

```
In [1]: 1 #Loading the required libraries
        2
        3 import numpy as np
        4 import pandas as pd
        5 from collections import Counter
        6 import matplotlib.pyplot as plt
        7 import seaborn as sns
```

```
In [2]: 1 #The two types of dataset which are required are:
        2
        3 #1] Listing Dataset
        4 #2] Reviews Dataset
```

```
In [3]: 1 #Loading the Listings dataset
        2 listings = pd.read_csv(r"C:\Users\sanji\Downloads\Listings.csv\Listings.csv")
```

C:\Users\sanji\AppData\Local\Temp\ipykernel\_14928\3171851516.py:2: DtypeWarning: Columns (5,13) have mixed types. Specify dtype option on import or set low\_memory=False.

```
listings = pd.read_csv(r"C:\Users\sanji\Downloads\Listings.csv\Listings.csv", encoding = 'latin-1')
```

```
In [4]: 1 #Loading the Reviews dataset
        2 reviews = pd.read_csv(r"C:\Users\sanji\Downloads\Reviews.csv\Reviews.csv")
```

```
In [5]: 1 # Displaying the first and last rows of the dataset
```

```
In [6]: 1 listings.head(5)
```

```
Out[6]:
```

	listing_id	name	host_id	host_since	host_location	host_response_time	host_response_rate
0	281420	Beautiful Flat in le Village Montmartre, Paris	1466919	2011-12-03	Paris, Ile-de-France, France	NaN	NaN
1	3705183	39 mÃÂ² Paris (Sacre CÃÂur)	10328771	2013-11-29	Paris, Ile-de-France, France	NaN	NaN
2	4082273	Lovely apartment with Terrace, 60m2	19252768	2014-07-31	Paris, Ile-de-France, France	NaN	NaN
3	4797344	Cosy studio (close to Eiffel tower)	10668311	2013-12-17	Paris, Ile-de-France, France	NaN	NaN
4	4823489	Close to Eiffel Tower - Beautiful flat : 2 rooms	24837558	2014-12-14	Paris, Ile-de-France, France	NaN	NaN

5 rows × 33 columns

In [7]: 1 reviews.head(5)

Out[7]:

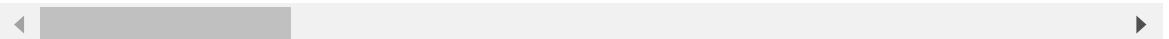
	listing_id	review_id	date	reviewer_id
0	11798	330265172	2018-09-30	11863072
1	15383	330103585	2018-09-30	39147453
2	16455	329985788	2018-09-30	1125378
3	17919	330016899	2018-09-30	172717984
4	26827	329995638	2018-09-30	17542859

In [8]: 1 listings.tail(5)

Out[8]:

	listing_id	name	host_id	host_since	host_location	host_response_time	host_response_rate
279707	38338635	Appartement T2 neuf prÃs du tram T3a Porte ...	31161181	2015-04-13	Paris, Ile-de-France, France		NaN
279708	38538692	Cozy Studio in Montmartre	10294858	2013-11-27	Paris, Ile-de-France, France		NaN
279709	38683356	Nice and cosy mini-appartement in Paris	2238502	2012-04-27	Paris, Ile-de-France, France		NaN
279710	39659000	Charming apartment near Rue Saint Maur / Oberk...	38633695	2015-07-16	Paris, Ile-de-France, France		NaN
279711	40219504	Cosy apartment with view on Canal St Martin	6955618	2013-06-17	Paris, Ile-de-France, France		NaN

5 rows × 33 columns



In [9]: 1 reviews.tail(5)

Out[9]:

	listing_id	review_id	date	reviewer_id
5373138	47779342	726766332	2021-01-25	283094516
5373139	47823964	727963021	2021-01-31	76411977
5373140	47896175	728548625	2021-02-02	71370946
5373141	47900451	727399287	2021-01-29	109011160
5373142	47998038	730320626	2021-02-11	276790978

