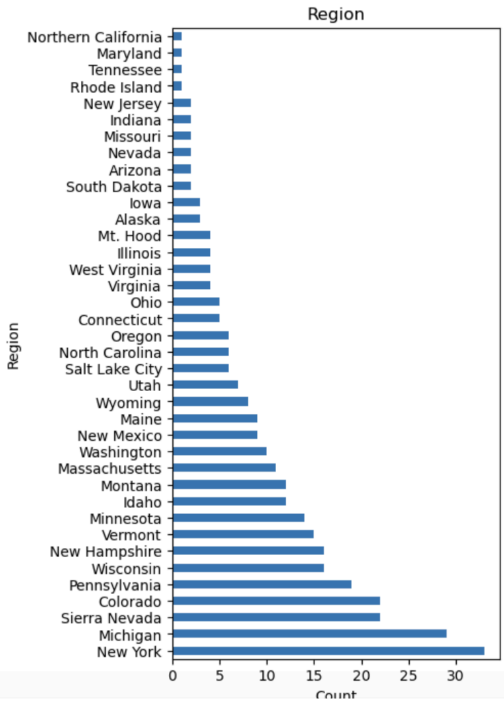
Big Mountain Ski Resort:Ticket Pricing Strategy Report

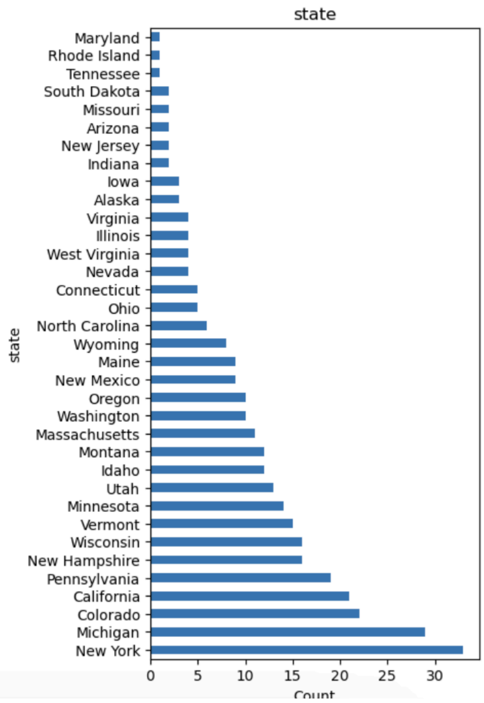
Problem Statement

What opportunities exist for Big Mountain Resort to optimize its pricing strategy, better capitalize on its facilities, and reduce operating costs of $1,540,000 by next season, while comparing its ticket value to the facilities offered and competitor resorts?

Data Wrangling

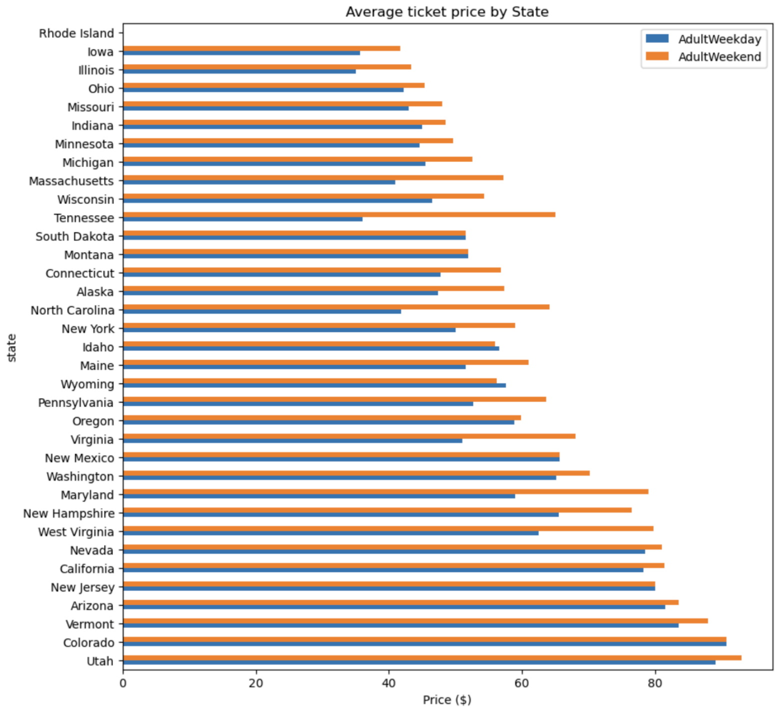
1. Handled missing values and outliers in both numerical and categorical features.
2. Explored the relationship between **region** and **state** in the data. Found that there are more unique regions than states.
3. Visualized the distribution of resorts by **region** and **state** to support decisions about treating states uniformly or differently.

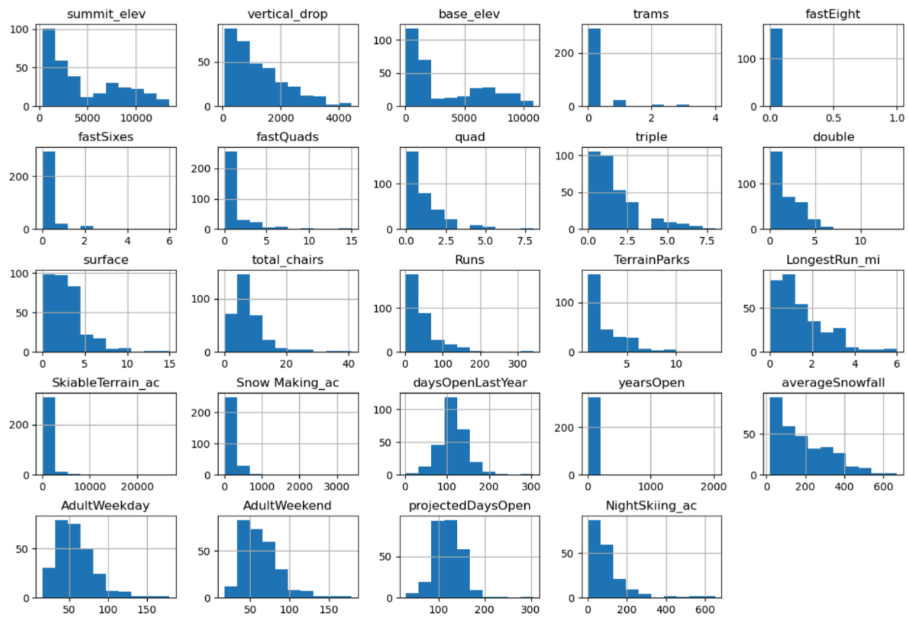




Price Distribution Analysis

- Analyzed how ticket prices vary by **state** and whether they target **weekday** or **weekend** visitors.
- Plotted distributions of key features to better understand value differences among resorts.

