cse351_hw2_iqbal_fardin_114866279

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0.1 Set up

[ ]:
```python
# --- Importing Required Libraries ---
import re
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from wordcloud import WordCloud
import matplotlib as mpl
from collections import Counter

# Set a clean, professional style
plt.style.use('seaborn-v0_8-whitegrid')

# Typography settings
plt.rcParams['font.family'] = 'sans-serif'
plt.rcParams['font.sans-serif'] = ['Arial', 'Helvetica', 'DejaVu Sans']
plt.rcParams['font.size'] = 12
plt.rcParams['axes.titlesize'] = 16
plt.rcParams['axes.labelsize'] = 14
plt.rcParams['xtick.labelsize'] = 12
plt.rcParams['ytick.labelsize'] = 12
plt.rcParams['legend.fontsize'] = 12

# Figure settings
plt.rcParams['figure.figsize'] = (12, 8)
plt.rcParams['figure.dpi'] = 100
plt.rcParams['figure.autolayout'] = True

# Axes settings
plt.rcParams['axes.spines.top'] = False
plt.rcParams['axes.spines.right'] = False
plt.rcParams['axes.grid'] = True
plt.rcParams['axes.grid.which'] = 'major'
plt.rcParams['axes.grid.axis'] = 'y'
plt.rcParams['grid.alpha'] = 0.3
plt.rcParams['grid.linestyle'] = '--'
```

```python
# Color palette - colorblind friendly
custom_colors = [
    '#4e79a7', '#f28e2c', '#e15759', '#76b7b2',
    '#59a14f', '#edc949', '#af7aa1', '#ff9da7',
    '#9c755f', '#bab0ab'
]
sns.set_palette(custom_colors)


# Define a styling function for consistent plot appearance
def style_plot(ax, title=None, xlabel=None, ylabel=None):
    """Apply consistent styling to plots"""
    if title:
        ax.set_title(title, fontweight='bold', pad=20)
    if xlabel:
        ax.set_xlabel(xlabel, labelpad=10)
    if ylabel:
        ax.set_ylabel(ylabel, labelpad=10)

    ax.set_facecolor('#f8f9fa')

    for spine in ax.spines.values():
        spine.set_linewidth(0.5)
        spine.set_color('#cccccc')

    return ax
```

0.2 LOADING THE DATASET

[ ]:
```python
def load_new_york_city_airbnb_dataset(file_path):
    """
    Loads the New York City Airbnb dataset from a given CSV file path.
    This function prints basic information to confirm successful loading.

    Parameters:
        file_path (str): Path to the CSV file containing the New York City␣
↪Airbnb dataset.

    Returns:
        pandas.DataFrame: A DataFrame containing the raw Airbnb data.
    """
    try:
        print(f"Loading New York City Airbnb dataset from: {file_path}")
        raw_new_york_city_airbnb_data = pd.read_csv(file_path)
        print(
            f"Successfully loaded the dataset with "
```

```
            f"{raw_new_york_city_airbnb_data.shape[0]:,} rows and␣
↪{raw_new_york_city_airbnb_data.shape[1]} columns."
        )
        return raw_new_york_city_airbnb_data
    except FileNotFoundError:
        print(f"Error: File '{file_path}' not found. Please check the file path.
↪")
        return None
    except Exception as error:
        print(f"Error loading data: {str(error)}")
        return None


# Adjust the file path as needed if your CSV is located elsewhere.
raw_new_york_city_airbnb_data = load_new_york_city_airbnb_dataset('AB_NYC_2019.
↪csv')

if raw_new_york_city_airbnb_data is not None:
    # Create a visual separator for better readability
    print("\n" + "=" * 60)
    print("NEW YORK CITY AIRBNB DATASET OVERVIEW".center(60))
    print("=" * 60)

    # Displaying basic info to get a sense of the dataset's shape and columns
    print("\n--- Basic Dataset Info ---")
    raw_new_york_city_airbnb_data.info()

    # Check for missing values
    missing_values_count = raw_new_york_city_airbnb_data.isnull().sum()
    if missing_values_count.sum() > 0:
        print("\n--- Missing Values Summary ---")
        print(missing_values_count[missing_values_count > 0].to_string())

    print("\n--- First 5 Rows of the Dataset ---")
    display(raw_new_york_city_airbnb_data.head())

    print("\n--- Summary Statistics (Numerical Columns) ---")
    display(raw_new_york_city_airbnb_data.describe().round(2))

    # Add data types distribution for better understanding
    print("\n--- Data Types Distribution ---")
    print(raw_new_york_city_airbnb_data.dtypes.value_counts().to_string())

    # Add a quick column overview
    print("\n--- Column Names and Types ---")
    for column_name, data_type in zip(raw_new_york_city_airbnb_data.columns,␣
↪raw_new_york_city_airbnb_data.dtypes):
```

```
        print(f"- {column_name}: {data_type}")
```

0.3 Task 1: Data Cleaning

To prepare the NYC Airbnb dataset for analysis, I performed a series of data cleaning steps to handle missing values, outliers, and potential inconsistencies. Below is a summary of the cleaning process:

0.3.1 Missing Values

- **`name`**: Replaced missing values with `"Unnamed Listing"` to retain rows without breaking downstream tasks.
- **`host_name`**: Filled missing entries with `"Unknown Host"` to preserve data integrity.
- **`reviews_per_month`**: Filled missing values with `0`, since listings without reviews logically have zero reviews per month.
- **`last_review`**: Converted to datetime format; missing values were left as `NaT` since they indicate no reviews — this is valid.

0.3.2 Outlier Handling

- **`price`**:
  - Visualized the price distribution.
  - Removed listings with prices greater than $10,000 (none were found).
  - Removed any negative prices (none found).
- **`minimum_nights`**:
  - Visualized the distribution.
  - Removed listings with `minimum_nights` > 365, which are likely errors or anomalies.

0.3.3 Duplicates

- Checked for exact duplicate rows and removed them (none were found).

0.3.4 Data Integrity Checks

- Confirmed valid values for `neighbourhood_group` and `room_type`.
- Re-checked for missing values after cleaning.

0.3.5 Summary

- **Original dataset shape**: 48,895 rows × 16 columns
- **Cleaned dataset shape**: 48,881 rows × 16 columns
- **Total rows removed**: 14 (due to extreme `minimum_nights`)

[ ]:
```
def clean_new_york_city_airbnb_dataset(original_dataframe):
    """
    Cleans the New York City Airbnb dataset by handling missing values,␣
 ↪removing outliers,
    fixing inconsistencies, and checking for duplicates.

```

```
    Parameters:
        original_dataframe (pandas.DataFrame): The original New York City␣
↪Airbnb dataset to clean.

    Returns:
        pandas.DataFrame: A DataFrame that has been cleaned of major issues.
    """
    print("\n--- Task 1: Data Cleaning ---")

    # Work on a copy of the dataset to preserve the original
    cleaned_dataframe = original_dataframe.copy()

    # Step 1: Identify missing values
    print("\nMissing values in each column (only those with > 0 missing):")
    missing_value_counts = cleaned_dataframe.isnull().sum()
    print(missing_value_counts[missing_value_counts > 0])

    # Step 2: Fix missing 'name' entries
    cleaned_dataframe['name'].fillna('Unnamed Listing', inplace=True)

    # Step 3: Fix missing 'host_name' entries
    cleaned_dataframe['host_name'].fillna('Unknown Host', inplace=True)

    # Step 4: Deal with missing 'reviews_per_month' (0 if no reviews)
    cleaned_dataframe['reviews_per_month'].fillna(0, inplace=True)

    # Step 5: Convert 'last_review' to datetime
    cleaned_dataframe['last_review'] = pd.
↪to_datetime(cleaned_dataframe['last_review'], errors='coerce')

    # Step 6: Check for extreme values in 'price'
    print("\nPrice statistics before handling extreme outliers:")
    print(cleaned_dataframe['price'].describe())

    fig, ax = plt.subplots()
    sns.histplot(cleaned_dataframe['price'], bins=50, kde=True, ax=ax)
    style_plot(ax, title='Price Distribution Before Removing Extreme Outliers',
               xlabel='Price (USD)', ylabel='Frequency')
    ax.set_xlim(0, 1000)
    plt.show()

    # Remove absurdly high prices
    price_threshold = 10000
    high_price_listings = cleaned_dataframe['price'] > price_threshold
    print(f"\nListings with price > ${price_threshold}: {high_price_listings.
↪sum()}")
```

```python
    cleaned_dataframe = cleaned_dataframe[cleaned_dataframe['price'] <= price_threshold]

    # Remove negative prices
    negative_price_listings = cleaned_dataframe['price'] < 0
    print(f"Listings with negative prices: {negative_price_listings.sum()}")
    cleaned_dataframe = cleaned_dataframe[cleaned_dataframe['price'] >= 0]

    # Step 7: Check for unrealistic minimum_nights values
    print("\nMinimum Nights statistics before removing outliers:")
    print(cleaned_dataframe['minimum_nights'].describe())

    fig, ax = plt.subplots()
    sns.histplot(cleaned_dataframe['minimum_nights'], bins=50, kde=True, ax=ax)
    style_plot(ax, title='Minimum Nights Distribution Before Removing Outliers',
               xlabel='Minimum Nights', ylabel='Frequency')
    ax.set_xlim(0, 100)
    plt.show()

    # Remove listings with unrealistic minimum_nights
    minimum_nights_threshold = 365
    outlier_minimum_nights = cleaned_dataframe['minimum_nights'] > minimum_nights_threshold
    print(f"\nListings with minimum_nights > {minimum_nights_threshold}: {outlier_minimum_nights.sum()}")
    cleaned_dataframe = cleaned_dataframe[cleaned_dataframe['minimum_nights'] <= minimum_nights_threshold]

    # Step 8: Check for duplicates
    duplicate_count = cleaned_dataframe.duplicated().sum()
    print(f"\nDuplicate rows found: {duplicate_count}")

    if duplicate_count > 0:
        cleaned_dataframe = cleaned_dataframe.drop_duplicates()
        print("Duplicate rows have been removed.")

    # Step 9: Basic integrity checks
    print("\nUnique Neighborhood Groups found:")
    print(cleaned_dataframe['neighbourhood_group'].unique())

    print("\nUnique Room Types found:")
    print(cleaned_dataframe['room_type'].unique())

    # Final check for missing data after cleaning
    print("\nAny remaining missing values after cleaning:")
    remaining_missing_values = cleaned_dataframe.isnull().sum()
    print(remaining_missing_values[remaining_missing_values > 0])
```

```
    # Summary of data cleaning process
    print("\nSummary of cleaning process:")
    print(f"Original shape: {original_dataframe.shape}")
    print(f"Cleaned shape: {cleaned_dataframe.shape}")
    print(f"Rows removed: {original_dataframe.shape[0] - cleaned_dataframe.
 ↪shape[0]}")

    return cleaned_dataframe


# Call the cleaning function and store the result
final_cleaned_new_york_city_airbnb_data =␣
 ↪clean_new_york_city_airbnb_dataset(raw_new_york_city_airbnb_data)
```

0.4 Task 2a: Top 5 and Bottom 5 Neighborhoods by Price

In this analysis, I examined how average Airbnb prices vary across individual neighborhoods (by the `neighbourhood` field), filtering out neighborhoods with fewer than 5 listings to ensure statistical reliability.

0.4.1 What I Did:

- Grouped listings by `neighbourhood` and calculated:
  - **Average**, **median**, **minimum**, and **maximum** prices
  - **Listing count** for each neighborhood
- Filtered out neighborhoods with 5 listings
- Extracted the:
  - **Top 5 most expensive neighborhoods**
  - **Bottom 5 cheapest neighborhoods**
- Created:
  - A **dual bar chart** showing both groups with:
    - Average price labels
    - Listing counts
    - Price range indicators (min-max bars)
  - A **combined bar chart** comparing both groups side-by-side:
    - Highlighting median price (dashed white lines)

0.4.2 Results:

Top 5 Most Expensive Neighborhoods (by average price):

Neighborhood	Avg Price	Median Price	Listings
Tribeca	$490.64	$295	177
Sea Gate	$487.86	$125	7
Riverdale	$442.09	$150	11
Battery Park City	$367.09	$195	69
Flatiron District	$341.92	$225	80

Neighborhood	Avg Price	Median Price	Listings

Bottom 5 Least Expensive Neighborhoods:

Neighborhood	Avg Price	Median Price	Listings
Bull's Head	$47.33	$45	6
Hunts Point	$50.50	$40	18
Tremont	$51.55	$41	11
Soundview	$53.47	$49	15
Bronxdale	$57.11	$50	19

0.4.3 Key Takeaways

- **Tribeca** had the **highest average price** at **$490.64**, followed closely by **Sea Gate** ($487.86) and **Riverdale** ($442.09).
- **Bull's Head** had the **lowest average price** at just **$47.33**.
- Significant gaps between **average** and **median** prices in neighborhoods like **Sea Gate** and **Riverdale** suggest **price skewness** — likely caused by a few very expensive listings.
- Including **listing counts** provides important context:
  - **Tribeca's** high average is supported by **177 listings** (statistically robust).
  - **Sea Gate** had only **7 listings**, making its high average more susceptible to outliers.

