Big Mountain Resort Pricing Strategy Analysis

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1 Introduction

Big Mountain Resort's pricing strategy currently does not account for the **$1.54M** annual operating cost associated with a newly constructed chair lift. This brings into light the fact that Big Mountain's ticket price does not have any reflection of facility value whatsoever. Because of this issue, Big Mountain is unable to properly determine areas high yield investment opportunities or cost saving strategies. In order to create a new pricing strategy built around facility value, more than 300 competitors within the ski-resort market were analyzed to determine Big Mountain's market position.

2 Analysis and Model Development

Through careful data wrangling and exploratory data analysis, 227 suitable resorts were identified for use in model construction, taking into account 25 unique features of interest. Initial analysis of ticket pricing determined **Weekend Ticket Prices** to be most suitable for further analysis, leading to **Weekday Ticket Prices** to be dropped from consideration.

Additional data related to states was brought in to further augment the ski resort dataset, providing state-level information on each resort such as resort density and population density. However no direct correlation between state and ticket price was identified, shifting the focus of model development to resort-level features. Through Principal Component Analysis strong correlations with resort-level features could be observed, however these relationships suggested non-linearity and multicollinearity which would be problematic for model development.

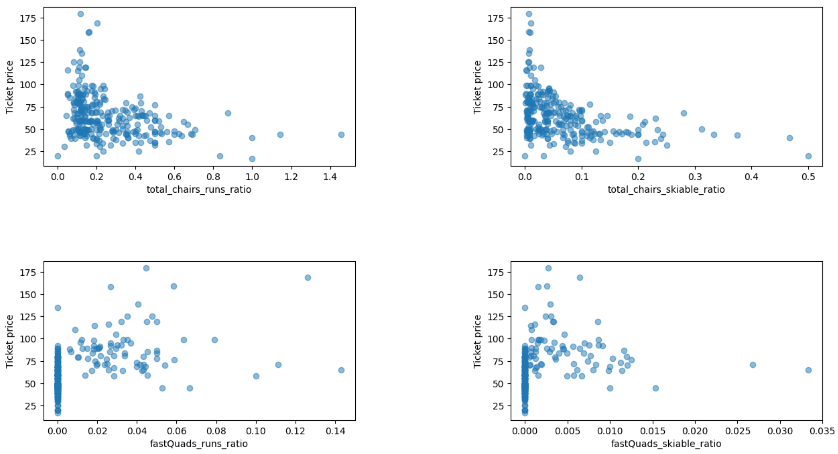

Figure 1: Top Ticket Price/Feature Correlations

Initial development began on a **Linear Regression** model with **Mean Ticket Price** as a baseline for comparison. Early versions of the Linear model showcased high variance and over fitting to the training data, suggesting the presence of redundant features within the model. Through the use of **SelectKBest** and **GridSearchCV** methods with $k = 8$ the number of features was reduced significantly. These features were determined to be: **Vertical Drop, Snow Making (acres), Total Chairs, Total Fast Quads, Total Runs, Longest Run (miles), Total Trams, and Skiable Terrain (acres)**. Numerical missing data was imputed with the **Median Value** for the relevant category. This model gives a **Mean Absolute Error Mean Value of 10.50** with a **Mean Absolute Error Standard Deviation of 1.622** and a **Mean Squared Error of 11.79**.

A second model was developed using a Random Forest Regressor approach for comparison with the Linear model. Using Cross-Validation techniques, the Random Forest model was ultimately selected as the best approach, yielding significantly more consisted and reliable predictive power and accuracy. This model gives a **Mean Absolute Error Mean Value of 9.645** with a **Mean Absolute Error Standard Deviation of 1.353** and a **Mean Squared Error of 9.538**.

Using the Random Forest Regressor model to predict the ticket price for Big Mountain Resort yields a value of **$95.87**. When considering the model error of roughly $9.6 this prediction indicates that there is already opportunity to increase ticket pricing without any further changes to resort facilities. However, this model was developed based on the assumption that other resorts are basing their ticket prices based on facility value and not simply setting them arbitrarily.

3 Recommendations

Big Mountain holds a superior Market position in each of the relevant facility categories when compared against competitors within the market. This showcases a strong opportunity for further price increases based around facility value. Testing the Random forest model against various investment scenarios yields interesting results. Expansion of current facilities is also to be a promising investment strategy. Four scenarios were tested.

The first scenario of interest has to do with **closing unpopular runs**. The model predicts that **closing one run will not affect revenue**. Closing more would significantly decrease support for higher ticket prices, but **if 3 runs are closed, closing 4 or 5 would not impact revenue**.

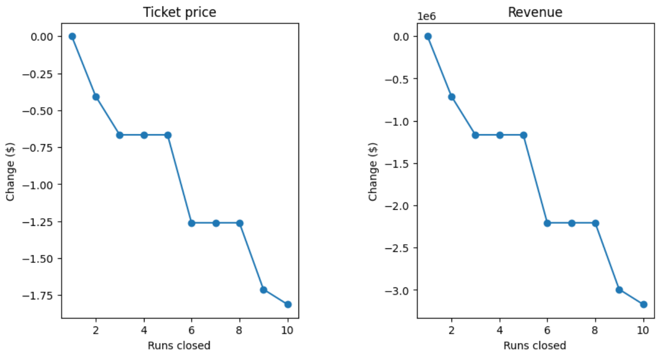

Figure 2: Analysis of Run Closure Scenario

The second scenario tested how an **increase in vertical drop by 150 feet plus installing an additional chair lift**. This change would increase support for ticket price by **$8.61**, yielding $15,065,471 over the course of a season.

The third scenario tested how the changes made with **scenario 2 plus an additional 2 acres of snow making**. This change would increase support for ticket price by **$9.90**, yielding $17,322,717 over the course of a season.

The fourth scenario showed no affect on ticket price. Changing the length of the longest run does not seem to be a strong investment opportunity.

Scenarios two and three show that with an increase in vertical drop and snow making coverage, the total annual cost of installing a new chair lift could be covered profitably.

Next steps for the development of this model would be to improve documentation to allow analysts to expedited training of analysts in its use. Further developments to this model could come in the form of system integration and user accessibility. By creating a user friendly interface, and potentially integrating it with current analysis software this could allow leadership to test more scenarios without further developer interaction.