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Currently Big Mountain Resort's ticket pricing strategy is to charge a premium above the average price of resorts in its market segment - this is achieved based on their current average weekend price of $81 when the market segment average is $64. But could they be charging more?

Big Mountain also does not have a strong sense of what facilities matter most to visitors, particularly which ones they're most likely to pay more for. This hampers investment strategy and this is why management is looking for a predictive model for ticket price based on a number of features boasted by the resort. The model will be used to provide guidance for Big Mountain's pricing and future facility investment plans.

1. Data Wrangling + Exploratory Data Analysis:
With this purpose in mind we dove into the data provided on all 328 of the ski resorts in the market segment. The initial pass through revealed a few oddities that needed to be cleaned up - for example one resort reported being open for 2019 years, and another resort claimed to have 26,819 acres when in reality it was only 1819 acres. The column data on Fast Eight was entirely removed due to a 50%+ resorts having missing values, and only 1 resort claiming to have this feature.

A distinct feature for ticket pricing was that many resorts priced Weekend and Weekday tickets the same. And given that we had more data reported for Weekend Ticket pricing, we choose to focus on this parameter.

To go a step beyond the given data we wanted to consider if state statistics would be important to a pricing model. State population and total area in square miles was incorporated, looking at information such as resorts per state, state total days open, total night skiing acreage available etc. During our exploratory data analysis phase the relationship between state and ticket prices was not obvious - which was good news as it offers justification for treating all states equally, and work towards building a pricing model that considers all states together.

During EDA we looked at a correlation heat map in addition to scatterplots of features with respect to ticket price and several positive correlations stood out. Snow making acreage, vertical drop, fast Quads, total # of runs, total chairs in particular seemed to encourage higher ticket prices. It should be remembered though, that as we explore data looking at how a given feature is correlated with ticket price this does not imply causation.

2. Model Preprocessing with feature engineering + Algorithms used to build the model with evaluation metric:

- Models were evaluated based on the following metrics: Coefficient of determination, Mean Absolute Error, and Mean Squared Error (R^2, MAE, and MSE respectively).

- Baseline'd model performance using the average price as a ticket price predictor.
- Built a refined linear model using cross-validation determining which and how many features were optimal for price prediction.
- Built a Random Forest Regressor model, also utilizing cross-validation.
- ***Model Conclusion: Random Forest Regressor Model had the best performance*** with a Mean Absolute Error (MAE) of $9.54 dollars on our test data subset. This was a huge improvement on the $19.13 dollars MAE of using just the average price.

During this stage we pursued several feature engineering techniques. First we imputed missing values trying both the mean and median where it was found the median was the better parameter. Next we scaled the features to have zero mand and unit variance as a preprocessing step to our machine learning algorithm. And our best model selected the top 4 features of importance, which were fastQuads, Runs, Snow Making acreage, and Vertical drop.

3. Winning Model, Scenario Modeling, and Pricing Recommendation:

Random Forest Regressor Model was the winning model and predicted that Big Mountain Resort would be charging $95.87 for their weekend tickets. This is almost a $16 increase compared to the current $81.00 they are charging.

Using our winning model we looked at four scenarios.

1) Permanently closing down up to 10 of the least used runs.
2) Increase vertical drop by adding a run, and requiring installation of an additional chair.
3) Same as 2) but adding 2 acres of snow making cover.
4) Increase the longest run by 0.2 miles and add 4 acres of snow coverage.

The model determined closing one run makes no difference. Closing 2 and 3 successively reduces support for ticket price and so revenue. If Big Mountain closes down 3 runs, it seems they may as well close down 4 or 5 as there's no further loss in ticket price. Increasing the closures down to 6 or more leads to a large drop. Scenario 2 increased support for ticket price by $1.99, which equals an increase of $3,574,638 over the course of a year. Scenarios 3 and 4 had no added support for higher ticket prices.

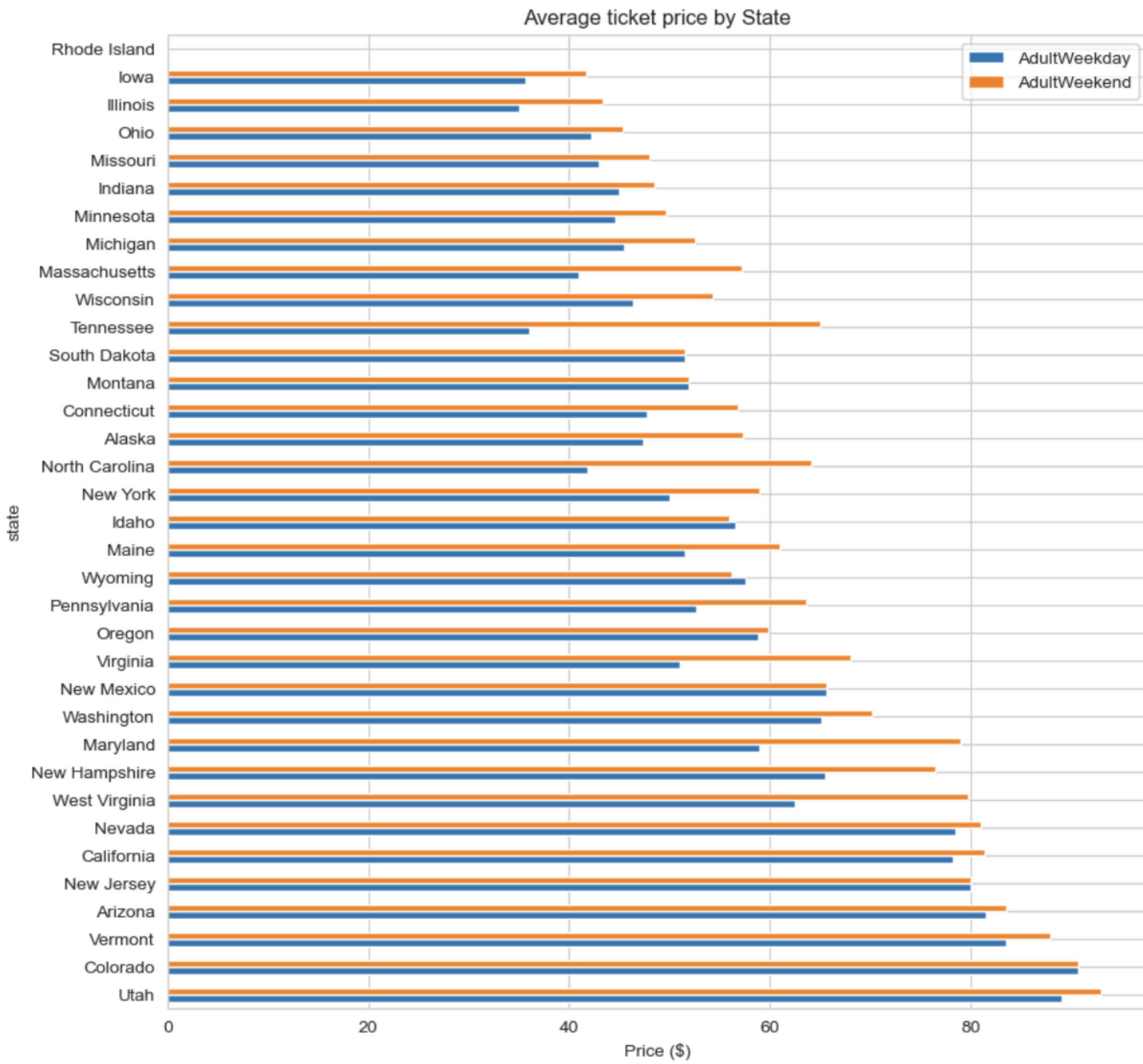
4. Conclusion and Future Scope of Work:

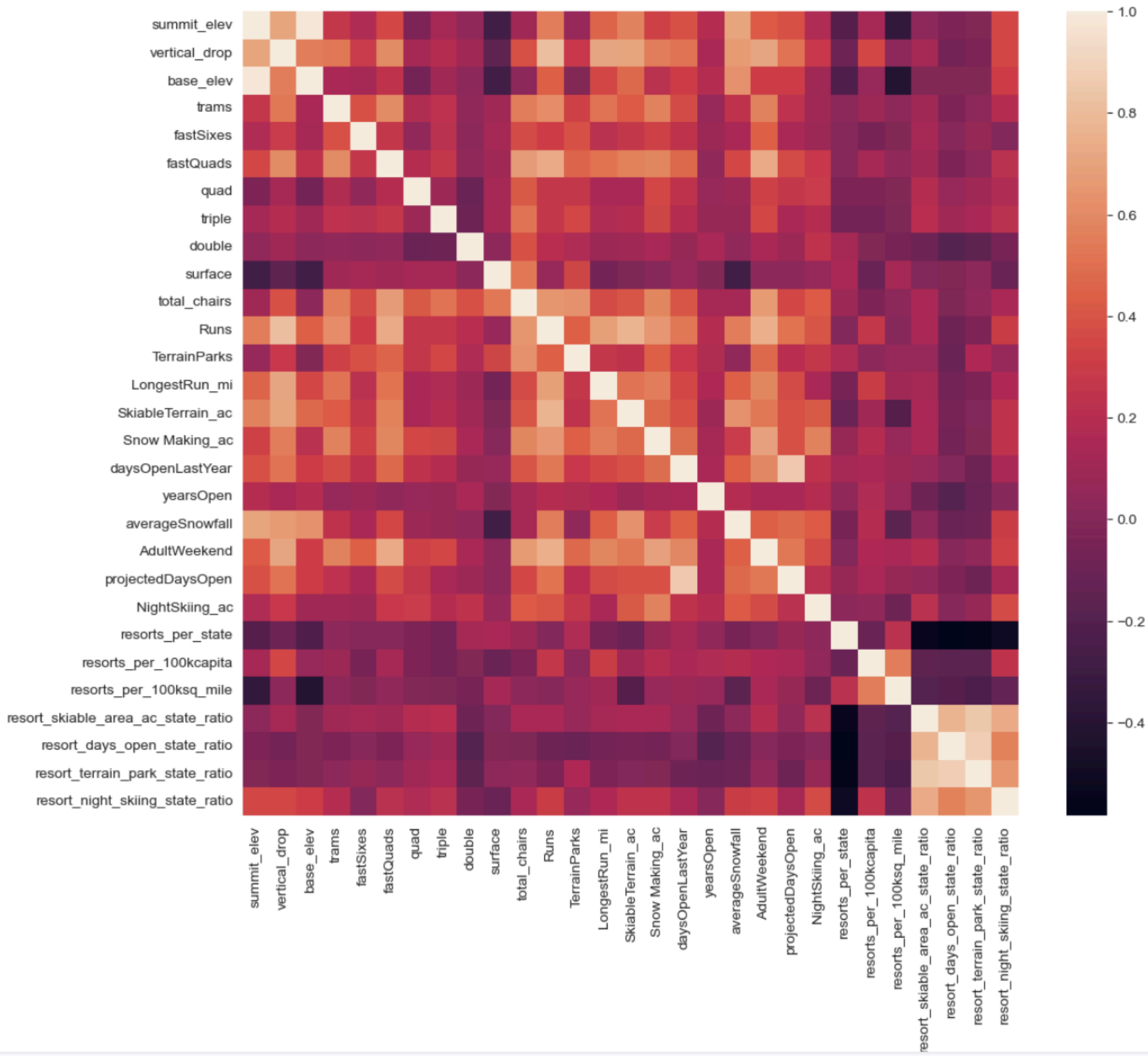
By using machine learning and the Random Forest Regressor Model we are able to provide Big Mountain a robust pricing model for their ticket prices. Here the model suggests raising ticket prices from $81 up to almost $96, and we also provided justification for closing down at least 1 run, and increasing vertical drop by adding another run.

Next steps would be to work with Big Mountain’s key stakeholders to work through the different recommendations and how they can implement change. Furthermore, by building out a model dashboard we would like to provide Big Mountain’s data analysts tools so they can adapt to changes in real time.

Relevant Figures:

1. Data Wrangling + Exploratory Data Analysis:





summit_elev
vertical_drop
base_elev
trams
fastSixes
fastQuads
quad
triple
double
surface
total_chairs
Runs
TerrainParks
LongestRun_mi
SkiableTerrain_ac
Snow Making_ac
daysOpenLastYear
yearsOpen
averageSnowfall
AdultWeekend
projectedDaysOpen
NightSkiing_ac
resorts_per_state
resorts_per_100kcapita
resorts_per_100ksq_mile
resort_skiable_area_ac_state_ratio
resort_days_open_state_ratio
resort_terrain_park_state_ratio
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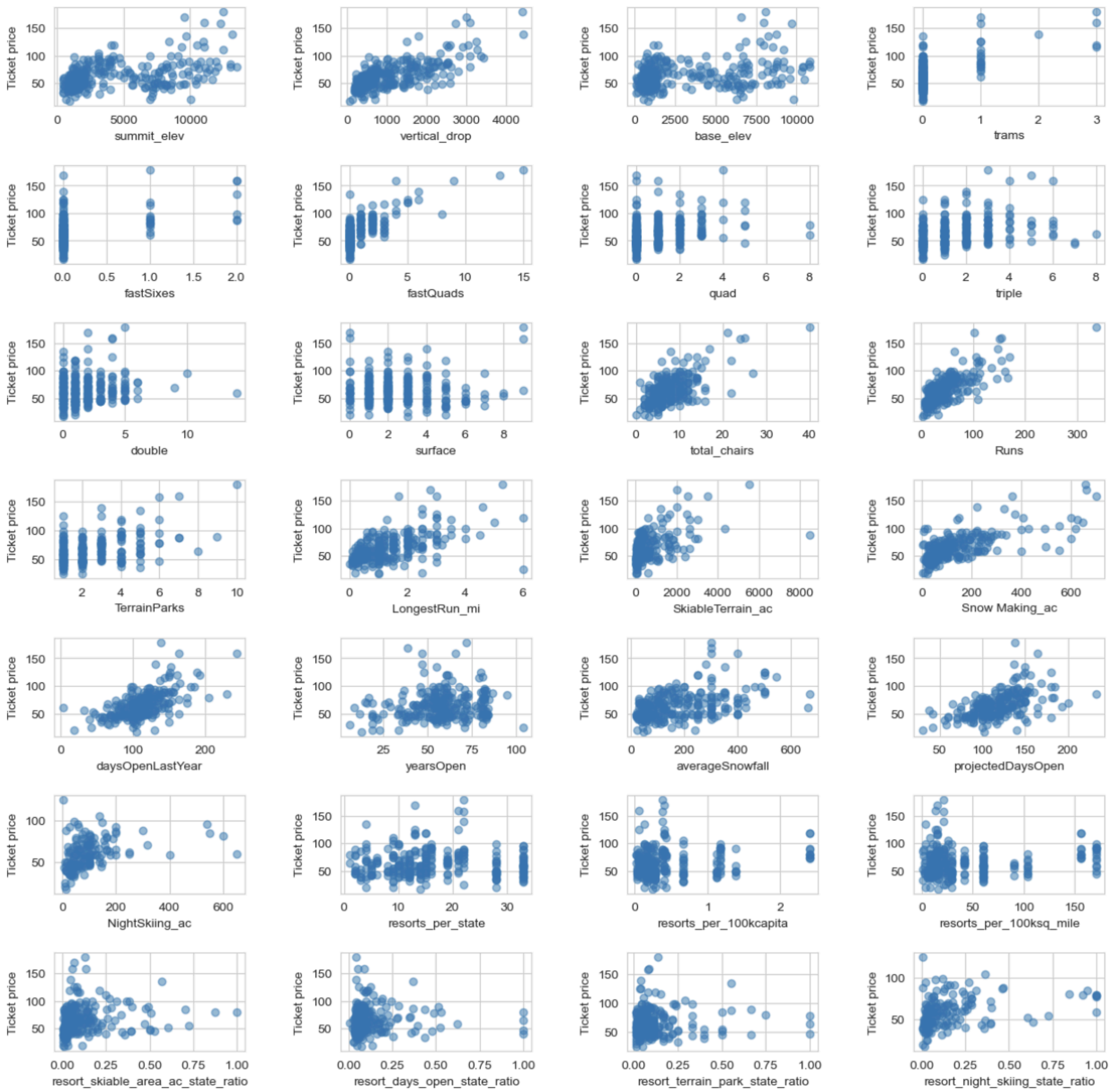
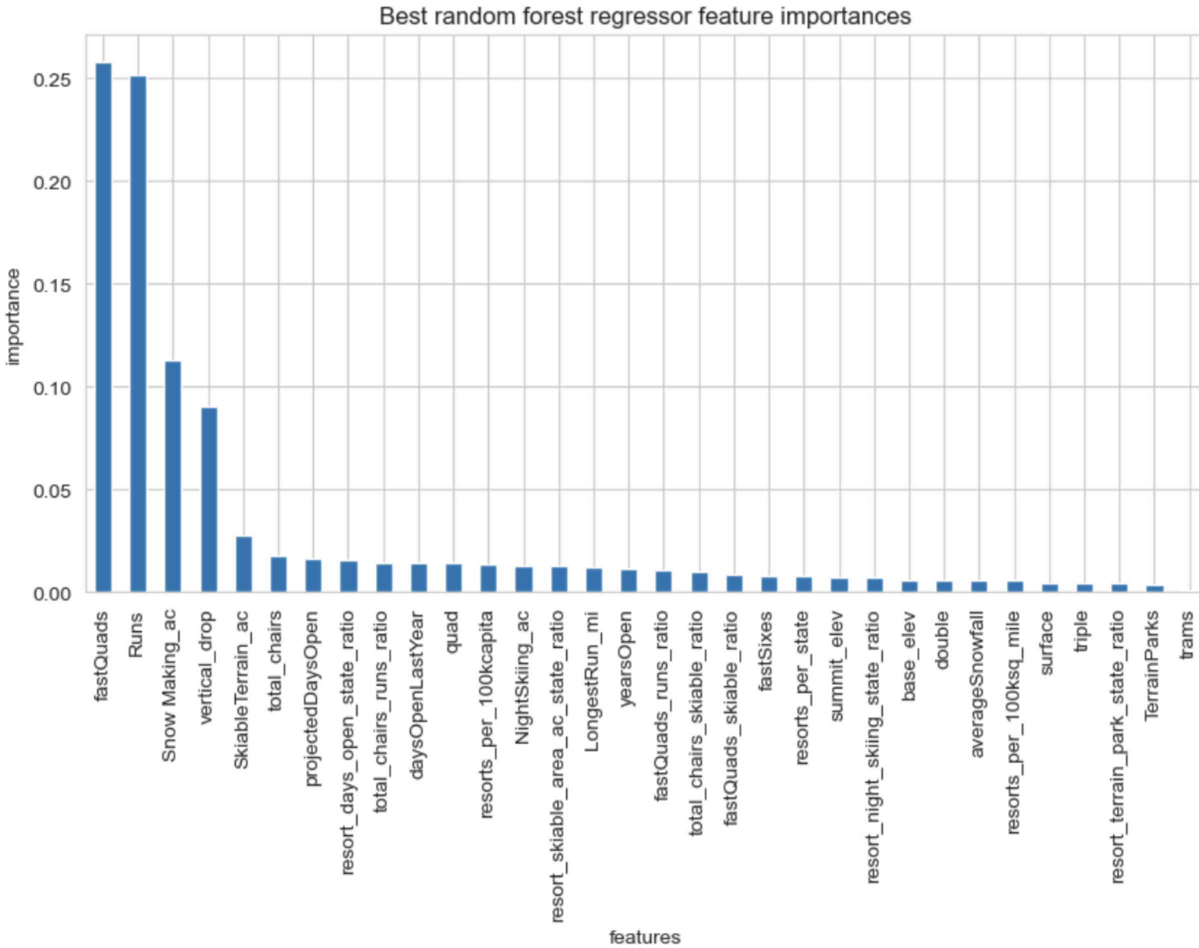
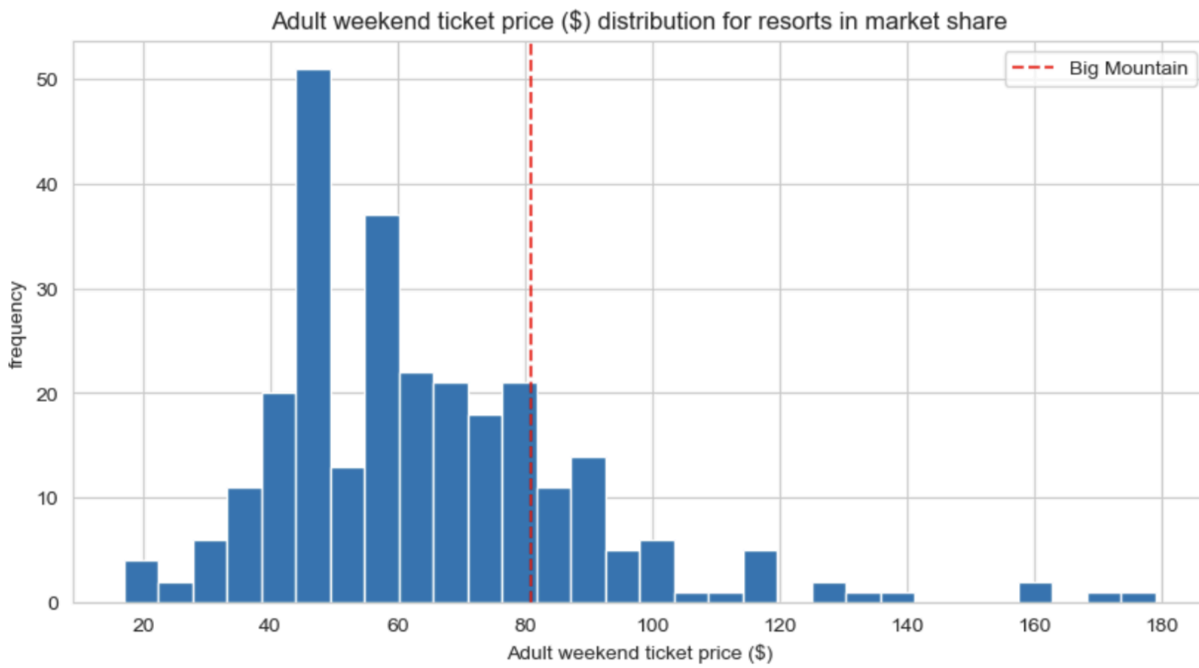
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

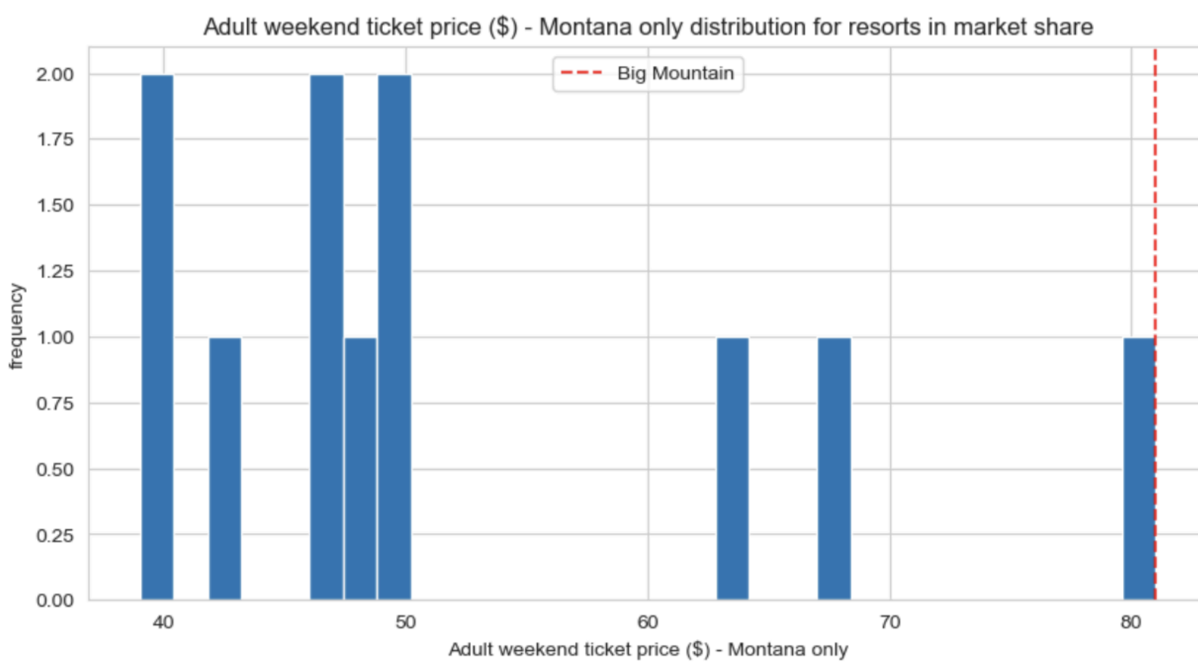


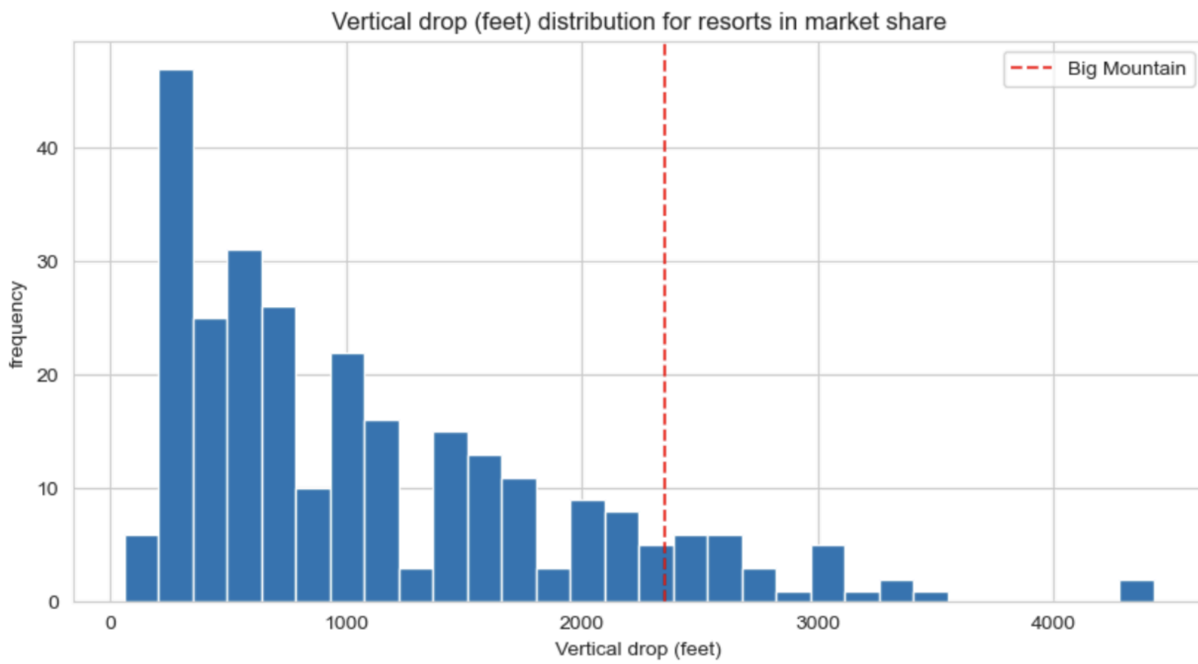
2. Model Preprocessing with feature engineering + Algorithms used to build the model with evaluation metric:

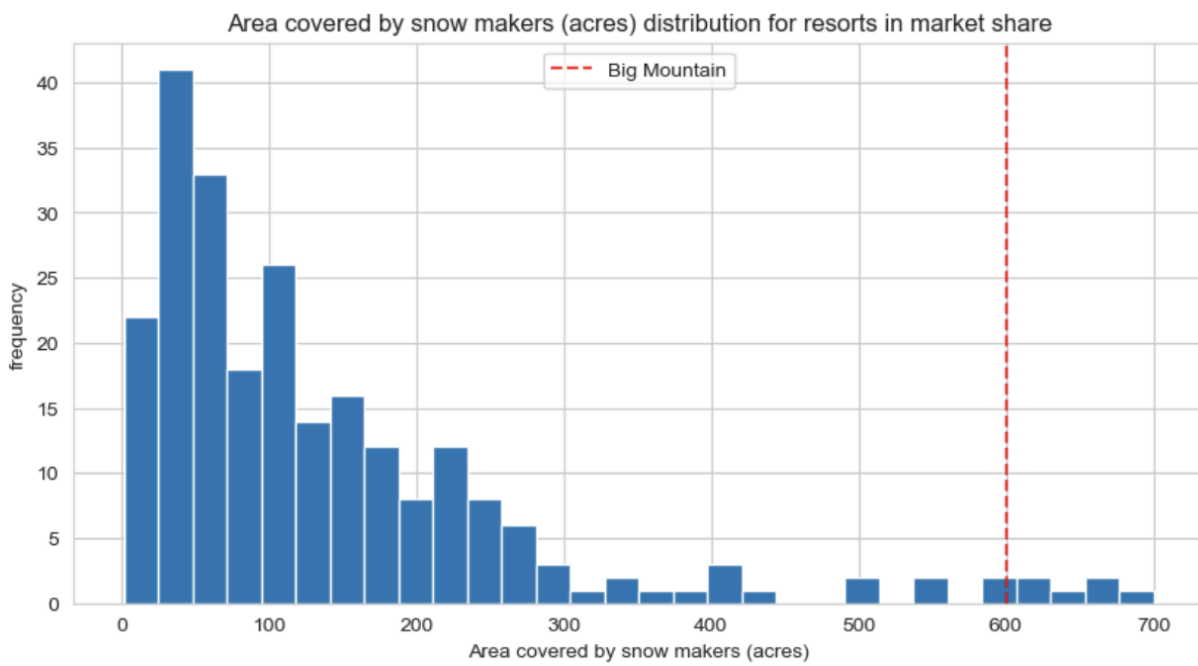


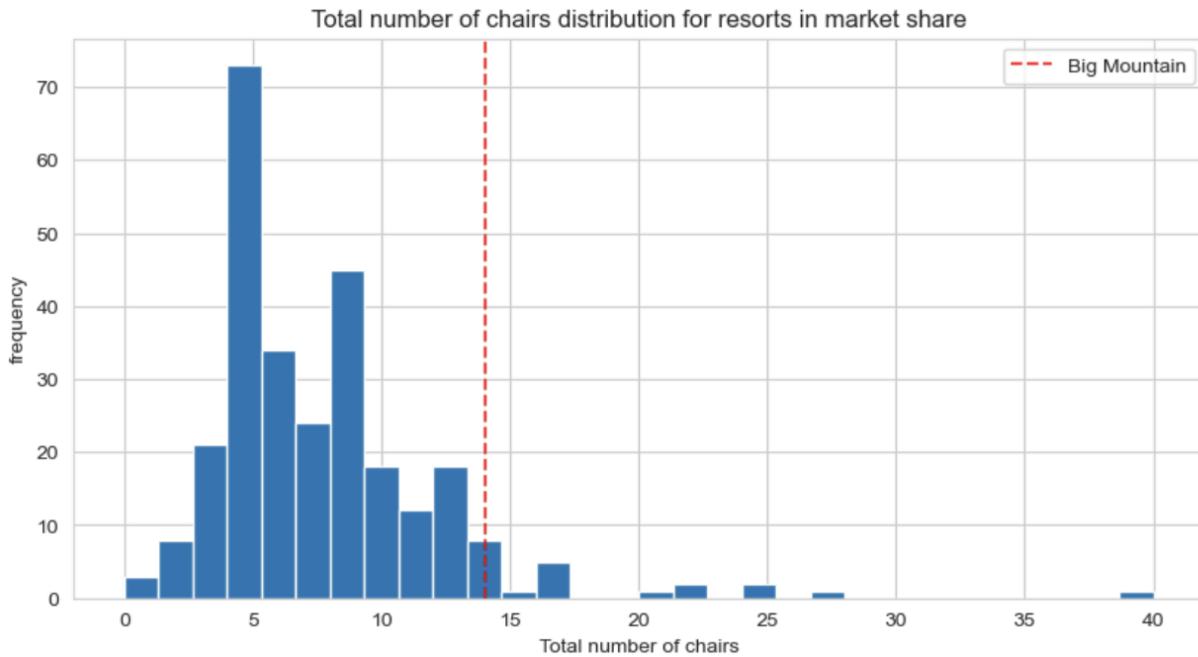
<u>3. Winning Model, Scenario Modeling, and Pricing Recommendation:</u>


Adult weekend ticket price ($) distribution for resorts in market share
Big Mountain
frequency
0
10
20
30
40
50
20
40
60
80
100
120
140
160
180
Adult weekend ticket price ($)

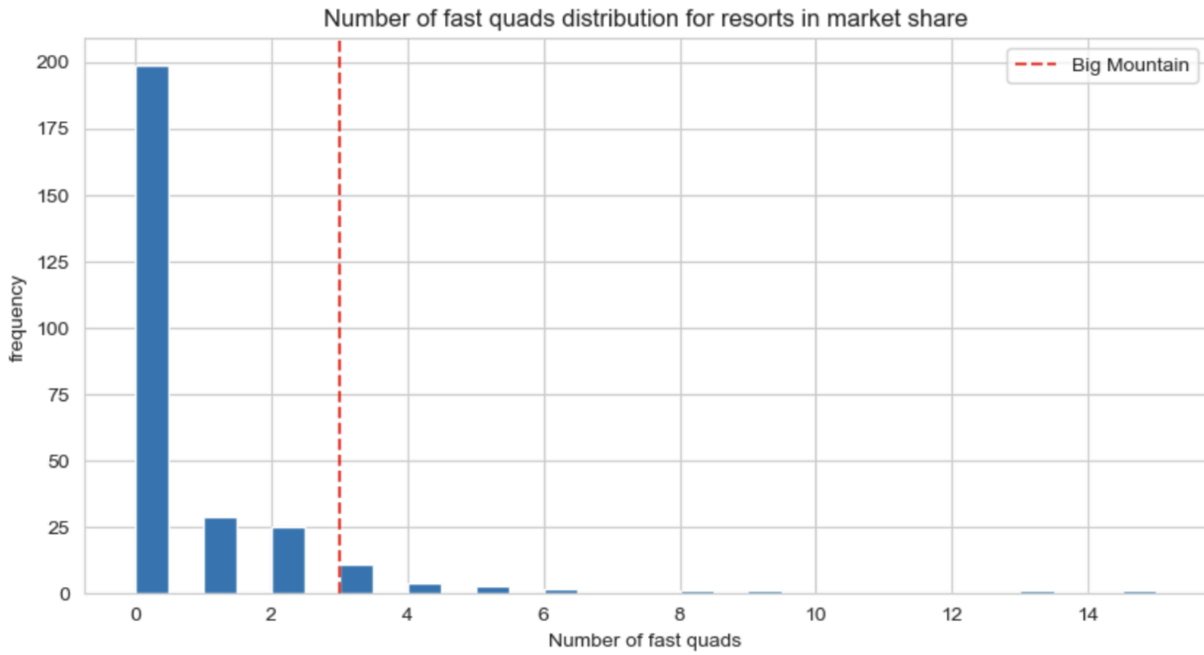

Adult weekend ticket price ($) - Montana only distribution for resorts in market share
Big Mountain
frequency
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
40
50
60
70
80
Adult weekend ticket price ($) - Montana only

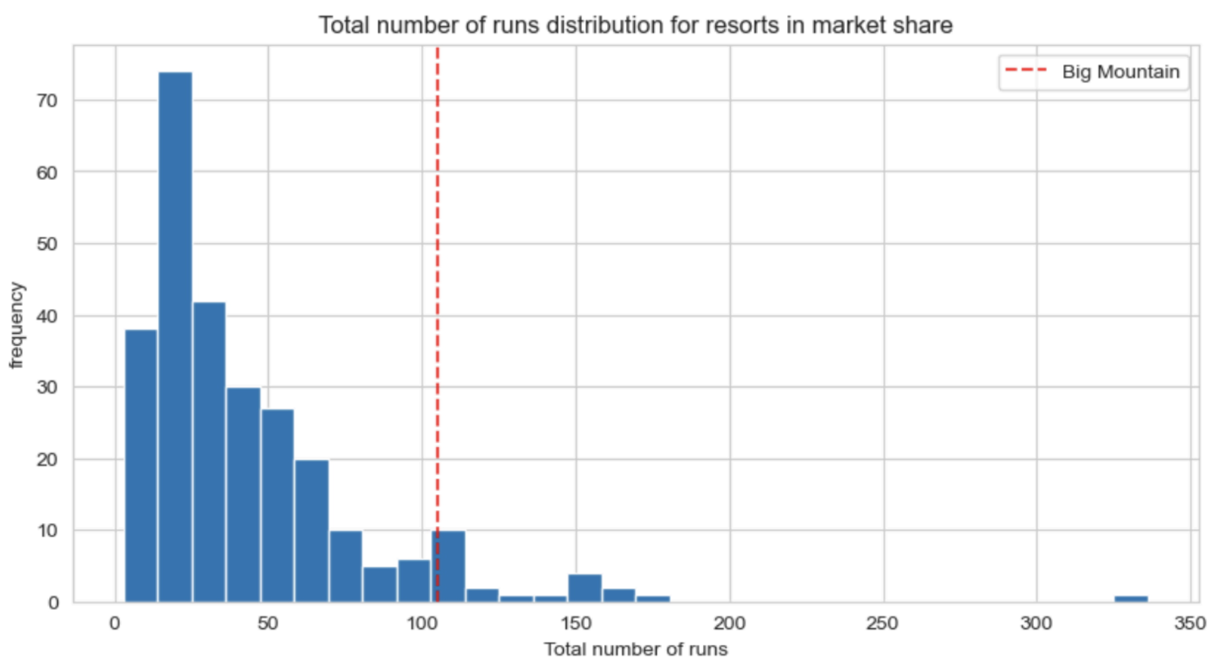

Vertical drop (feet) distribution for resorts in market share
Big Mountain
frequency
0
10
20
30
40
0
1000
2000
3000
4000
Vertical drop (feet)

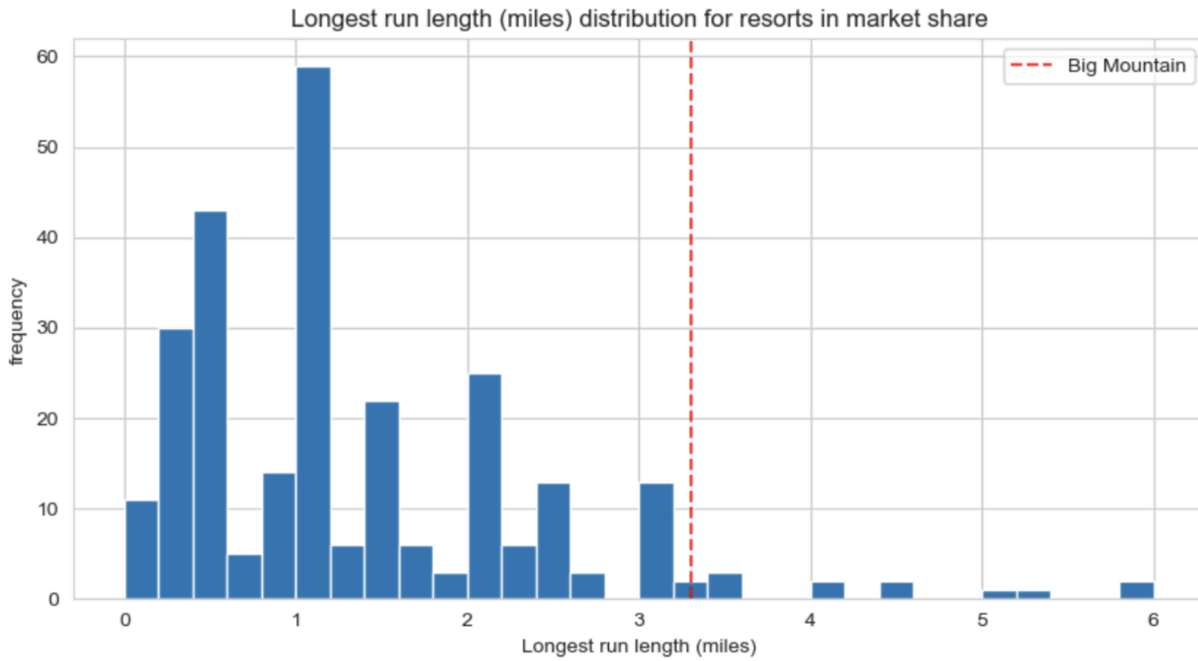

Area covered by snow makers (acres) distribution for resorts in market share
Big Mountain
frequency
0
5
10
15
20
25
30
35
40
0
100
200
300
400
500
600
700
Area covered by snow makers (acres)

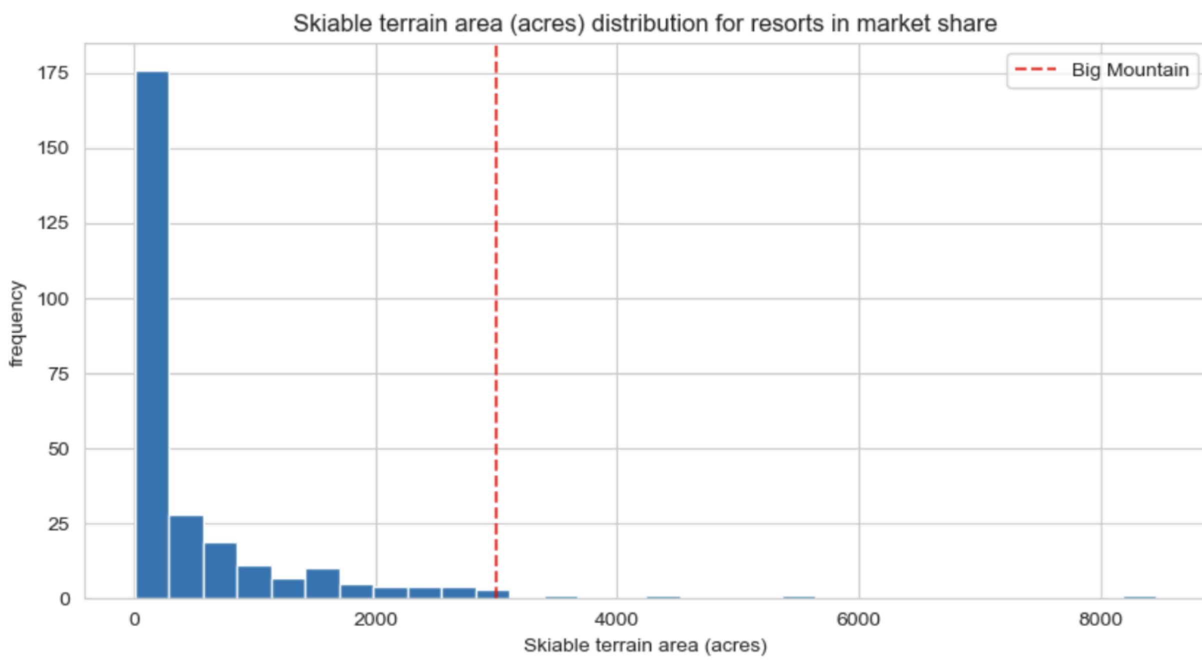


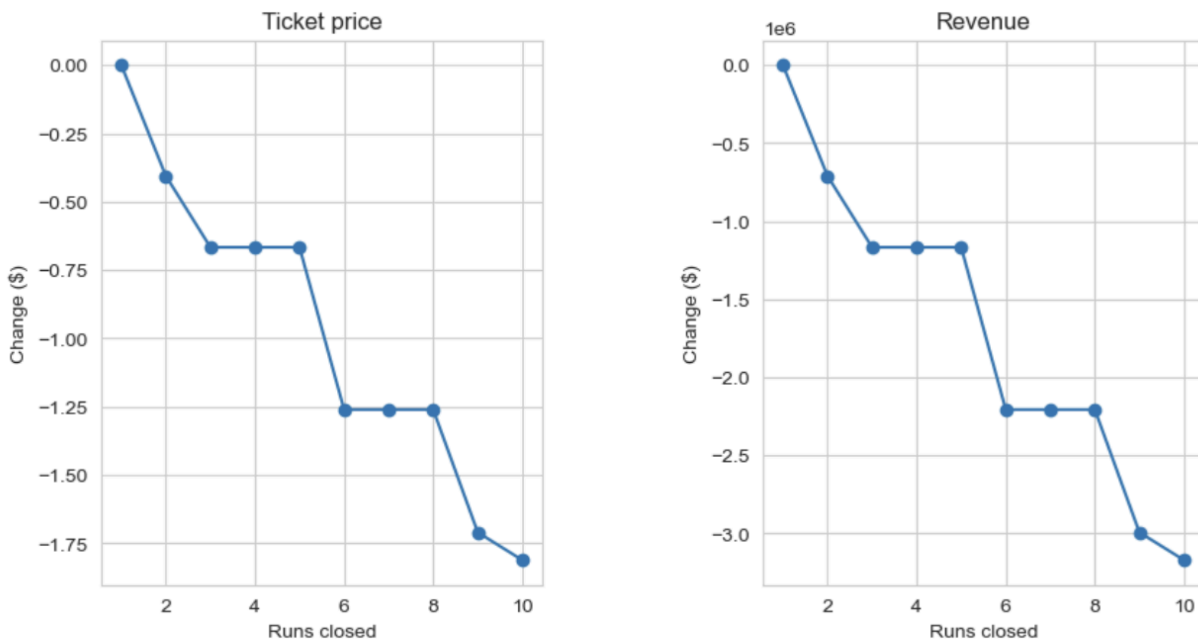
Total number of chairs distribution for resorts in market share
Big Mountain
frequency
0
10
20
30
40
50
60
70
0
5
10
15
20
25
30
35
40
Total number of chairs


Number of fast quads distribution for resorts in market share
Big Mountain
frequency
0
25
50
75
100
125
150
175
200
0
2
4
6
8
10
12
14
Number of fast quads


Total number of runs distribution for resorts in market share
Big Mountain
frequency
0
10
20
30
40
50
60
70
0
50
100
150
200
250
300
350
Total number of runs


Longest run length (miles) distribution for resorts in market share
Big Mountain
frequency
Longest run length (miles)
0
1
2
3
4
5
6
0
10
20
30
40
50
60


Skiable terrain area (acres) distribution for resorts in market share
Big Mountain
frequency
Skiable terrain area (acres)
0
2000
4000
6000
8000
0
25
50
75
100
125
150
175


Ticket price
0.00
−0.25
−0.50
−0.75
−1.00
−1.25
−1.50
−1.75
Change ($)
2
4
6
8
10
Runs closed
Revenue
1e6
0.0
−0.5
−1.0
−1.5
−2.0
−2.5
−3.0
Change ($)
2
4
6
8
10
Runs closed