Assignment 3: Policy Gradients (DDPG and REINFORCE)

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Background

This exercise requires you to solve various continous control problems in OpenAI-Gym.

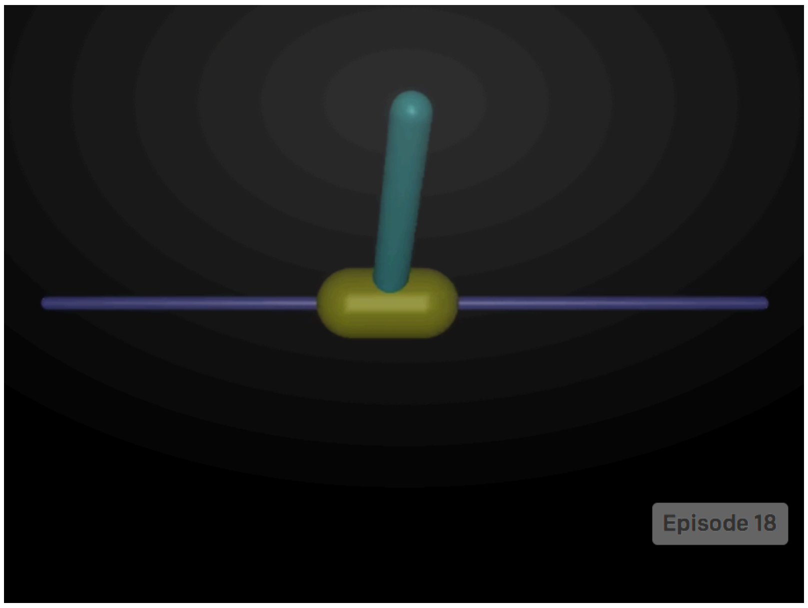
DDPG is policy gradient actor critic method for continous control which is off policy. It tackles the curse of dimensionality / loss of performance faced when discretizing a continous action domain. DDPG uses similiar "tricks" as DQN to improve the stability of training, including a replay buffer and target networks.

Furthermore, you will implement REINFORCE for discrete and continous environments, and as a bonus compare the sample efficiency and performance with DQN and DDPG.

DDPG paper: https://arxiv.org/pdf/1509.02971.pdf (https://arxiv.org/pdf/1509.02971.pdf)

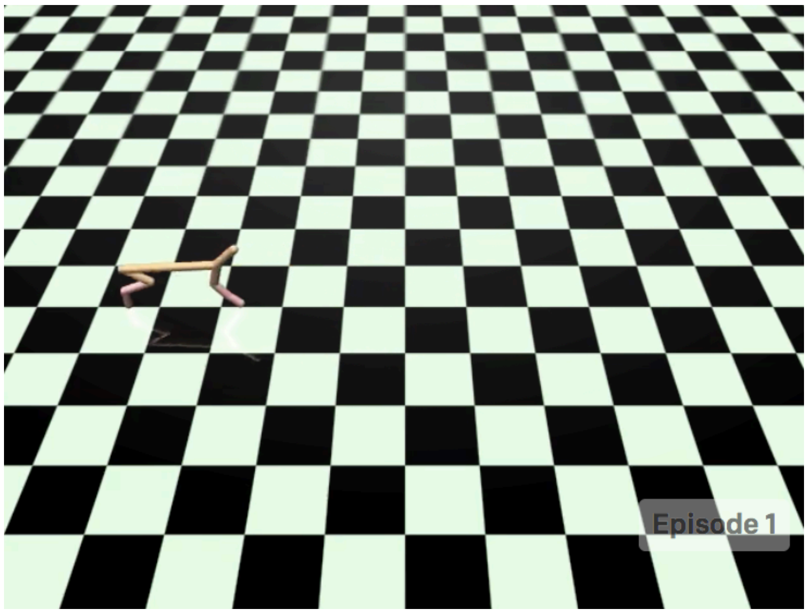
Environments:

InvertedPendulum-v2 environment:



Pendulum-v0 environment:

Halfcheetah-v2 environment:



Setup environment for Actor Critic

- inline plotting
- gym
- directory for logging videos

In [1]:

```
%matplotlib inline
import matplotlib.pyplot as plt
import numpy as np
import random
import math

#environment
import gym
import os
import time
#pytorch
import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.autograd import Variable

logging_interval = 20
animate_interval = logging_interval * 5
logdir='./DDPG/'
```

Set up gym environment

The code below does the following for you:

- Wrap environment, log videos, setup CUDA variables (if GPU is available)
- Record action and observation space dimensions
- Fix random seed for determinisitic training

In [2]:

```
VISUALIZE = True
SEED = 0
MAX_PATH_LENGTH = 500
NUM_EPISODES = 12000
GAMMA=0.99
BATCH_SIZE = 128

# Environments to be tested on
# env_name = 'InvertedPendulum-v1'
# env_name = 'Pendulum-v0'
env_name = 'HalfCheetah-v1'

# wrap gym to save videos
env = gym.make(env_name)
if VISUALIZE:
    if not os.path.exists(logdir):
        os.mkdir(logdir)
    env = gym.wrappers.Monitor(env, logdir, force=True, video_callable=lambda episod
env._max_episodes_steps = MAX_PATH_LENGTH

# check observation and action space
discrete = isinstance(env.action_space, gym.spaces.Discrete)
obs_dim = env.observation_space.shape[0]
act_dim = env.action_space.n if discrete else env.action_space.shape[0]

if discrete:
    print("This is a discrete action space, probably not the right algorithm to use"

# set random seeds
torch.manual_seed(SEED)
np.random.seed(SEED)

# make variable types for automatic setting to GPU or CPU, depending on GPU availab
use_cuda = torch.cuda.is_available()
FloatTensor = torch.cuda.FloatTensor if use_cuda else torch.FloatTensor
LongTensor = torch.cuda.LongTensor if use_cuda else torch.LongTensor
ByteTensor = torch.cuda.ByteTensor if use_cuda else torch.ByteTensor
Tensor = FloatTensor
```

```
[2018-05-15 18:15:02,522] Making new env: HalfCheetah-v1
[2018-05-15 18:15:02,888] Clearing 4 monitor files from previous run (
because force=True was provided)
```

Demonstrate your understanding of the simulation:

For the environments mentioned above ('Pendulum-v0', 'HalfCheetah-v2', 'InvertedPendulum-v2'),

- describe the reward system
- describe the each state variable (observation space)
- describe the action space
- when is the environment considered "solved"?

Ans:

Pendulum-v0

- reward = -(theta^2 + 0.1*theta_dt^2 + 0.001*action^2)
- x1 = cos(theta) within [-1,1]; x2 = sin(theta) within [-1,1]; x3 = theta_dot within [-8,8] where theta is the angular of the pendulum, and theta_dot is the angular velocity of the pendulum.
- A joint effore within [-2,2]
- In general, the pendulum starts randomly at angle from -pi to pi, with random velocity between -1 and 1. There is no specific termination, so I have to manual set up a maximum number of steps for one episode. Also, to optimize this model, we want the pendulum to remain at zero angle (vertical), with least angular velocity as well as the least effort.

HalfCheetah-v1

- To produce reward in each step, there are two ingredients, one is called reward_control and the other called reward_run. reward_ctrl = - 0.1 * np.square(action).sum(), where action has 6 dimensions, reward_run = (xposafter - xposbefore)/self.dt. Therefore, the reward = reward_ctrl + reward_run which is a scalar.

- State space

```
  (name)    (joint)     (parameter)
- rootx     slider      position (m)
- rootz     slider      position (m)
- rooty     hinge       angle (rad)
- bthigh    hinge       angle (rad)
- bshin     hinge       angle (rad)
- bfoot     hinge       angle (rad)
- fthigh    hinge       angle (rad)
- fshin     hinge       angle (rad)
- ffoot     hinge       angle (rad)
- rootx     slider      velocity (m/s)
- rootz     slider      velocity (m/s)
- rooty     hinge       angular velocity (rad/s)
- bthigh    hinge       angular velocity (rad/s)
- bshin     hinge       angular velocity (rad/s)
- bfoot     hinge       angular velocity (rad/s)
- fthigh    hinge       angular velocity (rad/s)
- fshin     hinge       angular velocity (rad/s)
- ffoot     hinge       angular velocity (rad/s)
```

- Action space

```
  (name)   (actuator)   (parameter):
- bthigh    hinge       torque (N m)
- bshin     hinge       torque (N m)
- bfoot     hinge       torque (N m)
- fthigh    hinge       torque (N m)
- fshin     hinge       torque (N m)
- ffoot     hinge       torque (N m)
```

- When the total reward with in 500 steps for one episode greater than 1500, we consider the cheetah is being well trained.

InvertedPendulum-v1

- reward is 1 for each step
- x1 = cart position, x2 = pole position, x3 = cart velocity, x4 = pole angular velocity
- a1 = the force impose on cart
- when the average reward greater than 500, we consider the inverted pendulum is being well balanced

Implement an action normalization class:

To train across various environments, it is useful to normalize action inputs and outputs between [-1, 1]. This class should take in actions and implement forward and reverse functions to map actions between [-1, 1] and [action_space.low, action_space.high].

Using the following gym wrapper, implement this class.

- https://github.com/openai/gym/blob/78c416ef7bc829ce55b404b6604641ba0cf47d10/gym/core.py (https://github.com/openai/gym/blob/78c416ef7bc829ce55b404b6604641ba0cf47d10/gym/core.py)
- i.e. we are overriding the outputs scale of actions.

In [4]:

```
class NormalizeAction(gym.ActionWrapper):
    def action(self, act):
        # [-1, 1] => [action_space.low, action_space.high]
        #tanh outputs (-1,1) from tanh, need to be [action_space.low, action_space.h
        act = (act + 1)/2  #[-1, 1] => [0,1]
        act = act * (self.action_space.high - self.action_space.low)
        act = act + self.action_space.low
        return act

    def reverse_action(self, act):
        # [action_space.low, action_space.high] => [-1,1]
        #reverse of that above
        act = act - self.action_space.low
        act = act / (self.action_space.high - self.action_space.low)
        act = act * 2 - 1
        return act
```

DDPG

Write a weight syncing function

In contrast to DQN, DDPG uses soft weight sychronization. At each time step following training, the actor and critic target network weights are updated to track the rollout networks.

- target_network.weights <= target_network.weights * (1 - tau) + source_network.weights * (tau)

In [5]:

```
def weightSync(target_model, source_model, tau = 0.001):
    # soft update
    for parameter_target, parameter_source in zip(target_model.parameters(), source_
        parameter_target.data.copy_((1 - tau) * parameter_target.data + tau * parame
```

Write a Replay class that includes all the functionality of a replay buffer

DDPG is an off policy actor-critic method and an identical replay buffer to that used for the previous assignment is applicable here as well (do not include the generate_minibatch method in your Replay class this time). Like before, your constructor for Replay should create an initial buffer of size 1000 when you instantiate it.

The replay buffer should kept to some maximum size (60000), allow adding of samples and returning of samples at random from the buffer. Each sample (or experience) is formed as (state, action, reward, next_state, done).

In [6]:

```
class Replay():
    def __init__(self):
        self.capacity = 60000
        self.memory = []
        self.position = 0
        self.gamma = 0.99

    def initialize(self, init_length, envir):
        st = envir.reset()
        for _ in range(init_length):
            a = envir.action_space.sample()
            st1, r, done, info = envir.step(a)
            # normalizing action
            # [action_space.low, action_space.high] => [-1,1]
            a = envir.reverse_action(a)
            self.push((st, a, st1, r, done))
            if done: st = envir.reset()
            else : st = st1

    def push(self, transition):
        if len(self.memory) < self.capacity:
            self.memory.append(None)
        self.memory[self.position] = transition
        self.position = (self.position + 1) % self.capacity

    def generateMinibatch(self, batch_size):
        batch_memory = random.sample(self.memory, batch_size) #return a list
        batch_memory = list(zip(*batch_memory))

        batch_st = Variable(FloatTensor(batch_memory[0]))
        batch_at = Variable(FloatTensor(batch_memory[1]))
        batch_st1 = Variable(FloatTensor(batch_memory[2]))
        batch_r = Variable(torch.unsqueeze(FloatTensor(batch_memory[3]),1))
        batch_done = torch.unsqueeze(FloatTensor(batch_memory[4]),1)

        return batch_st, batch_at, batch_st1, batch_r, batch_done

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

Write an Ornstein Uhlenbeck process class for exploration noise

The proccess is described here:

- https://en.wikipedia.org/wiki/Ornstein–Uhlenbeck_process (https://en.wikipedia.org/wiki/Ornstein–Uhlenbeck_process)
- http://math.stackexchange.com/questions/1287634/implementing-ornstein-uhlenbeck-in-matlab (http://math.stackexchange.com/questions/1287634/implementing-ornstein-uhlenbeck-in-matlab)

You should implement:

- a step / sample method
- reset method

Use theta = 0.15, mu = 0, sigma = 0.3, dt = 0.01

In [8]:

