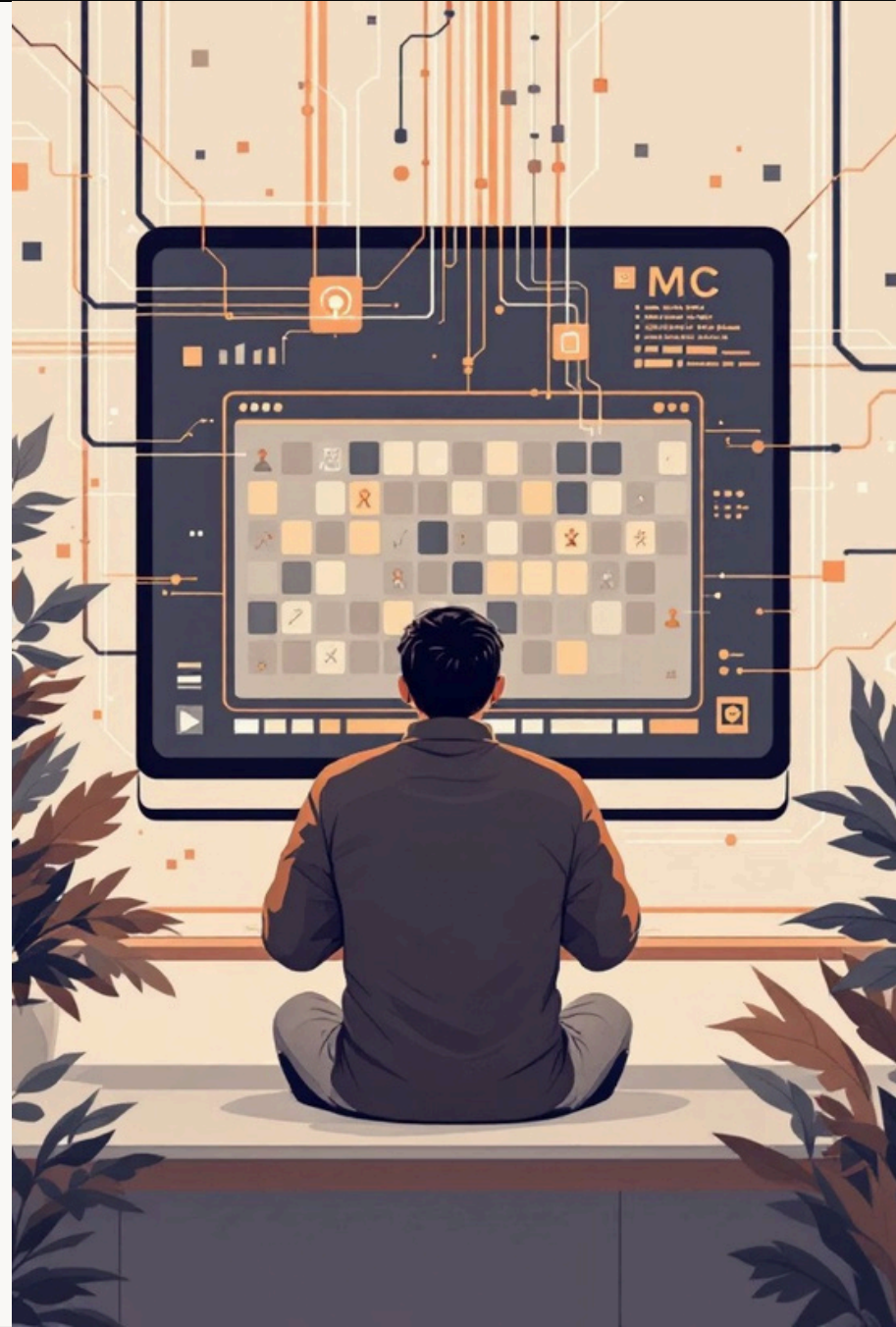
# Team Conquer

Team Number 73

- Ritvik Shrivastav
- Prashasth Immanuel
- Kamal Enoch
- Bharat Reddy

# GRPO Fine-Tuning of Llama-3.1-8B using Unsloth

Accelerated by AMD MI300X



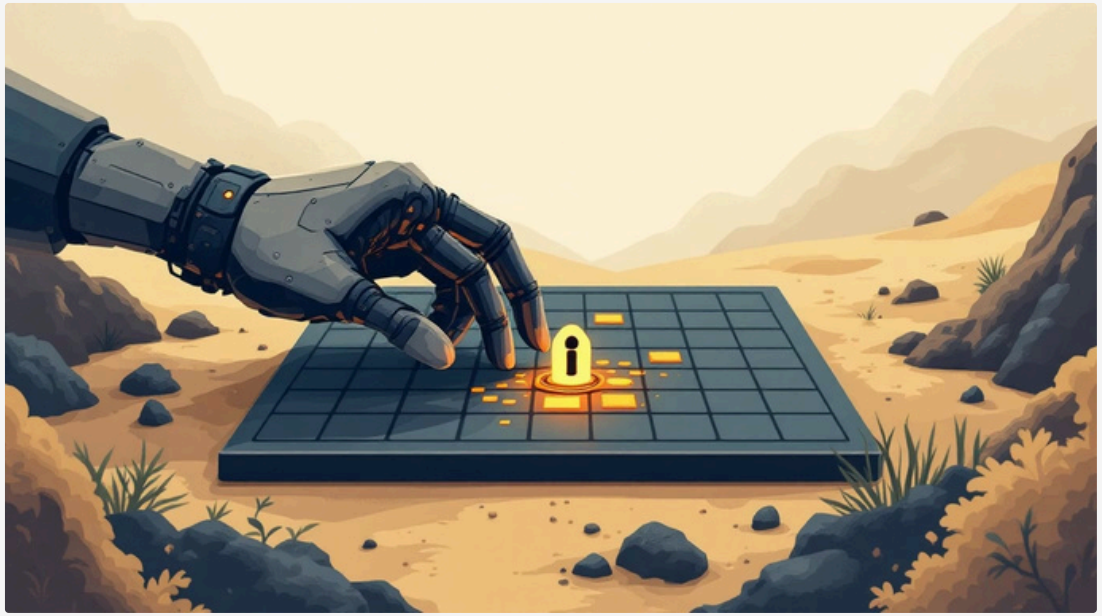
# Problem Statement: Mastering Minesweeper

### Structured Action Output

The LLM must generate actions in a precise JSON format for system interpretation.

### Optimize Full-Game Win Rate

Success is measured by complete board wins, not merely survival or partial clearance.



# System Architecture: A Powerful Stack

## Base Model: Llama-3.1-8B

A strong foundation for general language understanding and generation.

## Fine-Tuning: GRPO

Utilizing Group Relative Policy Optimization for enhanced stability and exploration.

## Acceleration: Unsloth

4-bit quantization and LoRA techniques for efficient fine-tuning.

