

Learning from Learners: Adapting Reinforcement Learning Agents to be



DI TECNOLOGIA

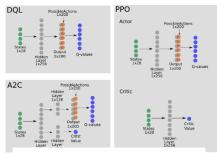
Competitive in a Card Game

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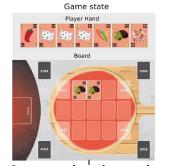
Chef's Hat Multiplayer Competitive Card Game and Simulation Environment



Reinforcement Learning Agents for Learning a Competitive Strategy



Three types of learning agents



Gamestate based on cards at hand and current cards at the board



Action space: 199 different combinations of a discard action and one pass action

Three evaluation scenarios and performance measures over 100 games





Vs Mvself

Vs Random





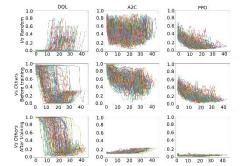
Model Victories Random1 Random2 Random3 $\begin{array}{c} 10.6 \pm \! 1.8 \\ 13.5 \pm \! 3.58 \\ 6.2 \pm \! 1.83 \end{array}$ DQL 66.8 ±5.69 9.7 ±3.13 12.9 ±4.66 A2C PPO 65.1 ±5.19 83.1 ±4.18 $\begin{array}{c} 12.1 \ \pm 4.35 \\ 6.0 \ \pm 2.28 \end{array}$ 9.3 ±3.1 4.7 ±2.19 vs. Myself Model Gen-1 Gen-25 Gen-50 Random 19.4 ±4.78 25.4 ±4.39 16.9 ±3.36 **42.9** ±7.06 **34.5** ±7.12 **40.3** ±3.52 $\begin{array}{c} 12.9 \ \pm 6.64 \\ 11 \ \pm 2.86 \\ 10.3 \ \pm 4.1 \end{array}$ DQL A2C PPO vs. Others Model Before training After training DQL A2C PPO Random 35.9 ±3.11 18.9 ±3.51 $\substack{35.9\ \pm 3.11\\4.9\ \pm 2.84}$ 42.8 ±5.06 2.4 ±0.8 48.5 ±40.6 3.3 ±1.85

vs. Random

Performance results after training for a thousand games.

Contributions

Strategy Emergence Observation



Each agent adopted a specific strategy, and adapted it when playing against each other.



Chef's Hat

Simulation Environment

https://github.com/pablovin/ChefsHatGYM

DQL

Trained Agents

A2C

PPO