```
class OrnsteinUhlenbeckProcess():
#     def __init__(self, mu=np.zeros(act_dim), sigma=0.3, theta=.15, dimension=1e-2,
    # for inverted pendulum and pendulum above
    def __init__(self, mu=np.zeros(act_dim), sigma=0.05, theta=.25, dimension=1e-2,
        self.theta = theta
        self.mu = mu
        self.sigma = sigma
        self.dt = dimension
        self.x0 = x0
        self.reset()

    def step(self):
        x = self.x_prev + self.theta * (self.mu - self.x_prev) * self.dt + \
                self.sigma * np.sqrt(self.dt) * np.random.normal(size=self.mu.shape
        self.x_prev = x
        return x

    def reset(self):
        self.x_prev = self.x0 if self.x0 is not None else np.zeros_like(self.mu)

    def __repr__(self):
        return 'OrnsteinUhlenbeckActionNoise(mu={}, sigma={})'.format(self.mu, self.
```

Write a Deep Neural Network class that creates a dense network of a desired architecture for actor and critic networks

Actor

- input and hidden layer activation function: ReLU
- output activation function: Tanh
- hidden_state sizes: 400
- state and action sizes: variable
- number of hidden layers: 2
- batch normalization applied to all hidden layers
- weight initialization: normal distribution with small variance.

Critic

- input and hidden layer activation function: ReLU
- output activation function: None
- hidden_state sizes: 300, 300 + action size
- state and action sizes: variable
- number of hidden layers: 2
- batch normalization applied to all hidden layers prior to the action input
- weight initialization: normal distribution with small variance.

Good baselines can be found in the paper.

In [9]:

```
# ----------------------------------------------------
# actor model, MLP
# ----------------------------------------------------
# 2 hidden layers, 400 units per layer, tanh output to bound outputs between -1 and

class actor(nn.Module):
    def __init__(self, input_size, output_size):
        super(actor, self).__init__()
        self.fc1 = nn.Linear(input_size, 400)
        self.bn1 = nn.BatchNorm1d(400) # batchnormalization
        self.fc2 = nn.Linear(400, 400)
        self.bn2 = nn.BatchNorm1d(400) # batchnormalization
        self.fc3 = nn.Linear(400, output_size)

        # parameters initialization
#         nn.init.xavier_normal_(self.fc1.weight)
#         nn.init.xavier_normal_(self.fc2.weight)
#         nn.init.xavier_normal_(self.fc3.weight)
#         nn.init.normal_(self.fc1.bias)
#         nn.init.normal_(self.fc2.bias)
#         nn.init.normal_(self.fc3.bias)
```

```
    def forward(self, x):
        x = F.relu(self.fc1(x))
        x = self.bn1(x)  # turn off for inverted-pendulum -v1
        x = F.relu(self.fc2(x))
        x = self.bn2(x)  # turn off for inverted-pendulum -v1

        outputs = F.tanh(self.fc3(x))
        return outputs



# ----------------------------------------------------
# critic model, MLP
# ----------------------------------------------------
# 2 hidden layers, 300 units per layer, ouputs rewards therefore unbounded
# Action not to be included until 2nd layer of critic (from paper). Make sure to fo

class critic(nn.Module):
    def __init__(self, state_size, action_size, output_size):
        super(critic, self).__init__()

        self.fc1 = nn.Linear(state_size, 300)
        self.bn1 = nn.BatchNorm1d(300) # batchnormalization
        self.fc2 = nn.Linear(300 + action_size, 300)
        self.fc3 = nn.Linear(300, output_size)

        # parameters initialization
#         nn.init.xavier_normal_(self.fc1.weight)
#         nn.init.xavier_normal_(self.fc2.weight)
#         nn.init.xavier_normal_(self.fc3.weight)
#         nn.init.normal_(self.fc1.bias)
#         nn.init.normal_(self.fc2.bias)
#         nn.init.normal_(self.fc3.bias)

    def forward(self, states, actions):
        x = F.relu(self.fc1(states))
        x = self.bn1(x)  # turn off for inverted-pendulum -v1
        x = torch.cat((x, actions), 1) # actions only join at second layer
        x = F.relu(self.fc2(x))

        outputs = self.fc3(x)
        return outputs
```

Define DDPG class to encapsulate definition, rollouts, and training

- gamma = 0.99
- actor_lr = 1e-4
- critic_lr = 1e-3
- critic l2 regularization = 1e-2
- noise decay
- noise class
- batch_size = 128
- optimizer: Adam
- loss (critic): mse

Furthermore, you can experiment with action versus parameter space noise. The standard implimentation works with action space noise, howeve parameter space noise has shown to produce excellent results.

In [10]:

```
class DDPG:
    def __init__(self, obs_dim, act_dim, critic_lr = 1e-3, actor_lr = 1e-4, gamma =
        self.gamma = GAMMA
        self.batch_size = BATCH_SIZE

        # actor
        self.actor = actor(input_size = obs_dim, output_size = act_dim).type(FloatTe
        self.actor_target = actor(input_size = obs_dim, output_size = act_dim).type(
        self.actor_target.load_state_dict(self.actor.state_dict())

        # critic
        self.critic = critic(state_size = obs_dim, action_size = act_dim, output_si
        self.critic_target = critic(state_size = obs_dim, action_size = act_dim, out
        self.critic_target.load_state_dict(self.critic.state_dict())

        # optimizers
        self.optimizer_actor = torch.optim.Adam(self.actor.parameters(), lr = actor_
        self.optimizer_critic = torch.optim.Adam(self.critic.parameters(), lr = crit

        # critic loss
        self.critic_loss = nn.MSELoss()

        # noise
        self.noise = OrnsteinUhlenbeckProcess(dimension = act_dim, num_steps = NUM_I

        # replay buffer
        self.replayBuffer = Replay()


    def train(self):
        # sample from Replay
        b_st, b_at, b_st1, b_r, b_d = self.replayBuffer.generateMinibatch(self.batch
```

```
        ## update critic (create target for Q function)
        # below is for target actor network
        targetActorPredict_b_at1 = self.actor_target(b_st1)

        #below is for target critic network
        mask = 1 - b_d   # if done is true, change the target to just reward
        batch_Q_next = self.critic_target(b_st1, targetActorPredict_b_at1)
        QQ_next = Variable((batch_Q_next.data * mask).view(self.batch_size, 1))
        b_Q_critic_target = b_r + self.gamma*(QQ_next)


        # below is for behavior critic network
        b_Q_critic_behaviorQ = self.critic(b_st, b_at)

        ## critic optimizer and backprop step (feed in target and predicted values t
        critic_loss = self.critic_loss(b_Q_critic_behaviorQ, b_Q_critic_target.detac
        self.optimizer_critic.zero_grad()
        critic_loss.backward()
        self.optimizer_critic.step()

        ## update actor (formulate the loss wrt which actor is updated)
        # below is for behavior actor network
        b_at_actor_behavior = self.actor(b_st)
        # below is for behavior critic network
        b_Q_critic_behaviorP = self.critic(b_st, b_at_actor_behavior)

        ## actor optimizer and backprop step (loss_actor.backward())
        loss_actor = -1. * b_Q_critic_behaviorP
        loss_actor = loss_actor.mean()

        self.optimizer_actor.zero_grad()
        loss_actor.backward()
        self.optimizer_actor.step()

        # sychronize target network with fast moving one
        weightSync(self.critic_target, self.critic)
        weightSync(self.actor_target, self.actor)
```

Create an instance of your DDPG object

- Print network architectures, confirm they are correct

In [11]:

```
ddpg = DDPG(obs_dim = obs_dim, act_dim = act_dim)
print(ddpg.actor)
print(ddpg.critic)
```

```
actor(
  (fc1): Linear(in_features=17, out_features=400, bias=True)
  (bn1): BatchNorm1d(400, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (fc2): Linear(in_features=400, out_features=400, bias=True)
  (bn2): BatchNorm1d(400, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (fc3): Linear(in_features=400, out_features=6, bias=True)
)
critic(
  (fc1): Linear(in_features=17, out_features=300, bias=True)
  (bn1): BatchNorm1d(300, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (fc2): Linear(in_features=306, out_features=300, bias=True)
  (fc3): Linear(in_features=300, out_features=1, bias=True)
)
```

Train DDPG on different environments

Early stopping conditions:

- avg_val > 500 for "InvertedPendulum"
- avg_val > -150 for "Pendulum"
- avg_val > 1500 for "HalfCheetah"

In [12]:

```
env = NormalizeAction(env) # remap action values for the environment
avg_val = 0

#for plotting
running_rewards_ddpg = []
step_list_ddpg = []
step_counter = 0

# set term_condition for early stopping according to environment being used
# term_condition = -150 # Pendulum
# term_condition = 500 # inverted pendulum
term_condition = 1500 # halfcheetah
ddpg.replayBuffer.initialize(1000, env)

for itr in range(NUM_EPISODES):
    state = env.reset() # get initial state
    animate_this_episode = (itr % animate_interval == 0) and VISUALIZE
    total_reward = 0
```

```
    while True: # for each episode, we loop each step in this episode
        ddpg.noise.reset()
        if animate_this_episode:
            env.render()
            time.sleep(0.05)
        # use actor to get action, add ddpg.noise.step() to action
        # remember to put NN in eval mode while testing (to deal with BatchNorm laye
        # to train mode after you're done getting the action
        var_state = Variable(torch.unsqueeze(FloatTensor(state),0), requires_grad=Fa
        ddpg.actor.eval()
        cuda_tensor_action = ddpg.actor(var_state)
        ddpg.actor.train()

        action = cuda_tensor_action.data[0].cpu().numpy()
        action = action + ddpg.noise.step()
        # below already include [-1,1] => [action_space.low, action_space.high]
        new_state, reward, done, _ = env.step(action)
        total_reward += reward

        ddpg.replayBuffer.push((state, action, new_state, reward, done))
        # step action, get next state, reward, done (keep track of total_reward)
        # populate ddpg.replayBuffer
        ddpg.train() ###################### update network (per step) in one episod
        step_counter += 1
        state = new_state
        if done: break

    if avg_val > term_condition and itr >100 : break

    running_rewards_ddpg.append(total_reward) # return of this episode
    step_list_ddpg.append(step_counter)

    avg_val = avg_val * 0.95 + 0.05*running_rewards_ddpg[-1]
    print("Average value: {} for episode: {}".format(avg_val,itr))

print('Done')
```

```
[2018-05-15 18:16:02,781] Starting new video recorder writing to /data
sets/home/85/185/chs140/ECE276C/PA3/DDPG/openaigym.video.0.3152.video0
00000.mp4
[2018-05-15 18:16:02,784] GLFW error: 65544, desc: b'X11: RandR gamma
ramp support seems broken'
[2018-05-15 18:16:02,825] GLFW error: 65544, desc: b'Linux: Failed to
watch for joystick connections in /dev/input: No such file or director
y'
[2018-05-15 18:16:02,826] GLFW error: 65544, desc: b'Linux: Failed to
open joystick device directory /dev/input: No such file or directory'

Average value: -17.843247096416302 for episode: 0
Average value: -36.08468524747259 for episode: 1
Average value: -54.33420902731596 for episode: 2
Average value: -71.70057412910461 for episode: 3
Average value: -59.74418617579752 for episode: 4
Average value: -62.580942535612834 for episode: 5
Average value: -73.82833487779708 for episode: 6
```

```
Average value: -75.82835487779706 for episode: 6
Average value: -81.68708376415621 for episode: 7
Average value: -89.20755442592052 for episode: 8
```

Plot rewards over multiple training runs

This is provided to generate and plot results for you.

In [15]:

```
def numpy_ewma_vectorized_v2(data, window):
    alpha = 2 /(window + 1.0)
    alpha_rev = 1-alpha
    n = data.shape[0]

    pows = alpha_rev**(np.arange(n+1))

    scale_arr = 1/pows[:-1]
    offset = data[0]*pows[1:]
    pw0 = alpha*alpha_rev**(n-1)

    mult = data*pw0*scale_arr
    cumsums = mult.cumsum()
    out = offset + cumsums*scale_arr[::-1]
    return out
```

DDPG Inverted-Pendulum-v1

In [13]:

```
np.save('ddpg_inverted_pendulum_reward.npy', running_rewards_ddpg)
np.save('ddpg_inverted_pendulum_step.npy', step_list_ddpg)
```

In [14]:

```
plt.figure()
out = numpy_ewma_vectorized_v2(np.array(running_rewards_ddpg),20)
step_list_ddpg = np.array(step_list_ddpg)
plt.plot(step_list_ddpg, out)
plt.title('Training reward over multiple runs')
plt.xlabel('Number of steps')
plt.ylabel('Cumulative reward')
plt.show()
```

In [19]:

