Importing Required Librarires

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from warnings import filterwarnings
filterwarnings('ignore')
from sklearn.cluster import KMeans
from scipy import stats
from sklearn.model_selection import train_test_split
from category_encoders import CatBoostEncoder,TargetEncoder
from sklearn.preprocessing import PowerTransformer
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score,mean_squared_error,mean_absolute_percentage_error
import statsmodels.api as sma
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import GradientBoostingRegressor
from xgboost import XGBRegressor
from catboost import CatBoostRegressor
from sklearn.neural_network import MLPRegressor
```

In [2]:

```
# set the plot size using 'rcParams'
# once the plot size is set using 'rcParams', it sets the size of all the forthcoming plots in t
# pass width and height in inches to 'figure.figsize'

plt.rcParams['figure.figsize'] = [15,8]

# Creating custom color
colors = ['#97C1A9','#DCDCDC','#AFC197','#9AC197','#97C1BE','#97C1A2','#C1979A',
          '#A997C1','#77AE8F','#DCDCDC','#67A481','#C197AF']
```

Reading the dataset and viewing first five rows

In [3]:

```
pd.set_option('display.max_columns',22)
```

In [4]:

```
df = pd.read_csv('Airbnb_Price.csv')

df.head()
```

Out[4]:

	City	Day	realSum	room_type	room_shared	room_private	person_capacity	host_is_supe
0	Amsterdam	Weekday	194.033698	Private room	False	True	2	
1	Amsterdam	Weekday	344.245776	Private room	False	True	4	
2	Amsterdam	Weekday	264.101422	Private room	False	True	2	
3	Amsterdam	Weekday	433.529398	Private room	False	True	4	
4	Amsterdam	Weekday	485.552926	Private room	False	True	2	

Checking the shape and dimension of dataset

In [5]:

```
print(f'The dataset has {df.shape[0]} rows and {df.shape[1]} columns')
```

```
The dataset has 51707 rows and 21 columns
```

In [6]:

```
print(f'The dimension of the dataset is {df.ndim}')
```

```
The dimension of the dataset is 2
```

Checking the datatype, number of non null values and name of each variable in the dataset

In [7]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51707 entries, 0 to 51706
Data columns (total 21 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   City                        51707 non-null  object 
 1   Day                         51707 non-null  object 
 2   realSum                     51707 non-null  float64
 3   room_type                   51707 non-null  object 
 4   room_shared                 51707 non-null  bool   
 5   room_private                51707 non-null  bool   
 6   person_capacity             51707 non-null  int64  
 7   host_is_superhost           51707 non-null  bool   
 8   multi                       51707 non-null  int64  
 9   biz                         51707 non-null  int64  
 10  cleanliness_rating          51707 non-null  int64  
 11  guest_satisfaction_overall  51707 non-null  int64  
 12  bedrooms                    51707 non-null  int64  
 13  dist                        51707 non-null  float64
 14  metro_dist                  51707 non-null  float64
 15  attr_index                  51707 non-null  float64
 16  attr_index_norm             51707 non-null  float64
 17  rest_index                  51707 non-null  float64
 18  rest_index_norm             51707 non-null  float64
 19  lng                         51707 non-null  float64
 20  lat                         51707 non-null  float64
dtypes: bool(3), float64(9), int64(6), object(3)
memory usage: 7.2+ MB
```

Checking for the missing values. Displaying number of missing values per column

In [8]:

```
missing_values = pd.DataFrame({'Number of missing values':df.isnull().sum(),
                               'Percentage of missing values':df.isnull().sum()/len(df)})

missing_values
```

Out[8]:

	Number of missing values	Percentage of missing values
City	0	0.0
Day	0	0.0
realSum	0	0.0
room_type	0	0.0
room_shared	0	0.0
room_private	0	0.0
person_capacity	0	0.0
host_is_superhost	0	0.0
multi	0	0.0
biz	0	0.0
cleanliness_rating	0	0.0
guest_satisfaction_overall	0	0.0
bedrooms	0	0.0
dist	0	0.0
metro_dist	0	0.0
attr_index	0	0.0
attr_index_norm	0	0.0
rest_index	0	0.0
rest_index_norm	0	0.0
lng	0	0.0
lat	0	0.0

From above dataframe we can see that there are no missing values present in the dataset

Dropping of irrelevant columns from the dataset

We can drop room_shared and room_private columns as they are subset of room_type column and attr_index , rest_index as there is normalised values of those columns is already there.

In [9]:

```
df.drop(columns = ['room_shared','room_private'] , inplace = True)
```

Checking for the descriptive statistics of the dataset

In [10]:

```
df.describe(include = 'object').T
```

Out[10]:

	count	unique	top	freq
City	51707	10	London	9993
Day	51707	2	Weekend	26207
room_type	51707	3	Entire home/apt	32648

From above report we could infer that :-

1) There are 10 unique cities listed and majority of the properties are listed from the city London with frequency of 9993

2) Majority of the bookings was made on weekends than weekdays

3) For room type most customers preferred entire home or apartment

In [11]:

```
df.describe().T
```

Out[11]:

	count	mean	std	min	25%	50%	75%
realSum	51707.0	279.879591	327.948386	34.779339	148.752174	211.343089	319.694286
person_capacity	51707.0	3.161661	1.298545	2.000000	2.000000	3.000000	4.000000
multi	51707.0	0.291353	0.454390	0.000000	0.000000	0.000000	1.000000
biz	51707.0	0.350204	0.477038	0.000000	0.000000	0.000000	1.000000
cleanliness_rating	51707.0	9.390624	0.954868	2.000000	9.000000	10.000000	10.000000
guest_satisfaction_overall	51707.0	92.628232	8.945531	20.000000	90.000000	95.000000	99.000000
bedrooms	51707.0	1.158760	0.627410	0.000000	1.000000	1.000000	1.000000
dist	51707.0	3.191285	2.393803	0.015045	1.453142	2.613538	4.263077
metro_dist	51707.0	0.681540	0.858023	0.002301	0.248480	0.413269	0.737840
attr_index	51707.0	294.204105	224.754123	15.152201	136.797385	234.331748	385.756381
attr_index_norm	51707.0	13.423792	9.807985	0.926301	6.380926	11.468305	17.415082
rest_index	51707.0	626.856696	497.920226	19.576924	250.854114	522.052783	832.628988
rest_index_norm	51707.0	22.786177	17.804096	0.592757	8.751480	17.542238	32.964603
lng	51707.0	7.426068	9.799725	-9.226340	-0.072500	4.873000	13.518825
lat	51707.0	45.671128	5.249263	37.953000	41.399510	47.506690	51.471885

In [ ]:

```

```

Univariate Analysis

In [12]:

```
df.columns
```

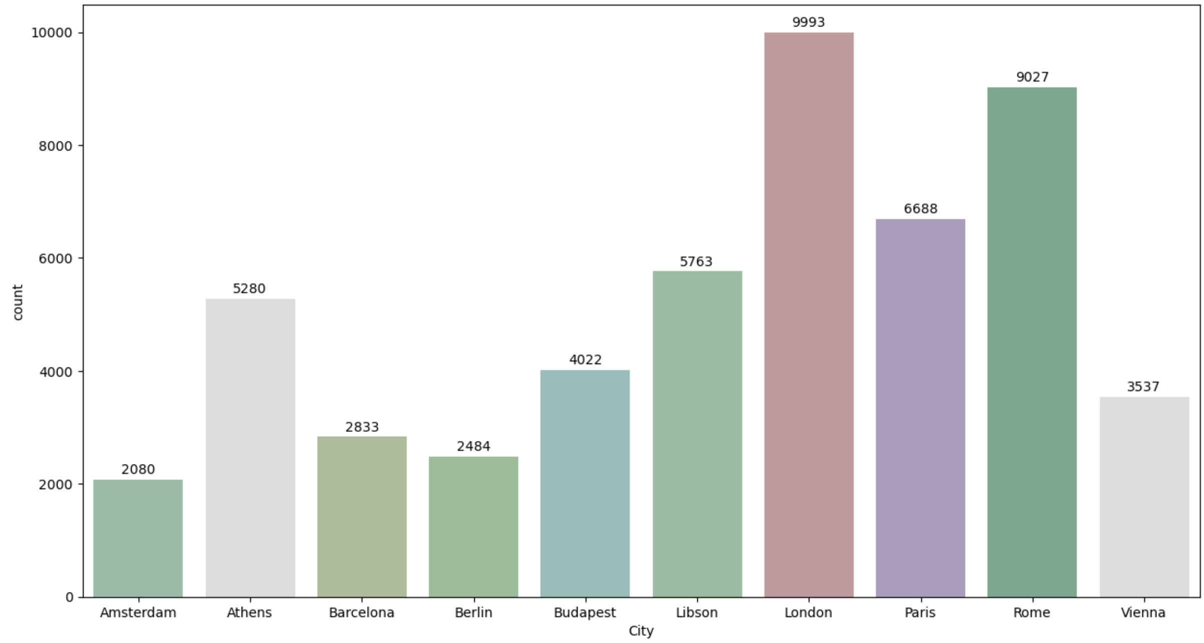
Out[12]:

```
Index(['City', 'Day', 'realSum', 'room_type', 'person_capacity',
       'host_is_superhost', 'multi', 'biz', 'cleanliness_rating',
       'guest_satisfaction_overall', 'bedrooms', 'dist', 'metro_dist',
       'attr_index', 'attr_index_norm', 'rest_index', 'rest_index_norm', 'lng',
       'lat'],
      dtype='object')
```

City

In [13]:

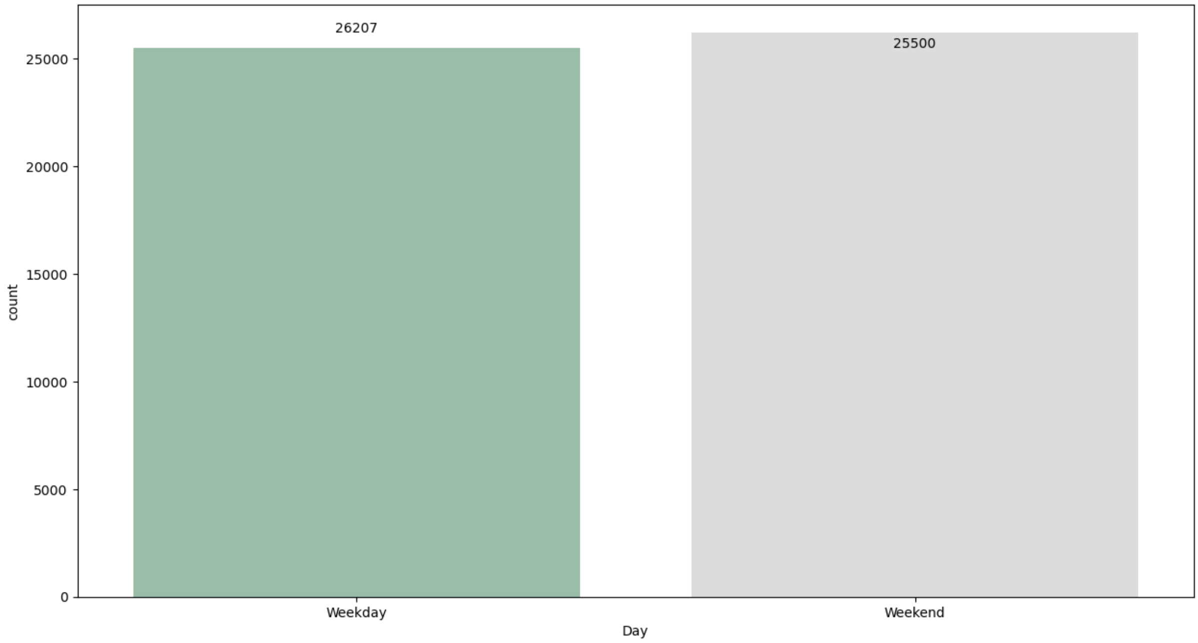
```
sns.countplot(df['City'].sort_values() , palette = colors )

for i,v in enumerate(df['City'].value_counts().sort_index()):
    plt.text(x = i , y = v + 100, s = v , ha = 'center')

