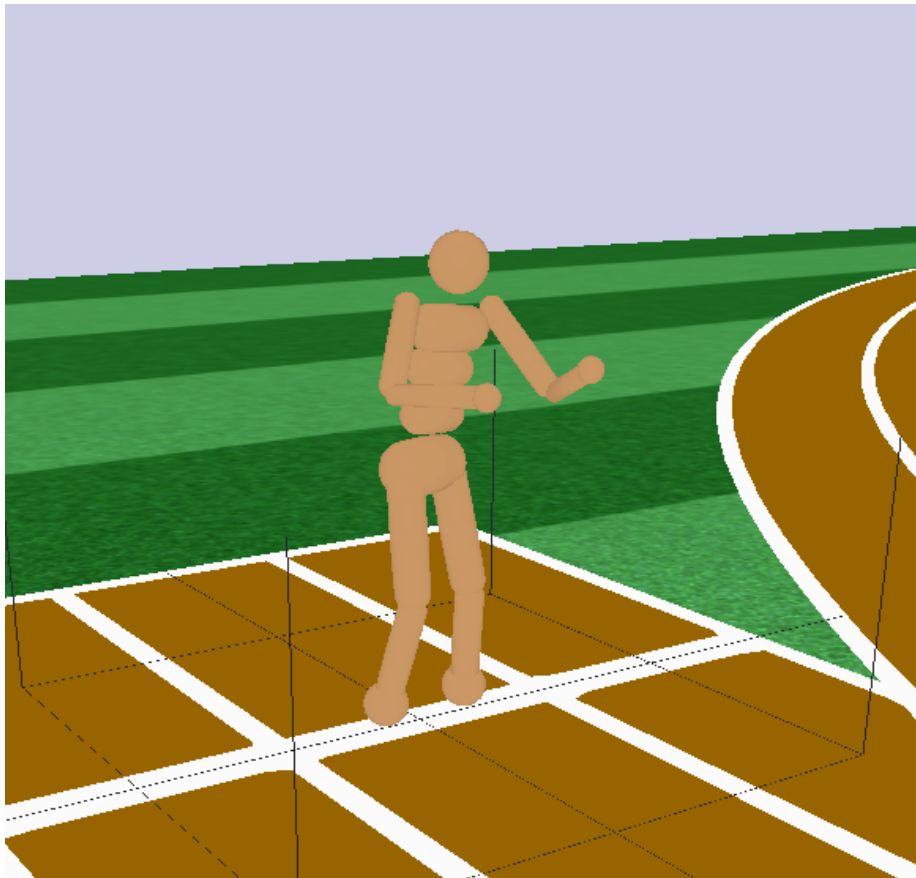


Capstone Report

Arise and walk, by Deep Deterministic Policy Gradient algorithm

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1 Definition of the problem

1.1 Project Overview

With this project, I want to tackle an important task of robotics: the ability of a humanoid to walk. This is a really interesting problem since we, humans, learn to walk without any feedback from another agent, just by a training process. The parents doesn't teach anything to the kids, the kids just learns. I think this is very interesting to build such model of artificial intelligence in order to to understand our brain a little bit more.

The anthropologic reason is not the only reason that task is important, it is also important to build autonomous walking robots able to progress on every fields. There are several areas of actions: In war, such a robot will be able to reach wounded soldier to give medical treatment or bring the soldier back to a safe place. It will avoid a medic human to risk his life in order to do that. In hospital, we will gain time by giving task to the walking robot so doctors and nurses will have more time to give to the patient. In every day life, we will be able to get near from the future described by movies like "I-Robot". Even if it questions the place of the robot in human society, I think making this kind of robot is still a goal to reach in order to send the robot in places human cannot or with difficulty go, like to another planet.

I am talking about walking but a neural network able to make a robot walk sure will be able to tackle another difficult task. The difficulty in those task is their continuous observation spaces. Indeed, in order to make a robot walk, we have two possibilities. The first one is to learn over pixels of the environment. I didn't choose this one because I don't think a human learn to walk from its sight but rather from its body. That why I chose to watch the position of its joints. With pixels, we will be able to train the humanoid to watch its steps but only after it is able to walk.

1.2 Problem Statement

The goal of this project, precisely, is to train a 3D avatar to walk forward on a plane fields. I will use OpenAI Gym [1] as an interface to the environment because it gives a simple and general way to use all kind of environment. For 3-dimensional avatar, it provides a binding for Mujoco library but since this library is paid, I will use a free similar one called Roboschool¹ which proposes few environments among the one I will use, RoboschoolHumanoid-v1. I am planning to use Reinforcement Learning to tackle this task with the Deep Deterministic Policy Gradient algorithm (Lillicrap et al.), an actor-critic algorithm. It is "Deep" because the actor and the critic is designed with deep neural networks. This algorithm is mostly used when the environment is a continuous space and since this environment never changes in our case (it is a plane field without changes), we can use a deterministic policy.

