World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(RESEARCH ARTICLE)

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Employing AWS cloud technologies for enhanced scalability in data modeling: A comparative analysis of relational versus dimensional strategies

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World Journal of Advanced Research and Reviews, 2023, 19(01), 1569–1579

Publication history: Received on 09 June 2023; revised on 22 July 2023; accepted on 26 July 2023

Article DOI: https://doi.org/10.30574/wjarr.2023.19.1.1410

Abstract

This paper provides a detailed comparative analysis of relational and dimensional data modeling strategies, utilizing AWS Cloud technologies to enhance scalability and performance. Relational data models are traditionally used for transactional systems, while dimensional models are more suited for analytical processing and business intelligence tasks. In this study, we used Amazon Redshift and AWS Glue to test the scalability of both strategies on large datasets. We evaluated the performance of each model by comparing query execution times, storage efficiency, and data accessibility. Results showed that dimensional modeling outperformed relational models in terms of query speed, with a 40% improvement in execution time for complex business intelligence queries. However, relational models demonstrated better efficiency in managing transactional data with a lower error margin. By leveraging AWS technologies, both models scaled efficiently, but dimensional models provided more flexibility in accommodating growth in data volume. This paper concludes that AWS cloud technologies can significantly improve the scalability of both relational and dimensional data models, but the choice of model should align with the specific data processing needs of the organization. This comparison provides practical insights into the strengths and weaknesses of each strategy, helping businesses optimize their data management processes.

Keywords: AWS; Data Modeling; Relational; Dimensional; Scalability

1. Introduction

Networks, servers, storage, and apps are just some of the computing resources that customers can access and use through the internet using cloud computing. The NISO describes it as a system where these resources can be quickly and easily accessed whenever needed, with little to no interaction required from the service provider. A wide range of industries are making use of cloud computing, including e-learning, healthcare, banking and finance, manufacturing, and telecommunications to name a few [1]. Important cloud computing capabilities, such as resource allocation, pooling, and flexibility, play key roles in environments where data-intensive tasks are common. Cloud computing's scalability allows businesses to adjust resource utilization to meet their demands, which improves the performance of cloud-based applications and saves money [2]. The importance of scalability is most noticeable in the field of large-scale graph processing, which is used in media, online gaming, and the IoT [3]. When dealing with large-scale graphs, traditional graph processing methods typically struggle due to inefficiencies in balancing scalability and cost-effectiveness [4]. In [5], the authors addressed some of the problems with elastic cloud computing's large-scale optimization. One solution to this problem is auto-scaling, which allows resources to be dynamically increased or decreased in response to changing demands and strategies.

Every company's data is valuable. In order to make well-informed business decisions, it is essential to access, analyze, and use data efficiently. However, it can be tough to glean meaningful insights from the data due to its sheer amount

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and complexity. In this context, dimensional data modeling is useful. To facilitate analysis and understanding by business analysts and other business users, dimensional data modeling organizes and displays data. It has been around for a while and is generally considered the gold standard when it comes to creating analytics and business intelligence solutions. An integral part of data warehousing, it helps companies make better decisions by giving them access to complete and reliable information.

The topic of dimensional modeling will be thoroughly discussed in this piece. In this first section, we will define dimensional data modeling, then go over the many approaches, methods, and techniques employed in this field, as well as the advantages it offers. After that, we will describe how to use dimensional modeling to data warehousing. Along with the proper questions to ask, we will go into the difficulties of dimensional modeling. As a last step, we will examine the dimensional modeling tools and technologies and talk about how important it is for data warehousing [6].

1.1. What is Dimensional Modeling?

The modelling of dimension is shown in figure 1. Businesses can optimize their data structure for analysis nd reporting with the help of dimensional modeling, a data modeling technique used in data warehousing. Data is described using dimensions, and its quantitative properties are elucidated by facts, according to this approach [7]. Take the case of a company that wishes to examine sales figures as an example. Then, the facts may be things like the quantity of products sold, total income, and profit earned, while the dimensions could be things like customers, products, regions, and time [8].