```
# env = NormalizeAction(env) # remap action values for the environment
state = env.reset() # get initial state
while True: # for each episode, we loop each step in this episode
    ddpg.noise.reset()
    env.render()
    time.sleep(0.05)
    # use actor to get action, add ddpg.noise.step() to action
    # remember to put NN in eval mode while testing (to deal with BatchNorm layers)
    # to train mode after you're done getting the action
    var_state = Variable(torch.unsqueeze(FloatTensor(state),0), requires_grad=False)

    ddpg.actor.eval()
    cuda_tensor_action = ddpg.actor(var_state)
    action = cuda_tensor_action.data[0].cpu().numpy()
    action = action + ddpg.noise.step()
    # below already include [-1,1] => [action_space.low, action_space.high]
    new_state, reward, done, _ = env.step(action)
    # step action, get next state, reward, done (keep track of total_reward)
    # populate ddpg.replayBuffer
    state = new_state
    if done: break

print('done')
```

done

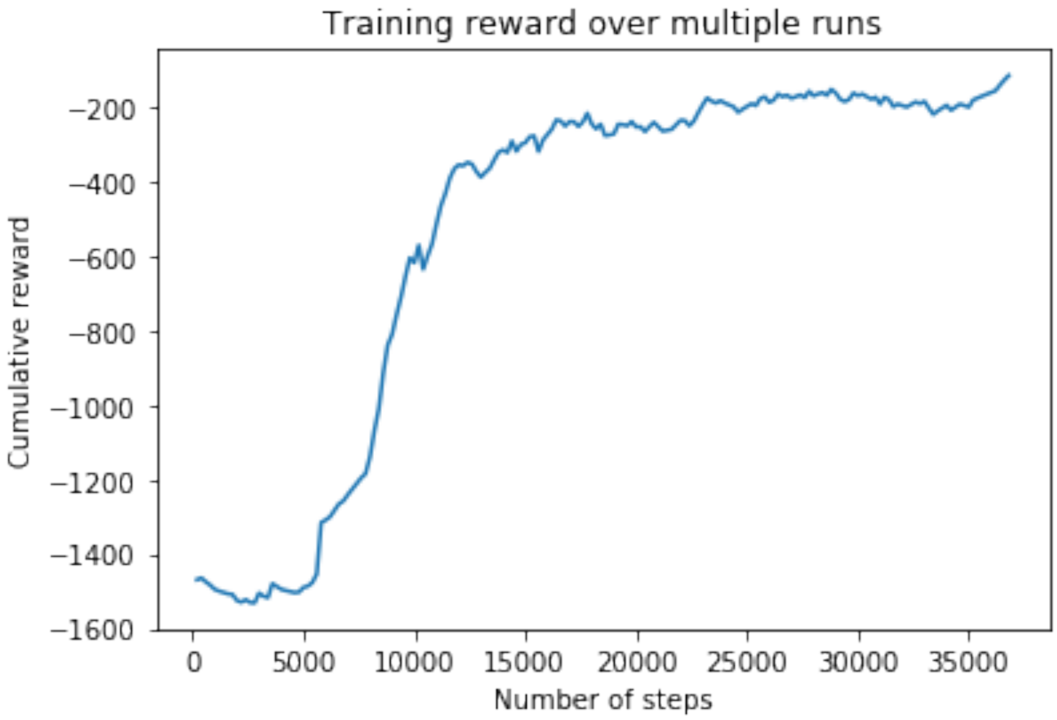
DDPG Pendulum-v0

In [14]:

```
np.save('ddpg_pendulum_reward.npy', running_rewards_ddpg)
np.save('ddpg_pendulum_step.npy', step_list_ddpg)
```

In [16]:

```
plt.figure()
out = numpy_ewma_vectorized_v2(np.array(running_rewards_ddpg),20)
step_list_ddpg = np.array(step_list_ddpg)
plt.plot(step_list_ddpg, out)
plt.title('Training reward over multiple runs')
plt.xlabel('Number of steps')
plt.ylabel('Cumulative reward')
plt.show()
```



In [19]:

```
# env = NormalizeAction(env) # remap action values for the environment
state = env.reset() # get initial state
while True: # for each episode, we loop each step in this episode
    ddpg.noise.reset()
    env.render()
    time.sleep(0.05)
    # use actor to get action, add ddpg.noise.step() to action
    # remember to put NN in eval mode while testing (to deal with BatchNorm layers)
    # to train mode after you're done getting the action
    var_state = Variable(torch.unsqueeze(FloatTensor(state),0), requires_grad=False

    ddpg.actor.eval()
    cuda_tensor_action = ddpg.actor(var_state)
    action = cuda_tensor_action.data[0].cpu().numpy()
    action = action + ddpg.noise.step()
    # below already include [-1,1] => [action_space.low, action_space.high]
    new_state, reward, done, _ = env.step(action)
    # step action, get next state, reward, done (keep track of total_reward)
    # populate ddpg.replayBuffer
    state = new_state
    if done: break

print('done')
```

done

DDPG HalfCheetah-v1

In [13]:

```
np.save('ddpg_halfcheetah_reward.npy', running_rewards_ddpg)
np.save('ddpg_halfcheetah_step.npy', step_list_ddpg)
```

In [16]:

```
plt.figure()
out = numpy_ewma_vectorized_v2(np.array(running_rewards_ddpg),20)
step_list_ddpg = np.array(step_list_ddpg)
plt.plot(step_list_ddpg, out)
plt.title('Training reward over multiple runs')
plt.xlabel('Number of steps')
plt.ylabel('Cumulative reward')
plt.show()
```

In [ ]:

```
# env = NormalizeAction(env) # remap action values for the environment
state = env.reset() # get initial state
while True: # for each episode, we loop each step in this episode
    ddpg.noise.reset()
    env.render()
    time.sleep(0.05)
    # use actor to get action, add ddpg.noise.step() to action
    # remember to put NN in eval mode while testing (to deal with BatchNorm layers)
    # to train mode after you're done getting the action
    var_state = Variable(torch.unsqueeze(FloatTensor(state),0), requires_grad=False

    ddpg.actor.eval()
    cuda_tensor_action = ddpg.actor(var_state)
    action = cuda_tensor_action.data[0].cpu().numpy()
    action = action + ddpg.noise.step()
    # below already include [-1,1] => [action_space.low, action_space.high]
    new_state, reward, done, _ = env.step(action)
    # step action, get next state, reward, done (keep track of total_reward)
    # populate ddpg.replayBuffer
    state = new_state
    if done: break

print('done')
```

REINFORCE

In this section you will implement REINFORCE, with modifications for batch training. It will be for use on both discrete and continous action spaces.

Policy Parametrization

Define a MLP which outputs a distribution over the action preferences given input state. For the discrete case, the MLP outputs the likelihood of each action (softmax) while for the continuous case, the output is the mean and standard deviation parametrizing the normal distribution from which the action is sampled.

In [3]:

```
# ----------------------------------------------------
# Policy parametrizing model, MLP
# ----------------------------------------------------
# 1 or 2 hidden layers with a small number of units per layer (similar to DQN)
# use ReLU for hidden layer activations
# softmax as activation for output if discrete actions, linear for continuous contro
# for the continuous case, output_dim=2*act_dim (each act_dim gets a mean and std_de

class mlp(nn.Module):
```

```
    # For discrete, it is the number of actions for outputs
    # For continuous, it is the dimension of action
    def __init__(self, Dim_state, num_outputs, disct):
        super(mlp, self).__init__()
        self.disct = disct
        if self.disct == True:
            self.fc1 = nn.Linear(Dim_state, 50)
            self.fc2 = nn.Linear(50, 50)
            self.fc3 = nn.Linear(50, num_outputs)
            # parameters initialization
#             nn.init.xavier_normal_(self.fc1.weight)
#             nn.init.xavier_normal_(self.fc2.weight)
#             nn.init.xavier_normal_(self.fc3.weight)
#             nn.init.normal_(self.fc1.bias)
#             nn.init.normal_(self.fc2.bias)
#             nn.init.normal_(self.fc3.bias)

        else:
            self.fc1 = nn.Linear(Dim_state, 50)
            self.fc2 = nn.Linear(50, 50)
            self.fc_mu = nn.Linear(50, num_outputs)
            self.fc_sigma = nn.Linear(50, num_outputs)


            # parameters initialization
#             nn.init.xavier_normal_(self.fc1.weight)
#             nn.init.xavier_normal_(self.fc2.weight)

#             nn.init.xavier_normal_(self.fc_mu.weight)
#             nn.init.xavier_normal_(self.fc_sigma.weight)

#             nn.init.normal_(self.fc1.bias)
#             nn.init.normal_(self.fc2.bias)

#             nn.init.normal_(self.fc_mu.bias)
#             nn.init.normal_(self.fc_sigma.bias)


    def forward(self, x):
        if self.disct == True:
            x = F.relu(self.fc1(x))
            x = F.relu(self.fc2(x))
            x = self.fc3(x)
            actions_prob = F.softmax(x, dim=1)
            return actions_prob
        else:
            x = F.relu(self.fc1(x))
            x = F.relu(self.fc2(x))

            mu = self.fc_mu(x)
            sigma = self.fc_sigma(x)
            return [mu, sigma]
```

Define a function that samples an action from the policy distribtion parameters obtained as output of the MLP. The function should return the action and the log-probability (log_odds) of taking that action.

In [4]:

```
def sample_action(logit, disct):
    # logit is the output of the softmax/linear layer
    # discrete is a flag for the environment type
    # Hint: use Categorical and Normal from torch.distributions to sample action anc
    # Note that log_probability in this case translates to ln(\pi(a|s))
    if disct == True:
        action_distribution=torch.distributions.Categorical(logit)
        action = action_distribution.sample()
        log_odds = action_distribution.log_prob(action)

    else : # continuous
        mean = logit[0]
        cov = F.softplus(logit[1])
        action_distribution = torch.distributions.normal.Normal(mean, cov)
        action = action_distribution.sample()
        log_odds = action_distribution.log_prob(action)
    return action, log_odds
```

Create a function update_policy that defines the loss function and updates the MLP according to the REINFORCE update rule (ref. slide 24 of Lec 7 or page 330 of Sutton and Barto (2018)). The update algorithm to be used below is slightly different: instead of updating the network at every time-step, we take the gradient of the loss averaged over a batch of timesteps (this is to make SGD more stable). We also use a baseline to reduce variance.

The discount factor is set as 1 here.

In [5]:

```
def reward2go(rewards, gamma =1):
    r2g = []
    acc_r = 0
    for r in reversed(rewards):
        acc_r = acc_r * gamma + r
        r2g.append(acc_r)
    return r2g[::-1]


def update_policy(paths, net):
    # paths: a list of paths (complete episodes, used to calculate return at each t
    # net: MLP object

    num_paths = len(paths)
    rew_cums = []
    log_odds = []
    # calculated as "reward to go"

    for path in paths:
        # rew_cums should record return at each time step for each path
        rew_cums += reward2go(path['reward'])
        # log_odds should record log_odds obtained at each timestep of path
        log_odds += path['log_odds']
        # calculated as "reward to go"

    # make log_odds, rew_cums each a vector
    rew_cums = np.array(rew_cums)
    log_odds = np.array(log_odds)
    rew_cums = (rew_cums - rew_cums.mean()) / (rew_cums.std() + 1e-5) # create base
    # calculate policy loss and average over paths
    policy_loss = -rew_cums.dot(log_odds)/ num_paths

    # take optimizer step
    optimizer.zero_grad()
    policy_loss.sum().backward()  # sum for cheetah, or may delete this sum for othe
    optimizer.step()
```

Set up environment and instantiate objects. Your algorithm is to be tested on one discrete and two continuous environments.

In [6]:

```
use_cuda = torch.cuda.is_available()
FloatTensor = torch.cuda.FloatTensor if use_cuda else torch.FloatTensor
LongTensor = torch.cuda.LongTensor if use_cuda else torch.LongTensor
ByteTensor = torch.cuda.ByteTensor if use_cuda else torch.ByteTensor
Tensor = FloatTensor

# Select Environment

######discrete environment:
```

```
######discrete environment:
# env_name='CartPole-v0'

######continous environments:
# env_name='InvertedPendulum-v1'
env_name = 'HalfCheetah-v1'


# Make the gym environment
env = gym.make(env_name)
visualize = False
# animate=visualize
learning_rate = 1e-3

max_path_length=None
min_timesteps_per_batch = 2000  # sets the batch size for updating network

# Set random seeds
seed=0
torch.manual_seed(seed)
np.random.seed(seed)


# Saving parameters
logdir='./REINFORCE/'

if visualize:
    if not os.path.exists(logdir):
        os.mkdir(logdir)
    env = gym.wrappers.Monitor(env, logdir, force=True, video_callable=lambda episoc

env._max_episodes_steps = min_timesteps_per_batch


# Is this env continuous, or discrete?
discrete = isinstance(env.action_space, gym.spaces.Discrete)


# Get observation and action space dimensions
obs_dim = env.observation_space.shape[0]
act_dim = env.action_space.n if discrete else env.action_space.shape[0]

# Maximum length for episodes
max_path_length = max_path_length or env.spec.max_episode_steps

# Make network object (remember to pass in appropriate flags for the type of action
# net = mlp(*args)
net = mlp(Dim_state = obs_dim, num_outputs = act_dim, disct = discrete).type(FloatTe

# Make optimizer
optimizer = torch.optim.Adam(net.parameters(), lr = learning_rate)
print(net)
```

```
[2018-05-15 14:26:39,297] Making new env: HalfCheetah-v1
```

```
[2018-05-15 14:26:39,630] Finished writing results. You can upload the
m to the scoreboard via gym.upload('/datasets/home/85/185/chs140/ECE27
6C/PA3/DDPG')
```

