Enhancing Hotel Services through Customer Reviews Insights by Leveraging Airbnb and Hotel Feedback.

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Abstract

This project explores how hotels can enhance their services through customer review insights by leveraging Airbnb and hotel feedback. By analyzing reviews from both Airbnb and hotels through text mining techniques, I will be able to identify what are the most frequent terms, what are the most frequent phrases. I will also perform sentiment analysis to train models to classify the Airbnb reviews into negative, positive and neutral using Bing lexicon. This project aims to identify critical factors that influence customer satisfaction and dissatisfaction. The findings are intended to help traditional hotels develop strategies according to the market demand analysis and dynamics. Hotels can leverage positive Airbnb feedback and identify negative feedback to improve their services and stay competitive. This paper is just for study purposes since it was collected from one hotel.

Keywords: Hotel, Airbnb, customer reviews, service, text mining.

1. Introduction

In recent years, the rise of platforms like Airbnb has significantly disrupted the traditional hotel industry. With millions of listings worldwide, Airbnb has rapidly become a major competitor, offering personalized and unique accommodation options that have reshaped consumer preferences. This shift has made it increasingly challenging for hotels to meet modern customer expectations. For traditional hotels to identify and address gaps in their service, customer feedback plays a critical role in attracting and retaining new guests. Leveraging data-driven insights has, therefore, become essential for the hotel industry to adapt and compete in an evolving market.

1.1 Problem and Purpose of the Study

Traditional hotels are finding it challenging to compete with platforms like Airbnb, which offer unique, personalized accommodations that cater to modern travelers. Although customer reviews contain valuable feedback, many hotels struggle to analyze and leverage this data to improve their service and remain competitive.

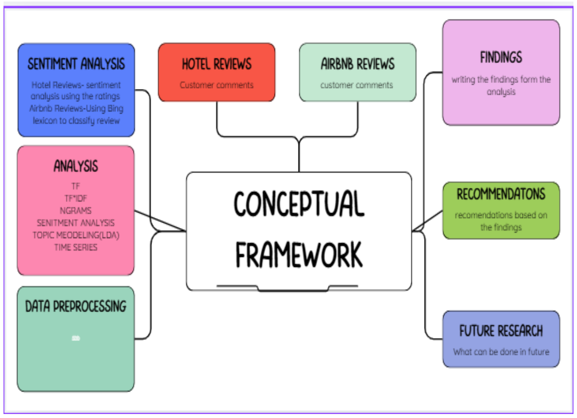
The purpose of the study is to try to address how the hotels can leverage both the positive customer feedback from Airbnb and also work on the hotel's negative feedback to enhance their service. Carrying text mining analysis provides actionable insights for hotels to improve their services and better meet guest expectations.

2. Literature Review

The paper by Torres et al. (2015) discusses the importance of consumer-generated feedback (CGF) in the hotel industry, focusing on improving service quality. The research highlights that word-of-mouth has expanded through digital platforms, allowing consumer opinions to reach a larger audience. The paper examines how hotels can use CGF, including positive and negative reviews, to improve operations, such as modifying training programs and policies. It explores the value that hotel managers place on feedback, how they balance positive and negative reviews, and how this feedback impacts perceived service quality. The study also identifies patterns in how managers use CGF to enhance customer experience, emphasizing that systematic use of feedback can lead to quality improvements. The paper concludes that while hotels focus more on addressing negative feedback, paying attention to positive feedback is equally important for maintaining high service standards. Also a paper done by Andrea Galvan on "How Airbnb Disrupts the Hotel Industry" highlights Airbnb's impact on traditional hotels, causing revenue losses and declining bookings. Despite these disruptions, Airbnb generates significant economic benefits, contributing over $100 billion globally and supporting local businesses, particularly in lesser-known destinations, through guest spending and increased travel.

2. 1 Conceptual Framework

The conceptual framework for this study centers on using text-mining techniques to analyze Airbnb and hotel reviews for service improvement in hotels. By focusing on customer reviews, the study aims to identify patterns of satisfaction and dissatisfaction. Positive Airbnb reviews will offer insights into successful practices that hotels can adopt to improve their services. Negative reviews will reveal specific areas where hotels can enhance their offerings. Through techniques like term frequency (TF), TF-IDF, and n-grams, the study will extract meaningful insights to help hotels optimize their services and better meet customer expectations.



3. Research Questions

The study intends to address the following research questions.

1. How can hotels leverage positive feedback from Airbnb reviews to enhance their service offering?

1.1. What are the most frequently mentioned positive aspects of Airbnb stays?

1.2. What unique attributes are specifically praised in positive Airbnb reviews compared to other reviews?

2. What are the most common service-related complaints from hotel customers, and how do they compare them to the negative feedback from Airbnb reviews?

2.1 What are the most frequently mentioned service-related complaints in hotel and Airbnb reviews?

2.2 How do the sentiments in hotel reviews compare to those in Airbnb reviews when it comes to service-related complaints?

3 How can hotels systematically address areas of dissatisfaction highlighted in negative Hotel reviews?

4 Are there seasonal pattern trends for satisfaction/dissatisfaction based on the Airbnb dataset since it has a date?

5 Does customer experience significantly differ between hotels and Airbnb?

By addressing these operationalized research questions, the study seeks to contribute and provide insights on how hotels can be able to tailor their services to address the customer's complaints to stay competitive in the industry.

4. Data Availability

The names of the dataset are Hotel reviews and Airbnb Reviews. I renamed trip advisor hotel reviews to hotel reviews. Both datasets are found in Kaggle. The URL for hotel reviews is https://www.kaggle.com/datasets/andrewmvd/trip-advisor-hotel-reviews/code, and the URL for Airbnb reviews is https://www.kaggle.com/datasets/muhammadahmedansari/airbnb-dataset. The genre of my dataset is customer reviews. Both datasets consist of reviews of the feedback collected from Airbnb and hotels. Hotel reviews have two variables: reviews (text) and ratings (numerical). Airbnb Reviews has six variables, including Listing ID, review ID, Date of review, reviewer ID, reviewer name, and comments. Both datasets provide text-based reviews, which are the key elements for text mining.

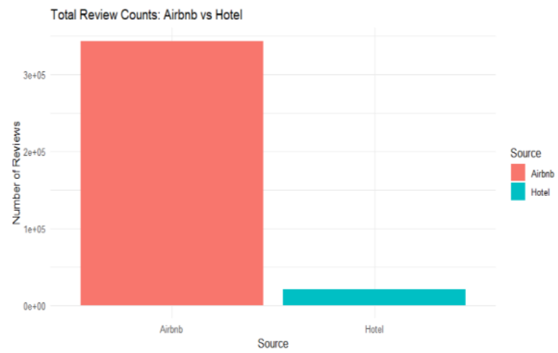
The hotel reviews dataset contains textual reviews from customers and their associated ratings. The Airbnb reviews dataset contains a textual comment that customers shared about their experience during their stay. Through analyzing these comments, one could learn about customer satisfaction and its key drivers, service improvement, and comparison analysis to understand the difference between satisfaction and expectations in Airbnb and hotels. The questions to explore include the most common reasons for customer satisfaction/dissatisfaction, seasonal pattern trends (especially for the Airbnb dataset as it includes dates), and whether customer experiences significantly differ between hotel and Airbnb. The Airbnb reviews dataset has 342,904 comments, and the Hotel reviews dataset has 20,491 reviews. Both datasets are open to the public via Kaggle. They are large, rich in information, and structured for meaningful insights. These datasets will allow hotels to learn from Airbnb's positive reviews and improve their service delivery accordingly.

5. Methodology

The Cross Industry Standard Process for Data Mining (CRISP-DM) methodology comprises of six stages. The first stage is to determine the purpose of the study, the second is exploring the availability and nature of the data, the third is data preparation, the fourth is developing and assessing the model, the fifth is Evaluating the findings, and the sixth is deploying the results.

5.1 Methodology; Data Preparation

To begin with, import your datasets and name them Hotelreviews and Airbnbreviews, respectively. After importing, I did check for the missing rows in both my datasets and removed the missing values. The next step was to tokenize the datasets and created a sentiment classification for the hotel reviews based on the rating. I did this by assigning ratings of 4 and above as positive, 3 as neutral, and 2 and below as negative. I, therefore, explored the data before any preprocessing and generated the term frequencies to see the most appearing words in the datasets. For the Aibnbreviews, since the dataset lacked ratings, I classified the sentiment using a dictionary-based approach by leveraging the Bing lexicon to identify positive and negative words within the reviews. The reviews, which were neither positive nor negative, were classified as neutral. I applied the term frequency and TF* IDF to both datasets to extract key satisfaction drivers by identifying frequently used words and phrases. I then detected trigrams in the hotel dataset and quad grams in the Airbnb dataset to find common word combinations, which will help uncover patterns in the data. I used the date field for the Airbnb dataset to perform seasonal trend analysis to track sentiment variations over time. I also performed TF *IDF in both datasets and applied the word cloud sentiment and box plot sentiments. Finally, I conducted a comparative analysis between hotel and Airbnb reviews to determine differences in customer experiences using sentiment classification across both platforms. This comprehensive approach will help extract actionable insights to improve hotel services. The following bar chart represents the number of observations for the two data sources.



