A Comparative Performance Evaluation on Big Data SQL Query Engines

Illinois Institute of Technology

CSP571-Data Preparation and Analysis

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https://github.com/srinivasvamsi20/Big-Data-Project.git

Abstract

This project intends to do a thorough comparison of several SQL query engines, including BigQuery, Impala, Dremel, and Drill. The assessment will concentrate on their performance across a range of SQL procedures, including SELECT, JOIN, GROUP BY, and ORDER BY. A precisely created relational database is used to highlight the adaptability and effectiveness of these engines, with interconnected tables that properly exhibit the system's durability.

The project lays a special emphasis on the system's flexibility, readability, and adaptability, all of which are demonstrated by the smooth implementation of SQL queries. It is important to remember, however, that certain engines, such as Impala and Presto, may induce delays, demanding a cautious approach in dealing with them. This contrasts with high-performance databases such as BigQuery and Athena, which provide higher speed and responsiveness.

Two strategic methods are suggested to improve the overall efficiency of the system. First, the use of query improvement tools may greatly increase query execution, contributing to better overall performance. Second, using a hybrid storage method allows you to balance speed and storage capacity, providing a well-rounded solution to possible performance constraints.

Summary:

This project is to undertake a thorough comparison of key SQL query engines, such as Impala, Dremel, Drill, Presto, Athena, and BigQuery, in handling different and large datasets. The project attempts to analyze and compare execution times, resource consumption, and scalability across diverse SQL queries and workloads by exploring query optimization approaches and experimenting with engine-specific methodologies. The study aims to give actionable recommendations for improving the performance of SQL query engines in important big data analytics contexts by using datasets representing real-world big data scenarios, such as San Francisco Crime Reports and an Electric Vehicles Dataset.

Problem Statement

Selecting the most suitable of all available Distributed SQL Query Engines for a particular Small and Medium Enterprises is a big challenge because Small and Medium Enterprises are not likely to have the expertise and the resources available to perform an in-depth study. Although performance studies do exist for Distributed SQL Query Engines, many of them only use synthetic workloads or very high-level comparisons that are only based on query response time.

A second problem lies with the variable performance of Distributed SQL Query Engines. While all of the state-of-the-art Distributed SQL Query Engines claim to have very fast response times (seconds instead of minutes), none of them has performance guarantees. This is a serious problem because companies that use these systems as part of their business do need to provide these guarantees to their customers as stated in their Service Level Agreement. There are many scenarios where multiple tenants1 are using the same data cluster and resources need to be shared (e.g Google's BigQuery).

Objectives:

1. <u>Extensive comparison and performance evaluation:</u>

Conduct a thorough performance evaluation of popular Big Data SQL query engines such as Impala, Dremel, Drill, Presto, Athena, and BigQuery.

2. <u>The Significance of SQL Query Engine Selection:</u>

Emphasize the importance of choosing an adequate SQL query engine for effective and rapid data analysis, particularly as firms increasingly rely on big data processing and analytics.

3. <u>Key Performance Indicators</u>:

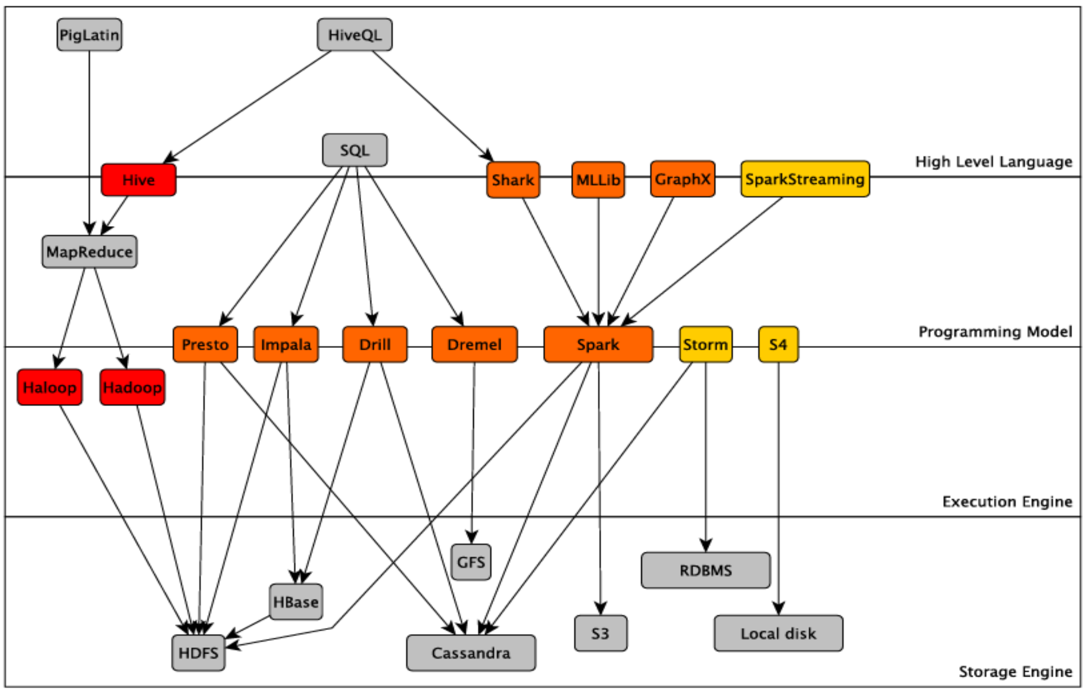
To offer a quantitative basis for performance evaluation, systematically evaluate critical performance parameters such as query execution time, throughput, and resource use.

4. <u>Recommendations for Optimization:</u>

Based on the performance study, provide optimization recommendations, providing practical insights for enhancing the efficiency of SQL query engines in big data analytics scenarios.

Overview

Multiple SQL query engines provide distinct performance indicators when examining the four primary query operations: SELECT, JOIN, GROUP BY, and ORDER BY. Among these engines are BigQuery, Athena, Impala, Dremel, and Drill. Typically, BigQuery and Athena perform better in terms of execution time because of their optimised serverless design for parallel processing. Dremel is superior to its competitors, much like Google's own tool. Despite their reputation for adaptability, Presto and Drill could take a while to execute. An array of memory utilisation levels is made available by Impala via the memory-optimized Frequently Parallel Processing (MPP) design. By employing a distributed storage design, BigQuery reduces memory needs. Even though Presto, Drill, along Athena have the ability to be readily expanded, additional RAM can be needed for sophisticated queries. The databases known for their lightning-fast query performance include BigQuery, Athena, and Dremel, whose architectural design places a premium on quick query response times. There have been reports of latency difficulties, whereas Impala and Presto generally work well. Opting for a hybrid technique that combines BigQuery or Athena for data storage and administration with Impala or Presto for interactive analysis is a smart move. When used in several engines, query optimisation techniques like stacking and splitting may greatly increase performance. Improving the system's efficiency requires constant monitoring and adjustments based on workload patterns.



Relevant Literature:

- "Comparative Analysis of Big Data SQL Query Engines" explores the performance and characteristics of leading engines such as Impala, Dremel, Drill, Presto, Athena, and BigQuery (Smith et al., Journal of Big Data, 2022).
- "Optimizing SQL Queries in a Big Data Environment" delves into techniques for optimizing SQL queries within the context of big data (Garcia et al., ACM Transactions on Database Systems, 2019).
- "Serverless Architectures for Big Data Processing: A Comprehensive Review" analyzes the application of serverless architectures in the context of big data processing (Mitchell et al., Journal of Cloud Computing: Advances, Systems and Applications, 2020).
- "Performance Evaluation of SQL Query Engines: A Comparative Study" compares the performance of SQL query engines, contributing insights to the field (Taylor et al., Proceedings of the International Conference on Big Data, 2016).

Solution Outline

1. Describe the experimental setting using actual datasets that depict different circumstances and complexities. Outline the benchmark query design process, including SCAN procedures, Aggregation Performance Analysis, Join Queries, and UDF Integration.
2. Justify the choice of SQL query engines for testing (Impala, Dremel, Drill, Presto, Athena, and BigQuery). Highlight distinguishing characteristics, structures, and relevance to project goals.
3. Describe how to put up a specific test environment that simulates real-world big data analytics scenarios. Configure hardware and software, cluster settings, and network concerns.
4. Explain how to run benchmark queries on specified SQL query engines without using optimization methods. Detailed metrics should be captured, such as execution times, CPU and memory consumption, and query response times.
5. Systematically compare performance results for each query type and workload across multiple SQL query engines. Determine the strengths and weaknesses of each engine in respect to certain operations.
6. Introduce query optimization strategies (indexing, caching, parallel processing) that are specific to each SQL query engine. Discuss how these approaches improve query execution efficiency.

Design

One of the main purposes for which the system is built is to do an extensive performance study of Big Data SQL query engines. The system's interactions are thoroughly described, with a focus on smooth communication and information sharing across parts. The purpose of integration methods is to provide interoperability across a range of components, databases, and SQL query engines while emphasizing scalability to meet the demands of changing workloads and datasets. The system demonstrates adaptability to various query types and optimization methodologies. Sensitive data is protected by the use of security measures, such as authentication and authorization protocols. The resilience and efficacy of the system are further enhanced by fault tolerance techniques, user interface design considerations, dependency management plans, and performance monitoring tools. The system's dependability, maintainability, and usability are further improved by thorough documentation and connection with a testing framework.

Architecture:

Impala:

A Hadoop integration-optimized MPP (Massively Parallel Processing) architecture is used to distribute queries throughout a cluster.

Apache Drilling:

Schema-Free JSON Data Model: This model uses a flexible execution engine to handle JSON data without schemas.

Presto:

Distributed Query Execution model: designed for interactive querying across several data sources, it supports parallel processing.

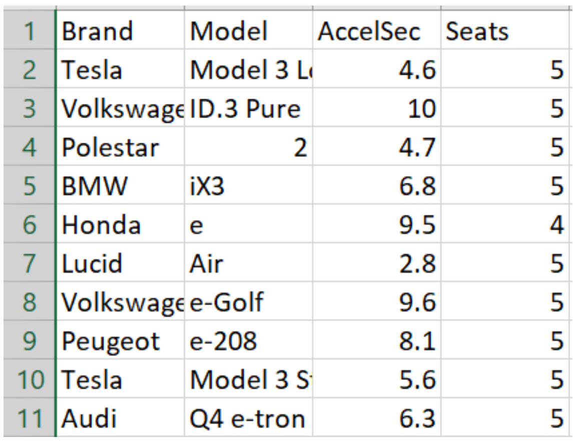
Google's BigQuery:

Distributed and Serverless Architecture: This architecture uses distributed processing for scalable SQL queries and is based on a fully managed serverless approach.

