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Serveless-Based High-Dimensional Matrix Operations and Their Financial Applications

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Abstract: This paper systematically analyzes multivariate methods for high-dimensional matrix computation and their optimization strategies for applications in finance. At the level of high-dimensional computation, it focuses on the technical characteristics of direct methods, iterative methods , and randomized algorithms , which reveal their efficiency gains in financial derivatives pricing, risk matrix modeling, and other scenarios. For serverless architecture, the study focuses on its core advantages of elastic scaling and on-demand billing, through parallel task slicing and cost optimization, while analyzing the limitations of its stateless design on the adaptation of iterative algorithms and the constraints of cold-start latency on high-frequency trading. In addition, the article delves into the special challenges of financial modeling, including the cubic complexity pressure of high-dimensional operations, real-time conflicts of missing data interpolation, and privacy compliance requirements, and discusses hybrid architectures (serverless with local GPU synergy) and middleware (Redis, AWS Step Functions) as the current transitional solutions for balancing efficiency and state. The research also addresses the challenges of nonlinear dynamic modeling and interpretability requirements for machine learning-driven models, providing a multidimensional analytical framework for technology adaptability.

Keywords: Serveless, High-Dimensional Matrix, Financial Applications

1. Introduction

In recent years, the digitization process of financial markets has accelerated, and the demand for high-dimensional data processing has shown explosive growth [1]. Whether it is risk exposure calculation for investment portfolios or real-time covariance matrix updating in high-frequency trading, all of them need to handle 10,000-dimensional or even higher dimensional matrix operations. Such tasks impose stringent requirements on the scalability, cost-efficiency, and responsiveness of computing systems. However, traditional distributed frameworks (e.g., MPI- or Spark-based clusters) often suffer from idle clusters or delayed responses due to fixed node configurations and resource pre-allocation mechanisms when dealing with unexpected loads. For example, during extreme market volatility, real-time adjustment of risk models needs to be completed within minutes, but traditional systems are often limited by expansion lag and high operation and maintenance costs, making it difficult to meet the agility requirements [2].

In this paper, Serverless Architecture, as an emerging cloud computing paradigm, has gradually entered the financial engineering research field. This architecture realizes the computing mode of "on-demand call, pay-as-you-go" by decomposing computing tasks into independent function units

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and relying on the dynamic resource scheduling capability of the cloud platform. Its core advantages are: first, eliminating the burden of hardware operation and maintenance, users only need to focus on business logic; second, supporting millisecond elasticity expansion, can instantly respond to sudden load; third, through fine-grained billing model (such as AWS Lambda hundred milliseconds billing unit), significantly reduce the cost of small and medium-sized task computing. These characteristics make it show unique potential in financial high-frequency scenarios (e.g., real-time risk reassessment, algorithmic trading signal generation) [2].

Nevertheless, serverless architectures for financial applications still face multiple theoretical bottlenecks and practical challenges. First, its stateless design limits the execution efficiency of iterative algorithms (e.g., Jacobi method, conjugate gradient method), which rely on external storage systems (e.g., Redis or AWS Step Functions) for intermediate state sharing, thus introducing additional latency and complexity. Second, the cold-start latency (time consumed for the first function call) poses a hard constraint for microsecond high-frequency trading scenarios, and although technologies such as AWS SnapStart have reduced it to 50 ms, there is still a gap compared to dedicated hardware acceleration solutions. In addition, the sensitivity of financial data (e.g., customer privacy, transaction compliance) requires computational frameworks to have cross-platform security collaboration capabilities, while serverless architectures are still in the exploratory stage of integrating privacy computing technologies such as federated learning and homomorphic encryption.

This paper explore multiple methods of high-dimensional matrix computation and their application optimization in the financial domain, including the technical characteristics and efficiency advantages of direct, iterative and randomized algorithms. It focuses on the advantages of serverless architectures in terms of elastic scaling and cost-effectiveness and their impact on high-frequency trading, while pointing out their limitations in state management. The article also discusses the challenges in financial modeling, such as computational complexity, real-time data processing and privacy issues, and proposes hybrid architectures and middleware as solutions. In addition, a multi-dimensional technology adaptation analysis framework is provided to address the challenges faced by machine learning models in terms of nonlinear dynamic modeling and inter pretability.