In [10]:

```
1 # Check for missing values in listings
2
3 print(listings.isnull().sum())
```

```
listing_id      0
name            173
host_id         0
host_since      165
host_location   840
host_response_time 128782
host_response_rate 128782
host_acceptance_rate 113087
host_is_superhost 165
host_total_listings_count 165
host_has_profile_pic 165
host_identity_verified 165
neighbourhood   0
district       242700
city           0
latitude       0
longitude      0
property_type   0
room_type       0
accommodates    0
bedrooms       29435
amenities       0
price          0
minimum_nights  0
maximum_nights  0
review_scores_rating 91405
review_scores_accuracy 91713
review_scores_cleanliness 91665
review_scores_checkin 91771
review_scores_communication 91687
review_scores_location 91775
review_scores_value 91785
instant_bookable 0
dtype: int64
```

In [11]:

```
1 # Checking for missing values in reviews
2
3 print(reviews.isnull().sum())
```

```
listing_id      0
review_id       0
date            0
reviewer_id     0
dtype: int64
```

In [12]:

```
1 # Handling missing values (example: filling or dropping)
2
3 listings.fillna({'price': listings['price'].median()}, inplace=True)
4 reviews.dropna(inplace=True)
```

```
In [13]: 1 # Converting columns to appropriate data types (example: price to numer
2
3 listings['price'] = listings['price'].replace('[\$,]', '', regex=True)
4 listings['price']
```

```
Out[13]: 0          53.0
1         120.0
2          89.0
3          58.0
4          60.0
...
279707    120.0
279708     60.0
279709     50.0
279710    105.0
279711     70.0
Name: price, Length: 279712, dtype: float64
```

```
In [14]: 1 #Descriptive statsitics
```

```
In [15]: 1 listings.describe()
```

```
Out[15]:
```

	listing_id	host_id	host_response_rate	host_acceptance_rate	host_total_listings
count	2.797120e+05	2.797120e+05	150930.000000	166625.000000	279712
mean	2.638196e+07	1.081658e+08	0.865939	0.827168	
std	1.442576e+07	1.108570e+08	0.283744	0.289202	
min	2.577000e+03	1.822000e+03	0.000000	0.000000	
25%	1.384462e+07	1.720656e+07	0.900000	0.780000	
50%	2.767098e+07	5.826911e+07	1.000000	0.980000	
75%	3.978485e+07	1.832853e+08	1.000000	1.000000	
max	4.834353e+07	3.901874e+08	1.000000	1.000000	712

```
In [16]: 1 reviews.describe()
```

```
Out[16]:
```

	listing_id	review_id	reviewer_id
count	5.373143e+06	5.373143e+06	5.373143e+06
mean	1.602989e+07	3.486753e+08	9.808133e+07
std	1.198676e+07	2.061019e+08	9.080596e+07
min	2.577000e+03	2.820000e+02	1.000000e+00
25%	5.332708e+06	1.666435e+08	2.390206e+07
50%	1.450814e+07	3.425727e+08	6.697814e+07
75%	2.414496e+07	5.334045e+08	1.528936e+08
max	4.826387e+07	7.356237e+08	3.903385e+08

```
In [17]: 1 #Visualisation
```

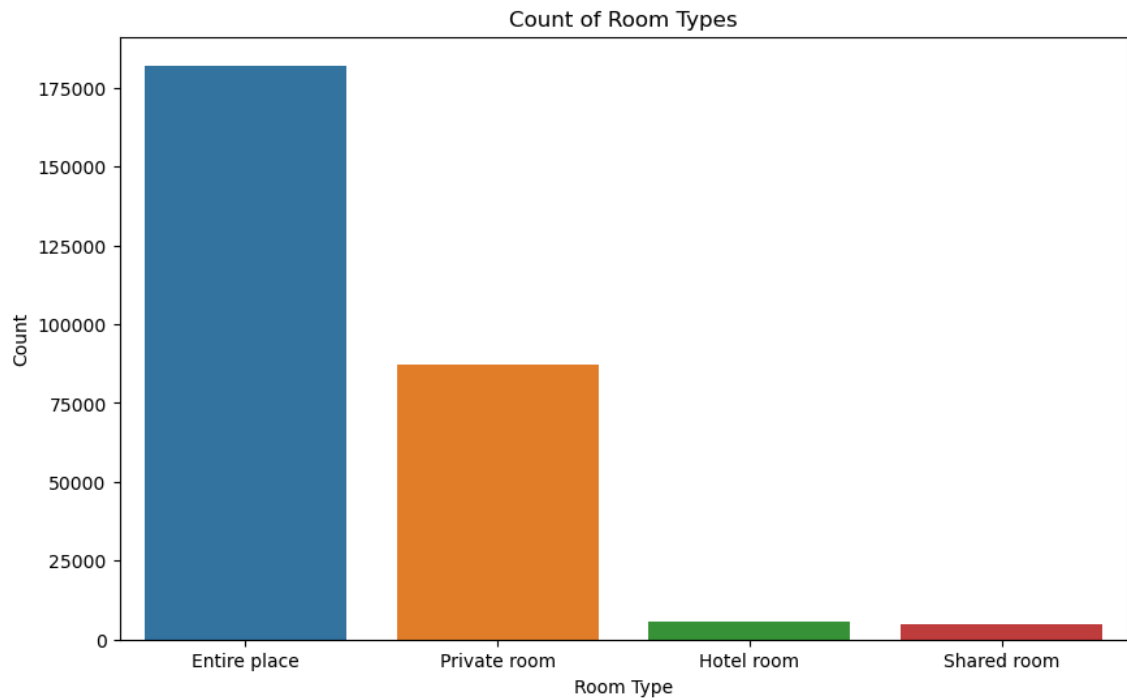
## Scenario 1: Distribution of listing prices

```
In [18]: 1 plt.figure(figsize=(10, 6))
2 sns.histplot(listings['price'], bins=50, kde=True)
3 plt.title('Distribution of Listing Prices')
4 plt.xlabel('Price')
5 plt.ylabel('Frequency')
6 plt.show()
7
```



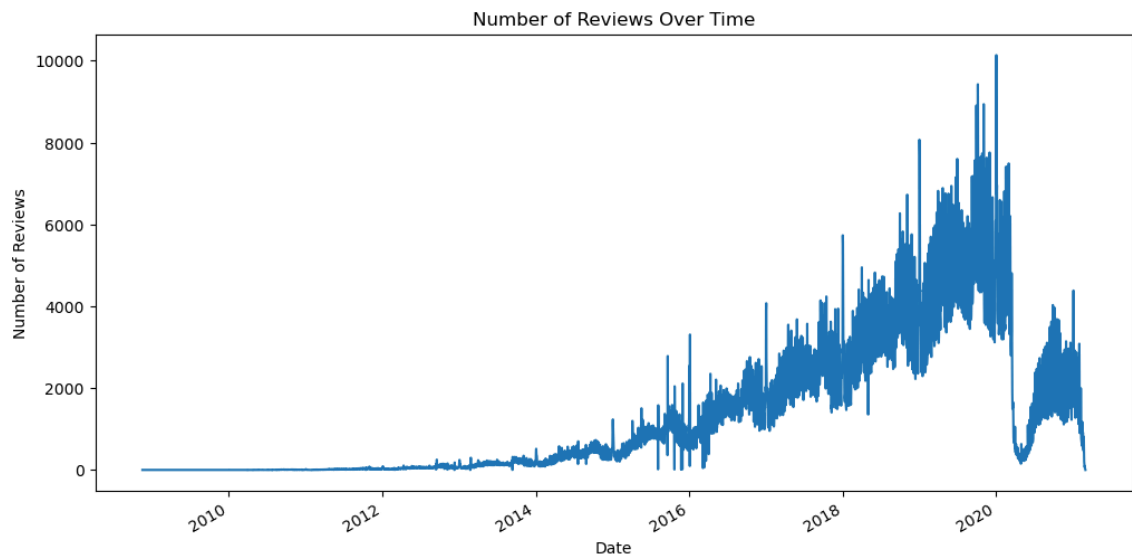
## Scenario 2: Room type Analysis

```
In [19]: 1 plt.figure(figsize=(10, 6))
2         sns.countplot(data=listings, x='room_type', order=listings['room_type']
3         plt.title('Count of Room Types')
4         plt.xlabel('Room Type')
5         plt.ylabel('Count')
6         plt.show()
7
```



