Data Mining Course - Project #1

Professors:
Dr. Farahani, Dr. Kheradpishe

Ali Nikkhah - 99422197

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New York City Airbnb Open Data

Abstract

Since 2008, guests and hosts have used Airbnb to expand on traveling possibilities and present a more unique, personalized way of experiencing the world. Today, Airbnb became one of a kind service that is used and recognized by the whole world. Data analysis on millions of listings provided through Airbnb is a crucial factor for the company. These millions of listings generate a lot of data - data that can be analyzed and used for security, business decisions, understanding of customers' and providers' (hosts) behavior and performance on the platform, guiding marketing initiatives, implementation of innovative additional services and much more.

source: https://www.kaggle.com/dgomonov/new-york-city-airbnb-open-data

Data Source

This dataset has around 49,000 observations in it with 16 columns and it is a mix between categorical and numeric values.

Working with data

در ابتدا داده را بارگذاری کرده و ستون ها و ویژگی های آن را برسی می‌کنیم.

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from matplotlib import font_manager
from bidi.algorithm import get_display
from arabic_reshaper import reshape
font_dirs = ['./fonts/']
font_files = font_manager.findSystemFonts(fontpaths=font_dirs)

font_list = font_manager.createFontList(font_files)
font_manager.fontManager.ttflist.extend(font_list)

plt.rcParams['font.family'] = "Vazir"
```

In [2]:
```
ny=pd.read_csv("AB_NYC_2019.csv")
ny
```

Out[2]:

	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
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9	2018-10-19	0.21	6	365
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45	2019-05-21	0.38	2	355
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0	NaN	NaN	1	365
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270	2019-07-05	4.64	1	194
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9	2018-11-19	0.10	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
48890	36484665	Charming one bedroom - newly renovated rowhouse	8232441	Sabrina	Brooklyn	Bedford-Stuyvesant	40.67853	-73.94995	Private room	70	2	0	NaN	NaN	2	9
48891	36485057	Affordable room in Bushwick/East Williamsburg	6570630	Marisol	Brooklyn	Bushwick	40.70184	-73.93317	Private room	40	4	0	NaN	NaN	2	36
48892	36485431	Sunny Studio at Historical Neighborhood	23492952	Ilgar & Aysel	Manhattan	Harlem	40.81475	-73.94867	Entire home/apt	115	10	0	NaN	NaN	1	27
48893	36485609	43rd St. Time Square-cozy single bed	30985759	Taz	Manhattan	Hell's Kitchen	40.75751	-73.99112	Shared room	55	1	0	NaN	NaN	6	2
48894	36487245	Trendy duplex in the very heart of Hell's Kitchen	68119814	Christophe	Manhattan	Hell's Kitchen	40.76404	-73.98933	Private room	90	7	0	NaN	NaN	1	23

48895 rows × 16 columns

می‌توان دید که در کل ۴۸۸۹۵ سطر و ۱۶ ستون داریم.

In [3]:
```
ny.head()
```

Out[3]:

	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
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9	2018-10-19	0.21	6	365
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45	2019-05-21	0.38	2	355
2	3647	THE VILLAGE OF HARLEM....NEW YORK !	4632	Elisabeth	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0	NaN	NaN	1	365
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270	2019-07-05	4.64	1	194
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9	2018-11-19	0.10	1	0

In [4]:
```
ny.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 48895 entries, 0 to 48894
Data columns (total 16 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  
dtypes: float64(3), int64(7), object(6)
memory usage: 6.0+ MB
```

پس نگاهی اجمالی بر داده می‌توان دید که ۱۶ ستون اطلاعات مهمی را در بردارند و می‌توان برای تحلیل از هر یک از آنها استفاده کرد، همچنین برخی موارد ناقص هم وجود دارد که باید آنها تمیز کنیم.

In [5]:
```
num_cols=ny.select_dtypes(exclude="object").columns
num_cols
```

Out[5]:
```
Index(['id', 'host_id', 'latitude', 'longitude', 'price', 'minimum_nights',
       'number_of_reviews', 'reviews_per_month',
       'calculated_host_listings_count', 'availability_365'],
      dtype='object')
```

In [6]:
```
cat_cols=ny.select_dtypes(include="object").columns
cat_cols
```

Out[6]:
```
Index(['name', 'host_name', 'neighbourhood_group', 'neighbourhood',
       'room_type', 'last_review'],
      dtype='object')
```

In [7]:
```
ny.dtypes
```

Out[7]:
```
id                                  int64
name                               object
host_id                             int64
host_name                          object
neighbourhood_group                object
neighbourhood                      object
latitude                          float64
longitude                         float64
room_type                          object
price                               int64
minimum_nights                      int64
number_of_reviews                   int64
last_review                        object
reviews_per_month                 float64
calculated_host_listings_count      int64
availability_365                    int64
dtype: object
```

داده شامل ۱۰ ویژگی کمی (numerical) و ۶ ویژگی کیفی (categorical) است

In [8]:
```
ny.isnull().sum()
```

Out[8]:
```
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
dtype: int64
```

ستون هایی که شامل کمبود داده هستند: last_review, host_name, last_review, reviews_per_month

با توجه به ماهیت داده، این ستون ها ارزش چندانی ندارند بنابراین میتوان از آنها چشم پوشی کرد. در مورد ستون reviews_per_month می‌توانیم داده نال را با 0 جایگزین کنیم.

In [9]:
```
ny=ny.drop(["id","host_name","last_review"],axis=1)
ny.head()
```

Out[9]:

	name	host_id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
0	Clean & quiet apt home by the park	2787	Brooklyn	Kensington	40.64749	-73.97237	Private room	149	1	9	0.21	6	365
1	Skylit Midtown Castle	2845	Manhattan	Midtown	40.75362	-73.98377	Entire home/apt	225	1	45	0.38	2	355
2	THE VILLAGE OF HARLEM....NEW YORK !	4632	Manhattan	Harlem	40.80902	-73.94190	Private room	150	3	0	NaN	1	365
3	Cozy Entire Floor of Brownstone	4869	Brooklyn	Clinton Hill	40.68514	-73.95976	Entire home/apt	89	1	270	4.64	1	194
4	Entire Apt: Spacious Studio/Loft by central park	7192	Manhattan	East Harlem	40.79851	-73.94399	Entire home/apt	80	10	9	0.10	1	0

In [10]:
```
ny=ny.fillna({"reviews_per_month":0})
```

In [11]:
```
ny.isnull().sum()
```

Out[11]:
```
name                              16
host_id                            0
neighbourhood_group                0
neighbourhood                      0
latitude                           0
longitude                          0
room_type                          0
price                              0
minimum_nights                     0
number_of_reviews                  0
reviews_per_month                  0
calculated_host_listings_count     0
availability_365                   0
dtype: int64
```

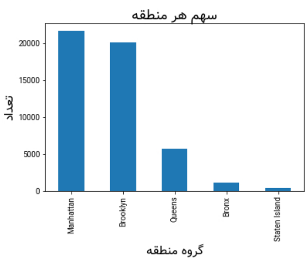
In [12]:
```
ny.duplicated().sum()
```

Out[12]:
```
0
```

Data Analysis

In [13]:
```
ny.neighbourhood_group.value_counts().plot(kind="bar")
plt.title(get_display(reshape("سهم هر منطقه")), fontsize=18)
plt.xlabel(get_display(reshape("گروه منطقه")), fontsize= 16)
plt.ylabel(get_display(reshape("تعداد")), fontsize= 16)
```

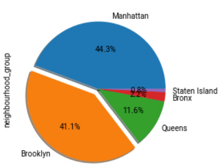
Out[13]:
```
Text(0, 0.5, 'دادعت')
```



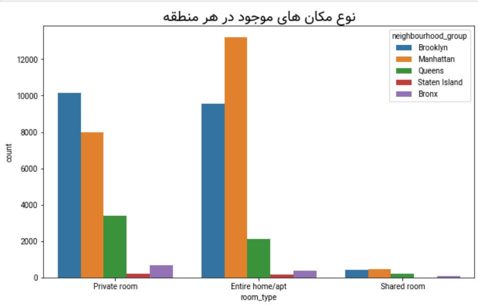
Manhatten و Brooklyn بیشترین سهم از تعداد هتل را دارند.

In [14]:
```
ny['neighbourhood_group'].value_counts().plot.pie(explode=[0,0.1,0,0,0],autopct='%1.1f%%',shadow=True)
```

Out[14]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fc7b47c0240>
```



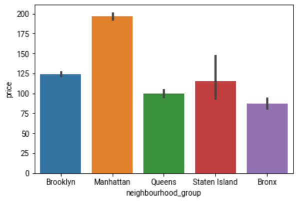
In [15]:
```
plt.figure(figsize=(10,6))
sns.countplot(x = 'room_type',hue = "neighbourhood_group",data = ny)
plt.title(get_display(reshape("نوع مکان های موجود در هر منطقه")), fontsize=18)
plt.show()
```



سهم هر منطقه از انواع مکان قابل مشاهده است.

In [16]:
```python
sns.barplot(data=ny,x="neighbourhood_group",y="price")
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc7b48252b0>



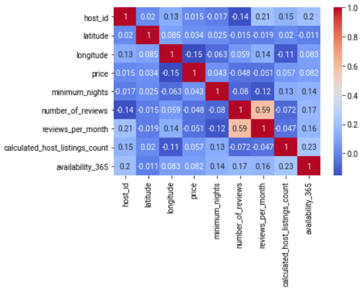
با مشاهده نمودار منطقه-قیمت بالا میتوان دید که Manhattan بیشترین قیمت را دارد.

In [17]:
```python
ny["price"].describe()
```

Out[17]:
```
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
```

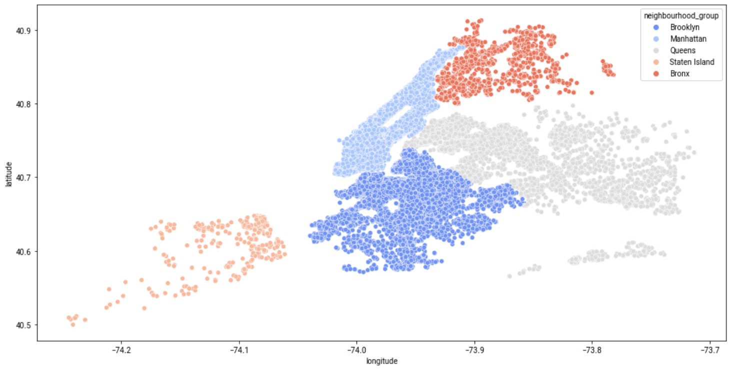
In [18]:
```python
sns.heatmap(ny.corr(),annot=True,cmap="coolwarm")
```

Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x7fc7b4684ef0>



با مشاهده نمودار هیت مپ بالا می‌توان دید که وابستگی قوی بین هیچ یک از ویژگی ها وجو ندارد بجز number_of_reviews , reviews_per_month

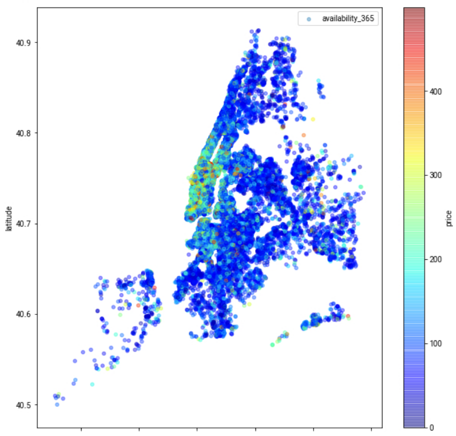
In [19]:
```python
f,ax = plt.subplots(figsize=(16,8))
ax = sns.scatterplot(y=ny.latitude,x=ny.longitude,hue=ny.neighbourhood_group,palette="coolwarm")
plt.show()
```



نمودار طول و عرض جغرافیایی از مناطق موجود

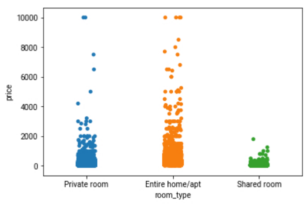
In [20]:
```python
plt.figure(figsize=(10,6))
ny1=ny[ny.price<500]

ny1.plot(kind='scatter', x='longitude',y='latitude',label='availability_365',c='price',cmap=plt.get_cmap('jet'),colorbar=True,alpha=0.4,figsize=(10,10))

plt.show()
```

<Figure size 720x432 with 0 Axes>



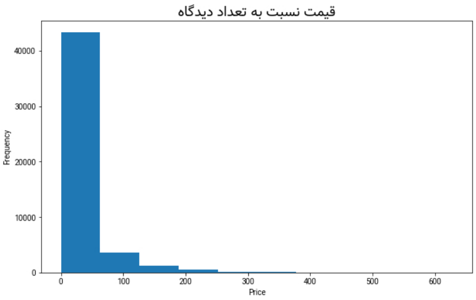
نمودار مقایسه قیمت نسبت به عرض جغرافیایی

In [21]:
```python
sns.stripplot(data=ny,x='room_type',y='price',jitter=True)

plt.show()
```



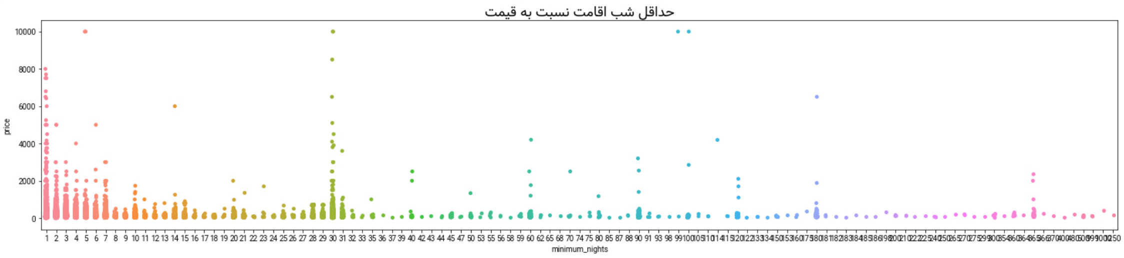
می‌توان فهمید که انواع مکان بازه قیمتی مختلفی دارند.

In [22]:
```python
plt.figure(figsize=(10,6))
ny['number_of_reviews'].plot(kind='hist')
plt.xlabel("Price")
plt.title(get_display(reshape("قیمت نسبت به تعداد دیدگاه")), fontsize=18)

plt.show()
```



مکان هایی که کمترین قیمت را دارند(زیر ۵۰ دلار) دارای بیشترین تعداد دیدگاه هستند.

In [23]:
```python
f,ax = plt.subplots(figsize=(25,5))
plt.title(get_display(reshape("حداقل شب اقامت نسبت به قیمت")), fontsize=18)
ax=sns.stripplot(data=ny,x='minimum_nights',y='price',jitter=True,)

plt.show()
```



مکان هایی که دارای حداقل شب اقامت کمتری هستند دارای قیمت بالاتری هم هستند.

مکان های دارای بیشترین تعداد دیدگاه

In [24]:
```python
ny1=ny.sort_values(by=['number_of_reviews'],ascending=False).head(100)
ny1.head()
```

Out[24]:

	name	host_id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
11759	Room near JFK Queen Bed	47621202	Queens	Jamaica	40.66730	-73.76831	Private room	47	1	629	14.58	2	333
2031	Great Bedroom in Manhattan	4734398	Manhattan	Harlem	40.82085	-73.94025	Private room	49	1	607	7.75	3	293
2030	Beautiful Bedroom in Manhattan	4734398	Manhattan	Harlem	40.82124	-73.93838	Private room	49	1	597	7.72	3	342
2015	Private Bedroom in Manhattan	4734398	Manhattan	Harlem	40.82264	-73.94041	Private room	49	1	594	7.57	3	339
13495	Room Near JFK Twin Beds	47621202	Queens	Jamaica	40.66939	-73.76975	Private room	47	1	576	13.40	2	173

مقایسه مدل های مختلف

فرض می‌کنیم داده ها از رگرسیون خطی پیروی می‌کنند

In [25]:
```python
import statsmodels.api as sm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error,r2_score
from sklearn import preprocessing
from sklearn.feature_selection import RFE

import warnings
warnings.filterwarnings('ignore')

# ny["name"]
# ny["name"] = pd.concat([ny, pd.get_dummies(ny['name'],sparse=True)], axis=1)

# pd.concat([ny, pd.get_dummies(ny['name']).astype(np.int8)],axis=1)
```

In [26]:
```python
# ny["name"] = pd.concat([ny, pd.get_dummies(ny['name'],sparse=True)], axis=1)


ny["name"] = pd.get_dummies(ny['name'])
ny["neighbourhood_group"]= pd.get_dummies(ny['neighbourhood_group'])
ny["neighbourhood"]= pd.get_dummies(ny['neighbourhood'])
ny["room_type"]= pd.get_dummies(ny['room_type'])
```

In [27]:
```python
ny
```

Out[27]:

	name	host_id	neighbourhood_group	neighbourhood	latitude	longitude	room_type	price	minimum_nights	number_of_reviews	reviews_per_month	calculated_host_listings_count	availability_365
0	0	2787	0	0	40.64749	-73.97237	0	149	1	9	0.21	6	365
1	0	2845	0	0	40.75362	-73.98377	1	225	1	45	0.38	2	355
2	0	4632	0	0	40.80902	-73.94190	0	150	3	0	0.00	1	365
3	0	4869	0	0	40.68514	-73.95976	1	89	1	270	4.64	1	194
4	0	7192	0	0	40.79851	-73.94399	1	80	10	9	0.10	1	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...
48890	0	8232441	0	0	40.67853	-73.94995	0	70	2	0	0.00	2	9
48891	0	6570630	0	0	40.70184	-73.93317	0	40	4	0	0.00	2	36
48892	0	23492952	0	0	40.81475	-73.94867	1	115	10	0	0.00	1	27
48893	0	30985759	0	0	40.75751	-73.99112	0	55	1	0	0.00	6	2
48894	0	68119814	0	0	40.76404	-73.98933	0	90	7	0	0.00	1	23

48895 rows × 13 columns

Model 1

In [28]:
```python
X=ny.drop('price',axis=1)
y=ny['price']
```

In [29]:
```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)
```

In [30]:
```python
lr=LinearRegression()
lr.fit(X_train,y_train)
y_pred=lr.predict(X_test)
r2_score(y_test,y_pred)
```

Out[30]:
```
0.12475900377581894
```

با استفاده از مدل SLR (Superwise linear regression) به دقت ۱۲.۴۷٪ می‌رسیم که می‌تواند قیمت مکان ها را نسبت به ویژگی های مختلف پیش بینی کند.

Model 2

In [31]:
```python
rfe = RFE(lr, 7)
#Transforming data using RFE
X_rfe = rfe.fit_transform(X,y)
#Fitting the data to model
lr.fit(X_rfe,y)
print(rfe.support_)
print(rfe.ranking_)
```

```
[ True False  True  True  True  True  True False False  True False False]
[1 6 1 1 1 1 1 5 2 1 4 3]
```

In [32]:
```python
#no of features
nof_list=np.arange(1,10)
high_score=0
#Variable to store the optimum features
nof=0
```

```python
score_list =[]
for n in range(len(nof_list)):
    X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.3, random_state = 0)
    lr = LinearRegression()
    rfe = RFE(lr,nof_list[n])
    X_train_rfe = rfe.fit_transform(X_train,y_train)
    X_test_rfe = rfe.transform(X_test)
    lr.fit(X_train_rfe,y_train)
    score = lr.score(X_test_rfe,y_test)
    score_list.append(score)
    if(score>high_score):
        high_score = score
        nof = nof_list[n]
print("Optimum number of features: %d" %nof)
print("Score with %d features: %f" % (nof, high_score))
```

```
Optimum number of features: 9
Score with 9 features: 0.103964
```

با استفاده از مدل بازگشتی حذف ویژگی (recurssive feature elimination model) به دقت ۱۰.۳۹٪ می‌رسیم. با ۹ ویژگی

Model 3

In [33]:

```python
xc=sm.add_constant(X)
lm=sm.OLS(y,xc).fit()
lm.summary()
```

Out[33]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.091
Model:	OLS	**Adj. R-squared:**	0.091
Method:	Least Squares	**F-statistic:**	410.3
Date:	Mon, 05 Apr 2021	**Prob (F-statistic):**	0.00
Time:	20:20:15	**Log-Likelihood:**	-3.3504e+05
No. Observations:	48895	**AIC:**	6.701e+05
Df Residuals:	48882	**BIC:**	6.702e+05
Df Model:	12		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-5.227e+04	1966.959	-26.576	0.000	-5.61e+04	-4.84e+04
name	-35.0187	228.940	-0.153	0.878	-483.743	413.706
host_id	9.662e-08	1.49e-08	6.493	0.000	6.75e-08	1.26e-07
neighbourhood_group	-48.6887	7.726	-6.302	0.000	-63.831	-33.546
neighbourhood	11.7782	36.036	0.327	0.744	-58.853	82.409
latitude	238.8920	20.167	11.845	0.000	199.363	278.421
longitude	-576.3336	23.887	-24.128	0.000	-623.152	-529.515
room_type	114.0089	2.130	53.525	0.000	109.834	118.184
minimum_nights	-0.0324	0.052	-0.622	0.534	-0.134	0.070
number_of_reviews	-0.1875	0.031	-6.051	0.000	-0.248	-0.127
reviews_per_month	-4.5483	0.870	-5.228	0.000	-6.254	-2.843
calculated_host_listings_count	-0.1122	0.033	-3.369	0.001	-0.178	-0.047
availability_365	0.1886	0.009	22.061	0.000	0.172	0.205

Omnibus:	110027.366	**Durbin-Watson:**	1.849
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	971923441.228
Skew:	21.285	**Prob(JB):**	0.00
Kurtosis:	692.387	**Cond. No.**	1.97e+11

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.97e+11. This might indicate that there are
strong multicollinearity or other numerical problems.

In [34]:

```python
X=X.drop("minimum_nights",axis=1)
```

In [35]:

```python
xc=sm.add_constant(X)
lm=sm.OLS(y,xc).fit()
lm.summary()
```

Out[35]:

OLS Regression Results

Dep. Variable:	price	**R-squared:**	0.091
Model:	OLS	**Adj. R-squared:**	0.091
Method:	Least Squares	**F-statistic:**	447.5
Date:	Mon, 05 Apr 2021	**Prob (F-statistic):**	0.00
Time:	20:20:15	**Log-Likelihood:**	-3.3504e+05
No. Observations:	48895	**AIC:**	6.701e+05
Df Residuals:	48883	**BIC:**	6.702e+05
Df Model:	11		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-5.222e+04	1965.198	-26.574	0.000	-5.61e+04	-4.84e+04
name	-34.8508	228.938	-0.152	0.879	-483.572	413.871
host_id	9.693e-08	1.49e-08	6.518	0.000	6.78e-08	1.26e-07
neighbourhood_group	-48.6003	7.724	-6.292	0.000	-63.740	-33.460
neighbourhood	11.8360	36.036	0.328	0.743	-58.794	82.466
latitude	238.4899	20.157	11.832	0.000	198.982	277.998
longitude	-575.8552	23.874	-24.120	0.000	-622.649	-529.061
room_type	113.9376	2.127	53.570	0.000	109.769	118.106
number_of_reviews	-0.1869	0.031	-6.035	0.000	-0.248	-0.126
reviews_per_month	-4.5029	0.867	-5.194	0.000	-6.202	-2.804
calculated_host_listings_count	-0.1138	0.033	-3.426	0.001	-0.179	-0.049
availability_365	0.1878	0.008	22.234	0.000	0.171	0.204

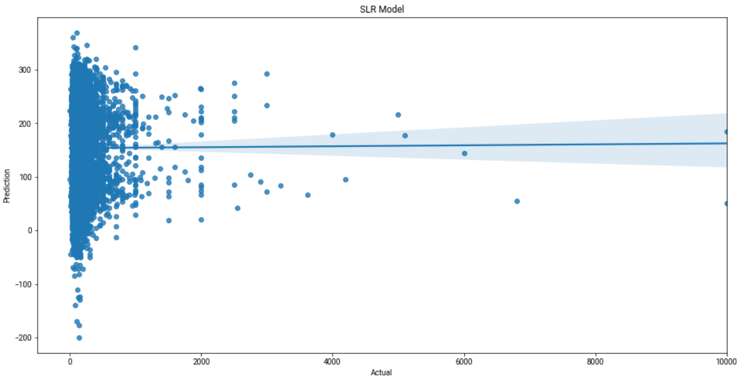
Omnibus:	110015.557	**Durbin-Watson:**	1.849
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	971217224.795
Skew:	21.279	**Prob(JB):**	0.00
Kurtosis:	692.136	**Cond. No.**	1.97e+11

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.97e+11. This might indicate that there are
strong multicollinearity or other numerical problems.

با استفاده از مدل OLS و حذف سه ویژگی: name, neighbouhood, minimum nights به دقت ۹.۱٪ می‌رسیم

بنابراین از مدل ۱ (SLR) استفاده می‌کنیم چون دقت بالاتری (%۱۲.۴۷) نسبت به بقیه مدل ها دارد.

In [36]:
```
plt.figure(figsize=(16,8))
sns.regplot(y_test,y_pred)
plt.xlabel('Actual')
plt.ylabel('Prediction')
plt.title("SLR Model")
plt.grid(False)
plt.show()
```



همانطور که قابل مشاهده است تراکم بسیار زیادی در بازه ۰ تا ۱۰۰۰ وجود دارد.
دقت مدل کم است زیرا داده ها به طور مساوی در امتداد خط رگرسیون خطی پخش نمی‌شوند.

In [ ]: