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Cognitive Query Routing (CQR): Reinforcement learning for adaptive query processing in hybrid databases

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Abstract

Modern database systems increasingly adopt hybrid architectures that integrate multiple specialized engines such as row-store and column-store processing, in-memory and disk-based execution, or transactional and analytical components. While these architectures offer flexibility and performance benefits, they introduce significant challenges in query routing and resource allocation. This paper presents Cognitive Query Routing (CQR), a reinforcement learning-based framework for adaptive query processing in hybrid database environments. CQR leverages deep reinforcement learning to dynamically route queries to optimal execution engines based on workload characteristics, system state, and performance feedback. We synthesize foundational adaptive query processing concepts with recent advances in learned optimization and present a comprehensive framework that addresses the multi-engine routing problem. Our analysis demonstrates how CQR extends classical adaptive processing techniques while incorporating cognitive routing principles to achieve robust, explainable query execution in heterogeneous database architectures.

Keywords: Adaptive Query Processing; Reinforcement Learning; Hybrid Databases; Query Routing; HTAP Systems; Cognitive Systems

1. Introduction

The landscape of database management systems has undergone a profound transformation over the past two decades, evolving from monolithic, single-purpose architectures to sophisticated hybrid systems that seamlessly integrate multiple specialized processing engines [1]. This architectural evolution has been driven by the recognition that no single storage or processing paradigm can efficiently handle the diverse spectrum of modern data workloads. Contemporary database systems must simultaneously support high-throughput transactional queries that demand strong consistency guarantees, complex analytical scans requiring columnar data organization, and increasingly, computationally intensive machine learning workloads with user-defined functions [2]. The emergence of hybrid transactional/analytical processing (HTAP) systems represents a culmination of this trend, where traditional boundaries between operational and analytical databases dissolve in favor of unified platforms capable of serving multiple workload patterns concurrently [3]. However, this architectural flexibility introduces a fundamental challenge

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that has become central to modern database research: how to intelligently route each incoming query to the most appropriate execution engine while continuously adapting to dynamic workload shifts, system resource constraints, and evolving performance characteristics.

Traditional query optimization approaches, which have served as the foundation of database systems for decades, rely fundamentally on static cost models and compile-time decision-making processes that cannot adapt to runtime conditions or learn from execution feedback [4]. These classical optimizers make irreversible decisions based on statistical estimates of data distributions, selectivity predictions, and assumed system states—all of which may diverge significantly from actual runtime conditions [5]. The limitations of static optimization become particularly acute in hybrid database environments where multiple engines with distinct performance characteristics compete for shared resources, and where workload compositions shift unpredictably throughout the day [6]. Classical adaptive query processing (AQP) techniques, pioneered by seminal work on eddies and state modules, introduced runtime adaptivity through mechanisms that could dynamically reorder operators and adjust execution strategies based on observed data characteristics [1, 3]. These foundational AQP approaches demonstrated the value of runtime adaptation and established core principles of continuous query processing that remain influential today. However, early adaptive techniques were designed primarily for single-engine environments and employed relatively simple routing heuristics that lack the sophisticated decision-making capabilities required for intelligent multi-engine query routing in contemporary hybrid systems.

The emergence of reinforcement learning (RL) as a powerful optimization paradigm has opened transformative possibilities for adaptive database systems that can learn optimal routing policies through systematic experience rather than relying solely on hand-crafted heuristics or analytical cost models [5]. Reinforcement learning provides a principled mathematical framework for sequential decision-making under uncertainty, where an agent learns to select actions that maximize cumulative rewards through trial-and-error interaction with its environment [6]. The application of RL to database query optimization represents a natural evolution of adaptive processing concepts, extending the reactive adaptivity of classical AQP systems with proactive learning capabilities that can discover complex patterns in workload behavior and system performance [7]. Recent systems have demonstrated the viability and effectiveness of RL-based query optimization in production environments, showing that learned policies can outperform traditional optimizers while adapting continuously to workload evolution [8]. The SkinnerDB system, which applies multi-armed bandit algorithms to adaptive join ordering, achieved regret-bounded performance guarantees while demonstrating practical deployability in real database workloads [6, 7]. These successes validate the core premise that database systems can benefit from learning-based optimization, though existing work has primarily focused on specific optimization problems such as join ordering or operator selection rather than addressing the broader challenge of multi-engine query routing in hybrid architectures.

The query routing problem in hybrid databases presents unique challenges that distinguish it from both traditional query optimization and classical adaptive processing [9]. Unlike join ordering, where the action space grows with query complexity, engine routing involves selecting from a fixed set of execution engines, each optimized for different access patterns and workload characteristics [10]. Row-oriented storage engines excel at point queries, updates, and transactional workloads that access complete records, while column-oriented engines provide superior performance for analytical scans that aggregate over large datasets with selective column access [11]. Modern hybrid systems increasingly incorporate specialized engines for machine learning workloads, where the presence and characteristics of user-defined functions significantly impact optimal execution strategies [9, 10]. The routing decision must account not only for static query characteristics such as join complexity, predicate selectivity, and aggregation requirements—but also for dynamic system state including current engine load, resource availability, cache warmth, and ongoing contention patterns [12]. This creates a high-dimensional decision space where optimal routing policies depend on complex interactions between query properties and runtime system conditions, making hand-crafted routing rules brittle and difficult to maintain as workload patterns evolve.

Real-world database workloads exhibit significant temporal dynamics that further complicate the routing problem [13]. Enterprise systems typically experience predictable daily patterns where transactional workloads dominate during business hours while analytical queries increase during off-peak periods, but these patterns are punctuated by unpredictable events such as year-end processing, marketing campaigns, or system migrations—that can dramatically shift workload composition [14]. Static routing policies that perform optimally for one workload distribution may degrade substantially when faced with different query mixes or resource availability patterns. The veDB-HTAP system deployed at ByteDance demonstrates how production HTAP environments must handle highly variable workload patterns where the ratio of transactional to analytical queries can shift by orders of magnitude within hours [14]. Adaptive routing systems must therefore incorporate mechanisms for continuous learning that allow policies to track workload evolution, detecting shifts in query patterns and adjusting routing strategies accordingly without requiring

manual intervention or offline retraining. This requirement for continuous adaptation under production constraints where excessive exploration can impact user-facing performance—represents a key challenge that distinguishes database query routing from many other RL application domains.

