Big Mountain Resort Pricing Analysis Report

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Objective

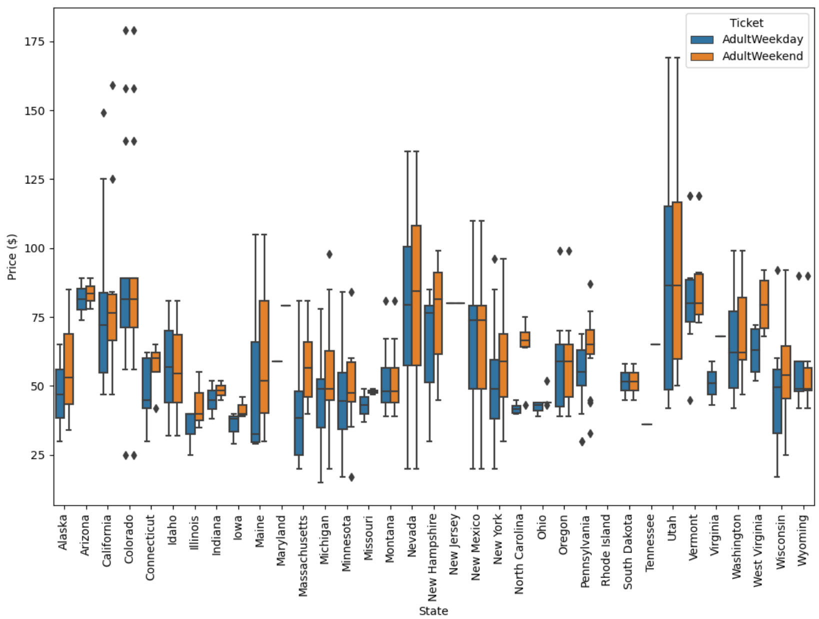
Big Mountain Resort is a prominent ski resort in Montana, that serves about 350K visitors per year for all ski/snowboard levels. Currently, the resort is pricing their premium tickets above market, and recently installed chair lifts costing $1.5M to accommodate the visitors. The resort is seeking guidance on optimizing ticket prices, reducing operational costs, understanding the importance of various facilities compared to others, and exploring changes to support the current or higher ticket prices.

Problem

Big Mountain Resort is seeking to increase revenue through optimizing its price strategy and facilities usage, based on data gathered from competitive resorts across the US. Is it possible for Big Mountain to increase revenue for the next season through cost-cutting measures while considering facility importance, optimizing ticket prices, and operational efficiency or expansion? How can we create a pricing model that can determine a competitive price for customers while representing the significance of the resort's facilities?

Data Wrangling

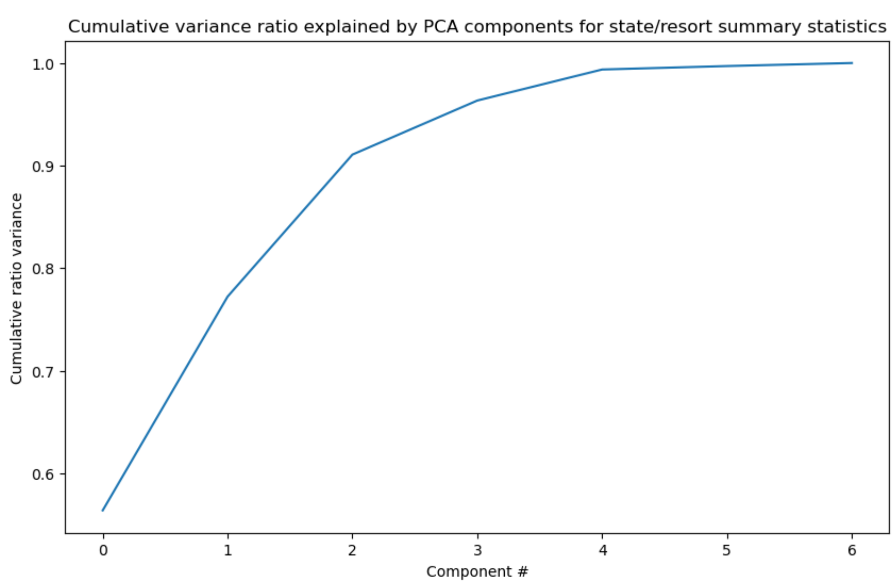
That data set has several important data fields like weekday/weekend prices, skiable terrains, total vertical drop, number of lifts, total runs, and fast quads. AdultWeekend vs AdultWeekday prices were inspected. After inspection, it was discovered 15-16% of values were missing ticket prices, and weekday prices had more values missing. Most states had a premium price much higher on weekends compared to their weekday prices, shown in the box plot below. Because of this, AdultWeekday was removed, and fastEight column was dropped since most values were null or missing.



