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Guided Capstone Project Report

****Please see the end of this report for the associated figures!***

Introduction

Big Mountain Resort aims to refine its ticket pricing to enhance revenue while preserving a positive guest experience. Currently, tickets are set at $81, but data evaluation indicates this may be insufficient compared to comparable resorts. The purpose of this project was to assess resort data, highlight key elements impacting pricing, and propose an ideal ticket price that corresponds with the resort's standards and future expansion plans.

Understanding the Problem

The task was to establish a pricing strategy that more accurately represents the resort's value while considering anticipated enhancements, like a new chair lift. The aim was to determine a price that maximizes revenue without adversely affecting demand.

Data Preparation

To guarantee precise analysis, the initial step involved cleaning and organizing the data:

- Addressing missing values to avoid gaps in the analysis
- Standardizing formats to ensure all data points were uniform
- Integrating various data sources, including resort characteristics, pricing, and operational expenses

After the data was cleaned, this now served as the basis for all subsequent analyses (Figure 1: Data Cleaning Overview).

Exploring the Data

Analyzing trends in the data provided significant insights:

- Current Pricing vs. Market Value – at $81, tickets appear undervalued when compared to similar resorts.
- Facility Influence on Pricing – aspects such as vertical drop, number of runs, and snowmaking capacity significantly affect pricing potential (Figure 2: Price vs. Facility Features).
- Seasonal Trends – adjusting prices during peak season could further enhance revenue.

Feature Engineering and Pre-processing

To create precise pricing models, I did the following:

- Identify key features such as resort size, amenities, and competition.
- Develop new features that more accurately depicted resort quality.
- Transforming the data through normalization of numerical values and encoding of categorical data.

These measures ensured the dataset was prepared for the predictive modeling (Figure 3: Feature Engineering Process)

Modeling and Key Findings

Multiple models were assessed to find the most effective method for predicting optimal pricing:

- Baseline model: utilized the current average ticket price as the baseline.
- Linear regression: offered basic predictions but ultimately failed to capture the complex relationships.
- Random forest regressor: surpasses all other models by adeptly managing nonlinear relationships.

Following this evaluation of performance metrics, the Random Forest model emerged as the most precise, demonstrating the lowest error and best predictive outcomes (Figure 4: Model Performance Comparison).

Scenario Testing and Recommended Pricing

Using the Random Forest model, various pricing scenarios were evaluated:

- New Optimal Price: the model indicates that the resort could feasibly charge $94 per ticket without compromising demand.
- Operational Cost Impact: introducing a new chair lift would raise costs by roughly $2 per ticket, yet with the new price of $94, the resort would continue to experience considerable revenue growth.
- Facility Upgrades: improving snowmaking capabilities and increasing vertical drop further justifies this pricing change.

Final Recommendation:

Raise ticket prices from $81 to $94 to better reflect the resort's value, account for operational enhancements, and increase revenue.

Conclusion

This project demonstrated that Big Mountain Resort has potential to modify its pricing strategy without compromising demand. By raising the ticket price to $94, the resort can better match its quality offerings while also preparing for future expansion. The insights obtained from this analysis offer a solid basis for making informed, data-driven decisions that will promote long-term success.

Next Steps

To enhance and expand upon these findings, upcoming efforts could concentrate on:

- Further detailed cost analysis to improve profitability estimates.
- Customer segmentation to implement dynamic pricing strategies.
- An interactive dashboard for experimenting with various pricing scenarios in real time.
- Continuous model updates to adapt to market trends and guest preferences.

By adopting a data-informed strategy, Big Mountain Resort is ideally positioned to optimize its pricing strategy, boost guest satisfaction, and increase profitability in a competitive market.

FIGURES

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 12  surface            277 non-null    int64
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 15  TerrainParks       233 non-null    float64
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 23  projectedDaysOpen  236 non-null    float64
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Figure 1: Data Cleaning Overview

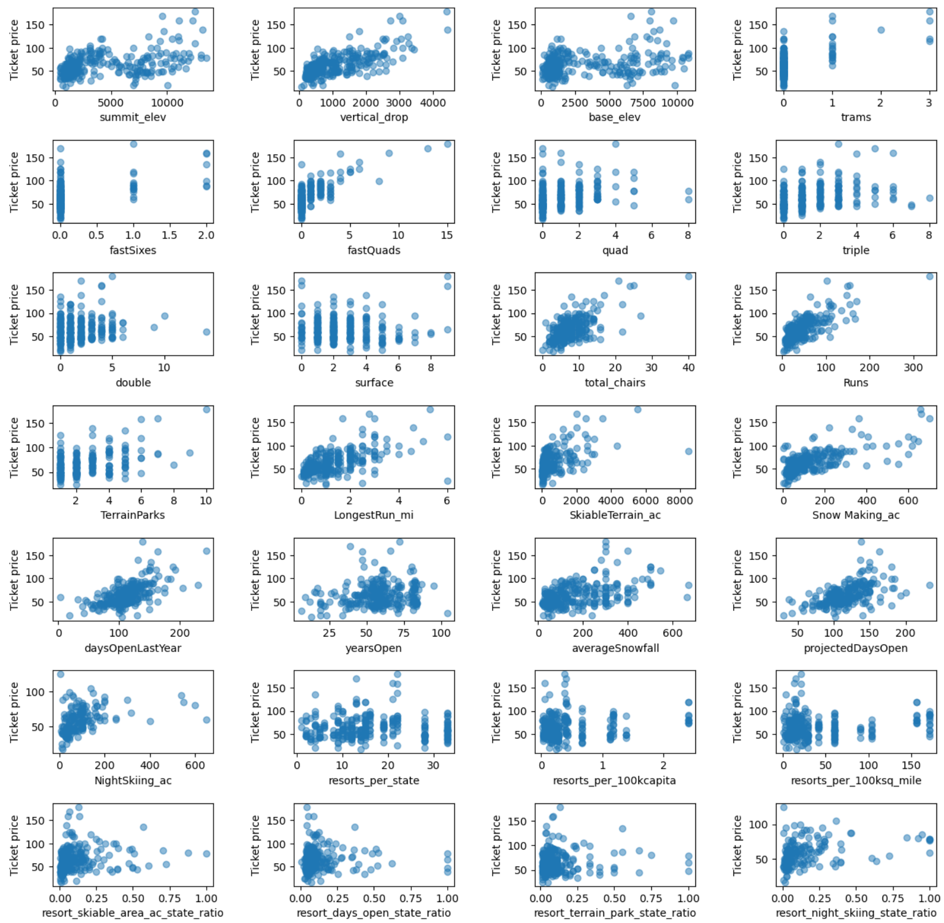

Figure 2: Price vs. Facility Features

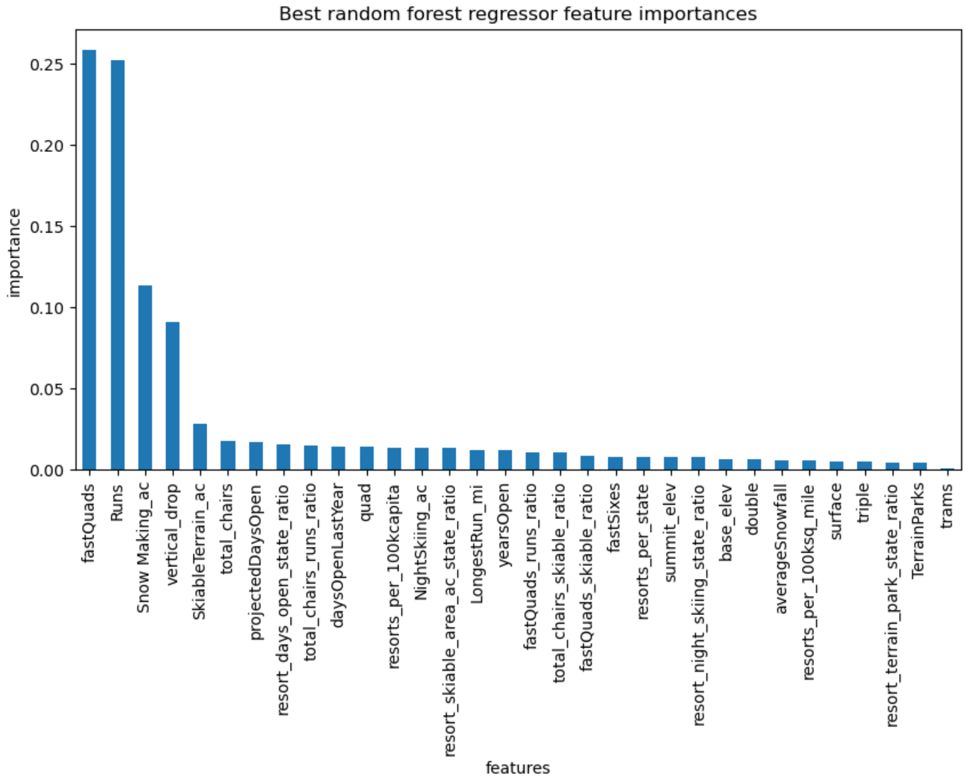

Figure 3: Feature Engineering Process

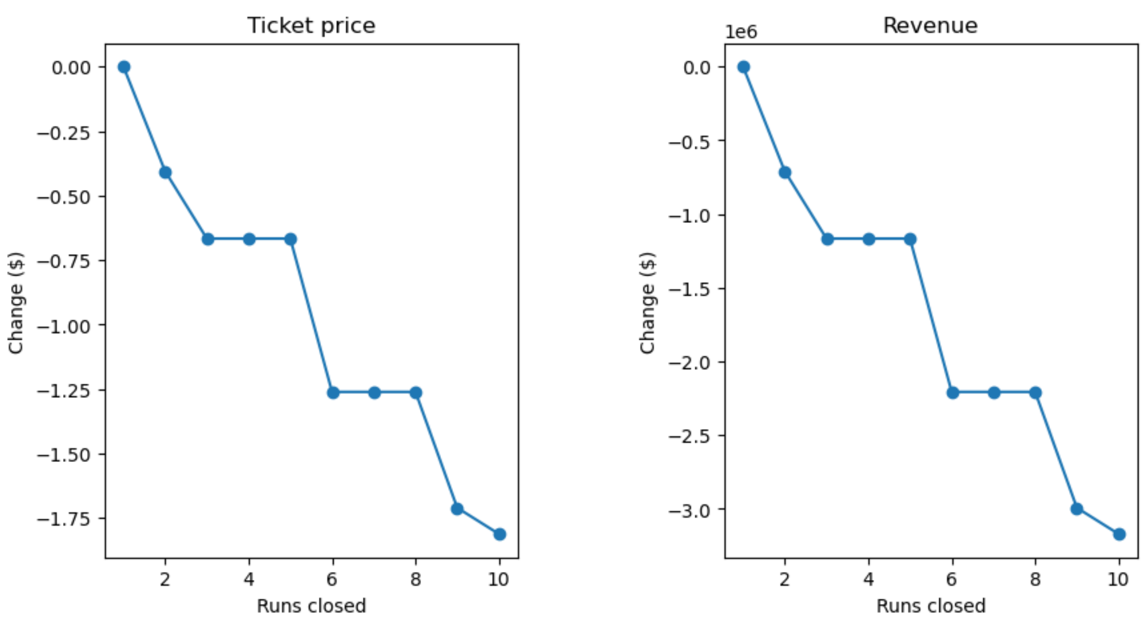

Figure 4: Model Performance Comparison