- Assignment: 1.2 R/Python Refresher
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- Course: DSC630-T301
- Week1: Introduction to Predictive Analytics
- Date: 03/15/2025

Load necessary packages

In [1]:
```
import pandas as pd
import numpy as np
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt
import seaborn as sns
```

Load the AirBnB dataset, from source: https://www.kaggle.com/datasets/arianazmoudeh/airbnbopendata/data

In [2]:
```
airbnb_df = pd.read_csv(r"Airbnb_Open_Data.csv", encoding="utf-8", low_memory = False)
airbnb_df.head()
```

Out[2]:

	id	NAME	host id	host_identity_verified	host name	neighbourhood group	neighbourhood	lat	
0	1001254	Clean & quiet apt home by the park	80014485718	unconfirmed	Madaline	Brooklyn	Kensington	40.64749	-7
1	1002102	Skylit Midtown Castle	52335172823	verified	Jenna	Manhattan	Midtown	40.75362	-7
2	1002403	THE VILLAGE OF HARLEM....NEW YORK !	78829239556	NaN	Elise	Manhattan	Harlem	40.80902	-7
3	1002755	NaN	85098326012	unconfirmed	Garry	Brooklyn	Clinton Hill	40.68514	-7
4	1003689	Entire Apt: Spacious Studio/Loft by central park	92037596077	verified	Lyndon	Manhattan	East Harlem	40.79851	-7

5 rows × 26 columns

Check for columns and its datatype

In [3]:

```
airbnb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 102599 entries, 0 to 102598
Data columns (total 26 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   id                              102599 non-null  int64  
 1   NAME                            102349 non-null  object 
 2   host id                         102599 non-null  int64  
 3   host_identity_verified          102310 non-null  object 
 4   host name                       102193 non-null  object 
 5   neighbourhood group             102570 non-null  object 
 6   neighbourhood                   102583 non-null  object 
 7   lat                             102591 non-null  float64
 8   long                            102591 non-null  float64
 9   country                         102067 non-null  object 
 10  country code                    102468 non-null  object 
 11  instant_bookable                102494 non-null  object 
 12  cancellation_policy             102523 non-null  object 
 13  room type                       102599 non-null  object 
 14  Construction year               102385 non-null  float64
 15  price                           102352 non-null  object 
 16  service fee                     102326 non-null  object 
 17  minimum nights                  102190 non-null  float64
 18  number of reviews               102416 non-null  float64
 19  last review                     86706 non-null   object 
 20  reviews per month               86720 non-null   float64
 21  review rate number              102273 non-null  float64
 22  calculated host listings count  102280 non-null  float64
 23  availability 365                102151 non-null  float64
 24  house_rules                     50468 non-null   object 
 25  license                         2 non-null       object 
dtypes: float64(9), int64(2), object(15)
memory usage: 20.4+ MB
```

Check for some dataset NAs, uniqueness

In [4]:

```python
df_state = []
columns = airbnb_df.columns
for i in columns :
    types = airbnb_df[i].dtypes
    unique_value = airbnb_df[i].nunique()
```

```
    nan_value= airbnb_df[i].isnull().sum()
    value_count= airbnb_df[i].isnull().count()
    nan_percentage= round(nan_value/value_count*100,2)
    duplicated= airbnb_df.duplicated().sum()

    df_state.append ([i , types , unique_value , nan_value, nan_percentage,duplicated])

df_state = pd.DataFrame(df_state)
df_state.columns =['Name of column' , 'Types' ,'Unique_data' , 'NAN value', "NAN_percentage","Duplicated"]
df_state.style.highlight_max(color = 'orange', axis = 0)
```

Out [4]:

	Name of column	Types	Unique_data	NAN value	NAN_percentage	Duplicated
0	id	int64	102058	0	0.000000	541
1	NAME	object	61281	250	0.240000	541
2	host id	int64	102057	0	0.000000	541
3	host_identity_verified	object	2	289	0.280000	541
4	host name	object	13190	406	0.400000	541
5	neighbourhood group	object	7	29	0.030000	541
6	neighbourhood	object	224	16	0.020000	541
7	lat	float64	21991	8	0.010000	541
8	long	float64	17774	8	0.010000	541
9	country	object	1	532	0.520000	541
10	country code	object	1	131	0.130000	541
11	instant_bookable	object	2	105	0.100000	541
12	cancellation_policy	object	3	76	0.070000	541
13	room type	object	4	0	0.000000	541
14	Construction year	float64	20	214	0.210000	541
15	price	object	1151	247	0.240000	541
16	service fee	object	231	273	0.270000	541
17	minimum nights	float64	153	409	0.400000	541
18	number of reviews	float64	476	183	0.180000	541
19	last review	object	2477	15893	15.490000	541
20	reviews per month	float64	1016	15879	15.480000	541
21	review rate number	float64	5	326	0.320000	541
22	calculated host listings count	float64	78	319	0.310000	541

	Name of column	Types	Unique_data	NAN value	NAN_percentage	Duplicated
23	availability 365	float64	438	448	0.440000	541
24	house_rules	object	1976	52131	50.810000	541
25	license	object	1	102597	100.000000	541

Perform basic data cleanup

In [5]:
```
# Remove $ and comma from columns with prices
col_to_clean=['price','service fee']
for col in col_to_clean:
    airbnb_df[col] = airbnb_df[col].str.replace('$', '', regex=False)  # Remove dollar sign
    airbnb_df[col] = airbnb_df[col].str.replace(',', '', regex=False)  # Remove commas
    airbnb_df[col] = airbnb_df[col].astype(float)
```

In [6]:
```
# Drop duplicates
airbnb_df = airbnb_df.drop_duplicates()
```

In [7]:
```
# Drop columns not needed
columns_to_drop = ['id', 'host id', 'NAME', 'host name', 'lat', 'long', 'country', 'country code',
                   'last review', 'house_rules', 'license', 'reviews per month']

# Drop the columns
airbnb_df = airbnb_df.drop(columns=columns_to_drop)
```

In [8]:
```
# Standardize data
label_encoder = LabelEncoder()

# Convert each object column to numeric using LabelEncoder
for column in airbnb_df.select_dtypes(include=['object','bool']).columns:
    airbnb_df[column] = label_encoder.fit_transform(airbnb_df[column])
```

In [9]:
```
airbnb_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 102058 entries, 0 to 102057
Data columns (total 14 columns):
 #   Column                          Non-Null Count   Dtype  
---  ------                          --------------   -----  
 0   host_identity_verified          102058 non-null  int64  
 1   neighbourhood group             102058 non-null  int64  
 2   neighbourhood                   102058 non-null  int64  
 3   instant_bookable                102058 non-null  int64  
 4   cancellation_policy             102058 non-null  int64  
 5   room type                       102058 non-null  int64  
 6   Construction year               101844 non-null  float64
 7   price                           101811 non-null  float64
 8   service fee                     101785 non-null  float64
 9   minimum nights                  101658 non-null  float64
 10  number of reviews               101875 non-null  float64
 11  review rate number              101739 non-null  float64
 12  calculated host listings count  101739 non-null  float64
 13  availability 365                101610 non-null  float64
dtypes: float64(8), int64(6)
memory usage: 11.7 MB
```

In [10]:

```
airbnb_df.describe()
```

Out[10]:

	host_identity_verified	neighbourhood group	neighbourhood	instant_bookable	cancellation_policy	room type	Co
count	102058.000000	102058.000000	102058.000000	102058.000000	102058.000000	102058.000000	1018
mean	0.503665	1.688697	108.382645	0.499490	1.001862	0.973476	20
std	0.505621	0.768401	69.539642	0.502056	0.817010	1.031060	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	20
25%	0.000000	1.000000	52.000000	0.000000	0.000000	0.000000	20
50%	1.000000	2.000000	97.000000	0.000000	1.000000	0.000000	20
75%	1.000000	2.000000	178.000000	1.000000	2.000000	2.000000	20
max	2.000000	7.000000	224.000000	2.000000	3.000000	3.000000	20

Write a summary of your data and identify at least two questions to explore visually with your data

Assumptions on columns

1. price: The listing price per night.
2. number of reviews: The number of reviews the listing has received.
3. room type: The type of room (Entire home/apt, Private room, Shared room, and Hotel).
4. neighbourhood group: The general area or borough.
5. availability 365: The number of days the listing is available in a year.
6. bedrooms: number of bedrooms.
7. bathrooms: number of bathrooms.

Summary

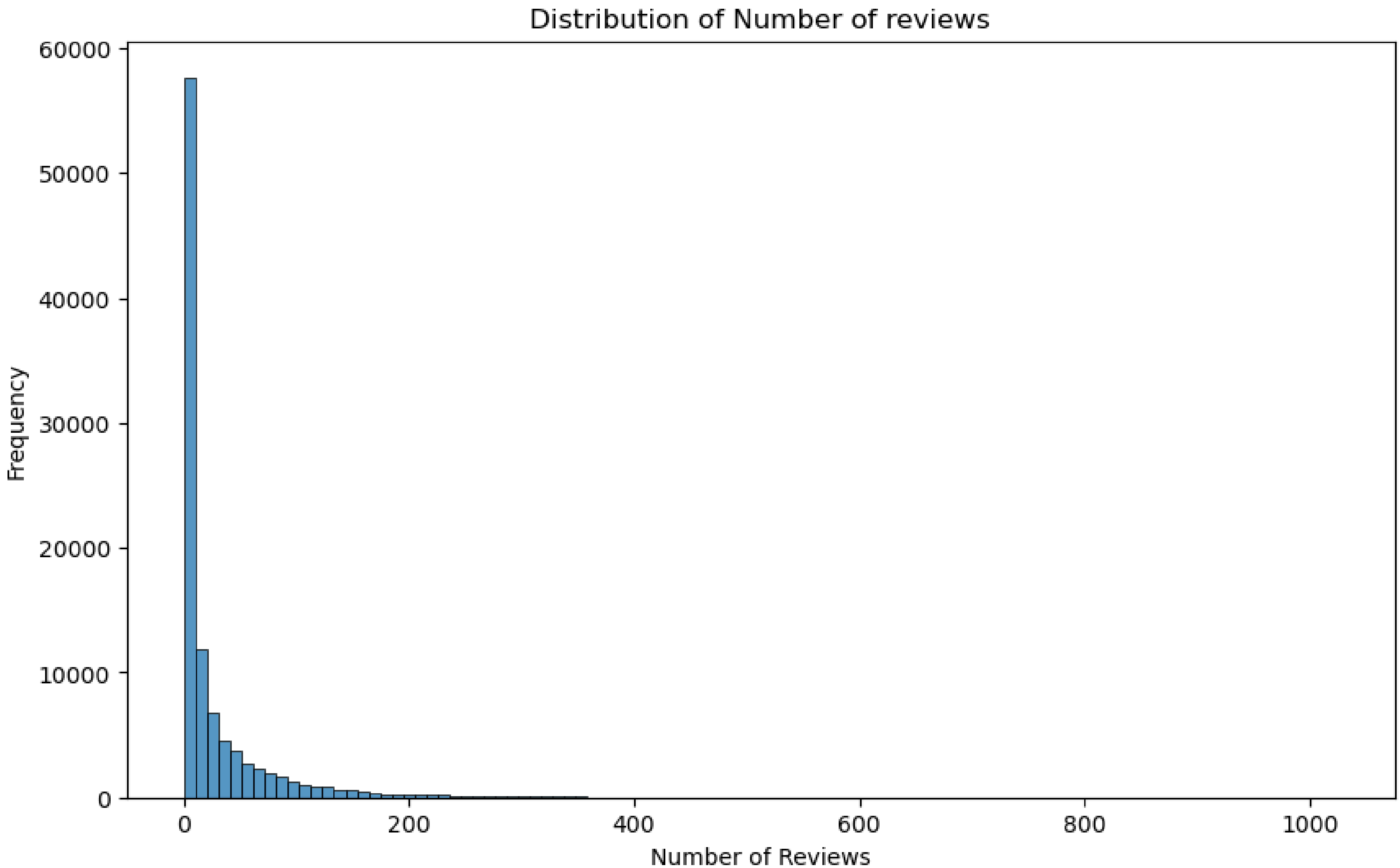
1. The AirBnb dataset is taken from Kaggle source (https://www.kaggle.com/datasets/arianazmoudeh/airbnbopendata/data).
2. Initial dataset has 102,599 records with 26 columns. After performing basic cleanup it was 102058 rows and 14 columns.

Questions to explore the data set visually

1. Is there a correlation between the number of reviews and the availability of a listing?
2. How does the distribution of listing prices vary across different room types?

Create a histogram or bar graph from your data.

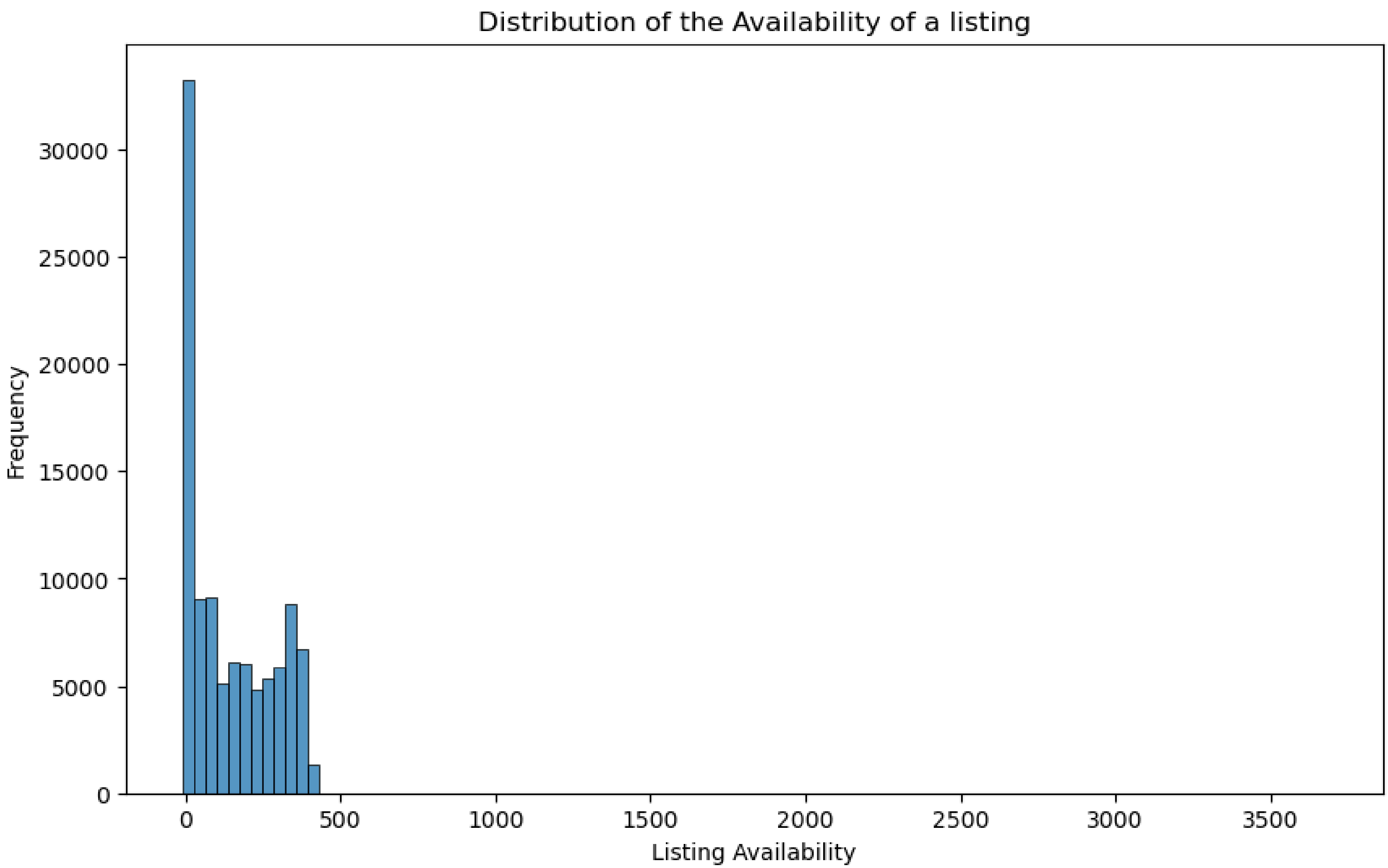
In [11]:
```python
# Histogram of Number of reviews
plt.figure(figsize=(10, 6))
sns.histplot(airbnb_df['number of reviews'], bins=100) #bins adjust the amount of bars in the graph.
plt.title('Distribution of Number of reviews')
plt.xlabel('Number of Reviews')
plt.ylabel('Frequency')
plt.show()
```



Number of Reviews: The histogram of listing prices shows shows a right-skewed distribution, indicating that most are in the lower range, with a few very in very high reviews.

In [12]:
```
# Histogram of Availability of listing
plt.figure(figsize=(10, 6))
sns.histplot(airbnb_df['availability 365'], bins=100) #bins adjust the amount of bars in the graph.
plt.title('Distribution of the Availability of a listing')
plt.xlabel('Listing Availability')
```

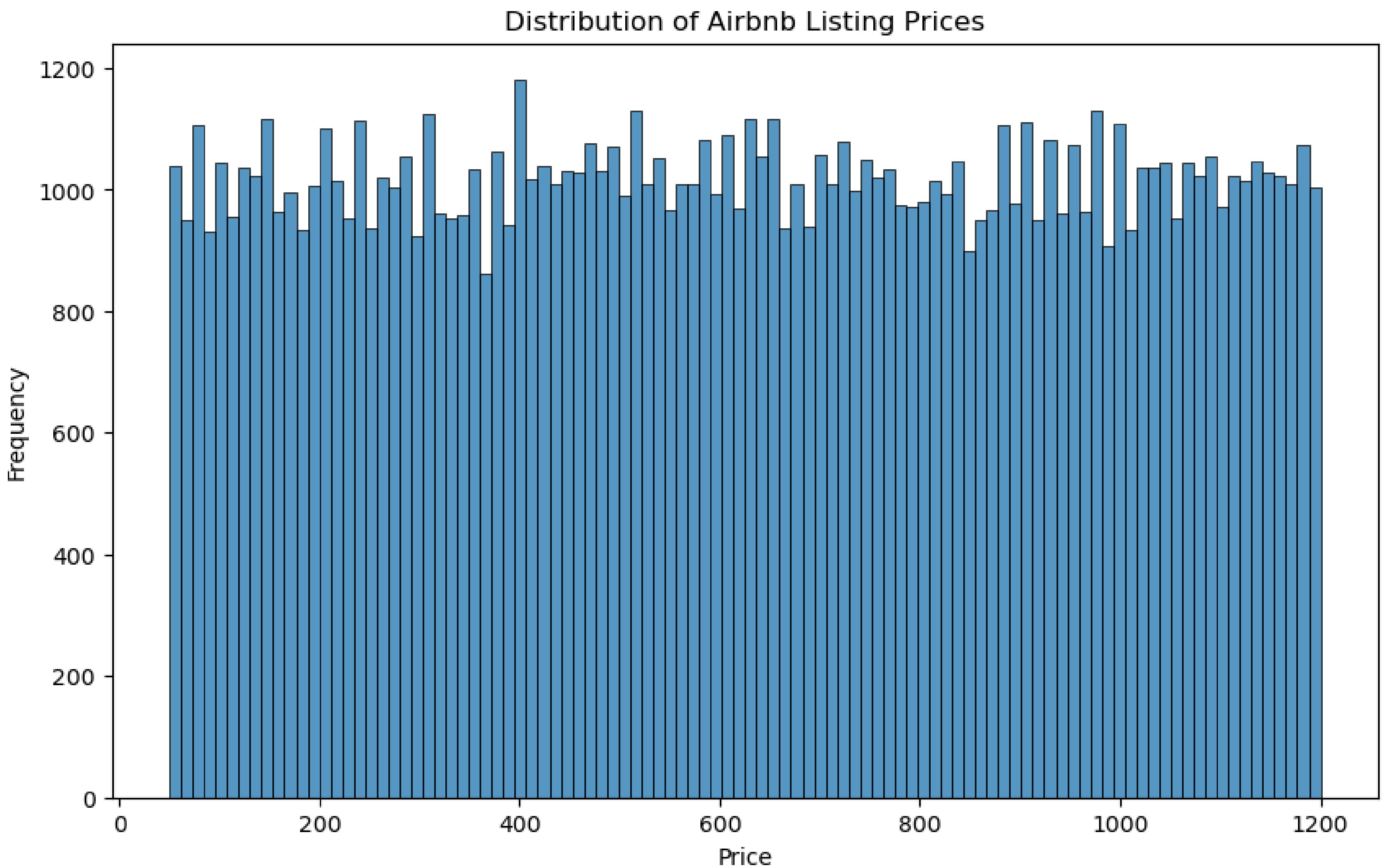
```
plt.ylabel('Frequency')
plt.show()
```



Listing Availability: Histogram is right-skewed, but with short tail. The number of frequency of distribution is also less.

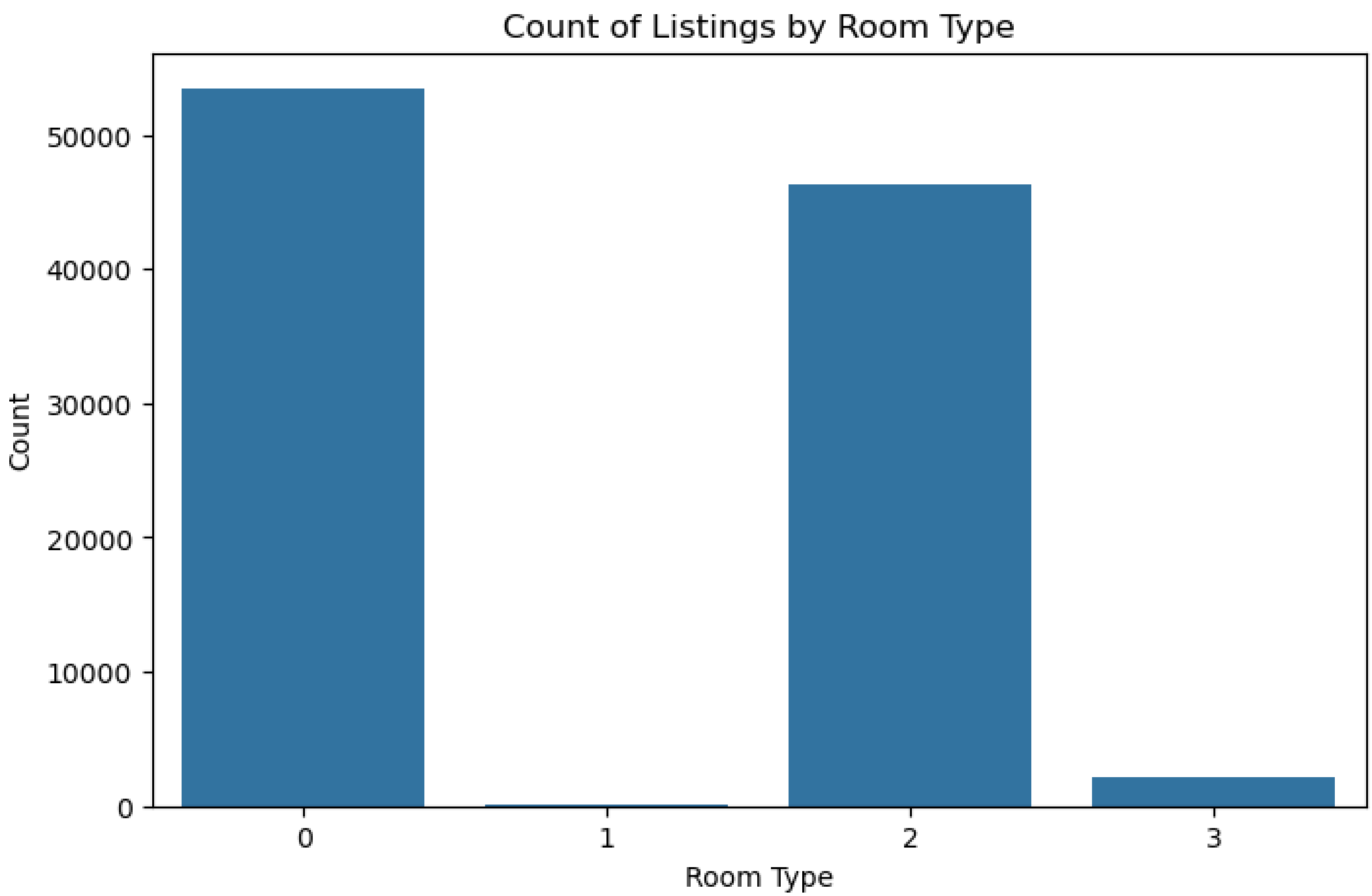
In [13]:
```
# Histogram of listing prices
plt.figure(figsize=(10, 6))
sns.histplot(airbnb_df['price'], bins=100) #bins adjust the amount of bars in the graph.
```

```python
plt.title('Distribution of Airbnb Listing Prices')
plt.xlabel('Price')
plt.ylabel('Frequency')
plt.show()
```



Price Distribution: The histogram of listing prices shows a uniform distribution, indicating that most listings are in similar price range.

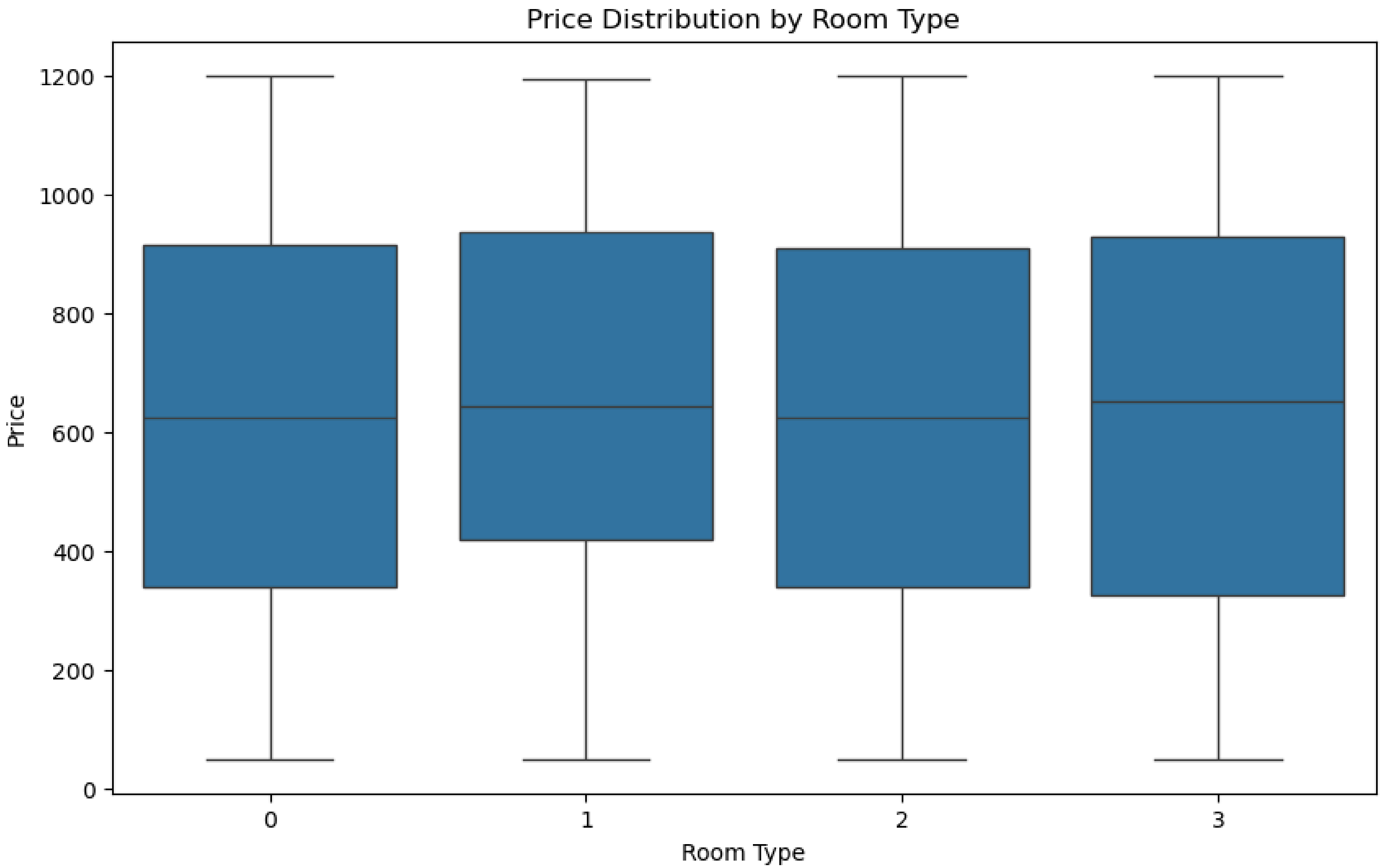
In [14]:
```
# Bar graph of room type counts
plt.figure(figsize=(8, 5))
sns.countplot(data=airbnb_df, x='room type')
plt.title('Count of Listings by Room Type')
plt.xlabel('Room Type')
plt.ylabel('Count')
plt.show()
```



Room Type Distribution: The bar graph of room types reveals that "Entire home/apt" and "Shared room" are the most common listing types.

Create a boxplot from your data.

In [15]:
```
# Boxplot of prices by room type
plt.figure(figsize=(10, 6))
sns.boxplot(data=airbnb_df, x='room type', y='price')
plt.title('Price Distribution by Room Type')
plt.xlabel('Room Type')
plt.ylabel('Price')
plt.show()
```

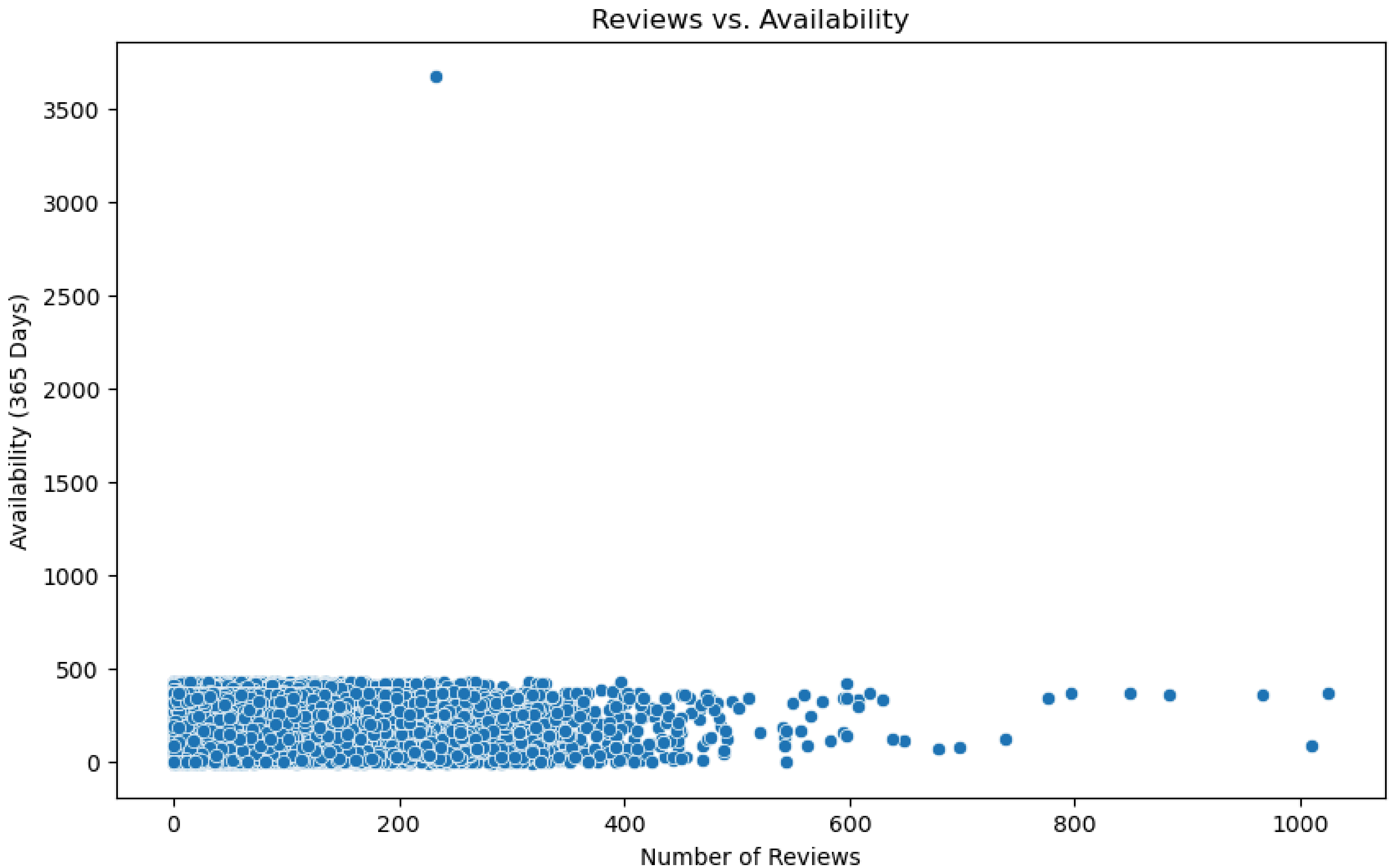


Price by Room Type: The boxplot illustrates all Room Types listings generally have similar prices.

Create a bivariate plot from your data.

In [16]:
```
# Scatter plot of reviews vs. availability
plt.figure(figsize=(10, 6))
```

```python
sns.scatterplot(data=airbnb_df, x='number of reviews', y='availability 365')
plt.title('Reviews vs. Availability')
plt.xlabel('Number of Reviews')
plt.ylabel('Availability (365 Days)')
plt.show()
```

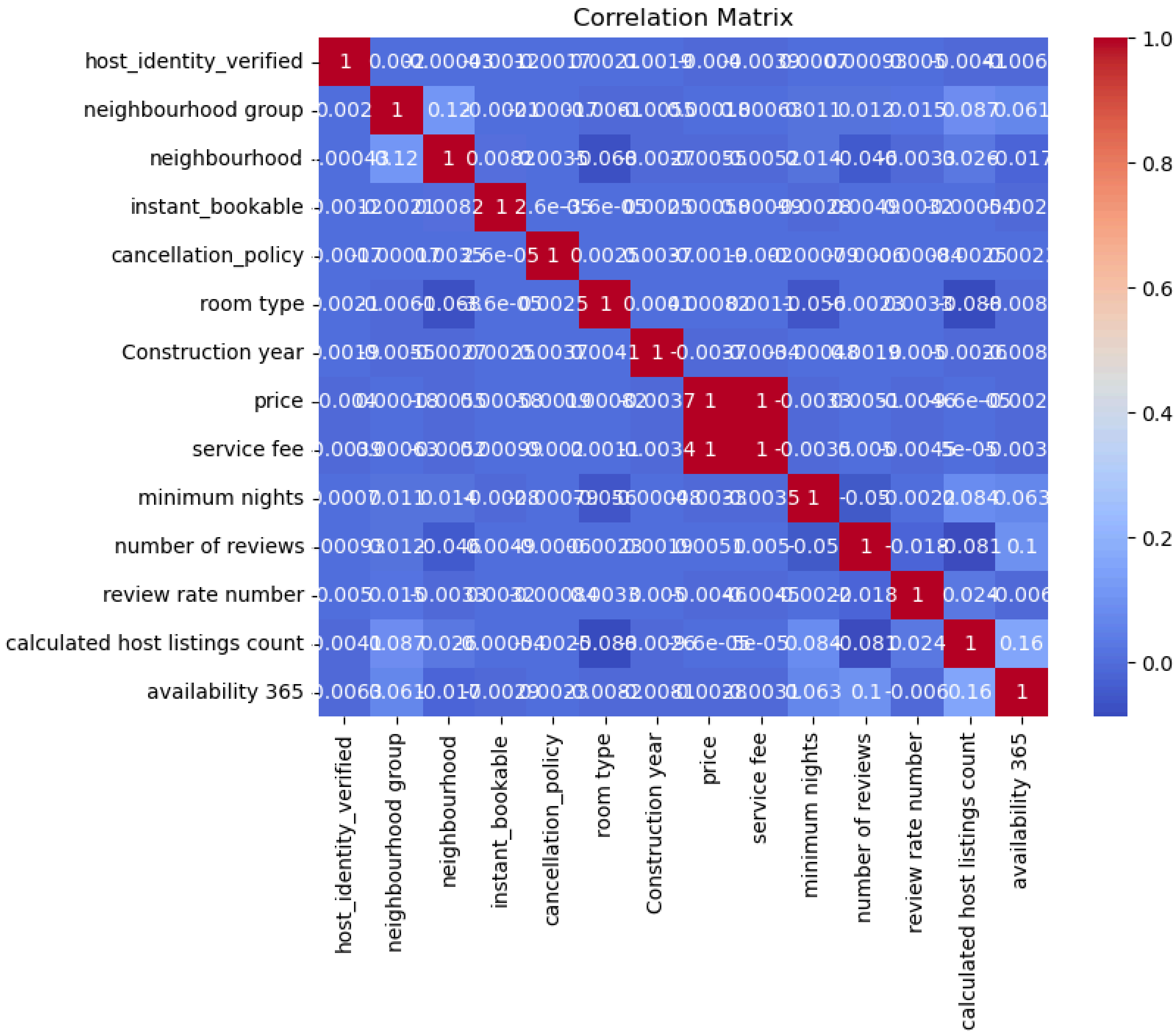


Reviews vs. Availability: The scatter plot is concentrated towards low to medium number of reviews with low score on availability. There seems to be an outlier with number of reviews as well.

Create any additional visualizations that will help to answer the question(s) you want to answer.

In [18]:

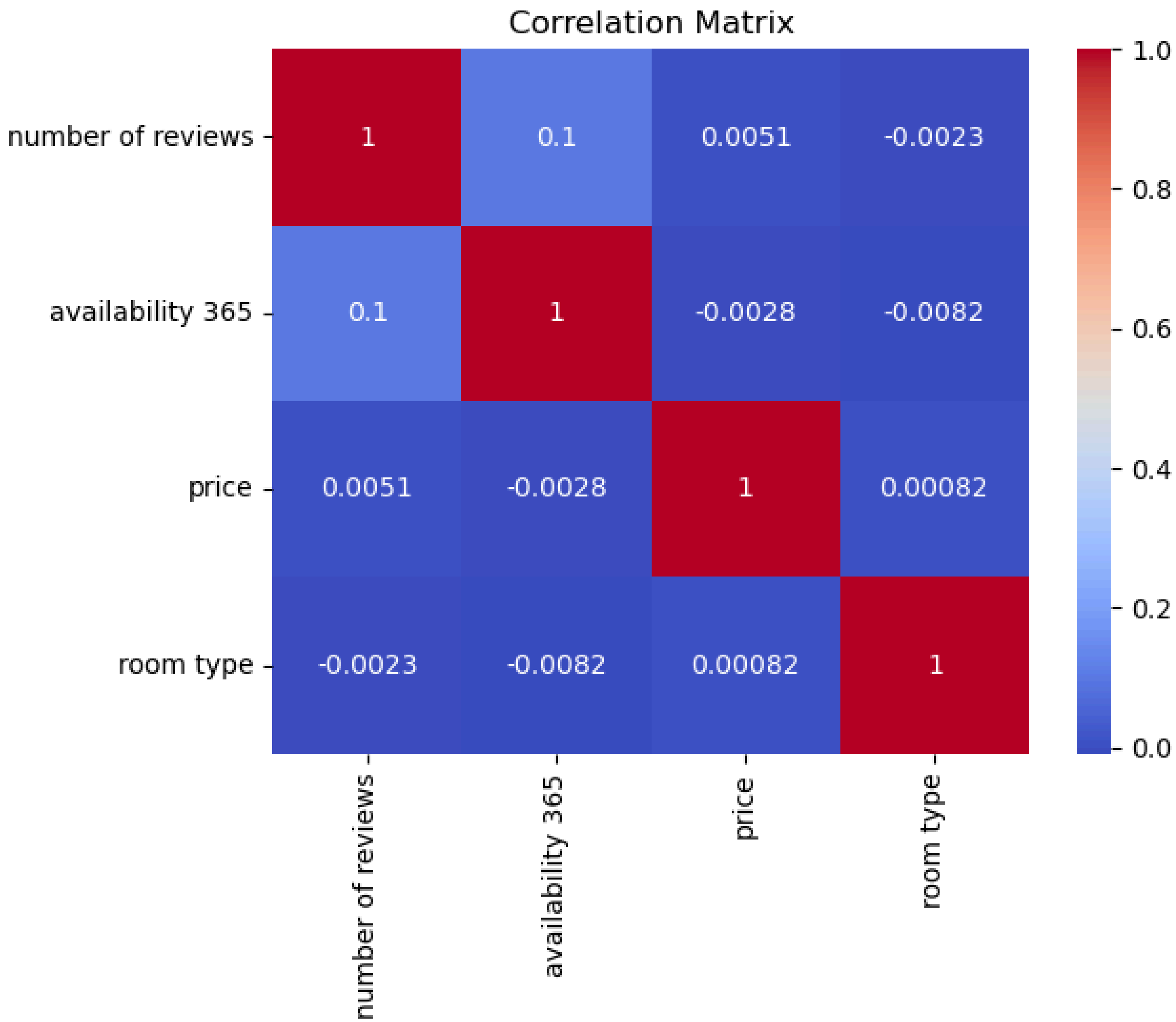
```
# Heatmap of correlation matrix
plt.figure(figsize=(8, 6))
correlation_matrix = airbnb_df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```


Correlation Matrix
host_identity_verified
neighbourhood group
neighbourhood
instant_bookable
cancellation_policy
room type
Construction year
price
service fee
minimum nights
number of reviews
review rate number
calculated host listings count
availability 365
1.0
0.8
0.6
0.4
0.2
0.0

Correlation Matrix: The heatmap of the correlation matrix indicates that there is no strong linear correlation between most numerical variables. However strong correlation is between Price and Service Fee

Perform correlation matrix on the selected column

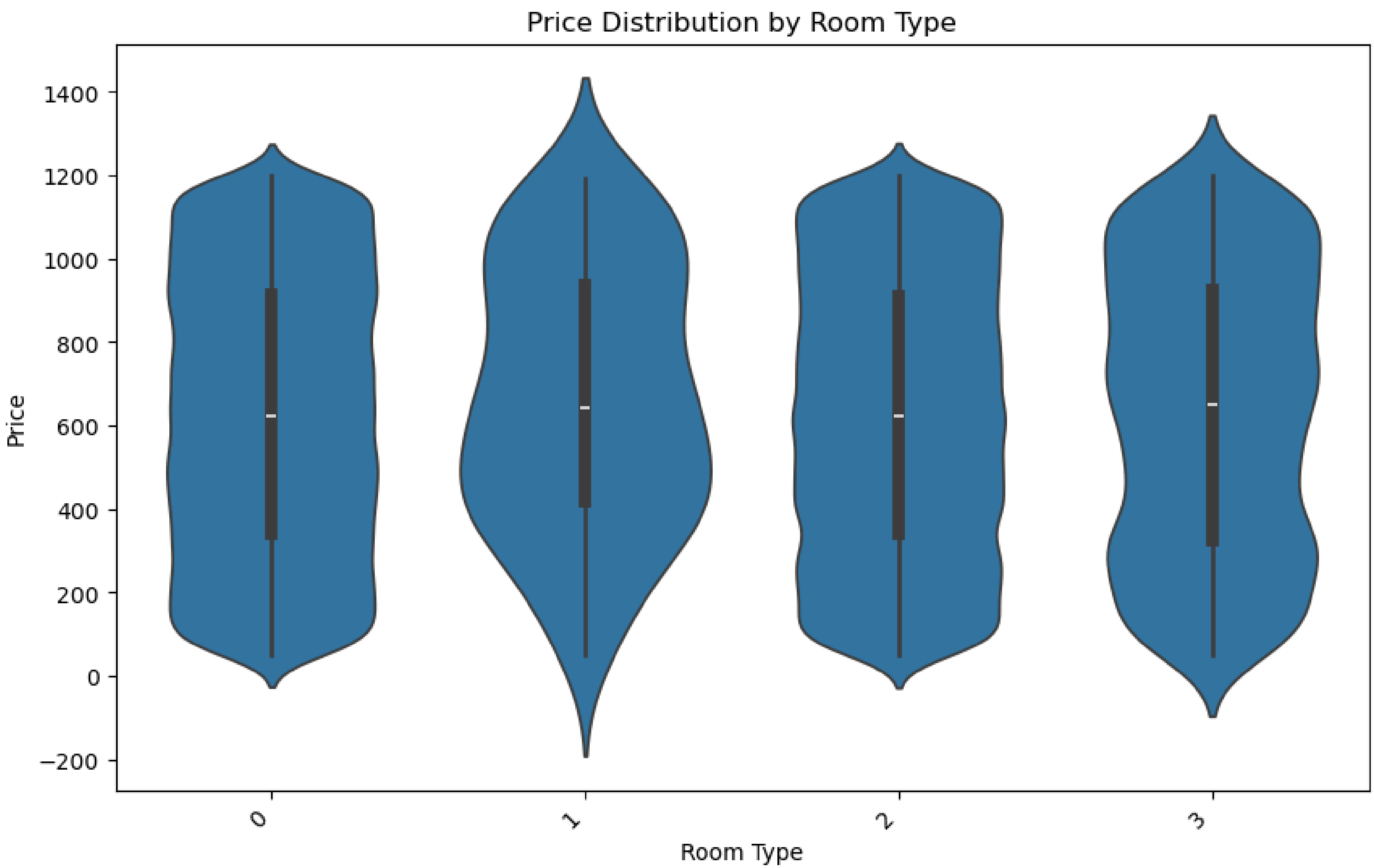
In [24]:
```
selected_columns = ['number of reviews', 'availability 365', 'price', 'room type']
df_selected = airbnb_df[selected_columns]
correlation_matrix = df_selected.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



Correlation Matrix: The heatmap of the correlation matrix indicates a weak linear relation between 'Number of Reviews' and 'Availability 365'

In [28]:
```
# Violin plot of Price by Room Type
plt.figure(figsize=(10, 6))
sns.violinplot(data=airbnb_df, x='room type', y='price')
plt.title('Price Distribution by Room Type')
plt.xlabel('Room Type')
```

```
plt.ylabel('Price')
plt.xticks(rotation=45, ha='right')
plt.show()
```



The violin plot shows that price distributions are uniform on Entire home/apt and Shared room, while Private room distribution looks normal.

Conclusion

Is there a correlation between the number of reviews and the availability of a listing?

1. Distribution of 'Number of Reviews' and 'Availability of listing' are both right skewed exhibiting similar behavior.
2. The scatter plot between them are concentrated towards low to medium number of reviews with low score on availability. There seems to be an outlier as well that can be analyzed further.
3. Correlation Matrix between 'Number of Reviews' and 'Availability of listing' is 0.1 indicating a weak linear relation.

Based on the above results of visualization there seems to be a weak linear relation but they are not conclusive and needs further analysis to support the theory.

How does the distribution of listing prices vary across different room types?

1. Distribution of 'listing Prices' is uniform, and based on bar chart the rental usage is higher on "Entire home/apt" and "Shared room"
2. Box plot on 'Price Distribution by Room Type' shows similar mean prices on all the types of Rooms.
3. The violin plot shows that price distributions are uniform on Entire home/apt and Shared room, while Private room distribution looks normal.
4. Correlation Matrix between 'Price' and 'Room Type' is 0.00082 indicating a very weak linear relation.

Based on the above results of visualization there seems to be a no relation but them, however based on violin plot the 'Private Room' distribution looks normal and 'Entire home/apt' and 'Shared room' are uniform and needs to be analyzed further

In [ ]:

```

```