

Increasing the Upper Bound for the EvoMan Game Competition

Gabriel-Codrin **Cojocaru** Sergiu-Andrei **Dinu** (presenter)
Eugen **Croitoru**

Faculty of Computer Science "Al. I. Cuza" University Iasi, Romania

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Introduction

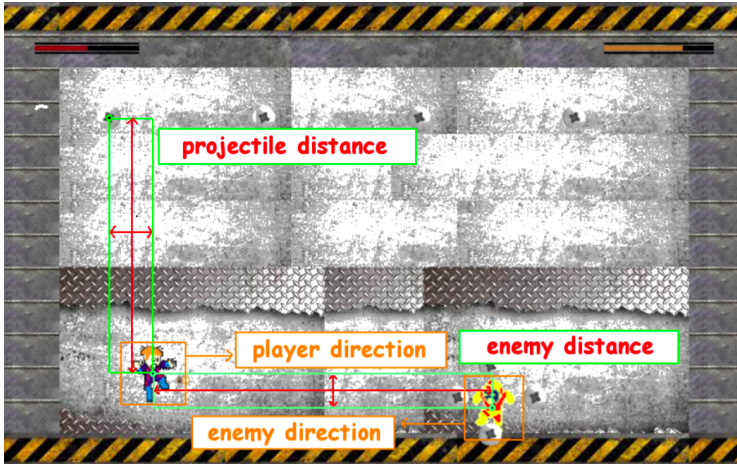
Problem description

Search Algorithms

Results

Introduction: Game

- ▶ Aim: play the Megaman/EvoMan game



Introduction: Motivation

- ▶ Games are an opportunity to improve our algorithms.
- ▶ They can be low-cost simulators for interesting problems or topics.
- ▶ EvoMan was used by a competition at WCCI 2020 (where we placed second).
- ▶ We found out that we can greatly improve on the upper bound provided.

Introduction: The difference

- ▶ The initial competition required training with 4 opponents, and testing on all 8.
- ▶ Our approach works better on simply fighting each opponent.
- ▶ It significantly improves the state of the art results.

Problem description: Evaluation

$$gain = 100.01 + player_life - enemy_life$$

- ▶ Both start with 100 life points.
- ▶ the absolute maximum score is 200.01.
- ▶ There are 8 opponents, each with a different strategy.
- ▶ There are 5 difficulty levels, each lowering the damage the player does, and increasing the damage the player takes.

Problem description: Agent

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- ▶ Each frame, we can perform 5 actions (e.g. move left, shoot).
- ▶ We chose to place an ANN in this loop.
- ▶ We also remember the past 2 frames' sensors values, and our past 2 actions, for a total of 62 inputs.

Search Algorithms: 2-stage approach

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 - ▶ Random initialisation.
 - ▶ Q-Learning.
 - ▶ Genetic Algorithm (GA).
 - ▶ Particle Swarm Optimisation (PSO).

Search Algorithms: 2-stage approach

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 - ▶ Particle Swarm Optimisation (PSO).
- ▶ then use an exploitative algorithm to refine that game-playing strategy. We've only used a Proximal Policy Optimisation (PPO) algorithm for this stage.

Search Algorithms: initial comparison

Method	Q-Learning	GA	PSO	Random init.
Result (approx. median)	-5	46	59	117

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- ▶ No pre-exploration algorithm performed better than random initialisation.
- ▶ The game is too difficult for basic strategies to constitute the basis for optimal strategies (a misleading / trap function landscape).

Results: Experiment

- ▶ PPO ran for between 1000 to 3000 epochs, per opponent, 30 repeats for each datapoint.
- ▶ Time: 1000 epochs require ≈ 10000000 (10M) Evoman frames.
- ▶ We ran specialised and generalised PPO models.
- ▶ Specialised means 8 models, 1 for each of the 8 opponents, 1000 epochs.
- ▶ Generalised means 1 model for all 8 opponents, 3000 epochs.

Results: vs the upper bound

Table: PPO generalised vs PPO specialised vs NEAT specialised,
difficulty = 2

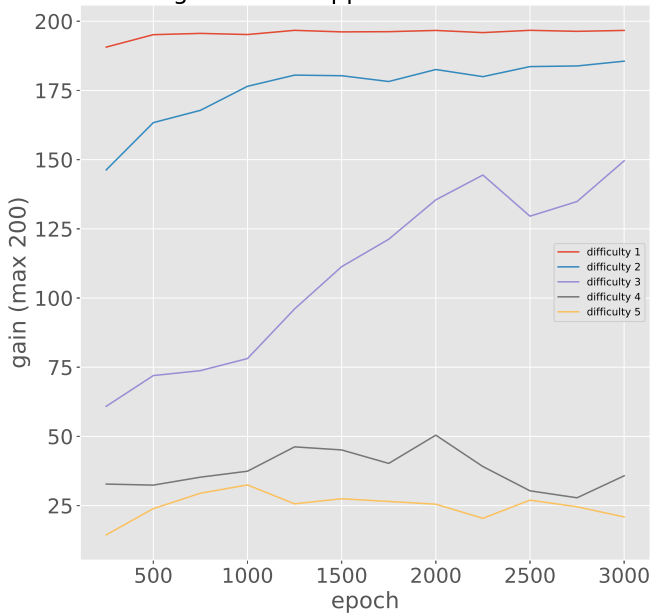
Opponent	PPO gen.	PPO spec.	NEAT spec.
1	199.54	199.67	190.01
2	200.01	199.61	194.01
3	194.81	199.94	180.01
4	180.61	195.95	194.01
5	187.77	198.03	194.01
6	174.43	199.67	173.01
7	183.07	197.73	177.01
8	169.31	195.07	186.01
harmonic mean	185.57	198.19	185.67

Results: all difficulties, generalised

Table: PPO (generalised) trained against all opponents (Gain)

Opponent	Difficulty				
	1	2	3	4	5
1	200.01	199.54	170.75	155.48	41.08
2	200.01	200.01	182.81	168.81	168.51
3	199.38	194.81	164.31	127.54	130.61
4	186.14	180.61	154.23	181.58	60.28
5	196.56	187.77	185.34	142.41	158.31
6	196.35	174.43	179.19	23.84	9.88
7	199.26	183.07	95.40	8.01	8.28
8	196.57	169.31	123.00	41.34	10.01
harmonic mean	196.68	185.57	149.57	35.76	20.89

PPO trained against all 8 opponents at different difficulties



Results: all difficulties, specialised

Table: PPO (specialised), trained 1000 epochs (gain)

Opponent	Difficulty			
	2	3	4	5
1	199.68	196.51	189.21	166.01
2	199.61	199.91	199.21	197.18
3	199.94	199.51	147.21	72.28
4	195.95	196.14	198.81	191.23
5	198.03	193.38	191.73	196.71
6	199.67	195.18	196.85	198.76
7	197.73	192.45	184.85	176.01
8	195.07	185.37	178.05	172.61
harmonic mean	198.19	194.7	184.12	154.58

Results: percentage of games lost

Table: PPO - percentage of games lost

Opp.	Difficulty								
	Generalised					Specialised			
	1	2	3	4	5	2	3	4	5
1	0	0	20	23.33	100	0	0	0	13.33
2	0	0	0	0	0	0	0	0	0
3	0	0	0	13.33	3.33	0	0	36.67	100
4	0	0	0	0	60	0	0	0	0
5	0	0	0	0	0	0	0	0	0
6	0	0	0	100	100	0	0	0	0
7	0	0	56.66	100	100	0	0	0	0
8	0	0	10	100	100	0	0	0	0

Conclusions

- ▶ We have surpassed the state-of-the-art through an exploitative and time-consuming algorithm.
- ▶ It is a difficult, misleading problem, since optimal game-playing strategies cannot be easily inferred from suboptimal strategies.
- ▶ Thus, the cascade method cannot work well. A memetic algorithm (e.g. GSO + PPO) seems feasible.



Evoman: Game-playing Competition for WCCI 2020,
<http://pesquisa.ufabc.edu.br/hal/Evoman.html>



Evoman: Game-playing Competition for WCCI 2020, results
<http://pesquisa.ufabc.edu.br/hal/Evoman.html#results>



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