```



Day

In [14]:

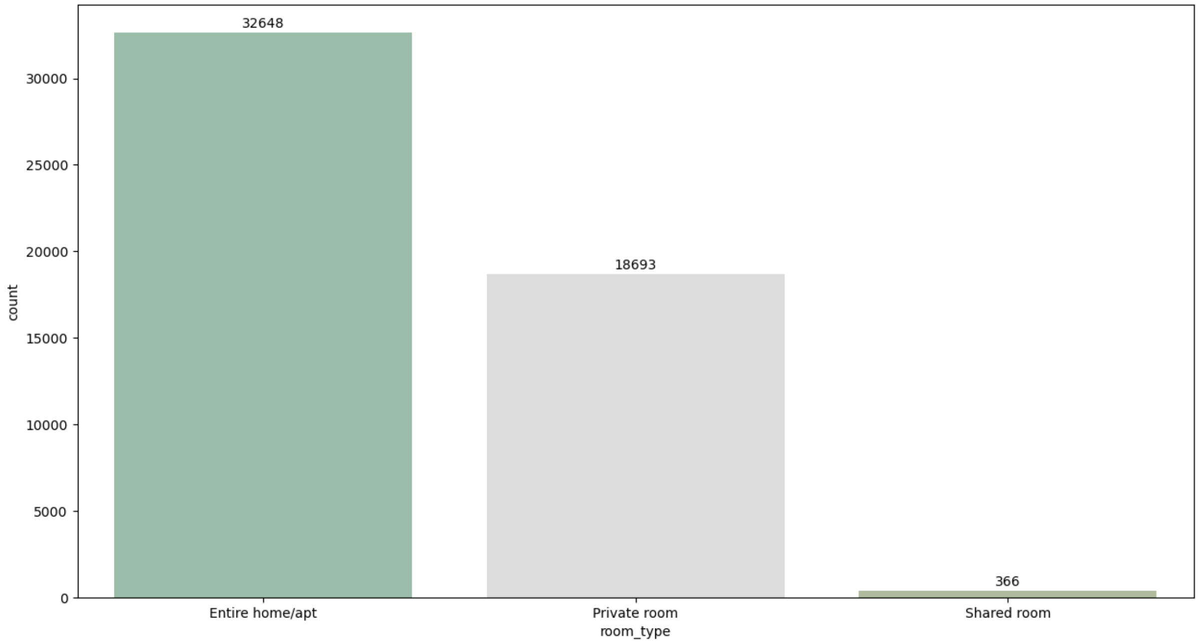
```
sns.countplot(df['Day'] , palette = colors)

for i,v in enumerate(df['Day'].value_counts()):
    plt.text(x = i , y = v , s = v , ha = 'center')
```



Room_type

In [15]:

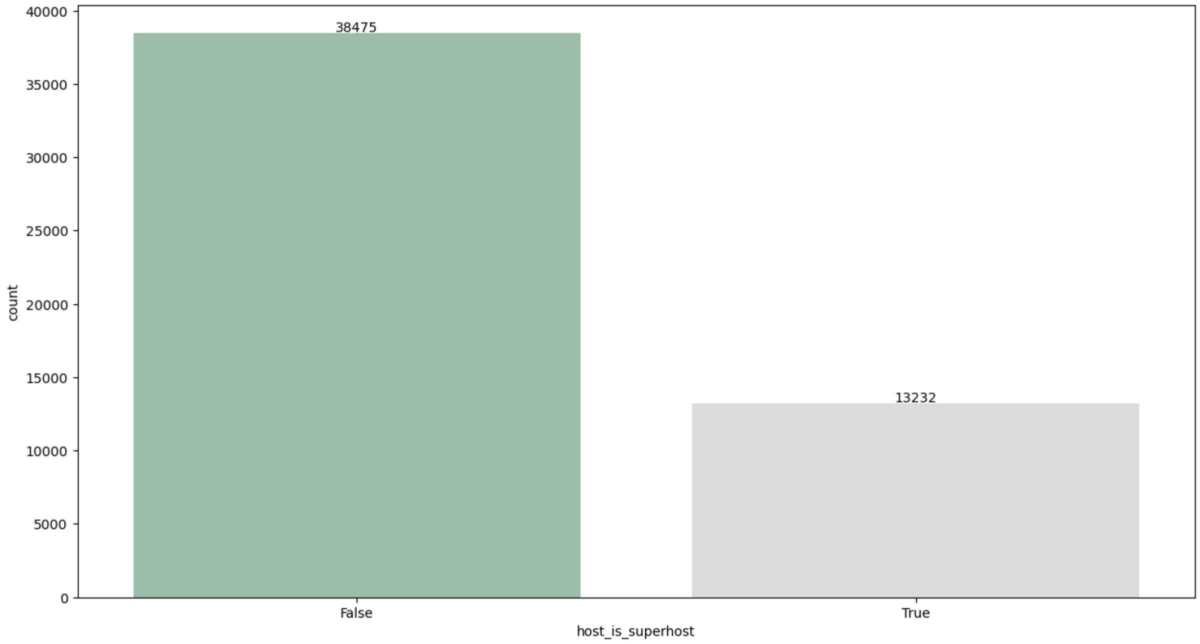
```
sns.countplot(df['room_type'].sort_values(), palette = colors)

for i,v in enumerate(df['room_type'].value_counts().sort_index()):
    plt.text(x = i , y = v + 300, s  = v , ha = 'center')
```



host_is_superhost

In [16]:

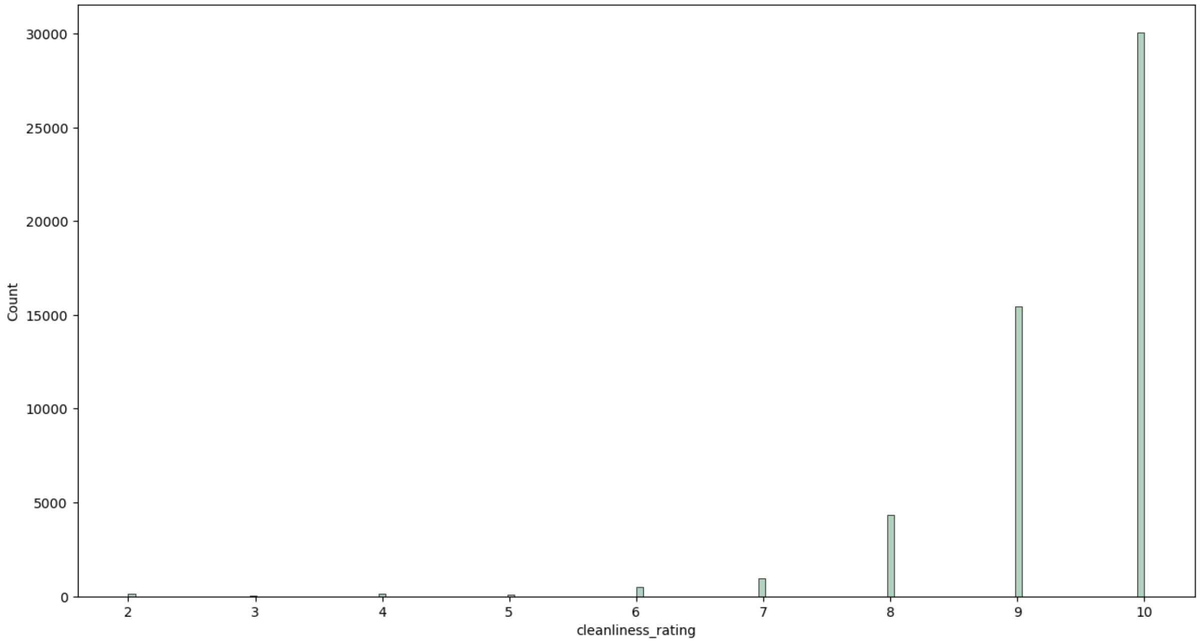
```
sns.countplot(df['host_is_superhost'].sort_values() , palette = colors)

for i,v in enumerate(df['host_is_superhost'].value_counts().sort_index()):
    plt.text(x = i , y = v + 100, s= v , ha = 'center')
```



cleanliness_rating

In [17]:

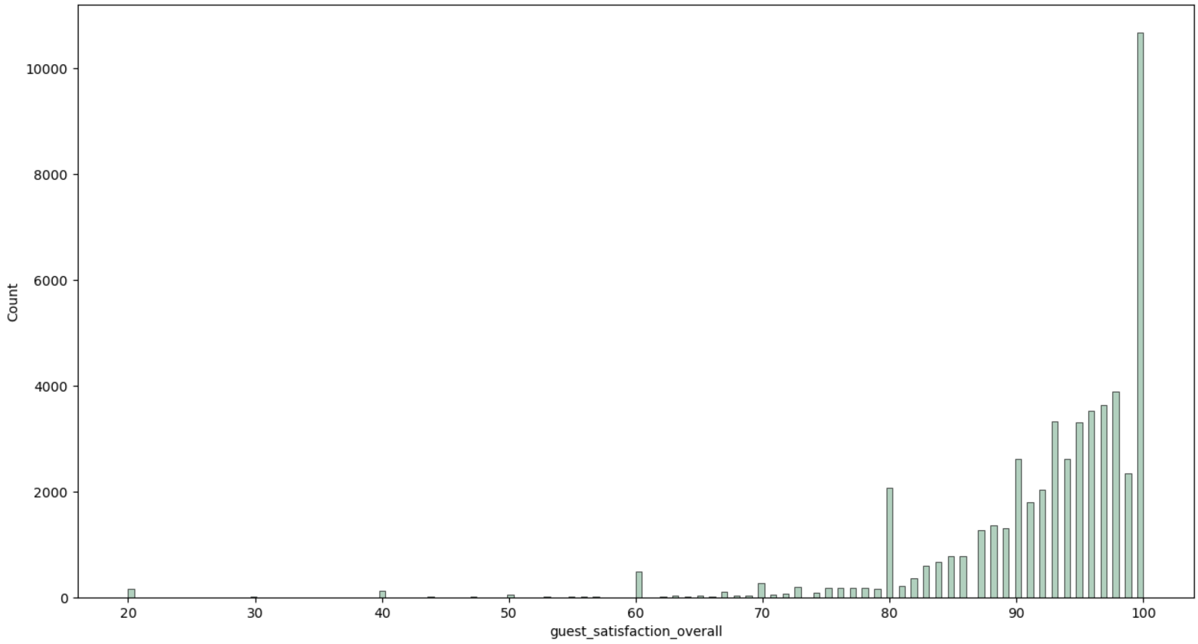
```
sns.histplot(df['cleanliness_rating'] , color = '#97C1A9')
plt.show()
```



Guest_satisfaction_overall

In [18]:

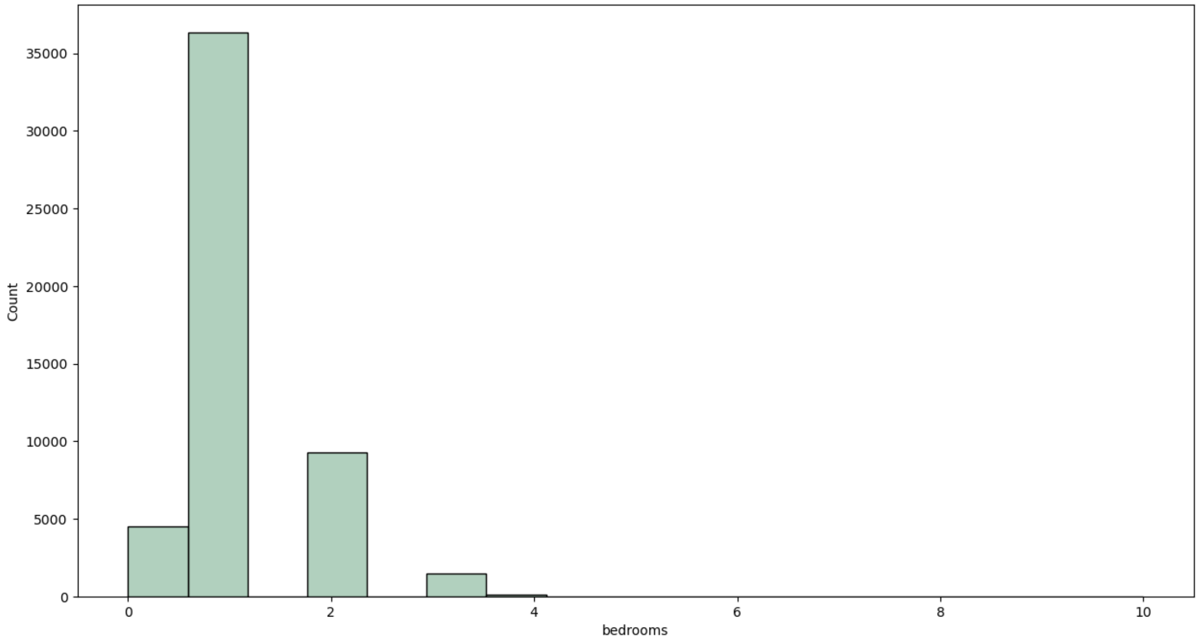
```
sns.histplot(df['guest_satisfaction_overall'] , color = '#97C1A9')
plt.show()
```



Bedrooms

In [19]:

```
sns.histplot(df['bedrooms'] , color = '#97C1A9')
plt.show()
```

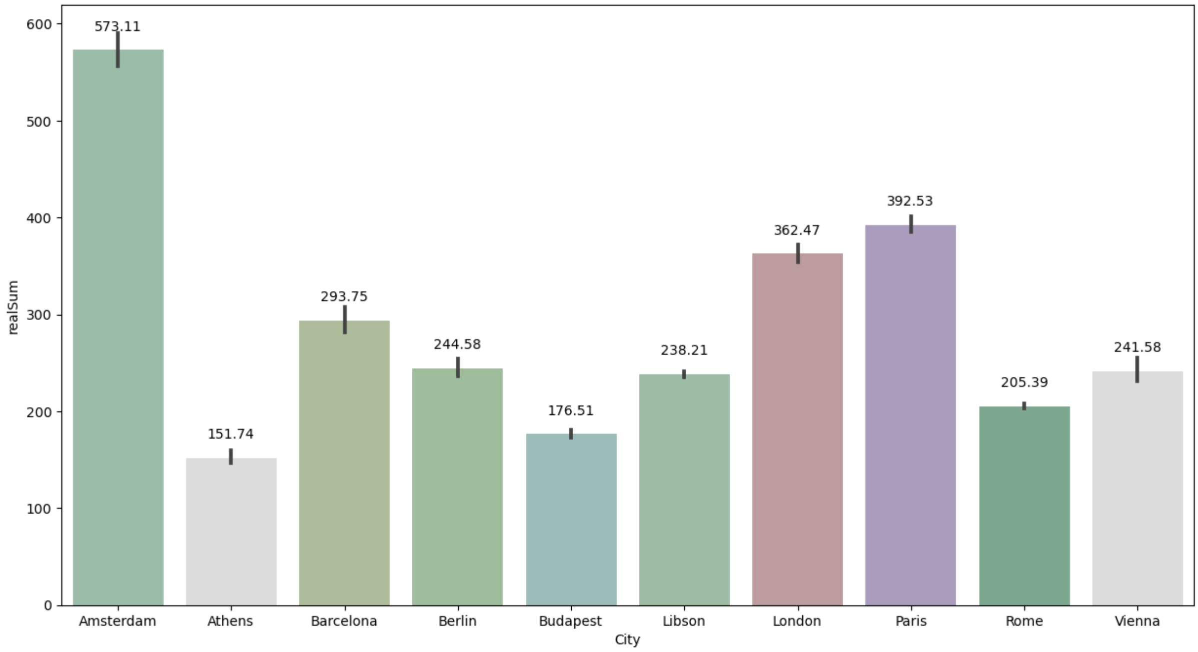


Bivariate Analysis

City vs Price

In [20]:

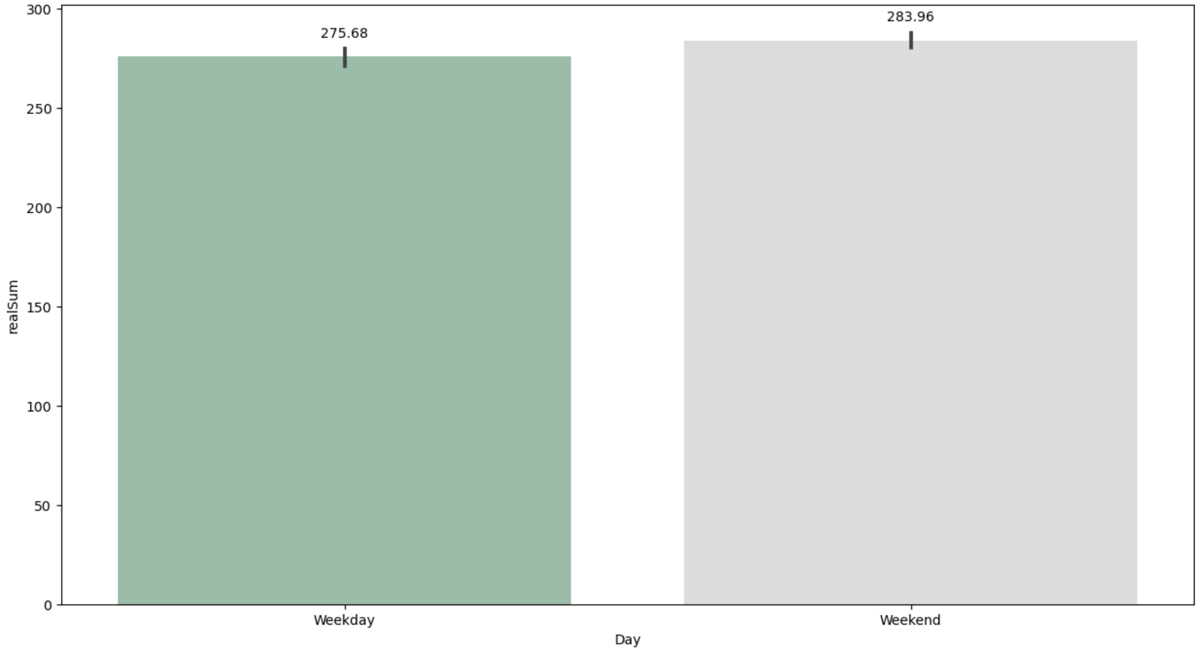
```
sns.barplot(df['City'].sort_values(),df['realSum'] , palette = colors)

for i,v in enumerate(df.groupby(by = 'City')['realSum'].mean()):
    plt.text(x = i, y = v + 20, s= round(v,2) , ha = 'center')
```



Day vs Price

In [21]:

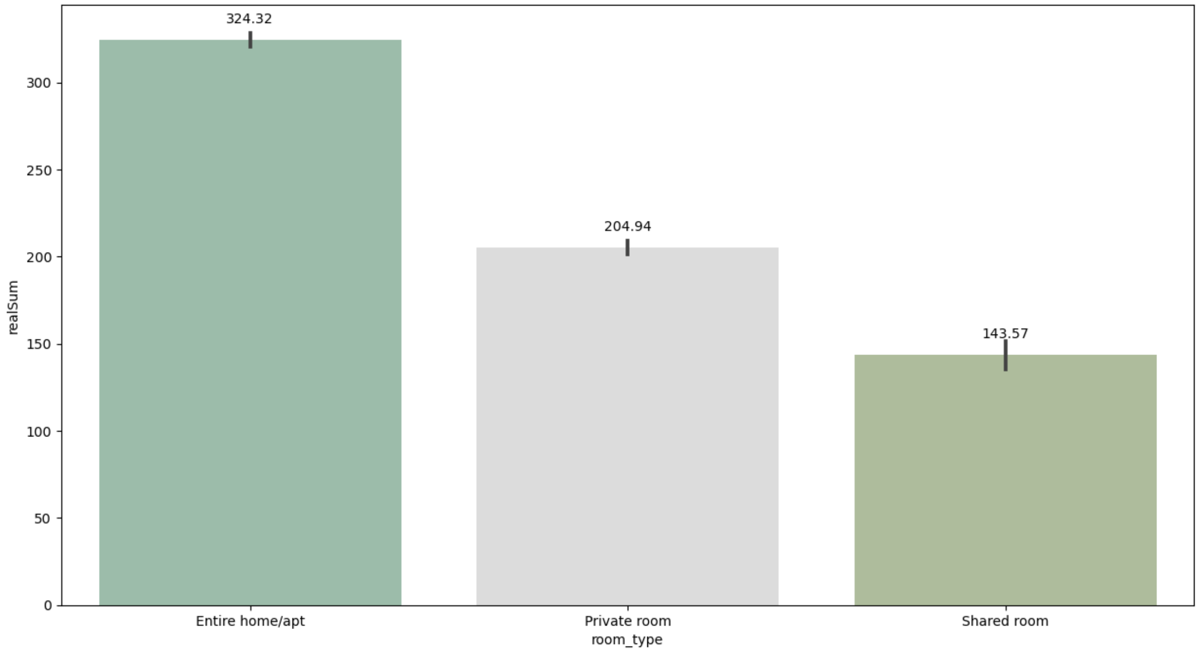
```
sns.barplot(df['Day'].sort_values(),df['realSum'],palette = colors)

for i,v in enumerate(df.groupby('Day')['realSum'].mean()):
    plt.text(x =i , y = v+10, s=round(v,2) , ha ='center')
```



Room_type vs Price

In [22]:

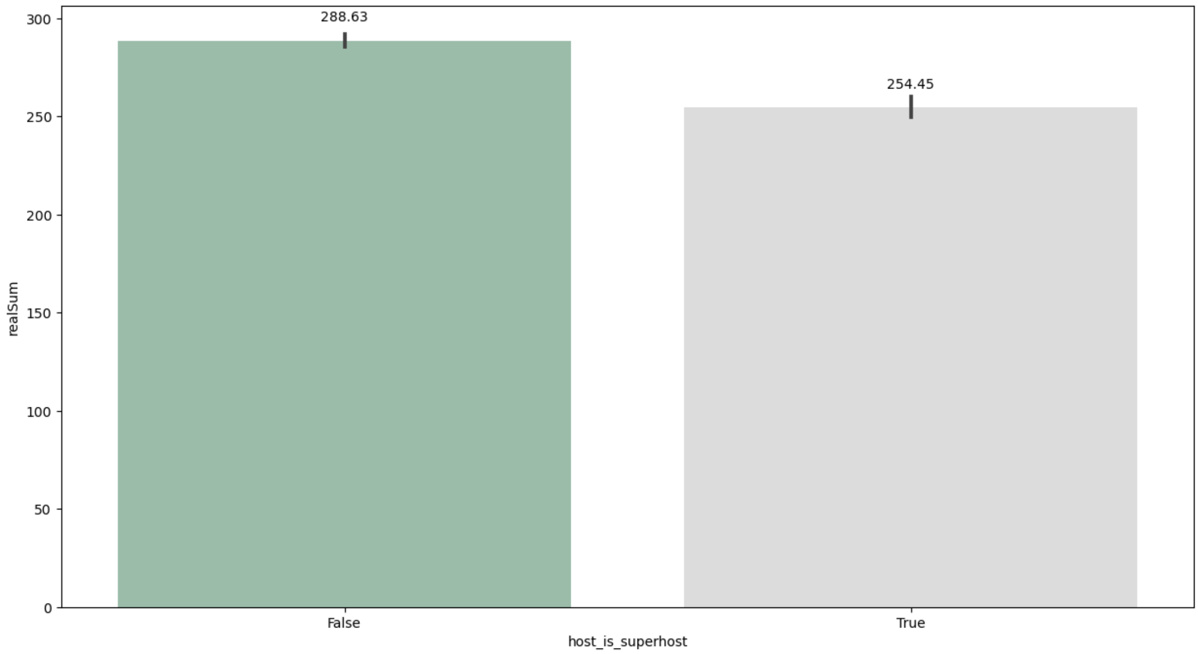
```
sns.barplot(df['room_type'].sort_values(),df['realSum'],palette=colors)

for i,v in enumerate(df.groupby('room_type')['realSum'].mean()):
    plt.text(x=i , y=v + 10, s= round(v,2) , ha='center')

