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 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, but poker has a very large game tree
  - Won't take advantage of imperfect opponent
- State of the art poker bot: **Pluribus**
  - Uses self-play to iteratively converge at the equilibrium
  - Leverages Monte Carlo Counterfactual Regret Minimization

Using LLMs

- Transformer models like ChatGPT / GPT-4 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.an*Expected$h$(EV) $R(h)$:**

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

    - $P(h)$ 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 (Guaranteed Reward Policy Optimization):**
  - **Monotonic Improvement:**
    Provides theoretical guarantees for steady policy improvement.
  - **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:**
  - High-performance PyTorch code with haT4 or A100written GPU kernels.
  - Improved memory utilization through typecasting.
  - Scalability: Fine-tuning 8B parameter models on modest GPU setups (e.g., Colab T4).

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:
  $$W' = W + BA$$

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: Guaranteed Reward Policy Optimization (GRPO)**
  - **Justification:**
    - GRPO provides theoreti guarantees for steady policy improvement.
    - 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.

**Limits Encountered & Adaptations&

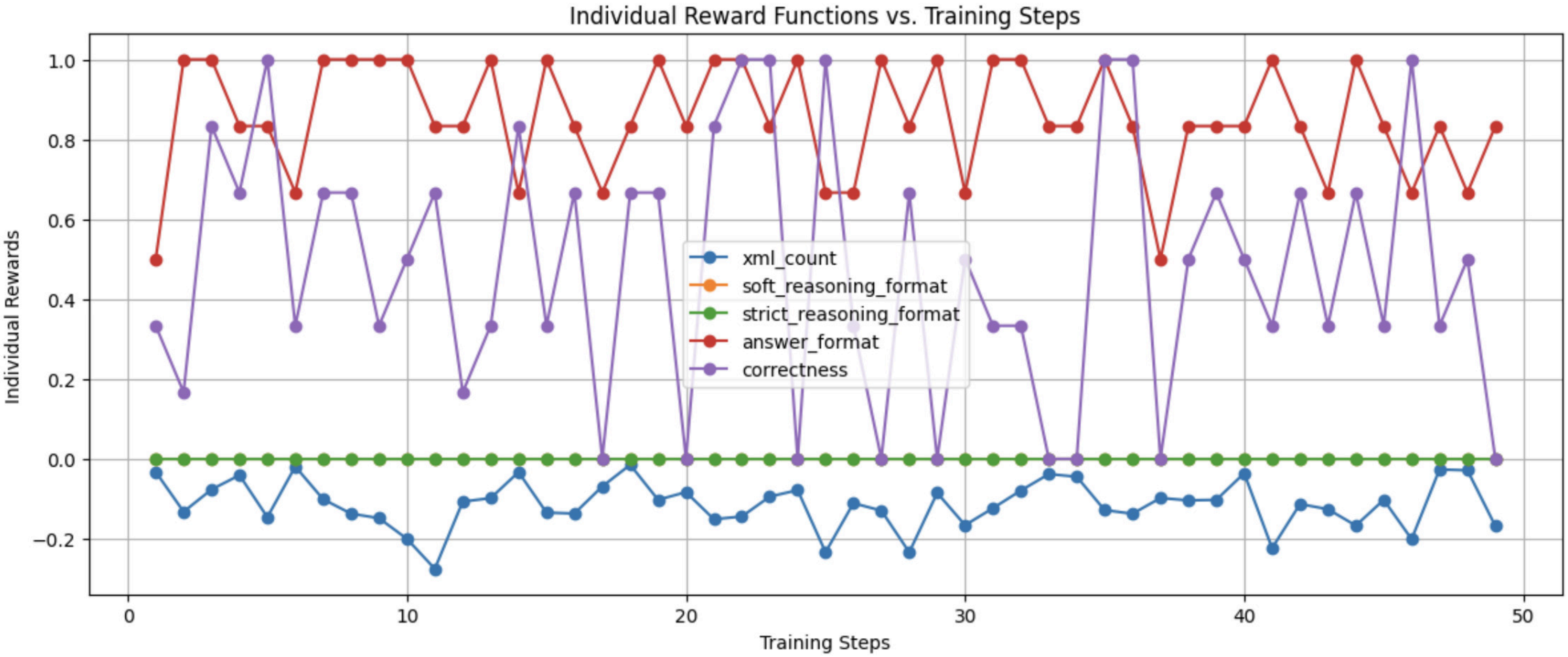
- **Computational Resources:**
  - Initially limited to a T4 GPU on Colab, leading to frequent disconnections and slow iteration.
  - Challenges in accessing scalable GPU resources on platforms like Google Cloud.
- **Impact on Model Training:**
  - Slow training and iteration speeds forced us to adjust 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.

Results

Individual Reward Functions vs. Training Steps
xml_count
soft_reasoning_format
strict_reasoning_format
answer_format
correctness
Individual Rewards
Training Steps
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
0
200
400
600
800
1000


Overall Reward vs. Training Steps
Total Reward
Overall Reward
Training Steps
2.5
2.0
1.5
1.0
0.5
0.0



Individual Reward Functions vs. Training Steps
Individual Rewards
Training Steps
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
0
10
20
30
40
50
xml_count
soft_reasoning_format
strict_reasoning_format
answer_format
correctness


Overall Reward vs. Training Steps
Total Reward
Overall Reward
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
Training Steps

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

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.

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 snippets for reinforcement learning tasks.