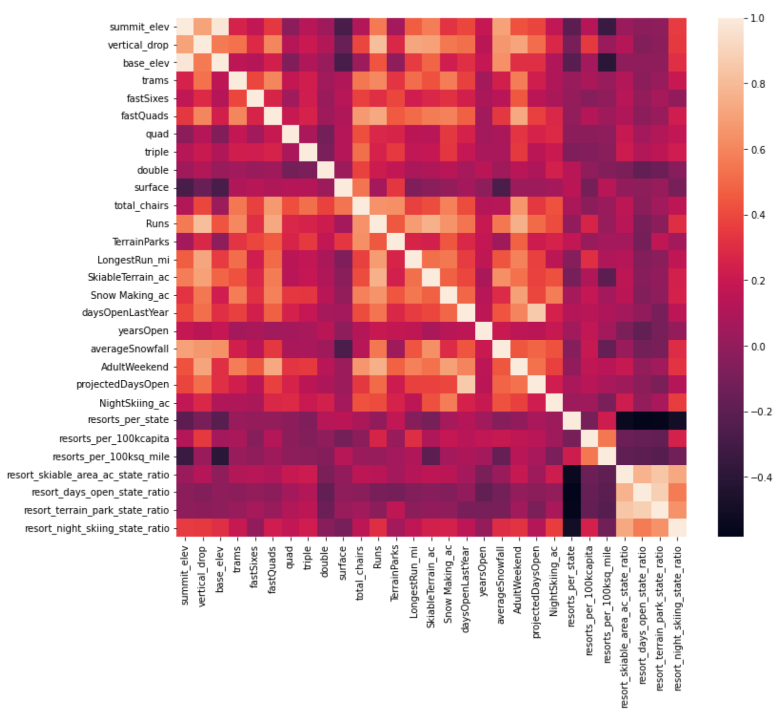
Summary of my recommendations for Big Mountain Resort

By Vincent Tolentino

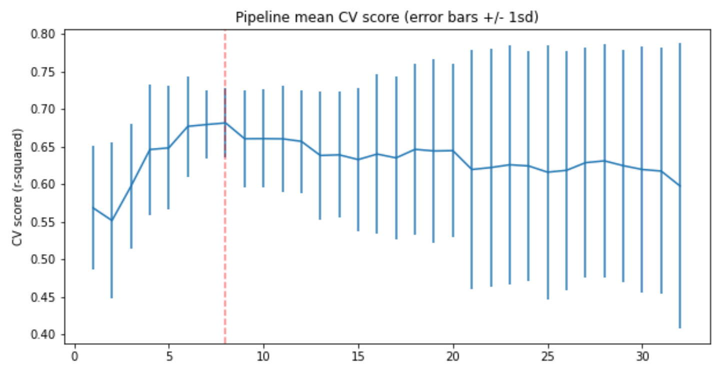
The problem we face with Big Mountain Resort (BMR) is ticket pricing. Initially, the strategy of BMR was to price their tickets at a premium above the average of other resort ticket prices, however, they posed a problem: arbitrarily setting ticket prices in this fashion can be detrimental in the long term and sustainable revenue cannot be accurately predicted. Therefore, a better utilization of repricing strategy that takes into account not only ticket prices, but other features of our resort must be created in order to increase ticket revenue and offset operating costs as well as predict an accurate ticket price model that will be reliable for years to come. With this in mind, we tackle the problem of *creating a ticket pricing model that will increase revenue for BMR and with that increased revenue, reduce operating costs by at least 20% by the next fiscal year.*

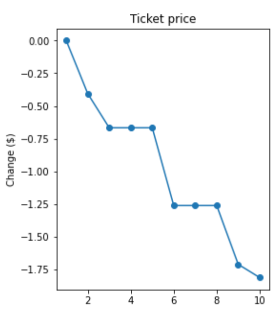
I started with a raw dataset of over 300 different resorts from across the country. This data, in order to be worked on by our eventual price model, had to be cleaned and organized so that we can work with it effectively. Things like missing data and duplicate values had to be dealt with. Identifying outliers in the data also proved to be useful so that outliers and incorrect data could be removed from skewing our results. With the addition of outside data including state populations and state areas were added to our data to help with further analysis into our ticket price model. With our data cleaned, I could move on to the Exploratory Data Analysis, which will help us pinpoint what more we can do with our dataset.

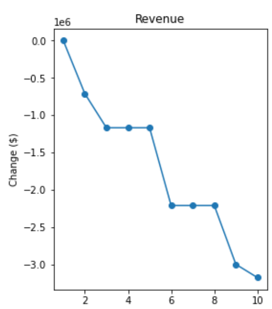


Additional calculations based on ratios (i.e. ratios of population density and resort density, etc.) could be done on the cleaned data set. Scaling this data also proved noteworthy and through the principle components analysis, or PCA, we were able to control the variance between the data points in our set. With this, we can find correlations between the features of each resort to identify those with which we can work with and give us insight into what our data means. The heatmap example on the previous page can show what types of correlations we can find within our dataset.

Diving into the preprocessing aspect of our ticket modeling, we start by separating with a train/test split in order to train our model on a subset of our data which will then be tested on another subset for accuracy. Mean absolute error (MAE) and Mean squared error (MSE) calculations were used to further analyze our projected ticket prices. In order to set up our model, we must impute missing values in the data using the median of the values due to the skew of the predictor feature distributions and scaling that data, and using a linear regression model on our scaled data to predict our train and test sets through a pipeline, which can perform all of these steps within a pipeline and it's fit method. Refining our model was assessed using cross-validation, we can find the best number of features to select (k) within our model to find the most accurate and best 'k' to use, as seen in this graph to the right, which selected 8 as the best k value. Using a Random Forest Model, we can utilize all these features of our linear regression model, with a marginal improvement on our figures. In the end, the Random Forest Model was chosen based on a lower cross-validation MAE and less variability within the model.







Putting our model to work proved to be worthwhile when given a list of scenarios by BMR to work with. Running through the scenarios resulted in a model that suggested a decrease in the amount of runs at BMR would necessitate a decrease in ticket price if more than 5 runs were closed (as seen in the figure above), however, a significant increase in price would be prompted by increasing a vertical drop and adding a chairlift for the drop. The increase in price by $1.99 would generate $3,474,638 per season, which is more than enough to cover operating costs and generate a significant amount of revenue for the resort, as the cost of the chairlift would amount to $1,540,000. With this in mind, we can safely improve

BMR with minimal effort and maximum gain by increasing ticket pricing slightly, and adding in the additional chair lift and increasing the vertical drop.

In conclusion, we can clearly see there is a benefit to creating a model for ticket pricing as opposed to arbitrarily picking a price based on average ticket prices of other resorts. It lends insight into what features of BMR and other ski resorts affect ticket pricing and how adding and subtracting these features can significantly raise or decrease ticket prices. Future improvements to our model can be done by adding additional information like operating costs of facilities and more insightful ticket sales data. This can further increase the efficacy of our model. If this new data is added, we can go back and test our Linear Regression Model and our Random Forest Model to see if there is a marked difference in performance. Quite possibly, we may need to adjust our choice based on those results. Future potential scenarios can further our insight into how to mold and shape the ticket prices of BMR. Factors that were not originally taken into consideration by the executives at BMR (like vertical drop, and number of chairs for example) are now included in the ticket price modeling, which will more accurately define the price of future tickets at this resort.