test

April 15, 2021

Import packages.

[1]:
```
import gym
import numpy as np
import matplotlib.pyplot as plt
import dual_sourcing
```

Set up configurations for the environment.

[3]:
```
CONFIG = {'Lr': 5, 'Le': 1, 'cr': 100, 'ce': 105, 'lambda': 10,
          'h': 1, 'b': 19, 'starting_state': [0]*7, 'max_order': 20,␣
 ↪'max_inventory': 1000}
```

Make an instance of the environment.

[4]:
```
env = gym.make('DualSourcing-v0', config=CONFIG)
```

Print the environment settings.

[5]:
```
print(env.state)
print(env.action_space)
print(env.observation_space)
```

```
[0 0 0 0 0 0 0]
MultiDiscrete([21 21])
MultiDiscrete([  21   21   21   21   21   21 1000])
```

Test the step function.

[6]:
```
env.seed(0)
env.state = [0] * 7
print(env.step([8, 2]))
print('***')
env.state = [5, 4, 5, 6, 6, 2, 2]
print(env.step([3, 1]))
```

```
(array([  0,   0,   0,   0,   8,   2, -10]), 0, 10, {})
***
(array([ 4,  5,  6,  6,  3,  1, -2]), -812, 11, {})
```

Evaluate an estimate of the value function for a certain policy by doing multiple episodes of simulation.

[39]:
```
def evaluate(env, n_episodes, numiters, policy, *args):
    # env: gym environment
    # n_episodes: number of total episodes to run (outer iteration)
    # numiters: number of time steps (inner iteration)
    # policy: policy function
    # *args: arguments in the policy function

    av_reward = np.zeros(n_episodes)

    for i in range(n_episodes):
        av_r = 0
        env.reset() # reset environment
        for t in range(numiters):
            action = policy(*args)
            state, reward, demand, info = env.step(action)
            if t > 100 and np.abs( av_r / (t+1) - (av_r + reward) / (t+2))  <␣
 ↪1e-4: # convergence is spotted
                break
            av_r = av_r + reward
        av_reward[i] = av_r / (t+1)
#         print(t)

    return np.mean(av_reward), np.std(av_reward) # return average reward and std
```

We need to decide on some policy that will not make the average reward blow up. As a result, we write the following function to plot the average reward vs. time step as a guidance.

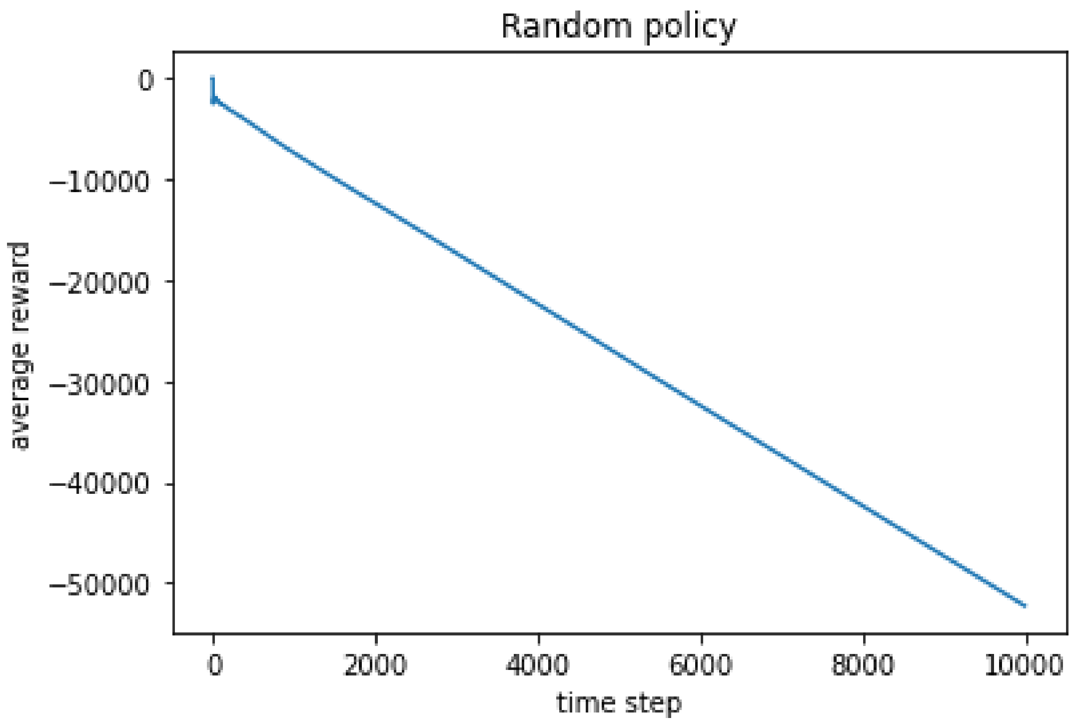
[18]:
```
def convergence_test(env, numiters, policy, *args):

    cum_reward = np.zeros(numiters)
    av_reward = np.zeros(numiters)

    env.reset() # reset environment
    for t in range(numiters-1):
        action = policy(*args)
        state, reward, demand, info = env.step(action)
        cum_reward[t+1] = cum_reward[t] + reward
        av_reward[t+1] = cum_reward[t+1] / (t+1)

    plt.plot(range(numiters), av_reward)
    plt.xlabel('time step')
    plt.ylabel('average reward')
```

(1) Random policy.

[16]:
```python
def random_policy(env):
    return env.action_space.sample()
```

[20]:
```python
convergence_test(env, 10000, random_policy, env)
plt.title('Random policy')
```

[20]: Text(0.5, 1.0, 'Random policy')



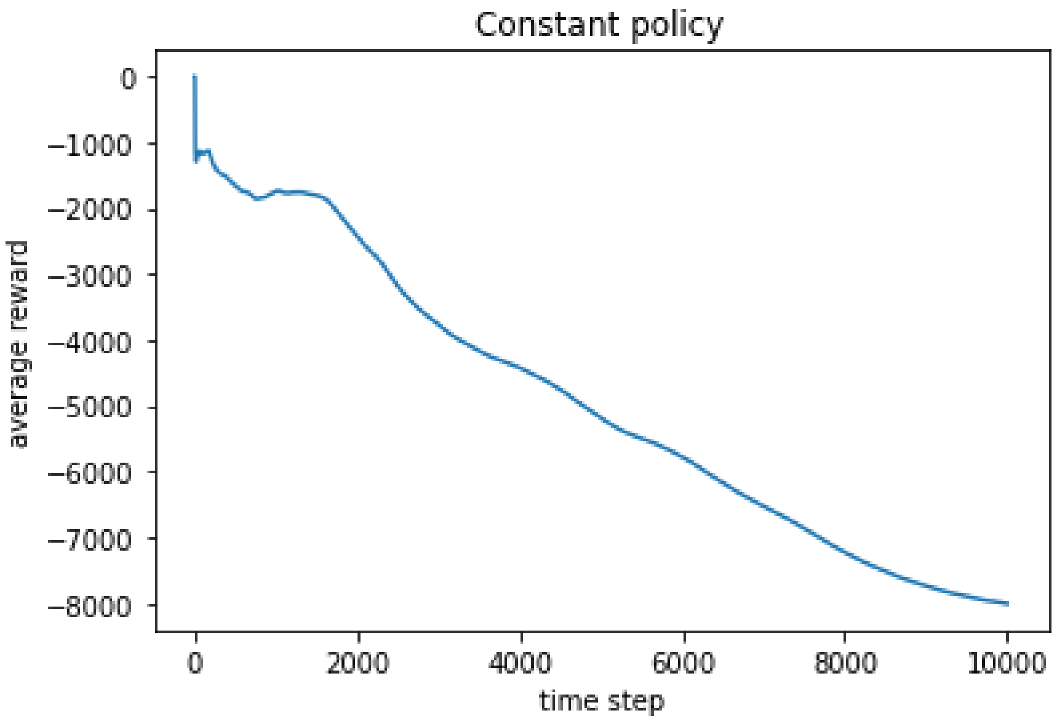
It is obvious that random policy cannot guarantee convergence.

(2) Constant policy.

[21]:
```python
def constant_policy(action):
    return action
```

[24]:
```python
convergence_test(env, 10000, constant_policy, np.array([0,10]))
plt.title('Constant policy')
```

[24]: Text(0.5, 1.0, 'Constant policy')



Constant policy is also not a good candidate.

(3) TBS policy

We shortly walk through the TBS policy here for consistency. A TBS policy $\pi_{r,S}$ is characterized by two parameters $r \in \mathbb{Z}_+$ and $S \in \mathbb{Z}_+$. In each period, the policy always orders r products from R and follows an order-up-to rule from E, where we maintain the express inventory position above S. That is to say, for all time step t, we set

$$
\begin{aligned}
q_t^r &= r \\
q_t^e &= \max\left(0, S - \hat{I}_t\right),
\end{aligned}
$$

where

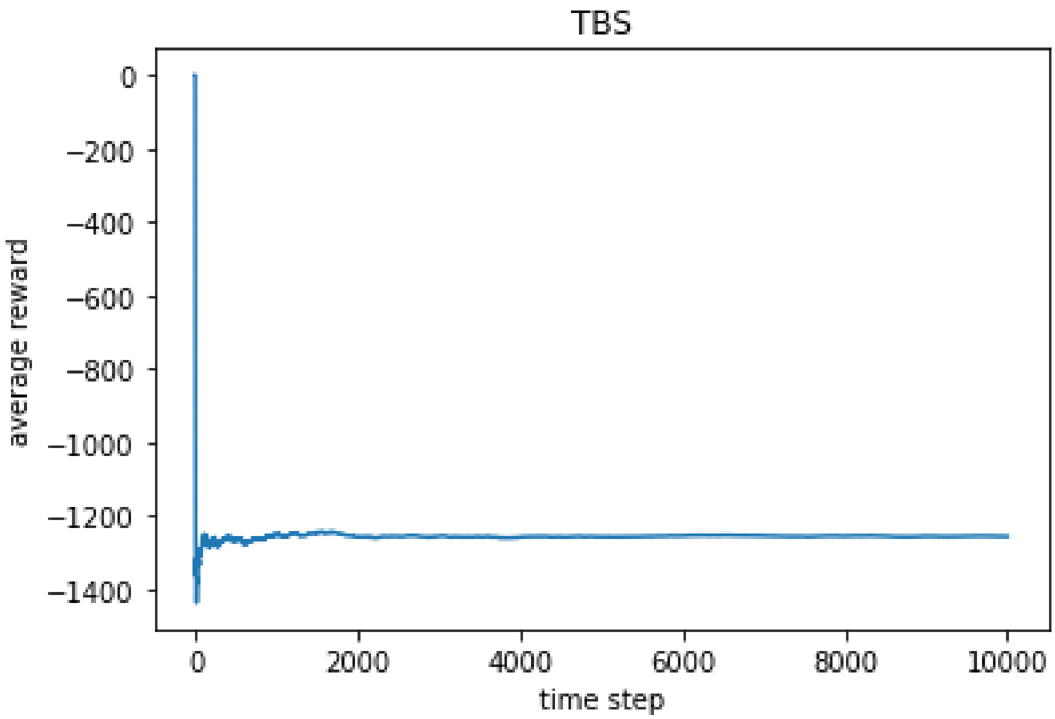
$$
\hat{I}_t := I_t + \sum_{i=t-L_e}^{t-1} q_i^e + \sum_{i=t-L_r}^{t-L_r+L_e} q_i^r
$$

is the so-called inventory position, which corresponds to the net inventory at the start of period t plus all orders to be received in periods $t, \ldots, t + L_e$.

[25]:
```
def TBS(env, r, S):
    ip = np.sum(env.state[1:(env.Le+1)]) + np.sum(env.state[env.Lr:])
    return r, max(0, S-ip)
```

[27]:
```
convergence_test(env, 10000, TBS, env, 5, 3)
plt.title('TBS')
```

[27]: Text(0.5, 1.0, 'TBS')



Eureka!

As a final step, we use the TBS policy to do the estimation and report the mean as well as the standard deviation.

[40]:
```
evaluate(env, 100, 5000, TBS, env, 5, 3)
```

[40]: (-1251.030088094656, 9.175726521778662)

We conclude that for TBS policy with parameter $r = 5, S = 3$, the estimate for the value function is -1251 and the standard deviation is 9.176.