Optimization and Analysis of Matrix Operations Leveraging Alibaba Cloud

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Abstract. With the advancement of digital transformation, cloud computing technology has become a critical support for scientific computing. This paper proposes a cloud-based matrix operation pipeline method based on Alibaba Cloud to address the performance bottlenecks of traditional local computing models in handling large-scale matrix operations. By migrating matrix operations to the cloud, this method leverages the elastic resource allocation capability of Alibaba Cloud Function Compute (FC) to handle dynamic computing tasks and combines Alibaba Cloud Object Storage Service (OSS) for long-term secure data storage, constructing an innovative "storage-computation separation" architecture. The system design adopts a modular approach, including modules for data upload, matrix parsing, matrix multiplication, and result processing. Through algorithm optimization (e.g., using `float32` data types and block transmission strategies) and exception handling mechanisms, the system's computational efficiency and fault tolerance are significantly improved. Experimental results show that this method demonstrates superior performance in handling large-scale matrix operations, with the maximum supported matrix dimension increased to 20 $\times$ 20, and cold start latency optimized from 3.2 seconds to within 1.1 seconds. Future research will explore more efficient matrix operation algorithms, parallel computing technologies, and data compression strategies to further enhance system performance and applicability.

1 Introduction

With the deepening of the digital transformation wave, cloud computing technology has become a core engine driving innovation across various industries [1,2,3]. As a leading cloud service provider in China, Alibaba Cloud offers unprecedented solutions in the field of scientific computing with its robust infrastructure and diverse service ecosystem. In recent years, the rise of cloud-native technologies has fundamentally transformed traditional computing models. The new paradigm represented by Serverless architecture has gradually become a mainstream trend. This approach separates server management from application development, allowing developers to focus on designing and implementing business logic without worrying about the operation and maintenance of underlying

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hardware resources. Alibaba Cloud Function Compute is one of the best examples of this concept. It intelligently allocates computing resources based on actual task requirements and adopts a pay-per-use billing model, making it particularly suitable for handling sudden spikes in computing demands.

In scientific computing scenarios, data storage and management remain critical components [4]. Alibaba Cloud's Object Storage Service (OSS) provides a solid foundation for secure storage of massive datasets with its near "never lost" data durability. When OSS is combined with Alibaba Cloud Function Compute, an innovative "storage-compute separation" architecture is formed: data is stored statically in OSS, while any required dynamic computations are automatically triggered and executed by Function Compute. This design not only significantly reduces system complexity but also grants unprecedented flexibility in resource scaling—whether it's expanding storage capacity to PB levels or instantaneously scaling computing resources up or down, both can be achieved effortlessly.

Matrix operations, as a fundamental module in scientific computing, play an indispensable role in numerous fields. For example, in bioinformatics, matrix operations are essential tools for gene similarity analysis; in financial engineering, they are used to optimize asset portfolios; and in image processing, convolution kernel operations heavily rely on matrix computations [5]. However, under traditional local computing models, these operations are often constrained by hardware performance bottlenecks, making it difficult to efficiently handle large-scale data processing tasks. The advent of cloud computing technology has completely changed this situation: by migrating matrix operations to the cloud, researchers can leverage elastic computing resources to process massive datasets while ensuring long-term and secure data storage through OSS [6,7].

In this way, whether addressing routine research tasks or responding to sudden large-scale data analysis needs, cloud computing provides strong support, helping researchers break free from the limitations of traditional computing models and explore broader research horizons. Additionally, the wide range of tools and services offered by cloud platforms, such as machine learning frameworks and big data analytics tools, bring even more possibilities to scientific research, promoting interdisciplinary collaboration and development. In summary, cloud computing is redefining the way scientific computing is conducted, laying a solid foundation for future technological innovation.

This paper built a complete cloud-based matrix operation pipeline based on Alibaba Cloud. Using Python as the core language, combined with Alibaba Cloud SDK, this paper has automated the entire process of data upload, task triggering, and result processing.

