Problem Identification

Big Mountain Resort recently added a new chair to increase the distribution of visitors across the mountain. However, this has added $1.54M in operational costs. The goal of this project was to find a way to recover those operational costs and keep the profit margin around 9.2%. From the limited data that I received, I concurred that the best way to do this was by raising ticket prices.

I used data from a csv file that contained information about ski resorts from all around the country. The file included lots of features such as weekday and weekend ticket prices, days open last year and projected days open, summit and base elevation, number of chairs and trams, total skiing area, longest run, etc. Most of these features were used in the final model. The response variables for this problem were the weekday and weekend prices, as those were the variables we want to change to increase revenue.

Data Preprocessing Steps of Note

There was a decent amount of data cleanup, particularly because there were many NaN values. To deal with these, I would either fill them with 0 or with the mean of the rest of the data in the column. Also, I removed the 'Region' column since it was almost always the same as the 'State' values.

I used the interquartile range (IQR) of the data to construct the model. However, when I deleted all the outlier resorts, the number of records reduced drastically. The original dataset held data for 330 resorts, but the IQR dataset only held records for 176 resorts. Furthermore, Big Mountain Resort had multiple outlier features and therefore was not included in the IQR dataset.

After creating a correlation matrix, I calculated that I need to remove the base elevation feature because of its correlation with other features.

In conclusion, the dataset that I used to start creating models did not include the 'Region' or 'base_elev' columns and lost almost half its records due to outliers in the data.

Model Description and Performance

To work on this problem, I created three different linear models. The first model included the data I just described. The dataset consisted of the 176 records that were within the IQR and did not include region or base elevation data. Since I still included the state for each record, I created dummy features in order to proceed with the model. This first model did not do well, resulting in an enormous explained variance (EA) and mean absolute error (MAE) (see figure below).

To improve the model, I removed the state column and the dummy features. We can't control what state a lodge is located in anyway, so it isn't a huge loss. This second model was a significant improvement. The EAS was around .53 and the MAE around 7.37.

However, some of the most influential factors were elevation. For my third model, I removed the summit elevation (base elevation had already been removed at this point). The EAS and MAE were very similar.

Model	Explained Variance	Mean Absolute Error	Features Dropped
Model 1.	-2.8054739133297618e+22	348372736122.40326	-
Model 2.	0.5325426531233336	7.373969726141045	'state'
Model 3.	0.5266658380003129	7.645321928693999	'state','summit_elev','base_elev'

Model Findings

I originally used the third model to predict the ticket prices, since it didn't make sense to use a model where elevation was a major factor. However, when I used the model to predict the Adult Weekend prices, the result was ~$77, which is $4 less than the current price. Since it doesn't make sense to decrease ticket prices to increase revenue, I decided to try out the second model. That model showed that we should increase the Adult Weekend ticket price to $87.66. This result makes a lot more sense for the context of the problem. When I used this model for Adult Weekday prices, the result was $85.84.

Conclusion

So will these ticket increases help? Will they help cover the operational costs of the new chair and keep us at a profit margin of 9.2%? According to our current prices ($81 for both Weekday and Weekend) and average number of visitors (~350,000), we currently make a revenue of $28,350,000. With a profit margin of 9.2%, that means that the current profit is $2,608,200. The additional operational costs, reduces this profit to $1,068,200. The operational costs of the new chair takes more than half of our current profit. This also means that our total operational costs equates to $27,281,800.

If we raise ticket prices by the bare minimum recommendation (for simplicity, we'll raise both weekday and weekend prices to $85.84) the revenue will be $30,044,000. This means that the new profit will be $2,762,200 (an increase of $1,694,000 and therefore covers the costs of the new chair). This also puts us at a profit margin exactly at 9.2%.

If we raise ticket prices to $87.66, the revenue is $30,681,000, which gives us a profit of $3,399,200 and a profit margin of 11.1%.

It looks like this model was a success. Even if we raise the ticket prices by less than $5, we can make up the operational costs of the chair and stick to our profit margin.

There were other ways we could have increased revenue, like keeping the resort open longer this season. Is raising ticket prices the best option? I created plots of some of the data and noticed an interesting trend: Big Mountain Resort offers more/better features than most resorts. Even though our prices are on the higher end, there are plenty of resorts that charge more and offer far less. Even with the increase in prices, our customers are getting a good deal. Below are some of the features that I plotted. These plots make it obvious that Big Mountain Resort (symbolized by the red dot) offers the higher end of these features (sometimes being a total outlier) and therefore can justify the slightly higher prices.