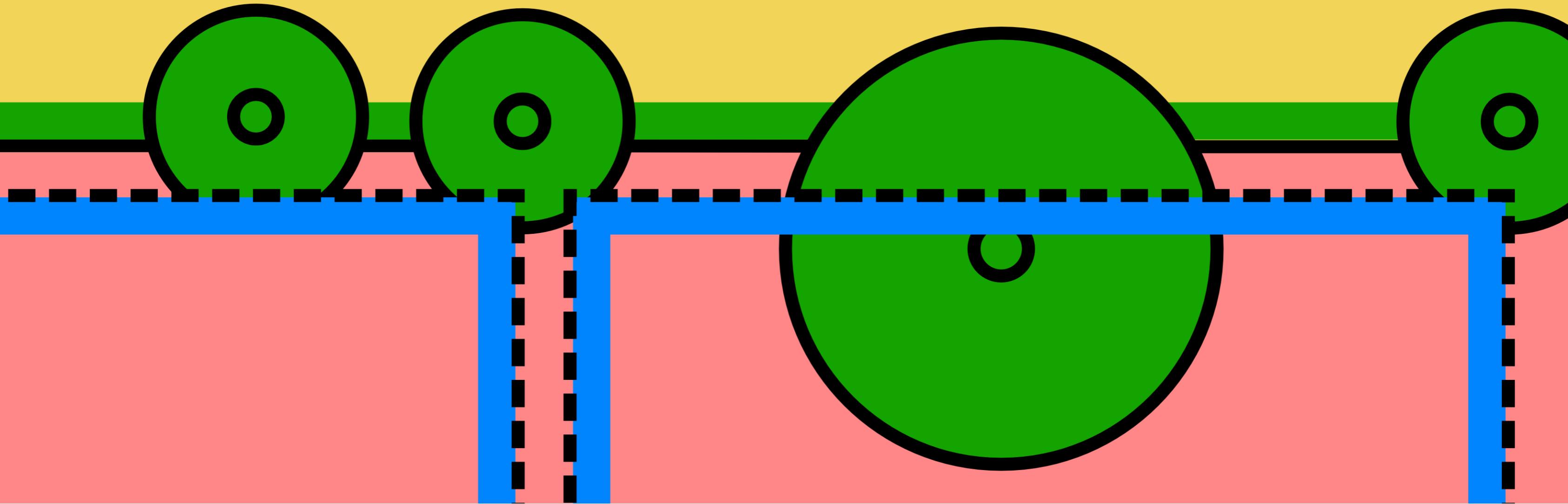


Digital Urban Land-Use Planning – How AI Systems Understand Development Plans

October 30th / Michael Schwarz



Moin! 🙌

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Studied **Computer Science M.Sc.**
with specialization in **Data Science**
at the TUAS Augsburg



Digitale Visitenkarte: <https://zeeg.me/schwamic>



Master Thesis

The aim of my master's thesis was to analyse the extent to which *Multimodal Large Language Models* are able to understand *Development Plans*. The investigations for the design and evaluation of an ai system explicitly relate to the *text comprehension of dev-plans*.



15.05.2024 – 06.09.2024

Process Steps



**Domain
Knowledge**



**Multimodal Large
Language Models**



**Experiments &
Evaluation**



Would you like a short recap?

URBAN LAND-USE PLANNING / DEVELOPMENT PLAN

Documents of a Development Plan

**Plan
Drawing**

**Explanation
of Symbols**

**Text
Part**

**Geo
Referenzing**

PDF, Image

PDF, Image

PDF, Image

TIF, TFW

Data
Types

DWG, DXF, XPlanGML

Docx, XPlanGML

Docx, XPlanGML (partly)

Documents of a Development Plan (2024)

