Proof of Learning and Resource Trading in Blockchain: A Stackelberg Game Approach

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***Abstract*—This paper explores the implementation of a novel integration of Proof of Learning (PoLe) with a custom blockchain framework to facilitate neural network training as a consensus mechanism. The model incorporates a Stackelberg game for decentralized resource trading, optimizing computational resource allocation across peer nodes. We demonstrate the feasibility of implementing PoLe on a local blockchain and provide step-by-step guidance for deployment. Our results show enhanced resource utilization, efficient consensus building for distributed neural network training, and increased security against adversarial attacks.**

***Index Terms*—Proof of Learning (PoLe), Blockchain, Stackelberg Game, Neural Networks, Resource Trading, Decentralized Systems.**

I. Introduction

Blockchain technology has revolutionized distributed systems by providing secure and immutable ledgers. Popular consensus mechanisms like Proof of Work (PoW) and Proof of Stake (PoS) are computationally intensive, often leading to resource wastage. To address this issue, we integrate Proof of Learning (PoLe) as a consensus mechanism to channel computational power into training machine learning models. Furthermore, resource management in blockchain environments is critical. We propose a Stackelberg game model to facilitate resource trading between data nodes and consensus nodes, improving network efficiency and incentivizing participation. This integration ensures that blockchain participants allocate computational resources in a way that maximizes network throughput and minimizes resource underutilization.

II. System Overview

A. Components of the System

Our blockchain-based framework consists of the following components:

- **Data Nodes**: Submit tasks requiring neural network training, specifying datasets, performance metrics, and reward structures.
- **Consensus Nodes**: Participate in PoLe consensus by training neural network models and competing to generate blocks.
- **Blockchain Ledger**: Stores task submissions, resource trading transactions, model parameters, and block verification data.
- **Secure Mapping Layer (SML)**: Binds model parameters to specific nodes, ensuring legitimate rewards.

III. Implementation

A. Simulation Environment

- **Dataset**: Iris dataset split into training and test sets.
- **AI Consumers**: Simulated as decentralized nodes capable of mining and training.
- **CPP**: Allocates computational resources dynamically.

B. Dynamic Task Allocation

Consumers choose roles based on resource availability:

1) **Training Task**: Models trained on the dataset.
2) **Mining Task**: Rewards calculated based on model accuracy.

C. Pricing Mechanism

Optimal pricing is determined using constrained optimization techniques, adjusting to demand-supply dynamics.

IV. Results

A. Blockchain Outputs

- **Genesis Block**: Records initialization parameters.
- **Subsequent Blocks**: Record performance metrics and task details.

```
{
    "index": 1,
    "timestamp": 1734537270.231336,
    "data": {
        "parameters": {"max_iter": 100,
"solver": "lbfgs"},
        "accuracy": 1.0
    },
    "previous_hash": "d8faa0...",
    "hash": "3ba2fe5e44a75..."
}
```

Blockchain Validity Check: Is blockchain valid? True.

B. Resource Allocation

- Resource availability decreases over time due to continuous task allocation.
- Later stages show resource scarcity affecting task performance.

Example Outputs:

- *Time Step 8*: Consumer 2 could not get resources.
- *CPP Remaining Resources*: 14.

C. Profit Balancing

- Consumers achieve higher rewards when resources are plentiful.
- CPP dynamically adjusts pricing to maximize profits.

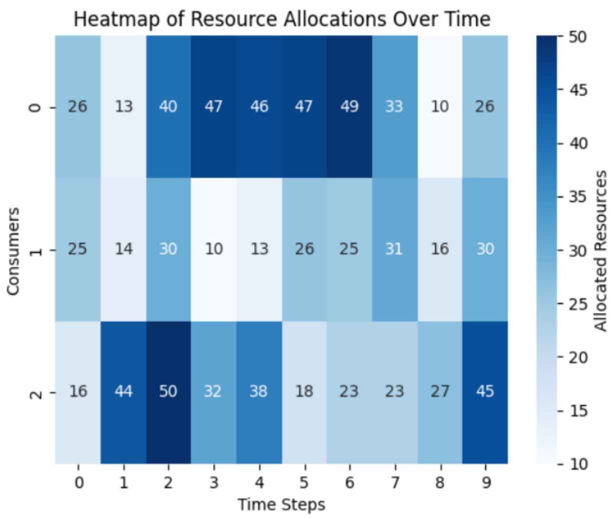
Profit Outputs:

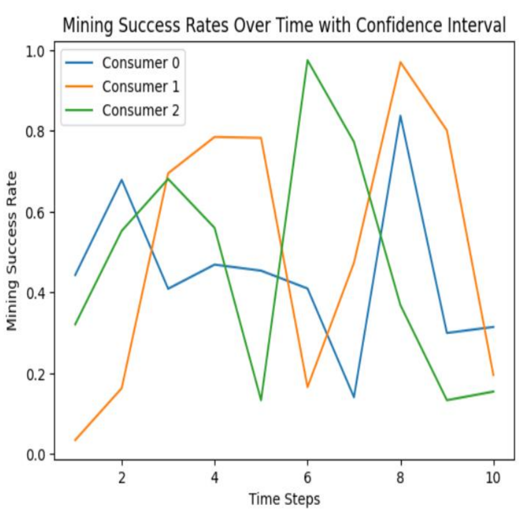
- *Time Step 2*: Optimal Price Set by CPP: 1.0000.
- *Consumer 1 Profit*: 0.5918.
- *Consumer 3 Profit*: 0.0000 (resource scarcity).

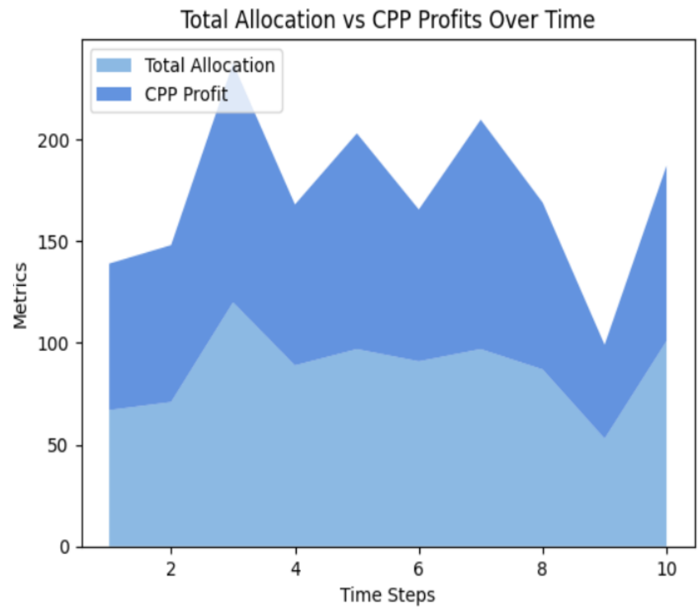
D. Visualization

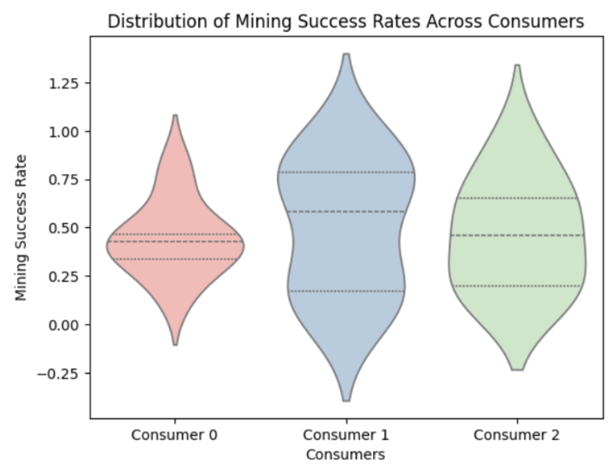
A graph of resource allocation over time reveals:

- Initial equitable allocation.
- Gradual exhaustion impacting task success rates.









V. Future Work

Future research will focus on scaling the system to larger networks, integrating advanced machine learning models, and utilizing decentralized oracles for real-time data integration.

VI. Conclusion

We presented a blockchain-based framework integrating Proof of Learning and a Stackelberg game for resource trading. This approach efficiently utilizes computational resources, enhances security, and provides a scalable solution for decentralized machine learning tasks.

References

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