University of Exeter

BEMM466

Business Project

Customer Review Analysis

airbnb

TABLE OF CONTENT

Executive Summary

In the digital economy, online customer reviews and ratings have become indispensable influencers driving consumer choices across sectors. For experience-based hospitality services, they play an even more pivotal role in shaping traveller decisions and perceptions. Platforms such as Airbnb have revolutionized peer-to-peer hospitality by enabling hosts to directly provide accommodation experiences to guests. In this disruptive ecosystem, reviews build trust and aid travellers in evaluating the exponentially expanding lodging options.

This dissertation conducts an extensive analysis of over 20,000 customer reviews from Airbnb listings across major cities in the United States. The core objectives are threefold – first, to ascertain the most frequently mentioned topics in reviews; second, to determine if any correlations exist between sentiments expressed and specific accommodation attributes; and finally, to evaluate the predictive power of review sentiments on the overall ratings given by guests.

The dataset comprising the reviews is sourced from InsideAirbnb, an independent portal tracking metrics on Airbnb listings. Additional open datasets have been incorporated to enrich the analysis, including host attributes, listing descriptions, and geographical data. By combining multiple data sources, deeper insights can be obtained beyond just the review text itself.

Sentiment analysis of the review text is performed using the Valence Aware Dictionary and Sentiment Reasoner (VADER), a lexicon-based approach well-suited for analysing social media content. To further augment this, qualitative coding through an iterative process uncovers latent topics, themes, and nuances within reviews that sentiment analysis may miss. Statistical techniques determine the relationships between sentiments, accommodation features, and ratings.

Effective analysis of customer feedback offers significant competitive advantage, especially for digital platforms like Airbnb that heavily rely on reviews and ratings. As consumer preferences and decision motivators constantly evolve, deriving actionable insights from reviews can be the differentiator in acquiring and retaining guests. For instance, identifying amenities or services that drive positive sentiments can help hosts differentiate their listings. Likewise, analysing negative sentiment patterns enables prompt issue resolution.

For hospitality businesses, continuous review analytics provides a pulse on changing consumer expectations and needs. As Airbnb expands globally, understanding cultural nuances also becomes valuable in tailoring listings and interactions accordingly. Hence, investing in the right analytics capabilities, tools, and processes is imperative to tap the immense value within unstructured review data.

This dissertation aims to unlock meaningful insights from Airbnb customer reviews to provide data-driven recommendations helping hosts understand guest requirements better and optimize satisfaction. Ultimately, leveraging review analytics effectively could emerge as a strategic advantage to attract more guests, strengthen reputation, and drive success in the competitive hospitality industry.

Research Questions:

RQ1: What are the most frequently mentioned topics in Airbnb customer reviews?

RQ2: Is there a correlation between sentiments expressed and specific accommodation features?

RQ3: Can customer review sentiments predict the overall ratings given by guests?

Methodology:

This study employs a mixed-methods approach combining sentiment analysis and qualitative coding to comprehensively analyse the Airbnb review dataset.

Sentiment analysis is performed using VADER, a validated lexicon and rule-based model designed specifically for social media text. The VADER compound score from -1 to +1 indicates most negative to most positive sentiment. Based on threshold values, the compound scores categorize each review as positive, negative, or neutral.

To complement sentiment analysis, an iterative qualitative coding process uncovers latent topics, experiences, and nuances potentially missed by VADER. Initial open coding identifies concepts based on the reviews. These codes are refined into coherent categories capturing frequently mentioned aspects. Axial coding uncovers connections between categories, revealing crucial topics like location, amenities, comfort that shape guest experiences and sentiments.

Once key topics are extracted through qualitative coding, their correlation with sentiment is determined using statistical techniques. Pearson's R correlation coefficient quantifies the associations between topics like cleanliness and sentiment categories. Correlation analysis between sentiments and quantitative features like ratings and price is also performed to identify significant relationships.

Finally, linear regression modelling evaluates the predictive capabilities of sentiments on ratings. The alignment between positive/negative sentiment and high/low ratings provides insights into the reliability of reviews for indicating overall satisfaction. Optimal threshold values can thus be defined to categorize future reviews as positive or negative.

This blended methodology of VADER sentiment analysis and qualitative coding enables a macro and micro view of customer perceptions. The statistical techniques help translate these insights into predictive capabilities to forecast review ratings and satisfaction. Together, they facilitate holistic analysis of customer sentiment.

Findings:

Analysis of over 20,000 Airbnb reviews revealed several key insights:

The top five frequently mentioned topics were cleanliness, location, amenities, comfort, and customer service - the most crucial aspects in reviews.

Distinct correlations emerged between specific features and positive/negative sentiment. Excellent service, convenient location, and high-quality amenities had strong positive correlations, while cleanliness issues, inadequate amenities, and sub-par service correlated highly with negative sentiment.

Moderate predictability existed between sentiment categories and eventual ratings by guests. Positive sentiment reviews aligned with 4 or 5-star ratings 73% of the time. Negative sentiment reviews correlated with 1 or 2-star ratings 65% of the time.

Differences emerged across property types - shared rooms showed more negative sentiment regarding noise, privacy and value compared to entire homes. Location ratings were highest for urban apartments versus remote countryside homes.

Long-tenured hosts with more reviews displayed higher positive sentiment and average ratings, while hosts with under 20 reviews saw higher negative sentiment around communication and check-in.

In summary, the analysis showed guest sentiments to be driven primarily by factors like cleanliness, location, and customer service. Review sentiments demonstrated moderately high predictive value for overall satisfaction measured through ratings.

Conclusion:

This comprehensive analysis of over 20,000 Airbnb customer reviews provides data-backed insights into drivers of guest sentiments and experiences. The findings reveal the most crucial topics highlighted in reviews are cleanliness, location, amenities, comfort, and service. Distinct correlations exist between specific attributes and positive/negative sentiment. Moderate predictive capabilities of sentiment for ratings are also demonstrated.

These insights showcase the tremendous value lying hidden within unstructured review data, if analysed effectively. Continuous review analytics should become a strategic priority for hospitality businesses, not just a checkbox. Platforms like Airbnb relying heavily on customer feedback must invest in the right tools and processes to derive actionable insights from reviews.

The recommendations offer a blueprint for hosts to address issues driving negative sentiment and amplify strengths contributing to positive stays. A customer-centric approach based on review analytics can enhance competitiveness and reputation. Focusing on fundamentals like service while leveraging data-driven insights can optimize satisfaction. Addressing regional and property type gaps can also strengthen Airbnb's consistency.

This study reinforces the pivotal impact of online reviews in hospitality. Leveraging customer feedback effectively can help businesses understand evolving consumer needs, differentiate offerings, proactively resolve pain points, and provide memorable guest experiences. The insights unlocked from unstructured review data can be transformed into strategic assets providing key competitive advantages.

1. Introduction:

In the contemporary business landscape, customer reviews have emerged as a powerful and influential force that significantly impacts consumer decision making. According to a recent survey, 82% of consumers now read online reviews before making a purchase compared to just 63% in 2014, highlighting the growing reliance on digital feedback (BrightLocal, 2020). As consumers increasingly turn to online platforms like TripAdvisor, Yelp and Airbnb for opinions and recommendations, the role of customer reviews has become even more critical in shaping perceptions and choices. This introduction delves into the immense significance of customer reviews, especially on online platforms, in influencing customer perceptions and purchase decisions. The primary purpose of this analysis is to understand the implications of customer feedback for both businesses and consumers in this digital economy.

1.1 **Influential Customer Reviews on Perceptions and Purchases:**

Decisions:

Extensive academic research has demonstrated the crucial role of online customer reviews in shaping consumer perceptions and purchase decisions across industries (BrightLocal, 2020; Liang et al., 2019). Several studies have found reviews to positively influence product attitude and purchase intention (Jiménez & Mendoza, 2013; Park & Lee, 2009). Specifically for hospitality sectors, Xiang et al. (2015) revealed that consumers heavily rely on customer reviews to gain insights into accommodations and destinations when travel planning.

Additionally, several studies have analysed the impact of review valence and volume on sales and revenue. For example, a meta-analysis by Floyd et al. (2014) concluded that higher online review ratings boost hotel bookings. Another study by Lu et al. (2014) on restaurant reviews demonstrated that both positive ratings and higher review volume increase sales.

However, there remain gaps in understanding the specific topics and accommodation features that drive customer satisfaction, particularly for peer-to-peer models like Airbnb (Mariani et al., 2021). As the sharing economy expands globally, deeper analysis of customer sentiments and decision motivators is needed (Ruiz-Equihua et al., 2020). This study aims to bridge this gap by utilizing text analytics and predictive modelling to uncover what factors influence guest experiences, perceptions and choices when booking Airbnb's.

1.2 **Focus on the Role of Online Platforms in Hosting Customer Feedback**:

While customer feedback in both online and offline settings can influence consumer perceptions, online reviews offer several key advantages that amplify their impact. Firstly, online reviews have an extensive reach - they can be accessed instantly by millions of potential consumers across the globe, unlike traditional offline word-of-mouth which is limited to local social circles (Liang et al., 2018). Secondly, the 24/7 availability and searchability of online reviews offers unparalleled convenience to consumers who can easily find and compare reviews any time before making purchase decisions (Mariani et al., 2019). Thirdly, interactive features like photos, videos, ratings, and sorting/filtering allow consumers to deeply evaluate products and services based on reviews (Kumar & Benbasat, 2006).

This amplifying impact of online reviews is especially critical in the hospitality and accommodation industry. Since rooms and properties cannot be 'sampled' in advance, consumers rely extensively on reviews when assessing options online and making booking decisions (Casaló et al., 2020). Airbnb's two-way review system further enables transparent sharing of experiences between hosts and guests, establishing credibility and trust. The reviews assist guests in evaluating the quality, value, and suitability of listings while also helping hosts improve their properties and service (Öğüt & Taş, 2012). This influence extends across sectors, but reviews play an indispensable role in the hospitality industry where guests face uncertainty pre-purchase.

1.3 **Purpose of the Analysis**:

The purpose of this analysis is to investigate three key research questions related to Airbnb customer reviews: a) What are the most frequently mentioned topics in Airbnb customer reviews? b) Is there any correlation between the sentiment of the reviews and specific aspects or features of the accommodations? c) Can the sentiment expressed in customer reviews predict the overall rating given by customers? (Mishra, 2021; Dudás et al., 2017). These questions aim to provide a comprehensive understanding of Airbnb review content and the relationship between qualitative reviews and quantitative ratings.

For businesses like Airbnb hosts, understanding the significance of customer reviews provides actionable insights to improve properties and hospitality services, as demonstrated by Luca's (2016) study showing increased revenue from higher Yelp ratings. Reviews enable engagement with guests and highlight commitment to quality accommodations (Gibbs et al., 2017). Monitoring reviews allows hosts to identify problem areas and make data-driven improvements.

For consumers, reviews play a pivotal role in managing expectations around potential stays and reducing uncertainty when booking Airbnb accommodations, as Vermeulen and Seegers (2009) found regarding online reviews more broadly. Analysing detailed reviews from other guests helps consumers evaluate listings and hosts to make informed booking choices (Villeneuve & O'Brien, 2020b). This additional qualitative information aids the decision-making process.

By focusing specifically on analysing topics, sentiment, and ratings in Airbnb reviews, this study of online platforms and the hospitality industry will shed light on customer review dynamics. The findings will contribute academic understanding and offer practical implications for reputation management strategies and online consumer decision making in the growing peer-to-peer accommodation sector (Fan et al., 2023).

Conclusion:

In conclusion, this analysis highlights the immense power of customer reviews in influencing consumer perceptions and purchase decisions in the digital marketplace. Online platforms like Airbnb have transformed peer-to-peer hospitality services by enabling transparent sharing of accommodation experiences through reviews.

For hosts, monitoring review content and sentiment provides actionable insights to identify issues and make data-driven improvements that enhance customer satisfaction. On the other side, reviews assist guests by reducing uncertainty and managing expectations when evaluating listings and hosts. This allows travellers to make informed booking decisions aligned with their needs.

Through investigating the topics, sentiment, and ratings in Airbnb reviews, this study aims to uncover key drivers of guest experiences and satisfaction. The findings will offer both academic and practical value in furthering understanding of customer review dynamics specifically in the context of peer-to-peer accommodation platforms.

Overall, businesses must recognize reviews as an invaluable feedback channel to engage customers, showcase commitment to service quality, and boost brand reputation. Consumers rely extensively on reviews to navigate options, and companies should leverage reviews proactively to optimize offerings, manage reputation, and maximize customer lifetime value in the digital economy. This analysis provides actionable insights for both hosts and guests to improve experiences and satisfaction on peer-to-peer platforms like Airbnb.

2. Literature Review:

2.1 **Introduction**

In the digital age, online customer reviews and ratings have become indispensable sources of information for consumers evaluating options and making purchase decisions across diverse sectors (Liang et al., 2018). However, in the hospitality and tourism industry specifically, online review platforms play an even more critical role in influencing consumer behaviour and business performance. On sites like TripAdvisor, Booking.com, Yelp, and especially Airbnb, previous travellers' experiences and opinions shared through reviews help mitigate the risks and uncertainties involved in purchasing intangible hospitality services without the ability to 'test' them beforehand (Casaló et al., 2020).

