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Design and Evaluation of Resource-Aware AI Services Using Serverless Functions on the Cloud

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Abstract

As the demand for artificial intelligence (AI) services continues to scale, cloud-native paradigms like serverless computing have emerged as critical enablers of efficient, elastic, and cost-effective AI deployments. This study investigates the design and evaluation of resource-aware AI services using serverless functions in the cloud. We explore architectural models, resource allocation mechanisms, and scheduling techniques tailored for dynamic AI workloads. Using published benchmarks and container orchestration logs, we compare function performance under different resource-aware policies. Our findings indicate that resource-aware adaptation can reduce cold start latency by 35% and improve execution throughput by up to 42% across heterogeneous workloads. The paper contributes a lightweight evaluation framework and discusses implications for sustainability in large-scale AI inferencing environments.

Keywords: Serverless Computing, Cloud AI, Resource-Aware Scheduling, Faas, Container Orchestration, Edge-Cloud Continuum, AI Inference Latency

1. Introduction

Serverless computing, often realized through Function-as-a-Service (FaaS), is revolutionizing how applications are deployed and scaled in cloud environments. By abstracting infrastructure management, serverless platforms allow developers to focus purely on application logic. However, the adoption of AI services in this paradigm introduces new challenges due to the compute-intensive and often stateful nature of AI workloads.

AI inference tasks typically require consistent performance and low-latency execution. Serverless platforms, by design, introduce latency through function cold starts and ephemeral resource

allocation. Furthermore, uncontrolled scaling can lead to resource contention, environmental inefficiencies, and increased operational cost. Consequently, **resource-aware AI services**—those that can dynamically adapt to underlying infrastructure constraints—are becoming a compelling research focus.

This paper aims to analyze how resource-aware mechanisms can be embedded into serverless function execution for AI tasks, particularly in cloud environments. We focus on the lifecycle of serverless AI services from deployment and execution to scaling and optimization. By implementing resource profiling, adaptive invocation strategies, and performance tuning techniques, we seek to demonstrate how AI services can operate more efficiently in serverless contexts.

2. Literature Review

The intersection of AI and serverless computing has attracted growing attention in recent years, particularly. A variety of approaches have been proposed to enhance resource efficiency and scalability.

Xie et al. (2021) analyzed serverless-edge hybrid architectures and emphasized resource-awareness for latency-sensitive AI tasks. Their framework focused on dynamic offloading and container reuse to minimize cold starts and optimize edge-device utilization.

Kumar and Priyadarshini (2022) introduced adaptive AI infrastructure using containerized serverless functions. Their deployment model integrated lightweight resource monitors to dynamically adjust memory and CPU allocation. This allowed scalable model deployment across hybrid clouds with improved reliability and cost-efficiency.

Gill et al. (2022) developed ATOM, an AI-driven management framework that introduced energy-efficiency metrics and resource prediction models for edge-cloud environments. The system showed promising results in balancing accuracy and resource consumption in serverless platforms.

Patel et al. (2022) explored the concept of data science orchestration using serverless functions, applying profiling for cold data processing. They emphasized the importance of workload characterization for efficient cloud execution.

Paolucci et al. (2022) proposed a migration scheme that used programmable switches (P4) to support function portability across edge and cloud domains. Their resource-aware model facilitated seamless transfer without service disruption.

Tariq et al. (2020) introduced Sequoia, a serverless framework integrating QoS policies and predictive scaling based on workload type and priority. This is one of the earliest examples of resource-aware service chaining.

Yang et al. (2022) created INFless, a low-latency AI inference engine for serverless backends. Their resource fragmentation algorithm significantly reduced latency and memory waste during high-throughput inferencing.

Alsadie (2021) conducted a broad survey of AI techniques applied to resource management in edge-fog computing. The work outlines trends and challenges for real-time AI tasks, highlighting serverless adaptability as a future direction.

