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Pouya Tobias Strand Nikoui s165946 | Marius Cristian Mic s193282 | Francisc Vlad Loghin s193204
Technical University of Denmark

Introduction

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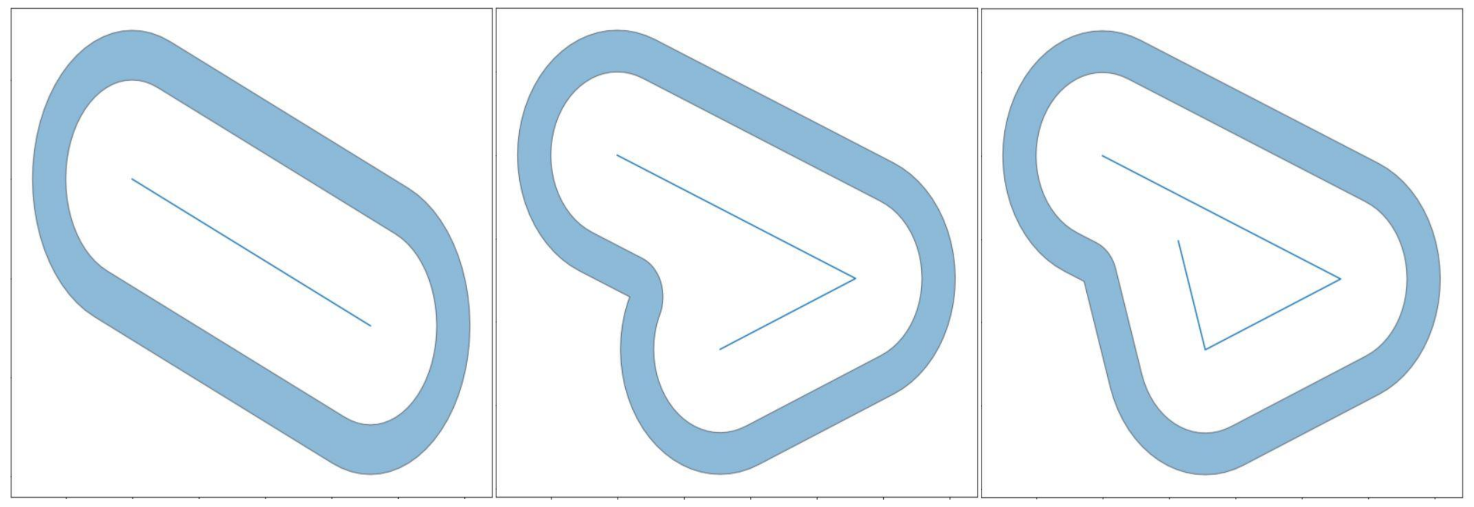

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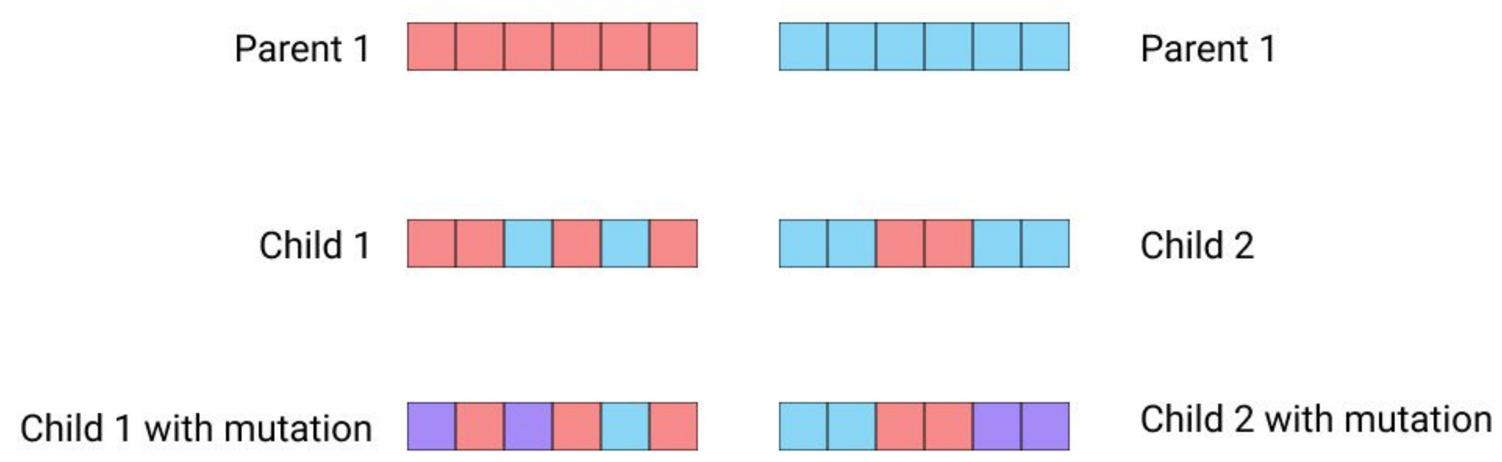

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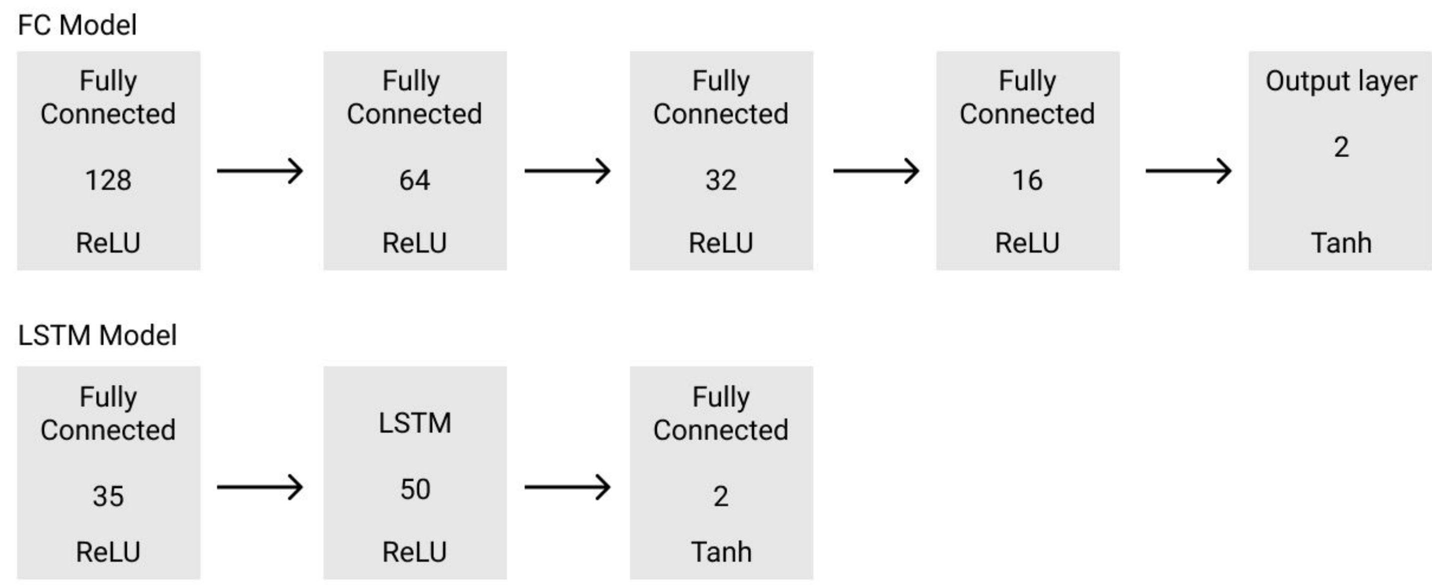

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In this report distance based penalties have been utilized to determine whether the subsequent state following a given action is desirable. Agents are originally penalized for hitting a wall or neither hitting a wall or the goal (A), however an additional penalty has been implemented for the distance to the goal of the new state being larger than the previous one (B). The fitness is thus the total penalty and the child generation is then selected, to some top limit, by ranking the results from least to greatest. The penalty functions are:

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Number of Agents	Number of Generations	Crossovers	Mutation Power	Top Limit
100	51	20	0.1	10

The highest fitness among all the agents, which is negative in this case, was plotted for each generation. Below it is seen that, for a map with zero turns, the fitness fluctuates over time however the general trend is increasing and should converge toward zero given enough time.

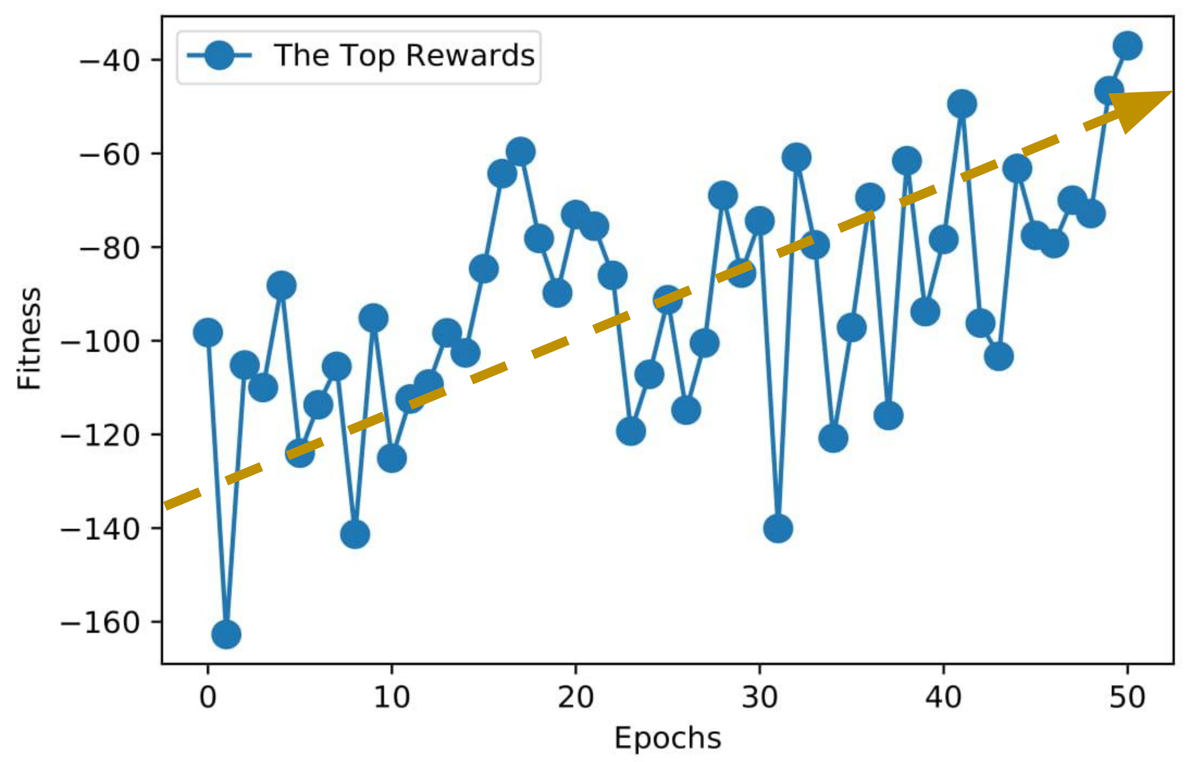

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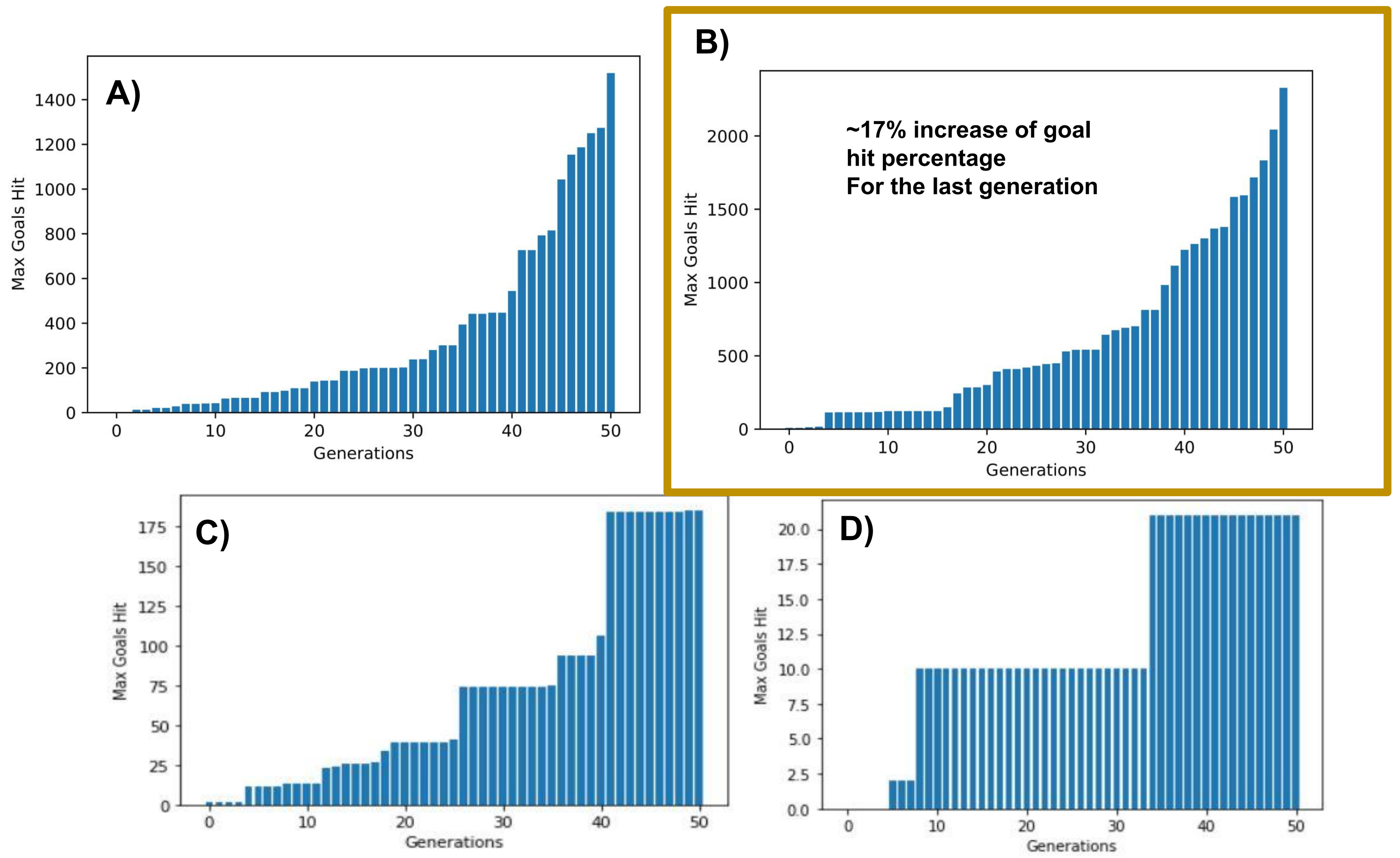
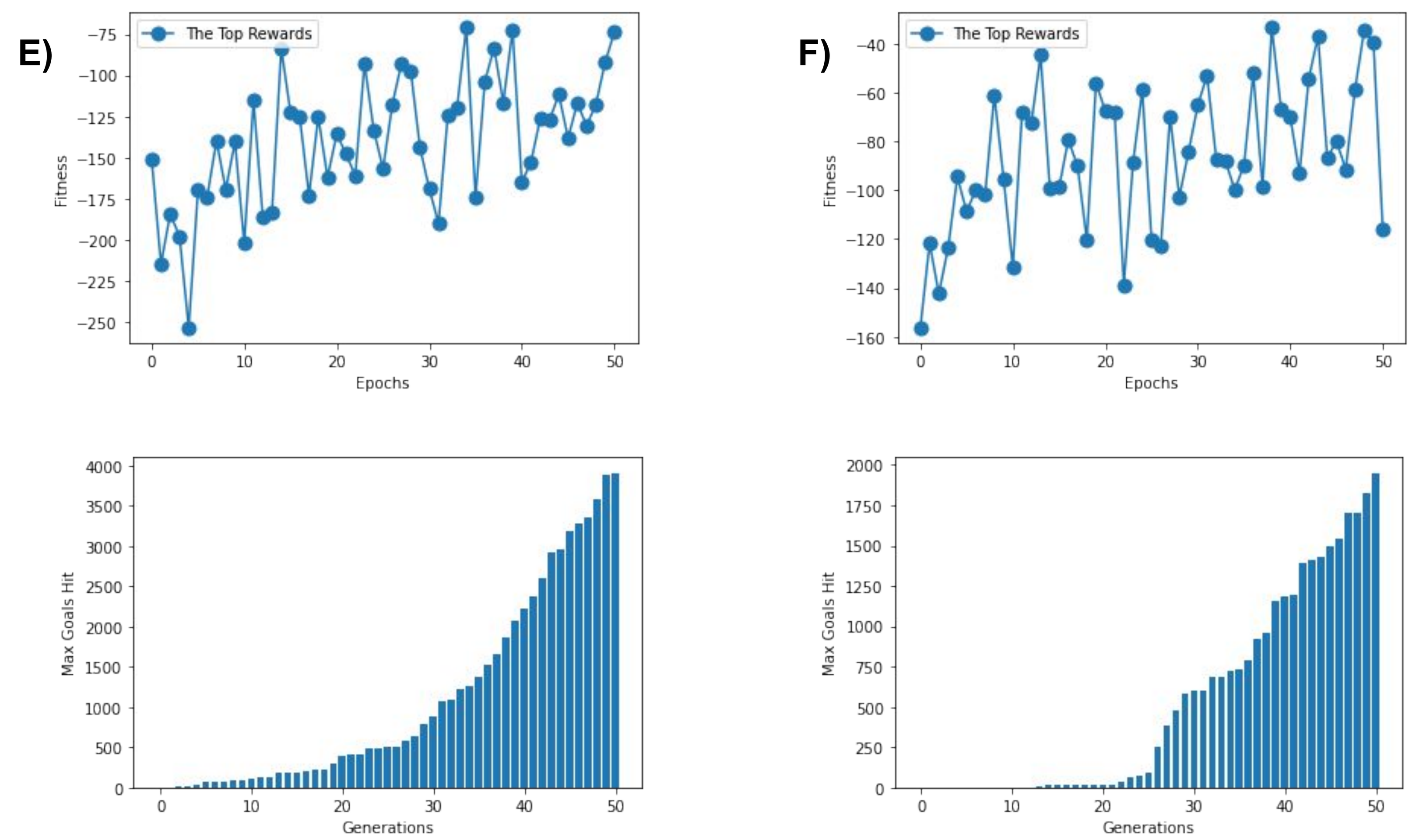
Figure A and B show the cumulative goals hit without and with the additional penalty implementation, respectively. The additional penalty drastically outperforms the original algorithm. From the three stages of curriculum learning (0,1,2 turns) in figure B, C, D it is seen that the network learns over time and can apply what it learned to a more difficult task effectively.