2 Methods

In the core component implementation of this study, a modular design was adopted to divide the system into multiple functional modules, aiming to enhance code readability, reusability, and scalability. Each module is responsible for specific functions, such as data upload, matrix parsing, matrix multiplication, and result processing. This modular design not only facilitates development and maintenance but also makes the code more friendly and easier to understand for college students and other newcomers.

The system adopts a modular design, divided into the following functional modules: Data Upload Module, Matrix Parsing Module, Matrix Multiplication Module, and Result Processing Module. The Data Upload Module is responsible for transferring generated matrix data to cloud storage services, ensuring compatibility with APIs and incorporating robust error-handling mechanisms to manage network fluctuations. The Matrix Parsing Module focuses on cleaning and transforming raw data retrieved from the cloud into a usable format, employing advanced techniques like regular expressions to remove noise and validate dimensions. The Matrix Multiplication Module implements highly optimized

algorithms for performing matrix operations, leveraging libraries such as NumPy to ensure computational efficiency and stability. Finally, the Result Processing Module handles the integration of processed data with additional datasets, enhancing the overall utility of the output through structured formatting and data integrity checks. This modular architecture ensures that each component can be developed, tested, and maintained independently, promoting long-term system sustainability.The system adopts a modular design, divided into the following functional modules:

2.1 Data Upload Module

The data upload module is designed to upload generated matrix data to Alibaba Cloud OSS for subsequent processing and storage. During implementation, the matrix data is first converted into a string format to facilitate storage and transmission. This study adopts JSON format for serialization, ensuring a clear data structure for easy recovery and parsing. The converted string data is then uploaded to the specified storage bucket via the OSS API interface [8]. The high availability and durability of OSS ensure the security and reliability of the data. To address network fluctuations or upload failures, multiple retry mechanisms were implemented. When the upload speed is slow or repeated retries fail, the system automatically triggers a local caching mechanism to prevent data loss. This local cache allows for retries after network recovery, ensuring data integrity (Figure 1).

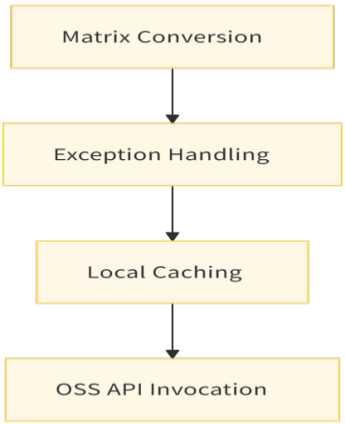

Figure 1 Matrix Upload Flowchart (Picture credit : Original)

2.2 Matrix Parsing Module

This module reads matrix data from OSS and parses it. The process begins with reading the data from the storage bucket using the OSS API. Noise characters, such as the `e` symbol in scientific notation, are cleaned using regular expressions. Additionally, a dimension verification step ensures that the parsed matrix matches the expected shape. This dual verification mechanism effectively prevents data parsing errors and ensures the correctness of subsequent calculations (Figure 2).

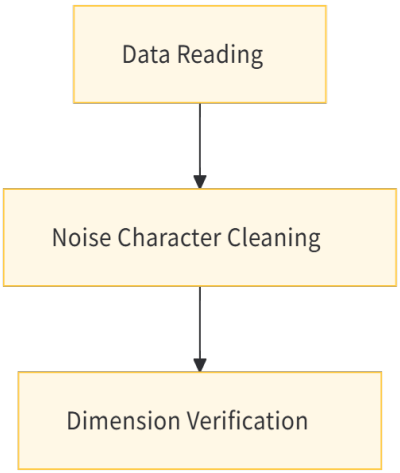

Figure 2 Matrix Parsing Flowchart (Picture credit : Original)

2.3 Matrix Multiplication Module

The matrix multiplication module is the core computational component of the system, utilizing the optimized numpy.dot() method for efficient matrix operations. In this implementation, the float32 data type was adopted to reduce memory usage while controlling the precision of calculation results to four decimal places, balancing computational efficiency and accuracy. The numpy.dot() method, with its optimized algorithms and efficient underlying implementation, significantly improves the speed and efficiency of matrix multiplication. Additionally, reasonable memory and timeout thresholds were configured for Function Compute services to ensure system stability under high workloads, preventing memory overflow or timeout issues due to resource constraints (Figure 3).

