Continuous_control_2

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This file is a continuation of Continuous Control in the same folder
The reason I have started a new file is because I wanted to keep the old file as evidence of the work done to get to this point. Otherwise it is the same

1 Continuous Control

You are welcome to use this coding environment to train your agent for the project. Follow the instructions below to get started!

1.0.1 1. Start the Environment

Run the next code cell to install a few packages. This line will take a few minutes to run!

```
In [6]: !pip -q install ./python
```

```
tensorflow 1.7.1 has requirement numpy>=1.13.3, but you'll have numpy 1.12.1 which is incompatib
ipython 6.5.0 has requirement prompt-toolkit<2.0.0,>=1.0.15, but you'll have prompt-toolkit 3.0.
```

The environments corresponding to both versions of the environment are already saved in the Workspace and can be accessed at the file paths provided below.
Please select one of the two options below for loading the environment.

```
In [7]: from unityagents import UnityEnvironment
        import numpy as np

        # select this option to load version 1 (with a single agent) of the environment
        env = UnityEnvironment(file_name='/data/Reacher_One_Linux_NoVis/Reacher_One_Linux_NoVis.

        # select this option to load version 2 (with 20 agents) of the environment
        # env = UnityEnvironment(file_name='/data/Reacher_Linux_NoVis/Reacher.x86_64')
```

```
INFO:unityagents:
'Academy' started successfully!
Unity Academy name: Academy
        Number of Brains: 1
```

```
        Number of External Brains : 1
        Lesson number : 0
        Reset Parameters :
                goal_speed -> 1.0
                goal_size -> 5.0
Unity brain name: ReacherBrain
        Number of Visual Observations (per agent): 0
        Vector Observation space type: continuous
        Vector Observation space size (per agent): 33
        Number of stacked Vector Observation: 1
        Vector Action space type: continuous
        Vector Action space size (per agent): 4
        Vector Action descriptions: , , ,
```

Environments contain ***brains*** which are responsible for deciding the actions of their associated agents. Here we check for the first brain available, and set it as the default brain we will be controlling from Python.

```
In [8]: # get the default brain
        brain_name = env.brain_names[0]
        brain = env.brains[brain_name]
```

1.0.2 2. Examine the State and Action Spaces

Run the code cell below to print some information about the environment.

```
In [9]: # reset the environment
        env_info = env.reset(train_mode=True)[brain_name]

        # number of agents
        num_agents = len(env_info.agents)
        print('Number of agents:', num_agents)

        # size of each action
        action_size = brain.vector_action_space_size
        print('Size of each action:', action_size)

        # examine the state space
        states = env_info.vector_observations
        state_size = states.shape[1]
        print('There are {} agents. Each observes a state with length: {}'.format(states.shape[0
        print('The state for the first agent looks like:', states[0])
        print(type(states[0]))
```

```
Number of agents: 1
Size of each action: 4
There are 1 agents. Each observes a state with length: 33
The state for the first agent looks like: [  0.00000000e+00  -4.00000000e+00   0.00000000e+00
```

```
  -0.00000000e+00  -0.00000000e+00  -4.37113883e-08   0.00000000e+00
   0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
   0.00000000e+00   0.00000000e+00  -1.00000000e+01   0.00000000e+00
   1.00000000e+00  -0.00000000e+00  -0.00000000e+00  -4.37113883e-08
   0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
   0.00000000e+00   0.00000000e+00   5.75471878e+00  -1.00000000e+00
   5.55726671e+00   0.00000000e+00   1.00000000e+00   0.00000000e+00
  -1.68164849e-01]
<class 'numpy.ndarray'>
```

```
In [10]: env_info = env.reset(train_mode=True)[brain_name]      # reset the environment
         states = env_info.vector_observations                  # get the current state (for eac
         scores = np.zeros(num_agents)                          # initialize the score (for each
         while True:
             actions = np.random.randn(num_agents, action_size) # select an action (for each age
             actions = np.clip(actions, -1, 1)                  # all actions between -1 and 1
             env_info = env.step(actions)[brain_name]           # send all actions to tne enviro
             next_states = env_info.vector_observations         # get next state (for each agent
             rewards = env_info.rewards                         # get reward (for each agent)
             dones = env_info.local_done                        # see if episode finished
             scores += env_info.rewards                         # update the score (for each age
             states = next_states                               # roll over states to next time
             if np.any(dones):                                  # exit loop if episode finished
                 break
         print('Total score (averaged over agents) this episode: {}'.format(np.mean(scores)))
```

```
Total score (averaged over agents) this episode: 0.0
```

When finished, you can close the environment. But note - don't do this if you plan to train the agent. I cannot find a way of re-starting it, other than completely refreshing this notebook. Broken pipe etc.

```
In [11]: # See comments above - don't close the environment. You can always just reset it!
         # env.close()
```

1.0.3 4. It's Your Turn!

Now it's your turn to train your own agent to solve the environment! A few **important notes**: - When training the environment, set `train_mode=True`, so that the line for resetting the environment looks like the following:

```
env_info = env.reset(train_mode=True)[brain_name]
```

- To structure your work, you're welcome to work directly in this Jupyter notebook, or you might like to start over with a new file! You can see the list of files in the workspace by clicking on ***Jupyter*** in the top left corner of the notebook.
- In this coding environment, you will not be able to watch the agents while they are training. However, ***after training the agents***, you can download the saved model weights to watch the agents on your own machine!

1.1 Proposed approach by DCFW

1. Use a DDPG actor-critic model to train the two agents (actor and critic).
2. Use the Udacity DDPG - pendulum code as a starter code to work with

```
In [12]: # first import torch modules
         import torch
         import torch.nn as nn
         import torch.nn.functional as F
         import torch.optim as optim
```

```
In [13]: # also import other required modules
         import random
         import pickle
         import copy
         from collections import deque, namedtuple
         import matplotlib.pyplot as plt
         %matplotlib inline
```

```
In [14]: # define helper function for initialising layers.
         # Note, pytorch does this automatically for the first intialisation.
         # Note, I believe Udacity code for DDPG pendulum was slightly wrong - used the output f
         # not the input features. To check out.
         def hidden_init(layer):
             """Helper function. Just returns the limits used for weights initialisation in the
             """
             f_out, f_in = layer.weight.data.size()
             lim = 1. / np.sqrt(f_in)
             return (-lim, lim)
```

1.2 Set up the Actor model

```
In [15]: # define the Actor. This is the agent that is going to try to learn the best policy
         class Actor(nn.Module):
             """Actor (Policy) Model"""

             def __init__(self, state_size, action_size, seed, fc1_units=256, fc2_units=128):
                 """Initialize parameters and build model.
                 Params
                 ======
                     state_size (int): Dimension of each state
                     action_size (int): Dimension of each action
                     seed (int): Random seed
                     fc1_units (int): Number of nodes in first hidden layer
                     fc2_units (int): Number of nodes in second hidden layer
                 """
                 super(Actor, self).__init__()
                 self.seed = torch.manual_seed(seed) # for reproducibility
                 self.fc1 = nn.Linear(in_features=state_size, out_features=fc1_units)
```

```
        self.fc2 = nn.Linear(fc1_units, fc2_units)
        self.fc3 = nn.Linear(fc2_units, action_size)
        self.reset_parameters()

    def reset_parameters(self):
        """reset the weighs of the layer to random uniform distribution (range = sqrt d
        self.fc1.weight.data.uniform_(*hidden_init(self.fc1))
        self.fc2.weight.data.uniform_(*hidden_init(self.fc2))
        self.fc3.weight.data.uniform_(-3e-3, 3e-3) # find out why hard-coded? Same for

    def forward(self, state):
        """Build an actor (policy) network that maps states -> actions"""
        x = F.relu(self.fc1(state))
        x = F.relu(self.fc2(x))
        return torch.tanh(self.fc3(x)) # INVESTIGATE this - whether better activation f
                                       # will map to between -1 and +1
```

1.3 Demonstrate / test some of the features of the Actor model

```
In [16]: # Demo some of the features of the Actor model
         actor = Actor(state_size=33, action_size=4, seed=42)
         print ('Actor summary:')
         print (actor)
         print ('\nSummary of second hidden layer')
         print (actor.fc2)
         print ('\nTorch tensor of the dimensions of second hidden layer:')
         print (actor.fc2.weight.data.size())
         print ('\nTorch initialises weights uniform random between +- sqrt(number of features i
         print ('\nTo check whether this is true, the min and max of second hidden layer are:')
         print (actor.fc2.weight.data.numpy().min(), actor.fc2.weight.data.numpy().max())
         print ('... and the sqrt of number of input features to second hidden layer of {} is:'
                .format(actor.fc2.weight.data.size()[1]))
         print (1. / np.sqrt(actor.fc2.weight.data.size()[1]))

         state = np.array([np.random.random() for i in range(33)])
         print ('\nCreated a random state of the following type (should be numpy array, like the
         print (type(state))
         print ('\nOutput from one forward pass of the model - should be tensor of size 4, corre
         print (actor.forward(torch.from_numpy(state).float()))

Actor summary:
Actor(
  (fc1): Linear(in_features=33, out_features=256, bias=True)
  (fc2): Linear(in_features=256, out_features=128, bias=True)
  (fc3): Linear(in_features=128, out_features=4, bias=True)
)

Summary of second hidden layer
```

```
Linear(in_features=256, out_features=128, bias=True)

Torch tensor of the dimensions of second hidden layer:
torch.Size([128, 256])

Torch initialises weights uniform random between +- sqrt(number of features in)

To check whether this is true, the min and max of second hidden layer are:
-0.0624967 0.0624897
... and the sqrt of number of input features to second hidden layer of 256 is:
0.0625

Created a random state of the following type (should be numpy array, like the Unity environment
<class 'numpy.ndarray'>

Output from one forward pass of the model - should be tensor of size 4, corresponding to the 4 a
tensor(1.00000e-02 *
       [ 5.2321, -7.0089, -2.3594, -1.1062])
```

