TECHNICAL DEEP DIVE · MCP ARCHITECTURE

Intelligent Request Routing in MCP Servers Using Embedded LLMs

How a small, purpose-built language model inside your MCP server can slash token costs, eliminate client-side orchestration complexity, and deliver dramatically smarter multi-tool responses.

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§ 01 — THE PROBLEM

Multi-Tool Routing: The Unsolved Problem Nobody Talks About

The Model Context Protocol has become the de facto standard for giving AI assistants access to external tools and data sources. Connect your CRM. Connect your analytics. Connect your file storage. In theory, a single AI assistant can now answer *"How did last quarter's email campaign affect our Shopify revenue, and does our QuickBooks profit-loss reflect that?"* by pulling from three different systems simultaneously.

In practice, this is where most MCP implementations quietly fall apart.

The challenge is not the protocol itself — MCP is well-designed. The challenge is routing: given a user's natural language question, which tools should be called, in what order, with what parameters, and how should the results be synthesized into a coherent answer? This is a fundamentally hard problem, and the dominant approaches all involve uncomfortable trade-offs.

> *"The question isn't whether your MCP server can access twenty data sources. The question is whether it can figure out which three of those twenty actually matter for the question in front of it — before it wastes 40,000 tokens finding out."*

To understand why this matters, we need to look at how the two dominant AI platforms handle multi-tool orchestration today — and why both approaches leave significant problems on the table.

§ 02 — CURRENT APPROACHES

How Today's Platforms Handle Multi-Tool Orchestration

Before describing what a better solution looks like, it's worth mapping the terrain of existing approaches. Two patterns dominate the market, each reflecting the architectural philosophy of the platform that popularized it.

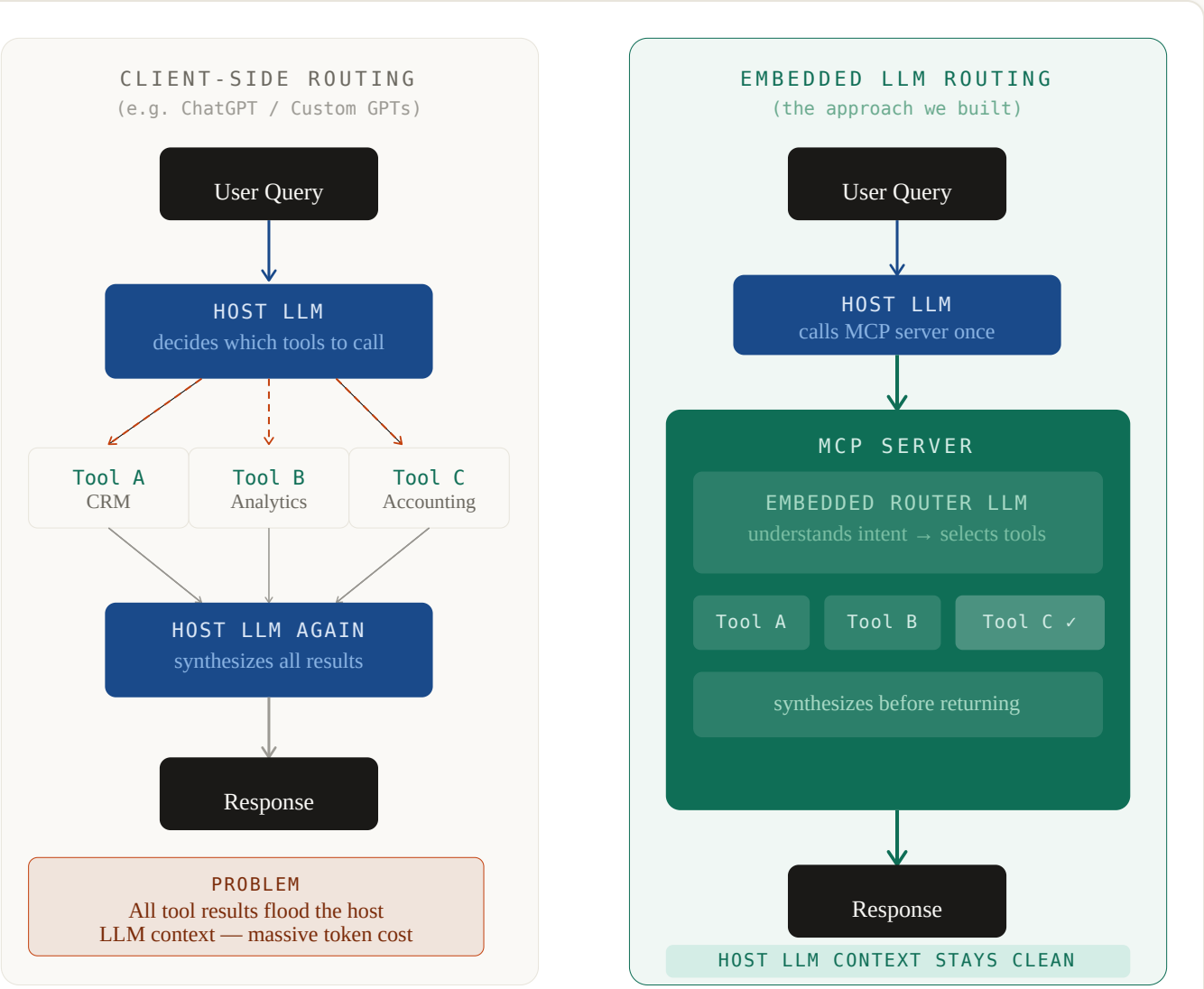

Figure 1. Two routing architectures compared. Left: client-side orchestration floods the host LLM context with raw tool results. Right: the embedded LLM router handles all orchestration server-side, returning a single synthesized response.

The Client-Side Approach: Powerful but Expensive

Platforms like OpenAI's Custom GPT framework and many LangChain-based implementations push the orchestration problem to the client — meaning the host LLM itself. When a user asks a complex question, the assistant examines every available tool, decides which to call, executes them in sequence or parallel, receives all the raw results, and then synthesizes a response.

This works. It also consumes enormous amounts of context window. When you have fifteen connected data sources and each tool call returns even a modest payload, you can easily exceed 20,000 tokens just in tool result data before the model writes a single word of response. At scale, this is economically and latency-wise untenable.

The Search-Based Approach: Smarter but Incomplete

Some architectures address this by exposing a search mechanism that lets the model query for relevant tools using keywords, load only the matched tools, and proceed. This reduces the tool list in context — but keyword search misses semantic intent. If a user asks *"What's making our revenue drop?"* and the relevant tool is named `GET_SHOPIFY_ORDER_SUMMARY`, the semantic distance between the query vocabulary and the tool name may cause the search to miss it entirely. The host LLM still receives raw tool outputs, so the token cost of results hasn't been addressed — only the cost of tool selection.

§ 03 — THE ARCHITECTURE

The Embedded Router: An LLM Inside Your MCP Server

The insight at the core of our approach is simple to state and non-obvious to implement: move the routing intelligence inside the MCP server itself. Instead of asking the host LLM to figure out which of your twenty tools to call, embed a small, fast, purpose-built language model inside the server that handles this decision transparently.

From the host LLM's perspective, it makes a single tool call. From the user's perspective, they get a synthesized answer that draws from exactly the right data sources. Everything in between — tool selection, parallel execution, result synthesis, error handling — happens inside the MCP server, invisible to the host model.

