Benchmarking Deep Learning for Cloud Resource Management: When More Data Doesn't Help

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Abstract

Deep learning has been widely explored for optimizing cloud resource management, promising efficient workload scheduling, cost reduction, and improved resource utilization. However, in our real-world deployment of a deep reinforcement learning-based (DRL) scheduler for VM allocation and scaling in a multi-cloud setting, we encountered surprising failures. Despite rigorous training on historical workload data, the model consistently underperformed compared to rule-based heuristics. In this paper, we analyze the causes behind this failure, identifying distribution shifts, delayed feedback loops, and interpretability bottlenecks as key contributors. We discuss the lessons learned and provide actionable recommendations for future work.

1 Introduction

Cloud computing platforms rely on efficient resource management to balance cost, performance, and scalability. Recent literature has demonstrated the potential of deep learning, particularly reinforcement learning, for dynamically allocating virtual machines (VMs) and optimizing resource utilization. Motivated by these successes, we developed a deep reinforcement learning-based scheduler trained on real-world cloud workload traces. However, despite exhaustive training and hyperparameter tuning, our model consistently failed to outperform traditional rule-based methods.

This paper provides a detailed analysis of our negative results, outlining the critical challenges we faced. Our findings contribute to the broader discourse on the applicability of deep learning in cloud computing, emphasizing the need for interpretability, data shift mitigation, and deployment-aware learning strategies.

2 Related Work

Previous studies have shown promising results in using deep learning for resource management:

- Mao et al. (2016) proposed a DRL-based scheduler for cluster resource allocation and demonstrated efficiency gains.
- Mirhoseini et al. (2017) applied reinforcement learning for chip placement and observed significant performance improvements.
- Fang et al. (2020) explored deep learning for auto-scaling cloud workloads, reporting better efficiency over traditional policies.

Despite these successes, the gap between research prototypes and real-world deployment remains significant. Our work contributes by documenting an in-

4 Observed Failures and Analysis

4.1 Failure to Generalize to Real-World Workloads

Despite achieving high performance during offline training, our model struggled in production due to **distribution shifts**. The workload patterns in the training dataset did not fully capture the dynamic and bursty nature of real-world traffic.

- **Issue**: The model learned static patterns but failed when new workload types emerged.
- **Analysis**: The reliance on historical data without dynamic adaptation limited generalization.

4.2 Delayed Feedback Loops Lead to Instability

Cloud resource allocation decisions often have **delayed effects**, where the impact of scaling decisions unfolds over time. The DRL model lacked mechanisms to account for these delays, leading to **oscillatory behaviors** in VM allocations.

- **Issue**: The model overreacted to transient workload spikes, leading to frequent scaling up/down.
- **Analysis**: Traditional rule-based heuristics, though simplistic, handled delayed feedback better due to built-in thresholds.

4.3 Poor Interpretability and Debugging Challenges

Unlike rule-based systems, deep learning models are inherently **black-box**, making it difficult to debug mispredictions. Operations teams found it challenging to trust the model's decisions due to a lack of explainability.

- **Issue**: The model's decisions were often counterintuitive, leading to resistance from cloud operators.
- **Analysis**: The absence of interpretability mechanisms (e.g., SHAP, LIME) hindered adoption.

4.4 Scalability Bottlenecks in Production Deployment

The DRL model required significant computational overhead, making real-time inference **impractical for large-scale deployments**.

- **Issue**: Model inference latency increased with the number of active VMs.
- **Analysis**: Traditional heuristics, while suboptimal, were **computationally efficient** and provided instant decisions.

5 Lessons Learned and Recommendations

Our negative results highlight key takeaways for applying deep learning in real-world cloud environments:

- **Handle Distribution Shifts Proactively**
  - Use adaptive learning techniques (e.g., continual learning) to accommodate changing workloads.
  - Incorporate uncertainty estimation to detect out-of-distribution inputs.
- **Model Delayed Effects Explicitly**
  - Use recurrent models or hybrid reinforcement learning approaches that account for delayed impact.
  - Augment training with simulated long-term effects rather than immediate rewards.
- **Improve Interpretability for Operator Trust**
  - Integrate explainability tools to make model decisions more transparent.
  - Develop hybrid approaches that combine ML with rule-based policies.
- **Optimize for Scalability and Efficiency**
  - Consider lightweight ML models or mixed approaches.
  - Benchmark against real-world constraints, not just offline datasets.

6 Conclusion

Our attempt to apply deep learning for cloud resource management faced unexpected failures due to distribution shifts, delayed feedback loops, interpretability gaps, and scalability constraints. These findings emphasize the need for realistic benchmarking and robust deployment strategies when applying deep learning to complex, dynamic environments.

Our experience serves as a cautionary tale and a learning opportunity for practitioners aiming to deploy deep learning in cloud-based decision systems. We encourage future research to bridge the gap between theoretical ML advancements and practical deployment challenges.

References

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