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Multi-Agent Reinforcement Learning Invades MMORPG: Lineage Clone Wars

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#GDC22

Agenda

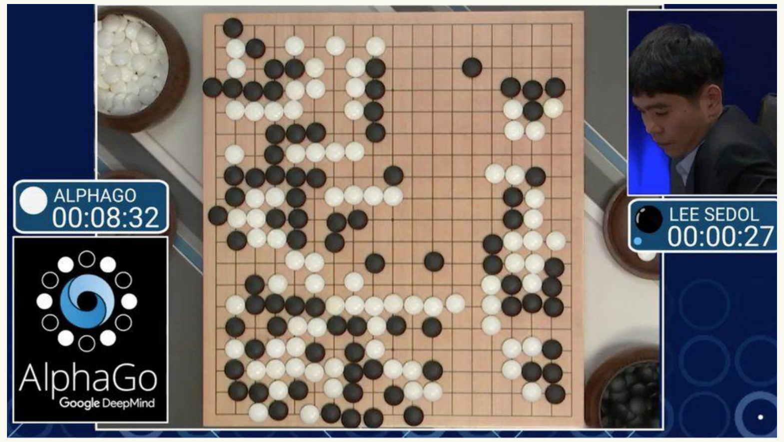
- Our Goal & Method
- Part I. Game Introduction
- Part II. Reinforcement Learning Method
- Part III. Reinforcement Learning Framework
- Conclusion

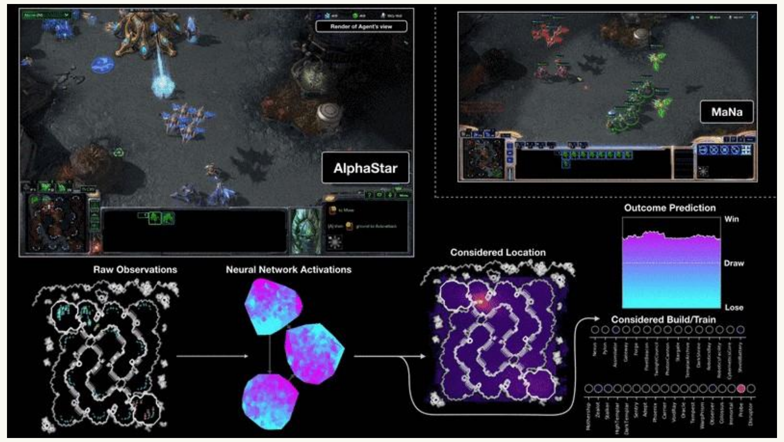
Our Goal

- Develop AIs that can fight against human users in large-scale battle
    - New gaming experience
    - Different kind of opponent

Our Method

- Reinforcement Learning
- Why reinforcement learning?
  - Human behavior is too complex for traditional methods (e.g., FSM, behavior tree)
  - Constant updates in MMORPG → easily update AIs with RL





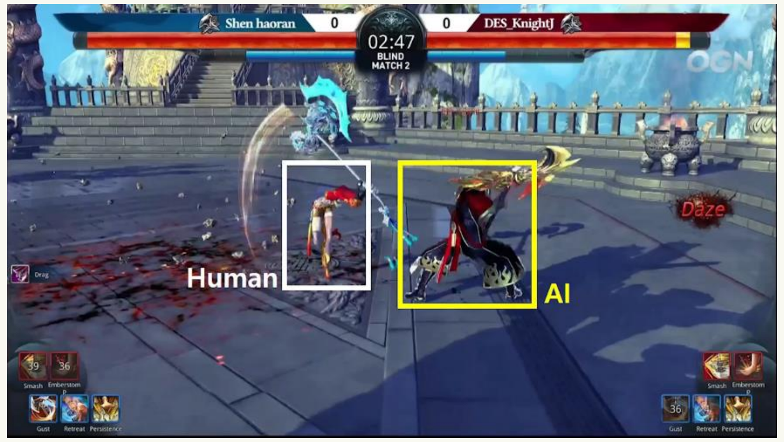
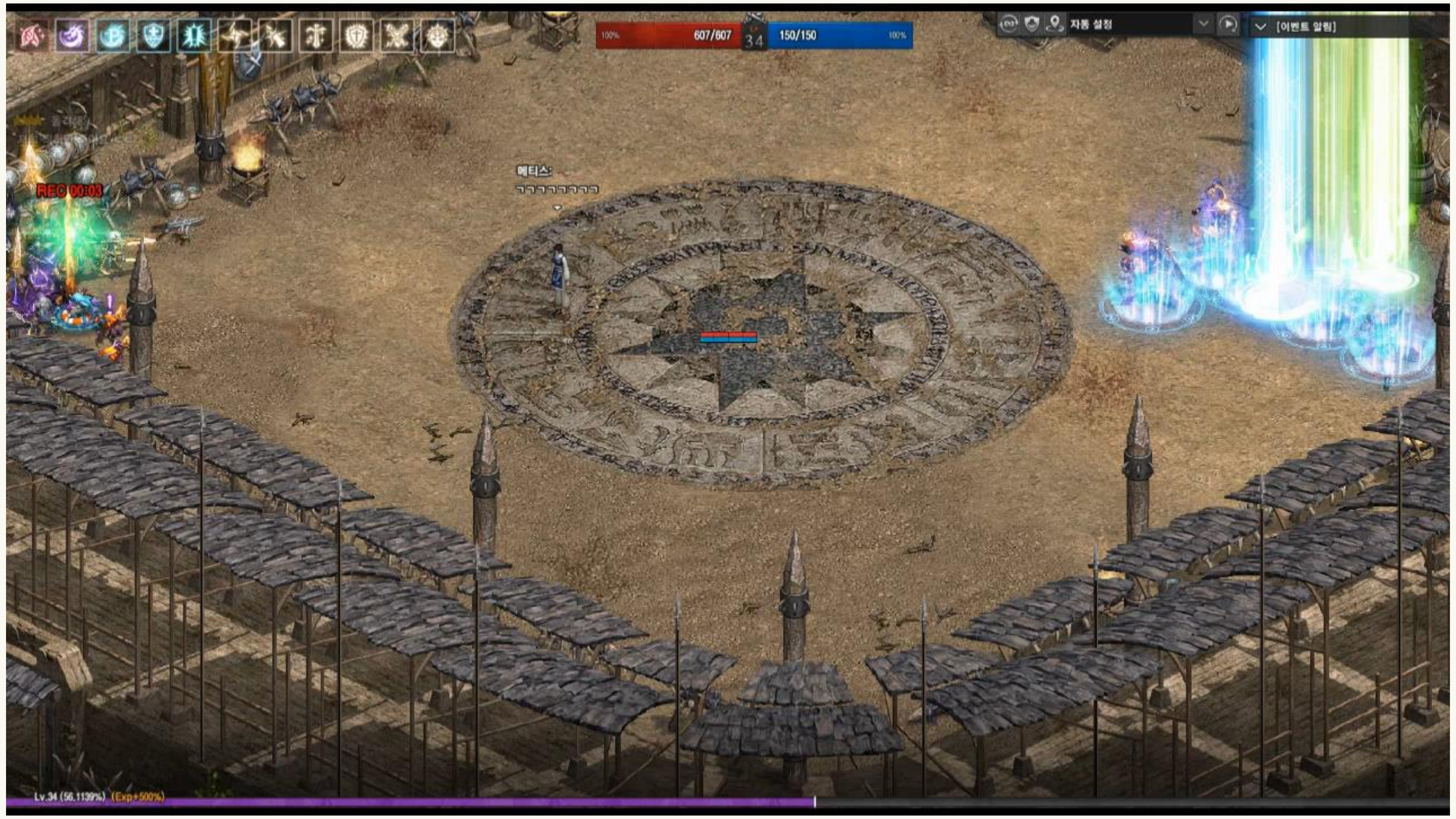


image ref :https://www.bbc.com/news/technology-35785875
https://deepmind.com/blog/article/alphastar-mastering-real-time-strategy-game-starcraft-ii
https://towardsdatascience.com/mastering-deep-reinforcement-learning-with-openais-new-spinning-up-in-deep-rl-package-b86b61ab6e54

Part I. Game Introduction

AI Content 1. Legend Reborn

- **Our goal:** create AIs that can win human players in 8 vs. 8 battle
- **Three key points**
  - Focus fire on specific targets
  - Position themselves depending on character class
  - Select skills appropriate in each situation

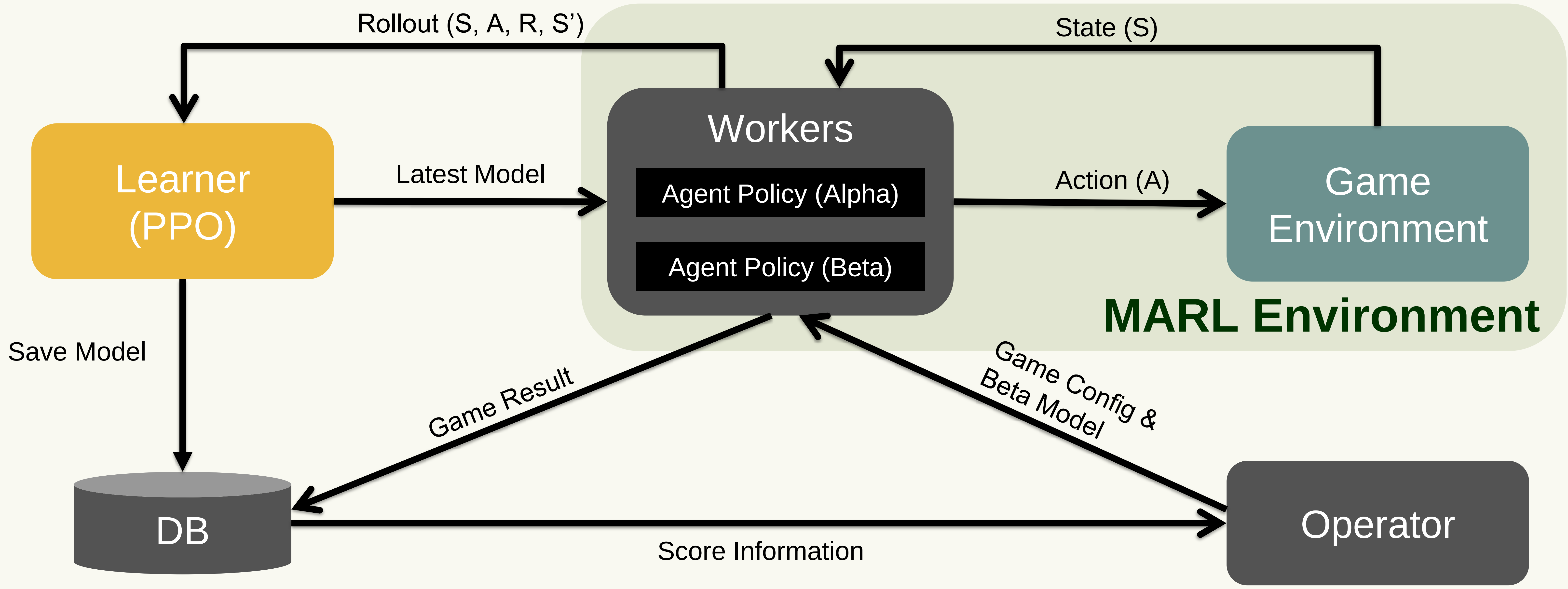


AI Content 2. Clone Wars

- **Our goal:** create AIs that behave like humans but provide more battle experience
    - Attack users
    - Hunt monsters
    - Raid bosses