Resource contention in multi-engine systems creates complex interdependencies where routing decisions affect not only individual query performance but overall system throughput and stability [13, 14]. When multiple execution engines share common resources—such as CPU cores, memory bandwidth, or I/O subsystems—the performance of one engine can be significantly impacted by load on other engines, creating dynamic performance characteristics that cannot be captured by static cost models [15]. A query routed to an engine that appears optimal based on historical performance may experience significant slowdowns if that engine is currently saturated or if critical data resides in another engine's cache. The cognitive routing literature from networking research has established that intelligent routing under resource contention requires systems that can perceive environmental state, learn from experience, and adapt decisions based on current conditions rather than fixed policies [15, 16, 17]. These cognitive routing principles—originally developed for packet routing in dynamic network environments—translate naturally to the database query routing context, where similar challenges of uncertain conditions, competing objectives, and resource constraints arise. Applying cognitive routing concepts to database systems requires careful adaptation of the underlying principles to account for database-specific characteristics, such as the semantic richness of queries compared to network packets and the diverse performance objectives beyond simple latency minimization.

The exploration-exploitation tradeoff, fundamental to all reinforcement learning applications, presents particularly acute challenges in production database environments where routing decisions directly impact user-facing application performance [6, 18]. Effective RL requires exploring alternative actions to discover potentially superior strategies, but excessive exploration in a live system can route queries to suboptimal engines, causing performance degradation that affects end users. Conservative exploration strategies that minimize user impact may fail to discover better routing policies quickly enough to adapt to workload changes, while aggressive exploration risks unacceptable performance variability. The Hydro system's approach to adaptive query processing for machine learning workloads demonstrates techniques for managing this tradeoff through confidence-based exploration that increases sampling of uncertain routing decisions while exploiting learned policies for familiar query patterns [9, 10]. Recent work on learned query optimization has further highlighted that systems must balance the benefits of learned policies against the risks of overfitting to training workloads, particularly when deployment workloads differ from training distributions [8]. These findings emphasize the importance of robust exploration strategies, continuous policy evaluation, and safety mechanisms that can detect and respond to performance degradation resulting from poor routing decisions.

This paper introduces Cognitive Query Routing (CQR), a comprehensive reinforcement learning framework that addresses the multi-engine query routing problem in hybrid database systems through principled integration of adaptive processing concepts, cognitive routing principles, and modern deep reinforcement learning techniques [19]. CQR formulates query routing as a Markov Decision Process where an RL agent learns to map high-dimensional state representations—comprising query features, system metrics, and workload context—to routing decisions that optimize multi-objective performance criteria including query latency, resource efficiency, and system throughput [20]. The framework incorporates mechanisms for continuous learning from execution feedback, enabling policies to adapt to workload evolution without offline retraining. To address production deployment requirements, CQR integrates safety mechanisms including fallback routing strategies, anomaly detection, and policy validation, while providing explainability interfaces that expose the reasoning behind routing decisions [21]. By synthesizing insights from decades of adaptive query processing research, recent advances in learned database optimization, and cognitive routing principles from networking systems, CQR establishes a comprehensive foundation for intelligent, adaptive query routing in heterogeneous database architectures. The framework's emphasis on practical deployment considerations—including cold-start mitigation, low-latency inference, and robust exploration strategies—distinguishes it from purely theoretical approaches and positions it for real-world adoption in production database systems.

2. Background and foundations

2.1. Adaptive Query Processing

Adaptive query processing emerged as a response to the limitations of traditional optimize-then-execute query processing models [2]. Classical query optimizers make decisions based on statistical estimates that may be inaccurate, and compile-time optimization cannot respond to runtime variations in data distributions, system load, or resource availability.

2.1.1. Eddies

The seminal work by Avnur and Hellerstein introduced eddies, a continuous adaptive query processing mechanism that routes tuples through query operators dynamically based on observed selectivities and costs [1]. Rather than fixing an operator order at compile time, eddies make per-tuple routing decisions, allowing the execution plan to adapt as data characteristics become apparent. This tuple-level adaptivity provides fine-grained responsiveness but introduces routing overhead and complexity.

2.1.2. State Modules (SteMs)

Raman and Hellerstein extended the eddy framework with state modules that encapsulate stateful operators (joins, aggregates) and provide uniform interfaces for tuple routing [3]. SteMs addressed challenges in routing tuples through operators that maintain internal state, enabling broader applicability of adaptive processing techniques.

2.1.3. Lifting the Burden of History

Deshpande's work on removing historical bias from adaptive routing decisions addressed a fundamental limitation of reactive systems [4]. Early routing decisions based on limited information can constrain future adaptivity. This research emphasized the importance of principled exploration strategies in adaptive systems, a concept that directly connects to reinforcement learning approaches.

Table 1 summarizes key characteristics of classical AQP approaches and their relationship to modern routing challenges.

Table 1 Comparison of adaptive query processing approaches

Approach	Adaptivity Granularity	Decision Mechanism	State Management	Multi-Engine Support
Eddies [1]	Per-tuple	Lottery scheduling	Implicit	Single engine
SteMs [3]	Per-tuple	Policy-based routing	Explicit modules	Single engine
History-free [4]	Per-tuple	Unbiased sampling	Distributed	Single engine
SkinnerDB [6]	Per-operator	RL policy (UCB)	Join state tracking	Single engine
Hydro [9]	Per-query segment	ML-driven routing	UDF-aware	Hybrid ML/DB
CQR (proposed)	Per-query	Deep RL policy	Engine state modeling	Full multi-engine

2.2. Reinforcement Learning for Query Optimization

The application of reinforcement learning to database query optimization represents a natural evolution of adaptive processing concepts. RL provides a principled framework for learning optimal policies through trial and error, balancing exploration and exploitation while optimizing for long-term objectives [5].

