

FinalProject

April 21, 2020

1 Applied Data Science Capstone - IBM Professional Certificate

1.0.1 Marcelo Porto

1.1 Introduction

The skills learned during this course give us tools to solve some interesting problem. If you are deciding to open a new business, it might be interesting to explore a city and find a neighborhood where your business is needed.

Let's say you want to open a coffee shop. It wouldn't be interesting to open in an area where there are 3 Starbucks' already. We can use the Foursquare API to find neighborhoods where there might be a need for your new coffee shop.

We can use clustering to find similar neighborhoods in the city that might support your plan: neighborhood X has a couple of coffee shops and it is similar to neighborhood Y. So it might be good to take our business to neighborhood Y if there isn't many coffee shops there already. Are neighborhoods X and Y similar enough if we remove coffee shops from the equation?

1.1.1 Target Audience

Prospective business owners could use this to find the best location for their business.

City officials or the appropriate city departments could use this project to identify areas to invest in and attract new business, enhancing the value of possible up-and-coming neighborhoods.

1.1.2 Data Required

Some cities do not have postal codes. Abu Dhabi, in the United Arab Emirates, is one of the cities. So first I will need to search for a list of neighborhoods in Abu Dhabi. Then, I will need to find coordinates for each one of these neighborhoods with the geopy service. After this is done, I will be able to search the city for different venues with the Foursquare API, using this data to cluster and compare neighborhoods.

For Abu Dhabi, [Wikipedia](#) provides a list of neighborhoods, which I can use to search for coordinates.

1.1.3 Structure

The Methodology section will explain how the process was done and methods applied. In Results, the findings will be presented along with the codes used. This reports ends with a brief discussion about the results and limitations of this exercise, and improvements that can be made.

1.2 Methodology

The Foursquare API will be used to extract information from business venues in the city. Geopy will be used to turn neighborhood names into latitude and longitude coordinates. The folium package will allow us to visualize these findings in beautiful interactive maps. And talking about beautiful, I will use the BeautifulSoup package to scrape neighborhood names for Abu Dhabi from Wikipedia.

Last but not least, I will apply K-means to cluster the neighborhoods based on what type of businesses are most common between them. After specifying how many clusters are to be created, this unsupervised machine learning algorithm chooses random points as cluster centers, and every other point is assigned to the closest center via the calculation of its Euclidean distances. The mean point of each cluster, or centroids, is calculated, and it becomes the new center for the cluster. This centroid minimizes the total squared distance of each point to the cluster center (Source: my thesis. Just trust me on this). There are limitations to this method, but this is out of the scope of this exercise.

All the coding here is done in Python, in a Jupyter Notebook, using the [IBM Skill Network Labs](#) platform, which is free and I **highly** recommend, it will make your life easier. As you can see, a Github repository is used to store the notebook. Feel free to clone it and use for your own learning!

(By the way, even though I am not using it here, I also suggest you to open an account on IBM Cloud. They have loads of free and cool resources for Data Science!)

1.3 Results

Note: Some outputs were cleared to make reading it easier.

Let's begin by loading and installing our tools!

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

import pandas as pd # library for data analysis
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)

import json # library to handle JSON files

!conda install -c conda-forge geopy --yes # uncomment this line if you haven't
    ↳ completed the Foursquare API lab
from geopy.geocoders import Nominatim # convert an address into latitude and
    ↳ longitude values

import requests # library to handle requests
from pandas.io.json import json_normalize # transform JSON file into a pandas
    ↳ dataframe

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

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

!conda install -c conda-forge folium=0.5.0 --yes # uncomment this line if you
↳ haven't completed the Foursquare API lab
import folium # map rendering library

print('Libraries imported.')
```

Collecting package metadata (current_repodata.json): done
Solving environment: done

Package Plan

environment location: /home/jupyterlab/conda/envs/python

added / updated specs:

- geopy

The following packages will be downloaded:

package	build		
geographiclib-1.50	py_0	34 KB	conda-forge
geopy-1.21.0	py_0	58 KB	conda-forge
Total:		92 KB	

The following NEW packages will be INSTALLED:

geographiclib	conda-forge/noarch::geographiclib-1.50-py_0
geopy	conda-forge/noarch::geopy-1.21.0-py_0

Downloading and Extracting Packages

geopy-1.21.0	58 KB	#####	100%
geographiclib-1.50	34 KB	#####	100%

Preparing transaction: done

Verifying transaction: done

Executing transaction: done

Collecting package metadata (current_repodata.json): done

Solving environment: failed with initial frozen solve. Retrying with flexible solve.

Collecting package metadata (repodata.json): done

Solving environment: done

Package Plan

environment location: /home/jupyterlab/conda/envs/python

added / updated specs:

- folium=0.5.0

The following packages will be downloaded:

package	build		
altair-4.1.0	py_1	614 KB	conda-forge
branca-0.4.0	py_0	26 KB	conda-forge
brotlipy-0.7.0	py36h8c4c3a4_1000	346 KB	conda-forge
chardet-3.0.4	py36h9f0ad1d_1006	188 KB	conda-forge
cryptography-2.8	py36h45558ae_2	628 KB	conda-forge
folium-0.5.0	py_0	45 KB	conda-forge
pandas-1.0.3	py36h830a2c2_1	11.1 MB	conda-forge
pysocks-1.7.1	py36h9f0ad1d_1	27 KB	conda-forge
toolz-0.10.0	py_0	46 KB	conda-forge
urllib3-1.25.9	py_0	92 KB	conda-forge
vincent-0.4.4	py_1	28 KB	conda-forge
Total:		13.1 MB	

The following NEW packages will be INSTALLED:

altair	conda-forge/noarch::altair-4.1.0-py_1
attrs	conda-forge/noarch::attrs-19.3.0-py_0
branca	conda-forge/noarch::branca-0.4.0-py_0
brotlipy	conda-forge/linux-64::brotlipy-0.7.0-py36h8c4c3a4_1000
chardet	conda-forge/linux-64::chardet-3.0.4-py36h9f0ad1d_1006
cryptography	conda-forge/linux-64::cryptography-2.8-py36h45558ae_2
entrypoints	conda-forge/linux-64::entrypoints-0.3-py36h9f0ad1d_1001
folium	conda-forge/noarch::folium-0.5.0-py_0
idna	conda-forge/noarch::idna-2.9-py_1
importlib-metadata	conda-forge/linux-64::importlib-metadata-1.6.0-py36h9f0ad1d_0
importlib_metadata	conda-forge/noarch::importlib_metadata-1.6.0-0
jinja2	conda-forge/noarch::jinja2-2.11.2-pyh9f0ad1d_0
jsonschema	conda-forge/linux-64::jsonschema-3.2.0-py36h9f0ad1d_1
markupsafe	conda-forge/linux-64::markupsafe-1.1.1-py36h8c4c3a4_1
pandas	conda-forge/linux-64::pandas-1.0.3-py36h830a2c2_1
pyopenssl	conda-forge/noarch::pyopenssl-19.1.0-py_1
pyrsistent	conda-forge/linux-64::pyrsistent-0.16.0-py36h8c4c3a4_0

```

pysocks          conda-forge/linux-64::pysocks-1.7.1-py36h9f0ad1d_1
pytz             conda-forge/noarch::pytz-2019.3-py_0
requests         conda-forge/noarch::requests-2.23.0-pyh8c360ce_2
toolz            conda-forge/noarch::toolz-0.10.0-py_0
urllib3          conda-forge/noarch::urllib3-1.25.9-py_0
vincent          conda-forge/noarch::vincent-0.4.4-py_1
zipp             conda-forge/noarch::zipp-3.1.0-py_0

```

Downloading and Extracting Packages

```

pysocks-1.7.1      | 27 KB      | ##### | 100%
cryptography-2.8   | 628 KB     | ##### | 100%
toolz-0.10.0       | 46 KB      | ##### | 100%
chardet-3.0.4      | 188 KB     | ##### | 100%
folium-0.5.0       | 45 KB      | ##### | 100%
urllib3-1.25.9     | 92 KB      | ##### | 100%
brotlipy-0.7.0     | 346 KB     | ##### | 100%
pandas-1.0.3       | 11.1 MB    | ##### | 100%
altair-4.1.0       | 614 KB     | ##### | 100%
branca-0.4.0       | 26 KB      | ##### | 100%
vincent-0.4.4      | 28 KB      | ##### | 100%

```

Preparing transaction: done

Verifying transaction: done

Executing transaction: done

Libraries imported.

First, let's test with some location, to see if there are entries in the Foursquare database for Abu Dhabi.