5.2 Modelling and Analytical Approaches

For Research Question 1, I used sentiment analysis with the Bing lexicon to classify reviews and identify aspects that customers appreciated the most. After classifying, I filtered the positive reviews and used term frequency (TF) to identify the top 20 most frequently mentioned positive terms. I also used TF-IDF to highlight unique attributes that are praised in positive reviews and N-grams to identify common phrases indicating key satisfaction. Packages used included tidytext, dplyr, ggplot2, wordcloud, and quanteda. For Research Question 2, I analyzed and compared the most common service-related complaints in both hotel and Airbnb reviews. For Research Question 2.1, I used the term frequency analysis to determine the most frequently mentioned complaints by tokenizing the reviews, removing stop words, and calculating word frequencies. I used a comparative bar chart and word cloud to visualize the most frequent complaint words for each dataset. For Research Question 2.2, I specifically focused on negative sentiment related to service issues by filtering reviews containing keywords like "service," "staff," "help," and "support". I then used box plot to visualize the distribution of negative sentiment scores for service-related complaints across Airbnb and hotel reviews, highlighting the differences between customer dissatisfaction in each context. For Research Question 3, I used topic modeling with Latent Dirichlet Allocation (LDA) to extract and analyze key themes present in negative hotel reviews and also applied sentiment analysis to evaluate dissatisfaction and help identify critical areas for improvement. Packages used were tidytext, quanteda, topicmodels, and ggplot2. For Research Question 4, I conducted seasonal trend analysis using lubridate to extract the month and year from Airbnb review dates and performed time-series analysis to calculate average sentiment scores by month to identify seasonal patterns in satisfaction or dissatisfaction. Packages used included lubridate, ggplot2, dplyr, and tidytext. Finally, for Research Question 5, I performed sentiment analysis on reviews from Airbnb and hotel datasets using tidytext, dplyr, and ggplot2. I combined the datasets and visualized the sentiment distribution through a bar chart and a box plot to compare customer sentiments across both sources.

6. Visualizations

The following visualizations were performed to try answer my project research questions.

Figure 1

This visual represents the word cloud sentiment for the hotel review. It shows the most frequently mentioned words in hotel reviews. Key terms like "hotel," "staff," "location," "service," and "clean" appear prominently, indicating that these aspects are often discussed by guests. This suggests that staff, location, and cleanliness are important themes in guest feedback.

The figure below shows the reviews for hotel which are mostly positive.

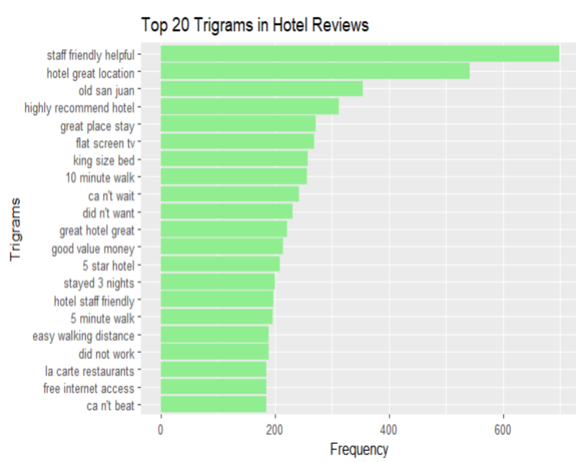


Figure 2

The graph below shows the word cloud sentiment with dominant words.It highlights commonly mentioned words like "Amsterdam," "location," "apartment," "stay," "host," and "clean." This indicates that guests often focus on the property's location, the quality of the apartment, and their overall experience with the host.

Figure 3

The graph below represents the top 30 postive words extracted from the positive sentiment analysis for Airbnb. The most prominent terms include "br," "stay," "Amsterdam," "location," and "apartment," which indicates that these are recurring themes in the reviews. Specifically, "Amsterdam" and "location" suggest that many guests are highlighting the convenience or attractiveness of the place they stayed. Also, words like "clean," "host," "nice," and "comfortable" suggest guests valued the cleanliness, hospitality, and comfort of their experience.

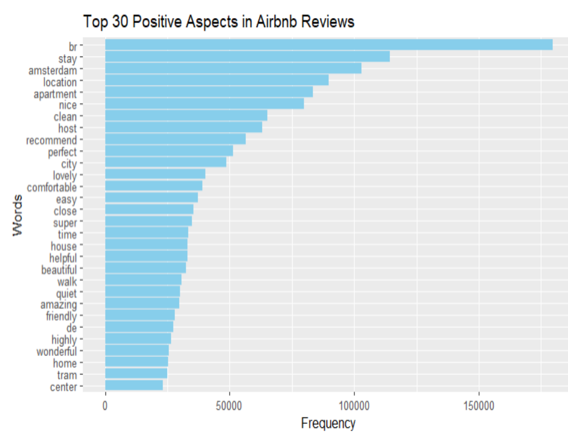


Figure 4

The bar chart below is TF-IDF representation of positive Airbnb reviews, highlighting unique attributes frequently mentioned by guests. The words with high TF-IDF scores include "perfect," "deal," "hostel," "entertainment," "rare," "factory," "helpfulness," and "friendly." These words suggest that guests appreciated aspects like value for money, good service, unique experiences, and access to entertainment, which contributed to their positive Airbnb experiences.

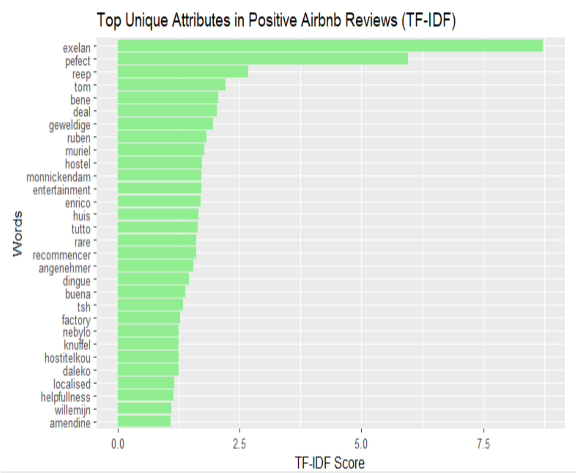


Figure 5

The graph below shows the top 20 bigrams mentioned in positive Airbnb reviews. Key phrases like "stay," "Amsterdam," "location," "apartment," and "nice" are among the most frequently occurring combinations. This suggests that guests value aspects related to their stay experience, specifically the location (such as Amsterdam), the quality of the apartment, and overall positive impressions like "clean," "host," and "recommend." These frequent bigrams help highlight what makes the stay satisfying for guests, focusing on location, comfort, cleanliness, and service.

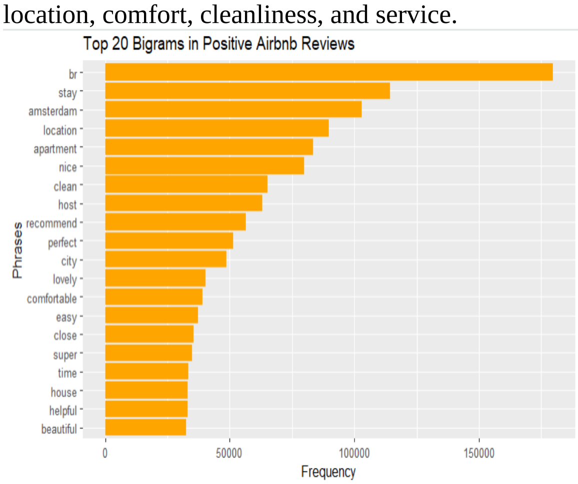


Figure 6

The bar chart below compares the most frequently mentioned negative aspects in Hotel and Airbnb reviews. The blue bars represent hotel complaints, while the red bars represent Airbnb complaints. In the hotel reviews, the most common complaints revolve around words such as "hotel," "stay," "staff," "night," and "service." This indicates that hotel guests were often dissatisfied with the overall experience, especially regarding staff interactions and the quality of service provided during their stay. In contrast, Airbnb reviews highlight words like "water," "bad," and "Amsterdam" as the most frequently mentioned negative aspects. This suggests that Airbnb guests faced more specific issues, such as problems with utilities like water and challenges related to certain locations..

Overall, hotel guests mostly reported dissatisfaction with general service and staff-related issues, whereas Airbnb guests tend to express concerns about specific amenities and property-related conditions. This comparison reveals that the nature of complaints differs between traditional hotels and Airbnb stays, with hotels facing service quality issues and Airbnb properties facing more localized or feature-specific complaints.

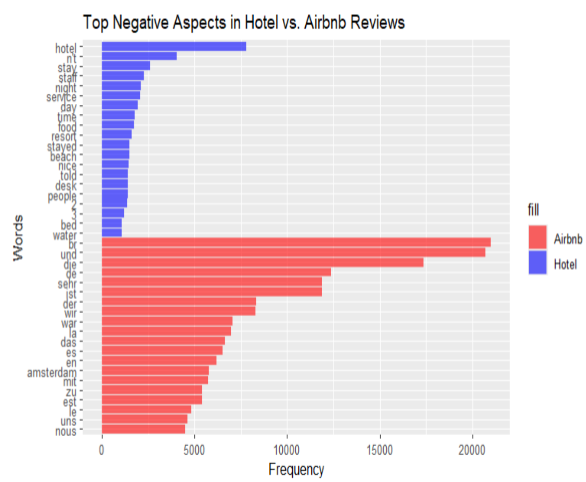


Figure 7 Sentiment distribution analysis for negative service-related reviews

The box plot shows the sentiment scores distribution for negative service-related complaints in Airbnb and hotel reviews. The Airbnb reviews, represented by the red box, have a wider range of negative sentiment scores, including more extreme values reaching below -20. This suggests that Airbnb guests tend to have a more negative experience regarding service, with a greater intensity of complaints. The variation in Airbnb complaints is also more extensive, indicating inconsistency in the quality of service across different properties.

In contrast, the hotel reviews, shown by the teal box, have a much narrower range of sentiment scores, remaining relatively close to zero with fewer extreme negative values. This implies that while service-related complaints exist, they are generally less severe and more consistent in hotels compared to Airbnb properties. Overall, hotels seem to provide a more stable level of service, whereas Airbnb experiences can vary widely, leading to more extreme negative sentiments

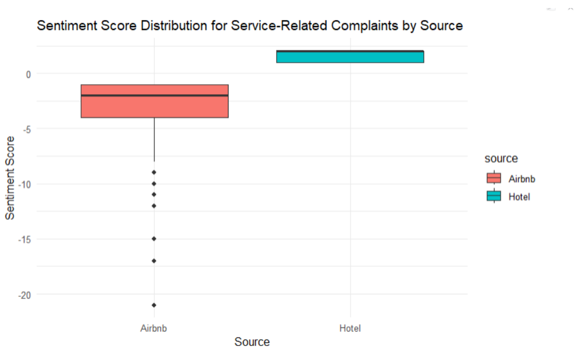


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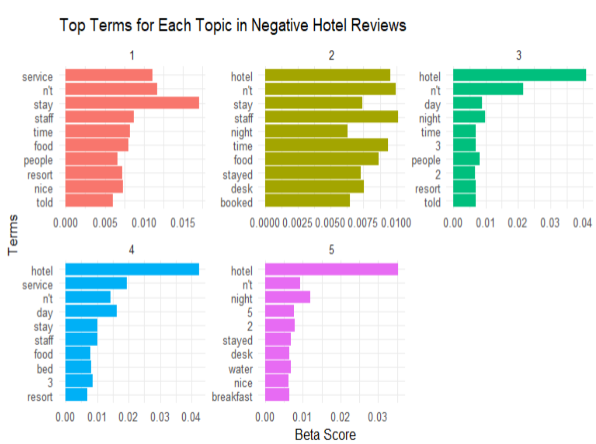
Fig 8 Topic Modeling (LDA)

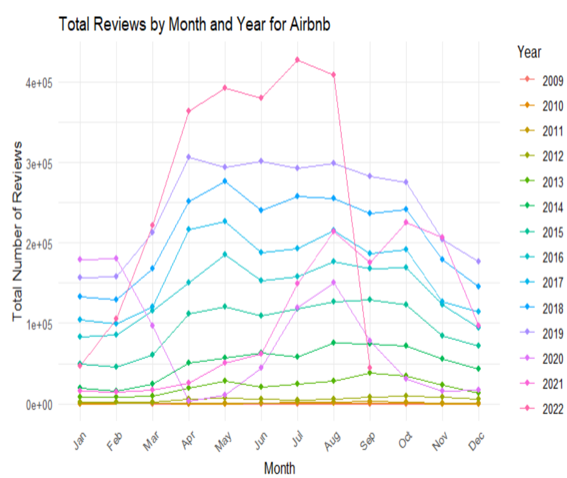
The first graph displays the top terms for each topic derived from negative hotel reviews using topic modeling (LDA). The analysis reveals distinct topics that customers frequently discuss in their negative feedback. Topic 1 emphasizes dissatisfaction with "service" and "staff," pointing to issues with customer support. Topic 2 highlights problems with "booking," "night stay," and overall experience. Topics 3, 4, and 5 also show frequent mentions of "staff," "stay," and "food," indicating recurring issues related to staff behavior, the quality of service, and amenities.



The word cloud presents an overview of the most frequently mentioned terms in negative hotel reviews. Words like "hotel," "service," "staff," "stay," "food," and "night" appear prominently, indicating these are common sources of dissatisfaction for guests. The frequent mentions of "service" and "staff" suggest that the quality of customer service and interactions with hotel staff are significant contributors to negative experiences. Additionally, terms like "time," "stay," and "food" suggest that guests are often unhappy with aspects of their stay, including meals and overall experience

Figure 9: Time-series Analysis

The trend analysis of Airbnb reviews by month and year shows a clear pattern in review activity throughout the year. Review volumes tend to peak during the summer months, particularly from May to August, with the highest number of reviews occurring in July for most years. This trend indicates that Airbnb experiences more activity and higher customer engagement during the summer, which aligns with vacation periods when people are more likely to travel. Conversely, the number of reviews tends to drop significantly from September onwards, reaching the lowest points in the winter months, particularly from November to January. This seasonal trend highlights that summer is the busiest period for Airbnb, likely driven by increased travel during warmer weather.



The trend analysis of total reviews across all years indicates a strong seasonal pattern. The number of reviews steadily increases from January, peaking in August, which suggests heightened activity during the summer months. After August, there is a sharp decline, with review counts dropping steadily through the fall and reaching their lowest levels in December. This trend highlights that Airbnb experiences high demand during the warmer months, likely due to increased travel during the summer vacation periods.

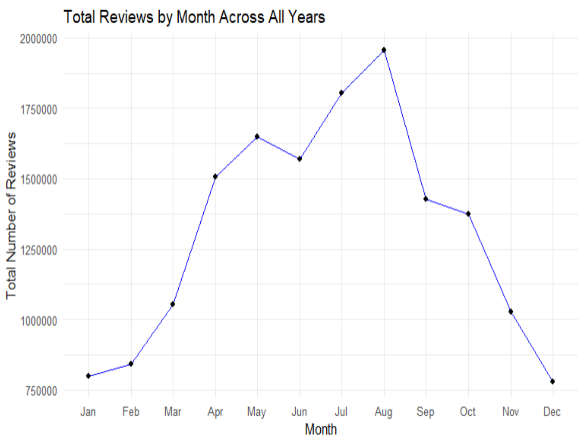
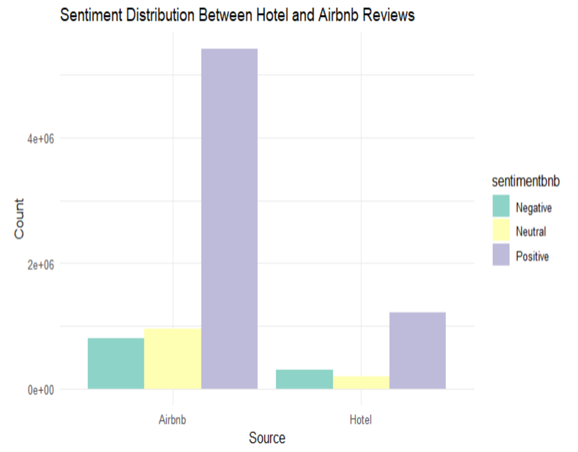
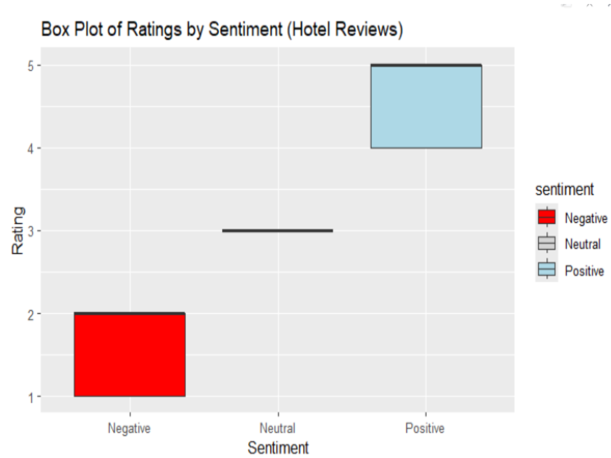


