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EDA project

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import missingno as msno
from scipy import stats
```

```
data = pd.read_csv('raw.csv')
data
```

	Bathrooms	Bedrooms	Beds	LocationName	NumGuests	NumReviews	Price	Rating	latitude	longitude	...	Number of Homes	Count of Abnb	Density of Abnb (%)	Average Abnb Price (by zipcode)	Average NumReviews (by zipcode)	Average Rating (by zipcode)	Average Number of Bathrooms (by zipcode)	Average Number of Bedrooms (by zipcode)	A c zi
0	1.0	1.0	1.0	Atlanta	2.0	7.0	38.0	Y	33.75515	-84.32992	...	5306.0	75	1.413494	104.743243	35.280702	4.944444	1.459459	1.845070	2.
1	1.0	1.0	1.0	Atlanta	2.0	15.0	38.0	N	33.82613	-84.33963	...	10537.2	96	0.911058	103.673684	21.169231	4.847458	1.281250	1.473118	1.
2	2.0	2.0	2.0	Atlanta	4.0	17.0	100.0	Y	33.75076	-84.37058	...	9114.4	200	2.194330	119.368687	40.400000	4.937500	1.375000	1.602094	1.
3	1.0	1.0	1.0	Atlanta	2.0	304.0	78.0	Y	33.77059	-84.33538	...	7808.0	130	1.664959	119.914729	44.063158	4.892857	1.292308	1.603306	1.
4	1.0	1.0	1.0	Atlanta	2.0	19.0	50.0	Y	33.79030	-84.40027	...	9343.6	190	2.033477	131.058511	28.444444	4.881679	1.326316	1.580838	1.
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
33140	1.0	1.0	2.0	Washington	5.0	159.0	67.0	N	38.90956	-77.03107	...	5300.0	123	2.320755	135.268293	52.009174	4.800000	1.262295	1.453704	2.
33141	2.0	1.0	4.0	Washington	1.0	28.0	49.0	Y	38.90920	-77.02622	...	5300.0	123	2.320755	135.268293	52.009174	4.800000	1.262295	1.453704	2.
33142	1.0	1.0	1.0	Washington	2.0	106.0	120.0	Y	38.88746	-76.99119	...	11794.8	410	3.476108	127.748768	54.344444	4.900289	1.196078	1.442708	2.
33143	1.0	1.0	2.0	Washington	3.0	296.0	70.0	Y	38.88535	-76.98183	...	11794.8	410	3.476108	127.748768	54.344444	4.900289	1.196078	1.442708	2.
33144	1.0	1.0	1.0	Alexandria	2.0	10.0	45.0	Y	38.84202	-77.07900	...	6201.6	419	6.756321	153.592233	38.372822	4.766537	1.215827	1.425000	1.

33145 rows × 40 columns

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 33145 entries, 0 to 33144
Data columns (total 40 columns):
 #   Column                                        Non-Null Count  Dtype  
---  ------                                        --------------  -----  
 0   Bathrooms                                     32697 non-null  float64
 1   Bedrooms                                      29818 non-null  float64
 2   Beds                                          32831 non-null  float64
 3   LocationName                                  32826 non-null  object 
 4   NumGuests                                     32831 non-null  float64
 5   NumReviews                                    32829 non-null  float64
 6   Price                                         32507 non-null  float64
 7   Rating                                        33145 non-null  object 
 8   latitude                                      33145 non-null  float64
 9   longitude                                     33145 non-null  float64
 10  zipcode                                       33145 non-null  int64  
 11  pop2016                                       33103 non-null  float64
 12  pop2010                                       33103 non-null  float64
 13  pop2000                                       33145 non-null  int64  
 14  cost_living_index (US avg. = 100)             33103 non-null  float64
 15  land_area (sq.mi.)                            33145 non-null  float64
 16  water_area (sq.mi.)                           33145 non-null  float64
 17  pop_density (people per mile)                 33145 non-null  int64  
 18  number of males                               33145 non-null  int64  
 19  number of females                             33145 non-null  int64  
 20  prop taxes paid 2016                          33058 non-null  float64
 21  median taxes (with mortgage                   29524 non-null  float64
 22  median taxes (no mortgage)                    29618 non-null  float64
 23  median house value                            29812 non-null  float64
 24  median houshold income                        33081 non-null  float64
 25  median monthly owner costs (with mortgage)    29784 non-null  float64
 26  median monthly owner costs (no mortgage)      29651 non-null  float64
 27  median gross rent                             32979 non-null  float64
 28  median asking price for vacant for-sale home/condo  33027 non-null  float64
 29  unemployment (%)                              33036 non-null  float64
 30  Number of Homes                               33103 non-null  float64
 31  Count of Abnb                                 33145 non-null  int64  
 32  Density of Abnb (%)                           33103 non-null  float64
 33  Average Abnb Price (by zipcode)               33145 non-null  float64
 34  Average NumReviews (by zipcode)               33145 non-null  float64
 35  Average Rating (by zipcode)                   33145 non-null  float64
 36  Average Number of Bathrooms (by zipcode)      33145 non-null  float64
 37  Average Number of Bedrooms (by zipcode)       33145 non-null  float64
 38  Average Number of Beds (by zipcode)           33145 non-null  float64
 39  Average Number of Guests (by zipcode)         33145 non-null  float64
dtypes: float64(32), int64(6), object(2)
memory usage: 10.1+ MB
```

```
display(data.head())
```