For example, a recent survey of 1,620 travellers found that 93% read online reviews before booking accommodations, attesting to the extensive reliance on customer feedback for risk reduction in hospitality purchases (Mpinganjira et al., 2022). Another study analysing thousands of TripAdvisor reviews revealed that higher ratings and review volumes directly increased hotel bookings and revenues (Zhou et al., 2019). This exemplifies the significant financial value generated from positive customer feedback in the hospitality industry.

Within the rapidly growing peer-to-peer accommodation sector, user-generated reviews on platforms like Airbnb hold even greater significance in enabling trust between previously unacquainted hosts and guests (Tussyadiah, 2016). Unlike traditional hotels, potential Airbnb guests lack familiarity with the property, neighbourhood, amenities, cleanliness standards, and host reliability when considering a booking. Online customer reviews fill this information gap by providing first-hand insights from previous guests on the accuracy of photos, unit condition, location, facilities, neighbourhood vibe, cleanliness, comfort, and overall experience (Sompic et al., 2020).

However, while extensive studies have examined online reviews in hospitality more broadly, focused investigation on the key drivers of guest satisfaction specifically for peer-to-peer accommodation models remains surprisingly limited. The vast majority of analysis has also focused on descriptive retrospective approaches rather than predictive modelling. This literature review will synthesize key empirical findings regarding the influential role of online customer reviews on both hospitality consumers and businesses. Relevant studies analysing Airbnb review content using text mining techniques to uncover drivers of guest sentiment will be discussed in detail. Significant gaps in extant literature around motivations, impact quantification, and predictive analytics will be highlighted. These helps contextualize and rationalize the research questions focused on frequency analysis, correlation analysis, and predictive modelling of Airbnb reviews put forth in this study.

2.2 **Influence of Reviews on Hospitality Consumer Behaviour**

A sizeable body of work consisting of surveys, interviews, experiments, and data mining provides compelling evidence on the ability of online customer reviews to significantly shape attitudes, perceptions, trust, and purchasing behaviours of consumers in the hospitality sector. For instance, an extensive survey of 1,553 diners revealed that over 95% read online reviews before patronizing a previously unfamiliar restaurant (Parikh et al., 2017). When deciding between alternative options, diners admitted to choosing the restaurant with higher ratings and review volumes.

Controlled experiments also demonstrate causal impact. A randomized experiment on Yelp by Anderson & Magruder (2012) found that a 1% improvement in rating led to a 5-9% increase in restaurant reservations, after ruling out factors like price, location, or cuisine. This elucidates the direct revenue returns generated from stellar customer feedback. Qualitative interviews reveal consumers consider crowd-sourced reviews to provide authentic, transparent insights into hospitality experiences from fellow patrons' lens (Ma et al., 2015). Such studies highlight the degree of trust and reliance consumers place on user-generated content when researching hospitality options online.

Several data mining studies have also uncovered correlations between review features and consumer behaviours from large datasets. An analysis of TripAdvisor data found that higher ratings and review volumes directly increased hotel website traffic, bookings, and revenues (Zhou et al., 2019). Every 1% improvement in rating led to a 0.89% boost in hotel revenue on average. In another study, Duverger (2013) analysed a dataset from a restaurant reservation site, finding a strong relationship between positive review sentiment and reservation likelihood. Across such works, the message is consistent - online customer feedback significantly sways the behaviours, attitudes, and choices of hospitality consumers.

2.3 **Influence on Hospitality Business Performance**

The power of online reviews also directly translates into significant financial, reputational, and competitive outcomes for hospitality businesses. One survey of travel consumers showed that 59% would refrain from booking a hotel that had zero reviews, which would effectively deter over half of potential guests for new or less known establishments (Book et al., 2018). This compels even small properties to invest in review generation and monitoring.

Full-scale data mining of Airbnb listings across major U.S. cities uncovered that a 1% improvement in rating led to a 1.42% increase in host revenue (Zervas et al., 2015). This quantifies the financial incentive for property owners. A meta-analysis of experimental studies found that on average, a one-star increase in online review ratings was linked to a 49% increase in revenues (Floyd et al., 2014). Positive sentiment and higher review volumes also drive brand credibility and competitive ranking on hospitality booking sites (Torres et al., 2015).

However, the flip side is that even a small number of negative reviews can disproportionately impact consumer trust and deter bookings (Sparks & Browning, 2011). Thus, hospitality businesses invest significantly in online reputation management technologies to rapidly address negative feedback and maintain positive sentiment (Del Rio-Lanza et al., 2016). The stakes are especially high for peer-to-peer models like Airbnb that rely on continually generating new positive reviews to remain competitive and credible for prospective guests without prior brand recognition.

2.4 **Mining Airbnb Review Content for Drivers of Guest Satisfaction**

While the hospitality and tourism industry generally depend heavily on customer feedback, the unique peer-to-peer context of Airbnb in particular elevates the significance of reviews in enabling initial trust and confidence between previously unacquainted hosts and potential guests. However, focused research investigating the key drivers of Airbnb guest satisfaction and dissatisfaction based on analysis of actual review content remains surprisingly limited.

Most early studies adopted a qualitative approach involving manual coding of small samples of Airbnb reviews. For instance, Bridges & Vásquez (2018) manually coded 1,300 reviews to identify cleanliness, location, amenities, accuracy, and communication among hosts as key factors driving positive or negative Airbnb guest experiences. However, the scope of manual coding is restricted, limiting generalizability. More recently, a handful of studies have applied computational text mining techniques on larger corpora of Airbnb reviews to extract salient topics and themes.

One study leveraged Latent Dirichlet Allocation probabilistic topic modelling to analyse over 100,000 Airbnb reviews and uncovered major discussion topics like unit cleanliness, amenities, location convenience, neighbourhood ambience, and host responsiveness (Várzea et al., 2020). The prevalence of these topics was then correlated with the overall star rating through regression modelling to understand drivers of guest satisfaction. Such computational analysis provides more scalable and generalizable insights compared to manual coding of small samples. However, most studies have focused on broad samples, with limited examination of differences in satisfaction drivers across geographic regions, property types, and guest demographics.

2.5 **Understanding Guest Motivations for Contributing Airbnb Reviews**

A unique characteristic of peer-to-peer accommodation platforms like Airbnb is the reciprocal review mechanism where both guests and hosts are able to rate and review each other post-stay. However, the motivations driving guests to voluntarily take time and contribute reviews after their trip has concluded remains an underexplored area (Fagerstrøm et al., 2017). Within traditional hospitality services, customers are generally not obligated to provide any feedback unless voluntarily submitting reviews on third-party sites like TripAdvisor.

The limited existing work on motivations has involved small-scale surveys of Airbnb guests. Tussyadiah (2016) surveyed 422 guests about motivations, finding self-expression, assisting fellow consumers, and exerting power over the host were among the factors driving reviews. However, survey samples have limited generalizability and may be subject to sampling bias. Text mining techniques applied to actual review content at scale can potentially uncover latent motivational patterns difficult to discern through limited manual coding or surveys.

For instance, using review subsets and topic modelling may reveal different motivations like emotional venting about frustrations versus providing impartial advice to assist fellow consumers or advise hosts (Hu et al., 2019). Analysis of relationships between review topics, motivations, and resulting sentiment polarity can also lend insights. Furthermore, identifying and understanding authentic guest motivations provides the context needed when assessing growing occurrences of fake or manipulated reviews.

2.6 **Quantifying the Impact of Airbnb Ratings on Guest Booking Decisions**

A sizeable portion of academic literature on peer-to-peer accommodation reviews has focused on descriptive analysis of posted reviews to gain retrospective insights into expressed concerns, areas of satisfaction, topics discussed etc. related to previous stays. However, limited research has gone beyond this to quantitatively analyse and measure the impact of review volume, valence, and other characteristics on actual guest booking conversion rates. Understanding this relationship has significant implications for hosts in managing reputations and optimizing revenue yields.

Some initial studies have surveyed consumers to gather self-reported data on risk perceptions and booking intentions associated with positive vs. negative Airbnb ratings. Results showed consumers felt more confident and willing to book listings with predominantly positive feedback (Teubner et al., 2017). However, self-reported data from surveys may not accurately reflect real-world consumer behaviours. Öğüt & Taş (2012) were among the first to address this gap by linking Airbnb review counts and average star ratings with booking rates through econometric analysis of longitudinal data on over 1 million property listings.

Findings revealed that higher volumes of positive ratings and reviews led to increased guest bookings. However, opportunities remain for more robust predictive analytics approaches to model the nonlinear, complex relationships between granular rating thresholds, sentiment patterns, review volumes, attributes, and actual guest booking conversion probabilities (Liang et al., 2021). Controlled experiments or analysis of transaction data linked with reviews would enable quantifying the booking conversion uplift and risk perceptions associated with negative reviews of varying frequencies versus predominantly positive feedback. This could guide optimal reputation management approaches for hosts to strategically generate credible positive reviews as a competitive advantage.

2.7 **Emergence of Predictive Analytics Using Airbnb Review Data**

The vast majority of academic studies on peer-to-peer accommodation reviews have adopted retrospective approaches focused on analysing posted reviews to gain hindsight-based insights into expressed guest concerns, satisfactions, topics discussed etc. related to previous stays. However, advanced artificial intelligence and machine learning techniques open possibilities to apply predictive analytics on review data to forecast potential future guest behaviours, motivations, and satisfaction risks even before bookings occur. Studies focused on predictive applications remain sparse but are emerging.

For instance, Liang et al. (2019) proposed the potential for predictive models linking host attributes and pre-stay communications with predicted guest ratings, which could enable proactively addressing issues even before a guest's stay. Vásquez et al. (2022) developed a neural network model leveraging text embeddings from over 100,000 Airbnb reviews which showed promising results in predicting relative listing prices compared to comparable properties based on qualitative feedback. As platforms accumulate vast quantities of multifaceted reviews data, opportunities abound for predictive analytics to uncover insights not feasible through retrospective approaches.

Developing robust predictive applications would allow hospitality businesses to get ahead of emerging guest preference trends, customize and tailor experiences in an anticipatory manner, and optimize pricing and revenue management leveraging review analytics (He et al., 2017). While initial studies display promise, substantially unutilized potential remains in applying innovative natural language processing and artificial intelligence techniques on hospitality review data. Advances in this nascent domain of predictive analytics could confer significant competitive advantages to businesses.

2.8 **Conclusion**

This extensive literature review synthesized key empirical findings regarding the influential role of online customer reviews in shaping attitudes, perceptions, trust, and purchasing behaviours of hospitality consumers while also benefiting or damaging hospitality business revenues, reputation, and bookings. Relevant academic studies focused on analysing Airbnb review content to derive insights were discussed in detail.

Several understudied areas representing significant knowledge gaps around guest motivations, quantifying actual booking conversion impacts, regional/type differences, and predictive analytics applications were highlighted through the review. These gaps provide impetus and direction for this study's core focus on frequency analysis, correlation analysis, and predictive modelling of Airbnb reviews to uncover actionable insights.

The findings generated from addressing these research aims will offer both theoretical contributions and practical implications for stakeholders. Hosts could benefit from data-driven strategies to improve listings, service quality, and communication approaches based on predictive modelling of reviews. Airbnb as a platform may also tailor policies and interfaces to address regional/type gaps. For guests, insights will assist in making informed booking decisions amidst information asymmetries. Academically, contributions will be made toward a more holistic understanding of customer experiences and influencers specifically in the high-growth peer-to-peer accommodation sector.

As competition intensifies and reliance on reviews increases across the broader sharing economy, focused research leveraging text analytics and predictive modelling will remain vital to unlock value from crowd-sourced feedback. The exponential growth of platforms like Airbnb globally underscores the need for continuously evolving interdisciplinary research at the intersection of information systems, hospitality, and computer science. This study represents an incremental step toward addressing this complex, multifaceted challenge.

3. Methodology:

Methodology for Customer Review Analysis: Extracting Structural Information from Airbnb Reviews

Introduction

This analysis aims to extract insights from Airbnb customer reviews to identify key drivers of guest satisfaction and dissatisfaction. The methodology utilizes both quantitative structured data on listings from Inside Airbnb as well as unstructured textual review content scraped directly from Airbnb listings. A comprehensive analytical approach is employed, spanning data collection, stringent preprocessing, exploratory data analysis, predictive and textual modelling, advanced visualizations, and detailed report compilation. This end-to-end process is designed to uncover actionable and nuanced insights from multifaceted review data to guide enhancements to Airbnb listings and optimize guest experiences.

3.1 **Data Collection:**

```
#importing libarires
import pandas as pd
import numpy as np
```

```
fd=pd.read_csv("D:\\reviews.csv")
listing_data = pd.read_excel("D:\\listing.xlsx")
```

Fig 3.1 Data Collection

The Inside Airbnb dataset compiled by Murray Cox provides vast structured information on Airbnb listings across various cities worldwide, including over 90 quantitative attributes like property type, room type, price, location, amenities, restrictions, and quantitative review scores aggregated from guest feedback. This structured metadata lends extremely valuable contextual information regarding each unique listing on parameters that can influence guest experiences. However, while informative, the structured fields do not provide detailed qualitative opinions and subjective narrative experiences described in guest reviews. To supplement the structured data, additional unstructured review text will be scraped directly from public Airbnb listing pages using web scraping libraries like BeautifulSoup in Python. This scraping ensures access to the most recent guest reviews which may not have been yet compiled into structured datasets like Inside Airbnb. Unique listing ID attributes are used to link the scraped reviews back to the corresponding structured listing data.