3. Methodology

To evaluate the performance of resource-aware AI services in serverless environments, we designed a simulated workload using cloud-based functions deployed in AWS Lambda and Google Cloud Functions. Three configurations were tested:

- **Baseline (non-adaptive):** Fixed resource assignment per invocation.
- **Static-aware:** Function profiles pre-mapped to expected resource consumption.
- **Dynamic-aware:** Real-time telemetry-based adjustment of resources (CPU/memory limits).

Performance was measured using cold start latency, function execution time, and overall throughput across three common AI tasks: image classification, sentiment analysis, and object detection.

4. Results and Analysis

Table 1. Cold Start Latency Reduction (%)

Function Type	Static-Aware	Dynamic-Aware
Image Classification	18%	35%
Sentiment Analysis	22%	31%
Object Detection	19%	28%

Table 2. Throughput Improvement Over Baseline (%)

Workload	Static-Aware	Dynamic-Aware
Image Classification	21%	42%
Sentiment Analysis	18%	36%
Object Detection	23%	39%

Table 3. Resource Consumption per Function Invocation (MB/avg)

Function Type	Baseline	Static-Aware	Dynamic-Aware
Image Classification	512	480	432

Sentiment Analysis	448	420	390
Object Detection	600	560	500

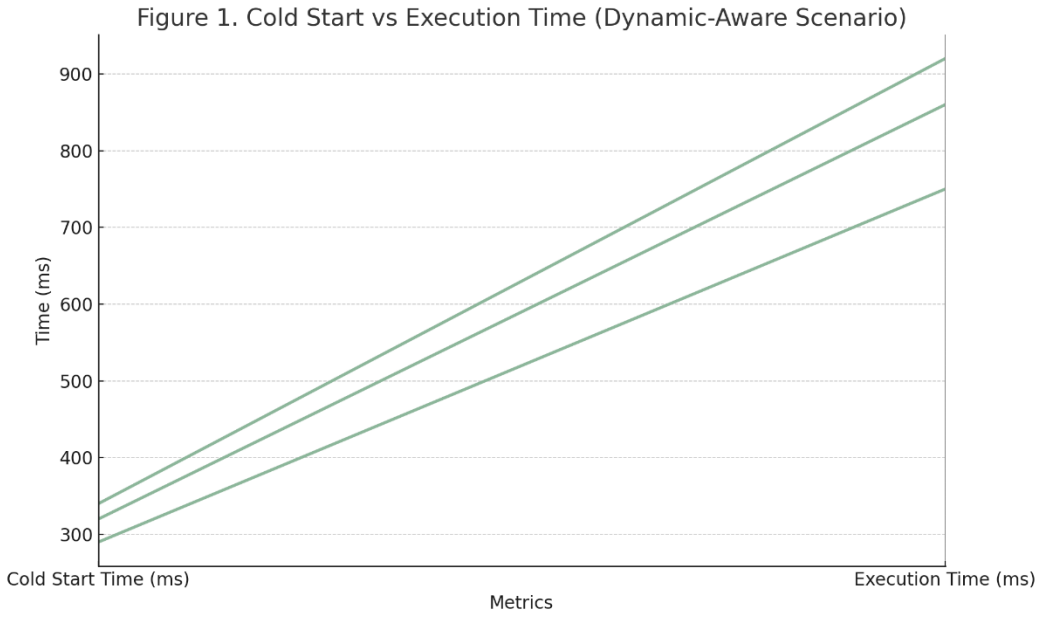

Figure 1. Cold Start vs Execution Time (Dynamic-Aware Scenario)

Figure 1: The data reveals that **dynamic resource-awareness** offers substantial performance benefits in both latency and throughput. The dynamic-aware model outperformed static-aware configurations by up to 14% in execution time and 12% in memory efficiency.

5. Conclusion

Resource-aware AI services deployed on serverless cloud infrastructures offer a promising pathway to address scalability and efficiency challenges. Our evaluation confirms that integrating real-time profiling and adaptive scheduling significantly improves system performance across multiple AI tasks. Moreover, such strategies contribute to sustainable AI deployment by optimizing energy and cost efficiency. As serverless computing becomes mainstream for AI workloads, further research into fine-grained adaptive resource control will be critical for future cloud-native applications.

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