Results (LSTM)

In order to investigate the performance of a different network, an RNN was tested. In figures E and F, the fitness and cumulative goals hits are plotted for maps of zero and one turn, respectively. A reduction of the plateaus are evident in the figure F, indicating that the training speed increased.



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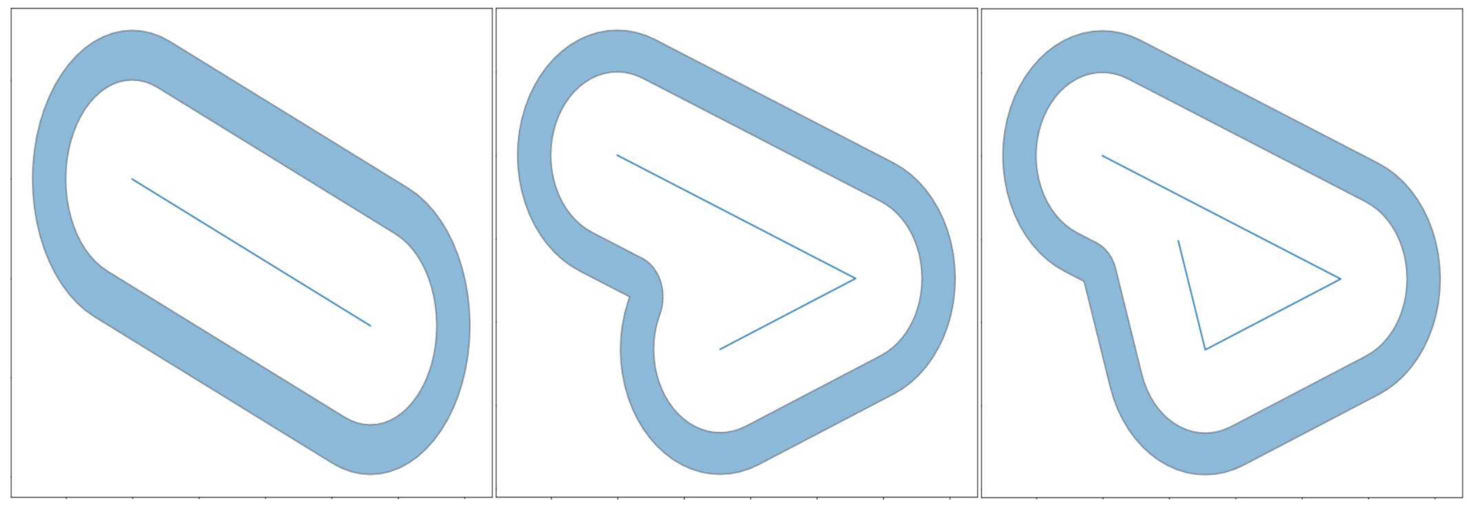

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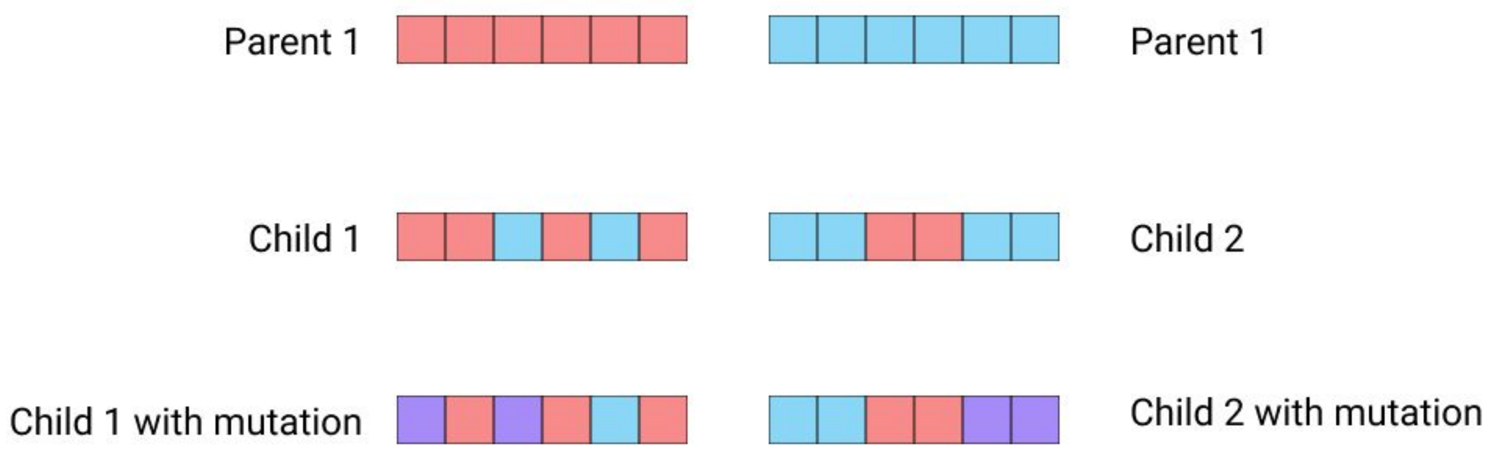

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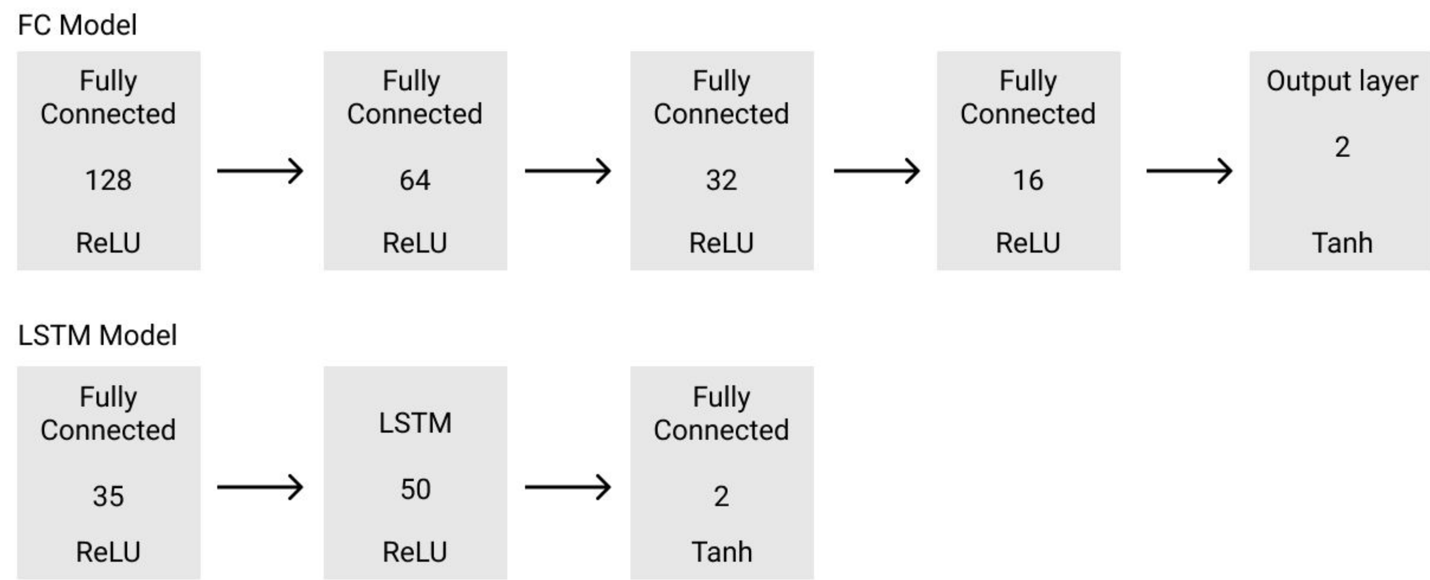

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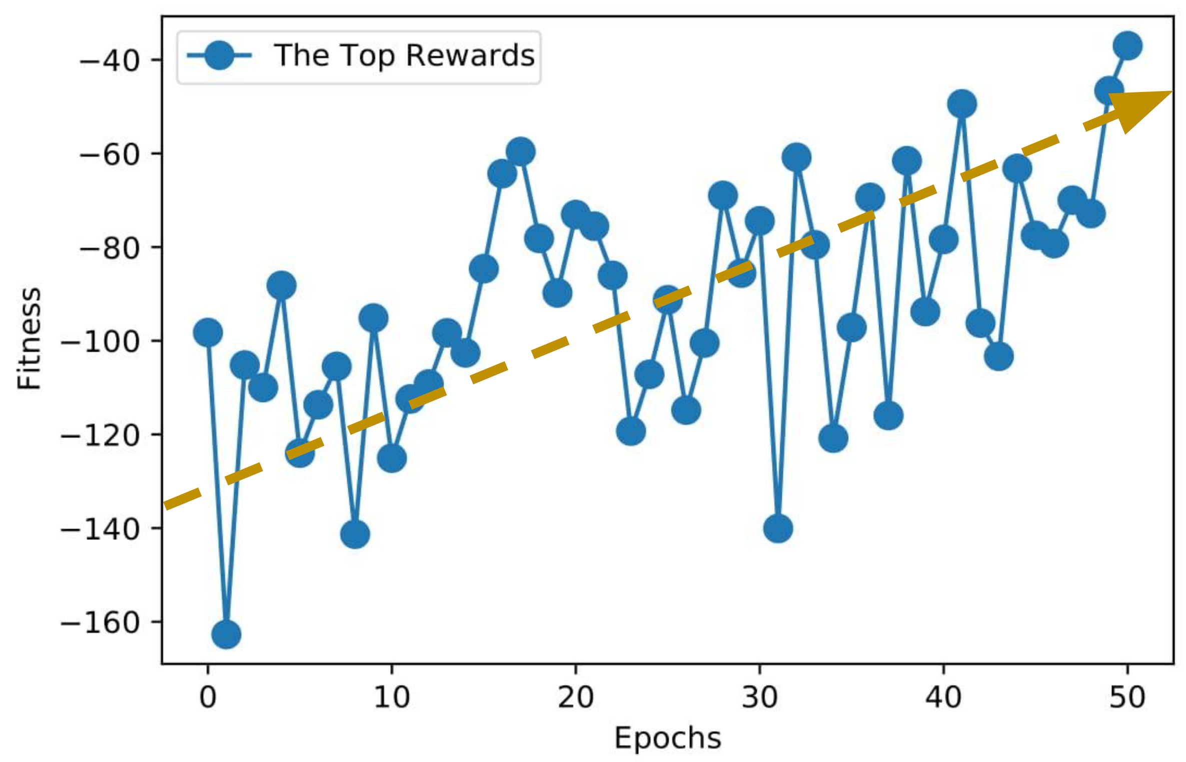

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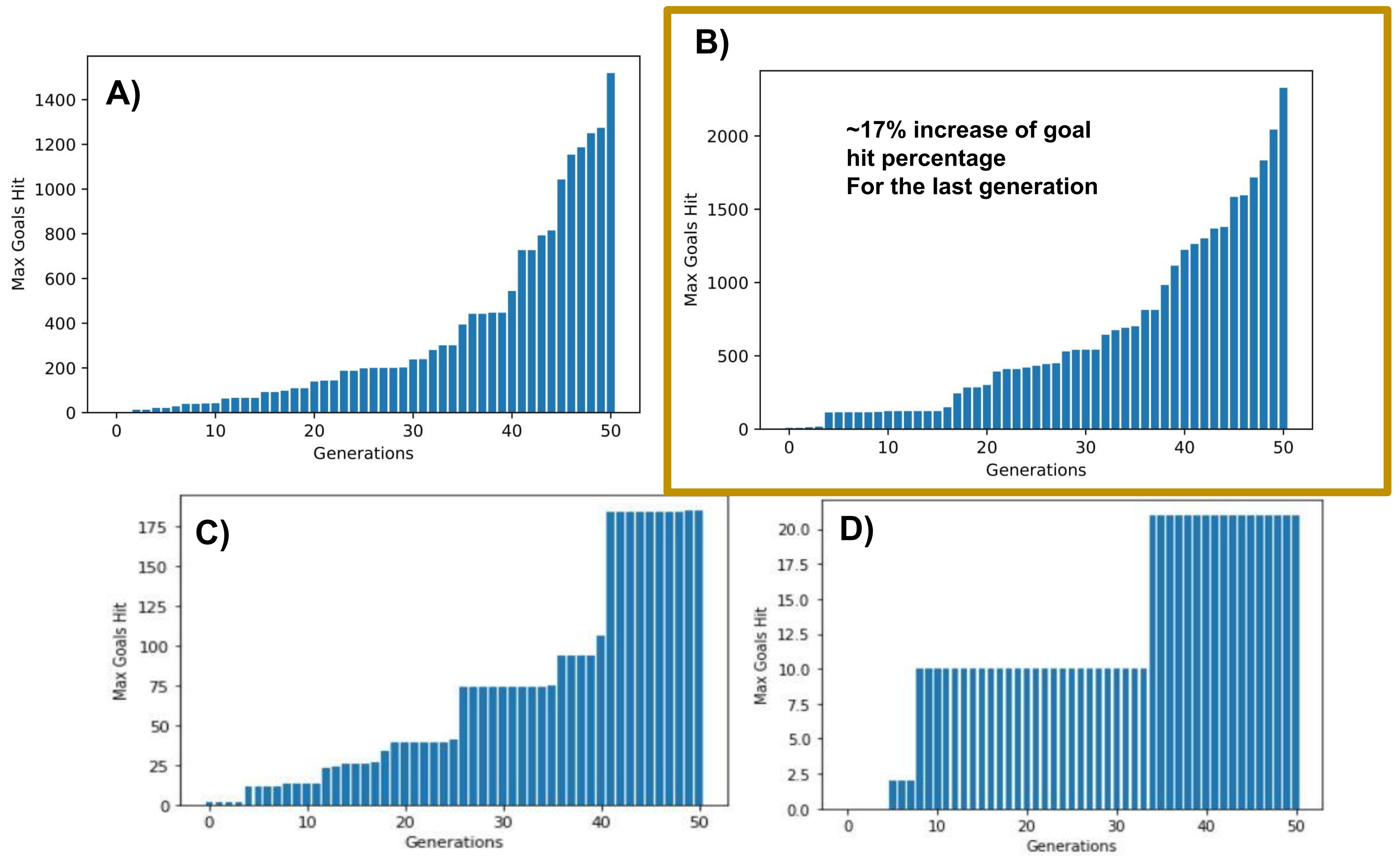

