A bout the data :

We make scraping the data from the Aribnb web site from suadi the data have sevene columns :

- url: the url of the items that have all the data
- name: the name of department
- header: the loaction of the place
- beds: the numbers of the beds in the departments
- bedrooms : the numbers of the rooms in departments
- date_range: how many day you will be stay in the departments
- price: the price of staying in the department
- rating: the rating of the people a bout the place

import libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

Read csv file

In [2]:
```
data  =  pd.read_csv("/kaggle/input/suida-arabia/saudi_arabia.csv")
```

Show the five first rows in the data

In [3]:
```
data.head()
```

Out[3]:

	Unnamed: 0	Exhibitor NeighborhoodThe Green (Self-entry) name	header	beds	bedrooms	date_range
0	0	Saleh's Cottage Saleh Cottage	Cabin in Samha	Saleh's Cottage Saleh Cottage	6 beds, · 2 bedrooms	Nov 12 – 17
1	1	Cypress cottage	Hut in Tabab	Cypress cottage	3 beds, · 2 bedrooms	May 1 – 6 $
2	2	Qishla	Apartment in Riyadh	Qishla	2 beds, · 2 bedrooms	Dec 15 – 20
3	3	Mabaat - Al Narjis - 424	Apartment in Riyadh	Mabaat - Al Narjis - 424	3 beds, · 2 bedrooms	Nov 12 – 17
4	4					

shape of the data

In [4]:
```
data.shape
```

Out[4]:
```
(3600, 8)
```

Show how many missing values in the columns

In [5]:
```
data.isnull().sum()
```

Out[5]:
```
Unnamed: 0      0
name            0
header          0
beds            0
bedrooms        0
date_range      0
price         854
rating         46
dtype: int64
```

Drop all the none value in the rows

In [6]:
```
data.dropna(inplace=True)
```

Here we can extract new features from bedrooms column the first numbers of the beds and the second the numbers of the rooms and others featrues

In [7]:
```
# Extract number of beds and number of bedrooms
data[['num_beds', 'num_bedrooms']] = data['bedrooms'].str.extract('(\d+) beds.*?
```

Fix the price values and delete the Doller sign and convert it to float type

In [8]:
```
data['price'] = data['price'].replace('[\$,]', '', regex=True).astype(float)
data['price'].head(3)
```

Out[8]:
```
2    162.0
3    205.0
4    244.0
Name: price, dtype: float64
```

This column has to value the first number represent the rating of place and the second represent the numbers of commints

In [9]:
```
data['rating'].head(2)
```

Out[9]:
```
2       5.0 (3)
3    4.86 (177)
Name: rating, dtype: object
```

In [10]:
```
# Assuming your DataFrame is named 'df' and the column is 'rating_and_comments'
data['ratingg'] = data['rating'].str.extract(r'(\d+\.\d+)').astype(float)
data['num_comments'] = data['rating'].str.extract(r'\((\d+)\)').astype(float)

# Display the resulting DataFrame
print(data[['ratingg', 'num_comments']].head(2))
```

```
   ratingg  num_comments
2     5.00           3.0
3     4.86         177.0
```

Drop unusefull columns after extracting of the new features

In [11]:
```
data = data.drop(columns=['rating' , 'bedrooms' , 'date_range' ,'Unnamed: 0' ])
```

Rename columns header

In [12]:
```
# Rename columns
data.rename(columns={'header':  'location'},  inplace=True)
```

How many locatioon we have ?

In [13]:
```
data['location'].value_counts()
```

Out[13]:

location	
Apartment in Riyadh	1147
Apartment in Jeddah	778
Condo in Riyadh	276
Condo in Jeddah	231
Home in Riyadh	182
Apartment in Makkah	31
Cabin in Jeddah	7
Apartment in King Abdullah Economic City	5
Chalet in Riyadh	5
Apartment in Mecca	4
Apartment in 3	الرياض
Villa in Riyadh	2
Villa in Dhahran	2
Chalet in Taif	1
Chalet in Mecca	1
Townhouse in Riyadh	1
Cottage in Umluj	1
Tiny home in Makkah Province	1
Hut in Taif	1
Room in Riyadh	1
Loft in Jeddah	1
Cabin in Taif	1
Villa in Jeddah	1
Cabin in At Taif	1
Chalet in Duba	1
Guesthouse in Tabuk Province	1
Guesthouse in Riyadh	1
Condo in Al Khobar	1
Villa in Abha	1
Cabin in Riyadh	1
Barn in Al Ula	1
Tiny home in Ragal Almaa	1
Vacation home in Riyadh	1
Loft in Riyadh City	1
Chalet in Abha	1
Place to stay in Riyadh	1
Farm stay in Al Atheeb	1
Farm stay in Jalajil	1
Barn in Riyadh	1
Barn in Jeddah	1
Home in Jeddah	1
Barn in Shlal	1

Name: count, dtype: int64

This problem called **Consistency**: Renaming the city names ensures that similar locations are represented consistently.

