Alex Beyer - ENME743 - ILA5 - Linear Policy Gradients

In [ ]:
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#Alex Beyer - ILA5 - Linear policy Gradients
#implements linear policy gradients with a gaussian potential (i think?) via a NN u

#necessary imports
import sklearn.preprocessing
import numpy as np
import gym
import matplotlib.pyplot as plt
import torch.nn.functional as func
import torch.optim as optim
import torch.nn as nn
import torch

#boilerplate setup
device = torch.device("cpu") #i ran this via CUDA but that throws errors for unsupp

#plotter class with data storage for later
class Plotter():
    def __init__(self):
        self.data = []

#actor-critic agent
class ActorCritic(nn.Module):
    def __init__(self, nStates, nActions, nHidden = 16):
        super(ActorCritic, self).__init__()
        #build NN
        self.nActions = nActions
        self.layer1 = nn.Linear(nStates, nHidden)
        self.layer2 = nn.Linear(nHidden, nHidden)
        self.layer3 = nn.Linear(nHidden, nActions)
        self.value = nn.Linear(nHidden, 1)
        self.to(device)

    #forward pass - I'm trying a different way to build this than in the NN homewor
    #personally I think this makes more sense but that's just how I think about the
    #expirimented a bit and relu for all 3 layers gives some interesting properties
    # but it still seems to correspond to great model preformance
    def forward(self, x):
        x = func.relu(self.layer1(x))
        x = func.relu(self.layer2(x))
        mu = func.relu(self.layer3(x)) #try different activators
        sigma = func.softmax(self.layer3(x), dim = -1) + .0001 #offset to prevent s
        dist = torch.distributions.Normal(mu.view(self.nActions).data, sigma.view(s
        value = self.value(x)
        return dist, value

#build the A2C trainer as a class which calls the ActorCritic agent class in itself
class A2C:
    def __init__(self, envName, gamma = .5, learnRate = .05, nEps = 100, nSteps = 1
        #store all the variables we'll need later
        self.envName = envName
        self.env = gym.make(envName)
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        self.model = ActorCritic(self.env.observation_space.shape[0], self.env.acti
        self.opt = optim.Adam(self.model.parameters(),learnRate)
        self.data = {"loss": []}
        self.nEps = nEps
        self.nEpsTest = nEpsTest
        self.nSteps = nSteps
        self.gamma = gamma

        #draw 10000 samples from the state space to initialize Q table
    def initStateScaler(self):
        ssSample = np.array([self.env.observation_space.sample() for x in range(100
        self.scaler = sklearn.preprocessing.StandardScaler()
        self.scaler.fit(ssSample)

    #continue to this as the model runs
    def scaleState(self, state):
        scaled = self.scaler.transform(np.array([state[0]]).reshape(1,-1))
        return scaled[0]

    #update the A2C policy
    def a2cUpdate(self, rewards, lProbs, values, state):
        qVals = []
        nextQ = 0
        pw = 0
        #apply the discount rate to the rewards found by the model, appending the t
        for reward in rewards[::-1]:
            nextQ += self.gamma ** pw * reward
            pw += 1
            qVals.append(nextQ)
        #update Q-table, stepping through in reverse to update
        qVals = qVals[::-1]
        qVals = torch.tensor(qVals)
        qVals = (qVals - qVals.mean()) / (qVals.std() + .000001) #offset to prevent
        #reset loss
        loss = 0
        for nextProb, value, nextQ in zip(lProbs, values, qVals):
            #update A2C parameters
            advantage = nextQ - value.item()
            actorLoss = -nextProb * advantage
            criticLoss = func.smooth_l1_loss(value[0], nextQ)
            loss += criticLoss + actorLoss

        self.opt.zero_grad()
        loss.min().backward()
        self.opt.step()

        #pass the current state into the actor-critic NN model to find the optimal
    def getNextAction(self, state):
        if type(state) is tuple:
            dist, value = self.model(torch.Tensor(state[0].reshape(1,-1)))
        else:
            dist, value = self.model(torch.Tensor(state))
        action = dist.sample().numpy()
        nextProb = dist.log_prob(torch.FloatTensor(action))
        return action, nextProb, value
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    #also define a test function to be callled immediately after training, in which
    def test(self, nEps, tEp):
        testReward = []
        #for each testing episode...
        for e in range(self.nEpsTest):
            #reinitialize our environment...
            state = self.env.reset()
            nextReward = []
            #and for each iteration of the testing episode...
            for t in range(self.nSteps):
                #run the same logic as the training step, but without updating para
                action, _, _ = self.getNextAction(state)
                _, reward, truncated, terminated, _ = self.env.step(action)
                nextReward.append(reward)
                if truncated or terminated:
                    break
                #and appending the reward to a list for return <-- this is what im
            testReward.append(sum(nextReward))
        return np.mean(testReward), np.std(testReward)

    #setup train loop
    def train(self):
        #initialize storage and zero score
        score = 0.0
        rewards = []
        muRewards = []
        sigmaRewards = []
        #setup initial Q-table
        self.initStateScaler()
        #for each episode...
        for e in range(self.nEps):
            #initialize empty storage...
            state = self.env.reset()
            score = 0.0
            stepNum = 0
            rewards = []
            lProbs = []
            values = []
            #then for each training run in the episode...
            for t in range(self.nSteps):
                #run the model, updating parameters and ending the episode if the m
                stepNum += 1
                if type(state) is tuple:
                    state = self.scaleState(state[0].reshape(1,-1))
                else:
                    state = self.scaleState(state.reshape(1,-1))
                action, nextProb, value = self.getNextAction(state)
                state, reward, truncated, terminated, _ = self.env.step(action)
                score += reward
                rewards.append(reward)
                values.append(value)
                lProbs.append(nextProb)
                if truncated or terminated:
                    break
            #appending the score to the list...
            rewards.append(score)
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            #updating the actor-critic parameters...
            self.a2cUpdate(rewards, lProbs, values, state)
            #while printing progress...
            if (e+1) % 2 == 0:
                print("ep {} got reward: {} in {} steps ".format(e+1, rewards[e], s
            if (e+1) % 10 == 0:
                nextMuReward, nextSigmaReward = self.test(self.nEpsTest,e)
                print('ave reward: {} \n w/stdev: {}'.format(nextMuReward, nextSigm
            #and saving episode mean statistics for plotting
            nextMuReward, nextSigmaReward = self.test(self.nEpsTest,e)
            muRewards.append(nextMuReward)
            sigmaRewards.append(nextSigmaReward)
        #finally, clean up
        self.env.close()
        return rewards, lProbs, values, muRewards, sigmaRewards

if __name__ == "__main__":
    A2C = A2C("MountainCarContinuous-v0")
    rewards, lProbs, values, muRewards, sigmaRewards = A2C.train()
    plt.plot(muRewards)
    plt.xlabel("Episode")
    plt.ylabel("Average Test Reward")
    plt.title("Average Test Reward by Episode")
    plt.show()
```

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ep 2 got reward: -0.013663550883247756 in 100 steps
ep 4 got reward: -0.05591936858420219 in 100 steps
ep 6 got reward: -0.002989107835262317 in 100 steps
ep 8 got reward: -0.0002443041850153316 in 100 steps
ep 10 got reward: -0.06328297020297136 in 100 steps
ave reward: -10.010159322163794
 w/stdev: 1.5862983481935455
ep 12 got reward: -0.3832364374074132 in 100 steps
ep 14 got reward: -0.0585127312231041 in 100 steps
ep 16 got reward: -0.013982870971291562 in 100 steps
ep 18 got reward: -0.12039669468051671 in 100 steps
ep 20 got reward: -0.06347591937954036 in 100 steps
ave reward: -9.595437594257694
 w/stdev: 1.4518556321429403
ep 22 got reward: -0.03025136508097468 in 100 steps
ep 24 got reward: -0.06806749418598237 in 100 steps
ep 26 got reward: -0.21018910467546448 in 100 steps
ep 28 got reward: -0.0666925161951415 in 100 steps
ep 30 got reward: -0.04646729462583608 in 100 steps
ave reward: -10.131185653359594
 w/stdev: 1.4212557778506094
ep 32 got reward: -0.0736640778023002 in 100 steps
ep 34 got reward: -0.007153154557226405 in 100 steps
ep 36 got reward: -0.07087265473249005 in 100 steps
ep 38 got reward: -0.04197126046853015 in 100 steps
ep 40 got reward: -0.006633605586193881 in 100 steps
ave reward: -10.121726971450554
 w/stdev: 1.5757775203692594
ep 42 got reward: -0.08162304328501513 in 100 steps
ep 44 got reward: -0.03528645156079371 in 100 steps
ep 46 got reward: -0.10413359548804238 in 100 steps
ep 48 got reward: -0.0703879671349629 in 100 steps
ep 50 got reward: -0.3203328737805592 in 100 steps
ave reward: -10.433343183406013
 w/stdev: 1.485128519262795
ep 52 got reward: -0.006795324925413926 in 100 steps
ep 54 got reward: -0.056446759803208124 in 100 steps
ep 56 got reward: -0.07826387226447339 in 100 steps
ep 58 got reward: -0.00029452174552818124 in 100 steps
ep 60 got reward: -0.14870100326857597 in 100 steps
ave reward: -9.238109423453707
 w/stdev: 0.8570624723326755
ep 62 got reward: -0.0625380627207278 in 100 steps
ep 64 got reward: -0.08753469931036761 in 100 steps
ep 66 got reward: -0.0009433177584555531 in 100 steps
ep 68 got reward: -0.0033402982428842876 in 100 steps
ep 70 got reward: -0.3430911245179246 in 100 steps
ave reward: -10.151623071833118
 w/stdev: 1.343972276230104
ep 72 got reward: -0.05265535810282565 in 100 steps
ep 74 got reward: -0.019974537815081652 in 100 steps
ep 76 got reward: -0.009523983301304018 in 100 steps
ep 78 got reward: -0.08071020129800424 in 100 steps
ep 80 got reward: -0.002174671452837984 in 100 steps
ave reward: -9.751493229433477
 w/stdev: 1.0857614325807703
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ep 82 got reward: -0.07412008168335547 in 100 steps
ep 84 got reward: -0.21480606241542688 in 100 steps
ep 86 got reward: -0.8045657459646464 in 100 steps
ep 88 got reward: -0.1160902178617107 in 100 steps
ep 90 got reward: -0.1561727917228396 in 100 steps
ave reward: -10.451563341789127
 w/stdev: 0.6528795154039805
ep 92 got reward: -0.6399018012691671 in 100 steps
ep 94 got reward: -0.00027102397835376824 in 100 steps
ep 96 got reward: -0.006555048761698857 in 100 steps
ep 98 got reward: -0.6607654803979188 in 100 steps
ep 100 got reward: -0.03010643366896062 in 100 steps
ave reward: -10.230303475004026
 w/stdev: 0.9328884881178395
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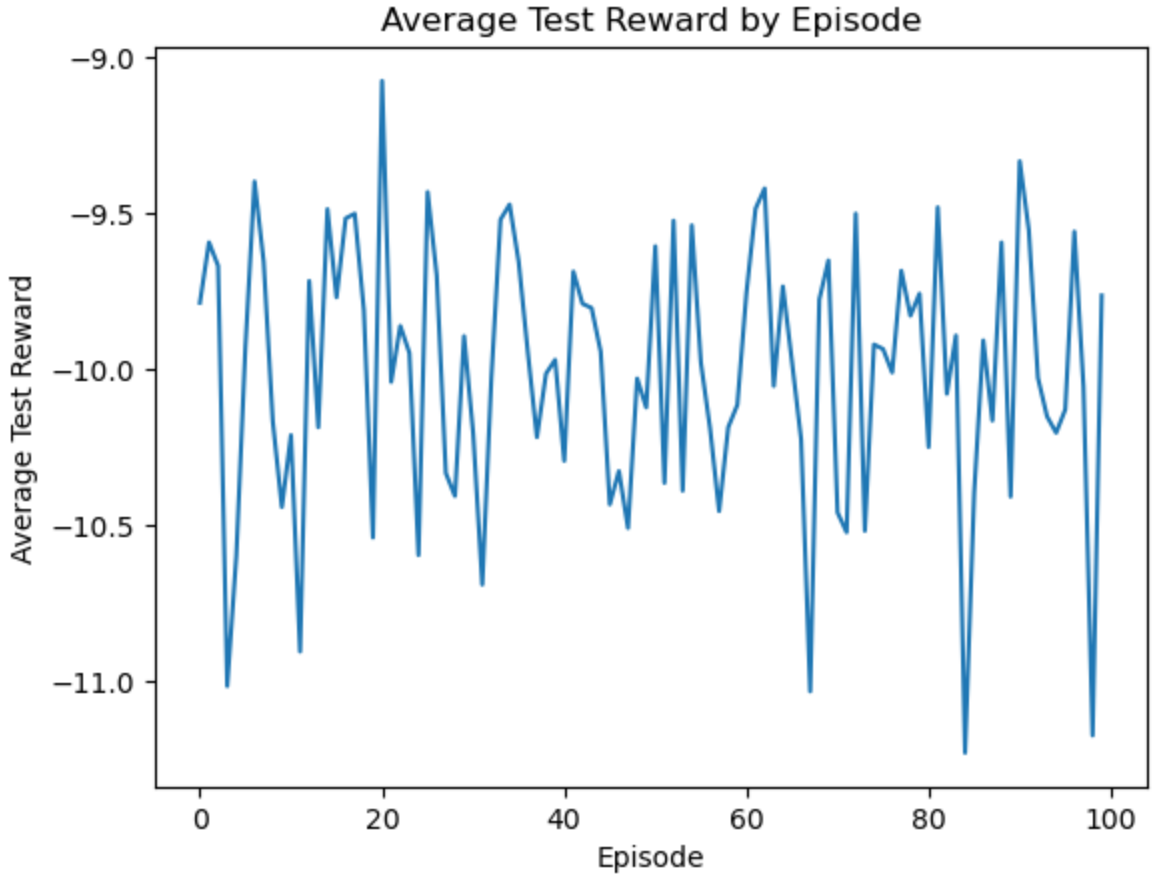

My algorithm runs a number of training episodes on the MountainCar, then runs a smaller number of testing episodes, taking the average reward from those for datapoints on the plot. The outputs we see in text form here are stats form the training episodes while the plot is testing episode specific. The reason the graph looks like this is because it's converging on a solution within the first batch of training episodes - what we're seeing is a model preforming almost as well as it can. Because there is always some amount of random exploration going on we'll always see some amount of oscillation in the average episode reward, just from the model attempting to explore and improve it's policy. Overall the model preforms excellently.