IBM Data Science Project: Select the best location for a new restaurant in Vancouver

In [ ]:

Background:

In [ ]:

For the IBM Data Science Capstone Project, we are trying to answer to the following business problem.

A restaurant business owner with multiple locations opened across Canada decides to open a new restaurant in Vancouver. The new unit is going to be focused on Asian cuisine, which is the main specialization gastronomy area on which the restaurants chain is focusing.

Considering the high real-estate prices across Vancouver, intense competition and the high rates that the restaurant plans to apply, one of the variable to decide upon is the right location. The intention of the owner is to find an optimal location in an area which is close to sceneries eating delights, high frequency tourist sections of the city and easily accessible to wealthier inhabitants.

The analysis can be driven by using unsupervised machine learning to create clusters of district areas potentially candidates for the optimal location. The new restaurant will be situated closest to culinary centers and tourist attractions.

Data:

To conduct the analysis we need the following sets of data:

1. List of the main districts of Vancouver which is obtained through a csv file. List of districts to be obtained from Wikipedia website: https://en.wikipedia.org/wiki/List_of_neighbourhoods_in_Vancouver (https://en.wikipedia.org/wiki/List_of_neighbourhoods_in_Vancouver)

1. Geo-coordinates of districts selected at point 1 above to be retrieved in using geocoder tool.

1. Venues from each district are collected using Foursquare API.

Problem solve:

After obtaining the complete data in the desired formatting, we apply the k-means methodology in order to create cluster of districts and determine areas where the restaurant should be located.

Analysis begins by uploading wiki data through csv. file and creating a list of districts of Vancouver, together with the geo-coordinates of each district. Basically, the imported list of districts is used in geocode python library to get the latitude and longitude of each district in the list. Districts and their coordinates are stored in a pandas dataframe format. When done, this includes the following details: Districts, Name, Latitude and Longitude.

The next step is to retrieve the venues of each district. This is completed with the help of Foursquare.com credentials via API. Data is retrieved in json format. We setup a limit of 100 venues for each district and a radius of 1000 meter from the coordinates of district center. In addition to that, we determine which venues are the most common within each district.

After collecting this additional data, a new data frame includes the districts and separate columns for "n" most common venues of each districts. At this stage, the columns look like this: Neighborhood, 1st most common venue, 2nd common venue and so on up to the 10th most common venue.

Unsupervised machine learning is applied by using the K-means methodology. In order to do this, first we need to use one-hot encode to create dummy variables to transform the venue categories values and allow the machine learning process.

K-means requires an optimal number of clusters to be used. For determining the appropriate district clustering, the parameter for the optimal number of clusters is identified by using silhouette score approach. We create a chart to show the silhouette scores for a range number of clusters. The highest score on the chart becomes the optimal number of clusters to initiate.

The number of clusters mentioned above is going to be used in the K-means process. The end result will have each district assigned with a cluster label into the data set.

Results:

The clustered data will let us know which cluster is the best for the solution of our problem. Most common venues and their frequency are a valuable indicator when considering the cluster to include the potential restaurant location. We advise the owner to consider district from the cluster where most of the lively part of the city is present with a lot of gastronomy and tourist venues on site.

Conclusion:

By using various Python libraries we are able to analyse and provide the output and recommendation to support decisional process. As a result, business owner selects the most profitable location with the most benefits available to his customers.

In [ ]:

```

```

Import of libraries:

In [1]:
```
import numpy as np
import pandas as pd
pd.set_option ('display.max_columns',None)
pd.set_option ('display.max_rows',None)
import json
!conda install -c conda-forge geopy #--yes
from geopy.geocoders import Nominatim
import requests
from pandas.io.json import json_normalize
import matplotlib.cm as cm
import matplotlib.colors as colors
from sklearn.cluster import KMeans
!conda install -c conda-forge folium=0.5.0 #--yes
import folium
print ('Imported')
```

```
Solving environment: done

## Package Plan ##

  environment location: /opt/conda/envs/Python36

  added / updated specs:
    - geopy


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    ca-certificates-2020.4.5.1 |       hecc5488_0         146 KB  conda-forge
    python_abi-3.6             |          1_cp36m           4 KB  conda-forge
    certifi-2020.4.5.1         |   py36h9f0ad1d_0         151 KB  conda-forge
    geopy-1.22.0               |     pyh9f0ad1d_0          63 KB  conda-forge
    openssl-1.1.1g             |       h516909a_0         2.1 MB  conda-forge
    geographiclib-1.50         |             py_0          34 KB  conda-forge
    ------------------------------------------------------------
                                           Total:         2.5 MB

The following NEW packages will be INSTALLED:

    geographiclib:   1.50-py_0            conda-forge
    geopy:           1.22.0-pyh9f0ad1d_0 conda-forge
    python_abi:      3.6-1_cp36m          conda-forge

The following packages will be UPDATED:

    ca-certificates: 2020.1.1-0                         --> 2020.4.5.1-hecc5488_
0     conda-forge
    certifi:         2020.4.5.1-py36_0                  --> 2020.4.5.1-py36h9f0a
d1d_0 conda-forge
    openssl:         1.1.1g-h7b6447c_0                  --> 1.1.1g-h516909a_0
conda-forge


Downloading and Extracting Packages
ca-certificates-2020 | 146 KB    | ##################################### | 10
0%
python_abi-3.6       | 4 KB      | ##################################### | 10
0%
certifi-2020.4.5.1   | 151 KB    | ##################################### | 10
0%
geopy-1.22.0         | 63 KB     | ##################################### | 10
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openssl-1.1.1g       | 2.1 MB    | ##################################### | 10
0%
geographiclib-1.50   | 34 KB     | ##################################### | 10
0%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
Solving environment: done
```

```
## Package Plan ##

  environment location: /opt/conda/envs/Python36

  added / updated specs:
    - folium=0.5.0


The following packages will be downloaded:

    package                    |            build
    ---------------------------|-----------------
    folium-0.5.0               |             py_0          45 KB  conda-forge
    branca-0.4.1               |             py_0          26 KB  conda-forge
    vincent-0.4.4              |             py_1          28 KB  conda-forge
    altair-4.1.0               |             py_1         614 KB  conda-forge
    ------------------------------------------------------------
                                           Total:         713 KB

The following NEW packages will be INSTALLED:

    altair:  4.1.0-py_1 conda-forge
    branca:  0.4.1-py_0 conda-forge
    folium:  0.5.0-py_0 conda-forge
    vincent: 0.4.4-py_1 conda-forge


Downloading and Extracting Packages
folium-0.5.0         | 45 KB     | ##################################### | 10
0%
branca-0.4.1         | 26 KB     | ##################################### | 10
0%
vincent-0.4.4        | 28 KB     | ##################################### | 10
0%
altair-4.1.0         | 614 KB    | ##################################### | 10
0%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
Imported
```