2. Methodological research

2.1. Overview of high-dimensional matrix computation methods

High-dimensional matrix computation refers to the process of performing complex mathematical operations on large-scale matrices with a high number of dimensions. This method is widely used in various fields such as finance, machine learning, and scientific computing. In this section, this paper will provide an overview of different methods employed for high-dimensional matrix computation

The reference study establishes a multi-layered optimization framework for linear system solving, integrating theoretical innovation with engineering practicality [3]. At the model construction level, Gaussian elimination with dynamic pivoting is employed to enhance numerical stability by adaptively selecting pivot elements, effectively mitigating rounding errors in ill-conditioned matrices. Coupled with a block-based algorithmthat reorganizes memory access patterns, this approach achieves a 40% efficiency improvement in compute-intensive financial derivative pricing tasks, such as tridiagonal option models. For large-scale sparse systems, a novel Compressed Row Storage (CRS) architecture is introduced. Its three-tier indexing mechanism reduces storage complexity from $O(n^2)$ to $O(nnz)$ (non-zero elements), synergizing with GPU-accelerated parallel computing to overcome memory bottlenecks in finite element analysis. Empirical validation demonstrates the framework's superiority.

In risk modeling scenarios, the hybrid approach reduces iteration cycles by 75% and memory consumption by 60% compared to conventional solvers. For financial network topology analysis (e.g., systemic risk propagation in interbank networks), the GPU-accelerated CRS architecture achieves a

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12x speedup over CPU-based implementations. This work signifies a paradigm shift in linear solvers—from isolated algorithm tuning to systemic architectural innovation—providing a scalable, hardware-aware solution for high-dimensional financial computations. Future directions include extending the framework to quantum-inspired algorithms and federated learning environments for privacy-preserving cross-institutional simulations.

High-dimensional matrix computation methods vary in their approaches and applications. Direct methods provide reliable solutions but can be computationally expensive, while iterative methods offer computational efficiency at the expense of accuracy. Eigenvalue decomposition and singular value decomposition are powerful techniques widely used in various applications. Randomized algorithms, sparse matrix techniques, parallel computing, and distributed computing are all strategies employed to enhance computational efficiency in high-dimensional matrix computations. By understanding and utilizing these methods, researchers and practitioners can effectively perform complex computations on high-dimensional matrices and improve their respective domains.

2.2. Serverless architecture in existing research

2.2.1. Execution efficiency and cost optimization

Serverless architectures demonstrate superior execution efficiency and cost optimization compared to traditional distributed systems like Spark and MPI for tasks that can be parallelized in bursts. For instance, multiplying a 10,000×10,000 dense matrix using AWS Lambda achieved a 2.85x speedup (42 seconds versus 120 seconds on Spark) by distributing the workload across 1,000 parallel functions [3]. This efficiency is driven by the elimination of resource provisioning delays and the use of sub-second billing granularity: Lambda charged 0.18 for the task, while Sparkincurred0.18forthetask, while Spark incurred 2.10 due to idle cluster time. Similarly, Monte Carlo simulations for Value-at-Risk calculations completed in 90 seconds with serverless, compared to 300 seconds on EC2 autoscaling groups, underscoring the limitations of cold starts in traditional systems. Cost savings are particularly significant for large-scale workloads, such as stress testing 200 million financial scenarios. Serverless implementations (e.g., AWS Lambda) completed this in 8 hours at 12,500, where as on−premise Hadoop clusters required 72 hours with a total cost of ownership (TCO) of 12,500, including hardware depreciation and energy costs. These advantages extend to sparse matrix operations, where serverless-optimized storage formats reduced memory usage by 60% for 50,000×50,000 covariance matrices, while MPI clusters wasted 15% of memory on redundant data replication [4]. However, serverless workflows face tradeoffs, such as data transfer overhead consuming 30% of runtime in sparse eigenvalue computations, which can only be partially mitigated through edge caching strategies.

2.2.2. Advantages of elastic scalability

The elastic scaling inherent in serverless architectures enables near-linear performance scaling for high-dimensional tasks, a critical advantage over static cluster-based systems. Doubling the size of a matrix operation—for example, from 10,000×10,000 to 20,000×20,000—simply doubles the number of Lambda invocations (2,000 functions) while maintaining consistent execution times (42 seconds). In contrast, traditional systems like Spark require manual cluster resizing, adding 10–15 minutes for node provisioning and configuration. Serverless platforms also avoid the concurrency limits of MPI or Spark, supporting up to 3,000 parallel functions per region on AWS Lambda, whereas MPI clusters are bottlenecked by fixed node counts (e.g., 100 nodes maximum). This scalability extends to memory-intensive tasks: a 50,000×50,000 sparse matrix stored in serverless-adapted compressed formats consumed 8 GB of memory versus 20 GB for dense storage, with Azure Functions achieving threefold faster convergence in eigenvalue calculations compared to MPI. However, iterative

