
Big Mountain Pricing Analysis

Problem Identification

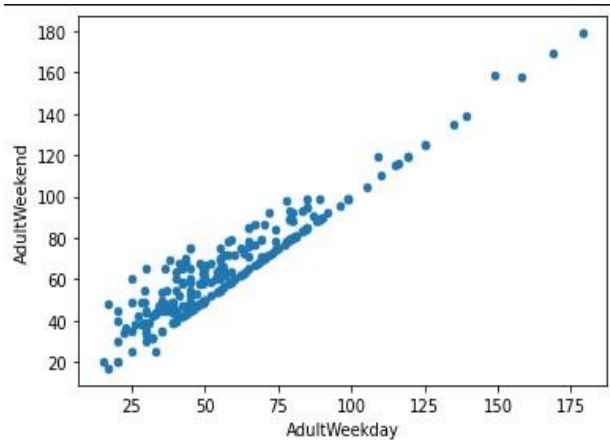
- **Problem:** ticket prices are not optimized in any way and need improvement.
- **Identifying Specifics:** ticket prices are based on the assets of the skiing resort, so these should dictate the price.
- **Potential Solution:** whether or not the skiing resort adds additional assets or removes some, the ticket prices should reflect this, such that a better profit is achieved.

Recommendations

- From the model used, a **ticket price change from \$81 to \$108** is supported.
- More specifically, an error of about \$10 accompanied this, but this still supports increasing the ticket price to \$98.
- Moreover, given the scenarios suggested, removing one run is fine, but any more and this may negatively impact the ticket price and revenue.
- Furthermore, adding a run with a greater vertical drop and an additional chair lift supported an additional \$3 price increase to the ticket.

(No other scenarios were predicted to make any difference)

EDA and Data Preparation



Before getting to the modelling part, a few important things to note about the data:

- Weekend Ticket Prices were used to predict, since they had less missing values and aside from that were directly proportional to Weekday Ticket Prices, as seen on the left.
- Certain data points were skewing data, and upon further inspection were obviously wrong, so they were corrected individually.
- From exploring the data, we suspected that the features Runs, total chairs, vertical drop and fastQuads would be the most important.
- As a standard practice in machine learning, the data was split into training and testing sets, meaning that not all was used for model training.

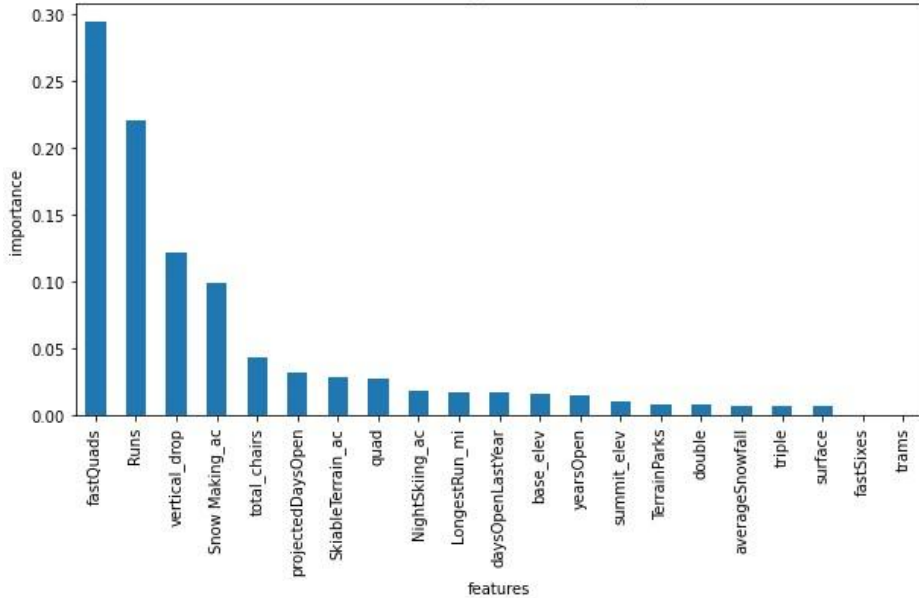
Modelling/Algorithms

Two Algorithms were used, Linear Regression and Random Forest:

- We used three different evaluation metrics, along with gridsearch (a method to optimize hyperparameters for the algorithms) to test both models.
- The Random Forest algorithm outputted better evaluation metrics across all three that were used, as compared to Linear Regression
- Thus, the Random Forest algorithm was used for the rest of the project.

Random Forest Analysis

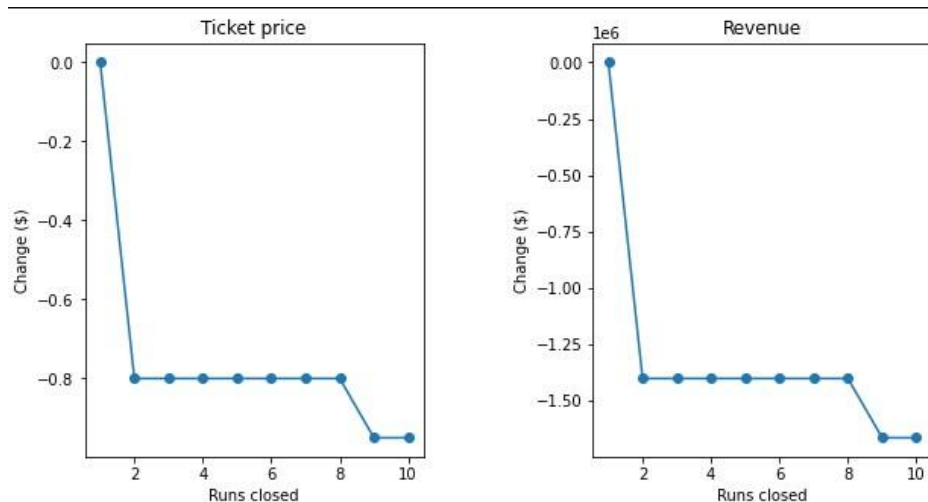
Best random forest regressor feature importances



The plot here shows the most important features when using the Random Forest Algorithm, and as expected, the features that were thought to be the most important are in the top five here.

Random Forest Predictions

- As mentioned before, the Random Forest Algorithm predicted that a price increase of up to \$108 is supported, and factoring in the \$10 error, this means a price range of \$98-118 ticket price.
- Out of the four scenarios, the only reasonable changes to consider would be to remove one run (see the plot to the right), and to add another run with a greater vertical drop and additional chair lift.



Conclusion

- Since the weekend and weekday ticket price were essentially the same, increasing the ticket price for either to something in the range of \$98-118 is supported.
- The other mentioned scenarios of removing a run or adding one with a greater vertical drop perhaps should be experimented with after.
- Before the modelling was performed, some data cleaning was performed, so in the future, improving on the original dataset would help improve the model or make other better models.
- More specifically, having data on the number of visitors and costs of assets would allow to make better or different predictions that would help ensure the model is accurate.