Big Ski Resort Price Modeling

06/29/2021

Outline

Objective: To leverage current facilities and strategically plan future investments.

How: Model ticket price based on the features from data collected and perform various scenarios of closing down or opening facilities to calculate the revenue generated from each scenario and make a sound data driven business decision.

Key steps in Data Science Method:

1. Problem Identification:
2. Data Wrangling:
3. Exploratory Data Analysis
4. Pre-processing and Training Data Development
5. Modeling

Problem Identification

Context: Big Mountain Resort recently installed an additional chair lift for $1540000. Can we justify increasing ticket price in order to cover for the investments?

Success criterion: We will be successful if we can increase ticket price such that we at least break-even the investment as soon as possible before the end of the season.

Scope: Build a model with the features available and predict the price of our resort.

Constraints: Price cannot be too high for example more than 25% of current price.

Data Source: csv file which contains information about various key resorts in the US.

Recommendation and key findings

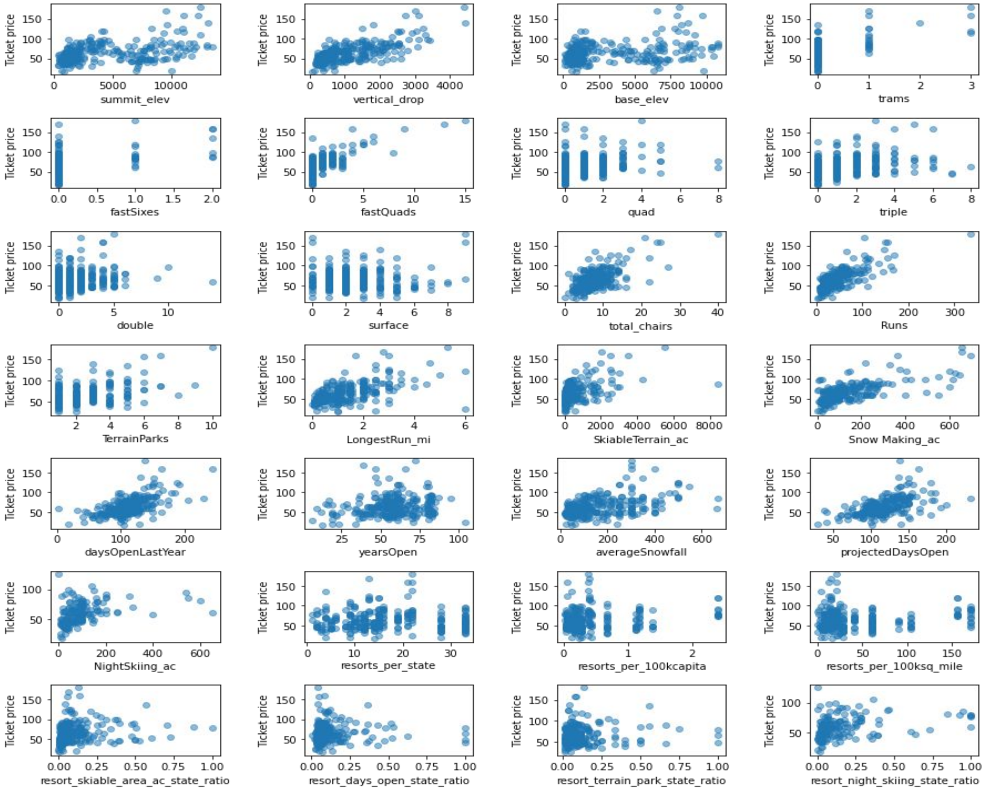
5 run closures, increasing vertical drop and installing additional chair lift

This would drive-up the revenues by $15000000 where as the investment was only $1500000 (10 times less)

Other scenarios of adding 2 acres of snow making cover and increasing the longest run by 0.2 miles didn’t yield significant revenues

Modeling results and analysis

Scatter plots of various features



Important features:

1. Vertical_drop
2. Snow Making_ac
3. total_chairs
4. fastQuads
5. Runs
6. LongestRun_mi
7. trams
8. SkiableTerrain_ac

Modeling results and analysis

Final pipeline chosen:

Imputer function: Median

Scaler function: None

Random Forest Regressor with n estimators = 69

Results:

Mean Absolute Error: $10.39

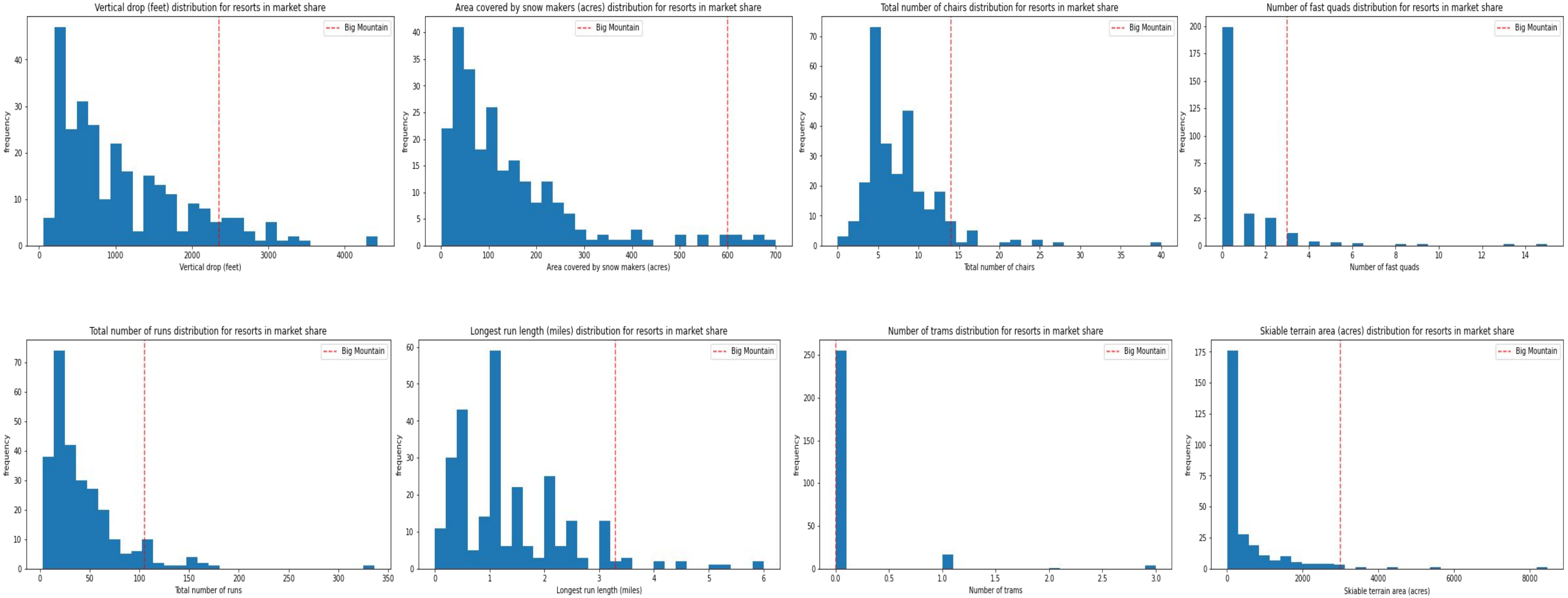
Standard Deviation: $1.47

Predicted ticket price: $95.87

Actual ticket price: $81 (more than one MAE off- quite big discrepancy)

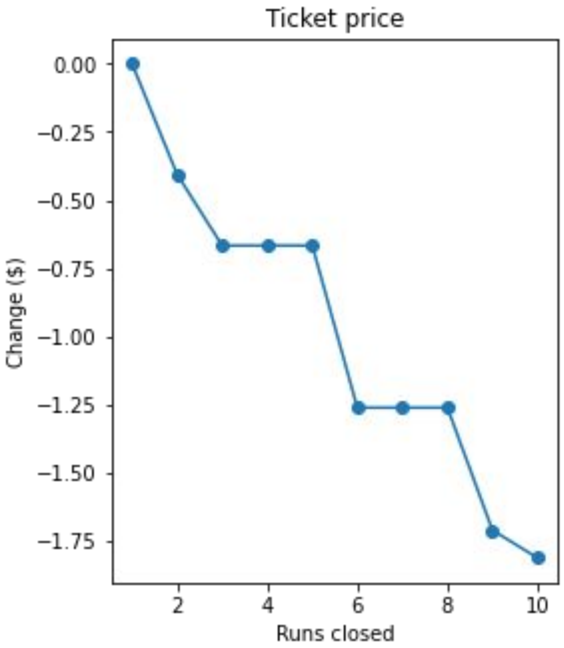
Modeling results and analysis

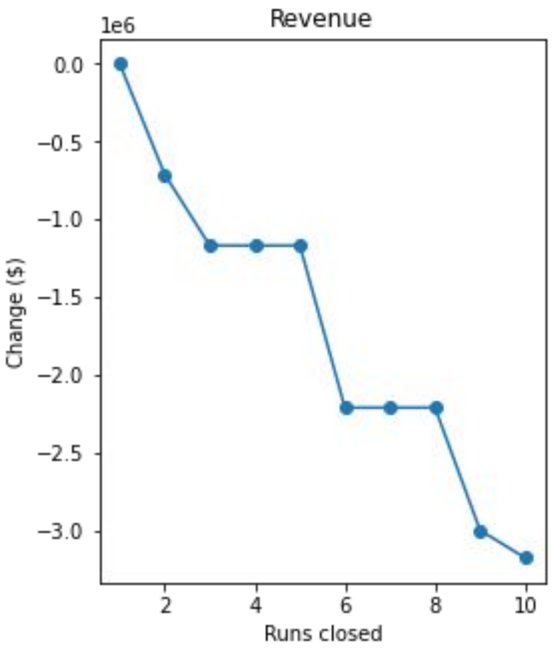
Big Mountain stance on important features



Modeling results and analysis

Ticket price/Revenue reduction with number of runs closed





Ideal runs closed would be 4 or 5, additional runs closed would result in sharp decline in revenues.

Summary and conclusion

Having operating costs would help improve our model and certainly help us to have a more understanding on the price discrepancy.

Big Mountain fares very well at important features so it is not surprising to see a high predicted price.

Since, we used a lot of resorts (276) for our model way more than what learning_curve suggested (40-50), so model can be assumed to be somewhat robust of wrong prices. This would lead us to believe that Big Mountain is underpricing for the facilities it has.

Create a dashboard that would help business leaders see the impact of feature changes on the revenue and make appropriate business decisions.