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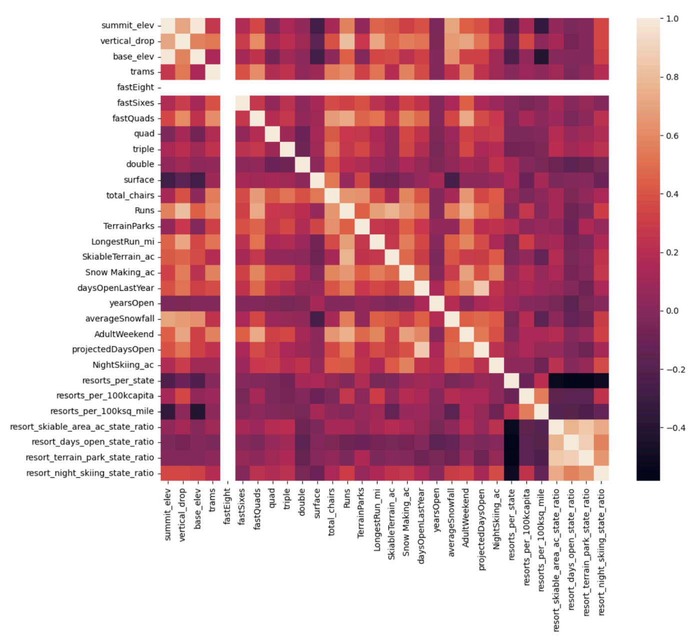
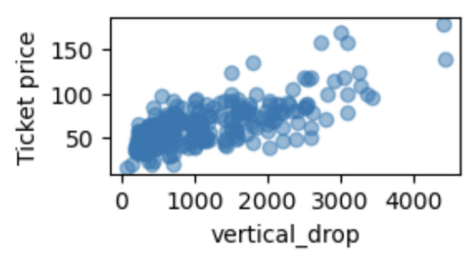
Big Mountain Resort seeks to revamp the pricing strategy for their weekend adult tickets using data-driven insights. Their goal is to set a competitive price that maximizes incoming revenue while considering market trends, resort amenities, and other factors that influence their pricing.

We started by collecting data on ski resorts across the United States, with features like elevation, terrain size, number of lifts, snowmaking capabilities, and state-level details like the number of resorts per state and population density. After data wrangling, cleaning the data, and handling missing values with imputation, we conducted some exploratory data analysis. We found a few trends emerged during this phase, including the strong correlation between features like vertical drop, snowmaking area, and the number of high-speed quad lifts with higher ticket prices. One interesting insight was that larger resorts did not always charge more for tickets, which indicates that a more premium experience could charge higher prices regardless of size. The following figures help to visualize these insights.



This correlation heatmap to the left shows relationships between key features and ticket prices.

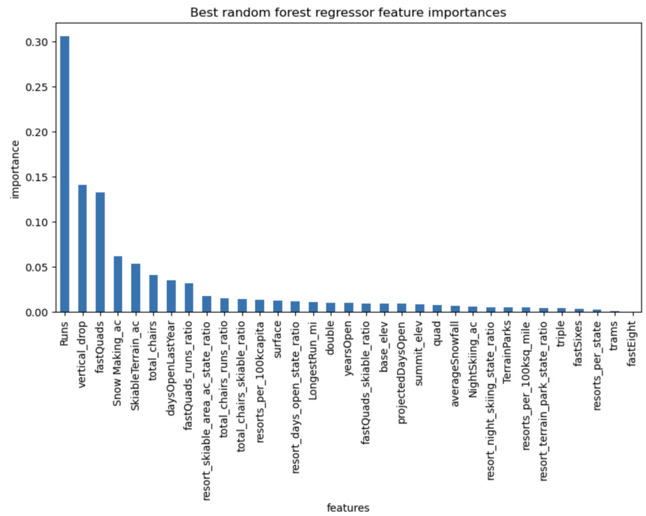


This scatterplot to the right pits vertical drop vs. ticket price, highlighting its strong positive correlation.

We then explored options for potential machine learning models. We first built a linear regression model, imputing missing values with the median and scaling the data to ensure consistent units across the different features. This model showed us some important insights, but we found that the model overfitted the training data. This resulted with a weaker performance on the test data. We then incorporated 'SelectKBest' into the model, which identified which features influenced ticket prices the most.

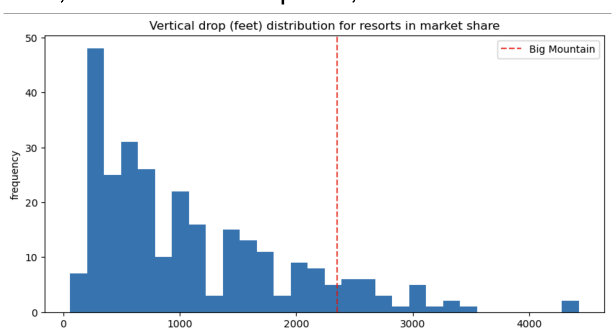
These features were vertical drop, snowmaking area, number of fast quads, and number of runs.

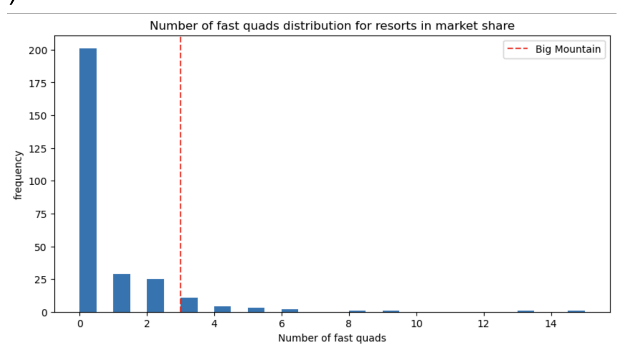
This bar chart shows us which features played an important role in determining ticket prices.

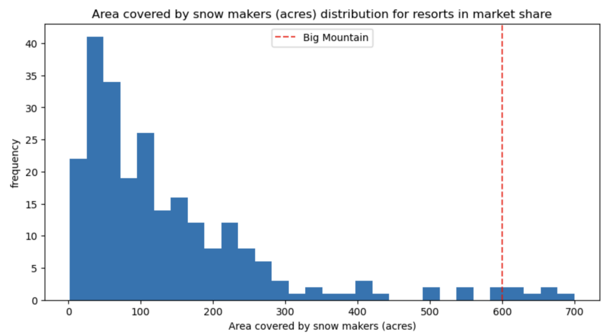


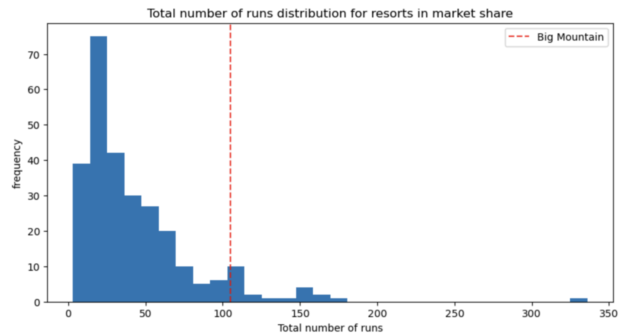
We then tried out using a random forest model, and as we used cross-validation, we found that this model performed better than the linear regression model. To further improve our random forest model, we used GridSearchCV to find the best hyperparameters. This resulted in deciding to impute missing values with the mean and skipping feature scaling, as this produced the best results. This model supported the same conclusion with the previous linear model, that vertical drop, fast quads, snowmaking area, and number of runs are the primary resort amenities that influence ticket prices.

We used the overall data from ski resorts in the US, and looked at where BM ranked among other resorts. We found that BM consistently ranked high with the features observed, especially our features that seemed to influence ticket price most(vertical drop, snowmaking area, number of fast quads, and number of runs).









We then used this model to predict an expected price for Big Mountain Resort, and the expected price came out to $92.19, with a mean absolute error of about $10. Through this model, our data supports that Big Mountain Resort could sustain a ticket price increase to approximately $85-$90. This price took into account the premium features that our resort offers, and is aligned with the prices of other resorts of similar caliber. We also find that as there is less competition within Montana as it has a less resort density, Big Mountain is able to be flexible with their pricing.

As we explored different scenarios with this model we built, we found several valuable insights. If we were to add a new chair lift and increase the vertical drop by 150 feet, we could allow an increase in ticket price of $1.24, which could see an $2.17 million increase in revenue. However, we would have to consider the costs of installation and operating this new lift, to better evaluate the return on investment. This increase in ticket price could be paired with closing less popular runs to further cut costs, as another scenario suggested closing 1-3 runs would have little to no effect on ticket price.

As for the scope of future work, Big Mountain could benefit from collecting more detailed data about its visitors. This would allow for us to create a model that could intake factors between ticket price and the number of visitors and the frequency of their visits. We could also potentially explore seasonal pricing strategies to adjust for peak demand periods. We could also continue exploring different scenarios with the model we created, with whatever business leadership sees would fit best.