Deep Q Networks

下面我们使用 open ai gym 环境中的 CartPole 来尝试实现一个简单的 DQN。

```
import torch
import torch.nn as nn
from torch.autograd import Variable
import numpy as np
import gym
```

定义一些超参数

```
batch_size = 32
lr = 0.01
epsilon = 0.9
gamma = 0.9
target_replace_iter = 100
memory_capacity = 2000
env = gym.make('CartPole-v0')
env = env.unwrapped
n_actions = env.action_space.n
n_states = env.observation_space.shape[0]
```

```
print('number of actions are: {}'.format(n_actions))
print('number of states are: {}'.format(n_states))
```

```
number of actions are: 2
number of states are: 4
```

这里使用 gym 自带的环境，关于 CartPole 的一些参数，我们同样可以像上一节课 MountainCar 一样找到，[地址](#) 在这里，通过这里可以看到，这个环境的观测的 4 个值分别是板的位置，板的速度，杆的角度以及杆顶端的速度，我们能够采取的动作就是 2 个，分别是向左移动杆和向右移动杆。

本质上，我们其实可以不用关心状态到底是什么，这些状态都可以作为神经网络的输入，输出就是每个动作的 value，可以让神经网络自己学会建立一个类似 Q 表的东西。

```
class q_net(nn.Module):
    def __init__(self, hidden=50):
        super(q_net, self).__init__()
```

```python
        self.fc = nn.Sequential(
            nn.Linear(n_states, hidden),
            nn.ReLU(True),
            nn.Linear(hidden, n_actions)
        )

        nn.init.normal(self.fc[0].weight, std=0.1) # 使用标准差是 0.1 的正态分布初始化
        nn.init.normal(self.fc[2].weight, std=0.1) # 使用标准差是 0.1 的正态分布初始化

    def forward(self, x):
        actions_value = self.fc(x)
        return actions_value
```

接下来我们定义一个 DQN 的过程作为一个类，在这个类中，我们会定义 dqn 的学习过程，dqn 的更新过程和之前讲个 q learning 的过程是很相同的

下面我们来实现整个过程

```python
class DQN(object):
    def __init__(self):
        self.eval_net, self.target_net = q_net(), q_net()

        self.learn_step_counter = 0
        self.memory_counter = 0
        self.memory = np.zeros((memory_capacity, n_states * 2 + 2)) # 当前的状态和动
作，之后的状态和动作
        self.optimizer = torch.optim.Adam(self.eval_net.parameters(), lr=lr)
        self.criterion = nn.MSELoss()

    def choose_action(self, s):
        '''
        根据输入的状态得到所有可行动作的价值估计
        '''
        s = Variable(torch.unsqueeze(torch.FloatTensor(s), 0))
        # input only one sample
        if np.random.uniform() < epsilon:  # greedy 贪婪算法
            actions_value = self.eval_net(s)
            action = torch.max(actions_value, 1)[1].data[0]
        else:  # random 随机选择
            action = np.random.randint(0, n_actions)
        return action

    def store_transition(self, s, a, r, s_):
        transition = np.hstack((s, [a, r], s_))
        # 用新的记忆替换旧的记忆
```

```
        index = self.memory_counter % memory_capacity
        self.memory[index, :] = transition
        self.memory_counter += 1

    def learn(self):
        # target net 的参数更新
        if self.learn_step_counter % target_replace_iter == 0:
            self.target_net.load_state_dict(self.eval_net.state_dict())
        self.learn_step_counter += 1

        # 取样记忆中的经历
        sample_index = np.random.choice(memory_capacity, batch_size)
        b_memory = self.memory[sample_index, :]
        b_s = Variable(torch.FloatTensor(b_memory[:, :n_states]))
        b_a = Variable(
            torch.LongTensor(b_memory[:, n_states:n_states + 1].astype(int)))
        b_r = Variable(
            torch.FloatTensor(b_memory[:, n_states + 1:n_states + 2]))
        b_s_ = Variable(torch.FloatTensor(b_memory[:, -n_states:]))

        # q_eval net 评估状态下动作的 value
        q_eval = self.eval_net(b_s).gather(1, b_a)  # shape (batch, 1) 选择对应 action 的动作
        q_next = self.target_net(
            b_s_).detach()  # detach from graph, don't backpropagate
        q_target = b_r + gamma * q_next.max(1)[0].view(batch_size, 1)  # shape (batch, 1)
        loss = self.criterion(q_eval, q_target) # mse 作为 loss 函数
        # 更新网络
        self.optimizer.zero_grad()
        loss.backward()
        self.optimizer.step()
```

```
dqn_trainer = DQN()
```

```
print('collecting experience ... ')
all_reward = []
for i_episode in range(300):
    s = env.reset()
    reward = 0
    while True:
#         env.render()
        a = dqn_trainer.choose_action(s)
```

```
        # 环境采取动作得到结果
        s_, r, done, info = env.step(a)

        # 修改奖励以便更快收敛
        x, x_dot, theta, theta_dot = s_
        r1 = (env.x_threshold - abs(x)) / env.x_threshold - 0.8
        r2 = (env.theta_threshold_radians - abs(theta)) / env.theta_threshold_radians
- 0.5
        r = r1 + r2

        dqn_trainer.store_transition(s, a, r, s_)

        reward += r
        if dqn_trainer.memory_counter > memory_capacity: # 记忆收集够开始学习
            dqn_trainer.learn()
            if done:
                print('Ep: {} | reward: {:.3f}'.format(i_episode, round(reward, 3)))
                all_reward.append(reward)
                break

        if done:
            break
        s = s_
```

```
collecting experience ...
Ep: 199 | reward: 1.720
Ep: 200 | reward: 4.116
Ep: 201 | reward: 2.598
Ep: 202 | reward: 7.261
Ep: 203 | reward: 1.570
Ep: 204 | reward: 1.191
Ep: 205 | reward: 2.557
Ep: 206 | reward: 2.822
Ep: 207 | reward: 1.788
Ep: 208 | reward: 3.345
Ep: 209 | reward: 2.787
Ep: 210 | reward: 2.718
Ep: 211 | reward: 21.747
Ep: 212 | reward: 2.514
Ep: 213 | reward: 1.504
Ep: 214 | reward: 5.059
Ep: 215 | reward: -1.003
Ep: 216 | reward: 5.880
Ep: 217 | reward: 25.360
Ep: 218 | reward: 19.871
```

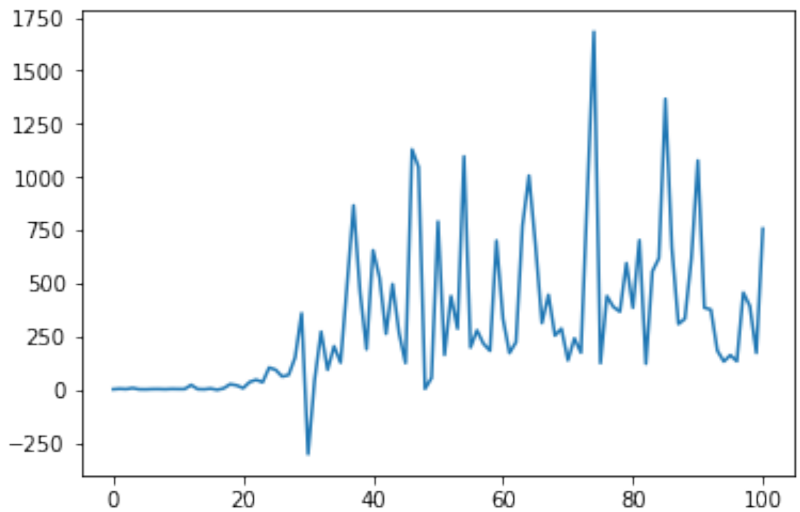
```
Ep: 219 | reward: 6.934
Ep: 220 | reward: 35.473
Ep: 221 | reward: 46.048
Ep: 222 | reward: 34.585
Ep: 223 | reward: 103.504
Ep: 224 | reward: 92.848
Ep: 225 | reward: 61.636
Ep: 226 | reward: 68.378
Ep: 227 | reward: 150.926
Ep: 228 | reward: 358.854
Ep: 229 | reward: -303.586
Ep: 230 | reward: 44.629
Ep: 231 | reward: 271.936
Ep: 232 | reward: 93.458
Ep: 233 | reward: 203.914
Ep: 234 | reward: 126.819
Ep: 235 | reward: 492.525
Ep: 236 | reward: 865.907
Ep: 237 | reward: 457.963
Ep: 238 | reward: 189.550
Ep: 239 | reward: 654.743
Ep: 240 | reward: 526.357
Ep: 241 | reward: 262.288
Ep: 242 | reward: 496.026
Ep: 243 | reward: 266.828
Ep: 244 | reward: 125.170
Ep: 245 | reward: 1129.094
Ep: 246 | reward: 1046.364
Ep: 247 | reward: 3.924
Ep: 248 | reward: 54.877
Ep: 249 | reward: 790.436
Ep: 250 | reward: 163.135
Ep: 251 | reward: 439.592
Ep: 252 | reward: 286.395
Ep: 253 | reward: 1096.519
Ep: 254 | reward: 198.122
Ep: 255 | reward: 278.892
Ep: 256 | reward: 215.559
Ep: 257 | reward: 182.856
Ep: 258 | reward: 700.339
Ep: 259 | reward: 333.089
Ep: 260 | reward: 172.095
Ep: 261 | reward: 222.899
Ep: 262 | reward: 770.689
Ep: 263 | reward: 1006.111
Ep: 264 | reward: 680.227
```

```
Ep: 265 | reward: 313.157
Ep: 266 | reward: 445.412
Ep: 267 | reward: 254.287
Ep: 268 | reward: 286.542
Ep: 269 | reward: 137.780
Ep: 270 | reward: 240.850
Ep: 271 | reward: 173.953
Ep: 272 | reward: 929.376
Ep: 273 | reward: 1682.483
Ep: 274 | reward: 124.281
Ep: 275 | reward: 439.573
Ep: 276 | reward: 388.455
Ep: 277 | reward: 366.418
Ep: 278 | reward: 594.223
Ep: 279 | reward: 385.194
Ep: 280 | reward: 702.398
Ep: 281 | reward: 121.711
Ep: 282 | reward: 555.598
Ep: 283 | reward: 617.005
Ep: 284 | reward: 1366.853
Ep: 285 | reward: 667.864
Ep: 286 | reward: 308.383
Ep: 287 | reward: 332.831
Ep: 288 | reward: 614.663
Ep: 289 | reward: 1077.267
Ep: 290 | reward: 385.115
Ep: 291 | reward: 375.811
Ep: 292 | reward: 183.127
Ep: 293 | reward: 132.291
Ep: 294 | reward: 161.788
Ep: 295 | reward: 133.430
Ep: 296 | reward: 455.821
Ep: 297 | reward: 392.828
Ep: 298 | reward: 172.488
Ep: 299 | reward: 756.369
```

```python
import matplotlib.pyplot as plt
%matplotlib inline
```

```python
plt.plot(all_reward)
```

```
[<matplotlib.lines.Line2D at 0x119000ba8>]
```



我们画出 reward 的曲线，可以发现奖励在不断变多，说明我们的 agent 学得越来越好，同时我们也可以实实在在地看到 agent 玩得怎么样，gym 提供了可视化的过程，但是 notebook 里面没有办法显示，我们可以使用运行 `dqn.py` 来看到 agent 玩的可视化视频。

另外，我们这里只使用了简单的多层神经网络来作为 dqn 的网络结构，网络的输入是杆的位置信息和角度等等，我们当然可以使用更加一般的输入，比如说每个状态都是一个图片的输入，那么这种方式更具有一般性，实现上几乎是一模一样，只需要改一改网络结构，同时 gym 中也可以得到每个屏幕的输出，具体可以看看 pytorch 的官方例子。