Part II. Reinforcement Learning Method

Overview of Our Learning Framework

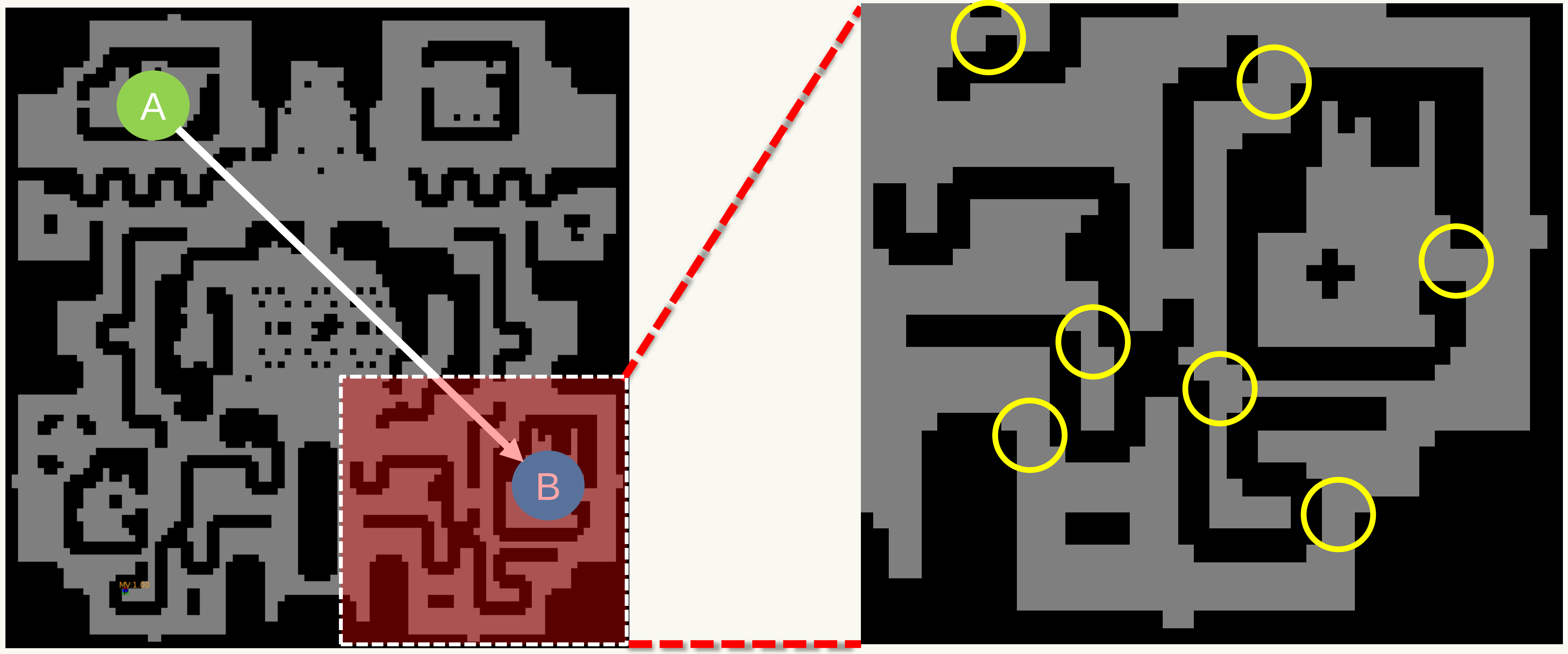


Practical Constraints

- **Limited training resources**
  - About 300 CPUs
- **Limited training time**
  - 1 week (before live service)
- **Constant updates**
  - Live service game
  - Additional training needed

Challenge 1: Geographic Complexity

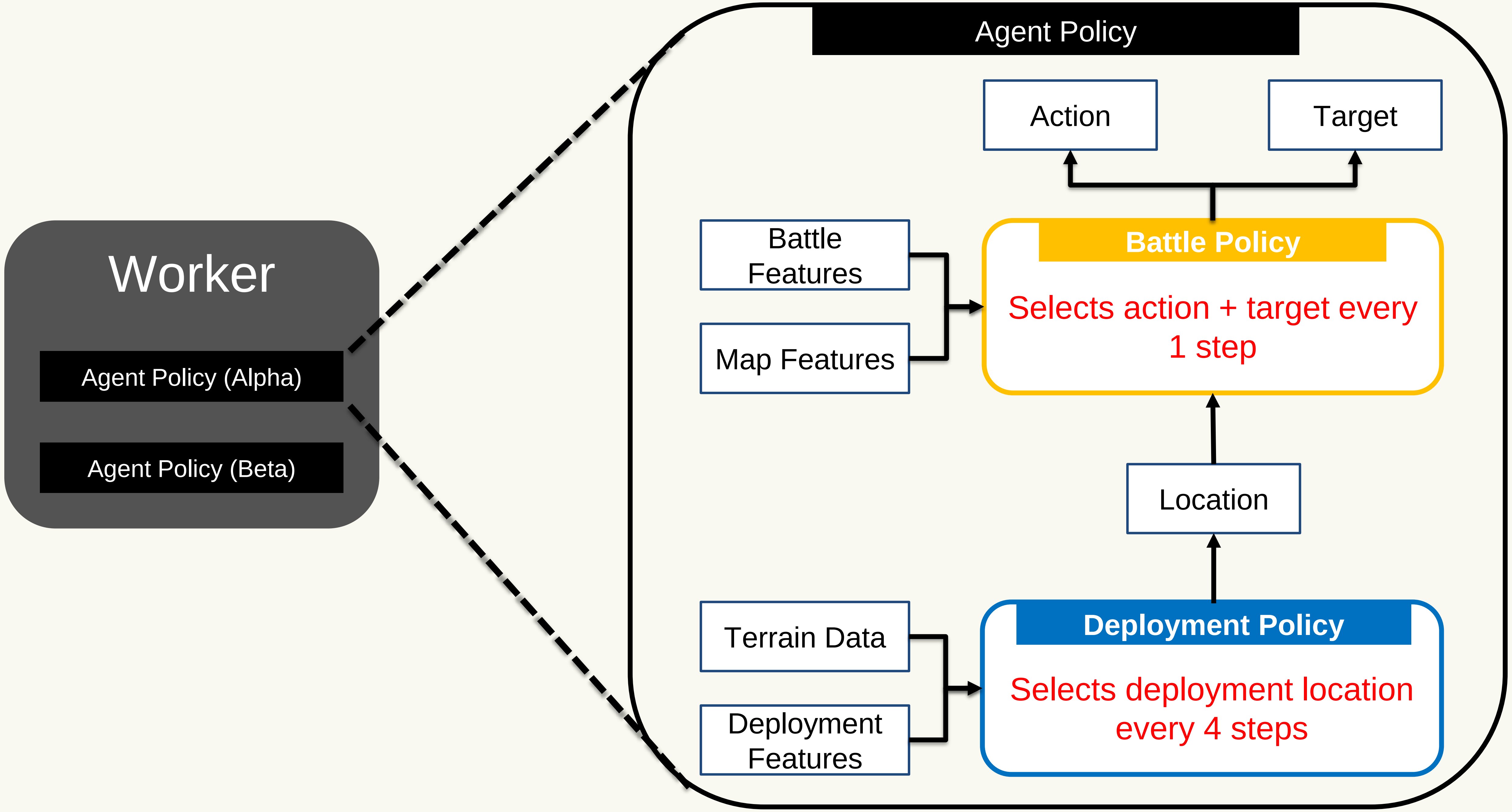
- Large map size + complex terrain



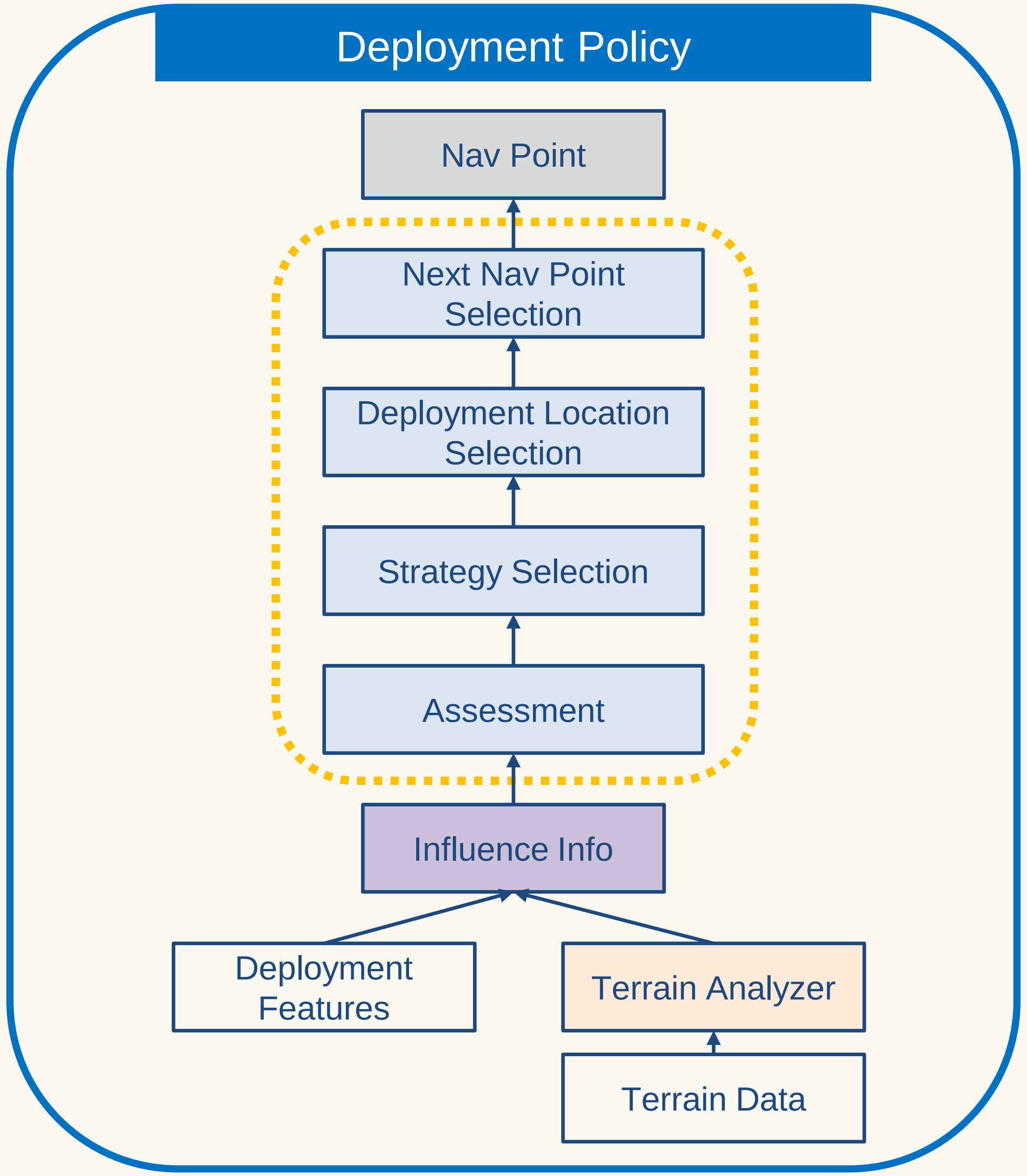
Time spent moving from
A → B: over 100 steps

Multiple narrow entryways
(Complex terrain)

Hierarchical Decision Structure

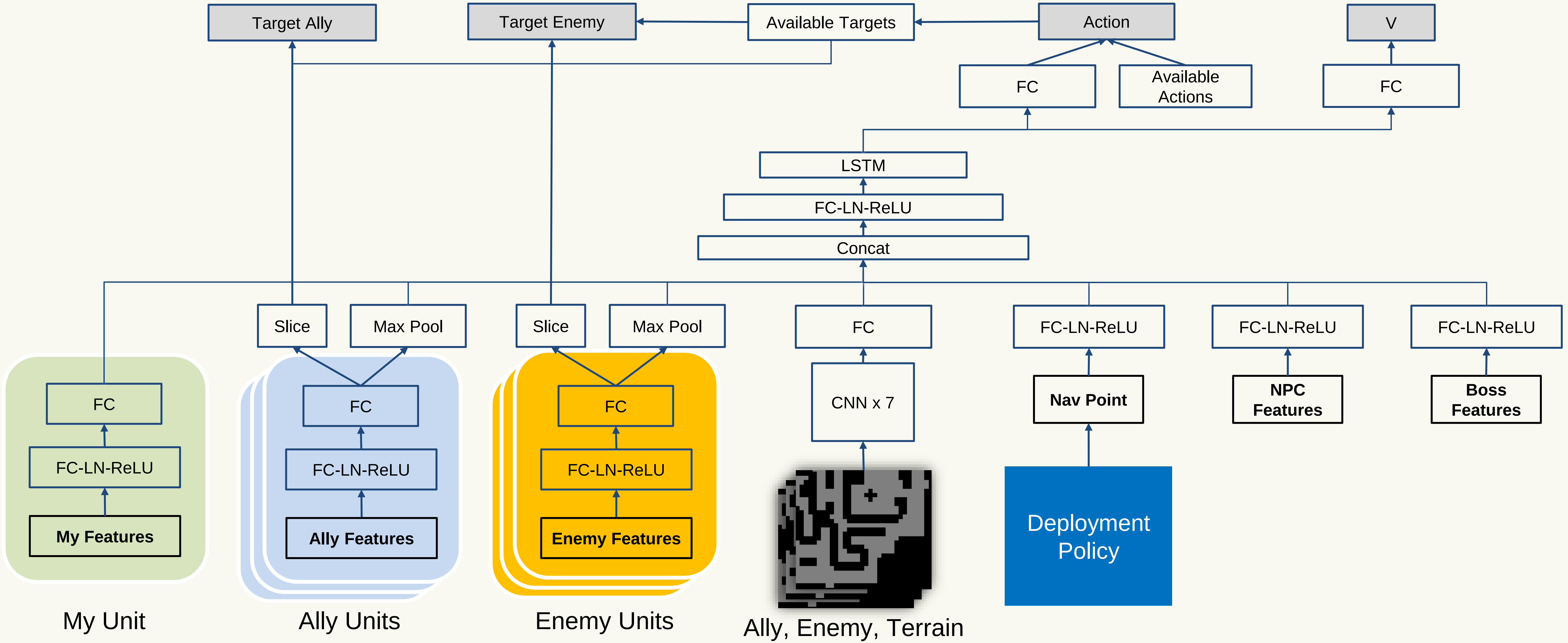


Deployment Policy

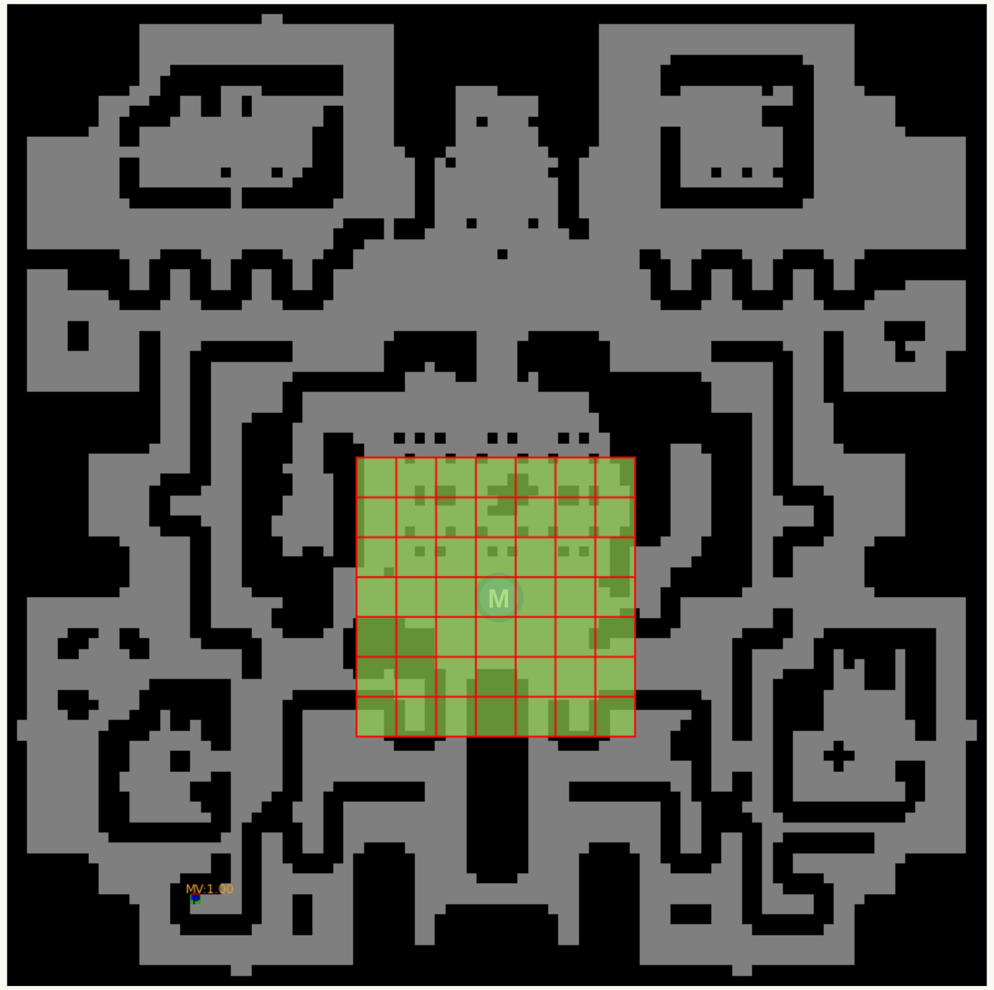


- Used to move agents to distant locations on a large map
  1. **[Influence Info]** calculates the influence of each team
  2. **[Assessment]** decides which team is dominant
  3. **[Strategy Selection]** selects strategy among offense, sweep, and defense
  4. **[Deployment Location Selection]** decides deployment location
  5. **[Next Nav Point Selection]** selects navigation points and feeds to battle policy

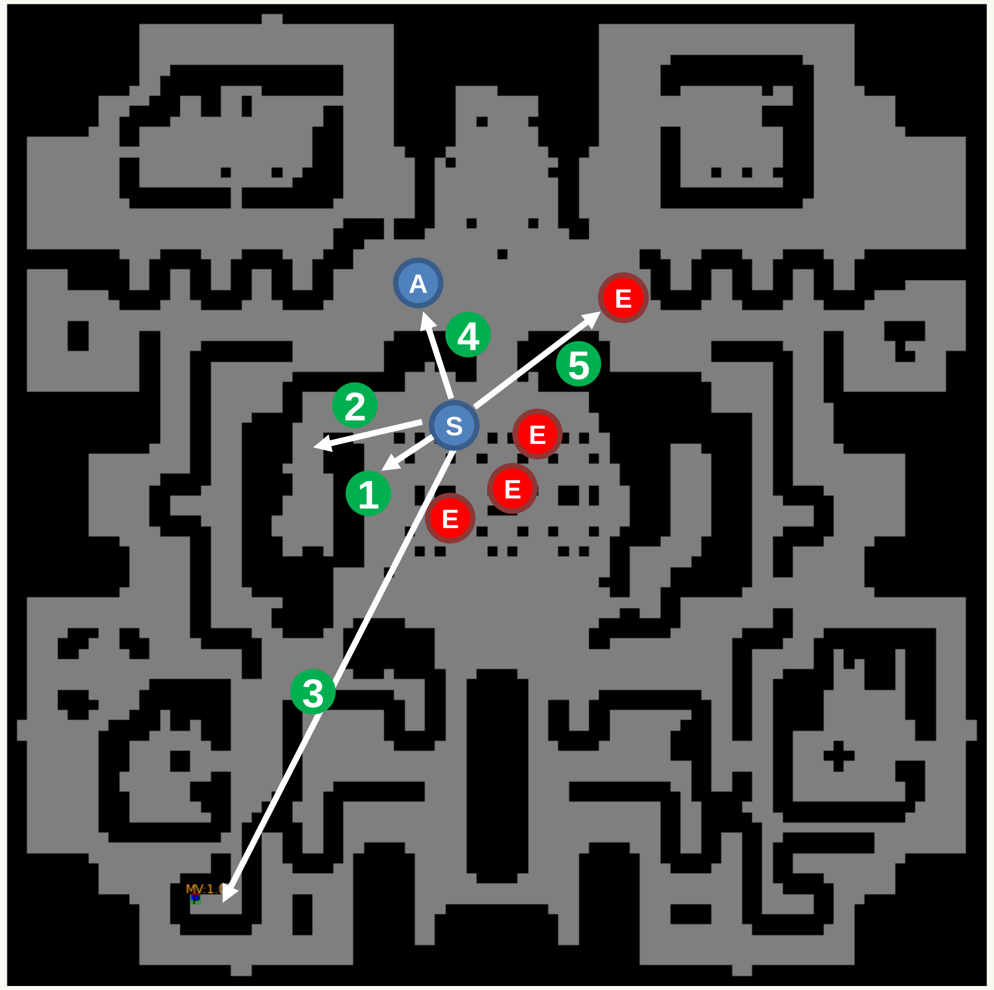
Battle Policy



Move Space Reduction



7x7 move points
[AI remains untrained]



Conceptualized move actions
[AI trained within 1 week]

Agent

- S Selected AI
- A Ally (AI)
- E Enemy (user)

Move Action

1. Hide behind wall
2. Retreat to close area
3. Retreat to distant area
4. Move to ally
5. Move to enemy

Challenge 2: Innumerable Combinations

- Numerous combinations of characters with different specifications

Number of participating characters: 8-16

Number of character classes: 10

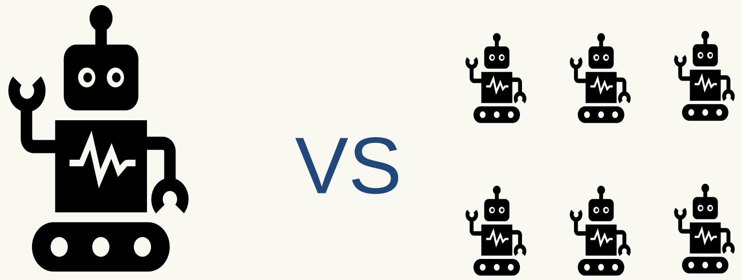
Range of character levels: 91-99

Types of character stats: 100+

Ex) STR, DEX, INT, CON, WIS, AGI, AC, etc.

Innumerable possible combinations

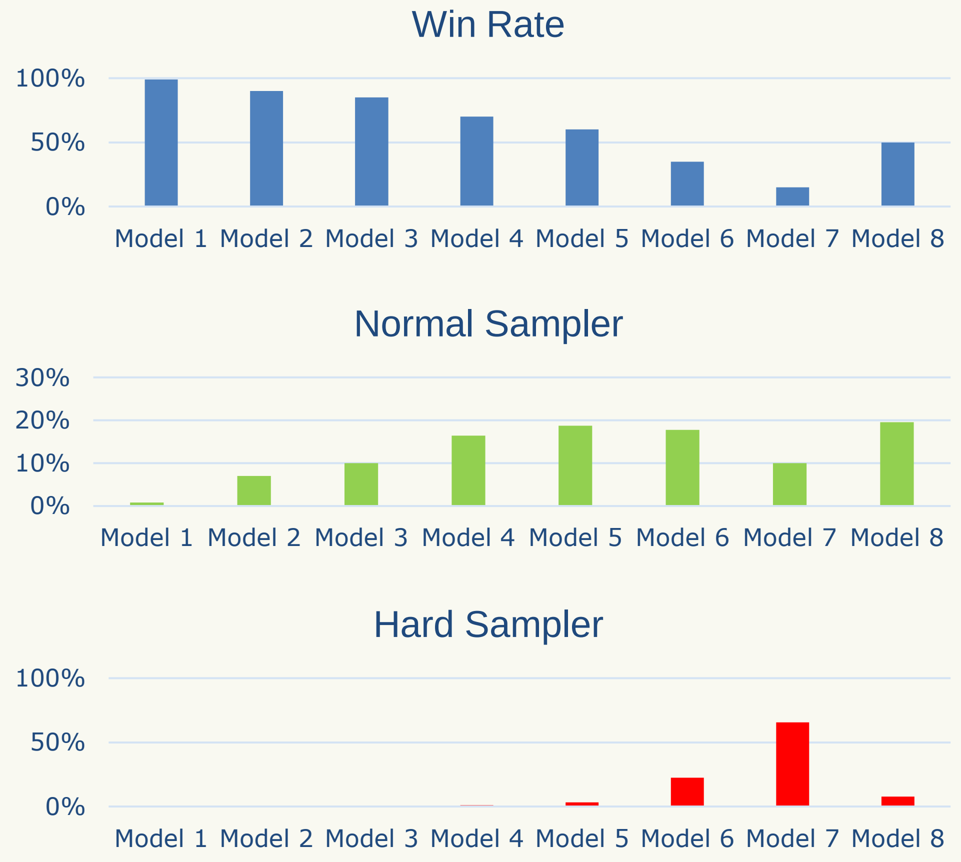
Sampling Methods for Self-Play Learning



Current Model

Past Model

Self-Play Learning



Model Sampling

- Random sampling → class combinations not used in real battles
- Combination sampling → combinations frequently used by users
  - At least 1 magician
  - At least X% melee class
  - 1-16 units per team
  - 30%↓ difference between number of ally and enemy units

Combination Sampling

Challenge 3: Behavior Shaping

- **Achieve human-likeness**
  - Example 1. AIs must occasionally prioritize their own life over allies
  - Example 2. AIs must stay close to their allies when preparing for battle
- **Make the game content fun for users**
  - Example 1. Fight to the death even when there is no chance of winning
  - Example 2. Behave aggressively → start more battles!

Reward Design for Behavior Shaping

- Achieve human-like behavior (e.g., prioritize their own life over allies')
  - -1.2 team reward if ally dies
  - Additional -0.6 individual reward if AI itself dies
- Encourage aggressive behavior
  - Penalty for time passed
- **Reward shaping: simple & effective way to satisfy the intentions of game designers**

Total Reward

Individual Reward

- -0.6 if I die
- -0.02 if no action
- 0.015 if ally is near
- 0.1 if I use buff
- 0.02 if I use debuff

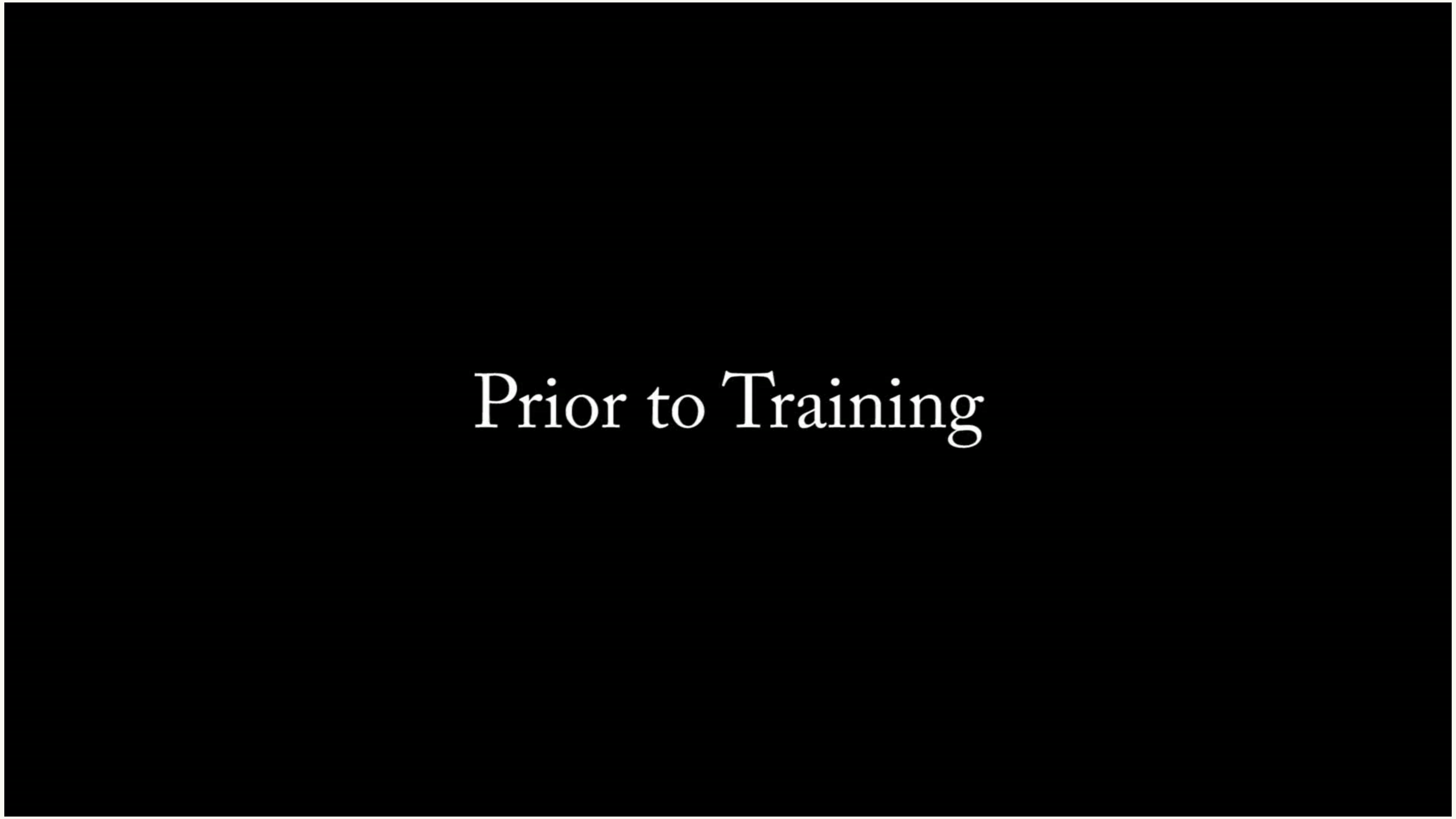
Team Reward

- -5×10^{-3} per tick
- -1.2 per dead ally
- 1.2 per dead enemy
- 0.08 per dead NPC
- 2.0 per dead boss

Other Training Methods We Used

- **Curriculum learning**
  - Make allies and enemies spawn close to each other X% of the time
- **Decay entropy loss coefficient**
  - Experience variety of actions → Increase probability of choosing better actions
- **Network surgery**
  - Respond to live service updates
  - Action-wise entropy loss → help AIs experience added skills

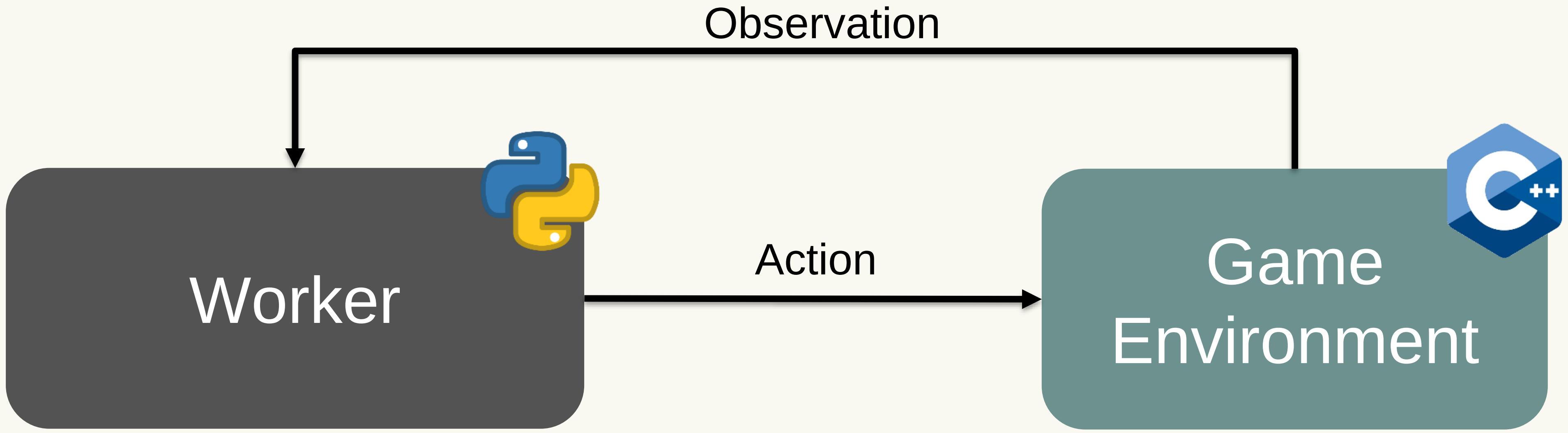
Video 1. Legend Reborn



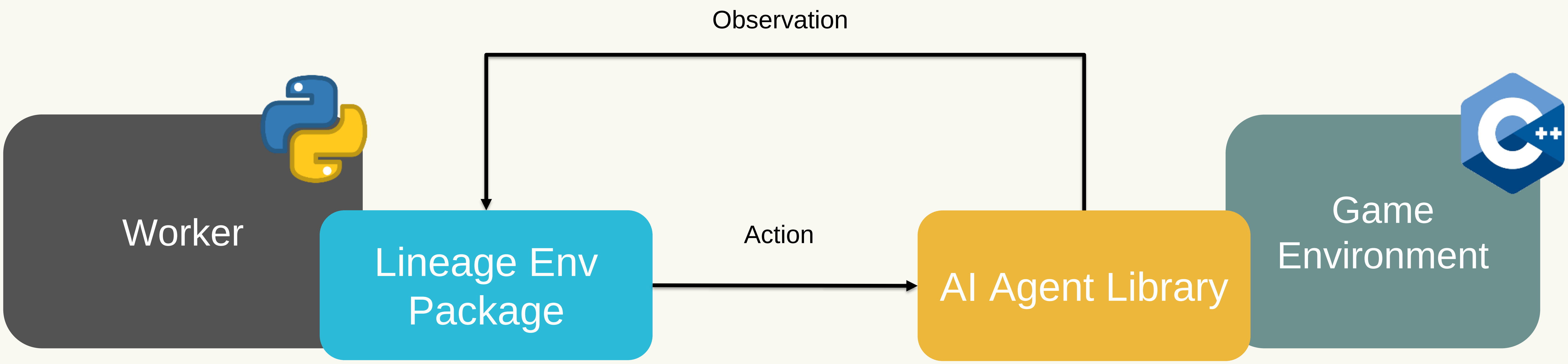
Video 2. Clone Wars

Part III. Reinforcement Learning Framework

Structure of Simulator



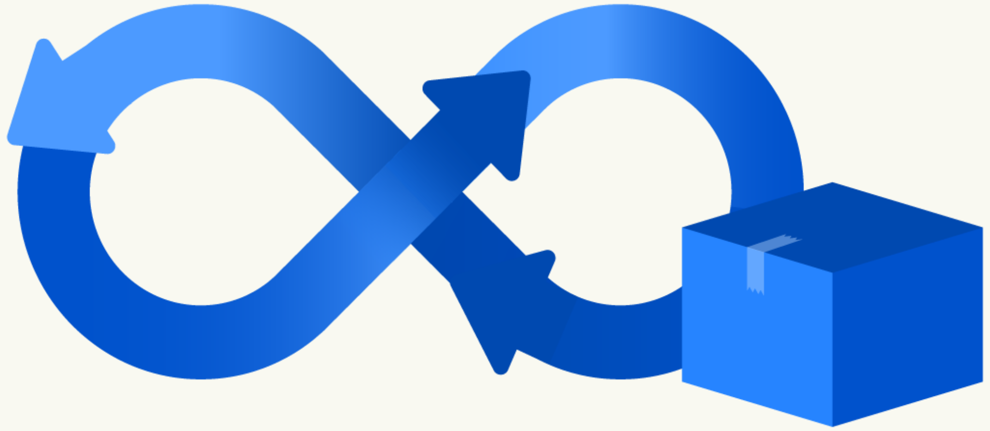
Structure of Simulator



RL Contents Development Pipeline

Challenge 1: Constant Game Updates

- **Reducing Simulator Development Cost**
  - Online game environments are constantly being updated
  - These updates affect the learning process
  - Without prompt support, the AI reveals weaknesses (e.g., AI fails to learn new skills)



110 environment updates in 20 days

Simulator Updating Process

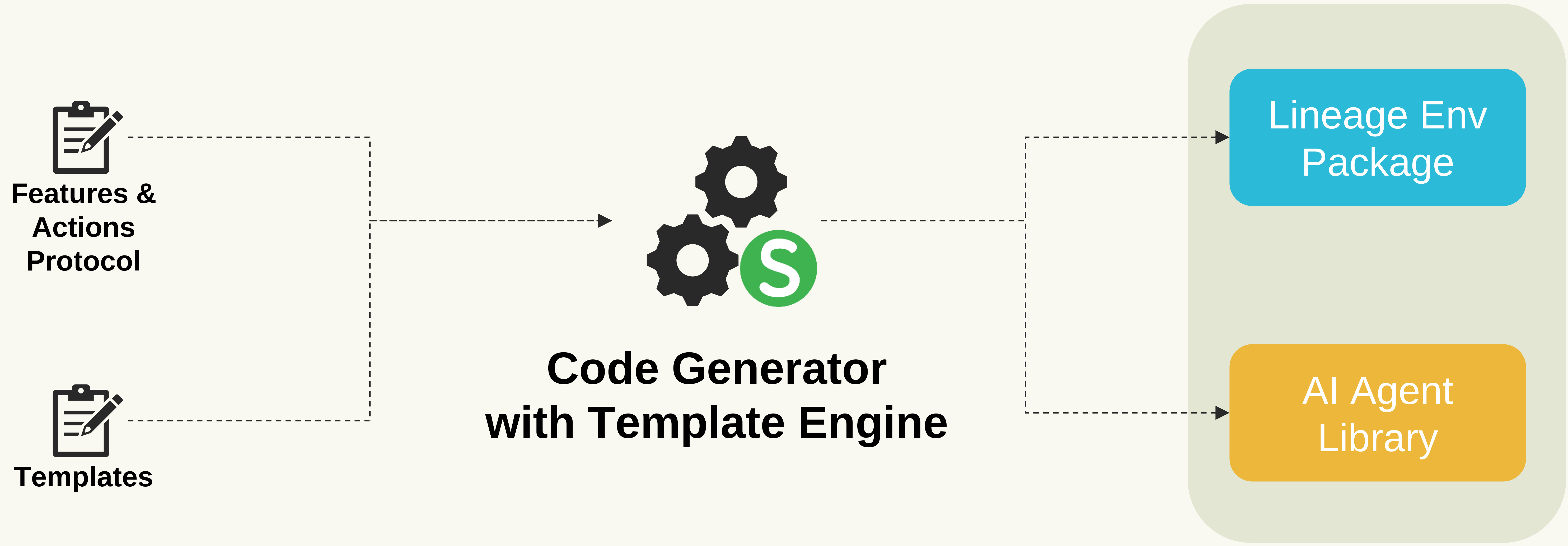
Check Requirements → Update Lineage Env Package → Update AI Agent Library → Distribute Simulator

Approx. 1 hour

Check Requirements → Generate (Env Package and AI Agent Library) → Distribute Simulator

Up to 10 min

The Automatic Code Generating System

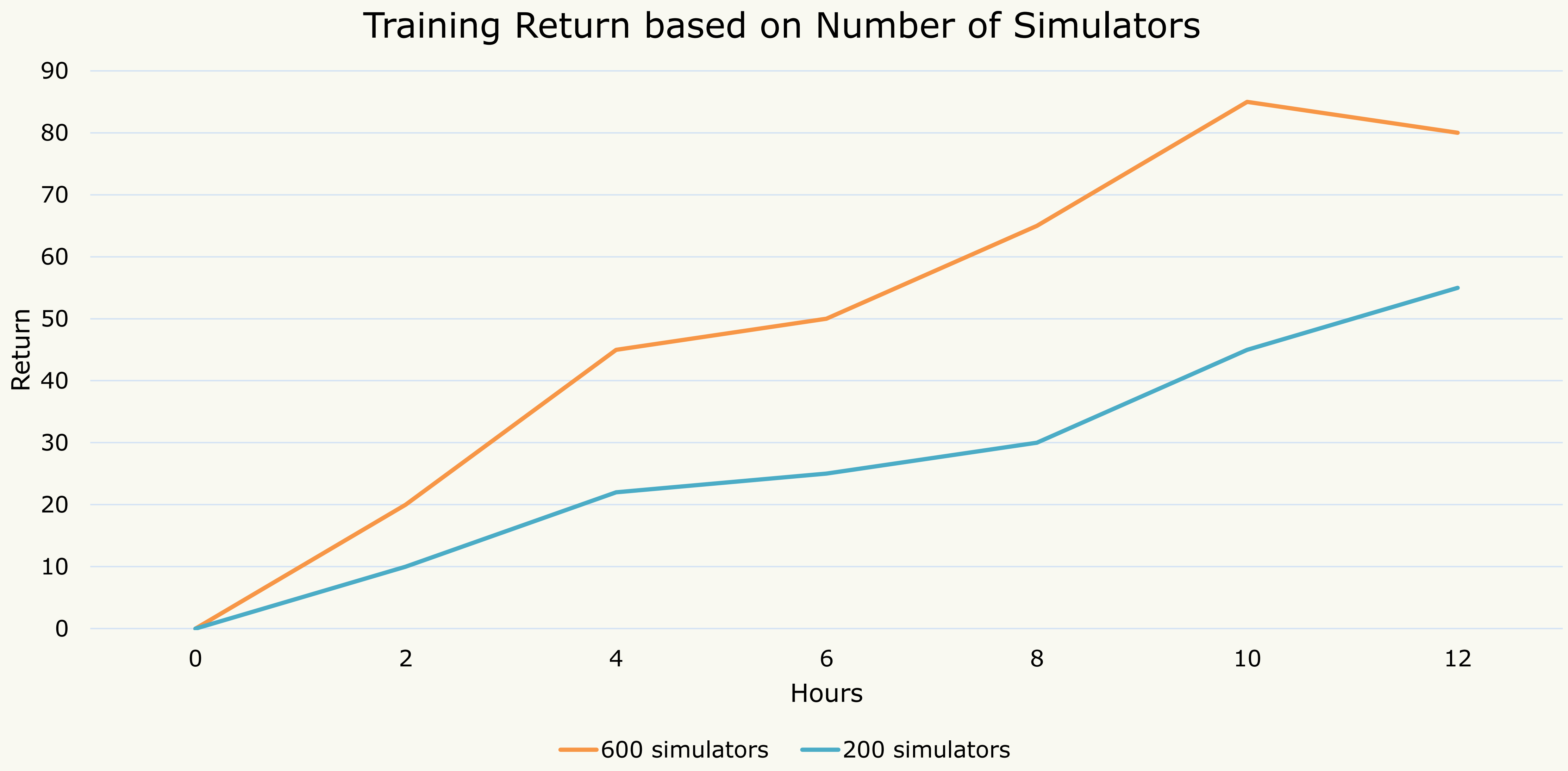


Automatic Code Generation

- **Results**
  - Observations and actions
  - Feature management
  - Simulation control API

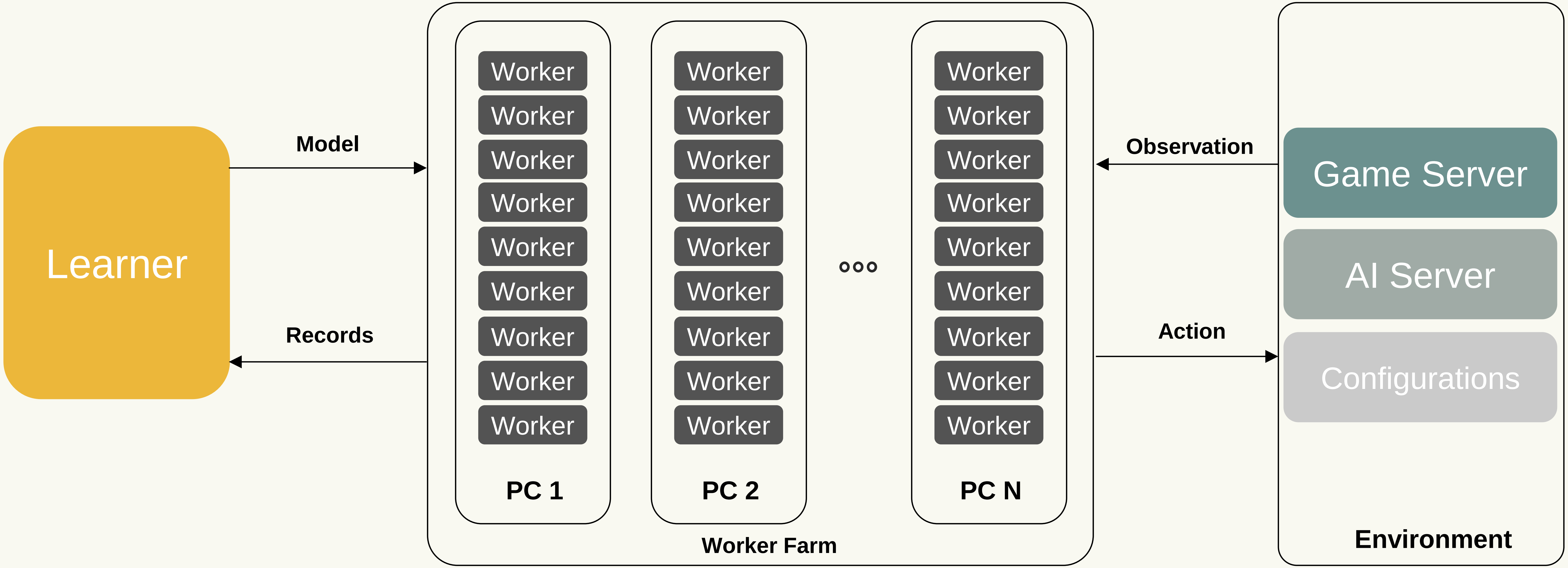
- **Effects**
  - Saving Coding Time
  - Eliminates mistakes
  - Improve productivity

