Balancing Ticket Prices and Resort Features for Optimal Profit

Carrie-Cate Jenkins

Big Mountain Resort is a ski resort located in Montana. Their current pricing strategy does not make the most of the facilities they offer. A new chair lift allows for better distribution of visitors across the mountain and increases this year's operating costs by $1,540,000. The resort needs data-driven strategies to cover this additional expense, increase profits, decrease costs, and plan for future investments. We used data analytics, statistical modeling, and machine learning to examine this problem and develop evidence-based business plans for Big Mountain Resort.

The data we used came from Alesha Eisen, the Database Manager at Big Mountain Ski Resort, in the form of a csv file containing information on various resorts. Originally, there were 330 observations (rows) in the dataset, one of which was Big Mountain Resort, and 27 columns, including information about each resort, its location, features, ticket prices, and more. Data cleaning resulted in a dataset with 25 columns and 277 rows and an additional dataset of summary information for resorts in each state. We examined this data to discover and analyze trends, create various statistical models to find the ticket price best supported by the data and information about changes the resort could make to increase ticket prices or decrease costs without lowering ticket prices.

The target feature for analysis was average ticket price. After looking more closely at prices by state, there did not appear to be a significant relationship. I chose the features to use for modeling by examining features that appeared to have possible correlation with ticket price: snowmaking ac, number of runs, vertical drop, number of chairs, and fast quad. I used the mean ticket price of $63.81 as a baseline with which to compare future models. Using the metrics R-squared, mean squared error, and mean absolute error, I examined how each model performed. I also used cross-validation to test the performance of each model and hyperparameter search to define the most impactful feature(s.). A linear regression model performed better than the means as it explained over 80% of the variance on the training set and over 70% on the test set. I also found that the most important feature was vertical drop followed by Snow Making_ac, (total_chairs,) fastQuads, and Runs. The linear model suggested that, on average, we'd expect to estimate a ticket price within $9 or so of the real price, which is an improvement from the within $19 that the baseline (mean) model offered. Next, I created and tested a random forest model that showed a lower mean absolute error than the previous model by almost $1 and exhibited less variability. Therefore, I determined that this was the strongest model tested. The random forest model shows that the most important features are fastQuads, followed by Runs, Snow Making_ac, vertical_drop, (and total chairs.) As the top features (parameters) overlap with those found in the linear regression model, our final model focused on these features.

When we used our model, it gives us a ticket price of $95.87 with an expected mean absolute error of $10.39. When compared to the rest of the ski resorts in the dataset, Big Mountain Resorts has better than average in nearly every feature and significantly better than average in snowmaking_ac, longest run, and skiable terrain_ac. These comparisons support the fact that the model recommends an increased ticket price. I recommend that Big Mountain Resort raise ticket prices to between $85 and $90, a $4-9 increase from their current price. The increase would add between $7,000,000 and $19,250,000 to the resort’s annual income, which would not only pay for the chair lift but also likely add opportunities for additional investments and improvements at the resort.

If the resort also wanted to decrease operating costs, our estimates show that closing one run would be acceptable without decreasing ticket price and would not reduce income, but closing any more than one would not support the current or higher ticket price. For future improvements, we found that adding one additional run and increasing the vertical drop by 150 feet would support an increase in ticket price by $1.99. Over the season, this could be expected to amount to an increase of about $3,474,638. To support these improvements, the resort would also need the resort to install another additional chair lift with the added cost of about $1,540,000. Within the first season, this would result in a net gain of about $1,934,638. If the resort also added 2 acres of snow making, it would not add further benefit. Similarly, increasing the longest run by .2 miles and adding 4 acres of snow making capability did not seem to add additional value. Therefore, I recommend adding one additional run and increasing the vertical drop by 150 feet.

Moving forward, our models and predict increase function could be used to examine the ticket price when changing any of the resort features that are in the model. As this dataset became outdated, we would need to edit the dataset and the model, but the same concepts could be used. As long as the resort could add, delete, or change data in the dataset as the values changed, and the models were edited to reflect these changes, these models could help the resort determine which features they might expand or add, how to adjust their ticket prices accordingly, and how this might effect the resort income. In this way, the resort could become as grand and profitable as its leadership could hope for.