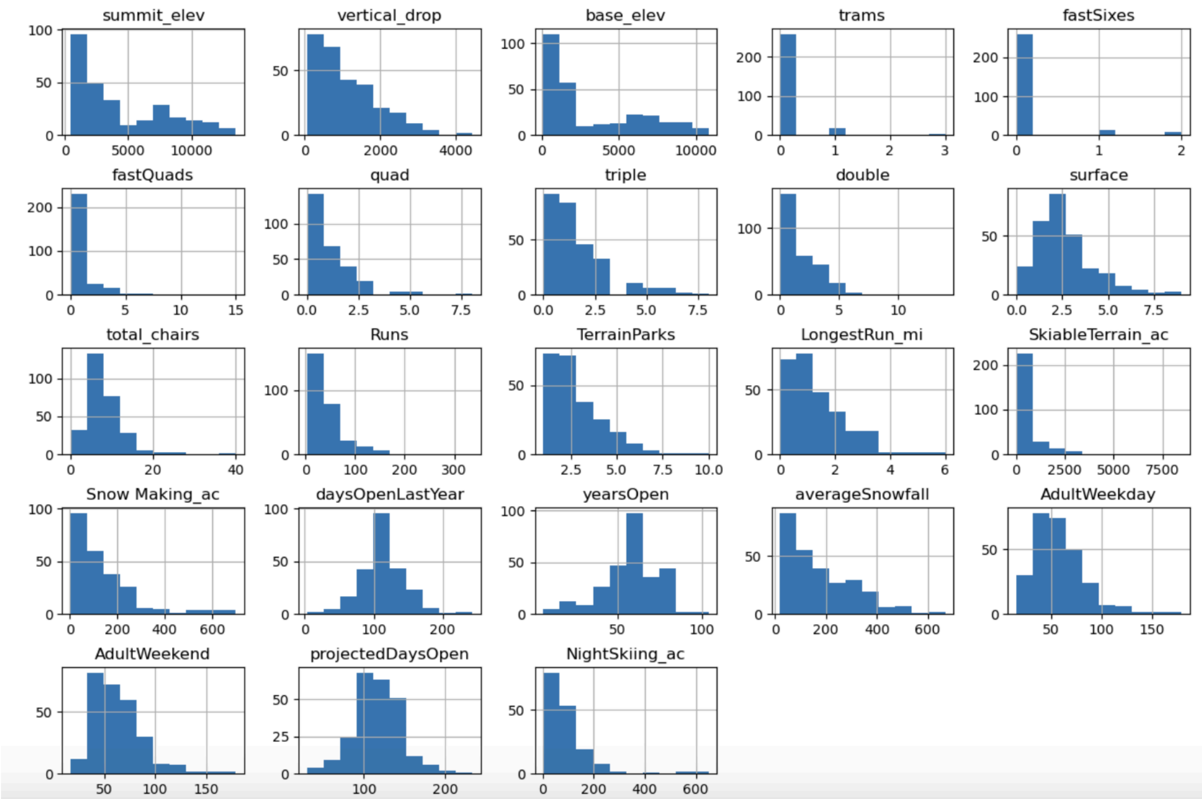




Key Findings & Red Flags:

- **SkiableTerrain_ac**: Clustered at the low end — may indicate smaller resorts dominate the data.
- **SnowMaking_ac**: Similar issue as SkiableTerrain — mostly low values.
- **fastEight**: Almost all values are 0, and half are missing — not a useful variable.
- **fastSixes**: Slightly more variation than fastEight, but still largely 0 — limited insight.
- **Trams**: Mostly 0, limited usefulness — flagged for low variance.
- **YearsOpen**: Appears to use calendar years (e.g., 2019) instead of years in operation — likely incorrect data entry.

7.Remove rows with no price data to get a clear distribution

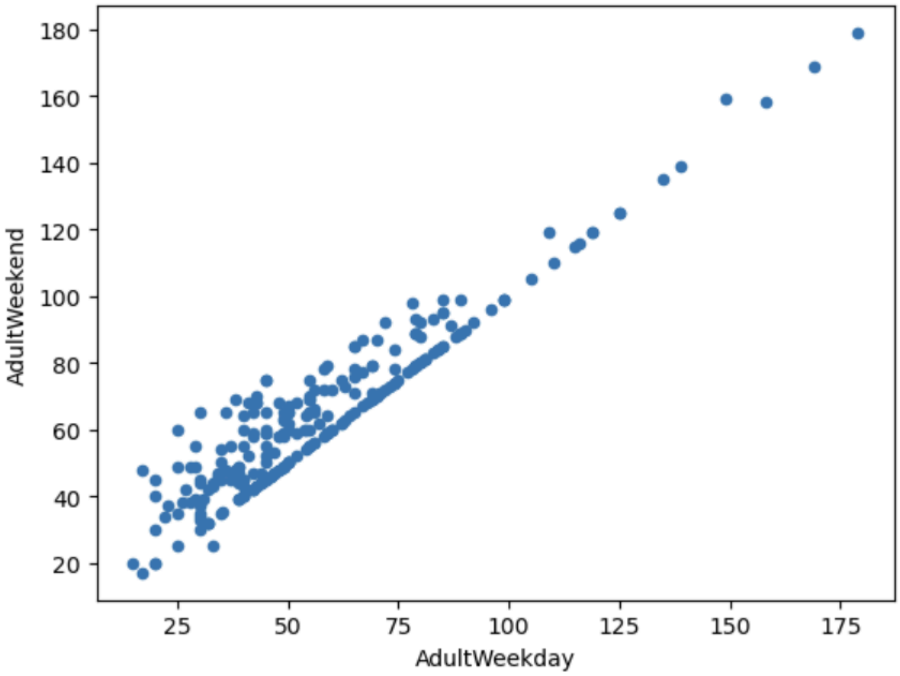


Data Cleaning Steps

1. **Removed rows with missing price data** to ensure clearer analysis of ticket price distributions.

2. **Cleaned weekday and weekend price data** to investigate any consistent patterns or relationships.

3. **Analyzed state population data** to identify possible correlations with resort data (e.g., pricing, features).

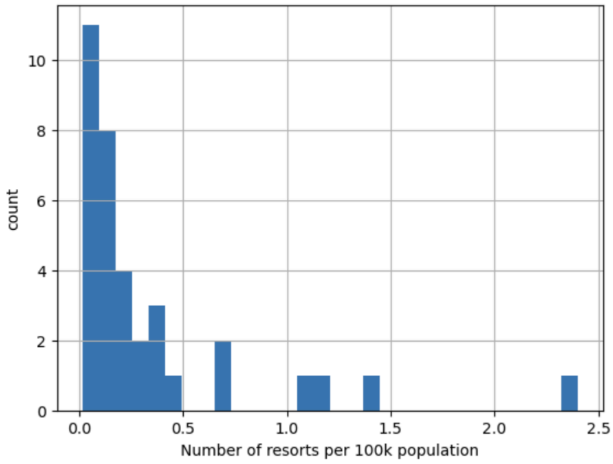


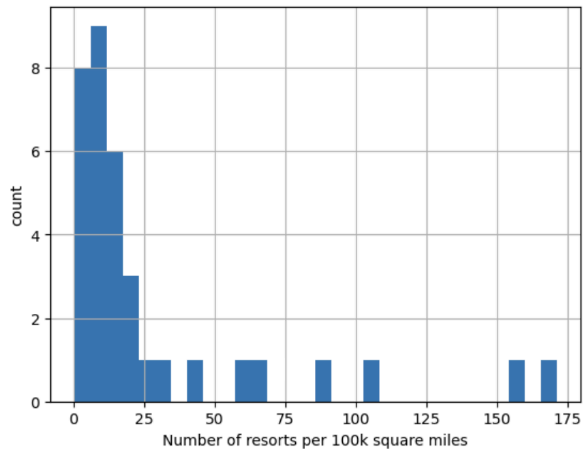
<u>Conclusion from Data Wrangling</u>

Now that the data is clean, we move forward with exploring it by investigating any consistent patterns or relationships between weekday and weekend price data, and analyzing state population data to identify possible correlations with resort data such as pricing and features

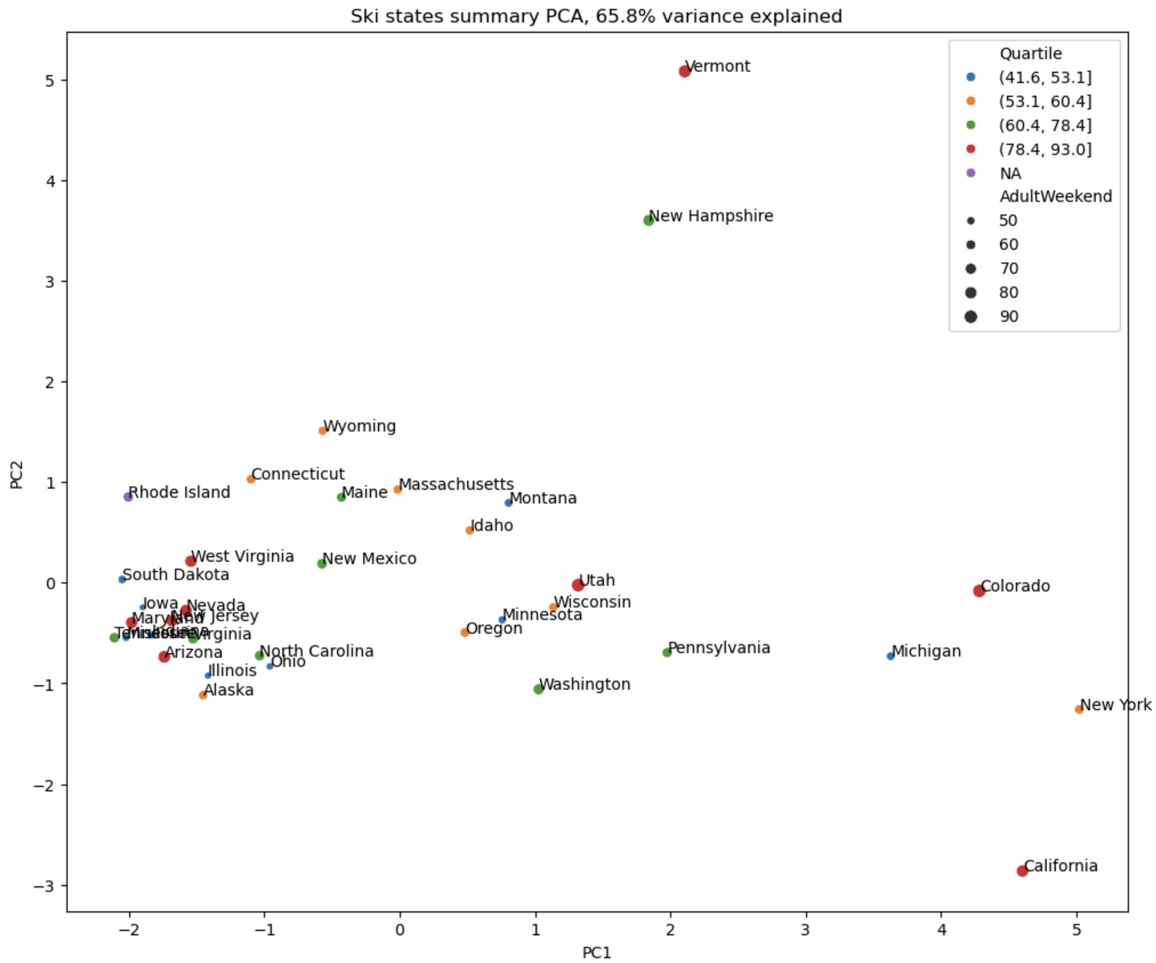
What we found

- The number of ski resorts in a state may be better explained by how many people live there or how much space is available per resort, rather than just the state's size or population—like in New York, where many resorts compete for a large population in a smaller area.

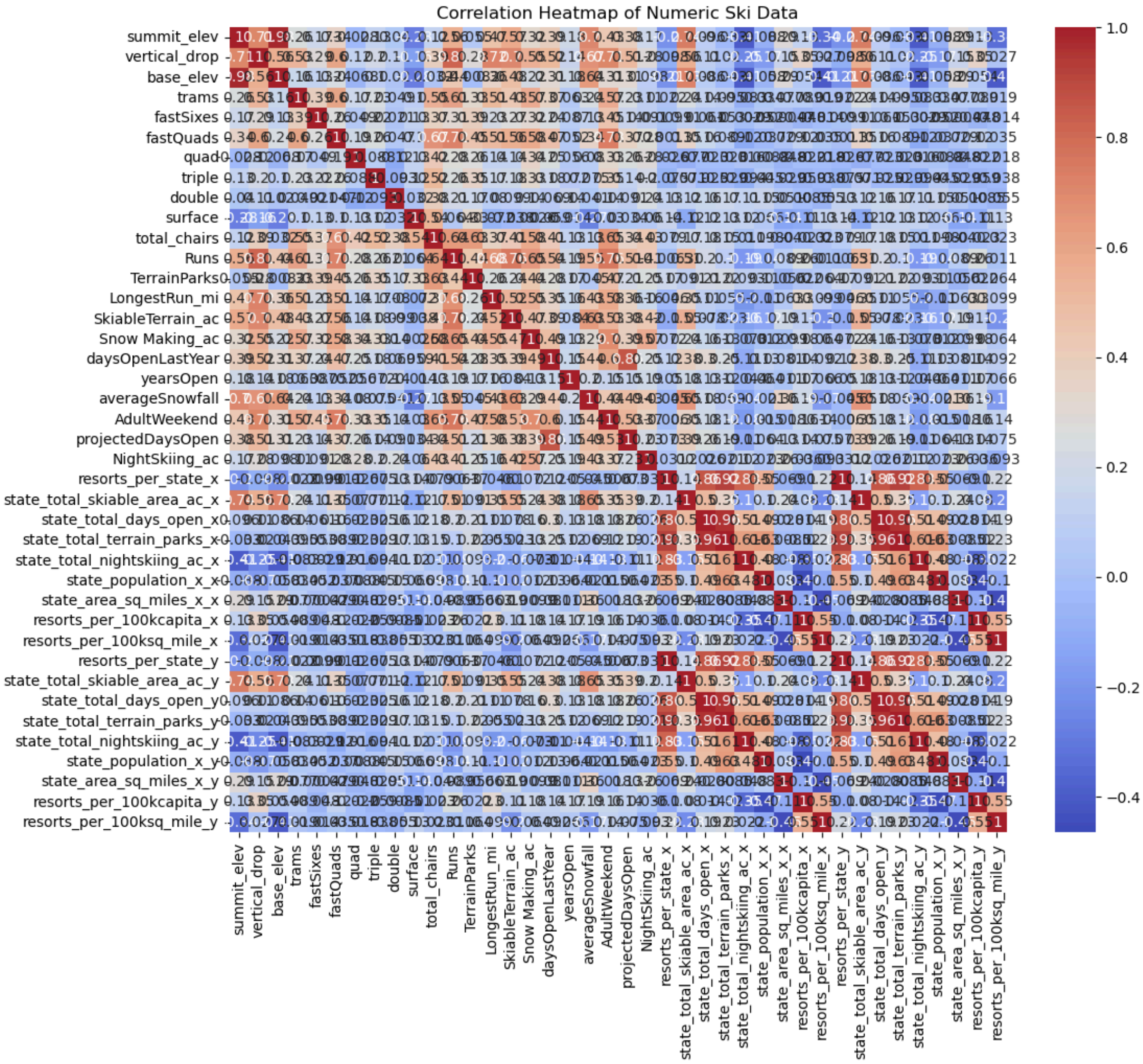




- Average ticket price by state



- Once we used PCA to explore our data, we came to the conclusion that each state could be treated equally to create a pricing model because no clear grouping was shown, but we have captured relevant data in features most likely to be important for solving the problem.



- **High multicollinearity exists among new ratio features**, and summit/base elevation are strongly correlated—as expected. More resorts in a state dilute the share of features, which explains the negative correlation with ratio-based variables.
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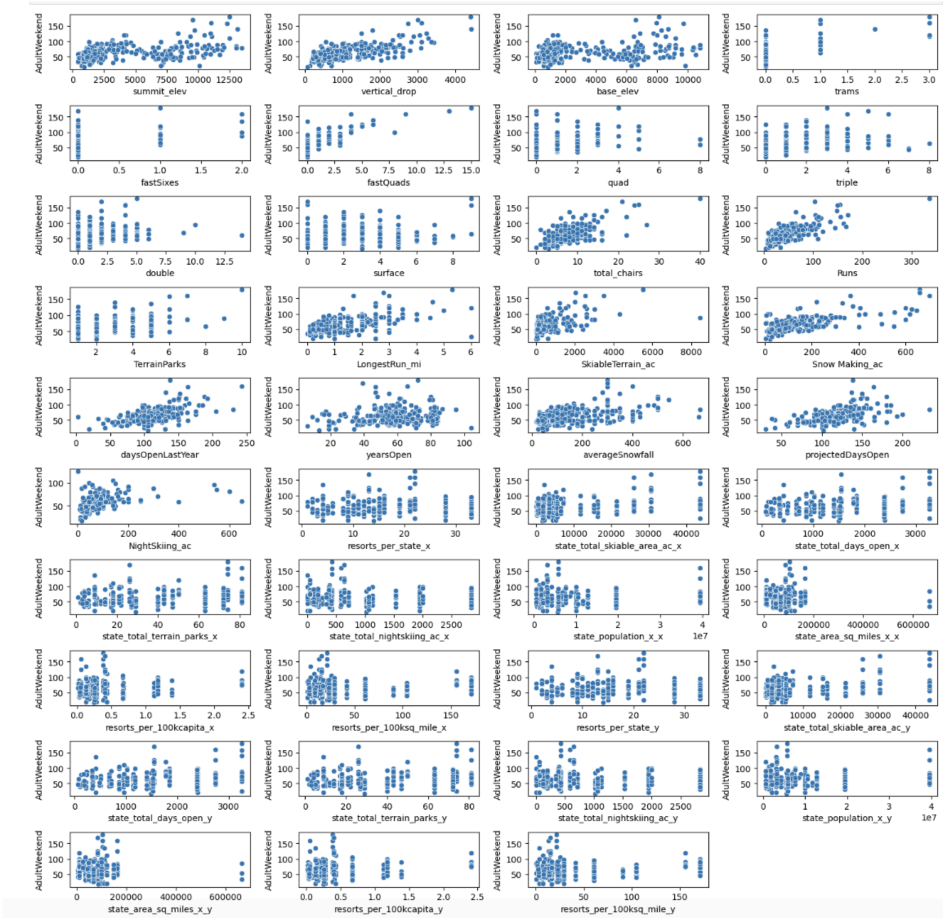
- **Key features positively correlated with higher weekend ticket prices** include the number of fastQuads, runs, snowmaking acreage, and total chairs—indicating visitors value infrastructure and snow reliability.

- **Snowmaking coverage and vertical drop influence pricing more than terrain size**, showing that guests prefer guaranteed snow and exciting elevation changes over large but inconsistent skiable areas.



- **Strong positive correlation** between vertical_drop and ticket price—bigger drops, higher value.
- **fastQuads** is a valuable feature—highly correlated with increased ticket prices.
- **Runs and total_chairs** show similar strong correlations—more infrastructure, higher prices.
- **resorts_per_100kcapita** reveals a nuanced trend

Findings:

- Higher chair-to-run ratios are linked to lower ticket prices, which is surprising at first.

- Resorts with fewer chairs per run tend to charge more, possibly aiming for a more exclusive experience.

- Mass-market resorts (lots of chairs, lower price) may focus on volume over exclusivity.

- Exclusive resorts (fewer chairs, higher price) likely serve fewer visitors but make more per person.

- A critical missing piece of data is the number of annual visitors, which would help confirm this pattern.

<u>Pipeline</u>

Modeling Steps

- Imputation:
  Median and mean strategies were used to fill missing values.

- Scaling:
  StandardScaler was applied to normalize data.

- Pipeline Construction

Algorithms Used

- Linear Regression

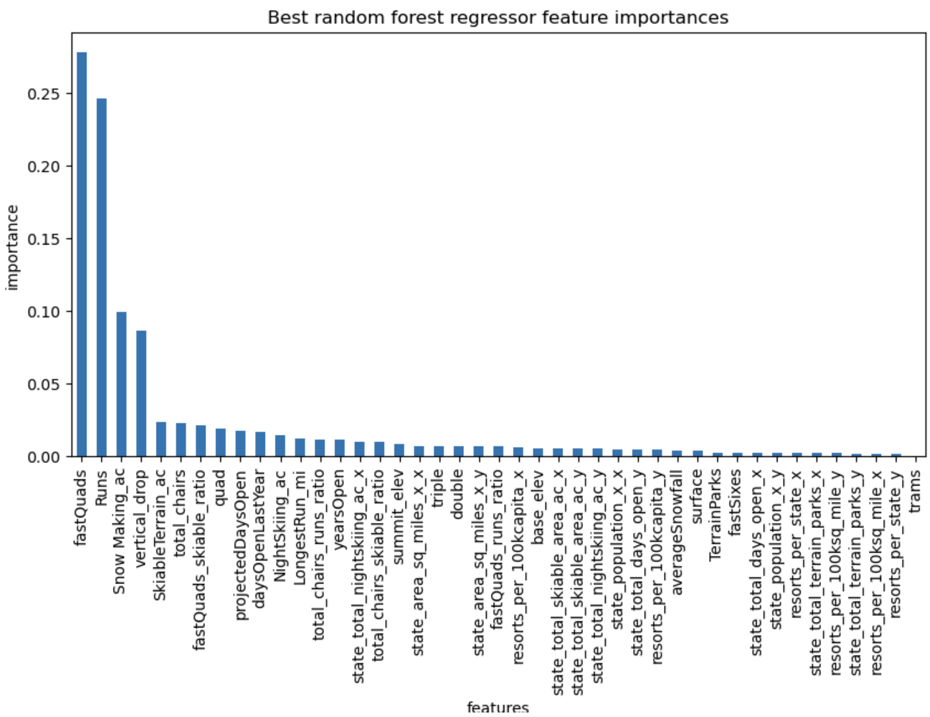
- Random Forest Regression

Evaluation Metrics

- R^2 Score: Measures how well the variance is explained.

- MAE (Mean Absolute Error): Average of absolute errors.

- MSE (Mean Squared Error): Penalizes larger errors more heavily.



- **Random forest regression** outperformed linear regression in terms of predictive power and handled feature interactions and non-linear relationships more effectively.

Conclusion

It is important to emphasize that Big Mountain ranks highly in snowmaking, a key feature for customers, and has the highest number of total chairs, enhancing its market position. While adding a new chair lift comes with an additional operating cost of 5,000 dollars per day, with 700 daily visitors buying an average of 5 tickets each (3,500 tickets/day), this results in about 1.43 dollar extra cost per ticket.

Our model shows that improvements such as those in Scenario 2 (e.g., increased lift capacity) could justify a price increase of more than $8, covering the lift's cost while boosting profit. Among the modeled scenarios, the most promising for further consideration include Scenario 2 plus a snowmaking upgrade, which led to the highest price increase, and smaller improvements like extending the longest run by 0.2 miles and adding 4 acres of snowmaking, which also produced positive results. These are lower-cost investments with clear returns that improve the resort's reputation and reliability. As for run closures, while they decrease ticket value, the effect is predictable, allowing for controlled experimentation, such as testing

Recommendations

- Conduct interviews with executives to understand their pricing strategy.
- Analyze competitor pricing to assess whether underpricing is widespread or specific to Big Mountain.
- Use the model to simulate the financial impact of adding or removing features (e.g., lifts, snowmaking).
- Align ticket pricing with facility value and market position to optimize revenue.

Future Scope of Work

Data Expansion: Incorporate more cost variables such as maintenance, labor, and seasonal visitor trends for a richer modeling foundation.

Business Tooling:

- Build an **interactive dashboard** for analysts to run pricing simulations independently.
- Create an **automated reporting system** with pre-built scenarios and outputs.
- Develop a **user-friendly interface** (e.g., a web app or API) for easy interaction with the model.