EVOLUTIONARY SELECTIVE IMITATION: INTERPRETABLE AGENTS BY IMITATION LEARNING WITHOUT A DEMONSTRATOR

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ABSTRACT

We propose a new method for training an agent via an evolutionary strategy (ES), in which we iteratively improve a set of samples to imitate: Starting with a random set, in every iteration we replace a subset of the samples with samples from the best trajectories discovered so far. The evaluation procedure for this set is to train, via supervised learning, a randomly initialised neural network (NN) to imitate the set and then execute the acquired policy against the environment. Our method is thus an ES based on a fitness function that expresses the effectiveness of imitating an evolving data subset. This is in contrast to other ES techniques that iterate over the weights of the policy directly. By observing the samples that the agent selects for learning, it is possible to interpret and evaluate the evolving strategy of the agent more explicitly than in NN learning. In our experiments, we trained an agent to solve the OpenAI Gym environment BIPEDALWALKER-V3 by imitating an evolutionarily selected set of only 25 samples with a NN with only a few thousand parameters. We further test our method on the Procgen game PLUNDER and show here as well that the proposed method is an interpretable, small, robust and effective alternative to other ES or policy gradient methods.
1 Introduction

Reinforcement learning (RL) agents are often effective at exploring their environment and find strategies that achieve high reward. These strategies can be counter-intuitive or unexpected. A core challenge of autonomous agent development is that it is difficult to deeply understand the strategy the agent discovered during training, before deployment to the real-world.

This problem is important because the strategies the agent discovered can be undesirable, exploitative or even dangerous in some point of their flow. For example, in the game COASTRUNNERS, OpenAI demonstrated [6] a racing agent that learned to exploit the game and achieve higher reward by crashing into other boats and repeatedly catching on fire, instead of actually finishing the race as the researchers intended. This game demonstrates the exploitative and counter-intuitive nature of strategies that can be discovered by reinforcement learning agents. In real-world scenario, the equivalent could be an automatic ship that learns to arrive faster by sailing in a way that danger the passengers on board. The concern of unexpected and dangerous agent behavior is growing in recent years as AI systems, and in particular robotic systems, become more widely adopted throughout the world.

The reason it is often difficult to fully understand trained policies is that the weights of a neural network (NN) are hard to interpret, which means researchers cannot rely on observing NN weights directly to understand the strategy the agent discovered. Instead, researchers often rely on observing their policy in simulations in attempt to understand their agents better. Simulations, however, often do not capture all of the possible states an agent would arrive at in the real-world, and relying on simulations is often not good enough to ensure the policy would not perform potentially damaging actions in the real-world.

Previous work attempted to help manage this problem. Incorporating human feedback in the reward loop [5] helps to ensure the agent is rewarded by following reasonable strategies, however human feedback can be demanding on human labor and be a limiting on the exploration of the agent. Visualizing NN weights, such as microscope by OpenAI [4], can help researcher to understand their policies, however, especially in Reinforcement learning where strategies are often complex, this method is limited in its application.

In this paper, we show that using Evolutionary Selective Imitation (ESI) we can generate policies that can be more easily interpretable, relieving the reliance on the NN weights to understand the policies. ESI is similar to other evolutionary strategies (ES), with the main difference of iterating over which samples are best to imitate, instead of iterating over the weights of the NN policy directly. The chosen imitation samples set, analogous to an airport baggage scanner, allow us to peak into the mind of the agent, so to speak, and develop a better understanding of the strategy the agent will follow. As an illustration, in the COASTRUNNERS example [6] mentioned above, researchers could potentially have observed ahead of deployment that the imitated samples focus on the specific section of the track the ship had learned to exploit, instead of the entire track, or perhaps observed suspicious samples in the set such that involve a ship set on fire. In our experiments, we present our method on PLUNDER and BIPED as an interpretable, robust and effective alternative to ES or Markov Decision Processes methods, such as policy gradient.