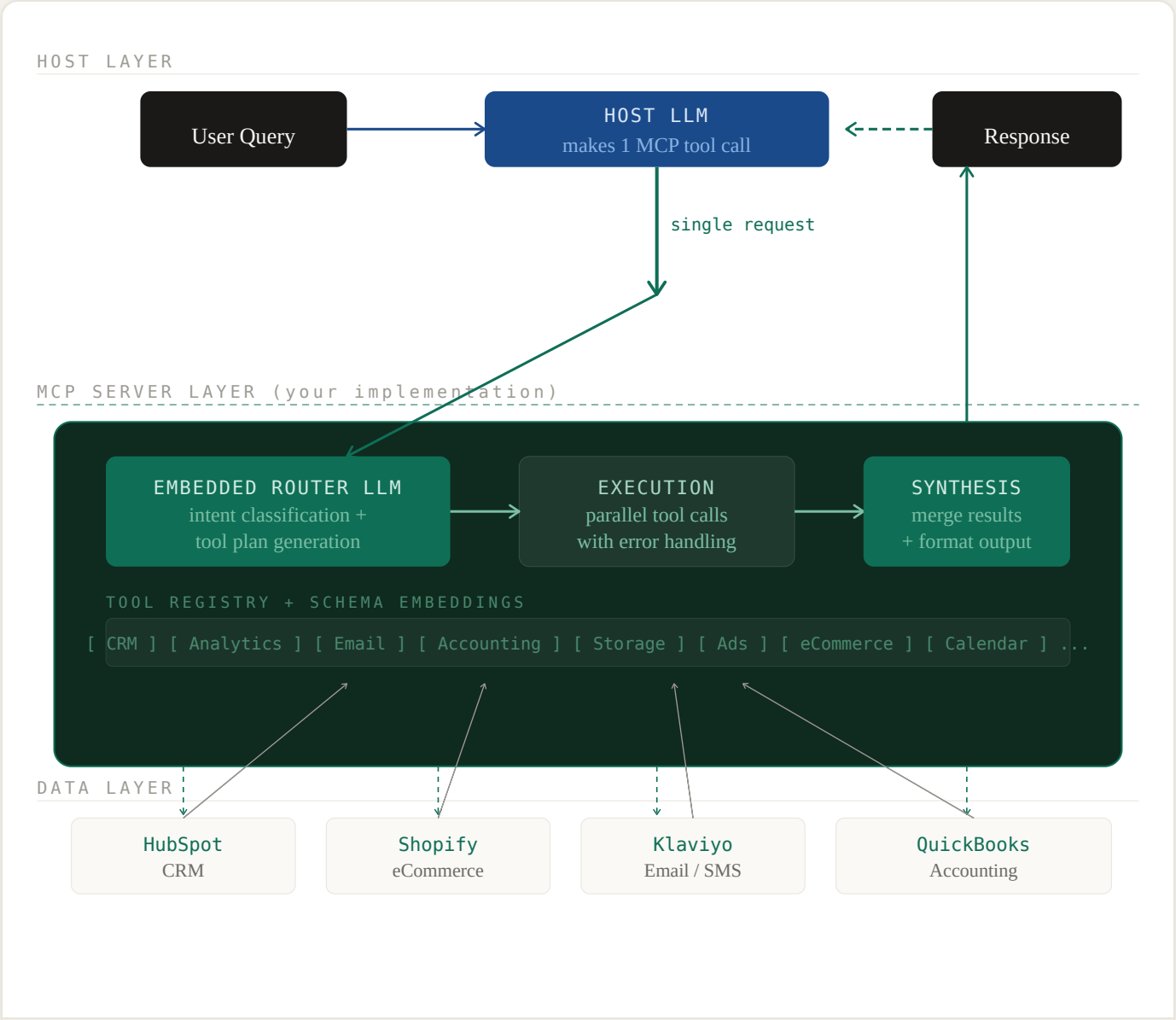

Figure 2. Full architecture of the embedded LLM routing system. The host LLM makes a single MCP tool call; everything inside the dashed green boundary is handled by the server — including intent classification, tool selection, parallel execution, and synthesis.

This architecture has a profound implication: the host LLM's context window is never contaminated with raw tool outputs. It sends a natural language question. It receives a clean, synthesized answer. The routing complexity — which was previously the host model's problem — is fully encapsulated.

1	N	1
MCP CALL FROM HOST LLM	TOOLS CALLED INTERNALLY (IN PARALLEL)	SYNTHESIZED RESPONSE RETURNED

§ 04 — THE ROUTING MECHANISM

How the Embedded Router Classifies Intent

The embedded router is not a general-purpose LLM. It is a small, fast model that has been given a precise and narrow job: read a natural language query, reason about which tools are needed to answer it, and produce a structured execution plan. It does not write prose. It does not explain itself. It outputs a deterministic JSON plan that the execution engine can act on immediately.

The router operates against a *tool schema registry* — a compact representation of every available tool that includes not just the tool's name and parameters, but semantic descriptions of what kinds of questions it can answer, what data it returns, and what its relationship is to other tools in the system.