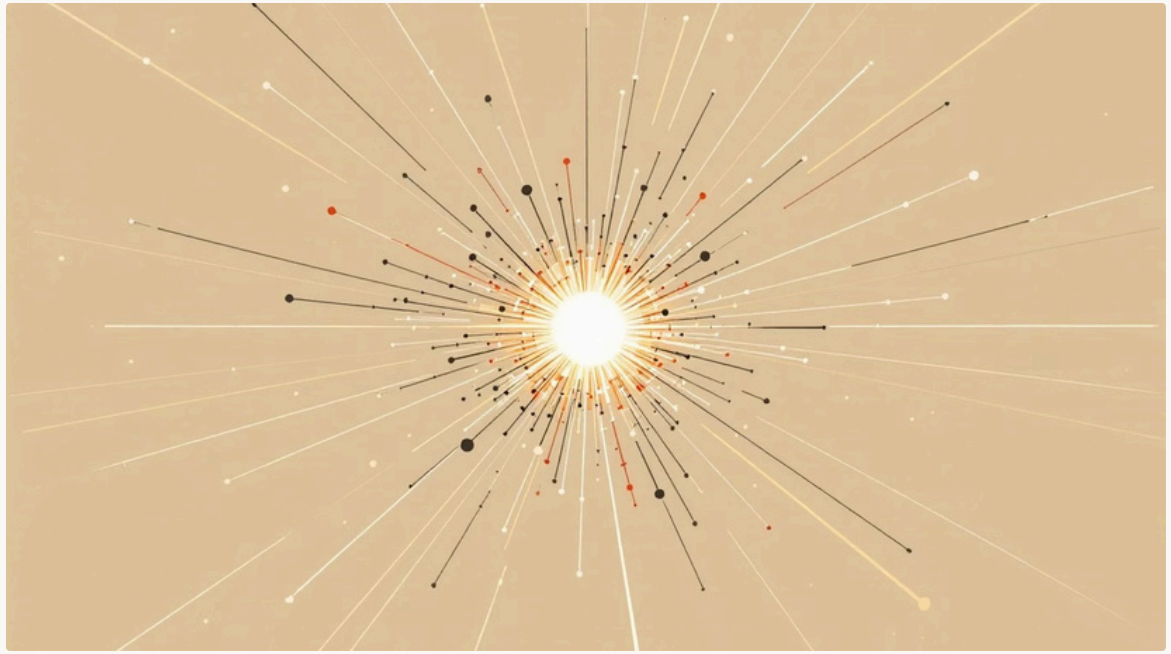
## Hardware: AMD MI300X GPUs

High-performance computing power for rapid experimentation and training.

## Custom Environment

Tailored Minesweeper simulator for targeted RL training.

# Why GRPO? Enhancing Stability and Exploration



Group Relative Policy Optimization (GRPO) offers significant advantages over standard PPO methods, particularly in environments requiring nuanced decision-making.

- ## Multiple Completions

  Generates several potential actions per board state, providing a richer learning signal.

- ## Relative Reward Comparison

  Compares rewards within a generated group, improving policy gradient stability.

- ## Encourages Exploration

  Reward variance within groups naturally fosters a more exploratory policy.

# Reward Shaping Strategy: Guiding the Agent

Carefully crafted reward signals are crucial for efficient learning in sparse-reward environments like Minesweeper.

## Valid JSON Output

Direct reward for adhering to the required output format.

## Legal Move Reward

Positive reinforcement for making valid game moves.

## Safe Reveal Bonus

Reward for uncovering safe cells, progressing towards the goal.