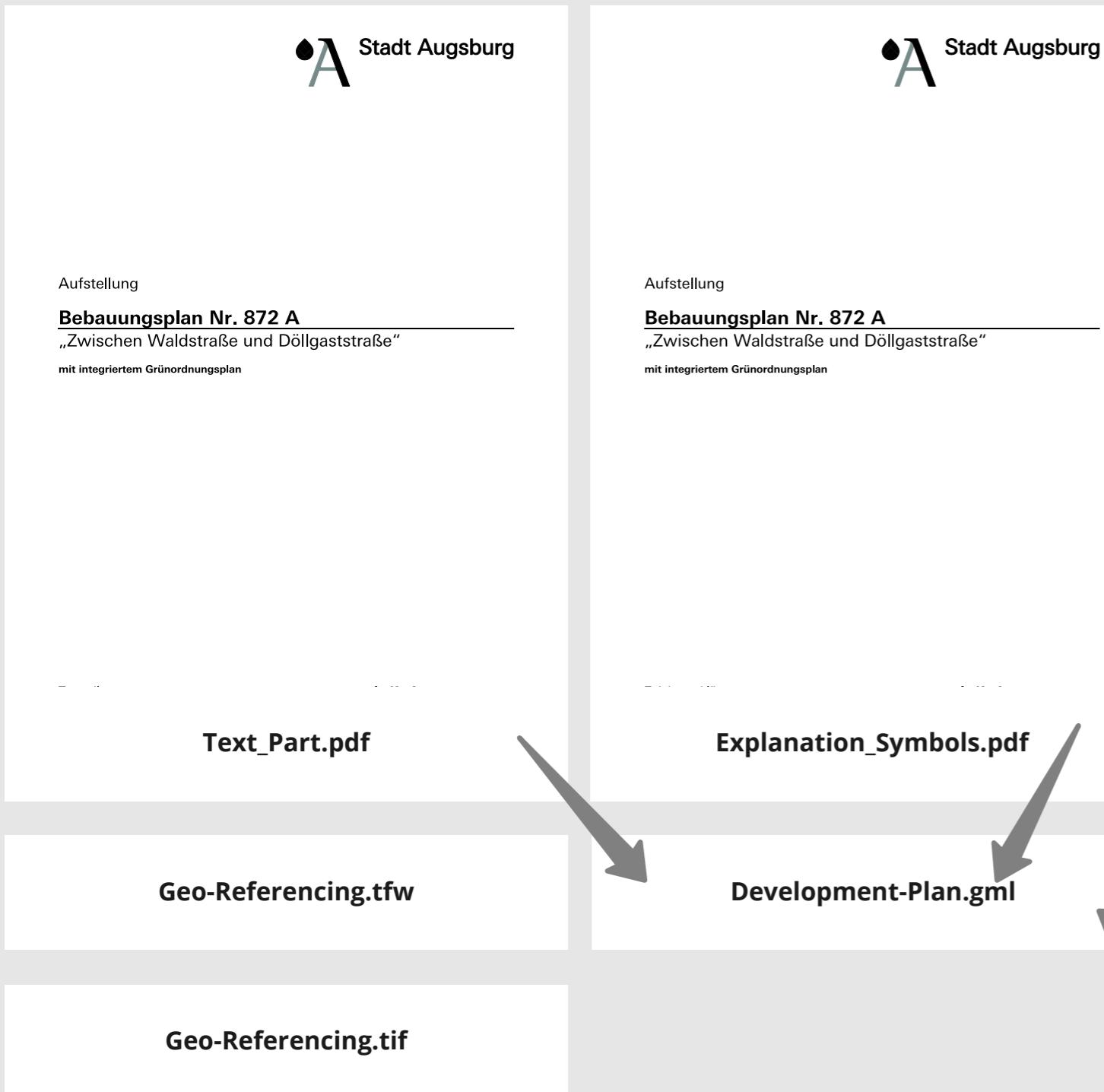


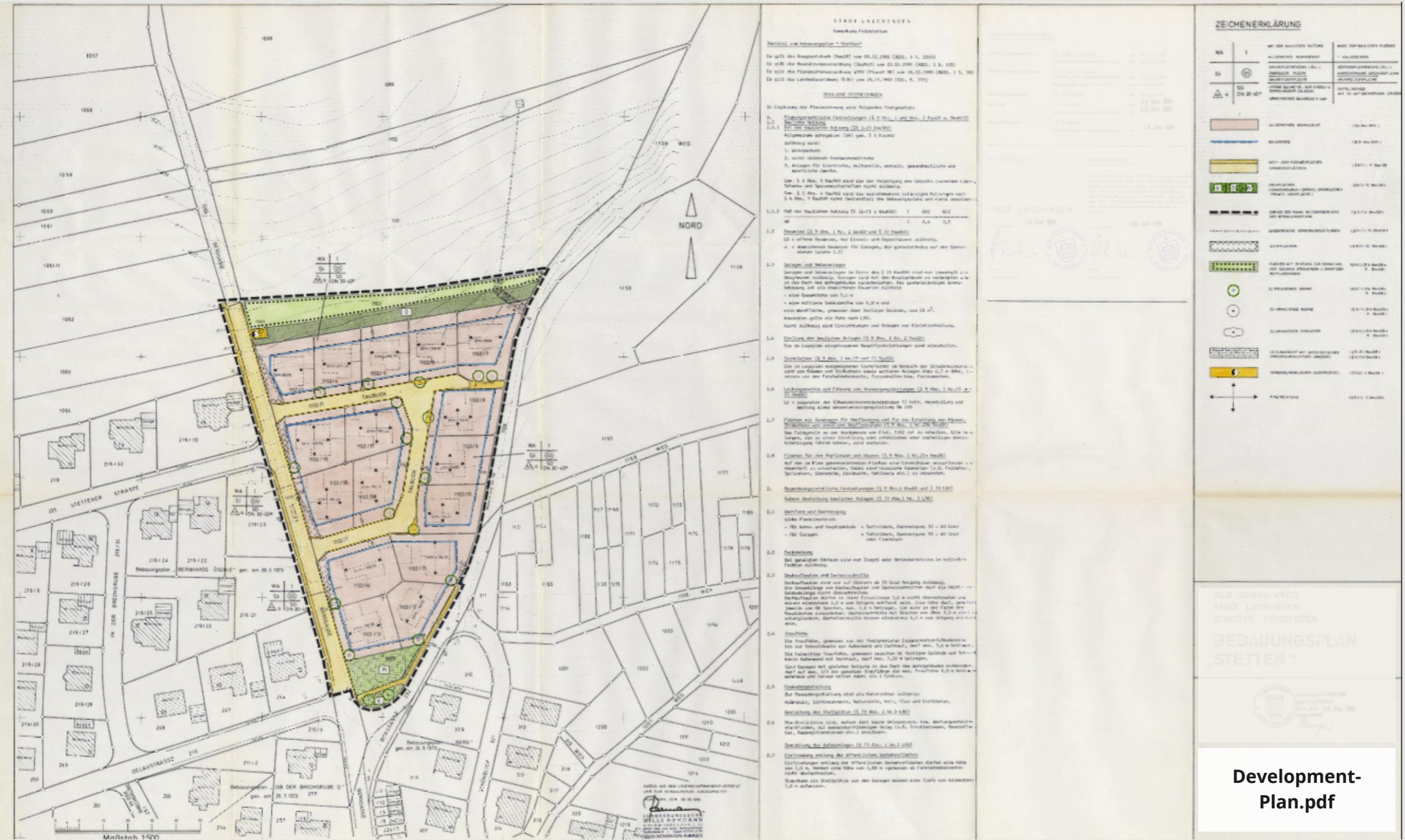
Figure 4

Documents of a Development Plan (1994)

Plan-Drawing.DWG/.DXF



Geo-Referencing.TIF/.TFW



MULTIMODAL LARGE LANGUAGE MODELS

Neural Networks

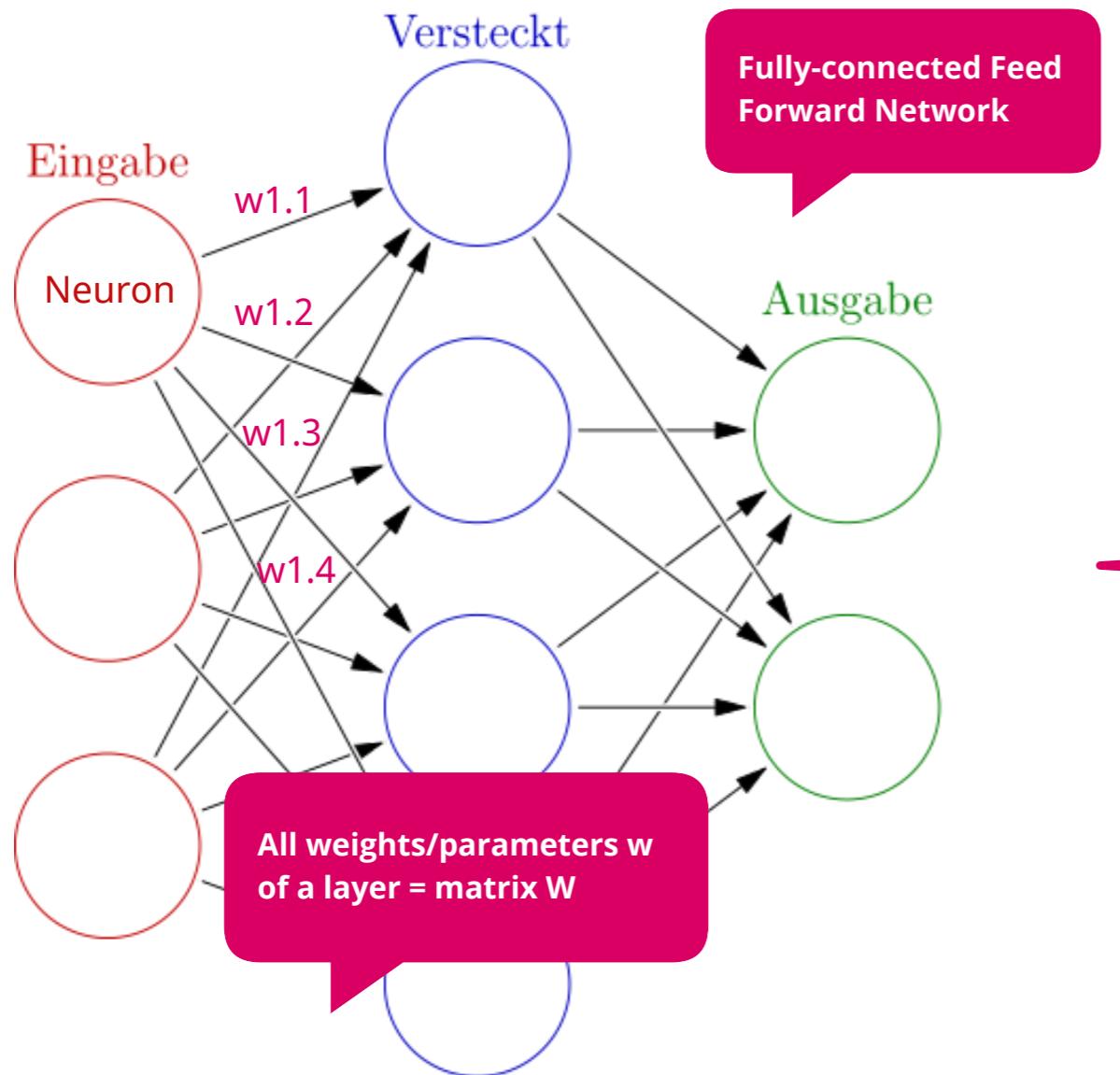


Figure 5

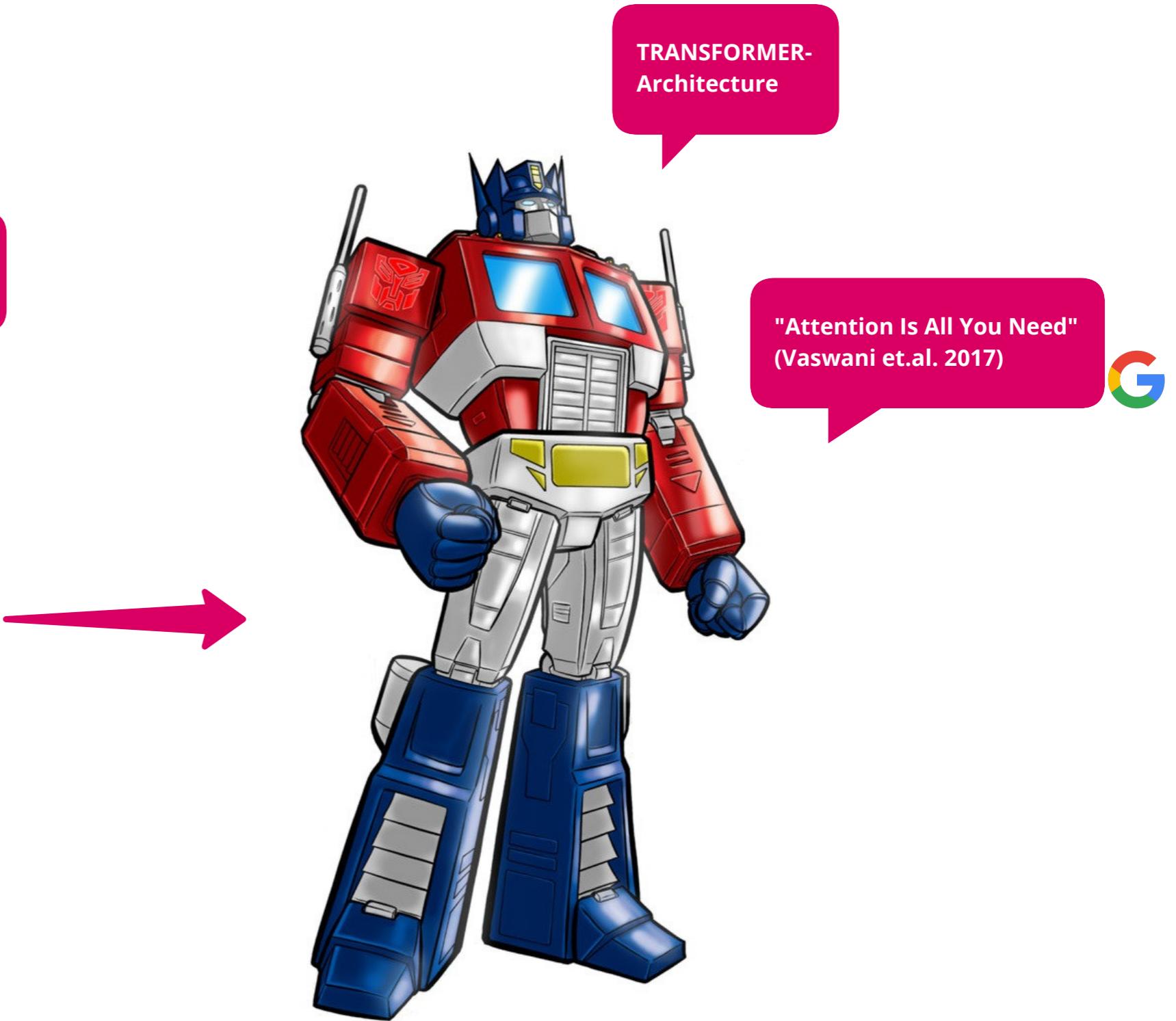


Figure 6

Machine Processing Of Language - Vector Representations

King + Woman - Man \approx Queen (Analogies) 😈

"Efficient Estimation of
Word Representations in
Vector Space"
(Mikolov et.al. 2013)

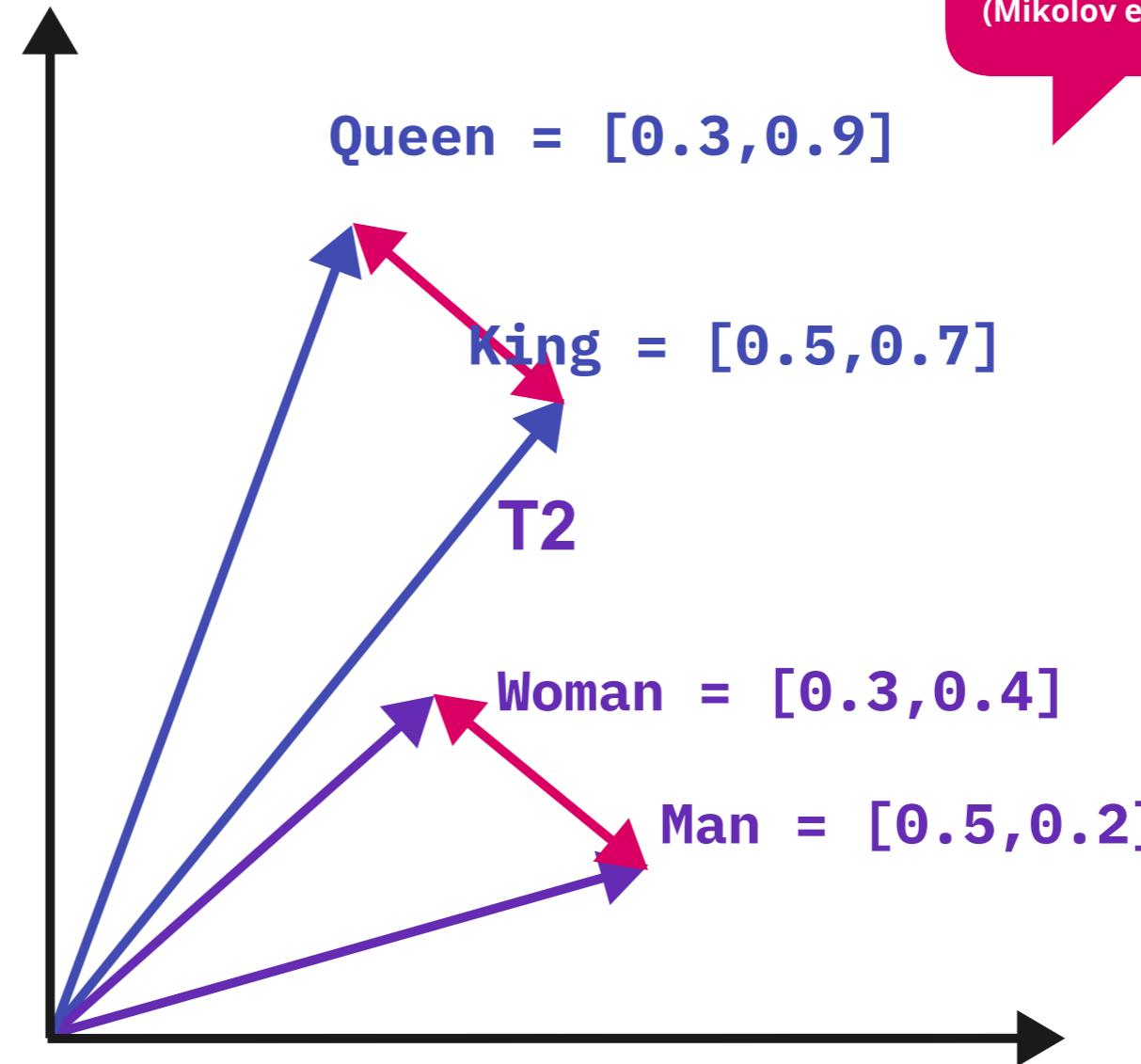
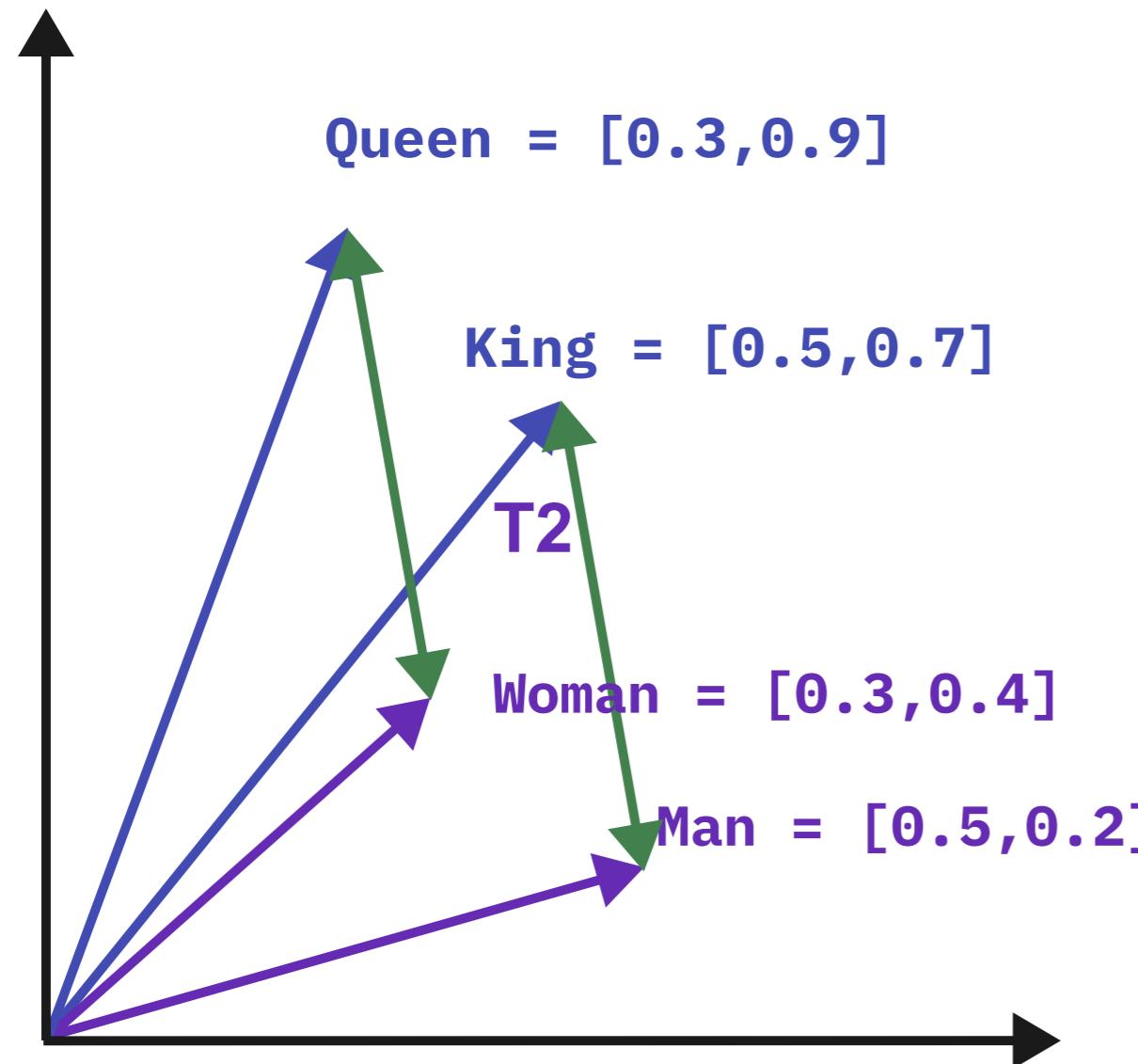
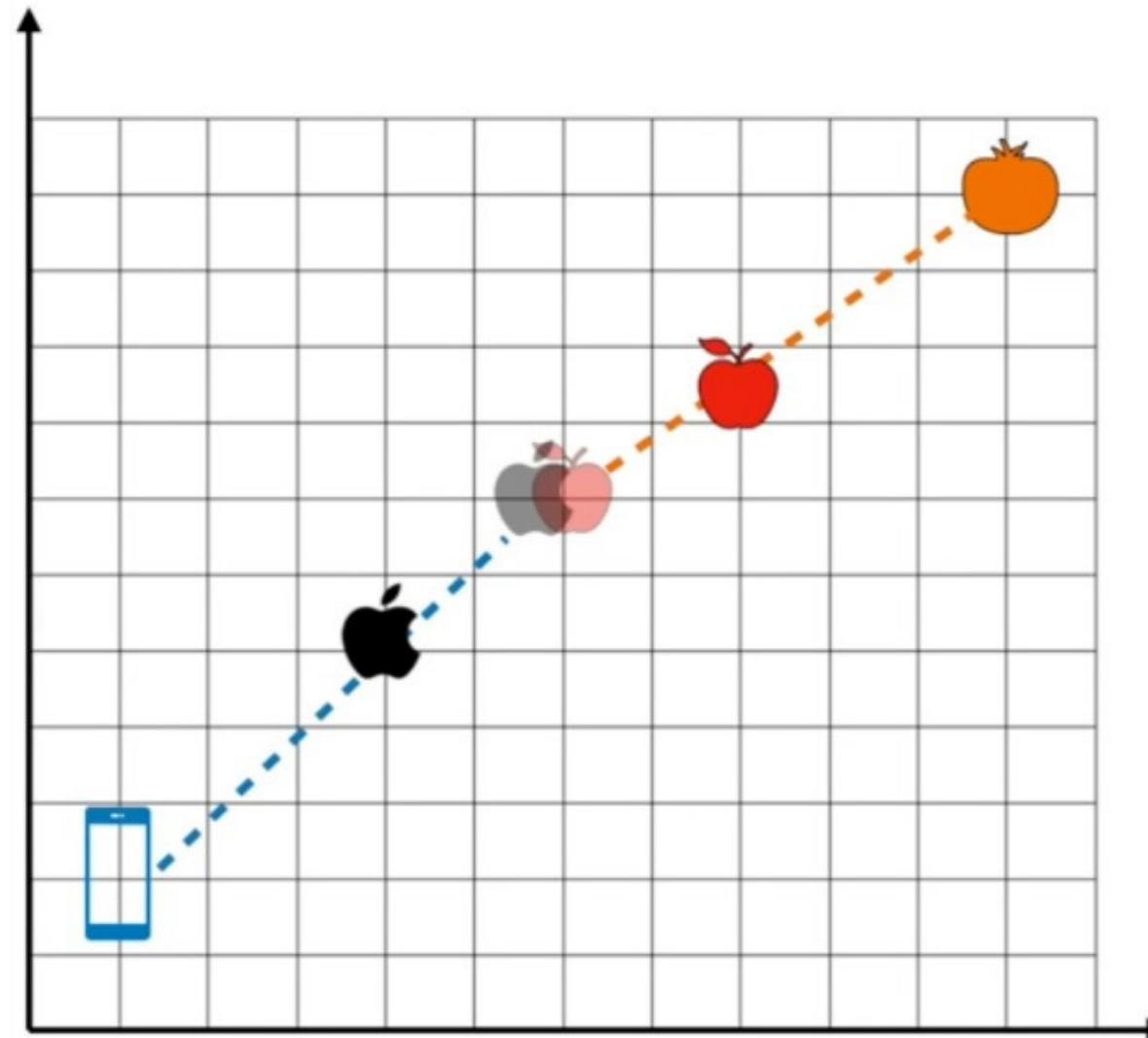


Figure 7

Machine Processing Of Language - Attention



please buy an **apple** and an **orange**

apple unveiled the new **phone**

Figure 8

Machine Processing Of Language + Vision via CLIP

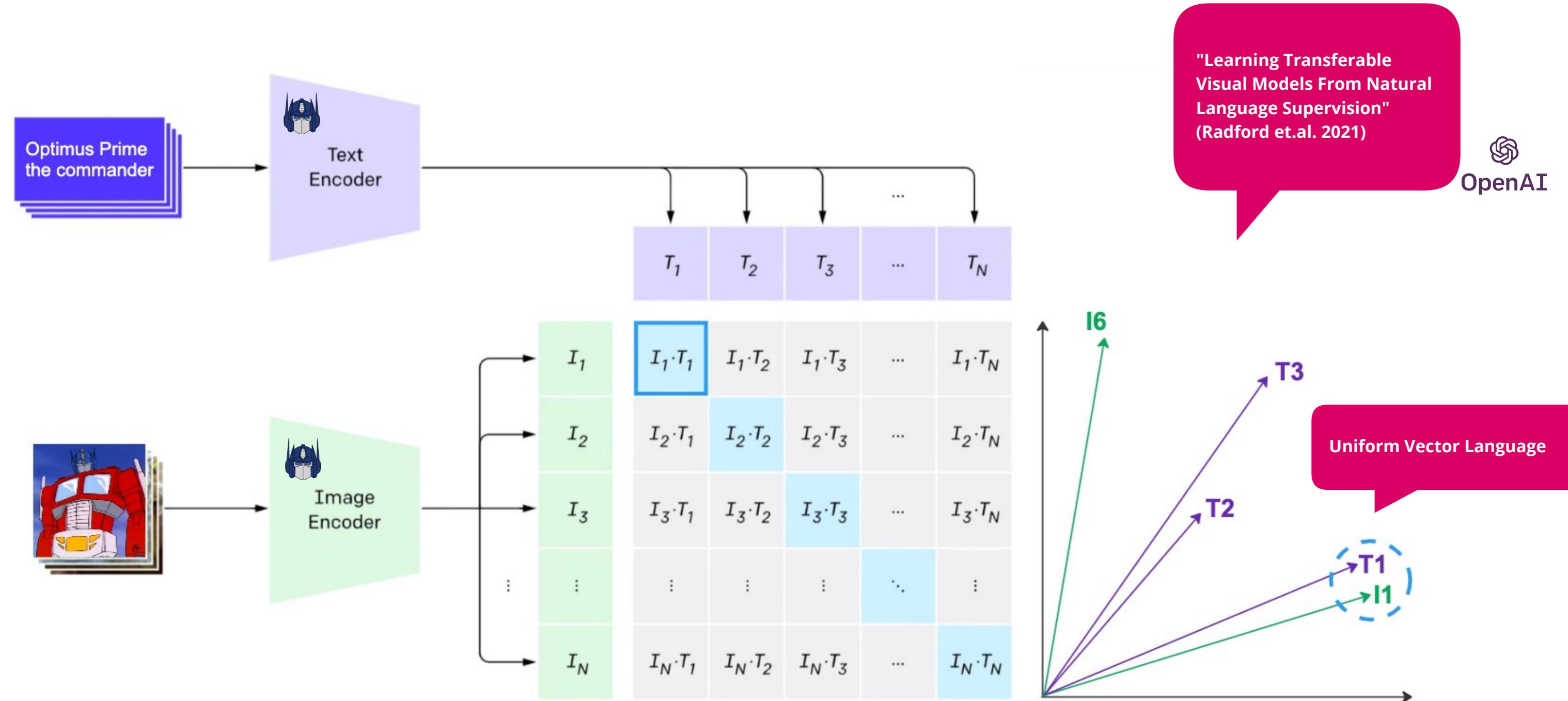


Figure 9

Large Language and Vision Assistant - LLaVA 1.0

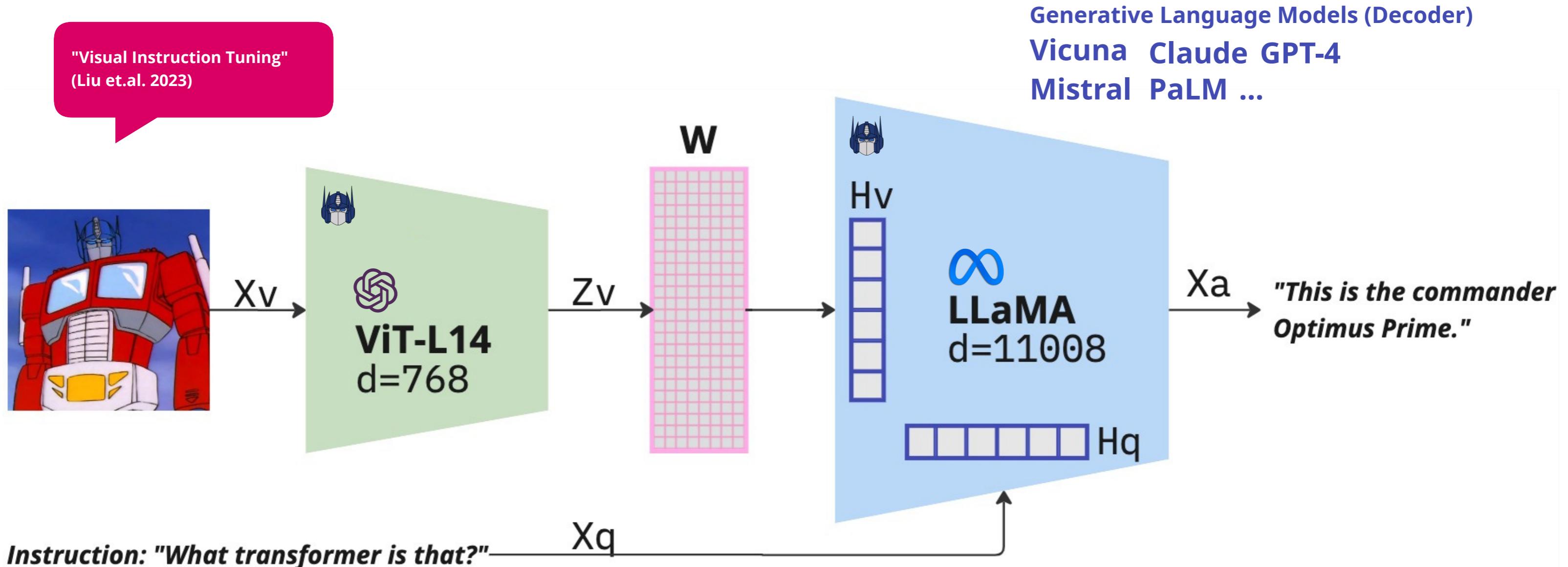
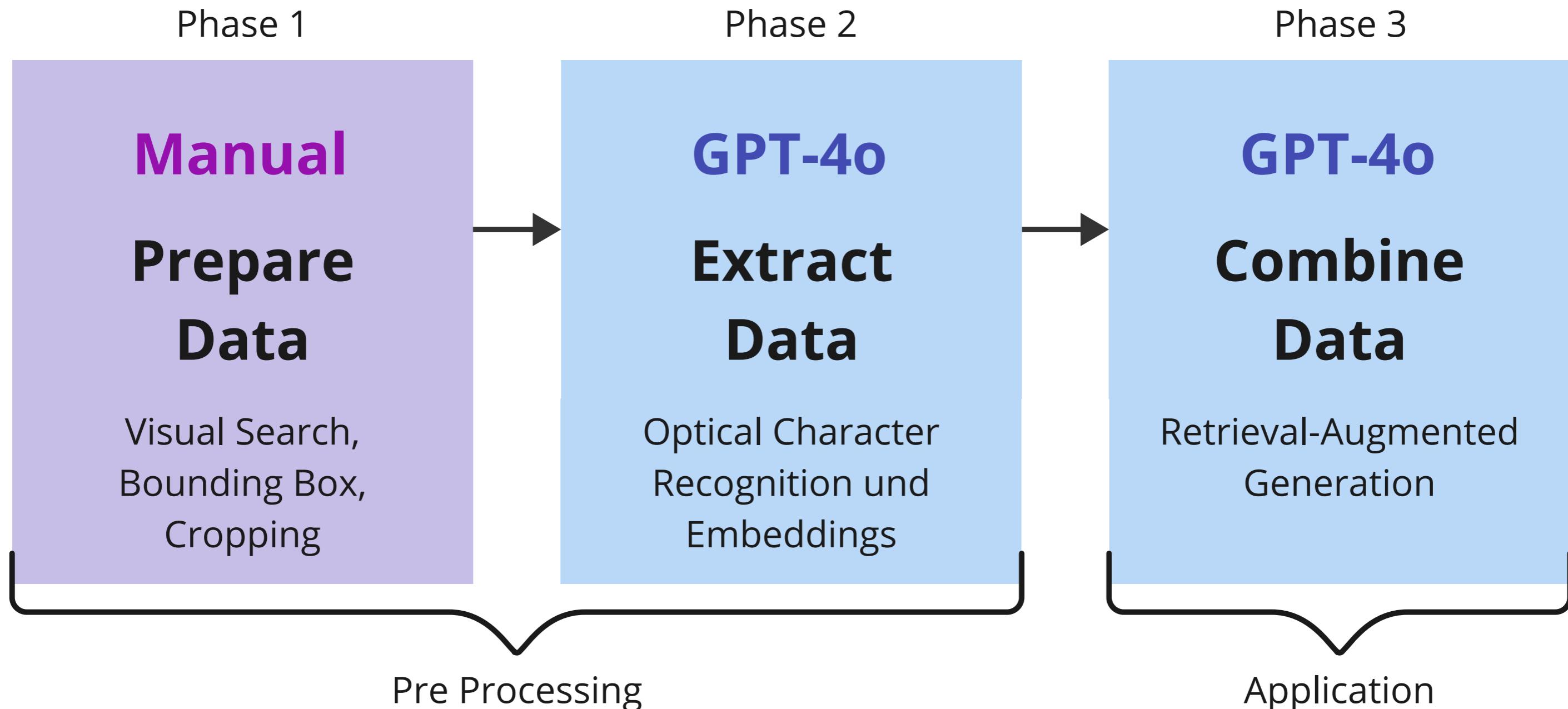


Figure 10

EXPERIMENTS & EVALUATION

Architecture – Prompt-Chain



Planning Permission Process - Final Result of GPT-4o [Phase 3]

Festsetzungen	Bauantrag	GPT-4o	widerspricht / entspricht	Korrekt	Konsistent
Art der baulichen Nutzungs 	<ul style="list-style-type: none"> Wohnhaus 	<ul style="list-style-type: none"> Erlaubt ist ein Gebäude im Allgemeinen Wohngebiet (WA) (§ 4 BauNVO). (Kapitel 1.1.1) 		3/3	3/3
Maß der baulichen Nutzungs 	<ul style="list-style-type: none"> Lageplan (zeichnerischer und schriftlicher Teil) GRZ 0,17 / GFZ 0,35 Zahl der Vollgeschosse II 	<ul style="list-style-type: none"> Die festgesetzte Grundflächenzahl (GRZ) ist 0,3 und die Geschossflächenzahl (GFZ) ist 0,5. (Kapitel 1.1.1) Es ist ein Vollgeschoss erlaubt. (Kapitel 1.1.3) 	 	3/3	3/3
Bauweise	<ul style="list-style-type: none"> Lageplan (zeichnerischer Teil) mit seitlichen Abstandsflächen 	<ul style="list-style-type: none"> Die festgesetzte Bauweise ist die offene Bauweise (0). (Kapitel 1.2) 	Das ist mir nicht bekannt.	3/3	3/3

Prompt Setup - Jupyter Notebooks

```
from utils.openai import OpenAI
from utils.runner import Runner

# Initialisierung
instructions = "Du bist ein Assistent zur getreuen Wiedergabe von Informationen aus einem Bebauungsplan. Achte auf Vollständigkeit."
chatGPT = OpenAI(instructions)
runner = Runner()
```

```
# Datenquelle
img_path = "../data/processed/bpläne/1_alles_in_einem_dokument/L04-ZE-TT-crop.png"
pdf_path = "../data/raw/bpläne/2_zeichnung_textteil_getrennt/F11-PZ-ZE.pdf"

# Aufgabe durchführen
instruction = 'In welchem Jahr ist der vorliegende Bebauungsplan in Kraft getreten? Ausgabe im JSON-Format: {"Gültig seit": <YYYY>}'
async def run():
    msg1 = await chatGPT.extractTextFromImage(instruction, img_path)
    msg2 = await chatGPT.extractTextFromImage(instruction, pdf_path, "pdf")
    return [msg1, msg2]
results = await runner.async_consistency_check(run)

# Ergebnisse speichern
msg1_l04_year, msg1_f11_year = results[0]
%store msg1_l04_year msg1_f11_year
```

„To what extent are MLLMs able to understand dev-plans?” [RQ1]



„How good is the quality of the extracted data?” [SQ1.1] - Phase2

- *SL-1A*: Plan drawing
- *SL-1B*: Symbol declaration document
- *SL-1C*: Text part document



„To what extent can an understanding of the extracted data be created?” [SQ1.2] - Phase3

- *SL-2A*: Extract information from collected *SL-1* data
- *SL-2B*: QA capabilities with regard to the known data from *SL-1*

How good is the quality of the extracted data?

