Capstone Report

Arise and walk, by Deep Deterministic Policy Gradient algorithm

Guitard Alan

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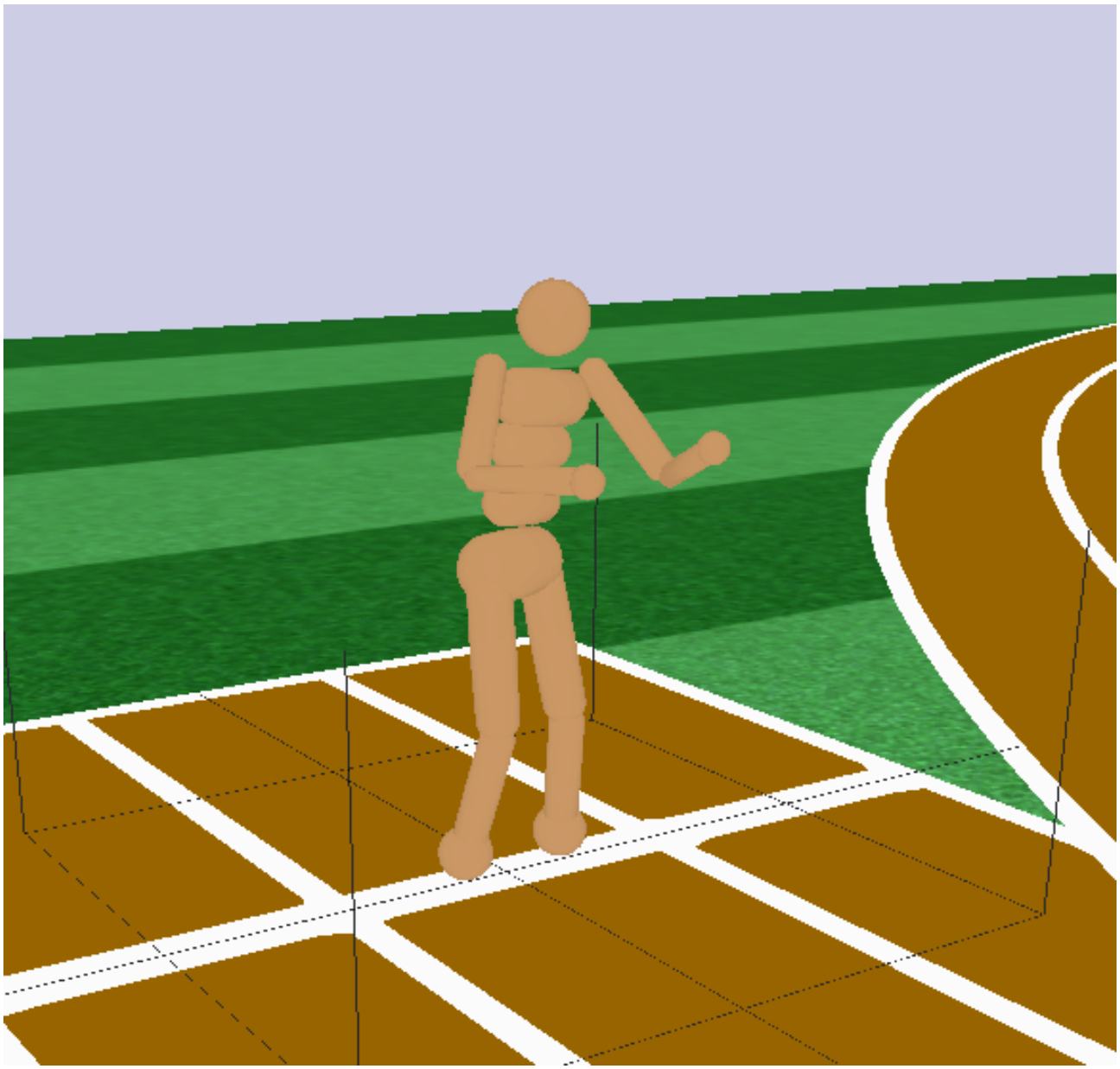


1 Definition of the problem

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 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 Roboschool[1] 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.

Actor Critic algorithm In Reinforcement Learning, many algorithms uses 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:

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

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:

$$\mu(s, a) = P(a_t = a | s_t = s) \tag{2}$$

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 chose 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 make an action that may lead to a bad state, the parent gives him a bad reward in order to change his behaviour (policy).

[1] https://github.com/openai/roboschool

1.3 Metrics

I will need two set of metrics because I have two kind 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 beggining 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 times. With these informations, I will be able to tell if my models is training well or if I have to adjust my parameters. When the body will start to have less fall, 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 axe 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

```
for n,j in enumerate(self.ordered_joints):
    j.set_motor_torque( self.power*j.power_coef \
                        *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 wether 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_collsion_cost**: The amount of feet collision taken during the last action

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.

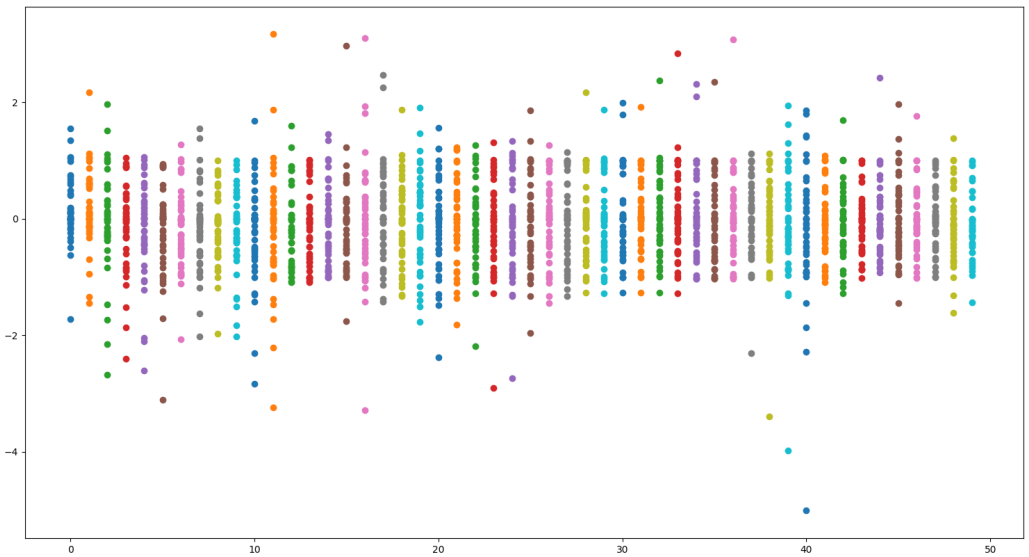


Figure 1: Roboschool environment

We can see that the majority of represented values is between -1 and 1. We guess easily that this easy the representation of joint values and their respective space, which correlates with the action state definition space. The other values represents 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. 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.

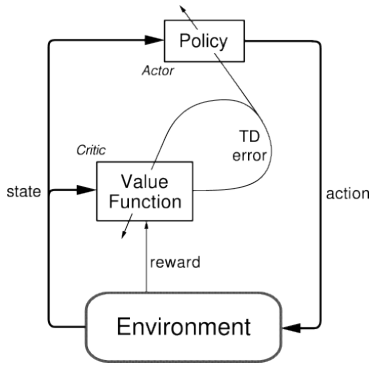


Figure 2: Actor-critic algorithm

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 beggining, 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":

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

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

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:

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

  end for
end for

Figure 3: Algorithm from Lillicrap et al. paper

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 OrnsteinâĂŞUhlenbeck 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 ?

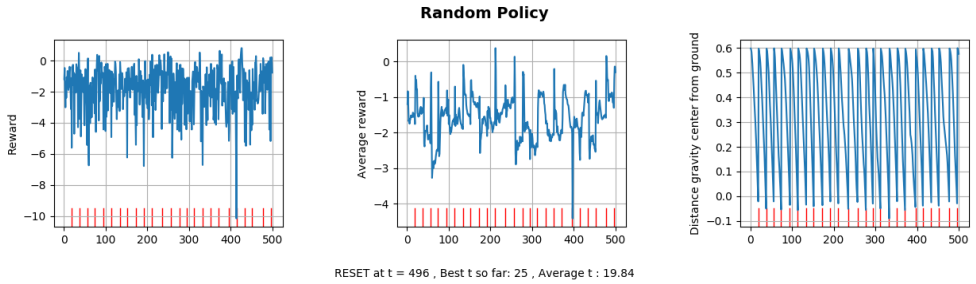
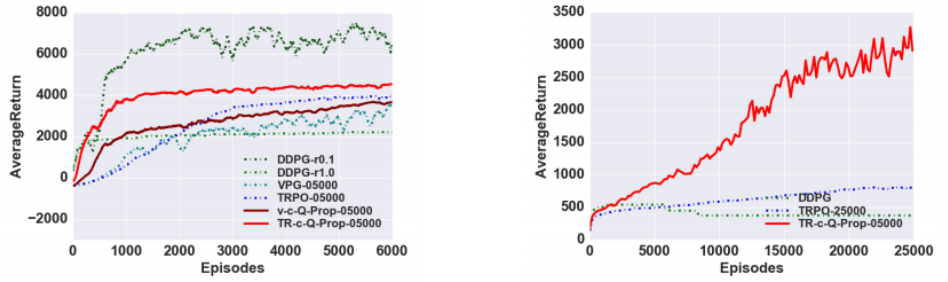


Figure 4: Random Policy

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



(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.

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.

3.2 Implementation

3.2.1 Project Structure

I present you on the fig. 6 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
        ├── matplotboard.py
        ├── memory.py
        ├── noise.py
        └── tensorboard.py
```

