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
  - Explore LLM capabilities for 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 (unexploitable decisions), which has limitations
    - Nash equilibria is hard to compute for multi-way zero sum games
    - Only able to calculate on a limited set of scenarios (ex. reduced bet sizes), since poker has a very large game tree
    - Fails to 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
- 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.
  - Ex. PPO, GRPO

PPO (Proximal Policy Optimization):

- Balances exploration and exploitation with clipping or penalty methods to ensure stable updates
- **Estimated Advantage:** $\hat{A}_t = Q(s_t, a_t) - V(s_t)$
- **Probability Ratio:** $\rho_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\text{old}}(a_t|s_t)}$
- **Clipped Objective:**
  $$L^{\text{CLIP}}(\theta) = \mathbb{E}_t\Big[\min\big(\rho_t(\theta)\,\hat{A}_t,\ \text{clip}(\rho_t(\theta), 1-\epsilon, 1+\epsilon)\,\hat{A}_t\big)\Big]$$
- **Result:** More stable training, preventing excessively large jumps in policy probability 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.
- **Empirical Advantages:**
  - Demonstrates superior performance compared to PPO in several benchmarks.

- Instead of training a separate value network as a baseline, GRPO uses group-based rewards as a reference.
- For each prompt (or state), the policy samples G completions/trajectories. Each completion y_i gets a reward r_i.
- The *group average* $\bar{r}$ is subtracted from each r_i to form the relative advantage $\hat{A}_i = r_i - \bar{r}$.
- This advantage says "How did completion i compare to the average in that group?"

$$L^{\mathrm{GRPO}}(\theta) = \hat{\mathbb{E}}_{s,\{y_i,r_i\}}\Big[\frac{1}{G}\sum_{i=1}^{G}\sum_{t}\min\big(\rho_{i,t}(\theta)\hat{A}_i, \mathrm{clip}(\rho_{i,t}(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_i\big)\Big]$$

Optimization & Reward Functions

- **Reward Function Design For Initial Training:**
  - **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.

Selecting GRPO & Refining the Model

- **Algorithm Choice: Group Relative Policy Optimization (GRPO)**
  - **Justification:**
    - Better than PPO for multi-agent situations
    - Requires much less compute (Unsloth)
    - Performs better in delayed reward situations, like Poker

- **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)
    - Tweaked reward functions to prevent reward hacking
  - **Hyperparameter Exploration:**
    - Exploration for reward thresholds for formatting/answers and learning rates
    - Iterative refinement based on model performance and observation of reward trends

Implementation Choices:

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)

- **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

- **Training via a New Loss Function:**
  - $f(B, A) = L(W + BA)$
    - Optimize this loss by taking gradient steps with respect to B and A
    - W is frozen
- **Parameter Counts:**
  - Originally: $O(dk)$
  - With LoRA: $O(r(d + k))$
- **In our implementation**
  - r is a hyperparameter: we use $r = 32$, $\frac{59{,}867{,}136}{3{,}000{,}000{,}000}$ (~2%) trainable parameters
  - Only need to save LoRA weights for each model

Fine-tuning and self play

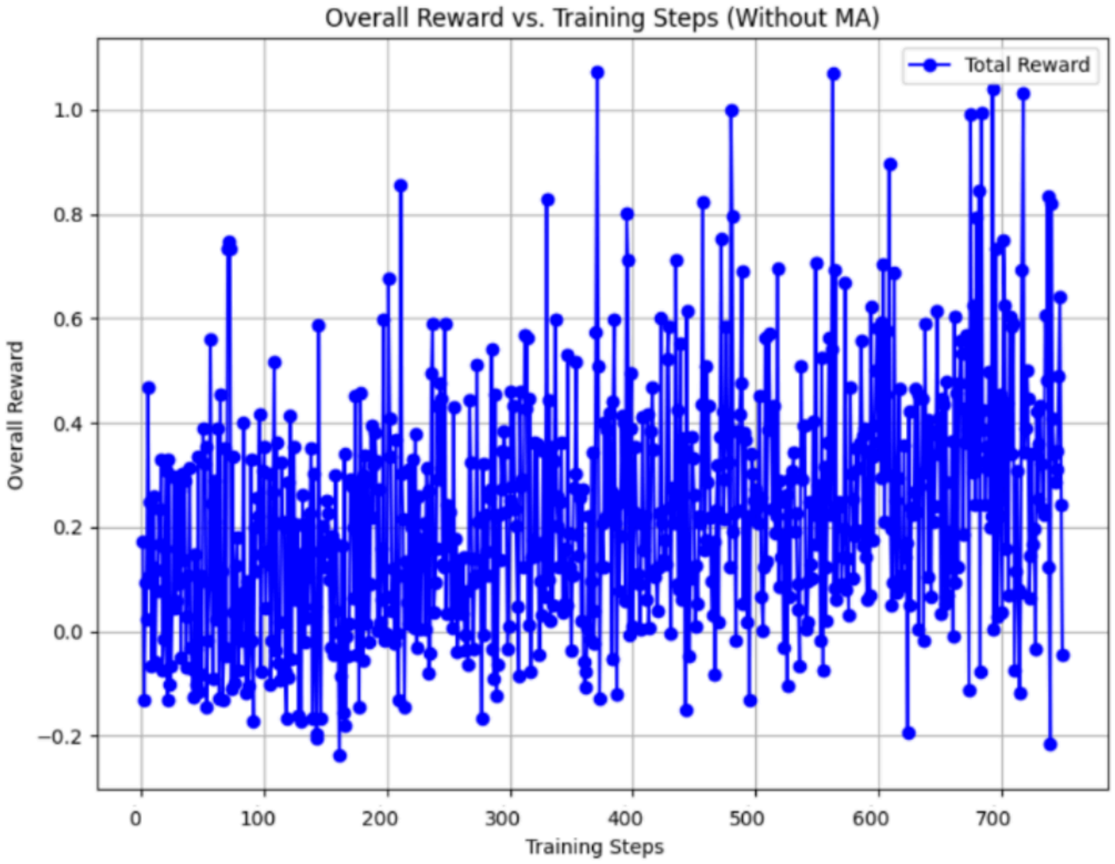
- **Initial Fine-Tuning:**
  - Used GRPO to train our model on a dataset of poker hands to learn foundations
  - **Dataset:** 500,000 poker hands from the **PokerBench** dataset

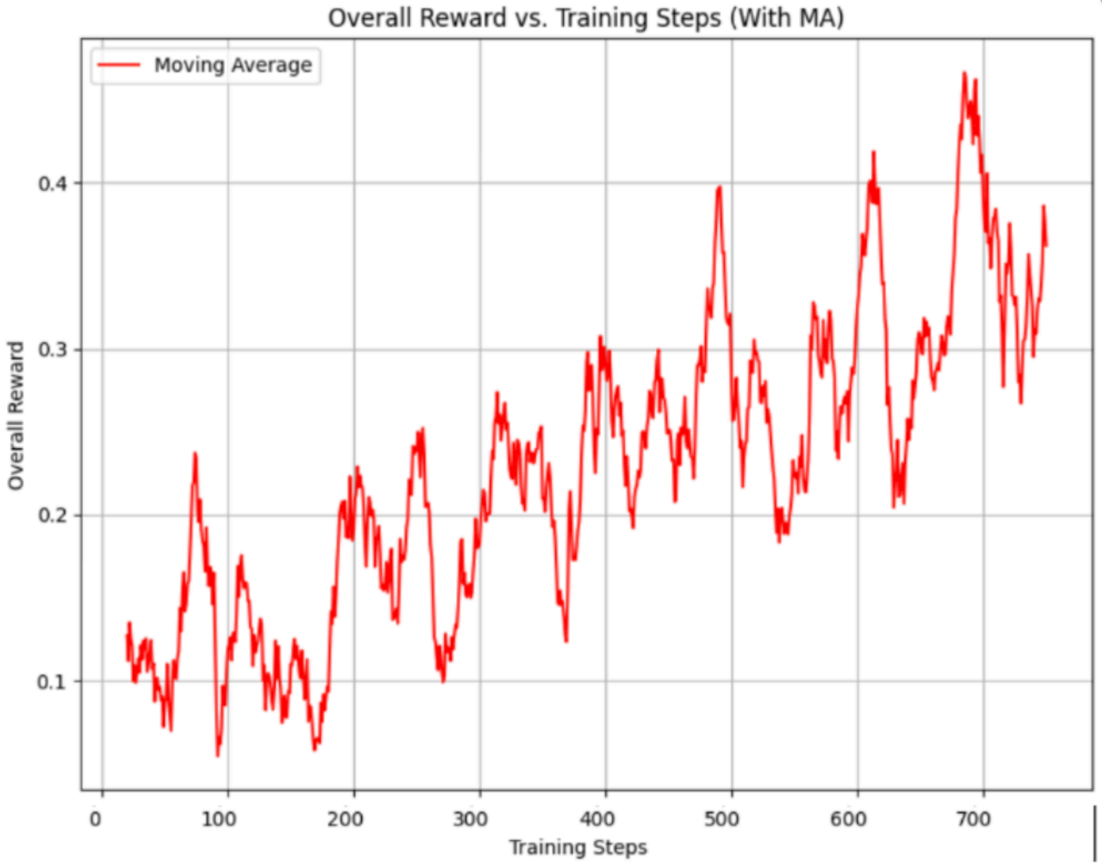
```
You are a specialist in playing 6-handed No Limit Texas Holdem. The following will be a game
scenario and you need to make the optimal decision.

Here is a game summary:

The small blind is 0.5 chips and the big blind is 1 chips. Everyone started with 100 chips.
The player positions involved in this game are UTG, HJ, CO, BTN, SB, BB.
In this hand, your position is BB, and your holding is [Seven of Diamond and Six of Diamond].
Before the flop, BTN raise 2.5 chips, and BB call. Assume that all other players that is not
mentioned folded.
The flop comes Ten Of Diamond, Six Of Heart, and Four Of Heart, then BB check, and BTN check.
The turn comes Eight Of Diamond, then BB check, and BTN bet 4 chips.


Now it is your turn to make a move.
To remind you, the current pot size is 9.0 chips, and your holding is [Seven of Diamond and Six
of Diamond].

Decide on an action based on the strength of your hand on this board, your position, and actions
before you. Do not explain your answer.
Your optimal action is:
```

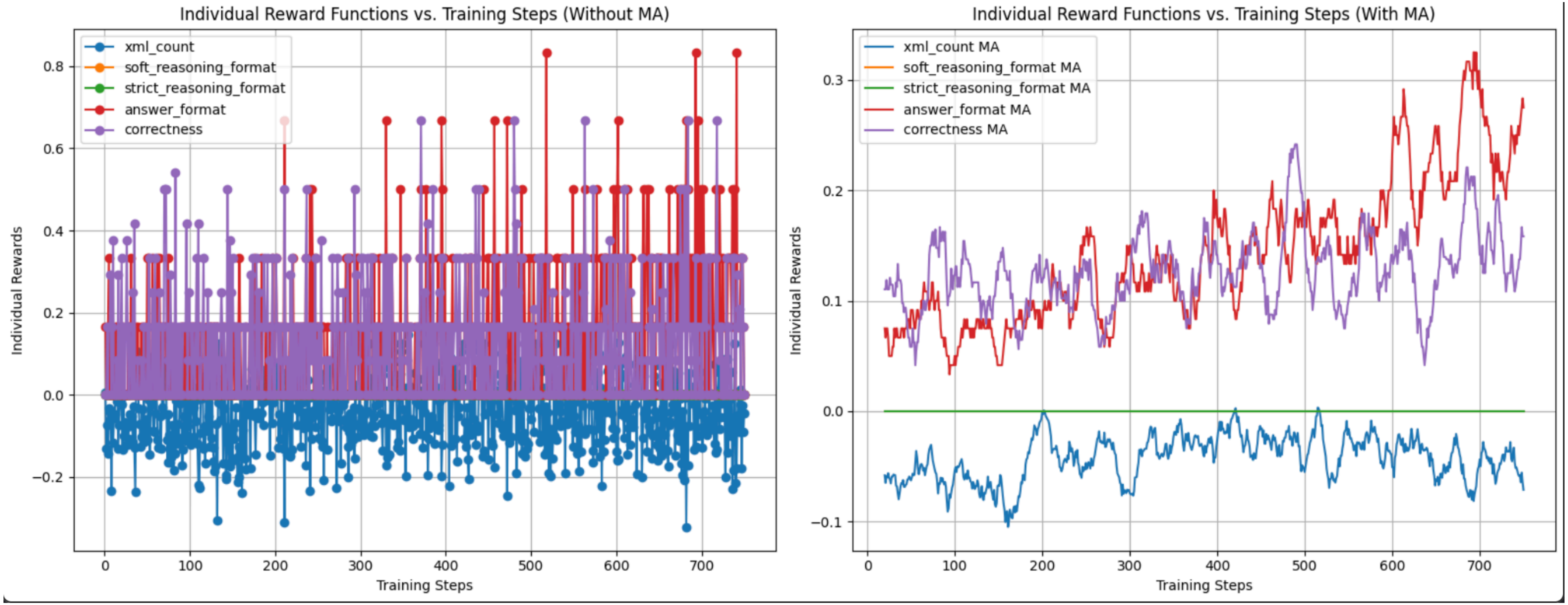
```
raise 13
```

- **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 for GRPO
  - Train on additional data, and then continue playing against itself
- Challenges: Long training time
  - 6 instances of our model have to conduct inference and give outputs
  - Due to randomness of poker, need many more simulations to observe long-term results

Results

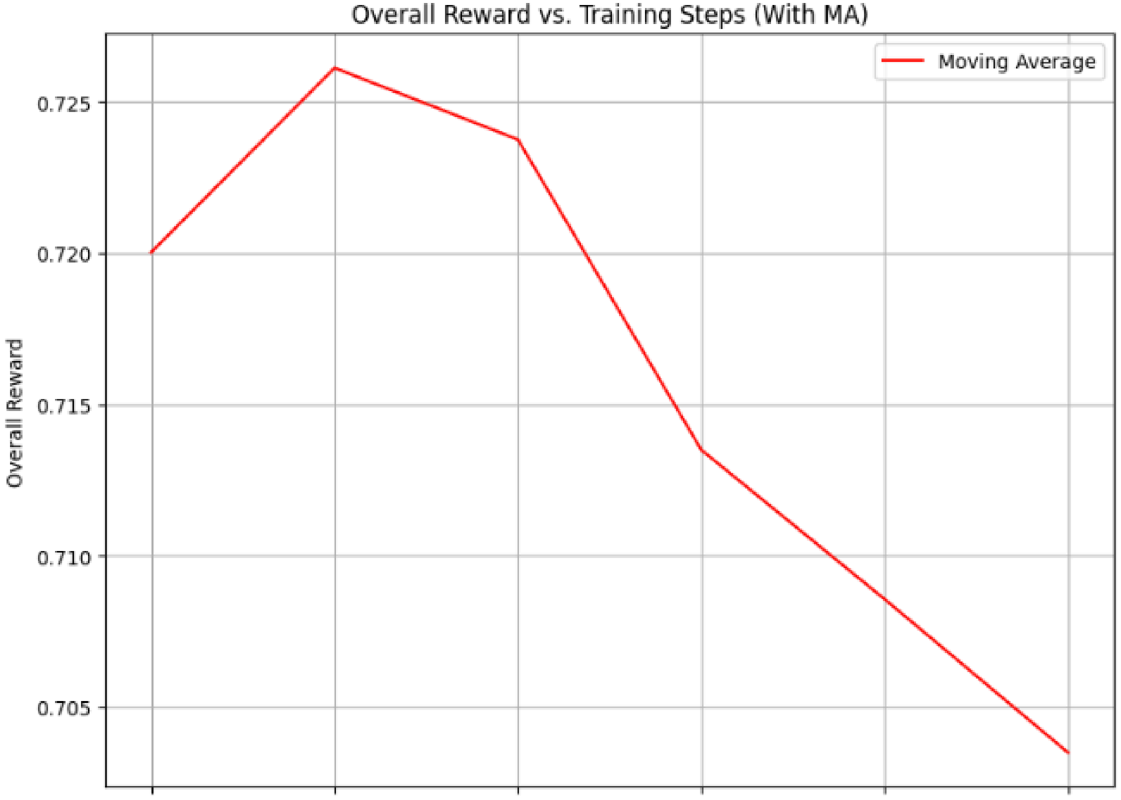

Overall Reward vs. Training Steps (Without MA)
Total Reward
Overall Reward
Training Steps
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
100
200
300
400
500
600
700


Overall Reward vs. Training Steps (With MA)
Moving Average
Overall Reward
Training Steps
0.4
0.3
0.2
0.1
0
100
200
300
400
500
600
700

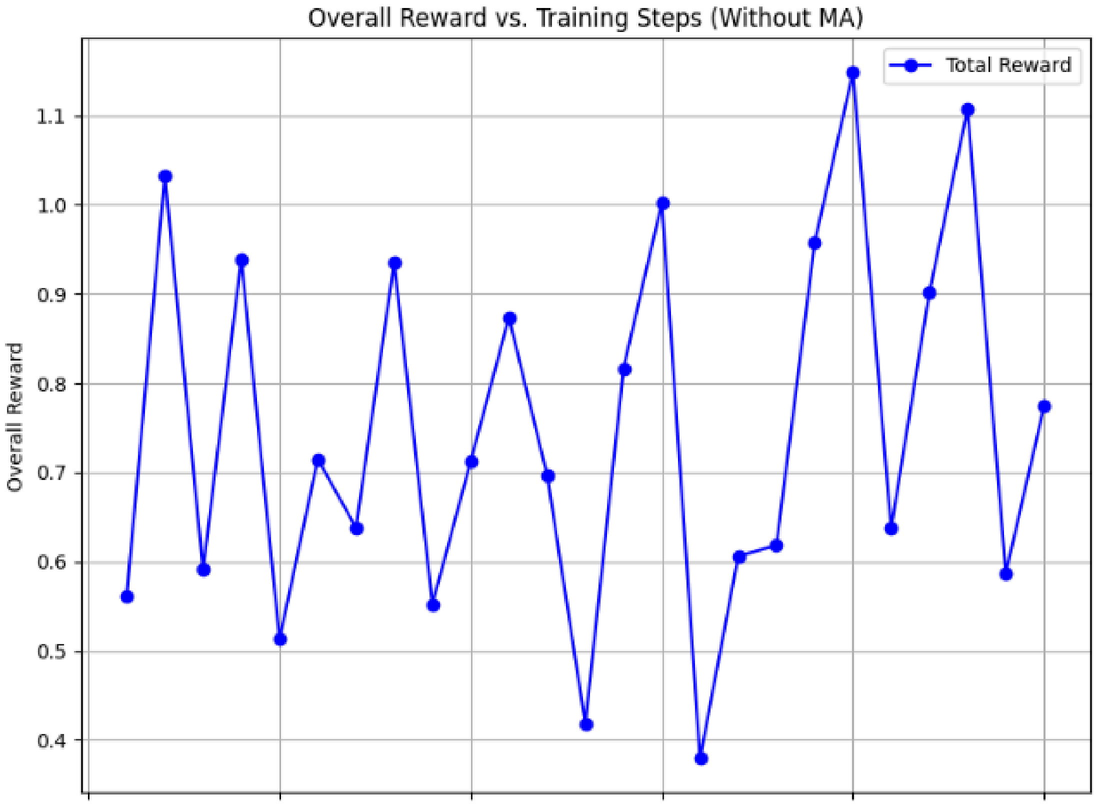


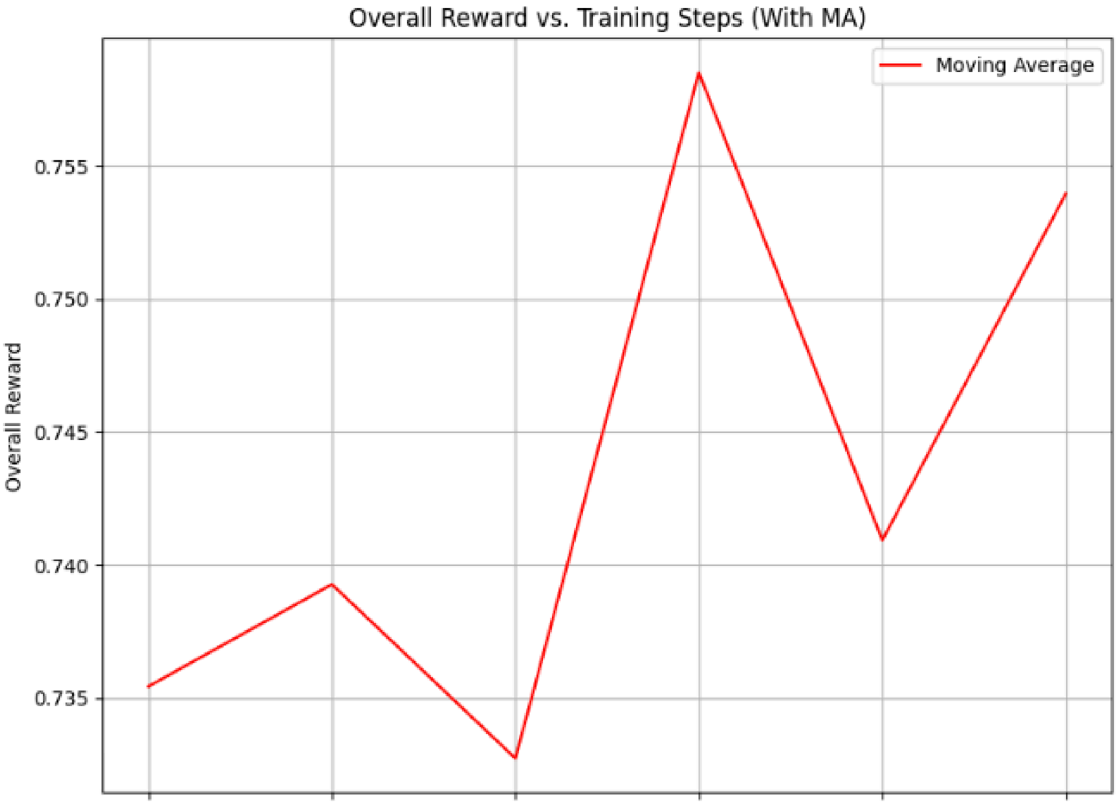
Individual Reward Functions vs. Training Steps (Without MA)
xml_count
soft_reasoning_format
strict_reasoning_format
answer_format
correctness
Individual Rewards
Training Steps
Individual Reward Functions vs. Training Steps (With MA)
xml_count MA
soft_reasoning_format MA
strict_reasoning_format MA
answer_format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

Rewards for Self Play Round 1

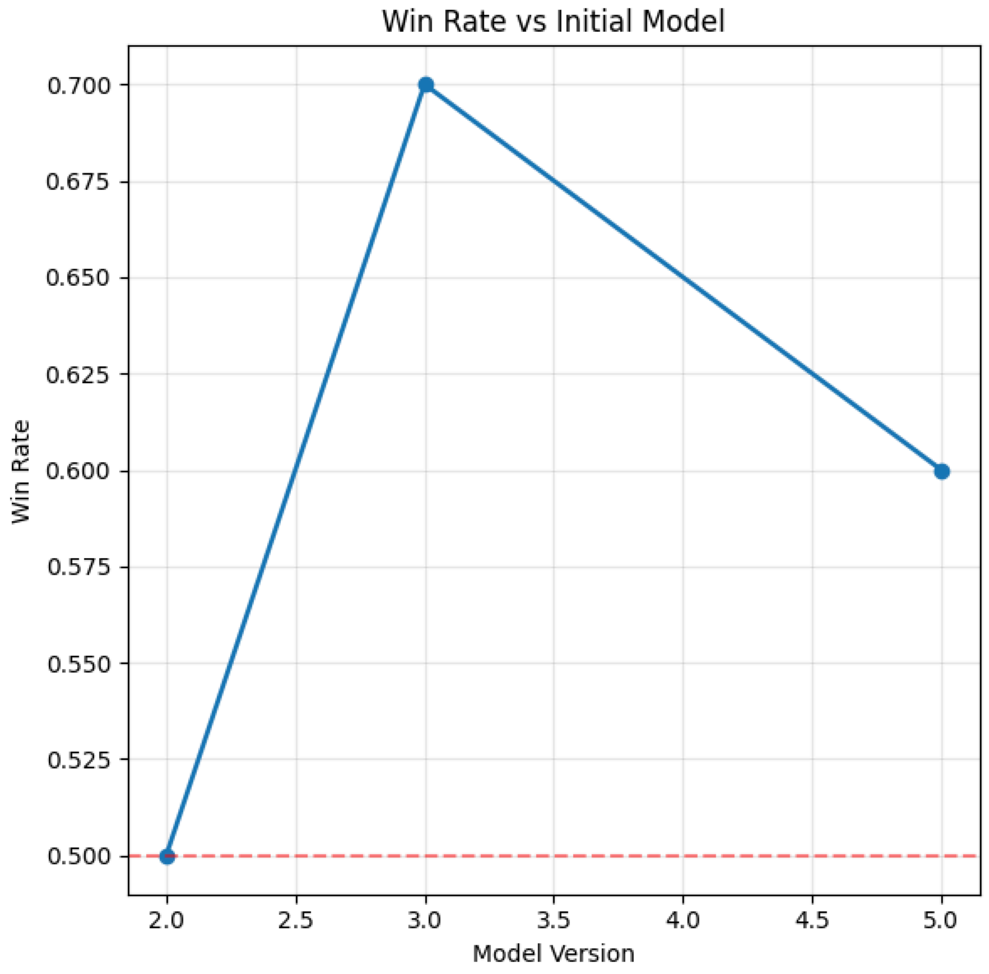


Rewards for Self Play Round 5





Model Winrate Progression



Self-Play Generated Data Example

You are a specialist in playing 6-handed No Limit Texas Holdem. The following will be a game scenario and you need to make the optimal decision. Here is a game summary: The small blind is 10 chips and the big blind is 20 chips. Everyone started with 1000 chips. The player positions involved in this game are UTG, HJ, CO, BTN, SB, BB. In this hand, your position is CO, and your holding is ['C2', 'C3']. Before the flop, TransformerPlayer6 declared call; TransformerPlayer1 declared call; TransformerPlayer2 declared fold; you declared call; TransformerPlayer4 declared call; TransformerPlayer5 declared call. The flop comes D3, D9, CK, then TransformerPlayer4 declared raise 20; TransformerPlayer5 declared fold; TransformerPlayer6 declared call; TransformerPlayer1 declared fold; you declared call. The turn comes ['D3', 'D9', 'CK', 'C9'], then TransformerPlayer4 declared call; TransformerPlayer6 declared raise 20. The river comes ['D3', 'D9', 'CK', 'C9', 'H9'], then TransformerPlayer4 declared fold. Now it is your turn to make a move. To remind you, the current pot size is {'main': {'amount': 260}, 'side': []} chips, and your holding is ['C2', 'C3']. Decide on an action based on the strength of your hand on this board, your position, and actions before you. Do not explain your answer. Your optimal action is:	raise 40

Results Overall

- **Fine-Tuning Improvements:** Model is improving and finding rewards during fine-tuning, demonstrating complex reasoning capabilities of LLMs
- **Self-Play Improvements:** Models further trained through self-play do better, showing potential for continued improvement through this pipeline

Project Reflection

Limits Encountered & Adaptations

- **Computational Resources:**
  - On an A100 GPU, fine-tuning on around 1000 PokerBench examples and 250 examples from self-play takes around 10 hours
  - 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 (ex. reduce LoRA r parameter size)
  - Required tuning reward functions to provide a denser, more continuous feedback signal.

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
- Converting PyPokerEngine outputs into prompts and labels for our self-play training

How The Project Evolved

- Trained initial model using **GRPO** and attempted self-play reinforcement learning with **PPO**.
- **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

- Figure out a way to assess what is a good "fold" during self-play to prevent biasing our model towards calling or raising during the self-play training
- Playing against other models (or humans) besides our own to evaluate performance
- Need way more training time and way more compute to achieve our goal

AI Tool Use

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