Dynamic Programming and Reinforcement Learning Assignment1 Report

Chih-Chieh Lin (2700266)
Yizhen Zhao (2658811)

November 15, 2020

1 Introduction

This Report describes our solutions and methods for solving airline revenue management problems. Regarding the four questions mentioned in this assignment, the relevant solutions will be placed in the following sections.

2 Total expected revenue and optimal policy

When it comes to total expected revenue, we consider the following value equation:

$$V_t(x) = max_{a=1,\ldots,n} \left\{ \sum_{i=1}^{a} \lambda_t\left(i\right)\left(f_a + V_{t+1}\left(x-1\right)\right) + \left(1 - \sum_{i=1}^{a} \lambda_t\left(i\right)\right) V_{t+1}\left(x\right) \right\}$$

By going through backward in time T, and forward in capacity C. For each time point and each capacity level, we calculated the probabilities of customers accept and reject each price of the class. Then use these variables mentioned above to calculate the value function at each time and capacity. At each step, we consider the state with maximum revenue (which means the value function with maximum value) as our optimal policy. Moreover, the total expected revenue is shown as follows.

$$V_{600}\left(100\right) = 30308.6057$$

3 Plot of Optimal policy

According to the methodology in Section 2, the optimal policy is obtained and shown in Figure 1.

From the figure 1 we could see that when we start from time 0, and we have enough capacity, the optimal policy suggests starting with the cheapest tickets (3rd class, the one in green color, which values 200 euros). As time goes on and capacity becomes limited, the strategy tend to sell the 2nd class tickets (the one in light yellow color, which values 300 euros). When both of capacity and time are extremely limited(when time reaches around 510 days and approximately 40 capacities left), the policy tend to sell the most expensive tickets (1st class, the one in red color, which values 500 euros) because at that condition, we do not have much time left and most of tickets were sold.

	average revenue	maximum revenue	minimum revenue
Price can go down	32297	35100	24600
Price cannot go down	31566	43000	23000

Table 1: Result of Simulation

4 Simulation

We simulate the demand of price at each time by using the random function in python. The condition of the simulation would look like Figure 3 and Figure 4. The Figure 3 shows the demand, price of policy and remaining capacity over time(from 0 to 600). The Figure 4 shows the same content but with different policy that the price cannot go down. Moreover, we run 1000 times on both optimal policies(price can/ cannot go down) with the same setting of random function. The simulation result would be shown in the Table 1.

5 When price cannot go down

We followed the same methodology in question a), but now price cannot go down. In this case, the total expected revenue has dropped by 5.8%:

$$V_{600}\,(100) = 28554.0905$$

The optimal policy with the constraint that price cannot go down is shown in Figure 2. As we could see the optimal policy also changed. The choice of selling the cheapest tickets (3rd class, which should be in green color) disappeared. It suggests starting with the 2nd class tickets, which values 300 euros. Even though there is still a lot of capacity left (around 80), it suggests starting selling 1st class tickets (the one in red color, which values 500 euros).

A Figures

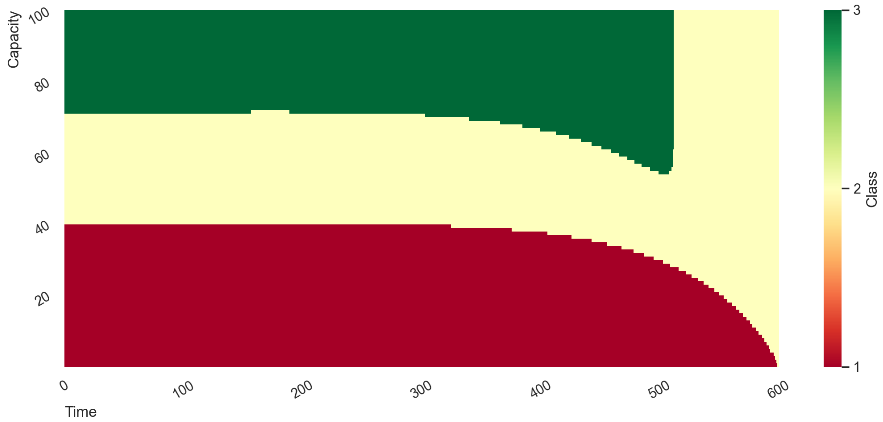

Figure 1: Optimal policy

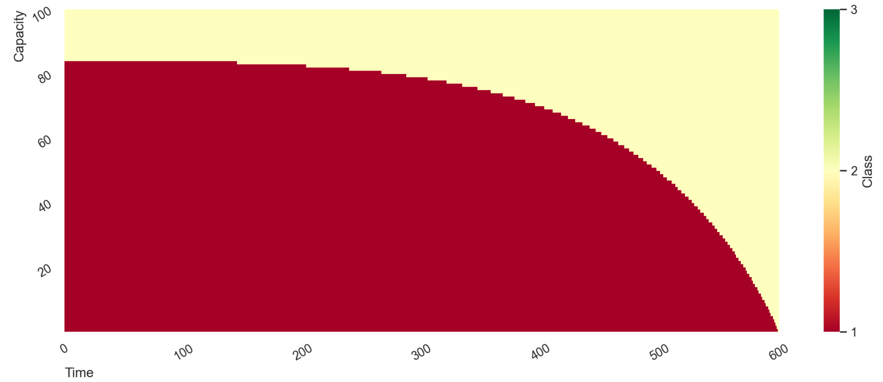

Figure 2: Optimal policy with constraint that price cannot go down

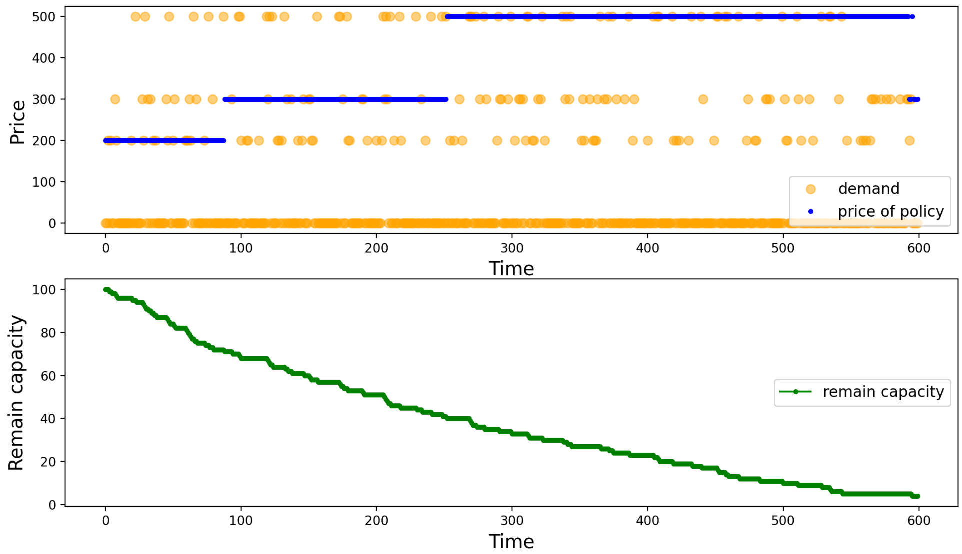

Figure 3: Simulation over time without constraint

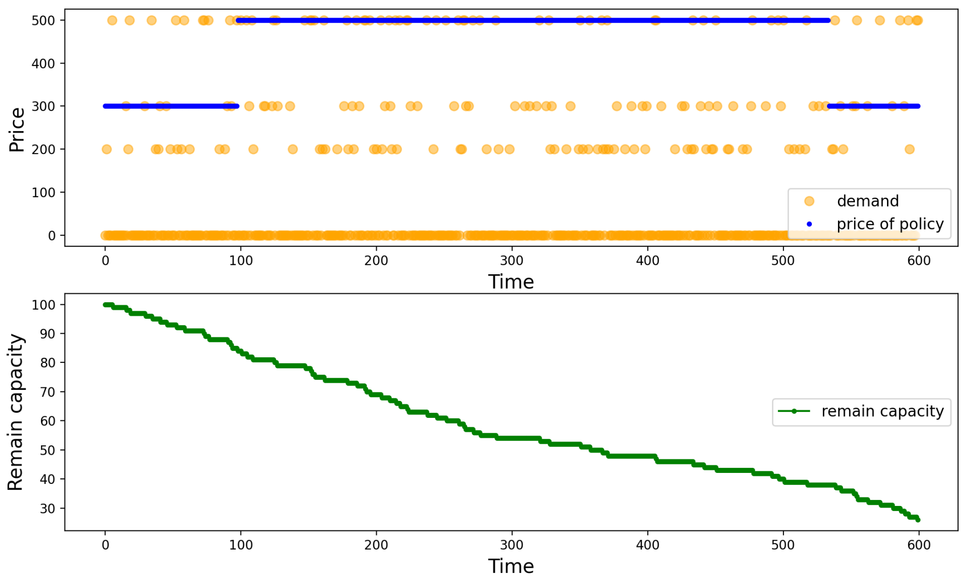

Figure 4: Simulation over time with constraint that price cannot go down