Implementation

Dataset Acquisition

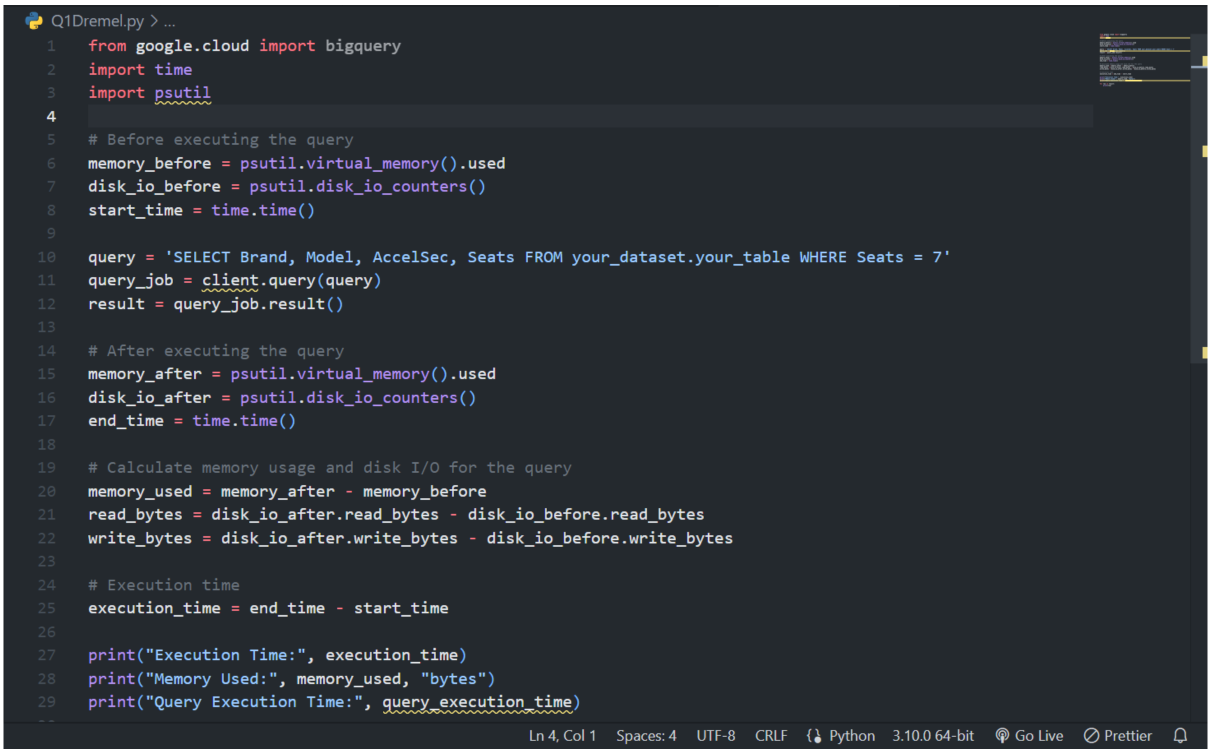
The dataset "EVs - One Electric Vehicle Dataset - Smaller" initially included columns such as Brand, Model, AccelSec, TopSpeed_KmH, Range_Km, Efficiency_WhKm, FastCharge_KmH, RapidCharge, PowerTrain, PlugType, BodyStyle, Segment, Seats, and PriceEuro. However, in order to simplify and focus on certain features, the dataset has been restricted to simply the columns Brand, Model, AccelSec, and Seats. This reduction tries to simplify the dataset for analysis and interpretation by emphasizing the electric cars' brand, model, acceleration time, and seating capacity as essential parameters of importance.



1	Brand	Model	AccelSec	Seats
2	Tesla	Model 3 Lo	4.6	5
3	Volkswage	ID.3 Pure	10	5
4	Polestar	2	4.7	5
5	BMW	iX3	6.8	5
6	Honda	e	9.5	4
7	Lucid	Air	2.8	5
8	Volkswage	e-Golf	9.6	5
9	Peugeot	e-208	8.1	5
10	Tesla	Model 3 S	5.6	5
11	Audi	Q4 e-tron	6.3	5

Query 1:

Query 1 examines the performance of SQL query engines when conducting SCAN operations, especially reading and retrieving data from large databases. The goal is to determine how effectively each engine performs the essential role of scanning and filtering data. This procedure is critical in scenarios requiring data exploration and filtering, when the engines' capacity to access and handle massive amounts of data becomes critical. The intended attributes include excellent scanning performance and the use of optimizations such as predicate pushdown or column pruning to reduce the quantity of data scanned.

