Big Mountain Pricing Strategy Analysis

Problem Statement

Big Mountain is currently pricing its offerings at $81.00, while a predictive model suggests a market-supported price of $97.96. This indicates a potential underpricing of $16.96. The aim is to identify the reasons behind this discrepancy, evaluate whether this would surprise executives, and provide data-driven recommendations for optimizing pricing and facility management.

Data Wrangling

Data wrangling involved collecting, cleaning, and organizing data from various sources to ensure it was suitable for analysis. Key data sources included:

1. Financial Records: Historical pricing, revenue, and operating costs (maintenance, staffing, energy).
2. Customer Surveys: Data on customer satisfaction, perceived value, and price sensitivity.
3. Visitor Demographics: Information on visitor age, income, and geographic origin.
4. External Factors: Weather patterns, economic conditions, and competitor actions.

Data Cleaning

- - Handling Missing Values: Imputed missing values using mean for numerical data and mode for categorical data.
- - Removing Duplicates: Ensured no duplicate records existed in the datasets.
- - Normalization: Scaled numerical features to a standard range to facilitate model training.

Data Transformation

- - Feature Encoding: Converted categorical variables into numerical.
- - Date Features: Extracted features such as month and season from date fields to analyze seasonal trends.

Exploratory Data Analysis (EDA)

EDA was conducted to uncover patterns, trends, and relationships in the data. Key findings included:

1. Revenue Trends: Seasonal peaks in revenue corresponded with holiday periods and winter months.
2. Customer Segmentation: Different customer segments showed varying levels of price sensitivity.

3. Competitive Analysis: Competitors' pricing strategies and their impact on Big Mountain's market share were analyzed.

Visualizations

1. Revenue Over Time: Line charts showing revenue trends across different months and years.
2. Customer Demographics: Bar charts and pie charts displaying the distribution of visitor age groups, income levels, and geographic origins.
3. Price Sensitivity: Histograms depicting customer responses to different price points.

Model Preprocessing with Feature Engineering

Feature Selection

Important features selected for the model included:

- - Historical pricing and revenue data.
- - Customer satisfaction scores.
- - Visitor demographics.
- - External factors like weather conditions and economic indicators.

Feature Engineering

- - Lag Features: Created lag features to capture the impact of past prices on current demand.
- - Interaction Terms: Generated interaction terms between customer demographics and price sensitivity.

Splitting the data into training (70%) and testing (30%) sets to evaluate model performance.

Algorithms Used to Build the Model

Multiple algorithms were tested to build the predictive pricing model. These included:

1. Linear Regression: Basic model to understand the linear relationship between features and price.
2. Random Forest: Ensemble method to capture non-linear interactions.
3. Gradient Boosting Machines (GBM): Used for its ability to handle complex relationships and interactions.

Evaluation Metric

- - Mean Absolute Error (MAE): Chosen as the primary evaluation metric to measure the average magnitude of errors in predictions without considering their direction.

Winning Model and Scenario Modelling

Winning Model

- - Gradient Boosting Machine (GBM) was selected as the winning model due to its superior performance, with a lower MAE compared to other models.

Scenario Modelling

1. Scenario 1: Increasing Vertical Drop and Adding a Chair Lift
   - Predicted to add $3,888,889 in seasonal revenue.
   - Required a feasibility study and cost-benefit analysis for implementation.

2. Scenario 2: Gradual Implementation of Run Closures
   - Identified least used runs for initial closure.
   - Monitored impact on revenue and customer satisfaction through pilot testing.

Visualizations

1. Model Performance: Comparison of MAE across different models using bar charts.
2. Revenue Impact of Scenarios: Projected revenue changes under different scenarios using bar and line charts.

Pricing Recommendation

Based on the model's findings, it is recommended to adjust the current pricing to align with the market-supported price of $97.96. Additionally:

1. Dynamic Pricing: Implement a dynamic pricing strategy that adjusts prices based on demand, seasonality, and competitor actions.
2. Customer Segmentation: Tailor pricing strategies for different customer segments to maximize revenue and customer satisfaction.

Conclusion

Big Mountain is currently underpricing its offerings by $16.96. By addressing data deficiencies, leveraging predictive models, and implementing strategic changes, the business can optimize pricing, enhance customer satisfaction, and boost revenue.

Future Scope of Work

Future improvements should focus on:

1. Enhancing Data Collection: Collect more granular data on operating costs, visitor behavior, and external factors.
2. Model Refinement: Continuously refine the predictive model with new data and advanced techniques.
3. Expanding Scenario Modeling: Explore additional scenarios and their potential impact on revenue and customer satisfaction.
4. Training and Documentation: Provide ongoing training and detailed documentation to ensure the model's effective use by business analysts.