¹<https://github.com/openai/roboschool>

Actor Critic algorithm In Reinforcement Learning, many algorithms use an action-value function. It is a function which returns the value of an action a from a state s following a policy μ . It is defined like this:

$$Q^\mu(s_t, a_t) = \mathbb{E}_{r_t, s_{t+1} \sim E}[r(s_t, a_t) + \gamma Q^\mu(s_{t+1}, \mu(s_{t+1}))] \quad (1)$$

Besides that, the policy is the map of probabilities for an agent to go to state s_{t+1} from state s by the action a :

$$\mu(s, a) = P(a_t = a | s_t = s) \quad (2)$$

The idea of actor-critic algorithms is to use the action-value function as a critic which will give the Q value of the action taken by the agent at each time step. The higher the Q is, the more the reward the agent will get by taking that action in that state. The agent, here called the actor, will follow a policy μ in order to choose the action and that policy will be updated by the output of the critic. In Layman's terms, the actor is a child playing in the sandbox and the critic is the parent watching him. When the child makes an action that may lead to a bad state, the parent gives him a bad reward in order to change his behaviour (policy).

1.3 Metrics

I will need two sets of metrics because I have two kinds of session for the body: it can walk and fail to stand or it can walk without falling. When the avatar will fall, I will restart the session, because to teach it to stand up is another kind of problem.

At the beginning of the training, the body will fall and fall again very quickly. So my metrics during that period will be the amount of time step it took before failing, the distance of the gravity center from the floor, the reward per action and the global average reward. Since the actor and critic are neural networks, I will also plot the loss of the critic network and their weights and biases, to check if it is changing over time. With these informations, I will be able to tell if my models are training well or if I have to adjust my parameters. When the body will start to have less falls, some of these metrics will not be informative anymore. I have to find metrics to evaluate the gait of the walk. For that, I will plot the angle of the current body position from the start position in respect to the axis the avatar will try to follow.

2 Analysis

2.1 Data Exploration: RoboschoolHumanoid-v1

2.1.1 Observation space

Definition An observation space, or state space, is the shape and the possible values an environment state could have. If the state is not continuous, we can calculate the state space by counting all possible values. For example, in a tic-tac-toe game, every square have 3 states so the state space is $3^9 = 19,683$. Here, our state is continuous, meaning that our possible values stands in a range. We can then just describe values and specify the range.

Our environment has an observation space of 44 float values in the range $[-5, 5]$ which is a concatenation a three vectors described as follows:

- **more**: It is a vector of 8 values defined as follows:
 - The distance between the last position of the body and the current one.
 - The sinus of the angle to the target.
 - The cosinus of the angle to the target.
 - The three next values is the X, Y and Z values of the matrix multiplication between
 - *
$$\begin{pmatrix} \cos(-yaw) & -\sin(-yaw) & 0 \\ \sin(-yaw) & \cos(yaw) & 0 \\ 0 & 0 & 1 \end{pmatrix}$$
 - * The speed vector of the body.
 - The roll value of the body
 - The pitch value of the body
- **j**: This is the current relative position of the joint described earlier and their current speed. The position is in the even position, and the speed in the odds (34 values).
- **feet_contact**: Boolean values, 0 or 1, for left and right feet, indicating if the respective feet is touching the ground or not.

2.1.2 Action space

Definition An action space is like observation space but for action an actor can take. In the tic-tac-toe example, the actor has 9 possible actions, which is playing in one of the square.

The action space is a vector of 17 float values in the range $[-1, 1]$. Each value corresponds to the joints of the avatar by this order in the XML file:

- abdomen_y
- abdomen_z
- abdomen_x
- right_hip_x
- right_hip_z
- right_hip_y
- right_knee
- left_hip_x
- left_hip_z
- left_hip_y
- left_knee
- right_shoulder1
- right_shoulder2
- right_elbow
- left_shoulder1
- left_shoulder2
- left_elbow

At each step, these values are applied to all the joints of the body by the code

```

1 for n,j in enumerate(self.ordered_joints):
2     j.set_motor_torque( self.power*j.power_coef \
3         *float(np.clip(a[n], -1, +1)) )

```

in the `apply_action` function in the class which extends the `gym.Env` class (`RoboschoolMujocoXmlEnv`) to set the torque value into the respective motor.

