Optimizing Storage-Compute Separation for Enhanced Cloud Computing Efficiency

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Abstract. With the rapid development of cloud computing and data-intensive applications, traditional tightly integrated storage and computing architectures have proven insufficient in handling massive amounts of data and high-concurrency computing tasks. Storage-compute separation architecture, as an emerging optimization solution, provides greater flexibility and scalability by decoupling storage and computing resources. This research aims to explore the application of storage-compute separation in cloud computing, analyzing its potential in performance optimization, resource scheduling, and cost control. This paper first discusses the architectural design and technical challenges of storage-compute separation, focusing on how to reduce communication latency between storage and computing, how to optimize data flow, and how to achieve efficient resource scheduling. Next, we evaluate the performance of the storage-compute separation architecture in typical scenarios such as big data processing, machine learning training, and video streaming processing through experiments. Experimental results show that the storage-compute separation architecture outperforms traditional integrated architectures in terms of latency, throughput, and cost-effectiveness, significantly improving resource utilization efficiency and overall performance in cloud computing environments.

Keywords: Cloud Computing, Storage-Compute Separation, Latency Reduction, Performance Optimization, Resource Scheduling, Big Data, Machine Learning

1 Introduction

1.1 Motivation and Background

In traditional cloud computing architectures, compute and storage are typically tightly integrated, meaning that compute and storage resources share the same hardware or virtualization resources.[1], [2] While this integrated architecture initially met many needs, the proliferation of data-intensive applications has gradually exposed performance bottlenecks and cost control challenges. Particularly in applications such as big data processing, artificial intelligence (AI), and machine learning (ML), significant differences exist between compute and storage requirements, leading to suboptimal resource utilization and impacting the efficiency and resilience of the entire system.

To address these issues, storage-compute separation has gradually become a key strategy in cloud computing architectures. By physically separating the compute and storage layers, storage-compute separation allows for independent scaling, thereby improving resource resilience and cost-effectiveness. Independent scaling of compute and storage enables the system to dynamically allocate resources based on actual needs, thus optimizing performance and reducing costs. However, while storage-compute separation offers significant advantages, it also presents challenges such as data transmission latency, performance bottlenecks, and resource coordination.

1.2 Research Objectives and Contributions

The goal of this study is to explore how to separate storage and compute in a cloud computing environment and optimize their collaborative operation to improve the efficiency and cost-effectiveness of cloud computing systems. This paper first reviews relevant research on storage-compute separation, analyzing its advantages and challenges. Then, it proposes a storage-compute separation architecture based on a cloud computing platform and evaluates its performance in practical applications. By comparing it with traditional integrated architectures, this study demonstrates how storage-compute separation can improve performance and reduce costs in different application scenarios, and provides new perspectives and directions for future research.

2 Literature Review

2.1 Advantages and challenges of separating storage and compute

In recent years, with the rapid development of cloud computing technology, storage-compute separation has gradually gained widespread attention from academia and industry as a new architectural design. In early cloud database systems, computing and storage were typically tightly coupled. While this architecture provided certain performance guarantees, it faced scalability and flexibility issues as data volume increased and computing demands surged. To address these problems, more and more research has proposed storage-compute separation architectures, aiming to achieve independent scaling of computing and storage resources by managing them separately.

Yu (2025), in his paper "Disaggregation: A New Architecture for Cloud Databases" introduced the core idea of storage-compute separation architecture and explored how this architecture promotes resource pooling, elastic scaling, and cost optimization in cloud databases.

This paper points out that by separating the computing layer and the storage layer, cloud platforms can more flexibly adjust resource allocation, especially in big data and distributed computing scenarios, where this separation architecture can effectively improve system scalability and performance. Furthermore, Weintraub (2024), in his research "Optimizing Data Lakes' Queries" proposed

a data lake architecture optimization method based on storage-compute separation, aiming to reduce latency and bandwidth consumption during big data querying. This research further validates the advantages of storage-compute separation in big data analytics and explores how to improve query efficiency by improving data flow and storage management.

