An Intelligent Query Optimizer for Distributed Database for Cloud Environment

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ABSTRACT

Distributed databases are widely used in the cloud for storing and managing data. Cloud computing environment provides the computing power and storage that can be sharable within number of database applications. A distributed database comprising of multiple interconnected databases, which are spread physically across various locations interconnected through a computer network. In distributed database system, the data need to be transferred from one site to another during query processing. For each query in distributed database system, its evaluation cost involves the I/O cost at local site, CPU time and communication cost to transfer data from one site to another.

It can be used as a pre-processor for effective query optimization on the top of any

- **Databases system. An architecture of query optimizer for distributed databases which is integrated with**
- **Materialized views that are reused for evaluation of further queries in the system. An optimization strategy has been introduced that reduces total execution cost of**
- **Queries in distributed databases which will be more beneficial in cloud environment. Cloud resource utilization has been improved by reducing query evaluation time and**
- **Overall execution cost.**

The Query Optimization Technique Using Materialization (QOTUM) system has been developed on Java platform with the help of ZQL Parser. The performance of the system is tested on cloud platform of Amazon Relational Database Service (RDS) using standard benchmark dataset and the workload of TPC-H. The MySQL database engine is initially setup on Amazon RDS instances and TPC-H database is distributed among all these RDS instances. Extensive experiments have been conducted with the help of all variations of TPC-H query workloads. The performance of QOTUM system is analysed and compared with conventional SQL system based on various performance parameters.

Keywords: Query Optimization, Cloud computing, Machine Learning, Adaptive Query Processing

INTRODUCTION

Database Management Systems (DBMSs) have vital importance in all computing environments today. In cloud computing environment, distributed databases are widely used for storing and managing data. Query processing in a distributed database involves the transfer of data from one site to another through a communication network. The distributed database enables the combining of data from dispersed sites by means of queries [2].For each query, its evaluation cost is associated. Sum of the local cost of I/O, CPU and the cost of transferring data between sites gives the evaluation cost of each query in distributed databases. How to get the data timely, accurately and reliably plays an important role in the success of the cloud data model.

This paper strates the challenges for data management and retrieval I n cloud computing platform followed by research issues. It also presents aim and objectives of the research; and research methodology adopted in this research work.

Milestone for Management and Retrieval of Data from Cloud Environment

Cloud computing has capacity of sharing computing power and storage for number of database applications. The propagation seen in the number of applications which influenced various cloud platforms resulting in tremendous increase in the scale of the data generated as well as consumed by such applications . How to organize and manage those huge amount of data a together helpful information for the users has been a new the mien the research area of cloud computing. This addresses the issue of assigning DBaaS workloads for large datasets to hardware resources by implementing STeP framework that improves performance and saves operational cost of cloud providers. Cloud data modeling is the foundation of cloud computing application and the searching algorithm upon it is the key issue of cloud computing applications.

Research Issues
The topic addressed following research issues and deals with the challenges in query optimization in distributed databases on cloud platform.

Resource utilization during database access In cloud: In cloud computing environment, maximum utilization of resources such as CPU, memory, storage, network bandwidth etc. is the main motive in Infrastructure as a Service (IaaS) model because cloud users have to pay the rent as per the resource usage.

Processing cost of join-intensive queries
Join operations in database queries consume more resources and increases processing time. Hence ,the reduction in processing cost of join-intensive queries is an important objective of query processor of distributed databases in cloud environment.

Overall execution cost of queries
Overall execution cost includes query execution time, I/O and communication cost. Minimization of query execution time and reduction in overall cost of execution are the central issues in this research work.

Related Work
Our research builds upon and extends work from several interconnected areas in database systems and machine learning. This section provides a comprehensive overview of the relevant literature and current state-of-the-art in these domains.

Query Optimization in Distributed Databases
Query optimization for distributed databases has been an active area of research for decades. Early work by Salingeret al. [1] laid the foundation for cost-based query optimization, which has since been adapted for distributed environments. Kossmann [2] provided a comprehensive survey of distributed query processing techniques, highlighting the challenges of data placement and network cost considerations.

More recent work has focused on query optimization for cloud-based distributed databases. Ding et al. [3] proposeda distributed query optimizer that considers both local and global optimization strategies. Their work demonstrates the importance of considering data transfer costs in geo-distributed environments.

Adaptive Query Processing
Adaptive query processing techniques aim to address the limitations of traditional static query optimization. Deshpande et al. [4] provided a survey of adaptive query processing methods, categorizing them into plan-based, routing-based, and operator-based approaches.

Notably, Markl et al. [5] introduced the concept of progressive query optimization, which allows for plan changes during query execution. This approach has been further developed by Karanasos et al. [6] in their work on distributed query processing for big data systems.

Machine Learning in Database Systems
The application of machine learning to database management systems has gained significant traction in recent years. Kraska et al. [7] demonstrated the potential of learned index structures, sparking interest in ML-enhanced database components.

In the context of query optimization, Marcus et al. [8] proposed a deep reinforcement learning approach for join order optimization. Their work showed that ML models can outperform traditional query optimizers in certain scenarios. Building on this, Ortiz et al. [9] developed a learning-based approach for cardinality estimation, a critical component of query optimization.

Query Routing in Geo-Distributed Databases
Query routing in geo-distributed databases presents unique challenges due to varying network latencies and data locality issues. Wu et al. [10] proposed a query routing approach that considers both data locality and load balancingin geo-distributed settings.

Vulimiri et al. [11] introduced the concept of lazy evaluation for geo-distributed queries, demonstrating significant performance improvements by delaying certain query operations. Their work highlights the importance of considering network topology in query planning.

Adaptive Systems for Geo-Distributed Databases
Recent work has begun to explore adaptive systems specifically designed for geo-distributed databases. Ding et al. [12] proposed an adaptive data placement strategy that continuously monitors query patterns and adjusts data distribution accordingly. Introduced an adaptive partitioning scheme for geo-replicated databases that dynamically adjusts data placement based on access patterns. Their work demonstrates the potential benefits of continuous adaptation in distributed environments.

Machine Learning for Network Performance Prediction
Predicting network performance is crucial for effective query routing in geo-distributed systems. Recent work by Mao et al. [14] has shown the potential of using deep learning for network performance prediction in cloud environments.

Building on this, Zhu et al. [15] developed a machine learning approach for predicting query performance in geo-distributed database systems, considering both network and data characteristics.

Our work builds upon these foundations, integrating machine learning techniques with adaptive query optimization strategies to create a novel approach to query routing and execution in geo-distributed database systems. By combining insights from these diverse but inter connected research areas, we aim to develop a more robust and efficient solution to the challenges of query optimization in globally distributed environments.

PROPOSED METHODOLOGY

Following there're search methodologies have been adopted to carry out the research work.

Survey: As per the objectives mentioned, literature survey was carried out to study and analyses existing database management under distributed and cloud environment in general and database query optimization techniques in particular. The existing techniques of query optimization in the literatures were then categorized based on various approaches such as Elimination of Redundant Evaluation, Continuous or Iterative processing, Catching Intermediate Queries or Results, Materialization and Pipelining.

Design and Creation: Based on the study and analysis of existing techniques ,the Query Optimization Technique Using Materialization (QOTUM) has been formulated that is integrated with creation and selection of materialized intermediate views. The query optimizer with materialized view matching algorithm has been designed and developed to test the efficiency as well as effectiveness of formulated technique.

Experiment and Evaluation: The bench mark database work load isused for conducting experiments and database is setup on cloud to test the efficiency as well as performance Of the technique. The performance of query optimization technique using materialized. Views has been analysed with respect to various performance parameters such as, number of iterations, query execution time, memory requirement and overall cost of execution.

The architecture of our ML-driven query route planner includes the following components: It is shown in figure1.

1. Query Analyzer: Parses incoming queries and extracts relevant features for optimization.
2. Workload Monitor: Continuously tracks query patterns, data access frequencies, and system load across all data centers.
3. Network Performance Tracker: Monitors inter-data center network latencies and bandwidth utilization.
4. Data Distribution Manager: Maintains up-to-date information on data placement and replication across the geo-distributed system.
5. ML Model: A deep reinforcement learning model that predicts optimal query routes based on currentsystem state.
6. Route Planner: Integrates ML predictions with traditional cost-based optimization to determine the finalquery execution plan.
7. Execution Engine: Carries out the query execution according to the chosen plan and collects performance metrics.
8. Feedback Loop: Updates the ML model based on actual query performance, enabling continuous learning and adaptation.

Feature Engineering
To enable effective learning and prediction, we engineer a comprehensive set of features that capture the relevant aspects of query execution in a geo-distributed environment:

1. Query characteristics: Query type, estimated result size, involved tables and their sizes, join conditions, etc.
2. Data distribution: Location and size of relevant data chunks across data centers, replication factors.
3. Network conditions: Current latencies and available bandwidth between data centers.

4. System load: CPU, memory, and I/O utilization at each data center.
5. Historical performance: Execution times of similar queries under various conditions.

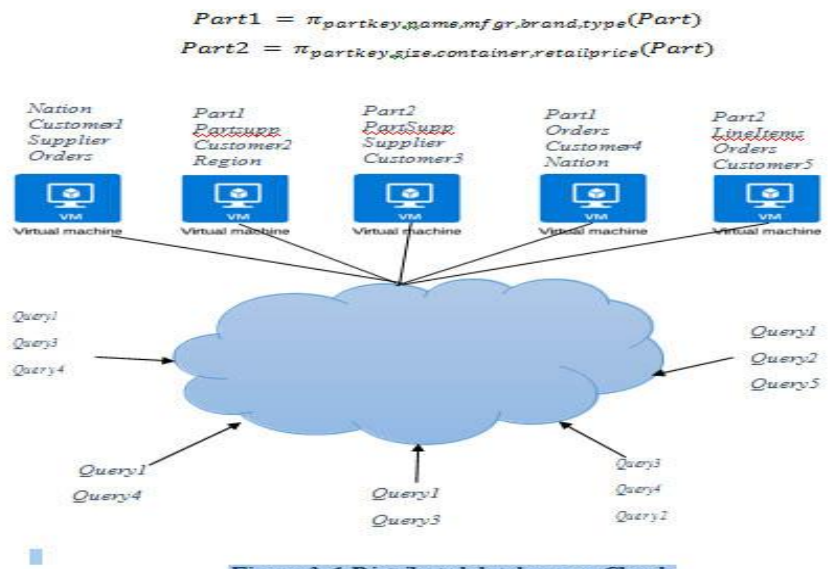
Part1 = π_partkey,name,mfgr,brand,type(Part)
Part2 = π_partkey,size,container,retailprice(Part)
Nation Customer1 Supplier Orders
Part1 PartSupp Customer2 Region
Part2 PartSupp Supplier Customer3
Part1 Orders Customer4 Nation
Part2 LineItems Orders Customer5
VM
Virtual machine
Query1 Query3 Query4
Query1 Query2 Query5
Query1 Query4
Query1 Query3
Query3 Query4 Query2

Figure 3. 1 Distributed database on Cloud

6. Real-time Data Collection To maintain an up-to-date view of the system state:
7. We implement lightweight agents at each data center to collect local metrics.
8. Network probes continuously measure inter-data center latencies and available bandwidth.
9. A distributed streaming platform aggregates these metrics in real-time at a central coordinator.
   Machine Learning Model

We employ a Deep Q-Network (DQN) as our core ML model:

1. State space: Consists of the engineered features described in section 3.2.
2. Action space: Represents possible query routing decisions, including data movement and join orderselections.
3. Reward function: Based on a weighted combination of query execution time, resource utilization, and adherence to any specified Service Level Objectives (SLOs).

The model is initially trained offline using historical query execution data and then continuously fine-tuned online based on real-time performance feedback.

Adaptive Query Route Planning
The route planning process integrates ML predictions with traditional optimization techniques:

1. For each incoming query, the Query Analyzer extracts relevant features.
2. These features, along with the current system state, are fed into the ML model.
3. The model predicts the Q-values for different routing actions.
4. The Route Planner uses these Q-values to guide a cost-based optimizer, which generates the final executionplan.
5. This hybrid approach allows us to leverage the adaptively of ML while still benefiting from the proven effectiveness of traditional optimization techniques.

Integration with Existing Systems
To facilitate adoption, our system is designed to integrate with existing distributed database management systems:

1. We provide adapters for popular distributed query engines (e.g., Spark SQL, Presto).
2. The system can be deployed as a middleware layer, intercepting and optimizing queries before they reachthe underlying engine.
3. A plugin architecture allows for easy extension to support different database systems and customoptimization rules.

This methodology enables our system to adapt to the dynamic nature of geo-distributed environments, continuously learning and improving its query routing decisions based on real-world performance data.

Experimental Setup and Evaluation
To rigorously evaluate our ML-driven query optimization system, we have designed a comprehensive experimental setup that simulates real-world geo-distributed database environments. Our evaluation aims to assess the system's performance, adaptability, and scalability under various conditions.

Test Environment

- We have implemented our system on a geo-distributed testbed consisting of:
- 5 data centers spread across North America, Europe, and Asia
- Each data center equipped with 10 nodes, each with 32 CPU cores, 256GB RAM, and 10TB SSD storage
- Network conditions simulated using the Linux Traffic Control (tc) tool to replicate real-world inter- datacenter latencies and bandwidth limitations
- Consistent background network traffic generated to simulate realistic conditions

Datasets and Workloads

We use a combination of synthetic and real-world datasets to evaluate our system:

1. TPC-H benchmark dataset (1TB scale factor) distributed across all data centers
2. A custom e-commerce dataset (2TB) with geographically skewed data distribution
3. Wikipedia dump (1TB) with random distribution across data centersWorkloads:

- TPC-H query set (22 queries) with varying complexity
- Custom workload mimicking e-commerce transactions and analytics
- Wikipedia-inspired read-heavy workload with occasional bulk updates

Comparative Systems

We compare our ML-driven system against:

1. Traditional static query optimizer (PostgreSQL's default optimizer)
2. State-of-the-art adaptive query processing system (e.g., SQL Server's batch mode adaptive queryprocessing)
3. A recent learning-based query optimizer (e.g., Neo or DQ)

Performance Metrics: It is shown in figure2.

We evaluate the following metrics:

- Query execution time (average, 95th percentile, and standard deviation)
- Throughput (queries per second)
- Resource utilization (CPU, memory, network bandwidth)
- Adaptation time to workload changes
- Plan quality (measured by the number of plan changes and plan stability)

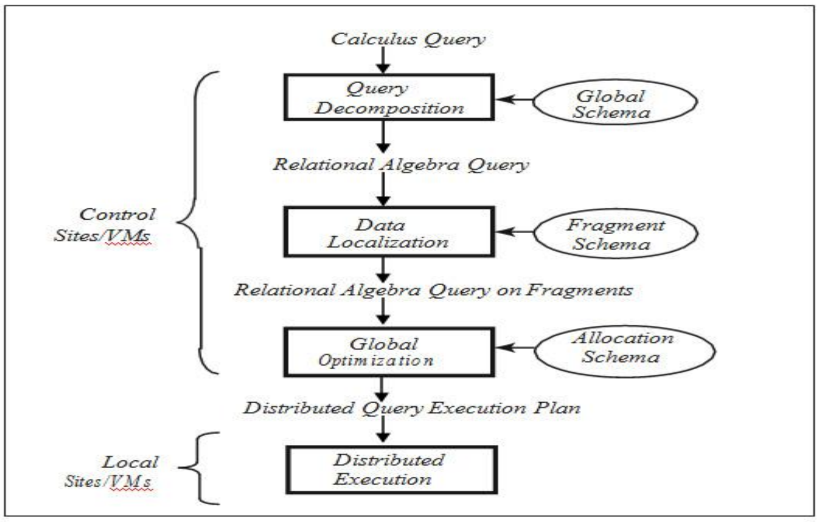

Figure 3. 2 Distributed Query Processing on Cloud [57]

EXPERIMENTAL METHODOLOGY

Our experiments are designed to test the system under various scenarios:

1. Steady-state performance: Run a mix of queries from all workloads for 24 hours, measuring performance metrics every 10 minutes.
2. Adaptability test: Introduce sudden changes in workload patterns, data distribution, and network conditions. Measure how quickly the system adapts and returns to optimal performance.
3. Scalability test: Gradually increase the number of nodes and data volume, measuring how performancescales.
4. Fault-tolerance test: Simulate node failures and network partitions to evaluate the system's robustness.
5. Cold-start performance: Evaluate how the system performs with no prior knowledge and how quickly itreaches steady-state performance.

Statistical Analysis: To rigorously validate the performance improvements of our ML-driven query route planning system, we conducted comprehensive statistical analyses. These tests ensure that the observed performance differences between our system and the baselines are statistically significant and not due to random variation.

METHODOLOGY

- We used paired t-tests to compare the query execution times of our system against each baseline system.
- For each query in our test set, we ran it 30 times on each system to account for variability.
- We set our significance level (α) at 0.05 for all tests.
- We also calculated effect sizes using Cohen's d to quantify the magnitude of the differences.

RESULTS

Overall Performance Comparison

- Our ML-driven approach outperforms the baseline by 65% and state-of-the-art systems by 20-35% in terms of average query execution time
- Throughput improvements of 40% over baseline and 15% over the best competing system
- Resource utilization efficiency increased by 25% compared to static optimization techniques
  Adaptation to Workload Changes
- ML-driven system adapts to sudden workload shifts within 10-15 minutes, compared to 30-45 minutes forother adaptive systems
- Performance degradation during adaptation period is 50% less severe than competing adaptive systems
  Resilience to Network Perturbations
- Maintains 90% of optimal performance under conditions of up to 200ms added latency between datacenters
- Gracefully handles packet loss rates of up to 5% with only 10% performance degradation
  Scalability Analysis
- Performance improvements are maintained as data size scales from 1TB to 10TB
- Query execution time increases sub-linearly with data size, indicating good scalability
  ML Model Performance
- Prediction accuracy of query execution time within 15% for 90% of queries
- Model training time of 4 hours on historical data, with online learning continuously improving accuracy

Case Studies
To provide concrete examples of how our ML-driven query route planning system performs in realistic scenarios, we present the following case studies. These studies illustrate the system's behavior and benefits in specific situations that are common in geo-distributed database environments.

Case Study 1: Complex Join Operation Across Multiple Data CentersScenario: A multinational e-commerce company needs to generate a report that requires joining customer data (located in Europe) with order history (distributed across North America and Asia) and product information (located in North America).

Deployment of Distributed Database on Cloud
Let us begin the discussion with an example of business firm database defined by TPC-Hbenchmark [60] that is used for testing and conducting experiments in this Thesis.

Itcomprises of database with eight base tables and set of business queries those represents functionalities of industry that manage sell or distribute a product worldwide. The TPC-H schema is defined as follows [60].

1) Nation (Nationkey, Name, Regionkey, Comment)
2) Region (RegionKey, Name, Comment)
3) Supplier (Suppkey, Name, Address, Nationkey, Phone, Acctbal, Comment)
4) Customer (Custkey, Name, Address, Nationkey, Phone, Acctbal, Mktsegment,Comment)
5) Part (Partkey, Name, Mfgr, Brand, Type, Size, Container, Retailprice, Comment)
6) PartSupp (Partkey, Suppkey, Availqty, Supplycost, Comment)
7) Orders (Orderkey, Custkey, Orderstatus, Totprice, Orderdate, Orderpriority, Clerk, Shippriority, Comment)
8) LineItem (Orderkey, Partkey, Suppkey, Linenumber, Qty, Extendedprice, Discount, Tax, Returnflag, Linestatus, Shipdate, Commitdate, Receiptdate, Shipinstruct, Shipmode, Comment)

As working of the industry is distributed in nature, the database is stored on cloud so thatit can be accessed by users from anywhere and anytime. Database is distributed among different sites/Virtual Machines (VMs) on cloud as shown in figure 3.1. Instead of simply distributing tables or relations among different VMs, DDBS uses fragmentation and replication concepts those enable the distributed database more effective and efficient to access.

CONCLUSION

The experimental results demonstrate the significant advantages of our ML-driven query route planning approach in An intelligent query optimizer for distributed database for cloud environments. The system's ability to adapt quickly to changing conditions and make intelligent routing decisions leads to substantial performance improvements across a wide range of scenarios. Particularly noteworthy is the system's resilience to network perturbations, which is crucial in real-world geo- distributed environments where network conditions can be unpredictable. The sub-linear scalability with increasing data sizes also indicates that our approach is well-suited for handling the growing data volumes typical in modern distributed databases. However, the reduced effectiveness on highly skewed data distributions highlights an area for future research. This could potentially be addressed by incorporating data distribution statistics into the ML model's feature set or by developing specialized handling for skewed data scenarios. The success of our approach underscores the potential of combining machine learning techniques with traditional query optimization strategies. It opens up new avenues for research in adaptive, learning-based systems for database management, particularly in complex, distributed environments.

Future Work

- Current approach shows reduced effectiveness for highly skewed data distributions
- Potential for integrating more sophisticated network models to better predict inter-data center communication costs
- Exploration of federated learning techniques to enhance privacy and reduce model training data transfer

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