Capstone Project - Part 1&2

March 23, 2020

1 Capstone Project - New Restaurant in Town

1.1 Project by Erick Daniel Rodriguez

1.1.1 1. Introduction

Mexico city is one of the most populated cities around the world, the city is divided in sixteen main boroughs, using statistical government data from Mexico City (INEGI) and with the Foursquare API, this project will try to find which boroughs are similar according to the different venues located in each borough.

1.1.2 2. Data

2.1 Data description The data that will be used for this project will be:

- Number of restaurants within the area of each borough
  - Foursquare API
- Population and job occupation division of each borough
  - Statistics data from 2017 of Mexico City (https://www.datatur.sectur.gob.mx/ITxEF_Docs/CDMX_A
- Borough coordinates
  - Open StreetMap (https://www.openstreetmap.org/relation/1376330)

2.2 Data preparation The first step will be to import the libraries that will be used.

[1]:
```
import numpy as np # library to handle data in a vectorized manner

import tabula as tb # library for PDF to DataFrame conversion

import pandas as pd # library for data analsysis

from geopy.geocoders import Nominatim # convert an address into latitude and␣
↪longitude values

# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors
```

```
import matplotlib.pyplot as plt
%matplotlib inline

# import k-means from clustering stage
from sklearn.cluster import KMeans
from sklearn.preprocessing import MinMaxScaler

import folium # map rendering library

import json # library to handle JSON files
from pandas.io.json import json_normalize # tranform JSON file into a pandas␣
↪dataframe
import requests # library to handle requests

print('Libraries imported.')
```

```
Libraries imported.
```

Creat dataframes from the "Statistics data from 2017 of Mexico City" report using the library Tabula.

[2]:
```
file_path = "https://www.datatur.sectur.gob.mx/ITxEF_Docs/CDMX_ANUARIO_PDF.pdf"
#Convert the file
occupation = tb.read_pdf(file_path, pages=331)
```

We have downloaded the employed population by delegation and its percentage distribution according to occupational division by March 15th of 2015 from the report, now we will look at the data and make the relevant adjustments.

[3]:
```
occupation=occupation[0] # Here we will index it to 0
occupation
```

[3]:

	Unnamed: 0	Total	Unnamed: 1 \
0	NaN	NaN	NaN
1	Delegación	NaN	Funcionarios,
2	NaN	NaN	profesionistas,
3	NaN	NaN	técnicos y
4	NaN	NaN	administrativos b/
5	Ciudad de México	4 033 273	43.91
6	Álvaro Obregón	351 409	42.30
7	Azcapotzalco	180 813	48.17
8	Benito Juárez	223 843	69.81
9	Coyoacán	280 561	54.74
10	Cuajimalpa de Morelos	91 063	41.60
11	Cuauhtémoc	269 664	51.26
12	Gustavo A. Madero	498 501	40.56
13	Iztacalco	175 194	46.45
14	Iztapalapa	786 218	34.80

15	La Magdalena Contreras	105 951	35.87	
16	Miguel Hidalgo	187 477	58.87	
17	Milpa Alta	55 323	22.99	
18	Tláhuac	149 382	33.15	
19	Tlalpan	307 257	44.49	
20	Venustiano Carranza	194 371	42.44	
21	Xochimilco	176 246	35.35	

	División ocupacional a/		Unnamed: 2	Unnamed: 3
0		(Porcentaje)	NaN	NaN
1	Trabajadores	Trabajadores	Comerciantes y	No
2	agropecuarios	en la industria c/	trabajadores en	especificado
3		NaN	servicios diversos d/	NaN
4		NaN	NaN	NaN
5	0.39	14.63	39.44	1.62
6	0.14	16.55	39.34	1.66
7	0.02	14.19	35.99	1.63
8	0.01	5.02	24.04	1.12
9	0.04	10.44	32.04	2.74
10	0.26	16.85	39.82	1.46
11	0.06	8.13	38.54	2.02
12	0.10	16.79	41.49	1.06
13	0.15	14.20	38.10	1.09
14	0.10	18.50	45.30	1.31
15	0.23	17.55	43.50	2.86
16	0.07	6.87	31.84	2.35
17	6.95	22.31	46.97	0.79
18	1.30	19.69	44.95	0.91
19	0.72	15.09	37.91	1.80
20	0.04	12.52	43.57	1.44
21	2.66	17.43	41.93	2.63

We can notice there is a problem with the first few rows of the dataframe, therefore, these first rows will be deleted and new ones will be added also considering new titles.

[4]:
```
occupation.drop(occupation.head(6).index,inplace=True)
occupation
```

[4]:

	Unnamed: 0	Total	Unnamed: 1	División ocupacional a/	\
6	Álvaro Obregón	351 409	42.30	0.14	16.55
7	Azcapotzalco	180 813	48.17	0.02	14.19
8	Benito Juárez	223 843	69.81	0.01	5.02
9	Coyoacán	280 561	54.74	0.04	10.44
10	Cuajimalpa de Morelos	91 063	41.60	0.26	16.85
11	Cuauhtémoc	269 664	51.26	0.06	8.13
12	Gustavo A. Madero	498 501	40.56	0.10	16.79
13	Iztacalco	175 194	46.45	0.15	14.20

```
14              Iztapalapa  786 218      34.80              0.10 18.50
15  La Magdalena Contreras  105 951      35.87              0.23 17.55
16          Miguel Hidalgo  187 477      58.87               0.07 6.87
17              Milpa Alta   55 323      22.99              6.95 22.31
18                 Tláhuac  149 382      33.15              1.30 19.69
19                 Tlalpan  307 257      44.49              0.72 15.09
20     Venustiano Carranza  194 371      42.44              0.04 12.52
21              Xochimilco  176 246      35.35              2.66 17.43

   Unnamed: 2 Unnamed: 3
6       39.34       1.66
7       35.99       1.63
8       24.04       1.12
9       32.04       2.74
10      39.82       1.46
11      38.54       2.02
12      41.49       1.06
13      38.10       1.09
14      45.30       1.31
15      43.50       2.86
16      31.84       2.35
17      46.97       0.79
18      44.95       0.91
19      37.91       1.80
20      43.57       1.44
21      41.93       2.63
```