Challenge 2: Maximizing Number of Simulations

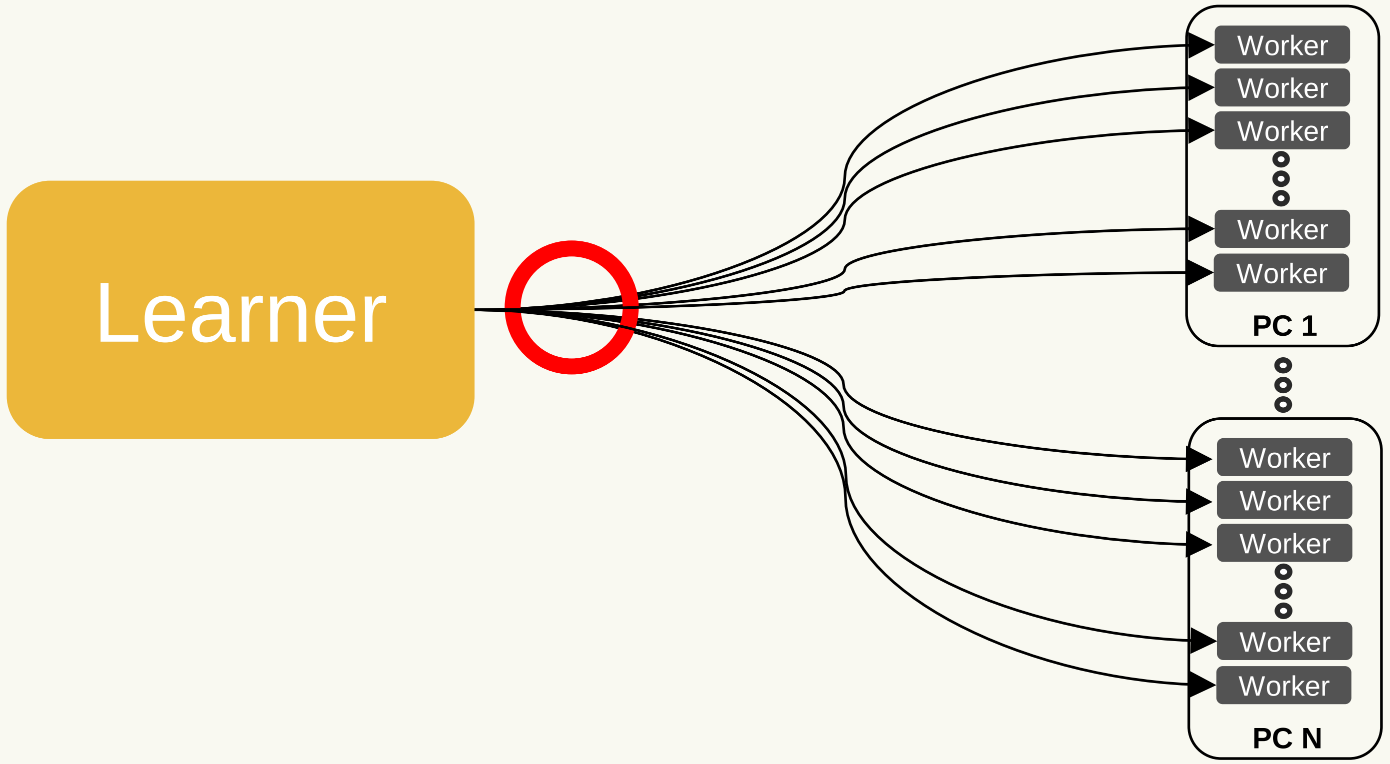


- DRL model learns through data
- More simulations and data required

Training System

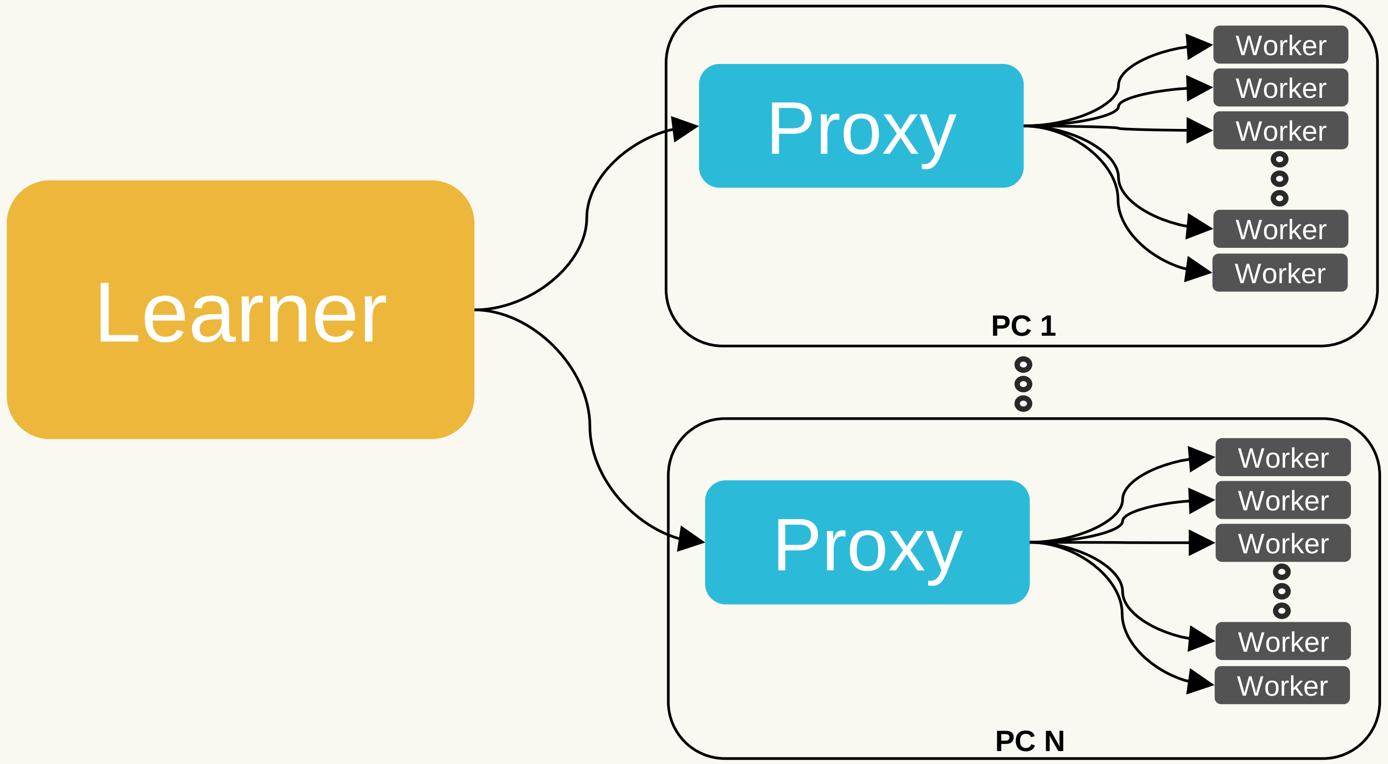


Reducing Network Traffic



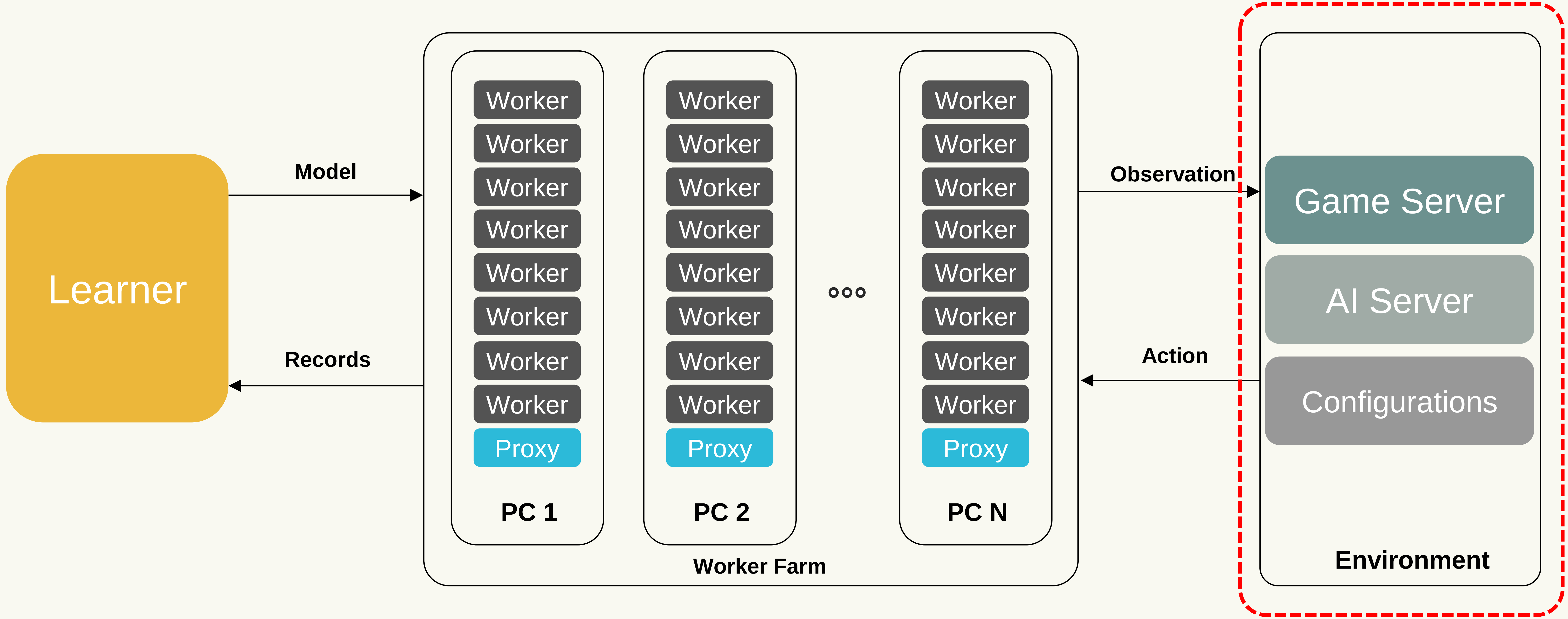
- Learner sends a model to each worker every 5 seconds
- Increased number of workers leads to amount of traffic beyond network capacity

Reducing Network Traffic

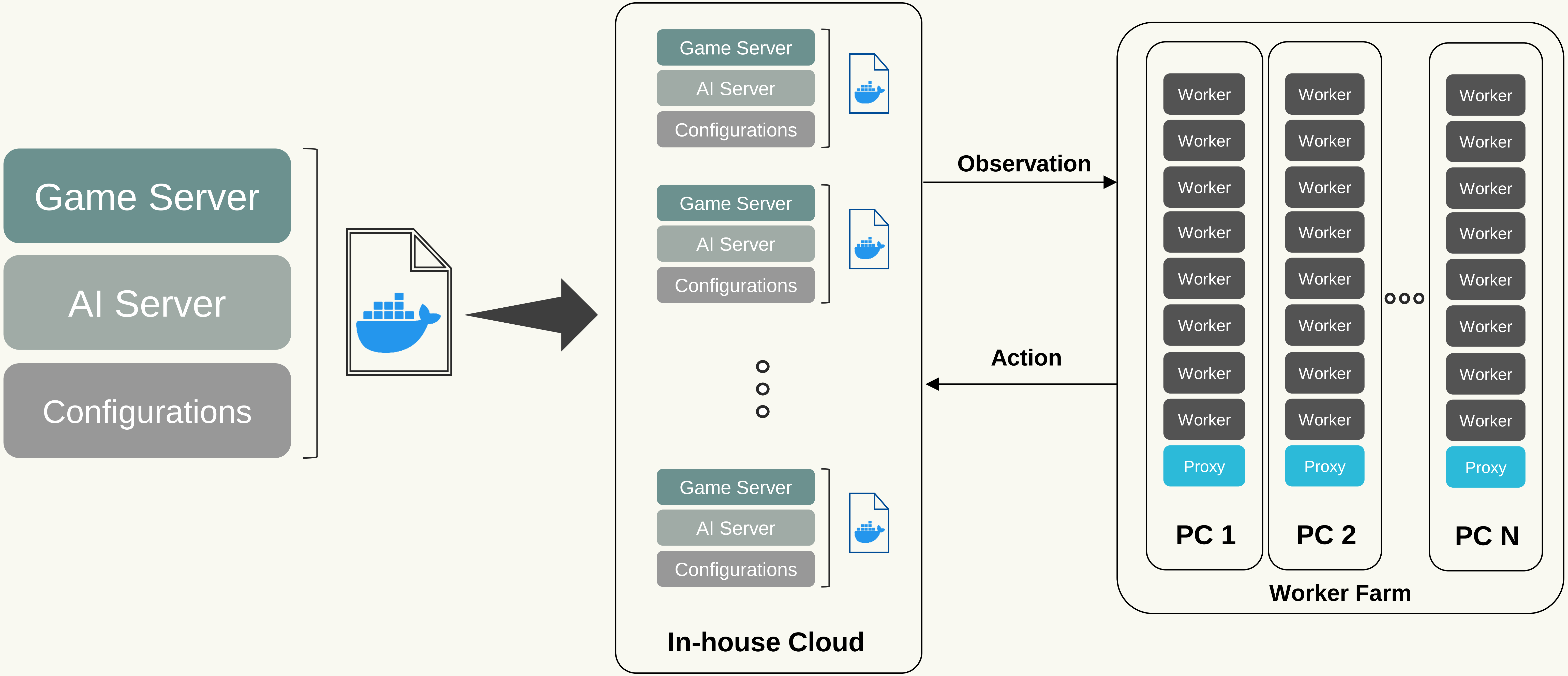


- Sending models only to the proxy process of each PC greatly reduces network traffic
- Proxy process publishes models to local workers