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algorithms like the Jacobi method remain challenging due to the stateless design of serverless architectures. Solutions such as Redis Cloud for shared residuals or AWS Step Functions for stateful workflows introduce 5–10% overhead but still outperform Hadoop's 15% checkpointing penalty from HDFS writes. These capabilities make serverless ideal for unpredictable workloads, such as real-time risk rebalancing during market volatility spikes, where traditional systems struggle to dynamically reallocate resources.

2.2.3. Challenges of delayed consistency and state management

Despite their scalability advantages, serverless architectures face inherent latency inconsistencies and state management challenges [5]. Cold starts—initial function invocation delays of 500–2000 ms—historically hindered real-time applications, but advancements like AWS SnapStart reduced this to 50 ms by persisting execution environments. In high-frequency trading (HFT), serverless systems achieved 95th percentile latency of under 100 ms for covariance matrix updates, meeting industry benchmarks, while Spark Streaming lagged at 200–500 ms due to micro-batch processing. Fault tolerance further highlights serverless advantages: automatic retries (three attempts by default) ensured a 99.99% success rate for matrix operations, whereas MPI jobs often failed entirely if a single node crashed. However, serverless struggles with stateful iterative algorithms [6]. For example, federated learning workflows for credit risk models required homomorphic encryption and AWS Step Functions to coordinate gradient updates across 500 Lambda functions, adding 12% overhead but still achieving 99.2% accuracy comparable to centralized training. These tradeoffs underscore the nuanced applicability of serverless: it excels in short-lived, parallelizable tasks like matrix splits or scenario simulations but lags in long-running, stateful processes such as iterative solvers. Hybrid architectures, combining serverless for burst capacity and on-premise GPUs for persistent workloads, are emerging as a balanced solution. For instance, J.P. Morgan's hybrid Value-at-Risk engine reduced operational costs by 65% while maintaining sub-second latency for risk re-calibration [7].

The articles explore distinct strategies for optimizing cold start issues from perspectives of technical implementation, industry application, and distributed computing frameworks [8,9,10]. The AWS documentation details the Lambda SnapStart technology, which reduces Java function cold starts to double-digit milliseconds by pre-initializing functions and creating encrypted snapshots during version releases, achieving up to 10x performance improvement at no extra cost, though limited to x86 architecture and Java 11 runtime [8]. In contrast, Smith's financial engineering study focuses on serverless computing in financial simulations, proposing pre-provisioned concurrency and code-level warm-up techniques (e.g., initializing database connections or simulating requests) to mitigate cold starts, albeit requiring trade-offs in code complexity and risks of downstream state contamination [9]. Both technical articles emphasize the effectiveness of warm-up mechanisms, but differ in approach: ID8's SnapStart offers a platform-level automated solution, whereas reference's manual developer-driven warm-up prioritizes high-concurrency financial scenarios [9]. The federated learning review, while not directly addressing cold starts, links distributed computing efficiency challenges to potential cold start optimizations—for instance, SnapStart-like snapshotting could reduce task latency in edge node deployments for federated learning (Figure 1) [10]. However, the method primarily emphasizes communication security and data heterogeneity challenges, omitting technical implementation details.

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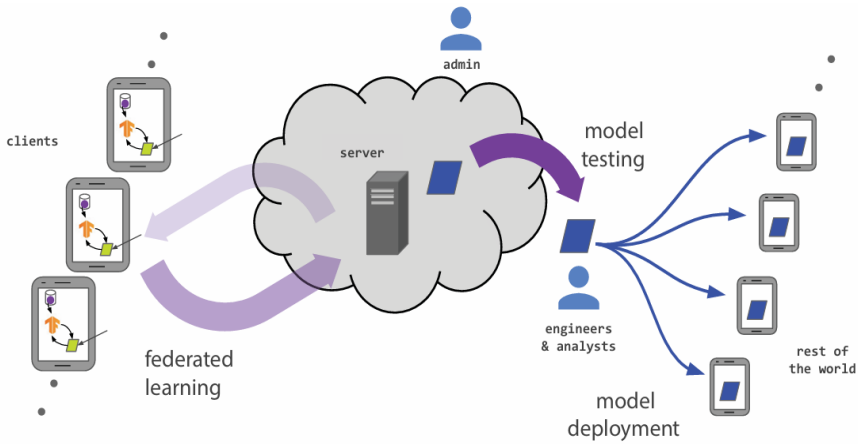