```



Host_is_superhost vs Price

In [23]:

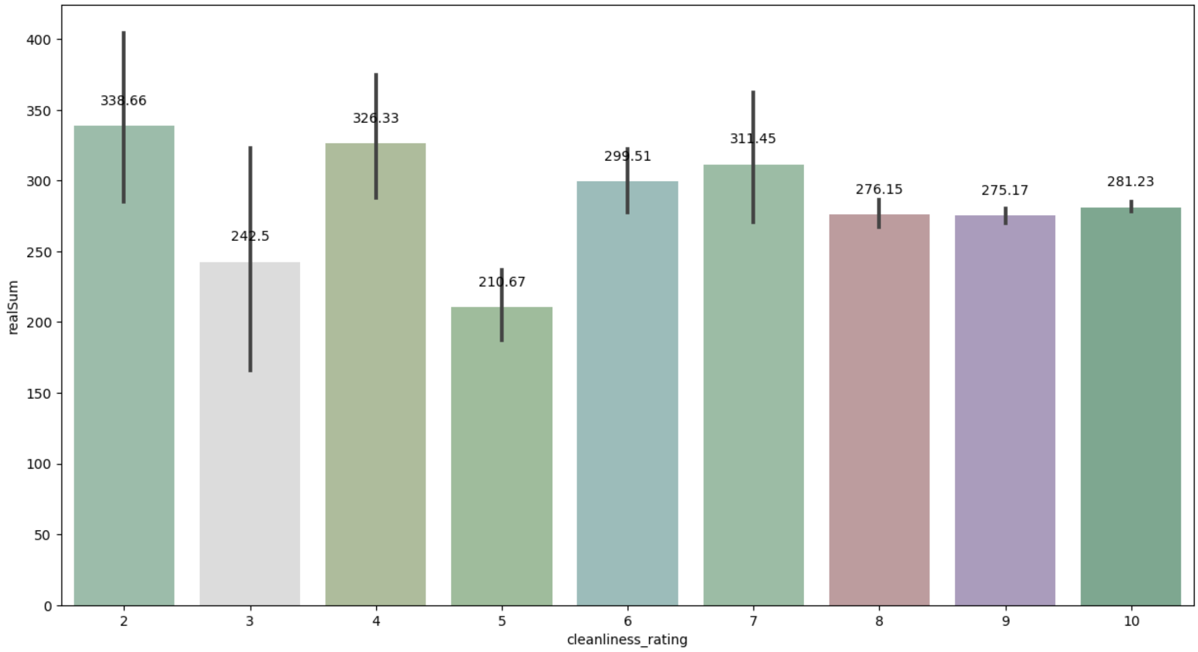
```
sns.barplot(df['host_is_superhost'],df['realSum'],palette=colors)

for i,v in enumerate(df.groupby('host_is_superhost')['realSum'].mean()):
    plt.text(x=i , y=v + 10 , s=round(v,2) , ha='center')
```



Cleanliness_rating vs Price

In [24]:

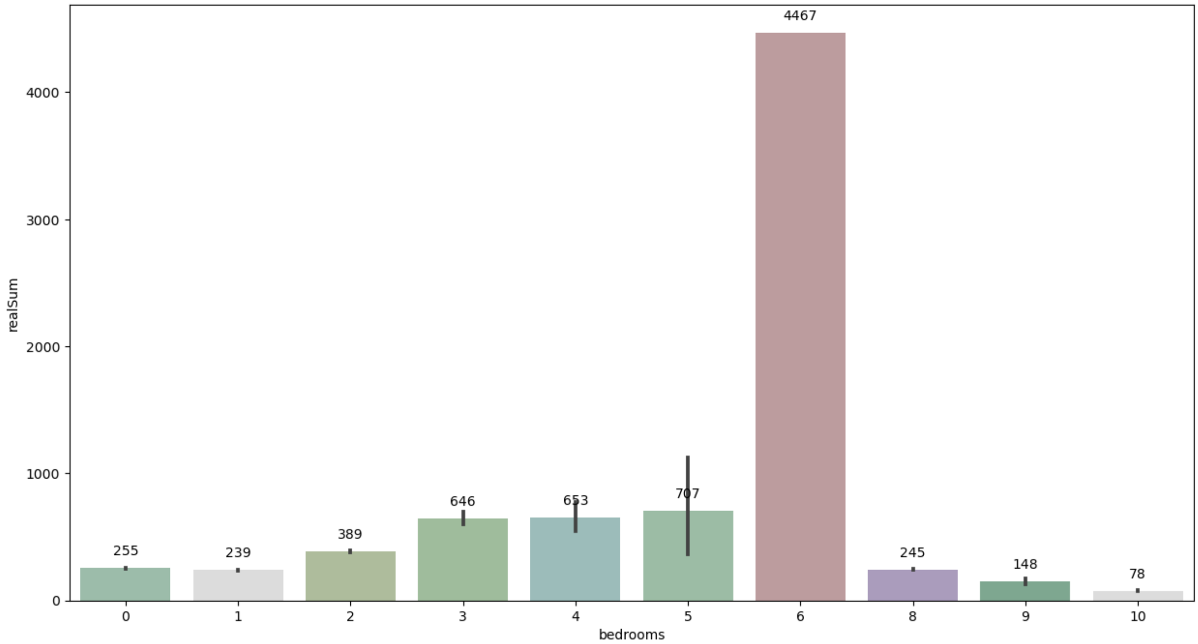
```
sns.barplot(df['cleanliness_rating'],df['realSum'],palette = colors)

for i,v in enumerate(df.groupby('cleanliness_rating')['realSum'].mean()):
    plt.text(x=i , y=v + 15, s=round(v,2), ha= 'center')
```



Bedrooms vs Price

In [25]:

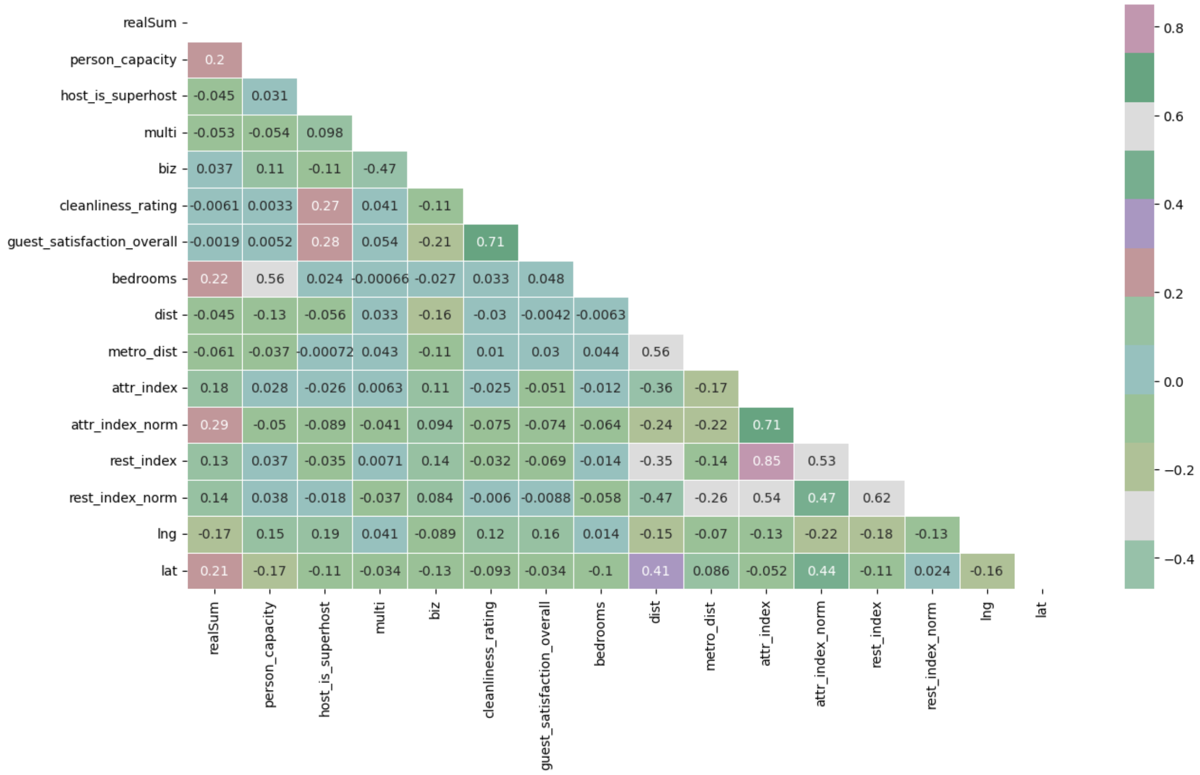
```
sns.barplot(df['bedrooms'],df['realSum'],palette=colors)

for i,v in enumerate(df.groupby('bedrooms')['realSum'].mean()):
    plt.text(x=i , y=v + 100, s=round(v) , ha='center')
```



Mutivariate Analysis

In [26]:

```
sns.heatmap(df.corr() , cmap = colors , mask = np.triu(df.corr()) , linewidth=0.5, annot = True
plt.show()
```



Feature Engineering

A new column named "Region" will be created by leveraging the latitude and longitude values of each city.

In [27]:

```
df['City'].unique()
```

Out[27]:

```
array(['Amsterdam', 'Athens', 'Barcelona', 'Berlin', 'Budapest', 'Libson',
       'London', 'Paris', 'Rome', 'Vienna'], dtype=object)
```

In [28]:

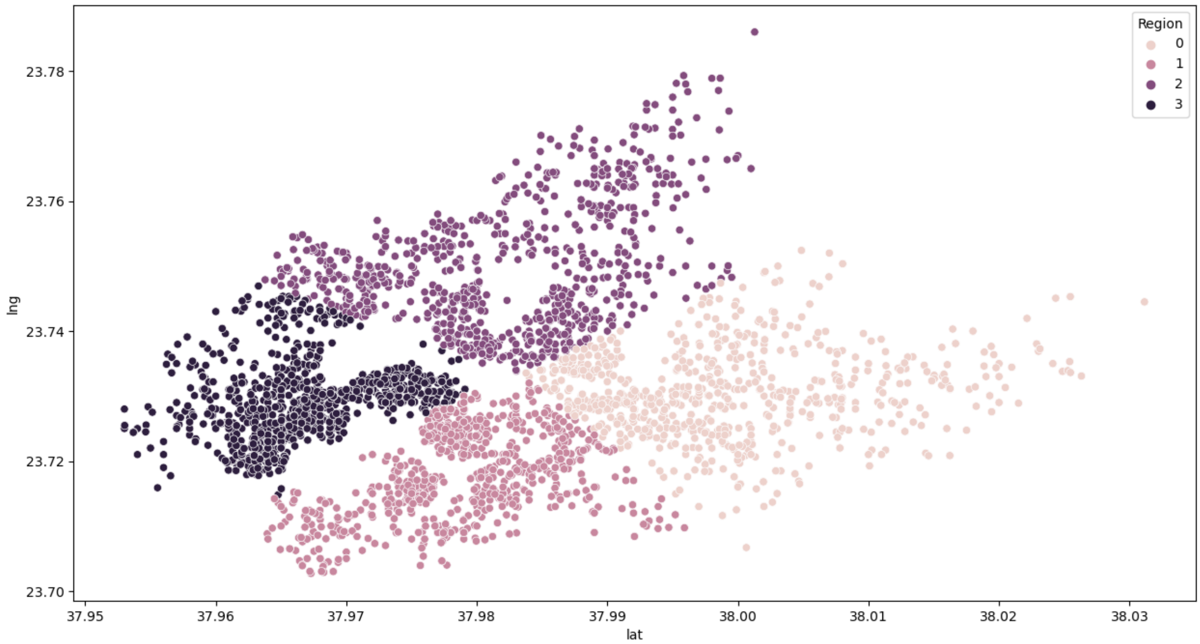
```
df_amsterdam = df[df['City'] == 'Amsterdam']
df_athens = df[df['City'] == 'Athens']
df_barcelona = df[df['City'] == 'Barcelona']
df_berlin = df[df['City'] == 'Berlin']
df_budapest = df[df['City'] == 'Budapest']
df_lisbon = df[df['City'] == 'Libson']
df_london = df[df['City'] == 'London']
df_paris = df[df['City'] == 'Paris']
df_rome = df[df['City'] == 'Rome']
df_vienna = df[df['City'] == 'Vienna']
```

