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Homes Experiences

Airbnb your home

Where	Check in	Check out	Who
Search destinations	Add dates	Add dates	Add guests

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Airbnb Listings EDA Project: New York 2025

- Kruthika P

Amazing views · Icons · Farms · Amazing pools · A-frames · Containers · Beachfront · OMG! · Countrys

Filters

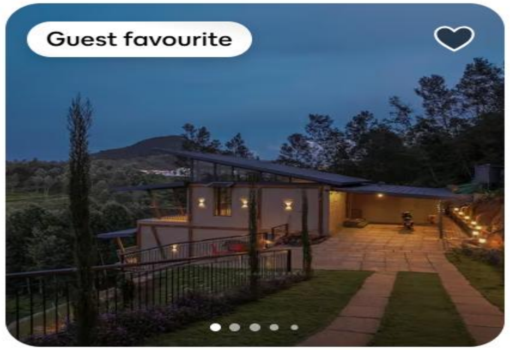
Prices include all fees

Nandi Hills, India ★ 4.97

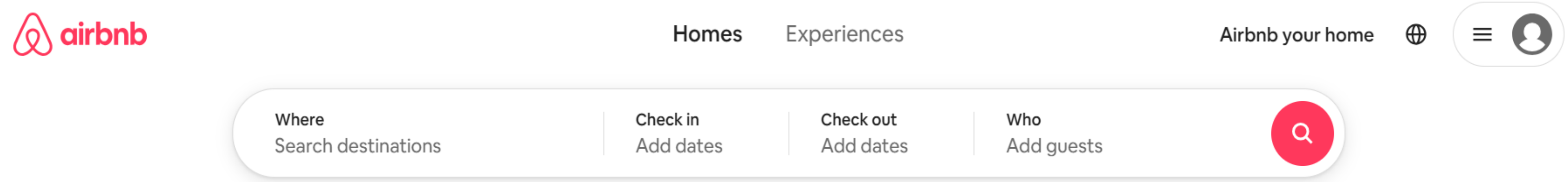
Kotagiri, India ★ 5.0

Show map

Nandi Hills, India ★ 4.87

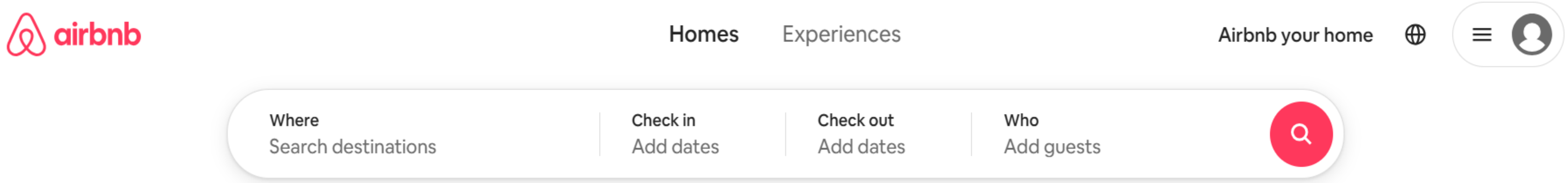


Kotagiri, India ★ 4.91



Project Overview

This project performs Exploratory Data Analysis (EDA) on New York Airbnb data to uncover trends and patterns in rental listings. Using libraries like Pandas, Numpy, Matplotlib, Seaborn for cleaning, visualization and analysis.



Objective

The goal of this project is to:

- Analyze room types, prices, and availability across different neighborhoods.
- Understand host behavior and listing patterns.
- Detect potential outliers in prices.
- Provide recommendations for guests and hosts based on insights.

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Where Search destinations | Check in Add dates | Check out Add dates | Who Add guests

Dataset Overview

- Data source – Kaggle
- Number of rows and columns – 20770 X 22
- Key variables / Features - Latitude, Longitude, Price, Minimum nights, Number of reviews, Reviews per month, Availability 365, Beds, Neighbourhood group

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Import libraries

```
[ ]  import pandas as pd
     import numpy as np
     import matplotlib.pyplot as plt
     import seaborn as sns
```

Loading dataset

```
from google.colab import files
uploaded = files.upload()


df = pd.read_csv('airbnb.csv', encoding='latin1')  # or encoding='latin1'
df.head()
```

Data exploration

```
df.head()
```

```
df.tail()
```

```
df.shape
```

```
df.info()
```

```
df.describe()
```

Data cleaning

```
df.isnull().sum()

#dropping the missing value rows
df.dropna(inplace=True)

df.isnull().sum()
```

	0
id	0
name	0
host_id	0
host_name	0
neighbourhood_group	0
neighbourhood	0

```
# Handling duplicate datas
df.duplicated().sum()

#dropping duplicate records
df.drop_duplicates(inplace=True)
df.duplicated().sum()
```

```
np.int64(0)
```

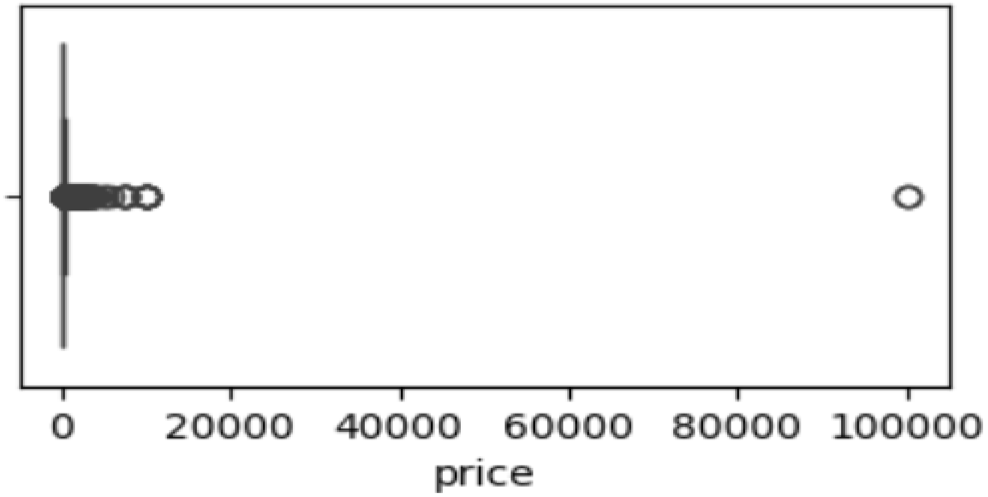
```
# Type casting
df.dtypes

df['id']=df['id'].astype(object)
df.dtypes
df['host_id']=df['host_id'].astype(object)
df.dtypes
```

EDA – Univariate Analysis

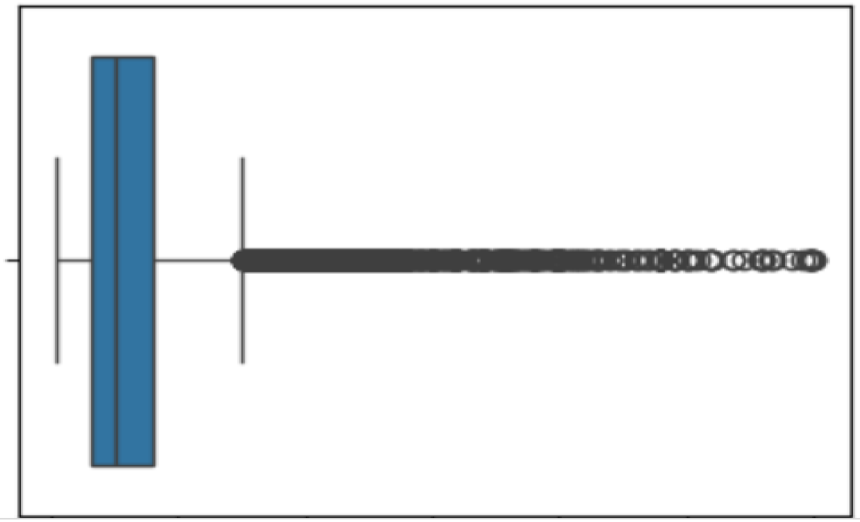
Checking Outliers for price column

```
plt.figure(figsize=(4,2))
sns.boxplot(data=df,x='price')
plt.show()
```




```
data=df[df['price']<1500]
```

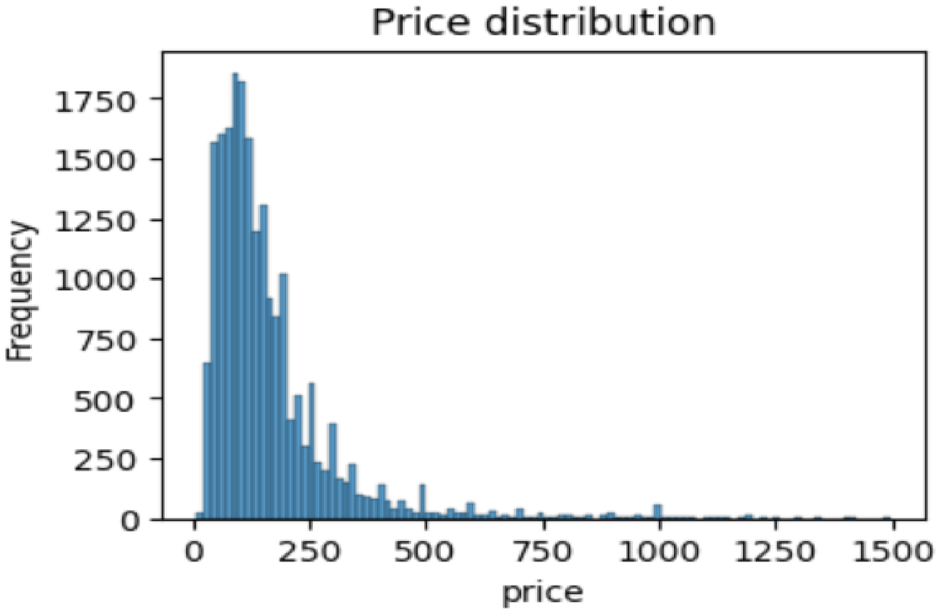
```
plt.figure(figsize=(4,3))
sns.boxplot(data=data,x='price')
plt.show()
```



EDA – Univariate Analysis

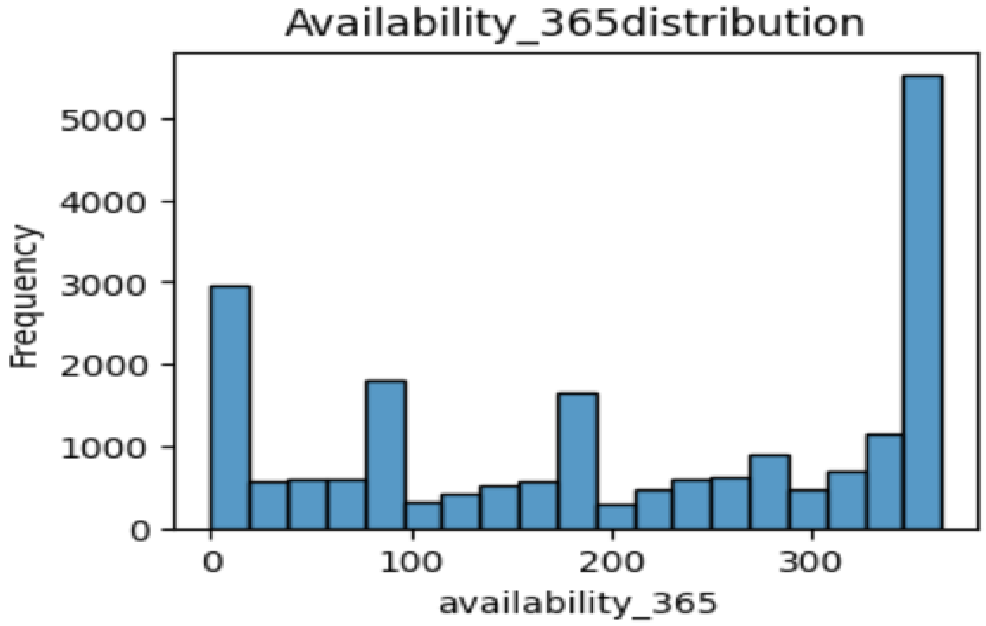
Data distribution of price column

```
plt.figure(figsize=(4,3))
sns.histplot(data=data,x='price',bins=100)
plt.title('Price distribution')
plt.ylabel('Frequency')
plt.show()
```



Data distribution of Availability 365 column

```
plt.figure(figsize=(4,3))
sns.histplot(data=df,x='availability_365')
plt.title('Availability_365distribution')
plt.ylabel('Frequency')
plt.show()
```



EDA – Univariate Analysis

Data summary of neighbourhood group with price

```
data.groupby('neighbourhood_group')['price'].mean()
```

neighbourhood_group	price
Bronx	107.990506
Brooklyn	155.138317
Manhattan	204.146014
Queens	121.681939
Staten Island	118.780069

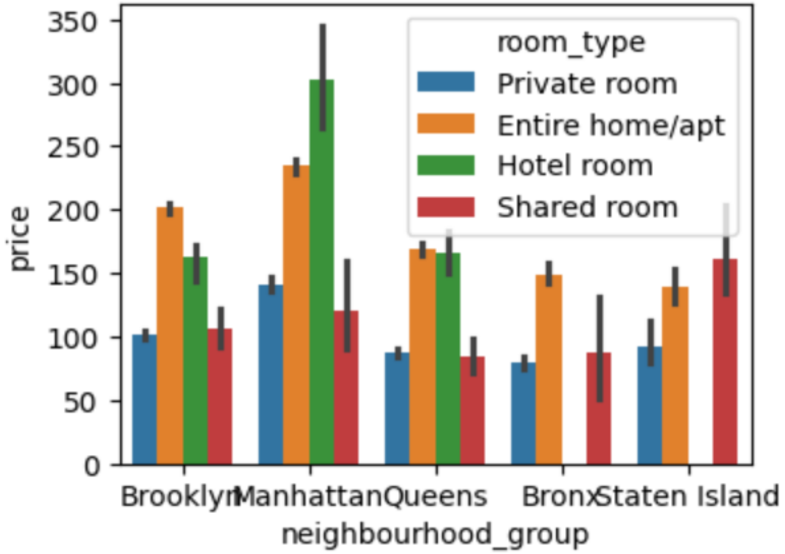
Feature engineering

```
data['price per bed']= data['price']/data['beds']
data.head()
```

EDA – Bivariate Analysis

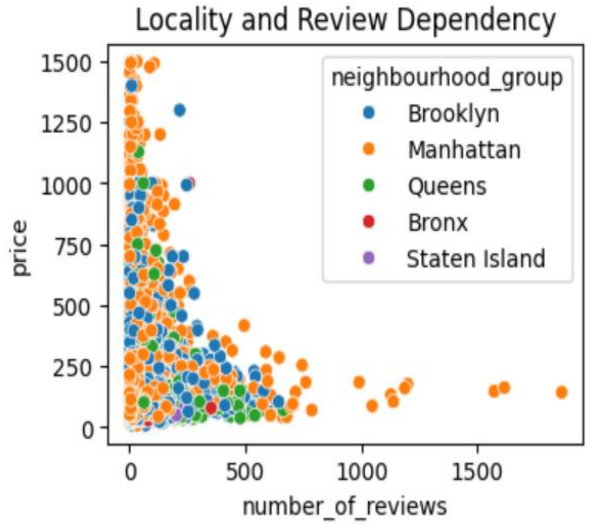
Price dependency on room type

```
plt.figure(figsize=(4,3))
sns.barplot(data=data,x='neighbourhood_group',y='price',hue='room_type')
plt.show()
```



Price relationship with number of reviews

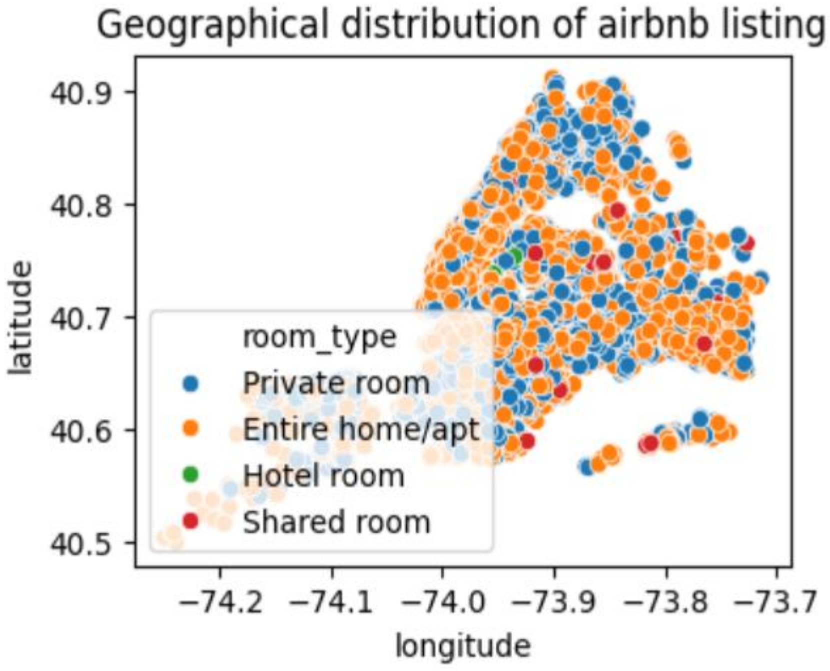
```
plt.figure(figsize=(4,3))
sns.scatterplot(data=data,x='number_of_reviews',y='price',hue='neighbourhood_group')
plt.title('Locality and Review Dependency')
plt.show()
```



EDA – Bivariate Analysis

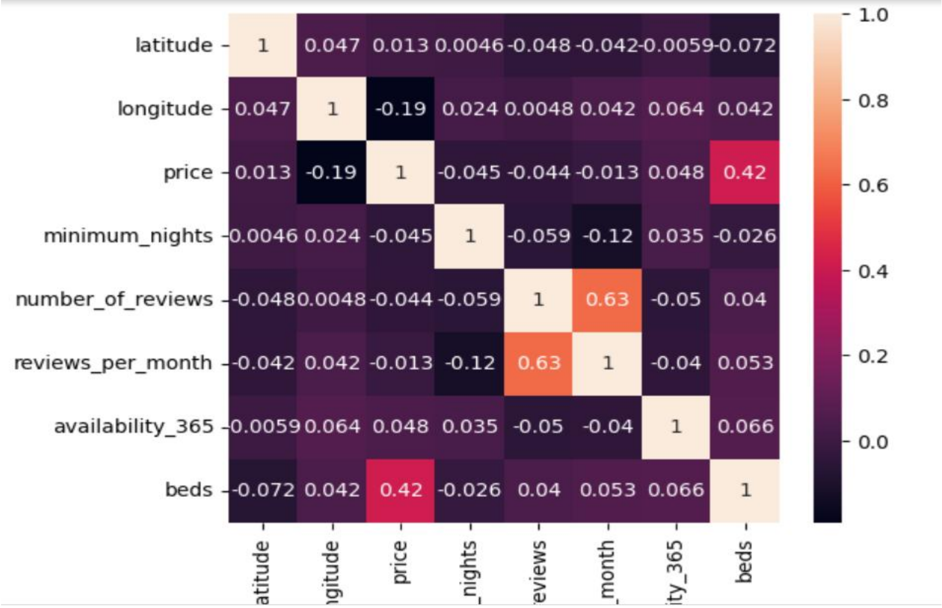
Geographical distribution of Airbnb listing

```
plt.figure(figsize=(4,3))
sns.scatterplot(data=data,x='longitude',y='latitude',hue='room_type')
plt.title("Geographical distribution of airbnb listing")
plt.show()
```



Correlation between numerical columns

```
plt.figure(figsize=(7,6))
corr=data[['latitude','longitude','price','minimum_nights','number_of_reviews',
          'reviews_per_month','availability_365','beds']].corr()
corr
sns.heatmap(data=corr,annot=True)
plt.show()
```



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Key Insights

1. Price Trends:

- **Manhattan** has the most expensive listings, followed by Brooklyn.
- **Entire homes/apartments** cost significantly more than private or shared rooms.

2. Room Type Distribution:

- **Entire homes/apartments** are the most common, but **private rooms** offer budget-friendly options.

3. Outliers in Price:

- Few listings priced at **$10,000+** were detected, indicating the need to filter such extreme values.

4. Availability Patterns:

- Listings with **high availability** tend to have lower prices and more reviews, likely due to better guest experience.

5. Host Behavior:

- Some hosts manage **multiple listings**, indicating a trend toward professional hosting.

Recommendations

- **For Guests:**
  - Look for listings with high availability and good reviews for a better experience.
  - **Private rooms** in Brooklyn offer affordable stays compared to Manhattan.
- **For Hosts:**
  - Improve **availability** and **review response rates** to attract more bookings.
  - Manage pricing effectively to compete within the borough's market.

Conclusion

This project offers valuable insights into the New York Airbnb market, helping both guests and hosts make informed decisions. By using **EDA techniques**, I have identified key trends and developed actionable recommendations. Future improvements can involve advanced analytics and predictive modeling to further enhance the findings.

Thank you