```
mlp(
  (fc1): Linear(in_features=17, out_features=50, bias=True)
  (fc2): Linear(in_features=50, out_features=50, bias=True)
  (fc_mu): Linear(in_features=50, out_features=6, bias=True)
  (fc_sigma): Linear(in_features=50, out_features=6, bias=True)
)
```

Run REINFORCE

Run REINFORCE for CartPole, InvertedPendulum, and HalfCheetah.

In [7]:

```
n_iter = 1000
min_timesteps_per_batch = 2000  # sets the batch size for updating network
avg_reward = 0
avg_rewards = []
step_list_reinforce = []
total_steps = 0
episodes = 0

for itr in range(n_iter): # loop for number of optimization steps
    paths = []
    steps = 0
    while True: # loop to get enough timesteps in this batch --> if episode ends th
        ob = env.reset()
        animate_this_episode = (itr % animate_interval == 0) and visualize
        obs, acs, rews, log_odds = [], [], [], []
        obs.append(ob)

        while True: # loop for episode inside batch
            if animate_this_episode:
                env.render()
                time.sleep(0.05)
            # get parametrized policy distribution from net using current state ob
            net.eval()
            var_ob = Variable(torch.unsqueeze(FloatTensor(ob),0), requires_grad=Fals
            distribution_parameters = net(var_ob)

            net.train()
            # sample action and get log-probability (log_odds) from distribution
            cuda_tensor_ac, log_odd= sample_action(logit = distribution_parameters ,
            ac = cuda_tensor_ac.data[0].cpu().numpy()

            # step environment, record reward, next state
            ob, rew, done, _ = env.step(ac)
            # append to obs, acs, rewards, log_odds
            obs.append(ob)
```

```
            acs.append(ac)
            rews.append(rew)
            log_odds.append(log_odd)

            # if done, restart episode till min_timesteps_per_batch is reached
            steps += 1

            if done:
                episodes = episodes + 1
                break

        path = {"observation" : obs,
                "reward" : np.array(rews),
                "action" : (acs),
                "log_odds" : log_odds}

        paths.append(path)
        if steps > min_timesteps_per_batch: break

    update_policy(paths, net)  # use all complete episodes (a batch of timesteps) re
    if itr == 0: avg_reward = path['reward'].sum()

    else: avg_reward = avg_reward * 0.95 + 0.05 * path['reward'].sum()

    if avg_reward > 1500: break
    # inverted 500, half_cheetah 1500, cartpole 200
    total_steps += steps
    print(avg_reward,end='\r')
    avg_rewards.append(avg_reward)
    step_list_reinforce.append(total_steps)
    if itr % logging_interval == 0: print('Average reward: {}'.format(avg_reward))

env.close()
print('done')
```

```
Average reward: -631.3082183173344
Average reward: -619.8083439120957
Average reward: -479.22020007268867
Average reward: -535.6534700193245
Average reward: -483.31511565534953
Average reward: -700.0253135620237
Average reward: -539.8485582303404
Average reward: -486.3342675842881
Average reward: -573.6608333884494
Average reward: -762.6001722762232
done.59865768538844
```

Reinforce CartPole-v0

In [22]:

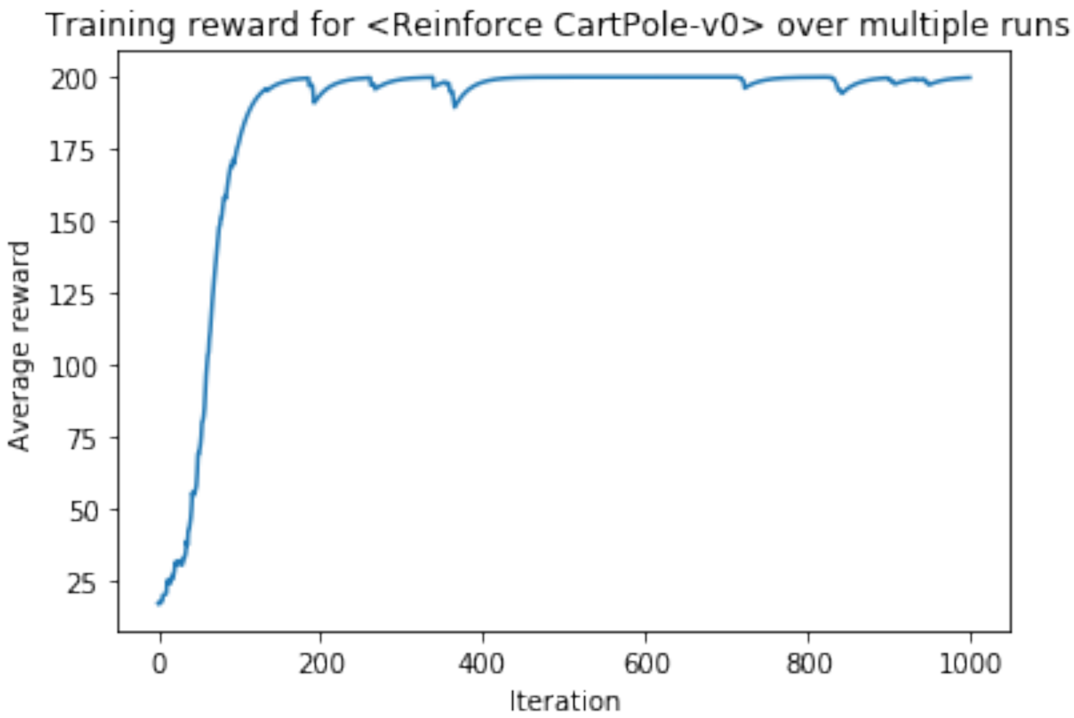
```
np.save('reinforce_cartpole_reward.npy', avg_rewards)
np.save('reinforce_cartpole_step.npy', step_list_reinforce)
```

In [14]:

```
plt.plot(avg_rewards)
plt.title('Training reward for <Reinforce CartPole-v0> over multiple runs ')
plt.xlabel('Iteration')
plt.ylabel('Average reward')
```

Out[14]:

```
Text(0,0.5,'Average reward')
```



In [19]:

```python
env_name='CartPole-v0'

# Make the gym environment
env = gym.make(env_name)
visualize = True
animate=visualize
learning_rate = 1e-3

max_path_length=None
min_timesteps_per_batch = 2000  # sets the batch size for updating network

# Set random seeds
seed=0
torch.manual_seed(seed)
np.random.seed(seed)

use_cuda = torch.cuda.is_available()
FloatTensor = torch.cuda.FloatTensor if use_cuda else torch.FloatTensor
LongTensor = torch.cuda.LongTensor if use_cuda else torch.LongTensor
ByteTensor = torch.cuda.ByteTensor if use_cuda else torch.ByteTensor
Tensor = FloatTensor

# Saving parameters
logdir='./REINFORCE/'

if visualize:
    if not os.path.exists(logdir):
        os.mkdir(logdir)
    env = gym.wrappers.Monitor(env, logdir, force=True, video_callable=lambda episod

env._max_episodes_steps = min_timesteps_per_batch


# Is this env continuous, or discrete?
discrete = isinstance(env.action_space, gym.spaces.Discrete)

# Get observation and action space dimensions
obs_dim = env.observation_space.shape[0]
act_dim = env.action_space.n if discrete else env.action_space.shape[0]

# Maximum length for episodes
max_path_length = max_path_length or env.spec.max_episode_steps
```

```
[2018-05-15 10:00:46,789] Making new env: CartPole-v0
[2018-05-15 10:00:46,795] Clearing 2 monitor files from previous run (
because force=True was provided)
```

In [21]:

```
########### for saving optimal model video

ob = env.reset()
while True:
    env.render()
    time.sleep(0.05)
    # get parametrized policy distribution from net using current state ob
    net.eval()
    var_ob = Variable(torch.unsqueeze(FloatTensor(ob),0), requires_grad=False)
    distribution_parameters = net(var_ob)
    # sample action and get log-probability (log_odds) from distribution
    cuda_tensor_ac, log_odd= sample_action(logit = distribution_parameters , disct =
    ac = cuda_tensor_ac.data[0].cpu().numpy()
    # step environment, record reward, next state
    new_ob, rew, done, _ = env.step(ac)
    ob = new_ob
    if done: break
print('done')
```

done

Reinforce Inverted Pendulum-v1

In [39]:

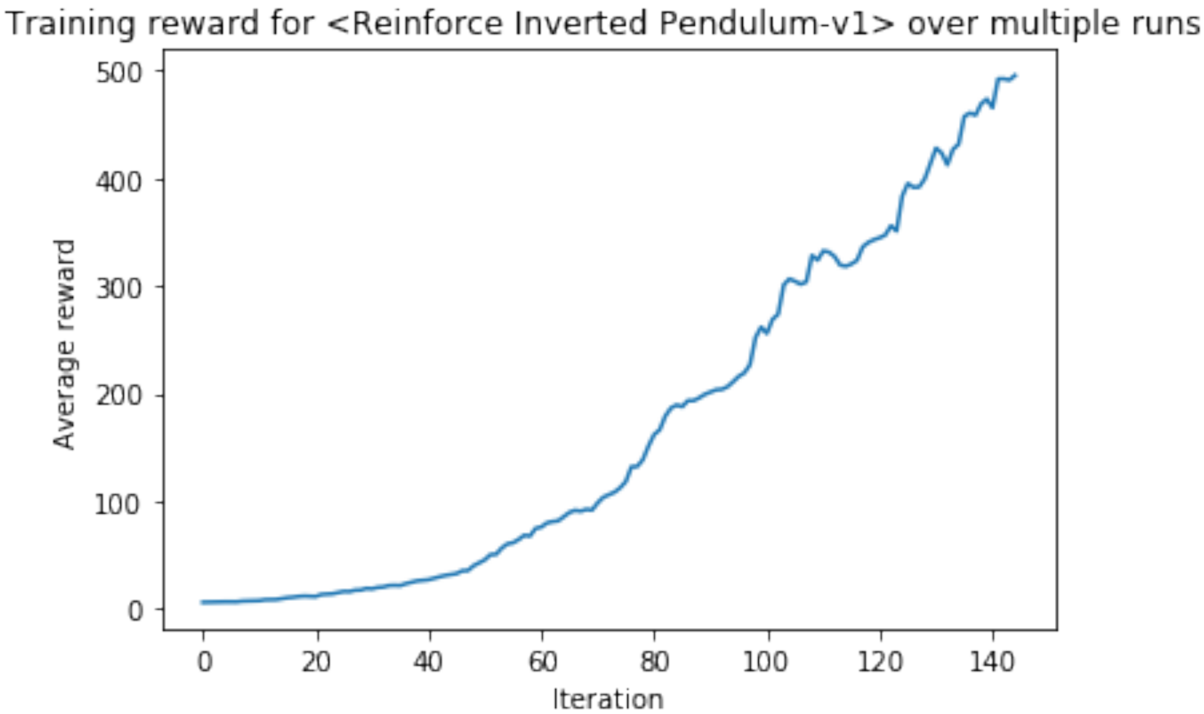
```
np.save('reinforce_inverted_pendulum_reward.npy', avg_rewards)
np.save('reinforce_inverted_pendulum_step.npy', step_list_reinforce)
```

In [12]:

```
plt.plot(avg_rewards)
plt.title('Training reward for <Reinforce Inverted Pendulum-v1> over multiple runs
plt.xlabel('Iteration')
plt.ylabel('Average reward')
```

Out[12]:

```
Text(0,0.5,'Average reward')
```



In [41]:

```
env_name='InvertedPendulum-v1'

# Make the gym environment
env = gym.make(env_name)
visualize = True
animate=visualize
learning_rate = 1e-3

max_path_length=None
min_timesteps_per_batch = 2000  # sets the batch size for updating network

# Set random seeds
seed=0
torch.manual_seed(seed)
np.random.seed(seed)

use_cuda = torch.cuda.is_available()
FloatTensor = torch.cuda.FloatTensor if use_cuda else torch.FloatTensor
LongTensor = torch.cuda.LongTensor if use_cuda else torch.LongTensor
ByteTensor = torch.cuda.ByteTensor if use_cuda else torch.ByteTensor
Tensor = FloatTensor

# Saving parameters
logdir='./REINFORCE/'

if visualize:
    if not os.path.exists(logdir):
        os.mkdir(logdir)
    env = gym.wrappers.Monitor(env, logdir, force=True, video_callable=lambda episod

env._max_episodes_steps = min_timesteps_per_batch


# Is this env continuous, or discrete?
discrete = isinstance(env.action_space, gym.spaces.Discrete)

# Get observation and action space dimensions
obs_dim = env.observation_space.shape[0]
act_dim = env.action_space.n if discrete else env.action_space.shape[0]

# Maximum length for episodes
max_path_length = max_path_length or env.spec.max_episode_steps
```

```
[2018-05-15 10:17:45,697] Making new env: InvertedPendulum-v1
[2018-05-15 10:17:45,705] Clearing 6 monitor files from previous run (
because force=True was provided)
```

In [43]:

