Chile: best comuna to place a Coffee Shop

Coursera IBM Data Science final Capstone project

1- Introduction/Business problem

I live in Chile and also love coffee. I've always dreamed about putting a Coffe shop somewhere, but of course the question that arise immediately is "where?". Here, I'll try to answer that question by using some of the techniques learned on this IBM Data Science courses. Chile is subdivided on Regions and Comunas, being this Comunas as large Neighborhoods. Please, keep in mind that.

I'll focus on the Metropolitan Region of Chile: is where I live and the one with the most variety of business and restaurants, and of course, coffee shops. Also, is the Region where the Capital belongs, Santiago de Chile, and the one with most income of all the country. But of course, the same analysis can be applied to a different Region on Chile or even a different country, since the algorithms that I'll apply will be, of couse, generic. The only thing that maybe will be different is the data treatment, but the methodology will be the same.

2-Data Description

To solve the business problem described above, I'll work with the following data:

- A Wikipedia page where is the info I need: Latitude and Longitude for each Comuna in Chile, divided by Region. The page is the following: https://es.wikipedia.org/wiki/Anexo:Comunas_de_Chile (https://es.wikipedia.org/wiki/Anexo:Comunas_de_Chile)
- Also, on this table, there are two more indicators tha will help me on my analysis: the Population Density (Habitants/Km^2) and the IDH (Indice de Desarrollo Humano or Human Development Index). The Density will help me to know and approximate of how many Coffee shops per habitant are there, and the IDH will help me to choose the Comuna with better incomes, since one of the indicators for that number is precisely that one. Also, the comunas with better IDH have better infraestructure, more educated habitants and more tourism, which is better for a Coffe shop.
- I'll also use the foursquare data to get, by comuna, the most common venues and then, by using K-means algorithm, group the comunas and choose the one that looks best to place the Coffee shop. Then, I'll work with the most representative group and get the number of Coffee shops existant (using again Foursquare data), get the number of coffee shops per habitant and with that number, choose the best comuna to place my shop.

I'll be using maps to visualize, first, all the comunas in the Metropolitan region and then the ones that I'll use, and also to visualize the cluster generated by the K-means algorithm. To finally make my choice I think that maybe a Choropleth map will be useful, or maybe a Horizontal plot bar will be enough: Whatever suits best to show the results to the stakeholders.

3-Methodoly

As I already said above, I'm going to use the data available on a wikipedia, which has the geo coordinates for each Comuna and also other data that it's interesting for me to use.

First, import the necessary libraries:

In [1]:
```
import pandas as pd
from bs4 import BeautifulSoup
import requests
import numpy as np
from sklearn.cluster import KMeans
import folium # map rendering library
# Matplotlib and associated plotting modules
import matplotlib.cm as cm
import matplotlib.colors as colors
import matplotlib.pyplot as plt
```

Now, I'm going to use Beautiful Soup with Pandas to get the table from the Wikipedia page and transform it into a Pandas Dataframe:

In [2]:
```
res = requests.get("https://es.wikipedia.org/wiki/Anexo:Comunas_de_Chil
e")
soup = BeautifulSoup(res.content,'html')
table = soup.find_all('table')[0]
df = pd.read_html(str(table))[0]
df.head()
```

Out[2]:

	CUT (Código Único Territorial)	Nombre	Unnamed: 2	Provincia	Región	Superficie(km²)	Población2020	Dens
0	15101	Arica	NaN	Arica	Arica y Parinacota	4.7994	247.552	
1	15102	Camarones	NaN	Arica	Arica y Parinacota	3.927	1.233	
2	15201	Putre	NaN	Parinacota	Arica y Parinacota	5.9025	2.515	
3	15202	General Lagos	NaN	Parinacota	Arica y Parinacota	2.2444	810.000	
4	1101	Iquique	NaN	Iquique	Tarapacá	2.2421	223.463	

OK, looks good, but not good enough. On the next step, I'm going to clean up a bit the Dataframe, deleting unnecessary columns and rename others for better habndling.

In [3]:
```python
# Deleting some columns...
df.drop(["CUT (Código Único Territorial)","Unnamed: 2","Provincia","Supe
rficie(km²)","Población2020","IDH 2020"],axis=1,inplace=True)
# renaming...
df.rename(columns = {'Nombre':'Comuna','Región':'Region', 'Densidad(ha
b./km²)':'Densidad','IDH 2020.1':'IDH'}, inplace = True)
df.head()
```

Out[3]:

	Comuna	Region	Densidad	IDH	Latitud	Longitud
0	Arica	Arica y Parinacota	51.60	Alto	-18°27'18"	-70°17'24"
1	Camarones	Arica y Parinacota	0.31	Alto	-19°1'1.2"	-69°52'1.2"
2	Putre	Arica y Parinacota	0.43	Alto	-18°12'0"	-69°34'58.8"
3	General Lagos	Arica y Parinacota	0.36	Medio	-17°39'10.8"	-69°38'6"
4	Iquique	Tarapacá	996.00	Alto	-20°14'38.4"	-70°8'20.4"

That's better. But there's still one problem: the Latitude and Longitude on the DF is in degrees, minutes, seconds format. To make it work with Foursquare, I need it to be in decinal format. So, I'm going to change it: first, creating a function to do that and then applying it to the corresponding columns:

In [4]:
```python
# Function to change the value of Lat and Long from degrees to decimal f
ormat.
def grados_a_decimal(valor):
    delimitador_parte_entera=valor.find("°")
    parte_entera=valor[0:delimitador_parte_entera]
    delimitador_minutos=valor.find("'")
    minutos=valor[delimitador_parte_entera+1:delimitador_minutos]
    delimitador_segundos=valor.find('"')
    segundos=valor[delimitador_minutos+1:delimitador_segundos]
    valor_decimal=float(parte_entera)-float(minutos)/60-float(segundos)/
3600
    return valor_decimal
```

In [5]:
```python
# Applying the function to the corresponding columns
df['Latitud'] = df['Latitud'].apply(lambda x: grados_a_decimal(x))
df['Longitud'] = df['Longitud'].apply(lambda x: grados_a_decimal(x))
df.head()
```

Out[5]:

	Comuna	Region	Densidad	IDH	Latitud	Longitud
0	Arica	Arica y Parinacota	51.60	Alto	-18.455	-70.290
1	Camarones	Arica y Parinacota	0.31	Alto	-19.017	-69.867
2	Putre	Arica y Parinacota	0.43	Alto	-18.200	-69.583
3	General Lagos	Arica y Parinacota	0.36	Medio	-17.653	-69.635
4	Iquique	Tarapacá	996.00	Alto	-20.244	-70.139

Done! I'm ready to select the Region in what I'm interested to work, which is the Region Metropolitana. So, let's select a subset of the whole Dataframe to work with.