Figure 6: Project structure

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 3.3.1 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:

```
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:

```
def samples(self, batch_size)
```

We need to get random samples, not last one or older one, but random, in order to break their temporal 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 defintion 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:

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

For the implemenation, I have three steps:

1. Compute the gradients:

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

2. Normalize with size of batches:

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

3. Applying gradients:

```
self.opt = tf.train.AdamOptimizer(
    self.lr).apply_gradients(
        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:

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

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:

```
# Get samples of memory
states, actions, rewards, next_states, dones = \
    self.memory.samples(self.params.batch_size)

with tf.variable_scope("train_critic"):
    # Predicted actions
    next_actions = self.tf_session.run(
        self.target_actor_model.output,
        feed_dict={
            self.target_actor_model.input_ph: next_states
        })

    if self.params.action_range:
        next_actions = (next_actions +
                        self.params.action_range/2
        ) / self.params.action_range

    # Compute the Q+1 value with next s+1 and a+1
    Q_next = self.tf_session.run(
          self.target_critic_model.Q,
          feed_dict={
              self.target_critic_model.input_state_ph: next_states,
              self.target_critic_model.input_action_ph: next_actions
          })

    # gamma is the discounted factor
    Q_next = self.params.gamma * Q_next * (1 - dones)
    Q_next = np.add(Q_next, rewards)

    # Train the critic network and get gradients
    feed_critic = {
        self.critic_model.input_state_ph: states,
        self.critic_model.input_action_ph: actions,
        self.critic_model.true_target_ph: Q_next
    }
    self.critic_loss, _, critic_action_gradient = \
        self.tf_session.run(
            [self.critic_model.loss, self.critic_model.opt,
             self.critic_model.action_gradients],
        feed_dict=feed_critic)

    with tf.variable_scope("train_actor"):
        # Train the actor network with the critic gradients
        feed_actor = {
            self.actor_model.input_ph: states,
            self.actor_model.action_gradients: \
                 critic_action_gradient[0]
        }
```

```
        self.actor_loss, _ = self.tf_session.run(
            [self.actor_model.loss,
             self.actor_model.opt],
             feed_dict=feed_actor)

    with tf.variable_scope("soft_update"):
        # Update target network
        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.

```
self.update_critic_target =
   [self.ct_params[i].assign(
                tf.multiply(self.c_params[i],
                            self.params.tau) +
                tf.multiply(self.ct_params[i],
                            1. - self.params.tau))
        for i in range(len(self.ct_params))]

self.update_actor_target =
   [self.at_params[i].assign(
                tf.multiply(self.a_params[i],
                            self.params.tau) +
                tf.multiply(self.at_params[i],
                            1. - self.params.tau))
        for i in range(len(self.at_params))]

```

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:

```
for j in range(self.params.epochs):

    noise_scale = (self.params.initial_noise_scale *
                self.params.noise_decay ** j) * (
                    self.act_high - self.act_low)

    action = self.act(state)
    if self.params.noisy and j < self.params.noise_threshold:
        action += self.noise() * noise_scale
        action = np.clip(action, self.act_low, self.act_high)

    new_state, reward, done, info = self.env.step(action)

    # Put the current environment in the memory
```

```
    # State interval is [-5;5] and action range is [-1;1]
    self.memory.remember(state, action, \
                         reward * self.params.reward_multiply, \
                         new_state, done, \
                         state_range=self.params.state_range, \
                         action_range=self.params.action_range)

    # Train the network
    self.train()

    # Reset the environment if done
    self.reset(done)

    # Render the environment
    self.render()

    # Plot needed values
    self.plotting(state=state, reward=reward, \
                  c_loss=self.critic_loss, \
                  a_loss=self.actor_loss)

    # Change current state
    state = new_state
```

3.2.7 Implementation complication

When I start to train my humanoid agent, it nerver learns anything. I then decided to test on a simpler environment to see if this came from the difficulty of the environment or from my implementation. In other words, I wanted to make sure the way I implemented Deep Deterministic Policy Gradients was correct. I then try to perform it the Pendulum[2] environment. The goal of that environment is to make the pendulum standing up in balance. At first, it didn't succeed so I had to review my code to notice the way computed the loss of my critic. The problem was that the $tf.mean\_squared\_error$ function (or equivalent) sum the squared difference but without divided by batch size like in the paper. I took a lot of time to notice and when I did, my network succeed to make the pendulum stay as shown in the Fig. 7.

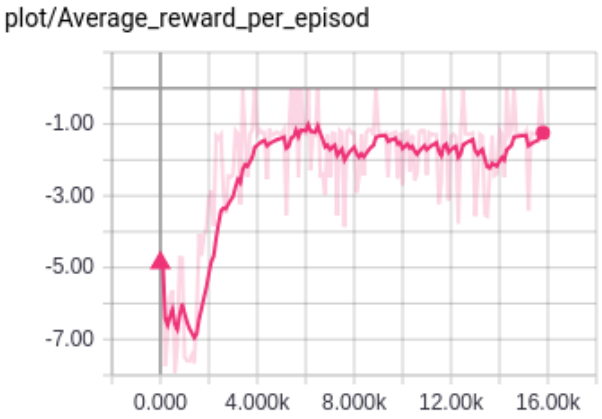


Figure 7: Results of pendulum environment

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.

[1] Roboschool 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.

[2] `https://github.com/openai/gym/wiki/Pendulum-v0`

3.3 Refinement

3.3.1 Hyper Parameters

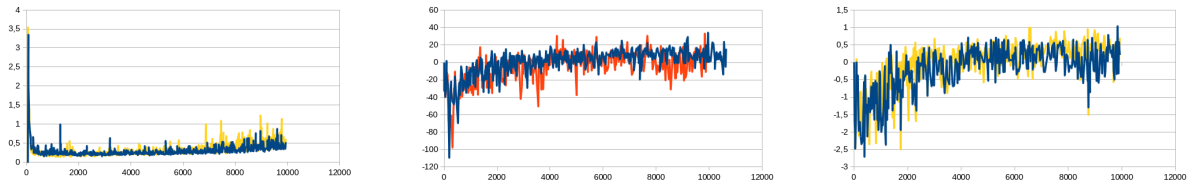
I present in this section every arguments of my programs. It was really usefull to quickly test many hyper parameters in order to see how does it affects the training.

Name	Description	Value for training
device	Choose CPU or GPU to perform TF operation	`gpu`
plot	Choose the plotting library	`tensorflow`
render	Render the environment[3]	false
reset	Reset the environment at final states	`true`
train	Train network	`true`
load_weights	Load previously saved weights	`false`
epochs	Number of epochs	10000
steps	Number of action during one epoch	100
batch_size	Number of samples to train from the momery	64
warm_up_step	Epoch to wait before training	64
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]`
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`
actor_learning_rate	Learning rate for the actor	0.0001
critic_learning_rate	Learning rate for the critic	0.001
gamma	Discounted factor	0.99
dropout	percent of dropout to use after dense layers	0
epsilon_greedy	use epsilon-greedy exploration process	false
noise_threshold	At which epochs the program stops adding noise to actions	500
noise_decay	The noise decay factor	0.99
reward_multiply	Multiply every reward with to reward more when good action is taken and less when a bad one is taken.	1
sigma	Used in the computation of noise, representing the variance	0.2
tau	Used in soft target update function	0.001
theta	Used in the computation of noise, representing the center	0.15

Table 1: Hyper parameters description and definition for training purpose

3.3.2 Baselines

First of all, we can show the results in fig. 8 of my implemenation with parameters used in the original paper, summarized in 3.3.1.



(a) Critic loss (b) Reward per episod (c) Average reward per episod

Figure 8: Results with parameters from original paper

The two lines in the figure is describing is two different run, to validate the stability. That first attempt to solve the problem is not conclusive but the agent still learns something until around 3000 epochs but nothing after. At that epochs, the loss doesn't decrease anymore either. It seems that the agent learn to stay stand but doesn't learn to go forward. To do that, I need to play with hyper-parameters or by adding some new logic. The noise may be decreased over time to get better rewards, the learning rate can also be decayed to prevent the decreased of the critic loss or the reward can be scaled by a factor, for instance.

Another explanation is that the agent needs more epochs to learn a good policy. The goal of tweaking parameters will then be to improve the learning speed, in order to not wait one million epoch to get a good policy.

3.3.3 Batch size

First, I tested the effect of differents lengths of batch size to see if it can improve the learning or decrease the time when convergence happens. The fig. 9 shows the reward given by each episod and that the batch size length does not affect the training. I will then stay on 128 like in the paper of Lillicrap et al..

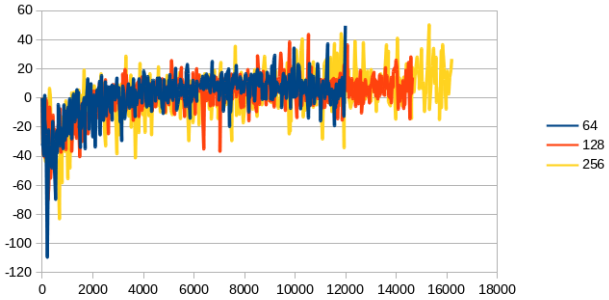


Figure 9: Reward per episode - Study of batch size length effect on training

3.3.4 Noise decay

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 beggining to learn a good policy. For that, I am scaling the noise with the a scale computed by the follwing formula:

$$N = e^{-j*\alpha} \tag{6}$$

, j being the current number of epoch, α the noise decay factor. To choose the best α, I plotted the N for each epochs during 10000 epochs and choose the α who plot the better line. The chosen one is 0.0005 and plots the line in fig. 10.

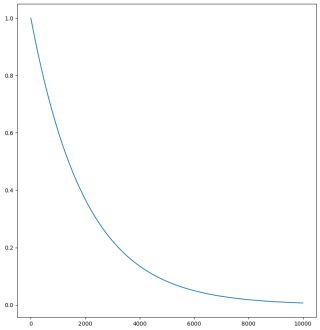


Figure 10: Value of noise decay factor over time when α is 0.0005

3.3.5 Learning rate decay

3.3.6 Reward scale

4 Results

4.1 Model Evaluation and Validation

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 dificult to understand when we just read the theory without actually using it). In contrary, the most chanllenging 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.

References

[1] Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym, 2016.

[2] Shixiang Gu, Timothy Lillicrap, Zoubin Ghahramani, Richard E. Turner, and Sergey Levine. Q-prop: Sample-efficient policy gradient with an off-policy critic. In *Proceedings International Conference on Learning Representations 2017*. OpenReviews.net, April 2017. URL `https://arxiv.org/pdf/1611.02247.pdf`.

[3] Timothy P. Lillicrap, Jonathan J. Hunt, Alexander Pritzel, Nicolas Heess, Tom Erez, Yuval Tassa, David Silver, and Daan Wierstra. Continuous control with deep reinforcement learning. *CoRR*, abs/1509.02971, 2015. URL `https://arxiv.org/pdf/1509.02971.pdf`.