An Advanced Methodological Optimization of Stochastic Gradient Descent for High-Dimensional Big Data Analysis in Computational Systems

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Abstract. The acceleration of high-dimensional big data analysis is paramount in the evolution of computational science. This paper presents an advanced optimization technique for the stochastic gradient descent (SGD) algorithm, fine-tuned for efficiency in complex datasets. Leveraging adaptive learning rates and momentum tuning, our method significantly reduces convergence time while maintaining accuracy. Experimental results demonstrate enhanced performance across various computational platforms, establishing a new benchmark for data-driven decision-making processes.

Keywords: Stochastic Gradient Descent, Big Data Analysis, Computational Systems, Adaptive Learning Rates, High-Dimensional Data, Optimization Techniques, Data-Driven Decision Making

Introduction

In the era of digital transformation, the explosion of big data analytics has introduced unprecedented challenges and opportunities within computational systems. The increased volume, velocity, and variety of data necessitate efficient processing techniques, particularly when handling high-dimensional datasets. Stochastic Gradient Descent (SGD) has emerged as a cornerstone algorithm in this domain due to its scalability and simplicity in optimization problems. However, conventional SGD techniques often struggle with slow convergence rates and suboptimal solutions when applied to complex, high-dimensional spaces. This paper addresses these limitations by introducing a novel methodological optimization of the SGD algorithm tailored for high-dimensional big data frameworks. Our approach incorporates adaptive learning rates and momentum tuning, which collectively enhance the algorithm's convergence speed and precision. The techniques proposed are empirically validated through comprehensive simulations, comparing our optimized SGD against traditional methodologies across diverse computational scenarios. The paper is structured as follows: Section 2 provides an in-depth review of existing optimization strategies in stochastic gradient descent. Section 3 elaborates on our proposed methodological enhancements, while Section 4 discusses the experimental setup and results. Finally, Section 5 concludes with insights on practical applications and future research directions.

References

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