Course Title:

Data Science (数据科学)

(Semester: Fall 2021)

Dr. Oluwarotimi W. SAMUEL

Research Center for Neural Engineering
Shenzhen Institutes of Advanced Technology
Chinese Academy of Sciences

Contact: (Email: <u>samuel@siat.ac.cn</u> & <u>timitex92@gmail.com</u>)

Phone: +86-15814491870

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Exploratory Data Analysis (EDA)

- **□** Outline for today's lecture
 - ✓ Explorative Data Analysis
 - ✓ Case Study I: Using Online Dataset
 - ✓ Case Study II: Using Online Dataset

Exploratory Data Analysis (EDA)

□ **Objective:** This lecture will focus on Exploratory Data Analysis with emphases on Case studies.

□ Expectation: At the end of this lecture, students are expected to understand the procedure for Exploring and Analyzing data when carrying out a Data Science projects.

✓ Data exploration and analysis is an approach similar to whereby visual tools are employed to understand the characteristics of the data.

✓ Exploratory data analysis is an approach of analyzing data sets to summarize their main characteristics.

Data Exploration



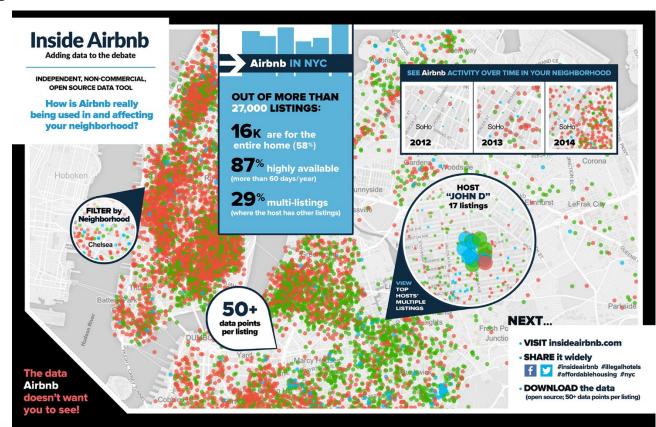
☐ Importance of Data Exploration:

- ✓ Helps to determine the cleaning processes that should be applied
- ✓ Helps us to determine the right tool for analysis
- ✓ May provide Data Scientists with pre-knowledge of inherent trend/s in the dataset
- ✓ Helps us to select the appropriate machine learning model/s

☐ Case Study:

Airbnb--Provide data that quantifies the impact of short-term rentals on housing and residential communities; and also provides a platform to support advocacy for policies to protect our cities from the impacts of short-term rentals.

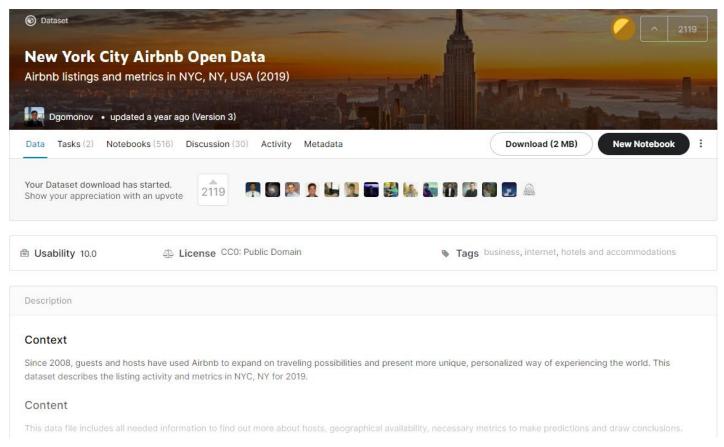
http://insideairbnb.com/about.html





☐ Exploring Data Visualization (Case Study)

Dataset



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

☐ Case Study:

First, relevant libraries are imported (numpy, pandas, matplolib, seaborn, etc.) to work with the Airbnb data.

```
###... Import all relevant libraries...###

import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import numpy as np # linear algebra

import matplotlib.pyplot as plt

import seaborn as sn
```

☐ Case Study:

Next, we read the csv file that contained the data using read_csv function provided by the Pandas library. And then display the first 5 records in the Dataframe(df)

```
###... Loading the Dataset ...###

# Read the CSV file that contains the dataset using read_csv function

# Display the first 5 records in the pandas dataframe (df)

# df = pd.read_csv('Airbnb_NYC_2019.csv', low_memory=False)

# df.head() df: {DataFrame: (48895, 16)}
```

☐ Case Study:

Displaying the first 5 records in the data frame:

	id	name	host_id	host_name	neighbourhood_group	neighbourhood	latitude
0	2539	Clean & quiet apt home by the park	2787	John	Brooklyn	Kensington	40.64749
1	2595	Skylit Midtown Castle	2845	Jennifer	Manhattan	Midtown	40.75362
2	3647	THE VILLAGE OF HARLEMNEW YORK!	4632	Elisabeth	Manhattan	Harlem	40.80902
3	3831	Cozy Entire Floor of Brownstone	4869	LisaRoxanne	Brooklyn	Clinton Hill	40.68514
4	5022	Entire Apt: Spacious Studio/Loft by central park	7192	Laura	Manhattan	East Harlem	40.79851

☐ Case Study:

Next, we tried to check the data types of all the columns in the data frame:

☐ Case Study:

data types in df:

```
id
                                      int64
                                     object
name
                                      int64
host id
host name
                                     object
neighbourhood group
                                     object
neighbourhood
                                     object
                                    float64
latitude
longitude
                                    float64
                                     object
room type
                                      int64
price
                                      int64
minimum nights
number of reviews
                                      int64
last review
                                     object
                                    float64
reviews per month
calculated host listings count
                                      int64
availability 365
                                      int64
dtype: object
```

☐ Case Study:

Next, we tried describing some basic statistics of the data in each column of the data frame using the "describe" ()" method.

```
# Describing some basic statistics of the data in each column of the data frame

df.describe() df: {DataFrame: (48895, 16)}

+
```

☐ Case Study:

Basic Statistics

```
df.describe() df: {DataFrame: (48895, 16)}
```



mean 1.901714e+07 6.762001e+07 40.728949 -73.952170 152.720687 7.029962 23.274466 1.373221 std 1.098311e+07 7.861097e+07 0.054530 0.046157 240.154170 20.510550 44.550582 1.680442 min 2.539000e+03 2.438000e+03 40.499790 -74.244420 0.000000 1.000000 0.000000 0.010000 25% 9.471945e+06 7.822033e+06 40.690100 -73.983070 69.000000 1.000000 1.000000 0.190000 50% 1.967728e+07 3.079382e+07 40.723070 -73.9352680 106.000000 3.000000 5.000000 5.000000 24.000000 2.020000		id	host_id	latitude	longitude	price	minimum_nights	number_of_reviews	reviews_r
std 1.098311e+07 7.861097e+07 0.054530 0.046157 240.154170 20.510550 44.550582 1.680442 min 2.539000e+03 2.438000e+03 40.499790 -74.244420 0.000000 1.000000 0.000000 0.010000 25% 9.471945e+06 7.822033e+06 40.690100 -73.983070 69.000000 1.000000 1.000000 0.190000 50% 1.967728e+07 3.079382e+07 40.723070 -73.955680 106.000000 3.000000 5.000000 0.720000 75% 2.915218e+07 1.074344e+08 40.763115 -73.936275 175.000000 5.000000 24.000000 2.020000	count	4.889500e+04	4.889500e+04	48895.000000	48895.000000	48895.000000	48895.000000	48895.000000	38843.000
min 2.539000e+03 2.438000e+03 40.499790 -74.244420 0.000000 1.000000 0.000000 0.010000 25% 9.471945e+06 7.822033e+06 40.690100 -73.983070 69.000000 1.000000 1.000000 0.190000 50% 1.967728e+07 3.079382e+07 40.723070 -73.955680 106.000000 3.000000 5.000000 5.000000 0.720000 75% 2.915218e+07 1.074344e+08 40.763115 -73.936275 175.000000 5.000000 24.000000 2.020000	mean	1.901714e+07	6.762001e+07	40.728949	-73.952170	152.720687	7.029962	23.274466	1.373221
25% 9.471945e+06 7.822033e+06 40.690100 -73.983070 69.000000 1.000000 1.000000 0.190000 50% 1.967728e+07 3.079382e+07 40.723070 -73.955680 106.000000 3.000000 5.000000 5.000000 0.720000 75% 2.915218e+07 1.074344e+08 40.763115 -73.936275 175.000000 5.000000 24.000000 2.020000	std	1.098311e+07	7.861097e+07	0.054530	0.046157	240.154170	20.510550	44.550582	1.680442
50% 1.967728e+07 3.079382e+07 40.723070 -73.955680 106.000000 3.000000 5.000000 0.720000 75% 2.915218e+07 1.074344e+08 40.763115 -73.936275 175.000000 5.000000 24.000000 2.020000	min	2.539000e+03	2.438000e+03	40.499790	-74.244420	0.000000	1.000000	0.000000	0.010000
75 % 2.915218e+07 1.074344e+08 40.763115 -73.936275 175.000000 5.000000 24.000000 2.020000	25%	9.471945e+06	7.822033e+06	40.690100	-73.983070	69.000000	1.000000	1.000000	0.190000
	50%	1.967728e+07	3.079382e+07	40.723070	-73.955680	106.000000	3.000000	5.000000	0.720000
max 3.648724e+07 2.743213e+08 40.913060 -73.712990 10000.000000 1250.000000 629.000000 58.50000	75%	2.915218e+07	1.074344e+08	40.763115	-73.936275	175.000000	5.000000	24.000000	2.020000
	max	3.648724e+07	2.743213e+08	40.913060	-73.712990	10000.000000	1250.000000	629.000000	58.500000

☐ Case Study:

Next, Checking for null values.

```
# Checking for null values

df.isnull().sum() df: {DataFrame: (48895, 16)}
```

```
id
                                         0
name
                                        16
host id
                                         0
host name
                                        21
neighbourhood group
                                         0
neighbourhood
latitude
longitude
room type
                                         0
price
minimum nights
                                         0
number of reviews
last review
                                     10052
reviews per month
                                     10052
calculated host listings count
                                         0
availability 365
dtype: int64
```

☐ Case Study:

Next, we need to drop some columns:

After a quick analysis, I deiced to drop less effective variables such as the:

- ✓ last_review, id, host_name, since some values are missing in these columns.
- ✓ I have also filled the NaN values of reviews_per_month with "zero" (0) and name by NoName.

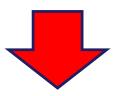
☐ Case Study:

```
# After careful analysis, we have to drop some less effective columns (attributes)

# last_review,id, host_name

df.drop(['id','host_name','last_review'], axis = 1,inplace=True) df: {DataFrame: (48895, 13)}

df.shape df: {DataFrame: (48895, 13)}
```



```
# Also, I have filled the NaN values of reviews_per_month with zero and name by NoName df.reviews_per_month.fillna(value=0,inplace=True) df: {DataFrame: (48895, 13)} df.name.fillna("NoName", inplace=True) df: {DataFrame: (48895, 13)}
```

☐ Case Study:

Next, we then check again to see if 'null' values still exist to be sure we are on the right path...

```
# Check to be sure if 'null' values still exist
df.isnull().sum() df: {DataFrame: (48895, 13)}
```

```
name 0 0 host_id 0 0 neighbourhood_group 0 neighbourhood 0 latitude 0 longitude 0 croom_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
```

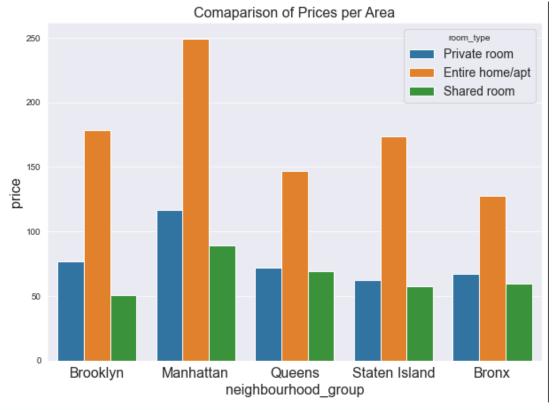
☐ Case Study:

Graphical explorations:

Exploring the prices of apartments/accommodation in the 5 neighborhood areas of NYC

☐ Case Study:

Graphical explorations:



☐ Case Study:

The above bar plot concludes that:

- ✓ Manhattan is the most expensive region in neighborhood group
- ✓ The price of entire home/apt is more than any other room type.
- ✓ Bronx is the cheapest among neighborhood groups.

☐ Case Study:

Graphical explorations:

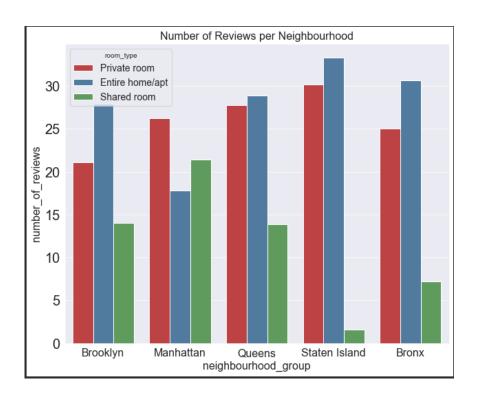
Analyze the Number of Reviews given per

Neighbourhood.

```
# Number of Review per neighbourhood
sns.set_style('darkgrid')
plt.figure(figsize=(10,8))
plt.title('Number of Reviews per Neighbourhood')
plt.rc('axes',titlesize=14)
sns.barplot(data=df,x='neighbourhood_group', y='number_of_reviews',hue='room_type',ci=None,palette='Set1', saturation=0.6)
```

☐ Case Study:

Analyze the Number of Reviews given per Neighbourhood.



☐ Case Study:

Graphical explorations:

Exploring the distribution of listings across the neighborhood in NYC.

```
# Determining the distribution of listings across the neighbourhoods

# plt.figure(figsize=(16, 6))

sns.set_style('darkgrid')

plt.figure(figsize=(10,7))

plt.rc('xtick',labelsize=16)

plt.rc('axes',labelsize=16)

plt.rc('axes',titlesize=16)

plt.rc('legend',fontsize=14)

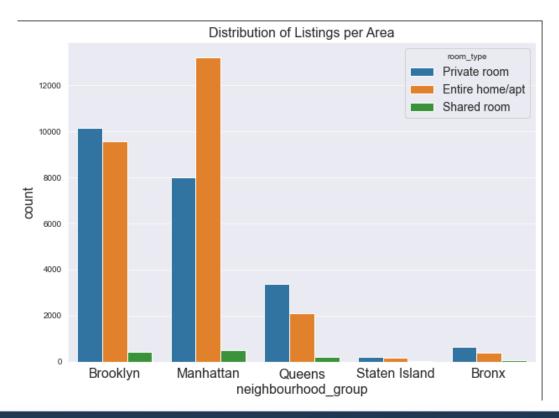
plt.title('Distribution of Listings per Area')

sns.countplot(df.neighbourhood_group,hue=df.room_type) df: {DataFrame:
```

☐ Case Study:

Graphical explorations: Exploring the distribution of

listings across NYC



☐ Case Study:

The above count plot concludes:

- ✓ Staten Island and Bronx have the least number of entries in the listings.
- ✓ Shared rooms are less available in the listings.
- ✓ Manhattan and Brooklyn neighborhoods have far more entries in the listings.

☐ Case Study:

Graphical explorations: Distribution of Neighbouhood by groups...

```
# Exploring the Distribution of neighbourhood by groups

plt.figure(figsize=(9,8))

plt.title('Distribution of Neighbourhood Groups')

plt.rc('axes',titlesize=14)# Here I have compared the prices of all Neighbouhoods with

sns.scatterplot(data=df,x='latitude',y='longitude',# sns.set_style('darkgrid')

hue='neighbourhood_group',# plt.figure(figsize=(10,7))

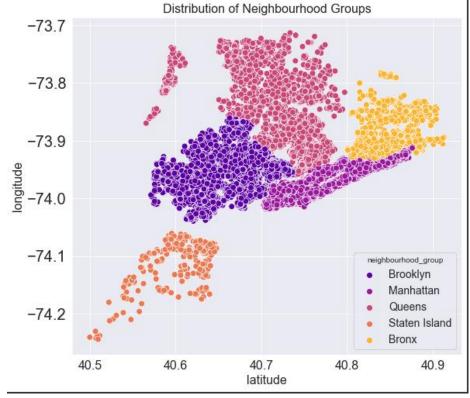
palette='plasma',# plt.rc('xtick',labelsize=16)

s=60)# plt.rc('axes',labelsize=16)
```

☐ Case Study:

Graphical explorations: Distribution of neighborhood by

groups...



☐ Case Study:

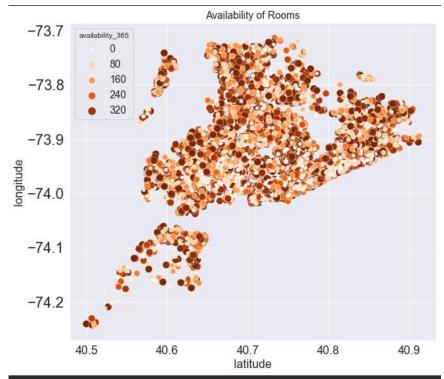
Graphical explorations: Analyzing accommodation availability...

☐ Case Study:

Graphical explorations: Analyzing accommodation

availability...

Here I have shown which rooms have the most availability



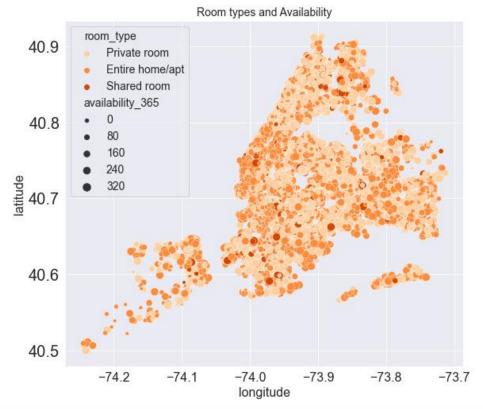
☐ Case Study:

Graphical explorations: Analyzing Room types and Availability...

☐ Case Study:

Graphical explorations: Analyzing Room types and

Availability...



☐ Case Study:

Graphical explorations:

✓ We like to explore the correlation level among the data variables.

```
# Exploring the correlation level among the data variables.

corrmat = df.corr() df: {DataFrame: (48895, 13)}

plt.subplots(figsize=(12,9))

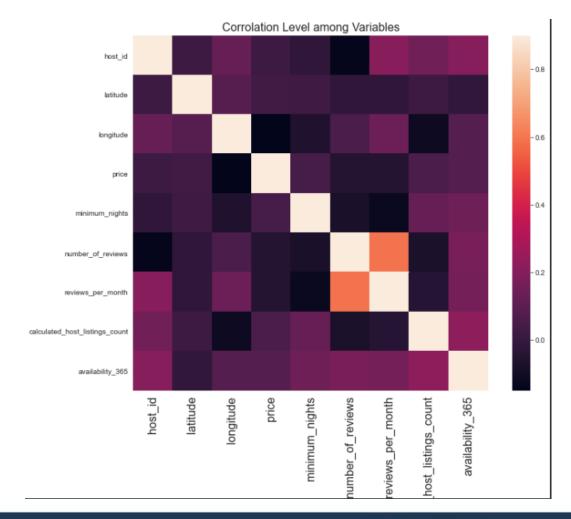
sns.heatmap(corrmat, vmax=0.9, square=True) corrmat: {DataFrame: (9, 9)}

plt.title('Corrolation Level among Variables')
```

☐ Case Study:

Graphical

explorations:



☐ Case Study:

Graphical explorations:

The above plot concludes: The above graph presents the correlation level among data variables. We can observe that none of the variables are strictly correlated between each other.



□ Data Exploration :

✓ In summary, exploring your data helps you observe hidden patterns that enables you determine the kind of analysis and model to adopt.

Questions and Comments!

Thank You



中国科学院深圳先进技术研究院

SHENZHEN INSTITUTES OF ADVANCED TECHNOLOGY
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