

Coen's AI Notes and Links

(by several intelligences cooperating)

2025-10-10

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1. Introduction

Welcome! This is a Work-in-Progress, a collection of notes on AI I am collecting and which I use when talking about or giving workshops about AI and GenAI. The newest version of this pdf can be downloaded from the next chapter.

Do NOT read this from beginning to end... instead look at the Index for relevant chapters and dive in...

Questions about this all? [Try to ask here](#)

I advise to get hands-on as soon as possible!

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.

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 filthy rich at the expense of lots 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

2. How to download

The latest PDF version of this book is available for download.

You can get it directly from [this GitHub link](#).

To download, click the download button on the GitHub page.

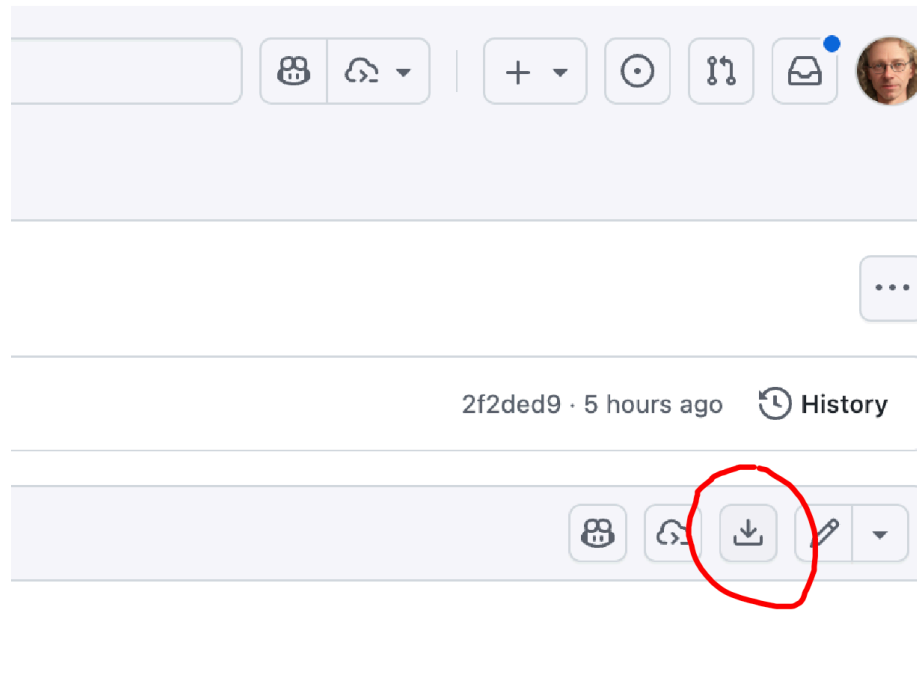


Figure 2.1: How to download the file on Github

Or use this QR code to get to the download location.



Figure 2.2: QR code for download link

Part I

AI Literacy

3. Diving into AI: some AI Literacy

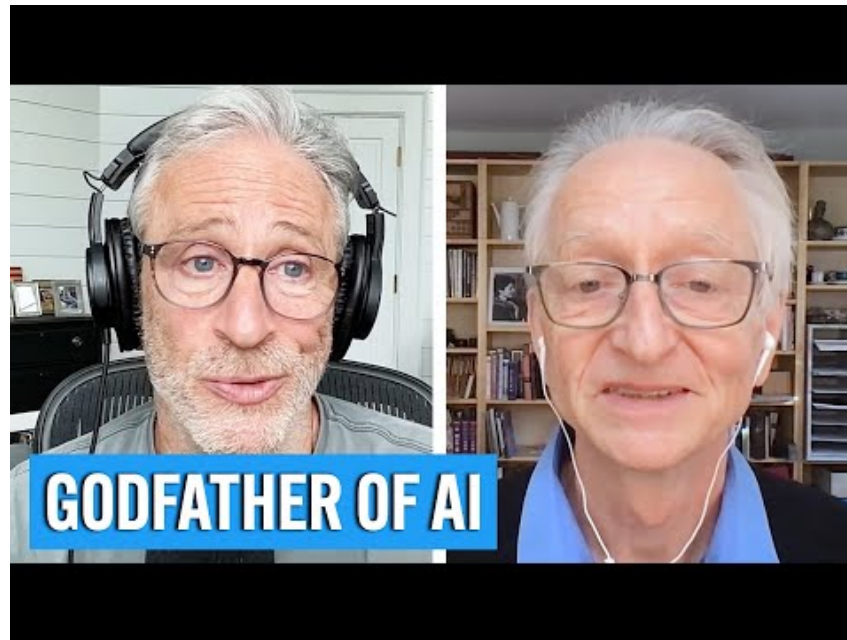
3.1 Key Tools to Get Started

- [ChatGPT](#) - well, maybe...
- [Perplexity.AI](#) - The AI-powered search engine that gives links to sources and suggests follow-up questions.
- [Comet](#) - The browser from Perplexity that has AI browsing built-in.
- [Cursor](#) - The AI-powered development environment we're using right now!

3.2 Some Core Concepts to Explore

- **Large Language Models (LLMs):** What they are and how they work.
- **Generative AI:** Creating new things with AI.
- **Training Data:** The information (like text, images, or code) used to teach an AI.
- **Prompt Engineering:** The art and science of writing effective instructions to get the best results from an AI.
- **Neural Networks:** The brain-inspired models that power much of modern AI.
- **Supervised vs. Unsupervised Learning:** Different ways that machines can learn from data.
- **Computer Vision:** How computers see and interpret the visual world.
- **Natural Language Processing (NLP):** How computers understand and process human language.
- **AI Ethics & Bias:** The important considerations of fairness, safety, and transparency in AI.

3.3 Your Next Steps in AI



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3.4 AI Jargon Buster

- **Prompt:** The question or instruction you give to an AI.
- **Hallucination:** When an AI confidently states incorrect or nonsensical information as if it were a fact.
- **Model:** The core AI program that has been trained on data to perform a specific task (e.g., GPT-4 is a language model).

4. AI Literacy Scenarios

5. Scenario: Transcribing and Summarizing a Meeting (Locally and Privately)

One of the most practical and impressive uses of AI is to automatically transcribe a meeting and then have an AI assistant summarize it for you. This guide will walk you through how to do this yourself, using tools that are easy to install and that keep all your data private on your own computer.

5.1 Why Local Tools? A Note on Privacy

When you record a meeting, the contents can be sensitive. Using an online transcription or summarization service means you are sending that data to a company's servers. While many services have strong privacy policies, the most secure way to handle confidential information is to never let it leave your machine in the first place.

The tools recommended here run **100% offline**. Your audio files and transcripts

are processed on your computer and are never sent over the internet. This gives you complete control and peace of mind.

5.2 The Tools You'll Need

We'll use a two-step process with two different, user-friendly applications:

1. **For Transcription:** We need an app that turns your audio recording into a text file.
 - **On macOS:** We recommend [MacWhisper](#).
 - **On Windows:** We recommend [WhisperDesktop](#).
2. **For Summarization:** We'll use a tool that can run a powerful AI language model locally on your machine to create the summary and action items.
 - **On both macOS and Windows:** We recommend [LM Studio](#).

5.3 Step 1: Transcribing Your Meeting

First, let's turn that audio file into text.

5.3.1 Installation

- **macOS:**
 1. Go to the [MacWhisper website](#).
 2. Download, unzip, and drag the application to your **Applications** folder.
- **Windows:**
 1. Go to the [WhisperDesktop releases page](#).
 2. Download the `.exe` file from the most recent release.

3. On first run, the app will automatically download the required AI model files.

5.3.2 Usage

Both applications are very straightforward: 1. Open the app. 2. Drag and drop your audio file (e.g., an `.mp3` or `.wav` file) into the app window. 3. Click the “Transcribe” button. 4. Wait for the magic to happen! When it’s done, you can copy the full text or save it as a text file.

You now have a complete transcript of your meeting!

