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# Airline Ticket Pricing

## Introduction

As anyone that has traveled by airplane can attest to, airline ticket prices are in a constant state of flux. For most consumers, the most apparent factors that influence airline prices include: the amount of distance traveled, the popularity of the air route (e.g. NY to LA vs. CHI to SF), the number of days before departure, and socio-political factors (e.g. war, pandemics, travel ban, etc…) specific to the arrival and departure locations. Considering these factors, consumers have some sense of what a reasonable price should be. And these "reasonable" prices are determined by the airline companies that set them.

For our project, we wanted to try and model the pricing strategy that an airline company would use for a given flight in order to see how reasonable prices are determined.

## Our Approach

Our model considers pricing a direct flight from Chicago, IL, USA to Monterrey, Mexico on a Wednesday. Through some research, we determined that the seating capacity for a Boeing-737, the most commonly used airplane for relatively short international flights, is around 220. Thus, we chose 220 as the maximum number of seats on the flight. We also chose 7 days as the maximum number of days before departure when customers would start buying tickets.

Our pricing strategy is modeled as a Markov Decision Process, where each state includes the number of days left to departure and the number of seats left in intervals of 10 seats on the flight:

$State\ I = \{\#\ of\ days\ before\ departure,\ \#\ of\ seats\ left\}$

The actions taken at each state are drawn from the following set of prices ($): {300, 400, 500, 600, 700, 800}.

*Action k* = {300, 400, 500, 600, 700, 800}

The number of people that are interested in buying tickets on a given day was modeled as a random variable with a Poisson distribution of mean ($\lambda$) equal to the total number of seats divided by the total number of days in the model. In other words, we assumed that the average number of people interested in buying a ticket was constant every day. We also created a discrete probability distribution function for the chance that a customer was willing to pay a given price.

$\lambda$ = *total # of seats/ maximum # of days left before departure* = 220 / 7 = 31.4

*Number of people interested in buying a ticket* = N ~ Poisson($\lambda$)

q(p) = *chance that someone is willing to buy a ticket at price p* =

| Price | 800.00 | 700.00 | 600.00 | 500.00 | 400.00 | 300.00 |
|---|---|---|---|---|---|---|
| Probability | 0.09 | 0.12 | 0.16 | 0.18 | 0.21 | 0.24 |

*Number of people that buy a ticket on a given day at a given price* = Np ~ Poisson ($\lambda$ * q(p))

The reward or revenue function for a given state and price was simply the price multiplied with the expected number of people buying tickets:

$R(I, k) = p * E[Np] = p * \lambda * q(p)$

The transition probabilities were calculated by finding the value of the Poisson distribution function for the number of seats sold during a given state transition:

P(j | I, k) = P( Poisson ($\lambda$) = (*#of seats left in j*) – (*# of seats left in i*))

We then formulated the Markov Decision Process as a linear program and used Excel's linear solver to find optimal constraint values for each state:

$$\min \sum_j f(i)$$

$$\text{s.t. } f(i) - R(i,k) + \sum_j P(j|i,k) * f(j) \text{ for all } i,k \geq 0$$

We made our pricing decisions by looking at which state's constraint values were 0; a value of 0 indicates that the price set for that specific constraint provides the optimal amount of revenue for the given state.

## Results

We found that price increases occur when either there is only one day to departure or when there is a scarcity of seats. As long as there are more than 50 unsold seats left on the flight, the price should be set at the lowest in the range of prices, $300, up until the last day of departure.

On any given day before the last day, our model shows that when there are less than 50 unsold seats in the flight the price increases rapidly with respect to the decrease in the number of unsold seats. If there are between 50 and 30 seats left, the price should be increased to $400; between 30 and 20 seats left, the price should increase further to $500; between 20 and 10 seats left, the price should increase further still to $600; finally, if there are below 10 seats left in the flight, the price should be increased to $700.

On the last day before departure, the price should be raised from $300 to $400 as long as there are more than 50 unsold seats left on the flight. Below 50 unsold seats, and the price increases as described above except for one exception: the price increases to $500 if there are between 40 and 30 seats left. Our model also shows that setting the price to $800 doesn't provide optimal revenue for any state.

## Analysis

For the most part, the results from our model seem to be fairly intuitive. It makes sense that the price increases as the number of unsold seats decreases and as the day to departure comes closer. However, it was interesting to note how quickly the price increased as the number of unsold seats went below 50. It's hard to say whether or not airline companies increase their ticket prices at a similar rate when the number of unsold seats sinks below some level.

The fact that the model found that setting the price to $800 never provided optimal revenue shows that $800, as one would expect, is an "unreasonable" price. In order to confirm this, we wanted to see if increasing the granularity in the number of seats left from intervals of 10 seats to simply one seat decreases would give us conditions where setting the price to $800 would make sense; however, due to the computational constraints of Excel's solver, we weren't able to compute an answer. Similarly, increasing the maximum amount of days before departure wasn't computational possible. The failed attempts to accomplish this and the evolution of our linear program can be seen in the extra sheets of our Model's Excel document named Try 1, Try 2, and Try 3.

If we were to further develop this linear program, we would try to consider changing the way we estimated the customer's willingness to pay. For our estimate of this probability, we considered that the willingness to pay for each customer depended only on the price.  A better model would be one that also considers the days left until departure, where the closer it is to the deadline, the more desperate the customer is to buy the ticket. We could include this in our model by using two separate probabilities or possibly combine them in some way. This change in our model would make it better approximate reality.