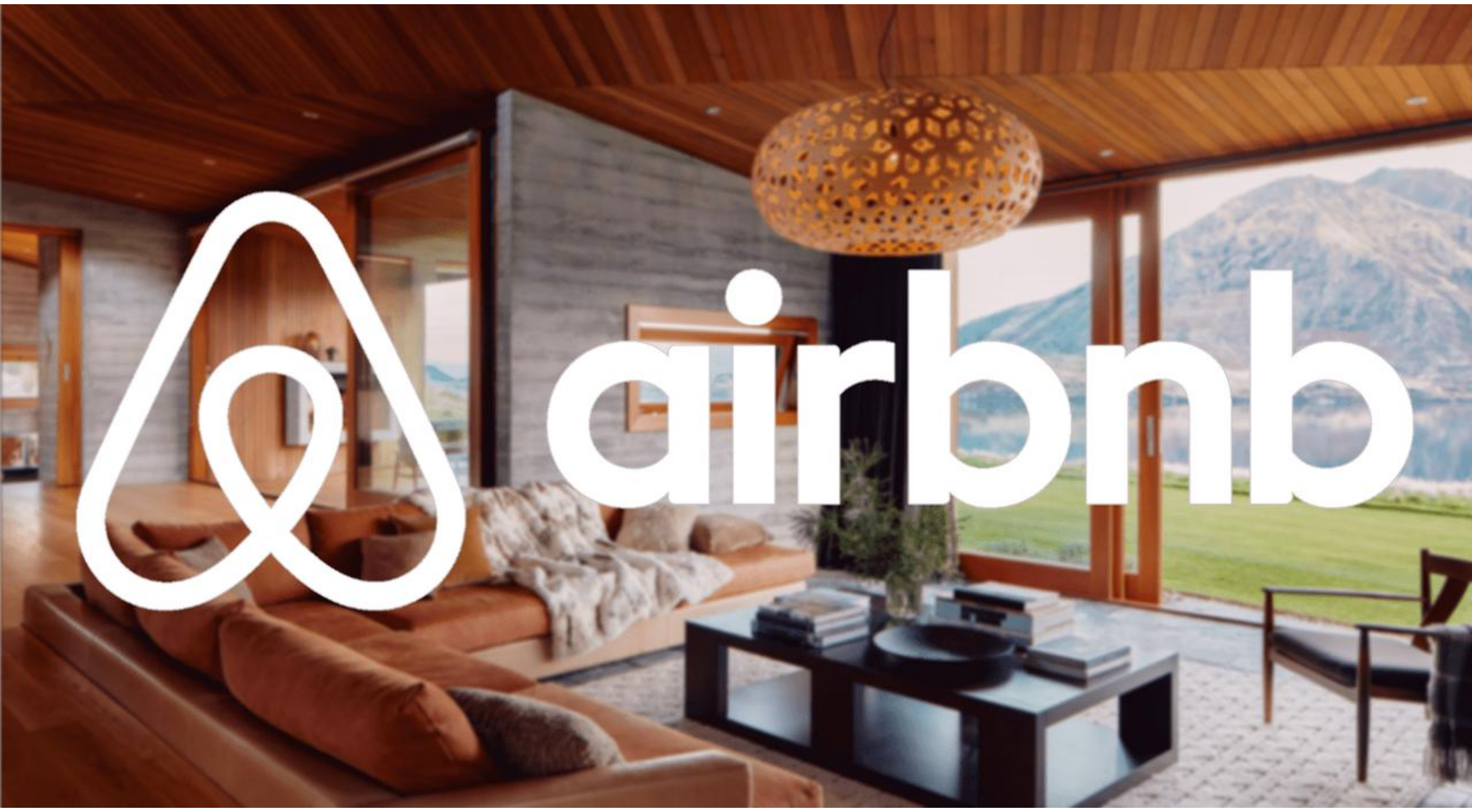



# A1: Text Mining Report on Airbnb

## Uncovering Market Insights for Hosts and Platform Optimization

**Mar 13, 2025**

PRESENTED TO

**Professor Thomas Kurnicki**

PRESENTED BY

**Tirthankar Mukherjee**

**Business Analysis with Unstructured Data - DAT-7471- FMBANDD1**

**Hult International Business School**

# Executive Summary

This comprehensive analysis of Airbnb listing data highlights several key factors significantly influencing booking rates and pricing strategies. Listings with neighborhood descriptions that exude positive sentiment, particularly those featuring phrases like "walking distance," "metro station," and "restaurants bars," tend to attract more bookings. Pricing trends indicate that entire homes and apartments, primarily 'serviced apartments and villas' priced above $600, command premium rates. In contrast, shared rooms are priced considerably lower. Property size metrics, such as the number of bedrooms and bathrooms, strongly correlate with price points. While host response rates correlate negatively with pricing, they are likely crucial for enhancing guest satisfaction.

Based on these insights, Airbnb management is recommended to implement the following four strategic initiatives:

**Optimize Pricing Strategies:** Encourage hosts to focus on premium property types and utilize data-driven approaches to set competitive cleaning fees.

**Enhance Neighborhood Descriptions:** Guide hosts to incorporate high-impact phrases related to accessibility and amenities to attract more bookings.

**Improve Host Performance:** Develop training programs and offer superhost incentives to elevate host responsiveness and service quality.

**Leverage Text Analytics:** Use advanced text analytics to provide personalized guest recommendations and improve service offerings.

These strategies will enable hosts to maximize their revenue potential while aligning their listings closely with guest preferences for convenience, accessibility, and dining options.

## Visualizations & Text Mining Framework with Key Insights

***1. "Average Price by Room Type and Property Type"* visualization**: This bar chart lets viewers quickly identify which room type and property type combinations command the highest prices on the Airbnb platform. Entire home listings have higher average prices than private or shared rooms. At the same time, Serviced Apartments and Villas are the most expensive property types under "Private Room" based on the highest bars on the chart, followed by hotels and apartments. *(Appendix 1)*

***2. "Sentiment Analysis of Airbnb Summaries"*** is a series of bar charts, each representing the sentiment score derived from Airbnb summaries using different sentiment analysis methods. The AFINN lexicon in red has a sentiment score of approximately 15,000, identifying a relatively high positive emotional tone in the Airbnb summaries. The Bing lexicon in green and the NRC lexicon in blue, showing a sentiment score of around 12,000 and approximately 10,000, indicate a positive overall sentiment. *(Appendix 2)*

***3. "Correlation Heatmap of Numeric Variables"* visualization:** This correlation heatmap displays the pairwise correlations between different numeric variables in the Airbnb dataset. Strong positive correlations are visible between variables related to property size, such as bathrooms and beds. This indicates that listings with more bedrooms tend to have more bathrooms and can accommodate more guests. *(Appendix 3)*

***4. "Superhost vs. Non-Superhost Performance"* visualization:** The bar chart highlights that Superhosts positively impact guest engagement, as indicated by the higher average number of reviews and higher average review scores. However, the observation that the superhost has a smaller average price provides potential business insight implications: to promote superhosts and incentivize more hosts to go above and beyond. *(Appendix 4)*

***5. "Most Common Words in Airbnb Descriptions"* Word Cloud:** The word cloud summarizes key themes used in Airbnb listing descriptions, providing valuable insights for hosts to optimize their listings and attract more bookings like prominence of location, accessibility, and essential amenities indicating customer preference when searching for accommodations. *(Appendix 5)*

***6. Bigram Network of Neighborhood Descriptions*****:** The bigram network visualization effectively summarizes frequent relationships in the text data of neighborhood descriptions. It reveals clusters of terms like “coffee shops” and "Bondi Beach," offering insights into what makes neighborhoods desirable in Airbnb listings. The visualization can inform hosts about what features of their location they should emphasize in their descriptions to attract more bookings. *(Appendix 6)*

***7. “Top 20 Bigrams in Neighborhood Descriptions”*** **visualization:** This horizontal bar chart highlights the importance of walkability, proximity to key amenities, and locations in describing Airbnb neighborhoods and can influence how listings are worded. The bigram "walking distance" and “5 minutes” are used the most, clearly standing out as key elements in neighborhood descriptions. *(Appendix 7)*

## Airbnb Data Analysis Dashboard Summary

The dashboard combines filtering capabilities with visual and tabular data presentations to help users understand pricing patterns, review trends, and content themes data through multiple analytical perspectives. The interface is divided into two main components:

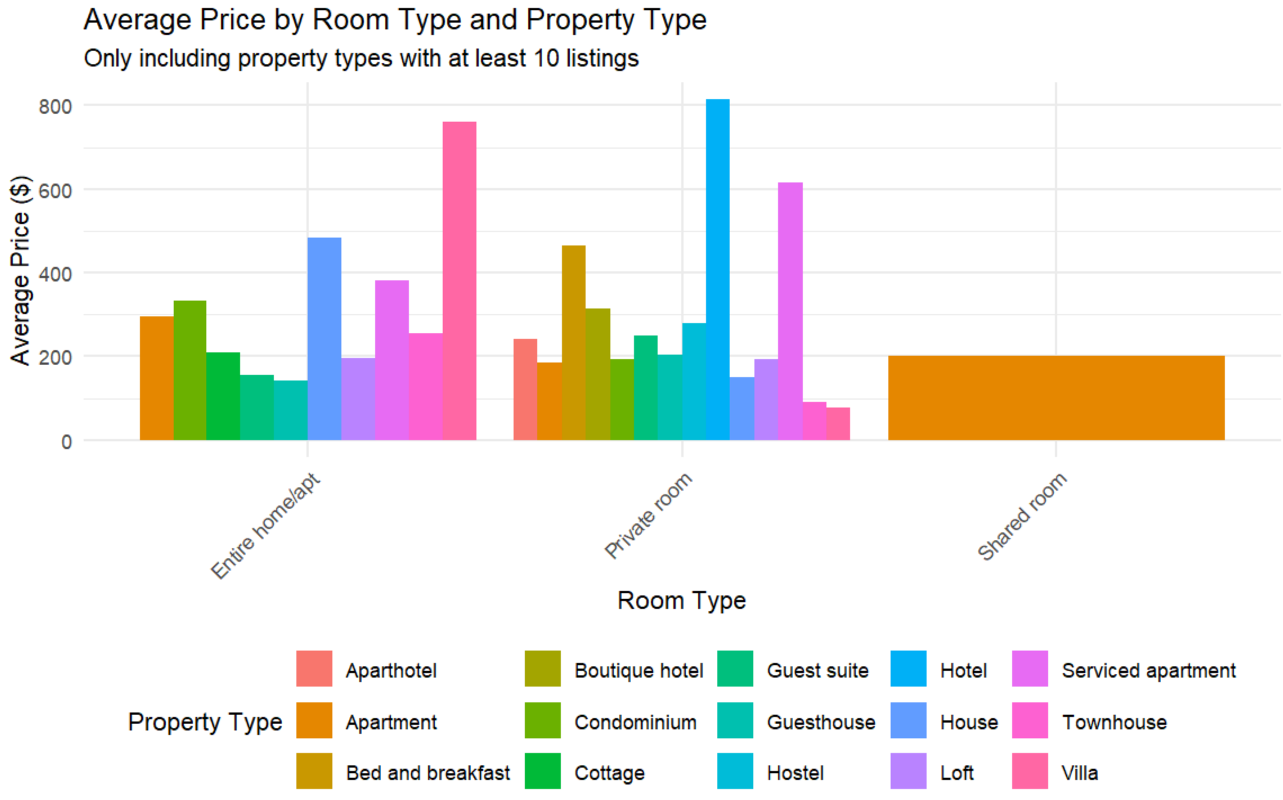
1. Sidebar Controls- This section includes a *room type selector, price range slider,* and *superhosts-only* checkbox.

2. Main Content Area- This section uses a tabbed interface to organize different analytical views like a price analysis tab (to compare average prices of rooms and properties), reviews tab (visualize review counts by room type), text analysis tab (a word cloud visualizing the most frequent terms in listing descriptions), and data table tab (comprehensive listing details including name, type, price, and amenities). *(Appendix 8.A, 8.B)*

This dashboard allows managers to make strategic decisions about Airbnb market positioning.

# Appendix

Appendix 1: Description of the "Average Price by Room Type and Property Type" visualization



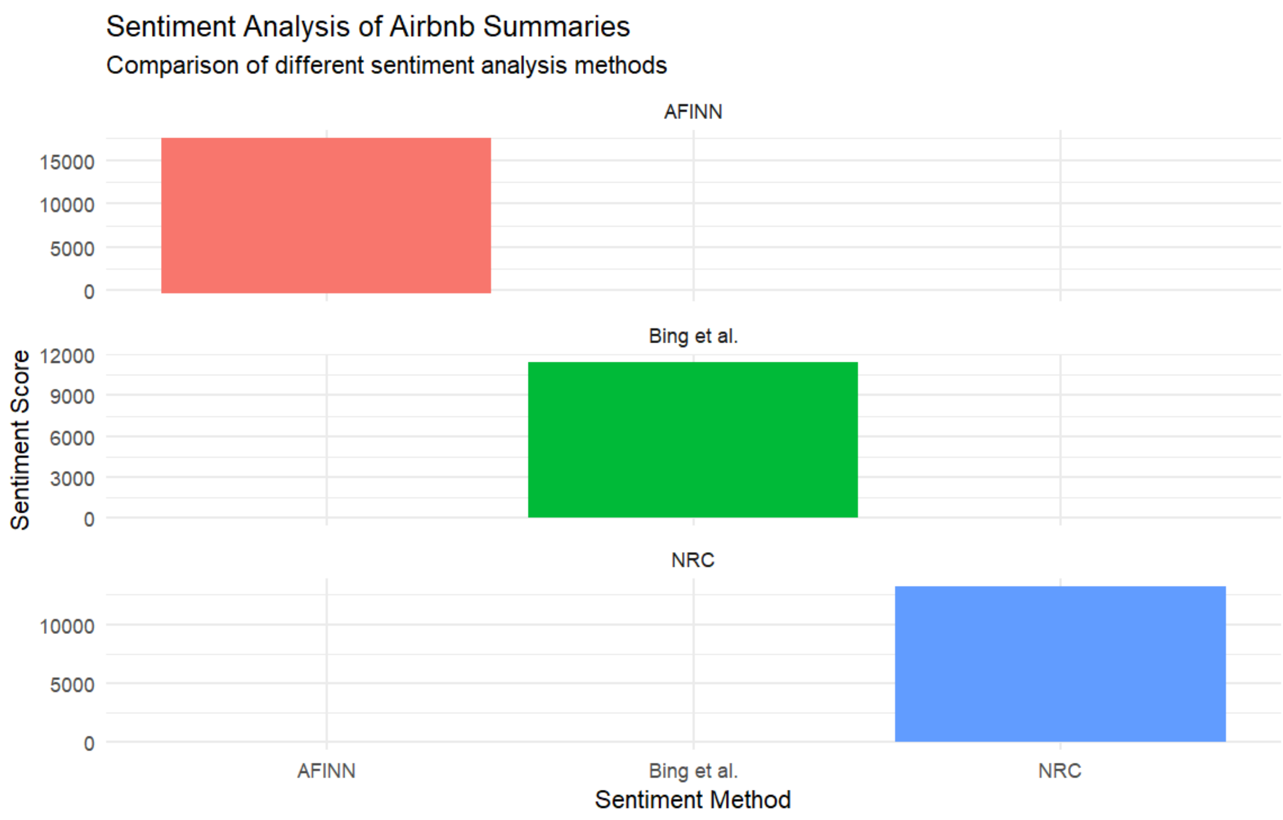

**Axes:**

- **X-axis**: Represents Room Type. The three room types are "Entire home/apt," "Private room," and "Shared room."
- **Y-axis**: Represents Average Price ($). The scale ranges from 0 to 800.