2.1.3 Reward

Definition A reward is a value given the information if the action was good or not given the state. The definition of the reward function is a critical aspect of reinforcement learning since it is the one who gives the most valuable information during the training.

The reward is a sum of 5 computed values:

- **alive**: -1 or +1 whether is on the ground or not
- **progress**: potential minus the old potential. The potential is defined by the speed multiplied by the distance to target point, to the negative.
- **electricity_cost**: The amount of energy needed for the last action
- **joints_at_limit_cost**: The amount of collision between joints of body during the last action
- **feet_collision_cost**: The amount of feet collision taken during the last action

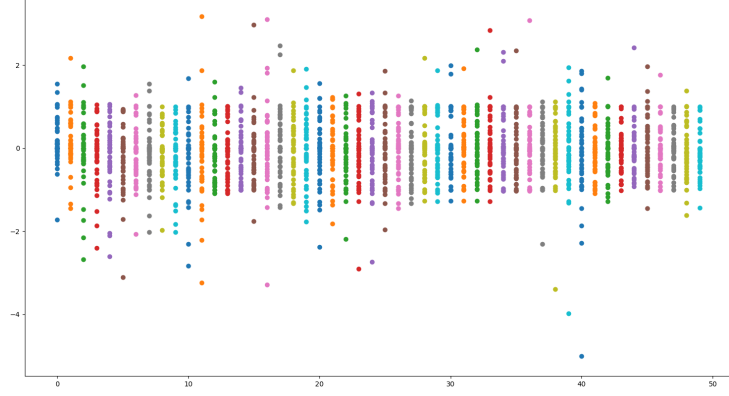


Figure 1: Roboschool environment

2.2 Exploratory Visualization

The fig. 1 shows the distribution of observation space during 500 epochs when only random actions are taken. The observation space is defined in the interval -5 and 5, so does the ordinate axis.

We can see that the majority of represented values is between -1 and 1. We guess easily that this is due to the representation of joint values and their respective space, which correlates with the action state definition space. The other values represent the more and j vector presented earlier in section 2.1.1.

2.3 Algorithm and Techniques

Deep Deterministic Policy Gradient In DDPG, instead of compute manually the Q value and the μ , we use neural networks, one for the actor and one for the critic. The figure 2 shows how such a model can train.

The Temporal Difference learning (TD Error in the figure) is a machine learning technique to, basically, let a network able to train with a little guess of the future. In our case of walking, the critic should not only see the next state but also estimate the chance the actor has to fall because of the action it took. To do that, we will use target actor and target critic network. It is, at the beginning, a copy of the actor and the critic but we will use these networks to compute the target action for a state and Q_{t+1} and, at each time steps, we will update their weights $\theta^{Q'}$ with the actual network weights θ^Q by the following formula called "soft update":

$$\theta^{Q'} \leftarrow \tau \theta^Q + (1 - \tau) \theta^{Q'} \quad (3)$$

Not using target networks will cause divergence and none of the model will learn a good policy or a good Q -value function.

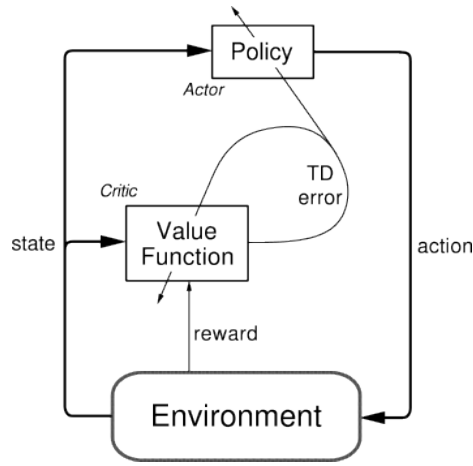


Figure 2: First, the environment gives the first state to the actor and it chose the action following the policy. The action is given back to the environment and a reward is computed, meaning how good the action was for that state, and sent to the critic network. The critic computes the Q value of that action by minimizing the loss and gives the error to the actor in order to let him train on it.

We need to also design a Replay buffer to store transition (s_t, a, r, s_{t+1}) and train over minibatch of random transition. In that way, we break temporal correlations between transition and minimize variance between our possible bad predictions.

A last thing we need to introduce is exploration noise. We want to add some noise to the action the actor take during training in order to let it explore its world with some randomness. A good way to compute noise is the Ornstein–Uhlenbeck process, which is also known as Brownian motion.

The figure 3 describes the algorithm in a pseudo-code. The reader can see that the actor doesn't learn the classical way, i.e. by minimizing its loss. Instead of that, its weights is updated with the gradient of the critic network after it trained.