1.4 Set up the Critic model

The critic is trying to learn the value-action of the state environment rather than the policy.
This will help speed up the learning rather than trying to learn the policy just on its own.

```
In [17]: class Critic(nn.Module):
             """Critic (Value) Model"""

             def __init__(self, state_size, action_size, seed, fcs1_units=256, fc2_units=128):
                 """Initialize parameters and build model.
                 Params
                 ======
                     state_size (int): Dimension of each state
                     action_size (int): Dimension of each action
                     seed (int): Random seed
                     fcs1_units (int): Number of nodes in the first hidden layer
                     fc2_units (int): Number of nodes in the second hidden layer
                 """
                 super(Critic, self).__init__()
                 self.seed = torch.manual_seed(seed)
                 self.fcs1 = nn.Linear(in_features=state_size, out_features=fcs1_units)
                 # note the difference in output units to input units - we are going to concaten
                 self.fc2 = nn.Linear(fcs1_units + action_size, fc2_units)
                 self.fc3 = nn.Linear(fc2_units, 1)
                 self.reset_parameters()

             def reset_parameters(self):
                 """reset the weighs of the layer to random uniform distribution (range = sqrt o
```

```
            self.fcs1.weight.data.uniform_(*hidden_init(self.fcs1))
            self.fc2.weight.data.uniform_(*hidden_init(self.fc2))
            self.fc3.weight.data.uniform_(-3e-3, 3e-3)

        def forward(self, state, action):
            """Build a critic (value) network that maps (state, action) pairs -> Q-values."
            xs = F.relu(self.fcs1(state))
            # we now need to add in the actions - why do we not do this at the first layer?
            t_xs = torch.transpose(xs, 0, 1)
            t_action = torch.transpose(action, 0, 1)
            x = torch.transpose(torch.cat((t_xs, t_action)), 0,1) # check whether I need to
            x = F.relu(self.fc2(x))
            x = self.fc3(x) # no need to put through an activation layer, as we want the VA
            return x
```

```
In [18]: # Examine the Critic model - no need to do the full exploration as for the Actor
         c = Critic(state_size=33, action_size=4, seed=42)
         print (c)
```

```
Critic(
  (fcs1): Linear(in_features=33, out_features=256, bias=True)
  (fc2): Linear(in_features=260, out_features=128, bias=True)
  (fc3): Linear(in_features=128, out_features=1, bias=True)
)
```

```
In [19]: # create some dummy states and actions to check the forward pass
         state = np.random.random((128,33))
         state = torch.from_numpy(state).float()

         actions = np.random.random((128,4))
         actions = torch.from_numpy(actions).float()

         # check the forward pass. This should create a scalar value for the state action pair.
         out =c.forward(state=state, action=actions)
         print (out.shape)
```

```
torch.Size([128, 1])
```

1.4.1 Identify the device being used. We need to do this in the set up of the main Agent

NOTE - set up and test the model using CPU first, then run training on GPU

```
In [20]: device = torch.device("cuda:0" if torch.cuda.is_available() else "cpu")
         print('device has been set, it is: {}'.format(device))
         if device.type == 'cuda':
             print('We are using GPU for TRAINING')
         else:
             print('We are using CPU to set up and test')
```

```
device has been set, it is: cuda:0
We are using GPU for TRAINING
```

1.5 Set up the DEFAULT hyper-parameters

These have been taken from the Udacity Deep Reinforcement Learning DDPG-pendulum code, as a starting point to explore the hyper-parameters

```
In [21]: BUFFER_SIZE = int(1e5)  # replay buffer size, Udacity_pendulum = 1e5
         BATCH_SIZE = 128        # minibatch size, Udacity_pendulum = 128
         GAMMA = 0.99            # discount factor, Udacity_pendulum = 0.99
         TAU = 1e-3              # for soft update of target parameters, Udacity_pendulum = 1e-3
         LR_ACTOR = 1e-4         # learning rate of the actor , Udacity_pendulum = 1e-4
         LR_CRITIC = 1e-3        # learning rate of the critic, Udacity_pendulum = 1e-3
         WEIGHT_DECAY = 0        # L2 weight decay, Udacity_pendulum = 0
```

```
In [22]: # define OUNoise which is used to add a bit of noise if you want a little
         # more exploratory action - you add it to the calculated action vector
         class OUNoise:
             """Ornstein-Uhlenbeck process"""

             def __init__(self, size, seed, mu=0., theta=0.15, sigma=0.2):
                 """Initialize parameters and noise process"""
                 self.mu = mu * np.ones(size)
                 self.theta = theta
                 self.sigma = sigma
                 self.seed = random.seed(seed)
                 self.reset()

             def reset(self):
                 """Reset the internal state (=noise) to mean (mu)"""
                 self.state = copy.copy(self.mu)

             def sample(self, epsilon=1.0):
                 """Update internal state and return it as a noise sample"""
                 x = self.state
                 dx = self.theta * (self.mu - x) + epsilon* self.sigma * np.array(
         #             [random.random() for i in range(len(x))])
                     [random.random() -0.5 for i in range(len(x))])
                 self.state = x + dx
                 return self.state
```

```
In [23]: # demonstrate the funcition of OUNoise
         oun = OUNoise(size=(5), seed=101)
         print ('Before: {}'.format(oun.state))
         print ('After: {}'.format(oun.sample(epsilon=0.5)))
```

```
Before: [ 0.  0.  0.  0.  0.]
After: [ 0.00811521 -0.03052455  0.04652511  0.04239764 -0.00328613]
```

```
In [24]: # define the Replay Buffer - re-using paths multiple times
         class ReplayBuffer:
             """Fixed size buffer to store experience tuples"""

             def __init__(self, action_size, buffer_size, batch_size, seed):
                 """Initialize a ReplayBuffer object.
                 Params
                 ======
                     buffer_size (int): maximum size of buffer
                     batch_size (int): size of each training batch
                 """
                 self.action_size = action_size
                 self.memory = deque(maxlen= buffer_size)
                 self.batch_size = batch_size
                 self.experience = namedtuple("Experience", field_names=[
                     "state", "action", "reward", "next_state", "done"
                 ])
                 self.seed = random.seed()

             def add(self, state, action, reward, next_state, done):
                 """Add a new experinece to the ReplayBuffer memory"""
                 e = self.experience(state, action, reward, next_state, done)
                 self.memory.append(e)

             def sample(self):
                 """Randomly sample a batch of experiences from memory"""
                 experiences = random.sample(self.memory, k=self.batch_size)

                 states = torch.from_numpy(np.vstack([e.state for e in experiences
                             if e is not None])).float().to(device)
                 actions = torch.from_numpy(np.vstack([e.action for e in experiences
                             if e is not None])).float().to(device)
                 rewards = torch.from_numpy(np.vstack([e.reward for e in experiences
                             if e is not None])).float().to(device)
                 next_states = torch.from_numpy(np.vstack([e.next_state for e in experiences
                             if e is not None])).float().to(device)
                 dones = torch.from_numpy(np.vstack([e.done for e in experiences
                             if e is not None]).astype(np.uint8)).float().to(device)

                 return (states, actions, rewards, next_states, dones)

             def len(self):
                 """Return the current size of the internal memory"""
                 return len(self.memory)
```

```
In [25]: class Agent():
             """Interacts and learns from the environment
             Uses the Actor and Critic in tandem"""

             def __init__(self, hypers):
                 """Initialize an Agent object.

                 Params
                 ======
                     state_size (int): dimension of each state
                     action_size (int): dimension of each action
                     random_seed (int): random seed
                 """

                 self.state_size = hypers['state_size']
                 self.action_size = hypers['action_size']
                 self.seed = hypers['random_seed']
                 self.actor_fc1_units = hypers['actor_fc1_units']
                 self.actor_fc2_units = hypers['actor_fc2_units']
                 self.lr_actor = hypers['lr_actor']
                 self.critic_fcs1_units = hypers['critic_fcs1_units']
                 self.critic_fc2_units = hypers['critic_fc2_units']
                 self.lr_critic = hypers['lr_critic']
                 self.weight_decay = hypers['weight_decay']
                 self.learn_every = hypers['learn_every']
                 self.oun_mu = hypers['oun_mu']
                 self.oun_theta = hypers['oun_theta']
                 self.oun_sigma = hypers['oun_sigma']
                 self.buffer_size = hypers['buffer_size']
                 self.batch_size = hypers['batch_size']
                 self.gamma = hypers['gamma']
                 self.tau = hypers['tau']
                 self.learn_counter = 0

                 # Actor Network (w/ Target Network)
                 self.actor_local = Actor(self.state_size, self.action_size, self.seed,
                                          self.actor_fc1_units, self.actor_fc2_units ).to(device
                 self.actor_target = Actor(self.state_size, self.action_size, self.seed,
                                          self.actor_fc1_units, self.actor_fc2_units).to(device)
                 self.actor_optimizer = optim.Adam(self.actor_local.parameters(),
                                         lr=self.lr_actor)

                 # Critic Network (w/Target Network)
                 self.critic_local = Critic(self.state_size, self.action_size, self.seed,
                                           self.critic_fcs1_units, self.critic_fc2_units).to(dev
                 self.critic_target = Critic(self.state_size, self.action_size, self.seed,
                                            self.critic_fcs1_units, self.critic_fc2_units).to(de
                 self.critic_optimizer = optim.Adam(self.critic_local.parameters(),
```

```
                                lr=self.lr_critic, weight_decay= self.weight_decay)

        # Noise process
        self.noise = OUNoise(self.action_size, self.seed, self.oun_mu, self.oun_theta,

        # Replay memory
        self.memory = ReplayBuffer(self.action_size, self.buffer_size, self.batch_size,
                                   self.seed)

    def step(self, state, action, reward, next_state, done):
        """Save the experience in the reply memory, and use random
        sample from buffer to learn"""
        # save the experience /reward etc
        self.memory.add(state, action, reward, next_state, done)

        # check there are enough samples in memory, and then learn
        if self.memory.len() > self.batch_size and self.learn_counter % self.learn_ever
            experiences = self.memory.sample()
            self.learn(experiences, self.gamma)
        self.learn_counter +=1

    def act(self, state, add_noise=True, epsilon=1.0):
        """Returns actions for a given state as per current policy"""
        state = torch.from_numpy(state).float().to(device)
        # forward pass through the actor neural net to give actions
        self.actor_local.eval()
        # turn off autograd for this one step as it speeds this up (and we don't need i
        with torch.no_grad():
            action = self.actor_local(state).cpu().data.numpy()
        self.actor_local.train()
        if add_noise:
            action += self.noise.sample(epsilon)
        return np.clip(action, -1, 1) # it is bounded to +/-1

    def reset(self):
        self.noise.reset()

    def learn(self, experiences, gamma):
        """Update policy and value parameters using given batch of experience tuples.
        Q_targets = r +  * critic_target(next_state, actor_target(next_state))
        where:
            actor_target(state) -> action
            critic_target(state, action) -> Q-value

        Params
        ======
            experiences (Tuple[torch.Tensor]): tuple of (s, a, r, s', done) tuples
            gamma (float): discount factor
```

```
        """
        states, actions, rewards, next_states, dones = experiences

        # -------------------update critic-----------------------#
        actions_next = self.actor_target(next_states)
        Q_targets_next = self.critic_target(next_states, actions_next)
        # Compute Q targets for current states (y_i)
        Q_targets = rewards + (gamma * Q_targets_next * (1- dones))
        # Compute critic loss
        Q_expected = self.critic_local(states, actions)
        critic_loss = F.mse_loss(Q_expected, Q_targets)
        # Minimise the loss
        self.critic_optimizer.zero_grad()
        critic_loss.backward()
        self.critic_optimizer.step()

        # -------------------update actor ------------------------#
        # compute actor loss
        actions_pred = self.actor_local(states)
        # remember - we are doing gradient ASCENT for actor policy
        # so turn it negative and run gradient descent....
        actor_loss = -self.critic_local(states, actions_pred).mean()
        # Minimize the loss (=maximise the gain in grad ascent)
        self.actor_optimizer.zero_grad()
        actor_loss.backward()
        self.actor_optimizer.step()

        # -------------------update target networks --------------#
        self.soft_update(self.critic_local, self.critic_target, self.tau)
        self.soft_update(self.actor_local, self.actor_target, self.tau)

    def soft_update(self, local_model, target_model, tau):
        """Soft update model parameters.
        _target = *_local + (1 - )*_target

        Params
        ======
            local_model: PyTorch model (weights will be copied from)
            target_model: PyTorch model (weights will be copied to)
            tau (float): interpolation parameter
        """
        for target_param, local_param in zip(
            target_model.parameters(), local_model.parameters()):
                target_param.data.copy_(tau*local_param.data +
                    (1.0-tau) * target_param.data)
```

We now need to set up the hyper-parameters, because we pass these into the agent at the start.

```
In [26]: def set_up_hyperparameters(**kwargs):
             """return a hyper-parameter dictionary to use in training"""
             # populate the dictionary first with the default ones. We will over-write them as u
             hypers = {
                 'state_size': 33,
                 'action_size': 4,
                 'random_seed': 101,
                 'buffer_size': BUFFER_SIZE,
                 'batch_size': BATCH_SIZE,
                 'gamma': GAMMA,
                 'tau': TAU,
                 'lr_actor': LR_ACTOR,
                 'lr_critic': LR_CRITIC,
                 'weight_decay': WEIGHT_DECAY,
                 'learn_every': 5,
                 # now we are onto dcfw 'defaults',
                 'n_episodes': 300, # number of episodes - set at 300 to see early results, othe
                 'max_t': 1000, # this needs to be 1,000, or otherwise set the loop to while Tru
                 'print_every': 50,
                 'oun_mu': 0.,
                 'oun_theta': 0.15,
                 'oun_sigma': 0.2,
                 'actor_fc1_units': 256,
                 'actor_fc2_units': 128,
                 'critic_fcs1_units': 256,
                 'critic_fc2_units': 128,
                 'save_every': 20,
                 'save_name': '_default',
                 'save_data_name': '_data_default',
                 'load_from_actor': '',
                 'load_from_critic': ''
                 }

             for key, value in kwargs.items():
                 hypers[key] = value

             return hypers

In [27]: def pprint(hypers):
             print ('Hyper-parameters used')
             for key, value in hypers.items():
                 if len(key)> 14:
                     print(key,"\t", value)
                 elif len(key) >6:
                     print (key,"\t\t", value)
                 else:
                     print(key, "\t\t\t",value)
             return None
```

```
In [28]: hypers = set_up_hyperparameters(n_episodes=300, batch_size=16)
         pprint(hypers)

Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  16
gamma                          0.99
tau                           0.001
lr_actor                   0.0001
lr_critic                   0.001
weight_decay                   0
learn_every                   5
n_episodes                   300
max_t                             1000
print_every                   50
oun_mu                           0.0
oun_theta                  0.15
oun_sigma                  0.2
actor_fc1_units           256
actor_fc2_units           128
critic_fcs1_units           256
critic_fc2_units           128
save_every                   20
save_name                   _default
save_data_name                   _data_default
load_from_actor
load_from_critic
```

So, now we have the actor and critic set up, as well as the Agent which combines the two when interacting with the enviroment. Run the folllowing cell, to check the environment is still operating, if not run the cells at the start of the workbook again.

```
In [29]: agent = Agent(hypers=hypers)
         agent.actor_optimizer

Out[29]: Adam (
         Parameter Group 0
             amsgrad: False
             betas: (0.9, 0.999)
             eps: 1e-08
             lr: 0.0001
             weight_decay: 0
         )
```

Train the agent!

```
In [30]: def ddpg(hypers):
             """Run the DDPG agent through episodes, using Actor and Critic"""

             agent = Agent(hypers=hypers)
             if hypers['load_from_actor']:
                 agent.actor_local.load_state_dict(hypers['load_from_actor'])

             if hypers['load_from_critic']:
                 agent.critic_local.load_state_dict(hypers['load_from_critic'])

             n_episodes = hypers['n_episodes']
             max_t = hypers['max_t']
             print_every = hypers['print_every']
             save_every = hypers['save_every']
             check_point_actor = 'checkpoint_actor_' + hypers['save_name']+'_'
             check_point_critic = 'checkpoint_critic_' + hypers['save_name']+'_'
             scores_deque = deque(maxlen = 100) # this is the test we are using - have to get av
             scores=[]
             epsilon = 1
             for i_episode in range(1, n_episodes +1):
                 env_info = env.reset(train_mode=True)[brain_name]
                 state =env_info.vector_observations
                 agent.reset() # note - this resets the noise only!
         #         epsilon *= EPSILON_RATE

                 score=0
                 while True:
         #         for t in range(max_t):
                     action = agent.act(state, epsilon)
                     env_info = env.step(action)[brain_name]
                     next_state = env_info.vector_observations
                     reward = env_info.rewards
                     done = env_info.local_done
                     agent.step(state, action, reward, next_state, done)
                     state = next_state
                     score += reward[0]
                     if done[0]:
                         break
                 scores_deque.append(score)
                 scores.append(score)
                 print('\rEpisode {} of {}\tAvg Score: {:.2f}'.format(i_episode, n_episodes, np.
                 if i_episode % save_every == 0:
                     torch.save(agent.actor_local.state_dict(), check_point_actor + str(i_episod
                     torch.save(agent.critic_local.state_dict(), check_point_critic + str(i_epis
                     with open(hypers['save_data_name']+'.pkl', 'wb') as file:
                         pickle.dump(scores, file)
                 if i_episode % print_every == 0:
                         print('\rEpisode {}\tAvg Score: {:.2f}'.format(i_episode, np.mean(score
```

