

# IL RE BOMBA

## Improving Pokémon AI Traning With NSGA-II

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August 24, 2022



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## Pokémon

Pokémon uses a turn-based system: at the start of each turn, both sides can choose to attack, use an item, switch the Pokémons for another in their party. The Pokemon who strikes first is determined by the Move's Priority and the Pokémons Speed. Each Pokémon uses moves to reduce their opponent's HP until one of them faints, i.e. their HP reach 0. If all of a player's Pokémons faint, the player loses the battle.

Figure 1: Pokémon battle

*Reinforcement learning (RL)* is an area of Machine Learning where an agent receives a reward based on the action it has performed. Actions allow the agent to transition from a state to another. The final objective is to learn a policy to reach a terminal state with the best reward achievable.

## Deep Q-Learning

The reinforcement learning technique we have employed is called *Deep Q-Learning*, which maps input states to a pair of actions and Q-values using an Artificial Neural Network. *Q-Learning* is based on the *Q-function*, namely  $Q : S \times A \rightarrow R$ , which returns - given a state-action pair ( $s, a \in S \times A$ ) - the expected discounted reward ( $r \in R$ ) for future states.



*NSGA-II* is a Evolutionary Algorithm that allows to produce *Pareto-equivalent* (or non-dominated) solutions of a multi-objective optimisation problem.

## General idea

The idea is that, given that the search space is very big - there are  $10^{354}$  different ways a Pokémon battle can start, and each turn has at most 306 different outcomes (and only for a single player) - we would like to positively bias our model with a controlled search, removing particularly useless moves, i.e. consider for the most Pareto-equivalent solutions.



## Genotype representation

Generally, in a Pokémon battle two actions are possible, i.e. performing a move or a switch. Moreover, depending on the type of battle, it may be necessary to specify the target of the move. To encode such a thing, we came up with the following genotype: each Pokémon is represented using two genes, i.e. action and target (optional) ( $a, t$ ). The whole genotype tells us who is going to perform what on whom.

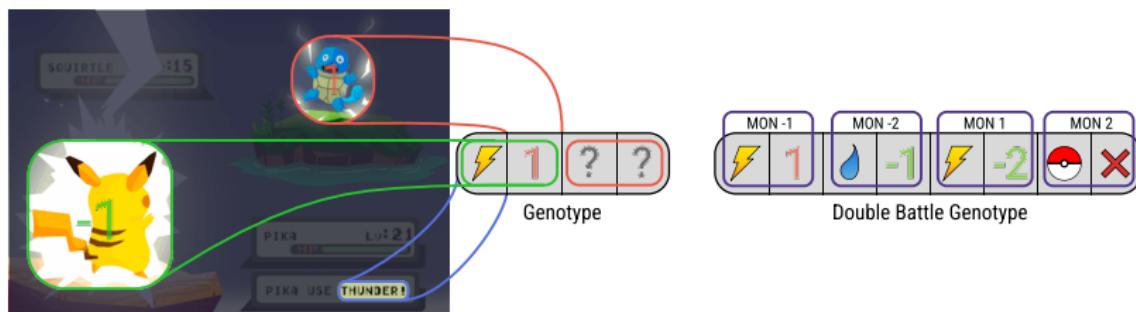


Figure 2: Genotype representation

## Genetic operators - Mutation

Mutation is performed for each gene in a genotype with probability  $P_m = 10\%$ : both the action and the target may be mutated, meaning that it is possible to go from a move to a switch (and vice-versa).