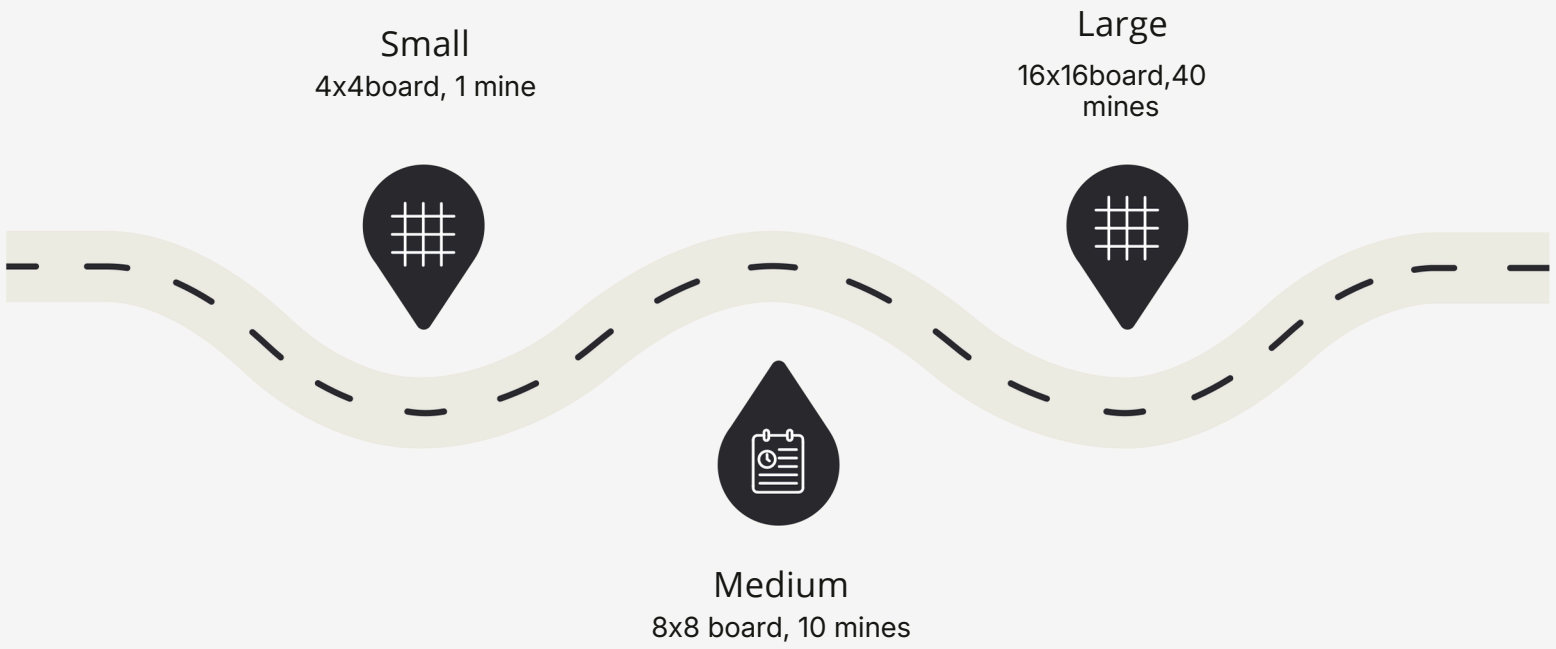
## Penalties

Negative rewards for bombs, invalid actions, or redundant moves.

## Terminal Win Bonus

Significant positive reward upon successfully clearing the entire board.

# Curriculum Learning: From Simple to Complex




- Start with small boards (e.g., 4x4 with 1 mine) to establish basic policy.
- Gradually increase board size and mine density as performance improves.
- Ensures early positive learning signals, preventing policy collapse.
- Reduces the chances of the agent resorting to random guessing on complex boards.

# Evaluation Methodology: Measuring Success

1

## Deterministic Inference

Utilizing greedy decoding to ensure consistent and reproducible action selection.

2

## Full-Episode Gameplay

Evaluating the agent across entire games, from start to finish, for comprehensive results.