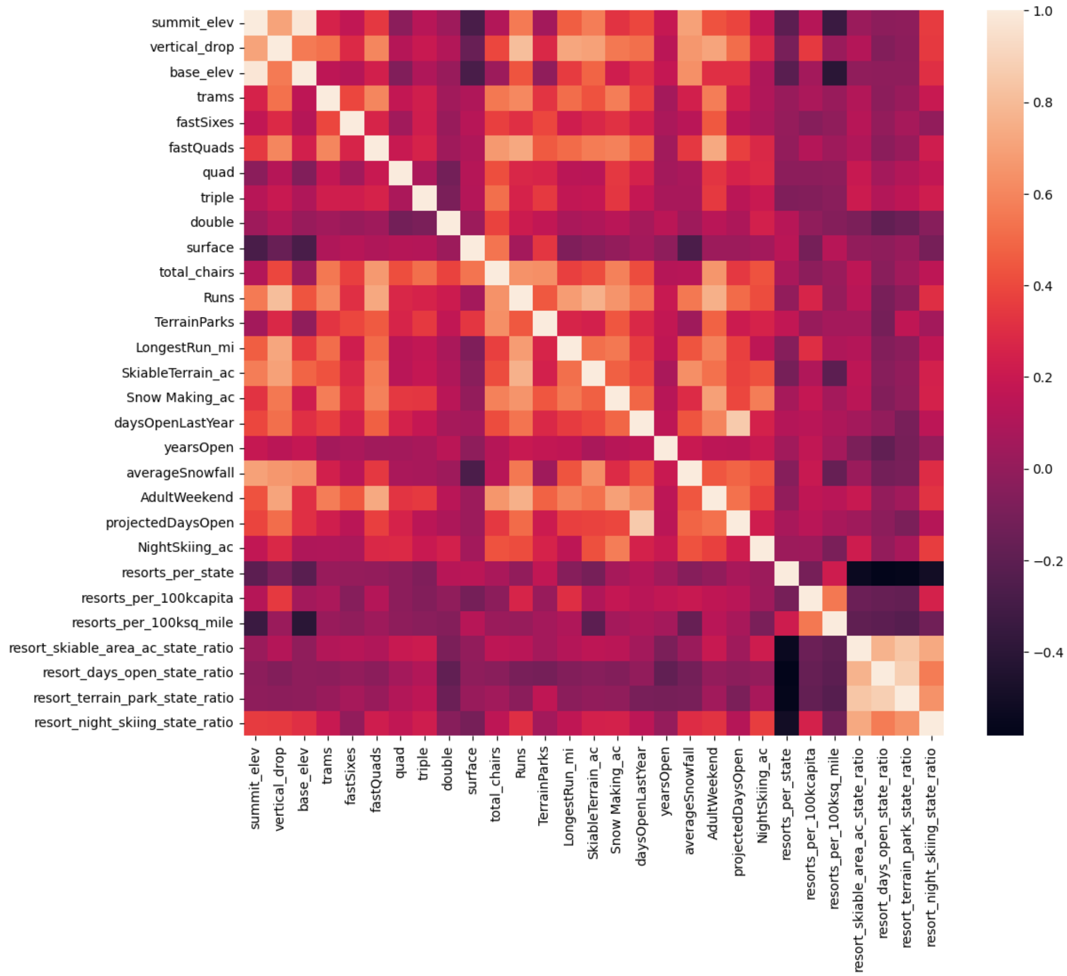
Exploratory Data Analysis

The preference for night skiing in northern/eastern states may stem from shorter daylight hours, prompting the extension of skiing days. The comparison of states does not require absolute size; rather, it focuses on the ratio of resorts serving the given population and area. Analyzing the number of resorts per 100k population and per 100k square miles eliminates larger states. The process involves scaling the data to normalize it, bringing it to a mean of 0.

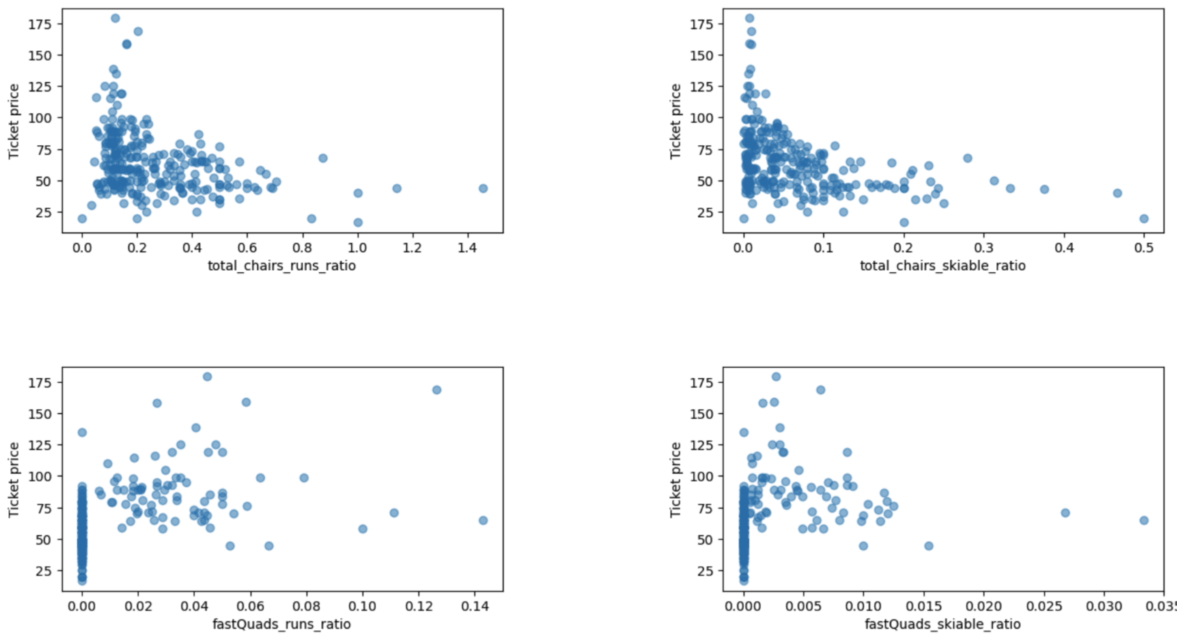
Shifting focus to ticket prices, Principal Component Analysis (PCA) provided summary statistics for state/resort differentiation, enhancing insights into weekend ticket prices.



A correlation heatmap identified strong correlations, such as summit/base elevation, night skiing, and resorts per capita. Exploring the "AdultWeekend" field revealed correlations with factors like snow making and runs.



Scatter plots highlighted significant correlations, including vertical drop and projected days open. Lastly, the correlation between ticket prices and chair/runs, skiable areas, along with having a quad lift, could impact ticket prices positively.