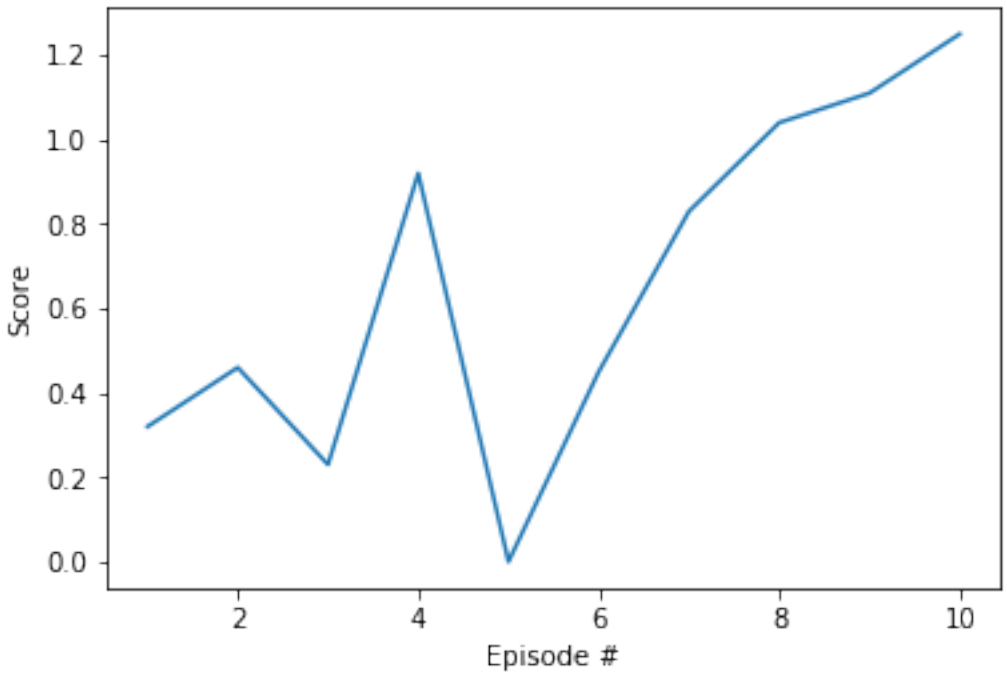
```
                if np.mean(scores_deque) > 30:
                    print ('Task completed on episode {}'.format(i_episode))
                    torch.save(agent.actor_local.state_dict(), check_point_actor + '_SOLVED')
                    torch.save(agent.critic_local.state_dict(), check_point_critic + '_SOLVED')
                    with open(hypers['save_data_name']+'.pkl', 'wb') as file:
                        pickle.dump(scores, file)
                    break
            return scores
```

```
In [31]: hypers = set_up_hyperparameters(n_episodes=10, save_name='test', print_every = 5)
```

```
In [32]: scores = ddpg(hypers)
```

```
Episode 5        Avg Score: 0.89: 0.89
Episode 10        Avg Score: 0.47: 0.47
```

```
In [33]: fig = plt.figure()
         ax = fig.add_subplot(111)
         plt.plot(np.arange(1, len(scores)+1), scores)
         plt.ylabel('Score')
         plt.xlabel('Episode #')
         plt.show()
```



OK, let's try running that for a bit longer

```
In [24]: hypers = set_up_hyperparameters(n_episodes=300, save_name='test', print_every = 5, acto
                                         critic_fcs1_units=128)

In [25]: pprint(hypers)

Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.0001
lr_critic                   0.001
weight_decay                   0
n_episodes                  300
max_t                             1000
print_every                  5
oun_mu                             0.0
oun_theta                  0.15
oun_sigma                  0.2
actor_fc1_units           128
actor_fc2_units           128
critic_fcs1_units           128
critic_fc2_units           128
save_every                   20
save_name                   test
load_from_actor
load_from_critic


In [34]: from workspace_utils import active_session

In [27]: with active_session():
             scores == ddpg(hypers)

1
Episode 1 of 300        Avg Score: 0.002
Episode 2 of 300        Avg Score: 0.363
Episode 3 of 300        Avg Score: 0.354
Episode 4 of 300        Avg Score: 0.525
Episode 5        Avg Score: 0.74e: 0.74
6
Episode 6 of 300        Avg Score: 0.737
Episode 7 of 300        Avg Score: 0.708
Episode 8 of 300        Avg Score: 0.689
Episode 9 of 300        Avg Score: 0.6910
Episode 10        Avg Score: 0.66e: 0.66
```

```
11
Episode 11 of 300        Avg Score: 0.6012
Episode 12 of 300        Avg Score: 0.5513
Episode 13 of 300        Avg Score: 0.5314
Episode 14 of 300        Avg Score: 0.5615
Episode 15        Avg Score: 0.56e: 0.56
16
Episode 16 of 300        Avg Score: 0.5817
Episode 17 of 300        Avg Score: 0.6218
Episode 18 of 300        Avg Score: 0.6619
Episode 19 of 300        Avg Score: 0.7120
Episode 20        Avg Score: 0.75e: 0.75
21
Episode 21 of 300        Avg Score: 0.8122
Episode 22 of 300        Avg Score: 0.7823
Episode 23 of 300        Avg Score: 0.8124
Episode 24 of 300        Avg Score: 0.8125
Episode 25        Avg Score: 0.81e: 0.81
26
Episode 26 of 300        Avg Score: 0.8327
Episode 27 of 300        Avg Score: 0.8528
Episode 28 of 300        Avg Score: 0.8329
Episode 29 of 300        Avg Score: 0.8330
Episode 30        Avg Score: 0.80e: 0.80
31
Episode 31 of 300        Avg Score: 0.7832
Episode 32 of 300        Avg Score: 0.7733
Episode 33 of 300        Avg Score: 0.8234
Episode 34 of 300        Avg Score: 0.8135
Episode 35        Avg Score: 0.83e: 0.83
36
Episode 36 of 300        Avg Score: 0.8437
Episode 37 of 300        Avg Score: 0.8538
Episode 38 of 300        Avg Score: 0.8839
Episode 39 of 300        Avg Score: 0.9040
Episode 40        Avg Score: 0.90e: 0.90
41
Episode 41 of 300        Avg Score: 0.9042
Episode 42 of 300        Avg Score: 0.9143
Episode 43 of 300        Avg Score: 0.9144
Episode 44 of 300        Avg Score: 0.9345
Episode 45        Avg Score: 0.96e: 0.96
46
Episode 46 of 300        Avg Score: 1.0047
Episode 47 of 300        Avg Score: 1.0448
Episode 48 of 300        Avg Score: 1.0649
Episode 49 of 300        Avg Score: 1.0850
Episode 50        Avg Score: 1.09e: 1.09
```

```
51
Episode 51 of 300        Avg Score: 1.1152
Episode 52 of 300        Avg Score: 1.1153
Episode 53 of 300        Avg Score: 1.1154
Episode 54 of 300        Avg Score: 1.1355
Episode 55        Avg Score: 1.12e: 1.12
56
Episode 56 of 300        Avg Score: 1.1257
Episode 57 of 300        Avg Score: 1.1158
Episode 58 of 300        Avg Score: 1.1059
Episode 59 of 300        Avg Score: 1.1060
Episode 60        Avg Score: 1.11e: 1.11
61
Episode 61 of 300        Avg Score: 1.1262
Episode 62 of 300        Avg Score: 1.1263
Episode 63 of 300        Avg Score: 1.1364
Episode 64 of 300        Avg Score: 1.1365
Episode 65        Avg Score: 1.12e: 1.12
66
Episode 66 of 300        Avg Score: 1.1267
Episode 67 of 300        Avg Score: 1.1168
Episode 68 of 300        Avg Score: 1.1169
Episode 69 of 300        Avg Score: 1.1270
Episode 70        Avg Score: 1.12e: 1.12
71
Episode 71 of 300        Avg Score: 1.1272
Episode 72 of 300        Avg Score: 1.1273
Episode 73 of 300        Avg Score: 1.1274
Episode 74 of 300        Avg Score: 1.1275
Episode 75        Avg Score: 1.11e: 1.11
76
Episode 76 of 300        Avg Score: 1.1177
Episode 77 of 300        Avg Score: 1.1178
Episode 78 of 300        Avg Score: 1.1079
Episode 79 of 300        Avg Score: 1.0980
Episode 80        Avg Score: 1.09e: 1.09
81
Episode 81 of 300        Avg Score: 1.1082
Episode 82 of 300        Avg Score: 1.0983
Episode 83 of 300        Avg Score: 1.0984
Episode 84 of 300        Avg Score: 1.0985
Episode 85        Avg Score: 1.09e: 1.09
86
Episode 86 of 300        Avg Score: 1.0987
Episode 87 of 300        Avg Score: 1.0988
Episode 88 of 300        Avg Score: 1.0989
Episode 89 of 300        Avg Score: 1.0890
Episode 90        Avg Score: 1.08e: 1.08
```

```
91
Episode 91 of 300        Avg Score: 1.0892
Episode 92 of 300        Avg Score: 1.0893
Episode 93 of 300        Avg Score: 1.0894
Episode 94 of 300        Avg Score: 1.0895
Episode 95        Avg Score: 1.07e: 1.07
96
Episode 96 of 300        Avg Score: 1.0797
Episode 97 of 300        Avg Score: 1.0698
Episode 98 of 300        Avg Score: 1.0699
Episode 99 of 300        Avg Score: 1.06100
Episode 100        Avg Score: 1.06e: 1.06
101
Episode 101 of 300        Avg Score: 1.07102
Episode 102 of 300        Avg Score: 1.07103
Episode 103 of 300        Avg Score: 1.08104
Episode 104 of 300        Avg Score: 1.07105
Episode 105        Avg Score: 1.07e: 1.07
106
Episode 106 of 300        Avg Score: 1.08107
Episode 107 of 300        Avg Score: 1.08108
Episode 108 of 300        Avg Score: 1.08109
Episode 109 of 300        Avg Score: 1.09110
Episode 110        Avg Score: 1.09e: 1.09
111
Episode 111 of 300        Avg Score: 1.10112
Episode 112 of 300        Avg Score: 1.11113
Episode 113 of 300        Avg Score: 1.12114
Episode 114 of 300        Avg Score: 1.12115
Episode 115        Avg Score: 1.12e: 1.12
116
Episode 116 of 300        Avg Score: 1.12117
Episode 117 of 300        Avg Score: 1.15118
Episode 118 of 300        Avg Score: 1.14119
Episode 119 of 300        Avg Score: 1.15120
Episode 120        Avg Score: 1.14e: 1.14
121
Episode 121 of 300        Avg Score: 1.13122
Episode 122 of 300        Avg Score: 1.14123
Episode 123 of 300        Avg Score: 1.14124
Episode 124 of 300        Avg Score: 1.15125
Episode 125        Avg Score: 1.15e: 1.15
126
Episode 126 of 300        Avg Score: 1.15127
Episode 127 of 300        Avg Score: 1.15128
Episode 128 of 300        Avg Score: 1.16129
Episode 129 of 300        Avg Score: 1.16130
Episode 130        Avg Score: 1.17e: 1.17
```

```
131
Episode 131 of 300        Avg Score: 1.18132
Episode 132 of 300        Avg Score: 1.19133
Episode 133 of 300        Avg Score: 1.18134
Episode 134 of 300        Avg Score: 1.19135
Episode 135        Avg Score: 1.19e: 1.19
136
Episode 136 of 300        Avg Score: 1.20137
Episode 137 of 300        Avg Score: 1.21138
Episode 138 of 300        Avg Score: 1.21139
Episode 139 of 300        Avg Score: 1.20140
Episode 140        Avg Score: 1.21e: 1.21
141
Episode 141 of 300        Avg Score: 1.22142
Episode 142 of 300        Avg Score: 1.21143
Episode 143 of 300        Avg Score: 1.21144
Episode 144 of 300        Avg Score: 1.20145
Episode 145        Avg Score: 1.21e: 1.21
146
Episode 146 of 300        Avg Score: 1.20147
Episode 147 of 300        Avg Score: 1.19148
Episode 148 of 300        Avg Score: 1.18149
Episode 149 of 300        Avg Score: 1.18150
Episode 150        Avg Score: 1.19e: 1.19
151
Episode 151 of 300        Avg Score: 1.18152
Episode 152 of 300        Avg Score: 1.19153
Episode 153 of 300        Avg Score: 1.19154
Episode 154 of 300        Avg Score: 1.19155
Episode 155        Avg Score: 1.20e: 1.20
156
Episode 156 of 300        Avg Score: 1.19157
Episode 157 of 300        Avg Score: 1.20158
Episode 158 of 300        Avg Score: 1.19159
Episode 159 of 300        Avg Score: 1.20160
Episode 160        Avg Score: 1.20e: 1.20
161
Episode 161 of 300        Avg Score: 1.21162
Episode 162 of 300        Avg Score: 1.21163
Episode 163 of 300        Avg Score: 1.20164
Episode 164 of 300        Avg Score: 1.21165
Episode 165        Avg Score: 1.23e: 1.23
166
Episode 166 of 300        Avg Score: 1.22167
Episode 167 of 300        Avg Score: 1.24168
Episode 168 of 300        Avg Score: 1.23169
Episode 169 of 300        Avg Score: 1.22
```

```
---------------------------------------------------------------------------

KeyboardInterrupt                         Traceback (most recent call last)

<ipython-input-27-a72f977eb422> in <module>()
  1 with active_session():
----> 2     scores == ddpg(hypers)


<ipython-input-23-e264218eaf4e> in ddpg(hypers)
 35             reward = env_info.rewards
 36             done = env_info.local_done
---> 37             agent.step(state, action, reward, next_state, done)
 38             state = next_state
 39             score += reward[0]


<ipython-input-19-0d9d9539aa90> in step(self, state, action, reward, next_state, done)
 63         if self.memory.len() > self.batch_size:
 64             experiences = self.memory.sample()
---> 65             self.learn(experiences, self.gamma)
 66
 67     def act(self, state, add_noise=True, epsilon=1.0):


<ipython-input-19-0d9d9539aa90> in learn(self, experiences, gamma)
116         # Minimize the loss (=maximise the gain in grad ascent)
117         self.actor_optimizer.zero_grad()
--> 118         actor_loss.backward()
119         self.actor_optimizer.step()
120


/opt/conda/lib/python3.6/site-packages/torch/tensor.py in backward(self, gradient, retai
 91                 products. Defaults to ``False``.
 92         """
---> 93         torch.autograd.backward(self, gradient, retain_graph, create_graph)
 94
 95     def register_hook(self, hook):


/opt/conda/lib/python3.6/site-packages/torch/autograd/__init__.py in backward(tensors, g
 87     Variable._execution_engine.run_backward(
 88         tensors, grad_tensors, retain_graph, create_graph,
---> 89         allow_unreachable=True)  # allow_unreachable flag
 90
 91
```

```
        KeyboardInterrupt:


In [23]: hypers = set_up_hyperparameters(n_episodes=300, save_name='run2', print_every = 10, act
                                         critic_fcs1_units=256, batch_size=256)

In [24]: pprint(hypers)

Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  256
gamma                          0.99
tau                           0.001
lr_actor                   0.0001
lr_critic                   0.001
weight_decay                   0
learn_every                   5
n_episodes                  300
max_t                             1000
print_every                   10
oun_mu                             0.0
oun_theta                   0.15
oun_sigma                   0.2
actor_fc1_units           256
actor_fc2_units           128
critic_fcs1_units           256
critic_fc2_units           128
save_every                    20
save_name                   run2
load_from_actor
load_from_critic


In [ ]: with active_session():
            scores == ddpg(hypers)
```

I actually did run with those parameters for 300 episodes, but didn't save the print-outs. It was very slow learning - getting to only 1.45 average after 300 esisodes. Therefore will try to increase the learning rate for both?

```
In [32]: hypers = set_up_hyperparameters(n_episodes=300, save_name='run3', print_every = 20, act
                                         critic_fcs1_units=256, batch_size=128, lr_actor = 1e-3,

In [33]: pprint(hypers)
```

```
Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.001
lr_critic                   0.005
weight_decay                   0
learn_every                   5
n_episodes                   300
max_t                             1000
print_every                   20
oun_mu                             0.0
oun_theta                  0.15
oun_sigma                  0.2
actor_fc1_units          256
actor_fc2_units          128
critic_fcs1_units           256
critic_fc2_units          128
save_every                   20
save_name                  run3
load_from_actor
load_from_critic
```

```
In [34]: with active_session():
             scores == ddpg(hypers)
```

```
Episode 20        Avg Score: 0.57e: 0.57
Episode 40        Avg Score: 0.36e: 0.36
Episode 60        Avg Score: 0.25e: 0.25
Episode 80        Avg Score: 0.19e: 0.19
Episode 100        Avg Score: 0.15e: 0.15
Episode 120        Avg Score: 0.04e: 0.04
Episode 140        Avg Score: 0.02e: 0.02
Episode 160        Avg Score: 0.01e: 0.01
Episode 180        Avg Score: 0.01e: 0.01
Episode 200        Avg Score: 0.01e: 0.01
Episode 220        Avg Score: 0.01e: 0.01
Episode 240        Avg Score: 0.01e: 0.01
Episode 260        Avg Score: 0.01e: 0.01
Episode 280        Avg Score: 0.02e: 0.02
Episode 300        Avg Score: 0.02e: 0.02
```

Well. That was pretty disastrous!

Next effort - move the learning rates back down to, say 5e-4 each.

```
In [36]: hypers = set_up_hyperparameters(n_episodes=300, save_name='run4', print_every = 20, act
                                         critic_fcs1_units=256, batch_size=128, lr_actor = 5e-4,
         pprint(hypers)
```

```
Hyper-parameters used
state_size                 33
action_size                 4
random_seed                 101
buffer_size                 100000
batch_size                 128
gamma                        0.99
tau                         0.001
lr_actor                  0.0005
lr_critic                  0.0005
weight_decay                  0
learn_every                 5
n_episodes                  300
max_t                          1000
print_every                 20
oun_mu                           0.0
oun_theta                  0.15
oun_sigma                  0.2
actor_fc1_units           256
actor_fc2_units           128
critic_fcs1_units           256
critic_fc2_units           128
save_every                   20
save_name                  run4
load_from_actor
load_from_critic
```

```
In [37]: with active_session():
             scores == ddpg(hypers)
```

```
Episode 20        Avg Score: 0.91e: 0.91
Episode 40        Avg Score: 0.78e: 0.78
Episode 60        Avg Score: 0.58e: 0.58
Episode 80        Avg Score: 0.63e: 0.63
Episode 100        Avg Score: 0.78e: 0.78
Episode 120        Avg Score: 1.07e: 1.07
Episode 140        Avg Score: 1.50e: 1.50
Episode 160        Avg Score: 2.06e: 2.06
Episode 180        Avg Score: 2.57e: 2.57
Episode 200        Avg Score: 3.34e: 3.34
Episode 220        Avg Score: 4.21e: 4.21
Episode 240        Avg Score: 5.24e: 5.24
```

```
Episode 260        Avg Score: 5.93e: 5.93
Episode 280        Avg Score: 7.10e: 7.10
Episode 300        Avg Score: 7.68e: 7.68
```

OK, so at this point, I returned to Udacity website - the session had closed itself down. But the checkpoints had worked, and the weights saved..... but annoyingly I called them the same name, so the critic weights over-rode the actor weights. As it looked like there was some promise to training, I'll fix the code, so that the critic weights are saved also. But I will run the training with more episodes.

```
In [41]: hypers = set_up_hyperparameters(n_episodes=1000, save_name='run4', print_every = 20, ac
                                        critic_fcs1_units=256, batch_size=128, lr_actor = 5e-4,
         pprint(hypers)

Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.0005
lr_critic                   0.0005
weight_decay                   0
learn_every                   5
n_episodes                   1000
max_t                             1000
print_every                   20
oun_mu                             0.0
oun_theta                  0.15
oun_sigma                  0.2
actor_fc1_units           256
actor_fc2_units           128
critic_fcs1_units           256
critic_fc2_units           128
save_every                    20
save_name                   run4
save_data_name                    _data_default
load_from_actor
load_from_critic


In [42]: with active_session():
             scores == ddpg(hypers)

Episode 20        Avg Score: 0.41re: 0.41
Episode 40        Avg Score: 0.68re: 0.68
```

```
Episode 60        Avg Score: 0.64re: 0.64
Episode 80        Avg Score: 0.74re: 0.74
Episode 100        Avg Score: 0.95re: 0.95
Episode 120        Avg Score: 1.30re: 1.30
Episode 140        Avg Score: 1.66re: 1.66
Episode 160        Avg Score: 2.02re: 2.02
Episode 180        Avg Score: 2.46re: 2.46
Episode 200        Avg Score: 2.81re: 2.81
Episode 220        Avg Score: 3.20re: 3.20
Episode 240        Avg Score: 3.78re: 3.78
Episode 260        Avg Score: 4.47re: 4.47
Episode 280        Avg Score: 5.05re: 5.05
Episode 300        Avg Score: 5.78re: 5.78
Episode 320        Avg Score: 6.25re: 6.25
Episode 340        Avg Score: 6.61re: 6.61
Episode 360        Avg Score: 7.11re: 7.11
Episode 380        Avg Score: 7.58re: 7.58
Episode 400        Avg Score: 7.62re: 7.62
Episode 420        Avg Score: 8.04re: 8.04
Episode 440        Avg Score: 8.09re: 8.09
Episode 460        Avg Score: 8.18re: 8.18
Episode 480        Avg Score: 8.23re: 8.23
Episode 500        Avg Score: 8.43re: 8.43
Episode 520        Avg Score: 8.47re: 8.47
Episode 540        Avg Score: 8.51re: 8.51
Episode 560        Avg Score: 8.43re: 8.43
Episode 580        Avg Score: 8.15re: 8.15
Episode 600        Avg Score: 7.79re: 7.79
Episode 620        Avg Score: 7.25re: 7.25
Episode 640        Avg Score: 7.13re: 7.13
Episode 660        Avg Score: 6.61re: 6.61
Episode 680        Avg Score: 6.44re: 6.44
Episode 700        Avg Score: 6.16re: 6.16
Episode 720        Avg Score: 5.91re: 5.91
Episode 740        Avg Score: 5.30re: 5.30
Episode 760        Avg Score: 4.86re: 4.86
Episode 780        Avg Score: 4.25re: 4.25
Episode 800        Avg Score: 3.97re: 3.97
Episode 820        Avg Score: 4.30re: 4.30
Episode 840        Avg Score: 4.43re: 4.43
Episode 860        Avg Score: 4.47re: 4.47
Episode 880        Avg Score: 4.82re: 4.82
Episode 900        Avg Score: 4.93re: 4.93
Episode 920        Avg Score: 4.70re: 4.70
Episode 940        Avg Score: 4.34re: 4.34
Episode 960        Avg Score: 4.62re: 4.62
Episode 980        Avg Score: 4.20re: 4.20
Episode 1000        Avg Score: 3.90re: 3.90
```

Hmm, not so good. Try reducing the theta - exploring too much?

```
In [44]: hypers = set_up_hyperparameters(n_episodes=300, save_name='run5', print_every = 20, act
                                         critic_fcs1_units=256, batch_size=128, lr_actor = 5e-4,
         pprint(hypers)
```

```
Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.0005
lr_critic                   0.0005
weight_decay                   0
learn_every                   5
n_episodes                   300
max_t                             1000
print_every                   20
oun_mu                           0.0
oun_theta                  0.05
oun_sigma                  0.2
actor_fc1_units           256
actor_fc2_units           128
critic_fcs1_units           256
critic_fc2_units           128
save_every                   20
save_name                   run5
save_data_name                    _data_default
load_from_actor
load_from_critic
```

```
In [45]: with active_session():
             scores == ddpg(hypers)
```

```
Episode 20        Avg Score: 0.86e: 0.86
Episode 40        Avg Score: 1.02e: 1.02
Episode 60        Avg Score: 1.13e: 1.13
Episode 80        Avg Score: 1.33e: 1.33
Episode 100        Avg Score: 1.71e: 1.71
Episode 120        Avg Score: 2.42e: 2.42
Episode 140        Avg Score: 3.24e: 3.24
Episode 160        Avg Score: 4.54e: 4.54
Episode 180        Avg Score: 5.79e: 5.79
```

```
Episode 200        Avg Score: 7.19e: 7.19
Episode 220        Avg Score: 8.52e: 8.52
Episode 240        Avg Score: 10.06: 10.06
Episode 260        Avg Score: 11.11: 11.11
Episode 280        Avg Score: 12.44: 12.44
Episode 300        Avg Score: 13.09: 13.09
```

Training appears good. Yippee!. Continue training, but with loaded weights.

```
In [51]: hypers = set_up_hyperparameters(n_episodes=1000, save_name='run6', print_every = 20, ac
                                        critic_fcs1_units=256, batch_size=128, lr_actor = 5e-4,
                                         lr_critic = 5e-4, oun_theta=0.05)
         pprint(hypers)
```

```
Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.0005
lr_critic                   0.0005
weight_decay                   0
learn_every                   5
n_episodes                   1000
max_t                             1000
print_every                  20
oun_mu                            0.0
oun_theta                  0.05
oun_sigma                  0.2
actor_fc1_units           256
actor_fc2_units           128
critic_fcs1_units           256
critic_fc2_units           128
save_every                   20
save_name                   run6
save_data_name                    _data_default
load_from_actor
load_from_critic
```

```
In [52]: with active_session():
             scores_2 = ddpg(hypers)
```

```
Episode 20        Avg Score: 0.39re: 0.39
Episode 40        Avg Score: 0.21re: 0.21
```

```
Episode 60        Avg Score: 0.23re: 0.23
Episode 80        Avg Score: 0.29re: 0.29
Episode 100        Avg Score: 0.38re: 0.38
Episode 120        Avg Score: 0.52re: 0.52
Episode 140        Avg Score: 0.82re: 0.82
Episode 160        Avg Score: 1.12re: 1.12
Episode 180        Avg Score: 1.41re: 1.41
Episode 200        Avg Score: 1.69re: 1.69
Episode 220        Avg Score: 1.86re: 1.86
Episode 240        Avg Score: 2.20re: 2.20
Episode 260        Avg Score: 2.51re: 2.51
Episode 280        Avg Score: 2.74re: 2.74
Episode 300        Avg Score: 3.10re: 3.10
Episode 320        Avg Score: 3.41re: 3.41
Episode 340        Avg Score: 3.64re: 3.64
Episode 360        Avg Score: 3.78re: 3.78
Episode 380        Avg Score: 3.99re: 3.99
Episode 400        Avg Score: 4.01re: 4.01
Episode 420        Avg Score: 4.17re: 4.17
Episode 440        Avg Score: 4.41re: 4.41
Episode 460        Avg Score: 4.74re: 4.74
Episode 480        Avg Score: 5.35re: 5.35
Episode 500        Avg Score: 5.99re: 5.99
Episode 520        Avg Score: 6.87re: 6.87
Episode 540        Avg Score: 7.40re: 7.40
Episode 560        Avg Score: 8.05re: 8.05
Episode 580        Avg Score: 8.43re: 8.43
Episode 600        Avg Score: 9.00re: 9.00
Episode 620        Avg Score: 9.32re: 9.32
Episode 640        Avg Score: 10.08e: 10.08
Episode 660        Avg Score: 10.72e: 10.72
Episode 680        Avg Score: 11.86e: 11.86
Episode 700        Avg Score: 12.87e: 12.87
Episode 720        Avg Score: 14.19e: 14.19
Episode 740        Avg Score: 15.99e: 15.99
Episode 760        Avg Score: 17.73e: 17.73
Episode 780        Avg Score: 19.05e: 19.05
Episode 800        Avg Score: 20.58e: 20.58
Episode 820        Avg Score: 21.83e: 21.83
Episode 840        Avg Score: 21.90e: 21.90
Episode 860        Avg Score: 22.81e: 22.81
Episode 880        Avg Score: 23.58e: 23.58
Episode 900        Avg Score: 23.60e: 23.60
Episode 920        Avg Score: 23.32e: 23.32
Episode 940        Avg Score: 23.84e: 23.84
Episode 960        Avg Score: 24.42e: 24.42
Episode 980        Avg Score: 24.88e: 24.88
Episode 1000        Avg Score: 26.20e: 26.20
```

Those results looked good - just not enough time. I might tweak the learning rate slightly higher, but otherwise let it run for longer. I also added code to pickle the data in stages so we can graph it, even if the connection with the server is lost.

```
In [35]: hypers = set_up_hyperparameters(n_episodes=2000, save_name='run7', print_every = 20, ac
                                         critic_fcs1_units=256, batch_size=128, lr_actor = 8e-4,
                                          lr_critic = 8e-4, oun_theta=0.05, save_data_name='run7_
         pprint(hypers)

Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.0008
lr_critic                   0.0008
weight_decay                    0
learn_every                  5
n_episodes                  2000
max_t                             1000
print_every                  20
oun_mu                             0.0
oun_theta                  0.05
oun_sigma                  0.2
actor_fc1_units          256
actor_fc2_units          128
critic_fcs1_units           256
critic_fc2_units          128
save_every                   20
save_name                   run7
save_data_name                   run7_data_
load_from_actor
load_from_critic


In [36]: with active_session():
             scores = ddpg(hypers)

Episode 20        Avg Score: 0.11re: 0.11
Episode 40        Avg Score: 0.06re: 0.06
Episode 60        Avg Score: 0.13re: 0.13
Episode 80        Avg Score: 0.19re: 0.19
Episode 100        Avg Score: 0.24re: 0.24
Episode 120        Avg Score: 0.39re: 0.39
```

```
Episode 140        Avg Score: 0.53re: 0.53
Episode 160        Avg Score: 0.63re: 0.63
Episode 180        Avg Score: 0.66re: 0.66
Episode 200        Avg Score: 0.72re: 0.72
Episode 220        Avg Score: 0.68re: 0.68
Episode 240        Avg Score: 0.69re: 0.69
Episode 260        Avg Score: 0.70re: 0.70
Episode 280        Avg Score: 0.73re: 0.73
Episode 300        Avg Score: 0.69re: 0.69
Episode 320        Avg Score: 0.76re: 0.76
Episode 340        Avg Score: 0.78re: 0.78
Episode 360        Avg Score: 0.83re: 0.83
Episode 380        Avg Score: 0.86re: 0.86
Episode 400        Avg Score: 0.98re: 0.98
Episode 420        Avg Score: 0.98re: 0.98
Episode 440        Avg Score: 0.99re: 0.99
Episode 460        Avg Score: 0.96re: 0.96
Episode 480        Avg Score: 1.01re: 1.01
Episode 500        Avg Score: 0.97re: 0.97
Episode 520        Avg Score: 0.99re: 0.99
Episode 540        Avg Score: 0.90re: 0.90
Episode 560        Avg Score: 0.87re: 0.87
Episode 580        Avg Score: 0.90re: 0.90
Episode 600        Avg Score: 0.91re: 0.91
Episode 620        Avg Score: 0.86re: 0.86
Episode 640        Avg Score: 0.99re: 0.99
Episode 660        Avg Score: 1.02re: 1.02
Episode 680        Avg Score: 0.96re: 0.96
Episode 700        Avg Score: 0.92re: 0.92
Episode 720        Avg Score: 0.85re: 0.85
Episode 740        Avg Score: 0.61re: 0.61
Episode 760        Avg Score: 0.47re: 0.47
Episode 780        Avg Score: 0.43re: 0.43
Episode 800        Avg Score: 0.44re: 0.44
Episode 820        Avg Score: 0.50re: 0.50
Episode 840        Avg Score: 0.65re: 0.65
Episode 860        Avg Score: 0.79re: 0.79
Episode 880        Avg Score: 0.81re: 0.81
Episode 900        Avg Score: 0.80re: 0.80
Episode 920        Avg Score: 0.82re: 0.82
Episode 940        Avg Score: 0.84re: 0.84
Episode 960        Avg Score: 0.82re: 0.82
Episode 980        Avg Score: 0.85re: 0.85
Episode 1000        Avg Score: 0.85re: 0.85
Episode 1020        Avg Score: 0.86re: 0.86
Episode 1040        Avg Score: 0.87re: 0.87
Episode 1060        Avg Score: 0.94re: 0.94
Episode 1080        Avg Score: 0.90re: 0.90
```

```
Episode 1100        Avg Score: 0.93re: 0.93
Episode 1120        Avg Score: 0.95re: 0.95
Episode 1140        Avg Score: 0.92re: 0.92
Episode 1160        Avg Score: 0.88re: 0.88
Episode 1180        Avg Score: 0.88re: 0.88
Episode 1200        Avg Score: 0.90re: 0.90
Episode 1220        Avg Score: 0.89re: 0.89
Episode 1240        Avg Score: 0.88re: 0.88
Episode 1260        Avg Score: 0.87re: 0.87
Episode 1280        Avg Score: 0.87re: 0.87
Episode 1300        Avg Score: 0.84re: 0.84
Episode 1320        Avg Score: 0.85re: 0.85
Episode 1340        Avg Score: 0.87re: 0.87
Episode 1360        Avg Score: 0.83re: 0.83
Episode 1380        Avg Score: 0.86re: 0.86
Episode 1400        Avg Score: 0.85re: 0.85
Episode 1420        Avg Score: 0.85re: 0.85
Episode 1440        Avg Score: 0.87re: 0.87
Episode 1460        Avg Score: 0.90re: 0.90
Episode 1480        Avg Score: 0.90re: 0.90
Episode 1500        Avg Score: 0.87re: 0.87
Episode 1520        Avg Score: 0.86re: 0.86
Episode 1540        Avg Score: 0.82re: 0.82
Episode 1560        Avg Score: 0.81re: 0.81
Episode 1580        Avg Score: 0.78re: 0.78
Episode 1600        Avg Score: 0.77re: 0.77
Episode 1620        Avg Score: 0.81re: 0.81
Episode 1640        Avg Score: 0.83re: 0.83
Episode 1660        Avg Score: 0.87re: 0.87
Episode 1680        Avg Score: 0.87re: 0.87
Episode 1700        Avg Score: 0.95re: 0.95
Episode 1720        Avg Score: 0.94re: 0.94
Episode 1740        Avg Score: 0.92re: 0.92
Episode 1760        Avg Score: 0.88re: 0.88
Episode 1780        Avg Score: 0.91re: 0.91
Episode 1800        Avg Score: 0.84re: 0.84
Episode 1820        Avg Score: 0.83re: 0.83
Episode 1840        Avg Score: 0.87re: 0.87
Episode 1860        Avg Score: 0.91re: 0.91
Episode 1880        Avg Score: 0.92re: 0.92
Episode 1900        Avg Score: 0.92re: 0.92
Episode 1920        Avg Score: 0.94re: 0.94
Episode 1940        Avg Score: 0.90re: 0.90
Episode 1960        Avg Score: 0.89re: 0.89
Episode 1980        Avg Score: 0.86re: 0.86
Episode 2000        Avg Score: 0.84re: 0.84
```

Did not work - revert the learning rate back down (even lower). And re-try....