**Data Representation**:

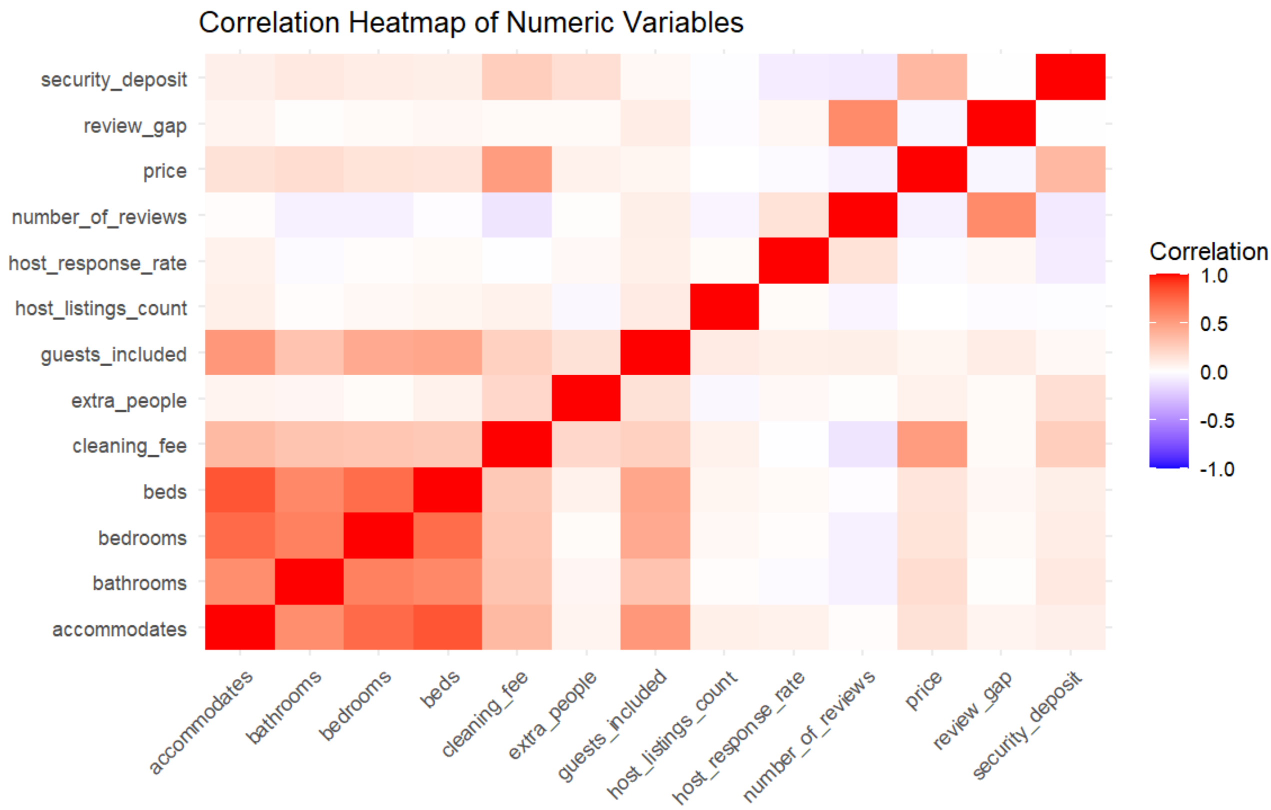
- Each bar represents a specific combination of room type and property type.
- The height of each bar corresponds to the average price for that combination.
- Bars are color-coded to distinguish between different property types, with a legend provided beneath the chart.

Appendix 2: Description of the sentiment analysis visualization for the Airbnb dataset:




The y-axis represents the **Sentiment Score**, and the x-axis represents the **Sentiment Method**.

Appendix 3: Description of the "Correlation Heatmap of Numeric Variables" visualization for the Airbnb dataset:



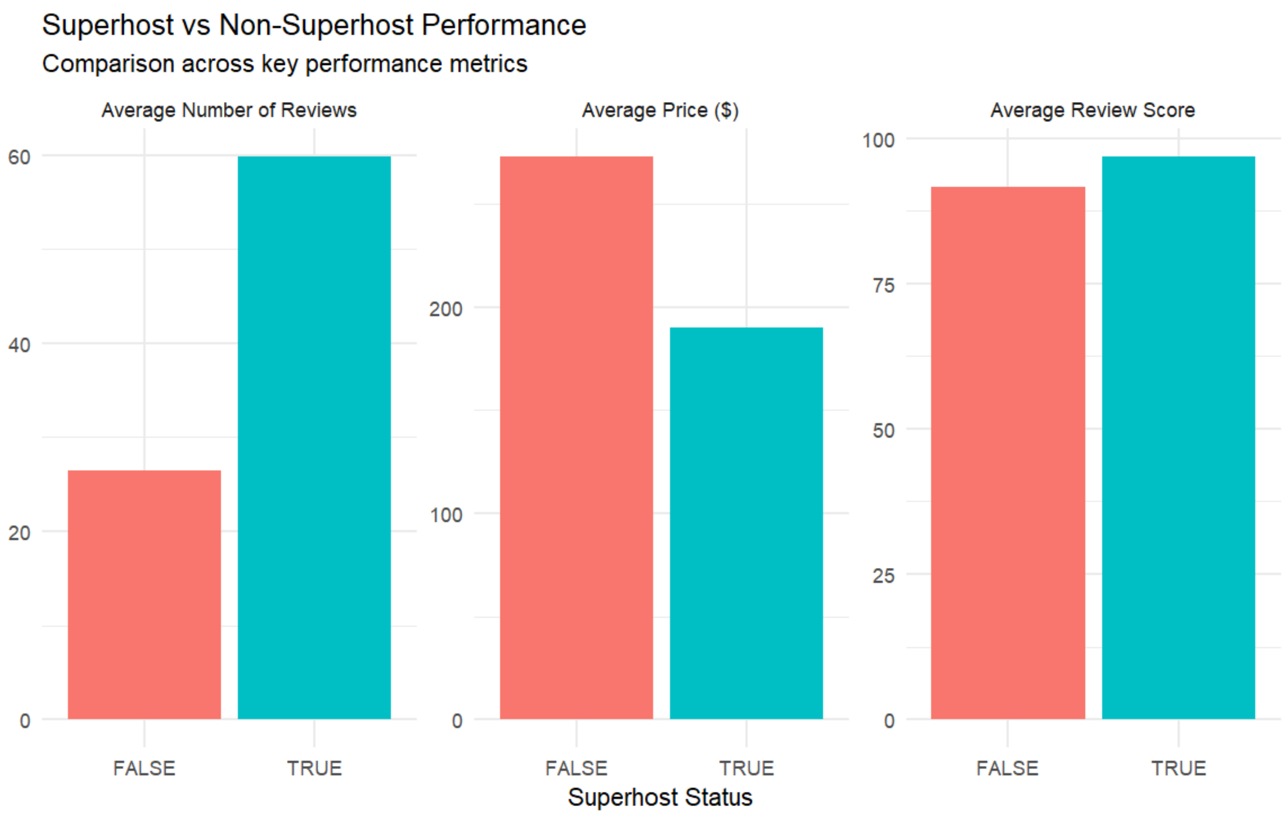

**Cells**: Each cell at the intersection of a row and a column represents the correlation coefficient between the two corresponding variables.

**Color Coding**: The cells are colored according to the strength and direction of the correlation:

- **Red** indicates a positive correlation. The intensity of the red color represents the strength of the positive correlation (darker red = stronger positive correlation).
- **White**: Indicates a correlation close to zero (no or very weak correlation).
- **Blue** Indicates a negative correlation. The intensity of the blue color represents the strength of the negative correlation (darker blue = stronger negative correlation).

**Color Scale**: A color scale (legend) is provided to the right of the heatmap, mapping the color intensities to correlation values ranging from -1.0 to 1.0.

Appendix 4: "Superhost vs Non-Superhost Performance: Comparison across key performance metrics", comparing the performance of Airbnb listings based on whether the host is a Superhost (TRUE) or not (FALSE)



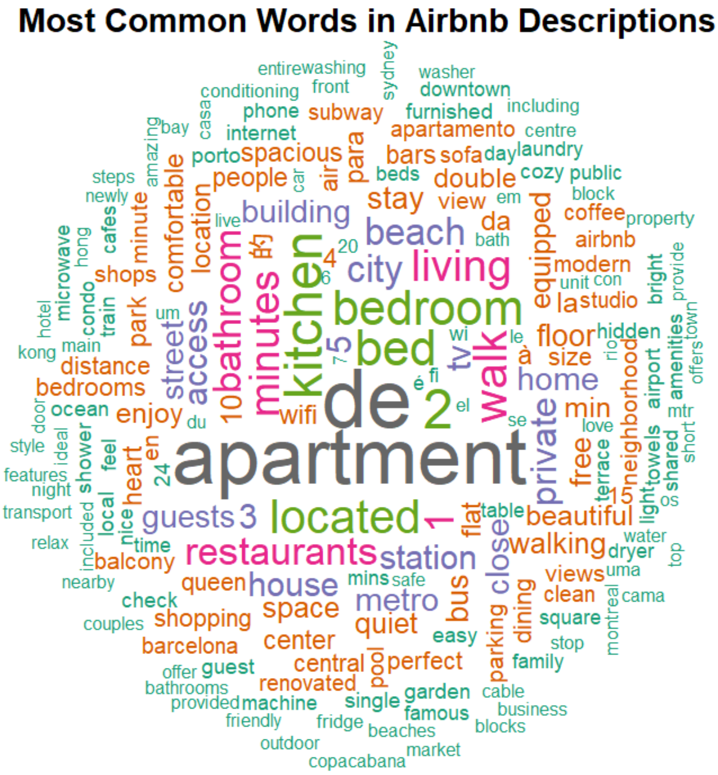

**X-axis**: Superhost Status (FALSE/TRUE).

*Average Number of Reviews:* **Y-axis**: *Average Number of Reviews.* The turquoise bar is significantly higher than the coral bar, indicating that listings managed by Superhosts tend to have a much higher average number of reviews than those managed by non-Superhosts.

*Average Price:* **Y-axis**: *Average Price.* On average, the listings managed by non-Superhosts have a higher price than those managed by Superhosts, possibly to break even owing to fewer customers.

*Average Review Score:* **Y-axis**: *Average Review Score.* The bar graph suggests that listings managed by Superhosts generally have higher average review scores.

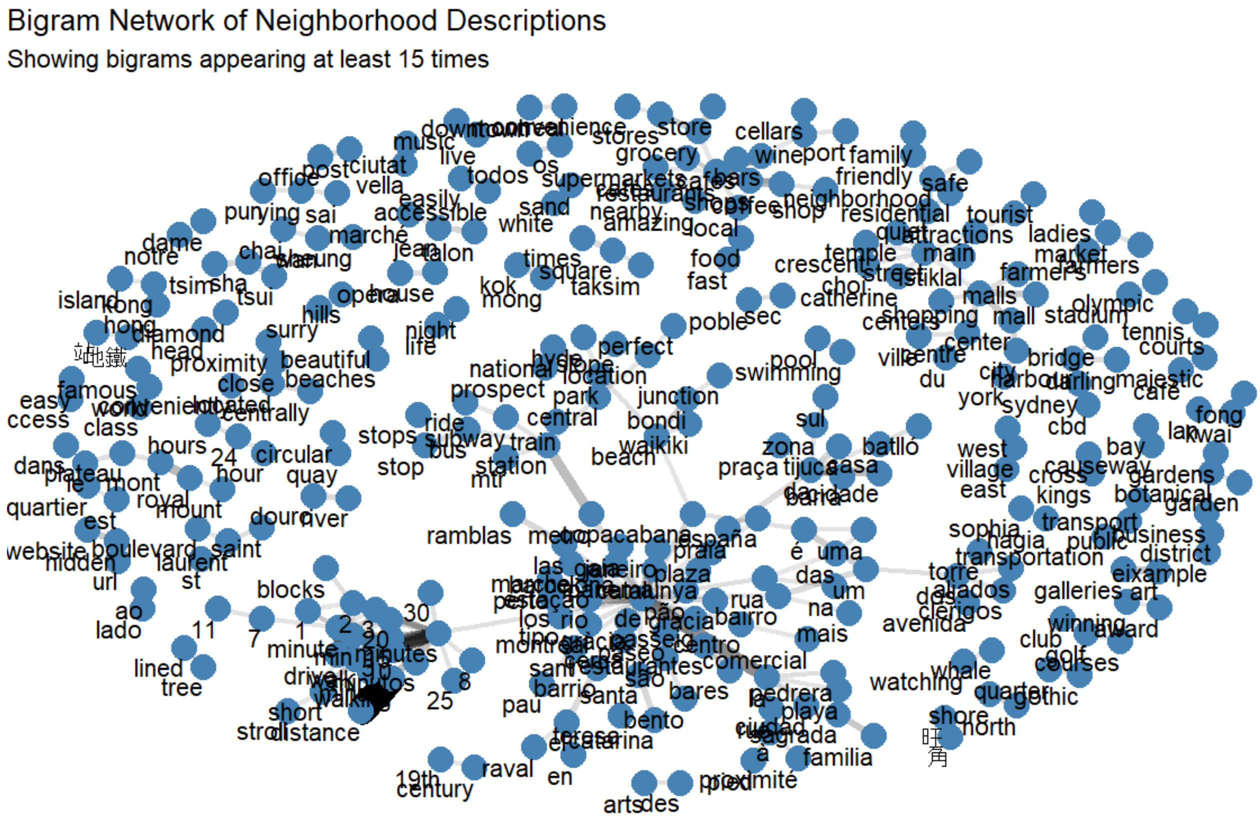
Appendix 5: **Word Cloud** titled “Most Common Words in Airbnb Descriptions.”




**Dominant Words**: Due to its size, the most prominent word is “apartment.” Other significant words include “minutes,” “located,” “restaurants,” “kitchen,” and “bedroom.” These suggest that descriptions often focus on property type, location, amenities, and the number of bedrooms.

**Descriptive Adjectives**: Adjectives like “beautiful,” “cozy,” “comfortable,” “modern,” and “quiet” give insight into how hosts are describing their properties to attract customers.

Appendix 6: **Bigram Network of Neighborhood Descriptions**

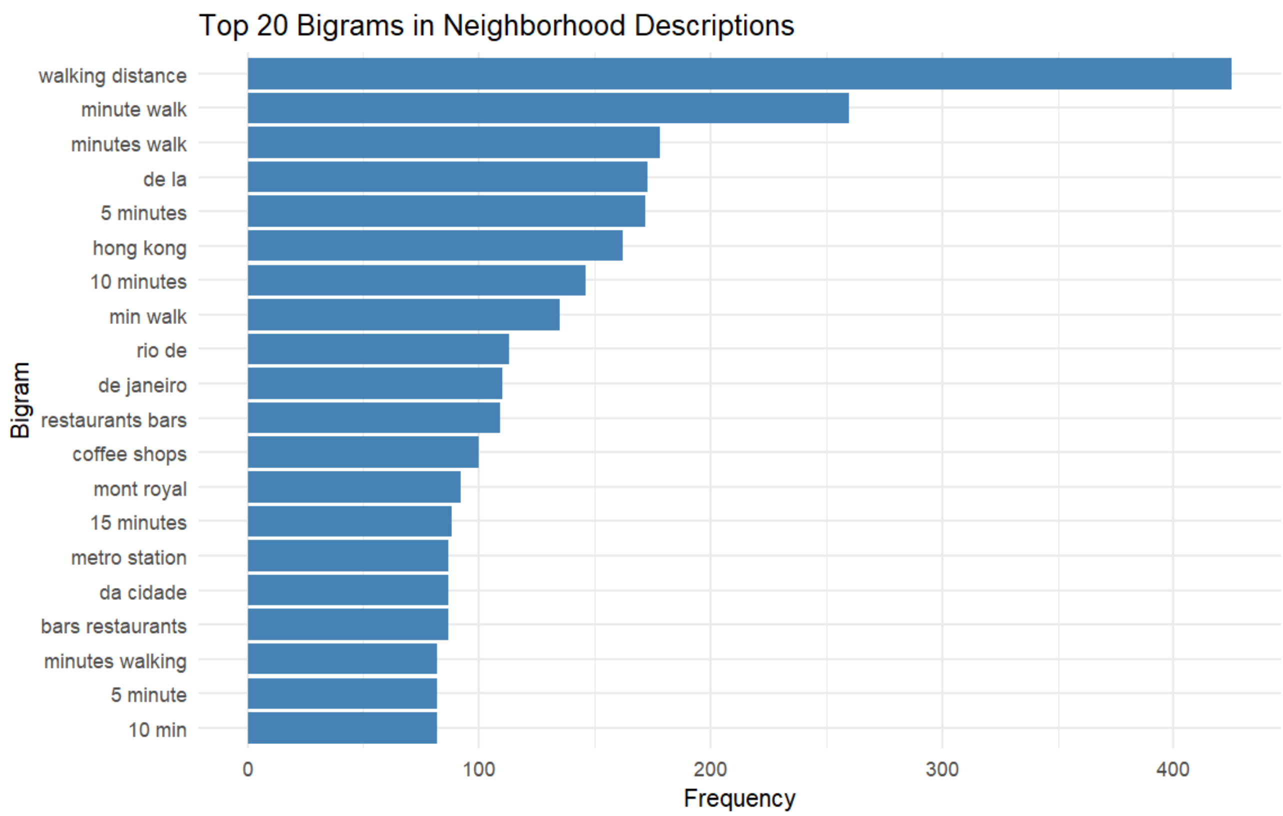



**Nodes:** Each word or phrase (bigram) is represented as a node (a blue circle). The label of each node is the bigram itself.

**Edges:** Lines connect the nodes, representing the co-occurrence of these words or phrases within the neighborhood descriptions. The thickness of the line suggests the frequency of their co-occurrence, with thicker lines indicating more frequent pairings.

**Layout:** The nodes are arranged in a force-directed layout where connected nodes are drawn closer together and disconnected nodes are pushed further apart. This allows clusters of related terms to emerge.

Appendix 7: Horizontal bar chart titled “Top 20 Bigrams in Neighborhood Descriptions”.



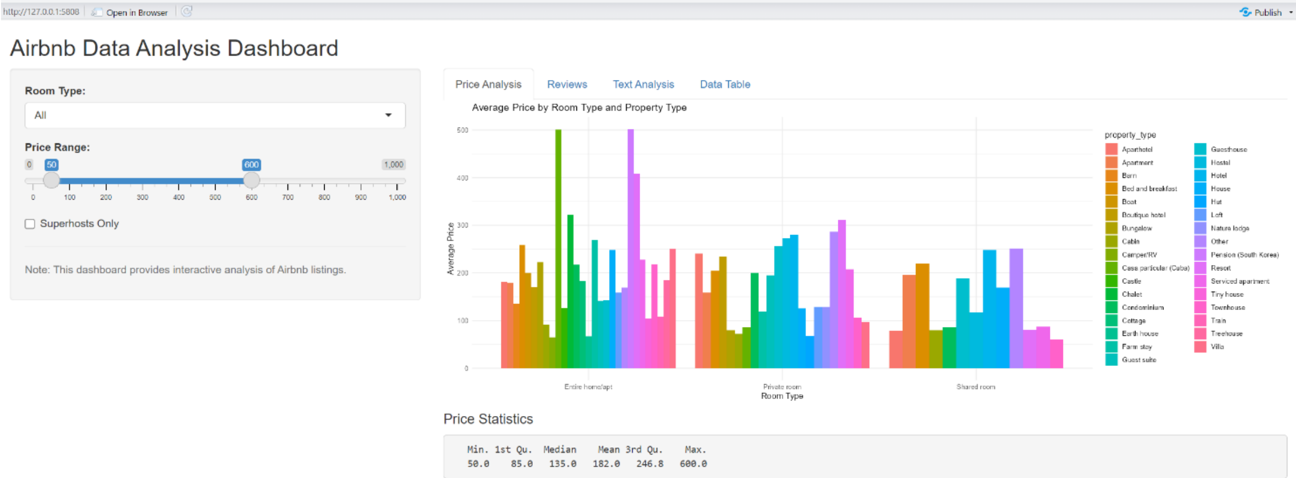

**Y-axis:** The y-axis lists the 20 most frequent bigrams. Each bigram is a pair of words often appearing together in the neighborhood descriptions. Examples include "walking distance," "minute walk," "restaurants bars," and location-specific phrases like "hong kong," "rio de," and "de janeiro." The bigrams are ordered from top to bottom according to frequency (highest to lowest).

**X-axis:** The x-axis represents the frequency or count of each bigram in the dataset. The scale extends from 0 to 400.

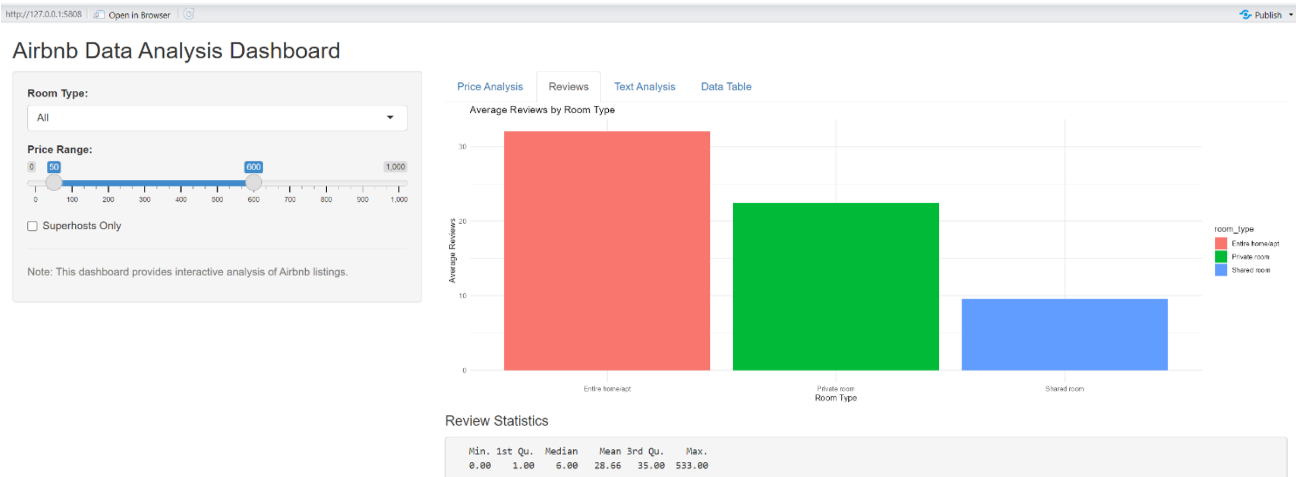
**Bars:** Each bigram has a horizontal bar extending from the y-axis to a point corresponding to its frequency on the x-axis. The bars are all colored in blue.

# Appendix 8.A: Description of the Airbnb Data Analysis Dashboard

## *Price Analysis Tab:*

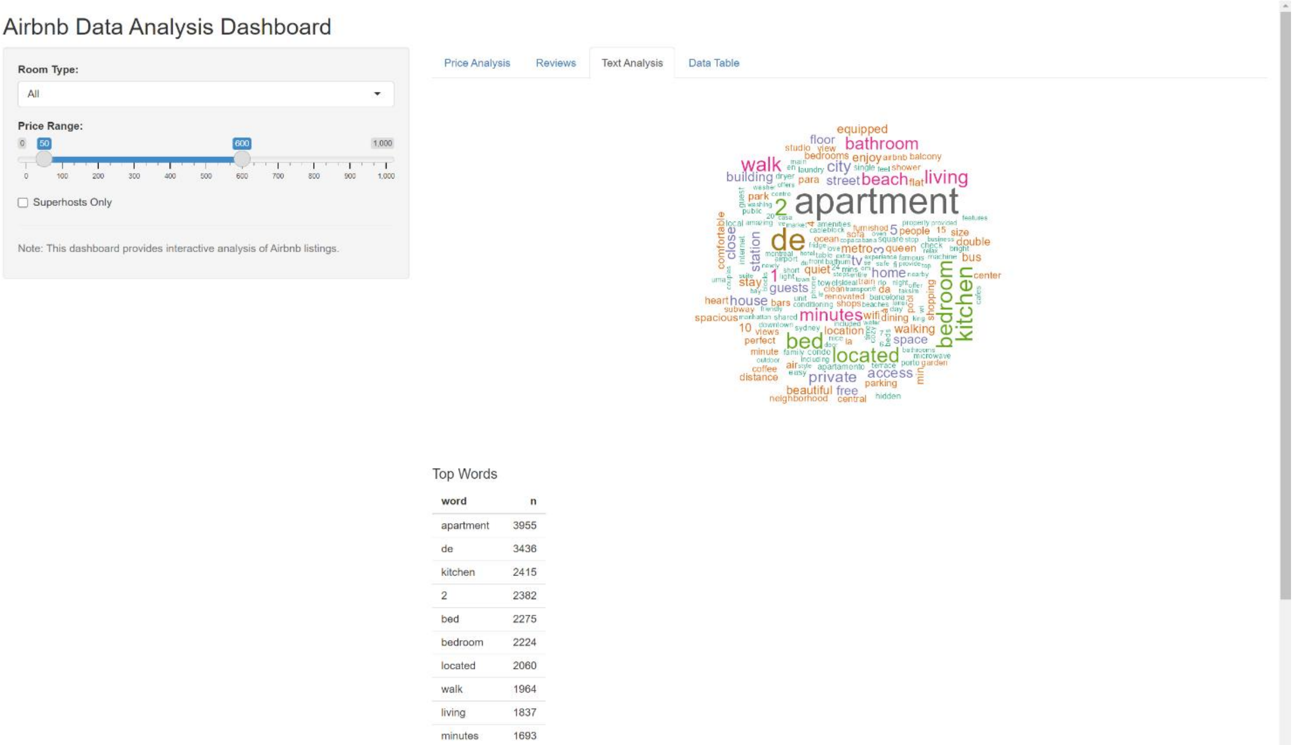



## *Reviews Tab:*

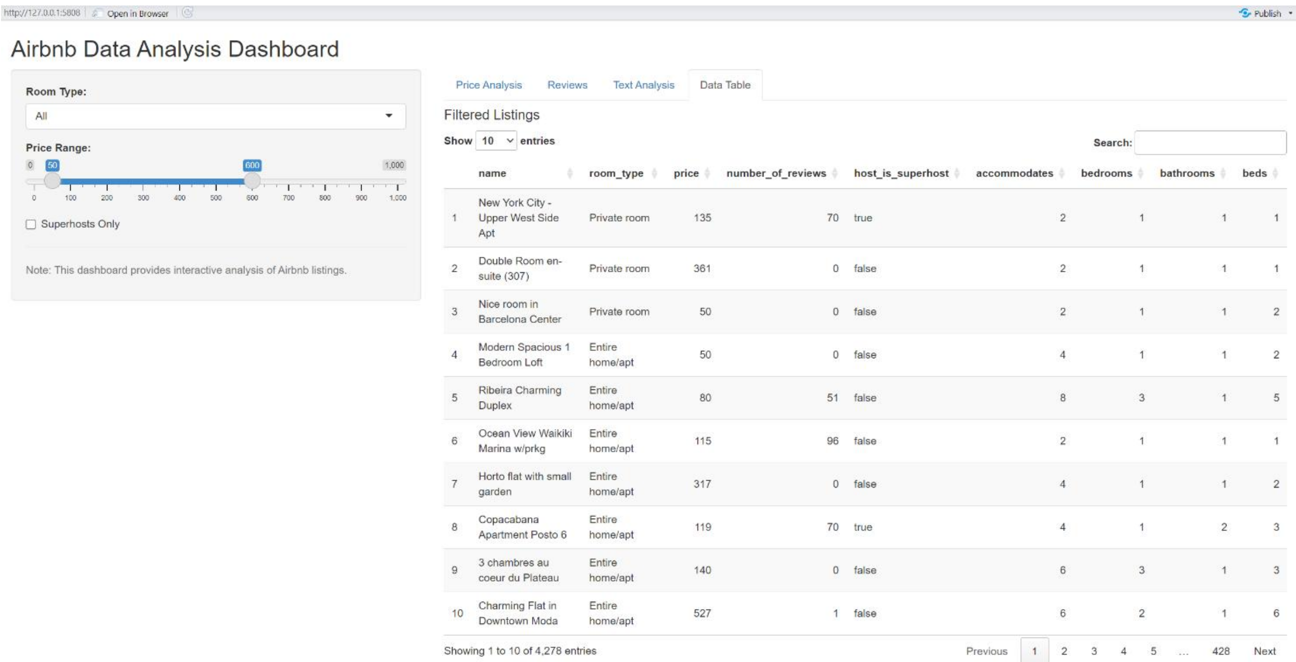


## Appendix 8.B: Description of the Airbnb Data Analysis Dashboard

### *Text Analysis Tab:*




### *Data Table Tab:*



Appendix 9: R-Script

Appendix 9.A: Setup and Configuration

```r
# ==============================================================================
# Assignment A1 : AIRBNB DATA ANALYSIS PIPELINE
# ==============================================================================
# Author: Tirthankar Mukherjee
# University: Hult International Business School
# Course: Business Analysis with Unstructured Data - DAT-7471 - FMBANDD1
# Program: Master of Business Analytics Dual Degree
# Professor: Thomas Kurnicki
# Date: March 13, 2025
# Description: Comprehensive analysis of Airbnb listing data to identify key
#              factors influencing listing performance and revenue
# ==============================================================================

#---------------------------------------------------------------------------
# ----------------- SETUP AND CONFIGURATION ------------------------------
#---------------------------------------------------------------------------
# Install required packages if not already installed
required_packages <- c("mongolite", "tidyverse", "tidytext", "wordcloud",
                       "ggplot2", "caret", "shiny", "lubridate", "dplyr",
                       "tidyr", "igraph", "ggraph", "RColorBrewer")

# Check and install missing packages
new_packages <- required_packages[!(required_packages %in% installed.packages()[,"Package"])]
if(length(new_packages) > 0) {
  install.packages(new_packages)
}

# Load all required libraries
lapply(required_packages, library, character.only = TRUE)

# Set default theme for consistent visualization
theme_set(theme_minimal())