Import the list of Vancouver districts from the csv file:

In [210]:
```
import types
import pandas as pd
from botocore.client import Config
import ibm_boto3

def __iter__(self): return 0

# @hidden_cell
# The following code accesses a file in your IBM Cloud Object Storage. It incl
udes your credentials.
# You might want to remove those credentials before you share the notebook.
client_c144cdf0deb84a7aac796d8ae3fcce3f = ibm_boto3.client(service_name='s3',
    ibm_api_key_id='vB17kp4Lt5iATNwQuNzYxz4tR4mJNJeeuuAP08afu0yd',
    ibm_auth_endpoint="https://iam.cloud.ibm.com/oidc/token",
    config=Config(signature_version='oauth'),
    endpoint_url='https://s3-api.us-geo.objectstorage.service.networklayer.co
m')

body = client_c144cdf0deb84a7aac796d8ae3fcce3f.get_object(Bucket='wk1-donotdel
ete-pr-1kj4zznzzph6uq',Key='Districts Vancouver 2.csv')['Body']
# add missing __iter__ method, so pandas accepts body as file-like object
if not hasattr(body, "__iter__"): body.__iter__ = types.MethodType( __iter__,
body )

# If you are reading an Excel file into a pandas DataFrame, replace `read_csv`
by `read_excel` in the next statement.
df_data_1 = pd.read_csv(body)
df_data_1.head()
```

Out[210]:

	District	Name
0	Vancouver-Downtown	Downtown
1	Vancouver-False Creek	False Creek
2	Vancouver-Fraserview	Fraserview
3	Vancouver-Hastings	Hastings
4	Vancouver-Arbutus ridge	Arbutus ridge

Retrieve list of districts, dimensions of data imported to df_data_1:

In [211]:
```
df_data_1.shape
```

Out[211]: (17, 2)

The Vancouver districts retrieved.

In [212]:
```
df_data_1
```

Out[212]:

	District	Name
0	Vancouver-Downtown	Downtown
1	Vancouver-False Creek	False Creek
2	Vancouver-Fraserview	Fraserview
3	Vancouver-Hastings	Hastings
4	Vancouver-Arbutus ridge	Arbutus ridge
5	Vancouver-Kingsway	Kingsway
6	Vancouver-Langara	Langara
7	Vancouver-Mount Pleasant	Mount Pleasant
8	Vancouver-Renfrew-Collingwood	Renfrew-Collingwood
9	Vancouver-Yaletown	Yaletown
10	Vancouver-West End	West End
11	Vancouver-Marpole	Marpole
12	North Vancouver-Seymour	North Seymour
13	Vancouver-Kitsilano	Kitsilano
14	North Vancouver-Garibaldi	North Garibaldi
15	Vancouver-Burrard	Burrard
16	Vancouver-Little Mountain	Little Mountain

We add to the dataframe the latitude and longitude columns to get ready for geo-coordinates retrieval:

In [213]:
```
column_names = ['District','Name','Latitude','Longitude']
```

In [214]:
```
neighbors = pd.DataFrame (columns=column_names)
```

In [215]:
```
neighbors
```

Out[215]:

District	Name	Latitude	Longitude

Get the geo-coordinates for each district in the df_data_1 range:

In [216]:
```
#import geopy.geocoders
#from geopy.geocoders import Nominatim
#geolocator = Nominatim(user_agent = "my-application")
district = df_data_1 ['District']
name = df_data_1 ['Name']
location = None
latitude = None
longitude = None
for data in range (0,len(district)):
    dt = district [data]
    nm = name [data]

    import geopy.geocoders
    from geopy.geocoders import Nominatim
    geolocator = Nominatim(user_agent = "my-application")
    location = geolocator.geocode ('{}'.format(dt))
    latitude = location.latitude
    longitude = location.longitude
     #print ('The geographical coordinates are {},{}.'.format(latitude,longitu
de))
    neighbors = neighbors.append ({'District':dt,'Name':nm,'Latitude': locatio
n.latitude,'Longitude':location.longitude},ignore_index = True)
```

We get the following table:

In [217]:
```
neighbors.head()
```

Out[217]:

	District	Name	Latitude	Longitude
0	Vancouver-Downtown	Downtown	49.283393	-123.117456
1	Vancouver-False Creek	False Creek	49.274751	-123.106131
2	Vancouver-Fraserview	Fraserview	49.218416	-123.073287
3	Vancouver-Hastings	Hastings	49.280673	-123.032600
4	Vancouver-Arbutus ridge	Arbutus ridge	49.240968	-123.167001

In [218]:
```
neighbors
```
Out[218]:

	District	Name	Latitude	Longitude
0	Vancouver-Downtown	Downtown	49.283393	-123.117456
1	Vancouver-False Creek	False Creek	49.274751	-123.106131
2	Vancouver-Fraserview	Fraserview	49.218416	-123.073287
3	Vancouver-Hastings	Hastings	49.280673	-123.032600
4	Vancouver-Arbutus ridge	Arbutus ridge	49.240968	-123.167001
5	Vancouver-Kingsway	Kingsway	49.256732	-123.089712
6	Vancouver-Langara	Langara	49.219437	-123.118026
7	Vancouver-Mount Pleasant	Mount Pleasant	49.263330	-123.096588
8	Vancouver-Renfrew-Collingwood	Renfrew-Collingwood	49.242024	-123.057679
9	Vancouver-Yaletown	Yaletown	49.276322	-123.120956
10	Vancouver-West End	West End	49.284131	-123.131795
11	Vancouver-Marpole	Marpole	49.209223	-123.136150
12	North Vancouver-Seymour	North Seymour	49.556758	-123.045975
13	Vancouver-Kitsilano	Kitsilano	49.269410	-123.155267
14	North Vancouver-Garibaldi	North Garibaldi	49.740507	-123.083205
15	Vancouver-Burrard	Burrard	49.285636	-123.119815
16	Vancouver-Little Mountain	Little Mountain	49.241853	-123.113496

In [219]:
```
neighbors.shape
```
Out[219]:
```
(17, 4)
```

Test for Vancouver coordinates:

In [220]:
```
import geopy.geocoders
from geopy.geocoders import Nominatim
geolocator = Nominatim(user_agent = "my-application")
location = geolocator.geocode ('Vancouver')
latitude = location.latitude
longitude = location.longitude
print ('Coordinate Vancouver {}, {}.'.format (latitude, longitude))
```
```
Coordinate Vancouver 49.2608724, -123.1139529.
```

Visualize data by using the folium library to create a visual map of the districts located across Vancouver.

In [221]:
```
map_vancouver = folium.Map(location=[latitude,longitude], zoom_start=11)
for lat,lng, district in zip (neighbors['Latitude'], neighbors ['Longitude'],
neighbors ['District']):
    label = '{}'.format (district)
    label = folium.Popup (label, parse_html = True)
    folium.CircleMarker(
        [lat,lng],
        radius=2,
        popup=label,
        color='blue',
        fill = True,
        fill_color = '#3186cc',
        fill_opacity = 0.7,
        parse_html = False).add_to(map_vancouver)
map_vancouver
```

Out[221]: Make this Notebook Trusted to load map: File -> Trust Notebook

Credential obtained from Foursquare website client account:

In [222]:
```
CLIENT_ID = 'DYYSKBE12XEO3QDIGIMQJOMKUSUSZ5XE1AQETKDHQJIOJV1E'
CLIENT_SECRET = 'HYKY5BPGPSMAA2SPTWO025FCX201MONU4E55MNRR1ALXCAMX'
VERSION = '20190823'
print ('Client_Id' + CLIENT_ID)
print ('Client_Secret:' + CLIENT_SECRET)
```

```
Client_IdDYYSKBE12XEO3QDIGIMQJOMKUSUSZ5XE1AQETKDHQJIOJV1E
Client_Secret:HYKY5BPGPSMAA2SPTWO025FCX201MONU4E55MNRR1ALXCAMX
```

Get the first district from the list together with its geo coordinates:

For the same district, retrieve from Foursquare the first 100 venues within a radius of 1000 meters:

Json detail format for the 100 venues:

Define the venue caterories:

In [227]:
```
def get_category_type (row):
    try: categories_list = row ['categories']
    except: categories_list = row ['venue.categories']
    if len(categories_list) == 0:
        return None
    else:
        return categories_list [0]['name']
```

In [228]:
```
venues = results ['response']['groups'][0]['items']
nearby_venues = json_normalize (venues)
filtered_columns = ['venue.name','venue.id','venue.categories','venue.locatio
n.lat','venue.location.lng']
nearby_venues
nearby_venues = nearby_venues.loc [:, filtered_columns]
nearby_venues ['venue.categories'] = nearby_venues.apply (get_category_type, a
xis=1)
nearby_venues.head()
```

Out[228]:

	venue.name	venue.id	venue.categories	venue.location.lat	venue.location.lng
0	Rosewood Hotel Georgia	4d5ec8ce29ef236ae0cb9059	Hotel	49.283429	-123.118911
1	Gotham Steakhouse & Cocktail Bar	4aa7f22bf964a520214e20e3	Steakhouse	49.282830	-123.115865
2	Hawksworth Restaurant	4d2cce46ae3a8cfa4067bf70	Lounge	49.283362	-123.119462
3	SEPHORA	4aa73bb9f964a5206b4c20e3	Cosmetics Shop	49.284092	-123.117204
4	Abercrombie & Fitch	4fcbf990e4b09ba63c216a21	Clothing Store	49.282274	-123.118685

In [254]:
```
nearby_venues.columns = [col.split(".") [-1] for col in nearby_venues.columns]
nearby_venues.head()
```

Out[254]:

	name	id	categories	lat	lng
0	Rosewood Hotel Georgia	4d5ec8ce29ef236ae0cb9059	Hotel	49.283429	-123.118911
1	Gotham Steakhouse & Cocktail Bar	4aa7f22bf964a520214e20e3	Steakhouse	49.282830	-123.115865
2	Hawksworth Restaurant	4d2cce46ae3a8cfa4067bf70	Lounge	49.283362	-123.119462
3	SEPHORA	4aa73bb9f964a5206b4c20e3	Cosmetics Shop	49.284092	-123.117204
4	Abercrombie & Fitch	4fcbf990e4b09ba63c216a21	Clothing Store	49.282274	-123.118685

Create a function to help us get the venue categories for all districts:

In [230]:
```
def getNearbyVenues (names, latitudes, longitudes, radius = 1000):

    venues_list=[]
    for name, lat, lng in zip (names, latitudes, longitudes):
        print(name)

        url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&clie
nt_secret={}&v={}&ll={},{}&radius={}&limit={}'.format (
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        results = requests.get(url).json() ["response"]['groups'][0]['items']

        venues_list.append ([(
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

    nearby_venues = pd.DataFrame ([item for venue_list in venues_list for item
in venue_list])
    nearby_venues.columns = ['Neighborhood',
                             'Neighborhood Latitudine',
                             'Neighborhood Longitude',
                             'Venue',
                             'Venue Latitude',
                             'Venue Longitude',
                             'Venue Category']
    return (nearby_venues)
```

In [231]:
```
vancouver_venues = getNearbyVenues (names=neighbors ['District'],latitudes =ne
ighbors['Latitude'], longitudes = neighbors ['Longitude'])
```

```
Vancouver-Downtown
Vancouver-False Creek
Vancouver-Fraserview
Vancouver-Hastings
Vancouver-Arbutus ridge
Vancouver-Kingsway
Vancouver-Langara
Vancouver-Mount Pleasant
Vancouver-Renfrew-Collingwood
Vancouver-Yaletown
Vancouver-West End
Vancouver-Marpole
North Vancouver-Seymour
Vancouver-Kitsilano
North Vancouver-Garibaldi
Vancouver-Burrard
Vancouver-Little Mountain
```

In [257]:
```
print(vancouver_venues.shape)
vancouver_venues.head(10)
```

```
(1113, 7)
```

Out[257]:

	Neighborhood	Neighborhood Latitudine	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Vancouver-Downtown	49.283393	-123.117456	Rosewood Hotel Georgia	49.283429	-123.118911	Hotel
1	Vancouver-Downtown	49.283393	-123.117456	Gotham Steakhouse & Cocktail Bar	49.282830	-123.115865	Steakhouse
2	Vancouver-Downtown	49.283393	-123.117456	Hawksworth Restaurant	49.283362	-123.119462	Lounge
3	Vancouver-Downtown	49.283393	-123.117456	SEPHORA	49.284092	-123.117204	Cosmetics Shop
4	Vancouver-Downtown	49.283393	-123.117456	Abercrombie & Fitch	49.282274	-123.118685	Clothing Store
5	Vancouver-Downtown	49.283393	-123.117456	Hyatt Regency Vancouver	49.284934	-123.120407	Hotel
6	Vancouver-Downtown	49.283393	-123.117456	Vancouver Art Gallery	49.282827	-123.120457	Art Gallery
7	Vancouver-Downtown	49.283393	-123.117456	The Keg Steakhouse + Bar - Dunsmuir	49.283438	-123.116363	Restaurant
8	Vancouver-Downtown	49.283393	-123.117456	Mogu: Japanese Street Eats	49.284118	-123.117531	Food Truck
9	Vancouver-Downtown	49.283393	-123.117456	Disney store	49.281689	-123.119850	Toy / Game Store

We get a total of 1113 venues to inspect.

In [ ]:

Determine the number of distinct venue categories for each distict district:

In [233]:
```
vancouver_venues.groupby('Neighborhood').count()
```

Out[233]:

Neighborhood	Neighborhood Latitudine	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Vancouver-Arbutus ridge	27	27	27	27	27	27
Vancouver-Burrard	100	100	100	100	100	100
Vancouver-Downtown	100	100	100	100	100	100
Vancouver-False Creek	100	100	100	100	100	100
Vancouver-Fraserview	38	38	38	38	38	38
Vancouver-Hastings	50	50	50	50	50	50
Vancouver-Kingsway	100	100	100	100	100	100
Vancouver-Kitsilano	100	100	100	100	100	100
Vancouver-Langara	17	17	17	17	17	17
Vancouver-Little Mountain	55	55	55	55	55	55
Vancouver-Marpole	47	47	47	47	47	47
Vancouver-Mount Pleasant	100	100	100	100	100	100
Vancouver-Renfrew-Collingwood	79	79	79	79	79	79
Vancouver-West End	100	100	100	100	100	100
Vancouver-Yaletown	100	100	100	100	100	100

In [234]:
```
print('{} unique categories'.format(len(vancouver_venues['Venue Category'].unique())))
```

```
198 unique categories
```

One hot encoding for machine learning:

In [273]:
```
vancouver_onehot = pd.get_dummies(vancouver_venues[['Venue Category']], prefix
="",prefix_sep="")
vancouver_onehot['Neighborhood'] = vancouver_venues ['Neighborhood']
fixed_columns = [vancouver_onehot.columns[-1]]+ list(vancouver_onehot.columns
[:-1])
vancouver_onehot = vancouver_onehot[fixed_columns]
vancouver_onehot.head()
```

Out[273]:

	Neighborhood	Accessories Store	American Restaurant	Amphitheater	Art Gallery	Arts & Crafts Store	Asian Restaurant	Athletics & Sports
0	Vancouver-Downtown	0	0	0	0	0	0	0
1	Vancouver-Downtown	0	0	0	0	0	0	0
2	Vancouver-Downtown	0	0	0	0	0	0	0
3	Vancouver-Downtown	0	0	0	0	0	0	0
4	Vancouver-Downtown	0	0	0	0	0	0	0

In [274]:
```
vancouver_onehot.shape
```

Out[274]: (1113, 199)

Group data by neighborhood and by the mean of frequency of each venue category:

In [275]:
```
vancouver_grouped = vancouver_onehot.groupby('Neighborhood').mean().reset_inde
x()
vancouver_grouped.head(20)
```

Out[275]:

	Neighborhood	Accessories Store	American Restaurant	Amphitheater	Art Gallery	Arts & Crafts Store	Asian Restaurant	Athletics & Sports
0	Vancouver-Arbutus ridge	0.00	0.000000	0.00	0.00	0.00	0.037037	0.000000
1	Vancouver-Burrard	0.00	0.010000	0.00	0.01	0.01	0.000000	0.000000
2	Vancouver-Downtown	0.01	0.000000	0.00	0.01	0.01	0.000000	0.000000
3	Vancouver-False Creek	0.00	0.000000	0.00	0.00	0.00	0.030000	0.000000
4	Vancouver-Fraserview	0.00	0.000000	0.00	0.00	0.00	0.000000	0.000000
5	Vancouver-Hastings	0.00	0.020000	0.02	0.00	0.00	0.020000	0.000000
6	Vancouver-Kingsway	0.00	0.000000	0.00	0.00	0.01	0.010000	0.000000
7	Vancouver-Kitsilano	0.00	0.010000	0.00	0.00	0.00	0.010000	0.000000
8	Vancouver-Langara	0.00	0.058824	0.00	0.00	0.00	0.000000	0.000000
9	Vancouver-Little Mountain	0.00	0.000000	0.00	0.00	0.00	0.000000	0.018182
10	Vancouver-Marpole	0.00	0.021277	0.00	0.00	0.00	0.000000	0.000000
11	Vancouver-Mount Pleasant	0.00	0.000000	0.00	0.00	0.02	0.000000	0.000000
12	Vancouver-Renfrew-Collingwood	0.00	0.012658	0.00	0.00	0.00	0.037975	0.000000
13	Vancouver-West End	0.00	0.000000	0.00	0.01	0.00	0.010000	0.000000
14	Vancouver-Yaletown	0.00	0.010000	0.00	0.01	0.00	0.000000	0.000000

Check for the top 5 most common venues in each neighborhood:

In [276]:
```
for hood in vancouver_grouped['Neighborhood']:
    print(" "+hood+" ")
    temp = vancouver_grouped[vancouver_grouped['Neighborhood'] == hood].T.rese
t_index()
    temp.columns = ['venue','freq']
    temp = temp.iloc[1:]
    temp['freq'] = temp['freq'].astype(float)
    temp=temp.round({'freq':2})
    print(temp.sort_values('freq',ascending=False).reset_index(drop=True).head
(5))
    print('\n')
```

```
 Vancouver-Arbutus ridge
             venue  freq
0  Sushi Restaurant  0.11
1            Bakery  0.07
2       Coffee Shop  0.07
3              Park  0.07
4   Bubble Tea Shop  0.04


 Vancouver-Burrard
                venue  freq
0               Hotel  0.10
1        Dessert Shop  0.05
2      Sandwich Place  0.04
3  Japanese Restaurant  0.04
4          Food Truck  0.04


 Vancouver-Downtown
           venue  freq
0          Hotel  0.11
1   Dessert Shop  0.05
2    Coffee Shop  0.05
3  Sandwich Place  0.04
4     Restaurant  0.04


 Vancouver-False Creek
             venue  freq
0      Coffee Shop  0.07
1      Pizza Place  0.05
2           Bakery  0.05
3             Café  0.04
4  Asian Restaurant  0.03


 Vancouver-Fraserview
         venue  freq
0  Pizza Place  0.11
1     Bus Stop  0.08
2  Bus Station  0.05
3  Gas Station  0.05
4         Park  0.05


 Vancouver-Hastings
                         venue  freq
0  Theme Park Ride / Attraction  0.14
1                         Park  0.06
2             Sushi Restaurant  0.04
3                  Event Space  0.04
4                         Café  0.04


 Vancouver-Kingsway
                   venue  freq
0  Vietnamese Restaurant  0.10
```

```
1                Bakery  0.06
2           Pizza Place  0.05
3           Coffee Shop  0.04
4      Sushi Restaurant  0.04


 Vancouver-Kitsilano
         venue  freq
0  Coffee Shop  0.11
1       Bakery  0.05
2  Yoga Studio  0.04
3   Restaurant  0.03
4         Café  0.03


 Vancouver-Langara
             venue  freq
0         Bus Stop  0.18
1             Park  0.12
2     Liquor Store  0.06
3  Bubble Tea Shop  0.06
4      Coffee Shop  0.06


 Vancouver-Little Mountain
                   venue  freq
0            Coffee Shop  0.09
1     Chinese Restaurant  0.07
2  Vietnamese Restaurant  0.05
3         Farmers Market  0.05
4                   Café  0.05


 Vancouver-Marpole
                   venue  freq
0       Sushi Restaurant  0.06
1    Japanese Restaurant  0.06
2     Chinese Restaurant  0.06
3            Pizza Place  0.04
4  Vietnamese Restaurant  0.04


 Vancouver-Mount Pleasant
                   venue  freq
0                Brewery  0.08
1            Coffee Shop  0.08
2                 Bakery  0.06
3  Vietnamese Restaurant  0.04
4       Sushi Restaurant  0.04


 Vancouver-Renfrew-Collingwood
                   venue  freq
0  Vietnamese Restaurant  0.13
1     Chinese Restaurant  0.11
2               Bus Stop  0.08
3       Asian Restaurant  0.04
```

```
4           Bus Station  0.04


 Vancouver-West End
                venue  freq
0               Hotel  0.08
1        Dessert Shop  0.05
2  Japanese Restaurant  0.05
3              Bakery  0.05
4      Sandwich Place  0.03


 Vancouver-Yaletown
               venue  freq
0              Hotel  0.09
1  Italian Restaurant  0.04
2               Café  0.04
3        Yoga Studio  0.03
4   Sushi Restaurant  0.03
```

Create the dataframe with the neighborhoods and their most common venues:

In [277]:
```
num_top_venues =5
def return_most_common_venues(row,num_top_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)
    return row_categories_sorted.index.values[0:num_top_venues]
```

In [278]:
```
num_top_venues = 10
indicators = ['st','nd','rd']
columns =['Neighborhood']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most common venue'.format(ind+1,indicators[ind]))
    except:
        columns.append('{} Most common venue'.format(ind+1))

neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['Neighborhood'] = vancouver_grouped['Neighborhood'
]

for ind in np.arange(vancouver_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind,1:] = return_most_common_venues(vanco
uver_grouped.iloc[ind,:], num_top_venues)
neighborhoods_venues_sorted.head()
```

Out[278]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Most common venue	
0	Vancouver-Arbutus ridge	Sushi Restaurant	Coffee Shop	Park	Bakery	Burger Joint	Ice Cream Shop	Bubble Tea Shop	
1	Vancouver-Burrard	Hotel	Dessert Shop	Food Truck	Japanese Restaurant	Sandwich Place	Coffee Shop	Plaza	F
2	Vancouver-Downtown	Hotel	Dessert Shop	Coffee Shop	Restaurant	Sandwich Place	Plaza	Food Truck	F
3	Vancouver-False Creek	Coffee Shop	Bakery	Pizza Place	Café	Brewery	Sandwich Place	Asian Restaurant	F
4	Vancouver-Fraserview	Pizza Place	Bus Stop	Gas Station	Bus Station	Park	Sporting Goods Shop	Convenience Store	E

Machine learning:

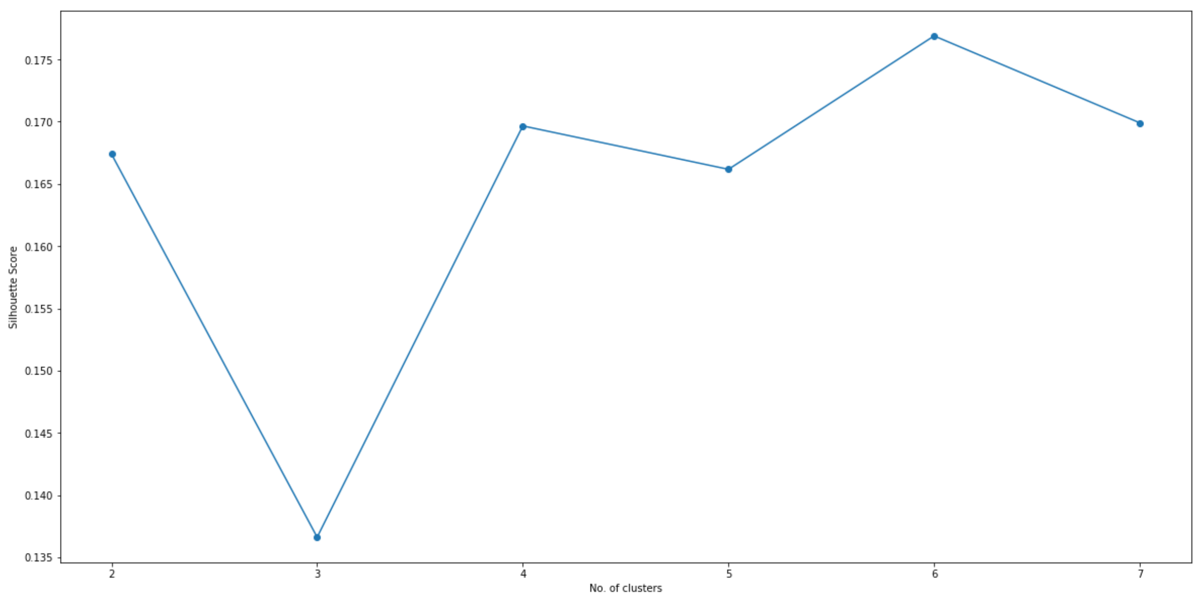
In [279]:
```
#import matplotlib as mlp
import matplotlib.pyplot as plt
%matplotlib inline

def plot(x, y, xlabel, ylabel):
    plt.figure(figsize=(20, 10))
    plt.plot(np.arange(2,x),y,'o-')
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.xticks(np.arange(2,x))
    plt.show()
```

Display a chart with silhouette scores to determine de number of clusters

In [280]:
```
max_range = 8

vancouver_grouped_clustering = vancouver_grouped.drop ('Neighborhood',1)

from sklearn.metrics import silhouette_samples, silhouette_score

indices = []
scores = []

for kclusters in range (2, max_range) :

    kmc = vancouver_grouped_clustering
    kmeans = KMeans (n_clusters = kclusters, init = 'k-means++', random_state
= 0).fit_predict(kmc)

    score = silhouette_score (kmc,kmeans)

    indices.append(kclusters)
    scores.append(score)
```

Find the optimal number of clusters:

In [281]:
```
plot(max_range, scores, "No. of clusters", "Silhouette Score")
```



Apply K-means for the optimal number of clusters: 6 is the number of cluster to use. This is where the score is the highest.

In [282]:
```
kmeans = KMeans(n_clusters=6, random_state=0).fit(vancouver_grouped_clustering
)

kmeans.labels_[0:10]
```

Out[282]:
```
array([1, 2, 2, 1, 0, 5, 1, 1, 3, 4], dtype=int32)
```

In [283]:
```
vancouver_grouped_clustering.head()
```

Out[283]:

	Accessories Store	American Restaurant	Amphitheater	Art Gallery	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	Auto Dealership	BB Joi
0	0.00	0.00	0.0	0.00	0.00	0.037037	0.0	0.0	0
1	0.00	0.01	0.0	0.01	0.01	0.000000	0.0	0.0	0
2	0.01	0.00	0.0	0.01	0.01	0.000000	0.0	0.0	0
3	0.00	0.00	0.0	0.00	0.00	0.030000	0.0	0.0	0
4	0.00	0.00	0.0	0.00	0.00	0.000000	0.0	0.0	0

New dataframe with top venues for each neighborhoods and cluster labels:

In [284]:
```
neighbors.rename(columns={'District':'Neighborhood'}, inplace=True)
neighbors.head()
```

Out[284]:

	Neighborhood	Name	Latitude	Longitude
0	Vancouver-Downtown	Downtown	49.283393	-123.117456
1	Vancouver-False Creek	False Creek	49.274751	-123.106131
2	Vancouver-Fraserview	Fraserview	49.218416	-123.073287
3	Vancouver-Hastings	Hastings	49.280673	-123.032600
4	Vancouver-Arbutus ridge	Arbutus ridge	49.240968	-123.167001

In [285]:
```
neighborhoods_venues_sorted.head()
```

Out[285]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Most common venue	
0	Vancouver-Arbutus ridge	Sushi Restaurant	Coffee Shop	Park	Bakery	Burger Joint	Ice Cream Shop	Bubble Tea Shop	
1	Vancouver-Burrard	Hotel	Dessert Shop	Food Truck	Japanese Restaurant	Sandwich Place	Coffee Shop	Plaza	F
2	Vancouver-Downtown	Hotel	Dessert Shop	Coffee Shop	Restaurant	Sandwich Place	Plaza	Food Truck	F
3	Vancouver-False Creek	Coffee Shop	Bakery	Pizza Place	Café	Brewery	Sandwich Place	Asian Restaurant	F
4	Vancouver-Fraserview	Pizza Place	Bus Stop	Gas Station	Bus Station	Park	Sporting Goods Shop	Convenience Store	E

In [286]:
```
neighborhoods_venues_sorted.insert(0,'Cluster Labels', kmeans.labels_)
vancouver_merged = neighbors
vancouver_merged = vancouver_merged.join (neighborhoods_venues_sorted.set_inde
x('Neighborhood'), on='Neighborhood')
vancouver_merged
```

Out[286]:

	Neighborhood	Name	Latitude	Longitude	Cluster Labels	1st Most common venue	2nd Most common venue	3rd Mos commo venu
0	Vancouver-Downtown	Downtown	49.283393	-123.117456	2.0	Hotel	Dessert Shop	Coffe Shc
1	Vancouver-False Creek	False Creek	49.274751	-123.106131	1.0	Coffee Shop	Bakery	Pizz Plac
2	Vancouver-Fraserview	Fraserview	49.218416	-123.073287	0.0	Pizza Place	Bus Stop	Ga Static
3	Vancouver-Hastings	Hastings	49.280673	-123.032600	5.0	Theme Park Ride / Attraction	Park	Them Pai
4	Vancouver-Arbutus ridge	Arbutus ridge	49.240968	-123.167001	1.0	Sushi Restaurant	Coffee Shop	Pai
5	Vancouver-Kingsway	Kingsway	49.256732	-123.089712	1.0	Vietnamese Restaurant	Bakery	Pizz Plac
6	Vancouver-Langara	Langara	49.219437	-123.118026	3.0	Bus Stop	Park	Bubb Tea Shc
7	Vancouver-Mount Pleasant	Mount Pleasant	49.263330	-123.096588	1.0	Coffee Shop	Brewery	Bakeı
8	Vancouver-Renfrew-Collingwood	Renfrew-Collingwood	49.242024	-123.057679	4.0	Vietnamese Restaurant	Chinese Restaurant	Bus Stc
9	Vancouver-Yaletown	Yaletown	49.276322	-123.120956	2.0	Hotel	Italian Restaurant	Cai
10	Vancouver-West End	West End	49.284131	-123.131795	2.0	Hotel	Dessert Shop	Japanes Restaurai
11	Vancouver-Marpole	Marpole	49.209223	-123.136150	4.0	Chinese Restaurant	Sushi Restaurant	Japanes Restaurai
12	North Vancouver-Seymour	North Seymour	49.556758	-123.045975	NaN	NaN	NaN	Na
13	Vancouver-Kitsilano	Kitsilano	49.269410	-123.155267	1.0	Coffee Shop	Bakery	Yoç Stud
14	North Vancouver-Garibaldi	North Garibaldi	49.740507	-123.083205	NaN	NaN	NaN	Na
15	Vancouver-Burrard	Burrard	49.285636	-123.119815	2.0	Hotel	Dessert Shop	Foc Truc
16	Vancouver-Little Mountain	Little Mountain	49.241853	-123.113496	4.0	Coffee Shop	Chinese Restaurant	Cai

In [287]:
```
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]


markers_colors = []
for lat, lon, poi, cluster in zip(vancouver_merged['Latitude'], vancouver_merged['Longitude'], vancouver_merged['Neighborhood'], vancouver_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + 'Cluster' + str(cluster), parse_html=True)
    folium.CircleMarker(
        [lat, lon],
        radius =5,
        popup=label,
        #color=rainbow[cluster-1],
        fill=True,
        #fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[287]: Make this Notebook Trusted to load map: File -> Trust Notebook

Clusters map visualize above.

Breakdown of nebighborhoods by cluster label:

In [288]:
```
#Cluster 1 - outer district
vancouver_merged.loc[vancouver_merged['Cluster Labels'] == 0, vancouver_merged
.columns[[0]+list(range(5, vancouver_merged.shape[1]))]]
```

Out[288]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Most common venue	8 co
2	Vancouver-Fraserview	Pizza Place	Bus Stop	Gas Station	Bus Station	Park	Sporting Goods Shop	Convenience Store	Elec

In [289]:
```
#Cluster 2
vancouver_merged.loc[vancouver_merged['Cluster Labels'] == 1, vancouver_merged
.columns[[0]+list(range(5, vancouver_merged.shape[1]))]]
```

Out[289]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Most common venue
1	Vancouver-False Creek	Coffee Shop	Bakery	Pizza Place	Café	Brewery	Sandwich Place	Asian Restaurant
4	Vancouver-Arbutus ridge	Sushi Restaurant	Coffee Shop	Park	Bakery	Burger Joint	Ice Cream Shop	Bubble Tea Shop
5	Vancouver-Kingsway	Vietnamese Restaurant	Bakery	Pizza Place	Coffee Shop	Sushi Restaurant	Mexican Restaurant	Café
7	Vancouver-Mount Pleasant	Coffee Shop	Brewery	Bakery	Sushi Restaurant	Vietnamese Restaurant	Pizza Place	Park
13	Vancouver-Kitsilano	Coffee Shop	Bakery	Yoga Studio	Restaurant	Vegetarian / Vegan Restaurant	Pizza Place	Board Shop

In [290]:
```
#Cluster 3
vancouver_merged.loc[vancouver_merged['Cluster Labels'] == 2, vancouver_merged
.columns[[0]+list(range(5, vancouver_merged.shape[1]))]]
```

Out[290]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Most common venue
0	Vancouver-Downtown	Hotel	Dessert Shop	Coffee Shop	Restaurant	Sandwich Place	Plaza	Food Truck
9	Vancouver-Yaletown	Hotel	Italian Restaurant	Café	Yoga Studio	Japanese Restaurant	Park	Seafood Restaurant
10	Vancouver-West End	Hotel	Dessert Shop	Japanese Restaurant	Bakery	Food Truck	Park	Café
15	Vancouver-Burrard	Hotel	Dessert Shop	Food Truck	Japanese Restaurant	Sandwich Place	Coffee Shop	Plaza

In [291]:
```
#Cluster 4 - outer district
vancouver_merged.loc[vancouver_merged['Cluster Labels'] == 3, vancouver_merged
.columns[[0]+list(range(5, vancouver_merged.shape[1]))]]
```

Out[291]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Most common venue	8 Mos commo venu
6	Vancouver-Langara	Bus Stop	Park	Bubble Tea Shop	Coffee Shop	Café	Liquor Store	Sandwich Place	Fie

In [292]:
```
#Cluster 5
vancouver_merged.loc[vancouver_merged['Cluster Labels'] == 4, vancouver_merged
.columns[[0]+list(range(5, vancouver_merged.shape[1]))]]
```

Out[292]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Mc comm ven
8	Vancouver-Renfrew-Collingwood	Vietnamese Restaurant	Chinese Restaurant	Bus Stop	Bus Station	Asian Restaurant	Park	Groce Stc
11	Vancouver-Marpole	Chinese Restaurant	Sushi Restaurant	Japanese Restaurant	Vietnamese Restaurant	Bus Stop	Bubble Tea Shop	Piz Pla
16	Vancouver-Little Mountain	Coffee Shop	Chinese Restaurant	Café	Farmers Market	Vietnamese Restaurant	Japanese Restaurant	Sporti Goo Sh

In [293]:
```
#Cluster 6 - outer district
vancouver_merged.loc[vancouver_merged['Cluster Labels'] == 5, vancouver_merged
.columns[[0]+list(range(5, vancouver_merged.shape[1]))]]
```

Out[293]:

	Neighborhood	1st Most common venue	2nd Most common venue	3rd Most common venue	4 Most common venue	5 Most common venue	6 Most common venue	7 Most common venue	8 Mo comm ven
3	Vancouver-Hastings	Theme Park Ride / Attraction	Park	Theme Park	Café	Sushi Restaurant	Coffee Shop	Soccer Field	Eve Spa

Cluster number 5 contains districts where a lot of Asian cuisine venues are already located, probably not a suitable area for the new restaurant due to increased competition over the same niche.

Based on cluster segmentation above, we learn that in cluster 3 the hotel category is the top venue, which might not be a right candidate for our restaurant.

Clusters data shows us that the number 1,4 and 6 clusters are outer districts, therefore might not want to setup the restaurant location around them.

Cluster number 2 is the largest cluster out of the total of 6. It contains many gastronomy related venues. They range from coffee shops, backeries, sushi and pizza places to various restaurants such as those with Vietnamese, Italian or mexican gastronomy. Based on this, we can advise the owner of the new restaurant to consider places inside this cluster as potential location. Cluster number 2 area is the one that the business would best benefit from. Districts inside this cluster are the best candidates due to its restaurant places but also due to its central location in down town part of the city where tourists are most interested visiting.

In [ ]:

In [ ]: