AgentCon Zurich

I’m speaking at AgentCon Zürich!

Feb 04, 2026 Swiss Life, Grubenstrasse 49 - 8045 Zürich

TypeAgent: From RAG to Structured RAG: Building Long-Context, Precise, and Fast AI Systems

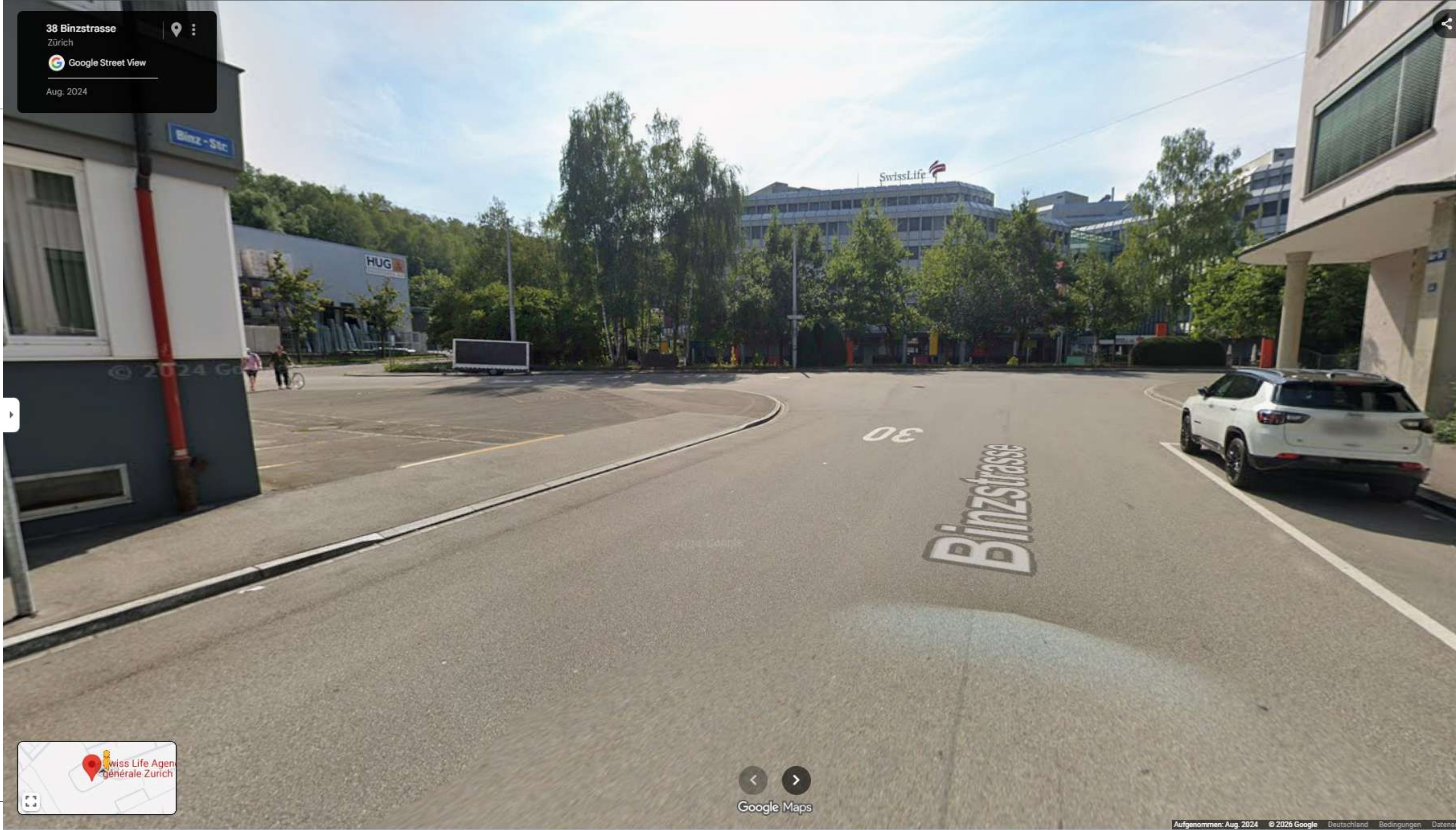
Bernhard Merkle

neo4j global AI community Microsoft SwissLife

About me…

SICK

Sensor Intelligence.


38 Binzstrasse
Zürich
Google Street View
Aug. 2024
Binz-Str
HUG
SwissLife
© 2024 Google
30
Binzstrasse
Swiss Life Agen
générale Zurich
Google Maps
Aufgenommen: Aug. 2024
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Deutschland
Bedingungen
Datens

30
Binzstrasse
Google Maps

HH GG 2308

SICK

Google maps
Street View
google.com/streetview

Lufthansa
STAR ALLIANCE
STAR ALLIANCE
479
Lufthansa
Quick
Check-in
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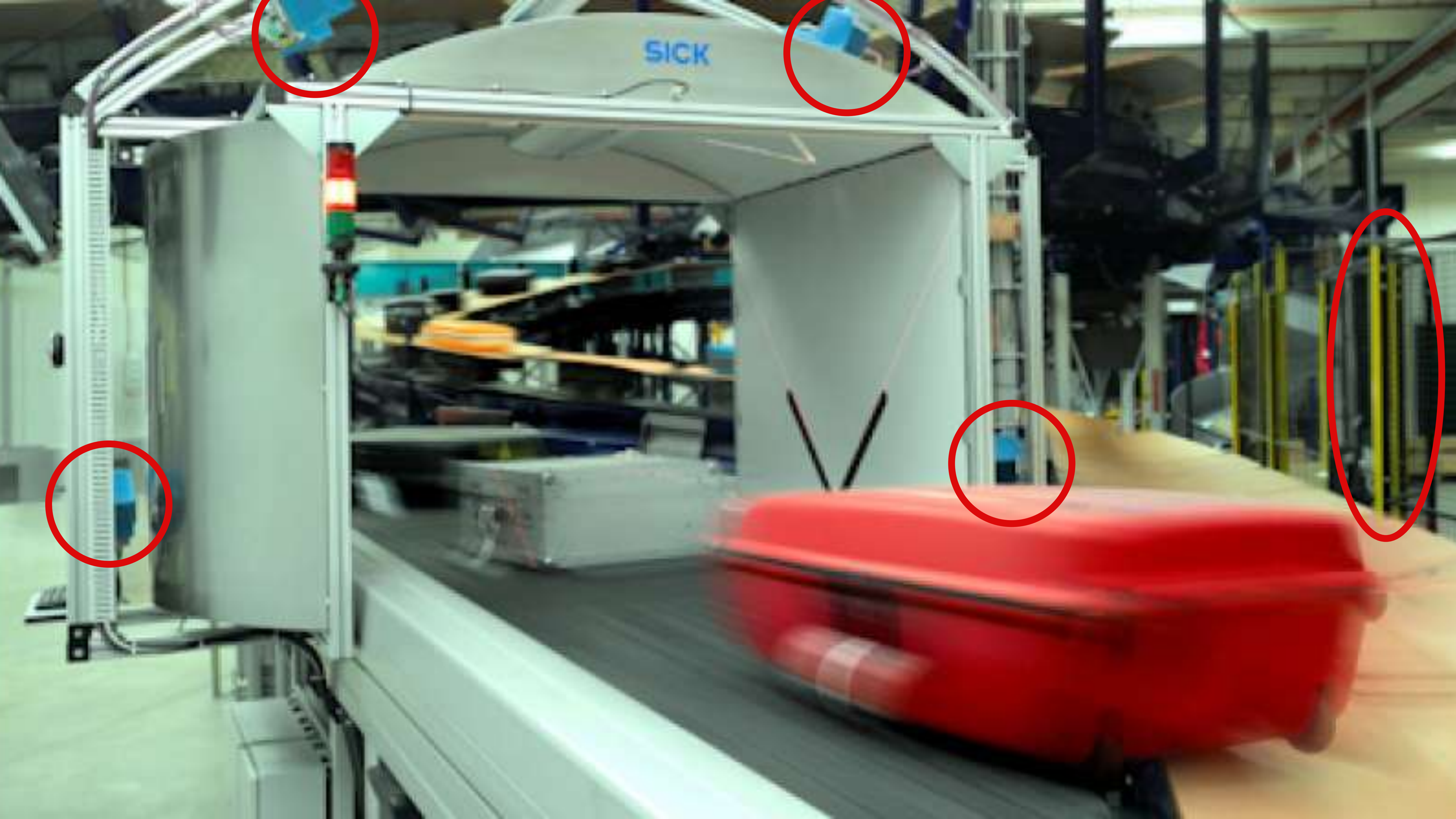
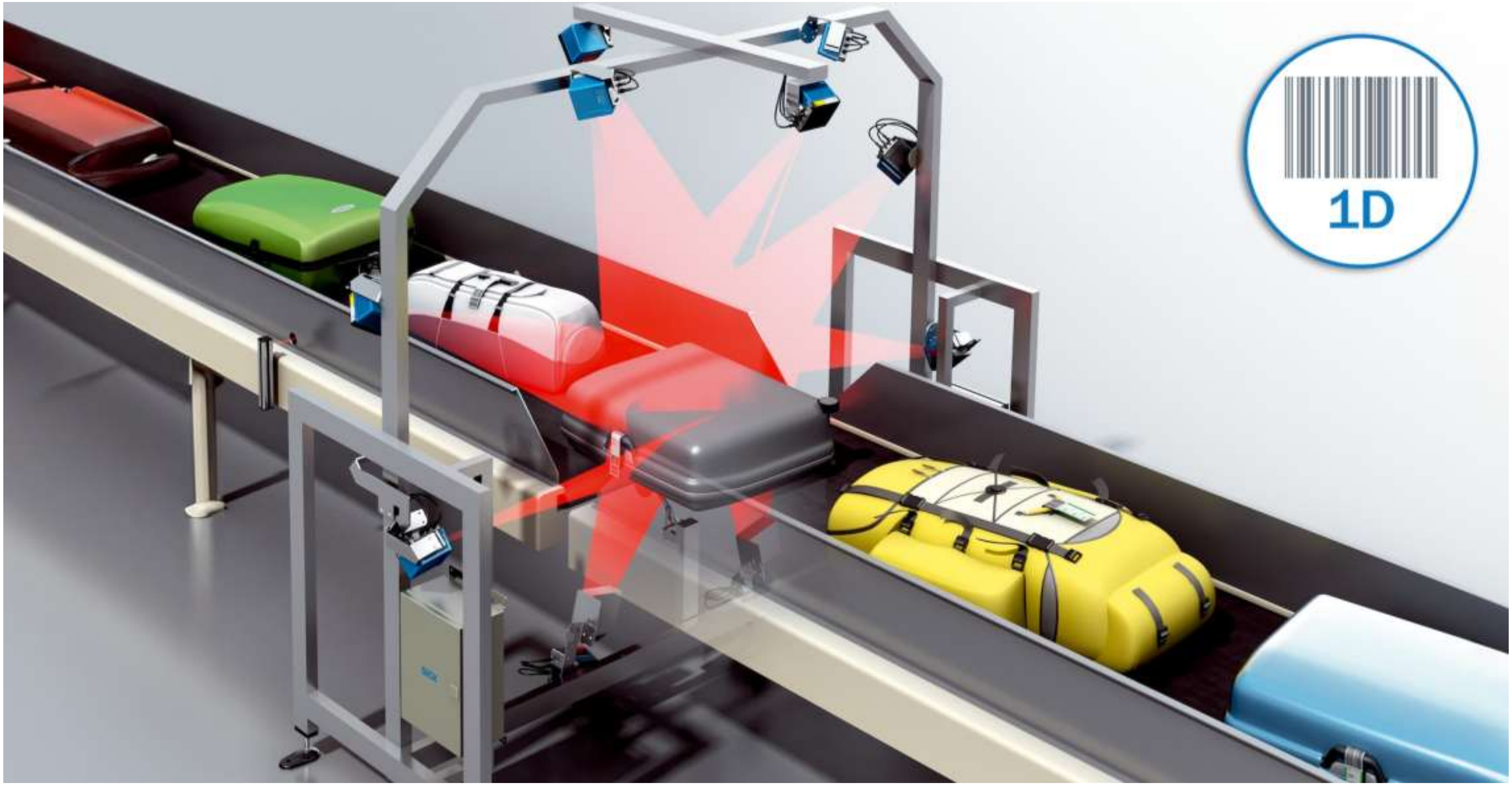
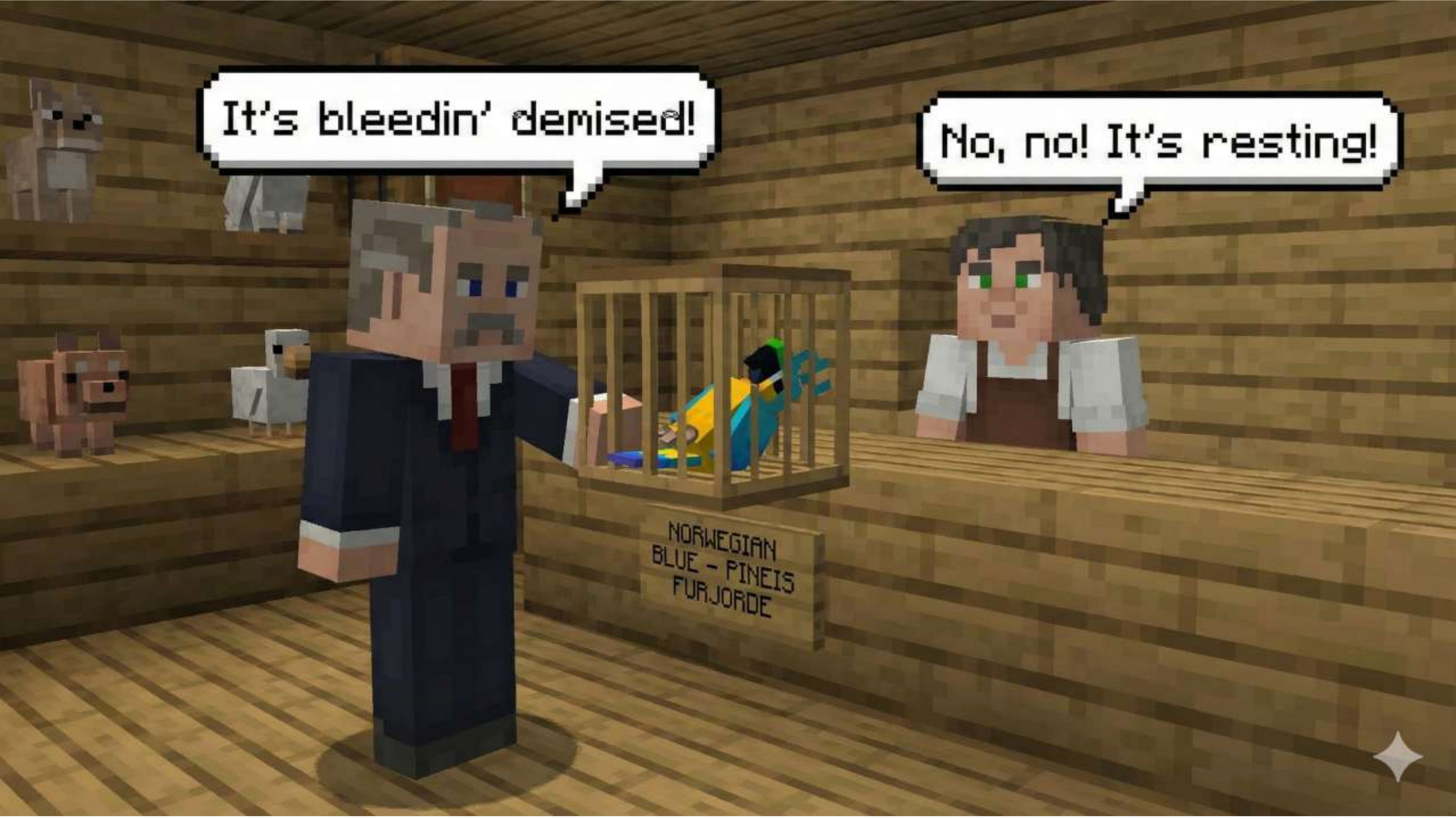

SICK


1D

SICK
AI

SICK
LECTOR
SICK
SICK
LECTOR
SICK
SICK
Lector 85x

THE PARROT
IS DEAD
TS


It's bleedin' demised!
No, no! It's resting!
NORWEGIAN BLUE - PINEIS FURJORDE

AGENTIC
WORKFLOWS
GITHUB & AI
AGENTIC
WORKFLOW

LLM vs RAG vs AI Agent vs Agentic AI

Aspect	LLM	RAG	AI AGENT	Agentic Ai
Definition	A smart text generator. You ask it something, it writes back an answer.	An AI that searches through your documents before answering your question.	An AI helper that can plan steps, use different tools, and complete whole tasks for you.	A team of AI workers where each one has a different job, and they work together to finish big projects.
Architecture	Your question → AI brain → Answer	Your question → Searches your files → Reads relevant parts → Writes answer using what it found	Your goal → Makes a plan → Uses tools it needs → Checks results → Adjusts and continues → Finishes task	Your goal → Manager assigns tasks → Researcher AI does its part → Writer AI does its part → Reviewer AI checks → Team delivers final result
Core Components	One AI model that learned from tons of text.	AI model plus a searchable library of your documents.	AI brain plus access to tools like search, calculator, file creators.	Multiple AI workers, shared memory they all access, manager that coordinates them.
Primary Functionality	Creates text by guessing what word should come next, like autocomplete on your phone.	Answers questions using information from your actual files and documents.	Breaks down your goal into steps, picks the right tools, and works until it's done.	Different AI specialists work together, pass information between them, and coordinate like a real team.
Typical Use Case	Writing emails, posts, stories, or getting quick explanations.	Answering questions about company policies, product guides, or research papers.	Research projects, collecting and organizing data, creating content packages.	Marketing campaigns, big research projects, running ongoing business processes.
Tool Integration	Works alone. Can't connect to	Can read your documents but	Can use web search, spreadsheets, calculators	Each team member uses whatever tools it needs for its

LLM writes, I cave all tage writes vean more data and cultidy nreeky ronfi̇ed ne sk sa ios of the here.
LLM writes.
RAG knows.
Agent acts.
Agentic AI manages.

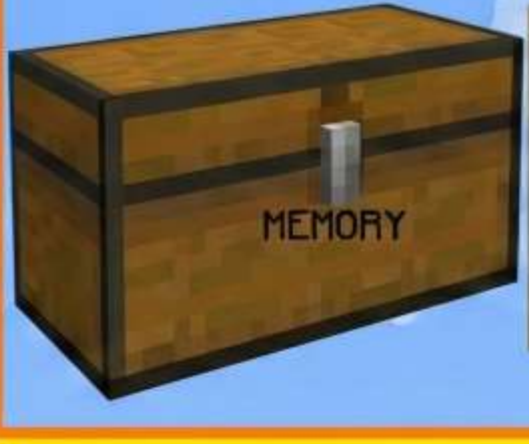
Problems with Classic-RAG

- ⚠ The "Lost in the Middle" Problem
  - ⚠ Lack of Global Context (The "Needle in a Haystack")
  - ⚠ Semantic Disconnect (The "Keyword Trap")
  - ⚠ Retrieval Noise and "Garbage In, Garbage Out"

- ⚠ Retrieval recall and precision are not really good
  - ⚠ Useage of much compute and data for....
  - ⚠ tokens, embeddings with no real semantic…
  - ⚠ context windows is limited, workaround, not efficient…

RAG
Structured-RAG
RAG PILE
RAG PILE
STRUCTURED-RAG STRUCTURE
STRUCTURED-RAG STRUCTURE

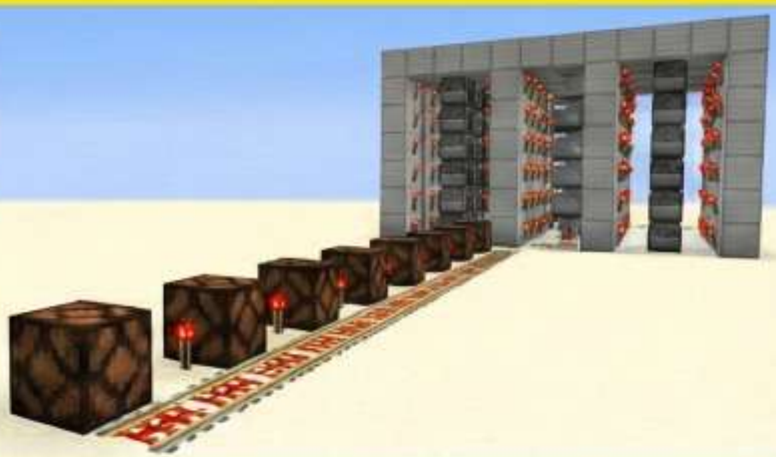
Review: Classic RAG (Retrieval-Augmented Generation)



Agents need memory
- To recall relevant past interactions
- To retrieve relevant documents

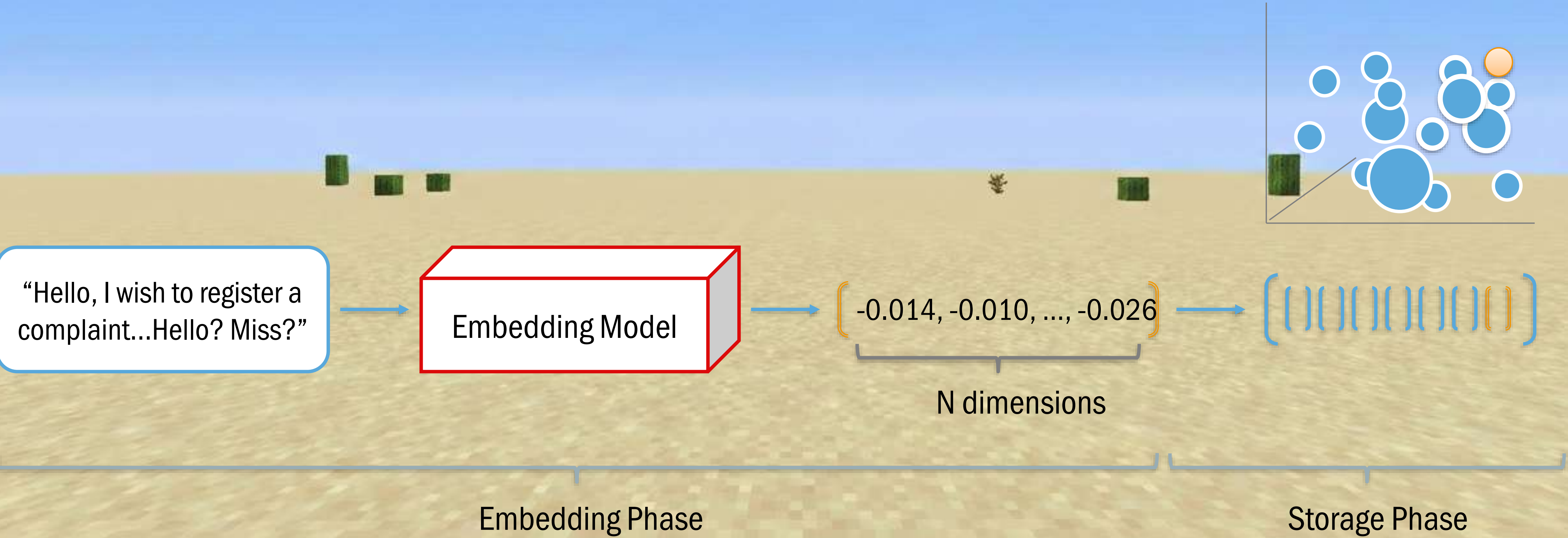
Classic RAG uses embeddings

Embeddings require a (fast) roundtrip to a service maintained by an LLM provider



For best results:
- Chop long documents up in chunks
- Use batching

Classic RAG – Embedding Storage



“Hello, I wish to register a complaint…Hello? Miss?”

Embedding Model

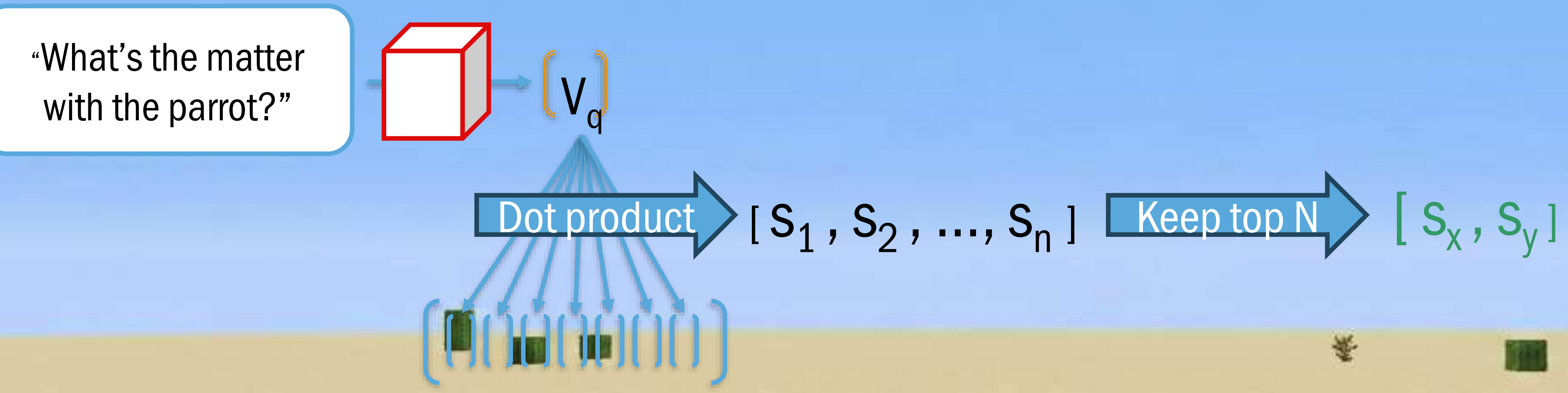
-0.014, -0.010, …, -0.026

N dimensions

Embedding Phase

Storage Phase

Classic RAG – Embedding Retrieval



“What’s the matter with the parrot?”

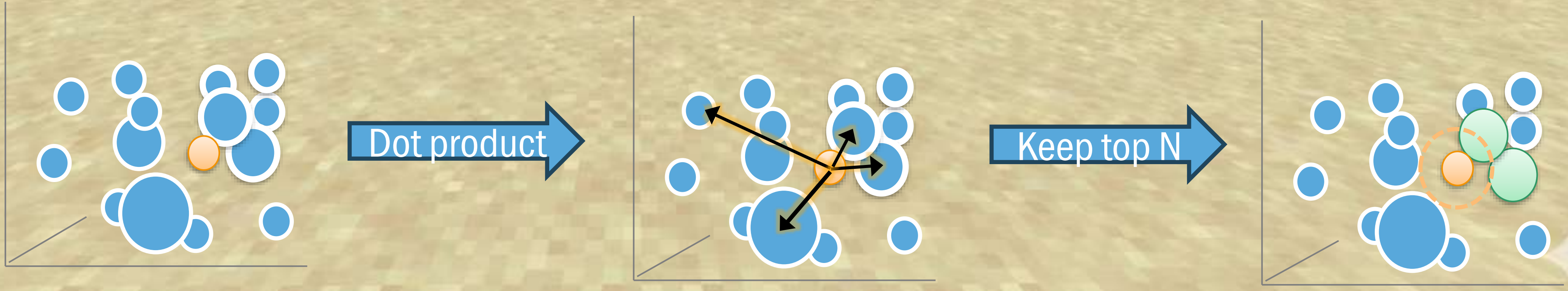
V_q

Dot product

$[\, s_1 , s_2 , \ldots, s_n \,]$

Keep top N

$[\, s_x , s_y \,]$



Dot product

Keep top N

Classic RAG:

Pros

- Well understood (mostly).
- Easy to deploy.

Cons

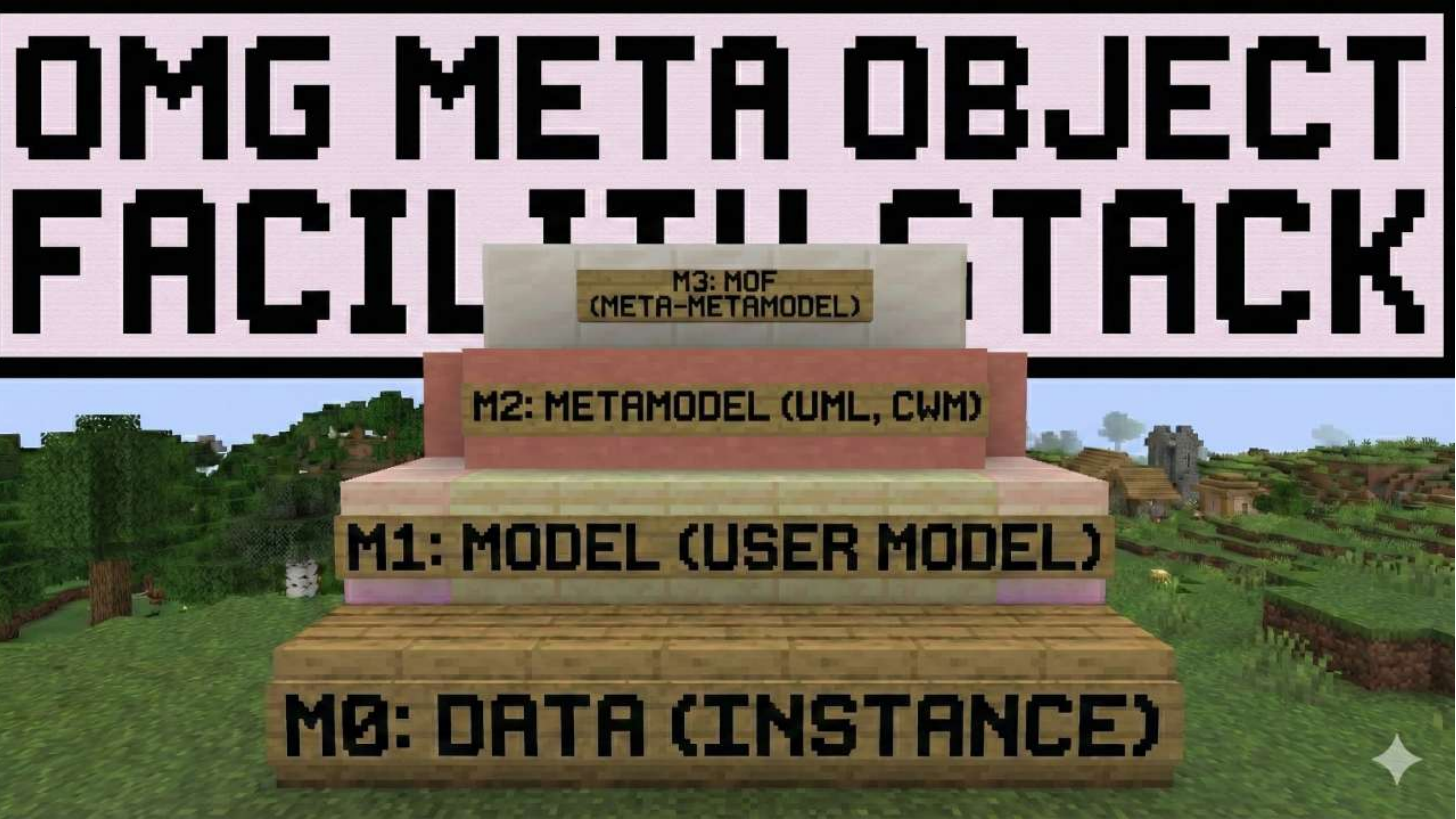
- Expensive and complicated.
- Take up lots of space.
- Large input strings give “mushy” results, near many things, not all that near anything in your query.

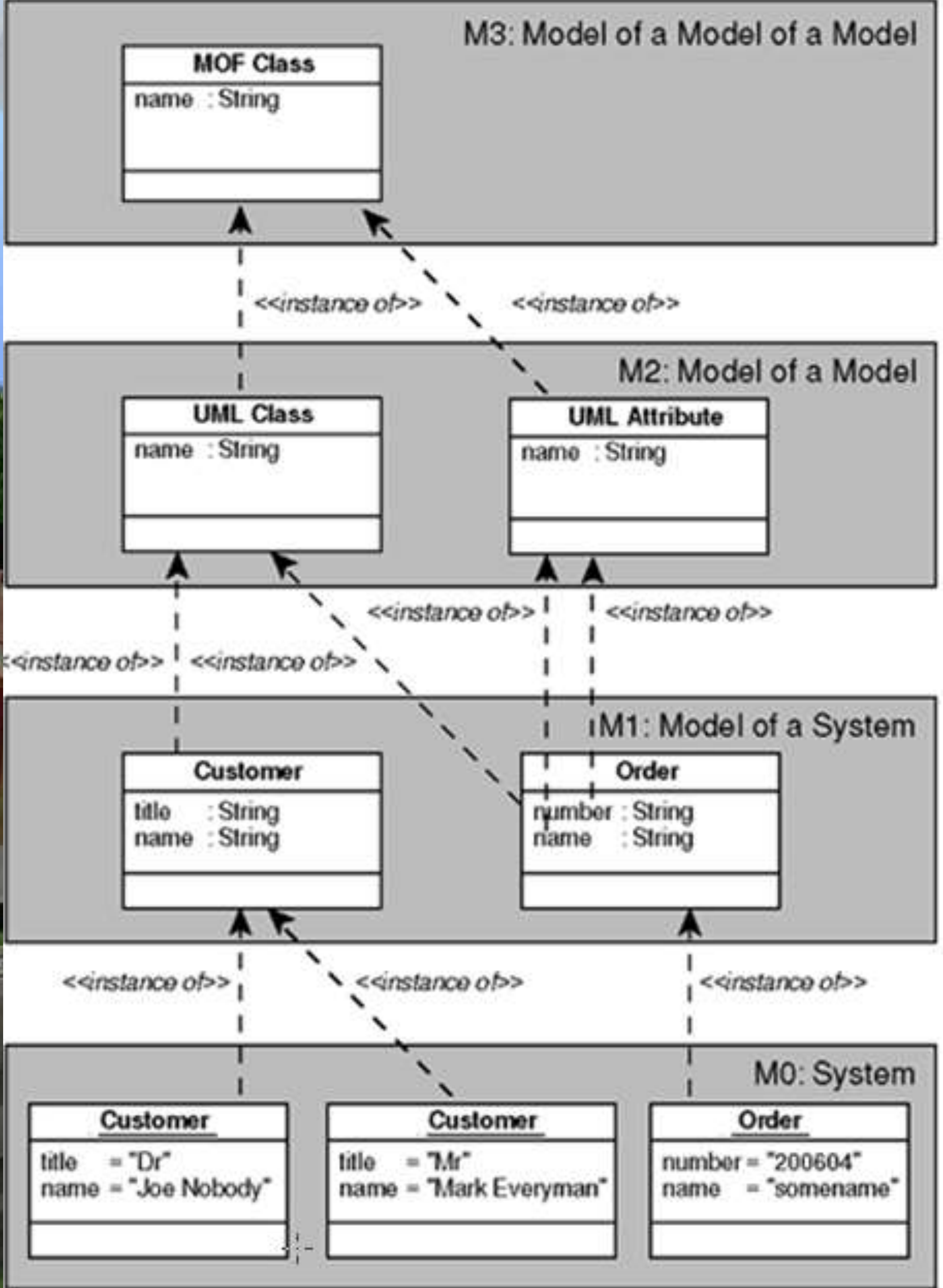
AND NOW FOR
SOMETHING
COMPLETELY
DIFFERENT ...
WANDA
DEAD PARROT

META-META
IS
BETTER
BETTER...
WANDA
DEAD PARROT

META–META
IS
BETTER
BETTER....
WANDA
DEAD PARROT

OMG META OBJECT FACILITY STACK




M3: Model of a Model of a Model
MOF Class
name : String
<<instance of>>
<<instance of>>
M2: Model of a Model
UML Class
name : String
UML Attribute
name : String
<<instance of>>
<<instance of>>
<<instance of>>
<<instance of>>
M1: Model of a System
Customer
title : String
name : String
Order
number : String
name : String
<<instance of>>
<<instance of>>
<<instance of>>
M0: System
Customer
title = "Dr"
name = "Joe Nobody"
Customer
title = "Mr"
name = "Mark Everyman"
Order
number = "200604"
name = "somename"

OMG

Structured RAG:

1. Ingestion

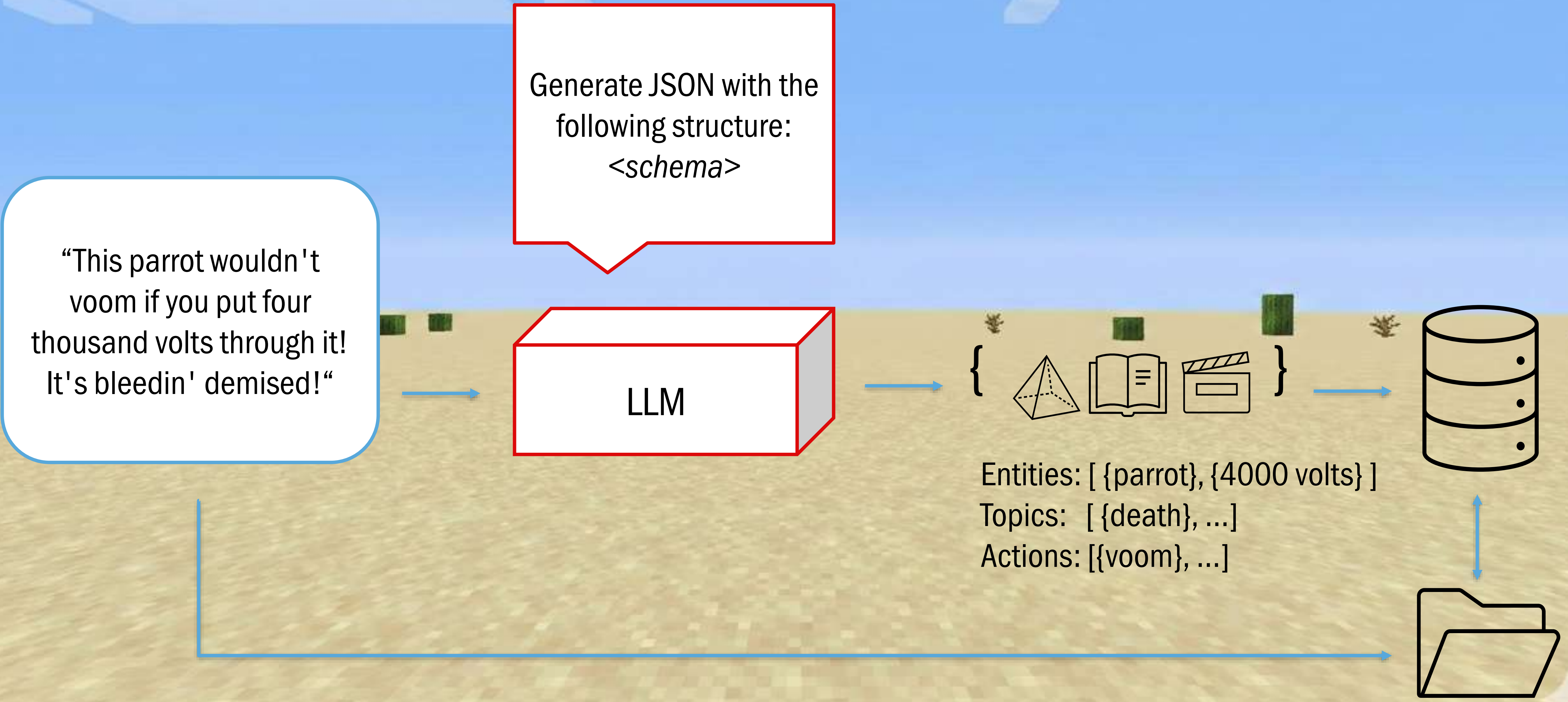
Run each input string through an LLM that extracts “knowledge” from it.

Knowledge: entities (people, places, etc.), actions, topics, relationships, etc.

Store knowledge nuggets in a classic database and create indexes over them.

The database is easily queried – it’s classic computer science.

Structured RAG – Ingestion Pipeline



“This parrot wouldn't voom if you put four thousand volts through it! It's bleedin' demised!“

Generate JSON with the following structure: *<schema>*

Entities: [{parrot}, {4000 volts}]
Topics: [{death}, ...]
Actions: [{voom}, ...]

Structured RAG:

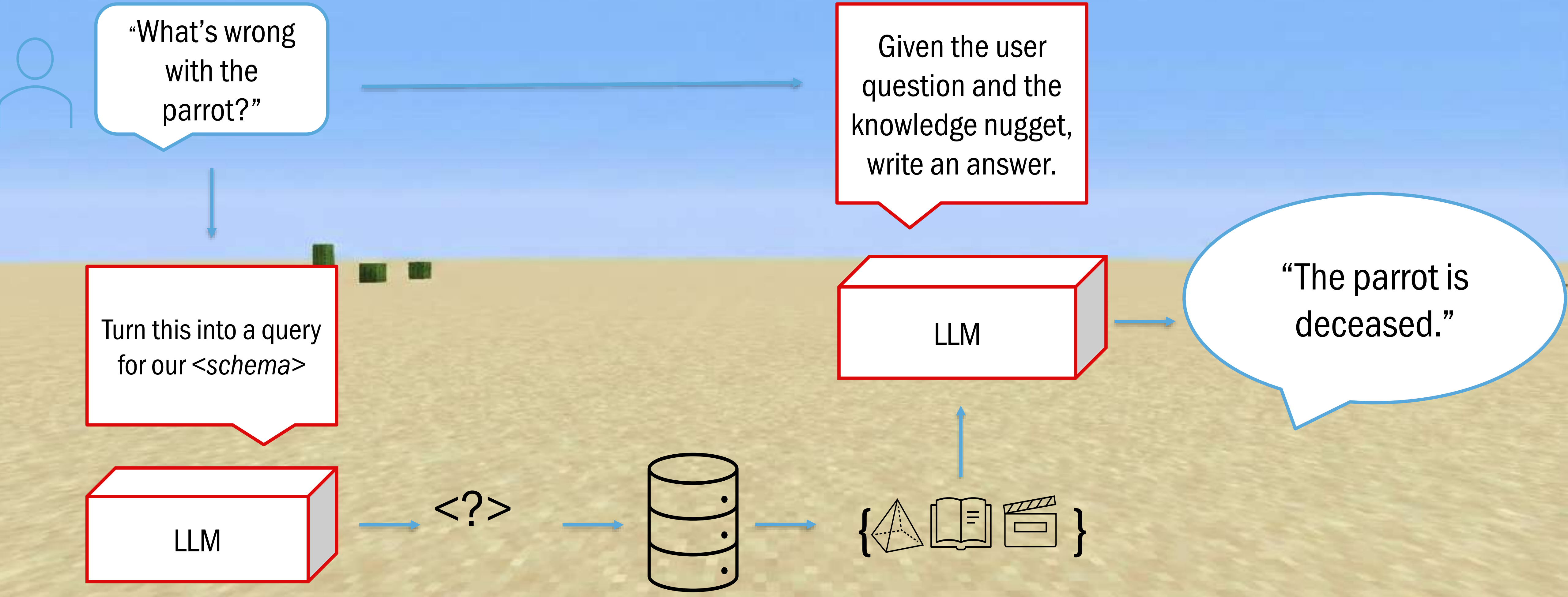
2. Querying

Turn user question into an (abstracted) database query.

Run the query, producing {Entities, Topics, Actions}.

Produce answer from best query results.

Structured RAG – Query Pipeline



“What’s wrong with the parrot?”

Turn this into a query for our <*schema*>

LLM

<?>

Given the user question and the knowledge nugget, write an answer.

LLM

“The parrot is deceased.”

Structured RAG evaluated

Retrieval recall and precision are better due to extraction and storage of knowledge nuggets, which can be queried more precisely, generating higher information density, leading to better answers.

Scalable to much larger conversation histories: indexing approach needs less compute and data.

Can do inference over knowledge nuggets. E.g. *artist*(*Palin*) → *person*(*Palin*), which helps with e.g. “what people did we talk about yesterday?”

Some knowledge can be extracted without consulting an LLM (e.g. email headers).

Bulk ingestion is slower, due to the use of an LLM instead of just embeddings.

Classic RAG vs Structured RAG

Feature	Classic RAG	Structured RAG
Logic	Semantic similarity (Vectors)	Typed Conversations & Schema-based indexing
Memory	Flat document chunks	Hierarchical, human-like memory
Precision	Lower (suffers from "context drift")	Higher (resolves pronouns + state)
Efficiency	Often requires large contexts	Distills logic into faster, smaller models

Structured RAG vs (Knowledge) Graph RAG

Feature	Structured RAG (TypeAgent)	Knowledge Graph RAG (GraphRAG)
Core Structure	Typed Schemas (TypeScript/JSON)	Nodes & Edges (Triplets)
Philosophy	"Logical distillation" of conversation.	"Relational mapping" of a corpus.
Primary Goal	Precise agent memory & task state.	Multi-hop reasoning & global summaries.
Indexing Unit	Conversations, turns, and entities.	Entities, relationships, and communities.
Search Method	Schema-driven lookup & pronoun resolution.	Graph traversal & community summarization.
Best For...	"What was the third book we discussed?"	"What are the common themes in these 1,000 files?"

Structured RAG vs (Knowledge) Graph RAG

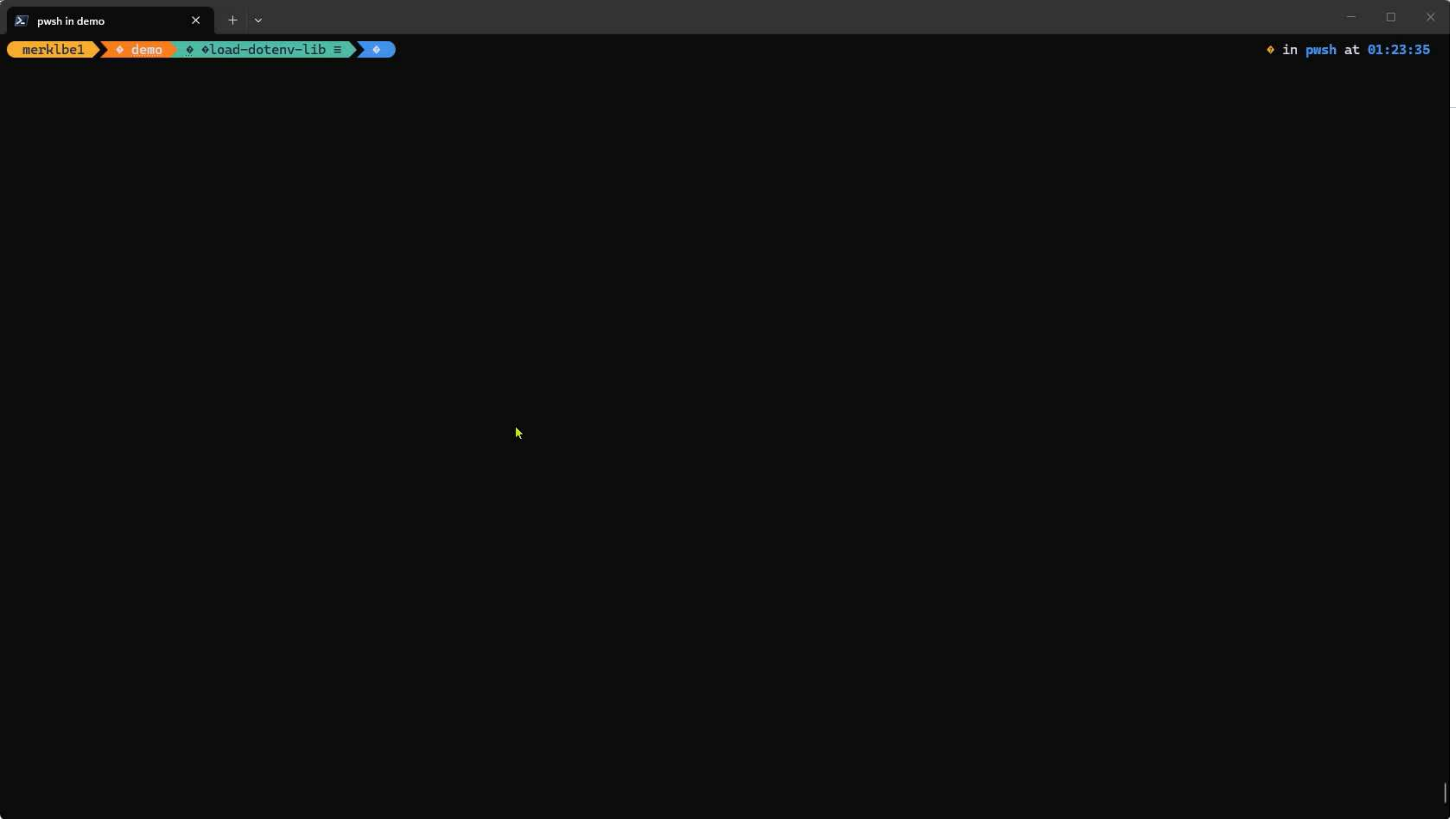
- 1. The Core Mechanism
  - Structured RAG: ses KnowPro to extract a "logical structure" from conversation
  - Graph RAG: It builds a network of entities (nodes) and their interactions (edges)

- 2. Information Density vs. Connectivity
  - Structured RAG prioritizes density control. It distills a long conversation into a compact, structured representation that fits within the "attention budget" of smaller, faster models. It is about making the model's memory more efficient.
  - GraphRAG prioritizes connectivity. It is less about saving tokens and more about ensuring that the model can find "hidden" relationships. For example, if Document A mentions a person and Document B mentions a company they own, GraphRAG links them so the LLM can answer questions about the person's business interests.

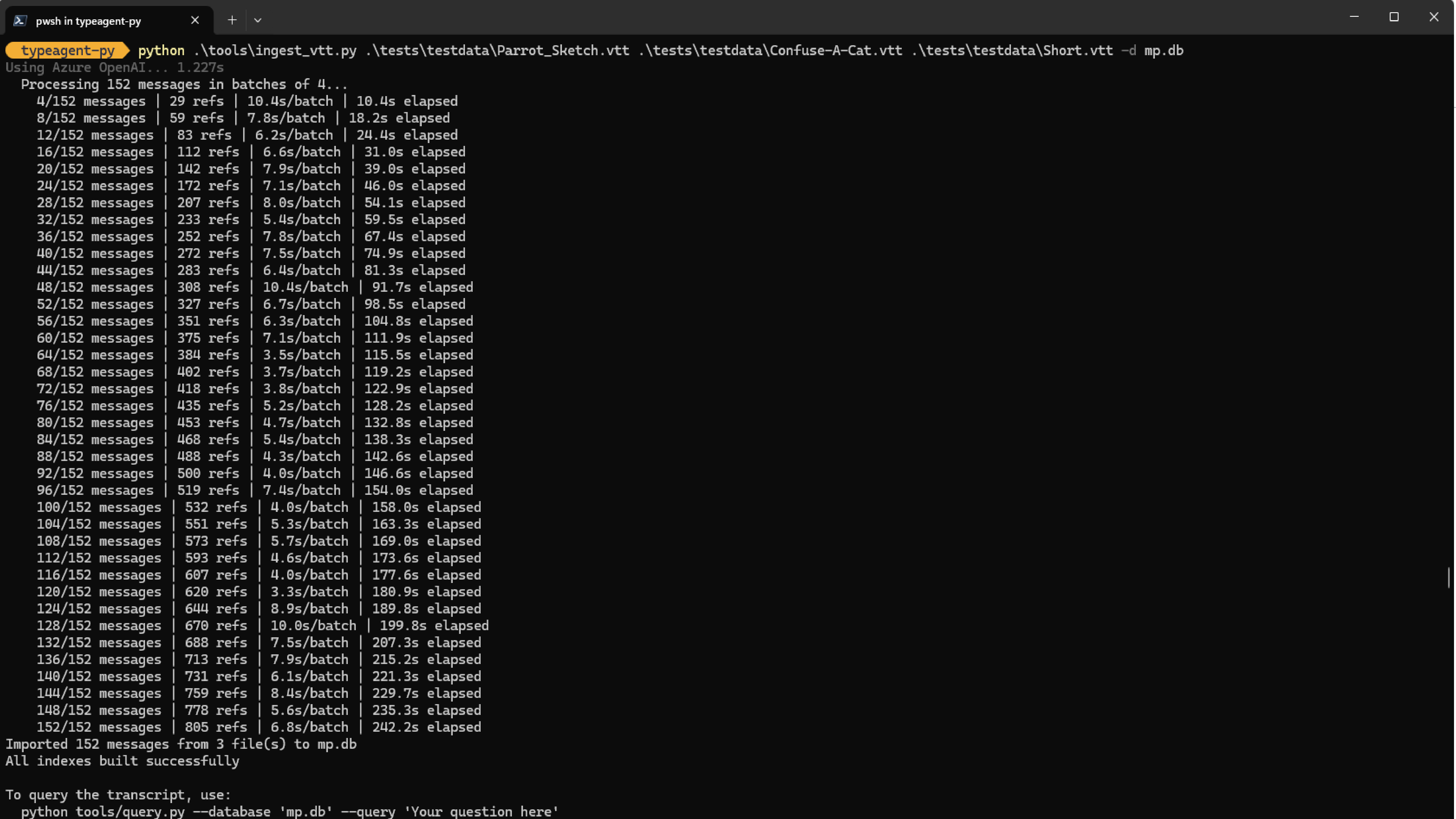
Structured RAG vs (Knowledge) Graph RAG

- 3. Use Case Focus
  - Structured RAG is built for agents that do work.
    superior because it maintains the "logical thread.“
  - GraphRAG is built for analysis.
    standard for "Tell me the overall sentiment of these research papers“

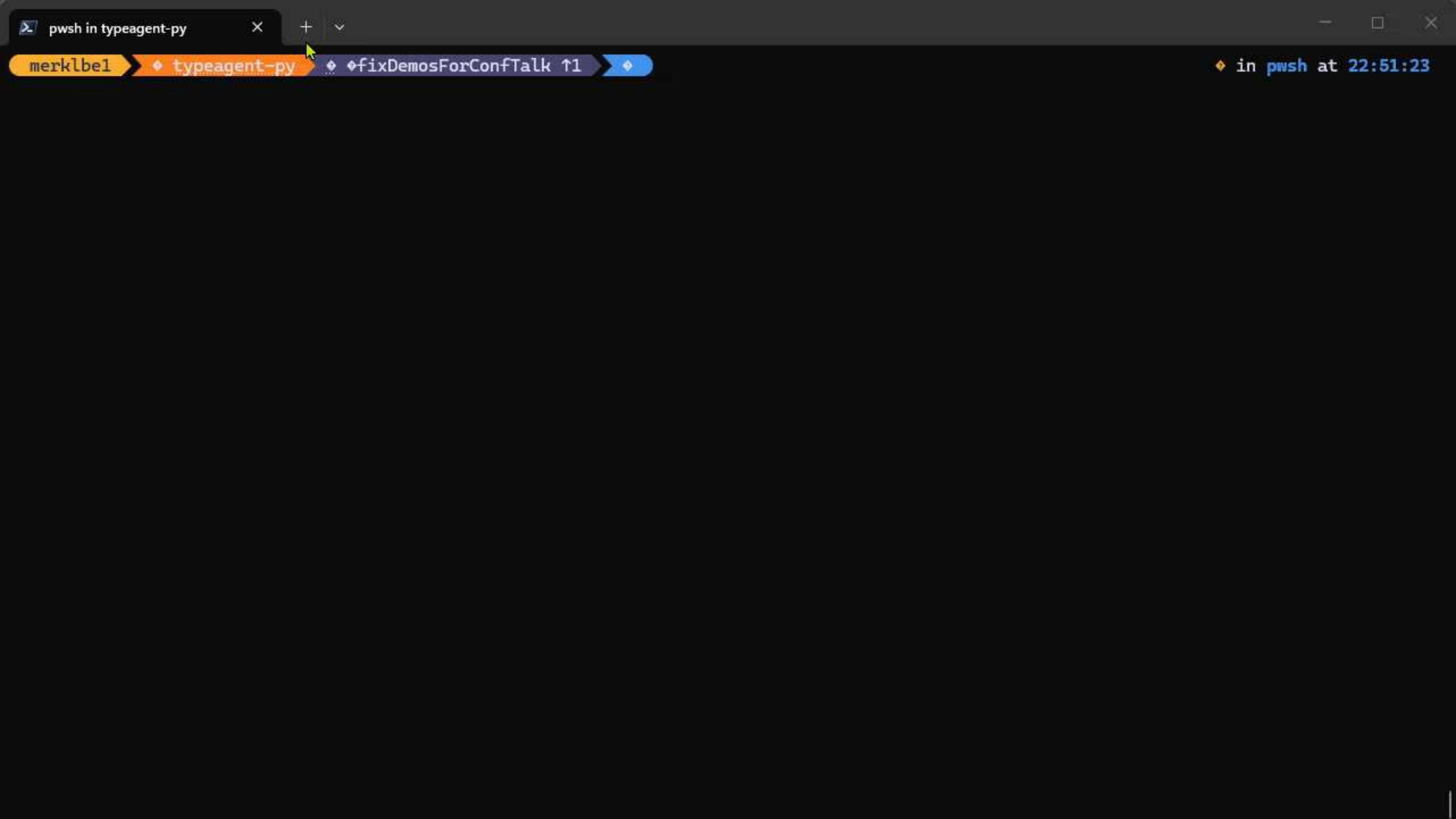
- 4. Developer Experience
  - Structured RAG relies on Schema-as-Code.
    You define what your memory looks like using TypeScript interfaces.
    The system ensures the LLM populates these structures strictly.
  - GraphRAG relies on Ontology Extraction.
    The system often discovers the structure itself (unsupervised) or
    uses a pre-defined graph schema to map out the world.



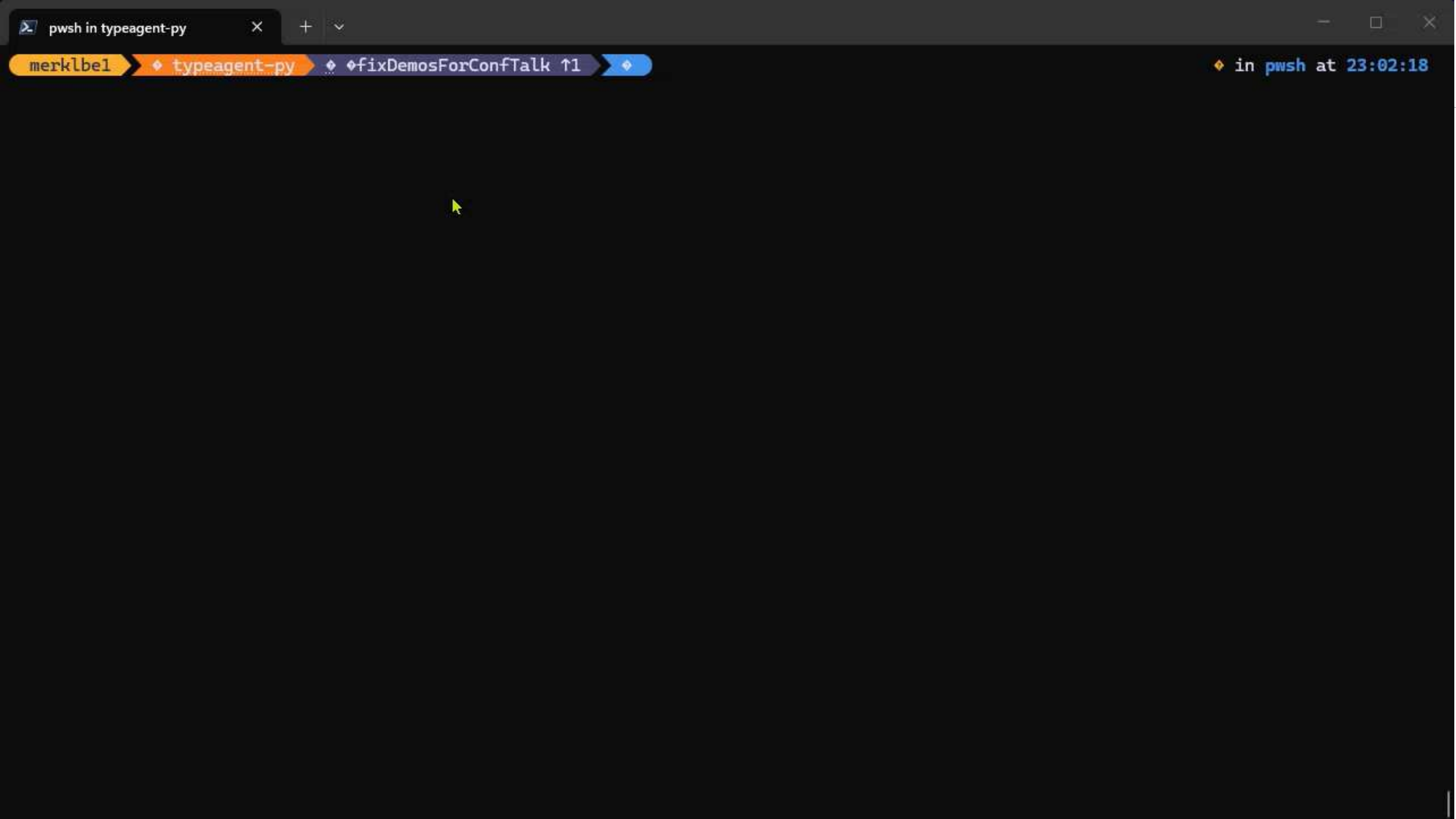
```
merklbe1 � demo � �load-dotenv-lib ≡ �                                   � in pwsh at 01:23:35
```



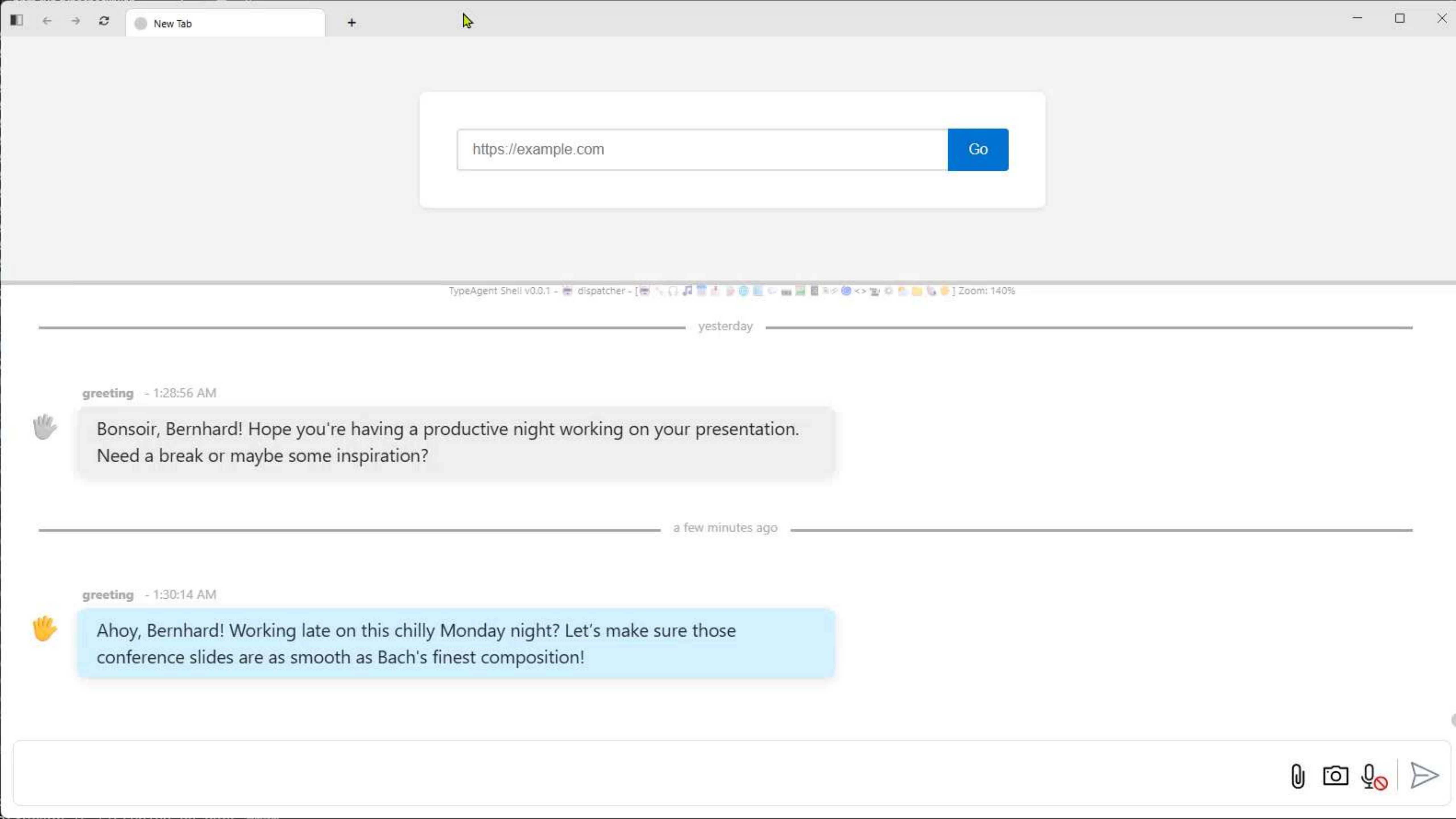
```
typeagent-py  python .\tools\ingest_vtt.py .\tests\testdata\Parrot_Sketch.vtt .\tests\testdata\Confuse-A-Cat.vtt .\tests\testdata\Short.vtt -d mp.db
Using Azure OpenAI... 1.227s
  Processing 152 messages in batches of 4...
    4/152 messages | 29 refs | 10.4s/batch | 10.4s elapsed
    8/152 messages | 59 refs | 7.8s/batch | 18.2s elapsed
    12/152 messages | 83 refs | 6.2s/batch | 24.4s elapsed
    16/152 messages | 112 refs | 6.6s/batch | 31.0s elapsed
    20/152 messages | 142 refs | 7.9s/batch | 39.0s elapsed
    24/152 messages | 172 refs | 7.1s/batch | 46.0s elapsed
    28/152 messages | 207 refs | 8.0s/batch | 54.1s elapsed
    32/152 messages | 233 refs | 5.4s/batch | 59.5s elapsed
    36/152 messages | 252 refs | 7.8s/batch | 67.4s elapsed
    40/152 messages | 272 refs | 7.5s/batch | 74.9s elapsed
    44/152 messages | 283 refs | 6.4s/batch | 81.3s elapsed
    48/152 messages | 308 refs | 10.4s/batch | 91.7s elapsed
    52/152 messages | 327 refs | 6.7s/batch | 98.5s elapsed
    56/152 messages | 351 refs | 6.3s/batch | 104.8s elapsed
    60/152 messages | 375 refs | 7.1s/batch | 111.9s elapsed
    64/152 messages | 384 refs | 3.5s/batch | 115.5s elapsed
    68/152 messages | 402 refs | 3.7s/batch | 119.2s elapsed
    72/152 messages | 418 refs | 3.8s/batch | 122.9s elapsed
    76/152 messages | 435 refs | 5.2s/batch | 128.2s elapsed
    80/152 messages | 453 refs | 4.7s/batch | 132.8s elapsed
    84/152 messages | 468 refs | 5.4s/batch | 138.3s elapsed
    88/152 messages | 488 refs | 4.3s/batch | 142.6s elapsed
    92/152 messages | 500 refs | 4.0s/batch | 146.6s elapsed
    96/152 messages | 519 refs | 7.4s/batch | 154.0s elapsed
    100/152 messages | 532 refs | 4.0s/batch | 158.0s elapsed
    104/152 messages | 551 refs | 5.3s/batch | 163.3s elapsed
    108/152 messages | 573 refs | 5.7s/batch | 169.0s elapsed
    112/152 messages | 593 refs | 4.6s/batch | 173.6s elapsed
    116/152 messages | 607 refs | 4.0s/batch | 177.6s elapsed
    120/152 messages | 620 refs | 3.3s/batch | 180.9s elapsed
    124/152 messages | 644 refs | 8.9s/batch | 189.8s elapsed
    128/152 messages | 670 refs | 10.0s/batch | 199.8s elapsed
    132/152 messages | 688 refs | 7.5s/batch | 207.3s elapsed
    136/152 messages | 713 refs | 7.9s/batch | 215.2s elapsed
    140/152 messages | 731 refs | 6.1s/batch | 221.3s elapsed
    144/152 messages | 759 refs | 8.4s/batch | 229.7s elapsed
    148/152 messages | 778 refs | 5.6s/batch | 235.3s elapsed
    152/152 messages | 805 refs | 6.8s/batch | 242.2s elapsed
Imported 152 messages from 3 file(s) to mp.db
All indexes built successfully

To query the transcript, use:
  python tools/query.py --database 'mp.db' --query 'Your question here'
```



```
merklbe1 � typeagent-py � �fixDemosForConfTalk ↑1 �                    � in pwsh at 22:51:23
```



```
merklbe1 ◆ typeagent-py ◆ ◆fixDemosForConfTalk ↑1 ◆                                   ◆ in pwsh at 23:02:18
```



TypeAgent Shell v0.0.1 - dispatcher - [ ] Zoom: 140%

yesterday

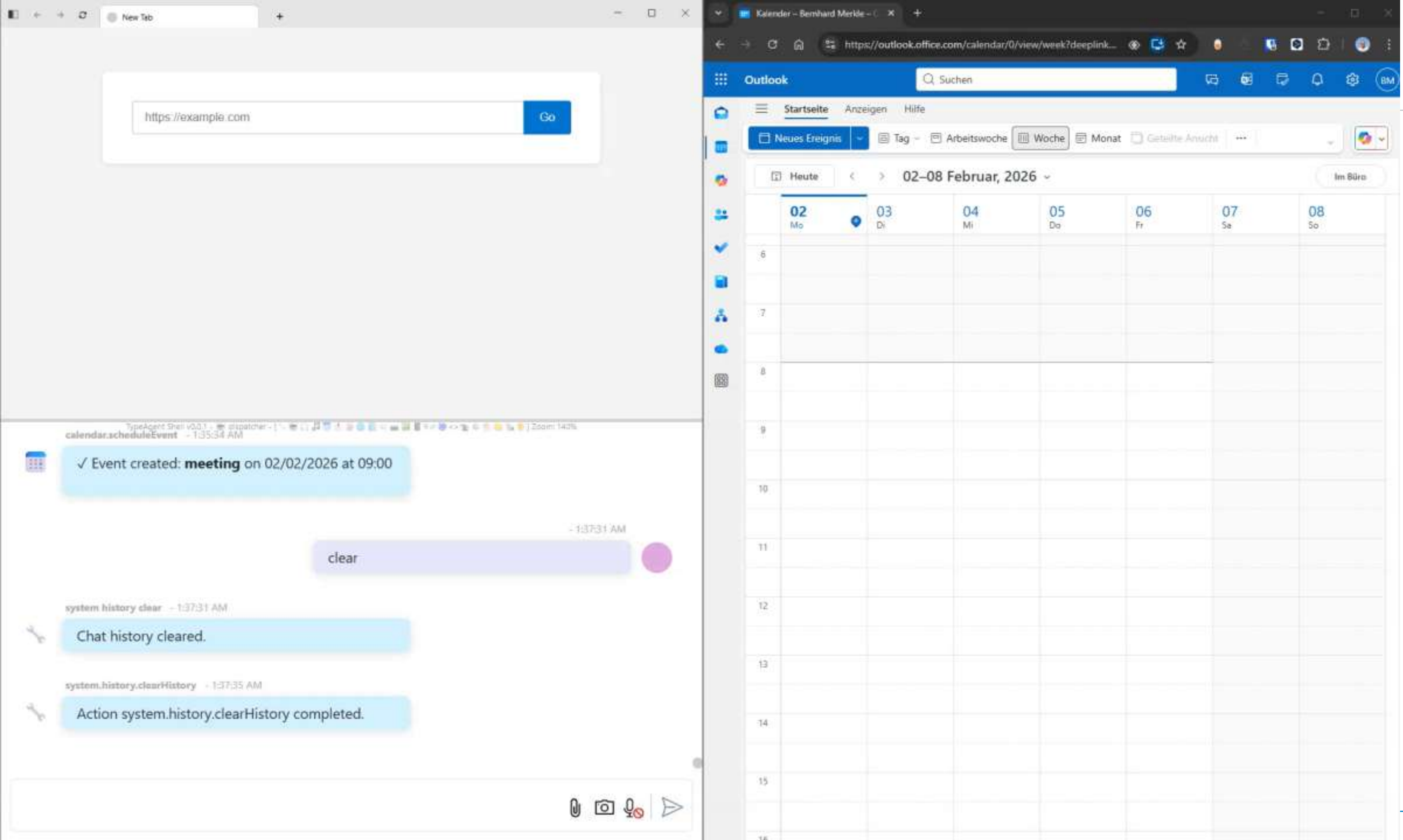
greeting - 1:28:56 AM

Bonsoir, Bernhard! Hope you're having a productive night working on your presentation. Need a break or maybe some inspiration?

a few minutes ago

greeting - 1:30:14 AM

Ahoy, Bernhard! Working late on this chilly Monday night? Let’s make sure those conference slides are as smooth as Bach's finest composition!



calendar.scheduleEvent - 1:35:34 AM

✓ Event created: **meeting** on 02/02/2026 at 09:00

- 1:37:31 AM

clear

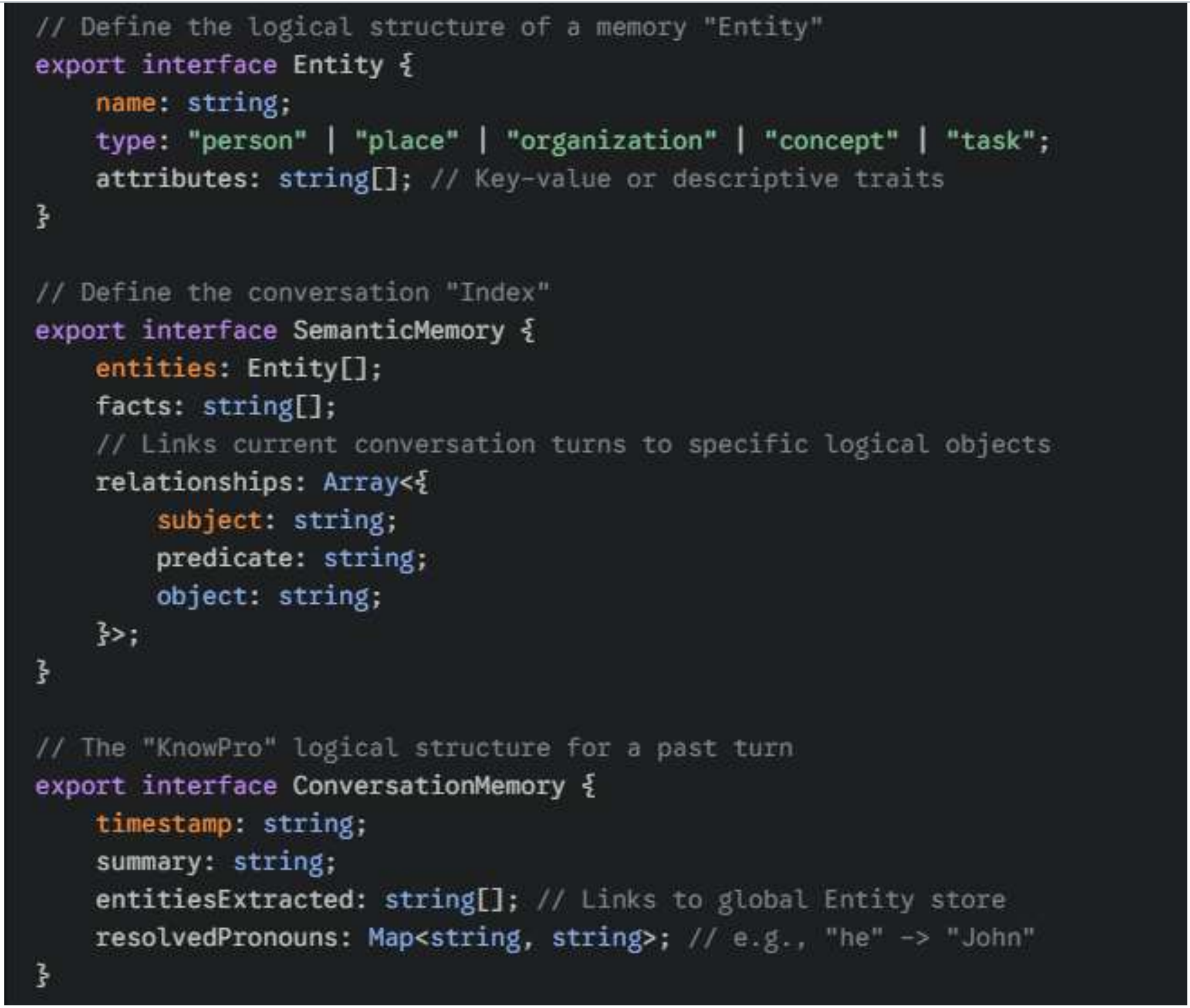
system history clear - 1:37:31 AM

Chat history cleared.

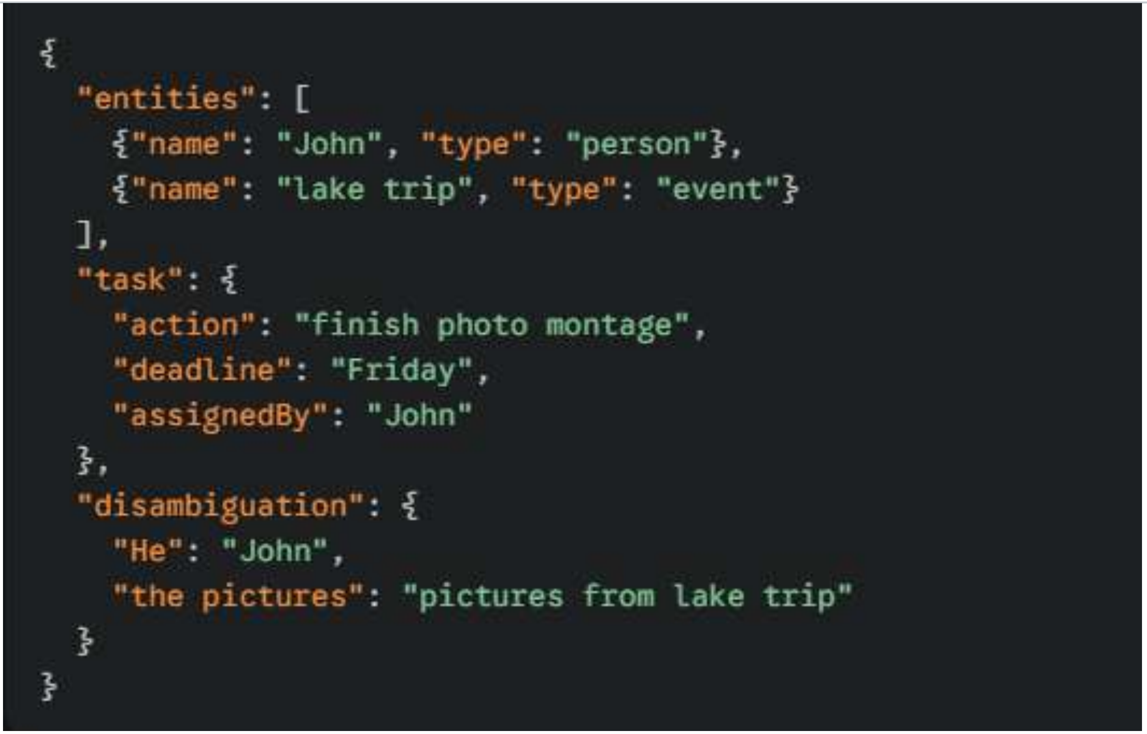
system.history.clearHistory - 1:37:35 AM

Action system.history.clearHistory completed.

KnowPro" system for extracting logical structure from text



```
// Define the logical structure of a memory "Entity"
export interface Entity {
    name: string;
    type: "person" | "place" | "organization" | "concept" | "task";
    attributes: string[]; // Key-value or descriptive traits
}

// Define the conversation "Index"
export interface SemanticMemory {
    entities: Entity[];
    facts: string[];
    // Links current conversation turns to specific logical objects
    relationships: Array<{
        subject: string;
        predicate: string;
        object: string;
    }>;
}

// The "KnowPro" logical structure for a past turn
export interface ConversationMemory {
    timestamp: string;
    summary: string;
    entitiesExtracted: string[]; // Links to global Entity store
    resolvedPronouns: Map<string, string>; // e.g., "he" -> "John"
}
```

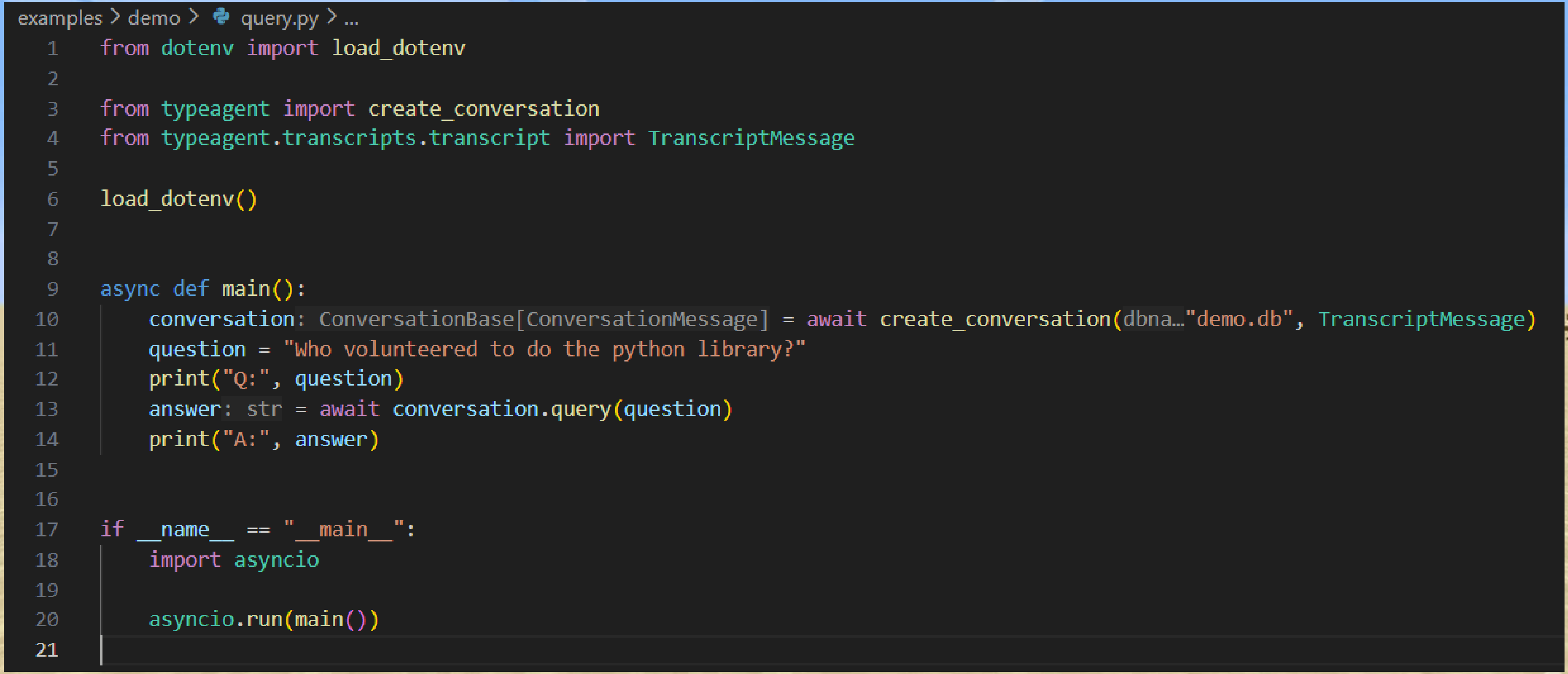


```
{
  "entities": [
    {"name": "John", "type": "person"},
    {"name": "lake trip", "type": "event"}
  ],
  "task": {
    "action": "finish photo montage",
    "deadline": "Friday",
    "assignedBy": "John"
  },
  "disambiguation": {
    "He": "John",
    "the pictures": "pictures from lake trip"
  }
}
```

KnowPro Folder (TypeScript): Look for index.ts and ontology.ts. These files define how the system builds "Indices" of conversations that are logically linked rather than just vector-indexed.

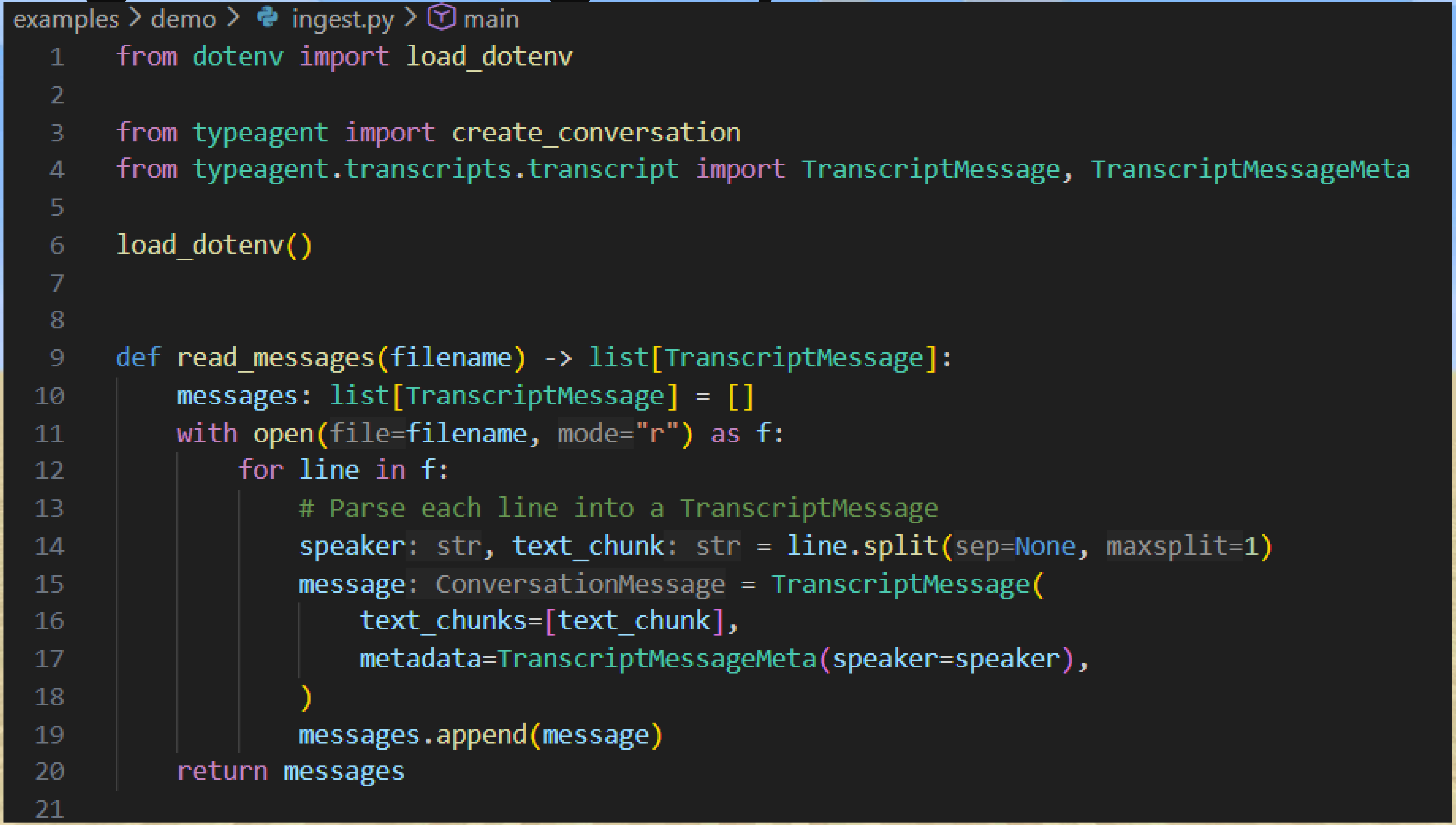
typeagent-py (Python): Look at the typeagent/know_pro directory. It translates these TypeScript interfaces into Pydantic models, which act as the structured schema for Python-based agents.

Query database



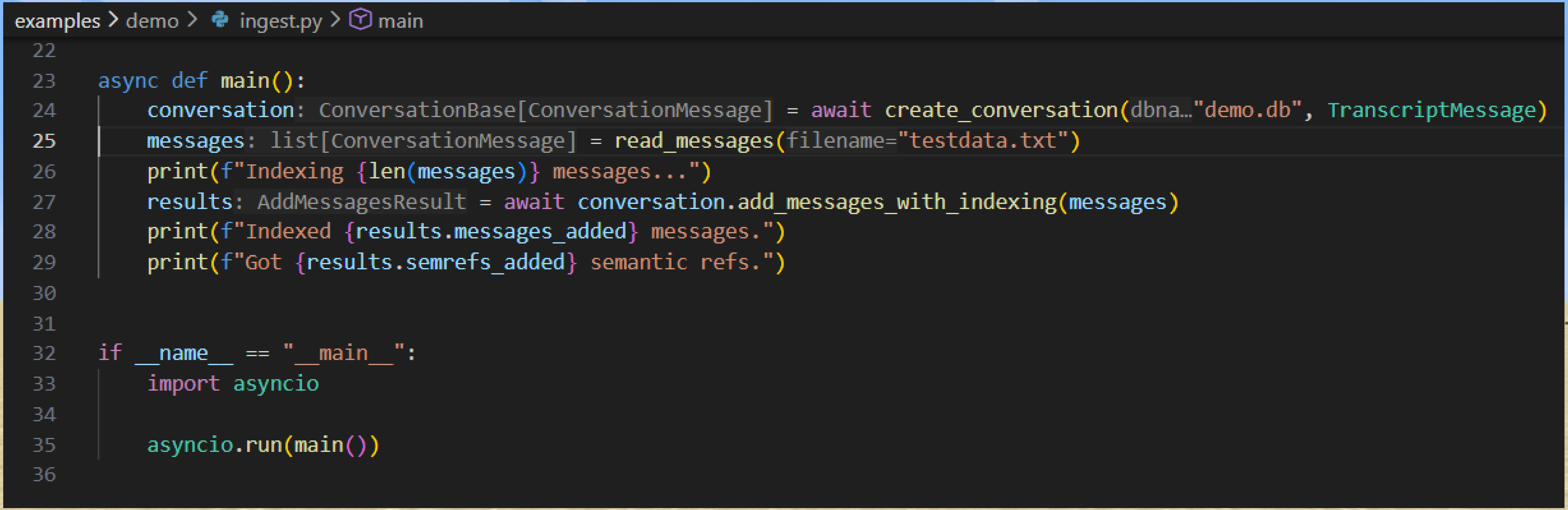
```python
from dotenv import load_dotenv

from typeagent import create_conversation
from typeagent.transcripts.transcript import TranscriptMessage

load_dotenv()


async def main():
    conversation: ConversationBase[ConversationMessage] = await create_conversation(dbna…"demo.db", TranscriptMessage)
    question = "Who volunteered to do the python library?"
    print("Q:", question)
    answer: str = await conversation.query(question)
    print("A:", answer)


if __name__ == "__main__":
    import asyncio

    asyncio.run(main())

```

Ingest Messages 1/2



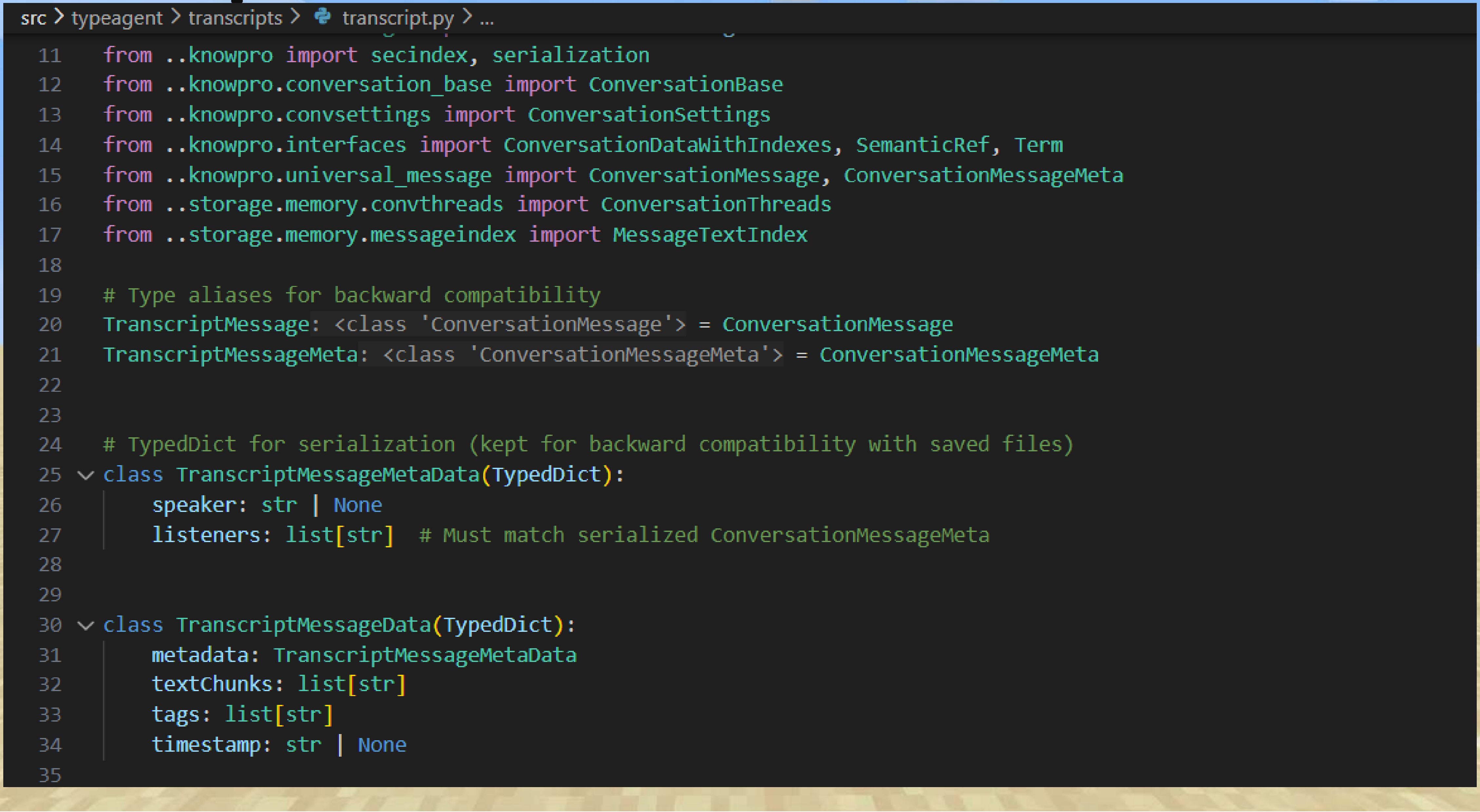
```python
from dotenv import load_dotenv

from typeagent import create_conversation
from typeagent.transcripts.transcript import TranscriptMessage, TranscriptMessageMeta

load_dotenv()


def read_messages(filename) -> list[TranscriptMessage]:
    messages: list[TranscriptMessage] = []
    with open(file=filename, mode="r") as f:
        for line in f:
            # Parse each line into a TranscriptMessage
            speaker: str, text_chunk: str = line.split(sep=None, maxsplit=1)
            message: ConversationMessage = TranscriptMessage(
                text_chunks=[text_chunk],
                metadata=TranscriptMessageMeta(speaker=speaker),
            )
            messages.append(message)
    return messages

```

Ingest Messages 2/2



```python

async def main():
    conversation: ConversationBase[ConversationMessage] = await create_conversation(dbna…"demo.db", TranscriptMessage)
    messages: list[ConversationMessage] = read_messages(filename="testdata.txt")
    print(f"Indexing {len(messages)} messages...")
    results: AddMessagesResult = await conversation.add_messages_with_indexing(messages)
    print(f"Indexed {results.messages_added} messages.")
    print(f"Got {results.semrefs_added} semantic refs.")


if __name__ == "__main__":
    import asyncio

    asyncio.run(main())

```

Knowpro: Datastructures



src > typeagent > transcripts > transcript.py > ...

```python
from ..knowpro import secindex, serialization
from ..knowpro.conversation_base import ConversationBase
from ..knowpro.convsettings import ConversationSettings
from ..knowpro.interfaces import ConversationDataWithIndexes, SemanticRef, Term
from ..knowpro.universal_message import ConversationMessage, ConversationMessageMeta
from ..storage.memory.convthreads import ConversationThreads
from ..storage.memory.messageindex import MessageTextIndex

# Type aliases for backward compatibility
TranscriptMessage: <class 'ConversationMessage'> = ConversationMessage
TranscriptMessageMeta: <class 'ConversationMessageMeta'> = ConversationMessageMeta


# TypedDict for serialization (kept for backward compatibility with saved files)
class TranscriptMessageMetaData(TypedDict):
    speaker: str | None
    listeners: list[str]  # Must match serialized ConversationMessageMeta


class TranscriptMessageData(TypedDict):
    metadata: TranscriptMessageMetaData
    textChunks: list[str]
    tags: list[str]
    timestamp: str | None

```

Summary: Structured RAG

- ✓ Retrieval recall and precision are better (knowledge nuggets)
- ✓ can be queried more precisely, generating higher information density
- ✓ → Better Answers
- ✓ Scalable to much larger conversation histories
- ✓ indexing approach needs less compute and data
- ✓ Some knowledge can be extracted without consulting an
- ✓ More lightweight than (Knowledge) GraphRAG

- ⚠ research project, early stage...
- ⚠ Bulk ingestion is slower (LLM usage)...

Sources:

- **Code**
- **Structured-RAG**
  - https://github.com/microsoft/TypeAgent (Initial TS Implementation Umesh Madan and Steven Lucco)
  - https://github.com/microsoft/typeagent-py (Python Port of TypeAgent Guido van Rossum)

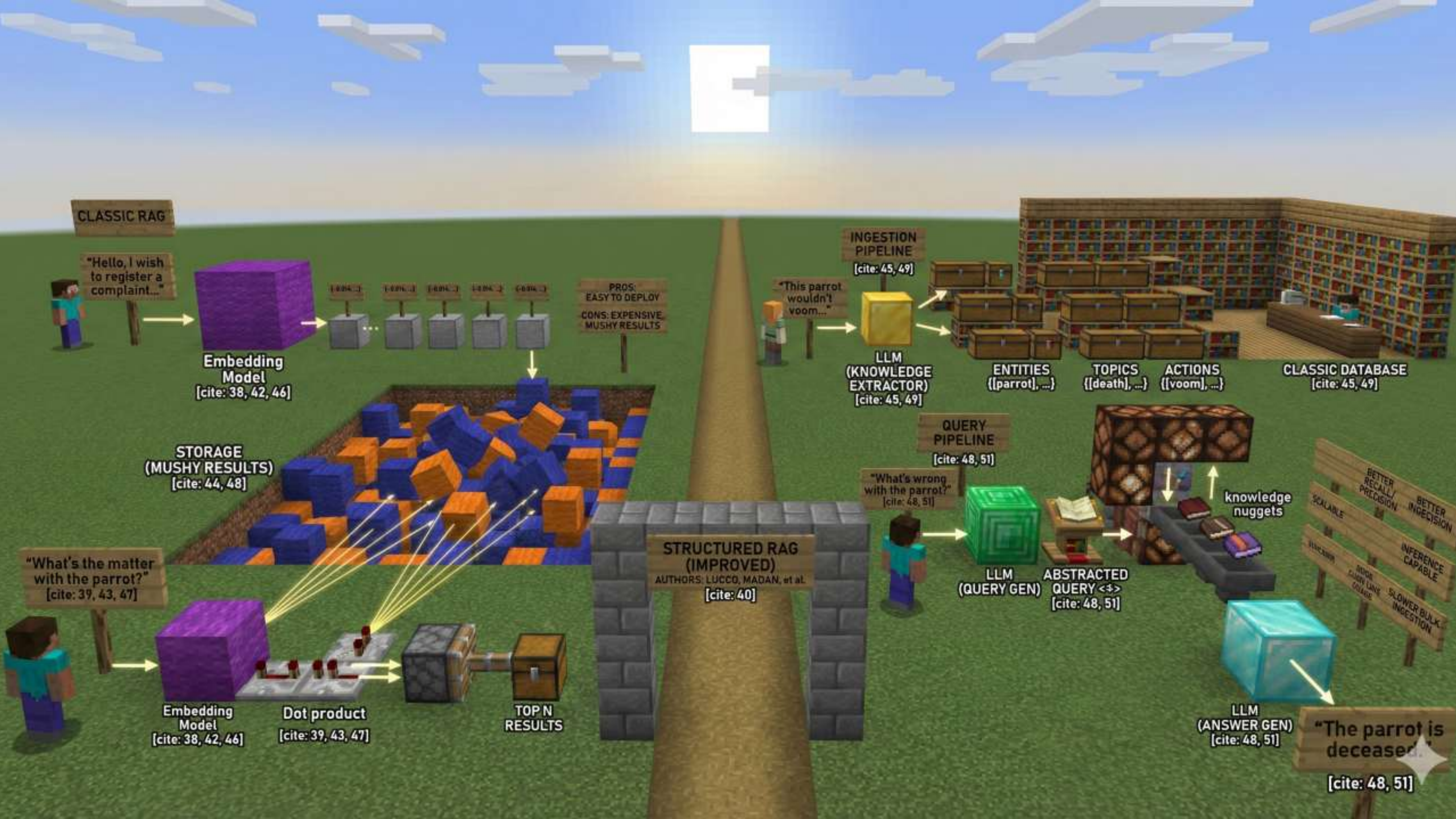
- **Graph-RAG**
  - https://github.com/microsoft/graphrag
  - https://github.com/neo4j/neo4j-graphrag-python

- **Collections**
  - https://github.com/graphrag
  - https://github.com/Andrew-Jang/RAGHub
  - https://github.com/DEEP-PolyU/Awesome-GraphRAG

Sources:

- **Presentations:**
- **Microsoft Build 2025: *"Making Agent Memory Better and Agent Actions Faster with TypeAgent“***
  https://www.youtube.com/watch?v=acbUy2oZqmA
- **PyBay 2025: *“Structured RAG is better than RAG“***
  https://www.youtube.com/watch?v=-klESD7iB-s

- **Guidos Talk:** https://github.com/microsoft/typeagent-py/blob/main/docs/StructuredRagPyBay25.pdf
- **Images generated via** https://gemini.google.com/


CLASSIC RAG
"Hello, I wish to register a complaint..."
Embedding Model [cite: 38, 42, 46]
PROS: EASY TO DEPLOY
CONS: EXPENSIVE, MUSHY RESULTS
STORAGE (MUSHY RESULTS) [cite: 44, 48]
"What's the matter with the parrot?" [cite: 39, 43, 47]
Embedding Model [cite: 38, 42, 46]
Dot product [cite: 39, 43, 47]
TOP N RESULTS
STRUCTURED RAG (IMPROVED)
AUTHORS: LUCCO, MADAN, et al.
[cite: 40]
INGESTION PIPELINE [cite: 45, 49]
"This parrot wouldn't voom..."
LLM (KNOWLEDGE EXTRACTOR) [cite: 45, 49]
ENTITIES {[parrot], ...}
TOPICS {[death], ...}
ACTIONS {[voom], ...}
CLASSIC DATABASE [cite: 45, 49]
QUERY PIPELINE [cite: 48, 51]
"What's wrong with the parrot?" [cite: 48, 51]
LLM (QUERY GEN)
ABSTRACTED QUERY <+> [cite: 48, 51]
knowledge nuggets
BETTER RECALL/ PRECISION
BETTER INGECISION
SCALABLE
INFERENCE CAPABLE
SLOWER BULK INGESTION
LLM (ANSWER GEN) [cite: 48, 51]
"The parrot is deceased." [cite: 48, 51]