![Imitation Data](image)

**Figure 1:** Starting with random weights, our policy learned to walk in the BIPED problem after it was trained to imitate five samples. This set of five samples, each composed of a pair (observation, action), was iteratively mutated and improved in an evolutionary process of 40 million steps. The approximations of the five observations that have evolved, as taken from the walking sequence, are given under ‘imitation data’. Below them is the walking sequence performed by the agent after it was trained on the five samples. We illustrate here that by observing the evolutionarily selected samples, we can develop better understanding of the strategy of the agent and the type of walk it will have when deployed.

2 Related Work

2.1 Interpretability

Increasing the interpretability of agents in RL is an active research area and a variety of methods have been developed for that purpose [15]. A comprehensive survey of visual interpretability of deep learning was carried out by [24]. Ref. [23] introduced a method to produce, using a NN, programs that explain learnt policies, such that the policies are more easily interpreted, amendable and verifiable than neural networks. Ref. [9] developed more easily interpretable architecture of deep Q-networks that achieved state-of-the-art training reward, however the features extracted were found to be shallow. OpenAI offers a utility to visualize layers and neurons of a NN [4], which can be used to analyze the features extracted from a NN. Relying on interpreting NN directly, however, was demonstrated to be fragile to systematic perturbations [8], such that two visually indistinguishable inputs assigned to the same label can have very different interpretations by common interpretation methods.
Similarly to these methods, the interpretability of the control policy of an agent is an intended consequence of ESI. However, ESI helps researchers understand their policy by developing through a selection of states that can be examined, relieving the reliance on the NN weights to understand the policy.

The gained interpretability of the policy allows us to better reduce the risk of the policy acting in damaging and unintentional manner after deployment. Specifically, Amodei et al. [1] surveyed applications that lead to unintended and harmful behavior, and categorised these behaviors according to their origination. Using their categorization, our approach is intended to help to avoid negative side-effects and reward hacking, and to achieve scalable oversight and robustness to distributional shift.

2.2 Evolutionary Strategies

Evolutionary strategies (ES) have been demonstrated as simple and effective methods in a variety of challenging RL tasks such as Atari games [12,21] and control of simulated robots [11]. Recently, ES [22] was used to evolve small agents that learned to solve vision tasks by directing attention to selectively chosen pixels. This selective attention also provide the benefit of interpretability, which can be gained by observing which pixels of the image the agent chose to attend to. Similarly to these method, ESI uses evolutionary techniques to solve RL environments. In contrast to these examples, however, ESI does not use the evolutionary strategy to improve the weights of the policy directly, but instead to improve a set of samples to imitate with imitation learning.

ES has similarities to ESI that we want to exploit as well as to extend here. One important benefit of ES was demonstrated by OpenAI [20] when solving problems by distributing the computational load on a large cluster. Following this demonstration by OpenAI, ESI can similarly be distributed on a large cluster of machines. Because each episode is composed of iterations that can run independently, by running all of the iterations of an episode in parallel, we can share the workload load between the machines and combine the results only once by the end of the episode.

2.3 Imitation Learning

Our method uses a form of imitation learning to develop the policy of the agent. In imitation learning, a.k.a. learning from demonstration, a policy learns to generalize over a set of state and actions achieved through a demonstrator. This method was found to be effective, among others, with self-driving vehicles [3, 18] and robotic motion [14, 17]. A comprehensive review of the method can be found in [2].

There is a variety of methods that use imitation learning to improve the effectiveness of a learning agent. Expert demonstrations were found to improve the efficiency of RL techniques and to solve tasks where RL alone is ineffective [16]. These demonstrations were also shown to be used to improve the effectiveness of RL in the case where these demonstrations are imperfect [13]. Furthermore, combining imitation learning with interventions, such that the agent learns behaviour from a demonstration via imitation learning, and then leverage intervention data to improve further, was found to improve learning over imitation learning alone [10]. A recent example of imitation learning to solve difficult tasks was demonstrated [19] to learn a solution by studying a single expert demonstration. The main difference of our approach and other methods mentioned here, is that we do not require prior demonstration to start the imitation process. Instead our policy starts with a trajectory generated by executing the random policy on the environment, and iteratively improves the imitation data through an evolutionary process. Another difference to the method demonstrated by [19] is that our method focuses on the beginning of the evolving solution that is then expanded towards the further stages of the behaviour, rather than learned backwards from the goal.

3 Selective Imitation

Selective imitation is motivated by learning of skill from demonstration in humans. Even for complex demonstra-
tions, and humans are able to choose important aspects and discernible aspects, and only these parts are then imitated, while distractors are ignored. For example, a young child can watch a professional soccer player on TV and try to imitate some of his moves with his playmates. If the professional slips and loses the ball, the child will recognize the slip was a mistake and will not attempt to imitate that. Even if the professional player does not perform a mistake, most of the time, he would perform actions that are too difficult and advanced for the child to learn, or that are not crucial for success, such as running with the ball or waiting for the ball to come. The child would know not to pay too much attention to this behavior.

Inspired by such examples, we propose a method that uses an evolutionary algorithm to solve the credit assignment problem, i.e. how to learn which parts of a demonstration should be imitated. The advantage of ESI is that the set of imitated samples provides utility, which is more useful than a data-independent exploration strategy. ESI begins randomly and improves upon a selection of samples chosen from the best trajectories encountered so far in the environment. In every learning step ESI chooses the set that yields the policy that provides the best trajectory, and continues this process recursively to discover better samples to imitate, as will be further explored in the Method section.

### 3.1 Interpretability by Implicit Data Selection

Policies developed by ESI are more interpretable because, in contrast to the “black box” nature of the weights of a NN, the samples the policy chose to imitate can be observed. This is important because the strategy the agent developed during training, can often be hard to anticipate by researchers (a.k.a. the control problem), and observing the agent in simulations is often not sufficient to ensure intentional behaviour and not accidentally overlook aspects of the strategy that can be dangerous or exploitative. In analogy to a code review, observing the samples the policy imitated allows us to look inside the policy, understand the policies strategy better, and look for any suspicious or unintended samples. In addition to preventing unintentional behavior, better understanding of the policy can also assist researchers to debug and improve sub-optimal performance. Researchers can also analyze specific training samples that caused sub-optimal behavior; when an undesirable behavior is observed, unlike black-box policies, a researcher can directly search the imitation data, determine what part is responsible and better understand the source of the behavior.

### 3.2 Efficiency and Flexibility

The resulting NN policy can often be small (thousands of parameters). Because the NN is trained in a supervised fashion on a small number of samples, only a small NN is required to fully imitate the data.

This method can be used to improve upon an existing human demonstration. This can be done by initializing the method with an expert demonstration of solving the environment made by a skilled individual, instead of a randomly generated one. In this way the algorithm would improve upon the existing demonstration to reach potentially higher results than could have been reached with a random initialization, while still remaining creative.

Each method episode can also be distributed among many independent machines, as demonstrated by OpenAI [20]. In every episode, iterations run independently from one another, and as such, these iterations can be parallelised effectively in a computer cluster.

### 4 Methods

We use an iterative, evolutionary approach to find the best set of samples to imitate \( A = (s_j, a_j, r_j)_{j=0}^M \), called the active set. In every iteration the active set is mutated to produce a new set of samples \( Q_i \), which is imitated using supervised learning to teach a neural network policy \( \pi_i(\theta) \) to be executed on the environment and create a trajectory \( T_i = (s_j, a_j, r_j)_{j=0}^J \). The overall best trajectory encountered in any iteration thus far \( \hat{T} = (\hat{s}_j, \hat{a}_j, \hat{r}_j)_{j=0}^J \), as measured by the total reward sum \( \sum_{j=0}^J \hat{r}_j \), is recorded.

| \( M \) | Size of active set |
| --- | --- |
| \( N \) | Number of iterations per episode |
| \( \lambda \) | Percentage of samples replaced every mutation |
| \( P \) | Number of samples replaced every mutation |
| \( A \) | Active set |
| \( A' \) | Subset of the active set |
| \( T \) | Best trajectory thus far |
| \( T' \) | Subset of the best trajectory thus far |
| \( e \) | Episode number |
| \( L_e \) | Sampling limit of episode |
| \( i \) | Iteration number |
| \( Q_i \) | Imitation data of iteration |
| \( \pi_i(\theta) \) | Iteration policy |
| \( T_i \) | Iteration policy execution trajectory |
| \( j \) | Step number |
| \( s_j \) | State |
| \( a_j \) | Action |
| \( r_j \) | Reward |

Table 1: List of variables and parameters.

The size of the active set is \( M \) and it is mutated such that some samples are replaced with new samples from the best trajectory, as explained in Fig. 2. The mutation of the active set in every iteration \( Q_i \) is the result of union \( Q_i = A' \cup T' \) of samples from the active set \( A' \) and samples from the best trajectory \( T' \). \( A' \) is composed of \( M - P \) randomly selected samples from the active set \( (s_l, a_l, r_l)_{l=0}^{M-P} \subseteq A \). \( T' \) is composed of \( P \) randomly selected samples from the best trajectory \( (s_l, a_l, r_l)_{l=0}^{P} \subseteq \hat{T} \), where \( P = M \cdot \lambda \).
In every iteration, a policy uses imitation learning to imitate the active set. That is, the training of the policy \( \pi_{\theta} \) is done with supervised learning, such that the policy learns to minimize the error between the predicted action of a state \( \pi_{\theta}(s_t) \), to the demonstrated action of the state \( a_t \). The formula for the error would thus be \( \sum_{t=0}^{T} ||\pi_{\theta}(s_t) - a_t||^2 \). The weights of the policy would be initialised randomly in every iteration and trained to optimize this error. In our experiments, we used a 1-hidden layer CNN for PLUNDER environment, and 1-hidden layer simple NN for BIPED as the agent.

In order to improve over the course of the entire task, the agent must combine information learned in previous steps with new information which means here to explore new samples for imitation learning. To balance exploration and iterative improvement, in every iteration the algorithm mutates the active set by keeping only some of the samples and replacing the other with new samples from the best trajectory found until now. The best trajectory from which new samples are taken is updated regularly throughout the execution (see Fig. 2) and also provides new samples to be imitated. This balance encourages the agent to explore thoroughly during an episode before it is updated and the dominance of these samples would prevent a qualitatively better strategy to emerge. Instead of updating the imitation data, new samples to be imitated. This balance encourages the exploration of more complex strategies such that the agent can succeed in more difficult environments, but this increases computational cost in training, an increased risk of overfitting, and more human labor required to fully examine the imitation data.

The complexity of the policy is controlled by a hyperparameter \( M \) (see Table 1) that sets the number of samples in the active set that is imitated by the policy. A larger number of samples can in principle support the formation of more complex strategies such that the agent can succeed in more difficult environments, but this increases computational cost in training, an increased risk of overfitting, and more human labor required to fully examine the imitation data.

### Algorithm 1 Evolutionary Selective Imitation

1: **procedure** **Main**

**Ensure:** Hyperparameters set

2: Initiate \( M, N, L_0, \lambda \)

**Ensure:** Variables initiated

3: \( \text{bestTraj} \leftarrow \text{random trajectory} \) \( \tilde{T} \) \( \triangleright \) best so far

4: \( L_e \leftarrow L_0 \)

5: \( \text{activeSet} \leftarrow \text{random subset of} \text{bestTraj} \text{of size} \)

6: \( M \)

7: **while** creating new episodes **do**

8: \( L_e \leftarrow L_{e-1} + 1 \) \( \triangleright \) Increase scope

9: **while** running \( \text{itersPerEpisode} \) iterations **do**

10: \( \text{MutateSet} \leftarrow M, N, L_e, \lambda, \tilde{T}, A \)

11: \( \text{imitationData} \leftarrow \text{MutateSet} \)

12: \( \text{Train} \pi_{i}(\theta) \) on \( \text{imitationData} \)

13: \( \text{Execute} \pi_{i}(\theta) \) \( \triangleright \) run iteration policy

14: \( \text{iterationTraj} \leftarrow (s_j, a_j, r_j)_{j=0}^{J} \)

15: \( \text{if} \sum_{j=0}^{J} r_j > \sum_{j=0}^{\tilde{J}} \tilde{r}_j \) \( \text{then} \)

16: \( \text{bestTraj} \leftarrow \text{iterationTraj} \)

17: \( \text{bestPolicy} \leftarrow \pi_{i}(\theta) \)

18: \( \text{bestPolicyData} \leftarrow \text{imitationData} \)

19: **return** bestPolicy

### Algorithm 2 MutateSet

1: **Summary:** Replaces part of \( \text{activeSet} \) with samples from \( \text{bestTraj} \) and returns new set.

2: **procedure** MutateSet(\( M, N, L_e, \lambda, \tilde{T}, A \))

3: \( P \leftarrow M \cdot \lambda \) \( \triangleright \) mutation size

4: \( \text{new} \leftarrow \text{random subset of} (s_j, a_j, r_j)_{j=0}^{L_e} \) of size \( P \)

5: \( \text{kept} \leftarrow \text{random subset of} A \) of size \( (M - P) \)

6: \( \text{newActiveSet} \leftarrow \text{new} \cup \text{kept} \)

7: **return** newActiveSet
5 Experiments

The goal of our experiments is the study of the effectiveness and the robustness of policies that are generated by ESI. We also want to find out whether the behavior of the agent is predictable based on the data that it has chosen to imitate. Lastly, we are going to test the importance of factors, such as exploration strength and active set size, on the results. We evaluated the method on two tasks, namely: BipedalWalker-v3 (Biped for short) and Plunder (Easy difficulty) from Procgen (environment from OpenAI). Hyperparameters will have to be chosen differently in order to account for the specificity of each game.

5.1 Hyperparameters

|       | Biped | Plunder |
|-------|-------|---------|
| $M$   | 25    | 160     |
| $N$   | 125   | 30      |
| $L_0$ | 5     | 20      |
| $\lambda$ | 0.5  | 0.5     |
| $K$   | 15    | 15      |
| $\eta$ | 0.005 | 0.005   |
| $T$   | 200   | 200     |

Table 2: Hyperparameters used in our experiments (Biped and Plunder). $K$ (batch size), $\eta$ (learning rate) and $T$ (number of back propagation iterations) refer to the hyperparameters used in the imitation neural network, which were similar for Biped and Plunder.

To create agents that imitate the samples in every iteration (25 in Biped and 160 in Plunder) (see Table 2), we used a simple single-hidden-layer neural network. In Biped we used 40 hidden nodes for a total of 2,804 parameters. In Plunder we used a CNN with 128 nodes in the hidden layer for a total of 58,539 parameters. Achieving good scores with such small number of parameters demonstrates an advantage of learning strategies with imitation learning on a few selected samples.

The range of hyperparameters tried is described in Figs. 5-9 and the final hyperparameter setting was chosen to maximize reward in the respective game, under computational constraints. To run the experiments we use a 64-bit Windows 10 computer with Intel(R) Core(TM) i7-10510U CPU @ 1.80GHz, 16.0 GB RAM, and the software Python 3, Pytorch v1.4.0, NumPy v1.18.1.

5.2 Bipedal Walker

In Biped (OpenAI Gym v0.17.0), the aim is the control of a robot, as shown in Fig. 3, and to reach the end of a route by controlling the velocity of the knee and hip joints (4 DoF) of a simple robotic walker. The reward is calculated based on the distance traverse by the robot. Reaching the end incurs +300 points, and falling leads to -100 points. Applying torque costs small number of points, such that the choice of the gait type is important for achieving a higher score. Solving Biped is defined as achieving an average reward of 300 points over 100 consecutive trials. Our experiments (see Fig. 4) of running the algorithm for 40 million steps developed a policy that achieved an average reward of 300.02 ± 36.99 over the required 100 trials.

As the agent is trained on more training steps, as demonstrated in Fig. 4, the reward increases as result of better data to imitate being discovered. The variance of the reward is large in the first few million of training steps as result of variance in the number of steps it requires to learn a simple walking sequence.

In Fig. 5 we show the effect of the active set size on the effectiveness of the agent. As we increase the active set size, more pairs $(s_j, a_j)$ are imitated which entails the development of more complex strategies. This, however, exposes...
Figure 5: Average and standard deviation of 10 experiments expressing the reward after 40 million training steps on BIPED as function of the active set size, i.e. the number of observations that are imitated by the policy.

We also demonstrate that the proposed method can develop an agent that achieves a score of $217.2 \pm 4.99$ in average of 100 consecutive runs in BIPED by imitating only five samples. Each sample is composed of a pair $(s_j, a_j)$. In Fig. 1, we present the graphical representation of all the states in the sample set. With the knowledge that these are all the samples the agent chose to imitate; we know this set of samples encompasses the entire strategy. Through this set, we can interpret the agent better before deployment. This is thus an example of the benefit of interpretability that is inherent in using ESI.

Figure 6: Screenshot of Plunder environment. Circle image in lower left corner signifies the type of the target ships, and the ship above are the potential targets to destroy.

5.3 Plunder

We chose to evaluate the agent on PLUNDER (Difficulty: Easy) environment of Procgen (OpenAI package Procgen v0.9.4 [7]) for the purpose of assessing the generalization of the agent and to measure its effectiveness in a pixel-based environment. Procgen is a benchmark developed by OpenAI that helps to measure the robustness of an agent by separating training and evaluation to different sets of procedurally generated levels. In environments that are part of Procgen, the agent first trains on a limited number of levels, 200 in this paper, for several iterations and then evaluated on a different set of 1,000 levels to gauge not only the effectiveness of the strategy it developed, but also the ability of the agent to not overfit to the 200 training levels.

In PLUNDER, a player is tasked, under time constraints, to control a ship with the aim of destroying target ships specified by a symbol in the bottom-left corner, as shown.
in Fig. 6. Levels are different from each other by the color and symbol of the target ship and the order and number of their appearance in the game. The reward evaluation metric is calculated based on the number of target ships destroyed and the number of friendly ships that were not shot at.

Our agent was trained on 200 training levels and achieved an average score of 12.8 when evaluated on 1,000 unseen levels (see Fig. 7). In comparison, OpenAI used PPO to achieve 5.07 as the baseline result in Ref. [7]. This result, in comparison to the baselines in Procgen paper, demonstrates the robustness that comes from using simple policies developed by ESI on the PLUNDER environment, however, we found that we could not replicate these results on some other games in Procgen, such as Starpilot or Bossfight.

In addition, we tested PLUNDER for how well the policy does as function of the active set size it trains on (see Fig. 8). There is a general increasing trend of reward as the policy becomes more complex by imitating a larger set of samples. However, as mentioned in the methods section, more complex strategies are harder to understand, can overfit the training set and require more computations in training, so that it is recommended to keep the active set smaller.

We also tested to measure how well the policy does as a function of the level of exploration. In every iteration, the policy decides to drop a random subset of the samples it imitates and replaces them with new samples. The larger the subset it drops, the higher the ‘mutation strength’ is, the higher the exploration of the policy is. This has resemblance to the noise factor in evolutionary strategies; high value would mean more exploration at the cost of higher difficulty to converge effectively and precisely. The reward as function of the percentage of samples replaced in every iteration is given in Fig. 9. As we can see, a combination approach of exploration (replacing some of the samples) and exploitation (saving the best samples gathered thus far from previous episodes) achieves a higher score. The trade-off peaks at 0.5, which means replacing half the samples in every iteration.

6 Conclusion

We have proposed a training method that enables inspection of the strategy that an agent discovers during training, by providing a set of critical samples from the agents behaviour. This inspection can help to gather insight and to interpret the learnt strategy. Our method employs imitation learning to imitate a selected set of samples, but it does not require any demonstration to mimic. Instead, the agent recursively iterates over a set of samples and, starting from a random trajectory, evolves a specific, small set of imitation data to train on. It is able to maintain a good learning process by the evolutionary choice of data, which appears to be an effective method of data selection for imitation. As demonstrated, by imitating only 25 samples ESI solved the BIPED control task, and by observing this data we can develop an understanding of the strategy of the agent without the need to rely on simulated experiments. We further demonstrated in the PLUNDER game that the resulting agent is effective and robust, and requires only a few thousand parameters.

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