Assignment 2: Deep Q Learning and Policy Gradient

2022-2023 fall quarter, CS269 Seminar 5: Reinforcement Learning. Department of Computer Science at University of California, Los Angeles. Course Instructor: Professor Bolei ZHOU. Assignment author: Zhenghao PENG.

Double-click (or enter) to edit

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Welcome to the assignment 2 of our RL course. This assignment consists of three parts:

- Section 2: Implement Q learning in tabular setting (20 points)
- Section 3: Implement Deep Q Network with pytorch (30 points)
- Section 4: Implement policy gradient method REINFORCE with pytorch (30 points)
- Section 5: Implement policy gradient method with baseline (20 points)

Section 0 and Section 1 set up the dependencies and prepare some useful functions.

The experiments we'll conduct and their expected goals:

1. Naive Q learning in FrozenLake (should solve)
2. DQN in CartPole (should solve)
3. DQN in MetaDrive-Easy (should solve)
4. DQN in MetaDrive-Hard (>50 return)
5. Policy Gradient w/o baseline in CartPole (w/ and w/o advantage normalization) (should solve)
6. Policy Gradient w/o baseline in MetaDrive-Easy (should solve)
7. Policy Gradient w/ baseline in CartPole (w/ advantage normalization) (should solve)
8. Policy Gradient w/ baseline in MetaDrive-Easy (should solve)
9. Policy Gradient w/ baseline in MetaDrive-Hard (>50 return)

Section 0: Dependencies

Please install the following dependencies.

Notes on MetaDrive

MetaDrive is a lightweight driving simulator which we will use for DQN and Policy Gradient methods. It can not be run on M1-chip Mac. We suggest using Colab or Linux for running MetaDrive.

Please ignore this warning from MetaDrive: `WARNING:root:BaseEngine is not launched, fail to sync seed to engine!`

Notes on Colab

We have several cells used for installing dependencies for Colab only. Please make sure they are run properly.

You don't need to install python packages again and again after **restarting the runtime**, since the Colab instance still remembers the python envionment after you installing packages for the first time. But you do need to rerun those packages installation script after you **reconnecting to the runtime** (which means Google assigns a new machine to you and thus the python environment is new).

```
!pip install "gym[classic_control,box2d]<0.20.0" seaborn pandas
!pip install torch
!pip install "pyglet<2.0.0"
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/pub
Collecting gym[box2d,classic_control]<0.20.0
  Downloading gym-0.19.0.tar.gz (1.6 MB)
     |████████████████████████████████| 1.6 MB 5.5 MB/s
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/dist-packages (0.11.
Requirement already satisfied: pandas in /usr/local/lib/python3.7/dist-packages (1.3.5)
Requirement already satisfied: numpy>=1.18.0 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: cloudpickle<1.7.0,>=1.2.0 in /usr/local/lib/python3.7/dis
Collecting pyglet>=1.4.0
  Downloading pyglet-2.0.0-py3-none-any.whl (966 kB)
     |████████████████████████████████| 966 kB 19.9 MB/s
Collecting box2d-py~=2.3.5
  Downloading box2d_py-2.3.8-cp37-cp37m-manylinux1_x86_64.whl (448 kB)
     |████████████████████████████████| 448 kB 23.9 MB/s
Requirement already satisfied: matplotlib>=2.2 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: scipy>=1.0 in /usr/local/lib/python3.7/dist-packages (fr
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/l
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages (
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packa
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (from
Building wheels for collected packages: gym
  Building wheel for gym (setup.py) ... done
  Created wheel for gym: filename=gym-0.19.0-py3-none-any.whl size=1663117 sha256=279d7
  Stored in directory: /root/.cache/pip/wheels/ef/9d/70/8bea53f7edec2fdb4f98d9d64ac9f11
```

```
Successfully built gym
Installing collected packages: pyglet, gym, box2d-py
  Attempting uninstall: gym
    Found existing installation: gym 0.25.2
    Uninstalling gym-0.25.2:
      Successfully uninstalled gym-0.25.2
Successfully installed box2d-py-2.3.8 gym-0.19.0 pyglet-2.0.0
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
Requirement already satisfied: torch in /usr/local/lib/python3.7/dist-packages (1.12.1+c
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-packag
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/publ
Collecting pyglet<2.0.0
  Downloading pyglet-1.5.27-py3-none-any.whl (1.1 MB)
     |████████████████████████████████| 1.1 MB 8.9 MB/s
Installing collected packages: pyglet
  Attempting uninstall: pyglet
    Found existing installation: pyglet 2.0.0
    Uninstalling pyglet-2.0.0:
      Successfully uninstalled pyglet-2.0.0
Successfully installed pyglet-1.5.27
```

```
# Install MetaDrive, a lightweight driving simulator
!pip install git+https://github.com/metadriverse/metadrive

# Test whether MetaDrive is properly installed. No error means the test is passed.
!python -m metadrive.examples.profile_metadrive --num-steps 1000
```

```
Collecting pygame
  Downloading pygame-2.1.2-cp37-cp37m-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
     |████████████████████████████████| 21.8 MB 13.0 MB/s
Requirement already satisfied: tqdm in /usr/local/lib/python3.7/dist-packages (from m
Collecting yapf
  Downloading yapf-0.32.0-py2.py3-none-any.whl (190 kB)
     |████████████████████████████████| 190 kB 42.2 MB/s
Requirement already satisfied: seaborn in /usr/local/lib/python3.7/dist-packages (fro
Collecting panda3d==1.10.8
  Downloading panda3d-1.10.8-cp37-cp37m-manylinux1_x86_64.whl (53.2 MB)
     |████████████████████████████████| 53.2 MB 1.1 MB/s
Collecting panda3d-gltf
  Downloading panda3d_gltf-0.13-py3-none-any.whl (25 kB)
Collecting panda3d-simplepbr
  Downloading panda3d_simplepbr-0.10-py3-none-any.whl (10 kB)
Requirement already satisfied: pillow in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: pytest in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: opencv-python-headless in /usr/local/lib/python3.7/dis

Requirement already satisfied: lxml in /usr/local/lib/python3.7/dist-packages (from m
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-packages (from
Requirement already satisfied: cloudpickle<1.7.0,>=1.2.0 in /usr/local/lib/python3.7/
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.7/dist-
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (fr
```

```
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-packages (fr
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-packages
Requirement already satisfied: atomicwrites>=1.0 in /usr/local/lib/python3.7/dist-pac
Requirement already satisfied: attrs>=17.4.0 in /usr/local/lib/python3.7/dist-package
Requirement already satisfied: more-itertools>=4.0.0 in /usr/local/lib/python3.7/dist
Requirement already satisfied: py>=1.5.0 in /usr/local/lib/python3.7/dist-packages (f
Requirement already satisfied: pluggy<0.8,>=0.5 in /usr/local/lib/python3.7/dist-pack
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (
Building wheels for collected packages: metadrive-simulator
  Building wheel for metadrive-simulator (setup.py) ... done
  Created wheel for metadrive-simulator: filename=metadrive_simulator-0.2.5.2-py3-nor
  Stored in directory: /tmp/pip-ephem-wheel-cache-t11v1lzn/wheels/d8/bc/9c/530116e897
Successfully built metadrive-simulator
Installing collected packages: panda3d, panda3d-simplepbr, yapf, pygame, panda3d-gltf
Successfully installed metadrive-simulator-0.2.5.2 panda3d-1.10.8 panda3d-gltf-0.13 p
Successfully registered the following environments: ['MetaDrive-validation-v0', 'Meta
Start to profile the efficiency of MetaDrive with 1000 maps and ~8 vehicles!
:device(error): Error adding inotify watch on /dev/input: No such file or directory
:device(error): Error opening directory /dev/input: No such file or directory
Finish 100/1000 simulation steps. Time elapse: 0.4430. Average FPS: 225.7563, Average
Finish 200/1000 simulation steps. Time elapse: 1.0274. Average FPS: 194.6667, Average
Finish 300/1000 simulation steps. Time elapse: 1.5479. Average FPS: 193.8095, Average
Finish 400/1000 simulation steps. Time elapse: 2.2328. Average FPS: 179.1511, Average
Finish 500/1000 simulation steps. Time elapse: 3.0118. Average FPS: 166.0130, Average
Finish 600/1000 simulation steps. Time elapse: 3.7379. Average FPS: 160.5194, Average
Finish 700/1000 simulation steps. Time elapse: 4.2994. Average FPS: 162.8148, Average
Finish 800/1000 simulation steps. Time elapse: 5.0923. Average FPS: 157.1004, Average
Finish 900/1000 simulation steps. Time elapse: 5.5501. Average FPS: 162.1582, Average
Finish 1000/1000 simulation steps. Time elapse: 6.1108. Average FPS: 163.6449, Averag
Total Time Elapse: 6.111, average FPS: 163.641, average number of vehicles: 9.385.
```

```
# If you are using Colab, please run the following script EACH time you disconnect from a Run

!apt-get install -y xvfb python-opengl
!pip install pyvirtualdisplay
```

```
Reading package lists... Done
Building dependency tree
Reading state information... Done
The following package was automatically installed and is no longer required:
  libnvidia-common-460
Use 'apt autoremove' to remove it.
The following additional packages will be installed:
  freeglut3
Suggested packages:
  libgle3
The following NEW packages will be installed:
  freeglut3 python-opengl xvfb
0 upgraded, 3 newly installed, 0 to remove and 4 not upgraded.
Need to get 1,355 kB of archives.
After this operation, 8,005 kB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu bionic/universe amd64 freeglut3 amd64 2.8.1-3 [7
Get:2 http://archive.ubuntu.com/ubuntu bionic/universe amd64 python-opengl all 3.1.0+df
Get:3 http://archive.ubuntu.com/ubuntu bionic-updates/universe amd64 xvfb amd64 2:1.19.
```

```
Fetched 1,355 kB in 2s (903 kB/s)
Selecting previously unselected package freeglut3:amd64.
(Reading database ... 123942 files and directories currently installed.)
Preparing to unpack .../freeglut3_2.8.1-3_amd64.deb ...
Unpacking freeglut3:amd64 (2.8.1-3) ...
Selecting previously unselected package python-opengl.
Preparing to unpack .../python-opengl_3.1.0+dfsg-1_all.deb ...
Unpacking python-opengl (3.1.0+dfsg-1) ...
Selecting previously unselected package xvfb.
Preparing to unpack .../xvfb_2%3a1.19.6-1ubuntu4.11_amd64.deb ...
Unpacking xvfb (2:1.19.6-1ubuntu4.11) ...
Setting up freeglut3:amd64 (2.8.1-3) ...
Setting up python-opengl (3.1.0+dfsg-1) ...
Setting up xvfb (2:1.19.6-1ubuntu4.11) ...
Processing triggers for man-db (2.8.3-2ubuntu0.1) ...
Processing triggers for libc-bin (2.27-3ubuntu1.6) ...
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/pub
Collecting pyvirtualdisplay
  Downloading PyVirtualDisplay-3.0-py3-none-any.whl (15 kB)
Installing collected packages: pyvirtualdisplay
Successfully installed pyvirtualdisplay-3.0
```

```
# If you are using Colab, please run the following script EACH time you restart the Runtime.
import os
os.environ['SDL_VIDEODRIVER']='dummy'

from pyvirtualdisplay import Display
display = Display(visible=0, size=(400, 300))
display.start()
```

```
<pyvirtualdisplay.display.Display at 0x7f12cf831650>
```