2.4 Benchmark

The most basic benchmark we have to test is the random benchmark. What will happen in a worse case scenario ?

The figure 4 shows that the agent fall and fall again, without any chance to stand. The relevant information here is the average reward. The average reward of the random policy over 500 epochs is between -1 and -2 and the agent never lives more than 30 epochs.

Now we have a low benchmark, we have to dig into previous work of the community in order to find the state-of-the-art paper for that task. The work of Lillicrap et al. in their paper called *Continuous control with deep reinforcement Learning* does not show results with a humanoid environment but they did reach a good policy

Algorithm 1 DDPG algorithm

Randomly initialize critic network $Q(s, a|\theta^Q)$ and actor $\mu(s|\theta^\mu)$ with weights θ^Q and θ^μ .
Initialize target network Q' and μ' with weights $\theta^{Q'} \leftarrow \theta^Q, \theta^{\mu'} \leftarrow \theta^\mu$
Initialize replay buffer R
for episode = 1, M **do**
 Initialize a random process \mathcal{N} for action exploration
 Receive initial observation state s_1
 for t = 1, T **do**
 Select action $a_t = \mu(s_t|\theta^\mu) + \mathcal{N}_t$ according to the current policy and exploration noise
 Execute action a_t and observe reward r_t and observe new state s_{t+1}
 Store transition (s_t, a_t, r_t, s_{t+1}) in R
 Sample a random minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from R
 Set $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1}|\theta^{\mu'})|\theta^{Q'})$
 Update critic by minimizing the loss: $L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i|\theta^Q))^2$
 Update the actor policy using the sampled gradient:

$$\nabla_{\theta^\mu} \mu|_{s_i} \approx \frac{1}{N} \sum_i \nabla_a Q(s, a|\theta^Q)|_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s|\theta^\mu)|_{s_i}$$

Update the target networks:

$$\begin{aligned}\theta^{Q'} &\leftarrow \tau \theta^Q + (1 - \tau) \theta^{Q'} \\ \theta^{\mu'} &\leftarrow \tau \theta^\mu + (1 - \tau) \theta^{\mu'}\end{aligned}$$

end for
end for

Figure 3: Algorithm from Lillicrap et al. paper

for 2d walker. Another more recent studies[2] shows results of different algorithm including DDPG.

The figure 5 emphases that maybe DDPG is not a good choice to such a complex environment like Humanoid because DDPG is really sensitive about hyper-parameters changes. I still want to try to teach a robot to walk with that algorithm by increasing the depth of the networks for example and see what happened.

3 Methodology

3.1 Data Preprocessing

The Roboschool environment is made for educational and research purpose. In that matter, a lot of useful data preprocessing is already made. For the observation vector, after building it as explained in section 2.1.1, the value is clipped between -5 and 5, meaning that if the environment provides a value outside of these bounds, the value is set to the nearest bounds. This is the same for action space but the value is clipped between -1 and 1.

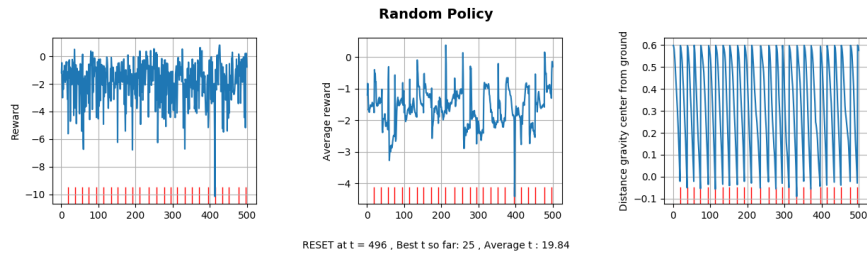
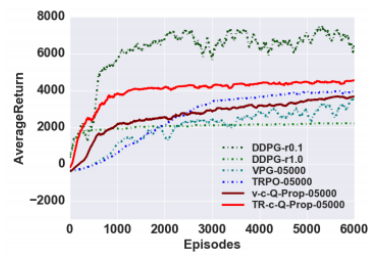
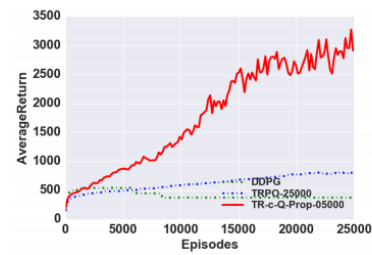


Figure 4: Random Policy



(a) Comparing algorithms on HalfCheetah-v1.



(b) Comparing algorithms on Humanoid-v1.