Limited Performance from Using a Single Server



Server Expansion



Challenge 3: Detecting Abnormalities

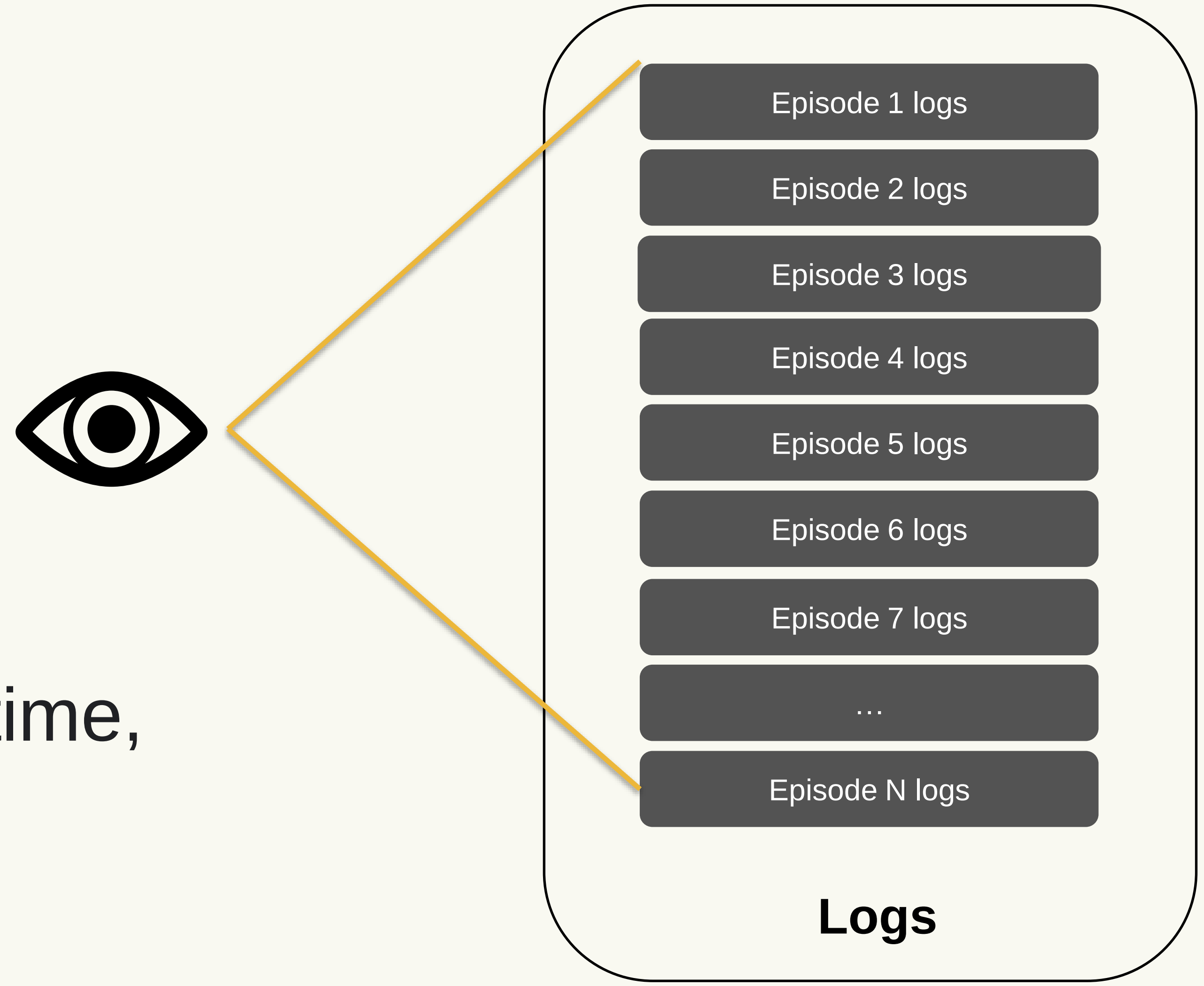
- Performing prompt analyses and responses to abnormal AI behavior
  - Too many games to analyze
  - Over 1,000 workers required to run 24/7

Saving Information to Detect Abnormalities

- Information that needs to be saved: features and packets at every step
- Process information used in the Lineage env package such as functions and parameters are already being logged

Watcher

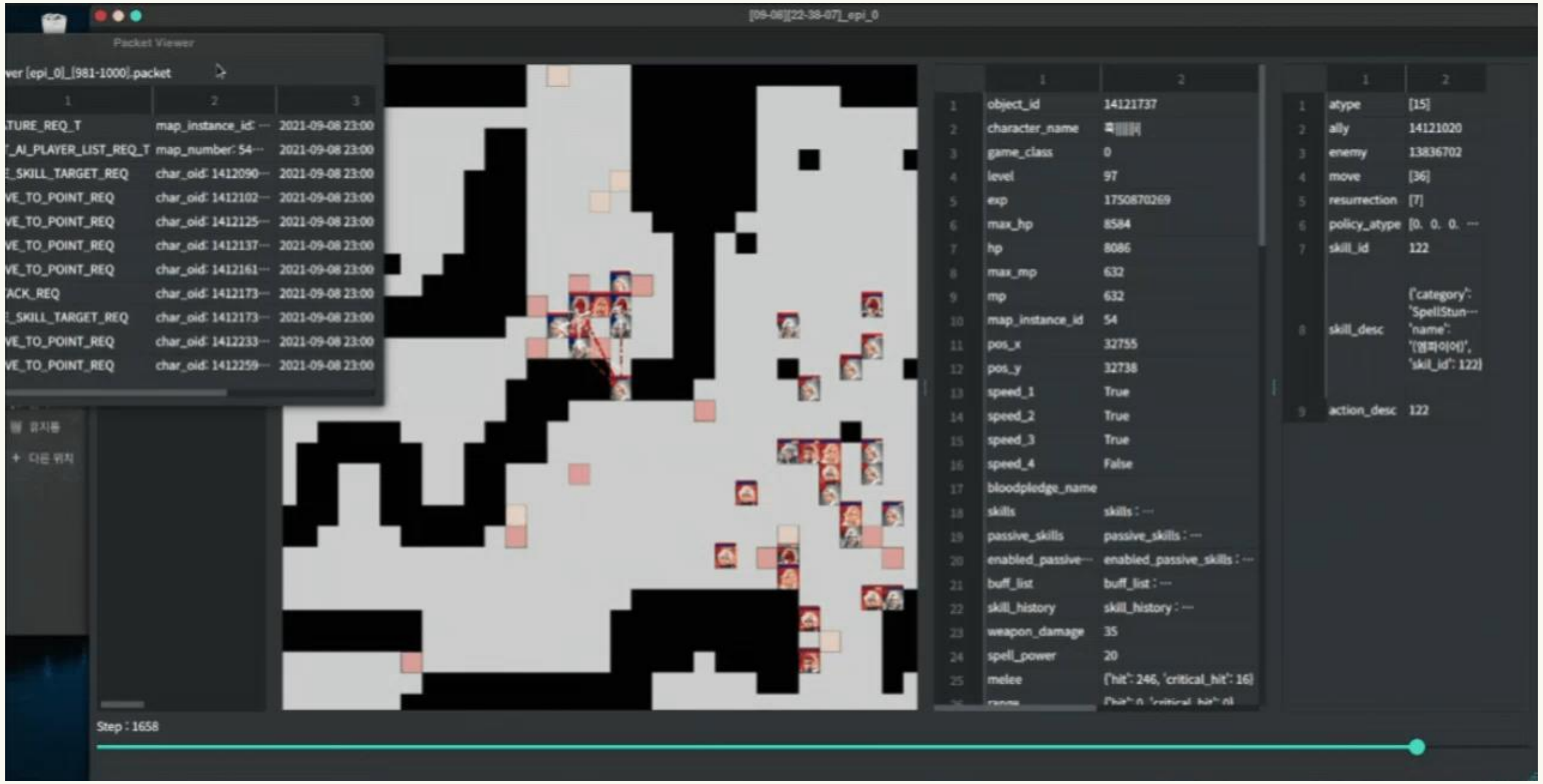
- Abnormality
  - Feature
  - Packets
- Game statistics
  - E.g., The Average kills of AI, The battle time, The maximum number of players



Visualization Tools

Game Environment
- Packet
- Feature

AI Behaviors
- Policy
- Decision
- Feature



Conclusion

- Reinforcement Learning Method
  - Hierarchical decision structure, model sampling & combination sampling, reward shaping
  - Successfully train AIs within 1 week with about 300 CPU cores
- Reinforcement Learning Framework
  - Code automatic generation system, Docker for Windows → reduce time & cost of updating environment
  - Abnormality detection and analysis tools → solve game environment issues & conduct AI behavior analysis
- We were able to create AIs for large-scale battle in MMORPG with MARL

THANK YOU

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