

The Semantic Layer: Teaching AI What Your **Data** **Means**

Why most enterprise AI agents are guessing, what it costs, and how a semantic layer turns isolated data silos into a map your agents can actually follow.

Every enterprise AI initiative eventually hits the same wall. The model is capable. The data exists. And yet the agent hallucinates, burns through tokens, and produces answers nobody on the team would trust without checking by hand. The missing piece is rarely the model — it is the layer that tells the agent what the data means. This paper explains what a semantic layer is, why skipping it quietly decides the fate of the whole system, and how to build one.

01 The part most teams skip

Connect an agent directly to your databases, document stores, and APIs, and you have built something that looks complete on an architecture diagram — and behaves like a stranger in your building. On every single task, the agent has to discover where data sits, guess what a column called `cpty_id` refers to, and infer how a trade relates to an invoice. It does this work again on the next task. And the next.

The consequences are predictable and measurable:

- **Hallucination under ambiguity.** When the meaning of data is not provided, the model fills the gap with plausible fiction. It does not know that "Volume" means MWh in one system and contract count in another — so it guesses.
- **Token burn on rediscovery.** Every task pays the full cost of exploring schemas, sampling tables, and reasoning about structure — work whose results are thrown away when the session ends.
- **Answers nobody can act on.** Correct-sounding results built on wrong joins are worse than errors: they look right. Someone must verify every answer by hand, which silently deletes the business case.

Without a semantic layer, you have isolated data silos connected to agents that must find out for themselves where data sits and what it means — on every single request.

02 What a semantic layer actually is

A semantic layer is a machine-readable description of your business: what exists, what it means, and how it connects. We think of it as a **data mesh with meaning** — a weighted graph of semantics that is designed for AI consumption, not just for human documentation.

The critical shift is in when the agent uses it. A well-built semantic layer is consulted **during reasoning, before data access**. The agent first understands the territory — which sources are authoritative for which concepts, how entities relate, which rules apply — and only then executes precise, targeted queries. Understanding precedes retrieval. That single ordering change is where most of the quality and cost gains come from.

The three layers of the model

LAYER	WHAT IT DESCRIBES	EXAMPLE
Business layer	The top-level view: business objects, capabilities, and domains as the organisation talks about them.	Counterparty, Trade, Commodity, Invoice, Environmental Product.
Data ontology	How those things relate — the rules and relationships that make the domain coherent.	A counterparty is party to a trade; a trade delivers a commodity and is billed on an invoice.
Schema & named graph	The real tables, fields, and graph structures in source systems, tied back to the business meaning above.	trades.cpty_id → Counterparty.id, with lineage and access classification.

This is not exotic technology. Mature standards exist for expressing ontologies — RDF(S) and OWL for the model itself, SHACL and similar frameworks for validating that data actually conforms to it. The hard part is not the tooling. It is the modelling discipline: writing down, precisely, how your business fits together. Once that is written down properly, it becomes a map the agent can follow.

ONTOLOGY, IN ONE SENTENCE

An ontology is to your business what a schema is to a database: a formal description of the nature, structure, and meaning of what exists — except it spans all your systems, and it is written so that a machine can reason over it.

03 What changes for the agent

With the semantic layer in place, the agent's job changes character. Instead of exploring, it navigates:

- **Sharper questions.** The agent knows which system is authoritative for a concept and asks it directly, instead of federating vague queries across everything.
- **Grounded answers.** Responses are anchored in defined business meaning, with the relationships that justify them — auditable rather than plausible.
- **Lower cost per task.** Meaning is handed to the model up front, once, instead of being rediscovered from raw data on every request. The saved tokens compound across every interaction, every day.
- **Better multi-step reasoning.** Complex questions — the multi-table, cross-domain questions your best analysts ask — are exactly where semantic grounding helps most.

THE EVIDENCE

17% → 54%

CORRECT ANSWERS ON AN ENTERPRISE SQL BENCHMARK, SAME LLM, AFTER ADDING A KNOWLEDGE-GRAPH VIEW OF THE SAME DATABASE [1]

3.2×

ACCURACY MULTIPLE, WITH THE LARGEST GAINS ON COMPLEX MULTI-TABLE QUESTIONS

98.2%

MID-TIER MODEL ACCURACY ON SEMANTIC-LAYER QUERIES VS. 100% FOR A FRONTIER MODEL — UNDER TWO POINTS APART ONCE THE FOUNDATION IS IN PLACE [2]

Benchmarks consistently show the same pattern: giving the model a semantic view of the data raises answer quality far more than upgrading the model does — and it lets a smaller, cheaper model match a frontier one.

04 Building it: how we approach the work

Phase 1 — Discovery and domain modelling

We start with the business, not the databases: which domains the agents will operate in, which questions they must answer, which decisions they support. From that we derive the business layer — the objects and capabilities that matter — and only then map them down to real systems. Modelling everything is a failure mode; modelling what the use cases touch is the discipline.

Phase 2 — Ontology design and validation

The relationships get formalised: entities, relationship types, cardinalities, business rules. We use open standards so the result is portable and testable, and we validate the ontology against real data early — an ontology that does not survive contact with production data is documentation, not architecture.

Phase 3 — Connection and consumption

The named-graph layer ties the model to live sources: schema mappings, lineage, and the access classification each element carries (public, internal, confidential — the semantic layer is also where data governance becomes machine-readable). Finally, the layer is exposed to the agents so it participates in reasoning: as context during planning, and as the map that guides retrieval.

What to avoid

- **The big-bang ontology.** Eighteen months of modelling before the first agent ships. Model one domain deeply, prove the gain, expand.
- **Documentation theatre.** A wiki describing your data is not a semantic layer. If an agent cannot traverse it programmatically at reasoning time, it does not count.

- **Skipping validation.** An ontology nobody checks against real data drifts into fiction — and agents grounded in fiction hallucinate with confidence.

05 The least glamorous part — and the one that decides everything

The semantic layer will never demo as well as an agent that talks. It is invisible when it works. But it is the line between a system people trust and one they quietly stop opening. Get it right, and agents ask sharper questions, give grounded answers, and cost less to run. Skip it, and every other investment in the stack — the models, the orchestration, the memory — performs below its potential, because everything downstream reasons over data it does not understand.

In our three-pillar architecture, the semantic layer is Pillar 1 for a reason: it is the foundation the other two stand on. The engineered agent system (Pillar 2) routes work across it; the memory (Pillar 3) consolidates experience on top of it. The companion papers in this series cover each in depth.

Where m2-consulting comes in

We have modelled semantic layers for regulated industries — banking, FinTech, energy trading — and connected them to production agent systems. If your agents are guessing, we can usually show you where and what it costs within a short assessment.

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[1] Sequeda, Allemang & Jacob, "A Benchmark to Understand the Role of Knowledge Graphs on Large Language Model's Accuracy for Question Answering on Enterprise SQL Databases," 2023, arXiv:2311.07509; analysis by dbt Labs, "The Semantic Layer as the Data Interface for LLMs."

[2] dbt Labs, "Semantic Layer vs. Text-to-SQL: 2026 Benchmark Update," April 2026.

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