Enhancing airbnb Bookings in Rio de Janeiro

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Executive Summary

The analysis of Airbnb's operations in Rio de Janeiro reveals some exciting opportunities for boosting booking success and fine-tuning our market strategy. We've seen that promoting the 'instant_book' feature can make a real difference in booking rates—it's like a shortcut to securing reservations without the back-and-forth. Another big takeaway is that improving how hosts and guests interact could be a game-changer. Offering incentives or better support could smooth things out and turn more inquiries into bookings. Plus, tailoring our listing strategies to match what travellers want in each neighbourhood could really pay off. By diving deep into segmentation and staying on top of what the competition is doing, we can keep our edge and keep growing in Rio.

<u>Important Links:</u>

GitHub Repository

- https://github.com/mishzaharieva/Airbnb_Project

GitHub Webpage

- https://mishzaharieva.github.io/Airbnb_Project/

Introduction

Airbnb operates as a two-sided marketplace connecting guests with hosts through various booking channels: 'contact_me', 'book_it', and 'instant_book'. These channels influence how guests and hosts interact, thereby impacting booking rates. This report focuses on optimizing the guest-host matching process in Rio de Janeiro to increase booking rates by improving interaction dynamics and streamlining the booking experience.

Key Metrics and Hypotheses

Hypotheses:

1. Different contact channels (Instant Book, Book It, Contact Me) have varying impacts on booking success rates, with Contact Me expected to have the lowest rate.
2. The number of interactions between hosts and guests influences booking rates.
3. Listings with more total reviews are likely to have higher booking success rates.
4. Certain property types (e.g., entire homes, private rooms) have higher booking success rates than others (e.g., shared rooms).
5. Listings in popular or highly rated neighbourhoods have higher booking success rates.
6. Lower response times are associated with higher booking success rates.
7. Quicker booking confirmations result in higher booking success rates.

Key Metrics:

1. Conversion Rate by Contact Channel: Evaluates booking success rates across 'contact_me', 'book_it', 'instant_book' to optimize channel effectiveness.
2. Impact of Number of Interactions (m_interactions): Analyses how host-guest interactions affect booking success, optimizing communication strategies.
3. Booking Success Rate by Review Count: Segments success rates based on listing reviews to leverage social proof.
4. Booking Success Rate by Property Type: Validates which property types attract higher bookings for strategic listing optimizations.
5. Booking Success Rate by Neighbourhood: Analyses success rates across Rio de Janeiro neighbourhoods to target marketing efforts.
6. Impact of Response Time on Booking Success Rate: Explores how host response times influence booking completion rates.
7. Impact of Booking Time on Booking Success Rate: Evaluates efficiency in the booking process on overall success rates.

Methodology

Data Sources:

1. Contacts Data Set: Contains guest inquiries and host interactions.
   - Columns: id_guest_anon, id_host_anon, id_listing_anon, ts_interaction_first, ts_reply_at_first, ts_accepted_at_first, ts_booking_at, ds_checkin_first, ds_checkout_first, m_guests, m_interactions, m_first_message_length_in_characters, contact_channel_first, guest_user_stage_first.
2. Listings Dataset: Provides details on each listing in Rio de Janeiro.
   - Columns: id_listing_anon, room_type, listing_neighborhood, total_reviews.
3. Users Dataset: Profiles of Airbnb users.
   - Columns: id_user_anon, words_in_user_profile, country.

Data Cleaning and Prepping:

4. Investigated and managed null values, focusing on critical columns (ts_interaction_first, ts_accepted_at_first, ts_booking_at, ts_reply_at_first).
5. Integrated contacts and listings datasets, handling missing data (removed 219 rows).
6. Created binary indicator columns (booking_completed, host_replied, host_accepted, interaction_occurred).
7. Calculated additional columns (response_time, booking_time) to analyse host responsiveness and booking efficiency.
8. Ensured data integrity through checks for duplicates and thorough cleaning.

Exploratory Data Analysis (EDA)

Hypothesis Testing:

1. Contact Channels and Booking Success:
   - Used bar charts to compare booking success rates across 'contact_me', 'book_it', 'instant_book'.
2. Property Type and Contact Channel Interaction:
   - Analysed interaction patterns between property types and contact channels using bar charts.
3. Neighbourhood and Contact Channel Interaction:
   - Heatmap analysis of success rates by contact channel across Rio de Janeiro neighbourhoods.
4. Interactions and Booking Success:
   - Box plot comparing interactions for successful and unsuccessful bookings.
5. Reviews and Booking Success:
   - Histograms and bar plots to analyse review counts and their impact on booking success.
6. Property Types and Booking Success:
   - Bar charts showing success rates for different property types.
7. Neighbourhoods and Booking Success:
   - Bar charts displaying success rates across Rio de Janeiro neighbourhoods.

Summary Statistics and Correlation Analysis:

8. Reviewed numerical data distributions and central tendencies.

9. Utilized correlation heatmaps to explore relationships between features and booking success.

Machine Learning Approach

Data Pre-Processing:

1. Handled categorical variables (get_dummies for contact_channel_first, listing_neighborhood, room_type).
2. Ensured completeness and integrity of the dataset.

Model Selection and Explanation:

1. Linear Relationship Models:
    - Logistic Regression: Analysed predictors' impact on booking completion.
    - LASSO Regression: Featured selection and regularization for robustness.
2. Non-linear Relationship Models:

- Decision Trees: Captured complex feature interactions.
- Random Forest: Improved accuracy through ensemble learning.
- XGBoost: Enhanced performance with gradient boosting.
    - Performing Cross Validation: Implemented to optimize model reliability and ensure genuine predictive power.

Data Preparation:

1. Feature Engineering: Included m_interactions, contact_channel_first, total_reviews, listing_neighborhood, host_replied, host_accepted, room_type.
2. Data Splitting: Divided into training (80%) and testing (20%) sets for model evaluation.

Models Training and Evaluation:

1. Each model (Logistic Regression, LASSO Regression, Decision Trees, Random Forest, XGBoost) was fitted to the training data.
2. Predictions were made for both training and testing datasets to evaluate model performance.
3. Feature Importance: Analysed feature importance scores from each model to identify variables impacting booking success rates.
4. Evaluation Metrics: Used evaluation metrics (such as accuracy, precision, recall, F1-score) for both training and testing datasets to assess model performance.
5. Confusion Matrix: Utilized confusion matrices for all models to understand the distribution of predicted versus actual outcomes and to evaluate model effectiveness.

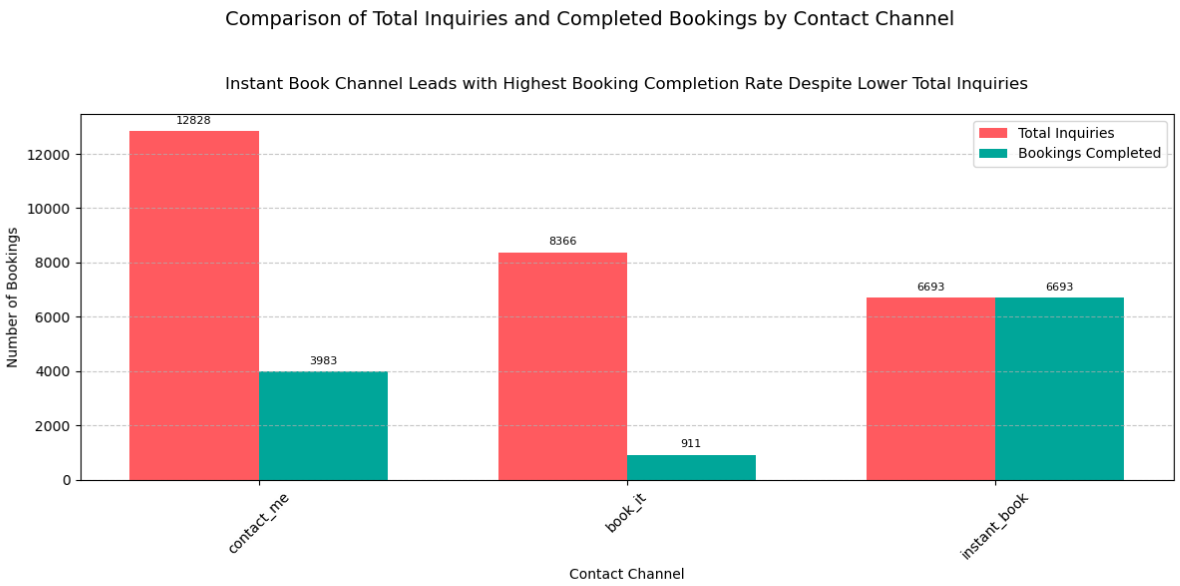
Results

Exploratory Data Analysis (EDA)

Hypothesis Testing:

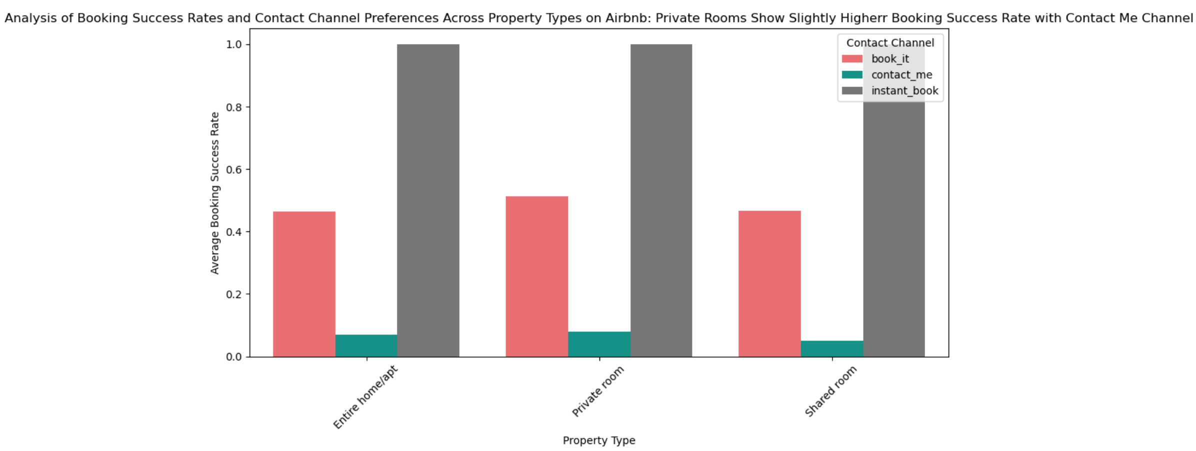
1. Effectiveness of Contact Channels

The analysis of booking success rates across different contact channels ('contact_me', 'book_it', 'instant_book') reveals significant variations. Notably, while 'contact_me' generates a high volume of inquiries, it results in the lowest booking success rate among the channels, confirming the hypothesis that it is less effective for securing bookings.

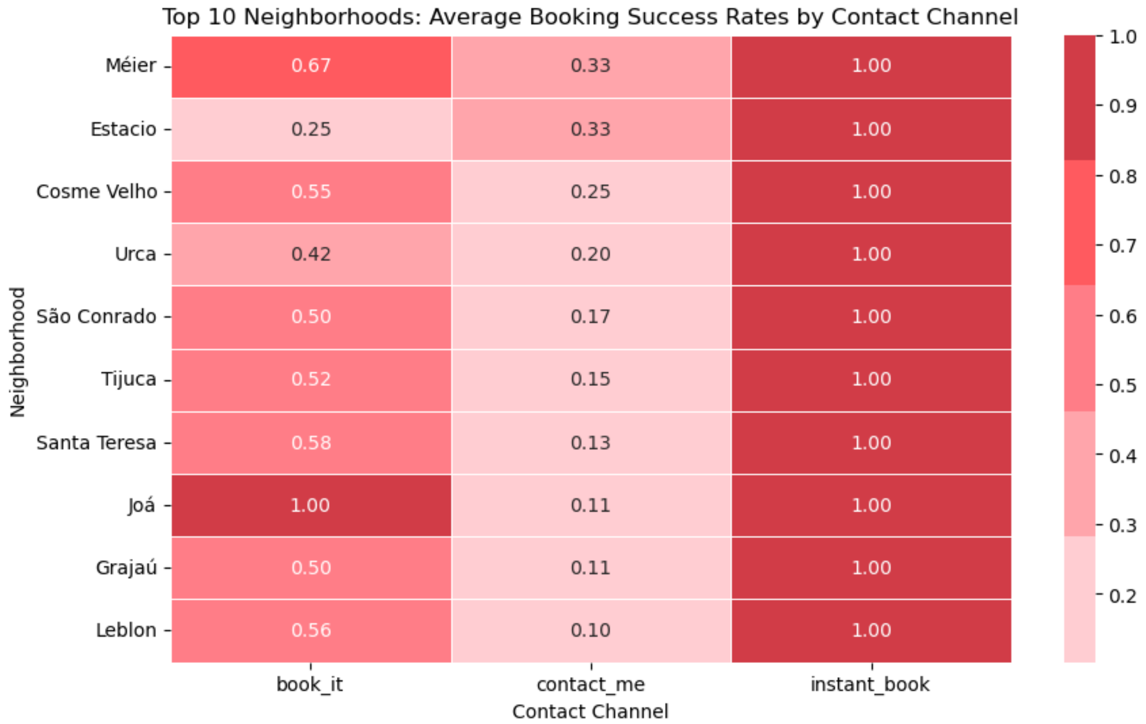


2. Property Type and Contact Channel Interaction:

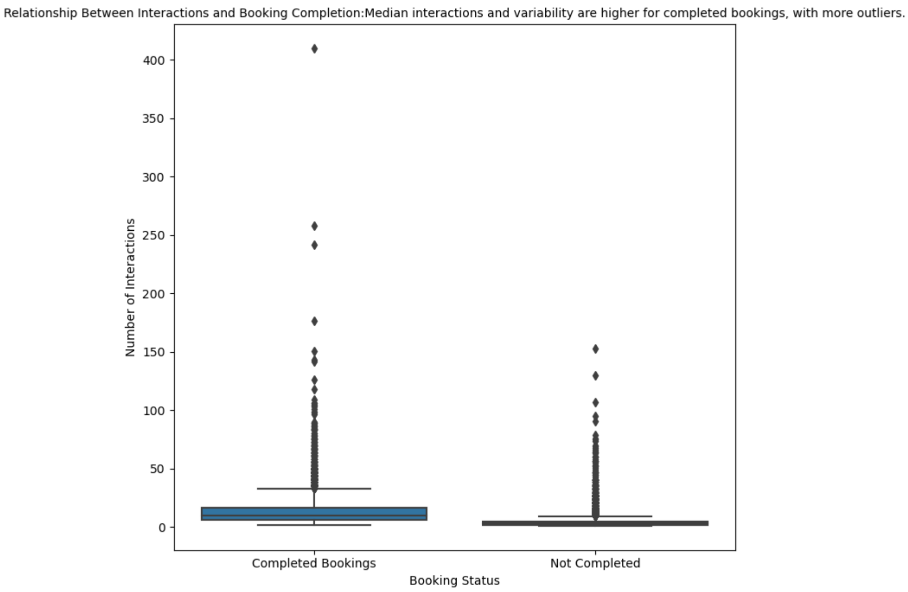
Notably, the 'instant_book' channel demonstrates a 100% success rate, indicating that bookings made through this channel are invariably accepted. Conversely, the 'contact_me' channel exhibits a lower overall acceptance rate. Among the different property types, private rooms achieve the highest acceptance rate for 'contact_me' bookings.



