An EDA Case Study: Real Estate in Vancouver, BC, Canada

VANCOUVER LOOKOUT AT HARBOUR CENTRE TOWER, Source: [https://www.AAA.com]

Author
Kasra Heidarinezhad

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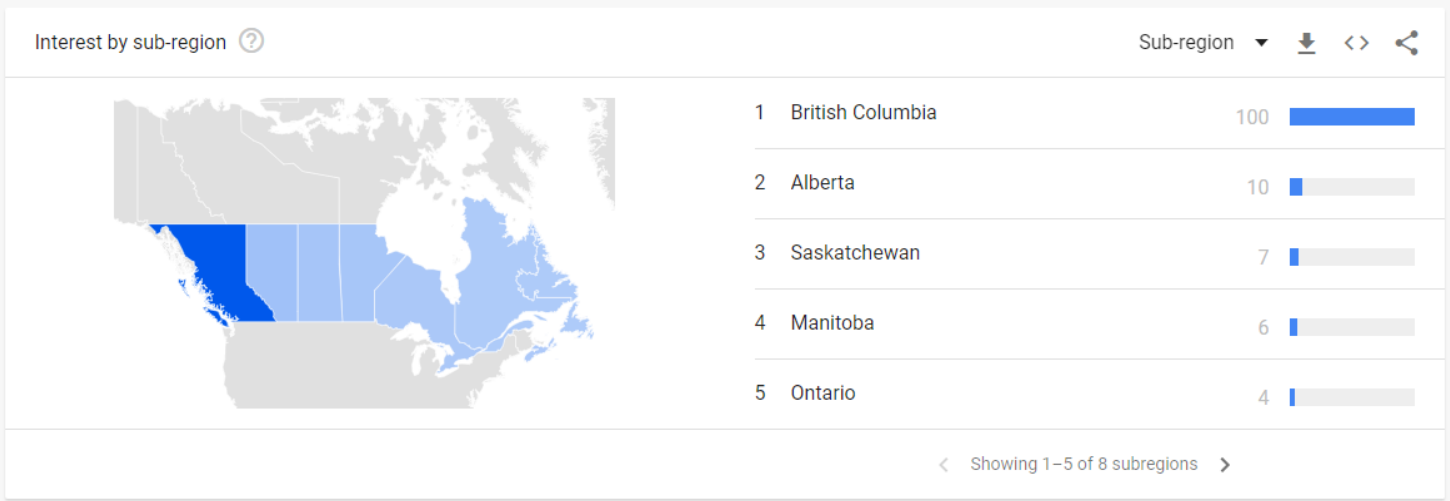
Section 1 Introduction

Nowadays, finding an affordable house in Canada is very difficult. Study of Google Trends data[1] shows that British Columbia, especially Vancouver got higher ranking in search **Vancouver real estate** keywords between searchers among all provinces in Canada [Picture 1].



[Figure 1] Google Trends output for "Vancouver real estate" comparison in Canada. (Screenshot by the author)

[1] https://trends.google.com

According to Statista[2] , Vancouver ranks 7th most expensive residential property markets worldwide in 2020. To finding a reasonable price property, there are couple of different resource in the market. For example websites such as Realtor.com and Redfin.com. In this project, we decided to analysis real estate market in Vancouver, BC, Canada with retrieving listing detail from one of existing resource.

Objective of this analyses of housing market, visualize statistic feature and finally predicting sales price in house listing via statistic data modeling.

Section 2 Creating data source, data cleaning, missing values

First step is to get data to analysis. You have two choice here: First is to link a government agency or real estate license to use as a part of research (does not work for me). Second choice is scraping data. In this article, we kept going with the second option. Finding resource is next challenge of this project. To choice a good option among the existing resource, I considered two following options:
1- Comprehensively of data that providing by a website
2- Difficulty of accessing to data within website
After a quite study and considering above mentioned factors, we decided to going to Zillow[3].

2-1 Web Scraping with Python

Required Libraries

Here we list a major required libraries. For easiness, we could throw all of them in a RequiredLibraries.txt file and run: pip install RequiredLibraries.txt.

```
import os
from bs4 import BeautifulSoup
from selenium import webdriver
from selenium.webdriver.common.keys import Keys
from selenium.webdriver.common.by import By
import warnings
import numpy as np
import pandas as pd
import lxml
from lxml.html.soupparser import fromstring
import prettify
import htmltext
import requests
import re
import json
```

Web Headers

Zillow throw Captchas so when you try and run a request.get(url) type of function. So way to get around this is by adding headers to the request function as you can see below:

```
#add headers in case you use chromedriver (captchas are no fun); namely used for chromedriver
req_headers = {
    'accept': 'text/html,application/xhtml+xml,application/xml;q=0.9,image/webp,image/apng,*/*;q=0.8',
    'accept-encoding': 'gzip, deflate, br',
    'accept-language': 'en-US,en;q=0.8',
    'upgrade-insecure-requests': '1',
    'user-agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/61.0.3163.100 Safari/537.36'
}
```

[2] https://www.statista.com/statistics/1040698/most-expensive-property-markets-worldwide
[3] https://Zillow.com

Furthermore, following step is done to complete job:

- Parse data from urls in looping through pages
- Create and append Data Frames
- Export Data frame to csv file
- Complete source
- Plot to rule them all

Here is complete code and result

```
import requests
import re
import json
import pandas as pd
import warnings
warnings.filterwarnings('ignore')

#add headers in case you use chromedriver (captchas are no fun); namely used for chromedriver
req_headers = {
    'accept': 'text/html,application/xhtml+xml,application/xml;q=0.9,image/webp,image/apng,*/*;q=0.8',
    'accept-encoding': 'gzip, deflate, br',
    'accept-language': 'en-US,en;q=0.8',
    'upgrade-insecure-requests': '1',
    'user-agent': 'Mozilla/5.0 (Windows NT 10.0; Win64; x64) AppleWebKit/537.36 (KHTML, like Gecko) Chrome/61.0.3163.100 Safari/537.36'
}

with requests.Session() as s:
    data_list = []
    resp = s.get('https://www.zillow.com/homes/for_sale/Vancouver,-BC_rb/', headers=req_headers)
    data = json.loads(re.search(r'!--(\{"queryState".*?)-->', resp.text).group(1))
    data_list.append(data)

    for pages in range(1,20):   #just grabbing the first 20 pages
        resp = s.get('https://www.zillow.com/homes/for_sale/Vancouver,-BC_rb/'+str(pages+1)+'_p/', headers=req_headers)
        data = json.loads(re.search(r'!--(\{"queryState".*?)-->', resp.text).group(1))
        data_list.append(data)

df = pd.DataFrame()

def make_frame(frame):
    for i in data_list:
        for item in i['cat1']['searchResults']['listResults']:
            frame = frame.append(item, ignore_index=True)
    return frame

df = make_frame(df)

df = df.drop('hdpData', 1) #drop cols
df = df.drop_duplicates(subset='zpid', keep="last") #drop dupes

#filters
df['zestimate'] = df['zestimate'].fillna(0)
df['best_deal'] = df['unformattedPrice'] - df['zestimate']
df = df.sort_values(by='best_deal',ascending=True)

df.to_csv('zillow_original.csv', encoding='utf-8')
```

Result: raw data

zpid	int64
id	float64
providerListingId	object
imgSrc	object
hasImage	object
carouselPhotos	object
detailUrl	object
statusType	object
statusText	object
countryCurrency	object

price	int64
unformattedPrice	object
address	object
addressStreet	object
addressCity	object
addressState	object
addressZipcode	bool
isUndisclosedAddress	int64
beds	int64
baths	float64
area	int64
latLong	object
isZillowOwned	bool
variableData	object
badgeInfo	float64
isSaved	bool
isUserClaimingOwner	bool
isUserConfirmedClaim	bool
pgapt	object
sgapt	object
zestimate	int64
shouldShowZestimateAsPrice	bool
has3DModel	bool
hasVideo	bool
isHomeRec	bool
info1String	object
brokerName	object
hasAdditionalAttributions	bool
isFeaturedListing	bool
availabilityDate	float64
list	bool
relaxed	bool
hasOpenHouse	object
openHouseStartDate	object
openHouseEndDate	object
openHouseDescription	object
streetViewMetadataURL	object
streetViewURL	object
best_deal	int64

Note

Keep in mind that it uses anti-scraping techniques like captchas, IP blocking, and honeypot traps to prevent its data from scraping. We do think our IP/device is probably blacklisted by now
Congratulation: First step done!

2-2 Data Cleaning

Data cleaning involves identifying and correcting any errors or inconsistencies in the data, such as missing values, duplicate records or incorrect data types. This is an important step because it helps to ensure that the data is complete and accurate, which is necessary for building reliable models. For this purpose, some columns that are not likely to help in data analysis and predicting the target variable are dropped from the original data frame.

2-3 Missing Values

It is important to fill in missing data with NaN (Not a Number) because it allows you to identify missing values in your data clearly. Filling missing values with NaN allows us to identify which values are missing and take appropriate action easily. Here, the missing values in the columns 'Volume', 'Interior', 'Availability', 'Garage', 'Upkeep Status,' 'Specification', 'Location Type', 'Number of floors', 'Details of Garden', 'Details of Storage', 'Number of Bedrooms', 'Details of Balcony', Number of Bathrooms and Description of Storage are addressed by filling it with NaN values.

After data cleaning, shape of data is like result:

```
df = pd.read_csv("zillow.csv")
print(f"Number of samples: {df.shape[0]}")
print(f"Number of features in set: {df.shape[1]}")
print("Features:")
print(df.dtypes)
```

Result:
Number of samples: 800
Number of features in set: 18
Features:

index	int64
zpid	int64
id	int64
imgSrc	object
detailUrl	object
TypeofProperty	object
formattedprice	object
Price	int64
address	object
addressStreet	object
addressZipcode	object
beds	float64
baths	float64
area	int64
latLong	object
has3DModel	bool
brokerName	object
best_deal	int64
dtype	object

Section 3 Data visualization

Here we did two Types of visualization:

1- Data visualization with Python libraries
2- Data visualization with Tableau

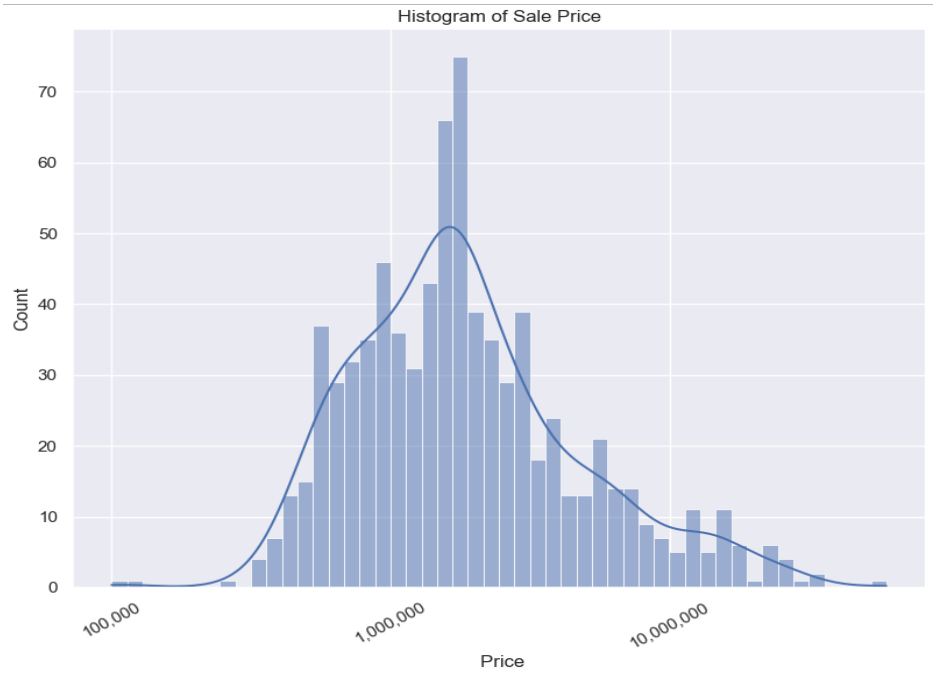
3-1 Data visualization with Python libraries

Here we did some codding to create a shape of data and histogram.

First and most important feature of statistics is Histogram, extracted by following code, result in [Figure 2]

```
# histogram of target=price variable
sns.set_theme()
graph = sns.displot(data=propertyListFrame, x="Price", kde=True, log_scale=True, bins=50)
graph.set(title="Histogram of Sale Price")
for ax in graph.axes.flat:
    ax.xaxis.set_major_formatter(tkr.FuncFormatter(lambda x, p: format(int(x), ',')))
plt.xticks(rotation=30)
plt.show()
```

Result:



[Figure 2] Histogram of real estate price in Vancouver. (Image by the author)

Let's have a look in to the other four major statistic parameter:

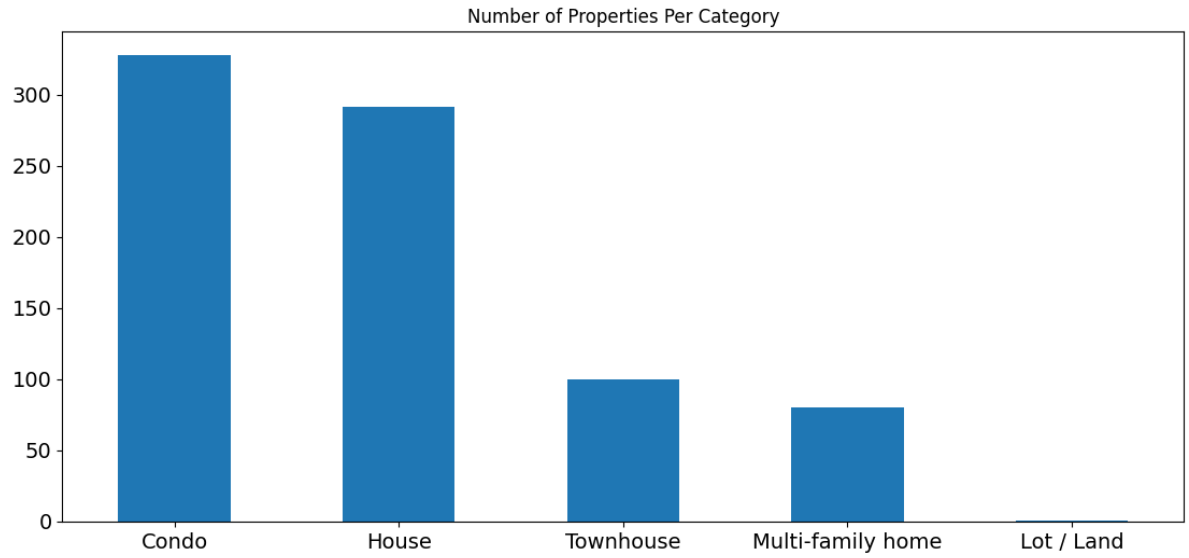
Mean: 3,164,698.75 CA$
Median: 1,675,000.00 CA$
Skewness: 4.6598
Kurtosis: 33.9900

Discussion: It shows the distribution of the price of properties in Vancouver, BC, is relatively high positive skewness (the mean is greater than the median). In the prediction model, this will cause, the less accurate in the price prediction. In the other hand, high kurtosis represents heavy tails meaning more outliers.

1- Statistics per category: **Type of property**
Let's take a look to distribution of numbers in listing base of type of property:

```
df['TypeofProperty'] = df['TypeofProperty'].str.strip()
graph = df['TypeofProperty'].value_counts()
graph.plot(kind='bar', fontsize=14, title="Number of Properties Per Category", rot=0)
plt.show()
```

Result:



[Figure 3] Number per category: Type of property (Image by the author)

As [Figure 3] suggest, number of Condo (Apartments) and houses are significant part of our listing.

2- Statistics per category: Activity of brokers

Here we did some coding to see distribution of numbers in listing base of brokers:

```
propertyListFrame['brokerName'] = propertyListFrame['brokerName'].str.strip()
type(propertyListFrame['brokerName'][0])
print(propertyListFrame['brokerName'].nunique())
df['TypeofProperty'].value_counts()
```

Result:

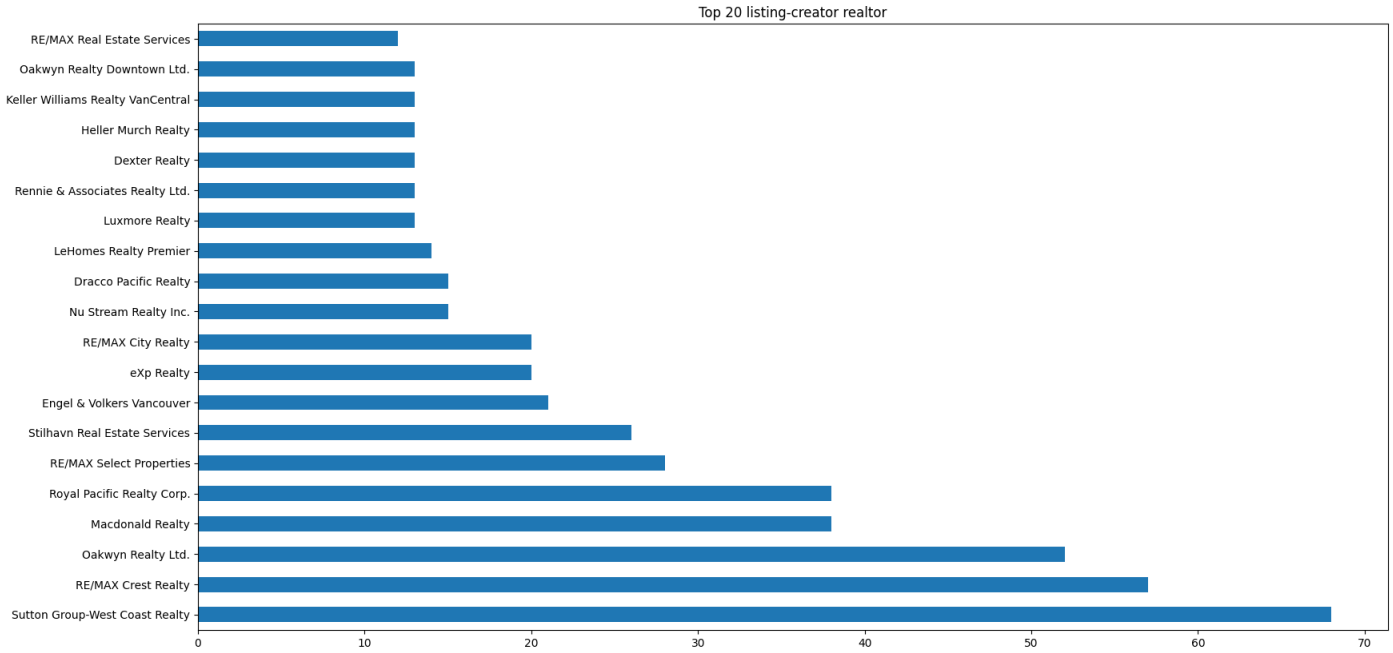
119

Condo	328
House	291
Townhouse	100
Multi-family home	80

As results shows, 119 individual brokers exist in our listing means some of them created more than one record in our property table. In continue, we plot top 20 realtor histogram [Figure 4].
We used matplotlib.pyplot to extract more helpful plots

```
df['brokerName'] = df['brokerName'].str.strip()
#print(df['brokerName'].nunique())   #print number of brokers
graph = df['brokerName'].value_counts()[:20]
graph.plot(kind='barh', fontsize=10, title="Top 20 listing-creator realtor")
plt.show()
```

Result:

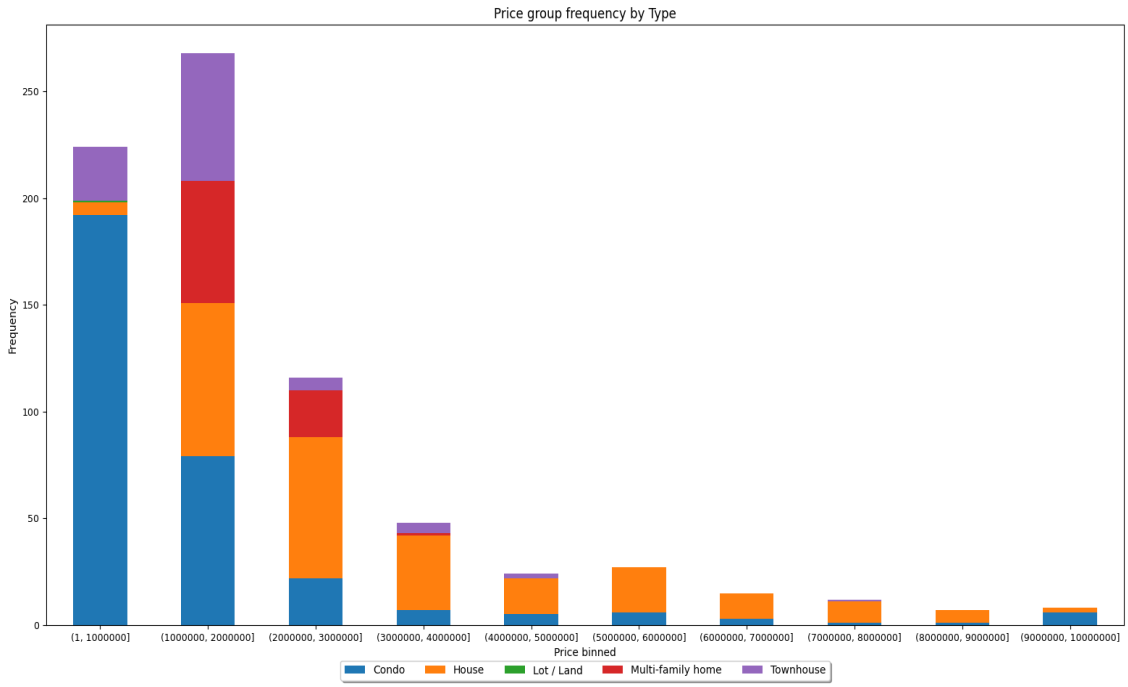


[Figure 4] Top 20 realtor histogram (Image by the author)

3- Statistics per category: **Price range**

We continue by creating a price range histogram to observe number of each type of property. [Figure 5]

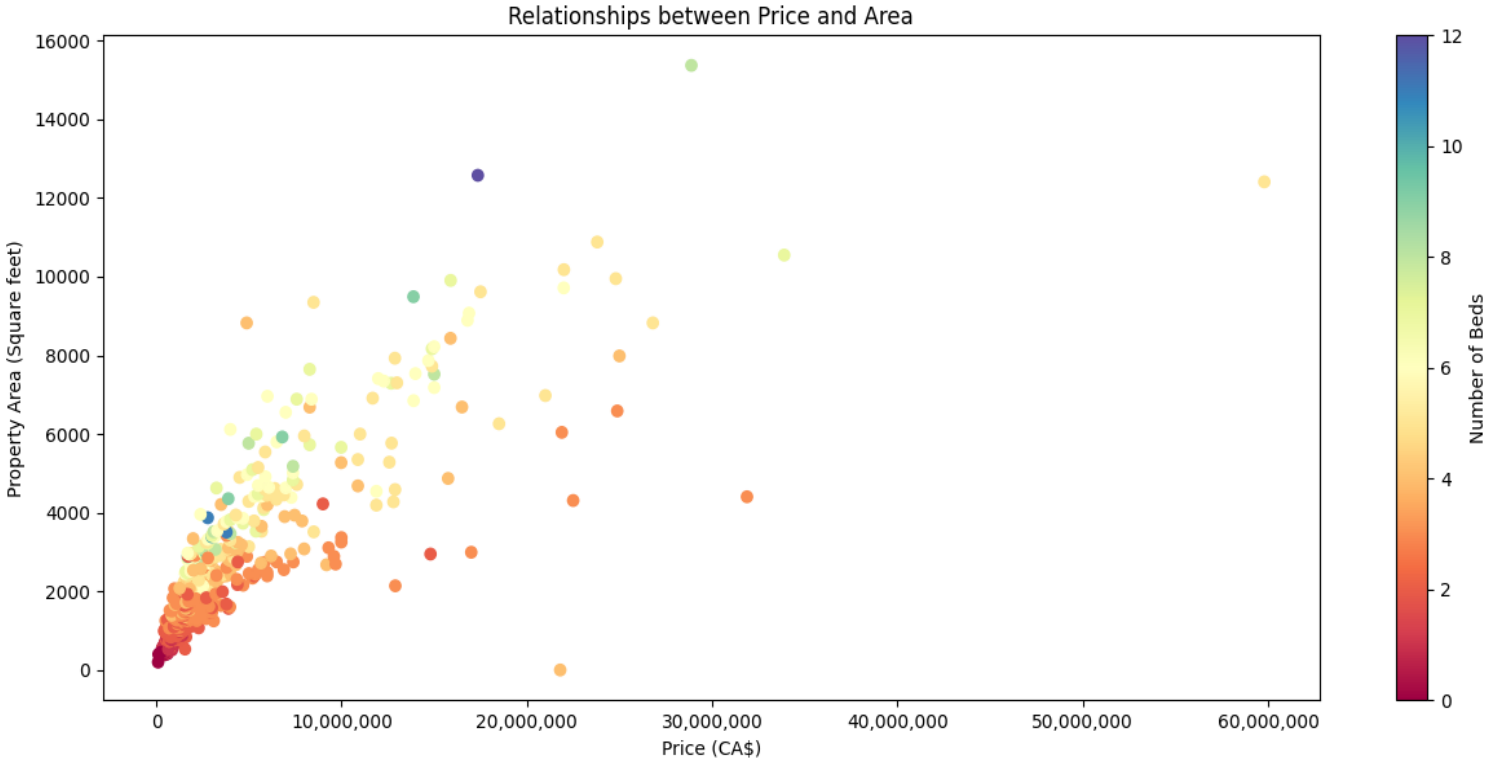
```
df1 = pd.read_csv('zillow.cs
df = df1[['Price', 'TypeofProperty' ]]
df['binned_price'] = pd.cut(df.Price, [1, 1000000, 2000000, 3000000, 4000000, 5000000, 6000000, 7000000, 8000000, 9000000, 10000000])
df.groupby('binned_price')['TypeofProperty'].value_counts()
df.drop('Price',axis=1,inplace=True)
df_reshaped = df.pivot_table(index=['binned_price'], columns=['TypeofProperty'], aggfunc=len)
df_reshaped.plot(kind='bar', stacked=True, ylabel='Frequency', xlabel='Price binned',title='Price group frequency by Type', rot=0, fontsize=9)
plt.legend(loc='upper center', bbox_to_anchor=(0.5, -0.05),fancybox=True, shadow=True, ncol=8)
plt.show()
```



[Figure 5] Histogram - Group by: Type of Property/ Price range science (Image by the author)

4- Scatter plot of distribution Statistics per category: **Area - number of beds** [Figure 6]

```
properties = pd.read_csv("zillow.csv")
plt.rcParams.update( {'figure.figsize':(10,8), 'figure.dpi':100})
plt.scatter(x=properties.Price, y=properties.area, c=properties.beds, cmap='Spectral')
plt.colorbar(label="Number of Beds")
plt.title('Relationships between Price and Area')
plt.xlabel('Price')
plt.ylabel('Property Area')
current_values = plt.gca().get_xticks()
plt.gca().set_xticklabels(['{:,.0f}'.format(x) for x in current_values])
plt.show()
```



[Figure 6] Scatter plot of distribution of price based of area and number of beds (Image by the author)

5- Geographical property distribution category: **Map – type of peroperty**

Finally, let's take a look to geographical property distribution in the Vancouver area [Figure 7]. For this purpose I used **folium** library. But it is necessary to do some pre-process to separate we used different color for each category of property. As you can see, it increase performance of visualization considerably.

Property location Analysis with Folium

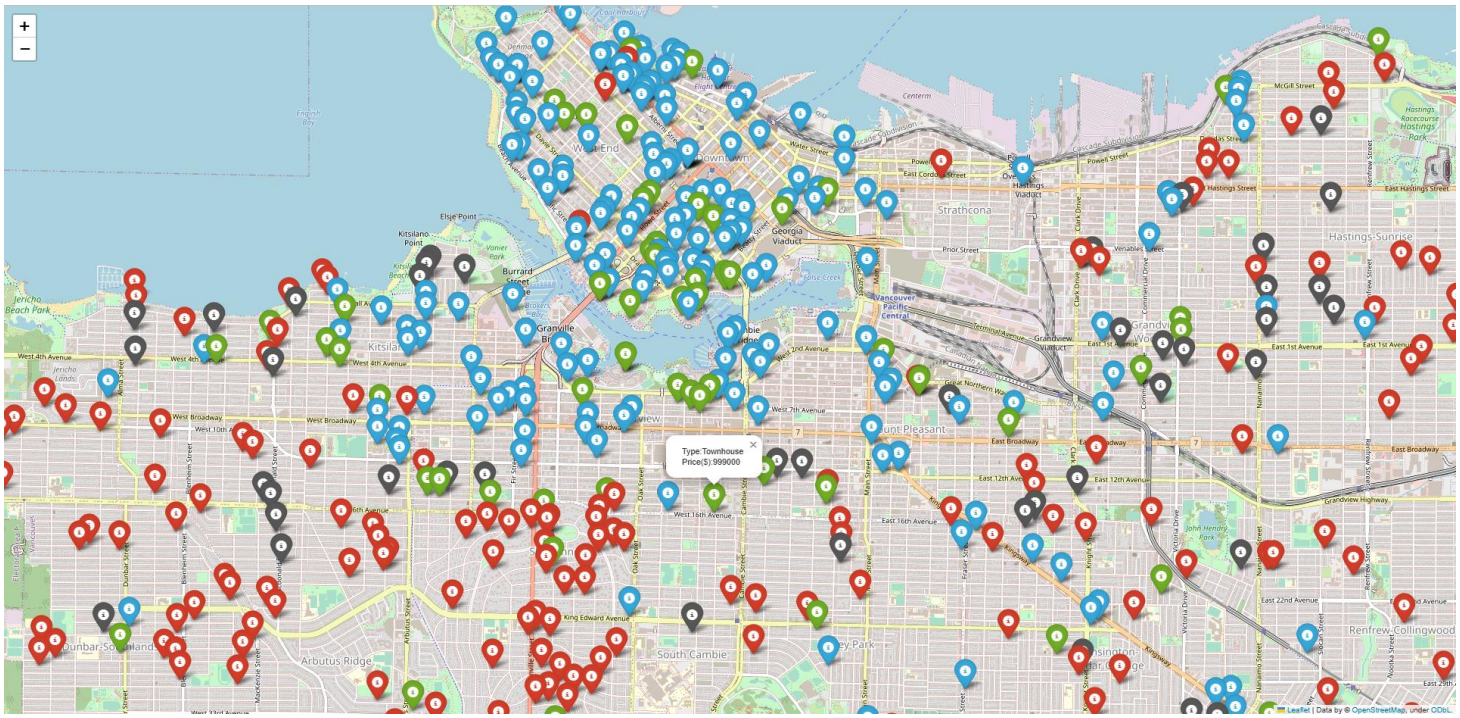
```
import pandas as pd
import folium
from folium.plugins import MarkerCluster     # Import folium MousePosition plugin
from folium.plugins import MousePosition     # Import folium DivIcon plugin
from folium.features import DivIcon

df = pd.read_csv('zillow.csv')
drawable_df = df[df.Lat > 0.0]

mapit = folium.Map( location=[49.261505,  -123.05453], zoom_start=12 )
for index, drawable_df in drawable_df.iterrows():
    if     drawable_df["TypeofProperty"]=='Condo': c = 'blue'
    elif   drawable_df["TypeofProperty"]=='Townhouse':  c = 'green'
    elif   drawable_df["TypeofProperty"]=='Multi-family home': c = 'gray'
    else:  c = 'red'

    folium.Marker(
                location = [drawable_df['Lat'], drawable_df['Long']],
                radius=15 ,
                icon=folium.Icon(color= c ) ,
                popup = f'Type:{drawable_df["TypeofProperty"]}\n Price($):{drawable_df["Price"]}'
                ).add_to(mapit)
mapit.save('map.html')
mapit.show_in_browser()
```

Result:



[Figure 7] Geographical property distribution in the Vancouver map (Image by the author)

6- Geographical Per Canada: **Map – Number**

This chart is not directly part of this project, but closely shows the ability of `matplotlib` in case of country distribution data. [Figure 8]

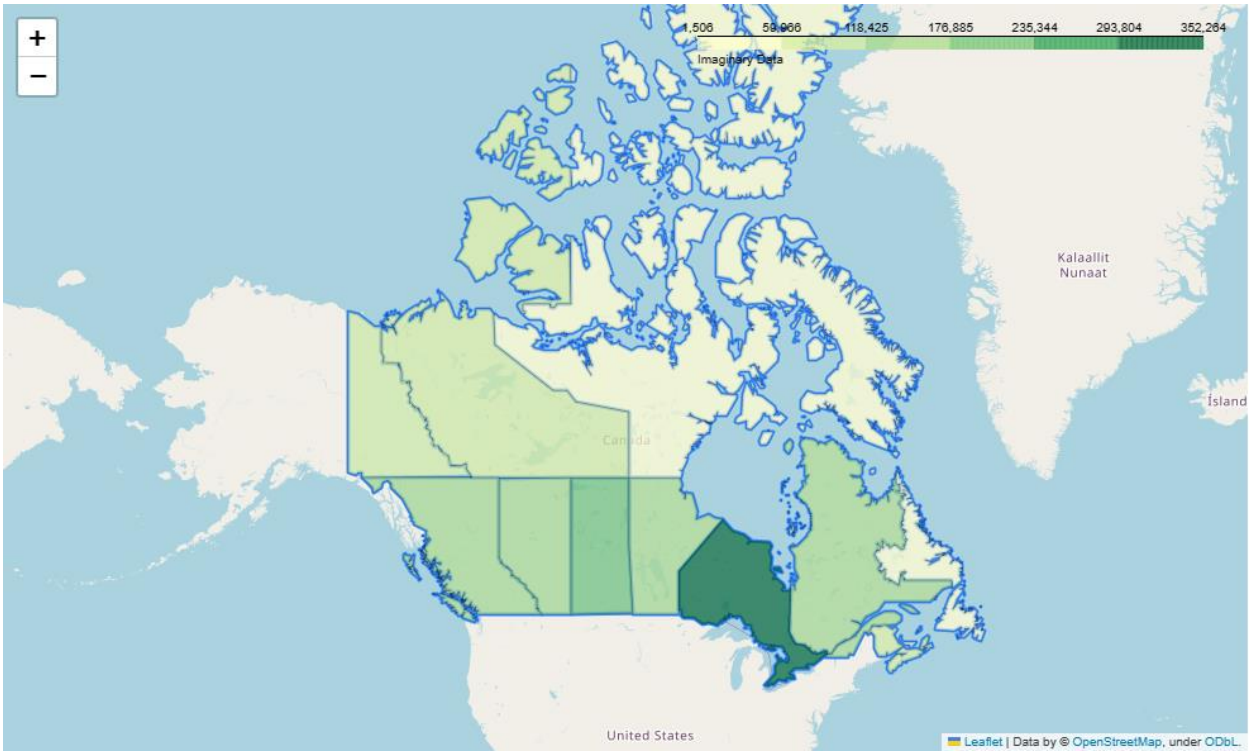
```
import pandas as pd
import geopandas as gpd
import matplotlib.pyplot as plt
import folium
```

```
can_map = folium.Map(location=[48, -102], zoom_start=3)   # Create the map object
c_data = {
  'Alberta': 144284.48,
  'British Columbia': 141222.06000000017,
  'Manitoba': 134337.96999999994,
  'New Brunswick': 115727.67000000001,
  'Newfoundland': 6885.140000000001,
  'Northwest Territories': 91755.44000000002,
  'Nova Scotia': 80136.18000000005,
  'Nunavut': 1506.4300000000014,
  'Ontario': 352263.50999999983,
  'Prince Edward Island': 28742.2,
  'Quebec': 138658.87999999998,
  'Saskatchewan': 177314.26000000013,
  'Yukon Territory': 74404.80000000003
}
```

```
folium.GeoJson(gdf).add_to(can_map)  # Add the GeoJSON data to the map

folium.Choropleth(
    geo_data=gdf,
    name="choropleth",
    data=c_data,
    columns=['Province', 'Profit'],
    key_on='feature.properties.NAME',
    fill_color="YlGn",
    fill_opacity=0.7,
    line_opacity=0.2,
    legend_name="Imaginary Data",
).add_to(can_map)

can_map
```

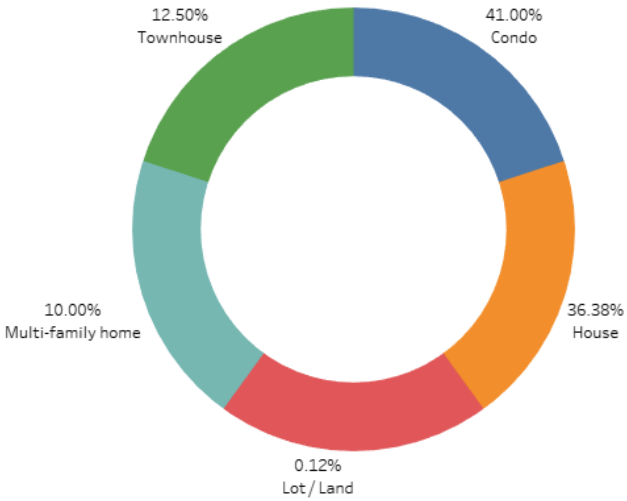


[Figure 8] Geographical distribution in Canada categorized by province (Image by the author)

3-2 Data visualization with Tableau

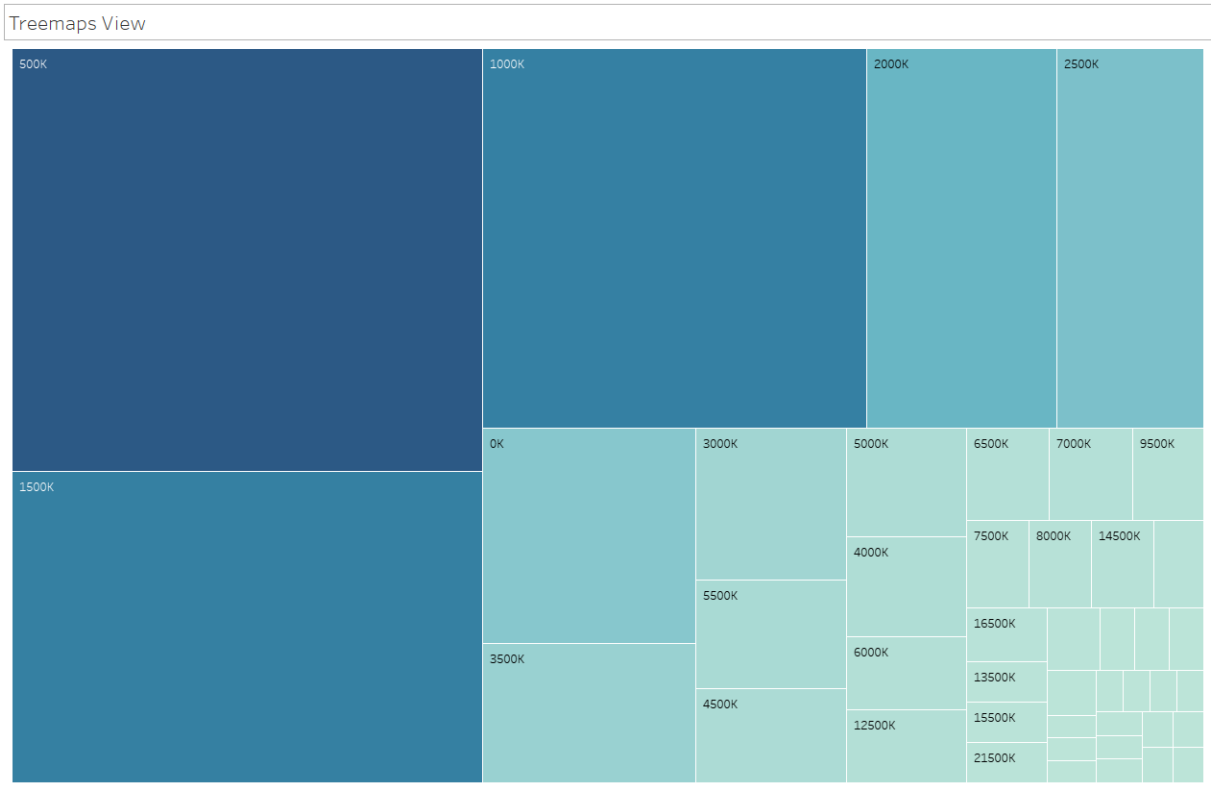
Tableau is a data visualization and business intelligence software that helps users to see and understand their data. It allows to create interactive dashboards, charts, and maps to gain insights from their data. It also has built-in collaboration features, so teams can share their findings and work together on projects. Here we used Tableau (Public) to carry out some visualization.

Chart 1: Percentage of each type of property for sale based on percentage of all [Figure 9]



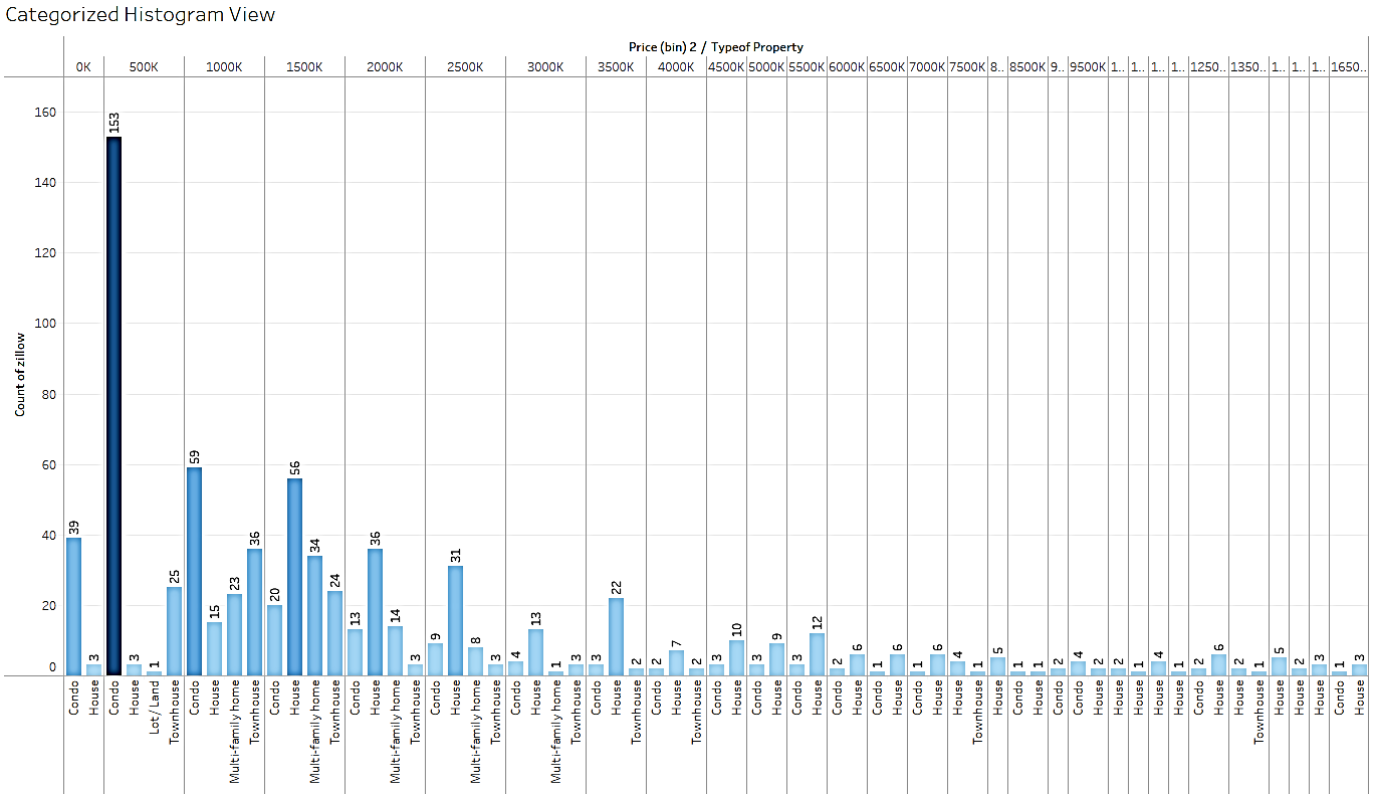
[Figure 9] Donut chart shows the percentage of each type of property for sale based on percentage of all (Image by the author)

Chart 2: Treemap view to demonstrations the distribution real estate based on price-range category [Figure 9]



[Figure 10] Treemap view shows the distribution based on price-range category (Image by the author)

Chart 3: Categorized histogram displays the distribution of listing based on Price (range)-Type category [figure 11]



[Figure 10] Categorized histogram view shows the distribution based on Price(range)-Type category (Image by the author)
[https://public.tableau.com/app/profile/kasra.heidarinezhad]

Section 4 Database, SQL and Query

To manipulate data, we created a database named: VancouverProperties.db with a table named: VancouverPropertiesTable with sqlite DBMS. Afterward, data is extracted by SELECT statement:

Query 1: A complete list of real estate in table

```
from pathlib import Path
import sqlite3

properties = pd.read_csv("zillow.csv")
Path('VancouverProperties.db').touch()
db_conn = sqlite3.connect('VancouverProperties.db')
db_cursor = db_conn.cursor()

properties.to_sql('VancouverPropertiesTable', db_conn, if_exists='append', index=False)
db_vancouverproperties_init_query = pd.read_sql(''' SELECT * FROM VancouverPropertiesTable ''', db_conn)
db_vancouverproperties_init_query
```

Result:

index	zpid	id	imgSrc	...	latLong	has3DModel	brokerName	best_deal
0	614	2070285804	2070285804	https://photos.zillowstatic.com/fp/f67e9aa377a...	...	{'latitude': 49.286182, 'longitude': -123.11589}	0	None	1058000
1	49	2066436476	2066436476	https://photos.zillowstatic.com/fp/b0831a45b64...	...	{'latitude': 49.261505, 'longitude': -123.05453}	0	eXp Realty	419900

2	136	2067490635	2067490635	https://photos.zillowstatic.com/fp/76674f8faeb...	...	{}	0	Park Georgia Realty Ltd.	438800
3	411	2060499969	2060499969	https://photos.zillowstatic.com/fp/85669420760...	...	{'latitude': 49.243015, 'longitude': -123.05983}	0	Nu Stream Realty Inc.	449000
4	636	2060854306	2060854306	https://photos.zillowstatic.com/fp/91c1798b32d...	...	{'latitude': 49.286224, 'longitude': -123.14085}	0	Team 3000 Realty Ltd.	599900
..	...	...	...	...	...	...	...	...	...
795	323	314427630	314427630	https://photos.zillowstatic.com/fp/02c6a12b34b...	...	{'latitude': 49.289257, 'longitude': -123.12097}	0	Macdonald Realty	4350000
796	201	2061702036	2061702036	https://photos.zillowstatic.com/fp/cc0fd71a6dd...	...	{'latitude': 49.27208, 'longitude': -123.12038}	0	RE/MAX Crest Realty	3250000
797	750	314427938	314427938	https://photos.zillowstatic.com/fp/3dd1f4e2611...	...	{'latitude': 49.274944, 'longitude': -123.12518}	0	Macdonald Realty	4398000
798	632	2071582184	2071582184	https://photos.zillowstatic.com/fp/47de178e771...	...	{}	0	eXp Realty	7870000
799	549	314346775	314346775	https://photos.zillowstatic.com/fp/0d5302ad0c1...	...	{'latitude': 49.256756, 'longitude': -123.13778}	0	Royal Pacific Realty Corp.	13888000

Query 2: List of real estate by filtering: Kingsway Street, and sorting

```
data_stat = pd.read_sql(''' SELECT zpid, TypeofProperty, Price, beds, addressStreet, area
                            FROM VancouverPropertiesTable
                            WHERE addressStreet LIKE '%Kingsway%'
                            ORDER BY Price DESC ''', db_conn)
data_stat
```

Result:

0	2061711245	Condo	990000	3.0	2220 Kingsway #NE802	1140
1	2063168941	Condo	830000	2.0	2220 Kingsway #1612	812
2	2065888823	Condo	748888	2.0	760 Kingsway #310	880
3	2063497103	Condo	699000	2.0	2689 Kingsway #910	746
4	2060658439	Condo	659900	2.0	488 Kingsway #W407	780
5	2060941923	Townhouse	649800	1.0	2435 Kingsway #204	528
6	2060248755	Condo	618000	2.0	2973 Kingsway #102	861
7	2060723406	Condo	575000	1.0	1239 Kingsway #208	569
8	2060561370	Condo	459000	0.0	1432 Kingsway St #351	459
9	2060499969	Condo	449000	0.0	2239 Kingsway #109	415

Query 3: Average condo price (CA$) and area (Square feet)

```
data_stat_Avg = pd.read_sql(''' SELECT AVG(Price)AS Avg_price_condo , TypeofProperty, AVG(area) AS Avg_area
                                FROM VancouverPropertiesTable
                                WHERE TypeofProperty == 'Condo'  ''', db_conn)
```

Result:

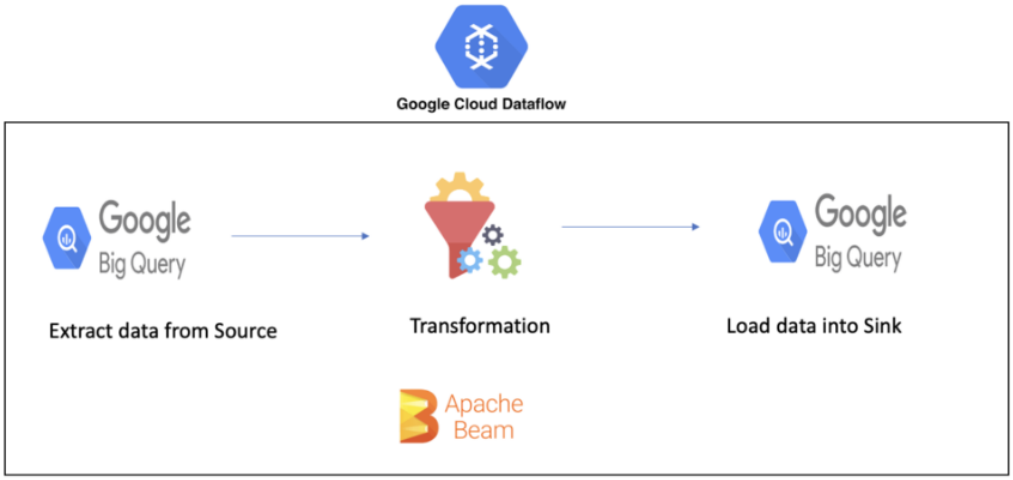
Avg_price_condo	TypeofProperty	Avg_area
1.797490e+06	Condo	1129.859756

Section 5 Statistical data modeling

Section 6 Building a data pipeline with Google Dataflow and Apache Beam

In this section, we continue our job by creating a data-parallel processing pipeline with GCP [4]. Among existing tools, we work with Google Cloud Dataflow, a fully-managed, serverless data processing service that provides a programming model for batch and stream processing, with support for distributed processing back-end, Apache Beam.

[4] Google Cloud Platform



[Figure 11] BigQuery data pipeline using Google Cloud Dataflow/Apache Beam [source [5]]

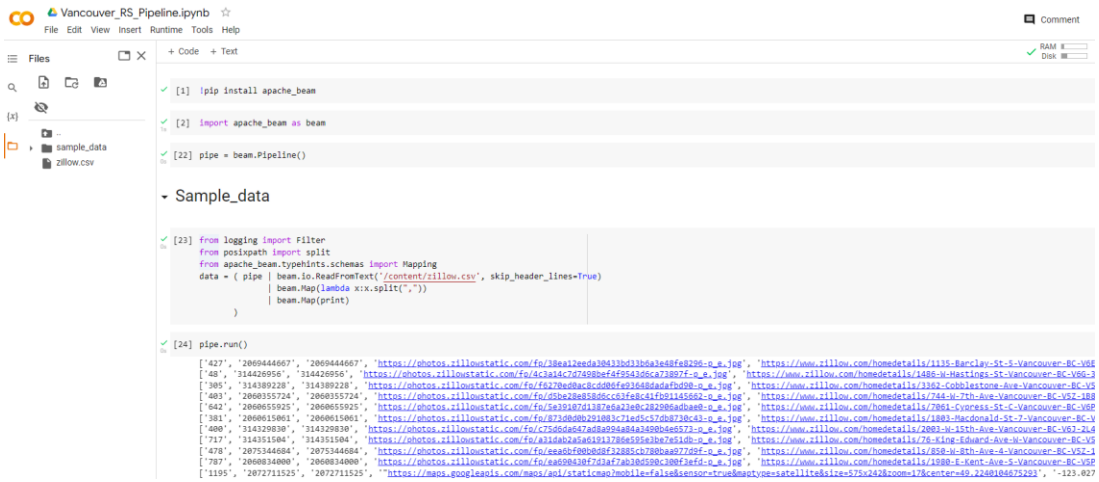
To build and execute data pipeline ETL, we follow next steps.

First of all we enabled Dataflow and Bigquery APIs. Afterwards we create a cloud storage bucket in the nearest region and store the Zillow.csv data file in the bucket.

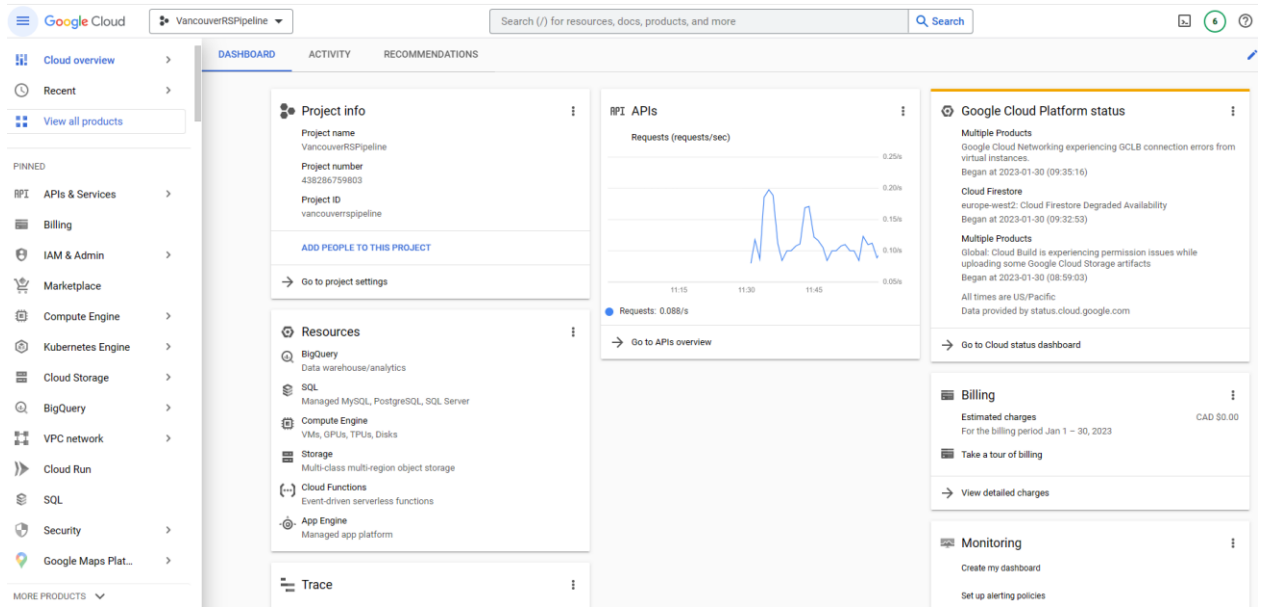
This phase includes following steps:

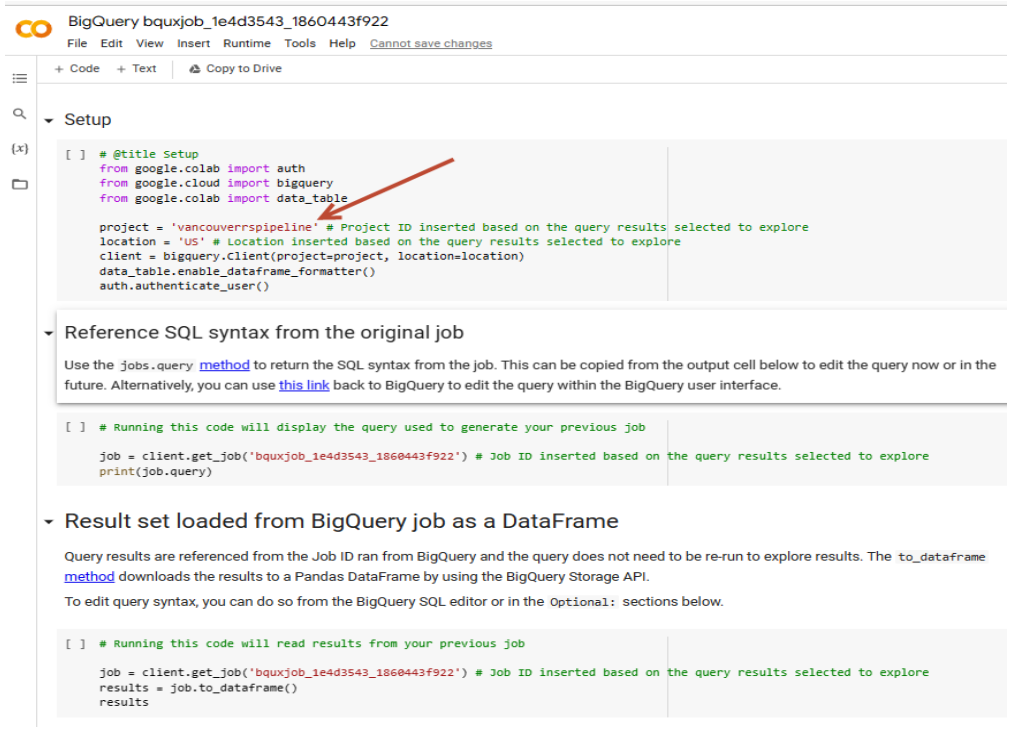
1- Read input data file into a pcollection: Input data for pipelines can be in any form: csv or json. We used Zillow.csv that created in previous section.
2- Create new pcollection(s) by applying filters, transforms on existing pcollection
3- Create new pcollection(s) by grouping: GroupByKey
4- Create new pcollection(s) by combining pcollection s: CoGroupByKey
5- Apply aggregate functions: count, sum
6- Mapping the result to convert into a dictionary format
7- Dumping the pipeline output into BigQuery table sink

Here we have some code snapshot and screenshot of GCP environment:



[5] https://www.revisitclass.com





Here we can see descriptive result of run bigQuery with above criteria. They include count, mean, std, min, max, 25%, 50%, 75% and max.

Show descriptive statistics using describe()

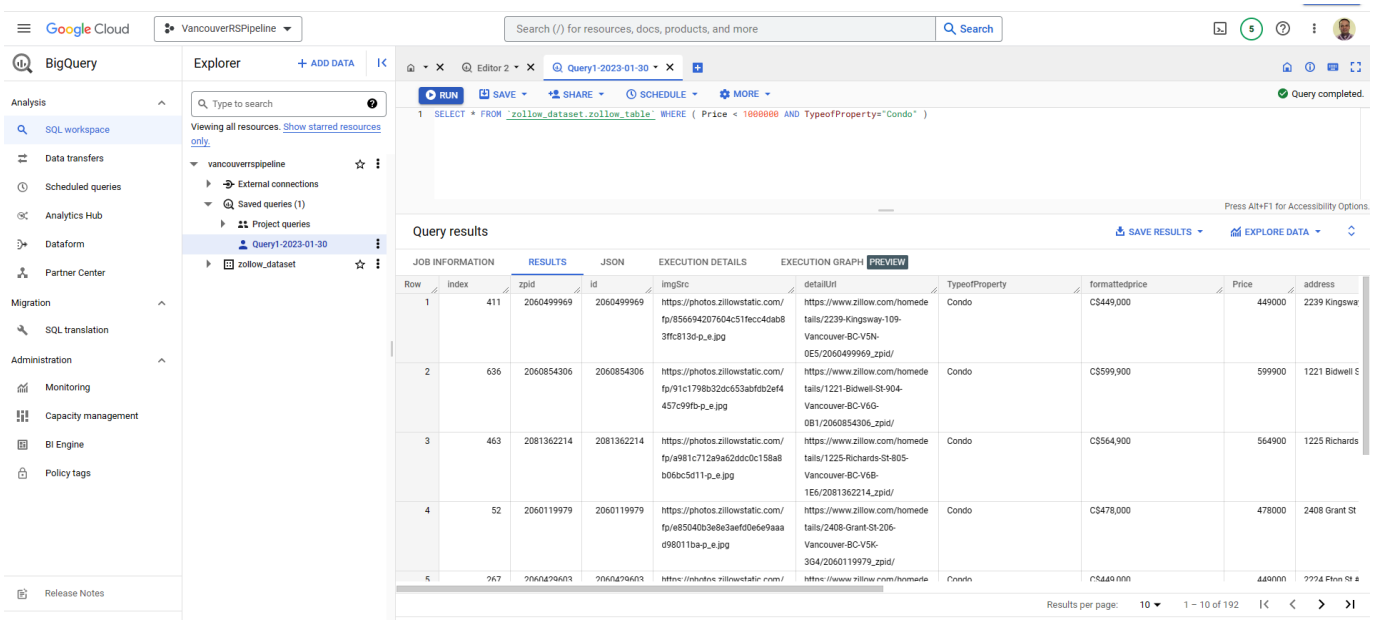
Use the pandas DataFrame.describe() method to generate descriptive statistics. Descriptive statistics include those that summarize the central tendency, dispersion and shape of a dataset's distribution, excluding NaN values. You may also use other Python methods to interact with your data.

```
[5] results.describe()
```

1 to 8 of 8 entries Filter

level_0	index	zpid	id	Price	beds	baths	area	Lat	Long	best_deal
count	192.0	192.0	192.0	192.0	192.0	192.0	192.0	192.0	192.0	192.0
mean	407.5260416666667	1999112127.890625	1999112127.890625	677814.1927083334	1.4010416666666667	1.3385416666666667	732.0572916666666	39.00038559895833	-97.46146818749999	677814.1927083334
std	290.9767795362299	328600253.37105954	328600253.37105954	177427.6615062614	0.6557030983826607	0.4744508628840805	203.20662851702156	20.059090241841872	50.1274005715234	177427.6615062614
min	40.0	314324455.0	314324455.0	319000.0	0.0	1.0	383.0	0.0	-123.211754	319000.0
25%	164.75	2060218579.75	2060218579.75	550750.0	1.0	1.0	567.0	49.214969499999995	-123.132186	550750.0
50%	344.0	2060835838.5	2060835838.5	649450.0	1.0	1.0	719.0	49.2636105	-123.10145	649450.0
75%	608.0	2062338753.5	2062338753.5	811750.0	2.0	2.0	860.25	49.277709	-123.03229375000001	811750.0
max	1199.0	2081362214.0	2081362214.0	999999.0	3.0	2.0	1350.0	49.29315	0.0	999999.0

Show 25 per page



Section 7 Conclusion

In this study, we have walked through to providing required data about real estate market in Vancouver, BC. Canada, we scraped data, preprocessed and did some basic statistical procedure. Afterward. We had some visualization with Python and Tableau to demonstration feature of distribution of real estate based on diversity and category. We also carried out some data manipulate through database specially SQL and SELECT statement. Finally we tried to predict housing price with LR model based on data in hand.

To be sure, prediction property price is a challenging problem. In our case, it may be more appropriate to use non-linear models or other types of statistical analysis. Additionally, it is important to be aware of the assumptions of LR, such as linearity, independence of errors, and normality of errors and check if these assumptions are met before applying LR. It is also worth considering other factors that may be affecting the relationship between the variables, such as outliers or multi-collinearity.

Multivariable LR is a powerful tool that allows researchers to examine the multiple factors that contribute to social experiences and control for the influence of spurious effects. It also helps in creating refined graphs of relationships through regression lines, which can be a straightforward and accessible way of presenting results. Understanding LR coefficients enables us to understand both the direction and strength of the relationship between variables. Also, the F-test and R-square help us to understand the explanatory power of statistical models. However, care is needed to examine variables and construct them in forms that are amenable to this approach, such as creating dummy variables. They also need to examine findings carefully and test for concerns such as collinearity or patterns among residuals. Despite this, LRs are quite forgiving of minor breaches of these assumptions and can produce some of the most useful information on the relationships between variables.

Based on our dataset, using of LR is not recommended, because the direction of the correlation is not clear from the scatter plot. A scatter plot is a useful tool for visualizing the relationship between two variables and can provide insight into whether a linear relationship may exist. If the scatter plot shows a clear pattern, such as a positive or negative correlation, it is more likely that a LR model will provide useful results. However, in our case, the scatter plot [Figure 6] shows a complex pattern or no clear relationship.

Appendix

List of Figures

Keywords

data pipline, json, big data, bigquery, GCP, data science, data mining, ETL (Extract-Transform-Load), Github, pandas, GeoJson, machine learning, mathplotlib, scraping, pyspark, apache spark, apache beam, data visualization, tableau, folium, seaborn, sqlite3, nampy, web scraping, google dataflow

The Tools

Anaconda, Python, SQL, Tableau (Public), Google Cloud Platform (GCP), Google Colab, Google Trends

Author
Kasra Heidarinezhad (Data scientist)
(604) 442-3332
Kasra.Heydarinezhad@gmail.com
www.linkedin.com/in/kasra-heidarinezhad
www.Github.com/kasraheidarinezhad