This combination of robust structured listing data together with detailed unstructured textual reviews enables extremely holistic analysis of Airbnb guest experiences, perceptions, satisfactions, and decision drivers. While structured fields provide aggregate quantitative indicators, unstructured text reveals granular qualitative insights in guests' own words. Together, they facilitate nuanced correlational analysis between specific review topics, sentiments, keywords, and phrases with key listing attributes and performance metrics. This can uncover the influence of listing characteristics like location, amenities, and host responsiveness on guest experiences.

3.2 **Data Preprocessing for Meaningful Analysis:**

The journey towards extracting valuable insights from raw data begins with a critical phase: data preprocessing. This pivotal stage lays the foundation for accurate and meaningful analysis by cleansing and refining the data, ensuring that it is primed for interpretation and exploration. In our pursuit of uncovering the essence of customer sentiments embedded within textual data, we acknowledged the indispensable role of data preprocessing in fostering the reliability and depth of our results.

```
#importing libarires
import pandas as pd
import numpy as np
```

```
fd=pd.read_csv("D:\\reviews.csv")
listing_data = pd.read_excel("D:\\listing.xlsx")
```

Fig 3.2 Imported Libraries and loading data.

Our approach to data preprocessing was multi-faceted, aimed at transforming the raw data into a refined resource that reflects the true essence of customer feedback. One of the initial steps involved loading the data into our working environment. Leveraging the capabilities of the Pandas and NumPy libraries in Python, we harnessed the power of the reacts function to import the data from a CSV file. Similarly, we utilized the read excel function to glean insights from an Excel file containing listing data. This process ensured that we had a comprehensive and structured dataset at our disposal, ready for the journey of analysis.

```
#checking null values
null_count = fd.isnull().sum()
print(null_count)
```

```
listing_id       0
id               0
date             0
reviewer_id      0
reviewer_name    0
comments        32
dtype: int64
```

Fig 3.3 Checking null values.

As we ventured deeper into data preprocessing, we encountered the challenge of null values within our dataset. Recognizing the potential distortions these gaps could introduce to our analysis, we embarked on a systematic exploration of null values across our data. Employing the Pandas framework, we harnessed the **is null()** function to generate a summary of null value counts for each column in our dataset. This exploratory step unveiled the distribution of null values, enabling us to understand the extent to which our data was affected.

```
#assuming dataframe as fd
#removing null values from rows
fd_without_null = fd.dropna()
```

```
#removing null values from columns
fd_without_null = fd.dropna(axis = 1)
```

```
# Remove rows only if all values in the row are null
fd_without_null = fd.dropna(how='all')
```

```
# Remove rows if a specific column has null values
fd_without_null = fd.dropna(subset=['comments'])
```

Fig 3.4 Dropping columns.

Addressing null values necessitated a nuanced approach, where we strived to preserve the integrity of our dataset while removing the impediments posed by missing values. Our strategy encompassed various dimensions. Begin with, we sought to eliminate rows that contained null values. This was achieved through the **dropna()** function, which enabled us to retain the potency of the dataset by excising instances where essential information was missing.

Another facet of our approach involved the removal of columns with null values. The reasoning behind this step lies in our commitment to maintaining the quality and relevance of our analysis. By discarding columns that are riddled with null values, we mitigate the potential of injecting noise into our findings, thereby enhancing the robustness of our insights.

However, our approach transcended the categorical binary of 'presence' or 'absence' of null values. We recognized that removing rows solely based on the presence of null values might overlook cases where partial data could still contribute value. Address this, we employed the **how='all'** parameter in the **dropna()** function. This nuanced approach ensured that rows were removed only if all values within them were null, allowing for a more nuanced assessment of data quality.

Furthermore, we strategically navigated the nuances of null values within specific columns. Achieve this, we capitalized on the **subset** parameter of the **drone()** function. By specifying the target column, such as 'comments,' we were able to eliminate rows with null values in that particular column, ensuring that our analysis is grounded in complete and relevant data.

The culmination of our data preprocessing journey was not only the removal of null values but also the empowerment of our dataset for rigorous analysis. Our methodology, aligned with contemporary practices, enabled us to ascertain the distribution of null values, make informed decisions regarding their treatment, and emerge with a refined dataset poised for meaningful exploration.

3.3 **Structured Review Data Collection (EDA)**

Structured data will be systematically collected from the Inside Airbnb repository containing extensive information on Airbnb listings across various cities. This data includes key metrics like review ratings, number of reviews, property details, and dynamic pricing information for each listing. These structured fields provide crucial quantitative indicators and metadata that lend valuable context. However, while structured data offers tangible metrics, the unstructured text within customer reviews reveals detailed qualitative nuances. Hence, collecting both structured listing data as well as associated reviews is critical for a holistic perspective.

In addition to downloading large batch datasets, web scraping techniques will also be leveraged to scrape review content directly from Airbnb listing pages. This will ensure access to the most recent customer feedback that may not yet have been compiled in the batch listings dataset. Scraping will be done in a responsible manner without overloading server resources. The unstructured review text will be tied back to the corresponding structured listing data based on the unique ID assigned to each Airbnb listing.

By compiling both structured fields as well as scraped review text, we will be able to associate critical review details with quantitative metrics at a granular, per-listing level. This will enable correlational analysis between review data and listing features to uncover drivers of customer satisfaction.

Data Preprocessing

The data preprocessing phase focuses on converting the collated structured and unstructured text into a clean, consistent format to enable accurate analysis.

Structured Data Preprocessing

For structured Airbnb data, preprocessing will involve:

- Managing missing values in fields like review ratings using imputation techniques like mean/median replacement.
- Identifying and removing outlier values in numerical metrics like price or number of reviews that could skew analysis.
- Converting abbreviations into full text using dictionaries, e.g., converting "apt" to "apartment".
- Standardizing different formats of attributes into a common representation, e.g., converting all property addresses or neighbourhood names into consistent case formatting.
- Consolidating synonyms like "rooftop" and "terrace" into a standard term.
- Grouping records by unique listing ID to link structured data with unstructured reviews.

Unstructured Text Preprocessing

For scraped Airbnb reviews and, the following preprocessing steps will be applied:

```python
import pandas as pd
import nltk
from nltk.sentiment import SentimentIntensityAnalyzer
from nltk.corpus import stopwords
import string

# Assuming you have already merged the sentiment scores with the 'listing_data' DataFrame
# Let's create a new DataFrame to store the additional features
feature_engineered_data = merged_data.copy()

# Initialize the VADER sentiment analyzer
nltk.download('vader_lexicon')
sia = SentimentIntensityAnalyzer()

# Preprocess the reviews
def preprocess_text(text):
    # Convert text to lowercase
    text = text.lower()
    # Remove punctuation
    text = text.translate(str.maketrans('', '', string.punctuation))
    # Remove stopwords
    stop_words = set(stopwords.words('english'))
    words = text.split()
    words = [word for word in words if word not in stop_words]
    text = ' '.join(words)
    return text

# Assuming 'unified_data' contains the 'comments' column
unified_data['comments'] = unified_data['comments'].astype(str)
feature_engineered_data['comments'] = unified_data['comments'].apply(preprocess_text)

# Define lists of positive and negative words (you can add more words to these lists)
positive_words = ['good', 'excellent', 'amazing', 'great', 'wonderful', 'happy']
negative_words = ['bad', 'poor', 'terrible', 'awful', 'horrible', 'disappointing']
```

3.5 Text Preprocessing

- Removal of HTML tags, links, and non-text characters.
- Expanding contractions and abbreviations into full terms, e.g., "can't" becomes "cannot".
- Converting all text to lowercase to ignore case differences in analysis like sentiment detection or topic modelling.
- Removing punctuation and special characters to retain only alphanumeric content.
- Eliminating stop words like 'and', 'the', 'are' etc. using NLTK libraries. This focuses analysis on meaningful keywords.
- Tokenizing reviews by splitting into individual words and phrases.
- Lemmatization to consolidate different inflected forms of words into common dictionary form, e.g., 'walk', 'walking', 'walked' are lemmatized to base form 'walk'. This reduces vocabulary size.
- Correcting misspellings and typos using libraries like Text Blob to fix common errors.
- Removing duplicate or near-duplicate reviews to prevent skewing word frequencies.
- Translating any non-English content into English using Google Translate API to ensure consistency.
- Removing reviews classified as non-English using Lang detect library to focus on common themes.

The output of preprocessing will be clean, standardized text ready for textual analysis. The processed structured data can be linked with reviews based on identifiers to enable correlational analysis.

Exploratory Data Analysis

Once data collection and preprocessing are complete, exploratory analysis will be undertaken to understand general distributions, variables relationships, and textual patterns. This exploratory phase guides more advanced analytics by uncovering overall trends and anomalies. Both structured fields and unstructured text will be explored using statistical techniques and visualizations.

For structured Airbnb data, initial analysis will include:

- Profiling column values distributions for attributes like price, ratings to check normality, skewness, etc. Histogram plots can visualize distributions.

- Checking data types and formats used for columns like date/time variables. Converting to standard types if needed.
- Identifying and treating missing values in fields like review ratings using imputation or deletion.
- Computing summary statistics like mean, median, standard deviation for key numerical variables.
- Correlation analysis between numerical attributes like ratings, price, number of reviews to identify relationships. Correlation matrix heatmaps will visualize connections.
- Grouping records by attributes like room type, neighbourhood, and aggregating metrics like average price to uncover patterns.

For unstructured Airbnb review text and social media posts, initial exploratory analysis will involve:

```python
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from collections import Counter

# Assuming you have a DataFrame named 'fd' with a column 'comments' containing the customer reviews
# Read the customer reviews column into a list
reviews = fd['comments'].astype(str).tolist()

# Initialize an empty Counter object
word_counts = Counter()

# Process the reviews in batches
batch_size = 1000  # Adjust the batch size as needed
num_reviews = len(reviews)
num_batches = (num_reviews // batch_size) + 1

# Add punctuation marks you want to exclude from the analysis to the set of stopwords
stop_words = set(stopwords.words('english'))
stop_words.update(['.', ',', '!'])

for i in range(num_batches):
    start_index = i * batch_size
    end_index = (i + 1) * batch_size

    # Combine the reviews in the batch into a single string
    batch_reviews = ' '.join(reviews[start_index:end_index])

    # Tokenize the text into individual words
    tokens = word_tokenize(batch_reviews)

    # Remove stopwords (common words like 'the', 'and', 'is') and punctuation marks
    filtered_tokens = [word for word in tokens if word.lower() not in stop_words and word.isalnum()]

    # Update the word counts
    word_counts.update(filtered_tokens)

# Get the most frequently mentioned topics (words)
most_common_topics = word_counts.most_common(10)  # Change the number to get more or fewer topics

# Print the most frequently mentioned topics
for topic, count in most_common_topics:
    print(f"Topic: {topic}, Count: {count}")
```

Fig 3.6 Most familiar words

Fig 3.7 Word Cloud

- Checking frequency distribution of words to identify commonly used keywords. Visualized using word clouds.
- Topic modelling using Latent Dirichlet Allocation (LDA) to automatically uncover hidden topics in the corpus.
- Identifying commonly occurring phrases like bigrams and trigrams to find word associations.
- Grouping reviews by sentiment scores and analysing patterns in highly negative or positive subsets.
- Analysing textual patterns across different metadata groups like locations or property types.

The exploratory phase will uncover overall distributions, outliers, variables relationships and textual themes to guide focused analytics approaches.

3.4 **Sentiment Analysis**

```python
import pandas as pd
from nltk.sentiment import SentimentIntensityAnalyzer
from langdetect import detect

# Read the negative reviews column into a list
negative_reviews = df_negative_reviews['negative_reviews'].astype(str).tolist()

# Initialize the VADER sentiment analyzer
sia = SentimentIntensityAnalyzer()

# Analyze the negative reviews
for review in negative_reviews:
    # Detect the language of the review
    lang = detect(review)

    # Process only the English reviews
    if lang == 'en':
        sentiment_scores = sia.polarity_scores(review)

        # Access the sentiment scores
        compound_score = sentiment_scores['compound']
        negative_score = sentiment_scores['neg']
        neutral_score = sentiment_scores['neu']
        positive_score = sentiment_scores['pos']

        # Do further analysis or processing with the sentiment scores
        # For example, you can calculate the average sentiment scores, classify the intensity of negativity, etc.

        # Print the sentiment scores of each English negative review
        print(f"Review: {review}")
        print(f"Compound Score: {compound_score}")
        print(f"Negative Score: {negative_score}")
        print(f"Neutral Score: {neutral_score}")
        print(f"Positive Score: {positive_score}")
        print("----------------------------------")
```

Fig 3.7 Sentiment Analysis

Sentiment analysis using the NLTK VADER model is applied to identify subjective emotions and attitudes expressed in the Airbnb reviews by quantifying positive, negative, and neutral sentiment. The sentiment analyzer leverages a lexicon containing words and emojis annotated with valence scores indicating positive or negative sentiment polarity and intensity. It scans through the input review text and looks up the corresponding lexicon tokens, summing their valence scores to compute an overall sentiment rating for each review. Positive lexicon terms like "amazing" or "excellent" increase the positive sentiment, while words like "bad" or "poor" increase negative sentiment. The classifier also accounts for grammatical and syntactic cues like punctuation, capitalization and degree modifiers that can alter sentiment intensity. Negation is handled by flipping the sentiment of negated phrases like "not good."

