CS294-112 Deep Reinforcement Learning HW1 Q3 Behavioral Cloning

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Libraries

In [1]:
```
%matplotlib inline
import pickle
import tensorflow as tf
import numpy as np
import tf_util
import gym
import load_policy
import datetime
import argparse
import sklearn.utils as sku
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import normalize, StandardScaler
import matplotlib.pyplot as plt
from IPython.display import HTML, display
```

Preparing the Data

In [2]:
```
def get_train_test_splits(obs_file, act_file, train_amount = None):
    print('loading expert observations and actions data')

    obs = np.load(obs_file).astype(np.float32)
    scaler = StandardScaler().fit(obs)
    obs = scaler.transform(obs).astype(np.float32)

    act = np.squeeze(np.load(act_file).astype(np.float32))

    if train_amount == None:
        return obs, None, act, None, scaler
    n_samples = obs.shape[0]
    obs_train, obs_test = train_test_split(obs, train_size = train_amoun
t)
    act_train, act_test = train_test_split(act, train_size = train_amoun
t)
    return obs_train, obs_test, act_train, act_test, scaler
```

Hyperparameters

In [3]:
```
obs_file, act_file = ("obs_Ant-v1112809102017.npy", "act_Ant-v1112809102017.npy")
# ("obs_Hopper-v1044909042017.npy", "act_Hopper-v1044909042017.npy")
# ("obs_Humanoid-v1044209042017.npy", "act_Humanoid-v1044209042017.npy")
# ("obs_Ant-v1112809102017.npy", "act_Ant-v1112809102017.npy")
# ("obs_Reacher-v1113609102017.npy", "act_Reacher-v1113609102017.npy")
# ("obs_HalfCheetah-v1114209102017.npy", "act_HalfCheetah-v1114209102017.npy")
# ("obs_Walker2d-v1115109102017.npy", "act_Walker2d-v1115109102017.npy")
creature = "Ant"
num_iters = 20000
batch_size = 100
learning_rate = 0.001
```

Train My Policy

In [4]:
```
sess = tf.InteractiveSession()
obs_train, obs_test, act_train, act_test, scaler =
get_train_test_splits(obs_file, act_file)
print obs_train.shape
print act_train.shape
num_obs_features = obs_train.shape[1]
num_act_features = act_train.shape[1]

x = tf.placeholder(tf.float32, shape=[None, num_obs_features])
y_ = tf.placeholder(tf.float32, shape=[None, num_act_features])

layer1 = tf.contrib.layers.fully_connected(x, num_obs_features, activati
on_fn = tf.nn.tanh, weights_initializer=tf.contrib.layers.xavier_initial
izer())
layer2 = tf.contrib.layers.fully_connected(layer1, num_obs_features, act
ivation_fn = tf.nn.tanh, weights_initializer=tf.contrib.layers.xavier_in
itializer())
y = tf.contrib.layers.fully_connected(layer2, num_act_features, activati
on_fn = None,
weights_initializer=tf.contrib.layers.xavier_initializer())

policy_fn = tf_util.function([x], y)

loss = tf.nn.l2_loss(y_ - y) / batch_size

train_step = tf.train.AdamOptimizer(learning_rate).minimize(loss)
tf.global_variables_initializer().run()
losses = []
for i in range(num_iters):
    x_batch, y_batch = sku.shuffle(obs_train, act_train, n_samples = bat
ch_size)
    a, loss_now = sess.run(fetches=[train_step, loss], feed_dict={x: x_b
atch, y_: y_batch})
    if (i % (num_iters/10) == 0):
        print "iter #", i
        losses.append(loss_now)
```

```
loading expert observations and actions data
(20000, 111)
(20000, 8)
iter # 0
iter # 2000
iter # 4000
iter # 6000
iter # 8000
iter # 10000
iter # 12000
iter # 14000
iter # 16000
iter # 18000
```

In [5]:
```
print losses
```

```
[1.5730798, 0.0041882098, 0.0021985422, 0.0022251981, 0.0017148277, 0.0
018956367, 0.0014221952, 0.0012696092, 0.0014165604, 0.0014482593]
```

In [6]:
```
# correct_prediction = tf.equal(tf.argmax(y, 1), tf.argmax(y_, 1))
# accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
# print sess.run(accuracy, feed_dict={x: obs_test, y_: act_test})
```

Run My Policy

In [7]:
```
env = gym.make(creature + "-v1")
max_steps = env.spec.timestep_limit

returns = []
observations = []
actions = []
for i in range(20):
#     print('iter', i)
    obs = env.reset()
    done = False
    totalr = 0.
    steps = 0
    while not done:
        action = policy_fn(scaler.transform(obs[None,:]).astype('float3
2'))
        observations.append(obs)
        actions.append(action)
        obs, r, done, _ = env.step(action)
        totalr += r
        steps += 1
#         env.render()
#         if steps % 100 == 0: print("%i/%i"%(steps, max_steps))
        if steps >= max_steps:
            break
    returns.append(totalr)

print('returns', returns)
print('mean return', np.mean(returns))
print('std of return', np.std(returns))

my_data = {'observations': np.array(observations),
               'actions': np.array(actions)}
```

```
[2017-09-10 23:40:06,247] Making new env: Ant-v1
```

```
('returns', [4828.8983074055695, 4831.0657919480209, 4871.588131238344
4, 4690.9101505301323, 5021.2595768729643, 4928.2746530856039, 4880.835
6549256059, 4812.5590721329954, 4754.5010128405293, 4637.6080232776903,
4770.1393127355605, 4861.814041478503, 4828.4675562487946, 4758.5004617
430013, 4855.9849644054375, 4758.8032705891728, 4731.8348826969859, 491
1.3045144043472, 4776.8819480952661, 5009.3720312597798])
('mean return', 4826.0301678957157)
('std of return', 94.683920861485731)
```

Results

All tasks were run on a NN with two hidden layers, tanh activation, 20000 sample points, 20000 training iterations, batch size of 100, and learning rate of 0.001.

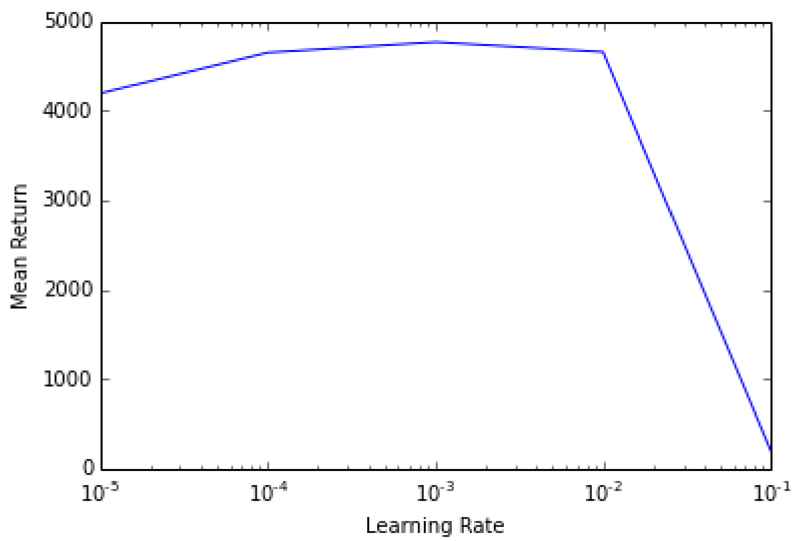
In [8]:
```
data = [["Task", "My Mean of Returns", "My SD of Returns", "Expert Mean of Returns", "Expert SD of Returns"],
         ["Ant", 4852.5017230854846, 74.23980300289098, 4782.1609172421513, 132.55560311907271],
         ["Walker2d", 4995.4266902009167, 1242.6555393075696, 5534.9265519203136, 44.500248612112557],
         ["Hopper", 1722.4381911703872, 1216.7809772698199, 3777.9972139025776, 3.2057125353927498],
         ["Reacher", -4.8619283516599729, 1.6960560957721855, -3.8987745270062617, 1.8182523276231009],
         ["Humanoid", 10385.595408411633, 52.941800608114725, 10411.367006191223, 64.386553835708511],
         ["HalfCheetah", 4049.217485821292, 92.03040403417107, 4158.3969968545998, 46.971685827755344],
         ]

display(HTML(
    '<table><tr>{}</tr></table>'.format('</tr><tr>'.join('<td>{}</td>'.format('</td><td>'.join(str(_) for _ in row)) for row in data))))
```

Task	My Mean of Returns	My SD of Returns	Expert Mean of Returns	Expert SD of Returns
Ant	4852.50172309	74.2398030029	4782.16091724	132.555603119
Walker2d	4995.4266902	1242.65553931	5534.92655192	44.5002486121
Hopper	1722.43819117	1216.78097727	3777.9972139	3.20571253539
Reacher	-4.86192835166	1.69605609577	-3.89877452701	1.81825232762
Humanoid	10385.5954084	52.9418006081	10411.3670062	64.3865538357
HalfCheetah	4049.21748582	92.0304040342	4158.39699685	46.9716858278

In [11]:
```
mean_returns = []
obs_train, obs_test, act_train, act_test, scaler =
get_train_test_splits(obs_file, act_file)
num_obs_features = obs_train.shape[1]
num_act_features = act_train.shape[1]

lr_list = [0.00001, 0.0001, 0.001, 0.01, 0.1]
for learning_rate in lr_list:
    print "training with learning rate:", learning_rate
    sess = tf.InteractiveSession()

    x = tf.placeholder(tf.float32, shape=[None, num_obs_features])
    y_ = tf.placeholder(tf.float32, shape=[None, num_act_features])

    layer1 = tf.contrib.layers.fully_connected(x, num_obs_features, acti
vation_fn = tf.nn.tanh, weights_initializer=tf.contrib.layers.xavier_ini
tializer())
    layer2 = tf.contrib.layers.fully_connected(layer1, num_obs_features,
```

```
 activation_fn = tf.nn.tanh, weights_initializer=tf.contrib.layers.xavie
r_initializer())
    y = tf.contrib.layers.fully_connected(layer2, num_act_features, acti
vation_fn = None, weights_initializer=tf.contrib.layers.xavier_initializ
er())

    policy_fn = tf_util.function([x], y)

    loss = tf.nn.l2_loss(y_ - y) / batch_size

    train_step = tf.train.AdamOptimizer(learning_rate).minimize(loss)
    tf.global_variables_initializer().run()
    for i in range(num_iters):
        x_batch, y_batch = sku.shuffle(obs_train, act_train, n_samples =
 batch_size)
        a, loss_now = sess.run(fetches=[train_step, loss], feed_dict={x:
 x_batch, y_: y_batch})

    env = gym.make(creature + "-v1")
    max_steps = env.spec.timestep_limit

    returns = []
    observations = []
    actions = []
    for i in range(20):
        obs = env.reset()
        done = False
        totalr = 0.
        steps = 0
        while not done:
            action = policy_fn(scaler.transform(obs[None,:]).astype('flo
at32'))
            observations.append(obs)
            actions.append(action)
            obs, r, done, _ = env.step(action)
            totalr += r
            steps += 1
            if steps >= max_steps:
                break
        returns.append(totalr)

    mean_returns.append(np.mean(returns))

    sess.close()

plt.plot(lr_list, mean_returns)
plt.ylabel('Mean Return')
plt.xlabel('Learning Rate')
plt.xscale('log')
plt.show()
```

```
loading expert observations and actions data
training with learning rate: 1e-05

[2017-09-10 23:47:42,828] Making new env: Ant-v1

training with learning rate: 0.0001

[2017-09-10 23:49:12,298] Making new env: Ant-v1

training with learning rate: 0.001

[2017-09-10 23:50:35,083] Making new env: Ant-v1

training with learning rate: 0.01

[2017-09-10 23:52:00,258] Making new env: Ant-v1

training with learning rate: 0.1

[2017-09-10 23:53:28,583] Making new env: Ant-v1
```



In [10]:
```python
print creature
```

```
Ant
```

The graph above shows how performance varies with the value of the learning rate. I chose to experiment with this hyperparameter because it can greatly affect the optimization of the loss function. If the learning rate is too high, it is easy to overshoot a local optimum in the cost function. If the learning rate is too low, then it is hard to learn anything given a fixed number of training iterations.

Appendix of Expert Returns

Hopper expert returns:

('returns', [3771.9336598726591, 3774.6625045070514, 3779.9935082891625, 3771.5253685435282, 3777.3681930911616, 3778.839472656417, 3778.72690636986, 3780.420514438782, 3778.5508451495007, 3777.3928509435241, 3780.6255379793006, 3775.5027294050469, 3776.7569006634217, 3780.9128980517853, 3782.9810844516765, 3773.5071795005179, 3782.8216694611729, 3778.8721318571479, 3781.2896818439012, 3777.2606409759246])

('mean return', 3777.9972139025776) ('std of return', 3.2057125353927498)

Humanoid expert returns:

('returns', [10426.901581297876, 10354.999386314665, 10518.526981022384, 10362.961354650473, 10397.952862427941, 10446.38337188637, 10430.008532411424, 10393.84011458044, 10354.894427755571, 10462.98034042896, 10478.465784041504, 10294.904552806682, 10486.55218058908, 10467.231468828335, 10418.502544063733, 10508.646297411087, 10427.947459059114, 10364.952755875134, 10331.624674666315, 10299.063453707358])

('mean return', 10411.367006191223) ('std of return', 64.386553835708511)

Reacher expert returns:

('returns', [-4.186911948636455, -5.2678239265846116, -6.0242261321475707, -3.372837307792369, -4.1526844029394097, -4.8800377997838567, -3.7797431463669269, -1.7708528883578709, -7.7285160804080837, -1.9489484559423917, -6.678527275516446, -4.1668850712442085, -5.0495028527687227, -1.43408737401054, -0.82961070795971548, -3.5888372914308166, -1.5595323005597548, -2.5248902640517321, -5.6329022633401271, -3.3981330502836196])

('mean return', -3.8987745270062617) ('std of return', 1.8182523276231009)

Ant expert returns:

('returns', [4634.3406190538553, 4679.9912036002106, 4953.8808445439299, 4990.3345743233913, 4890.1763907943932, 4707.2176554932867, 4829.1796412666581, 4666.6558116610486, 4849.3110733590174, 4724.8338142283865, 4740.5009526333615, 4833.1880590325636, 4682.7170248359034, 4761.0720917128101, 4462.971570585778, 4938.5729851855885, 4712.6437039011062, 4748.6394716855511, 4814.7542912273575, 5022.2365657188247])

('mean return', 4782.1609172421513) ('std of return', 132.55560311907271)