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continuous action spaces such as Robotics. It is similar to Trust Region Policy Optimization (TRPO) but follows a simpler algorithm making it computionally less
        costly. It was proposed in the following a research paper Proximal Policy Optimization Algorithms by OpenAl (arxiv link)
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        Implementation Note:

    Impletated from scratch in python using following libraries - tensorflow, numpy, gym, opency, matplotlib.

    Tested for Bipedal walker environment of OpenAl.

        Importing necessary libraries
In [1]: seed=1
         import os
         #os.environ["CUDA VISIBLE DEVICES"] = "-1"
        os.environ['TF_DETERMINISTIC_OPS'] = '1'
        os.environ['PYTHONHASHSEED']=str(seed)
         import numpy as np
        np.random.seed(seed)
         import tensorflow as tf
         tf.random.set_seed(seed)
        from tensorflow.keras.models import Model
        from tensorflow.keras.layers import Flatten, Dense ,Input,concatenate ,Conv2D,Conv2DTranspose,\
        MaxPooling2D, AveragePooling2D, LSTM , Reshape, TimeDistributed, ReLU, LeakyReLU, Dropout, BatchNormalization
        from tensorflow.keras.optimizers import Adam, Adagrad
        from tensorflow.keras import regularizers
        from tensorflow.keras.callbacks import ModelCheckpoint
        from tensorflow.keras import backend as K
         import warnings
         import glob
         import math
         import cv2
         from matplotlib import pyplot as plt
         import pickle
        from collections import deque
        from tqdm import tqdm, trange
         import gym
         import imageio
        from datetime import datetime
        from copy import copy , deepcopy
        TanH=tf.keras.layers.Activation('tanh')
        Sigmoid=tf.keras.layers.Activation('sigmoid')
        Basic settings and paths
In [2]: train ppo agent=True
         env_name = 'BipedalWalker-v2'
         exp_root_path='exps/ppo_exp_1'
         if not os.path.exists(exp_root_path): os.makedirs(exp_root_path)
        Hyper-parameters setting
In [3]: params dict={
          actor lr' : 0.001,
         'critic_lr': 0.001,
         '_value coef' : 0.5,
         '_entropy_coef' : 0.01,
          gamma': 0.99,
         ' Lambda' : 0.95,
         ' clip epsilon' : 0.05,
         '_advantage' : 10,
         ' time steps' : 2000,
         '_episodes' : 1000,
         '_train steps': 5
        param_str='Time : '+str(datetime.now()) +'\n'+'Exp Name : ' + exp_root_path+'\n'
        for key in params_dict.keys():
            param_str += str( key + ' = '+str(params_dict[key]) + '\n' )
        with open(exp_root_path+'/params.txt','w') as file:
            file.write(param_str)
        Class definations
        1. Class Actor():
                Class for creating actor Network inheriting tensorflow.keras Model class
                -> __init__ : Layer definations
                -> call() : Network building
        2. Class Critic():
                Class for creating actor Network inheriting tensorflow.keras Model class
                -> __init__ : Layer definations
                -> call() : Network building
        3. Class Memory():
                Class for storing data samples and retriving when necessary. Each data sample to be stored consists of : state , acti
            on , mean, std, value, mask, reward
                -> append(data sample) appends one sample into memory
                -> retrive() -> data sample, retrives all the stored samples and cleares memory
        4. Class Environment():
                A wrapper around OpenAI environment.
                -> reset() resets the environment
                -> step() takes action and returns observation, reward, terminal, info
                -> render() renders current environment image
                -> close() closes environment instance
        5. CLass PPO_Model():
                 Takes all the hyper-parameters as input.
                -> calc_gae_values : Calculates generalized advantage estimations from values, rewards and masks
                -> calc_actor_loss : Calculates actor loss
                -> train actor : Trains actor model with calculated loss
                -> calc critic loss : Calculate critic loss
                -> train critic : Trains Critic model with calculated loss
                -> test model : Test the actor model for environment and returns test reward
                -> get_log_probability : calculates log of gaussian probabilities from action , mean and std
                -> get entropy : calculates entropy from std
In [4]: class Environment():
            def __init__(self, seed=seed):
                self.env= gym.make(env_name)
                self.env.seed(seed)
                self.n_states = self.env.observation_space.shape[0]
                self.n_actions = self.env.action_space.shape[0]
            def reset(self):
                return self.env.reset()
            def step(self,action):
                action = np.clip(action, -1.0, 1.0)
                observation, reward, done, info = self.env.step(action)
                if reward == -100:
                     reward=-2
                mask = not done
                return observation, reward, mask, info
            def render(self,opt):
                 return self.env.render(opt)
             def close(self):
                self.env.close()
         class Actor(Model):
            def init (self, n act):
                 super(Actor, self).__init__()
                self.d1 = Dense(512, activation='relu')
                self.d2 = Dense(256, activation='relu')
                self.mean = Dense(n_act)
                self.tanh = TanH
                self.sigmoid = Sigmoid
                self.std = Dense(n_act)
            def call(self, x):
                x = self.d1(x)
                x = self.d2(x)
                mean = self.mean(x)
                mean = self.tanh(mean)
                std = self.std(x)
                std = self.sigmoid(std)
                return mean, std+10e-10
        class Critic(Model):
            def init (self):
                 super(Critic, self).__init__()
                 self.d1 = Dense(512, activation='relu')
                self.d2 = Dense(256, activation='relu')
                self.value = Dense(1)
            def call(self, x):
                x = self.d1(x)
                x = self.d2(x)
                value = self.value(x)
                 return value
        class Memory():
                 def __init__(self,_len=None,n_states=None,n_actions=None):
                     self. len= len
                     self.n states=n states
                    self.n actions=n actions
                     self.clear()
                def clear(self):
                     len=self. len
                    self.curr_states = np.zeros((_len,self.n_states),dtype=np.float32)
                     self.old_actions = np.zeros((_len,self.n_actions),dtype=np.float32)
                     self.values = np.zeros((_len,1),dtype=np.float32)
                     self.masks = np.zeros(( len,1),dtype=np.float32)
                     self.rewards = np.zeros((_len,1),dtype=np.float32)
                     self.old_means = np.zeros((_len,self.n_actions),dtype=np.float32)
                    self.old stds = np.zeros(( len,self.n actions),dtype=np.float32)
                     self.i=0
                def append(self, state, action, mean, std, q_value, mask, reward):
                     self.curr_states[self.i,:]=state
                     self.old_actions[self.i,:]=action
                     self.old means[self.i,:]=mean
                     self.old_stds[self.i,:]=std
                    self.values[self.i,:]=q_value
                     self.masks[self.i,:]=mask
                     self.rewards[self.i,:]=reward
                     self.i+=1
                def retrive(self):
                    curr_states=self.curr_states.copy()
                     old_actions=self.old_actions.copy()
                     old means=self.old means.copy()
                     old stds=self.old stds.copy()
                     values=self.values.copy()
                     rewards=self.rewards.copy()
                     masks = self.masks.copy()
                     self.clear()
                     return curr states, old actions, old means, old stds, values, rewards, masks
         class PPO_Model():
            def __init__(self,n_actions=None,_actor_lr = 0.001, _critic_lr = 0.001,_value_coef=0.5,_entropy_coef=0.01,_gamma=0.99,
                         _lambda=0.95,_clip_epsilon=0.05,_advantage= 10, _time_steps=2000,_episodes=1000,_train_steps=5):
                 self. actor=Actor(n actions)
                self._critic=Critic()
                self._actor_opt= Adam(_actor_lr)
                self._critic_opt= Adam(_critic_lr)
                self. value coef= value coef
                self. entropy coef= entropy coef
                self. gamma= gamma
                self. lambda= lambda
                self. clip epsilon= clip epsilon
                self. advantage= advantage
                self. time steps = time steps
                self._episodes = _episodes
                self._train_steps = _train_steps
            def calc gae values(self, n values, n masks, n rewards):
                 target qvals = []
                for i in range(len(n_rewards)-self._advantage):
                    values=n values[i:i+self. advantage+1]
                     rewards=n_rewards[i:i+self._advantage]
                     masks=n masks[i:i+self. advantage]
                     gae=0
                     for j in range(self._advantage):
                         delta = rewards[j] + self._gamma * values[j + 1] * masks[j] - values[j]
                         gae += ((self._gamma * self._lambda)**j) * masks[j] * delta
                     target_qvals.append(gae + values[0])
                adv = np.array(target_qvals) - n_values[:-self._advantage-1]
                return target_qvals, (adv - np.mean(adv)) / (np.std(adv) + 1e-10)
            def calc_actor_loss(self, mean, std, old_mean, old_std, old_action, advantage_raw):#, rewards, values):
                old_probs = self.get_log_probs(old_action,old_mean,old_std)
                new probs = self.get log probs(old action, mean, std)
                entropy loss = self.get entropy(std)
                ratio = K.exp(new_probs-old_probs)
                p1 = ratio * advantage raw
                p2 = K.clip(ratio, min_value=1 - self._clip_epsilon, max_value=1 + self._clip_epsilon) * advantage_raw
                actor_loss = K.mean(K.minimum(p1, p2))
                 total loss = -actor loss - self. entropy coef * entropy loss
                return total loss
            @tf.function
            def train_actor_network(self,curr_states,old_mean,old_std,old_actions,advantage_raw):
                 advantage_raw=tf.cast(advantage_raw, tf.float32)
                with tf.GradientTape() as tape:
                     mean, std = self._actor(curr_states, training=True)
                    act_loss = self.calc_actor_loss(mean, std, old_mean, old_std, old_actions, advantage_raw)
                    gradients = tape.gradient(act_loss, self._actor.trainable_variables)
                     self. actor opt.apply gradients(zip(gradients, self. actor.trainable variables))
                return act loss
            @tf.function
            def calc_critic_loss(self,_values,_target_rewards):
                     batch size= values.shape[0]
                     critic_loss=self._value_coef*2*tf.reduce_sum(tf.square(_target_rewards-_values))/batch_size
                     return critic loss
            @tf.function
            def train_critic_network(self, states, target_rewards):
                with tf.GradientTape() as tape:
                     values=self._critic(states)
                     values=tf.cast(values,tf.float32)
                     target_rewards=tf.cast(target_rewards, tf.float32)
                     critic_loss=self.calc_critic_loss(values, target_rewards)
                    gradients = tape.gradient(critic_loss, self._critic.trainable_variables)
                     self._critic_opt.apply_gradients(zip(gradients, self._critic.trainable_variables))
                return critic loss
            @tf.function
            def get_log_probs(self,_actions,mean,std):
                 _actions=tf.cast(_actions,tf.float32)
                mean=tf.cast(mean, tf.float32)
                std=tf.cast(std,tf.float32)
                 var = -0.5*((actions-mean)/(std))**2
                _coef = 1/(std*tf.sqrt(2*np.pi))
                _probs = _coef*tf.cast(tf.exp(_var),tf.float32)
                log probs = tf.math.log( probs)
                return log probs
            def get_entropy(self, std):
                 entropy = 0.5 * (tf.math.log(2 * np.pi * std ** 2) + 1)
                return entropy
            def test_reward(self,i_seed):
                 env=Environment(seed=i_seed)
                state = env.reset()
                mask = True
                total_reward = 0
                while mask:
                     state_input = K.expand_dims(state, 0)
                     mean, std = self._actor(state_input)
                     act=np.random.normal(mean, std)[0]
                     next_state, reward, mask, _ = env.step(mean[0])
                     state = next state
                     total_reward += reward
                 env.close()
                 return total reward
        Brief Flow Chart of the training algorithm
                                                                   PPO
                                        Calc GAE
                                                                                             . Collect samples
                         For n in (3,2,1):
                                                                              Policy Network
                              delta : rewards[ n ] + gamma * values [ n+1 ]
                              gae : delta + gamma * lambda * gae
                                                                                              Action
                          gae = gae + values[1]
                                                                                                     Environment
                      3. Train
                                                                               Critic Network
                                        Train Actor
                       Actor
                          mean , std : Actor (states)
                                                                  2. Calc
                          prob_a: probability(old actions, old mean, old std)
                                                                  GAE's
                          prob_b : probability(old actions, new mean, new std)
                          ratio: prob_a / prob_b
                          Norm_GAE = normalize(GAE's)
                                                                   1st GAE
                                                                                   Calc GAE
                                                                                                     1st Data Sample
                          p1 : ratio * Norm_GAE
                         p2 : clip(ratio, 1- epsilon, 1+epilon) * Norm_GAE
                                                                                                     2nd Data Sample
                                                                                Calc GAE
                                                                  2nd GAE
                          loss : mean( minimum(p1,p2))
                                                                                                     3rd Data Sample
                          Actor.grads.minimize(loss)
                                                                                                     4th Data Sample
                                                                  3rd GAE
                                                                             Calc GAE
                          4. Train
                                                                                                     5th Data Sample
                                         Train Critic
                          Critic
                                                                                                     6th Data Sample
                                q_values : Critic ( states)
                                loss: (target_q_values - q_values)**2
                               Critic.grads.minimize(loss)
        The training loop
In [5]: if train ppo agent==True:
            # Creating envronment
            env=Environment()
            n states= env.n states
            n actions = env.n actions
            state = env.reset()
            rewards log=[]
            max reward=0
            ppo_model=PPO_Model(n_actions=env.n_actions,**params_dict)
            ppo memory = Memory( len=(ppo model. time steps+ppo model. advantage), n states=n states, n actions=n actions)
            for episode in range(ppo_model._episodes):
                 state_input = None
                 sum reward=0
                sum reward log=0
                for itr in trange(ppo_model._time_steps+ppo_model._advantage):
                     state_input = K.expand_dims(state, 0)
                     mean, std = ppo_model._actor(state_input)
                     q_value = ppo_model._critic(state_input)
                     action = np.random.normal(mean, std)[0]
                     observation, reward, mask, info = env.step(action)
                     sum reward+=reward
                    ppo_memory.append(state,action,mean,std,q_value,mask,reward)
                     state = observation
                     if not mask: # mask is invert of done / terminal
                         sum_reward_log=copy(sum_reward)
                         sum reward=0
                         env.reset()
                 curr_states,old_actions,old_means,old_stds,values,rewards,masks = ppo_memory.retrive()
                 state_input=K.expand_dims(state, 0)
                q_value = ppo_model._critic(state_input)
                 values=np.concatenate([values,q_value],axis=0)
                for _ in trange(ppo_model._train_steps):
                         adv = ppo_model._advantage
                         target_qvals, advantages = ppo_model.calc_gae_values(values, masks, rewards)
                         ppo_model.train_actor_network(curr_states[:-adv],old_means[:-adv],old_stds[:-adv],old_actions[:-adv],advantages)
                         ppo model.train_critic_network(curr_states[:-adv], target_qvals)
                avg_reward = np.mean([ppo_model.test_reward(i) for i in trange(5)])
                print('episode :',episode,'reward :',sum_reward_log)
                print('total test reward=' + str(avg_reward))
                 if avg reward >=max reward:
                     ppo_model._actor.save_weights(exp_root_path+'/ppo_best_actor.hdf5')
                    ppo model. critic.save weights(exp root path+'/ppo best critic'+'.hdf5')
                    best eps=episode
                    max reward = avg reward
                rewards_log.append([sum_reward_log,avg_reward])
                env.reset()
            env.close()
            plt.plot(rewards_log)
        Note: Training output is removed for ease of reading.
        Train and Test rewards
In [6]: if train_ppo_agent==True:
            f=open(exp_root_path+'/ppo-biped-loss.pkl','wb')
            pickle.dump(rewards log,f)
            f.close()
        else:
            f=open(exp_root_path+'/ppo-biped-loss.pkl','rb')
            rewards_log=pickle.load(f)
            f.close()
        fig,axes=plt.subplots(nrows=1,ncols=1,figsize=(20,4))
         axes.plot(rewards_log)
        axes.legend(['train reward', 'test reward'])
        axes.grid()
        axes.axhline(y=250, color='b', linestyle='--')
        fig.savefig(exp_root_path+'/bipedal-ppo.png')
                test reward
         150
         100
          50
         -50
        Test on Bipedal Environment ¶
In [7]: env = Environment()
         if train_ppo_agent == False:
            ppo model=PPO Model(n actions=env.n actions, **params_dict)
         _actor=ppo_model._actor
         actor(np.ones((1,env.n_states)))
         _actor.load_weights(exp_root_path+'/ppo_best_actor.hdf5')
In [8]: state=env.reset()
         i=0
         ter_count=0
         img save path=exp root path+'/bipedal ppo/'
         if not os.path.exists(img_save_path): os.makedirs(img_save_path)
         while True:
            action=_actor(state.reshape(1,24))
            state,rwd,mask,info=env.step(action[0][0])
            img=env.render('rgb_array')
            cv2.imwrite(img_save_path+str(i)+'.jpg',img)
            i+=1
             if mask==False:
                     ter count+=1
                     state=env.reset()
             if ter_count==5:
                      break
        env.close()
In [9]: fnames=[img_save_path+str(i)+'.jpg' for i in range(1000)]
         with imageio.get_writer(img_save_path+'bipedal_ppo.gif', mode='I') as writer:
            for fname in tqdm(fnames):
                 image = imageio.imread(fname)
                 writer.append_data(image)
                                                                                               1000/1000 [00:24<00:00, 40.69it/s]
        Saved GIF of test results
```

Thank You!

Proxilmal Policy Optimization ¶

PPO is a state of the art algorithm in the field of Reinforcement learning. It has proven record of performing well in sophisticated envoronments especially with