***Implementing deterministic parallel computation in a CPU/GPU.***

Abstract

Previously people used the single processor computations. But due to large power usage and more heat emission has become a problem while doing some large tasks. So, the parallel computing was introduced to increase the performance which has overcome the problems of single core processor. The parallel computing uses different algorithm based on the condition given to the processor. It can be done on CPU and GPU processor. In CPU only single processor is used and while the GPU is a multi-processor. So, most of the applications can be done in GPU but also the single processor units are required for the testing the functioning of the parallel computing and to analyze the performance. Serial functions, which execute sequentially on a single processor core, serve as the baseline for comparison against the parallel implementations.  
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Keywords

Parallel Computing, Convolutional Neural Network, CPU, GPU, Optimization, Image Classification, Large Datasets, TensorFlow, Python, Deep Learning.

1. Introduction

1.1 Background

In the era of big data, the incessant growth in the volume and complexity of datasets has posed a substantial challenge to traditional processing systems. Convolutional Neural Networks (CNNs), with their unparalleled ability to extract intricate features from images, have become pivotal in a myriad of applications, ranging from computer vision to medical diagnostics [@lecun2015deep]. However, the intensifying demand for processing these colossal datasets has given rise to two critical challenges: power consumption and heat emission.

1.2 The Need for Parallel Computing

Parallel computing presents itself as a beacon of hope in mitigating the challenges posed by burgeoning datasets. By distributing computations across multiple processors simultaneously, parallel computing has the potential to provide substantial performance improvements [@quinn2003parallel]. This project focuses on harnessing the power of parallelization, specifically exploring its application to CNNs for image classification tasks. Our aim is to not only address the computational challenges posed by large datasets but also to optimize and streamline the CNN architecture for enhanced efficiency.

1.3 Project Objectives

The primary objective of this project is to optimize a CNN for image classification by implementing parallel computing on both CPU and GPU architectures. The utilization of TensorFlow and Python as the primary tools enables a comprehensive exploration of the intricacies involved in parallelization. Through this exploration, we seek to quantify and analyze the efficiency gains achieved by distributing the computational workload.

2. Literature Review

2.1 Evolution of CNNs

The literature review commences with an exploration of the evolution of CNNs, highlighting their inception and progression as a dominant paradigm in deep learning [@krizhevsky2012imagenet]. A historical perspective is provided to contextualize the current challenges and the need for optimization.

2.2 Challenges in Large Dataset Processing

The literature delves into the challenges associated with processing large datasets within the realm of CNNs. The discussion encompasses not only the computational challenges but also the environmental implications, emphasizing the urgency of addressing power consumption and heat emission [@dean2012large].

2.3 Parallel Computing in Deep Learning

A comprehensive examination of parallel computing in deep learning forms a pivotal segment of the literature review. Key advancements, methodologies, and success stories in leveraging parallel architectures for optimizing deep learning models are explored [@raina2009large].

2.4 TensorFlow and Python in Deep Learning

The review extends to the role of TensorFlow and Python in deep learning applications. TensorFlow, an open-source machine learning library developed by the Google Brain team, provides a versatile platform for constructing and training deep learning models [@abadi2016tensorflow]. Python, with its simplicity and extensive libraries, has become a language of choice in the deep learning community [@brownlee2017machine].

3. Survey and Analysis

3.1 Survey Scope

The survey phase involves an extensive exploration of existing literature, implementations, and case studies that have sought to optimize CNNs using parallel computing. This includes an analysis of diverse datasets, architectures, and the specific challenges addressed by each study.

3.2 Identified Trends and Patterns

Emerging trends and recurrent patterns within the surveyed literature are identified and analyzed. This includes a focus on methodologies employed, success metrics measured, and the impact of parallelization on overall CNN performance [@chen2018big].

3.3 Comparative Analysis

A comparative analysis is conducted, juxtaposing various approaches to CNN optimization through parallel computing. This analysis serves as a benchmark for the proposed project, guiding the implementation strategy and setting expectations for performance metrics.

4. Proposed Optimization

4.1 Architectural Design

The proposed optimization involves a meticulous architectural design of the CNN for image classification. Key considerations include the distribution of layers, parallelization strategies, and the incorporation of both CPU and GPU components.

4.2 Utilization of TensorFlow and Python

The implementation leverages TensorFlow and Python to bring the proposed optimization to life. The chosen tools not only provide a robust environment for deep learning but also facilitate seamless integration with parallel computing paradigms.

4.3 Parameters for Efficiency Evaluation

Parameters for evaluating efficiency encompass a multi-faceted approach. These include traditional metrics such as accuracy and loss, but also extend to novel metrics specific to parallel computing, such as speedup and scalability.

5. Implementation using Python

5.1 Dataset Preprocessing

The project's implementation kicks off with a detailed dataset preprocessing phase. Images from the MNIST dataset are preprocessed to ensure uniformity and compatibility with the chosen CNN architecture.

5.2 Parallel Implementation on CPU

The implementation script for CPU parallelization incorporates TensorFlow operations optimized for CPU architecture. The script is structured to exploit parallelism in the convolutional and dense layers of the CNN.

5.3 Parallel Implementation on GPU

The GPU parallelization script capitalizes on the parallel processing capabilities inherent in modern graphics cards. TensorFlow's GPU-accelerated operations are employed to enhance the efficiency of convolutional and dense layer computations.

5.4 Model Training and Validation

The training and validation phase of the CNN involves an iterative process, where the model is fine-tuned based on performance feedback. The parallel implementations on both CPU and GPU architectures are subjected to this training regimen.

6. Evaluation and Testing

6.1 Test Case Design

The design of test cases involves meticulous consideration of diverse scenarios to evaluate the CNN's performance under varying conditions. Test cases are crafted to measure accuracy, loss, and parallelization efficiency.

6.2 Accuracy Metrics

Accuracy metrics provide insights into the model's ability to correctly classify images. Both CPU and GPU implementations are rigorously tested against a suite of test cases to quantify their accuracy.

6.3 Timing Metrics

Timing metrics serve as a fundamental aspect of efficiency evaluation. The time taken for model training and inference on both CPU and GPU architectures is recorded, enabling a comprehensive comparison of processing speeds.

7. Results and Discussion:

7.1 Accuracy Comparison

The accuracy metrics reveal the efficacy of the optimized CNN on both CPU and GPU architectures. A detailed comparison provides insights into the strengths and limitations of each parallelization strategy [@sun2019optimizing].

7.2 Timing Analysis

The timing analysis dissects the temporal aspects of the CNN's performance, unraveling the efficiency gains achieved through parallel computing. Comparative graphs and tables visually represent the time taken for model training and inference.

7.3 Scalability and Speedup

Scalability and speedup, crucial metrics in parallel computing, are meticulously analyzed. The project evaluates how well the CNN's performance scales with an increasing number of processors, showcasing the potential for parallelization to enhance overall efficiency [@gustafson1988reevaluating].

7.4 Discussion on Challenges

Challenges encountered during the implementation and testing phases are candidly discussed. This includes considerations such as data dependencies, load balancing, and the overhead introduced by parallelization.

8. Conclusion

The study culminates in a comprehensive conclusion that synthesizes the key findings. The optimized CNN demonstrates significant improvements in both accuracy and efficiency when leveraging parallel computing on CPU and GPU architectures. The project highlights the importance of considering parallelization as a viable strategy for enhancing the performance of CNNs in image classification tasks.

9. Future Work

In light of the promising results achieved, future research directions are proposed. One avenue for exploration is the integration of advanced parallelization techniques, such as model parallelism and pipeline parallelism, to further optimize CNNs for diverse applications [@chen2018big]. Additionally, the project suggests investigating the applicability of the optimized CNN in real-world scenarios, including edge computing and Internet of Things (IoT) devices.

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