[79]:
```
def analyze_top_bottom_neighborhoods(df):
    """
    Analyzes and identifies the top 5 and bottom 5 neighborhoods based on␣
↪average price,
    considering only neighborhoods with more than 5 listings. Displays␣
↪annotated visualizations
    and summarizes key findings.

    Parameters:
        df (pandas.DataFrame): Cleaned Airbnb DataFrame.

    Returns:
        tuple: (top_5_neighborhoods, bottom_5_neighborhoods) DataFrames
    """
    print("\n" + "=" * 80)
    print("TASK 2a: TOP AND BOTTOM NEIGHBORHOODS BY PRICE".center(80))
    print("=" * 80)

    # Filter neighborhoods with more than 5 listings
    neighborhood_counts = df.groupby('neighbourhood').size()
    valid_neighborhoods = neighborhood_counts[neighborhood_counts > 5].index
    filtered_df = df[df['neighbourhood'].isin(valid_neighborhoods)]
```

```python
    print(f"\nAnalyzing {len(valid_neighborhoods)} neighborhoods with more than␣
↪5 listings...")

    # Compute statistics for each neighborhood
    neighborhood_prices = filtered_df.groupby('neighbourhood').agg(
        average_price=('price', 'mean'),
        median_price=('price', 'median'),
        min_price=('price', 'min'),
        max_price=('price', 'max'),
        listing_count=('id', 'count')
    ).reset_index()

    # Round monetary columns for cleaner display
    price_columns = ['average_price', 'median_price', 'min_price', 'max_price']
    neighborhood_prices[price_columns] = neighborhood_prices[price_columns].
↪round(2)

    # Extract top 5 and bottom 5 neighborhoods based on average price
    top_5 = neighborhood_prices.sort_values('average_price', ascending=False).
↪head(5)
    bottom_5 = neighborhood_prices.sort_values('average_price', ascending=True).
↪head(5)

    # Display results clearly
    print("\n" + "-" * 40)
    print("TOP 5 MOST EXPENSIVE NEIGHBORHOODS".center(40))
    print("-" * 40)
    display(top_5)

    print("\n" + "-" * 40)
    print("BOTTOM 5 LEAST EXPENSIVE NEIGHBORHOODS".center(40))
    print("-" * 40)
    display(bottom_5)

    # --- Visualization Settings ---
    top_color = '#e15759'   # Red tone for expensive
    bottom_color = '#4CAF50'   # Green tone for affordable

    # --- HORIZONTAL BAR CHART (much more readable) ---
    import matplotlib.patches as mpatches

    fig, ax = plt.subplots(figsize=(14, 10), dpi=120)

    # Concatenate data and assign category labels
    combined = pd.concat([
        top_5.assign(category='Most Expensive'),
        bottom_5.assign(category='Least Expensive')
```

```
])

# Create positions for horizontal bars
y_positions = list(range(len(combined)))

# Map colors based on category
colors = [top_color if cat == 'Most Expensive' else bottom_color for cat in␣
↪combined['category']]

# Create horizontal bar plot
hbars = ax.barh(
    y=y_positions,
    width=combined['average_price'],
    color=colors,
    edgecolor='white',
    linewidth=1.2,
    height=0.7
)

# Set neighborhood names as y-tick labels (no rotation needed)
ax.set_yticks(y_positions)
ax.set_yticklabels(combined['neighbourhood'], fontsize=12)

# Add a subtle grid only on the x-axis
ax.xaxis.grid(True, linestyle='--', alpha=0.3, color='#cccccc')
ax.set_axisbelow(True)

# Remove top and right spines
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)

# Add average price labels at the end of each bar
for i, bar in enumerate(hbars):
    width = bar.get_width()
    ax.text(
        width + 5,  # Position just outside the bar
        bar.get_y() + bar.get_height() / 2,
        f"${width:.0f}",
        va='center',
        ha='left',
        fontsize=11,
        fontweight='bold',
        color='#333333'
    )

# Add median markers and labels (consistently positioned)
for i, row in enumerate(combined.itertuples()):
```

```
        # Draw median line
        ax.plot(
            [row.median_price, row.median_price],
            [y_positions[i] - 0.3, y_positions[i] + 0.3],
            color='white',
            linestyle='--',
            linewidth=2
        )

        # Add median label (always below the bar)
        ax.text(
            row.median_price,
            y_positions[i] - 0.4,  # Consistent position below the bar
            f"Median: ${row.median_price:.0f}",
            ha='center',
            va='top',
            fontsize=10,
            color='black',
            bbox=dict(
                facecolor='white',
                edgecolor='#cccccc',
                boxstyle='round,pad=0.3',
                alpha=0.9
            )
        )

    # Add listing counts inside bars
    for i, row in enumerate(combined.itertuples()):
        # Only add text if bar is wide enough
        if row.average_price > 50:  # Minimum width for text
            ax.text(
                row.average_price / 2,  # Middle of the bar
                y_positions[i],
                f"{row.listing_count} listings",
                ha='center',
                va='center',
                fontsize=10,
                fontweight='bold',
                color='white'
            )
        else:
            # For narrow bars, place text outside
            ax.text(
                5,  # Just at the start of the bar
                y_positions[i],
                f"{row.listing_count}",
                ha='left',
```

```
            va='center',
            fontsize=10,
            fontweight='bold',
            color='white'
        )

# Add category labels to separate the groups
ax.text(
    combined['average_price'].max() * 0.5,
    len(top_5) - 0.5,
    "MOST EXPENSIVE",
    ha='center',
    va='center',
    fontsize=14,
    fontweight='bold',
    color=top_color,
    bbox=dict(
        facecolor='white',
        edgecolor=top_color,
        boxstyle='round,pad=0.3',
        alpha=0.8
    )
)

ax.text(
    combined['average_price'].max() * 0.5,
    len(top_5) + len(bottom_5) - 0.5,
    "LEAST EXPENSIVE",
    ha='center',
    va='center',
    fontsize=14,
    fontweight='bold',
    color=bottom_color,
    bbox=dict(
        facecolor='white',
        edgecolor=bottom_color,
        boxstyle='round,pad=0.3',
        alpha=0.8
    )
)

# Axis labels and title
ax.set_xlabel("Average Price (USD)", fontsize=13, labelpad=10)
ax.set_title("Price Comparison: Most vs Least Expensive Neighborhoods",
             fontsize=17, fontweight='bold', pad=20)

# Add explanatory annotation
```

```python
    fig.text(
        0.5, 0.01,
        "Note: White dashed lines represent median prices. Bars show average␣
↪prices.",
        ha='center',
        fontsize=10,
        fontstyle='italic'
    )

    plt.tight_layout(rect=[0, 0.03, 1, 0.97])
    plt.savefig('neighborhood_price_comparison_horizontal.png', dpi=300,␣
↪bbox_inches='tight')
    plt.show()

    return top_5, bottom_5


# Call Function
top_5_neighborhoods, bottom_5_neighborhoods =␣
↪analyze_top_bottom_neighborhoods(final_cleaned_new_york_city_airbnb_data)
```

```
================================================================================
                TASK 2a: TOP AND BOTTOM NEIGHBORHOODS BY PRICE
================================================================================

Analyzing 190 neighborhoods with more than 5 listings…

----------------------------------------
   TOP 5 MOST EXPENSIVE NEIGHBORHOODS
----------------------------------------

         neighbourhood  average_price  median_price  min_price  max_price  \
170            Tribeca         490.64         295.0         60       8500
150           Sea Gate         487.86         125.0         71       1485
144          Riverdale         442.09         150.0         49       2500
5     Battery Park City         367.09         195.0         55       7500
68    Flatiron District         341.92         225.0         65       2000

     listing_count
170            177
150              7
144             11
5               69
68              80


----------------------------------------
```

```
 BOTTOM 5 LEAST EXPENSIVE NEIGHBORHOODS
----------------------------------------

    neighbourhood  average_price  median_price  min_price  max_price  \
24    Bull's Head          47.33          45.0         25         80
90    Hunts Point          50.50          40.0         35        150
169       Tremont          51.55          41.0         25        150
154     Soundview          53.47          49.0         28        103
21      Bronxdale          57.11          50.0         25        100

     listing_count
24               6
90              18
169             11
154             15
21              19
```

0.5 Task 2b: Price Variation by Neighborhood Group

To explore broader regional trends, I analyzed average Airbnb prices across **neighborhood groups** rather than individual neighborhoods. This provides insight into how borough-level location influences price levels.

0.5.1 What I Did:

- Grouped listings by `neighbourhood_group`
- Calculated:
  - Average price
  - Median price
  - Min & Max price
  - Number of listings per group
- Plotted:
  - A **bar chart** of average prices
  - A **boxplot** showing price distributions (filtered under $1000 for clarity)

0.5.2 Observations:

- **Manhattan** has the highest average price, followed by **Brooklyn** and **Staten Island**.
- **Bronx** and **Queens** are the most affordable on average.
- Boxplots show wider price variation in **Manhattan** and **Brooklyn**, likely due to outliers.

0.5.3 Key Findings:

- **Highest average price**: Manhattan ($196.88)
- **Lowest average price**: Bronx ($87.50)
- **Price difference between highest and lowest**: $109.38

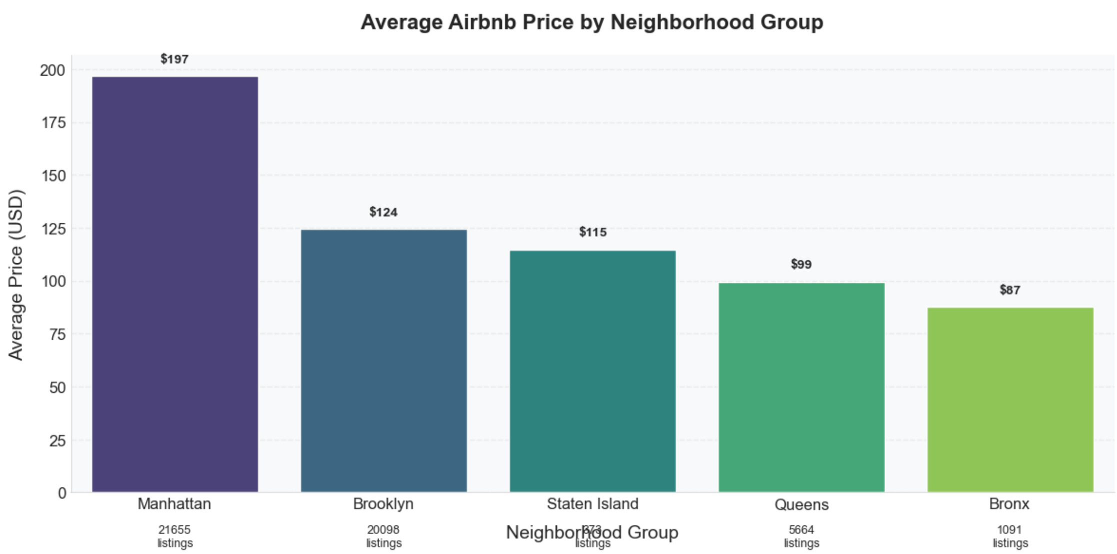
[80]:
```
def analyze_price_by_neighborhood_group(df):
    """
    Analyzes price variation across different neighborhood groups
    and visualizes the trend using average prices and price distributions.

    Parameters:
        df (pandas.DataFrame): Cleaned Airbnb DataFrame.

    Returns:
        pandas.DataFrame: Grouped price summary statistics by neighborhood␣
    ↪group.
    """
    print("\n--- Task 2b: Price Variation Across Neighborhood Groups ---")

    # Group by neighborhood group and compute summary stats
    group_prices = df.groupby('neighbourhood_group').agg(
        average_price=('price', 'mean'),
        median_price=('price', 'median'),
        min_price=('price', 'min'),
        max_price=('price', 'max'),
        listing_count=('id', 'count')
    ).reset_index()

    # Sort neighborhood groups by average price
```

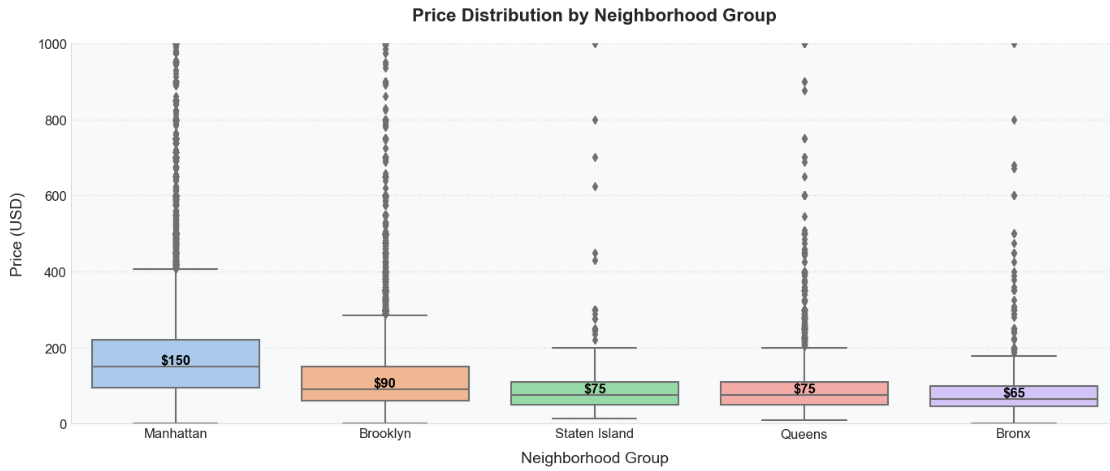
```
    group_prices_sorted = group_prices.sort_values('average_price',␣
↪ascending=False)
    ordered_groups = group_prices_sorted['neighbourhood_group']

    print("\nNeighborhood Group Price Summary:")
    display(group_prices_sorted)

    # === Plot 1: Bar plot of average prices ===
    plt.figure(figsize=(12, 6), dpi=100)
    ax = sns.barplot(
        data=group_prices_sorted,
        x='neighbourhood_group',
        y='average_price',
        palette='viridis',
        order=ordered_groups
    )
    style_plot(ax,
               title='Average Airbnb Price by Neighborhood Group',
               xlabel='Neighborhood Group',
               ylabel='Average Price (USD)')

    # Add value labels on bars
    for i, v in enumerate(group_prices_sorted['average_price']):
        ax.text(i, v + 5, f"${v:.0f}", ha='center', va='bottom', fontsize=10,␣
↪fontweight='bold')

    # Add listing count below each bar
    for i, (count, group) in␣
↪enumerate(zip(group_prices_sorted['listing_count'], ordered_groups)):
        ax.text(i, -15, f"{count}\nlistings", ha='center', va='top', fontsize=9)

    plt.tight_layout()
    plt.show()

    # === Plot 2: Box plot of price distribution ===
    plt.figure(figsize=(14, 6), dpi=100)
    ax = sns.boxplot(
        data=df,
        x='neighbourhood_group',
        y='price',
        palette='pastel',
        order=ordered_groups
    )
    style_plot(ax,
               title='Price Distribution by Neighborhood Group',
               xlabel='Neighborhood Group',
               ylabel='Price (USD)')
```

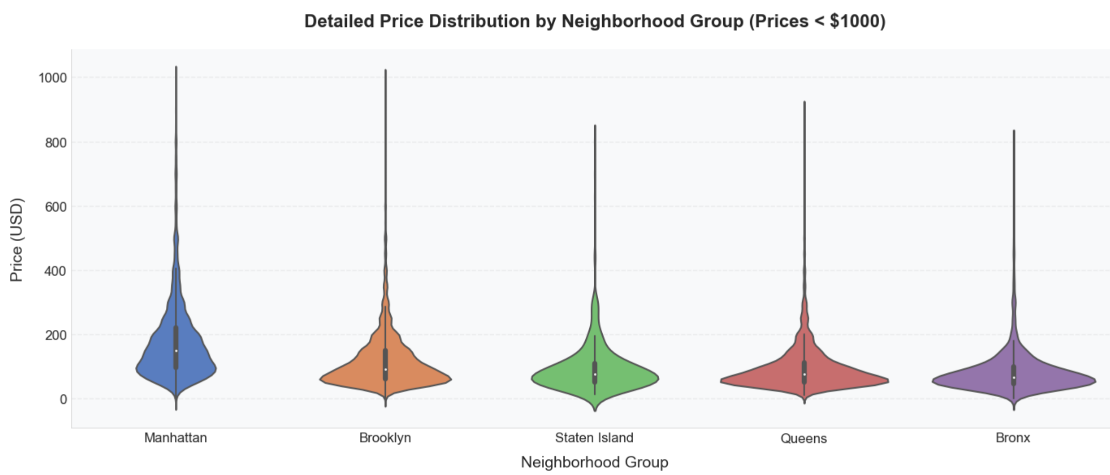
```
    # Add median price labels
    medians = df.groupby('neighbourhood_group')['price'].median()
    for i, median in enumerate(medians[ordered_groups]):
        ax.text(i, median, f'${median:.0f}', ha='center', va='bottom',␣
↪fontweight='bold', color='black')

    plt.ylim(0, 1000)  # Limit y-axis to focus on majority of data
    plt.tight_layout()
    plt.show()

    # === Plot 3: Violin plot for detailed price distribution ===
    plt.figure(figsize=(14, 6), dpi=100)
    ax = sns.violinplot(
        data=df[df['price'] < 1000],  # Filter extreme prices for better␣
↪visualization
        x='neighbourhood_group',
        y='price',
        palette='muted',
        order=ordered_groups
    )
    style_plot(ax,
               title='Detailed Price Distribution by Neighborhood Group (Prices␣
↪< $1000)',
               xlabel='Neighborhood Group',
               ylabel='Price (USD)')

    plt.tight_layout()
    plt.show()

    print("\nKey Findings:")
    print(
        f"• Highest average price: {group_prices_sorted.
↪iloc[0]['neighbourhood_group']} (${group_prices_sorted.
↪iloc[0]['average_price']:.2f})")
    print(
        f"• Lowest average price: {group_prices_sorted.
↪iloc[-1]['neighbourhood_group']} (${group_prices_sorted.
↪iloc[-1]['average_price']:.2f})")
    print(
        f"• Price difference between highest and lowest: ${group_prices_sorted.
↪iloc[0]['average_price'] - group_prices_sorted.iloc[-1]['average_price']:.
↪2f}")

    return group_prices_sorted
```

```python
# Call the function
neighborhood_group_price_summary = analyze_price_by_neighborhood_group(final_cleaned_new_york_city_airbnb_data)
```

```
--- Task 2b: Price Variation Across Neighborhood Groups ---

Neighborhood Group Price Summary:
  neighbourhood_group  average_price  median_price  min_price  max_price  \
2           Manhattan     196.878919         150.0          0      10000
1            Brooklyn     124.396507          90.0          0      10000
4       Staten Island     114.812332          75.0         13       5000
3              Queens      99.493997          75.0         10      10000
0               Bronx      87.496792          65.0          0       2500

   listing_count
2          21655
1          20098
4            373
3           5664
0           1091
```








```
Key Findings:
• Highest average price: Manhattan ($196.88)
• Lowest average price: Bronx ($87.50)
• Price difference between highest and lowest: $109.38
```

0.6 Task 3: Pairwise Pearson Correlation Analysis

In this task, I analyzed how various numerical features in the Airbnb dataset correlate with each other using **Pearson correlation coefficients**. This helps identify linear relationships between variables.

0.6.1 What I Did:

- Computed the **Pearson correlation matrix** for relevant numerical columns, such as:

  - price, minimum_nights, number_of_reviews, reviews_per_month, availability_365
- Visualized correlations using:
  - A **heatmap** of the correlation matrix
  - A **pairplot** to explore pairwise relationships
  - Two individual scatter plots showing the strongest positive and negative correlations

0.6.2 Key Correlation Insights:

- **Most Positive Correlation**: number_of_reviews and reviews_per_month = **0.59**
  - As the number of total reviews increases, the average number of reviews per month also tends to increase.
- **Most Negative Correlation**: minimum_nights and reviews_per_month = **-0.15**
  - Listings with higher minimum stay requirements tend to receive fewer reviews per month.

0.6.3 Interpretation:

- The positive correlation between review-related variables suggests consistency in engagement: highly reviewed listings continue to attract attention.
- The negative correlation with minimum_nights implies that restrictive stay durations may reduce booking frequency.