City names mapping

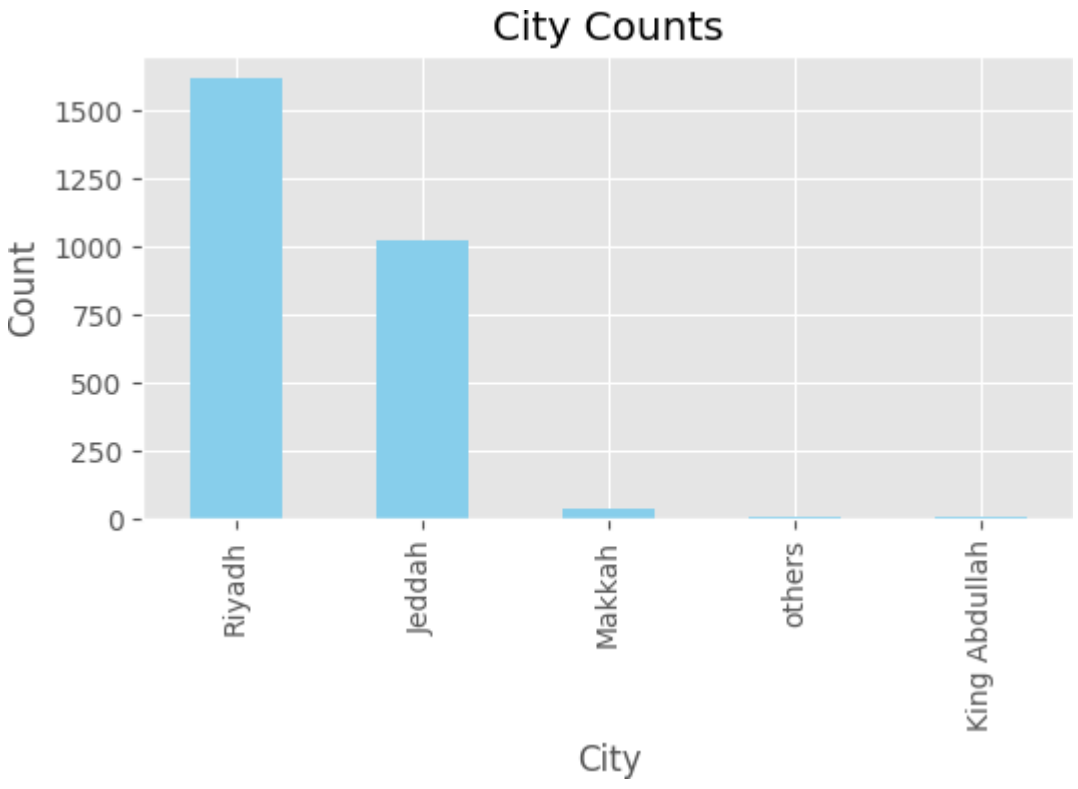
In [14]:

```
import pandas as pd
import re
# City names
# City names mapping
mapping = { 'Apartment in Riyadh': "Riyadh", 'Apartment in Jeddah': "Jeddah", 'C
            'Apartment in Makkah': "Makkah", 'Condo in Jeddah': "Jeddah", 'Home i
            'Apartment in King Abdullah Economic City': "King Abdullah", 'Apartme
            'Hotel in Makkah': "Makkah", 'Apartment in  Muhammadiyah, Jeddah': "J
            'Apartment in Mecca': "Makkah", 'Chalet in Riyadh': "Riyadh", 'Condo
```

```
            'Room in Riyadh': "Riyadh", 'Home in Jeddah': "Jeddah", 'Villa in Riy
            'Hut in Jeddah': "Jeddah", 'Cabin in Jeddah': "Jeddah", 'Hut in Taif'
            'Apartment in Diriyah': "others", 'Guest suite in Riyadh': "Riyadh",
            'Condo in Al Khobar': "others", 'Chalet in Duba': "others", 'Chalet i
            'Vacation home in Riyadh': "Riyadh", 'Tiny home in Ragal Almaa': "oth
            'Place to stay in Riyadh': "Riyadh", 'Farm stay in Jalajil': "others"
            'Ranch in AlUla': "others" , 'Cabin in At Taif': "others", 'Villa in
            'Guesthouse in Makkah': "Makkah"}

# Apply mapping to the 'city' column
data['location'] = data['location'].map(mapping)
```

Count the occurrences of each city

In [15]:
```
# Count the occurrences of each city
city_counts = data['location'].value_counts()

# Plotting
plt.figure(figsize=(6, 3))
city_counts.plot(kind='bar', color='skyblue')
plt.title('City Counts')
plt.xlabel('City')
plt.ylabel('Count')

# Display the plot
plt.show()
```



In [16]:
```
data.columns
```

Out[16]:
```
Index(['name', 'location', 'beds', 'price', 'num_beds', 'num_bedrooms',
       'ratingg', 'num_comments'],
      dtype='object')
```

In [17]:
```
data2 = data.drop(columns=[  'beds'  , 'name'])
```

show the types of the columns

In [18]:
```
data2.dtypes
```

Out[18]:
```
location        Object
price          float64
num_beds        Object
num_bedrooms    Object
ratingg        float64
num_comments   float64
dtype: object
```

In [19]:
```
data2.dropna(inplace=True)
```

- Once you have **converted** the **data types**, you can then enter the data into the model.
- The **model** will then be able to learn the **relationships** between the data and make more **accurate predictions**.

In [20]:
```
# Convert columns to recommended data types
data2['location'] = data2['location'].astype(str)
data2['price'] = data2['price'].astype(float)
data2['num_beds'] = data2['num_beds'].astype(int)
data2['num_bedrooms'] = data2['num_bedrooms'].astype(int)
data2['ratingg'] = data2['ratingg'].astype(float)
data2['num_comments'] = data2['num_comments'].astype(int)
```

- Describe method to display summary statistics (count, mean, std, min, 25%, 50%, 75%, and max) for numeric columns.
- It also shows the mean and median for specific columns.

In [21]:
```
data2.describe()
```

Out[21]:

	price	num_beds	num_bedrooms	ratingg	num_comments
count	2139.000000	2139.000000	2139.000000	2139.000000	2139.000000
mean	156.085554	3.043478	2.135577	4.909719	21.863955
std	97.589496	1.381922	0.889783	0.128036	17.694838
min	48.000000	1.000000	1.000000	3.250000	3.000000
25%	104.000000	2.000000	2.000000	4.850000	10.000000
50%	133.000000	3.000000	2.000000	5.000000	16.000000
75%	158.000000	4.000000	2.000000	5.000000	33.000000
max	447.000000	8.000000	5.000000	5.000000	178.000000

analysis and recommendations

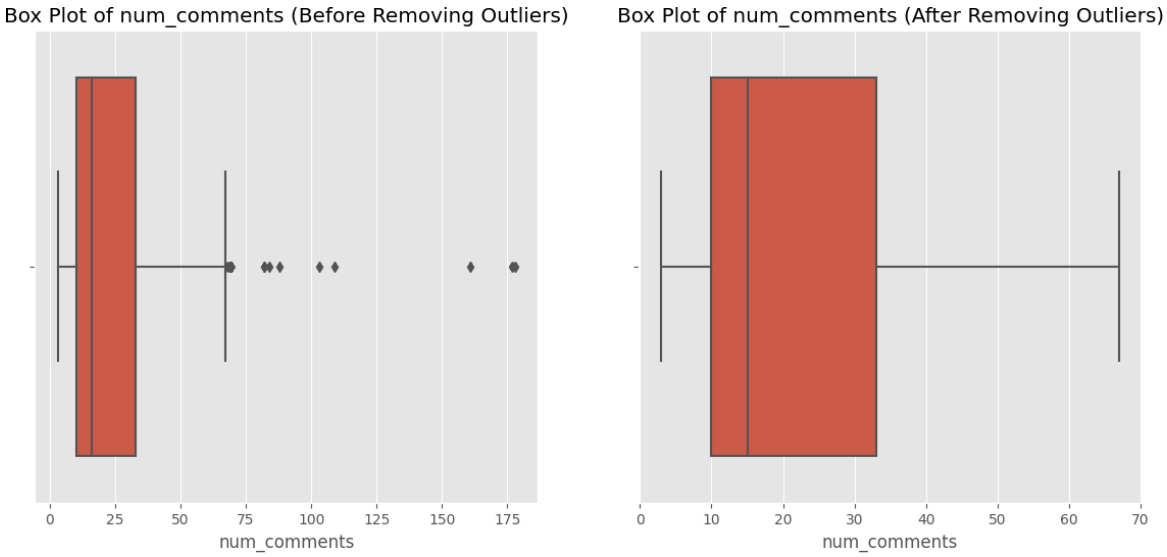
- **Price**:
  - **Analysis**: The mean price is $156.54 with a standard deviation of $97.80. The minimum price is $48, and the maximum is $448.
  - **Recommendation**: - Check for outliers in the price column. - You can use box plots or other visualizations to identify extreme values. - you might choose to remove or adjust outliers.
- **num_comments**:
  - **Analysis**: The mean number of comments is approximately 21.81 with a standard deviation of 17.69. The minimum number of comments is 3, and the maximum is 178.
  - **Recommendation**: - Check for outliers in the number of comments. - If there are properties with an exceptionally high number of comments, investigate whether these are legitimate data points or if there are any data entry errors

- **function to make plot and remove outliers**

In [22]:
```
import matplotlib.pyplot as plt
import seaborn as sns

# Function to remove outliers
def remove_outliers(df, column):
    Q1 = df[column].quantile(0.25)
    Q3 = df[column].quantile(0.75)
    IQR = Q3 - Q1

    # Define the boundaries for outliers
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    # Remove outliers
    df_no_outliers = df[(df[column] >= lower_bound) & (df[column] <= upper_bound

    return df_no_outliers

# Function to create box plot
def plot_box_plots(df, column):
    df_no_outliers = remove_outliers(df, column)  # Define df_no_outliers here

    plt.figure(figsize=(14, 6))

    # Before removing outliers
    plt.subplot(1, 2, 1)
    sns.boxplot(x=df[column])
    plt.title(f'Box Plot of {column} (Before Removing Outliers)')

    # After removing outliers
    plt.subplot(1, 2, 2)
    sns.boxplot(x=df_no_outliers[column])
    plt.title(f'Box Plot of {column} (After Removing Outliers)')

    plt.show()
```

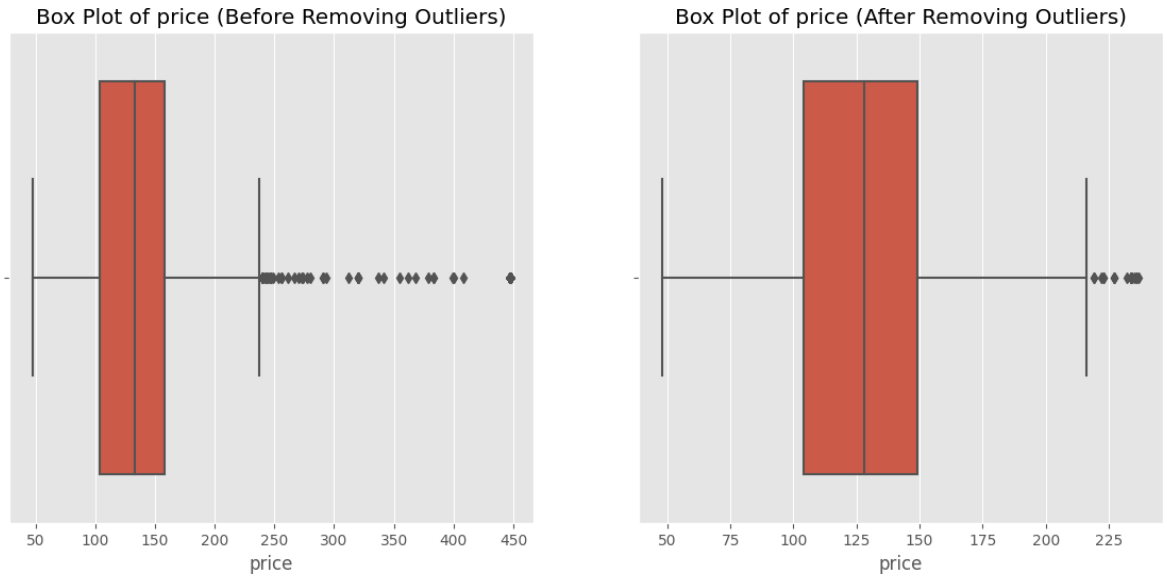
- **Remove outliers in the num_comments**

In [23]:
```
# Create and display the box plots before and after removing outliers
plot_box_plots(data2, 'num_comments')
# Remove outliers
data3 = remove_outliers(data2, 'num_comments')
```



- **remove outliers from price**

In [24]:
```
# Create and display the box plots before and after removing outliers
plot_box_plots(data3, 'price')
# Remove outliers
data4 = remove_outliers(data3, 'price')
```



- **Most famous city in Sudia Arabia**

we looking teh plot we sea the Riyadh has the heghest price

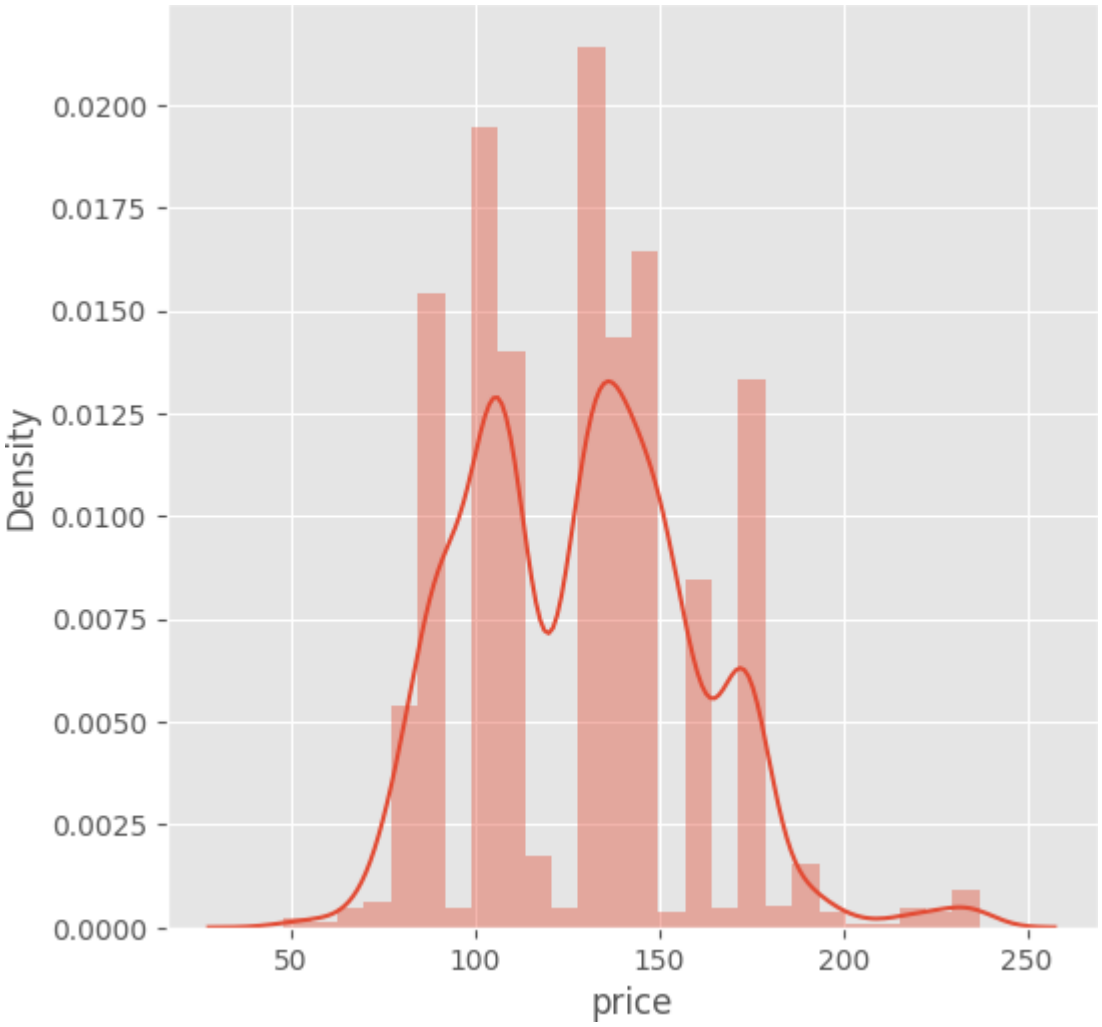
In [25]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='location', y='price', data=data4)
```

```
plt.title('Relationship between Location and Price')
plt.show()
```

Distribution of House priceing

In [26]:
```
plt.figure(figsize=(6,6))
sns.distplot(data4['price'])
plt.show()
```

```
/tmp/ipykernel_20/1307547860.py:2:  UserWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see
https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751

  sns.distplot(data4['price'])
```



- **make encoded for categorical columns**

In [27]:
```
data5_encoded = pd.get_dummies(data4, columns=['location'], prefix='location')
data5_encoded
```

Out[27]:

	price	num_beds	num_bedrooms	ratingg	num_comments	location_Jeddah	loc
2	162.0	2	2	5.00	3	False	
7	176.0	2	2	4.93	67	False	
9	105.0	3	2	4.88	33	False	
15	57.0	1	1	4.90	21	True	
17	115.0	3	2	5.00	5	False	
...	...	...	...	...	...	...	
3592	139.0	4	2	5.00	3	False	
3594	111.0	5	3	5.00	4	True	
3595	91.0	3	2	5.00	11	False	
3598	133.0	3	2	4.81	16	False	
3599	173.0	1	1	5.00	10	False	

1805 rows × 10 columns

- **check if there Replace spaces with NaN**

In [28]:
```
# Replace spaces with NaN
data5_encoded.replace(' ', pd.NA, inplace=True)
# Drop rows with any null values
data5_encoded  = data5_encoded.dropna()
# Display the cleaned DataFrame
print("DataFrame after removing rows with null values or spaces:")
print(data5_encoded)
```

```
DataFrame after removing rows with null values or spaces:
      price  num_beds  num_bedrooms  ratingg  num_comments  location_Jeddah  \
2     162.0         2             2     5.00             3            False
7     176.0         2             2     4.93            67            False
9     105.0         3             2     4.88            33            False
15     57.0         1             1     4.90            21             True
17    115.0         3             2     5.00             5            False
...     ...       ...           ...      ...           ...              ...
3592  139.0         4             2     5.00             3            False
3594  111.0         5             3     5.00             4             True
3595   91.0         3             2     5.00            11            False
3598  133.0         3             2     4.81            16            False
3599  173.0         1             1     5.00            10            False

      location_King Abdullah  location_Makkah  location_Riyadh  \
2                      False            False             True
7                      False            False             True
9                      False            False             True
15                     False            False            False
17                     False            False             True
...                      ...              ...              ...
3592                   False            False             True
3594                   False            False            False
3595                   False            False             True
3598                   False            False             True
3599                   False            False             True

      location_others
2               False
7               False
9               False
15              False
17              False
...               ...
3592            False
3594            False
3595            False
3598            False
3599            False

[1805 rows x 10 columns]
```

- **convert the value of the encoded columns from True to 1 and False to 0**

In [29]:
```
# Assuming you have a DataFrame named data5_encoded
data5_encoded[['location_Jeddah', 'location_King Abdullah', 'location_Makkah', '
```

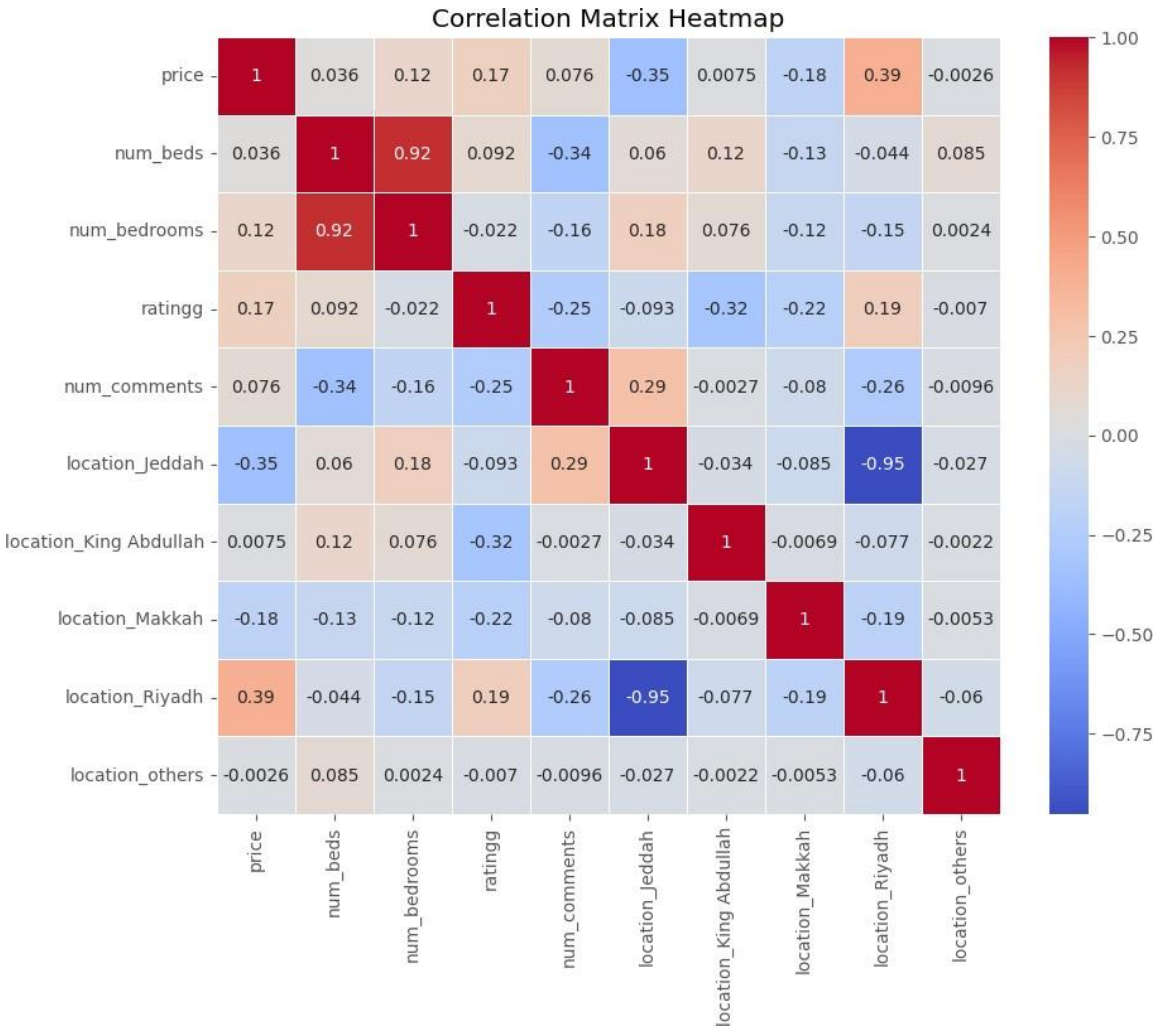
- **convert the type of the num beds and num bedrooms**

In [30]:
```
data5_encoded['num_beds'] = data5_encoded['num_beds'].astype(int)
data5_encoded['num_bedrooms'] = data5_encoded['num_bedrooms'].astype(int)
```

show the corrlation between the columns

In [31]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

```
# Create a correlation matrix
correlation_matrix = data5_encoded.corr()

# Create a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



In [32]:
```
X = data5_encoded.drop(['price'] , axis='columns')
X.head(3)
```

Out[32]:

	num_beds	num_bedrooms	ratingg	num_comments	location_Jeddah	location_King Abdullah
2	2	2	5.00	3	0	0
7	2	2	4.93	67	0	0
9	3	2	4.88	33	0	0

In [33]:
```
y = data5_encoded.price
y.head(3)
```

Out[33]:
```
2    162.0
7    176.0
9    105.0
Name: price, dtype: float64
```

In [34]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2 ,  random_
```

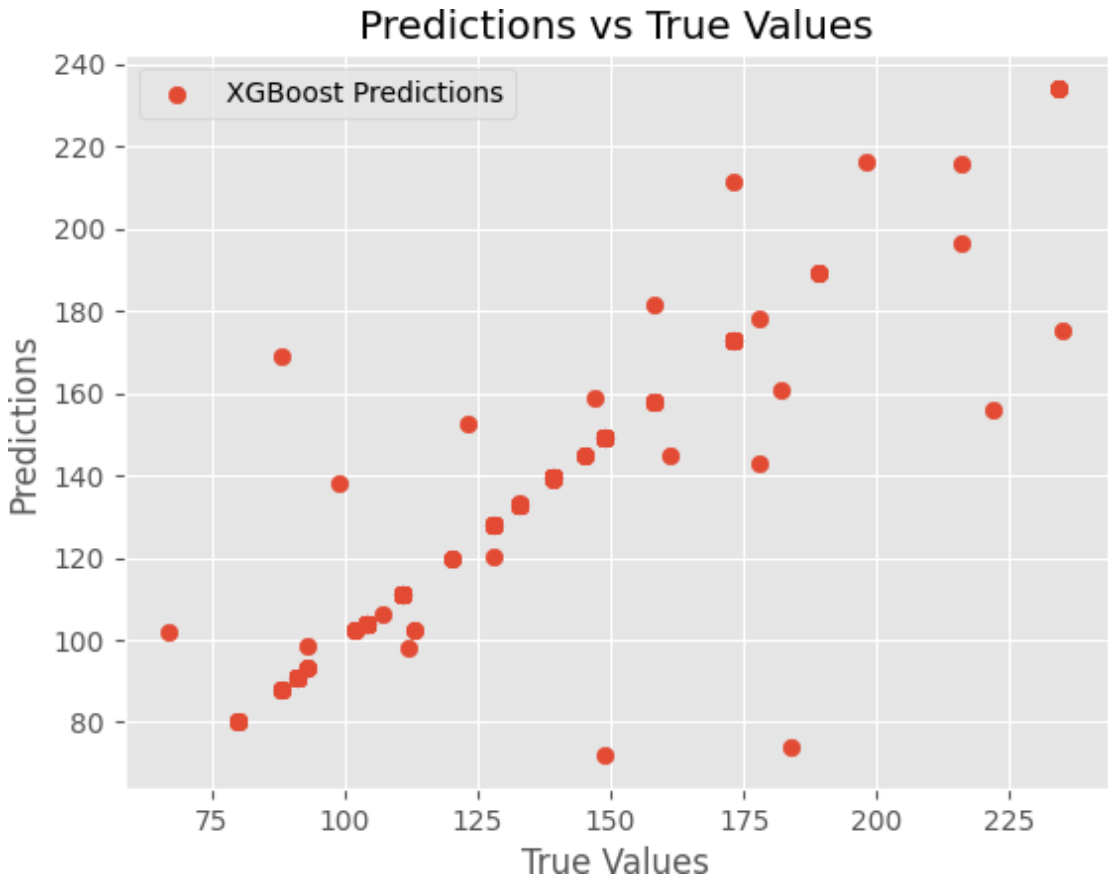
Evaluate model performance

In [35]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from xgboost import XGBRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
import seaborn as sns


# Train Linear Regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
lr_predictions = lr_model.predict(X_test)

# Train K-Nearest Neighbors model
knn_model = KNeighborsRegressor()
knn_model.fit(X_train, y_train)
knn_predictions = knn_model.predict(X_test)

# Train Decision Tree model
dt_model = DecisionTreeRegressor()
dt_model.fit(X_train, y_train)
dt_predictions = dt_model.predict(X_test)

# Train Random Forest model
rf_model = RandomForestRegressor()
rf_model.fit(X_train, y_train)
rf_predictions = rf_model.predict(X_test)

# Train XGBoost model
xgb_model = XGBRegressor()
xgb_model.fit(X_train, y_train)
xgb_predictions = xgb_model.predict(X_test)

# Function to evaluate model performance
def evaluate_model(model, predictions, y_true):
    mse = mean_squared_error(y_true, predictions)
    r2 = r2_score(y_true, predictions)
    print(f"Mean Squared Error: {mse}")
    print(f"R^2 Score: {r2}")

# Evaluate models
print("Linear Regression:")
evaluate_model(lr_model, lr_predictions, y_test)
```

```
print("\nK-Nearest Neighbors:")
evaluate_model(knn_model, knn_predictions, y_test)

print("\nDecision Tree:")
evaluate_model(dt_model, dt_predictions, y_test)

print("\nRandom Forest:")
evaluate_model(rf_model, rf_predictions, y_test)

print("\nXGBoost:")
evaluate_model(xgb_model, xgb_predictions, y_test)

# Create a heatmap for correlation matrix of model predictions
predictions_df = pd.DataFrame({'Linear Regression': lr_predictions,
                               'K-Nearest Neighbors': knn_predictions,
                               'Decision Tree': dt_predictions,
                               'Random Forest': rf_predictions,
                               'XGBoost': xgb_predictions})
```

```
Linear Regression:
Mean Squared Error: 635.4651264050899
R^2 Score: 0.3658874129080978

K-Nearest Neighbors:
Mean Squared Error: 158.34626038781164
R^2 Score: 0.8419907676147829

Decision Tree:
Mean Squared Error: 151.32413446223867
R^2 Score: 0.8489979474780436

Random Forest:
Mean Squared Error: 87.16940510419228
R^2 Score: 0.9130161283616292

XGBoost:
Mean Squared Error: 114.74648161885897
R^2 Score: 0.885497747562241
```

In [37]:
```
# Optionally, plot predictions against true values
plt.scatter(y_test, xgb_predictions, label='XGBoost Predictions')
plt.xlabel('True Values')
plt.ylabel('Predictions')
plt.legend()
plt.title('Predictions vs True Values')
plt.show()
```


Predictions vs True Values
XGBoost Predictions
Predictions
True Values
240
220
200
180
160
140
120
100
80
75
100
125
150
175
200
225

Saudi Arabia Condo Price Predictions Report

Hypothesis:

In predicting Saudi Arabia condo prices, we hypothesize that the number of bedrooms, the number of beds, and the location will significantly influence the property's rental price. We expect that properties with more bedrooms and beds will have higher rental prices. Additionally, we anticipate that the location of the property will be a crucial factor, with prices varying across different cities in Saudi Arabia.

Saudi Arabia Condo Price Predictions Report

About the Data:

The dataset was obtained by scraping data from the Airbnb website in Saudi Arabia. It contains information on rental properties with the following columns:

name: The name of the property.

header: The location of the property.

beds: The number of beds in the property.

bedrooms: The number of bedrooms in the property.

date_range: The duration of stay in the property.

price: The price of staying in the property.

rating: The rating of the property.

Data Cleaning and Exploration:

Data Shape:

The dataset has a shape of (3600, 8).

Missing Values:

There are missing values in the 'price' and 'rating' columns.

Handling Missing Values:

Rows with missing values are dropped.

Feature Engineering:

Extracted features from the 'bedrooms' column to create 'num_beds' and 'num_bedrooms'.

Cleaned and converted 'price' values to float.

Extracted 'rating' and 'num_comments' from the original 'rating' column.

Drop Unnecessary Columns:

Dropped unnecessary columns: 'rating', 'bedrooms', 'date_range', 'Unnamed: 0'.

Location Mapping:

Mapped and renamed locations for consistency.

Data Analysis:

Location Distribution:

Most locations are in Riyadh and Jeddah.

Price Distribution:

The mean price is $156.54, with a minimum of $48 and a maximum of $448.

There are potential outliers in the data.

Number of Comments Distribution:

The mean number of comments is approximately 21.81, with a minimum of 3 and a maximum of 178.

There are potential outliers in the data.

Data Encoding and Cleaning:

One-Hot Encoding:

Applied one-hot encoding to the 'location' column.

Replace Spaces:

Replaced spaces with NaN and dropped rows with null values.

Convert Boolean Columns:

Converted boolean columns to 1 and 0.

Convert Data Types:

Converted data types for 'num_beds', 'num_bedrooms', and other relevant columns.

Data Correlation:

A heatmap was created to visualize the correlation matrix of the cleaned dataset.

Model Building and Evaluation:

Trained and evaluated several regression models:

Linear Regression:

MSE: 635.47

R^2 Score: 0.37

K-Nearest Neighbors:

MSE: 158.35

R^2 Score: 0.84

Decision Tree:

MSE: 151.32

R^2 Score: 0.85

Random Forest:

MSE: 87.17

R^2 Score: 0.91

XGBoost:

MSE: 114.75

R^2 Score: 0.89

Conclusion:

The Random Forest model performed the best among the models evaluated, with the lowest MSE and highest R^2 score.

Further analysis and fine-tuning of the model could improve predictive performance.

Consideration of outliers in the data is recommended for more accurate predictions.

Hypothesis Validation:

The results of our regression models support our hypothesis. The number of bedrooms, the number of beds, and the location significantly influence condo prices in Saudi Arabia. The Random Forest model, which takes into account these features, provided the most accurate predictions. Adjustments and enhancements to the model, considering outliers and additional features, could further improve its performance.

References:

https://pandas.pydata.org/

https://scikit-learn.org/stable/

https://matplotlib.org/