Predicting Big Mountain Ski Resort's Fair Market Ticket Price

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1 Problem Introduction

Over the years, Big Mountain Ski Resort has grown and developed into a top-tier ski resort in the United States — yet it is not priced as such. Spurred by the addition of a new chairlift this offseason and its associated operating costs hitting the books, Big Mountain management has launched a data-driven investigation into the resort's pricing strategy to settle the matter.

As the data scientist, I sought to use data to understand which resort features can command a higher lift ticket price. I created a model to predict how Big Mountain's lift tickets should be priced according to how its amenities stack up to those of its competitors. Using this strategy, I aimed to answer the question, "Based on the resort's amenities, what should Big Mountain's ticket prices be in order to recoup the $1.54M increase in operating costs this year while keeping profit margins at or above 10%?"

2 Dataset

The dataset contains data from 330 U.S. ski resorts. The data consist of 24 quantitative measures as well as name, state, and region information for each resort. Before I could begin my analysis I cleaned the data, eliminating a category with 50% missing values and removing any entries that lacked price information since they wouldn't be useful for my analysis. I also took a look at the distributions of numerical data to check for any obvious outliers and data entry issues. I cleaned up a couple erroneous data points and felt the distributions appeared reasonable to move forward.

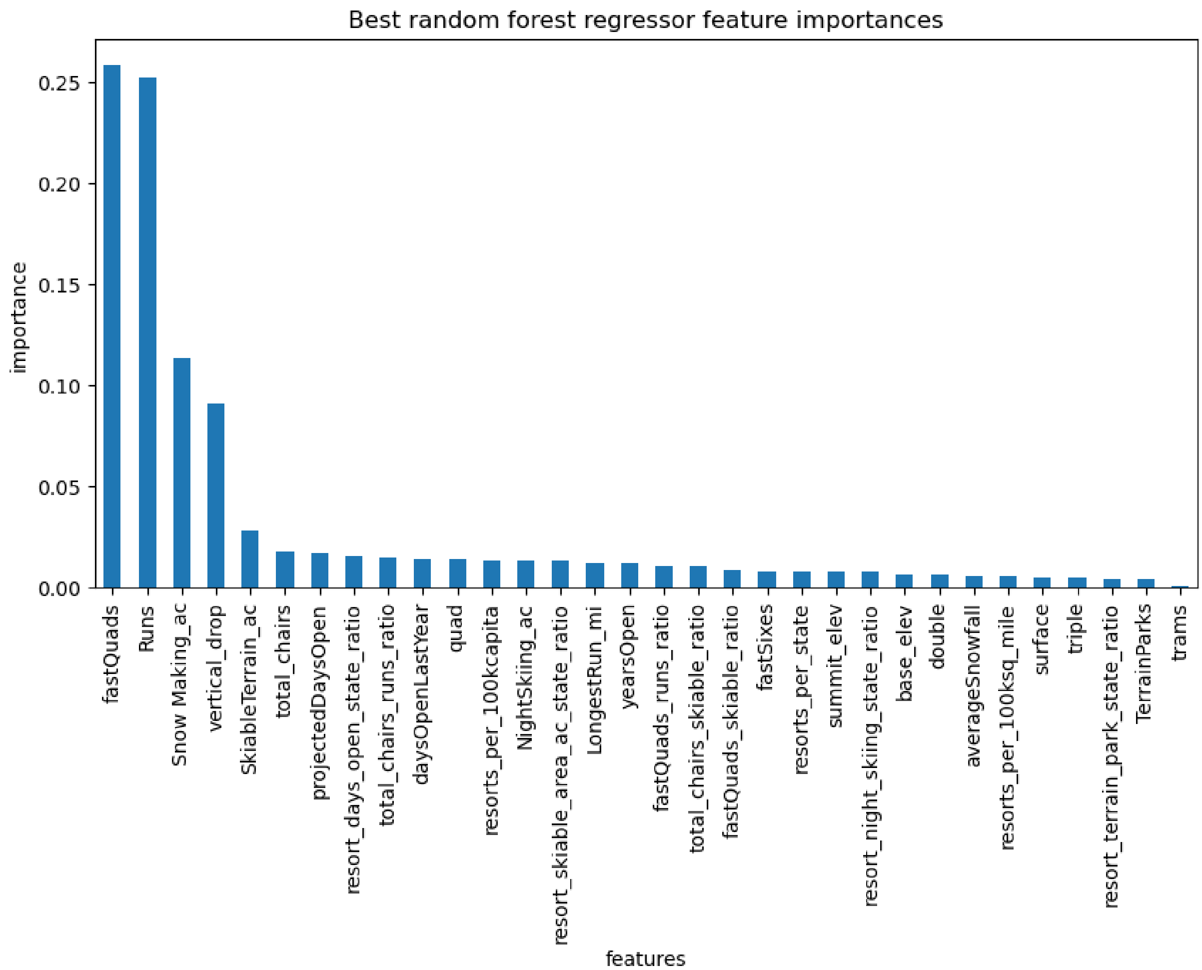
3 Exploratory Analysis

In order to determine if Big Mountain should be evaluated against all other resorts or just those in Montana, I brought in some additional state and population data. I created a number of per-state metrics, including resort density, total number of resorts, total skiable area, and total ski days. With 7 total metrics, I turned to Principal Component Analysis to explore the variance between the skiing markets in different states. I determined that there was no correlation between the state in which a resort is located and its ticket price. I moved forward in my analysis confident that I could compare all resorts in the dataset fairly, without having to account for skewed pricing in certain states.

I then looked for other patterns within the data, creating scatter plots and a heat map to examine correlations between features. The preliminary analysis seemed to show ticket price correlated more strongly with vertical drop, number of runs, number of fast quad chairs, and snow making acreage.

4 Pre-Processing and Training

I created a modeling pipeline in order to efficiently evaluate a number of strategies for pre-processing the data. I compared a linear regression model with a random forest model, using 5-fold cross-validation to optimize the parameters of each model. Ultimately, the best performing model was a random forest with median imputing, no feature scaling, and 69 estimators. As shown in the graph below, the model placed highest emphasis on the number of fast quad chairs, then the number of runs, snow making acreage, total vertical drop, and skiable terrain acreage. The rest of the features were treated fairly equally with low importance. The random forest model outperformed the linear model on the test data by about 20% with a mean absolute error of $9.54



5 Modeling

After re-fitting the model to the entirety of the ski resort data, I used the model to estimate Big Mountain's ticket price. The predicted price for Big Mountain, based on its lineup of features, is $95.87. Even accounting for a mean absolute error of $10.39 , Big Mountain certainly should raise its ticket prices in order to accurately reflect its status as a first-rate ski resort.

6 Conclusion

In a market context, this price increase makes perfect sense. Among all ski resorts in the U.S., Big Mountain ranks as follows:

- 93rd percentile for number of total runs
- 93rd percentile for number of fast quad chairs
- 97th percentile for snow making acreage
- 98th percentile for skiable terrain acreage
- 89th percentile for total vertical drop

Despite these elite characteristics, Big Mountain's ticket price is only in the 81st percentile. The resort is clearly missing out on extra revenue due to inaccurate pricing of its product.

Addressing the initial problem statement, this price increase of $14.87 would cover the $1.54M cost 16 times over. Assuming attendance is unchanged, a price increase of only $0.88 per lift ticket would cover the new operating cost. Even accounting for the maximum error, the model supported a price increase of at least $4.48, so covering the increased operating cost should negatively affect the resort's profit margins.

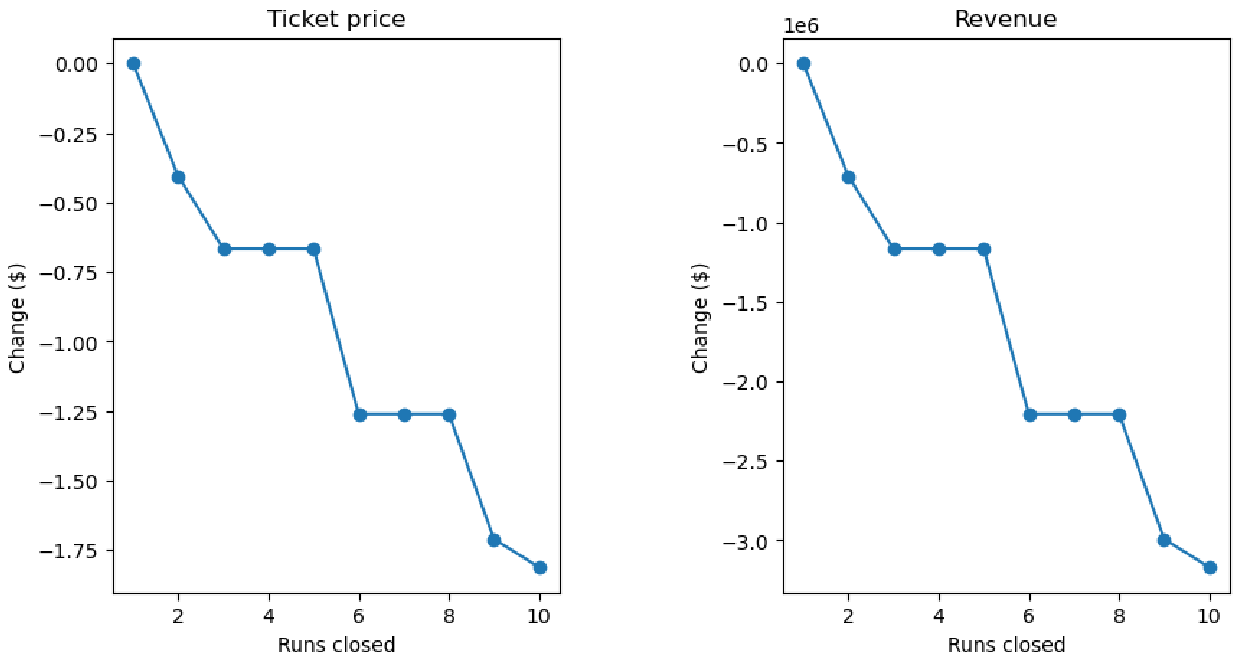
7 Future Recommendations

Big Mountain is considering a number of measures to either cut costs or increase revenue. These changes would affect the parameters that the model treated as most important. As such, I changed the parameters and used the model to predict the resulting ticket price.

One proposed change was to increase the length of the longest run to 3.5 miles, which would add 4 acres of snow making. The model did not support a price increase in response to this change, though it would undoubtedly cost money to implement. As such, this change is not recommended.

Another set of proposed changes involved adding a run beyond the bottom of the current base area. This change would necessitate an additional chairlift and would increase the total vertical drop of the resort by 150 feet. It also may require an additional 2 acres of snow making. I used the model to evaluate this change with and without snow making. The model supported the addition of the run and chairlift, showing a predicted ticket price increase of $1.99. That increase would expand out to a revenue increase of almost $3.5M over the course of the season. By contrast, the additional snow making acreage would not justify a further price increase and is not recommended unless the run is unusable without it.

The final proposed change was to close up to 10 unpopular runs, therefore saving on costs. The model showed that a single run closure should not impact ticket prices, but that further closures should correlate with a lower ticket price and therefore lower revenue. This trend is illustrated on the graphs below. Closing 10 runs corresponded to a ticket price decrease of $1.81 and a season-long revenue loss of over $300,000. It is impossible to say whether these changes would be offset by decreased operating costs without the relevant data.


Ticket price
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
−1.50
−1.75
Change ($)
2
4
6
8
10
Runs closed
Revenue
1e6
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
Change ($)
2
4
6
8
10
Runs closed