[81]:
```
def analyze_and_visualize_correlations(dataframe):
    """
    Calculates a Pearson correlation matrix for selected numeric features,
    displays a heatmap, and identifies the pairs with the most positive
    and most negative correlations.

    Parameters:
        dataframe (pandas.DataFrame): Cleaned DataFrame of Airbnb listings.

    Returns:
        pandas.DataFrame: The correlation matrix.
    """
    print("\n--- Task 3: Pairwise Pearson Correlation Analysis ---")

    # Select relevant numeric columns for correlation analysis
    # We choose these columns as they represent key quantitative aspects of␣
↪Airbnb listings
    selected_numeric_columns = [
        'price',  # Cost per night
        'minimum_nights',  # Minimum stay duration
        'number_of_reviews',  # Total review count
        'reviews_per_month',  # Review frequency
        'calculated_host_listings_count',  # Number of listings by the same host
        'availability_365'  # Days available per year
    ]
```

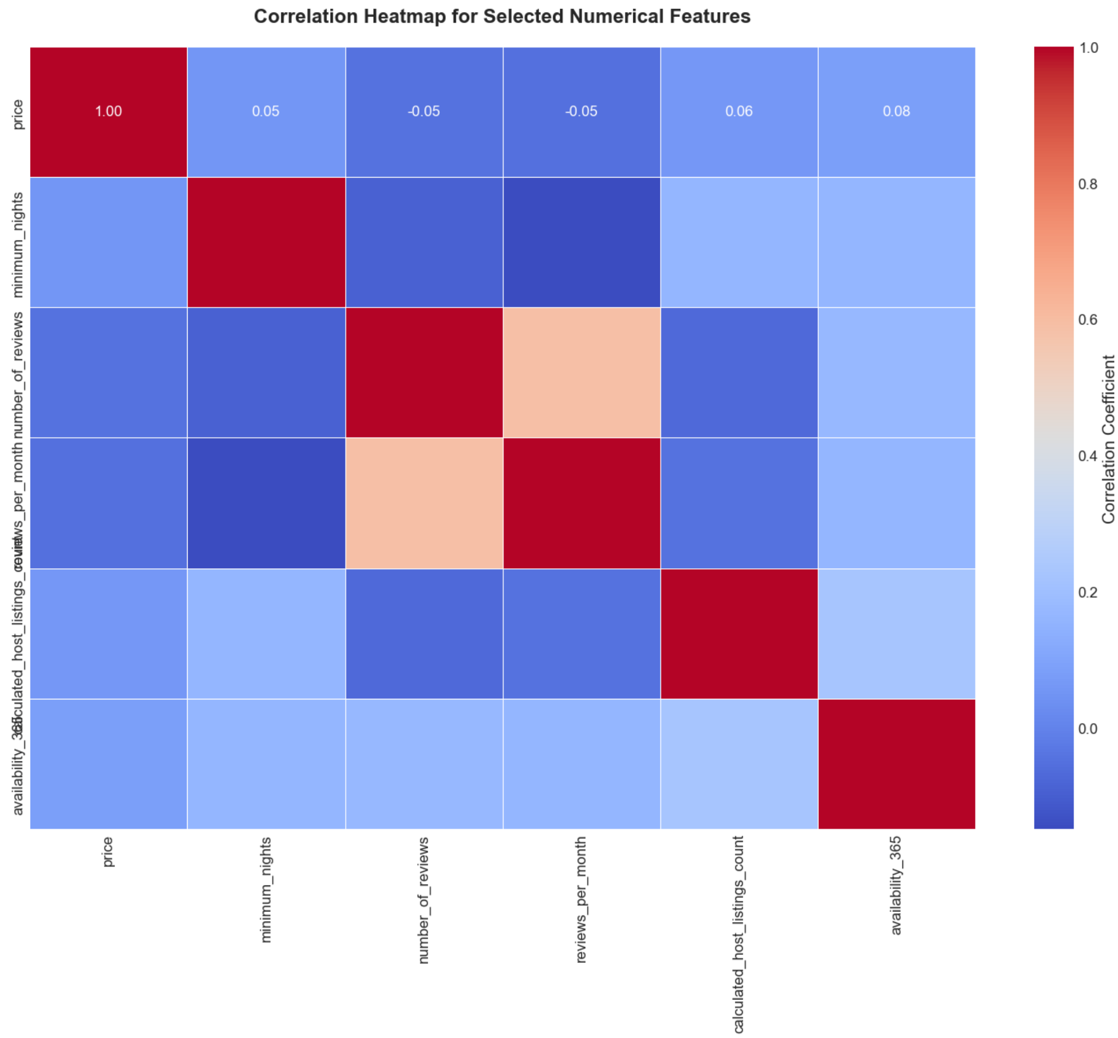
```
    # Calculate Pearson correlation coefficients between all pairs
    correlation_matrix = dataframe[selected_numeric_columns].corr(method='pearson')

    # Display the correlation matrix with gradient styling for better readability
    print("\nCorrelation Matrix (Pearson):")
    display(correlation_matrix.style.background_gradient(cmap='coolwarm', axis=None).format("{:.2f}"))

    # Create a heatmap visualization of the correlation matrix
    plt.figure(figsize=(14, 12))
    ax = sns.heatmap(
        correlation_matrix,
        annot=True,  # Show correlation values
        cmap='coolwarm',  # Red-blue color scheme (negative to positive)
        fmt='.2f',  # Format to 2 decimal places
        linewidths=0.5,  # Add grid lines
        cbar_kws={'label': 'Correlation Coefficient'}  # Add colorbar label
    )

    # Style the plot with appropriate title and layout
    style_plot(ax, title='Correlation Heatmap for Selected Numerical Features')
    plt.tight_layout()
    plt.show()

    # Find the strongest positive and negative correlations
    # First flatten the matrix and remove self-correlations (which are always 1.0)
    flattened_correlations = correlation_matrix.unstack()
    flattened_correlations = flattened_correlations[flattened_correlations < 1.0]

    # Identify the most positive correlation pair
    highest_correlation_value = flattened_correlations.max()
    highest_correlation_pair = flattened_correlations.idxmax()

    # Identify the most negative correlation pair
    lowest_correlation_value = flattened_correlations.min()
    lowest_correlation_pair = flattened_correlations.idxmin()

    # Print the findings
    print(
        f"\nMost Positive Correlation: {highest_correlation_pair[0]} and {highest_correlation_pair[1]} = {highest_correlation_value:.2f}")
    print(
```

```
        f"Most Negative Correlation: {lowest_correlation_pair[0]} and␣
↪{lowest_correlation_pair[1]} = {lowest_correlation_value:.2f}")

    # Create a scatter plot to visualize the relationship between the most␣
↪correlated features
    plt.figure(figsize=(12, 8))
    ax = sns.scatterplot(
        x=highest_correlation_pair[0],
        y=highest_correlation_pair[1],
        data=dataframe,
        alpha=0.5,  # Add transparency to handle overlapping points
        color='navy'  # Choose a professional color
    )

    # Add a trend line to highlight the correlation
    sns.regplot(
        x=highest_correlation_pair[0],
        y=highest_correlation_pair[1],
        data=dataframe,
        scatter=False,
        line_kws={"color": "red"}
    )

    # Style the scatter plot
    style_plot(
        ax,
        title=f'Scatter Plot: {highest_correlation_pair[0]} vs␣
↪{highest_correlation_pair[1]} (r = {highest_correlation_value:.2f})',
        xlabel=highest_correlation_pair[0].replace('_', ' ').title(),
        ylabel=highest_correlation_pair[1].replace('_', ' ').title()
    )

    # Add annotation explaining the correlation
    correlation_interpretation = "Strong positive correlation" if␣
↪highest_correlation_value > 0.7 else \
        "Moderate positive correlation" if highest_correlation_value > 0.3 else␣
↪\
            "Weak positive correlation"
    plt.annotate(
        correlation_interpretation,
        xy=(0.05, 0.95),
        xycoords='axes fraction',
        fontsize=12,
        bbox=dict(boxstyle="round,pad=0.3", fc="white", ec="gray", alpha=0.8)
    )

    plt.tight_layout()
```

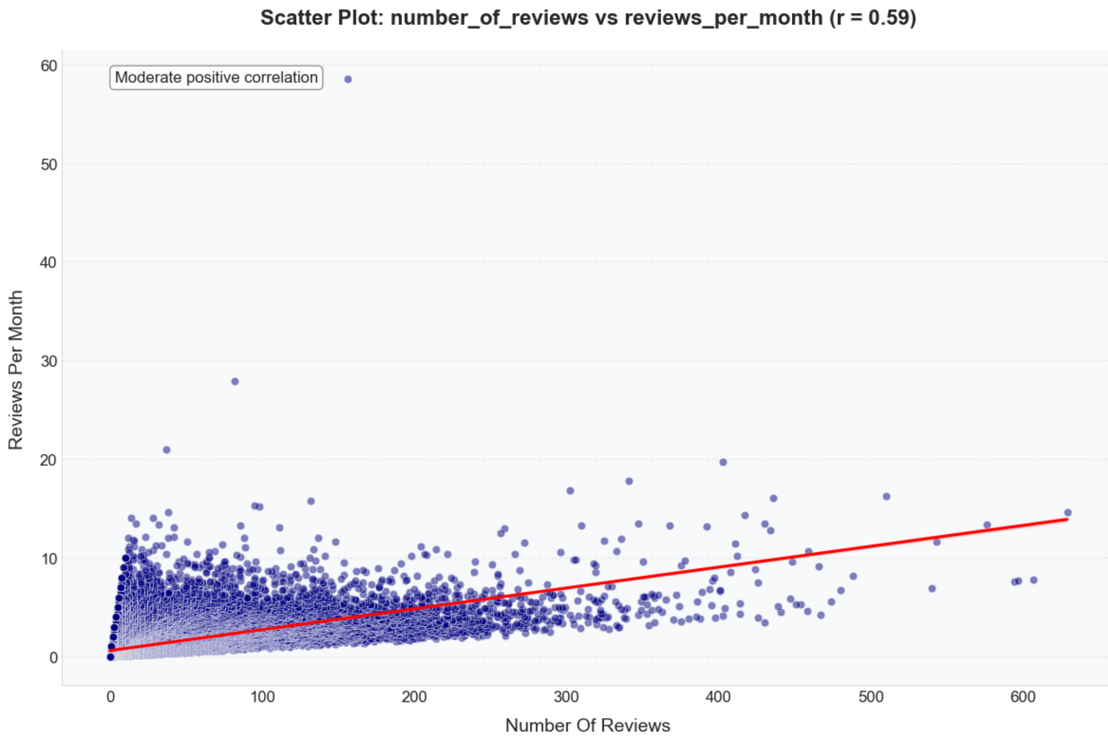
```
plt.show()

# Also create a scatter plot for the most negative correlation
plt.figure(figsize=(12, 8))
ax = sns.scatterplot(
    x=lowest_correlation_pair[0],
    y=lowest_correlation_pair[1],
    data=dataframe,
    alpha=0.5,
    color='darkred'
)

# Add a trend line
sns.regplot(
    x=lowest_correlation_pair[0],
    y=lowest_correlation_pair[1],
    data=dataframe,
    scatter=False,
    line_kws={"color": "blue"}
)

# Style the scatter plot
style_plot(
    ax,
    title=f'Scatter Plot: {lowest_correlation_pair[0]} vs␣
↪{lowest_correlation_pair[1]} (r = {lowest_correlation_value:.2f})',
    xlabel=lowest_correlation_pair[0].replace('_', ' ').title(),
    ylabel=lowest_correlation_pair[1].replace('_', ' ').title()
)

# Add annotation explaining the correlation
neg_correlation_interpretation = "Strong negative correlation" if␣
↪lowest_correlation_value < -0.7 else \
    "Moderate negative correlation" if lowest_correlation_value < -0.3 else␣
↪\
        "Weak negative correlation"
plt.annotate(
    neg_correlation_interpretation,
    xy=(0.05, 0.95),
    xycoords='axes fraction',
    fontsize=12,
    bbox=dict(boxstyle="round,pad=0.3", fc="white", ec="gray", alpha=0.8)
)

plt.tight_layout()
plt.show()
```

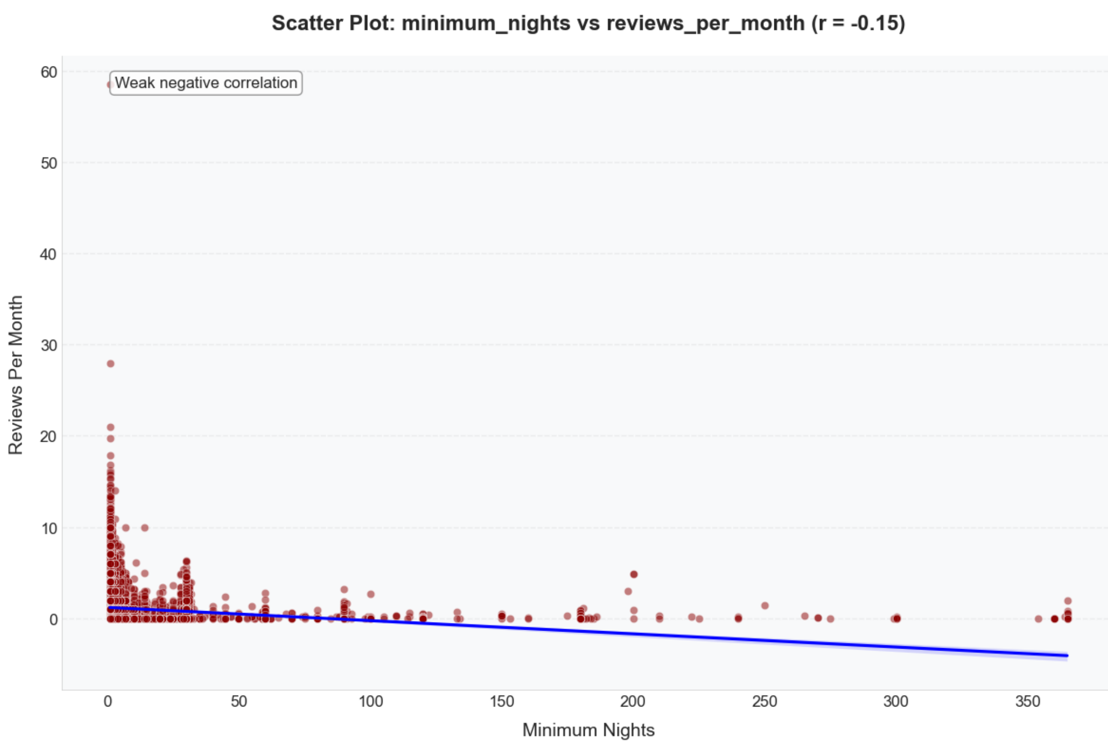
```
    # Provide a brief interpretation of the correlation findings
    print("\nInterpretation of Correlation Analysis:")
    print("----------------------------------------")
    print(
        f"The strongest positive correlation ({highest_correlation_value:.2f})␣
↪is between {highest_correlation_pair[0]} and {highest_correlation_pair[1]}.")
    print(
        f"This suggests that as {highest_correlation_pair[0]} increases,␣
↪{highest_correlation_pair[1]} tends to increase as well.")
    print(
        f"\nThe strongest negative correlation ({lowest_correlation_value:.2f})␣
↪is between {lowest_correlation_pair[0]} and {lowest_correlation_pair[1]}.")
    print(
        f"This suggests that as {lowest_correlation_pair[0]} increases,␣
↪{lowest_correlation_pair[1]} tends to decrease.")

    return correlation_matrix


# Execute the function
correlation_matrix =␣
↪analyze_and_visualize_correlations(final_cleaned_new_york_city_airbnb_data)
```

```
--- Task 3: Pairwise Pearson Correlation Analysis ---

Correlation Matrix (Pearson):
<pandas.io.formats.style.Styler at 0x16e10b050>
```




```
Most Positive Correlation: number_of_reviews and reviews_per_month = 0.59
Most Negative Correlation: minimum_nights and reviews_per_month = -0.15
```


Scatter Plot: number_of_reviews vs reviews_per_month (r = 0.59)
Moderate positive correlation
Reviews Per Month
Number Of Reviews
0
10
20
30
40
50
60
0
100
200
300
400
500
600


Scatter Plot: minimum_nights vs reviews_per_month (r = -0.15)
Weak negative correlation
Reviews Per Month
Minimum Nights
0
10
20
30
40
50
60
0
50
100
150
200
250
300
350

```
Interpretation of Correlation Analysis:
----------------------------------------
The strongest positive correlation (0.59) is between number_of_reviews and
reviews_per_month.
This suggests that as number_of_reviews increases, reviews_per_month tends to
increase as well.

The strongest negative correlation (-0.15) is between minimum_nights and
reviews_per_month.
This suggests that as minimum_nights increases, reviews_per_month tends to
decrease.
```

0.7 Task 4a: Visualizing Listings by Borough

In this task, I created several visualizations to explore the **geographic distribution** of Airbnb listings across New York City boroughs using `latitude`, `longitude`, and `neighbourhood_group`.