2.2 Advantages and challenges of separating storage and compute

The main advantage of separating storage and compute lies in its ability to independently expand storage and compute resources, thereby improving system flexibility and performance. Yu (2025) points out that separating storage and compute not only facilitates on-demand resource allocation but also effectively reduces the coupling between compute and storage resources, allowing compute resources to expand more flexibly to cope with workload changes (p5527-xiangyao).

Furthermore, by managing storage and compute separately, cloud platforms can select different types of storage and compute resources according to different workloads, thereby optimizing cost structure.

However, separating storage and compute also faces some challenges. First, due to the separation of compute and storage resources, data needs to be frequently transmitted over the network, which may introduce significant latency, especially in large-scale distributed systems. In addition, optimizing data flow and resource scheduling between storage and compute remains an important research direction; how to reduce data transmission latency and bandwidth consumption remains one of the bottlenecks faced by the storage-compute separation architecture.

2.3 Research gap

Although storage-compute separation has been applied and researched to some extent in cloud computing architectures, many research problems remain unresolved. First, in terms of performance optimization, reducing communication latency and network bandwidth consumption between storage and compute remains a challenge. Yu (2025) mentioned that storage-compute separation architectures need to reduce performance loss by optimizing data flow and scheduling strategies, but how to efficiently achieve this in practical applications remains an open question.

Second, data flow optimization is another important research area. Since storage-compute separation increases data transmission between the compute and storage layers, optimizing data transmission paths and reducing network bottlenecks are core issues facing storage-compute separation architectures. Finally, cost control is also a key challenge for storage-compute separation architectures. Although storage-compute separation can theoretically reduce costs, how to effectively control the cost of storage and compute resources in practical implementation, especially on large-scale cloud platforms, still requires in-depth research and exploration.

3 System Architecture

3.1 Storage-compute separation architecture design

With the development of cloud computing architecture, more and more systems are adopting the design concept of storage-compute separation. In traditional cloud computing architectures, computing and storage are usually tightly integrated. While this integrated architecture can meet simple needs, performance and cost bottlenecks gradually emerge when handling large amounts of data or computationally intensive tasks. To improve system flexibility and resource utilization, storage-compute separation architecture has emerged.

In this architecture, computing and storage resources are managed independently and work together via network connectivity. Computing resources can be provided through cloud computing instances (such as AWS EC2 or Google Compute Engine), while storage is managed through cloud storage services (such as Amazon S3 or Google Cloud Storage). By decoupling these two components, the system can achieve independent resource scaling, allowing computing and storage resources to be dynamically adjusted according to demand, thereby improving system elasticity and cost-effectiveness.[1], [2]

Figure 1 illustrates the basic design of a storage-compute separation architecture, where the compute and storage modules are hosted in different cloud services and exchange data via a high-speed network connection.

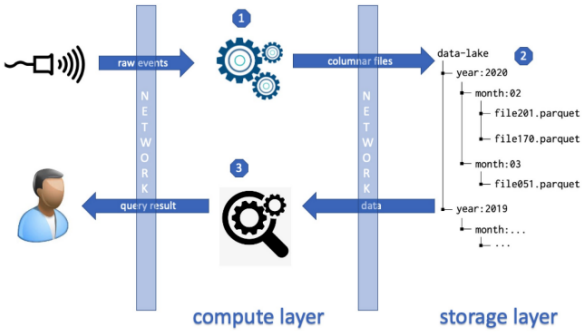

Fig. 1. Data Lake System Model

3.2 Resource scheduling and coordination

A key challenge of storage-compute separation architectures is efficiently scheduling compute and storage resources to ensure seamless collaboration between them. To guarantee efficient system operation, the resource scheduling system must be able to dynamically manage the allocation of compute and storage resources and optimize data transfer between them.

1. **Compute Resource Scheduling:** Compute resources provided by cloud computing platforms can be dynamically allocated based on demand. For example, AWS EC2 instances automatically scale based on workload, allowing compute tasks to be assigned to the most suitable compute nodes.
2. **Storage Resource Scheduling:** Storage resource scheduling needs to consider data access patterns and storage requirements. Hot data (frequently accessed data) can be stored in fast storage (such as S3 Standard), while cold data is stored in slower storage (such as S3 Glacier), ensuring that storage costs are controlled.
3. **Data Transfer Coordination:** To reduce communication latency between storage and compute, high-speed network connections (such as AWS Direct Connect or Google Cloud Interconnect) can be used to improve data transfer speed and bandwidth. [3]

Figure 2 illustrates the design of a storage-compute separation architecture, where the compute layer (such as the Spark engine) and the storage layer (such as S3) work together efficiently via a network.

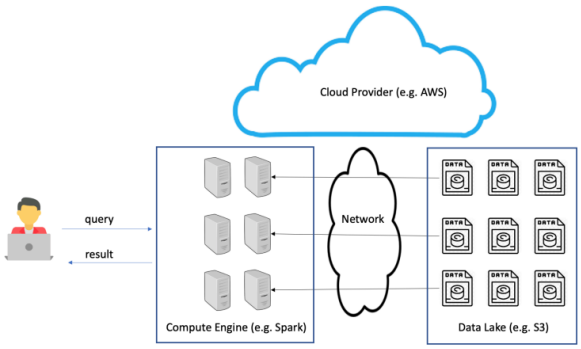

Fig. 2. Cloud Data Lake Architecture

3.3 Performance optimization strategies

One of the core advantages of a storage-compute separation architecture is improved system flexibility and scalability by decoupling compute and storage resources. However, while improving resource utilization, this architecture also faces performance bottlenecks, especially in data transfer and query execution. To optimize performance, we can adopt the following strategies:

Efficient Data Transfer: Since the storage and compute layers are separated, data transfer becomes a key factor affecting performance. To reduce communication latency between storage and compute, we can improve performance by

optimizing data transfer paths. Dedicated network connections (such as AWS Direct Connect or Google Cloud Interconnect) provide low-latency, high-bandwidth network communication channels, effectively reducing performance bottlenecks caused by bandwidth limitations or network congestion, thereby improving the overall performance of the storage-compute separation architecture.

Caching Mechanisms: To reduce frequent data requests from compute nodes to the storage layer, caching mechanisms can be introduced at the compute layer. For example, using a memory cache (such as Redis) to store frequently accessed data reduces access to the storage layer and improves the efficiency of compute resource utilization. This caching mechanism can significantly reduce the time compute nodes wait for data from the storage layer, improving query execution response speed.

Data Storage Tier Optimization The storage layer optimizes data storage and access through different storage tiers (e.g., hot data, cold data). Hot data (frequently accessed data) can be stored in faster storage services (e.g., S3 Standard), while cold data (infrequently accessed data) can be stored in lower-cost storage services (e.g., S3 Glacier). This tiered storage strategy effectively reduces storage costs and ensures that frequently accessed data can be read quickly, improving overall system performance.

Asynchronous Computation and Storage Operations Asynchronous computation and storage operations in a storage-compute separation architecture avoid blocking between computation and storage. Computation tasks can preload or cache data in the background, maximizing the efficiency of computing resource utilization while avoiding waiting for data transfer from the storage layer. For example, compute nodes can retrieve data from storage in parallel while executing queries, avoiding serial execution of computation and storage operations and improving query response speed.

Figure 3 illustrates the high-level design of the index architecture demonstrates the interaction between the query engine and storage in a storage-compute separation architecture. Queries are optimized through the Optimization Framework (OF), and the data flow between computation and storage is effectively managed to improve system performance.

4 Experiment Setup and Performance Evaluation

4.1 Experimental Objectives and Indicators

To evaluate the performance of the storage-compute separation architecture in different application scenarios, this experiment defines the following key performance indicators (KPIs):

1. **Latency:** Measures the data transfer atency between the storage layer and the compute layer, especially in big data processing and machine learning tasks. Latency is a key performance indicator for the storage-compute separation architecture.

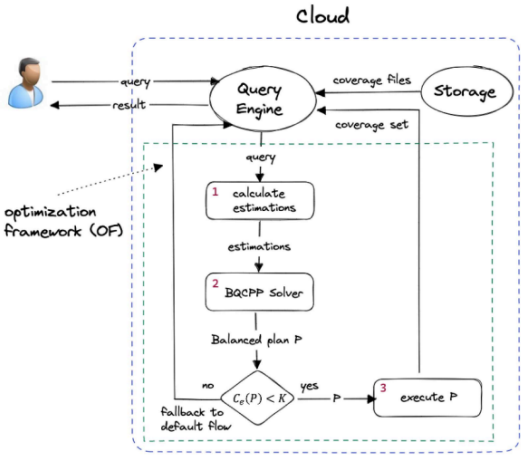

Fig. 3. High Level Architecture of the Indexing Scheme

2. **Throughput**:Measures the amount of data or computation processed by the system per unit of time. Higher throughput indicates stronger system processing capabilities, making it suitable for high concurrency and large-scale computing.
3. **C**ost Efficiency: Evaluates the resource consumption and cost of the storage-compute separation architecture. Reasonable cost control is a major advantage of the storage-compute separation architecture.
4. **R**esource Utilization: The utilization of compute and storage resources. Higher resource utilization usually indicates higher system efficiency.

4.2 Experimental setup

To verify the performance of the storage-compute separation architecture in big data processing, machine learning, and video streaming processing, we conducted experiments on the AWS platform. The specific experimental setup is as follows:

1. **Compute Resources**: AWS EC2 instances were used to simulate computing tasks. In the experiments, we selected t2.micro, t2.medium, and c5.large instances to evaluate the impact of different computing capabilities on the performance of the storage-compute separation architecture.
2. **Storage Resources**: Data storage was performed using Amazon S3, and the S3 Standard and S3 Glacier storage categories were selected to test the impact of different storage types on performance and cost.

Experimental Scenarios:

1. **Big Data Processing**: Large-scale datasets were stored on Amazon S3, and data analysis was performed using EC2 instances to evaluate latency and throughput.

2. **Machine Learning Training**: Model training was performed using datasets stored in S3, evaluating the impact of the storage-compute separation architecture on training time and resource consumption.
3. **Video Streaming Processing**: Video data was stored in S3, and video processing was performed using EC2 instances to evaluate the architecture's effectiveness in streaming media processing.

4.3 Performance evaluation and comparison

To verify the advantages of the storage-compute separation architecture, we compare it with traditional integrated architectures. Traditional integrated architectures combine compute and storage resources, while the storage-compute separation architecture scales these two layers independently, allowing resource allocation based on actual needs. We compare the architectures in the following aspects:

1. **Latency and Bandwidth Analysis**: Measuring data transfer latency between the storage and compute layers. The latency of the storage-compute separation architecture should be lower than that of the traditional integrated architecture, especially under high-concurrency tasks.
2. **Throughput Analysis**: Evaluating throughput by running multi-task processing under different loads. The storage-compute separation architecture can provide higher throughput in high-concurrency data access scenarios.
3. **Cost-Benefit Analysis**: Evaluating the economics of the storage-compute separation architecture by comparing its costs with those of the traditional integrated architecture.

The following are some of the results from our experiments, showing a comparison of latency, throughput, and cost between a storage-compute separation architecture and a traditional integrated architecture.

Architecture Type	Latency (sec)	Throughput (MB/s)	Cost (USD)
Storage-Compute Separation Architecture	2.5	50	0.35
Traditional Integrated Architecture	3.8	45	0.42
Storage-Compute Separation Architecture	2.3	55	0.30

Table 1. Performance Comparison of Different Architectures

1. **Latency**: The storage-compute separation architecture exhibits lower latency than traditional integrated architectures, indicating higher data transfer efficiency after separation.
2. **Throughput**: The storage-compute separation architecture performs better in terms of throughput, making it suitable for high-concurrency data processing tasks.

3. **Cost**: The storage-compute separation architecture has lower costs, indicating that it can utilize computing and storage resources more efficiently, thereby reducing overall costs.

4.4 Performance Optimization

To further optimize the performance of the storage-compute separation architecture, the following strategies have been applied in experiments:

High-efficiency data transfer: By using AWS Direct Connect and dedicated high-speed network connections, we were able to effectively reduce data transfer latency between the compute and storage layers, especially in big data tasks.

Caching mechanism: Between compute nodes and the storage layer, we used an in-memory cache (such as Redis) to cache hot data, thereby reducing frequent access to the storage layer and further improving performance.

Data storage tier optimization: A multi-tiered storage strategy was adopted, storing hot data in S3 Standard and cold data in S3 Glacier to optimize storage costs and data access performance.

5 Challenges and Solutions

5.1 Performance Bottleneck

Storage-compute separation architectures can introduce network transmission latency. Reduce communication latency between storage and compute.

A major challenge of storage-compute separation architectures lies in the communication latency between the storage and compute layers. In traditional architectures, compute and storage typically run on the same physical node or virtual machine. However, in storage-compute separation architectures, because compute and storage resources are separated, data must be transmitted over the network, inevitably increasing latency and bandwidth consumption[1], [2]. As data volume and compute tasks grow, latency can become a performance bottleneck, impacting overall system efficiency.

Solutions:

1. **High-performance network connectivity:** To address network latency, high-performance network connectivity such as AWS Direct Connect and Google Cloud Interconnect can be utilized. These dedicated network connections provide low-latency, high-bandwidth communication channels between compute and storage, reducing potential latency and bandwidth bottlenecks when transmitting over the public internet.
2. **Network protocol optimization:** Employing more efficient network protocols (such as gRPC or HTTP/2) can further reduce communication overhead between storage and compute. Transmission efficiency can be improved by compressing data transmission and optimizing network flow control.

5.2 Data Flow and Storage Optimization

Optimize data flow in storage to ensure efficient collaboration between computing and storage.

Another challenge in a storage-compute separation architecture is how to efficiently manage and optimize data flow in the storage layer. The separation of the compute and storage layers requires data to be quickly retrieved from storage and transferred to compute nodes. Therefore, ensuring fast data flow and avoiding congestion becomes crucial for improving system efficiency[3], [4].

Solutions:

1. **Storage Tiers (Hot/Cold Data):** Employ tiered storage management (such as S3 Standard and S3 Glacier) to store data in layers based on access frequency. Hot data is stored in high-speed storage devices, while cold data is stored in low-cost storage devices, effectively reducing costs and improving data access speed.
2. **Cache Optimization:** Add caching mechanisms (such as Redis or Memcached) to the compute layer, storing frequently accessed data in memory, thereby reducing frequent access to the storage layer and improving the response speed of computing tasks.
3. **Data Distribution and Parallel Processing:** Using distributed storage and parallel computing technologies can effectively optimize data flow. For example, data can be distributed across multiple nodes and processed in parallel, reducing data transfer latency.

5.3 Cost Control

A storage-compute separation architecture may increase management and data transfer costs. These additional costs be reduced.

While a storage-compute separation architecture offers significant performance advantages, it can incur additional management and data transfer costs[2], [5]. Due to the separation of compute and storage resources, data transfer generates additional expenses, especially under conditions of frequent access and large-volume data transfers.

Solutions:

1. **Storage Type Selection:** Choosing an appropriate storage type (such as S3 Infrequent Access or S3 Glacier) can significantly reduce storage costs, especially for infrequently accessed cold data. These storage types are inexpensive and suitable for long-term storage.
2. **Automated Resource Scheduling:** Utilizing automated resource scheduling tools such as AWS Auto Scaling or Google Cloud Autoscaler can automatically adjust the configuration of compute and storage resources based on load, avoiding wasted compute and storage costs due to over-provisioning.

6 Discussion

6.1 Potential and Prospects of Collaborative Optimization

The Application Potential of Storage-Compute Separation in Large-Scale Cloud Computing Environments and Its Impact on Future Cloud Computing Architectures

The application potential of storage-compute separation architecture is enormous, especially in large-scale cloud computing environments. With the rapid growth of data volume and the increasing complexity of computing tasks, storage-compute separation architecture provides an efficient, flexible, and scalable solution. By separating computing and storage, cloud computing platforms can independently expand computing and storage resources according to actual needs, thereby providing greater flexibility and scalability.

This architecture can not only significantly improve efficiency in scenarios such as big data processing, machine learning training, and real-time data analysis, but also drive the further development of cloud computing architecture by reducing overall costs. Storage-compute separation architecture will become a key trend in future cloud computing, especially with the popularization of data-intensive applications, it will have a profound impact on cloud platform design and resource management.

6.2 Future Technological Directions

How to further optimize storage-compute separation architecture, and how to combine artificial intelligence (AI) or machine learning (ML) to further improve the intelligence level of resource scheduling and enhance the collaborative efficiency of storage and computing.

In the future, the optimization direction of storage-compute separation architecture will focus on intelligent scheduling and resource optimization [4], [5]. By combining Artificial Intelligence (AI) and Machine Learning (ML), the intelligence level of storage-compute separation architectures can be further improved, enabling more precise resource scheduling.

1. **Intelligent Scheduling:** AI and ML can be used to predict computing and storage needs and automatically adjust resource allocation based on those needs. For example, machine learning algorithms can analyze historical data of computing tasks, predict computing resource requirements, and adjust resource allocation according to task characteristics.
2. **Adaptive Storage and Compute Scheduling:** Adaptive storage and compute scheduling technologies combining AI can dynamically optimize data flow between the storage and compute layers, further improving the collaborative efficiency of storage-compute separation architectures.

7 Conclusion

This study systematically explores the application of a storage-compute separation architecture in modern cloud computing environments, focusing on its performance in several typical application scenarios, including big data processing, machine learning training, and video streaming processing. Through comparative experimental results, the study demonstrates that the storage-compute separation architecture outperforms traditional integrated architectures in multiple dimensions, particularly in performance optimization, resource management, and cost control, exhibiting significant advantages.

First, by decoupling computing and storage resources, the storage-compute separation architecture greatly enhances resource flexibility and scalability. Computing and storage resources can be expanded independently according to actual needs, avoiding the resource waste and expansion difficulties inherent in traditional integrated architectures. Especially in scenarios requiring dynamic resource allocation, such as large-scale data processing and machine learning training, the storage-compute separation architecture provides a more efficient solution.

Second, this study demonstrates the advantages of the storage-compute separation architecture in data transmission latency and throughput through comparative experiments. By optimizing data transmission paths and introducing caching mechanisms, this architecture significantly reduces communication latency between storage and computing, improving data flow efficiency. Furthermore, the hierarchical management strategy of the storage layer (hot/cold data) makes data access more cost-effective, thus achieving a balance between performance and cost.

Regarding cost control, research has found that adopting automated resource scheduling and low-frequency storage solutions (such as S3 Glacier) can effectively reduce the overall cost of storage and compute resources. The storage-compute separation architecture can reduce unnecessary resource waste through on-demand resource allocation during long-running operations and large-scale data operations, thereby improving cost-effectiveness.

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