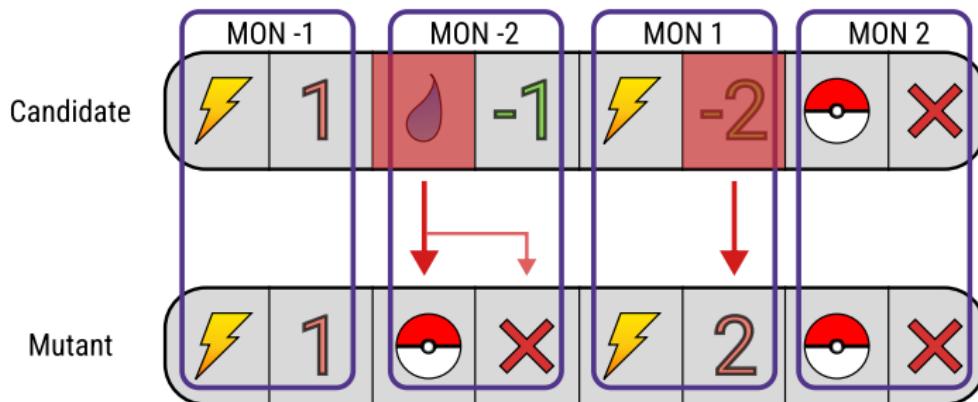


Figure 3: Mutation

Instead, we used Uniform Crossover in a particular way: given that each Pokémon is represented by a valid  $(a, t)$  pair, we perform crossover by selecting the whole pair from one of the parents to avoid inconsistencies. Furthermore, crossover is performed with  $P_c = 100\%$ , and  $P_{bias} = 50\%$  (i.e. the bias towards a certain offspring).

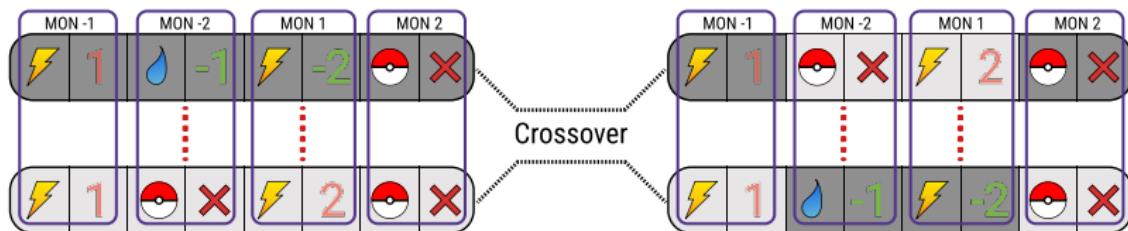


Figure 4: Recombination

# Objective & Optimisation

Concerning the *Pareto front* we have considered four variables with the following optimisation problem:

$$\underline{x} = (x_1, x_2, x_3, x_4) \in \mathbb{R}^4 \quad \text{where } \mathbb{R}^4 = \{(x_1, x_2, x_3, x_4) : 0 \leq x_1, x_2, x_3, x_4 \leq 100\}$$

where  $x_1$  is the damage dealt by the ally Pokémons to the opponents,  $x_2 is the damage dealt by the opponents' Pokémons to the allies,  $x_3$  is the health points remaining of the player's Pokémons and  $x_4$  is the health points remaining of the opponent's Pokémons.$

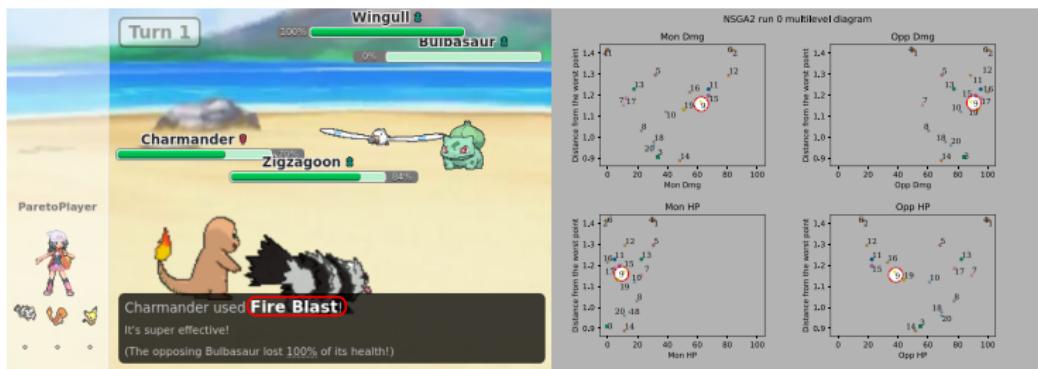


Figure 5: Recombination

The agent architecture is a four-layer deep *Multilayer Perceptron (MLP)*, which employs *ReLU* as activation function. In particular:

- input and output layers size depend on the type of battle the network is facing (e.g. a 4 VS 4 battle implies a size of 244 input neurons);
- two hidden hidden layers of size 256 and 128, respectively.

The standard agent uses a simple  $\varepsilon$ -greedy policy:

- it starts from a probability  $P_r = 1.0$  to perform a random action;
- it linearly decreases to  $P_r = 0.1$  in the first 40% of the training;
- for the remaining 60% of the training it linearly decreases to  $P_r = 0.01$ .

## ParetoPlayer

*ParetoPlayer* embeds the Pareto search of non-dominated moves:

- it performs a random move chosen from the ones returned by *NSGA-II* with 70% probability;
- a completely random one with 30% probability.



# Program structure

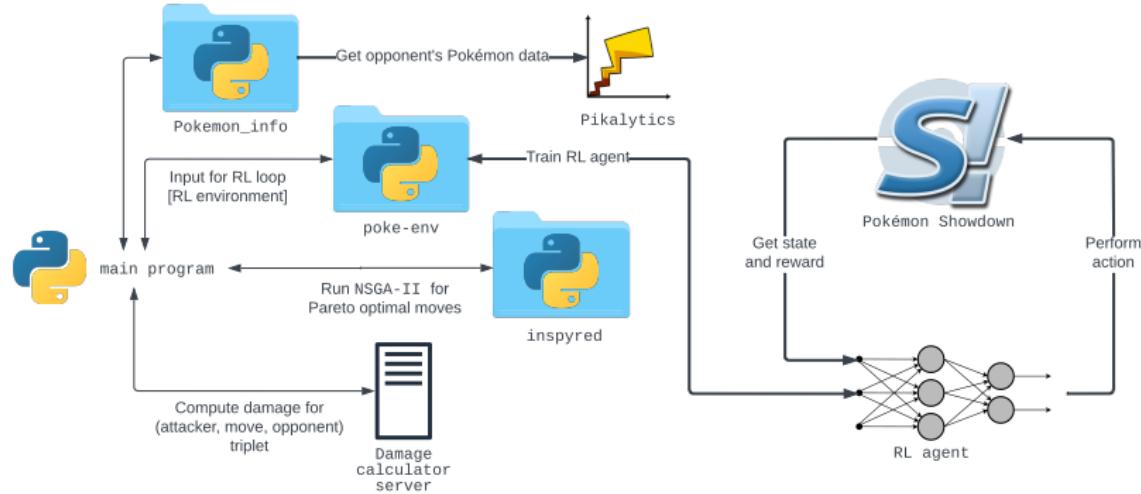


Figure 6: Program structure

All agents were trained by having them fight against *MaxDamagePlayer*, i.e. a bot which always chooses the combination of moves that deals the highest amount of damage.

A

B

# Live Demo

We have tested both the normality and the statistical significance of the proposed solution with the employment of the following graphical and analytical tools:

## Normality

- Quantile-Quantile plot
- Shapiro-Wilk test
- Kolmogorov-Smirnov normality test

## Statistical significance

- Box plot
- t-test
- Wilcoxon rank mean test



Several situations were considered, such as:

- 2 VS 2 battle with a static teams;
- 2 VS 2 battle with a single victory condition;
- 2 VS 2 battle with teams sampled randomly from a pool of possible Pokémons.

The main difficulties we have encountered concern:

- Damage calculator
- Hyperparameters selection and topology search
- Pokémon double battles
- Pokémon battle switches



# Contributions

Thanks for your attention!



## Repositories

- pareto-epsilon-greedy-RL
- poke-env (modified)
- Pokemon\_info

## Collaborators' Github

- Simone Alghisi
- Samuele Bortolotti
- Massimo Rizzoli
- Erich Robbi

