

CADENZA: Compiling Natural-Language Intent into Task-Specific Operator DAGs for Semantic Query Processing

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Semantic query processing engines (SQPEs) extend relational query processing with *semantic operators* that are executed via model inference over unstructured data. Optimizing such queries is inherently multi-objective: model inference dominates latency and monetary cost, and outputs are stochastic and backend-dependent, so quality must be optimized alongside efficiency. Existing SQPE optimizers do not expose each semantic operator instance's intermediate task outputs as a relational optimization object, leaving optimization unable to filter, reorder, route, threshold, or jointly tune them. We present CADENZA, which compiles each semantic operator *instance*—a template bound to a natural-language *intent*—into an intent-specific plan space of typed task DAGs and selects an executable plan under user-specified quality–latency–cost trade-offs. CADENZA introduces *task-extended relational algebra* (TxRA), a conservative extension of relational algebra with task-specific operators. The *logical planner* synthesizes seed TxRA plans, applies structural rewrites whose safety conditions are checked from operator dependencies, and enumerates semantics-guided alternatives from alternative-generation templates. The *physical planner* compiles each task-specific operator into a router over heterogeneous backends and jointly tunes routing cutpoints, backend parameters, and relational thresholds with Bayesian optimization. On SemBench, CADENZA improves the scenario-level averages of quality, latency, and cost by up to +0.49, 165.7×, and 310.3×, respectively, relative to state-of-the-art.

CCS Concepts: • **Information systems** → **Query optimization**; **Database query processing**; • **Computing methodologies** → *Natural language processing*.

Additional Key Words and Phrases: Semantic Operators, Large Language Models, Query Optimization, Multi-Objective Optimization, Task-Specific Operators

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1 Introduction

With the advent of Large Language Models (LLMs), a new class of *semantic query processing engines* (SQPEs) has emerged [1, 9, 21, 24, 27, 32, 34]. SQPEs extend relational query processing with *semantic operators* whose behavior is specified in natural language and executed via model inference over unstructured table data (e.g., text, images, audio). These operators mirror core relational operators (e.g., SemFilter, SemJoin, SemMap) while replacing hand-written UDF pipelines with prompt-driven matching, extraction, and reasoning as first-class operators. We distinguish a semantic

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```

SELECT b.BrandName, COUNT(*) AS NumFlagged
FROM Products p JOIN Brands b ON p.BrandId = b.BrandId
WHERE p.Category IN ('Supplements', 'Cosmetics')
      AND SemFilter('Compliance-sensitive claims (e.g., "FDA
approved") appear on the package labels in {p.Image}.')
GROUP BY b.BrandName;

```

Fig. 1. A semantic operator instance embedded in SQL.

operator template (a fixed algebraic operator such as `SemFilter`) from an instance, which binds the template to concrete inputs and an *intent*—a natural-language specification of the operator’s semantic goal. Figure 1 shows a representative query where `SemFilter` acts as a predicate over product images, flagging items whose package labels appear to contain compliance-sensitive claims.

Because semantic operators invoke expensive and inherently uncertain inference, SQPEs face a multi-objective optimization problem [27]. Model-backed steps can dominate end-to-end latency and monetary cost [14, 24, 27], while semantic outputs are non-deterministic and backend-dependent. Semantic query optimization is thus best viewed as selecting plans that balance quality, latency, and cost rather than minimizing a single metric.

Existing SQPE optimizers [9, 21, 24, 27, 30, 32, 34] do not expose each semantic operator instance’s internal task structure as a relational optimization object, leaving optimization unable to filter, reorder, route across heterogeneous backends, threshold, or jointly tune its intermediate task outputs. Figure 2 illustrates four such patterns. *Direct LLM* is a monolithic LLM call per row, the simplest supported execution pattern. *Proxy Cascade* represents LOTUS-style [24] proxy execution, where a cheaper model or embedding score decides which tuples escalate to the LLM. *Reduced Context* represents Palimpsest/Abacus-style [21, 27] reduced-context execution, where the input is chunked and only the top- k chunks are fed to the LLM. *Pipeline Rewrite* represents DocETL-style [30] pipeline-level decomposition. None of these expose intermediate task outputs to relational optimization.

Our key insight is that an intent-specific decomposition of a semantic operator instance into a DAG of typed sub-operators turns its intermediate task outputs into relational attributes that optimization can filter, reorder, route across heterogeneous backends, threshold, and jointly tune. For example, the filter in Figure 1 can be achieved by an OCR step that extracts text from each label, followed by a `TxtQA` step that checks whether the text contains a compliance-sensitive claim, where each step is served by a model whose capacity matches its difficulty.

However, achieving this goal raises three challenges (C), each motivating a desideratum (D). (C1) Intent is given in open-ended natural language with no algebraic form, so the optimizer must (D1) synthesize an intent-specific DAG of typed sub-operators. (C2) The right backend for a sub-operator is input-dependent: some tuples are best handled by deterministic rules, others by specialized models, and the residual hard cases require LLMs—a heterogeneity that requires (D2) per-tuple dispatch over heterogeneous backends. (C3) The plan space is multi-objective and plan evaluation is expensive, so (D3) search must be sample-efficient and budget-bounded.

We present CADENZA¹, a semantic operator optimizer that addresses these three desiderata. Given an instance with its intent and a user-specified preference (w_q, w_l, w_c) over quality, latency, and cost, the *logical planner* synthesizes an intent-dependent *plan space* of sub-operator DAGs (D1), and the *physical planner* compiles each sub-operator into tailored implementations (D2) and tunes via

¹In music, a cadenza is a structured yet improvisational passage that adapts the performance to the specific piece; analogously, CADENZA synthesizes and tunes a bespoke execution plan for each intent instance. The full version, including the appendix, is available at arXiv:2606.29151.

Bayesian optimization (D3). CADENZA focuses on optimizing individual semantic operator instances; joint optimization across operators is orthogonal to our focus. Crucially, per-operator optimization already captures most gains: even on multi-operator queries, composing locally optimized instances substantially outperforms state-of-the-art baselines (§7.2).

We formalize such sub-operators in *task-extended relational algebra* (TxRA), a conservative extension of relational algebra. TxRA keeps *relational* operators (e.g., σ , π , $\bowtie$) intact for deterministic schema and dataflow manipulation, but adds *task-specific* operators perform inference over typed attributes and expose their outputs as relational attributes (e.g., OCR returns text, and TxtQA/VQA return an answer with a confidence score, each appended to its input row).

The logical planner translates a semantic operator instance into a TxRA DAG (i.e., a logical plan). Unlike traditional DBMSs, where the query explicitly determines the logical plan structure (e.g., SQL), its intent is given as open-ended natural language with no algebraic form. To address D1, the planner thus (i) synthesizes a small set of seed plans via an iterative draft-refine loop under a fixed LLM budget, and (ii) expands them with two mechanisms: *correctness-preserving structural rewrites* and *semantics-guided alternative generation*. Structural rewrites are dependency-based algebraic rewrites whose preconditions are checked from schemas and dataflow. In contrast, semantic alternatives such as decomposition and proxy substitution are not assumed to be equivalence-preserving; they enlarge the candidate plan space and are selected empirically using the validation/teacher signals used by the physical optimizer. For example, Figure 1’s query yields a seed plan such as $\text{Products} \rightarrow \text{VQA}(\text{Image}, q) \rightarrow \sigma_{\text{Answer}=\text{Yes} \wedge \text{Score} \geq \lambda}$, for which decomposition produces an alternative $\text{Products} \rightarrow \text{OCR}(\text{Image}) \rightarrow \text{TxtQA}(\text{txt}, q) \rightarrow \sigma_{\text{Answer}=\text{Yes} \wedge \text{Score} \geq \lambda}$, where q is the predicate. Crucially, LLM usage is confined to budgeted seed-plan generation; most exploration comes from the mechanisms.

The physical planner takes the candidate logical plans produced by the logical planner, finds the best physical plan for each logical plan, and selects the overall winner under the user’s quality, latency, and cost preferences. To address D2, the planner synthesizes a *data-aware router* per task-specific operator: per tuple, it scores input difficulty and dispatches the tuple to one of heterogeneous backend families—*symbolic* (deterministic rules), *specialized* (compact task-tuned models), *general-purpose* (foundation models), and *composite* (multi-stage pipelines)—via tunable cutpoints. For instance, an OCR router may dispatch easy labels to a distilled OCR model and escalate difficult images to a vision LLM. To address D3, the planner jointly tunes the physical plan’s parameter space Θ —consisting of the router’s cutpoints, per-backend knobs, and parameters of relational operators (e.g., score thresholds λ)—with Bayesian optimization under a fixed evaluation budget. Neither data-aware routing nor Bayesian optimization is new in isolation. Our contribution is the SQPE-specific physical parameterization: routing is attached to each task-specific operator, and its cutpoints are exposed together with backend and relational parameters as one physical optimization problem. For deployment, we select a single Pareto-optimal plan by maximizing a user-weighted utility; to approximate the Pareto frontier, we instead optimize hypervolume. To ensure practicality, the planner also enforces runtime safety and manages optimization overhead.

CADENZA does not cost every subplan as classical optimizers do: with no reliable closed-form cost/quality model for task-specific operators, costing a (sub)plan is not a cheap formula lookup but an execution on samples. Since each candidate is a short task-specific DAG, whole-plan BO evaluation is affordable, whereas subplan-level costing would require BO-style evaluation for many operator/sub-DAG fragments. Moreover, unlike dynamic-programming (DP)-style optimization or interleaved search that prunes plans via partial evaluation, our staged design is necessary because synthesized plans are open-ended and can violate DP’s optimal-substructure assumption: intermediate outputs (e.g., noisy OCR) may be corrected downstream, so early pruning may discard the eventual winner.