### Scenario 3 : How many number of reviews do we get over time?

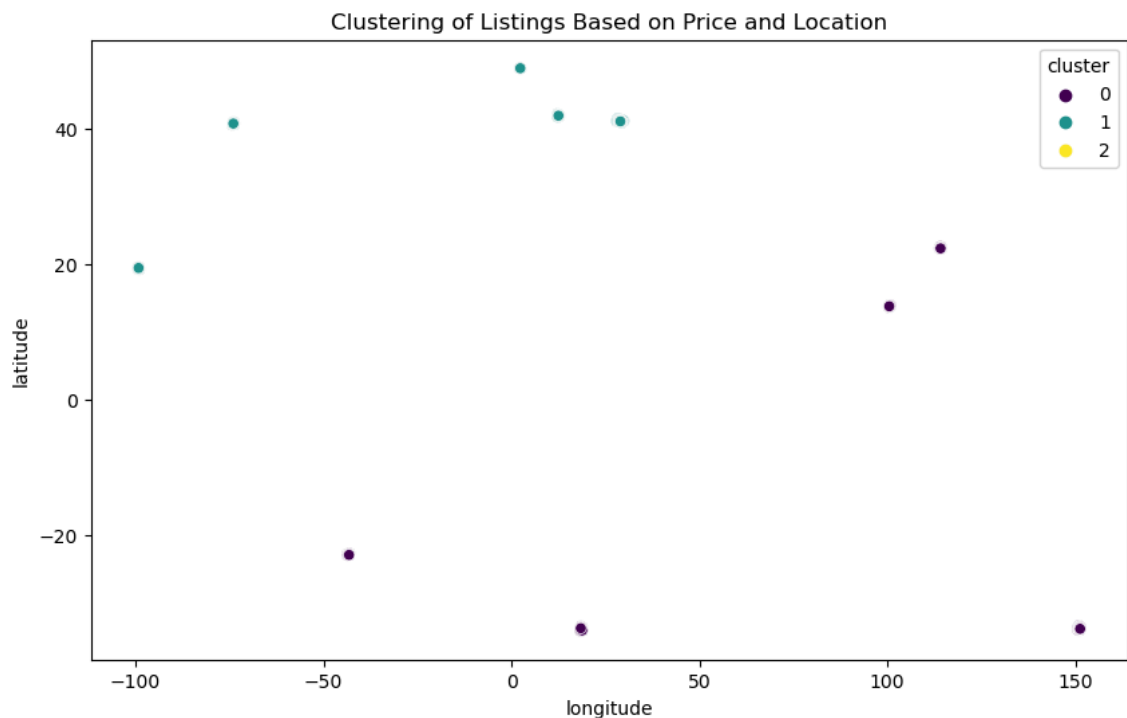
```
In [20]: 1 reviews['date'] = pd.to_datetime(reviews['date'])
2 plt.figure(figsize=(12, 6))
3 reviews['date'].value_counts().sort_index().plot()
4 plt.title('Number of Reviews Over Time')
5 plt.xlabel('Date')
6 plt.ylabel('Number of Reviews')
7 plt.show()
8
```



## Scenario 4 : What is the clustering of listings based on prices and locations?

```
In [21]: 1 from sklearn.cluster import KMeans
2 from sklearn.preprocessing import StandardScaler
3
4 features = listings[['price', 'latitude', 'longitude']]
5 scaler = StandardScaler()
6 scaled_features = scaler.fit_transform(features)
7
8 kmeans = KMeans(n_clusters=3)
9 kmeans.fit(scaled_features)
10
11 listings['cluster'] = kmeans.labels_
12
13 plt.figure(figsize=(10, 6))
14 sns.scatterplot(data=listings, x='longitude', y='latitude', hue='cluster')
15 plt.title('Clustering of Listings Based on Price and Location')
16 plt.show()
17
18
```

C:\Users\sanji\anaconda3\Lib\site-packages\sklearn\cluster\\_kmeans.py:141  
 2: FutureWarning: The default value of `n\_init` will change from 10 to 'auto' in 1.4. Set the value of `n\_init` explicitly to suppress the warning  
 super().\_check\_params\_vs\_input(X, default\_n\_init=10)





