You, the leadership at Big Mountain Resort, came to us with an important question: Is the current pricing strategy of simply applying a price uplift to the average lift ticket price of surrounding resorts the right one? Or is there a chance that (as a premier resort with many features that set it apart from its local competitors) Big Mountain was under-leveraging its facilities and leaving potential Revenue on the table? This also led naturally to an additional question: If there are features which customers do care about to the degree that they justify a higher ticket price, are there other features that matter much less, and can be discontinued to achieve a sizable cost savings? These are the questions we sought to answer through our analysis.

The dataset that we used for this analysis contains a large amount of information around each of 330 ski resorts around the United States. This includes descriptive data, such as Resort Name, State, Region, and so on, as well as important numerical measures, like skiable acreage, vertical drop, and the number of lifts. The measures around which the analysis hinged, however, were the Weekday and Weekend Adult Lift Ticket Prices. We employed the following process: Clean the data, find which measures were most strongly correlated with Ticket Price, build and test a model designed to output ticket price based on a list of features, and then use that model with Big Mountain’s specific feature list to determine the highest price point that might be supported by the market.

The data cleaning process primarily involved the removal of records with null values. Unfortunately, roughly 14% of the total rows contained no ticket price data. This rendered them unhelpful to our analysis, so these records were removed. It was also during this process that we made a decision regarding whether to use one or both of the available lift ticket prices (Weekday and Weekend). A simple comparison showed that for the resorts on the higher end, there was no difference in price between the two ticket types. As such, we removed the Weekday price from consideration and focused only on the Weekend prices.

Chart, scatter chart

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Fig. 1: Correlation between Weekday and Weekend prices for all resorts.

There is a noticeable straight line representing resorts where the two prices are equal.

With the data cleaned, the primary consideration influencing our analytical methodology became the dimensionality of the data. With so many variables to consider, it was important to rescale them all in an attempt to find which of them had the largest impact on the variability of the data. Once rescaled, it became a matter of charting the correlation between each individual measure and the associated ticket price for that resort. Through that process, several notable trends emerged. Vertical drop, number of chairs, number of runs, fast quads, snowmaking area, and days open all seem well-correlated to ticket price.

With several key features in hand, the next step was to design and test a machine learning model that could take said features as inputs and return a predicted price. But before we could proceed with that, we needed to set a baseline, which was to simply employ the mean value as a predictor. If the model could not outperform the baseline, then it wouldn’t be useful and would require a fresh restart. In the case of our data, the Mean Average Error (a measure of prediction accuracy) for the Mean was 18.79, which essentially means that you could typically expect to be off by roughly $19 if you based your prediction strictly on the average of known values.

Baseline established, it became time to create our two models. This involved splitting our data into two baskets; a learning set for training the model, and a testing set for actually evaluating our results.

 The first model evaluated was a linear model. To prepare the model, the data needed to be scaled, and missing values needed to be imputed. There was little effect on this model between using the mean or median to impute. After running against the test set, this model significantly outperformed the straight average with a MAE around $10. The next model assessed was a Random Forest model. It similarly needed scaling and the blank values imputed, but after fine-tuning it was able to provide a comparison of the most and least important features for predicting ticket price. It also greatly outperformed the average, with an MAE around 9 dollars.

In the end, we're choosing the Random Forest model for our analysis as it has a slightly lower MAE (~$9 vs ~$10) as well as a lower level of variability when compared to the linear model.

All that remained at this point was to run the model on the full dataset, and then use it to predict the ideal ticket price based on Big Mountain’s feature list. Based on our analysis, it appears that with the specific mix of features that Big Mountain offers could support a price of up to **$92.39,** significantly higher than the current price of $81. Even with the mean average error of $10.44, this implies that there is likely room to raise prices and still be supported by the market.

The last step in our analysis was to use our model to evaluate the specific changes proposed by management. These options were:

1. Permanently closing down up to 10 of the least used runs. This doesn't impact any other resort statistics.
2. Increase the vertical drop by adding a run to a point 150 feet lower down but requiring the installation of an additional chair lift to bring skiers back up, without additional snow making coverage
3. Same as number 2, but adding 2 acres of snow making cover
4. Increase the longest run by 0.2 mile to boast 3.5 miles length, requiring an additional snow making coverage of 4 acres

For these changes, we found the following:

Scenario 1: While closing 1-4 runs has what could be a manageable negative impact on ticket price (<$1.50), closing additional runs causes the modeled price and associated Revenue to drop precipitously, implying a case of rapidly diminishing returns on pursuing that option.

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Fig. 2: Modeled impact of number of runs closed vs. merited ticket price.

As noted, closing more than 4-5 runs has an immediate and significant negative impact on Revenue.

Scenario 2: Using the average # of 5 ski days per customer, we came to the conclusion that this upgrade would warrant an approximately **$1.31 in additional ticket price increase, or roughly 2.3 million dollars in additional annual Revenue**. Given that the estimated installation and maintenance price-tag for this improvement is ~1.5 million dollars, it's likely that this has the potential to add significant profit for Big Mountain.

Scenario 3: Adding additional ski-making acreage as part of this improvement project did not appear to increase potential Revenue at all, and is not recommended.

Scenario 4: This proposed upgrade showed no impact on the modeled price at all. This is not surprising given how low the “Longest Run” feature was on the list of impactful variables for our model.

With regard to influence on sustainable ticket price, Scenario 1 (closing runs to reduce costs), and Scenario 2 (adding more runs and lifts) appear to be the most impactful. Even though they seem to run counter to each other, if the newly created runs are significantly more popular than the ones being closed, both could still have a positive effect on the bottom line.

In conclusion, our analysis reveals that there already exists an opportunity for Big Mountain Resort to secure additional Revenue by increasing its ticket prices, and some of the proposed changes (specifically Scenarios 1&2) provide the chance to merit an even higher price while also reducing operating costs and positively impacting the bottom line.