```
!sudo apt-get install swig  # swig 설치
!pip install box2d gymnasium[box2d]
```

숨겨진 출력 표시

```
!git clone https://github.com/Soggeum/20242R0136COSE47402.git
%cd 20242R0136COSE47402/FinalProject/lunar-lander
```

숨겨진 출력 표시

```
import gymnasium as gym
import pygame
import numpy as np
import matplotlib.pyplot as plt
import itertools
```

```
import agent_class as agent
```

Initialize environment and agent

```
# We first create the environment on which we will later train the agent
env = gym.make('LunarLander-v3')

# We need to know the dimensionality of the state space, as well as how many
# actions are possible
N_actions = env.action_space.n
observation, info = env.reset()
N_state = len(observation)

print('dimension of state space =',N_state)
print('number of actions =',N_actions)
```

```
dimension of state space = 8
number of actions = 4
```

```
# We create an instance of the agent class.
# At initialization, we need to provide
# - the dimensionality of the state space, as well as
# - the number of possible actions

parameters = {'N_state':N_state, 'N_actions':N_actions}

my_agent = agent.dqn(parameters=parameters)
# to train via the actor-critic algorithm, use this line:
# my_agent = agent.actor_critic(parameters=parameters)
```

Train agent

```
# We train the agent on the LunarLander-v3 environment.
# Setting verbose=True allows us to follow the progress of the training

training_results = my_agent.train(environment=env,
                                  verbose=True)
```

episode	return (this episode)	minimal return (last 20 episodes)	mean return (last 20 episodes)
100	-63.745	-333.606	-133.189
200	-137.825	-247.144	-97.487
300	-48.600	-399.012	-79.365
400	64.748	-264.094	-57.653
500	-11.198	-108.507	-5.500
600	-50.319	-182.694	21.444
700	92.862	-234.553	-12.551
800	230.056	-98.974	178.076
900	266.220	-7.204	208.497
1000	244.970	-212.061	163.451
1053	201.835	200.804	238.148

```
# the method my_agent.train() from the previous cell returns a dictionary
# with training stats, namely:
# - duration of each episode during training,
# - return of each episode during training
# - the total number of training epochs at the end of each episode
# - the total number of steps simulated at the end of each episode
```

```
training_results.keys()
```

```
dict_keys(['episode_durations', 'epsiode_returns', 'n_training_epochs', 'n_steps_simulated', 'training_completed'])
```

Plot training stats

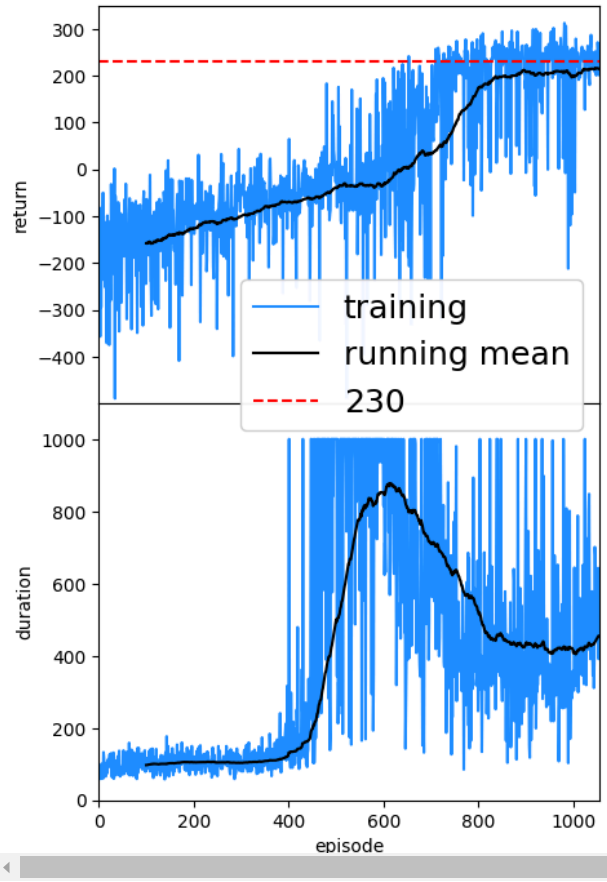
```
# Plot both the return per episode and the duration per episode during
# training, together with their running average over 20 consecutive episodes

N = 100 # number of episodes for running average

def running_mean(x,N=100):
        x_out = np.zeros(len(x)-N,dtype=float)
        for i in range(len(x)-N):
                x_out[i] = np.mean(x[i:i+N+1])
        return x_out

def plot_returns_and_durations(training_results,filename=None):
    fig,axes = plt.subplots(2,1,figsize=(5,8))
    fig.subplots_adjust(hspace=0.0001)
    #
    # return as a function of episode
    ax = axes[0]
    x = training_results['epsiode_returns']
    t = np.arange(len(x)) + 1
    #
    ax.plot(t,x,label='training',color='dodgerblue',)
    # add running mean
    x = running_mean(x=x,N=N)
    t = np.arange(len(x)) + N
    ax.plot(t,x,color='black',label='running mean')
    #
    ax.axhline(230,ls='--',
               label='230',
                       color='red')
    #
    ax.set_ylim(-499,350)
    ax.set_xticks([])
    ax.set_xlim(0,len(t)+100)
    ax.set_xlabel(r'episode')
    ax.set_ylabel(r'return')
    #
    #
    ax = axes[1]
    x = training_results['episode_durations']
    t = np.arange(len(x)) + 1
    #
    ax.plot(t,x,label='training',color='dodgerblue',)
    # add running mean
    x = running_mean(x=x,N=N)
    t = np.arange(len(x)) + N
    ax.plot(t,x,color='black',label='running mean')
    #
    ax.axhline(1200,ls='--', # draw line outside of plot scale,
                label='230', # to get the red dotted line into the legend
                       color='red')
    #
    ax.set_ylim(0,1100)
    ax.set_xlim(0,len(t)+100)
    ax.set_xlabel(r'episode')
    ax.set_ylabel(r'duration')
    ax.legend(loc='upper right',bbox_to_anchor=(1.,1.35),
                                framealpha=0.95,
                       fontsize=18)
    #
    plt.show()
    if filename != None:
        fig.savefig(filename,bbox_inches='tight')
    plt.close(fig)

plot_returns_and_durations(training_results=training_results)
```



Create gameplay video using trained agent

First we create a "live" video that pops up and shows Lunar Lander gameplay performed by the agent

```
# There is the issue that the game window freezes when running gym games
# in jupyter notebooks, see https://github.com/openai/gym/issues/2433
# We here use the fix from that website, which is to use the following
# wrapper class:
class PyGameWrapper(gym.Wrapper):
    def render(self, **kwargs):
        retval = self.env.render( **kwargs)
        for event in pygame.event.get():
            pass
        return retval
```

```
# Create a wrapped environment
env = PyGameWrapper(gym.make('LunarLander-v3',render_mode='human'))

N_episodes = 100

result_string = 'Run {0}: duration = {1}, total return = {2:7.3f}'

for j in range(N_episodes):
    state, info = env.reset()

    total_reward = 0
    for i in itertools.count():
        #env.render()

        action = my_agent.act(state)
        state, reward, terminated, truncated, info = env.step(action)
        done = terminated or truncated
        total_reward += reward

        if done:
            print(result_string.format(j+1,i+1,total_reward))
            break

env.close()
```

```
Run 1: duration = 248, total return =  14.514
Run 2: duration = 377, total return = 248.985
Run 3: duration = 230, total return = 265.657
Run 4: duration = 369, total return = 191.265
Run 5: duration = 238, total return = 242.310
```

```
Run 6: duration = 269, total return = 239.245
Run 7: duration = 323, total return = 248.480
Run 8: duration = 381, total return = 218.104
Run 9: duration = 246, total return = 252.300
Run 10: duration = 470, total return = 221.463
Run 11: duration = 366, total return = 228.637
Run 12: duration = 264, total return = 225.442
Run 13: duration = 412, total return = 236.490
Run 14: duration = 397, total return = 226.231
Run 15: duration = 411, total return = 244.396
Run 16: duration = 277, total return = 256.117
Run 17: duration = 235, total return = 252.910
Run 18: duration = 465, total return = 257.295
Run 19: duration = 294, total return = 259.867
Run 20: duration = 242, total return = 242.040
Run 21: duration = 282, total return = 270.701
Run 22: duration = 318, total return = 260.515
Run 23: duration = 1000, total return = 133.132
Run 24: duration = 403, total return = 242.232
Run 25: duration = 500, total return = 248.794
Run 26: duration = 1000, total return = 146.760
Run 27: duration = 418, total return = 236.674
Run 28: duration = 297, total return = 224.078
Run 29: duration = 740, total return = 201.677
Run 30: duration = 277, total return = 261.403
Run 31: duration = 1000, total return = 144.660
Run 32: duration = 347, total return = 262.270
Run 33: duration = 1000, total return = 162.782
Run 34: duration = 267, total return =  37.562
Run 35: duration = 337, total return = 258.332
Run 36: duration = 1000, total return = 134.772
Run 37: duration = 344, total return = 254.130
Run 38: duration = 1000, total return = 105.749
Run 39: duration = 1000, total return = 143.841
Run 40: duration = 595, total return = 230.054
Run 41: duration = 322, total return = 241.073
Run 42: duration = 286, total return = 237.698
Run 43: duration = 1000, total return = 142.797
Run 44: duration = 408, total return = 252.662
Run 45: duration = 402, total return = 262.550
Run 46: duration = 319, total return = 230.427
Run 47: duration = 350, total return = 249.565
Run 48: duration = 316, total return = 222.992
Run 49: duration = 379, total return = 220.360
Run 50: duration = 493, total return = 278.496
Run 51: duration = 346, total return = 248.227
Run 52: duration = 485, total return = 248.675
Run 53: duration = 332, total return = 265.492
Run 54: duration = 582, total return = 234.948
Run 55: duration = 473, total return = 230.542
Run 56: duration = 1000, total return = 120.883
Run 57: duration = 389, total return = 252.505
Run 58: duration = 246, total return = 244.084
```

We also create a video file containing 20 games played by the agent

```
import gymnasium as gym
from gymnasium.wrappers import RecordEpisodeStatistics, RecordVideo

num_eval_episodes = 100

env = gym.make("LunarLander-v3", render_mode="rgb_array")  # replace with your environment
env = RecordVideo(env, video_folder="my_video", name_prefix="eval",
                  episode_trigger=lambda x: True)

env = RecordEpisodeStatistics(env, buffer_length=num_eval_episodes)

for episode_num in range(num_eval_episodes):
    obs, info = env.reset()

    episode_over = False
    while not episode_over:
        action = my_agent.act(state)
        #action = env.action_space.sample()  # replace with actual agent
        obs, reward, terminated, truncated, info = env.step(action)

        episode_over = terminated or truncated
env.close()

print(f'Episode time taken: {env.time_queue}')
print(f'Episode total rewards: {env.return_queue}')
print(f'Episode lengths: {env.length_queue}')
```

```
Episode time taken: deque([0.311925, 0.28265, 0.292123, 0.163196, 0.311078, 0.443475, 0.424414, 0.180685, 0.256797, 0.250661, 0.195404, 0.184452, 0.17
Episode total rewards: deque([-833.6724371955099, -737.1552930177 51, -769.1016327150238, -358.9979936134969, -499.80505331710754, -830.4024996506721,
Episode lengths: deque([87, 79, 85, 53, 63, 87, 74, 51, 77, 69, 57, 51, 51, 71, 87, 80, 64, 50, 53, 51, 56, 58, 62, 52, 64, 78, 51, 71, 80, 62, 83, 75
```