Figure 5: Average return over episodes in HalfCheetah-v1 and Humanoid-v1 during learning, comparing Q-Prop against other model-free algorithms. Q-Prop with vanilla policy gradient outperforms TRPO on HalfCheetah. Q-Prop significantly outperforms TRPO in convergence time on Humanoid.

3.2 Implementation

3.2.1 Project Structure

I present you below the structure of my project:

```

/
├── params.json
├── main_walk.py
├── walk
│   ├── agents
│   │   ├── abstract_env.py
│   │   ├── abstract_humanoid.py
│   │   ├── abstract_bipedal.py
│   │   ├── abstract_inverted_pendulum.py
│   │   ├── ac_policy.py
│   │   └── random_policy.py
│   ├── models
│   │   └── actor_critic.py
│   └── utils
│       ├── array_utils.py
│       └── board.py

```

```

├── matplotlibboard.py
├── memory.py
├── noise.py
└── tensorboard.py

```

In the `agents` folder, the `abstract_env.py` file is meant to be the super class of every policy I could implement, managing operation that every environment has to manage like instancing the plotting library or resetting the environment and its variables. You can see I implemented the subclasses for the environment `InvertedPendulum` and `BipedalWalker`. In the `models` folder, we have our actor and critic networks definitions. In the `utils` folder, we have all classes used by our algorithm to make it work properly like visualization class, data structure and noise definition. The last thing I need to precise is that a lot of parameters in my program is written in `params.json` and read at runtime. By this way, I can search for the good set of parameters without entering into the code. I will explain in section 3.3.3 this file precisely after my implementation description.

3.2.2 Replay buffer

To implement that task, I started by writing the replay buffer. I created a class `Memory` which holds a queue as a member in order to store tuple of (s_t, a, r, s_{t+1}) . I defined the first method as follow:

```

1 def remember(self, state, action, reward, next_state, done,
    state_range=None, action_range=None)

```

The `done` value is a boolean telling if the state is terminal or not. The state and the action range is a value to normalize the respective vector between 0 and 1. I think by this way neural networks will have better performance because input is less sparsed. If not `None`, these values must be equal to the range between low and high value (2 for action and 10 for state in our case).

The second needed method to define is the one to get samples from the queue randomly:

```

1 def samples(self, batch_size)

```

We need to get random sample, not last one or older one, but random, in order to break their correlations which would lead to decrease the performance of the model.

3.2.3 Neural networks: Actor and Critic

Keras vs Tensorflow In the beginning, to design my networks, I used Keras but this library is high-level API over Theano, Tensorflow and CNTK. It means that when we use it, we lose some control over the low-level API in order to be more readable and easy to implement. Since I will need to compute gradients and applying it to another networks, I understand that it will be more easy to do that in Tensorflow and it will be a good occasion to start to learn it.

The Actor The actor model is composed by fully-connected layers followed by Rectified Linear Unit activation function and then by batch normalization, because it gives better training speed and efficiency. The ReLU function is defined as follow: $f(x) = \max(0, x)$. The input is a shape of 44 float values for the state and the output is a shape of 17 float values activated by hyperbolic tangent because the range of the action values is equal to definition range of the hyperbolic tangent, $[-1, 1]$.

The Critic The critic model is composed by two inputs, one for the state and one for the action. The state input is followed by two dense layers activated by ReLU and batch normalization. The action input is concatenated just before the last layer of the state network. That layer is also followed by ReLU activation and batch normalization. These two layers is then added and followed by the output layer, a single-node one representing the Q-value of the state-action pair.

Target networks In our training process, when we have to do inferences from next actions or next states, we have to use actor target network and critic target network. These identical network has been recently shown to increase stability during the training and decrease variance of outputs.

3.2.4 Training

The Actor To train the actor network, we must define operations capable of applying the sampled policy gradients computed by critic network. The mathematical term is:

$$\nabla_{\theta^\mu} J \approx \frac{1}{N} \sum_i \nabla_{\alpha} Q(s, a | \theta^Q) | s = s_i, a = \mu(s_i) \nabla_{\theta^\mu \mu(s | \theta^\mu) | s_i} \quad (4)$$

For the implementation, I have three steps:

1. Compute the gradients:

```
1 self.unnormalized_actor_gradients = tf.gradients(
2     self.output, self.network_params, -self.action_gradients)
```

2. Normalize with size of batches:

```
1 self.actor_gradients = list(
2     map(
3         lambda x: tf.div(x, self.batch_size),
4         self.unnormalized_actor_gradients))
```

3. Applying gradients:

```
1 self.opt = tf.train.AdamOptimizer(
2     self.lr).apply_gradients(
3         zip(self.actor_gradients, self.network_params))
```