3. Neighbourhood Listing and Contact Channel Interaction:
    - Instant Book: All neighbourhoods achieve a 100% booking success rate.
    - Book It: Joá (100%), Santa Teresa (57.86%), and Tijuca (51.72%) have relatively higher success rates.
    - Contact Me: This channel generally has lower success rates. The highest success rates are in Méier (33.33%), Estácio (33.33%), and Cosme Velho (25%).



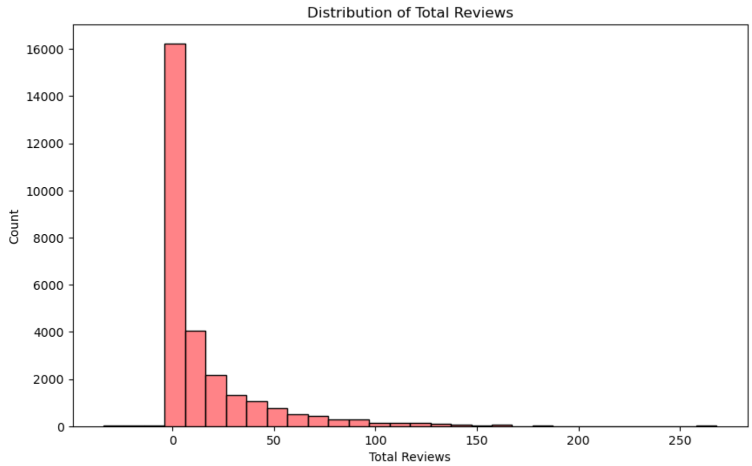
4. Interactions and Booking Success
    - Completed bookings have a higher median number of interactions.
    - Greater variability and more outliers with high interactions are observed for completed bookings.
    - This supports the hypothesis that more interactions between hosts and guests lead to higher booking success rates.



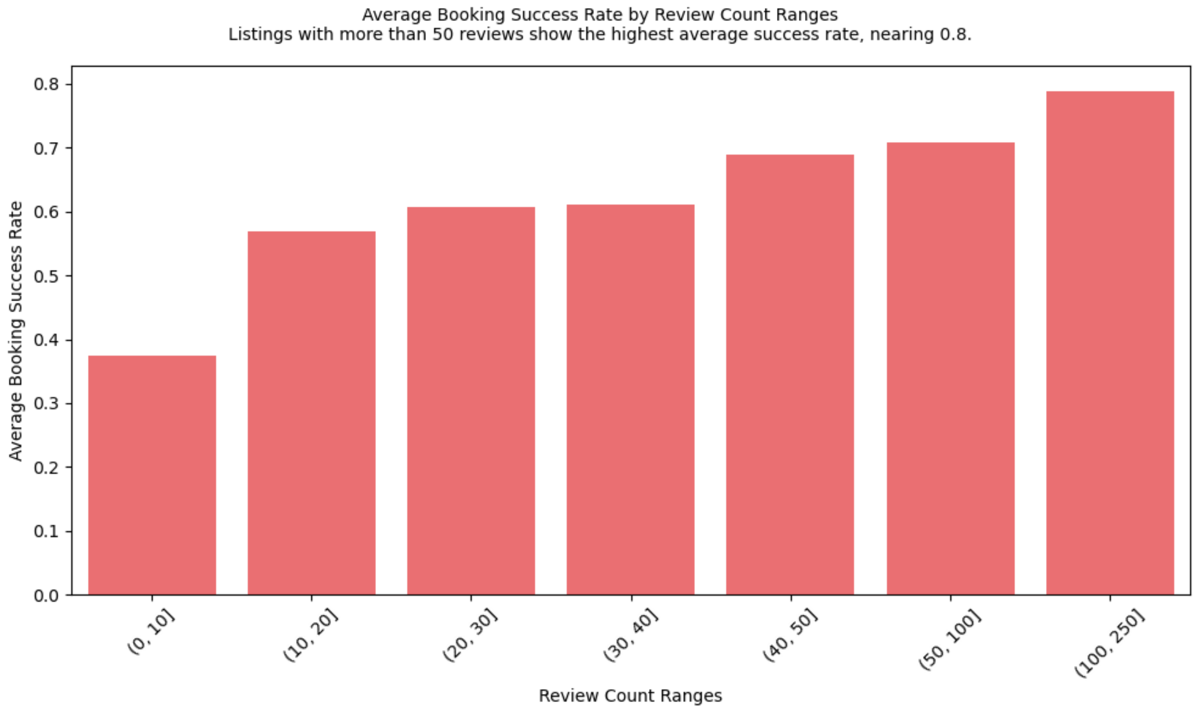
3. Impact of Reviews on Booking Success

The histogram indicates that the distribution is heavily right skewed. This suggests that there are many listings with very few reviews (0-10), and progressively fewer listings with a higher number of reviews.

The majority of listings have fewer reviews (0-10), with a sharp decline in the number of listings as review counts increase, indicating a highly skewed distribution.

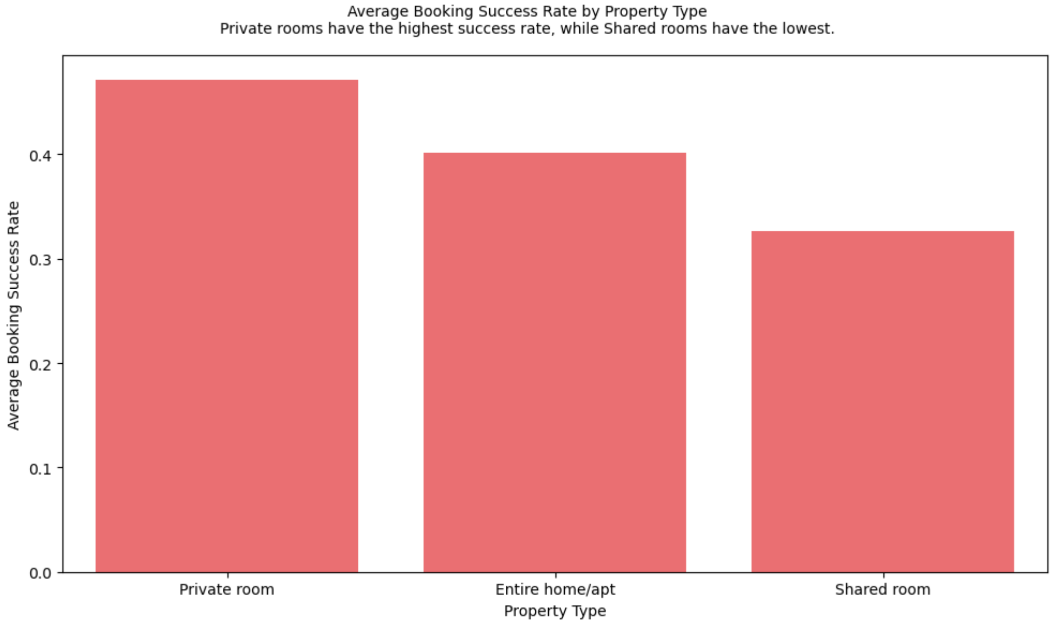


Looking at the bar chart graph, it is evident that listings with more than 50 reviews, especially those with 100-250 reviews, exhibit the highest average booking success rate, approaching 0.8.



4. Property Type and Booking Success

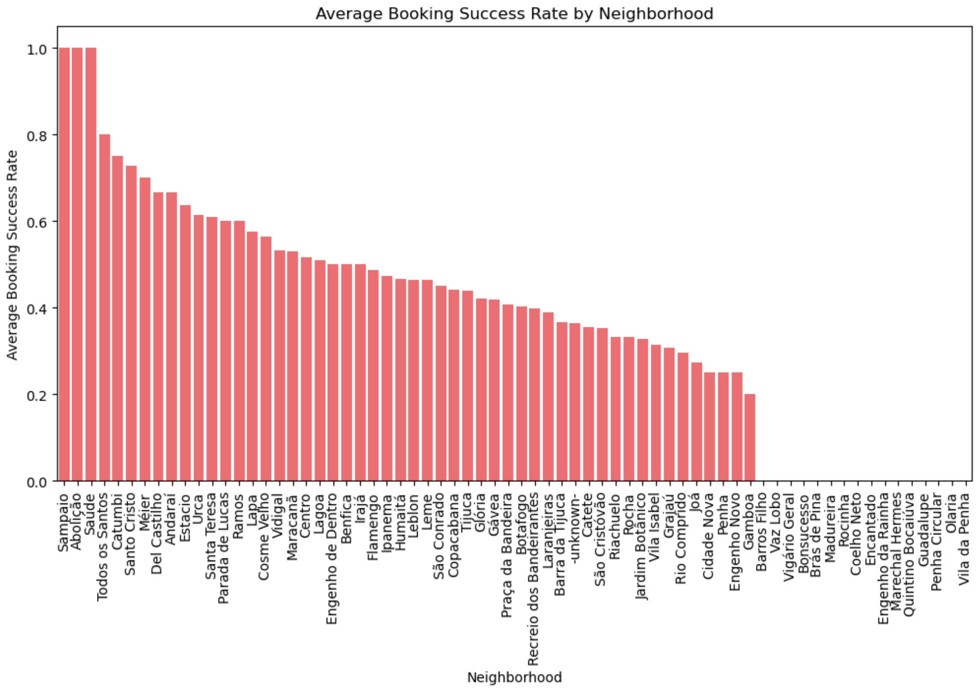
Looking at the bar chart, it is evident that the Private room property type has the highest success rate, while the Shared room type has the lowest success rate.



5. Neighbourhood Influence on Booking Success

There is a varied success rates across neighbourhoods, with some showing notably higher rates than others.

Top 10 Neighbourhoods: Sampaio, Abolição, Saúde, Todos os Santos, Catumbi, Santo Cristo, Méier, Andaraí, Del Castilho, Estacio.



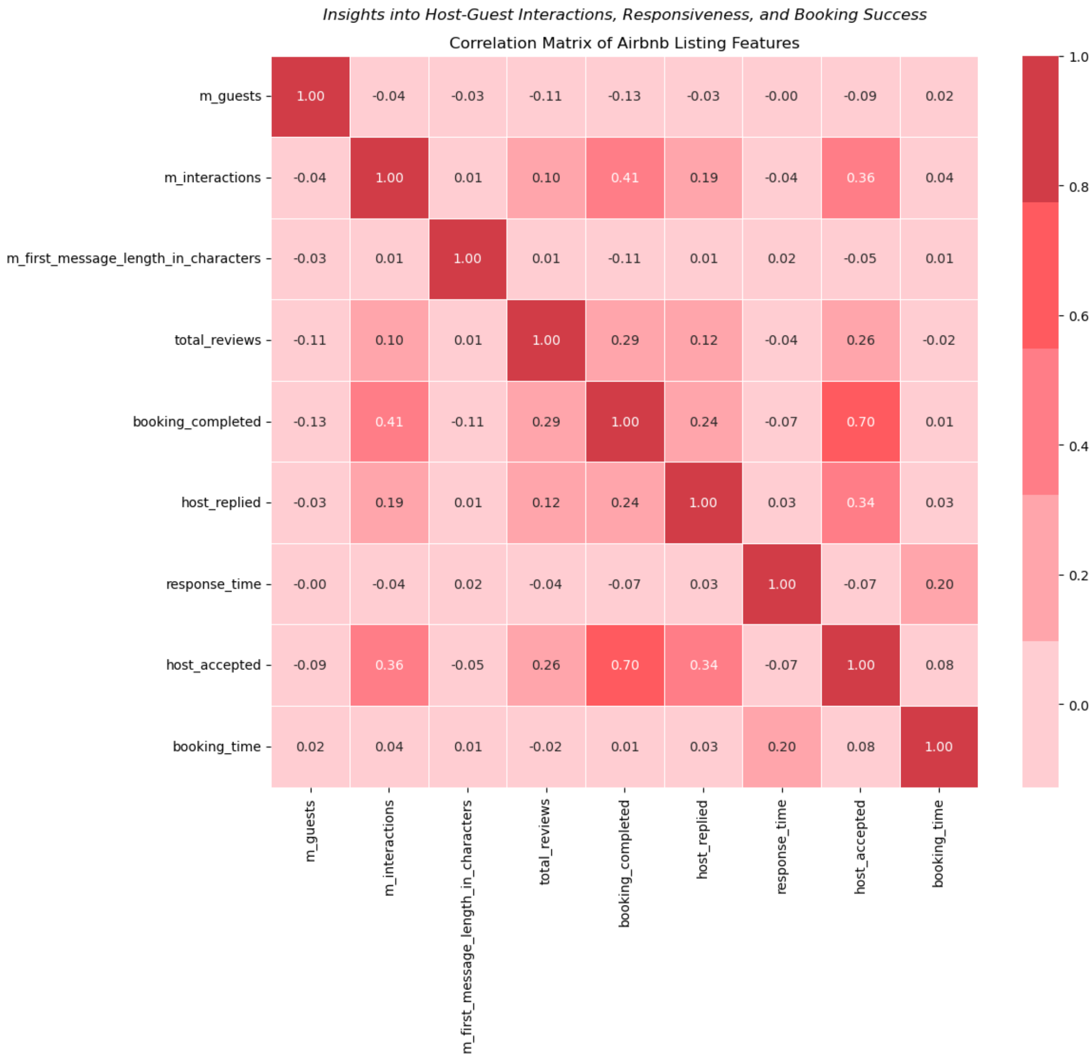
Summary Statistics and Correlation Analysis:

1. **Summary statistics of the data.**

- The mean for booking_completed is 42%, host_reply_rate is 92%, and host_acceptance_rate is 58%.
- On average, the first message sent by a guest contains 193 characters.
- On average, the total number of messages sent by both the guest and the host is 8.2.
- On average, the response time is 821 minutes/ 13 hours and 41 minutes
- On average, the booking time is 461 minutes/ 7 hours and 41 minutes

2. **Correlation heatmap highlights relationships such as:**

- m_interactions and host_acceptance_rate have a positive correlation of 0.36, indicating that more interactions between the host and guest are associated with a higher likelihood of the host accepting the booking. A similar relationship can be seen with booking_completed.
- host_reply_rate shows a positive correlation of 0.24 with booking_completed, suggesting that increased host responsiveness correlates with higher booking rates.
- host_acceptance_rate and booking_completed exhibit a very strong positive correlation of 0.7, indicating a robust relationship between host acceptance and booking completion rates.
- response_time has a very slight negative correlation of -0.07 with booking completion. This suggests that as response time increases, there is a slight decrease in booking completion rates.
- booking_time has a very slight positive correlation of 0.01 with booking completion. This indicates that as booking time increases slightly, booking completion rates also tend to increase.



	m_guests	m_interactions	m_first_message_length_in_characters	total_reviews	booking_completed	host_replied	response_time	host_accepted	booking_time
m_guests	1.00	-0.04	-0.03	-0.11	-0.13	-0.03	-0.00	-0.09	0.02
m_interactions	-0.04	1.00	0.01	0.10	0.41	0.19	-0.04	0.36	0.04
m_first_message_length_in_characters	-0.03	0.01	1.00	0.01	-0.11	0.01	0.02	-0.05	0.01
total_reviews	-0.11	0.10	0.01	1.00	0.29	0.12	-0.04	0.26	-0.02
booking_completed	-0.13	0.41	-0.11	0.29	1.00	0.24	-0.07	0.70	0.01
host_replied	-0.03	0.19	0.01	0.12	0.24	1.00	0.03	0.34	0.03
response_time	-0.00	-0.04	0.02	-0.04	-0.07	0.03	1.00	-0.07	0.20
host_accepted	-0.09	0.36	-0.05	0.26	0.70	0.34	-0.07	1.00	0.08
booking_time	0.02	0.04	0.01	-0.02	0.01	0.03	0.20	0.08	1.00

