Spring 2024 6.8200 Computational Sensorimotor Learning Assignment 4

In this assignment, we will work on learning from demonstrations.

You will need to **answer the bolded questions** and **fill in the missing code snippets** (marked by **TODO**).

There are **145** total points to be had in this PSET and an addition **30 bonus** points. `ctrl-f` for "pts" to ensure you don't miss questions.

```
!pip install numpy==1.23.1 > /dev/null 2>&1
!pip install "setuptools<58.0.0" > /dev/null 2>&1
!pip install pybullet > /dev/null 2>&1
!pip install git+https://github.com/taochenshh/easyrl.git > /dev/null
2>&1
!pip install git+https://github.com/Improbable-AI/airobot.git >
/dev/null 2>&1
!pip install gym pyvirtualdisplay > /dev/null 2>&1
!apt-get install -y xvfb python-opengl ffmpeg > /dev/null 2>&1
!apt install chromium-browser xvfb
!apt install xvfb
```

```
Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
The following additional packages will be installed:
  apparmor libfontenc1 libfuse3-3 liblzo2-2 libudev1 libxfont2
libxkbfile1 snapd squashfs-tools
  systemd-hwe-hwdb udev x11-xkb-utils xfonts-base xfonts-encodings
xfonts-utils xserver-common
Suggested packages:
  apparmor-profiles-extra apparmor-utils fuse3 zenity | kdialog
The following NEW packages will be installed:
  apparmor chromium-browser libfontenc1 libfuse3-3 liblzo2-2 libxfont2
libxkbfile1 snapd
  squashfs-tools systemd-hwe-hwdb udev x11-xkb-utils xfonts-base
xfonts-encodings xfonts-utils
  xserver-common xvfb
The following packages will be upgraded:
  libudev1
1 upgraded, 17 newly installed, 0 to remove and 37 not upgraded.
Need to get 34.2 MB of archives.
After this operation, 128 MB of additional disk space will be used.
Get:1 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64
apparmor amd64 3.0.4-2ubuntu2.3 [595 kB]
Get:2 http://archive.ubuntu.com/ubuntu jammy/main amd64 liblzo2-2
```

```
amd64 2.10-2build3 [53.7 kB]
Get:3 http://archive.ubuntu.com/ubuntu jammy/main amd64 squashfs-tools
amd64 1:4.5-3build1 [159 kB]
Get:4 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64
libudev1 amd64 249.11-0ubuntu3.12 [78.2 kB]
Get:5 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 udev
amd64 249.11-0ubuntu3.12 [1,557 kB]
Get:6 http://archive.ubuntu.com/ubuntu jammy/main amd64 libfuse3-3
amd64 3.10.5-1build1 [81.2 kB]
Get:7 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64 snapd
amd64 2.58+22.04.1 [23.8 MB]
Get:8 http://archive.ubuntu.com/ubuntu jammy-updates/universe amd64
chromium-browser amd64 1:85.0.4183.83-0ubuntu2.22.04.1 [49.2 kB]
Get:9 http://archive.ubuntu.com/ubuntu jammy/main amd64 libfontenc1
amd64 1:1.1.4-1build3 [14.7 kB]
Get:10 http://archive.ubuntu.com/ubuntu jammy/main amd64 libxfont2
amd64 1:2.0.5-1build1 [94.5 kB]
Get:11 http://archive.ubuntu.com/ubuntu jammy/main amd64 libxkbfile1
amd64 1:1.1.0-1build3 [71.8 kB]
Get:12 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64
systemd-hwe-hwdb all 249.11.5 [3,228 B]
Get:13 http://archive.ubuntu.com/ubuntu jammy/main amd64 x11-xkb-utils
amd64 7.7+5build4 [172 kB]
Get:14 http://archive.ubuntu.com/ubuntu jammy/main amd64 xfonts-
encodings all 1:1.0.5-0ubuntu2 [578 kB]
Get:15 http://archive.ubuntu.com/ubuntu jammy/main amd64 xfonts-utils
amd64 1:7.7+6build2 [94.6 kB]
Get:16 http://archive.ubuntu.com/ubuntu jammy/main amd64 xfonts-base
all 1:1.0.5 [5,896 kB]
Get:17 http://archive.ubuntu.com/ubuntu jammy-updates/main amd64
xserver-common all 2:21.1.4-2ubuntu1.7~22.04.8 [28.6 kB]
Get:18 http://archive.ubuntu.com/ubuntu jammy-updates/universe amd64
xvfb amd64 2:21.1.4-2ubuntu1.7~22.04.8 [863 kB]
Fetched 34.2 MB in 1s (61.0 MB/s)
Preconfiguring packages ...
Selecting previously unselected package apparmor.
(Reading database ... 121752 files and directories currently
installed.)
Preparing to unpack .../apparmor_3.0.4-2ubuntu2.3_amd64.deb ...
Unpacking apparmor (3.0.4-2ubuntu2.3) ...
Selecting previously unselected package liblzo2-2:amd64.
Preparing to unpack .../liblzo2-2_2.10-2build3_amd64.deb ...
Unpacking liblzo2-2:amd64 (2.10-2build3) ...
Selecting previously unselected package squashfs-tools.
Preparing to unpack .../squashfs-tools_1%3a4.5-3build1_amd64.deb ...
Unpacking squashfs-tools (1:4.5-3build1) ...
Preparing to unpack .../libudev1_249.11-0ubuntu3.12_amd64.deb ...
Unpacking libudev1:amd64 (249.11-0ubuntu3.12) over (249.11-
0ubuntu3.10) ...
```

```
Setting up libudev1:amd64 (249.11-0ubuntu3.12) ...
Selecting previously unselected package udev.
(Reading database ... 121960 files and directories currently
installed.)
Preparing to unpack .../udev_249.11-0ubuntu3.12_amd64.deb ...
Unpacking udev (249.11-0ubuntu3.12) ...
Selecting previously unselected package libfuse3-3:amd64.
Preparing to unpack .../libfuse3-3_3.10.5-1build1_amd64.deb ...
Unpacking libfuse3-3:amd64 (3.10.5-1build1) ...
Selecting previously unselected package snapd.
Preparing to unpack .../snapd_2.58+22.04.1_amd64.deb ...
Unpacking snapd (2.58+22.04.1) ...
Setting up apparmor (3.0.4-2ubuntu2.3) ...
Created symlink
/etc/systemd/system/sysinit.target.wants/apparmor.service →
/lib/systemd/system/apparmor.service.
Setting up liblzo2-2:amd64 (2.10-2build3) ...
Setting up squashfs-tools (1:4.5-3build1) ...
Setting up udev (249.11-0ubuntu3.12) ...
invoke-rc.d: could not determine current runlevel
invoke-rc.d: policy-rc.d denied execution of start.
Setting up libfuse3-3:amd64 (3.10.5-1build1) ...
Setting up snapd (2.58+22.04.1) ...
Created symlink /etc/systemd/system/multi-user.target.wants/snapd.aa-
prompt-listener.service → /lib/systemd/system/snapd.aa-prompt-
listener.service.
Created symlink
/etc/systemd/system/multi-user.target.wants/snapd.apparmor.service
→ /lib/systemd/system/snapd.apparmor.service.
Created symlink
/etc/systemd/system/multi-user.target.wants/snapd.autoimport.service →
/lib/systemd/system/snapd.autoimport.service.
Created symlink
/etc/systemd/system/multi-user.target.wants/snapd.core-fixup.service →
/lib/systemd/system/snapd.core-fixup.service.
Created symlink
/etc/systemd/system/multi-user.target.wants/snapd.recovery-chooser-
trigger.service → /lib/systemd/system/snapd.recovery-chooser-
trigger.service.
Created symlink
/etc/systemd/system/multi-user.target.wants/snapd.seeded.service →
/lib/systemd/system/snapd.seeded.service.
Created symlink
/etc/systemd/system/cloud-final.service.wants/snapd.seeded.service
→ /lib/systemd/system/snapd.seeded.service.
Unit /lib/systemd/system/snapd.seeded.service is added as a dependency
to a non-existent unit cloud-final.service.
Created symlink
/etc/systemd/system/multi-user.target.wants/snapd.service →
```

```
/lib/systemd/system/snapd.service.
Created symlink /etc/systemd/system/timers.target.wants/snapd.snap-
repair.timer → /lib/systemd/system/snapd.snap-repair.timer.
Created symlink /etc/systemd/system/sockets.target.wants/snapd.socket
→ /lib/systemd/system/snapd.socket.
Created symlink /etc/systemd/system/final.target.wants/snapd.system-
shutdown.service → /lib/systemd/system/snapd.system-shutdown.service.
Selecting previously unselected package chromium-browser.
(Reading database ... 122193 files and directories currently
installed.)
Preparing to unpack .../00-chromium-browser_1%3a85.0.4183.83-
0ubuntu2.22.04.1_amd64.deb ...
=> Installing the chromium snap
==> Checking connectivity with the snap store
===> System doesn't have a working snapd, skipping
Unpacking chromium-browser (1:85.0.4183.83-0ubuntu2.22.04.1) ...
Selecting previously unselected package libfontenc1:amd64.
Preparing to unpack .../01-libfontenc1_1%3a1.1.4-1build3_amd64.deb ...
Unpacking libfontenc1:amd64 (1:1.1.4-1build3) ...
Selecting previously unselected package libxfont2:amd64.
Preparing to unpack .../02-libxfont2_1%3a2.0.5-1build1_amd64.deb ...
Unpacking libxfont2:amd64 (1:2.0.5-1build1) ...
Selecting previously unselected package libxkbfile1:amd64.
Preparing to unpack .../03-libxkbfile1_1%3a1.1.0-1build3_amd64.deb ...
Unpacking libxkbfile1:amd64 (1:1.1.0-1build3) ...
Selecting previously unselected package systemd-hwe-hwdb.
Preparing to unpack .../04-systemd-hwe-hwdb_249.11.5_all.deb ...
Unpacking systemd-hwe-hwdb (249.11.5) ...
Selecting previously unselected package x11-xkb-utils.
Preparing to unpack .../05-x11-xkb-utils_7.7+5build4_amd64.deb ...
Unpacking x11-xkb-utils (7.7+5build4) ...
Selecting previously unselected package xfonts-encodings.
Preparing to unpack .../06-xfonts-encodings_1%3a1.0.5-0ubuntu2_all.deb
...
Unpacking xfonts-encodings (1:1.0.5-0ubuntu2) ...
Selecting previously unselected package xfonts-utils.
Preparing to unpack .../07-xfonts-utils_1%3a7.7+6build2_amd64.deb ...
Unpacking xfonts-utils (1:7.7+6build2) ...
Selecting previously unselected package xfonts-base.
Preparing to unpack .../08-xfonts-base_1%3a1.0.5_all.deb ...
Unpacking xfonts-base (1:1.0.5) ...
Selecting previously unselected package xserver-common.
Preparing to unpack .../09-xserver-common_2%3a21.1.4-
2ubuntu1.7~22.04.8_all.deb ...
Unpacking xserver-common (2:21.1.4-2ubuntu1.7~22.04.8) ...
Selecting previously unselected package xvfb.
Preparing to unpack .../10-xvfb_2%3a21.1.4-
2ubuntu1.7~22.04.8_amd64.deb ...
Unpacking xvfb (2:21.1.4-2ubuntu1.7~22.04.8) ...
```

```
Setting up libfontenc1:amd64 (1:1.1.4-1build3) ...
Setting up xfonts-encodings (1:1.0.5-0ubuntu2) ...
Setting up systemd-hwe-hwdb (249.11.5) ...
Setting up chromium-browser (1:85.0.4183.83-0ubuntu2.22.04.1) ...
update-alternatives: using /usr/bin/chromium-browser to provide
/usr/bin/x-www-browser (x-www-browser) in auto mode
update-alternatives: using /usr/bin/chromium-browser to provide
/usr/bin/gnome-www-browser (gnome-www-browser) in auto mode
Setting up libxkbfile1:amd64 (1:1.1.0-1build3) ...
Setting up libxfont2:amd64 (1:2.0.5-1build1) ...
Setting up x11-xkb-utils (7.7+5build4) ...
Setting up xfonts-utils (1:7.7+6build2) ...
Setting up xfonts-base (1:1.0.5) ...
Setting up xserver-common (2:21.1.4-2ubuntu1.7~22.04.8) ...
Setting up xvfb (2:21.1.4-2ubuntu1.7~22.04.8) ...
Processing triggers for man-db (2.10.2-1) ...
Processing triggers for dbus (1.12.20-2ubuntu4.1) ...
Processing triggers for udev (249.11-0ubuntu3.12) ...
Processing triggers for fontconfig (2.13.1-4.2ubuntu5) ...
Processing triggers for hicolor-icon-theme (0.17-2) ...
Processing triggers for libc-bin (2.35-0ubuntu3.4) ...
/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_0.so.3 is not a
symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind.so.3 is not a symbolic
link

/sbin/ldconfig.real: /usr/local/lib/libtbbbind_2_5.so.3 is not a
symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc.so.2 is not a
symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbbmalloc_proxy.so.2 is not a
symbolic link

/sbin/ldconfig.real: /usr/local/lib/libtbb.so.12 is not a symbolic
link

Reading package lists... Done
Building dependency tree... Done
Reading state information... Done
xvfb is already the newest version (2:21.1.4-2ubuntu1.7~22.04.8).
0 upgraded, 0 newly installed, 0 to remove and 37 not upgraded.
```

```python
import os
import torch
import gym
import pickle
import pprint
```

```
import time
import pybullet as p
import pybullet_data as pd
import pybullet_envs
import airobot as ar
import numpy as np
np.bool = np.bool_
import pandas as pd
import matplotlib.pyplot as plt
import torch.optim as optim
import torch.nn.functional as F
from typing import Any
from matplotlib import animation
from IPython.display import HTML
from matplotlib import pylab
from dataclasses import dataclass
from airobot import Robot
from airobot.utils.common import quat2euler
from airobot.utils.common import euler2quat
from gym import spaces
from gym.envs.registration import registry, register
from tensorboard.backend.event_processing.event_accumulator import
EventAccumulator
from tqdm.notebook import tqdm
from torch import nn
from torch.utils.data import Dataset
from torch.utils.data import DataLoader
from pathlib import Path
from copy import deepcopy
from itertools import count
from easyrl.agents.ppo_agent import PPOAgent
from easyrl.utils.common import save_traj
from easyrl.configs import cfg
from easyrl.configs import set_config
from easyrl.configs.command_line import cfg_from_cmd
from easyrl.engine.ppo_engine import PPOEngine
from easyrl.models.categorical_policy import CategoricalPolicy
from easyrl.models.diag_gaussian_policy import DiagGaussianPolicy
from easyrl.models.mlp import MLP
from easyrl.models.value_net import ValueNet
from easyrl.agents.base_agent import BaseAgent
from easyrl.utils.torch_util import DictDataset
from easyrl.utils.torch_util import load_state_dict
from easyrl.utils.torch_util import load_torch_model
from easyrl.runner.nstep_runner import EpisodicRunner
from easyrl.utils.torch_util import save_model
from easyrl.utils.torch_util import action_entropy
from easyrl.utils.torch_util import action_from_dist
from easyrl.utils.torch_util import action_log_prob
```

```
from easyrl.utils.torch_util import clip_grad
from easyrl.utils.common import set_random_seed
from easyrl.utils.gym_util import make_vec_env
from easyrl.utils.common import load_from_json
from easyrl.utils.torch_util import freeze_model
from easyrl.utils.torch_util import move_to
from easyrl.utils.torch_util import torch_float
from easyrl.utils.torch_util import torch_to_np
from base64 import b64encode
from IPython import display as ipythondisplay
%matplotlib inline
```

```
/usr/local/lib/python3.10/dist-packages/gym/envs/registration.py:440:
UserWarning: WARN: The `registry.env_specs` property along with
`EnvSpecTree` is deprecated. Please use `registry` directly as a
dictionary instead.
  logger.warn(
```

```
from google.colab import drive

drive.mount('/content/drive/')
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
Mounted at /content/drive/
```

```
from pyvirtualdisplay import Display
display = Display(visible=0, size=(1400, 900))
display.start()
```

```
<pyvirtualdisplay.display.Display at 0x7ca1d0080670>
```

```
def play_video(video_dir, video_file=None, video_id=None):
    """
      Parameters:
      - video_dir (str): The directory path where video files are
located. This is used if `video_file` is not provided.
      - video_file (str, optional): The path to a specific video file
to play. If None, the function searches for
        'render_video.mp4' in `video_dir`.

      Returns:
        - None: This function does not return any value. It directly
displays the video within the IPython notebook.
    """
    if video_file is None:
```

```
        video_dir = Path(video_dir)
        video_files = list(video_dir.glob(f'**/render_video.mp4'))
        if video_id is not None:
            video_files = [x for x in video_files if f'{video_id:06d}'
in x.as_posix()]
        video_files.sort()
        video_file = video_files[-1]
    else:
        video_file = Path(video_file)
    compressed_file = video_file.parent.joinpath('comp.mp4')
    os.system(f"ffmpeg -i {video_file} -filter:v 'setpts=2.0*PTS' -
vcodec libx264 {compressed_file.as_posix()}")
    mp4 = open(compressed_file.as_posix(),'rb').read()
    data_url = "data:video/mp4;base64," + b64encode(mp4).decode()
    ipythondisplay.display(HTML("""
    <video width=400 controls>
        <source src="%s" type="video/mp4">
    </video>
    """ % data_url))

# read tf log file
def read_tf_log(log_dir):
    """
        Parameters:
      - log_dir (str): The directory path where TensorFlow log files
are located. The function searches for files
        starting with 'events.' within this directory and its
subdirectories.

      Returns:
      - Tuple[List[int], List[float], List[float]]: A tuple containing
three lists:
          - steps (List[int]): A list of steps at which each episode's
success rate was recorded.
          - returns (List[float]): A list of mean returns for each
episode.
          - success_rate (List[float]): A list of success rates for
each episode.
        Returns None if no log files are found or if there's an error
in extracting scalar values.
    """
    log_dir = Path(log_dir)
    print(f'Log dir is : {log_dir}, exists :
{os.path.exists(log_dir)}')
    log_files = list(log_dir.glob(f'**/events.*'))
    if len(log_files) < 1:
        return None
    log_file = log_files[0]
    event_acc = EventAccumulator(log_file.as_posix())
```

```python
    event_acc.Reload()
    tags = event_acc.Tags()
    try:
        scalar_success = event_acc.Scalars('train/episode_success')
        success_rate = [x.value for x in scalar_success]
        steps = [x.step for x in scalar_success]
        scalar_return = event_acc.Scalars('train/episode_return/mean')
        returns = [x.value for x in scalar_return]
    except:
        return None
    return steps, returns, success_rate


def plot_curves(data_dict, title):
    """
        Parameters:
      - data_dict (Dict[str, List[List[float]]]): A dictionary where
each key is a label string and each value is a list
        containing two lists: the first list for x-values and the
second for y-values of the curve.
      - title (str): The title of the plot.

      This function does not return anything. It directly displays the
plot.
    """
    # {label: [x, y]}
    fig, ax = plt.subplots(figsize=(8, 6))
    labels = data_dict.keys()
    for label, data in data_dict.items():
        x = data[0]
        y = data[1]
        ax.plot(x, y, label=label)
    ax.set_title(title)
    ax.legend()

def set_random_seed(seed):
    """
        Parameters:
       - seed (int): set random seed.
    """
    np.random.seed(seed)
    torch.manual_seed(seed)

# set random seed
seed = 0
set_random_seed(seed=seed)
```

Environment (Pusher)

In this assignment, we will use the Pusher environment that we used in HW3. We modified the environment so that the goal locations are randomly sampled within a small region. Below, we specify the goal bounds using the variable self._goal_bounds.

```
class URRobotPusherGym(gym.Env):
    """
    A gym environment for a robot arm to learn pushing objects towards
a goal position in a simulated environment.

    Attributes:
    - action_space (gym.spaces.Box): The action space of the
environment, defining the allowed actions.
    - observation_space (gym.spaces.Box): The observation space of the
environment, defining the structure of observations.
    - robot (Robot): The robot object, providing an interface to
control and retrieve information from the robot arm.
    """
    def __init__(self,
                 action_repeat=10,
                 gui=False,
                 max_episode_length=30,
                 dist_threshold=0.05):
        """
        Initializes the gym environment with specified parameters.
        Parameters:
        - action_repeat (int, optional): The number of times an action
is repeated. Defaults to 10.
        - gui (bool, optional): If True, the PyBullet GUI is enabled
for visualization. Defaults to False.
        - max_episode_length (int, optional): The maximum length of an
episode. Defaults to 30.
        - dist_threshold (float, optional): The distance threshold to
consider the task as successful. Defaults to 0.05.
        """
        self._action_repeat = action_repeat
        self._max_episode_length = max_episode_length
        self._dist_threshold = dist_threshold

        self._xy_bounds = np.array([[0.23, 0.78],  # [xmin, xmax]
                                    [-0.35, 0.3]])  # [ymin, ymax]
        self._goal_bounds = np.array([[0.3, 0.65],  # [xmin, xmax]
                                      [0.0, 0.25]])  # [ymin, ymax]
        self.robot = Robot('ur5e_stick',
                           pb_cfg={'gui': gui,
                                   'realtime': False,
                                   'opengl_render':
torch.cuda.is_available()})
```

```
        self._arm_reset_pos = np.array([-0.38337763,
                                        -2.02650575,
                                        -2.01989619,
                                        -0.64477803,
                                        1.571439041,
                                        -0.38331266])
        self._table_id =
self.robot.pb_client.load_urdf('table/table.urdf',
                                                        [.5, 0, 0.4],
                                                        euler2quat([0,
0, np.pi / 2]),
                                                        scaling=0.9)

        # create a ball at the start location (for visualization
purpose)
        self._start_pos = np.array([0.45, -0.32, 1.0])
        self._start_urdf_id = self.robot.pb_client.load_geom('sphere',
size=0.04, mass=0,

base_pos=self._start_pos,
                                                             rgba=[1,
1, 0, 0.8])

        # create a ball at the goal location
        self._goal_pos = np.array([0.5, 0.2, 1.0])
        self._goal_urdf_id = self.robot.pb_client.load_geom('sphere',
size=0.04, mass=0,

base_pos=self._goal_pos,
                                                            rgba=[1,
0, 0, 0.8])

        # disable the collision checking between the robot and the
ball at the goal location
        for i in
range(self.robot.pb_client.getNumJoints(self.robot.arm.robot_id)):

self.robot.pb_client.setCollisionFilterPair(self.robot.arm.robot_id,

self._goal_urdf_id,
                                                        i,
                                                        -1,

enableCollision=0)
        # disable the collision checking between the robot and the
ball at the start location
        for i in
range(self.robot.pb_client.getNumJoints(self.robot.arm.robot_id)):

self.robot.pb_client.setCollisionFilterPair(self.robot.arm.robot_id,
```

```
self._start_urdf_id,
                                                        i,
                                                        -1,

enableCollision=0)

        self._box_pos = np.array([0.45, -0.1, 0.996])
        self._box_id = self.robot.pb_client.load_geom('cylinder',
size=[0.05, 0.05], mass=1.,

base_pos=self._box_pos,
                                                      rgba=[1., 0.6,
0.6, 1])

        self.robot.pb_client.changeDynamics(self._box_id, -1,
lateralFriction=0.9)

        self.robot.pb_client.setCollisionFilterPair(self._box_id,

self._start_urdf_id,
                                                    -1,
                                                    -1,
                                                    enableCollision=0)
        self.robot.pb_client.setCollisionFilterPair(self._box_id,

self._goal_urdf_id,
                                                    -1,
                                                    -1,
                                                    enableCollision=0)

        self._action_bound = 1.0
        self._ee_pos_scale = 0.04
        self._action_high = np.array([self._action_bound] * 2)
        self.action_space = spaces.Box(low=-self._action_high,
                                       high=self._action_high,
                                       dtype=np.float32)
        state_low = np.full(len(self._get_obs()), -float('inf'))
        state_high = np.full(len(self._get_obs()), float('inf'))
        self.observation_space = spaces.Box(state_low,
                                            state_high,
                                            dtype=np.float32)
        self.reset()

    def reset(self):
        """
        Resets the environment to its initial state and returns the
initial observation.

        Returns:
```

```
        - state (np.ndarray): The initial observation of the
environment after reset.
        """
        self.robot.arm.set_jpos(self._arm_reset_pos,
ignore_physics=True)
        self.robot.pb_client.reset_body(self._box_id,
base_pos=self._box_pos)

        starts = self._goal_bounds[:, 0]
        ends = self._goal_bounds[:, 1]
        width = ends - starts
        # different from HW3, we are setting the goal to a random
location
        ran = np.random.random(2)
        goal_pos = starts + width * ran
        goal_pos = np.append(goal_pos, 1)
        self._goal_pos = goal_pos
        self.robot.pb_client.reset_body(self._goal_urdf_id,
base_pos=self._goal_pos)

        self._t = 0
        self._ref_ee_pos = self.robot.arm.get_ee_pose()[0]
        self._ref_ee_ori = self.robot.arm.get_ee_pose()[1]
        return self._get_obs()

    def step(self, action):
        """
        Applies an action to the environment and returns the next
state, reward, done flag, and additional information.

        Parameters:
        - action (np.ndarray): The action to be applied to the
environment.

        Returns:
        - state (np.ndarray): The next state of the environment after
applying the action.
        - reward (float): The reward resulting from the action.
        - done (bool): The done flag indicating if the episode has
ended.
        - info (dict): Additional information about the step,
including success and collision indicators.
        """
        previous_state = self._get_obs()
        collision = self._apply_action(action)
        self._t += 1
        state = self._get_obs()

        reward, info = self._get_reward(state=state, action=action,
previous_state=previous_state)
```

```
        done = self._t >= self._max_episode_length or info['success']
        info['collision'] = collision
        return state, reward, done, info

    def _get_reward(self, state, action, previous_state):
        """
        Calculates the reward for the current action based on the
state of the environment and the action taken.

        Parameters:
        - state (np.ndarray): The current state of the environment,
including the gripper's and object's positions.
        - action (np.ndarray): The action taken by the agent.
        - previous_state (np.ndarray): The state of the environment
before the current action was taken.

        Returns:
        - reward (float): The calculated reward based on the distance
of the object to the goal, the distance between the gripper and the
object, and whether the object has reached the goal.
        - info (dict): A dictionary containing additional information
about the current step, including whether the goal has been
successfully reached ('success': bool).
        """
        object_pos = state[2:4]
        dist_to_goal = np.linalg.norm(object_pos - self._goal_pos[:2])
        success = dist_to_goal < self._dist_threshold
        gripper_pos = state[:2]
        prev_object_pos = previous_state[2:4]
        prev_dist_to_goal = np.linalg.norm(prev_object_pos -
self._goal_pos[:2])

        gripper_obj_dist = np.linalg.norm(gripper_pos - object_pos)
        reach_reward = -gripper_obj_dist
        touch_reward = int(gripper_obj_dist < 0.08) * 0.03 if
dist_to_goal < prev_dist_to_goal else 0

        push_reward = np.exp(-dist_to_goal * 8) * 1. if touch_reward >
0 else 0
        if success:
            push_reward += 10
        reward = touch_reward + push_reward + reach_reward
        info = dict(success=success)
        return reward, info

    def _get_obs(self):
        """
        Retrieves the current observation of the environment, which
includes the position of the gripper and the position of the object
relative to the goal.
```

```
        Returns:
        - state (np.ndarray): An array containing the current
positions of the gripper and the object, as well as the goal position.
        """
        gripper_pos = self.robot.arm.get_ee_pose()[0][:2]
        object_pos, object_quat =
self.robot.pb_client.get_body_state(self._box_id)[:2]
        state = np.concatenate([gripper_pos, object_pos[:2],
self._goal_pos[:2]])
        return state

    def _apply_action(self, action):
        """
        Applies the given action to the environment, moving the
robot's end effector accordingly.

        Parameters:
        - action (np.ndarray): The desired movement action for the
robot's end effector, specified as a displacement in the x and y
directions.

        Returns:
        - (bool): False if the new position is within predefined
bounds (collision).
        """
        if not isinstance(action, np.ndarray):
            action = np.array(action).flatten()
        if action.size != 2:
            raise ValueError('Action should be [d_x, d_y].')
        # we set dz=0
        action = np.append(action, 0)
        pos, quat, rot_mat, euler = self.robot.arm.get_ee_pose()
        pos += action[:3] * self._ee_pos_scale
        pos[2] = self._ref_ee_pos[2]
        # if the new position is out of the bounds, then we don't
apply the action
        if not np.logical_and(np.all(pos[:2] >= self._xy_bounds[:,
0]),
                              np.all(pos[:2] <= self._xy_bounds[:,
1])):
            return False

        # move the end-effector to the new position
        jnt_pos = self.robot.arm.compute_ik(pos, ori=self._ref_ee_ori)
        for step in range(self._action_repeat):
            self.robot.arm.set_jpos(jnt_pos)
            self.robot.pb_client.stepSimulation()

        return False
```

```
    def render(self, mode='human', **kwargs):
        """
        Renders the environment. If mode is 'human', the environment
is visualized.

        Parameters:
        - mode (str, optional): The mode of rendering. Defaults to
'human'.

        Returns:
        - rgb (np.ndarray): An RGB array of the scene if mode is not
'human'.
        """
        robot_base = self.robot.arm.robot_base_pos
        self.robot.cam.setup_camera(focus_pt=robot_base,
                                    dist=2,
                                    yaw=85,
                                    pitch=-20,
                                    roll=0)
        rgb, _ = self.robot.cam.get_images(get_rgb=True,
                                           get_depth=False)
        return rgb


module_name = __name__

env_name = 'URPusher-v1'
if env_name in registry.env_specs:
    del registry.env_specs[env_name]
register(
    id=env_name,
    entry_point=f'{module_name}:URRobotPusherGym',
)
```

```
/usr/local/lib/python3.10/dist-packages/gym/envs/registration.py:440:
UserWarning: WARN: The `registry.env_specs` property along with
`EnvSpecTree` is deprecated. Please use `registry` directly as a
dictionary instead.
  logger.warn(
```

Learning from Demonstrations

To generate a dataset of demonstrations to learn from, we've provided you a pre-trained expert model.

```
# Download the expert model
!wget --no-check-certificate -r 'https://docs.google.com/uc?
```

```
export=download&id=1vlOBeo3caEbl17JEEyxRWbCnFZ--dyXH' -O
pusher_expert_model.pt

WARNING: combining -O with -r or -p will mean that all downloaded
content
will be placed in the single file you specified.

--2024-03-16 17:43:41--  https://docs.google.com/uc?
export=download&id=1vlOBeo3caEbl17JEEyxRWbCnFZ--dyXH
Resolving docs.google.com (docs.google.com)... 108.177.127.113,
108.177.127.139, 108.177.127.102, ...
Connecting to docs.google.com (docs.google.com)|
108.177.127.113|:443... connected.
HTTP request sent, awaiting response... 303 See Other
Location: https://drive.usercontent.google.com/download?
id=1vlOBeo3caEbl17JEEyxRWbCnFZ--dyXH&export=download [following]
--2024-03-16 17:43:42--
https://drive.usercontent.google.com/download?
id=1vlOBeo3caEbl17JEEyxRWbCnFZ--dyXH&export=download
Resolving drive.usercontent.google.com
(drive.usercontent.google.com)... 172.217.218.132,
2a00:1450:4013:c08::84
Connecting to drive.usercontent.google.com
(drive.usercontent.google.com)|172.217.218.132|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 167875 (164K) [application/octet-stream]
Saving to: ‘pusher_expert_model.pt’

pusher_expert_model 100%[===================>] 163.94K  --.-KB/s    in
0.001s

2024-03-16 17:43:43 (129 MB/s) - ‘pusher_expert_model.pt’ saved
[167875/167875]

FINISHED --2024-03-16 17:43:43--
Total wall clock time: 2.0s
Downloaded: 1 files, 164K in 0.001s (129 MB/s)
```

Utility functions

```
def create_actor(env):
    """
    Creates an actor model for a given environment using a Diagonal
Gaussian policy architecture.

https://github.com/taochenshh/easyrl/blob/master/easyrl/models/diag_ga
ussian_policy.py

    Parameters:
    - env (gym.Env): The environment for which the actor is being
```

```
created. The observation and action spaces of the environment are used
to define the input and output dimensions of the model.

    Returns:
    - actor (nn.Module): An instance of `DiagGaussianPolicy`,
initialized with the specified architecture and ready for training or
inference.
    """
    ob_dim = env.observation_space.shape[0]
    action_dim = env.action_space.shape[0]
    actor_body = MLP(input_size=ob_dim,
                     hidden_sizes=[64],
                     output_size=64,
                     hidden_act=nn.Tanh,
                     output_act=nn.Tanh)
    actor = DiagGaussianPolicy(actor_body,
                               in_features=64,
                               action_dim=action_dim)
    return actor

def load_expert_agent(env, device,
expert_model_path='pusher_expert_model.pt'):
    """
    Loads an expert agent model from a specified file path.

    Parameters:
    - env (gym.Env): The environment associated with the expert agent.
Used to create an actor model with appropriate dimensions.
    - device (torch.device): The device on which the model should be
loaded.
    - expert_model_path (str, optional): The file path to the expert
model's state dictionary. Defaults to 'pusher_expert_model.pt'.

    Returns:
    - expert_agent (BasicAgent): A `BasicAgent` instance with the
actor loaded from the specified checkpoint.
    """
    expert_actor = create_actor(env=env)
    expert_agent = BasicAgent(actor=expert_actor)
    print(f'Loading expert model from: {expert_model_path}.')
    ckpt_data = torch.load(expert_model_path, map_location=f'cpu')
    load_state_dict(expert_agent.actor,
                    ckpt_data['actor_state_dict'])
    freeze_model(expert_agent.actor)
    return expert_agent

def generate_demonstration_data(expert_agent, env, num_trials):
    """
    Generates demonstration data by running inference with an expert
agent in the environment.
```

```
    Parameters:
    - expert_agent (BasicAgent): The expert agent used to generate the
demonstrations.
    - env (gym.Env): The environment in which the agent will generate
demonstrations.
    - num_trials (int): The number of trials to run for generating
demonstrations.

    Returns:
    - trajs (list): A list of trajectories generated by the expert
agent. Each trajectory contains observations, actions, rewards, and
other trajectory-specific information collected during the trial.
    """
    return run_inference(expert_agent, env, num_trials,
return_on_done=True)

def run_inference(agent, env, num_trials, return_on_done=False,
sample=True, disable_tqdm=False, render=False):
    """
    Runs inference with a given agent in the environment for a
specified number of trials.

    Parameters:
    - agent (BasicAgent): The agent to run inference with.
    - env (gym.Env): The environment in which to run the agent.
    - num_trials (int): The number of trials to run.
    - return_on_done (bool, optional): Whether to return immediately
after an episode is done. Defaults to False.
    - sample (bool, optional): Whether to sample actions from the
policy distribution. Defaults to True.
    - disable_tqdm (bool, optional): Whether to disable the tqdm
progress bar. Defaults to False.
    - render (bool, optional): Whether to render the environment.
Defaults to False.

    Returns:
    - trajs (list): A list of trajectories from the inference runs.
Each trajectory contains observations, actions, rewards, and other
episode-specific information.
    """
    runner = EpisodicRunner(agent=agent, env=env)
    trajs = []
    for trial_id in tqdm(range(num_trials), desc='Run',
disable=disable_tqdm):
        env.reset()
        traj = runner(time_steps=cfg.alg.episode_steps,
                      sample=sample,
                      return_on_done=return_on_done,
                      evaluation=True,
```

```
                       render_image=render)
        trajs.append(traj)
    return trajs

def eval_agent(agent, env, num_trials, disable_tqdm=False,
render=False):
    """
    Evaluates the given agent in the environment across a specified
number of trials.

    Parameters:
    - agent (BasicAgent): The agent to evaluate.
    - env (gym.Env): The environment in which to evaluate the agent.
    - num_trials (int): The number of trials to perform for the
evaluation.
    - disable_tqdm (bool, optional): Whether to disable the tqdm
progress bar during evaluation. Defaults to False.
    - render (bool, optional): Whether to render the environment
during evaluation. Defaults to False.

    Returns:
    - success_rate (float): The rate of successful episodes.
    - ret_mean (float): The mean return across all trials.
    - ret_std (float): The standard deviation of the return across all
trials.
    - rets (list): A list of returns from each trial.
    - successes (list): A list of boolean values indicating whether
each trial was successful.
    """
    trajs = run_inference(agent, env, num_trials, return_on_done=True,
                          disable_tqdm=disable_tqdm, render=render)
    tsps = []
    successes = []
    rets = []
    for traj in trajs:
        tsps = traj.steps_til_done.copy().tolist()
        rewards = traj.raw_rewards
        infos = traj.infos
        for ej in range(rewards.shape[1]):
            ret = np.sum(rewards[:tsps[ej], ej])
            rets.append(ret)
            successes.append(infos[tsps[ej] - 1][ej]['success'])
        if render:
            save_traj(traj, 'tmp')
    ret_mean = np.mean(rets)
    ret_std = np.std(rets)
    success_rate = np.mean(successes)
    return success_rate, ret_mean, ret_std, rets, successes
```

```
@dataclass
class BasicAgent:
    """
    A basic agent class for reinforcement learning, encapsulating a
policy actor model.

    Attributes:
    - actor (nn.Module): The neural network model that acts as the
policy actor for the agent.

    Methods:
    - get_action(ob, sample=True, *args, **kwargs): Generates an
action for a given observation by sampling from the policy actor's
output distribution. Returns the action along with information such as
log probability and entropy of the action.
    """
    actor: nn.Module

    def __post_init__(self):
        move_to([self.actor],
                device=cfg.alg.device)

    @torch.no_grad()
    def get_action(self, ob, sample=True, *args, **kwargs):
        t_ob = torch_float(ob, device=cfg.alg.device)
        # the policy returns a multi-variate gaussian distribution
        act_dist, _ = self.actor(t_ob)
        # sample from the distribution
        action = action_from_dist(act_dist,
                                  sample=sample)
        # get the log-probability of the sampled actions
        log_prob = action_log_prob(action, act_dist)
        # get the entropy of the action distribution
        entropy = action_entropy(act_dist, log_prob)
        action_info = dict(
            log_prob=torch_to_np(log_prob),
            entropy=torch_to_np(entropy),
        )
        return torch_to_np(action), action_info

def set_configs(exp_name='bc'):
    set_config('ppo')
    cfg.alg.seed = seed
    cfg.alg.num_envs = 1
    cfg.alg.episode_steps = 150
    cfg.alg.max_steps = 600000
    cfg.alg.device = 'cuda' if torch.cuda.is_available() else 'cpu'
    cfg.alg.env_name = 'URPusher-v1'
    cfg.alg.save_dir =
Path.cwd().absolute().joinpath('data').as_posix()
```

```
    cfg.alg.save_dir += f'/{exp_name}'
    setattr(cfg.alg, 'diff_cfg', dict(save_dir=cfg.alg.save_dir))

    print(f'====================================')
    print(f'      Device:{cfg.alg.device}')
    print(f'====================================')
```

Generating demonstrations

Now that you've downloaded the expert policy model, let's load the expert agent.

```
# load the expert agent
set_configs()
env = make_vec_env(cfg.alg.env_name,
                   cfg.alg.num_envs,
                   seed=cfg.alg.seed)
expert_agent = load_expert_agent(env, device=cfg.alg.device)
```

```
[INFO][2024-03-16 17:43:56]: Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
INFO:EasyRL:Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
[INFO][2024-03-16 17:43:56]: Creating 1 environments.
INFO:EasyRL:Creating 1 environments.
[INFO][2024-03-16 17:43:56]: Load in OpenGL!
INFO:AIRobot:Load in OpenGL!

====================================
      Device:cuda
====================================

/usr/local/lib/python3.10/dist-packages/gym/spaces/box.py:128:
UserWarning: WARN: Box bound precision lowered by casting to float32
  logger.warn(f"Box bound precision lowered by casting to
{self.dtype}")
/usr/local/lib/python3.10/dist-packages/gym/core.py:317:
DeprecationWarning: WARN: Initializing wrapper in old step API which
returns one bool instead of two. It is recommended to set
`new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/wrappers/step_api_compatib
ility.py:39: DeprecationWarning: WARN: Initializing environment in old
step API which returns one bool instead of two. It is recommended to
set `new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/core.py:256:
DeprecationWarning: WARN: Function `env.seed(seed)` is marked as
```

```
deprecated and will be removed in the future. Please use
`env.reset(seed=seed)` instead.
  deprecation(

Loading expert model from: pusher_expert_model.pt.
```

Agent is a class encapsulating has an `actor` network that returns a tuple in its forward pass: `(action_distribution, output_of_MLP)`

```
expert_agent

BasicAgent(actor=DiagGaussianPolicy(
  (body): MLP(
    (fcs): ModuleList(
      (0): Linear(in_features=6, out_features=64, bias=True)
      (1): Tanh()
      (2): Linear(in_features=64, out_features=64, bias=True)
      (3): Tanh()
    )
  )
  (head_mean): Linear(in_features=64, out_features=2, bias=True)
))
```

Let's check how good the expert policy is and visualize its performance using `eval_agent` which takes an agent and evaluates it in a specified environment.

This function will return to you the succes rate over all trajectories, the mean and standard deviation of total returns, the total returns of each trajectory, and the success of each trajectory.

```
success_rate, ret_mean, ret_std, rets, successes =
eval_agent(expert_agent, env, 500)
# you might see some variance in the success rate here,
# if you rollout the policies more times, the success rate will be
more stable
print(f'\n Expert policy success rate:{success_rate}') # It takes < 1
minute in T4.
```

{"model_id":"2fc59af969664d02a00f8f1b605ab6b2","version_major":2,"version_minor":0}

```
/usr/local/lib/python3.10/dist-packages/gym/utils/
passive_env_checker.py:174: UserWarning: WARN: Future gym versions
will require that `Env.reset` can be passed a `seed` instead of using
`Env.seed` for resetting the environment random number generator.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:190: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `return_info` to return information from the
environment resetting.
  logger.warn(
```

```
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:195: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `options` to allow the environment
initialisation to be passed additional information.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `reset()` method
was expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `reset()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:227: DeprecationWarning: WARN: Core environment is written in old
step API which returns one bool instead of two. It is recommended to
rewrite the environment with new step API.
  logger.deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:233: DeprecationWarning: `np.bool8` is a deprecated alias for
`np.bool_`.  (Deprecated NumPy 1.24)
  if not isinstance(done, (bool, np.bool8)):
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `step()` method was
expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `step()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
```

```
 Expert policy success rate:0.87
```

```
# if you set `render=True`, it will save each evaluation trajectory in
`tmp`
# and you can use `play_video` to visually check the trajectory
success_rate, ret_mean, ret_std, rets, successes =
eval_agent(expert_agent, env, 5, render=True) # It takes < 1 minute in
T4.
```


{"model_id":"fcc1ffed7e33486b82650c0f2bbc278a","version_major":2,"vers
ion_minor":0}


```
/usr/local/lib/python3.10/dist-packages/gym/core.py:43:
DeprecationWarning: WARN: The argument mode in render method is
deprecated; use render_mode during environment initialization instead.
See here for more information: https://www.gymlibrary.ml/content/api/
  deprecation(
```

```
play_video('tmp', video_id=2)
```

```
<IPython.core.display.HTML object>
```

Finally, let's generate a dataset of 50 expert demonstrations. Note that data is usually acquired not from optimal deomonstrations but from the real world.

```
# Each trajectory is a dataclass containing a list of objects
containing "step data".
# Step data contains- observation: ndarry[float],
action:ndarry[float], action_info: Dict[log_prob: 1x1 ndarry[float],
entropy: 1x1 ndarry[float]],
#                     next_observation: ndarry[float], reward: 1x1
ndarry[float], done: 1x1 ndarry[bool]

# Trajectory class:
https://github.com/taochenshh/easyrl/blob/master/easyrl/utils/data.py

expert_trajs = generate_demonstration_data(expert_agent=expert_agent,
                                           env=env,
                                           num_trials=50) # It takes <
1 minute in T4.
```

{"model_id":"057c44c404b34d298304c1f075760db9","version_major":2,"vers
ion_minor":0}

```
/usr/local/lib/python3.10/dist-packages/gym/utils/
passive_env_checker.py:174: UserWarning: WARN: Future gym versions
will require that `Env.reset` can be passed a `seed` instead of using
`Env.seed` for resetting the environment random number generator.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:190: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `return_info` to return information from the
environment resetting.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:195: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `options` to allow the environment
initialisation to be passed additional information.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `reset()` method
was expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `reset()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
```

```
py:227: DeprecationWarning: WARN: Core environment is written in old
step API which returns one bool instead of two. It is recommended to
rewrite the environment with new step API.
  logger.deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:233: DeprecationWarning: `np.bool8` is a deprecated alias for
`np.bool_`.  (Deprecated NumPy 1.24)
  if not isinstance(done, (bool, np.bool8)):
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `step()` method was
expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `step()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
```

```
#### The class Trajectory and the function create_trajectories() are
added by me
# Trajectory class has data fields that correspond to the format
accepted by the TrajDataset
# create_trajectories is a helper function that converts the
trajectories returned by generate_demonstration_data into a format
that can be accepted by the TrajDataset class

# class StepData:
#     ob: Any = None
#     state: Any = None
#     action: Any = None
#     # store action infomation such as log probability, entropy
#     action_info: Any = None
#     next_ob: Any = None
#     next_state: Any = None
#     reward: Any = None
#     done: Any = None
#     info: Any = None
#     extra: Any = None

# A class that stores a single trajectory consisting of a sequence of
observations and actions
class Trajectory:
    obs: Any = None
    actions: Any = None

    def __init__(self, obs, actions):
        self.obs = obs
        self.actions = actions

# function for creating a list of Trajectory from expert trajectories
def create_trajectories(trajectories):
```

```
  trajs = []
  for traj in trajectories:
    obs = []
    actions = []
    for step_data in traj.traj_data:
      obs.append(step_data.ob)
      actions.append(step_data.action)
    trajs.append(Trajectory(obs, actions))

  return trajs

# convert the trajectories into a format that is accepted by
TrajDataset
trajectories = create_trajectories(expert_trajs)
```

Behavior Cloning (BC)

Q1: (30 pts total) Now that we have expert demonstrations, let's use supervised learning (behavior cloning) to clone expert behavior and analyze the results.

Basic methodology for this task:

1. Obtain expert data (Done!)

(TO-DO)

1. Instantiate model using the `create_actor(env)` function, which given an environment creates a special torch.nn.Module that uses a diagonal gaussian policy. The model takes an observation as input and outputs types `(torch.Distribution, torch.nn.Module)`
2. Instantiate agent using newly created model
3. Use expert demonstrations to train agent with the function `train_bc_agent` to optimize policy in respect to loss function.
4. Evaluate agent using `eval_agent`

There is a TO-DO section for optimizing policy with expert data.

```
class TrajDataset(Dataset):
    """
    A dataset class for handling trajectory data for reinforcement
learning models.

    Attributes:
    - states (np.ndarray): An array of states from the trajectories.
    - actions (np.ndarray): An array of actions corresponding to the
states.

    Methods:
    - __init__(trajs): Initializes the dataset with trajectories,
concatenating states and actions.
```

```
    - __len__(): Returns the number of samples in the dataset.
    - __getitem__(idx): Retrieves a sample by index, returning a
dictionary with 'state' and 'action'.
    - add_traj(traj=None, states=None, actions=None): Adds additional
trajectories or individual states and actions to the dataset.
    """
    def __init__(self, trajs):
        """
        Initializes the TrajDataset with trajectories data.

        Parameters:
        - trajs (list of Trajectory): A list of trajectories. Each
trajectory should have an 'obs' attribute for observations and an
'actions' attribute for actions.
        """
        states = []
        actions = []
        for traj in trajs:
            states.append(traj.obs)
            actions.append(traj.actions)
        self.states = np.concatenate(states, axis=0)
        self.actions = np.concatenate(actions, axis=0)

    def __len__(self):
        """
        Returns the total number of samples (state-action pairs)
available in the dataset.

        Returns:
        - int: The number of samples in the dataset.
        """
        return self.states.shape[0]

    def __getitem__(self, idx):
        """
        Retrieves a single sample from the dataset at the specified
index.

        Parameters:
        - idx (int): The index of the sample to retrieve.

        Returns:
        - sample (dict): A dictionary containing the 'state' and
'action' for the sample at the given index.
        """
        sample = dict()
        sample['state'] = self.states[idx]
        sample['action'] = self.actions[idx]
        return sample
```

```
    def add_traj(self, traj=None, states=None, actions=None):
        """
        Adds new trajectory data to the dataset. The method can add
data from a trajectory object or from separate arrays of states and
actions.

        Parameters:
        - traj (Trajectory, optional): A new trajectory object to add
to the dataset. Default is None.
        - states (np.ndarray, optional): An array of new states to add
to the dataset. Default is None.
        - actions (np.ndarray, optional): An array of new actions to
add to the dataset. Default is None.
        """
        if traj is not None:
            self.states = np.concatenate((self.states, traj.obs),
axis=0)
            self.actions = np.concatenate((self.actions,
traj.actions), axis=0)
        else:
            self.states = np.concatenate((self.states, states),
axis=0)
            self.actions = np.concatenate((self.actions, actions),
axis=0)


def train_bc_agent(agent, trajs, max_epochs=5000, batch_size=256,
lr=0.0005, disable_tqdm=True):
    """
    Trains a behavior cloning agent using trajectory data.

    Parameters:
    - agent: The agent to be trained.
    - trajs: A list of trajectories for training. Each trajectory
contains observations and actions.
    - max_epochs (int, optional): The maximum number of training
epochs. Defaults to 5000.
    - batch_size (int, optional): The batch size for training.
Defaults to 256.
    - lr (float, optional): The learning rate for the optimizer.
Defaults to 0.0005.
    - disable_tqdm (bool, optional): Whether to disable the tqdm
progress bar. Defaults to True.

    Returns:
    - agent: The trained agent.
    - logs (dict): A dictionary containing training logs, including
losses and epoch numbers.
    - dataset_size (int): The size of the training dataset.
    """
```

```
    dataset = TrajDataset(trajs)
    dataloader = DataLoader(dataset,
                            batch_size=batch_size,
                            shuffle=True)
    optimizer = optim.Adam(agent.actor.parameters(),
                           lr=lr)
    pbar = tqdm(range(max_epochs), desc='Epoch', disable=disable_tqdm)
    logs = dict(loss=[], epoch=[])
    for iter in pbar:
        avg_loss = []
        for batch_idx, sample in enumerate(dataloader):
            states = sample['state'].float().to(cfg.alg.device)
            expert_actions =
sample['action'].float().to(cfg.alg.device)
            optimizer.zero_grad()
            #### TODO: optimize the policy with the expert data,
            #### save the loss in a variable named as 'loss' (10 pts)
            #### (hint: think about how agent looks like and what it
returns.)

            # get the agent actions given the states
            action_distribution, _ = agent.actor(states)
            actions = action_from_dist(action_distribution)

            # calculate the loss between the agent's actions and the
expert's actions
            loss = F.mse_loss(actions, expert_actions)
            # loss = loss_fn(actions, expert_actions)

            ####
            loss.backward()
            optimizer.step()
            pbar.set_postfix({'loss': loss.item()})
            avg_loss.append(loss.item())
        logs['loss'].append(np.mean(avg_loss))
        logs['epoch'].append(iter)
    return agent, logs, len(dataset)

'''
2. Instantiate model using the create_actor(env) function, which given
an environment creates a special torch.nn.Module that uses a diagonal
gaussian policy. The model takes an observation as input and outputs
types (torch.Distribution, torch.nn.Module)
3. Instantiate agent using newly created model
4. Use expert demonstrations to train agent with the function
train_bc_agent to optimize policy in respect to loss function.
5. Evaluate agent using eval_agent
'''

# instantiate model using the create_actor(env)
```

```
model = create_actor(env)

# instantiate agent using the model
agent = BasicAgent(model)

# get the trajectories in the format required by the dataset from
expert trajectories
trajectories = create_trajectories(expert_trajs)

# train the agent using bc on expert trajectories
trained_agent, logs, dataset_size = train_bc_agent(agent,
trajectories)

# evaluate the agent using eval_agent
success_rate, ret_mean, ret_std, rets, successes =
eval_agent(trained_agent, env, 5, render=True) # It takes < 1 minute
in T4.
```

{"model_id":"13535a99fcaa4a6e87684d4981190bef","version_major":2,"version_minor":0}

```
/usr/local/lib/python3.10/dist-packages/gym/core.py:43:
DeprecationWarning: WARN: The argument mode in render method is
deprecated; use render_mode during environment initialization instead.
See here for more information: https://www.gymlibrary.ml/content/api/
  deprecation(
```

```
# if you set `render=True`, it will save each evaluation trajectory in
`tmp`
# and you can use `play_video` to visually check the trajectory
success_rate, ret_mean, ret_std, rets, successes =
eval_agent(trained_agent, env, 5, render=True) # It takes < 1 minute
in T4.
```

{"model_id":"2cbb1b12bd654ea1ae05c510f6c07e84","version_major":2,"version_minor":0}

```
play_video('tmp', video_id=14) # this works!!
```

```
<IPython.core.display.HTML object>
```

(20 pts): In the real-world collecting expert demonstrations can be expensive. It would be ideal if we can learn a good policy with only a few demonstrations. To gain an understanding of how much data is necessary, lets measure the performance of the learned policy with varying amounts of expert data. Fill in the missing code and train a BC policy using `train_bc_agent` (the default hyperparameters should be sufficient) with $1, 3, 15, 25, 50$ expert trajectories (note that we've already generated 50 trajectories above so you can just index into these!). You should store each of the trained agents (as well as the mean and std of return) for future comparison in later parts of this assignment.

Once you have trained the BC policy, evaluate your policy on 200 episodes and plot the average success rate (returned by 'eval_agent') as a function of the number of expert transitions used in training. Note that not all trajectories have the same length. We can think of the number of expert transitions as the number of supervised learning examples or in other words, dataset size (which is returned by `train_bc_agent`).

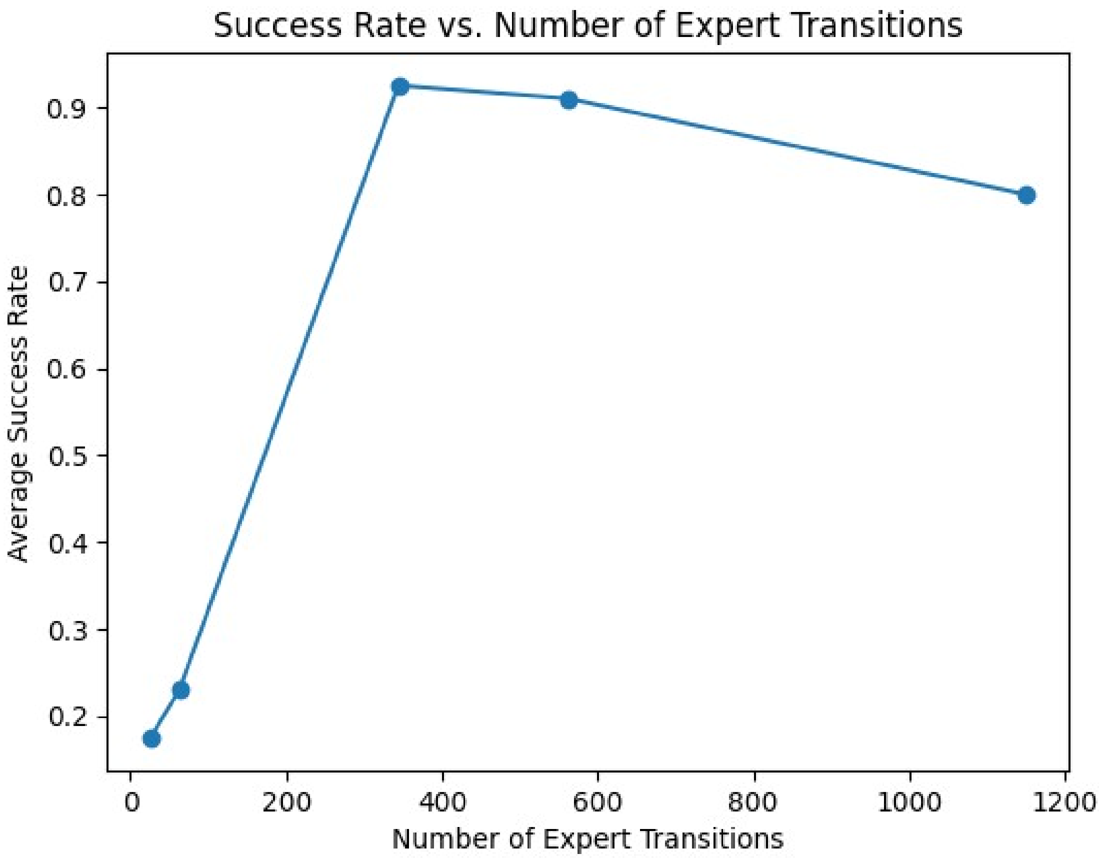
```
num_trajs = [1, 3, 15, 25, 50]
bc_success_rates = []
bc_steps = []
bc_agents = dict()
bc_rets = dict()

num_episodes = 200

#### TODO:  It takes ~10 minutes in T4.
for num_traj in num_trajs:
    # Use a subset of expert trajectories
    subset_trajs = expert_trajs[:num_traj]
    trajectories = create_trajectories(subset_trajs) # create
trajectories in the format required by TrajDataset

    # Train BC agent with subset of data
    agent = BasicAgent(create_actor(env))
    agent, logs, dataset_size = train_bc_agent(agent, subset_trajs)

    bc_steps.append(dataset_size)

    # Store the trained agent
    bc_agents[num_traj] = agent

    # Evaluate the agent
    print(f'Evaluating for expert demonstrations provided :
{num_traj}')
    success_rate, ret_mean, ret_std, rets, successes =
eval_agent(agent, env, num_trials=num_episodes)

    # Store the results
    bc_success_rates.append(success_rate)
    bc_rets[num_traj] = (ret_mean, ret_std)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
Evaluating for expert demonstrations provided : 1
```

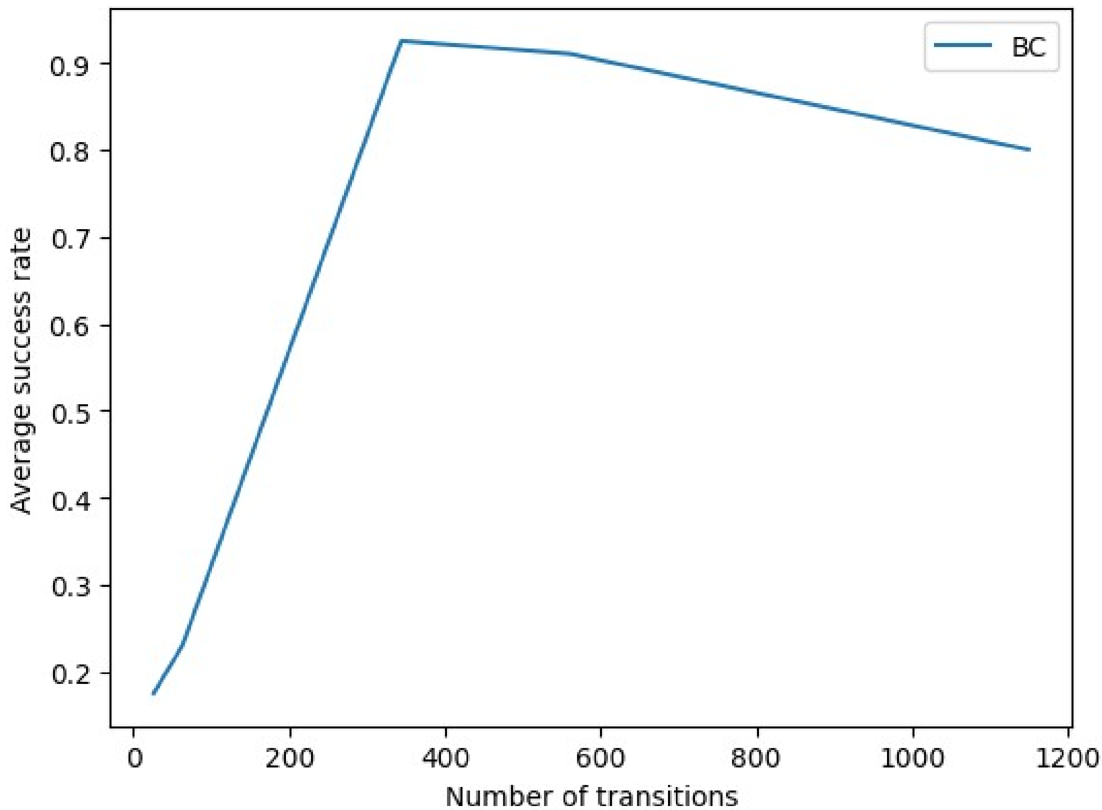
{"model_id":"5249b381079d4a74b1b0d5f68b9976d3","version_major":2,"version_minor":0}

```
Evaluating for expert demonstrations provided : 3

{"model_id":"93916ef33c0149c2890357edfdc20953","version_major":2,"version_minor":0}

Evaluating for expert demonstrations provided : 15

{"model_id":"37400a83a8124ec3a135be1d551f9da0","version_major":2,"version_minor":0}

Evaluating for expert demonstrations provided : 25

{"model_id":"ec86c518c5494b11b4ecbe4bcbb1d0da","version_major":2,"version_minor":0}

Evaluating for expert demonstrations provided : 50

{"model_id":"74b2e3572b34493c9b13df773143d5c5","version_major":2,"version_minor":0}

# # Plot the average success rate as a function of the number of expert transitions
plt.plot(bc_steps, bc_success_rates, marker='o')
plt.xlabel('Number of Expert Transitions')
plt.ylabel('Average Success Rate')
plt.title('Success Rate vs. Number of Expert Transitions')
plt.show()
###########################################################
```




```python
# Save BC experiments. Not saved between runtimes. Download from
runtime drive files to save progress.
# Change destination path as desired.
PATH = "/content/drive/MyDrive/Colab_Notebooks"
os.makedirs(PATH, exist_ok=True)

with open(f'{PATH}/bc_agent.pkl', 'wb') as f:
    data = [bc_agents, bc_steps, bc_success_rates, bc_rets]
    pickle.dump(data, f)

# load bc experiments
PATH = "/content/drive/MyDrive/Colab_Notebooks"
with open(f'{PATH}/bc_agent.pkl', 'rb') as f:
    bc_agents, bc_steps, bc_success_rates, bc_rets = pickle.load(f)

plt.plot(bc_steps, bc_success_rates, label='BC')
plt.xlabel("Number of transitions")
plt.ylabel("Average success rate")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x7ca00ad92d40>
```



DAgger

Q2:(40 pts total) As we have learned in the class, behavior cloning suffers from co-variate shift. One way to mitigate this issue is using DAgger. The key idea of DAgger is as follows:

1. Train a behavior cloned policy π_{θ_k} by using an expert dataset D
2. Rollout the current policy π_{θ_k} and get a trajectory $(s_0, a_0, s_1, a_1, \ldots)$.
3. Query the expert again and get the expert actions $(a_0^{¿}, a_1^{¿}, \ldots)$. We can add these extra expert demonstration data $D_k = (s_0, a_0^{¿}, s_1, a_1^{¿}, \ldots)$ to D: $D = D \cup D_k$.
4. Optimize the current policy again with the aggregated dataset D.
5. Repeat step 2 to 4.

In the following section, you will finish implementing the DAgger algorithm.

```
@dataclass
class DaggerAgent:
    """
    A class for the DAgger (Dataset Aggregation) agent, incorporating
both learned and expert policies.

    Attributes:
    - actor (nn.Module): The learned policy model.
    - expert_actor (nn.Module): The expert policy model, used for
```

```
generating corrective actions.
    - lr (float): The learning rate for the optimizer.

    Methods:
    - __post_init__(): Initializes the agent, moves models to the
specified device, and freezes the expert model.
    - get_action(ob, sample=True, *args, **kwargs): Generates an
action from the learned policy and retrieves the corresponding expert
action. Returns both along with additional action information.
    - optimize(data, **kwargs): Optimizes the learned policy using
given data, which includes states and expert actions.
    - save_model(is_best=False, step=None): Saves the state dictionary
of the learned policy model.
    """
    actor: nn.Module
    expert_actor: nn.Module
    lr: float

    def __post_init__(self):
        """
        Post-initialization method for the DaggerAgent. This method is
automatically called after the object is initialized.

        It moves the actor and expert_actor models to the specified
device and freezes the parameters of the expert_actor to prevent it
from being updated during training.
        """
        move_to([self.actor, self.expert_actor],
                device=cfg.alg.device)
        freeze_model(self.expert_actor)
        self.optimizer = optim.Adam(self.actor.parameters(),
                                    lr=self.lr)

    @torch.no_grad()
    def get_action(self, ob, sample=True, *args, **kwargs):
        """
        Generates an action for a given observation using the learned
policy and also retrieves the corresponding expert action.

        Parameters:
        - ob (np.ndarray): The current state/observation.
        - sample (bool, optional): Whether to sample from the policy
distribution (True) or take the mean action (False). Defaults to True.

        Returns:
        - action (np.ndarray): The action generated by the learned
policy.
        - action_info (dict): A dictionary containing additional
information about the action, such as log probability ('log_prob'),
entropy ('entropy'), and the expert action ('exp_act').
```

```
        """
        t_ob = torch_float(ob, device=cfg.alg.device)
        # the policy returns a multi-variate gaussian distribution
        act_dist, _ = self.actor(t_ob)
        # sample from the distribution
        action = action_from_dist(act_dist,
                                  sample=sample)
        # get the log-probability of the sampled actions
        log_prob = action_log_prob(action, act_dist)
        # get the entropy of the action distribution
        entropy = action_entropy(act_dist, log_prob)
        action_info = dict(
            log_prob=torch_to_np(log_prob),
            entropy=torch_to_np(entropy),
        )


        action_info['exp_act'] = None
        ##### TODO (10 pts): get the expert action from the expert
policy and set "action_info['exp_act']" to this action.
        ##### as before, the policy returns a multi-variate gaussian
distribution.
        act_dist_expert, _ = self.expert_actor(t_ob)
        action_info['exp_act'] = action_from_dist(act_dist_expert,
                                                  sample=sample)

        ###############################################

        return torch_to_np(action), action_info

    def optimize(self, data, **kwargs):
        """
        Optimizes the learned policy using given batch data.

        Parameters:
        - data (dict): A batch of data containing 'state' and
'action', where 'state' is the input to the model and 'action' is the
target action from the expert policy.

        Returns:
        - optim_info (dict): A dictionary containing optimization
information such as the loss ('loss') and gradient norm ('grad_norm')
after the optimization step.
        """
        for key, val in data.items():
            data[key] = torch_float(val, device=cfg.alg.device)
        ob = data['state']
        exp_act = data['action']

        #### TODO (10 pts): optimize the policy
```

```
        act_dist, _ = self.actor(data['state'])
        action = action_from_dist(act_dist)
        loss = F.mse_loss(action, exp_act)

        ##############################
        self.optimizer.zero_grad()
        loss.backward()

        grad_norm = clip_grad(self.actor.parameters(),
                              cfg.alg.max_grad_norm)
        self.optimizer.step()

        optim_info = dict(
            loss=loss.item(),
            grad_norm=grad_norm,
        )
        return optim_info

    def save_model(self, is_best=False, step=None):
        """
        Saves the state dictionary of the actor model.

        Parameters:
        - is_best (bool, optional): Flag indicating if the current
model is the best model to be saved. Defaults to False.
        - step (int, optional): The current training step or epoch,
used for naming the saved model file. Defaults to None.
        """
        data_to_save = {
            'actor_state_dict': self.actor.state_dict()
        }
        save_model(data_to_save, cfg.alg, is_best=is_best, step=step)

@dataclass
class DaggerEngine:
    agent: Any
    runner: Any
    env: Any
    trajs: Any

    def __post_init__(self):
        """
        Initializes the DaggerEngine with the provided components and
pre-existing trajectory data.
        """
        self.dataset = TrajDataset(self.trajs)

    def train(self):
        """
        Trains the agent using DAgger (Dataset Aggregation) algorithm.
```

```
Repeatedly evaluates the current policy,
        collects new trajectories using the current policy augmented
with expert actions, and updates the policy based on the aggregated
dataset.

        Returns:
        - dataset_sizes (list): A list of dataset sizes after each
evaluation interval, indicating the growth of the training dataset
over time.
        - success_rates (list): A list of success rates evaluated at
each evaluation interval during training.
        """
        success_rates = []
        dataset_sizes = []
        self.cur_step = 0
        for iter_t in tqdm(count()):
            if iter_t % cfg.alg.eval_interval == 0:
                success_rate, ret_mean, ret_std, rets, successes =
eval_agent(self.agent,

self.env,

200,

disable_tqdm=True)
                success_rates.append(success_rate)
                dataset_sizes.append(len(self.dataset))
            # rollout the current policy and get a trajectory
            traj = self.runner(sample=True, get_last_val=False,
time_steps=cfg.alg.episode_steps)
            # optimize the policy
            self.train_once(traj)
            if self.cur_step > cfg.alg.max_steps:
                break
        return dataset_sizes, success_rates

    def train_once(self, traj):
        """
        Performs a single iteration of policy update using a newly
collected trajectory.

        Parameters:
        - traj (Trajectory): A trajectory collected using the current
policy, consisting of states, actions, rewards, and additional info.
        """
        self.cur_step += traj.total_steps

        action_infos = traj.action_infos
        exp_act = torch.stack([ainfo['exp_act'] for ainfo in
action_infos])
```

```
        self.dataset.add_traj(states=traj.obs,
                              actions=exp_act.cpu())
        rollout_dataloader = DataLoader(self.dataset,
                                        batch_size=cfg.alg.batch_size,
                                        shuffle=True,
                                       )
        optim_infos = []
        for oe in range(cfg.alg.opt_epochs):
            for batch_ndx, batch_data in
enumerate(rollout_dataloader):
                optim_info = self.agent.optimize(batch_data)
                optim_infos.append(optim_info)

def train_dagger(expert_actor, trajs, actor=None):
    """
    Initializes and trains a DAgger agent using provided trajectories
and expert policy.

    Parameters:
    - expert_actor: The expert policy model used to guide the DAgger
training process.
    - trajs: Pre-collected trajectories from the expert policy to
bootstrap the DAgger algorithm.
    - actor (optional): An initial policy model to start training
with. If None, a new actor is created.

    Returns:
    - dagger_agent: The trained DAgger agent.
    - dataset_sizes: A list of dataset sizes through the training,
indicating how much data was used at each stage.
    - success_rates: A list of success rates evaluated at various
points during training, indicating the performance of the trained
agent.
    """
    expert_actor = deepcopy(expert_actor)
    actor = deepcopy(actor)
    set_configs('dagger')
    cfg.alg.episode_steps = 30
    cfg.alg.max_steps = 1200
    cfg.alg.eval_interval = 1
    cfg.alg.log_interval = 1
    cfg.alg.batch_size = 256
    cfg.alg.opt_epochs = 500
    set_random_seed(cfg.alg.seed)
    env = make_vec_env(cfg.alg.env_name,
                       cfg.alg.num_envs,
                       seed=cfg.alg.seed)
    env.reset()
    if actor is None:
```

```
        actor = create_actor(env=env)
    dagger_agent = DaggerAgent(actor=actor, expert_actor=expert_actor, 
lr=0.001)
    runner = EpisodicRunner(agent=dagger_agent, env=env)
    engine = DaggerEngine(agent=dagger_agent,
                          env=env,
                          runner=runner,
                          trajs=trajs)
    dataset_sizes, success_rates = engine.train()
    return dagger_agent, dataset_sizes, success_rates

set_configs('dagger')
cfg.alg.episode_steps = 30
cfg.alg.max_steps = 1200
cfg.alg.eval_interval = 1
cfg.alg.log_interval = 1
cfg.alg.batch_size = 256
cfg.alg.opt_epochs = 500
print(cfg.alg.max_grad_norm)
```

```
[INFO][2024-03-16 17:56:47]: Alogrithm type:<class 
'easyrl.configs.ppo_config.PPOConfig'>
INFO:EasyRL:Alogrithm type:<class 
'easyrl.configs.ppo_config.PPOConfig'>

====================================
      Device:cuda
====================================
None
```

(20 pts): Complete the missing code for `DaggerAgent` (define the loss function and optimize the policy). Train a DAgger agent using `train_dagger` with the behaviorally cloned agent that was trained on just one demonstration as the initial policy, π_{θ_k}, the same demonstration as the initial dataset, D, and the expert that will provide expert actions as our pre-trained expert model. Note: for train_dagger, pass in the agent's actor, not the agent itself.

Similar to Q1, plot the success rate curves for both DAgger and BC as a function of the number of expert transitions (e.g., dataset size) available at training. Your DAgger and BC curves should reach similarly high performance with enough data while DAgger will reach a high success rate earlier.

```
dagger_agent = None
dagger_steps = None
dagger_success_rates = None

#### TODO: train DAgger agent and plot the success rate curves for BC 
and DAgger together
#### It takes ~20 minutes in T4

# get the BC agent that was trained on just 1 expert demonstration
```

```
bc_agent = bc_agents[1]
dagger_agent, dagger_steps, dagger_success_rates =
train_dagger(expert_agent.actor, expert_trajs, bc_agent.actor)
######################################################################
####################

# Save results
with open(f'{PATH}/dagger_agent.pkl', 'wb') as f:
  data = [dagger_agent, dagger_steps, dagger_success_rates]
  pickle.dump(data, f)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
[INFO][2024-03-16 00:11:36]: Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
INFO:EasyRL:Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
[INFO][2024-03-16 00:11:36]: Creating 1 environments.
INFO:EasyRL:Creating 1 environments.
[INFO][2024-03-16 00:11:36]: Load in OpenGL!
INFO:AIRobot:Load in OpenGL!

====================================
      Device:cuda
====================================

/usr/local/lib/python3.10/dist-packages/gym/spaces/box.py:128:
UserWarning: WARN: Box bound precision lowered by casting to float32
  logger.warn(f"Box bound precision lowered by casting to
{self.dtype}")
/usr/local/lib/python3.10/dist-packages/gym/core.py:317:
DeprecationWarning: WARN: Initializing wrapper in old step API which
returns one bool instead of two. It is recommended to set
`new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/wrappers/step_api_compatib
ility.py:39: DeprecationWarning: WARN: Initializing environment in old
step API which returns one bool instead of two. It is recommended to
set `new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/core.py:256:
DeprecationWarning: WARN: Function `env.seed(seed)` is marked as
deprecated and will be removed in the future. Please use
`env.reset(seed=seed)` instead.
```

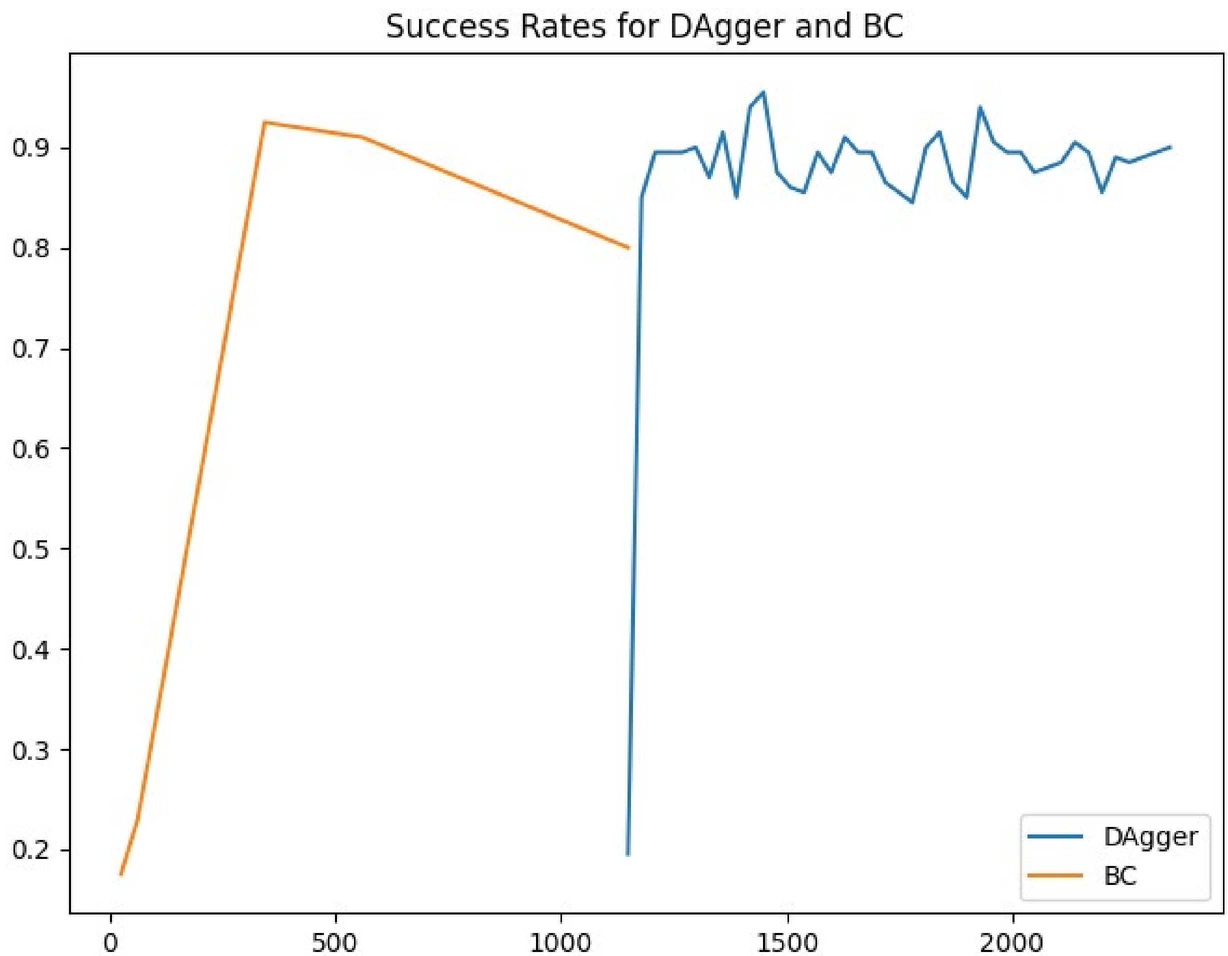
```
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:174: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed a `seed` instead of using `Env.seed` for
resetting the environment random number generator.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:190: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `return_info` to return information from the
environment resetting.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:195: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `options` to allow the environment
initialisation to be passed additional information.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `reset()` method
was expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `reset()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
```

{"model_id":"cc8d216543594c95abf0961ca8c5b6d9","version_major":2,"vers
ion_minor":0}

```
/usr/local/lib/python3.10/dist-packages/gym/utils/
passive_env_checker.py:227: DeprecationWarning: WARN: Core environment
is written in old step API which returns one bool instead of two. It
is recommended to rewrite the environment with new step API.
  logger.deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:233: DeprecationWarning: `np.bool8` is a deprecated alias for
`np.bool_`.  (Deprecated NumPy 1.24)
  if not isinstance(done, (bool, np.bool8)):
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `step()` method was
expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `step()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
```

```python
# load DAGGER experiments
with open(f'{PATH}/dagger_agent.pkl', 'rb') as f:
    dagger_agent, dagger_steps, dagger_success_rates = pickle.load(f)
```

```python
## Plot the curves of DAgger and BC against expert transitions

plot_curves({
    'DAgger': [dagger_steps, dagger_success_rates],
    'BC': [bc_steps, bc_success_rates]
}, 'Success Rates for DAgger and BC')
```



RL Finetune

Q3 (40 pts total): In DAgger, an expert is required to query the optimal action at every step during training time. However, an expert may not always be available. In the context of autonomous vehicles, for behavior cloning an expert driver is only required to collect the initial dataset of expert demonstrations while for DAgger we would need an expert to see everything the vehicle does and relabel the data in a continuous cycle during all of training. Clearly this approach does not scale, especially if obtaining these expert labels is costly.

In such cases where an expert is unavailable during the training process, if we have access to the reward function in addition to a few demonstrations, then we can combine RL and behavior cloning to improve performance.

In the following section, we will use PPO to finetune the behavior-cloned policy. We have provided you with a `train_ppo` function that you are free to modify. Note that typically we use multi-process to roll out many agents in parallel in PPO. It typically leads to faster and more stable learning. One way to get around parallelization is to have one policy update step after collecting many rollouts with the same policy. Here, our environment terminates after 30 steps and gets reset, but `episode_steps` is set to 900, so we will have 30 agents' rollout experience for every single step of policy optimization.

```
#### TODO: use PPO to finetune the behavior cloned policies (the ones
#### that are trained with 1 and 3 demonstration trajectories
respectively)
#### There is no implementation question in this code block.
def train_ppo(actor=None, save_dir=None, max_steps=1000000):
    """
    Finetunes a policy using the Proximal Policy Optimization (PPO)
algorithm.

    Parameters:
    - actor (optional): An initial policy model to finetune. If None,
a new actor is created.
    - save_dir (str, optional): Directory to save trained models and
logs.
    - max_steps (int, optional): The maximum number of steps to run
the PPO training.

    Returns:
    - agent: The trained PPO agent.
    - engine: The PPO training engine used for the training process.
    - save_dir: The directory where the trained models and logs are
saved.
    """
    set_config('ppo')
    cfg.alg.num_envs = 1
    cfg.alg.episode_steps = 900
    cfg.alg.max_steps = max_steps
    cfg.alg.deque_size = 20
    cfg.alg.eval_interval = 10
    cfg.alg.log_interval = 1
    cfg.alg.device = 'cuda' if torch.cuda.is_available() else 'cpu'
    cfg.alg.env_name = 'URPusher-v1'
    cfg.alg.save_dir =
Path.cwd().absolute().joinpath('data').as_posix()
    cfg.alg.save_dir += '/rl_finetune' if save_dir is None else
f'/{save_dir}'
    setattr(cfg.alg, 'diff_cfg', dict(save_dir=cfg.alg.save_dir))
```

```
    print(f'=====================================')
    print(f'      Device:{cfg.alg.device}')
    print(f'      Total number of steps:{cfg.alg.max_steps}')
    print(f'=====================================')

    set_random_seed(cfg.alg.seed)
    env = make_vec_env(cfg.alg.env_name,
                       cfg.alg.num_envs,
                       seed=cfg.alg.seed)
    env.reset()
    ob_size = env.observation_space.shape[0]

    if actor is None:
        actor = create_actor(env=env)
    actor = deepcopy(actor)

    critic_body = MLP(input_size=ob_size,
                     hidden_sizes=[64],
                     output_size=64,
                     hidden_act=nn.Tanh,
                     output_act=nn.Tanh)

    critic = ValueNet(critic_body, in_features=64)
    agent = PPOAgent(actor=actor, critic=critic, env=env)
    runner = EpisodicRunner(agent=agent, env=env)
    engine = PPOEngine(agent=agent,
                       runner=runner)
    engine.train()
    return agent, engine, cfg.alg.save_dir

# pusher environment with the environment trained from scratch
# PATH = "/content/drive/MyDrive/Colab_Notebooks"
save_dir_scratch = 'tmp/ppo_scratch'
ppo_agent_scratch, ppo_engine_scratch, dir_scratch =
train_ppo(save_dir=save_dir_scratch, max_steps=10000)

# get the BC actor that was trained on 3 demonstrations
bc_agent = bc_agents[3]
save_dir_finetuned = 'tmp/ppo_finetuned'
ppo_agent_finetuned, ppo_engine_finetuend, dir_finetuned =
train_ppo(actor=bc_agent.actor, save_dir=save_dir_finetuned,
max_steps=10000)
```

```
[INFO][2024-03-16 18:01:40]: Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
INFO:EasyRL:Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
[INFO][2024-03-16 18:01:40]: Creating 1 environments.
INFO:EasyRL:Creating 1 environments.
```

```
[INFO][2024-03-16 18:01:40]: Load in OpenGL!
INFO:AIRobot:Load in OpenGL!

====================================
      Device:cuda
      Total number of steps:10000
====================================

/usr/local/lib/python3.10/dist-packages/gym/spaces/box.py:128:
UserWarning: WARN: Box bound precision lowered by casting to float32
  logger.warn(f"Box bound precision lowered by casting to
{self.dtype}")
/usr/local/lib/python3.10/dist-packages/gym/core.py:317:
DeprecationWarning: WARN: Initializing wrapper in old step API which
returns one bool instead of two. It is recommended to set
`new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/wrappers/step_api_compatib
ility.py:39: DeprecationWarning: WARN: Initializing environment in old
step API which returns one bool instead of two. It is recommended to
set `new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/core.py:256:
DeprecationWarning: WARN: Function `env.seed(seed)` is marked as
deprecated and will be removed in the future. Please use
`env.reset(seed=seed)` instead.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:174: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed a `seed` instead of using `Env.seed` for
resetting the environment random number generator.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:190: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `return_info` to return information from the
environment resetting.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:195: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `options` to allow the environment
initialisation to be passed additional information.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `reset()` method
was expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `reset()` method is
```

```
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
[ERROR][2024-03-16 18:01:42]: Not a valid git repo:
/usr/local/lib/python3.10/dist-packages
ERROR:EasyRL:Not a valid git repo: /usr/local/lib/python3.10/dist-
packages
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:227: DeprecationWarning: WARN: Core environment is written in old
step API which returns one bool instead of two. It is recommended to
rewrite the environment with new step API.
  logger.deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:233: DeprecationWarning: `np.bool8` is a deprecated alias for
`np.bool_`.  (Deprecated NumPy 1.24)
  if not isinstance(done, (bool, np.bool8)):
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `step()` method was
expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `step()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
[INFO][2024-03-16 18:01:42]: Exploration steps: 0
INFO:EasyRL:Exploration steps: 0
[INFO][2024-03-16 18:01:42]: Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/ckpt_000000000000.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/ckpt_000000000000.pt.
[INFO][2024-03-16 18:01:42]: Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/model_best.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/model_best.pt.
[INFO][2024-03-16 18:02:11]: Exploration steps: 9000
INFO:EasyRL:Exploration steps: 9000
[INFO][2024-03-16 18:02:11]: Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/ckpt_000000009000.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/ckpt_000000009000.pt.
[INFO][2024-03-16 18:02:11]: Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/model_best.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_scratch/seed_0/model/model_best.pt.
[INFO][2024-03-16 18:02:17]: Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
INFO:EasyRL:Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
[INFO][2024-03-16 18:02:17]: Creating 1 environments.
INFO:EasyRL:Creating 1 environments.
```

```
[INFO][2024-03-16 18:02:17]: Load in OpenGL!
INFO:AIRobot:Load in OpenGL!

====================================
      Device:cuda
      Total number of steps:10000
====================================

[ERROR][2024-03-16 18:02:19]: Not a valid git repo:
/usr/local/lib/python3.10/dist-packages
ERROR:EasyRL:Not a valid git repo: /usr/local/lib/python3.10/dist-
packages
[INFO][2024-03-16 18:02:19]: Exploration steps: 0
INFO:EasyRL:Exploration steps: 0
[INFO][2024-03-16 18:02:19]: Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/ckpt_000000000000.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/ckpt_000000000000.pt.
[INFO][2024-03-16 18:02:19]: Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/model_best.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/model_best.pt.
[INFO][2024-03-16 18:02:51]: Exploration steps: 9000
INFO:EasyRL:Exploration steps: 9000
[INFO][2024-03-16 18:02:51]: Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/ckpt_000000009000.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/ckpt_000000009000.pt.
[INFO][2024-03-16 18:02:51]: Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/model_best.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_finetuned/seed_0/model/model_best.pt.
```

(20 pts): Compare the learning curves (both the return curve and the success rate curve) of the following two cases:

1. A policy trained from scratch for the pusher environment
2. A finetuned behavior-cloned policy with RL (specifically here, use the BC agent trained with 3 demonstration trajectories from Q1, i.e., bc_agents[3])

- This should be a fixed value across all steps.

For 10k time steps and 300k time steps, train both agents and make two separate plots for a total of 4 plots. One analyzing the return and the other analyzing success rates.

Return Plot: the number of steps (# of steps) X (return for rl_scratch and rl_finetune). Plot the average return with its uncertainty (standard deviation) as a shade with alpha=0.25

Success Rate Plot: the number of steps (# of steps) X (success for rl_scratch and rl_finetune). Include the average success rate for the **BC agent** trained on 3 demonstrations without any fine-turning in this plot as a separate color (you should've cached this from Q1).

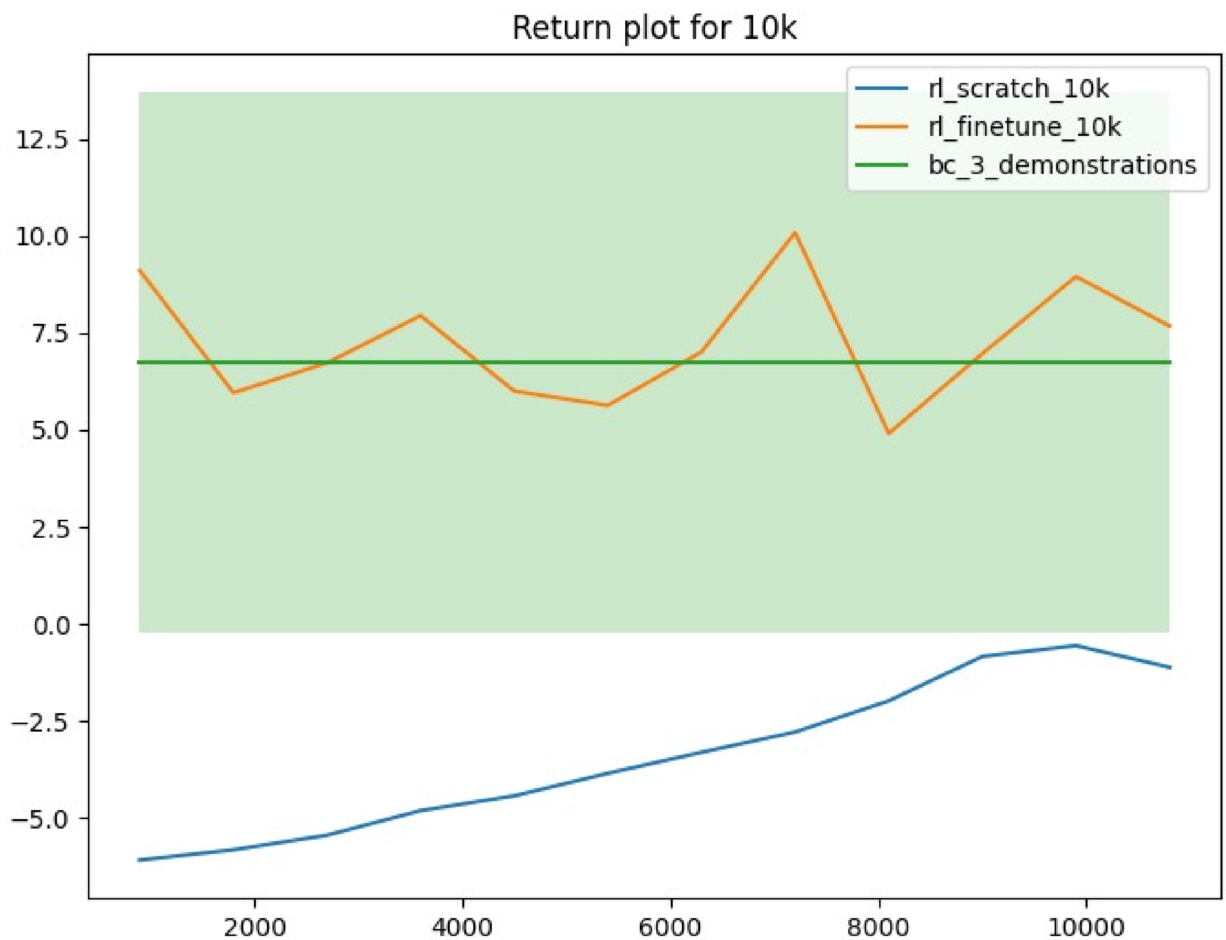
Note: we provide the data for the 300k training, no need to implement the 300k trained agents yourself

```
# It takes ~3 minutes in T4 for 10K steps.
# TODO: Plots for 10k time steps. The `plot_curves()` function may be
useful.

# Custom function for plotting curves with uncertainty (using standard
deviation for uncertainty)
def plot_curves_with_uncertainty(data_dict, title):
    """
    Parameters:
    - data_dict (Dict[str, List[List[float]]]): A dictionary where
each key is a label string and each value is a list
      containing three lists: the first list for x-values, the second
for y-values (mean), and the third for standard deviation.
    - title (str): The title of the plot.

    This function does not return anything. It directly displays the
plot.
    """
    fig, ax = plt.subplots(figsize=(8, 6))  # Adjusted size for better
visibility
    for label, data in data_dict.items():
        x = data[0]
        y_mean = data[1]
        if len(data) == 3:
            y_std = data[2]
        else:
            y_std = np.zeros_like(y_mean)

        # y_std = data[2]

        # Plot mean
        ax.plot(x, y_mean, label=label)

        # Plot uncertainty (standard deviation) as a shaded area
        ax.fill_between(x, y_mean - y_std, y_mean + y_std, alpha=0.25)

    ax.set_title(title)
    ax.legend()
    plt.show()

## PLOT 1 -- (# of steps) X (return for rl_scratch and rl_finetune),
and the average return of the BC agent with its uncertainty
steps_scratch, returns_scratch, success_rate_scratch =
read_tf_log('data/tmp/ppo_scratch/seed_0/log')
steps_finetuned, returns_finetuned, success_rate_finetuned =
read_tf_log(f'data/tmp/ppo_finetuned/seed_0/log')
```

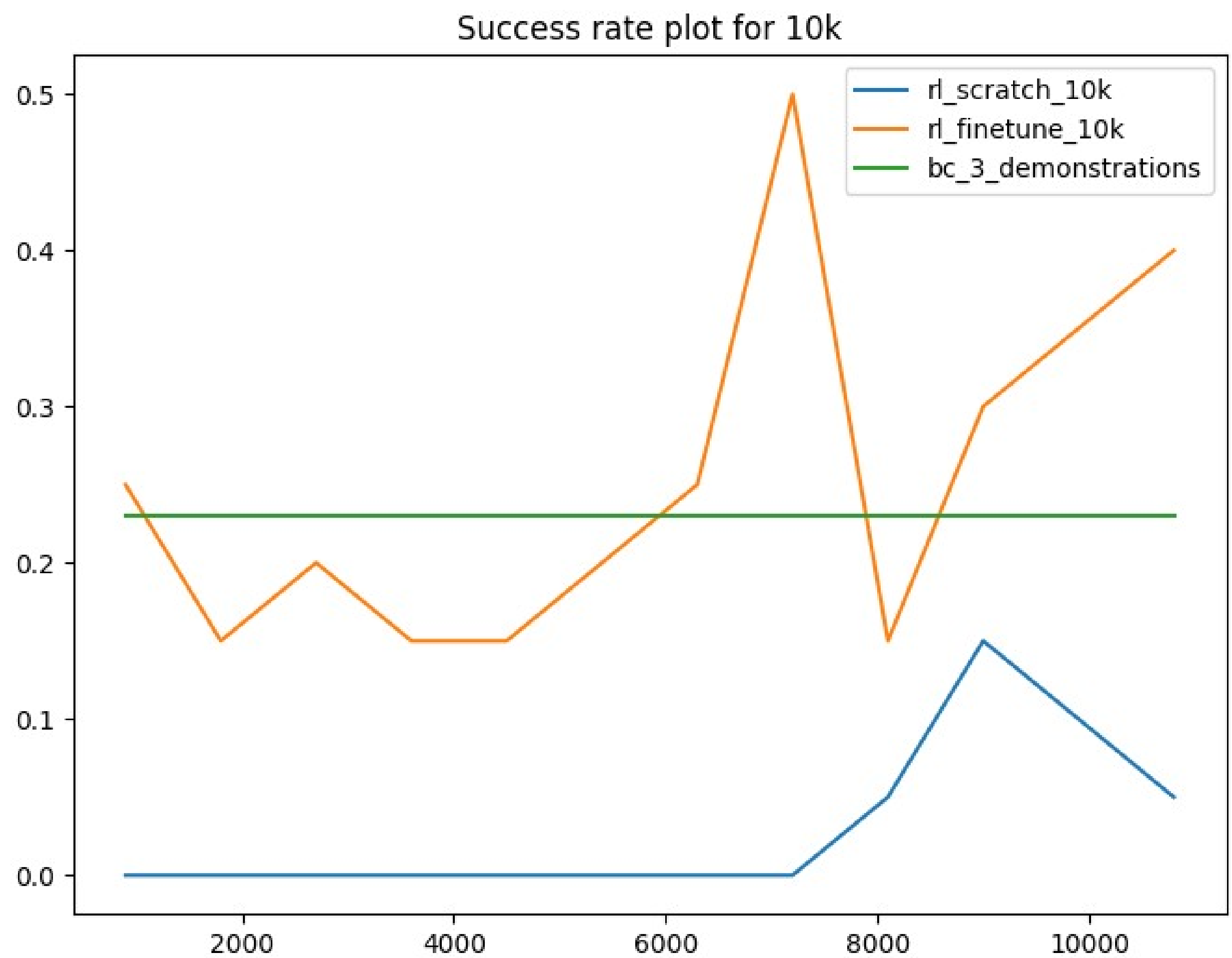
```
# FOR the BC agent -- with 3 demonstrations -- num_trajs = [1, 3, 15,
25, 50] -- Cached from Q1
num_demonstrations = 3
bc_success_rate = bc_success_rates[1] #since success rate is just an
array and it would index into 1 (for num_demonstrations = 3)
bc_average_return = bc_rets[num_demonstrations][0]
bc_std = bc_rets[num_demonstrations][1]

print(f'BC agent with {num_demonstrations} demonstrations, average
return -- {bc_average_return}, uncertainty -- {bc_std}')

plot_curves_with_uncertainty({
    'rl_scratch_10k': [steps_scratch, returns_scratch],
    'rl_finetune_10k': [steps_finetuned, returns_finetuned],
    'bc_3_demonstrations': [steps_scratch,
[bc_average_return]*len(steps_scratch), bc_std]}, 'Return plot for
10k')


## PLOT 2 -- (# of steps) X (success rate for rl_scratch and
rl_finetune) & average success rate of the BC agent with 3
demonstrations (cached from Q1)
plot_curves({
    'rl_scratch_10k': [steps_scratch, success_rate_scratch],
    'rl_finetune_10k': [steps_finetuned, success_rate_finetuned],
    'bc_3_demonstrations' : [steps_scratch, [bc_success_rate] *
len(steps_scratch)]}, 'Success rate plot for 10k')
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
Log dir is : data/tmp/ppo_scratch/seed_0/log, exists : True
Log dir is : data/tmp/ppo_finetuned/seed_0/log, exists : True
BC agent with 3 demonstrations, average return -- 6.73768424987793,
uncertainty -- 6.953542709350586
```



Return plot for 10k
rl_scratch_10k
rl_finetune_10k
bc_3_demonstrations
12.5
10.0
7.5
5.0
2.5
0.0
−2.5
−5.0
2000
4000
6000
8000
10000




```
# Download the results of the model trained with only PPO and finetuned trained for 300k steps
!wget --no-check-certificate -r 'https://drive.google.com/uc?export=download&id=1GNNd4iShD6fgsjLw6GJSVj169JlPLDZt' -O rl_scratch_results.csv
!wget --no-check-certificate -r  'https://drive.google.com/uc?export=download&id=10EWpvU0pS5vS1zx1oKytNwYRQJjsd3XS' -O rl_finetune_results.csv
```

```
WARNING: combining -O with -r or -p will mean that all downloaded content
will be placed in the single file you specified.

--2024-03-16 19:07:57--  https://drive.google.com/uc?export=download&id=1GNNd4iShD6fgsjLw6GJSVj169JlPLDZt
Resolving drive.google.com (drive.google.com)... 108.177.119.138, 108.177.119.100, 108.177.119.113, ...
Connecting to drive.google.com (drive.google.com)|108.177.119.138|:443... connected.
HTTP request sent, awaiting response... 303 See Other
```

```
Location: https://drive.usercontent.google.com/download?
id=1GNNd4iShD6fgsjLw6GJSVj169JlPLDZt&export=download [following]
--2024-03-16 19:07:57--
https://drive.usercontent.google.com/download?
id=1GNNd4iShD6fgsjLw6GJSVj169JlPLDZt&export=download
Resolving drive.usercontent.google.com
(drive.usercontent.google.com)... 108.177.127.132,
2a00:1450:4013:c07::84
Connecting to drive.usercontent.google.com
(drive.usercontent.google.com)|108.177.127.132|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 16117 (16K) [application/octet-stream]
Saving to: ‘rl_scratch_results.csv’

rl_scratch_results. 100%[===================>]  15.74K  --.-KB/s    in
0s

2024-03-16 19:07:58 (73.4 MB/s) - ‘rl_scratch_results.csv’ saved
[16117/16117]

FINISHED --2024-03-16 19:07:58--
Total wall clock time: 0.7s
Downloaded: 1 files, 16K in 0s (73.4 MB/s)
WARNING: combining -O with -r or -p will mean that all downloaded
content
will be placed in the single file you specified.

--2024-03-16 19:07:58--  https://drive.google.com/uc?
export=download&id=10EWpvU0pS5vS1zx1oKytNwYRQJjsd3XS
Resolving drive.google.com (drive.google.com)... 108.177.119.138,
108.177.119.100, 108.177.119.113, ...
Connecting to drive.google.com (drive.google.com)|
108.177.119.138|:443... connected.
HTTP request sent, awaiting response... 303 See Other
Location: https://drive.usercontent.google.com/download?
id=10EWpvU0pS5vS1zx1oKytNwYRQJjsd3XS&export=download [following]
--2024-03-16 19:07:58--
https://drive.usercontent.google.com/download?
id=10EWpvU0pS5vS1zx1oKytNwYRQJjsd3XS&export=download
Resolving drive.usercontent.google.com
(drive.usercontent.google.com)... 108.177.127.132,
2a00:1450:4013:c07::84
Connecting to drive.usercontent.google.com
(drive.usercontent.google.com)|108.177.127.132|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 14773 (14K) [application/octet-stream]
Saving to: ‘rl_finetune_results.csv’

rl_finetune_results 100%[===================>]  14.43K  --.-KB/s    in
0s
```

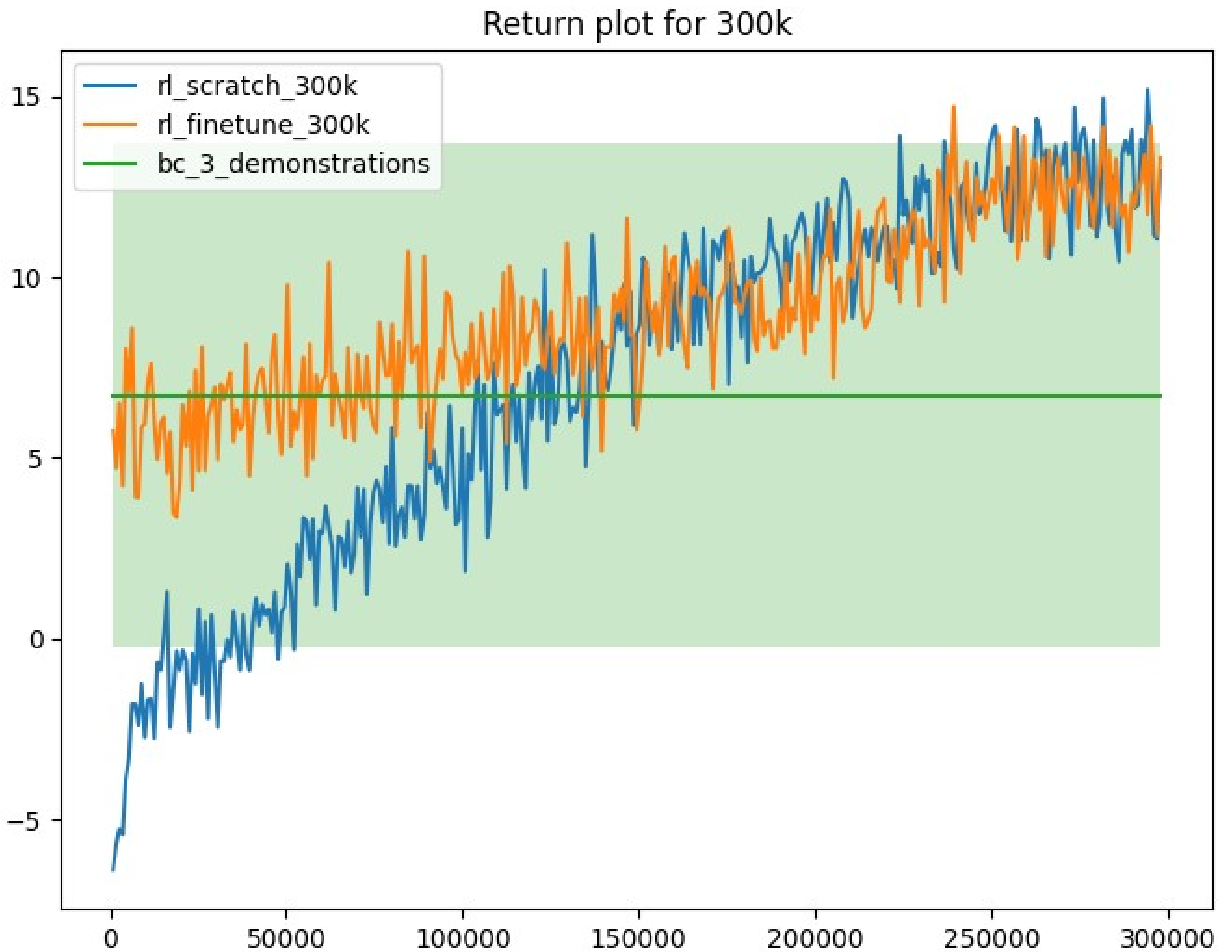
```
2024-03-16 19:07:59 (96.1 MB/s) - ‘rl_finetune_results.csv’ saved
[14773/14773]

FINISHED --2024-03-16 19:07:59--
Total wall clock time: 1.1s
Downloaded: 1 files, 14K in 0s (96.1 MB/s)
```

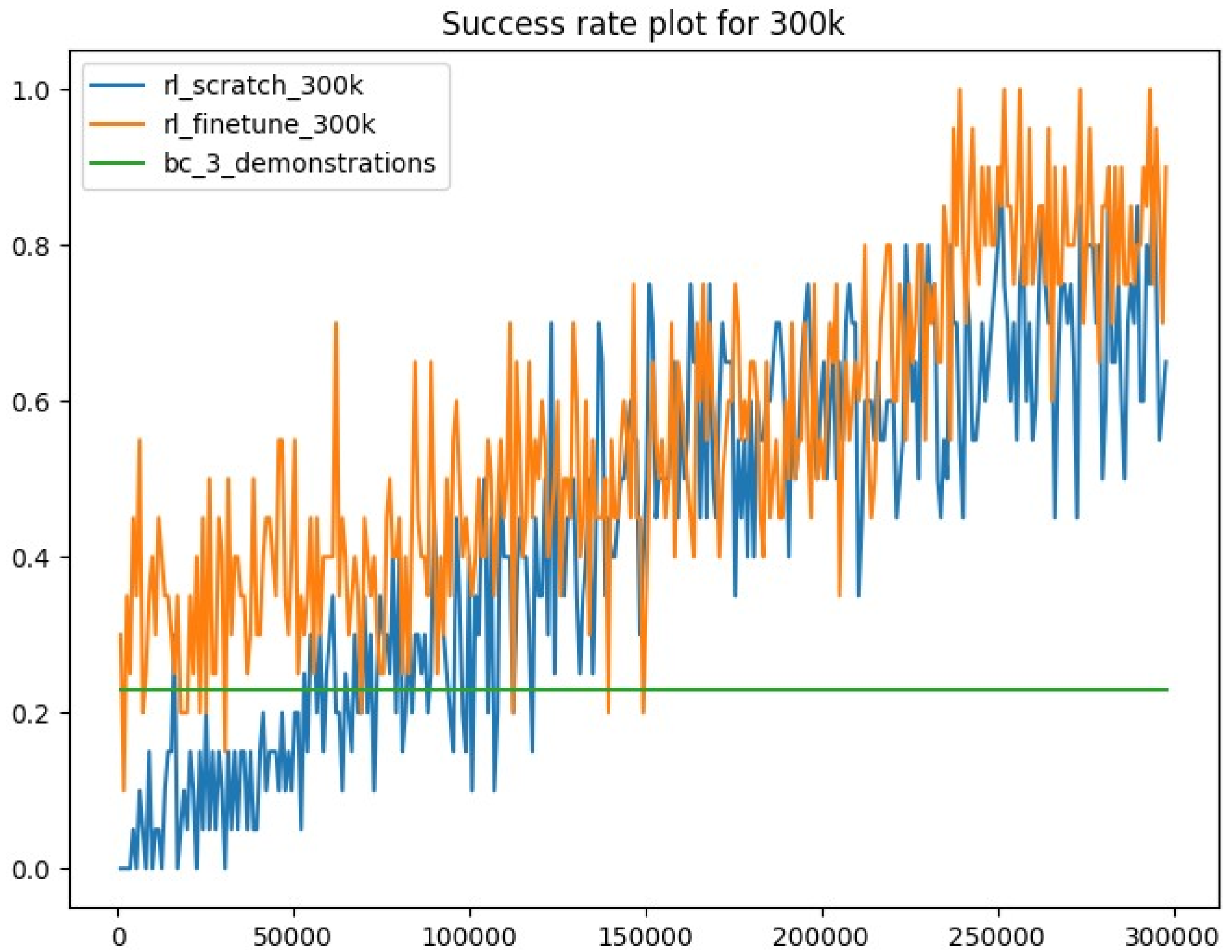
```
# load data for 300k steps
df = pd.read_csv("rl_scratch_results.csv")
scratch_steps, scratch_returns, scratch_success_rate = df["steps"],
df["returns"], df["success_rate"]

df = pd.read_csv("rl_finetune_results.csv")
finetune_steps, finetune_returns, finetune_success_rate = df["steps"],
df["returns"], df["success_rate"]
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
# TODO: Plots for 300k time steps.
# PLOT 1 -- (# of steps) X (returns for rl_scratch and rl_finetune on
300k steps) & average return of the BC agent (with 3 demonstrations)
with uncertainty
plot_curves_with_uncertainty({
    'rl_scratch_300k': [scratch_steps, scratch_returns],
    'rl_finetune_300k': [finetune_steps, finetune_returns],
    'bc_3_demonstrations': [scratch_steps,
[bc_average_return]*len(scratch_steps), bc_std]}, 'Return plot for
300k')

# PLOT 2 -- (# of steps) X (success rate for rl_scratch and
rl_finetune on 300k steps) & average success rate of the BC agent with
3 demonstrations
plot_curves({
    'rl_scratch_300k': [scratch_steps, scratch_success_rate],
    'rl_finetune_300k': [finetune_steps, finetune_success_rate],
    'bc_3_demonstrations' : [scratch_steps, [bc_success_rate] *
len(scratch_steps)]}, 'Success rate plot for 300k')
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```


Return plot for 300k
rl_scratch_300k
rl_finetune_300k
bc_3_demonstrations
15
10
5
0
−5
0
50000
100000
150000
200000
250000
300000



Q (10 pts): Do you see any difference in performance at the end of training? Why do `rl_scratch` and `rl_finetune` converge to the same success rate?

A: We don't see any noticeable difference in performance at the end of training, and that `rl_scratch` and `rl_finetune` converge to the same success rate. This could be because both the agents had sufficient steps (300k) to explore the environment and optimize their policies. We see that `rl_finetune` starts with a better initial policy, and hence, its success_rate and return are higher initially than `rl_scratch`, giving at an advantage. However, this advantage diminishes, as the `rl_scratch` policy catches up (given sufficient number of steps).

Q (10 pts): What about in comparison to the BC agent without fine-tuning? If so, describe them in detail.

A: Here, the BC agent learns solely from expert demonstrations using supervised learning to mimic the behavior of the expert. Although, this leads to decent performance as the number of demonstrations increase (in the plot in Q1), the BC agent is limited by the quality and variety of the expert data. On the other, PPO learns from interactions with the environment, and optimizes its policy based on the rewards received, allowing it to discover strategies not present in the demonstrations. In essence, BC agent would struggle with generalization if there aren't enough diverse demonstrations from the expert, which could be seen from its high variance (uncertainty) even though its mean return is comparable to RL policies. The mean success rate is much lower than the RL policies, indicating that it performs poorly compared to the RL policies, which improve their policies by continuously interacting with the environment.

Suboptimal Demonstrations

Q4 (35 pts total): In many cases, we might not have a good expert model available. Thus, the demonstrations we get from the expert will not be optimal. In the following section, we will use a sub-optimal expert model to generate the demonstration data, use such data to train a BC agent, and see if the policy can be improved by RL.

```
# Download the suboptimal expert model
!wget --no-check-certificate -r 'https://docs.google.com/uc?
export=download&id=1AzWwGkOcZxrx43kNhD-7TPj06bIKRSXX' -O
pusher_suboptimal_expert_model.pt
```

```
WARNING: combining -O with -r or -p will mean that all downloaded
content
will be placed in the single file you specified.

--2024-03-16 19:16:10--  https://docs.google.com/uc?
export=download&id=1AzWwGkOcZxrx43kNhD-7TPj06bIKRSXX
Resolving docs.google.com (docs.google.com)... 108.177.119.138,
108.177.119.113, 108.177.119.100, ...
Connecting to docs.google.com (docs.google.com)|
108.177.119.138|:443... connected.
HTTP request sent, awaiting response... 303 See Other
Location: https://drive.usercontent.google.com/download?
id=1AzWwGkOcZxrx43kNhD-7TPj06bIKRSXX&export=download [following]
--2024-03-16 19:16:11--
https://drive.usercontent.google.com/download?id=1AzWwGkOcZxrx43kNhD-
7TPj06bIKRSXX&export=download
Resolving drive.usercontent.google.com
(drive.usercontent.google.com)... 108.177.127.132,
2a00:1450:4013:c07::84
Connecting to drive.usercontent.google.com
(drive.usercontent.google.com)|108.177.127.132|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 167811 (164K) [application/octet-stream]
Saving to: ‘pusher_suboptimal_expert_model.pt’

pusher_suboptimal_e 100%[===================>] 163.88K  --.-KB/s    in
0.002s

2024-03-16 19:16:12 (104 MB/s) - ‘pusher_suboptimal_expert_model.pt’
saved [167811/167811]

FINISHED --2024-03-16 19:16:12--
```

```
Total wall clock time: 1.2s
Downloaded: 1 files, 164K in 0.002s (104 MB/s)
```

```
# same as before, let's load a suboptimal expert model
set_configs()
env = make_vec_env(cfg.alg.env_name,
                   cfg.alg.num_envs,
                   seed=cfg.alg.seed)
sub_expert_agent = load_expert_agent(env, device=cfg.alg.device,
expert_model_path='pusher_suboptimal_expert_model.pt')
```

```
[INFO][2024-03-16 19:21:07]: Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
INFO:EasyRL:Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
[INFO][2024-03-16 19:21:07]: Creating 1 environments.
INFO:EasyRL:Creating 1 environments.
[INFO][2024-03-16 19:21:07]: Load in OpenGL!
INFO:AIRobot:Load in OpenGL!

====================================
      Device:cuda
====================================
Loading expert model from: pusher_suboptimal_expert_model.pt.
```

```
# let's see how good the expert model is
# It takes < 1 minute in T4
success_rate, ret_mean, ret_std, rets, successes =
eval_agent(sub_expert_agent, env, 500)
print(f'Expert policy success rate:{success_rate}')
```


```
{"model_id":"9e722d41e9684dbf895d452aeb4f6cee","version_major":2,"vers
ion_minor":0}
```


```
/usr/local/lib/python3.10/dist-packages/gym/utils/
passive_env_checker.py:174: UserWarning: WARN: Future gym versions
will require that `Env.reset` can be passed a `seed` instead of using
`Env.seed` for resetting the environment random number generator.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:190: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `return_info` to return information from the
environment resetting.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:195: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `options` to allow the environment
initialisation to be passed additional information.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `reset()` method
```

```
was expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.py:165: UserWarning: WARN: The obs returned by the `reset()` method is not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.py:227: DeprecationWarning: WARN: Core environment is written in old step API which returns one bool instead of two. It is recommended to rewrite the environment with new step API.
  logger.deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.py:233: DeprecationWarning: `np.bool8` is a deprecated alias for `np.bool_`.  (Deprecated NumPy 1.24)
  if not isinstance(done, (bool, np.bool8)):
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.py:141: UserWarning: WARN: The obs returned by the `step()` method was expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.py:165: UserWarning: WARN: The obs returned by the `step()` method is not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")

Expert policy success rate:0.632
```

```python
# let's use this suboptimal expert model to generate some demonstrations
# It takes < 1 minute in T4
sub_expert_trajs = generate_demonstration_data(expert_agent=sub_expert_agent,
                                               env=env,
                                               num_trials=50)
```

{"model_id":"e5561db067f4406e8784bb656af4dd45","version_major":2,"version_minor":0}

Q4.1 (10 pts): Similar to Q1, train a BC policy using `train_bc_agent` with $1, 3, 15, 25, 50$ suboptimal trajectories. Once you have trained the BC policy (cloned on suboptimal data), evaluate your policy on 200 episodes and plot the average success rate (returned by 'eval_agent') as a function of the number of expert transitions used in training.

```python
num_trajs = [1, 3, 15, 25, 50]
bc_success_rates_sub = []
bc_steps_sub = []
bc_agents_sub = dict()

num_episodes = 200
# TODO same as before, run BC with 1, 3, 15, 25, 50 demonstrations respectively
```

```
# It takse ~5 minutes in T4
for num_traj in num_trajs:
  # get a subset of suboptimal trajectories
  subset_trajs = sub_expert_trajs[:num_traj]
  # convert trajectories to the format required by TrajDataset
  # trajectories = create_trajectories(subset_trajs)

  # train a bc agent on this subset of suboptimal data
  agent = BasicAgent(create_actor(env))
  agent, logs, dataset_size = train_bc_agent(agent, subset_trajs)

  bc_steps_sub.append(dataset_size)

  # store the trained agent
  bc_agents_sub[num_traj] = agent

  # evaluate the agent
  print(f'Evaluating for suboptimal expert demonstrations :
{num_traj}')
  success_rate, ret_mean, ret_std, rets, successes = eval_agent(agent,
env, num_trials=num_episodes)

  # store the results
  bc_success_rates_sub.append(success_rate)
###########################################################

with open(f'{PATH}/bc_agent_sub.pkl', 'wb') as f:
    data = [bc_agents_sub, bc_steps_sub, bc_success_rates_sub]
    pickle.dump(data, f)
```

```
/usr/local/lib/python3.10/dist-packages/ipykernel/ipkernel.py:283:
DeprecationWarning: `should_run_async` will not call `transform_cell`
automatically in the future. Please pass the result to
`transformed_cell` argument and any exception that happen during
thetransform in `preprocessing_exc_tuple` in IPython 7.17 and above.
  and should_run_async(code)
```

```
Evaluating for suboptimal expert demonstrations : 1
```

{"model_id":"cedce2490eae475595d5c22d91e735be","version_major":2,"version_minor":0}

```
Evaluating for suboptimal expert demonstrations : 3
```

{"model_id":"1ca16abf1918422585bee4e2b10a7b46","version_major":2,"version_minor":0}

```
Evaluating for suboptimal expert demonstrations : 15
```

{"model_id":"65ac4fcf250643a0a08f1b5e49316166","version_major":2,"version_minor":0}

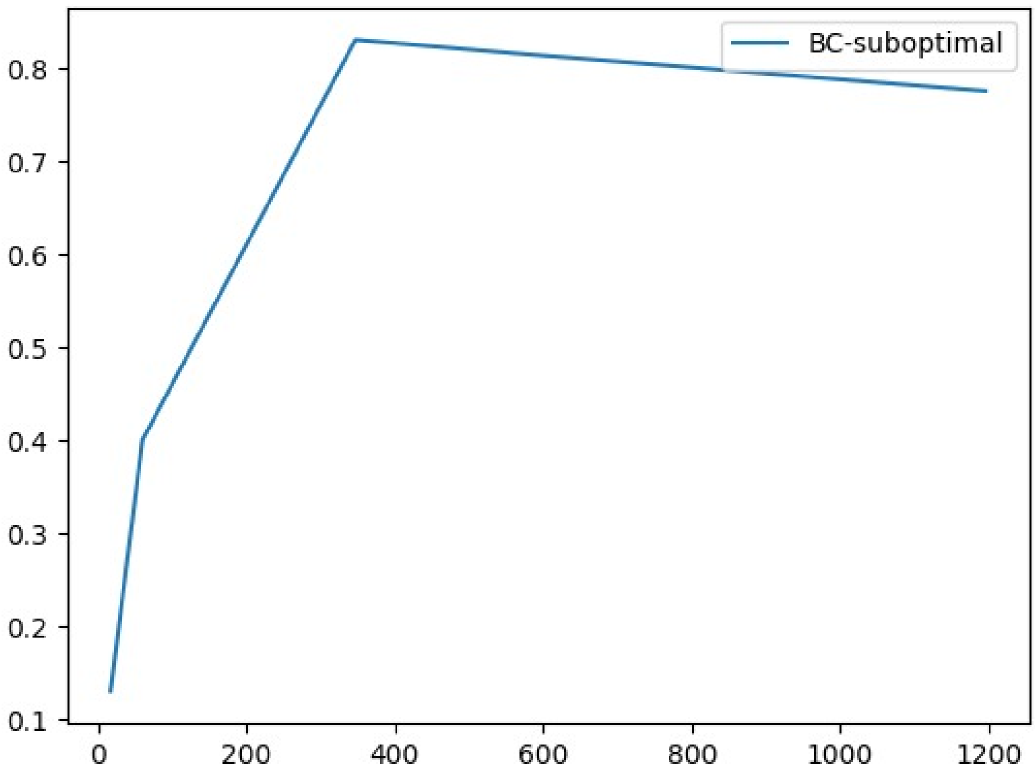
```
Evaluating for suboptimal expert demonstrations : 25
```

{"model_id":"decbd6c880194c729990621ce7ab180c","version_major":2,"version_minor":0}

```
Evaluating for suboptimal expert demonstrations : 50
```

{"model_id":"2da60c4bc58041a287684968d3c0191e","version_major":2,"version_minor":0}

```
with open(f'{PATH}/bc_agent_sub.pkl', 'rb') as f:
    bc_agents_sub, bc_steps_sub, bc_success_rates_sub = pickle.load(f)

plt.plot(bc_steps_sub, bc_success_rates_sub, label='BC-suboptimal')
plt.legend()

<matplotlib.legend.Legend at 0x7ca038207a30>
```



Q4.2 (25 pts): Similar to in Q3, run RL-finetune with the behavior-cloned policy trained from 3 suboptimal demonstration trajectories using 10k and 300k steps. Plot the return and success rate of the agent. On the same graph, also plot the same values for the 'from scratch' and RL-finetuned agents trained on 3 optimal demonstrations policies with the corresponding amount of steps. You should have a total of 4 graphs.

- Return Plot: the number of steps (# of steps) X return for *rl_scratch, rl_finetune_suboptimal, rl_finetune_optimal*

- Second Plot: the number of steps (# of steps) X success rate for *rl_scratch, rl_finetune_suboptimal, rl_finetune_optimal*

Does RL-finetune help improve the policy performance? Describe your observations.

A: From the graphs, we can see that for this setting (block pushing), RL-finetune does help, even with suboptimal demonstrations. We can see from the graphs of success_rate and return below for 10k steps, that both `rl_finetune_suboptimal` and `rl_finetune_optimal` achieve similar performance and outperform `rl_scratch`. However, we see that this advantage starts to diminish as the number of steps increase. In the grpah of 300k steps, we see that the `rl_scratch` policy catches and performs similarly to `rl_finetune_suboptimal` and `rl_finetune_optimal`. Although finetuning does help achieve better performance initially; training on a sufficient number of steps may allow `rl_scratch` to catch upto policies that are initialized from BC.

```
# finetuning RL policies with the behavior cloned policy from 3
suboptimal demonstration trajectories using 10k steps.
num_steps = 10000

# # RL policy trained on scratch -- not required to be run -- results
available from Q3
# save_dir_suboptimal_scratch = 'tmp/ppo_suboptimal_scratch'
# ppo_agent_suboptimal_scratch, ppo_engine_suboptimal_scratch,
dir_suboptimal_scratch =
train_ppo(save_dir=save_dir_suboptimal_scratch, max_steps=num_steps) #
no agent specified, will train from scratch

# get the bc agent trained on 3 demonstrations
bc_actor_suboptimal = bc_agents_sub[3].actor
save_dir_suboptimal_finetuned = 'tmp/ppo_suboptimal_finetuned'
ppo_agent_suboptimal_finetuned, ppo_engine_suboptimal_finetuned,
dir_suboptimal_finetuned = train_ppo(actor=bc_actor_suboptimal,
save_dir=save_dir_suboptimal_finetuned, max_steps=num_steps)
```

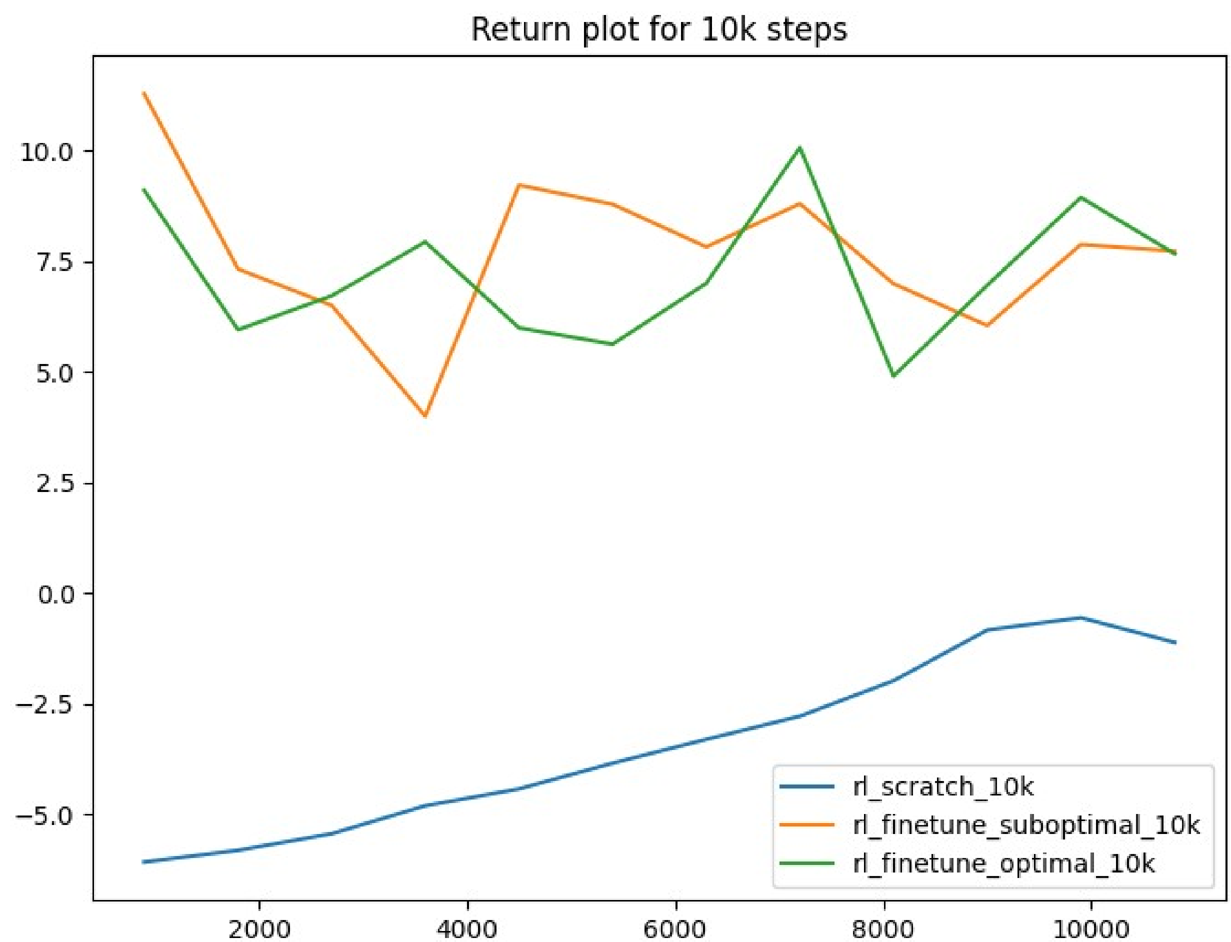
```
[INFO][2024-03-16 19:47:12]: Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
INFO:EasyRL:Alogrithm type:<class
'easyrl.configs.ppo_config.PPOConfig'>
[INFO][2024-03-16 19:47:12]: Creating 1 environments.
INFO:EasyRL:Creating 1 environments.
[INFO][2024-03-16 19:47:12]: Load in OpenGL!
INFO:AIRobot:Load in OpenGL!

====================================
      Device:cuda
      Total number of steps:10000
====================================

/usr/local/lib/python3.10/dist-packages/gym/spaces/box.py:128:
UserWarning: WARN: Box bound precision lowered by casting to float32
  logger.warn(f"Box bound precision lowered by casting to
```

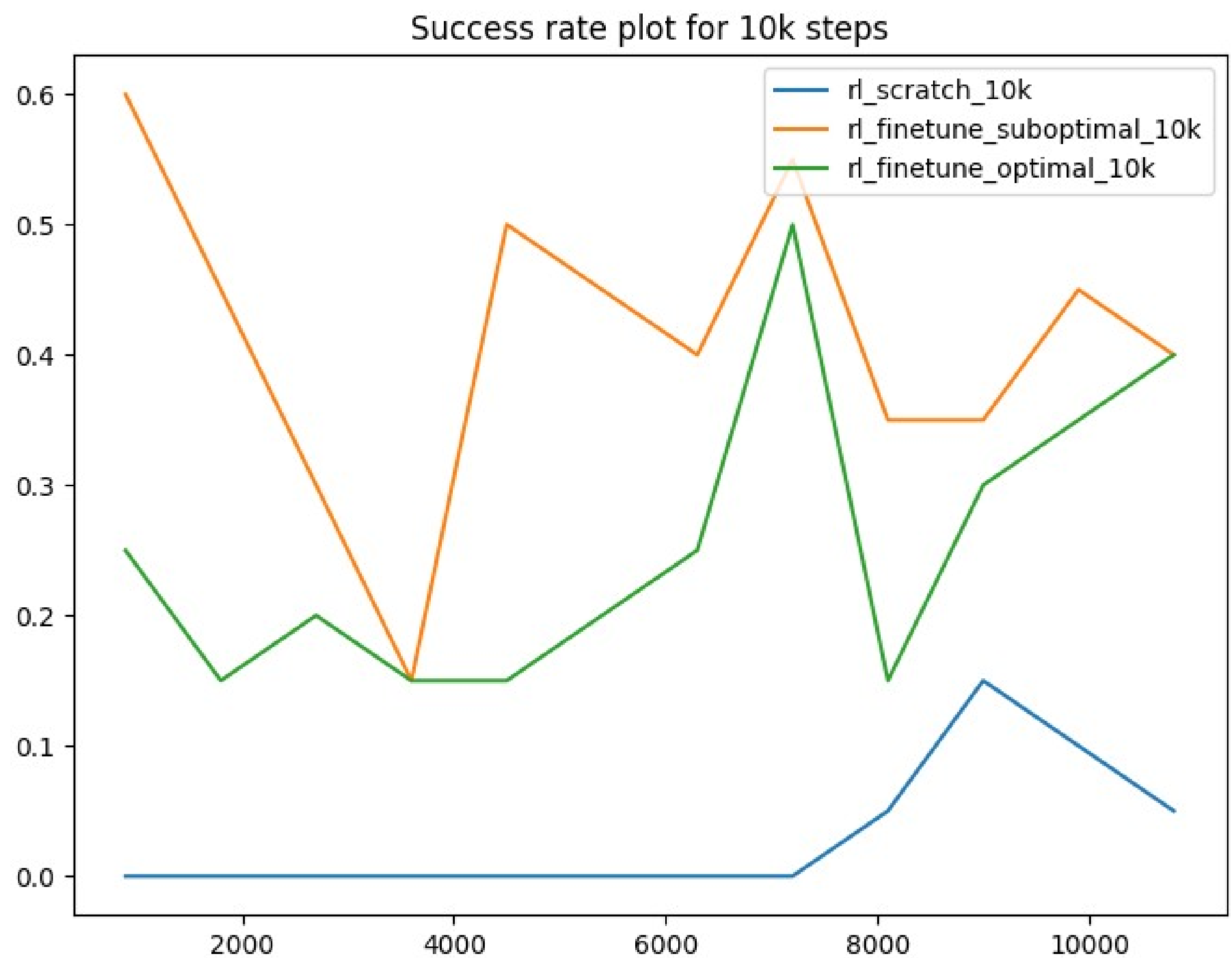
```
{self.dtype}")
/usr/local/lib/python3.10/dist-packages/gym/core.py:317:
DeprecationWarning: WARN: Initializing wrapper in old step API which
returns one bool instead of two. It is recommended to set
`new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/wrappers/step_api_compatib
ility.py:39: DeprecationWarning: WARN: Initializing environment in old
step API which returns one bool instead of two. It is recommended to
set `new_step_api=True` to use new step API. This will be the default
behaviour in future.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/core.py:256:
DeprecationWarning: WARN: Function `env.seed(seed)` is marked as
deprecated and will be removed in the future. Please use
`env.reset(seed=seed)` instead.
  deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:174: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed a `seed` instead of using `Env.seed` for
resetting the environment random number generator.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:190: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `return_info` to return information from the
environment resetting.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:195: UserWarning: WARN: Future gym versions will require that
`Env.reset` can be passed `options` to allow the environment
initialisation to be passed additional information.
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `reset()` method
was expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `reset()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
[ERROR][2024-03-16 19:47:14]: Not a valid git repo:
/usr/local/lib/python3.10/dist-packages
ERROR:EasyRL:Not a valid git repo: /usr/local/lib/python3.10/dist-
packages
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:227: DeprecationWarning: WARN: Core environment is written in old
step API which returns one bool instead of two. It is recommended to
rewrite the environment with new step API.
```

```
  logger.deprecation(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:233: DeprecationWarning: `np.bool8` is a deprecated alias for
`np.bool_`.  (Deprecated NumPy 1.24)
  if not isinstance(done, (bool, np.bool8)):
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:141: UserWarning: WARN: The obs returned by the `step()` method was
expecting numpy array dtype to be float32, actual type: float64
  logger.warn(
/usr/local/lib/python3.10/dist-packages/gym/utils/passive_env_checker.
py:165: UserWarning: WARN: The obs returned by the `step()` method is
not within the observation space.
  logger.warn(f"{pre} is not within the observation space.")
[INFO][2024-03-16 19:47:14]: Exploration steps: 0
INFO:EasyRL:Exploration steps: 0
[INFO][2024-03-16 19:47:14]: Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/ckpt_000000000
000.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/ckpt_000000000
000.pt.
[INFO][2024-03-16 19:47:14]: Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/model_best.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/model_best.pt.
[INFO][2024-03-16 19:47:46]: Exploration steps: 9000
INFO:EasyRL:Exploration steps: 9000
[INFO][2024-03-16 19:47:46]: Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/ckpt_000000009
000.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/ckpt_000000009
000.pt.
[INFO][2024-03-16 19:47:46]: Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/model_best.pt.
INFO:EasyRL:Saving checkpoint:
/content/data/tmp/ppo_suboptimal_finetuned/seed_0/model/model_best.pt.

# read the data first using read_tf_log for rl_finetuned_suboptimal
steps_suboptimal_finetuned, returns_suboptimal_finetuned,
success_rate_suboptimal_finetuned =
read_tf_log(dir_suboptimal_finetuned)

# TODO: Plot comparison of 3 agents trained with 10k and 300k steps. 4
graphs total.
## PLOT 1 -- (# of steps) X (return for rl_scratch, return for
rl_finetune_suboptimal, rl_finetune_optimal) -- 10k steps
plot_curves({
    'rl_scratch_10k': [steps_suboptimal_finetuned, returns_scratch],
    'rl_finetune_suboptimal_10k': [steps_suboptimal_finetuned,
```

```
returns_suboptimal_finetuned],
    'rl_finetune_optimal_10k': [steps_suboptimal_finetuned,
returns_finetuned],
}, 'Return plot for 10k steps')

## PLOT 2 -- (# of steps) X  (success rate for rl_scratch,
rl_finetune_suboptimal, rl_finetune_optimal) -- 10k steps
plot_curves({
    'rl_scratch_10k': [steps_suboptimal_finetuned,
success_rate_scratch],
    'rl_finetune_suboptimal_10k': [steps_suboptimal_finetuned,
success_rate_suboptimal_finetuned],
    'rl_finetune_optimal_10k': [steps_suboptimal_finetuned,
success_rate_finetuned],
}, 'Success rate plot for 10k steps')
```

```
Log dir is : /content/data/tmp/ppo_suboptimal_finetuned, exists : True
```

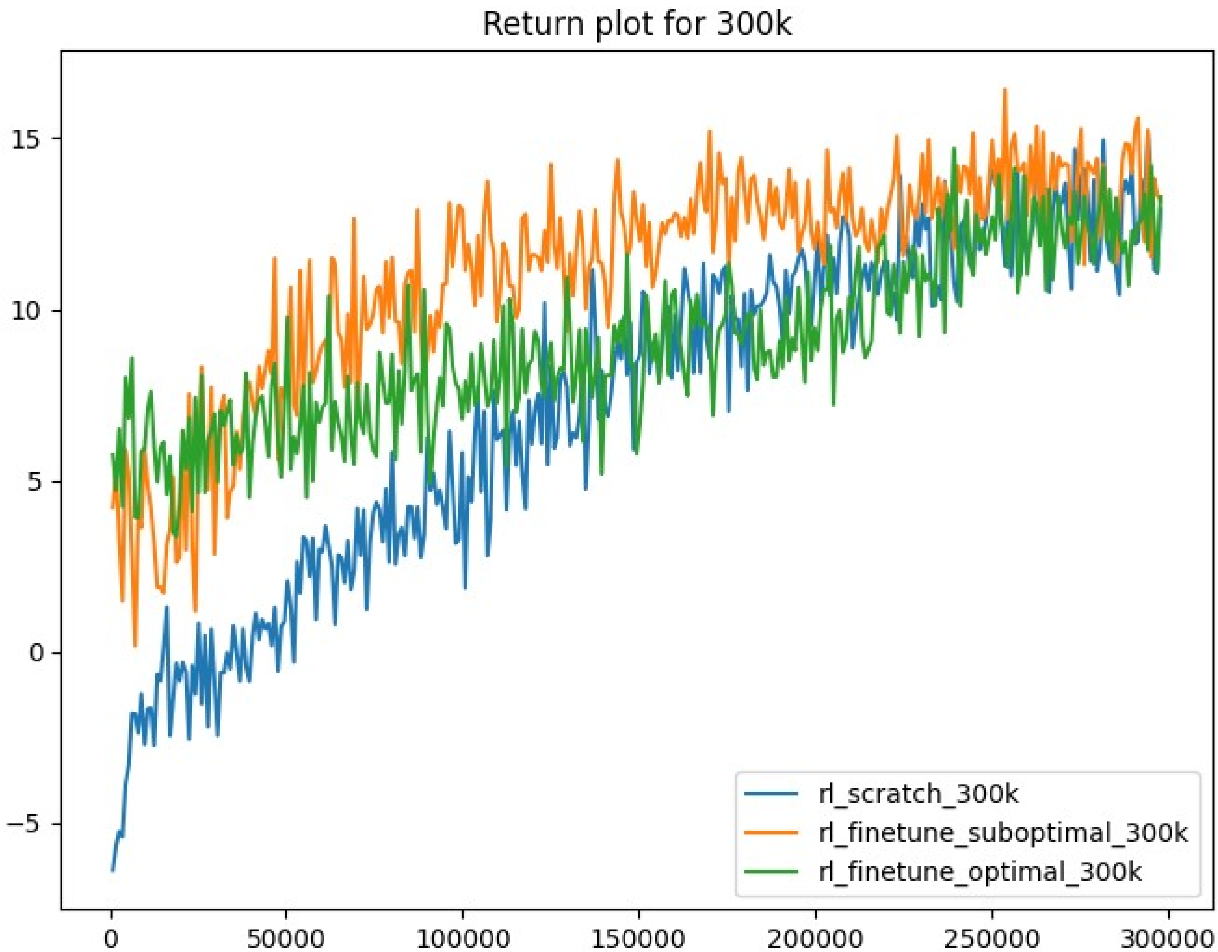


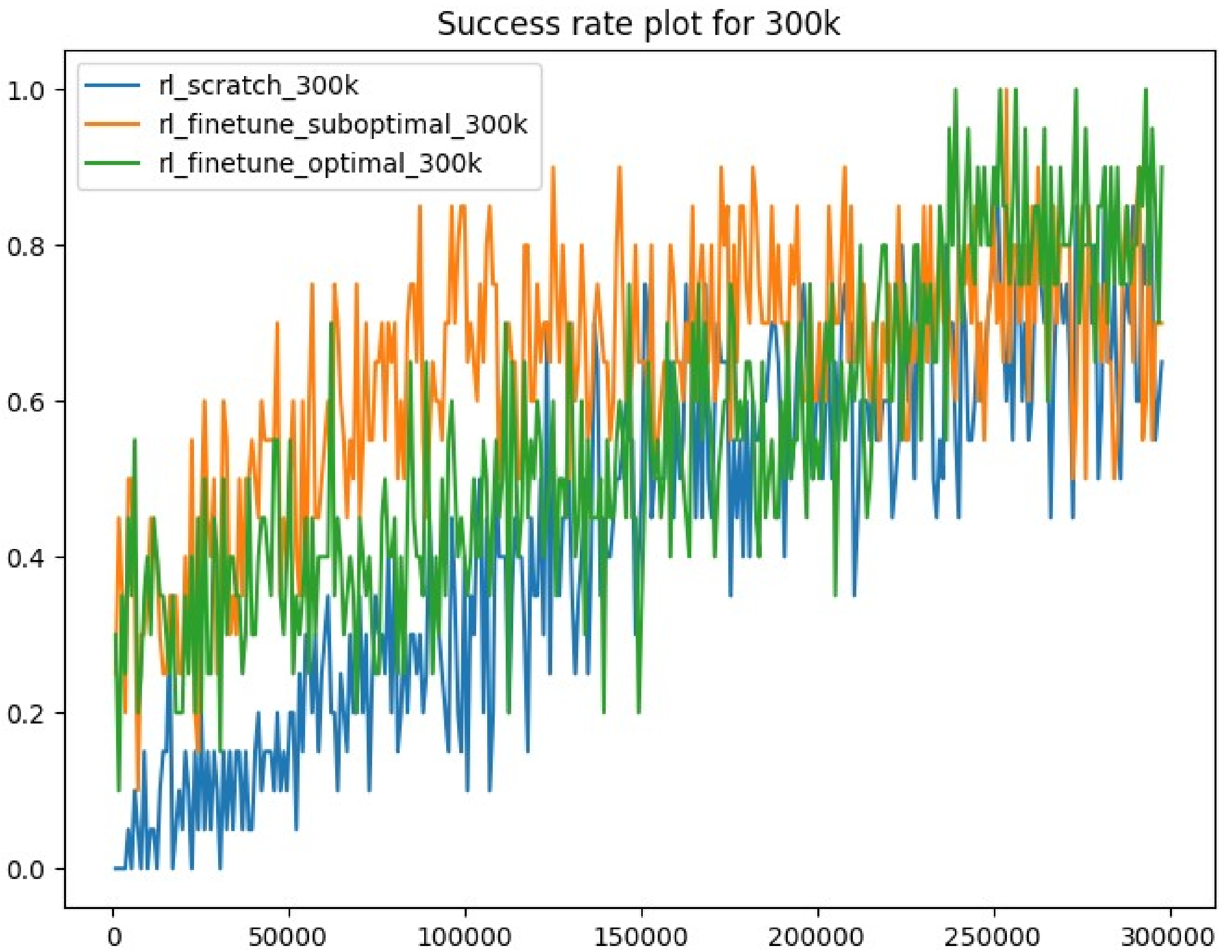



```
!wget --no-check-certificate -r  'https://drive.google.com/uc?export=download&id=1uxWNFfOswOW7qlEPCJgPdr_xefvJBUkx' -O rl_finetune_sub_results.csv

# load data for finetune suboptimal agent trained on 300k steps
df = pd.read_csv("rl_finetune_sub_results.csv")
finetune_sub_steps, finetune_sub_returns, finetune_sub_success_rate = df["steps"], df["returns"], df["success_rate"]
```

```
WARNING: combining -O with -r or -p will mean that all downloaded content
will be placed in the single file you specified.

--2024-03-16 19:35:45--  https://drive.google.com/uc?export=download&id=1uxWNFfOswOW7qlEPCJgPdr_xefvJBUkx
Resolving drive.google.com (drive.google.com)... 108.177.119.139, 108.177.119.100, 108.177.119.113, ...
Connecting to drive.google.com (drive.google.com)|108.177.119.139|:443... connected.
HTTP request sent, awaiting response... 303 See Other
```

```
Location: https://drive.usercontent.google.com/download?
id=1uxWNFfOswOW7qlEPCJgPdr_xefvJBUkx&export=download [following]
--2024-03-16 19:35:46--
https://drive.usercontent.google.com/download?
id=1uxWNFfOswOW7qlEPCJgPdr_xefvJBUkx&export=download
Resolving drive.usercontent.google.com
(drive.usercontent.google.com)... 108.177.127.132,
2a00:1450:4013:c07::84
Connecting to drive.usercontent.google.com
(drive.usercontent.google.com)|108.177.127.132|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 15014 (15K) [application/octet-stream]
Saving to: ‘rl_finetune_sub_results.csv’

rl_finetune_sub_res 100%[===================>]  14.66K  --.-KB/s    in
0s

2024-03-16 19:35:47 (98.8 MB/s) - ‘rl_finetune_sub_results.csv’ saved
[15014/15014]

FINISHED --2024-03-16 19:35:47--
Total wall clock time: 1.4s
Downloaded: 1 files, 15K in 0s (98.8 MB/s)

# Plots for the 300k steps
## PLOT 1 -- (# of steps) X (return for rl_scratch, return for
rl_finetune_suboptimal, rl_finetune_optimal)
total_steps = len(finetune_returns)

plot_curves({
    'rl_scratch_300k': [finetune_sub_steps[:total_steps],
scratch_returns[:total_steps]],
    'rl_finetune_suboptimal_300k': [finetune_sub_steps[:total_steps],
finetune_sub_returns[:total_steps]],
    'rl_finetune_optimal_300k': [finetune_sub_steps[:total_steps],
finetune_returns[:total_steps]],
}, 'Return plot for 300k')

## PLOT 2 -- (# of steps) X (success_rate for rl_scratch,
rl_finetune_suboptimal, rl_finetune_optimal)
plot_curves({
    'rl_scratch_300k': [finetune_sub_steps[:total_steps],
scratch_success_rate[:total_steps]],
    'rl_finetune_suboptimal_300k': [finetune_sub_steps[:total_steps],
finetune_sub_success_rate[:total_steps]],
    'rl_finetune_optimal_300k': [finetune_sub_steps[:total_steps],
finetune_success_rate[:total_steps]],
}, 'Success rate plot for 300k')
```


Return plot for 300k
15
10
5
0
−5
0
50000
100000
150000
200000
250000
300000
rl_scratch_300k
rl_finetune_suboptimal_300k
rl_finetune_optimal_300k



More Advanced Ideas (Bonus, Optional)

So far, we have seen how behavior cloning, DAgger, and behavior cloning with RL finetuning work. There are many more ideas one can try to make use of the demonstration data. For example, we can optimize the policy with the RL loss and behavior-cloning loss together as done in this work - Learning Complex Dexterous Manipulation with Deep Reinforcement Learning and Demonstrations, Equation (6) - discussed in lecture.

Try to implement it yourself on the Pusher environment. You are free to use any publicly avaiable RL library. You can also try out a sparse-reward setting for the Pusher environment with expert demonstrations.

Q (20 pts): Plot the return as well as the success rate curves. Compare the curves with the curves from the RL-scratch (training with RL from scratch) experiment.

A:

Survey (bonus points, 10 pts)

Please fill out this anonymous survey and enter the code below to receive credit. Thanks!

Code: oh_reward_my_reward

```
# Converts notebook to HTML page for download. Change path as
neccessary
!jupyter nbconvert --to html '/content/drive/My Drive/Colab
Notebooks/csl/hw4/lfd_solutions.ipynb'
```