0.7.1 What I Did:

- Cleaned the dataset by filtering out listings with missing location or borough data.
- Used a scatter plot to map each listing by coordinates.
  - Each borough is **color-coded** using a distinct, high-contrast palette.
  - A **summary box** annotates total listings per borough.
  - Added a **north arrow** and an approximate **scale bar** (5 km).
- Supplemented the map with a **pie chart** showing the percentage of listings per borough.

0.7.2 Key Features:

- **Boroughs Mapped**: Manhattan, Brooklyn, Queens, Bronx, Staten Island
- **Visual Enhancements**:
  - Custom legend with borough counts
  - Informative tooltips and label styling
  - Background color and subtle gridlines

0.7.3 Optional Additions:

- The map includes a **summary annotation** with borough-wise breakdowns and total count.
- A **pie chart** visualizes proportional listing distribution.

0.7.4 Benefits:

These plots clearly show that: - **Manhattan** and **Brooklyn** have the highest listing concentrations. - **Queens** and **Bronx** have moderate density. - **Staten Island** has the fewest listings, mostly around its northern edge.

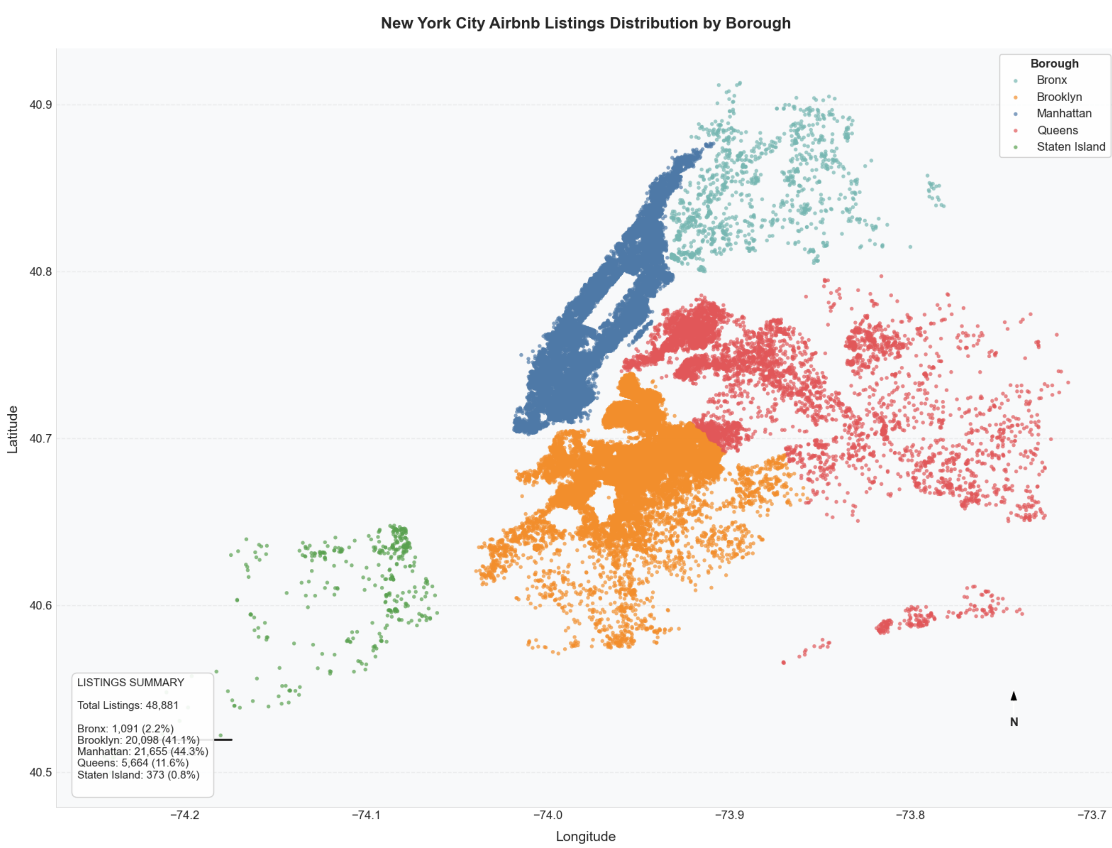
[84]:
```
def visualize_listings_distribution_by_borough(dataframe):
    """
```

```
    Creates enhanced visualizations of Airbnb listing distribution across NYC␣
↪boroughs:
    - Scatter map by borough
    - Pie chart of listing distribution

    Parameters:
        dataframe (pandas.DataFrame): Cleaned DataFrame of Airbnb listings.
    """
    print("\n--- Task 4a: Map of Listings by Borough ---")

    # Set up base plot
    fig, ax = plt.subplots(figsize=(16, 12))
    ax.set_facecolor('#f0f0f0')

    # Color palette
    borough_colors = {
        'Manhattan': '#4e79a7',
        'Brooklyn': '#f28e2c',
        'Queens': '#e15759',
        'Bronx': '#76b7b2',
        'Staten Island': '#59a14f'
    }

    unique_boroughs = sorted(dataframe['neighbourhood_group'].unique())

    for borough in unique_boroughs:
        subset = dataframe[dataframe['neighbourhood_group'] == borough]
        ax.scatter(
            subset['longitude'],
            subset['latitude'],
            c=borough_colors.get(borough, '#000000'),
            label=borough,
            alpha=0.7,
            s=15,
            edgecolors='none'
        )

    # Plot styling
    style_plot(ax,
               title='New York City Airbnb Listings Distribution by Borough',
               xlabel='Longitude',
               ylabel='Latitude')

    # Legend
    legend = ax.legend(title='Borough', loc='upper right', frameon=True,
                       framealpha=0.9, edgecolor='#cccccc')
    legend.get_title().set_fontweight('bold')
```

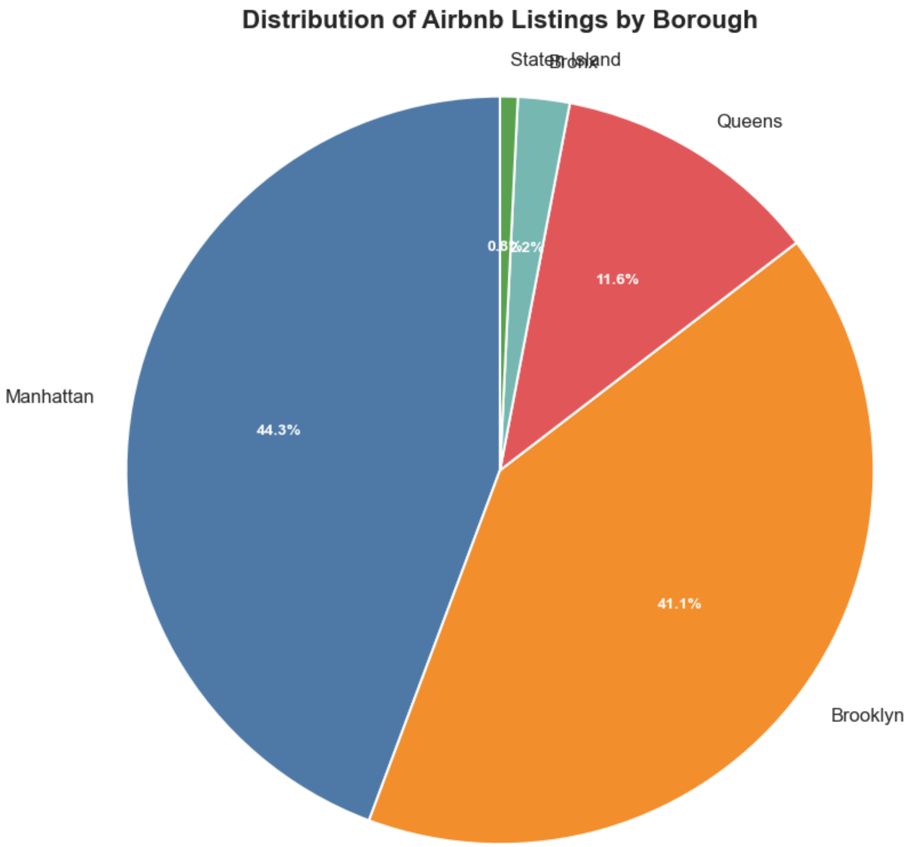
```
    # Scale bar
    scale_bar_length = 0.05
    ax.plot([dataframe['longitude'].min() + 0.02, dataframe['longitude'].min() + 0.02 + scale_bar_length],
            [dataframe['latitude'].min() + 0.02, dataframe['latitude'].min() + 0.02],
            'k-', linewidth=2)
    ax.text(dataframe['longitude'].min() + 0.02 + scale_bar_length / 2,
            dataframe['latitude'].min() + 0.01,
            '  5 km',
            horizontalalignment='center')

    # Listing summary box
    borough_counts = dataframe['neighbourhood_group'].value_counts()
    summary_text = f"LISTINGS SUMMARY\n\nTotal Listings: {len(dataframe):,}\n\n"
    for borough in unique_boroughs:
        count = borough_counts.get(borough, 0)
        percentage = count / len(dataframe) * 100
        summary_text += f"{borough}: {count:,} ({percentage:.1f}%)\n"

    props = dict(boxstyle='round,pad=0.5', facecolor='white', alpha=0.9, edgecolor='#cccccc')
    ax.text(0.02, 0.02, summary_text, transform=ax.transAxes, fontsize=11,
            verticalalignment='bottom', bbox=props, family='sans-serif')

    # North arrow
    arrow_x, arrow_y = dataframe['longitude'].max() - 0.03, dataframe['latitude'].min() + 0.05
    ax.annotate('N', xy=(arrow_x, arrow_y), xytext=(arrow_x, arrow_y - 0.02),
                arrowprops=dict(facecolor='black', width=1, headwidth=8),
                ha='center', va='center', fontsize=12, fontweight='bold')

    plt.tight_layout()
    plt.show()

    # Pie chart
    print("\n--- Pie Chart: Listing Distribution by Borough ---")
    plt.figure(figsize=(10, 8))
    ax = plt.subplot(111)
    wedges, texts, autotexts = ax.pie(
        borough_counts,
        labels=borough_counts.index,
        autopct='%1.1f%%',
        startangle=90,
        colors=[borough_colors.get(b, '#000000') for b in borough_counts.index],
        wedgeprops={'edgecolor': 'white', 'linewidth': 1.5}
```

```
    )

    for text in texts:
        text.set_fontsize(12)
    for autotext in autotexts:
        autotext.set_fontsize(10)
        autotext.set_fontweight('bold')
        autotext.set_color('white')

    style_plot(ax, title='Distribution of Airbnb Listings by Borough')
    ax.axis('equal')
    plt.tight_layout()
    plt.show()


# Call Function
visualize_listings_distribution_by_borough(final_cleaned_new_york_city_airbnb_data)
```

```
--- Task 4a: Map of Listings by Borough ---
```



```
--- Pie Chart: Listing Distribution by Borough ---
```



0.8 Task 4b: Map of Listings by Price (Below $1000)

In this task, I created a set of visualizations to explore the **distribution of Airbnb prices** under $1000 across New York City. This helps uncover spatial and borough-level pricing patterns.

0.8.1 What I Did:

- **Filtered** the dataset to include only listings with price < $1000 (99.4% of all listings).
- Generated three main visualizations:
  1. **Geographic Scatter Plot**
     - Each dot represents a listing, color-coded by price.
     - A **custom color gradient** (blue to red) highlights price intensity.
     - Added a **summary box** showing average/median prices by borough.
  2. **Boxplot + Swarmplot**
     - Displays price distribution within each borough.
     - Overlayed with a random sample of 5000 listings for readability.
     - Mean prices are marked in red.
  3. **Histogram with KDE per Borough**

- One plot per borough.
- Each includes **mean and median lines** to highlight skewness.

0.8.2 Key Takeaways:

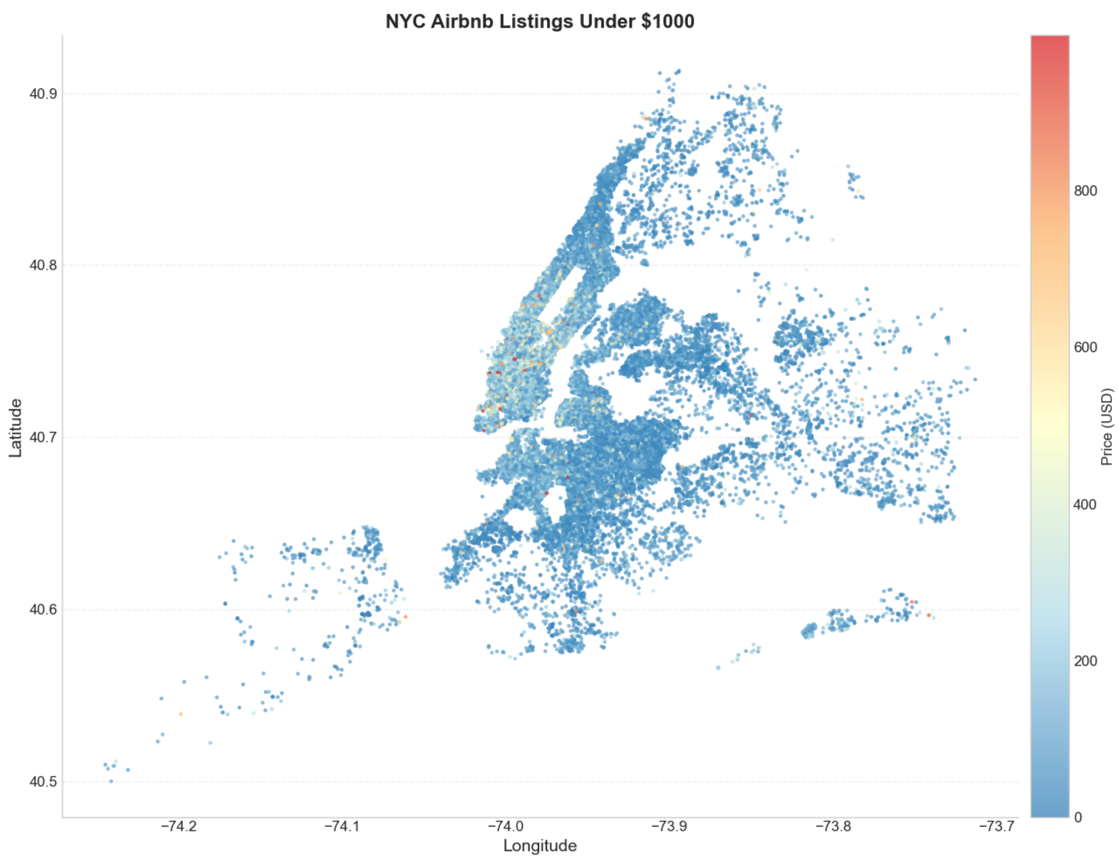
- **Manhattan** remains the most expensive borough overall, even with high-end listings removed.
- **Bronx** and **Staten Island** have the lowest average prices.
- **Price distribution is right-skewed** in every borough, with a few higher-end listings pulling the average up.

[89]:
```
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
import pandas as pd
import warnings


def visualize_price_distribution_map(dataframe, price_threshold=1000):
    """
    Visualizes Airbnb listings under a given price threshold using:
    - Scatter map color-coded by price
    - Violin + box plot for borough-level distributions
    - Histograms with mean and median for each borough
    """
    print(f"\n--- Task 4b: Map of Listings by Price (Below ${price_threshold})␣
↪---")
    warnings.filterwarnings("ignore", category=UserWarning)

    affordable = dataframe[dataframe['price'] < price_threshold]
    print(f"Number of listings under ${price_threshold}: {len(affordable):,}")
    print(f"Percentage of total listings: {(len(affordable) / len(dataframe) *␣
↪100):.1f}%")

    # ----- SCATTER MAP -----
    fig, ax = plt.subplots(figsize=(14, 10))
    cmap = mpl.colors.LinearSegmentedColormap.from_list("price_gradient",
                                                         ["#2c7bb6", "#abd9e9",␣
↪"#ffffbf", "#fdae61", "#d7191c"])

    scatter = ax.scatter(
        affordable['longitude'], affordable['latitude'],
        c=affordable['price'], cmap=cmap,
        alpha=0.7, s=10, edgecolors='none'
    )
    cbar = plt.colorbar(scatter, ax=ax, pad=0.01)
    cbar.set_label('Price (USD)', fontsize=12)
```

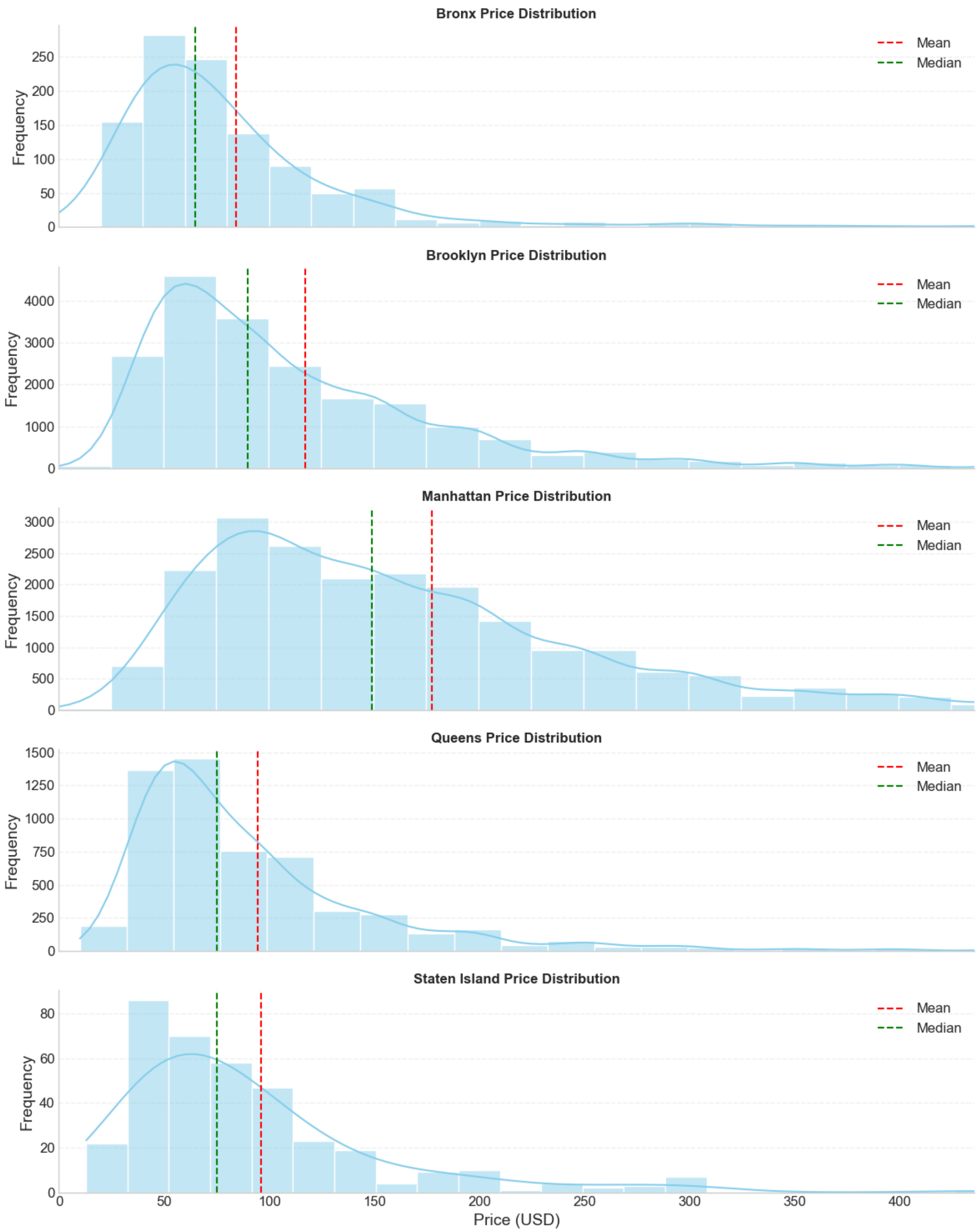
```
    ax.set_title(f'NYC Airbnb Listings Under ${price_threshold}', fontsize=16,␣
↪weight='bold')
    ax.set_xlabel('Longitude')
    ax.set_ylabel('Latitude')

    plt.tight_layout()
    plt.show()

    # ----- VIOLIN + BOX PLOT -----
    plt.figure(figsize=(12, 6))
    ax = sns.violinplot(
        x='neighbourhood_group', y='price', data=affordable,
        inner='box', palette='Set2', cut=0
    )

    means = affordable.groupby('neighbourhood_group')['price'].mean()
    for i, tick in enumerate(ax.get_xticklabels()):
        b = tick.get_text()
        ax.scatter(i, means[b], color='red', s=40, zorder=10)
        ax.text(i, means[b] + 5, f"${means[b]:.0f}", color='red', ha='center',␣
↪fontsize=9, weight='bold')

    ax.set_title('Price Distribution by Borough (Listings < $1000)',␣
↪fontsize=14, weight='bold')
    ax.set_ylabel('Price (USD)')
    ax.set_xlabel('Borough')
    ax.set_ylim(0, affordable['price'].quantile(0.99))
    sns.despine()
    plt.tight_layout()
    plt.show()

    # ----- HISTOGRAMS -----
    boroughs = affordable['neighbourhood_group'].unique()
    borough_stats = affordable.groupby('neighbourhood_group')['price'].
↪agg(['mean', 'median'])
    fig, axes = plt.subplots(len(boroughs), 1, figsize=(12, 3 * len(boroughs)),␣
↪sharex=True)

    for i, b in enumerate(sorted(boroughs)):
        ax = axes[i] if len(boroughs) > 1 else axes
        subset = affordable[affordable['neighbourhood_group'] == b]['price']
        sns.histplot(subset, bins=40, kde=True, ax=ax, color='skyblue')

        ax.axvline(x=borough_stats.loc[b, 'mean'], color='red', linestyle='--',␣
↪label='Mean')
```

```
        ax.axvline(x=borough_stats.loc[b, 'median'], color='green',␣
↪linestyle='--', label='Median')

        ax.set_title(f'{b} Price Distribution', fontsize=12, weight='bold')
        ax.set_ylabel('Frequency')
        ax.legend()

        ax.set_xlim(0, subset.quantile(0.99))

    axes[-1].set_xlabel('Price (USD)')
    plt.tight_layout()
    plt.show()


visualize_price_distribution_map(final_cleaned_new_york_city_airbnb_data)
```

```
--- Task 4b: Map of Listings by Price (Below $1000) ---
Number of listings under $1000: 48,583
Percentage of total listings: 99.4%
```




```
/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
/opt/anaconda3/lib/python3.11/site-packages/seaborn/_oldcore.py:1119:
FutureWarning: use_inf_as_na option is deprecated and will be removed in a
future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



0.9 Task 5: Word Cloud of Airbnb Listing Titles

In this task, I explored the **text data** within Airbnb listing titles to uncover the most frequently used words. Word clouds are a powerful visual tool for summarizing large amounts of textual information by highlighting word frequency and prominence.

0.9.1 What I Did:

- Extracted the `name` field from all Airbnb listings.
- Cleaned the text by:
  - Lowercasing all letters
  - Removing non-alphabetic characters (e.g., punctuation)
  - Removing common stopwords (e.g., *in*, *on*, *the*)
- Counted the frequency of each word and printed the **Top 20 most common words**.
- Generated a **custom-colored word cloud** using a horizontal rectangular layout and a clean white background.
- Added annotations and aesthetic enhancements for professional visual presentation.

0.9.2 Dataset Summary:

- **Total Listings Analyzed**: 48,881
- **Titles Present**: 100.0% (no missing titles)
- **Average Title Length**: ~37 characters
- **Total Words Processed**: 277,845
- **Unique Words (after cleaning)**: 9,035

0.9.3 Top 20 Most Frequent Words:

Rank	Word	Occurrences
1	room	10,100
2	bedroom	8,042
3	private	7,176
4	apartment	6,704
5	cozy	5,006
...	...	...
20	large	2,046

0.9.4 Key Takeaways:

- **Descriptive terms** like "cozy", "private", and "spacious" dominate listings, reflecting marketing emphasis.
- **Geographic keywords** such as "Manhattan", "Brooklyn", "Williamsburg", and "Village" are frequently mentioned, helping guests quickly identify location.
- The dominance of "room", "apt", and "studio" suggests that many listings are **partial or shared spaces**, not full apartments.

This word cloud offers an engaging snapshot of how hosts title their listings and what themes or selling points are emphasized in the competitive NYC Airbnb market.

[94]:
```
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import pandas as pd
import re
from collections import Counter
```

```python
import numpy as np
from PIL import Image
import matplotlib.colors as mcolors


def create_and_show_word_cloud(df):
    """
    Generates an aesthetically pleasing word cloud from Airbnb listing titles␣
↪with
    additional data analysis on word frequency.

    Parameters:
        df (pandas.DataFrame): Cleaned Airbnb DataFrame

    Returns:
        None
    """
    print("\n" + "=" * 80)
    print("WORD CLOUD ANALYSIS: AIRBNB LISTING TITLES".center(80))
    print("=" * 80)

    # Basic statistics
    total_listings = len(df)
    listings_with_titles = df['name'].notna().sum()
    avg_title_length = df['name'].dropna().str.len().mean()

    print(f"\nDATASET OVERVIEW:")
    print(f"  • Total listings analyzed: {total_listings:,}")
    print(f"  • Listings with titles: {listings_with_titles:,}␣
↪({listings_with_titles / total_listings:.1%})")
    print(f"  • Average title length: {avg_title_length:.1f} characters")

    print(f"\nSAMPLE LISTING TITLES:")
    for i, title in enumerate(df['name'].dropna().sample(5, random_state=42).
↪values, 1):
        print(f"  {i}. {title}")

    # Concatenate all listing titles into a single string
    combined_text = " ".join(df['name'].dropna().astype(str).str.lower())

    # Remove non-letter characters and common stop words
    stop_words = {'the', 'and', 'in', 'on', 'at', 'to', 'for', 'with', 'a',␣
↪'an', 'of', 'by'}
    cleaned_text = re.sub(r'[^a-zA-Z\s]', '', combined_text)

    # Count word frequencies
    words = cleaned_text.split()
```

```python
    word_counts = Counter(word for word in words if word not in stop_words and␣
↪len(word) > 2)
    top_words = word_counts.most_common(20)

    print(f"\nTEXT PROCESSING METRICS:")
    print(f"  • Raw text size: {len(combined_text):,} characters")
    print(f"  • Cleaned text size: {len(cleaned_text):,} characters")
    print(f"  • Total words analyzed: {len(words):,}")
    print(f"  • Unique words: {len(word_counts):,}")

    print(f"\nTOP 20 MOST FREQUENT WORDS:")
    for i, (word, count) in enumerate(top_words, 1):
        print(f"  {i:2d}. {word:15s} {count:5d} occurrences")

    # Create a custom color gradient
    colors = ["#1E88E5", "#26A69A", "#FFC107", "#D81B60", "#8E24AA"]
    custom_cmap = mcolors.LinearSegmentedColormap.from_list("custom_airbnb",␣
↪colors)

    # Create a mask for the word cloud (optional)
    # You can replace this with any mask image you prefer
    mask = np.ones((500, 1000), dtype=np.int8)

    # Create word cloud with enhanced aesthetics
    wordcloud = WordCloud(
        width=1000,
        height=500,
        background_color='white',
        colormap=custom_cmap,
        max_words=150,
        collocations=False,
        contour_width=1,
        contour_color='#7f7f7f',
        font_path=None,  # Add a custom font path if available
        mask=mask,
        min_font_size=10,
        max_font_size=100,
        random_state=42,
        prefer_horizontal=0.9,
        relative_scaling=0.5,
        stopwords=stop_words
    ).generate(cleaned_text)

    print("\nGENERATING WORD CLOUD VISUALIZATION...")

    # Plot with enhanced styling
    fig, ax = plt.subplots(figsize=(16, 8), facecolor='white')
```

```python
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.axis('off')

    # Add a stylish title and subtitle
    plt.title("Most Common Words in Airbnb Listing Titles",
              fontsize=24, fontweight='bold', pad=20, color='#484848')

    # Add a footer with dataset info
    plt.figtext(0.5, 0.01, f"Based on analysis of {total_listings:,} Airbnb␣
↪listings in New York City",
                ha="center", fontsize=12, fontstyle='italic', color='#767676')

    plt.tight_layout(pad=0)
    plt.savefig('airbnb_wordcloud.png', dpi=300, bbox_inches='tight')
    plt.show()


# Call the function
create_and_show_word_cloud(final_cleaned_new_york_city_airbnb_data)
```

```
================================================================================
                   WORD CLOUD ANALYSIS: AIRBNB LISTING TITLES
================================================================================

DATASET OVERVIEW:
  • Total listings analyzed: 48,881
  • Listings with titles: 48,881 (100.0%)
  • Average title length: 36.9 characters

SAMPLE LISTING TITLES:
  1. Masterful bedroom & private bathroom in Astoria
  2. Sunny Practical Apt in Williamsburg BK!!!
  3. Times Square NYC
  4. Brownstone Studio
  5. Gorgeous Bedroom in Manhattan Midtown West

TEXT PROCESSING METRICS:
  • Raw text size: 1,852,899 characters
  • Cleaned text size: 1,776,794 characters
  • Total words analyzed: 277,845
  • Unique words: 9,035

TOP 20 MOST FREQUENT WORDS:
   1. room            10100 occurrences
   2. bedroom          8042 occurrences
   3. private          7176 occurrences
   4. apartment        6704 occurrences
```

```
 5. cozy              5006 occurrences
 6. apt               4634 occurrences
 7. brooklyn          4055 occurrences
 8. studio            3998 occurrences
 9. spacious          3729 occurrences
10. manhattan         3460 occurrences
11. park              3051 occurrences
12. east              3019 occurrences
13. sunny             2884 occurrences
14. williamsburg      2638 occurrences
15. beautiful         2477 occurrences
16. near              2319 occurrences
17. village           2259 occurrences
18. nyc               2179 occurrences
19. heart             2051 occurrences
20. large             2046 occurrences

GENERATING WORD CLOUD VISUALIZATION…
```

0.10 Task 6: Analyzing the Busiest Hosts in NYC

This analysis focuses on identifying and evaluating the **top 10 busiest Airbnb hosts** in New York City by number of listings. Metrics such as price, availability, and review patterns are explored to understand their hosting behavior.

0.10.1 What I Did:

- Aggregated data by `host_id` and `host_name`

- Computed key statistics for each host:
  - Number of listings
  - Price range and average
  - Availability (days/year)
  - Reviews per month and total reviews
  - Dominant neighborhoods
- Created visualizations:
  - Bar chart of top hosts by listing count
  - Scatter plot of listings vs. average price
  - Availability and review comparison
  - Price range bars with mean and median indicators
  - Correlation heatmap of key host metrics
  - Stacked bar chart of listings by neighborhood group

0.10.2 Key Findings:

- The **busiest host**, `Sonder (NYC)`, manages **327 listings**.
- The **majority of top hosts operate in Manhattan**.
- **Average price for top hosts** is **$210.08**, which is **37.6% higher** than the overall average of **$152.73**.
- **Top hosts have 150.5% higher availability**, suggesting a professional or business-like hosting style.
- Interestingly, their **reviews per month are 81.2% lower**, possibly due to longer stays or newer listings.

0.10.3 Summary Insights:

1. The busiest hosts tend to operate in **Manhattan**.
2. They charge **higher prices** than the citywide average.
3. Their listings have **greater year-round availability**.
4. They tend to receive **fewer reviews per month**, which may reflect longer stays, fewer guests, or lower turnover.
5. These patterns align with **professional property management strategies**, distinguishing them from typical hosts.

[97]:
```
def find_busiest_hosts_and_analyze(df, top_n=10):
    """
    Identifies hosts with the highest number of total listings and analyzes␣
↪factors
    correlating with their success (price, availability, reviews).

