How to Build a Token-Free AI Platform

Your data supplies every answer through deterministic retrieval; the language model stays optional, adding a natural voice, never the answer itself.

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Abstract

Many systems marketed as "AI assistants" answer questions whose answers already exist in a structured corpus: a catalogue, a schema, a policy set, a ticket history, a configuration store. The default implementation wraps a large language model (LLM) in retrieval-augmented generation (RAG), paying generated tokens for every answer, with results that can vary between runs and with cost, latency, and data residency to manage. We argue that a large and identifiable class of these tasks needs no generation at all, and we present a general, domain-agnostic method for building zero-token assistants, systems that consume zero generative LLM tokens on the answer path. The method has three parts: (1) a decision framework for recognising when a task is retrieval-shaped rather than generation-shaped; (2) a reusable architecture with deterministic intent routing, structure-first retrieval with an approximate-nearest-neighbour (ANN) fallback, and similarity scoring hardened by domain scoping, rule-based alignment, and confidence calibration; and (3) an optional, grounded, time-boxed LLM layer that never sits on the answer path. We give a step-by-step build recipe any team can follow, illustrate it across several domains, and analyse cost, determinism, and applicability against the RAG baseline. A fielded enterprise schema-migration assistant serves as the anchor case study, but the method itself is independent of any domain.

Keywords. zero-token systems, deterministic retrieval, intent classification, sentence embeddings, approximate nearest neighbour, retrieval-augmented generation, LLM cost, reproducibility, design pattern.

1. Introduction

The common way to build a knowledge assistant in 2024–2025 is to place a large language model (LLM) at its centre and feed it context through retrieval-augmented generation (RAG) [6]. RAG is a wonderful tool for open-ended synthesis. For questions whose answer already exists as one or more rows in a corpus the organisation controls, however, sending every request through a token-metered generator is worth weighing against four practical considerations:

1. **Cost per answer.** Every query consumes input and output tokens; at interactive scale the recurring bill grows with usage.
2. **Consistency.** The same question can return differently worded answers on different runs, which makes results harder to reproduce and to audit.
3. **Staying within the data.** A model may occasionally include entities that are not in the corpus [5, 8], which matters when the answer goes on to drive an action.
4. **Latency and dependency.** Answers rely on a remote API, coupling an internal tool to an external service's availability, rate limits, and data-residency posture.

Our thesis is simple: a large, recognisable class of assistant tasks is a retrieval and similarity problem, not a generation problem, and for that class an assistant can be built that spends zero generative tokens on the answer path. "Zero-token" here means no billed generative inference to produce an answer; a small local embedding encoder may still turn text into vectors for similarity search, but it is not a generative model, emits no billed tokens, and its corpus vectors are precomputed once.

This paper turns that thesis into a method any team can apply, in any domain.

Contributions.

- A decision framework (Section 2) for judging whether a task is zero-token-able, with a practical decision tree (Figure 1).
- A domain-agnostic reference architecture (Section 3) whose logic is independent of the domain it serves.
- A step-by-step build recipe (Section 4, Figure 4) covering routing, retrieval, similarity scoring, rule hardening, calibration, and safe optional use of an LLM.
- Worked instantiations across domains (Section 5) showing the same recipe serve schema migration, a service catalogue, product reconciliation, and policy lookup.
- An analytical evaluation (Section 6) against RAG, and an honest account of when not to remove the LLM (Section 7).

The pattern echoes a classic systems idea, specialise the common case [12]: pay the expensive, general mechanism (generation) only for the genuinely open-ended tail, and answer the structured majority with cheap, deterministic machinery.

2. When Is a Task Zero-Token-Able?

Not every task should shed its LLM. The first and most valuable step of the method is a diagnosis. A task is a strong candidate for the zero-token treatment when the following hold; each is a property of the task, not of any technology.

C1. Closed answer space. Every valid answer is (or is assembled from) entries in a corpus you control, a table, catalogue, schema, or document set. The system selects and ranks; it does not invent.

C2. Enumerable operations. The kinds of request are finite and nameable ("look up X", "map X to Y", "list the parts of Z", "what precedes W"). You can write them down; there are tens, not thousands.

C3. Ground truth exists. There is a correct answer that a domain expert could confirm, so correctness is checkable rather than a matter of taste.

C4. Reproducibility or audit matters. The same input should give the same output, and stakeholders need to see why an answer was produced.

C5. Cost, latency, privacy, or offline use press. The task runs at scale, must be fast, must stay on-premise, or must work without an external API.

Conversely, anti-signals favour keeping generation: the task requires novel prose, summarisation across many sources, subjective or creative judgement, or free-form conversation whose value is the wording. C1–C3 are the decisive tests; C4–C5 turn a viable candidate into a compelling one. Figure 1 renders this as a decision tree a practitioner can walk in minutes.