3

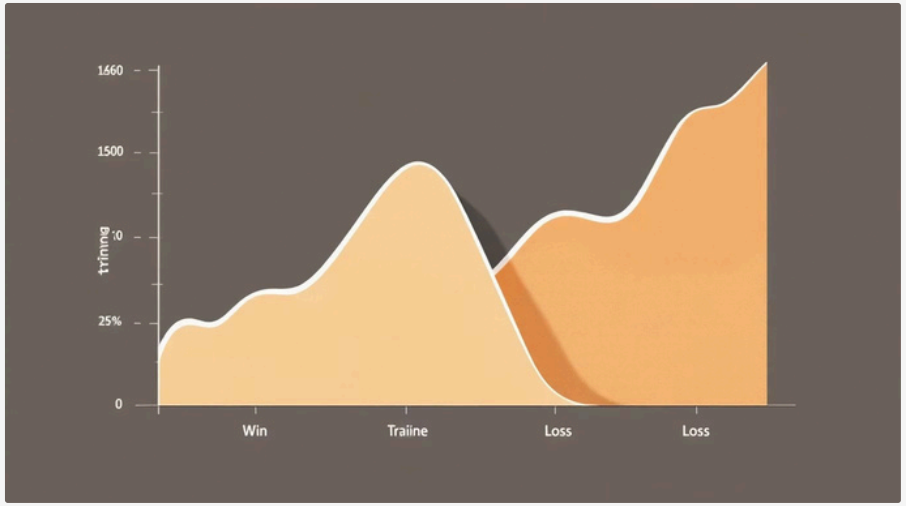
## Key Metrics

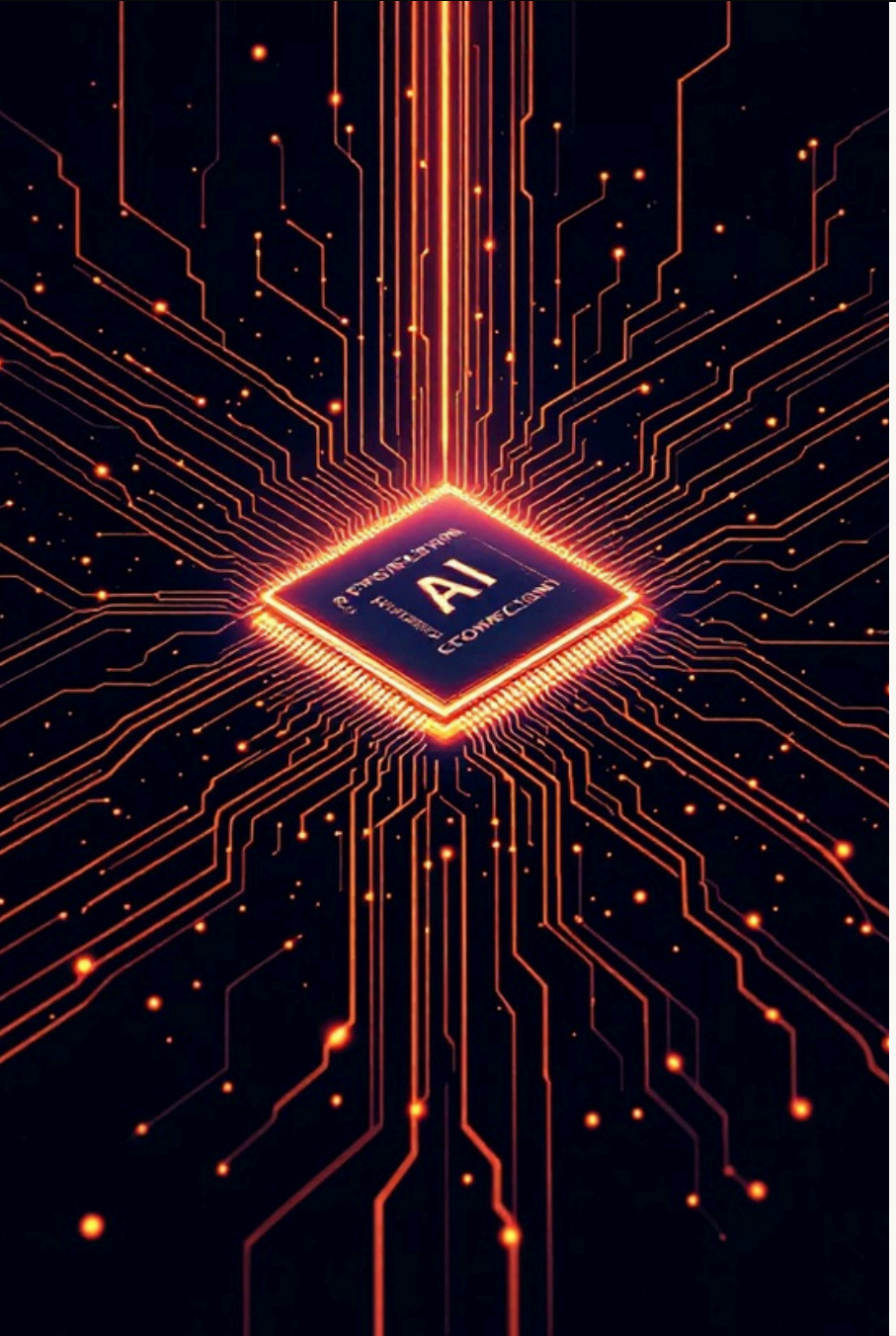
Tracking Win Percentage, Loss Percentage, and Invalid Action Percentage.

4

## Periodic Evaluation

Regular checks during training to monitor progress and identify potential issues.






# Key Learnings & Insights

## Reward Shaping is Paramount

Effective reward design significantly outweighs marginal gains from increased model size.

## Exploration is Critical

Mechanisms promoting exploration are essential for discovering optimal policies.

## Curriculum Accelerates Convergence

Structured curriculum learning speeds up the training process.

## Unsloth + MI300X Power

This combination enables rapid iteration and experimentation, crucial for RL development.