

Capstone Project Report: Big Mountain Resort

Introduction

Big Mountain Resort wants to adjust ticket prices to increase revenue while keeping guests happy. Current tickets are \$81, below the market value. The goal was to find the key factors influencing price and recommend an updated ticket rate.

Problem Statement

Design a pricing strategy that reflects the resort's value, especially with upcoming upgrades like a new chair lift, aiming to maximize revenue without reducing demand.

Data Preparation

- Cleaned data: filled missing values, removed duplicates
- Standardized formats and combined resort features, pricing, and cost data
- Created a reliable dataset for analysis

Exploratory Analysis

- Tickets are undervalued at \$81
- Key price drivers: vertical drop, number of runs, snowmaking
- Peak-season pricing could further boost revenue

Modeling

- Tested Linear Regression and Random Forest models
- Random Forest performed best, capturing complex relationships

Findings & Recommendations

- Optimal ticket price: **\$94** without hurting demand
- New chair lift adds ~\$2 per ticket, still profitable
- Planned upgrades support higher pricing
- **Recommendation:** Raise tickets from \$81 → \$94

Conclusion

Big Mountain Resort can increase prices safely, better reflecting its value and supporting future growth.

Next Steps

- Analyze costs for profitability
- Consider customer segmentation for dynamic pricing
- Build a dashboard for scenario testing
- Update models regularly to track market trends

FIGURES -

```

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12  surface                277 non-null   int64
13  total_chairs           277 non-null   int64
14  Runs                   274 non-null   float64
15  TerrainParks           233 non-null   float64
16  LongestRun_mi          272 non-null   float64
17  SkiableTerrain_ac      275 non-null   float64
18  Snow Making_ac         240 non-null   float64
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20  yearsOpen               277 non-null   float64
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22  AdultWeekend           277 non-null   float64
23  projectedDaysOpen      236 non-null   float64
24  NightSkiing_ac         163 non-null   float64
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memory usage: 56.3+ KB

```

Fig1 - Data Cleaning Overview

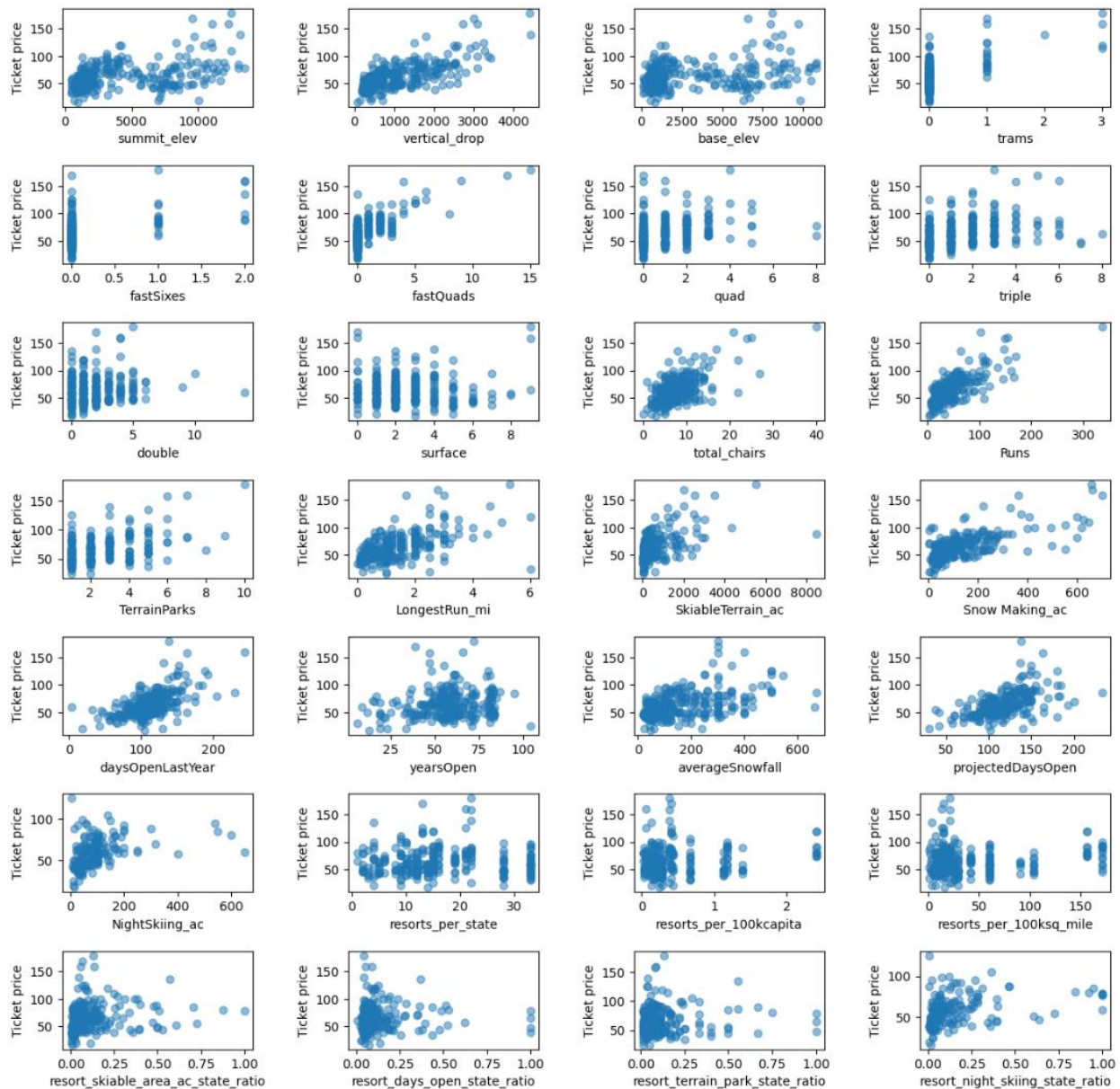


Fig2- Price vs Facility Features

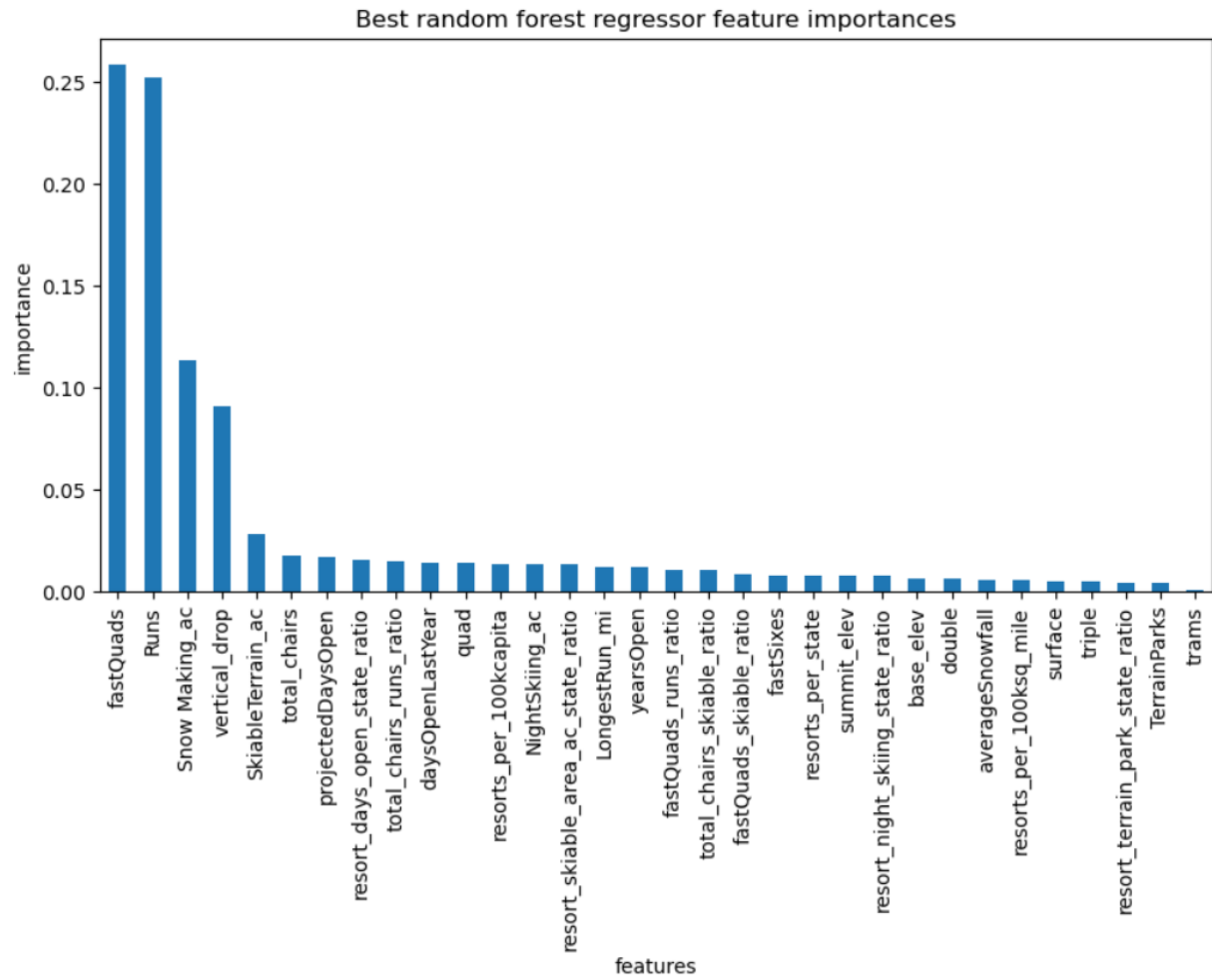


Fig3 – Feature Engineering Process.

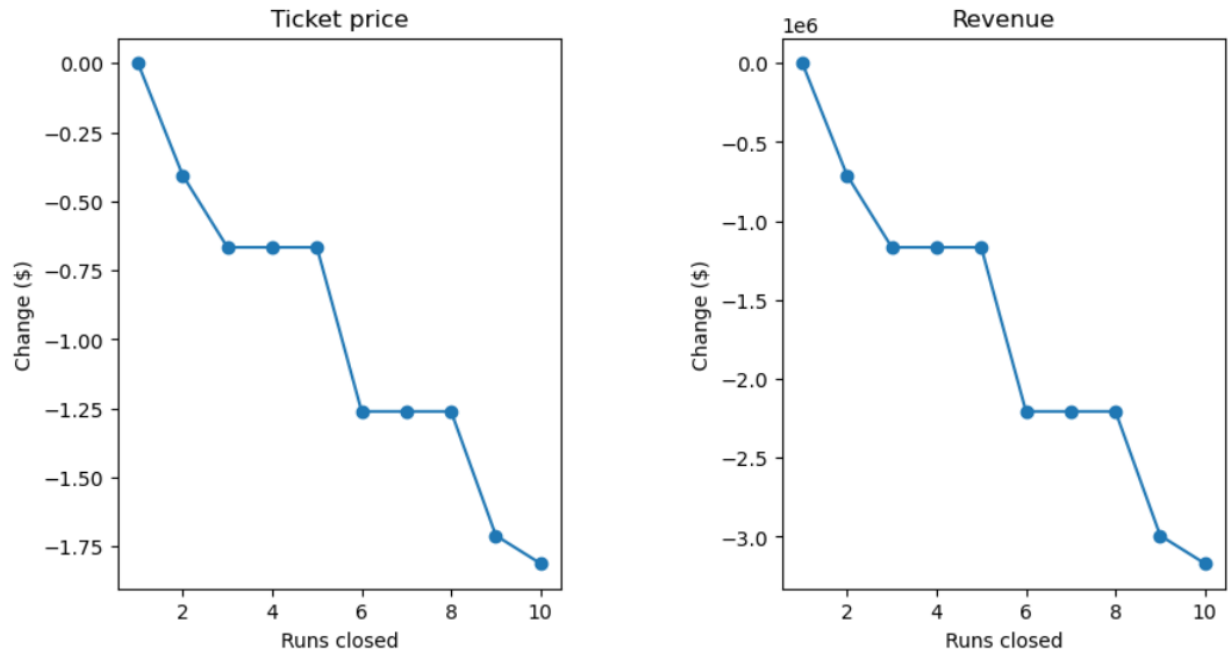


Fig4 – Model Performance Comparison