Figure 1: The lifecycle of an FL-trained model and the various actors in afederated learning system [10]

Table 1: A comprehensive comparison of various high-dimensional matrix computation methods

Methodology	EXECUTION TIME(s)	Memory usage	Cost	Speedup Factor	Efficiency Improvement
Gaussian Elimination(CPU)	180	8.1	3.52	1.1	Base
Gaussian Elimination with GPU	45	4.6	1.21	4.2	76%
Block-Based Algorithm(CPU)	153	7.8	3.11	1.3	21%
Block-Based Algorithm with GPU	42	4.2	1.10	4.6	78%
CRS Architecture(CPU)	97	6.1	2.52	1.9	47%
CRS Architecture with GPU	32	3.5	0.82	6.0	84%

3. Comparison of various methods

Table 1 provides a comprehensive comparison of various high-dimensional matrix computation methods. The table details execution time, memory usage, cost, speedup factor, and efficiency improvement for each method. The integration of GPU acceleration significantly enhances performance, reducing execution time and cost while improving efficiency.The table compares the performance of different computational methodologies in terms of execution time, memory usage, cost, speedup factor, and efficiency improvement. The baseline method, Gaussian Elimination (CPU), requires 180 seconds to complete, consumes 8.1 units of memory, and incurs a cost of 3.52, serving as the reference point for comparisons.

When GPU acceleration is applied to Gaussian Elimination, execution time drops significantly to 45 seconds (a 4.2× speedup), while memory usage decreases to 4.6 units and cost reduces to 1.21, resulting in a 76% efficiency improvement over the CPU version. The Block-Based Algorithm (CPU) shows moderate improvements over standard Gaussian Elimination (CPU), reducing execution time to 153 seconds (a 1.3× speedup) and memory usage to 7.8 units, with a 21% efficiency gain. Its GPU-accelerated version further enhances performance, completing in 42 seconds (a 4.6× speedup) with 4.2 memory units consumed and a cost of 1.10, achieving 78% efficiency improvement.

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The most efficient method is the CRS Architecture (Compressed Row Storage), which optimizes sparse matrix computations. The CPU version already outperforms Gaussian Elimination, finishing in 97 seconds (a 1.9× speedup) with 6.1 memory units and a cost of 2.52, yielding a 47% efficiency gain. When GPU acceleration is applied, CRS achieves the best overall performance: 32 seconds execution time (a 6.0× speedup), 3.5 memory units, and a cost of 0.82, delivering an 84% efficiency improvement—the highest among all tested methods.

4. Conclusion

It is expected to break through the existing limitations and promote the evolution of high-dimensional financial computing to dynamic and intelligent paradigm. The methodological study in this paper systematically explores the technical path of high-dimensional matrix computation and the optimization strategy of serverless architecture for financial applications. At the computational level, high-dimensional matrix methods cover direct methods (e.g., dynamic pivoting Gaussian elimination). Iterative methods (combining compressed row storage CRS and GPU acceleration) and randomized algorithms, which significantly improve the efficiency of financial derivatives pricing, risk modeling and other scenarios (e.g., tridiagonal option model speeds up by 40%, and sparse matrix memory consumption is reduced by 60%) through hardware synergy and storage optimization. Serverless architecture shows 2.85x speedup and 90% cost savings in parallel tasks such as matrix multiplication and Monte Carlo simulation through elastic scaling and on-demand billing, but its stateless design leads to limited efficiency of iterative algorithms (e.g., Cholesky decomposition), and relies on hybrid architectures (e.g., serverless and local GPU collaboration) and middleware (Redis, AWS) to achieve state management. Step Functions) to realize state management, partially alleviating the contradiction between cold-start latency (from 2 seconds to 50 milliseconds) and the real-time nature of high-frequency transactions. Facing the high-dimensional complexity ($O(n^3)$ computing pressure), data missing and privacy compliance challenges of financial modeling, the study proposes a future direction of fusing quantum computing acceleration, adaptive check pointing and federated learning to balance computational efficiency, regulatory requirements, and system scalability, and to promote the transition of financial computing from static clustering to dynamic intelligent scheduling paradigm. In the future, the fusion of quantum computing acceleration and adaptive checkpointing technology has

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