Section 1: Building abstract class and helper functions

```
# Run this cell without modification

# Import some packages that we need to use
import gym
import numpy as np
import pandas as pd
import seaborn as sns
from collections import deque
import copy
from gym.error import Error
from gym import logger, error
import torch
import torch.nn as nn
import time
from IPython.display import clear_output
```

```python
from gym.envs.registration import register
import copy
import json
import os
import subprocess
import tempfile
import time
import IPython
import PIL
import pygame


def wait(sleep=0.2):
    clear_output(wait=True)
    time.sleep(sleep)


def merge_config(new_config, old_config):
    """Merge the user-defined config with default config"""
    config = copy.deepcopy(old_config)
    if new_config is not None:
        config.update(new_config)
    return config



def test_random_policy(policy, env):
    _acts = set()
    for i in range(1000):
        act = policy(0)
        _acts.add(act)
        assert env.action_space.contains(act), "Out of the bound!"
    if len(_acts) != 1:
        print(
            "[HINT] Though we call self.policy 'random policy', " \
            "we find that generating action randomly at the beginning " \
            "and then fixing it during updating values period lead to better " \
            "performance. Using purely random policy is not even work! " \
            "We encourage you to investigate this issue."
        )


# We register a non-slippery version of FrozenLake environment.
try:
    register(
        id='FrozenLakeNotSlippery-v1',
        entry_point='gym.envs.toy_text:FrozenLakeEnv',
        kwargs={'map_name' : '4x4', 'is_slippery': False},
        max_episode_steps=200,
        reward_threshold=0.78, # optimum = .8196
    )
```

```python
except Error:
    print("The environment is registered already.")


def _render_helper(env, mode, sleep=0.1):
    ret = env.render(mode)
    if sleep:
        wait(sleep=sleep)
    return ret


def animate(img_array):
    """A function that can generate GIF file and show in Notebook."""
    path = tempfile.mkstemp(suffix=".gif")[1]
    images = [PIL.Image.fromarray(frame) for frame in img_array]
    images[0].save(
        path,
        save_all=True,
        append_images=images[1:],
        duration=0.05,
        loop=0
    )
    with open(path, "rb") as f:
        IPython.display.display(
            IPython.display.Image(data=f.read(), format='png'))


def evaluate(policy, num_episodes=1, seed=0, env_name='FrozenLake8x8-v1',
             render=None, existing_env=None, max_episode_length=1000,
             sleep=0.0, verbose=False):
    """This function evaluate the given policy and return the mean episode
    reward.
    :param policy: a function whose input is the observation
    :param num_episodes: number of episodes you wish to run
    :param seed: the random seed
    :param env_name: the name of the environment
    :param render: a boolean flag indicating whether to render policy
    :return: the averaged episode reward of the given policy.
    """
    if existing_env is None:
        env = gym.make(env_name)
        env.seed(seed)
    else:
        env = existing_env
    rewards = []
    frames = []
    if render: num_episodes = 1
    for i in range(num_episodes):
        obs = env.reset()
        act = policy(obs)
        ep_reward = 0
```

```
        for step_count in range(max_episode_length):
            obs, reward, done, info = env.step(act)
            act = policy(obs)
            ep_reward += reward

            if verbose and step_count % 50 == 0:
                print("Evaluating {}/{} episodes. We are in {}/{} steps. Current episode rewa
                    i + 1, num_episodes, step_count + 1, max_episode_length, ep_reward
                ))

            if render:
                frames.append(_render_helper(env, render, sleep))
                wait(sleep=0.05)
            if done:
                break
        rewards.append(ep_reward)
    if render:
        env.close()
    return np.mean(rewards), {"frames": frames}
```

```
pygame 2.1.2 (SDL 2.0.16, Python 3.7.15)
Hello from the pygame community. https://www.pygame.org/contribute.html
```

```
# Run this cell without modification

DEFAULT_CONFIG = dict(
    seed=0,
    max_iteration=20000,
    max_episode_length=200,
    evaluate_interval=10,
    evaluate_num_episodes=10,
    learning_rate=0.01,
    gamma=0.8,
    eps=0.3,
    env_name='FrozenLakeNotSlippery-v1'
)

class AbstractTrainer:
    """This is the abstract class for value-based RL trainer. We will inherent
    the specify algorithm's trainer from this abstract class, so that we can
    reuse the codes.
    """

    def __init__(self, config):
        self.config = merge_config(config, DEFAULT_CONFIG)

        # Create the environment
        self.env_name = self.config['env_name']
        self.env = gym.make(self.env_name)
```

```
        # Apply the random seed
        self.seed = self.config["seed"]
        np.random.seed(self.seed)
        self.env.seed(self.seed)

        # We set self.obs_dim to the number of possible observation
        # if observation space is discrete, otherwise the number
        # of observation's dimensions. The same to self.act_dim.
        if isinstance(self.env.observation_space, gym.spaces.box.Box):
            assert len(self.env.observation_space.shape) == 1
            self.obs_dim = self.env.observation_space.shape[0]
            self.discrete_obs = False
        elif isinstance(self.env.observation_space,
                        gym.spaces.discrete.Discrete):
            self.obs_dim = self.env.observation_space.n
            self.discrete_obs = True
        else:
            raise ValueError("Wrong observation space!")

        if isinstance(self.env.action_space, gym.spaces.box.Box):
            assert len(self.env.action_space.shape) == 1
            self.act_dim = self.env.action_space.shape[0]
        elif isinstance(self.env.action_space, gym.spaces.discrete.Discrete):
            self.act_dim = self.env.action_space.n
        elif isinstance(self.env.action_space, gym.spaces.MultiDiscrete):
            MetaDrive-Tut-Easy-v0
        else:
            raise ValueError("Wrong action space! {}".format(self.env.action_space))

        self.eps = self.config['eps']


    def process_state(self, state):
        """
        Process the raw observation. For example, we can use this function to
        convert the input state (integer) to a one-hot vector.
        """
        return state

    def compute_action(self, processed_state, eps=None):
        """Compute the action given the processed state."""
        raise NotImplementedError(
            "You need to override the Trainer.compute_action() function.")

    def evaluate(self, num_episodes=50, *args, **kwargs):
        """Use the function you write to evaluate current policy.
        Return the mean episode reward of 50 episodes."""
        if "MetaDrive" in self.env_name:
            kwargs["existing_env"] = self.env
        result, eval_infos = evaluate(self.policy, num_episodes, seed=self.seed,
```

```
                        env_name=self.env_name, *args, **kwargs)
        return result, eval_infos

    def policy(self, raw_state, eps=0.0):
        """A wrapper function takes raw_state as input and output action."""
        return self.compute_action(self.process_state(raw_state), eps=eps)

    def train(self):
        """Conduct one iteration of learning."""
        raise NotImplementedError("You need to override the "
                                  "Trainer.train() function.")


# Run this cell without modification

def run(trainer_cls, config=None, reward_threshold=None):
    """Run the trainer and report progress, agnostic to the class of trainer
    :param trainer_cls: A trainer class
    :param config: A dict
    :param reward_threshold: the reward threshold to break the training
    :return: The trained trainer and a dataframe containing learning progress
    """
    if config is None:
        config = {}
    trainer = trainer_cls(config)
    config = trainer.config
    start = now = time.time()
    stats = []
    total_steps = 0

    try:
        for i in range(config['max_iteration'] + 1):
            stat = trainer.train()
            stat = stat or {}
            stats.append(stat)
            if "episode_len" in stat:
                total_steps += stat["episode_len"]
            if i % config['evaluate_interval'] == 0 or \
                    i == config["max_iteration"]:
                reward, _ = trainer.evaluate(
                    config.get("evaluate_num_episodes", 50),
                    max_episode_length=config.get("max_episode_length", 1000)
                )
                print("({:.1f}s,+{:.1f}s) Iter {}, {}episodic return"
                      " is {:.2f}. {}".format(
                            time.time() - start,
                            time.time() - now,
                            i,
                            "" if total_steps == 0 else "Step {}, ".format(total_steps),
                            reward,
                            {k: round(np.mean(v), 4) for k, v in stat.items()
```

```
                                if not np.isnan(v) and k != "frames"
                                }
                                      if stat else ""
                          ))
                    now = time.time()
                if reward_threshold is not None and reward > reward_threshold:
                    print("In {} iteration, episodic return {:.3f} is "
                          "greater than reward threshold {}. Congratulation! Now we "
                          "exit the training process.".format(
                        i, reward, reward_threshold))
                    break
        except Exception as e:
            print("Error happens during training: ")
            raise e
        finally:
            if hasattr(trainer.env, "close"):
                trainer.env.close()
                print("Environment is closed.")

        return trainer, stats
```

Section 2: Q-Learning

(20/100 points)

Q-learning is an off-policy algorithm who differs from SARSA in the computing of TD error.

Unlike getting the TD error by running policy to get `next_act` a' and compute:

$r + \gamma Q(s', a') - Q(s, a)$

as in SARSA, in Q-learning we compute the TD error via:

$r + \gamma \max_{a'} Q(s', a') - Q(s, a)$.

The reason we call it "off-policy" is that the next-Q value is not computed for the "behavior policy", instead, it is a "virtural policy" that always takes the best action given current Q values.

```
a = np.ones((16, 4))
print(a[0, :] - a[0])
```

```
[0. 0. 0. 0.]
```

Section 2.1: Building Q Learning Trainer

```
# Solve the TODOs and remove `pass`
```

```
# Managing configurations of your experiments is important for your research.
Q_LEARNING_TRAINER_CONFIG = merge_config(dict(
    eps=0.3,
), DEFAULT_CONFIG)


class QLearningTrainer(AbstractTrainer):
    def __init__(self, config=None):
        config = merge_config(config, Q_LEARNING_TRAINER_CONFIG)
        super(QLearningTrainer, self).__init__(config=config)
        self.gamma = self.config["gamma"]
        self.eps = self.config["eps"]
        self.max_episode_length = self.config["max_episode_length"]
        self.learning_rate = self.config["learning_rate"]

        # build the Q table
        self.table = np.zeros((self.obs_dim, self.act_dim))

    def compute_action(self, obs, eps=None):
        """Implement epsilon-greedy policy

        It is a function that take an integer (state / observation)
        as input and return an interger (action).
        """
        if eps is None:
            eps = self.eps

        # [TODO] You need to implement the epsilon-greedy policy here.
        if np.random.uniform(0, 1) < eps:
          action = self.env.action_space.sample()
        else:
          action = np.argmax(self.table[obs, :])

        return action

    def train(self):
        """Conduct one iteration of learning."""
        # [TODO] Q table may be need to be reset to zeros.
        # if you think it should, than do it. If not, then move on.

        obs = self.env.reset()
        for t in range(self.max_episode_length):
            act = self.compute_action(obs)

            next_obs, reward, done, _ = self.env.step(act)

            # [TODO] compute the TD error based on the next observation and current reward

            td_error = reward + self.gamma * max(self.table[next_obs, :]) - self.table[obs][a
```

```
        # [TODO] compute the new Q value
        # hint: use TD error, self.learning_rate and current Q value
        new_value = self.table[obs][act] + self.learning_rate * td_error

        self.table[obs][act] = new_value
        obs = next_obs
        if done:
            break
```

Section 2.2: Use Q Learning to train agent in FrozenLake

```
# Run this cell without modification

q_learning_trainer, _ = run(
    trainer_cls=QLearningTrainer,
    config=dict(
        max_iteration=5000,
        evaluate_interval=50,
        evaluate_num_episodes=50,
        env_name='FrozenLakeNotSlippery-v1'
    ),
    reward_threshold=0.99
)
```

```
(0.4s,+0.4s) Iter 0, episodic return is 0.00.
(1.0s,+0.5s) Iter 50, episodic return is 0.00.
(1.5s,+0.5s) Iter 100, episodic return is 0.00.
(2.0s,+0.5s) Iter 150, episodic return is 0.00.
(2.5s,+0.5s) Iter 200, episodic return is 0.00.
(3.1s,+0.7s) Iter 250, episodic return is 0.00.
(3.8s,+0.7s) Iter 300, episodic return is 0.00.
(4.2s,+0.4s) Iter 350, episodic return is 0.00.
(4.8s,+0.6s) Iter 400, episodic return is 0.00.
(5.5s,+0.7s) Iter 450, episodic return is 0.00.
(6.0s,+0.4s) Iter 500, episodic return is 0.00.
(6.4s,+0.4s) Iter 550, episodic return is 0.00.
(7.0s,+0.6s) Iter 600, episodic return is 0.00.
(7.5s,+0.5s) Iter 650, episodic return is 0.00.
(8.1s,+0.5s) Iter 700, episodic return is 0.00.
(8.5s,+0.4s) Iter 750, episodic return is 0.00.
(9.0s,+0.5s) Iter 800, episodic return is 0.00.
(9.5s,+0.5s) Iter 850, episodic return is 0.00.
(10.1s,+0.6s) Iter 900, episodic return is 0.00.
(10.5s,+0.4s) Iter 950, episodic return is 0.00.
(11.2s,+0.6s) Iter 1000, episodic return is 0.00.
(11.7s,+0.6s) Iter 1050, episodic return is 0.00.
(12.2s,+0.5s) Iter 1100, episodic return is 0.00.
(12.7s,+0.5s) Iter 1150, episodic return is 0.00.
(13.3s,+0.6s) Iter 1200, episodic return is 0.00.
(13.7s,+0.4s) Iter 1250, episodic return is 0.00.
```

```
(14.2s,+0.5s) Iter 1300, episodic return is 0.00.
(14.8s,+0.6s) Iter 1350, episodic return is 0.00.
(15.4s,+0.7s) Iter 1400, episodic return is 0.00.
(16.2s,+0.8s) Iter 1450, episodic return is 0.00.
(16.8s,+0.6s) Iter 1500, episodic return is 0.00.
(17.2s,+0.4s) Iter 1550, episodic return is 0.00.
(17.3s,+0.0s) Iter 1600, episodic return is 1.00.
In 1600 iteration, episodic return 1.000 is greater than reward threshold 0.99. Congratu
Environment is closed.
```

```
# Run this cell without modification

# Render the learned behavior
_ = evaluate(
    policy=q_learning_trainer.policy,
    num_episodes=1,
    env_name=q_learning_trainer.env_name,
    render="human",  # Visualize the behavior here in the cell
    sleep=0.0  # The time interval between two rendering frames
)
```

```
  (Right)
SFFF
FHFH
FFFH
HFFG
```

Section 3: Implement Deep Q Learning in Pytorch

(30 / 100 points)

In this section, we will implement a basic neural network and Deep Q Learning with Pytorch, a powerful deep learning framework. Before start, you need to make sure using `pip install torch` to install it (see Section 0).