2.2.1. SkinnerDB

Trummer et al.'s SkinnerDB system demonstrated the viability of RL for adaptive join ordering [6], [7]. SkinnerDB treats query execution as a sequential decision problem where the system selects join operators dynamically based on accumulated rewards. The system employs upper confidence bound (UCB) algorithms from multi-armed bandit theory to achieve regret-bounded performance guaranteeing that execution cost converges toward optimal plans.

The key insight of SkinnerDB is that query execution can be decomposed into a sequence of smaller decisions (which join to execute next), each informed by observations from previous decisions. This decomposition reduces the action space compared to full plan enumeration while maintaining near-optimal performance. However, SkinnerDB focuses on single-engine join ordering rather than multi-engine routing.

2.2.2. Learned Query Optimization

Zhang et al. analyzed the tradeoffs between traditional adaptive processing and learned optimization approaches [8]. Their work highlighted that learned methods excel when training workloads are representative of execution workloads,

but may struggle with workload shifts. This finding emphasizes the importance of continuous learning and adaptation in production systems a core design principle for CQR.

2.2.3. Cognitive Routing Principles

The term "cognitive routing" originates from network and communications research, where it describes routing protocols that learn from experience and adapt to network conditions [15]. Wu et al. defined cognitive routing as decision-making that incorporates environmental awareness, learning capabilities, and intelligent adaptation [15].

Key principles from cognitive routing that inform CQR design include

2.2.4. Environmental Perception

Systems must accurately observe and represent relevant state information, including both query characteristics and system conditions.

2.2.5. Learning from Experience

Routing decisions should improve over time through feedback from execution outcomes rather than relying solely on a priori models.

2.2.6. Adaptive Decision-Making

Policies must adjust to changing conditions, including workload shifts and system dynamics.

2.2.7. Multi-Objective Optimization

Real-world routing often involves multiple competing objectives (latency, throughput, resource utilization) requiring sophisticated tradeoff management.

These principles translate naturally to the database query routing context, where systems must route queries across heterogeneous engines based on learned policies that adapt to workload evolution.

3. CQR framework architecture

The Cognitive Query Routing framework comprises several integrated components that collectively enable intelligent, adaptive query routing in hybrid database systems.

Figure 1 presents the high-level architecture, which we detail in the following subsections.

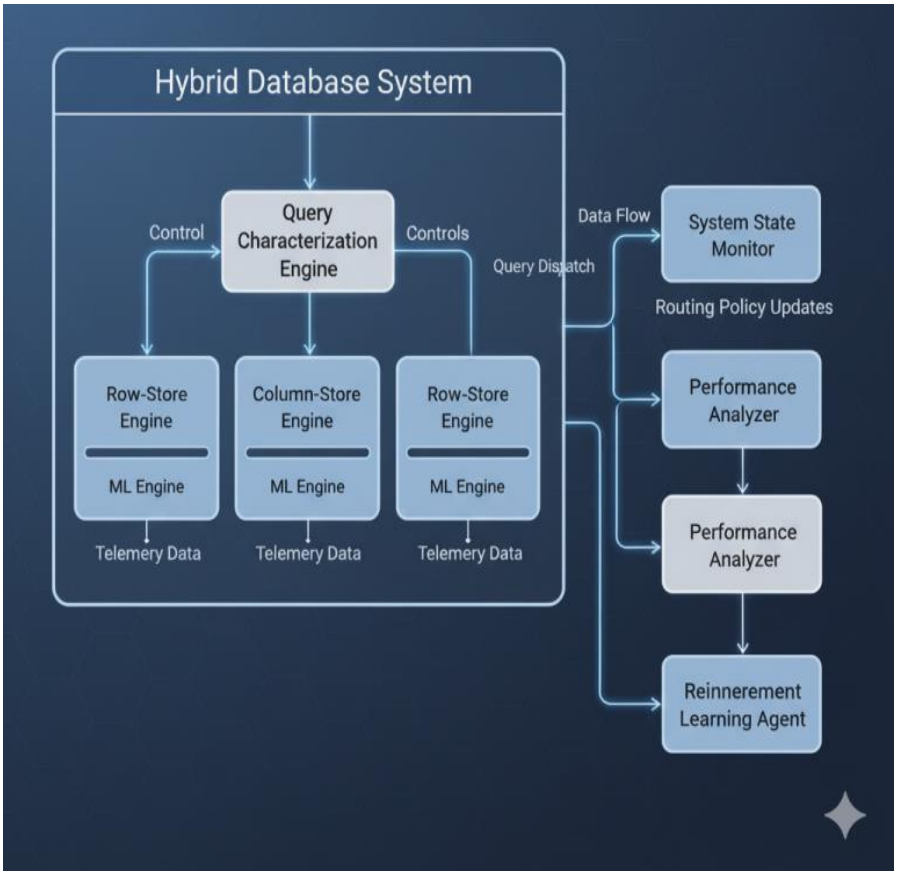


Figure 1 Hybrid Database Architecture with Ai-Driven Routing

A detailed system diagram showing the architecture of a hybrid database system with multiple specialized engines (row-store, column-store, ML engine). The diagram should include components labeled "Query Characterization Module," "System State Monitor," "Reinforcement Learning Agent," "Routing Decision Engine," and "Performance Analyzer," connected by arrows indicating data flow. Use a modern, professional tech visualization style with soft colors and clear labels.

3.1. Query Characterization Module

The Query Characterization Module extracts feature from incoming queries that inform routing decisions. Effective feature extraction is critical for RL-based routing, as the quality of state representation directly impacts policy learning [9], [11].

3.1.1. Syntactic Features

These include query structure characteristics such as the number and types of joins, presence of aggregations, subquery complexity, and predicate selectivity estimates. While traditional optimizers use these features for cost estimation, CQR treats them as components of the RL state space.