```
########### for saving optimal model video

ob = env.reset()
while True:
    env.render()
    time.sleep(0.05)
    # get parametrized policy distribution from net using current state ob
    net.eval()
    var_ob = Variable(torch.unsqueeze(FloatTensor(ob),0), requires_grad=False)
    distribution_parameters = net(var_ob)
    # sample action and get log-probability (log_odds) from distribution
    cuda_tensor_ac, log_odd= sample_action(logit = distribution_parameters , disct =
    ac = cuda_tensor_ac.data[0].cpu().numpy()
    # step environment, record reward, next state
    new_ob, rew, done, _ = env.step(ac)
    ob = new_ob
    if done: break
print('done')
```

done

Reinforce HalfCheetah-v1

In [8]:

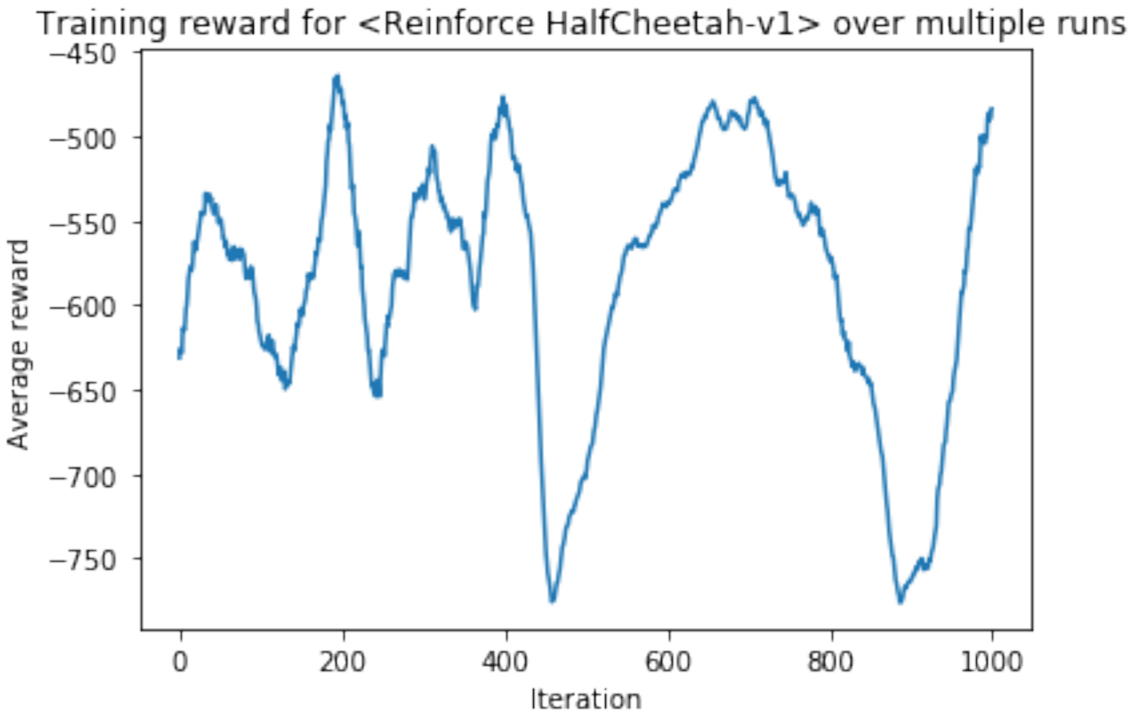
```
np.save('reinforce_halfcheetah_reward.npy', avg_rewards)
np.save('reinforce_halfcheetah_step.npy', step_list_reinforce)
```

In [10]:

```
plt.plot(avg_rewards)
plt.title('Training reward for <Reinforce HalfCheetah-v1> over multiple runs ')
plt.xlabel('Iteration')
plt.ylabel('Average reward')
```

Out[10]:

```
Text(0,0.5,'Average reward')
```



In [11]:

```
env_name='HalfCheetah-v1'

# Make the gym environment
env = gym.make(env_name)
visualize = True
animate=visualize
learning_rate = 1e-3

max_path_length=None
min_timesteps_per_batch = 2000  # sets the batch size for updating network

# Set random seeds
seed=0
torch.manual_seed(seed)
np.random.seed(seed)

use_cuda = torch.cuda.is_available()
FloatTensor = torch.cuda.FloatTensor if use_cuda else torch.FloatTensor
LongTensor = torch.cuda.LongTensor if use_cuda else torch.LongTensor
ByteTensor = torch.cuda.ByteTensor if use_cuda else torch.ByteTensor
Tensor = FloatTensor

# Saving parameters
logdir='./REINFORCE/'

if visualize:
    if not os.path.exists(logdir):
        os.mkdir(logdir)
    env = gym.wrappers.Monitor(env, logdir, force=True, video_callable=lambda episod

env._max_episodes_steps = min_timesteps_per_batch


# Is this env continuous, or discrete?
discrete = isinstance(env.action_space, gym.spaces.Discrete)

# Get observation and action space dimensions
obs_dim = env.observation_space.shape[0]
act_dim = env.action_space.n if discrete else env.action_space.shape[0]

# Maximum length for episodes
max_path_length = max_path_length or env.spec.max_episode_steps
```

```
[2018-05-15 15:42:06,135] Making new env: HalfCheetah-v1
[2018-05-15 15:42:06,150] Clearing 4 monitor files from previous run (
because force=True was provided)
```

In [13]:

```
ob = env.reset()
while True:
    env.render()
    time.sleep(0.05)
    # get parametrized policy distribution from net using current state ob
    net.eval()
    var_ob = Variable(torch.unsqueeze(FloatTensor(ob),0), requires_grad=False)
    distribution_parameters = net(var_ob)
    # sample action and get log-probability (log_odds) from distribution
    cuda_tensor_ac, log_odd= sample_action(logit = distribution_parameters , disct =
    ac = cuda_tensor_ac.data[0].cpu().numpy()
    # step environment, record reward, next state
    new_ob, rew, done, _ = env.step(ac)
    ob = new_ob
    if done: break
print('done')
```

```
done
```

BONUS (15% extra)

Compare average returns for CartPole (discrete action space) when using REINFORCE and DQN. Since in REINFORCE we update the network after a set number of steps instead of after every episode, plot the average rewards as a function of steps rather than episodes for both DQN and REINFORCE. You will need to make minor edits to your DQN code from the previous assignment to record average returns as a function of time_steps.

Similarly, compare REINFORCE with DDPG on InvertedPendulum and HalfCheetah using steps for the x-axis.

You may use the example code provided below as a reference for the graphs.

DQN

1.1 DQN environment setup

In [25]:

```
 # import your DQN and format your average returns as defined above
import gym
import numpy as np
import matplotlib.pyplot as plt

from collections import namedtuple
import random
import torch
import torch.nn as nn
```

```
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.autograd import Variable

# Create the CartPole game environment
env = gym.make('CartPole-v0')
env.reset()
use_cuda = torch.cuda.is_available()
# use_cuda = False
FloatTensor = torch.cuda.FloatTensor if use_cuda else torch.FloatTensor
LongTensor = torch.cuda.LongTensor if use_cuda else torch.LongTensor
ByteTensor = torch.cuda.ByteTensor if use_cuda else torch.ByteTensor

class Net(nn.Module):
# Define your network here
    def __init__(self, state_size, action_size, hidden_size):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(state_size, hidden_size)
        self.fc1.weight.data.normal_(0, 0.1)   # initialization
        self.out = nn.Linear(hidden_size, action_size)
        self.out.weight.data.normal_(0, 0.1)   # initialization
    def forward(self, x):
        x = self.fc1(x)
        x = F.tanh(x)
        Qs_actions = self.out(x) # Q value for one state, at different actions
        return Qs_actions

class QNetwork:
    def __init__(self, learning_rate, state_size, action_size, hidden_size, alpha_de
        self.LR = learning_rate
        self.state_size = state_size
        self.action_size = action_size
        self.hidden_size = hidden_size
        self.alpha_decay = alpha_decay
        self.model = Net(self.state_size, self.action_size, self.hidden_size)
        self.optimizer = torch.optim.Adam(self.model.parameters(), lr=self.LR)
        self.criterion = nn.MSELoss()

    def learn(self, batch_Q_behavior, batch_Q_target):
        loss = self.criterion(batch_Q_behavior, batch_Q_target)
        self.optimizer.zero_grad()
        loss.backward()
        self.optimizer.step()
```

```
[2018-05-15 13:02:24,780] Making new env: CartPole-v0
```

1.2 DQN replay buffer

In [26]:

```
class Replay():
    def __init__(self, max_size):
        self.capacity = max_size
        self.memory = []
        self.position = 0
        self.gamma = 0.99

    def initialize(self, init_length, envir):
        st = env.reset()
        for _ in range(init_length):
            a = np.random.randint(2, size=1)
            st1, r, done, info = env.step(int(a))
            self.push((st, a, st1, r, done))
            if done: st = env.reset()
            else : st = st1

    def push(self, transition):
        if len(self.memory) < self.capacity:
            self.memory.append(None)
        self.memory[self.position] = transition
        self.position = (self.position + 1) % self.capacity

    def generate_minibatch(self, DQN, targetDQN, batch_size):

        batch_memory = random.sample(self.memory, batch_size) #return a list
        batch_memory = list(zip(*batch_memory))

        batch_st = Variable(FloatTensor(batch_memory[0]))
        batch_at = Variable(LongTensor(batch_memory[1]))
        batch_st1 = Variable(FloatTensor(batch_memory[2]))
        batch_r = Variable(torch.unsqueeze(FloatTensor(batch_memory[3]),1))
        batch_done = FloatTensor(batch_memory[4])

        batch_Q_behavior = DQN.model(batch_st).gather(1, batch_at)
        mask = 1. - batch_done
        batch_Q_next = targetDQN.model(batch_st1).detach()

        QQ_next = Variable((batch_Q_next.max(1)[0].data * mask).view(batch_size, 1)
        batch_Q_target = batch_r + self.gamma*(QQ_next)
        return batch_Q_behavior, batch_Q_target

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

1.3 DQN training

In [27]:

```
learning_rate = 0.01
action_size = env.action_space.n
state_size = env.observation_space.shape[0]
hidden_size = 64
alpha_decay = 0.1
batch_size = 500

DQN = QNetwork(learning_rate, state_size, action_size, hidden_size, alpha_decay)
targetDQN = QNetwork(learning_rate, state_size, action_size, hidden_size, alpha_deca
# set targetDQN weights to DQN weights
# for ex. targetDQN.model.weights = DQN.model.weights (syntax given here is for rep
targetDQN.model.load_state_dict(DQN.model.state_dict())
replay = Replay(max_size=10000) ## Initialize Replay Buffer
replay.initialize(init_length=1000, envir=env) ## Populate the initial experience bu
if use_cuda:
    print('run gpu !')
    targetDQN.model.cuda()
    DQN.model.cuda()
else:
    print('gpu not activited !')

# Runtime parameters
num_episodes = 2000            # max number of episodes to learn from
gamma = 0.99                   # future reward discount
max_steps = 500                # cut off simulation after this many steps
# Exploration parameters
min_epsilon = 0.01             # minimum exploration probability
decay_rate = 5/num_episodes    # exponential decay rate for exploration prob
returns = np.zeros(num_episodes)
step_list_DQN = []
total_steps = 0
avg_reward = 0
avg_rewards = []
logging_interval = 100


for ep in range(1, num_episodes): # ep now is for one iteration
    paths = []
    steps = 0
    while True: #  paths = a number of episode, but restricted by step> 2000 break
        total_reward = 0
        epsilon = min_epsilon + (1.0 - min_epsilon)*np.exp(-decay_rate*ep)
    # --> start episode
        state = env.reset()
        rews = []
        for step in range(max_steps): # path = one episode
            # generate the steps in each episode
            # explore/exploit and get action using DQN
            if random.random()<= epsilon:
                action = np.random.randint(2, size=1)
            else:
                var_state = Variable(torch.unsqueeze(FloatTensor(state),0))# here c
                DQN.model.eval()
                Qs_actions = DQN.model.forward(var_state) # shape of (1, 2) variabl
```

```
                Qs_actions = DQN.model.forward(var_state) # shape of (1, 2) variabl
                DQN.model.train()
                cuda_tensor_action = torch.max(Qs_actions,1)[1].data
                action = cuda_tensor_action.cpu().numpy()

            new_state, reward, done, _ = env.step(int(action))
            rews.append(reward)
            replay.push((state, action, new_state, reward, done))
            steps += 1
        # perform action and record new_state, action, reward
        # populate Replay experience buffer
            if done:  break
            else: state = new_state
        # <-- end episode
        path={'reward':np.array(rews)}
        paths.append(path)
        if steps > 2000: break

    batch_Q_behavior, batch_Q_target = replay.generate_minibatch(DQN, targetDQN, bat
    DQN.learn(batch_Q_behavior, batch_Q_target)
    targetDQN.model.load_state_dict(DQN.model.state_dict())

    avg_reward = avg_reward * 0.95 + 0.05 * path['reward'].sum()
    total_steps += steps
    avg_rewards.append(avg_reward)
    step_list_DQN.append(total_steps)
    if ep % logging_interval == 0: print('Average reward: {}'.format(avg_reward))
print('finished training')
```

...

1.4 DQN Cartpole Results

In [28]:

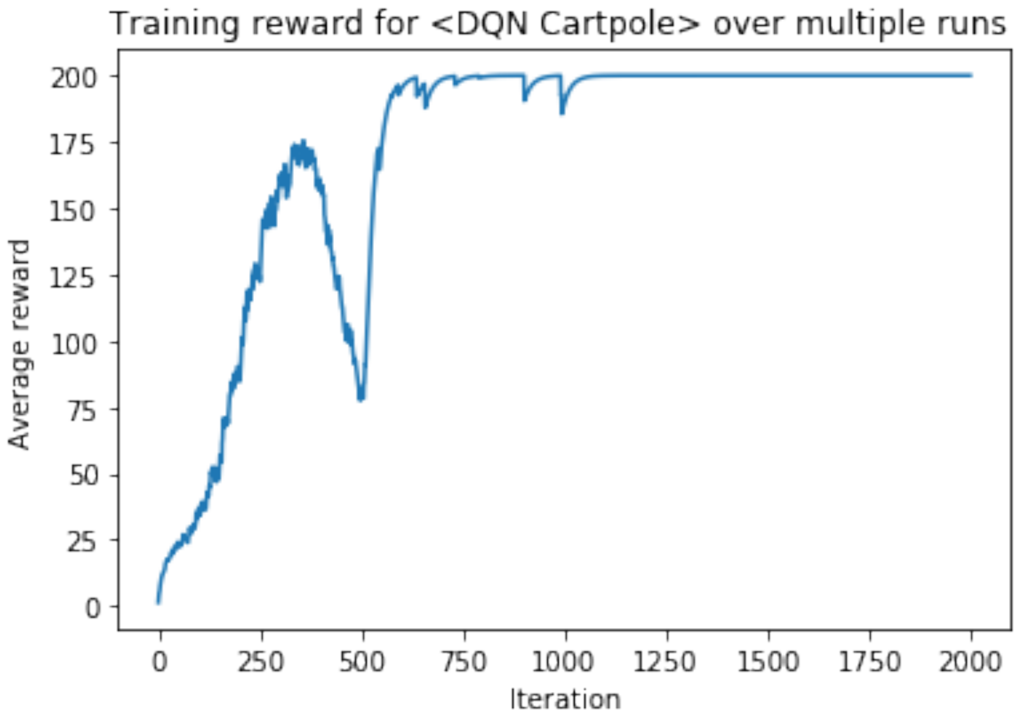
```
np.save('DQN_cartpole_reward.npy', avg_rewards)
np.save('DQN_cartpole_step.npy', step_list_DQN)
```

In [29]:

```
plt.plot(avg_rewards)
plt.title('Training reward for <DQN Cartpole> over multiple runs ')
plt.xlabel('Iteration')
plt.ylabel('Average reward')
```

Out[29]:

```
Text(0,0.5,'Average reward')
```



DQN vs Reinforce

CartPole (discrete action space)

In [4]:

```
running_rewards_ddpg=np.load('DQN_cartpole_reward.npy')
step_list_DQN=np.load('DQN_cartpole_step.npy')

avg_rewards = np.load('reinforce_cartpole_reward.npy')
step_list_reinforce = np.load('reinforce_cartpole_step.npy')
```

In [5]:

```
plt.figure()
out = numpy_ewma_vectorized_v2(np.array(running_rewards_ddpg),20)
plt.plot(step_list_DQN, out)
plt.title('Training reward over multiple runs')
plt.xlabel('Number of steps')
plt.ylabel('Cumulative reward')
plt.plot(step_list_reinforce, avg_rewards)
plt.legend(['DQN', 'REINFORCE'])
plt.show()
```

DDPG vs Reinforce

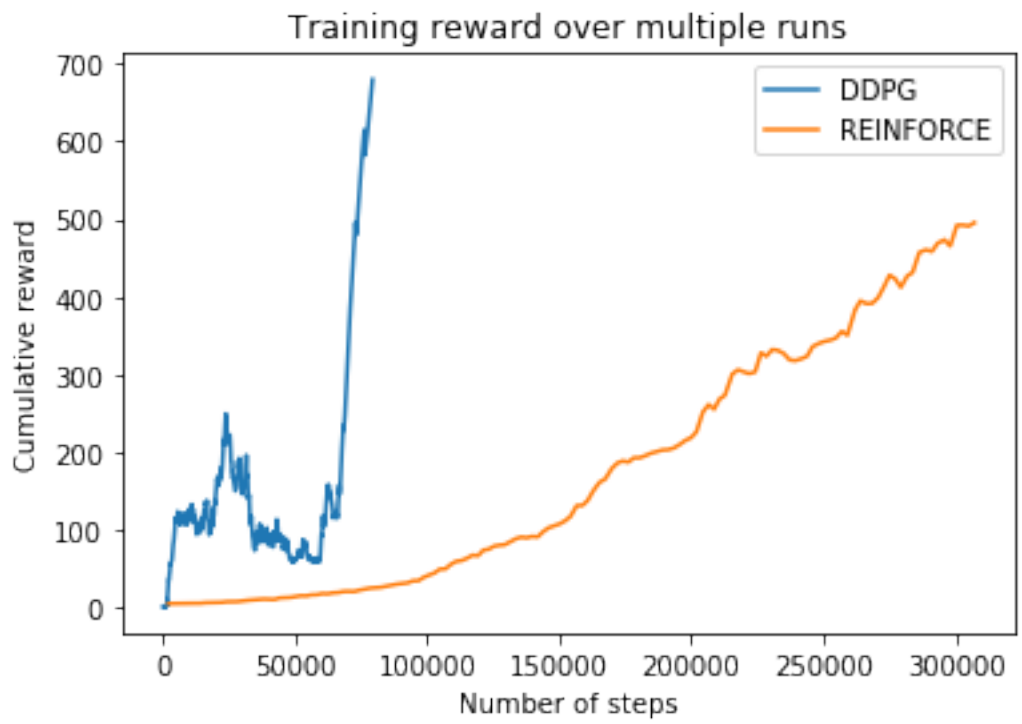
Inverted Pendulum-v1

In [17]:

```
running_rewards_ddpg=np.load('ddpg_inverted_pendulum_reward.npy')
step_list_ddpg=np.load('ddpg_inverted_pendulum_step.npy')

avg_rewards = np.load('reinforce_inverted_pendulum_reward.npy')
step_list_reinforce = np.load('reinforce_inverted_pendulum_step.npy')
```

In [18]:

```
plt.figure()

out = numpy_ewma_vectorized_v2(np.array(running_rewards_ddpg),20)
plt.plot(step_list_ddpg, out)
plt.title('Training reward over multiple runs')
plt.xlabel('Number of steps')
plt.ylabel('Cumulative reward')
plt.plot(step_list_reinforce, avg_rewards)
plt.legend(['DDPG', 'REINFORCE'])

plt.show()
```



HalfCheetah-v1

In [17]:

```
running_rewards_ddpg=np.load('ddpg_halfcheetah_reward.npy')
step_list_ddpg=np.load('ddpg_halfcheetah_step.npy')

avg_rewards = np.load('reinforce_halfcheetah_reward.npy')
step_list_reinforce = np.load('reinforce_halfcheetah_step.npy')
```

In [18]:

```
plt.figure()
out = numpy_ewma_vectorized_v2(np.array(running_rewards_ddpg),20)
plt.plot(step_list_ddpg, out) # or plt.plot(step_list_DQN, out)
plt.title('Training reward over multiple runs')
plt.xlabel('Number of steps')
plt.ylabel('Cumulative reward')
plt.plot(step_list_reinforce, avg_rewards)
plt.legend(['DDPG', 'REINFORCE'])

plt.show()
```

Assignment 3: Policy Gradients (DDPG and REINFORCE)

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Background

This exercise requires you to solve various continous control problems in OpenAI-Gym.

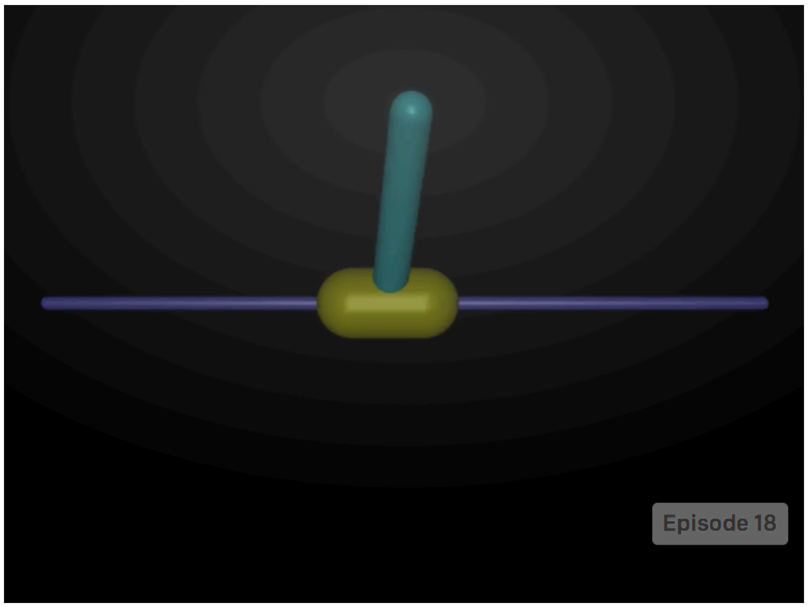
DDPG is policy gradient actor critic method for continous control which is off policy. It tackles the curse of dimensionality / loss of performance faced when discretizing a continous action domain. DDPG uses similiar "tricks" as DQN to improve the stability of training, including a replay buffer and target networks.

Furthermore, you will implement REINFORCE for discrete and continous environments, and as a bonus compare the sample efficiency and performance with DQN and DDPG.

DDPG paper: https://arxiv.org/pdf/1509.02971.pdf (https://arxiv.org/pdf/1509.02971.pdf)

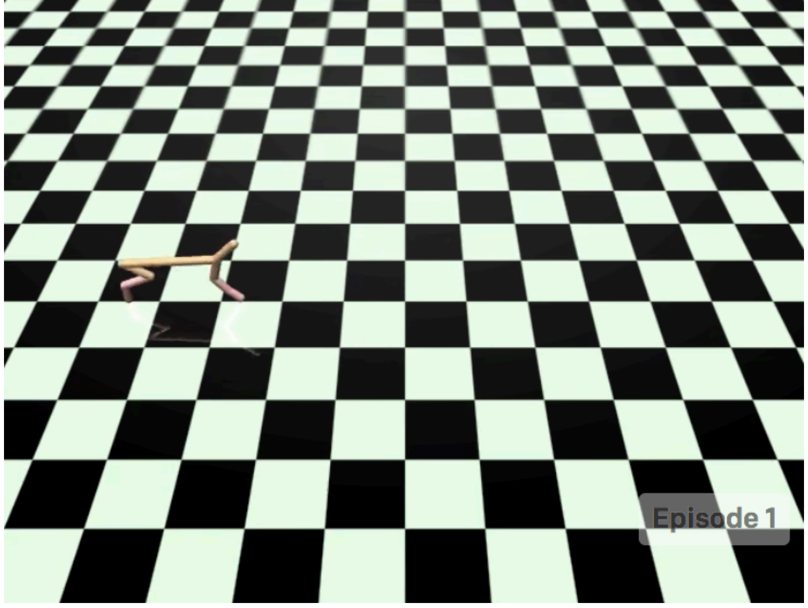
Environments:

InvertedPendulum-v2 environment:



Pendulum-v0 environment:

Halfcheetah-v2 environment:



Setup environment for Actor Critic

- inline plotting
- gym
- directory for logging videos

In [1]:

Set up gym environment

The code below does the following for you:

- Wrap environment, log videos, setup CUDA variables (if GPU is available)
- Record action and observation space dimensions
- Fix random seed for determinisitic training

In [2]:

```
[2018-05-15 18:15:02,522] Making new env: HalfCheetah-v1
[2018-05-15 18:15:02,888] Clearing 4 monitor files from previous run (
because force=True was provided)
```

Demonstrate your understanding of the simulation:

For the environments mentioned above ('Pendulum-v0', 'HalfCheetah-v2', 'InvertedPendulum-v2'),

- describe the reward system
- describe the each state variable (observation space)
- describe the action space
- when is the environment considered "solved"?

Ans:

Pendulum-v0

- reward = -(theta^2 + 0.1*theta_dt^2 + 0.001*action^2)
- x1 = cos(theta) within [-1,1]; x2 = sin(theta) within [-1,1]; x3 = theta_dot within [-8,8] where theta is the angular of the pendulum, and theta_dot is the angular velocity of the pendulum.
- A joint effore within [-2,2]
- In general, the pendulum starts randomly at angle from -pi to pi, with random velocity between -1 and 1. There is no specific termination, so I have to manual set up a maximum number of steps for one episode. Also, to optimize this model, we want the pendulum to remain at zero angle (vertical), with least angular velocity as well as the least effort.

HalfCheetah-v1

- To produce reward in each step, there are two ingredients, one is called reward_control and the other called reward_run. reward_ctrl = - 0.1 * np.square(action).sum(), where action has 6 dimensions, reward_run = (xposafter - xposbefore)/self.dt. Therefore, the reward = reward_ctrl + reward_run which is a scalar.

- State space

```
  (name)    (joint)     (parameter)
- rootx     slider      position (m)
- rootz     slider      position (m)
- rooty     hinge       angle (rad)
- bthigh    hinge       angle (rad)
- bshin     hinge       angle (rad)
- bfoot     hinge       angle (rad)
- fthigh    hinge       angle (rad)
- fshin     hinge       angle (rad)
- ffoot     hinge       angle (rad)
- rootx     slider      velocity (m/s)
- rootz     slider      velocity (m/s)
- rooty     hinge       angular velocity (rad/s)
- bthigh    hinge       angular velocity (rad/s)
- bshin     hinge       angular velocity (rad/s)
- bfoot     hinge       angular velocity (rad/s)
- fthigh    hinge       angular velocity (rad/s)
- fshin     hinge       angular velocity (rad/s)
- ffoot     hinge       angular velocity (rad/s)
```

- Action space

```
  (name)   (actuator)   (parameter):
- bthigh    hinge       torque (N m)
- bshin     hinge       torque (N m)
- bfoot     hinge       torque (N m)
- fthigh    hinge       torque (N m)
- fshin     hinge       torque (N m)
- ffoot     hinge       torque (N m)
```

- When the total reward with in 500 steps for one episode greater than 1500, we consider the cheetah is being well trained.

InvertedPendulum-v1

- reward is 1 for each step
- x1 = cart position, x2 = pole position, x3 = cart velocity, x4 = pole angular velocity
- a1 = the force impose on cart
- when the average reward greater than 500, we consider the inverted pendulum is being well balanced

Implement an action normalization class:

To train across various environments, it is useful to normalize action inputs and outputs between [-1, 1]. This class should take in actions and implement forward and reverse functions to map actions between [-1, 1] and [action_space.low, action_space.high].

Using the following gym wrapper, implement this class.

- https://github.com/openai/gym/blob/78c416ef7bc829ce55b404b6604641ba0cf47d10/gym/core.py (https://github.com/openai/gym/blob/78c416ef7bc829ce55b404b6604641ba0cf47d10/gym/core.py)
- i.e. we are overriding the outputs scale of actions.

```
In [4]:
```

DDPG

Write a weight syncing function

In contrast to DQN, DDPG uses soft weight sychronization. At each time step following training, the actor and critic target network weights are updated to track the rollout networks.

- target_network.weights <= target_network.weights * (1 - tau) + source_network.weights * (tau)

```
In [5]:
```

Write a Replay class that includes all the functionality of a replay buffer

DDPG is an off policy actor-critic method and an identical replay buffer to that used for the previous assignment is applicable here as well (do not include the generate_minibatch method in your Replay class this time). Like before, your constructor for Replay should create an initial buffer of size 1000 when you instantiate it.

The replay buffer should kept to some maximum size (60000), allow adding of samples and returning of samples at random from the buffer. Each sample (or experience) is formed as (state, action, reward, next_state, done).

```
In [6]:
```

Write an Ornstein Uhlenbeck process class for exploration noise

The proccess is described here:

- https://en.wikipedia.org/wiki/Ornstein–Uhlenbeck_process (https://en.wikipedia.org/wiki/Ornstein–Uhlenbeck_process)
- http://math.stackexchange.com/questions/1287634/implementing-ornstein-uhlenbeck-in-matlab (http://math.stackexchange.com/questions/1287634/implementing-ornstein-uhlenbeck-in-matlab)

You should implement:

- a step / sample method
- reset method

Use theta = 0.15, mu = 0, sigma = 0.3, dt = 0.01

In [8]:

```

```

Write a Deep Neural Network class that creates a dense network of a desired architecture for actor and critic networks

Actor

- input and hidden layer activation function: ReLU
- output activation function: Tanh
- hidden_state sizes: 400
- state and action sizes: variable
- number of hidden layers: 2
- batch normalization applied to all hidden layers
- weight initialization: normal distribution with small variance.

Critic

- input and hidden layer activation function: ReLU
- output activation function: None
- hidden_state sizes: 300, 300 + action size
- state and action sizes: variable
- number of hidden layers: 2
- batch normalization applied to all hidden layers prior to the action input
- weight initialization: normal distribution with small variance.

Good baselines can be found in the paper.

In [9]:

Define DDPG class to encapsulate definition, rollouts, and training

- gamma = 0.99
- actor_lr = 1e-4
- critic_lr = 1e-3
- critic l2 regularization = 1e-2
- noise decay
- noise class
- batch_size = 128
- optimizer: Adam
- loss (critic): mse

Furthermore, you can experiment with action versus parameter space noise. The standard implimentation works with action space noise, howeve parameter space noise has shown to produce excellent results.

In [10]:

Create an instance of your DDPG object

- Print network architectures, confirm they are correct

In [11]:

```
actor(
  (fc1): Linear(in_features=17, out_features=400, bias=True)
  (bn1): BatchNorm1d(400, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (fc2): Linear(in_features=400, out_features=400, bias=True)
  (bn2): BatchNorm1d(400, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (fc3): Linear(in_features=400, out_features=6, bias=True)
)
critic(
  (fc1): Linear(in_features=17, out_features=300, bias=True)
  (bn1): BatchNorm1d(300, eps=1e-05, momentum=0.1, affine=True, track_
running_stats=True)
  (fc2): Linear(in_features=306, out_features=300, bias=True)
  (fc3): Linear(in_features=300, out_features=1, bias=True)
)
```

Train DDPG on different environments

Early stopping conditions:

- avg_val > 500 for "InvertedPendulum"
- avg_val > -150 for "Pendulum"
- avg_val > 1500 for "HalfCheetah"

In [12]:

```
```

```
[2018-05-15 18:16:02,781] Starting new video recorder writing to /data
sets/home/85/185/chs140/ECE276C/PA3/DDPG/openaigym.video.0.3152.video0
00000.mp4
[2018-05-15 18:16:02,784] GLFW error: 65544, desc: b'X11: RandR gamma
ramp support seems broken'
[2018-05-15 18:16:02,825] GLFW error: 65544, desc: b'Linux: Failed to
watch for joystick connections in /dev/input: No such file or director
y'
[2018-05-15 18:16:02,826] GLFW error: 65544, desc: b'Linux: Failed to
open joystick device directory /dev/input: No such file or directory'
```

```
Average value: -17.843247096416302 for episode: 0
Average value: -36.08468524747259 for episode: 1
Average value: -54.33420902731596 for episode: 2
Average value: -71.70057412910461 for episode: 3
Average value: -59.74418617579752 for episode: 4
Average value: -62.580942535612834 for episode: 5
Average value: -73.82833487779708 for episode: 6
Average value: -81.68708376415621 for episode: 7
Average value: -89.20755442592052 for episode: 8
```

Plot rewards over multiple training runs

This is provided to generate and plot results for you.

In [15]:

```
```

DDPG Inverted-Pendulum-v1

In [13]:

```
```

In [14]:

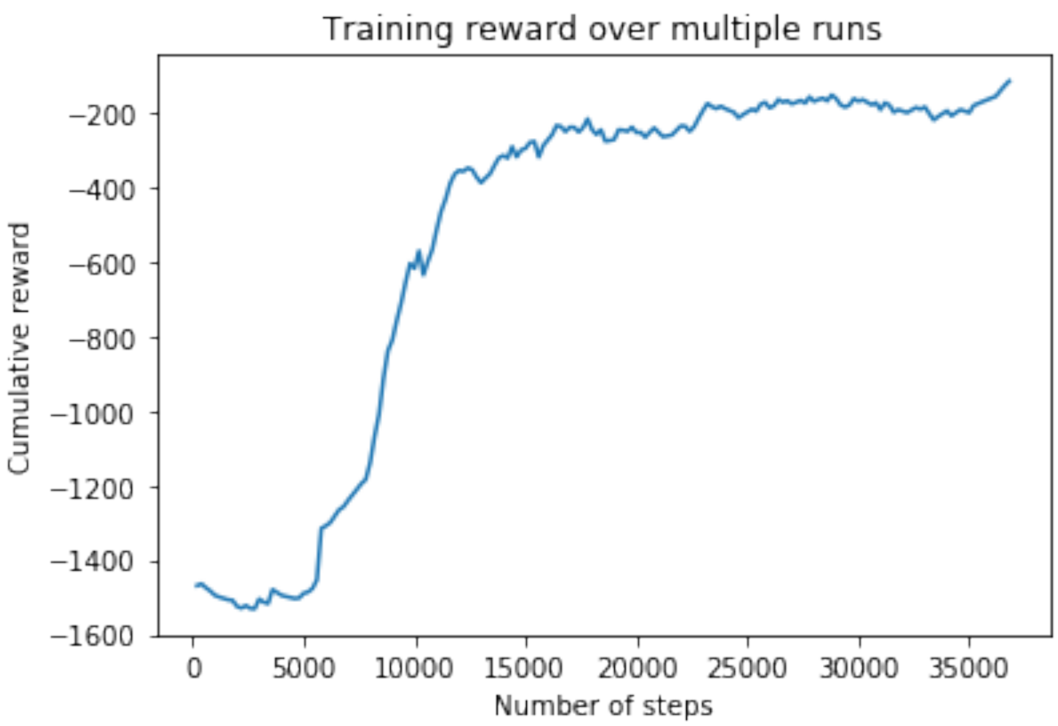
In [19]:

done

DDPG Pendulum-v0

In [14]:

In [16]:



In [19]:

done

DDPG HalfCheetah-v1

In [13]:

In [16]:

In [ ]:

REINFORCE

In this section you will implement REINFORCE, with modifications for batch training. It will be for use on both discrete and continous action spaces.

Policy Parametrization

Define a MLP which outputs a distribution over the action preferences given input state. For the discrete case, the MLP outputs the likelihood of each action (softmax) while for the continuous case, the output is the mean and standard deviation parametrizing the normal distribution from which the action is sampled.

In [3]:

Define a function that samples an action from the policy distribtion parameters obtained as output of the MLP. The function should return the action and the log-probability (log_odds) of taking that action.

In [4]:

```
```

Create a function update_policy that defines the loss function and updates the MLP according to the REINFORCE update rule (ref. slide 24 of Lec 7 or page 330 of Sutton and Barto (2018)). The update algorithm to be used below is slightly different: instead of updating the network at every time-step, we take the gradient of the loss averaged over a batch of timesteps (this is to make SGD more stable). We also use a baseline to reduce variance.

The discount factor is set as 1 here.

In [5]:

```
```

Set up environment and instantiate objects. Your algorithm is to be tested on one discrete and two continuous environments.

In [6]:

```
```

```
[2018-05-15 14:26:39,297] Making new env: HalfCheetah-v1
[2018-05-15 14:26:39,630] Finished writing results. You can upload the
m to the scoreboard via gym.upload('/datasets/home/85/185/chs140/ECE27
6C/PA3/DDPG')
```

```
mlp(
  (fc1): Linear(in_features=17, out_features=50, bias=True)
  (fc2): Linear(in_features=50, out_features=50, bias=True)
  (fc_mu): Linear(in_features=50, out_features=6, bias=True)
  (fc_sigma): Linear(in_features=50, out_features=6, bias=True)
)
```

Run REINFORCE

Run REINFORCE for CartPole, InvertedPendulum, and HalfCheetah.

In [7]:

```
Average reward: -631.3082183173344
Average reward: -619.8083439120957
Average reward: -479.22020007268867
Average reward: -535.6534700193245
Average reward: -483.31511565534953
Average reward: -700.0253135620237
Average reward: -539.8485582303404
Average reward: -486.3342675842881
Average reward: -573.6608333884494
Average reward: -762.6001722762232
done.59865768538844
```

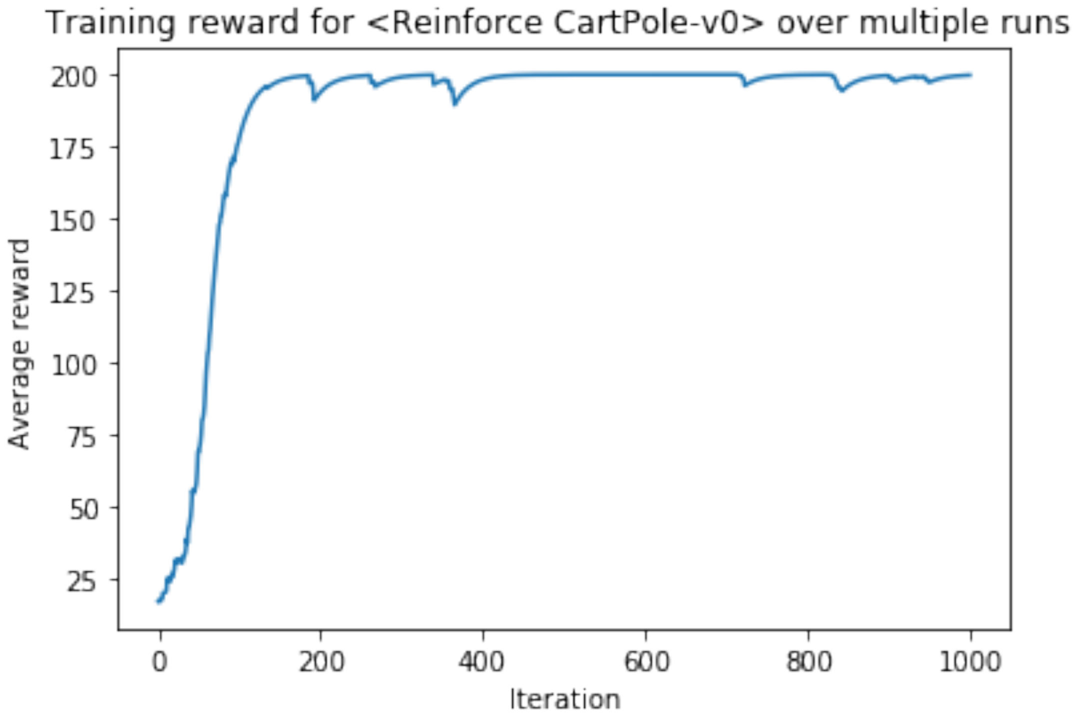
Reinforce CartPole-v0

In [22]:

In [14]:

Out[14]:

```
Text(0,0.5,'Average reward')
```



In [19]:

```
[2018-05-15 10:00:46,789] Making new env: CartPole-v0
[2018-05-15 10:00:46,795] Clearing 2 monitor files from previous run (
because force=True was provided)
```

In [21]:

```
done
```

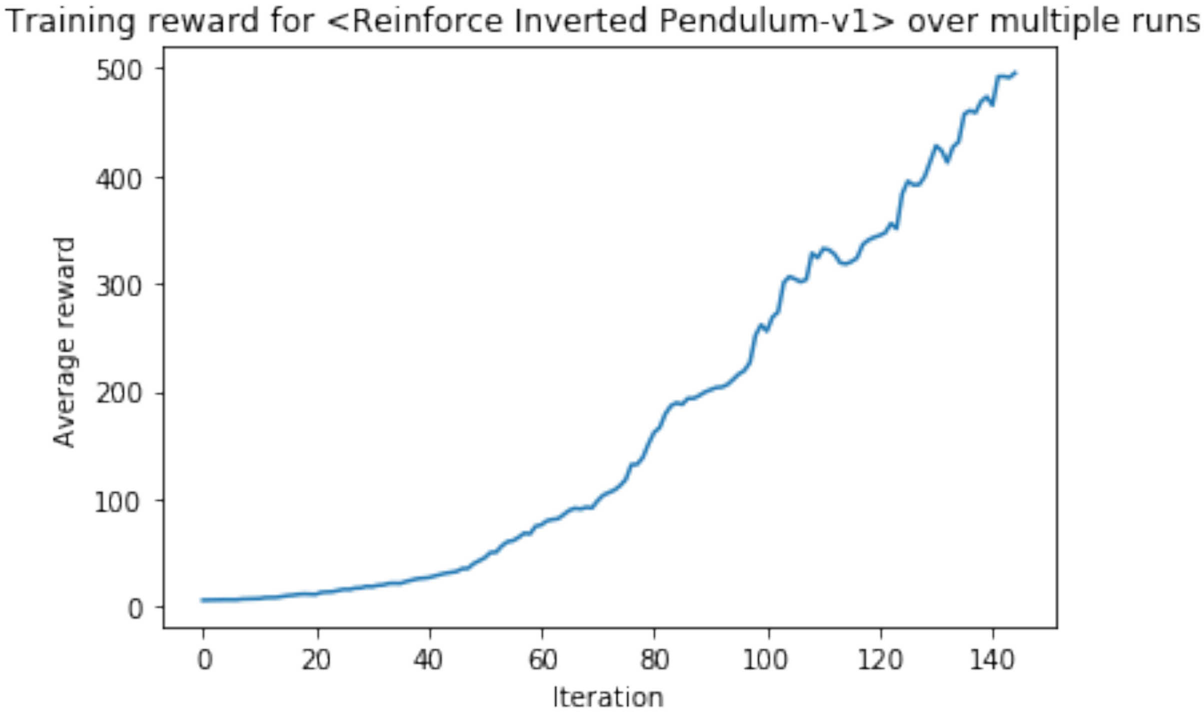
Reinforce Inverted Pendulum-v1

In [39]:

In [12]:

Out[12]:

Text(0,0.5,'Average reward')



In [41]:

```
[2018-05-15 10:17:45,697] Making new env: InvertedPendulum-v1
[2018-05-15 10:17:45,705] Clearing 6 monitor files from previous run (
because force=True was provided)
```

In [43]:

done

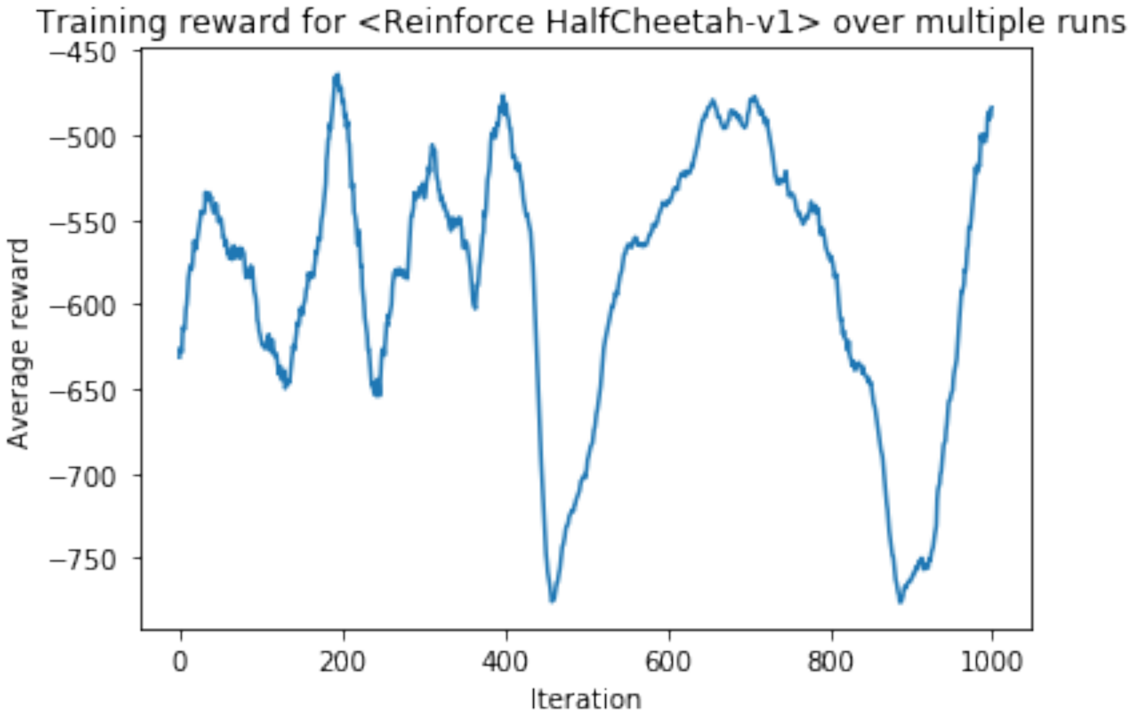
Reinforce HalfCheetah-v1

In [8]:

In [10]:

Out[10]:

Text(0,0.5,'Average reward')



In [11]:

[2018-05-15 15:42:06,135] Making new env: HalfCheetah-v1
[2018-05-15 15:42:06,150] Clearing 4 monitor files from previous run (
because force=True was provided)

In [13]:

```
done
```

BONUS (15% extra)

Compare average returns for CartPole (discrete action space) when using REINFORCE and DQN. Since in REINFORCE we update the network after a set number of steps instead of after every episode, plot the average rewards as a function of steps rather than episodes for both DQN and REINFORCE. You will need to make minor edits to your DQN code from the previous assignment to record average returns as a function of time_steps.

Similarly, compare REINFORCE with DDPG on InvertedPendulum and HalfCheetah using steps for the x-axis.

You may use the example code provided below as a reference for the graphs.

DQN

1.1 DQN environment setup

In [25]:

```
[2018-05-15 13:02:24,780] Making new env: CartPole-v0
```

1.2 DQN replay buffer

In [26]:

1.3 DQN training

In [27]:

...

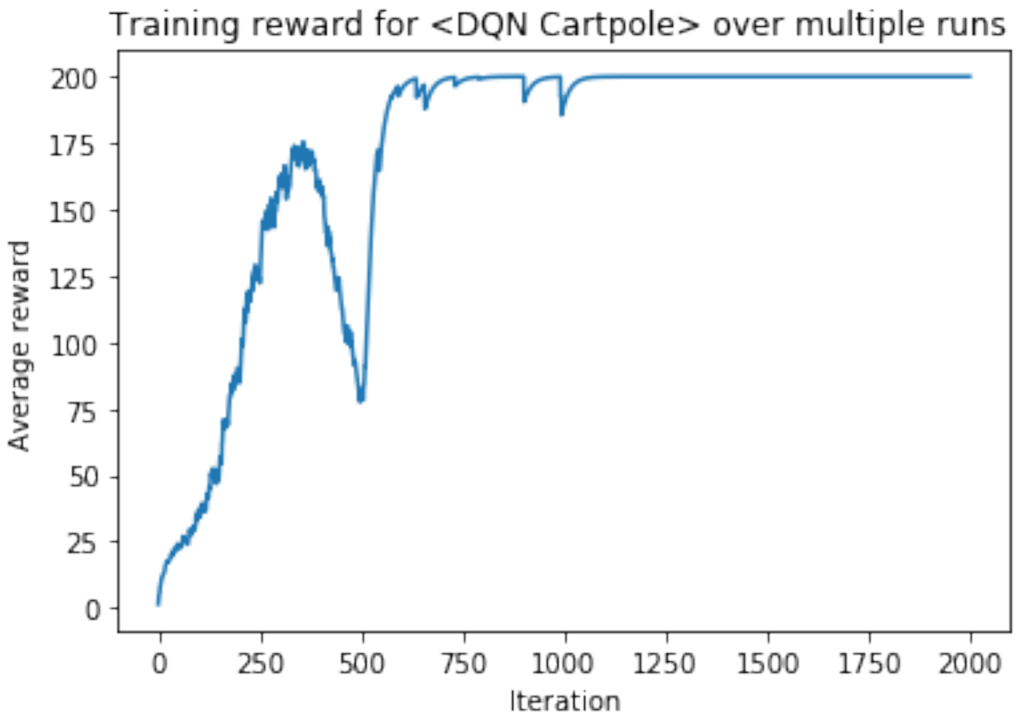
1.4 DQN Cartpole Results

In [28]:

In [29]:

Out[29]:

```
Text(0,0.5,'Average reward')
```



DQN vs Reinforce

CartPole (discrete action space)

In [4]:

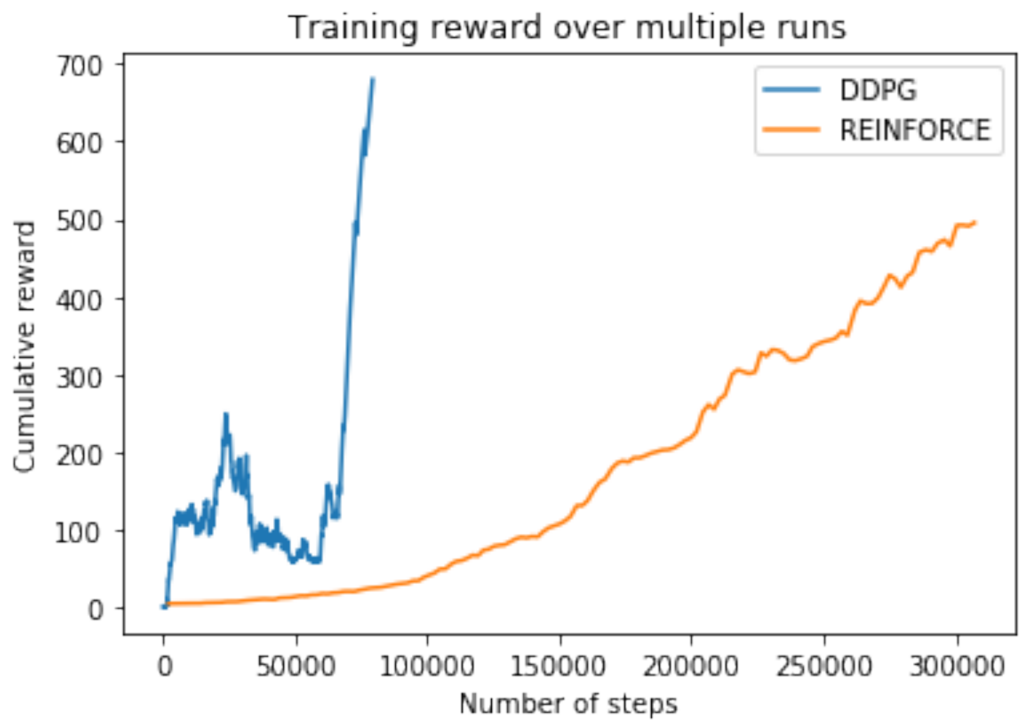
In [5]:

DDPG vs Reinforce

Inverted Pendulum-v1

In [17]:

In [18]:



HalfCheetah-v1

In [17]:

In [18]: