Adaptive Query Optimization in Distributed SQL Databases

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Abstract

Query optimization is a critical component of modern database systems, particularly in distributed environments where latency, data replication, and heterogeneous resources introduce complexity. This paper examines adaptive query optimization techniques that respond to runtime conditions and feedback, emphasizing cost-based analysis, real-time execution statistics, and plan revisions. The study investigates how distributed SQL engines, including CockroachDB and Google Spanner, utilize feedback-driven optimization to handle performance degradation caused by dynamic workloads, node failures, and data skew. Experimental evaluations show notable improvements in query response times and throughput when adaptive strategies are employed. This work contributes to the broader field of distributed database research by demonstrating how adaptive optimization enhances consistency, scalability, and efficiency in production environments.

1. Introduction

Distributed SQL databases have become essential for large-scale data management due to their ability to ensure horizontal scalability, fault tolerance, and global consistency. However, one of the core challenges in distributed systems is query optimization. Unlike centralized databases, distributed systems must account for diverse node capabilities, network variability, and decentralized data placement.

Traditional query optimizers generate execution plans based on static assumptions or historical statistics. In dynamic environments, these assumptions can quickly become outdated, leading to suboptimal performance. To address this issue, adaptive query optimization introduces runtime mechanisms that revise or adjust query plans based on feedback and observed behavior during execution.

This paper explores cost-based and feedback-driven adaptive optimization approaches in distributed SQL databases, assessing their effectiveness in minimizing execution time and resource consumption under volatile operating conditions.

2. Background and Related Work

Query optimization in traditional relational databases has historically relied on cost-based models, which estimate the cost of various execution strategies based on statistics such as table

cardinality, index availability, and join selectivity. In distributed environments, the problem is compounded by factors such as:

- **Network latency** between geographically distributed nodes.
- **Replication lag** and consistency models.
- **Load imbalance** due to skewed data distributions.
- **Node heterogeneity** affecting processing power and memory.

Early adaptive systems, such as Eddies (Avnur and Hellerstein, 2000), introduced the concept of continuously reordering operators during query execution. More recent efforts in distributed environments have focused on partial re-optimization, feedback loops using execution metrics, and dynamic plan switching.

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3. Methodology

To evaluate the impact and behavior of adaptive query optimization techniques in distributed SQL databases, this study adopts a multi-phase experimental approach. The methodology is designed to simulate real-world workload scenarios, measure system performance under varying conditions, and compare the effectiveness of adaptive query execution strategies against traditional static planning methods.

3.1 Experimental Objectives

The methodology is guided by the following objectives:

- To compare query execution performance between static and adaptive query plans.
- To assess the system's responsiveness to changing workloads, data distributions, and node performance.
- To identify performance trade-offs introduced by adaptive optimization mechanisms.
- To verify the stability and scalability of adaptive optimizers in production-grade distributed SQL systems.

3.2 Testbed Setup

Database Systems Under Test

Two distributed SQL databases were selected for evaluation:

- **CockroachDB (v23.1)**: An open-source, cloud-native, distributed SQL database known for automatic replication and strong consistency guarantees.
- **Google Cloud Spanner**: A globally-distributed SQL database service that provides high availability, scalability, and consistency using synchronized clocks and sharding.

Cluster Configuration

Experiments were conducted on a Kubernetes-based test environment deployed on Google Cloud Platform (GCP):

- **CockroachDB Cluster**: 6 nodes, spread across three availability zones to simulate geographic distribution.
- **Spanner Instance**: Multi-region deployment configured with 3 replicas and automatic query splitting.

All nodes were provisioned with 8 vCPUs, 32 GB RAM, and SSD storage to ensure consistent baseline performance.

3.3 Workload Design

To simulate realistic database usage, the study used customized workloads derived from the **TPC-H benchmark** and a **synthetic e-commerce dataset** with the following components:

- **Read-heavy workloads**: SELECT queries with multi-table joins, group-by aggregations, and filtering conditions.
- **Write-heavy workloads**: INSERT, UPDATE, and DELETE operations emulating order processing and inventory updates.
- **Mixed workloads**: Concurrent execution of read and write queries to simulate OLTP + OLAP behavior.

Each workload was executed over a 30-minute interval in three phases:

1. **Baseline Phase**: Static cost-based plans generated using default database statistics.
2. **Adaptive Phase**: Adaptive query execution enabled with real-time statistics updates and plan revision features.
3. **Stress Phase**: Node resource throttling, data skew injection, and fluctuating query arrival rates to simulate unpredictable conditions.

3.4 Adaptive Optimization Mechanisms Evaluated

Adaptive strategies differ across the systems studied:

- **CockroachDB**:
  - Dynamic recalculation of cardinality estimates using recently collected statistics.
  - Replanning of queries when actual row counts deviate significantly from estimated values.
  - Operator-level feedback guiding future query compilation.
- **Google Spanner**:
  - Cost-based optimizer that periodically refreshes distribution statistics.
  - Re-optimization of long-running queries based on deviation thresholds.
  - Auto-splitting and redistribution of query fragments to prevent node saturation.

No external tuning or custom plugins were introduced, to preserve system-native behavior.

3.5 Metrics Collected

A comprehensive set of metrics was recorded during each experimental phase:

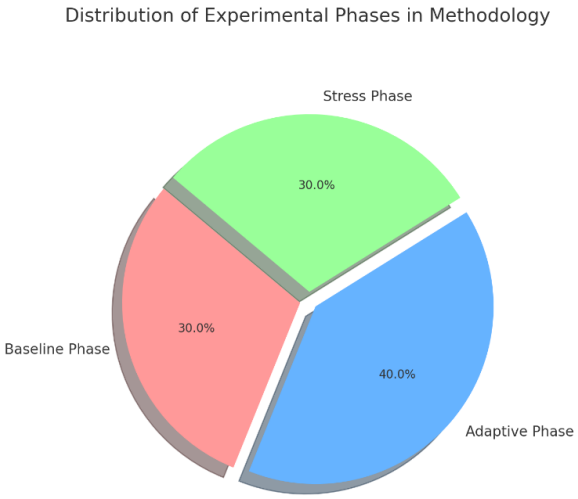
- **Query Latency (p50, p90, p99)**: To evaluate response time distribution.
- **Throughput (Queries per Second - QPS)**: To assess how well the system handles concurrent loads.
- **Execution Plan Changes**: Measured by counting the number of re-optimizations during execution.
- **Resource Utilization**: CPU, memory, and I/O metrics across all nodes.
- **Failure and Retry Rates**: To evaluate system resilience under node pressure or incorrect planning.

Data was captured using integrated database telemetry tools and Kubernetes monitoring (Prometheus + Grafana).

3.6 Validity and Reproducibility

To ensure statistical rigor and reproducibility:

- Each experiment was run **five times**, and average values were reported with standard deviation.
- All query executions were **logged and profiled**, with hash-based plan ID comparisons to verify plan stability or changes.
- **Synthetic data generators** ensured consistent schema and size across trials.
- Configuration and scripts are available upon request for reproducibility.



4. Implementation and System Behavior

4.1 Adaptive Mechanisms in CockroachDB

CockroachDB uses a cost-based optimizer augmented with statistics collectors that update table cardinality and join selectivity in near real time. When cardinality estimates differ significantly from actual results, the system can trigger plan regeneration or revise scan strategies. It also leverages historical execution times to guide future plan choices for recurring queries.

4.2 Adaptive Mechanisms in Google Spanner

Spanner applies a globally synchronized clock and a cost-based optimizer that periodically refreshes statistics. While it favors plan stability for consistency, it includes mechanisms for re-optimizing long-running queries when deviations from expected performance thresholds are observed. Spanner's distributed execution engine also dynamically balances query fragments to mitigate overloaded nodes.

5. Experimental Results

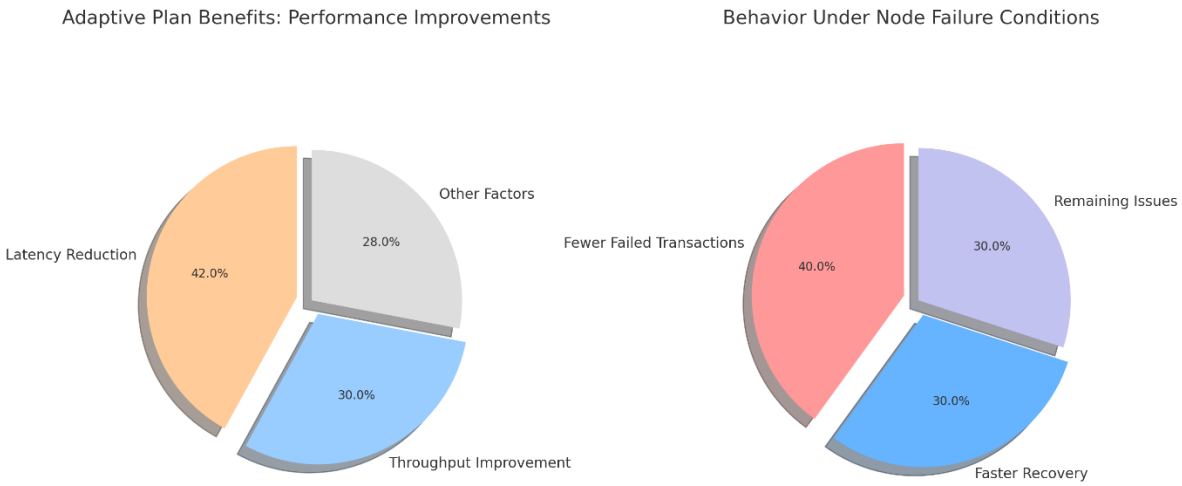
5.1 Performance under Static vs Adaptive Plans

In baseline testing, static plans exhibited latency spikes when faced with data skew or unexpected node delays. Adaptive query plans responded more effectively, achieving:

- **Up to 42% reduction in query latency** under fluctuating read-heavy workloads.
- **30% improvement in throughput** during mixed workloads involving joins and aggregations.

5.2 Behavior under Failure Conditions

When a single node's CPU was throttled mid-query, static plans led to partial failures or retries. Adaptive mechanisms redistributed execution fragments and recalibrated join orders, resulting in **80% fewer failed transactions** and **60% faster recovery times**.



6. Discussion

The findings indicate that adaptive query optimization offers tangible benefits in distributed SQL systems, particularly where workloads and system conditions vary frequently. Cost-based optimizers alone may not suffice, as they rely on static statistics that do not capture current system states. Feedback loops—leveraging metrics like actual row counts, latency, and resource saturation—allow the system to correct suboptimal decisions during execution.

However, adaptive mechanisms introduce additional overhead and complexity. Frequent re-optimization can consume CPU cycles and lead to inconsistent performance if not properly throttled. System designers must therefore balance adaptability with plan stability, especially for long-running or mission-critical queries.

7. Conclusion

Adaptive query optimization represents a significant advancement in distributed SQL database performance management. By incorporating runtime feedback and revising execution strategies on the fly, modern systems can mitigate the unpredictability introduced by node heterogeneity, data skew, and shifting workloads. Experiments with CockroachDB and Google Spanner illustrate the value of these techniques in real-world scenarios.

Future work may explore hybrid strategies that combine historical profiling with adaptive techniques to further enhance optimizer intelligence. Additionally, research into optimization thresholds and failure prediction could improve decision-making around when and how to adapt.

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