1. Importing Dependencies & Loading Dataset

```
#Importing Dependencies
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
#Loading Dataset
data=pd.read_csv("/content/sample_data/airbnb_dataset.csv",encoding_errors='ignore')
```

2. Initial Exploration

#Print top 5 rows
data.head()

₹		id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude	room
	0	1312228.0	Rental unit in Brooklyn · ★5.0 · 1 bedroom	7130382	Walter	Brooklyn	Clinton Hill	40.683710	-73.964610	F
	1	45277537.0	Rental unit in New York ·★4.67 · 2 bedrooms ·	51501835	Jeniffer	Manhattan	Hell's Kitchen	40.766610	-73.988100	hoı
	2	971000000000000000000000000000000000000	Rental unit in New York **4.17 · 1 bedroom ·	528871354	Joshua	Manhattan	Chelsea	40.750764	-73.994605	hoı
	3	3857863.0	Rental unit in New York * \$\ddot 4.64 \cdot 1 bedroom \cdot \dots	19902271	John And Catherine	Manhattan	Washington Heights	40.835600	-73.942500	ſ
	4	40896611.0	Condo in New York · ★4.91 · Studio · 1 bed · 1	61391963	Stay With Vibe	Manhattan	Murray Hill	40.751120	-73.978600	hoı

5 rows × 22 columns

#Print last 5 rows
data.tail()

→	•••						.		
<u> </u>		id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude	longitude
2	20765	24736896.0	Rental unit in New York *4.75 1 bedroom	186680487	Henry D	Manhattan	Lower East Side	40.711380	-73.991560
2	20766	2835711.0	Rental unit in New York *4.46 1 bedroom		Aspen	Manhattan	Greenwich Village	40.730580	-74.000700
2	20767	51825274.0	Rental unit in New York • *4.93 • 1 bedroom •		Jeff	Manhattan	Hell's Kitchen	40.757350	-73.99343(
2	20768	783000000000000000000000000000000000000	Rental unit in New York · ★5.0 · 1 bedroom · 1		Marissa	Manhattan	Chinatown	40.713750	-73.991470
2	20769	566000000000000000000000000000000000000	Rental unit in Queens · ★4.89 · 1 bedroom · 1		Glenroy	Queens	Rosedale	40.658874	-73.72865 ⁻
Print		. Rows & Columns							
) (2	20724,	22)							
ata.in → <c In Da</c 	nfo() class ndex: nta co	'pandas.core.frame.Dat 20724 entries, 0 to 20	caFrame'> 0769						
		olumn 		Non-Null Cour					
0		ame		20724 non-nul 20724 non-nul	_				
2		ost_id		20724 non-nul	9				
3		ost_name eighbourhood_group		20724 non-nul 20724 non-nul	9				
5	ne	eighbourhood		20724 non-nul	ll object				
6 7		atitude ongitude		20724 non-null 20724 non-null					
8		ongitude oom_type		20724 non-nul 20724 non-nul					
9) pr	rice		20724 non-nul	ll float6	4			
		nimum_nights umber_of_reviews		20724 non-null 20724 non-null					
		ast_review		20724 non-nul					
1	.3 re	eviews_per_month		20724 non-nul	ll float6	4			
		alculated_host_listings vailability_365	_count	20724 non-nul 20724 non-nul					
		umber_of_reviews_ltm		20724 non-nul					
		cense		20724 non-nul					

20724 non-null object

17 license

 18
 rating
 20724 non-null object

 19
 bedrooms
 20724 non-null object

 20
 beds
 20724 non-null int64

 21
 baths
 20724 non-null object

dtypes: float64(9), int64(1), object(12)

memory usage: 3.6+ MB

Generate descriptive statistics for numeric columns (count, mean, std, min, quartiles, max) data.describe()

\Rightarrow		latitude	longitude	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host
	count	20724.000000	20724.000000	20724.000000	20724.000000	20724.000000	20724.000000	
	mean	40.726843	-73.939155	187.732195	28.566396	42.592646	1.257529	
	std	0.060320	0.061442	1023.539393	33.560272	73.534712	1.905221	
	min	40.500314	-74.249840	10.000000	1.000000	1.000000	0.010000	
	25%	40.684150	-73.980760	80.000000	30.000000	4.000000	0.210000	
	50%	40.722937	-73.949599	125.000000	30.000000	14.000000	0.650000	
	75%	40.763132	-73.917430	199.000000	30.000000	49.000000	1.800000	
	max	40.911147	-73.713650	100000.000000	1250.000000	1865.000000	75.490000	

3. Data Cleaning

#Checking null values
data.isnull().sum()

$\overline{\Rightarrow}$		0
	id	0
	name	0
	host_id	0
	host_name	0
	neighbourhood_group	0
	neighbourhood	7
	latitude	7
	longitude	7
	room_type	7
	price	34
	minimum_nights	7
	number_of_reviews	7
	last_review	7
	reviews_per_month	7
	calculated_host_listings_count	7
	availability_365	7
	number_of_reviews_ltm	7
	license	0
	rating	0
	bedrooms	0
	beds	0
	baths	0

dtype: int64

```
#Dropping all null rows
data.dropna(inplace=True)
```

#Checking total Duplicate rows
data.duplicated().sum()

→ np.int64(0)

#printing all duplicate rows
data[data.duplicated()]

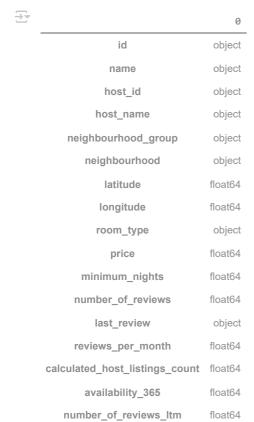


id name host_id host_name neighbourhood_group neighbourhood latitude longitude room_type price ... last_re

0 rows × 22 columns

#Dropping all duplicate rows
data.drop_duplicates(inplace=True)

#Checking Data type of Columns
data.dtypes



license

rating

bedrooms

beds baths object

object

object int64

object

dtype: object

#Changing the data-type of column 'id' to object
data['id']=data['id'].astype(object)

#Changing the data-type of column 'host_id' to object
data['host_id']=data['host_id'].astype(object)

4. Data Analysis

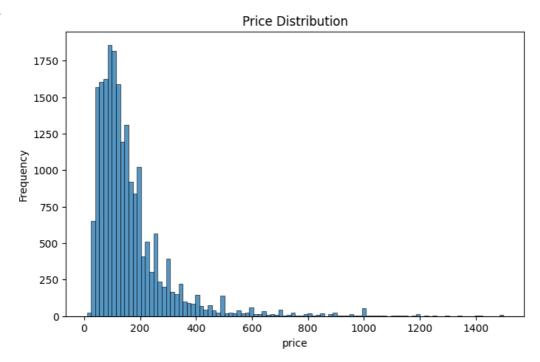
4.A. Univariate Analysis

#new dataframe with price less than 1500 to remove price outliers
df=data[data['price']<1500]
#Boxplot of Price Distribution
plt.title('Price Distribution')
sns.boxplot(data=df,x='price')
plt.show()</pre>



#Histogram of Price Distribution
plt.figure(figsize=(8,5))
plt.title('Price Distribution')
sns.histplot(data=df,x='price',bins=100)
plt.ylabel('Frequency')
plt.show()

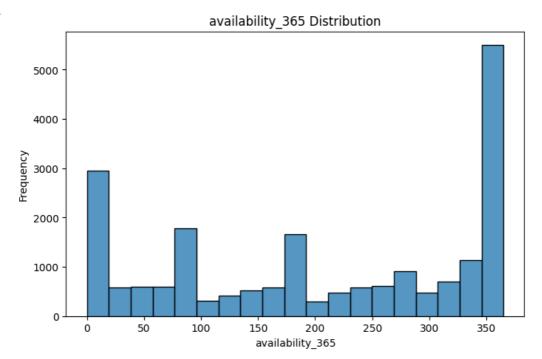




#Histogram of availability_365 Distribution
plt.figure(figsize=(8,5))

plt.title('availability_365 Distribution')
sns.histplot(data=df,x='availability_365')
plt.ylabel('Frequency')
plt.show()

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#Average Price of each neighbourhood group
df.groupby(by='neighbourhood_group')['price'].mean()

₹		price
	neighbourhood_group	
	Bronx	107.990506
	Brooklyn	155.138317
	Manhattan	204.076470
	Queens	121.681939

dtype: float64

Staten Island

4.B. Feature Engineering

#Adding a new column named 'price per bed' to dataframe 'df'
df['price_per_bed']=df['price']/df['beds']

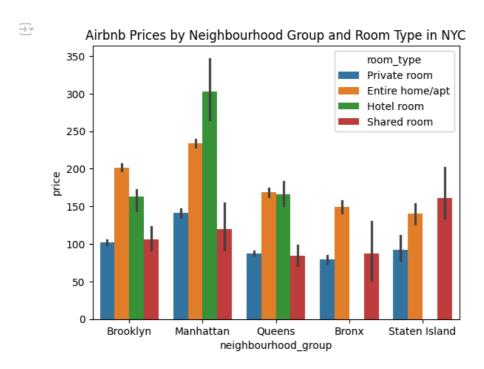
118.780069

#Average Price per bed of each neighbourhood group
df.groupby(by='neighbourhood_group')['price_per_bed'].mean()

dtype: float64

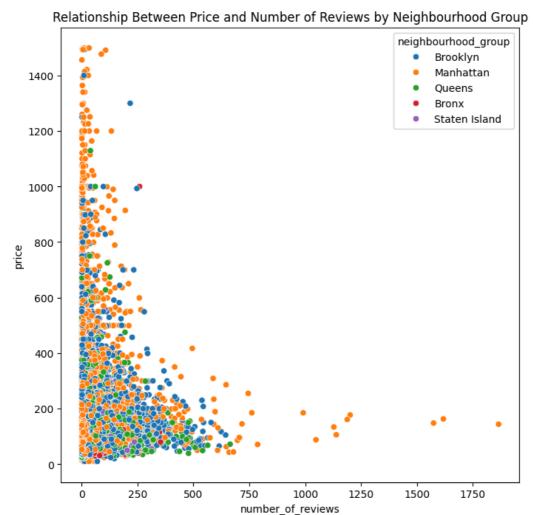
4.C. Bivariate Analysis

#Barplot of Airbnb Prices by Neighbourhood Group and Room Type in NYC
sns.barplot(data=df,x='neighbourhood_group',y='price',hue='room_type')
plt.title('Airbnb Prices by Neighbourhood Group and Room Type in NYC')
plt.show()

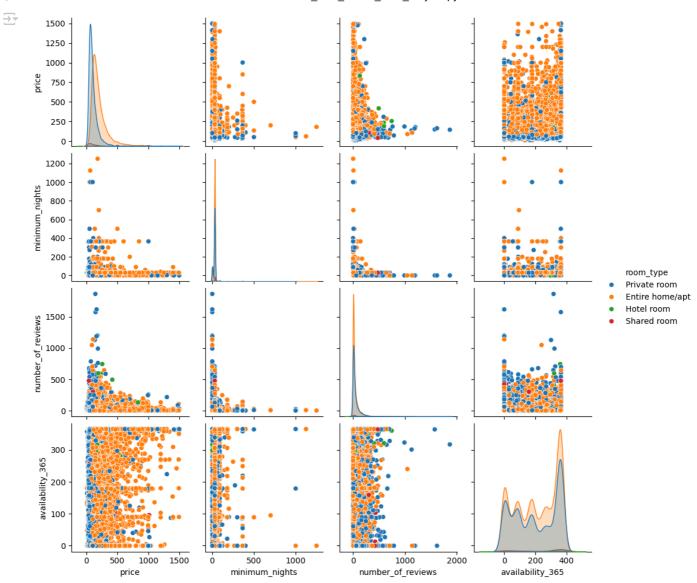


#Relationship Between Price and Number of Reviews by Neighbourhood Group
plt.figure(figsize=(8,8))
plt.title('Relationship Between Price and Number of Reviews by Neighbourhood Group')
sns.scatterplot(data=df,x='number_of_reviews',y='price', hue='neighbourhood_group')
plt.show()





#Pairwise Relationships Between Listing Attributes by Room Type
sns.pairplot(data=df,vars=['price','minimum_nights','number_of_reviews','availability_365'], hue='room_type')
plt.show()



```
# Geographical distribution of Airbnb listings
plt.figure(figsize=(10,7))
plt.title('Geographical distribution of Airbnb listings')
sns.scatterplot(data=df,x='longitude',y='latitude',hue='room_type')
plt.show()
```

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