In [29]:

```
#Amsterdam
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_amsterdam[['lat','lng']])
lab=kmod.labels_
df_amsterdam['Region']=lab
sns.scatterplot(df_amsterdam['lat'],df_amsterdam['lng'],hue=df_amsterdam['Region'])
df_amsterdam['Region']=df_amsterdam['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```

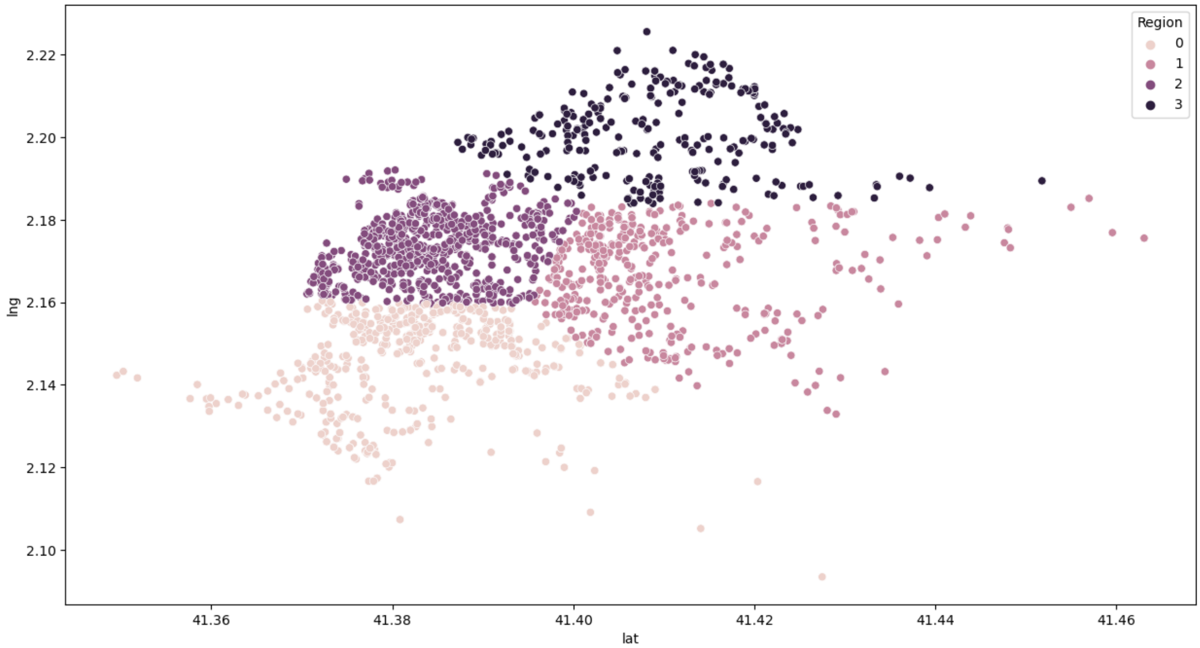
In [30]:

```
#Athens
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_athens[['lat','lng']])
lab=kmod.labels_
df_athens['Region']=lab
sns.scatterplot(df_athens['lat'],df_athens['lng'],hue=df_athens['Region'])
df_athens['Region']=df_athens['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



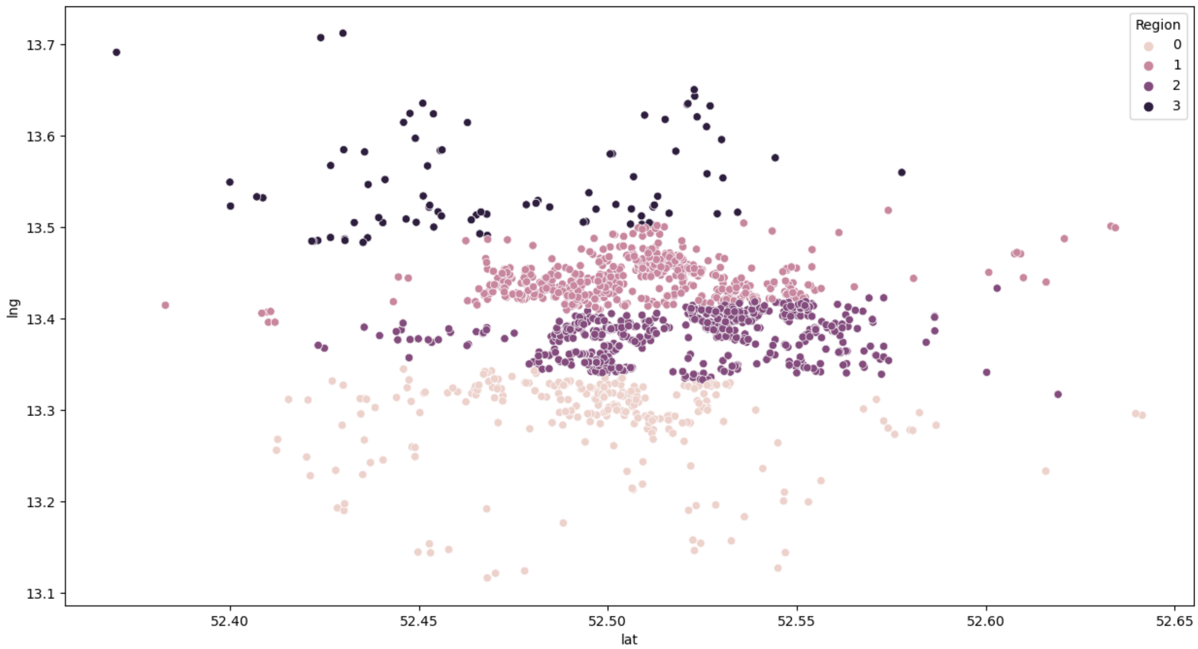
In [31]:

```
#Barcelona
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_barcelona[['lat','lng']])
lab=kmod.labels_
df_barcelona['Region']=lab
sns.scatterplot(df_barcelona['lat'],df_barcelona['lng'],hue=df_barcelona['Region'])
df_barcelona['Region']=df_barcelona['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



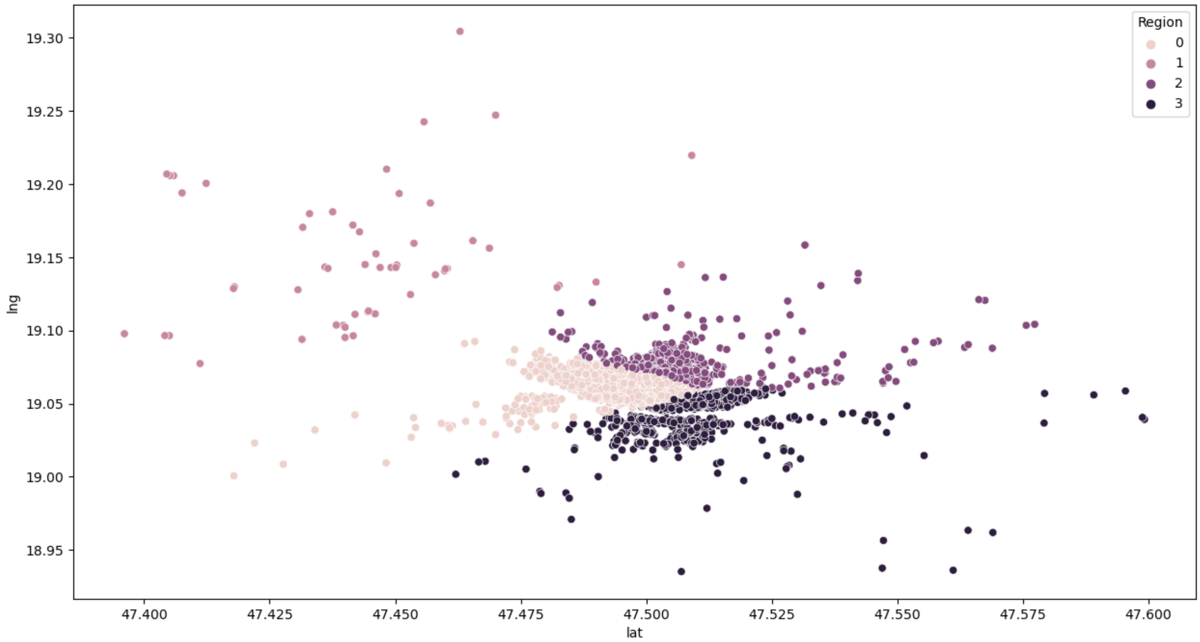
In [32]:

```
#Berlin
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_berlin[['lat','lng']])
lab=kmod.labels_
df_berlin['Region']=lab
sns.scatterplot(df_berlin['lat'],df_berlin['lng'],hue=df_berlin['Region'])
df_berlin['Region']=df_berlin['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