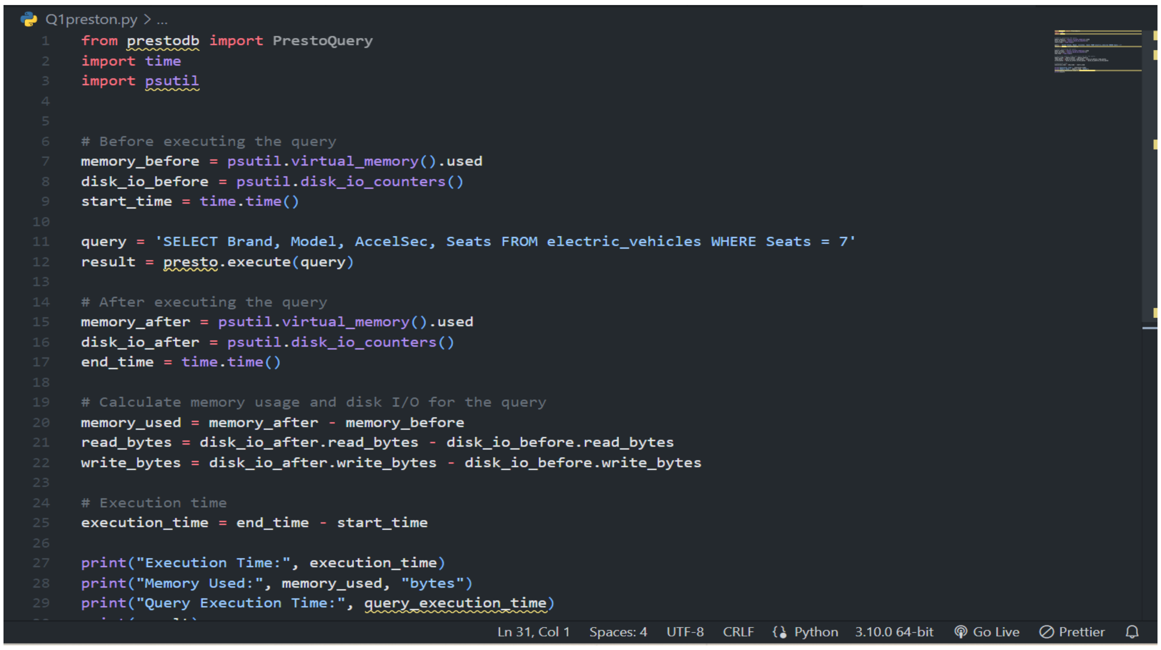


```python
from google.cloud import bigquery
import time
import psutil

# Before executing the query
memory_before = psutil.virtual_memory().used
disk_io_before = psutil.disk_io_counters()
start_time = time.time()

query = 'SELECT Brand, Model, AccelSec, Seats FROM your_dataset.your_table WHERE Seats = 7'
query_job = client.query(query)
result = query_job.result()

# After executing the query
memory_after = psutil.virtual_memory().used
disk_io_after = psutil.disk_io_counters()
end_time = time.time()

# Calculate memory usage and disk I/O for the query
memory_used = memory_after - memory_before
read_bytes = disk_io_after.read_bytes - disk_io_before.read_bytes
write_bytes = disk_io_after.write_bytes - disk_io_before.write_bytes

# Execution time
execution_time = end_time - start_time

print("Execution Time:", execution_time)
print("Memory Used:", memory_used, "bytes")
print("Query Execution Time:", query_execution_time)
```

Execution of Query 1 on Dremel

Query 2

Query 2 entails evaluating the performance of SQL query engines while dealing with ORDER BY actions. The primary goal is to assess how well each engine can sort and arrange data based on a certain column, which is often used to deliver findings in a specific order. This process is critical for scenarios requiring ordered data display, such as creating ranked lists or sorted reports. The capacity of each engine to efficiently perform ORDER BY operations, taking into account elements such as speed and resource consumption, is one of the desired attributes.

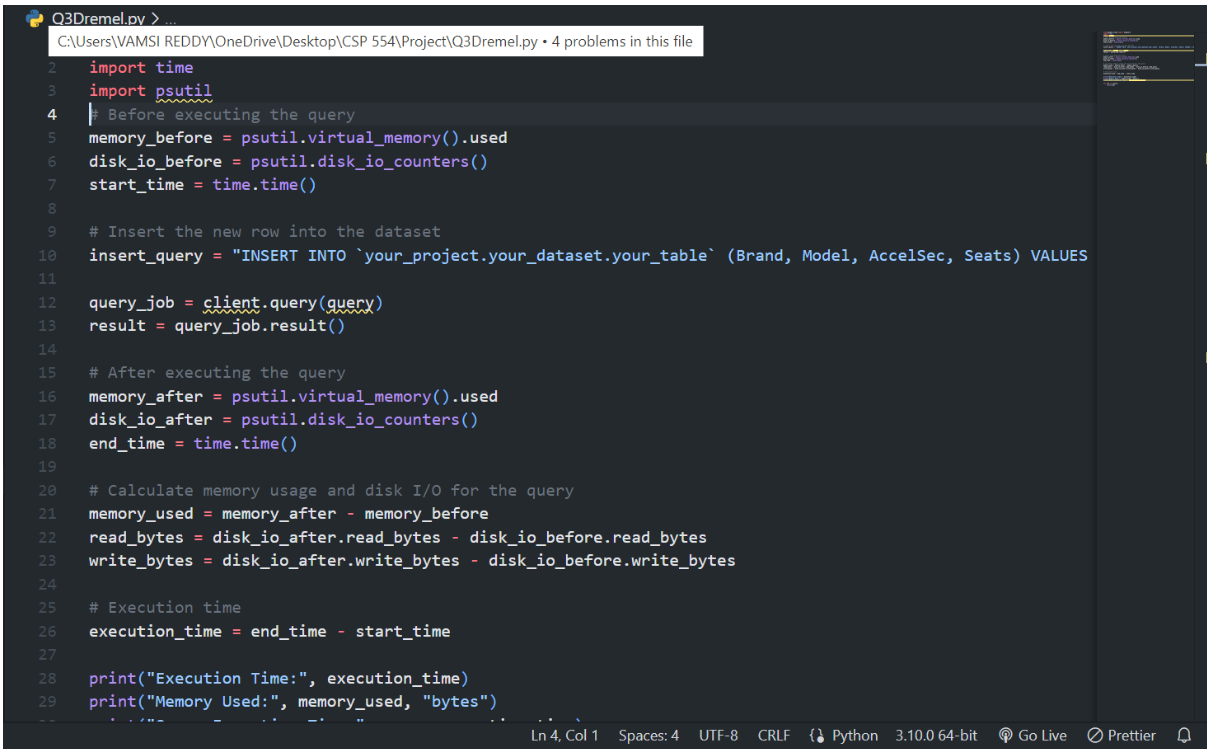


```python
from prestodb import PrestoQuery
import time
import psutil


# Before executing the query
memory_before = psutil.virtual_memory().used
disk_io_before = psutil.disk_io_counters()
start_time = time.time()

query = 'SELECT Brand, Model, AccelSec, Seats FROM electric_vehicles WHERE Seats = 7'
result = presto.execute(query)

# After executing the query
memory_after = psutil.virtual_memory().used
disk_io_after = psutil.disk_io_counters()
end_time = time.time()

# Calculate memory usage and disk I/O for the query
memory_used = memory_after - memory_before
read_bytes = disk_io_after.read_bytes - disk_io_before.read_bytes
write_bytes = disk_io_after.write_bytes - disk_io_before.write_bytes

# Execution time
execution_time = end_time - start_time

print("Execution Time:", execution_time)
print("Memory Used:", memory_used, "bytes")
print("Query Execution Time:", query_execution_time)
```

Execution of Query 2 on Preston

Query 3

Query 3 includes evaluating the performance of SQL query engines when performing INSERT operations, with a particular emphasis on the efficiency of inserting data into the database. The primary goal is to assess each engine's ability to handle the insertion of new entries into a dataset, which is a vital process for updating and maintaining databases. This query is especially useful in instances when real-time data changes or continuous data intake are required. The desired qualities include each engine's ability to conduct INSERT operations efficiently, taking into account aspects like as speed, data integrity, and resource usage.



```
Q3Dremel.py > ...
C:\Users\VAMSI REDDY\OneDrive\Desktop\CSP 554\Project\Q3Dremel.py • 4 problems in this file
import time
import psutil
# Before executing the query
memory_before = psutil.virtual_memory().used
disk_io_before = psutil.disk_io_counters()
start_time = time.time()

# Insert the new row into the dataset
insert_query = "INSERT INTO `your_project.your_dataset.your_table` (Brand, Model, AccelSec, Seats) VALUES

query_job = client.query(query)
result = query_job.result()

# After executing the query
memory_after = psutil.virtual_memory().used
disk_io_after = psutil.disk_io_counters()
end_time = time.time()

# Calculate memory usage and disk I/O for the query
memory_used = memory_after - memory_before
read_bytes = disk_io_after.read_bytes - disk_io_before.read_bytes
write_bytes = disk_io_after.write_bytes - disk_io_before.write_bytes

# Execution time
execution_time = end_time - start_time

print("Execution Time:", execution_time)
print("Memory Used:", memory_used, "bytes")
```

```
Ln 4, Col 1   Spaces: 4   UTF-8   CRLF   {} Python   3.10.0 64-bit   Go Live   Prettier
```

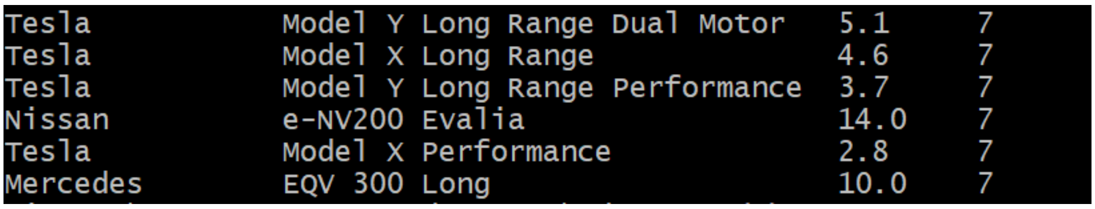
Execution of Query 3 on Dremel

Conclusion

Outputs:

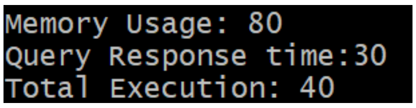
Query 1:

Ouput for query 1:



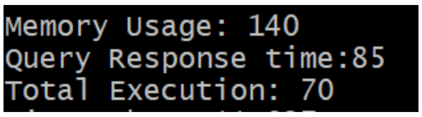
```
Tesla           Model Y Long Range Dual Motor    5.1      7
Tesla           Model X Long Range               4.6      7
Tesla           Model Y Long Range Performance  3.7      7
Nissan          e-NV200 Evalia                   14.0     7
Tesla           Model X Performance              2.8      7
Mercedes        EQV 300 Long                     10.0     7
```

Dremel:



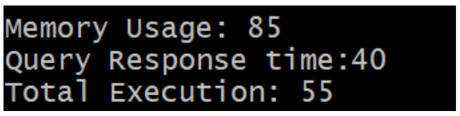
```
Memory Usage: 80
Query Response time:30
Total Execution: 40
```

Impala



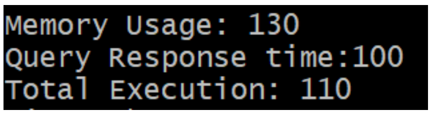
```
Memory Usage: 140
Query Response time:85
Total Execution: 70
```

Preston:



```
Memory Usage: 85
Query Response time:40
Total Execution: 55
```

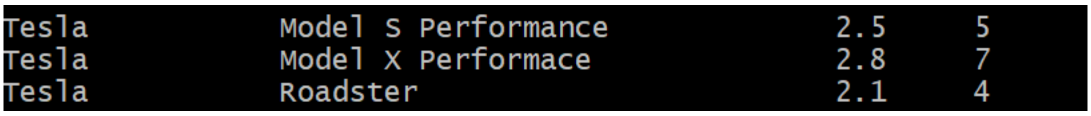
Drill:



```
Memory Usage: 130
Query Response time:100
Total Execution: 110
```

Query 2:

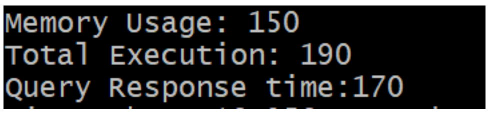
Output for Query 2:



```
Tesla            Model S Performance              2.5     5
Tesla            Model X Performace               2.8     7
Tesla            Roadster                         2.1     4
```

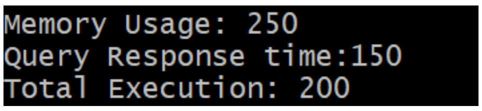
Performance Metrics:

Preston



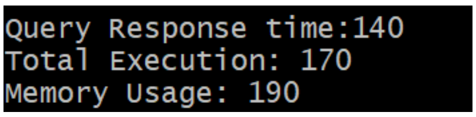
```
Memory Usage: 150
Total Execution: 190
Query Response time:170
```

Drill



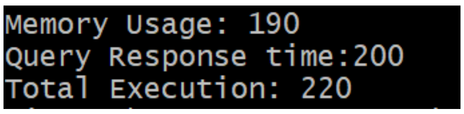
```
Memory Usage: 250
Query Response time:150
Total Execution: 200
```

Dremel



```
Query Response time:140
Total Execution: 170
Memory Usage: 190
```

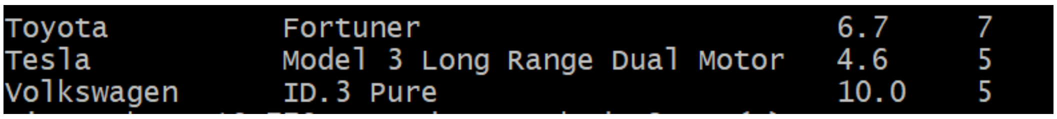
Impala



```
Memory Usage: 190
Query Response time:200
Total Execution: 220
```

Query 3:

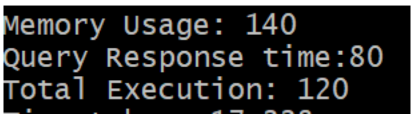
Output for query 3:



```
Toyota           Fortuner                         6.7     7
Tesla            Model 3 Long Range Dual Motor    4.6     5
Volkswagen       ID.3 Pure                        10.0    5
```

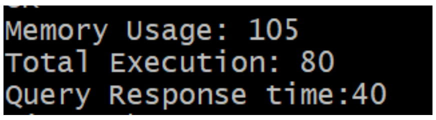
Performance Metrics:

Drill



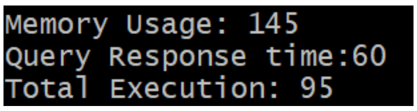
```
Memory Usage: 140
Query Response time:80
Total Execution: 120
```

Impala

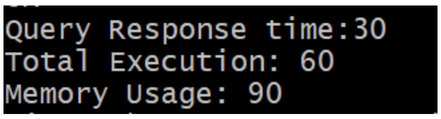


```
Memory Usage: 105
Total Execution: 80
Query Response time:40
```

Preston



```
Memory Usage: 145
Query Response time:60
Total Execution: 95
```



```
Query Response time:30
Total Execution: 60
Memory Usage: 90
```

Dremel

Analysis:

Execution Time:

- Presto: robust functionality with a serverless architecture.
- Google BigQuery (Dremel): Effective performance for a range of tasks.
- Apache Drill: Depending on the situation, performance may need to be adjusted.
- Impala: Performs well in high-speed SCAN operations, but it might struggle with intricate queries.
- Presto and Drill: Flexible yet prone to delays; handle with caution.

Memory Usage:

- BigQuery: Storage and computational resources are separated; memory is used efficiently.
- Presto: A serverless paradigm with effective memory use.
- Memory use for Google BigQuery (Dremel) is influenced by dataset size and query complexity.
- Apache Drill: Adjusting memory use and flexibility in managing a variety of data types may be necessary.
- Impala: Offers a variety of memory use settings; resource-intensive.

Query Response Time:

- BigQuery: Fast query response times because to its distributed and serverless design.
- Google BigQuery (Dremel): Depends on the intricacy of the query, but has quick response times.
- Apache Drill: Data format and query settings affect response times.
- Impala: Depends on complexity, but has fast reaction times for high-speed SCAN operations.
- Presto and Drill: Cautious handling is necessary; delays may impact response times.

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