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# Deep Deterministic Policy Gradient for Regularity Rally in TORCS Simulator

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**Deep Deterministic Policy Gradient for Regularity Rally in TORCS Simulator**
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*Dedicato a*
*Donald Knuth*

# Abstract

This thesis is a report for the Excellence Course Project developed during the degree's last year.

The aim of this thesis is to study an application of Deep Reinforcement Learning by training a sensor-based autonomous car to drive in a Regularity Rally, which is, a type of motor sport race with the purpose of driving in the minimum time at a specified average speed. In order to achieve the goal, Deep Deterministic Policy Gradient (DDPG) algorithm has been applied.

This report will briefly introduce Reinforcement Learning theory, show how the project has been implemented and its results.

A sister project focusing on Speed Racing has been developed by Dylan Savoia.

# Contents

# Chapter 1

# Introduction

Reinforcement Learning is a branch of Artificial Intelligence that studies algorithms to teach an agent how to act in an environment. Some applications of this subject are robotics, advertising, business and chemistry.

In most cases reinforcement learning algorithms are initially applied on games which, generally, represent complex environments that can easily become suitable for Reinforcement Learning problems. Important examples of games impact on Reinforcement Learning are chess and GO: beating humans on these two strategy games, in facts, have been the first challenges of Reinforcement Learning.

For this project the environment chosen is TORCS, an open source car simulator that can be easily controlled through Python APIs.

# Chapter 2

# TORCS

TORCS (The Open Racing Car Simulator) is an open-source 3D car racing simulator released for the first time in 1997 and developed by Bernhard Wymann (project leader), Christos Dimitrakakis (simulation, sound, AI) and Andrew Sumner (graphics, tracks).

**Figure 2.1.** Classic View of a TORCS car in a race

## 2.1 Simulated Car Racing Championship

Simulated Car Racing Championship is an international competition with the goal to design a pre-programmed driver that can compete on unknown tracks first alone and then against other autonomous drivers.

The drivers perceive the environment through a number of sensors that describe relevant features of the car surroundings (e.g., the track limits, the position of near-by obstacles), of the car state (the fuel level, the engine RPMs, the current gear, etc.), and the current game state (lap time, number of lap, etc.).

The competition software extends the original TORCS architecture by adding a client-server module, real time events simulation and an abstraction layer between the driver code and the race server. [1]

**Table 2.1.** Description of TORCS available sensors

| **Name** | **Range** | **Description** |
|---|---|---|
| angle | $[-\pi, +\pi]$ (rad) | Angle between the car direction and the direction of the track axis |
| curLapTime | $[0, +\infty)$ (s) | Time elapsed during current lap |
| damage | $[0, +\infty)$ (point) | Current damage of the car |
| distFromStart | $[0, +\infty)$ (m) | Distance of the car from the start line along the track line |
| distRaced | $[0, +\infty)$ (m) | Distance covered by the car from the beginning of the race |
| focus | $[0, 200]$ (m) | Vector of 5 range finder sensors: each sensor returns the distance between the track edge and the car within a range of 200 meters |
| fuel | $[0, +\infty)$ (l) | Current fuel level |
| gear | $-1, 0, 1, \ldots 6$ | Current gear: -1 is reverse, 0 is neutral and the gear from 1 to 6 |
| lastLapTime | $[0, +\infty)$ (s) | Time to complete the last lap |
| opponents | $[0, 200]$ (m) | Vector of 36 opponent sensors. |
| racePos | $1, 2, \ldots N$ | Position in the race with respect to other cars |
| rpm | $[0, +\infty)$ (rpm) | Number of rotation per minute of the car engine |
| speedX | $(-\infty, +\infty)$ (km/h) | Speed of the car along the longitudinal axis of the car. |
| speedY | $(-\infty, +\infty)$ (km/h) | Speed of the car along the transverse axis of the car |
| speedZ | $(-\infty, +\infty)$ (km/h) | Speed of the car along the Z axis of the car |

**Table 2.1.** Description of TORCS available sensors (continued)

| **Name** | **Range** | **Description** |
|---|---|---|
| track | $[0, 200]$ (m) | Vector of 19 range finder sensors: each sensors returns the distance between the track edge and the car within a range of 200 meters |
| trackPos | $(-\infty, +\infty)$ | Distance between the car and the track axis |
| wheelSpinVel | $[0, +\infty)$ (rad/s) | Vector of 4 sensors representing the rotation speed of wheels |
| z | $(-\infty, +\infty)$ (m) | Distance of the car mass center from the surface of the track along the Z axis |

**Table 2.2.** Description of TORCS available effectors

| **Name** | **Range** | **Description** |
|---|---|---|
| accel | $[0, 1]$ | Virtual gas pedal |
| brake | $[0, 1]$ | Virtual brake pedal |
| clutch | $[0, 1]$ | Virtual clutch pedal |
| gear | $1, 2, \ldots 6$ | Gear Value |
| steering | $[-1, 1]$ | Steering value |
| focus | $[-90, 90]$ | Focus direction |
| meta | $0, 1$ | Ask competition to restart the race |

# Chapter 3

# Reinforcement Learning

Machine Learning is an application of Artificial Intelligence that studies algorithms and methods that can automatically learn and improve from experience without being explicitly programmed.

Typically Machine Learning methods are divided in three main categories: supervised learning, unsupervised learning and reinforcement learning.

The former's goal is to learn a mapping from inputs $x$ to outputs $y$, given a labeled set of input-output pairs called training set; the second focuses on finding "interesting patterns" in data; [2] the latter, is the problem faced by an agent that must learn behavior through trial-and-error interactions with a dynamic environment.

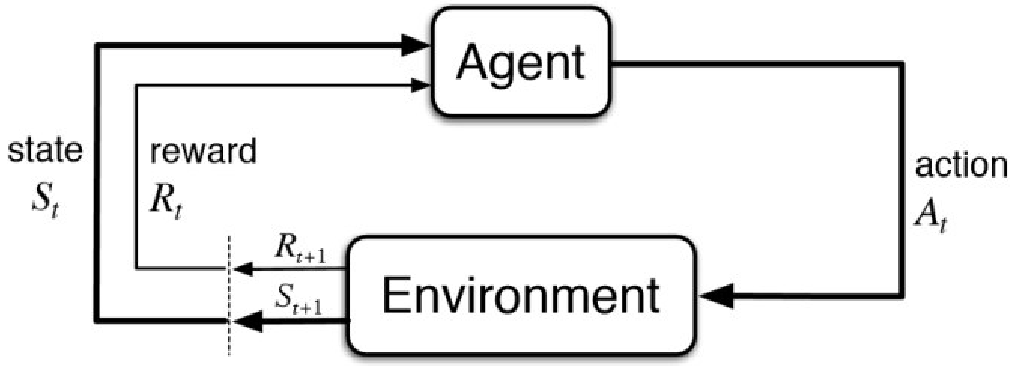
In the standard Reinforcement-Learning (RL) model, also known as Markov Decision Process, an agent is connected to an environment with which it can interact. Every time an action is performed, the agent receives its current state in the environment with the gained reward, that can be positive or negative.

Formally, in Markov Decision Process a model is defined by:

- a set of environment states $S$
- a set of agent actions $A$
- a set of scalar rewards $R$

Reinforcement Learning focuses to learn a behavior that maximizes the expected cumulative reward. [3]

**Figure 3.1.** The agent-environment interaction in a Markov decision process [4]




The cumulative reward at each time step t can be written as:

$$G_t = R_{t+1} + R_{t+2} + \dots \ = \sum_{k=0}^{T} R_{t+k+1} \tag{3.1}$$

The equation just defined is also called finite-horizon model, but it is not always appropriate: in many cases the precise length of the agent's life is not known in advance, so it is preferable to use the infinite-horizon discounted model, which can be defined in the following way:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1} \tag{3.2}$$

The infinite-horizon discounted model takes the long-run reward of the agent into account, but rewards that are received in the future are geometrically discounted according to discount factor $\gamma$. The expected return given a certain state-action tuple is called value function:

$$V(s,a) = E[G_t \mid S_t = s, A_t = a] \tag{3.3}$$

## 3.1 Bellman Equation

The value learned at time $t$ strongly depends on the function learned at time $t-1$, this relation is described by the Bellman Equation:

$$\begin{align}
V(s,a) &= E[G_t \mid S_t = s, A_t = a] \tag{3.4}\\
&= E[R_{t+1} + \gamma R_{t+2} + \gamma^2 R_{t+3} + \cdots \mid S_t = s, A_t = a] \tag{3.5}\\
&= E[R_{t+1} + \gamma(R_{t+2} + \gamma R_{t+3} + \dots) \mid S_t = s, A_t = a] \tag{3.6}\\
&= E[R_{t+1} + \gamma G_{t+1} \mid S_t = s, A_t = a] \tag{3.7}\\
&= E[R_{t+1} + \gamma V(S_{t+1}) \mid S_t = s, A_t = a] \tag{3.8}
\end{align}$$

## 3.2 Monte Carlo and TD Learning

A Reinforcement learning model could be learned in two ways:

- Monte Carlo: rewards are given at the end of the game and the agent learns on the cumulative reward.

$$V(S_t) = V(S_t) + \alpha[G_t - V(S_t)] \tag{3.9}$$

- Temporal Difference (TD) Learning: every step the agent gets the reward and model is updated.

$$V(S_t) = V(S_t) + \alpha[R_{t+1} + \gamma V(S_t + 1) - V(S_t)] \tag{3.10}$$

With long episodes TD Learning is preferable because using only the cumulative reward could penalize good actions chosen in bad episodes and reward bad actions taken in good episodes.

## 3.3 Approaches to solve a RL problem

There are three main approaches to solve a Reinforcement Learning problem: value based, policy based and model based.

From these three methods take place other ones, like actor critic, that are simply the mixture of the basic ones.

### 3.3.1 Value based

Value based class of algorithms aims to build a value function of states (or of state-action pairs) that estimate "how good" it is for the agent to be in a given state (or how good it is to perform a given action in a given state). The notion of "how good" here is defined in terms of future rewards that can be expected. One of the simplest and most popular value based algorithms is Q-learning (Watkins, 1989).

Basically Q-learning keeps a lookup table of values $Q(s, a)$ with one entry for every state-action pair that estimates the expected cumulative reward. The value function Q can be defined in the following way:

$$Q(s, a) = E(\sum_{k=0}^{\infty} \gamma^k r_t + k \mid s_t = s, a_t = a) \tag{3.11}$$

Once the value function is known (or estimated) it is possible to apply *argmax* to chose the action that would give the highest reward in a specific state.

### 3.3.2 Policy based

In policy based Reinforcement Learning the goal is to optimize the policy function $\pi$ without using a value function. The policy takes in input the state and returns the action the agent should take:

$$a = \pi(s) \tag{3.12}$$

It is possible to define a deterministic policy, which returns the same action at a given state or a stochastic one that outputs a distribution probability over actions at a given state.

### 3.3.3 Model based

Model based algorithms goal is to build a model of the environment in order to take the right action at a given state. This approach is less general than the other two, in facts, for every environment it is necessary to build a specific model.

### 3.3.4 Actor-Critic

If the value function is learned in addition to the policy, we would get Actor-Critic algorithm:

- Critic: updates value function parameters w and depending on the algorithm it could be action-value $Q(a \mid s, w)$ or state-value $V(s, w)$.
- Actor: updates policy parameters $\theta$, in the direction suggested by the critic, $\pi(a \mid s, \theta)$.

This class of algorithms is very powerful and it is the one we will focus on, since it is implemented in Deep Deterministic Policy Gradient.

# Chapter 4

# Reinforcement Learning Algorithms Improvements

This Chapter focuses on some improvements that could be adopted while implementing a Reinforcement Learning algorithm in order to gain better performance and handle some problems that could be easily encountered.

## 4.1 Deep Learning

The adoption of Neural Networks (NN) in Reinforcement Learning gave birth to the so called Deep Reinforcement Learning. Using NNs to model policies and value functions is easier to handle continuous domain states and actions. An important example of this approach is Deep Q-Learning.

### 4.1.1 Deep Q-Learning

Deep Q-Learning is an improvement of Q-Learning that uses Neural Networks instead of tables to estimate the value function. Q-Learning is very powerful but it can only be used with discrete actions and states while the deep version allows also continuous inputs.

## 4.2 Target Function

When using TD value based models, and in particular Deep Q-Learning, the value learned at time $t$ has a strong dependency on the function learned at time $t-1$ as pointed out by the Bellman Equation.

For Q-Learning, the Bellman Equation could be expressed in the following way:

$$NewQ(s,a) = Q(s,a) + \alpha[R(s,a) + \gamma maxQ(s',a') - Q(s,a)] \tag{4.1}$$

The new Q value for a state-action tuple is the current Q value plus the learning rate $\alpha$ times the reward for taking that action at that state added to the difference between the discounted maximum expected future reward given the next state-action tuple and the current Q value.

What value based models try to do is minimize the error between real value function and the estimated one. The error is calculated by taking the difference between predicted Q target (maximum possible value from the next state) and the current Q value. When using Neural Networks, weights could be updated by multiplying the error and gradient of the Q value:

$$\Delta w = \alpha[(R + \gamma max_a Q(s', a, w)) - Q(s, a, w)]\nabla_w Q(s, a, w) \tag{4.2}$$

Since the Q target is not known, it needs to be estimated together with the Q value, but using the same same weights for estimating both makes a big correlation between the target and the error that leads to slow learning.

Instead of using the same weights, Google DeepMind introduced the notion of fixed Q-targets, which is, the use of a separate network with a fixed parameter for estimating the target that is updated every $\tau$ step by copying the same parameters of the Q Network.

## 4.3 Exploration-Exploitation trade off

Since RL tries to maximize the cumulative reward, it is frequent that the model reaches local maximum points, which is, in the most of the times, due to a greedy behavior of the model that try to exploits current knowledge that is initially weak.

To avoid the model to exploit the "closest" source of rewards, in the training phase, it is necessary to add some noise to the actions in order to allow the agent to explore the entire environment and reach a better maximum point.

This problem is well-known as the "dilemma of exploration and exploitation". [4] A classic approach to partially solve this problem is the $\epsilon$-greedy policy: every step with probability $\epsilon$ a greedy action is taken and with probability $1 - \epsilon$ a non-greedy random action is taken.

## 4.4 Replay Buffer

Replay Buffer or Experience Replay is a technique that consists in keeping buffer that stores the tuples (s, a, r, s') of the various steps.

At each step, the training routine picks a batch of examples from the buffer and uses them to update the model. This is quite useful because avoids forgetting previous experiences and reduces correlation between experiences.

# Chapter 5

# Deep Deterministic Policy Gradient

**Algorithm 1** Deep Deterministic Policy Gradient

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

$$\nabla_{\theta^\mu} J \approx \frac{1}{n} \sum_i \nabla_a Q(s, a \mid \theta^Q) \mid_{s=s_i, a=\mu(s_i)} \nabla_{\theta^\mu} \mu(s \mid \theta^\mu) \mid_{s_i}$$

    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**

In 2016 Google Deepmind Researches created an algorithm based on the actor critic approach to apply Reinforcement Learning in environments with continuous action domain and continuous action spaces: Deep Deterministic Policy Gradient (DDPG).

Described in the paper “Continuous control with Deep Reinforcement Learning”, DDPG is the mixture of Deep Q-Learning and Deterministic Policy Gradient.[5]

# Chapter 6

# Implementation

What follows is an explanation of the Project Implementation with some pieces of code and instructions to allow the reader to replicate it.

## 6.1 Environment

As explained in Section 2.1, the environment is completely developed in the Simulated Car Racing Championship Software that is available at the following Git Hub repository with a readme file that explains how to compile and install it: `https://github.com/fmirus/torcs-1.3.7`. To interact with the simulator the developer Naoto Yoshida created a Python API that allows programmers to communicate with the environment with OpenAI-like methods. A detailed readme of the API is available at the following link: `https://github.com/ugo-nama-kun/gym_torcs`. Here is a small piece of code that shows how gym torcs can be used to drive a TORCS car.

```
from gym_torcs import TorcsEnv

#### Generate a Torcs environment
env = TorcsEnv(vision=False, throttle=True)

# reset environment
ob = env.reset()

# choose an action [steering, throttle, brake]
action = [0., 1., 0.]

# single step
ob, reward, done, _ = env.step(action)

# shut down torcs
env.end()
```

## 6.2 DDPG in Tensorflow

Deep Deterministic Policy Gradient implementation has been coded in Python Tensorflow using the Keras high-level API. The code has not been written from scratch, but starting from an old implementation based on the old version of Keras that is now deprecated. The original project owned by Ben Lau can be found at the following link: `http://yanpanlau.github.io/2016/10/11/Torcs-Keras.html`

### 6.2.1 Critic Network

Critic Network consists in a class that contains four methods. The constructor __init__ that initializes the parameters and instatiates the Critic Network and the Target Critic Network.

```python
class CriticNetwork(object):
    def __init__(self, sess, state_size, action_size, BATCH_SIZE, TAU, LEARNING_RATE):
        self.sess = sess
        self.BATCH_SIZE = BATCH_SIZE
        self.TAU = TAU
        self.LEARNING_RATE = LEARNING_RATE
        self.action_size = action_size
        K.set_session(sess)
        self.model, self.action, self.state = self.create_critic_network(state_size, action_size)
        self.target_model, self.target_action, self.target_state = self.create_critic_network(state_size, action_size)
        self.action_grads = tf.gradients(self.model.output, self.action)
        self.sess.run(tf.initialize_all_variables())
```

The gradients method evaluates estimated value gradient on actions to train the Actor Network.

```python
    def gradients(self, states, actions):
        return self.sess.run(self.action_grads, feed_dict={
            self.state: states,
            self.action: actions
        })[0]
```

target_train that updates target network as explained in Section 5

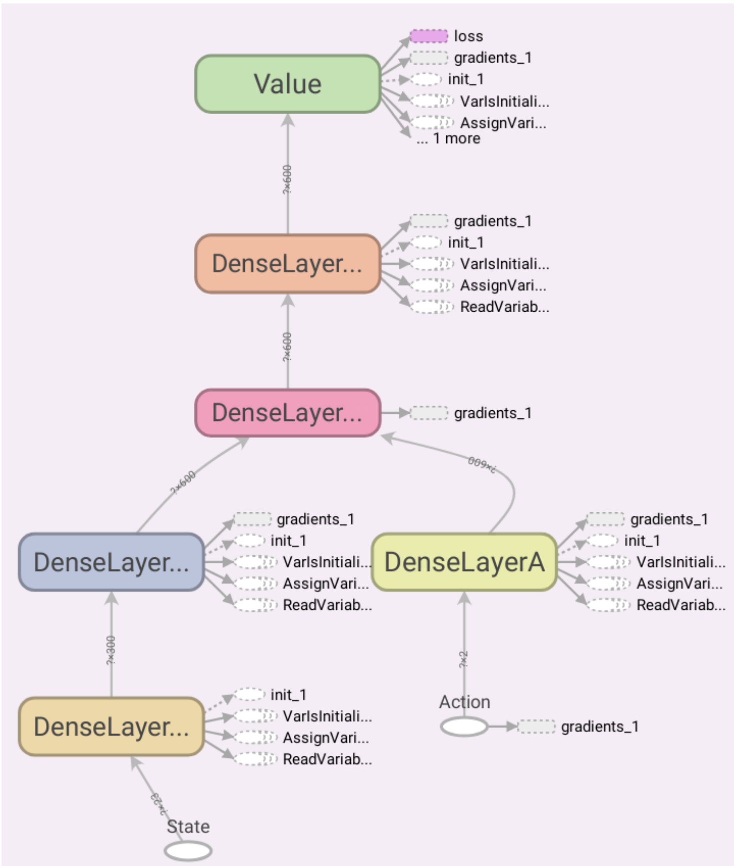
```python
    def target_train(self):
        critic_weights = self.model.get_weights()
        critic_target_weights = self.target_model.get_weights()
        for i in range(len(critic_weights)):
            critic_target_weights[i] = self.TAU * critic_weights[i] + (1 - self.TAU)* critic_target_weights[i]
        self.target_model.set_weights(critic_target_weights)
```

create_critic_network method builds the Critic Neural Network by concatenating the input layers (state and action) with two hidden layers made respectively of 300 and 600 neurons.

```python
    def create_critic_network(self, state_size,action_dim):
```

```
        print("Now we build the model")
        S = Input(shape=[state_size])
        A = Input(shape=[action_dim],name='action2')
        w1 = Dense(HIDDEN1_UNITS, activation='relu')(S)
        a1 = Dense(HIDDEN2_UNITS, activation='linear')(A)
        h1 = Dense(HIDDEN2_UNITS, activation='linear')(w1)
        h2 = add([h1,a1])
        h3 = Dense(HIDDEN2_UNITS, activation='relu')(h2)
        V = Dense(action_dim,activation='linear')(h3)
        model = Model(inputs=[S,A],outputs=V)
        adam = Adam(lr=self.LEARNING_RATE)
        model.compile(loss='mse', optimizer=adam)
        return model, A, S
```

**Figure 6.1.** Tensorboard graph of Critic Network



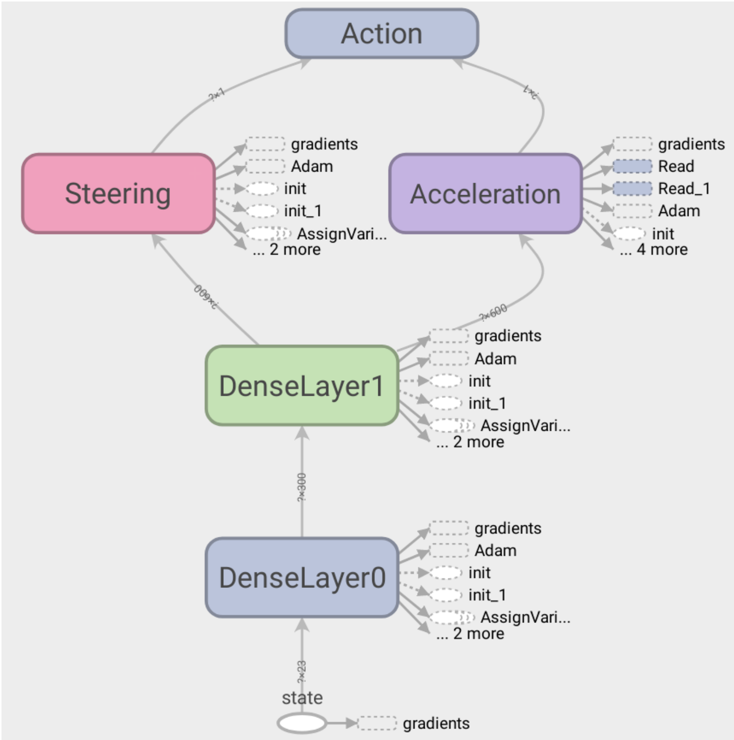

## 6.3 Actor Network

Actor Network realization is quite similar except for training method and the neural network initialization routine. In facts, the neural network input is just the agent state and the output is composed of the three commands the agent every step controls. The full implementation is provided in the next piece of code.

```python
class ActorNetwork(object):
    def __init__(self, sess, state_size, action_size, BATCH_SIZE, TAU, LEARNING_RATE):
        self.sess = sess
        self.BATCH_SIZE = BATCH_SIZE
        self.TAU = TAU
        self.LEARNING_RATE = LEARNING_RATE
        K.set_session(sess)
        self.model , self.weights, self.state = self.create_actor_network(state_size, action_size)
        self.target_model, self.target_weights, self.target_state = self.create_actor_network(state_size, action_size)
        self.action_gradient = tf.placeholder(tf.float32,[None, action_size])
        self.params_grad = tf.gradients(self.model.output, self.weights, -self.action_gradient)
        grads = zip(self.params_grad, self.weights)
        self.optimize = tf.train.AdamOptimizer(LEARNING_RATE).apply_gradients(grads)
        self.sess.run(tf.initialize_all_variables())

    def train(self, states, action_grads):
        self.sess.run(self.optimize, feed_dict={
            self.state: states,
            self.action_gradient: action_grads
        })

    def target_train(self):
        actor_weights = self.model.get_weights()
        actor_target_weights = self.target_model.get_weights()
        for i in range(len(actor_weights)):
            actor_target_weights[i] = self.TAU * actor_weights[i] + (1 - self.TAU)* actor_target_weights[i]
        self.target_model.set_weights(actor_target_weights)

    def create_actor_network(self, state_size,action_dim):
        print("Now we build the model")
        S = Input(shape=[state_size])
        h0 = Dense(HIDDEN1_UNITS, activation='relu')(S)
        h1 = Dense(HIDDEN2_UNITS, activation='relu')(h0)
        Steering = Dense(1,activation='tanh',kernel_initializer=variance_scaling(scale=1e-4, distribution='normal'), bias_initializer=variance_scaling(scale=1e-4, distribution='normal'))(h1)
        Acceleration = Dense(1,activation='sigmoid', kernel_initializer=variance_scaling(scale=1e-4, distribution='normal'), bias_initializer=variance_scaling(scale=1e-4, distribution='normal'))(h1)
        Brake = Dense(1,activation='sigmoid', kernel_initializer=variance_scaling(scale=1e-4, distribution='normal'), bias_initializer=variance_scaling(scale=1e-4, distribution='normal'))(h1)
        V = concatenate([Steering,Acceleration,Brake])
        model = Model(inputs=S, outputs=V)
        return model, model.trainable_weights, S
```

Since acceleration and brake take values between 0 and 1 and steering value is between -1 and 1, in create_actor_network method, the Critic Network output layer parameters are initialized with a normal distribution scaled of a 1e-4 factor.

**Figure 6.2.** Tensorboard graph of Actor Network




## 6.4 Model Update

The main work is done by the updated routine that is run right after an action is taken every step. At first the environment is reset and the first state is stored observed.

```
ob = env.reset()
s_t = np.hstack((ob.angle, ob.track, ob.trackPos, ob.speedX, ob.speedY,
        ob.speedZ, ob.wheelSpinVel/100.0, ob.rpm))
```

After that, a loop over the max number of steps starts. The actor predicts an action, to which some noise is added and the agent interacts with the environment by sending the chosen action and a new observation is made.

```
for j in range(max_steps):
    loss = 0
    epsilon -= 1.0 / EXPLORE
    a_t = np.zeros([1,action_dim])
    noise_t = np.zeros([1,action_dim])
    a_t_original = actor.model.predict(s_t.reshape(1, s_t.shape[0]))
    noise_t[0][0] = train_indicator * max(epsilon, 0) * OU.function(
        a_t_original[0][0], 0.0 , 0.60, 0.10)
```

```
    noise_t[0][1] = train_indicator * max(epsilon, 0) * OU.function(
        a_t_original[0][1], 0.6 , 1.00, 0.10)
    noise_t[0][2] = train_indicator * max(epsilon, 0) * OU.function(
        a_t_original[0][2], -0.1 , 1.00, 0.05)
    #The following code do the stochastic brake
    if random.random() <= 0.1:
        print("********Now we apply the brake***********")
        noise_t[0][2] = train_indicator * max(epsilon, 0) * OU.function
            (a_t_original[0][2], 0.1 , 1.00, 0.10)
    for x in range(action_dim):
        a_t[0][x] = a_t_original[0][x] + noise_t[0][x]
    ob, r_t, done, info = env.step(a_t[0])
    s_t1 = np.hstack((ob.angle, ob.track, ob.trackPos, ob.speedX, ob.
        speedY, ob.speedZ, ob.wheelSpinVel/100.0, ob.rpm))
```

The tuple (state, action, reward, next_state) is then stored in the replay buffer. A batch of samples is picked from the replay buffer and for each sample the Target Q value is calculated, as well as the real value.

Critic is trained by minimizing the mean squared error by the estimated Q value and the calculated Q value. Actor update is more complex: for every sample, actor predicts the action for the state and the value gradient is calculated on it, after that actor is trained by maximizing the value function over the state-action tuple.

Finally, Target networks are updated.

```
    buff.add(s_t, a_t[0], r_t, s_t1, done)
    batch = buff.getBatch(BATCH_SIZE)
    states = np.asarray([e[0] for e in batch])
    actions = np.asarray([e[1] for e in batch])
    rewards = np.asarray([e[2] for e in batch])
    new_states = np.asarray([e[3] for e in batch])
    dones = np.asarray([e[4] for e in batch])
    y_t = np.asarray([e[1] for e in batch])
    target_q_values = critic.target_model.predict([new_states, actor.
        target_model.predict(new_states)])
    for k in range(len(batch)):
        if dones[k]:
            y_t[k] = rewards[k]
        else:
            y_t[k] = rewards[k] + GAMMA*target_q_values[k]
    if (train_indicator):
        loss += critic.model.train_on_batch([states,actions], y_t)
        a_for_grad = actor.model.predict(states)
        grads = critic.gradients(states, a_for_grad)
        actor.train(states, grads)
        actor.target_train()
        critic.target_train()
    total_reward += r_t
    s_t = s_t1
```

## 6.5 Ornstein–Uhlenbeck Noise

To avoid the model to exploit and guarantee exploration OU Noise is used. The definition and its implementation are the following:

$$dx_t = \theta(\mu - x_t)\,dt + \sigma\,dW_t \tag{6.1}$$

```
class OU(object):
    def function(self, x, mu, theta, sigma):
        return theta * (mu - x) + sigma * np.random.randn(1)
```

$\theta$ means how "fast" the variable reverts towards the mean. $\mu$ represents the equilibrium or the mean value. $\sigma$ is the degree of volatility of the noise. In the project the chosen parameters for steering, acceleration and brake are the following:

**Table 6.1.** OU Noise parameters for TORCS effectors

| **Action** | $\theta$ | $\mu$ | $\sigma$ |
|---|---|---|---|
| steering | 0.60 | 0.00 | 0.30 |
| acceleration | 1.00 | 0.60 | 0.10 |
| brake | 1.00 | -0.10 | 0.05 |

### 6.5.1 Stochastic Brake

As suggested by Ben Lau in his implementation it has been added stochastic brake: during the exploration phase, 10% of the times brake is hit while 90% it isn't. This is meant to lead to agent learning to brake before and during turns, otherwise agent would not understand the brake functionality and remain stuck at the same position for the whole race. Stochastic Brake is applied by adding some OU Noise with probability 0.1 and following parameters:

**Table 6.2.** OU Noise parameters for TORCS effectors

| **Action** | $\theta$ | $\mu$ | $\sigma$ |
|---|---|---|---|
| brake | 1.00 | 0.10 | 0.10 |

## 6.6 Reward Shaping

Since the aim of this project is to teach the agent to drive and to maintain a specified speed, the reward should be maximum when the speed is exactly the selected one, the angle between car axis and track is close to zero and the car position is approximately at the center of the track. The implemented reward function definition is the following:

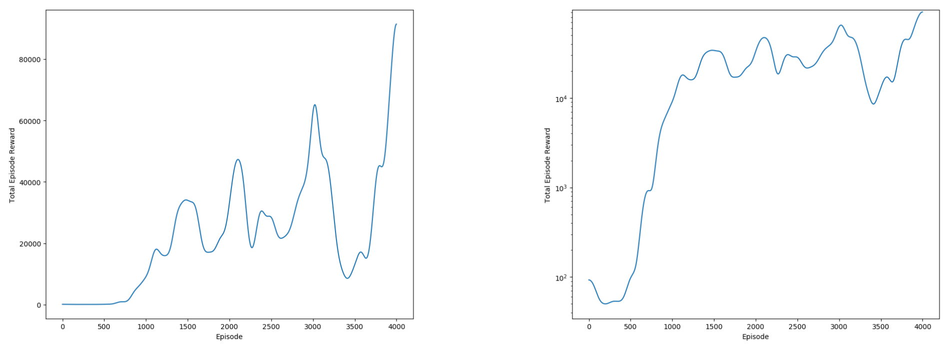
$$r(s) = \begin{cases} 200, & \text{if car out of track or backward} \\ (cos\theta + (1-d))(-v^2 + vv^*), & \text{else} \end{cases} \tag{6.2}$$

Where $\theta$ is the angle between car axis and track, $v$ is the car speed, $v^*$ is the specified speed and $d$ is the normalized distance between the car and the track edge.

# Chapter 7

# Training and Evaluation

Training phase has been run making 4000 episodes. Car started moved randomly, which often led it out of track and low reward. After about 600 episodes reward started increasing since car learned how to stay in the middle of the track, but it still was not at the maximum. Reward kept increasing until the agent understood how to maintain a certain average speed by pushing the throttle pedal and the brake one.




**(a)** Plot with linear y scale **(b)** Plot with logarithmic y scale

**Figure 7.1.** Total Reward Plots

Due to OU process, reward results noised but it is clear how the episode reward kept growing up during the reward phase. Reward plot noise could also due to the chosen reward shaping, in fact in long episodes the agent accumulated high rewards since it stood in track for but in short episodes negative reward had an higher impact on total reward. This problem has been hilighted by Gal Dalal et al. in Safe Exploration in Continuous Action Spaces [6] but it extremely depends on the environment.

Agent has been trained only on a track (Corkscrew), while testing phase has been done on four different tracks. Test Results are shown in the following table.

**Table 7.1.** OU Noise parameters for TORCS effectors

| **Track** | **Mean Reward** | **Episodes** |
|---|---|---|
| Corkscrew | 27770 | 20 |

- On Corkscrew the agent gets a mean reward of 27770 over 20 episodes.
- On

# Chapter 8

# Conclusions

This project was intended to teach a car how to keep the track and maintain a certain speed. Reinforcement Learning, and in particular, Deep Deterministic Policy Gradient demonstrated to be powerful algorithms to train agents in continuous state-action space.

The two dealt problems are generally faced separately in Control Engineering: for example Cruise Control implemented in cars, which is responsible for keeping a constant speed is usually faced with a classic feedback loop.

Moreover, the agent has been trained only considering sensors while it is possible to use also the car vision. Probably by using car camera the model would have been better but slower, or even not possible to train on a Personal Computer.

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