AIR BNB Price Prediction

Problem Statement

- The purpose of this project is to explore the data using pyspark and predict the price of an Airbnb listing from features extracted from the listings using SparkML.

Data Source

- https://www.kaggle.com/stevezhenghp/airbnb-price-prediction
- Number of columns : 29
- Number of Rows : 74112
- Dataset Size: 99MB

Data Source details

```
df.printSchema()
```

```
root
 |-- id: string (nullable = true)
 |-- log_price: double (nullable = true)
 |-- property_type: string (nullable = true)
 |-- room_type: string (nullable = true)
 |-- amenities: string (nullable = true)
 |-- accommodates: integer (nullable = true)
 |-- bathrooms: double (nullable = true)
 |-- bed_type: string (nullable = true)
 |-- cancellation_policy: string (nullable = true)
 |-- cleaning_fee: boolean (nullable = true)
 |-- city: string (nullable = true)
 |-- description: string (nullable = true)
 |-- first_review: string (nullable = true)
 |-- host_has_profile_pic: string (nullable = true)
 |-- host_identity_verified: string (nullable = true)
 |-- host_response_rate: string (nullable = true)
 |-- host_since: string (nullable = true)
 |-- instant_bookable: string (nullable = true)
 |-- last_review: string (nullable = true)
 |-- latitude: double (nullable = true)
 |-- longitude: double (nullable = true)
 |-- name: string (nullable = true)
 |-- neighbourhood: string (nullable = true)
 |-- number_of_reviews: integer (nullable = true)
 |-- review_scores_rating: double (nullable = true)
 |-- thumbnail_url: string (nullable = true)
 |-- zipcode: string (nullable = true)
 |-- bedrooms: double (nullable = true)
 |-- beds: double (nullable = true)
```

```
id                     - AIRBNB unique ID
log_price              - Price for the AIRBNB
property type          - Apartment/house/villa
room type              - Entire house/sharing/single room
amenities              - TV/Wifi/Hot water
accommodates           - Accomodates how many people
bathroom               - How many bathrooms
bed_type               - Real bed/couch/airbed
Cancellation policy     - Strict/Flexible
cleaning fees          - True/False
description            - Description
first_review           - first review date
host_has_profile pic - True/False
host_identity_verified- True/False
host_response_rate     - Percentage
host_since             - Date
instant_bookable       - True/False
last_review            - Date
latitude               - Latitude position
longitude              -Longitude position
name                   - Name of the AIRBNB
neighbourhood          - Neigborhood places
number_of_reviews      - Total number of reviews
review_scores_rating - Average rating for the AIRBNB
thumbnail_url          - URL for the AIRBNB website
zipcode                - Zipcode of the location
bedrooms               - Number of bedrooms
beds                   - Number of beds
```

Displaying the first row of the dataframe

```
df.show(n=1,truncate=False,vertical=True)
```

```
-RECORD 0-------------------------------------------------------------------------------------------------------------------
 id                     | 6304928
 log_price              | 5.1298987149230735
 property_type          | Apartment
 room_type              | Entire home/apt
 amenities              | {"Wireless Internet","Air conditioning",Kitchen,Heating,"Family/kid friendly",Washer,Dryer,"Smoke detector","Fire
 accommodates           | 7
 bathrooms              | 1.0
 bed_type               | Real Bed
 cancellation_policy    | strict
 cleaning_fee           | true
 city                   | NYC
 description            | Enjoy travelling during your stay in Manhattan. My place is centrally located near Times Square and Central Park
 first_review           | 2017-08-05
 host_has_profile_pic   | t
 host_identity_verified | f
 host_response_rate     | 100%
 host_since             | 2017-06-19
 instant_bookable       | t
 last_review            | 2017-09-23
 latitude               | 40.766115415949685
 longitude              | -73.98903992265213
 name                   | Superb 3BR Apt Located Near Times Square
 neighbourhood          | Hell's Kitchen
 number_of_reviews      | 6
 review_scores_rating   | 93.0
 thumbnail_url          | https://a0.muscache.com/im/pictures/348a55fe-4b65-452a-b48a-bfecb3b58a66.jpg?aki_policy=small
 zipcode                | 10019
 bedrooms               | 3.0
 beds                   | 3.0
only showing top 1 row
```

Total count of each property type

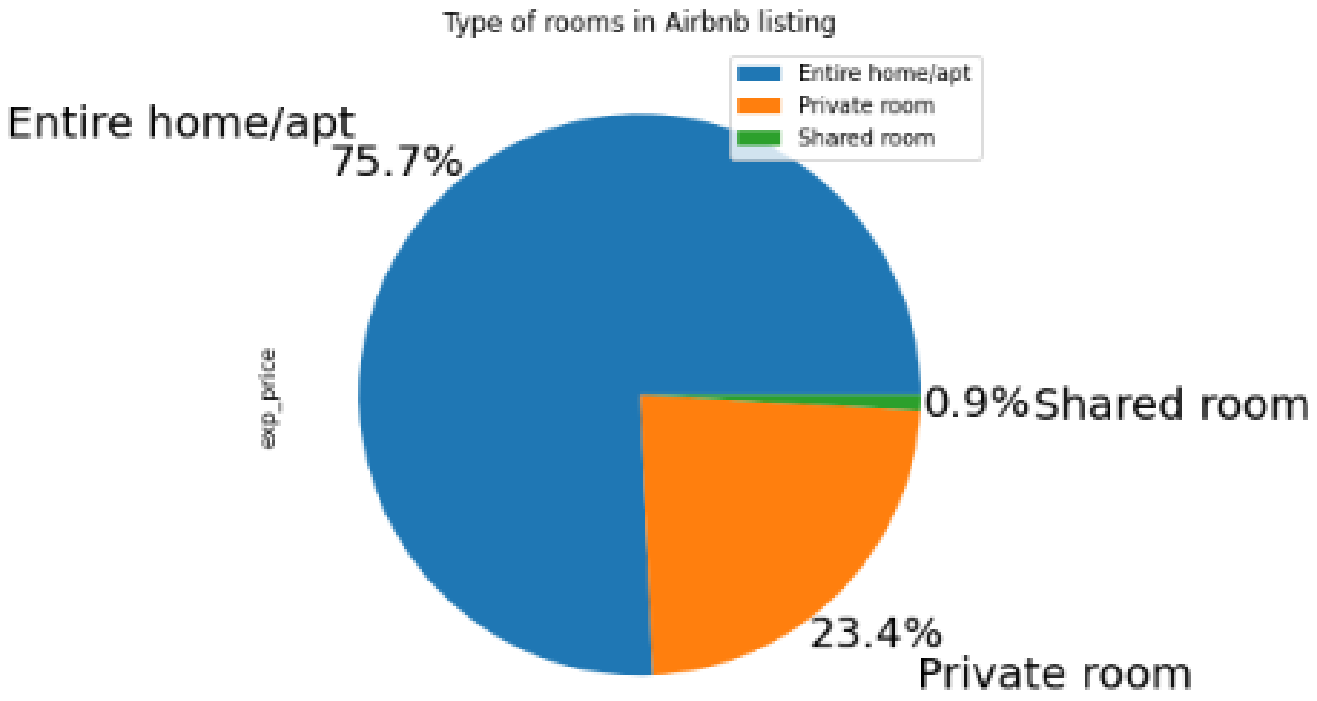
```
SELECT property_type,count(id) as Total_count
FROM price
group by property_type
order by Total_count desc

"""
print("Total count based on property type")
spark.sql(query).show()
```

```
Total count based on property type
+--------------------+-----------+
|       property_type|Total_count|
+--------------------+-----------+
|           Apartment|      24750|
|               House|       8903|
|         Condominium|       1421|
|           Townhouse|        940|
|                Loft|        719|
|          Guesthouse|        335|
|               Other|        331|
|     Bed & Breakfast|        286|
|            Bungalow|        216|
|         Guest suite|         97|
|                Dorm|         90|
|               Villa|         68|
|              In-law|         61|
|              Hostel|         46|
|               Cabin|         45|
|           Camper/RV|         35|
|                Boat|         35|
|      Boutique hotel|         32|
|           Timeshare|         30|
|Serviced apartment|           12|
+--------------------+-----------+
only showing top 20 rows
```

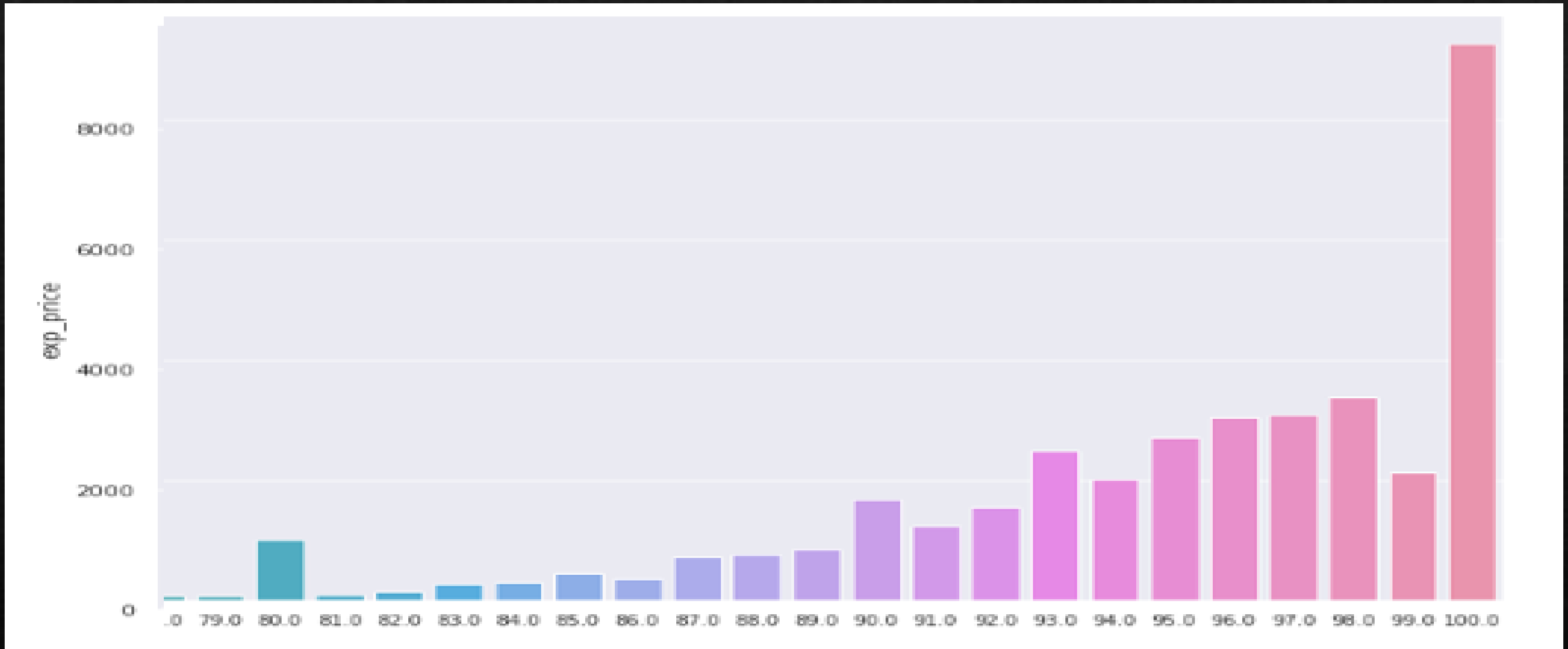
Type of rooms available in Airbnb listings

```
df1.groupby(['room_type']).sum().plot(kind='pie',y= 'exp_price',radius = 1,title=
 "Type of rooms in Airbnb listing",autopct='%1.1f%%',fontsize=20,figsize=(6, 6),pctdistance=1.2,labeldistance=1.4)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e813be210>
```



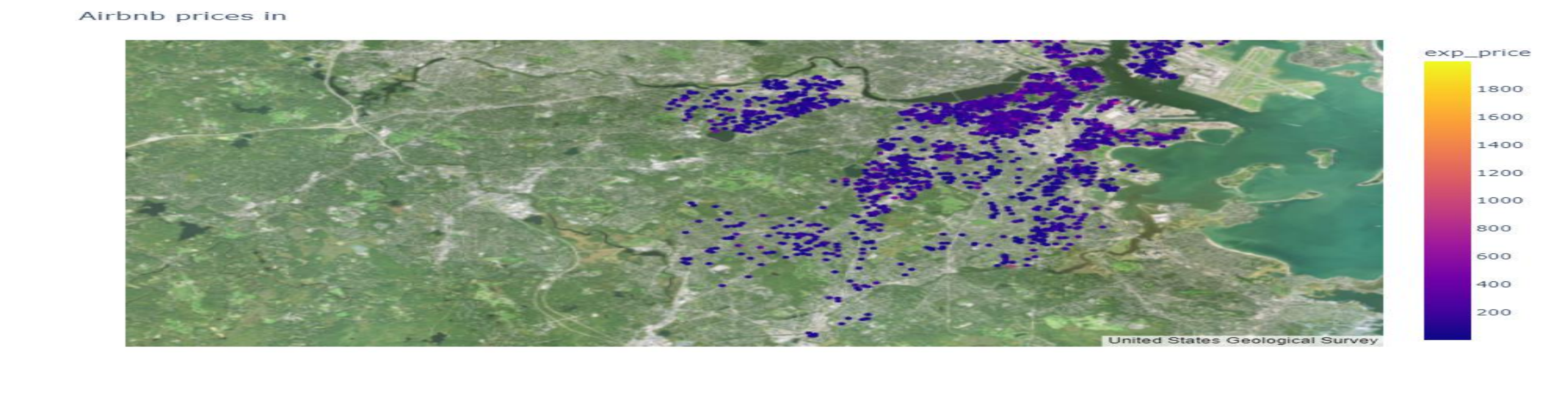
Is there any correlation between the price and rating of the Airbnb listing?



It could be inferred from the above graph that, the price of the Airbnb listing is proportional to the rating

Location of the Airbnb listings along with the price

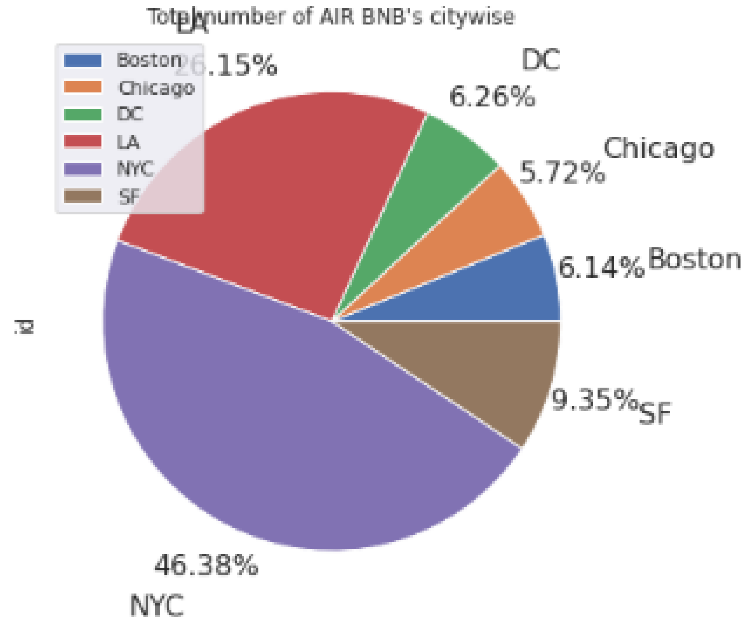
```
fig = px.scatter_mapbox(df1,lat="latitude",lon="longitude",hover_data=['name'],color='exp_price',zoom=10)
fig.update_layout(
            title = f'Airbnb prices in ',geo_scope='usa',width=1000, height=600,mapbox_style="white-bg",
            mapbox_layers=[{
                 "below": 'traces',"sourcetype": "raster","sourceattribution": "United States Geological Survey",
                 "source": ["https://basemap.nationalmap.gov/arcgis/rest/services/USGSImageryOnly/MapServer/tile/{z}/{y}/{x}"]
              }]
    )
fig.show()
```



Which city has the highest number of Airbnbs?

```
df1.groupby(['city']).count().plot(kind='pie',y= 'id',radius = 1,title=
 "Total number of AIR BNB's citywise",autopct='%1.2f%%',fontsize=16,figsize=(6, 6),pctdistance=1.2,labeldistance=1.4)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f4e80eab510>
```



Does the rating of Airbnb listing depend on the cancellation policy?

```
df.createOrReplaceTempView('cancellation')

query = """
SELECT cancellation_policy,count(cancellation_policy),sum(review_scores_rating)/count(review_scores_rating) as avg_rating
FROM cancellation
group by cancellation_policy
order by avg_rating desc

"""
print("Cancellation policy")
spark.sql(query).show()
```

```
Cancellation policy
+-------------------+--------------------------+-----------------+
|cancellation_policy|count(cancellation_policy)|       avg_rating|
+-------------------+--------------------------+-----------------+
|           moderate|                     11386|95.08598278587739|
|           flexible|                      7342|94.55107600108963|
|             strict|                     19733|93.82673693812396|
|     super_strict_30|                        33|89.33333333333333|
|     super_strict_60|                         6|85.66666666666667|
+-------------------+--------------------------+-----------------+
```

From the above figures, it could be inferred that the rating doesn't depend on the cancellation policy

Correlation of the feature variables with the log_price

```
import six
for i in df4.columns:
    if not( isinstance(df4.select(i).take(1)[0][0], six.string_types)):
        print( "Correlation to log_price for ", i, df4.stat.corr('log_price',i))
```

```
Correlation to log_price for  log_price 1.0
Correlation to log_price for  accommodates 0.5821216346150896
Correlation to log_price for  bathrooms 0.3066494495230136
Correlation to log_price for  latitude 0.000853903764855051
Correlation to log_price for  longitude -0.05823807457798872
Correlation to log_price for  number_of_reviews -0.012968757197144054
Correlation to log_price for  review_scores_rating 0.07742280233346707
Correlation to log_price for  bedrooms 0.4808712214477055
Correlation to log_price for  beds 0.4471387234238176
```

Linear Regression to predict the Log_price based on the features of the listings

```
(trainingData, testData) = df4.randomSplit([0.8, 0.2])
```

```
lr = LinearRegression(featuresCol = 'features', labelCol='log_price', maxIter=10, regParam=0.3, elasticNetParam=0.8)
lr_model = lr.fit(trainingData)
print("Coefficients: " + str(lr_model.coefficients))
print("Intercept: " + str(lr_model.intercept))
```

Decision Tree Regressor

Decision Tree Regressor

```
from pyspark.ml.regression import DecisionTreeRegressor
dt = DecisionTreeRegressor(featuresCol ='features', labelCol = 'log_price')
dt_model = dt.fit(trainingData)
dt_predictions = dt_model.transform(testData)
dt_evaluator = RegressionEvaluator(
    labelCol="log_price", predictionCol="prediction", metricName="rmse")
rmse = dt_evaluator.evaluate(dt_predictions)
print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

```
Root Mean Squared Error (RMSE) on test data = 0.060637
```

Gradient Boosting Regressor

```
[ ]  gbt_evaluator = RegressionEvaluator(
         labelCol="log_price", predictionCol="prediction", metricName="rmse")
     rmse = gbt_evaluator.evaluate(gbt_predictions)
     print("Root Mean Squared Error (RMSE) on test data = %g" % rmse)
```

```
Root Mean Squared Error (RMSE) on test data = 0.0635137
```

```
[ ]  print("R Squared (R2) on test data = %g" % gbt_evaluator.evaluate(gbt_predictions))
```

```
R Squared (R2) on test data = 0.0635137
```

THANK YOU