Big Mountain Price Analysis Report

Kaley Wong
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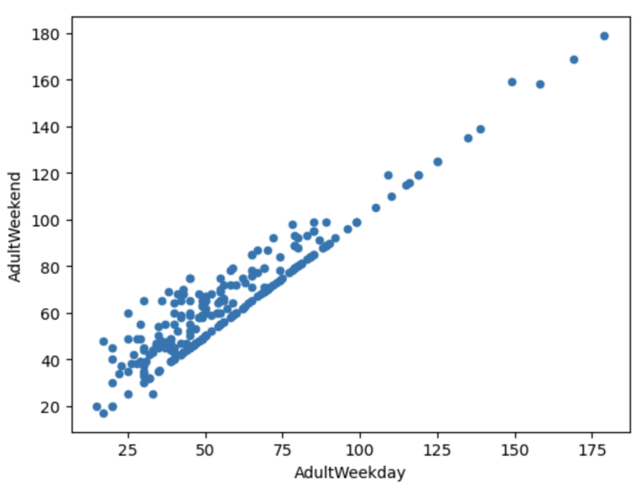
Introduction:

Big Mountain Resort, located in Montana, is a popular ski destination that offers stunning views and diverse terrains across 105 trails. With approximately 350,000 annual visitors, the resort recently invested in an additional chair lift to improve visitor distribution, increasing their operational cost by $1,540,000. The resort's business is concerned about maximizing revenue while maintaining competitiveness, the resort seeks data-driven insights to refine its pricing strategy. Through market analysis and visitor data, we will help Big Mountain Resort set an optional ticket price and identify cost-saving measures or enhancements to support revenue growth.

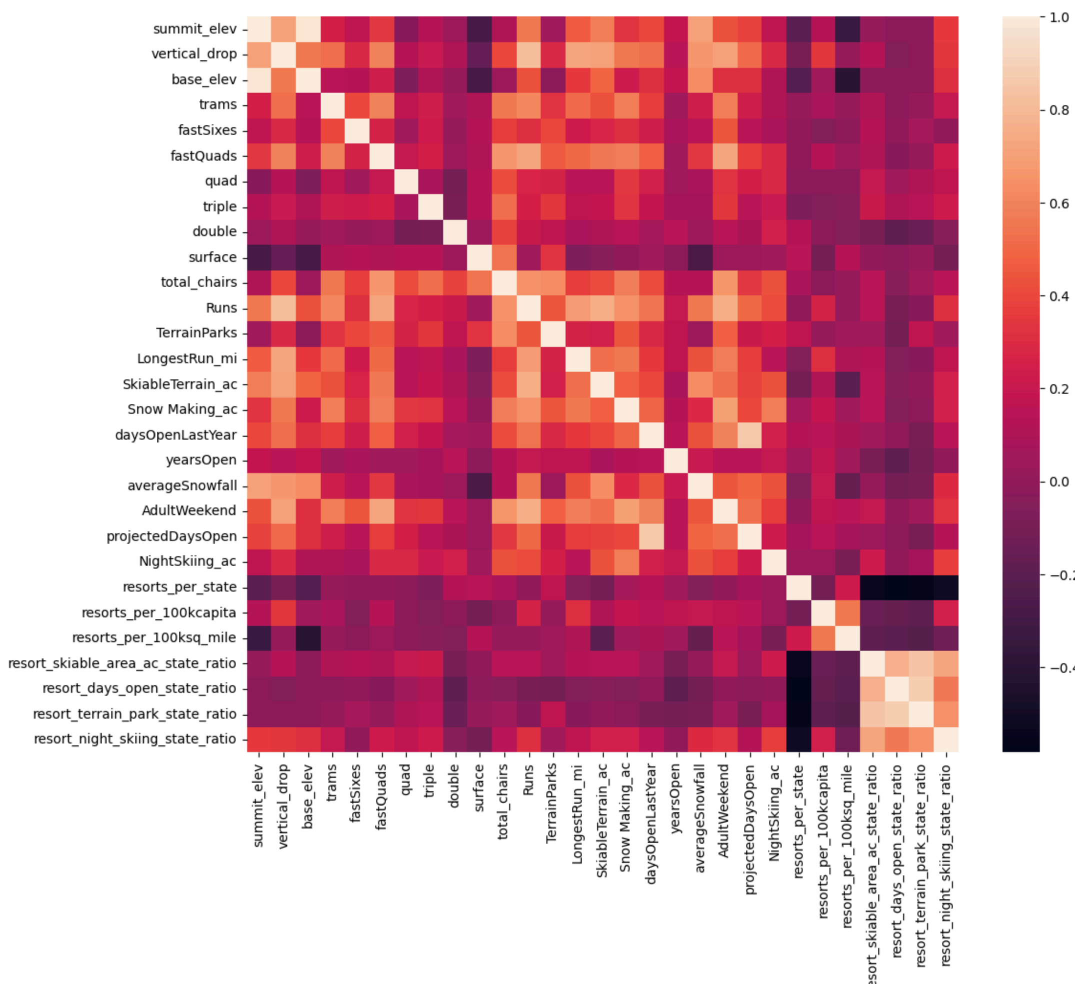
Problem:
How can we develop a pricing model that strikes a balance between competitiveness for customers and accurately reflects the value of Big Mountain Resort's facilities?

Data Wrangling:
With the data that we were provided, the most relevant features in our data set were total vertical drop, number of lifts, weekday/weekend price, and total number or runs for each resort. The feature we focused on the most on was weekday vs weekend ticket price to see if there was a clear difference between the two. We can see in the graph below, most states had the same pricing for weekday and weekend.



More specifically, we see that the distribution for weekday and weekend prices in Montana are equal. Looking more into the data, we found missing values for both weekday and weekend prices. The weekend prices have fewer missing values than weekdays, so we dropped the weekend column in the data set. We also decided to drop the fastEight column because half of the values are missing and all but the other values are zero. Once we finished cleaning our data wrangling and cleaning, we ended up with a data frame with 277 rows and 25 columns.

Exploratory Data Analysis:
To understand the data better and uncover useful insights, we need to explore patterns and trends within it. First, we looked at how the number of ski resorts in an area compares to the population and land area, but this didn't provide much useful information for Big Mountain Resort. However, it helped clarify some initial thoughts. Next, I examined how factors like vertical drop, years open, and skiable areas relate to ticket prices in each state. This required a detailed analysis, revealing that the first two factors explain most of the variation. Focusing on these, I compared them to ticket prices using a scatter plot. To better understand the relationship between price and these factors, I created a heatmap, which provides a clearer visualization of their connections.



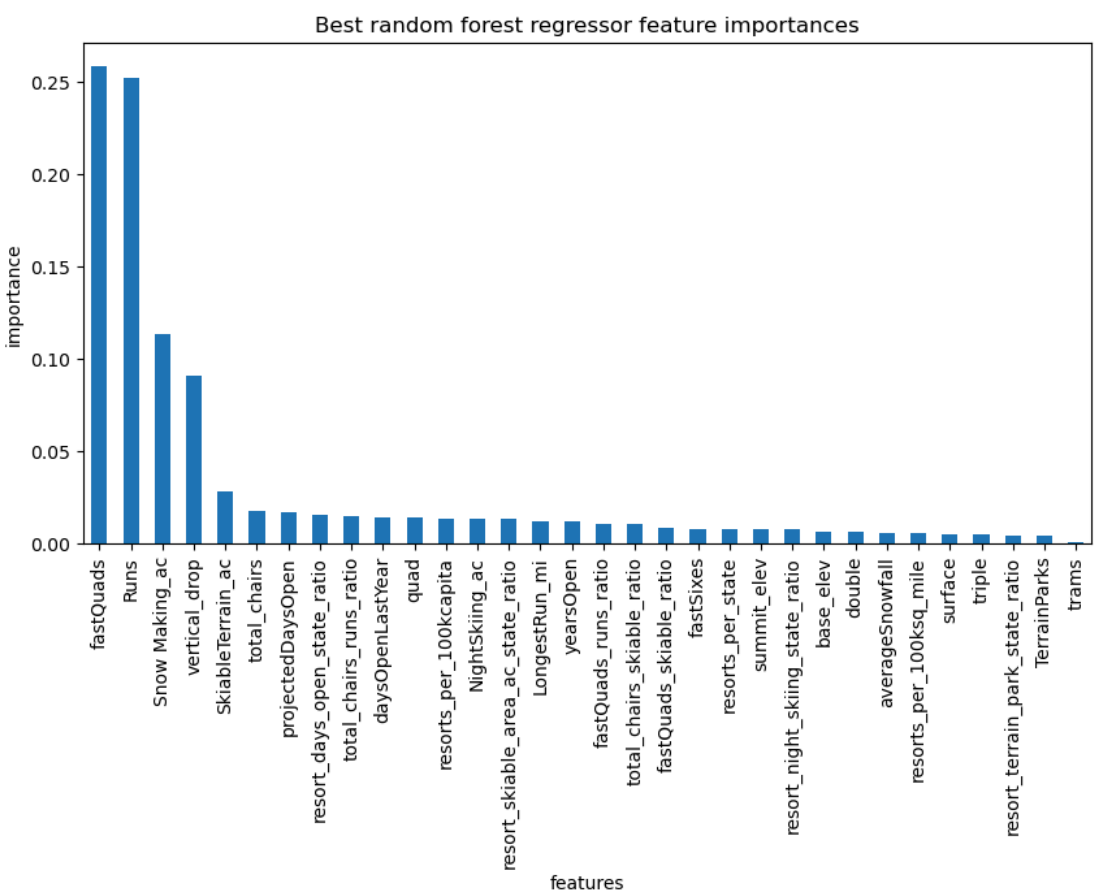
If we look at the relationships in “AdultWeekend”, the row shows that there is a clear positive correlation between fastQuads, Runs, SnowMaking_AC, and resort_night_skiing_ratios. We can use the features from above, to build a model that can help up determine a new data-based ticket price.

Processing and Training the Data:

We built several machine learning models to help predict ticket prices for our resort. The first few steps we did was split our data into a 70/30 test/train set to minimize bias in our evaluation and validation process. Following those steps, we found the approximate average ticket price to be $63.81, and we calculated the mean square error of $19, which represents that by average we would expect our ticket price to be off by $19.

The first model we created was using linear regression where we found our biggest positive features were vertical_drop, Snow Making_ac, total_chairs, and fastQuads. From our cross-validation, we found the mean absolute error was $10.50 and the mean absolute error from our test split was $11.79.

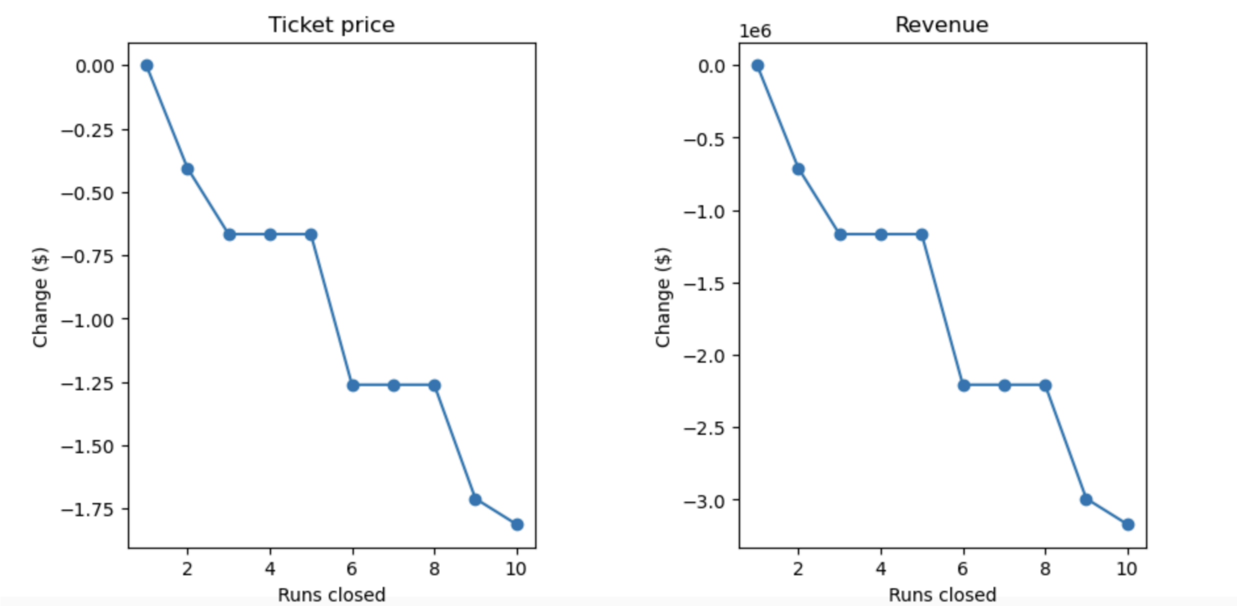
The second model we created was the random forest model where we found our top four features were fastQuads, Runs, Snow Making_ac, and vertical_drop. From our cross validation, we found the mean absolute error was $9.64 and the mean absolute errorAE from our test split was $9.54.



Comparing the two methods above, we should use the random forest model since it is more consistent and shows less variability since we have a lower cross-validation mean absolute error by almost $1.

Modeling:

The first potential scenario we came across was to permanently shut down 10 of the lease used runs. By modeling this, we saw that closing 1 run does not make a difference, closing 2 or 3 runs lowers the ticket price and as well as the revenue. But if the resort is planning to drop 3 runs, might as well close 4 or 5 runs since there wouldn't be any further loss in ticket price.



The second potential scenario is to add a run, increase the vertical drop by 150 feet and install an additional chair lift. With this, we see that these changes support an increase of price tickets by about 2 dollars, with an annual revenue of 3474638 dollars. We also added 2 acres of snow making to see if this would make the situation worse or better, and with the addition of 2 acres of snow, it makes no difference from the 3 previous features alone.

The Big Mountain tickets currently cost $81per ticket, and our model predicted we should be charging $95.87, which is about a $14 difference. Our expected mean absolute error was $10.39, which we can interpret as there is still room to increase the price of tickets.

Conclusion:

Big Mountain Resort is currently undercharging for the range of services they provide. Based on this analysis, they excel in several key factors that influence pricing, suggesting they should increase their ticket price by at least $10. Additionally, the resort could save significant costs by not opening all of their runs simultaneously. Despite receiving 350,000 visitors annually, not every run is fully utilized every day, leading to unnecessary expenses. According to a predictive analysis using the Random Forest Model, Big Mountain Resort can keep up to 5 runs closed without experiencing a substantial decline in revenue.