3.1.2. Semantic Features

For ML-centric workloads, the presence and characteristics of user-defined functions significantly impact optimal engine selection [9], [10]. CQR extracts UDF complexity indicators, data dependency patterns, and potential parallelization opportunities. The Hydro system demonstrated that UDF-aware routing can significantly improve performance in ML query workloads [9].

3.1.3. Workload Context

Individual query features alone are insufficient for optimal routing decisions. CQR incorporates workload context features including recent query arrival patterns, historical performance for similar queries, and time-of-day patterns that may indicate workload shifts [13].

3.2. System State Monitor

The System State Monitor continuously observes execution engine states, resource utilization, and performance metrics. This component provides the environmental awareness necessary for cognitive routing [15].

3.2.1. Engine-Specific Metrics

Each engine in the hybrid system reports current load, queue depths, cache states, and resource consumption. For HTAP systems, this includes tracking whether engines are currently executing transactional or analytical workloads [14], [22].

3.2.2. Resource Availability

Global resource metrics (CPU utilization, memory pressure, I/O bandwidth consumption) inform routing decisions by indicating contention and capacity constraints. The veDB-HTAP system demonstrated the importance of resource-aware routing in ByteDance's production environment [14].

3.2.3. Performance Feedback

Completed query execution times, resource consumption, and error conditions provide the reward signals necessary for RL policy updates [6]. This feedback loop enables continuous learning and policy refinement.

3.3. Reinforcement Learning Agent

The RL Agent implements the core decision-making logic, selecting target engines for incoming queries based on learned policies. The agent architecture must balance learning efficiency with execution overhead.

3.3.1. Policy Network

Deep neural networks approximate the routing policy, mapping state representations to engine selection probabilities. The network architecture must handle high-dimensional state spaces while maintaining low inference latency [19]. We discuss specific architectural choices in Section IV.

3.3.2. Experience Replay

To stabilize learning and improve sample efficiency, CQR maintains a replay buffer of past routing decisions and their outcomes [15]. Experience replay allows the agent to learn from historical data, reducing the amount of exploration needed in production systems a critical consideration for user-facing databases.

3.3.3. Exploration Strategy

Balancing exploration and exploitation is fundamental to RL [6]. CQR implements adaptive exploration strategies that adjust exploration rates based on policy confidence, workload stability, and system criticality. During stable periods with high confidence, the system exploits learned policies; during workload shifts or when encountering novel query patterns, exploration increases to discover potentially better routing strategies.

3.4. Routing Decision Engine

The Routing Decision Engine translates the RL agent's engine selections into concrete query dispatching, handling practical considerations like connection management and failover.

3.4.1. Policy Execution

The engine implements the routing policy by directing queries to selected engines, managing execution contexts, and handling any necessary query rewriting or parameter adaptation required by target engines [22].

3.4.2. Fallback Mechanisms

Production systems require robust handling of engine failures or unexpected performance degradation. CQR implements safety mechanisms that override RL decisions when engines become unavailable or performance deviates significantly from expectations [11].

3.4.3. Explainability Interface

To support debugging and system understanding, CQR provides explanations for routing decisions, including which features most influenced engine selection and confidence estimates for the chosen action [21]. Recent work on query

performance explanation through large language models provides complementary approaches to understanding routing decisions [21].

3.5. Performance Analyzer

The Performance Analyzer processes execution feedback to generate reward signals and detect anomalies that may indicate policy degradation or workload shifts.

3.5.1. Reward Computation

The analyzer transforms raw performance metrics into scalar rewards that guide RL learning. Reward design must balance multiple objectives query latency, resource efficiency, and throughput while remaining simple enough to enable effective learning [5]. We detail reward formulation in Section IV-C.

3.5.2. Anomaly Detection

Sudden performance changes may indicate workload shifts, system failures, or policy degradation. The analyzer detects such anomalies and can trigger policy reevaluation or increased exploration [8].

3.5.3. Policy Evaluation

Periodic offline evaluation assesses policy quality using counterfactual reasoning—estimating how alternative routing decisions would have performed. This evaluation informs decisions about policy updates and exploration rate adjustments [6].

4. Reinforcement learning formulation

The query routing problem can be formulated as a Markov Decision Process (MDP), providing a principled framework for applying reinforcement learning techniques [5], [6]. This section details the MDP components and discusses algorithm selection for the CQR framework.

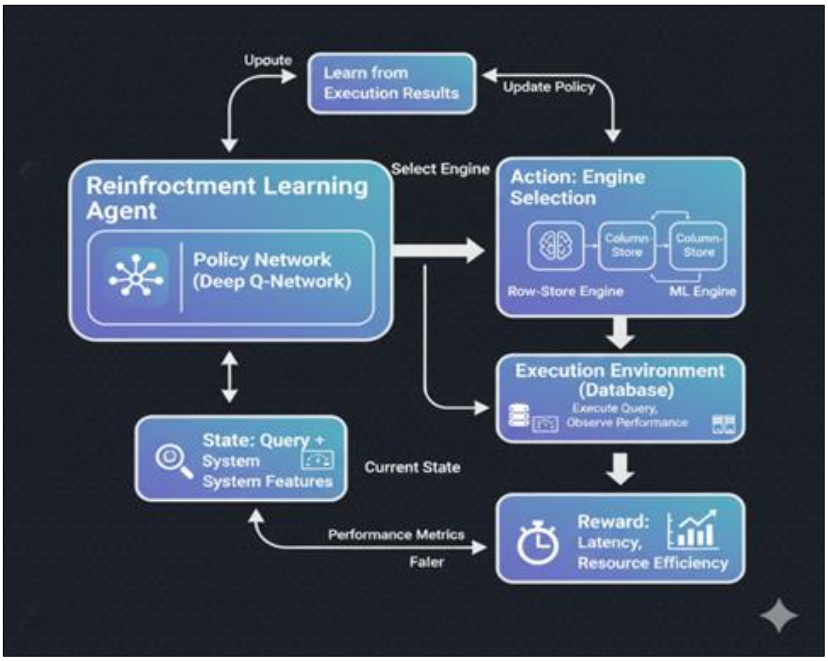


Figure 2 Reinforcement Learning for Database Query Routing

A conceptual diagram showing a reinforcement learning process for database query routing. Include labeled boxes for State (query + system features), Action (engine selection), Reward (latency, resource efficiency), and Policy Network (Deep Q-Network), with feedback arrows showing learning from execution results. Use an academic AI-diagram style with gradients and icons.

4.1. State Space Representation

The state space S captures all information relevant to routing decisions at query arrival time. A state $s \in S$ is a vector comprising:

4.1.1. Query Features f_q

These include query complexity metrics (number of tables, join count, predicate count), estimated selectivity, presence of aggregations and sorting, and UDF characteristics [9]. For query q, we represent these as a fixed-length feature vector extractable in $O(1)$ time through query analysis.

4.1.2. System State f_s

Engine-specific metrics including current queue depths $\{d_1, d_2, ..., d_n\}$ for n engines, resource utilization percentages, and cache warmth indicators [14]. For HTAP systems, this includes transaction isolation state and consistency requirements [13].

4.1.3. Historical Context f_h

Recent workload characteristics including query arrival rates, performance trends for similar queries, and time-based features that capture temporal patterns [18]. The context window size presents a tradeoff between information richness and state space dimensionality.

The complete state representation is:

$$s = [\mathbf{f}_q, \mathbf{f}_s, \mathbf{f}_h]$$

Table 2: summarizes key state space components and their dimensions.

Table 2 State space components for query routing

Component	Features	Dimensionality	Update Frequency	Source
Query Structure	Join count, table count, predicate count	10-20	Per query	Query parser
Query Semantics	Aggregations, UDFs, sorting, grouping	8-15	Per query	Query analyzer
Selectivity Estimates	Predicate selectivity, cardinality estimates	5-10	Per query	Statistics
Engine Queue Depths	Current queue size per engine	n (num engines)	Continuous	Engine monitors
Resource Utilization	CPU, memory, I/O per engine	$3n$	Continuous (1s)	System metrics
Cache States	Cache hit rates, warm data indicators	$2n$	Continuous (10s)	Engine internals
Workload Context	Arrival rate, query mix, time features	15-25	Continuous (1s)	Workload tracker
Historical Performance	Recent latency, success rates	10-20	Per query	Execution log

4.2. Action Space and Engine Selection

The action space A comprises the set of available execution engines. For a hybrid system with n engines, $A = \{e_1, e_2, ..., e_n\}$, where each action $a \in A$ represents routing the query to engine e_a.

4.2.1. Discrete Action Space

Unlike join order selection in SkinnerDB where action spaces grow with query complexity [6], the engine routing action space remains constant regardless of query characteristics. This property simplifies policy learning and enables efficient policy representation through standard classification neural networks.

4.2.2. Action Constraints

Certain queries may have execution constraints that restrict valid actions. For example, transactional queries requiring strong consistency may only be routable to certain engines [13], [14]. CQR incorporates constraint satisfaction by masking invalid actions during policy evaluation.

4.2.3. Hybrid Engine Execution

Some systems support splitting a single query across multiple engines—for instance, executing joins on a row-store while pushing aggregations to a column-store [13]. CQR can be extended to support such hybrid execution by expanding the action space to include engine combinations, though this significantly increases action space complexity.

4.3. Reward Function Design

The reward function $R(s,a,s')$ quantifies the quality of routing query in state s to engine a, transitioning to state s'. Effective reward design is critical for learning useful policies [5], [6].

4.3.1. Primary Performance Objective

Query execution latency forms the primary component of the reward signal. For a query completing in time t seconds, we can define a latency-based reward:

$$r_{\text{latency}} = -\log(1+t)$$

The logarithmic transformation prevents extreme latencies from dominating learning while maintaining sensitivity to performance differences across the typical latency range.

4.3.2. Resource Efficiency

To encourage resource-efficient routing, we incorporate penalties for excessive resource consumption:

$$r_{\text{resource}} = -\alpha\left(\text{CPU}_{\%} + \text{Memory}_{\%} + \text{IO}_{\%}\right)$$

where α is a weighting factor balancing resource efficiency against latency [14].

4.3.3. Throughput Optimization

System-level throughput can be incentivized by rewarding routing decisions that maintain balanced load across engines:

$$r_{\text{balance}} = \beta \cdot \left(1 - \sigma(\text{load distributions})\right)$$

where σ denotes standard deviation of engine loads and β weights the importance of load balancing [22].

4.3.4. Combined Reward

The complete reward function combines these components:

$$R(s,a,s') = r_{\text{latency}} + r_{\text{resource}} + r_{\text{balance}} + r_{\text{penalty}}$$

where r_{penalty} includes negative rewards for constraint violations or execution failures.

Table 3 compares reward formulations from related systems.

Table 3 Reward Function Comparison Across Systems

System	Primary Objective	Secondary Objectives	Reward Formulation	Time Horizon
SkinnerDB [6]	Join execution cost	Regret minimization	Negative cost	Per-join step
Hydro [9]	UDF execution time	Resource usage	Negative latency + penalty	Per-query
veDB-HTAP [14]	Mixed workload latency	Engine balance	Weighted multi-objective	Per-query
AutoQuo [12]	Plan execution time	Robustness	Adaptive cost function	Per-plan
CQR (proposed)	Query latency	Resources + throughput	Multi-component with balancing	Per-query

4.4. Policy Learning Algorithm

CQR employs deep Q-learning with experience replay as the core RL algorithm, chosen for its sample efficiency and stability in high-dimensional state spaces [15], [19].

4.4.1. Deep Q-Network (DQN)

The action-value function $Q(s,a)$ is approximated by a deep neural network with parameters θ. The network takes state s as input and outputs Q-values for each possible action (engine). The routing policy selects the action with maximum Q-value:

$$\pi(s)=\arg\max_{a} Q(s,a;\theta)$$

- **Network Architecture**: The DQN architecture consists of:
  - Input layer accepting the state vector
  - Multiple fully connected hidden layers with ReLU activation
  - Dropout layers for regularization
  - Output layer with n units (one per engine) representing Q-values
  - Hidden layer sizes typically range from 128-512 units, balancing representation capacity with inference speed [19].

4.4.2. Training Procedure

The network is trained to minimize the temporal difference error:

$$L(\theta)=E_{(s,a,r,s')\sim D}\left[\left(r+\gamma\max_{a'} Q(s',a';\theta^{-})-Q(s,a;\theta)\right)^2\right]$$

where D is the experience replay buffer, γ is the discount factor, and θ^{-} represents parameters of a target network that is periodically updated to stabilize learning [15].

4.4.3. Exploration Strategy

CQR implements ϵ-greedy exploration with adaptive ϵ decay. During stable periods, ϵ decreases to prioritize exploitation; when workload shifts are detected, ϵ temporarily increases to explore new optimal routing strategies [8].

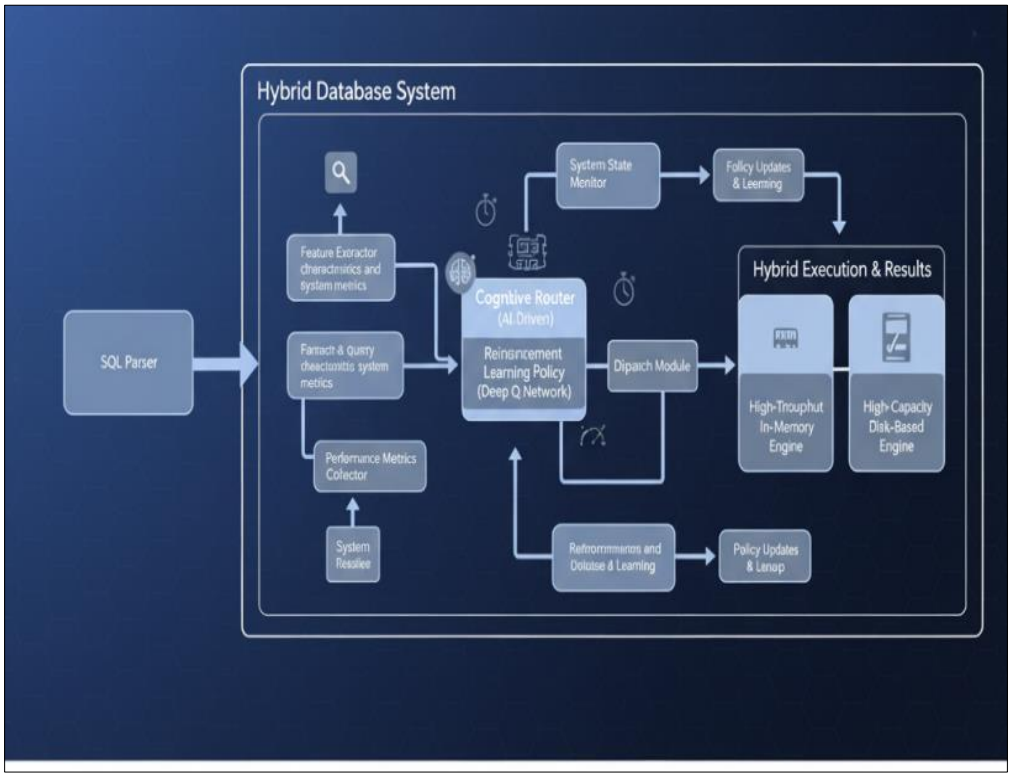
4.4.4. Alternative Algorithms

- While DQN provides a strong baseline, CQR's architecture supports alternative RL algorithms including:
- Actor-Critic methods for continuous policy improvement
- Policy gradient methods for handling large action spaces in hybrid execution scenarios
- Multi-armed bandit algorithms (UCB, Thompson Sampling) for simpler deployment with lower overhead [6], [18]

The algorithm selection depends on system requirements, with simpler methods appropriate for constrained environments and sophisticated deep RL suitable for complex hybrid systems with diverse workloads [7], [11].

5. Implementation considerations

Deploying CQR in production database systems requires addressing several practical challenges beyond the core RL formulation.



An illustration showing integration points of the Cognitive Query Routing framework inside an existing hybrid database architecture. Depict the query flow from parser → feature extractor → RL policy → engine dispatch → feedback loop. Include components for in-memory and disk-based systems. Style should resemble a software architecture whitepaper graphic.

Figure 3 Cognitive Query Routing Integration in Hybrid Architecture

5.1. Integration with Existing Systems

5.1.1. Query Interception

CQR must intercept queries after parsing but before execution plan generation. This integration point allows feature extraction from the parsed query structure while maintaining compatibility with engine-specific optimizers [22]. Systems like ShannonBase demonstrate practical patterns for workload routing integration [22].

5.1.2. Minimal Overhead

Routing decisions must add minimal latency to query execution. State feature extraction and policy inference should complete in milliseconds. This constraint favors lightweight feature sets and efficient neural network architectures [11]. Hydro's architecture demonstrates that careful feature engineering can maintain sub-millisecond routing overhead even for complex ML queries [9].

5.1.3. Compatibility

The framework must accommodate engines with different query language support, transaction semantics, and data representations. Query rewriting may be necessary to translate between engine-specific dialects [13].

5.2. Training and Deployment

5.2.1. Cold Start Problem

Initially, the RL agent has no learned policy and must explore randomly or use heuristic fallbacks. Techniques to mitigate cold start include

- Pre-training on synthetic workloads or simulations [8]
- Warm-starting with heuristic policies based on simple rules
- Conservative exploration that favors safe, general-purpose engines initially

5.2.2. Online Learning

Production deployment requires online learning where the policy improves during live operation. This introduces challenges in balancing exploration (which may degrade user-facing performance) with exploitation [6]. CQR addresses this through

- Low baseline exploration rates (1-5%) during stable operation
- Confidence-based exploration where uncertain states trigger higher exploration
- Scheduled exploration windows during low-traffic periods

5.2.3. Continuous Adaptation

Workload characteristics evolve over time, requiring continuous policy updates. Zhang et al. emphasize that learned optimizers must adapt to workload drift to maintain effectiveness [8]. CQR implements sliding window training where recent experiences have higher weight, allowing the policy to track workload evolution.

5.3. Safety and Reliability

5.3.1. Fallback Mechanisms

When the RL policy selects engines that fail or perform unexpectedly poorly, the system must recover gracefully. CQR implements multi-level fallbacks

- Automatic retry on alternative engines after timeout
- Fallback to heuristic routing if RL-selected engines repeatedly fail
- Emergency mode using default engine selection during system instability

5.3.2. Policy Validation

Before deploying updated policies, offline validation assesses performance on held-out queries. Only policies demonstrating improvement over baseline are deployed to production [11].

5.3.3. Explainability

Production systems require understanding of routing decisions for debugging and optimization. CQR provides explanation through

- Feature importance scores indicating which state components most influenced decisions [21]
- Confidence estimates for routing choices
- Alternative engine recommendations with estimated performance differences

5.4. Scalability Considerations

5.4.1. Distributed Deployment

Large-scale systems may require distributed CQR deployment where multiple routing agents operate independently. Coordination mechanisms can synchronize learning across agents, sharing experience and policy updates [14].

5.4.2. State Space Pruning

As the number of engines and features grows, state dimensionality can become unwieldy. Feature selection techniques identify the most informative state components, reducing dimensionality while maintaining policy quality [9].

5.4.3. Action Space Management

For systems with many specialized engines, the action space can become large. Hierarchical routing first selecting engine categories, then specific engines—can simplify learning [18].

Table 4 summarizes implementation challenges and mitigation strategies.

Table 4 Implementation challenges and mitigation strategies

Challenge	Impact	Mitigation Strategy	Related Work
Cold start	Poor initial performance	Pre-training, heuristic warm-start, conservative exploration	[8]
Exploration overhead	User-facing latency impact	Low baseline exploration, confidence-based adaptive exploration	[6]
Workload drift	Policy degradation over time	Continuous learning, sliding window training, drift detection	[8]
Engine failures	Query execution failures	Multi-level fallbacks, automatic retry, health monitoring	[11]
Feature extraction latency	Routing overhead	Efficient parsing, feature caching, lightweight representations	[9]
High-dimensional state	Learning difficulty	Feature selection, dimensionality reduction, hierarchical representation	[9]
Multiple objectives	Conflicting optimization goals	Multi-objective reward design, Pareto optimization	[14]
Distributed deployment	Coordination complexity	Experience sharing, federated learning, policy synchronization	[14]

6. Related work

The CQR framework builds upon three primary research threads: adaptive query processing, reinforcement learning for databases, and cognitive routing systems. This section surveys key contributions in each area and positions CQR relative to existing work.

6.1. Classical Adaptive Query Processing

The foundational work on adaptive query processing established core principles that inform modern approaches. Avnur and Hellerstein's eddies introduced the concept of per-tuple routing through query operators [1], demonstrating that dynamic plan adaptation could outperform static optimization under cardinality estimation errors. The eddy framework influenced subsequent work on adaptive execution strategies.

Raman and Hellerstein's state modules extended eddies to handle stateful operators [3], addressing practical challenges in building fully adaptive query processors. Their work established architectural patterns for encapsulating operator state while maintaining routing flexibility.

Deshpande's work on lifting historical bias [4] highlighted the importance of principled exploration in adaptive systems, directly anticipating later connections to reinforcement learning. The comprehensive survey by Deshpande et al. [2] and later reflections by Babu [23] provide taxonomies of adaptive techniques and identify open research directions that CQR addresses.

6.2. Reinforcement Learning for Query Optimization

The application of RL to query optimization represents a significant evolution beyond reactive adaptive processing. Tzoumas and Sellis first proposed combining eddies with reinforcement learning [5], framing the routing problem as an RL task where the system learns from execution feedback.

SkinnerDB by Trummer et al. [6], [7] demonstrated practical RL-based query optimization, achieving regret-bounded join ordering through multi-armed bandit algorithms. SkinnerDB's success validated the RL approach for adaptive query processing, though it focused on single-engine join selection rather than multi-engine routing. The SkinnerMT extension by Wei et al. [24, 25] further improved robustness through parallelization.

Recent learned query optimization work by Zhang et al. [8] analyzed the limitations of learned approaches under workload shift, emphasizing the need for continuous adaptation—a core design principle of CQR. The AutoQuo system [12] applied RL to adaptive plan optimization, demonstrating industry interest in learned optimization techniques.

6.3. ML-Centric Adaptive Processing

The emergence of ML workloads in database systems has motivated specialized adaptive processing approaches. The Hydro system by Kakkar et al. [9], [10] introduced adaptive query processing specifically designed for ML queries with user-defined functions. Hydro's routing policies adapt to UDF characteristics and execution patterns, demonstrating significant performance improvements over static optimization.

The Aero system [11] further advanced ML-centric adaptive processing, incorporating sophisticated cost models for ML operators. These systems demonstrate the value of workload-specific adaptation, though they focus on ML queries rather than general hybrid database routing.

6.4. HTAP and Hybrid Database Systems

Modern HTAP systems face challenges similar to those addressed by CQR. Song's work on rethinking query optimization in HTAP databases [13] highlighted the need for dynamic plan adaptation as workloads shift between transactional and analytical patterns.

The veDB-HTAP system from ByteDance [14] represents a state-of-the-art production HTAP system with intelligent workload routing. veDB-HTAP routes queries between row and column engines using cost models enhanced with machine learning, demonstrating the practical feasibility of learned routing in large-scale production systems. ShannonBase [22] provides similar intelligent routing capabilities, showing industry convergence toward learned optimization.

6.5. Cognitive Routing Systems

The cognitive routing literature from networking and communications provides theoretical foundations for CQR. Wu et al. [15] defined cognitive routing based on deep reinforcement learning, establishing principles of environmental awareness, learning, and adaptation that directly apply to database routing.

Work by Gupta et al. [16] and Al-Rawi et al. [17] applied RL to routing in cognitive radio networks, demonstrating successful deployment of learned routing policies in resource-constrained, dynamic environments—challenges analogous to those in database systems.

Alanazi's reinforcement learning-based query routing [18] applied RL to peer-to-peer query routing, demonstrating the generality of RL approaches across different routing contexts. Recent work on deep RL routing frameworks [19] provides architectural patterns applicable to CQR implementation.

6.6. Explainability and System Understanding

The emergence of explainability requirements in learned database systems has motivated work on understanding routing decisions. Recent work by Xiu et al. [21] on query performance explanation through large language models demonstrates complementary approaches to understanding why specific engines perform better for particular queries. Integrating such explanation capabilities with CQR could enhance debuggability and user trust in learned routing systems. Properly explained works can also help proper understandings especially in plant medicine[26]

FUTURE DIRECTIONS AND CONCLUSION

A futuristic concept illustration showing intelligent data routing in a multi-engine database cluster. Depict neural pathways symbolizing reinforcement learning decisions, with icons for cloud databases, AI optimization, and workload balancing. Use a high-tech visualization with glowing neural lines and data nodes to symbolize cognition and adaptivity

Figure 4 Cognitive Data Routing

7. Future research directions

7.1. Several promising directions extend the CQR framework

Multi-Query Optimization: Current CQR formulation routes individual queries independently. Future work could incorporate multi-query optimization where routing decisions consider interactions between concurrent queries, optimizing system-wide throughput rather than individual query latency [14].

7.2. Transfer Learning

Policies learned on one database system could potentially transfer to similar systems or workloads. Investigating transfer learning approaches could reduce cold-start costs and enable faster deployment across multiple installations [8].

7.3. Hierarchical Reinforcement Learning

For systems with many specialized engines, hierarchical RL could decompose routing into multiple levels—first selecting engine categories, then specific engines within categories. This decomposition could improve learning efficiency in complex environments [18].

7.4. Federated Learning

In multi-tenant or distributed database deployments, federated learning approaches could enable policy learning across installations while preserving data privacy. Tenants could benefit from collective experience without sharing sensitive workload information [14].

7.5. Integration with LLM-Based Optimization

Recent advances in large language model-based query optimization [21] could complement CQR. LLMs could provide natural language explanations for routing decisions or suggest feature engineering improvements based on query patterns.

7.6. Hardware-Aware Routing

Modern hardware heterogeneity (CPUs, GPUs, specialized accelerators) creates opportunities for hardware-aware query routing. Extending CQR to route queries to appropriate hardware resources represents a promising research direction [9].

8. Conclusion

This paper presented Cognitive Query Routing (CQR), a comprehensive reinforcement learning framework for adaptive query processing in hybrid database systems. CQR addresses the fundamental challenge of intelligent query routing across multiple specialized execution engines by combining classical adaptive processing principles with modern deep reinforcement learning techniques.

The framework provides several key advances over existing approaches

- **Multi-Engine Support**: Unlike single-engine adaptive systems like eddies [1] or SkinnerDB [6], CQR explicitly addresses routing across heterogeneous engines with different capabilities and performance characteristics.
- **Principled Learning**: By formulating routing as a Markov Decision Process, CQR enables systematic policy learning that balances multiple objectives while providing theoretical foundations for convergence and optimality analysis.
- **Production-Ready Design**: The framework incorporates practical considerations including safety mechanisms, explainability, and integration patterns necessary for production deployment, drawing on lessons from systems like veDB-HTAP [14] and Hydro [9].
- **Continuous Adaptation**: CQR 's online learning mechanisms enable continuous adaptation to workload evolution, addressing the workload drift challenges identified by Zhang et al. [8] while maintaining stable production performance.

The convergence of adaptive query processing, reinforcement learning, and hybrid database architectures represents a significant evolution in database system design. As databases increasingly adopt specialized engines for different workload patterns transactional processing, analytical queries, ML workloads, and graph processing—the need for intelligent, adaptive routing will only intensify.

CQR demonstrates that cognitive routing principles from network systems [15], [16], [17] translate effectively to database contexts, where similar challenges of resource contention, dynamic conditions, and multi-objective optimization arise. The framework's emphasis on explainability [21] and safety mechanisms addresses critical requirements for production database deployments where incorrect routing decisions directly impact user-facing applications.

The success of recent systems like SkinnerDB [6], [7], Hydro [9], [10], and veDB-HTAP [14] validates the core premise that learned, adaptive routing can significantly improve performance over static optimization. CQR synthesizes insights from these systems into a comprehensive framework applicable across diverse hybrid database architectures.

Looking forward, the integration of reinforcement learning into database query processing represents more than an incremental optimization technique it signals a fundamental shift toward systems that learn from experience rather than relying solely on analytical cost models. As workloads become increasingly diverse and unpredictable, the ability to adapt continuously through learning will become essential for achieving robust, efficient query execution.

The challenges outlined in this paper from state representation and reward design to safety mechanisms and explainability provide a roadmap for researchers and practitioners deploying learned optimization in production systems. While significant work remains in areas like transfer learning, multi-query optimization, and hardware-aware routing, the foundational principles established by CQR provide a solid basis for continued advancement.

In conclusion, Cognitive Query Routing represents a synthesis of decades of adaptive query processing research with modern reinforcement learning techniques, addressing the practical challenges of routing queries in contemporary hybrid database systems. By providing a principled framework for continuous learning and adaptation, CQR enables databases to automatically discover and exploit optimal routing strategies, improving performance while reducing the manual tuning burden on database administrators. As database systems continue to evolve toward greater specialization and heterogeneity, frameworks like CQR will become increasingly critical for realizing the performance potential of hybrid architectures.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

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