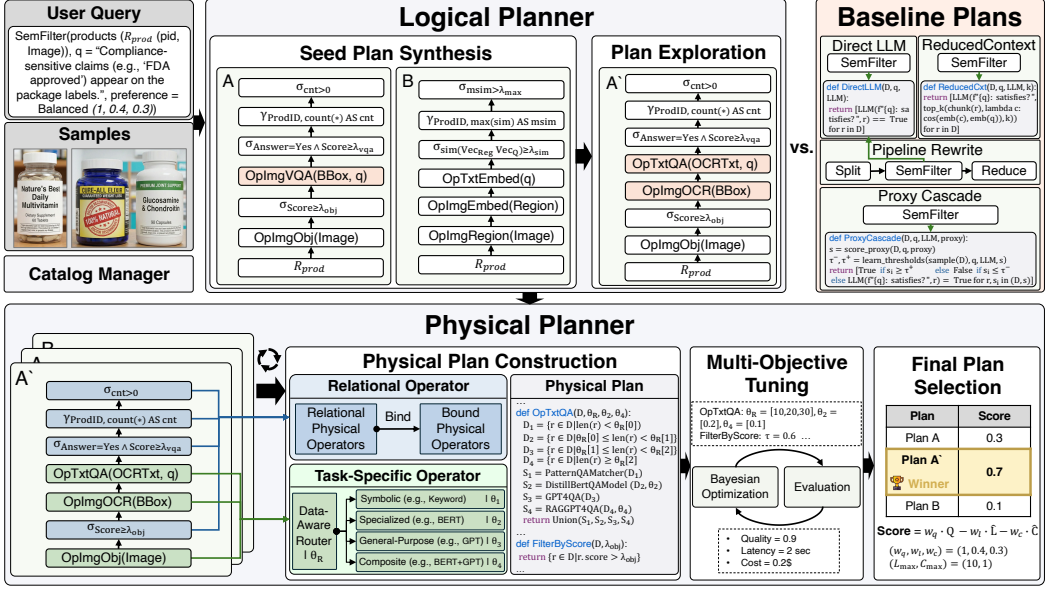


Fig. 2. Overview of the CADENZA architecture illustrating an end-to-end workflow example with representative baseline plans. For clarity, implementation-level optimizations that apply uniformly across plans (e.g., LLM batching) are not shown.

CADENZA is explicitly *budget-aware* and *anytime*: it searches over candidate logical and physical plans under fixed evaluation budgets, returning the best plan found so far and improving monotonically with additional search. This is a deliberate design choice aligned with real deployments, where each additional candidate incurs model inference and evaluation cost. To control backend stochasticity without inflating evaluation cost, we run a single evaluation per BO trial and treat it as a noisy observation in the surrogate, then re-evaluate only the final top- K physical plans for robust selection.

Contributions. This work makes the following contributions:

- We present CADENZA, an SQPE-level optimizer that compiles a semantic operator instance into TxRA plans and selects an executable plan under quality–latency–cost preferences.
- We introduce task-extended relational algebra, which adds task-specific operators to relational operators, enabling semantic processing to be expressed and optimized as an operator DAG.
- We develop a logical planner that synthesizes seed TxRA plans, applies structural rewrites, and enumerates semantics-guided alternatives from alternative-generation templates.
- We propose a physical planner that compiles logical plans into physical plans with a data-aware router over family-specific implementations, exposing router cutpoints, backend parameters, and relational thresholds for joint tuning.
- We evaluate CADENZA on SemBench [18] and show up to +0.49 quality and 165.7×/310.3× latency/cost improvements in scenario-level averages over state-of-the-art baselines.

Section 2 provides an overview of CADENZA and formalizes the optimization problem; Sections 4–5 present the logical and physical planners; Sections 6–7 describe implementation and evaluation; Section 8 discusses related work; and Section 9 concludes.

2 An Overview of CADENZA

This section overviews CADENZA. We first formalize the semantic operator optimization problem and objectives (§2.1), then present the system architecture through a motivating example (§2.2)).

2.1 Semantic Operator Optimization Problem

We formalize the optimization problem as finding a Pareto-optimal plan over quality, cost, and latency. For deployment, we select one Pareto-optimal plan which maximizes a user-weighted utility U .

- **Semantic Operator Instance (SO_I):** An instantiation of a semantic operator template with a natural-language *intent* I that specifies the operator's semantic goal. It denotes an intended transformation $SO_I : \text{Rel}_{\text{in}} \rightarrow \text{Rel}_{\text{out}}$.
- **Logical Plan ($\mathcal{L}$):** A DAG of typed logical operators specifying *what* computation performs SO_I . We denote the set of valid logical plans as $\mathbb{L}(SO_I)$.
- **Physical Plan ($\mathcal{P}$):** A concrete, executable realization of a logical plan, where each operator is bound to a specific implementation and parameters (some tunable). The search space is the union of all such realizations:

$$\mathbb{S}(SO_I) = \bigcup_{\mathcal{L} \in \mathbb{L}(SO_I)} \mathbb{P}(\mathcal{L}).$$

Optimization Goal. Given a semantic operator instance, we optimize over the plan space $\mathbb{S}$ under three competing objectives: maximize quality $Q(\mathcal{P})$ while minimizing latency $L(\mathcal{P})$ and monetary cost $C(\mathcal{P})$. For deployment, we select a single plan by maximizing a user-weighted scalar utility $U(\mathcal{P}) = w_q Q(\mathcal{P}) - w_l \hat{L}(\mathcal{P}) - w_c \hat{C}(\mathcal{P})$ for weights $w_q, w_l, w_c \geq 0$ (at least one positive; setting a weight to 0 omits that metric), where $\hat{L}(\mathcal{P})$ and $\hat{C}(\mathcal{P})$ denote normalized latency and cost, respectively. With all positive weights, the selected plan is Pareto-optimal in the (Q, L, C) trade-off space.

Pareto Optimality of Utility Maximization. Suppose $\mathcal{P}^*$ is not Pareto-optimal. Then there exists $\mathcal{P}' \in \mathbb{S}$ such that $Q(\mathcal{P}') \geq Q(\mathcal{P}^*)$, $\hat{L}(\mathcal{P}') \leq \hat{L}(\mathcal{P}^*)$, and $\hat{C}(\mathcal{P}') \leq \hat{C}(\mathcal{P}^*)$, with at least one inequality strict. Because $w_q, w_l, w_c > 0$, we have $U(\mathcal{P}') - U(\mathcal{P}^*) = w_q(Q(\mathcal{P}') - Q(\mathcal{P}^*)) + w_l(\hat{L}(\mathcal{P}^*) - \hat{L}(\mathcal{P}')) + w_c(\hat{C}(\mathcal{P}^*) - \hat{C}(\mathcal{P}')) > 0$, which contradicts the optimality of $\mathcal{P}^*$. $\square$

Constrained Optimization. Constrained-optimization formulations (e.g., $\max Q$ subject to $L \leq L_{\text{max}}$) are also supported by modifying the BO procedure, e.g., by adding budget-violation penalties to the BO scoring objective; the utility-based interface is our default for its simplicity.

2.2 System Architecture

CADENZA takes as input (i) a semantic operator instance, (ii) the input relation(s) containing unstructured attributes, (iii) an optional validation set, and (iv) an optional user-specified preference over quality, latency, and cost. It outputs an executable physical operator DAG—a fully bound plan with concrete implementations and tuned parameters. As illustrated in Figure 2 (light gray boxes), the architecture consists of three main components:

Catalog Manager Maintains the operator catalog, which enumerates relational and task-specific operators and implementations.

Logical Planner (§4) Determines *what* to compute by decomposing the user's intent into a DAG of typed logical operators.

Physical Planner (§5) Determines *how* to compute it by compiling the logical plan into a physical plan with tunable parameters and tunes them via Bayesian Optimization.

User-Specified Preference. The preference is implemented as weights $(w_q, w_l, w_c) \geq 0$ over quality, latency, and cost (a 0 weight omits that metric). This weighted-utility formulation is a pragmatic deployment interface that provides a simple soft-preference mechanism for top- k plan selection, consistent with prior work on rank-aware query optimization [13, 20]. Fine-grained weights offer maximum flexibility, but for non-expert users we provide a discrete preset that maps to predefined weights—*quality-first* (1, 0.1, 0.1), *balanced* (1, 0.4, 0.3) (default), and *efficiency-first* (0.1, 1, 1).

Validation Set. Following prior work [24, 27], we estimate a plan’s quality, latency, and cost on a small labeled validation set. If not provided, we sample tuples and label them once with a configurable teacher model; this one-time cost is included in optimization overhead and the labels are reused across all candidates. Our goal is not to predict exact accuracy but to rank candidate plans correctly. Empirically, this ranking remains stable even with moderate teacher noise (e.g., 10–20% errors on hard samples), since bad plans (e.g., overly aggressive symbolic filters) fail on easy cases the teacher gets right, while good plans correlate well with the teacher’s decisions. Final evaluations are performed separately.

Logical Plan Exploration (Figure 2, Top). The logical planner explores different strategies to realize the intent. First, it generates a small set of initial seed plans. under a fixed LLM budget. It then expands these seeds using two mechanisms: dependency-checked structural rewrites and semantics-guided alternative generation. In our running example:

- **Plan A (direct).** Find candidate objects and ask VQA the intent *directly* per object—“does this object satisfy q ?”; a product passes if any object affirms it ($Y_{\text{ProdID}, \text{count}(*)} \rightarrow \sigma_{\text{cnt} > 0}$).
- **Plan B (proxy).** Embed image regions and the intent text into a shared space and ask a *proxy* question—“is any region close to the intent?”; a product passes if its maximum region–intent similarity exceeds λ_{max} ($Y_{\text{ProdID}, \text{max}(\text{sim})} \rightarrow \sigma_{\text{msim} > \lambda_{\text{max}}}$).

Subsequently, **Plan Exploration** proposes **Plan A’**, which replaces the monolithic VQA operator with an $\text{OCR} \rightarrow \text{TxtQA}$ alternative (highlighted in red in Figure 2). This alternative is not assumed to be equivalent a priori; it is compiled, tuned, and ranked under the same quality–latency–cost objective.

Physical Plan Construction (Figure 2, Bottom). For each discovered logical plan, the physical planner compiles it into a physical plan with tunable parameters by binding each logical operator to a concrete physical implementation.

- **Relational Operators:** Predicates such as $\sigma_{\text{Score} \geq \lambda}$ are compiled into standard filters with a tunable parameter λ .