5.4 Step 2: Summarizing with a Local AI

Now, let’s take that wall of text and turn it into a neat summary and a list of action items.

5.4.1 Installation of LM Studio

1. Go to the [LM Studio website](#) and download the installer for your operating system (Mac or Windows).
2. Run the installer and follow the on-screen instructions.

5.4.2 Downloading an AI Model

LM Studio is a home for AI models. Before you can chat with one, you need to download it. 1. Open LM Studio. 2. Click on the **Search** icon () in the left-hand menu. 3. In the search bar, type a model name. A good, versatile model to start with is “**Mistral 7B Instruct**”. 4. You’ll see a list of different versions. Look for one that is a good balance of size and quality. The versions marked with **Q4_K_M** are often a good choice. 5. Click the **Download**

button next to the model you choose. This might take a while as the file is several gigabytes.

5.4.3 Creating the Summary

1. Once the model is downloaded, click on the **Chat** icon () in the left-hand menu.
2. At the top of the screen, make sure your downloaded model is selected.
3. Now you can chat with your local AI! Copy the transcript from Step 1 and paste it into the chat box using a prompt like the one in the example below.

5.5 Putting It All Together: The Full Workflow

Here is an example of what your prompt and the AI's response might look like inside LM Studio.

You:

Hello! I have a transcript of a team meeting here. Could you summarize it for me and create minutes with action points? I have anonymized the speakers' names to Speaker A, B, and C.

Here is the text:

```
[Speaker A]: Good morning everyone. Let's start with the progress on Project Sunflower. How are we d
[Speaker B]: Good morning. I've run the latest tests on the new module. It looks good, but the perfo
[Speaker A]: Understood. Can you make an analysis of that and come up with a proposal?
[Speaker B]: Sure, I'll put it on my list.
[Speaker C]: I'd like to touch on the marketing campaign we're launching next week. The visuals have
```

[Speaker A]: Who was supposed to deliver those?

[Speaker B]: That would be me. I have a first draft ready, but I wanted to wait for the latest details of the technical specifications.

[Speaker C]: Great, thank you!

[Speaker A]: Perfect. Then we'll close here. Good work everyone.

Local AI Assistant (running in LM Studio):

Of course! Here is a summary and the minutes of the meeting.

5.5.1 Summary

During the meeting, the status of “Project Sunflower” was discussed. The new module is functional, but there are performance issues on the staging environment, likely due to unoptimized database queries. Additionally, an update was given on the upcoming marketing campaign; the visuals have been approved, but the texts for social media posts are still needed.

5.5.2 Minutes and Action Points

Attendees: Speaker A, Speaker B, Speaker C

Date: [Current Date]

Subject: Progress on Project Sunflower & Marketing Campaign

Discussion Points:

1. **Status of Project Sunflower:**
 - The new module has been tested and is functional.
 - There are performance issues on the staging environment.
2. **Status of Marketing Campaign:**
 - Visuals have been approved by the client.
 - Texts for social media posts are not yet final.

Action Points:

- **[Speaker B]:** Analyze the database queries of the new module and come up with a proposal for optimization.
- **[Speaker B]:** Deliver the final texts for the social media posts to Speaker C by the end of the day.

And that's it! You've successfully gone from an audio recording to a complete set of meeting minutes, without your data ever leaving your computer. You're now an AI-powered, privacy-conscious productivity wizard!

6. Beyond the Prompt: The Power of AI Context

A simple prompt is just a question. But to get truly powerful results from an AI, you need to master the art of providing **context**. This chapter, inspired by best practices from tools like [Cursor](#), reframes this crucial skill for everyone, not just programmers.

6.1 What is Context?

Think of context as a **briefing you give to a human assistant**. The better the briefing, the better the result. You wouldn't just tell an assistant "write a report" without giving them the source material. The same is true for AI.

Context is all the relevant information you provide *along with* your prompt. This can include:

- **Pasting in text:** Providing the specific email you want to reply to, or the article you want summarized.
- **Setting the scene:** Telling the AI who it is ("You are a friendly, expert marketer") and who you are ("I am a beginner learning about this topic").
- **Providing examples:** Giving it a sample of the writing style you want it to adopt.
- **Referencing the conversation:** Using the information discussed earlier in your chat.