In [6]:
```
df_metropolitana = df[df['Region'] == "Metropolitana de Santiago"].reset
_index(drop=True)
df_metropolitana.head()
```

Out[6]:

	Comuna	Region	Densidad	IDH	Latitud	Longitud
0	Santiago	Metropolitana de Santiago	21.8759	Muy alto	-33.437222	-70.657222
1	Cerrillos	Metropolitana de Santiago	4.2360	Alto	-33.500000	-70.716667
2	Cerro Navia	Metropolitana de Santiago	12.9513	Medio	-33.422000	-70.735000
3	Conchalí	Metropolitana de Santiago	12.6540	Alto	-33.380000	-70.675000
4	El Bosque	Metropolitana de Santiago	12.2857	Alto	-33.567000	-70.675000

Let's check how many rows are in our new dataframe:

In [7]:
```
df_metropolitana.shape
```

Out[7]: (52, 6)

Nice. 52 is correct, that's the total number of Comunas on the Region Metropolitana.

Now, let's visualize the data a little bit. How about checking the comunas on a map, to check how centered they are, and more important, let's put a different color to identify them by the IDH factor. Let's translate it the range a little bit:

- Muy Alto: Very high - Blue
- Alto: High - Green
- Medio: Medium - Yellow
- Bajo: Low - Orange

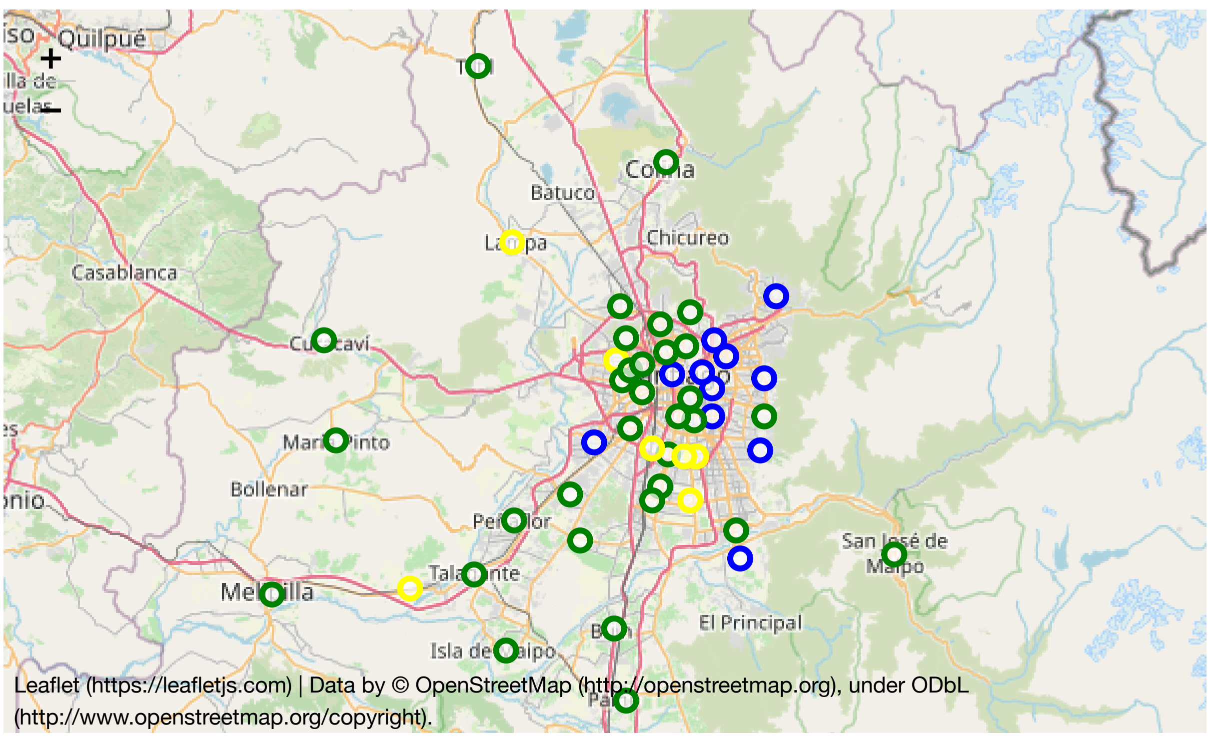
In [8]:
```python
latitude=-33.6027831
longitude=-71.299166

map_metropolitana = folium.Map(location=[latitude, longitude], zoom_start=9)

# add markers to map
for lat, lng, label, idh in zip(df_metropolitana['Latitud'], df_metropolitana['Longitud'], df_metropolitana['Comuna'], df_metropolitana['IDH']):
    label = folium.Popup(label, parse_html=True)
    if idh == 'Muy alto': color='blue'
    elif idh == 'Alto': color='green'
    elif idh == 'Medio': color='yellow'
    else: color='orange'
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color=color,
        fill=True,
        fill_color='white',
        fill_opacity=0.7,
        parse_html=False).add_to(map_metropolitana)

map_metropolitana
```

Out[8]:



OK, looks good, but I need to filter a little bit more the data. First, I'm interested only in the Comunas that have 'High' or 'Very high' IDH, so, lets filter them:

In [9]:
```
df_metropolitana = df_metropolitana.query('IDH == "Muy alto" or IDH == "Alto"').reset_index(drop=True)
df_metropolitana.shape
```

Out[9]:
```
(45, 6)
```

OK, only. 7 comunas has an IDH lower than 'High'.

The other issue is that the Region Metropolitana has a very extensive territory, and I'm not particularly interested in the Comunas that are too far away from the center of the Region, since this Comunas are considered more "Rural", so, the people living there are not particularly a target for a Coffee shop. So. lets' eliminate them:

In [10]:
```
df_metropolitana = df_metropolitana.query('Latitud > -33.59 and Latitud < -33.34 and Longitud >-70.79 and Longitud < -70.5').reset_index(drop=True)
df_metropolitana.shape
```

Out[10]:
```
(28, 6)
```

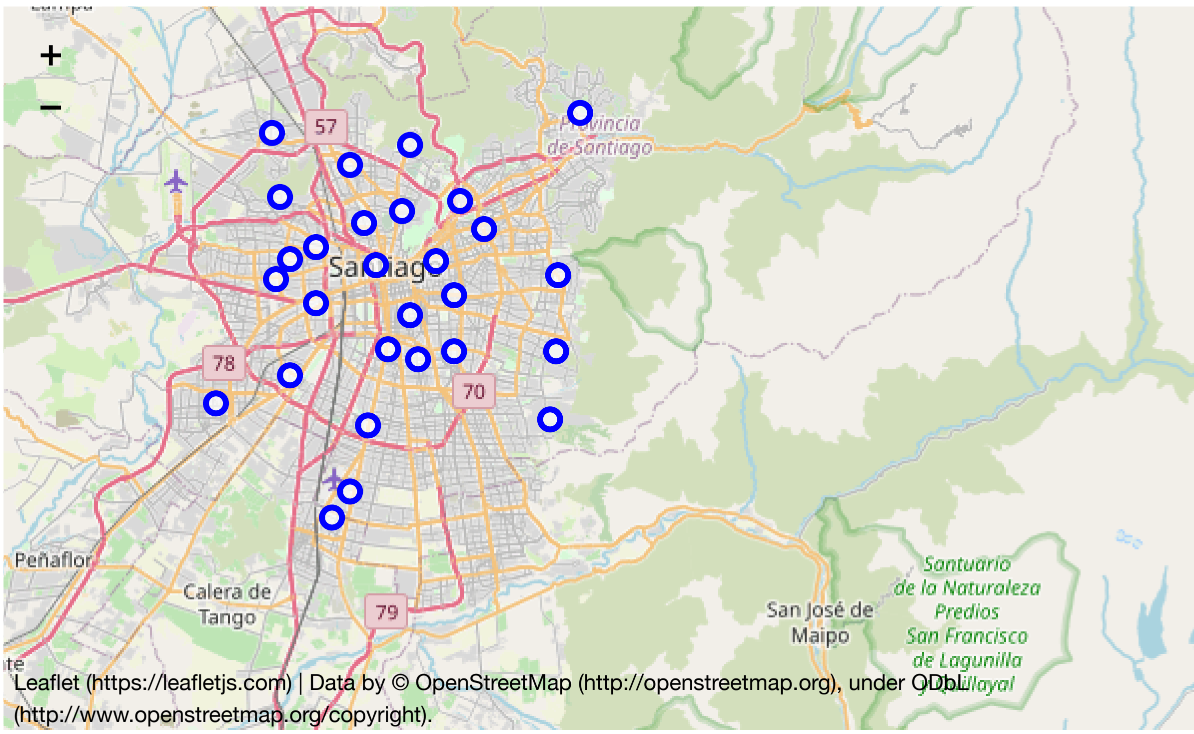
OK! I have cut down 24 Comunas, and I'm ready to work with the remaining 28. Let's visualize them on a map again:

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

# add markers to map
for lat, lng, label, idh in zip(df_metropolitana['Latitud'], df_metropolitana['Longitud'], df_metropolitana['Comuna'], df_metropolitana['IDH']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        popup=label,
        color='blue',
        fill=True,
        fill_color='white',
        fill_opacity=0.7,
        parse_html=False).add_to(map_metropolitana)

map_metropolitana
```

Out[11]:



OK, Now I'm ready to have fun with Foursquare. First, lets' initialize some useful variables:

In [57]:
```python
# Here are the credentials, remove the info to upload the file.
```

In [13]:
```python
VERSION = '20201229' # Foursquare API version
LIMIT = 100 # A default Foursquare API limit value
```

First, I'm going to reuse a function from the lectures where we get the nearby venues given a location. Instead of use 500 m around, we are going to go a little bit bigger: 5 km. Why? because, as I said on the Introduction part, Comunas are like LARGE neighborhoods. So, in average, I think that look at the locations around 5 km is good to get enough information.

In [16]:
```
# using the function of the lab
def getNearbyVenues(names, latitudes, longitudes, radius=5000):
    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        # 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]['ite
ms']
        # 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 = ['Comuna',
                  'Comuna Latitude',
                  'Comuna Longitude',
                  'Venue',
                  'Venue Latitude',
                  'Venue Longitude',
                  'Venue Category']
    return(nearby_venues)
```

OK, let's use the function to get the venues:

In [17]:
```
metropolitana_venues = getNearbyVenues(names=df_metropolitana['Comuna'],
                                   latitudes=df_metropolitana['Latitud'
],
                                   longitudes=df_metropolitana['Longitu
d']
                                  )
```

In [18]:
```
metropolitana_venues
```

Out[18]:

	Comuna	Comuna Latitude	Comuna Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Santiago	-33.437222	-70.657222	Plaza de Bolsillo - Santiago Centro	-33.436778	-70.655481	Plaza
1	Santiago	-33.437222	-70.657222	FuriSushi	-33.436130	-70.662690	Sushi Restaurant
2	Santiago	-33.437222	-70.657222	La Fête Chocolat	-33.442606	-70.651286	Candy Store
3	Santiago	-33.437222	-70.657222	Libreria Manantial	-33.438549	-70.651361	College Bookstore
4	Santiago	-33.437222	-70.657222	Starbucks	-33.433253	-70.658200	Coffee Shop
...	...	...	...	...	...	...	...
2724	San Bernardo	-33.582000	-70.687000	Hiper Lider	-33.546332	-70.667430	Supermarket
2725	San Bernardo	-33.582000	-70.687000	Feria San Rafael	-33.581776	-70.638947	Farmers Market
2726	San Bernardo	-33.582000	-70.687000	Metro de Santiago, Línea 4A	-33.564491	-70.641212	Metro Station
2727	San Bernardo	-33.582000	-70.687000	Plaza Prat	-33.547001	-70.657854	Plaza
2728	San Bernardo	-33.582000	-70.687000	Parque Avenida Observatorio	-33.564351	-70.639249	Park

2729 rows × 7 columns

Let's count how many venues we got for each Comuna:

In [20]:
```
metropolitana_venues.groupby('Comuna').count()
```

Out[20]:

	Comuna Latitude	Comuna Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Comuna						
Cerrillos	100	100	100	100	100	100
Conchalí	100	100	100	100	100	100
El Bosque	100	100	100	100	100	100
Estación Central	100	100	100	100	100	100
Huechuraba	100	100	100	100	100	100
Independencia	100	100	100	100	100	100
La Cisterna	54	54	54	54	54	54
La Florida	100	100	100	100	100	100
La Reina	100	100	100	100	100	100
Las Condes	100	100	100	100	100	100
Lo Barnechea	97	97	97	97	97	97
Lo Prado	100	100	100	100	100	100
Macul	100	100	100	100	100	100
Maipú	100	100	100	100	100	100
Pedro Aguirre Cerda	100	100	100	100	100	100
Peñalolén	100	100	100	100	100	100
Providencia	100	100	100	100	100	100
Pudahuel	100	100	100	100	100	100
Quilicura	100	100	100	100	100	100
Quinta Normal	100	100	100	100	100	100
Recoleta	100	100	100	100	100	100
Renca	99	99	99	99	99	99
San Bernardo	79	79	79	79	79	79
San Joaquín	100	100	100	100	100	100
San Miguel	100	100	100	100	100	100
Santiago	100	100	100	100	100	100
Vitacura	100	100	100	100	100	100
Ñuñoa	100	100	100	100	100	100

Let's find out how many categories we got:

In [21]:
```
print('There are {} uniques categories.'.format(len(metropolitana_venues
['Venue Category'].unique())))
```

```
There are 230 uniques categories.
```

OK, now let's prepare the data to work with the K-means algorithm and let the machine learning do their magic to group our Comunas and find out which ones are more suitable for our Coffee shop. First, let's transform the data into Onehot Encoding:

In [22]:
```
metropolitana_onehot = pd.get_dummies(metropolitana_venues[['Venue Categ
ory']], prefix="", prefix_sep="")
metropolitana_onehot.insert(0, "Comuna", metropolitana_venues['Comuna'],
True)
metropolitana_onehot.head()
```

Out[22]:

	Comuna	Accessories Store	Airport	American Restaurant	Amphitheater	Antique Shop	Arcade	Arepa Restaurant	Argen Resta
0	Santiago	0	0	0	0	0	0	0	
1	Santiago	0	0	0	0	0	0	0	
2	Santiago	0	0	0	0	0	0	0	
3	Santiago	0	0	0	0	0	0	0	
4	Santiago	0	0	0	0	0	0	0	

5 rows × 231 columns

Let's group by the Dataframe by Comuna by taking the mean on each category:

In [23]:
```
metropolitana_grouped=metropolitana_onehot.groupby('Comuna').mean().reset_index()
metropolitana_grouped
```

Out[23]:

	Comuna	Accessories Store	Airport	American Restaurant	Amphitheater	Antique Shop	Arcade	Arepa Restaurant
0	Cerrillos	0.00	0.01	0.000000	0.00	0.00	0.00	0.01
1	Conchalí	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
2	El Bosque	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
3	Estación Central	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
4	Huechuraba	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
5	Independencia	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
6	La Cisterna	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
7	La Florida	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
8	La Reina	0.00	0.00	0.010000	0.01	0.00	0.00	0.00
9	Las Condes	0.00	0.00	0.010000	0.00	0.00	0.00	0.00
10	Lo Barnechea	0.00	0.00	0.010309	0.00	0.00	0.00	0.00
11	Lo Prado	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
12	Macul	0.01	0.00	0.000000	0.01	0.00	0.00	0.00
13	Maipú	0.00	0.00	0.000000	0.00	0.00	0.00	0.01
14	Pedro Aguirre Cerda	0.00	0.00	0.000000	0.00	0.01	0.00	0.00
15	Peñalolén	0.00	0.00	0.000000	0.00	0.00	0.01	0.00
16	Providencia	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
17	Pudahuel	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
18	Quilicura	0.00	0.00	0.010000	0.00	0.00	0.00	0.00
19	Quinta Normal	0.01	0.00	0.000000	0.00	0.00	0.00	0.00
20	Recoleta	0.00	0.00	0.010000	0.00	0.00	0.00	0.00
21	Renca	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
22	San Bernardo	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
23	San Joaquín	0.01	0.00	0.000000	0.00	0.00	0.00	0.00
24	San Miguel	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
25	Santiago	0.00	0.00	0.000000	0.00	0.00	0.00	0.00
26	Vitacura	0.00	0.00	0.010000	0.00	0.00	0.00	0.00
27	Ñuñoa	0.00	0.00	0.000000	0.01	0.00	0.00	0.00

28 rows × 231 columns

OK, looks good. With this data frame I'm ready to get the 10 most common venues by Comuna. So let's define a function to do that:

In [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]
```

And now we use it:

In [27]:
```
num_top_venues = 10
indicators = ['st', 'nd', 'rd']
# create columns according to number of top venues
columns = ['Comuna']
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
comuna_venues_sorted = pd.DataFrame(columns=columns)
comuna_venues_sorted['Comuna'] = metropolitana_grouped['Comuna']

for ind in np.arange(metropolitana_grouped.shape[0]):
    comuna_venues_sorted.iloc[ind, 1:] = return_most_common_venues(metro
politana_grouped.iloc[ind, :], num_top_venues)

comuna_venues_sorted.head()
```

Out[27]:

	Comuna	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue
0	Cerrillos	Sushi Restaurant	Chinese Restaurant	Gym	Sandwich Place	Ice Cream Shop	Park	Restaurant
1	Conchalí	Furniture / Home Store	Sushi Restaurant	Sandwich Place	Soccer Field	Peruvian Restaurant	Chinese Restaurant	Convenience Store
2	El Bosque	Chinese Restaurant	Pizza Place	Sushi Restaurant	Seafood Restaurant	Pharmacy	Flea Market	Gym
3	Estación Central	Sushi Restaurant	Sandwich Place	Peruvian Restaurant	Park	Plaza	Coffee Shop	Bakery
4	Huechuraba	Peruvian Restaurant	Ice Cream Shop	Restaurant	Sushi Restaurant	Coffee Shop	Burger Joint	Soccer Field

Finally, now that we have the 10 more common venue types by comuna sorted, we can use the K-means algorithm to let it group automatically the Comunas.