Fig 9 Sentiment Analysis Distribution

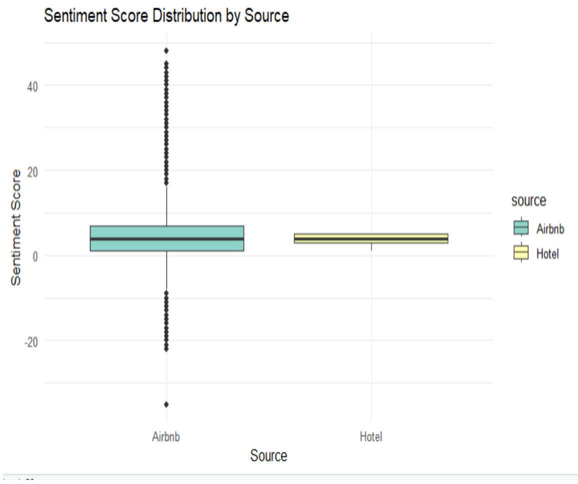
The bar chart below represents the sentiment distribution between hotel and Airbnb reviews. The majority of Airbnb reviews are classified as positive, indicated by the large bar, while the number of negative and neutral reviews is comparatively much lower. For hotel reviews, there is also a significant proportion of positive sentiments, though the overall number of reviews is much smaller compared to Airbnb. Negative and neutral reviews are less frequent in both datasets. These insights suggest that Airbnb receives a higher volume of positive feedback than hotels, which could imply a generally higher satisfaction level among Airbnb guests compared to hotel guests. The difference in the distribution also indicates that customers may perceive Airbnb accommodations more favorably due to their personalized and unique experiences.



The box plot shows the sentiment score distribution for Airbnb and hotel reviews. Airbnb reviews have a wider range of sentiment scores, with a larger box suggesting greater variability in customer feedback. There are also several outliers for Airbnb, both positive and negative, indicating a wider spread of extreme opinions. In contrast, hotel reviews have a smaller interquartile range, showing more consistency in sentiment scores and fewer extreme values.



Overall, Airbnb reviews are more diverse in terms of customer satisfaction, whereas hotel reviews tend to cluster more closely, implying more uniform feedback. This variation may reflect the broader range of experiences that Airbnb offers compared to traditional hotels.



7. Findings

The findings from my analysis reveal how hotels can effectively use customer reviews from both Airbnb and hotel feedback to enhance their services. By analyzing reviews from Airbnb and traditional hotels, I identified key factors that influence customer satisfaction and dissatisfaction, which can serve as a guide for improvements in the hotel industry. Airbnb reviews highlighted positive aspects such as "location," "host friendliness," and "cleanliness." These recurring themes suggest that Airbnb guests value a personalized stay, comfort, and proximity to attractions. Traditional hotels can learn from this by enhancing the uniqueness of their offerings and improving customer service quality. Using TF-IDF analysis, specific attributes like "entertainment" and "friendly hosts" were found to contribute to memorable experiences, which hotels could adopt to create a more engaging guest experience.

Hotel reviews often mentioned dissatisfaction with "service," "staff," and "overall quality," highlighting the need for improved customer interactions and service standards. Airbnb reviews were more focused on issues such as "water" and property conditions, indicating a need to address specific amenities. To enhance guest experiences, hotels should prioritize staff training, improve service quality, and ensure consistent positive interactions, while Airbnb hosts should focus on amenities and property maintenance.

The Sentiment analysis showed a higher proportion of positive feedback for Airbnb compared to hotels, suggesting a generally more favorable perception of Airbnb stays. However, Airbnb reviews displayed more variability in satisfaction, whereas hotels had more consistent feedback, potentially indicating a lack of personalization. Hotels could benefit from diversifying and tailoring their offerings to enhance guest satisfaction.

Topic modeling using LDA highlighted key areas of dissatisfaction in hotel reviews, such as "service," "staff," "stay quality," and "food." Addressing these issues could significantly improve the guest experience.

Additionally, the trend analysis of Airbnb reviews showed clear seasonal patterns, with peaks in review activity during summer months, suggesting an increase in travel during these periods. These seasonal insights can help hotels adjust marketing strategies, promotions, and service offerings to accommodate the increased demand.

The analysis also revealed that terms like "service," "staff," and "food" were frequently mentioned in negative hotel reviews, highlighting these as key areas of dissatisfaction. Improving these aspects could help hotels address recurring complaints effectively.

By leveraging positive aspects from Airbnb and addressing areas of dissatisfaction, hotels can enhance their services, improve guest satisfaction, and remain competitive in an evolving hospitality market. This analysis provides a comprehensive approach to understanding market dynamics and implementing targeted improvements to meet the needs of modern travelers.