Without context, the AI has to guess. And when it guesses, you get generic, boring, and often unhelpful answers.

6.2 A Practical Example: Replying to an Email

Let's see context in action.

Bad Prompt (No Context)

"Draft a polite and professional email saying I can't make it."

The AI will produce a generic, fill-in-the-blanks template. It's not very helpful because it lacks any specific details.

Good Prompt (With Context)

“I need to reply to this email. **[Paste the full text of the original email here]**. Please draft a polite and professional reply explaining that I can’t make the ‘Project Phoenix’ meeting on Wednesday because of a conflict, but I am very interested. Ask if they can send me the minutes and suggest I’m available to connect next week.”

See the difference? By providing the original email and clear instructions, you’ve given the AI all the context it needs to draft a perfect, ready-to-send reply.

6.3 The “Context Window”: An AI’s Short-Term Memory

It’s important to know that every AI has a limited memory, called a “**context window**.” This is the maximum amount of information (your prompt, the text you’ve pasted, the conversation history) that the model can “see” at one time.

If your conversation gets very long, the AI might start to “forget” things you discussed at the beginning. If you notice the AI losing track, it might be time to start a new conversation to give it a fresh, clean context to work with.

7. Searching for stuff

How can I find what I need?

- perplexity.ai
- <https://www.rankmyai.com/>

8. AI Overview

8.1 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 II

AI

9. GenAI

Recent:

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

9.1 What is GenAI?

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

9.2 GPT - Generative Pre-Trained Transformer

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

9.3 Prompting

... and some sources with tips how to prompt every day...

- [Prompting basics](#)
- [Prompting ChatGPT4.1](#)
- [Look for course with 'Prompting' in name: https://www.deeplearning.ai/short-courses/](https://www.deeplearning.ai/short-courses/)
- [Ruben Hassid: RISE](#)
- [In cursor.ai course: Info about 'managing your context in cursor](#)
- [mention of Llama Prompt Optimization](#)

9.4 Hallucinating

When nonsense comes out of an LLM (or out of a Human by the way) we call it hallucination. Some questions can trigger hallucination.

9.4.1

9.4.2 ‘Which day do I have to put the garbage can out on the street?’

Some LLMs will give you a Date when you ask for one, a percentage when you ask for one, even when the LLM could not possibly give an answer to your question. If you ask which day you should put my garbage out and the LLM mentions a Date without having a clue where you are then you can be sure it just made up a Date (because you asked for a Date).

9.4.3 ‘Can you help me find my lost keys?’

9.4.4 ‘Can you create an image of a watch that says it is 3 o’ clock?’

Try it. You will find that a picture of a clock often shows 10:10. You could ask [perplexity.ai](#): Why does a generated image of a clock point to 10:10?

9.5 RAG - Retrieval Augmented Generation

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

9.6 Active Inference

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

9.7 Running LLM’s locally

On your laptop/desktop or on a company server:

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

9.8 Coding with GenAI

- [cursor course: AI Fundamentals](#)

- [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 \(AI in neovim, free\)](#)

9.9 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](#)

9.10 GenAI

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

9.11 Some more sites, nice to play around with

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

10. AI versus education

10.1 Media & Opinions

- [bron: word-geen-ai-zombie-zo-blijf-je-kritisch-in-een-wereld-vol-ai](#)
- [bron: ICT maakt eigen ‘zelf in te kleuren’ AI-opleiding mogelijk](#)
- [Saçan: Schuurpapier voor het onderwijs...](#)
- [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](#)
- [Three things chess can teach us...](#)

10.2 Tools, Best Practices & lesson material

- [EduGenai \(Npuls\)](#)
- [How to cite ChatGPT? Use AI Archive](#)
- [npuls: AI-GO Raamwerk-AI-Geletterdheid-in-het-Onderwijs](#)
- [aiarchives.org](#)
- [You did it together with AI? Make a statement!](#)

- [hbo-i-outcomes-example-generator chatbot](#)
- <https://roadmap.sh/ai>

11. Jobs and AI

July 2025

- Music: Fake or real?
- FD: ai vervangt de programmeur nog niet
- pabo-wint-aan-populariteit-ict-en-fysio-juist-niet
- UWV: Kansrijke beroepen 2025-2026

12. Resources and References GenAI

12.1 How to mention that you did use AI?

- fontys.libguides.com/apa/AI

12.2 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).

