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Paper Talk: “Go with the Flow - Reinforcement Learning in Turn-Based Battle Video Games”

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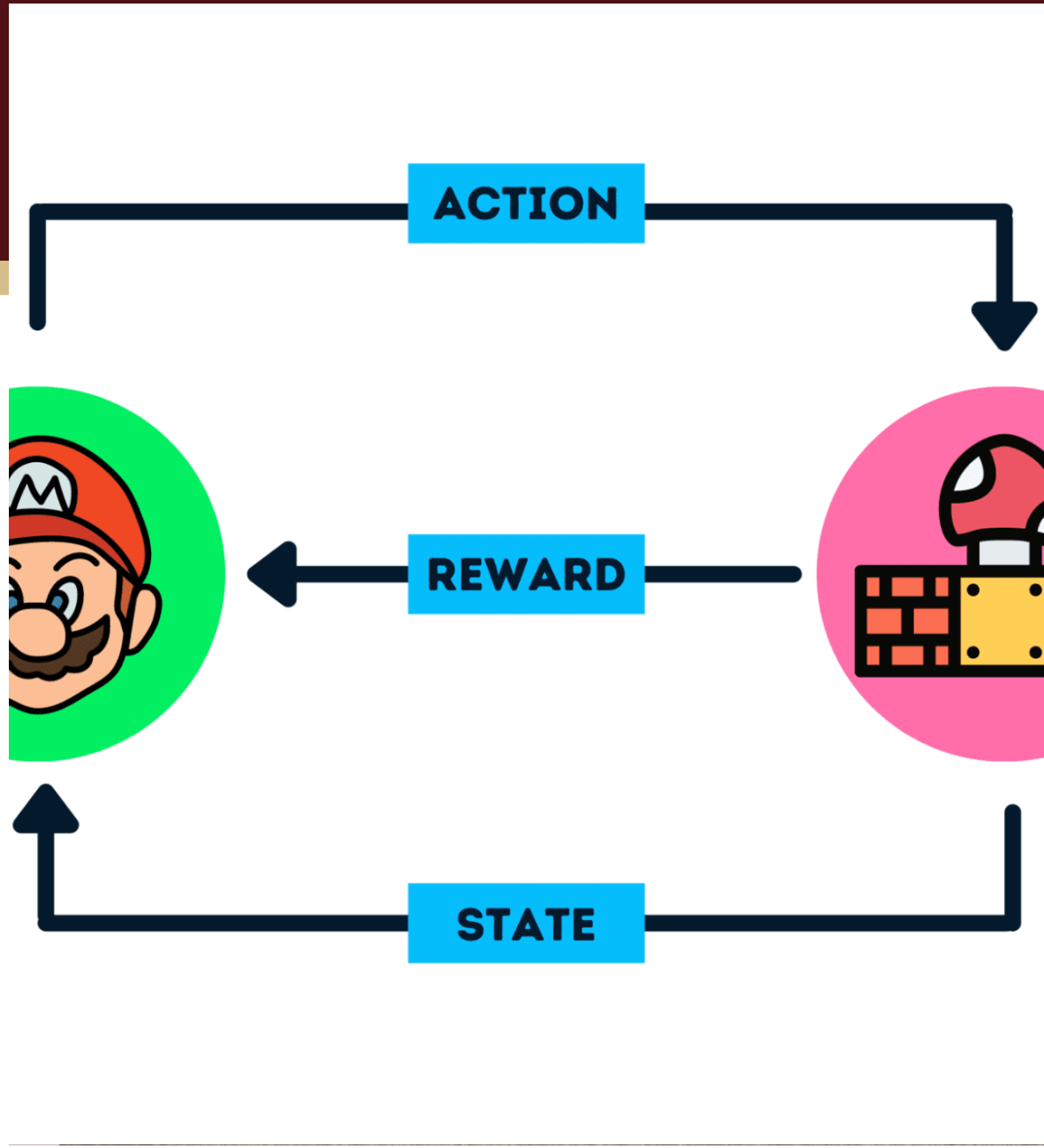
Venue: IVA 2020

