

Big Mountain Resort: Data-Driven Ticket Pricing & Investment Strategy Report

Problem Statement

Big Mountain Resort aims to use data from 330 comparable U.S. ski resorts to build a predictive pricing model that identifies the main drivers of ticket prices and recommends an optimal and competitive price for the upcoming season. The goals are to (a) evaluate whether the current ticket price reflects true market value, (b) recommend a competitive pricing strategy if misaligned, and (c) identify opportunities for revenue growth and operational investment. By applying these insights, the resort seeks to increase overall revenue by 10% by next fiscal year.

Data Wrangling

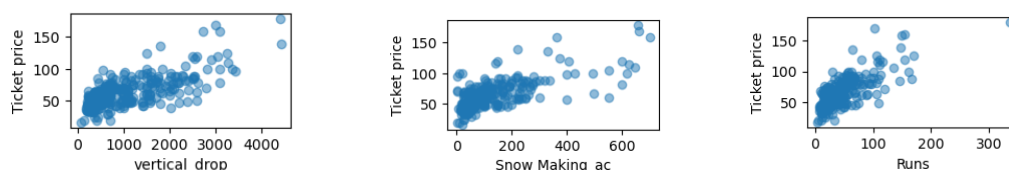
The original dataset included 330 resorts (including the Big Mountain Resort) and 27 variables describing ticket prices, terrain, lifts, snowmaking, season length, and more. Key steps in data cleaning included:

- Removing features with excessive missingness (*fastEight*) and correcting incorrect or outlier values (e.g., *SkiableArea*, *yearsOpen*).
- Dropping rows without pricing data and selecting *AdultWeekend* as the target due to greater completeness.

After cleaning, the dataset was reduced to 277 rows and 25 features, consistent and ready for analysis.

Exploratory Data Analysis (EDA)

Our exploratory analysis examined how resort characteristics vary across states and how they influence pricing. For example, Montana has substantial land area but relatively few resorts, while New York has the highest resort count but limited skiable terrain. Principal Component Analysis showed that the first two components explained over 75% of the variance, with Vermont and New Hampshire standing out due to high resort density and night-skiing availability. Several features such as vertical drop, fast quads, snowmaking capacity, total chairs, total runs, and a resort's share of statewide night-skiing displayed strong positive correlations with ticket price. These insights informed feature selection and highlighted the need to manage multicollinearity among competition-related ratios.

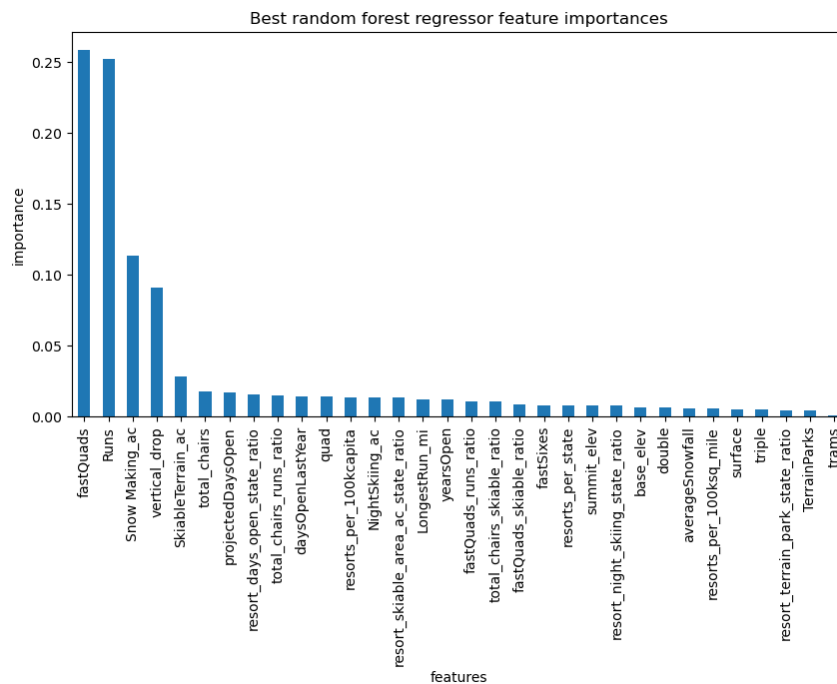


Model Preprocessing & Feature Engineering

Before modeling, Big Mountain Resort was set aside for final prediction, and the remaining data was split into a 70/30 train–test set. Non-numeric variables (*i.e.* *Name*, *State*, *Region*) were removed, missing values were imputed using the median, and numeric features were standardized, particularly for the linear regression model. Feature selection and cross-validation were used to identify the most influential predictors. As a benchmark, a mean-prediction baseline produced a high mean absolute error (MAE) of about \$19, confirming the need for more sophisticated modelling.

Algorithms & Evaluation

We evaluated two primary models: a linear regression with scaled features and a Random Forest Regressor. The linear model performed well, explaining roughly 80% of the variance in training data and 70% in the test set, with an MAE of about \$9. Its top predictors included vertical drop, snowmaking capacity, fast quads, total chairs, and runs. The Random Forest model achieved slightly better accuracy, reducing MAE by about a dollar, and demonstrated greater stability while reinforcing the same key price drivers. The Random Forest Regressor was selected as the final model due to its stronger and more robust performance.



Winning Model & Scenario Modelling

Big Mountain currently charges \$81 for a weekend lift ticket, while the Random Forest model predicts an optimal market-aligned price of approximately \$95.87. Even after accounting for the model's MAE (~\$10), the analysis strongly suggests the resort is undervaluing its offering. Scenario modeling showed that expanding vertical drop provides the largest pricing impact, increasing the predicted ticket price by about \$8.61. Adding additional snowmaking on top of this expansion yields only a modest further lift, bringing the total increase to roughly \$9.90.

Other scenarios, such as run closures or extending the longest run, produced minimal improvements. Overall, vertical drop expansion clearly emerged as the most impactful investment for increasing pricing potential.

Pricing Recommendation

We recommend the following:

1. Adopt a phased price increase, paired with customer-feedback monitoring and sales tracking.
2. Further explore the vertical drop expansion scenario—either through a planning pilot or willingness-to-pay surveys.
3. Conduct targeted market research to validate model assumptions around customer perception and competitor pricing.

Big Mountain’s strong facility profile supports this adjustment. The resort ranks near the higher end of its peers in vertical drop, snowmaking capacity, total chairs, number of fast quads, total runs, and skiable terrain. These features enhance its attractiveness and help justify a higher ticket price. A modest increase could also help offset the recent \$1.54 million lift installation cost, especially given roughly 350,000 annual visitors.

Conclusion

This analysis suggests that Big Mountain Resort is likely underpricing its offerings relative to comparable resorts nationwide. By implementing a data-driven pricing strategy and evaluating high-impact investment opportunities, particularly the vertical drop expansion, the resort is well positioned to meet its target of increasing revenue by 10% next year. The Random Forest model provides a strong, reliable foundation for future scenario planning and operational decision-making.

Future Scope of Work

To further strengthen the model and enhance business insights, the following steps are recommended:

- Integrate data on operating cost, maintenance, and labor data to support more profit-oriented pricing decisions.
- Collect visitor demographic and demand data to estimate price elasticity.
- Incorporate customer satisfaction scores and survey responses to understand perceived value.
- Develop an interactive dashboard for leadership to simulate pricing/investment scenarios in real time.
- Update the model annually using new data to track shifts in industry pricing trends.