12.3 Online Platforms

- spacy.io : NLP

12.4 (Short) Courses

- [Short courses at Deeplearning.ai](https://www.deeplearning.ai)
 - Implementations of papers
 - Benchmarks
 - State-of-the-art tracking

12.5 Code Repositories

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

12.6 Community Resources

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

12.7 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)

13. No-Code / Low Code

Worth looking at:

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

Part III

AI Act Europe

14. AI Act Resources and References

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

Part IV

Train, Fine Tune, RAG

15. 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.

16. RAG: Retrieval Augmented Generation

Good to know about if you are in the AI field.

- [deeplearning.ai course: Chat with your data](#)

17. Finetune

18. 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](#)

19. Visual Recognition

CLIP-models, dyno, yolo, resnet, alexnet.

Part V

Data

20. Finding and Preparing Data

20.1 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.

20.2 Popular Data Sources

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

Part VI

Related subjects and tools

21. Tools

21.1 Agents

21.1.1 Agent Development Kit

- [HF: Introduction to Agents](#)
- <https://google.github.io/adk-docs/><https://google.github.io/adk-docs/>

21.1.2 Open Agent Platform

- docs.oap.langchain.com

21.2 MCP - Model Context Protocol

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

- modelcontextprotocol.info/
- [Example Clients](#)
- mcpservers.org

- github.com/r-huijts
- Servers
- Greg Isenberg/Ras Mic explaining MCP
- short course MCP at deeplearning.ai
- Ruud [mijn-nieuwe-mcp-server-laat-ai-zichzelf-actief tegenspreken](#)

22. Agents

22.1 Agent Development Kit

- [HF: Introduction to Agents](#)
- <https://google.github.io/adk-docs/><https://google.github.io/adk-docs/>

22.2 Open Agent Platform

- docs.oap.langchain.com

23. MCP - Model Context Protocol

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

- modelcontextprotocol.info/
- [Example Clients](#)
- mcpservers.org
- github.com/r-huijts
- [Servers](#)
- [Greg Isenberg/Ras Mic explaining MCP](#)
- [short course MCP at deeplearning.ai](#)
- [Ruud mijn-nieuwe-mcp-server-laait-ai-zichzelf-actief tegenspreken](#)

24. ACP - Agent Communication Protocol

To let Agents communicate, no matter what framework the Agents were built in.

- agentcommunicationprotocol.dev
- deeplearning.ai on ACP

25. Div tools that could be interesting

26. Journalism and AI

- [stichtingrpo.nl: introductie-ai-kompas](#)
- [Hey Aftonbladet \(chatbot\): What do YOU want to know?](#)

Part VII

Neuron & Network

27. If you prefer a story...

The story that follows right here explains the ideas behind a Neural Network from a technical perspective. If you would rather read an Instructive Story, a Saga, read it online at: [Lonn's neural-net-saga](#). Scroll down a bit and start reading 'The Percy Chronicles: A Neural Network Saga'. At the end of that story you will find some python to get hands-on with.

28. Understanding the Perceptron

28.1 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.