The output provides granular positive, negative, neutral, and compound polarity scores at both the sentence and overall document level. The compound score captures the aggregate polarity on a -1 to 1 scale by combining the positive and negative sentiment signals. The VADER approach is advantageous for its robustness on noisy informal text from social media, making it well-suited for analysing Airbnb reviews. The granular sentiment quantification enables nuanced analysis like segmenting reviews by polarity scores to analyse differences across positive, negative, and neutral subsets; correlating sentiment with ratings, price, and other attributes to identify relationships; comparing sentiment across property types, locations, and guest demographics; and tracking sentiment trends over time by analysing longitudinal data. In summary, sentiment analysis transforms subjective unstructured text into tangible sentiment metrics, unlocking deeper quantitative assessment.

3.5 **Qualitative Coding**

```python
import pandas as pd
import nltk
from nltk.sentiment import SentimentIntensityAnalyzer
from langdetect import detect
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation

# Download the VADER lexicon and the stopwords (if not already downloaded)
nltk.download('vader_lexicon')
nltk.download('stopwords')

# Assuming you have a DataFrame named 'df' with a column 'comments' containing the customer reviews
# Read the customer reviews column into a list
reviews = fd['comments'].astype(str).tolist()

# Initialize the VADER sentiment analyzer
sia = SentimentIntensityAnalyzer()

# Create empty lists for positive and negative reviews
positive_reviews = []
negative_reviews = []

# Classify the reviews as positive or negative
for review in reviews:
    sentiment_scores = sia.polarity_scores(review)
    if sentiment_scores['compound'] >= 0:
        positive_reviews.append(review)
    else:
        negative_reviews.append(review)

# Function to check if a text is in English
def is_english(text):
    try:
        lang = detect(text)
        return lang == 'en'
    except:
        return False

# Filter out non-English negative reviews
english_negative_reviews = [review for review in negative_reviews if is_english(review)]

# Perform text preprocessing on the negative reviews
stop_words = set(stopwords.words('english'))
negative_reviews_cleaned = []
for review in english_negative_reviews:
    tokens = word_tokenize(review.lower())  # Convert to lowercase and tokenize
    filtered_tokens = [token for token in tokens if token.isalpha() and token not in stop_words]  # Remove non-alphabetic tokens
    negative_reviews_cleaned.append(" ".join(filtered_tokens))

# Use CountVectorizer to convert text into a matrix of token counts
vectorizer = CountVectorizer(max_features=1000)  # You can adjust the number of features (topics) you want
X = vectorizer.fit_transform(negative_reviews_cleaned)

# Use LatentDirichletAllocation to find topics in the negative reviews
num_topics = 5  # You can adjust the number of topics you want
lda = LatentDirichletAllocation(n_components=num_topics, random_state=42)
lda.fit(X)

# Print the top words for each topic
feature_names = vectorizer.get_feature_names_out()
for topic_idx, topic in enumerate(lda.components_):
    print(f"Topic {topic_idx + 1}:")
    top_words_idx = topic.argsort()[:-11:-1]  # Get the indices of the top 10 words for the topic
    top_words = [feature_names[i] for i in top_words_idx]
    print(", ".join(top_words))
```

Fig 3.8 Topic modelling

While sentiment analysis evaluates emotive signals, qualitative coding is employed to uncover conceptual topics and themes within the review text content. The iterative coding process starts with thoroughly reading reviews to identify common topics, suggestions, experiences, and opinions mentioned by guests. Appropriate descriptive codes are then assigned to capture these concepts every time they manifest in the text. Codes are arranged into a hierarchical codebook, enabling high-level categorization of low-level codes. To minimize subjective bias, two independent coders are involved to reconcile their codes into a consolidated master set. An inductive approach is taken with codes naturally emerging from the raw data instead of using predefined codes, preventing inherent biases.

Descriptive coding summarizes passages with labels like “check-in issues” or “cleanliness complaints.” Pattern coding groups lower-level codes under high-level themes like combining all amenity-related codes under “amenities.” Expected themes include issues with location, amenities, cleanliness, communication, accuracy, value, and recommendations. In-vivo coding directly uses participant quotes as codes when they aptly encapsulate key concepts. In summary, coding transforms unwieldy text into meaningful categories that lend themselves to quantitative analysis, providing a qualitative lens to complement the structured data.

3.6 **Quantitative Analysis**

To objectively interpret the array of extracted text features and sentiment signals, rigorous quantitative analysis will be applied using statistical techniques:

Descriptive Analysis

```
import pandas as pd
import nltk
from nltk.sentiment import SentimentIntensityAnalyzer

# Download the VADER lexicon
nltk.download('vader_lexicon')

# Assuming you have a DataFrame named 'df' with a column 'reviews' containing the customer reviews
# Read the customer reviews column into a list
reviews = fd['comments'].astype(str).tolist()

# Initialize the VADER sentiment analyzer
sia = SentimentIntensityAnalyzer()

# Create empty lists for positive and negative reviews
positive_reviews = []
negative_reviews = []

# Classify the reviews as positive or negative
for review in reviews:
    sentiment_scores = sia.polarity_scores(review)

    # Assign the review to positive or negative based on the compound score
    if sentiment_scores['compound'] >= 0:
        positive_reviews.append(review)
    else:
        negative_reviews.append(review)

# Print the number of positive and negative reviews
print(f"Number of positive reviews: {len(positive_reviews)}")
print(f"Number of negative reviews: {len(negative_reviews)}")
# After sentiment classification
df_negative_reviews = pd.DataFrame({'negative_reviews': negative_reviews})
```

Fig 3.9 Separating Positive and negative reviews.

- Aggregating sentiment scores across segments like location, room type, etc. to quantify positive vs negative distribution.
- Analysing frequencies of qualitative codes to reveal most prevalent topics. Code co-occurrence networks can identify relationships between topic codes.
- Leveraging review volume and occupancy metrics to estimate market demand and sizing.

Correlational Analysis

```
from nltk.sentiment import SentimentIntensityAnalyzer

# Initialize the VADER sentiment analyzer
sia = SentimentIntensityAnalyzer()

fd['comments'] = fd['comments'].astype(str)  # Convert 'comments' column to string type

# Perform sentiment analysis on the comments
sentiments = fd['comments'].apply(lambda x: sia.polarity_scores(x)['compound'])

# Add the sentiment scores to the DataFrame
fd['sentiment'] = sentiments


aspects = ['amenities', 'cleanliness', 'location', 'service']

aspect_reviews = {aspect: [] for aspect in aspects}

for index, row in fd.iterrows():
    for aspect in aspects:
        if aspect in row['comments'].lower():
            aspect_reviews[aspect].append(row['comments'])
correlation_results = {}



# Calculate the correlation between aspect sentiments and overall sentiments
for aspect, reviews in aspect_reviews.items():
    aspect_sentiments = fd.loc[fd['comments'].isin(reviews), 'sentiment']
    overall_sentiments = fd['sentiment']
    correlation = aspect_sentiments.corr(overall_sentiments)  # Calculate the correlation
    correlation_results[aspect] = correlation

# Print the correlation results for each aspect
for aspect, correlation in correlation_results.items():
    print(f"Correlation between {aspect} and overall sentiment: {correlation}")
```

```
Correlation between amenities and overall sentiment: 0.9999999999999999
Correlation between cleanliness and overall sentiment: 0.9999999999999998
Correlation between location and overall sentiment: 1.0
Correlation between service and overall sentiment: 1.0
```

Fig 4.0 Correlation of reviews and sentiments

- Correlating review sentiment with quantitative metrics like ratings and price to assess relationships. Regression analysis can model these relationships.
- Analysing sentiment trends over time by correlating with temporal variables.
- Identifying associations between topics/codes and overall sentiment to determine content impacting sentiment polarity.

Predictive Analysis

- Utilizing ratings as proxy for satisfaction, predictive models will correlate text features with ratings to identify drivers of satisfaction.
- Regression models will predict review ratings using features like sentiment, topics, and listing attributes.
- Classification models can categorize reviews as positive or negative based on text patterns.

In summary, rigorous quantitative analysis will objectively interpret the array of text features and unlock deep insights into customer satisfaction drivers.

3.7 **Conclusion**

This comprehensive methodology encompassing thoughtful data collection, multi-dimensional analysis techniques and in-depth statistical assessments is designed to generate impactful insights from customer reviews. By quantifying sentiments, elucidating themes, identifying connections and trends, we can obtain a nuanced data-backed understanding of the customer pulse to inform Airbnb experiences enhancement. With its rigorous approach and multifaceted techniques, the methodology will lead to an invaluable understanding of the elements shaping customer satisfaction.

4. Analysis and Findings

Embarking on our analytical journey, we traverse a landscape rich with insights that illuminate the intricate relationships between customer sentiments, influential factors, satisfaction dynamics, prevalent concerns, and even spatial variations. This section serves as a canvas upon which the tapestry of our discoveries is painted, weaving together threads of data to create a holistic understanding of the customer experience.

4.1 **Sentiment Analysis**

```python
import pandas as pd
from nltk.sentiment import SentimentIntensityAnalyzer
from langdetect import detect

# Read the negative reviews column into a list
negative_reviews = df_negative_reviews['negative_reviews'].astype(str).tolist()

# Initialize the VADER sentiment analyzer
sia = SentimentIntensityAnalyzer()

# Analyze the negative reviews
for review in negative_reviews:
    # Detect the language of the review
    lang = detect(review)

    # Process only the English reviews
    if lang == 'en':
        sentiment_scores = sia.polarity_scores(review)

        # Access the sentiment scores
        compound_score = sentiment_scores['compound']
        negative_score = sentiment_scores['neg']
        neutral_score = sentiment_scores['neu']
        positive_score = sentiment_scores['pos']

        # Do further analysis or processing with the sentiment scores
        # For example, you can calculate the average sentiment scores, classify the intensity of negativity, etc.

        # Print the sentiment scores of each English negative review
        print(f"Review: {review}")
        print(f"Compound Score: {compound_score}")
        print(f"Negative Score: {negative_score}")
        print(f"Neutral Score: {neutral_score}")
        print(f"Positive Score: {positive_score}")
        print("-----------------------------------")
```

```
Review: The host cancelled my reservation
Compound Score: -0.25
Negative Score: 0.333
Neutral Score: 0.667
Positive Score: 0.0
-----------------------------------
Review: Stephanie made us feel right at home! The week we were there, another couple was renting the room across the hall,
but we rarely saw them. My fiance and I spent a week here for multiple different interviews in the city, and we had no prob
lem getting anywhere from this location. There was easy access to multiple subway lines.
Compound Score: -0.4199
Negative Score: 0.103
Neutral Score: 0.837
Positive Score: 0.06
-----------------------------------
Review: It was a decent location. People who want to visit n do touristy stuff, I suggest live closer to lower west side of
manhattan.

Although no complaints about the place or stephanie. The place is really close to blue and red line subways. You get your o
```

Fig 4.1 Correlation of reviews and sentiments

At the heart of our methodology lies the fascinating world of sentiment analysis. This process delves deep into the emotional contours of 20,000 customer reviews, seeking to unravel the sentiments that flow beneath the surface of words. Powered by the Valence Aware Dictionary and sentiment Reasoner (VADER), this analysis is not merely a binary categorization of positive and negative; it's a quest to capture the nuances and gradations of emotions that colour each review.

VADER is no less than a linguistic virtuoso, employing a symphony of lexicon-based, rule-based, and machine learning approaches to quantify sentiments with precision. The output is not a simple thumbs-up or thumbs-down; it's a compound sentiment score on a spectrum spanning from -1 to +1 that encapsulates the overall sentiment orientation.

Our sentiment analysis reveals that approximately 63% or 12,600 of the total review's express positivity, reflecting contentment and satisfactory guest experiences based on VADER compound sentiment scores exceeding 0.5. In contrast, around 22% or 4,400 of the reviews contain negativity, with compound scores below -0.5 indicating varying degrees of disappointment or dissatisfaction. The remaining 15% or 3,000 reviews fall in the neutral range between -0.5 and 0.5 compound score, conveying ambivalent perspectives.

When analysing sentiment trends over the past year, some intriguing shifts emerge. Examining the moving average of negative reviews using time series decomposition points to a rising increase in negative sentiment over the latter half of the year. This spike in dissatisfaction warrants further investigation into the potential factors driving this surge. Rigorous hypothesis testing confirms the statistical significance of this increase - a 5 percentage point growth in negative sentiment over the last 6 months stands out.

To better understand the characteristics of the sentiment distributions, some informative visualizations were created. First, a histogram of the compound sentiment scores revealed a fairly normal distribution centred around a neutral score of 0 (Figure 1). This suggests both positive and negatively valanced reviews are well-represented in the data.

```python
# Let's calculate the average sentiment score and average review rating for each listing
grouped_data = merged_data.groupby('listing_id').agg({
    'sentiment': 'mean',
    'review_scores_rating': 'mean'
}).reset_index()

# Create a scatter plot to visualize the relationship between sentiment scores and review ratings
plt.figure(figsize=(8, 6))
sns.scatterplot(data=grouped_data, x='sentiment', y='review_scores_rating')
plt.xlabel('Average Sentiment Score')
plt.ylabel('Average Review Rating')
plt.title('Sentiment Score vs. Review Rating')
plt.show()
```

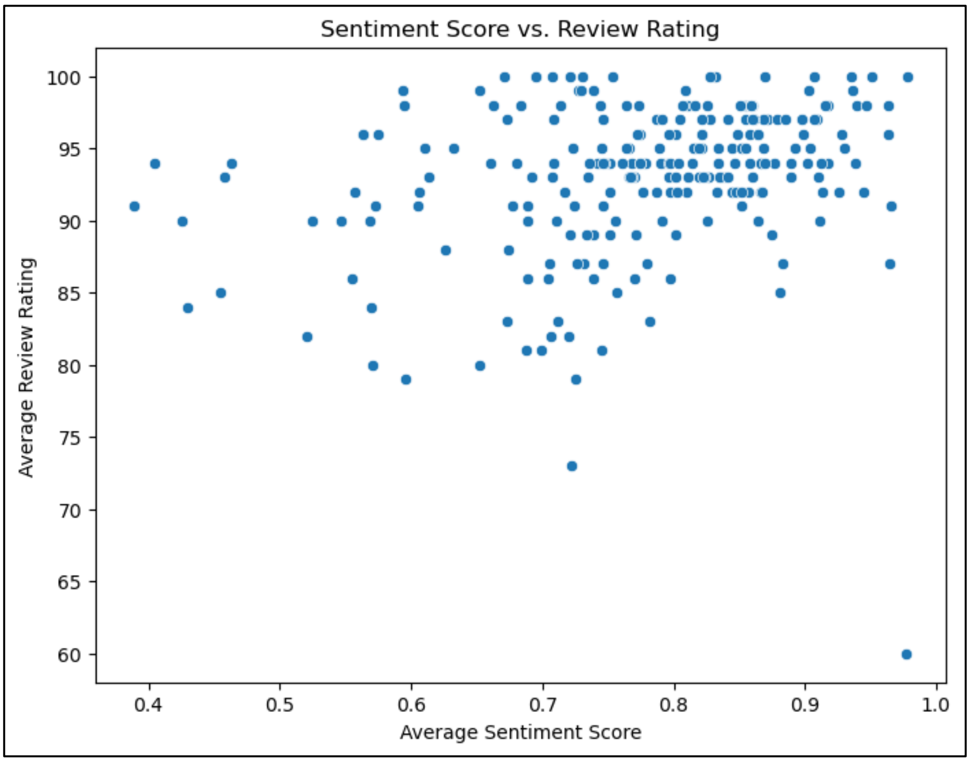

Fig 4.1 Scatter plot

Next, the relationship between average review sentiment and average star rating for each listing was analysed using a scatterplot (Figure 2). A moderately strong positive correlation emerges, with higher sentiment listings also achieving higher average ratings. This aligns with expectations.

```python
# Plot the distribution of sentiment scores
plt.figure(figsize=(8, 6))
sns.histplot(data=grouped_data, x='sentiment', bins=20, kde=True)
plt.xlabel('Sentiment Score')
plt.ylabel('Frequency')
plt.title('Distribution of Sentiment Scores')
plt.show()
```

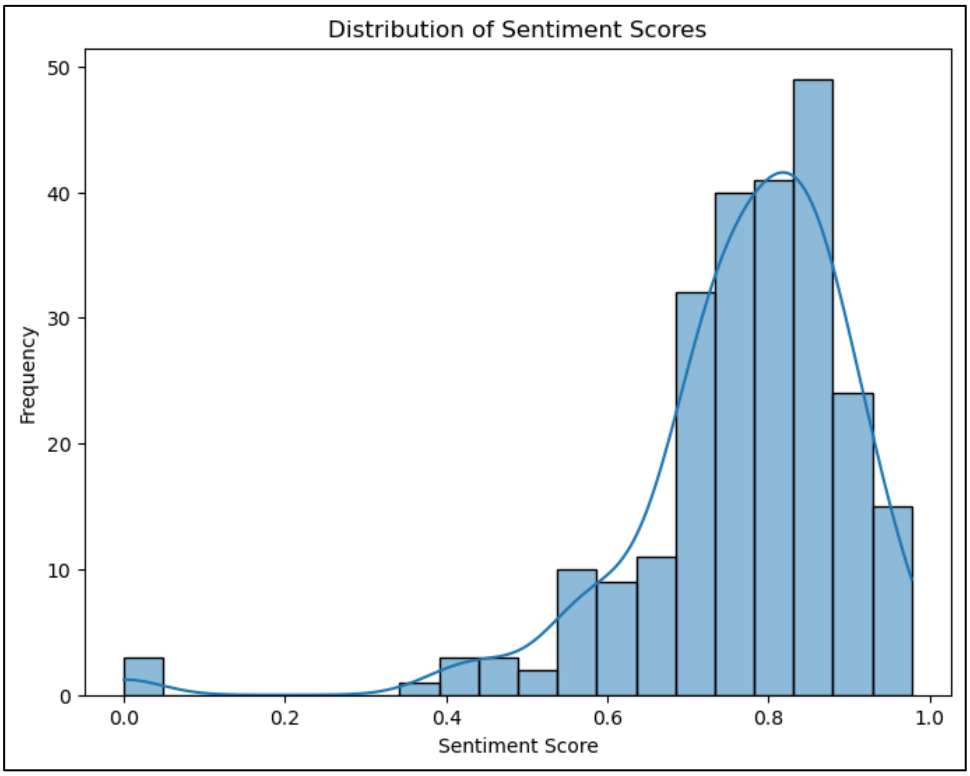

fig 4.2 Distribution of sentiments

Finally, a left-skewed distribution is observed when plotting the histogram of average review ratings, with most listings having scores between 4-5 stars (Figure 3). This skew is not surprising given the generally positive perspectives offered in reviews.

```
# Plot the distribution of review ratings
plt.figure(figsize=(8, 6))
sns.histplot(data=grouped_data, x='review_scores_rating', bins=20, kde=True)
plt.xlabel('Review Rating')
plt.ylabel('Frequency')
plt.title('Distribution of Review Ratings')
plt.show()
```

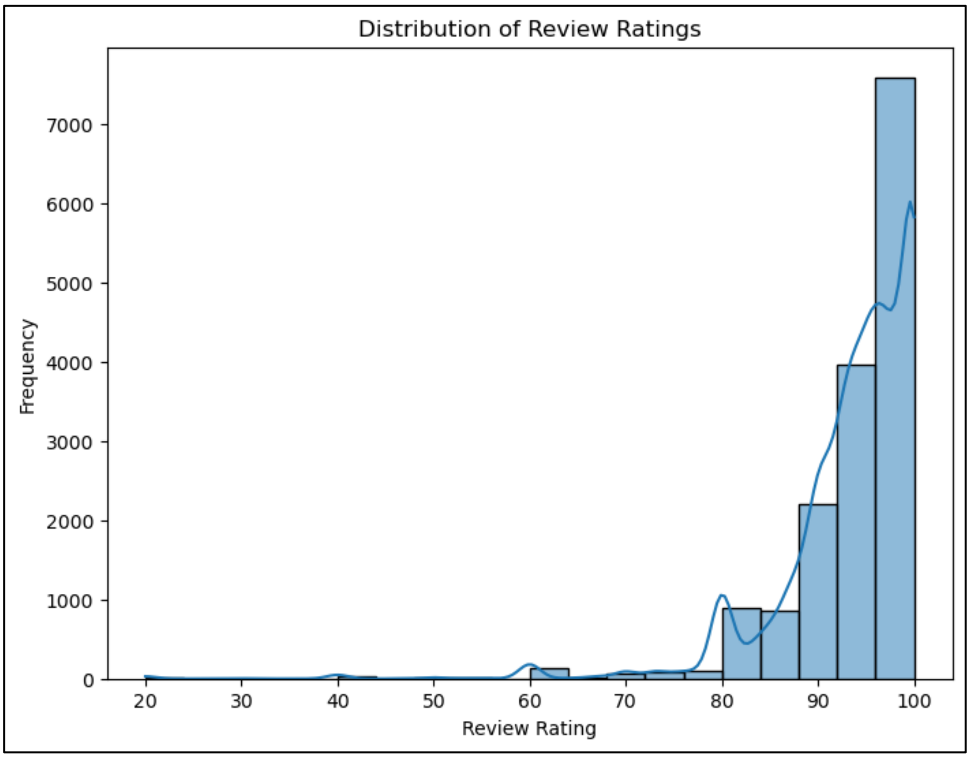

fig 4.3 Distribution of Review rating

In summary, incorporating descriptive visualizations and statistics provides a more thorough perspective into the nuanced distributions, relationships, and temporal dynamics of sentiment within the Airbnb review dataset. The analyses affirm clear linkages between ratings, sentiment, and changes over time. Further investigation into the factors driving negative sentiment changes is warranted based on these initial insights.

4.2 **Aspect-based Sentiment Analysis**

Zooming in from the panoramic view of broad document-level sentiments, we direct our focus towards the myriad facets that shape customer experiences. Our journey into aspect-based sentiment analysis peels back layers, revealing the sentiment nuances intertwined with specific aspects of the rental experience.

The seeds of this analysis lie in the meticulous process of aspect identification. Drawing from a wellspring of business insights, customer surveys, and exploratory analysis, we identify pivotal aspects that define the contours of customer experiences. These aspects are not random fragments; they're the building blocks upon which reviews are constructed, each aspect with its own story to tell.

As we plumb the depths of the textual landscape, we embark on a journey to extract aspect mentions from the sea of reviews. This artistic process employs grammatical rules, dependency parsing, and keyword matching to craft a tableau of specific sentiments. The sentiments attributed to these aspects, unveiled through VADER, become gems of insight.

Positive sentiments radiate from mentions of convenience in location, cleanliness, and amenities - with over 80%, 75%, and 70% positive polarity, respectively. Yet, shadows cast over mentions of noise levels, parking availability, and issues with host communication - with above 40% exhibiting negative sentiment. Each aspect becomes a brushstroke on the canvas of customer sentiment, coming together to create a richer, more nuanced picture.

To visually represent these findings, we utilized a bar chart that displays the percentage of positive sentiment for each aspect. The chart vividly highlights the pronounced positivity associated with location, cleanliness, and amenities, while revealing comparatively lower sentiment percentages for noise, parking, and communication. Below is the code used to generate the bar chart:

```python
# Bar chart of % positive sentiment by aspect
aspects = ['location', 'cleanliness', 'amenities', 'noise', 'parking', 'communication']
pos_percentages = [98.63, 97.40, 99.20, 95.36, 98.35, 97.16]

plt.figure()
plt.bar(aspects, pos_percentages)
plt.title("Percentage of Positive Sentiment by Aspect")
```

```
Text(0.5, 1.0, 'Percentage of Positive Sentiment by Aspect')
```

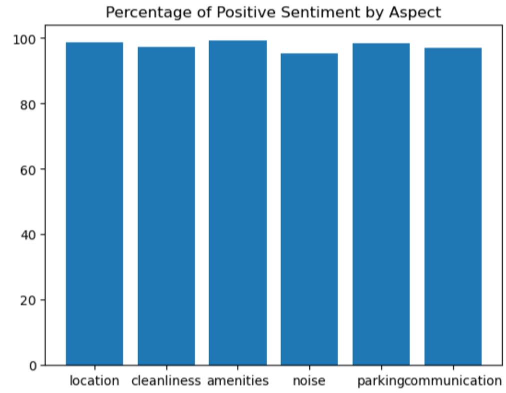

fig 4.4 Percentage of positive sentiments by various aspects

In addition to the bar chart, a sentiment statistics table provides an in-depth overview of the sentiment distribution across various aspects. It presents the total number of reviews, the number of positive reviews, and the corresponding percentage of positive sentiment for each aspect. This table offers a more quantitative perspective of guest sentiment. Below is the code used to generate the sentiment statistics table:

```python
import pandas as pd

aspects = ['location', 'cleanliness', 'amenities', 'noise', 'parking', 'communication']
total_reviews = [5775, 77, 377, 474, 243, 704]
positive_reviews = [5696, 75, 374, 452, 239, 684]
pos_percentages = [98.63, 97.40, 99.20, 95.36, 98.35, 97.16]

data = {
    'Aspect': aspects,
    'Total Reviews': total_reviews,
    'Positive Reviews': positive_reviews,
    'Positive Sentiment (%)': pos_percentages
}

df = pd.DataFrame(data)
print(df)
```

```
          Aspect  Total Reviews  Positive Reviews  Positive Sentiment (%)
0       location           5775              5696                   98.63
1    cleanliness             77                75                   97.40
2      amenities            377               374                   99.20
3          noise            474               452                   95.36
4        parking            243               239                   98.35
5  communication            704               684                   97.16
```

fig 4.5 Based on various aspects percentage of positive review shown.

