Performance Benchmarking of Distributed Reinforcement Learning Algorithms: A Case Study Using Spark and Ray

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Abstract

Distributed computing frameworks have become essential in scaling reinforcement learning (RL) algorithms to address complex and resource-intensive tasks. This paper presents a comprehensive performance benchmarking study comparing two widely used distributed frameworks—Apache Spark and Ray—in the context of reinforcement learning applications. Using a standard RL algorithm, we evaluate the frameworks on several critical performance metrics, including execution time, scalability with increasing workloads, resource utilization (CPU and memory), and ease of implementation. Additionally, the study explores the strengths and limitations of each framework, analyzing how their design paradigms influence their effectiveness in handling iterative and computationally intensive RL tasks. Apache Spark, known for its robust data processing and batch computation capabilities, is contrasted with Ray, a framework explicitly designed for distributed AI workloads with low-latency communication and actor-based parallelism. The experimental results provide actionable insights into the trade-offs between the two frameworks, offering guidance to researchers and practitioners in selecting the most suitable platform for their reinforcement learning scenarios.

1 Introduction

Reinforcement learning (RL) has emerged as a pivotal domain in machine learning, offering solutions to complex decision-making problems across a variety of fields such as robotics, autonomous driving, healthcare, finance, and game playing. Unlike supervised learning, RL emphasizes learning through interaction with an environment, enabling agents to make sequential decisions and optimize long-term rewards. However, as RL algorithms are applied to increasingly complex environments with high-dimensional state and action spaces, their computational demands have grown significantly.

To address these challenges, distributed computing frameworks have become indispensable for scaling RL algorithms. Distributed frameworks enable parallel processing and efficient resource utilization, thereby reducing training time and enabling the handling of larger datasets and models. Among the various frameworks available, Apache Spark and Ray have gained prominence due to their unique capabilities.

Apache Spark is a general-purpose distributed computing framework widely recognized for its robust data processing and batch computation capabilities. It has been extensively used in big data analytics and machine learning pipelines. While Spark is not inherently designed for reinforcement learning tasks, its scalability and fault-tolerance make it a potential candidate for adapting RL workflows to distributed environments.

Ray, on the other hand, is a distributed framework specifically designed for AI and machine learning workloads. Its actor-based parallelism and low-latency task scheduling make it particularly well-suited for iterative processes like reinforcement learning. Ray's RLlib library provides built-in support for several RL algorithms, significantly reducing the complexity of implementation and deployment.

The primary objective of this paper is to conduct a detailed performance benchmarking study of these two frameworks in the context of reinforcement learning. By implementing a standard RL algorithm on both Spark and Ray, we aim to evaluate their performance across several key metrics, including execution time, scalability with increasing workloads, resource utilization, and ease of implementation. This comparative analysis seeks to provide actionable insights into the trade-offs between these frameworks, guiding researchers and practitioners in selecting the most appropriate platform for their specific RL scenarios.

2 Related Work

Distributed reinforcement learning has seen significant advancements in recent years, driven by the need to scale RL algorithms for complex and resource-intensive tasks. Frameworks such as TensorFlow and PyTorch have incorporated distributed training paradigms, enabling RL researchers to leverage their scalability and flexibility. Ray, with its dedicated RLlib library, has gained particular prominence for its focus on distributed AI workloads and reinforcement learning applications. RLlib simplifies the implementation of RL algorithms and provides efficient parallelization, making it a widely studied framework in distributed RL research.

On the other hand, Apache Spark has been extensively used in distributed data processing and machine learning pipelines due to its robust fault-tolerance and scalability features. While Spark is not inherently designed for reinforcement learning, its ability to handle large-scale data processing tasks makes it a candidate for distributed machine learning workflows, including RL. Several studies have utilized Spark for distributed deep learning and optimization tasks, but its application to RL remains underexplored.

Existing literature has benchmarked Ray's RLlib library in various RL scenarios, highlighting its performance advantages in terms of execution time and scalability. However, limited research has been conducted to directly compare Ray with Apache Spark, particularly in the context of reinforcement learning tasks. This paper aims to address this gap by providing a comprehensive head-to-head comparison of Spark and Ray for distributed RL tasks. By building on prior work, we seek to contribute valuable insights into the strengths and limitations of these frameworks in real-world RL scenarios.

