UNVEILING THE SECRETS OF AIRBNB IN NYC: DATA METHODOLOGY

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MARCH 2024

2. Creating features

2.1 categorizing the "availability_365" column into 5 categories

```
def availability_365_categories_function(row):
    """
    Categorizes the "minimum_nights" column into 5 categories
    """
    if row <= 1:
        return 'very Low'
    elif row <= 100:
        return 'Low'
    elif row <= 200 :
        return 'Medium'
    elif (row <= 300):
        return 'High'
    else:
        return 'very High'
```

2.2 categorizing the "minimum_nights" column into 5 categories

```python
def minimum_night_categories_function(row):
    """
    Categorizes the "minimum_nights" column into 5 categories
    """
    if row <= 1:
        return 'very Low'
    elif row <= 3:
        return 'Low'
    elif row <= 5 :
        return 'Medium'
    elif (row <= 7):
        return 'High'
    else:
        return 'very High'
```

2.3 categorizing the "number_of_reviews" column into 5 categories

```python
def number_of_reviews_categories_function(row):
    """
    Categorizes the "number_of_reviews" column into 5 categories
    """
    if row <= 1:
        return 'very Low'
    elif row <= 5:
        return 'Low'
    elif row <= 10 :
        return 'Medium'
    elif (row <= 30):
        return 'High'
    else:
        return 'very High'
```

2.4 categorizing the "price" column into 5 categories

```
inp0.price.describe()
```

```
count    48895.000000
mean       152.720687
std        240.154170
min          0.000000
25%         69.000000
50%        106.000000
75%        175.000000
max      10000.000000
Name: price, dtype: float64
```

3. Fixing columns

```
# To see Non-Null counts and data types
inp0.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 20 columns):
 #   Column                          Non-Null Count  Dtype  
---  ------                          --------------  -----  
 0   id                              48895 non-null  int64  
 1   name                            48879 non-null  object 
 2   host_id                         48895 non-null  int64  
 3   host_name                       48874 non-null  object 
 4   neighbourhood_group             48895 non-null  object 
 5   neighbourhood                   48895 non-null  object 
 6   latitude                        48895 non-null  float64
 7   longitude                       48895 non-null  float64
 8   room_type                       48895 non-null  object 
 9   price                           48895 non-null  int64  
 10  minimum_nights                  48895 non-null  int64  
 11  number_of_reviews               48895 non-null  int64  
 12  last_review                     38843 non-null  object 
 13  reviews_per_month               38843 non-null  float64
 14  calculated_host_listings_count  48895 non-null  int64  
 15  availability_365                48895 non-null  int64  
 16  availability_365_categories     48895 non-null  object 
 17  minimum_night_categories        48895 non-null  object 
 18  number_of_reviews_categories    48895 non-null  object 
 19  price_categories                48895 non-null  object 
dtypes: float64(3), int64(7), object(10)
memory usage: 7.5+ MB
```

Fix: reviews_per_month is of object Dtype. datetime64 is a better Dtype for this column.

```
inp0.last_review = pd.to_datetime(inp0.last_review)
inp0.last_review
```

```
0        2018-10-19
1        2019-05-21
2               NaT
3        2019-05-07
4        2018-11-19
            ...
48890           NaT
48891           NaT
48892           NaT
48893           NaT
48894           NaT
Name: last_review, Length: 48895, dtype: datetime64[ns]
```

4. Data types

4.1 Categorical

```
inp0.columns
```

```
Index(['id', 'name', 'host_id', 'host_name', 'neighbourhood_group',
       'neighbourhood', 'latitude', 'longitude', 'room_type', 'price',
       'minimum_nights', 'number_of_reviews', 'last_review',
       'reviews_per_month', 'calculated_host_listings_count',
       'availability_365', 'availability_365_categories',
       'minimum_night_categories', 'number_of_reviews_categories',
       'price_categories'],
      dtype='object')
```

```
# Categorical nominal
categorical_columns = inp0.columns[[0,1,3,4,5,8,16,17,18,19]]
categorical_columns
```

```
Index(['id', 'name', 'host_name', 'neighbourhood_group', 'neighbourhood',
       'room_type', 'availability_365_categories', 'minimum_night_categories',
       'number_of_reviews_categories', 'price_categories'],
      dtype='object')
```

4.2 Numerical

```
numerical_columns = inp0.columns[[9,10,11,13,14,15]]
numerical_columns
```

```
Index(['price', 'minimum_nights', 'number_of_reviews', 'reviews_per_month',
       'calculated_host_listings_count', 'availability_365'],
      dtype='object')
```

```
inp0[numerical_columns].describe()
```

	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
count	48895.000000	48895.000000	48895.000000	38843.000000	48895.000000	48895.000000
mean	152.720687	7.029962	23.274466	1.373221	7.143982	112.781327
std	240.154170	20.510550	44.550582	1.680442	32.952519	131.622289
min	0.000000	1.000000	0.000000	0.010000	1.000000	0.000000
25%	69.000000	1.000000	1.000000	0.190000	1.000000	0.000000
50%	106.000000	3.000000	5.000000	0.720000	1.000000	45.000000
75%	175.000000	5.000000	24.000000	2.020000	2.000000	227.000000
max	10000.000000	1250.000000	629.000000	58.500000	327.000000	365.000000

4.3 Coordinates and date

```
coordinates = inp0.columns[[5,6,12]]
inp0[coordinates]
```

	neighbourhood	latitude	last_review
0	Kensington	40.64749	2018-10-19
1	Midtown	40.75362	2019-05-21
2	Harlem	40.80902	NaT
3	Clinton Hill	40.68514	2019-05-07
4	East Harlem	40.79851	2018-11-19
...	...	...	...
48890	Bedford-Stuyvesant	40.67853	NaT
48891	Bushwick	40.70184	NaT
48892	Harlem	40.81475	NaT
48893	Hell's Kitchen	40.75751	NaT
48894	Hell's Kitchen	40.76404	NaT

48895 rows × 3 columns

5. Missing values

```
# To see the number of missing values
inp0.isnull().sum()
```

```
id                                0
name                             16
host_id                           0
host_name                        21
neighbourhood_group               0
neighbourhood                     0
latitude                          0
longitude                         0
room_type                         0
price                             0
minimum_nights                    0
number_of_reviews                 0
last_review                   10052
reviews_per_month             10052
calculated_host_listings_count    0
availability_365                  0
availability_365_categories       0
minimum_night_categories          0
number_of_reviews_categories      0
price_categories                  0
dtype: int64
```

- Two columns (last_review , reviews_per_month) has around 20.56% missing values. name and host_name has 0.3% and 0.4 % missing values

- We need to see if the values are, MCAR: It stands for Missing completely at random. The reason behind the missing value is not dependent on any other features or if it is MNAR: It stands for Missing not at random. There is a specific reason behind the missing value.

- There is no dropping or imputation of columns as we are just analyzing the dataset and not making a model.Also most of the features are important for our analysis.

5.1 Missing values Analysis

```
# Selecting the data with missing values for 'last_review' feature
inp1 = inp0.loc[inp0.last_review.isnull(),:]
```

5.2 Missing values Analysis ('neighbourhood_group' feature)

```
# Count of 'neighbourhood_group' with missing values
inp1.groupby('neighbourhood_group').neighbourhood_group.count()
```

```
neighbourhood_group
Bronx             215
Brooklyn         3657
Manhattan        5029
Queens           1092
Staten Island      59
Name: neighbourhood_group, dtype: int64
```

```
# Count of 'neighbourhood_group'
inp0.groupby('neighbourhood_group').neighbourhood_group.count()
```

```
neighbourhood_group
Bronx             1091
Brooklyn         20104
Manhattan        21661
Queens            5666
Staten Island      373
Name: neighbourhood_group, dtype: int64
```

```python
(inp1.groupby('neighbourhood_group').neighbourhood_group.count()/inp0.groupby('neighbourhood_group').neighbourhood_group.count())*100
```

```
neighbourhood_group
Bronx            19.706691
Brooklyn         18.190410
Manhattan        23.216841
Queens           19.272856
Staten Island    15.817694
Name: neighbourhood_group, dtype: float64
```

```python
((inp1.groupby('neighbourhood_group').neighbourhood_group.count()/inp0.groupby('neighbourhood_group').neighbourhood_group.count())*100).mean()
```

```
19.240898461107257
```

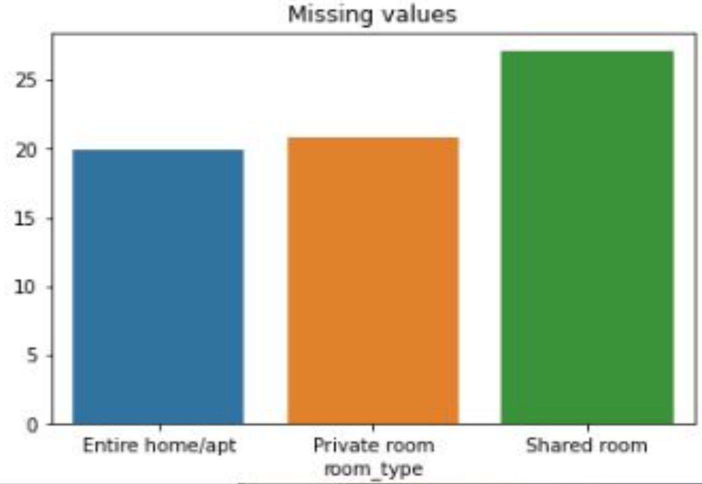
- Each neighbourhood_group has about 19 % missing values in 'last_review' feature.

5.3 Missing values Analysis ('room_type' feature)

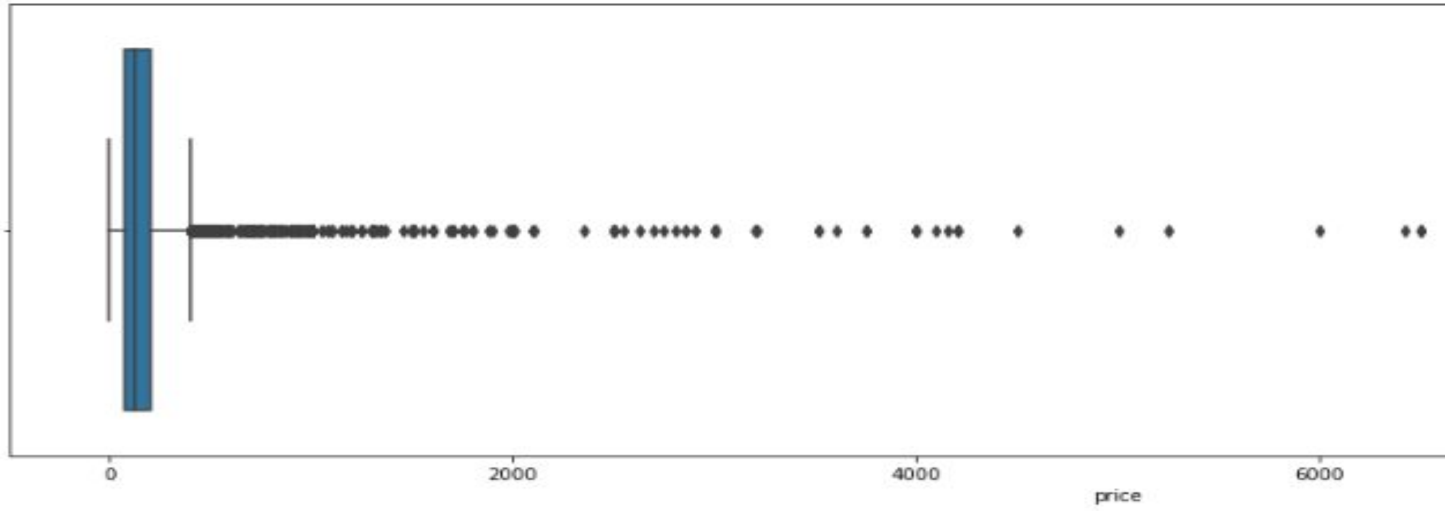
```
# Count of 'room_type' with missing values
inp3 = (inp1.groupby('room_type').room_type.count()/inp0.groupby('room_type').room_type.count())*100
inp3
```

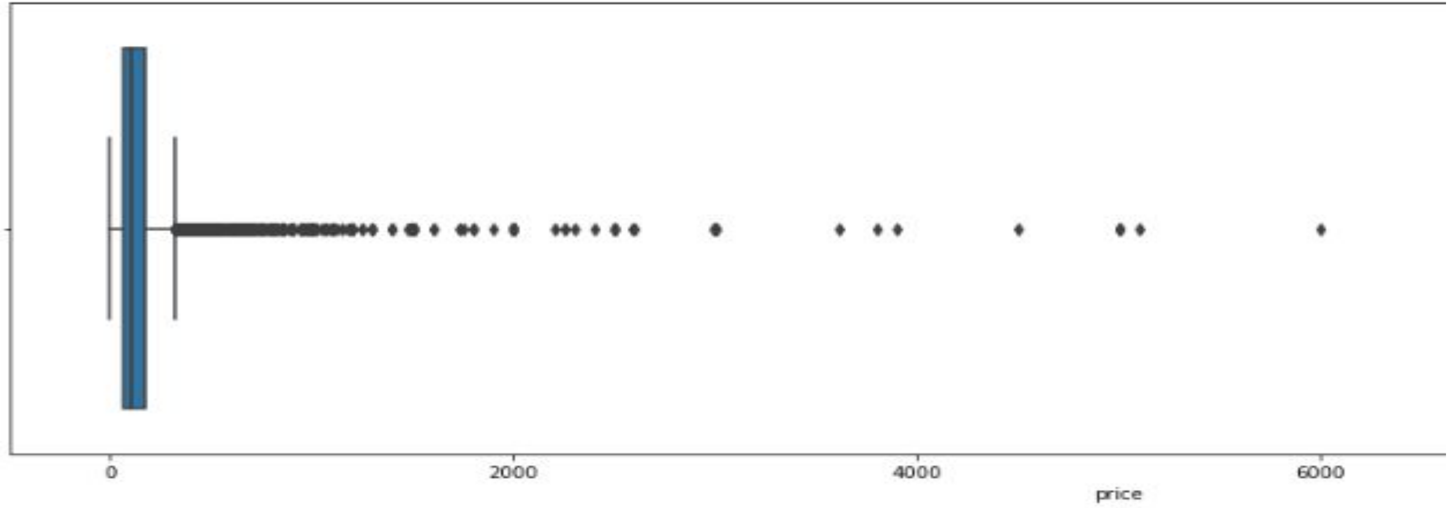
```
room_type
Entire home/apt    19.981109
Private room       20.877004
Shared room        27.068966
Name: room_type, dtype: float64
```

```
plt.title('Missing values')
sns.barplot(x = inp3.index, y = inp3.values)
plt.show()
```



'Shared room' has the highest missing value percentage (27 %) for 'last_review' feature while to other room types has only about 20 %.





- The pricing is higher when 'last_review' feature is missing .

- reviews are less likely to be given for shared rooms

- When the prices are high reviews are less likely to be given

- The above analysis seems to show that the missing values here are not MCAR (missing completely at random)

6. Univariate Analysis

6.1 name

```
inp0.name.value_counts()
```

```
Hillside Hotel                                         18
Home away from home                                    17
New york Multi-unit building                           16
Brooklyn Apartment                                     12
Loft Suite @ The Box House Hotel                       11
                                                       ..
Brownstone garden 2 bedroom duplex, Central Park        1
Bright Cozy Private Room near Columbia Univ             1
1 bdrm/large studio in a great location                 1
Cozy Private Room #2 Two Beds Near JFK and J Train      1
Trendy duplex in the very heart of Hell's Kitchen       1
Name: name, Length: 47896, dtype: int64
```

6.2 host_id

```
inp0.host_id.value_counts()
```

```
219517861    327
107434423    232
30283594     121
137358866    103
16098958      96
            ...
23727216       1
89211125       1
19928013       1
1017772        1
68119814       1
Name: host_id, Length: 37457, dtype: int64
```

6.3 host_name

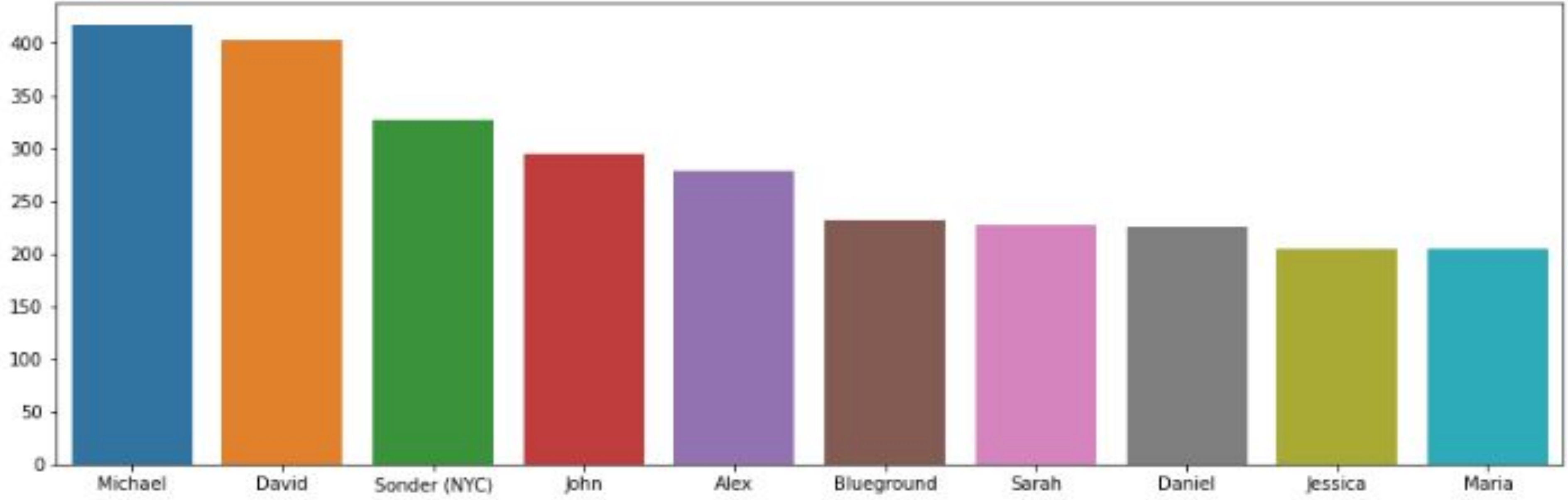
```
inp0.host_name.value_counts()
```

```
Michael              417
David                403
Sonder (NYC)         327
John                 294
Alex                 279
                    ...
Rhonycs                1
Brandy-Courtney        1
Shanthony              1
Aurore And Jamila      1
Ilgar & Aysel          1
Name: host_name, Length: 11452, dtype: int64
```

```
inp0.host_name.value_counts().index[:10]
```

```
Index(['Michael', 'David', 'Sonder (NYC)', 'John', 'Alex', 'Blueground',
       'Sarah', 'Daniel', 'Jessica', 'Maria'],
      dtype='object')
```

```
# Top 10 host's
plt.figure(figsize=(15,5))
sns.barplot(x = inp0.host_name.value_counts().index[:10] , y = inp0.host_name.value_counts().values[:10])
plt.show()
```

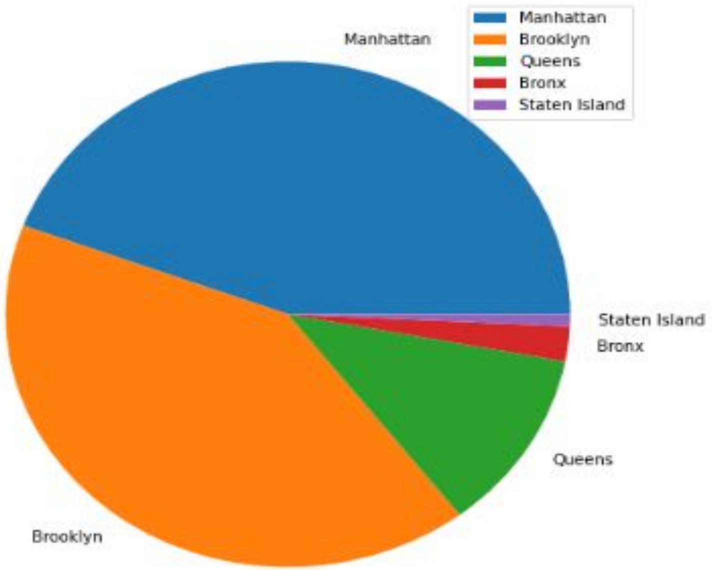


6.4 neighbourhood_group

```
inp0.neighbourhood_group.value_counts()
```

```
Manhattan        21661
Brooklyn         20104
Queens            5666
Bronx             1091
Staten Island      373
Name: neighbourhood_group, dtype: int64
```

```
plt.figure(figsize=(8,8))
plt.pie(x = inp0.neighbourhood_group.value_counts(normalize= True) * 100,labels = inp0.neighbourhood_group.value_counts(normalize= True).index)
plt.legend()
plt.show()
```



What are the neighbourhoods they need to target?

81 % of the listing are Manhattan and Brooklyn neighbourhood_group

6.5 neighbourhood

```
inp0.neighbourhood.value_counts()
```

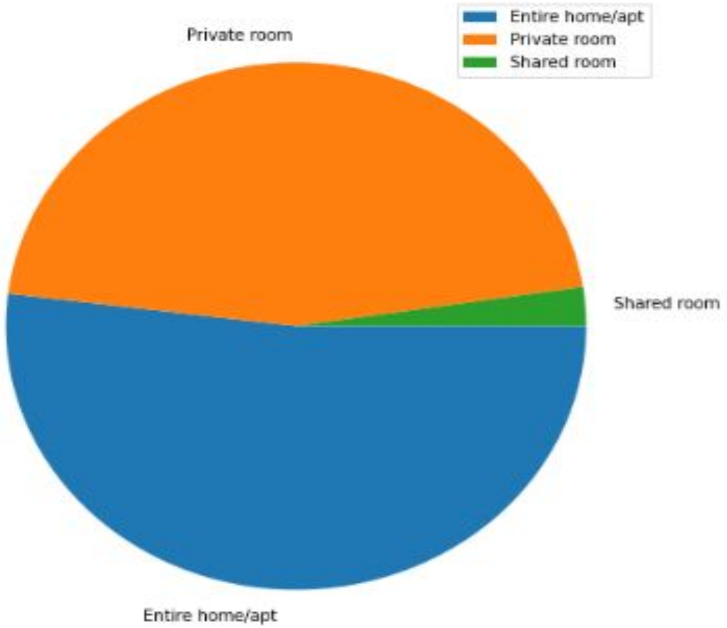
```
Williamsburg          3920
Bedford-Stuyvesant    3714
Harlem                2658
Bushwick              2465
Upper West Side       1971
                      ...
Fort Wadsworth           1
Richmondtown             1
New Dorp                 1
Rossville                1
Willowbrook              1
Name: neighbourhood, Length: 221, dtype: int64
```

6.6 room_type

```
inp0.room_type.value_counts()
```

```
Entire home/apt    25409
Private room       22326
Shared room         1160
Name: room_type, dtype: int64
```

```
plt.figure(figsize=(8,8))
plt.pie(x = inp0.room_type.value_counts(normalize= True) * 100,labels = inp0.room_type.value_counts(normalize= True).index,counterclock=False)
plt.legend()
plt.show()
```



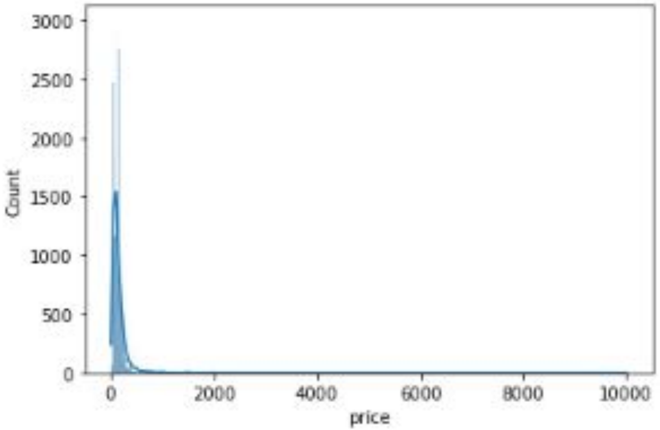
6.7 price

```
inp0.price.value_counts()
```

```
100    2051
150    2047
50     1534
60     1458
200    1401
       ...
780       1
386       1
888       1
483       1
338       1
Name: price, Length: 674, dtype: int64
```

```
sns.histplot(data = inp0.price,kde = True)
```

<AxesSubplot:xlabel='price', ylabel='Count'>



6.8 minimum_nights

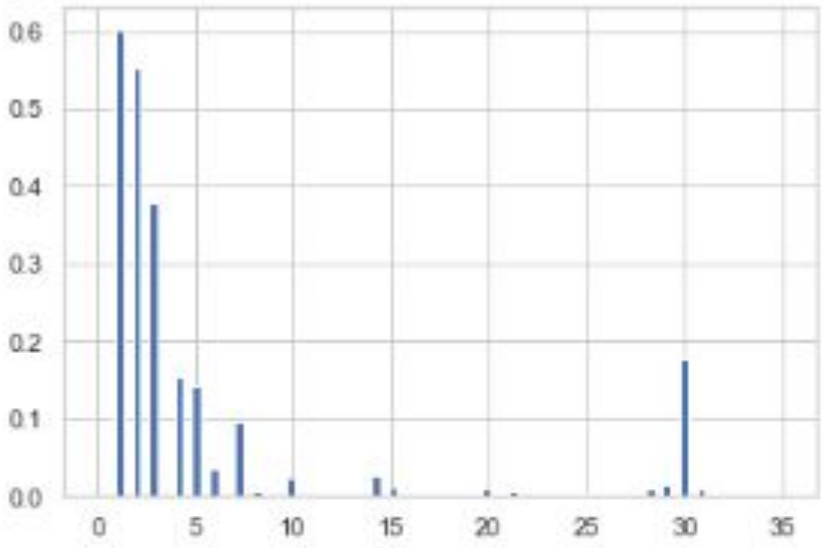
```
inp0.minimum_nights.value_counts()
```

```
1      12720
2      11696
3       7999
30      3760
4       3303
       ...
186        1
366        1
68         1
87         1
36         1
Name: minimum_nights, Length: 109, dtype: int64
```

```
inp0.minimum_nights.describe()
```

```
count    48895.000000
mean         7.029962
std         20.510550
min          1.000000
25%          1.000000
50%          3.000000
75%          5.000000
max       1250.000000
Name: minimum_nights, dtype: float64
```

```
plt.hist(data = inp0, x = 'minimum_nights',bins=80,range=(0,35),density=True)
plt.show()
```

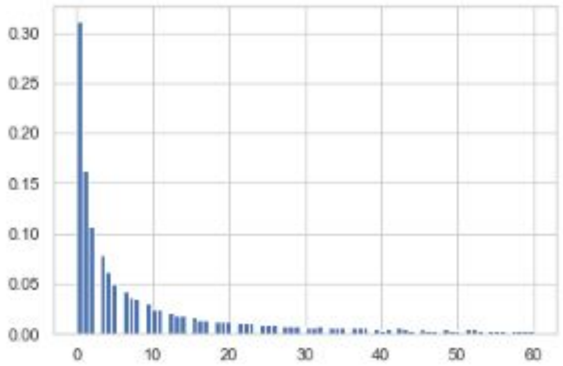


6.9 number_of_reviews

```
inp0.number_of_reviews.describe()
```

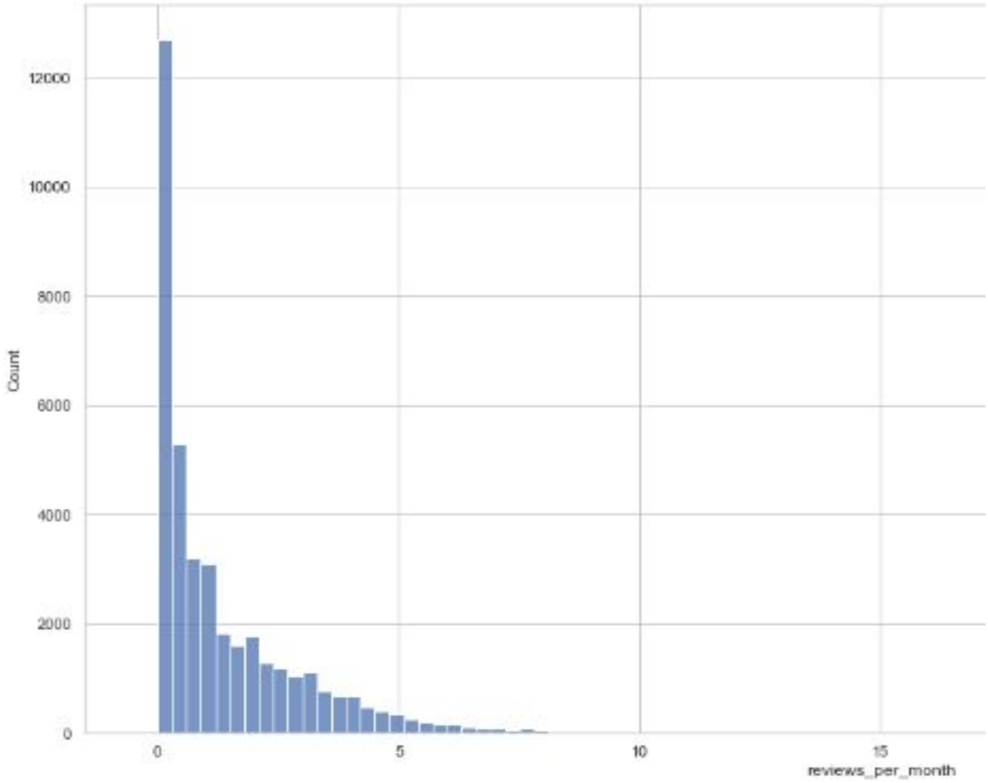
```
count    48895.000000
mean        23.274466
std         44.550582
min          0.000000
25%          1.000000
50%          5.000000
75%         24.000000
max        629.000000
Name: number_of_reviews, dtype: float64
```

```
plt.hist(data = inp0, x = 'number_of_reviews',bins=80,range=(0,60),density=True)
plt.show()
```



6.10 reviews_per_month

```
plt.figure(figsize = (20,10))
sns.histplot(data = inp0, x = 'reviews_per_month',bins=100,binrange=(0,30))
plt.show()
```




```
inp0.reviews_per_month.describe()
```

```
count    38843.000000
mean         1.373221
std          1.680442
min          0.010000
25%          0.190000
50%          0.720000
75%          2.020000
max         58.500000
Name: reviews_per_month, dtype: float64
```

6.11 calculated_host_listings_count

```
inp0.calculated_host_listings_count.describe()
```

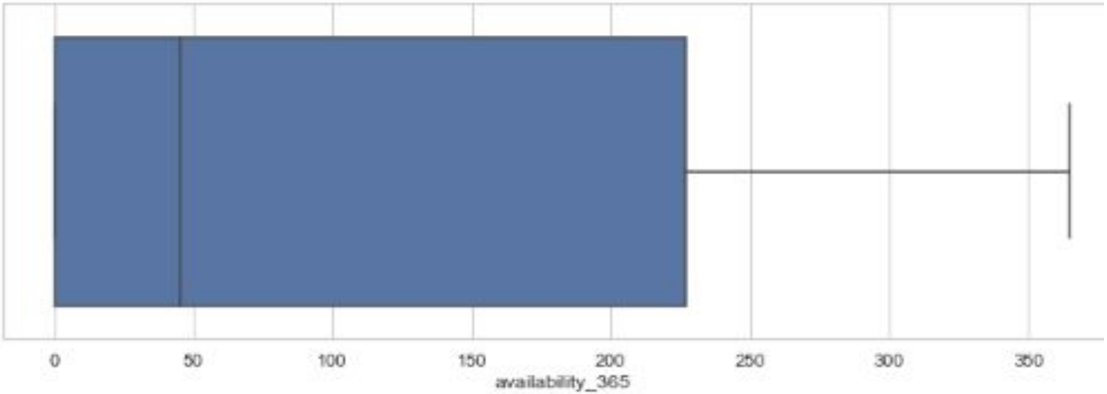
```
count    48895.000000
mean         7.143982
std         32.952519
min          1.000000
25%          1.000000
50%          1.000000
75%          2.000000
max        327.000000
Name: calculated_host_listings_count, dtype: float64
```

6.12 availability_365

```
inp0.availability_365.describe()
```

```
count    48895.000000
mean       112.781327
std        131.622289
min          0.000000
25%          0.000000
50%         45.000000
75%        227.000000
max        365.000000
Name: availability_365, dtype: float64
```

```
plt.figure(figsize = (12,4))
sns.boxplot(data = inp0 , x = 'availability_365')
plt.show()
```

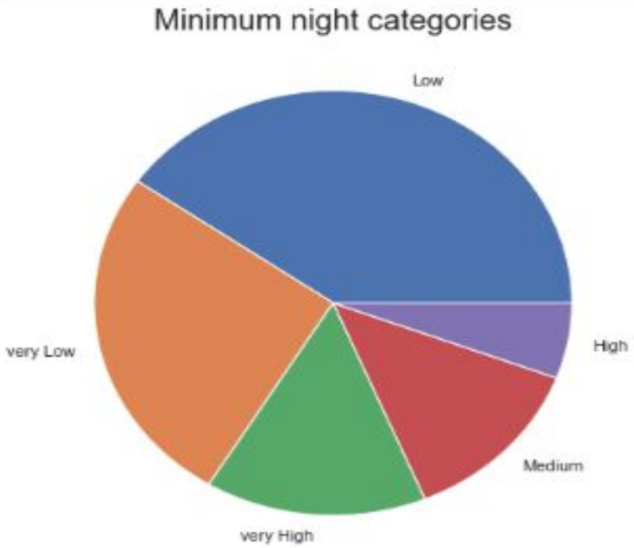


6.13 minimum_night_categories

```
inp0.minimum_night_categories.value_counts(normalize= True)*100
```

```
Low          40.280192
very Low     26.014930
very High    14.997444
Medium       12.960425
High          5.747009
Name: minimum_night_categories, dtype: float64
```

```
plt.figure(figsize=(12,7))
plt.title('Minimum night categories', fontdict={'fontsize': 20})
plt.pie(x = inp0.minimum_night_categories.value_counts(),labels=inp0.minimum_night_categories.value_counts().index)
plt.show()
```

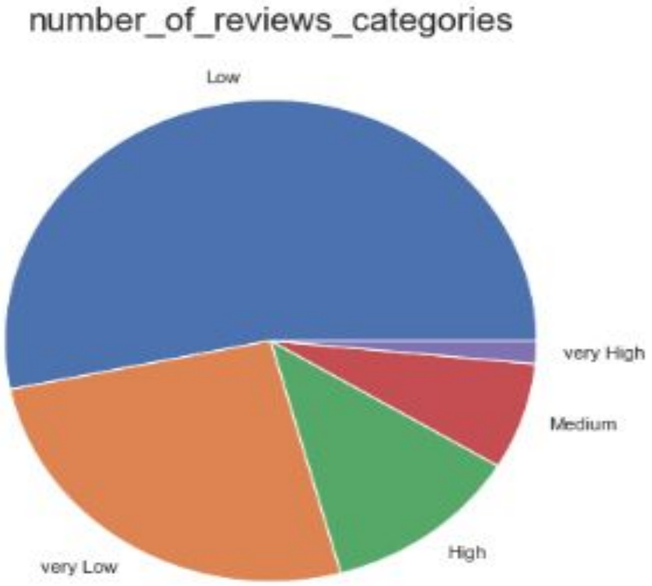


6.14 number_of_reviews_categories

```
inp0.number_of_reviews_categories.value_counts(normalize=True)*100
```

```
Low          53.240618
very Low     26.014930
High         12.052357
Medium        7.164332
very High     1.527764
Name: number_of_reviews_categories, dtype: float64
```

```
plt.figure(figsize=(12,7))
plt.title('number_of_reviews_categories', fontdict={'fontsize': 20})
plt.pie(x = inp0.number_of_reviews_categories.value_counts(),labels=inp0.number_of_reviews_categories.value_counts().index)
plt.show()
```

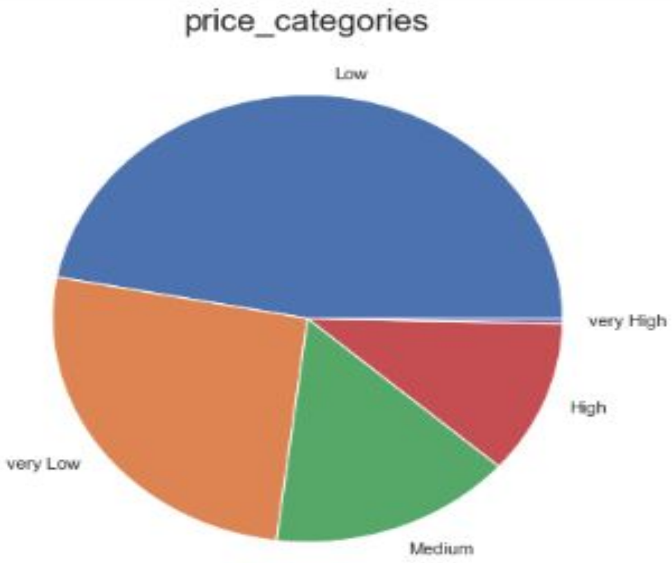


6.15 price_categories

```
inp0['price_categories'].value_counts()
```

```
Low          22998
very Low     12720
Medium        7556
High          5447
very High      174
Name: price_categories, dtype: int64
```

```
plt.figure(figsize=(12,7))
plt.title('price_categories', fontdict={'fontsize': 20})
plt.pie(x = inp0.price_categories.value_counts(),labels=inp0.price_categories.value_counts().index,)
plt.show()
```



What is the pricing ranges preferred by customers?

'Low' price ranges are preferred by customers followed by very 'Low' price ranges.

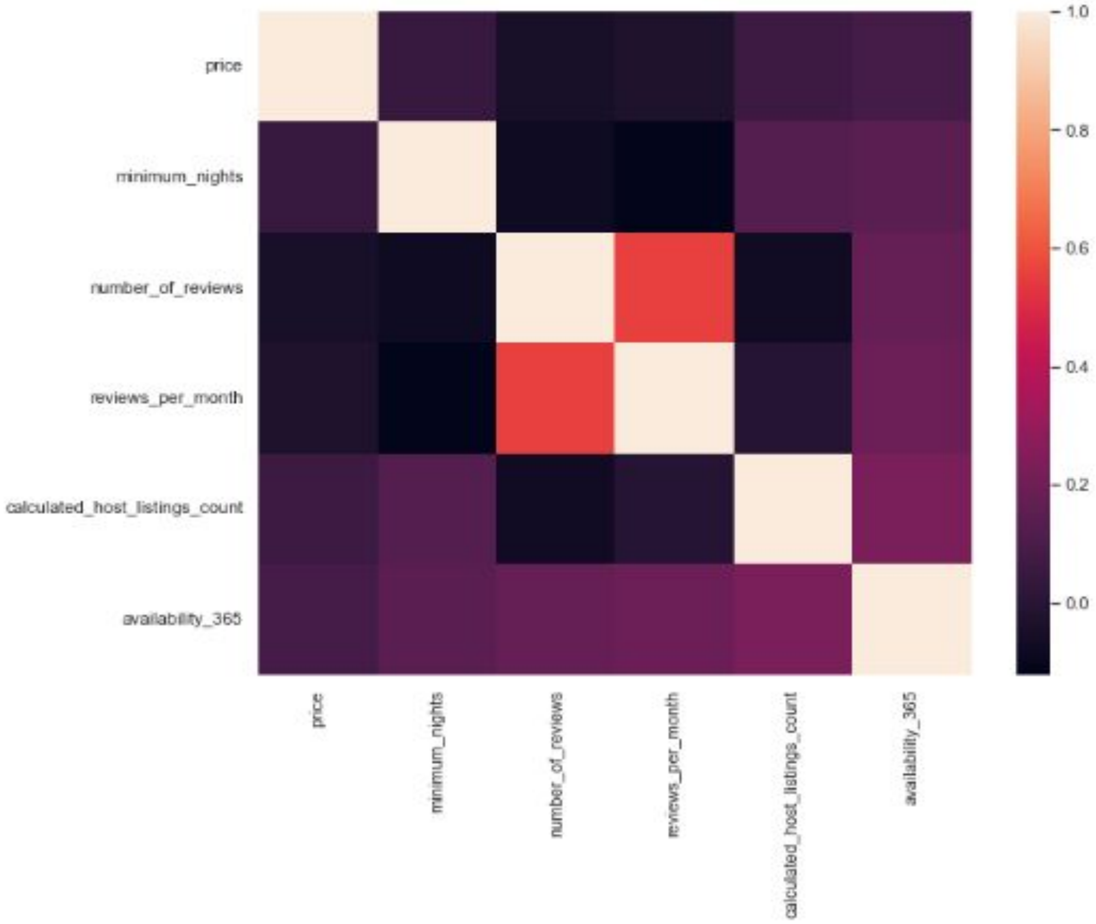
7. Bivariate and Multivariate Analysis

7.1 Finding the correlations

```
inp0[numerical_columns].corr()
```

	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
price	1.000000	0.042799	-0.047954	-0.030608	0.057472	0.081829
minimum_nights	0.042799	1.000000	-0.080116	-0.121702	0.127960	0.144303
number_of_reviews	-0.047954	-0.080116	1.000000	0.549868	-0.072376	0.172028
reviews_per_month	-0.030608	-0.121702	0.549868	1.000000	-0.009421	0.185791
calculated_host_listings_count	0.057472	0.127960	-0.072376	-0.009421	1.000000	0.225701
availability_365	0.081829	0.144303	0.172028	0.185791	0.225701	1.000000

```
plt.figure(figsize=(10,8))
sns.heatmap(data = inp0[numerical_columns].corr())
plt.show()
```



7.2 Finding Top correlations

```
corr_matrix = inp0[numerical_columns].corr().abs()

#the matrix is symmetric so we need to extract upper triangle matrix without diagonal (k = 1)

sol = (corr_matrix.where(np.triu(np.ones(corr_matrix.shape), k=1).astype(bool))
                 .stack()
                 .sort_values(ascending=False))
```

```
corr_matrix
```

	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
price	1.000000	0.042799	0.047954	0.030608	0.057472	0.081829
minimum_nights	0.042799	1.000000	0.080116	0.121702	0.127960	0.144303
number_of_reviews	0.047954	0.080116	1.000000	0.549868	0.072376	0.172028
reviews_per_month	0.030608	0.121702	0.549868	1.000000	0.009421	0.185791
calculated_host_listings_count	0.057472	0.127960	0.072376	0.009421	1.000000	0.225701
availability_365	0.081829	0.144303	0.172028	0.185791	0.225701	1.000000

```python
# Top meaningful correlations
sol[1:8]
```

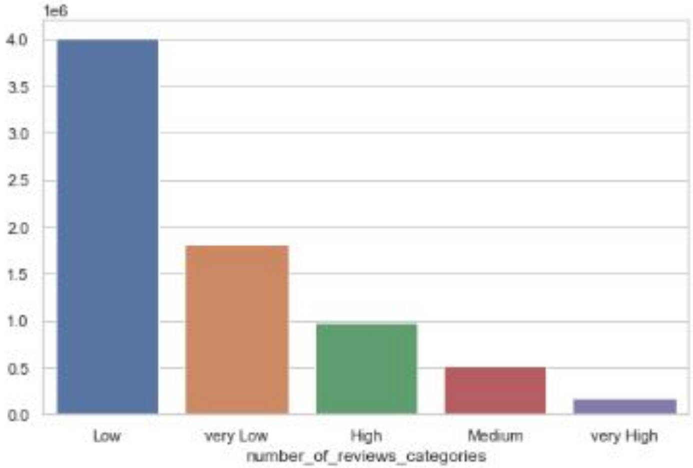
```
calculated_host_listings_count  availability_365                  0.225701
reviews_per_month               availability_365                  0.185791
number_of_reviews               availability_365                  0.172028
minimum_nights                  availability_365                  0.144303
                                calculated_host_listings_count    0.127960
                                reviews_per_month                 0.121702
price                           availability_365                  0.081829
dtype: float64
```

7.3 number_of_reviews_categories and prices

```
# prices for each of reviews_categories
x1 = inp0.groupby('number_of_reviews_categories').price.sum().sort_values(ascending = False)
x1
```

```
number_of_reviews_categories
Low          4002323
very Low     1806531
High          971346
Medium        508647
very High     178431
Name: price, dtype: int64
```

```
plt.figure(figsize=(8,5))
sns.barplot(x = x1.index,y = x1.values)
plt.show()
```



What is the pricing ranges preferred by customers?

The total price for 'Low' or 'very Low' number_of_reviews_categories are high.

.4 ('room_type' and 'number_of_reviews_categories')

```
inp0.room_type.value_counts()
```

```
Entire home/apt    25409
Private room       22326
Shared room         1160
Name: room_type, dtype: int64
```

```
pd.crosstab(inp0['room_type'], inp0['number_of_reviews_categories'])
```

number_of_reviews_categories	High	Low	Medium	very High	very Low
room_type					
Entire home/apt	3809	14909	1960	504	4227
Private room	1950	10769	1494	226	7887
Shared room	134	354	49	17	606

The various kinds of properties that exist w.r.t. customer preferences.?

Entire home/apt have more reviews than Shared rooms

'Shared room' are less likely to give reviews. only 16 %

7.5 'room_type' and 'price_categories'

```
pd.crosstab(inp0['room_type'], inp0['price_categories'])
```

price_categories	High	Low	Medium	very High	very Low
room_type					
Entire home/apt	3714	13086	4262	120	4227
Private room	1620	9597	3170	52	7887
Shared room	113	315	124	2	606

7.6 'room_type' and 'reviews_per_month'

```
inp0.room_type.value_counts()
```

```
Entire home/apt    25409
Private room       22326
Shared room         1160
Name: room_type, dtype: int64
```

```
inp0.groupby('room_type').reviews_per_month.mean()
```

```
room_type
Entire home/apt    1.306578
Private room       1.445209
Shared room        1.471726
Name: reviews_per_month, dtype: float64
```

```
inp0.groupby('room_type').reviews_per_month.median()
```

```
room_type
Entire home/apt    0.66
Private room       0.77
Shared room        0.98
Name: reviews_per_month, dtype: float64
```

For each 'room_type' there are ~1.4 reviews per month on average.

7.7 minimum_night_categories and reviews_per_month

```
inp0.groupby('minimum_night_categories').reviews_per_month.sum().sort_values()
```

```
minimum_night_categories
High           1227.57
very High      2235.19
Medium         4689.73
very Low      20395.49
Low           24792.06
Name: reviews_per_month, dtype: float64
```

Customers are more likely to leave reviews for low number of minimum nights

Adjustments in the existing properties to make it more customer-oriented. ?

minimum_nights should be on the lower side to make properties more customer-oriented

7.8 'availability_365_categories', 'price_categories' and 'reviews_per_month'

```
inp0.availability_365_categories.value_counts()
```

```
very Low     17941
Low          11829
very High     8108
Medium        5792
High          5225
Name: availability_365_categories, dtype: int64
```

If the combination of availability and price is very high, reviews_per_month will be low on average.

Very high availability and very low price are likely to get more reviews.

		reviews_per_month
availability_365_categories	price_categories	
High	High	0.598431
	Low	2.200373
	Medium	1.056111
	very High	0.342308
	very Low	3.289381
Low	High	0.638307
	Low	1.783956
	Medium	0.883844
	very High	0.803750
	very Low	2.896114
Medium	High	0.591070
	Low	1.993565
	Medium	1.157492
	very High	0.517500
	very Low	2.893918
very High	High	0.428464
	Low	1.490562
	Medium	0.694283
	very High	0.276571
	very Low	2.206077
very Low	High	0.337780
	Low	0.506051
	Medium	0.276970
	very High	0.480588
	very Low	0.673759