[5]:
```
occupation.columns = ['Borough', 'Total', '%A', '%B', '%C', '%D']
occupation
```

[5]:
```
                  Borough    Total     %A          %B     %C    %D
6           Álvaro Obregón  351 409  42.30  0.14 16.55  39.34  1.66
7             Azcapotzalco  180 813  48.17  0.02 14.19  35.99  1.63
8            Benito Juárez  223 843  69.81   0.01 5.02  24.04  1.12
9                 Coyoacán  280 561  54.74  0.04 10.44  32.04  2.74
10   Cuajimalpa de Morelos   91 063  41.60  0.26 16.85  39.82  1.46
11              Cuauhtémoc  269 664  51.26   0.06 8.13  38.54  2.02
12       Gustavo A. Madero  498 501  40.56  0.10 16.79  41.49  1.06
13               Iztacalco  175 194  46.45  0.15 14.20  38.10  1.09
14              Iztapalapa  786 218  34.80  0.10 18.50  45.30  1.31
15  La Magdalena Contreras  105 951  35.87  0.23 17.55  43.50  2.86
16          Miguel Hidalgo  187 477  58.87   0.07 6.87  31.84  2.35
17              Milpa Alta   55 323  22.99  6.95 22.31  46.97  0.79
18                 Tláhuac  149 382  33.15  1.30 19.69  44.95  0.91
19                 Tlalpan  307 257  44.49  0.72 15.09  37.91  1.80
20     Venustiano Carranza  194 371  42.44  0.04 12.52  43.57  1.44
21              Xochimilco  176 246  35.35  2.66 17.43  41.93  2.63
```

There is a problem with column "%B", the column is displaying two values, therefore, this must be changed in order to have two different columns.

[6]:
```
nums1, nums2 = list(), list()
for vals in occupation['%B'].values:
    nums = [float(i) for i in vals.split()]
    nums1.append(nums[0])
    nums2.append(nums[1])

occupation['%B'] = nums1
occupation['%B2'] = nums2 # Temporary name for the splitted of the column
occupation
```

[6]:

	Borough	Total	%A	%B	%C	%D	%B2
6	Álvaro Obregón	351 409	42.30	0.14	39.34	1.66	16.55
7	Azcapotzalco	180 813	48.17	0.02	35.99	1.63	14.19
8	Benito Juárez	223 843	69.81	0.01	24.04	1.12	5.02
9	Coyoacán	280 561	54.74	0.04	32.04	2.74	10.44
10	Cuajimalpa de Morelos	91 063	41.60	0.26	39.82	1.46	16.85
11	Cuauhtémoc	269 664	51.26	0.06	38.54	2.02	8.13
12	Gustavo A. Madero	498 501	40.56	0.10	41.49	1.06	16.79
13	Iztacalco	175 194	46.45	0.15	38.10	1.09	14.20
14	Iztapalapa	786 218	34.80	0.10	45.30	1.31	18.50
15	La Magdalena Contreras	105 951	35.87	0.23	43.50	2.86	17.55
16	Miguel Hidalgo	187 477	58.87	0.07	31.84	2.35	6.87
17	Milpa Alta	55 323	22.99	6.95	46.97	0.79	22.31
18	Tláhuac	149 382	33.15	1.30	44.95	0.91	19.69
19	Tlalpan	307 257	44.49	0.72	37.91	1.80	15.09
20	Venustiano Carranza	194 371	42.44	0.04	43.57	1.44	12.52
21	Xochimilco	176 246	35.35	2.66	41.93	2.63	17.43

The column is now correctly splitted, however, the column was sent to the end of the dataframe, so we have to place it in the correct order.

[7]:
```
occupation=occupation[['Borough', 'Total', '%A', '%B', '%B2','%C', '%D']]
occupation.columns = ['Borough', 'Total', '%A', '%B', '%C', '%D', '%E']
occupation.style.set_caption("Employed population by delegation and its␣
 ↪percentage distribution according to occupational division")
occupation
```

[7]:

	Borough	Total	%A	%B	%C	%D	%E
6	Álvaro Obregón	351 409	42.30	0.14	16.55	39.34	1.66
7	Azcapotzalco	180 813	48.17	0.02	14.19	35.99	1.63
8	Benito Juárez	223 843	69.81	0.01	5.02	24.04	1.12
9	Coyoacán	280 561	54.74	0.04	10.44	32.04	2.74
10	Cuajimalpa de Morelos	91 063	41.60	0.26	16.85	39.82	1.46
11	Cuauhtémoc	269 664	51.26	0.06	8.13	38.54	2.02
12	Gustavo A. Madero	498 501	40.56	0.10	16.79	41.49	1.06

13	Iztacalco	175	194	46.45	0.15	14.20	38.10	1.09
14	Iztapalapa	786	218	34.80	0.10	18.50	45.30	1.31
15	La Magdalena Contreras	105	951	35.87	0.23	17.55	43.50	2.86
16	Miguel Hidalgo	187	477	58.87	0.07	6.87	31.84	2.35
17	Milpa Alta	55	323	22.99	6.95	22.31	46.97	0.79
18	Tláhuac	149	382	33.15	1.30	19.69	44.95	0.91
19	Tlalpan	307	257	44.49	0.72	15.09	37.91	1.80
20	Venustiano Carranza	194	371	42.44	0.04	12.52	43.57	1.44
21	Xochimilco	176	246	35.35	2.66	17.43	41.93	2.63

We now have the correct order. The dataframe is divided by borough. The meaning of each column is the following: * Borough = Name of the borough

- Total = Total population
- %A = officers, directors and managers; professionals and technicians; as well as auxiliary workers in administrative activities.
- %B = Agricultural workers.
- %C = Craft workers; as well as industrial machinery operators, assemblers, drivers and transport drivers.
- %D = Merchants, sales employees, and sales agents; workers in personal services and surveillance; as well as workers in elementary and support activities.
- %E = Not specified

Now we will get the latitude and longitude of the neighbourhoods, which are retrieved using Open Street Map Geocoding

[8]:
```
#Get Latitude and Longitude for suburbs
address= occupation['Borough']
geolocater= Nominatim(user_agent="mexico_city-explorer")
location=[]
empty=[]

def getcoords(add):
    try:
        coords= geolocater.geocode(add, timeout=10)
        location.append([add, coords.latitude, coords.longitude])
        print("the coords are {}".format(location[-1]))

    except GeocoderTimedOut:
        return getcoords(add)

    except:
        empty.append([add])
        print("Couldn't find coords of {}".format(empty[-1]))

for add in address:
```

```
        getcoords(add)
```

```
the coords are ['Álvaro Obregón', 19.318148049999998, -99.2778443631872]
the coords are ['Azcapotzalco', 19.4858148, -99.18420573027606]
the coords are ['Benito Juárez', 20.8169666, -98.17826806649418]
the coords are ['Coyoacán', 19.32804005, -99.15106340693589]
the coords are ['Cuajimalpa de Morelos', 19.3187067, -99.32320297716439]
the coords are ['Cuauhtémoc', 19.4416128, -99.1518637]
the coords are ['Gustavo A. Madero', 19.518545449999998, -99.1436399464875]
the coords are ['Iztacalco', 19.39897535, -99.09531197032297]
the coords are ['Iztapalapa', 19.3428293, -99.04689193846701]
the coords are ['La Magdalena Contreras', 19.27547005, -99.26333858358939]
the coords are ['Miguel Hidalgo', 19.429614049999998, -99.19863845640572]
the coords are ['Milpa Alta', 19.138028, -99.05892017210884]
the coords are ['Tláhuac', 19.26950425, -99.00409684032508]
the coords are ['Tlalpan', 19.200877, -99.21701240427146]
the coords are ['Venustiano Carranza', 16.30898425, -92.6379347298267]
the coords are ['Xochimilco', 19.23697845, -99.0823001406525]
```

Now we trasnform the obtained borough latitude and longitude values into a dataframe.

[9]:
```
CDMX=pd.DataFrame(location, columns=['Borough','Latitude','Longitude'])
CDMX
```

[9]:

	Borough	Latitude	Longitude
0	Álvaro Obregón	19.318148	-99.277844
1	Azcapotzalco	19.485815	-99.184206
2	Benito Juárez	20.816967	-98.178268
3	Coyoacán	19.328040	-99.151063
4	Cuajimalpa de Morelos	19.318707	-99.323203
5	Cuauhtémoc	19.441613	-99.151864
6	Gustavo A. Madero	19.518545	-99.143640
7	Iztacalco	19.398975	-99.095312
8	Iztapalapa	19.342829	-99.046892
9	La Magdalena Contreras	19.275470	-99.263339
10	Miguel Hidalgo	19.429614	-99.198638
11	Milpa Alta	19.138028	-99.058920
12	Tláhuac	19.269504	-99.004097
13	Tlalpan	19.200877	-99.217012
14	Venustiano Carranza	16.308984	-92.637935
15	Xochimilco	19.236978	-99.082300

We can also obtain the latitude and longitude of Mexico City as a whole

[10]:
```
address = 'Mexico City'

geolocator = Nominatim(user_agent="mexico_city-explorer")
location = geolocator.geocode(address)
```

```
latitude_CDMX = location.latitude
longitude_CDMX = location.longitude
print('The geograpical coordinate of Mexico City are {}, {}.'.
 ↪format(latitude_CDMX, longitude_CDMX))
```

```
The geograpical coordinate of Mexico City are 19.4326296, -99.1331785.
```

We now create a map of Mexico City in order to see the division by each borough, this is created with the library folium. An important consideration is that some names on the labels will have an odd format, this is due to the fact that some borough names have accents.

[11]:
```
# Creates map of Mexico City using latitude and longitude values
map_CDMX = folium.Map(location=[latitude_CDMX, longitude_CDMX], zoom_start=10)

# Add markers to map
for lat, lng, borough in zip(CDMX['Latitude'], CDMX['Longitude'],␣
 ↪CDMX['Borough']):
    label = '{}'.format(borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_CDMX)

map_CDMX
```

[11]:
```
<folium.folium.Map at 0x1a1f4f1510>
```

Map looks great, however there are two locations which are incorrectly placed (Not in Mexico City) therefore, I will correct this by adding a string to the borough name, this way Open Street Map will know exactly the boroughs we need.

[12]:
```
#Get Latitude and Longitude for suburbs
address= occupation['Borough'].astype(str) + ', Mexico City' # Added string to␣
 ↪help API know exact location
geolocater= Nominatim(user_agent="mexico_city-explorer")
location=[]
empty=[]

def getcoords(add):
    try:
        coords= geolocater.geocode(add, timeout=10)
        location.append([add, coords.latitude, coords.longitude])
```

```
        print("the coords are {}".format(location[-1]))

    except GeocoderTimedOut:
        return getcoords(add)

    except:
        empty.append([add])
        print("Couldn't find coords of {}".format(empty[-1]))

for add in address:
        getcoords(add)
```

```
the coords are ['Álvaro Obregón, Mexico City', 19.318148049999998,
-99.2778443631872]
the coords are ['Azcapotzalco, Mexico City', 19.4858148, -99.18420573027606]
the coords are ['Benito Juárez, Mexico City', 19.3804695, -99.1632429340113]
the coords are ['Coyoacán, Mexico City', 19.32804005, -99.15106340693589]
the coords are ['Cuajimalpa de Morelos, Mexico City', 19.3187067,
-99.32320297716439]
the coords are ['Cuauhtémoc, Mexico City', 19.4326296, -99.1331785]
the coords are ['Gustavo A. Madero, Mexico City', 19.518545449999998,
-99.1436399464875]
the coords are ['Iztacalco, Mexico City', 19.39897535, -99.09531197032297]
the coords are ['Iztapalapa, Mexico City', 19.3428293, -99.04689193846701]
the coords are ['La Magdalena Contreras, Mexico City', 19.27547005,
-99.26333858358939]
the coords are ['Miguel Hidalgo, Mexico City', 19.429614049999998,
-99.19863845640572]
the coords are ['Milpa Alta, Mexico City', 19.138028, -99.05892017210884]
the coords are ['Tláhuac, Mexico City', 19.26950425, -99.00409684032508]
the coords are ['Tlalpan, Mexico City', 19.200877, -99.21701240427146]
the coords are ['Venustiano Carranza, Mexico City', 19.432396,
-99.08806284470657]
the coords are ['Xochimilco, Mexico City', 19.23697845, -99.0823001406525]
```

[13]:
```
CDMX_new=pd.DataFrame(location, columns=['Borough','Latitude','Longitude'])
CDMX_new
```

[13]:

	Borough	Latitude	Longitude
0	Álvaro Obregón, Mexico City	19.318148	-99.277844
1	Azcapotzalco, Mexico City	19.485815	-99.184206
2	Benito Juárez, Mexico City	19.380470	-99.163243
3	Coyoacán, Mexico City	19.328040	-99.151063
4	Cuajimalpa de Morelos, Mexico City	19.318707	-99.323203
5	Cuauhtémoc, Mexico City	19.432630	-99.133178
6	Gustavo A. Madero, Mexico City	19.518545	-99.143640
7	Iztacalco, Mexico City	19.398975	-99.095312

```
8              Iztapalapa, Mexico City  19.342829 -99.046892
9   La Magdalena Contreras, Mexico City  19.275470 -99.263339
10         Miguel Hidalgo, Mexico City  19.429614 -99.198638
11             Milpa Alta, Mexico City  19.138028 -99.058920
12                Tláhuac, Mexico City  19.269504 -99.004097
13                Tlalpan, Mexico City  19.200877 -99.217012
14     Venustiano Carranza, Mexico City  19.432396 -99.088063
15              Xochimilco, Mexico City  19.236978 -99.082300
```

[14]:
```
# Creates map of Mexico City using latitude and longitude values
map_CDMX_new = folium.Map(location=[latitude_CDMX, longitude_CDMX],␣
 ↪zoom_start=10)

# Add markers to map
for lat, lng, borough in zip(CDMX_new['Latitude'], CDMX_new['Longitude'],␣
 ↪CDMX_new['Borough']):
    label = '{}'.format(borough)
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='#3186cc',
        fill_opacity=0.7,
        parse_html=False).add_to(map_CDMX_new)

map_CDMX_new
```

[14]:
```
<folium.folium.Map at 0x1a1f5f9450>
```

All locations are now placed correctly. This ends the first section of the capstone project, on the next part we will begin to use the Foursquare API in order to start the clustering analysis.

1.1.3 3. Exploring Mexico City's Boroughs

The first thing we need to set is the Foursquare API credentials and version

[15]:
```
CLIENT_ID = 'WBF3HABTS4VOJEDTJQ4F1C2SXJMHGQUD3DWCTE2YJOIIRSJS' # your␣
 ↪Foursquare ID
CLIENT_SECRET = 'AOTYKKKNKYLJC2FHAP3KDOYUOEZO2BLRAFPRUUONZFHGVLOF' # your␣
 ↪Foursquare Secret
VERSION = '20180605' # Foursquare API version

print('Your credentails:')
```

```
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID: WBF3HABTS4VOJEDTJQ4F1C2SXJMHGQUD3DWCTE2YJ0IIRSJS
CLIENT_SECRET:A0TYKKKNKYLJC2FHAP3KDOYUOEZO2BLRAFPRUUONZFHGVLOF
```

Define a function which will return the venues from the Foursquare API of the different boroughs given the coordinates from the previous dataframe.

[16]:
```
def getNearbyVenues(names, latitudes, longitudes, radius=5000):

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

        # create the API request URL
        url = 'https://api.foursquare.com/v2/venues/explore?
↪&client_id={}&client_secret={}&v={}&ll={},{}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lng,
            radius,
            LIMIT)

        # make the GET request
        results = requests.get(url).json()["response"]['groups'][0]['items']

        # return only relevant information for each nearby venue
        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 = ['Borough',
                  'Borough Latitude',
                  'Borough Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
```

```
                  'Venue Category']

    return(nearby_venues)
```

Now that the function is defined, we can search for venues for each borough.

[17]:
```
LIMIT = 100
radius = 5000
CDMX_venues = getNearbyVenues(names=CDMX_new['Borough'],
                                    latitudes=CDMX_new['Latitude'],
                                    longitudes=CDMX_new['Longitude'],
                                    radius = radius
                                   )
```

```
Álvaro Obregón, Mexico City
Azcapotzalco, Mexico City
Benito Juárez, Mexico City
Coyoacán, Mexico City
Cuajimalpa de Morelos, Mexico City
Cuauhtémoc, Mexico City
Gustavo A. Madero, Mexico City
Iztacalco, Mexico City
Iztapalapa, Mexico City
La Magdalena Contreras, Mexico City
Miguel Hidalgo, Mexico City
Milpa Alta, Mexico City
Tláhuac, Mexico City
Tlalpan, Mexico City
Venustiano Carranza, Mexico City
Xochimilco, Mexico City
```

Here we can see how many venues were returned from our function

[18]:
```
print('{} venues were returned by Foursquare.'.format(CDMX_venues.shape[0]))
print('There are {} uniques categories.'.format(len(CDMX_venues['Venue␣
 ↪Category'].unique())))
```

```
1384 venues were returned by Foursquare.
There are 228 uniques categories.
```

Interesting, now we can take a look at some of the data.

[19]:
```
CDMX_venues.head()
```

[19]:

	Borough	Borough Latitude	Borough Longitude	\
0	Álvaro Obregón, Mexico City	19.318148	-99.277844	
1	Álvaro Obregón, Mexico City	19.318148	-99.277844	
2	Álvaro Obregón, Mexico City	19.318148	-99.277844	
3	Álvaro Obregón, Mexico City	19.318148	-99.277844	

```
4  Álvaro Obregón, Mexico City         19.318148         -99.277844

                                  Venue  Venue Latitude  Venue Longitude  \
0             Club Ecuestre San Francisco       19.327934       -99.259696
1                         Café del Bosque       19.327297       -99.279234
2                                Mexitaco       19.320944       -99.263044
3  Parque Nacional Desierto de los Leones       19.322098       -99.308918
4                         Vista Al Bosque       19.339868       -99.266400

       Venue Category
0                Farm
1                Café
2          Taco Place
3                Park
4  Golf Driving Range
```

Latitude and longitude data from each borough will be constantly repeating through this dataframe, since we already know those values, we can drop them.

[20]:
```
CDMX_venues=CDMX_venues.drop(['Borough Latitude', 'Borough Longitude'], axis=1)
CDMX_venues
```

[20]:
```
                         Borough                                  Venue  \
0     Álvaro Obregón, Mexico City            Club Ecuestre San Francisco
1     Álvaro Obregón, Mexico City                        Café del Bosque
2     Álvaro Obregón, Mexico City                               Mexitaco
3     Álvaro Obregón, Mexico City  Parque Nacional Desierto de los Leones
4     Álvaro Obregón, Mexico City                        Vista Al Bosque
…                             …                                      …
1379      Xochimilco, Mexico City              Café "La Espalda De Dios"
1380      Xochimilco, Mexico City                                   Oxxo
1381      Xochimilco, Mexico City                                   oxxo
1382      Xochimilco, Mexico City                     micheladas bravas
1383      Xochimilco, Mexico City                      kiosko Nativitas

      Venue Latitude  Venue Longitude      Venue Category
0           19.327934       -99.259696                Farm
1           19.327297       -99.279234                Café
2           19.320944       -99.263044          Taco Place
3           19.322098       -99.308918                Park
4           19.339868       -99.266400  Golf Driving Range
…                 …                …                   …
1379        19.261851       -99.098765         Snack Place
1380        19.249399       -99.057915   Convenience Store
1381        19.246790       -99.083033    Department Store
1382        19.247730       -99.056815             Brewery
1383        19.245127       -99.091991          Theme Park
```

```
[1384 rows x 5 columns]
```

This new data frame looks sharper.

Now we can take a look at how many venue categories there are, since the data will be repeating for each column (latitude, longitude and venue), it will be created a new data frame just to make it more appealing.

[21]:
```
CDMX_venues_count=CDMX_venues.drop(['Venue', 'Venue Latitude', 'Venue␣
↪Longitude'], axis=1).groupby('Borough').count()
CDMX_venues_count
```

[21]:

Borough	Venue Category
Azcapotzalco, Mexico City	100
Benito Juárez, Mexico City	100
Coyoacán, Mexico City	100
Cuajimalpa de Morelos, Mexico City	58
Cuauhtémoc, Mexico City	100
Gustavo A. Madero, Mexico City	100
Iztacalco, Mexico City	100
Iztapalapa, Mexico City	100
La Magdalena Contreras, Mexico City	100
Miguel Hidalgo, Mexico City	100
Milpa Alta, Mexico City	4
Tlalpan, Mexico City	22
Tláhuac, Mexico City	100
Venustiano Carranza, Mexico City	100
Xochimilco, Mexico City	100
Álvaro Obregón, Mexico City	100

There are only three boroughs with few venues, let's see now what kind of categories are on each zone.

We apply one hot encoding, this will help the ML algorithm to know which are existants.

[22]:
```
# One hot encoding
CDMX_onehot = pd.get_dummies(CDMX_venues[['Venue Category']], prefix="",␣
↪prefix_sep="")

# Add neighborhood column back to dataframe
CDMX_onehot['Borough'] = CDMX_venues['Borough']

# Move neighborhood column to the first column
fixed_columns = [CDMX_onehot.columns[-1]] + CDMX_onehot.columns[:-1].values.
↪tolist()
CDMX_onehot = CDMX_onehot[fixed_columns]
```

```
CDMX_onehot.head()
```

[22]:

	Borough	Accessories Store	Airport Lounge	Airport Service	American Restaurant	Arepa Restaurant	Argentinian Restaurant	Art Gallery	Art Museum	Asian Restaurant	…	Travel Lounge	University	Vegetarian / Vegan Restaurant	Veterinarian	Vineyard	Water Park	Wine Shop	Wings Joint	Women's Store	Yoga Studio
0	Álvaro Obregón, Mexico City	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0	0	0	0	0	0
1	Álvaro Obregón, Mexico City	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0	0	0	0	0	0
2	Álvaro Obregón, Mexico City	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0	0	0	0	0	0
3	Álvaro Obregón, Mexico City	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0	0	0	0	0	0
4	Álvaro Obregón, Mexico City	0	0	0	0	0	0	0	0	0	…	0	0	0	0	0	0	0	0	0	0

[5 rows x 229 columns]

Group them by borough and reset the index just in case.

[23]:
```
CDMX_grouped = CDMX_onehot.groupby('Borough').mean().reset_index()
CDMX_grouped.head()
```

[23]:

	Borough	Accessories Store	Airport Lounge
0	Azcapotzalco, Mexico City	0.0	0.0

```
1          Benito Juárez, Mexico City                0.0             0.0
2              Coyoacán, Mexico City                 0.0             0.0
3  Cuajimalpa de Morelos, Mexico City                0.0             0.0
4             Cuauhtémoc, Mexico City                0.0             0.0

   Airport Service  American Restaurant  Arepa Restaurant  \
0              0.0                 0.00               0.0
1              0.0                 0.00               0.0
2              0.0                 0.00               0.0
3              0.0                 0.00               0.0
4              0.0                 0.02               0.0

   Argentinian Restaurant  Art Gallery  Art Museum  Asian Restaurant  …  \
0                    0.00         0.01        0.00              0.00  …
1                    0.00         0.02        0.02              0.00  …
2                    0.01         0.01        0.02              0.00  …
3                    0.00         0.00        0.00              0.00  …
4                    0.00         0.04        0.07              0.02  …

   Travel Lounge  University  Vegetarian / Vegan Restaurant  Veterinarian  \
0            0.0        0.00                           0.00          0.01
1            0.0        0.01                           0.01          0.00
2            0.0        0.01                           0.00          0.00
3            0.0        0.00                           0.00          0.00
4            0.0        0.00                           0.02          0.00

   Vineyard  Water Park  Wine Shop  Wings Joint  Women's Store  Yoga Studio
0  0.000000        0.00        0.0         0.01           0.00         0.00
1  0.000000        0.01        0.0         0.00           0.00         0.03
2  0.000000        0.00        0.0         0.00           0.00         0.00
3  0.017241        0.00        0.0         0.00           0.00         0.00
4  0.000000        0.00        0.0         0.00           0.01         0.01

[5 rows x 229 columns]
```

Next, we will define a function in order to get the most common venues (by category) for each borough.

[24]:
```
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]
```

Let's apply the previous function to all the boroughs.

[25]:
```
num_top_venues = 10
indicators = ['st', 'nd', 'rd']

# Create columns according to number of top venues
columns = ['Borough']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indicators[ind]))
    except:
        columns.append('{}th Most Common Venue'.format(ind+1))

# Create a new dataframe
boroughs_venues_sorted = pd.DataFrame(columns=columns)
boroughs_venues_sorted['Borough'] = CDMX_grouped['Borough']

for ind in np.arange(CDMX_grouped.shape[0]):
    boroughs_venues_sorted.iloc[ind, 1:] =␣
 ↪return_most_common_venues(CDMX_grouped.iloc[ind, :], num_top_venues)

boroughs_venues_sorted.apply(np.roll, shift=1)
```

[25]:

	Borough	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
0	Álvaro Obregón, Mexico City	Mexican Restaurant	Park	Ice Cream Shop	Seafood Restaurant
1	Azcapotzalco, Mexico City	Mexican Restaurant	Taco Place	Ice Cream Shop	Bakery
2	Benito Juárez, Mexico City	Ice Cream Shop	Mexican Restaurant	Coffee Shop	Food Truck
3	Coyoacán, Mexico City	Ice Cream Shop	Mexican Restaurant	Bakery	Burger Joint
4	Cuajimalpa de Morelos, Mexico City	Mexican Restaurant	Park	Restaurant	Trail
5	Cuauhtémoc, Mexico City	Mexican Restaurant	Art Museum	Bakery	Theater
6	Gustavo A. Madero, Mexico City	Mexican Restaurant	Taco Place	Burger Joint	Coffee Shop
7	Iztacalco, Mexico City	Taco Place			
8	Iztapalapa, Mexico City	Taco Place			
9	La Magdalena Contreras, Mexico City	Taco Place			
10	Miguel Hidalgo, Mexico City	Mexican Restaurant			
11	Milpa Alta, Mexico City	Factory			
12	Tlalpan, Mexico City	Mexican Restaurant			
13	Tláhuac, Mexico City	Mexican Restaurant			
14	Venustiano Carranza, Mexico City	Taco Place			
15	Xochimilco, Mexico City	Mexican Restaurant			

```
7     Mexican Restaurant            Restaurant                Bakery
8     Mexican Restaurant                Bakery        Breakfast Spot
9     Mexican Restaurant  Gym / Fitness Center        Ice Cream Shop
10        Ice Cream Shop                Museum  Gym / Fitness Center
11          Camera Store              Mountain    Mexican Restaurant
12            Steakhouse          Soccer Field              Mountain
13            Taco Place                   Gym    Seafood Restaurant
14    Mexican Restaurant                Bakery        Airport Lounge
15            Taco Place            Restaurant        Ice Cream Shop

    5th Most Common Venue 6th Most Common Venue 7th Most Common Venue  \
0             Coffee Shop    Italian Restaurant            Restaurant
1             Coffee Shop        Breakfast Spot              Pharmacy
2     Japanese Restaurant            Taco Place           Yoga Studio
3             Coffee Shop        Breakfast Spot            Taco Place
4                Mountain          Dessert Shop            Taco Place
5          Ice Cream Shop                 Hotel           Art Gallery
6          Ice Cream Shop                 Café            Restaurant
7             Music Venue           Coffee Shop             Racetrack
8            Burger Joint    Seafood Restaurant             BBQ Joint
9      Seafood Restaurant           Coffee Shop                  Café
10                 Hotel        Breakfast Spot                  Park
11            Food Stand     Food & Drink Shop                  Food
12  Outdoors & Recreation    Athletics & Sports                 Trail
13            Pizza Place                Plaza             BBQ Joint
14            Pizza Place           Coffee Shop          Burger Joint
15            Flower Shop     Convenience Store           Wings Joint

      8th Most Common Venue 9th Most Common Venue 10th Most Common Venue
0               Taco Place              Mountain                 Bakery
1               Food Truck          Cupcake Shop   Gym / Fitness Center
2   Health & Beauty Service                 Café              Pet Store
3     Performing Arts Venue                Plaza         Clothing Store
4             Historic Site          Burger Joint  Outdoors & Recreation
5                     Plaza            Taco Place         History Museum
6        Spanish Restaurant        Clothing Store            Pizza Place
7      Gym / Fitness Center               Stadium           Burger Joint
8               Restaurant  Fast Food Restaurant             Food Truck
9               Food Truck                  Farm               Mountain
10                 Bakery           Food Court                Dog Run
11             Flower Shop          Flea Market               Festival
12                 Bakery                  Farm      Convenience Store
13                 Garden          Soccer Field             Restaurant
14       Seafood Restaurant      Baseball Stadium                   Park
15     Other Great Outdoors               Brewery       Sushi Restaurant
```

Run k-means to cluster the city into 5 clusters.

[26]:
```
# set number of clusters
kclusters = 5

CDMX_grouped_clustering = CDMX_grouped.drop('Borough', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).
 ↪fit(CDMX_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
```

[26]:
```
array([1, 0, 0, 3, 0, 1, 1, 1, 1, 0], dtype=int32)
```

Now there will be a new dataframe that includes the cluster as well as the top 10 venues for each borough.

1.1.4 4. Results and conclusions

[27]:
```
boroughs_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)
CDMX_merged=CDMX_new
CDMX_merged=CDMX_merged.merge(boroughs_venues_sorted, on = 'Borough')

CDMX_merged
```

[27]:

	Borough	Latitude	Longitude	Cluster Labels	\
0	Álvaro Obregón, Mexico City	19.318148	-99.277844	0	
1	Azcapotzalco, Mexico City	19.485815	-99.184206	1	
2	Benito Juárez, Mexico City	19.380470	-99.163243	0	
3	Coyoacán, Mexico City	19.328040	-99.151063	0	
4	Cuajimalpa de Morelos, Mexico City	19.318707	-99.323203	3	
5	Cuauhtémoc, Mexico City	19.432630	-99.133178	0	
6	Gustavo A. Madero, Mexico City	19.518545	-99.143640	1	
7	Iztacalco, Mexico City	19.398975	-99.095312	1	
8	Iztapalapa, Mexico City	19.342829	-99.046892	1	
9	La Magdalena Contreras, Mexico City	19.275470	-99.263339	1	
10	Miguel Hidalgo, Mexico City	19.429614	-99.198638	0	
11	Milpa Alta, Mexico City	19.138028	-99.058920	2	
12	Tláhuac, Mexico City	19.269504	-99.004097	1	
13	Tlalpan, Mexico City	19.200877	-99.217012	4	
14	Venustiano Carranza, Mexico City	19.432396	-99.088063	1	
15	Xochimilco, Mexico City	19.236978	-99.082300	1	

	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	\
0	Mexican Restaurant	Park	Ice Cream Shop	
1	Mexican Restaurant	Taco Place	Ice Cream Shop	

```
2         Ice Cream Shop    Mexican Restaurant           Coffee Shop
3         Ice Cream Shop    Mexican Restaurant               Bakery
4     Mexican Restaurant                  Park           Restaurant
5     Mexican Restaurant           Art Museum               Bakery
6     Mexican Restaurant           Taco Place          Burger Joint
7             Taco Place    Mexican Restaurant           Restaurant
8             Taco Place    Mexican Restaurant               Bakery
9             Taco Place    Mexican Restaurant  Gym / Fitness Center
10    Mexican Restaurant        Ice Cream Shop               Museum
11               Factory          Camera Store             Mountain
12    Mexican Restaurant           Taco Place                  Gym
13    Mexican Restaurant           Steakhouse          Soccer Field
14            Taco Place    Mexican Restaurant               Bakery
15    Mexican Restaurant           Taco Place           Restaurant

   4th Most Common Venue  5th Most Common Venue 6th Most Common Venue  \
0     Seafood Restaurant           Coffee Shop    Italian Restaurant
1                 Bakery           Coffee Shop        Breakfast Spot
2             Food Truck    Japanese Restaurant           Taco Place
3           Burger Joint           Coffee Shop        Breakfast Spot
4                  Trail              Mountain          Dessert Shop
5                Theater         Ice Cream Shop                Hotel
6            Coffee Shop         Ice Cream Shop                Café
7                 Bakery           Music Venue          Coffee Shop
8         Breakfast Spot          Burger Joint    Seafood Restaurant
9         Ice Cream Shop     Seafood Restaurant          Coffee Shop
10  Gym / Fitness Center                 Hotel        Breakfast Spot
11    Mexican Restaurant            Food Stand     Food & Drink Shop
12    Seafood Restaurant           Pizza Place                 Plaza
13              Mountain  Outdoors & Recreation    Athletics & Sports
14        Airport Lounge           Pizza Place          Coffee Shop
15        Ice Cream Shop           Flower Shop     Convenience Store

   7th Most Common Venue    8th Most Common Venue 9th Most Common Venue  \
0             Restaurant              Taco Place              Mountain
1               Pharmacy              Food Truck          Cupcake Shop
2            Yoga Studio  Health & Beauty Service                 Café
3             Taco Place   Performing Arts Venue                Plaza
4             Taco Place           Historic Site          Burger Joint
5            Art Gallery                  Plaza            Taco Place
6             Restaurant      Spanish Restaurant        Clothing Store
7              Racetrack    Gym / Fitness Center                Stadium
8              BBQ Joint              Restaurant  Fast Food Restaurant
9                   Café              Food Truck                  Farm
10                  Park                  Bakery            Food Court
11                  Food             Flower Shop           Flea Market
12             BBQ Joint                  Garden          Soccer Field
```

```
13                 Trail                   Bakery                   Farm
14          Burger Joint       Seafood Restaurant      Baseball Stadium
15           Wings Joint     Other Great Outdoors                Brewery

   10th Most Common Venue
0                  Bakery
1    Gym / Fitness Center
2               Pet Store
3          Clothing Store
4   Outdoors & Recreation
5          History Museum
6             Pizza Place
7            Burger Joint
8              Food Truck
9                Mountain
10                Dog Run
11               Festival
12             Restaurant
13      Convenience Store
14                   Park
15       Sushi Restaurant
```

Now let's see how our clusters look in the map.

[28]:
```
# create map
map_clusters = folium.Map(location=[latitude_CDMX, longitude_CDMX],␣
 ↪zoom_start=11)

# set color scheme for the clusters
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]

# add markers to the map
markers_colors = []
for lat, lon, poi, cluster in zip(CDMX_merged['Latitude'],␣
 ↪CDMX_merged['Longitude'], CDMX_merged['Borough'], CDMX_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
```

[28]:
```
<folium.folium.Map at 0x1a1f732210>
```

If we look at the map we can notice the five different clusters, however, three of them are alone, clearly outliers, which makes sense since this boroughs are on the outskirts of town, as we recall, these where the boroughs that had the least venues (not at least 100, which was our maximum). Aside from that we can notice that there is not a clear division between "Cluster 0" and "Cluster 1". Let's try to find out why.

To give equal importance to all features, we need to scale the continuous features.

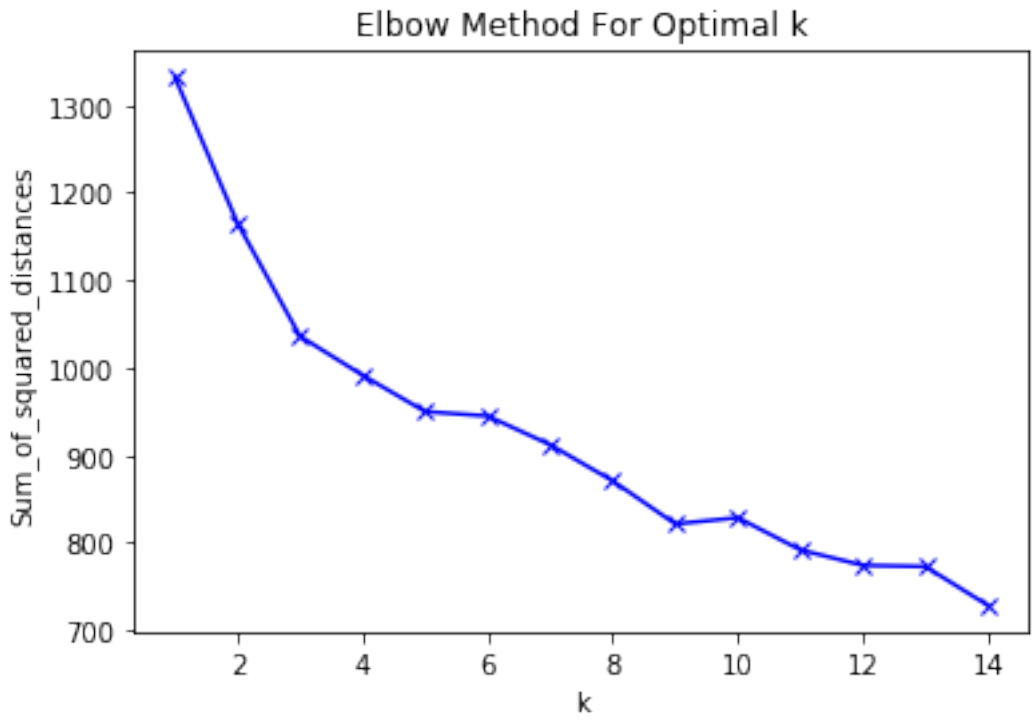
[29]:
```
mms = MinMaxScaler()
mms.fit(CDMX_onehot.drop(['Borough'], axis=1))
data_transformed = mms.transform(CDMX_onehot.drop(['Borough'], axis=1))
```

For each k value, we will initialise k-means and use the inertia attribute to identify the sum of squared distances of samples to the nearest cluster centre.

[30]:
```
Sum_of_squared_distances = []
K = range(1,15)
for k in K:
    km = KMeans(n_clusters=k)
    km = km.fit(data_transformed)
    Sum_of_squared_distances.append(km.inertia_)
```

Below is a plot of sum of squared distances for k in the range specified above.

[31]:
```
plt.plot(K, Sum_of_squared_distances, 'bx-')
plt.xlabel('k')
plt.ylabel('Sum_of_squared_distances')
plt.title('Elbow Method For Optimal k')
plt.show()
```



As we can see, there is not a clear "arm" so we can not find the "elbow" to determine how many number of clusters would be ideal, this could mean that even just one cluster could fit our dataframe, which is not ideal for the scope of this project, however it is an interesting project result, one reason could be that many of the venues are taco places or mexican restaurants for all the different boroughs.

Let's now create a dataframe only for Taco Places and Mexican Restaurants.

[32]:
```
CDMX_Taco_Places = CDMX_venues[(CDMX_venues['Venue Category'].str.
 ↪contains('Taco Place', regex=False))].groupby(['Borough']).count()
CDMX_Mexican_Restaurant = CDMX_venues[(CDMX_venues['Venue Category'].str.
 ↪contains('Mexican Restaurant', regex=False))].groupby(['Borough']).count()

CDMX_Mexican_Restaurant.drop(['Venue Longitude', 'Venue', 'Venue Latitude'],␣
 ↪axis = 1, inplace = True)
CDMX_Taco_Places.drop(['Venue Longitude', 'Venue', 'Venue Latitude'], axis = 1,␣
 ↪inplace = True)

CDMX_Mexican_Restaurant.rename(columns = {'Venue Category':'Number of Mexican␣
 ↪Restaurants'}, inplace=True)
CDMX_Taco_Places.rename(columns = {'Venue Category':'Number of Taco Places'},␣
 ↪inplace=True)
```

[33]:
```
Mexican_food=CDMX_Mexican_Restaurant.merge(CDMX_Taco_Places, on = 'Borough')
Mexican_food['Total'] = Mexican_food.sum(axis=1)
Mexican_food
```

[33]:

Borough	Number of Mexican Restaurants	Number of Taco Places	Total
Azcapotzalco, Mexico City	25	12	37
Benito Juárez, Mexico City	8	4	12
Coyoacán, Mexico City	6	3	9
Cuajimalpa de Morelos, Mexico City	17	2	19
Cuauhtémoc, Mexico City	10	4	14
Gustavo A. Madero, Mexico City	18	14	32
Iztacalco, Mexico City	12	20	32
Iztapalapa, Mexico City	17	20	37
La Magdalena Contreras, Mexico City	13	19	32
Miguel Hidalgo, Mexico City	6	1	7
Tláhuac, Mexico City	15	10	25
Venustiano Carranza, Mexico City	9	22	31
Xochimilco, Mexico City	16	11	27
Álvaro Obregón, Mexico City	12	3	15

As we recall:

[34]:
```
print('There are {} uniques venue categories.'.format(len(CDMX_venues['Venue␣
↪Category'].unique())))
```

```
There are 228 uniques venue categories.
```

And in many of the boroughs, just 2 venue categories accounted for close to 30% of the venues, as someone who lives in Mexico, not surprised that the most common category venue for each borough is a Mexican Restaurant or a Taco Place, we do enjoy our food!

[35]:
```
Mexican_food[['Number of Mexican Restaurants', 'Number of Taco Places']].
 ↪plot(kind='barh', figsize=(15, 9), width = 0.8)
plt.ylabel('Borough')
plt.title('Number of restaurants')
plt.show()
```