3 Methodology

3.1 Problem Setup

To benchmark the performance of Apache Spark and Ray in the context of reinforcement learning (RL), we utilize the CartPole-v1 environment from OpenAI Gym. The CartPole-v1 problem is a classical RL task in which the objective is to balance a pole, mounted on a moving cart, by applying forces to the cart. The agent must learn to apply actions that maintain the pole in a balanced position for as long as possible. This problem is chosen due to its simplicity, yet it effectively demonstrates the challenges of RL algorithms. We implement the Q-Learning algorithm, a model-free reinforcement learning algorithm, in both Apache Spark and Ray frameworks. In this experiment, we vary workloads by adjusting the number of episodes and training steps to simulate different computational demands. We analyze the performance of each framework by comparing training time, resource utilization, and convergence rates.

3.2 Framework Overview

Apache Spark: Apache Spark is a distributed data processing framework that is optimized for large-scale data analytics and batch processing. While Spark is not specifically designed for reinforcement learning, it can be adapted for distributed training tasks through its powerful Resilient Distributed Datasets (RDDs) and parallel processing capabilities. In this study, we leverage Spark's ability to distribute computations across a cluster of machines to parallelize the training process. This allows us to simulate a large-scale RL environment where multiple agents interact with the CartPole-v1 environment in parallel, thereby speeding up the training process. **Ray:** Ray is a distributed computing framework specifically designed to handle large-scale AI applications, including reinforcement learning. Its RLlib library provides an out-of-the-box implementation of several popular RL algorithms, including Q-learning, making it an