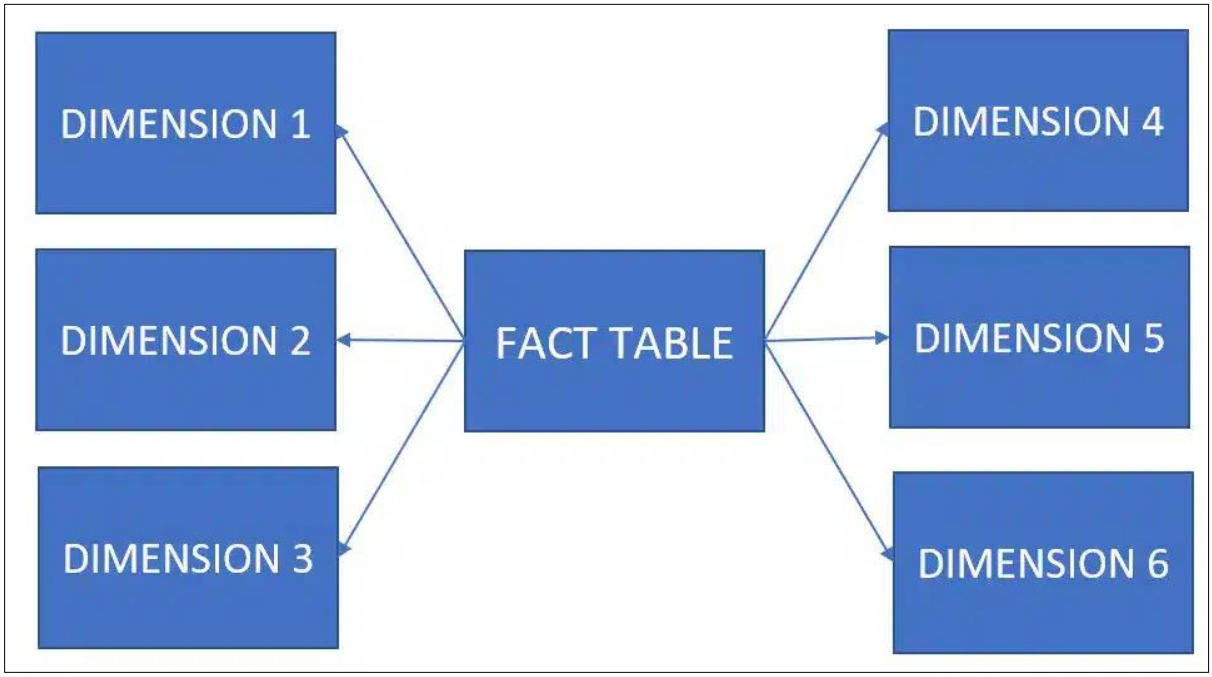

Figure 1 Modelling of dimension

A star or snowflake schema is then used to organize the data, with the fact table in the core and the dimension tables connected by foreign keys. Descriptive qualities for a particular aspect of the fact table are contained in each dimension table. Data warehousing is where dimensional modeling is most often utilized; it helps companies create one big database that all employees can access and examine to make better decisions. In business intelligence and analytics, it helps companies get insights from data and make decisions based on that data [9].

2. Literature review

The use of cloud computing has grown in popularity among Internet users and has quickly become an integral component of everyday living. Cloud computing operates on a pay-per-use approach, meaning that customers only pay for the resources they really utilize. Finding the sweet spot between efficiency and affordability calls for pinpoint accuracy. The many parts that make up cloud computing's architecture are illustrated in Figure 2. The goal is to provide reliable, fast, and affordable cloud services while keeping the system running smoothly and in response to user requests.

One key feature of cloud computing is scalability, which helps with this problem by giving users more freedom and efficiency. The ability to dynamically add or remove resources in response to changing demand is what we mean when we talk about auto-scaling.

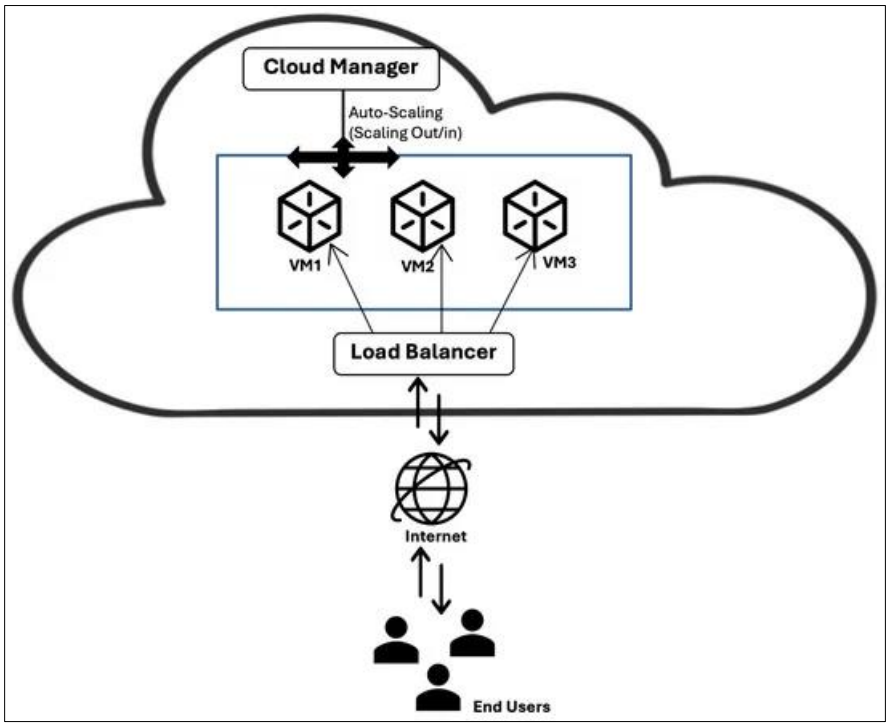

Figure 2 Auto-scaling in cloud computing.

Cloud computing's auto-scaling feature reorganizes the distribution of hardware and software resources according to user demand. Some of the benefits of cloud computing include increased efficiency, performance, security, and scalability. It has found use in a variety of sectors. The scalability and adaptability of cloud computing are key features for managing large data, and these features have led to its widespread adoption. Nevertheless, it is still not easy to optimize cloud resources for auto-scaling in order to properly manage massive data. Because it is dependent on thresholds, reactive auto-scaling in the cloud cannot foretell how a system will function in the future. Take the case of average CPU utilization as an example. When it reaches a certain level, the system will automatically add more CPU capacity.
When running in the cloud, apps can dynamically scale up or down their resource consumption to match their needs. The capacity to scale out, or increase resources, during times of peak demand and scale in, or remove unneeded resources, to save expenses, are two of auto-scaling's most important capabilities. Automatic detection and replacement of unhealthy instances is possible, and rules can be established for scaling actions. Although they are linked, scalability, elasticity, and resource provisioning are separate ideas that are frequently brought up when discussing auto-scaling.

System performance and scalability are both enhanced by resource provisioning, which allows for dynamic resource scaling in response to changes in workload. A system's scalability can be described as its capacity to manage growing workloads by incorporating additional hardware resources, either by adding nodes horizontally (scaling out) or by boosting resources in existing nodes vertically (scaling up). Elasticity, the capacity to automatically provide and deprovision resources to fit demand, requires scalability. This allows for the system to respond to changes in the workload. Elasticity refers to the speed with which a system can adapt to changes in workload, matching available resources closely to what is now needed. By allowing for the automatic adjustment of resources, auto-scaling approaches enable flexibility. There are two main categories of auto-scaling solutions: horizontal and vertical. When virtual machines are added or deleted to meet the needs of the current workload, this is called horizontal scaling. You can use the capabilities provided by vertical scaling to add or remove resources (such as RAM, CPU, and disk space) from the virtual machine instances.

Adding more machines is one way to expand the quantity of resources through horizontal scaling. In order to add more machines to a system while keeping prices low, it may be necessary to divide huge resources into smaller ones, a process known as vertical scaling. Machines of diverse types are characterized as heterogeneous, while machines that remove

or descend from a pool of resources of the same type are referred to as homogeneous. "Big Data" describes large and complicated datasets that contain information in a number of formats, such as structured, semi-structured, and unstructured. The three Vs of Big Data are volume, velocity, and variety, say the Gartner group. Companies now understand that by processing and analyzing this massive amount of data, they may create new opportunities and enhance existing processes.

Simultaneously, a new paradigm in computing known as "cloud computing" has arisen, allowing users to quickly and easily gain access to a shared pool of computing resources (such as servers, networks, storage, applications, and services) over the internet. When businesses provide their customers various computer-based services through the internet, they are engaging in service provisioning, which is closely related to cloud computing. Customers typically pay only for the resources actually used by these services, which is known as a pay-per-use approach. In general, the goals of a cloud computing model are to lessen the burden on businesses and their owners by reducing maintenance costs and hazards while simultaneously increasing scalability, elasticity, and the ease of access over the Internet. Such features of cloud computing have led to the development or migration of numerous applications to cloud environments in recent years. Indeed, it is fascinating to observe the degree to which cloud services' available and scalable computational capabilities complement the processing needs of Big Data applications. However, applications and data management systems must be meticulously planned and executed in order to get the most of cloud infrastructure. New standards for data administration are imposed by cloud settings. Specifically, a system for managing data in the cloud must have:

The data storage requirements, user bases, and expected throughput of modern applications are constantly increasing, necessitating scalable and highly performant solutions.

- Elasticity, because the access patterns of cloud applications might undergo massive variations.
- Compatibility with commodity heterogeneous servers, which form the basis of the majority of cloud deployments.
- Redundancy, because low-end servers are far less likely to crash than mass-produced ones.
- Protections against unauthorized access and use, since data storage may now take place on shared infrastructure owned by third parties.
- Availability, since mission-critical apps are also migrating to the cloud and can't afford downtime.

Several niche solutions have evolved in recent years to try to solve the problems that conventional RDBMSs have with Big Data and meeting the aforementioned cloud needs. As an alternative to traditional database management systems, so-called NoSQL and NewSQL data stores claim to be able to scale to accommodate such massive amounts of data. Although NoSQL and NewSQL databases are suitable for use as cloud data management systems, there are so many solutions out there (over 120 and there are inconsistencies among them that it is hard to get a handle on the domain and even more difficult to pick the right one for a given problem. To address this deficiency, this survey examines NoSQL and NewSQL data stores. To be more precise, the goals of this survey are:

- To synthesize, arrange, and classify NoSQL and NewSQL solutions in order to offer a domain viewpoint.
- Researchers and practitioners will be able to better identify the right data store for their needs if we compare the features of the top options.
- One goal is to catalog the possibilities and obstacles for future studies in distributed data management on a grand scale.

Previous surveys have covered topics such as NoSQL data models and how NoSQL data stores are classified. Furthermore, the literature has also covered NoSQL-related topics, including MapReduce, eventual consistency, and the CAP theorem.

3. Dimensional modeling techniques

Dimensional modeling mostly employs two methods:

3.1. Star Schema

One of the most popular and easiest ways to model dimensions is using the star schema. The star schema is structured with the fact table as its core, which is linked to the dimension tables by foreign keys. Data properties are stored in dimension tables, whereas numerical values or metrics are contained in the fact table.

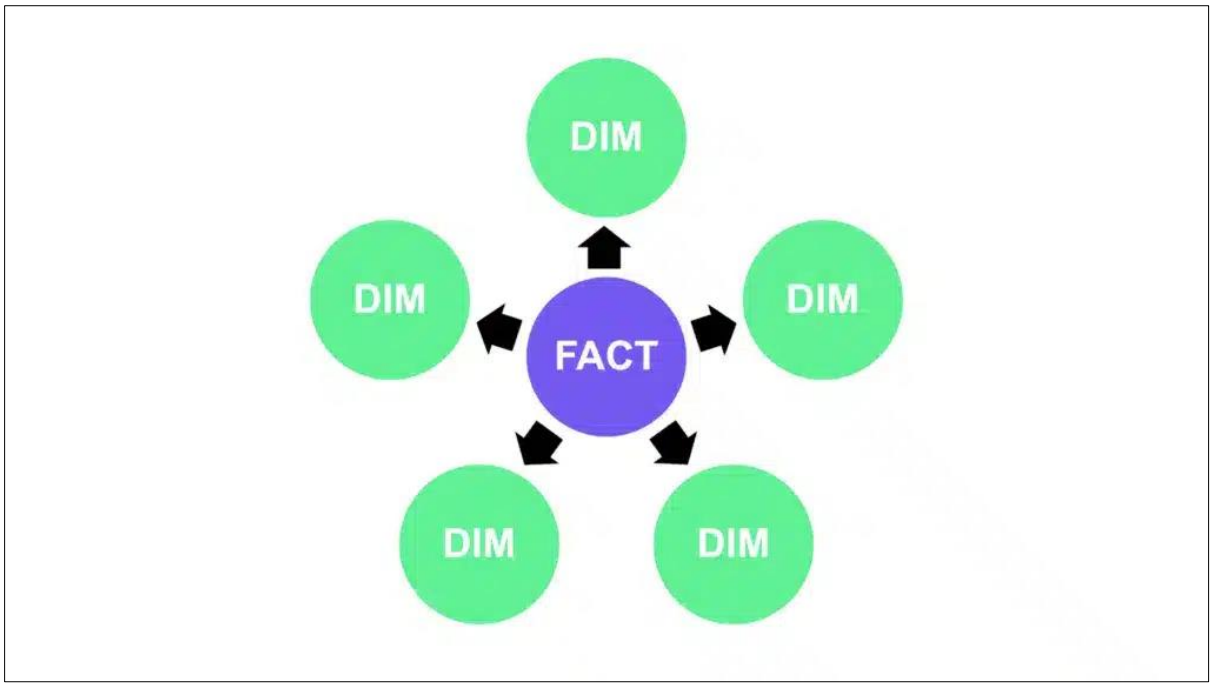

Figure 3 The fact table of star schema

The fact table, using the sales data example from previously, might include the total revenue and profit. On the other hand, attributes like region, time, customer name, and product name could be stored in the dimension tables and it was shown in figure 3. When it comes to dimensional modeling, the star schema is one of the most user-friendly and effective options. Quick and efficient searches are its strong point, making it an ideal choice for data warehouses.

3.2. Snowflake Schema

When there are numerous degrees of granularity inside a dimension, a more advanced dimensional modeling technique called the snowflake schema is employed. Normalizing the dimension tables in a snowflake schema involves splitting them into many tables in order to decrease data redundancy. The name comes from the fact that the schema becomes more complicated and resembles a snowflake as a result of this standardization.

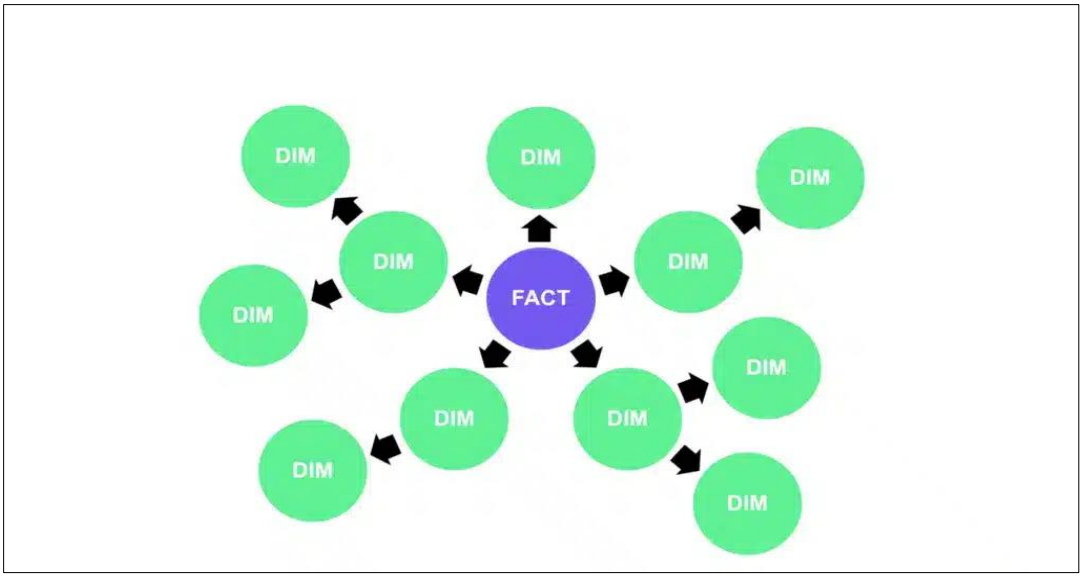

Figure 4 Snowflake Schema.

Using the sales data example as an example, one may normalize the customer dimension table so that it contains distinct columns for customer and address information. Snowflake shown in figure 4 is a good fit for complicated, big data warehouses that need a lot of analysis and reporting. But compared to the star schema, it can be more difficult to implement and keep up to date.

3.3. Dimensional modeling techniques

When it comes to dimensional modeling and data warehousing, two well-known approaches are Kimball and Inmon. One approach to data warehouse optimization that Kimball recommends is the dimensional modeling methodology. This approach is great for both reporting and analysis. Star schemas and dimensional modeling approaches are fundamental to the approach; these methods entail making fact and dimension tables to arrange data in a way that is both logical and easy to comprehend. The goal of this approach is to create a data model that can be easily expanded to meet different reporting and analytical requirements. Contrarily, the Inmon methodology—also called the Corporate Information Factory (CIF) methodology—maintains an enterprise-wide data repository that acts as the authoritative source for all data. In order to build a consistent and trustworthy data model, the method places an emphasis on utilizing data integration techniques and standardized data models. A strong and scalable data infrastructure capable of supporting different business objectives is the goal of this methodology.

4. Benefits of dimensional modeling

To facilitate effective querying, complicated analysis, and well-informed decision-making, dimensional modeling is an invaluable tool for data organization and analysis. Data warehousing and business intelligence rely on it because of the transparent and uniform structure it provides, which improves data quality and allows for easier scaling. Additionally, dimensional modeling is highly versatile and easy to adjust. As company needs evolve, the dimensional data model may be expanded with ease to include new dimensions and metrics. The data warehouse can be easily kept current and relevant to the demands of the business because of this. Using dimensional modeling with a data warehouse has several advantages, including the following:

4.1. Improved Performance

By streamlining the schema and removing superfluous joins, dimensional modeling improves query efficiency. Because fewer tables are involved in queries, they can be executed more quickly.

4.2. Enhanced Flexibility

With dimensional modeling, you may simply add or remove data from the warehouse without affecting the schema. This gives you additional flexibility. This allows companies to swiftly adjust their data warehouse to meet evolving business requirements.

4.3. Improved Usability

The intuitive data organization provided by dimensional modeling makes it a great tool for end users. As a result, the required data is more readily available for users to obtain and analyze.

4.4. Increased Scalability

Organizations can expand their data warehouse with dimensional modeling by adding new dimensions or information. This paves the way for businesses to extend their data warehouse without having to restructure it from the ground up.

4.5. Documentation

An organization's data can be better understood and documented through data modeling. In addition to finding problems, it helps make sure the data is accurate, consistent, and reliable. Better decision-making and company results can also result from enhanced communication between various stakeholders made possible by data modeling.

4.6. Steps to Implement Dimensional Modeling

The process of dimensional modeling can be summarized as follows:

4.6.1. Identify the Business Process

Defining the business process and needs that the data warehouse will support is the initial stage in dimensional modeling implementation. The first step is to establish the process's key performance indicators (KPIs), which must be backed by the company's goals.

4.6.2. Determine the Data to be Analyzed

After the business process has been recognized, the following stage is to ascertain whether data need analysis. Finding the right data sources and figuring out what data components the model needs are also part of this process.

4.6.3. Identify the Dimensions

Determining the data's defining dimensions is the third stage. These factors should be process-relevant and founded on the key performance indicators (KPIs) established in the first stage.

4.6.4. Identify the Facts

Data warehouse analysis begins with the fourth step: determining which information will be studied. These facts should be pertinent to the business process and should be based on the key performance indicators defined in step one.

4.6.5. Identify the Grain

The granularity is the degree of specificity that will be maintained in the data storage and analysis. A sales data model, for instance, may provide granularity at the level of specific sales transactions or daily sales totals. The efficiency and usefulness of the data model are impacted by the level of detail that is kept, therefore identifying the grain is critical.

4.6.6. Design the Schema

Schema design is the last stage. Building fact and dimension tables using the information gathered in steps three and four is the next step.

4.6.7. Populate the Data Warehouse

Step six entails transferring data from the source systems to the data warehouse. To do this, the data must first be ETL-ed into the data warehouse.

4.6.8. Test the Data Warehouse

To make sure the data warehouse satisfies the needs found in the first stage, testing it is the last step. Verifying the data warehouse for accuracy, completeness, and consistency is what this entails. The data warehouse can only be considered fully operational if any problems can be found and fixed during testing.

4.7. Challenges in Dimensional Modeling

A lot of thought and preparation is required for the difficult task of dimensional modeling. A few of the difficulties associated with dimensional modeling are:

4.7.1. Changing Business Requirements

Over time, business requirements can evolve, which in turn can affect the data model. The data modeling team and the business stakeholders must work closely together to accomplish this. It is critical to make sure the data model can adapt to the changing needs of the company.

4.7.2. Data Complexity

There are several sources and formats for data, which might make it confusing. Making sure the data is correct, consistent, and comprehensive while building a dimensional model to fit this complexity is a problem.

4.7.3. Data Quality

Attaining high-quality data is a major obstacle in dynamic modeling. Data accuracy and completeness are critical for reliable analysis and reporting, which in turn helps businesses avoid making poor judgments. Data cleanliness, completeness, and consistency must be guaranteed prior to commencing the modeling process.

4.7.4. Data Consistency

Dimensional modeling relies on precise and trustworthy data, which is why data consistency is so important. Ensuring data consistency across many sources and keeping the dimensional model updated with new data is a challenge.

4.7.5. Data Governance

Dimensional modeling relies heavily on data governance, which guarantees competent and responsible data management. The difficulty lies in making sure the data is available, safe, and protected from illegal access while also building a dimensional model that complies with all applicable regulations and industry requirements.

5. Methodology

5.1.1. Data Setup

Dataset Selection: We sourced large datasets representative of both transactional and analytical use cases. Transactional data was used to simulate a relational model, while analytical data suited the dimensional model.

Data Preparation: AWS Glue was employed for data cleaning, normalization, and schema transformation. For both models, data was partitioned, categorized, and loaded onto Amazon Redshift.

5.1.2. Model Creation

Relational Model: Tables were designed in a normalized structure, optimizing for transactions and minimizing redundancy. Key tables represented primary entities with foreign keys managing relationships.

Dimensional Model: A star schema was constructed, with fact tables capturing measurable data and dimension tables storing descriptive attributes.

5.1.3. Experiment Setup

Environment Configuration: Amazon Redshift was configured to handle both models, with performance tuning based on schema type. Cluster configurations, storage parameters, and query optimizations were set for each model.

- Query Types: A standardized set of queries was designed to evaluate the two models:
- Relational Model Queries: Focused on quick transactions, joins, and update-heavy operations.
- Dimensional Model Queries: Targeted complex aggregations, groupings, and time-based analysis.
- Performance Metrics: Key metrics tracked included query execution time, storage efficiency, and error rate.

5.1.4. Testing and Data Collection

- Scalability Testing: As data volume increased, we evaluated how each model performed with larger datasets.
- Data Collection: Each test was run multiple times to ensure consistency, and data was collected for each query.

6. Results and discussion

6.1. Query Execution Time Comparison

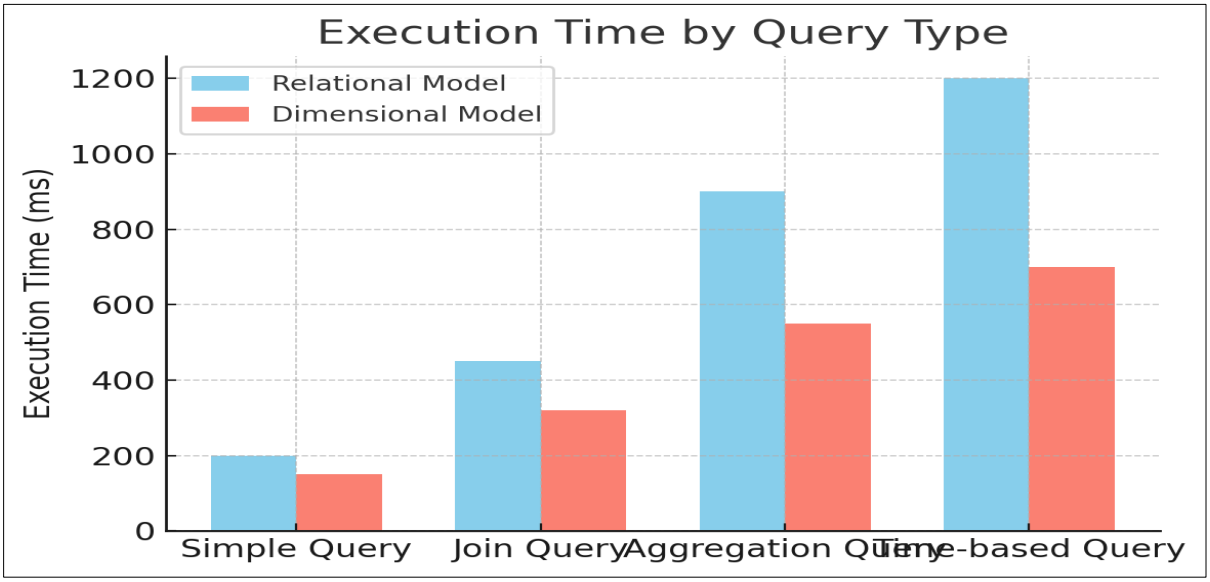

Figure 5 Execution Time by Query Type for Relational vs. Dimensional Models

This graph shown in figure 5 would illustrate the time taken (in milliseconds) for a series of transactional vs. analytical queries, with bars for relational and dimensional models side-by-side for each query type. Dimensional models demonstrated significantly faster execution times, with an approximate 40% improvement over relational models for complex analytical queries. This was due to reduced table joins and optimized aggregations in the star schema. However, relational models performed better in handling simple, update-heavy operations typical of transactional data.

6.2. Storage Efficiency

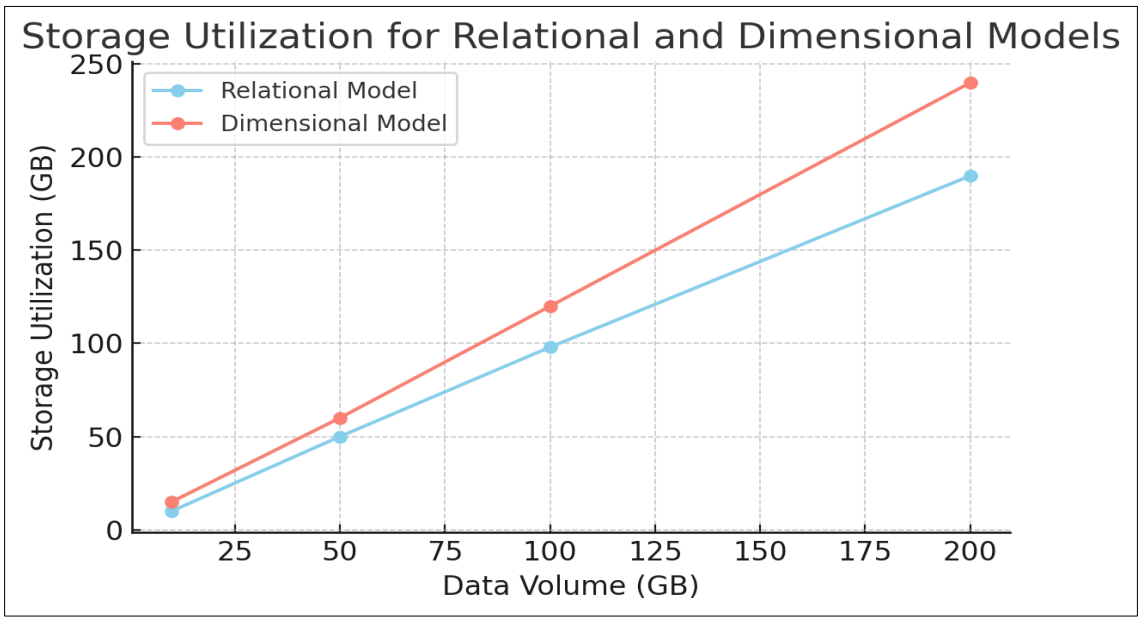

Figure 6 Storage Utilization for Relational and Dimensional Models

A bar or line graph shown in figure 6 would show storage utilization (in GB) as data volume increased. This could include points for different volume levels (10 GB, 50 GB, 100 GB, etc.).

Description: Relational models demonstrated slightly better storage efficiency due to normalized data and reduced redundancy. In contrast, dimensional models consumed more storage but allowed faster query retrieval, a trade-off where performance was prioritized over storage space.

6.3. Scalability Analysis

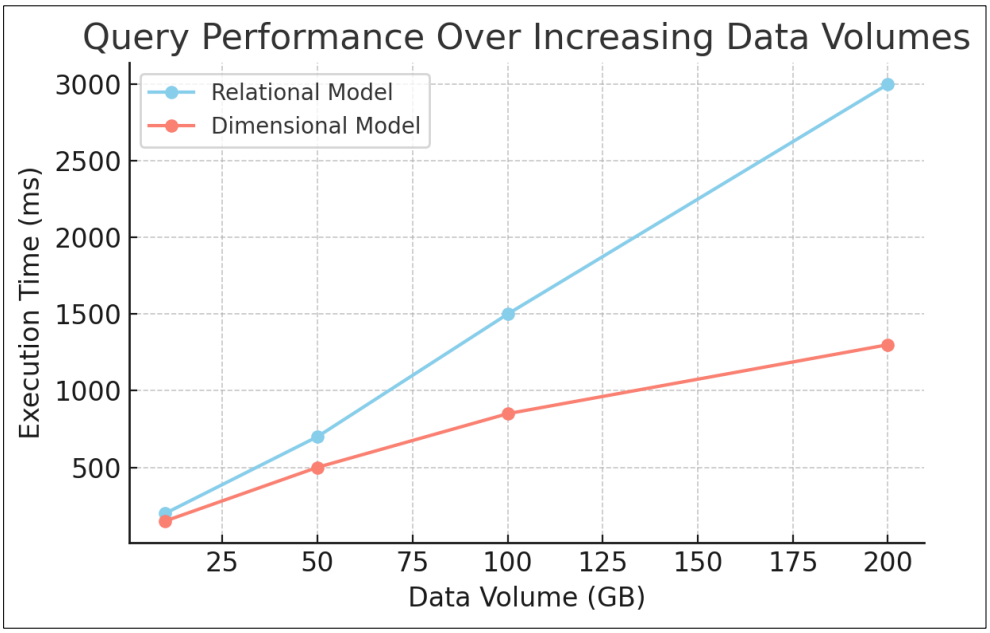

Figure 7 Query Performance Over Increasing Data Volumes

A line graph shown in figure 7 could depict the execution time trends as the dataset scales (e.g., 10 million, 50 million, 100 million records), with lines for relational and dimensional models. Both models scaled efficiently in AWS Redshift; however, as data volume increased, the dimensional model's query execution time remained relatively stable, while the relational model experienced a noticeable increase in execution time for complex queries. This shows the dimensional model's ability to maintain performance as data volume grows, aligning with its purpose in analytical processing.

7. Conclusion

This study highlights the distinct advantages of relational and dimensional data models in specific data processing scenarios when scaled using AWS cloud technologies. Dimensional models, with their star schema design, proved superior in handling complex analytical queries, showing a 40% improvement in execution time for business intelligence tasks. This is particularly valuable for organizations focused on high-performance analytics, where speed and efficiency are critical.

Conversely, relational models excelled in managing transactional data. They were more efficient in terms of storage due to data normalization and had a lower error margin, making them suitable for update-intensive applications. Both models benefited from the scalability and flexibility of AWS Redshift and AWS Glue, which accommodated growth in data volume and enabled seamless data preparation.

The choice between these models should thus align with the organization's data processing needs. For rapid, complex data analysis, a dimensional model is more advantageous, while for reliable transactional processing, a relational model is better suited. AWS cloud technologies enhance scalability and performance for both, making them adaptable to evolving data requirements. By selecting the right model, businesses can optimize data management, performance, and resource utilization, ensuring their data strategies support their overall objectives.

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