In [28]:
```
# set number of clusters
kclusters = 5
metropolitana_grouped_clustering = metropolitana_grouped.drop('Comuna', 1)
# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(metropolitana_grouped_clustering)
# check cluster labels generated for each row in the dataframe
kmeans.labels_
```

Out[28]:
```
array([0, 4, 0, 2, 4, 2, 3, 0, 1, 1, 1, 2, 2, 0, 1, 4, 1, 2, 4, 2, 1, 0,
       0, 2, 2, 2, 1, 1], dtype=int32)
```

Good. We have our groups. Let's add them to a DataFrame:

In [29]:
```
# adding the cluster labels
comuna_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)
metropolitana_merged = df_metropolitana

# Let's use right join, just in case not all the Comunas on the df_metropolitana are on the comunas_venues_sorted
metropolitana_merged = metropolitana_merged.join(comuna_venues_sorted.set_index('Comuna'), on='Comuna',how='right')

metropolitana_merged.head()
```

Out[29]:

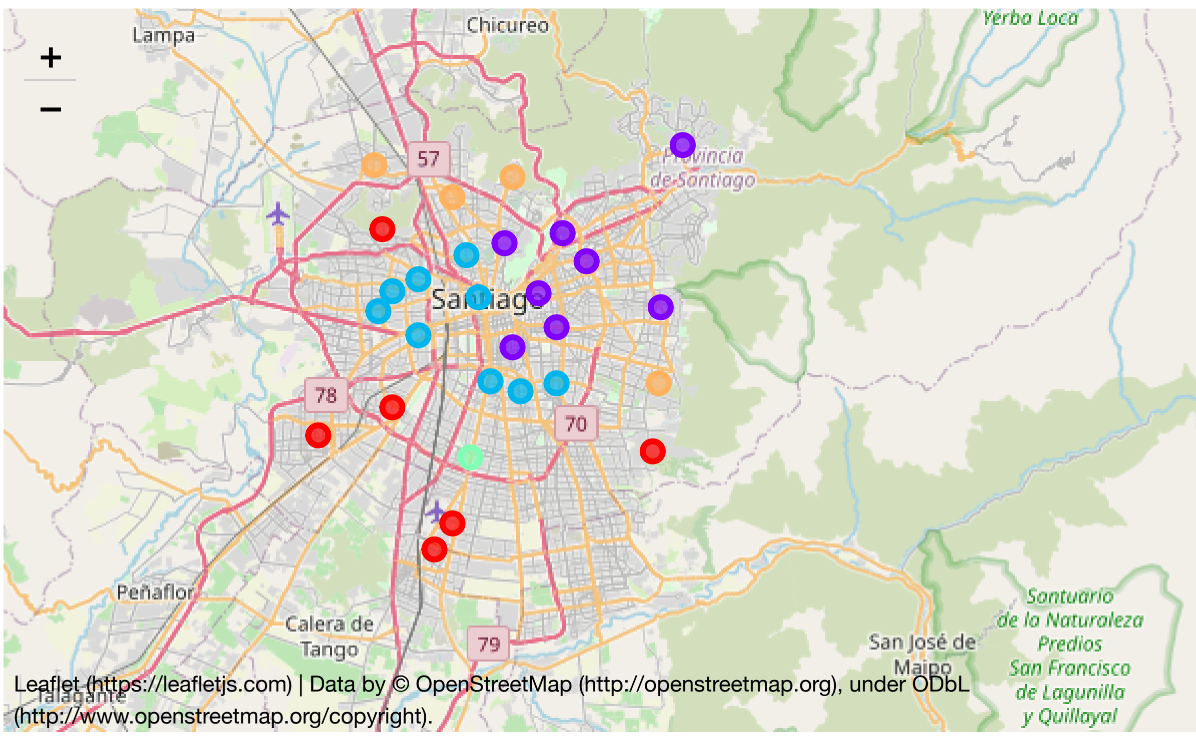
	Comuna	Region	Densidad	IDH	Latitud	Longitud	Cluster Labels	1st Most Common Venue	2nd Most Common Venue
0	Santiago	Metropolitana de Santiago	21.8759	Muy alto	-33.437222	-70.657222	2	Park	Coffee Shop
1	Cerrillos	Metropolitana de Santiago	4.2360	Alto	-33.500000	-70.716667	0	Sushi Restaurant	Chinese Restaurant
2	Conchalí	Metropolitana de Santiago	12.6540	Alto	-33.380000	-70.675000	4	Furniture / Home Store	Sushi Restaurant
3	El Bosque	Metropolitana de Santiago	12.2857	Alto	-33.567000	-70.675000	0	Chinese Restaurant	Pizza Place
4	Estación Central	Metropolitana de Santiago	13.7861	Alto	-33.459000	-70.699000	2	Sushi Restaurant	Sandwich Place

Let's visualize it again this result on a Folium map:

In [31]:
```
# create map
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=10)
# 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(metropolitana_merged['Latitud'], metro
politana_merged['Longitud'], metropolitana_merged['Comuna'], metropolita
na_merged['Cluster Labels']):
    label = folium.Popup(str(poi) + ' Cluster ' + str(cluster), parse_ht
ml=True)
    folium.CircleMarker(
        [lat, lon],
        radius=5,
        popup=label,
        color=rainbow[cluster-1],
        fill=True,
        fill_color=rainbow[cluster-1],
        fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

Out[31]:



Good. Let's examine the clusters to have a better idea of which one is the best candidate for our business:

Cluster 0

More focused on Oriental restaurants and pizza places, I think we can discard this one.

In [32]:
```
metropolitana_merged.loc[metropolitana_merged['Cluster Labels'] == 0, metropolitana_merged.columns[[0] + list(range(5, metropolitana_merged.shape[1]))]]
```

Out[32]:

	Comuna	Longitud	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Com V
1	Cerrillos	-70.716667	0	Sushi Restaurant	Chinese Restaurant	Gym	Sandwich Place	Ice Cream Shop	
3	El Bosque	-70.675000	0	Chinese Restaurant	Pizza Place	Sushi Restaurant	Seafood Restaurant	Pharmacy	M
8	La Florida	-70.538000	0	Sushi Restaurant	Chinese Restaurant	Pizza Place	Gym	Bakery	Resta
14	Maipú	-70.766667	0	Sushi Restaurant	Bar	Park	Pizza Place	Sandwich Place	Ch Resta
23	Renca	-70.723000	0	Restaurant	Sushi Restaurant	Pharmacy	Chinese Restaurant	Park	
27	San Bernardo	-70.687000	0	Pizza Place	Chinese Restaurant	Flea Market	Park	Sushi Restaurant	

Cluster 1

This is more interesting cluster, where all the comunas have a Coffee Shop on the top 5 most common venues. Also, we see a lots of Bakery shops and nonetheless, parks and gyms, where our target audience usually hangs out.

In [33]:
```
metropolitana_merged.loc[metropolitana_merged['Cluster Labels'] == 1, metropolitana_merged.columns[[0] + list(range(5, metropolitana_merged.shape[1]))]]
```

Out[33]:

	Comuna	Longitud	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Co
9	La Reina	-70.532000	1	Bakery	Coffee Shop	Restaurant	Plaza	Park	Fa
10	Las Condes	-70.583333	1	Hotel	Coffee Shop	Bakery	Park	Plaza	
11	Lo Barnechea	-70.516667	1	Gym	Restaurant	Park	Bakery	Coffee Shop	Sh
15	Ñuñoa	-70.604000	1	Bakery	Peruvian Restaurant	Coffee Shop	Sandwich Place	Plaza	Rest
16	Pedro Aguirre Cerda	-70.633667	1	Park	Bakery	Peruvian Restaurant	Pizza Place	Coffee Shop	Rest
18	Providencia	-70.616000	1	Park	Bakery	Coffee Shop	Peruvian Restaurant	Sandwich Place	Rest
22	Recoleta	-70.640000	1	Park	Coffee Shop	Scenic Lookout	Hotel	Restaurant	Fa
26	Vitacura	-70.600000	1	Hotel	Park	Restaurant	Coffee Shop	Sandwich Place	L

Cluster 2

Again, and interesting group, with Coffee shops on the top 5. But, we don't see a lots of parks here, more like oriental restaurants again.

In [34]:
```
metropolitana_merged.loc[metropolitana_merged['Cluster Labels'] == 2, metropolitana_merged.columns[[0] + list(range(5, metropolitana_merged.shape[1]))]]
```

Out[34]:

	Comuna	Longitud	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Santiago	-70.657222	2	Park	Coffee Shop	Pizza Place	Theater	Sushi Restaurant
4	Estación Central	-70.699000	2	Sushi Restaurant	Sandwich Place	Peruvian Restaurant	Park	Plaza
6	Independencia	-70.666000	2	Park	Coffee Shop	Pizza Place	Tea Room	Farmers Market
12	Lo Prado	-70.726000	2	Sushi Restaurant	Sandwich Place	Chinese Restaurant	Bakery	Nightclub
13	Macul	-70.604000	2	Sandwich Place	Sushi Restaurant	Peruvian Restaurant	Coffee Shop	Ice Cream Shop
19	Pudahuel	-70.716667	2	Sushi Restaurant	Peruvian Restaurant	Bakery	Nightclub	Bar
21	Quinta Normal	-70.699000	2	Sushi Restaurant	Coffee Shop	Sandwich Place	Peruvian Restaurant	Bar
24	San Joaquín	-70.628000	2	Sushi Restaurant	Bakery	Pizza Place	Sandwich Place	Coffee Shop
25	San Miguel	-70.649444	2	Pizza Place	Sushi Restaurant	Sandwich Place	Bakery	Peruvian Restaurant

Cluster 3

I thon we can discard this comuna, no Coffee shops here, more oriental restaurants and pizza places.

In [35]:
```
metropolitana_merged.loc[metropolitana_merged['Cluster Labels'] == 3, metropolitana_merged.columns[[0] + list(range(5, metropolitana_merged.shape[1]))]]
```

Out[35]:

	Comuna	Longitud	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7 C
7	La Cisterna	-70.663	3	Sushi Restaurant	Park	Pizza Place	Bar	Bakery	Liquor Store	

Cluster 4

The last cluster is again not interesting. Seems to be more focused on a more 'family' kind of people, and the Coffee shops are only at the 5th most common value and below. We can discard this one.

In [36]:
```
metropolitana_merged.loc[metropolitana_merged['Cluster Labels'] == 4, metropolitana_merged.columns[[0] + list(range(5, metropolitana_merged.shape[1]))]]
```

Out[36]:

	Comuna	Longitud	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	(
2	Conchalí	-70.675000	4	Furniture / Home Store	Sushi Restaurant	Sandwich Place	Soccer Field	Peruvian Restaurant	R
5	Huechuraba	-70.634000	4	Peruvian Restaurant	Ice Cream Shop	Restaurant	Sushi Restaurant	Coffee Shop	
17	Peñalolén	-70.533333	4	Pizza Place	Farmers Market	Restaurant	Sushi Restaurant	Chinese Restaurant	
20	Quilicura	-70.729000	4	Clothing Store	Sushi Restaurant	Furniture / Home Store	Department Store	Restaurant	I(

The way I see it, the real fight is between Cluster 1 and 2, But I'll choose cluster 1 because the other popular places are more like to have people interested in attend a Coffee shop. The presence of Gyms, parks and Hotels tips the scales on it's favor. So, let's work with it.

In [37]:
```
best_cluster=metropolitana_merged.loc[metropolitana_merged['Cluster Labe
ls'] == 1].reset_index(drop=True)
best_cluster
```

Out[37]:

	Comuna	Region	Densidad	IDH	Latitud	Longitud	Cluster Labels	1st Most Common Venue	2nd Mos Commo Venu
0	La Reina	Metropolitana de Santiago	4.3587	Muy alto	-33.443000	-70.532000	1	Bakery	Coffe Sho
1	Las Condes	Metropolitana de Santiago	3.3410	Muy alto	-33.416667	-70.583333	1	Hotel	Coffe Sho
2	Lo Barnechea	Metropolitana de Santiago	121.1000	Muy alto	-33.350000	-70.516667	1	Gym	Restaurar
3	Ñuñoa	Metropolitana de Santiago	14.7171	Muy alto	-33.454000	-70.604000	1	Bakery	Peruvia Restaurar
4	Pedro Aguirre Cerda	Metropolitana de Santiago	10.7803	Alto	-33.466333	-70.633667	1	Park	Baker
5	Providencia	Metropolitana de Santiago	11.2677	Muy alto	-33.435000	-70.616000	1	Park	Baker
6	Recoleta	Metropolitana de Santiago	11.8793	Alto	-33.406000	-70.640000	1	Park	Coffe Sho
7	Vitacura	Metropolitana de Santiago	3.4562	Muy alto	-33.400000	-70.600000	1	Hotel	Par

Let's define a function to get the number of Coffee shops for each comuna selected:

In [39]:
```
# function to get the list of number of coffe shops on the Comunas selec
ted, on a radius of 5k
def getCoffeShopsNumber(names, latitudes, longitudes, radius=5000):
    coffee_shops_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        # create the API request URL
        search_category = '4bf58dd8d48988d1e0931735' #category for #coff
ee shop

        url='https://api.foursquare.com/v2/venues/explore?client_id={}&c
lient_secret={}&v={}&ll={},{}&categoryId={}&radius={}&limit={}'.format(
            CLIENT_ID,
            CLIENT_SECRET,
            VERSION,
            lat,
            lon,
            search_category,
            radius,
            LIMIT)

        number_of_coffeshops = requests.get(url).json()["response"]['tot
alResults']
        coffee_shops_list.append(number_of_coffeshops)

    return(coffee_shops_list)
```

In [40]:
```
coffee_shops_list=getCoffeShopsNumber(names=best_cluster['Comuna'],
                                      latitudes=best_cluster['Latitud'],
                                      longitudes=best_cluster['Longitud']
                                     )
```

In [41]:
```
best_cluster['Coffee Shops N']=coffee_shops_list
best_cluster
```

Out[41]:

	Comuna	Region	Densidad	IDH	Latitud	Longitud	Cluster Labels	1st Most Common Venue	2nd Mos Commo Venu
0	La Reina	Metropolitana de Santiago	4.3587	Muy alto	-33.443000	-70.532000	1	Bakery	Coffe Sho
1	Las Condes	Metropolitana de Santiago	3.3410	Muy alto	-33.416667	-70.583333	1	Hotel	Coffe Sho
2	Lo Barnechea	Metropolitana de Santiago	121.1000	Muy alto	-33.350000	-70.516667	1	Gym	Restaurar
3	Ñuñoa	Metropolitana de Santiago	14.7171	Muy alto	-33.454000	-70.604000	1	Bakery	Peruvia Restaurar
4	Pedro Aguirre Cerda	Metropolitana de Santiago	10.7803	Alto	-33.466333	-70.633667	1	Park	Baker
5	Providencia	Metropolitana de Santiago	11.2677	Muy alto	-33.435000	-70.616000	1	Park	Baker
6	Recoleta	Metropolitana de Santiago	11.8793	Alto	-33.406000	-70.640000	1	Park	Coffe Sho
7	Vitacura	Metropolitana de Santiago	3.4562	Muy alto	-33.400000	-70.600000	1	Hotel	Par

Now, let's make the calculation of roughly, amount of coffee shops per habitants, using the 'Densidad' (Density) value:

In [42]:
```
# making the calculation: we're going to divide the number of coffee sho
ps by the density of each Comuna, to check how many coffee shops are per
habitant
coffee_shops_per_hab=[]
for densidad,coffee_shops in zip(best_cluster['Densidad'],best_cluster[
'Coffee Shops N']):
    coffee_shops_per_hab.append(coffee_shops/densidad)