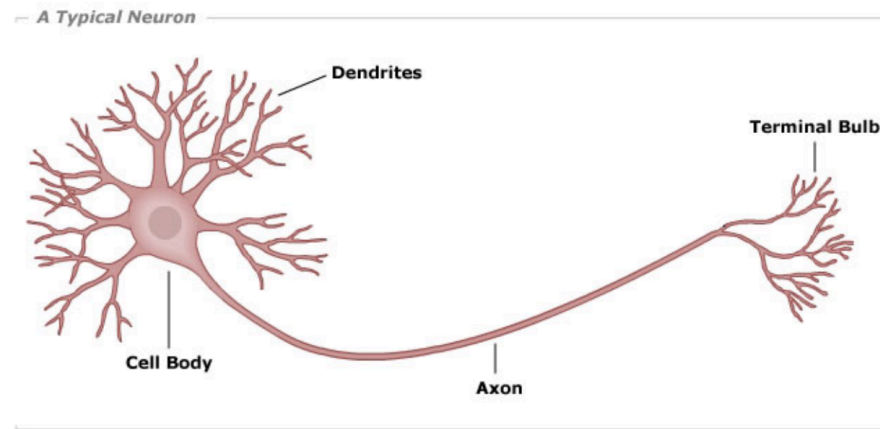


Figure 28.1: A typical biological neuron structure

28.2 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.

28.2. FROM BIOLOGY TO MACHINE: IMPLEMENTING A PERCEPTRON⁸⁷

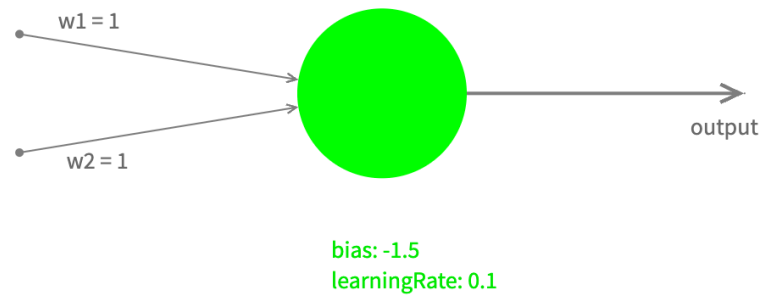


Figure 28.2: Perceptron's architectural diagram

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: $z := w1*x1 + w2*x2 + bias$
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:

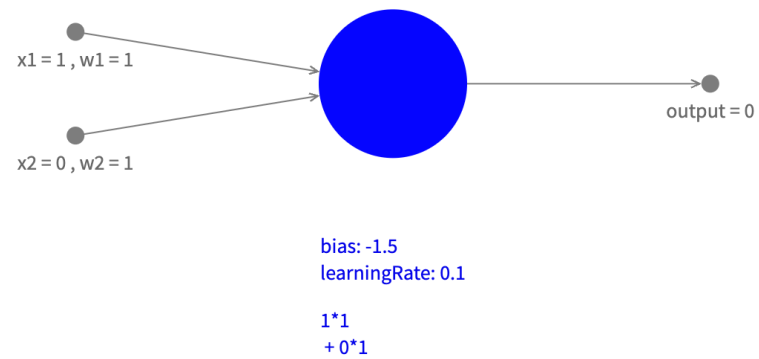


Figure 28.3: Perceptron's architectural diagram

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

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

Input 1	Input 2	Output
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?

28.3 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).

28.4 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.

28.5 Reference

- [wikipedia: perceptron](#)

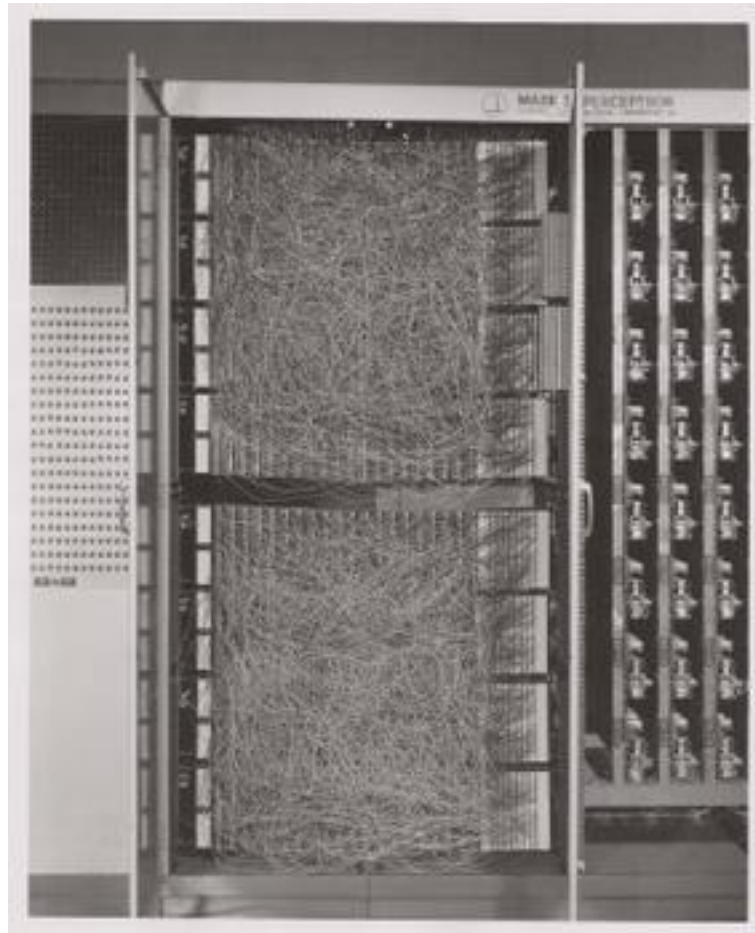


Figure 28.4: The Mark I Perceptron machine, the first implementation of the perceptron algorithm (source: wikipedia)

29. 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.

