Big Mountain Resort Revenue Increase Recommendation

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6/11/2024

Problem Statement

The big mountain ski resort in Montana has a visiting population of 350,000 every year and has 11 lifts, 2 T-bars and 1 magic carpet in order to accommodate skiers of all levels and abilities. However, the resort has installed another chair lift that will help increase the distribution of visitors across the, that costs another $1,540,000 in operating costs. The resort' pricing strategy so far has been to charge above the market value over the average price of resorts in its market segment, which is not a very sustainable solution.
So, the ski-resort would like to increase its revenue by at least 10% by monetizing its other facilities or increasing the ticket prices *without* cutting costs on its current ticket prices.

Data

We had to manipulate the data provided to us in order for us to model it efficiently and get a reasonable outcome. In addition to cleaning the dataset of any missing values, missing columns and fact checking our data for any anomalous values, and determining what features are important to help us make our prediction we also had to answer the following questions:

- Should we try to find the target variable by state or region?
- What target variable must we use – AdultWeekday tickets or Adult Weekend tickets

In *Fig 1* given below, we noticed that Montana has 12 resorts and is in the top 13 of the states with the most amount of market share in resorts. Given this, we thought it makes more sense to group the target variable by state rather than region because it allows for a more detailed and accurate analysis of the market, especially in states with significant resort presence like Montana. This granularity can help in identifying state-specific trends and opportunities that would be less apparent at the regional level. In terms of the target variable we decided to go along with predicting the **Adult Weekend Prices**, even though the Adult Weekday Prices and Adult Weekend Prices are the same in terms of the values and averages (see *Fig 2*) due to more cleanliness of the data in the variable.

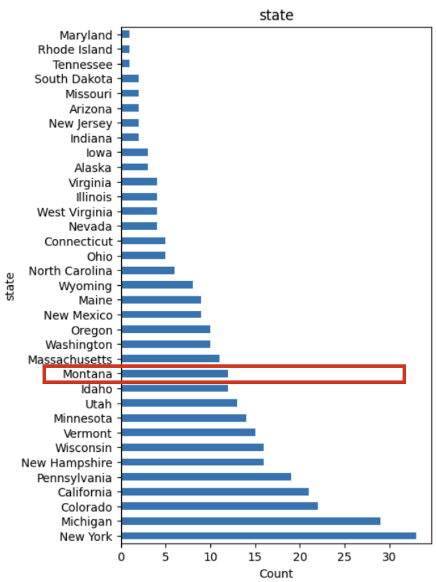

Fig 1: Visualization of number of resorts by state

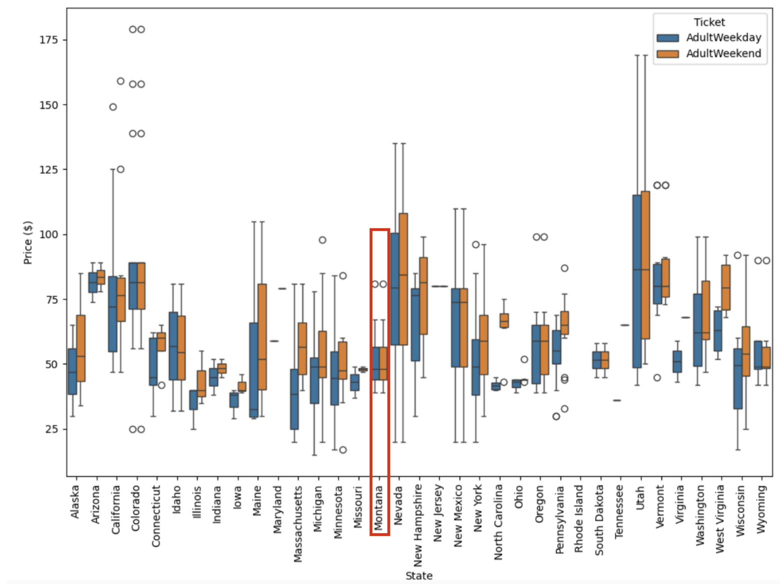

Fig 2: Visualization of average Adult Weekday and Adult Weekend Prices

Data Analysis

Our main objective of doing Data Analysis on our data before we jumped into modeling it was to:

1. Understand the correlations between various features and the AdultWeekendPrice so that we know which features to experiment with when getting a prediction from our model
2. Build new features that would strengthen the quality of the prediction of our model

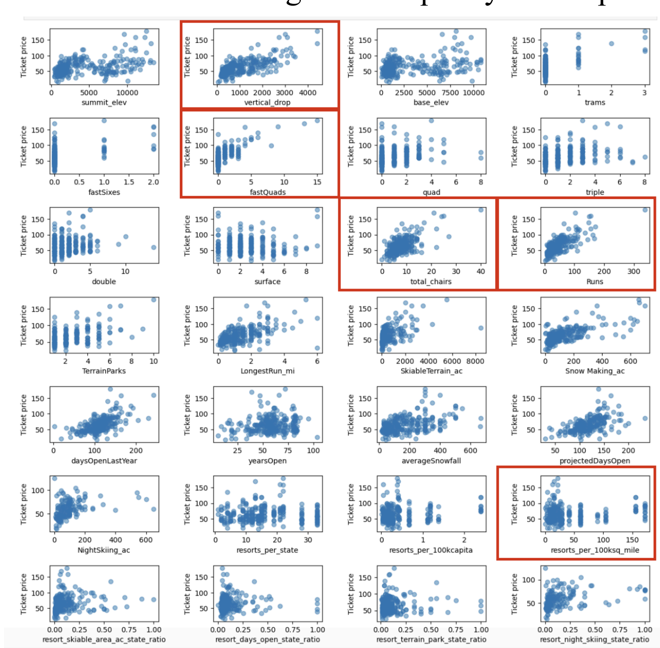

Fig 3: Correlation of various resort features with ticket price

If you look at Fig 3 above, we discovered that vertical_drop, Runs, fastQuads and total_chairs have the highest positive correlation with the ticket prices. Furthermore, we also discovered that when there is a lower number of resorts per capita, there is a greater variability of pricing of the tickets of the resorts. The ticket prices could climb as the number of resorts increases as it indicates a popular area for skiing with plenty of demand. The lower ticket prices with states with fewer resorts indicates a lower demand for skiing in those states. Lastly, we also engineered 4 new features shown in *Fig 4*, and discovered that the more chairs a resort has to move people around, relative to the number of runs, ticket prices fall and they stay pretty low.

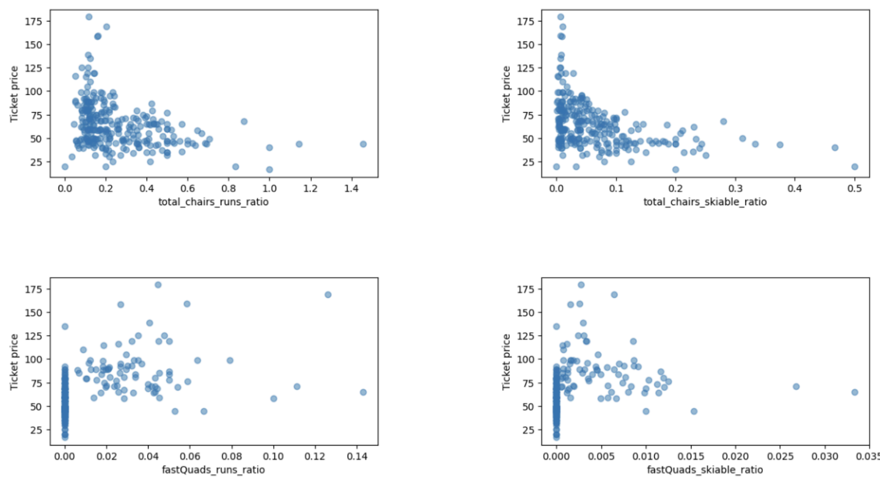

Fig 4: Visualization newly engineered features correlated with the ticket price

Modeling

We first took leadership's original technique of using the mean as a predictor for the baseline model, and we ended up getting a 63.8. This was a very poor prediction and yielded an MAE metric of 19.14 (just for context, an MAE tells us on average how far away from the true value the prediction is)
Then we created two models:

1. Linear regression with imputing missing values with the median and cross validating with k number of features
2. Random forest with cross validation and hyperparameter tuning (number of estimators, scaling, and imputing strategy of median or mean being the hyperparameters)

We ended up choosing the Random Forest model because it had an MAE of 9.5, as opposed to Linear Regression that has an MAE of 10.5. We also visualized (see *Fig 5* below) what four features the that the best Random Regressor model used to make it's prediction from and they ended up being fastQuads, Runs, Snow Making_ac and vertical_drop (pretty similar to the features that we found had a strong correlation with the ticket prices in the EDA section).

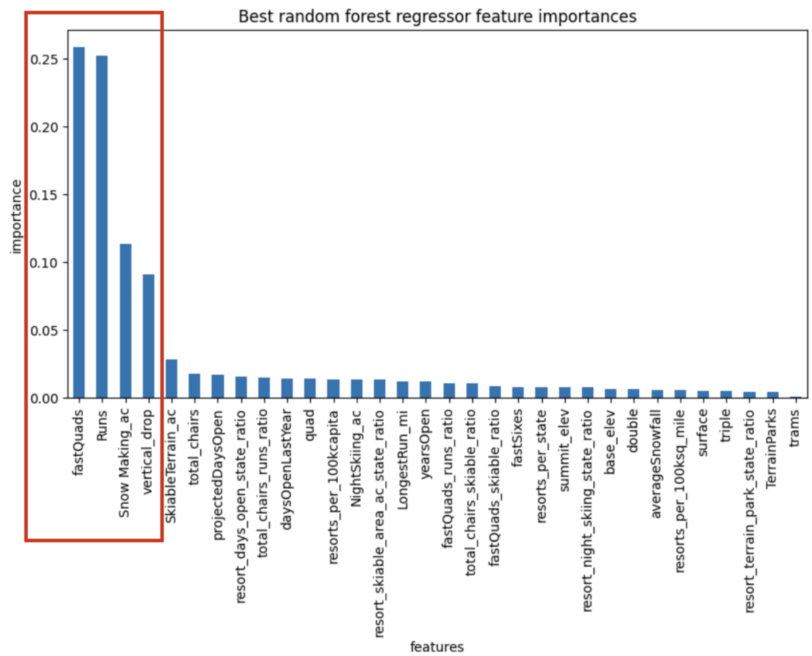

Fig 5: Feature importances of the best Random Forest Regressor model

Pricing Recommendation using chosen Random Forest Model

Using our new Random Forest Model, we got a modeled price of $95.87, when the actual price of the resort was $81.00. The mean absolute error is $10.39, which suggests that there is still room for a lot of increase. Given that there was room for increase in the pricing, we looked at some of the options that the business had shortlisted in order to increase the revenue of the tickets or cutting current costs on certain facilities. In the table given below you will see the short listed option and our corresponding finding.

Short-listed Option	Finding
Permanently closing down up to 10 of the least used runs.	The resort can close up to 4 or 5 without a substantive blow to their ticket price (See *Fig 6*) below
Increase the vertical drop by adding a run to a point 150 feet lower down but requiring the installation of an additional chair lift to bring skiers back up, without additional snow making coverage	This scenario just increased the support ticket price by $1.99.

Same as above, but adding 2 acres of snow making cover	Same as above
Increase the longest run by 0.2 mile to boast 3.5 miles length, requiring an additional snow making coverage of 4 acres	This scenario led to no change in the ticket price.

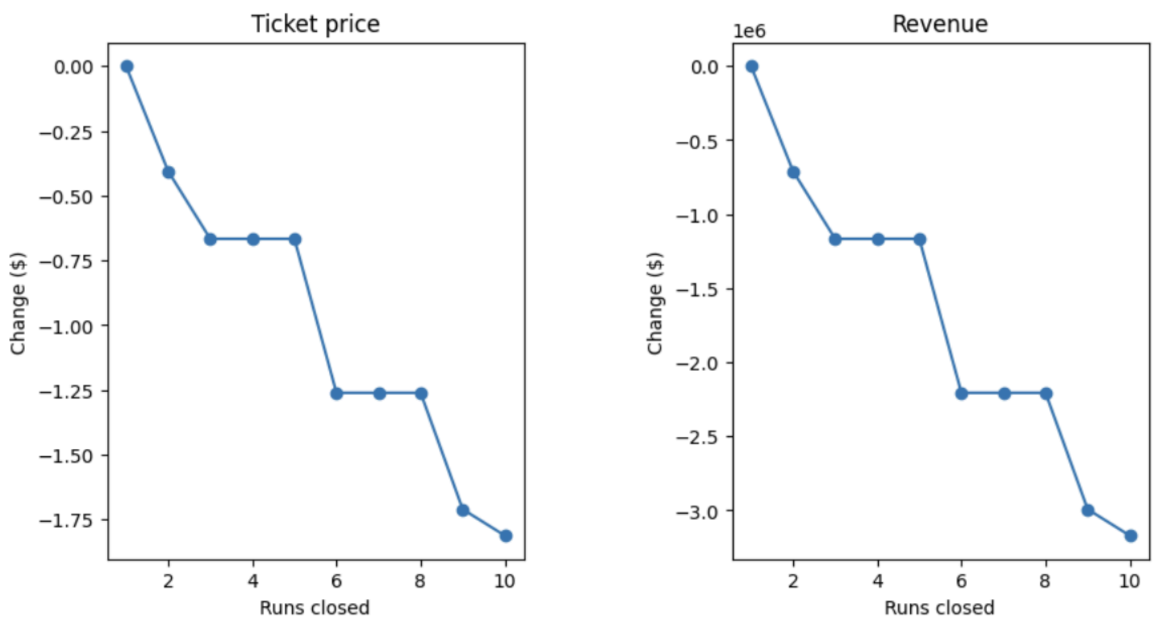

Fig 6: Visualization of change in ticket pricing as the number of runs close

Conclusion

Based on the modeling and analysis we did above, here are some recommendations we suggest to the leadership:

- Conduct a pilot closure of up to four runs and monitor the impact on visitor satisfaction and ticket sales.
- Market some of the facilities that Big Mountain Resort has opposed to other resorts (one of the highest vertical drops, extensive snow making capabilities, high total number of chair lifts, diverse range of runs, longest runs compared to other resorts and large amounts of skiable terrain) and gradually use the unique facilities to increase the price to $95.87

Future Scope of Work

Note that the modeled price was much higher than the original price here ($95.87 as opposed to $81.00). In the next iteration for a better model, we could augment our dataset with the following features for a better prediction:

- The salaries and the number of the employees who maintain these facilities.
- The cost of the food and beverages sold at the resort
- The varying costs during different seasons of the year

We can also iterate on this model based on the impact it has on the number of visitors visiting the ski resort on a bi-yearly or yearly cadence (ex. If the ticket prices increase, this could reduce the number of visitors which is currently 350,000 over the season.)