Pre-Processing and Training Data

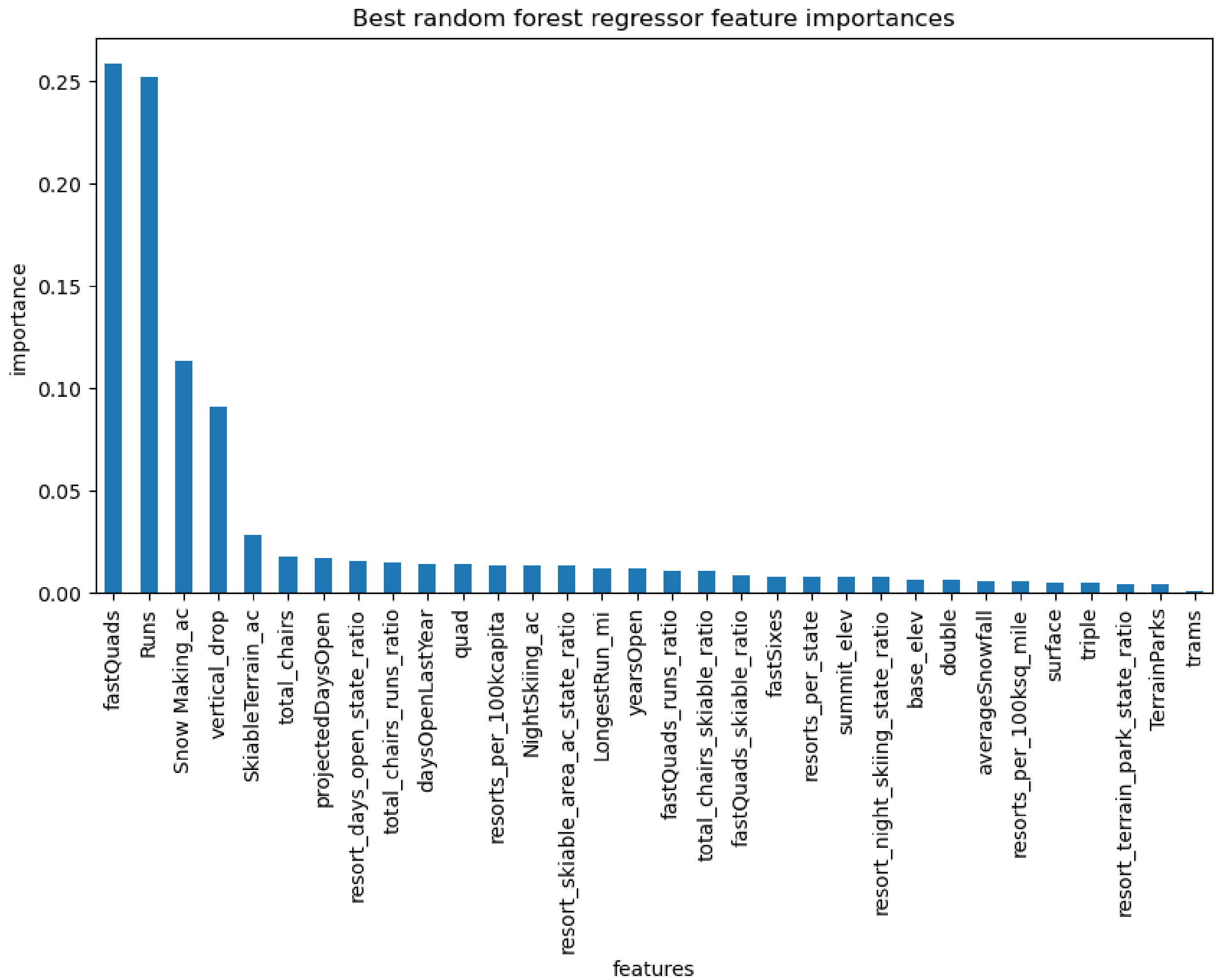
The analysis begins by using the mean value as the simplest model, serving as a baseline, and implementing a 70/30 Train/Test Split to minimize biases or overfitting. Comparing the mean to sklearn's DummyRegressor using metrics, particularly R2 (coefficient of determination), is important.

R2 measures the proportion of variance in the dependent variable predicted by the model. The baseline model predicts the mean (R2 = 0), while a perfect model has no residual error (R2 = 1). Metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE) provide insights into the difference between predicted and actual values.

The analysis using the mean as a predictor resulted in equaling 0, as expected. While R2 explains variance, MAE and MSE offer information on the proximity of predictions to true values.

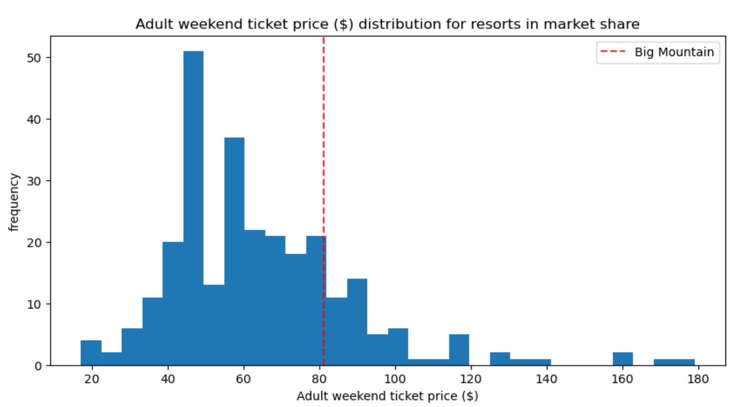
The mean did not support since Absolute Error was $19, which is too high. With the regression performed, the result was $9, however, additional steps could be taken to refine the results.

Moreover, pipelines were created for both linear regression and a random regressor, with the latter outperforming the former. Cross-validation showed significant variability, leading to the application of best_params, which revealed that only 8 features were optimal for the model. The learning_curve function was used to assess the need for the full training size, indicating that a training size of around 40 is sufficient quantity of data. The chart below identifies that 'fastQuad', 'Runs', 'Snow Making', 'vertical drop', and 'skiable terrain' are important values within the dataset.



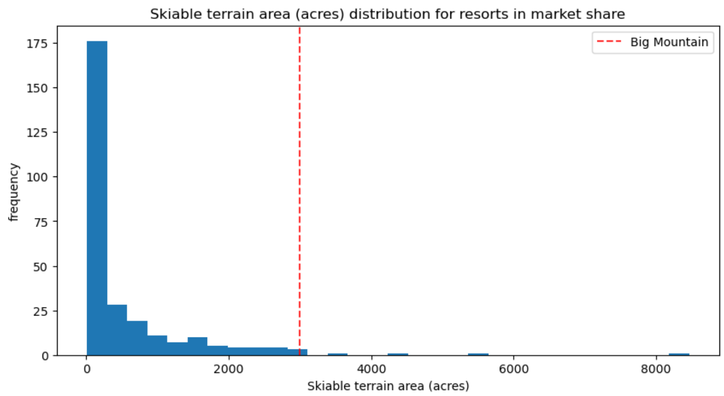
Modeling

The current price for an adult ticket is $81 and the three pricing models were tested. To create a pricing model, I used the top components and method of regression identified in the previous section. The following features are identified by the model as of positive importance: vertical_drop, snow_making, total chairs, fastQuards, runs/longest runs, trams, and skiable terrain.

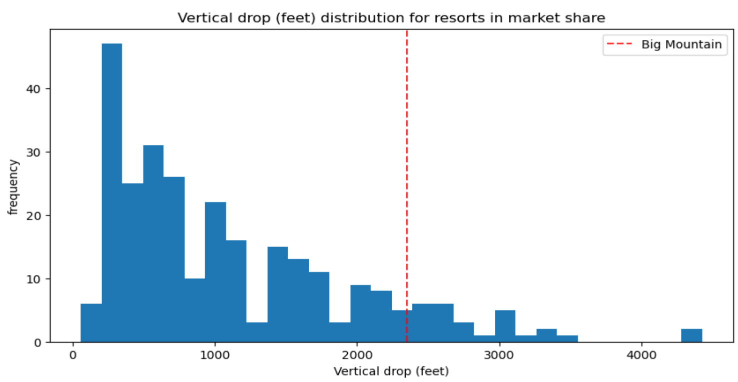


Big Mountain adult weekend price ranks competitively across resorts offering similar services.

