Guided Capstone Project Report

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Big Mountain Resort, a ski resort located in Montana, with access to 105 trails. Every year about 350,000 people ski or snowboard at Big Mountain. These are serviced by 11 lifts, 2 T-bars, and 1 magic carpet for novice skiers. Big Mountain Resort has recently installed an additional chair lift that increases their operating costs by $1,540,000 this season. Big Mountain follows a pricing strategy where they charge more than the average price compared to other resorts in their market segment. This premium pricing strategy has limitations. There is a suspicion that Big Mountain is not fully capitalizing on its facilities. The business wants guidance on how to select a better value for their ticket prices. They are also considering making some changes, such as reducing costs without reducing ticket prices or potentially increasing ticket prices.

Our primary objective is to develop a predictive model capable of estimating ticket prices for Big Mountain Resort.

Data Wrangling

Data wrangling methods includes cleaning, correction, and augmentation processes to prepare data for the modeling of resort ticket prices. The 'fastEight' column, with over 50% missing values, was dropped. Records with missing pricing data were dropped as the goal was to model resort ticket prices. A suspicious value for ‘SkiableTerrain_ac’ was corrected using other data. A possible erroneous value for ‘Snow Making_ac’ was removed as it had missing pricing data, and the value could not be estimated reliably. Dataset augmented with state population and size data, as well as number of resorts in each market segment per state.

Figure 1. Relationship between weekday and weekend prices.

The dataset contained two types of ticket prices: Adultweekday and Adultweekend. Weekend and weekday prices for the resort in focus, Big Mountain, were found to be same, at $81. Additionally, across some states, there was notable variation in ticket prices, with certain states having distinctly higher or lower prices compared to others. We also saw that when the weekday price approached $100, there was typically no distinction between weekend and weekday prices as shown in Figure 1. For the analysis, the decision was made to treat weekday and weekend prices the same for Big Mountain, taking the weekend price as the target ticket price.

Exploratory Data Analysis:

Two different analytical approaches, PCA for outlier identification and a Seaborn correlation heatmap for understanding feature relationships, were applied during the exploratory data analysis. The outlier states, namely Vermont, New Hampshire, New York, and California, were identified through PCA but were found not to significantly impact ticket prices. The crucial insights were gained when analyzing a seaborn correlation heatmap, rather than the PCA-scaled dataset. This revealed that ticket prices are notably influenced by these features: 'Vertical Drop', 'FastQuads', 'total_chairs' and 'Runs', shown in Figure 2. The correlation analysis suggests that focusing on those features is optimal for modeling ticket prices.

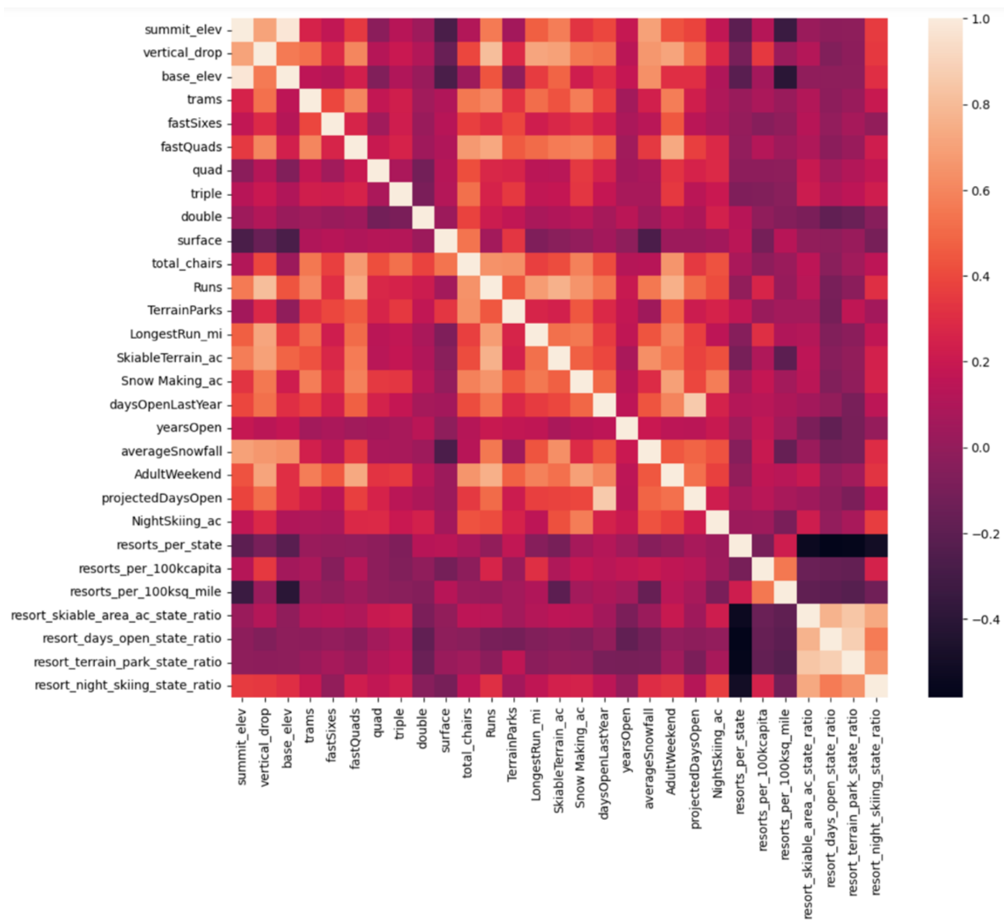

Figure 2. Relationships amongst the features.

Preprocessing

Preprocessing analysis involves a systematic approach, including baseline models, feature engineering, pipeline creation, and the selection of an advanced model (Random Forest). The calculated average ticket price of $63.81 was used as a baseline for comparison. The predicted ticket prices were off by around $19 from the actual prices when using the mean as the predictor. Such a large error suggests that the mean is not an accurate predictor for ticket prices in this scenario. Linear regression models were then trained and evaluated, both manually and through sklearn metrics, showing better performance. Specifically, the predictions from these models were, on average, $9 away from the actual ticket prices, indicating better accuracy compared to the initial average-based approach. The use of the pipeline provided an efficient way to achieve these results, allowing for faster progress with confidence in the model's performance. The analysis extended to Random Forest regression, where a pipeline was created and hyperparameters tuned. The top four dominant features as shown in Figure 3 were found ‘fastQuads’, ‘Runs’, ‘Snow Making_ac’, ‘vertical_drop’ that are in common with the linear regression model. The conclusion suggests that the Random Forest Regression model provides better predictive performance with lower MAE values (nearly $1 lower) and reduced variability compared to the Linear Regression model.

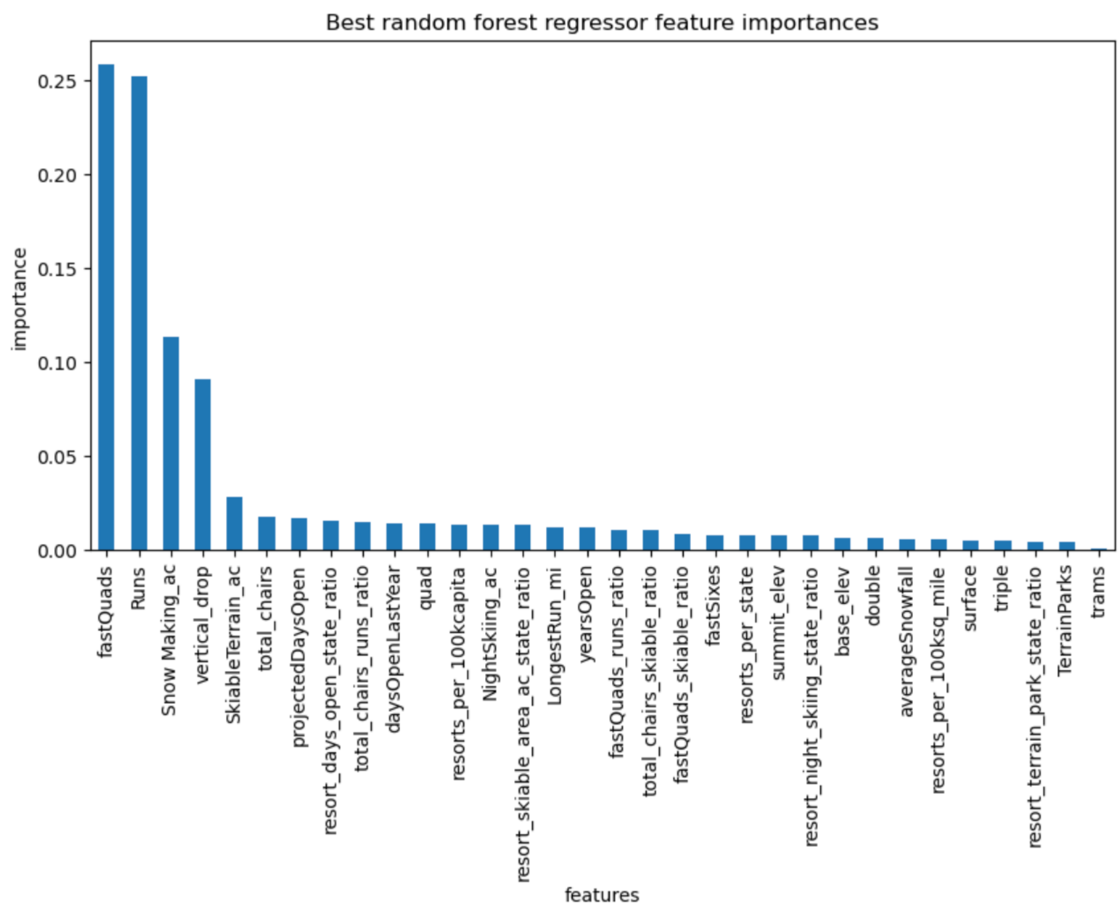

Figure 3. Random forest's feature importance.

Modeling

The predictive model for ticket prices at Big Mountain Resort suggests an ideal price of $95.87, while the actual price is $81.00, indicating a potential to increase ticket prices. This difference between the predicted price and the actual price is about $14.87, which is larger than what we expected, with an average error of $10.39. This suggests that there might be room to increase the ticket price at Big Mountain. Exploring various scenarios, the impact of closing runs, adding new runs, expanding snowmaking, and extending the longest run was evaluated. Modeling scenarios 1 indicated that closing one run has no impact on ticket prices or revenue. However, closing 2 or 3 runs decreases support for ticket prices and revenue. If 3 runs are closed, there's little difference between closing 4 or 5, as it doesn't further reduce ticket prices. However, closing 6 or more runs results in a significant drop in ticket prices and revenue as shown in Figure 4.

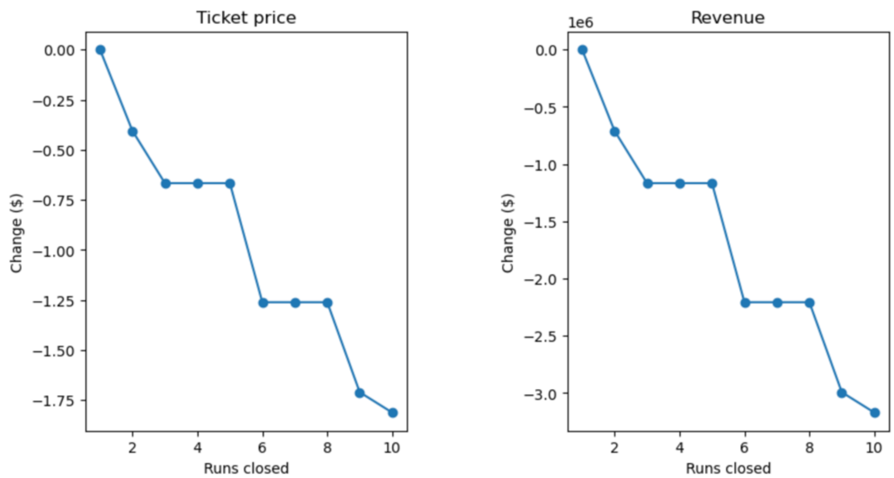

Figure 4. Ticket price and revenue change for modeling scenarios 1.

Scenarios 2, adding a new run, increasing vertical drop, and installing a chair lift could support a $1.99 increase in ticket prices, generating approximately $3,474,638 in additional revenue. By making these improvements and raising ticket prices by $1.99, Big Mountain Resort expects to generate a net additional revenue of approximately $1,934,638 ($3,474,638 - $1,540,000) over the season. Scenarios 3 and 4 indicated that additional snowmaking or extending the longest run did not significantly affect ticket prices, emphasizing the importance of other features in determining pricing and visitor attraction. The best scenario for Big Mountain Resort was Scenario 2, involving adding a new run, increasing vertical drop, and installing an additional chair lift.

Conclusion

In conclusion, the analysis suggests that there is an opportunity for Big Mountain Resort to increase the current ticket price of $81.00. The predictive model indicates an ideal ticket price of $95.87, and the observed difference of $14.87 between the predicted and actual price, with an average error of $10.39, suggests that a price adjustment, potentially an increase, could be considered.

Based on the analysis and scenarios evaluated, the suggested approach for increasing ticket prices at Big Mountain Resort involves implementing Scenario 2. Adding a new run increases the variety and attractiveness of the skiing experience. Increasing the vertical drop enhances the skiing terrain, providing a more thrilling experience. Installing an extra chair lift improves the accessibility and efficiency of transportation within the resort. Implementing these changes is predicted to support a $1.99 increase in ticket prices. Over the season, this improvement is expected to generate approximately $3,474,638 in additional revenue. In scenario 1, there may be room to close some runs, but careful consideration is needed to avoid negative consequences. Additionally, continued focus on key features identified in the model is crucial for informed decision-making regarding pricing and resort enhancements.

Future Work

The model has limitations due to the absence of crucial data like operating costs and other pricing elements such as season passes. Having additional information would have provided a more comprehensive understanding of how the resort sets its prices. Discrepancies between the modeled and actual prices for Big Mountain may be influenced by unaccounted factors or outliers. To ensure the model's utility, feedback from business executives is essential, and if deemed useful, creating an accessible tool for business analysts to test scenarios independently could enhance its practicality. This could involve implementing a user-friendly dashboard for swift and easy scenario testing.