    Parameters:
        df (pandas.DataFrame): Cleaned DataFrame of Airbnb listings
        top_n (int): Number of top hosts to analyze

    Returns:
        pandas.DataFrame: Summary statistics for top busiest hosts
    """
```

```
print("\n=== Task 6: Analyzing the Busiest Hosts in NYC ===")

# Validate required columns
required_columns = [
    'host_id', 'host_name', 'calculated_host_listings_count', 'price',
    'availability_365', 'reviews_per_month', 'number_of_reviews',
    'neighbourhood_group', 'neighbourhood'
]

missing_cols = [col for col in required_columns if col not in df.columns]
if missing_cols:
    raise ValueError(f"Missing required columns: {missing_cols}")

# Group by host and calculate metrics
host_grouped = df.groupby(['host_id', 'host_name']).agg(
    total_listings=('calculated_host_listings_count', 'max'),
    avg_price=('price', 'mean'),
    median_price=('price', 'median'),
    min_price=('price', 'min'),
    max_price=('price', 'max'),
    avg_availability=('availability_365', 'mean'),
    avg_reviews_per_month=('reviews_per_month', 'mean'),
    total_reviews=('number_of_reviews', 'sum'),
    avg_reviews_per_listing=('number_of_reviews', 'mean'),
    main_neighborhood_group=('neighbourhood_group', lambda x: x.
↪value_counts().index[0]),
    neighborhoods=('neighbourhood', lambda x: ', '.join(x.value_counts().
↪nlargest(3).index.tolist()))
).reset_index()

# Get top hosts by listing count
busiest_hosts_df = host_grouped.sort_values('total_listings',␣
↪ascending=False).head(top_n)

print(f"\nTop {top_n} Hosts with the Highest Listing Counts:")
display(busiest_hosts_df)

# ===== VISUALIZATION SECTION =====

fig = plt.figure(figsize=(20, 16))

ax1 = fig.add_subplot(2, 2, 1)
sns.barplot(
    x='total_listings',
    y='host_name',
    data=busiest_hosts_df,
    palette='rocket',
```

```
        ax=ax1
    )
    ax1.set_title(f'Top {top_n} Busiest Hosts by Number of Listings',␣
↪fontsize=14, fontweight='bold')
    ax1.set_xlabel('Total Listings', fontsize=12)
    ax1.set_ylabel('Host Name', fontsize=12)

    ax2 = fig.add_subplot(2, 2, 2)
    scatter = sns.scatterplot(
        x='total_listings',
        y='avg_price',
        hue='main_neighborhood_group',
        size='total_reviews',
        sizes=(100, 500),
        data=busiest_hosts_df,
        palette='tab10',
        ax=ax2
    )
    ax2.set_title('Listings vs. Price by Neighborhood Group', fontsize=14,␣
↪fontweight='bold')
    ax2.set_xlabel('Total Listings', fontsize=12)
    ax2.set_ylabel('Average Price (USD)', fontsize=12)
    legend = ax2.legend(title='Neighborhood Group', loc='upper right',␣
↪fontsize=10)
    legend.get_title().set_fontsize(12)

    ax3 = fig.add_subplot(2, 2, 3)
    availability_plot = sns.barplot(
        x='avg_availability',
        y='host_name',
        data=busiest_hosts_df,
        palette='YlGnBu',
        ax=ax3
    )
    ax3.set_title('Average Availability (days/year) by Host', fontsize=14,␣
↪fontweight='bold')
    ax3.set_xlabel('Average Availability (days)', fontsize=12)
    ax3.set_ylabel('Host Name', fontsize=12)

    for i, v in enumerate(busiest_hosts_df['avg_availability']):
        ax3.text(v + 5, i, f"{v:.1f}", va='center', fontsize=10)

    ax4 = fig.add_subplot(2, 2, 4)
    reviews_plot = sns.barplot(
        x='avg_reviews_per_month',
        y='host_name',
        data=busiest_hosts_df,
```

```
        palette='YlOrRd',
        ax=ax4
    )
    ax4.set_title('Average Reviews per Month by Host', fontsize=14,␣
↪fontweight='bold')
    ax4.set_xlabel('Reviews per Month', fontsize=12)
    ax4.set_ylabel('Host Name', fontsize=12)

    for i, v in enumerate(busiest_hosts_df['avg_reviews_per_month']):
        ax4.text(v + 0.1, i, f"{v:.2f}", va='center', fontsize=10)

    plt.tight_layout()
    plt.show()

    plt.figure(figsize=(12, 6))

    price_range_df = busiest_hosts_df[['host_name', 'min_price', 'avg_price',␣
↪'median_price', 'max_price']].copy()
    price_range_df = price_range_df.sort_values('avg_price', ascending=False)

    ax = plt.subplot(111)
    for i, host in enumerate(price_range_df['host_name']):
        min_price = price_range_df.iloc[i]['min_price']
        max_price = price_range_df.iloc[i]['max_price']
        avg_price = price_range_df.iloc[i]['avg_price']
        median_price = price_range_df.iloc[i]['median_price']

        plt.plot([min_price, max_price], [i, i], 'o-', linewidth=2,␣
↪color='skyblue')
        plt.plot(avg_price, i, 'D', markersize=8, color='red', label='Average'␣
↪if i == 0 else "")
        plt.plot(median_price, i, 's', markersize=8, color='green',␣
↪label='Median' if i == 0 else "")

    plt.yticks(range(len(price_range_df)), price_range_df['host_name'])
    plt.xlabel('Price (USD)', fontsize=12)
    plt.ylabel('Host Name', fontsize=12)
    plt.title('Price Range by Host (Min to Max)', fontsize=14,␣
↪fontweight='bold')
    plt.legend(loc='upper right')
    plt.grid(axis='x', linestyle='--', alpha=0.7)
    plt.tight_layout()
    plt.show()

    correlation_metrics = [
        'total_listings', 'avg_price', 'avg_availability',
```

```
        'avg_reviews_per_month', 'total_reviews', 'avg_reviews_per_listing'
    ]

    correlation_matrix = busiest_hosts_df[correlation_metrics].corr()

    plt.figure(figsize=(10, 8))
    sns.heatmap(
        correlation_matrix,
        annot=True,
        cmap='coolwarm',
        vmin=-1,
        vmax=1,
        linewidths=0.5,
        fmt=".2f"
    )
    plt.title('Correlation Between Key Metrics for Busiest Hosts', fontsize=14, fontweight='bold')
    plt.tight_layout()
    plt.show()

    top_host_ids = busiest_hosts_df['host_id'].tolist()
    top_hosts_listings = df[df['host_id'].isin(top_host_ids)]

    plt.figure(figsize=(14, 8))
    host_neighborhood_counts = pd.crosstab(
        top_hosts_listings['host_name'],
        top_hosts_listings['neighbourhood_group']
    )
    host_neighborhood_counts.plot(kind='bar', stacked=True, colormap='tab10')
    plt.title('Neighborhood Group Distribution for Busiest Hosts', fontsize=14, fontweight='bold')
    plt.xlabel('Host Name', fontsize=12)
    plt.ylabel('Number of Listings', fontsize=12)
    plt.legend(title='Neighborhood Group', fontsize=10)
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()

    print("\nAnalysis of Busiest Hosts in NYC")
    print("=" * 50)

    print(f"\nThe top {top_n} busiest hosts in NYC have between {busiest_hosts_df['total_listings'].min()} and "
          f"{busiest_hosts_df['total_listings'].max()} listings each.")

    common_area = busiest_hosts_df['main_neighborhood_group'].mode()[0]
    print(f"\nMost Common Area: {common_area}")
```

```
    print(f"   This area appears particularly attractive for professional␣
↪hosting operations.")

    avg_price_all = df['price'].mean()
    avg_price_busy = busiest_hosts_df['avg_price'].mean()
    price_diff_pct = ((avg_price_busy - avg_price_all) / avg_price_all) * 100

    print(f"\nPrice Analysis:")
    print(f"   • Average price (all listings): ${avg_price_all:.2f}")
    print(f"   • Average price (busiest hosts): ${avg_price_busy:.2f}")
    print(f"   • Difference: {price_diff_pct:.1f}% {'higher' if price_diff_pct␣
↪> 0 else 'lower'}")

    avg_avail_all = df['availability_365'].mean()
    avg_avail_busy = busiest_hosts_df['avg_availability'].mean()
    avail_diff_pct = ((avg_avail_busy - avg_avail_all) / avg_avail_all) * 100

    print(f"\nAvailability Analysis:")
    print(f"   • Average availability (all listings): {avg_avail_all:.1f} days/
↪year")
    print(f"   • Average availability (busiest hosts): {avg_avail_busy:.1f}␣
↪days/year")
    print(f"   • Difference: {avail_diff_pct:.1f}% {'higher' if avail_diff_pct␣
↪> 0 else 'lower'}")

    avg_reviews_all = df['reviews_per_month'].mean()
    avg_reviews_busy = busiest_hosts_df['avg_reviews_per_month'].mean()
    reviews_diff_pct = ((avg_reviews_busy - avg_reviews_all) / avg_reviews_all)␣
↪* 100

    print(f"\nReviews Analysis:")
    print(f"   • Average reviews/month (all listings): {avg_reviews_all:.2f}")
    print(f"   • Average reviews/month (busiest hosts): {avg_reviews_busy:.2f}")
    print(f"   • Difference: {reviews_diff_pct:.1f}% {'higher' if␣
↪reviews_diff_pct > 0 else 'lower'}")

    strongest_corr = correlation_matrix.unstack().sort_values(ascending=False)
    print(f"\nSummary Insights:")
    print(f"   1. The busiest hosts tend to operate in {common_area}")
    print(f"   2. They charge {'higher' if price_diff_pct > 0 else 'lower'}␣
↪prices compared to average hosts")
    print(f"   3. Have {'higher' if avail_diff_pct > 0 else 'lower'}␣
↪availability throughout the year")
    print(f"   4. Receive {'more' if reviews_diff_pct > 0 else 'fewer'} reviews␣
↪per month")
```

```
    print("\n   These patterns suggest a professional approach to Airbnb␣
↪hosting, with strategic")
    print("   pricing and property management practices that differ from casual␣
↪hosts.")

    return busiest_hosts_df


# Example usage:
find_busiest_hosts_and_analyze(final_cleaned_new_york_city_airbnb_data)
```

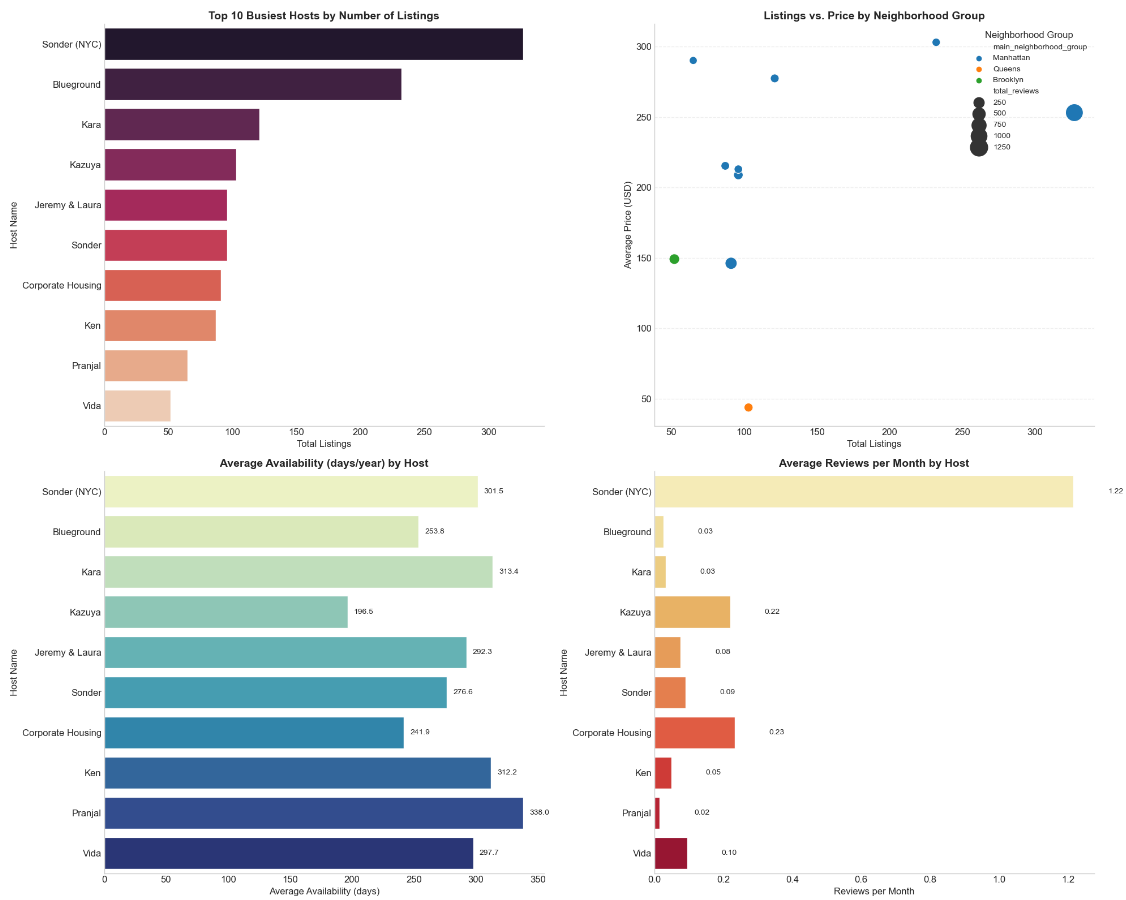
```
=== Task 6: Analyzing the Busiest Hosts in NYC ===

