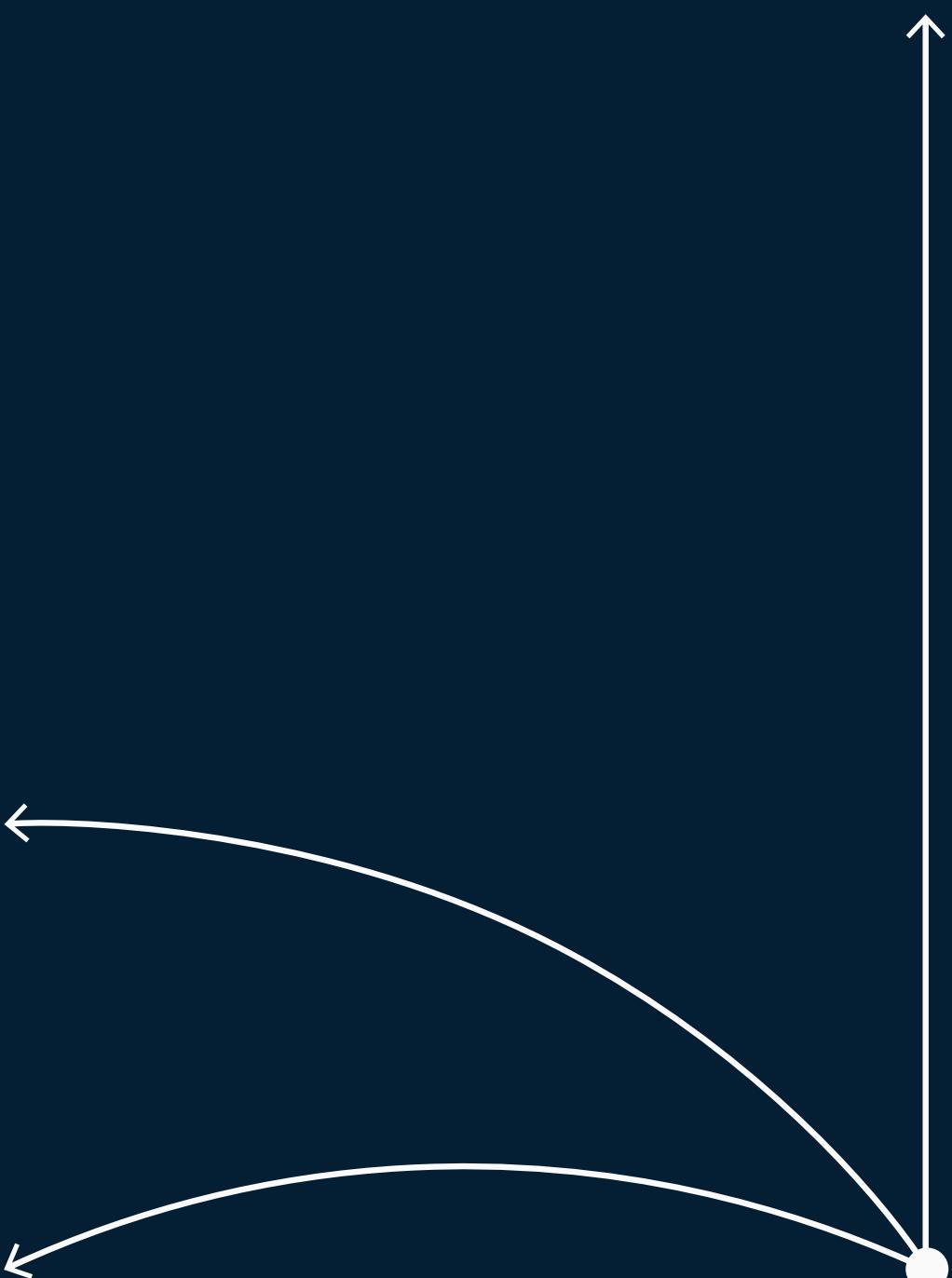


# Context Engineering in Agentic AI: The Power of the Semantic Layer

London AI Agentic Meetup

Thursday, 2025-09-25

**Leonardo Ubbiali**



# Leonardo Ubbiali



Entrepreneur, YC W24 Alumn.  
Ex MoonPay, Babylon, Yoox.

Email: leo@visumlabs.com

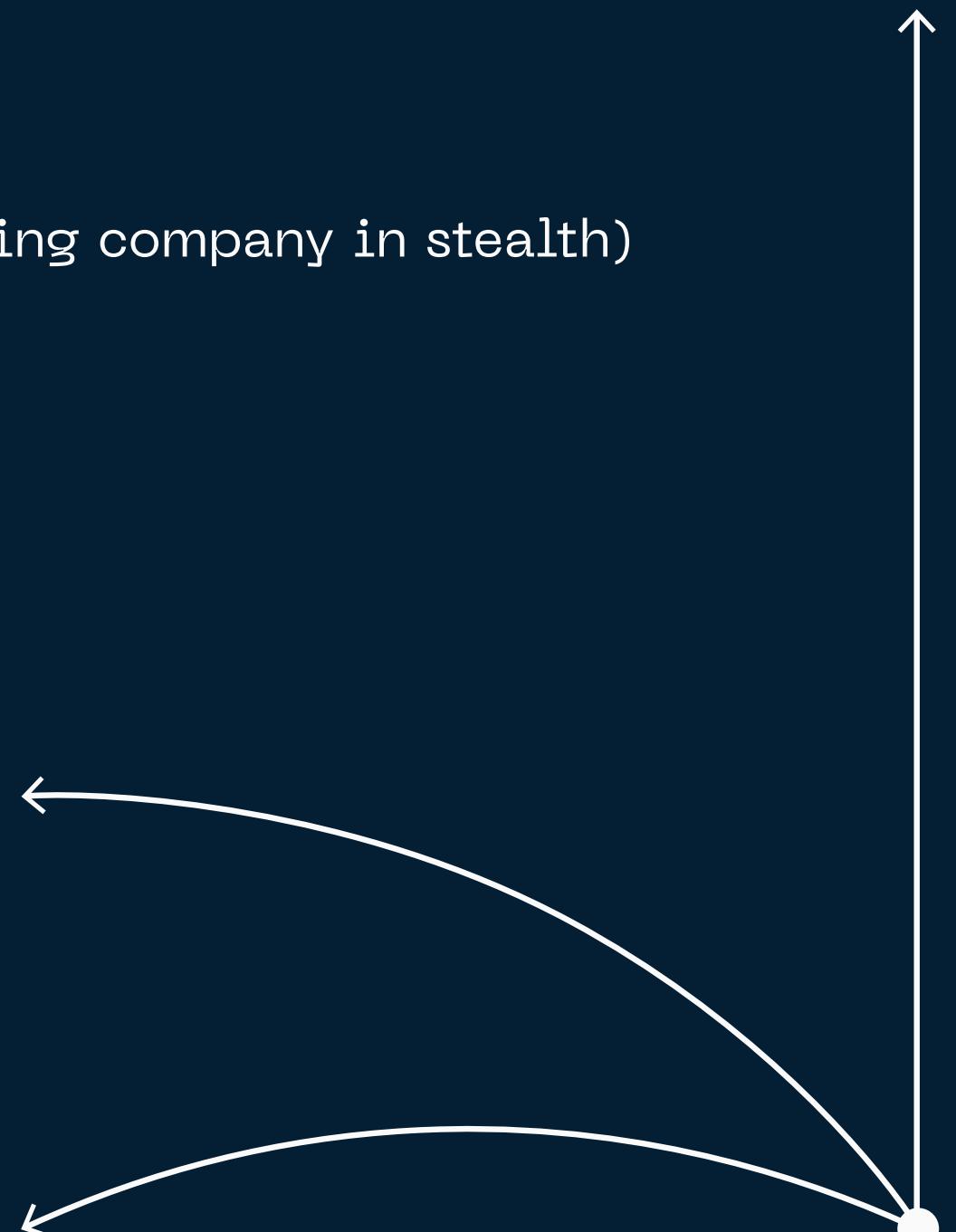
Now helping companies implement data and AI systems (consulting company in stealth)



X

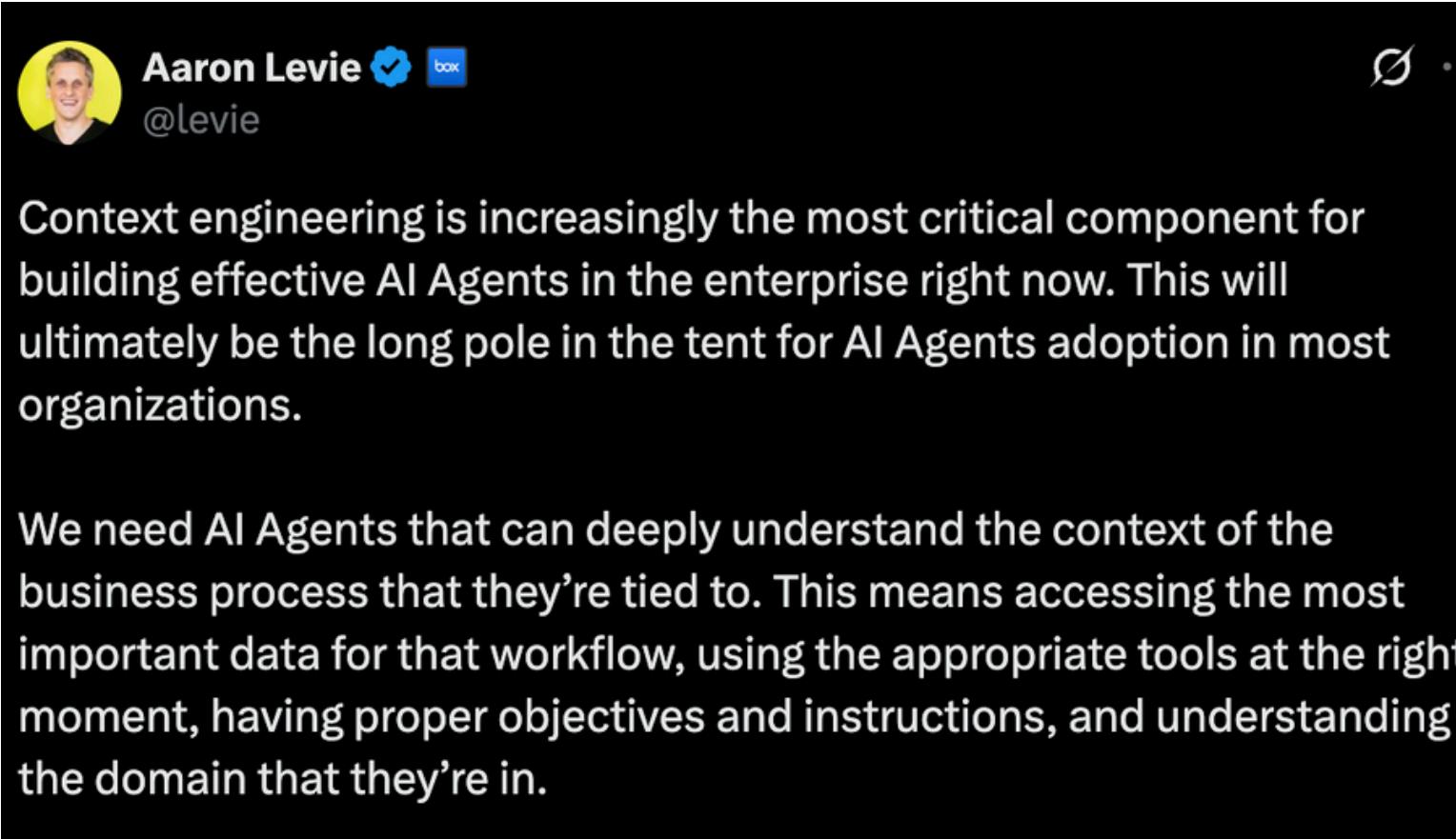


LinkedIn



# Context Over Prompts

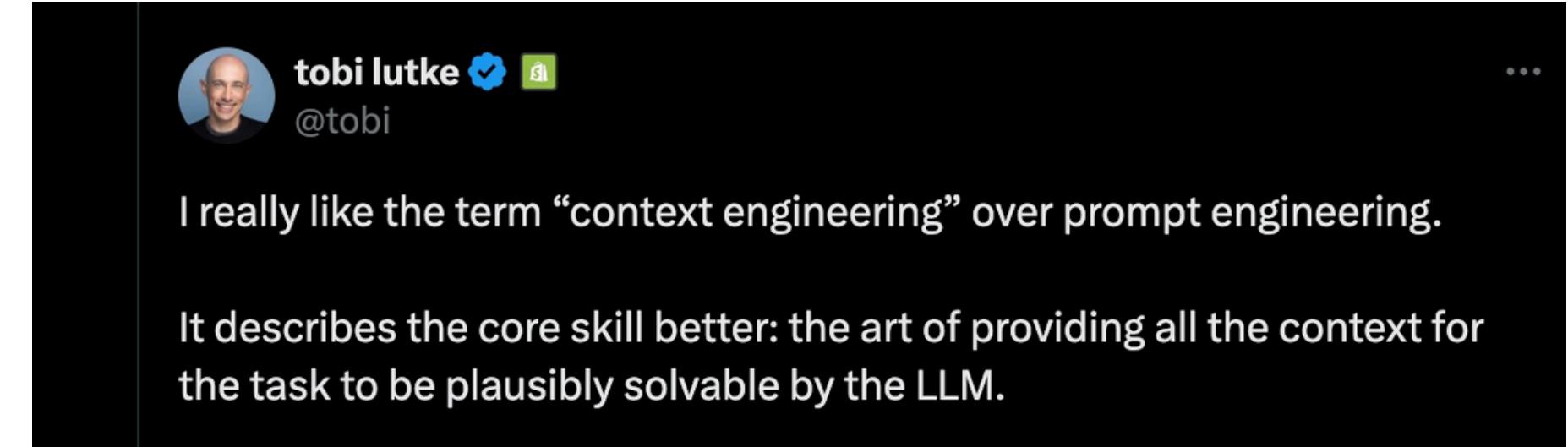
Context Engineering – Not Just Prompt Engineering



Aaron Levie    
@levie

Context engineering is increasingly the most critical component for building effective AI Agents in the enterprise right now. This will ultimately be the long pole in the tent for AI Agents adoption in most organizations.

We need AI Agents that can deeply understand the context of the business process that they're tied to. This means accessing the most important data for that workflow, using the appropriate tools at the right moment, having proper objectives and instructions, and understanding the domain that they're in.

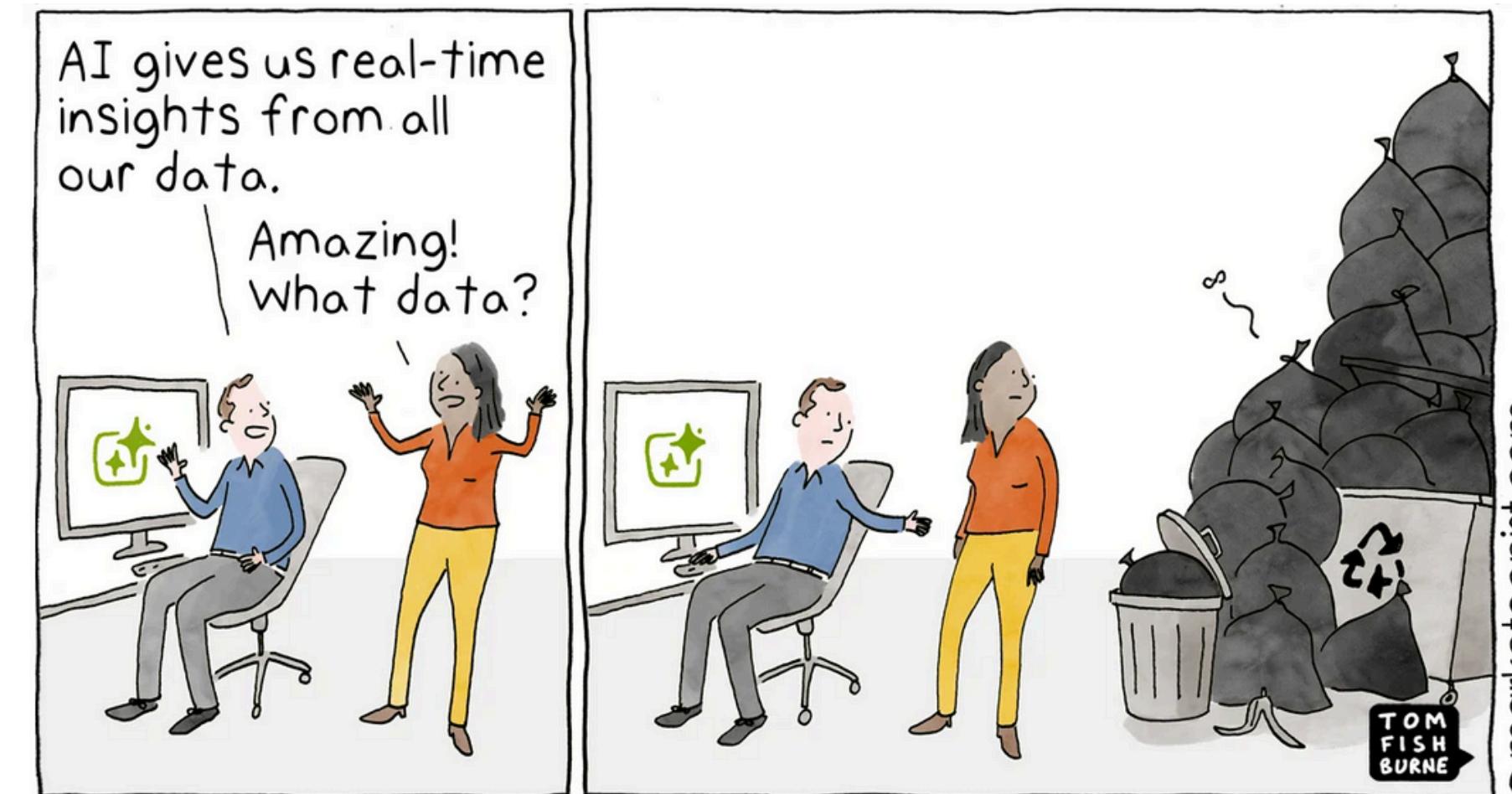


tobi lutke    
@tobi

I really like the term “context engineering” over prompt engineering. It describes the core skill better: the art of providing all the context for the task to be plausibly solvable by the LLM.

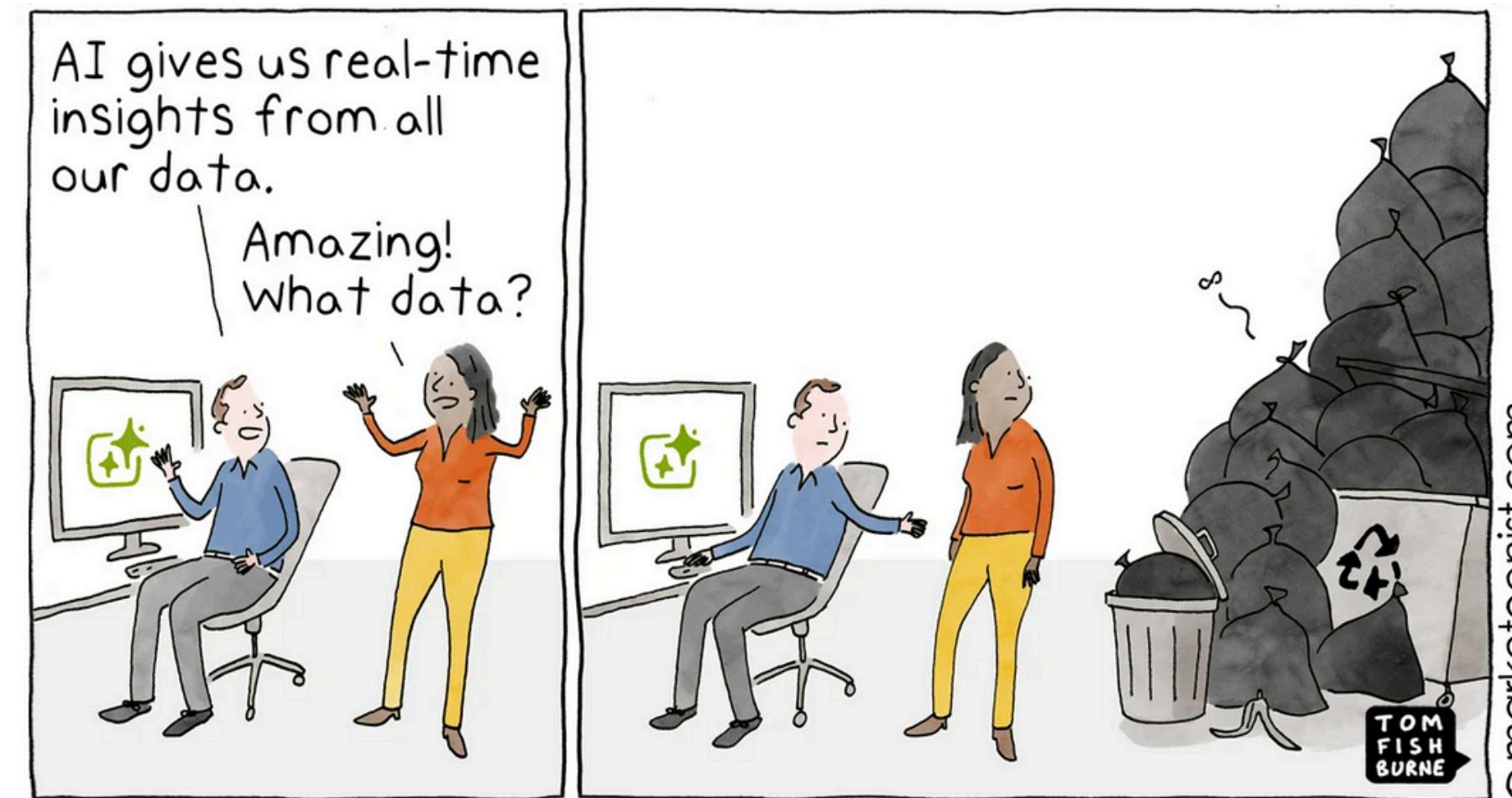
# Why AI Agents Fail Without Data Context

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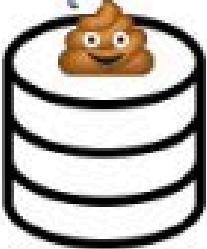


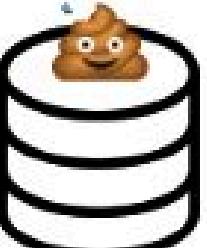
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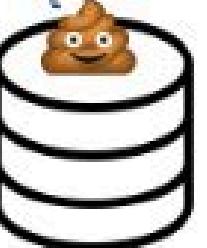
1. Data is fragmented; definitions and KPIs differ by team
2. LLMs often hallucinate and misinterpret data structure/meaning
3. Business logic is NOT just SQL tables—context is the missing ingredient

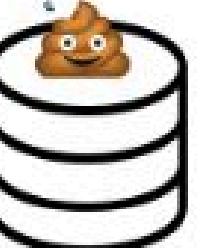


# Shit in Shit Out


$$+ \text{ Machine Learning } = \text{💩}$$


$$+ \text{ Artificial Intelligence } = \text{💩}$$


$$+ \text{ Generative AI } = \text{💩}$$


$$+ \text{ Agentic AI } = \begin{matrix} \text{💩} & \text{💩} & \text{💩} \\ \text{💩} & \text{💩} & \text{💩} \\ \text{💩} & \text{💩} & \text{💩} \end{matrix}$$

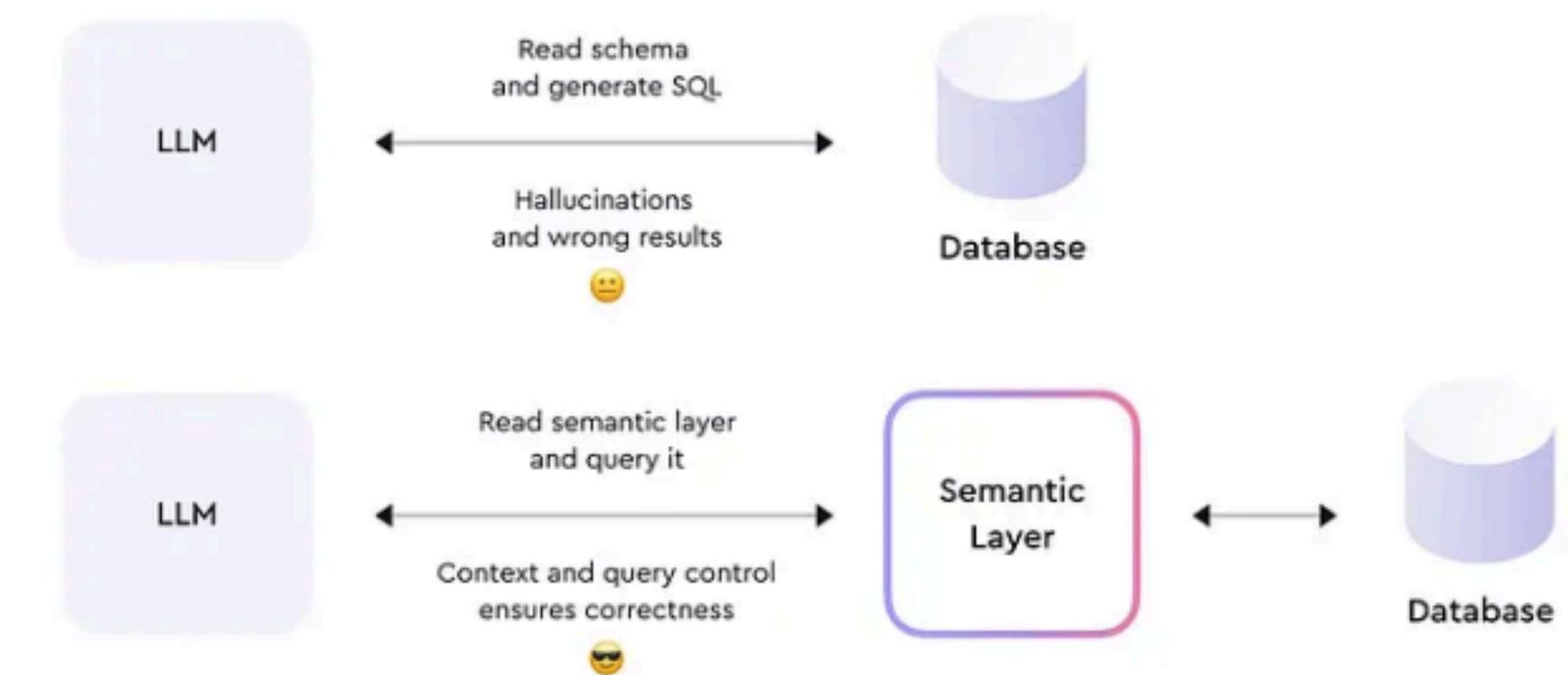
# What Is a Semantic Layer?

A semantic layer for AI is a business-friendly abstraction that sits between raw data and AI applications, translating complex technical data into understandable business concepts and relationships.

It provides a unified, authoritative view of data by embedding business logic, metrics, and rules, acting as a shared source of truth that teaches AI systems to interpret and act on data with business context

# What Is a Semantic Layer?

- Sits between your raw data and business users/AI

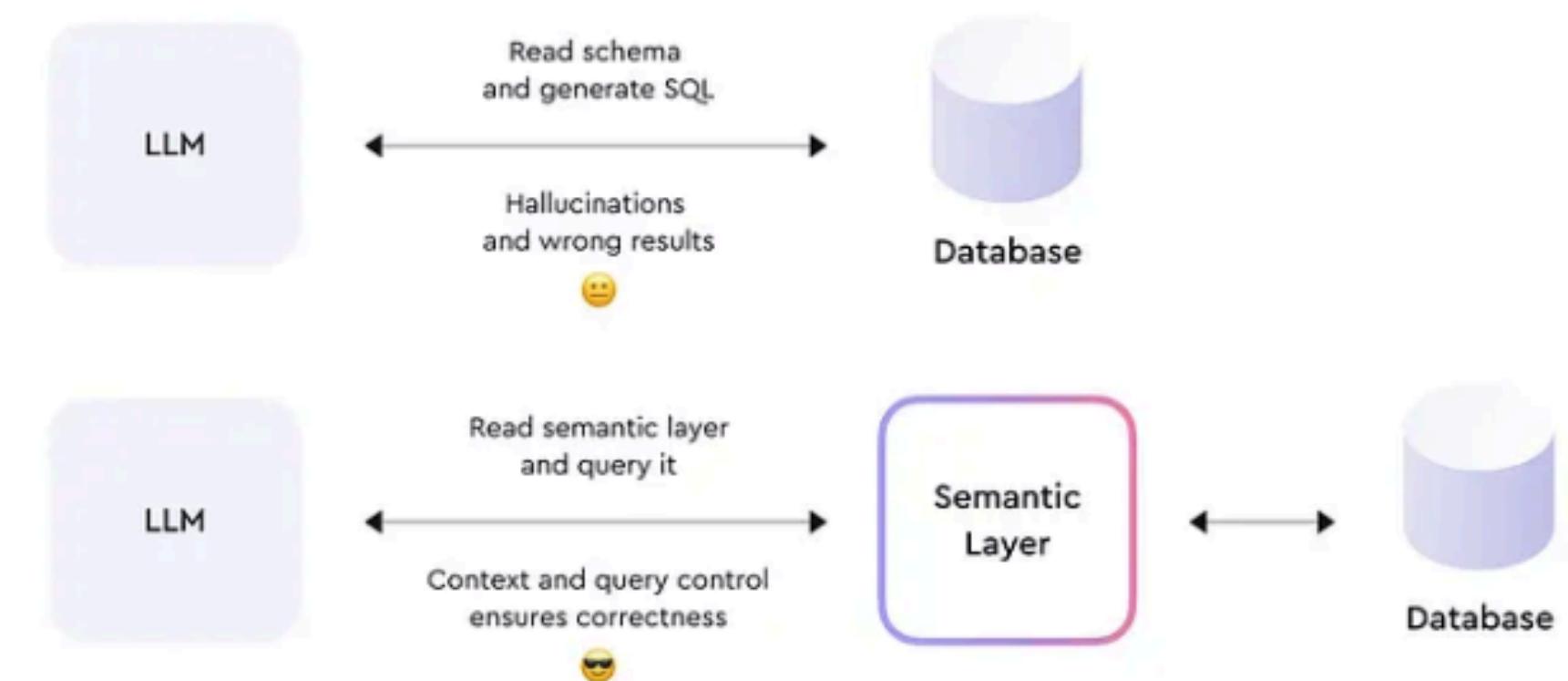


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Sources:  
[Cube Semantic Layer explainer](#)

# What Is a Semantic Layer?

- Sits between your raw data and business users/AI
- Maps technical schema to shared, business-friendly concepts

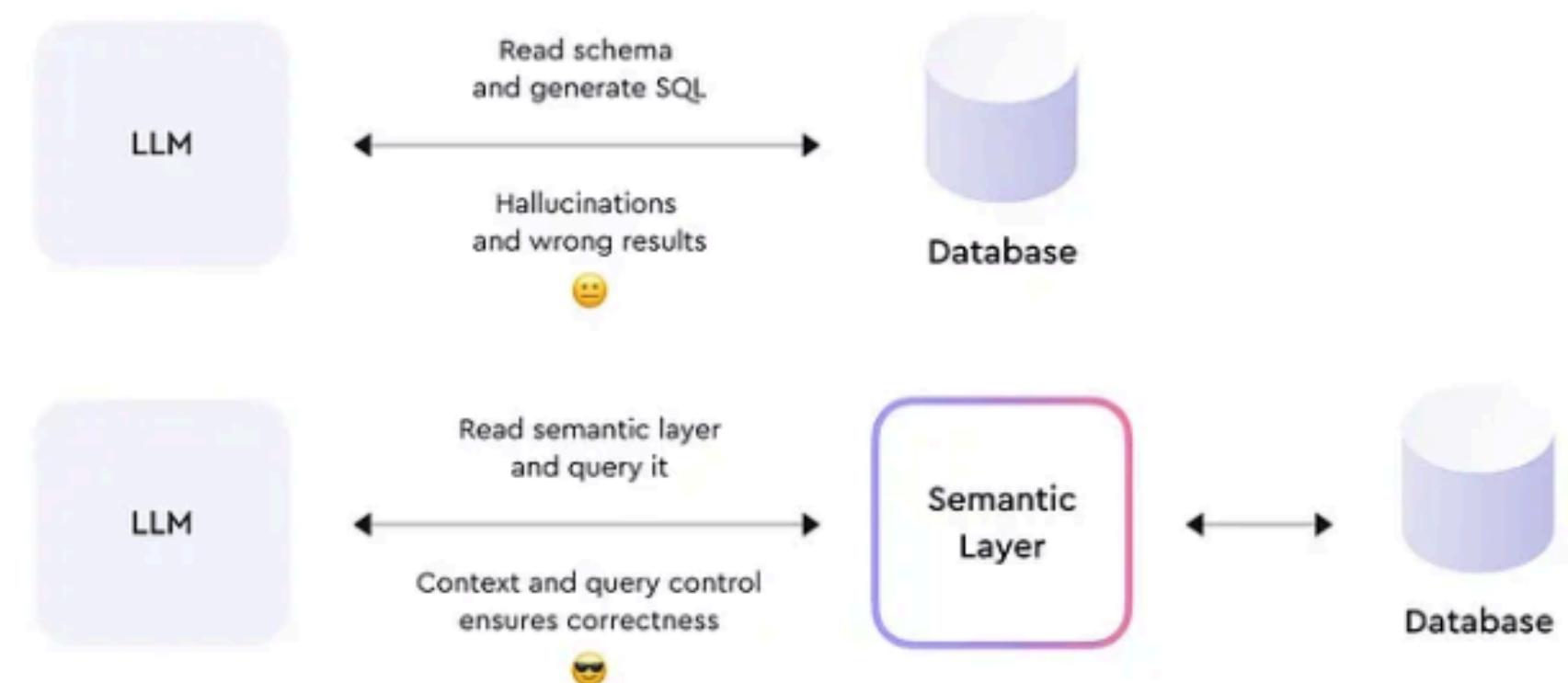


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# What Is a Semantic Layer?

- Sits between your raw data and business users/AI
- Maps technical schema to shared, business-friendly concepts
- Abstracts SQL and joins into understandable logic



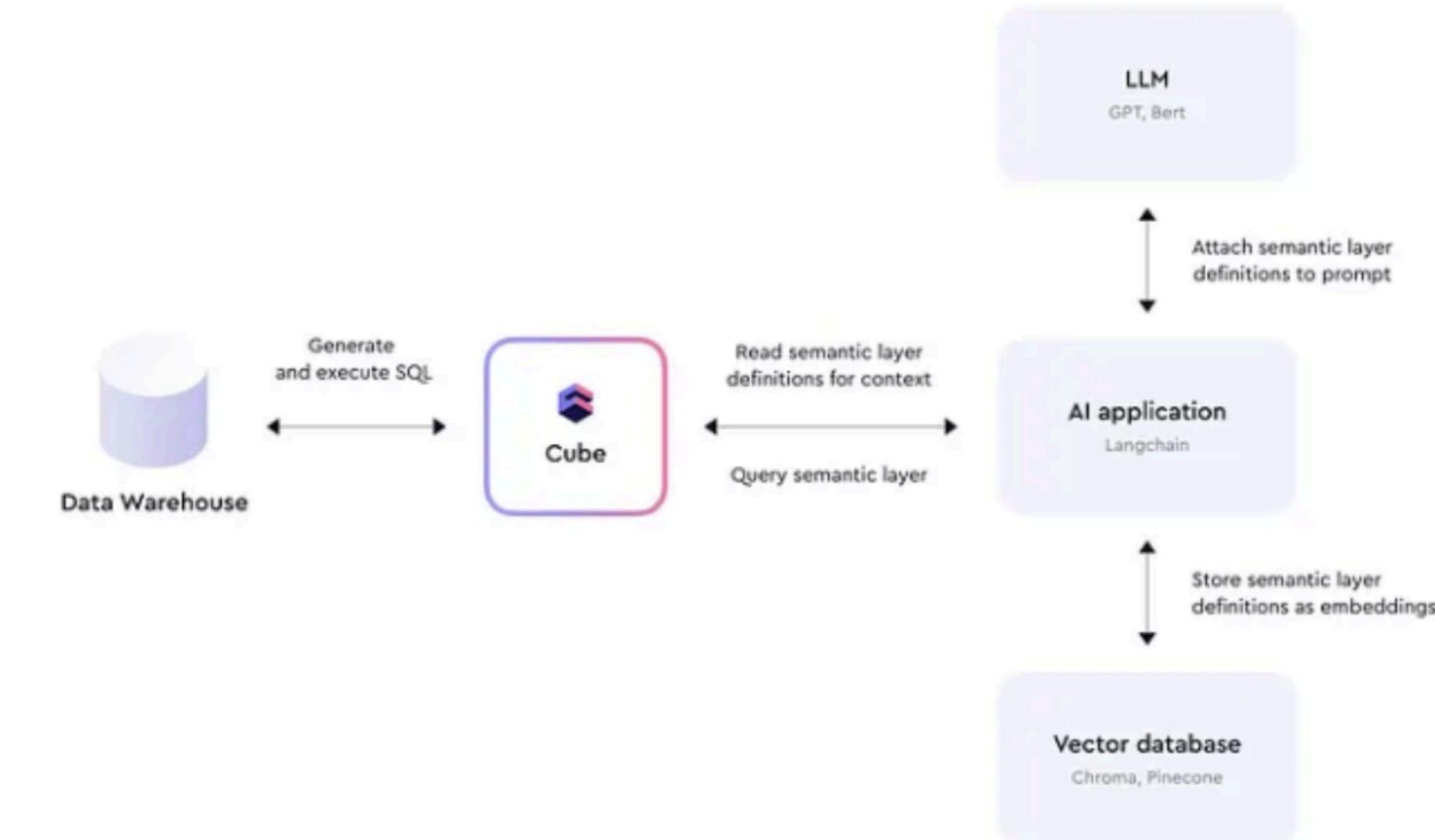
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# Why Context Engineering matters

## 1. No AI without consistent data:

AI needs high-quality, consistent data via a universal semantic layer..



# Why Context Engineering matters

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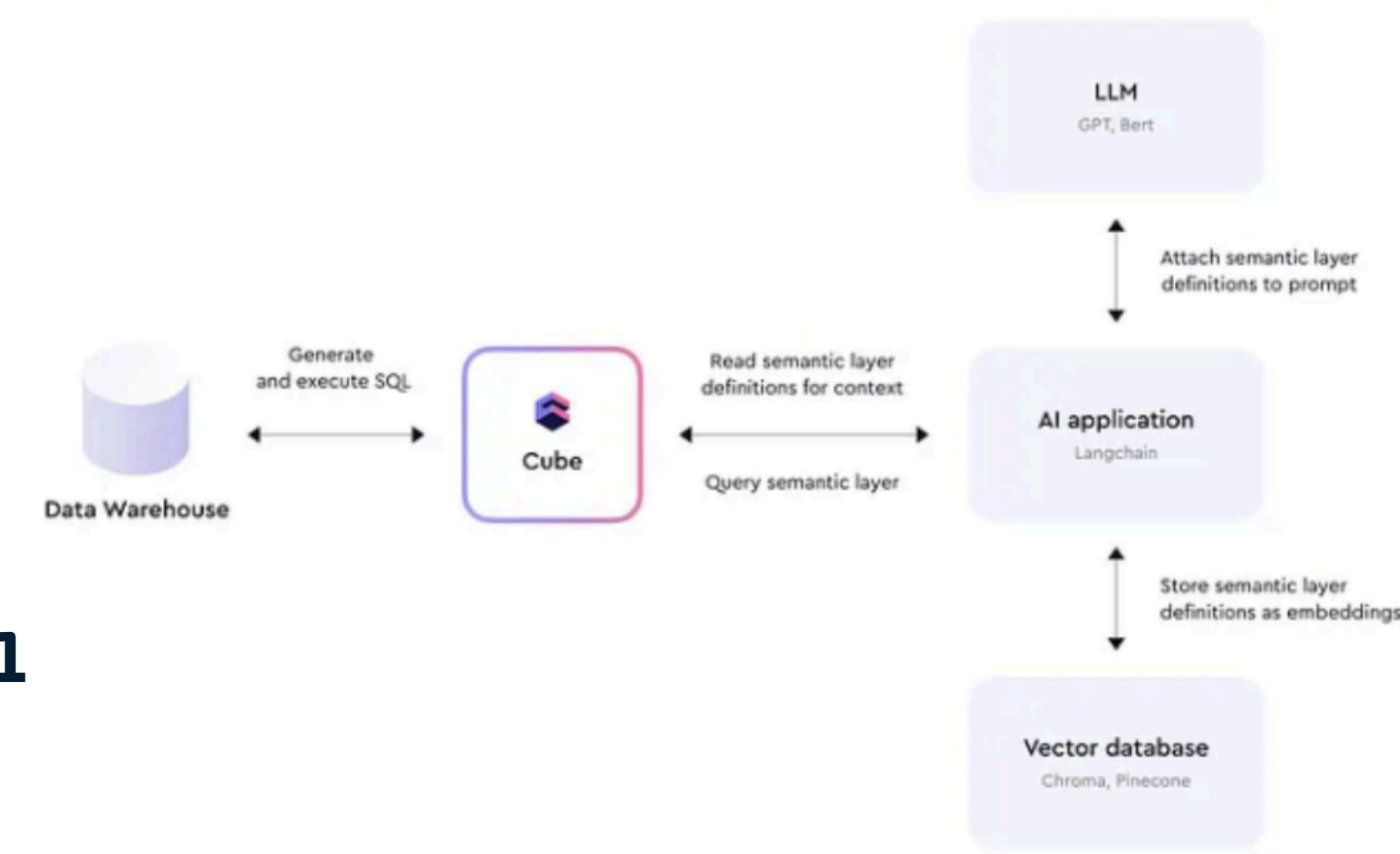
AI needs high-quality, consistent data via a universal semantic layer..

## 2. The rise of agentic AI:

Agentic AI requires accurate, consistent inputs ensured by a semantic layer.

## 3. The benefits of an AI-ready universal semantic layer:

A semantic layer connects data and powers AI applications.



# Anatomy of a Semantic Layer

## **A modern semantic layer includes:**

- A metric store: centralised definitions of KPIs and calculations
- A modelling layer: mappings from business concepts to tables and joins
- APIs and SDKs: so tools (LLMs, Agentic Workflows, BI tools) can access it
- Lineage tracking and version control: to trace changes over time

# Sematic Layer – an example

```
None

metrics:
  - name: total_revenue
    label: Total Revenue
    model: ref('orders')
    calculation_method: sum
    expression: amount
    description: "Sum of all order amounts"
    timestamp: order_date
    time_grains: [day, week, month, year]

  - name: order_count
    label: Order Count
    model: ref('orders')
    calculation_method: count
    description: "Number of orders placed"
    timestamp: order_date
    time_grains: [day, week, month, year]

dimensions:
  - name: customer_id
    type: string
    description: "Unique ID for the customer"

  - name: country
    type: string
    description: "Country of the customer"

  - name: order_date
    type: date
    description: "Date when the order was placed"
```

# Quantitative Impact: Real LLM Results

- Benchmark ([paper\_semantic\_layer.pdf], Table 1, Fig. 6, 8, p.9–11):
- GPT-4 Zero-shot on raw SQL: 16.7% accuracy
- GPT-4 using Knowledge Graph/Semantic Layer: 54.2% accuracy



**3X**  
improvement  
(especially on complex questions)

# Quantitative Impact: Real LLM Results

## A BENCHMARK TO UNDERSTAND THE ROLE OF KNOWLEDGE GRAPHS ON LARGE LANGUAGE MODEL'S ACCURACY FOR QUESTION ANSWERING ON ENTERPRISE SQL DATABASES

TECHNICAL REPORT

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November 14, 2023

### ABSTRACT

Enterprise applications of Large Language Models (LLMs) hold promise for question answering on enterprise SQL databases. However, the extent to which LLMs can accurately respond to enterprise questions in such databases remains unclear, given the absence of suitable Text-to-SQL benchmarks tailored to enterprise settings. Additionally, the potential of Knowledge Graphs (KGs) to enhance LLM-based question answering by providing business context is not well understood. This study aims to evaluate the accuracy of LLM-powered question answering systems in the context of enterprise questions and SQL databases, while also exploring the role of knowledge graphs in improving accuracy. To achieve this, we introduce a benchmark comprising an enterprise SQL schema in the insurance domain, a range of enterprise queries encompassing reporting to metrics, and a contextual layer incorporating an ontology and mappings that define a knowledge graph. Our primary finding reveals that question answering using GPT-4, with zero-shot prompts directly on SQL databases, achieves an accuracy of 16%. Notably, this accuracy increases to 54% when questions are posed over a Knowledge Graph representation of the enterprise SQL database. Therefore, investing in Knowledge Graph provides higher accuracy for LLM powered question answering systems.

“

Using GPT-4 and [zero-shot prompting](#), enterprise natural language questions over enterprise SQL databases achieved 16.7% accuracy. This accuracy increased to 54.2% when a Knowledge Graph representation of the SQL database was used, thus an accuracy improvement of 37.5 [percentage points].

	w/o KG (SQL)	w/ KG (SPARQL)	Improvement
All Questions	16.7%	54.2%	37.5%
Low Question/Low Schema	25.5%	71.1%	45.6%
High Question/Low Schema	37.4%	66.9%	29.5%
Low Question/High Schema	0%	35.7%	35.7%
High Question/High Schema	0%	38.5%	38.5%

Table 1: Average Overall Execution Accuracy (AOEA) of Overall and Quadrant Results

# **Semantic Layer, Ontology, Knowledge Graph:**

## Clear Definitions

# Semantic Layer

<b>Definition</b>	An abstraction layer that translates complex technical data models into unified, business-friendly concepts, metrics, and relationships.
<b>Purpose</b>	To provide consistent, reusable definitions for KPIs, metrics, and business concepts— <b>enabling self-service analytics, LLM query generation, and governance.</b>
<b>Typical Form</b>	Logical mappings, metrics catalogs, normalized business concepts, YAML/JSON/SQL configs (e.g., dbt Semantic Layer, Cube, Looker).
<b>Granularity</b>	Coarse to mid-grain (tables, columns, metrics, business terms).
<b>Key Use Cases</b>	Trusted BI, LLM-powered analytics, metrics standardization, semantic search, agentic AI.
<b>Example</b>	"ARR" is always: <code>SUM(revenue) WHERE type = 'subscription'</code> across all reporting tools.

# Ontology

<b>Definition</b>	A formal specification that defines types, properties, and relationships for concepts in a domain, often as machine-readable rules.
<b>Purpose</b>	To specify the formal structure and meaning of domain knowledge— <b>defining the building blocks</b> (types, properties, allowed associations, hierarchies).
<b>Typical Form</b>	OWL, RDF, UML diagrams, class/property definitions (e.g., Palantir Foundry Ontology, Blindata).
<b>Granularity</b>	Fine to mid-grain (definition of classes/"things", properties, value sets, relationships, rules, constraints).
<b>Key Use Cases</b>	Knowledge modeling, interoperability, disambiguation, translating domain expertise to structural rules, reasoning.
<b>Example</b>	"Person" has attributes: name, birthdate; "worksFor" links Person to Organization.

# Knowledge Graph

<b>Definition</b>	A network of interconnected entities (nodes) and their relationships (edges), typically realized as a graph, built using an ontology or data model plus actual organizational data.
<b>Purpose</b>	To organize and contextualize data by linking real-world entities and facts together— <b>enabling advanced search, inference, and context-aware AI/agent workflows.</b>
<b>Typical Form</b>	Graph databases (Neo4j, AWS Neptune), RDF triples, property graphs populated with real business data.
<b>Granularity</b>	Instance-level (actual organizations, people, transactions, products) with links and context.
<b>Key Use Cases</b>	Smart search/recommendations, context-aware agents, RAG, relationship inference, entity resolution, explainable AI.
<b>Example</b>	Leonardo Ubbiali (Person) worksFor Visum Labs (Company), livesIn London (Location) — relationships discoverable and explorable.

# How They Work Together



**Ontology** sets the rules and definitions ("menu").

Ref: Jeremy Ravenel LinkedIn analogy

# How They Work Together



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**Semantic Layer** makes those rules practical for data and analytics users ("recipe book using menu items").

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# How They Work Together

- **Ontology** sets the rules and definitions ("menu").
- **Semantic Layer** makes those rules practical for data and analytics users ("recipe book using menu items").
- **Knowledge Graph** applies both to connect and contextualize actual data/entities ("the meal, actually prepared and plated, with all associations and traces recorded").

Ref: Jeremy Ravenel LinkedIn analogy

# In Agentic AI & Analytics

## Semantic Layer

The semantic layer helps LLMs interpret and generate precise SQL/metrics. Without it, LLMs hallucinate or misinterpret.

## Ontology

Ensures the terms/relationships LLMs use match business reality and remain interoperable.

## Knowledge Graph:

Gives agents/LLMs a contextual map of all entities and their interrelationships, enabling advanced RAG, fact-checking, and reasoning.

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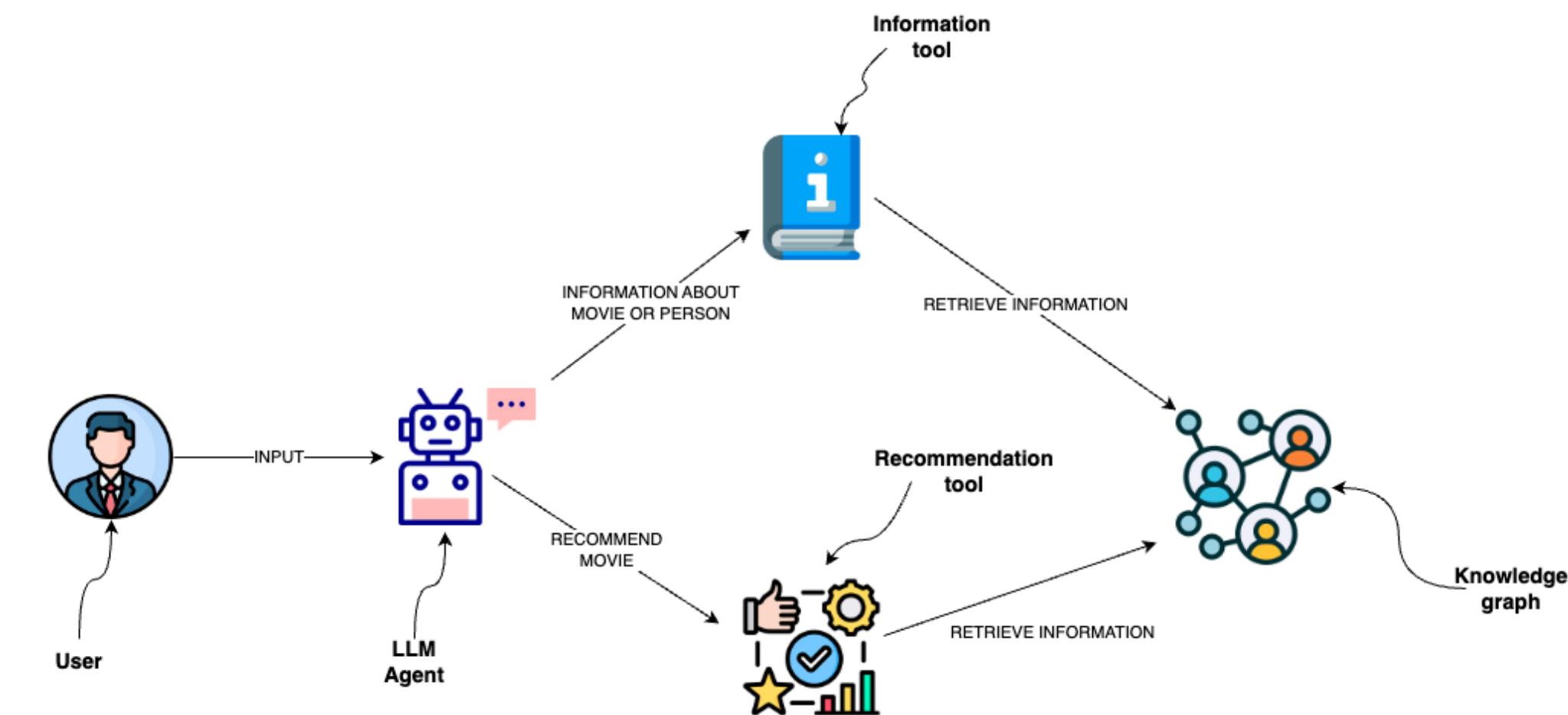
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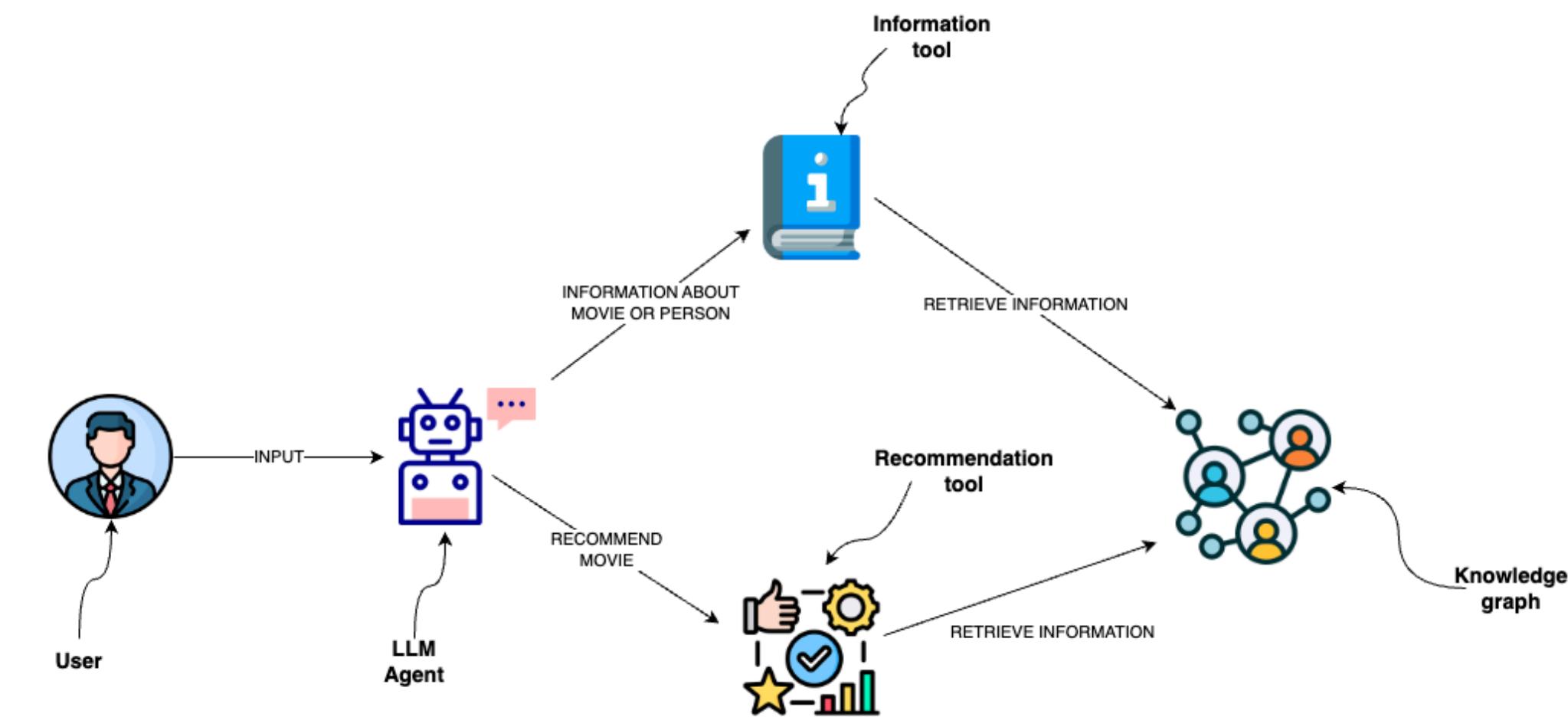
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# How to implement it

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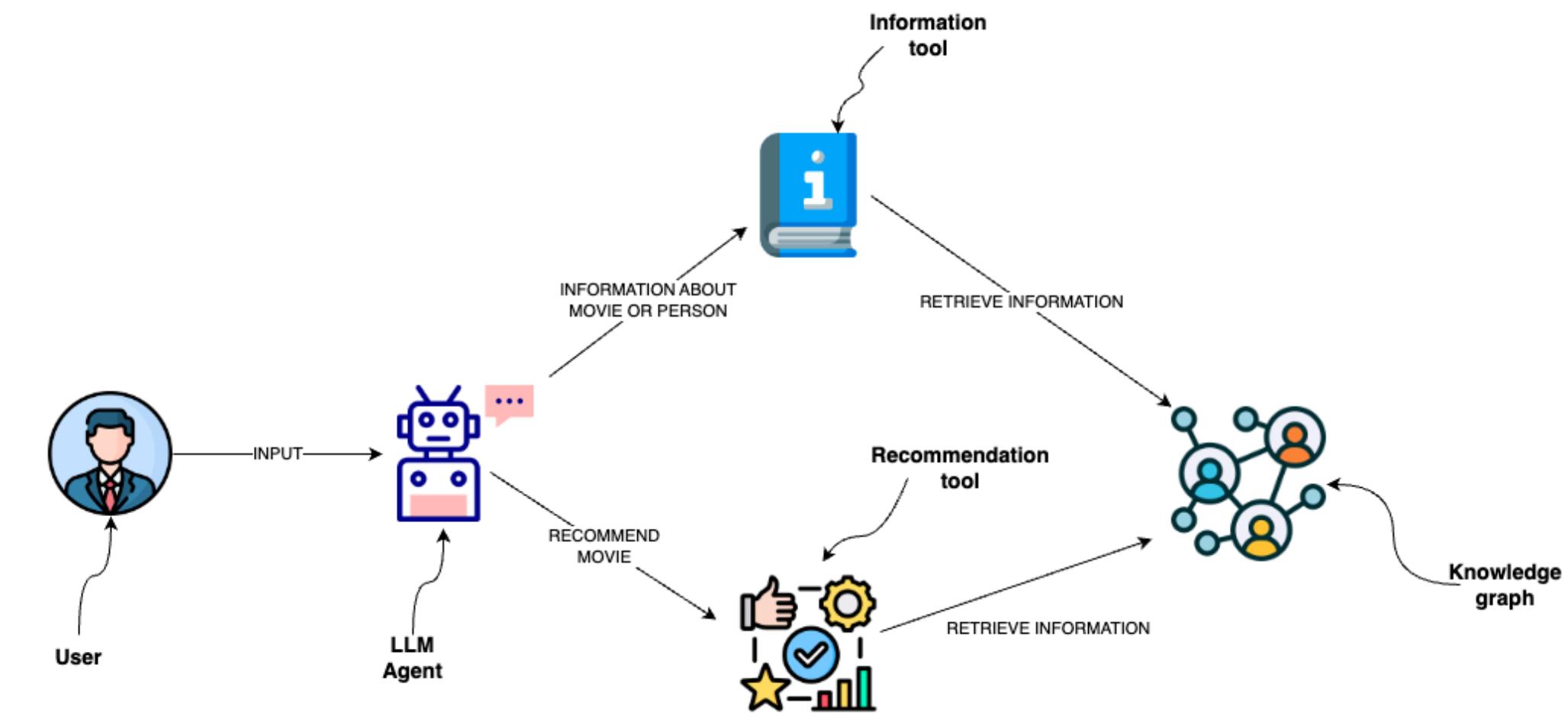


# How to implement it

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**3.** Make layer accessible for API/RAG/agent use



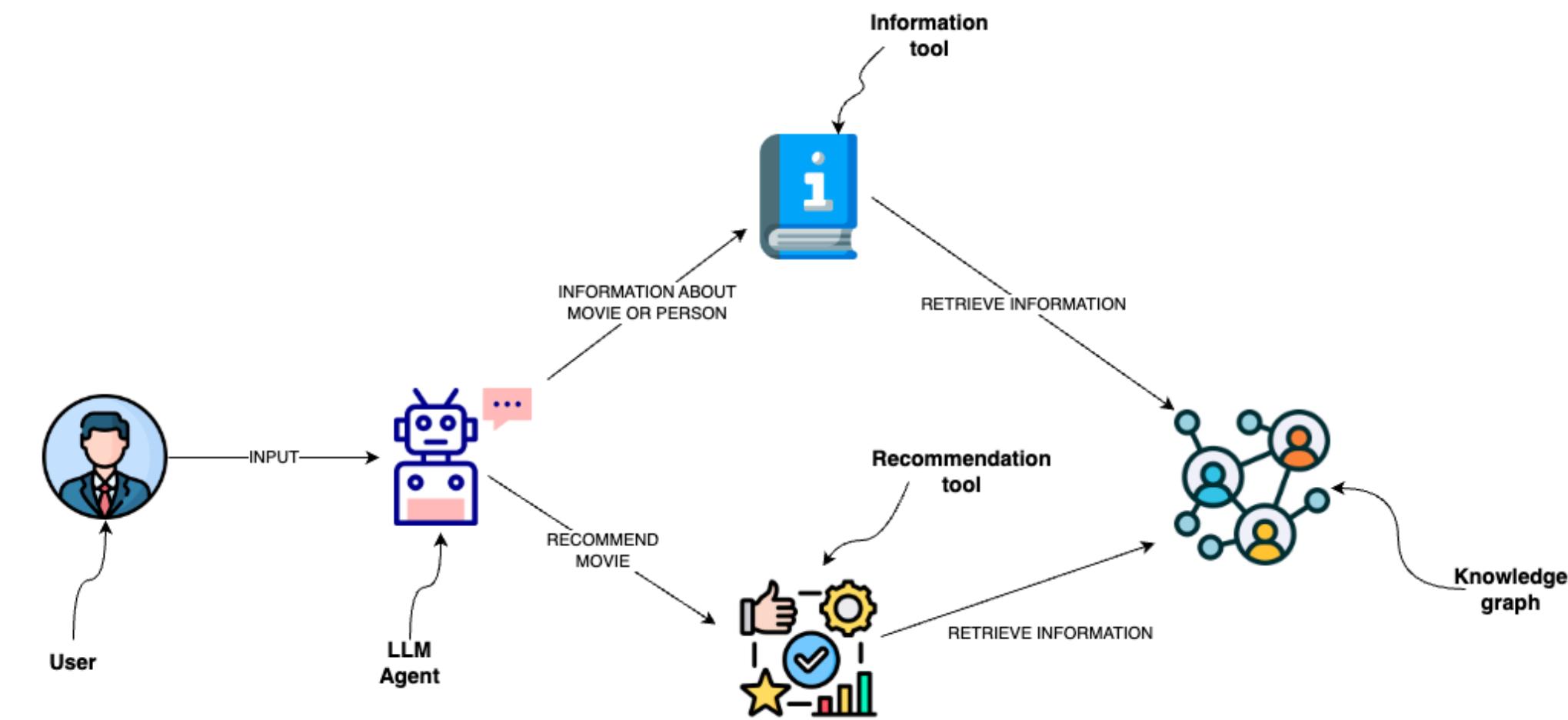
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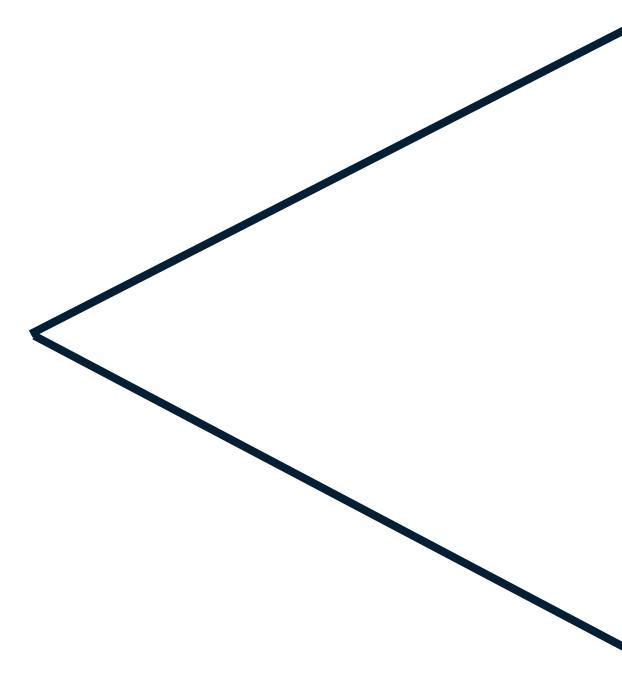
**3.** Make layer accessible for API/RAG/agent use

**4.** Create feedback/update loops for continuous improvement



# The Challenge: Keeping the Layer Updated

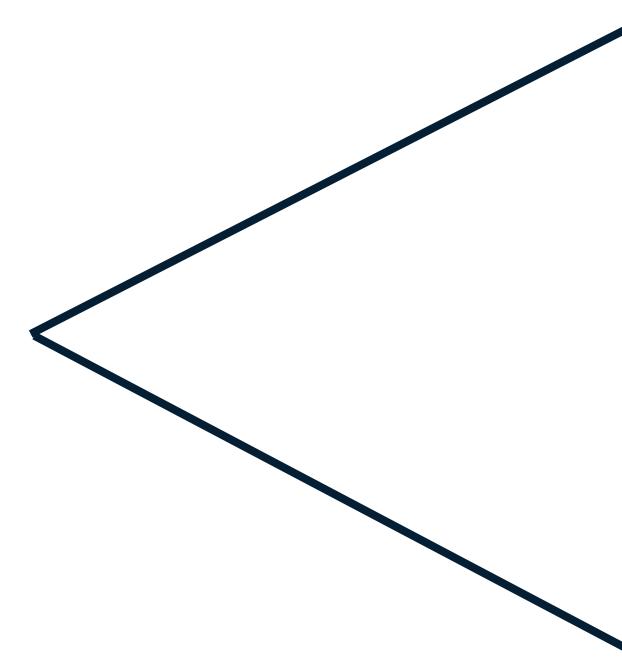
Challenge



- Biggest risk:**  
Out-of-date logic,  
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- Requires versioning,**  
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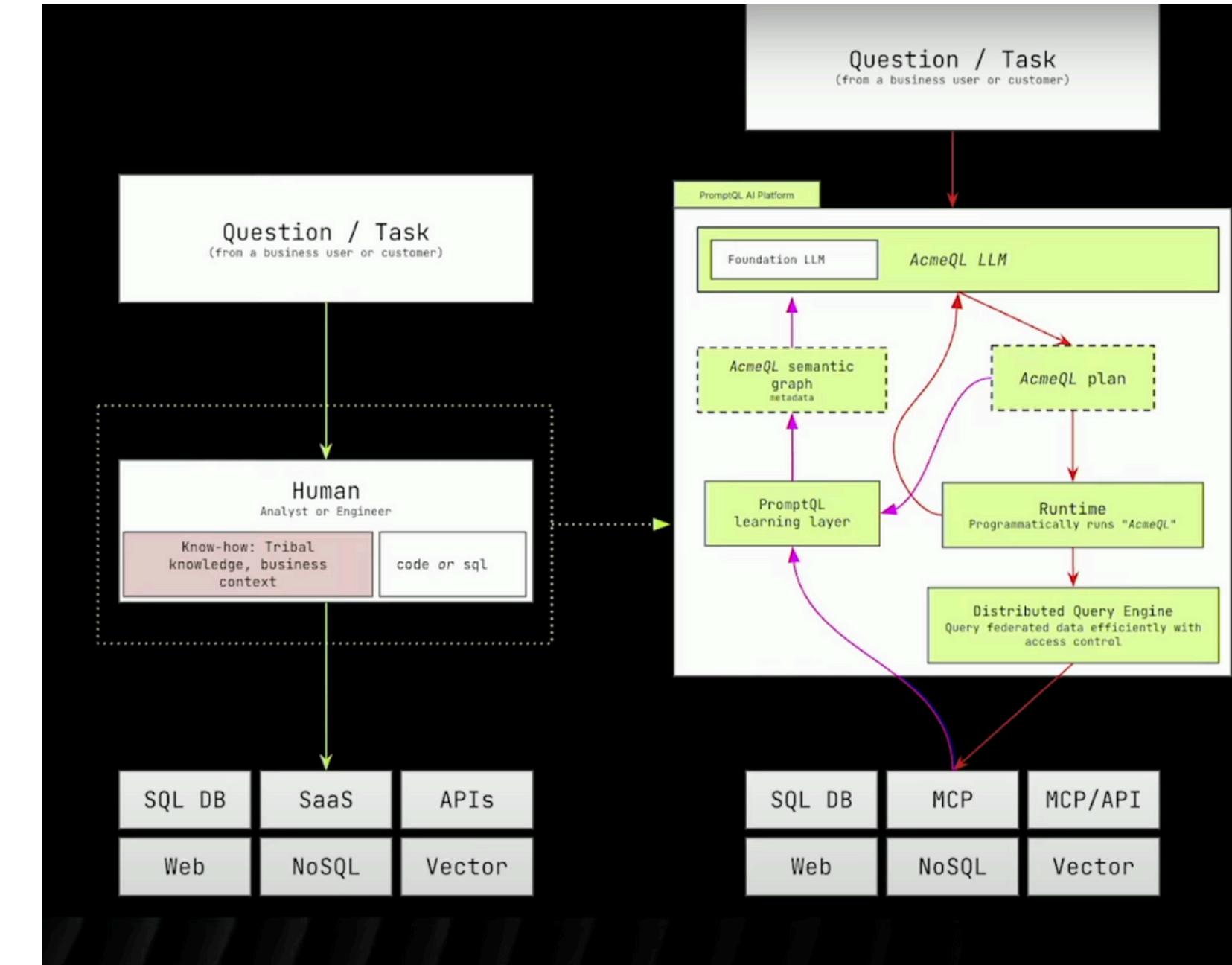
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**Requires versioning,**

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# The Future: Self-Updating, Agentic Semantic Layers

- Semantic layers that evolve as agents and users interact
- • Automated lineage, explainability, and version control
- “Semantic layer becomes the OS for enterprise AI”



Reference: Thoughtspot agentic semantic layer

# Intensive Hands-On Workflow Building

01

Treat LLMs as dumb (but very fast and cocky) data analysts

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- ∅1 Treat LLMs as dumb (but very fast and cocky) data analysts
- ∅2 Give them context and boundaries (whip the cocky analyst)

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- ∅1 Treat LLMs as dumb (but very fast and cocky) data analysts
- ∅2 Give them context and boundaries (whip the cocky data analyst)
- ∅3 Ensure the context evolves with the business logic

# Questions?