```

Appendix 9.B: Data Connection and Loading

```
#-------------------------------------------------------------------------
# ----------------- DATA CONNECTION AND LOADING ---------------------------
#-------------------------------------------------------------------------
# MongoDB connection details
# Note: In production, consider storing credentials in environment variables
connection_string <- 'mongodb+srv://mukherjeetirthankar:tirthA25@a1textmining.9gdz0.mongodb.net/?retryWı

# Initialize MongoDB connection
airbnb_collection <- mongo(
  collection = "listingsAndReviews",
  db = "sample_airbnb",
  url = connection_string
)

# Function to clean and preprocess Airbnb data
clean_airbnb_data <- function(data) {
  # Data cleaning and type conversion
  data %>%
    mutate(
      # Convert currency string to numeric
      price = as.numeric(gsub("[\\$,]", "", price)),

      # Convert date strings to Date objects
      last_review = as.Date(last_review),
      first_review = as.Date(first_review),

      # Calculate duration between first and last review in days
      review_gap = as.numeric(difftime(last_review, first_review, units = "days")),

      # Extract and clean host response rate
      host_response_rate = as.numeric(gsub("%", "", host$host_response_rate)) / 100,

      # Convert listing details to numeric
      accommodates = as.numeric(accommodates),
      bedrooms = as.numeric(bedrooms),
      bathrooms = as.numeric(bathrooms),
      beds = as.numeric(beds),

      # Extract additional host information
      host_is_superhost = host$host_is_superhost,
      host_identity_verified = host$host_identity_verified,
      host_listings_count = as.numeric(host$host_listings_count)
    )
}

# Fetch and preprocess all data
# Warning: This operation may require significant memory
airbnb <- airbnb_collection$find() %>% clean_airbnb_data()
```

Appendix 9.C: Exploratory Data Analysis

```r
#-------------------------------------------------------------------------
#------------------- EXPLORATORY DATA ANALYSIS ---------------------------
#-------------------------------------------------------------------------

# Function to summarize dataset
summarize_dataset <- function(data) {
  # Basic dataset summary
  cat("Dataset Summary:\n")
  cat("Number of listings:", nrow(data), "\n")
  cat("Number of variables:", ncol(data), "\n")
  cat("Date range:", min(data$first_review, na.rm = TRUE), "to",
      max(data$last_review, na.rm = TRUE), "\n")

  # Missing values summary
  missing_values <- data %>%
    summarise(across(everything(), ~sum(is.na(.)))) %>%
    pivot_longer(everything(), names_to = "variable", values_to = "missing_count") %>%
    filter(missing_count > 0) %>%
    arrange(desc(missing_count))

  if(nrow(missing_values) > 0) {
    cat("\nVariables with missing values:\n")
    print(missing_values)
  }
}

# Run initial data summary
summarize_dataset(airbnb)
```

Appendix 9.D: Price Analysis

```
#-----------------------------------------------------------------------------
# -------------------- PRICE ANALYSIS -----------------------------------
#-----------------------------------------------------------------------------
# Analyze how price varies by room type and property type
price_analysis <- airbnb %>%
  # Group data for aggregation
  group_by(room_type, property_type) %>%
  # Calculate metrics for each group
  summarise(
    avg_price = mean(price, na.rm = TRUE),
    median_price = median(price, na.rm = TRUE),
    min_price = min(price, na.rm = TRUE),
    max_price = max(price, na.rm = TRUE),
    total_listings = n(),
    avg_reviews = mean(number_of_reviews, na.rm = TRUE),
    .groups = "drop"  # Drop grouping after summarization
  ) %>%
  # Filter out uncommon property types for clearer visualization
  filter(total_listings >= 10)

# Visualization: Average Price by Room Type and Property Type
plot_price_by_room_property <- function(data) {
  ggplot(data, aes(x = room_type, y = avg_price, fill = property_type)) +
    geom_bar(stat = "identity", position = "dodge") +
    labs(
      title = "Average Price by Room Type and Property Type",
      subtitle = "Only including property types with at least 10 listings",
      x = "Room Type",
      y = "Average Price ($)",
      fill = "Property Type"
    ) +
    theme(
      axis.text.x = element_text(angle = 45, hjust = 1),
      legend.position = "bottom",
      legend.box = "horizontal"
    )
}

# Generate and display the price analysis plot
plot_price_by_room_property(price_analysis)


```

Appendix 9.E: Host Performance Analysis

```r
#---------------------------------------------------------------------------
#---------------- HOST PERFORMANCE ANALYSIS -----------------------------
#---------------------------------------------------------------------------
# Analyze how host characteristics affect listing performance
host_performance <- airbnb %>%
  # Filter out entries with missing response rate
  filter(!is.na(host$host_response_rate)) %>%
  # Group by superhost status
  group_by(host_is_superhost) %>%
  # Calculate metrics for each group
  summarise(
    avg_response_rate = mean(host_response_rate, na.rm = TRUE),
    avg_price = mean(price, na.rm = TRUE),
    avg_reviews = mean(number_of_reviews, na.rm = TRUE),
    avg_review_scores = mean(review_scores$review_scores_rating, na.rm = TRUE),
    total_listings = n(),
    .groups = "drop"
  )

# Visualization: Superhost vs Non-Superhost Performance
plot_superhost_performance <- function(data) {
  # Prepare data for visualization by pivoting to long format
  plot_data <- data %>%
    select(host_is_superhost, avg_price, avg_reviews, avg_review_scores) %>%
    pivot_longer(
      cols = c(avg_price, avg_reviews, avg_review_scores),
      names_to = "metric",
      values_to = "value"
    ) %>%
    mutate(
      # Create readable labels for the metrics
      metric = case_when(
        metric == "avg_price" ~ "Average Price ($)",
        metric == "avg_reviews" ~ "Average Number of Reviews",
        metric == "avg_review_scores" ~ "Average Review Score",
        TRUE ~ metric
      )
    )

  # Create the plot
  ggplot(plot_data, aes(x = host_is_superhost, y = value, fill = host_is_superhost)) +
    geom_bar(stat = "identity") +
    facet_wrap(~ metric, scales = "free_y") +
    labs(
      title = "Superhost vs Non-Superhost Performance",
      subtitle = "Comparison across key performance metrics",
      x = "Superhost Status",
      y = NULL
    ) +
    theme(legend.position = "none")
}

# Generate and display the host performance plot
plot_superhost_performance(host_performance)
```

Appendix 9.F: Text Mining on Descriptions

```r
#---------------------------------------------------------------------------
#---------------- TEXT MINING ON DESCRIPTIONS ----------------------------
#---------------------------------------------------------------------------
# Process and analyze listing descriptions to identify key terms

# Function to process text and remove stop words
process_text <- function(data, text_column, id_column = "name") {
  data %>%
    select(!!sym(id_column), !!sym(text_column)) %>%
    # Filter out missing text values
    filter(!is.na(!!sym(text_column))) %>%
    # Tokenize text into individual words
    unnest_tokens(word, !!sym(text_column)) %>%
    # Remove stop words that don't add meaning
    anti_join(stop_words) %>%
    # Count word frequency
    count(word, sort = TRUE)
}

# Process descriptions for analysis
description_tokens <- process_text(airbnb, "description")

# Create word cloud of most common words in descriptions
create_wordcloud <- function(token_data, max_words = 200, title = "Word Cloud") {
  # Set up plotting device
  par(mar = c(0, 0, 2, 0))

  # Generate word cloud
  wordcloud(
    words = token_data$word,
    freq = token_data$n,
    max.words = max_words,
    colors = brewer.pal(8, "Dark2"),
    random.order = FALSE,
    rot.per = 0.35,
    scale = c(3, 0.5)
  )

  # Add title
  title(main = title)
}

# Generate and display the description word cloud
create_wordcloud(
  description_tokens,
  max_words = 200,
  title = "Most Common Words in Airbnb Descriptions"
)
```

Appendix 9.G: Sentiment Analysis

```r
#---------------- SENTIMENT ANALYSIS ON LISTING SUMMARIES ----------------
#-------------------------------------------------------------------------
# Analyze the sentiment of listing summaries to identify emotional tone

# Function to perform sentiment analysis using multiple lexicons
analyze_sentiment <- function(token_data) {
  # AFINN sentiment analysis (numerical scores)
  afinn_sentiment <- token_data %>%
    inner_join(get_sentiments("afinn")) %>%
    group_by(name) %>%
    summarise(sentiment = sum(value), .groups = "drop") %>%
    mutate(method = "AFINN")

  # Bing and NRC sentiment analysis (categorical)
  bing_and_nrc_sentiment <- bind_rows(
    # Bing lexicon (positive/negative)
    token_data %>%
      inner_join(get_sentiments("bing")) %>%
      mutate(method = "Bing et al."),

    # NRC lexicon (positive/negative only)
    token_data %>%
      inner_join(get_sentiments("nrc") %>%
                   filter(sentiment %in% c("positive", "negative"))) %>%
      mutate(method = "NRC")
  ) %>%
    # Count positive and negative words
    count(method, sentiment) %>%
    # Reshape data for visualization
    pivot_wider(names_from = sentiment, values_from = n, values_fill = 0) %>%
    # Calculate net sentiment
    mutate(sentiment = positive - negative)

  # Combine results from different methods
  bind_rows(afinn_sentiment, bing_and_nrc_sentiment)
}

# Process and tokenize summaries
summary_tokens <- airbnb %>%
  select(name, summary) %>%
  filter(!is.na(summary)) %>%
  unnest_tokens(word, summary) %>%
  filter(!is.na(word)) %>%
  anti_join(stop_words)

# Perform sentiment analysis
combined_sentiments <- analyze_sentiment(summary_tokens)

# Visualization: Sentiment Analysis Results
plot_sentiment_analysis <- function(sentiment_data) {
  ggplot(sentiment_data, aes(method, sentiment, fill = method)) +
    geom_col(show.legend = FALSE) +
    facet_wrap(~method, ncol = 1, scales = "free_y") +
    labs(
```

517:1 (Untitled) R Script

Appendix 9.H: Neighborhood Bigram Analysis

```r
#---------------------- NEIGHBORHOOD BIGRAM ANALYSIS ---------------------------
#-------------------------------------------------------------------------------
# Analyze neighborhood descriptions using bigrams to identify location features

# Function to process text into n-grams
process_ngrams <- function(data, text_column, n = 2, id_column = "name", min_count = 1) {
  # Create ngrams from text
  ngrams <- data %>%
    filter(!is.na(!!sym(text_column))) %>%
    unnest_tokens(
      ngram,
      !!sym(text_column),
      token = "ngrams",
      n = n
    )

  # For bigrams, separate into component words and filter stop words
  if (n == 2) {
    ngrams <- ngrams %>%
      separate(ngram, c("word1", "word2"), sep = " ") %>%
      filter(!word1 %in% stop_words$word) %>%
      filter(!word2 %in% stop_words$word) %>%
      filter(!is.na(word1) & !is.na(word2)) %>%
      count(word1, word2, sort = TRUE) %>%
      filter(n >= min_count)
  } else {
    # For other n-grams, just count occurrences
    ngrams <- ngrams %>%
      count(ngram, sort = TRUE) %>%
      filter(n >= min_count)
  }

  return(ngrams)
}

# Process neighborhood descriptions into bigrams
neighborhood_bigrams <- process_ngrams(
  airbnb,
  "neighborhood_overview",
  n = 2,
  min_count = 10
)

# Visualization: Top Bigrams Bar Chart
plot_top_bigrams <- function(bigram_data, top_n = 20) {
  bigram_data %>%
    head(top_n) %>%
    unite(bigram, word1, word2, sep = " ") %>%
    ggplot(aes(x = reorder(bigram, n), y = n)) +
    geom_col(fill = "steelblue") +
    coord_flip() +
    labs(
      title = paste("Top", top_n, "Bigrams in Neighborhood Descriptions"),
      x = "Bigram",
```

```r
# Visualization: Bigram Network Graph
plot_bigram_network <- function(bigram_data, min_count = 10) {
  # Filter bigrams by minimum count
  filtered_bigrams <- bigram_data %>%
    filter(n >= min_count)

  # Create network graph
  bigram_graph <- filtered_bigrams %>%
    graph_from_data_frame()

  # Plot the graph
  ggraph(bigram_graph, layout = "fr") +
    geom_edge_link(aes(edge_alpha = n, edge_width = n), show.legend = FALSE) +
    geom_node_point(color = "steelblue", size = 5) +
    geom_node_text(aes(label = name), vjust = 1.5, hjust = 1) +
    labs(
      title = "Bigram Network of Neighborhood Descriptions",
      subtitle = paste("Showing bigrams appearing at least", min_count, "times")
    ) +
    theme_void()
}

# Generate and display the bigram network
plot_bigram_network(neighborhood_bigrams, min_count = 15)

```

Appendix 9.I: TF-IDF Analysis

```r
#-------------------------------------------------------------------------
#----------------------- TF-IDF ANALYSIS ------------------------------
#-------------------------------------------------------------------------

# Identify distinctive terms in neighborhood descriptions using TF-IDF

# Function to perform TF-IDF analysis on bigrams
analyze_tfidf <- function(data, text_column, grouping_var = "neighborhood_cleansed") {
  # Process text into bigrams
  bigrams <- data %>%
    filter(!is.na(!!sym(text_column)) & !is.na(!!sym(grouping_var))) %>%
    unnest_tokens(
      bigram,
      !!sym(text_column),
      token = "ngrams",
      n = 2
    ) %>%
    separate(bigram, c("word1", "word2"), sep = " ") %>%
    filter(!word1 %in% stop_words$word) %>%
    filter(!word2 %in% stop_words$word) %>%
    filter(!is.na(word1) & !is.na(word2)) %>%
    unite(bigram, word1, word2, sep = " ")

  # Calculate TF-IDF
  bigrams %>%
    count(!!sym(grouping_var), bigram) %>%
    bind_tf_idf(bigram, !!sym(grouping_var), n) %>%
    arrange(desc(tf_idf))
}

# Analyze TF-IDF if neighborhood_cleansed is available
if ("neighborhood_cleansed" %in% names(airbnb)) {
  neighborhood_tfidf <- analyze_tfidf(
    airbnb,
    "neighborhood_overview",
    "neighborhood_cleansed"
  )

  # Display top TF-IDF terms by neighborhood
  top_tfidf_terms <- neighborhood_tfidf %>%
    group_by(neighborhood_cleansed) %>%
    slice_max(order_by = tf_idf, n = 5) %>%
    ungroup()

  print(top_tfidf_terms)
}
```

Appendix 9.J: Correlation Analysis

```r
#---------------------------------------------------------------------------
#----------------------- CORRELATION ANALYSIS ---------------------------
#---------------------------------------------------------------------------
# Analyze correlations between numeric variables

# Function to calculate correlations between numeric variables
calculate_correlations <- function(data) {
  # Select numeric columns
  numeric_cols <- data %>%
    select(where(is.numeric)) %>%
    # Remove columns with too many NAs
    select_if(function(x) mean(!is.na(x)) > 0.5)

  # Calculate correlation matrix
  cor_matrix <- cor(numeric_cols, use = "pairwise.complete.obs")

  # Convert to long format for visualization
  cor_data <- as.data.frame(cor_matrix) %>%
    rownames_to_column("variable1") %>%
    pivot_longer(-variable1, names_to = "variable2", values_to = "correlation")

  return(cor_data)
}

# Calculate correlations
correlations <- calculate_correlations(airbnb)

# Visualization: Correlation Heatmap
plot_correlation_heatmap <- function(cor_data) {
  ggplot(cor_data, aes(x = variable1, y = variable2, fill = correlation)) +
    geom_tile() +
    scale_fill_gradient2(
      low = "blue",
      mid = "white",
      high = "red",
      midpoint = 0,
      limits = c(-1, 1)
    ) +
    theme(
      axis.text.x = element_text(angle = 45, hjust = 1),
      axis.title = element_blank()
    ) +
    labs(
      title = "Correlation Heatmap of Numeric Variables",
      fill = "Correlation"
    )
}

# Generate and display correlation heatmap
plot_correlation_heatmap(correlations)
```