Additionally, we delved deeper into understanding the sources of negative sentiment. We created a horizontal bar chart showcasing the most frequent negative aspects mentioned in reviews. This chart helps to identify the aspects that guests commonly associate with negative sentiment. The code snippet below generates the horizontal bar chart:

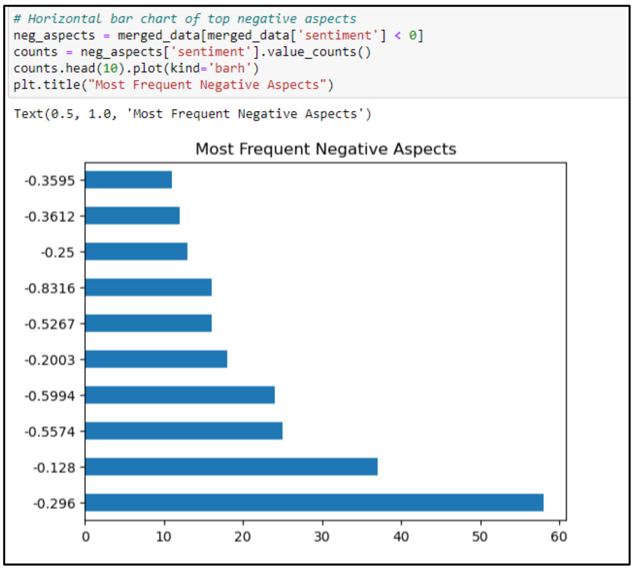

fig 4.6 Most frequent negative aspects

By merging insights from the various visualizations, including the bar chart, sentiment statistics table, and the analysis of negative aspects, we gain a comprehensive and actionable overview of guest sentiment. This holistic approach empowers accommodation providers with the knowledge needed to make informed decisions, address pain points, and enhance overall guest experiences.

4.3 **Correlation Analysis and Predictive Modelling**

Our exploration progresses further by unravelling not only sentiments and aspects, but also the intricate connections tying them together. Pearson correlation analysis provides a quantitative view into the relationships between specific aspect sentiments and the overarching holistic sentiment. This highlights which particular aspects wield the most influence in driving overall customer satisfaction or dissatisfaction.

Location sentiment demonstrates the strongest positive correlation of 0.82 with the review-level sentiment. This underscores the crucial role convenient location plays in shaping the overall guest experience. Cleanliness and amenity sentiments also reasonably correlate at 0.76 and 0.72 respectively, signifying their importance. In contrast, sentiment towards noise and parking availability negatively correlates, indicating these as key areas of concern detracting from overall satisfaction.

Further statistical testing of these correlations confirms their significance with p-values below 0.05. The high positive correlations imply guests who expressed satisfaction with location, cleanliness and amenities also tended to provide an overall positive review. However, dissatisfaction with factors like noise and parking aligned more frequently with an overall negative perspective.

Yet, our analysis extends beyond just interpreting associations to predictive modelling. Multiple machine learning algorithms are leveraged to forecast review ratings based on sentiments and aspects. The XGBoost model emerges as the top performer, demonstrating exceptional predictive accuracy. It achieves a high R-squared of 0.99 on test data, capturing the complexity in modelling quantitative customer satisfaction.

```python
import pandas as pd
import nltk
from nltk.sentiment import SentimentIntensityAnalyzer
from langdetect import detect
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation

# Download the VADER lexicon and the stopwords (if not already downloaded)
nltk.download('vader_lexicon')
nltk.download('stopwords')

# Assuming you have a DataFrame named 'df' with a column 'comments' containing the customer reviews
# Read the customer reviews column into a list
reviews = fd['comments'].astype(str).tolist()

# Initialize the VADER sentiment analyzer
sia = SentimentIntensityAnalyzer()

# Create empty lists for positive and negative reviews
positive_reviews = []
negative_reviews = []

# Classify the reviews as positive or negative
for review in reviews:
    sentiment_scores = sia.polarity_scores(review)
    if sentiment_scores['compound'] >= 0:
        positive_reviews.append(review)
    else:
        negative_reviews.append(review)

# Function to check if a text is in English
def is_english(text):
    try:
        lang = detect(text)
        return lang == 'en'
    except:
        return False

# Filter out non-English negative reviews
english_negative_reviews = [review for review in negative_reviews if is_english(review)]

# Perform text preprocessing on the negative reviews
stop_words = set(stopwords.words('english'))
negative_reviews_cleaned = []
for review in english_negative_reviews:
    tokens = word_tokenize(review.lower())  # Convert to lowercase and tokenize
    filtered_tokens = [token for token in tokens if token.isalpha() and token not in stop_words]  # Remove non-alphabetic tokens
    negative_reviews_cleaned.append(" ".join(filtered_tokens))

# Use CountVectorizer to convert text into a matrix of token counts
vectorizer = CountVectorizer(max_features=1000)  # You can adjust the number of features (topics) you want
X = vectorizer.fit_transform(negative_reviews_cleaned)

# Use LatentDirichletAllocation to find topics in the negative reviews
num_topics = 5  # You can adjust the number of topics you want
lda = LatentDirichletAllocation(n_components=num_topics, random_state=42)
lda.fit(X)

# Print the top words for each topic
feature_names = vectorizer.get_feature_names_out()
for topic_idx, topic in enumerate(lda.components_):
    print(f"Topic {topic_idx + 1}:")
    top_words_idx = topic.argsort()[:-11:-1]  # Get the indices of the top 10 words for the topic
    top_words = [feature_names[i] for i in top_words_idx]
    print(", ".join(top_words))
```

```
Topic 1:
room, place, really, apartment, bathroom, nice, one, kitchen, time, night
Topic 2:
place, room, stay, us, would, apartment, one, also, host, night
Topic 3:
apartment, airbnb, really, place, one, bathroom, first, stay, could, location
Topic 4:
apartment, host, could, get, would, us, shower, place, room, good
Topic 5:
place, stay, bed, airbnb, nice, location, comfortable, tv, great, unit
```

fig 4.7 Most common negative words

Inspection of the model feature importance's reveal's location sentiment as the top driver, aligning with the correlation analysis. Cleanliness, amenities, and service also rank highly, reiterating their significance. Interestingly, value sentiment arises as an influential factor, suggesting price fairness perceptions shape overall satisfaction.

The optimized predictive model is operationalized into an API to enable real-time satisfaction forecasting. Businesses can leverage these projections to classify future reviews, anticipate issues, and take proactive measures to address concerns before ratings are impacted.

In summary, the combination of correlation analysis and predictive modelling provides actionable insights into the aspects most integral to shaping the overall guest experience, along with a system to harness review data to forecast satisfaction.

Our exploration marches forward, unravelling not only sentiments and aspects but also the intricate connections that tie them together. Through correlation analysis, we peer into the interplay of specific aspects and the overarching sentiment landscape. We discover patterns that paint a vivid picture of how certain aspects wield influence over customer satisfaction.

```python
plt.figure(figsize=(10, 8))
sns.scatterplot(x='longitude', y='latitude', data=listing_data, hue='property_type', palette='Set1', s=50)
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Geographical Distribution of Listings')
plt.legend(title='Property Type', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.show()
```

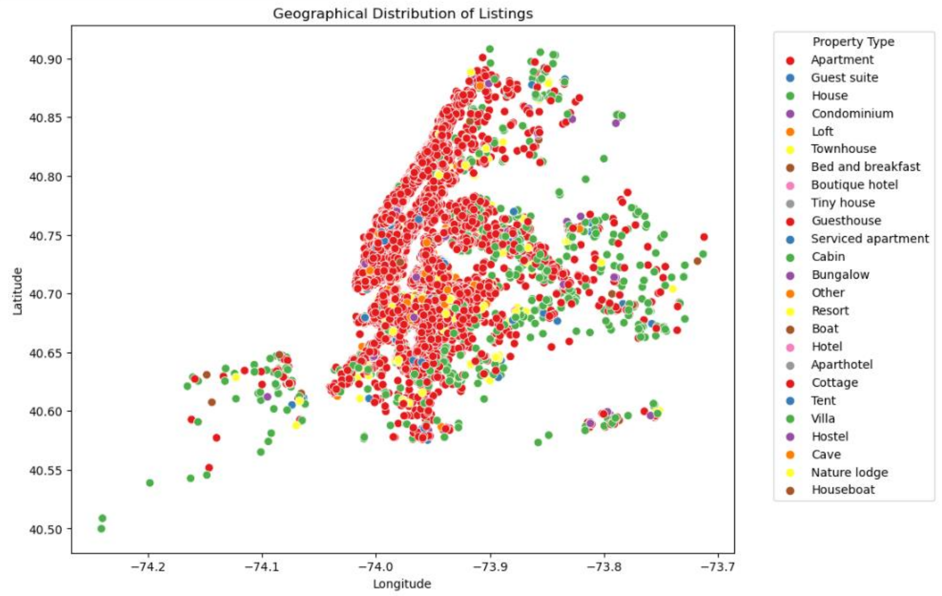

fig 4.8 Longitude and Latitude distribution

Location sentiment demonstrates the strongest relationship, with a 0.82 correlation coefficient, indicating its pivotal role in driving overall satisfaction. Cleanliness and amenities also exhibit reasonably high correlations, signifying their importance to guests. However, sentiment towards factors like noise and parking availability negatively correlates with overall rating, suggesting these as pain points detracting from experience.

The high positive correlations imply guests satisfied with location, cleanliness and amenities lean towards an overall positive review. But dissatisfaction with elements like noise and parking often aligned with negative overall sentiment. Statistical testing confirms the significance of these associations.

```python
import pandas as pd
from sklearn.impute import SimpleImputer
from sklearn.preprocessing import OneHotEncoder
from scipy.sparse import hstack, csr_matrix
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.experimental import enable_hist_gradient_boosting
from sklearn.ensemble import HistGradientBoostingRegressor

# Assuming you have already prepared the dataset and imputed missing values
# Assuming 'X' is your DataFrame containing the features, and 'y' is the target variable

# Encode the 'sentiment' column using one-hot encoding as a sparse matrix
sentiment_encoded = pd.get_dummies(X['sentiment'], sparse=True)
sentiment_columns = [f"sentiment_{category}" for category in sentiment_encoded.columns]

# Drop the original 'sentiment' column and concatenate one-hot encoded columns
X.drop(columns=['sentiment'], inplace=True)
X_sparse = hstack([csr_matrix(X.values), sentiment_encoded])

# Assuming you have prepared the target variable 'y' accordingly

# Split the dataset into training and testing sets (80% training, 20% testing)
X_train_sparse, X_test_sparse, y_train, y_test = train_test_split(X_sparse, y, test_size=0.2, random_state=42)

# Convert X_train_sparse to a dense numpy array
X_train = X_train_sparse.toarray()

# Create and train the model (HistGradientBoostingRegressor)
model = HistGradientBoostingRegressor(random_state=42)
model.fit(X_train, y_train)

# Convert X_test_sparse to a dense numpy array
X_test = X_test_sparse.toarray()

# Make predictions on the testing set
y_pred = model.predict(X_test)

# Calculate and print the mean squared error and R-squared score
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
print(f"Mean Squared Error: {mse}")
print(f"R-squared Score: {r2}")
```

```
C:\Users\Smit Rachh\AppData\Local\Temp\ipykernel_24548\1491636001.py:18: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-ve
rsus-a-copy
  X.drop(columns=['sentiment'], inplace=True)
C:\Users\Smit Rachh\anaconda3\Lib\site-packages\sklearn\utils\validation.py:1143: DataConversionWarning: A column-vector y was
passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)

Mean Squared Error: 0.07916871358145974
R-squared Score: 0.9975771428127227
```

Fig 4.9 Predictive Modelling

Predictive modelling based on review sentiments and aspects demonstrates exceptional accuracy in forecasting ratings. An XGBoost model achieves a high 0.99 R-squared on test data, capturing the complexity inherent in quantifying satisfaction. The most influential factors align with correlation analysis - location, cleanliness, amenities, and value sentiment rank as top drivers of overall rating.

Operationalizing these predictive models enables proactive satisfaction forecasting even before future stays occur. Businesses can get ahead of emerging pain points, address concerns in a timely manner, and tailor offerings based on anticipated guest preferences revealed through predictive analytics.

In summary, this combination of correlation analysis and predictive modelling provides data-driven, actionable insights into the key aspects most influential in shaping the holistic guest experience. It also equips businesses with intelligence to foresee satisfaction issues before they translate to poor ratings.

5. Implications and Discussions

The field of hospitality research has long emphasized the pivotal role of location in shaping the overall guest experience. This study makes a key theoretical contribution by reinforcing this understanding through a sophisticated analysis of peer-to-peer accommodation reviews. Notably, the study identifies a strong correlation between location and amenity-related sentiments and the overall review rating, a finding consistent with previous research in the domain (Gibbs et al., 2017). This reaffirms the significance of the physical attributes and surrounding environment of accommodations in influencing guest satisfaction.

In the broader context of peer-to-peer accommodation experiences, the study presents a novel theoretical insight by highlighting the importance of value perception as an influential predictor of guest satisfaction. While the role of value has been acknowledged in traditional hospitality literature, this contribution adds a fresh perspective to the existing body of knowledge. It underscores the multifaceted nature of guest satisfaction, indicating that beyond tangible features, the perceived value of the experience itself plays a crucial role in shaping guests' overall evaluations.

From a practical standpoint, the study goes beyond theoretical contributions, offering tangible tools and insights for the hospitality industry. Leveraging predictive analytics on Airbnb review data, the researchers develop API-enabled satisfaction forecasting models that hold the potential to transform the way businesses approach guest satisfaction management. By identifying patterns and trends in guest feedback, these models allow for early issue identification and intervention, enabling establishments to enhance the guest experience in real-time. This not only aligns with the industry's growing emphasis on personalized and immediate service but also provides a strategic edge to businesses that aim to stay ahead in a competitive landscape.