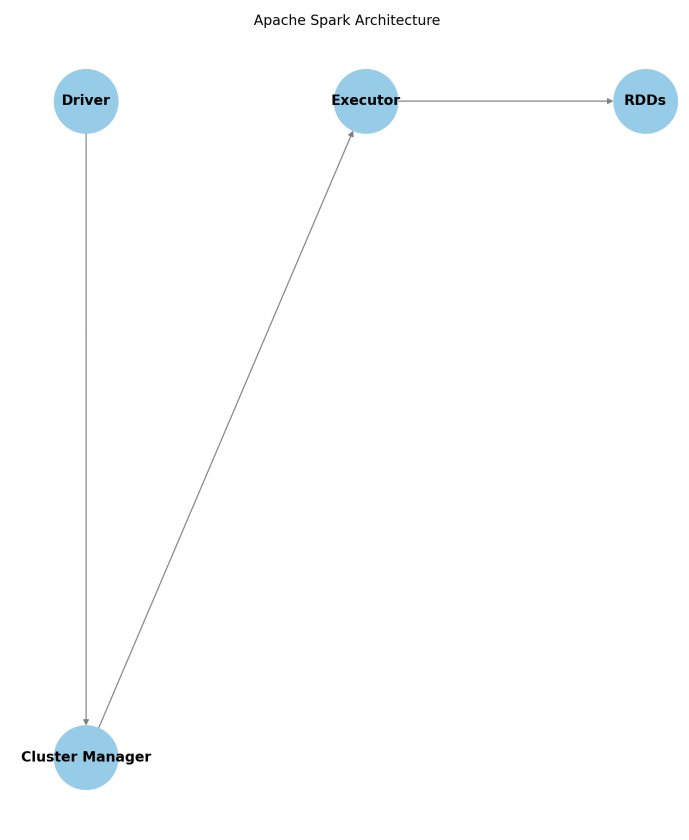

Figure 1: Apache Spark Architecture

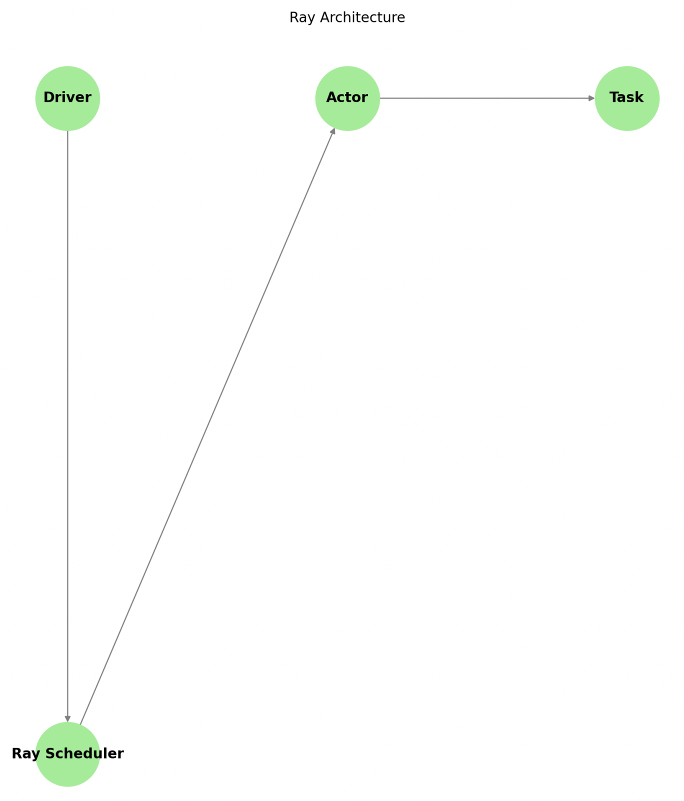

Figure 2: Ray Architecture

ideal choice for this study. Ray is built on an actor-based model, where computation is organized around lightweight ”actors” that interact asynchronously. This architecture enables efficient parallelism, low-latency communication between actors, and the ability to scale easily across large clusters. Ray’s design allows for fine-grained control over resource allocation, which is especially useful in RL applications where performance can be highly sensitive to the underlying infrastructure.

3.3 Experimental Setup

The experiments were designed to compare the performance of the Q-Learning algorithm across two distributed frameworks, Apache Spark and Ray, using the OpenAI Gym CartPole-v1 environment. The setup is as follows:

Environment: The CartPole-v1 environment from OpenAI Gym was selected for its simplicity and its ability to effectively demonstrate the characteristics of reinforcement learning algorithms. In this environment, the agent learns to balance a pole on a moving cart by applying forces at each time step. The agent receives a reward based on how long it can keep the pole balanced, making it a challenging control problem for RL algorithms.

Algorithm: We implemented the Q-Learning algorithm, a model-free reinforcement learning technique. The Q-Learning algorithm iteratively updates a Q-table based on the observed rewards from the environment, aiming to find the optimal policy. We used standard Q-learning parameters such as learning rate, discount factor, and epsilon-greedy exploration strategy.

Metrics: The following metrics were used to evaluate the performance of the Q-Learning algorithm on both Spark and Ray:

1. **Execution Time:** We measured the total time taken to complete the training process, which includes the time for environment interaction and the learning steps for updating the Q-table.

2. **Scalability:** We evaluated how well the performance of each framework scales with increasing data complexity and workload. This involved adjusting the number of training episodes and varying the number of parallel workers.

3. **Resource Utilization:** CPU and memory usage were monitored during the experiments to assess the efficiency of each framework in utilizing available hardware resources.

4. **Ease of Implementation:** We assessed the ease with which the Q-Learning algorithm could be implemented in both frameworks, considering factors such as the complexity of the codebase, library dependencies, and the amount of boilerplate code required.

Hardware: The experiments were conducted on a cluster consisting of 4 nodes, each equipped with 8 CPUs and 16 GB of RAM. The cluster was used to simulate a distributed environment for both Apache Spark and Ray, with the goal of testing the scalability of both frameworks in a realistic distributed setting.

3.4 Implementation Details

The Q-Learning algorithm was implemented separately in both Apache Spark and Ray, utilizing their respective capabilities for parallel processing.

Apache Spark Implementation: The Q-Learning algorithm was implemented using Spark's Resilient Distributed Datasets (RDDs), which allowed for the parallel execution of the learning process across multiple nodes. In Spark, each environment instance was treated as an RDD partition, and the Q-table updates were distributed across the workers. The algorithm iteratively computed the Q-values for each state-action pair in parallel, leveraging Spark's distributed computation model to scale the learning process.