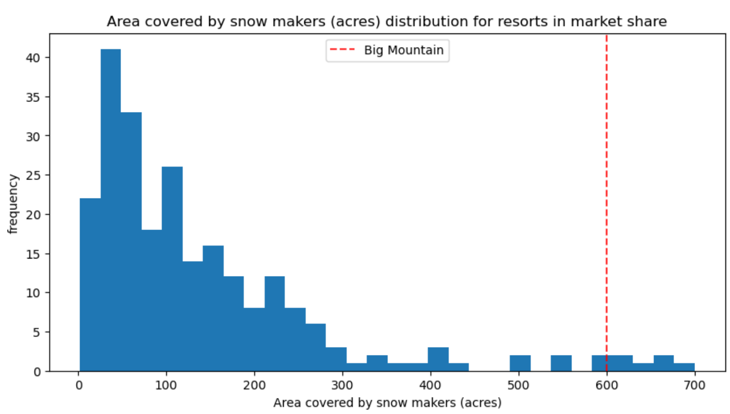
Before determining a price, the charts below explore how Big Mountain ranks across these categories:



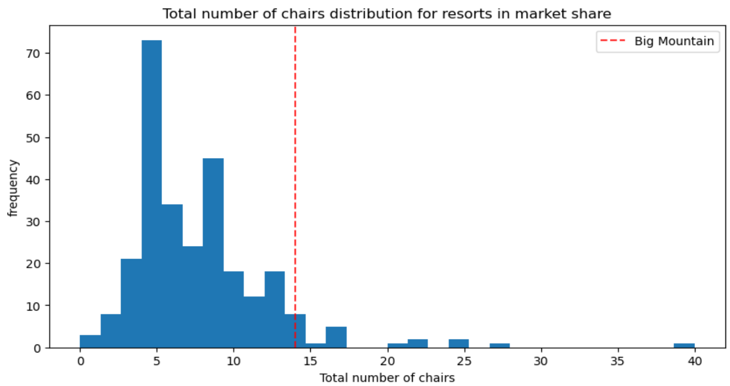
Skiable Terrain: Big Montana is amongst the resorts with the largest amount of skiable terrain.



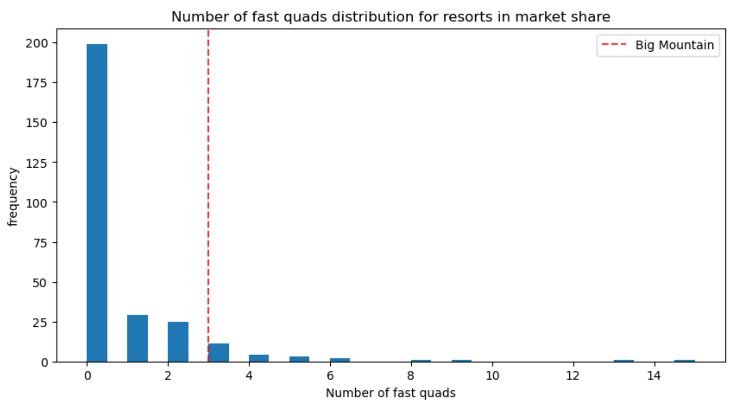
Vertical Drop: Other resorts are offering more despite Big Mountain doing well in terms of vertical drops.



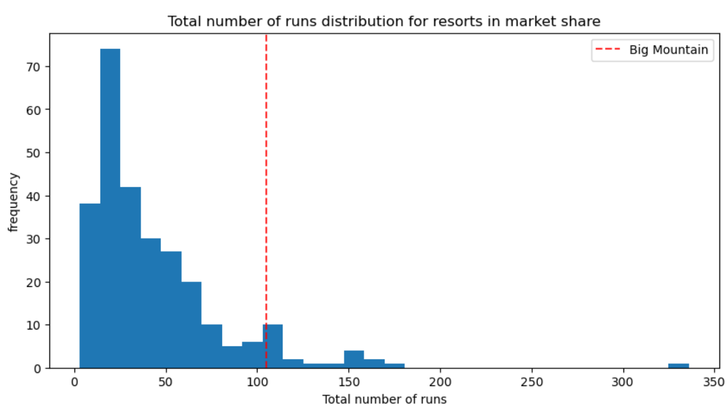
Snow Makers: Big Mountain ranks very high in the market of snow making.



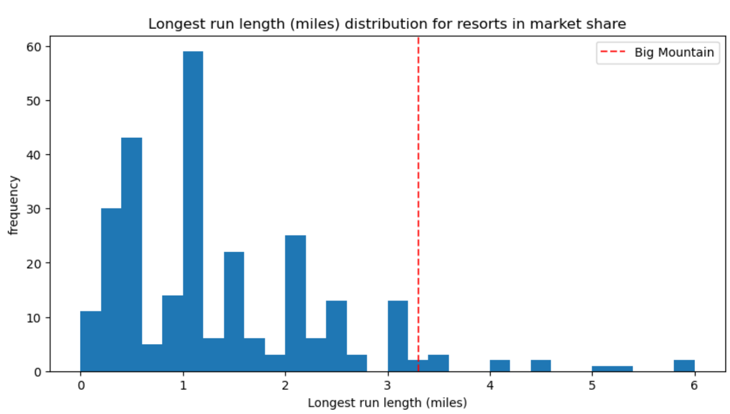
Total # of chairs: Big Mountain has amongst the highest number of total chairs.



Fast Quads: Big Mountain has 3, while most do not, despite some outliers having more the resort remains competitive.

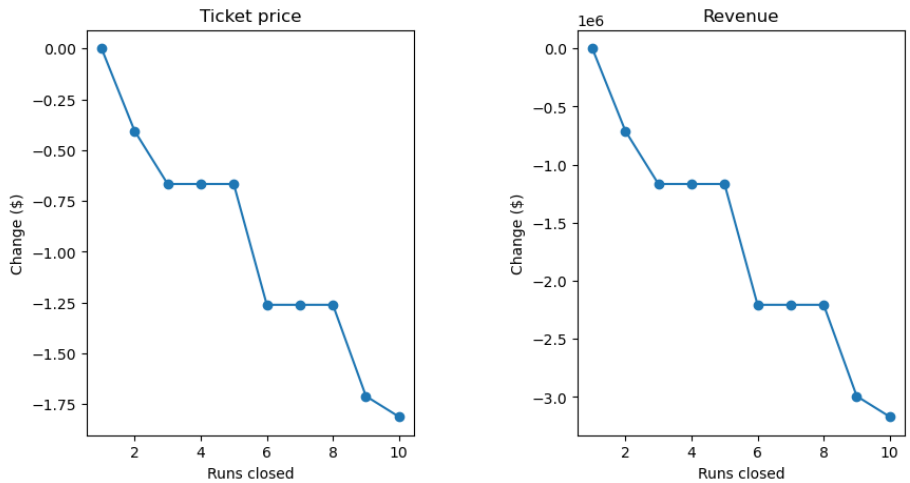


Total Runs: Big Mountain ranks fairly high, despite some resorts with more.



Total Long Runs: Big Mountain has one of the longest runs. Generally long runs are rare.

Now that we have explored some of Big Mountain's competitive geographical advantages, let’s explore the models that were tested. Closing the least-used run won't affect revenue, but shutting down runs ranked 2nd to 5th may weaken support for the current ticket price, as shown in the plot below.



The pricing model with the most positive impact anticipates a revenue increase of 3.47M dollars. This projection is based on raising the ticket price by $1.99, adding a new run 150 feet lower, and installing a new chair lift, assuming an average of 5 days of skiing for 350,000 visitors in the upcoming season. It's crucial to note that the model does not factor in additional capital and operation costs, as this information is unavailable. Adding the new chair lift is expected to increase operating costs by $1.54M.

Recommendations

This pricing model recommendation would raise the price above $83, or higher, however, this would require Big Mountain to make enhancements to the facility to support the increase. The resort price is already positioned competitively compared to other resorts offering similar amenities. Improving Big Mountain's facility to charge higher prices aims to attract more visitors, capitalizing on its geographical advantage. This strategy strengthens its competitive position in a favorable market cycle.

To enhance the model further, I would also recommend the company to gather and collect additional data from the following sources: operating cost, visitor volume across the U.S., customer market survey preferences, expectations, and willingness to pay for specific amenities and services, and continuing competitive market analysis. In addition, we could also assemble a cross-functional team of business experts to explore the model and validate the business assumptions through testing.