Guided Capstone Report

Introduction:

Big Mountain recently installed a new chair lift to increase the distribution of visitors on the mountain. It is likely that the resort's premium pricing is not being maximized. In order to succeed, we need to know what services and facilities make Big Mountain stand out from other competitive resorts and adjust the pricing accordingly. Since the new lift increases maintenance costs, we need to know how this new lift helps improve the distribution of visitors throughout the mountain. One possible constraint we might encounter is that we may not have sufficient relevant data. The stakeholders to provide key insight to is are Director of Operations Jimmy Blackburn and Database Manager Alesha Eisen. The data used is from a .csv file provided by Alesha Eisen. The goal is to create a machine learning model to predict the price Big Mountain should charge depending their place in the market

Problem Statement:

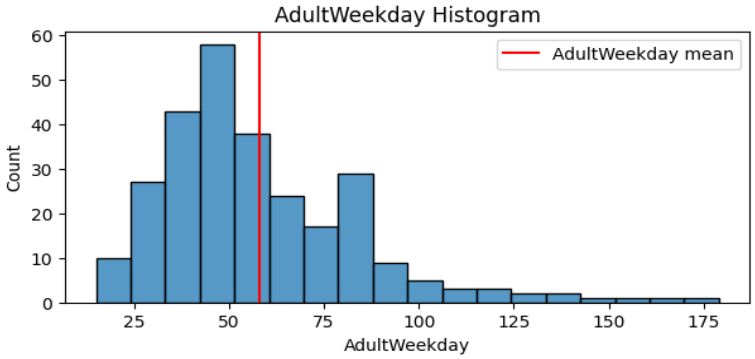
What opportunities exist for Big Mountain to recoup the increased operational cost of $1.54 million over the next year through modification of pricing or optimization of importance of their facilities?

Data Wrangling:

The provided data contains 26 descriptive features of 328 unique ski resorts. Some of these features are name, region, state, summit elevation as well as adult weekday price and adult weekend price. The last two being potential target features.

There were a few rows that did not include any price data and were therefore dropped. The fastEight feature contained heavily imbalanced classes and would not provide any useful insight so it was also dropped. The yearsOpen feature contained a value of 2019 that was most likely an input error that was corrected to match the remaining data of the column.

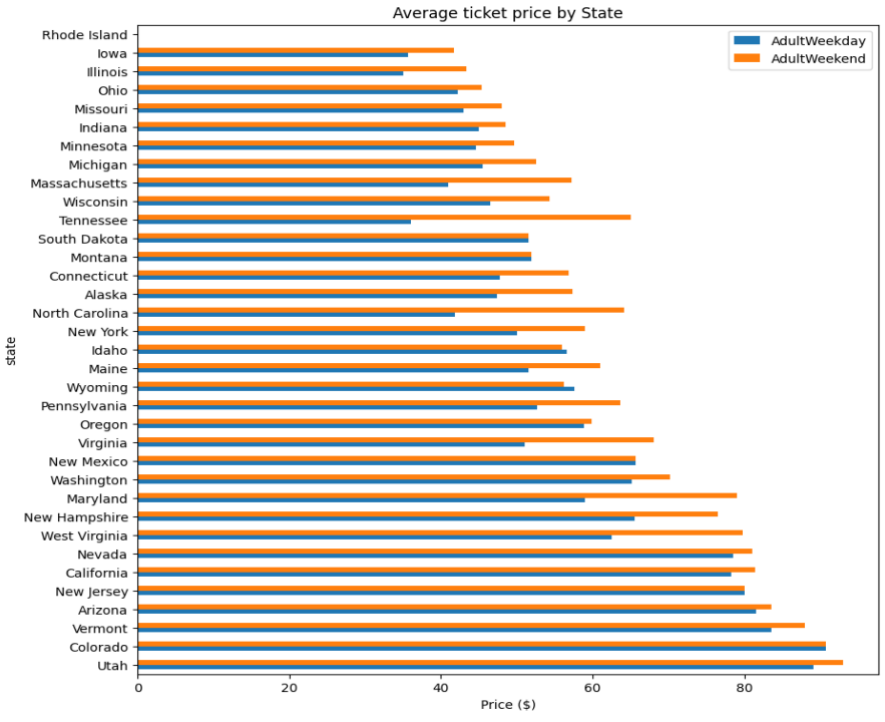
Data about state population was acquired from Wikipedia to create features such as resorts_per_state, resorts_per_100kcapita, resorts_per_100ksq_mile, resort_skiable_area_ac_state_ratio, resort_days_open_state_ratio, resort_terrain_park_state_ratio, and resort_night_skiing_state_ratio.



Exploratory Data Analysis:

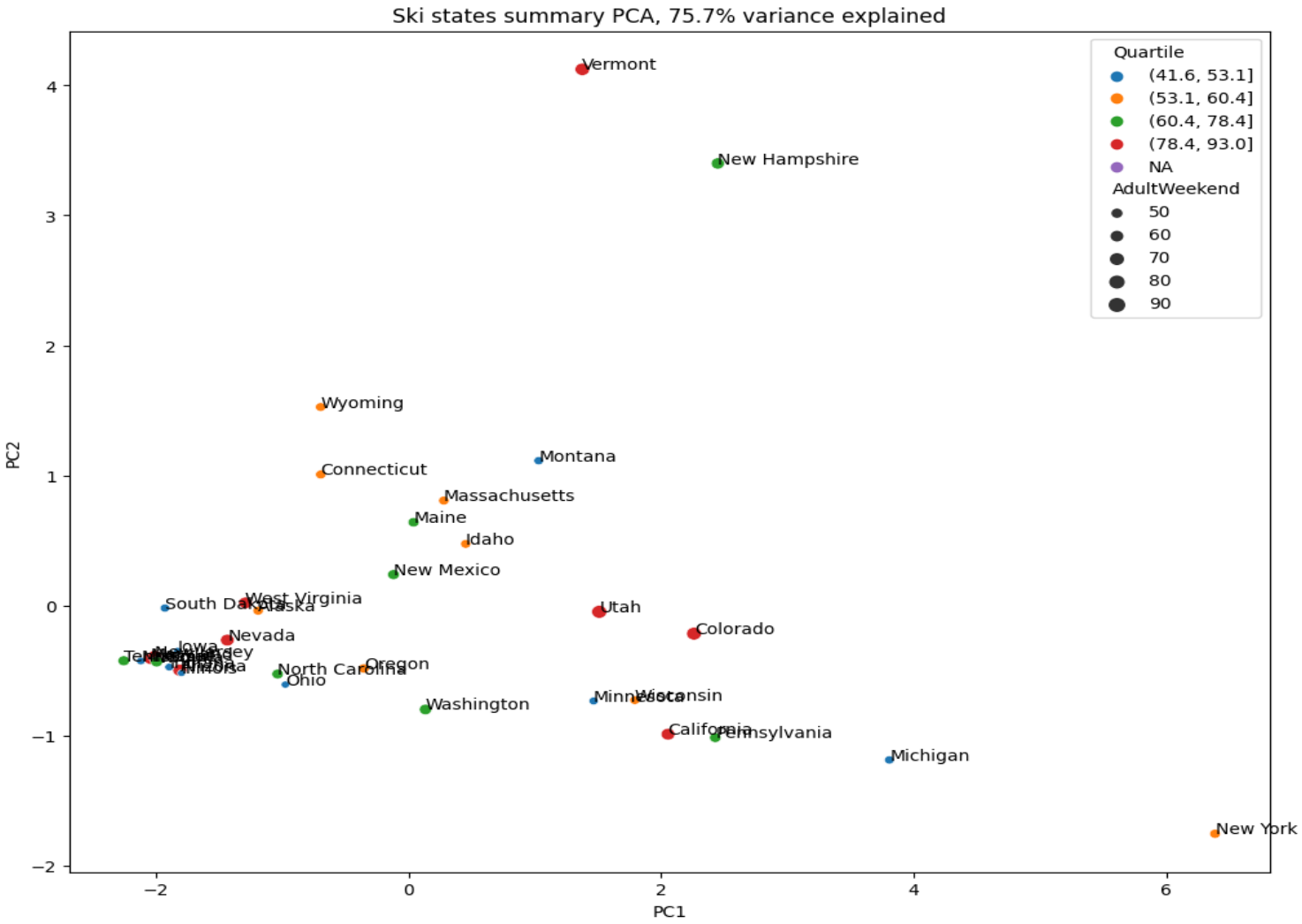
There were a few notable discoveries found while exploring each column. Firstly, the target feature of AdultWeekend is right-skewed with an average of 64.28.