- **Task-Specific Operators:** Complex operators are compiled into an implementation that incorporates a data-aware router to dispatch tuples to family-specific implementations. For example, OpTxtQA in Plan A’ dispatches tuples across various implementations (symbolic matching, a distilled QA model, a strong general-purpose LLM, and a composite RAG-style), using cheap input features such as text length with a tunable threshold θ_R , together with per-family parameters such as a confidence threshold (θ_2) and a similarity threshold (θ_4) (see “Physical Plan” in Figure 2). When available, the compiler reuses the cataloged implementation for each family; otherwise, it generates the missing family-specific implementations and synthesizes the router.

Multi-Objective Tuning. For each candidate logical plan, CADENZA tunes the parameters of its compiled physical plan using Bayesian optimization on the validation set. The optimizer maximizes a scalar utility that trades off Quality (Q), Latency (L), and Cost (C). We estimate L_{max} and C_{max} via an LLM-only execution on the validation set. For stability, we use logarithmic scaling (details in §5).

Final Plan Selection. After tuning each candidate logical plan, CADENZA compares the resulting best tuned physical plans and selects the overall winner by the same scalar utility. As shown in the “Final Plan Selection” table, plan A’ is selected because its tuned physical plan preserves high accuracy via the OCR–TxtQA pipeline while reducing cost relative to the VQA approach (Plan A).

Stability under Stochastic Planning. Model inferences can be stochastic, so repeated optimization runs may follow different trajectories and select a different final best plan for the same query. We therefore focus on stability at the level of outcome metrics (Q, L, C) (or a scalar utility) rather than exact plan identity. To reduce run-to-run variance, we (i) control avoidable randomness using deterministic decoding when available, (ii) treat each BO trial as a noisy observation and (iii) smooth residual noise by re-evaluating the final top- K candidates multiple times and selecting via an aggregated score (e.g., median/mean), optionally requiring an improvement margin ϵ before replacing the incumbent.

3 Task-Extended Relational Algebra

Semantic operator instances are specified by open-ended natural-language intents and executed via costly, uncertain inference over unstructured data. Treating an instance as a black-box UDF hides intermediate signals and blocks classical transformations such as pushdown and commutation. Meanwhile, classical relational algebra cannot express semantics-dependent predicates over such modalities. We therefore introduce *task-extended relational algebra* (TxRA), a conservative extension that encapsulates inference behind *typed tasks* and exposes their outputs as relational attributes, enabling semantic processing to be optimized as an operator DAG.

As in relational algebra (RA), TxRA separates the logical specification of an operator from its physical realization: a task-specific operator declares *what task* to perform (e.g., OCR, extracting text from an image, with output schema (txt:Text)), independent of *how* it is implemented (e.g., for OCR, a vision LLM vs. Tesseract vs. a distilled OCR model). A TxRA query thus forms an operator DAG amenable to two kinds of plan exploration. *Structural* rewrites, derived from schema and dependency contracts, follow classical RA transformations such as pushdown and commutation. *Semantic* alternatives, such as VQA to OCR $\rightarrow$ TextQA, are not assumed to be equivalence-preserving by default. §4.3 details both mechanisms.

Types, Domains, and Carrier Set. Let $\mathbb{T}$ be a type universe, where each $\tau \in \mathbb{T}$ has a carrier domain $\mathcal{D}_\tau$. Let $\mathbb{D} = \{\mathcal{D}_\tau \mid \tau \in \mathbb{T}\}$ be the set of such domains, partitioned as $\mathbb{D} = \mathbb{D}_{\text{syn}} \cup \mathbb{D}_{\text{sem}}$ where $\mathbb{D}_{\text{syn}}$ contains structured domains supporting deterministic comparisons (e.g., Int, Float), and $\mathbb{D}_{\text{sem}}$ contains domains of semantic objects (e.g., Text, Image). We write $\text{Rel}_\mathbb{T}$ for the set of typed relations whose attributes have types in $\mathbb{T}$ (equivalently, range over domains in $\mathbb{D}$). For example, in a product relation $r(\text{pid}:\text{Int}, \text{img}:\text{Image})$, pid is in $\mathbb{D}_{\text{syn}}$ and img is in $\mathbb{D}_{\text{sem}}$. Values in $\mathbb{D}_{\text{sem}}$ support identity equality and syntactic predicates (e.g., on file size or hash for img), while latent semantics-dependent predicates (e.g., on its label text or depicted brand) are expressed via task-specific operators.

Algebra Definition. We define $\text{TxRA} = (\text{Rel}_\mathbb{T}, \Omega_{\text{rel}} \cup \Omega_{\text{task}})$, where Ω_{rel} denotes relational operators and Ω_{task} denotes task-specific operators. All operators are closed over $\text{Rel}_\mathbb{T}$.

Relational Operators (Ω_{rel}). Ω_{rel} comprises standard relational operators (e.g., $\sigma, \pi, \bowtie, \gamma$) with well-typed deterministic predicates over $\mathbb{D}_{\text{syn}}$. For $\mathbb{D}_{\text{sem}}$, we permit only deterministic predicates over raw content or metadata (e.g., exact match/regex/length for Text, and IDs/hashes/basic metadata for Image); thus, joins are keyed only by $\mathbb{D}_{\text{syn}}$ attributes or deterministic identifiers from $\mathbb{D}_{\text{sem}}$, while meaning-based matching is expressed via Ω_{task} . Schema and cardinality semantics follow classical relational algebra.

Task-Specific Operators (Ω_{task}). Let $\mathcal{T}$ be a task space. A task $t \in \mathcal{T}$ is a typed (possibly stochastic) computation with signature

$$\text{sig}(t) : (\tau_1, \dots, \tau_m) \rightarrow \text{Rel}_{\mathbb{T}},$$

where inputs may include semantic types (e.g., Text, Image). For example, $\text{OCR} : \text{Image} \rightarrow (\text{txt}:\text{Text})$ extracts text from an image, $\text{TxtQA}_{\varphi} : \text{Text} \rightarrow (\text{answer}:\text{Text}, \text{Score}:\text{Float})$ answers a parameterized question φ over text, and $\text{ImgCls} : \text{Image} \rightarrow (\text{label}:\text{Text})$ classifies an image. Since tasks may be stochastic, $\llbracket t \rrbracket$ induces a distribution over output relations $\Delta(\text{Rel}_{\mathbb{T}})$; we accordingly define plan equivalence *in distribution* to state transformation correctness.

A *task-specific operator* correlates t with each tuple of an input relation r by binding t to attributes $\bar{B}$, in the table-valued LATERAL/Apply (CROSS APPLY) style:

$$\text{Apply}_{t(\bar{B})}(r) = \bigsqcup_{x \in \text{occ}(r)} \{x\} \times t(x[\bar{B}]).$$

For example, $\text{Apply}_{\text{OCR}(\text{img})}(r)$ extracts text from each `img` and appends it as a new attribute `txt`, yielding a relation with schema $(\text{pid}:\text{Int}, \text{img}:\text{Image}, \text{txt}:\text{Text})$. For readability, we depict this in pipeline form (e.g., $r \rightarrow \text{Op}$) as shorthand for $\text{Apply}_{t(\bar{B})}(r)$ with the declared bindings. Semantics-dependent predicates are expressed by composing with relational operators, e.g., $\sigma_{\psi}(\text{Apply}_{t(\bar{B})}(r))$, where ψ is a well-typed predicate over $\mathbb{D}_{\text{syn}}$ output attributes.

Example (Decomposing an Image Claim Filter). Let $r(\text{pid} : \text{Int}, \text{img} : \text{Image})$ be a relation of products. Consider an intent I : “Flag products whose package label contains compliance-sensitive claims (e.g., ‘FDA approved’).” We realize this intent by composing OCR and TxtQA_{φ} introduced above, with φ asking whether the extracted text contains a compliance claim. A TxRA plan for the semantic filter is (omitting a final projection):

$$\sigma_{\text{answer}=\text{“yes”} \wedge \text{Score} \geq \lambda}(\text{Apply}_{\text{TxtQA}_{\varphi}(\text{txt})}(\text{Apply}_{\text{OCR}(\text{img})}(r))).$$

Here, the intermediate OCR outputs become ordinary attributes that are passed to TxtQA_{φ} , while the final decision is expressed as a standard relational filter over $(\text{answer}, \text{Score})$.

Conservativity. If we restrict $\mathbb{D}_{\text{sem}} = \emptyset$ and $\Omega_{\text{task}} = \emptyset$, then TxRA reduces to classical relational algebra over $\mathbb{D}_{\text{syn}}$.

Algebraic Properties and Reorderability. We model tasks as side-effect-free, tuple-wise computations that append attributes via Apply . A sufficient condition to reorder two task-specific operators Op_1 and Op_2 is that neither consumes attributes produced by the other. Let $\text{Attr}(Op)$ be attributes generated by Op and $\text{Free}(Op)$ be required input attributes; then a safe commutativity condition is:

$$\text{Free}(Op_1) \cap \text{Attr}(Op_2) = \emptyset \wedge \text{Free}(Op_2) \cap \text{Attr}(Op_1) = \emptyset.$$

Similarly, a filter σ_{ψ} can be pushed below Apply whenever ψ does not reference attributes produced by the task.

For example, $\text{Apply}_{\text{OCR}(\text{img})}$ and $\text{Apply}_{\text{TxtQA}_{\varphi}(\text{txt})}$ cannot be reordered since $\text{Free}(\text{TxtQA}) \cap \text{Attr}(\text{OCR}) = \{\text{txt}\}$, whereas an independent $\text{Apply}_{\text{ImgCls}(\text{img})}$ shares no attribute dependency and swaps freely. Likewise, $\sigma_{\text{answer}=\text{“yes”} \wedge \text{Score} \geq \lambda}$ cannot be pushed below $\text{Apply}_{\text{TxtQA}_{\varphi}}$ as it references its outputs, but a syntactic $\sigma_{\text{filesize}(\text{img}) > X}$ pushes below all Apply ’s.