29.1 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

29.1.1 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

29.1.2 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)
```

29.2 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

29.3 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.

30. Understanding Perceptron Limitations

30.1 The XOR Problem: A Classic Challenge

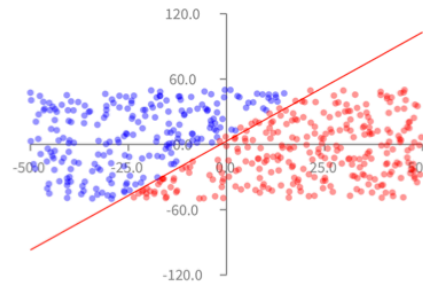
While Perceptrons are powerful tools for many classification tasks, they face a fundamental limitation: they can only solve linearly separable problems. The classic example of this limitation is the XOR (exclusive OR) function.

30.1.1 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

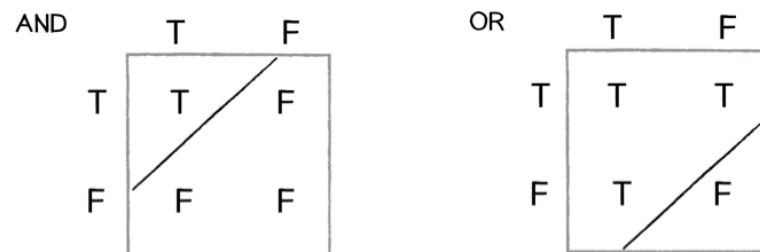
Figure 30.1: Visual representation of XOR problem

30.1.2 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



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Figure 30.2: Attempted linear separation of XOR

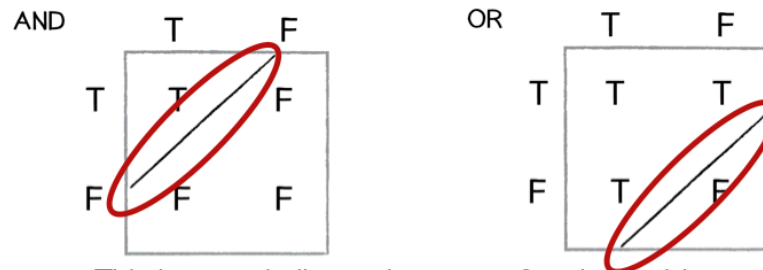
As you can see, no single straight line can separate the points where output should be 1 (blue) from points where output should be 0 (red).

30.2 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

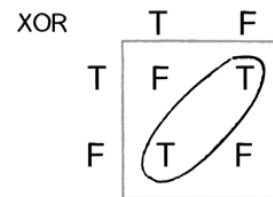
39

Figure 30.3: 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

Figure 30.4: Complete neural network solution

30.3 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.

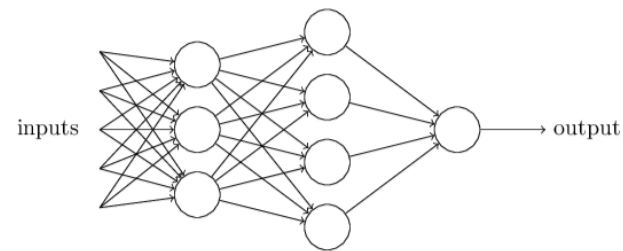
31. Introduction to Neural Networks

31.1 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



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Figure 31.1: Basic neural network architecture

31.2 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 Percep-

trons

3. **Output Layer:** Produces the final result

31.2.1 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

31.3 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

31.4 Creating a Simple Network

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

Neural Networks can

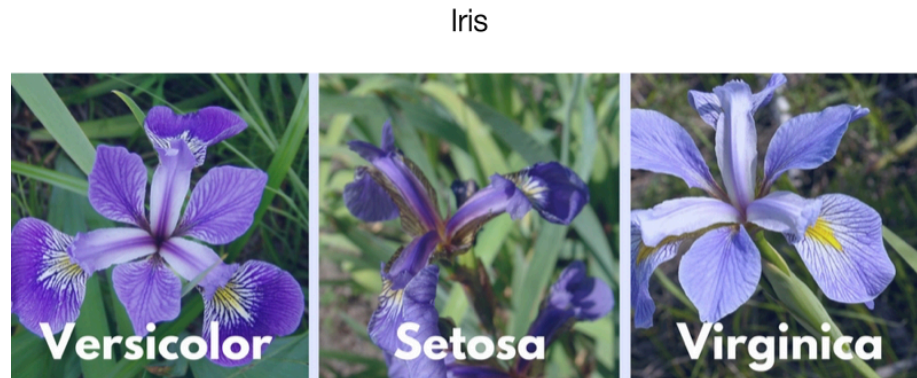
1. solve problems that are more difficult.
2. Handle complex pattern recognition
3. Learn hierarchical features automatically
4. Scale well to large problems

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

32. Practical Example: Classifying Iris Flowers

32.1 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.



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Figure 32.1: Different types of Iris flowers

32.2 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**.

32.3 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.

33. The Mathematics Behind Neural Networks

33.1 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.

33.2 The Building Blocks

33.2.1 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: $a = f(z)$

33.2.2 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

33.3 The Learning Process

33.3.1 1. Forward Propagation

Information flows through the network.

33.3.2 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.

34. Exploring Neural Network Architectures

34.1 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.

34.2 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

34.3 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

34.4 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

34.5 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

34.6 Autoencoders

Self-learning networks:

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

34.7 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

34.8 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

34.9 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.

35. Resources and References AI

35.1 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](#)

35.2 Video Courses and Tutorials

35.2.1 1. Foundational Series

- [3Blue1Brown Neural Networks](#)
 - Visual explanations
 - Mathematical intuition
 - Clear animations

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

35.2.2 2. Programming Tutorials

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

35.2.3 3. Advanced Topics

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

35.3 Online Platforms

35.3.1 1. Interactive Learning

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

35.3.2 2. Research Papers

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

35.3.3 3. Code Repositories

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

35.4 Community Resources

35.4.1 1. Forums and Discussion

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

35.4.2 2. Blogs and Newsletters

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

35.4.3 3. Tools and Libraries

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

35.5 Academic Papers

35.5.1 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)

35.5.2 Podcasts

- [MLST: Machine Learning Street Talk](#)
- [Brainport/Iman interviews Sepp Hochreiter: XLSTM](#)
- other podcasts from this series: ‘Deep Dives with Iman’.
- [Fontys AI Garage](#)

35.5.3 Other

- email news letter: alphasignal.ai

Part VIII

Experiments

36. Experiments

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

37. 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/>

38. 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.

39. MCP Client

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