The Critic I defined training operations for the critic with a mean squared error loss function and the ADAM optimizer, with learning rate defined in parameters and minimizing the loss. Since the learning is on batch and the environment constantly evolving, I need to divide the loss by the size of the batch before back-propagation. The formula is defined as follow:

$$L = \frac{1}{N} \sum_i (y_i - Q(s_i, a_i | \theta^\mu))^2 \quad (5)$$

with N the size of the batch. The difficulty in my implementation comes a lot from that formula because I thought the function in Tensorflow who compute the mean squared error computed exactly this formula but I noticed that it sums without divided by the batch size. The loss was still decreasing so it misguided me and when I added the division, the loss was increasing but the reward as well. It is normal to see the loss increasing since the environment is moving as we go along with the training.

Process Here comes the salt and pepper of Deep Deterministic Policy Gradients. I need here to train the critic network first, computing the gradients and apply it to the actor network. Here the complete code which is basically the implementation of the figure 3:

```

1 # Get samples of memory
2 states, actions, rewards, next_states, dones = \
3     self.memory.samples(self.params.batch_size)
4
5 with tf.variable_scope("train_critic"):
6     # Predicted actions
7     next_actions = self.tf_session.run(
8         self.target_actor_model.output,
9         feed_dict={
10             self.target_actor_model.input_ph: next_states
11         })
12
13     if self.params.action_range:
14         next_actions = (next_actions +
15                         self.params.action_range/2
16                     ) / self.params.action_range
17
18     # Compute the Q+1 value with next s+1 and a+1
19     Q_next = self.tf_session.run(
20         self.target_critic_model.Q,
21         feed_dict={
22             self.target_critic_model.input_state_ph: next_states,
23             self.target_critic_model.input_action_ph:
24                 next_actions
25         })
26
27     # gamma is the discounted factor
28     Q_next = self.params.gamma * Q_next * (1 - dones)
29     Q_next = np.add(Q_next, rewards)
30
31     # Train the critic network and get gradients

```

```

31 feed_critic = {
32     self.critic_model.input_state_ph: states,
33     self.critic_model.input_action_ph: actions,
34     self.critic_model.true_target_ph: Q_next
35 }
36 self.critic_loss, _, critic_action_gradient = \
37     self.tf_session.run(
38         [self.critic_model.loss, self.critic_model.opt,
39          self.critic_model.action_gradients],
40         feed_dict=feed_critic)
41
42 with tf.variable_scope("train_actor"):
43     # Train the actor network with the critic gradients
44     feed_actor = {
45         self.actor_model.input_ph: states,
46         self.actor_model.action_gradients: \
47             critic_action_gradient[0]
48     }
49     self.actor_loss, _ = self.tf_session.run(
50         [self.actor_model.loss,
51          self.actor_model.opt],
52         feed_dict=feed_actor)
53
54 with tf.variable_scope("soft_update"):
55     # Update target network
56     self._update_target_network()

```

Here is the step by step explanation:

- We get temporally not-correlated batch from memory.
- We compute next actions with next states.
- We compute the expected reward Q_{next} with next states and next actions.
- We ponderate (or ignoring if the state is final) by the gamma parameters, i.e the discounted factor.
- We use it as a label to train the critic network and get gradients.
- We can then apply these gradients the actor to train it.
- Finally, we update target networks with soft update function.

```

1 self.update_critic_target =
2     [self.ct_params[i].assign(
3         tf.multiply(self.c_params[i],
4                     self.params.tau) +
5         tf.multiply(self.ct_params[i],
6                     1. - self.params.tau))
7     for i in range(len(self.ct_params))]
8
9 self.update_actor_target =
10    [self.at_params[i].assign(
11        tf.multiply(self.a_params[i],
12                    self.params.tau) +
13        tf.multiply(self.at_params[i],

```

```

14         1. - self.params.tau))
15         for i in range(len(self.at_params))]
16

```

3.2.5 Noise

In my first implementation, I used a ϵ -greedy algorithm to explore the environment. It was a decaying asymptotic-to-zero function used to generate less and less random actions over time. But then I discovered noise function to reduce variance and increase stability over taken actions, like Ornstein-Uhlenbeck noise. It computes a vector of float equal to the shape passed in parameters and we can add it to the action given by the actor. I used $\sigma = 0.2$ and $\theta = 0.15$.