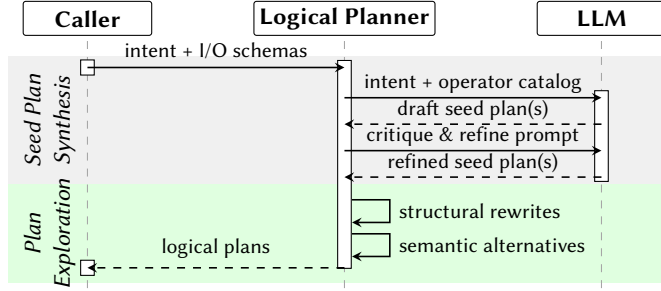


Fig. 3. The workflow of CADENZA's logical planner: seed synthesis (gray) and plan exploration (green).

Table 1. Currently supported task-specific logical operators for text and image.

Modality	Category	Operator	Output Schema	Description
Text	Structural	OpTxtSplit	$R_{Spl}(\text{SegIdx}, \text{Content})$	Segments text into ordered units (e.g., sentences) for indexing.
		OpTxtOutline	$R_{Out}(\text{SecIdx}, \text{ParentIdx}, \text{Level}, \text{Title}, \text{Content})$	Extracts hierarchical sections and their logical structure.
		OpTxtTable	$R_{Tab}(\text{TabIdx}, \text{RowIdx}, \text{ColName}, \text{CellValue})$	Deconstructs embedded tables into relational rows and columns.
	Attributive	OpTxtNER	$R_{NER}(\text{Entity}, \text{Score}, \text{Word})$	Identifies and classifies entity spans.
		OpTxtCls	$R_{Cls}(\text{Label}, \text{Score})$	Predicts labels for a text from a given label set with scores.
		OpTxtSenti	$R_{Snt}(\text{Polarity}, \text{Score})$	Identifies sentiment polarity per aspect.
		OpTxtQA	$R_{QA}(\text{Answer}, \text{Score})$	Extracts the answer value with its confidence score
		OpTxtClaim	$R_{CIm}(\text{ClaimSpan}, \text{Verdict}, \text{EvdSpan}, \text{Score})$	Identifies claim spans and validates factuality with evidence.
	Associative	OpTxtRel	$R_{Rel}(\text{Subject}, \text{Predicate}, \text{Object}, \text{Score})$	Extracts semantic triples representing factual relationships.
		OpTxtEvent	$R_{Evt}(\text{EvtIdx}, \text{Type}, \text{Role}, \text{Argument}, \text{Score})$	Extracts event frames as role-argument bindings.
		OpTxtNLI	$R_{NLI}(\text{Label}, \text{Score})$	Determines the logical inference relationship between two texts.
		OpTxtCoref	$R_{Ref}(\text{ClusterIdx}, \text{Span}, \text{Mention})$	Groups mentions referencing the same entity into clusters.
	Generative	OpTxtPairScore	$R_{Sim}(\text{Score})$	Quantifies semantic similarity or relevance between a text pair.
		OpTxtSum	$R_{Sum}(\text{Summary})$	Condenses the input text into a concise summary.
		OpTxtTrans	$R_{Trn}(\text{Translation})$	Converts the input text into a specified target language.
		OpTxtRewrite	$R_{Rew}(\text{Content})$	Paraphrases or modifies text style while preserving meaning.
	Latent	OpTxtEmbed	$R_{Vec}(\text{Vector})$	Encodes text into a vector representation.
Image	Structural	OpImgRegion	$R_{Reg}(\text{RegIdx}, \text{BBox}, \text{Mask})$	Segments the image into indexed regions (boxes or masks).
		OpImgOCR	$R_{OCR}(\text{Text}, \text{Score})$	Extracts text content with spatial coordinates.
	Attributive	OpImgCls	$R_{Cls}(\text{Label}, \text{Score})$	Classifies the entire image into categories.
		OpImgObj	$R_{Obj}(\text{BBox}, \text{Label}, \text{Score})$	Detects objects with bounding boxes and class labels.
		OpImgKeypnt	$R_{Kpt}(\text{KptIdx}, \text{Point}, \text{Label})$	Identifies semantic keypoints (e.g., joints, landmarks).
		OpImgVQA	$R_{QA}(\text{Answer}, \text{Score})$	Answers natural language questions about the image.
	Associative	OpImgSceneRel	$R_{SGG}(\text{Subject}, \text{Predicate}, \text{Object}, \text{Score})$	Extracts visual relationships (scene graph triples).
		OpImgPairScore	$R_{Sim}(\text{Score})$	Quantifies visual similarity between an image pair.
	Generative	OpImgCap	$R_{Cap}(\text{Caption})$	Generates a descriptive caption for the image.
		OpImgEdit	$R_{Edit}(\text{Image})$	Generates a modified image based on constraints.
	Latent	OpImgEmbed	$R_{Vec}(\text{Vector})$	Encodes the image into a dense vector representation.

4 Logical Planner

In this section, we present the logical planner. We first describe our task-specific logical operators (§4.1), then present seed plan synthesis (§4.2), and finally describe plan exploration via structural rewrites and semantics-guided alternative generation (§4.3). Figure 3 summarizes the workflow. We tested the logical planner on TPC-H queries specified as intents with I/O schemas, and found that it recovers the required relational structure—including multi-way joins—without introducing unnecessary operators.

4.1 Task-Specific Logical Operators

Task-specific operators map unstructured inputs to structured relations that can be processed by relational operators. We address two design questions: (i) the granularity of task-specific operators, and (ii) how to organize the operator set in a database-centric way.

Granularity. We define each task-specific logical operator at the level of a common *task formulation* in standard ML model ecosystems (e.g., Hugging Face): a reusable computation with a typed signature and a stable output schema independent of any backend. The catalog is task-family based rather than workload-specific. Each operator corresponds to a common ML task formulation in standard model ecosystems such as Hugging Face Tasks. For example, OpTxtSenti specializes text classification with a sentiment label space, rather than encoding a Movie scenario-specific rule.

Task Categories. We group task-specific operators by the *database role* of their outputs into five categories: *Structural* (indexes substructures such as segments/regions), *Attributive* (unary descriptors such as labels/answers), *Associative* (relations over elements or pairs, e.g., triples/NLI), *Generative* (derived artifacts as new semantic objects), and *Latent* (vectors for similarity-based retrieval).

Current Operator Set and Extensibility. Table 1 lists the supported text and image operators. New operators are added by registering a task signature and assigning a category.

4.2 Seed Plan Synthesis

Given a semantic operator instance, the planner performs up to B_{log} synthesis attempts; each attempt runs *draft plan synthesis* followed by *plan refinement* and yields at most one seed plan. To keep LLM usage budgeted, refinement is capped by b_{ref} LLM-invoking verification/repair rounds, while deterministic checks do not count.

4.2.1 Draft Plan Synthesis. Each attempt begins by generating a *draft* seed plan that outlines a plausible sequence of reasoning steps for the instance. The planner prompts an LLM with the intent, input/output schemas, the operator catalog, and a short history of previous plans to discourage repetition and encourage structural diversity (e.g., after a VQA-centric draft, a later attempt may explore an embedding-based alternative). Here, extensibility is a core design principle of CADENZA; since the planner uses in-context learning over the prompt-provided operator catalog, adding a new modality (e.g., video) or a domain-specific operator typically only requires registering its signature and description in the catalog, without fine-tuning or retraining. While the catalog provides the primary vocabulary, drafts may include non-catalog placeholders when needed; each placeholder must declare a typed signature and explicit output schema to remain type-checkable.

4.2.2 Plan Refinement. Drafts may be ill-formed (e.g., unsupported operators, invalid wiring, or schema mismatches). The planner refines each draft via a compile-time fix loop: it runs a deterministic verifier to collect all errors and return a concrete report, prompts an LLM to revise the draft to satisfy the report, and repeats until the verifier passes or the refinement budget is exhausted. Once verifier-clean, the planner performs *catalog grounding*, rewriting non-catalog placeholders or composite steps into equivalent subgraphs of catalog primitives when possible. For example, if a filter predicate references a non-existent attribute (Ans), the verifier reports the missing field and the revision updates the predicate to use the correct upstream output attribute. Similarly, the placeholder OpTxtImgSim is grounded into OpImgEmbed→OpTxtEmbed.

4.3 Plan Exploration

Plan exploration expands each seed plan via two mechanisms. Structural rewrites follow the classical optimizer model: correctness-preserving transformations whose preconditions are checked from plan wiring, I/O bindings, and operator contracts. Semantic alternatives exploit task-level knowledge (e.g., partitionability, modality conversion) to propose additional plans without assuming equivalence, and are retained only if their compiled physical plans improve the quality-latency-cost trade-off on the validation/teacher signal.

4.3.1 Structural Rewrites. Structural rewrites are the only plan-exploration steps that we treat as correctness-preserving algebraic rewrites. They require only (i) data dependencies (I/O bindings) and (ii) an operator contract over schema and cardinality. In TxRA, each task-specific operator is a per-tuple Apply that appends a known output schema, thus we apply classical transformations whenever the dependency conditions from §3 hold. Concretely, two operators commute (and can be reordered) whenever $\text{Free}(Op_1) \cap \text{Attr}(Op_2) = \emptyset$ and $\text{Free}(Op_2) \cap \text{Attr}(Op_1) = \emptyset$. A filter σ_ψ can be pushed below an Apply when ψ does not reference task-produced attributes. Our prototype implements two rules: FILTERPUSHDOWN and COMMUTATIVEREORDERING.

4.3.2 Semantics-Guided Alternative Generation. Beyond structural rewrites, useful alternatives often require task-level properties that are not implied by schema or cardinality contracts. We therefore do not present semantic alternatives as equivalence rules. Instead, each semantic alternative is generated by an alternative-generation template: it proposes a new typed DAG that may be cheaper or more accurate for a particular intent/data distribution, and the optimizer decides whether to keep it through validation/teacher-based plan ranking. Some templates can be equivalence-preserving under additional task-specific assumptions, such as lossless partitioning, but CADENZA does not rely on that assumption for correctness; it treats the generated plan as an alternative. Our prototype uses two high-impact templates for unstructured workloads.