```

[ ]: #Test with Abu Dhabi
CLIENT_ID = 'yourid' # your Foursquare ID
CLIENT_SECRET = 'yoursecret' # your Foursquare Secret
VERSION = '20200401' # Foursquare API version
neighborhood_latitude =24.4539
neighborhood_longitude =54.3773
# type your answer here
LIMIT = 100 # limit of number of venues returned by Foursquare API
radius = 500 # define radius
url = 'https://api.foursquare.com/v2/venues/explore?
->&client_id={} &client_secret={} &v={} &ll={},{} &radius={} &limit={}'.format(
    CLIENT_ID,
    CLIENT_SECRET,
    VERSION,
    neighborhood_latitude,
    neighborhood_longitude,
    radius,
    LIMIT)

```

```
url # display URL

results = requests.get(url).json()
results
```

```
[3]: # function that extracts the category of the venue
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']
```

```
[4]: venues = results['response']['groups'][0]['items']

nearby_venues = json_normalize(venues) # flatten JSON

# filter columns
filtered_columns = ['venue.name', 'venue.categories', 'venue.location.lat',
                    ↪ 'venue.location.lng']
nearby_venues = nearby_venues.loc[:, filtered_columns]

# filter the category for each row
nearby_venues['venue.categories'] = nearby_venues.apply(get_category_type,
                    ↪ axis=1)

# clean columns
nearby_venues.columns = [col.split(".")[1] for col in nearby_venues.columns]

nearby_venues.head()
```

/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages/ipykernel_launcher.py:3: FutureWarning: pandas.io.json.json_normalize is deprecated, use pandas.json_normalize instead

This is separate from the ipykernel package so we can avoid doing imports until

```
[4]:
```

	name	categories	lat	lng
0	Umm Al Emarat Park) (Park		24.453300	54.381092
1	Home Bakery	Bakery	24.453337	54.381018
2	Café Arabia	Café	24.455760	54.379318
3	Mushrif palace park	Park	24.453375	54.374729
4	Murjan Asfar Hotel Apartment	Hotel	24.453511	54.377871

```
[5]: nearby_venues.shape
```

```
[5]: (5, 4)
```

Ok, apparently there are some. Let's plot these venues in a map of Abu Dhabi.

```
[6]: # create map of AD using latitude and longitude values
latitude = 24.4539
longitude = 54.3773
#neighborhood_latitude =24.4539
#neighborhood_longitude =54.3773
map_AD = folium.Map(location=[latitude, longitude], zoom_start=10)

# add markers to map
for lat, lng, borough, neighborhood in zip(nearby_venues['lat'],
    ↪nearby_venues['lng'], nearby_venues['name'], nearby_venues['categories']):
    label = '{} , {}'.format(neighborhood, 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_AD)

map_AD
```

```
[6]: <folium.folium.Map at 0x7fb4cd72bdd8>
```

Cool! Now, those are venues. There are no postal codes in Abu Dhabi.

We can find a list of neighborhoods on Wikipedia.

Let's see if I can find coordinates for one of these neighborhoods, Al Karama.

```
[7]: address = 'Al Karama, Abu Dhabi, United Arab Emirates'

geolocator = Nominatim(user_agent="foursquare_agent")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print(latitude, longitude)
```

```
25.244402800000003 55.30475541735386
```

Alright, it works. There aren't that many, so I could probably copy the list to a spreadsheet and load here as a csv file.

But that's no fun. Let's scrape the Wikipedia page to get the Neighborhood names, using the BeautifulSoup package.

```
[8]: import requests
website_url = requests.get('https://en.wikipedia.org/wiki/Abu_Dhabi').text
!pip install BeautifulSoup4
from bs4 import BeautifulSoup
soup = BeautifulSoup(website_url, 'html.parser')
```

Collecting BeautifulSoup4

Downloading https://files.pythonhosted.org/packages/e8/b5/7bb03a696f2c9b7af792a8f51b82974e51c268f15e925fc834876a4efa0b/beautifulsoup4-4.9.0-py3-none-any.whl (109kB)

| | 112kB 6.1MB/s eta 0:00:01

Collecting soupsieve>1.2 (from BeautifulSoup4)

Downloading https://files.pythonhosted.org/packages/05/cf/ea245e52f55823f19992447b008bcbb7f78efc5960d77f6c34b5b45b36dd/soupsieve-2.0-py2.py3-none-any.whl

Installing collected packages: soupsieve, BeautifulSoup4

Successfully installed BeautifulSoup4-4.9.0 soupsieve-2.0

The output is pretty long, so I suggest collapsing it for a better read of the notebook. But printing the whole thing is necessary to find what we want. Or you can check the source code of the page.

```
[ ]: print(soup)
```

That was long, so I'm suppressing it for the purpose of your reading. By inspecting our "soup", we see that the list is under the class "div-col columns column-width".

```
[ ]: #div-col columns column-width
hoods = soup.find(class_="div-col columns column-width")
print(hoods)
```

To get just the name of the neighborhood, we use this code:

```
[11]: hoods.a.text
```

```
[11]: 'Al Aman'
```

I'll create a dataframe for the neighborhoods and iterate over our "soup" to get all the names.

```
[12]: header=["Neighborhood", "Lat", "Lon"]

df = pd.DataFrame(columns=header)
hoods_rows = hoods.find_all('a')
for tr in hoods_rows:
    row = tr.text

    df = df.append({'Neighborhood': row}, ignore_index=True)
```



```
[13]: df
```

```
[13]:
```

	Neighborhood	Lat	Lon
0	Al Aman	NaN	NaN
1	Al Bateen	NaN	NaN
2	Al Dhafrah	NaN	NaN
3	Al Falah	NaN	NaN
4	Al Karama	NaN	NaN
5	Al Khubeirah	NaN	NaN
6	Al Lulu Island	NaN	NaN
7	Al Madina	NaN	NaN
8	Al Maryah Island	NaN	NaN
9	Al Manaseer	NaN	NaN
10	Al Manhal	NaN	NaN
11	Al Maqtaa	NaN	NaN
12	Al Markaziyah	NaN	NaN
13	Al Meena	NaN	NaN
14	Al Moroor	NaN	NaN
15	Al Mushrif	NaN	NaN
16	Al Muzoon	NaN	NaN
17	Al Nahyan	NaN	NaN
18	Al Qubesat	NaN	NaN
19	Al Ras Al Akhdar	NaN	NaN
20	Al Reef	NaN	NaN
21	Al Reem Island	NaN	NaN
22	Al Rehhan	NaN	NaN
23	Al Rowdah	NaN	NaN
24	Al Shamkha	NaN	NaN
25	Bani Yas	NaN	NaN
26	Al Zaab	NaN	NaN
27	Al Zahiyah	NaN	NaN
28	Al Zahraa	NaN	NaN
29	Al Khalidyah	NaN	NaN
30	Bain Al Jisrain	NaN	NaN
31	Hideriyyat	NaN	NaN
32	Khalifa City	NaN	NaN
33	Marina Village	NaN	NaN
34	Masdar City	NaN	NaN
35	Mohammed Bin Zayed City	NaN	NaN
36	Saadiyat Island	NaN	NaN
37	Shakhbout City	NaN	NaN
38	Officers City	NaN	NaN
39	Qasr El Bahr	NaN	NaN
40	Qasr El Shatie	NaN	NaN
41	Yas Island	NaN	NaN
42	Al Samha	NaN	NaN

Great! Now we can put that into the geocoder to get our coordinates.

```
[14]: address = '{}', Abu Dhabi, United Arab Emirates'
geolocator = Nominatim(user_agent="foursquare_agent")

for i in range(0, df.shape[0]):
    hood = df.iloc[i,0]
    location = geolocator.geocode(address.format(hood))
    if location is not None:
        df.iloc[i,1] = location.latitude
        df.iloc[i,2] = location.longitude
```

```
[15]: df
```

```
[15]:
```

	Neighborhood	Lat	Lon
0	Al Aman	24.432	54.4266
1	Al Bateen	24.2151	55.6263
2	Al Dhafrah	24.4761	54.3694
3	Al Falah	24.4447	54.7282
4	Al Karama	25.2444	55.3048
5	Al Khubeirah	24.4652	54.3368
6	Al Lulu Island	24.4996	54.3457
7	Al Madina	24.3409	54.4907
8	Al Maryah Island	24.5021	54.3902
9	Al Manaseer	NaN	NaN
10	Al Manhal	24.4666	54.366
11	Al Maqtaa	24.4346	54.4544
12	Al Markaziyah	24.4933	54.3667
13	Al Meena	NaN	NaN
14	Al Moroor	NaN	NaN
15	Al Mushrif	24.4369	54.391
16	Al Muzoon	NaN	NaN
17	Al Nahyan	24.4684	54.3852
18	Al Qubesat	NaN	NaN
19	Al Ras Al Akhdar	NaN	NaN
20	Al Reef	24.4577	54.6737
21	Al Reem Island	24.4867	54.4105
22	Al Rehhan	NaN	NaN
23	Al Rowdah	24.4564	54.3596
24	Al Shamkha	24.3885	54.7184
25	Bani Yas	NaN	NaN
26	Al Zaab	NaN	NaN
27	Al Zahiyah	24.4933	54.3799
28	Al Zahraa	24.4392	54.4352
29	Al Khalidiyah	NaN	NaN
30	Bain Al Jisrain	24.4092	54.4954
31	Hideriyyat	NaN	NaN

32	Khalifa City	24.4214	54.5774
33	Marina Village	NaN	NaN
34	Masdar City	24.4259	54.6193
35	Mohammed Bin Zayed City	24.3279	54.5624
36	Saadiyat Island	24.5303	54.4409
37	Shakhbout City	24.3622	54.631
38	Officers City	24.3824	54.535
39	Qasr El Bahr	24.4746	54.3966
40	Qasr El Shatie	NaN	NaN
41	Yas Island	24.4864	54.6091
42	Al Samha	NaN	NaN

We couldn't find all the neighborhoods, but that's ok, we still got plenty for this exercise.
Let's remove the ones without coordinates.

```
[16]: df=df.dropna()
```

```
[17]: df.reset_index(inplace=True,drop=True)
df
```

```
[17]:
```

	Neighborhood	Lat	Lon
0	Al Aman	24.432	54.4266
1	Al Bateen	24.2151	55.6263
2	Al Dhafrah	24.4761	54.3694
3	Al Falah	24.4447	54.7282
4	Al Karama	25.2444	55.3048
5	Al Khubeirah	24.4652	54.3368
6	Al Lulu Island	24.4996	54.3457
7	Al Madina	24.3409	54.4907
8	Al Maryah Island	24.5021	54.3902
9	Al Manhal	24.4666	54.366
10	Al Maqtaa	24.4346	54.4544
11	Al Markaziyah	24.4933	54.3667
12	Al Mushrif	24.4369	54.391
13	Al Nahyan	24.4684	54.3852
14	Al Reef	24.4577	54.6737
15	Al Reem Island	24.4867	54.4105
16	Al Rowdah	24.4564	54.3596
17	Al Shamkha	24.3885	54.7184
18	Al Zahiyah	24.4933	54.3799
19	Al Zahraa	24.4392	54.4352
20	Bain Al Jisrain	24.4092	54.4954
21	Khalifa City	24.4214	54.5774
22	Masdar City	24.4259	54.6193
23	Mohammed Bin Zayed City	24.3279	54.5624
24	Saadiyat Island	24.5303	54.4409
25	Shakhbout City	24.3622	54.631

26	Officers City	24.3824	54.535
27	Qasr El Bahr	24.4746	54.3966
28	Yas Island	24.4864	54.6091

Now we can plot these in a map:

```
[18]: # create map of Abu Dhabi using latitude and longitude values
latitude = 24.4539
longitude = 54.3773
map_AD = folium.Map(location=[latitude, longitude], zoom_start=10)

# add markers to map
for lat, lng, neighborhood in zip(df['Lat'], df['Lon'], df['Neighborhood']):
    label = '{}'.format(neighborhood)
    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_AD)

map_AD
```

```
[18]: <folium.folium.Map at 0x7fb4cce6aa58>
```

We use the Foursquare API to find venues in these neighborhoods.
Let's use that trusty function that was provided in the course.

```
[19]: def getNearbyVenues(names, latitudes, longitudes, radius=500):

    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 = ['Neighborhood',
                        'Neighborhood Latitude',
                        'Neighborhood Longitude',
                        'Venue',
                        'Venue Latitude',
                        'Venue Longitude',
                        'Venue Category']

return(nearby_venues)

```

Running the function...

```

[20]: AD_venues = getNearbyVenues(names=df['Neighborhood'],
                                latitudes=df['Lat'],
                                longitudes=df['Lon']
                                )

```

```

Al Aman
Al Bateen
Al Dhafrah
Al Falah
Al Karama
Al Khubeirah
Al Lulu Island
Al Madina
Al Maryah Island
Al Manhal
Al Maqtaa
Al Markaziyah
Al Mushrif
Al Nahyan
Al Reef

```

Al Reem Island
 Al Rowdah
 Al Shamkha
 Al Zahiyah
 Al Zahraa
 Bain Al Jisrain
 Khalifa City
 Masdar City
 Mohammed Bin Zayed City
 Saadiyat Island
 Shakhbout City
 Officers City
 Qasr El Bahr
 Yas Island

Now we have a list of venues with coordinates for each neighborhood.
 Let's just look at the first 10 entries.

```
[36]: AD_venues.head(10)
```

```
[36]:
```

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	\
0	Al Aman	24.431990	54.42655	
1	Al Aman	24.431990	54.42655	
2	Al Aman	24.431990	54.42655	
3	Al Aman	24.431990	54.42655	
4	Al Aman	24.431990	54.42655	
5	Al Aman	24.431990	54.42655	
6	Al Dhafrah	24.476147	54.36936	
7	Al Dhafrah	24.476147	54.36936	
8	Al Dhafrah	24.476147	54.36936	
9	Al Dhafrah	24.476147	54.36936	

		Venue	Venue Latitude	Venue Longitude	\
0		Subway	24.435156	54.425187	
1	Novotel Abu Dhabi	Al Bustan	24.429431	54.429166	
2		McDonald's	24.434646	54.424393	
3		Cafe Bonjour Bonsoir	24.429314	54.428250	
4		Adagio Aparthotel	24.429396	54.428604	
5		Coffee Planet	24.434725	54.423094	
6		Jumeirah Etihad Tower	24.476051	54.367716	
7		Starbucks ()	24.477430	54.371626	
8		Gudee Pizza & Café	24.477860	54.371012	
9	Al Shater Hassan	Restaurant	24.478750	54.369562	

	Venue Category
0	Sandwich Place
1	Hotel
2	Fast Food Restaurant

```

3           Café
4           Hotel
5       Coffee Shop
6           Hotel
7       Coffee Shop
8       Pizza Place
9   Falafel Restaurant

```

How many unique type of businesses do we have in Abu Dhabi?

```
[37]: print('There are {} unique businesses.'.format(len(AD_venues['Venue Category'].
→unique())))
```

There are 125 unique businesses.

```
[58]: AD_venues.groupby('Neighborhood').count()
```

```
[58]:
```

	Neighborhood	Latitude	Neighborhood	Longitude	Venue	\
Neighborhood						
Al Aman		6		6	6	
Al Dhafrah		32		32	32	
Al Karama		38		38	38	
Al Khubeirah		17		17	17	
Al Lulu Island		1		1	1	
Al Madina		3		3	3	
Al Manhal		7		7	7	
Al Maqtaa		27		27	27	
Al Markaziyah		39		39	39	
Al Maryah Island		56		56	56	
Al Mushrif		4		4	4	
Al Nahyan		29		29	29	
Al Reef		12		12	12	
Al Reem Island		1		1	1	
Al Rowdah		8		8	8	
Al Shamkha		2		2	2	
Al Zahiyah		68		68	68	
Al Zahraa		4		4	4	
Bain Al Jisrain		27		27	27	
Khalifa City		4		4	4	
Masdar City		6		6	6	
Mohammed Bin Zayed City		1		1	1	
Officers City		1		1	1	
Saadiyat Island		1		1	1	
Shakhbout City		1		1	1	
Yas Island		100		100	100	

```
Venue Latitude  Venue Longitude  Venue Category
```

Neighborhood			
Al Aman	6	6	6
Al Dhafrah	32	32	32
Al Karama	38	38	38
Al Khubeirah	17	17	17
Al Lulu Island	1	1	1
Al Madina	3	3	3
Al Manhal	7	7	7
Al Maqtaa	27	27	27
Al Markaziyah	39	39	39
Al Maryah Island	56	56	56
Al Mushrif	4	4	4
Al Nahyan	29	29	29
Al Reef	12	12	12
Al Reem Island	1	1	1
Al Rowdah	8	8	8
Al Shamkha	2	2	2
Al Zahiyah	68	68	68
Al Zahraa	4	4	4
Bain Al Jisrain	27	27	27
Khalifa City	4	4	4
Masdar City	6	6	6
Mohammed Bin Zayed City	1	1	1
Officers City	1	1	1
Saadiyat Island	1	1	1
Shakhbout City	1	1	1
Yas Island	100	100	100

We see we have a problem with our data here. There are a few neighborhoods with very few entries. We could attempt to increase the radius of search. Or find another data source. For this exercise we will limit our analysis to those areas with at least 5 businesses.

```
[70]: temp = AD_venues.groupby('Neighborhood').count()
      id = temp.index[temp.iloc[:,0] >= 5]
```

```
[74]: #rpt[rpt['STK_ID'].isin(stk_list)]
      AD_venues = AD_venues[AD_venues['Neighborhood'].isin(id)]
```

What type of venue is more frequent in each neighborhood?
How are we going to cluster these together? To start to answer these questions, we turn the venues into dummy variables.
We can get the dummies with one hot encoding.

```
[75]: # one hot encoding
      AD_onehot = pd.get_dummies(AD_venues[['Venue Category']], prefix="",
      ↪prefix_sep="")
```



```
# add neighborhood column back to dataframe
AD_onehot['Neighborhood'] = AD_venues['Neighborhood']

# move neighborhood column to the first column
fixed_columns = [AD_onehot.columns[-1]] + list(AD_onehot.columns[:-1])
AD_onehot = AD_onehot[fixed_columns]

AD_onehot.head()
```

```
[75]:  Women's Store  Afghan Restaurant  African Restaurant  Airport Terminal  \
0           0           0           0           0           0
1           0           0           0           0           0
2           0           0           0           0           0
3           0           0           0           0           0
4           0           0           0           0           0

      American Restaurant  Arcade  Asian Restaurant  BBQ Joint  Bakery  Beach  \
0           0           0           0           0           0           0
1           0           0           0           0           0           0
2           0           0           0           0           0           0
3           0           0           0           0           0           0
4           0           0           0           0           0           0

      Bed & Breakfast  Bistro  Bookstore  Boutique  Bowling Alley  \
0           0           0           0           0           0
1           0           0           0           0           0
2           0           0           0           0           0
3           0           0           0           0           0
4           0           0           0           0           0

      Breakfast Spot  Buffet  Burger Joint  Cafeteria  Café  Candy Store  \
0           0           0           0           0           0           0
1           0           0           0           0           0           0
2           0           0           0           0           0           0
3           0           0           0           0           1           0
4           0           0           0           0           0           0

      Chinese Restaurant  Clothing Store  Cocktail Bar  Coffee Shop  \
0           0           0           0           0
1           0           0           0           0
2           0           0           0           0
3           0           0           0           0
4           0           0           0           0