[RQ1][SQ1.1] – Phase2

- GPT-4o was able to extract text information in *adequate quality BUT depends very much on the pre-processing and visual structure* of the dev-plan documents.
- Accordingly, it can be assumed that GPT-4o extracts content mostly *based on visual characteristics*, so that *domain specific connections can be overlooked or misinterpreted*.
- Limitations also became apparent, such as the *lack of geo referencing*.



In order *to achieve reliable and high quality, the MLLM would have to be trained for specific tasks and learn domain knowledge.*

To what extent can an understanding of the extracted data be created? [RQ1][SQ1.2] – Phase3

- MLLMs such as GPT-4o have a *sufficient understanding of language to correctly link domain-specific content* with each other and to deal with user instructions.
- However, the understanding of MLLMs is *strongly dependent on the expertise provided*, which was also illustrated in the step "Bauweise".
- Likewise, *GPT-4o did not question the context information provided*, which indicates that *GPT-4o has little domain specific understanding*.



For a robust understanding, the MLLM would need to learn basic domain knowledge and retrieval evaluation skills.

„Can MLLMs understand the contents of machine-readable development plans at least as well as humans can?“ [RQ2]

 *GPT-4o can not understand dev-plans as well as humans can.* However, the results also show that a *human and MLLM as a team, may be able to understand dev-plans better* than a human could without the support of AI.

- *GPT-4o did not have to figure out which test steps are relevant for the permission process of the construction project.*
- GPT-4o is *currently not able to carry out geo-referencing or a precise comparison between a dev-plan and a construction plan*, which severely *limits the number of feasible test steps* within an permission process.
- *The strengths of GPT-4o are its ability to recognise associations and relationships* between text content.
- This allows information to be *extracted and searched efficiently*. Accordingly, GPT-4o was able to *achieve very good results in the minimal RAG application* on the basis of the contextual knowledge provided.

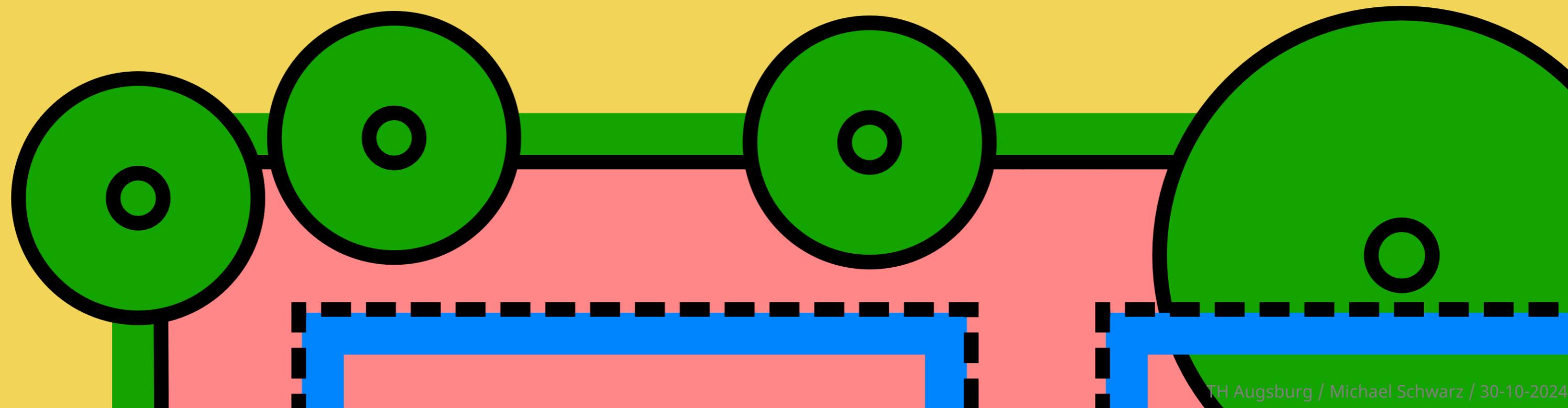
Further Research Opportunities



Possible applications of **MLLMs** for **RAG scenarios** in the field of urban land use planning.



Pre-train **CNN** models to extract **graphical unstructured information** from dev-plans reliably.



MANY THANKS!



for the great projects we did together
during my Master's programme!

- *Study Project: Mobile App for Managing Building and Room Data for AI-Supported Analyses*
- *Master Thesis: Digital Urban Land-Use Planning - How AI Systems Understand Development Plans*

Links & Sources

- [**Master Thesis \(GitHub\)**](#)
- [**Huggingface \(Transformer\) / LangChain / LLamaIndex**](#)

Figure 1 und 2: THA Prof. Fina, Skript Umfeldplanung 2023

Figure 3: <https://www.musterhaus.net/ratgeber/bebauungsplan-lesen-und-verstehen>

Figure 4: Bebauungsplan der Stadt Augsburg

Figure 5: https://wikimedia.org/wikipedia/neural_network_de.svg.png

Figure 6: http://img3.wikia.nocookie.net/_cb20140629204205

Figure 7: <https://www.researchgate.net/figure/The-classical-king-woman-man-queen-example>

Figure 8: https://www.youtube.com/watch?v=UPtG_38Oq8o

Figure 9: Darstellung angelehnt an <https://arxiv.org/abs/2103.00020>

Figure 10: Darstellung angelehnt an <https://arxiv.org/abs/2304.08485>