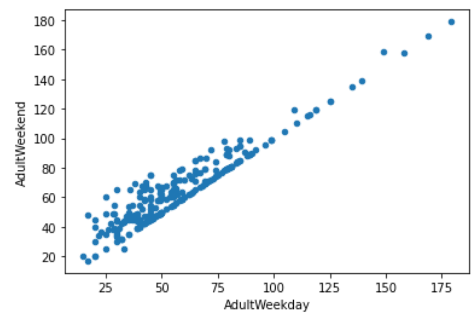
1. Problem Statement

Can adjusting Big Mountain Resort's ticket pricing based on high-impact facility features (such as lift count, vertical drop, and skiable terrain) — rather than using the regional average — increase pricing competitiveness and revenue potential by at least 10% within the next ski season, without negatively affecting customer satisfaction or visitor volume?

Our objective was to develop an interpretable model using data about features and ticket pricing from 330 US based ski resorts, in order to increase pricing competitiveness for Big Mountain. Currently, Big Mountain's pricing strategy does not consider how its specific offerings compare with competitors, potentially resulting in lost revenue or pricing misalignment. Ultimately, we hope to use comparative data in the same market to evaluate Big Mountain's pricing position relative to its facility offerings.

2. Data Wrangling

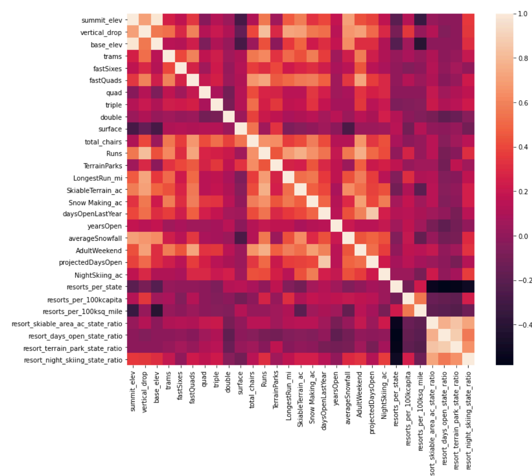
The dataset was cleaned and prepared for analysis. We dropped all rows in our dataset with no price data, ensured there were no duplicate resorts, dropped the column 'fastEight' (which had more than half of its values missing), and replaced suspicious values in the data (e.g. the very large snow making acres of Heavenly Mountain Resort). We also investigated the relationship between states and regions, specifically the distribution of resorts by region and state and ticket prices by state, ultimately finding that New York dominates the number of resorts per state while Utah is the most expensive state on average. Finally, we looked into our target feature: **ticket price data**.



There is a clear line where weekend and weekday prices are equal, however weekend prices higher than weekday prices seem to be restricted to resorts under $100 ticket pricing. Generally, we will focus on the '**AdultWeekend**' prices going forward.

3. Exploratory Data Analysis (EDA)

We then performed EDA to look for the features most relevant to ticket pricing, also including crucial ratios into our data (e.g. resorts per 100k capita or 100k sq mile). We disentangled this web of relationships via PCA, creating a feature correlation heatmap (lighter squares indicate large correlation). Zooming into this heatmap and focusing on our target feature ('AdultWeekend' ticket price), we saw that the number of **fast quads, vertical drop, runs, total chairs, and snow making acreage** stood out in determining price, indicating these features are crucial in pricing strategies across the market.



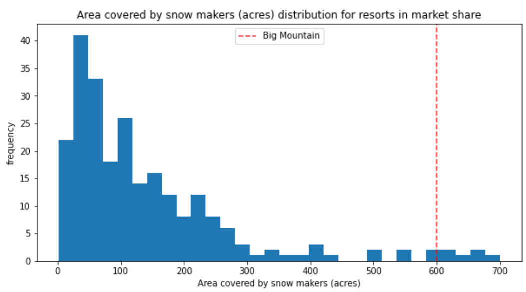
4. Modeling Preprocessing and Training

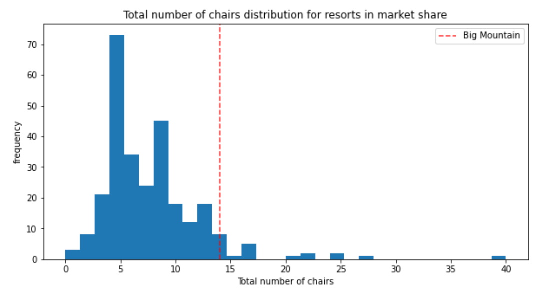
Next, we began the process of model selection and training. Firstly, we imputed missing values with the median values for those features (having determined this leads to the best model performance in predicting price by using metric values to determine performance). We built some pipelines to scale the data, train the model, make predictions, and assess model performance. We tested both a logistic regression linear model, in which we used Grid Search Cross-Validation to keep track of the best number of features to include in our model, as well as a random forest model assessed through 5-fold cross-validation. Ultimately, we found that the **random forest model produced systematically lower errors and less variability** (implying consistency in model performance). Thus, we opted to use the random forest model, as it also surfaced key interpretable features consistent with the linear model, while capturing more complexity in the data.

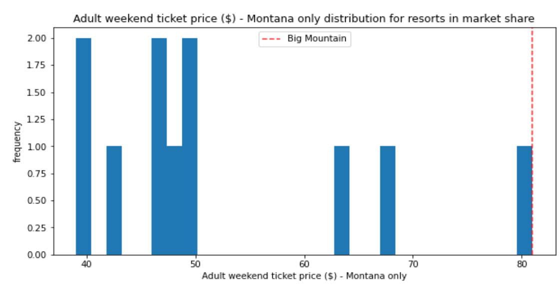
5. Modeling

Using our random forest model pipeline, we then refit our model on all the available data (of course excluding Big Mountain data). We calculated the expected Big Mountain ticket price from our model, determining that **Big Mountain's modelled price is $95.87, a whole $14.87 dollars more than its actual price**. Even with the expected mean absolute error of our model ($10.39), this suggests a whole lot of room for an increase in price, based on Big Mountain's resort features. This result is optimistic, but should be considered within the limitations of the model and the market context. Specifically, our dataset only includes ticket prices as resort prices, omitting fixed costs, variable costs, and seasonal adjustments. The model also does not consider information about customers' purchasing behaviors.

Our data suggests that Big Mountain is very competitive relative to the US market in terms of its total number of chairs, fast quads, number of runs, skiable terrain, and numerous other features. This explains ticket underpricing.

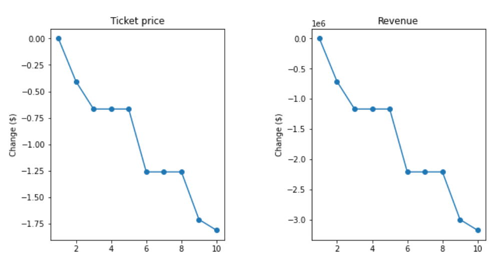






Nonetheless, we must consider the fact that Big Mountain Resort is located in the state of Montana. **Big Mountain Resort has some of the highest ticket prices in the whole state of Montana**, despite our model suggesting it being undervalued relative to the overall US market. Thus, external constraints related to location, such as competition in the area or community agreements about prices, may be limiting Big Mountain's ability to raise prices further.

We also modeled various scenarios, such as closing runs in the resort. According to our model, closing 1 run results in no change in projected ticket price, while decreasing more than 1 results in a decrease. Our model also suggests that if you remove 3 runs, you may as well change up to 5, however dropping more than 5 leads in a large price drop.



We also modeled scenarios in which we added a run, increased vertical drop (adding increase in snow making acreage to account for the extension), and added a chair. From our modeling, we concluded that adding a small amount of snow making acreage changed very little in the ticket price, and that extending the longest run by 0.2 miles would result in no net change in price.

6. Conclusion & Recommendations

Ultimately, our recommendation based on our model, is that **Big Mountain Resort can increase its ticket pricing** to match the overall US market. However, this increase must be considered relative to the local market of Montana, in which case local limitations may suggest that Big Mountain should instead decrease costs by cutting some of the resort features which would have otherwise made it more competitive in the overall US market. This model can be used to test various scenarios and evaluate the impact of changing the facilities offerings. Our model can be used efficiently to predict budgeting for future investments.