      Convenience Store  Cosmetics Shop  Cupcake Shop  Department Store  \
0           0           0           0           0
1           0           0           0           0
```

2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

	Dessert Shop	Donut Shop	Electronics Store	Ethiopian Restaurant	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Falafel Restaurant	Fast Food Restaurant	Filipino Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	1	0	
3	0	0	0	
4	0	0	0	

	Fish & Chips Shop	Flower Shop	Food & Drink Shop	Food Court	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	French Restaurant	Fried Chicken Joint	Furniture / Home Store	Gift Shop	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Go Kart Track	Greek Restaurant	Grocery Store	Gym	Gym / Fitness Center	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Gym Pool	Gymnastics Gym	Harbor / Marina	Health & Beauty Service	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Hookah Bar	Hostel	Hot Spring	Hotel	Hotel Bar	IT Services	\
--	------------	--------	------------	-------	-----------	-------------	---

0	0	0	0	0	0	0
1	0	0	0	1	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	0
4	0	0	0	1	0	0

	Ice Cream Shop	Indian Restaurant	Italian Restaurant	Japanese Restaurant	\
0	0		0	0	0
1	0		0	0	0
2	0		0	0	0
3	0		0	0	0
4	0		0	0	0

	Jewelry Store	Juice Bar	Korean Restaurant	Lebanese Restaurant	\
0	0	0		0	
1	0	0		0	
2	0	0		0	
3	0	0		0	
4	0	0		0	

	Lingerie Store	Lounge	Medical Center	Mediterranean Restaurant	\
0	0	0	0		0
1	0	0	0		0
2	0	0	0		0
3	0	0	0		0
4	0	0	0		0

	Mexican Restaurant	Middle Eastern Restaurant	Miscellaneous Shop	\
0		0	0	0
1		0	0	0
2		0	0	0
3		0	0	0
4		0	0	0

	Moroccan Restaurant	Movie Theater	Multiplex	Nail Salon	Neighborhood	\
0		0	0	0	Al Aman	
1		0	0	0	Al Aman	
2		0	0	0	Al Aman	
3		0	0	0	Al Aman	
4		0	0	0	Al Aman	

	Nightclub	Optical Shop	Pakistani Restaurant	Park	Peruvian Restaurant	\
0	0	0		0		0
1	0	0		0		0
2	0	0		0		0
3	0	0		0		0
4	0	0		0		0

	Pet Store	Pharmacy	Pizza Place	Playground	Plaza	Pool	Pub	Racetrack	\
0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	

	Residential Building (Apartment / Condo)	Resort	Restaurant	\
0		0	0	
1		0	0	
2		0	0	
3		0	0	
4		0	0	

	Sandwich Place	Seafood Restaurant	Shawarma Place	Shoe Store	\
0	1	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Shopping Mall	Snack Place	South Indian Restaurant	Spa	\
0	0	0		0	0
1	0	0		0	0
2	0	0		0	0
3	0	0		0	0
4	0	0		0	0

	Sporting Goods Shop	Sports Bar	Steakhouse	Supermarket	Sushi Restaurant	\
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	0	0	0	0	

	Tennis Court	Theater	Theme Park	Theme Park Ride / Attraction	\
0	0	0	0		0
1	0	0	0		0
2	0	0	0		0
3	0	0	0		0
4	0	0	0		0

	Theme Restaurant	Toy / Game Store	Turkish Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	

3	0	0	0
4	0	0	0

	Vegetarian / Vegan Restaurant	Wine Bar
0	0	0
1	0	0
2	0	0
3	0	0
4	0	0

```
[76]: AD_grouped = AD_onehot.groupby('Neighborhood').mean().reset_index()
      AD_grouped
```

```
[76]:
```

	Neighborhood	Women's Store	Afghan Restaurant	African Restaurant \
0	Al Aman	0.000000	0.000000	0.000000
1	Al Dhafrah	0.000000	0.000000	0.000000
2	Al Karama	0.000000	0.000000	0.000000
3	Al Khubeirah	0.000000	0.000000	0.000000
4	Al Manhal	0.000000	0.000000	0.000000
5	Al Maqtaa	0.000000	0.000000	0.000000
6	Al Markaziyah	0.000000	0.000000	0.000000
7	Al Maryah Island	0.017857	0.017857	0.000000
8	Al Nahyan	0.000000	0.000000	0.000000
9	Al Reef	0.000000	0.000000	0.000000
10	Al Rowdah	0.000000	0.000000	0.000000
11	Al Zahiyah	0.000000	0.000000	0.014706
12	Bain Al Jisrain	0.000000	0.000000	0.000000
13	Masdar City	0.000000	0.000000	0.000000
14	Yas Island	0.000000	0.000000	0.010000

	Airport Terminal	American Restaurant	Arcade	Asian Restaurant \
0	0.000000	0.000000	0.00	0.000000
1	0.000000	0.000000	0.00	0.000000
2	0.000000	0.000000	0.00	0.105263
3	0.000000	0.000000	0.00	0.000000
4	0.000000	0.000000	0.00	0.000000
5	0.037037	0.000000	0.00	0.000000
6	0.000000	0.025641	0.00	0.051282
7	0.000000	0.035714	0.00	0.000000
8	0.000000	0.034483	0.00	0.034483
9	0.000000	0.000000	0.00	0.000000
10	0.000000	0.000000	0.00	0.000000
11	0.000000	0.000000	0.00	0.029412
12	0.000000	0.000000	0.00	0.000000
13	0.000000	0.000000	0.00	0.000000
14	0.000000	0.010000	0.01	0.000000

	BBQ Joint	Bakery	Beach	Bed & Breakfast	Bistro	Bookstore \
0	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000
1	0.000000	0.031250	0.03125	0.000000	0.000000	0.000000
2	0.000000	0.078947	0.00000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000
5	0.000000	0.037037	0.00000	0.000000	0.000000	0.000000
6	0.000000	0.025641	0.00000	0.025641	0.000000	0.000000
7	0.000000	0.035714	0.00000	0.000000	0.017857	0.000000
8	0.000000	0.068966	0.00000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000
11	0.014706	0.000000	0.00000	0.029412	0.000000	0.014706
12	0.000000	0.000000	0.00000	0.000000	0.000000	0.037037
13	0.000000	0.000000	0.00000	0.000000	0.000000	0.000000
14	0.000000	0.010000	0.00000	0.000000	0.000000	0.010000

	Boutique	Bowling Alley	Breakfast Spot	Buffet	Burger Joint \
0	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.000000	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000	0.037037
6	0.000000	0.025641	0.025641	0.000000	0.000000
7	0.017857	0.000000	0.000000	0.017857	0.017857
8	0.000000	0.000000	0.000000	0.000000	0.034483
9	0.000000	0.000000	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.000000	0.000000	0.000000
11	0.029412	0.000000	0.014706	0.000000	0.029412
12	0.000000	0.000000	0.000000	0.000000	0.037037
13	0.000000	0.000000	0.000000	0.000000	0.000000
14	0.000000	0.000000	0.000000	0.000000	0.030000

	Cafeteria	Café	Candy Store	Chinese Restaurant	Clothing Store \
0	0.000000	0.166667	0.00	0.000000	0.000000
1	0.000000	0.093750	0.00	0.000000	0.031250
2	0.026316	0.026316	0.00	0.000000	0.000000
3	0.000000	0.235294	0.00	0.000000	0.000000
4	0.000000	0.428571	0.00	0.000000	0.000000
5	0.000000	0.185185	0.00	0.000000	0.000000
6	0.000000	0.076923	0.00	0.025641	0.000000
7	0.000000	0.089286	0.00	0.035714	0.000000
8	0.000000	0.172414	0.00	0.000000	0.000000
9	0.000000	0.000000	0.00	0.000000	0.000000
10	0.000000	0.625000	0.00	0.000000	0.000000
11	0.000000	0.044118	0.00	0.029412	0.029412

12	0.000000	0.037037	0.00	0.000000	0.000000
13	0.000000	0.166667	0.00	0.000000	0.000000
14	0.000000	0.110000	0.01	0.010000	0.040000

	Cocktail Bar	Coffee Shop	Convenience Store	Cosmetics Shop	\
0	0.000000	0.166667	0.000000	0.000000	
1	0.000000	0.031250	0.000000	0.000000	
2	0.000000	0.000000	0.026316	0.000000	
3	0.000000	0.235294	0.000000	0.000000	
4	0.000000	0.142857	0.000000	0.000000	
5	0.000000	0.074074	0.037037	0.000000	
6	0.000000	0.000000	0.000000	0.000000	
7	0.017857	0.071429	0.000000	0.017857	
8	0.000000	0.103448	0.034483	0.000000	
9	0.000000	0.083333	0.083333	0.000000	
10	0.000000	0.250000	0.000000	0.125000	
11	0.000000	0.044118	0.000000	0.014706	
12	0.037037	0.111111	0.000000	0.000000	
13	0.000000	0.000000	0.000000	0.000000	
14	0.000000	0.070000	0.000000	0.020000	

	Cupcake Shop	Department Store	Dessert Shop	Donut Shop	\
0	0.000000	0.000000	0.000000	0.000000	
1	0.000000	0.031250	0.000000	0.000000	
2	0.000000	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.000000	0.058824	
4	0.000000	0.000000	0.000000	0.000000	
5	0.000000	0.000000	0.037037	0.000000	
6	0.000000	0.025641	0.000000	0.025641	
7	0.000000	0.000000	0.017857	0.000000	
8	0.034483	0.000000	0.068966	0.000000	
9	0.000000	0.000000	0.000000	0.000000	
10	0.000000	0.000000	0.000000	0.000000	
11	0.000000	0.014706	0.044118	0.000000	
12	0.000000	0.000000	0.000000	0.000000	
13	0.000000	0.000000	0.000000	0.000000	
14	0.000000	0.030000	0.010000	0.000000	

	Electronics Store	Ethiopian Restaurant	Falafel Restaurant	\
0	0.000000	0.000000	0.000000	
1	0.000000	0.000000	0.031250	
2	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.000000	
4	0.000000	0.000000	0.000000	
5	0.000000	0.000000	0.000000	
6	0.000000	0.000000	0.000000	
7	0.000000	0.000000	0.000000	

8	0.000000	0.000000	0.034483
9	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.000000
11	0.029412	0.014706	0.000000
12	0.000000	0.000000	0.000000
13	0.000000	0.000000	0.000000
14	0.010000	0.000000	0.000000

	Fast Food Restaurant	Filipino Restaurant	Fish & Chips Shop	Flower Shop \
0	0.166667	0.000000	0.00	0.000000
1	0.062500	0.031250	0.00	0.000000
2	0.000000	0.000000	0.00	0.000000
3	0.117647	0.000000	0.00	0.000000
4	0.000000	0.000000	0.00	0.000000
5	0.037037	0.000000	0.00	0.000000
6	0.128205	0.025641	0.00	0.000000
7	0.000000	0.000000	0.00	0.017857
8	0.000000	0.000000	0.00	0.068966
9	0.000000	0.000000	0.00	0.000000
10	0.000000	0.000000	0.00	0.000000
11	0.044118	0.000000	0.00	0.000000
12	0.000000	0.000000	0.00	0.000000
13	0.166667	0.000000	0.00	0.000000
14	0.010000	0.000000	0.01	0.000000

	Food & Drink Shop	Food Court	French Restaurant	Fried Chicken Joint \
0	0.000000	0.00	0.000000	0.0000
1	0.000000	0.00	0.000000	0.0625
2	0.000000	0.00	0.000000	0.0000
3	0.000000	0.00	0.000000	0.0000
4	0.000000	0.00	0.000000	0.0000
5	0.000000	0.00	0.037037	0.0000
6	0.000000	0.00	0.000000	0.0000
7	0.000000	0.00	0.017857	0.0000
8	0.000000	0.00	0.034483	0.0000
9	0.000000	0.00	0.000000	0.0000
10	0.000000	0.00	0.000000	0.0000
11	0.000000	0.00	0.014706	0.0000
12	0.037037	0.00	0.037037	0.0000
13	0.000000	0.00	0.000000	0.0000
14	0.000000	0.01	0.010000	0.0000

	Furniture / Home Store	Gift Shop	Go Kart Track	Greek Restaurant \
0	0.0000	0.000000	0.00	0.000000
1	0.0625	0.000000	0.00	0.000000
2	0.0000	0.000000	0.00	0.000000
3	0.0000	0.000000	0.00	0.000000

4	0.0000	0.000000	0.00	0.000000
5	0.0000	0.000000	0.00	0.000000
6	0.0000	0.000000	0.00	0.000000
7	0.0000	0.000000	0.00	0.017857
8	0.0000	0.000000	0.00	0.000000
9	0.0000	0.000000	0.00	0.000000
10	0.0000	0.000000	0.00	0.000000
11	0.0000	0.014706	0.00	0.000000
12	0.0000	0.037037	0.00	0.000000
13	0.0000	0.000000	0.00	0.000000
14	0.0300	0.010000	0.01	0.010000

	Grocery Store	Gym	Gym / Fitness Center	Gym Pool	Gymnastics Gym \
0	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.031250	0.000000	0.000000	0.000000	0.000000
2	0.000000	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.058824	0.000000	0.000000
4	0.000000	0.000000	0.000000	0.000000	0.000000
5	0.037037	0.037037	0.000000	0.037037	0.000000
6	0.000000	0.025641	0.000000	0.000000	0.000000
7	0.000000	0.000000	0.000000	0.000000	0.000000
8	0.000000	0.000000	0.034483	0.000000	0.000000
9	0.000000	0.166667	0.000000	0.000000	0.083333
10	0.000000	0.000000	0.000000	0.000000	0.000000
11	0.000000	0.014706	0.014706	0.000000	0.000000
12	0.000000	0.037037	0.000000	0.000000	0.000000
13	0.000000	0.000000	0.000000	0.000000	0.000000
14	0.000000	0.000000	0.000000	0.000000	0.000000

	Harbor / Marina	Health & Beauty Service	Hookah Bar	Hostel \
0	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000
2	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.025641	0.000000	0.000000
7	0.000000	0.000000	0.000000	0.000000
8	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.000000	0.000000
11	0.000000	0.000000	0.014706	0.014706
12	0.037037	0.000000	0.000000	0.000000
13	0.000000	0.000000	0.000000	0.000000
14	0.000000	0.000000	0.020000	0.000000

Hot Spring	Hotel	Hotel Bar	IT Services	Ice Cream Shop \
------------	-------	-----------	-------------	------------------

0	0.000000	0.333333	0.000000	0.00	0.000000
1	0.000000	0.031250	0.000000	0.00	0.031250
2	0.000000	0.000000	0.000000	0.00	0.026316
3	0.000000	0.000000	0.000000	0.00	0.058824
4	0.142857	0.142857	0.000000	0.00	0.000000
5	0.000000	0.037037	0.000000	0.00	0.000000
6	0.000000	0.128205	0.025641	0.00	0.025641
7	0.000000	0.017857	0.000000	0.00	0.000000
8	0.000000	0.000000	0.000000	0.00	0.000000
9	0.000000	0.000000	0.000000	0.00	0.000000
10	0.000000	0.000000	0.000000	0.00	0.000000
11	0.000000	0.058824	0.000000	0.00	0.029412
12	0.000000	0.074074	0.000000	0.00	0.000000
13	0.000000	0.000000	0.000000	0.00	0.000000
14	0.000000	0.000000	0.000000	0.01	0.010000

	Indian Restaurant	Italian Restaurant	Japanese Restaurant	Jewelry Store \
0	0.000000	0.000000	0.000000	0.000000
1	0.062500	0.000000	0.000000	0.000000
2	0.447368	0.000000	0.026316	0.000000
3	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000	0.000000
5	0.037037	0.037037	0.000000	0.000000
6	0.025641	0.051282	0.000000	0.000000
7	0.017857	0.035714	0.017857	0.035714
8	0.000000	0.034483	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.000000	0.000000
11	0.073529	0.000000	0.000000	0.000000
12	0.037037	0.074074	0.037037	0.000000
13	0.000000	0.166667	0.000000	0.000000
14	0.010000	0.040000	0.010000	0.000000

	Juice Bar	Korean Restaurant	Lebanese Restaurant	Lingerie Store \
0	0.000000	0.000000	0.000000	0.00
1	0.000000	0.000000	0.000000	0.00
2	0.000000	0.026316	0.000000	0.00
3	0.058824	0.000000	0.000000	0.00
4	0.000000	0.000000	0.000000	0.00
5	0.000000	0.000000	0.000000	0.00
6	0.000000	0.000000	0.000000	0.00
7	0.000000	0.000000	0.000000	0.00
8	0.000000	0.034483	0.000000	0.00
9	0.000000	0.000000	0.000000	0.00
10	0.000000	0.000000	0.000000	0.00
11	0.014706	0.000000	0.000000	0.00
12	0.000000	0.000000	0.037037	0.00

13	0.000000	0.000000	0.000000	0.00
14	0.010000	0.000000	0.000000	0.01

	Lounge	Medical Center	Mediterranean Restaurant	Mexican Restaurant \
0	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000
2	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.142857	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000
6	0.025641	0.000000	0.000000	0.000000
7	0.035714	0.000000	0.017857	0.035714
8	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.000000	0.000000
11	0.000000	0.000000	0.000000	0.000000
12	0.000000	0.000000	0.000000	0.000000
13	0.000000	0.000000	0.000000	0.000000
14	0.000000	0.000000	0.000000	0.000000

	Middle Eastern Restaurant	Miscellaneous Shop	Moroccan Restaurant \
0	0.000000	0.000000	0.000000
1	0.156250	0.000000	0.000000
2	0.026316	0.000000	0.000000
3	0.058824	0.000000	0.000000
4	0.000000	0.000000	0.000000
5	0.074074	0.000000	0.000000
6	0.000000	0.000000	0.025641
7	0.035714	0.000000	0.000000
8	0.034483	0.000000	0.000000
9	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.000000
11	0.088235	0.014706	0.000000
12	0.037037	0.000000	0.000000
13	0.000000	0.000000	0.000000
14	0.020000	0.000000	0.000000

	Movie Theater	Multiplex	Nail Salon	Nightclub	Optical Shop \
0	0.000000	0.000000	0.000000	0.000000	0.00
1	0.062500	0.000000	0.000000	0.000000	0.00
2	0.000000	0.000000	0.000000	0.000000	0.00
3	0.000000	0.000000	0.000000	0.000000	0.00
4	0.000000	0.000000	0.000000	0.000000	0.00
5	0.000000	0.000000	0.000000	0.000000	0.00
6	0.025641	0.000000	0.000000	0.000000	0.00
7	0.000000	0.017857	0.000000	0.000000	0.00
8	0.000000	0.000000	0.034483	0.000000	0.00

9	0.000000	0.000000	0.000000	0.000000	0.00
10	0.000000	0.000000	0.000000	0.000000	0.00
11	0.014706	0.000000	0.000000	0.000000	0.00
12	0.000000	0.000000	0.000000	0.037037	0.00
13	0.000000	0.000000	0.000000	0.000000	0.00
14	0.030000	0.000000	0.000000	0.000000	0.01

	Pakistani Restaurant	Park	Peruvian Restaurant	Pet Store	Pharmacy \
0	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.026316	0.026316	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000	0.037037
6	0.000000	0.025641	0.000000	0.000000	0.000000
7	0.000000	0.000000	0.017857	0.000000	0.000000
8	0.000000	0.000000	0.000000	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.083333	0.000000
10	0.000000	0.000000	0.000000	0.000000	0.000000
11	0.000000	0.000000	0.000000	0.000000	0.000000
12	0.000000	0.000000	0.000000	0.000000	0.000000
13	0.000000	0.000000	0.000000	0.000000	0.000000
14	0.000000	0.000000	0.000000	0.000000	0.000000

	Pizza Place	Playground	Plaza	Pool	Pub	Racetrack \
0	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
1	0.031250	0.000000	0.000000	0.000000	0.000000	0.00
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
5	0.037037	0.000000	0.000000	0.000000	0.000000	0.00
6	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
7	0.000000	0.000000	0.017857	0.017857	0.000000	0.00
8	0.034483	0.000000	0.000000	0.000000	0.000000	0.00
9	0.083333	0.000000	0.000000	0.250000	0.000000	0.00
10	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
11	0.029412	0.014706	0.000000	0.000000	0.014706	0.00
12	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
13	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
14	0.010000	0.000000	0.000000	0.000000	0.000000	0.01

	Residential Building (Apartment / Condo)	Resort	Restaurant \
0	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000
2	0.000000	0.000000	0.026316
3	0.000000	0.000000	0.000000
4	0.000000	0.000000	0.000000

5	0.000000	0.037037	0.037037
6	0.000000	0.025641	0.025641
7	0.017857	0.017857	0.000000
8	0.000000	0.000000	0.000000
9	0.083333	0.000000	0.000000
10	0.000000	0.000000	0.000000
11	0.000000	0.000000	0.014706
12	0.000000	0.000000	0.037037
13	0.000000	0.000000	0.000000
14	0.000000	0.010000	0.000000

	Sandwich Place	Seafood Restaurant	Shawarma Place	Shoe Store \
0	0.166667	0.000000	0.000000	0.000000
1	0.000000	0.031250	0.000000	0.000000
2	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.058824	0.000000
4	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.025641	0.000000	0.000000
7	0.000000	0.000000	0.000000	0.017857
8	0.034483	0.034483	0.000000	0.000000
9	0.000000	0.000000	0.000000	0.000000
10	0.000000	0.000000	0.000000	0.000000
11	0.014706	0.000000	0.000000	0.000000
12	0.000000	0.000000	0.000000	0.000000
13	0.000000	0.000000	0.000000	0.000000
14	0.020000	0.000000	0.000000	0.000000

	Shopping Mall	Snack Place	South Indian Restaurant	Spa \
0	0.000000	0.00000	0.000000	0.000000
1	0.000000	0.03125	0.000000	0.000000
2	0.000000	0.00000	0.026316	0.000000
3	0.000000	0.00000	0.000000	0.000000
4	0.000000	0.00000	0.000000	0.000000
5	0.037037	0.00000	0.000000	0.000000
6	0.000000	0.00000	0.000000	0.000000
7	0.017857	0.00000	0.000000	0.017857
8	0.000000	0.00000	0.000000	0.000000
9	0.000000	0.00000	0.000000	0.000000
10	0.000000	0.00000	0.000000	0.000000
11	0.029412	0.00000	0.000000	0.000000
12	0.037037	0.00000	0.000000	0.074074
13	0.166667	0.00000	0.000000	0.000000
14	0.010000	0.00000	0.000000	0.000000

	Sporting Goods Shop	Sports Bar	Steakhouse	Supermarket \
0	0.00	0.000000	0.000000	0.000000

1	0.00	0.000000	0.000000	0.000000
2	0.00	0.000000	0.000000	0.026316
3	0.00	0.000000	0.000000	0.058824
4	0.00	0.000000	0.000000	0.000000
5	0.00	0.000000	0.000000	0.000000
6	0.00	0.025641	0.000000	0.000000
7	0.00	0.000000	0.035714	0.017857
8	0.00	0.000000	0.000000	0.000000
9	0.00	0.000000	0.000000	0.000000
10	0.00	0.000000	0.000000	0.000000
11	0.00	0.000000	0.000000	0.000000
12	0.00	0.000000	0.037037	0.000000
13	0.00	0.000000	0.000000	0.166667
14	0.04	0.000000	0.030000	0.010000

	Sushi Restaurant	Tennis Court	Theater	Theme Park	\
0	0.000000	0.000000	0.00	0.00	
1	0.000000	0.000000	0.00	0.00	
2	0.000000	0.000000	0.00	0.00	
3	0.000000	0.000000	0.00	0.00	
4	0.000000	0.000000	0.00	0.00	
5	0.000000	0.000000	0.00	0.00	
6	0.000000	0.000000	0.00	0.00	
7	0.035714	0.000000	0.00	0.00	
8	0.000000	0.000000	0.00	0.00	
9	0.000000	0.083333	0.00	0.00	
10	0.000000	0.000000	0.00	0.00	
11	0.000000	0.000000	0.00	0.00	
12	0.000000	0.000000	0.00	0.00	
13	0.166667	0.000000	0.00	0.00	
14	0.000000	0.000000	0.01	0.03	

	Theme Park Ride / Attraction	Theme Restaurant	Toy / Game Store	\
0	0.00	0.000000	0.00	
1	0.00	0.000000	0.00	
2	0.00	0.026316	0.00	
3	0.00	0.000000	0.00	
4	0.00	0.000000	0.00	
5	0.00	0.000000	0.00	
6	0.00	0.000000	0.00	
7	0.00	0.000000	0.00	
8	0.00	0.000000	0.00	
9	0.00	0.000000	0.00	
10	0.00	0.000000	0.00	
11	0.00	0.000000	0.00	
12	0.00	0.000000	0.00	
13	0.00	0.000000	0.00	

14	0.12	0.000000	0.03
----	------	----------	------

	Turkish Restaurant	Vegetarian / Vegan Restaurant	Wine Bar
0	0.00000	0.000000	0.000000
1	0.03125	0.000000	0.000000
2	0.00000	0.026316	0.000000
3	0.00000	0.000000	0.000000
4	0.00000	0.000000	0.000000
5	0.00000	0.000000	0.000000
6	0.00000	0.000000	0.000000
7	0.00000	0.000000	0.017857
8	0.00000	0.000000	0.000000
9	0.00000	0.000000	0.000000
10	0.00000	0.000000	0.000000
11	0.00000	0.000000	0.014706
12	0.00000	0.000000	0.000000
13	0.00000	0.000000	0.000000
14	0.00000	0.000000	0.000000

We now have the frequency for each neighborhood.
What are the top 5 venues for each neighborhood?

```
[77]: num_top_venues = 5

for hood in AD_grouped['Neighborhood']:
    print("----"+hood+"----")
    temp = AD_grouped[AD_grouped['Neighborhood'] == hood].T.reset_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(num_top_venues))
    print('\n')
```

----Al Aman----

	venue	freq
0	Hotel	0.33
1	Fast Food Restaurant	0.17
2	Coffee Shop	0.17
3	Sandwich Place	0.17
4	Café	0.17

----Al Dhafrah----

	venue	freq
0	Middle Eastern Restaurant	0.16
1	Café	0.09

2	Movie Theater	0.06
3	Fried Chicken Joint	0.06
4	Fast Food Restaurant	0.06

----Al Karama----

	venue	freq
0	Indian Restaurant	0.45
1	Asian Restaurant	0.11
2	Bakery	0.08
3	Supermarket	0.03
4	Park	0.03

----Al Khubeirah----

	venue	freq
0	Coffee Shop	0.24
1	Café	0.24
2	Fast Food Restaurant	0.12
3	Supermarket	0.06
4	Shawarma Place	0.06

----Al Manhal----

	venue	freq
0	Café	0.43
1	Hotel	0.14
2	Hot Spring	0.14
3	Medical Center	0.14
4	Coffee Shop	0.14

----Al Maqtaa----

	venue	freq
0	Café	0.19
1	Middle Eastern Restaurant	0.07
2	Coffee Shop	0.07
3	Burger Joint	0.04
4	French Restaurant	0.04

----Al Markaziyah----

	venue	freq
0	Fast Food Restaurant	0.13
1	Hotel	0.13
2	Café	0.08
3	Asian Restaurant	0.05
4	Italian Restaurant	0.05

----Al Maryah Island----

	venue	freq
0	Café	0.09
1	Coffee Shop	0.07
2	Mexican Restaurant	0.04
3	Jewelry Store	0.04
4	Sushi Restaurant	0.04

----Al Nahyan----

	venue	freq
0	Café	0.17
1	Coffee Shop	0.10
2	Flower Shop	0.07
3	Bakery	0.07
4	Dessert Shop	0.07

----Al Reef----

	venue	freq
0	Pool	0.25
1	Gym	0.17
2	Tennis Court	0.08
3	Pet Store	0.08
4	Residential Building (Apartment / Condo)	0.08

----Al Rowdah----

	venue	freq
0	Café	0.62
1	Coffee Shop	0.25
2	Cosmetics Shop	0.12
3	Women's Store	0.00
4	Multiplex	0.00

----Al Zahiyah----

	venue	freq
0	Middle Eastern Restaurant	0.09
1	Indian Restaurant	0.07
2	Hotel	0.06
3	Dessert Shop	0.04
4	Fast Food Restaurant	0.04

----Bain Al Jisrain----

	venue	freq
0	Coffee Shop	0.11
1	Spa	0.07
2	Italian Restaurant	0.07
3	Hotel	0.07
4	Lebanese Restaurant	0.04

----Masdar City----

	venue	freq
0	Shopping Mall	0.17
1	Sushi Restaurant	0.17
2	Italian Restaurant	0.17
3	Fast Food Restaurant	0.17
4	Café	0.17

----Yas Island----

	venue	freq
0	Theme Park Ride / Attraction	0.12
1	Café	0.11
2	Coffee Shop	0.07
3	Italian Restaurant	0.04
4	Sporting Goods Shop	0.04

Let's put this information in a dataframe, with the top 5 most common venues for each neighborhood.

```
[78]: #This function sorts the venues in descending order
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]
```

```
[79]: num_top_venues = 5

indicators = ['st', 'nd', 'rd']

# create columns according to number of top venues
columns = ['Neighborhood']
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
neighborhoods_venues_sorted = pd.DataFrame(columns=columns)
neighborhoods_venues_sorted['Neighborhood'] = AD_grouped['Neighborhood']

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

neighborhoods_venues_sorted.head()
```

```
[79]:
```

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	\
0	Al Aman	Hotel	Coffee Shop	
1	Al Dhafrah	Middle Eastern Restaurant	Café	
2	Al Karama	Indian Restaurant	Asian Restaurant	
3	Al Khubeirah	Café	Coffee Shop	
4	Al Manhal	Café	Hot Spring	

	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Fast Food Restaurant	Sandwich Place	Café
1	Fried Chicken Joint	Furniture / Home Store	Fast Food Restaurant
2	Bakery	Ice Cream Shop	Cafeteria
3	Fast Food Restaurant	Donut Shop	Gym / Fitness Center
4	Medical Center	Coffee Shop	Hotel

Let's have a look at the whole thing...

```
[80]: neighborhoods_venues_sorted
```

```
[80]:
```

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	\
0	Al Aman	Hotel	Coffee Shop	
1	Al Dhafrah	Middle Eastern Restaurant	Café	
2	Al Karama	Indian Restaurant	Asian Restaurant	
3	Al Khubeirah	Café	Coffee Shop	
4	Al Manhal	Café	Hot Spring	
5	Al Maqtaa	Café	Coffee Shop	
6	Al Markaziyah	Fast Food Restaurant	Hotel	
7	Al Maryah Island	Café	Coffee Shop	
8	Al Nahyan	Café	Coffee Shop	
9	Al Reef	Pool	Gym	
10	Al Rowdah	Café	Coffee Shop	
11	Al Zahiyah	Middle Eastern Restaurant	Indian Restaurant	
12	Bain Al Jisrain	Coffee Shop	Spa	
13	Masdar City	Sushi Restaurant	Italian Restaurant	
14	Yas Island	Theme Park Ride / Attraction	Café	

	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
--	-----------------------	-----------------------	-----------------------

0	Fast Food Restaurant	Sandwich Place	Café
1	Fried Chicken Joint	Furniture / Home Store	Fast Food Restaurant
2	Bakery	Ice Cream Shop	Cafeteria
3	Fast Food Restaurant	Donut Shop	Gym / Fitness Center
4	Medical Center	Coffee Shop	Hotel
5	Middle Eastern Restaurant	Pharmacy	Shopping Mall
6	Café	Italian Restaurant	Asian Restaurant
7	Sushi Restaurant	Middle Eastern Restaurant	American Restaurant
8	Dessert Shop	Flower Shop	Bakery
9	Pizza Place	Convenience Store	Coffee Shop
10	Cosmetics Shop	Wine Bar	Donut Shop
11	Hotel	Coffee Shop	Fast Food Restaurant
12	Hotel	Italian Restaurant	Lebanese Restaurant
13	Café	Supermarket	Fast Food Restaurant
14	Coffee Shop	Clothing Store	Sporting Goods Shop

Now we can attempt to cluster these neighborhoods based on how similar its businesses are.

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

AD_grouped_clustering = AD_grouped.drop('Neighborhood', 1)

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

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:5]
```

```
[81]: array([0, 1, 3, 1, 2], dtype=int32)
```

```
[82]: # add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster_Labels', kmeans.labels_)

AD_merged = df

# merge AD_grouped with AD_data to add latitude/longitude for each neighborhood
AD_merged = AD_merged.join(neighborhoods_venues_sorted,
    ↳set_index('Neighborhood'), on='Neighborhood')

AD_merged.head()
```

```
[82]: Neighborhood    Lat    Lon Cluster_Labels    1st Most Common Venue \
0      Al Aman      24.432  54.4266           0.0                Hotel
1      Al Bateen    24.2151  55.6263           NaN                NaN
2      Al Dhafrah   24.4761  54.3694           1.0  Middle Eastern Restaurant
3      Al Falah     24.4447  54.7282           NaN                NaN
```

4	Al Karama	25.2444	55.3048	3.0	Indian Restaurant
---	-----------	---------	---------	-----	-------------------

	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue \
0	Coffee Shop	Fast Food Restaurant	Sandwich Place
1	NaN	NaN	NaN
2	Café	Fried Chicken Joint	Furniture / Home Store
3	NaN	NaN	NaN
4	Asian Restaurant	Bakery	Ice Cream Shop

	5th Most Common Venue
0	Café
1	NaN
2	Fast Food Restaurant
3	NaN
4	Cafeteria

[83] : AD_merged

	Neighborhood	Lat	Lon	Cluster_Labels \
0	Al Aman	24.432	54.4266	0.0
1	Al Bateen	24.2151	55.6263	NaN
2	Al Dhafrah	24.4761	54.3694	1.0
3	Al Falah	24.4447	54.7282	NaN
4	Al Karama	25.2444	55.3048	3.0
5	Al Khubeirah	24.4652	54.3368	1.0
6	Al Lulu Island	24.4996	54.3457	NaN
7	Al Madina	24.3409	54.4907	NaN
8	Al Maryah Island	24.5021	54.3902	1.0
9	Al Manhal	24.4666	54.366	2.0
10	Al Maqtaa	24.4346	54.4544	1.0
11	Al Markaziyah	24.4933	54.3667	1.0
12	Al Mushrif	24.4369	54.391	NaN
13	Al Nahyan	24.4684	54.3852	1.0
14	Al Reef	24.4577	54.6737	4.0
15	Al Reem Island	24.4867	54.4105	NaN
16	Al Rowdah	24.4564	54.3596	2.0
17	Al Shamkha	24.3885	54.7184	NaN
18	Al Zahiyah	24.4933	54.3799	1.0
19	Al Zahraa	24.4392	54.4352	NaN
20	Bain Al Jisrain	24.4092	54.4954	1.0
21	Khalifa City	24.4214	54.5774	NaN
22	Masdar City	24.4259	54.6193	1.0
23	Mohammed Bin Zayed City	24.3279	54.5624	NaN
24	Saadiyat Island	24.5303	54.4409	NaN
25	Shakhbout City	24.3622	54.631	NaN
26	Officers City	24.3824	54.535	NaN
27	Qasr El Bahr	24.4746	54.3966	NaN

28 Yas Island 24.4864 54.6091 1.0

	1st Most Common Venue	2nd Most Common Venue \
0	Hotel	Coffee Shop
1	NaN	NaN
2	Middle Eastern Restaurant	Café
3	NaN	NaN
4	Indian Restaurant	Asian Restaurant
5	Café	Coffee Shop
6	NaN	NaN
7	NaN	NaN
8	Café	Coffee Shop
9	Café	Hot Spring
10	Café	Coffee Shop
11	Fast Food Restaurant	Hotel
12	NaN	NaN
13	Café	Coffee Shop
14	Pool	Gym
15	NaN	NaN
16	Café	Coffee Shop
17	NaN	NaN
18	Middle Eastern Restaurant	Indian Restaurant
19	NaN	NaN
20	Coffee Shop	Spa
21	NaN	NaN
22	Sushi Restaurant	Italian Restaurant
23	NaN	NaN
24	NaN	NaN
25	NaN	NaN
26	NaN	NaN
27	NaN	NaN
28	Theme Park Ride / Attraction	Café

	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Fast Food Restaurant	Sandwich Place	Café
1	NaN	NaN	NaN
2	Fried Chicken Joint	Furniture / Home Store	Fast Food Restaurant
3	NaN	NaN	NaN
4	Bakery	Ice Cream Shop	Cafeteria
5	Fast Food Restaurant	Donut Shop	Gym / Fitness Center
6	NaN	NaN	NaN
7	NaN	NaN	NaN
8	Sushi Restaurant	Middle Eastern Restaurant	American Restaurant
9	Medical Center	Coffee Shop	Hotel
10	Middle Eastern Restaurant	Pharmacy	Shopping Mall
11	Café	Italian Restaurant	Asian Restaurant
12	NaN	NaN	NaN

13	Dessert Shop	Flower Shop	Bakery
14	Pizza Place	Convenience Store	Coffee Shop
15	NaN	NaN	NaN
16	Cosmetics Shop	Wine Bar	Donut Shop
17	NaN	NaN	NaN
18	Hotel	Coffee Shop	Fast Food Restaurant
19	NaN	NaN	NaN
20	Hotel	Italian Restaurant	Lebanese Restaurant
21	NaN	NaN	NaN
22	Café	Supermarket	Fast Food Restaurant
23	NaN	NaN	NaN
24	NaN	NaN	NaN
25	NaN	NaN	NaN
26	NaN	NaN	NaN
27	NaN	NaN	NaN
28	Coffee Shop	Clothing Store	Sporting Goods Shop

Since we used our original dataframe some of the neighborhoods in which no venues were found on Foursquare reappeared here.

Let's drop these NA's. Also we will change the cluster values to integer.

```
[84]: AD_merged=AD_merged.dropna()
      AD_merged['Cluster_Labels'] = AD_merged.Cluster_Labels.astype(int)
```

```
/home/jupyterlab/conda/envs/python/lib/python3.6/site-
packages/ipykernel_launcher.py:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy

```
[85]: AD_merged
```

```
[85]:
```

	Neighborhood	Lat	Lon	Cluster_Labels \
0	Al Aman	24.432	54.4266	0
2	Al Dhafrah	24.4761	54.3694	1
4	Al Karama	25.2444	55.3048	3
5	Al Khubeirah	24.4652	54.3368	1
8	Al Maryah Island	24.5021	54.3902	1
9	Al Manhal	24.4666	54.366	2
10	Al Maqtaa	24.4346	54.4544	1
11	Al Markaziyah	24.4933	54.3667	1
13	Al Nahyan	24.4684	54.3852	1
14	Al Reef	24.4577	54.6737	4
16	Al Rowdah	24.4564	54.3596	2

18	Al Zahiyah	24.4933	54.3799	1
20	Bain Al Jisrain	24.4092	54.4954	1
22	Masdar City	24.4259	54.6193	1
28	Yas Island	24.4864	54.6091	1

	1st Most Common Venue	2nd Most Common Venue	\
0	Hotel	Coffee Shop	
2	Middle Eastern Restaurant	Café	
4	Indian Restaurant	Asian Restaurant	
5	Café	Coffee Shop	
8	Café	Coffee Shop	
9	Café	Hot Spring	
10	Café	Coffee Shop	
11	Fast Food Restaurant	Hotel	
13	Café	Coffee Shop	
14	Pool	Gym	
16	Café	Coffee Shop	
18	Middle Eastern Restaurant	Indian Restaurant	
20	Coffee Shop	Spa	
22	Sushi Restaurant	Italian Restaurant	
28	Theme Park Ride / Attraction	Café	

	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Fast Food Restaurant	Sandwich Place	Café
2	Fried Chicken Joint	Furniture / Home Store	Fast Food Restaurant
4	Bakery	Ice Cream Shop	Cafeteria
5	Fast Food Restaurant	Donut Shop	Gym / Fitness Center
8	Sushi Restaurant	Middle Eastern Restaurant	American Restaurant
9	Medical Center	Coffee Shop	Hotel
10	Middle Eastern Restaurant	Pharmacy	Shopping Mall
11	Café	Italian Restaurant	Asian Restaurant
13	Dessert Shop	Flower Shop	Bakery
14	Pizza Place	Convenience Store	Coffee Shop
16	Cosmetics Shop	Wine Bar	Donut Shop
18	Hotel	Coffee Shop	Fast Food Restaurant
20	Hotel	Italian Restaurant	Lebanese Restaurant
22	Café	Supermarket	Fast Food Restaurant
28	Coffee Shop	Clothing Store	Sporting Goods Shop

Now we can map the neighborhoods differentiating the clusters with different colors.

```
[86]: # create map
map_clusters = folium.Map(location=[latitude, longitude], 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(AD_merged['Lat'], AD_merged['Lon'],
    ↪AD_merged['Neighborhood'], AD_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

```

[86]: <folium.folium.Map at 0x7fb4ca8455f8>

Let's inspect cluster 1, the most common one.

```

[87]: AD_merged.loc[AD_merged['Cluster_Labels'] == 1, AD_merged.columns[[0] +
    ↪list(range(4, AD_merged.shape[1]))]]

```

[87]:	Neighborhood	1st Most Common Venue	2nd Most Common Venue	\
2	Al Dhafrah	Middle Eastern Restaurant		Café
5	Al Khubeirah		Café	Coffee Shop
8	Al Maryah Island		Café	Coffee Shop
10	Al Maqtaa		Café	Coffee Shop
11	Al Markaziyah	Fast Food Restaurant		Hotel
13	Al Nahyan		Café	Coffee Shop
18	Al Zahiyah	Middle Eastern Restaurant		Indian Restaurant
20	Bain Al Jisrain		Coffee Shop	Spa
22	Masdar City	Sushi Restaurant		Italian Restaurant
28	Yas Island	Theme Park Ride / Attraction		Café

	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
2	Fried Chicken Joint	Furniture / Home Store	Fast Food Restaurant
5	Fast Food Restaurant	Donut Shop	Gym / Fitness Center
8	Sushi Restaurant	Middle Eastern Restaurant	American Restaurant
10	Middle Eastern Restaurant	Pharmacy	Shopping Mall
11	Café	Italian Restaurant	Asian Restaurant
13	Dessert Shop	Flower Shop	Bakery
18	Hotel	Coffee Shop	Fast Food Restaurant
20	Hotel	Italian Restaurant	Lebanese Restaurant

22	Café	Supermarket	Fast Food Restaurant
28	Coffee Shop	Clothing Store	Sporting Goods Shop

We can already get some insights from this table. We see that our business idea, a coffee shop, is very present in most areas. But let's take a look at Al Zahiyah.

```
[88]: AD_merged.loc[AD_merged['Neighborhood'] == 'Al Zahiyah']
```

```
[88]: Neighborhood    Lat    Lon Cluster_Labels    1st Most Common Venue \
18    Al Zahiyah    24.4933    54.3799            1 Middle Eastern Restaurant

    2nd Most Common Venue 3rd Most Common Venue 4th Most Common Venue \
18    Indian Restaurant            Hotel            Coffee Shop

    5th Most Common Venue
18    Fast Food Restaurant
```

Ok, coffee shop appears only in 4th place. So perhaps there is an opportunity here. This could give a potential business owner a starting point to hers/his research.

I would like to remove coffee shops from the equation and recluster (is that a word?) the neighborhoods. It would be nice to see if maybe we get different neighborhoods that might be clustered together, which could suggest that a coffee shop would be a good investment in area X, because neighborhood Y has a couple, but it was clustered together with X when we removed coffee shops.

However, our current database does not have enough venues to attempt this.

Before we go, let's take a look at our other clusters.

```
[89]: AD_merged.loc[AD_merged['Cluster_Labels'] == 0, AD_merged.columns[[0] +
↳list(range(4, AD_merged.shape[1]))]]
```

```
[89]: Neighborhood 1st Most Common Venue 2nd Most Common Venue \
0    Al Aman            Hotel            Coffee Shop

    3rd Most Common Venue 4th Most Common Venue 5th Most Common Venue
0    Fast Food Restaurant    Sandwich Place            Café
```

```
[90]: AD_merged.loc[AD_merged['Cluster_Labels'] == 2, AD_merged.columns[[0] +
↳list(range(4, AD_merged.shape[1]))]]
```

```
[90]: Neighborhood 1st Most Common Venue 2nd Most Common Venue \
9    Al Manhal            Café            Hot Spring
16    Al Rowdah            Café            Coffee Shop

    3rd Most Common Venue 4th Most Common Venue 5th Most Common Venue
9    Medical Center            Coffee Shop            Hotel
16    Cosmetics Shop            Wine Bar            Donut Shop
```

```
[91]: AD_merged.loc[AD_merged['Cluster_Labels'] == 3, AD_merged.columns[[0] +
↳list(range(4, AD_merged.shape[1]))]]
```

```
[91]: Neighborhood 1st Most Common Venue 2nd Most Common Venue \
4      Al Karama      Indian Restaurant      Asian Restaurant

      3rd Most Common Venue 4th Most Common Venue 5th Most Common Venue
4              Bakery      Ice Cream Shop      Cafeteria
```

```
[92]: AD_merged.loc[AD_merged['Cluster_Labels'] == 4, AD_merged.columns[[0] +
↳list(range(4, AD_merged.shape[1]))]]
```

```
[92]: Neighborhood 1st Most Common Venue 2nd Most Common Venue \
14      Al Reef      Pool      Gym

      3rd Most Common Venue 4th Most Common Venue 5th Most Common Venue
14      Pizza Place      Convenience Store      Coffee Shop
```

For this last cluster we see Al Reef, which is an up-and-coming residential area. Maybe it could use another coffee shop?

1.4 Discussion and Final Thoughts...

As you can see, there a lot of tools to work with here and make some interesting analysis. Of course, we could always use more data. We can find the locations of the other neighborhoods, even if we have to do it manually.

We showed that there aren't many venues listed on Foursquare for some areas. We could use other databases to see if we get better results. It would also be interesting to integrate this with information about if an area is a business area or a more residential one. As mentioned, we can also explore further the clustering method as well.

However, even with limitations, even if we do not get clear cut conclusions for this exercise, we do get some things from it: * We can at least get some insights and give a direction or focus for our research/work. * This was a great learning experience. Even though I had seen most of these methods during my Master's, I had done everything with R. A refreshment on the subject with Python was a great way to learn a new programming language. * Also, there was much more learned during the course that is not being used in this report. SQL, for example. Plus, as already mentioned in the Methodology, I was presented to a couple of really cool platforms to code and do analysis on, in IBM Skills Network Labs and IBM Cloud with Watson services. Have a look on those.

Thank you for reading this.

```
[ ]:
```