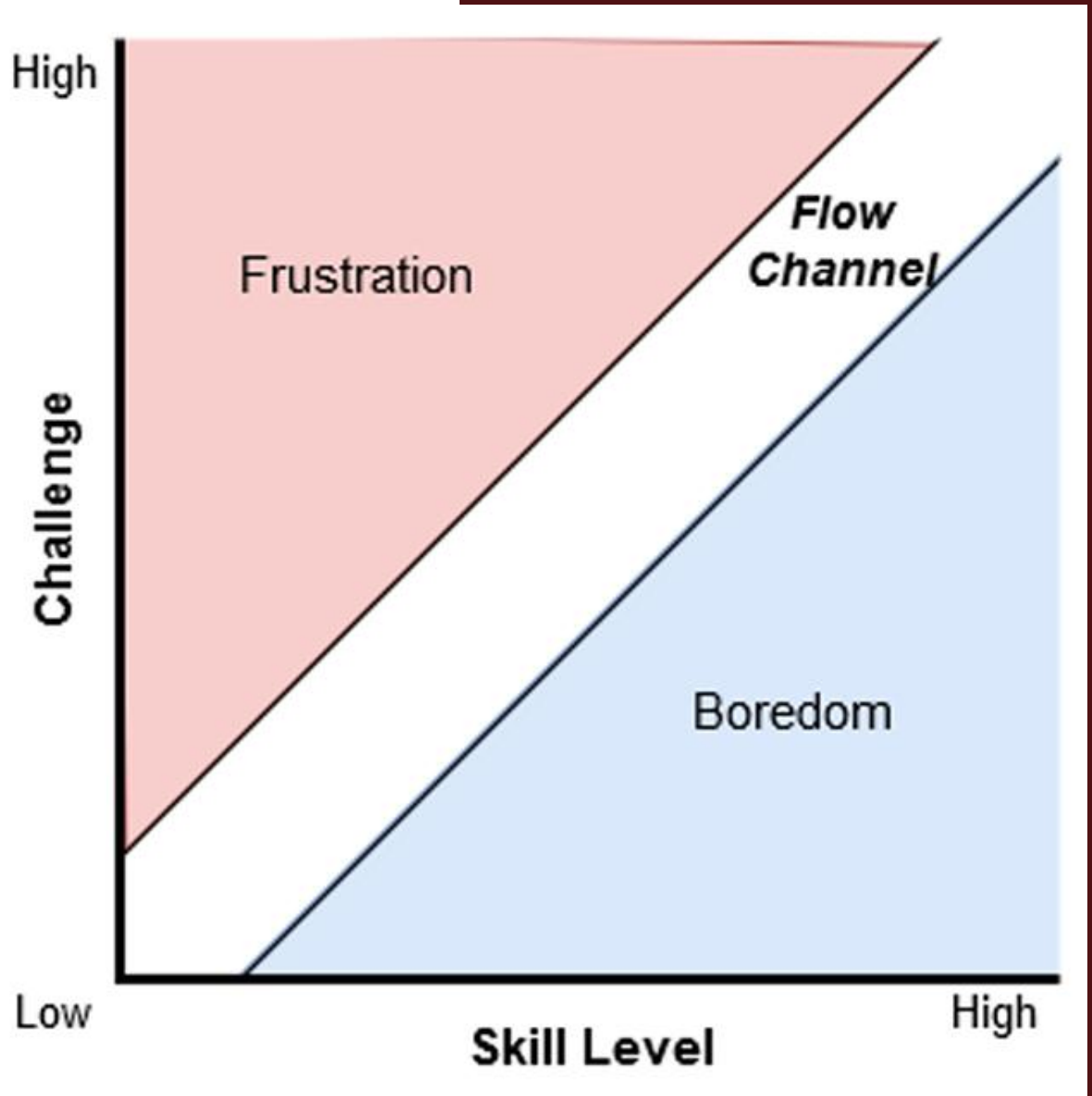
Presented by Joseph Nikhil Reddy Maramreddy

Presented as part of the Final Project for course CS 5325.001



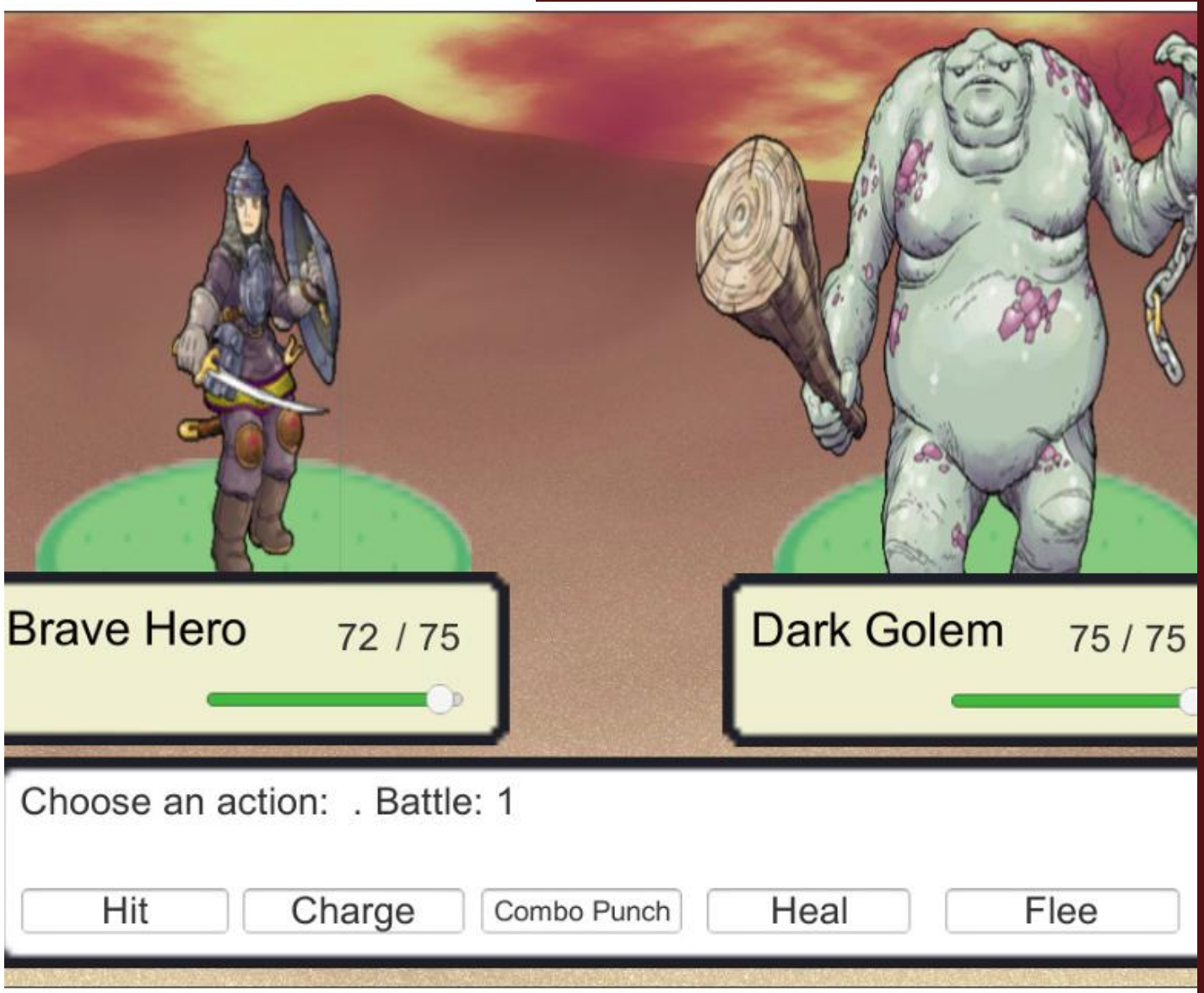
Motivation & Problem Statement

- Traditional games use fixed difficulty levels (Easy/Medium/Hard).
- These fail to adapt to each player's skill level.
- Too easy → boredom; too hard → frustration.
- Dynamic Difficulty Adjustment (DDA) aims to keep players in flow - a balanced challenge.



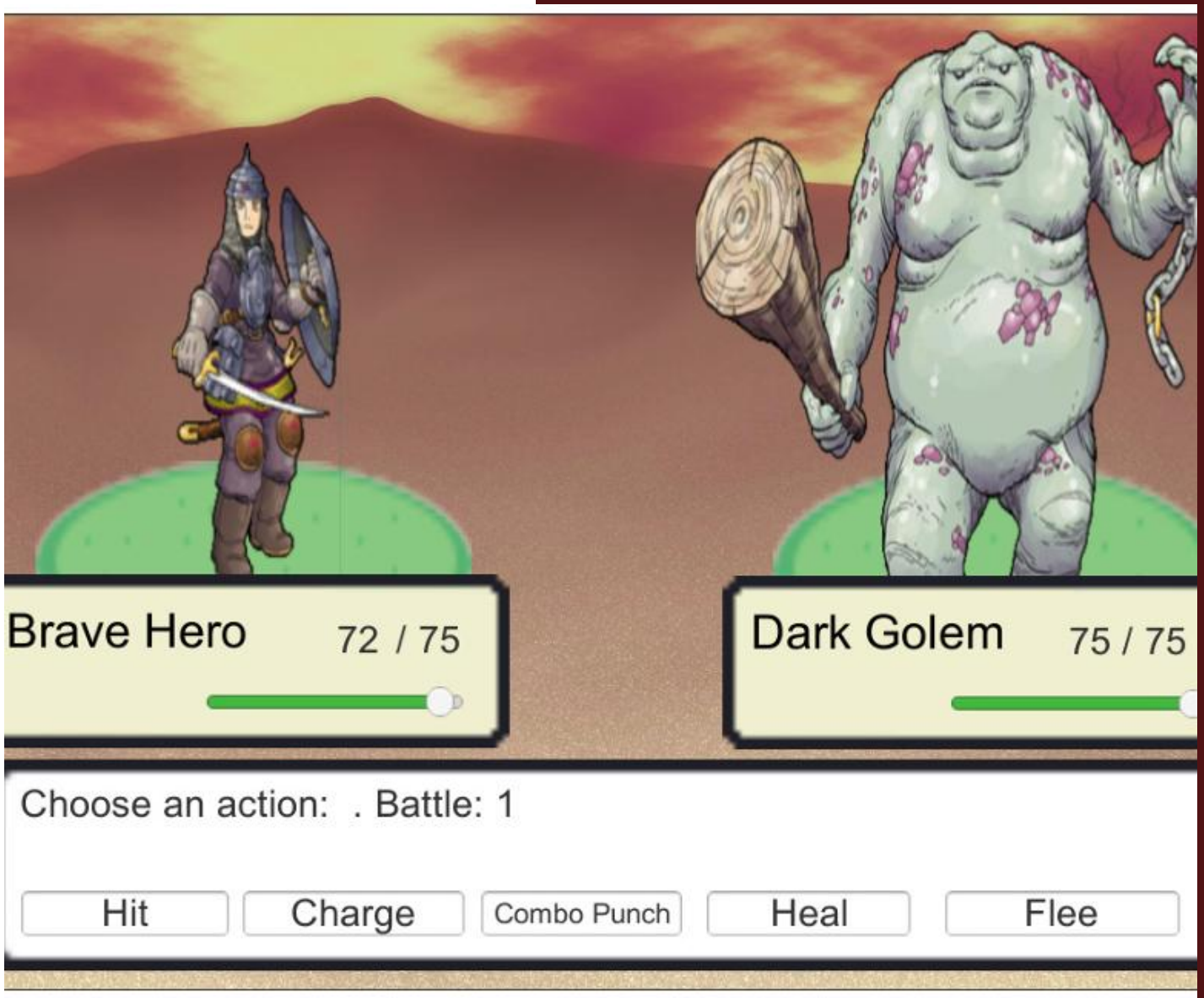
Approach Overview

- Built a 2D turn-based battle game (similar to classic RPG fights).
- Implemented a Reinforcement Learning (SARSA) agent as the opponent.
- Used RL to adjust gameplay dynamically (learning from ongoing battles).
- Evaluated both agent behavior and player engagement through experiments.



Game Mechanics

- Each side (player & agent) starts with 75 HP.
- Player chooses from 5 moves: Hit, Charge, Combo, Heal and Flee.
- The AI also has these moves (no Flee).
- Battles end when one side's HP ≤ 0.



Reinforcement Learning Setup

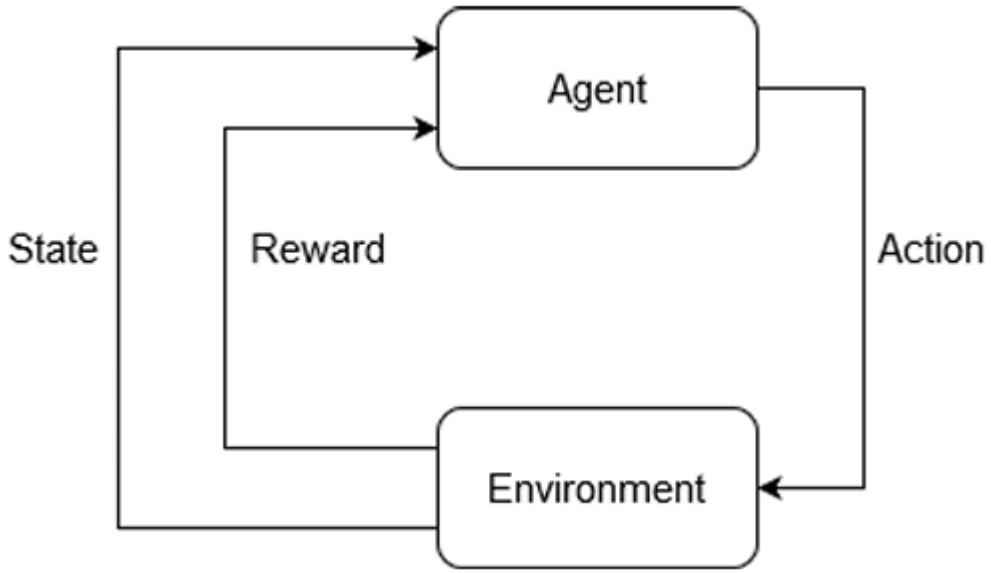
- Algorithm: SARSA (on-policy RL).

$$Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma Q(s', a') - Q(s, a)]$$

- States: 17 discrete HP-difference bands (e.g., equal HP, player ahead, AI ahead).
- Actions: Hit, Charge, Combo, Heal.
- Reward:
  - +100 for winning, −100 for losing (or ±50 variant).
  - Rewards swapped after 5 wins/losses → Dynamic Difficulty Adjustment.

Reinforcement Learning Setup

Diagram of the SARSA algorithm.



The states for the SARSA RL agent.

State	Player HP	Agent HP
0	75	==
1	[51-74]	==
2	[31-50]	==
3	[16-30]	==
4	[1-15]	==
5	<Agent HP	[66-74]
6	<Agent HP	[46-65]
7	<Agent HP	[31-45]
8	<Agent HP	[16-30]
9	<Agent HP	[1-15]
10	[66-74]	<Player HP
11	[46-65]	<Player HP
12	[31-45]	<Player HP
13	[16-30]	<Player HP
14	[1-15]	<Player HP
15	0	-
16	-	0

Experiment Design

- **Participants:** 4 players (2M, 2F, ages 20 - 40).
- **Games:** 10 game configurations (varying reward magnitude & exploration rate).
- **Each game:** 30 battles.
- **Measures:**
  - Player move usage
  - Agent's action evolution
  - HP trends per battle
  - Player feedback via **Game Experience Questionnaire (GEQ)**

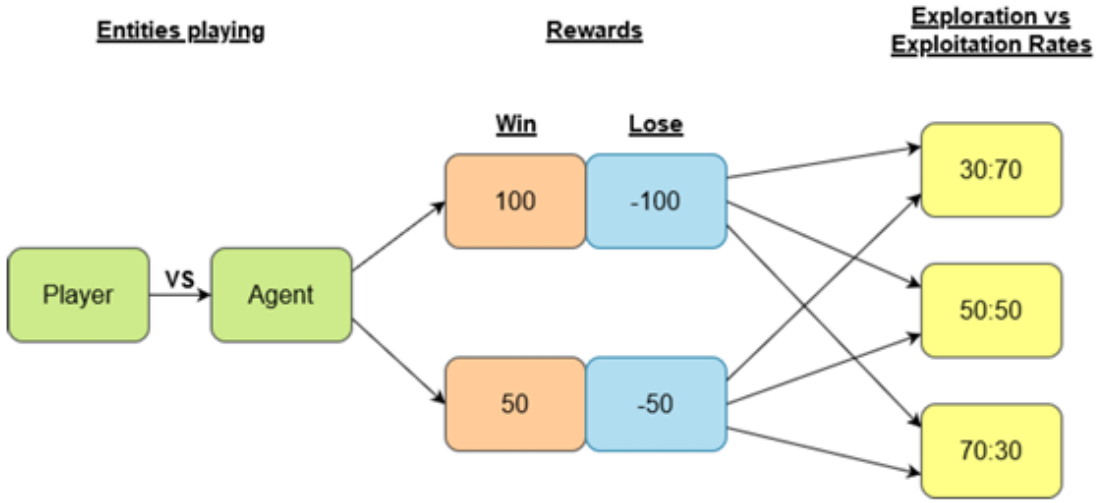


Figure 4: tree diagram with all possible parameters choices.

Results: Agent Learning Behavior

- Early training → agent overused Heal, leading to long matches.
- Later → agent learned to balance between attacking and healing.
- (30% exploration / 70% exploitation) gave best results - balanced challenge.
- Agent move distributions (combo, heal, etc.)
- HP traces over battles (showing more balanced fights).

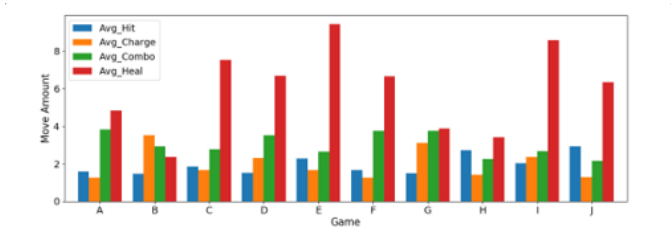


Figure 6: RL agent's average moves over 10 games (A-J).

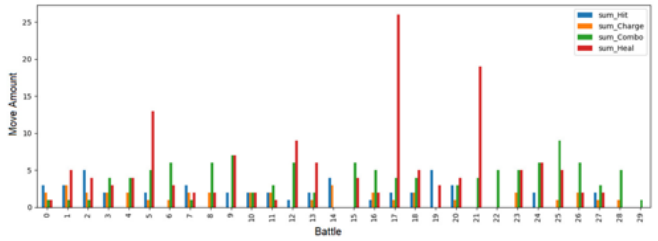


Figure 7: RL agent's moves sum in the 30 battles of game A.

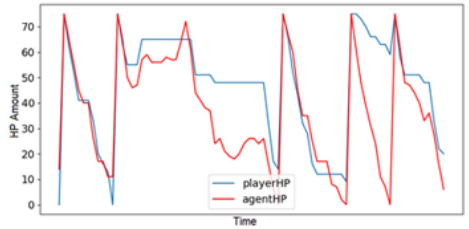


Figure 8: Player's and agent's HPs from battles $[16-20]$ of game A.

Results: Player Experience

- Measured via **GEQ** (challenge, competence, effort, flow).
- RL-based AI produced **balanced challenge and engagement**.
- Fixed Easy AI → boring; Hard AI → frustrating.
- RL opponents often scored highest for flow and enjoyment.

Gameplay type pairs	success	skillful	challenge	effort
easy vs hard	**0.03**	1	**0.001**	**0.001**
easy vs 50-50	1	1	**0.001**	**0.005**
easy vs 70-30	0.107	1	**0.001**	**0.001**
easy vs 30-70	1	1	**0.001**	**0.001**
hard vs 50-50	0.085	1	0.067	0.848
hard vs 70-30	1	1	**0.011**	0.107
hard vs 30-70	**0.002**	0.522	0.239	0.957
50-50 vs 70-30	1	1	1	1
50-50 vs 30-70	0.239	0.811	0.368	1
70-30 vs 30-70	0.1	0.811	1	1

Table 3: results of paired t-tests computed between all the combinations of gameplay types. Significant p-values ($p < .05$) after Bonferroni correction are highlighted in bold.

Limitations

1. **Small state space & simple environment.** Results may not scale to complex games.
2. **Reward swapping heuristic** (after 5 wins/losses) may cause abrupt difficulty shifts.
3. **Small participant pool** → limited statistical significance.
4. **Heal-spamming artifact** shows incomplete reward shaping.
5. **No comparison to other RL methods** (e.g., Q-learning).

My Implementation Plan

- Implement a simplified SARSA agent in Python with:
  - 17-state representation (HP difference).
  - 4 actions (Hit, Charge, Combo, Heal).
  - Reward swapping for adaptive difficulty.
- Simulate training and visualize:
  - Agent learning curve.
  - HP difference per battle.
  - Move distribution evolution.
- If time permits, I also want to make a small project using a game engine.

Feasibility

- Because the SARSA algorithm and state-reward structure are straightforward to implement in Python or Unity, the project requires only basic computational resources.
- The RL agent operates on a discrete state-action space with small-scale training data; hence, this project is computationally feasible without GPUs or large datasets.
- Any potential challenges that can arise during experiments, such as reward tuning or overuse of specific actions (e.g., Heal), can be managed through controlled simulation and logging.

Thank You!

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CS 5325.001 – Reinforcement Learning

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