

Importing necessary libraries

```
In [13]: import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

```
In [14]: #Reading CSV File which was saved earlier and gathered data using API calls.
df=pd.read_csv("datawithPrices.csv")
pd.set_option('display.max_columns', None)
df.head(10)
```

Out[14]:

| | Unnamed: 0 | Place Name | Category | PostalCode | Borough | Neighborhood | Latitude | Longitude | HousingPrice |
|---|------------|-----------------------------------|----------------------|------------|------------------|---|-----------|------------|--------------|
| 0 | 2 | Elgin & Winter Garden Theatre Ctr | Music Venue | M5B | Downtown Toronto | Garden District, Ryerson | 43.657162 | -79.378937 | 2200 |
| 1 | 11 | Carville Mill Park | Park | M5B | Downtown Toronto | Garden District, Ryerson | 43.657162 | -79.378937 | 2200 |
| 2 | 23 | Hina's Beauty Care | Hair Salon | M5B | Downtown Toronto | Garden District, Ryerson | 43.657162 | -79.378937 | 2200 |
| 3 | 34 | Richmond Station | American Restaurant | M5H | Downtown Toronto | Richmond, Adelaide, King | 43.650571 | -79.384568 | 2200 |
| 4 | 44 | Cactus Club Cafe | American Restaurant | M5H | Downtown Toronto | Richmond, Adelaide, King | 43.650571 | -79.384568 | 2200 |
| 5 | 46 | Markham Corners | Shopping Mall | M5H | Downtown Toronto | Richmond, Adelaide, King | 43.650571 | -79.384568 | 2200 |
| 6 | 54 | Cherry beach sports fields | Soccer Field | M5H | Downtown Toronto | Richmond, Adelaide, King | 43.650571 | -79.384568 | 2200 |
| 7 | 63 | Metro Grill | Fast Food Restaurant | M5H | Downtown Toronto | Richmond, Adelaide, King | 43.650571 | -79.384568 | 2200 |
| 8 | 82 | Toca | Bar | M5V | Downtown Toronto | CN Tower, King and Spadina, Railway Lands, Har... | 43.628947 | -79.394420 | 2200 |
| 9 | 87 | Akira Back Toronto | Japanese Restaurant | M5V | Downtown Toronto | CN Tower, King and Spadina, Railway Lands, Har... | 43.628947 | -79.394420 | 2200 |

```
In [15]: df.shape
```

(1242, 9)

```
In [16]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1242 entries, 0 to 1241
Data columns (total 9 columns):
#   Column          Non-Null Count  Dtype
---  -
0   Unnamed: 0      1242 non-null  int64
1   Place Name      1242 non-null  object
2   Category        1242 non-null  object
3   PostalCode      1242 non-null  object
4   Borough         1242 non-null  object
5   Neighborhood    1242 non-null  object
6   Latitude        1242 non-null  float64
7   Longitude       1242 non-null  float64
8   HousingPrice    1242 non-null  int64
dtypes: float64(2), int64(2), object(5)
memory usage: 87.5+ KB
```

Most common place type in the data is Restaurant.

```
In [17]: df.Category.value_counts()
```

Out[17]:

| | |
|---|----|
| Restaurant | 53 |
| Park | 52 |
| Café | 50 |
| Bakery | 44 |
| Diner | 39 |
| .. | |
| Laser Tag Center | 1 |
| Aquarium | 1 |
| Pest Control Service | 1 |
| Karaoke Bar | 1 |
| Dumpling Restaurant | 1 |
| Name: Category, Length: 274, dtype: int64 | |

No null values in the dataset.

```
In [18]: df.isnull().sum()
```

Out[18]:

| | |
|--------------|---|
| Unnamed: 0 | 0 |
| Place Name | 0 |
| Category | 0 |
| PostalCode | 0 |
| Borough | 0 |
| Neighborhood | 0 |
| Latitude | 0 |
| Longitude | 0 |
| HousingPrice | 0 |
| dtype: int64 | |

```
In [19]: #Unique Values
unique_values = pd.DataFrame(
    columns=['Unique Values']
)
for row in list(df.columns.values):
    unique_values.loc[row] = [df[row].nunique()]
unique_values
```

Out[19]:

| | Unique Values |
|--------------|---------------|
| Unnamed: 0 | 1242 |
| Place Name | 1242 |
| Category | 274 |
| PostalCode | 101 |
| Borough | 13 |
| Neighborhood | 101 |
| Latitude | 101 |
| Longitude | 73 |
| HousingPrice | 13 |

No missing data in the dataset.

```
In [20]: missing_data = pd.DataFrame(
    df.isnull().sum(),
    columns=['Missing Values']
)
missing_data
```

Out[20]:

| | Missing Values |
|--------------|----------------|
| Unnamed: 0 | 0 |
| Place Name | 0 |
| Category | 0 |
| PostalCode | 0 |
| Borough | 0 |
| Neighborhood | 0 |
| Latitude | 0 |
| Longitude | 0 |
| HousingPrice | 0 |

```
In [21]: data_types = pd.DataFrame(
    df.dtypes,
    columns=['Data Type']
)
data_types
```

Out[21]:

| | Data Type |
|--------------|-----------|
| Unnamed: 0 | int64 |
| Place Name | object |
| Category | object |
| PostalCode | object |
| Borough | object |
| Neighborhood | object |
| Latitude | float64 |
| Longitude | float64 |
| HousingPrice | int64 |

Data Quality Report

```
In [22]: dq_report = data_types.join(missing_data).join(unique_values)
dq_report
```

Out[22]:

| | Data Type | Missing Values | Unique Values |
|--------------|-----------|----------------|---------------|
| Unnamed: 0 | int64 | 0 | 1242 |
| Place Name | object | 0 | 1242 |
| Category | object | 0 | 274 |
| PostalCode | object | 0 | 101 |
| Borough | object | 0 | 13 |
| Neighborhood | object | 0 | 101 |
| Latitude | float64 | 0 | 101 |
| Longitude | float64 | 0 | 73 |
| HousingPrice | int64 | 0 | 13 |

Analysis of the data - Overall data quality is good. It has more than 1200 columns and no missing or null values in the dataset. Target column HousingPrice is there to predict its values later on using machine learning models.