	Bathrooms	Bedrooms	Beds	LocationName	NumGuests	NumReviews	Price	Rating	latitude	longitude	...	Number of Homes	Count of Abnb	Density of Abnb (%)	Average Abnb Price (by zipcode)	Average NumReviews (by zipcode)	Average Rating (by zipcode)	Average Number of Bathrooms (by zipcode)	Average Number of Bedrooms (by zipcode)	Avera Numb of Be (zipcod
0	1.0	1.0	1.0	Atlanta	2.0	7.0	38.0	Y	33.75515	-84.32992	...	5306.0	75	1.413494	104.743243	35.280702	4.944444	1.459459	1.845070	2.1466
1	1.0	1.0	1.0	Atlanta	2.0	15.0	38.0	N	33.82613	-84.33963	...	10537.2	96	0.911058	103.673684	21.169231	4.847458	1.281250	1.473118	1.6875
2	2.0	2.0	2.0	Atlanta	4.0	17.0	100.0	Y	33.75076	-84.37058	...	9114.4	200	2.194330	119.368687	40.400000	4.937500	1.375000	1.602094	1.9250
3	1.0	1.0	1.0	Atlanta	2.0	304.0	78.0	Y	33.77059	-84.33538	...	7808.0	130	1.664959	119.914729	44.063158	4.892857	1.292308	1.603306	1.9538
4	1.0	1.0	1.0	Atlanta	2.0	19.0	50.0	Y	33.79030	-84.40027	...	9343.6	190	2.033477	131.058511	28.444444	4.881679	1.326316	1.580838	1.9684

5 rows × 40 columns

```
display(data.describe())
```

	Bathrooms	Bedrooms	Beds	NumGuests	NumReviews	Price	latitude	longitude	zipcode	pop2016	...	Number of Homes	Count of Abnb	Density of Abnb (%)	
count	32697.000000	29818.000000	32831.000000	32831.000000	32829.000000	32507.000000	33145.000000	33145.000000	33145.000000	33103.000000	...	33103.000000	33145.000000	33103.000000	33
mean	1.215891	1.474479	1.940148	3.528373	51.086296	117.885071	36.700842	-97.464214	57754.753990	34018.967163	...	13607.586865	739.072077	36.405024	
std	0.547114	0.839045	1.421961	2.260288	62.151818	97.025832	5.198376	21.231474	36716.353574	22522.663845	...	9009.065538	1167.458959	96.259056	
min	0.000000	1.000000	0.000000	1.000000	2.000000	10.000000	25.452690	-122.544590	2108.000000	69.000000	...	27.600000	1.000000	0.003440	
25%	1.000000	1.000000	1.000000	2.000000	11.000000	63.000000	32.749120	-122.259300	19147.000000	15504.000000	...	6201.600000	114.000000	0.805234	
50%	1.000000	1.000000	1.000000	3.000000	28.000000	90.000000	37.796110	-90.079520	70118.000000	33392.000000	...	13356.800000	284.000000	2.234994	
75%	1.000000	2.000000	2.000000	4.000000	67.000000	139.000000	40.647290	-75.181480	94112.000000	45420.000000	...	18168.000000	703.000000	5.538630	
max	9.000000	10.000000	20.000000	16.000000	1099.000000	999.000000	47.742760	-70.983350	98177.000000	114602.000000	...	45840.800000	4143.000000	330.488194	

8 rows × 38 columns

(1) (5 marks) Propose 4 questions (non-predictive and non-trivial) that you believe are interesting to explore and can be answered using the provided dataset (at least 3 question should be answered using hypothesis test). Briefly describe why you think those questions are interesting to whom. You can answer this question in a markdown cell of your ipynb file.

1. Is there a relationship between the average price of Airbnb listings in the same location and the median household income?

   Why is it interesting? Investors may find this useful in understanding how economic issues affect pricing.

2. Is the average price of real estate higher in densely populated areas?

   Why is it interesting? Travelers may find this information useful in understanding the price differences between less populated and more inhabited urban areas.

3. Does the daily cost have a substantial correlation with the number of bedrooms?

   Why is it interesting? For prospective hosts who wish to tailor their pricing strategy according to the size of their house, this is helpful.

4. Do regions with lower unemployment rates have a larger percentage of 5-star listings?

```
missing_count = data.isnull().sum()
missing_percentage = (missing_count / len(data)) * 100

missing_summary = pd.DataFrame({
    'Missing count': missing_count,
    'Missing percentage': missing_percentage
})
print(missing_summary)
```

```
median houshold income                                    64
median monthly owner costs (with mortgage)              3361
median monthly owner costs (no mortgage)                3494
median gross rent                                        166
median asking price for vacant for-sale home/condo      118
unemployment (%)                                         109
Number of Homes                                           42
Count of Abnb                                              0
Density of Abnb (%)                                       42
Average Abnb Price (by zipcode)                            0
Average NumReviews (by zipcode)                            0
Average Rating (by zipcode)                                0
Average Number of Bathrooms (by zipcode)                   0
Average Number of Bedrooms (by zipcode)                    0
Average Number of Beds (by zipcode)                        0
Average Number of Guests (by zipcode)                      0

                                                   Missing percentage
Bathrooms                                                    1.351637
Bedrooms                                                    10.037713
Beds                                                         0.947353
LocationName                                                 0.962438
NumGuests                                                    0.947353
NumReviews                                                   0.953387
Price                                                        1.924876
Rating                                                       0.000000
latitude                                                     0.000000
longitude                                                    0.000000
zipcode                                                      0.000000
pop2016                                                      0.126716
pop2010                                                      0.126716
pop2000                                                      0.000000
cost_living_index (US avg. = 100)                            0.126716
land_area (sq.mi.)                                           0.000000
water_area (sq.mi.)                                          0.000000
pop_density (people per mile)                                0.000000
number of males                                              0.000000
number of females                                            0.000000
prop taxes paid 2016                                         0.262483
median taxes (with mortgage                                 10.924725
median taxes (no mortgage)                                  10.641122
median house value                                          10.055815
median houshold income                                       0.193091
median monthly owner costs (with mortgage)                  10.140293
median monthly owner costs (no mortgage)                    10.541560
median gross rent                                            0.500830
median asking price for vacant for-sale home/condo           0.356011
unemployment (%)                                             0.328858
Number of Homes                                              0.126716
Count of Abnb                                                0.000000
Density of Abnb (%)                                          0.126716
Average Abnb Price (by zipcode)                              0.000000
Average NumReviews (by zipcode)                              0.000000
Average Rating (by zipcode)                                  0.000000
Average Number of Bathrooms (by zipcode)                     0.000000
Average Number of Bedrooms (by zipcode)                      0.000000
Average Number of Beds (by zipcode)                          0.000000
Average Number of Guests (by zipcode)                        0.000000
```

(2) (15 marks) Analyze the quality of data (all columns) and report statistics of missing data and their missing mechanism and why did you choose this mechanism, and how will handle these nulls (there's no one true solution but you must explain your reasons in a separate markdown and you must missingno package to support your claims), the report must answer the following questions

2.1 does missing value exit in the table?

- The dataset does indeed have missing values in a few of its columns.

2.2 Where are the missing data?

- House-specific columns like Bathrooms, Bedrooms, Beds, LocationName, Number of Guests, and Number of Reviews are missing data.
- characteristics of the economy and population, such as median taxes, median house value, prop taxes paid in 2016, pop2016, and pop2010.
- The number of homes and the density of Airbnbs by zipcode are two aggregated Airbnb features with a minor amount of missing data.

