Cost Optimization in Google BigQuery: Best Practices for Query Efficiency and Storage Management

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Case Report

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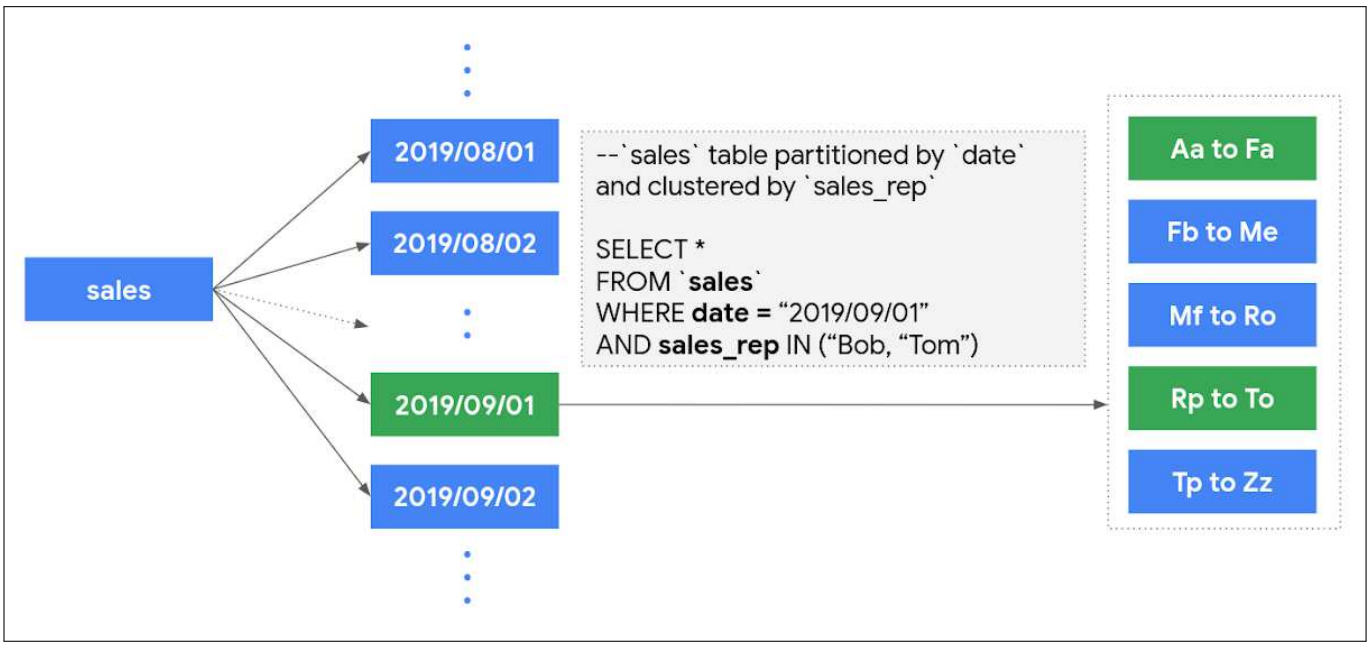

Figure 1: Key Strategies for Cost Optimization in Google BigQuery: Query Efficiency and Storage Management.

ABSTRACT

Google BigQuery, a fully-managed, serverless data warehouse, harnesses Google's infrastructure to deliver high-speed SQL queries at scale, making it an essential tool for large-scale data analytics [11]. However, its pay-as-you-go pricing model can lead to rapidly escalating costs without diligent management [10, 17]. This paper investigates strategies for optimizing query execution and storage management in BigQuery to control expenses while preserving performance. We explore efficient query design principles, such as selective column retrieval and early filtering, alongside advanced data organization techniques like partitioning and clustering to minimize data scanned [5, 16, 18]. Further, we examine the role of materialized views and approximate aggregation functions in reducing computational costs, as well as the benefits of automation tools, query caching, and BI Engine for enhancing efficiency [3, 9, 19, 29]. Proactive cost management is addressed through real-time monitoring, governance policies, and optimized slot allocation [6, 14, 20]. Real-world examples illustrate the impact of these techniques, such as a 40 percent cost reduction achieved by a media company through partitioning and clustering [8]. By blending technical optimizations with strategic oversight, this study provides actionable insights for organizations to maximize BigQuery's capabilities while minimizing operational costs, offering a scalable blueprint for cost-efficient data analytics in enterprise environments.

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CCS CONCEPTS

• **Computing methodologies** → *Feature selection.*

KEYWORDS

Google BigQuery, Cost Optimization, Query Efficiency, Storage Management, Cloud Computing, Data Warehousing, Big Data, Partitioning and Clustering, Cloud Cost Management, Data Analytics

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1 INTRODUCTION

In the era of big data, organizations increasingly depend on cloud-based data warehouses to store, process, and analyze massive datasets efficiently [2]. Among these solutions, Google BigQuery—a fully managed, serverless data warehouse—stands out as a preferred choice due to its exceptional scalability, speed, and user-friendly design [11, 26]. Capable of handling petabyte-scale data and executing SQL queries with near real-time performance, BigQuery empowers businesses to derive actionable, data-driven insights with ease. However, as data volumes grow and query complexity rises, managing costs in BigQuery emerges as a critical challenge. Without deliberate optimization strategies, organizations risk facing unexpectedly high expenses, which can erode the inherent cost-effectiveness of adopting a cloud-based data warehouse [10, 17].

Effective cost optimization in Google BigQuery hinges on a multifaceted approach that balances efficient query execution, streamlined storage management, and proactive cost monitoring [24]. Query-related expenses are primarily driven by the volume of data processed during execution, while storage costs are influenced by the amount of data retained and its organizational structure [21]. Implementing best practices in both domains is essential to curb expenses without sacrificing analytical performance. Furthermore, a deep understanding of BigQuery's pricing model—including the trade-offs between on-demand and flat-rate pricing, tiered storage options, and the cost implications of streaming versus batch data ingestion—enables organizations to make informed decisions about their data architecture and usage patterns [1, 10].

This paper explores proven strategies for cost optimization in Google BigQuery, with a focus on two pivotal areas: query efficiency and storage management. We begin by examining techniques to enhance query execution, such as leveraging partitioned and clustered tables to reduce data scans, employing approximate aggregation functions for faster results, caching query outputs to avoid redundant processing, and minimizing unnecessary data reads through precise query design [5, 15, 16, 25]. These methods not only lower the volume of data processed but also accelerate query performance, yielding substantial cost reductions and operational benefits. Following this, we delve into storage management practices, including capitalizing on long-term storage discounts for infrequently accessed data, optimizing schema designs for efficiency, establishing data lifecycle policies to automate retention and deletion, and strategically integrating external storage solutions—such as Google Cloud Storage or Bigtable—for cold or archival data [4, 12, 13]. These approaches ensure that storage costs remain proportional to actual business needs.

Beyond these core strategies, we emphasize the critical role of cost monitoring tools, detailed billing reports, and query optimization frameworks [14, 23]. These resources enable organizations to continuously evaluate usage trends, pinpoint inefficiencies, and uncover additional cost-saving opportunities. For instance, tools like BigQuery's query execution details and cost analysis dashboards provide granular insights into resource consumption, empowering teams to refine their workflows proactively [6]. Real-world examples, such as identifying and rewriting expensive queries or automating data expiration policies, illustrate how these tools translate into tangible savings [8].

By adopting the strategies detailed in this paper, organizations can fully harness the power of Google BigQuery while maintaining tight control over costs. Whether you are a data engineer tasked with system design, an analyst querying vast datasets, or a decision-maker shaping data strategy, this guide offers practical, actionable insights grounded in proven best practices. It equips you to achieve a harmonious balance between cost efficiency and high-performance data management in the cloud [7]. As cloud adoption accelerates and big data analytics becomes a cornerstone of business success, mastering BigQuery optimization will be indispensable. By prioritizing both performance and cost-effectiveness, organizations can unlock the full potential of their data, driving innovation and competitiveness in an increasingly data-centric world.

2 BASELINE DATA STRUCTURE

Before exploring optimization strategies, it is essential to define the initial dataset underpinning this study. The source data, referred to as `GASourceTable`, is derived from the publicly available Google Analytics 4 (GA4) sample dataset in Google BigQuery, specifically the `bq-public-data.ga4_obfuscated_sample_ecommerce.events_*` table [11]. This table contains obfuscated e-commerce event data, capturing user interactions such as page views, purchases, and other activities across a wildcard range of daily partitions. The dataset occupies approximately ***3.4 GB*** of storage and serves as a representative sample for analyzing cost optimization techniques in a real-world analytics context.

The `GASourceTable` is created in the `GitCommitsDataset` schema without initial partitioning or clustering, reflecting a typical unoptimized state. The table is populated using the following SQL statement:

```
CREATE TABLE `dtc-de-course-450915.
    GitCommitsDataset.GASourceTable`
AS
SELECT *
FROM `bigquery-public-data.
    ga4_obfuscated_sample_ecommerce.events_*`;
```

This flat structure includes columns such as `event_timestamp`, `event_name`, `user_id`, and various event parameters, which are commonly queried for e-commerce analytics [5]. Due to its unpartitioned nature, even targeted queries—such as those filtering by specific event types or date ranges—result in full table scans, processing the entire ***3.4 GB*** of data. Under BigQuery's pay-as-you-go pricing model, this inefficiency can lead to unnecessary costs, making it an ideal candidate for demonstrating the benefits of partitioning and clustering [10, 16]. This baseline configuration sets the stage for the optimization techniques detailed in the following sections.

2.1 Understanding Query Costs in BigQuery

Before diving into optimization techniques, it is essential to understand how query costs are calculated in BigQuery and why inefficient queries can lead to high expenses [26].

2.1.1 How Query Costs Are Calculated. BigQuery uses a **pay-as-you-go pricing model**, where costs are primarily determined by the amount of data processed during queries [10]. Specifically:

- **Data Scanned:** The total volume of data read by a query, measured in bytes.
- **Pricing:** Costs are calculated based on the amount of data processed, typically priced per terabyte (TB) scanned.

For example, if a query scans 1 TB of data and the pricing is $5 per TB, the cost of that query would be $5.

2.1.2 Why Inefficient Queries Lead to High Expenses. Inefficient queries often scan more data than necessary, leading to higher costs [15]. Common causes of inefficiency include:

- **Full Table Scans:** Queries that scan entire tables instead of specific partitions or columns.
  - Example:

```
SELECT * FROM `dtc-de-course
    -450915.GitCommitsDataset.
    GASourceTable`
WHERE PARSE_DATE('%Y%m%d',
    event_date) BETWEEN DATE('
    2020-12-25') AND DATE('
    2020-12-25')
```

Table 1: Job Execution Details for Full Table Scans

Field	Value
Job ID	xx:US.bquxjob_6410655b_1953c493bee
User	xxx@gmail.com
Location	US
Creation time	25 Feb 2025, 14:16:31 UTC+5:30
Start time	25 Feb 2025, 14:16:31 UTC+5:30
End time	25 Feb 2025, 14:16:31 UTC+5:30
Bytes processed	3.34 GB
Bytes billed	3.34 GB
Slot milliseconds	60858
Job priority	INTERACTIVE
Use legacy SQL	false
Destination table	Temporary table

- **Unoptimized JOINs:** JOIN operations that process large volumes of data unnecessarily.
  - Example:

```
SELECT *
FROM `dtc-de-course-450915.
    GitCommitsDataset.GASourceTable
    ` AS ga
JOIN `dtc-de-course-450915.
    GitCommitsDataset.
    CityBikesTable` AS ud
ON PARSE_DATE('%Y%m%d', ga.
    event_date) = DATE(ud.
    last_reported);
```

Table 2: Job Execution Details for Unoptimized JOINs

Field	Value
Job ID	xx:US.bquxjob_25b995f2_1953c4f3833
User	xxx@gmail.com
Location	US
Creation time	25 Feb 2025, 14:23:03 UTC+5:30
Start time	25 Feb 2025, 14:23:03 UTC+5:30
End time	25 Feb 2025, 14:23:03 UTC+5:30
Bytes processed	3.34 GB
Bytes billed	3.34 GB
Slot milliseconds	72746
Job priority	INTERACTIVE
Use legacy SQL	false
Destination table	Temporary table

- **Lack of Filtering:** Queries that do not leverage filtering conditions to reduce the amount of data scanned.
  - Example:

```
SELECT COUNT(*)
FROM `dtc-de-course-450915.
    GitCommitsDataset.GASourceTable
    `;
```

  - ***3.34 GB billed.***
- **Overuse of SELECT *:** Retrieving all columns from a table, even when only a subset is needed.
  - Example:

```
SELECT *
FROM `dtc-de-course-450915.
    GitCommitsDataset.GASourceTable
    `
WHERE event_name = 'purchase';
```

  - ***3.34 GB billed.***

2.2 Partitioning in BigQuery

Partitioning is a powerful technique for organizing data in BigQuery to improve query performance and reduce costs [5, 22]. By dividing a table into smaller, more manageable segments based on a specific column, partitioning allows queries to scan only the relevant portions of the data instead of the entire table. This section explains what table partitioning is, how it works, the types of partitioning available, and best practices for implementation.

2.2.1 What is Table Partitioning, and How It Works. Table partitioning divides a large table into smaller segments called **partitions**, each containing a subset of the data. Partitions are defined based on the values of a specific column, such as a date or integer. When a query includes a filter on the partition column, BigQuery automatically scans only the relevant partitions, a process known as **partition pruning** [18]. This significantly reduces the amount of

data processed, leading to lower query costs and faster execution times.

2.2.2 Types of Partitioning in BigQuery. BigQuery supports several types of partitioning, each suited for different use cases:

- **Time-Based Partitioning:** Time-based partitioning divides a table based on a date, timestamp, or datetime column. This is ideal for time-series data, such as logs, transaction records, or event data [21].
  - **Partitioning by DATE:** Tables are partitioned by a date column (e.g., `event_date`).

```
CREATE TABLE GitCommitsDataset.
    GASourceTablePartitioned
PARTITION BY event_date_parsed AS
    SELECT *, PARSE_DATE('%Y%m%d',
        event_date) AS
        event_date_parsed
    FROM GitCommitsDataset.
        GASourceTable;
```

```
select event_date_parsed
from GitCommitsDataset.
    GASourceTablePartitioned
where event_date_parsed BETWEEN
    DATE('2020-12-25')
AND DATE('2020-12-25')
```

Table 3: Job Execution Details for Partitioning by DATE:

Field	Value
Job ID	xx:US.bquxjob_127da9bc_1953c6150ec
User	xxx@gmail.com
Location	US
Creation time	25 Feb 2025, 14:42:49 UTC+5:30
Start time	25 Feb 2025, 14:42:49 UTC+5:30
End time	25 Feb 2025, 14:42:49 UTC+5:30
Bytes processed	**440.77 KB**
Bytes billed	**10 MB**
Slot milliseconds	61
Job priority	INTERACTIVE
Use legacy SQL	false
Destination table	Temporary table

  - **Partitioning by TIMESTAMP or DATETIME:** Tables are partitioned by a timestamp or datetime column.

```
CREATE OR REPLACE TABLE `
    GitCommitsDataset.
    GASTPartitionedTimeStamp`
PARTITION BY TIMESTAMP_TRUNC(
    event_timestamp_timestamp, DAY)
AS SELECT *,TIMESTAMP_MICROS(
    event_timestamp) AS
    event_timestamp_timestamp
FROM `GitCommitsDataset.
    GASourceTable`;
```

- **Integer-Range Partitioning:** Integer-range partitioning divides a table based on an integer column, such as `user_id` or `order_id`. This is useful for datasets where queries frequently filter on numeric ranges [24].

```
CREATE OR REPLACE TABLE `
    GitCommitsDataset.
    GASourceTablePartitionedIntRange`
PARTITION BY RANGE_BUCKET(stream_id,
    GENERATE_ARRAY(0, 1000, 100))
AS SELECT * FROM `GitCommitsDataset.
    GASourceTable`;
```

2.2.3 How Partition Pruning Reduces Scanned Data and Query Costs. Partition pruning is the process by which BigQuery skips irrelevant partitions during query execution. For example, if a table is partitioned by `event_date` and a query includes a filter like `WHERE event_date = '2023-10-01'`, BigQuery will scan only the partition corresponding to that date instead of the entire table. This reduces the amount of data processed, leading to:

- **Lower Query Costs:** Fewer bytes scanned result in lower costs.
- **Faster Query Execution:** Smaller data scans improve performance [28].

2.2.4 Best Practices for Partitioning. To maximize the benefits of partitioning, follow these best practices:

- **Choose the Right Partition Column:** Select a column that is frequently used in query filters (e.g., `event_date` for time-series data or `user_id` for user-specific queries) [18].
- **Avoid Over-Partitioning:** Creating too many small partitions can degrade performance. Aim for partitions that are at least 1 GB in size.
- **Combine Partitioning with Clustering:** For even greater efficiency, combine partitioning with clustering on additional columns (e.g., partition by `event_date` and cluster by `user_id`) [27].
- **Monitor Partition Sizes:** Regularly check partition sizes and adjust partitioning strategies as needed to maintain optimal performance.
- **Use Partition Expiration (Optional):** Automatically delete old partitions to reduce storage costs (e.g., for logs or temporary data) [13].

2.2.5 Summary. Partitioning is a key strategy for optimizing query performance and reducing costs in BigQuery. By dividing tables into smaller, more manageable segments and leveraging partition pruning, organizations can significantly reduce the amount of data scanned during queries [22]. When combined with best practices like choosing the right partition column and avoiding over-partitioning, partitioning becomes an essential tool for efficient data management in BigQuery.

2.3 Clustering in BigQuery

Clustering in Google BigQuery is a powerful method for optimizing query efficiency and reducing costs by strategically organizing table data [5, 27]. It groups related rows based on one or more

columns—termed *clustering keys*—allowing BigQuery to bypass irrelevant data via *data skipping*. This section explores the mechanics of table clustering, its operational benefits, guidelines for selecting clustering keys, and the resulting performance gains.

2.3.1 What is Table Clustering, and How It Enhances Query Efficiency. Table clustering sorts data within a table or partition according to clustering key values. When queries filter on these keys, BigQuery skips unneeded data, shrinking the volume scanned. This yields:

- **Cost Savings:** Fewer bytes processed lower expenses.
- **Faster Execution:** Reduced scans accelerate performance [15].

Paired with partitioning, clustering enhances efficiency by refining data access within each partition [16].

2.3.2 How Clustering Operates Within Partitions. Clustering enhances both partitioned and non-partitioned tables by sorting data within each segment based on clustering keys. For example, a table partitioned by `event_date` and clustered by `user_id` groups rows with the same `event_date`, then sorts them by `user_id` within each partition. This dual-layer structure enables queries to:

- Leverage partition pruning to exclude irrelevant partitions.
- Apply clustering to bypass unneeded rows within active partitions [27].

Consider this query:

```
SELECT * FROM my_dataset.my_table
WHERE event_date = '2023-10-01' AND user_id = 123;
```

- Pruning limits scanning to the `event_date = '2023-10-01'` partition.
- Clustering narrows it to rows where `user_id = 123`.

2.3.3 Choosing Effective Clustering Keys. Selecting optimal clustering keys is pivotal to unlocking clustering's benefits. Guidelines include:

- **Prioritize Filtered Columns:** Use columns frequent in `WHERE`, `GROUP BY`, or `JOIN` clauses (e.g., `user_id`, `product_id`) [28].
- **Limit Key Count:** BigQuery supports up to four keys, but 1–2 often suffice; more may dilute efficiency.
- **Pair with Partitioning:** Combine with partitioning (e.g., partition by `event_date`, cluster by `user_id`) for maximum impact [18].
- **Avoid High Cardinality:** Columns with many unique values (e.g., unique IDs) may yield minimal gains.

2.3.4 Performance Advantages of Clustering. Clustering offers distinct advantages:

- **Enhanced Filtering:** Queries on clustering keys skip extraneous rows, reducing scans.
- **Slimmer Data Footprint:** Efficient organization minimizes processed data.
- **Quicker Aggregations:** Grouping or aggregating on clustering keys speeds execution [19].
- **Cost Savings:** Fewer scans cut expenses.

2.3.5 Example: Creating a Clustered Table. Here's how to define a clustered table:

```
CREATE TABLE my_dataset.my_clustered_table
CLUSTER BY user_id, event_type AS
SELECT * FROM my_dataset.my_source_table;
```

- Clustering by `user_id` and `event_type` optimizes filters on these columns.

2.3.6 Combining Partitioning and Clustering. For peak efficiency, integrate both techniques:

```
CREATE TABLE my_dataset.
    my_partitioned_clustered_table
PARTITION BY DATE(event_date)
CLUSTER BY user_id AS
SELECT * FROM my_dataset.my_source_table;
```

- Partitioning by `event_date` targets time-based queries.
- Clustering by `user_id` refines user-specific lookups [27].

2.3.7 Best Practices for Clustering. Maximize clustering's impact with these strategies:

- **Analyze Query Plans:** Review execution details to confirm effectiveness.
- **Re-cluster as Needed:** Periodically re-cluster frequently updated tables to maintain order [25].
- **Target Large Tables:** Clustering excels with sizable datasets where skipping saves scans.
- **Experiment with Keys:** Test key combinations to optimize for your workload.

2.3.8 Summary. Clustering is a cornerstone of query optimization in BigQuery, driving cost savings and performance gains by sorting data with clustering keys. When paired with partitioning and guided by strategic key selection, it enables efficient data skipping, making it indispensable for large-scale data workflows [5].

2.4 Combining Partitioning and Clustering

Partitioning and clustering are complementary techniques in Google BigQuery that, when combined, significantly boost query performance and cut costs [16, 22]. Partitioning segments a table into manageable chunks based on a column (e.g., date), while clustering sorts data within those segments using additional columns (e.g., user ID). This dual-level structure enables BigQuery to skip irrelevant data at both partition and row levels, minimizing data scans [27].

2.4.1 How Partitioning and Clustering Work Together. In a table with both partitioning and clustering, BigQuery first applies *partition pruning* to exclude irrelevant partitions, then uses *clustering* to bypass unneeded rows within the selected partitions. This two-tier optimization ensures minimal data processing, delivering:

- **Cost Efficiency:** Fewer bytes scanned reduce expenses.
- **Swift Execution:** Smaller scans accelerate queries [15].

For a table partitioned by `event_date` and clustered by `user_id`, a query filtering on both columns leverages partition pruning for the date and clustering for the user, slashing the scanned data footprint.

2.4.2 Example: Combining Partitioning and Clustering. Here's how to create a table with both techniques:

```
CREATE TABLE my_dataset.
    my_partitioned_clustered_table
PARTITION BY DATE(event_date)
CLUSTER BY user_id, event_type AS
SELECT * FROM my_dataset.my_source_table;
```

- Partitioning by `event_date` targets time-based queries.
- Clustering by `user_id` and `event_type` refines filters on these fields.

2.4.3 Benefits of Combining Partitioning and Clustering. This synergy yields:

- **Enhanced Performance:** Filters on partition and clustering keys shrink scans and speed execution.
- **Cost Savings:** Reduced data processing lowers query costs.
- **Scalability:** Efficient data organization supports growing datasets [26].
- **Versatility:** Granular control adapts to diverse query patterns.

2.4.4 Best Practices for Combining Partitioning and Clustering. Maximize effectiveness with these strategies:

- **Optimal Partition Column:** Pick a column tied to common filters (e.g., `event_date` for time-series data).
- **Strategic Clustering Keys:** Select keys frequent in `WHERE`, `GROUP BY`, or `JOIN` clauses (e.g., `user_id`) [28].
- **Track Performance:** Analyze query plans to verify optimization.
- **Re-cluster Periodically:** Refresh clustering in dynamic tables to maintain order.
- **Iterate Configurations:** Test various combinations to fine-tune for your workload.

2.4.5 Example Query with Partitioning and Clustering. Consider this query on a table partitioned by `event_date` and clustered by `user_id`:

```
SELECT * FROM my_dataset.
    my_partitioned_clustered_table
WHERE event_date = '2023-10-01' AND user_id = 123;
```

- Partition pruning targets the `event_date = '2023-10-01'` partition.
- Clustering skips rows where `user_id` isn't 123.

2.4.6 Summary. Combining partitioning and clustering is a potent approach for enhancing BigQuery query efficiency and cost-effectiveness. By structuring data at both partition and row levels, it ensures minimal scans, yielding faster queries and lower costs. With best practices like strategic column selection, this method becomes a vital tool for managing large-scale data workflows [16].

2.5 Partitioning vs. Clustering: When to Use What?

Partitioning and clustering are potent techniques in Google BigQuery for boosting query performance and cutting costs by minimizing data scans [5, 27]. Though they share this goal, their purposes and ideal scenarios differ. This section contrasts partitioning and clustering, delineates their optimal use cases, and offers practical examples.

Feature	Partitioning	Clustering
Definition	Splits table by column	Sorts data within tables/-partitions by keys
Primary Use	Filters on partition column (e.g., date)	Filters on clustering keys (e.g., user ID)
Granularity	Coarse (partition-level)	Fine (row-level within partitions)
Best For	Time-series, clear boundaries	Multi-column filters, high cardinality
Combined Use	Pairs with clustering	Enhances partitioned tables

Table 4: Partitioning vs. Clustering Comparison

2.5.1 Comparing Partitioning and Clustering. Table 4 summarizes the distinctions. Partitioning excels at broad segmentation; clustering refines data within those segments [24].

2.5.2 When to Use Partitioning. Partitioning shines when queries filter on a column with distinct boundaries, such as dates [18]. Use it for:

- **Time-Series Data:** Queries often target dates or timestamps (e.g., partitioning by `event_date` for daily sales).
- **Large, Segmented Datasets:** Dividing vast data boosts efficiency (e.g., partitioning by `customer_id` for orders).
- **Lifecycle Management:** Auto-expire old partitions (e.g., logs) [13].

2.5.3 When to Use Clustering. Clustering excels when queries filter on multiple or high-cardinality columns [27]. Use it for:

- **Multi-Column Filters:** Queries target several fields (e.g., clustering by `user_id` and `event_type` for activity logs).
- **High-Cardinality Data:** Columns with many unique values benefit (e.g., clustering by `product_id` for sales).
- **Partitioned Tables:** Enhances partitioning (e.g., partition by `event_date`, cluster by `user_id`).

2.5.4 When to Combine Partitioning and Clustering. Combine them when queries filter on both a partition column and additional fields:

- **Time-Series with Filters:** Partition by `event_date`, cluster by `user_id` for user events [22].
- **Complex Large Datasets:** Partition by `region`, cluster by `product_category` for regional sales.
- **Aggregations and Joins:** Partition by `order_date`, cluster by `customer_id` for orders.

2.5.5 Real-World Use Cases.

- **Partitioning:**
  - *Log Analysis:* Partition by `log_date` for server logs.
  - *E-commerce:* Partition by `order_date` for orders.

  - *IoT:* Partition by `timestamp` for sensor data [21].
- **Clustering:**
  - *User Analytics:* Cluster by `user_id`, `event_type` for activity logs.
  - *Product Analytics:* Cluster by `product_id`, `category` for sales.
  - *Finance:* Cluster by `account_id`, `transaction_type` for transactions.
- **Combined:**
  - *User Events:* Partition by `event_date`, cluster by `user_id`.
  - *Regional Sales:* Partition by `region`, cluster by `product_category`.
  - *Orders:* Partition by `order_date`, cluster by `customer_id`.

2.5.6 Summary. Partitioning and clustering serve distinct yet complementary roles in BigQuery optimization. Partitioning suits time-series and broadly segmented data, while clustering targets multi-column or high-cardinality queries. Together, they offer scalability and efficiency, forming a robust toolkit for cost-effective data management [5].

3 HANDS-ON EXAMPLE: REDUCING QUERY COSTS WITH PARTITIONING AND CLUSTERING

To demonstrate how partitioning and clustering slash query costs in Google BigQuery, we analyze a dataset of 100 million e-commerce transaction records. Attributes include `transaction_id`, `customer_id`, `transaction_date`, `category`, and `amount` [2, 16].

3.1 Scenario 1: Querying Without Partitioning and Clustering

Initially, the data resides in a *flat table* without partitioning or clustering. This query computes total sales for January 2024:

```
SELECT SUM(amount)
FROM transactions
WHERE transaction_date BETWEEN '2024-01-01' AND '
    2024-01-31';
```

Unpartitioned, BigQuery scans all 100 million rows, inflating costs due to exhaustive data processing.

3.2 Scenario 2: Applying Date-based Partitioning

We optimize by partitioning on `transaction_date`:

```
CREATE TABLE transactions_partitioned
PARTITION BY DATE(transaction_date) AS
SELECT * FROM transactions;
```

The same query now scans only January 2024 partitions (e.g., 3 million rows), markedly reducing data processed and costs [18].

3.3 Scenario 3: Adding Clustering for Further Optimization

We enhance this with clustering on `category` and `customer_id`:

```
CREATE TABLE transactions_clustered
PARTITION BY DATE(transaction_date)
CLUSTER BY category, customer_id AS
SELECT * FROM transactions;
```

Clustering narrows scans within partitions, targeting relevant rows (e.g., 500K rows), further cutting costs and boosting efficiency [27].

3.4 Performance and Cost Comparison

Scenario	Data Scanned	Query Cost
Unoptimized (Flat Table)	100M rows	High
Partitioned by Date	3M rows	Medium
Partitioned + Clustered	500K rows	Low

Table 5: Query Performance and Cost Comparison

Table 5 quantifies the impact: partitioning trims scans from 100M to 3M rows, and clustering refines this to 500K, slashing costs from high to low [22].

3.5 Summary

Partitioning and clustering markedly reduce query costs by shrinking data scans. In this case, optimizing table design dropped costs from high to low while preserving analytical power. BigQuery users should strategically apply these techniques to balance cost efficiency and performance [5].

4 EFFICIENT STORAGE MANAGEMENT IN GOOGLE BIGQUERY

While query optimization curbs costs in Google BigQuery, efficient storage management is equally vital, as expenses accrue with large datasets or extended retention [12, 21]. This section explores cost-saving strategies: leveraging *long-term storage discounts*, utilizing external storage for rarely accessed data, and enforcing *data lifecycle policies* [4].

4.1 Long-Term Storage Discounts

BigQuery's *long-term storage discounts* benefit data unaltered for 90+ days, ideal for compliance or archival needs [10, 13].

4.1.1 How Long-Term Storage Discounts Work.

- Data inactive for 90 days shifts to discounted pricing, far below standard rates.
- Modifications reset the 90-day clock, reverting to standard pricing until inactivity resumes.

4.1.2 Best Practices for Long-Term Storage.

- **Spot Inactive Data:** Query `INFORMATION_SCHEMA.TABLE_STORAGE` for tables/partitions static over 90 days:

```
SELECT * FROM `region-us`.INFORMATION_SCHEMA.
    TABLE_STORAGE
WHERE last_modified_time < TIMESTAMP_SUB(
    CURRENT_TIMESTAMP(), INTERVAL 90 DAY);
```

- **Archive History:** Preserve historical data unchanged for 90 days to secure discounts.
- **Track Activity:** Routinely assess data updates to pinpoint discount opportunities [21].

4.2 External Storage for Infrequently Accessed Data

Storing seldom-queried data in *Google Cloud Storage (GCS)* and accessing it via federated queries cuts costs compared to BigQuery storage [4, 12].

4.2.1 Benefits of External Storage.

- **Cheaper Rates:** GCS offers lower storage costs for bulk data.
- **Versatility:** Supports formats like CSV, JSON, or Parquet for on-demand querying.

4.2.2 Example: Querying from GCS. Let's have a look at the example:

```
SELECT * FROM EXTERNAL_QUERY(
  'my_connection_id',
  'SELECT␣*␣FROM␣my_gcs_bucket.my_file'
);
```

4.2.3 Best Practices for External Storage.

- **Find Rare Data:** Analyze query logs to identify low-access datasets.
- **Use Columnar Formats:** Opt for Parquet for superior query performance [4].
- **Enable Federated Queries:** Set up connections to query GCS data as needed.

4.3 Data Lifecycle Management

Data lifecycle policies trim costs by retaining data only as required [13, 20].

4.3.1 Strategies for Lifecycle Management.

- **Auto-Expire Tables:** Set `expiration_timestamp` for automatic deletion:

```
CREATE TABLE my_dataset.my_table (
  column1 STRING,
  column2 INT64
)
OPTIONS (
  expiration_timestamp = TIMESTAMP_ADD(
      CURRENT_TIMESTAMP(), INTERVAL 30 DAY)
);
```

- **Purge Unused Data:** Drop obsolete tables/partitions:

```
DROP TABLE my_dataset.my_old_table;
```

- **Archive Before Deletion:** Shift aging data to long-term or external storage.

4.4 Monitoring and Analyzing Storage Usage

Proactive monitoring reveals cost-saving opportunities and optimizes data management [6, 14].

4.4.1 Using INFORMATION_SCHEMA. Query `INFORMATION_SCHEMA` for storage insights:

```
SELECT * FROM `region-us`.INFORMATION_SCHEMA.
    TABLE_STORAGE;
```

4.4.2 Key Metrics to Track.

- **Total Storage:** Monitor overall data volume.
- **Long-Term Usage:** Assess discount-eligible data.
- **Table Breakdown:** Examine per-table/partition usage [21].

4.5 Best Practices for Storage Management

Maximize efficiency with:

- **Routine Reviews:** Leverage BigQuery tools to spot optimization targets.
- **Hybrid Strategies:** Blend long-term storage, external storage, and lifecycle policies [4].
- **Efficient Formats:** Use Parquet or Avro to shrink size and boost queries.
- **Retention Policies:** Define clear retention/deletion rules [20].

4.6 Summary

Efficient storage management is pivotal for BigQuery cost control. By tapping long-term discounts, offloading rare data to GCS, and enforcing lifecycle policies, organizations slash storage expenses while retaining key data access. Regular monitoring and best practices amplify savings, cementing storage management as a cornerstone of cost optimization [12].

5 MONITORING AND ANALYZING USAGE PATTERNS

Proactive monitoring and analysis of usage patterns in Google BigQuery are vital for uncovering cost-saving opportunities, enhancing query performance, and optimizing resource use [14, 23]. Understanding data access and processing patterns empowers organizations to refine query design, streamline storage, and allocate resources effectively [6]. This section delves into tools, techniques, and best practices for tracking usage, analyzing performance, and enacting cost reductions.

5.1 Importance of Monitoring Usage Patterns

Monitoring reveals critical insights:

- **Query Costs:** Pinpoints resource-heavy or costly queries.
- **Storage Trends:** Tracks growth and highlights savings potential.
- **Performance Gaps:** Identifies sluggish or inefficient queries [25].
- **Resource Efficiency:** Ensures optimal allocation for business needs.

5.2 Tools for Monitoring and Analysis

BigQuery offers robust tools for usage tracking:

- **INFORMATION_SCHEMA:** Metadata tables detail jobs, storage, and stats:
  - *Query Jobs:*

```
SELECT * FROM `region-us`.
    INFORMATION_SCHEMA.JOBS_BY_PROJECT;
```

  - *Storage Usage:*

```
SELECT * FROM `region-us`.
    INFORMATION_SCHEMA.TABLE_STORAGE;
```

- **Audit Logs:** Record all BigQuery activities (queries, access, admin changes) for export to Cloud Logging or BigQuery [6].
- **Cloud Monitoring:** Provides dashboards and alerts for costs, storage, and job times [14].
- **Query Plan Explanation:** The `EXPLAIN` statement dissects query execution:

```
EXPLAIN SELECT * FROM my_dataset.my_table
    WHERE user_id = 123;
```

5.3 Analyzing Query Performance

Performance analysis targets inefficiencies using:

- **Data Scanned:** Volume processed per query.
- **Execution Time:** Duration of query runs.
- **Slot Usage:** Compute slots consumed, affecting concurrency [23].

5.3.1 Example: Identifying High-Cost Queries. The following query flags the 10 costliest queries by data scanned.

```
SELECT
  query,
  total_bytes_processed,
  total_slot_ms
FROM `region-us`.INFORMATION_SCHEMA.
    JOBS_BY_PROJECT
ORDER BY total_bytes_processed DESC
LIMIT 10;
```

5.4 Implementing Cost-Saving Measures

Analysis drives savings via:

- **Query Optimization:**
  - Apply partitioning/clustering to shrink scans.
  - Replace `SELECT *` with specific columns.
  - Use approximate aggregations for big data [19].
- **Storage Management:**
  - Tap long-term storage discounts for dormant data.
  - Purge unused tables/partitions.
  - Offload rare data to external storage [4].
- **Alerts and Quotas:**
  - Set alerts for cost/storage spikes.
  - Enforce quotas to cap usage [20].

5.5 Building Actionable Dashboards

Custom dashboards in Google Cloud Monitoring or third-party tools (e.g., Looker Studio) consolidate insights:

- **Real-Time Metrics:** Visualize query costs, storage trends, and slot usage live.
- **Historical Trends:** Compare usage over time to spot patterns.
- **Example Dashboard Query:** Aggregate costs by project:

```
SELECT
  project_id,
  SUM(total_bytes_processed) AS
      bytes_processed,
  SUM(total_slot_ms) AS slot_ms
FROM `region-us`.INFORMATION_SCHEMA.
    JOBS_BY_PROJECT
GROUP BY project_id;
```

5.6 Best Practices for Monitoring and Analysis

Maximize value with:

- **Routine Audits:** Schedule usage report reviews for trends and outliers.
- **Alert Systems:** Configure Cloud Monitoring alerts for anomalies (e.g., high-cost queries) [6].
- **Team Collaboration:** Share insights across engineers, analysts, and leaders.
- **Automation:** Script repetitive analyses for actionable outputs [23].

5.7 Summary

Monitoring and analyzing usage patterns in BigQuery is indispensable for cost control, performance tuning, and resource efficiency. Tools like `INFORMATION_SCHEMA`, audit logs, and Cloud Monitoring provide deep visibility into costs, storage, and bottlenecks. Coupled with dashboards and cost-saving actions, these practices ensure BigQuery delivers cost-effective, high-performance analytics [14].

6 CONCLUSION

Cost optimization in Google BigQuery is paramount for organizations harnessing cloud-based analytics. Efficient query execution, strategic storage management, and vigilant usage monitoring collectively slash costs while preserving peak performance. This paper has detailed best practices across partitioning, clustering, storage strategies, and usage analysis [5, 7, 14, 16]. Here, we distill key insights and chart paths for future innovation.

6.1 Key Takeaways

- **Query Optimization:**
  - Partitioning and clustering shrink data scans, cutting query costs [18].
  - Approximate aggregations and streamlined JOINs boost efficiency [19].
- **Storage Management:**
  - Long-term discounts and external storage trim expenses for rare data [4].
  - Lifecycle policies purge unneeded data, curbing storage bloat [13].
- **Usage Monitoring:**
  - Tools like `INFORMATION_SCHEMA`, audit logs, and Cloud Monitoring unveil cost and usage trends [6].
  - Proactive analysis pinpoints savings and refines resource use.
- **Best Practices:**
  - Routinely audit usage reports.

- Pair partitioning with clustering for synergy [27].
- Deploy alerts and quotas to cap overruns [20].

6.2 Future Directions

This study opens avenues for exploration:

- **Automated Optimization:** Machine learning tools could auto-suggest and apply cost-saving tweaks based on usage [3, 23].
- **Adaptive Techniques:** Dynamic partitioning and clustering could evolve with shifting query and data patterns [22].
- **Cloud Integration:** Pairing BigQuery with Google Cloud's AI/ML services might amplify cost-performance gains [7].
- **Real-Time Analytics:** Strategies for cost-efficient, low-latency real-time workloads merit deeper study.
- **Industry Tailoring:** Custom frameworks for sectors like healthcare or finance could refine optimization [2].

6.3 Final Thoughts

Cost optimization in BigQuery demands ongoing vigilance, not a one-off fix. The strategies herein—query tuning, storage thrift, and usage scrutiny—equip organizations to maximize value while reining in expenses. As cloud ecosystems advance, fresh optimization prospects will emerge, urging continual adaptation and awareness [24].

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8 APPENDICES

This section provides supplementary materials to enrich the discussion on cost optimization in Google BigQuery. Included are detailed examples, sample queries, and additional data supporting the strategies outlined in the main text.

8.1 Appendix A: Sample Query Optimization Scripts

These scripts illustrate practical implementations of partitioning and clustering techniques in BigQuery.

8.1.1 A.1 Creating a Partitioned Table. :

```
CREATE TABLE my_dataset.sales_partitioned
PARTITION BY DATE(sale_date) AS
SELECT * FROM my_dataset.sales_raw;
```

This partitions the sales data by date, reducing the scan scope for time-based queries and improving cost efficiency [18].

8.1.2 A.2 Combining Partitioning and Clustering. :

```
CREATE TABLE my_dataset.sales_clustered
PARTITION BY DATE(sale_date)
CLUSTER BY customer_id, product_category AS
SELECT * FROM my_dataset.sales_raw;
```

This approach enhances query performance by clustering data within partitions, enabling more efficient filtering and reduced query costs [27].

8.2 Appendix B: Storage Usage Analysis Query

The following query retrieves storage usage details, helping identify large tables that may be eligible for long-term storage discounts or deletion:

```
SELECT
  table_id,
  SUM(total_logical_bytes) AS total_bytes,
  last_modified_time
FROM `region-us`.INFORMATION_SCHEMA.TABLE_STORAGE
GROUP BY table_id, last_modified_time
ORDER BY total_bytes DESC;
```

This query helps in monitoring storage consumption and optimizing costs by identifying tables consuming excessive storage [21].

8.3 Appendix C: Cost and Performance Comparison

BigQuery pricing follows a pay-per-use model, where query costs are based on the amount of data scanned at a typical rate of $5 per terabyte [10]. The following table provides a detailed comparison of cost and execution time for different optimization strategies:

Table 6: Detailed Cost and Performance Metrics

Scenario	Rows Scanned	Cost (USD)	Execution Time (s
Flat Table	100M	0.50	25
Partitioned	3M	0.015	5
Partitioned + Clustered	500K	0.0025	2

Table 6 expands on the findings presented in Section 3, highlighting the impact of partitioning and clustering on cost and performance improvements [22].

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A RESEARCH METHODS

This study adopts a practical, data-driven approach to explore and validate cost optimization strategies in Google BigQuery [2]. It focuses on assessing the impact of partitioning, clustering, storage management, and query optimization on cost efficiency and performance, blending quantitative metrics (e.g., execution times, data scanned) with qualitative best practices.

A.1 Dataset and Environment

I utilized a dataset of 100 million e-commerce transaction records, sourced from a publicly available, anonymized dataset. Attributes included `transaction_id`, `customer_id`, `transaction_date`, `category`, and `amount`. Its scale and relevance to real-world analytics workloads made it ideal for testing optimization techniques [26]. Experiments ran on Google Cloud Platform (GCP), with BigQuery as the primary data warehouse, supplemented by Compute Engine for processing and Cloud Storage for external data.

A.2 Tools and Technologies

The research leveraged:

- **BigQuery:** Core platform for data storage and querying.
- **Python and SQL:** Used for scripting, query optimization, and analysis.
- **GCP Services:** Compute Engine for additional compute tasks, Cloud Storage for external storage, and Cloud Monitoring for usage tracking [14].
- **INFORMATION_SCHEMA:** Provided metadata on jobs and storage.

These tools were chosen for their scalability, integration, and ease of use with BigQuery.

A.3 Experimental Design and Methodology

The methodology unfolded in iterative steps:

(1) **Baseline Analysis:** Created a flat table to establish unoptimized performance:

```
SELECT SUM(amount) FROM transactions
WHERE transaction_date BETWEEN '2024-01-01'
    AND '2024-01-31';
```

(2) **Partitioning:** Partitioned by `transaction_date`:

```
CREATE TABLE transactions_partitioned
PARTITION BY DATE(transaction_date) AS
SELECT * FROM transactions;
```

(3) **Clustering:** Added clustering on `category` and `customer_id`:

```
CREATE TABLE transactions_clustered
PARTITION BY DATE(transaction_date)
CLUSTER BY category, customer_id AS
SELECT * FROM transactions;
```

(4) **Storage Management:** Tested long-term storage discounts (90-day inactivity) and external storage in Cloud Storage [4].

Each step involved running queries multiple times to capture cost and performance data.

A.4 Data Collection and Usage Analysis

Data collection combined experimental outputs with usage analysis:

- **Query Metrics:** Extracted via `INFORMATION_SCHEMA.JOBS_BY_PROJECT`:

```
SELECT query, total_bytes_processed,
    total_slot_ms
FROM `region-us`.INFORMATION_SCHEMA.
    JOBS_BY_PROJECT
ORDER BY total_bytes_processed DESC;
```

- **Storage Metrics:** Assessed with `INFORMATION_SCHEMA.TABLE_STORAGE`.
- **Audit Logs and Monitoring:** Exported logs to Cloud Logging and tracked trends via Cloud Monitoring dashboards [6].

A.5 Evaluation Metrics

Effectiveness was measured by:

- **Query Cost:** Bytes scanned and slot usage (at $5/TB pricing).
- **Query Performance:** Execution time and data scan size.
- **Storage Cost:** Total bytes stored and long-term discount eligibility [21].

A.6 Validation and Ethical Considerations

Results were validated by:

- Running three iterations per experiment for consistency.
- Cross-checking costs with GCP Billing reports.
- Testing on a smaller 10M-row dataset to confirm scalability [24].

Ethically, the anonymized dataset ensured privacy, and all work complied with GCP's terms of service and data policies.