8. Recommendations

This project explores how hotels can enhance their services through customer review insights by leveraging both Airbnb and hotel feedback, using text mining techniques to identify critical factors that influence customer satisfaction and dissatisfaction. The findings are intended to help traditional hotels develop effective strategies according to market demand, and to remain competitive in the hospitality industry.

First, hotels should focus on the aspects that make Airbnb experiences highly appreciated by guests, such as "location," "host friendliness," and "cleanliness." Traditional hotels can leverage these insights by enhancing the uniqueness of their offerings, providing personalized services, and ensuring high standards of cleanliness.

Using techniques such as TF-IDF and sentiment analysis, it is evident that attributes like "entertainment," "helpfulness," and "friendly hosts" contribute significantly to positive experiences. Hotels can incorporate these elements to create more engaging and personalized stays, enhancing their appeal to guests. Improving service quality and staff interactions is also crucial.

Negative reviews for hotels often mentioned issues with "service," "staff," and "quality of stay." Hotels must invest in staff training programs that emphasize customer interaction, problem-solving, and empathy to address these areas of dissatisfaction. This will help improve the quality of guest interactions and provide a more positive experience, which is crucial in staying competitive against platforms like Airbnb.

Hotels should also address specific pain points commonly highlighted in negative Airbnb reviews, such as issues with utilities and property conditions. By ensuring the reliability of amenities and addressing property-related issues, hotels can reduce complaints and enhance guest satisfaction. Addressing these practical challenges will help bridge the gap between customer expectations and actual experiences, providing a more consistent quality of stay.

The sentiment analysis findings revealed that while Airbnb reviews had a higher proportion of positive feedback, the variability was also higher compared to hotel reviews. This suggests that while Airbnb provides a more personalized experience, there is inconsistency in service quality. Hotels can use this insight to maintain a balance—providing consistent service quality while introducing unique and personalized offerings to enhance customer satisfaction.

Seasonal trend analysis showed that Airbnb reviews peaked during the summer months of June to August, indicating that this is the peak travel season. Hotels can capitalize on this insight by tailoring marketing campaigns and promotions for the summer period, offering packages and special deals to attract more guests. This seasonal strategy will help hotels accommodate demand surges and effectively compete during high travel seasons.

Finally, topic modeling identified recurring issues in hotel reviews related to "service," "staff," "food," and "overall stay quality." Addressing these areas is key to enhancing guest satisfaction. Hotels should evaluate and improve their food offerings based on guest feedback and provide consistent service that meets or exceeds guest expectations. Enhancing these critical areas will address the root causes of dissatisfaction and contribute to an overall positive experience.

By leveraging the positive insights from Airbnb reviews, addressing negative feedback in their own operations, and making strategic improvements based on customer feedback, hotels can enhance their service offerings and improve guest satisfaction. This project highlights how data-driven insights from customer reviews can be effectively used to guide actionable improvements, enabling hotels to adapt to changing traveler preferences and remain competitive in the hospitality industry.

9. Limitations and Future Research

The limitations of this project is on the nature and scope of the datasets used. The hotel dataset was collected from a specific hotel in Texas, while the Airbnb dataset originated from a single host in Amsterdam. As a result, the findings of this analysis should not be generalized to represent all hotels or Airbnb properties globally or make broader conclusion. The findings provide insights specific to the articular hotel and Airbnb host involved in this study.

For future research, expanding the datasets to include multiple hotels across different regions and diverse Airbnb hosts from various locations would offer a more comprehensive understanding of the factors affecting guest satisfaction and dissatisfaction.

Further, future research could also explore the role of demographic factors, such as age, gender, and travel purpose, in shaping guest experiences and satisfaction. Understanding these nuances could help in tailoring marketing and service strategies to meet the needs of specific customer segments.

Finally, sentiment analysis could be refined by using advanced machine learning models for more accurate classification of guest feedback. By addressing these limitations and expanding the scope of future research, the hospitality industry can gain a deeper understanding of how to adapt its services to meet evolving customer needs effectively

10. Conclusion

In conclusion, this project has demonstrated the value of leveraging customer reviews from both Airbnb and hotels to enhance service quality in the hospitality industry. By employing text mining techniques such as sentiment analysis, TF-IDF, and topic modeling, significant insights into customer satisfaction and dissatisfaction were uncovered. Positive feedback from Airbnb highlights the importance of unique experiences, friendly hosts, and quality accommodations, while negative reviews from both platforms point to areas like service quality and staff interactions that need improvement. By focusing on these key areas and adjusting services based on customer preferences and seasonal trends, traditional hotels can better compete with platforms like Airbnb, ultimately enhancing guest experiences and staying relevant in a changing market.

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