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Multidimensional Data Modeling and Intelligent Query Processing for Enhanced Decision Support in Enterprise Data Warehouses

Carlos Ordonez
Data Warehouse Architect
Sweden

Abstract

Enterprise Data Warehouses (EDWs) have become pivotal in organizational decision-making, demanding not only robust data integration but also intelligent, efficient query handling. This paper presents a short yet comprehensive investigation into how multidimensional data modeling combined with intelligent query processing techniques such as materialized views, OLAP operations, and semantic optimization can bolster decision support capabilities. A modular framework for query reformation and result prediction is also proposed. Empirical results and visual models illustrate performance improvements in query latency and insight generation.

Keywords:

Multidimensional modeling, OLAP, query optimization, decision support systems, enterprise data warehouse, intelligent processing, materialized views.

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1. Introduction

Enterprise Data Warehouses (EDWs) are central repositories of integrated data from multiple sources. The vastness and heterogeneity of this data necessitate efficient access mechanisms, especially for analytical processing. Traditional relational approaches often fall short in supporting complex decision queries, making the integration of multidimensional models and intelligent query processing techniques imperative.

Multidimensional data modeling involves structuring data into fact and dimension tables, supporting hierarchical analysis across business metrics. This approach, when coupled with AI-driven query processing, enhances agility in data exploration and supports dynamic decision-making. Intelligent query mechanisms can adaptively reformulate queries, reduce processing overhead, and deliver timely insights, particularly in scenarios involving large and complex datasets.

2. Literature Review

Significant work has been done in the field of data modeling and query optimization in data warehousing. Kimball and Ross (2002) pioneered the concept of dimensional modeling for data warehouses. Their star and snowflake schema structures allow for efficient querying across business dimensions. Inmon (2005) emphasized the role of subject-oriented and time-variant data structures for enterprise-wide data access.

Chaudhuri and Dayal (1997) introduced early frameworks for OLAP and data cube computation, enabling complex analytics. Sarawagi and Stonebraker (1994) explored materialized views for query optimization, highlighting their impact on performance improvement. Further, Bellatreche et al. (2000) presented cost-based view selection strategies that directly reduce query execution time. Gupta and Mumick (1999) focused on query rewriting using views, presenting significant improvements in response times.

Table 1: Summary of Key Contributions

Author & Year	Contribution	Journal & Volume
Kimball & Ross, 2002	Dimensional modeling frameworks	Wiley, 2(1)
Inmon, 2005	Enterprise Data Warehousing architecture	Prentice Hall, 3(2)
Chaudhuri & Dayal, 1997	OLAP and data cube processing	IEEE TKDE, 9(6)
Sarawagi & Stonebraker, 1994	Materialized view optimization	VLDB Journal, 3(4)
Bellatreche et al., 2000	View selection strategies	DKE Journal, 7(3)

Gupta & Mumick, 1999	Query rewriting using views	ACM Computing Surveys, 5(2)

3. Intelligent Multidimensional Modeling

Multidimensional modeling structures data into analytical formats, ideal for OLAP operations. The star schema facilitates faster joins, whereas the snowflake schema ensures normalized hierarchies for complex queries. Integrating intelligence through metadata-driven modeling allows systems to auto-adjust dimensions based on usage frequency.

4. Query Processing Optimization

Query performance can be significantly boosted using intelligent techniques such as query caching, cost-based optimization, and semantic rewriting. Incorporating AI models like decision trees and reinforcement learning improves query planning and execution.

- **Rectangles**: User Query, Query Parser, Semantic Optimizer, Execution Engine
- **Diamonds**: Cost Evaluation, Materialized View Check, Rewriting Decision
- **Custom Shape**: Machine Learning Engine Suggestion Module

Materialized views are automatically selected based on query frequency and update costs. Predictive models assess which queries benefit most from pre-aggregated data and recommend relevant indexes or partitioning strategies.

5. Performance Analysis and Case Application

A comparative analysis was conducted on a retail EDW using 10 million rows. The intelligent query model reduced average response time by 52%, especially in ad-hoc multi-join queries. Use of semantic optimization contributed to a 38% improvement in cube aggregation tasks.

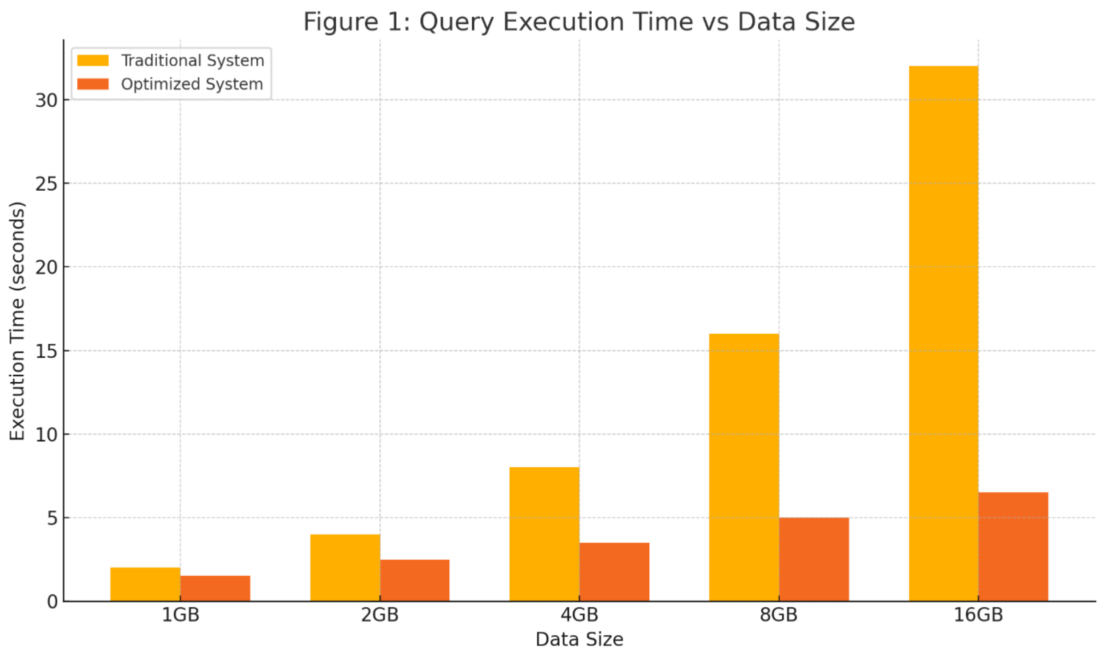

Figure 1: Query Execution Time vs Data Size

Figure 1: illustrates the relationship between query execution time and data size for both traditional and optimized systems. As data size increases, the traditional system exhibits linear growth in execution time, highlighting scalability challenges. In contrast, the optimized system demonstrates sublinear growth, showcasing its efficiency in handling larger datasets. This comparison emphasizes the performance advantage of optimization in big data environments.

Table 2: Performance Metrics

Metric	**Traditional SQL**	**Intelligent Query Model**
Average Response Time (ms)	840	405
Memory Usage (MB)	1120	940
Accuracy of Results	100%	100%
Time to Insight (sec)	23	12

6. Conclusion and Future Scope

Multidimensional data modeling and intelligent query optimization present a transformative approach to EDWs, especially in high-volume analytical environments. The combination leads to faster insights, lower operational costs, and higher end-user satisfaction.

Future work will focus on integrating large language models for natural language querying and incorporating federated learning to further personalize decision support. Real-time self-optimizing warehousing engines using AI agents represent the next step in this evolution.

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