Machine Learning Approach

The objective of the machine learning analysis is to predict booking success rates and identify the most influential factors. Based on the findings from my exploratory analysis, several variables appear to have substantial impact on booking success:

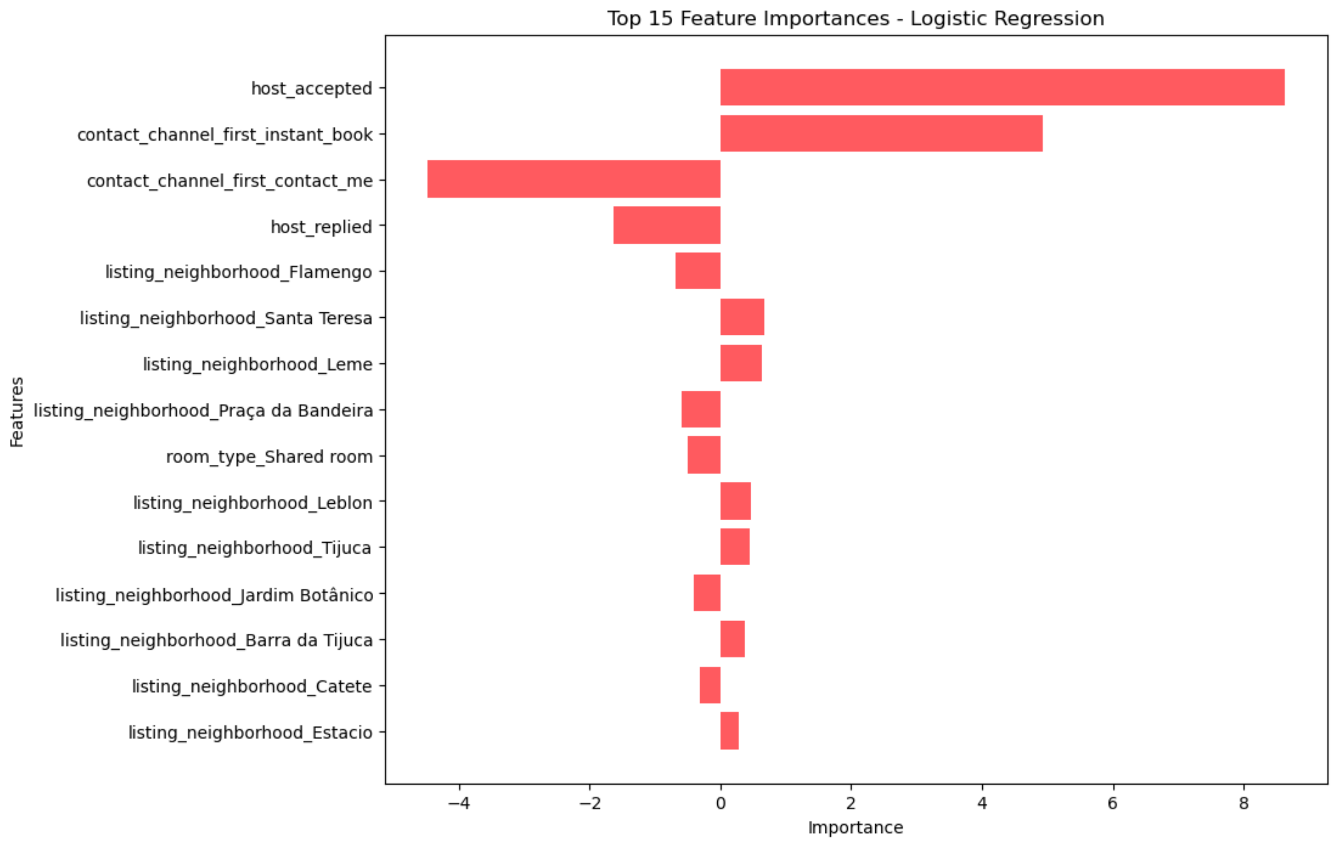
- Contact Channel
- Number of Interactions
- Reviews
- Property Type: Specific room_type and listing_neighbourhood characteristics affect the likelihood of booking success.
- Host Responsiveness

These variables, together with the booking rate, will be the focus for building the machine learning models. By analysing these factors, the aim is to optimize the guest-host matching process in Rio de Janeiro, enhancing the overall booking success rates.

Logistic Regression:

Key Findings:

- The logistic regression model highlights that features like host acceptance of bookings and availability of instant booking positively impact booking completion rates.
- The need for guests to contact hosts before booking and certain neighbourhood factors, like Flamengo, have a negative influence.
- Focusing on prompt acceptance and reducing pre-booking contact requirements could enhance booking success, while addressing specific neighbourhood challenges may also be beneficial.



Performance Metrics:

- Test Data:
  - Accuracy: The model correctly predicts 96% of all cases in the test data.
  - Precision: When the model predicts a positive outcome (booking completed), it is correct 96% of the time.
  - Recall: The model identifies 95% of all actual positive cases (completed bookings).
  - F1-score: This metric balances precision and recall, providing a harmonic mean of 96%.
- Training Data:
  - Accuracy: The model correctly predicts 97% of all cases in the training data.
  - Precision: When the model predicts a positive outcome, it is correct 97% of the time.
  - Recall: The model identifies 95% of all actual positive cases.
  - F1-score: The harmonic mean of precision and recall is 96%.

Overall Analysis:

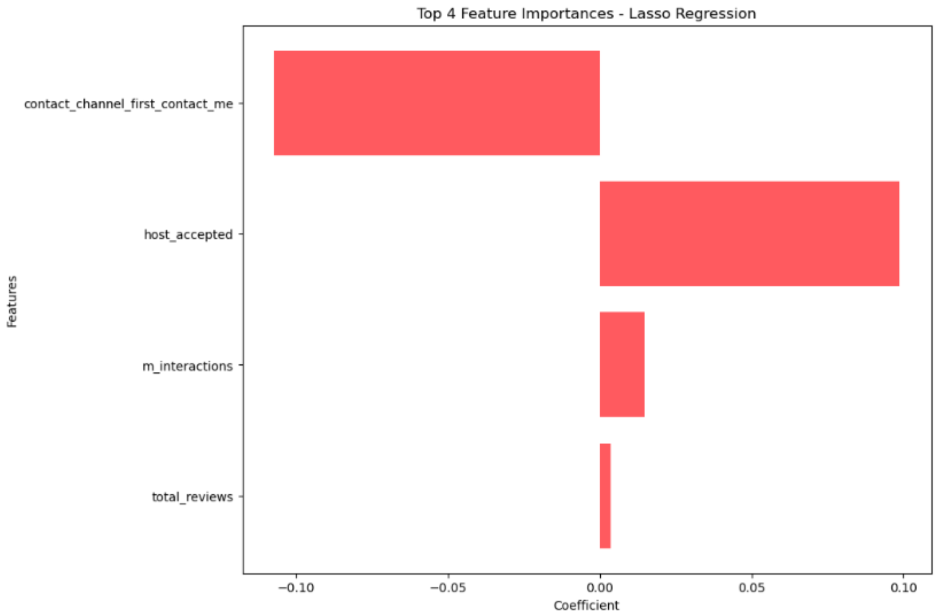
- Consistency: Metrics are consistent between training and test datasets, indicating good model generalization.
- Performance: High accuracy and balanced precision-recall trade-off suggest effective prediction of booking completions.
- Confusion Matrix: Shows strong performance with high true positives and true negatives, and relatively low false positives and false negatives.

LASSO Regression:

Using Lasso Regression for regularization improves model interpretability and helps prevent overfitting by penalizing the absolute values of the coefficients.