best_cluster['Coffee Shops per Habitant']=coffee_shops_per_hab

best_cluster
```

Out[42]:

	Comuna	Region	Densidad	IDH	Latitud	Longitud	Cluster Labels	1st Most Common Venue	2nd Mos Commo Venu
0	La Reina	Metropolitana de Santiago	4.3587	Muy alto	-33.443000	-70.532000	1	Bakery	Coffe Sho
1	Las Condes	Metropolitana de Santiago	3.3410	Muy alto	-33.416667	-70.583333	1	Hotel	Coffe Sho
2	Lo Barnechea	Metropolitana de Santiago	121.1000	Muy alto	-33.350000	-70.516667	1	Gym	Restaurar
3	Ñuñoa	Metropolitana de Santiago	14.7171	Muy alto	-33.454000	-70.604000	1	Bakery	Peruvia Restaurar
4	Pedro Aguirre Cerda	Metropolitana de Santiago	10.7803	Alto	-33.466333	-70.633667	1	Park	Baker
5	Providencia	Metropolitana de Santiago	11.2677	Muy alto	-33.435000	-70.616000	1	Park	Baker
6	Recoleta	Metropolitana de Santiago	11.8793	Alto	-33.406000	-70.640000	1	Park	Coffe Sho
7	Vitacura	Metropolitana de Santiago	3.4562	Muy alto	-33.400000	-70.600000	1	Hotel	Par

OK, we got everything we need to make our final decision. Let's plot the results:

In [54]:
```
df_plot=best_cluster[['Comuna','Coffee Shops per Habitant']]
df_plot.set_index('Comuna',inplace=True)
df_plot=df_plot.sort_values(by='Coffee Shops per Habitant', ascending=True)
df_plot
```

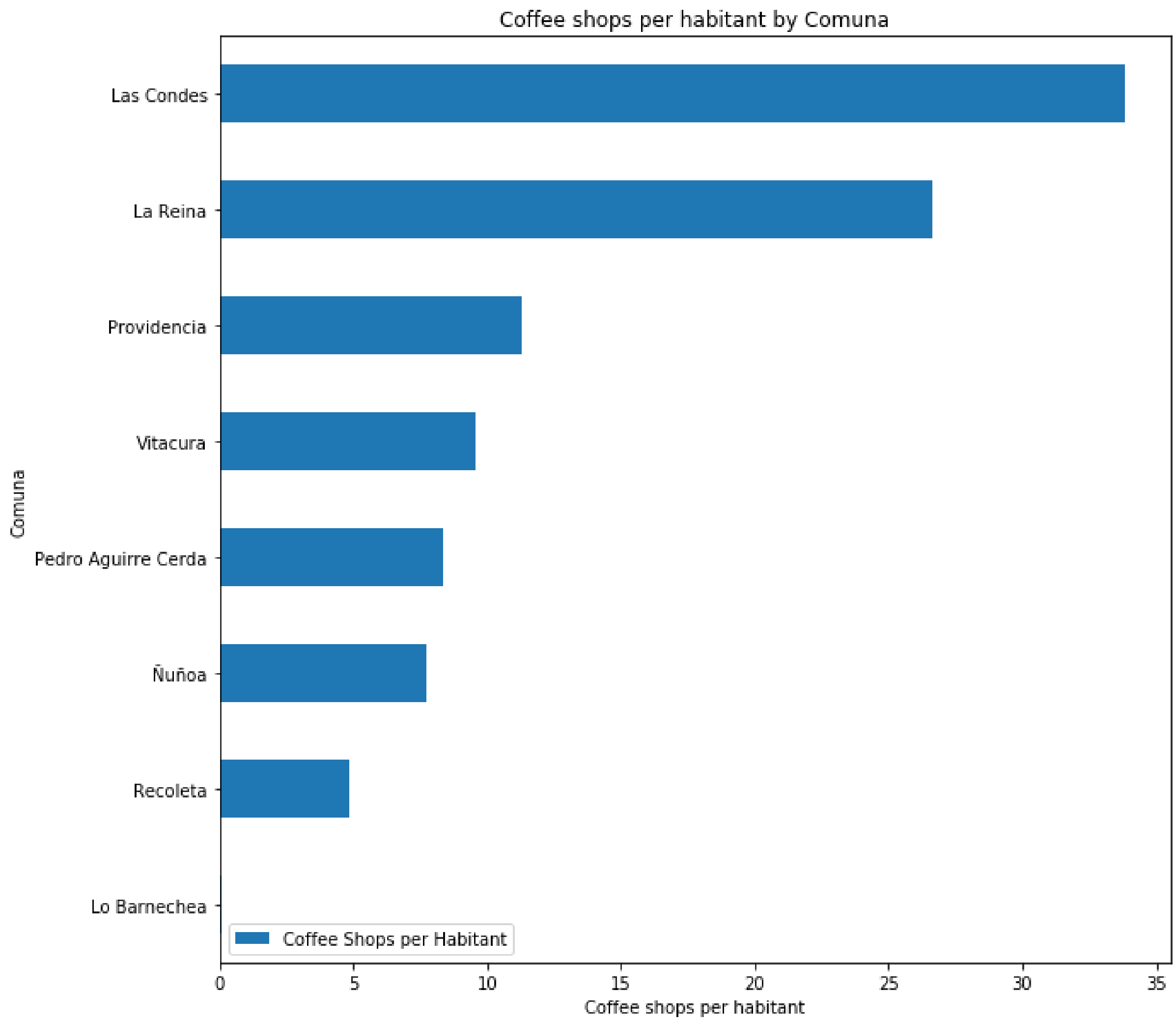
Out[54]:

	Coffee Shops per Habitant
Comuna	
Lo Barnechea	0.090834
Recoleta	4.882443
Ñuñoa	7.746091
Pedro Aguirre Cerda	8.348562
Vitacura	9.548059
Providencia	11.271156
La Reina	26.613440
Las Condes	33.822209

In [55]:
```
df_plot.plot(kind='barh', figsize=(10, 10))

plt.xlabel('Coffee shops per habitant')
plt.title('Coffee shops per habitant by Comuna')

plt.show()
```



OK. The amount of Coffee shops per habitan on Lo Barnechea is almost inexistant compare to the other Comunas, so, they are in clearly need for another one!

4- Results

After all the analysis ran on this set of Data, we can say that the best comuna to place our Coffee shop business is Lo Barnechea, since the amount of Coffee shops per habitant is surprisingly low in comparission with the other comunas on the same cluster.

Nowing a little bit abot the Comunas of the Region Metropolitana, I can say that this resuls are good enough, because on this case, Lo Barnechea has more or less the same incomes than the other comunas on the same cluster, like Las Condes or Vitacura, and the population on this Comunas are likely to share the same interest. Also, it has an IDH of 'Very high', so it's a good candidate enough. The exact location of the place is, of course, something to analyze further.

5- Discussion

Seeing the results, as I already said, the look good enough, but maybe the only thing that can be holds again the decision of putting the Coffee shop on Lo Barnechea is the distance of the comuna from the center of the Region. This Comuna is on the far-east of the Metropolitan region and is not a very good candidate if you want something near to the business center of Santiago. But, in that case, we can check the other Comunas that follow in the ranking, Recoleta and Ñuñoa, and they are very good candidates as well. So, in case that the stakeholders found that Lo Barnechea is located too far away, they can go and put the Coffee shop on Recoleta or Ñuñoa and the results will be similar.

Another thing that catch my attention was the low amount of data available on Foursquare for other regions in Chile. When I was doing this analysis I also tried on the regions of Valparaiso and O'higgins, but the amount of venues that I could get on Foursquare for that were too low, making the step of grouping by using the K-means algorithm was not clear enough to me. But, maybe with more data available, we'll be able to aplly the same methodology to any Region in Chile and maybe any city in the word.

6- Conclusion

The result of this report can be discussed further, and the exact location for the business place still needs to be analyzed, but I think that the methodology applied here can be used for almost any type of business and on every place in the world, that have, of course, a decent amount of data on Foursquare. For the business problem studied here, the results are pretty good enough, and I'm happy with them. Being me the stakeholder, I approve the results obtained.

In [ ]: