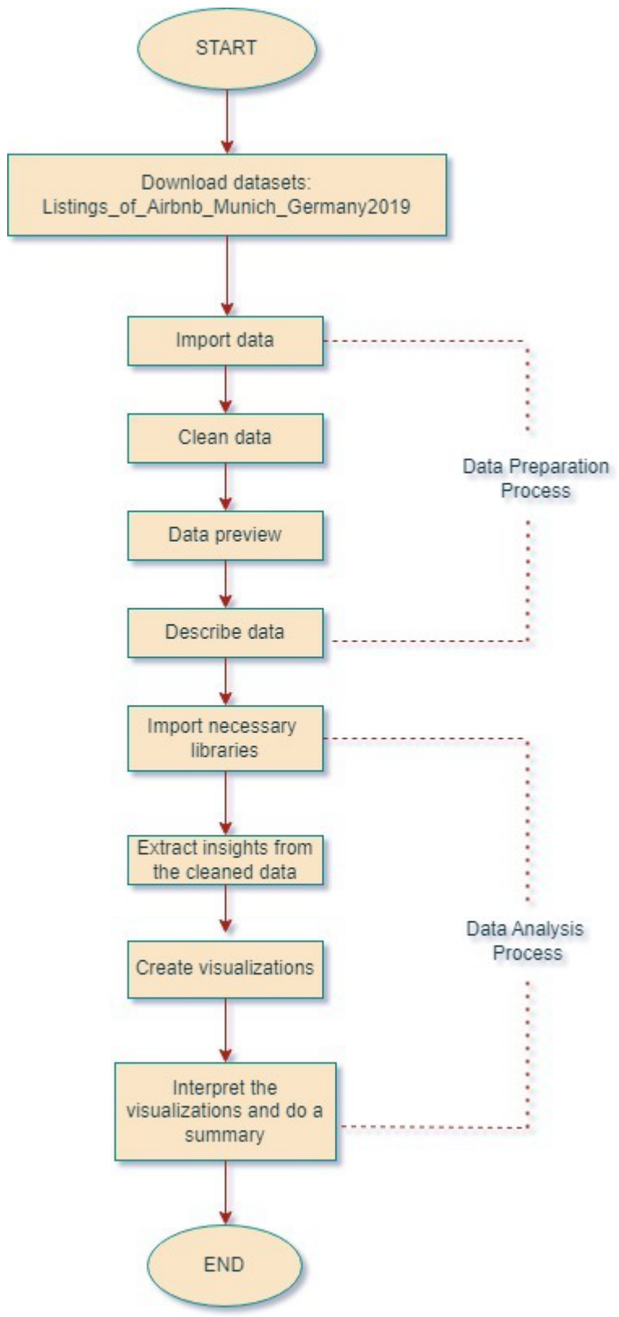
Data Preparation

```
from PIL import Image
img = Image.open("data preparation flowchart.jpeg")
display(img)
```



Data Import

```
import pandas as pd
data= pd.read_csv("listings_airbnb_munich.csv")
data
```

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_n
0	609851	Luxury 3 room flat close to Olympiapark	3024324	Christian	NaN	Maxvorstadt	48.15561	11.56736	Entire home/apt	200	
1	97945	Deluxw-Apartm. with roof terrace	517685	Angelika	NaN	Hadern	48.11492	11.48954	Entire home/apt	80	
2	114695	Apartment Munich/East with sundeck	581737	Stephan	NaN	Berg am Laim	48.12071	11.63758	Entire home/apt	95	
3	127383	City apartment next to Pinakothek	630556	Sonja	NaN	Maxvorstadt	48.15199	11.56482	Entire home/apt	120	
4	159634	Fancy, bright central roof top flat and homeof...	765694	Susana	NaN	Pasing-Obermenzing	48.13855	11.46586	Entire home/apt	60	
...	...	...	...	...	...	...	...	...	...	...	
5528	1560042	Frisch und freundlich in weiß-rot	1909709	Gabriele	NaN	Pasing-Obermenzing	48.15970	11.45158	Private room	38	
5529	1576125	Quiet and Relaxing Room with own Bath	8378646	Ralf	NaN	Allach-Untermenzing	48.17912	11.46728	Private room	38	
5530	1576417	Quiet and Relaxing Rooms with own Bath for 3Pe...	8378646	Ralf	NaN	Allach-Untermenzing	48.18063	11.46759	Private room	44	
5531	1583637	Comfortable & next to the Oktoberfest	3664843	Florian	NaN	Ludwigsvorstadt-Isarvorstadt	48.13296	11.55499	Private room	69	
5532	1585526	Tolle Altbauwohnung nahe Theresienwiese	7680306	Katharina	NaN	Schwanthalerhöhe	48.13850	11.52979	Private room	235	

5533 rows × 18 columns

```
num_entries = data.shape[0]
num_entries
```

```
5533
```

```
num_features = data.shape[1]
num_features
```

```
18
```

```
data.dtypes
```

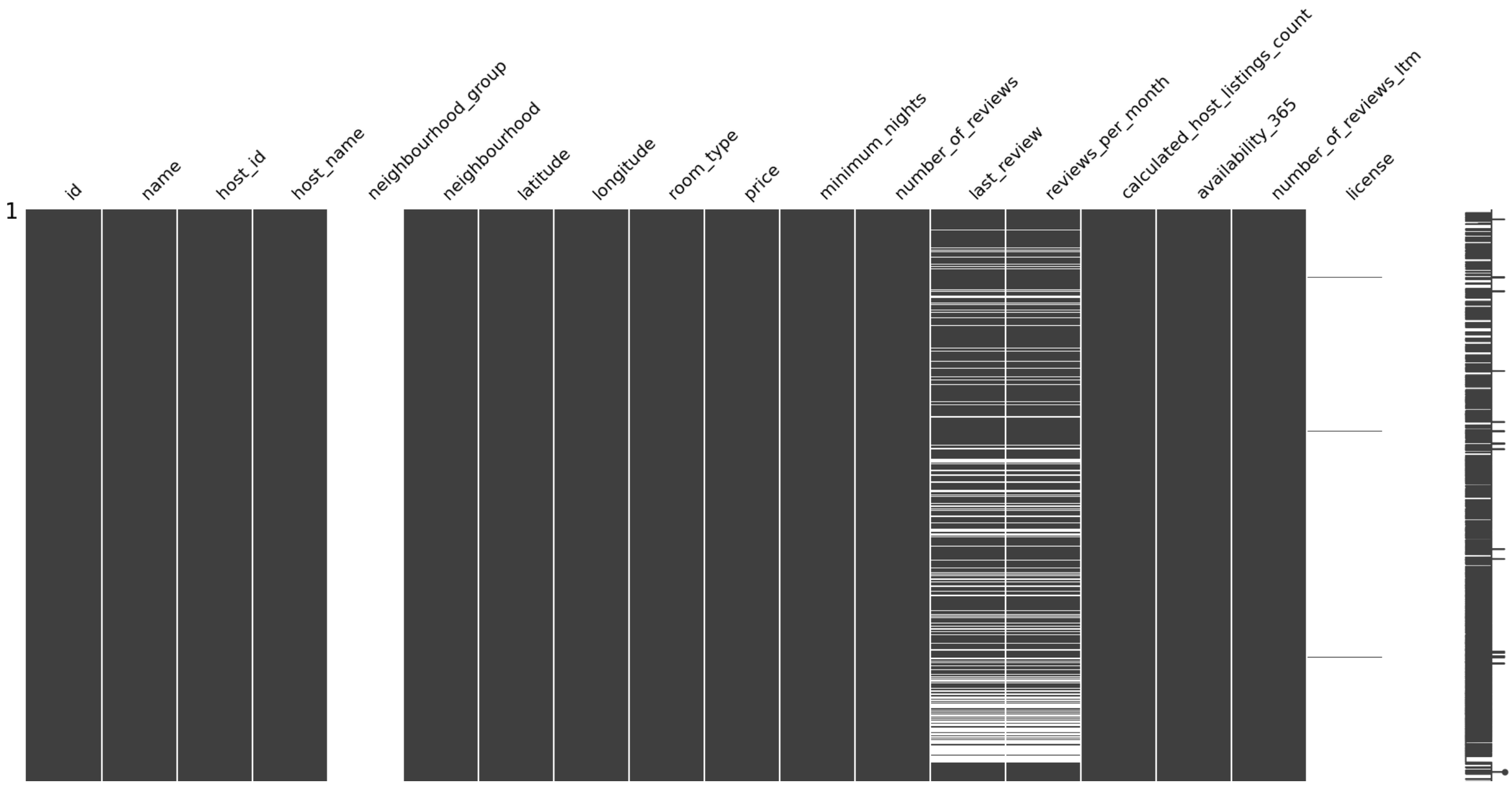
```
id                                int64
name                             object
host_id                           int64
host_name                        object
neighbourhood_group             float64
neighbourhood                    object
latitude                        float64
longitude                       float64
room_type                        object
price                             int64
minimum_nights                    int64
number_of_reviews                 int64
last_review                      object
reviews_per_month               float64
calculated_host_listings_count    int64
availability_365                  int64
number_of_reviews_ltm             int64
license                          object
dtype: object
```

Data Cleaning

Visualizing Missing Data

```
import missingno as msno
msno.matrix(data)
```

```
<Axes: >
```




```
columns_to_drop = ['id', 'host_id', 'host_name', 'neighbourhood_group','number_of_reviews', 'last_review', 'reviews_per_month',
                   'calculated_host_listings_count', 'number_of_reviews_ltm', 'license']
new_data = data.drop(columns_to_drop, axis=1)
new_data
```

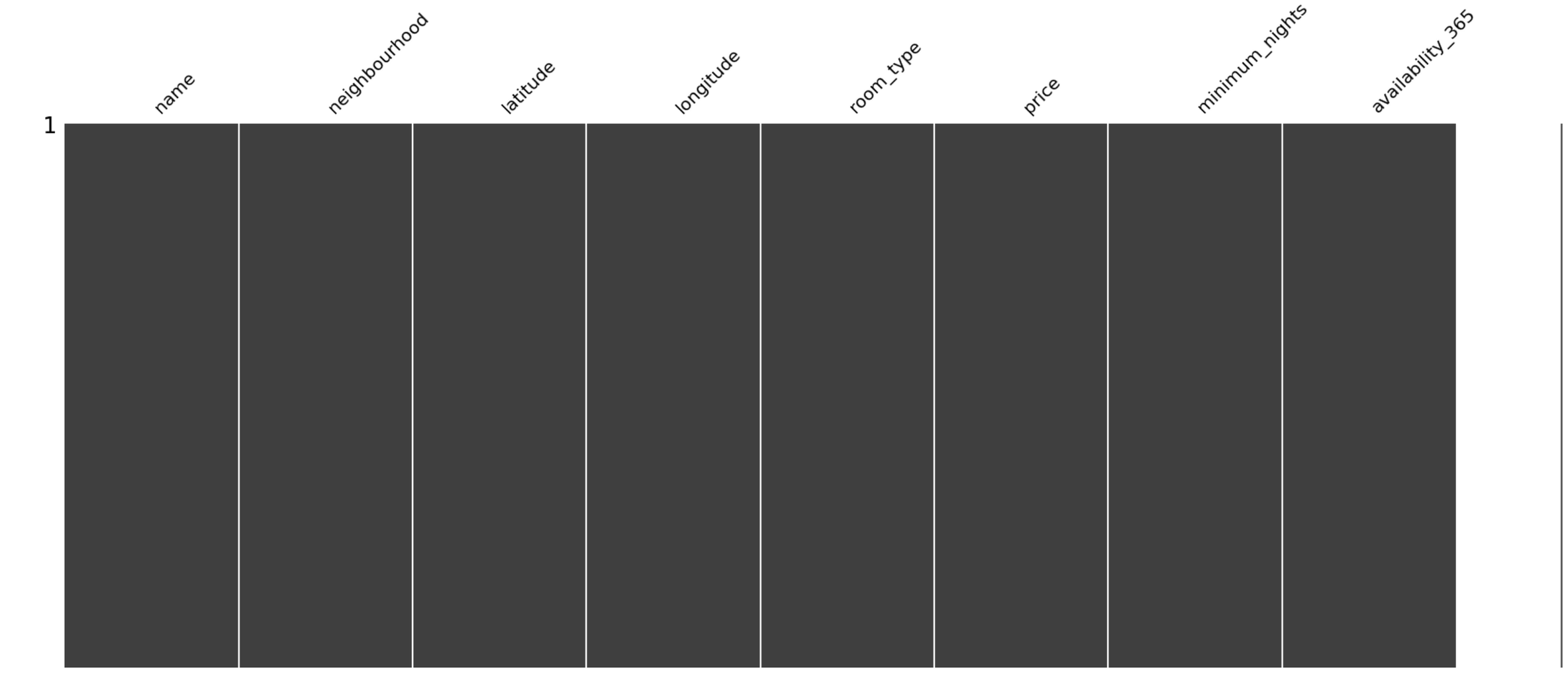
	name	neighbourhood	latitude	longitude	room_type	price	minimum_nights	availability_365
0	Luxury 3 room flat close to Olympiapark	Maxvorstadt	48.15561	11.56736	Entire home/apt	200	5	129
1	Deluxw-Apartm. with roof terrace	Hadern	48.11492	11.48954	Entire home/apt	80	2	86
2	Apartment Munich/East with sundeck	Berg am Laim	48.12071	11.63758	Entire home/apt	95	2	140
3	City apartment next to Pinakothek	Maxvorstadt	48.15199	11.56482	Entire home/apt	120	3	0
4	Fancy, bright central roof top flat and homeof...	Pasing-Obermenzing	48.13855	11.46586	Entire home/apt	60	2	1
...	...	...	...	...	...	...	...	...
5528	Frisch und freundlich in weiß-rot	Pasing-Obermenzing	48.15970	11.45158	Private room	38	1	117
5529	Quiet and Relaxing Room with own Bath	Allach-Untermenzing	48.17912	11.46728	Private room	38	1	0
5530	Quiet and Relaxing Rooms with own Bath for 3Pe...	Allach-Untermenzing	48.18063	11.46759	Private room	44	1	0
5531	Comfortable & next to the Oktoberfest	Ludwigsvorstadt-Isarvorstadt	48.13296	11.55499	Private room	69	2	0
5532	Tolle Altbauwohnung nahe Theresienwiese	Schwanthalerhöhe	48.13850	11.52979	Private room	235	3	365

5533 rows × 8 columns

For a cleaner and more objective analysis, these variables had been deleted since the variables that dropped will not be used in our analysis.

```
import missingno as msno
msno.matrix(new_data)
```

<Axes: >



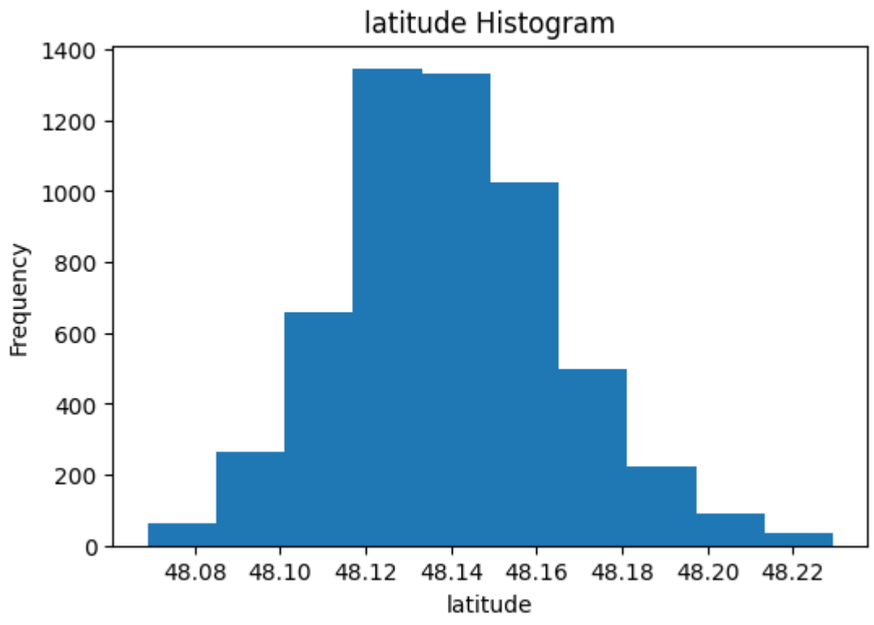

```
import pandas as pd
missing_percentage = new_data.isnull().mean()*100
missing_percentage
```

```
name               0.0
neighbourhood      0.0
latitude           0.0
longitude          0.0
room_type          0.0
price              0.0
minimum_nights     0.0
availability_365   0.0
dtype: float64
```

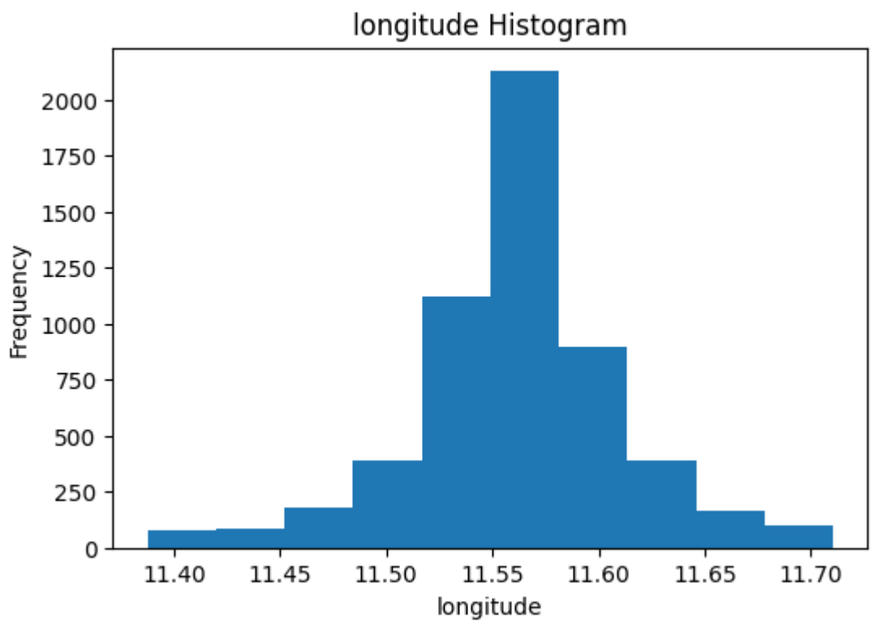
This dataset has practically no null values, therefore no null values treatment will be performed.

Outliers Detection and Treatment

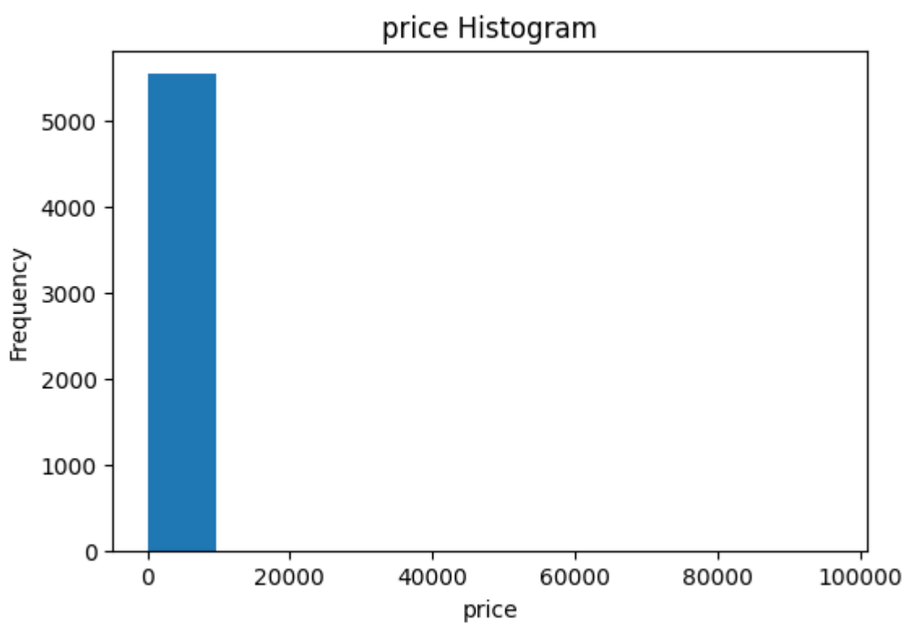
```
import pandas as pd
import matplotlib.pyplot as plt

plt.figure(figsize=(6, 4))
plt.hist(new_data['latitude'])
plt.title("latitude" + " Histogram")
plt.xlabel("latitude")
plt.ylabel("Frequency")
plt.show()
```



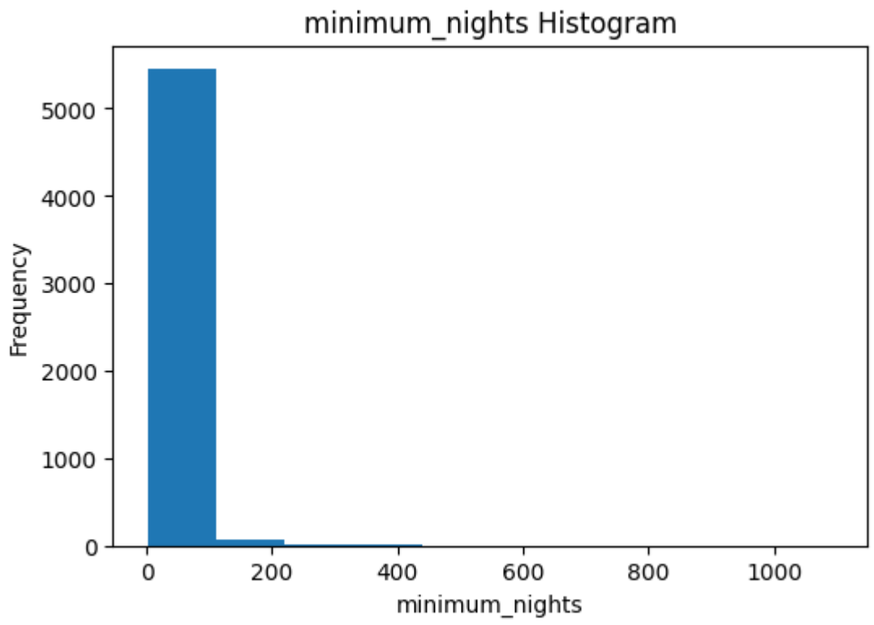

```
plt.figure(figsize=(6, 4))
plt.hist(new_data['longitude'])
plt.title("longitude" + " Histogram")
plt.xlabel("longitude")
plt.ylabel("Frequency")
plt.show()
```



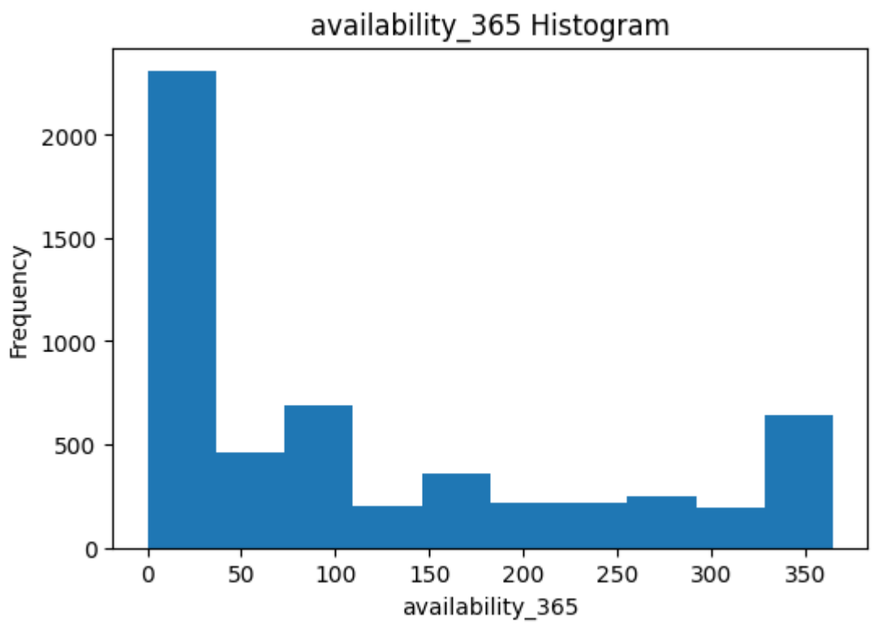
```
plt.figure(figsize=(6,4))
plt.hist(new_data['price'])
plt.title("price" + " Histogram")
plt.xlabel("price")
plt.ylabel("Frequency")

plt.show()
```




```
plt.figure(figsize=(6, 4))
plt.hist(new_data['minimum_nights'])
plt.title("minimum_nights" + " Histogram")
plt.xlabel("minimum_nights")
plt.ylabel("Frequency")
plt.show()
```




```
plt.figure(figsize=(6, 4))
plt.hist(new_data['availability_365'])
plt.title("availability_365" + " Histogram")
plt.xlabel("availability_365")
plt.ylabel("Frequency")
plt.show()
```



Through the five histogram, it is possible to verify the presence of outliers in the variables 'price' and 'minimum_nights'. The values do not follow a distribution and distort the entire graphical presentation.

```
new_data.describe()
```

	latitude	longitude	price	minimum_nights	availability_365
count	5533.000000	5533.000000	5533.000000	5533.000000	5533.000000
mean	48.139611	11.562330	170.836978	9.009398	114.627327
std	0.025659	0.048663	1308.536534	31.365482	125.219271
min	48.068870	11.387475	0.000000	1.000000	0.000000
25%	48.122560	11.538820	66.000000	1.000000	0.000000
50%	48.137080	11.564030	100.000000	2.000000	72.000000
75%	48.155700	11.585310	167.000000	4.000000	206.000000
max	48.229500	11.710610	96274.000000	1095.000000	365.000000

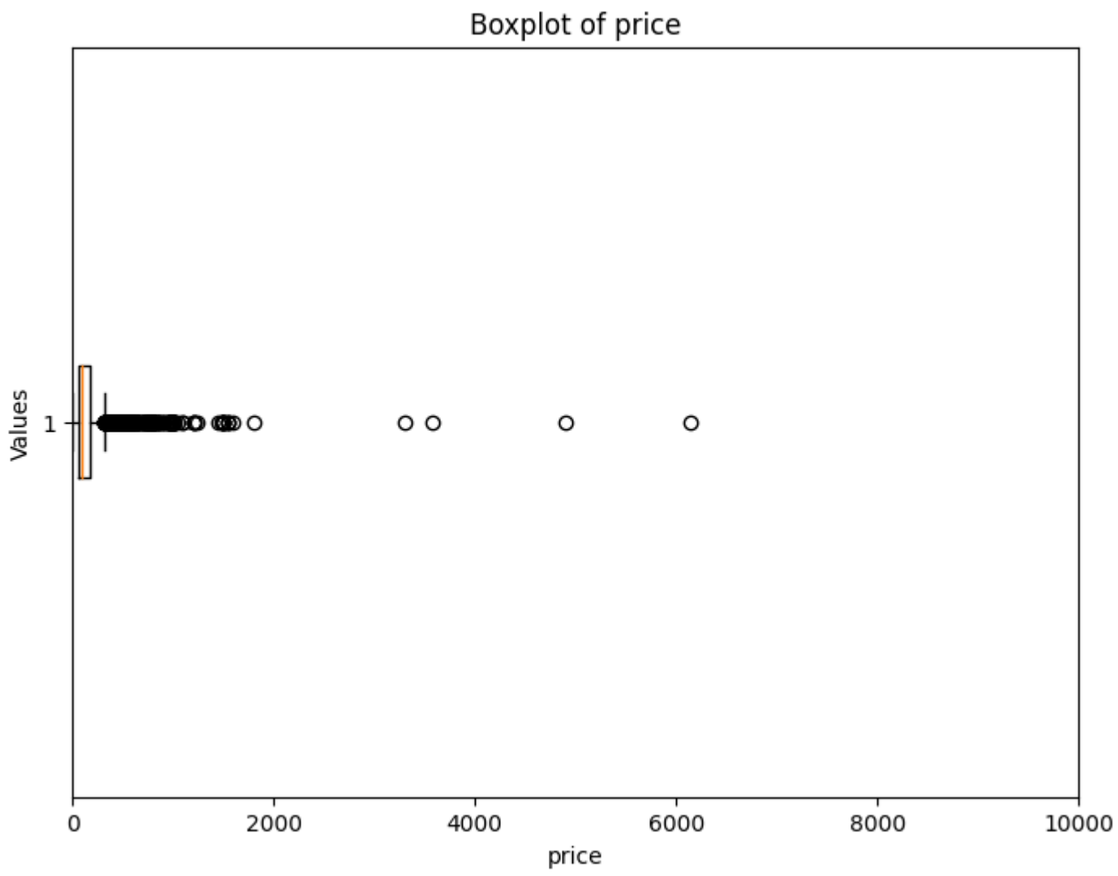
The variable 'price' has 75% of its values below 167, but its maximum value is 96274, which is well above the values obtained up to 75% of the dataset, which proves the presence of outliers.

The variable 'price' presents minimum values equal to 0. Understanding the Airbnb business, it is known that no one rents any property on Airbnb for free.

The variable 'minimum_nights' has 75% of its values below 4, but its maximum value is 1095, which is well above the values obtained up to 75% of the dataset, which proves the presence of outliers.

Boxplot for "Price"

```
plt.figure(figsize=(8, 6))
plt.boxplot(new_data['price'], vert=False)
plt.title('Boxplot of ' + 'price')
plt.xlabel('price')
plt.ylabel('Values')
plt.xlim(0,10000)
plt.show()
```




```
import numpy as np
import pandas as pd

outliers = new_data[new_data['price'] > 1000]
outliers_count = np.sum(new_data['price'] > 1000)
outliers_ratio = round(outliers_count / len(new_data), 3)

print("Outliers:")
print(outliers)
print("\nQuantity of Outliers:", outliers_count)
print("Outliers Ratio:", outliers_ratio)
```

```
     5217      Great flat for Oktoberfest - for couples or 4

                                       neighbourhood   latitude  longitude  \
251                                     Tudering-Riem  48.130710  11.695030
453                                 Schwanthalerhöhe  48.130360  11.543080
1722                                  Altstadt-Lehel  48.134160  11.576950
1864                                Sendling-Westpark  48.108340  11.526620
1875                                    Au-Haidhausen  48.120650  11.579480
2558                                      Maxvorstadt  48.150850  11.572580
3029                             Neuhausen-Nymphenburg  48.151790  11.530910
3182                                         Sendling  48.123690  11.546420
3382                          Ludwigsvorstadt-Isarvorstadt  48.133950  11.553670
3416                                Schwabing-West  48.168130  11.581460
3520                                  Berg am Laim  48.124082  11.605817
3583                                    Au-Haidhausen  48.128353  11.596788
3646                          Ludwigsvorstadt-Isarvorstadt  48.132094  11.566024
3999                          Ludwigsvorstadt-Isarvorstadt  48.136090  11.558870
4114                          Ludwigsvorstadt-Isarvorstadt  48.126840  11.558060
4133                                      Maxvorstadt  48.146160  11.546230
4616                             Milbertshofen-Am Hart  48.188591  11.558877
4679  Thalkirchen-Obersendling-Forstenried-Fürstenri...  48.077360  11.516680
4826  Thalkirchen-Obersendling-Forstenried-Fürstenri...  48.075393  11.517271
4858                             Neuhausen-Nymphenburg  48.158954  11.555540
5017                                         Moosach  48.170482  11.513101
5018                                         Moosach  48.170607  11.514607
5019                                         Moosach  48.170540  11.513202
5072                                  Altstadt-Lehel  48.137896  11.576529
5217                                     Obergiesing  48.116220  11.582400

           room_type  price  minimum_nights  availability_365
251   Entire home/apt   1050               5               192
```

```
Outliers Ratio: 0.005
```

```
import numpy as np
import pandas as pd

zero_price_values = new_data[new_data['price'] == 0]

print("\nValues where 'price' is equal to 0:")
print(zero_price_values)

outliers_count = np.sum(new_data['price'] == 0)
print("\nQuantity of Outliers:", outliers_count)

outliers_ratio = round(outliers_count / len(new_data), 3)
print("Outliers Ratio:", outliers_ratio)
```

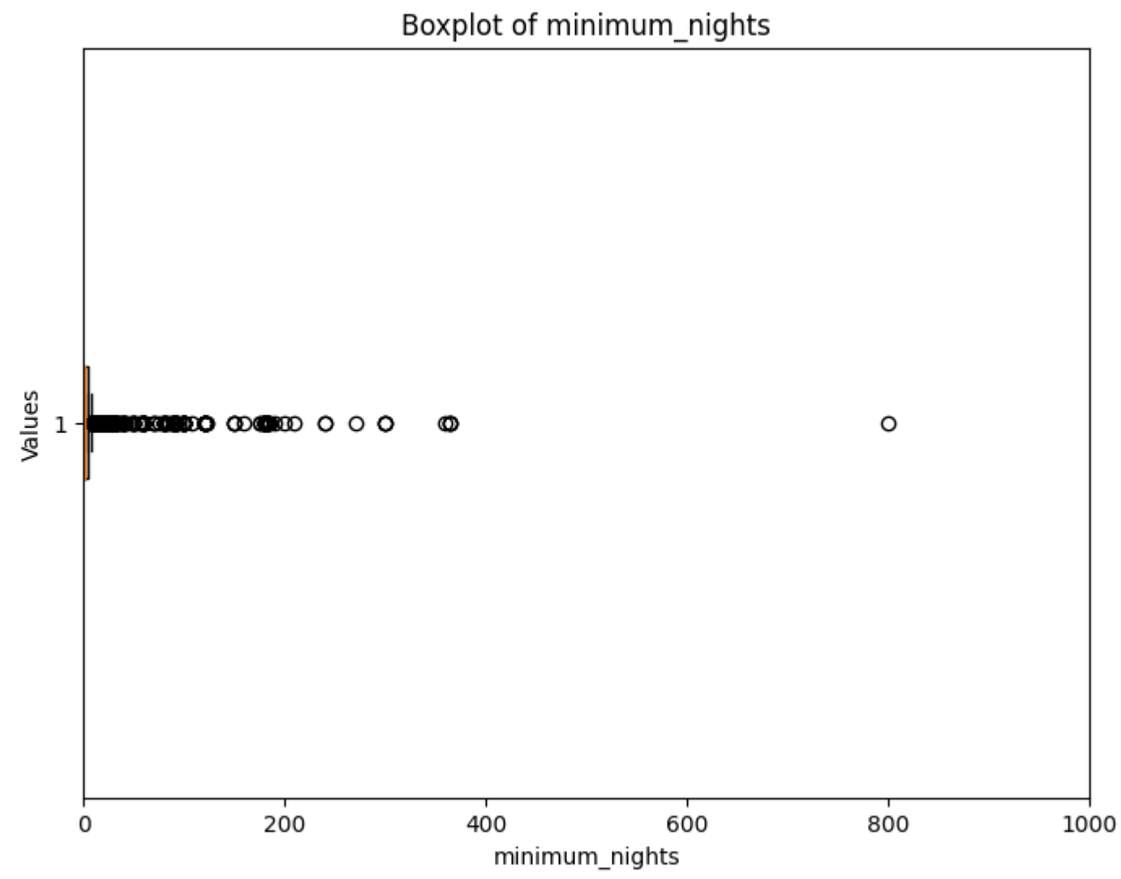
```
Values where 'price' is equal to 0:
                     name     neighbourhood  latitude  longitude   room_type  \
2123  Boutique Hotel Krone  Schwanthalerhöhe  48.13547   11.54717  Hotel room

      price  minimum_nights  availability_365
2123      0               1                 0

Quantity of Outliers: 1
Outliers Ratio: 0.0
```

Above, the boxplot for the variable 'price' visually shows the information contained in the summary statistics.

As a parameter, all data greater than 1000 will be considered an outlier in this analysis. Above also, we will see the quantity and ratio of these outliers and the values where 'price' is equal to 0.

Boxplot for "minimum_nights"

```
plt.figure(figsize=(8, 6))
plt.boxplot(new_data['minimum_nights'], vert=False)
plt.title('Boxplot of ' + 'minimum_nights')
plt.xlabel('minimum_nights')
plt.ylabel('Values')
plt.xlim(0,1000)

plt.show()
```




```
import numpy as np
import pandas as pd

outliers = new_data[new_data['price'] > 30]

outliers_count = np.sum(new_data['price'] > 30)
outliers_ratio = round(outliers_count / len(new_data), 3)

print("Outliers:")
print(outliers)
print("\nQuantity of Outliers:", outliers_count)
print("Outliers Ratio:", outliers_ratio)
```

```
Outliers:
                                                   name  \
0                  Luxury 3 room flat close to Olympiapark
1                         Deluxw-Apartm. with roof terrace
2                       Apartment Munich/East with sundeck
3                        City apartment next to Pinakothek
4     Fancy, bright central roof top flat and homeof...
...                                                 ...
5528                    Frisch und freundlich in weiß-rot
5529                Quiet and Relaxing Room with own Bath
5530  Quiet and Relaxing Rooms with own Bath for 3Pe...
5531                Comfortable & next to the Oktoberfest
5532              Tolle Altbauwohnung nahe Theresienwiese

                     neighbourhood  latitude  longitude        room_type  \
0                        Maxvorstadt  48.15561   11.56736  Entire home/apt
1                             Hadern  48.11492   11.48954  Entire home/apt
2                        Berg am Laim  48.12071   11.63758  Entire home/apt
3                        Maxvorstadt  48.15199   11.56482  Entire home/apt
4                  Pasing-Obermenzing  48.13855   11.46586  Entire home/apt
...                               ...       ...        ...              ...
5528               Pasing-Obermenzing  48.15970   11.45158     Private room
5529             Allach-Untermenzing  48.17912   11.46728     Private room
5530             Allach-Untermenzing  48.18063   11.46759     Private room
5531  Ludwigsvorstadt-Isarvorstadt  48.13296   11.55499     Private room
5532                Schwanthalerhöhe  48.13850   11.52979     Private room

      price  minimum_nights  availability_365
0       200               5               129
```

```
1        80               2                86
2        95               2               140
3       120               3                 0
4        60               2                 1
...     ...             ...               ...
5528     38               1               117
5529     38               1                 0
5530     44               1                 0
5531     69               2                 0
5532    235               3               365

[5420 rows x 8 columns]

Quantity of Outliers: 5420
Outliers Ratio: 0.98
```

Above, the boxplot for the variable 'minimum_nights' visually shows the information contained in the summary statistics.

As a parameter, all data greater than 30 will be considered an outlier in this analysis. Above also, we will see the quantity and ratio of these outliers.

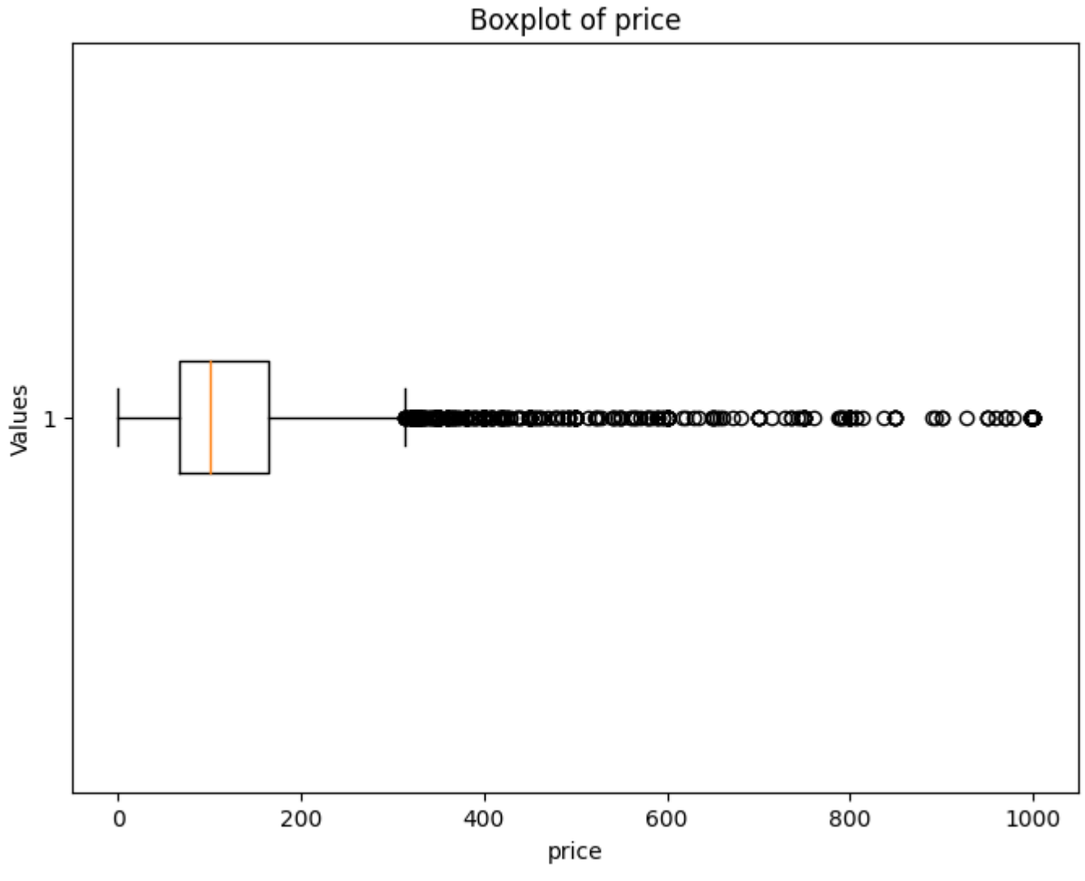
We had set parameters for both of them in which will be considered outliers since the amount of outliers are too many.

Removing Outliers and Creating Data Frame for Analysis

```
outliers = new_data[new_data['price'] > 1000]

cleaned_data = new_data.drop(outliers.index)

print("Cleaned Data:")
print(cleaned_data)
```

```
Cleaned Data:
                                                   name  \
0               Luxury 3 room flat close to Olympiapark
1                     Deluxw-Apartm. with roof terrace
2                    Apartment Munich/East with sundeck
3                     City apartment next to Pinakothek
4     Fancy, bright central roof top flat and homeof...
...                                                 ...
5528                 Frisch und freundlich in weiß-rot
5529              Quiet and Relaxing Room with own Bath
5530  Quiet and Relaxing Rooms with own Bath for 3Pe...
5531              Comfortable & next to the Oktoberfest
5532            Tolle Altbauwohnung nahe Theresienwiese

                     neighbourhood  latitude  longitude        room_type  \
0                       Maxvorstadt  48.15561   11.56736  Entire home/apt
1                            Hadern  48.11492   11.48954  Entire home/apt
2                       Berg am Laim  48.12071   11.63758  Entire home/apt
3                       Maxvorstadt  48.15199   11.56482  Entire home/apt
4                Pasing-Obermenzing  48.13855   11.46586  Entire home/apt
...                             ...       ...        ...              ...
5528             Pasing-Obermenzing  48.15970   11.45158     Private room
5529           Allach-Untermenzing  48.17912   11.46728     Private room
5530           Allach-Untermenzing  48.18063   11.46759     Private room
5531  Ludwigsvorstadt-Isarvorstadt  48.13296   11.55499     Private room
5532              Schwanthalerhöhe  48.13850   11.52979     Private room

      price  minimum_nights  availability_365
0       200               5               129
1        80               2                86
2        95               2               140
3       120               3                 0
4        60               2                 1
...     ...             ...               ...
5528     38               1               117
5529     38               1                 0
5530     44               1                 0
5531     69               2                 0
5532    235               3               365

[5508 rows x 8 columns]
```

```
plt.figure(figsize=(8, 6))
plt.boxplot(cleaned_data['price'], vert=False)
plt.title('Boxplot of ' + 'price')
plt.xlabel('price')
plt.ylabel('Values')
plt.show()
```

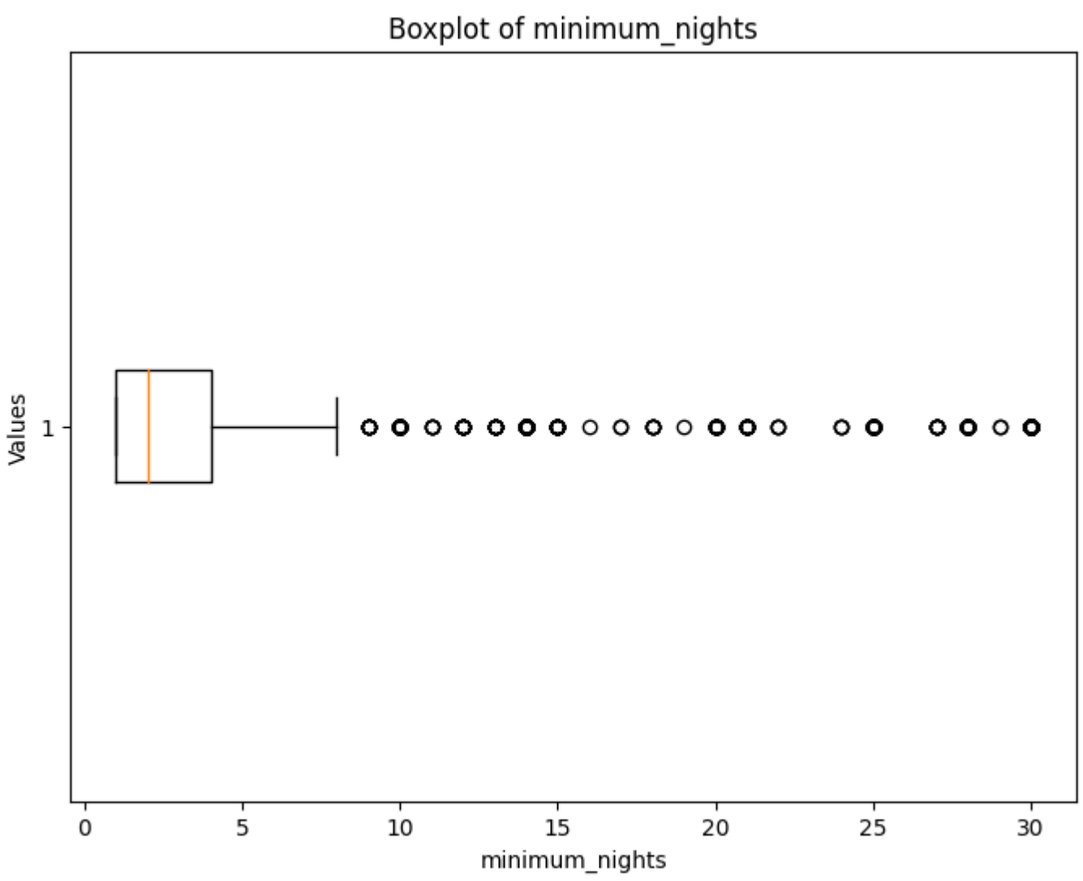



```
outliers = new_data[new_data['minimum_nights'] > 30]

# Remove outliers from the DataFrame
cleaned_data = new_data.drop(outliers.index)
```

```
# Display the cleaned data
print("Cleaned Data:")
print(cleaned_data)
```

```
Cleaned Data:
                                                   name  \
0                  Luxury 3 room flat close to Olympiapark
1                        Deluxw-Apartm. with roof terrace
2                     Apartment Munich/East with sundeck
3                      City apartment next to Pinakothek
4     Fancy, bright central roof top flat and homeof...
...                                                 ...
5528                   Frisch und freundlich in weiß-rot
5529               Quiet and Relaxing Room with own Bath
5530  Quiet and Relaxing Rooms with own Bath for 3Pe...
5531               Comfortable & next to the Oktoberfest
5532              Tolle Altbauwohnung nahe Theresienwiese

                     neighbourhood  latitude  longitude        room_type  \
0                        Maxvorstadt  48.15561   11.56736  Entire home/apt
1                            Hadern  48.11492   11.48954  Entire home/apt
2                        Berg am Laim  48.12071   11.63758  Entire home/apt
3                        Maxvorstadt  48.15199   11.56482  Entire home/apt
4                  Pasing-Obermenzing  48.13855   11.46586  Entire home/apt
...                               ...       ...        ...              ...
5528               Pasing-Obermenzing  48.15970   11.45158     Private room
5529             Allach-Untermenzing  48.17912   11.46728     Private room
5530             Allach-Untermenzing  48.18063   11.46759     Private room
5531  Ludwigsvorstadt-Isarvorstadt  48.13296   11.55499     Private room
5532                Schwanthalerhöhe  48.13850   11.52979     Private room

      price  minimum_nights  availability_365
0       200               5               129
1        80               2                86
2        95               2               140
3       120               3                 0
4        60               2                 1
...     ...             ...               ...
5528     38               1               117
5529     38               1                 0
5530     44               1                 0
5531     69               2                 0
5532    235               3               365

[5319 rows x 8 columns]
```

```
plt.figure(figsize=(8, 6))
plt.boxplot(cleaned_data['minimum_nights'], vert=False)
plt.title('Boxplot of ' + 'minimum_nights')
plt.xlabel('minimum_nights')
plt.ylabel('Values')
plt.show()
```



Finally, with the clean data frame created and treated, the analysis begins.

```
cleaned_data.describe()
```

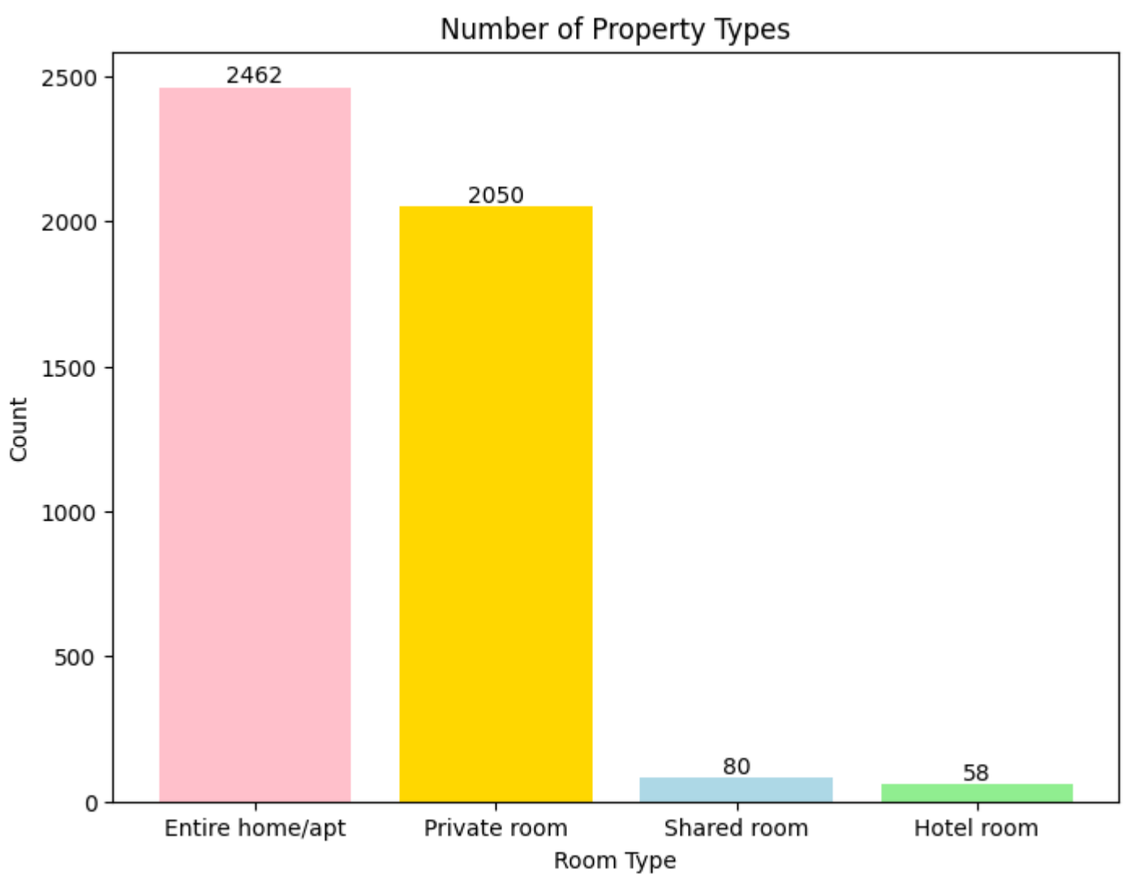
	latitude	longitude	price	minimum_nights	availability_365
count	5319.000000	5319.000000	5319.000000	5319.000000	5319.000000
mean	48.139530	11.562366	173.774206	4.480165	112.395187
std	0.025685	0.048759	1334.399578	6.571928	124.739760
min	48.068870	11.387475	0.000000	1.000000	0.000000
25%	48.122391	11.538725	68.000000	1.000000	0.000000
50%	48.137030	11.563940	100.000000	2.000000	67.000000
75%	48.155565	11.585520	170.000000	4.000000	202.000000
max	48.229500	11.710610	96274.000000	30.000000	365.000000

Exploratory Data Analysis

Objective 1:

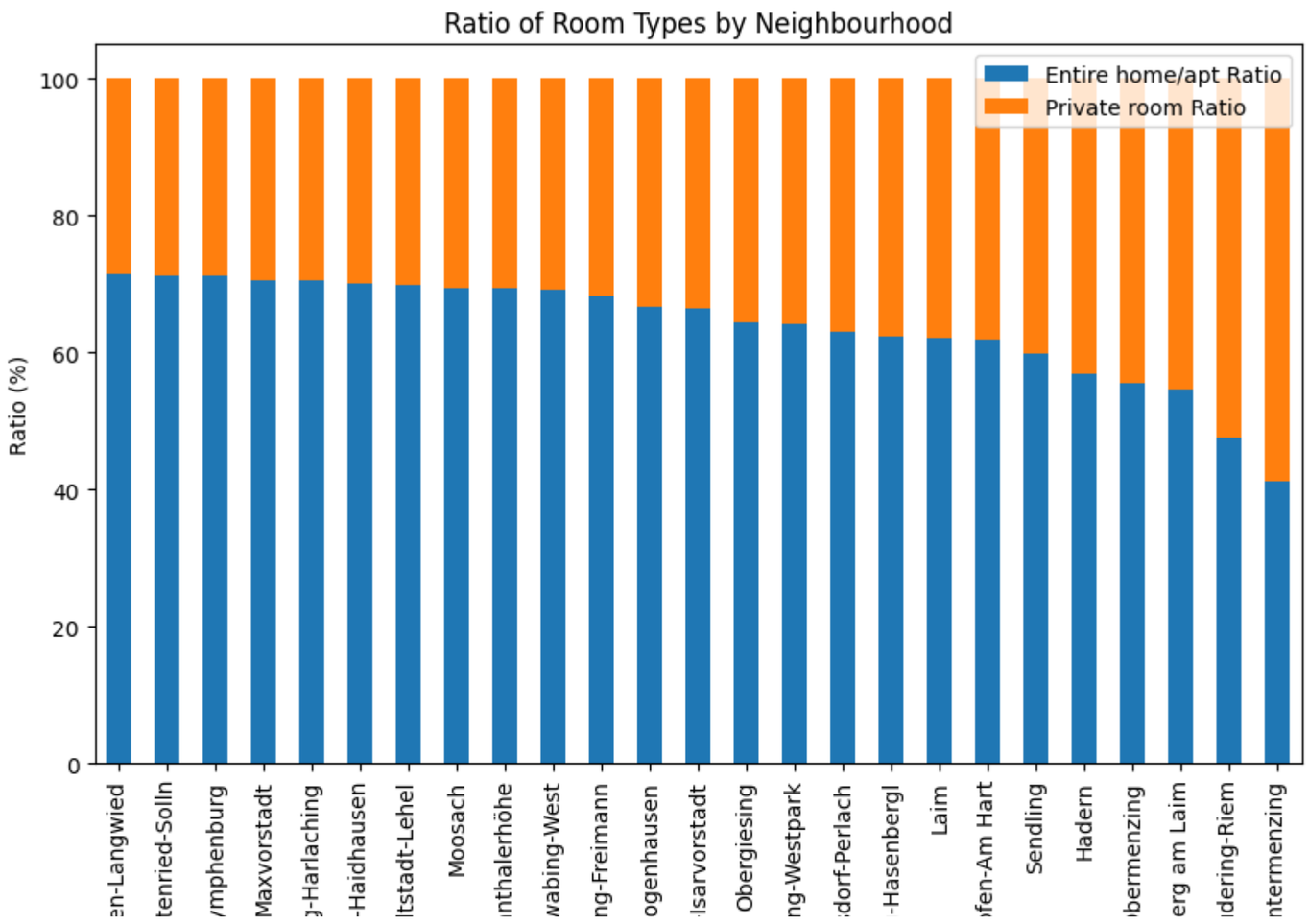
```
import pandas as pd
property_counts = new_data['room_type'].value_counts()
property_ratios = (property_counts / len(new_data) * 100).round(2).astype(str) + '%'

print("Number of Property Types:")
print(property_counts)
```

```
print()

print("Ratio of Property Types:")
print(property_ratios)

     Number of Property Types:
     Entire home/apt    3591
     Private room       1853
     Shared room          52
     Hotel room           37
     Name: room_type, dtype: int64

     Ratio of Property Types:
     Entire home/apt     64.9%
     Private room       33.49%
     Shared room         0.94%
     Hotel room          0.67%
     Name: room_type, dtype: object


import matplotlib.pyplot as plt

room_types = ['Entire home/apt', 'Private room', 'Shared room', 'Hotel room']
counts = [2462, 2050, 80, 58]
colors = ['#FFC0CB', '#FFD700', '#ADD8E6', '#90EE90']

plt.figure(figsize=(8, 6))
plt.bar(room_types, counts, color=colors)

for i, count in enumerate(counts):
    plt.text(i, count, str(count), ha='center', va='bottom')

plt.title("Number of Property Types")
plt.xlabel("Room Type")
plt.ylabel("Count")

plt.show()
```



As the property types 'Shared room' and 'Hotel room' are not relevant to the number of properties being rented on Airbnb in the city of Munich, we will continue this analysis in the neighbourhoods using only the property types 'Entire home/apt' and 'Private room'. In Munich, Germany, hotel rooms and shared rooms might not be as common as other property types for a variety of reasons. First off, shared rooms often offer little in the way of personal space or privacy, which may not be what most travellers like. Munich is a well-liked travel destination, drawing a variety of tourists who frequently seek out more secluded and pleasant lodgings. Additionally, Munich has a large supply of hotels with a variety of alternatives and amenities, which could reduce the demand for hotels with listings on Airbnb. Additionally, Munich's cultural tastes and accepted travel practices may have an impact on how popular shared rooms and hotel rooms are, with a stronger desire for complete homes or private rooms that offer a more individualised and opulent experience.

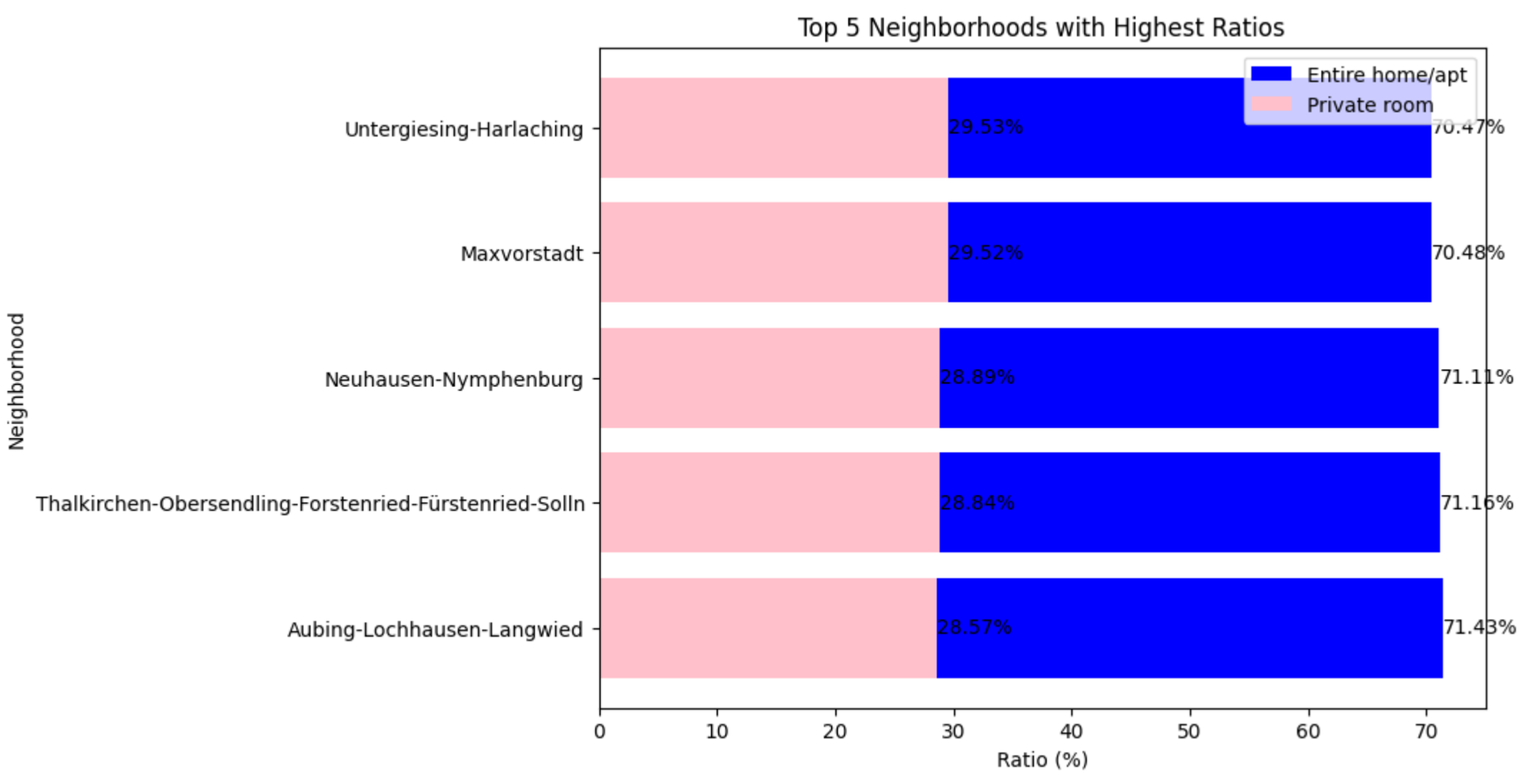
```
import matplotlib.pyplot as plt

grouped_data = grouped_data.sort_values(by='Entire home/apt Ratio', ascending=False)

fig, ax = plt.subplots(figsize=(10, 6))
grouped_data[['Entire home/apt Ratio', 'Private room Ratio']].plot(kind='bar', stacked=True, ax=ax)

plt.title('Ratio of Room Types by Neighbourhood')
plt.xlabel('Neighbourhood')
plt.ylabel('Ratio (%)')

plt.legend()

plt.xticks(rotation=90)

plt.show()
```



It can be seen that the distribution of property types in Munich is well balanced in most neighbourhoods. This indicates that both types of accommodations are available and in demand, providing a diverse range of options for travelers. A well-balanced distribution of property types can be beneficial for both hosts and guests. Hosts have the flexibility to offer different types of accommodations based on their property and preferences, while guests have the opportunity to choose the type of accommodation that suits their needs and preferences.

Below we can see the neighbourhoods where the proportion of property type 'Entire home/apt' is higher, so if the Airbnb user wants to stay in one of the neighbourhoods listed below, there is a greater chance that this user will find offers of this type property available.

```
import matplotlib.pyplot as plt


top_5_neighborhoods = grouped_data.head(5)


plt.figure(figsize=(8, 6))
plt.barh(top_5_neighborhoods.index, top_5_neighborhoods['Entire home/apt Ratio'], color='blue', label='Entire home/apt')
plt.barh(top_5_neighborhoods.index, top_5_neighborhoods['Private room Ratio'], color='pink', label='Private room')


for i, neighborhood in enumerate(top_5_neighborhoods.index):
    ratio_entire = top_5_neighborhoods.loc[neighborhood, 'Entire home/apt Ratio']
    ratio_private = top_5_neighborhoods.loc[neighborhood, 'Private room Ratio']
    plt.text(ratio_entire, i, f'{ratio_entire}%', va='center', color='black')
    plt.text(ratio_private, i, f'{ratio_private}%', va='center', color='black')


plt.title("Top 5 Neighborhoods with Highest Ratios")
plt.xlabel("Ratio (%)")
plt.ylabel("Neighborhood")
plt.legend()


plt.show()
```

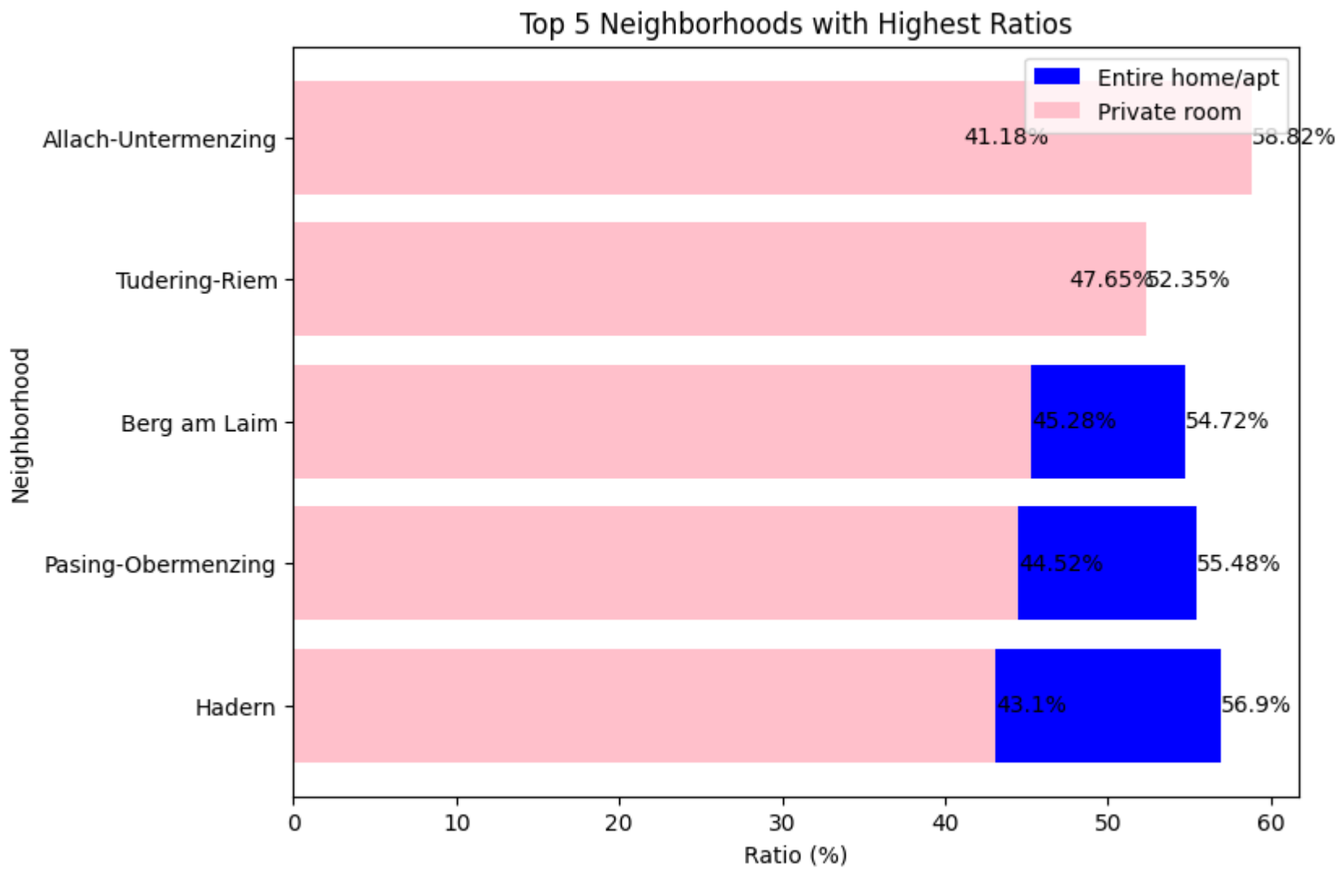


These neighbourhoods in Munich may have a higher concentration of residential properties or property owners who are more inclined to rent out their entire homes/apartments rather than individual rooms.

Now, we can see the neighbourhoods where the proportion of property type 'Private room' is higher, so if the Airbnb user wants to stay in one of the neighbourhoods listed below, there is a greater chance that this user will find offers for this type of property available.

```
import matplotlib.pyplot as plt

top_5_neighborhoods = grouped_data.tail(5)
```

```
plt.figure(figsize=(8, 6))
plt.barh(top_5_neighborhoods.index, top_5_neighborhoods['Entire home/apt Ratio'], color='blue', label='Entire home/apt')
plt.barh(top_5_neighborhoods.index, top_5_neighborhoods['Private room Ratio'], color='pink', label='Private room')

for i, neighborhood in enumerate(top_5_neighborhoods.index):
    ratio_entire = top_5_neighborhoods.loc[neighborhood, 'Entire home/apt Ratio']
    ratio_private = top_5_neighborhoods.loc[neighborhood, 'Private room Ratio']
    plt.text(ratio_entire, i, f'{ratio_entire}%', va='center', color='black')
    plt.text(ratio_private, i, f'{ratio_private}%', va='center', color='black')

plt.title("Top 5 Neighborhoods with Highest Ratios")
plt.xlabel("Ratio (%)")
plt.ylabel("Neighborhood")
plt.legend()

plt.show()
```



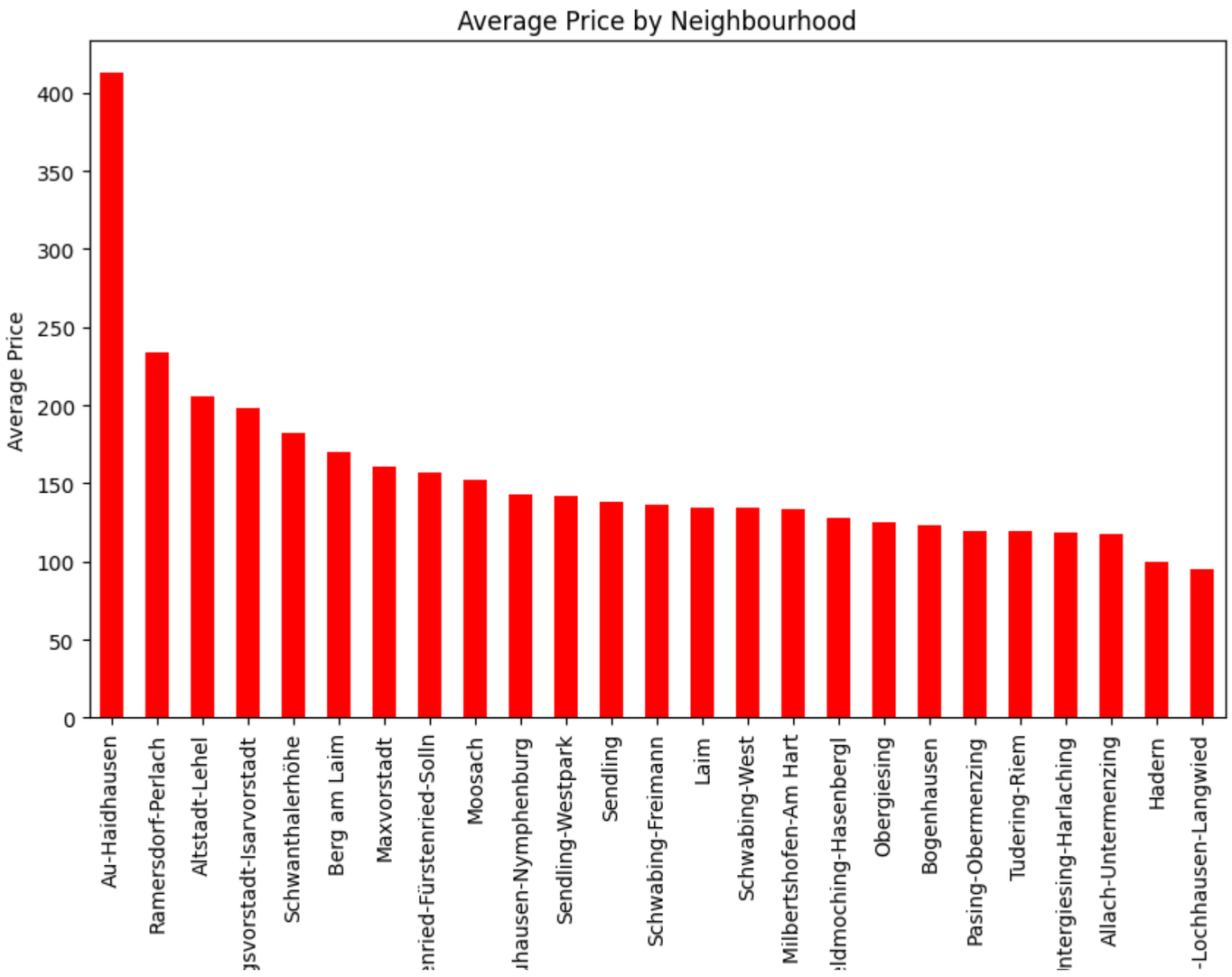
The unique characteristics of the neighborhoods, such as their location, amenities, atmosphere, or target audience, might make them more attractive for travelers or tenants seeking private room accommodations. For example, neighborhoods near universities or popular tourist destinations often have a higher demand for private rooms.

Objective 2:

```
selected_columns = ['neighbourhood', 'price']
selected_data = data[selected_columns]
average_price_by_neighbourhood = round(selected_data.groupby('neighbourhood')['price'].mean().sort_values(ascending=False),2)
average_price_by_neighbourhood
```

```
neighbourhood
Au-Haidhausen                                          412.64
Ramersdorf-Perlach                                     233.79
Altstadt-Lehel                                         206.05
Ludwigsvorstadt-Isarvorstadt                           198.49
Schwanthalerhöhe                                       182.61
Berg am Laim                                           170.39
Maxvorstadt                                            160.45
Thalkirchen-Obersendling-Forstenried-Fürstenried-Solln 156.63
Moosach                                                152.23
Neuhausen-Nymphenburg                                  142.49
Sendling-Westpark                                      142.08
Sendling                                               138.30
Schwabing-Freimann                                     136.52
Laim                                                   134.71
Schwabing-West                                         134.69
Milbertshofen-Am Hart                                  133.69
Feldmoching-Hasenbergl                                 127.97
Obergiesing                                            125.38
Bogenhausen                                            123.26
Pasing-Obermenzing                                     119.39
Tudering-Riem                                          119.02
Untergiesing-Harlaching                                118.72
Allach-Untermenzing                                    117.96
Hadern                                                 100.17
Aubing-Lochhausen-Langwied                              95.43
Name: price, dtype: float64
```

```
import matplotlib.pyplot as plt

neighbourhood_prices = new_data.groupby('neighbourhood')['price'].mean().sort_values(ascending=False)

plt.figure(figsize=(10, 6))
neighbourhood_prices.plot(kind='bar', color='red')
plt.title('Average Price by Neighbourhood')
plt.xlabel('Neighbourhood')
plt.ylabel('Average Price')
plt.xticks(rotation=90)
plt.show()
```



Above is the average property price per neighbourhood in Munich. We can see that there is a big price difference, where the average price in the most expensive neighbourhood is 412.64 and in the cheapest neighbourhood is 95.43.

```
highest_prices = round(new_data.groupby('neighbourhood')['price'].mean().nlargest(2),2)

lowest_prices = round(new_data.groupby('neighbourhood')['price'].mean().nsmallest(2),2)

print("Neighbourhoods with the Highest Prices:")
print(highest_prices)

print("\nNeighbourhoods with the Lowest Prices:")
print(lowest_prices)
```

```
Neighbourhoods with the Highest Prices:
neighbourhood
Au-Haidhausen         412.64
Ramersdorf-Perlach    233.79
Name: price, dtype: float64

Neighbourhoods with the Lowest Prices:
neighbourhood
Aubing-Lochhausen-Langwied     95.43
Hadern                        100.17
Name: price, dtype: float64
```

Objective 3:

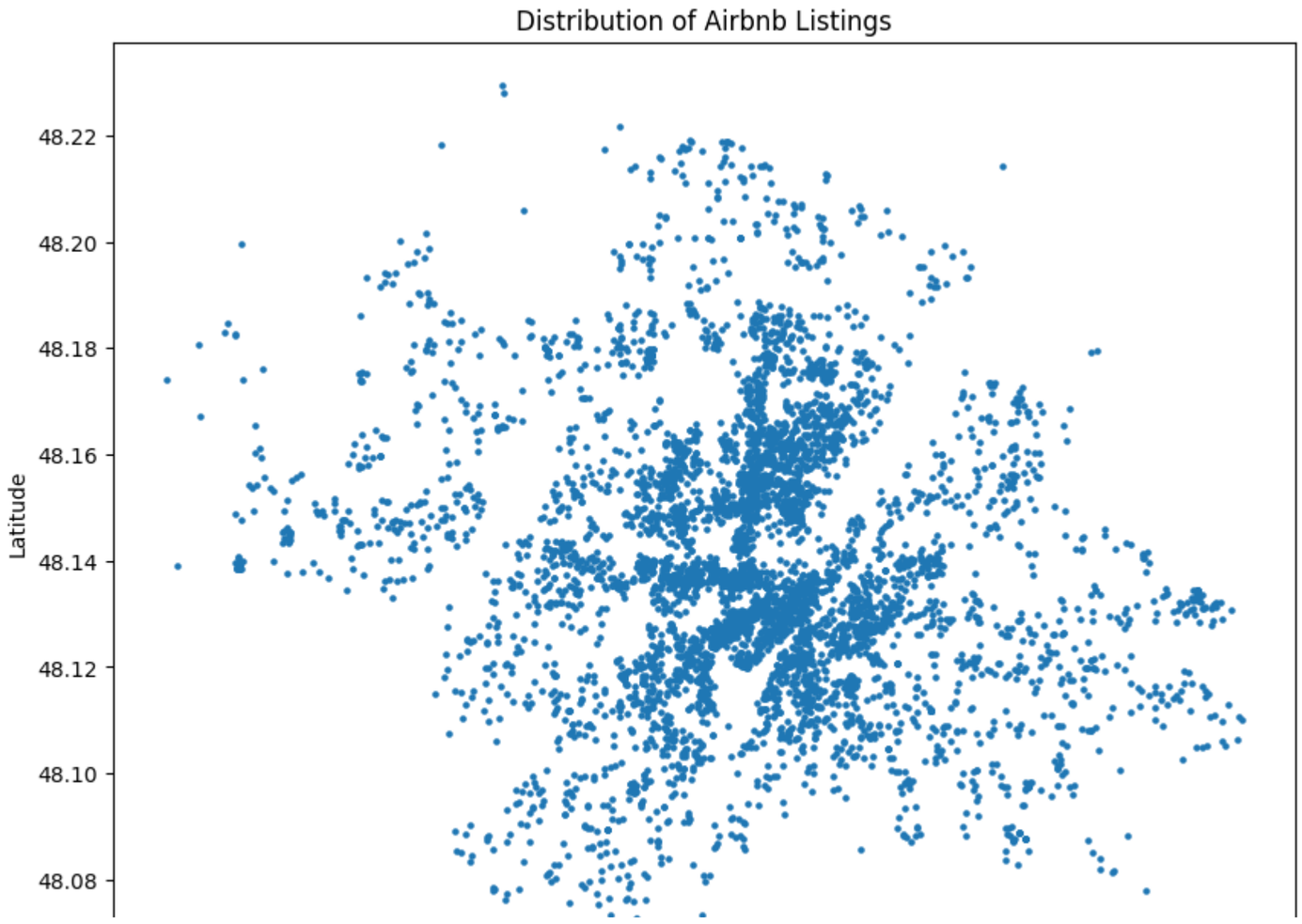
```
!pip install folium
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: folium in /usr/local/lib/python3.10/dist-packages (0.14.0)
Requirement already satisfied: branca>=0.6.0 in /usr/local/lib/python3.10/dist-packages (from folium) (0.6.0)
Requirement already satisfied: jinja2>=2.9 in /usr/local/lib/python3.10/dist-packages (from folium) (3.1.2)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from folium) (1.22.4)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from folium) (2.27.1)
Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2>=2.9->folium) (2.1.2)
Requirement already satisfied: urllib3<1.27,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->folium) (1.26.15)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->folium) (2022.12.7)
Requirement already satisfied: charset-normalizer~=2.0.0 in /usr/local/lib/python3.10/dist-packages (from requests->folium) (2.0.12)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->folium) (3.4)
```

```
!pip install geopandas
```

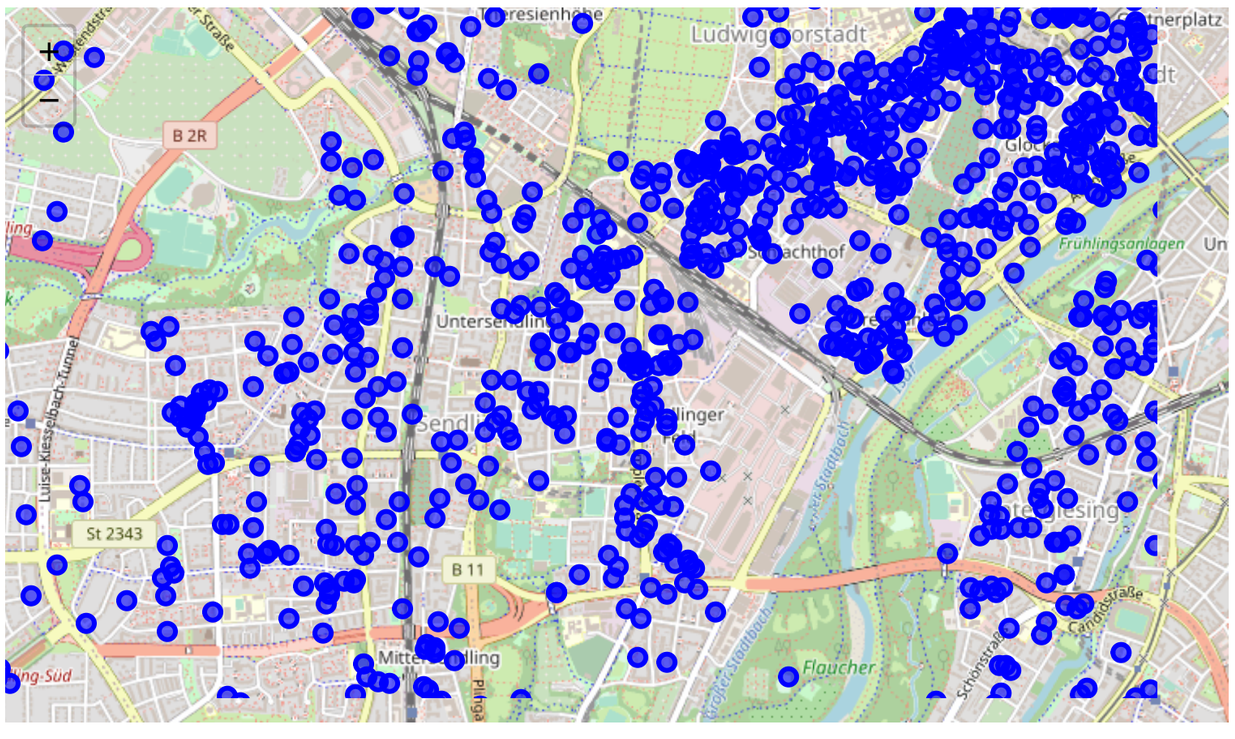
```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: geopandas in /usr/local/lib/python3.10/dist-packages (0.13.0)
Requirement already satisfied: fiona>=1.8.19 in /usr/local/lib/python3.10/dist-packages (from geopandas) (1.9.4.post1)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from geopandas) (23.1)
Requirement already satisfied: pandas>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from geopandas) (1.5.3)
Requirement already satisfied: pyproj>=3.0.1 in /usr/local/lib/python3.10/dist-packages (from geopandas) (3.5.0)
Requirement already satisfied: shapely>=1.7.1 in /usr/local/lib/python3.10/dist-packages (from geopandas) (2.0.1)
Requirement already satisfied: attrs>=19.2.0 in /usr/local/lib/python3.10/dist-packages (from fiona>=1.8.19->geopandas) (23.1.0)
Requirement already satisfied: certifi in /usr/local/lib/python3.10/dist-packages (from fiona>=1.8.19->geopandas) (2022.12.7)
Requirement already satisfied: click~=8.0 in /usr/local/lib/python3.10/dist-packages (from fiona>=1.8.19->geopandas) (8.1.3)
Requirement already satisfied: click-plugins>=1.0 in /usr/local/lib/python3.10/dist-packages (from fiona>=1.8.19->geopandas) (1.1.1)
Requirement already satisfied: cligj>=0.5 in /usr/local/lib/python3.10/dist-packages (from fiona>=1.8.19->geopandas) (0.7.2)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from fiona>=1.8.19->geopandas) (1.16.0)
Requirement already satisfied: python-dateutil>=2.8.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.1.0->geopandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.1.0->geopandas) (2022.7.1)
Requirement already satisfied: numpy>=1.21.0 in /usr/local/lib/python3.10/dist-packages (from pandas>=1.1.0->geopandas) (1.22.4)
```

```
import geopandas as gpd


selected_columns = ['latitude', 'longitude']
selected_data = data[selected_columns]

plt.figure(figsize=(10, 8))
plt.scatter(selected_data['longitude'], selected_data['latitude'], s=5, alpha=1.0)
plt.xlabel('Longitude')
plt.ylabel('Latitude')
plt.title('Distribution of Airbnb Listings')
plt.show()
```



Sparse areas or gaps on the scatter plot indicate regions in Munich with fewer Airbnb listings. These areas might be underrepresented or less popular for rentals, which could provide opportunities for market analysis or potential expansion of Airbnb services.

```
import folium

selected_columns = ['latitude', 'longitude']
selected_data = data[selected_columns]

m = folium.Map(selected_data=['latitude', 'longitude'], zoom_start=12)

for index, row in data.iterrows():
    folium.CircleMarker(location=[row['latitude'], row['longitude']],
                        radius=5,
                        color='blue',
                        fill=True,
                        fill_color='blue',
                        fill_opacity=0.6,
                        popup=row['neighbourhood']).add_to(m)

m
```



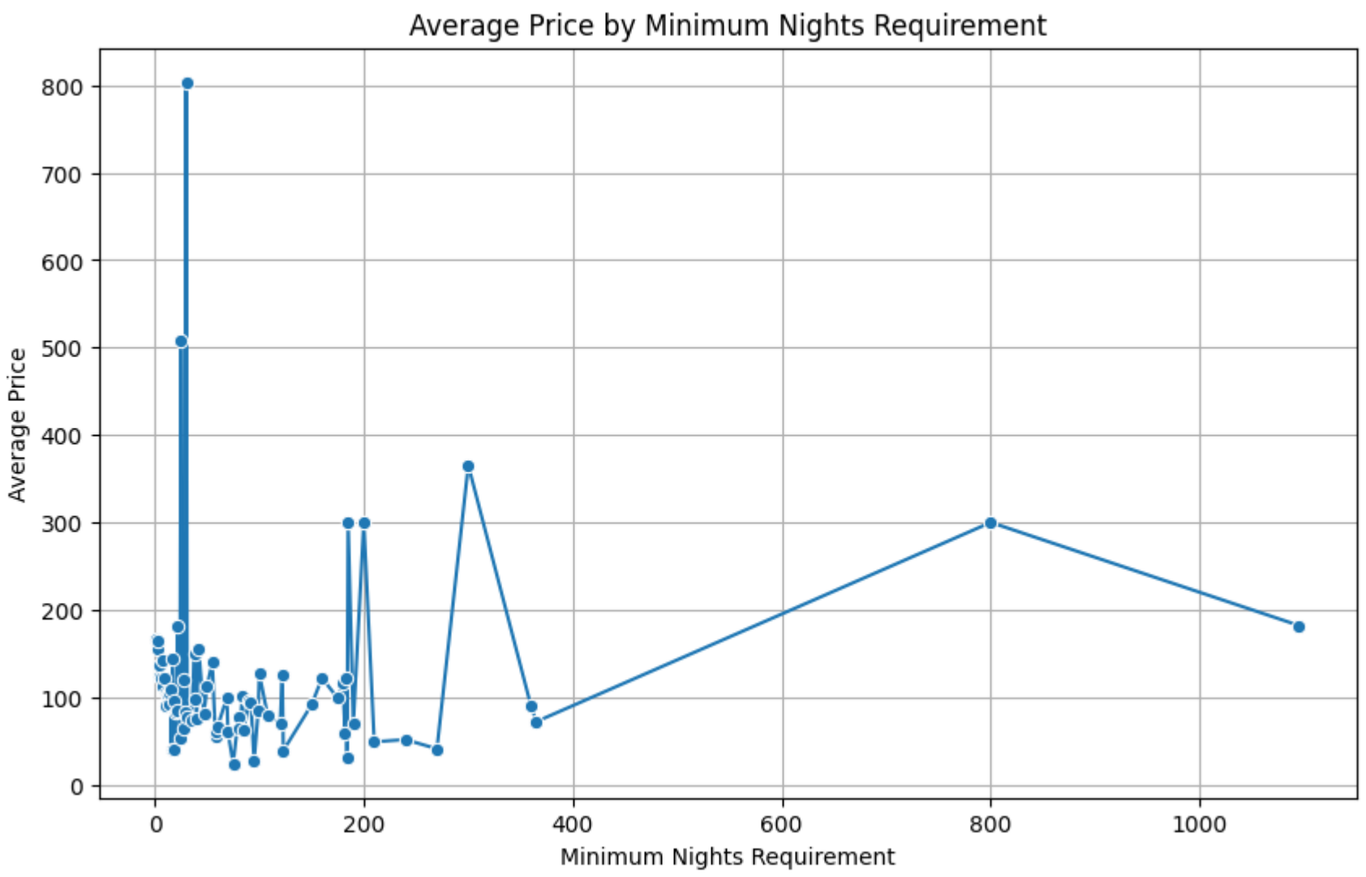
Above graph show more specific for the location with Airbnb activity. The graph provides a visual representation of the geographic distribution of Airbnb in Munich listings based on latitude and longitude coordinates. Each marker on the map represents a specific location. The density of markers indicates the concentration of Airbnb listings in different areas. We can observe clusters or hotspots where multiple markers are closely grouped together, indicating popular or densely populated areas for rentals. Sparse areas or gaps on the map with fewer markers indicate regions with lower Airbnb activity. These areas might be less popular for rentals, indicating potential gaps or opportunities for market analysis or expansion of Airbnb services. By examining the map, we can identify the proximity of Airbnb listings to specific points of interest such as tourist attractions, parks, transportation hubs, or commercial centers. This information can be useful for travelers or property owners in understanding the accessibility and desirability of different locations. The interactive nature of the map allows users to zoom in and out, as well as pan across different areas for a more detailed exploration of the distribution and patterns.

Objective 4:

```
selected_columns = ['minimum_nights', 'price']
selected_data = data[selected_columns]
round(selected_data.groupby('minimum_nights')['price'].mean().sort_values(ascending=False),2)
```

```
     minimum_nights
     30     803.81
     25     508.47
     300    365.33
     800    300.00
     200    300.00
             ...
     16      40.00
     123     39.00
     184     30.00
     95      27.00
     75      24.00
     Name: price, Length: 74, dtype: float64
```

```
import seaborn as sns
import matplotlib.pyplot as plt

selected_columns = ['minimum_nights', 'price']
selected_data = data[selected_columns]

average_price_by_minimum_nights = selected_data.groupby('minimum_nights')['price'].mean().reset_index()
plt.figure(figsize=(10, 6))
sns.lineplot(data=average_price_by_minimum_nights, x='minimum_nights', y='price', marker='o')
plt.title('Average Price by Minimum Nights Requirement')
plt.xlabel('Minimum Nights Requirement')
plt.ylabel('Average Price')
plt.grid(True)
plt.show()
```



From this we can determine the optimal minimum nights for maximizing rental income or occupancy rates, we can look for points on the graph that correspond to higher average prices. These points indicate the minimum nights requirement that yields higher rental prices, which can contribute to maximizing rental income or occupancy rates.

There is no trend that we can see between the minimum nights requirement and rental prices. It is because of rental prices are typically influenced by multiple factors, such as property size, location, amenities, and seasonal demand. The minimum nights requirement alone may not be the primary determinant of rental prices. We should consider analyzing the combined effect of multiple variables to gain a comprehensive understanding of the factors influencing rental prices.

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