Template 1: Partitioned Extraction. Some task-specific operators admit useful partitioned alternatives: the input is split into subrelations by a partitioner P , the task is applied to each partition, and the outputs are normalized and unioned. This template is equivalence-preserving only when the task is partition-local and the normalizer preserves all cross-partition identifiers needed by downstream operators. Otherwise, it is an approximate alternative that trades possible context loss for lower latency/cost:

$$\text{Apply}_t(r) \rightsquigarrow \text{Norm} \left(\biguplus_{s \in P(r)} \text{Apply}_t(s) \right). \quad (1)$$

Example. For entity extraction over a long PDF, the planner splits into pages, runs extraction per page in parallel, and normalizes span offsets before unioning results. *Benefit.* Enables intra-operator parallelism and mitigates context-window limits. *Validation role.* Because cross-partition context may matter, the resulting plan competes with non-partitioned plans and is selected only when it improves the measured quality–latency–cost trade-off.

Template 2: Cross-Modal Proxying. Some tasks admit cheaper alternatives by converting modalities through a conversion operator c , and then applying the task in the converted modality:

$$\text{Apply}_{t_{\text{img}}}(r) \rightsquigarrow \text{Apply}_{t_{\text{txt}}}(\text{Apply}_c(r)). \quad (2)$$

This alternative is not assumed to be semantically equivalent to the original image task; it is a proxy whose usefulness depends on the intent and data distribution. *Example.* To filter images containing a specific phrase, the planner applies OCR and then runs text filtering/classification over the extracted strings, instead of invoking a heavy vision model. *Benefit.* Enables modality switching and cheaper proxy execution when high-fidelity models are costly or unavailable. *Safeguard.* Because conversion can fail, CADENZA can compile this template with a physical fallback, e.g., routing empty or low-confidence OCR outputs to a stronger vision backend. The final decision is made by the same validation/teacher-based plan ranking used for other alternatives.

5 Physical Planner

In this section, we present the physical planner. We first describe the physical plan construction (§5.1), focusing on task-specific operators that compose family-specific implementations with a data-aware router. We then describe multi-objective tuning (§5.2), where Bayesian optimization tunes parameters on a validation set.

5.1 Physical Plan Construction

Algorithm 1 constructs a physical plan $\mathcal{P}$ and its tunable parameter space Θ from a logical plan $\mathcal{L}$. It initializes an empty plan and parameter space (Line 1) and traverses operators in topological order (Line 2). For each task-specific operator (Line 4), the compiler considers each synthesis directive $d \in \mathcal{D}$ (Line 6). The implementation catalog indexes entries by both the operator l and the directive d (i.e., backend family/style), so lookups are keyed by (d, l) (Line 7); otherwise, it synthesizes the missing implementation using the directive and the backend registry, which records available model-serving resources for task-specific inference and their instantiation interfaces (Line 9). It collects candidate implementations and their exposed parameters (Lines 12–13), then synthesizes a data-aware router (Line 16) and forms a composite operator (Line 18). For each relational operator (Line 19), it binds a concrete implementation from the catalog and exposes its tunable parameters (Line 20). Each bound operator is added to $\mathcal{P}$ (Line 22) and its parameters are aggregated into Θ (Line 23). Finally, the compiler copies the dataflow edges from $\mathcal{L}$ to $\mathcal{P}$ (Line 25) and returns $\mathcal{P}$ and Θ (Line 26).

SYNTHESIZEIMPL (Line 9). It materializes a concrete physical implementation for a task-specific logical operator l . It takes a synthesis directive $d \in \mathcal{D}$ —a prompt template that targets a backend family (symbolic, specialized, general-purpose, or composite) and encodes the intended implementation style (e.g., “use only foundation models” or “compose a multi-step pipeline”). Concretely, the planner instantiates this template with $(d, l, \mathcal{R})$ —the directive d , the operator specification of l (typed signature, input bindings, and output schema), and the backend registry $\mathcal{R}$, including only entries applicable to d and l to keep prompts compact. The LLM returns a callable implementation that satisfies the operator contract and declares its tunable parameters (e.g., confidence thresholds, top- k), which are added to the plan’s parameter space for tuning. For example, consider OpTxtQA. The planner synthesizes one candidate per backend family—a symbolic regex filter (no parameters), a specialized DISTILLBERT_QA variant with threshold θ_{qa} , a GPT4-based variant (no parameters), and a composite that prefilters with CLIPSIM and escalates to GPT4 with thresholds θ_{sim} and θ_{gpt} . Since synthesis may fail, SYNTHESIZEIMPL is paired with §6.3.

SYNTHESIZEROUTER (Line 16). Given candidate implementations $\mathcal{K} = \{I_1, \dots, I_N\}$, SYNTHESIZEROUTER constructs a data-aware router r that dispatches each input to an implementation based on its estimated difficulty. The router consists of: (i) *lightweight input-feature extraction* code, (ii) *scoring* code that maps these features to a scalar difficulty score $s \in [0, 1]$ (higher means “needs more semantic capability”), and (iii) *partitioning/dispatching* code. (i) and (ii) are synthesized by prompting an LLM with the operator specification, the ordered implementation set $\mathcal{K}$, and a router generation prompt. (iii) is then generated by instantiating a fixed bucketing-and-dispatch template which uses the scorer and $N-1$ tunable cutpoints to assign each row to one of N buckets and invoke the corresponding I_i . The features are cheap, non-inferential signals (e.g., text length/format; image resolution/aspect ratio, and simple pixel statistics). SYNTHESIZEROUTER is also paired with §6.3.

Percentile Bucketing with Softmax-Parameterized Masses. In practice, we bucket by *percentiles* rather than raw score thresholds, making routing depend on the relative ordering rather than absolute score values, which makes it less sensitive to score-distribution shifts. Concretely,

Algorithm 1 Physical Plan Construction

Input: $\mathcal{L}$ (logical plan DAG), C (implementation catalog), $\mathcal{D}$ (synthesis directives), $\mathcal{R}$ (backend registry)
Output: $\mathcal{P}$ (physical plan), Θ (tunable parameter space)

```

1:  $\mathcal{P} \leftarrow \text{EMPTYDAG}(); \Theta \leftarrow \emptyset$ 
2: for each  $l \in \text{TOPOLOGICALSORT}(\mathcal{L})$  do
3:    $\Theta_l \leftarrow \emptyset$ 
4:   if  $\text{ISTASKSPECIFIC}(l)$  then
5:      $\mathcal{K} \leftarrow \emptyset$ 
6:     for each  $d \in \mathcal{D}$  do
7:        $I \leftarrow \text{LOOKUPCATALOG}(C, d, l)$ 
8:       if  $I = \emptyset$  then
9:          $I \leftarrow \text{SYNTHESIZEIMPL}(d, l, \mathcal{R})$ 
10:      end if
11:      if  $I \neq \emptyset$  then
12:         $\mathcal{K} \leftarrow \mathcal{K} \cup \{I\}$ 
13:         $\Theta_l \leftarrow \Theta_l \cup \text{PARAMS}(I)$ 
14:      end if
15:    end for
16:     $r \leftarrow \text{SYNTHESIZEROUTER}(\mathcal{K})$ 
17:     $\Theta_l \leftarrow \Theta_l \cup \text{PARAMS}(r)$ 
18:     $p_{\text{spcf}} \leftarrow (r, \mathcal{K}); p \leftarrow p_{\text{spcf}}$ 
19:  else
20:     $(p_{\text{agn}}, \Theta_l) \leftarrow \text{BINDRELATIONALOP}(C, l); p \leftarrow p_{\text{agn}}$ 
21:  end if
22:   $\mathcal{P}.\text{ADDNODE}(p)$ 
23:   $\Theta \leftarrow \Theta \cup \Theta_l$ 
24: end for
25:  $\mathcal{P}.\text{LINKEDGESFROM}(\mathcal{L})$ 
26: return  $\mathcal{P}, \Theta$ 

```

we convert scores to rank-based percentiles $u \in (0, 1]$ and assign buckets using $N-1$ increasing percentile cutpoints τ via $k = \text{digitize}(u; \tau)$. To avoid ordered constraints on τ , we parameterize bucket masses with logits $\alpha \in \mathbb{R}^N$, define $\pi = \text{softmax}(\alpha) \in \Delta^{N-1}$, and set cutpoints by the CDF $\tau_k = \sum_{i=1}^k \pi_i$ for $k = 1, \dots, N-1$.

Precompilation. For the operators in Table 1, we precompile physical implementations offline as a caching mechanism for efficiency, except symbolic ones that require query-specific knowledge and are instantiated on demand. If an implementation is missing or the backend set changes, CADENZA synthesizes it at runtime.

5.2 Multi-Objective Tuning

Given a compiled physical plan $\mathcal{P}$ with tunable parameters Θ and a validation set $\mathcal{E}$, the physical planner tunes $\mathcal{P}$ under a fixed evaluation budget B_{tune} , defined in terms of optimization trials (i.e., maximum plan executions) using Bayesian optimization. For $b = 1, \dots, B_{\text{tune}}$, BO proposes $\theta_b \in \Theta$; we execute $\mathcal{P}(\theta_b)$ on $\mathcal{E}$ and measure quality, latency, and cost. This tunes both router parameters

and per-implementation parameters. As defined in §2.1, we select the final plan by maximizing $U(\mathcal{P})$ with normalized latency and cost. We use log normalization since latency and cost span orders of magnitude: it compresses extremes and reduces sensitivity to outliers, budget caps, and cap choices.

Tuning Practicalities. The Bayesian optimization procedure itself is standard and orthogonal to our contributions, as is handling high-dimensional mixed discrete–continuous search spaces [7, 8]. For efficiency, we cap each plan at 15 continuous parameters. To reduce sensitivity to initial random trials, we warm-start with a few hand-designed configurations spanning distinct backend regimes.

6 Implementation

In this section, we describe CADENZA’s implementation and deployment details. CADENZA is implemented in Python (~20K LoC) and currently supports text, image, and audio modalities.

6.1 System Environment & Stack

Core. CADENZA is implemented in Python (3.10+) and uses PyTorch (2.6+). For BO, we use BoTorch via Optuna’s BoTorch integration.

Integration. CADENZA is a standalone optimizer/executor with its own CLI: it can run through its own CLI without depending on any host SQPE. To interoperate with existing SQPEs, the host SQPE implements a small adapter: (i) a *dispatch hook* forwards the host’s semantic operator calls to CADENZA, (ii) *I/O adapters* exchange relations as `pandas.DataFrame`, and (iii) an *LM adapter* routes CADENZA’s LM calls through the host’s LM client; CADENZA itself remains unchanged. Our experiments use a LOTUS integration; the same pattern applies to other SQPEs.

Data Model. Operator inputs/outputs are passed through the adapter as Pandas DataFrames (Arrow-compatible when applicable), enabling vectorized execution and efficient batch inference (e.g., batching LLM or local model calls) rather than per-tuple invocation.

6.2 Optimization Overhead Management

Plan Caching. To amortize optimization cost, CADENZA caches optimized physical plans keyed by an *intent signature* that captures the intent-defining configuration. On a cache hit, CADENZA reuses the cached physical plan without re-optimizing. To handle data distribution drift, which can degrade synthesized symbolic rules and routers, we use two strategies. First, percentile bucketing relies on relative ranks and is thus less sensitive to minor score shifts. Second, cached plans are considered as valid only for a specific data profile. In production, we recommend periodic re-optimization to regenerate symbolic rules and re-tune parameters on fresh samples.

Adaptive Bypass. For small inputs where optimization overhead can dominate, CADENZA bypasses optimization and runs a default LLM-only execution. We use a simple cardinality heuristic $N \leq \tau$. We set $\tau=300$ from profiling the crossover between LLM-only and CADENZA execution; near this scale, only 16/55 queries favored LLM-only, so bypassing is a conservative guardrail and τ is configurable.

6.3 Robustness

Code Safety. LLM-synthesized code includes a small test wrapper (expected signature and required columns) and is smoke-tested on mock inputs. It then runs in an isolated runtime with static checks and timeouts to prevent unsafe operations and bound resource usage. If synthesized code fails the smoke test, CADENZA re-synthesizes it under a bounded timeout/attempt budget until it passes.

Error Recovery. At runtime, CADENZA handles transient failures with bounded retries and safe-mode fallback. If a synthesized code raises an exception or returns a confidence score below a safety margin (when available), we fall back to a default LLM to ensure completion even in the presence of synthesized code fragility.

7 Experiments

We seek to answer the following research questions about CADENZA:

- RQ1.** Does CADENZA achieve better end-to-end quality/latency/cost trade-offs than prior SQPE optimizers? (§7.2)
- RQ2.** How sensitive is CADENZA to its configurations? (§7.3)
- RQ3.** Which techniques of CADENZA account for its performance gains, and by how much? (§7.4)

Table 2. Overview of datasets used in each scenario.

Scenario	SF	Table	#Rows	Unstructured Columns Used
Movie	20000	Reviews	20000	ReviewText TEXT
Wildlife	4000	ImageData	4000	Image IMAGE , City TEXT ,
		AudioData	650	StationID TEXT Audio AUDIO , City TEXT , StationID TEXT
MMQA	300	LizzyCaplanText	300	Title TEXT , Text TEXT
		BenPiazzaText	300	Text TEXT
		TampaInternationalAirport	300	Airlines TEXT ,
		Images	300	Destinations TEXT Image IMAGE
Cars	100000	CarComplaint	99929	Summary TEXT
		CarImage	19156	Image IMAGE
		CarAudio	871	Audio AUDIO
E-Commerce	5000	StyleDetails	5000	ProductDisplayName TEXT , ProductDescriptors TEXT , Images IMAGE

Table 3. End-to-end average improvement of CADENZA over each baseline. Δ for Q is the arithmetic mean of $Q_{\text{CADENZA}} - Q_{\text{baseline}}$; $\times$ for L/C is the geometric mean of baseline/CADENZA. Queries unsupported or failed by a baseline are excluded.

System	Δ Q	$\times$ L	$\times$ C
LOTUS	+0.10	3.80 $\times$	4.88 $\times$
Palimpzest	+0.11	4.42 $\times$	21.83 $\times$
ThalamusDB	+0.28	4.33 $\times$	1.51 $\times$
DocETL	+0.08	13.19 $\times$	8.62 $\times$
Extended AFlow	+0.26	1.40 $\times$	1.96 $\times$
Extended DyFlow	+0.21	1.07 $\times$	1.40 $\times$

Table 4. Fraction of total latency/cost spent in optimization (summing over optimization-enabled queries), and an amortized variant that reuses cached plans per scenario.

Scenario	Overh.L%	Amort.L%	Overh.C%	Amort.C%
Movie	23.7	9.4	17.0	6.4
Wildlife	23.8	9.4	19.8	7.6
MMQA	20.1	7.7	15.2	5.6
Cars	17.2	5.9	15.3	4.5
E-Comm	16.1	6.0	15.8	5.9

7.1 Experimental Setup

7.1.1 Benchmark. We evaluate on SemBench [18], a benchmark for SQPEs that features diverse semantic operators over text, image, and audio data.² We enforce a uniform 24-hour per-query timeout. Table 2 summarizes dataset properties.

Movie. This scenario evaluates sentiment-aware analytics over movie text reviews. It contains 10 semantic queries (Q1–Q4: filters; Q5–Q7: joins; Q8: classification; Q9–Q10: rankings).

Wildlife. This scenario studies species presence and co-occurrence in camera-trap images and animal sound audio captures from Kaggle datasets, with species labels available as ground truth. It contains 10 semantic queries: Q1/Q3/Q7/Q10 are image filters over species (with downstream aggregations), Q2/Q4/Q8 are audio filters, and Q5/Q6/Q9 are multi-modal queries combining image and audio.

MMQA. This scenario evaluates question answering over heterogeneous tables, text, and images. It contains 11 semantic queries: Q1/Q3a/Q3f/Q4/Q5 and Q6a–Q6c are text filters/maps, Q7 is a text→image join, and Q2a–Q2b are image joins with an extraction.

Cars. This scenario combines vehicle metadata, NHTSA complaints, vehicle damage images, and engine-diagnostic audio. It contains 10 semantic queries: Q1/Q4/Q10 are text filters/maps, Q3/Q7/Q8 are image filters, Q2 is an audio filter, and Q5/Q6/Q9 are multi-modal queries combining text/image/audio.

E-Commerce. This scenario uses an online fashion retail dataset with structured product attributes, text descriptions, and images. It contains 14 semantic queries: Q1–Q2 are filters, Q3–Q4 maps, Q5–Q6 classifications, Q7–Q9 joins, Q10–Q11 are multi-stage 3-/4-way joins, Q12 a structured extraction, Q13 a cross-modal filter–join, and Q14 a filter with top- k ranking.

7.1.2 Measure. We measure efficiency by latency (seconds) and monetary cost (USD), and measure quality in $[0, 1]$ against ground truth: relative error (aggregation), F1 (retrieval), Spearman’s ρ (ranking), and ARI (grouping/classification). We repeat each experiment three times and report geometric means. For brevity, we denote **Q** as quality ($\uparrow$), **L** as latency ($\downarrow$), and **C** as monetary cost ($\downarrow$).

7.1.3 Environment. All experiments ran on a machine with 2× RTX 3090 (24 GB each), a 64-core Intel Xeon CPU, and 512 GB RAM. We accessed LLMs via Azure AI Foundry (no local GPUs) and report cost as Azure API charges plus estimated GPU cost for local models from runtime, using \$0.71/hour (NCasT4_v3) as a proxy. We used Global Standard, disabled content filters, and set temperature to 0.

²The Medical scenario was removed from SemBench due to licensing issues [29].

7.1.4 CADENZA Settings. We use GPT-4.1 for planning (parallelism 20); for fair comparison, adaptive bypass uses GPT-4.1-mini (for audio inputs, gpt-audio-mini) and disable plan caching. Unless otherwise noted, we use a 50-sample validation set, $B_{log} = 3$, 20 BO trials, and set $w_q=1.0$, $w_l=0.4$, $w_c=0.3$.

7.1.5 Competitors. We compare semantic-operator optimizers: Palimpzest [21] (with Abacus [27]), LOTUS [24], ThalamusDB [14], and DocETL [30]. We also extend and evaluate AFlow [40] and DyFlow [36]. For all applicable systems, we set parallelism to 20. Following [18], we exclude AOP [34], CAESURA [31], and Unify [32], which require natural-language inputs. We use a controlled setting where all systems share the same pool of foundation models and, where supported, specialized backends. For audio inputs, every baseline uses gpt-audio-mini.

LOTUS. LOTUS [24] optimizes semantic operators by approximating an oracle LLM-based algorithm using proxy models. We use LOTUS v1.1.4 and set the oracle LLM to GPT-4.1-mini (GPT-4.1 was too slow for some queries). For semantic filters, we use GPT-4.1-nano as the proxy; for semantic joins, we use e5-base-v2 (text) and clip-ViT-B-32 (image) embeddings as proxies following [18]. For fair comparison on top- k queries, we extend LOTUS with a Volcano-style pull executor that streams rows through semantic operators and cancels in-flight LLM calls once k outputs are produced.

Palimpzest. Palimpzest [21] integrates the Abacus, a cost-based optimizer [27], which compares physical operators under a chosen objective and constraints with an LLM judge. We use Palimpzest v1.1.1 with Abacus enabled and set MaxQualityAtFixedCost with a \$10 constraint.³ We provide GPT-4.1-nano, GPT-4.1-mini, GPT-4.1, and Text-Embedding-3-Small as candidates, with GPT-4.1 judge.

ThalamusDB. ThalamusDB [14] employs approximate query processing (AQP) with user-defined termination conditions (e.g., error bounds and token budgets), trading quality for efficiency via early stopping. Because our evaluation targets near-exact outputs, enabling AQP termination can stop execution before meeting the required quality. We therefore run ThalamusDB by setting the target error to zero and removing the token budget cap. We use ThalamusDB v0.1.15 and fix the LLM to GPT-4.1-mini.

DocETL. DocETL [30] rewrites a semantic operator pipeline with LLMs to improve quality only. We include DocETL v0.2.6 as a quality-oriented baseline, using GPT-4.1-mini as the default model and Text-Embedding-3-Small for embeddings, and run via its Python API with optimization enabled. Since DocETL currently supports only text inputs, we evaluate it only on text-only queries and disable result caching for fairness. DocETL frequently fails at runtime [24]; we report the average over three successful runs.

Extended AFlow. AFlow [40] is a state-of-the-art agentic workflow framework that searches over code-represented workflows using MCTS with validation-set execution feedback. We extend it with specialized-model nodes and a cost/latency-aware objective, and follow [40] by running 20 MCTS iterations with GPT-4.1 as the optimizer and the same validation set size as CADENZA.

Extended DyFlow. DyFlow [36] is an agentic workflow framework that iteratively designs workflows stage-by-stage with an LLM guided by validation-set feedback. We extend it with the same specialized-model nodes and cost/latency-aware objective, using GPT-4.1 as the driver and the same validation set size as CADENZA.

³Abacus supports multiple objectives, including MaxQuality, MinCost, MinLatency, MaxQualityAtFixedCost, MaxQualityAtFixedTime, MinCostAtFixedQuality, and MinTimeAtFixedQuality. Without an explicit budget constraint, MaxQuality can select prohibitively expensive plans (e.g., >\$1000), which exceed our budget.

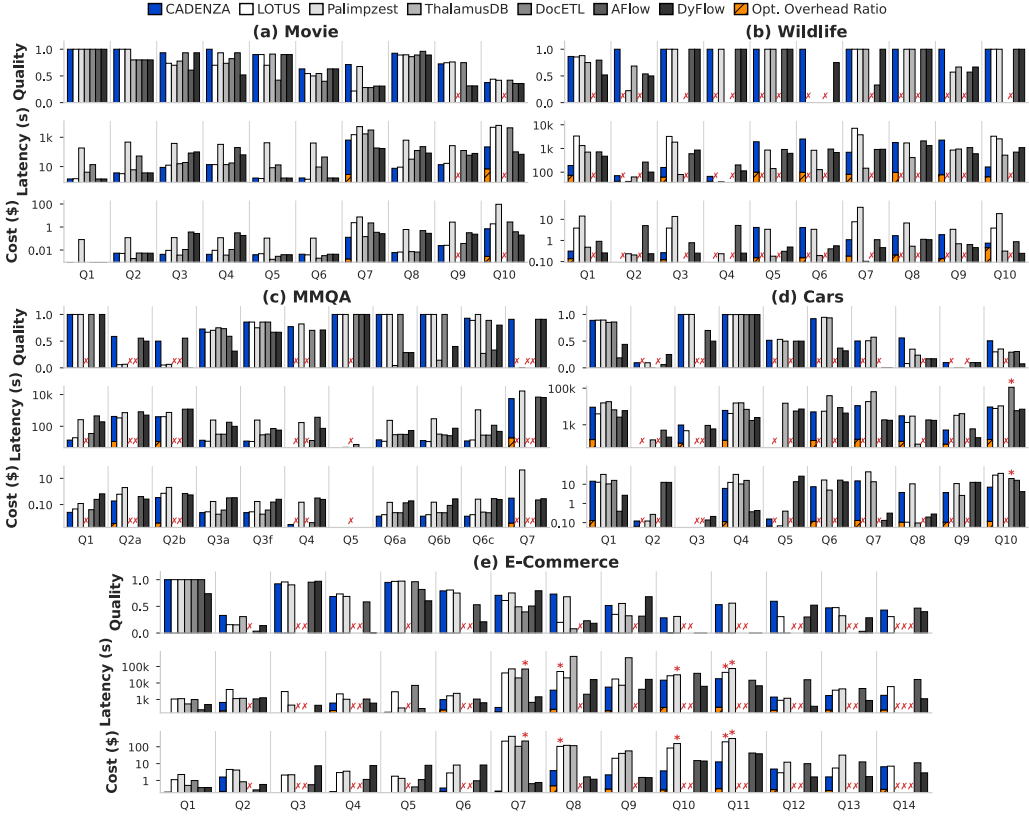


Fig. 4. End-to-end per-query Q/L/C across systems for each scenario.

7.1.6 Validation Set Setup. For fair comparison, all systems that consume a validation set—CADENZA, LOTUS, Palimpzest, DocETL, AFlow, and DyFlow—operate without human ground-truth labels: each uses an oracle LLM for proxy signals on unlabeled tuples.

7.2 End-to-End Query Performance

Table 3 summarizes CADENZA’s average relative performance across scenarios. Figure 4 visualizes per-query Q/L/C across systems. (×) denotes failures. (*) marks latency/cost extrapolated from timed-out runs by rerunning at a smaller scale (E-Comm, SF500) and scaling by the input-cardinality ratio (quality from the smaller run). Hatched bar segments indicate the optimization overhead fraction of the total, including optimization and execution. Overall, CADENZA achieves consistently strong quality–latency–cost trade-offs—even on multi-operator queries (e.g., Q7 in Wildlife, Q10–12 in E-Comm).

Movie (Figure 4(a)). On scenario-level averages, CADENZA improves Q by +0.15 (vs. DyFlow), L $21.0\times$ / C $120.1\times$ (vs. Palimpzest). For Q5, Q6, and Q7, CADENZA selects an OpTextSenti-based plan that requires far fewer LLM calls, resulting in low latency and cost. In contrast, LOTUS and DocETL use embedding similarity as a proxy, which is ill-suited for sentiment-based joins and leads to a notable drop in quality. Palimpzest executes LLM-based plans under a cost constraint by cascading from cheaper to more expensive models, improving quality over LOTUS but at a substantially higher cost. Palimpzest is slow and costly on Q8 and Q10 because it selects a Mixture-of-Agents [33] plan,

yet achieves only similar quality. AFlow and DyFlow remain competitive on easier cases but plateau on harder sentiment joins (e.g., Q7 $F1 = 0.31$); their search procedures tend to settle on parameter tweaks rather than discover better structures within the budget, yielding high cross-query variance. ThalamusDB skips Q9, Q10 (no ranking support). As shown in Table 4, CADENZA incurs about 24% latency and 17% cost overhead, amortizing to ~9% and ~6%.

Wildlife (Figure 4(b)). On scenario-level averages, CADENZA improves Q by +0.48 (vs. ThalamusDB), L $20.8\times$ / C $8.1\times$ (vs. LOTUS). LOTUS's latency is dominated by upfront prompt materialization: it eagerly constructs per-row prompts for the entire input, which can take nearly 30 minutes. Palimpzest avoids this upfront cost, but it often executes semantic filters with GPT-4.1, making inference expensive; moreover, its optimization alone can cost over \$1 while offering little quality improvement over LOTUS. In contrast, CADENZA selects plans with OplmgCls and tunes it to process data mostly by specialized backends, avoiding expensive LLM invocations and yielding faster, cheaper execution. AFlow shows high quality variance (Q7), and MCTS overhead increases latency and cost overall. As shown in Table 4, CADENZA adds ~24% latency and ~20% cost overhead, amortizing to ~9% and ~8%. In Q3 and Q10, ThalamusDB is fast but inaccurate: its early stopping checks whether the answer is stable under both extreme completions (default $t=0/1$), which for aggregation/ranking only indicates stability at the extremes and misses true-label concentrations that flip the top-1.

MMQA (Figure 4(c)). Most queries operate on inputs small enough to fall under CADENZA's bypass threshold. On the image-text logo joins (Q2a, Q2b), LOTUS, Palimpzest, and DyFlow apply a brute-force LLM oracle to every (image, text) pair, mistaking visually similar but distinct logos for matches and collapsing F1 to roughly 0.05–0.07. CADENZA instead chooses an OplmgCls-based join that scores pairs from visual representations and only escalates uncertain cases to an LLM verifier, lifting F1 to 0.59 / 0.50, on par with AFlow's specialized-model plan but without its MCTS overhead. On the large-scale join (Q7), LOTUS, ThalamusDB, and DocETL fail to complete, and Palimpzest's cost-driven cascade still enumerates every pair, while CADENZA, AFlow, and DyFlow all reach F1 0.91 by pruning pairs with cheap symbolic/specialized cues before any LLM call. ThalamusDB and DocETL lack operators required by several queries (map and image input queries, respectively).

Cars (Figure 4(d)). Cars is the most modality-rich scenario—each car may carry text, image, and audio modalities on top of structured fields (transmission, crash, fuel_type)—so the right plan typically gates an expensive modality operator behind a cheap structured filter. CADENZA picks exactly such plans: Q1 (“cars in a crash”) answers via the structured crash field alone ($F1$ 0.89), and Q3 (“manual transmission, damaged in images”) prunes by transmission before running OplmgCls on survivors ($F1$ 1.00). AFlow and DyFlow stick with image-classifier plans and miss the cheap structured filters, degrading to $F1$ 0.19 / 0.44 on Q1 and 0.70 / 0.50 on Q3 at no cost benefit; Q6 and Q7 show the same single-modality over-commit. Palimpzest cascades over the whole input rather than after a structured prefilter, spending \$15–\$33 on multi-modal queries to reach the $F1$ CADENZA hits at \$6–\$14. Q8 (“punctures and paint scratches on images”) is the clearest CADENZA win: every baseline conflates the two damage types under a single LLM oracle ($F1$ 0.08–0.35; LOTUS asks the LLM to verify both per image and collapses to $F1$ 0.08), while CADENZA stages a coarse OplmgCls scan followed by a selective LLM verifier on positives only, lifting $F1$ to 0.56. LOTUS, DocETL, and ThalamusDB cover only subsets of queries.

E-Commerce (Figure 4(e)). On scenario-level averages, CADENZA improves Q by +0.24 (vs. DyFlow), L $165.7\times$ / C $310.3\times$ (vs. DocETL). For Q1 (Reebok backpack filtering), we answer via simple keyword filtering over product name/description even without task-specific operators; for Q4 we use OplmgCls mainly with CLIP [26]. For Q3 and Q5 (text brand/category extraction), we

use OpTxtQA and process it with lightweight keyword-based and BART [19] zero-shot-based implementations for most inputs, routing only cue-missing or hard cases to an LLM backend. For Q6 (image category extraction), we use OpImgCls with cropping-based decomposition. Across these queries, the cheaper backends handle up to 91% of inputs. For join-heavy queries (Q7–Q9), we adopt a similar pair-level strategy: prune pairs using cheap brand/category/color cues and then apply selective LLM filtering to avoid quadratic blowups; for Q8, we instead rely on OpTextPairScore paired with OpImgCap. In contrast, baselines are overly reliant on LLMs or ill-suited proxies (e.g., embedding similarity), and LOTUS further loses quality on Q8 due to lack of multi-key joins. Q8 is particularly challenging due to its large join input (28 texts and 4,993 images), causing most baselines to exceed the 24-hour timeout. For Palimpzest, we disabled Abacus on join-heavy queries because the optimization input exceeded the embedding model’s maximum sequence length. AFlow also uses specialized models (e.g., CLIP and BART), but it largely sticks to its initial plan and makes only minor tweaks, so quality improves little; meanwhile, MCTS overhead makes it slower and more expensive. ThalamusDB lacks a map and thus skips Q3–Q6.

Takeaway. Current SQPEs do not expose a semantic operator instance’s intermediate task outputs as a physical optimization object, and often over-spend on easy inputs.

7.3 Sensitivity Analysis

To study sensitivity, we run analyses on the Movie scenario and report end-to-end performance as the geometric mean over queries where optimization is not skipped.

Table 5. Sensitivity to utility weights.

(w_q, w_l, w_c)	$Q \uparrow$	$L \text{ (s)} \downarrow$	$C \text{ ($) } \downarrow$
(1.0, 0.1, 0.1)	0.78	4251	4.82
(0.1, 1.0, 1.0)	0.41	104	0.08
(1.0, 0.4, 0.3)	0.65	355	0.30
(1.0, 0.9, 0.1)	0.52	143	0.09
(1.0, 0.1, 0.9)	0.59	181	0.09

7.3.1 Impact of Utility Weights. Table 5 reports sensitivity to the utility weights. Quality-centric weights (1.0, 0.1, 0.1) favor LLM-heavy plans, achieving the highest quality but also the largest latency and cost; BO can also slow down since many candidates remain LLM-intensive. Latency/cost-centric weights (0.1, 1.0, 1.0) largely avoids LLM calls and instead uses specialized or symbolic backends, reducing latency and cost at the expense of quality; the remaining cost mainly comes from early BO trials that still explore some LLM-including candidates. For intermediate settings with $w_q=1.0$, increasing the latency weight (and lowering the cost weight) favors specialized/symbolic choices, yielding lower latency and low cost but reduced quality. Shifting weight from latency to cost (from (1.0, 0.9, 0.1) to (1.0, 0.1, 0.9)) keeps cost low but increases latency and quality, suggesting more reliance on specialized backends than symbolic ones while avoiding expensive LLM calls. We use (1.0, 0.4, 0.3) by default as a stable middle ground.

7.3.2 Impact of BO Trials. Figure 5 reports sensitivity to the BO trial budget. With our warm-start initialization, BO shows limited randomness, but with only 5 trials it may select a plan before revealing each candidate’s full potential. As a result, it can choose a plan using OpTxtCls, which yields slightly higher quality (e.g., 0.68) but higher latency due to a larger model, while the OpTxtSenti-based plan is not tuned enough to expose its latency advantage. With 10 trials, BO typically uncovers the latency potential of OpTxtSenti-based plan, leading to a large latency drop and making it the preferred choice despite a small quality loss. With 20 trials, additional

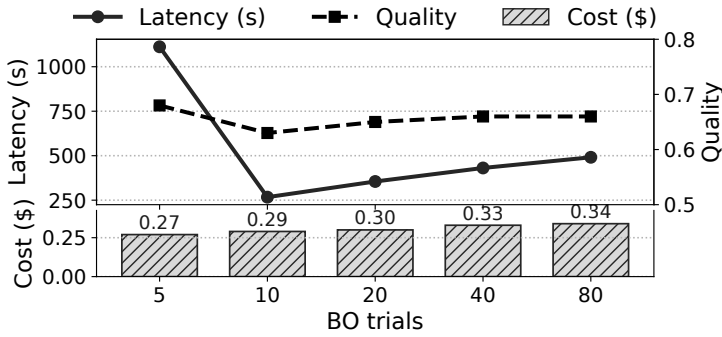


Fig. 5. Sensitivity to Bayesian optimization trials.

tuning slightly improves quality (e.g., 0.63→0.65) with router threshold tunings at the cost of extra tuning-time latency and cost, and beyond that further trials mainly increase tuning cost (dominated by LLM calls) without materially improving the final plan. In practice, the BO trial budget should depend on user intent and the size of the parameter space, which we leave for future work.

Takeaway. Plan selection responds predictably to the utility weights, so users can dial the Q/L/C trade-off without per-query tuning; in the evaluated parameter spaces, 20 tuning trials provide a stable trade-off.

7.4 Ablation Study

Table 6 reports a unified ablation that mixes additive build-up of the logical planning (rows 1–4, full physical) with leave-one-out on physical planning from Full CADENZA (rows 5–10). The ablation runs on SemBench together with BioDEX; queries handled by CADENZA’s adaptive bypass are excluded from the aggregation. **Tune** indicates whether the compiler-exposed parameters are jointly optimized. **BE** (Backends) $\in \{\text{All, SYM, SP, GP, COM}\}$: All = full pool, SYM = symbolic only, SP = specialized only, GP = general-purpose LLM only, COM = composite cascade. Router operates only over the All pool.

Table 6. Ablation study. Row 4 is Full CADENZA.

#	#Seed	Expl	Tune	Router	BE	Q↑	L (s)↓	C (\$)↓
1	—	—	—	—	GP	0.64	9,086	29.2
2	1	×	✓	✓	All	0.48	5,164	5.7
3	3	×	✓	✓	All	0.67	2,743	2.7
4	3	✓	✓	✓	All	0.71	2,975	3.0
5	3	✓	×	✓	All	0.62	5,847	7.9
6	3	✓	✓	×	All	0.63	6,896	16.6
7	3	✓	✓	—	SYM	0.30	237	0.04
8	3	✓	✓	—	SP	0.50	1,448	0.21
9	3	✓	✓	—	GP	0.65	7,800	23.5
10	3	✓	✓	—	COM	0.55	7,318	7.8

The logical build-up (rows 1–3) carries most of the Q gain. At seed=1 (row 2), Q drops because a single plan often turns out structurally weak—operators may be miswired or backends mismatched—and full physical cannot rescue a broken plan. Multi-seed (row 3) is the dominant single jump: candidate diversity gives the physical tuner and per-operator routers a richer plan space to exploit. Adding Expl (row 4) further raises Q on queries needing operator decomposition or modality switching, though the gain is amortized by queries already well-served.

On the physical side, disabling parameter tuning (row 5) is the most damaging: router cutpoints and other exposed parameters remain at their default settings, leading to poorly calibrated routing decisions. Removing Router (row 6) primarily inflates cost: the tuner can still pick the best backend per operator, but without per-tuple dispatch every input pays the same expensive tariff. Single-backend variants (rows 7–10) never recover Full’s trade-off: GP reaches comparable Q at 8× the cost; SYM is essentially free but only covers cue-rich queries.

Takeaway. Logical planning expands the achievable trade-off space; physical optimization—routing, backend-family choice, and joint parameter tuning—determines which trade-off is realized.

8 Related Work

Semantic Operator Optimization. LOTUS [24] approximates a reference LLM-based algorithm using proxy models. Palimpzest [21] integrates Abacus [27], a cost-based optimizer over a user-specified program whose semantic operators are each bound to a single logical operator, searching over transformations and implementations for that fixed structure. ThalamusDB [14] targets AQP via partial results and early termination, again on a single logical operator binding. AOP [34] and Unify [32] pre-register both general-purpose and symbolic backend implementations, using symbolic when applicable. DocETL [30] performs pipeline-level rewrites over document-processing operators (map, filter, reduce, split, gather, resolve, equijoin); the distinction is not whether a system can decompose, but what the decomposition exposes to the optimizer. DocETL does not expose decomposed task outputs as a relational physical optimization object, and its optimizer targets quality only. CADENZA instead compiles a semantic operator instance embedded in a relational query into a typed TxRA DAG, exposing intermediate task outputs as relational attributes that physical search can filter, threshold, reorder, bind per-task to symbolic, specialized, general-purpose, or composite backends, and jointly tune for Q/L/C.

LLM-based Query Planning. LLMs are widely used to construct multi-step plans, either by decomposing tasks into sub-steps (e.g., DECOMP [17]) or by interleaving reasoning with tool use (e.g., ReAct [38], ADAPT [25], Dart-LLM [35]). These approaches primarily target feasibility and typically lack transformation rules or explicit quality–cost optimization. Related systems refine programs or pipelines to improve end-task performance (e.g., MLE-STAR [22], Data-Interpreter [10], ADAS [11]). Closer to optimization, Archon [28] applies Bayesian optimization, AFlow [40] uses Monte Carlo Tree Search, and DyFlow [36] uses an LLM-driven dynamic redesign loop, but their search spaces are largely limited to code-represented LLM-call workflows and do not incorporate relational-style optimization or heterogeneous backends. Query-level model routing and cascading have also been studied [4–6, 23]. CADENZA differs in attaching routing to each task-specific operator and exposing its cutpoints together with backend and relational parameters as part of an SQPE physical plan.

UDF Optimization. Several systems extend SQL engines with ML/LLM capabilities by treating semantic processing as expensive UDFs that encapsulate model calls, e.g., Caesura [31], Amazon Redshift ML [1], BigQuery [9], EVA [15], VOCAL-UDF [39], and Aero [16]. They typically optimize a *fixed* logical plan and treat UDFs as black boxes, focusing on efficient execution; for example, Aero [16] uses adaptive execution to choose evaluation orders for black-box UDFs. In contrast, CADENZA exposes semantic processing via task-extended relational algebra, enabling intent-dependent decomposition and optimization rather than a monolithic UDF. Prior work on opening black-box UDFs (e.g., SQL inlining [2, 3], control-flow graph decomposition [37], and reorderability analysis [12]) is not designed for model-backed, task-specific operators and does not address intent-dependent plan synthesis or multi-objective tuning.

9 Conclusion

We presented CADENZA, a semantic operator optimizer that compiles each instance into a typed TxRA DAG, exposing intermediate task outputs as relational attributes for routing across heterogeneous backends and joint tuning via Bayesian optimization. CADENZA achieves up to +0.49 quality and $165.7\times/310.3\times$ latency/cost improvements on SemBench scenarios.

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