Poker Zero Final Presentation

Problem Definition

- **What are we solving?**
  - We aim to build a **reasoning model** for No-Limit Hold’em poker capable of decision-making under **incomplete information** and **adversarial conditions**.
- **Importance:**
  - Real-time strategic thinking, risk assessment, and adaptation.
  - Decision-making under uncertainty
- **Success Criteria**
  - **Win rate** (hands won, stack size, profit over time)
  - **Performance against GTO (Game Theory Optimal) strategies**

Prior Work

- Poker solvers often play game theory optimal poker, which is limited
  - Nash equilibria is hard to compute for multi-way zero sum games
  - Only able to calculate on a limited set of scenarios, since poker has a very large game tree
  - Won't take advantage of imperfect opponent

Using ML and LLMs

- State of the art poker bot: **Pluribus**
  - Uses self-play to iteratively converge close to the Nash Equilibrium
  - Leverages Monte Carlo Counterfactual Regret Minimization
- Transformer models like ChatGPT / GPT-4 also don't play GTO
- LLMs use less compute/resource consumption than CFR
- Can receive more information in the game tree

Modeling the Problem

- **Stochastic Nature of Poker:**
  - Poker is inherently random, with incomplete information and unpredictable outcomes

$$EV = \sum_{h \in H} P(h) \times R(h)$$

    - $P(h)$ is the probability of a hand outcome $R(h)$ is the corresponding reward.
- **Goal:** maximize total expected winnings over all rounds r
  - **Actions:** Possible moves (bet, raise, fold, call)

Modeling the Problem

- Reinforcement Learning (RL) naturally suited for sequential decision making problems and long term problems
- Setting up a basic framework
  - **States:** Game configurations, including hole cards, community cards, betting history, stack sizes
  - **Actions:** Possible moves (bet, raise, fold, call) & associated amounts
  - **Rewards:** Based on how good the actions are

Optimization Methods

- **Policy Gradient Methods:**
  Directly optimize the policy by maximizing the expected reward.
- **PPO (Proximal Policy Optimization):**
  Balances exploration and exploitation with clipping or penalty methods to ensure stable updates.

- **GRPO (Group Relative Policy Optimization):**
  - **Multi-Agent Environment**
    Adjusts an agent’s policy relative to a group baseline or relative to other agents’ policies.
  - **Reward-Centric Updates:**
    Focuses on adjusting policies based on long-term reward estimates.
  - **Empirical Advantages:**
    Demonstrates superior performance compared to PPO and TRPO in several benchmarks.
- **Relevance to Poker:**
  Enables strategic adaptation and robust performance in complex, adversarial settings.

Unsloth

- **Purpose:**
  An open-source Python framework optimized for fast fine-tuning and deployment of large language models.
- **Key Features:**
  - Optimized PyTorch code
  - Handwritten GPU kernels to speed up inference
  - Significantly reduced memory usage
  - Allows us to fine-tune 8B parameter models on a Colab T4 GPU

LoRA (Low Rank Adaptation)

- **Concept:**
  Introduces low-rank matrices into pretrained model layers to achieve efficient fine-tuning.
- **Benefit:**
  Significant performance gains with a minimal increase in parameters—ideal for adapting large models in resource-constrained environments.

Mathematical Formulation of LoRA

- **Pretrained Weight Matrix:**
  Let $W \in \mathbb{R}^{d \times k}$ be a pretrained weight matrix.
- **Low-Rank Update:**
  Approximate the weight update as:
  $$\Delta W = BA$$
  where:
  - $B \in \mathbb{R}^{d \times r}, A \in \mathbb{R}^{r \times k}, r \ll \min(d, k)$
- **Adapted Weights:**
  The new weight matrix is given by:
  $$W' = W + BA$$

Weight Update, Factorization, and Training Efficiency

- **Factorization & Weight Update:**
  - Originally: $O(dk)$ parameters
  - With LoRA: $O(r(d+k))$ parameters
- **Training via a New Loss Function:**
  - $f(B, A) = L(W_0 + BA)$
    - Optimize this loss by taking gradient steps with respect to B and A
    - W_0 is frozen
- **In our implementation**
  - r is a hyperparameter
  - We choose $r = 32$, about $\frac{59{,}867{,}136}{3{,}000{,}000{,}000}$ (~2%) of parameters are trainable

Optimization & Reward Functions

- **Reward Function Design:**
    - **For Initial Training:**
        - **Negative Reward:** Apply penalties for outputs that violate constraints.
        - **Zero Reward:** No reward for clearly incorrect moves.
    - **Partial Rewards:**
        - Reward for executing a correct action.
        - Additional reward for an almost correct action (e.g., bet size within ±20% of the optimal).
    - **Maximum Reward:**
        - Full reward for both the correct action and optimal bet sizing.

- **Why This Approach?**
  - Allows gradual, nuanced learning instead of an all-or-nothing reward.
  - Helps the model learn the subtleties of decision-making in an environment where perfect play is rare.

Selecting GRPO & Refining the Model

- **Algorithm Choice: Group Relative Policy Optimization (GRPO)**
  - **Justification:**
    - Suitable for poker's continuous and complex environment where isolated wins do not ensure overall success.

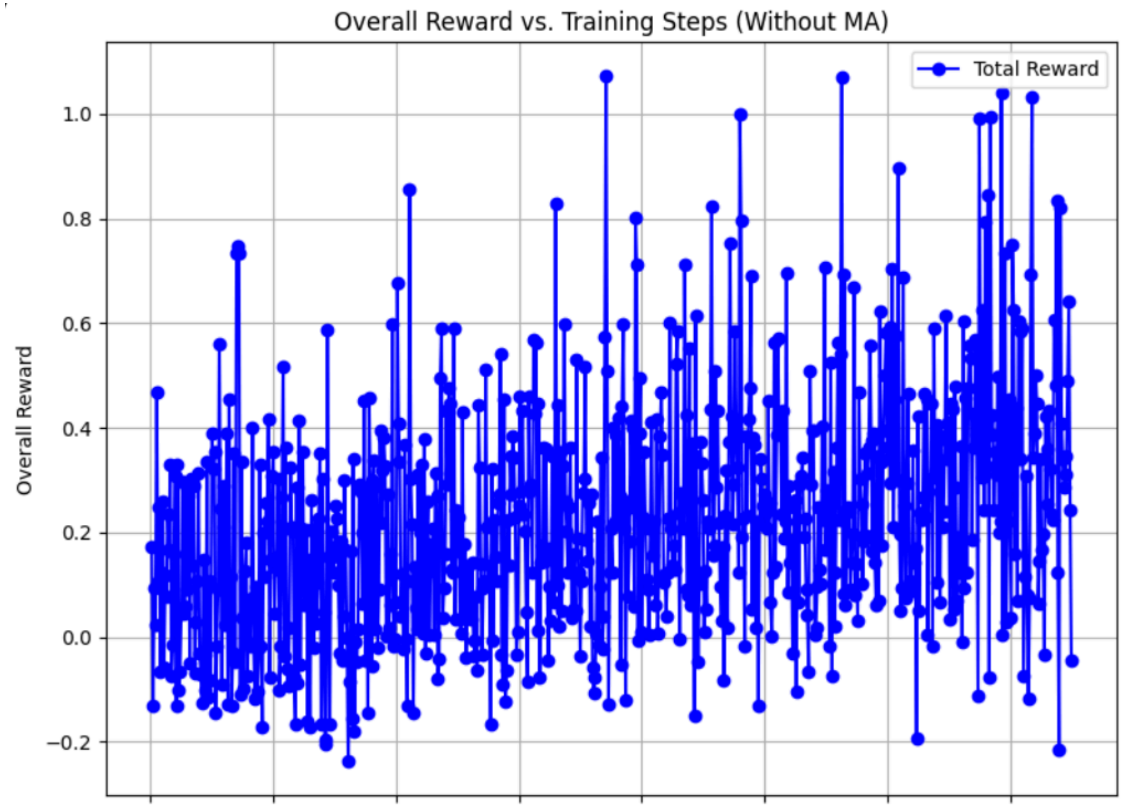
- **Tuning Procedure & Hyperparameters:**
  - **Reward Function Tuning:**
    - Began with rewards only for exact matches, but feedback was sparse.
    - Introduced partial credit for near-miss outputs (e.g., valid poker moves, near-optimal bet amounts).
  - **Hyperparameter Exploration:**
    - Systematic grid search over reward thresholds and learning rates.
    - Iterative refinement based on model performance and stability.

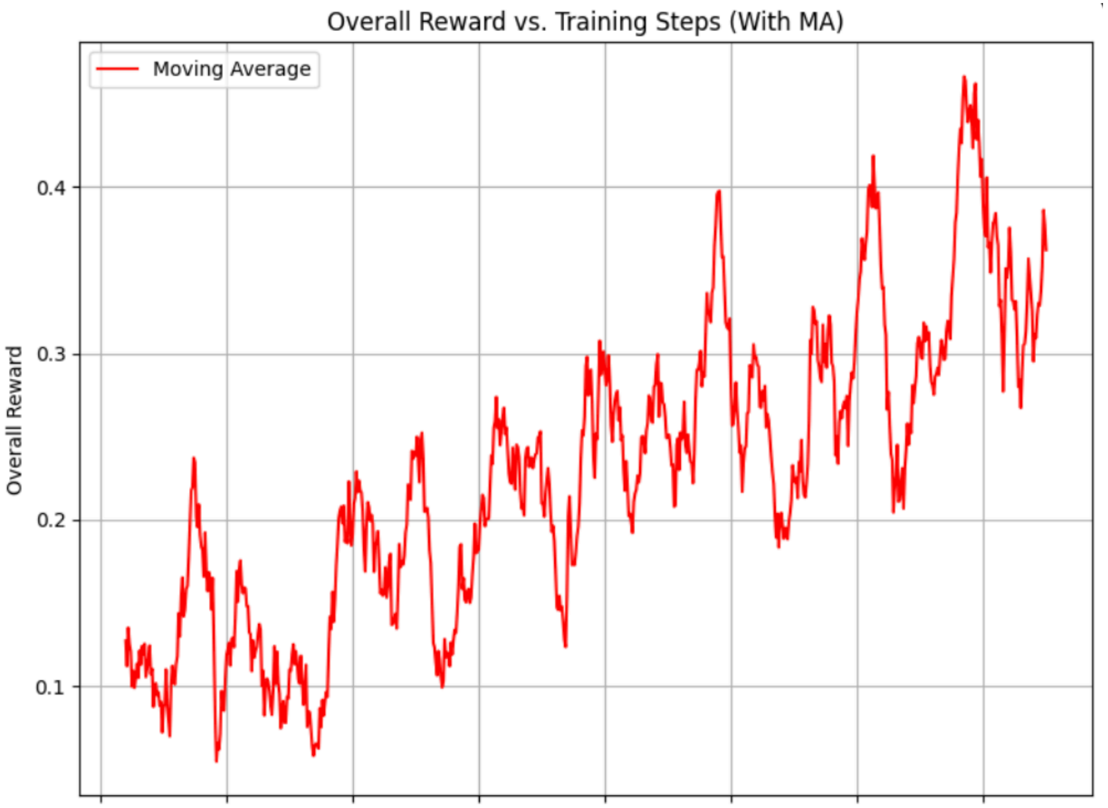
- **Implementation Choices:**
  - Leveraged the **Unsloth** framework to optimize GRPO training.
  - Utilized PyTorch for model development and integration, taking advantage of its efficient computation and GPU support.

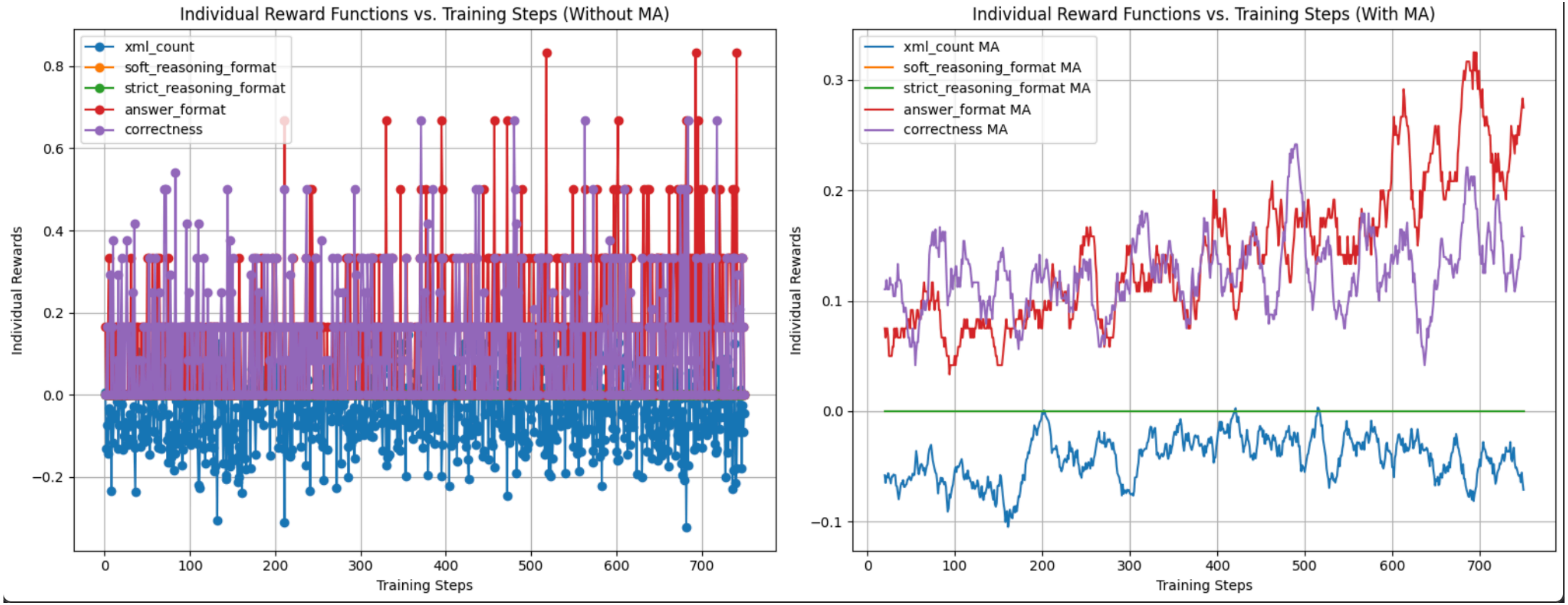
Self Play

- **PyPokerEngine**: A library for simulating poker games with AI bots
    - Used PyPokerEngine to make our model play against itself
- Model plays against earlier iterations of itself
    - Uses the output to generate additional training data
- Challenges: Took a long time to run
    - 6 instances of our model have to conduct inference and give outputs

Results

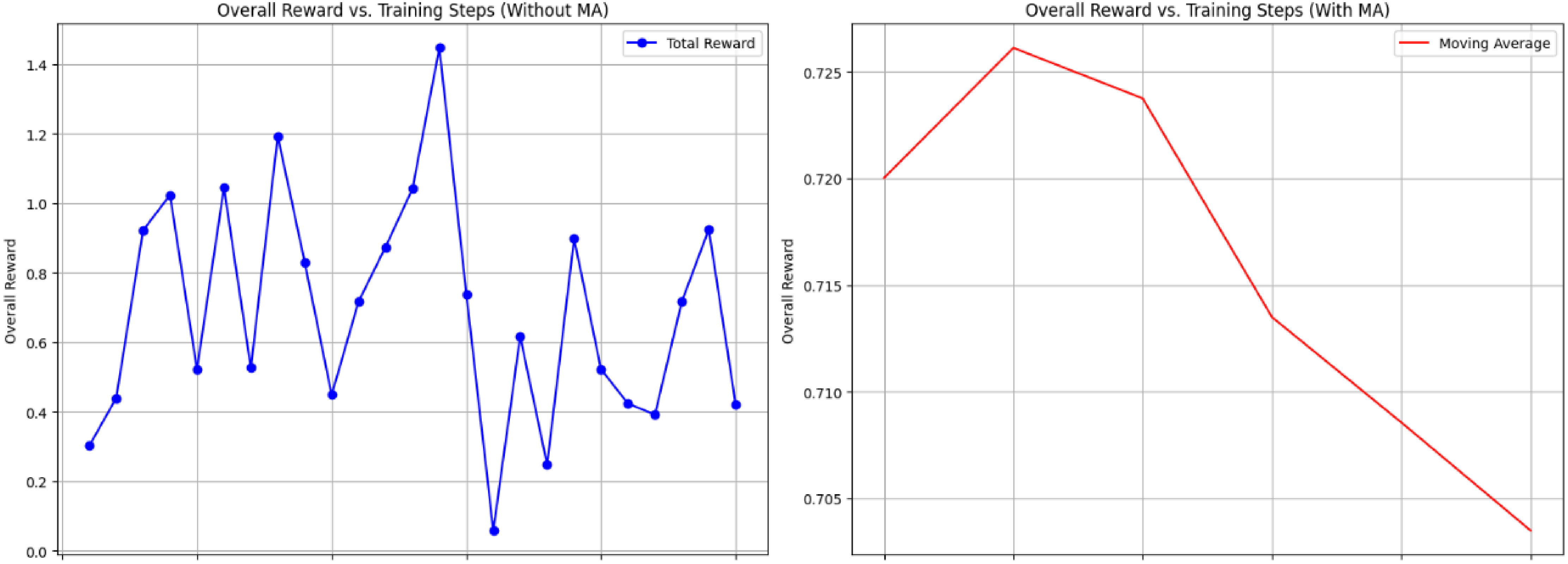

Overall Reward vs. Training Steps (Without MA)
Total Reward
Overall Reward
1.0
0.8
0.6
0.4
0.2
0.0
−0.2


Overall Reward vs. Training Steps (With MA)
Moving Average
Overall Reward
0.4
0.3
0.2
0.1

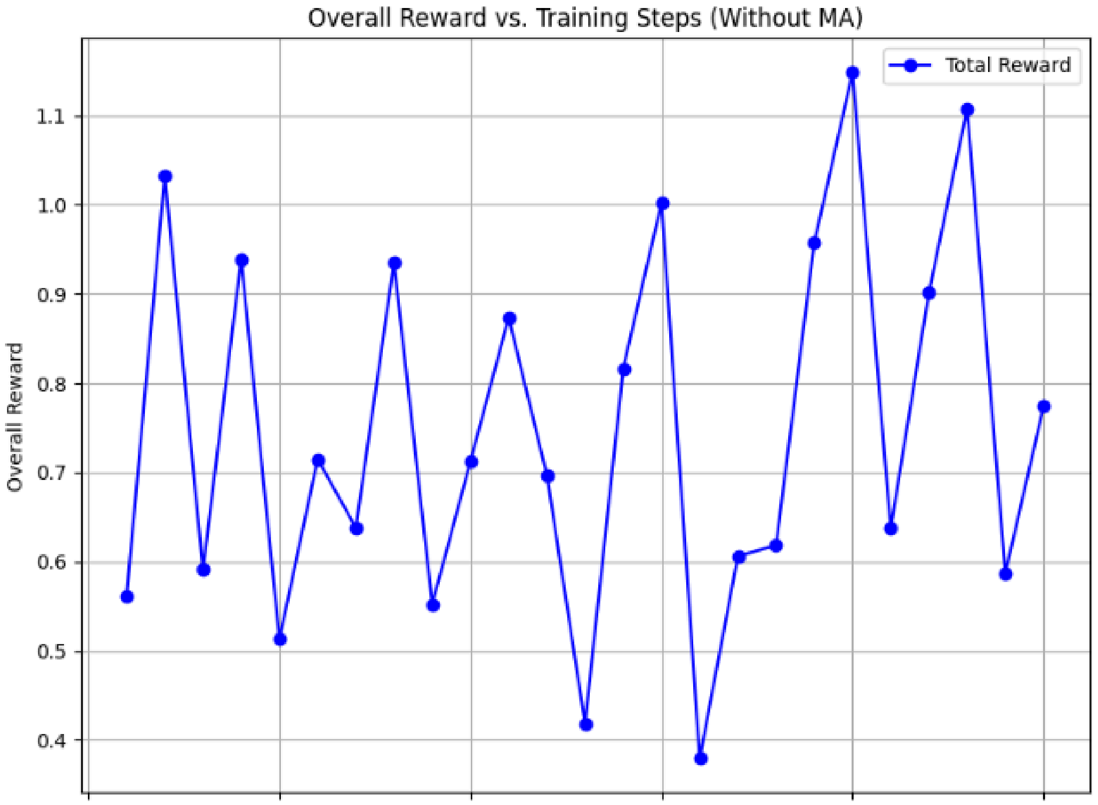


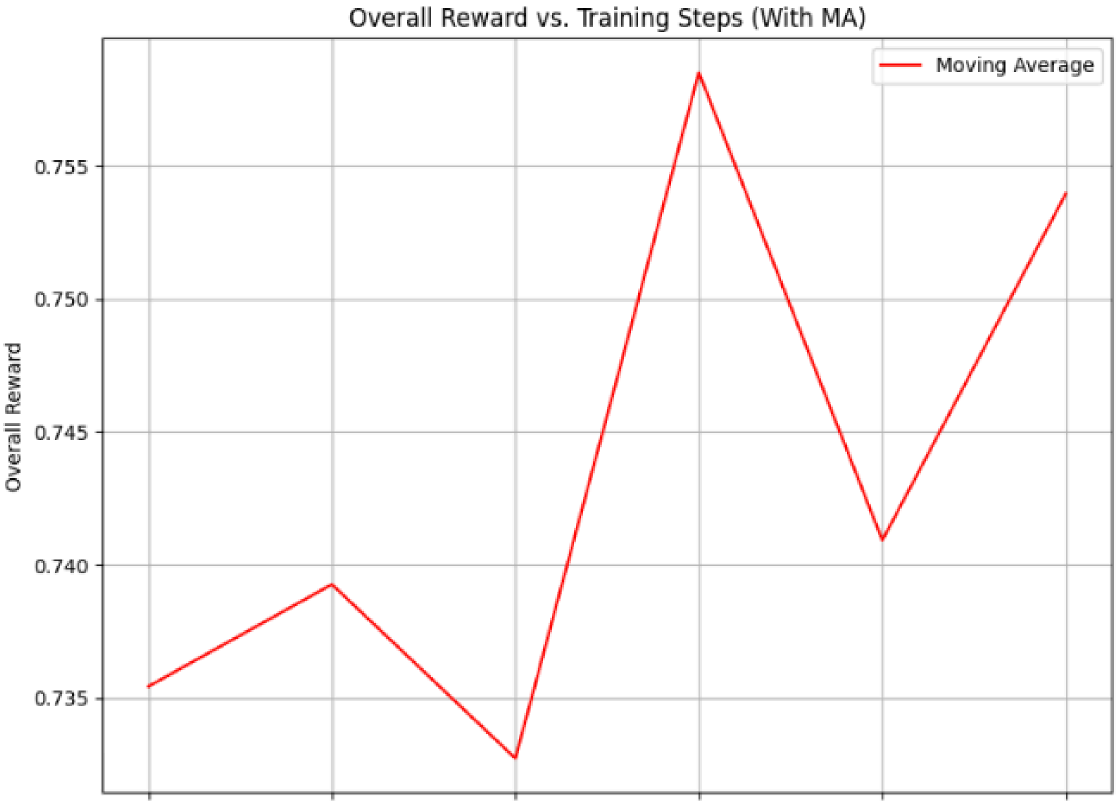
Individual Reward Functions vs. Training Steps (Without MA)
xml_count
soft_reasoning_format
strict_reasoning_format
answer_format
correctness
Individual Rewards
Training Steps
Individual Reward Functions vs. Training Steps (With MA)
xml_count MA
soft_reasoning_format MA
strict_reasoning_format MA
answer_format MA
correctness MA
Individual Rewards
Training Steps

Rewards for Self Play Round 1



Rewards for Self Play Round 5





Results Overall

- **Profit Rate:** Consistent improvement in win rates against older iterations of the models

How do your results compare to baseline methods or the literature?

- **Performance Metrics:**
  - **Reward Rate:** Upward trend of rewards over time

Demo

Showcase a demo or compelling visualization if applicable.

Compare expected progress with actual progress. Explain discrepancies.

Project Reflection

Limits Encountered & Adaptations

- **Computational Resources:**
  - Initially limited to a T4 GPU on Colab, leading to frequent disconnections and slow iteration.
  - Challenges in accessing scalable GPU resources on platforms like Google Cloud.
- **Impact on Model Training:**
  - Slow training and iteration speeds forced us to adjust our training framework.
  - Required tuning reward functions to provide a denser, more continuous feedback signal.

- **Adaptation Strategies:**
  - **Unsloth** played a critical role in speeding up our training cycles.
  - Optimization of training loops and hyperparameter searches to work within computational constraints.
  - Adoption of incremental learning strategies to mitigate resource limitations while still aiming for optimal performance.

Technical/Conceptual difficulties

- Understanding the complexity of poker strategies and how to model them effectively.
- Implementing reinforcement learning algorithms, especially in the context of self-play.

What part of the project workflow was easier than expected? Harder?

Easier

- Implementing basic reinforcement learning algorithms using **unsloth** directly within Colab.

Harder

- Debugging and tuning reinforcement learning models to converge effectively in self-play scenarios.

How the project evolved

- Trained initial model using **GRPO** and attempted self-play reinforcement learning with **PPO** to generate initial neural layers.
- **Challenge**: Model wasn't converging.
    - Shifted to using the self-play environment to generate additional training data for **GRPO**.
- Focused more on **self-play**, with multiple iterations of PokerZero playing each other to measure performance improvements.

For The Future

- Rewards come from correct moves AND winning the pot, so model receives less rewards for folds, even if they are correct
- Add additional analysis and provide rewards for good folds
- Playing against other models besides our own to evaluate performance
- Need way more training time and way more compute to achieve our goal

How did AI tools assist your project?

Specific Examples:

- **Literature Review**: Helped in understanding initial concepts and strategies for reinforcement learning.
- **Debugging**: Assisted in understanding complex algorithms and generating code