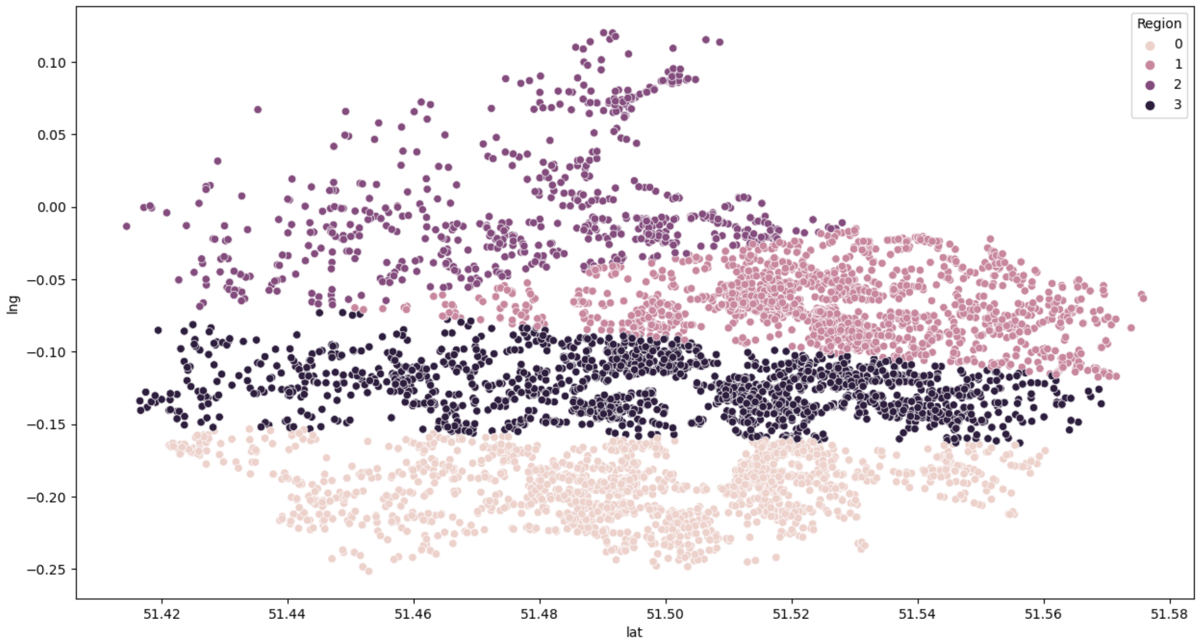
In [33]:

```
#Budapest
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_budapest[['lat','lng']])
lab=kmod.labels_
df_budapest['Region']=lab
sns.scatterplot(df_budapest['lat'],df_budapest['lng'],hue=df_budapest['Region'])
df_budapest['Region']=df_budapest['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



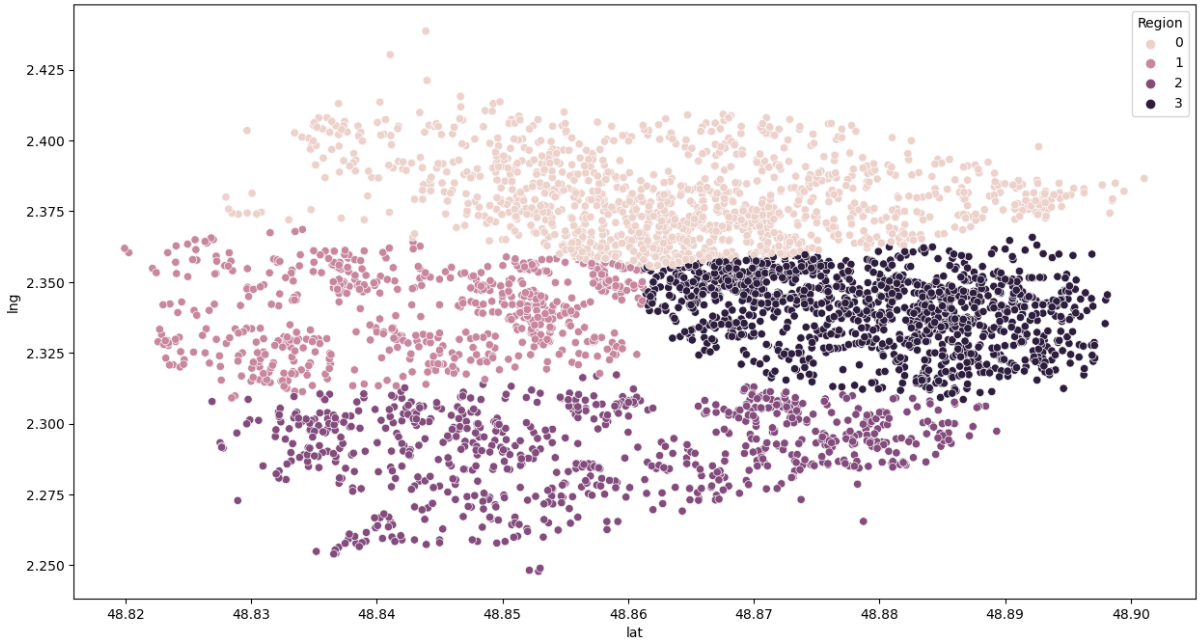
In [34]:

```
#London
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_london[['lat','lng']])
lab=kmod.labels_
df_london['Region']=lab
sns.scatterplot(df_london['lat'],df_london['lng'],hue=df_london['Region'])
df_london['Region']=df_london['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



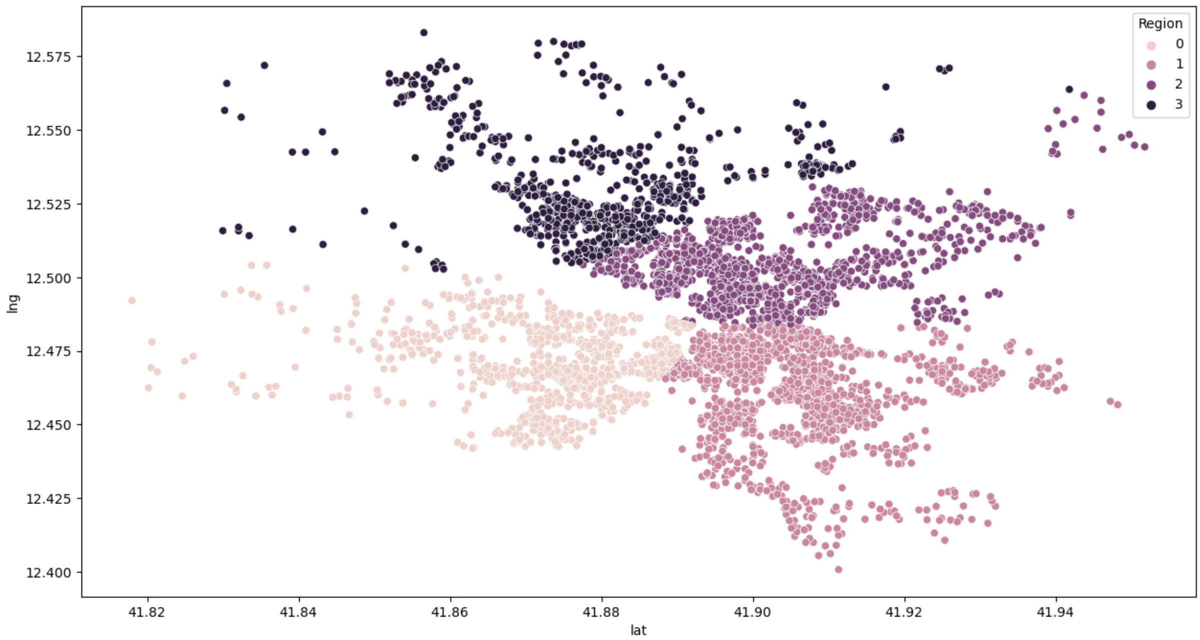
In [35]:

```
#Paris
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_paris[['lat','lng']])
lab=kmod.labels_
df_paris['Region']=lab
sns.scatterplot(df_paris['lat'],df_paris['lng'],hue=df_paris['Region'])
df_paris['Region']=df_paris['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



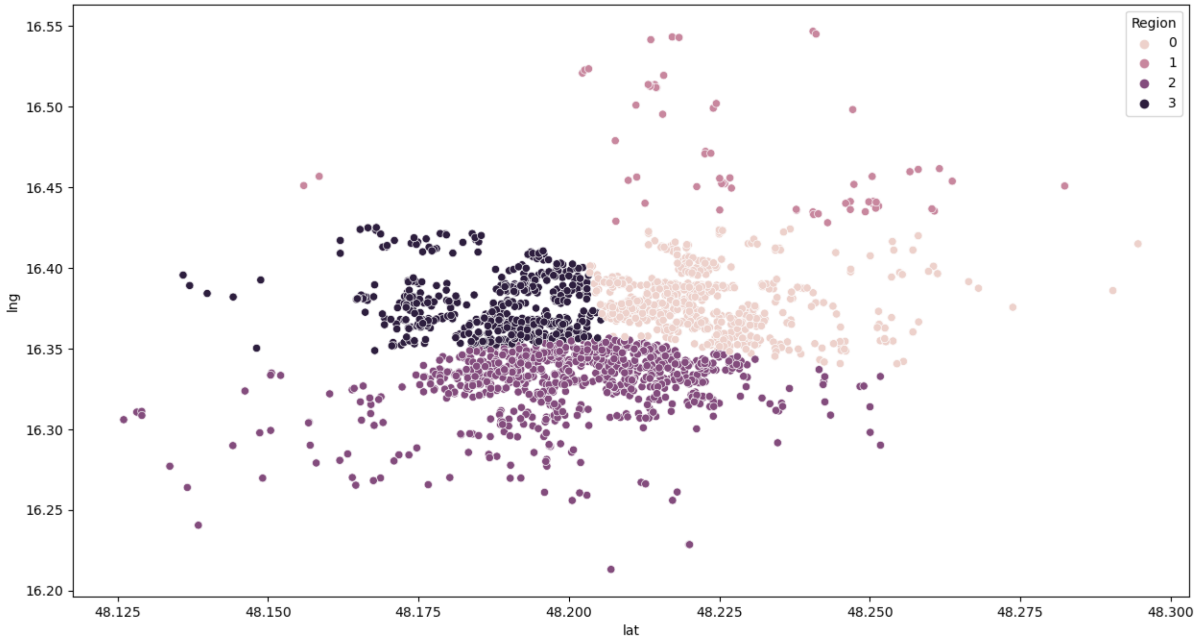
In [36]:

```
#Rome
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_rome[['lat','lng']])
lab=kmod.labels_
df_rome['Region']=lab
sns.scatterplot(df_rome['lat'],df_rome['lng'],hue=df_rome['Region'])
df_rome['Region']=df_rome['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



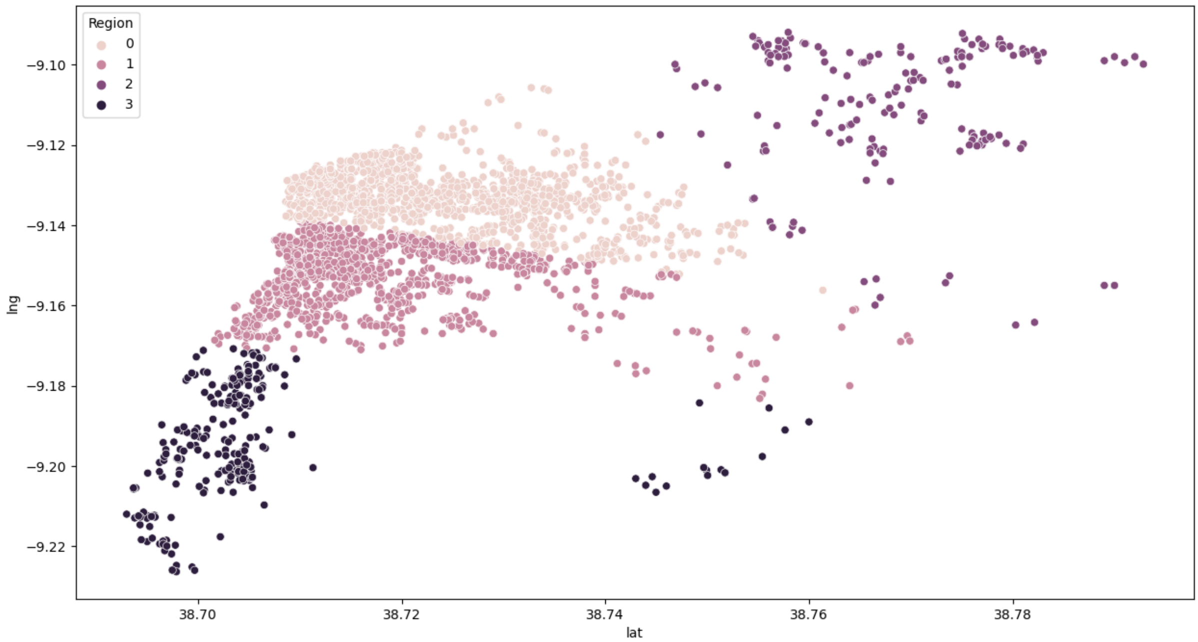
In [37]:

```
#Vienna
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_vienna[['lat','lng']])
lab=kmod.labels_
df_vienna['Region']=lab
sns.scatterplot(df_vienna['lat'],df_vienna['lng'],hue=df_vienna['Region'])
df_vienna['Region']=df_vienna['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



In [38]:

```
#Lisbon
km=KMeans(n_clusters=4, init='k-means++',random_state=20)
kmod=km.fit(df_lisbon[['lat','lng']])
lab=kmod.labels_
df_lisbon['Region']=lab
sns.scatterplot(df_lisbon['lat'],df_lisbon['lng'],hue=df_lisbon['Region'])
df_lisbon['Region']=df_lisbon['Region'].map({0:'West',1:'North',2:'South',3:'East'})
```



In [39]:

```
df = pd.concat([df_amsterdam,df_athens,df_barcelona,df_berlin,df_budapest,df_lisbon,df_london,d

df.head()
```

Out[39]:

	City	Day	realSum	room_type	person_capacity	host_is_superhost	multi	biz	cleanliness
0	Amsterdam	Weekday	194.033698	Private room	2	False	1	0	
1	Amsterdam	Weekday	344.245776	Private room	4	False	0	0	
2	Amsterdam	Weekday	264.101422	Private room	2	False	0	1	
3	Amsterdam	Weekday	433.529398	Private room	4	False	0	1	
4	Amsterdam	Weekday	485.552926	Private room	2	True	0	0	

In [40]:

```
df['Region'].isnull().sum()
```

Out[40]:

0

Dropping of individual latitude and longitude columns

In [41]:

```
df.drop(columns = ['lat','lng'],inplace = True)
```

Performing bining for guest satisfaction column. Creating 3 discrete bins namely score between 0-35 as poor , 36 - 70 as average and 71 - 100 as high

In [42]:

```
def binning(l):
    if l > 0 and l <= 35 :
        return 'Poor'
    elif l > 36 and l <= 70:
        return 'Average'
    else:
        return 'High'

df['guest_satisfaction_overall'] = df['guest_satisfaction_overall'].apply(binning)
```

Performing hypothesis testing to find the significant variables

Hypothesis :

H0 : There is no significant relationship between the dependent and independent variable

Ha : There is significant relationship between the dependent and independent variable

Significance level :

Considering significance level as 0.05

In [43]:

```
# Creating a dataframe to store the results of statistical results

statistical_result = pd.DataFrame(columns = ['Column','Pvalue','Remarks'])
```

In [44]:

```
num_cols = ['dist', 'metro_dist', 'attr_index_norm', 'rest_index_norm','attr_index','rest_index
cat_cols = ['City', 'Day', 'room_type', 'person_capacity','host_is_superhost', 'cleanliness_rat
            'guest_satisfaction_overall','bedrooms','Region']
```

In [45]:

```
# Numerical vs Categorical - f_oneway test

for i in cat_cols:
    groups =  [df.loc[df[i] == subclass , 'realSum'] for subclass
              in df[i].unique()]

    stat , pval = stats.f_oneway(*groups)

    statistical_result = statistical_result.append({'Column':i , 'Pvalue':pval,
                                                    'Remarks':'Reject H0' if pval <= 0.05 else '
                                                   ignore_index=True)
```

In [46]:

```
# Numerical vs Numerical - Pearsonr test

for i in num_cols:
    stat , pval = stats.pearsonr(df[i],df['realSum'])

    statistical_result = statistical_result.append({'Column':i , 'Pvalue':pval,
                                                    'Remarks':'Reject H0' if pval <= 0.05 else '
                                                   ignore_index=True)
```

In [47]:

```
statistical_result
```

Out[47]:

	Column	Pvalue	Remarks
0	City	0.000000e+00	Reject H0
1	Day	4.090175e-03	Reject H0
2	room_type	0.000000e+00	Reject H0
3	person_capacity	0.000000e+00	Reject H0
4	host_is_superhost	4.345181e-25	Reject H0
5	cleanliness_rating	9.461615e-04	Reject H0
6	guest_satisfaction_overall	5.707492e-04	Reject H0
7	bedrooms	0.000000e+00	Reject H0
8	Region	3.958731e-33	Reject H0
9	dist	2.563113e-24	Reject H0
10	metro_dist	7.376494e-44	Reject H0
11	attr_index_norm	0.000000e+00	Reject H0
12	rest_index_norm	6.507204e-238	Reject H0
13	attr_index	0.000000e+00	Reject H0
14	rest_index	5.763826e-208	Reject H0

Insights from statistical test

After performing statistical tests, all variables were found to be statistically significant. This suggests that each variable examined in the study has a meaningful relationship with the outcome. These findings indicate the importance of all variables in influencing the price variable.

Splitting the dataset randomly into train and test dataset using ratio of 70:30

In [48]:

```
x = df.drop(columns = 'realSum')
y = df['realSum']

xtrain , xtest , ytrain , ytest = train_test_split(x,y,test_size = 0.30 , random_state = 24)
```

Transforming of target variable

In [49]:

```
ytrain = np.array(ytrain).reshape(-1, 1)
ytest = np.array(ytest).reshape(-1, 1)
```

In [50]:

```
pt = PowerTransformer()

var = pt.fit(ytrain)
ytrain = var.transform(ytrain)
ytest = var.transform(ytest)
```

Encoding of Categorical variables

For columns like city , room_type , region CatBoost Encoding technique can be used

In [51]:

```
catboost_columns = ['City','room_type','Region']

for i in catboost_columns:

    var_city = CatBoostEncoder().fit(xtrain[i],ytrain)

    xtrain[i] = var_city.transform(xtrain[i])
    xtest[i] = var_city.transform(xtest[i])
```

For columns like day , host_is_superhost and guest_satisfaction we can replace with 0 and 1

In [52]:

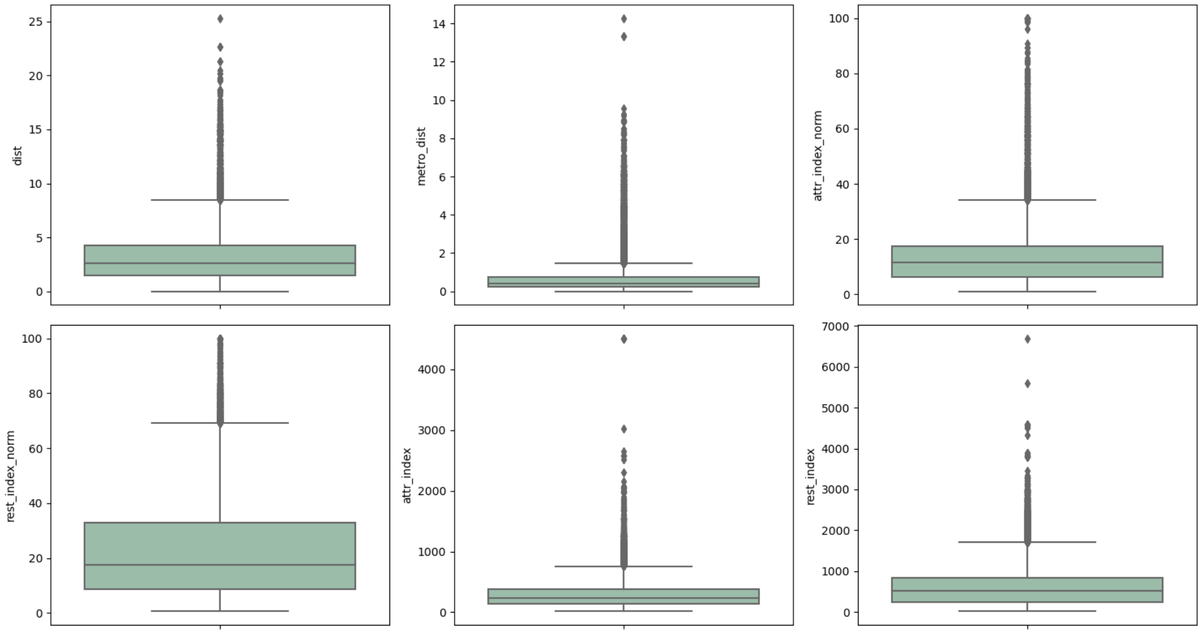
```
xtrain['Day'].replace({'Weekend':1,'Weekday':0},inplace=True)
xtest['Day'].replace({'Weekend':1,'Weekday':0},inplace=True)

xtrain['host_is_superhost'].replace({True:1,False:0},inplace=True)
xtest['host_is_superhost'].replace({True:1,False:0},inplace=True)

xtrain['guest_satisfaction_overall'].replace({'High':2,'Average':1,'Poor':0},inplace = True)
xtest['guest_satisfaction_overall'].replace({'High':2,'Average':1,'Poor':0},inplace = True)
```

Checking and treating of outliers

For training data

In [53]:

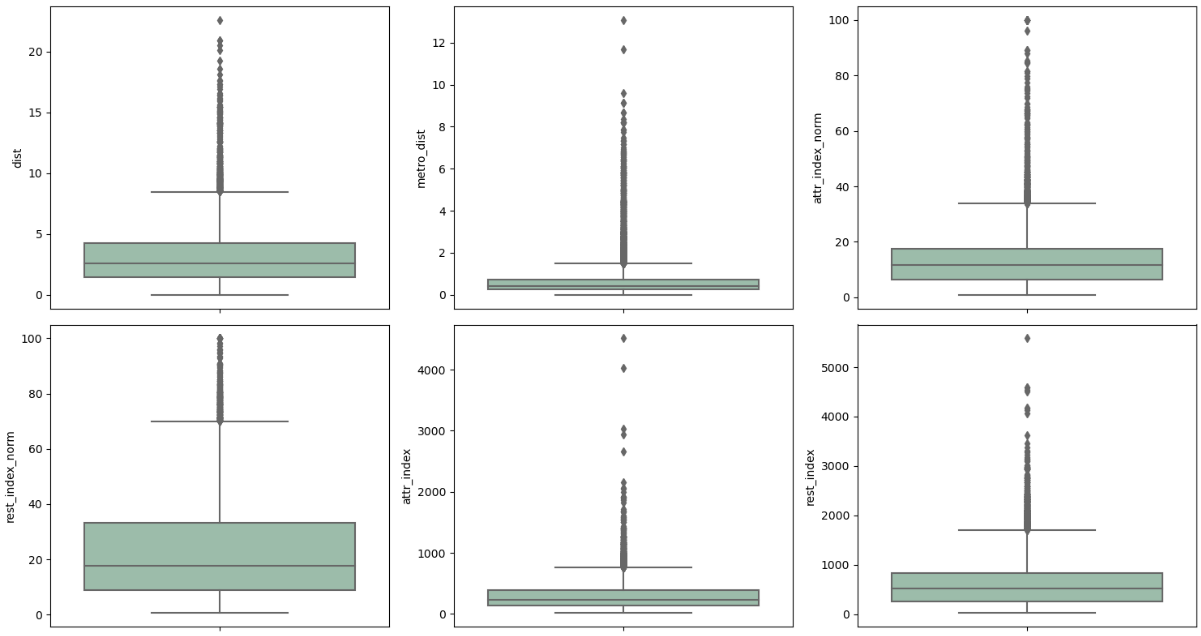
```
f,ax = plt.subplots(2,3)

for i,v in zip(num_cols,ax.flatten()):
    sns.boxplot(y = xtrain[i] , ax = v , palette = colors)

plt.tight_layout()
plt.show()
```



For testing data

In [54]:

```
f,ax = plt.subplots(2,3)

for i,v in zip(num_cols,ax.flatten()):
    sns.boxplot(y = xtest[i] , ax = v, palette = colors)

plt.tight_layout()
plt.show()
```



From above box plots it is clearly evident that there are outliers . By doing IQR method we tend lose data. Hence we go forward by doing transformation technique

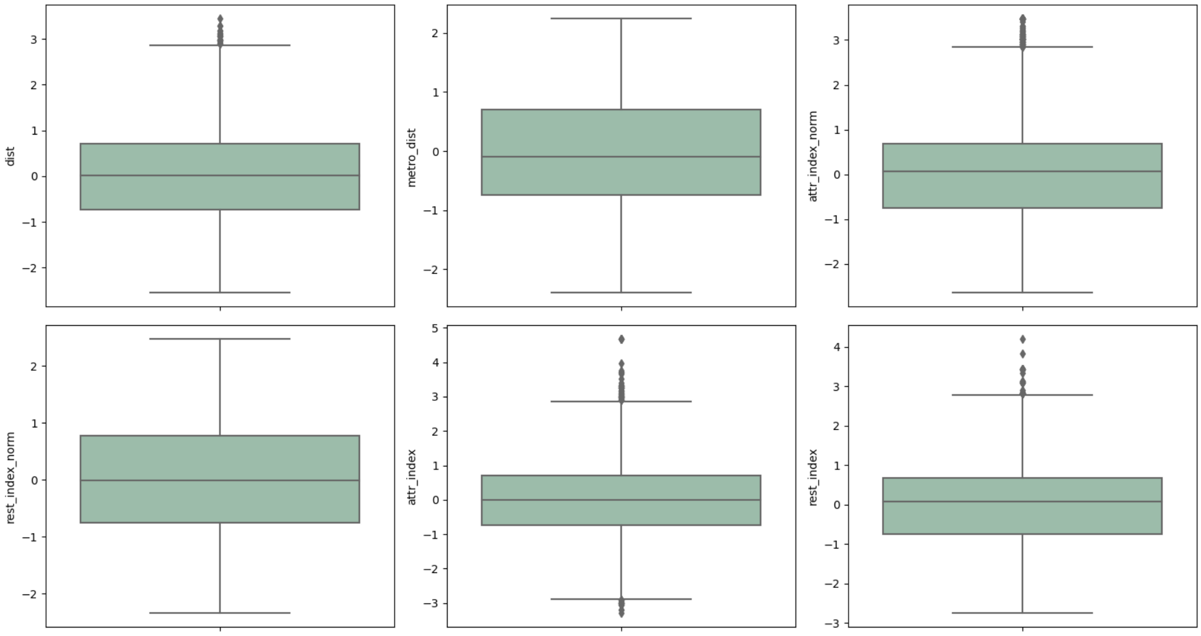
In [55]:

```
pt = PowerTransformer()

for i in num_cols:
    var = pt.fit(xtrain[[i]])

    xtrain[i] = var.transform(xtrain[[i]])
    xtest[i] = var.transform(xtest[[i]])
```

After treating outliers

In [56]:

```
f,ax = plt.subplots(2,3)

for i,v in zip(num_cols,ax.flatten()):
    sns.boxplot(y = xtrain[i] , ax = v , palette = colors)

plt.tight_layout()
plt.show()
```



Building a Base Model

Building a base model using Linear Regression as it is having the highest explanatory power compared to other models

In [57]:

```
xtrain
```

Out[57]:

	City	Day	room_type	person_capacity	host_is_superhost	multi	biz	cleanliness_rating	gues
31733	0.370252	1	0.255588	2	0	0	0	8	
6108	-0.974896	1	0.255588	3	1	1	0	10	
50254	-0.058587	1	0.255588	4	1	0	0	10	
17082	-0.019765	0	0.255588	4	0	0	1	9	
26349	0.370252	0	0.255588	4	0	0	1	7	
...	...	...	...	...	...	...	...	...	
21633	-0.019765	1	0.255588	4	0	0	1	10	
19857	-0.019765	1	0.255588	3	0	0	1	10	
14528	-0.612586	0	0.255588	4	1	0	1	10	
899	1.185099	0	0.255588	4	0	0	0	10	
45474	-0.315801	1	0.255588	4	0	0	1	9	

36194 rows × 17 columns

In [58]:

```
model_lr = sma.OLS(ytrain,sma.add_constant(xtrain)).fit()

model_lr.summary()
```

Out[58]:

OLS Regression Results

Dep. Variable:	y	**R-squared:**	0.662
Model:	OLS	**Adj. R-squared:**	0.662
Method:	Least Squares	**F-statistic:**	4170.
Date:	Sun, 30 Jul 2023	**Prob (F-statistic):**	0.00
Time:	01:53:31	**Log-Likelihood:**	-31721.
No. Observations:	36194	**AIC:**	6.348e+04
Df Residuals:	36176	**BIC:**	6.363e+04
Df Model:	17		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.2840	0.039	-33.172	0.000	-1.360	-1.208
City	1.0144	0.008	135.069	0.000	1.000	1.029
Day	0.0417	0.006	6.766	0.000	0.030	0.054
room_type	0.9831	0.011	91.493	0.000	0.962	1.004
person_capacity	0.1440	0.003	43.655	0.000	0.138	0.150
host_is_superhost	0.0347	0.007	4.658	0.000	0.020	0.049
multi	0.0760	0.008	9.707	0.000	0.061	0.091
biz	0.1838	0.008	23.842	0.000	0.169	0.199
cleanliness_rating	0.1089	0.004	28.447	0.000	0.101	0.116
guest_satisfaction_overall	-0.3027	0.019	-15.892	0.000	-0.340	-0.265
bedrooms	0.2466	0.006	40.590	0.000	0.235	0.258
dist	-0.0403	0.004	-9.021	0.000	-0.049	-0.032
metro_dist	0.0144	0.003	4.229	0.000	0.008	0.021
attr_index	-0.0166	0.012	-1.376	0.169	-0.040	0.007
attr_index_norm	0.3034	0.006	49.206	0.000	0.291	0.315
rest_index	0.0380	0.010	3.705	0.000	0.018	0.058
rest_index_norm	-0.0211	0.005	-4.208	0.000	-0.031	-0.011
Region	-0.1426	0.036	-3.918	0.000	-0.214	-0.071

Omnibus:	2811.223	**Durbin-Watson:**	1.995
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	7807.113
Skew:	0.433	**Prob(JB):**	0.00
Kurtosis:	5.104	**Cond. No.**	136.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [59]:

```
pred_train = model_lr.predict(sma.add_constant(xtrain))
pred_test = model_lr.predict(sma.add_constant(xtest))

r2_train = r2_score(ytrain,pred_train)
r2_test = r2_score(ytest,pred_test)
rmse_train = np.sqrt(mean_squared_error(ytrain,pred_train))
rmse_test = np.sqrt(mean_squared_error(ytest,pred_test))
mape_train = mean_absolute_percentage_error(ytrain,pred_train)
mape_test = mean_absolute_percentage_error(ytest,pred_test)
```

In [60]:

```
# Creating a dataframe to store values of metrics of both train and test data

performance_df = pd.DataFrame(columns = ['Model_Name','Train R2','Test R2','Train RMSE','Test RI
                                         ,'Train MAPE','Test MAPE','Remarks'])

performance_df
```

Out[60]:

Model_Name	Train R2	Test R2	Train RMSE	Test RMSE	Train MAPE	Test MAPE	Remarks

In [61]:

```
# Appending values of our base model to performance df

performance_df = performance_df.append({'Model_Name':'Base Model','Train R2':r2_train,'Test R2'
                                       'Train RMSE':rmse_train,'Test RMSE':rmse_test,'Train MAPI
                                       'Test MAPE':mape_test,'Remarks':'Base'},ignore_index=Tru

performance_df
```

Out[61]:

	Model_Name	Train R2	Test R2	Train RMSE	Test RMSE	Train MAPE	Test MAPE	Remarks
0	Base Model	0.66211	0.653968	0.581283	0.584654	56.088907	18.944154	Base

Building different models and evaluating using appropriate technique

In [62]:

```
# Creating a user defined function to store values of metrics to the dataframe

def model_performance(model , name):
    global performance_df
    pred_train = model.predict(xtrain)
    pred_test = model.predict(xtest)

    r2_train = r2_score(ytrain,pred_train)
    r2_test = r2_score(ytest,pred_test)
    rmse_train = np.sqrt(mean_squared_error(ytrain,pred_train))
    rmse_test = np.sqrt(mean_squared_error(ytest,pred_test))
    mape_train = mean_absolute_percentage_error(ytrain,pred_train)
    mape_test = mean_absolute_percentage_error(ytest,pred_test)

    # Defining a function for remarks

    def remarks(train,test):
        if abs(train - test) > 0.1 or train > 0.90:
            return 'Over Fit'
        elif train > 0.5 and test > 0.5:
            return 'Good Fit'
        else :
            return 'Under Fit'

    performance_df = performance_df.append({'Model_Name':name,'Train R2':r2_train,'Test R2':r2_
                                           'Test RMSE':rmse_test,'Train MAPE':mape_train,'Test M
                                            'Remarks':remarks(r2_train,r2_test)},ignore_index = 
```

In [63]:

```
# Creating a user defined function to highlight the rows which are good fit

def highlight_row(df):
    color_green = ['background-color : #97C1A9']*len(df)
    color_white = ['background-color : white']*len(df)

    if df['Remarks'] == 'Good Fit':
        return color_green
    else:
        return color_white
```

Decision Tree Model

In [64]:

```
model_dt = DecisionTreeRegressor().fit(xtrain,ytrain)

model_performance(model_dt,'Decision Tree')
```

Random Forest Model

In [65]:

```
model_rf = RandomForestRegressor().fit(xtrain,ytrain)

model_performance(model_rf,'Random Forest')
```

KNN

In [66]:

```
model_knn = KNeighborsRegressor().fit(xtrain,ytrain)

model_performance(model_knn, 'KNN')
```

AdaBoost

In [67]:

```
model_ab = AdaBoostRegressor().fit(xtrain,ytrain)

model_performance(model_ab,'AdaBoost')
```

Gradient Boosting

In [68]:

```
model_gb = GradientBoostingRegressor().fit(xtrain,ytrain)

model_performance(model_gb , 'Gradient Boosting')
```

XGBoost

In [69]:

```
model_xgb = XGBRegressor().fit(xtrain,ytrain)

model_performance(model_xgb, 'XGBoost')
```

Neural Network

In [70]:

```
model_nn = MLPRegressor().fit(xtrain,ytrain)

model_performance(model_nn, 'Neural Network')
```

CatBoost

In [71]:

```
model_cb = CatBoostRegressor().fit(xtrain,ytrain)

model_performance(model_cb, 'CatBoost')
```

```
Learning rate set to 0.072185
0:      learn: 0.9579867        total: 154ms    remaining: 2m 33s
1:      learn: 0.9195192        total: 159ms    remaining: 1m 19s
2:      learn: 0.8860296        total: 164ms    remaining: 54.5s
3:      learn: 0.8552237        total: 169ms    remaining: 42.1s
4:      learn: 0.8262818        total: 174ms    remaining: 34.6s
5:      learn: 0.7995746        total: 179ms    remaining: 29.6s
6:      learn: 0.7765343        total: 185ms    remaining: 26.3s
7:      learn: 0.7544273        total: 191ms    remaining: 23.7s
8:      learn: 0.7358304        total: 197ms    remaining: 21.7s
9:      learn: 0.7183826        total: 203ms    remaining: 20.1s
10:     learn: 0.7019796        total: 209ms    remaining: 18.8s
11:     learn: 0.6875885        total: 214ms    remaining: 17.6s
12:     learn: 0.6750950        total: 220ms    remaining: 16.7s
13:     learn: 0.6638052        total: 226ms    remaining: 15.9s
14:     learn: 0.6535420        total: 231ms    remaining: 15.2s
15:     learn: 0.6444852        total: 236ms    remaining: 14.5s
16:     learn: 0.6363529        total: 241ms    remaining: 13.9s
17:     learn: 0.6284220        total: 246ms    remaining: 13.4s
```

In [72]:

```
performance_df.style.apply(highlight_row,axis=1)
```

Out[72]:

	Model_Name	Train R2	Test R2	Train RMSE	Test RMSE	Train MAPE	Test MAPE	Remarks
0	Base Model	0.662110	0.653968	0.581283	0.584654	56.088907	18.944154	Base
1	Decision Tree	1.000000	0.690968	0.000000	0.552513	0.000000	18.530725	Over Fit
2	Random Forest	0.975647	0.819986	0.156056	0.421690	15.027987	6.076583	Over Fit
3	KNN	0.790124	0.669001	0.458122	0.571813	33.911501	11.833031	Over Fit
4	AdaBoost	0.478345	0.467755	0.722257	0.725098	80.480491	39.119074	Under Fit
5	Gradient Boosting	0.714418	0.702631	0.534399	0.541987	45.032207	13.096748	Good Fit
6	XGBoost	0.822820	0.753535	0.420927	0.493422	36.876970	14.070904	Good Fit
7	Neural Network	0.731129	0.709337	0.518527	0.535841	38.427753	8.117910	Good Fit
8	CatBoost	0.800137	0.753808	0.447060	0.493149	37.972769	10.085537	Good Fit

After assessing various models, it was observed that some models exhibited a significant drop in performance when applied to unseen data, indicating overfitting. However, there were models that consistently performed well on both training and unseen data. Notably, the XGB model outperformed other models in terms of performance. Hence, based on its superior performance and generalization ability, we can confidently consider the XGB model as our final choice.