Developing a Machine Learning Dynamic Pricing Algorithm from Historical Data on Movie Tickets and Using it to Acquire Optimal Ticket Prices

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ABSTRACT

Watching a movie at a theater is meant to be an enjoyable experience for the customer. No moviegoer should have to pay a high price for tickets just to have an unsatisfactory experience. Whether it's the low quality of the theater, the fact that only bad seats are available, or only non-optimal hours of the movie showing, no person would want to pay for tickets under these conditions. Therefore, my project is aims to use machine learning through linear/logistic regression to develop a dynamic pricing algorithm for optimal ticket prices. Implementing dynamic pricing in the movie industry will determine a price for movie tickets that will be beneficial for both sides. I gathered historical data on movie ticket prices over history, stored them in secure databases and then used machine learning to find a trend that can factor into the dynamic pricing algorithm. These prices that are obtained from the algorithm should lead to greater customer satisfaction. This satisfaction was measured by collecting data from a sample of people for their preference of price. The results led to the human test subjects to choose the prices from the algorithm over current ticket prices. Future work still needs to be made in order to improve on the algorithm but the potential and interest was there. Then, movie theaters will use this algorithm to offer ticket pricing that will lead to an increase in revenue and an increase in customer satisfaction.

1 Introduction

Imagine you are going to a new movie and you purchase your tickets ahead of time. This theater, however, does not ask you to pick the seats you wish to purchase the tickets for and so, once you arrive at the theater, all the seats are taken except for the front row. Now, you have to watch the entire movie with an uncomfortable seat and you still paid the same as the other customers, who enjoyed the movie comfortably. There could be many different conditions that could lead to an unsatisfactory experience at the theater. It could be the low quality of the theater, it could be the fact that only bad/undesirable seats are available, or it could be that the movie is only shown during non-optimal hours of the day (during usual work hours, 9-5). Regardless of which reason, no person would want to pay for tickets under these conditions or would pay for tickets with less enthusiasm.

As of right now, the movie theaters around the United States do not have an efficient solution to not selling every ticket for a movie. These theaters offer every ticket for a certain movie at the same price regardless of the unfavorable conditions that were mentioned before. For instance, every seat in the theater would have the same price for that certain movie. Similarly, the ticket price of the movie would be the same regardless of the time of the showing. These theaters just expect customers to pay whatever price they offer for the movies and they do not care about how many actual tickets are sold then. There is no solution taken to try and sell more tickets at those unfavorable times or at low quality theaters. Customers just wait for evening/night times for movies and only purchase tickets if any good seats are available and the quality of the movie theater is welcoming.

Now, suppose that the theater sold those bad seats for a cheaper price. Then maybe the customers would not consider these tickets or conditions to be such an inconvenience. Sure, they would not get the seat or would have to watch the movie at a time that they do not prefer, etc. but it would make them happier because they are paying less than people who did get lucky in regards to these conditions. This is a form of dynamic pricing. It was first introduced by American Airlines in 1980 and is now used in several fields in society (Kampakis, 2018). Dynamic pricing is a strategy where prices for a certain product continuously adjusts depending on real-time supply and demand. These prices can tend to vary depending on several different variables. It is an ideal strategy to factor in several issues that are associated with the movie ticket purchase. The dynamic pricing method will account for where a seat is located, how the quality of the theater is, what time the movie is showing, etc. I will be using this idea of dynamic pricing to fix the aforementioned problem with movie ticket pricing with a machine learning algorithm.

2 Background

When it comes to purchasing movie tickets, there has been no overall trend in the prices for the past 70 years. Even adjusting for inflation, the average price of a movie ticket has stayed around 8 or 9 dollars over the last 50 years (Webster, 2021). But, after focusing on the most recent decades, there is a potential increase in the average price. Research was conducted on the history of movie ticket prices and there was a substantial increase in the average price from 1959 to 1969 to $9.89 (Corcoran, 2019). Since 1969, the average ticket price has tended to fluctuate between increasing and decreasing per year, yielding no overall trend when looking at the 7 decades. However, honing in on just a few years shows a likely change. The past 3 decades, from the 1990s to 2010s, showed a slight increase in the average price (Suneson, 2019). So, a solution must be found in order to avoid this potential increasing trend and satisfy the customers' need of cheap ticket prices.

One way I proposed to achieve this solution was to use dynamic pricing on historical data of movie ticket prices. In most simplest terms, dynamic pricing is trying to find the highest amount a customer will be willing to pay for a good or service (Couto, 2020). It is the abstract model of selling the same product for different prices to different groups of customers. It takes several factors associated with the exchange into account and then offers various prices that seem fair to the different customers. The goal is to maximize revenue while keeping customer satisfaction still in mind. Dynamic pricing is usually implemented in two different ways: dynamic pricing based on groups and dynamic pricing based on time (Campbell, 2020). These methods are just as the titles say. Dynamic pricing based on groups use machine learning algorithms or statistical splicing to offer various prices to different groups depending on factors like location, income, demographics, etc. Dynamic pricing based on time is just offering various prices depending on the time of the day, 6 am vs 8 pm, or the time of the month, beginning of a month vs the end. There is no better way when you compare the two ways as there are several ways to implement both strategies. My aim is to focus on several factors at once, which includes time along with seats, quality of the theater, and more.

3 Related Work

As of now, there has not been any similar systems that use dynamic pricing to obtain movie tickets. However, my idea of using dynamic pricing was implemented first by American Airlines in 1980. They realized that customers were split into two different groups: people who preferred a cheap price and people who preferred great service (Kampakis, 2018). The main idea was to use customers’ information, like search history, to get a feel of what kind of fare class the customer would prefer and how much it calculates as the max the customer would pay (Perkins, 2018). They can offer different prices and choices depending on what the customer’s information portrays them to prefer.

As mentioned in the previous section, the movie cinema industry has stayed relatively constant in their ticket prices if you look at the trend for the past 50 years. However, looking at the most recent decades, there is a slight increase in the average ticket price, but no related work has been conducted in the movie industry to display the right offers to the users. This is why I believe a dynamic pricing solution would be very useful to help customers in this exchange, and with some changes, can make prices cheaper, which has been done in the industries of airlines, hotels, and many more.

4 System Design

To execute this project in the most efficient way, there were several design decisions that had to be made. The main decision, in my opinion, was which dataset to use for the analysis and training of the machine learning algorithm. Another design decision was which machine learning model to use for the dynamic pricing algorithm. Finally, the last project decision was for how to measure customer satisfaction after obtaining a ticket price from the algorithm.

4.1 Acquiring Datasets

Since this is a machine learning project at its core, getting accurate and reliable datasets is the first priority. The main objective of this project was to analyze historical data on movie ticket prices so clearly there is no way to do so without a dataset. However, finding a good dataset was not an easy task. At first, my goal was to find a dataset that includes movie ticket prices, the times of the showing, seat number, and other factors that I mentioned earlier would contribute heavily to a ticket price prediction. After researching many sites on Google, Kaggle, and other sources, I could not find any dataset that included all the factors that I had wanted to examine. I finally decided to settle for a somewhat reliable dataset that I found on Kaggle (Mobius, 2020). This dataset included ticket price, the time of the movie, and the ticket sales at that time. The formatting of the data was not ideal as the numbers were not to scale and some units were missing as well, especially for the prices and times. But, I was able to modify the data after inspecting the dataset and the values entered in the columns. After updating the columns of the dataset with scaled values and units of measurement, I considered the dataset as valid to be analyzed for a machine learning model.

4.2 The ML Model and Factors To Test

Now that a dataset has been found, an ideal machine learning model must be chosen to evaluate the data. The models that came to my mind were linear regression and potentially logistic regression (Shin, 2020). I believe both would be good methods to use given two sets of data to focus on. For instance, looking at the time a ticket of the movie and the number of tickets sold would be a great time to use either regression model to get a trend or prediction.

Now, I had to figure out which movie factors would I test for these ML models. At first, I realized using the time a movie is shown was not entirely enough for good dynamic pricing as it would just be standard pricing seen in several industries. A better measure of dynamic pricing based on time would be to factor in the time a ticket is purchased rather than the showing. This way, if a ticket is purchased well in advance of the showing or if the ticket was purchased a few moments before the showing, the price would change.

The issue with this is would you make the tickets cheaper or more expensive for both cases? It makes sense that a person should have to pay more if they try to purchase tickets last minute, but what if there are many open seats available right before the movie showing? Then, they can offer these tickets at cheaper prices to fill up the seats. In the opposite case, if theaters offer cheaper prices just to fill up open seats last minute, people will just wait until the prices are reduced to purchase.

Another example is concerning a newly released movie's popularity. It makes sense to have the price be cheaper if you purchase the tickets in advance but if the movie has a very high popularity, theaters would not have the price go down since the demand to purchase tickets is there regardless of price.

In this case, my goal would be to analyze when a ticket is purchased in comparison to the movie time showing (ex: 7 days before the showing time) and see the ticket prices and the amount of ticket sales. This would let me see if ticket prices changed over the time before the movie and if there was a rise in sales for certain times before the movie. In the same sense, I also want to see the capacity of certain movies to see if there are many open seats, and whether a cheaper price was offered last minute and purchased. This would show if offering cheap tickets right before the showing would lead to more revenue for theaters and in turn let customers watch movies for cheap. Another factor I want to observe is the popularity of a movie and whether the ticket price and amount of ticket sales was ever changed over time.

I decided to settle on linear regression for the machine learning model and have several linear best lines of fits for those factors above. I would use the actual linear regression models for the time a ticket is purchased and then use the popularity of a movie to separate the movies into which equation to use, to get the optimal price for purchasing tickets. For instance, if a movie is considered popular or has a rating of 4 or above, then it would not take the time into consideration and would just focus on other factors. In contrast, if the movie is not popular, then I would use the equation for time letting cheaper last minute prices and cheaper early purchased tickets.

Unfortunately, the dataset I found did not include these factors mentioned above, and only included the time of the movie showing. So I decided to settle on using linear regression for the machine learning model, focusing on the showing time for movies vs ticket price. Finding the best line of fit for a specific two columns of data would give me the general trend of those factors. Then, I would use the equation from this correlation to help formulate an overall algorithm, after gaining access to more factors from other datasets, to give an optimal ticket price.

4.3 Measurement of Customer Satisfaction

After the dynamic pricing algorithm has been developed, I will get prices using it. I will input the same factor values for current movie showings and see if customers would either pay the amount my algorithm offers for a movie ticket or if they would pay the original matinee price. So, in order to measure this customer satisfaction value, I will be collecting data from a sample of people over whether they prefer the dynamic pricing algorithm price or the original price. With this implementation, I would now have to obtain an IRB approval for this project.

An IRB approval is granted by a group of officials called the Institutional Review Board, or IRB board. This board has the authority to approve, modify, or reject research involving human subjects (FDA, 1998). Because I am now collecting data from human subjects on whether or not they prefer the algorithm price, I would need an IRB approval. Given the very limited and low risk task that I am asking the human subjects to perform, I believe that an IRB approval would be very easy to obtain for my project. Due to time constraints, I was not able to be granted IRB approval. Future work on this project, I will need to acquire IRB approval. If the customer satisfaction data showcases that my dynamic pricing algorithm prices were preferred, then my project would be ample evidence that implementing dynamic pricing for theaters will be a success.

5 Procedure

A procedure for the stakeholders and customers to execute this project is simple. The stakeholders in this case are the companies of movie theaters who are offering the ticket prices for movies. They would use the dynamic pricing algorithm behind the scenes to offer an ideal price for a movie ticket based on the factors associated with that particular movie ticket (timing, seats, etc.). The customers would not directly use the dynamic pricing algorithm, but, their choice of one ticket over another ticket would indirectly use the system.

6 Results

Given the limited dataset I had, the process I took was scanning the data and then performing a machine learning approach on the available factors that I believed should factor into ticket prices the most.

6.1 Graphing Show Time vs Ticket Price

I decided to analyze the correlation between the show time of a movie (what time in the day the movie is the movie being shown, ex: 4 pm) and the ticket price. I grouped all the data by the show time, based on 24 hour time, and then saw what the average ticket price was for movies that were shown at that time of day. I plotted the data to see if there was a linear trend between the show time and the ticket price. The graph is below in Figure 1.

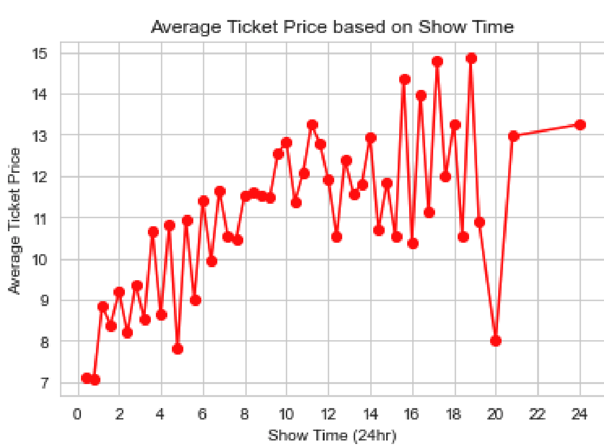

Figure 1: **Graphing the average ticket price based on the show time for a multitude of movies.**

6.2 Executing Linear Regression

The graph in Figure 1 was good evidence for the linear regression model to work. There looks to be an almost linear trend between the show time and the ticket price, besides a few outliers. I then began the linear regression technique on this data using the ordinary least squares (OLS) method. The goal was to find alpha and beta values to plug in to the equation,

$$y = \alpha + \beta * X \tag{1}$$

First, I calculated the mean of both the X, show time, and Y, ticket price, variables in order to estimate y. With these values, I found the covariance of the X and y and the variance of X, which are needed to calculate the alpha and beta values. The beta value was calculated from the sum of all the covariance of X and y values divided by the sum of all the variance of X values. The alpha value was from the mean of y subtracted by the product of the beta value and the mean of X. After all these steps, I found my alpha and beta values and was able to find the equation of the line of best fit (Shin, 2019). The equation to estimate the ticket price from the show time was,

$$y = 7.5769 + 0.3318 * X \tag{2}$$

6.3 Dynamic Pricing Algorithm Prices vs Actual Prices

Now that an equation was found, I implemented dynamic pricing and compared the prices given for current movies using my algorithm to their original ticket prices. I looked up ticket prices for 2 different movies: *Godzilla vs Kong* and *Mortal Kombat*. I found the price for these 2 movies at 3 times spread out throughout the day.

The first test was for the movie, *Godzilla vs Kong*. The ticket prices for this movie were: $11.60 at 11:00 am, $14.65 at 4:00 pm, and $14.65 at 10:20 pm. I then input these times as a 24 hour time format into the equation to find ticket prices, X = 11, 16, and 22.3. The dynamic pricing algorithm prices for this movie at the same times were: $11.23 at 11:00 am, $12.89 at 4:00 pm, and $14.98 at 10:20 pm.

The next movie to test was, *Mortal Kombat*. The ticket prices for this movie were: $11.60 at 11:20 am, $14.65 at 4:20 pm, and $14.65 at 10:00 pm. Same as before, I input these times into the equation to find ticket prices, X = 11.33, 16.33, and 22. The dynamic pricing algorithm prices for this movie at the same times were: $11.33 at 11:20 am, $12.99 at 4:20 pm, and $14.88 at 10:00 pm.

From these results, my dynamic pricing algorithm offered cheaper prices for early to afternoon times for movies as opposed to the original prices. However, for the late movie showings, the algorithm prices cost more than the original price. This is something I believe can be accounted for with more data to use to train the algorithm and get better prices for the customers through dynamic pricing.

6.4 **Testing the Algorithm Price on Test Customers and Getting their Preference**

The dynamic pricing algorithm gave prices for 2 movies given the time of the movie showing, so I used these results to measure customer satisfaction with these dynamic pricing algorithm prices. I collected data from 8 individual human test subjects on what their choice was between the original prices for the two movies or the prices given from the linear regression equation. 6 of the "customers" preferred my dynamic pricing ticket prices over the original prices as they were cheaper during the day and afternoon. But, the other 2 looked at the bigger picture of the dynamic pricing algorithm and noticed that tickets would become much more expensive for late movie showings, especially for movies that are not considered blockbusters. These 2 believed more data is needed to truly be able to implement this dynamic pricing algorithm over the current prices that are used. They did support the idea if the algorithm was trained more however. All in all, these results gave great feedback with a 75% satisfaction rate and with more datasets and training, I believe I can obtain the last 25% as well.

