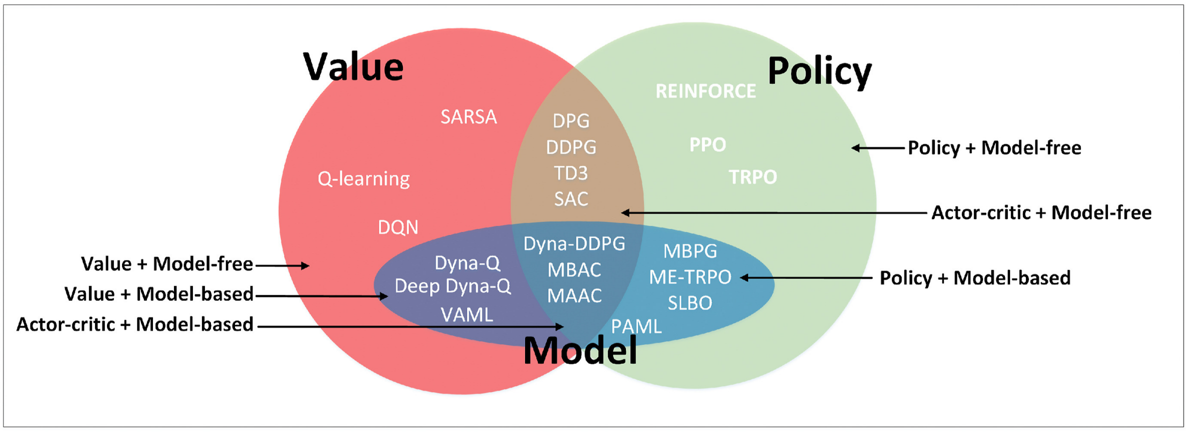
DDA 4230 Tutorial 10

Section 0: Outline

1. Overview of RL Algorithms
2. DQN

```
from collections import namedtuple
import numpy as np
import matplotlib.pyplot as plt
from tqdm import tqdm
import gym
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from torch.utils.data.sampler import BatchSampler, SubsetRandomSampler
```

Section 1: Overview of RL Algorithms



Classification of RL ALgorithms from A.T.D.Perera

Up to now, we have learned:

Tabular Methods:

- Value Iteration
- Policy Iteration
- Q-learning
- SARSA
- TD(λ)

Approximation Methods:

- REINFORCE
- REINFORCE with Baselines
- Actor Critic
- DQN

Section 2: DQN

CartPole

Consider the CartPole problem. A pole is attached by an un-actuated joint to a cart, which moves along a frictionless track. The system is controlled by applying a force of $+1$ or -1 to the cart. The pendulum starts upright, and the goal is to prevent it from falling over. A reward of $+1$ is provided for every timestep that the pole remains upright. The episode ends when the pole is more than 15 degrees from vertical, or the cart moves more than 2.4 units from the center. The state space is continuous and each state is a tuple of cart position, cart velocity, pole angle, and pole angular velocity. There are 2 discrete deterministic actions: Left and Right.

Note: CartPole-v0 defines "solving" as getting average undiscounted return of 195.0 over 100 consecutive trials

DQN

Q-Learning is an off-policy algorithm that learns about the greedy policy $a = \max_a Q(s, a; \theta)$ while using a different behaviour policy for acting in the environment/collecting data. This behaviour policy is usually an ϵ-greedy policy that selects the greedy action with probability $1 - \epsilon$ and a random action with probability ϵ to ensure good coverage of the state-action space.

To avoid computing the full expectation in the DQN loss, we can minimize it using stochastic gradient descent. If the loss is computed using just the last transition s, a, r, s', this reduces to standard Q-Learning.

Algorithm 2: Deep Q-learning

Initialize replay memory D with a fixed capacity
Initialize action value function $\hat{Q}$ with random weights $\mathbf{w}$
Initialize target action value function $\hat{Q}$ with weights $\mathbf{w}^- = \mathbf{w}$
for *episode* $k = 1, \ldots, K$ **do**
  Observe initial frame x_1 and pre-process frame to get state s_1
  for *time step* $t = 1, \ldots, T$ **do**
    Select action $a_t = \begin{cases} \text{random action} & \text{with probability } \epsilon \\ \arg\max_a \hat{Q}(s_t, a, \mathbf{w}) & \text{otherwise} \end{cases}$
    Execute action a_t in emulator and observe reward r_t and image x_{t+1}
    pre-process s_t, x_{t+1} to get s_{t+1}, and store transition (s_t, a_t, r_t, s_{t+1}) in D
    Sample uniformly a random minibatch of N transitions $\{(s_j, a_j, r_j, s_{j+1})\}_{j \in [N]}$ from D
    Set $y_j = r_j$ if episode ends at step $j + 1$, otherwise set $y_j = r_j + \gamma \max_{a'} \hat{Q}(s_{j+1}, a', \mathbf{w}^-)$
    Perform a stochastic gradient descent step on $J(\mathbf{w}) = \frac{1}{N} \sum_{j=1}^{N} (y_j - \hat{Q}(s_j, a_j, \mathbf{w}))^2$ with respect to $\mathbf{w}$
    Every C steps reset $\mathbf{w}^- = \mathbf{w}$

```python
class Net(nn.Module):
    # A Simple Q Network
    def __init__(self, dim_state, n_action):
        super(Net, self).__init__()
        self.fc1 = nn.Linear(dim_state, 128)
        self.fc2 = nn.Linear(128, n_action)

    def forward(self, x):
        x = torch.tanh(self.fc1(x))
        action_value = self.fc2(x)
        return action_value
```

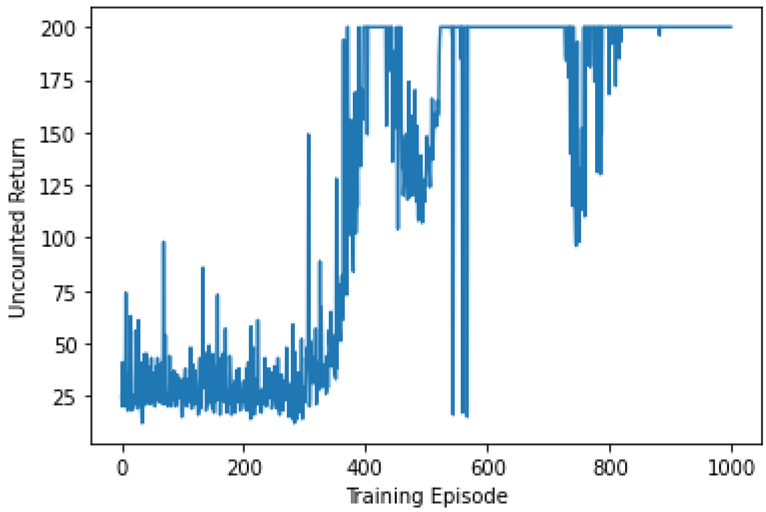
```python
class DQN():

    def __init__(self, capacity, learning_rate, batch_size, gamma, dim_state,
n_action):
        super(DQN, self).__init__()
        self.capacity = capacity
        self.learning_rate = learning_rate
        self.batch_size = batch_size
        self.gamma = gamma
        self.n_action = n_action
        self.dim_state = dim_state

        self.target_net, self.act_net = Net(
            dim_state, n_action), Net(dim_state, n_action)
        self.memory = [None]*self.capacity
        self.optimizer = optim.Adam(
            self.act_net.parameters(), self.learning_rate)
        self.loss_func = nn.MSELoss()

        self.memory_count = 0
        self.update_count = 0

    def select_action(self, state):
        state = torch.tensor(state, dtype=torch.float).unsqueeze(0)
        value = self.act_net(state)
        action_max_value, index = torch.max(value, 1)
        action = index.item()
        if np.random.rand(1) >= 0.9:  # epslion greedy
            action = np.random.choice(range(self.n_action), 1).item()
        return action

    def store_transition(self, transition):
        index = self.memory_count % self.capacity
        self.memory[index] = transition
        self.memory_count += 1
        return self.memory_count >= self.capacity

    def update(self):
        if self.memory_count >= self.capacity:
            state = torch.tensor([t.state for t in self.memory]).float()
            action = torch.LongTensor(
                [t.action for t in self.memory]).view(-1, 1).long()
            reward = torch.tensor([t.reward for t in self.memory]).float()
            next_state = torch.tensor(
```

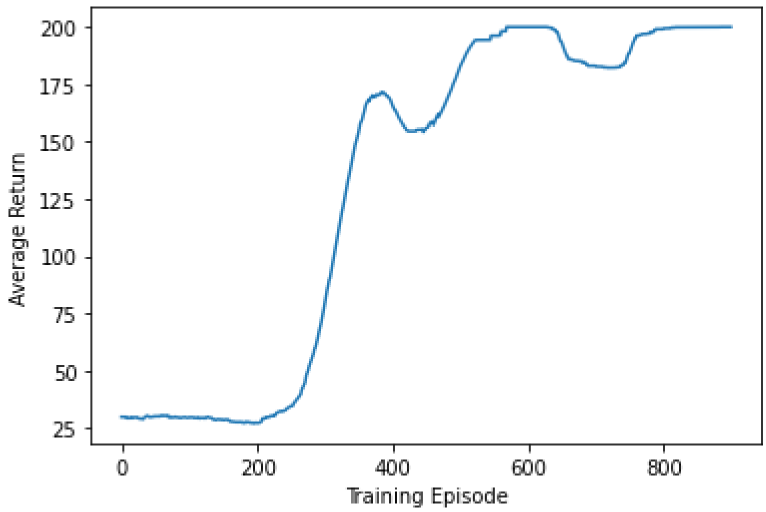
```
                [t.next_state for t in self.memory]).float()
            done = torch.tensor(
                [t.done for t in self.memory]).float()

            #reward = (reward - reward.mean()) / (reward.std() + 1e-7)
            with torch.no_grad():
                target_v = reward + (1-done)*self.gamma * \
                    self.target_net(next_state).max(1)[0]

            # Update...
            for index in
BatchSampler(SubsetRandomSampler(range(len(self.memory))),
batch_size=self.batch_size, drop_last=False):
                v = (self.act_net(state).gather(1, action))[index]
                loss = self.loss_func(target_v[index].unsqueeze(
                    1), (self.act_net(state).gather(1, action))[index])
                self.optimizer.zero_grad()
                loss.backward()
                self.optimizer.step()
                self.update_count += 1
                if self.update_count % 100 == 0:
                    self.target_net.load_state_dict(self.act_net.state_dict())
        else:
            pass
```

```
# Hyper-parameters
seed = 1
num_episodes = 1000
env = gym.make('CartPole-v0')
n_action = env.action_space.n
dim_state = env.observation_space.shape[0]

torch.manual_seed(seed)
env.seed(seed)

# Replay Buffer
Transition = namedtuple(
    'Transition', ['state', 'action', 'reward', 'next_state', 'done'])

capacity = 8000
learning_rate = 1e-3
batch_size = 256
gamma = 0.995

agent = DQN(capacity=capacity, learning_rate=learning_rate,
            batch_size=batch_size, gamma=gamma, dim_state=dim_state,
n_action=n_action)
return_list = []

for i_ep in tqdm(range(num_episodes)):
    state = env.reset()
    total_return = 0
    for t in range(200):
        # Choose Action
        action = agent.select_action(state)

        # Step in Env
```

```python
        next_state, reward, done, info = env.step(action)
        total_return += reward

        # Add transition to Buffer
        transition = Transition(state, action, reward, next_state, float(done))
        agent.store_transition(transition)
        state = next_state

        if done or t >= 199:
            # To facilitate our training, update per episode.
            agent.update()
            break
    return_list.append(total_return)
plt.plot(return_list)
plt.xlabel('Training Episode')
plt.ylabel('Uncounted Return')
plt.savefig('CartPole_DQN.png')
plt.show()
plt.close()
moving_average = [np.mean(return_list[i:(i+100)])
                  for i in range(num_episodes-100)]
plt.plot(moving_average)
plt.xlabel('Training Episode')
plt.ylabel('Average Return')
plt.savefig('CartPole_DQN_Average.png')
plt.show()
plt.close()
```

```
100%|██████████| 1000/1000 [10:16<00:00,  1.62it/s]
```





200
175
150
125
100
75
50
25
Average Return
0
200
400
600
800
Training Episode