RESTAURANT RATINGS CONSULTANCY REPORT

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Executive Summary

Leveraging supervised and unsupervised machine learning, particularly the Decision Tree Regressor model, this project aims to understand and predict restaurant ratings accurately. The model performs admirably, with low errors and a substantial R-squared score. Implementation of these data-driven insights can lead to a more enriched dining experience, tailored strategies for partner restaurants, and efficient decision-making. As FoodieBay navigates the dynamic and competitive food industry, this framework underscores its commitment to excellence, ensuring continued relevance and success in an evolving landscape.

BACCM framework

Need: FoodieBay requires a data-driven approach to improve customer satisfaction and optimize its restaurant partner strategies. There's a need to understand the factors influencing restaurant ratings and predict them accurately.

Stakeholders: The primary stakeholders include FoodieBay, its partner restaurants, and customers who rely on the platform for dining choices.

Value: Implementing data-driven insights will lead to an enhanced dining experience, tailored business strategies for partner restaurants, and efficient decision-making.

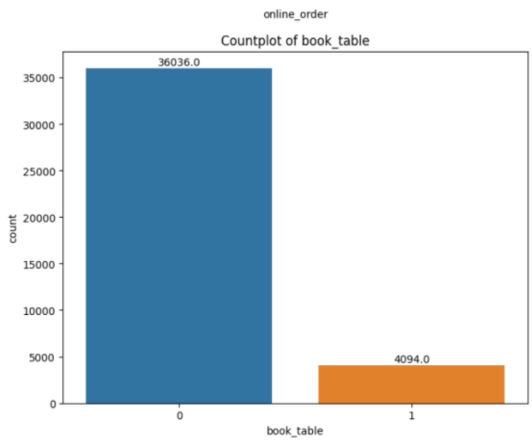
Solution: Leveraging supervised and unsupervised machine learning models, specifically the Decision Tree Regressor, provides a robust predictive tool for restaurant ratings.

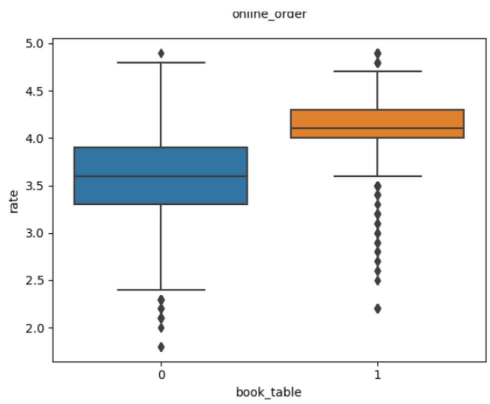
Change: The project introduces a shift towards data-centric decision-making, emphasizing continuous monitoring, model refinement, and collaboration with partner restaurants.

Context: In a dynamic and competitive food industry, data-driven insights are essential. FoodieBay's commitment to excellence and customer satisfaction drives the need for this framework, ensuring relevance and success in the evolving restaurant landscape.

Insights from Exploratory Data Analysis (EDA):

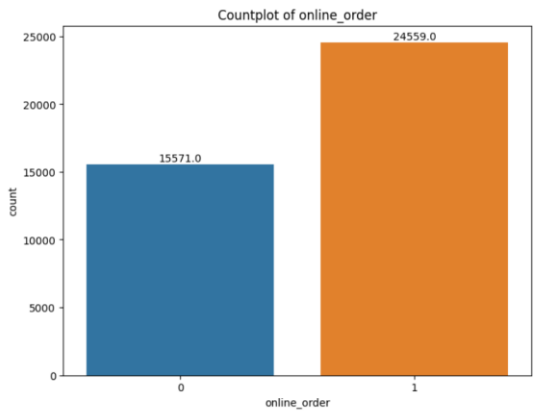
1) Of the 40131 observations, 36036 restaurants do not allow reservations for tables, whereas 4094 do allow. Additionally, the boxplot demonstrates that restaurants with table reservations had higher median ratings than restaurants without reservations, indicating that table reservations have a favourable effect on restaurant ratings.

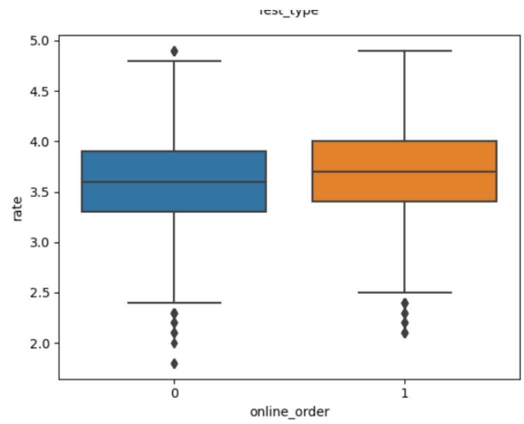




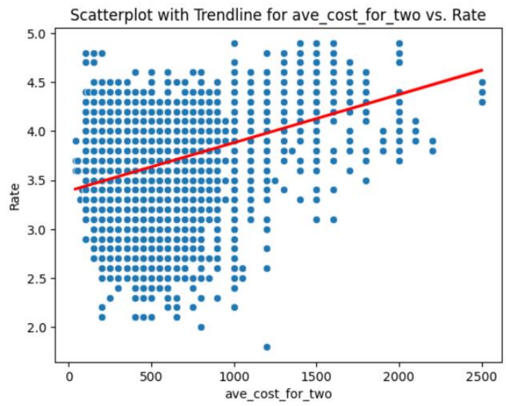
2) The dataset includes 24559 restaurants that allow online ordering, compared to 15571 that do not. Online ordering is available at 61% of the participating restaurants. The box plot

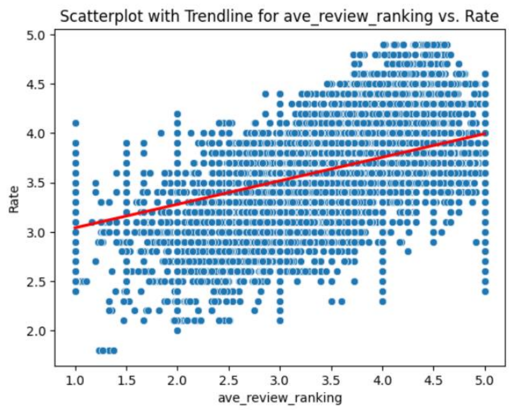
demonstrates that the median rating for restaurants with online ordering is marginally higher than the median rating for restaurants without online ordering, indicating that an increase in online orders is associated with a higher rating.



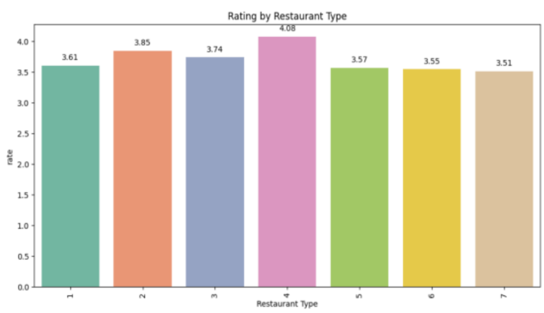


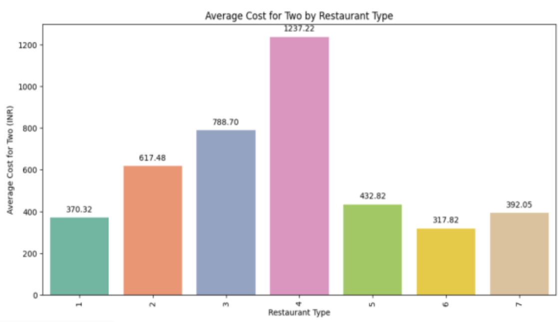
3) The average price for two and the overall ratings of restaurants have a positive association, indicating that more expensive restaurants typically have higher reviews. This can be because the food, service, and ambiance are superior. Additionally, there is a strong association between the average customer review score and the ratings, indicating that people tend to give higher ratings to establishments with better average review scores.





4) Casual Dining, Bar has the highest rating followed by Cafe and Casual Dining. Takeaway has the lowest average rating. On the other hand, the average cost for two is highest at casual dining, Bar restaurants, followed by casual dining and cafe. The lowest average cost for two is at Quick bites.





5) The best performing restaurants are Asia Kitchen by Mainland China, Flechazo, Punjab Grill and AB's - Absolute Barbecues. On the other hand, the worst performing restauraunts are Alibi - Maya International Hotel, Bhagini, Mast Kalandar and Bageecha. BTM city has the greatest number of restaurants at 4422.

Proposed Machine Learning Solution

The selected machine learning model for predicting restaurant ratings is the Decision Tree Regressor. The Decision Tree Regressor captures complex non-linear relationships between features and ratings, making it a valuable predictive tool.

Interpretation of Model Performance

The Decision Tree Regressor model performs well with a low Mean Absolute Error (MAE) of 0.204, small Mean Squared Error (MSE) of 0.081, Root Mean Square Error (RMSE) of 0.285, and a substantial R-squared (R2) score of 0.565, indicating strong predictive capability.

Pros

- Non-linear Relationships: Decision trees are capable of capturing non-linear relationships between features and the target variable, making them suitable for complex data patterns.
- Interpretability: Decision trees are easy to interpret and visualize, allowing stakeholders to understand how the model makes predictions.
- Robustness: Decision trees are less sensitive to outliers compared to linear regression, as they divide the data into segments based on thresholds.
- Feature Importance: Decision trees provide a measure of feature importance, helping identify which features have the most significant impact on ratings.

Cons

- Overfitting: Decision trees can be prone to overfitting, especially if they are deep and not appropriately pruned. Overfit models perform well on the training data but may not generalize well to new, unseen data.
- Instability: Small changes in the data can lead to significantly different decision tree structures, making them less stable than some other models.
- Limited Predictive Power: While decision trees are capable of capturing complex relationships, they may still struggle with capturing certain nuances in the data that other models can handle better.

Recommendations and Conclusions:

Recommendations of Business Applications:

- Enhanced Customer Experience: By understanding the factors that influence restaurant ratings, the platform can provide personalized restaurant recommendations and improve user satisfaction.
- Optimized Business Strategies: FoodieBay can offer tailored business solutions to its partner restaurants based on the identified factors that influence ratings.
- Efficient Decision-Making: The Decision Tree Regressor model can be integrated into FoodieBay's platform. This gives it the capability to make real-time predictions, helping users make informed dining choices.

Potential Benefits to Stakeholders:

Users: Users benefit from improved restaurant recommendations, leading to better dining experiences.

Partner Restaurants: Partner restaurants can optimize their services based on data-driven insights, potentially increasing their ratings and customer satisfaction.

FoodieBay: FoodieBay gains a competitive edge by offering data-driven solutions and improving user engagement.

Implications

- Enhanced Decision-Making: FoodieBay can now make data-driven decisions to improve the dining experience and optimize its business strategies.
- Customer-Centric Approach: They can tailor their platform to better match customer preferences, leading to increased user engagement and loyalty.
- Resource Allocation: They can identify underperforming restaurants and provide support or recommendations to improve ratings, ultimately driving business growth.
- Business Processes: FoodieBay should integrate the Decision Tree Regressor model into its recommendation system and business consulting services.

Recommendations for Further Improvement

- Regular Data Updates: Periodically update the dataset with new restaurant data and customer reviews to adapt to changing trends.
- Retraining Models: Revisit and retrain machine learning models as significant changes occur in the restaurant industry or user behavior.
- Customer Engagement: Continuously gather feedback from customers to fine-tune restaurant recommendations and enhance the user experience.
- Collaboration with Restaurants: Collaborate with partner restaurants to measure the impact of recommendations and optimizations, leading to mutually beneficial improvements.