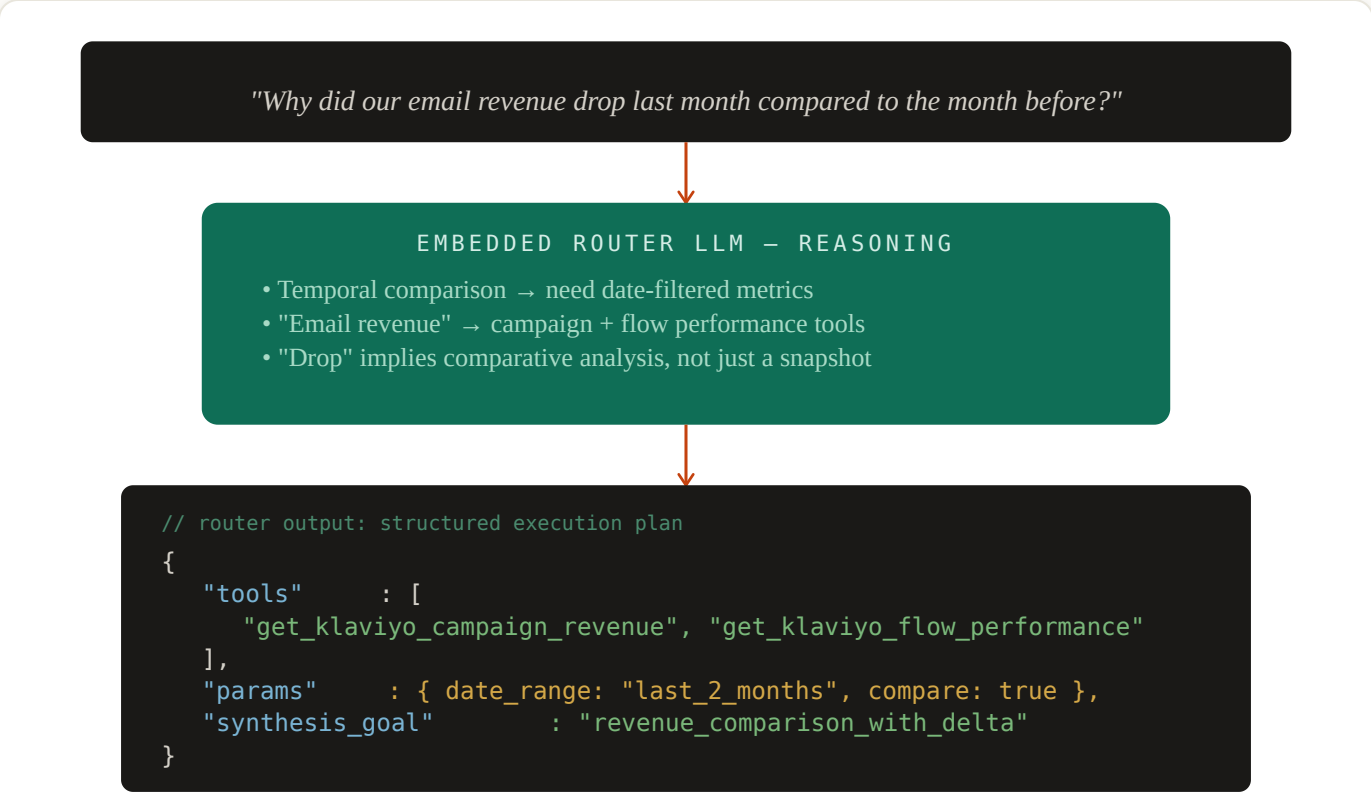

Figure 3. The embedded router analyzes query intent, maps it to semantic tool categories, and outputs a structured execution plan — all before a single external API call is made.