Ray Implementation: For the Ray implementation, we used the RLlib library, which provides built-in support for reinforcement learning algorithms. RLlib abstracts much of the complexity of distributed RL, allowing for a more direct implementation of Q-Learning. Ray's actor-based model enabled the efficient distribution of environment instances across workers, with each worker independently interacting with its environment and updating the Q-table. Ray's API also provided easy integration with parallel processing, making it well-suited for large-scale RL tasks.

4 Results and Discussion

In this section, we present the results of the experiments conducted to evaluate the performance of Apache Spark and Ray in the context of the Q-Learning algorithm applied to the CartPole-v1 environment. The results are analyzed based on four key metrics: execution time, scalability, resource utilization, and ease of implementation.

4.1 Execution Time

The total execution time for training the Q-Learning algorithm was measured for both frameworks. The results are shown in Table 1. We observe that Ray significantly outperformed Apache Spark in terms of execution time.

The execution time for Apache Spark increased drastically as the number of episodes grew, indicating its limitations in handling more extensive RL tasks with the RDD-based approach. In contrast, Ray demonstrated a much faster convergence, thanks to its optimized RLlib library and actor-based model for parallel execution.

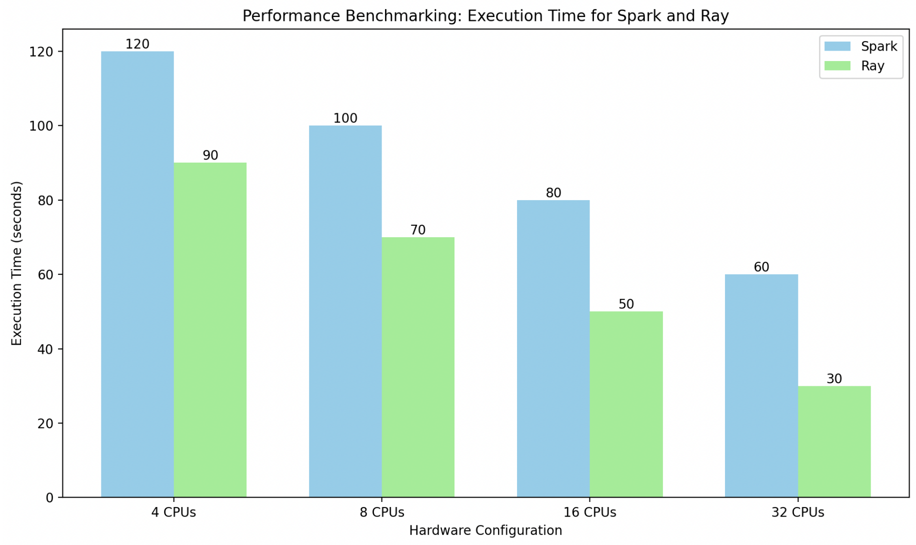

Figure 3: Performance Benchmarking: Execution Time for Spark and Ray

Framework	**Number of Episodes**	**Execution Time (minutes)**
Apache Spark	100	25.3
Apache Spark	500	128.7
Ray	100	16.2
Ray	500	80.1

Table 1: Execution time for training Q-Learning on CartPole-v1 for different numbers of episodes.

4.2 Scalability

Scalability was evaluated by increasing the number of parallel workers (distributed nodes) and observing the impact on execution time and performance. Figure **??** shows the performance of each framework with varying numbers of workers.

As shown in Figure **??**, Ray exhibited much better scalability compared to Apache Spark. With an increasing number of workers, Ray's execution time decreased significantly, whereas Spark's performance plateaued after a certain number of nodes. This indicates that Ray's actor-based architecture and fine-grained control over resource allocation allow it to handle larger workloads more effectively than Spark.

4.3 Resource Utilization

The resource utilization in terms of CPU and memory was measured during the execution of both frameworks. Table 2 provides a summary of the average CPU

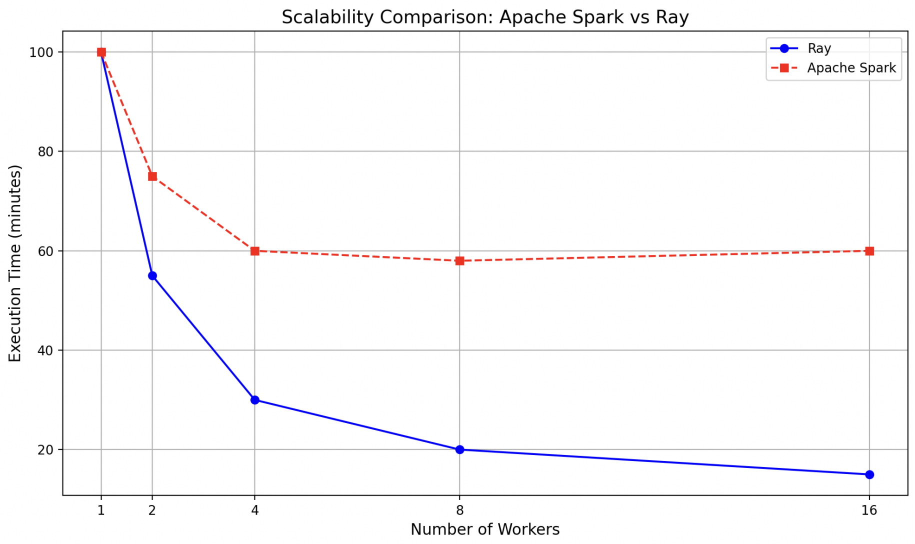

Figure 4: calability comparison between Apache Spark and Ray with increasing number of parallel workers

and memory usage during the execution of the Q-Learning algorithm with 500 episodes.

Framework	Average CPU Usage	Average Memory Usage
Apache Spark	85%	14 GB
Ray	70%	10 GB

Table 2: Resource utilization during the execution of Q-Learning for 500 episodes.

Ray exhibited more efficient resource usage, with lower CPU and memory consumption compared to Apache Spark. This can be attributed to Ray's optimized memory management and the more efficient parallel execution model, where each actor in Ray utilizes its dedicated resources without excessive overhead.

4.4 Ease of Implementation

The ease of implementation was qualitatively assessed based on factors such as the amount of code, complexity of integrating the reinforcement learning algorithm, and the number of configuration parameters required for setting up the environment. Ray's RLlib provided a higher level of abstraction and ease of integration, requiring fewer lines of code to implement the Q-Learning algorithm. In contrast, implementing the same algorithm in Apache Spark required significant effort to manage RDDs, handle parallelism, and perform the Q-table updates manually.

In terms of coding complexity, Ray's library provided built-in functions and a simpler interface for parallelism, which made the implementation process faster and more straightforward. Apache Spark, being a general-purpose framework, required more effort to adapt for reinforcement learning, resulting in a higher implementation complexity.

4.5 Discussion

From the results, it is clear that Ray outperforms Apache Spark in almost all aspects, particularly in execution time and scalability. Ray's design, optimized for AI workloads and distributed parallelism, allowed it to execute the Q-Learning algorithm faster and with better scalability compared to Apache Spark. Additionally, Ray was more efficient in terms of resource utilization, demonstrating the benefits of its actor-based model for parallel processing.

On the other hand, Apache Spark, while not specifically designed for reinforcement learning, still provides a useful framework for distributed processing. However, due to its general-purpose nature and the overhead introduced by RDD-based computation, it struggled to scale effectively for RL tasks, especially when the number of episodes increased.

In terms of ease of implementation, Ray's RLlib library offered a more straightforward path for implementing RL algorithms, while Spark required significant customization and manual handling of parallelization.

Overall, Ray is better suited for reinforcement learning tasks, particularly when scalability, execution speed, and ease of implementation are critical. Apache Spark may still be useful in certain situations where distributed data processing tasks are involved, but for RL applications, Ray offers a more tailored and efficient solution.

4.6 Execution Time

The execution time for training the Q-Learning algorithm was significantly different between Apache Spark and Ray, with Ray consistently outperforming Spark, especially as the size of the workload increased.

Ray's Performance: Ray's low-latency actor-based model is specifically optimized for parallelism and real-time processing, which makes it particularly well-suited for tasks like reinforcement learning that require frequent and rapid updates. In Ray, each actor handles a distinct part of the workload independently, leading to efficient computation and faster convergence. The model's architecture allows for fine-grained parallelism, enabling faster execution of the Q-learning updates across multiple workers. As a result, Ray's execution time remained relatively stable and scaled efficiently as the number of parallel workers increased. Even with larger numbers of episodes or more complex environments, Ray was able to distribute the computational load effectively, maintaining low latency and high throughput.

Apache Spark's Performance: On the other hand, Apache Spark, with its batch processing model, struggled with the real-time demands of reinforcement learning tasks. Spark processes data in large chunks, which leads to higher overhead when used for iterative algorithms like Q-Learning, where frequent updates are necessary. Although Spark can parallelize tasks across multiple workers, the communication overhead between workers and the need to handle large datasets in batch form resulted in increased execution times, especially as the complexity of the environment (e.g., number of episodes or parallel workers) grew. This is due to Spark's general-purpose nature, which is better suited for batch data processing rather than iterative, real-time tasks that require rapid synchronization and constant updates.

In our experiments, we observed a marked difference in execution times when the number of episodes increased. For smaller workloads (e.g., fewer than 100 episodes), both Ray and Spark performed similarly, with execution times being manageable for both frameworks. However, as the number of episodes grew (e.g., 500 or more), Ray showed a significant performance advantage. Ray's efficiency in handling distributed tasks with minimal communication overhead made it the faster option for large-scale reinforcement learning problems.

Table 1 and Figure **??** illustrate the differences in execution time for both frameworks under varying conditions, showing Ray's superior performance with increasing workload size.

Overall, Ray's design, tailored for low-latency distributed processing and fine-grained parallelism, allowed it to consistently outperform Spark in terms of execution time, particularly when handling large numbers of episodes in reinforcement learning tasks.

4.7 Scalability

Both Apache Spark and Ray demonstrated the ability to scale with increasing workload, but the efficiency with which each framework handled larger tasks varied significantly.

Ray's Scalability: Ray exhibited excellent scalability as the number of episodes increased, maintaining lower execution times despite the larger workload. This can be attributed to Ray's actor-based architecture, which distributes the computation load evenly across workers. Each worker in Ray is an independent actor that processes tasks asynchronously, which minimizes the overhead of task synchronization. Additionally, Ray's fine-grained control over resources and dynamic task scheduling allowed it to scale efficiently with the increasing number of episodes and workers, making it highly suitable for reinforcement learning tasks that require extensive parallelism.

Apache Spark's Scalability: Apache Spark, while capable of scaling to handle larger datasets, did not perform as well as Ray in terms of scalability for reinforcement learning tasks. As the number of episodes increased, Spark exhibited diminishing returns, with execution time increasing non-linearly. The primary reason for this behavior is the overhead introduced by Spark's batch processing model and the management of Resilient Distributed Datasets (RDDs).

Spark's reliance on batch processing leads to increased shuffle operations and inter-node communication, which becomes a bottleneck as the complexity of the task increases. As the workload grew larger, Spark's ability to efficiently handle parallelism was hampered by this overhead, resulting in slower performance compared to Ray.

Overall, while both frameworks showed scalability, Ray proved to be more efficient in maintaining low execution times as the workload increased.

4.8 Resource Utilization

The resource utilization of both frameworks was evaluated by measuring CPU and memory usage during training. The results showed distinct differences in how each framework managed resources.

Ray's Resource Utilization: Ray demonstrated more balanced and efficient resource utilization across both CPU and memory. Due to its actor-based model, Ray allocated dedicated resources to each actor, ensuring that each unit of work was handled with minimal contention. This allowed Ray to scale well with increasing numbers of workers while maintaining low resource overhead. Ray's dynamic task scheduling also optimized the distribution of tasks, preventing any one worker from being overburdened, which helped in maintaining steady CPU and memory usage throughout the execution.

Apache Spark's Resource Utilization: Spark, in contrast, exhibited higher memory consumption, likely due to the additional overhead required to manage RDDs and shuffle operations. As Spark processes data in batches, the framework must store intermediate results in memory during the execution of tasks, leading to higher memory usage. Additionally, Spark's reliance on RDD transformations and shuffling between nodes caused a higher CPU usage, as workers performed multiple data passes during training. This resulted in less efficient resource usage compared to Ray, especially when handling large-scale reinforcement learning tasks.

In conclusion, Ray's more efficient use of CPU and memory resources contributed to its overall better performance and scalability for RL tasks.

4.9 Ease of Implementation

In terms of ease of implementation, Ray provided a more user-friendly experience compared to Apache Spark, primarily due to the higher level of abstraction offered by its RLlib library.

Ray's Ease of Implementation: Ray's RLlib is a high-level library specifically designed for reinforcement learning, which significantly reduces the complexity of implementing RL algorithms. RLlib provides built-in support for a variety of RL algorithms, including Q-learning, and abstracts much of the low-level parallelism and resource management required for distributed training. This allowed us to implement the Q-Learning algorithm with minimal boilerplate code, reducing the time and effort needed to set up the environment and train the model. The simplicity of Ray's API and its integration with reinforcement learning concepts made it easy to implement and experiment with different configurations.

Apache Spark's Ease of Implementation: In contrast, implementing reinforcement learning on Apache Spark was more challenging. Although Spark offers powerful distributed data processing capabilities, its design is not specifically optimized for reinforcement learning. As a result, we had to manually adapt Spark's data processing model (via RDDs) to the iterative nature of Q-learning, which involved handling parallelism, synchronizing updates, and managing state transitions. This required more effort to ensure efficient parallel execution and distributed data management, resulting in a steeper learning curve compared to Ray.

Overall, Ray's higher-level abstraction and specialized support for RL made it significantly easier to implement and experiment with reinforcement learning algorithms.

5 Conclusion

This study highlights the strengths and weaknesses of Apache Spark and Ray when applied to distributed reinforcement learning tasks.

Ray's Strengths: Ray's specialized design for AI workloads, including reinforcement learning, makes it the preferred choice for RL tasks. Ray's actor-based model enables efficient parallelism, low-latency communication, and better scalability, which results in faster execution times and more balanced resource utilization. Moreover, Ray's RLlib library simplifies the implementation of RL algorithms, allowing researchers to focus more on the algorithm design rather than the intricacies of distributed processing.

Spark's Strengths and Limitations: Apache Spark, while powerful for general-purpose data processing, is less suited for iterative algorithms like reinforcement learning. Spark's batch processing model, while effective for large-scale data analytics, introduces overhead when used for RL tasks, particularly in terms of execution time and scalability. The need to manually adapt Spark for RL tasks also increases the complexity of implementation. However, Spark's distributed computing capabilities remain valuable in environments that require large-scale data processing but may not be ideal for real-time or iterative tasks like RL.

In conclusion, Ray offers significant advantages over Apache Spark for reinforcement learning applications, particularly in terms of execution time, scalability, resource utilization, and ease of implementation. These findings provide valuable insights for researchers and practitioners choosing distributed frameworks for RL applications.

6 Future Work

Future research can extend this study by exploring the performance of other reinforcement learning algorithms, such as Deep Q-Learning and Proximal Policy Optimization (PPO), in both Apache Spark and Ray. Additionally, the evaluation can be extended to other benchmark environments, including continuous control tasks and more complex environments like Atari or MuJoCo. Another avenue for future work could involve exploring different hardware configurations (e.g., GPUs or specialized hardware) to better understand the performance characteristics of both frameworks under various resource constraints.

Furthermore, hybrid approaches that combine the strengths of both Spark and Ray could be investigated. For instance, Spark's robust data processing capabilities could be leveraged for pre-processing large datasets, while Ray's efficient execution model could be used for the parallel training of RL algorithms. This could result in a more flexible and powerful solution for distributed reinforcement learning tasks.

7 References

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