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Big Mountain Resort Pricing Strategy Report

Problem Statement

Big Mountain Resort aims to evaluate whether its current weekend ticket prices reflect the value of its offerings compared to peer resorts. Our objective was to build a predictive model of AdultWeekend ticket prices using facility and state-level features to guide data-driven pricing and investment decisions.

Data Wrangling

The original dataset contained 330 ski resorts and 27 features. Big Mountain Resort was present and had no missing values. The cleaning process involved:

- Dropping the fastEight column (over 50% missing).
- Removing 47 rows (14%) missing AdultWeekend prices.
- Choosing AdultWeekend as the target due to lower missingness compared to AdultWeekday.
- Addressing issues like suspicious terrain values and invalid yearsOpen entries.

Final dataset: **282 rows** and **26 cleaned columns**, ready for modeling.

Exploratory Data Analysis (EDA)

We examined both resort-level and engineered state-level features:

- Categorical: state, Region, Name
- Numeric: elevations, lift types, runs, snowfall, skiable area
- Engineered: ratios of resort-to-state assets, per-capita resort density

Key observations:

- Strong correlations between price and features like vertical_drop, Runs, Snow Making_ac, and fastQuads.(See Figuare 1)
- No clear relationship between state label and ticket prices (confirmed via PCA).
- Engineered features like resort_night_skiing_state_ratio also showed predictive power.

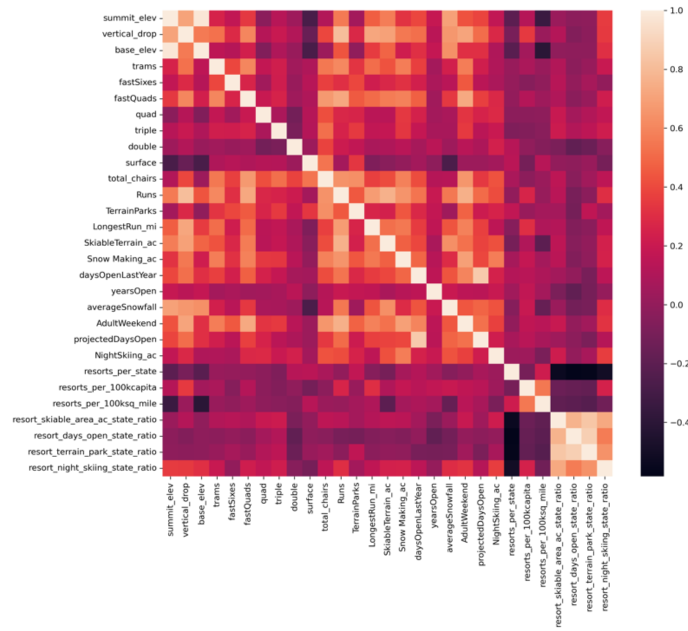

Figure 1: Correlation Heatmap of Numerical Features in the Ski Resort Dataset.

Model Preprocessing & Feature Engineering

Preprocessing steps included:

- Median imputation
- Feature scaling
- SelectKBest for feature selection

We engineered ratios to contextualize each resort's facilities within its state, including:

- resort_skiable_area_ac_state_ratio
- fastQuads_skiable_ratio
- total_chairs_runs_ratio

These helped normalize facility features across states and reduced noise from categorical variables like state.

Modeling & Evaluation

We trained and evaluated the following:

1. **Baseline model** (predicting mean): $R^2 \approx 0.0$
2. **Linear Regression**:
   - MAE ≈ $9 (cross-validation)
   - Selected top 8 features
3. **Random Forest Regressor**:
   - MAE ≈ $8
   - Less sensitive to outliers
   - More stable and higher-performing across folds

Winning model: **Random Forest Regressor** for its robustness, predictive strength, and interpretability.

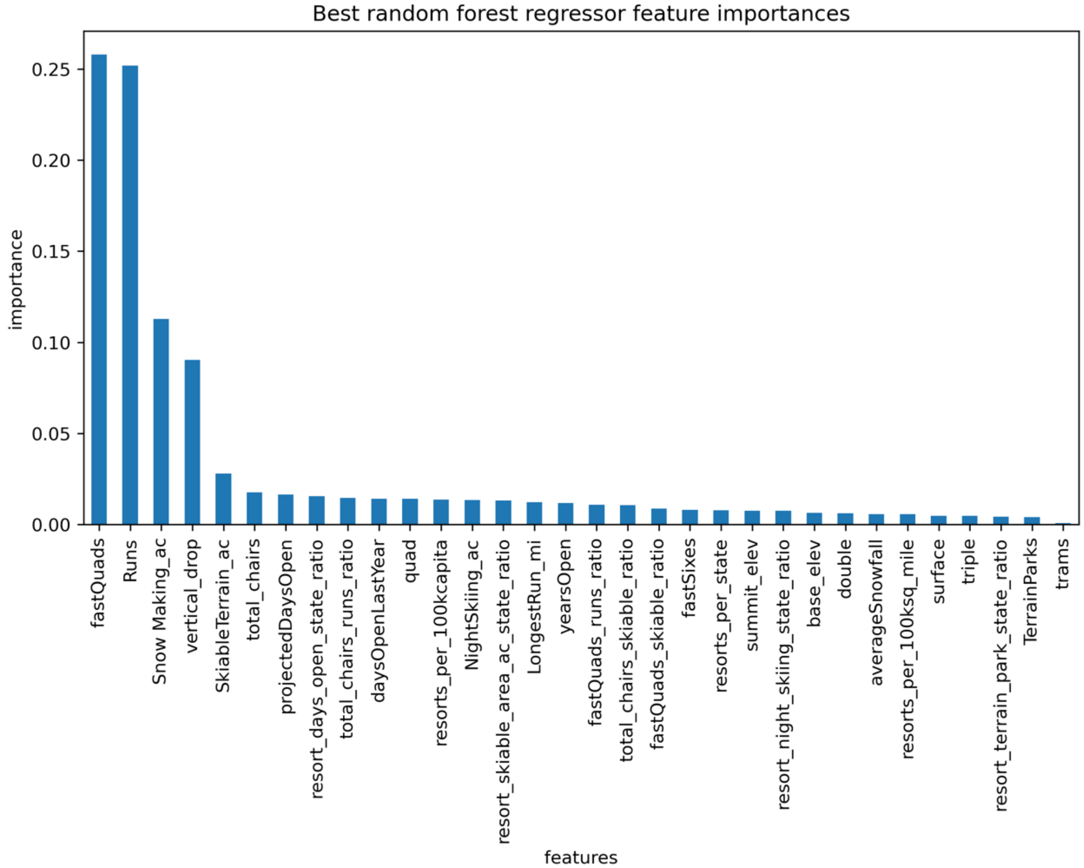

Figure 2: Random Forest Model – Feature Importance Plot

Business Scenario Modeling & Pricing Recommendation

Using the winning model, Big Mountain's predicted price is **~$64**, well above its actual price. This suggests the resort may be **undervalued**, possibly due to:

- Conservative pricing
- Limited brand visibility
- Local economic conditions

Recommendation: Consider a **moderate price increase**, e.g., to **$55–$60**, and:

- Review promotional strategies
- Reinvest in features with the highest model impact (e.g., fast lifts, snowmaking)
- Run A/B tests or collect visitor feedback on price sensitivity

Conclusion

Big Mountain Resort performs strongly on key pricing drivers but charges below model expectations. Our analysis shows the value it offers supports a higher ticket
price, and the model can inform future pricing and capital planning.

Future Scope of Work

- Incorporate cost, profit margin, and customer satisfaction data
- Track dynamic pricing (e.g., holidays, promotions)
- Enable analysts to use the model via a dashboard or Excel plug-in
- Explore unsupervised learning (e.g., clustering) to identify market segments