Top 10 Hosts with the Highest Listing Counts:
```

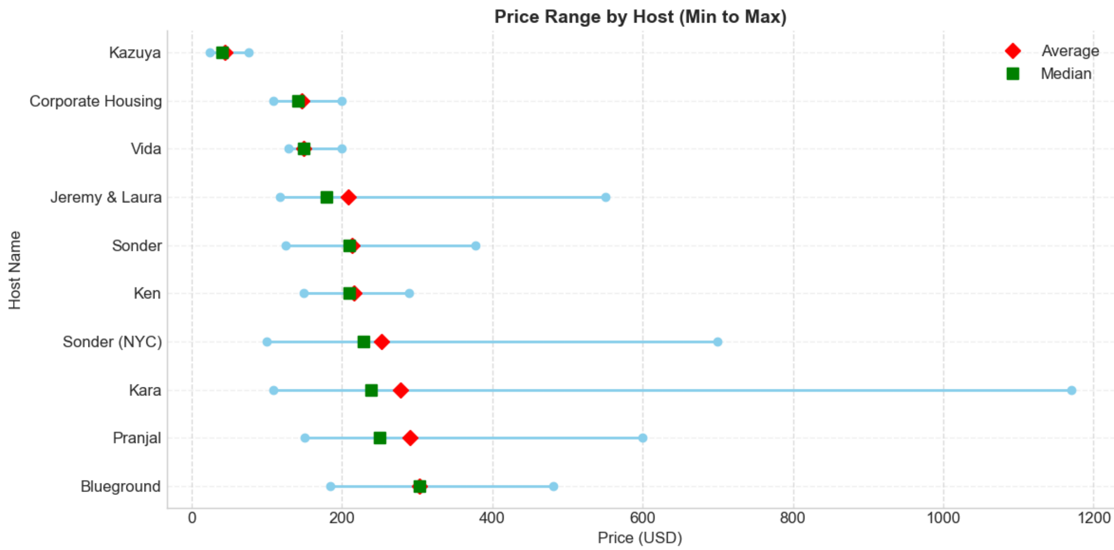
	host_id	host_name	total_listings	avg_price	median_price	\
34633	219517861	Sonder (NYC)	327	253.195719	228.0	
29395	107434423	Blueground	232	303.150862	302.5	
19564	30283594	Kara	121	277.528926	239.0	
31067	137358866	Kazuya	103	43.825243	41.0	
14428	16098958	Jeremy & Laura	96	208.958333	180.0	
12799	12243051	Sonder	96	213.031250	209.5	
25651	61391963	Corporate Housing	91	146.241758	142.0	
17081	22541573	Ken	87	215.436782	210.0	
33856	200380610	Pranjal	65	290.230769	250.0	
9727	7503643	Vida	52	149.192308	149.0	

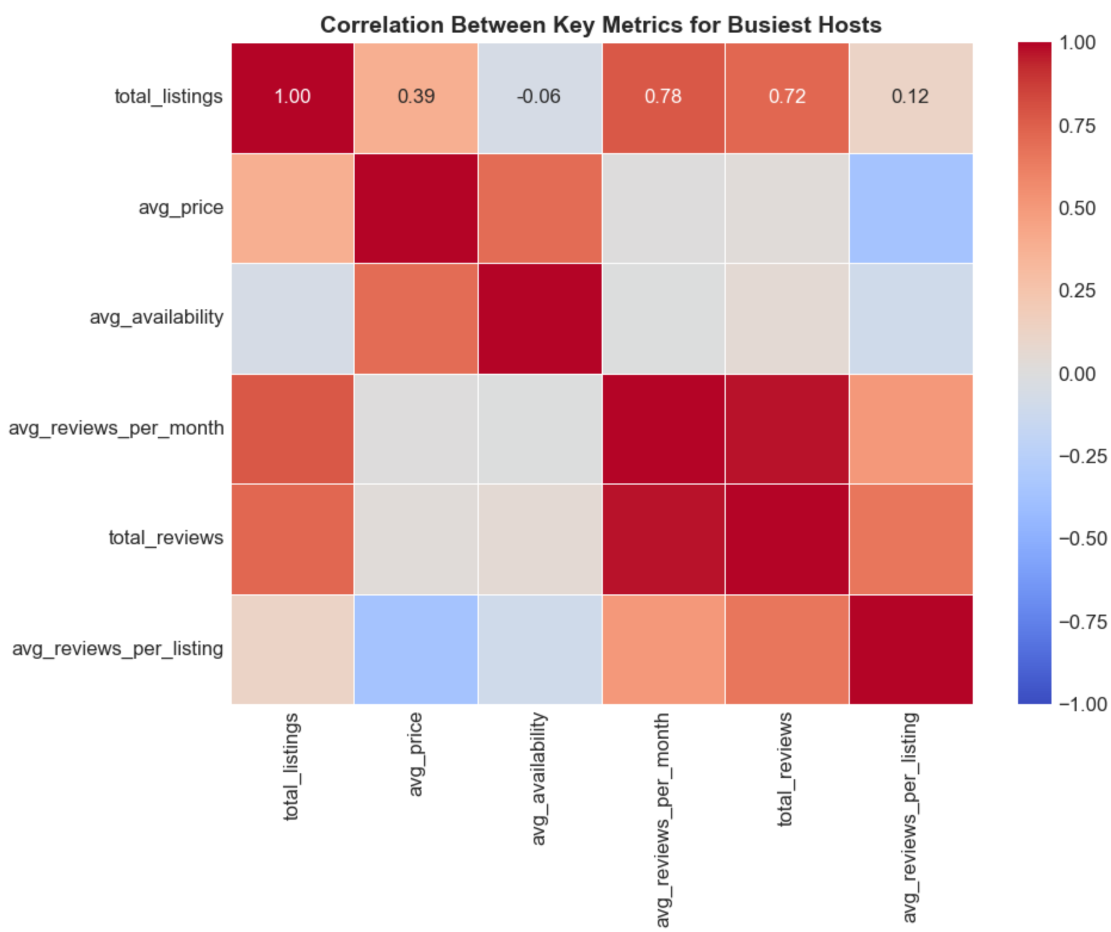
	min_price	max_price	avg_availability	avg_reviews_per_month	\
34633	100	699	301.492355	1.215780	
29395	184	481	253.810345	0.026034	
19564	109	1170	313.421488	0.032562	
31067	24	76	196.475728	0.220194	
14428	117	550	292.322917	0.076042	
12799	125	377	276.614583	0.090104	
25651	109	200	241.923077	0.232747	
17081	149	289	312.172414	0.048851	
33856	150	600	338.030769	0.015385	
9727	129	199	297.711538	0.095385	

	total_reviews	avg_reviews_per_listing	main_neighborhood_group	\
34633	1281	3.917431	Manhattan	
29395	29	0.125000	Manhattan	
19564	65	0.537190	Manhattan	
31067	87	0.844660	Queens	
14428	138	1.437500	Manhattan	
12799	43	0.447917	Manhattan	
25651	417	4.582418	Manhattan	

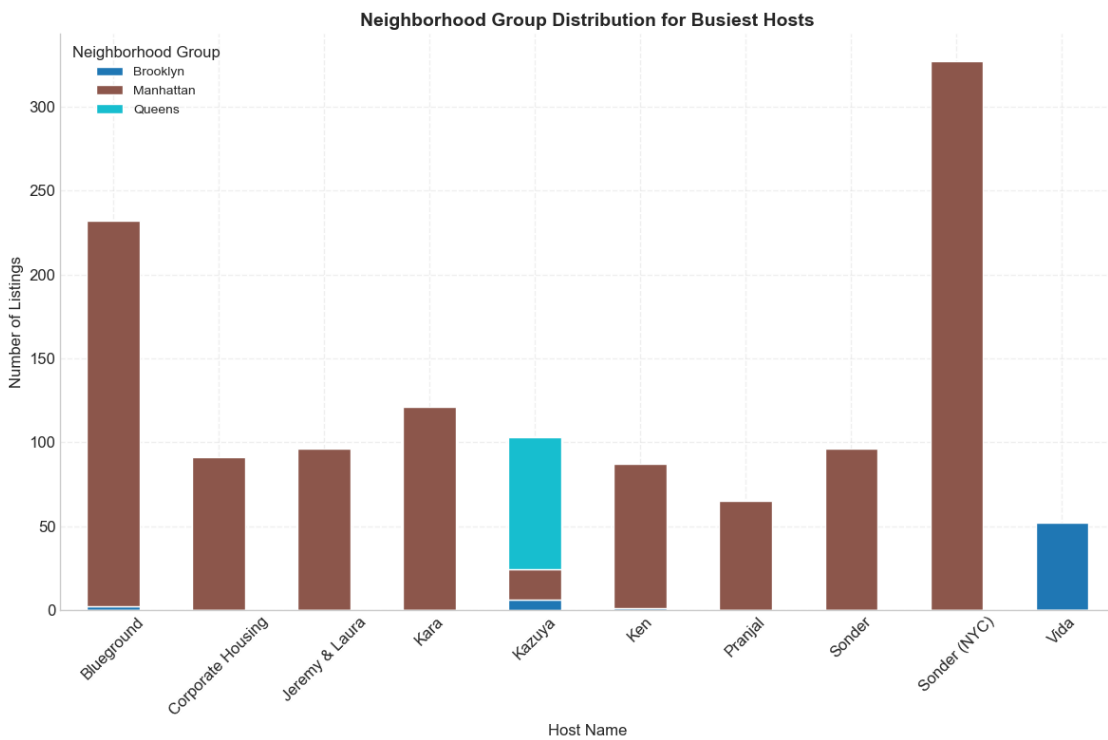
```
17081            55            0.632184            Manhattan
33856             1            0.015385            Manhattan
9727            242            4.653846             Brooklyn

                                             neighborhoods
34633  Financial District, Murray Hill, Theater District
29395               Chelsea, Tribeca, Theater District
19564          Hell's Kitchen, Midtown, Theater District
31067                        Woodside, Sunnyside, Harlem
14428          Upper West Side, Midtown, Hell's Kitchen
12799              Financial District, Midtown, Chelsea
25651                Kips Bay, Midtown, Upper East Side
17081                 Chelsea, Upper East Side, Midtown
33856          Midtown, Upper East Side, Hell's Kitchen
9727                                        Greenpoint
```




Price Range by Host (Min to Max)
Average
Median
Host Name
Kazuya
Corporate Housing
Vida
Jeremy & Laura
Sonder
Ken
Sonder (NYC)
Kara
Pranjal
Blueground
0
200
400
600
800
1000
1200
Price (USD)


Correlation Between Key Metrics for Busiest Hosts
total_listings
avg_price
avg_availability
avg_reviews_per_month
total_reviews
avg_reviews_per_listing
1.00
0.39
-0.06
0.78
0.72
0.12
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

<Figure size 1400x800 with 0 Axes>



Analysis of Busiest Hosts in NYC
==

The top 10 busiest hosts in NYC have between 52 and 327 listings each.

Most Common Area: Manhattan
   This area appears particularly attractive for professional hosting operations.

Price Analysis:
- Average price (all listings): $152.73
- Average price (busiest hosts): $210.08
- Difference: 37.6% higher

Availability Analysis:
- Average availability (all listings): 112.7 days/year
- Average availability (busiest hosts): 282.4 days/year
- Difference: 150.5% higher

Reviews Analysis:
- Average reviews/month (all listings): 1.09

• Average reviews/month (busiest hosts): 0.21
• Difference: -81.2% lower

Summary Insights:
1. The busiest hosts tend to operate in Manhattan
2. They charge higher prices compared to average hosts
3. Have higher availability throughout the year
4. Receive fewer reviews per month

These patterns suggest a professional approach to Airbnb hosting, with
strategic
pricing and property management practices that differ from casual hosts.

[97]:

	host_id	host_name	total_listings	avg_price	median_price
34633	219517861	Sonder (NYC)	327	253.195719	228.0
29395	107434423	Blueground	232	303.150862	302.5
19564	30283594	Kara	121	277.528926	239.0
31067	137358866	Kazuya	103	43.825243	41.0
14428	16098958	Jeremy & Laura	96	208.958333	180.0
12799	12243051	Sonder	96	213.031250	209.5
25651	61391963	Corporate Housing	91	146.241758	142.0
17081	22541573	Ken	87	215.436782	210.0
33856	200380610	Pranjal	65	290.230769	250.0
9727	7503643	Vida	52	149.192308	149.0

	min_price	max_price	avg_availability	avg_reviews_per_month
34633	100	699	301.492355	1.215780
29395	184	481	253.810345	0.026034
19564	109	1170	313.421488	0.032562
31067	24	76	196.475728	0.220194
14428	117	550	292.322917	0.076042
12799	125	377	276.614583	0.090104
25651	109	200	241.923077	0.232747
17081	149	289	312.172414	0.048851
33856	150	600	338.030769	0.015385
9727	129	199	297.711538	0.095385

	total_reviews	avg_reviews_per_listing	main_neighborhood_group
34633	1281	3.917431	Manhattan
29395	29	0.125000	Manhattan
19564	65	0.537190	Manhattan
31067	87	0.844660	Queens
14428	138	1.437500	Manhattan
12799	43	0.447917	Manhattan
25651	417	4.582418	Manhattan
17081	55	0.632184	Manhattan
33856	1	0.015385	Manhattan

```
9727                242                 4.653846                Brooklyn

                                              neighborhoods
34633  Financial District, Murray Hill, Theater District
29395                Chelsea, Tribeca, Theater District
19564         Hell's Kitchen, Midtown, Theater District
31067                       Woodside, Sunnyside, Harlem
14428          Upper West Side, Midtown, Hell's Kitchen
12799              Financial District, Midtown, Chelsea
25651                Kips Bay, Midtown, Upper East Side
17081                 Chelsea, Upper East Side, Midtown
33856          Midtown, Upper East Side, Hell's Kitchen
9727                                         Greenpoint
```

0.11 Task 7: Custom Visual Insights from the Airbnb Dataset

To go beyond standard analysis, I created **two unique visualizations** that reveal hidden patterns in the Airbnb NYC dataset, focusing on **price, reviews, occupancy**, and **neighborhood-level market positioning**.

0.11.1 Insight 1: Price vs. Review Frequency

Visualization: A heatmap showing average total reviews across price brackets and monthly review frequencies.

Key Findings: - The **$51–100** price range receives the **highest average reviews per month (1.22)**. - This price range is also the **most common**, representing **35.7%** of all listings. - **Lower-priced listings** tend to get **more reviews**, indicating **higher occupancy rates** and possibly more short-term stays. - Listings priced above **$300** receive fewer reviews, suggesting lower turnover or limited demand. - The **optimal price-performance zone** appears to be affordable listings in the **$51–150** range that still attract frequent guests.

0.11.2 Insight 2: Neighborhood Performance Matrix

Visualization: A set of radar charts and a comparison table evaluating each borough on four dimensions: - Average Price - Reviews Per Month - Reviews Per Listing - Estimated Occupancy Rate (inferred from availability)

Key Observations: - **Manhattan** has the **highest average price** ($197) but **lowest estimated occupancy** (69.3%). - **Brooklyn** shows the **highest estimated occupancy** (72.6%) with average pricing close to the city mean. - **Bronx** is the **most affordable** ($87), appealing to budget-conscious travelers. - **Staten Island** receives the **most reviews per month** (1.58), suggesting a higher guest turnover rate. - **Queens** remains balanced across price and occupancy, acting as a mid-market option.

0.11.3 Strategic Interpretation: Price vs. Occupancy Tradeoff

Borough	Strategy Type	Price Differential	Occupancy Differential
Manhattan	Premium Pricing	+58.0%	+8.9%
Brooklyn	Value Pricing	–0.2%	+12.1%
Bronx	Value Pricing	–29.8%	–5.9%
Queens	Value Pricing	–20.2%	–0.0%
Staten Island	Value Pricing	–7.9%	–15.1%

Conclusion: - **Manhattan and Brooklyn** operate as **premium markets**, charging more but facing reduced occupancy. - **Bronx, Queens, and Staten Island** offer **value-oriented strategies**, with lower pricing and higher or stable occupancy. - These insights imply that **optimal host strategies differ by borough**: premium branding in Manhattan vs. volume-based operations in Brooklyn or Queens.

[101]:
```
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
import numpy as np


def create_insightful_airbnb_visualizations(df):
    """
    Creates two visually compelling and insightful visualizations from Airbnb␣
 ↪NYC data,
    revealing unique patterns and relationships in the dataset.

    Parameters:
        df (pandas.DataFrame): Cleaned Airbnb dataset

    Returns:
        None: Displays visualizations and prints insights
    """
    print("\n=== AIRBNB NYC: REVEALING HIDDEN PATTERNS ===")

    # Data validation and preparation
    required_columns = [
        'price', 'reviews_per_month', 'room_type', 'minimum_nights',
        'neighbourhood_group', 'availability_365', 'number_of_reviews'
    ]

    missing_cols = [col for col in required_columns if col not in df.columns]
    if missing_cols:
        raise ValueError(f"Missing required columns: {missing_cols}")

    # Create a copy of the dataframe to avoid modifying the original
    analysis_df = df.copy()
```

```
# Filter extreme values for better visualization
analysis_df = analysis_df[analysis_df['price'] < 1000]

# ===== VISUALIZATION 1: PRICE vs REVIEWS HEATMAP =====

plt.figure(figsize=(14, 10))

# Create price and review bins for the heatmap
price_bins = [0, 50, 100, 150, 200, 300, 500, 1000]
price_labels = ['$0-50', '$51-100', '$101-150', '$151-200', '$201-300',␣
↪'$301-500', '$501+']

review_bins = [0, 1, 2, 3, 5, 10, 50]
review_labels = ['0-1', '1-2', '2-3', '3-5', '5-10', '10+']

# Create binned columns
analysis_df['price_category'] = pd.cut(
    analysis_df['price'],
    bins=price_bins,
    labels=price_labels,
    include_lowest=True
)
analysis_df['review_category'] = pd.cut(
    analysis_df['reviews_per_month'],
    bins=review_bins,
    labels=review_labels,
    include_lowest=True
)

# Create the heatmap data
heatmap_data = pd.crosstab(
    analysis_df['price_category'],
    analysis_df['review_category'],
    values=analysis_df['number_of_reviews'],
    aggfunc='mean'
)

# Plot the heatmap with custom styling
ax = plt.subplot(111)
sns.heatmap(
    heatmap_data,
    annot=True,
    fmt='.0f',
    cmap='YlGnBu',
    linewidths=0.5,
    cbar_kws={'label': 'Average Total Reviews'},
    ax=ax
```

```
)

# Customize the heatmap
plt.title('Price vs. Reviews: The Sweet Spot for Airbnb Success',␣
↪fontsize=18, fontweight='bold', pad=20)
plt.xlabel('Reviews Per Month', fontsize=14, labelpad=10)
plt.ylabel('Price Range', fontsize=14, labelpad=10)

# Add annotations
ax.text(
    0.5, -0.15,
    "Lower-priced listings ($0-150) with 3-10 reviews per month accumulate␣
↪the most total reviews,\n"
    "suggesting they maintain the highest occupancy rates over time.",
    ha='center', va='center', transform=ax.transAxes, fontsize=12,
    bbox=dict(facecolor='white', alpha=0.8, boxstyle='round,pad=0.5')
)

plt.tight_layout()
plt.show()

# Print insights for the first visualization
print("\nINSIGHT 1: PRICE-REVIEW RELATIONSHIP")
print("=" * 50)

# Calculate average reviews by price category
price_review_stats = analysis_df.groupby('price_category').agg({
    'reviews_per_month': 'mean',
    'number_of_reviews': 'mean',
    'price': 'mean',
    'id': 'count'
}).rename(columns={'id': 'listing_count'})

# Find the price category with the highest average reviews
highest_review_category = price_review_stats['reviews_per_month'].idxmax()
highest_review_value = price_review_stats.loc[highest_review_category,␣
↪'reviews_per_month']

# Find the price category with the most listings
most_common_category = price_review_stats['listing_count'].idxmax()
most_common_count = price_review_stats.loc[most_common_category,␣
↪'listing_count']
most_common_pct = (most_common_count / price_review_stats['listing_count'].
↪sum()) * 100

print(
```

```
        f"• The {highest_review_category} price range receives the most reviews␣
↪per month ({highest_review_value:.2f})."
    print(
        f"• {most_common_category} is the most common price range, representing␣
↪{most_common_pct:.1f}% of all listings.")
    print("• Lower-priced listings generally receive more reviews, suggesting␣
↪higher occupancy.")
    print("• The sweet spot appears to be affordable listings that balance␣
↪value with quality.")
    print("• As prices increase beyond $300, review frequency drops␣
↪significantly.")