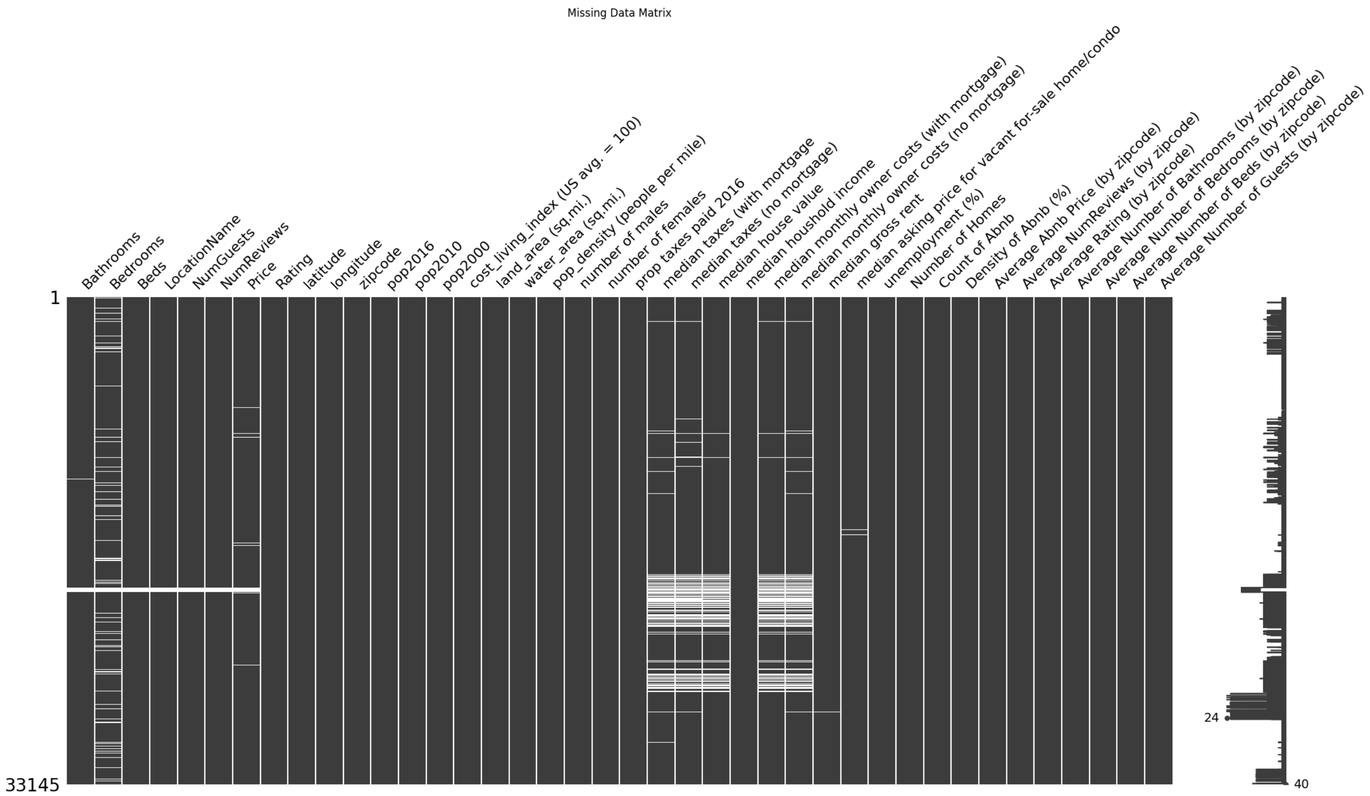
2.3 How much data is missing?

- Each column has a different percentage of missing data: At about 10.92%, median taxes (with mortgage) is the column with the largest percentage of missing data.
- Missing percentages range from 1% to 2% in columns such as Price, Bathrooms, and Prop Taxes Paid in 2016.
- Missing data is absent from the majority of aggregated Airbnb features (Average Abnb Price, etc.).

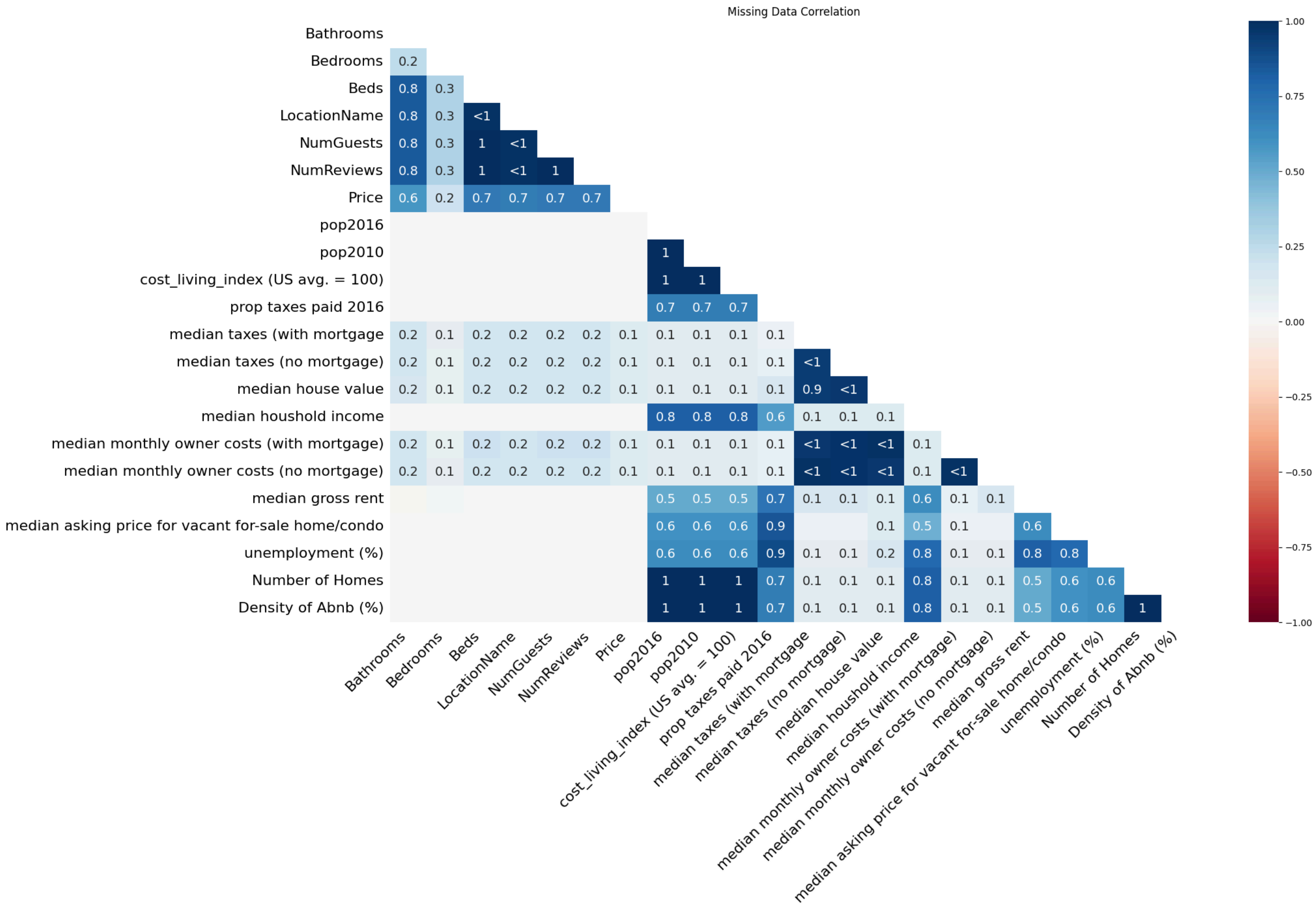
2.4 Are there any variables often missing together?

- Patterns of missing data may be revealed via a more thorough correlation study (using programs like Missingno's heatmap).
- For example, the median taxes with and without mortgages show comparable missing percentages, which suggests that these statistics are missing collectively.
- Patterns may be shared by bedrooms, median home value, and other economic indicators, indicating that missing values may be associated with particular zip codes or listings.

```
# Visualize missing data
msno.matrix(data)
plt.title("Missing Data Matrix")
plt.show()
```




```
msno.heatmap(data)
plt.title("Missing Data Correlation")
plt.show()
```




```
# Handle missing data (example: imputation for numerical and categorical columns)
numerical_cols = data.select_dtypes(include=[np.number]).columns
categorical_cols = data.select_dtypes(exclude=[np.number]).columns

# Imputation strategies
data[numerical_cols] = data[numerical_cols].fillna(data[numerical_cols].median())
data[categorical_cols] = data[categorical_cols].fillna(data[categorical_cols].mode().iloc[0])
```

- Explore outliers and duplicated, and how would you handle them (there's no one true solution but you must explain your reasons in a separate markdown), Briefly describe your step and findings.

Outlier Analysis

- Outliers will be identified using the Interquartile Range (IQR) method.
- Extreme values will be capped to reduce their influence on analysis. """

```
# Outlier handling for 'Price'
Q1 = data['Price'].quantile(0.25)
Q3 = data['Price'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR

outliers = data[(data['Price'] < lower_bound) | (data['Price'] > upper_bound)]
print(f"Number of outliers in 'Price': {len(outliers)}")
```

```
Number of outliers in 'Price': 2483
```

```
# Cap outliers
data['Price'] = np.where(data['Price'] < lower_bound, lower_bound,
                         np.where(data['Price'] > upper_bound, upper_bound, data['Price']))
```

```
# Duplicates Analysis
duplicates = data.duplicated()
print(f"Number of duplicate rows: {duplicates.sum()}")

# Remove duplicates
data = data.drop_duplicates()
```

```
Number of duplicate rows: 4266
```

---

(3) (15 marks) For the 4 questions you proposed in the first subquestion, what are the null hypothesis and alternative hypothesis? Perform statistical test to answer your question and report your findings.

Hypothesis Testing:

Question 1: Price vs. Population Density:

- Null Hypothesis: The average price and population density do not significantly correlate.
- Alternative Hypothesis: The average price and population density are significantly correlated.

```
correlation_result = stats.pearsonr(data['pop_density (people per mile)'], data['Price'])
print("Correlation Test Result for Population Density vs. Price:", correlation_result)
```

```
Correlation Test Result for Population Density vs. Price: PearsonRResult(statistic=0.00865278420080556, pvalue=0.1414527325389911)
```

Question 2: The Ratio of 5-Star Ratings to the Unemployment Rate

- It is hypothesized that the percentage of 5-star ratings is not considerably impacted by the unemployment rate.
- Another theory is that the percentage of 5-star reviews is strongly impacted by the unemployment rate.

```
# Convert Rating column to numeric, coercing errors into NaN
data['Rating'] = pd.to_numeric(data['Rating'], errors='coerce')

# Remove rows where Rating is NaN
low_unemployment = data[data['unemployment (%)'] <= data['unemployment (%)'].median()]['Rating'].dropna()
high_unemployment = data[data['unemployment (%)'] > data['unemployment (%)'].median()]['Rating'].dropna()

# Perform the t-test
ttest_result = stats.ttest_ind(low_unemployment, high_unemployment)
print("T-Test Result for Unemployment Rate vs. 5-Star Ratings:", ttest_result)
```

```
T-Test Result for Unemployment Rate vs. 5-Star Ratings: TtestResult(statistic=nan, pvalue=nan, df=nan)
<ipython-input-63-40d4efffd639>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Rating'] = pd.to_numeric(data['Rating'], errors='coerce')
```

Question 3: Price vs. Bedrooms:

- Null Hypothesis: The daily price is not much impacted by the number of bedrooms.
- Alternative Hypothesis: The daily cost is highly influenced by the number of bedrooms.

```
grouped = [data[data['Bedrooms'] == i]['Price'] for i in data['Bedrooms'].unique()]
anova_result = stats.f_oneway(*grouped)
print("ANOVA Test Result for Bedrooms vs. Price:", anova_result)
```

```
ANOVA Test Result for Bedrooms vs. Price: F_onewayResult(statistic=1804.6818795925049, pvalue=0.0)
```

Question 4: Average Price vs. Median Household Income:

- Null Hypothesis: The average price and median household income do not significantly correlate.
- Alternative Hypothesis: The average price and median household income are significantly correlated.

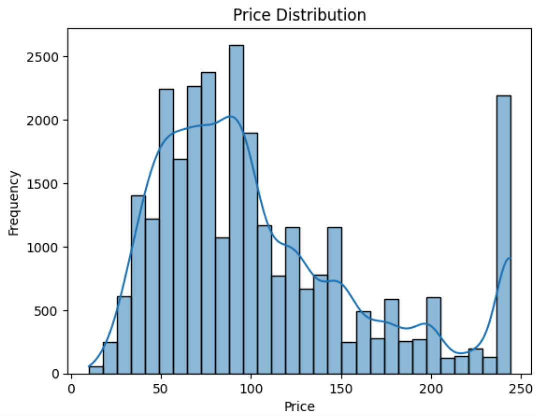
```
correlation_result_income = stats.pearsonr(data['median houshold income'], data['Price'])
print("Correlation Test Result for Median Household Income vs. Average Price:", correlation_result_income)
```

---

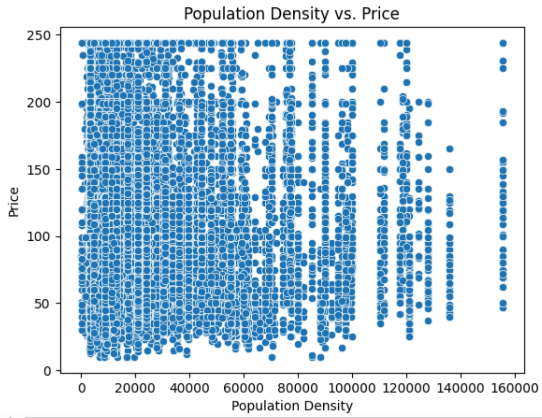
(4) (10 marks) Make some visualizations about your columns and explain what did you got from each visualization.

Visualization

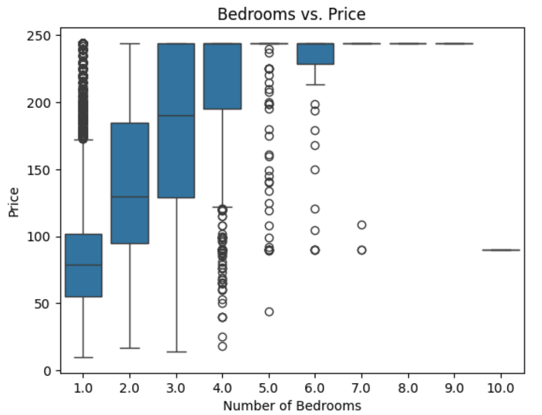
```
# Price Distribution
sns.histplot(data['Price'], bins=30, kde=True)
plt.title('Price Distribution')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```




```
# Population Density vs. Price
# plt.figure(figsize=(20, 14))
sns.scatterplot(x='pop_density (people per mile)', y='Price', data=data)
plt.title('Population Density vs. Price')
plt.xlabel('Population Density')
plt.ylabel('Price')
plt.show()
```




```
# Bedrooms vs. Price
# plt.figure(figsize=(14, 10))
sns.boxplot(x='Bedrooms', y='Price', data=data)
plt.title('Bedrooms vs. Price')
plt.xlabel('Number of Bedrooms')
plt.ylabel('Price')
plt.show()
```




```
# Median Household Income vs. Price
# plt.figure(figsize=(18, 14))
sns.scatterplot(x='median houshold income', y='Price', data=data)
plt.title('Median Household Income vs. Price')
plt.xlabel('Median Household Income')
plt.ylabel('Price')
plt.show()
```

(5) (5 marks) Briefly describe your feature engineering plan and code it (at least 3 columns should be involved).

Plan for Feature Engineering

1. Divide `Price` by `NumGuests` to create a `Price_per_Guest` feature.
2. Depending on whether `cost_living_index` is greater than the median, create a binary `High_Cost_Living` column.
3. Determine the average number of reviews for listings classified by `zipcode` and add `Avg_Reviews_Per_Zipcode`.

```
data['Price_per_Guest'] = data['Price'] / data['NumGuests']

median_cost_living = data['cost_living_index (US avg. = 100)'].median()
data['High_Cost_Living'] = data['cost_living_index (US avg. = 100)'] > median_cost_living
data['Avg_Reviews_Per_Zipcode'] = data.groupby('zipcode')['NumReviews'].transform('mean')

# Save the processed dataset
data.to_csv('processed_airbnb_data.csv', index=False)
print("Feature engineering completed and saved.")
```

```
<ipython-input-83-d12e796f8414>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['Price_per_Guest'] = data['Price'] / data['NumGuests']
<ipython-input-83-d12e796f8414>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  data['High_Cost_Living'] = data['cost_living_index (US avg. = 100)'] > median_cost_living
<ipython-input-83-d12e796f8414>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
```