There was also a difference in the number of resorts per state compared to number of resorts per region. The New York, Michigan, Sierra Nevada and Colorado regions had the highest number of resorts while New York, Michigan, Colorado and California were the states with the most amount of resorts.

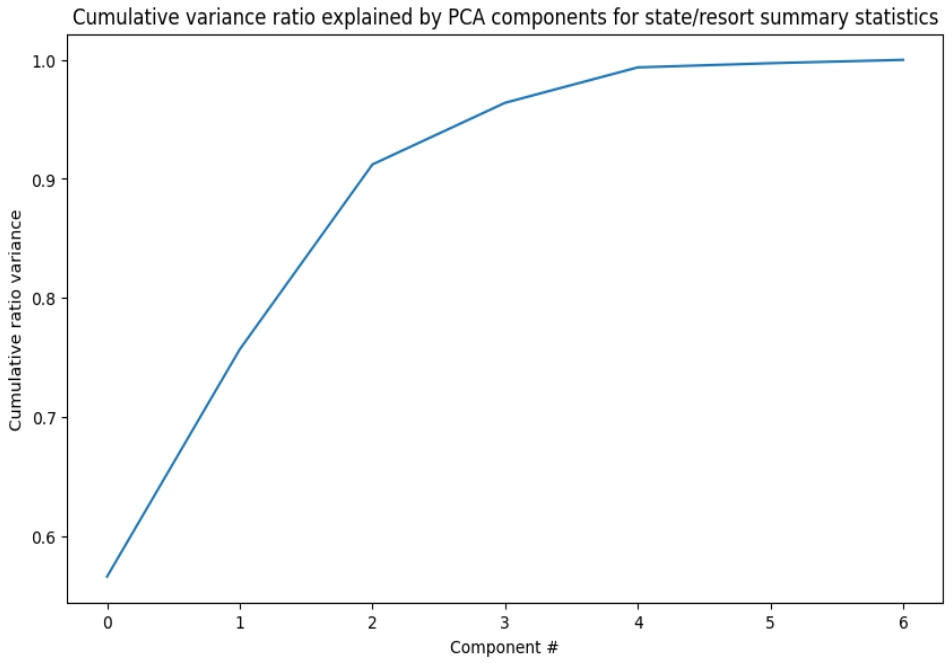


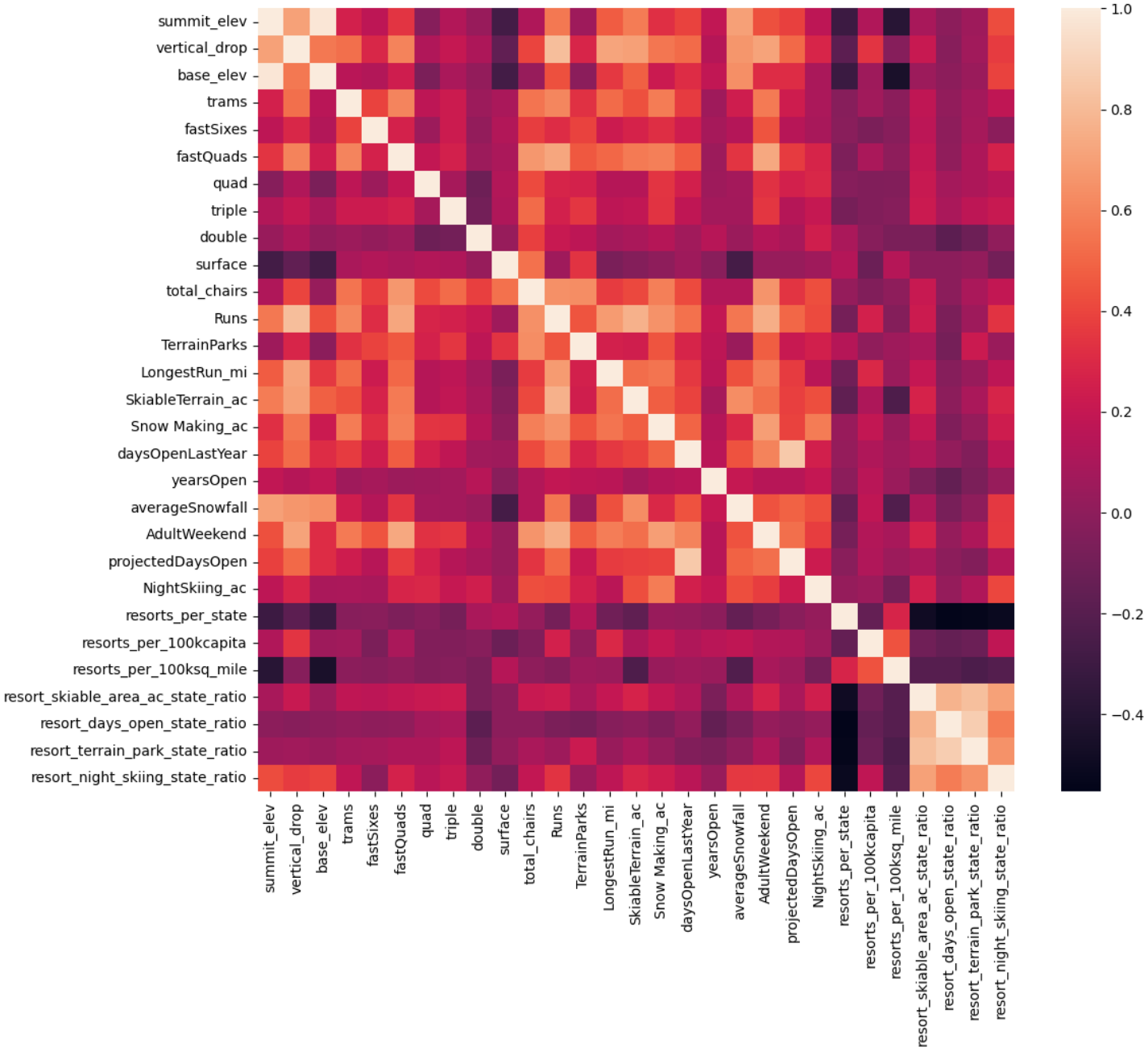
When examining the ticket prices per state, Utah, Colorado, Vermont an Arizona had the highest prices. But no clear pattern was found when examining the prices per state.

Principal component analysis was used to find patterns within the data. It was notable that the first two components account for over 75% of the variance while the first four component account for over 95% of the variance. Vermont, New Hampshire and New York appear to be outliers but there appears to be no clear pattern with the distribution of states with the first two components.



There were also a few features that were very closely correlated. Notably, Resort_night_skiing_state_ration and AdultWeekend as well as fast_quads, total_chairs, Snow Making_ac.





Preprocessing and Training:

A 70/30 train/test split was conducted on the data. Since there was still a bit of missing data, it was imputed with the median since some of the features had discrete values rather than continuous values. Finally, the data was scaled around 0 using a standard scaler algorithm.

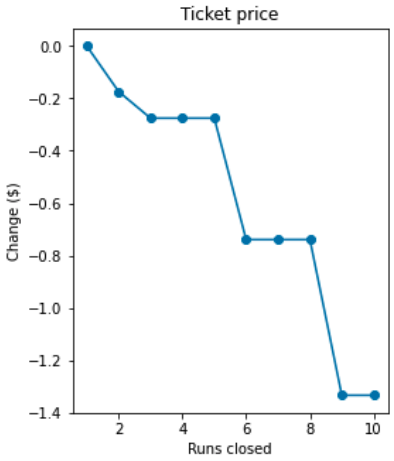
Modeling and Evaluation:

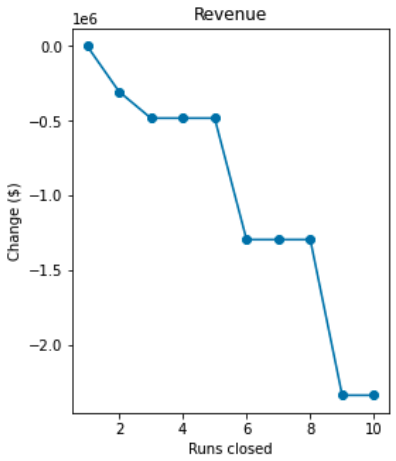
The data was used to build two models: a linear regression model and a random forest regressor model. Both models were created using five-fold

cross-validation and the grid search cross-validation technique was used to find optimal hyperparameters for each model. GridSearchCV was used to find the best selectbest_k value linear model as well as finding the best n estimators and best simple imputer strategy for the random forest model. The best linear regression model had an average cross-validation score of 0.633 with a standard deviation of 0.095 while the random forest regressor had an average cross-validation score he best of 0.713 with a standard deviation of 0.0701.

With a higher cross-validation score and a lower standard deviation, the random forest regressor is better at accurately predicting the price. Its most important features are Runs and fastQuads with Snow Making_ac and vertical_drop also being important.

A learning curve was used to determine if collecting more data would be required to find better results. This shows that the cross-validation scores level off by around 40-50 samples, indicating that there is sufficient data.





Results:

There were multiple scenarios to examine. The first scenario involved closing up to at least 10 of the least used runs. The closure of a single run makes no difference while closing 2 and 3 runs reduces the support for an increase in ticket price. Closing 4 and five runs produces the same loss in revenue as closing 3 runs and closing six or more runs leads to a large drop in ticket price and revenue.

The second scenario involves adding a run, increasing the vertical drop and installing a new chairlift. This scenario supports the increase in ticket price by $1.61 and over the season, this price increase is expected to amount to $2,815,217.

Scenario 3 involves adding a run, increasing the vertical drop by 150 feet, installing a new chairlift, and adding 2 acres of snow making. This scenario gave the same results as the second scenario.

The fourth and final scenario involves increasing the longest run by 0.2 miles and guarantee ints snow coverage by adding 4 acres of snow making capability. This scenario resulted in no difference.

Conclusion and Future Scope:

Comparing the four different scenarios, the second scenario yealds the best results. It will allow for an increase in price that will cover the seasonal operational cost of adding a new chairlift.

The model would have benefited greatly by having more data by both Big Mountain and other resorts. Some of these costs would be things like maitainance costs and operational costs. It seems that despite Big Mountain ranking highly in a lot of the facilities offered, it's prices were still too low. This justifies the sharp increase in price. I don't think this mismatch would come as a surprise to the business executives as they had predicted that they were underutilizing some of their facilities. The business could make use of this model by imputing different scenerios and reviewing the results.