Re-Evolutionary Algorithms

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Introduction

Motivation:
Policy gradient methods in reinforcement learning face the issue of lack of exploration. Evolutionary strategies is a black-box optimization algorithm to overcome local optima which suffer from low exploitation of the environment feedback signals.

Objective:
Our project is aimed at developing a hybrid evolutionary reinforcement learning algorithm (ERL) and apply it to a classic control problem to prove its superiority over the standalone algorithms. We implement a policy gradient algorithm (Advantage Actor Critic - A2C) and an evolutionary algorithm (ES) for the cartpole problem on OpenAI gym. Subsequently, we combine A2C with ES for the cartpole problem to show that it performs better than the standalone algorithms.

Environment:
A pole is attached to a cart which moves along a frictionless track. The system is controlled by moving the cart right or left. The pole starts upright and the goal is to prevent it from falling over. The objective of this task is to keep the cartpole upright continuously for 200 timesteps which corresponds to a reward of 200.

The Actor-Critic Architecture

The neural network architecture for the policy gradient and the value gradient functions are described. The policy gradient outputs a probability distribution for the policy from which actions are sampled and hence, the actor. The value gradient computes the advantage of taking a particular action given an observed state and hence, the critic.

Policy Gradient architecture which outputs predictions of each action

Value Gradient architecture using a single hidden layer

Evolutionary Strategies

Policy Gradient architecture which outputs predictions of each action

Value Gradient architecture using a single hidden layer

Figure 1: Cartpole Problem on OpenAI Gym

Evolutionary Actor-Critic

We combine ES and A2C iteratively in a sequence. Each iteration of algorithm spawns parameters and makes an update by choosing the best candidate. The weights updated by the ES is passed on to the policy gradient function of the A2C algorithm which performs a gradient descent update.

Figure 3: Vanilla E-A2C

ES spawns a population of parameters and A2C updates each member of the population by performing a series of gradient descent updates. Finally ES chooses the best parameter vector (based on the rewards obtained) in the population, and injects noise onto this parameter vector to generate the new population.

Figure 4: Evolutionary A2C

Results & Conclusions

Observations: The training converges when the average reward reaches 200 consistently. A2C reaches this state at around 75 epochs (5 episodes each) but it has a lot of variation due to the stochasticity in the selection of actions. ES has a lot of variation at the beginning but stabilizes after 150 epochs. Vanilla E-A2C reaches this state after 125 epochs. The evolutionary A2C is clearly superior to the other three algorithms in the sense that it is the quickest to converge and the variations in the reward are minimal after reaching this state.

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Future Work

Implement evolutionary DQN for the mountain car environment to show the exploration capability enhanced by ES

References