## Scenario 5: What are the most common types of Airbnb listings?

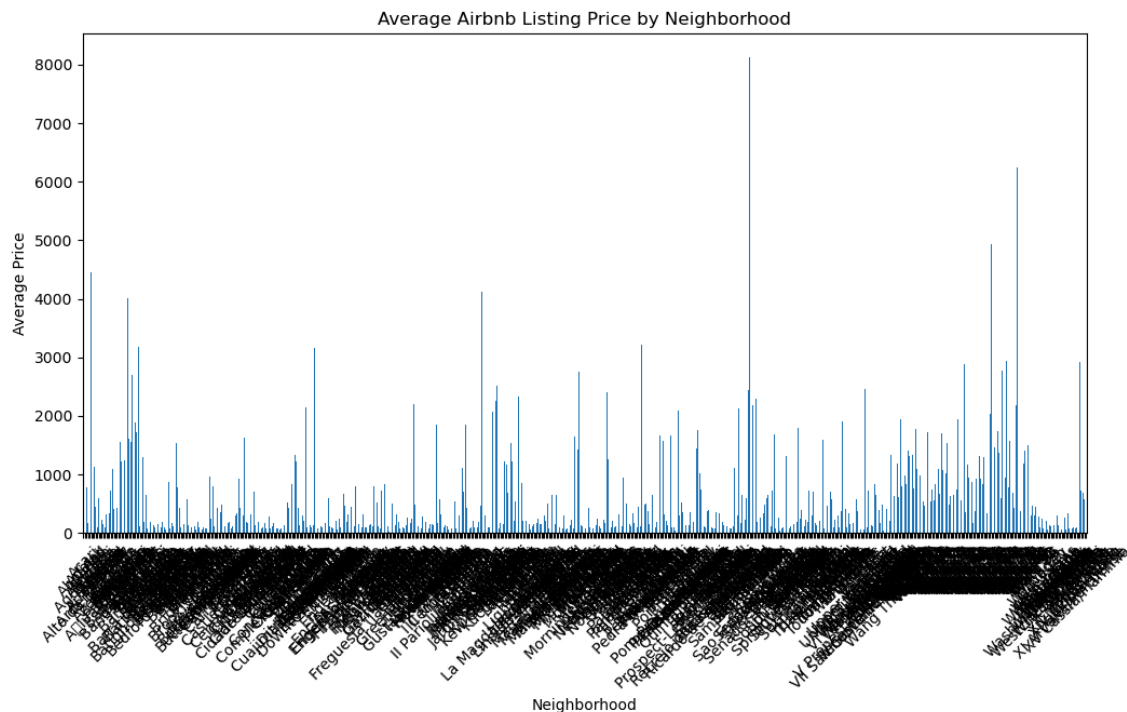
```
In [22]: 1 property_counts = listings['property_type'].value_counts()  
        2 print(property_counts)
```

```
Entire apartment          138989  
Private room in apartment  47322  
Private room in house     13292  
Entire house              13273  
Entire condominium        11250  
  
...  
Shared room in floor      1  
Shared room in parking space 1  
Shared room in tent       1  
Train                     1  
Tipi                      1  
Name: property_type, Length: 144, dtype: int64
```

## Scenario 6: How do listing prices vary across different neighborhoods or regions?

```
In [23]: 1 # Grouping by neighborhood and calculating average price
2 neighborhood_prices = listings.groupby('neighbourhood')['price'].mean()
3
4 # Plotting
5 neighborhood_prices.plot(kind='bar', figsize=(12, 6))
6 plt.xlabel('Neighborhood')
7 plt.ylabel('Average Price')
8 plt.title('Average Airbnb Listing Price by Neighborhood')
9 plt.xticks(rotation=45)
10 plt.show()
11
```

C:\Users\sanji\anaconda3\Lib\site-packages\IPython\core\pylabtools.py:152:  
 UserWarning: Glyph 129 (\x81) missing from current font.  
 fig.canvas.print\_figure(bytes\_io, \*\*kw)