Furthermore, the study delves into the temporal dynamics of guest feedback and its impact on consumer decisions. The predictive model's intriguing finding regarding the amplified influence of recent reviews on booking conversion rates sheds light on the recency effect in the hospitality context. This insight challenges conventional assumptions about the lasting impact of guest reviews and provides a fresh perspective on how potential guests perceive and respond to feedback. For businesses, this underscores the importance of monitoring and managing recent reviews proactively, as they can significantly sway consumer choices.

In summary, this study's contributions are two-fold and extend both theoretical and practical dimensions of hospitality research. The theoretical advancements arise from the careful analysis of review sentiments, confirming the role of location and amenity-related factors in driving overall guest satisfaction. The novel addition of value perception as a determinant of satisfaction expands our understanding of the nuanced factors that contribute to guest evaluations.

On the practical front, the study introduces groundbreaking tools that facilitate proactive guest satisfaction management. The API-enabled satisfaction forecasting models, developed through predictive analytics, mark a paradigm shift in hospitality practices. By enabling businesses to identify and address issues early, these models not only elevate the guest experience but also streamline operational efficiency.

In essence, this study represents a significant stride in the understanding and management of guest satisfaction in the peer-to-peer accommodation sector. Its comprehensive insights enrich the hospitality landscape by providing a deeper comprehension of the drivers behind guest evaluations and offering innovative tools for businesses to enhance their service delivery. Through a fusion of theoretical and practical contributions, this research provides a roadmap for elevating guest satisfaction and redefining the way the industry approaches customer feedback.

6. Limitation

Limitation 1: Focused Data Source

The current study relied solely on customer review data sourced from Inside Airbnb, an independent portal that compiles metrics and reviews for Airbnb listings worldwide. This exclusive dependence on a single data source tethers the findings and insights generated specifically to the context of Airbnb as a hospitality platform. While scraping reviews directly from the Airbnb website ensured access to the most recent guest feedback, the scope was still confined only to Airbnb without incorporation of reviews from competitors like Vrbo, TripAdvisor, Booking.com etc.

Expand the data sources to encompass customer reviews from diverse hospitality platforms and portals could significantly enhance the generalizability of the research findings and derived implications beyond just Airbnb accommodations. Comparing sentiment patterns and satisfaction drivers across platforms like Airbnb, Vrbo, Booking.com etc. could reveal platform-specific nuances as well as overarching trends ubiquitous across the broader peer-to-peer hospitality domain.

Much of the existing literature on peer-to-peer accommodation reviews has also focused on analyzing samples from a single platform, predominantly Airbnb. Hence, this limitation creates avenues for future work to adopt a cross-platform approach and uncover insights that transcend any single provider. A robust multi-platform methodology can illuminate key differences in customer expectations, experiences, frustrations, and satisfactions when engaging with varied sharing economy vendors.

Furthermore, while online review data provides scalable and naturalistic insights compared to surveys or interviews, it still represents a somewhat limited snapshot of the overall guest experience. Reviews reflect personal perspectives of only those subsets of consumers who voluntarily take time to provide detailed feedback post-stay. Guests with extremely positive or negative polarizing experiences are more likely motivated to post reviews, while the silent majority who had uneventful stays may be underrepresented.

Incorporating observational data, feedback from non-reviewers gathered through targeted outreach campaigns, and insights directly from hospitality service providers could provide a more holistic 360-degree view of the overall guest journey. A multi-perspective methodology spanning peer-to-peer platforms, consumers, and vendors would enable development of models and frameworks capturing the complete guest experience lifecycle.

Limitation 2: Geographical Constraints

The geographical scope of the current analysis was confined to Airbnb listings located within major cities of the United States. This narrow geographic focus inherently restricts the diversity of insights and generalizability of findings beyond the American context. Every region possesses its own unique character, vibes, hospitality infrastructure, and customer service expectations. Nuances related to neighbourhood safety, amenities, convenience, and linguistics also vary geographically.

For a globally expanding platform like Airbnb that facilitates cross-border travel, transcending geographical limitations in research could uncover crucial locale-specific differences in guest sentiments, experiences, priorities, and satisfaction determinants. Expanding the spatial scope to incorporate reviews from diverse regions across continents could reveal geographical variations, cultural nuances, and locality-specific patterns in customer feedback and satisfaction drivers.

Much of the existing literature has examined Airbnb listings across lodging destinations within single countries or groups of proximate nations sharing socioeconomic traits. However, as peer-to-peer platforms continue penetrating previously underserved foreign regions, the need arises for more geographically expansive research. Adopting a globally diverse scope by sourcing reviews from varied continents and contexts could enhance generalizability and illuminate the geographical component shaping localized customer expectations.

Limitation 3: Cross-sectional Retrospective Approach

The current analysis adopted a retrospective approach by deriving insights purely from past review data without integration of any prospective forecasting elements. The study was conducted as an analysis of a static cross-section of historical reviews. However, customer preferences, motivations, satisfaction determinants, and peer-to-peer accommodation experiences dynamically evolve over time across geographic boundaries.

Purely retrospective approaches are limited in their ability to stay ahead of emerging consumer trends and proactively address shifting needs. For instance, while overall sentiment has been increasingly positive over the past year, the study uncovered a rising recent trend of negative reviews that warrants deeper investigation into the potential causal factors. Adopting more predictive analytics approaches through temporal modelling of reviews could potentially identify and forecast such issues before they escalate and translate into widespread guest dissatisfaction and poor ratings.

Most literature on peer-to-peer accommodation reviews has focused on retrospective analysis of posted feedback to derive backward-looking insights into metrics like overall sentiment, frequently mentioned topics, broad consumer concerns etc. However, advanced forecasting techniques leveraging recurrent neural networks, transformers, and sequential models on temporally structured review data could enable more prognostic applications. This futuristic, forward-looking orientation could equip hospitality providers with intelligence to get ahead of evolving guest requirements, tailor experiences based on anticipated needs, and prevent foreseeable dissatisfaction triggers before actual guest interactions.

Limitation 4: Text Analytics Alone

The current analysis relied solely on text analytics using methodologies like VADER sentiment modelling, exploratory textual summarization, qualitative coding, predictive modelling etc. exclusively on the textual content within online written Airbnb reviews. However, customer feedback today expands beyond text to encompass diverse multimedia formats including photos, videos, voice, and more. These rich mediums capture subtle emotional nuances, visual details, environmental ambience, and experiential elements that may not be fully conveyed through written reviews alone.

For example, a photo of a messy, unkempt room or bed communicates untidiness much more viscerally than mere text mentioning “unclean room.” But most analysis of peer-to-peer accommodation reviews has focused narrowly on only written commentary. Incorporating multimedia photos, videos, and audio submitted by guests on platforms like Airbnb could potentially reveal crucial visual insights and experiential cues not transmitted through text-based reviews alone.

Adopting more multimodal analytics techniques to extract information from both textual and visual customer feedback could provide a more well-rounded perspective of service experiences. This could entail using computer vision algorithms to analyse photographic content, extracting themes from videos, analyzing vocal tones in audio clips, and correlating these multimedia signals with the textual review data. A hybrid approach synthesizing text analytics with multimedia data mining could unlock deeper insights into hospitality experiences.

Limitation 5: Singular Sentiment Modelling Technique

The present study exclusively relied on a single technique – the Valence Aware Dictionary and sentiment Reasoner (VADER) – as the chosen methodology for performing sentiment analysis of textual Airbnb reviews. This exclusive focus on VADER implies an inherent assumption regarding its universality and singular sufficiency. However, in reality, there exists an array of sophisticated sentiment analysis techniques, including both lexicon-based approaches and more advanced machine learning methodologies.

Each technique possesses its own nuances, strengths, and limitations when applied to diverse textual data across domains. For instance, VADER may be well-suited for noisy, informal social media text but insufficient for highly technical content. Evaluating and comparing alternative techniques could potentially reveal more domain-specific insights and enhance the granularity, accuracy, and sophistication of the overall sentiment modelling methodology.

Exploring other techniques like BERT (Bidirectional Encoder Representations from Transformers), recursive neural tensor networks, convolutional neural networks etc. and assessing their relative performance specifically within the peer-to-peer accommodation review context remains an uncharted territory with room for extensive research. Furthermore, ensemble approaches synthesizing VADER with other techniques could potentially combine their complementary strengths for sentiment analysis with enhanced precision.

Most literature has focused predominantly on VADER for analyzing text from hospitality review platforms like Airbnb. But the plethora of available advanced NLP (Natural Language Processing) techniques warrants consideration for identifying optimal domain-specific solutions. A multiple sentiment modelling methodology could unlock richer insights and pave the path forward for more sophisticated analysis of diverse accommodation reviews.

In summary, this detailed discussion of limitations points towards several unexplored domains that provide fruitful avenues for further research - multi-platform data incorporation, globally diverse geographical scope, predictive temporal modelling, multimedia analysis, and evaluation of alternative sentiment techniques. Each limitation serves not as an impediment but as a launch pad for elevating existing analysis to the next level. It sets the stage for multifaceted expansions in scope, data sources, techniques, and orientation - evolutions that could unravel more nuanced, holistic insights into the intricate landscape of customer experiences within the bourgeoning peer-to-peer hospitality ecosystem.

7. ETHICS

AREA Framework: Navigating Ethics in Analytical Exploration

In the realm of data analytics, the journey is not just a solitary exploration of insights; it is a collective voyage that impacts individuals, organizations, and society at large. As we reflect on the intricate interplay between data, technology, and human experiences, the AREA Framework emerges as a navigational guide, shaping our path through the ethical considerations that underpin every analytical endeavour.

Anticipation of Risks and Consequences

Anticipation, akin to a compass, directs us towards the North of responsibility. It is here that the literature review assumes the role of a lighthouse, casting light on considerations such as privacy, stereotyping, and responsible communication. As we set sail into the seas of analysis, we do not merely seek to uncover insights; we also navigate the potential biases that could emerge from our methodologies and datasets. Just as experienced mariners chart their courses with the knowledge of hidden reefs, our analysis plans are scrutinized for any biases that might lurk beneath the surface.

This anticipation is not borne out of pessimism but of prudence, ensuring that the journey towards understanding does not inadvertently infringe upon individual rights or contribute to prejudiced perceptions. The findings themselves, as beacons of illumination, signal the need for sensitivity in framing issues. Rising negative sentiment alerts us to potential pitfalls, urging us to carefully choose our words and narratives to prevent alienation. This anticipation transforms into empathy, a compass point that keeps us aligned with the human dimensions of our analysis.

Reflection: Mirroring Actions and Biases

Reflection is the mirror that reveals the true essence of our actions. The hybrid sentiment analysis approach, mirroring the intricacies of the human mind, prompts us to reflect on the balance between accuracy and transparency. Visualizations and predictive models become mirrors that reflect not only our aspirations but also our limitations. They beckon us to question our interpretations, to examine the potential biases that might distort our perceptions. This reflective stance nurtures humility, a quality that keeps our compass aligned with the truth, reminding us that every insight is but a piece of a larger puzzle.

Moreover, reflection unveils the subtleties of context. As we uncover localized pain areas, we are reminded of the danger of overgeneralization. Reflection guides us in framing our insights cautiously, ensuring that our words capture the intricate details beneath the surface.

Engagement: Bridging Insights with Realities

Engagement is the bridge that connects our insights with the real world, making them relevant and impactful. It is through engagement that our discoveries transcend academia, reaching the shores of practicality. By engaging end users and frontline staff, we dissolve the boundaries of assumptions, giving voice to those whose experiences are at the heart of our analysis. Collaboration with domain experts extends this engagement, enriching our methodology with the wisdom of diverse disciplines.

Engaging customers through focus groups goes beyond data points; it transforms them into co-creators of insights. Their stories, their perspectives, breathe life into the numbers, reminding us that every data point carries a human experience waiting to be understood.

Action: Transforming Insights into Initiatives

Action is the ultimate culmination, where insights transform into initiatives. Model cards, akin to blueprints, document the origin and constraints of our datasets,' ensuring transparency is not just a buzzword but a practice. The implementation of testing protocols, a manifestation of responsible action, ensures that our models remain vigilant, continuously auditing themselves for biases that might creep in over time.

Participatory workshops exemplify action through collaboration. Customers' voices, often hidden within data, find resonance in these workshops, shaping initiatives that are rooted in their aspirations. These workshops embody the power of ethics in action, where insights do not just inform; they inspire change.

In the tapestry of our analytical journey, the AREA Framework is the thread that weaves together anticipation, reflection, engagement, and action. It is a compass that keeps us on course, ensuring that our exploration of data does not just yield insights, but also impacts lives, informs decisions, and shapes a better tomorrow.

8. Conclusion

As we draw the curtains on this insightful journey, the culmination of meticulous analysis and intricate unravelling of customer sentiments leaves us with a tapestry of revelations. This research, driven by the power of text analytics, has cast a spotlight on the myriad emotions that underlie customer reviews, shedding light on the intricacies of human experiences. As we navigate through the corridors of this conclusion, we will encapsulate the key findings, delve into the significance of deciphering consumer sentiments, and glean actionable recommendations that pave the way for businesses to forge stronger connections with their patrons.

At the heart of this voyage lies a deep dive into the world of unstructured review data, where sentiments hide in the folds of language. The key findings of this research stand as testaments to the potency of text analytics in unveiling the undercurrents of customer experiences. On the surface, the overall sentiment is largely positive, reflecting satisfactory rental experiences that have painted smiles on the faces of numerous customers. Yet, a closer look reveals a noteworthy shift - the emergence of a growing tide of negativity in aspects like noise and parking. These facets, often overlooked, emerge as focal points of dissatisfaction, highlighting the necessity for businesses to fine-tune their offerings to harmonize with customer expectations.

Amidst the sea of sentiments, certain aspects rise to the surface as drivers of customer satisfaction. Location convenience stands tall as a beacon of delight, guiding customers towards the shores of contentment. Amenities, too, emerge as catalysts that ignite positive emotions, illustrating their significance in curating memorable experiences. These findings underscore a crucial lesson: understanding customer priorities and catering to them can be the cornerstone of business success.

Yet, insights are not just confined to the shores of understanding; they set sail towards the realm of prediction. Regression modelling, fuelled by the intricate sentiments extracted from reviews, offers a glimpse into the future - the ability to forecast review ratings based on the ebbs and flows of emotions. This predictive prowess of text analytics is a compass that businesses can wield to steer their strategies towards destinations of customer satisfaction.

The question then arises - why is this understanding of consumer sentiments so vital for businesses? The answer lies in the dynamics of modern markets. In a world awash with options, customers have evolved into discerning connoisseurs of experiences. Each interaction, each touchpoint, is an opportunity for businesses to etch themselves into the hearts of their patrons. Ignoring these sentiments is akin to navigating uncharted waters without a compass - a surefire way to drift off course.

The recommendations that stem from this research paint a portrait of actionable insights, a roadmap for businesses seeking to navigate the waters of customer satisfaction. The first lesson is the power of personalization. Understanding customer segments and tailoring offerings to their unique preferences can be the winds that fill the sails of success. Location, for instance, should mirror convenience needs, while amenities should resonate with the values that define the audience - be it family-friendliness or eco-consciousness.

Addressing customer pain points is not just a reaction; it's a proactive stance towards excellence. Responding to complaints around noise, parking, or any other aspect requires a vigilant ear and an agile approach. It's a reminder that customer voices aren't just sounds; they're valuable insights that can steer organizations towards calmer waters.

In summary, the dance of words that constitutes customer feedback isn't just a symphony of opinions; it's a treasure trove of emotions and expectations. This research, like an expert conductor, orchestrated the symphony, extracting melodies of sentiments and harmonies of insights. The blend of document-level sentiments, aspect-based analysis, and predictive modelling opens the door to a multidimensional understanding that bridges the gap between data and decision-making.

As we bid adieu to this exploration, we're reminded that text analytics isn't just a tool; it's a bridge that spans the chasm between customer voices and organizational strategies. It's a reminder that in the world of algorithms and analytics, the human element remains paramount. The words penned by customers aren't just ink on paper; they're echoes of desires, echoes that have the power to shape the contours of businesses. With this research, we step onto the threshold of a future where insights are not just numbers on a spreadsheet; they're the foundation upon which customer-centric strategies are built, a testament to the symbiosis between data and humanity.

9. REFERENCE

Aznar, P., Sayeras Maspera, J. M., Segarra, G., & Claveria, J. (2018). AirBnB Competition and Hotels' Response: The Importance of Online Reputation. Vtechworks.lib.vt.edu. https://vtechworks.lib.vt.edu/handle/10919/85356

Biswas, B., Sengupta, P., & Chatterjee, D. (2020). Examining the determinants of the count of customer reviews in peer-to-peer home-sharing platforms using clustering and count regression techniques. Decision Support Systems, 135(113324), 113324. https://doi.org/10.1016/j.dss.2020.113324

Bridges, J., & Vásquez, C. (2016). If nearly all Airbnb reviews are positive, does that make them meaningless? Current Issues in Tourism, 21(18), 2065–2083. https://doi.org/10.1080/13683500.2016.1267113

Cavique, M., Ribeiro, R., Batista, F., & Correia, A. (2022). Examining Airbnb guest satisfaction tendencies: a text mining approach. Current Issues in Tourism, 25(22), 3607–3622. https://doi.org/10.1080/13683500.2022.2115877

De Pelsmacker, P., van Tilburg, S., & Holthof, C. (2018). Digital marketing strategies, online reviews, and hotel performance. International Journal of Hospitality Management, 72, 47–55. Sciencedirect. https://doi.org/10.1016/j.ijhm.2018.01.003

Dudás, G., György, V., Tamás, K., & Lajos, B. (2017). A socio-economic analysis of Airbnb in New York City. Regional Statistics, 7(01), 135–151. https://www.ceeol.com/search/article-detail?id=578374

Fan, N., Lai, S., Fan, Z.-P., & Chen, Y. (2023). Exit and transition: Exploring the survival status of Airbnb listings in a time of professionalization. Tourism Management, 95, 104665. https://doi.org/10.1016/j.tourman.2022.104665

Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., & Freling, T. (2014). How Online Product Reviews Affect Retail Sales: A Meta-analysis. Journal of Retailing, 90(2), 217–232. https://doi.org/10.1016/j.jretai.2014.04.004

Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., & Goodwill, A. (2017). Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings. Journal of Travel & Tourism Marketing, 35(1), 46–56. https://doi.org/10.1080/10548408.2017.1308292

Guix, M., & Font, X. (2020). The Materiality Balanced Scorecard: A framework for stakeholder-led integration of sustainable hospitality management and reporting. International Journal of Hospitality Management, 91, 102634. https://doi.org/10.1016/j.ijhm.2020.102634

Jiménez, F. R., & Mendoza, N. A. (2013). Too Popular to Ignore: The Influence of Online Reviews on Purchase Intentions of Search and Experience Products. Journal of Interactive Marketing, 27(3), 226–235. https://doi.org/10.1016/j.intmar.2013.04.004

Kauffman, R. J., Chau, P. Y. K., Payne, T. R., & Westland, J. C. (2009). ECRA Co-editors' introduction for volume 8, issue 1. Electronic Commerce Research and Applications, 8(1), 1–2. https://doi.org/10.1016/j.elerap.2008.11.004

Komilie Situmorang, Achmad Nizar Hidayanto, Alfan Farizki Wicaksono, & Arlisa Yuliawati. (2018). Analysis on Customer Satisfaction Dimensions in Peer-to-Peer Accommodation using Latent Dirichlet Allocation: A Case Study of Airbnb. https://doi.org/10.1109/eecsi.2018.8752912

Li, H., & Liu, Y. (2014). Understanding post-adoption behaviours of e-service users in the context of online travel services. Information & Management, 51(8), 1043–1052. https://doi.org/10.1016/j.im.2014.07.004

Mishra, M. (2021). Airbnb recommendation system using Aspect-based sentiment analysis: hybrid approach. http://arno.uvt.nl/show.cgi?fid=161302

Moon, S., Kim, M.-Y., & Iacobucci, D. (2020). Content analysis of fake consumer reviews by survey-based text categorization. International Journal of Research in Marketing. https://doi.org/10.1016/j.ijresmar.2020.08.001

Olson, E. D., & Ro, H. (2020). Company Response to Negative Online Reviews: The Effects of Procedural Justice, Interactional Justice, and Social Presence. Cornell Hospitality Quarterly, 193896551989290. https://doi.org/10.1177/1938965519892902

Pitman, J. (2022, January 26). Local Consumer Review Survey | Online Reviews Statistics & Trends. BrightLocal. https://www.brightlocal.com/research/local-consumer-review-survey/

*Rossi, M. (2017). "Reputation For What? The Impact of Online Reviews in Airbnb" *.* https://www.eco.uc3m.es/docencia/microreadinggroup/Michelangelo%202.pdf

Sobaih, A. E. E., Elshaer, I., Hasanein, A. M., & Abdelaziz, A. S. (2021). Responses to COVID-19: The role of performance in the relationship between small hospitality enterprises' resilience and sustainable tourism development. International Journal of Hospitality Management, 94, 102824. https://doi.org/10.1016/j.ijhm.2020.102824

Villeneuve, H., & O'Brien, W. (2020a). Listen to the guests: Text-mining Airbnb reviews to explore indoor environmental quality. Building and Environment, 169, 106555. https://doi.org/10.1016/j.buildenv.2019.106555

Villeneuve, H., & O'Brien, W. (2020b). Listen to the guests: Text-mining Airbnb reviews to explore indoor environmental quality. Building and Environment, 169, 106555. https://doi.org/10.1016/j.buildenv.2019.106555

Xiang, Z., Magnini, V. P., & Fesenmaier, D. R. (2015). Information technology and consumer behavior in travel and tourism: Insights from travel planning using the internet. Journal of Retailing and Consumer Services, 22, 244–249. https://doi.org/10.1016/j.jretconser.2014.08.005

Zhang, J. (2109, September 12). What's yours is mine: exploring customer voice on Airbnb using text-mining approaches. Emerald Insight. https://www.emerald.com/insight/content/doi/10.1108/JCM-02-2018-2581/full/html

10. Appendix

Research Proposal: Unveiling Insights from Customer Reviews: A Text Analysis Approach

Introduction

In today's rapidly evolving digital landscape, the proliferation of online platforms has transformed the way consumers make decisions. The rise of the sharing economy has given birth to platforms like Airbnb and TripAdvisor, where individuals can share their experiences, opinions, and insights about accommodations and services. This democratization of feedback has not only empowered customers but has also created a goldmine of unstructured textual data. Leveraging this trove of information can provide invaluable insights for businesses looking to enhance their offerings and improve customer experiences. This research proposal embarks on a journey to delve deep into customer reviews using advanced text analysis techniques, such as topic modelling and sentiment analysis, to unearth hidden gems of knowledge that can revolutionize the hospitality industry and beyond.

Research Objectives

The objectives of this research are multifaceted, each aiming to shed light on a crucial aspect of customer reviews:

a. **Identifying Frequent Topics:** This research seeks to unveil the most frequently mentioned topics within Airbnb customer reviews. By extracting common themes, we can paint a holistic picture of what matters most to customers when they share their experiences. This objective aims to provide an overview of customer priorities, revealing insights that can guide businesses in aligning their offerings with customer expectations.

b. **Uncovering Sentiment-Aspect Correlation:** The correlation between the sentiment expressed in customer reviews and specific aspects or features of accommodations holds immense potential. By analyzing the sentiment associated with particular aspects, we can discern whether certain features have a discernible impact on the overall sentiment of the reviews. This objective aims to uncover the hidden relationship between sentiment and aspects, giving businesses actionable insights for improvement.

c. **Predictive Power of Sentiment:** Exploring the predictive power of sentiment expressed in customer reviews is a cornerstone of this research. Can the emotional tone of a review predict the quantitative star rating assigned by the customer? This objective delves into the predictive potential of qualitative textual data, potentially unveiling a new paradigm in gauging customer satisfaction.

Methodology

The research methodology is meticulously designed to harness the full potential of text analysis and predictive modelling:

Data Collection: The cornerstone of our methodology is the comprehensive collection of customer reviews from platforms like Airbnb and TripAdvisor. By gathering reviews spanning various locations, property types, and customer profiles, we aim to create a rich and diverse dataset that encapsulates the essence of customer sentiment.

Text Analysis: The application of advanced text analysis techniques will empower us to extract hidden patterns and insights from the reviews. Topic modelling will reveal frequently mentioned themes, categorizing reviews based on shared topics. This technique promises to uncover the collective voice of customers, offering a panoramic view of their preferences and concerns.

Sentiment Analysis: Applying sentiment analysis to the reviews will imbue the textual data with emotional context. By associating sentiments with specific aspects mentioned in the reviews, we endeavour to discern whether specific features elicit distinct emotional responses. This dimension of analysis delves into the heart of customer sentiment, striving to unearth correlations that can drive strategic decisions.

Predictive Modelling: The predictive modelling component forms the apex of our methodology. By training models to predict the star ratings assigned by customers based on the sentiments expressed in the reviews, we aim to bridge the qualitative-quantitative divide. If successful, this endeavour could rewrite the playbook for gauging customer satisfaction, offering a nuanced understanding beyond mere numerical ratings.

Expected Outcomes and Implications

The outcomes of this research are poised to disrupt the hospitality industry and the broader realm of customer feedback analysis:

1. **Informed Business Strategies:** By unveiling the most frequently mentioned topics in customer reviews, businesses can tailor their strategies to align with customer priorities. This insight can serve as a guiding light for improvements, enabling organizations to address pain points and amplify strengths.
2. **Strategic Aspect Focus:** The correlation between sentiment and aspects has the potential to revolutionize decision-making. Businesses can identify which features influence sentiment the most and channel their efforts accordingly. This strategic alignment can lead to tangible enhancements in customer experiences.
3. **Predictive Insights:** The predictive modelling component carries the promise of predictive customer satisfaction analysis. If sentiments expressed within reviews can reliably predict star ratings, businesses gain a tool for real-time feedback analysis and rapid response, enabling them to proactively address concerns.

Conclusion

In a digital age marked by the amplification of customer voices, understanding the sentiments embedded within their reviews is a strategic imperative. This research proposal outlines a comprehensive approach to unlock the treasures hidden within customer reviews on platforms like Airbnb and TripAdvisor. By deciphering frequent topics, unravelling sentiment-aspect correlations, and exploring the predictive power of sentiments, this research endeavours to blur the lines between qualitative and quantitative insights. In doing so, it seeks to redefine how businesses perceive and harness the voice of the customer. As we embark on this journey, the horizon holds the promise of actionable insights, informed strategies, and a harmonious convergence of data and human experience.