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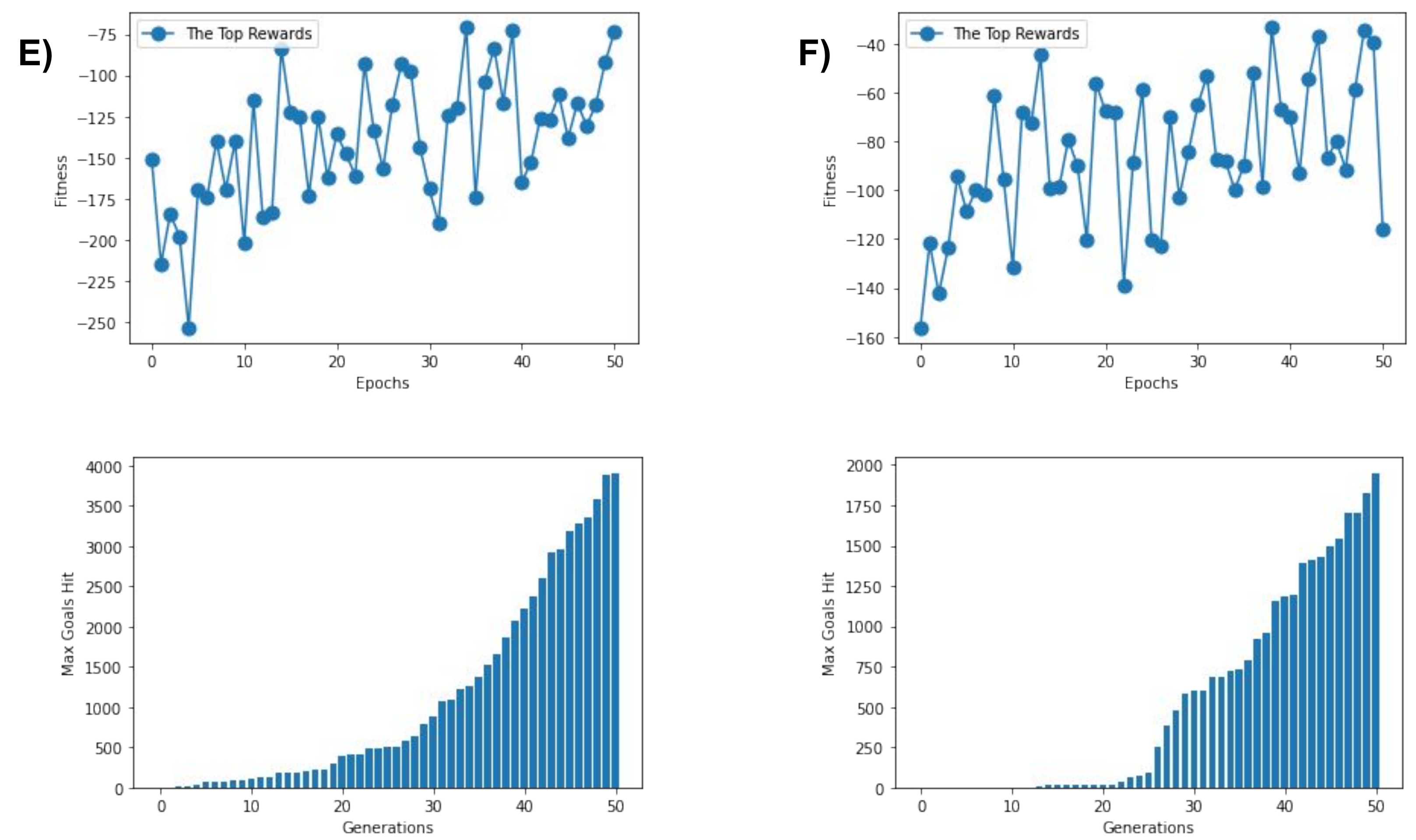

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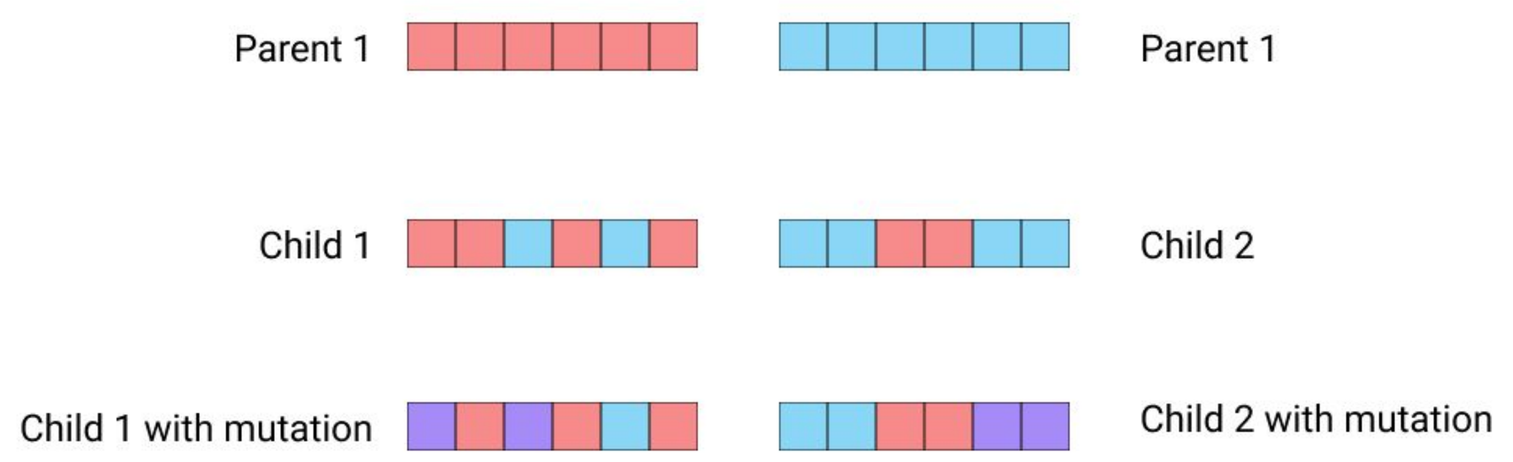

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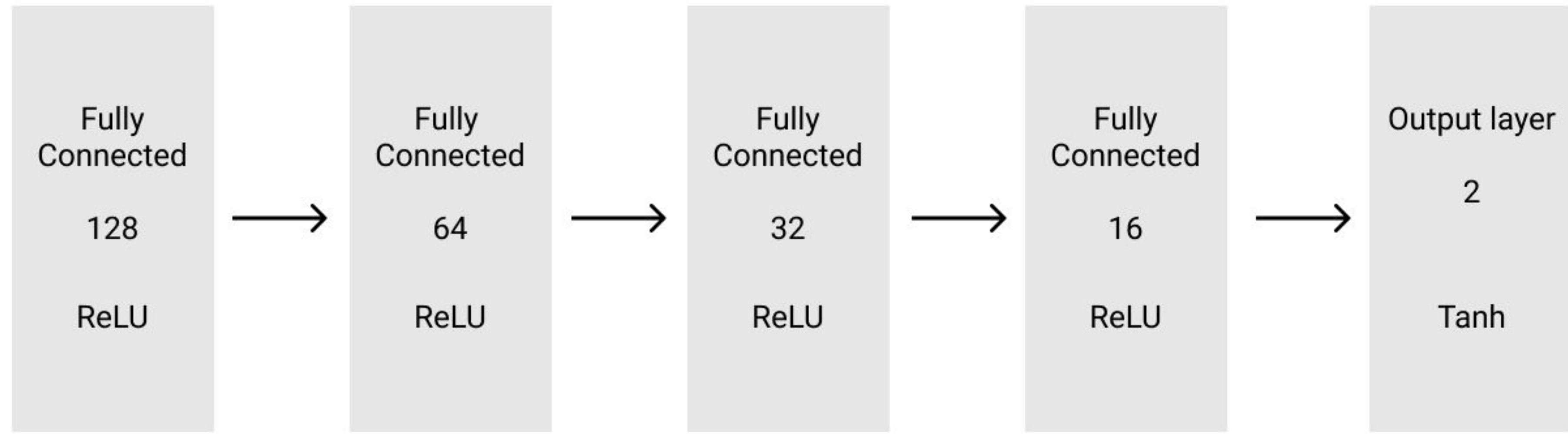