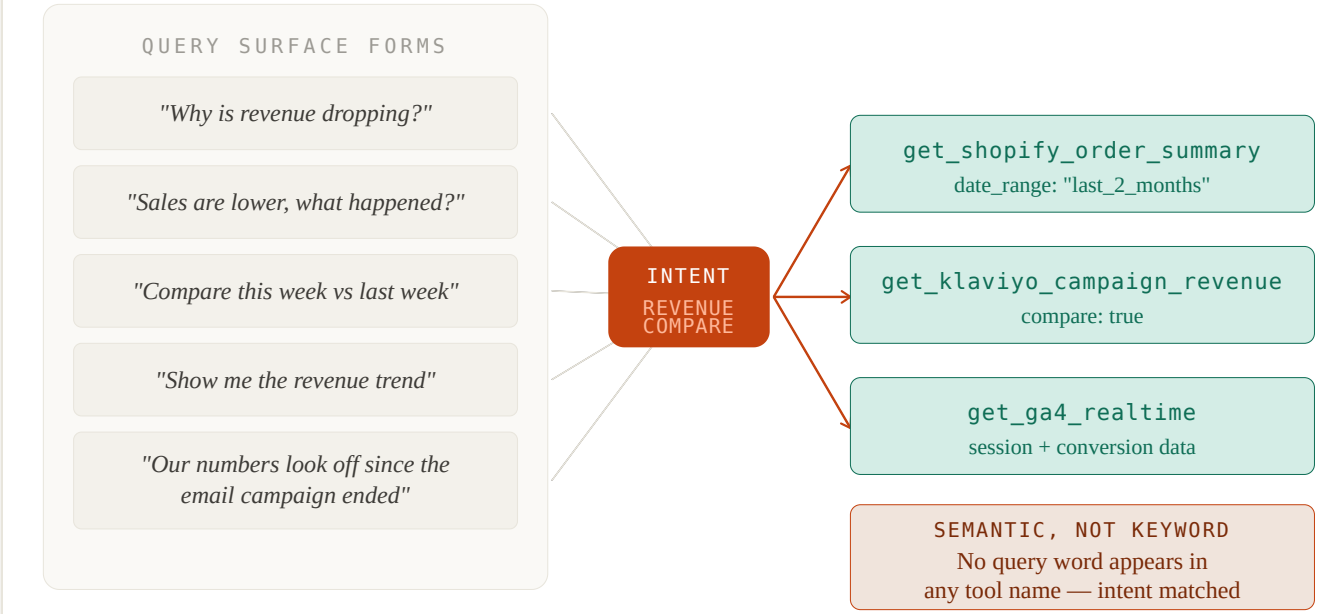

Figure 4. Semantic intent classification: five different phrasings of the same underlying question all collapse to the same intent category and tool calls — something keyword search cannot reliably achieve.

§ 05 — TOKEN ECONOMICS

The Token Cost Advantage: A Detailed Breakdown

Let's put concrete numbers to this. Assume a deployment with fifteen connected data sources, where the average tool call returns 1,500 tokens of raw output. A complex multi-source question might require calling five tools.

