Building with AI

Meet the team

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Agenda

1

Setup

Env setup
Quick LLM/AI basic concepts intro

2

RAG from ground up

Understanding the components of a RAG system from within

3

Agentic World

Everything got simpler with the agentic approach

4

Closing thoughts

Ideas and Resources to take for your use-cases

Setup

- Fetch the repo
- ./run_all.sh build
- ./run_all.sh start
- ./run_all.sh pull_model gemma3:4b
- ./run_all.sh start_model gemma3:4b
- ./pivot2025-shell.sh
- ./python3 chat_test.py

Basic concepts

Large Language Model

In simple words it’s a list of tokens with different weights

Basically massive precomputed neural network of interconnected tokens.

Current models are NOT open sourced, we only know the weights we don't know the relation between the words

Concepts

Large Language Model usage components

Prompt

Inference engine

Interface

Agents/tools (model tools and agents)

Model

Large Language Model usage components

Prompt – A template of communication with the LLM. Contains certain special tokens to mark positions with intent.

Inference engine – The engine that will run the prompt on the model, Ollama, LLamaCPP,

Interface – We need to send the data somehow. REST api, web page, app, etc

Large Language Model usage components

Where can we get models? Huggingface (for open souce), model provider APIs

Interesting models:

- LLama the model we will be using
- MS Phi models are interesting because they are SLMS (Small Language models)
- Gemma Google open weight models family

Layers

Closest to the metal

Optimizations here primarily speed up

Heart of the chain

Can finetune

Can Retrain

System Prompt

Previous conversation

Improve through RAG

The instructions for the newest task

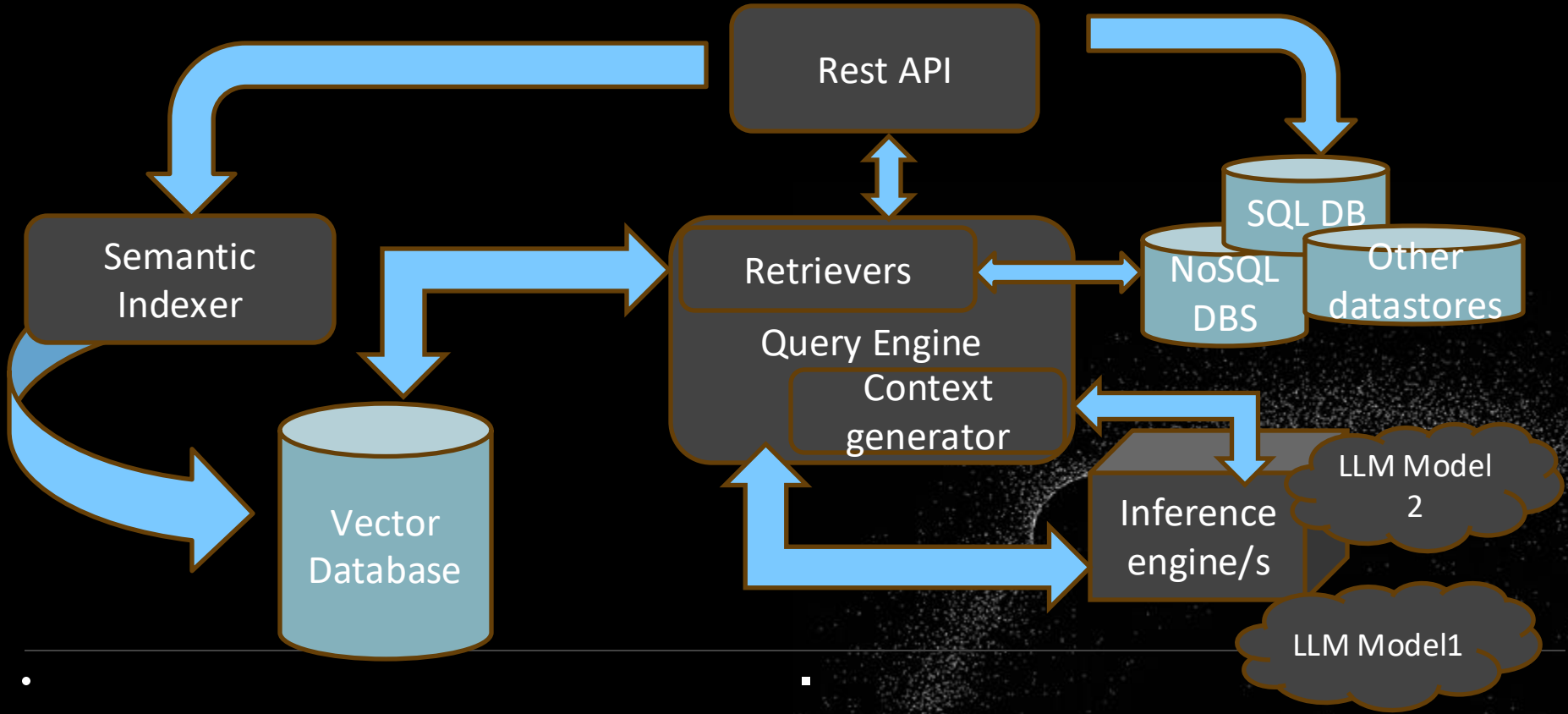
Can be improved through adaptive prompting

Models own self-directed interaction with real world

To gather data and effect action

RAG from ground up

Possible RAG architecture



RAG Step 1: Indexing

1. First we start by indexing data
   - We need to index it in such a way that we keep the semantic similarity.
   - Then we store it on the vector database.

But what is semantic similarity and how do we achieve it?!

- It can't be just a word, otherwise you would lose the semantic meaning.
  (And for that we already have fuzzy logic and BM25 full text search algorithms)

RAG Step 1: Indexing

We need pieces of information to which we will call chunks.

Chunks can be created by splitter

- A splitter will split the information based on textual characteristics of the information

Examples:

Text splitter, Character splitter, Recursive Character Splitter, Sentence splitter, Semantic splitting

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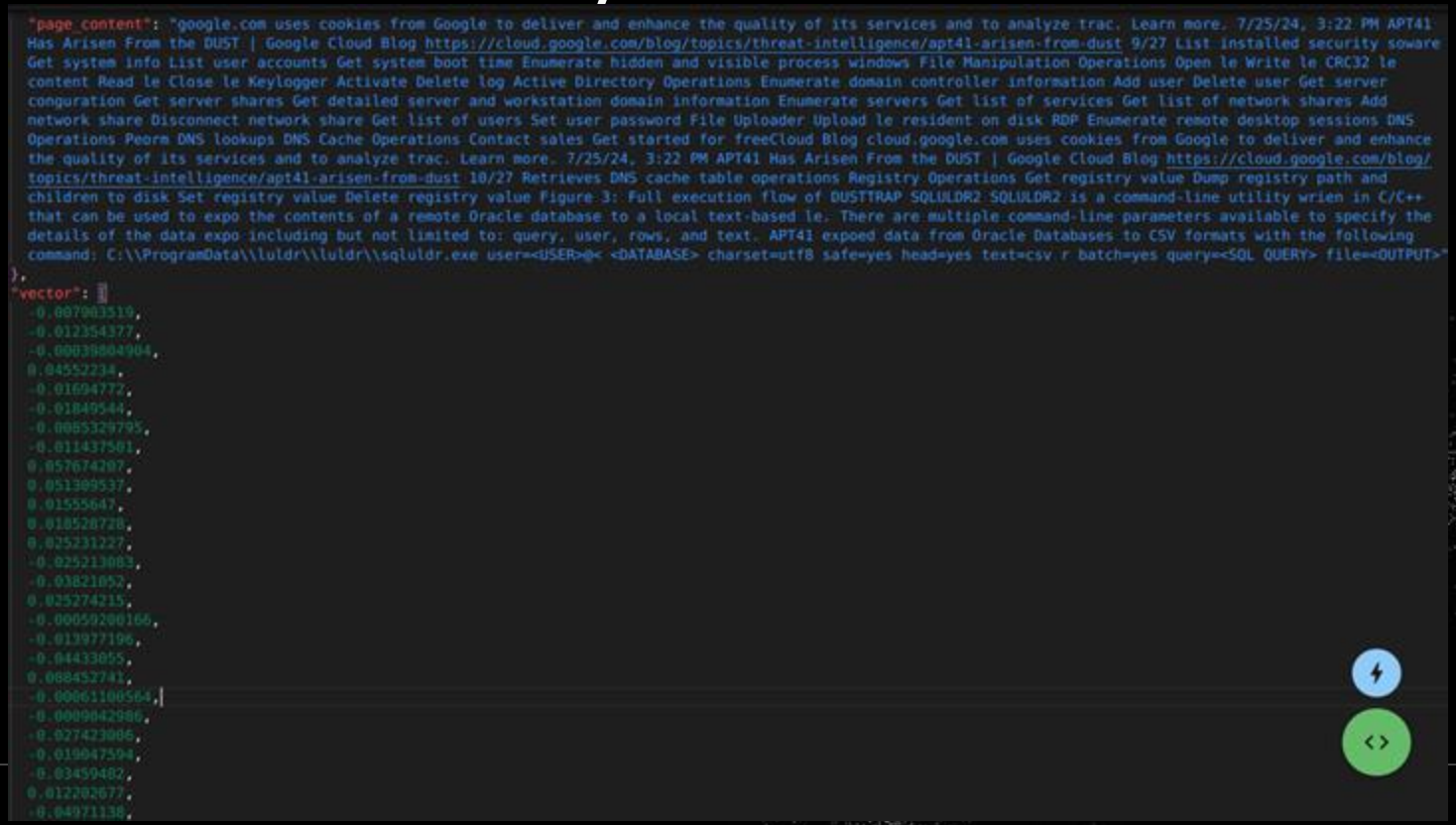
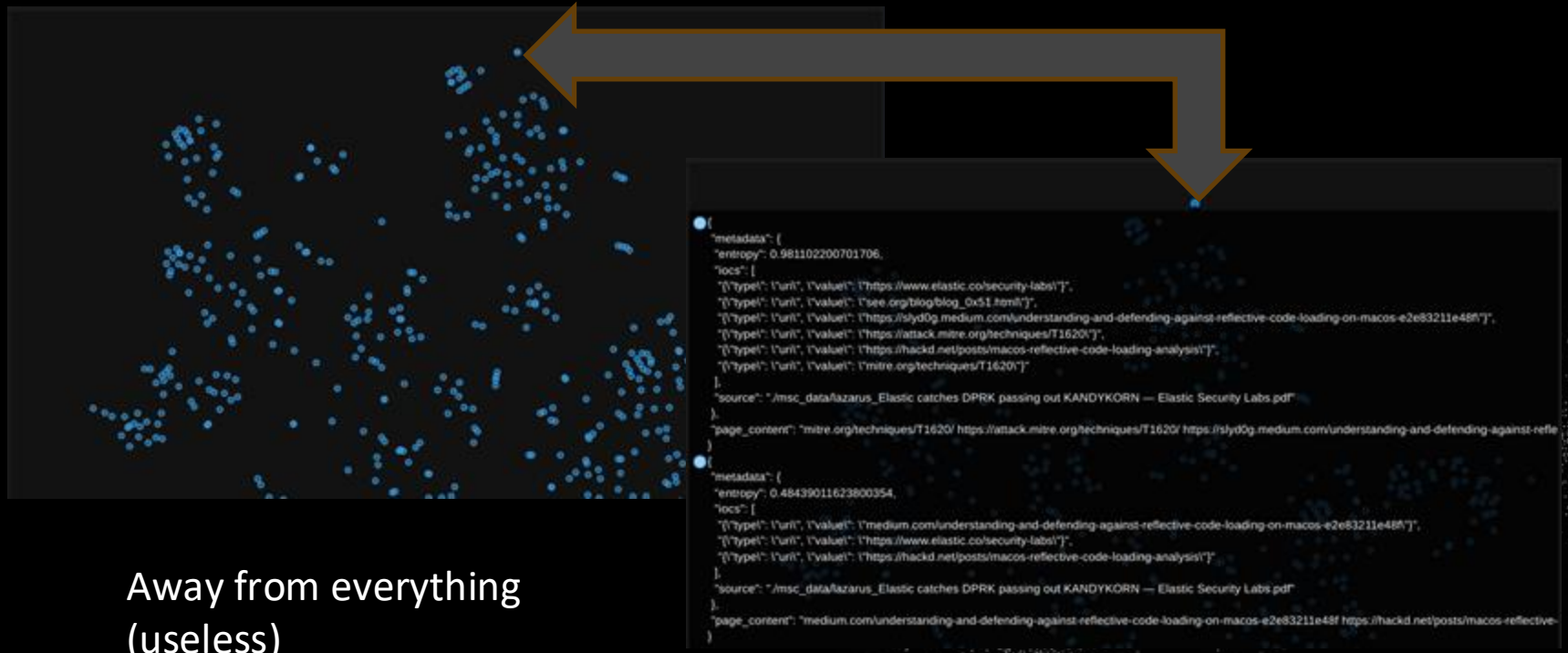
And we embed those chunks:

Embeddings are a vector of floats between -1 and 1

How to semantically index data



How to semantically index data



Away from everything
(useless)
content similar

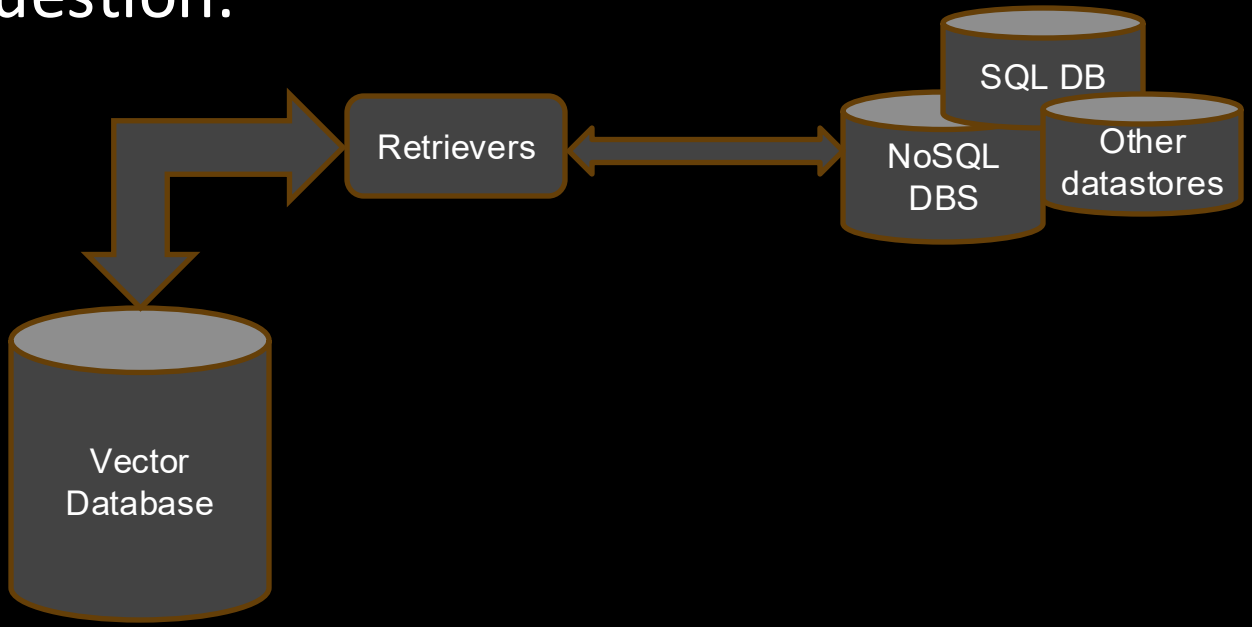
How to semantically index data

Not perfect but
we can see some
clustering

Retrievers

We want to retrieve the information relevant for our question.

Vector search
Hybrid search
Fulltext search
Others



Context generators

What is context?

Information that is given to the LLM to generate the answer.

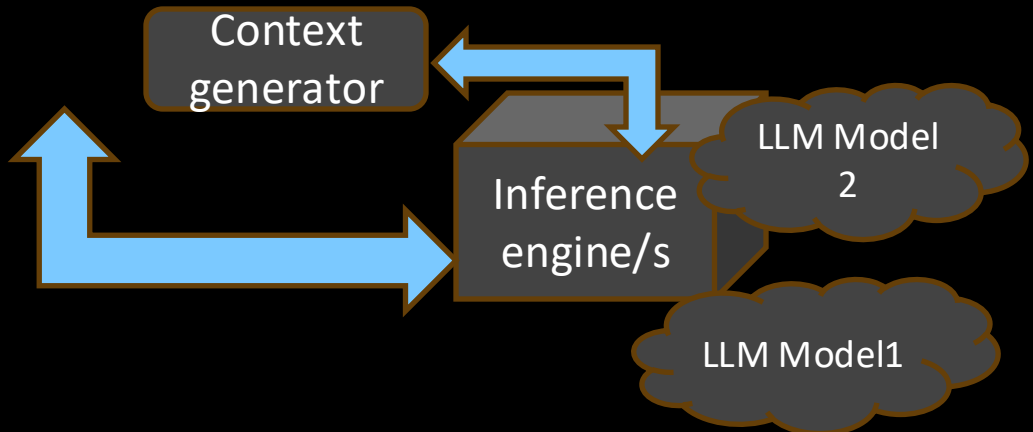
This information is collected from the available sources

It increases the LLM "knowledge" beyond the contents of the training dataset.

Context generators

What is context generator?

- Multiple sources of context
- Quality assurance
- Context merging and reranking
- Previous interactions
- AI agents



Context generators - advanced

- Merge all context and summarize
- Remove noise from the context
- Recursively search for more information
- Extract entities to increase focus
- Translate context for normalization
- Along with the question determine the best model to generate answers
- Enrich context with external metadata

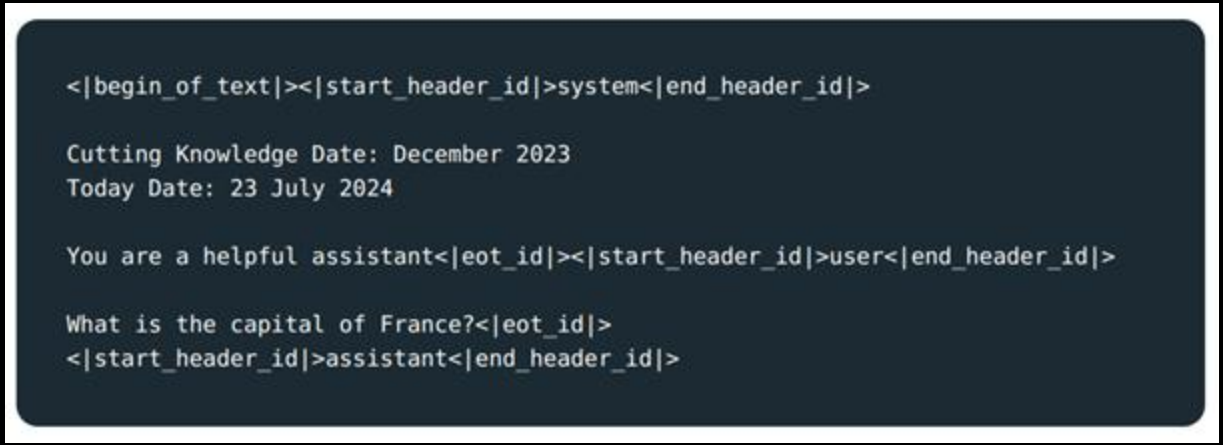
Prompts

The way to convey the LLM the context and make the question

Different models have different prompt formats.

Roles

- system
- assistant
- user
- ipython



Prompts - advanced

Run call tools

Run python code

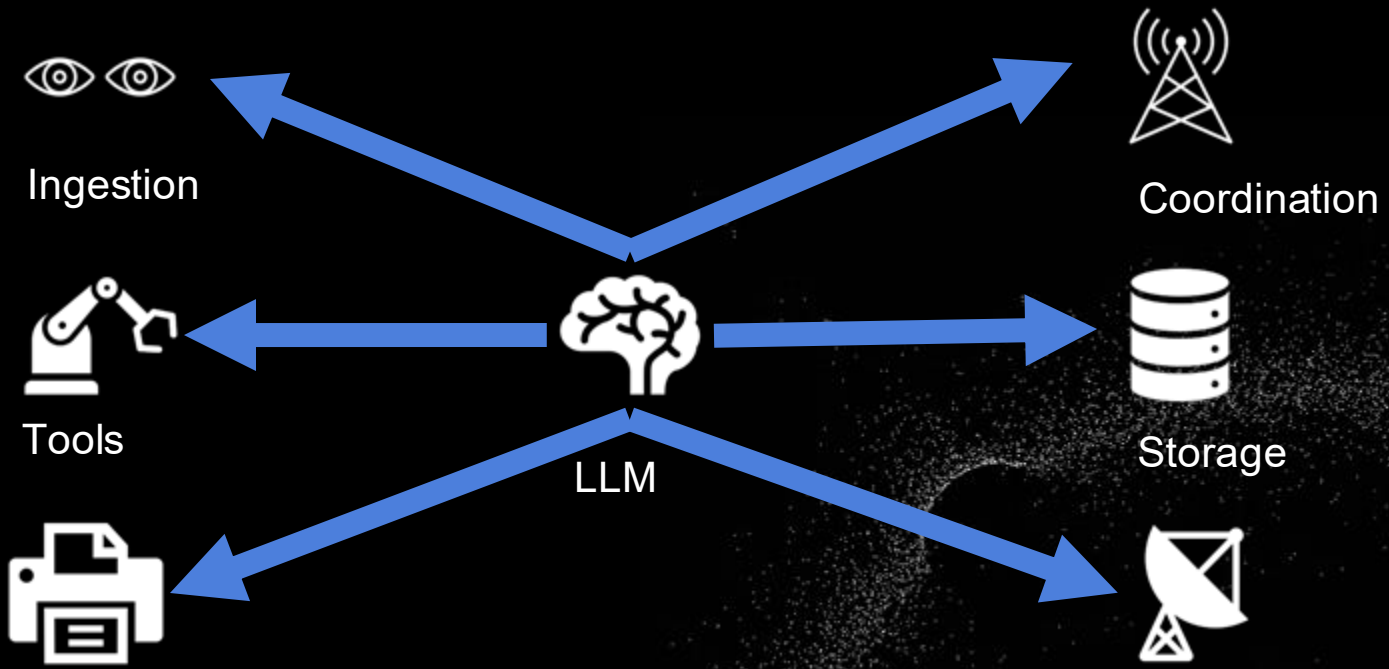
```
# for Search
<|python_tag|>
brave_search.call(query="...")
<|eom_id|>

# for Wolfram
<|python_tag|>
wolfram_alpha.call(query="...")
<|eom_id|>
```

Prompts - examples


```
  "reply": {
    "answer": "```\n[\n  {\n    \"text\": \"June 11, 2024\",\n    \"type\": \"DATE\"\n  },\n  {\n    \"text\": \"AhnLab\",\n    \
"type\": \"ORGANIZATION\"\n  },\n  {\n    \"text\": \"UAT-5394\",\n    \"type\": \"GROUP\"\n  },\n  {\n    \"text\": \"June 12, 2
024\",\n    \"type\": \"DATE\"\n  },\n  {\n    \"text\": \"95.164.86.148\",\n    \"type\": \"IP_ADDRESS\"\n  },\n  {\n    \"text\
": \"MoonPeak\",\n    \"type\": \"ORGANIZATION\"\n  },\n  {\n    \"text\": \"RDP\",\n    \"type\": \"SOFTWARE\"\n  },\n  {\n    \
"text\": \"Port 9999\",\n    \"type\": \"SOFTWARE\"\n  },\n  {\n    \"text\": \"July 4, 2024\",\n    \"type\": \"DATE\"\n  },\n
{\n    \"text\": \"27.255.81.118\",\n    \"type\": \"IP_ADDRESS\"\n  },\n  {\n    \"text\": \"July 5, 2024\",\n    \"type\": \"DA
TE\"\n  },\n  {\n    \"text\": \"Port 9966\",\n    \"type\": \"SOFTWARE\"\n  },\n  {\n    \"text\": \"167.88.173.173\",\n    \"ty
pe\": \"IP_ADDRESS\"\n  },\n  {\n    \"text\": \"Port 9936\",\n    \"type\": \"SOFTWARE\"\n  }\n]\n```",
    "nodes": [],
    "iocs": []
  },
  "request": {
    "query": "Since June 11, 2024, we saw a distinct shift in the actor's tactics with respect to setting up supporting infrastru
cture. After AhnLab's disclosure, UAT-5394 moved from hosting their malicious payloads on legitimate cloud storage providers to s
ystems and servers they now owned and controlled. It is likely that this move was made to preserve their infections from potentia
l shutdown of cloud locations by the service providers. \n95[.]164[.]86[.]148 is one of the earliest servers set up and actively
used by UAT-5394 since at least June 12, 2024, to host malicious artifacts (described in AhnLab's disclosure) and served as a Moo
nPeak C2 server on Port 9999 until at least July 4, 2024. This C2 server was accessed between this time frame, over RDP by 27[.]2
55[.]81[.]118, another  UAT-5394 IOC resolving multiple malicious domains registered by the threat actors. \nOn July 5, 2024, the
 threat actors now used 95[.]164[.]86[.]148 to RDP into a second malicious server, 167[.]88[.]173[.]173 which was already serving
 as a MoonPeak C2 on Port 9966. This RDP access to 167[.]88[.]173[.]173 resulted in a second deployment of MoonPeak's C2 on Port
9936. ",
```

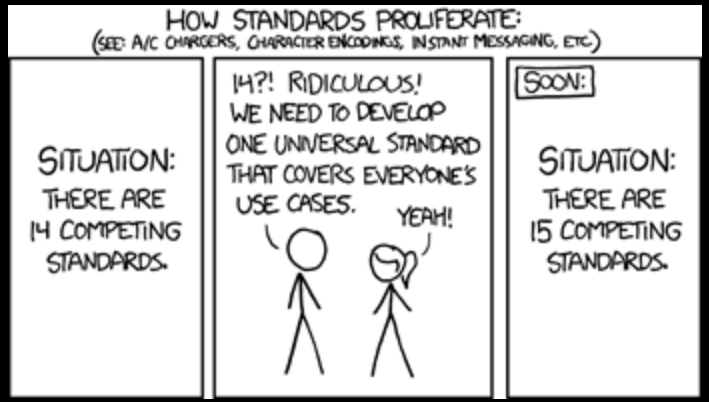
Agentic world

What is Orchestration?



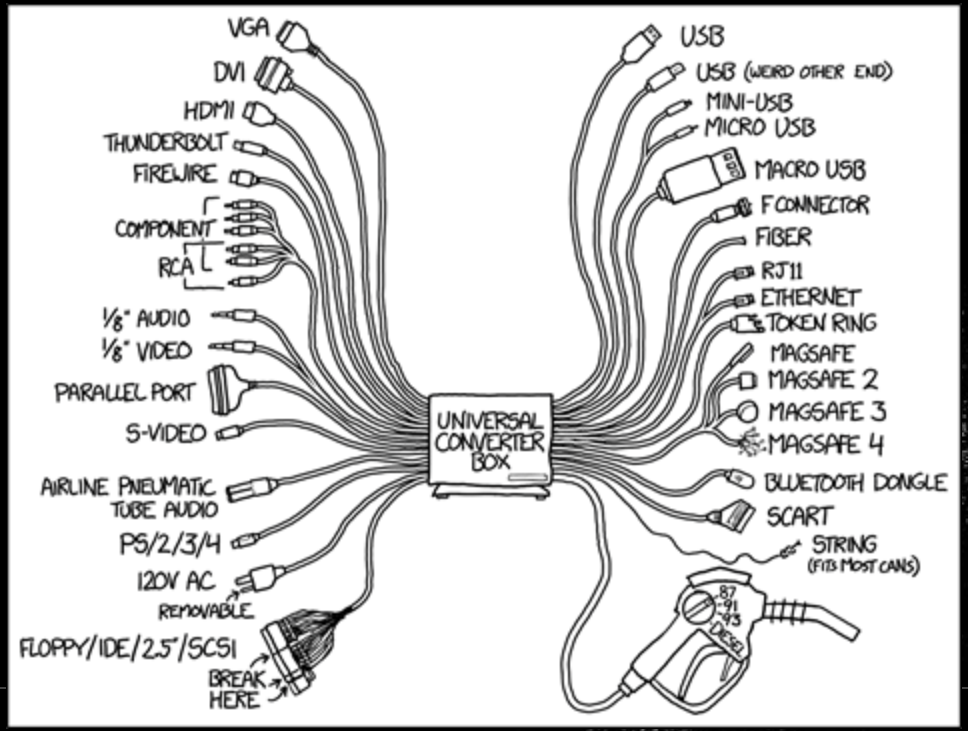
A Note about Orchestration Options

- There are many options

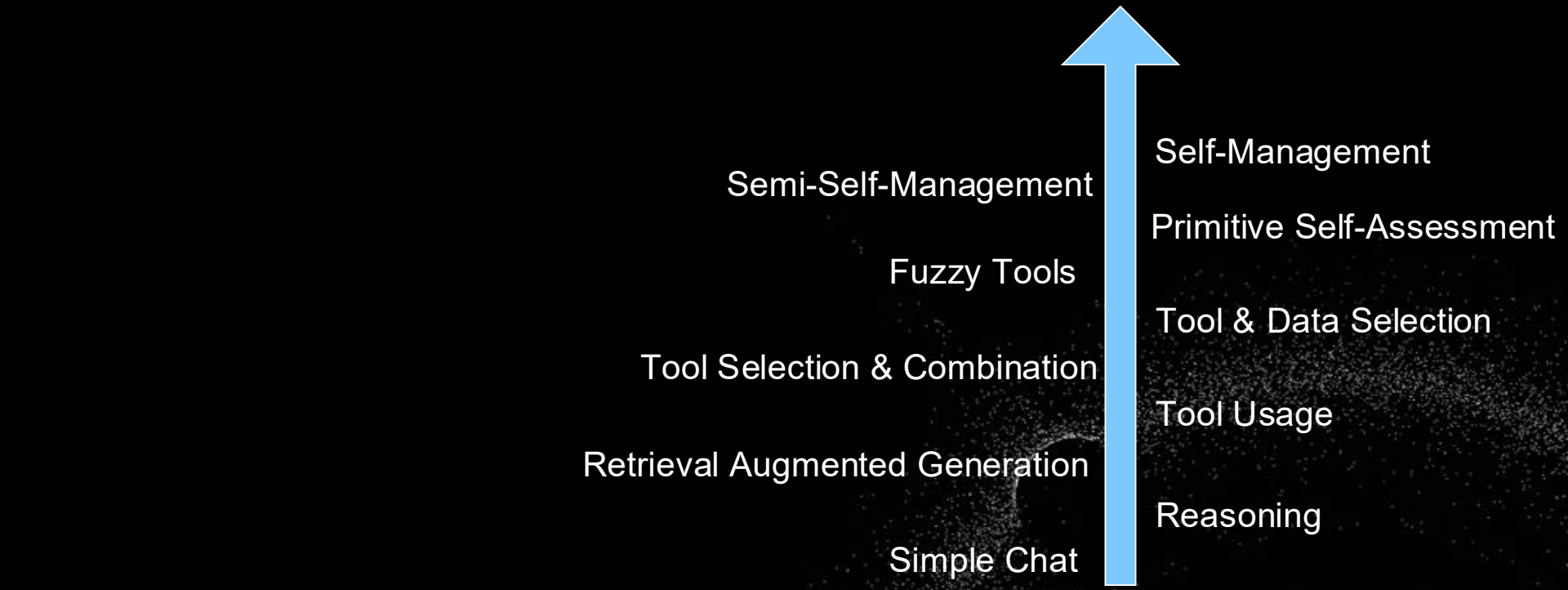


- Rigging
- Langchain
- Fence
- AutoGen
- Llama Index

This is real now – but you have to build the cables



Levels Of Autonomy



Levels Of Autonomy

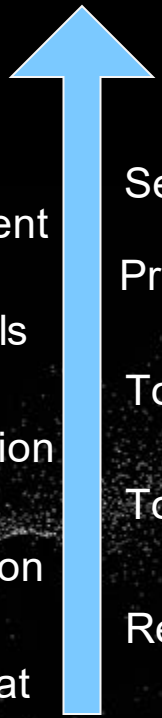
Semi-Self-Management

Fuzzy Tools

Tool Selection & Combination

Retrieval Augmented Generation

Simple Chat



Self-Management

Primitive Self-Assessment

Tool & Data Selection

Tool Usage

Reasoning

Levels Of Autonomy

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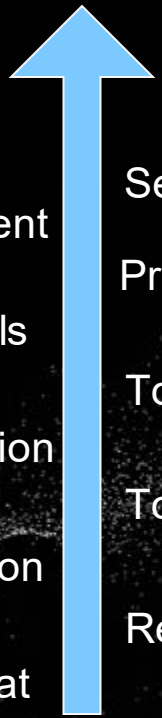


Self-Management

Primitive Self-Assessment

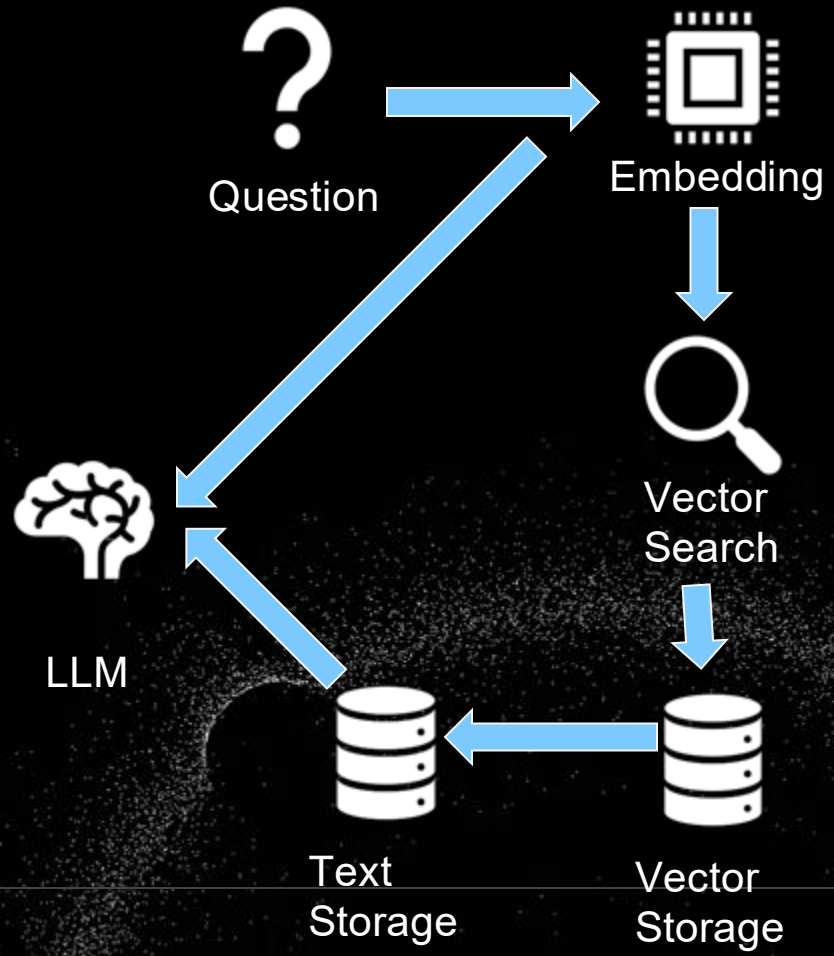
Tool & Data Selection

Tool Usage

Reasoning

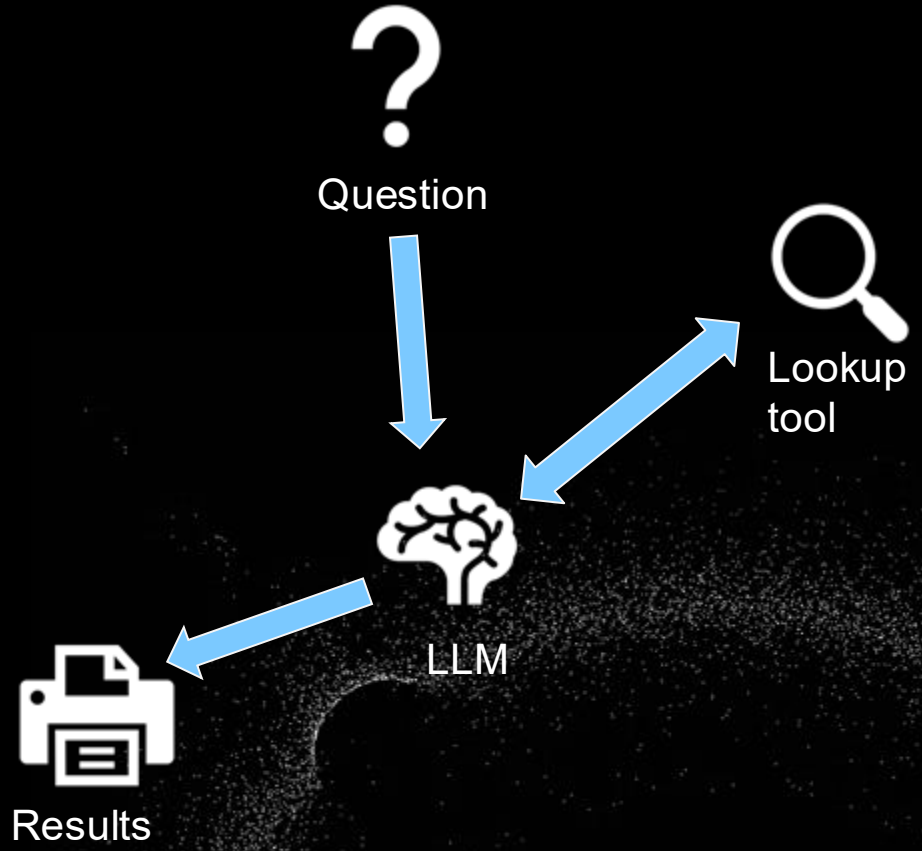
Retrieval Augmented Generation

- In this case the system always does the same things
- Works great for context-specific questions



Tool Usage: CEO view

- Now the tool is optional
- The LLM goes from just processing to reasoning
- The tool invocation and result processing is up to it



Tool Usage

- If you want the LLM to be able to pick a tool you need to make it optional
- This is when you REALLY need orchestration
- Now it can pick to trigger a tool or just directly answer

```python
from typing import Annotated
import requests
import rigging as rg

def get_weather(city: Annotated[str, "The city name to get weather for"]) -> str:
    "A tool to get the weather for a location"
    try:
        city = city.replace(" ", "+")
        return requests.get(f"http://wttr.in/{city}?format=2").text
    except:
        return "Failed to call the API"

chat = (
    await
    rg.get_generator("gpt-4o-mini")
    .chat("How is the weather in london?")
    .using(get_weather)
    .run()
)
print(chat)
print(chat.last)
chat = (
    await
    rg.get_generator("gpt-4o-mini")
    .chat("Who played Harry Potter?")
    .using(get_weather)
    .run()
)
print(chat)
print(chat.last)
```

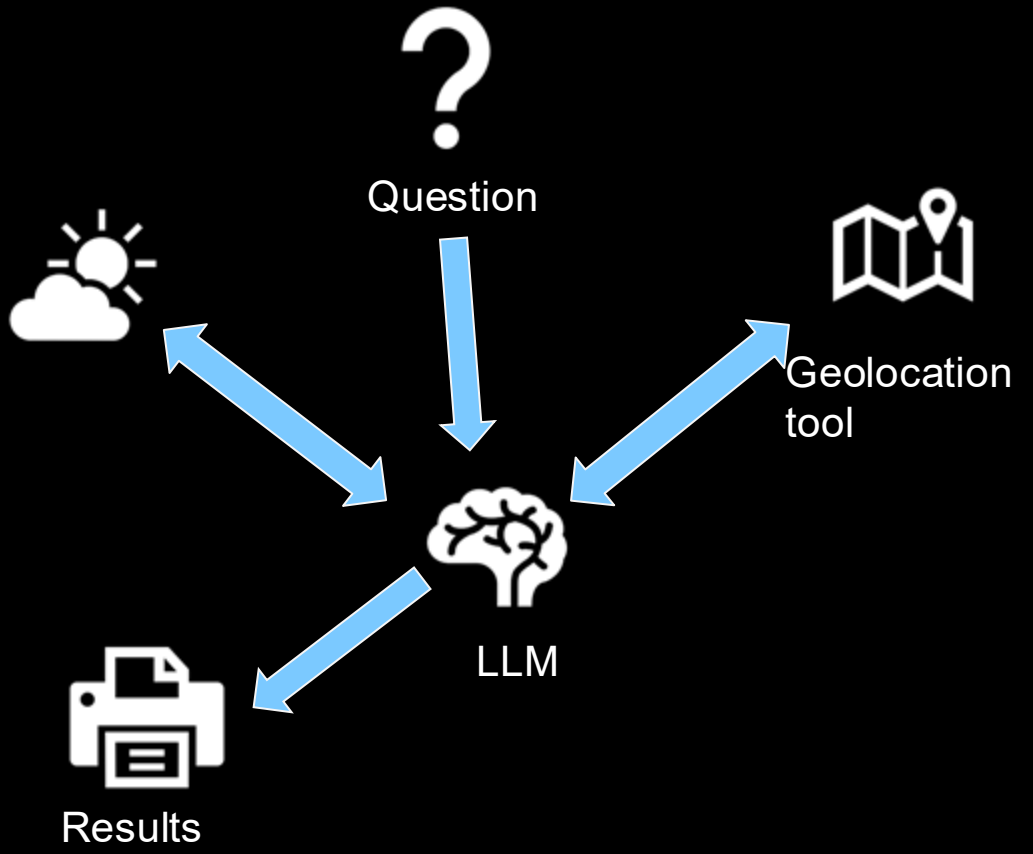
```
uuid=UUID('a5d5c278-3944-49d3-a24f-97f857296cc5') messages=[Message(role='user', parts=[], tool_calls=None, tool_call_id=None, content='How is the
weather in london?'), Message(role='assistant', parts=[], tool_calls=[ToolCall(id='call_LWzuoba7jn0YAAXZbZsGkd3Z', type='function', function=Funct
ionCall(name='get_weather', arguments='{"city":"London"}'))], tool_call_id=None, content=''), Message(role='tool', parts=[], tool_calls=None, tool
_call_id='call_LWzuoba7jn0YAAXZbZsGkd3Z', content='  +47°F  +6mph\n')] generated=[Message(role='assistant', parts=[], tool_calls=None, tool_
call_id=None, content='The current weather in London is sunny, with a temperature of 47°F and a light breeze at 6 mph.')] metadata={} stop_reason=
'stop' failed=False
[assistant]: The current weather in London is sunny, with a temperature of 47°F and a light breeze at 6 mph.
uuid=UUID('89079ec6-7528-4d92-9968-8dc7f99810b9') messages=[Message(role='user', parts=[], tool_calls=None, tool_call_id=None, content='Who played
Harry Potter?')] generated=[Message(role='assistant', parts=[], tool_calls=None, tool_call_id=None, content="Daniel Radcliffe played Harry Potter
in the film series adapted from J.K. Rowling's novels.")] metadata={} stop_reason='stop' failed=False
[assistant]: Daniel Radcliffe played Harry Potter in the film series adapted from J.K. Rowling's novels.
```

Let‘s eat our veggies

What I am thinking about	How Rigging does it
Reliability	Parsing & Templating
Response Validation	Callbacks & Mapping
Scaling	Iterating and Batching
Tools	Tools
Storing & Exporting	Serielization

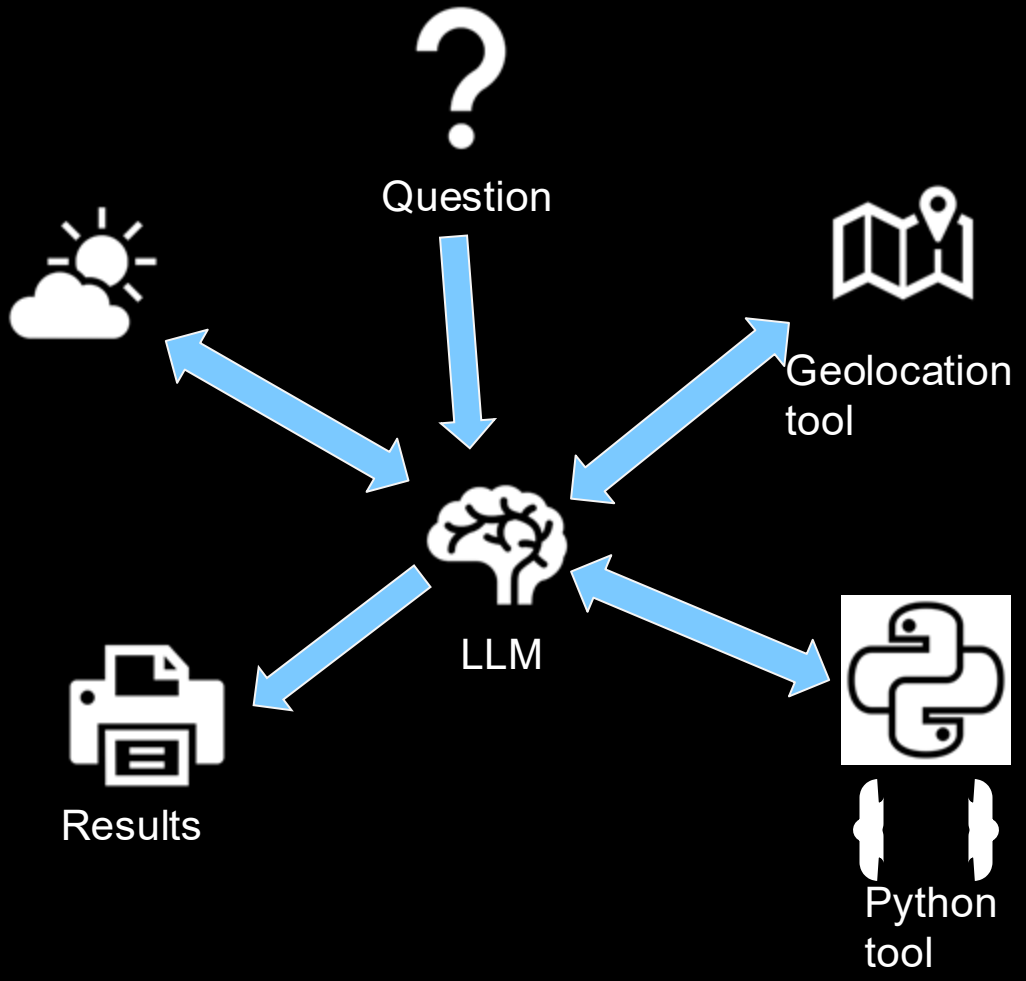
Tool Combinations: CEO view

- Now tools can be combined and activated together
- But again, the LLM is at the centre, calling the shots



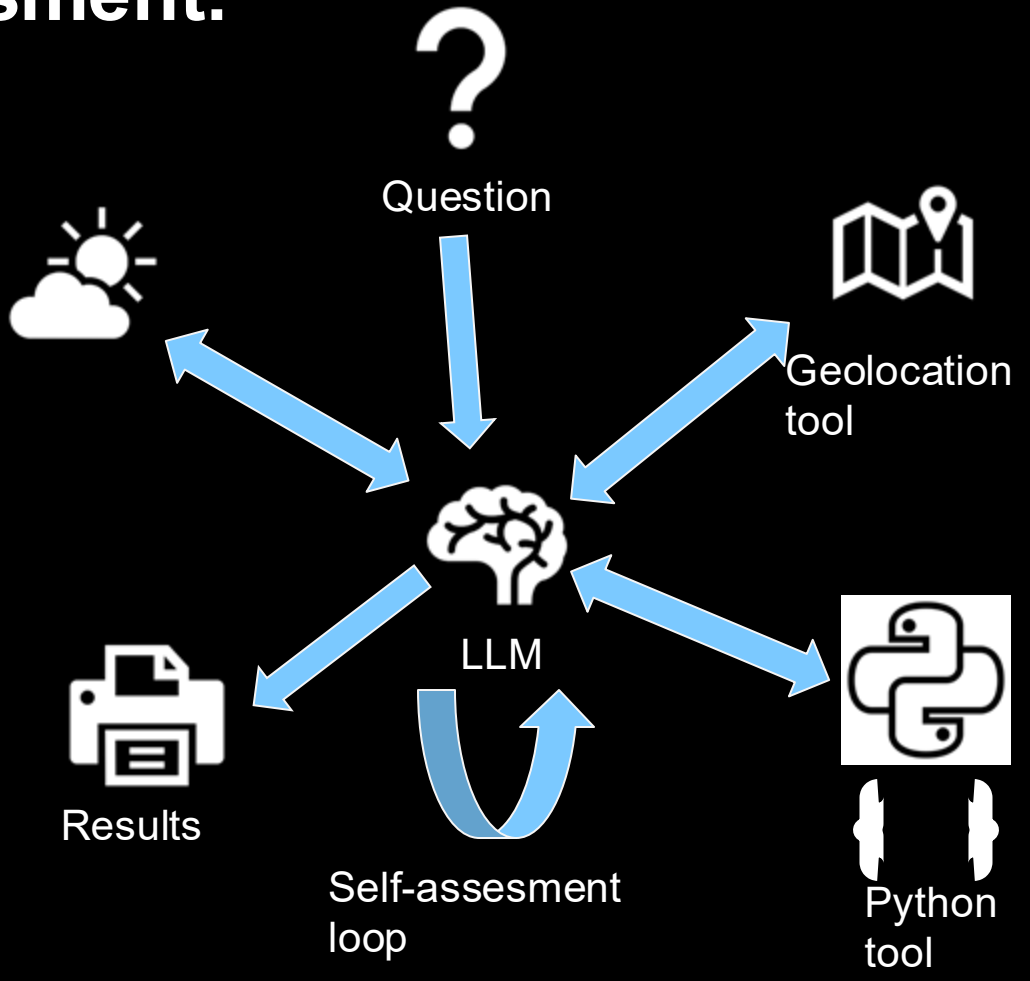
Fuzzy Tools: CEO View

- Fuzzy tools are more malleable
- Include a larger element of self-definition
- Good example is a basic python tool
- But again, the LLM is at the centre, calling the shots



Hardcoded Self-Assesment: CEO View

- Just a simple check for a certain type of XML tag
- Or a specific value
- Otherwise continuing in a loop



Let‘s get semi-autonomous

Information Ingestion	Self Management	Knowledge Management
Remote Analysis	Self-focus	Graph Memory
Data Enricher	Analysis Strategies	Pivot Classifier
Pivot Discovery	Concurrent Splitoffs	Completeness Explorer

Closing thoughts

Thank you