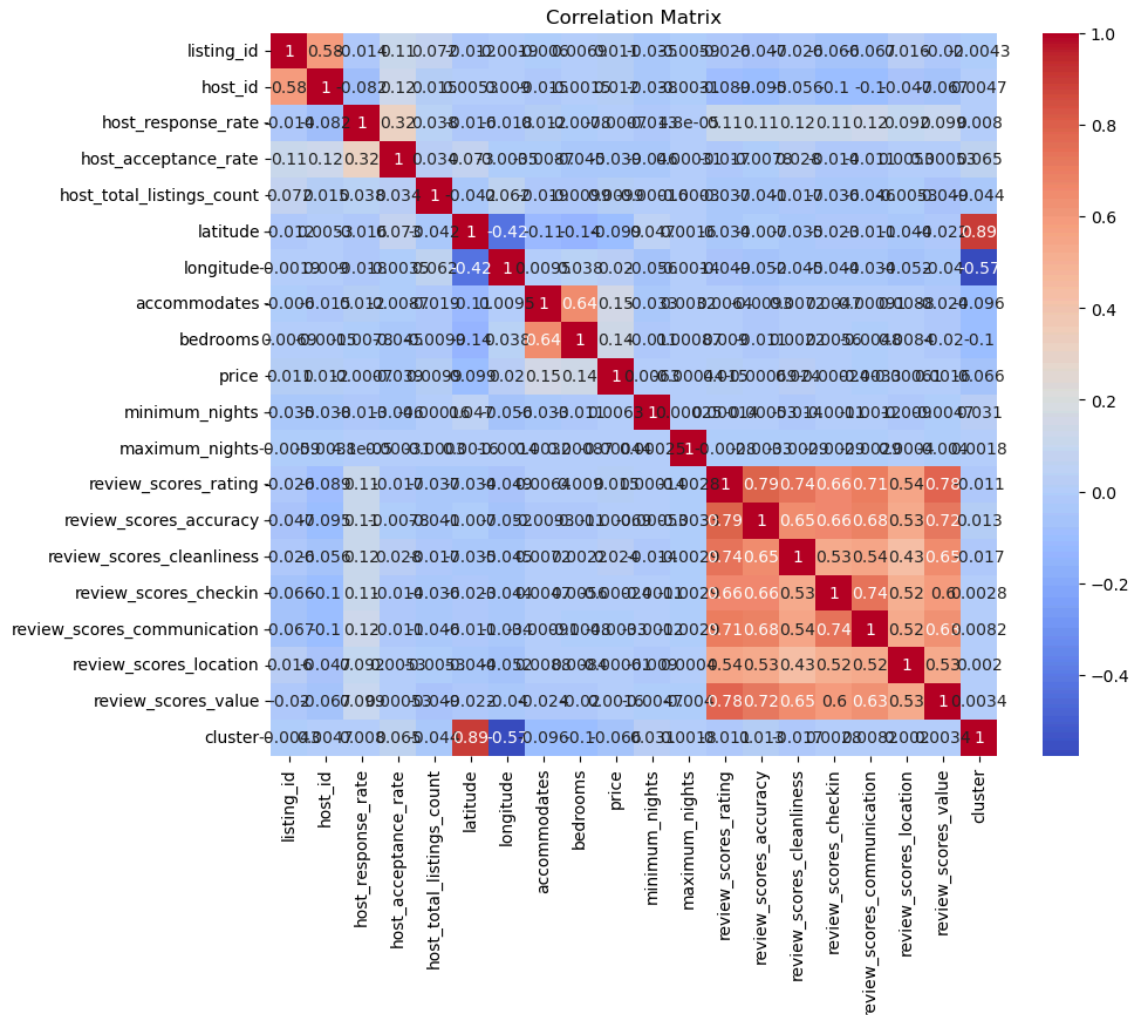


## Scenario 7: What are the key factors influencing listing prices?

```
In [24]: 1 # Correlation matrix
2 correlation_matrix = listings.corr()
3
4 # Plotting heatmap
5 plt.figure(figsize=(10, 8))
6 sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
7 plt.title('Correlation Matrix')
8 plt.show()
9
```

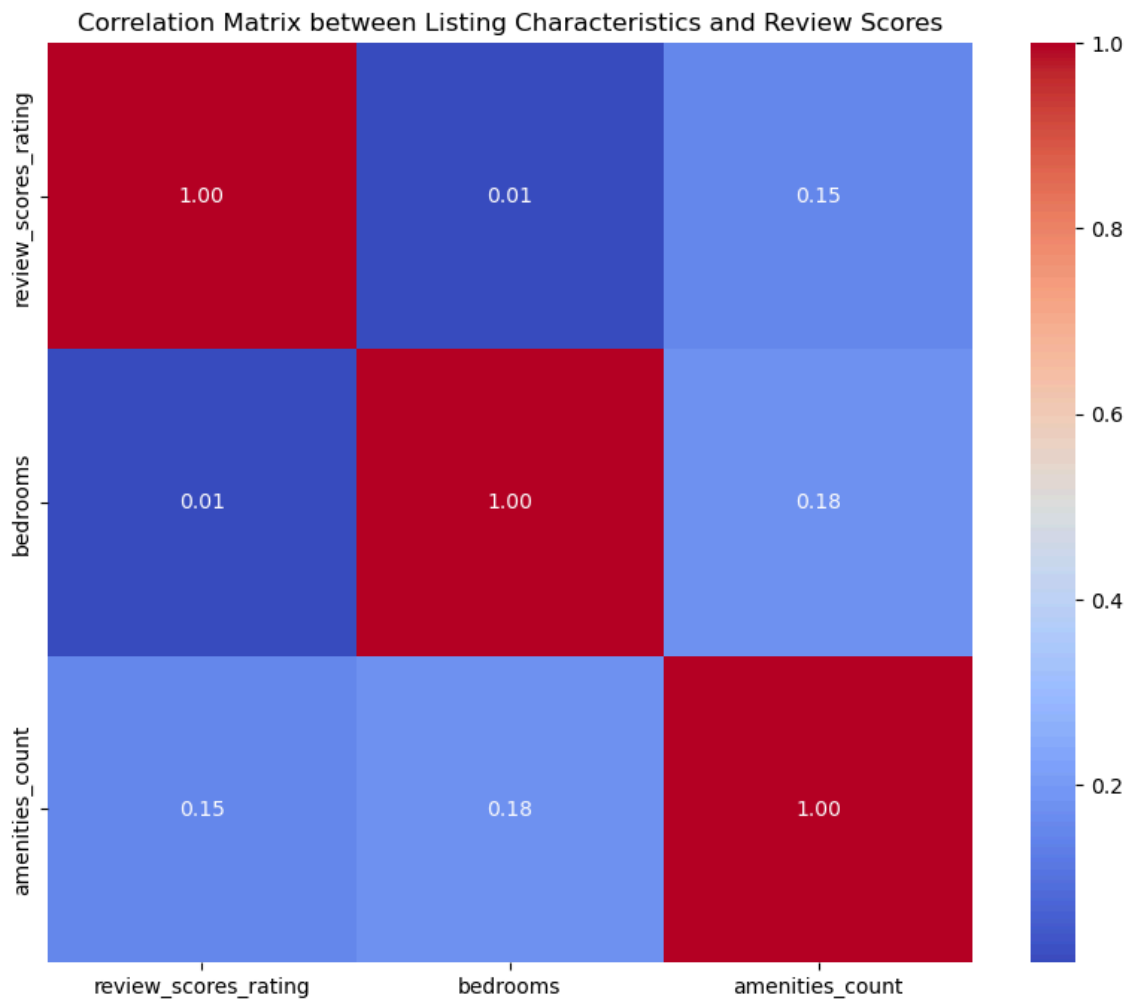
C:\Users\sanji\AppData\Local\Temp\ipykernel\_14928\598132496.py:2: FutureWarning: The default value of numeric\_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid columns or specify the value of numeric\_only to silence this warning.

```
correlation_matrix = listings.corr()
```



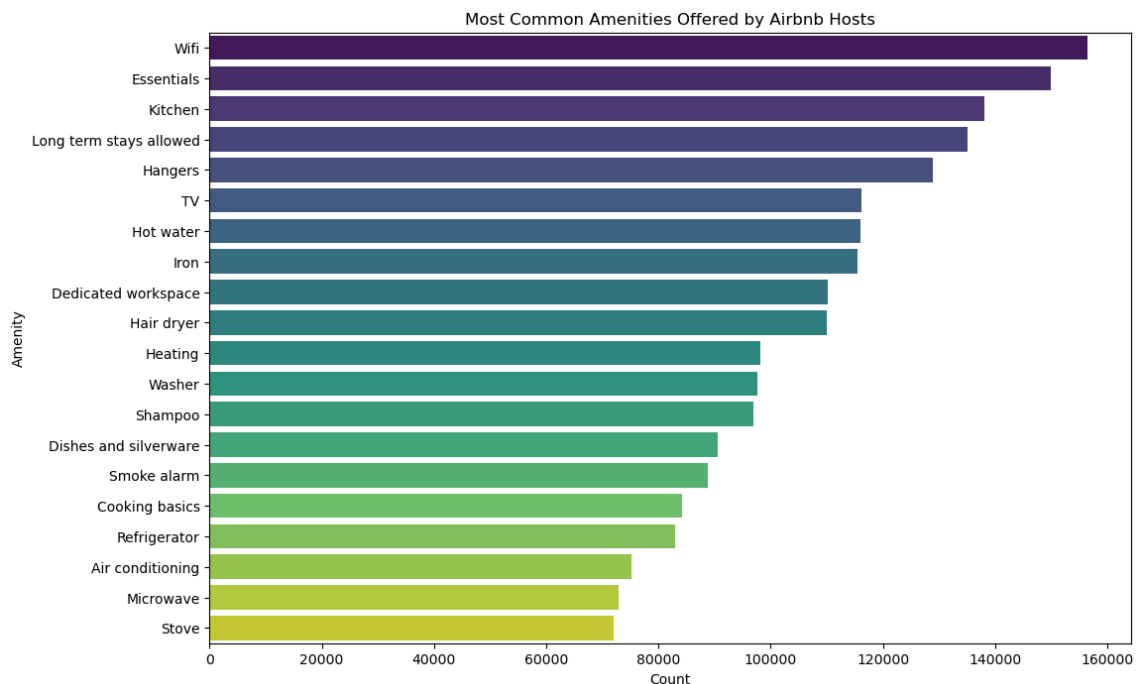
## Scenario 8: How do listing characteristics (e.g., number of bedrooms, amenities) correlate with review scores?

```
In [25]: 1 # Ensure relevant columns are present and without missing values
2 columns_of_interest = ['review_scores_rating', 'bedrooms', 'amenities']
3 listings = listings[columns_of_interest].dropna()
4
5 # Convert amenities to a numerical feature (e.g., count the number of amenities)
6 listings['amenities'] = listings['amenities'].str.strip('{}').str.replace(' ', '')
7 listings['amenities_count'] = listings['amenities'].apply(lambda x: len(x.split(',')))
8
9 # Select relevant numerical columns for correlation analysis
10 numerical_features = ['review_scores_rating', 'bedrooms', 'amenities_count']
11
12 # Calculate correlation matrix
13 correlation_matrix = listings[numerical_features].astype(float).corr()
14
15 # Plot heatmap
16 plt.figure(figsize=(10, 8))
17 sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
18 plt.title('Correlation Matrix between Listing Characteristics and Review Scores')
19 plt.show()
20
```



## Scenario 9: What are the most common amenities offered by Airbnb hosts?

```
In [26]: 1 # Assume the amenities column is a string with comma-separated values
2 # For example: "{Wifi, Kitchen, Heating}"
3 listings['amenities'] = listings['amenities'].str.strip('{}').str.replace(' ', '')
4
5 # Split amenities into a list
6 listings['amenities'] = listings['amenities'].apply(lambda x: x.split(','))
7
8 # Flatten the list of amenities and count the occurrences
9 amenities_list = [amenity.strip() for sublist in listings['amenities'] for amenity in sublist]
10 amenities_counter = Counter(amenities_list)
11
12 # Convert to DataFrame for easier plotting
13 amenities_df = pd.DataFrame(amenities_counter.items(), columns=['amenity', 'count'])
14 amenities_df = amenities_df.sort_values(by='count', ascending=False)
15
16 # Plot the most common amenities
17 plt.figure(figsize=(12, 8))
18 sns.barplot(data=amenities_df.head(20), x='count', y='amenity', palette='magma')
19 plt.xlabel('Count')
20 plt.ylabel('Amenity')
21 plt.title('Most Common Amenities Offered by Airbnb Hosts')
22 plt.show()
23
```



```
In [27]: 1
```

```
In [ ]: 1
2
```

```
In [ ]: 1
```

In [ ]:

1