7 **Conclusion**

In conclusion, the dynamic pricing method of using a machine learning algorithm through linear regression is a solution that has high potential. The results showcased that my dynamic algorithm was able to offer cheaper prices for movies when they were in early and afternoon times of the day. These are usually times when total ticket sales are low as evidenced by the data. The majority of the 8 human subjects preferred the price given from the dynamic pricing algorithm as opposed to the original prices. In response to two of the test "customers" point of views, I believe it is fair to conclude that my algorithm as it is right now will give expensive prices for movies at late night times, 7pm - 11pm, and would lead to very low customer satisfaction. Likewise though, the algorithm can offer really cheap prices for early morning times, 12am - 6am, which can lead to a loss of profit for the movie theater and businesses.

Regardless, this was a good start to create an overall ideal dynamic pricing algorithm. More data is needed that include the other factors I discussed in the beginning sections, such as seat location, time a ticket is purchased, popularity of the movie, and more. This will help train the algorithm to get more ideal prices than my current algorithm. For instance, the current algorithm can be modified to add in the seat location factor, popularity, and ticket purchase time. In its simplest form, the dynamic pricing algorithm will be of the form,

$$P = (a - b * T) + (S - \frac{C}{3}) * c \tag{3}$$

where P is the final ticket price, T is the time a movie ticket is purchased in days before the showing, S is the seat row #, and C is the theater capacity in rows. The coefficients, a, b, c, can be learned through linear regression from datasets containing the corresponding variables. If the popularity of a movie is high, rating greater than 3/5, using an if statement, theaters would use an equation like this,

$$P = (10 - 0.16 * T) + (S - \frac{C}{3}) * 0.25 \tag{4}$$

If the popularity of a movie is low, 3/5 or less, theaters would use an equation like this,

$$P = (6 + 0.33 * T) + (S - \frac{C}{3}) * 0.15 \tag{5}$$

In equation 4 and 5, I used some sample coefficients for these potential equations. When the movie is popular, then the prices will increase slightly as the purchase time gets closer to the showing, hence why there is a negative coefficient in front of *T*. The opposite has been done for the movies with no popularity as the prices would be cheaper as you get to closer to the showing time, to incentivize customers to fill up the seats. The part that is added to the linear regression is utilizing the seat location in the algorithm. If the seat is in the first few rows, which is found by looking at the first 3rd of the rows in the theater (C/3), the ticket price won't have to add the extra 0.15/0.25 cost for the seat row variable. If the seat is in a good location, then the ticket price will have to pay a little more and the amount that gets added increases as the seat goes higher up. The coefficient before seat location is higher for the popular movies so that the comfortable seats are still worth more.

Overall, the current dynamic pricing approach with machine learning was a good start to creating a dynamic pricing algorithm and acquiring more access to the other factors will only improve the current algorithm. All 8 of the test "customers" enjoyed the idea and really saw dynamic pricing as a means to get ideal ticket prices as a very promising idea. With more training, a dynamic pricing algorithm using machine learning to obtain optimal ticket prices is the future for the movie cinema industry.

8 Future Work

In my eyes, there is a lot of promising work that can still be done on my project. I was at a lack of a multitude of datasets that would have helped train my machine learning algorithm for dynamic pricing. WIth more access, I could have obtained more datasets that were reliable and included data on the several factors that should factor into the movie ticket prices. Accessing data on more factors will improve my algorithm from just focusing on only the time of the movie showing to a dynamic pricing algorithm that incorporates a multitude of factors to get an ideal ticket price. As mentioned before, having access to data saying when tickets are purchased as opposed to the actual movie showing is one of these factors that would be much better for the dynamic pricing algorithm. I also believe that more test subjects when collecting data would have been helpful as well.

I also believe that testing the algorithm was not as ideal as I had hoped for currently. Due to the pandemic, the earliest times for movies I could find were 11:00 am and the latest is right before midnight, so I was not able to compare my algorithm price against actual prices for movies at those times. So, for future work, once the pandemic has ended, I would test the prices from the dynamic pricing algorithm to get a glimpse from customers if these prices are enticing enough to visit a movie at late/early morning hours.

So clearly, there is more that can be done as there is much potential in this idea. With more work, movie theaters can see that all the pros outweigh the cons of dynamic pricing and they will implement dynamic pricing.

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