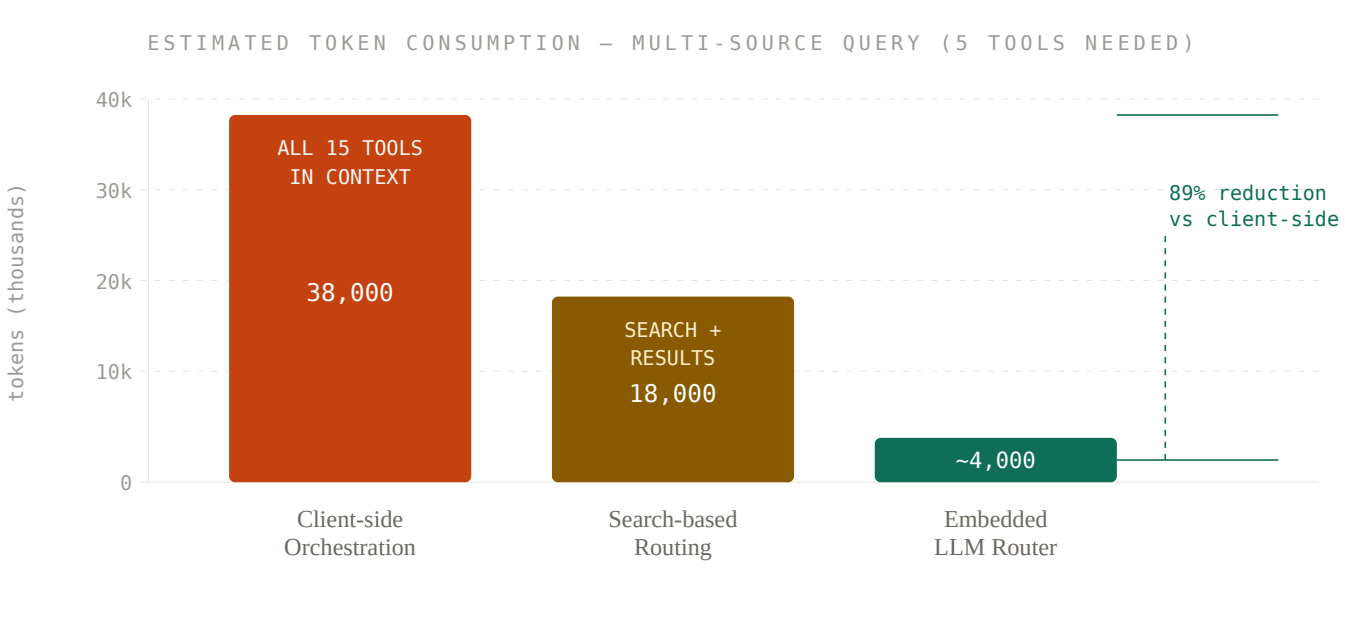

Figure 5. Comparative token consumption across routing approaches for a query requiring 5 tool calls (15 tools connected, average 1,500 tokens per result). The embedded router keeps the host LLM context clean — it only sees the synthesized answer, not raw tool outputs.

The key insight: in the embedded router approach, raw tool outputs *never enter the host LLM's context window*. The MCP server consumes them internally. The host only receives the final synthesized answer — typically 300–600 tokens regardless of how many tools were called. Token costs grow sub-linearly with the number of connected data sources.

CHARACTERISTIC	CLIENT-SIDE	SEARCH-BASED	EMBEDDED ROUTER
Host LLM context pollution	High — all raw results	Medium — matched results	None — synthesized only
Semantic routing accuracy	High (LLM decides)	Low (keyword match)	High (LLM decides)
Round-trips for routing	1 (then parallel calls)	2–3 (search → load → call)	0 (internal to server)
Cross-tool synthesis quality	High	Medium	High
Scales to 20+ tools	Poorly	Moderately	Well
Implementation complexity	Low (client handles it)	Medium	High (your server must)

§ 06 — REQUEST LIFECYCLE

Anatomy of a Routed Request

Let's trace a complete request from user query to synthesized response, examining each stage and what decisions are made along the way.

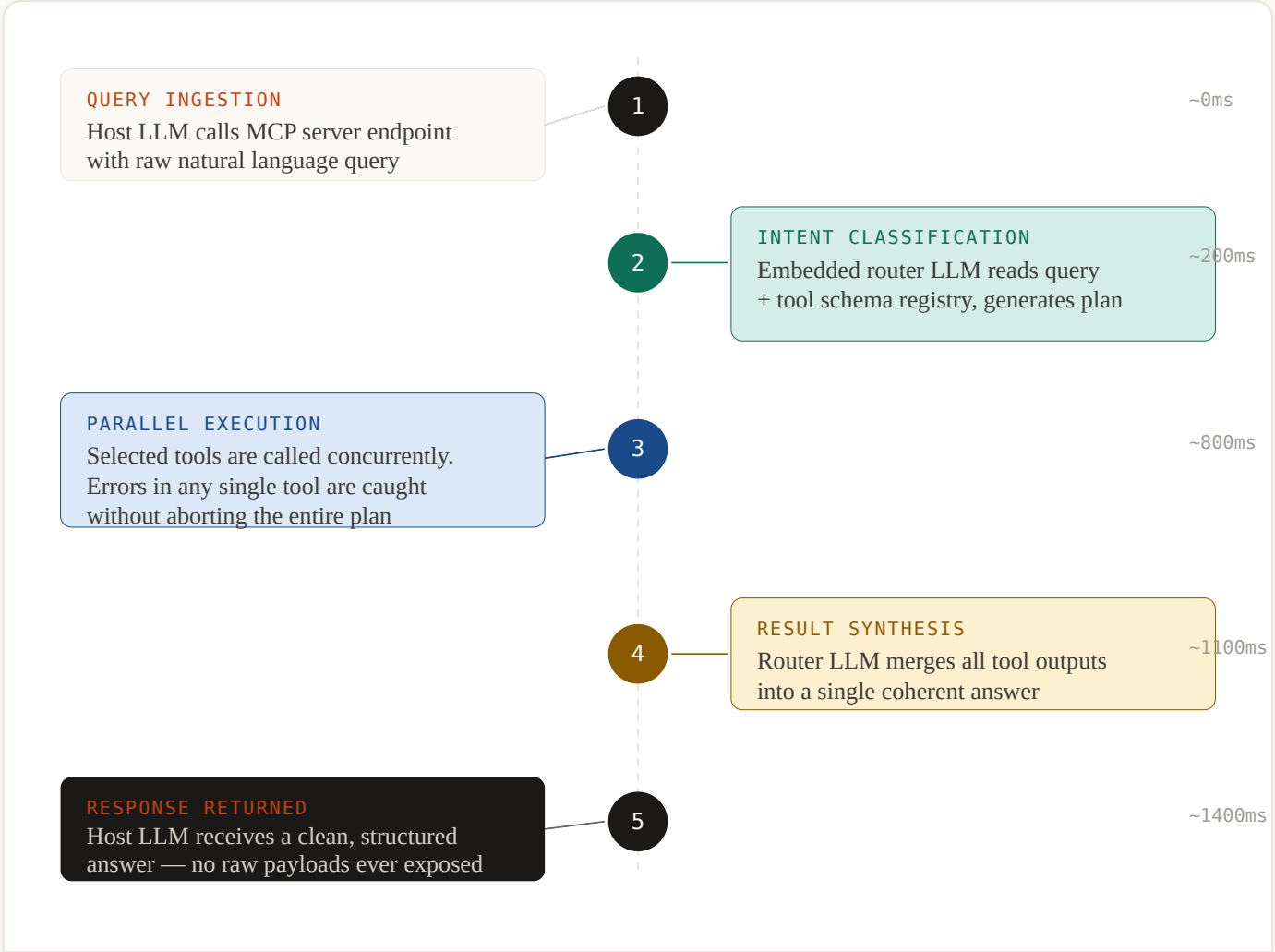

Figure 6. Complete request lifecycle. Timing estimates assume average API latency. The parallel execution phase (stage 3) is the dominant cost — running N tools in parallel rather than serially is critical to keeping total latency acceptable.

DESIGN PRINCIPLE: GRACEFUL DEGRADATION

When a tool call fails during parallel execution — a rate limit, a downstream API timeout — the embedded router synthesizes the best possible answer from the tools that succeeded. It explicitly annotates the gap: *"Revenue data from Shopify is unavailable — API timeout. Klaviyo email attribution and GA4 session data were retrieved successfully."* This transparency is far more useful than a generic error.

§ 07 — SCHEMA DESIGN

Designing Tool Schemas That the Router Can Reason About

The quality of routing is only as good as the schema information the router has access to. Writing tool schemas that are simultaneously machine-parseable and semantically rich enough for an LLM to reason about is perhaps the most underappreciated engineering challenge in this architecture.

Standard MCP tool schemas describe *what parameters a function takes*. Our routing schemas also describe *what kinds of questions the tool can answer*, *which other tools it is complementary to*, and *what data it returns in plain language*.

```
// Standard MCP schema — adequate for execution, poor for routing { "name":
"get_shopify_order_summary", "description": "Get summary of recent orders",
"inputSchema": { "start_date": "string", "end_date": "string" } } // Routing-
aware schema — enables semantic classification { "name":
"get_shopify_order_summary", "intent_tags": ["revenue", "sales", "ecommerce",
"orders", "trend"], "answers_questions_like": [ "How much did we sell this
month?", "Why is revenue dropping?", "What is our average order value?" ],
"complementary_tools": ["get_klaviyo_campaign_revenue", "run_ga4_report"],
"returns": "Revenue total, order count, AOV, top products by date range" }
```

The `COMPLEMENTARY_TOOLS` field is particularly powerful. It teaches the router which tools are frequently most useful together, enabling it to proactively build multi-tool execution plans for queries that only mention one domain but would benefit from correlated data.

> **CAUTION: SCHEMA DRIFT**
>
> Tool schemas are live documents. When you add a new data source, update an existing tool's return signature, or deprecate a connector, the router's schema registry must be updated in lockstep. Stale schemas are a silent failure mode — the router makes plausible-sounding decisions based on outdated information. Automated schema validation as part of your CI pipeline is not optional; it's foundational.

§ 08 — WHY IT MATTERS

What This Architecture Unlocks

The embedded LLM router is not an optimization — it's an architectural shift that changes what's possible in multi-tool AI deployments.

1

CONTEXT WINDOW PRESERVATION

The host LLM's context remains available for the actual conversation. When tool outputs don't consume the context window, the model can maintain longer histories, follow more complex instructions, and produce higher-quality synthesized responses.

2

UNLIMITED TOOL SCALE

With traditional approaches, adding a fifteenth or twentieth tool increases context window pressure significantly. With embedded routing, each new tool adds a small entry to the schema registry — but the host LLM never sees it unless it's needed. Fifty connected data sources remain performant on simple queries.

3

CROSS-SOURCE SYNTHESIS WITHOUT CLIENT-SIDE COMPLEXITY

Correlating data from Klaviyo, Shopify, and Google Analytics previously required careful client-side orchestration. The embedded router handles this transparently — it recognizes multi-source queries, calls all relevant tools, and returns a single synthesized answer.

4

REUSABLE ROUTING INTELLIGENCE ACROSS HOST MODELS

Because routing logic lives in the MCP server, you can swap host LLMs — Claude, GPT-4, an open-source model — without rebuilding orchestration. The server presents identical behavior regardless of what's calling it.

5

OBSERVABILITY AND CONTROL

Every routing decision is logged inside the MCP server. You can audit which tools were selected for which queries, identify misrouting patterns, improve schemas, and tune behavior — none of which is possible when routing happens inside the host LLM's opaque reasoning.

> *"The paradox of multi-tool AI is that more capability creates more complexity — unless you have a layer that absorbs that complexity before it reaches the host model. The embedded router is that layer."*

§ 09 — HONEST ASSESSMENT

Trade-offs and When Not to Use This Pattern

Architectural honesty requires acknowledging where this pattern adds cost and complexity. The embedded router is not a free lunch.

OPERATIONAL OVERHEAD

Running an embedded LLM inside your MCP server means running inference infrastructure. For low-traffic deployments, this cost may outweigh the token savings from optimized routing. The pattern becomes economical at scale — typically when you have more than five connected tools and handle a meaningful daily query volume.

WHEN SIMPLER APPROACHES ARE BETTER

If your MCP server exposes only 2–4 tools covering distinct, non-overlapping domains, the routing problem is trivial. A simple rule-based dispatcher or exposing all tools to the host LLM is perfectly adequate. The embedded router pays dividends when you have *many* tools with *overlapping* semantic domains — where a question about "revenue" might reasonably involve three different systems.

The schema maintenance burden is also real. Every tool must have a well-written, semantically rich schema. This requires ongoing attention as tools evolve, connectors are added, and the vocabulary of user queries shifts. Teams that underinvest in schema quality will find routing accuracy degrading silently and without obvious error messages.

Finally, pre-synthesis inside the server means you are making opinionated decisions about how to combine and present data before it reaches the host LLM. In most cases this is desirable. But if your use case requires the host model to reason directly over raw data — statistical analysis, anomaly detection, complex derived metrics — pre-synthesis may discard information the model needs.

§ 10 — CONCLUSION

The Next Frontier in MCP Server Design

The Model Context Protocol has solved the integration problem — connecting AI to the tools and data sources it needs. The next challenge is the orchestration problem: making multi-tool queries feel effortless, economical, and intelligent.

Embedded LLM routing moves intelligence to where the tools live, keeping the host model's context clean, reducing token costs dramatically, and enabling semantic routing accuracy that keyword search cannot match. It is not the only path forward — but it is the pattern that we have found most scalable as the number of connected data sources grows from five to twenty to fifty.

The best AI integrations are ones where the routing infrastructure is invisible. Users ask natural questions and receive coherent answers drawn from exactly the right sources. The complexity lives in the server. The conversation stays clean.