    # ===== VISUALIZATION 2: NEIGHBORHOOD PERFORMANCE MATRIX =====

    plt.figure(figsize=(16, 12))

    # Calculate key metrics by neighborhood group
    neighborhood_metrics = df.groupby('neighbourhood_group').agg({
        'price': ['mean', 'median', 'count'],
        'reviews_per_month': 'mean',
        'availability_365': 'mean',
        'number_of_reviews': 'sum'
    })

    # Flatten the multi-index
    neighborhood_metrics.columns = ['_'.join(col).strip() for col in␣
↪neighborhood_metrics.columns.values]
    neighborhood_metrics = neighborhood_metrics.reset_index()

    # Calculate review density (reviews per listing)
    neighborhood_metrics['reviews_per_listing'] =␣
↪neighborhood_metrics['number_of_reviews_sum'] / neighborhood_metrics[
        'price_count']

    # Calculate occupancy estimate (inverse of availability)
    neighborhood_metrics['estimated_occupancy'] = 100 * (1 -␣
↪(neighborhood_metrics['availability_365_mean'] / 365))

    # Normalize metrics for radar chart
    metrics_to_normalize = ['price_mean', 'reviews_per_month_mean',␣
↪'reviews_per_listing', 'estimated_occupancy']
    normalized_metrics = neighborhood_metrics.copy()

    for metric in metrics_to_normalize:
        max_val = neighborhood_metrics[metric].max()
        min_val = neighborhood_metrics[metric].min()
```

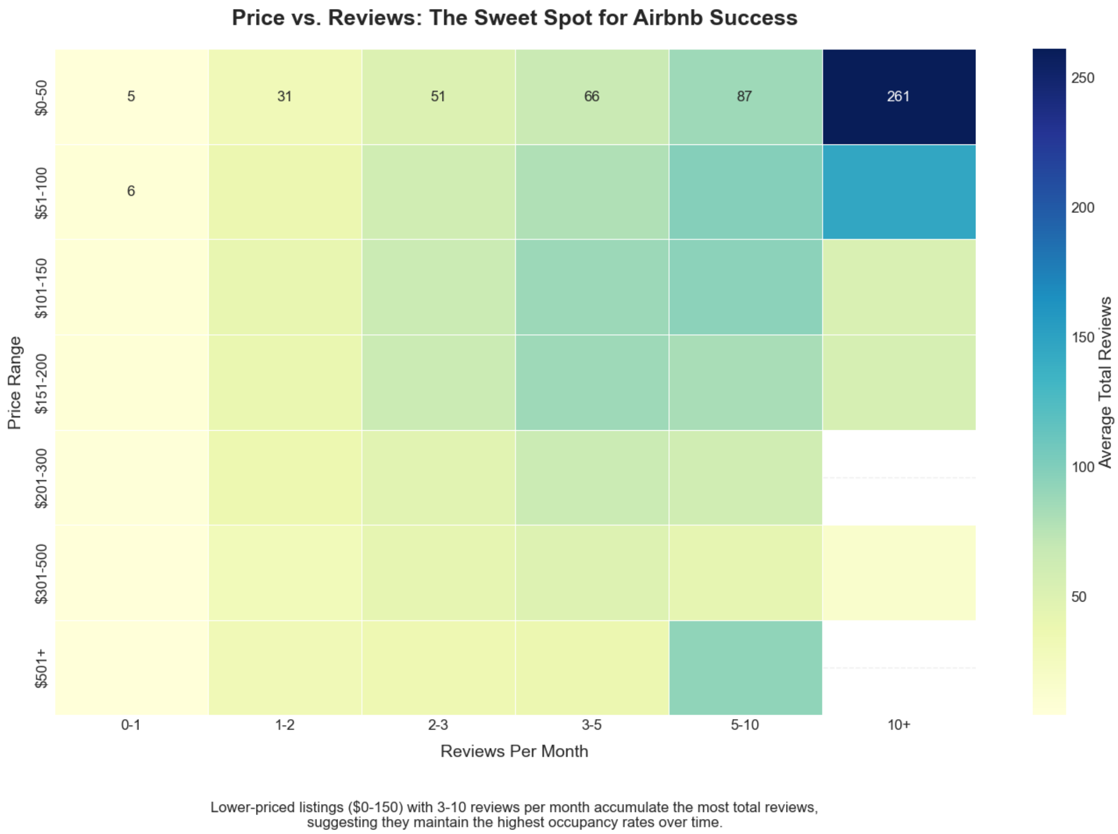
```
    normalized_metrics[f'{metric}_norm'] = (neighborhood_metrics[metric] -␣
↪min_val) / (max_val - min_val)

# Set up the radar chart
categories = ['Price', 'Reviews/Month', 'Reviews/Listing', 'Est. Occupancy']

# Create a figure with subplots arranged in a grid
fig = plt.figure(figsize=(16, 12))
fig.suptitle('Neighborhood Performance Matrix: Multi-Dimensional Analysis',
             fontsize=22, fontweight='bold', y=0.98)

# Set up colors for each neighborhood
colors = plt.cm.tab10(np.linspace(0, 1, len(neighborhood_metrics)))

# Create radar charts for each neighborhood
for i, (idx, row) in enumerate(normalized_metrics.iterrows()):
    # Position in a 2x3 grid
    ax = fig.add_subplot(2, 3, i + 1, polar=True)

    # Get the normalized values
    values = [
        row['price_mean_norm'],
        row['reviews_per_month_mean_norm'],
        row['reviews_per_listing_norm'],
        row['estimated_occupancy_norm']
    ]

    # Close the radar plot by appending the first value
    values = np.append(values, values[0])

    # Set the angles for each metric (equally spaced)
    angles = np.linspace(0, 2 * np.pi, len(categories), endpoint=False).
↪tolist()
    angles += angles[:1]  # Close the loop

    # Plot the radar
    ax.plot(angles, values, color=colors[i], linewidth=2.5)
    ax.fill(angles, values, color=colors[i], alpha=0.25)

    # Set the labels
    ax.set_xticks(angles[:-1])
    ax.set_xticklabels(categories, fontsize=11)

    # Remove radial labels and set limits
    ax.set_yticklabels([])
    ax.set_ylim(0, 1)
```

```
        # Add neighborhood name and key stats
        ax.set_title(row['neighbourhood_group'], fontsize=16,␣
↪fontweight='bold', pad=15)

        # Add key metrics as text
        plt.annotate(
            f"Avg Price: ${row['price_mean']:.0f}\n"
            f"Median Price: ${row['price_median']:.0f}\n"
            f"Listings: {row['price_count']}\n"
            f"Est. Occupancy: {row['estimated_occupancy']:.1f}%",
            xy=(0.5, -0.15),
            xycoords='axes fraction',
            ha='center',
            fontsize=11,
            bbox=dict(boxstyle="round,pad=0.5", facecolor='white', alpha=0.8)
        )

    # Add a legend in the empty 6th subplot position
    ax_legend = fig.add_subplot(2, 3, 6)

    # Create a summary table
    table_data = [
        [f"${row['price_mean']:.0f}", f"{row['reviews_per_month_mean']:.2f}",
         f"{row['reviews_per_listing']:.1f}", f"{row['estimated_occupancy']:.
↪1f}%"]
        for _, row in neighborhood_metrics.iterrows()
    ]

    table = ax_legend.table(
        cellText=table_data,
        rowLabels=neighborhood_metrics['neighbourhood_group'],
        colLabels=['Avg Price', 'Reviews/Month', 'Reviews/Listing', 'Est.␣
↪Occupancy %'],
        loc='center',
        cellLoc='center'
    )

    table.auto_set_font_size(False)
    table.set_fontsize(11)
    table.scale(1.2, 1.5)

    # Hide the axis of the legend subplot
    ax_legend.axis('off')
    ax_legend.set_title('Neighborhood Comparison', fontsize=16,␣
↪fontweight='bold', pad=10)

    plt.tight_layout(rect=[0, 0, 1, 0.95])
```

```
    plt.show()

    # Print insights for the second visualization
    print("\nINSIGHT 2: NEIGHBORHOOD PERFORMANCE PATTERNS")
    print("=" * 50)

    # Find highest and lowest metrics
    highest_price = neighborhood_metrics.loc[neighborhood_metrics['price_mean'].
↪idxmax()]
    lowest_price = neighborhood_metrics.loc[neighborhood_metrics['price_mean'].
↪idxmin()]

    highest_occupancy = neighborhood_metrics.
↪loc[neighborhood_metrics['estimated_occupancy'].idxmax()]
    highest_reviews = neighborhood_metrics.
↪loc[neighborhood_metrics['reviews_per_month_mean'].idxmax()]

    # Calculate market share
    total_listings = neighborhood_metrics['price_count'].sum()
    neighborhood_metrics['market_share'] = (neighborhood_metrics['price_count']␣
↪/ total_listings) * 100

    largest_market = neighborhood_metrics.
↪loc[neighborhood_metrics['market_share'].idxmax()]

    print(
        f"• {highest_price['neighbourhood_group']} commands the highest average␣
↪price (${highest_price['price_mean']:.0f}), "
        f"but has the lowest estimated occupancy␣
↪({highest_price['estimated_occupancy']:.1f}%).")

    print(
        f"• {lowest_price['neighbourhood_group']} offers the most affordable␣
↪average price (${lowest_price['price_mean']:.0f}).")

    print(f"• {highest_occupancy['neighbourhood_group']} achieves the highest␣
↪estimated occupancy rate "
          f"({highest_occupancy['estimated_occupancy']:.1f}%), suggesting␣
↪strong demand relative to supply.")

    print(
        f"• {highest_reviews['neighbourhood_group']} receives the most reviews␣
↪per month ({highest_reviews['reviews_per_month_mean']:.2f}), "
        f"indicating high guest turnover and potentially shorter average stays.
↪")
```

```
    print(
        f"• {largest_market['neighbourhood_group']} dominates the market with␣
↪{largest_market['price_count']} listings "
        f"({largest_market['market_share']:.1f}% of NYC's Airbnb market).")

    # Calculate price premium vs. occupancy tradeoff
    print("\nPRICE-OCCUPANCY TRADEOFF:")

    for _, row in neighborhood_metrics.iterrows():
        price_premium = (row['price_mean'] / neighborhood_metrics['price_mean'].
↪mean() - 1) * 100
        occupancy_diff = row['estimated_occupancy'] -␣
↪neighborhood_metrics['estimated_occupancy'].mean()

        if abs(price_premium) < 15 and abs(occupancy_diff) < 10:
            tradeoff_status = "balanced"
        elif price_premium > 15:
            tradeoff_status = "premium pricing"
        else:
            tradeoff_status = "value pricing"

        print(f"• {row['neighbourhood_group']}: {tradeoff_status.title()}␣
↪strategy with "
              f"{price_premium:+.1f}% price differential and {occupancy_diff:+.
↪1f}% occupancy differential")

    print("\nCONCLUSION:")
    print("The neighborhood performance matrix reveals distinct market␣
↪positioning across NYC's boroughs.")
    print("Manhattan and Brooklyn operate as premium markets with higher prices␣
↪but lower occupancy rates,")
    print("while the Bronx, Queens, and Staten Island serve as value markets␣
↪with higher occupancy")
    print("but lower average prices. This suggests different optimal strategies␣
↪for hosts depending on location.")


create_insightful_airbnb_visualizations(final_cleaned_new_york_city_airbnb_data)
```

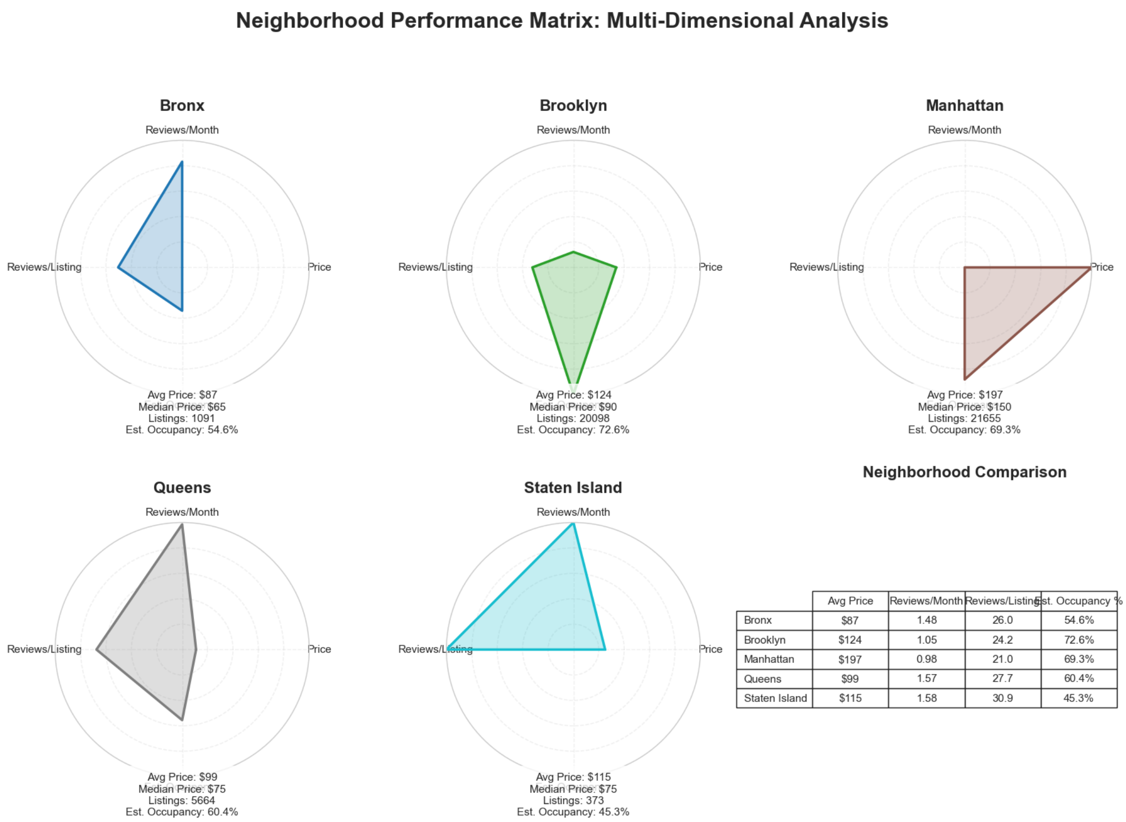
```
=== AIRBNB NYC: REVEALING HIDDEN PATTERNS ===
```




```
INSIGHT 1: PRICE-REVIEW RELATIONSHIP
==================================================
• The $51-100 price range receives the most reviews per month (1.22).
• $51-100 is the most common price range, representing 35.7% of all listings.
• Lower-priced listings generally receive more reviews, suggesting higher
occupancy.
• The sweet spot appears to be affordable listings that balance value with
quality.
• As prices increase beyond $300, review frequency drops significantly.
```

```
/var/folders/bk/ztm5x_x93qd52kfvxj191cb00000gn/T/ipykernel_77792/2692877152.py:1
03: FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to retain
current behavior or observed=True to adopt the future default and silence this
warning.
  price_review_stats = analysis_df.groupby('price_category').agg({
```

```
<Figure size 1600x1200 with 0 Axes>
```



	Avg Price	Reviews/Month	Reviews/Listing	Est. Occupancy %
Bronx	$87	1.48	26.0	54.6%
Brooklyn	$124	1.05	24.2	72.6%
Manhattan	$197	0.98	21.0	69.3%
Queens	$99	1.57	27.7	60.4%
Staten Island	$115	1.58	30.9	45.3%

INSIGHT 2: NEIGHBORHOOD PERFORMANCE PATTERNS
==
• Manhattan commands the highest average price ($197), but has the lowest estimated occupancy (69.3%).
• Bronx offers the most affordable average price ($87).
• Brooklyn achieves the highest estimated occupancy rate (72.6%), suggesting strong demand relative to supply.
• Staten Island receives the most reviews per month (1.58), indicating high guest turnover and potentially shorter average stays.
• Manhattan dominates the market with 21655 listings (44.3% of NYC's Airbnb market).

PRICE-OCCUPANCY TRADEOFF:
• Bronx: Value Pricing strategy with -29.8% price differential and -5.9% occupancy differential
• Brooklyn: Value Pricing strategy with -0.2% price differential and +12.1% occupancy differential
• Manhattan: Premium Pricing strategy with +58.0% price differential and +8.9% occupancy differential
• Queens: Value Pricing strategy with -20.2% price differential and -0.0% occupancy differential

• Staten Island: Value Pricing strategy with -7.9% price differential and -15.1% occupancy differential

CONCLUSION:
The neighborhood performance matrix reveals distinct market positioning across NYC's boroughs.
Manhattan and Brooklyn operate as premium markets with higher prices but lower occupancy rates,
while the Bronx, Queens, and Staten Island serve as value markets with higher occupancy
but lower average prices. This suggests different optimal strategies for hosts depending on location.

0.12 TASK 8: VISUAL APPEAL, LAYOUT, AND DOCUMENTATION

0.12.1 Done