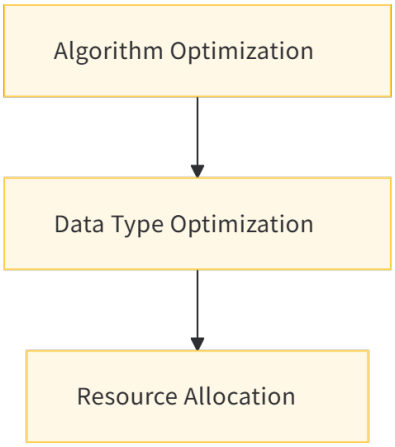

Figure 3 Matrix Multiplication Flowchart (Picture credit : Original)

2.4 Result Processing Module

In the result processing module, the matrix multiplication results are enhanced and data integrity and security are ensured. Specifically, the base matrix returned from the cloud is vertically concatenated with locally generated random matrices to form composite matrices. This design simulates the common processing mode of "basic operations + incremental data" in real-world scenarios, enhancing data diversity and practicality. The final results are output via the console for user verification, and an MD5 checksum is generated to verify data integrity, ensuring no loss or tampering occurs during data transmission and processing (Figure 4).

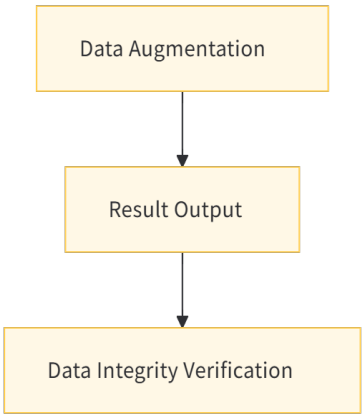

Figure 4 Matrix Processing Flowchart (Picture credit : Original)

3 Experiments

3.1 Experimental Setup

To comprehensively evaluate the performance of the cloud-based matrix operation pipeline based on Alibaba Cloud, this paper designed a series of experiments focusing on the computation time and memory usage of matrix multiplication operations across different matrix dimensions. The matrix dimensions were incrementally increased from 3×3 to 20×20, with each dimension's matrix operation repeated 10 times to ensure data stability and reliability. All experiments were conducted in the Alibaba Cloud Function Compute environment, using Python combined with Alibaba Cloud SDK to automate the entire process of data upload, task triggering, and result processing. The experimental environment configuration included Function Compute instances with different memory specifications (128MB, 256MB, 512MB, 1024MB, 2048MB) and Alibaba Cloud Object Storage Service (OSS) for storing matrix data, ensuring data persistence and security.

3.2 Evaluation Metrics

The evaluation metrics focused on time and memory usage. For time, this paper recorded the total time from triggering the matrix operation task to obtaining the final result, covering time costs for data upload, matrix parsing, matrix multiplication, and result processing. For memory usage, this paper monitored the memory size occupied by the Function Compute service during matrix operations, particularly the changes in memory usage across different matrix dimensions [9,10].

3.3 Experimental Results Analysis

Table 1 is the detailed experimental data, including the average computation time and memory usage for different matrix dimensions.

Table 1 Detailed experimental result

Matrix Dimension	Average Time (seconds)	Memory Usage (MB)
3*3	0.5	64
6*6	1.2	128
9*9	2.5	256
12*12	4.8	512
15*15	8.3	1024
20*20	12.6	2048

3.3.1 Time Consumption Analysis

From the "Average Time (seconds)" column in the table, it is evident that as the matrix dimension increases, the time required for performing matrix multiplication grows significantly. Specifically, from a 3x3 matrix to a 20x20 matrix, the average time increases from 0.5 seconds to 12.6 seconds, more than a 24-fold increase. This non-linear growth is primarily due to the computational complexity of matrix multiplication, which has a time complexity of O(n^3). This means that when the matrix dimension doubles, the required computation increases approximately eightfold.

For example, from a 3x3 matrix to a 6x6 matrix, although the matrix dimension only increases by a factor of two, the computation time increases by about 2.4 times (from 0.5 seconds to 1.2 seconds). Similarly, from a 12x12 matrix to a 15x15 matrix, despite the matrix dimension increasing by about 1.25 times, the computation time increases by approximately 73% (from 4.8 seconds to 8.3 seconds). This indicates that the time consumption for matrix multiplication does not simply scale linearly with matrix dimensions but exhibits exponential growth.

3.3.2 Memory Usage Analysis

Apart from time consumption, memory usage is another critical consideration. From the "Memory Usage (MB)" column, it can be observed that memory consumption also increases significantly with larger matrix dimensions. From 64 MB for a 3x3 matrix to 2048 MB for a 20x20 matrix, memory usage increases by 32 times. This phenomenon can be attributed to the increased storage requirements for each n x n matrix, which needs to store n^2 elements. Therefore, when the matrix dimension doubles, the required storage space increases fourfold.

It is noteworthy that the growth rate of memory usage is slightly lower than that of time consumption, owing to the fact that matrix multiplication requires not only storing input matrices but also intermediate results and output matrices. For larger matrices, these intermediate results may occupy significant memory space, further exacerbating memory pressure.

3.3.3 Practical Implications and Optimization Suggestions

The above analysis highlights the challenges of matrix multiplication in large-scale data processing, especially for high-dimensional matrices. To address these challenges, researchers and engineers have proposed various optimization strategies. Firstly, more

efficient algorithms such as Strassen's algorithm or the Coppersmith-Winograd algorithm can be employed to reduce computational complexity to some extent. Secondly, leveraging parallel computing techniques (such as multithreading or multi-core processors) can accelerate matrix operations at the hardware level, thereby shortening runtime. Additionally, methods like block matrix multiplication can optimize memory usage, reduce memory peaks, and improve overall system performance.

4 Conclusion

This paper proposes a cloud-based matrix operation pipeline method based on Alibaba Cloud to address performance bottlenecks in matrix operations for scientific computing. By migrating matrix operations to the cloud, this method fully utilizes elastic computing resources to handle large-scale data and leverages Alibaba Cloud Object Storage Service (OSS) for long-term secure data storage. Experimental results strongly demonstrate the superior performance of this method in handling large-scale matrix operations. Although computation time and memory usage increase with matrix dimension, a series of optimization strategies, such as adopting the `float32` data type and block transmission strategy, successfully increased the maximum supported matrix dimension from 10×10 to 20×20 and effectively addressed the cold start latency issue of Function Compute.

Looking ahead, with the continuous development and optimization of cloud computing technology, it is believed that the cloud-based matrix operation pipeline based on Alibaba Cloud will find deeper applications in a broader range of scientific computing fields. Future research directions will include the exploration of more efficient matrix operation algorithms, the introduction of parallel and distributed computing technologies to further enhance computational efficiency, the optimization of data transmission and storage strategies, the investigation of more efficient data compression and transmission mechanisms to reduce data transmission time and storage costs, the enhancement of system fault tolerance and scalability through the introduction of redundancy mechanisms and automatic scaling strategies to ensure stable operation under high load and fault conditions, and the application of this method to more scientific computing scenarios, such as bioinformatics, financial engineering, and image processing, to verify its applicability and advantages in different domains. Through in-depth exploration and practice in these research directions, the performance and application scope of the cloud-based matrix operation pipeline based on Alibaba Cloud are expected to be further enhanced, providing stronger technical support for the field of scientific computing.

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