightarrow Output layer
- Perfect for classification and regression tasks
- Examples: Our Iris classifier, handwriting recognition

23.3 Convolutional Neural Networks (CNN)

Inspired by the human visual cortex:

- Specialized for processing grid-like data (images, video)
- Uses convolution operations to detect patterns
- Excellent at feature extraction
- Applications: Image recognition, computer vision, medical imaging

23.4 Recurrent Neural Networks (RNN)

Networks with memory:

- Can process sequences of data
- Information cycles through the network
- Great for time-series data and natural language
- Applications: Language translation, speech recognition, stock prediction

23.5 Long Short-Term Memory (LSTM)

A sophisticated type of RNN:

- Better at remembering long-term dependencies
- Controls information flow with gates
- Solves the vanishing gradient problem
- Applications: Text generation, music composition

23.6 Autoencoders

Self-learning networks:

- Learn to compress and reconstruct data
- Useful for dimensionality reduction
- Can detect anomalies
- Applications: Data compression, noise reduction, feature learning

23.7 Generative Adversarial Networks (GAN)

Two networks competing with each other:

- Generator creates fake data
- Discriminator tries to spot fakes
- Through competition, both improve
- Applications: Creating realistic images, style transfer, data augmentation

23.8 Choosing the Right Architecture

The choice of architecture depends on:

1. Type of data (images, text, time-series)
2. Task requirements (classification, generation, prediction)
3. Available computational resources
4. Need for real-time processing

23.9 Future Directions

Neural network architectures continue to evolve:

- Hybrid architectures combining multiple types
- More efficient training methods
- Better handling of uncertainty
- Integration with other AI techniques

In the next section, we'll dive deeper into training these networks effectively.

Chapter 24

Resources and References AI

24.1 Books

1. Neural Networks and Deep Learning

- Author: Michael Nielsen
- [Free Online Book](#)
- Perfect for beginners and intermediate learners
- Clear explanations with interactive examples

2. Deep Learning

- Authors: Ian Goodfellow, Yoshua Bengio, Aaron Courville
- [Available Online](#)
- Comprehensive coverage of deep learning
- Industry standard reference

3. Agile AI in Pharo

- Author: Alexandre Bergel
- Practical implementation in Pharo
- Hands-on examples and exercises
- [Book Link](#)

24.2 Video Courses and Tutorials

24.2.1 1. Foundational Series

- [3Blue1Brown Neural Networks](#)

- Visual explanations
- Mathematical intuition
- Clear animations

<https://www.youtube.com/watch?v=O5xeyoRL95U>

24.2.2 2. Programming Tutorials

- [Fast.ai Deep Learning Course](#)
 - Practical approach
 - Top-down learning
 - Real-world applications

24.2.3 3. Advanced Topics

- [Stanford CS231n](#)
 - Computer Vision
 - Deep Learning
 - State-of-the-art techniques

24.3 Online Platforms

24.3.1 1. Interactive Learning

- [Kaggle Learn](#)
 - Hands-on exercises
 - Real datasets
 - Community support

24.3.2 2. Research Papers

- [arXiv Machine Learning](#)
 - Latest research
 - Open access
 - Preprint server

24.3.3 3. Code Repositories

- [Papers With Code](#)
 - Implementations of papers
 - Benchmarks
 - State-of-the-art tracking

24.4 Community Resources

24.4.1 1. Forums and Discussion

- [r/MachineLearning](#)
- [Cross Validated](#)
- [AI Stack Exchange](#)

24.4.2 2. Blogs and Newsletters

- [Distill.pub](#)
 - Interactive explanations
 - Visual learning
 - Deep insights

24.4.3 3. Tools and Libraries

- [TensorFlow](#)
- [PyTorch](#)
- [Scikit-learn](#)

24.5 Academic Papers

24.5.1 Foundational Papers

- “A Logical Calculus of Ideas Immanent in Nervous Activity” (McCulloch & Pitts, 1943)
- “Learning Internal Representations by Error Propagation” (Rumelhart et al., 1986)
- “Gradient-Based Learning Applied to Document Recognition” (LeCun et al., 1998)

Part VII

Experiments

Chapter 25

Experiments

Experiments, maybe incomplete... never finished, the whole reutemeteut!

Chapter 26

MCP hands-on

Diving in...

So MCP standardizes the way I can combine sources of info (like RAG?) with an LLM.

Duckduckgoing for ‘MCP vs ollama hands-on’ (adding CLI afterwards) gives me some links to look at, and after a closer look these still seem interesting:

- [agentic-rag-and-mcp](#)
- [Ollama MCP bridge](#)
- [ollama-mcp](#)
- <https://modelcontextprotocol.io/introduction>
- [lazy terminal](#)
- <https://apidog.com/blog/neovim-mcp-server/>

Chapter 27

to look at still:

- [agentic-rag-and-mcp](#)
- [Ollama MCP bridge](#)
- [ollama-mcp](#)
- <https://modelcontextprotocol.io/introduction>
- [lazy terminal](#)
- <https://apidog.com/blog/neovim-mcp-server/>

First I need an MCP client and an MCP server.

Chapter 28

MCP Client

- [5ire](#) looks nice.
- [oterm](#)