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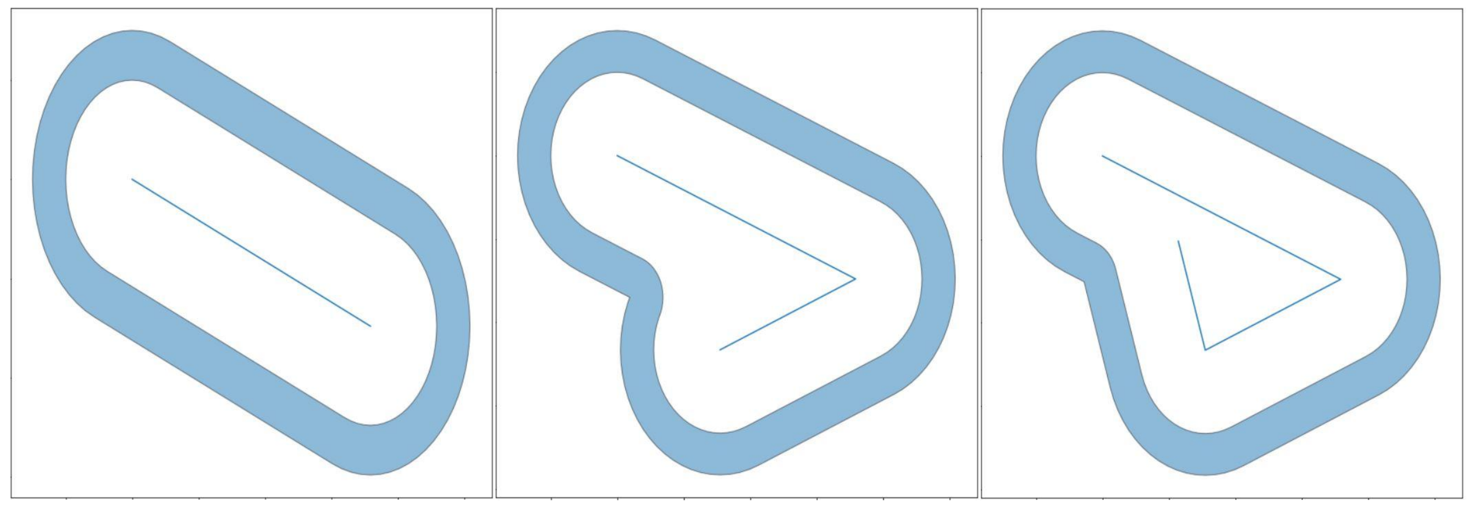

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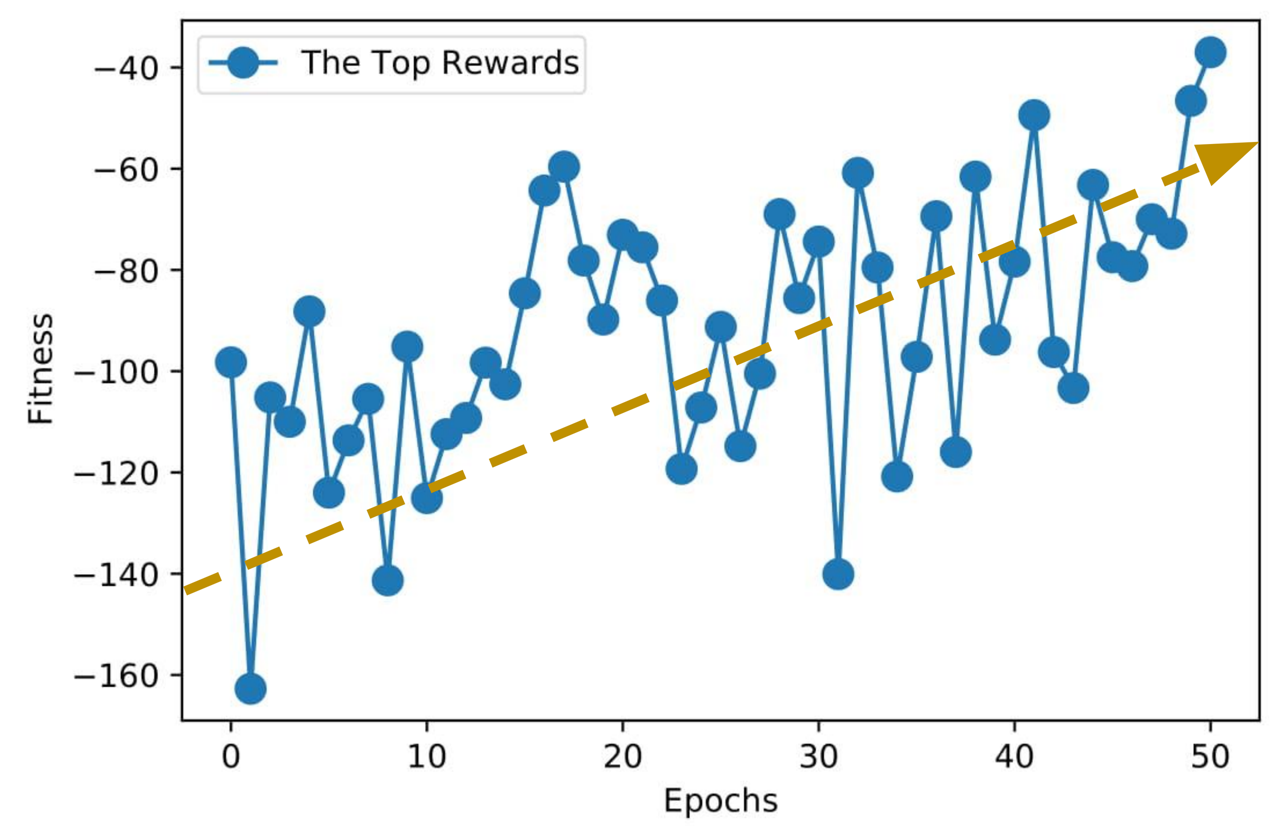

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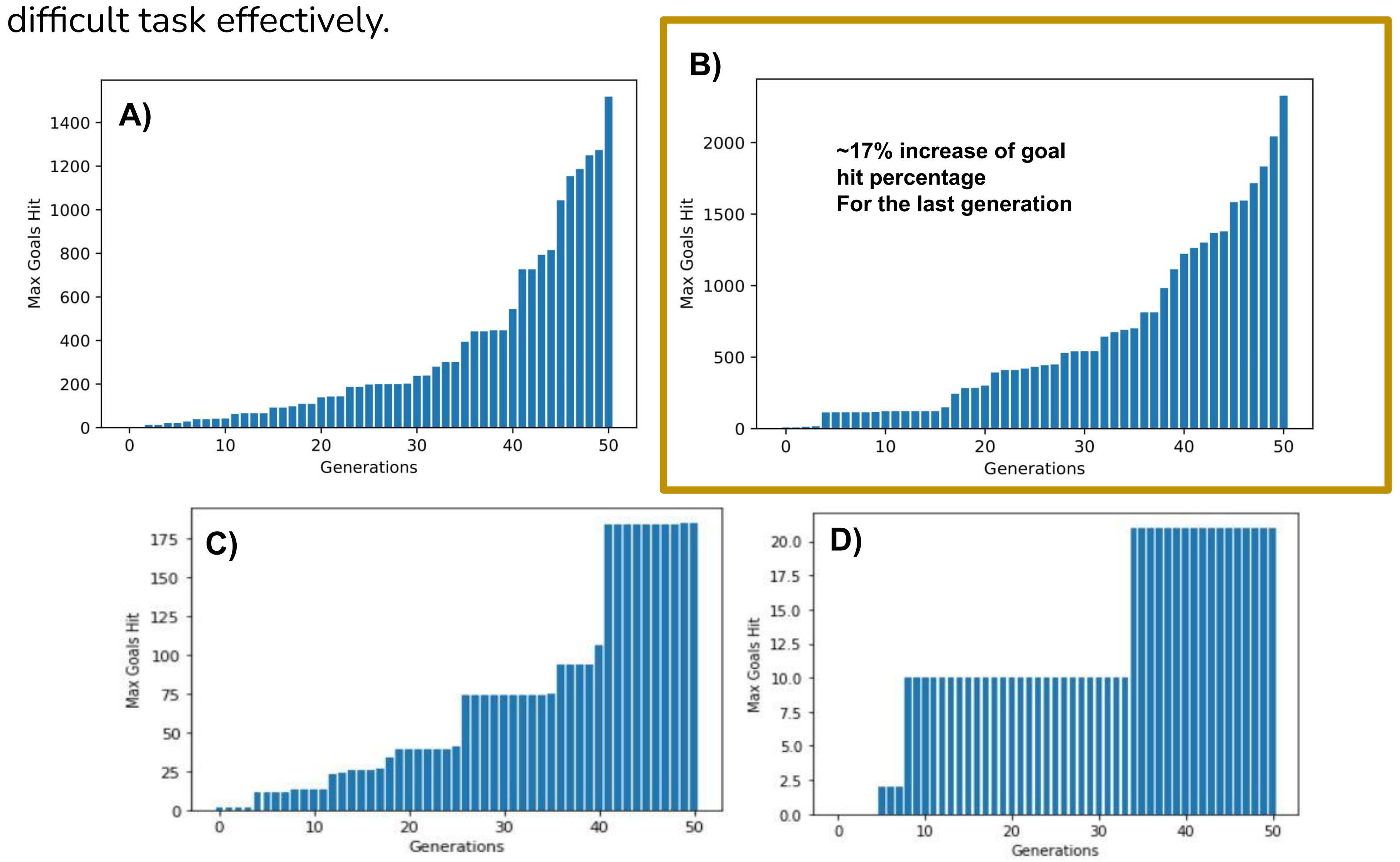

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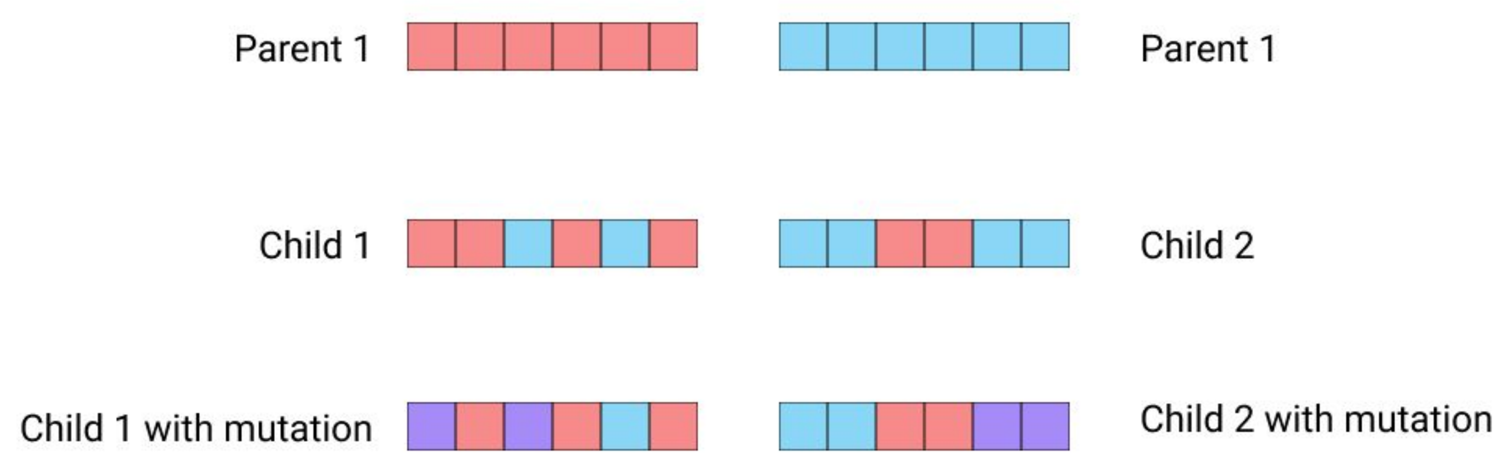

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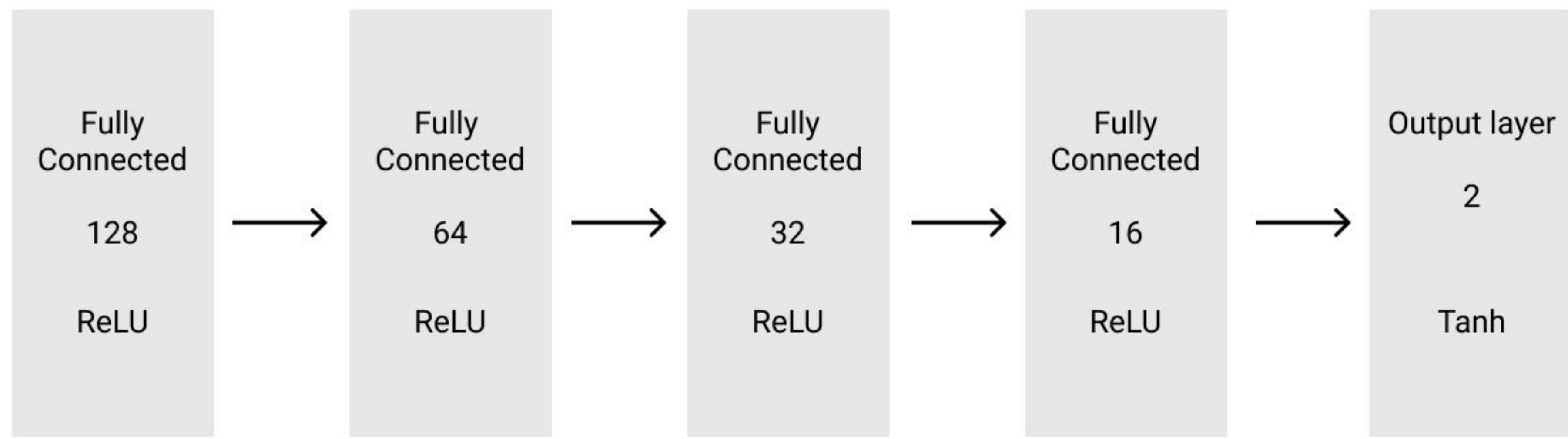

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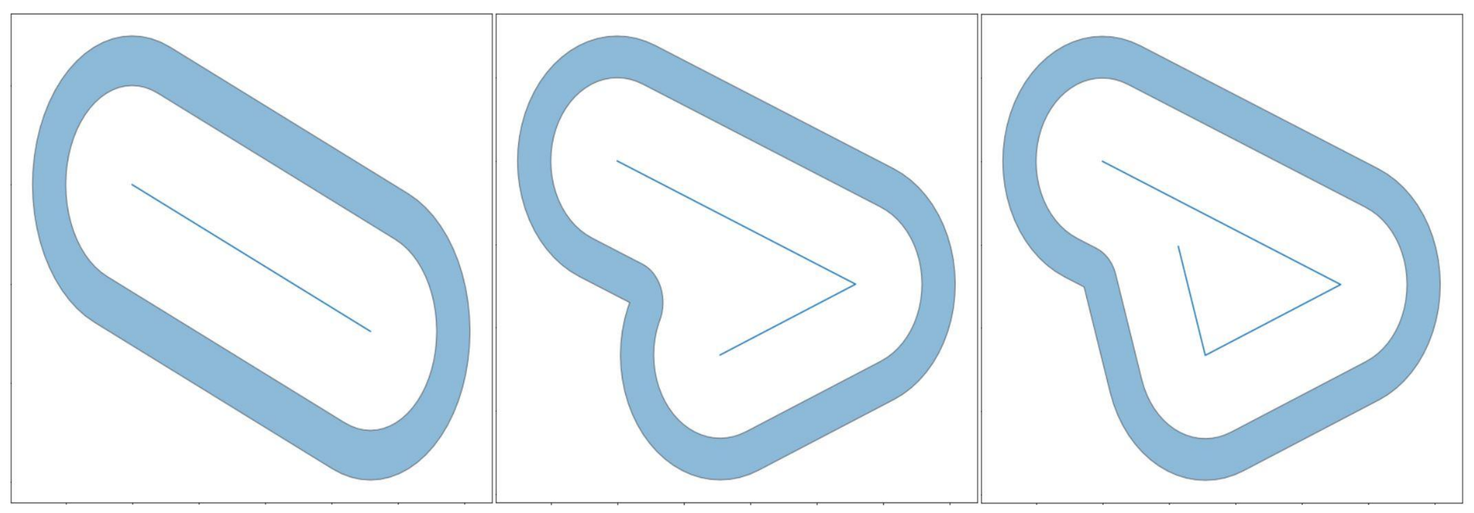

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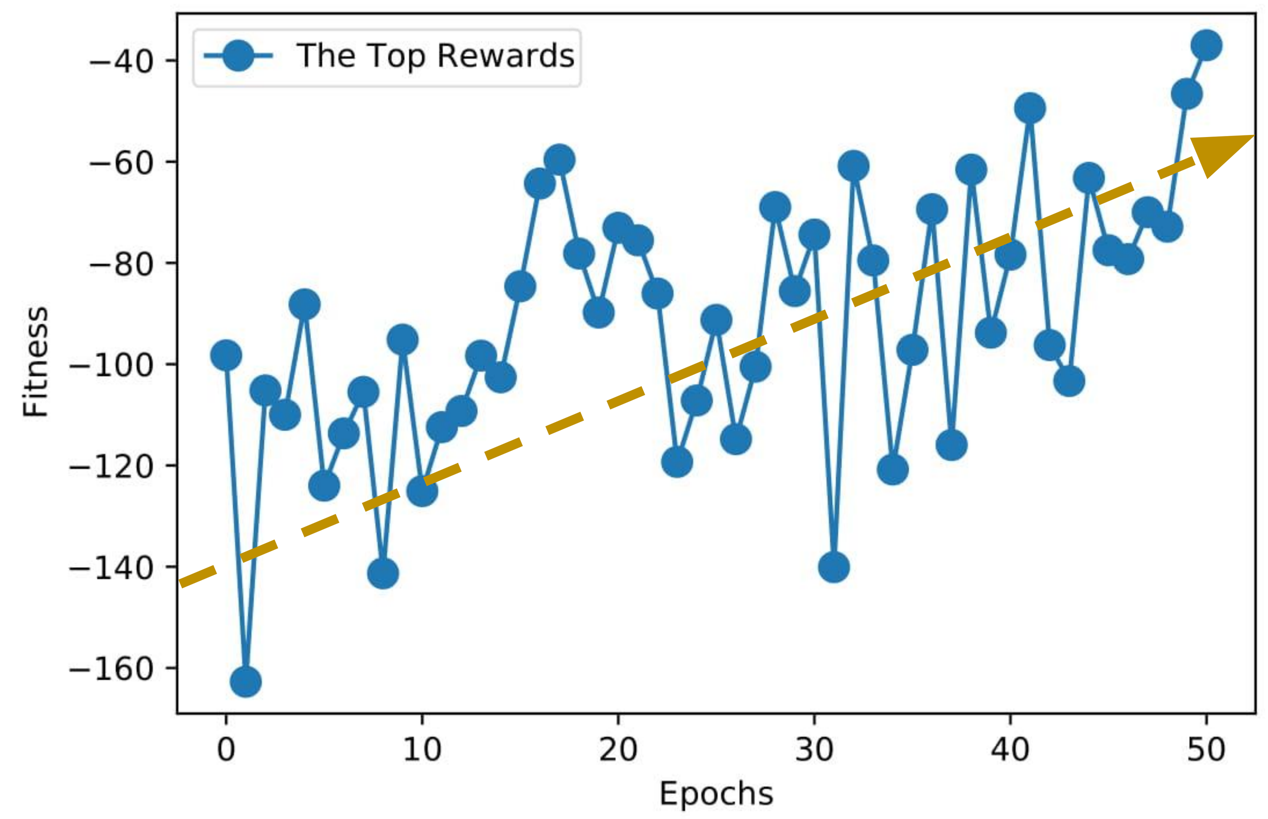

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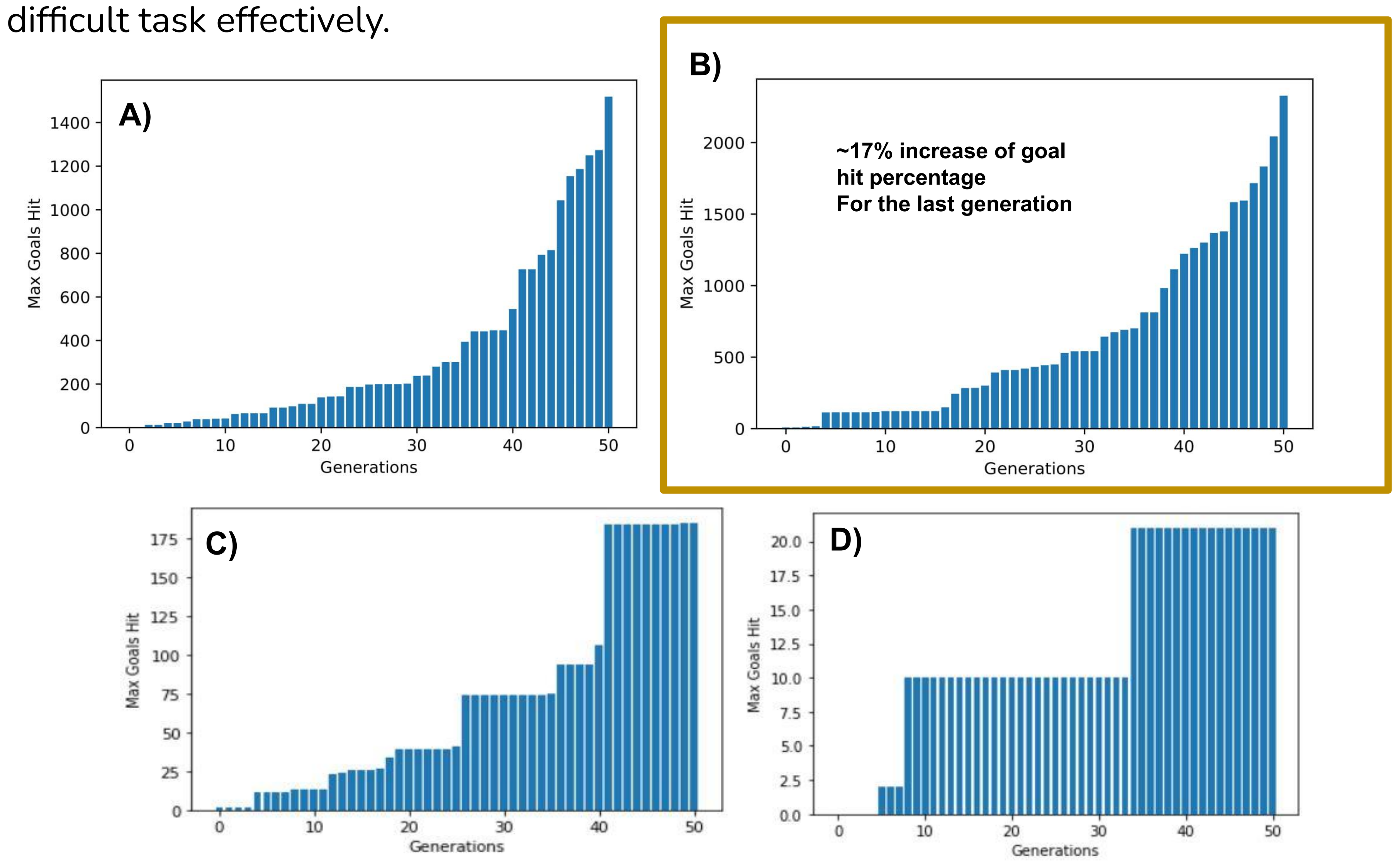

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