Key Findings:

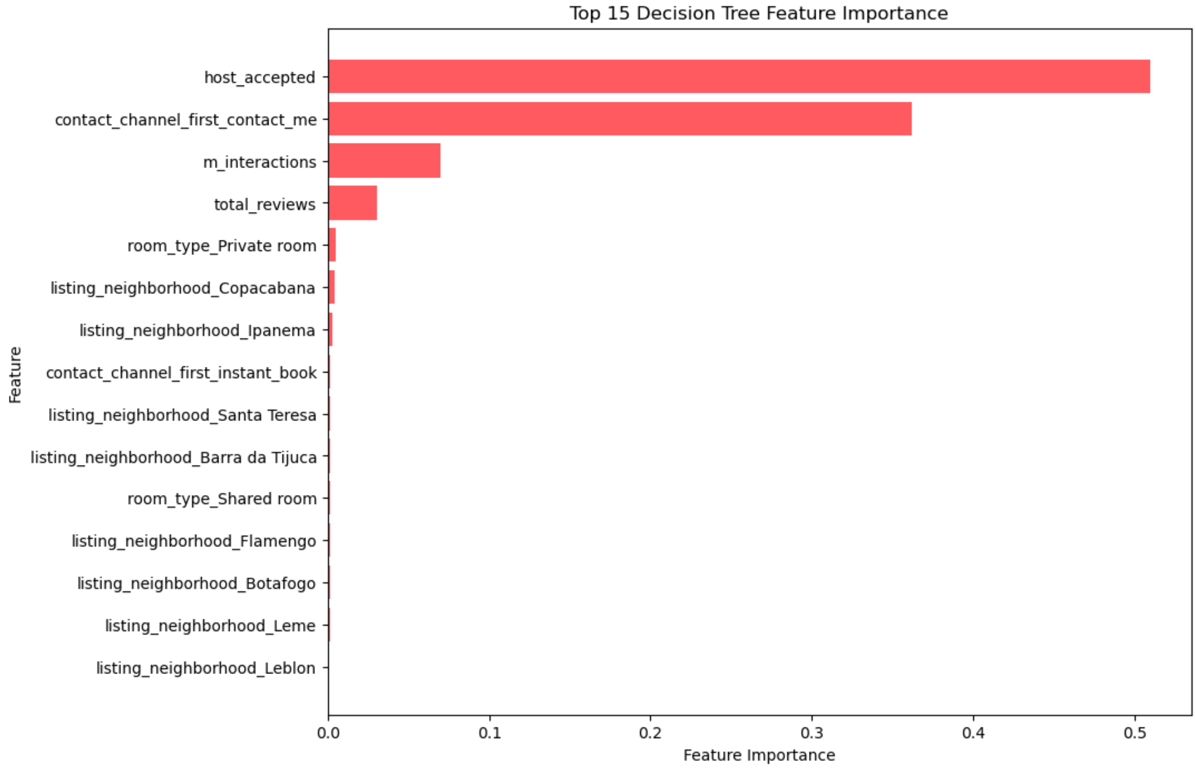
- The Lasso Regression model demonstrates robust performance in predicting booking completions in Rio de Janeiro, achieving an accuracy of 82% on the test dataset and 81% on the training data set.
- Key features such as contact_channel_first_contact_me negatively impact booking completion rates, while host_accepted interactions positively influence outcomes.
- Other features, including m_interactions and total_reviews, exhibit minimal impact. Moving forward, optimizing interaction channels and enhancing host responsiveness are critical for improving booking success rates.



Decision Trees:

Key Findings:

- Highly Important Features:
  - host_accepted (0.509760): This feature appears to be the most influential according to your model. It suggests that whether the host accepted the booking request or not plays a significant role in predicting the outcome.
  - contact_channel_first_contact_me (0.362077): The method of first contact between guest and host also shows strong importance. This could indicate that how initial communication is initiated impacts booking decisions or outcomes.
- Moderately Important Features:
  - m_interactions (0.069739): Number of interactions (possibly messages or inquiries) is also considered, albeit to a lesser extent than the above two features.
  - total_reviews (0.030311): The total number of reviews for the listing contributes to a lesser degree compared to the more decisive features.
- Less Important Features:
  - room_type_Private room (0.004832): This feature has some importance but significantly less compared to host_accepted and contact_channel_first_contact_me.



Performance Metrics:

- Test Data:
  - Accuracy: The model correctly predicts 95% of all cases in the test data.
  - Precision: When the model predicts a positive outcome (booking completed), it is correct 95% of the time.
  - Recall: The model identifies 94% of all actual positive cases (completed bookings).
  - F1-score: This metric balances precision and recall, providing a harmonic mean of 95%

- Training Data:
  - Accuracy: The model correctly predicts 99% of all cases in the training data.
  - Precision: When the model predicts a positive outcome (booking completed), it is correct 100% of the time.
  - Recall: The model identifies 98% of all actual positive cases (completed bookings).
  - F1-score: This metric balances precision and recall, providing a harmonic mean of 99%.

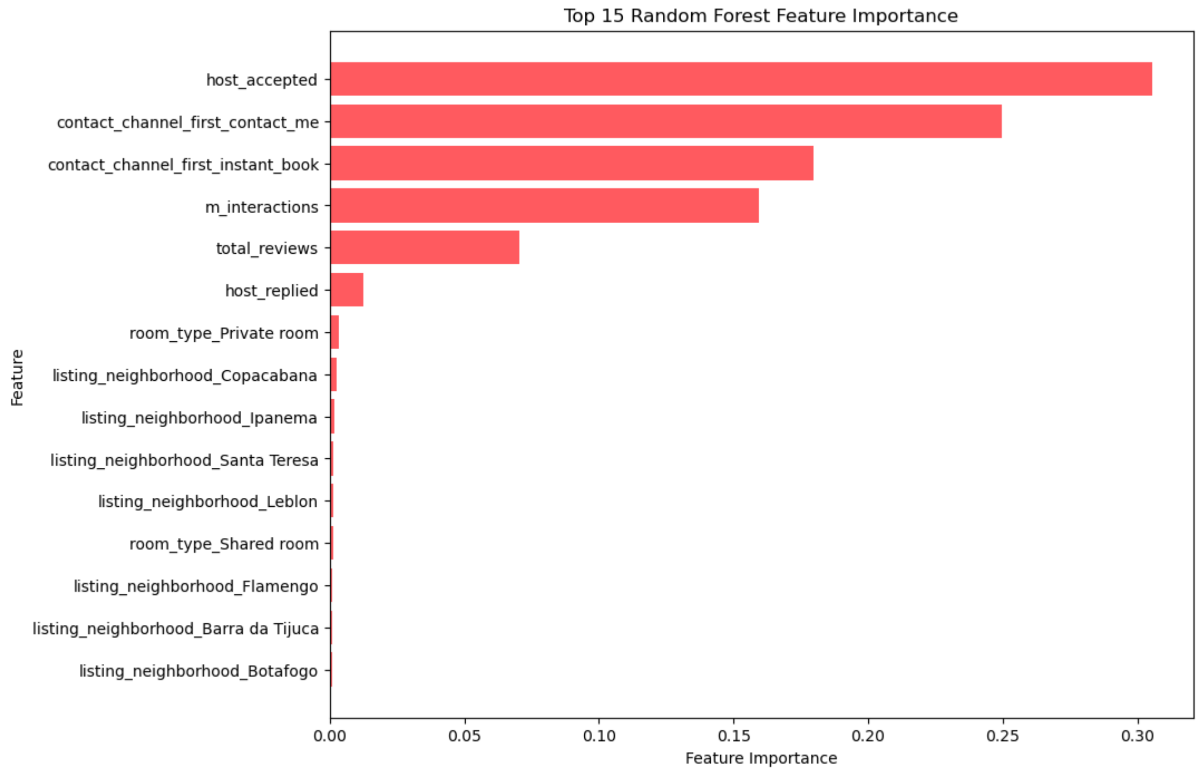
Overall Analysis:

- The Decision Tree model demonstrates high accuracy on both the training set (0.99) and the test set (0.95). This indicates that the model performs well in correctly predicting booking outcomes (accepted or not) based on the input features.
- Precision (ability of the classifier not to label as positive a sample that is negative) and recall (ability of the classifier to find all positive samples) are balanced, with slightly higher precision (0.95 for class 1) than recall (0.94 for class 1) on the test set. This suggests that when the model predicts a booking will be accepted (class 1), it is correct 95% of the time, and it correctly identifies 94% of all actual booking acceptances.
- The F1-score for class 1 is 0.94 on the test set, indicating a good balance between precision and recall. This metric is crucial as it combines both precision and recall into a single measure, providing a holistic view of the model's performance.
- The confusion matrices for both training and test sets show strong performance with high true positives (2155 in test set, 9117 in train set) and true negatives (3166 in test set, 12981 in train set). The number of false positives (120 in test set, 33 in train set) and false negatives (137 in test set, 178 in train set) is relatively low, indicating good predictive capability across classes

Random Forest:

Key Findings:

- Most influential features in predicting whether a booking is successful or not:
  - host_accepted: This feature has the highest importance, indicating that whether the host accepts bookings plays a significant role in the prediction.
  - contact_channel_first_contact_me and contact_channel_first_instant_book: These features also show high importance, suggesting that the method through which guests initiate contact or book instantly influences the prediction.
  - m_interactions and total_reviews: The number of interactions and total reviews received by the host contribute significantly to predicting booking outcomes.
  - host_replied: Whether the host replied to inquiries is also important, however to a lesser extent compared to other features.



Performance Metrics:

- Test Data:
  - Accuracy: The Random Forest model correctly predicts 97% of all cases in the test data.
  - Precision: When the model predicts a positive outcome (booking completed), it is correct 95% of the time.
  - Recall: The model identifies 96% of all actual positive cases (completed bookings).
  - F1-score: This metric balances precision and recall, providing a harmonic mean of 96%.
- Training Data:
  - Accuracy: The Random Forest model correctly predicts 99% of all cases in the training data.
  - Precision: When the model predicts a positive outcome (booking completed), it is correct 99% of the time.
  - Recall: The model identifies 99% of all actual positive cases (completed bookings).

    - F1-score: This metric balances precision and recall, providing a harmonic mean of 99%.

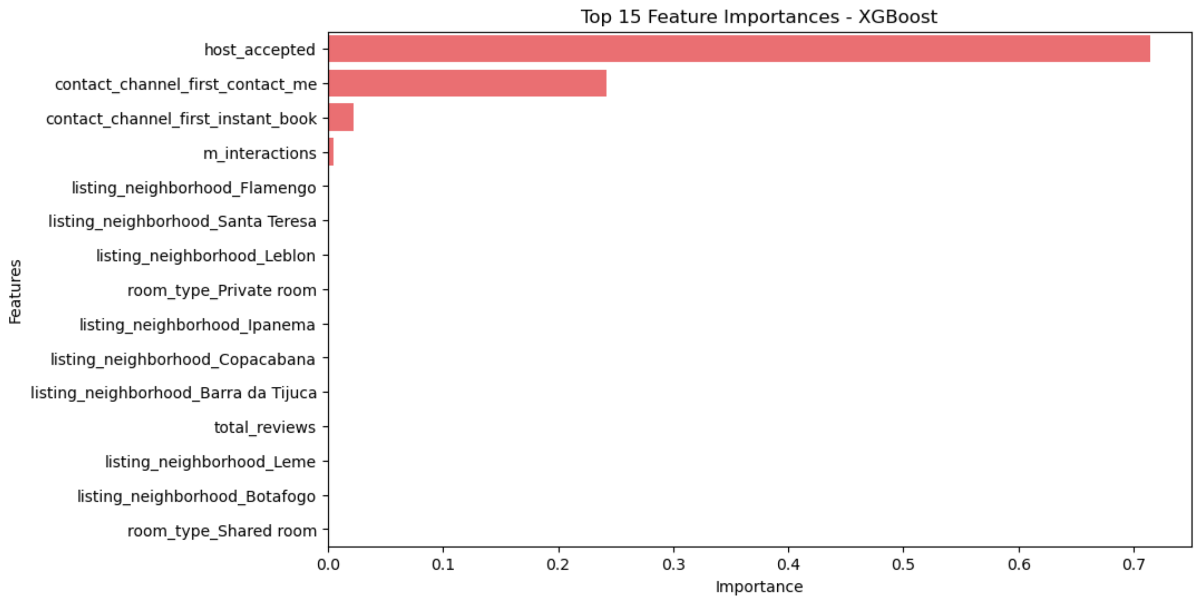
Overall Analysis:

- The Random Forest model demonstrates strong predictive performance in determining whether a booking will be successful or not. It achieves high accuracy on both the training (99%) and test (97%) datasets, indicating robust generalization capabilities.
- The model identifies several key features that significantly influence booking outcomes, including host acceptance of bookings, guest interaction methods, total reviews, and host responsiveness

XGBoost:

Key Findings:

- Feature Importance Interpretation:
    - host_accepted: This feature has the highest importance (0.714), indicating that whether the host accepts bookings plays a significant role in the model's predictions.
    - contact_channel_first_contact_me: This feature is also important (0.242), suggesting that the method of first contact with the host is a relevant predictor.
    - contact_channel_first_instant_book: Although less important (0.022), it still contributes to the model's decision-making process.
    - Other features: The remaining features have lower importance values (ranging from 0.004 to 0.0007), indicating they contribute less to the model's predictive power.



Performance Metrics:

- Test Data:
    - Accuracy: The XGBoost model achieves an accuracy of 97%, meaning it correctly predicts the class (booked or not booked) for 97% of the instances in the test dataset.
    - Precision: For class 0 (not booked), precision is 98%. This indicates that when the model predicts a listing will not be booked, it is correct 98% of the time.
    - Recall: For class 0, recall is 97%. This means that out of all actual instances where a listing was not booked, the model correctly identifies 97% of them.
    - F1-score: The F1-score is a balance between precision and recall. For class 0, the F1-score is 0.97, indicating a good balance between precision and recall.
- Training Data:
    - Accuracy: The XGBoost model achieves an accuracy of 97%, meaning it correctly predicts the class (booked or not booked) for 97% of the instances in the training dataset.
    - Precision: For class 0 (not booked), precision is 98%. This indicates that when the model predicts a listing will not be booked, it is correct 98% of the time.
    - Recall: For class 0, recall is 97%. This means that out of all actual instances where a listing was not booked, the model correctly identifies 97% of them.

    - F1-score: The F1-score is a balance between precision and recall. For class 0, the F1-score is 0.97, indicating a good balance between precision and recall.

Overall Analysis:

- Performance: The XGBoost model demonstrates robust performance with high accuracy (>97%) and balanced F1-scores for both classes (booked and not booked listings).
- Feature Importance: Key features such as host_accepted and contact_channel_first_contact_me significantly influence predictions, providing insights into factors driving booking outcomes.
- Next Steps: To optimize and further enhance the model's performance and reliability, I will use cross validation, to validate the learning model and ensure that the high performance is not due to overfitting but rather a reflection of the model's ability to perform well to new data.

Cross Validation Results:

- Consistency: The small standard deviations for both train and test errors indicate that the model performs consistently across different subsets of the data. Specifically, the average train error mean is approximately 3.13% with a standard deviation of about 0.03%, while the average test error mean is around 3.18% with a standard deviation of approximately 0.14%.
- Low Error Rates: The mean error rates for both train and test sets are low, with the model averaging a train error mean of 3.13% and a test error mean of 3.18%.
- Minimal Overfitting: The similarity between the train-error-mean (3.13%) and test-error-mean (3.18%) indicates that the model is not overfitting significantly; it performs well on both the training and validation sets.

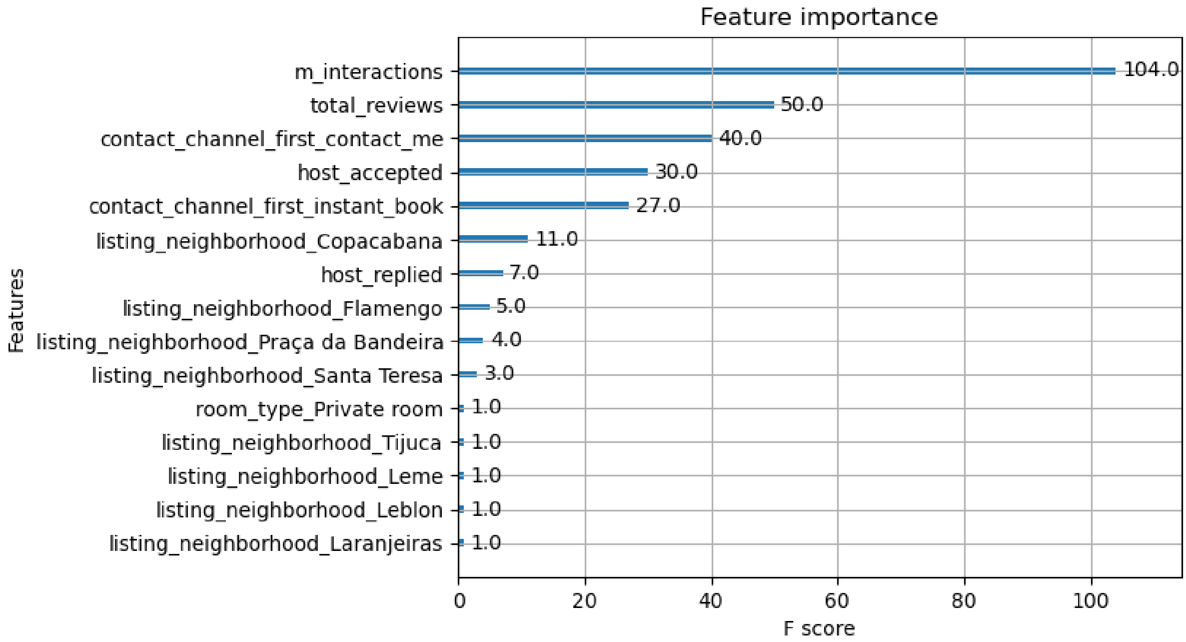
Performance Metrics:

- Test Data:
    - Precision:
        - Unsuccessful Booking (0.98): Out of all the instances predicted Unsuccessful Booking, 98% were correct.
        - Successful Booking (0.95): Out of all the instances predicted as Successful Booking, 95% were correct.
    - Recall:
        - Unsuccessful Booking (0.97): Out of all actual Unsuccessful Booking instances, 97% were correctly identified.
        - Successful Booking (0.97): Out of all actual Successful Booking instances, 97% were correctly identified.
    - F1-Score:
        - Unsuccessful Booking 0 (0.97) and Successful Booking (0.96): Indicates a balance between precision and recall for both.
- Training Data:
    - Precision:
        - Unsuccessful Booking (0.98): Out of all the instances predicted as Unsuccessful Booking, 98% were correct.
        - Successful Booking (0.96): Out of all the instances predicted as Successful Booking, 96% were correct.
    - Recall:
        - Unsuccessful Booking (0.97): Out of all actual Unsuccessful Booking instances, 97% were correctly identified.

        - Successful Booking (0.97): Out of all actual Successful Booking instances, 97% were correctly identified.
    - F1-Score:
        - Unsuccessful Booking (0.97) and Successful Booking (0.96): Indicates a balance between precision and recall for both.

Feature Importance:

- High Importance Features:
    - m_interactions: This feature has the highest importance score of 104.0, indicating it plays a significant role in predicting the target variable.
    - total_reviews: Also important with a score of 50.0, suggesting it contributes substantially to the model's predictions.
    - contact_channel_first_contact_me and contact_channel_first_instant_book: These features are moderately important, with scores of 40.0 and 27.0 respectively.



Conclusions & Recommendations

Conclusions

1. **Effectiveness of Contact Channels:**
    - The analysis reveals that the 'instant_book' channel consistently achieves the highest booking success rates, indicating its efficiency in converting inquiries into bookings without additional host confirmation.
    - 'Contact_me' and 'book_it' channels show lower success rates, suggesting opportunities for improvement in how these channels are utilized to increase booking success.
2. **Impact of Interaction Dynamics:**
    - Listings with higher numbers of interactions between hosts and guests tend to have higher booking success rates. This highlights the importance of fostering engagement through effective communication channels and responsive interactions.
    - Hosts with quicker response times exhibit higher booking success rates, emphasizing the need for prompt responsiveness to guest inquiries.
3. **Influence of Listing Attributes:**
    - Property types such as private rooms generally have higher booking success rates compared to shared rooms, indicating preferences among guests for certain accommodation types.
    - Neighbourhoods play a significant role in booking success, with some areas demonstrating notably higher success rates than others. This suggests potential for targeted marketing and promotion strategies based on location.
4. **Machine Learning Insights:**
    - Models such as Logistic Regression, Decision Trees, Random Forest, and XGBoost provide robust predictions of booking outcomes based on factors like host acceptance rates, interaction frequency, and property characteristics.
    - Feature importance analysis across models consistently highlights host acceptance, contact channels, and listing attributes as critical factors influencing booking success.

Recommendations

Based on the conclusions drawn from the analysis, here are targeted recommendations to enhance booking success in Rio de Janeiro:

1. **Optimize Contact Channels:**
    - **Recommendation:** Enhance the usability and visibility of the 'instant_book' feature across listings.
        - **Rationale:** Given its high success rate, promoting 'instant_book' could streamline the booking process, reducing friction and increasing immediate conversions.

        - **Estimated Impact:** High. This initiative leverages existing user behaviour and platform capabilities to directly boost booking rates.

2. **Improve Host-Guest Interaction:**
    - **Recommendation:** Implement incentives for hosts to improve responsiveness and increase interaction frequency with guests.
        - **Rationale:** Higher interaction volumes and quicker response times correlate with increased booking success. Incentives could include recognition badges, ranking boosts, or promotional placement for highly responsive hosts.
        - **Estimated Impact:** Moderate to High. Improving interaction dynamics directly enhances user experience and booking conversion rates.
3. **Enhance Listing Attributes and Location Strategies:**
    - **Recommendation:** Conduct targeted campaigns to highlight listings in neighbourhoods with historically high booking success rates.
        - **Rationale:** Neighbourhoods significantly impact booking success, presenting an opportunity to tailor marketing efforts to areas with proven demand.
        - **Estimated Impact:** Moderate. Strategic promotion of listings in high-performing neighbourhoods can attract more bookings from discerning guests seeking specific locations.

Prioritization

1. **Promote 'instant_book' Feature:** This recommendation ranks highest due to its potential to immediately impact booking conversions by simplifying the booking process and leveraging existing high success rates.
2. **Improve Host-Guest Interaction:** While crucial for long-term engagement and satisfaction, this initiative ranks slightly lower due to the need for sustained effort and incentivization to change host behaviour effectively.
3. **Enhance Listing Attributes and Location Strategies:** This initiative, though impactful, ranks third as it involves targeted marketing efforts and may require additional resources to optimize visibility and promotion effectively.

To address broader challenges in matching supply and demand beyond the current dataset, there is a need to consider some of the following approaches:

1. **Market Segmentation Analysis:**
    - Conduct detailed segmentation analysis to understand diverse guest preferences and behaviours in Rio de Janeiro. This could involve surveys, focus groups, or advanced analytics to uncover hidden patterns in user preferences.
2. **Competitive Landscape Assessment:**
    - Evaluate competitive platforms and market trends to identify emerging opportunities and threats. Understanding how competitors manage their supply and demand dynamics can provide strategic insights for Airbnb's approach.

3. **Dynamic Pricing Experiments:**
    - Implement dynamic pricing strategies based on real-time demand signals and competitive pricing intelligence. Experiment with pricing models that optimize both host earnings and guest affordability, potentially using machine learning models to predict optimal pricing.