Lab13 Report

st122314

Proximal Policy Optimization (PPO)

Actor and critic models

```
In [ ]:
```

process_device = "cuda"

```
# model.py
from torch import nn
from torch.distributions import normal
import torch
class Actor(nn.Module):
    def init (self, n states, n actions):
        super(Actor, self). init ()
        self.n_states = n_states
        self.n_actions = n_actions
        self.fc1 = nn.Linear(in features=self.n states, out features=64)
        self.fc2 = nn.Linear(in features=64, out features=64)
        self.mu = nn.Linear(in features=64, out features=self.n actions)
        self.log_std = nn.Parameter(torch.zeros(1, self.n_actions))
        for layer in self.modules():
            if isinstance(layer, nn.Linear):
                nn.init.orthogonal (layer.weight)
                layer.bias.data.zero_()
    def forward(self, inputs):
        x = inputs
        x = torch.tanh(self.fcl(x))
        x = torch.tanh(self.fc2(x))
        mu = self.mu(x)
        std = self.log std.exp()
        dist = normal.Normal(mu, std)
        return dist
class Critic(nn.Module):
    def init (self, n states):
        super(Critic, self).__init__()
        self.n_states = n_states
        self.fc1 = nn.Linear(in features=self.n states, out features=64)
        self.fc2 = nn.Linear(in features=64, out features=64)
        self.value = nn.Linear(in features=64, out features=1)
        for layer in self.modules():
            if isinstance(layer, nn.Linear):
                nn.init.orthogonal (layer.weight)
                layer.bias.data.zero ()
    def forward(self, inputs):
        x = inputs
        x = torch.tanh(self.fcl(x))
        x = torch.tanh(self.fc2(x))
        value = self.value(x)
        return value
```

Agent

```
# agent.py
# from model import Actor, Critic
from torch.optim import Adam
from torch import from numpy
import numpy as np
import torch
from torch.optim.lr scheduler import LambdaLR
class Agent:
    def init (self, env name, n iter, n states, action bounds, n actions, lr):
        self.env name = env name
        self.n iter = n iter
        self.action bounds = action bounds
        self.n actions = n actions
        self.n states = n states
        self.device = torch.device(process device)
        self.lr = lr
        self.current policy = Actor(n states=self.n states,
                                    n actions=self.n actions).to(self.device)
        self.critic = Critic(n states=self.n states).to(self.device)
        self.actor optimizer = Adam(self.current policy.parameters(), lr=self.lr, er
        self.critic optimizer = Adam(self.critic.parameters(), lr=self.lr, eps=1e-5)
        self.critic loss = torch.nn.MSELoss()
        self.scheduler = lambda step: max(1.0 - float(step / self.n iter), 0)
        self.actor scheduler = LambdaLR(self.actor optimizer, lr lambda=self.schedul
        self.critic scheduler = LambdaLR(self.actor optimizer, lr lambda=self.schedu
    def choose_dist(self, state):
        state = np.expand dims(state, 0)
        state = from numpy(state).float().to(self.device)
        with torch.no grad():
            dist = self.current policy(state)
        # action *= self.action bounds[1]
        # action = np.clip(action, self.action bounds[0], self.action bounds[1])
        return dist
    def get_value(self, state):
        state = np.expand dims(state, 0)
        state = from numpy(state).float().to(self.device)
        with torch.no grad():
            value = self.critic(state)
        return value.detach().cpu().numpy()
    def optimize(self, actor loss, critic loss):
        self.actor optimizer.zero grad()
        actor loss.backward()
        # torch.nn.utils.clip_grad_norm_(self.current_policy.parameters(), 0.5)
        # torch.nn.utils.clip grad norm (self.critic.parameters(), 0.5)
        self.actor optimizer.step()
```

```
self.critic optimizer.zero grad()
    critic loss.backward()
    # torch.nn.utils.clip grad norm (self.current policy.parameters(), 0.5)
    # torch.nn.utils.clip grad norm (self.critic.parameters(), 0.5)
    self.critic optimizer.step()
def schedule lr(self):
    # self.total scheduler.step()
    self.actor scheduler.step()
    self.critic scheduler.step()
def save weights(self, iteration, state rms):
    torch.save({"current_policy_state_dict": self.current policy.state dict(),
                "critic state dict": self.critic.state dict(),
                "actor optimizer state dict": self.actor optimizer.state dict(),
                "critic optimizer state dict": self.critic optimizer.state dict(
                "actor scheduler state dict": self.actor scheduler.state dict(),
                "critic scheduler state dict": self.critic scheduler.state dict(
                "iteration": iteration,
                "state rms mean": state rms.mean,
                "state_rms_var": state_rms.var,
                "state rms count": state rms.count}, self.env name + " weights.r
def load weights(self):
    checkpoint = torch.load(self.env name + " weights.pth")
    self.current policy.load state dict(checkpoint["current policy state dict"])
    self.critic.load_state_dict(checkpoint["critic_state_dict"])
    self.actor optimizer.load state dict(checkpoint["actor optimizer state dict"
    self.critic optimizer.load state dict(checkpoint["critic optimizer state dic
    self.actor scheduler.load state dict(checkpoint["actor scheduler state dict"
    self.critic scheduler.load state dict(checkpoint["critic scheduler state dic
    iteration = checkpoint["iteration"]
    state rms mean = checkpoint["state rms mean"]
    state rms var = checkpoint["state rms var"]
    return iteration, state rms mean, state rms var
def set to eval mode(self):
    self.current policy.eval()
    self.critic.eval()
def set to train mode(self):
    self.current policy.train()
    self.critic.train()
```

State normalization

```
In [ ]:
```

```
# running mean std.py
import numpy as np
class RunningMeanStd(object):
    # https://en.wikipedia.org/wiki/Algorithms for calculating variance#Parallel alg
    # -> It's indeed batch normalization :D
    def init (self, epsilon=1e-4, shape=()):
        self.mean = np.zeros(shape, 'float64')
        self.var = np.ones(shape, 'float64')
        self.count = epsilon
    def update(self, x):
        batch mean = np.mean(x, axis=0)
        batch var = np.var(x, axis=0)
        batch count = x.shape[0]
        self.update from moments(batch mean, batch var, batch count)
    def update from moments(self, batch mean, batch var, batch count):
        self.mean, self.var, self.count = update mean var count from moments(
            self.mean, self.var, self.count, batch mean, batch var, batch count)
def update mean var count from moments (mean, var, count, batch mean, batch var, batch
    delta = batch mean - mean
    tot_count = count + batch_count
    new mean = mean + delta * batch count / tot count
   m a = var * count
   m_b = batch_var * batch_count
   M2 = m a + m b + np.square(delta) * count * batch count / tot count
    new var = M2 / tot count
    new_count = tot_count
    return new mean, new var, new count
```

Evaluate model function

```
# test.py
import numpy as np
def evaluate_model(agent, env, state_rms, action_bounds):
    total rewards = 0
    s = env.reset()
    done = False
    while not done:
        s = np.clip((s - state_rms.mean) / (state_rms.var ** 0.5 + 1e-8), -5.0, 5.0)
        dist = agent.choose dist(s)
        action = dist.sample().cpu().numpy()[0]
        # action = np.clip(action, action_bounds[0], action bounds[1])
        next_state, reward, done, _ = env.step(action)
        # env.render()
        s = next_state
        total rewards += reward
    # env.close()
    return total rewards
```

```
# train.py
import torch
import numpy as np
import time
# from running mean std import RunningMeanStd
# from test import evaluate model
from torch.utils.tensorboard import SummaryWriter
class Train:
    def init (self, env, test env, env name, n iterations, agent, epochs, mini be
        self.env = env
        self.env name = env name
        self.test env = test env
        self.agent = agent
        self.epsilon = epsilon
        self.horizon = horizon
        self.epochs = epochs
        self.mini batch size = mini batch size
        self.n iterations = n iterations
        self.start time = 0
        self.state rms = RunningMeanStd(shape=(self.agent.n states,))
        self.running reward = 0
    @staticmethod
    def choose mini batch (mini batch size, states, actions, returns, advs, values, 1
        full_batch_size = len(states)
        for in range(full batch size // mini batch size):
            indices = np.random.randint(0, full batch size, mini batch size)
            yield states[indices], actions[indices], returns[indices], advs[indices]
                  log probs[indices]
    def train(self, states, actions, advs, values, log probs):
        values = np.vstack(values[:-1])
        log probs = np.vstack(log probs)
        returns = advs + values
        advs = (advs - advs.mean()) / (advs.std() + 1e-8)
        actions = np.vstack(actions)
        for epoch in range(self.epochs):
            for state, action, return_, adv, old_value, old_log_prob in self.choose_
                state = torch.Tensor(state).to(self.agent.device)
                action = torch.Tensor(action).to(self.agent.device)
                return_ = torch.Tensor(return_).to(self.agent.device)
                adv = torch.Tensor(adv).to(self.agent.device)
                old value = torch.Tensor(old value).to(self.agent.device)
                old_log_prob = torch.Tensor(old_log_prob).to(self.agent.device)
                value = self.agent.critic(state)
                # clipped value = old value + torch.clamp(value - old value, -self.e
                # clipped v loss = (clipped value - return ).pow(2)
                # unclipped_v_loss = (value - return_).pow(2)
                # critic loss = 0.5 * torch.max(clipped v loss, unclipped v loss).me
                critic loss = self.agent.critic loss(value, return )
```

```
new log prob = self.calculate log probs(self.agent.current policy, s
            ratio = (new log prob - old log prob).exp()
            actor loss = self.compute actor loss(ratio, adv)
            self.agent.optimize(actor loss, critic loss)
    return actor loss, critic loss
def step(self):
    state = self.env.reset()
    for iteration in range(1, 1 + self.n_iterations):
        states = []
        actions = []
        rewards = []
        values = []
        log probs = []
        dones = []
        self.start time = time.time()
        for t in range(self.horizon):
            # self.state rms.update(state)
            state = np.clip((state - self.state rms.mean) / (self.state rms.var
            dist = self.agent.choose dist(state)
            action = dist.sample()
            # action = np.clip(action, self.agent.action bounds[0], self.agent.action
            log_prob = dist.log_prob(action).cpu()
            action = action.cpu().numpy()[0]
            value = self.agent.get value(state)
            next state, reward, done, = self.env.step(action)
            states.append(state)
            actions.append(action)
            rewards.append(reward)
            values.append(value)
            log probs.append(log prob)
            dones.append(done)
            if done:
                state = self.env.reset()
            else:
                state = next state
        # self.state rms.update(next state)
        next_state = np.clip((next_state - self.state_rms.mean) / (self.state_rm
        next_value = self.agent.get_value(next_state) * (1 - done)
        values.append(next value)
        advs = self.get_gae(rewards, values, dones)
        states = np.vstack(states)
        actor loss, critic loss = self.train(states, actions, advs, values, log
        # self.agent.set weights()
        self.agent.schedule lr()
        eval rewards = evaluate model(self.agent, self.test env, self.state rms,
        self.state rms.update(states)
        self.print_logs(iteration, actor_loss, critic_loss, eval_rewards)
        print("iteration: ", iteration, "\teval rewards: ", eval rewards)
@staticmethod
def get_gae(rewards, values, dones, gamma=0.99, lam=0.95):
```

```
advs = []
    qae = 0
    dones.append(0)
    for step in reversed(range(len(rewards))):
        delta = rewards[step] + gamma * (values[step + 1]) * (1 - dones[step])
        gae = delta + gamma * lam * (1 - dones[step]) * gae
        advs.append(gae)
    advs.reverse()
    return np.vstack(advs)
@staticmethod
def calculate log probs(model, states, actions):
    policy distribution = model(states)
    return policy distribution.log prob(actions)
def compute actor loss(self, ratio, adv):
    pg loss1 = adv * ratio
    pg loss2 = adv * torch.clamp(ratio, 1 - self.epsilon, 1 + self.epsilon)
    loss = -torch.min(pg loss1, pg loss2).mean()
    return loss
def print logs(self, iteration, actor loss, critic loss, eval rewards):
    if iteration == 1:
        self.running reward = eval rewards
    else:
        self.running reward = self.running reward * 0.99 + eval rewards * 0.01
    if iteration % 100 == 0:
        print(f"Iter:{iteration} | "
              f"Ep Reward:{eval rewards:.3f} "
              f"Running_reward:{self.running_reward:.3f} | "
              f"Actor Loss:{actor loss:.3f}| "
              f"Critic Loss:{critic loss:.3f}| "
              f"Iter duration:{time.time() - self.start time:.3f} | "
              f"lr:{self.agent.actor scheduler.get last lr()}")
        self.agent.save weights(iteration, self.state rms)
    with SummaryWriter(self.env name + "/logs") as writer:
        writer.add scalar("Episode running reward", self.running reward, iterati
        writer.add scalar("Episode reward", eval rewards, iteration)
        writer.add_scalar("Actor loss", actor_loss, iteration)
        writer.add_scalar("Critic loss", critic_loss, iteration)
```

```
# You need a DISPLAY for GlfwContext. For Jupyter, try
# export LD_PRELOAD=/usr/lib/x86_64-linux-gnu/libGLEW.so
# xvfb-run -a -s "-screen 0 1400x900x24" jupyter lab --ip=<server-ip>
!echo $DISPLAY
```

```
In [ ]:
```

```
# Include this at the top of your colab code
import os
if not os.path.exists('.mujoco setup complete'):
    # Get the preregs
    !apt-get -gg update
    !apt-get -qq install -y libosmesa6-dev libgl1-mesa-glx libglfw3 libgl1-mesa-dev
    # Get Mujoco
    !mkdir ~/.mujoco
    !wget -q https://mujoco.org/download/mujoco210-linux-x86 64.tar.gz -O mujoco.tar
    !tar -zxf mujoco.tar.gz -C "$HOME/.mujoco"
    !rm mujoco.tar.gz
    # Add it to the actively loaded path and the bashrc path (these only do so much)
    !echo 'export LD LIBRARY PATH=$LD LIBRARY PATH:$HOME/.mujoco/mujoco210/bin' >> -
    !echo 'export LD PRELOAD=$LD PRELOAD:/usr/lib/x86 64-linux-gnu/libGLEW.so' >> ~/
    # THE ANNOYING ONE, FORCE IT INTO LDCONFIG SO WE ACTUALLY GET ACCESS TO IT THIS
    !echo "/root/.mujoco/mujoco210/bin" > /etc/ld.so.conf.d/mujoco ld lib path.conf
    !ldconfig
    # Install Mujoco-py
    !pip3 install -U 'mujoco-py<2.2,>=2.1'
    # run once
    !touch .mujoco setup complete
try:
    if mujoco run once:
        pass
except NameError:
    _mujoco_run_once = False
if not mujoco run once:
    # Add it to the actively loaded path and the bashrc path (these only do so much)
    try:
        os.environ['LD LIBRARY PATH'] = os.environ['LD LIBRARY PATH'] + ':/root/.mujoc
    except KeyError:
        os.environ['LD LIBRARY PATH']='/root/.mujoco/mujoco210/bin'
    try:
        os.environ['LD PRELOAD']=os.environ['LD PRELOAD'] + ':/usr/lib/x86 64-linux-
    except KeyError:
        os.environ['LD PRELOAD']='/usr/lib/x86 64-linux-gnu/libGLEW.so'
    # presetup so we don't see output on first env initialization
    import mujoco py
    mujoco run once = True
creating /usr/local/lib/python3.7/dist-packages/mujoco py/generated/ p
yxbld 2.1.2.14 37 linuxcpuextensionbuilder/lib.linux-x86 64-3.7
```

yxbld_2.1.2.14_37_linuxcpuextensionbuilder/lib.linux-x86_64-3.7 creating /usr/local/lib/python3.7/dist-packages/mujoco_py/generated/_p yxbld_2.1.2.14_37_linuxcpuextensionbuilder/lib.linux-x86_64-3.7/mujoco_py x86_64-linux-gnu-gcc -pthread -shared -Wl,-O1 -Wl,-Bsymbolic-functions -Wl,-Bsymbolic-functions -Wl,-z,relro -Wl,-Bsymbolic-functions -Wl,-z, relro -g -fdebug-prefix-map=/build/python3.7-dIfpci/python3.7-3.7.13=. -fstack-protector-strong -Wformat -Werror=format-security -Wdate-time -D_FORTIFY_SOURCE=2 /usr/local/lib/python3.7/dist-packages/mujoco_py/g enerated/_pyxbld_2.1.2.14_37_linuxcpuextensionbuilder/temp.linux-x86_6 4-3.7/usr/local/lib/python3.7/dist-packages/mujoco_py/cymj.o /usr/local/lib/python3.7/dist-packages/mujoco_py/generated/_pyxbld_2.1.2.14_37_linuxcpuextensionbuilder/temp.linux-x86_64-3.7/usr/local/lib/python3.7/dist-packages/mujoco_py/generated/_pyxbld_2.1.2.14_37_linuxcpuextensionbuilder/temp.linux-x86_64-3.7/usr/local/lib/python3.7/dist-packages/mujoco_py/gl/osmesashim.o -L/root/.mujoco/mujoco210/bin -Wl,--enable-new-dtags,-R/root/.mujoco/mujoco210/bin -lmujoco210 -lg

lewosmesa -losMesa -losMe

co_py/generated/_pyxbld_2.1.2.14_37_linuxcpuextensionbuilder/lib.linux

```
# play.py
from mujoco py.generated import const
from mujoco_py import GlfwContext
import numpy as np
import cv2
#GlfwContext(offscreen=True)
class Play:
    def init (self, env, agent, env name, max episode=1):
        self.env = env
        self.max episode = max episode
        self.agent = agent
        _, self.state_rms_mean, self.state_rms_var = self.agent.load_weights()
        self.agent.set to eval mode()
        self.device = torch.device(process_device)
        self.fourcc = cv2.VideoWriter fourcc(*'XVID')
        self.VideoWriter = cv2.VideoWriter(env name + ".avi", self.fourcc, 50.0, (25
    def evaluate(self):
        for _ in range(self.max_episode):
            s = self.env.reset()
            episode reward = 0
            for _ in range(self.env._max_episode_steps):
                s = np.clip((s - self.state rms mean) / (self.state rms var ** 0.5 +
                dist = self.agent.choose dist(s)
                action = dist.sample().cpu().numpy()[0]
                s , r, done, = self.env.step(action)
                episode reward += r
                if done:
                    break
                s = s
                # self.env.render(mode="human")
                # self.env.viewer.cam.type = const.CAMERA FIXED
                # self.env.viewer.cam.fixedcamid = 0
                # time.sleep(0.03)
                I = self.env.render(mode='rgb array')
                I = cv2.cvtColor(I, cv2.COLOR RGB2BGR)
                I = cv2.resize(I, (250, 250))
                self.VideoWriter.write(I)
                # cv2.imshow("env", I)
                # cv2.waitKey(10)
            print(f"episode reward:{episode reward:3.3f}")
        self.env.close()
        self.VideoWriter.release()
        cv2.destroyAllWindows()
```

```
In [ ]:
```

```
import gym
import os
import mujoco_py
# from agent import Agent
# from train import Train
# from play import Play
```

```
ENV_NAME = "InvertedDoublePendulum"
TRAIN_FLAG = True
test_env = gym.make(ENV_NAME + "-v2")
print(test_env.reset())
```

In []:

```
n_states = test_env.observation_space.shape[0]
action_bounds = [test_env.action_space.low[0], test_env.action_space.high[0]]
n_actions = test_env.action_space.shape[0]
```

```
# n_iterations = 500
n_iterations = 200
lr = 3e-4
epochs = 10
clip_range = 0.2
mini_batch_size = 64
T = 2048
```

```
In [ ]:
```

```
print(f"number of states:{n states}\n"
      f"action bounds:{action bounds}\n"
      f"number of actions:{n actions}")
if not os.path.exists(ENV NAME):
    os.mkdir(ENV NAME)
    os.mkdir(ENV_NAME + "/logs")
env = qym.make(ENV NAME + "-v2")
agent = Agent(n states=n states,
              n iter=n iterations,
              env_name=ENV_NAME,
              action bounds=action bounds,
              n actions=n actions,
              lr=lr)
if TRAIN FLAG:
    trainer = Train(env=env,
                    test_env=test_env,
                    env name=ENV NAME,
                    agent=agent,
                    horizon=T,
                    n iterations=n iterations,
                    epochs=epochs,
                    mini batch size=mini batch size,
                    epsilon=clip range)
    trainer.step()
player = Play(env, agent, ENV NAME)
player.evaluate()
```

Ant (4 legs animal)

```
In [ ]:
```

```
ENV_NAME = "Ant"
TRAIN_FLAG = True
test_env = gym.make(ENV_NAME + "-v2")

n_states = test_env.observation_space.shape[0]
action_bounds = [test_env.action_space.low[0], test_env.action_space.high[0]]
n_actions = test_env.action_space.shape[0]
```

```
In [ ]:
print(f"number of states:{n states}\n"
      f"action bounds: {action bounds} \n"
      f"number of actions:{n actions}")
if not os.path.exists(ENV NAME):
    os.mkdir(ENV NAME)
    os.mkdir(ENV NAME + "/logs")
env = qym.make(ENV NAME + "-v2")
agent = Agent(n states=n states,
              n iter=n iterations,
              env_name=ENV_NAME,
              action bounds=action bounds,
              n actions=n actions,
              lr=lr)
if TRAIN FLAG:
    trainer = Train(env=env,
                     test env=test env,
                     env name=ENV NAME,
                     agent=agent,
                     horizon=T,
                     n iterations=n iterations,
                     epochs=epochs,
                    mini batch size=mini batch size,
                     epsilon=clip range)
    trainer.step()
player = Play(env, agent, ENV NAME)
player.evaluate()
```

```
number of states:111
action bounds: [-1.0, 1.0]
number of actions:8
iteration: 1 eval rewards: -422.17374568866836
iteration: 2 eval rewards: -3243.8308376227956
iteration: 3
               eval rewards: -38.164450059129024
iteration: 4
             eval rewards: -186.24992453730675
iteration: 5 eval rewards: -398.9249271273701
iteration: 6 eval rewards: -125.90317860908169
iteration: 7
             eval rewards: -2682.0857415884975
iteration: 8 eval rewards: -60.19074124542881
iteration: 9
               eval rewards: -223.80968566426688
iteration: 10 eval rewards: -22.236191872180473
iteration: 11 eval_rewards: -46.47449037020863
iteration: 12 eval rewards: -112.72958757010065
iteration: 13 eval rewards: -198.86097335462006
iteration: 14 eval_rewards: -7.264166408747806
iteration: 15 eval rewards: -80.21478054630954
iteration: 16 eval rewards: -22.082756863453497
```

FetchPickAndPlace

```
In [ ]:
```

```
ENV NAME = "FetchPickAndPlace"
TRAIN FLAG = True
test env = gym.make(ENV NAME + "-v1")
n states = test env.observation space["observation"].shape[0]
n achieveds = test env.observation space["achieved goal"].shape[0]
n goals = test env.observation space["desired goal"].shape[0]
action_bounds = [test_env.action_space.low[0], test_env.action_space.high[0]]
n_actions = test_env.action space.shape[0]
print(n states)
print(n goals)
env dict = test env.reset()
state = env dict["observation"]
achieved goal = env dict["achieved goal"]
desired goal = env dict["desired goal"]
print(state)
print(achieved goal)
print(desired goal)
25
3
[ 1.34193265e+00 7.49100375e-01 5.34722720e-01 1.48432121e+00
  8.85913193e-01 4.24702091e-01 1.42388560e-01 1.36812818e-01
 -1.10020629e-01 2.91834773e-06 -4.72661656e-08 -3.85214084e-07
  5.92637053e-07 1.12208536e-13 -7.74656889e-06 -7.65027248e-08
  4.92570535e-05 1.88857148e-07 -2.90549459e-07 -1.18156686e-18
  7.73934983e-06 7.18103404e-08 -2.42928780e-06 4.93607091e-07
```

1.70999820e-071

[1.48432121 0.88591319 0.42470209] [1.24591882 0.63620262 0.42469975]

```
In [ ]:
```

```
state = env_dict["observation"]
achieved_goal = env_dict["achieved_goal"]

desired_goal = env_dict["desired_goal"]

#state = np.expand_dims(state, axis=0)
#goal = np.expand_dims(desired_goal, axis=0)

with torch.no_grad():
    x = np.append(state, desired_goal)
    x = from_numpy(x).float()
    print(x)
```

```
def set_state(env_dict):
    state = env_dict["observation"]
    achieved_goal = env_dict["achieved_goal"]
    desired_goal = env_dict["desired_goal"]

    return np.append(state, desired_goal)
```

```
def evaluate model(agent, env, state rms, action bounds):
    total rewards = 0
    s = env.reset()
    s = set state(s)
    done = False
    while not done:
        s = \text{np.clip}((s - \text{state rms.mean}) / (\text{state rms.var} ** 0.5 + 1e-8), -5.0, 5.0)
        dist = agent.choose dist(s)
        action = dist.sample().cpu().numpy()[0]
        # action = np.clip(action, action_bounds[0], action_bounds[1])
        next_state, reward, done, _ = env.step(action)
        next state = set state(next state)
        # env.render()
        s = next state
        total_rewards += reward
    # env.close()
    return total rewards
```

```
class Train:
        def __init__(self, env, test_env, env_name, n_iterations, agent, epochs, mini_ba
                self.env = env
                self.env name = env name
                self.test env = test env
                self.agent = agent
                self.epsilon = epsilon
                self.horizon = horizon
                self.epochs = epochs
                self.mini_batch_size = mini_batch_size
                self.n iterations = n iterations
                self.start_time = 0
                self.state rms = RunningMeanStd(shape=(self.agent.n states,))
                self.running reward = 0
        @staticmethod
        def choose mini batch (mini batch size, states, actions, returns, advs, values, 1
                full batch size = len(states)
                for in range(full batch size // mini batch size):
                        indices = np.random.randint(0, full batch size, mini batch size)
                        yield states[indices], actions[indices], returns[indices], advs[indices]
                                    log probs[indices]
        def train(self, states, actions, advs, values, log probs):
                values = np.vstack(values[:-1])
                log probs = np.vstack(log probs)
                returns = advs + values
                advs = (advs - advs.mean()) / (advs.std() + 1e-8)
                actions = np.vstack(actions)
                for epoch in range(self.epochs):
                        for state, action, return , adv, old value, old log prob in self.choose
                                state = torch.Tensor(state).to(self.agent.device)
                                action = torch.Tensor(action).to(self.agent.device)
                                return_ = torch.Tensor(return_).to(self.agent.device)
                                adv = torch.Tensor(adv).to(self.agent.device)
                                old value = torch.Tensor(old value).to(self.agent.device)
                                old log prob = torch.Tensor(old log prob).to(self.agent.device)
                                value = self.agent.critic(state)
                                # clipped value = old value + torch.clamp(value - old value, -self.e
                                # clipped_v_loss = (clipped_value - return_).pow(2)
                                # unclipped v loss = (value - return ).pow(2)
                                # critic loss = 0.5 * torch.max(clipped v loss, unclipped v loss).me
                                critic loss = self.agent.critic loss(value, return )
                                new_log_prob = self.calculate_log_probs(self.agent.current_policy, self.agent.current_policy, sel
                                ratio = (new log prob - old log prob).exp()
                                actor loss = self.compute actor loss(ratio, adv)
                                self.agent.optimize(actor loss, critic loss)
                return actor loss, critic loss
```

```
def step(self):
    state = self.env.reset()
    state = set state(state)
    for iteration in range(1, 1 + self.n iterations):
        states = []
        actions = []
        rewards = []
        values = []
        log probs = []
        dones = []
        self.start time = time.time()
        for t in range(self.horizon):
            # self.state rms.update(state)
            state = np.clip((state - self.state_rms.mean) / (self.state_rms.var
            dist = self.agent.choose dist(state)
            action = dist.sample()
            # action = np.clip(action, self.agent.action bounds[0], self.agent.action
            log prob = dist.log prob(action).cpu()
            action = action.cpu().numpy()[0]
            value = self.agent.get value(state)
            next_state, reward, done, _ = self.env.step(action)
            next_state = set_state(next_state)
            states.append(state)
            actions.append(action)
            rewards.append(reward)
            values.append(value)
            log probs.append(log prob)
            dones.append(done)
            if done:
                state = self.env.reset()
                state = set state(state)
            else:
                state = next state
        # self.state rms.update(next state)
        next state = np.clip((next state - self.state rms.mean) / (self.state rm
        next_value = self.agent.get_value(next_state) * (1 - done)
        values.append(next value)
        advs = self.get gae(rewards, values, dones)
        states = np.vstack(states)
        actor_loss, critic_loss = self.train(states, actions, advs, values, log_
        # self.agent.set weights()
        self.agent.schedule lr()
        eval rewards = evaluate model(self.agent, self.test env, self.state rms,
        self.state rms.update(states)
        self.print logs(iteration, actor loss, critic loss, eval rewards)
        print("iteration: ", iteration, "\teval_rewards: ", eval rewards)
@staticmethod
def get gae(rewards, values, dones, gamma=0.99, lam=0.95):
    advs = []
    gae = 0
    dones.append(0)
    for step in reversed(range(len(rewards))):
        delta = rewards[step] + gamma * (values[step + 1]) * (1 - dones[step]) -
        gae = delta + gamma * lam * (1 - dones[step]) * gae
```

```
advs.append(gae)
   advs.reverse()
    return np.vstack(advs)
@staticmethod
def calculate log probs(model, states, actions):
   policy distribution = model(states)
    return policy distribution.log prob(actions)
def compute actor loss(self, ratio, adv):
   pg loss1 = adv * ratio
   pg loss2 = adv * torch.clamp(ratio, 1 - self.epsilon, 1 + self.epsilon)
   loss = -torch.min(pg_loss1, pg loss2).mean()
   return loss
def print logs(self, iteration, actor loss, critic loss, eval rewards):
    if iteration == 1:
        self.running reward = eval rewards
   else:
        self.running reward = self.running reward * 0.99 + eval rewards * 0.01
    if iteration % 100 == 0:
        print(f"Iter:{iteration} | "
              f"Ep Reward:{eval rewards:.3f} "
              f"Running reward:{self.running reward:.3f}| "
              f"Actor Loss:{actor loss:.3f}| "
              f"Critic_Loss:{critic_loss:.3f}| "
              f"Iter_duration:{time.time() - self.start_time:.3f}| "
              f"lr:{self.agent.actor scheduler.get last lr()}")
        self.agent.save weights(iteration, self.state rms)
   with SummaryWriter(self.env name + "/logs") as writer:
        writer.add_scalar("Episode running reward", self.running_reward, iterati
        writer.add_scalar("Episode reward", eval_rewards, iteration)
        writer.add scalar("Actor loss", actor loss, iteration)
        writer.add_scalar("Critic loss", critic_loss, iteration)
```

```
#GlfwContext(offscreen=True)
class Play:
    def __init__(self, env, agent, env_name, max_episode=1):
        self.env = env
        self.max episode = max episode
        self.agent = agent
        , self.state rms mean, self.state rms var = self.agent.load weights()
        self.agent.set to eval mode()
        self.device = torch.device(process device)
        self.fourcc = cv2.VideoWriter fourcc(*'XVID')
        self.VideoWriter = cv2.VideoWriter(env_name + ".avi", self.fourcc, 50.0, (25)
    def evaluate(self):
        for in range(self.max episode):
            s = self.env.reset()
            s = set state(s)
            episode reward = 0
            for in range(self.env. max episode steps):
                s = np.clip((s - self.state rms mean) / (self.state rms var ** 0.5 +
                dist = self.agent.choose dist(s)
                action = dist.sample().cpu().numpy()[0]
                s , r, done, = self.env.step(action)
                s = set state(s )
                episode reward += r
                if done:
                    break
                s = s
                # self.env.render(mode="human")
                # self.env.viewer.cam.type = const.CAMERA FIXED
                # self.env.viewer.cam.fixedcamid = 0
                # time.sleep(0.03)
                I = self.env.render(mode='rgb array')
                I = cv2.cvtColor(I, cv2.COLOR RGB2BGR)
                I = cv2.resize(I, (250, 250))
                self.VideoWriter.write(I)
                # cv2.imshow("env", I)
                # cv2.waitKey(10)
            print(f"episode reward:{episode reward:3.3f}")
        self.env.close()
        self.VideoWriter.release()
        cv2.destroyAllWindows()
```

```
ENV_NAME = "FetchPickAndPlace"
TRAIN_FLAG = True
test_env = gym.make(ENV_NAME + "-v1")

n_states = test_env.observation_space["observation"].shape[0]
n_achieveds = test_env.observation_space["achieved_goal"].shape[0]
n_goals = test_env.observation_space["desired_goal"].shape[0]
action_bounds = [test_env.action_space.low[0], test_env.action_space.high[0]]
n_actions = test_env.action_space.shape[0]
```

```
In [ ]:
print(f"number of states:{n states}\n"
      f"action bounds:{action bounds}\n"
      f"number of actions:{n actions}")
if not os.path.exists(ENV NAME):
    os.mkdir(ENV NAME)
    os.mkdir(ENV_NAME + "/logs")
env = qym.make(ENV NAME + "-v1")
agent = Agent(n_states=n_states + n_goals,
              n iter=n iterations,
              env_name=ENV_NAME,
              action bounds=action bounds,
              n actions=n actions,
              lr=lr)
if TRAIN FLAG:
    trainer = Train(env=env,
                    test env=test env,
                    env name=ENV NAME,
                    agent=agent,
                    horizon=T,
                    n iterations=n iterations,
                    epochs=epochs,
                    mini batch size=mini batch size,
                    epsilon=clip range)
    trainer.step()
player = Play(env, agent, ENV NAME)
player.evaluate()
number of states:25
```

```
action bounds: [-1.0, 1.0]
number of actions:4
iteration: 1 eval rewards: -50.0
iteration: 2 eval_rewards: -50.0
iteration: 3 eval_rewards: -50.0
iteration: 4 eval rewards: -50.0
iteration: 5 eval rewards: -50.0
iteration: 6 eval_rewards: -50.0
iteration: 7 eval rewards: -50.0
iteration: 8 eval rewards: -50.0
iteration: 9 eval rewards: -50.0
iteration: 10 eval_rewards: -50.0
iteration: 11 eval rewards: -50.0
iteration: 12 eval rewards: -50.0
iteration: 13 eval_rewards: -50.0
iteration: 14 eval_rewards: -50.0
iteration: 15 eval rewards: -50.0
iteration: 16 eval rewards: -50.0
```

Deep Deterministic Policy Gradients (DDPG)

```
from torch import nn
import torch
from torch.nn import functional as F
import numpy as np
def init weights biases(size):
    v = 1.0 / np.sqrt(size[0])
    return torch.FloatTensor(size).uniform (-v, v)
class Actor(nn.Module):
    def __init__(self, n_states, n_actions, n_goals, n_hidden1=256, n_hidden2=256, r
        self.n states = n states[0]
        self.n actions = n actions
        self.n goals = n goals
        self.n hidden1 = n hidden1
        self.n hidden2 = n hidden2
        self.n hidden3 = n hidden3
        self.initial w = initial w
        super(Actor, self). init ()
        self.fc1 = nn.Linear(in features=self.n states + self.n goals, out features=
        self.fc2 = nn.Linear(in_features=self.n_hidden1, out_features=self.n_hidden2
        self.fc3 = nn.Linear(in features=self.n hidden2, out features=self.n hidden3
        self.output = nn.Linear(in features=self.n hidden3, out features=self.n acti
    def forward(self, x):
        x = F.relu(self.fcl(x))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        output = torch.tanh(self.output(x)) # TODO add scale of the action
        return output
class Critic(nn.Module):
    def __init__(self, n_states, n_goals, n_hidden1=256, n_hidden2=256, n_hidden3=25
        self.n states = n states[0]
        self.n goals = n goals
        self.n_hidden1 = n_hidden1
        self.n hidden2 = n hidden2
        self.n hidden3 = n hidden3
        self.initial_w = initial_w
        self.action size = action size
        super(Critic, self).__init__()
        self.fc1 = nn.Linear(in features=self.n states + self.n goals + self.action
        self.fc2 = nn.Linear(in_features=self.n_hidden1, out_features=self.n_hidden2
        self.fc3 = nn.Linear(in features=self.n hidden2, out features=self.n hidden3
        self.output = nn.Linear(in_features=self.n_hidden3, out_features=1)
    def forward(self, x, a):
        x = F.relu(self.fc1(torch.cat([x, a], dim=-1)))
        x = F.relu(self.fc2(x))
        x = F.relu(self.fc3(x))
        output = self.output(x)
        return output
```

```
import numpy as np
from copy import deepcopy as dc
import random
class Memory:
    def __init__(self, capacity, k_future, env):
        self.capacity = capacity
        self.memory = []
        self.memory counter = 0
        self.memory length = 0
        self.env = env
        self.future p = 1 - (1. / (1 + k future))
    def sample(self, batch size):
        ep indices = np.random.randint(0, len(self.memory), batch size)
        time_indices = np.random.randint(0, len(self.memory[0]["next_state"]), batch
        states = []
        actions = []
        desired_goals = []
        next states = []
        next_achieved_goals = []
        for episode, timestep in zip(ep indices, time indices):
            states.append(dc(self.memory[episode]["state"][timestep]))
            actions.append(dc(self.memory[episode]["action"][timestep]))
            desired goals.append(dc(self.memory[episode]["desired goal"][timestep]))
            next_achieved_goals.append(dc(self.memory[episode]["next_achieved_goal"]
            next states.append(dc(self.memory[episode]["next_state"][timestep]))
        states = np.vstack(states)
        actions = np.vstack(actions)
        desired_goals = np.vstack(desired_goals)
        next achieved goals = np.vstack(next achieved goals)
        next states = np.vstack(next states)
        her indices = np.where(np.random.uniform(size=batch size) < self.future p)
        future offset = np.random.uniform(size=batch size) * (len(self.memory[0]["ne
        future_offset = future_offset.astype(int)
        future t = (time indices + 1 + future offset)[her indices]
        future_ag = []
        for episode, f offset in zip(ep indices[her indices], future t):
            future_ag.append(dc(self.memory[episode]["achieved_goal"][f_offset]))
        future ag = np.vstack(future ag)
        desired goals[her indices] = future ag
        rewards = np.expand_dims(self.env.compute_reward(next_achieved_goals, desire
        return self.clip_obs(states), actions, rewards, self.clip_obs(next_states),
    def add(self, transition):
        self.memory.append(transition)
        if len(self.memory) > self.capacity:
            self.memory.pop(0)
        assert len(self.memory) <= self.capacity</pre>
```

```
def len__(self):
   return len(self.memory)
@staticmethod
def clip obs(x):
    return np.clip(x, -200, 200)
def sample for normalization(self, batch):
    size = len(batch[0]["next state"])
    ep indices = np.random.randint(0, len(batch), size)
   time indices = np.random.randint(0, len(batch[0]["next state"]), size)
    states = []
   desired goals = []
    for episode, timestep in zip(ep indices, time indices):
        states.append(dc(batch[episode]["state"][timestep]))
        desired goals.append(dc(batch[episode]["desired goal"][timestep]))
    states = np.vstack(states)
   desired goals = np.vstack(desired goals)
   her indices = np.where(np.random.uniform(size=size) < self.future p)
    future offset = np.random.uniform(size=size) * (len(batch[0]["next state"])
    future offset = future offset.astype(int)
    future t = (time indices + 1 + future offset)[her indices]
    future ag = []
    for episode, f_offset in zip(ep_indices[her_indices], future_t):
        future ag.append(dc(batch[episode]["achieved goal"][f offset]))
    future ag = np.vstack(future ag)
   desired goals[her indices] = future ag
   return self.clip obs(states), self.clip obs(desired goals)
```

```
!pip install mpi4py
Collecting mpi4py
  Downloading mpi4py-3.1.3.tar.gz (2.5 MB)
                                      \blacksquare | 2.5 MB 5.1 MB/s
  Installing build dependencies ... done
  Getting requirements to build wheel ... done
    Preparing wheel metadata ... done
Building wheels for collected packages: mpi4py
  Building wheel for mpi4py (PEP 517) ... done
  Created wheel for mpi4py: filename=mpi4py-3.1.3-cp37-cp37m-linux x86
64.whl size=2185319 sha256=83430d85c27cb47cdf848b108f935a7fb28a076584
ec5a6d59f7d28d0a298030
  Stored in directory: /root/.cache/pip/wheels/7a/07/14/6a0c63fa2c6e47
3c6edc40985b7d89f05c61ff25ee7f0ad9ac
Successfully built mpi4py
Installing collected packages: mpi4py
Successfully installed mpi4py-3.1.3
```

```
import threading
import numpy as np
from mpi4py import MPI
class Normalizer:
    def init (self, size, eps=1e-2, default clip range=np.inf):
        self.size = size
        self.eps = eps
        self.default clip range = default clip range
        # some local information
        self.local sum = np.zeros(self.size, np.float32)
        self.local_sumsq = np.zeros(self.size, np.float32)
        self.local count = np.zeros(1, np.float32)
        # get the total sum sumsq and sum count
        self.total sum = np.zeros(self.size, np.float32)
        self.total sumsq = np.zeros(self.size, np.float32)
        self.total count = np.ones(1, np.float32)
        # get the mean and std
        self.mean = np.zeros(self.size, np.float32)
        self.std = np.ones(self.size, np.float32)
        # thread locker
        self.lock = threading.Lock()
    # update the parameters of the normalizer
    def update(self, v):
        v = v.reshape(-1, self.size)
        # do the computing
        with self.lock:
            self.local_sum += v.sum(axis=0)
            self.local_sumsq += (np.square(v)).sum(axis=0)
            self.local count[0] += v.shape[0]
    # sync the parameters across the cpus
    def sync(self, local_sum, local_sumsq, local_count):
        local sum[...] = self. mpi average(local sum)
        local sumsq[...] = self. mpi average(local sumsq)
        local_count[...] = self._mpi_average(local_count)
        return local sum, local sumsq, local count
    def recompute stats(self):
        with self.lock:
            local count = self.local count.copy()
            local sum = self.local sum.copy()
            local_sumsq = self.local_sumsq.copy()
            # reset
            self.local count[...] = 0
            self.local sum[...] = 0
            self.local sumsq[...] = 0
        # sync the stats
        sync_sum, sync_sumsq, sync_count = self.sync(local_sum, local_sumsq, local_d
        # update the total stuff
        self.total sum += sync sum
        self.total sumsq += sync sumsq
        self.total count += sync count
        # calculate the new mean and std
        self.mean = self.total_sum / self.total_count
        self.std = np.sqrt(np.maximum(np.square(self.eps), (self.total sumsq / self.
            self.total sum / self.total count)))
```

```
# average across the cpu's data
def _mpi_average(self, x):
    buf = np.zeros_like(x)
    MPI.COMM_WORLD.Allreduce(x, buf, op=MPI.SUM)
    buf /= MPI.COMM_WORLD.Get_size()
    return buf

# normalize the observation
def normalize(self, v, clip_range=None):
    if clip_range is None:
        clip_range = self.default_clip_range
    return np.clip((v - self.mean) / self.std, -clip_range, clip_range)
```

Agent Class

```
import torch
from torch import from numpy, device
import numpy as np
# from models import Actor, Critic
# from memory import Memory
from torch.optim import Adam
from mpi4py import MPI
# from normalizer import Normalizer
class Agent:
    def __init__(self, n_states, n_actions, n_goals, action_bounds, capacity, env,
                 k future,
                 batch size,
                 action size=1,
                 tau=0.05,
                 actor lr=1e-3,
                 critic lr=1e-3,
                 gamma=0.98):
        self.device = device("cpu")
        self.n states = n states
        self.n actions = n actions
        self.n goals = n goals
        self.k_future = k_future
        self.action bounds = action bounds
        self.action size = action size
        self.env = env
        self.actor = Actor(self.n states, n actions=self.n actions, n goals=self.n g
        self.critic = Critic(self.n states, action size=self.action size, n goals=se
        self.sync networks(self.actor)
        self.sync networks(self.critic)
        self.actor target = Actor(self.n states, n actions=self.n actions, n goals=s
        self.critic target = Critic(self.n states, action size=self.action size, n g
        self.init_target_networks()
        self.tau = tau
        self.gamma = gamma
        self.capacity = capacity
        self.memory = Memory(self.capacity, self.k future, self.env)
        self.batch_size = batch_size
        self.actor lr = actor lr
        self.critic lr = critic lr
        self.actor optim = Adam(self.actor.parameters(), self.actor lr)
        self.critic_optim = Adam(self.critic.parameters(), self.critic_lr)
        self.state normalizer = Normalizer(self.n states[0], default clip range=5)
        self.goal normalizer = Normalizer(self.n goals, default clip range=5)
    def choose_action(self, state, goal, train_mode=True):
        state = self.state_normalizer.normalize(state)
        goal = self.goal normalizer.normalize(goal)
        state = np.expand dims(state, axis=0)
        goal = np.expand dims(goal, axis=0)
        with torch.no_grad():
            x = np.concatenate([state, goal], axis=1)
            x = from numpy(x).float().to(self.device)
```

```
action = self.actor(x)[0].cpu().data.numpy()
    if train mode:
        action += 0.2 * np.random.randn(self.n actions)
        action = np.clip(action, self.action bounds[0], self.action bounds[1])
        random actions = np.random.uniform(low=self.action bounds[0], high=self.
                                           size=self.n actions)
        action += np.random.binomial(1, 0.3, 1)[0] * (random actions - action)
   return action
def store(self, mini batch):
    for batch in mini batch:
        self.memory.add(batch)
   self. update normalizer(mini batch)
def init target networks(self):
    self.hard update networks(self.actor, self.actor target)
    self.hard update networks(self.critic, self.critic target)
@staticmethod
def hard update networks(local model, target model):
    target model.load state dict(local model.state dict())
@staticmethod
def soft update networks(local model, target model, tau=0.05):
    for t_params, e_params in zip(target_model.parameters(), local_model.paramet
        t_params.data.copy_(tau * e_params.data + (1 - tau) * t_params.data)
def train(self):
    states, actions, rewards, next states, goals = self.memory.sample(self.batc)
   states = self.state normalizer.normalize(states)
   next states = self.state normalizer.normalize(next states)
    goals = self.goal normalizer.normalize(goals)
    inputs = np.concatenate([states, goals], axis=1)
   next inputs = np.concatenate([next states, goals], axis=1)
    inputs = torch.Tensor(inputs).to(self.device)
   rewards = torch.Tensor(rewards).to(self.device)
   next inputs = torch.Tensor(next inputs).to(self.device)
   actions = torch.Tensor(actions).to(self.device)
   with torch.no grad():
        target q = self.critic target(next inputs, self.actor target(next inputs
        target returns = rewards + self.gamma * target q.detach()
        target returns = torch.clamp(target returns, -1 / (1 - self.gamma), 0)
   q_eval = self.critic(inputs, actions)
   critic_loss = (target_returns - q_eval).pow(2).mean()
   a = self.actor(inputs)
   actor loss = -self.critic(inputs, a).mean()
   actor_loss += a.pow(2).mean()
   self.actor_optim.zero_grad()
   actor loss.backward()
   self.sync grads(self.actor)
   self.actor optim.step()
```

```
self.critic optim.zero grad()
   critic loss.backward()
   self.sync grads(self.critic)
    self.critic optim.step()
   return actor loss.item(), critic loss.item()
def save weights(self):
   torch.save({"actor_state_dict": self.actor.state dict(),
                "state normalizer mean": self.state normalizer.mean,
                "state normalizer std": self.state normalizer.std,
                "goal normalizer mean": self.goal normalizer.mean,
                "goal_normalizer_std": self.goal_normalizer.std}, "FetchPickAndF
                #"goal normalizer std": self.goal normalizer.std}, "FetchSlide.g
                #"goal normalizer std": self.goal normalizer.std}, "HandReach.pt
def load weights(self):
    #checkpoint = torch.load("FetchSlide.pth")
   checkpoint = torch.load("FetchPickAndPlace.pth")
    #checkpoint = torch.load("FetchPickAndPlace.pth")
    actor state dict = checkpoint["actor state dict"]
    self.actor.load state dict(actor state dict)
    state normalizer mean = checkpoint["state normalizer mean"]
    self.state normalizer.mean = state normalizer mean
   state_normalizer_std = checkpoint["state normalizer std"]
   self.state normalizer.std = state normalizer std
   goal normalizer mean = checkpoint["goal normalizer mean"]
   self.goal normalizer.mean = goal normalizer mean
   goal normalizer std = checkpoint["goal normalizer std"]
    self.goal_normalizer.std = goal_normalizer_std
def set to eval mode(self):
   self.actor.eval()
    # self.critic.eval()
def update_networks(self):
    self.soft update networks(self.actor, self.actor target, self.tau)
    self.soft update networks(self.critic, self.critic target, self.tau)
def update normalizer(self, mini batch):
   states, goals = self.memory.sample for normalization(mini batch)
   self.state normalizer.update(states)
   self.goal normalizer.update(goals)
    self.state normalizer.recompute stats()
   self.goal normalizer.recompute stats()
@staticmethod
def sync networks(network):
   comm = MPI.COMM WORLD
    flat_params = _get_flat_params_or_grads(network, mode='params')
   comm.Bcast(flat_params, root=0)
   _set_flat_params_or_grads(network, flat_params, mode='params')
@staticmethod
def sync grads(network):
    flat grads = get flat params or grads(network, mode='grads')
   comm = MPI.COMM WORLD
```

Play class (run and record the vdo)

```
import torch
from torch import device
import numpy as np
import cv2
from gym import wrappers
from mujoco py import GlfwContext
#GlfwContext(offscreen=True)
from mujoco py.generated import const
class Play:
    def init (self, env, agent, max episode=4):
        self.env = env
        self.env = wrappers.Monitor(env, "./videos", video callable=lambda episode i
        self.max episode = max episode
        self.agent = agent
        self.agent.load weights()
        self.agent.set to eval mode()
        self.device = device("cuda" if torch.cuda.is available() else "cpu")
    def evaluate(self):
        for in range(self.max episode):
            env dict = self.env.reset()
            state = env_dict["observation"]
            achieved goal = env dict["achieved goal"]
            desired goal = env dict["desired goal"]
            while np.linalg.norm(achieved goal - desired goal) <= 0.05:</pre>
                env dict = self.env.reset()
                state = env dict["observation"]
                achieved goal = env dict["achieved goal"]
                desired goal = env dict["desired goal"]
            done = False
            episode reward = 0
            while not done:
                action = self.agent.choose action(state, desired goal, train mode=Fa
                next env dict, r, done, = self.env.step(action)
                next state = next env dict["observation"]
                next_desired_goal = next_env_dict["desired_goal"]
                episode reward += r
                state = next state.copy()
                desired_goal = next_desired_goal.copy()
                I = self.env.render(mode="rgb_array") # mode = "rgb_array"
                self.env.viewer.cam.type = const.CAMERA_FREE
                self.env.viewer.cam.fixedcamid = 0
                # I = cv2.cvtColor(I, cv2.COLOR RGB2BGR)
                # cv2.imshow("I", I)
                # cv2.waitKey(2)
            print(f"episode reward:{episode reward:3.3f}")
        self.env.close()
```

```
In [ ]:
```

```
import gym
# from agent import Agent
import matplotlib.pyplot as plt
from torch.utils.tensorboard import SummaryWriter
import numpy as np
# from play import Play
import mujoco py
import random
from mpi4py import MPI
import psutil
import time
from copy import deepcopy as dc
import os
import torch
ENV NAME = "FetchPickAndPlace-v1"
INTRO = False
Train = True
Play FLAG = False
MAX EPOCHS = 30
MAX CYCLES = 50
num updates = 40
MAX EPISODES = 2
memory_size = 7e+5 // 50
batch size = 256
actor lr = 1e-3
critic lr = 1e-3
gamma = 0.98
tau = 0.05
k future = 4
test env = gym.make(ENV NAME)
state shape = test env.observation space.spaces["observation"].shape
n actions = test env.action space.shape[0]
n_goals = test_env.observation_space.spaces["desired_goal"].shape[0]
action bounds = [test env.action space.low[0], test env.action space.high[0]]
to gb = lambda in bytes: in bytes / 1024 / 1024 / 1024
os.environ['OMP NUM THREADS'] = '1'
os.environ['MKL NUM THREADS'] = '1'
os.environ['IN MPI'] = '1'
def eval_agent(env_, agent_):
    total success rate = []
    running_r = []
    for ep in range(10):
        per success rate = []
        env_dictionary = env_.reset()
        s = env dictionary["observation"]
        ag = env dictionary["achieved goal"]
        g = env_dictionary["desired_goal"]
        while np.linalg.norm(ag - g) <= 0.05:</pre>
            env dictionary = env .reset()
            s = env dictionary["observation"]
            ag = env_dictionary["achieved_goal"]
            g = env_dictionary["desired_goal"]
        ep r = 0
        for t in range(50):
```

```
with torch.no grad():
                a = agent_.choose_action(s, g, train_mode=False)
            observation_new, r, _, info_ = env_.step(a)
s = observation_new['observation']
            g = observation new['desired goal']
            per success rate.append(info ['is success'])
            ep r += r
        total_success_rate.append(per_success_rate)
        if ep == 0:
            running r.append(ep r)
        else:
            running r.append(running r[-1] * 0.99 + 0.01 * ep r)
    total success rate = np.array(total success rate)
    local success rate = np.mean(total success rate[:, -1])
    global success rate = MPI.COMM WORLD.allreduce(local success rate, op=MPI.SUM)
    return global success rate / MPI.COMM WORLD.Get size(), running r, ep r
if INTRO:
    print(f"state shape:{state shape[0]}\n"
          f"number of actions:{n actions}\n"
          f"action boundaries:{action bounds}\n"
          f"max timesteps:{test env. max episode steps}")
    for in range(3):
        done = False
        test env.reset()
        while not done:
            action = test env.action space.sample()
            test_state, test_reward, test_done, test_info = test_env.step(action)
            # substitute_goal = test_state["achieved_goal"].copy()
            # substitute reward = test env.compute reward(
                   test state["achieved goal"], substitute goal, test info)
            # print("r is {}, substitute reward is {}".format(r, substitute reward))
            test env.render()
    exit(0)
env = gym.make(ENV_NAME)
env.seed(MPI.COMM WORLD.Get rank())
random.seed(MPI.COMM WORLD.Get rank())
np.random.seed(MPI.COMM_WORLD.Get_rank())
torch.manual seed(MPI.COMM WORLD.Get rank())
agent = Agent(n states=state shape,
              n actions=n actions,
              n goals=n goals,
              action bounds=action bounds,
              capacity=memory size,
              action_size=n_actions,
              batch size=batch size,
              actor lr=actor lr,
              critic lr=critic lr,
              gamma=gamma,
              tau=tau,
              k future=k future,
              env=dc(env))
if Train:
    t_success_rate = []
    total ac loss = []
    total_cr_loss = []
```

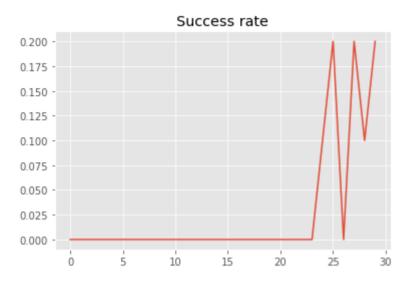
```
for epoch in range(MAX EPOCHS):
    start time = time.time()
    epoch actor loss = 0
   epoch critic loss = 0
    for cycle in range(0, MAX CYCLES):
        mb = []
        cycle actor loss = 0
        cycle critic loss = 0
        for episode in range(MAX EPISODES):
            episode dict = {
                "state": [],
                "action": [],
                "info": [],
                "achieved goal": [],
                "desired_goal": [],
                "next state": [],
                "next achieved goal": []}
            env dict = env.reset()
            state = env_dict["observation"]
            achieved goal = env dict["achieved goal"]
            desired goal = env dict["desired goal"]
            while np.linalg.norm(achieved goal - desired goal) <= 0.05:</pre>
                env dict = env.reset()
                state = env dict["observation"]
                achieved goal = env dict["achieved goal"]
                desired goal = env dict["desired goal"]
            for t in range(500):
                action = agent.choose action(state, desired goal)
                next env dict, reward, done, info = env.step(action)
                next state = next env dict["observation"]
                next achieved goal = next env dict["achieved goal"]
                next desired goal = next env dict["desired goal"]
                episode dict["state"].append(state.copy())
                episode dict["action"].append(action.copy())
                episode_dict["achieved_goal"].append(achieved_goal.copy())
                episode dict["desired goal"].append(desired goal.copy())
                state = next state.copy()
                achieved goal = next achieved goal.copy()
                desired goal = next desired goal.copy()
                if done:
                    break
            episode dict["state"].append(state.copy())
            episode_dict["achieved_goal"].append(achieved_goal.copy())
            episode dict["desired goal"].append(desired goal.copy())
            episode dict["next state"] = episode dict["state"][1:]
            episode_dict["next_achieved_goal"] = episode_dict["achieved_goal"][1
            mb.append(dc(episode dict))
        agent.store(mb)
        for n update in range(num updates):
            actor loss, critic loss = agent.train()
            cycle actor loss += actor loss
            cycle critic loss += critic loss
        epoch actor loss += cycle actor loss / num updates
        epoch critic loss += cycle critic loss /num updates
```

```
agent.update networks()
       ram = psutil.virtual memory()
        success_rate, running_reward, episode_reward = eval_agent(env, agent)
       total_ac_loss.append(epoch_actor_loss)
        total cr loss.append(epoch critic loss)
        if MPI.COMM WORLD.Get rank() == 0:
            t success rate.append(success rate)
            print(f"Epoch:{epoch}
                  f"Running reward:{running reward[-1]:.3f}| "
                  f"EP reward:{episode reward:.3f} "
                  f"Memory length:{len(agent.memory)}| "
                  f"Duration:{time.time() - start time:.3f}| "
                  f"Actor Loss:{actor loss:.3f}
                  f"Critic Loss:{critic loss:.3f}
                  f"Success rate:{success_rate:.3f}| "
                  f"{to_gb(ram.used):.1f}/{to_gb(ram.total):.1f} GB RAM")
            agent.save weights()
    if MPI.COMM WORLD.Get rank() == 0:
       with SummaryWriter("logs") as writer:
            for i, success rate in enumerate(t success rate):
                writer.add scalar("Success rate", success rate, i)
       plt.style.use('ggplot')
       plt.figure()
       plt.plot(np.arange(0, MAX EPOCHS), t success rate)
       plt.title("Success rate")
       plt.savefig("success rate.png")
       plt.show()
elif Play FLAG:
    player = Play(env, agent, max episode=100)
   player.evaluate()
```

```
Epoch:0 | Running reward:-50.000 | EP reward:-50.000 | Memory length:100 |
Duration:78.810 | Actor_Loss:0.517 | Critic_Loss:0.001 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch:1 | Running reward:-50.000 | EP reward:-50.000 | Memory length:200 |
Duration:80.369 | Actor_Loss:0.951 | Critic_Loss:0.005 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch:2 | Running reward:-50.000 | EP reward:-50.000 | Memory length:300 |
Duration:81.550 | Actor Loss:1.486 | Critic Loss:0.018 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch:3 | Running reward:-50.000 | EP reward:-50.000 | Memory length:400 |
Duration:82.133 | Actor Loss:1.880 | Critic Loss:0.011 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch:4 | Running_reward:-50.000 | EP_reward:-50.000 | Memory_length:500 |
Duration:81.919 | Actor Loss:2.033 | Critic Loss:0.009 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch:5 | Running reward:-50.000 | EP reward:-50.000 | Memory length:600 |
Duration:82.451 | Actor Loss:2.467 | Critic Loss:0.008 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch:6 | Running reward:-50.000 | EP reward:-50.000 | Memory length:700 |
Duration:83.077 | Actor Loss:2.400 | Critic Loss:0.021 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch: 7 | Running reward: -50.000 | EP reward: -50.000 | Memory length: 800 |
Duration:82.777 | Actor Loss:3.190 | Critic Loss:0.024 | Success rate:0.0
00 | 2.2/12.7 GB RAM
```

```
Epoch:8 | Running reward:-50.000 | EP reward:-50.000 | Memory length:900 |
Duration:81.397 | Actor Loss:2.705 | Critic Loss:0.031 | Success rate:0.0
00 | 2.2/12.7 GB RAM
Epoch: 9 | Running reward: -50.000 | EP reward: -50.000 | Memory length: 1000
| Duration:81.139 | Actor Loss:3.736 | Critic Loss:0.022 | Success rate:
0.000 | 2.2/12.7 GB RAM
Epoch:10 | Running reward:-50.000 | EP reward:-50.000 | Memory length:110
0 | Duration:81.164 | Actor_Loss:4.016 | Critic Loss:0.041 | Success rate:
0.000 | 2.2/12.7 GB RAM
Epoch:11 | Running reward:-50.000 | EP reward:-50.000 | Memory length:120
0 | Duration:81.285 | Actor Loss:4.518 | Critic Loss:0.019 | Success rate:
0.000 | 2.2/12.7 GB RAM
Epoch:12 | Running reward:-50.000 | EP reward:-50.000 | Memory length:130
0 | Duration:80.684 | Actor_Loss:3.391 | Critic Loss:0.068 | Success rate:
0.000 | 2.2/12.7 GB RAM
Epoch:13 | Running reward:-49.981 | EP reward:-50.000 | Memory length:140
0 | Duration:80.924 | Actor Loss:4.995 | Critic Loss:0.059 | Success rate:
0.000 | 2.2/12.7 GB RAM
Epoch:14 | Running reward:-50.000 | EP reward:-50.000 | Memory length:150
0 | Duration:81.189 | Actor Loss:4.600 | Critic_Loss:0.061 | Success rate:
0.000 | 2.2/12.7 GB RAM
Epoch:15 | Running reward:-50.000 | EP reward:-50.000 | Memory length:160
0 | Duration:80.574 | Actor Loss:4.808 | Critic Loss:0.091 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:16 | Running reward:-50.000 | EP reward:-50.000 | Memory length:170
0 | Duration:81.524 | Actor Loss:4.597 | Critic Loss:0.104 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:17 | Running reward:-50.000 | EP reward:-50.000 | Memory length:180
0 | Duration:83.427 | Actor Loss:5.433 | Critic Loss:0.231 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:18 | Running reward:-50.000 | EP reward:-50.000 | Memory length:190
0 | Duration:84.695 | Actor Loss:5.448 | Critic Loss:0.230 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:19 | Running reward:-50.000 | EP reward:-50.000 | Memory length:200
0 | Duration:83.121 | Actor_Loss:5.549 | Critic_Loss:0.093 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:20 | Running reward:-50.000 | EP reward:-50.000 | Memory length:210
0 | Duration:83.552 | Actor Loss:5.235 | Critic Loss:0.089 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:21 Running reward:-50.000 EP reward:-50.000 Memory length:220
0 | Duration:84.254 | Actor Loss:4.470 | Critic Loss:0.152 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:22 | Running reward:-49.981 | EP reward:-50.000 | Memory length:230
0 | Duration:85.156 | Actor Loss:4.656 | Critic Loss:0.126 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:23 | Running reward:-50.000 | EP reward:-50.000 | Memory length:240
0 | Duration:84.989 | Actor Loss:4.332 | Critic Loss:0.171 | Success rate:
0.000 | 2.3/12.7 GB RAM
Epoch:24 | Running reward:-49.634 | EP reward:-50.000 | Memory length:250
0 | Duration:84.048 | Actor_Loss:5.669 | Critic_Loss:0.164 | Success rate:
0.100 | 1.6/12.7 GB RAM
Epoch:25 | Running reward:-49.397 | EP reward:-50.000 | Memory length:260
0 | Duration:85.039 | Actor Loss:5.006 | Critic Loss:0.465 | Success rate:
0.200 | 1.6/12.7 GB RAM
Epoch:26 | Running reward:-49.903 | EP reward:-50.000 | Memory length:270
0 | Duration:84.347 | Actor_Loss:5.022 | Critic_Loss:0.156 | Success rate:
0.000 | 1.6/12.7 GB RAM
Epoch:27 | Running reward:-49.331 | EP reward:-50.000 | Memory length:280
0 | Duration:85.093 | Actor Loss:5.716 | Critic Loss:0.186 | Success rate:
0.200 | 1.6/12.7 GB RAM
Epoch:28 | Running_reward:-49.715 | EP_reward:-50.000 | Memory_length:290
```

0 | Duration:87.732 | Actor_Loss:6.281 | Critic_Loss:0.189 | Success rate: 0.100 | 1.7/12.7 GB RAM Epoch:29 | Running_reward:-49.203 | EP_reward:-50.000 | Memory_length:300 0 | Duration:90.424 | Actor_Loss:4.443 | Critic_Loss:0.323 | Success rate: 0.200 | 1.7/12.7 GB RAM



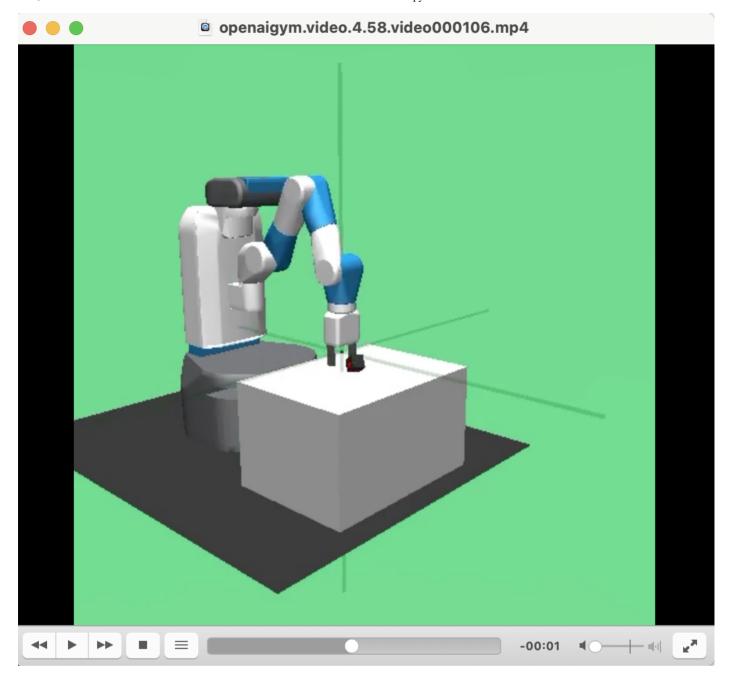
In [39]:

```
player = Play(env, agent, max_episode=100)
player.evaluate()

episode_reward:-50.000
episode_reward:-50.000
```

episode reward:-50.000 episode reward:-50.000 episode reward:-20.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode_reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode_reward:-31.000

episode reward:-50.000



Take Home

Humanoid with PPO

In this Lab, I have already tried InvertedDoublePendulu, Ant(4 legs animal) and FetchPickAndPlace for PPO. So, now I tried Humanoid for PPO take home exercise.

```
In [ ]:
```

```
ENV_NAME = "Humanoid"
TRAIN_FLAG = True
test_env = gym.make(ENV_NAME + "-v2")

n_states = test_env.observation_space.shape[0]
action_bounds = [test_env.action_space.low[0], test_env.action_space.high[0]]
n_actions = test_env.action_space.shape[0]
```

```
In [ ]:
```

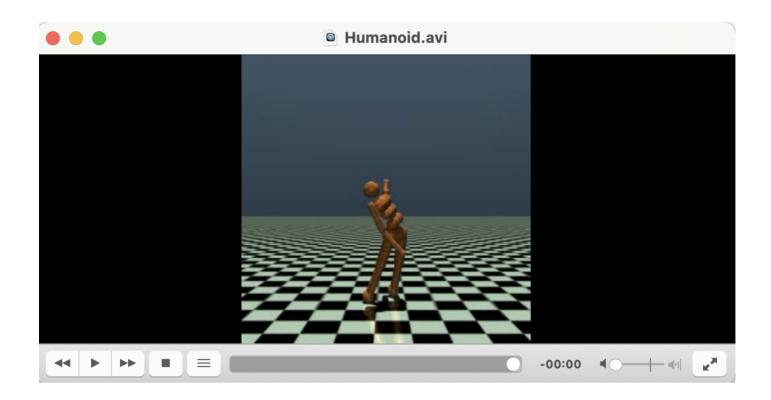
```
print(f"number of states:{n states}\n"
      f"action bounds: {action bounds}\n"
      f"number of actions:{n actions}")
if not os.path.exists(ENV NAME):
    os.mkdir(ENV NAME)
    os.mkdir(ENV NAME + "/logs")
env = qym.make(ENV NAME + "-v2")
agent = Agent(n states=n states,
              n iter=n iterations,
              env name=ENV NAME,
              action bounds=action bounds,
              n actions=n actions,
              lr=lr)
if TRAIN FLAG:
    trainer = Train(env=env,
                    test env=test_env,
                    env name=ENV NAME,
                    agent=agent,
                    horizon=T,
                    n iterations=n iterations,
                    epochs=epochs,
                    mini batch size=mini batch size,
                    epsilon=clip range)
    trainer.step()
player = Play(env, agent, ENV NAME)
player.evaluate()
number of states:376
action bounds: [-0.4, 0.4]
```

```
number of actions:17
iteration: 1
              eval rewards: 143.15736124981203
iteration: 2
               eval rewards: 131.4511843905099
iteration: 3
             eval rewards: 144.6173321616741
iteration: 4 eval_rewards: 93.28572179050539
iteration: 5 eval rewards: 98.52909047192348
           6 eval rewards: 176.85550847116176
iteration:
iteration: 7
             eval rewards: 222.288420580107
iteration: 8 eval rewards: 166.71971782433545
              eval rewards: 229.69841565937216
iteration: 9
iteration: 10 eval_rewards: 133.40805634697935
iteration: 11 eval_rewards: 156.350102919167
iteration: 12 eval rewards: 273.1542224001928
iteration: 13 eval rewards: 331.76494729778733
iteration: 14
               eval_rewards: 337.86891653585445
iteration: 15
               eval rewards: 239.13549677957872
iteration: 16
               eval rewards: 398.14874145346596
```

In Humanoid with PPO,

- evaluation rewards: 495.579.
- running reward: 432.703
- Actor_Loss:0.051
- Critic_Loss:107.269

• iteration: 500



HandReach with DDPG

Since I have already tried FetchPickAndPlace for DDPG, now I tried HandReach for DDPG take home exercise.

```
In [ ]:
```

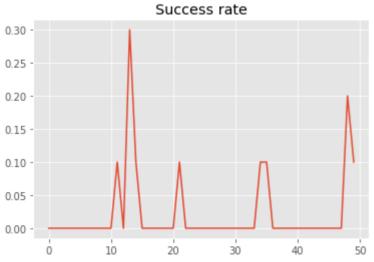
```
import gym
# from agent import Agent
import matplotlib.pyplot as plt
from torch.utils.tensorboard import SummaryWriter
import numpy as np
# from play import Play
import mujoco py
import random
from mpi4py import MPI
import psutil
import time
from copy import deepcopy as dc
import os
import torch
ENV NAME = "HandReach-v0"
# "RepeatCopy-v0"
# "ReversedAddition-v0"
# "FetchSlide-v1"
# "FetchPickAndPlace-v1"
INTRO = False
Train = True
Play FLAG = False
MAX EPOCHS = 50
MAX CYCLES = 50
num_updates = 40
MAX EPISODES = 2
memory size = 7e+5 // 50
batch size = 256
actor_lr = 1e-3
critic lr = 1e-3
qamma = 0.98
tau = 0.05
k future = 4
test env = gym.make(ENV NAME)
state shape = test env.observation space.spaces["observation"].shape
#state shape = test env.observation space.shape
n actions = test env.action space.shape[0]
n goals = test env.observation space.spaces["desired goal"].shape[0]
action_bounds = [test_env.action_space.low[0], test_env.action_space.high[0]]
to_gb = lambda in_bytes: in_bytes / 1024 / 1024 / 1024
os.environ['OMP_NUM_THREADS'] = '1'
os.environ['MKL_NUM_THREADS'] = '1'
os.environ['IN_MPI'] = '1'
def eval_agent(env_, agent_):
    total success rate = []
    running_r = []
    for ep in range(10):
        per_success_rate = []
        env dictionary = env .reset()
        s = env_dictionary["observation"]
        ag = env_dictionary["achieved_goal"]
        g = env_dictionary["desired_goal"]
        while np.linalg.norm(ag - g) <= 0.05:</pre>
            env dictionary = env .reset()
```

```
s = env dictionary["observation"]
            aq = env dictionary["achieved goal"]
            g = env dictionary["desired goal"]
        ep r = 0
        for t in range(50):
            with torch.no grad():
                a = agent .choose action(s, g, train mode=False)
            observation new, r, info = env .step(a)
            s = observation new['observation']
            g = observation new['desired goal']
            per success rate.append(info ['is success'])
            ep r += r
        total success rate.append(per success rate)
        if ep == 0:
            running r.append(ep r)
        else:
            running_r.append(running_r[-1] * 0.99 + 0.01 * ep_r)
    total success rate = np.array(total success rate)
    local success rate = np.mean(total success rate[:, -1])
    global success rate = MPI.COMM WORLD.allreduce(local success rate, op=MPI.SUM)
    return global success rate / MPI.COMM WORLD.Get size(), running r, ep r
if INTRO:
    print(f"state shape:{state shape[0]}\n"
          f"number of actions:{n actions}\n"
          f"action boundaries:{action bounds}\n"
          f"max timesteps:{test env. max episode steps}")
    for in range(3):
        done = False
        test env.reset()
        while not done:
            action = test env.action space.sample()
            test state, test reward, test done, test info = test env.step(action)
            # substitute goal = test state["achieved goal"].copy()
            # substitute reward = test env.compute reward(
                  test state["achieved goal"], substitute goal, test info)
            # print("r is {}, substitute_reward is {}".format(r, substitute_reward))
            test env.render()
    exit(0)
env = gym.make(ENV_NAME)
env.seed(MPI.COMM WORLD.Get rank())
random.seed(MPI.COMM WORLD.Get rank())
np.random.seed(MPI.COMM WORLD.Get rank())
torch.manual seed(MPI.COMM WORLD.Get rank())
agent = Agent(n states=state shape,
              n_actions=n_actions,
              n goals=n goals,
              action_bounds=action_bounds,
              capacity=memory_size,
              action size=n actions,
              batch size=batch size,
              actor lr=actor lr,
              critic lr=critic lr,
              gamma=gamma,
              tau=tau,
              k future=k future,
              env=dc(env))
```

```
if Train:
    t success rate = []
    total ac loss = []
    total cr loss = []
    for epoch in range(MAX EPOCHS):
        start time = time.time()
        epoch actor loss = 0
        epoch critic loss = 0
        for cycle in range(0, MAX CYCLES):
            mb = []
            cycle actor loss = 0
            cycle critic loss = 0
            for episode in range(MAX EPISODES):
                episode dict = {
                    "state": [],
                    "action": [],
                    "info": [],
                    "achieved goal": [],
                    "desired goal": [],
                    "next state": [],
                    "next achieved goal": []}
                env dict = env.reset()
                state = env dict["observation"]
                achieved_goal = env_dict["achieved goal"]
                desired goal = env dict["desired goal"]
                while np.linalg.norm(achieved goal - desired goal) <= 0.05:</pre>
                    env dict = env.reset()
                    state = env dict["observation"]
                    achieved goal = env dict["achieved goal"]
                    desired goal = env dict["desired goal"]
                for t in range(500):
                    action = agent.choose action(state, desired goal)
                    next env dict, reward, done, info = env.step(action)
                    next state = next env dict["observation"]
                    next achieved goal = next env dict["achieved goal"]
                    next desired goal = next env dict["desired goal"]
                    episode dict["state"].append(state.copy())
                    episode dict["action"].append(action.copy())
                    episode dict["achieved goal"].append(achieved goal.copy())
                    episode dict["desired goal"].append(desired goal.copy())
                    state = next state.copy()
                    achieved goal = next achieved goal.copy()
                    desired goal = next desired goal.copy()
                    if done:
                        break
                episode dict["state"].append(state.copy())
                episode dict["achieved goal"].append(achieved goal.copy())
                episode dict["desired goal"].append(desired goal.copy())
                episode_dict["next_state"] = episode_dict["state"][1:]
                episode_dict["next_achieved_goal"] = episode_dict["achieved_goal"][1
                mb.append(dc(episode_dict))
            agent.store(mb)
            for n update in range(num updates):
                actor loss, critic loss = agent.train()
```

```
cycle actor loss += actor loss
                cycle critic loss += critic loss
            epoch actor loss += cycle actor loss / num updates
            epoch critic loss += cycle critic loss /num updates
            agent.update networks()
        ram = psutil.virtual memory()
        success rate, running reward, episode reward = eval agent(env, agent)
        total ac loss.append(epoch actor loss)
        total cr loss.append(epoch critic loss)
        if MPI.COMM WORLD.Get rank() == 0:
            t success rate.append(success rate)
            print(f"Epoch:{epoch}|
                  f"Running reward:{running reward[-1]:.3f}| "
                  f"EP reward:{episode reward:.3f} "
                  f"Memory_length:{len(agent.memory)}| "
                  f"Duration:{time.time() - start_time:.3f}| "
                  f"Actor Loss:{actor loss:.3f} | "
                  f"Critic Loss:{critic loss:.3f}| "
                  f"Success rate:{success_rate:.3f}| "
                  f"{to gb(ram.used):.1f}/{to gb(ram.total):.1f} GB RAM")
            agent.save_weights()
    if MPI.COMM WORLD.Get rank() == 0:
        with SummaryWriter("logs") as writer:
            for i, success_rate in enumerate(t_success_rate):
                writer.add scalar("Success rate", success rate, i)
        plt.style.use('ggplot')
        plt.figure()
        plt.plot(np.arange(0, MAX EPOCHS), t success rate)
        plt.title("Success rate")
        plt.savefig("success rate.png")
        plt.show()
elif Play FLAG:
    player = Play(env, agent, max episode=100)
    player.evaluate()
```

Epoch:49 | Running_reward:-49.501 | EP_reward:-3.000 | Memory_length:5000 | Duration:106.909 | Actor_Loss:2.960 | Critic_Loss:0.030 | Success rate: 0.100 | 1.9/12.7 GB RAM

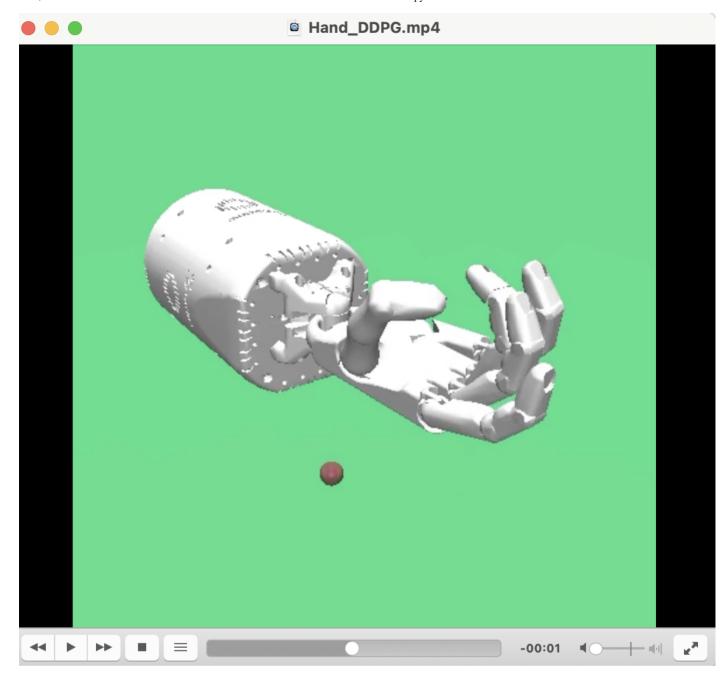


```
In [ ]:
```

```
player = Play(env, agent, max episode=100)
player.evaluate()
episode reward:-50.000
episode reward:-5.000
episode reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-49.000
episode reward:-50.000
episode reward:-49.000
episode reward:-50.000
episode reward:-50.000
episode_reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-4.000
episode_reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode_reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode reward:-19.000
episode reward:-50.000
episode reward:-50.000
episode reward:-50.000
episode_reward:-50.000
episode reward:-50.000
```

episode reward:-50.000

episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode_reward:-50.000 episode_reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-48.000 episode reward:-5.000 episode reward:-50.000 episode reward:-50.000 episode reward:-26.000 episode reward:-50.000 episode reward:-49.000 episode reward:-50.000 episode_reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000 episode reward:-50.000



In []:

localhost:8888/notebooks/Downloads/Lab13.ipynb