If you are not familiar with Pytorch, we suggest you to go through pytorch official quickstart tutorials:

1. quickstart
2. tutorial on RL

Different from the Q learning in Section 2, we will implement Deep Q Network (DQN) in this section. The main differences are summarized as follows:

DQN requires an experience replay memory to store the transitions. A replay memory is implemented in the following `ExperienceReplayMemory` class. It contains a certain amount of transitions: `(s_t, a_t, r_t, s_t+1, done_t)`. When the memory is full, the earliest transition is discarded to store the latest one.

The introduction of replay memory increases the sample efficiency (since each transition might be used multiple times) when solving complex task. However, you may find it learn slowly in this assignment since the CartPole-v0 is a relatively easy environment.

DQN has a delayed-updating target network. DQN maintains another neural network called the target network that has identical structure of the Q network. After a certain amount of steps has been taken, the target network copies the parameters of the Q network to itself. Normally, the update of target network is much less frequent than the update of the Q network, since the Q network is updated in each step.

The reason to leverage the target network is to stabilize the estimation of the TD error. In DQN, the TD error is evaluated as:

$$(r_t + \gamma \max_{a_{t+1}} Q^{target}(s_{t+1}, a_{t+1}) - Q(s_t, a_t))$$

The Q value of the next state is estimated by the target network, not the Q network that is being updated. This mechanism can reduce the variance of gradient because the next Q values is not influenced by the update of current Q network.

Section 3.1: Build DQN trainer

```
# Solve the TODOs and remove `pass`

from collections import deque
import random

class ExperienceReplayMemory:
    """Store and sample the transitions"""
    def __init__(self, capacity):
        # deque is a useful class which acts like a list but only contain
        # finite elements. When adding new element into the deque will make deque full with
        # `maxlen` elements, the oldest element (the index 0 element) will be removed.

        # [TODO] uncomment next line.
        self.memory = deque(maxlen=capacity)

    def push(self, transition):
        self.memory.append(transition)

    def sample(self, batch_size):
        return random.sample(self.memory, batch_size)
```

```
    def __len__(self):
        return len(self.memory)


# Solve the TODOs and remove `pass`

class PytorchModel(nn.Module):
    def __init__(self, num_inputs, num_actions, hidden_units=100):
        super(PytorchModel, self).__init__()

        print("Num inputs: {}, Num actions: {}".format(num_inputs, num_actions))

        # [TODO] Build a nn.Sequential object as the neural network with two layers.
        # The first hidden layer has `hidden_units` hidden units, followed by
        # a ReLU activation function.
        # The second hidden layer takes `hidden_units`-dimensional vector as input
        # and output another `hidden_units`-dimensional vector, followed by ReLU activation.
        # The third layer take the activation vector from the second hidden layer, who has
        # `hidden_units` elements, as input and return `num_actions` values.
        self.action_value = nn.Sequential(
            nn.Linear(num_inputs, hidden_units),
            nn.ReLU(),
            nn.Linear(hidden_units, hidden_units),
            nn.ReLU(),
            nn.Linear(hidden_units, num_actions)
        )


    def forward(self, obs):
        return self.action_value(obs)

# Test
test_pytorch_model = PytorchModel(num_inputs=3, num_actions=7, hidden_units=123)
assert isinstance(test_pytorch_model.action_value, nn.Module)
assert len(test_pytorch_model.state_dict()) == 6
assert test_pytorch_model.state_dict()["action_value.0.weight"].shape == (123, 3)
print("Name of each parameter vectors: ", test_pytorch_model.state_dict().keys())

print("Test passed!")
```

```
Num inputs: 3, Num actions: 7
Name of each parameter vectors:  odict_keys(['action_value.0.weight', 'action_value.0.bi
Test passed!
```

```
# Solve the TODOs and remove `pass`

DQN_CONFIG = merge_config(dict(
    parameter_std=0.01,
    learning_rate=0.01,
    hidden_dim=100,
```

```
    clip_norm=1.0,
    clip_gradient=True,
    max_iteration=1000,
    max_episode_length=1000,
    evaluate_interval=100,
    gamma=0.99,
    eps=0.3,
    memory_size=50000,
    learn_start=5000,
    batch_size=32,
    target_update_freq=500,  # in steps
    learn_freq=1,  # in steps
    n=1,
    env_name="CartPole-v0",
), Q_LEARNING_TRAINER_CONFIG)


def to_tensor(x):
    """A helper function to transform a numpy array to a Pytorch Tensor"""
    if isinstance(x, np.ndarray):
        x = torch.from_numpy(x).type(torch.float32)
    assert isinstance(x, torch.Tensor)
    if x.dim() == 3 or x.dim() == 1:
        x = x.unsqueeze(0)
    assert x.dim() == 2 or x.dim() == 4, x.shape
    return x


class DQNTrainer(AbstractTrainer):
    def __init__(self, config):
        config = merge_config(config, DQN_CONFIG)
        self.learning_rate = config["learning_rate"]
        super().__init__(config)

        self.memory = ExperienceReplayMemory(config["memory_size"])

        self.learn_start = config["learn_start"]
        self.batch_size = config["batch_size"]
        self.target_update_freq = config["target_update_freq"]
        self.clip_norm = config["clip_norm"]
        self.hidden_dim = config["hidden_dim"]
        self.max_episode_length = self.config["max_episode_length"]
        self.learning_rate = self.config["learning_rate"]
        self.gamma = self.config["gamma"]
        self.n = self.config["n"]


        self.step_since_update = 0
        self.total_step = 0

        # You need to setup the parameter for your function approximator.
```

```
        self.initialize_parameters()

    def initialize_parameters(self):
        self.network = None
        print("Setting up self.network with obs dim: {} and action dim: {}".format(self.obs_d
        self.network = PytorchModel(self.obs_dim, self.act_dim)

        self.network.eval()
        self.network.share_memory()

        # [TODO] Uncomment next few lines
        # Initialize target network, which is identical to self.network,
        # and should have the same weights with self.network. So you should
        # put the weights of self.network into self.target_network.

        self.target_network = PytorchModel(self.obs_dim, self.act_dim)
        self.target_network.load_state_dict(self.network.state_dict())

        self.target_network.eval()

        # Build Adam optimizer and MSE Loss.
        # [TODO] Uncomment next few lines
        self.optimizer = torch.optim.Adam(
            self.network.parameters(), lr=self.learning_rate
        )
        self.loss = nn.MSELoss()

    def process_state(self, state):
        """Preprocess the state (observation).

        If the environment provides discrete observation (state), transform
        it to one-hot form. For example, the environment FrozenLake-v0
        provides an integer in [0, ..., 15] denotes the 16 possible states.
        We transform it to one-hot style:

        original state 0 -> one-hot vector [1, 0, 0, 0, 0, 0, 0, 0, ...]
        original state 1 -> one-hot vector [0, 1, 0, 0, 0, 0, 0, 0, ...]
        original state 15 -> one-hot vector [0, ..., 0, 0, 0, 0, 0, 1]

        If the observation space is continuous, then you should do nothing.
        """
        if not self.discrete_obs:
            return state
        else:
            new_state = np.zeros((self.obs_dim,))
            new_state[state] = 1
        return new_state

    def compute_values(self, processed_state):
        """Compute the value for each potential action. Note that you
        should NOT preprocess the state here."""
```

```python
        values = self.network(processed_state).detach().numpy()
        return values

    def compute_action(self, processed_state, eps=None):
        """Compute the action given the state. Note that the input
        is the processed state."""

        values = self.compute_values(processed_state)
        assert values.ndim == 1, values.shape

        if eps is None:
            eps = self.eps

        if np.random.uniform(0, 1) < eps:
            action = self.env.action_space.sample()
        else:
            action = np.argmax(values)
        return action

    def train(self):
        s = self.env.reset()
        processed_s = self.process_state(s)
        act = self.compute_action(processed_s)
        stat = {"loss": [], "success_rate": np.nan}

        for t in range(self.max_episode_length):
            next_state, reward, done, info = self.env.step(act)
            next_processed_s = self.process_state(next_state)

            # Push the transition into memory.
            self.memory.push(
                (processed_s, act, reward, next_processed_s, done)
            )

            processed_s = next_processed_s
            act = self.compute_action(next_processed_s)
            self.step_since_update += 1
            self.total_step += 1

            if done:
                # print("INFO: ", info)
                if "arrive_dest" in info:
                    stat["success_rate"] = info["arrive_dest"]
                break

            if t % self.config["learn_freq"] != 0:
                # It's not necessary to update in each step.
                continue

            if len(self.memory) < self.learn_start:
                continue
```

```
elif len(self.memory) == self.learn_start:
    print("Current memory contains {} transitions, "
          "start learning!".format(self.learn_start))

batch = self.memory.sample(self.batch_size)

# Transform a batch of state / action / .. into a tensor.
state_batch = to_tensor(
    np.stack([transition[0] for transition in batch])
)
action_batch = to_tensor(
    np.stack([transition[1] for transition in batch])
)
reward_batch = to_tensor(
    np.stack([transition[2] for transition in batch])
)
next_state_batch = torch.stack(
    [transition[3] for transition in batch]
)
done_batch = to_tensor(
    np.stack([transition[4] for transition in batch])
)

# torch.Size([32, 4])
# torch.Size([1, 32])
# torch.Size([1, 32])
# torch.Size([32, 4])
# torch.Size([1, 32])

# td_error = reward + self.gamma * max(self.table[next_obs, :]) - self.table[obs]

# # [TODO] compute the new Q value
# # hint: use TD error, self.learning_rate and current Q value
# new_value = self.table[obs][act] + self.learning_rate * td_error


with torch.no_grad():
    # [TODO] Compute the Q values of next states
    # Q_t_plus_one = self.target_network(next_state_batch).gather(1, action_batch
    # Q_t_plus_one, _ = torch.max(self.target_network(next_state_batch), dim = 1)
    Q_t_plus_one = torch.max(self.target_network(next_state_batch), dim = 1)[0] #

    assert isinstance(Q_t_plus_one, torch.Tensor)
    assert Q_t_plus_one.dim() == 1


    # [TODO] Compute the target value of Q
    # print("self.gamma * Q_t_plus_one", (self.gamma * Q_t_plus_one).size())
    # print("torch.transpose(state_batch, 0, 1)[act].size()", torch.transpose(sta
    # print("reward_batch", reward_batch.size())
    # print((self.batch_size,))
```

```
            Q_target = (reward_batch + (1 - done_batch) + self.gamma * Q_t_plus_one)
            Q_target = Q_target.reshape(self.batch_size,)
            # print("Q_target.size()", Q_target.size())

            assert Q_target.shape == (self.batch_size,)

        # Collect the Q values in batch.
        self.network.train()
        q_out = self.network(state_batch)
        assert q_out.dim() == 2
        Q_t = q_out.gather(1, action_batch.long().view(-1, 1)).squeeze(-1)
        # print("Q_t", Q_t)
        # print("Q_target", Q_target)

        assert Q_t.shape == Q_target.shape

        # Update the network
        self.optimizer.zero_grad()
        loss = self.loss(input=Q_t, target=Q_target)
        loss_value = loss.item()
        stat['loss'].append(loss_value)
        loss.backward()

        # [TODO] Gradient clipping. Uncomment next line
        nn.utils.clip_grad_norm_(self.network.parameters(), self.clip_norm)

        self.optimizer.step()
        self.network.eval()

    if len(self.memory) >= self.learn_start and \
            self.step_since_update > self.target_update_freq:
        print("{} steps has passed since last update. Now update the"
              " parameter of the behavior policy. Current step: {}".format(
            self.step_since_update, self.total_step
        ))
        self.step_since_update = 0
        # [TODO] Copy the weights of self.network to self.target_network.
        self.target_network.load_state_dict(self.network.state_dict())

        self.target_network.eval()

    ret = {"loss": np.mean(stat["loss"]), "episode_len": t}
    if "success_rate" in stat:
        ret["success_rate"] = stat["success_rate"]
    return ret

def process_state(self, state):
    return torch.from_numpy(state).type(torch.float32)

def save(self, loc="model.pt"):
```

```
        torch.save(self.network.state_dict(), loc)

    def load(self, loc="model.pt"):
        self.network.load_state_dict(torch.load(loc))
```

Section 3.2: Test DQN trainer

```
# Run this cell without modification

# Build the test trainer.
test_trainer = DQNTrainer({})

# Test compute_values
fake_state = test_trainer.env.observation_space.sample()
processed_state = test_trainer.process_state(fake_state)
assert processed_state.shape == (test_trainer.obs_dim, ), processed_state.shape
values = test_trainer.compute_values(processed_state)
assert values.shape == (test_trainer.act_dim, ), values.shape

test_trainer.train()
print("Now your codes should be bug-free.")

_ = run(DQNTrainer, dict(
    max_iteration=20,
    evaluate_interval=10,
    learn_start=100,
    env_name="CartPole-v0",
))

test_trainer.save("test_trainer.pt")
test_trainer.load("test_trainer.pt")

print("Test passed!")
```

```
Setting up self.network with obs dim: 4 and action dim: 2
Num inputs: 4, Num actions: 2
Num inputs: 4, Num actions: 2
Now your codes should be bug-free.
Setting up self.network with obs dim: 4 and action dim: 2
Num inputs: 4, Num actions: 2
Num inputs: 4, Num actions: 2
(0.0s,+0.0s) Iter 0, Step 9, episodic return is 9.20. {'episode_len': 9.0}
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:3441: RuntimeWarning: M
  out=out, **kwargs)
/usr/local/lib/python3.7/dist-packages/numpy/core/_methods.py:189: RuntimeWarning: inval
  ret = ret.dtype.type(ret / rcount)
Current memory contains 100 transitions, start learning!
(0.4s,+0.4s) Iter 10, Step 116, episodic return is 10.80. {'loss': 0.2861, 'episode_len
(0.8s,+0.4s) Iter 20, Step 276, episodic return is 9.70. {'loss': 0.0368, 'episode_len'
```

```
Environment is closed.
Test passed!
```

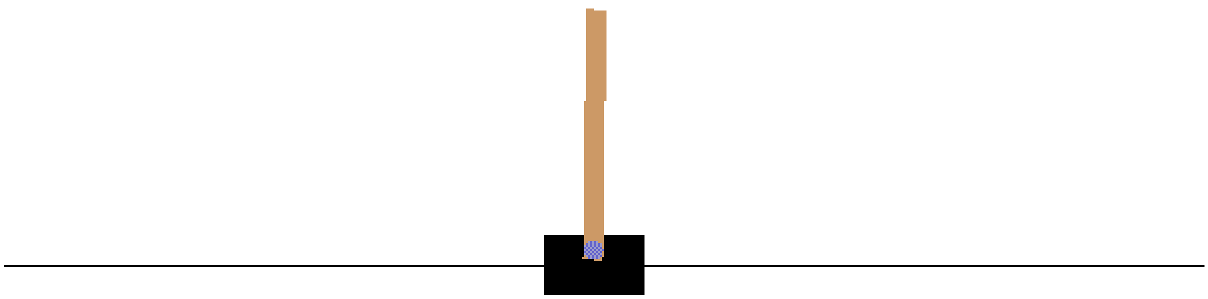
Section 3.3: Train DQN agents in CartPole

```
# Run this cell without modification

pytorch_trainer, pytorch_stat = run(DQNTrainer, dict(
    max_iteration=2000,
    evaluate_interval=50,
    learning_rate=0.01,
    clip_norm=10.0,
    memory_size=50000,
    learn_start=1000,
    eps=0.1,
    target_update_freq=1000,
    batch_size=32,
    env_name="CartPole-v0",
), reward_threshold=195.0)

reward, _ = pytorch_trainer.evaluate()
assert reward > 195.0, "Check your codes. " \
    "Your agent should achieve {} reward in 1000 iterations." \
    "But it achieve {} reward in evaluation.".format(195.0, reward)


pytorch_trainer.save("dqn_trainer_cartpole.pt")

# Should solve the task in 10 minutes
```

```
Current memory contains 1000 transitions, start learning!
1053 steps has passed since last update. Now update the parameter of the behavior pol
(1.4s,+1.3s) Iter 50, Step 1436, episodic return is 9.40. {'loss': 0.0229, 'episode_l
1013 steps has passed since last update. Now update the parameter of the behavior pol
(3.0s,+1.6s) Iter 100, Step 2087, episodic return is 9.20. {'loss': 0.0245, 'episode_
(4.6s,+1.5s) Iter 150, Step 2680, episodic return is 9.20. {'loss': 0.0261, 'episode_
1006 steps has passed since last update. Now update the parameter of the behavior pol
(6.1s,+1.5s) Iter 200, Step 3298, episodic return is 9.80. {'loss': 0.0361, 'episode_
1015 steps has passed since last update. Now update the parameter of the behavior pol
(8.2s,+2.1s) Iter 250, Step 4122, episodic return is 25.90. {'loss': 0.0407, 'episode
1018 steps has passed since last update. Now update the parameter of the behavior pol
(11.5s,+3.3s) Iter 300, Step 5327, episodic return is 21.20. {'loss': 0.047, 'episode
1009 steps has passed since last update. Now update the parameter of the behavior pol
1007 steps has passed since last update. Now update the parameter of the behavior pol
(15.9s,+4.4s) Iter 350, Step 7042, episodic return is 73.90. {'loss': 0.0958, 'episod
1054 steps has passed since last update. Now update the parameter of the behavior pol
1044 steps has passed since last update. Now update the parameter of the behavior pol
1061 steps has passed since last update. Now update the parameter of the behavior pol
1018 steps has passed since last update. Now update the parameter of the behavior pol
(27.5s,+11.6s) Iter 400, Step 11422, episodic return is 36.90. {'loss': 0.0496, 'epis
1065 steps has passed since last update. Now update the parameter of the behavior pol
```

```
1002 steps has passed since last update. Now update the parameter of the behavior pol
1076 steps has passed since last update. Now update the parameter of the behavior pol
(35.7s,+8.1s) Iter 450, Step 14583, episodic return is 16.20. {'loss': 0.0971, 'episc
1027 steps has passed since last update. Now update the parameter of the behavior pol
1034 steps has passed since last update. Now update the parameter of the behavior pol
(40.4s,+4.7s) Iter 500, Step 16283, episodic return is 15.30. {'loss': 0.1235, 'episc
1044 steps has passed since last update. Now update the parameter of the behavior pol
1034 steps has passed since last update. Now update the parameter of the behavior pol
(45.0s,+4.7s) Iter 550, Step 18104, episodic return is 53.60. {'loss': 0.1329, 'episc
1028 steps has passed since last update. Now update the parameter of the behavior pol
1059 steps has passed since last update. Now update the parameter of the behavior pol
(50.7s,+5.7s) Iter 600, Step 20325, episodic return is 143.30. {'loss': 0.2167, 'epis
1011 steps has passed since last update. Now update the parameter of the behavior pol
1069 steps has passed since last update. Now update the parameter of the behavior pol
1045 steps has passed since last update. Now update the parameter of the behavior pol
(59.5s,+8.8s) Iter 650, Step 23895, episodic return is 18.70. {'loss': 0.1272, 'episc
1037 steps has passed since last update. Now update the parameter of the behavior pol
(62.1s,+2.6s) Iter 700, Step 24917, episodic return is 17.70. {'loss': 0.0458, 'episc
1027 steps has passed since last update. Now update the parameter of the behavior pol
(64.6s,+2.5s) Iter 750, Step 25892, episodic return is 15.50. {'loss': 0.132, 'episod
1014 steps has passed since last update. Now update the parameter of the behavior pol
(67.5s,+2.9s) Iter 800, Step 26878, episodic return is 14.00. {'loss': 0.2647, 'episc
1011 steps has passed since last update. Now update the parameter of the behavior pol
1017 steps has passed since last update. Now update the parameter of the behavior pol
(72.2s,+4.8s) Iter 850, Step 28279, episodic return is 83.40. {'loss': 0.154, 'episod
1007 steps has passed since last update. Now update the parameter of the behavior pol
(75.7s,+3.5s) Iter 900, Step 29371, episodic return is 14.50. {'loss': 0.0946, 'episc
1024 steps has passed since last update. Now update the parameter of the behavior pol
(79.8s,+4.1s) Iter 950, Step 30873, episodic return is 106.50. {'loss': 0.2597, 'epis
1023 steps has passed since last update. Now update the parameter of the behavior pol
1056 steps has passed since last update. Now update the parameter of the behavior pol
1107 steps has passed since last update. Now update the parameter of the behavior pol
1061 steps has passed since last update. Now update the parameter of the behavior pol
(90.0s,+10.2s) Iter 1000, Step 34746, episodic return is 200.00. {'loss': 0.1904, 'ep
In 1000 iteration, episodic return 200.000 is greater than reward threshold 195.0. Co
Environment is closed.
```

```python
# Run this cell without modification

# Render the learned behavior
eval_reward, eval_info = evaluate(
    policy=pytorch_trainer.policy,
    num_episodes=1,
    env_name=pytorch_trainer.env_name,
    render="rgb_array",  # Visualize the behavior here in the cell
)

animate(eval_info["frames"])

print("DQN agent achieves {} return.".format(eval_reward))
```



Section 3.4: Train DQN agents in MetaDrive

```
# Run this cell without modification

def register_metadrive():
    from gym.envs.registration import register
    from gym import Wrapper
    try:
        from metadrive.envs import MetaDriveEnv
        from metadrive.utils.config import merge_config_with_unknown_keys
    except ImportError as e:
        print("Please install MetaDrive through: pip install git+https://github.com/decisionf
        raise e

    env_names = []
    try:
        class MetaDriveEnvD(Wrapper):
            def __init__(self, config, *args, **kwargs):
                super().__init__(MetaDriveEnv(config))
                self.action_space = gym.spaces.Discrete(int(np.prod(self.env.action_space.nve

        _make_env = lambda config=None: MetaDriveEnvD(config)

        env_name = "MetaDrive-Tut-Easy-v0"
        register(id=env_name, entry_point=_make_env, kwargs={"config": dict(
            map="S",
            start_seed=0,
            environment_num=1,
```

```
            horizon=200,
            discrete_action=True,
            discrete_steering_dim=3,
            discrete_throttle_dim=3
        )})
        env_names.append(env_name)

        env_name = "MetaDrive-Tut-Hard-v0"
        register(id=env_name, entry_point=_make_env, kwargs={"config": dict(
            map="CCC",
            start_seed=0,
            environment_num=10,
            discrete_action=True,
            discrete_steering_dim=5,
            discrete_throttle_dim=5
        )})
        env_names.append(env_name)
    except gym.error.Error as e:
        print("Information when registering MetaDrive: ", e)
    else:
        print("Successfully registered MetaDrive environments: ", env_names)
```

```
# Run this cell without modification

register_metadrive()
```

```
Successfully registered the following environments: ['MetaDrive-validation-v0', 'MetaDri
Successfully registered MetaDrive environments:  ['MetaDrive-Tut-Easy-v0', 'MetaDrive-Tu
```

```
# Run this cell without modification

# Build the test trainer.
test_trainer = DQNTrainer(dict(env_name="MetaDrive-Tut-Easy-v0"))

# Test compute_values
for _ in range(10):
    fake_state = test_trainer.env.observation_space.sample()
    processed_state = test_trainer.process_state(fake_state)
    assert processed_state.shape == (test_trainer.obs_dim, ), processed_state.shape
    values = test_trainer.compute_values(processed_state)
    assert values.shape == (test_trainer.act_dim, ), values.shape

    test_trainer.train()

print("Now your codes should be bug-free.")
test_trainer.env.close()
del test_trainer
```

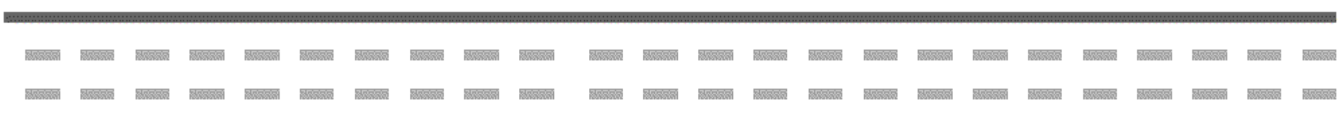
```
WARNING:root:BaseEngine is not launched, fail to sync seed to engine!
Setting up self.network with obs dim: 259 and action dim: 9
Num inputs: 259, Num actions: 9
Num inputs: 259, Num actions: 9
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:3441: RuntimeWarning: M
  out=out, **kwargs)
/usr/local/lib/python3.7/dist-packages/numpy/core/_methods.py:189: RuntimeWarning: inval
  ret = ret.dtype.type(ret / rcount)
Now your codes should be bug-free.
```

```
# Run this cell without modification

env_name = "MetaDrive-Tut-Easy-v0"

pytorch_trainer2, _ = run(DQNTrainer, dict(
    max_episode_length=200,
    max_iteration=5000,
    evaluate_interval=10,
    evaluate_num_episodes=10,
    learning_rate=0.0001,
    clip_norm=10.0,
    memory_size=1000000,
    learn_start=2000,
    eps=0.1,
    target_update_freq=5000,
    learn_freq=16,
    batch_size=256,
    env_name=env_name
), reward_threshold=120)


pytorch_trainer2.save("dqn_trainer_metadrive_easy.pt")
```

```
WARNING:root:BaseEngine is not launched, fail to sync seed to engine!
Setting up self.network with obs dim: 259 and action dim: 9
Num inputs: 259, Num actions: 9
Num inputs: 259, Num actions: 9
(3.8s,+3.8s) Iter 0, Step 199, episodic return is -0.57. {'episode_len': 199.0}
(10.6s,+6.9s) Iter 10, Step 2189, episodic return is -0.57. {'loss': 0.7809, 'episode_le
(18.3s,+7.6s) Iter 20, Step 4179, episodic return is -0.57. {'loss': 0.0433, 'episode_le
5200 steps has passed since last update. Now update the parameter of the behavior policy
(25.7s,+7.5s) Iter 30, Step 6169, episodic return is -0.01. {'loss': 0.0186, 'episode_le
(31.3s,+5.6s) Iter 40, Step 7199, episodic return is 125.58. {'loss': 0.0953, 'episode_l
In 40 iteration, episodic return 125.581 is greater than reward threshold 120. Congratul
Environment is closed.
```

```
# Run this cell without modification

# Render the learned behavior
```

```
# NOTE: The learned agent is marked by green color.
eval_reward, eval_info = evaluate(
    policy=pytorch_trainer2.policy,
    num_episodes=1,
    env_name=pytorch_trainer2.env_name,
    render="topdown",  # Visualize the behaviors in top-down view
    verbose=True
)

frames = [pygame.surfarray.array3d(f).swapaxes(0, 1) for f in eval_info["frames"]]

animate(frames)

print("DQN agent achieves {} return in MetaDrive easy environment.".format(eval_reward))
```



Section 3.5: Train agent to solve harder driving task using DQN!

We will train agent to solve a hard MetaDrive environment with multiple curved road segments. We will visualize the behavior of agent later.

The training log of my experiment is left below for your information. As you can see the performance is not good in terms of the zero success rate.

GOAL: achieve episodic return > 50.

BONUS!! can be earned if you can improve the training performance by adjusting hyper-parameters and optimizing code. Improvement means achieving > 0.0 success rate. However, I can't promise that it is feasible to use DQN algorithm to solve this task. Please creates a independent markdown cell to highlight your improvement.

```
# Solve the TODOs and remove `pass`

class PytorchModel(nn.Module):
    def __init__(self, num_inputs, num_actions, hidden_units=100):
        super(PytorchModel, self).__init__()

        print("Num inputs: {}, Num actions: {}".format(num_inputs, num_actions))

        # [TODO] Build a nn.Sequential object as the neural network with two layers.
        # The first hidden layer has `hidden_units` hidden units, followed by
        # a ReLU activation function.
        # The second hidden layer takes `hidden_units`-dimensional vector as input
        # and output another `hidden_units`-dimensional vector, followed by ReLU activation.
        # The third layer take the activation vector from the second hidden layer, who has
        # `hidden_units` elements, as input and return `num_actions` values.
```

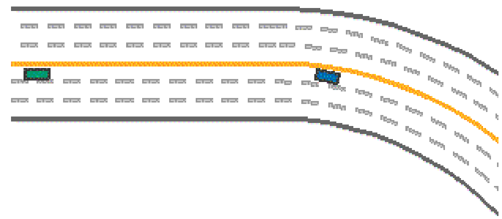
```
        self.action_value = nn.Sequential(
            nn.Linear(num_inputs, hidden_units),
            nn.ReLU(),
            nn.Linear(hidden_units, hidden_units),
            nn.ReLU(),
            nn.Linear(hidden_units, hidden_units),
            nn.ReLU(),
            nn.Linear(hidden_units, hidden_units),
            nn.ReLU(),
            nn.Linear(hidden_units, num_actions)
        )


    def forward(self, obs):
        return self.action_value(obs)


# Run this cell without modification
# (of course you can adjust hyper-parameters if you like)

# We might want to stop the training and restore later.
# Therefore, we don't use the `run` function but instead
# explicitly expose the trainer here.
# This can avoid the loss of trained agent if any unexpected error
# happens during training and thus you can stop at any time and then
# run next cell to see the visualization.
# This also allow us to save and restore the intermiedate agents if want.


metadrive_config = dict(
    max_episode_length=1000,
    max_iteration=5000,
    evaluate_interval=50,
    evaluate_num_episodes=5,
    learning_rate=0.0001,
    clip_norm=10.0,
    memory_size=1000000,
    learn_start=5000,
    eps=0.2,
    target_update_freq=5000,
    learn_freq=16,
    batch_size=258,
    env_name="MetaDrive-Tut-Hard-v0"
)

metadrive_reward_threshold = 1000

metadrive_trainer = DQNTrainer(metadrive_config)

# We might want to load trained trainer to pick up training:
if os.path.isfile("dqn_trainer_metadrive_hard.pt"):
    metadrive_trainer.load("dqn_trainer_metadrive_hard.pt")
```

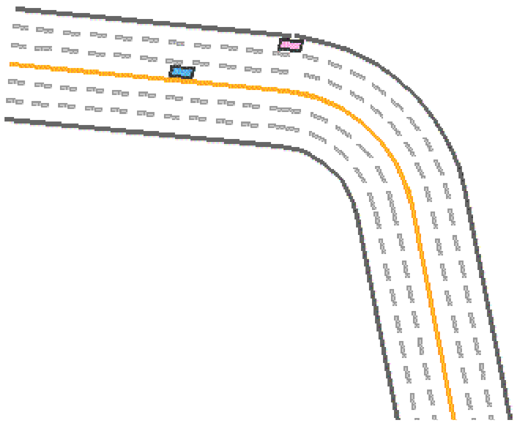
```python
metadrive_config = metadrive_trainer.config
start = now = time.time()
stats = []
total_steps = 0
try:
    for i in range(metadrive_config['max_iteration'] + 1):
        stat = metadrive_trainer.train()
        stat = stat or {}
        stats.append(stat)

        metadrive_trainer.save("dqn_trainer_metadrive_hard.pt")

        if "episode_len" in stat:
            total_steps += stat["episode_len"]
        if i % metadrive_config['evaluate_interval'] == 0 or \
                i == metadrive_config["max_iteration"]:
            reward, _ = metadrive_trainer.evaluate(
                metadrive_config.get("evaluate_num_episodes", 50),
                max_episode_length=metadrive_config.get("max_episode_length", 1000)
            )
            print("({:.1f}s,+{:.1f}s) Iter {}, {}episodic return"
                  " is {:.2f}. {}".format(
                        time.time() - start,
                        time.time() - now,
                        i,
                        "" if total_steps == 0 else "Step {}, ".format(total_steps),
                        reward,
                        {k: round(np.mean(v), 4) for k, v in stat.items()
                        if not np.isnan(v) and k != "frames"
                        }
                              if stat else ""
                  ))
            now = time.time()
        if metadrive_reward_threshold is not None and reward > metadrive_reward_threshold:
            print("In {} iteration, episodic return {:.3f} is "
                  "greater than reward threshold {}. Congratulation! Now we "
                  "exit the training process.".format(
                i, reward, metadrive_reward_threshold))
            break
except Exception as e:
    print("Error happens during training: ")
    raise e
finally:
    if hasattr(metadrive_trainer.env, "close"):
        metadrive_trainer.env.close()
        print("Environment is closed.")
```

```
5056 steps has passed since last update. Now update the parameter of the behavior pol
(2091.3s,+26.7s) Iter 3550, Step 310684, episodic return is -0.25. {'loss': 1.8117, '
```

```
(2122.0s,+30.7s) Iter 3600, Step 315114, episodic return is 55.99. {'loss': 1.619, 'e
5028 steps has passed since last update. Now update the parameter of the behavior pol
(2150.6s,+28.6s) Iter 3650, Step 319229, episodic return is 54.67. {'loss': 1.403, 'e
5066 steps has passed since last update. Now update the parameter of the behavior pol
(2176.8s,+26.2s) Iter 3700, Step 322996, episodic return is 54.30. {'loss': 1.1383, '
5074 steps has passed since last update. Now update the parameter of the behavior pol
(2207.5s,+30.7s) Iter 3750, Step 327536, episodic return is 52.44. {'loss': 1.8064, '
5008 steps has passed since last update. Now update the parameter of the behavior pol
(2235.9s,+28.4s) Iter 3800, Step 331792, episodic return is 58.82. {'loss': 1.7941, '
5080 steps has passed since last update. Now update the parameter of the behavior pol
(2262.5s,+26.7s) Iter 3850, Step 335939, episodic return is 57.47. {'loss': 1.8673, '
(2291.8s,+29.3s) Iter 3900, Step 340203, episodic return is 54.48. {'loss': 2.1193, '
5045 steps has passed since last update. Now update the parameter of the behavior pol
(2317.9s,+26.1s) Iter 3950, Step 344304, episodic return is 45.07. {'loss': 2.0082, '
5014 steps has passed since last update. Now update the parameter of the behavior pol
(2345.9s,+28.0s) Iter 4000, Step 348501, episodic return is 62.93. {'loss': 2.2177, '
5025 steps has passed since last update. Now update the parameter of the behavior pol
(2375.5s,+29.7s) Iter 4050, Step 352967, episodic return is 54.85. {'loss': 1.7875, '
5088 steps has passed since last update. Now update the parameter of the behavior pol
(2402.6s,+27.0s) Iter 4100, Step 357009, episodic return is 57.93. {'loss': 1.9405, '
5110 steps has passed since last update. Now update the parameter of the behavior pol
(2430.5s,+27.9s) Iter 4150, Step 361252, episodic return is 52.42. {'loss': 2.1129, '
(2454.2s,+23.7s) Iter 4200, Step 364918, episodic return is 53.81. {'loss': 2.223, 'e
5025 steps has passed since last update. Now update the parameter of the behavior pol
(2478.9s,+24.7s) Iter 4250, Step 368518, episodic return is 60.15. {'loss': 1.9067, '
5080 steps has passed since last update. Now update the parameter of the behavior pol
(2504.8s,+25.8s) Iter 4300, Step 372548, episodic return is 58.30. {'loss': 2.1726, '
5036 steps has passed since last update. Now update the parameter of the behavior pol
(2532.7s,+27.9s) Iter 4350, Step 376816, episodic return is 60.92. {'loss': 1.6555, '
5018 steps has passed since last update. Now update the parameter of the behavior pol
(2559.1s,+26.4s) Iter 4400, Step 380599, episodic return is 56.41. {'loss': 1.6445, '

(2584.9s,+25.8s) Iter 4450, Step 384393, episodic return is 55.02. {'loss': 1.7815, '
5080 steps has passed since last update. Now update the parameter of the behavior pol
(2613.7s,+28.8s) Iter 4500, Step 388930, episodic return is 58.58. {'loss': 1.6675, '
5068 steps has passed since last update. Now update the parameter of the behavior pol
(2641.6s,+27.9s) Iter 4550, Step 393111, episodic return is 57.78. {'loss': 1.5443, '
5082 steps has passed since last update. Now update the parameter of the behavior pol
(2672.0s,+30.4s) Iter 4600, Step 397620, episodic return is 54.31. {'loss': 1.6602, '
5083 steps has passed since last update. Now update the parameter of the behavior pol
(2696.4s,+24.4s) Iter 4650, Step 401472, episodic return is 52.80. {'loss': 2.4116, '
5064 steps has passed since last update. Now update the parameter of the behavior pol
(2726.1s,+29.7s) Iter 4700, Step 406025, episodic return is 54.75. {'loss': 2.9953, '
(2752.0s,+25.9s) Iter 4750, Step 410206, episodic return is -0.66. {'loss': 2.1858, '
5030 steps has passed since last update. Now update the parameter of the behavior pol
(2779.2s,+27.2s) Iter 4800, Step 414501, episodic return is 52.79. {'loss': 2.1456, '
5043 steps has passed since last update. Now update the parameter of the behavior pol
(2806.8s,+27.6s) Iter 4850, Step 418707, episodic return is 60.64. {'loss': 2.1959, '
5091 steps has passed since last update. Now update the parameter of the behavior pol
(2833.6s,+26.8s) Iter 4900, Step 422788, episodic return is 54.57. {'loss': 2.0302, '
5021 steps has passed since last update. Now update the parameter of the behavior pol
(2862.3s,+28.6s) Iter 4950, Step 427086, episodic return is 60.51. {'loss': 2.6268, '
5023 steps has passed since last update. Now update the parameter of the behavior pol
(2884.8s,+22.6s) Iter 5000, Step 430502, episodic return is 58.77. {'loss': 3.0463, '
Environment is closed.
```

```
# Run this cell without modification

# Render the learned behavior
# NOTE: The learned agent is marked by green color.
eval_reward, eval_info = evaluate(
    policy=metadrive_trainer.policy,
    num_episodes=1,
    env_name=metadrive_trainer.env_name,
    render="topdown",  # Visualize the behaviors in top-down view
    verbose=True
)

frames = [pygame.surfarray.array3d(f).swapaxes(0, 1) for f in eval_info["frames"]]

animate(frames)

print("DQN agent achieves {} return in MetaDrive hard environment.".format(eval_reward))
```





Section 4: Policy gradient methods - REINFORCE

(30 / 100 points)

Unlike supervised learning, in RL the optimization objective return is not differentiable w.r.t. the neural network parameters. This can be workaround via ***Policy Gradient***. It can be proved that policy gradient is an unbiased estimator of the gradient of the objective.

Concretely, let's consider such optimization objective:

$$Q = \mathbb{E}_{\text{possible trajectories}} \sum_t r(a_t, s_t) = \sum_{s_0, a_0, ..} p(s_0, a_0, \dots, s_t, a_t) r(s_0, a_0, \dots, s_t, a_t) = \sum_\tau p$$

wherein $\sum_t r(a_t, s_t) = r(\tau)$ is the return of trajectory $\tau = (s_0, a_0, \dots)$. We remove the discount factor for simplicity. Since we want to maximize Q, we can simply compute the gradient of Q w.r.t. parameter θ (which is implictly included in $p(\tau)$):

$$\nabla_\theta Q = \nabla_\theta \sum_\tau p(\tau) r(\tau) = \sum_\tau r(\tau) \nabla_\theta p(\tau)$$

Apply a famous trick: $\nabla_\theta p(\tau) = p(\tau) \dfrac{\nabla_\theta p(\tau)}{p(\tau)} = p(\tau) \nabla_\theta \log p(\tau)$.

Introducing a log term can change the product of probabilities to sum of log probabilities. Now we can expand the log of product above to sum of log:

$$p_\theta(\tau) = p(s_0, a_0, \dots) = p(s_0)\prod_t \pi_\theta(a_t|s_t)p(s_{t+1}|s_t, a_t)$$

$$\log p_\theta(\tau) = \log p(s_0) + \sum_t \log \pi_\theta(a_t|s_t) + \sum_t \log p(s_{t+1}|s_t, a_t)$$

You can find that the first and third term are not correlated to the parameter of policy $\pi_\theta(\cdot)$. So when we moving back to $\nabla_\theta Q$, we find

$$\nabla_\theta Q = \sum_\tau r(\tau)\nabla_\theta p(\tau) = \sum_\tau r(\tau)p(\tau)\nabla_\theta \log p(\tau) = \sum p_\theta(\tau)(\sum_t \nabla_\theta \log \pi_\theta(a_t|s_t))r(\tau)$$

When we sample sufficient amount of data from the environment, the above equation can be estimated via:

$$\nabla_\theta Q = \frac{1}{N}\sum_{i=1}^{N}[(\sum_t \nabla_\theta \log \pi_\theta(a_{i,t}|s_{i,t})(\sum_{t'=t}\gamma^{t'-t}r(s_{i,t'}, a_{i,t'}))]$$

This algorithm is called REINFORCE algorithm, which is a Monte Carlo Policy Gradient algorithm with long history. In this section, we will implement the it using pytorch.

The policy network is composed by two parts:

1. A basic neural network serves as the function approximator. It output raw values parameterizing the action distribution given current observation. We will reuse PytorchModel here.
2. A distribution layer builds upon the neural network to wrap the raw logits output from neural network to a distribution and provides API for sampling action and computing log probability.

Section 4.1: Build REINFORCE

```
# Run this cell without modification

class PGNetwork(nn.Module):
    def __init__(self, obs_dim, act_dim, hidden_units=128):
        super(PGNetwork, self).__init__()
        self.network = PytorchModel(obs_dim, act_dim, hidden_units)

    def forward(self, obs):
        logit = self.network(obs)

        # [TODO] Create an object of the class "torch.distributions.Categorical"
        #  with logit. Hint: don't mess up `logits`
        # Then sample an action from it.
        dist = torch.distributions.Categorical(logits=logit)
        action = dist.sample()
```

```
        return action

    def log_prob(self, obs, act):
        logits = self.network(obs)

        # [TODO] Create an object of the class "torch.distributions.Categorical"
        # Then get the log probability of the action `act` in this distribution.
        dist = torch.distributions.Categorical(logits=logits)
        log_prob = dist.log_prob(act)

        return log_prob

# Note that we do not implement GaussianPolicy here. So we can't
# apply our algorithm to the environment with continous action.



# Solve the TODOs and remove `pass`

PG_DEFAULT_CONFIG = merge_config(dict(
    normalize_advantage=True,

    clip_norm=10.0,
    clip_gradient=True,

    hidden_units=100,


    max_iteration=1000,

    train_batch_size=1000,
    gamma=0.99,
    learning_rate=0.01,


    env_name="CartPole-v0",

), DEFAULT_CONFIG)




class PGTrainer(AbstractTrainer):
    def __init__(self, config=None):
        config = merge_config(config, PG_DEFAULT_CONFIG)
        super().__init__(config)

        self.iteration = 0
        self.start_time = time.time()
        self.iteration_time = self.start_time
        self.total_timesteps = 0
        self.total_episodes = 0
```

```python
        # build the model
        self.initialize_parameters()

    def initialize_parameters(self):
        """Build the policy network and related optimizer"""
        # Detect whether you have GPU or not. Remember to call X.to(self.device)
        # if necessary.
        self.device = torch.device(
            "cuda" if torch.cuda.is_available() else "cpu"
        )

        # Build the policy network
        self.network = PGNetwork(
            self.obs_dim, self.act_dim,
            hidden_units=self.config["hidden_units"]
        ).to(self.device)

        # Build the Adam optimizer.
        self.optimizer = torch.optim.Adam(
            self.network.parameters(),
            lr=self.config["learning_rate"]
        )

    def to_tensor(self, array):
        """Transform a numpy array to a pytorch tensor"""
        return torch.from_numpy(array).type(torch.float32).to(self.device)

    def to_array(self, tensor):
        """Transform a pytorch tensor to a numpy array"""
        ret = tensor.cpu().detach().numpy()
        if ret.size == 1:
            ret = ret.item()
        return ret

    def save(self, loc="model.pt"):
        torch.save(self.network.state_dict(), loc)

    def load(self, loc="model.pt"):
        self.network.load_state_dict(torch.load(loc))

    def compute_action(self, observation, eps=None):
        """Compute the action for single observation. eps is useless here."""
        assert observation.ndim == 1
        # [TODO] Sample an action from action distribution given by the policy
        # Hint: The input of policy network is a batch of data, so you need to
        #  expand the first dimension of observation before feeding it to policy network.

        obs = to_tensor(observation).unsqueeze(0)
        action = self.network.forward(obs).item()

        return action
```

```python
def compute_log_probs(self, observation, action):
    """Compute the log probabilities of a batch of state-action pair"""
    # [TODO] Using the function of policy network to get log probs.
    # Hint: Remember to transform the data into tensor before feeding it.
    obs = to_tensor(observation)
    act = to_tensor(action)
    log_probs = self.network.log_prob(obs, act)

    return log_probs.squeeze(0)


def update_network(self, processed_samples):
    """Update the policy network"""
    advantages = self.to_tensor(processed_samples["advantages"])
    flat_obs = np.concatenate(processed_samples["obs"])
    flat_act = np.concatenate(processed_samples["act"])

    self.network.train()
    self.optimizer.zero_grad()

    log_probs = self.compute_log_probs(flat_obs, flat_act)

    assert log_probs.shape == advantages.shape, "log_probs shape {} is not " \
        "compatible with advantages {}".format(log_probs.shape, advantages.shape)

    # [TODO] Compute the loss using log probabilities and advantages.
    loss = -torch.sum(log_probs * advantages)

    loss.backward()

    # Clip the gradient
    torch.nn.utils.clip_grad_norm_(
        self.network.parameters(), self.config["clip_gradient"]
    )

    self.optimizer.step()
    self.network.eval()

    update_info = {
        "policy_loss": loss.item(),
        "mean_log_prob": torch.mean(log_probs).item(),
        "mean_advantage": torch.mean(advantages).item()
    }
    return update_info

# ===== Training-related functions =====
def collect_samples(self):
    """Here we define the pipeline to collect sample even though
    any specify functions are not implemented yet.
    """
```

```
iter_timesteps = 0
iter_episodes = 0
episode_lens = []
episode_rewards = []
episode_obs_list = []
episode_act_list = []
episode_reward_list = []
success_list = []
while iter_timesteps <= self.config["train_batch_size"]:
    obs_list, act_list, reward_list = [], [], []
    obs = self.env.reset()
    steps = 0
    episode_reward = 0
    while True:
        act = self.compute_action(obs)

        # print("ACT: ", act, type(act))

        next_obs, reward, done, step_info = self.env.step(act)

        obs_list.append(obs)
        act_list.append(act)
        reward_list.append(reward)

        obs = next_obs.copy()
        steps += 1
        episode_reward += reward
        if done or steps > self.config["max_episode_length"]:
            if "arrive_dest" in step_info:
                success_list.append(step_info["arrive_dest"])
            break
    iter_timesteps += steps
    iter_episodes += 1
    episode_rewards.append(episode_reward)
    episode_lens.append(steps)
    episode_obs_list.append(np.array(obs_list, dtype=np.float32))
    episode_act_list.append(np.array(act_list, dtype=np.float32))
    episode_reward_list.append(np.array(reward_list, dtype=np.float32))

# [TODO] Uncomment everything below and understand the data structure:
# The return `samples` is a dict that contains several fields.
# Each field (key-value pair) contains a list.
# Each element in list is a list represent the data in one trajectory (episode).
# Each episode list contains the data of that field of all time steps in that episode
# The return `sample_info` is a dict contains logging item name and its value.

samples = {
    "obs": episode_obs_list,
    "act": episode_act_list,
    "reward": episode_reward_list
}
```

```
    sample_info = {
        "iter_timesteps": iter_timesteps,
        "iter_episodes": iter_episodes,
        "performance": np.mean(episode_rewards),  # help drawing figures
        "ep_len": float(np.mean(episode_lens)),
        "ep_ret": float(np.mean(episode_rewards)),
        "episode_len": sum(episode_lens),
        "success_rate": np.mean(success_list)
    }
    return samples, sample_info

def process_samples(self, samples):
    """Process samples and add advantages in it"""
    values = []
    for reward_list in samples["reward"]:
        # reward_list contains rewards in one episode
        returns = np.zeros_like(reward_list, dtype=np.float32)
        Q = 0

        # [TODO] Scan the episode in a reverse order and compute the
        # discounted return at each time step. Fill the array `returns`
        # Each entry to the returns is the target Q value of current time step

        for i, r in reversed(list(enumerate(reward_list))):
          Q = Q * self.config["gamma"] + r
          returns[i] = Q

        values.append(returns)

    # We call the values advantage here.
    advantages = np.concatenate(values)
    # print("advan", advantages.shape)

    if self.config["normalize_advantage"]:
        # [TODO] normalize the advantage so that it's mean is
        # almost 0 and the its standard deviation is almost 1.
        mean, std = advantages.mean(), advantages.std()
        advantages = (advantages - mean)/std

    samples["advantages"] = advantages
    return samples, {}

# ===== Training iteration =====
def train(self):
    """Here we defined the training pipeline using the abstract
    functions."""
    info = dict(iteration=self.iteration)

    # [TODO] Uncomment the following block and go through the learning
    # pipeline.
```

```
        # Collect samples
        samples, sample_info = self.collect_samples()
        info.update(sample_info)

        # Process samples
        processed_samples, processed_info = self.process_samples(samples)
        info.update(processed_info)

        # Update the model
        update_info = self.update_network(processed_samples)
        info.update(update_info)


        now = time.time()
        self.iteration += 1
        self.total_timesteps += info.pop("iter_timesteps")
        self.total_episodes += info.pop("iter_episodes")

        # info["iter_time"] = now - self.iteration_time
        # info["total_time"] = now - self.start_time
        info["total_episodes"] = self.total_episodes
        info["total_timesteps"] = self.total_timesteps
        self.iteration_time = now

        # print("INFO: ", info)
        return info
```

Section 4.2: Test REINFORCE

```
# Run this cell without modification

# Test advantage computing
test_trainer = PGTrainer({"normalize_advantage": False})
test_trainer.train()
fake_sample = {"reward": [[2, 2, 2, 2, 2]]}
np.testing.assert_almost_equal(
    test_trainer.process_samples(fake_sample)[0]["reward"][0],
    fake_sample["reward"][0]
)
np.testing.assert_almost_equal(
    test_trainer.process_samples(fake_sample)[0]["advantages"],
    np.array([9.80199, 7.880798, 5.9402, 3.98, 2.], dtype=np.float32)
)

# Test advantage normalization
test_trainer = PGTrainer(
    {"normalize_advantage": True, "env_name": "LunarLander-v2"})
```

```
    {"normalize_advantage": True, "env_name": "LunarLander-v2"})
test_adv = test_trainer.process_samples(fake_sample)[0]["advantages"]
np.testing.assert_almost_equal(test_adv.mean(), 0.0)
np.testing.assert_almost_equal(test_adv.std(), 1.0)

# Test the shape of functions' returns
fake_observation = np.array([
    test_trainer.env.observation_space.sample() for i in range(10)
])
fake_action = np.array([
    test_trainer.env.action_space.sample() for i in range(10)
])
assert test_trainer.to_tensor(fake_observation).shape == torch.Size([10, 8])
assert np.array(test_trainer.compute_action(fake_observation[0])).shape == ()
assert test_trainer.compute_log_probs(fake_observation, fake_action).shape == \
       torch.Size([10])

print("Test Passed!")
```

```
Num inputs: 4, Num actions: 2
Num inputs: 8, Num actions: 4
Test Passed!
```

Section 4.3: Train REINFORCE in CartPole and see the impact of advantage normalization

```
# Run this cell without modification

pg_trainer_no_na, pg_result_no_na = run(PGTrainer, dict(
    learning_rate=0.01,
    max_episode_length=200,
    train_batch_size=200,
    env_name="CartPole-v0",
    normalize_advantage=False,  # <<== Here!

    evaluate_interval=10,
    evaluate_num_episodes=10,
), 195.0)
```

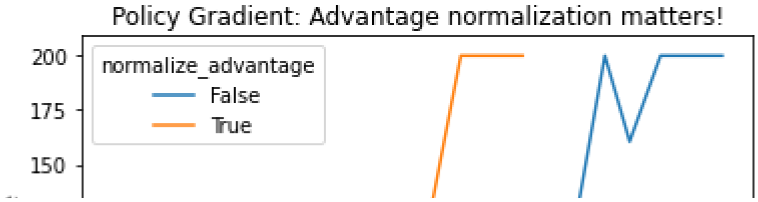
```
Num inputs: 4, Num actions: 2
(0.2s,+0.2s) Iter 0, Step 209, episodic return is 27.20. {'iteration': 0.0, 'performance
(1.2s,+1.0s) Iter 10, Step 2398, episodic return is 40.30. {'iteration': 10.0, 'performa
(2.6s,+1.4s) Iter 20, Step 4887, episodic return is 73.40. {'iteration': 20.0, 'performa
(4.6s,+2.0s) Iter 30, Step 8101, episodic return is 200.00. {'iteration': 30.0, 'perform
In 30 iteration, episodic return 200.000 is greater than reward threshold 195.0. Congrat
Environment is closed.
```

```
# Run this cell without modification

pg_trainer_na, pg_result_na = run(PGTrainer, dict(
    learning_rate=0.01,
    max_episode_length=200,
    train_batch_size=200,
    env_name="CartPole-v0",
    normalize_advantage=True,  # <<== Here!

    evaluate_interval=10,
    evaluate_num_episodes=10,
), 195.0)
```

```
Num inputs: 4, Num actions: 2
(0.2s,+0.2s) Iter 0, Step 202, episodic return is 19.60. {'iteration': 0.0, 'performance
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:3441: RuntimeWarning: M
  out=out, **kwargs)
/usr/local/lib/python3.7/dist-packages/numpy/core/_methods.py:189: RuntimeWarning: inval
  ret = ret.dtype.type(ret / rcount)
(1.3s,+1.1s) Iter 10, Step 2603, episodic return is 38.40. {'iteration': 10.0, 'performa
(3.2s,+1.9s) Iter 20, Step 5513, episodic return is 200.00. {'iteration': 20.0, 'perform
In 20 iteration, episodic return 200.000 is greater than reward threshold 195.0. Congrat
Environment is closed.
```

```
# Run this cell without modification
pg_result_no_na_df = pd.DataFrame(pg_result_no_na)
pg_result_na_df = pd.DataFrame(pg_result_na)
pg_result_no_na_df["normalize_advantage"] = False
pg_result_na_df["normalize_advantage"] = True

data=pd.concat([pg_result_no_na_df, pg_result_na_df]).reset_index()

ax = sns.lineplot(
    x="total_timesteps",
    y="performance",
    data=pd.concat([pg_result_no_na_df, pg_result_na_df]).reset_index(), hue="normalize_advan
)
ax.set_title("Policy Gradient: Advantage normalization matters!")
```

```
Text(0.5, 1.0, 'Policy Gradient: Advantage normalization matters!')
```



Section 4.4: Train REINFORCE in MetaDrive-Easy


```
# Run this cell without modification

env_name = "MetaDrive-Tut-Easy-v0"

pg_trainer_metadrive_easy, pg_trainer_metadrive_easy_result = run(PGTrainer, dict(
    train_batch_size=2000,
    normalize_advantage=True,
    max_episode_length=200,
    max_iteration=5000,
    evaluate_interval=10,
    evaluate_num_episodes=10,
    learning_rate=0.001,
    clip_norm=10.0,
    env_name=env_name
), reward_threshold=120)


pg_trainer_metadrive_easy.save("pg_trainer_metadrive_easy.pt")
```

```
WARNING:root:BaseEngine is not launched, fail to sync seed to engine!
Num inputs: 259, Num actions: 9
(8.9s,+8.9s) Iter 0, Step 2010, episodic return is 2.72. {'iteration': 0.0, 'performance
(53.3s,+44.5s) Iter 10, Step 22732, episodic return is 4.11. {'iteration': 10.0, 'perfor
(102.5s,+49.2s) Iter 20, Step 43434, episodic return is 6.10. {'iteration': 20.0, 'perfo
(155.9s,+53.4s) Iter 30, Step 64227, episodic return is 26.94. {'iteration': 30.0, 'perf
(214.1s,+58.2s) Iter 40, Step 84694, episodic return is 57.48. {'iteration': 40.0, 'perf
(281.1s,+67.0s) Iter 50, Step 105163, episodic return is 125.58. {'iteration': 50.0, 'pe
In 50 iteration, episodic return 125.581 is greater than reward threshold 120. Congratul
Environment is closed.
```

```
# Run this cell without modification

# Render the learned behavior
# NOTE: The learned agent is marked by green color.
eval_reward, eval_info = evaluate(
    policy=pg_trainer_metadrive_easy.policy,
    num_episodes=1,
    env_name=pg_trainer_metadrive_easy.env_name,
    render="topdown",  # Visualize the behaviors in top-down view
```

```
    verbose=True
)

frames = [pygame.surfarray.array3d(f).swapaxes(0, 1) for f in eval_info["frames"]]

animate(frames)

print("REINFORCE agent achieves {} return in MetaDrive easy environment.".format(eval_reward)
```

Section 5: Policy gradient with baseline

(20 / 100 points)

We compute the gradient of $Q = \mathbb{E}\sum_t r(a_t, s_t)$ w.r.t. the parameter to update the policy. Let's consider this case: when you take a so-so action that lead to positive expected return, the policy gradient is also positive and you will update your network toward this action. At the same time a potential better action is ignored.

To tackle this problem, we introduce the "baseline" when computing the policy gradient. The insight behind this is that we want to optimize the policy toward an action that are better than the "average action".

We introduce $b_t = \mathbb{E}_{a_t}\sum_{t'} \gamma^{t'-t} r(s_{t'}, a_{t'})$ as the baseline. It average the expected discount return of all possible actions at state s_t. So that the "advantage" achieved by action a_t can be evaluated via $\sum_{t'=t} \gamma^{t'-t} r(a_{t'}, s_{t'}) - b_t$

Therefore, the policy gradient becomes:

$$\nabla_\theta Q = \frac{1}{N}\sum_{i=1}^{N}[(\sum_t \nabla_\theta \log \pi_\theta(a_{i,t}|s_{i,t})(\sum_{t'} \gamma^{t'-t} r(s_{i,t'}, a_{i,t`}) - b_{i,t})]$$

In our implementation, we estimate the baseline via an extra network `self.baseline`, which has same structure of policy network but output only a scalar value. We use the output of this network to serve as the baseline, while this network is updated by fitting the true value of expected return of current state: $\mathbb{E}_{a_t}\sum_{t'} \gamma^{t'-t} r(s_{t'}, a_{t'})$

The state-action values might have large variance if the reward function has large variance. It is not easy for a neural network to predict targets with large variance and extreme values. In implementation, we use a trick to match the distribution of baseline and values. During training, we first collect a batch of target values: $\{t_i = \mathbb{E}_{a_t}\sum_{t'} \gamma^{t'-t} r(s_{t'}, a_{t'})\}_i$. Then we normalize all targets to a standard distribution with mean = 0 and std = 1. Then we ask the baseline network to fit such normalized targets.

When computing the advantages, instead of using the output of baseline network as the baseline b, we firstly match the baseline distribution with state-action values, that is we "de-standarize" the baselines. The transformed baselines $b' = f(b)$ should has the same mean and STD with the action values.

After that, we compute the advantage of current action: $adv_{i,t} = \sum_{t'} \gamma^{t'-t} r(s_{i,t'}, a_{i,t'}) - b'_{i,t}$

By doing this, we mitigate the instability of training baseline.

Hint: We suggest to normalize an array via: `(x - x.mean()) / max(x.std(), 1e-6)`. The max term can mitigate numeraical instability.

Section 5.1: Build PG method with baseline

```
class PolicyGradientWithBaselineTrainer(PGTrainer):
    def initialize_parameters(self):
        # Build the actor in name of self.policy
        super().initialize_parameters()

        # Build the baseline network using Net class.
        self.baseline = PytorchModel(
            self.obs_dim, 1, self.config["hidden_units"]
        ).to(self.device)

        self.baseline_loss = nn.MSELoss()

        self.baseline_optimizer = torch.optim.Adam(
            self.baseline.parameters(),
            lr=self.config["learning_rate"]
        )

    def process_samples(self, samples):
        # Call the original process_samples function to get advantages
        tmp_samples, _ = super().process_samples(samples)
        values = tmp_samples["advantages"]
        samples["values"] = values  # We add q_values into samples

        # [TODO] flatten the observations in all trajectories (still a numpy array)
        obs = np.concatenate(samples["obs"])

        assert obs.ndim == 2
        assert obs.shape[1] == self.obs_dim

        obs = self.to_tensor(obs)
        samples["flat_obs"] = obs

        # [TODO] Compute the baseline by feeding observation to baseline network
```

```
        # Hint: `baselines` is a numpy array with the same shape of `values`,
        #  that is: (batch size, )
        baselines = self.to_array(self.baseline(obs).squeeze(1))

        assert baselines.shape == values.shape

        # [TODO] Match the distribution of baselines to the values.
        # Hint: We expect to see baselines.std() almost equals to values.std(),
        #  and baselines.mean() almost equals to values.mean()
        baselines = (baselines - baselines.mean()) / max(baselines.std(), 1e-6)

        # Compute the advantage
        advantages = values - baselines
        samples["advantages"] = advantages
        process_info = {"mean_baseline": float(np.mean(baselines))}
        return samples, process_info

    def update_model(self, processed_samples):
        update_info = {}
        update_info.update(self.update_baseline(processed_samples))
        update_info.update(self.update_policy(processed_samples))
        return update_info

    def update_baseline(self, processed_samples):
        self.baseline.train()
        obs = processed_samples["flat_obs"]

        # [TODO] Normalize the values to mean=0, std=1.
        values = processed_samples["values"]
        values = (values - values.mean()) / max(values.std(), 1e-6)

        values = self.to_tensor(values[:, np.newaxis])

        baselines = self.baseline(obs)

        self.baseline_optimizer.zero_grad()
        loss = self.baseline_loss(input=baselines, target=values)
        loss.backward()

        # Clip the gradient
        torch.nn.utils.clip_grad_norm_(
            self.baseline.parameters(), self.config["clip_gradient"]
        )

        self.baseline_optimizer.step()
        self.baseline.eval()
        return dict(baseline_loss=loss.item())
```

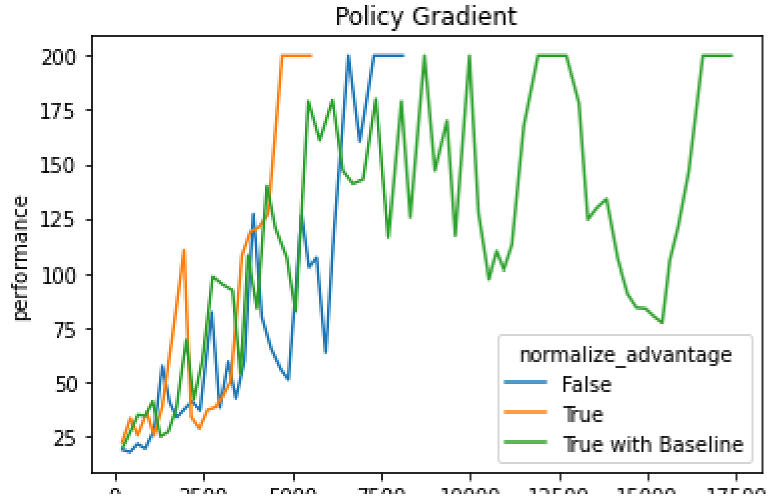
Section 5.2: Run PG w/ baseline in CartPole

```
# Run this cell without modification

pg_trainer_wb_cartpole, pg_trainer_wb_cartpole_result = run(PolicyGradientWithBaselineTrainer
    learning_rate=0.01,
    max_episode_length=200,
    train_batch_size=200,

    env_name="CartPole-v0",
    normalize_advantage=True,

    evaluate_interval=10,
    evaluate_num_episodes=10,
), 195.0)
```

```
Num inputs: 4, Num actions: 2
Num inputs: 4, Num actions: 1
/usr/local/lib/python3.7/dist-packages/numpy/core/fromnumeric.py:3441: RuntimeWarning: M
  out=out, **kwargs)
/usr/local/lib/python3.7/dist-packages/numpy/core/_methods.py:189: RuntimeWarning: inval
  ret = ret.dtype.type(ret / rcount)
(0.3s,+0.3s) Iter 0, Step 219, episodic return is 18.40. {'iteration': 0.0, 'performance
(2.0s,+1.7s) Iter 10, Step 2460, episodic return is 57.70. {'iteration': 10.0, 'performa
(4.5s,+2.5s) Iter 20, Step 5092, episodic return is 129.80. {'iteration': 20.0, 'perforn
(6.5s,+2.0s) Iter 30, Step 8311, episodic return is 182.70. {'iteration': 30.0, 'perforn
(8.2s,+1.7s) Iter 40, Step 11175, episodic return is 146.10. {'iteration': 40.0, 'perfor
(9.8s,+1.6s) Iter 50, Step 14434, episodic return is 84.30. {'iteration': 50.0, 'perforn
(11.8s,+2.0s) Iter 60, Step 17359, episodic return is 200.00. {'iteration': 60.0, 'perfo
In 60 iteration, episodic return 200.000 is greater than reward threshold 195.0. Congrat
Environment is closed.
```

```
# Run this cell without modification

pg_result_no_na_df = pd.DataFrame(pg_result_no_na)
pg_result_no_na_df["normalize_advantage"] = "False"
pg_result_na_df = pd.DataFrame(pg_result_na)
pg_result_na_df["normalize_advantage"] = "True"
pg_trainer_wb_cartpole_result_df = pd.DataFrame(pg_trainer_wb_cartpole_result)
pg_trainer_wb_cartpole_result_df["normalize_advantage"] = "True with Baseline"
pg_result_df = pd.concat([pg_result_no_na_df, pg_result_na_df, pg_trainer_wb_cartpole_result_
ax = sns.lineplot(
    x="total_timesteps",
    y="performance",
    data=pg_result_df, hue="normalize_advantage",
)
ax.set_title("Policy Gradient")
```

```
Text(0.5, 1.0, 'Policy Gradient')
```

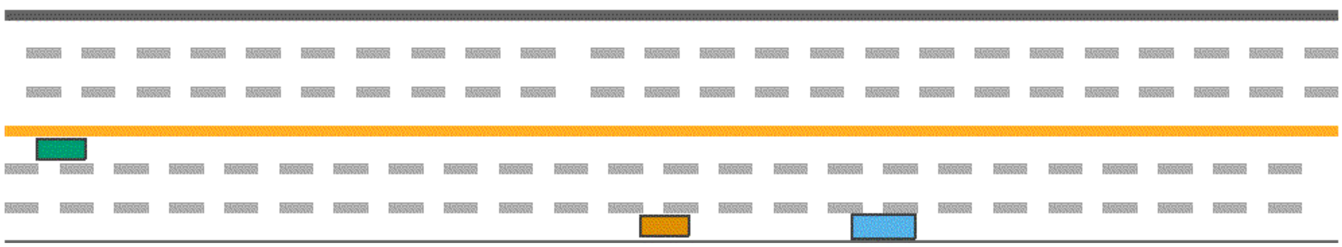


Section 5.3: Run PG w/ baseline in MetaDrive-Easy

```
# Run this cell without modification

env_name = "MetaDrive-Tut-Easy-v0"

pg_trainer_wb_metadrive_easy, pg_trainer_wb_metadrive_easy_result = run(
    PolicyGradientWithBaselineTrainer,
    dict(
        train_batch_size=2000,
        normalize_advantage=True,
        max_episode_length=200,
        max_iteration=5000,
        evaluate_interval=10,
        evaluate_num_episodes=10,
        learning_rate=0.001,
        clip_norm=10.0,
        env_name=env_name
    ),
    reward_threshold=120
)

pg_trainer_wb_metadrive_easy.save("pg_trainer_wb_metadrive_easy.pt")
```

```
WARNING:root:BaseEngine is not launched, fail to sync seed to engine!
Num inputs: 259, Num actions: 9
Num inputs: 259, Num actions: 1
(8.7s,+8.7s) Iter 0, Step 2163, episodic return is 2.90. {'iteration': 0.0, 'performance
(54.6s,+45.9s) Iter 10, Step 22652, episodic return is 7.54. {'iteration': 10.0, 'perfor
(111.2s,+56.6s) Iter 20, Step 43178, episodic return is 57.52. {'iteration': 20.0, 'perf
(176.1s,+64.8s) Iter 30, Step 63613, episodic return is 125.58. {'iteration': 30.0, 'per
In 30 iteration, episodic return 125.581 is greater than reward threshold 120. Congratul
Environment is closed.
```

```
# Run this cell without modification

# Render the learned behavior
# NOTE: The learned agent is marked by green color.
eval_reward, eval_info = evaluate(
    policy=pg_trainer_wb_metadrive_easy.policy,
    num_episodes=1,
    env_name=pg_trainer_wb_metadrive_easy.env_name,
    render="topdown",  # Visualize the behaviors in top-down view
    verbose=True
)

frames = [pygame.surfarray.array3d(f).swapaxes(0, 1) for f in eval_info["frames"]]

animate(frames)

print("PG agent achieves {} return in MetaDrive easy environment.".format(eval_reward))
```



```
# Run this cell without modification

pg_trainer_wb_metadrive_easy_result_df = pd.DataFrame(pg_trainer_wb_metadrive_easy_result)
pg_trainer_wb_metadrive_easy_result_df["with Baseline"] = True


pg_trainer_metadrive_easy_result_df = pd.DataFrame(pg_trainer_metadrive_easy_result)
pg_trainer_metadrive_easy_result_df["with Baseline"] = False

ax = sns.lineplot(
    x="total_timesteps",
    y="performance",
    data=pd.concat([pg_trainer_wb_metadrive_easy_result_df, pg_trainer_metadrive_easy_result_
    hue="with Baseline",
)
ax.set_title("Policy Gradient in MetaDrive: Baseline matters!")
```

```
Text(0.5, 1.0, 'Policy Gradient in MetaDrive: Baseline matters!')
```

Section 5.4: Run PG with baseline in MetaDrive-Hard

Goal: Acheive episodic return > 50.

BONUS!! can be earned if you can improve the training performance by adjusting hyper-parameters and optimizing code. Improvement means achieving > 0.0 success rate. However, I can't promise that it is feasible to use PG with or without algorithm to solve this task. Please creates a independent markdown cell to highlight your improvement.


```
# Run this cell without modification

env_name = "MetaDrive-Tut-Hard-v0"

pg_trainer_wb_metadrive_hard, pg_trainer_wb_metadrive_hard_result = run(
    PolicyGradientWithBaselineTrainer,
    dict(
        train_batch_size=4000,
        normalize_advantage=True,
        max_episode_length=1000,
        max_iteration=5000,
        evaluate_interval=10,
        evaluate_num_episodes=10,
        learning_rate=0.001,
        clip_norm=10.0,
        env_name=env_name
    ),
    reward_threshold=120
)

pg_trainer_wb_metadrive_hard.save("pg_trainer_wb_metadrive_hard.pt")
```

```
WARNING:root:BaseEngine is not launched, fail to sync seed to engine!
Num inputs: 259, Num actions: 25
Num inputs: 259, Num actions: 1
(79.1s,+79.1s) Iter 0, episodic return is 12.29.
(369.7s,+290.6s) Iter 10, episodic return is 15.48.
(626.9s,+257.2s) Iter 20, episodic return is 23.20.
(892.1s,+265.3s) Iter 30, episodic return is 18.92.
(1162.2s,+270.0s) Iter 40, episodic return is 43.23.
(1442.7s,+280.6s) Iter 50, episodic return is 53.04.
(1723.8s,+281.1s) Iter 60, episodic return is 54.52.
(2004.9s,+281.1s) Iter 70, episodic return is 51.89.
(2289.9s,+285.0s) Iter 80, episodic return is 55.25.
(2575.5s,+285.7s) Iter 90, episodic return is 54.94.
(2859.7s,+284.2s) Iter 100, episodic return is 56.15.
(3149.0s,+289.3s) Iter 110, episodic return is 51.85.
(3433.9s,+284.9s) Iter 120, episodic return is 55.86.
(3717.1s,+283.2s) Iter 130, episodic return is 59.07.
(4004.5s,+287.4s) Iter 140, episodic return is 58.09.
(4292.6s,+288.0s) Iter 150, episodic return is 56.94.
(4576.7s,+284.1s) Iter 160, episodic return is 57.04.
(4862.1s,+285.5s) Iter 170, episodic return is 53.65.
(5157.4s,+295.2s) Iter 180, episodic return is 58.56.
(5446.2s,+288.9s) Iter 190, episodic return is 56.86.
(5739.7s,+293.4s) Iter 200, episodic return is 59.26.
(6040.0s,+300.4s) Iter 210, episodic return is 57.42.
(6343.5s,+303.5s) Iter 220, episodic return is 55.03.
(6644.1s,+300.6s) Iter 230, episodic return is 54.90.
(6945.6s,+301.5s) Iter 240, episodic return is 57.98.
(7237.3s,+291.7s) Iter 250, episodic return is 56.16.
(7536.1s,+298.8s) Iter 260, episodic return is 57.55.
(7830.9s,+294.8s) Iter 270, episodic return is 54.40.
(8148.3s,+317.3s) Iter 280, episodic return is 57.98.
(8449.6s,+301.3s) Iter 290, episodic return is 61.01.
(8756.2s,+306.6s) Iter 300, episodic return is 54.13.
(9047.7s,+291.5s) Iter 310, episodic return is 59.33.
(9338.1s,+290.4s) Iter 320, episodic return is 57.23.
(9633.5s,+295.4s) Iter 330, episodic return is 54.47.
(9931.4s,+297.9s) Iter 340, episodic return is 56.07.
(10229.0s,+297.6s) Iter 350, episodic return is 52.66.
(10525.3s,+296.3s) Iter 360, episodic return is 49.64.
(10823.3s,+298.1s) Iter 370, episodic return is 52.30.
(11115.3s,+292.0s) Iter 380, episodic return is 56.77.
(11401.2s,+285.9s) Iter 390, episodic return is 56.82.
(11700.1s,+298.9s) Iter 400, episodic return is 56.29.
(11989.8s,+289.6s) Iter 410, episodic return is 54.98.
(12285.4s,+295.7s) Iter 420, episodic return is 54.42.
(12576.9s,+291.5s) Iter 430, episodic return is 56.84.
(12868.2s,+291.4s) Iter 440, episodic return is 55.23.
(13162.1s,+293.8s) Iter 450, episodic return is 52.74.
(13464.7s,+302.6s) Iter 460, episodic return is 60.56.
(13762.2s,+297.6s) Iter 470, episodic return is 54.78.
(14060.7s,+298.5s) Iter 480, episodic return is 58.03.
(14367.4s,+306.7s) Iter 490, episodic return is 58.77.
(14670.6s,+303.3s) Iter 500, episodic return is 59.09.
(14979.4s,+308.8s) Iter 510, episodic return is 53.65.
(15287.1s,+307.6s) Iter 520, episodic return is 59.32.
```

```
(15602.0s,+315.0s) Iter 530, episodic return is 59.06.
(15910.9s,+308.9s) Iter 540, episodic return is 56.38.
(16225.9s,+314.9s) Iter 550, episodic return is 55.74.
(16536.4s,+310.5s) Iter 560, episodic return is 53.87.
(16850.6s,+314.2s) Iter 570, episodic return is 50.71.
(17153.8s,+303.2s) Iter 580, episodic return is 56.33.
Environment is closed.
---------------------------------------------------------------------------
KeyboardInterrupt                         Traceback (most recent call last)
<ipython-input-94-ab4fd2e3d8c5> in <module>
     16         env_name=env_name
     17     ),
---> 18     reward_threshold=120
```

```
# Run this cell without modification

# Render the learned behavior
# NOTE: The learned agent is marked by green color.
eval_reward, eval_info = evaluate(
    policy=pg_trainer_wb_metadrive_hard.policy,
    num_episodes=1,
    env_name=pg_trainer_wb_metadrive_hard.env_name,
    render="topdown",  # Visualize the behaviors in top-down view
    verbose=True
)

frames = [pygame.surfarray.array3d(f).swapaxes(0, 1) for f in eval_info["frames"]]

animate(frames)

print("PG agent achieves {} return in MetaDrive hard environment.".format(eval_reward))
```

Conclusion and Discussion

In this assignment, we learn how to build naive Q learning, Deep Q Network and Policy Gradient methods.

In the next markdown cell, you can write whatever you like. Like the suggestion on the course, the confusing problems in the assignments, and so on.

If you want to do more investigation, feel free to open new cells via `Esc + B` after the next cells and write codes in it, so that you can reuse some result in this notebook. Remember to write sufficient comments and documents to let others know what you are doing.

Following the submission instruction in the assignment to submit your assignment. Thank you!