3.2.6 The Agent

Here is the main loop of the program:

```

1 for j in range(self.params.epochs):
2
3     noise_scale = (self.params.initial_noise_scale *
4                   self.params.noise_decay ** j) * (
5                   self.act_high - self.act_low)
6
7     action = self.act(state)
8     if self.params.noisy and j < self.params.noise_threshold:
9         action += self.noise() * noise_scale
10        action = np.clip(action, self.act_low, self.act_high)
11
12    new_state, reward, done, info = self.env.step(action)
13
14    # Put the current environment in the memory
15    # State interval is [-5;5] and action range is [-1;1]
16    self.memory.remember(state, action, \
17                        reward * self.params.reward_multiply, \
18                        new_state, done, \
19                        state_range=self.params.state_range, \
20                        action_range=self.params.action_range)
21
22    # Train the network
23    self.train()
24
25    # Reset the environment if done
26    self.reset(done)
27
28    # Render the environment
29    self.render()
30
31    # Plot needed values
32    self.plotting(state=state, reward=reward, \
33                 c_loss=self.critic_loss, \
34                 a_loss=self.actor_loss)
35
36    # Change current state
37    state = new_state

```

3.3 Refinement

3.3.1 Noise

To find the best tuning for my training, I changed the way I added the noise into the action, the learning operation of my actor network and its layer definition. For the noise, I added it every steps. It then produces a bad training making the loss of the critic network going up at around 1000 steps, which corresponds to around 50 epochs. Removing that noise at this moment does not removing the loss decreasing, as shown in the Fig. 6.

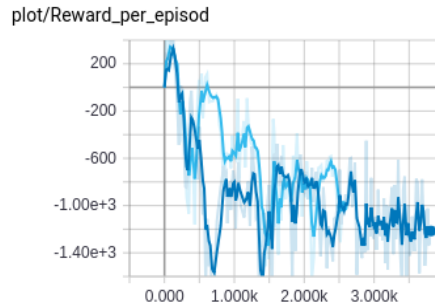


Figure 6: The light blue line is the run with noise removed at step 50, and the dark blue is with noise always added.

Since it does not affect the training (the reward is not affected either), I will keep adding noise until some convergence starts to occur. In the later work, I won't keep a good eye on the loss of the critic. The study of the noise addition makes me think that it is normal if the loss is increasing, since the environment is moving and the reward more and more difficult to compute. However, I added noise decay to decrease the noise over time. Since the agent learn over time, it should not need as much noise as the beginning to learn a good policy. For that, I am scaling the noise with the a scale computed by the following formula:

$$NS = (I * \alpha^t) * (high - low) \quad (6)$$

, I being the initial noise scale gave in parameters, α^t the noise decay factor ponderate over time and everything is scaled by the bound of actions.

3.3.2 Network definition

Thanks to the architecture of my code, I am able to change the model of the networks easily so I tuned these parameter a lot. A lot of paper written about DDPG [3] [4] used layers of 400 and 300 units with action added at the second layer in the critic network. I then decided to follow that benchmark since it gave good results with a lot of environment. In order to have a learning more efficient

¹Roboschool has a bug which lead to give vector of *inf* after the second reset when rendering, so when I train the networks, I don't render it.

and to see how a modification would effect, I changed the depth or the number of units. I found out that decreasing the number of units doesn't affect the quality of the learning but decreases the speed and building the networks deeper make the critic loss diverges very fast.

3.3.3 Hyper Parameters

I present in this section every arguments of my programs. It was really usefull to quickly test many hyper parameters in order to see how does it affects the training.

| Name | Description | Value for training |
|----------------------|---|--------------------|
| device | Choose CPU or GPU to perform TF operation | gpu |
| reset | Reset the environment at final states | true |
| render | Render the environment ² | false |
| plot | Choose the plotting library | tensorflow |
| train | Train network | true |
| noisy | Add noise to action outputs | true |
| load_weights | Load previously saved weights | false |
| batch_size | Number of samples to train from the momery | 128 |
| epochs | Number of epochs | 10000 |
| steps | Number of action during one epoch | 100 |
| noise_threshold | At which epochs the program stops adding noise to actions | 500 |
| warm_up_step | Epoch to wait before training | 128 |
| sigma | Used in the computation of noise, representing the variance | 0.2 |
| theta | Used in the computation of noise, representing the center | 0.15 |
| initial_noise_scale | the initial noise scale used in the computation of noise decay | 0.1 |
| noise_decay | The noise decay factor | 0.99 |
| actor_learning_rate | Learning rate for the actor | 0.0001 |
| critic_learning_rate | Learning rate for the critic | 0.001 |
| actor_batch_norm | Add batch normalization after dense layers of the actor network | true |
| critic_batch_norm | Add batch normalization after dense layers of the critic network | true |
| tau | Used in soft target update function | 0.001 |
| gamma | Discounted factor | 0.99 |
| actor_layers | Structure of actor network, depth and number of units in each layer | [400, 300] |
| critic_layers | Structure of critic network, depth and number of units in each layer | [400, 300] |
| reward_multiply | Multiply every reward with to reward more when good action is taken and less when a bad one is taken. | 1 |
| dropout | percent of dropout to use after dense layers | 0 |

Table 1: Hyper parameters description and definition for training purpose

4 Results

4.1 Model Evaluation and Validation

4.1.1 Implementation

Before validating the model, I wanted to make sure the way I implemented Deep Deterministic Policy Gradients was correct. I then try to perform it on a simpler environment such as Pendulum³ environment. The goal of that environment is to make the pendulum standing up in balance. My network succeed to make the pendulum stay as shown in the Fig. 7.

It shows the pendulum learn a good policy, the rewards is going up to converge at 4000 epochs. The rewards is defined in the range -inf to 0 so it is totally normal that the graph never shows a positive reward. In the render, the pendulum runs-up and when it is up, it keeps the position until the end of 100 epochs.

³<https://github.com/openai/gym/wiki/Pendulum-v0>



Figure 7: Results of pendulum environment

About validating the model, I designed it in tensorflow and plot in TensorBoard in order to check its structure.

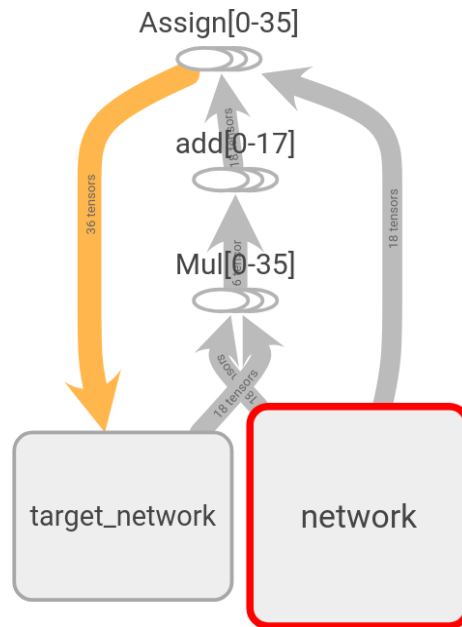


Figure 8: Soft target update operations graph

We can see in the fig. 8 the operations which handle the soft target update from networks to target networks.

4.1.2 Tweaking the model

Initially, I trained the model with batch normalization because it has shown in many cases that it can improve learning speed without decreasing the performance. However, the soft target update must be made differently for the batch normalization

layer than the dense one. So first of all, it is interesting to see how well it will performed without it. For dropout layer, I don't think forgetting some informations is a good trick to tackle that kind of problem because usually, this technique is used to prevent overfitting. Since DDPG is a deterministic policy, I don't think overfitting will be a crucial issue but it could help to not have the Q output in a local maxima.

4.1.3 Evaluation

4.2 Justification

5 Conclusion

5.1 Free-Form Visualization

5.2 Reflection

To tackle the problem, I first learned how Deep Deterministic Policy Gradients works by reading scientific paper on that subject. I then started my implementation starting by the replay buffer and then the DDPG algorithm itself. I added soft target update and noise addition after. Seeing that results was not good and resolving coding mistakes (which took me a lot of time as Tensorflow was new to me), I started to read more scientific paper and tried their results with their model architecture and their parameters. My agent started to learn how to stand but not how to walk, and it could be for two reasons: either in some ways I have a problem in my implementation of DDPG and the update of my gradients, either it must take time a lot of time (the time of the longest training I performed was 3 days). The paper from Lillicrap et al. shows that DDPG has the inconvenient to be efficient after a lot of training epochs.

The most interesting part of the project was to see how the changes in my implementation in terms of algorithm and parameters could change the behavior of the actor. It was also really interesting to learn techniques scientists often use to increase stability, performance or quality of results like noise addition or soft target update. Implementing the Deep Deterministic Policy Gradients was also really enriching because I learned to use Tensorflow and working directly with weights, biases and gradients and by that way increased my knowledge over how deep learning is working mathematically (which is rather difficult to understand when we just read the theory without actually using it). In contrary, the most challenging part was to actually validate my network.

5.3 Improvement

In terms of coding, a good improvement would be to be able to launch the training over a cloud, like AWS from Amazon or CloudML from Google. The training would be very faster and the validation of the model as well. About the algorithm I am

using, DDPG, Gu et al. shows that TRPO (Trust Region Policy Optimization) is more suitable for a 3d walking agent because it is more stable than DDPG during training. It would be interesting for me to actually validate that statement and learn about more algorithms as TRPO, Q-Prop or DQN.

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