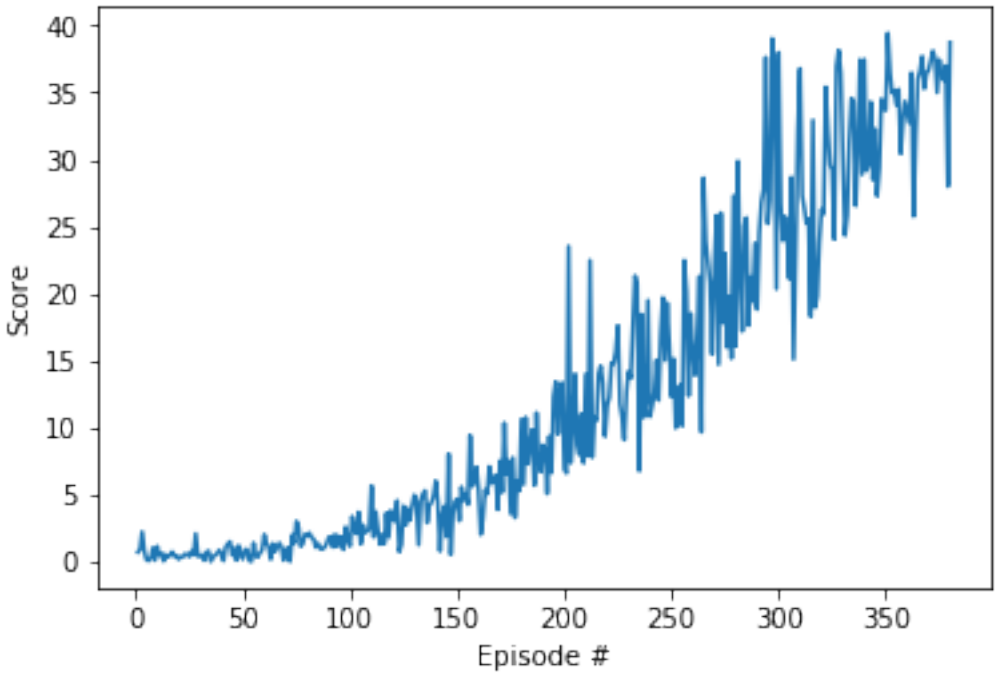
```
In [38]: hypers = set_up_hyperparameters(n_episodes=2000, save_name='run8', print_every = 50, ac
                                         critic_fcs1_units=256, batch_size=128, lr_actor = 3e-4,
                                          lr_critic = 3e-4, oun_theta=0.05, save_data_name='run8_
         pprint(hypers)

Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.0003
lr_critic                   0.0003
weight_decay                   0
learn_every                   5
n_episodes                   2000
max_t                             1000
print_every                   50
oun_mu                             0.0
oun_theta                  0.05
oun_sigma                  0.2
actor_fc1_units           256
actor_fc2_units           128
critic_fcs1_units           256
critic_fc2_units           128
save_every                   20
save_name                   run8
save_data_name                   run8_data_
load_from_actor
load_from_critic


In [39]: with active_session():
             scores = ddpg(hypers)

Episode 50        Avg Score: 0.60re: 0.60
Episode 100        Avg Score: 0.93re: 0.93
Episode 150        Avg Score: 2.27re: 2.27
Episode 200        Avg Score: 5.19re: 5.19
Episode 250        Avg Score: 10.22e: 10.22
Episode 300        Avg Score: 17.37e: 17.37
Episode 350        Avg Score: 25.14e: 25.14
Episode 380 of 2000        Avg Score: 30.21Task completed on episode 380
```

```
In [40]: fig = plt.figure()
         ax = fig.add_subplot(111)
         plt.plot(np.arange(1, len(scores)+1), scores)
         plt.ylabel('Score')
         plt.xlabel('Episode #')
         plt.show()
```




```
In [42]: plt.savefig('solved.jpg')
```

```
<matplotlib.figure.Figure at 0x7fb45026ce48>
```

Well, that was a bit easy - can see if I can get a higher score now? Changed the code in ddpg to get a score > 40 as a success measure.
The *only* change in the ddpg code below is the use of a score-target now, instead of hard-coded figure of 30

```
In [43]: def ddpg(hypers, score_target=30):
             """Run the DDPG agent through episodes, using Actor and Critic"""

             agent = Agent(hypers=hypers)
             if hypers['load_from_actor']:
                 agent.actor_local.load_state_dict(hypers['load_from_actor'])

             if hypers['load_from_critic']:
```

```
        agent.critic_local.load_state_dict(hypers['load_from_critic'])

    n_episodes = hypers['n_episodes']
    max_t = hypers['max_t']
    print_every = hypers['print_every']
    save_every = hypers['save_every']
    check_point_actor = 'checkpoint_actor_' + hypers['save_name']+'_'
    check_point_critic = 'checkpoint_critic_' + hypers['save_name']+'_'
    scores_deque = deque(maxlen = 100) # this is the test we are using - have to get av
    scores=[]
    epsilon = 1
    for i_episode in range(1, n_episodes +1):
        env_info = env.reset(train_mode=True)[brain_name]
        state =env_info.vector_observations
        agent.reset() # note - this resets the noise only!
#         epsilon *= EPSILON_RATE

        score=0
        while True:
#         for t in range(max_t):
            action = agent.act(state, epsilon)
            env_info = env.step(action)[brain_name]
            next_state = env_info.vector_observations
            reward = env_info.rewards
            done = env_info.local_done
            agent.step(state, action, reward, next_state, done)
            state = next_state
            score += reward[0]
            if done[0]:
                break
        scores_deque.append(score)
        scores.append(score)
        print('\rEpisode {} of {}\tAvg Score: {:.2f}'.format(i_episode, n_episodes, np.
        if i_episode % save_every == 0:
            torch.save(agent.actor_local.state_dict(), check_point_actor + str(i_episod
            torch.save(agent.critic_local.state_dict(), check_point_critic + str(i_epis
            with open(hypers['save_data_name']+'.pkl', 'wb') as file:
                pickle.dump(scores, file)
        if i_episode % print_every == 0:
                print('\rEpisode {}\tAvg Score: {:.2f}'.format(i_episode, np.mean(score
        if np.mean(scores_deque) > score_target:
            print ('Task completed on episode {}'.format(i_episode))
            torch.save(agent.actor_local.state_dict(), check_point_actor + '_SOLVED')
            torch.save(agent.critic_local.state_dict(), check_point_critic + '_SOLVED')
            with open(hypers['save_data_name']+'.pkl', 'wb') as file:
                pickle.dump(scores, file)
            break
    return scores
```

```
In [44]: hypers = set_up_hyperparameters(n_episodes=2000, save_name='run9', print_every = 50, ac
                                         critic_fcs1_units=256, batch_size=128, lr_actor = 3e-4,
                                          lr_critic = 3e-4, oun_theta=0.05, save_data_name='run8_
         pprint(hypers)

Hyper-parameters used
state_size                  33
action_size                  4
random_seed                  101
buffer_size                  100000
batch_size                  128
gamma                          0.99
tau                           0.001
lr_actor                   0.0003
lr_critic                   0.0003
weight_decay                    0
learn_every                   5
n_episodes                  2000
max_t                            1000
print_every                   50
oun_mu                             0.0
oun_theta                  0.05
oun_sigma                  0.2
actor_fc1_units          256
actor_fc2_units          128
critic_fcs1_units           256
critic_fc2_units          128
save_every                   20
save_name                  run9
save_data_name                   run8_data_
load_from_actor
load_from_critic


In [45]: with active_session():
             scores = ddpg(hypers, score_target=40)

Episode 50        Avg Score: 0.63re: 0.63
Episode 100        Avg Score: 1.10re: 1.10
Episode 150        Avg Score: 2.13re: 2.13
Episode 200        Avg Score: 3.77re: 3.77
Episode 250        Avg Score: 6.67re: 6.67
Episode 300        Avg Score: 9.06re: 9.06
Episode 350        Avg Score: 10.46e: 10.46
Episode 400        Avg Score: 10.96e: 10.96
Episode 450        Avg Score: 10.84e: 10.84
Episode 500        Avg Score: 11.25e: 11.25
Episode 550        Avg Score: 11.58e: 11.58
```

```
Episode 600        Avg Score: 10.75e: 10.75
Episode 650        Avg Score: 10.22e: 10.22
Episode 700        Avg Score: 10.64e: 10.64
Episode 750        Avg Score: 11.32e: 11.32
Episode 800        Avg Score: 11.95e: 11.95
Episode 850        Avg Score: 12.16e: 12.16
Episode 900        Avg Score: 13.09e: 13.09
Episode 950        Avg Score: 13.78e: 13.78
Episode 1000        Avg Score: 14.35e: 14.35
Episode 1050        Avg Score: 15.17e: 15.17
Episode 1100        Avg Score: 16.06e: 16.06
Episode 1150        Avg Score: 16.70e: 16.70
Episode 1200        Avg Score: 16.97e: 16.97
Episode 1250        Avg Score: 19.36e: 19.36
Episode 1300        Avg Score: 22.38e: 22.38
Episode 1350        Avg Score: 25.33e: 25.33
Episode 1400        Avg Score: 28.36e: 28.36
Episode 1450        Avg Score: 29.51e: 29.51
Episode 1500        Avg Score: 30.31e: 30.31
Episode 1550        Avg Score: 32.67e: 32.67
Episode 1600        Avg Score: 32.16e: 32.16
Episode 1650        Avg Score: 28.82e: 28.82
Episode 1700        Avg Score: 28.49e: 28.49
Episode 1750        Avg Score: 30.45e: 30.45
Episode 1800        Avg Score: 31.79e: 31.79
Episode 1850        Avg Score: 31.47e: 31.47
Episode 1900        Avg Score: 29.89e: 29.89
Episode 1950        Avg Score: 28.65e: 28.65
Episode 2000        Avg Score: 28.48e: 28.48
```

In [ ]: