# battle-neighborhoods-2

February 3, 2019

## 0.1 Coursera IBM Data Science Capstone Project

### 0.1.1 Battle of the Neighborhoods

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**Contents**



## 0.2 1. Introduction / Business Problem

This notebook corresponds to the final assignment of the Coursera *Applied Data Science Capstone* course, which is the final step for the *IBM Data Science Professional Certificate* specialization. The final capstone project consists on applying the methodologies learned during the specialization to solve a fictional business problem, ensuring that the Foursquare API data is used in part of the analysis.

For this project, I selected to work with selecting a suitable location for a fictional restaurant in Madrid city. Below is the business problem description:

Our customer, the restaurant chain "XYZ Fancy Dining" is interested in opening a new restaurant in Madrid. Madrid is one of the busiest cities in Europe, with more than three million residents and an average of almost 800.000 visitors each month. This would be our customer's second restaurant location, after having successfully opened a venue in Greenwich Village, a very lively neighborhood from Valencia city.

Considering that our customer has had very good results with their val location, they have requested our data science team to find a neighborhood with similar characteristics.
The problem question would be: **What neighborhood from Madrid has the most similar characteristics in terms of entertainment and dining options compared to El Carme in Valencia City?**

The data to be used for this project comes from three different locations:
* Foursquare. It is a local search-and-discovery service which provides information on different types of entertainment, drinking and dining venues. Foursquare has an API that can be used to query their database and find information related to the venues, such as location, overall category, reviews and tips.
* Madrid Neighborhood Names and geographic coordinates. Available on https://datos.madrid.es/, this is used to obtain the neighborhood location information from the city.
* Valencia City Neighborhood Names and geographic coordinates. Data available on http://mapas.valencia.es/lanzadera/opendata/Barrios/SHAPE

## 0.3 2. Data Preparation

On this section, we will consolidate the data from our three data sources into a new dataset we will use for the clustering process. First step is to process the Madrid Neighborhood data, which is available in a .shp file.

We will first import all libraries to be used on this section, and then proceed with the data wrangling.

```
In [581]: # Import required python libraries
          import pandas as pd
          import geopandas as gpd # The geopandas library allows working with geospatial data
          import numpy as np
          import folium
          import requests
          import matplotlib.pyplot as plt
          import seaborn as sns
          %matplotlib inline
```

### 0.3.1 2.1 Madrid Location Data

```
In [582]: #Import Neighborhoods geodata
          madrid_neighborhoods = gpd.read_file("data/neighborhoods-madrid/BARRIOS.shp")
```

Lets get some basic information on the imported data

```
In [583]: madrid_neighborhoods.head(3)

Out[583]:    OBJECTID  geodb_oid CODDIS      NOMDIS CODBAR CODDISTRIT CODBARRIO  \
          0       108        108     17  Villaverde    172          17      17-2
          1       109        109     17  Villaverde    173          17      17-3
          2       111        111     17  Villaverde    175          17      17-5

                   NOMBRE  ORIG_FID                                           geometry
          0  San Cristobal       107  POLYGON ((441930.8668000005 4466853.1887, 4419...
```

```
1       Butarque       108  POLYGON ((444144.8566044134 4464473.210504748,...
2    Los Angeles       110  POLYGON ((441147.7280000008 4466374.483400001,...
```

```
In [584]: madrid_neighborhoods.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 131 entries, 0 to 130
Data columns (total 10 columns):
OBJECTID      131 non-null int64
geodb_oid     131 non-null int64
CODDIS        131 non-null object
NOMDIS        131 non-null object
CODBAR        131 non-null object
CODDISTRIT    131 non-null object
CODBARRIO     131 non-null object
NOMBRE        131 non-null object
ORIG_FID      131 non-null int64
geometry      131 non-null object
dtypes: int64(3), object(7)
memory usage: 10.3+ KB
```

```
In [585]: #Check what is projection (Folium uses WSGS84, epsg=4326)
          madrid_neighborhoods.crs
```

```
Out[585]: {'init': 'epsg:25830'}
```

We can make some observations on the data source:
* As expected, all field names are in spanish, we will translate this to english. * The data source contains a "geometry" column which basically contains a polygon delimiting each neighborhood. We actually only need the coordinates of a point for each neighborhood, so we will need to obtain the center coordinates of each polygon (centroid), thankfully Geopandas can help us with that. * The coordinate system is not WGS84. To ensure compatibility with other data sources, we will need to translate to WGS84. Geopandas has a method to do this easily

```
In [586]: #Since Projection is not WGS84, use geopandas to_crs method to convert:
          madrid_neighborhoods =  madrid_neighborhoods.to_crs(epsg='4326')
          madrid_neighborhoods.crs
```

```
Out[586]: {'init': 'epsg:4326', 'no_defs': True}
```

```
In [587]: #Add Longitude/Latitutde coordinates using the centroid
          madrid_neighborhoods['Longitude'] = madrid_neighborhoods.centroid.x
          madrid_neighborhoods['Latitude'] = madrid_neighborhoods.centroid.y
```

```
In [588]: #Remove unnecessary columns, translate column names to english
          madrid_neighborhoods = madrid_neighborhoods[['NOMDIS','NOMBRE','geometry','Longitude
          madrid_neighborhoods.rename(columns={'NOMDIS':'District',
                                              'NOMBRE':'Neighborhood'}, inplace=True)
```

In [589]: 
```
#Check the dataset
madrid_neighborhoods.head(3)
```

Out[589]:
```
     District   Neighborhood  \
0  Villaverde  San Cristobal
1  Villaverde       Butarque
2  Villaverde    Los Angeles

                                            geometry  Longitude   Latitude
0  POLYGON ((-3.683790913754153 40.35021495613195...  -3.688372  40.340888
1  POLYGON ((-3.657513637252129 40.32892568402512...  -3.676254  40.337115
2  POLYGON ((-3.692967961823778 40.34584760766253...  -3.699137  40.355790
```

In [590]: 
```
#Drop the Geometry column, we will not use it anymore
madrid_neighborhoods.drop(columns=['geometry'], axis=1, inplace=True)
```

In [591]: 
```
#Add city Name (Will be used later)
madrid_neighborhoods['City']='Madrid'
```

In [592]: 
```
#Convert geopandas dataframe to Pandas dataframe
madrid_neighborhoods = pd.DataFrame(madrid_neighborhoods)
print(type(madrid_neighborhoods))
```

```
<class 'pandas.core.frame.DataFrame'>
```

In [593]: 
```
madrid_neighborhoods.iloc[19]
```

Out[593]:
```
District        Puente de Vallecas
Neighborhood              Entrevías
Longitude                 -3.67311
Latitude                   40.3748
City                        Madrid
Name: 19, dtype: object
```

In [594]: 
```
#Remove special spanish characters (investigate how to do this more efficiently)
madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.repla
madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.repla
madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.repla
madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.repla
madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.repla
#madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.rep
#madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.rep
```

In [595]: 
```
#Set District and Neighborhood to uppercase
madrid_neighborhoods['District'] = madrid_neighborhoods['District'].str.upper()
madrid_neighborhoods['Neighborhood'] = madrid_neighborhoods['Neighborhood'].str.uppe
```

In [596]: 
```
#Check the dataset
madrid_neighborhoods.head(3)
```

```
Out[596]:       District   Neighborhood  Longitude   Latitude    City
          0  VILLAVERDE  SAN CRISTOBAL  -3.688372  40.340888  Madrid
          1  VILLAVERDE       BUTARQUE  -3.676254  40.337115  Madrid
          2  VILLAVERDE    LOS ANGELES  -3.699137  40.355790  Madrid
```

```
In [597]: print('The number of neighborhoods in Madrid is: {}'.format(madrid_neighborhoods['Ne
          print('The number of districts in Madrid is: {}'.format(madrid_neighborhoods['Distri
```

```
The number of neighborhoods in Madrid is: 131
The number of districts in Madrid is: 21
```

### 0.3.2 2.2 Valencia Location Data

```
In [598]: # Import neighborhoods
          val_neighborhoods = gpd.read_file("http://mapas.valencia.es/lanzadera/opendata/Barri
```

Lets get some basic information on the imported data

```
In [599]: val_neighborhoods.head(3)
```

```
Out[599]:   codbarrio      nombre coddistbar coddistrit  \
          0         1  BENIFARAIG        171         17
          1         1   BENICALAP        161         16
          2         2   TORREFIEL        152         15

                                                      geometry
          0  POLYGON ((725499.03 4378693.39, 725477.797 437...
          1  POLYGON ((725164.733 4375392.58, 725187.044 43...
          2  POLYGON ((726040.348 4375385.446, 725995.041 4...
```

```
In [600]: val_neighborhoods.info()
```

```
<class 'geopandas.geodataframe.GeoDataFrame'>
RangeIndex: 88 entries, 0 to 87
Data columns (total 5 columns):
codbarrio     88 non-null object
nombre        88 non-null object
coddistbar    88 non-null object
coddistrit    88 non-null object
geometry      88 non-null object
dtypes: object(5)
memory usage: 3.5+ KB
```

```
In [601]: val_neighborhoods.crs
```

```
Out[601]: {'init': 'epsg:25830'}
```

We can make some observations on the data source:
* As expected, the field names are different than the Madrid dataset. We will need to readjust for it to be the same. * The data source contains a "point" column which contains the coordinates for each neighborhood. We should extract the Latitude/Longitude from this column * The coordinate system is not WGS84 (epsg = 4326). To ensure compatibility with other data sources, we will need to translate to WGS84. Geopandas has a method to do this easily

In [602]:
```
#Since Projection is not WGS84, use geopandas to_crs method to convert:
val_neighborhoods =  val_neighborhoods.to_crs(epsg='4326')
val_neighborhoods.crs
```

Out[602]:
```
{'init': 'epsg:4326', 'no_defs': True}
```

In [603]:
```
#Add Longitude/Latitutde coordinates using the centroid
val_neighborhoods['Longitude'] = val_neighborhoods.centroid.x
val_neighborhoods['Latitude'] = val_neighborhoods.centroid.y
```

In [604]:
```
#Remove unnecessary columns, translate column names to english
val_neighborhoods = val_neighborhoods[['nombre','coddistrit','geometry','Longitude',
val_neighborhoods.rename(columns={'coddistrit':'District',
                                  'nombre':'Neighborhood'}, inplace=True)
```

In [605]:
```
#Drop the Geometry column, we will not use it anymore
val_neighborhoods.drop(columns=['geometry'], axis=1, inplace=True)
```

In [606]:
```
#Reorganize columns
val_neighborhoods = val_neighborhoods[['District','Neighborhood','Longitude','Latitu
```

In [607]:
```
#Add city Name
val_neighborhoods['City']='Valencia'
```

In [608]:
```
#Convert geopandas dataframe to Pandas dataframe
val_neighborhoods = pd.DataFrame(val_neighborhoods)
print(type(val_neighborhoods))
```

```
<class 'pandas.core.frame.DataFrame'>
```

In [609]:
```
#Check the dataset
val_neighborhoods.head(3)
```

Out[609]:

| | District | Neighborhood | Longitude | Latitude | City |
|---|---|---|---|---|---|
| 0 | 17 | BENIFARAIG | -0.384621 | 39.525644 | Valencia |
| 1 | 16 | BENICALAP | -0.391002 | 39.493006 | Valencia |
| 2 | 15 | TORREFIEL | -0.376932 | 39.495198 | Valencia |

In [610]:
```
print('The number of neighborhoods in Valencia is: {}'.format(val_neighborhoods['Neig
print('The number of districts in Valencia is: {}'.format(val_neighborhoods['Distric
```

```
The number of neighborhoods in Valencia is: 88
The number of districts in Valencia is: 19
```

### 0.3.3 2.3 Madrid Population

In this part, we will create a dataset with the population per neighborhood. The data source for this dataset was downloaded from the Madrid databank, see: http://www-2.madrid.es/CSE6/control/menuCSE?filtro=NS&tablaSerie=SERIES

```
In [611]: madrid_population = pd.read_excel('data/population-madrid/population-madrid.xls', sk
          madrid_population.head()
```

```
Out[611]:   Distrito       Barrio   Edad  Total
          0   CENTRO      PALACIO  Total  22984
          1   CENTRO  EMBAJADORES  Total  45433
          2   CENTRO       CORTES  Total  10525
          3   CENTRO     JUSTICIA  Total  17205
          4   CENTRO  UNIVERSIDAD  Total  31809
```

```
In [612]: madrid_population.drop('Edad', axis=1, inplace=True)
          madrid_population.columns = ['District','Neighborhood','Population']
```

```
In [613]: #Check if by merging with madrid dataset we get the same amount of neighborhoods
          madrid_population.merge(madrid_neighborhoods, on='Neighborhood', how='inner').shape
```

```
Out[613]: (119, 7)
```

There are 131 neighborhoods in the Madrid dataset, however when matching with the population dataset (different source) we don't get a match for all the neighborhoods. Lets investigate which are different

```
In [614]: #Outer Join
          test = madrid_population.merge(madrid_neighborhoods, on='Neighborhood', how='outer')
          test[test.isnull().any(axis=1)]
```

```
Out[614]:               District_x                                     Neighborhood  \
          17                RETIRO                                    LOS JERONIMOS
          44    FUENCARRAL-EL PARDO                                  FUENTELARREINA
          45    FUENCARRAL-EL PARDO                                     PEÑA GRANDE
          46    FUENCARRAL-EL PARDO                                        EL PILAR
          52        MONCLOA-ARAVACA                                       ARGUELLES
          58                LATINA                                      LOS CARMENES
          64                LATINA                                       LAS AGUILAS
          106           VILLAVERDE                              VILLAVERDE ALTO C.H.
          111     VILLA DE VALLECAS                                 CASCO H.VALLECAS
          114            VICALVARO                                 CASCO H.VICALVARO
          125  SAN BLAS-CANILLEJAS                                     EL SALVADOR
          128              BARAJAS                                  CASCO H.BARAJAS
          131                  NaN  VILLAVERDE ALTO, CASCO HISTORICO DE VILLAVERDE
          132                  NaN                      CASCO HISTORICO DE VALLECAS
          133                  NaN                                          AGUILAS
          134                  NaN                                         CARMENES
```

```
135                 NaN                                        JERONIMOS
136                 NaN                                        ARGÜELLES
137                 NaN                                         SALVADOR
138                 NaN                       CASCO HISTORICO DE BARAJAS
139                 NaN                                            PILAR
140                 NaN                                       PEÑAGRANDE
141                 NaN                                    FUENTELAREINA
142                 NaN                     CASCO HISTORICO DE VICALVARO

     Population             District_y  Longitude   Latitude    City
17       7069.0                    NaN        NaN        NaN     NaN
44       3272.0                    NaN        NaN        NaN     NaN
45      44621.0                    NaN        NaN        NaN     NaN
46      46577.0                    NaN        NaN        NaN     NaN
52      24191.0                    NaN        NaN        NaN     NaN
58      17448.0                    NaN        NaN        NaN     NaN
64      51703.0                    NaN        NaN        NaN     NaN
106     45324.0                    NaN        NaN        NaN     NaN
111     40352.0                    NaN        NaN        NaN     NaN
114     34928.0                    NaN        NaN        NaN     NaN
125     11372.0                    NaN        NaN        NaN     NaN
128      7585.0                    NaN        NaN        NaN     NaN
131         NaN             VILLAVERDE  -3.708949  40.341448  Madrid
132         NaN       VILLA DE VALLECAS  -3.618222  40.345891  Madrid
133         NaN                 LATINA  -3.771087  40.381801  Madrid
134         NaN                 LATINA  -3.735930  40.401486  Madrid
135         NaN                 RETIRO  -3.685143  40.413744  Madrid
136         NaN       MONCLOA - ARAVACA  -3.717846  40.428209  Madrid
137         NaN   SAN BLAS - CANILLEJAS  -3.630974  40.445291  Madrid
138         NaN                BARAJAS  -3.578866  40.474005  Madrid
139         NaN   FUENCARRAL - EL PARDO  -3.709590  40.477140  Madrid
140         NaN   FUENCARRAL - EL PARDO  -3.725803  40.478783  Madrid
141         NaN   FUENCARRAL - EL PARDO  -3.741786  40.481107  Madrid
142         NaN              VICÁLVARO  -3.579807  40.388153  Madrid
```

In [615]:
```
#Update column names to match both dataframes
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'JERONIMOS', 'Neigh
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'FUENTELAREINA', 'N
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'PEÑAGRANDE', 'Neig
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'PILAR', 'Neighborh
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'ARGÜELLES', 'Neigh
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'CARMENES', 'Neighbo
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'AGUILAS', 'Neighbo
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'VILLAVERDE ALTO, C
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'CASCO HISTORICO DE
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'CASCO HISTORICO DE
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'SALVADOR', 'Neighbo
madrid_neighborhoods.loc[madrid_neighborhoods['Neighborhood'] == 'CASCO HISTORICO DE
```

```
In [616]: #Check if by merging with madrid dataset we get the same amount of neighborhoods
          madrid_population.merge(madrid_neighborhoods, on='Neighborhood').shape
```

```
Out[616]: (131, 7)
```

Now both dataframes match! We will use the madrid_population dataset later

### 0.3.4 2.4 Average Income per neighborhood dataset

This dataset contains the average income per neighborhood in madrid. Source file available on this link: https://www.madrid.es/UnidadesDescentralizadas/UDCEstadistica/Nuevaweb/Econom%C3%ADa/Re
The file was pre-processed in Excel

```
In [686]: madrid_income = pd.read_excel('data/income-madrid/income-madrid.xls')
          madrid_income.head()
```

```
Out[686]:   District Neighborhood  Average Income
          0   CENTRO      PALACIO        34675.85
          1   CENTRO  EMBAJADORES        25999.83
          2   CENTRO       CORTES        34952.68
          3   CENTRO     JUSTICIA        40314.88
          4   CENTRO  UNIVERSIDAD        30701.65
```

```
In [688]: #Check if by merging with madrid dataset we get the same amount of neighborhoods
          madrid_income.merge(madrid_neighborhoods, on='Neighborhood', how='inner').shape
```

```
Out[688]: (131, 7)
```

We have 131 neighborhoods, good to go!
We will use the madrid_income dataset later

### 0.3.5 2.5 Neighborhoods dataset

In this part, we will simply create a new dataset combining both Madrid and val neighborhood lists. This will be used later for clustering

```
In [617]: #Concatenate two dataframes
          neighborhoods = pd.concat([madrid_neighborhoods,val_neighborhoods])
```

```
In [618]: #Check random neighborhoods Madrid
          neighborhoods[neighborhoods['City']=='Madrid'].head(3)
```

```
Out[618]:      District   Neighborhood  Longitude   Latitude    City
          0  VILLAVERDE  SAN CRISTOBAL  -3.688372  40.340888  Madrid
          1  VILLAVERDE       BUTARQUE  -3.676254  40.337115  Madrid
          2  VILLAVERDE    LOS ANGELES  -3.699137  40.355790  Madrid
```

```
In [619]: #Check random neighborhoods Valencia
          neighborhoods[neighborhoods['City']=='Valencia'].head(3)
```

Out[619]:   District Neighborhood  Longitude   Latitude      City
```
0       17   BENIFARAIG  -0.384621  39.525644  Valencia
1       16    BENICALAP  -0.391002  39.493006  Valencia
2       15    TORREFIEL  -0.376932  39.495198  Valencia
```

In [620]:
```
#Count number of neighborhoods per city
neighborhoods.groupby('City')['Neighborhood'].count()
```

Out[620]:
```
City
Madrid      131
Valencia     88
Name: Neighborhood, dtype: int64
```

## 0.4 3. Methodology

### 0.4.1 3.1. Madrid Neighborhoods Visualization

In [621]:
```
#Obtain the coordinates from the dataset itself, just averaging Latitude/Longitude o
lat_madrid = madrid_neighborhoods['Latitude'].mean()
lon_madrid = madrid_neighborhoods['Longitude'].mean()
print('The geographical coordinates of Madrid are {}, {}'.format(lat_madrid, lon_madr
```

```
The geographical coordinates of Madrid are 40.42384071409435, -3.680098265322107
```

In [622]:
```
# Create a list of districts, to be used later
districts = madrid_neighborhoods['District'].unique().tolist()
```

In [623]:
```
# This code is to create a dictionary to map a random color to each borough.
# https://stackoverflow.com/questions/28999287/generate-random-colors-rgb/28999469 a
# https://stackoverflow.com/questions/3380726/converting-a-rgb-color-tuple-to-a-six-
district_color = {}
for district in districts:
    district_color[district]= '#%02X%02X%02X' % tuple(np.random.choice(range(256), s
```

In [624]:
```
# create map of Madrid using latitude and longitude values
map_madrid = folium.Map(location=[lat_madrid, lon_madrid], zoom_start=11, control_sca

# add markers to map
for lat, lng, district, neighborhood in zip(madrid_neighborhoods['Latitude'],
                                            madrid_neighborhoods['Longitude'],
                                            madrid_neighborhoods['District'],
                                            madrid_neighborhoods['Neighborhood']):
    label_text = district + ' - ' + neighborhood
    label = folium.Popup(label_text, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        tooltip = label_text,
        radius=4,
```

```
                    popup=label,
                    color=district_color[district],
                    fill=True,
                    fill_color=district_color[district],
                    fill_opacity=0.7).add_to(map_madrid)

        map_madrid
```

Out[624]: <folium.folium.Map at 0x28a8b4b2f28>

### 0.4.2 3.2. Explore Madrid and val Neighborhoods using the Foursquare API

```
In [625]: CLIENT_ID = 'TWOZ1RBXJLFNVXN1GCNRMXVTI3YQR5UWQIIKU1NB11VBQNAL' # your Foursquare ID
          CLIENT_SECRET = 'FKR5PXODGZ52EQH3PDEGCCERQLFRHZUPP2Q2MHF2MBHU41IE' # your Foursquare
          VERSION = '20180605' # Foursquare API version
          LIMIT = 200 # limit of number of venues returned by Foursquare API
          radius = 500 # define radius
```

Borrowing the function we used in the course lab (getNearbyVenues), and modifying it by adding the City and District Name

```
In [626]: def getNearbyVenues(names, districts, cities, latitudes, longitudes, radius=500):

              venues_list=[]
              for name, district, city, lat, lng in zip(names, districts, cities, latitudes, lo
                  print('Processing City: {}, District: {}, Neighborhood: {}'.format(city, dis

                  # create the API request URL
                  url = 'https://api.foursquare.com/v2/venues/explore?&client_id={}&client_sec
                      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,
                      district,
                      city,
                      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 venu
        nearby_venues.columns = ['Neighborhood',
                                 'District',
                                 'City',
                                 'Neighborhood Latitude',
                                 'Neighborhood Longitude',
                                 'Venue',
                                 'Venue Latitude',
                                 'Venue Longitude',
                                 'Venue Category']

        return(nearby_venues)
```

In [627]:
```
venues = getNearbyVenues(names=neighborhoods['Neighborhood'],
                         districts = neighborhoods['District'],
                         cities = neighborhoods['City'],
                         latitudes=neighborhoods['Latitude'],
                         longitudes=neighborhoods['Longitude'])
```

```
Processing City: Madrid, District: VILLAVERDE, Neighborhood: SAN CRISTOBAL
Processing City: Madrid, District: VILLAVERDE, Neighborhood: BUTARQUE
Processing City: Madrid, District: VILLAVERDE, Neighborhood: LOS ANGELES
Processing City: Madrid, District: VILLAVERDE, Neighborhood: LOS ROSALES
Processing City: Madrid, District: VILLAVERDE, Neighborhood: VILLAVERDE ALTO C.H.
Processing City: Madrid, District: USERA, Neighborhood: ORCASITAS
Processing City: Madrid, District: VILLA DE VALLECAS, Neighborhood: ENSANCHE DE VALLECAS
Processing City: Madrid, District: CARABANCHEL, Neighborhood: BUENAVISTA
Processing City: Madrid, District: LATINA, Neighborhood: CUATRO VIENTOS
Processing City: Madrid, District: USERA, Neighborhood: SAN FERMIN
Processing City: Madrid, District: VILLA DE VALLECAS, Neighborhood: CASCO H.VALLECAS
Processing City: Madrid, District: USERA, Neighborhood: ORCASUR
Processing City: Madrid, District: USERA, Neighborhood: ZOFIO
Processing City: Madrid, District: USERA, Neighborhood: PRADOLONGO
Processing City: Madrid, District: CARABANCHEL, Neighborhood: ABRANTES
Processing City: Madrid, District: CARABANCHEL, Neighborhood: PUERTA BONITA
Processing City: Madrid, District: USERA, Neighborhood: ALMENDRALES
Processing City: Madrid, District: VILLA DE VALLECAS, Neighborhood: SANTA EUGENIA
Processing City: Madrid, District: CARABANCHEL, Neighborhood: VISTA ALEGRE
Processing City: Madrid, District: PUENTE DE VALLECAS, Neighborhood: ENTREVIAS
Processing City: Madrid, District: LATINA, Neighborhood: LAS AGUILAS
Processing City: Madrid, District: PUENTE DE VALLECAS, Neighborhood: PALOMERAS SURESTE
Processing City: Madrid, District: PUENTE DE VALLECAS, Neighborhood: PALOMERAS BAJAS
Processing City: Madrid, District: ARGANZUELA, Neighborhood: LEGAZPI
Processing City: Madrid, District: USERA, Neighborhood: MOSCARDO
Processing City: Madrid, District: CARABANCHEL, Neighborhood: OPAÑEL
```

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Processing City: Madrid, District: PUENTE DE VALLECAS, Neighborhood: SAN DIEGO
Processing City: Madrid, District: PUENTE DE VALLECAS, Neighborhood: PORTAZGO
Processing City: Madrid, District: CARABANCHEL, Neighborhood: COMILLAS
Processing City: Madrid, District: LATINA, Neighborhood: CAMPAMENTO
Processing City: Madrid, District: ARGANZUELA, Neighborhood: CHOPERA
Processing City: Madrid, District: ARGANZUELA, Neighborhood: DELICIAS
Processing City: Madrid, District: LATINA, Neighborhood: ALUCHE
Processing City: Madrid, District: MORATALAZ, Neighborhood: PAVONES
Processing City: Madrid, District: VICÁLVARO, Neighborhood: VALDERRIVAS
Processing City: Madrid, District: CARABANCHEL, Neighborhood: SAN ISIDRO
Processing City: Madrid, District: VICÁLVARO, Neighborhood: VALDEBERNARDO
Processing City: Madrid, District: PUENTE DE VALLECAS, Neighborhood: NUMANCIA
Processing City: Madrid, District: RETIRO, Neighborhood: ADELFAS
Processing City: Madrid, District: ARGANZUELA, Neighborhood: ACACIAS
Processing City: Madrid, District: RETIRO, Neighborhood: PACIFICO
Processing City: Madrid, District: ARGANZUELA, Neighborhood: PALOS DE MOGUER
Processing City: Madrid, District: MORATALAZ, Neighborhood: FONTARRON
Processing City: Madrid, District: ARGANZUELA, Neighborhood: ATOCHA
Processing City: Madrid, District: LATINA, Neighborhood: LOS CARMENES
Processing City: Madrid, District: MORATALAZ, Neighborhood: VINATEROS
Processing City: Madrid, District: LATINA, Neighborhood: LUCERO
Processing City: Madrid, District: MORATALAZ, Neighborhood: HORCAJO
Processing City: Madrid, District: ARGANZUELA, Neighborhood: IMPERIAL
Processing City: Madrid, District: CENTRO, Neighborhood: EMBAJADORES
Processing City: Madrid, District: MORATALAZ, Neighborhood: MARROQUINA
Processing City: Madrid, District: RETIRO, Neighborhood: NIÑO JESUS
Processing City: Madrid, District: LATINA, Neighborhood: PUERTA DEL ANGEL
Processing City: Madrid, District: MORATALAZ, Neighborhood: MEDIA LEGUA
Processing City: Madrid, District: CENTRO, Neighborhood: CORTES
Processing City: Madrid, District: CENTRO, Neighborhood: SOL
Processing City: Madrid, District: RETIRO, Neighborhood: ESTRELLA
Processing City: Madrid, District: RETIRO, Neighborhood: LOS JERONIMOS
Processing City: Madrid, District: RETIRO, Neighborhood: IBIZA
Processing City: Madrid, District: CENTRO, Neighborhood: PALACIO
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: ARCOS
Processing City: Madrid, District: SALAMANCA, Neighborhood: GOYA
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: AMPOSTA
Processing City: Madrid, District: CENTRO, Neighborhood: JUSTICIA
Processing City: Madrid, District: SALAMANCA, Neighborhood: RECOLETOS
Processing City: Madrid, District: CENTRO, Neighborhood: UNIVERSIDAD
Processing City: Madrid, District: SALAMANCA, Neighborhood: FUENTE DEL BERRO
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: VENTAS
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: HELLIN
Processing City: Madrid, District: MONCLOA - ARAVACA, Neighborhood: ARGUELLES
Processing City: Madrid, District: SALAMANCA, Neighborhood: LISTA
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: PUEBLO NUEVO
Processing City: Madrid, District: SALAMANCA, Neighborhood: CASTELLANA
Processing City: Madrid, District: CHAMBERÍ, Neighborhood: ALMAGRO
```

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Processing City: Madrid, District: CHAMBERÍ, Neighborhood: TRAFALGAR
Processing City: Madrid, District: CHAMBERÍ, Neighborhood: ARAPILES
Processing City: Madrid, District: CHAMBERÍ, Neighborhood: GAZTAMBIDE
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: QUINTANA
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: SIMANCAS
Processing City: Madrid, District: SALAMANCA, Neighborhood: GUINDALERA
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: CONCEPCION
Processing City: Madrid, District: CHAMBERÍ, Neighborhood: RIOS ROSAS
Processing City: Madrid, District: CHAMBERÍ, Neighborhood: VALLEHERMOSO
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: SAN PASCUAL
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: CANILLEJAS
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: ROSAS
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: EL SALVADOR
Processing City: Madrid, District: SAN BLAS - CANILLEJAS, Neighborhood: REJAS
Processing City: Madrid, District: MONCLOA - ARAVACA, Neighborhood: CASA DE CAMPO
Processing City: Madrid, District: CHAMARTÍN, Neighborhood: EL VISO
Processing City: Madrid, District: CHAMARTÍN, Neighborhood: CIUDAD JARDIN
Processing City: Madrid, District: CHAMARTÍN, Neighborhood: PROSPERIDAD
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: SAN JUAN BAUTISTA
Processing City: Madrid, District: TETUÁN, Neighborhood: CUATRO CAMINOS
Processing City: Madrid, District: HORTALEZA, Neighborhood: PALOMAS
Processing City: Madrid, District: TETUÁN, Neighborhood: BELLAS VISTAS
Processing City: Madrid, District: CHAMARTÍN, Neighborhood: HISPANOAMERICA
Processing City: Madrid, District: HORTALEZA, Neighborhood: PIOVERA
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: COLINA
Processing City: Madrid, District: TETUÁN, Neighborhood: BERRUGUETE
Processing City: Madrid, District: BARAJAS, Neighborhood: ALAMEDA DE OSUNA
Processing City: Madrid, District: TETUÁN, Neighborhood: CASTILLEJOS
Processing City: Madrid, District: MONCLOA - ARAVACA, Neighborhood: ARAVACA
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: ATALAYA
Processing City: Madrid, District: CHAMARTÍN, Neighborhood: NUEVA ESPAÑA
Processing City: Madrid, District: HORTALEZA, Neighborhood: CANILLAS
Processing City: Madrid, District: BARAJAS, Neighborhood: CORRALEJOS
Processing City: Madrid, District: MONCLOA - ARAVACA, Neighborhood: VALDEZARZA
Processing City: Madrid, District: TETUÁN, Neighborhood: VALDEACEDERAS
Processing City: Madrid, District: TETUÁN, Neighborhood: ALMENARA
Processing City: Madrid, District: MONCLOA - ARAVACA, Neighborhood: VALDEMARIN
Processing City: Madrid, District: BARAJAS, Neighborhood: CASCO H.BARAJAS
Processing City: Madrid, District: MONCLOA - ARAVACA, Neighborhood: CIUDAD UNIVERSITARIA
Processing City: Madrid, District: MONCLOA - ARAVACA, Neighborhood: EL PLANTIO
Processing City: Madrid, District: HORTALEZA, Neighborhood: PINAR DEL REY
Processing City: Madrid, District: HORTALEZA, Neighborhood: APOSTOL SANTIAGO
Processing City: Madrid, District: CHAMARTÍN, Neighborhood: CASTILLA
Processing City: Madrid, District: CIUDAD LINEAL, Neighborhood: COSTILLARES
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: EL PILAR
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: PEÑA GRANDE
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: LA PAZ
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: FUENTELARREINA
```

```
Processing City: Madrid, District: BARAJAS, Neighborhood: TIMON
Processing City: Madrid, District: BARAJAS, Neighborhood: AEROPUERTO
Processing City: Madrid, District: HORTALEZA, Neighborhood: VALDEFUENTES
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: MIRASIERRA
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: VALVERDE
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: EL GOLOSO
Processing City: Madrid, District: FUENCARRAL - EL PARDO, Neighborhood: EL PARDO
Processing City: Madrid, District: VICÁLVARO, Neighborhood: CASCO H.VICALVARO
Processing City: Madrid, District: VICÁLVARO, Neighborhood: EL CAÑAVERAL
Processing City: Valencia, District: 17, Neighborhood: BENIFARAIG
Processing City: Valencia, District: 16, Neighborhood: BENICALAP
Processing City: Valencia, District: 15, Neighborhood: TORREFIEL
Processing City: Valencia, District: 5, Neighborhood: TORMOS
Processing City: Valencia, District: 5, Neighborhood: SANT ANTONI
Processing City: Valencia, District: 14, Neighborhood: BENIMACLET
Processing City: Valencia, District: 5, Neighborhood: MARXALENES
Processing City: Valencia, District: 4, Neighborhood: EL CALVARI
Processing City: Valencia, District: 5, Neighborhood: MORVEDRE
Processing City: Valencia, District: 5, Neighborhood: TRINITAT
Processing City: Valencia, District: 4, Neighborhood: LES TENDETES
Processing City: Valencia, District: 4, Neighborhood: CAMPANAR
Processing City: Valencia, District: 6, Neighborhood: JAUME ROIG
Processing City: Valencia, District: 1, Neighborhood: EL CARME
Processing City: Valencia, District: 6, Neighborhood: CIUTAT UNIVERSITARIA
Processing City: Valencia, District: 3, Neighborhood: EL BOTANIC
Processing City: Valencia, District: 6, Neighborhood: EXPOSICIO
Processing City: Valencia, District: 1, Neighborhood: LA SEU
Processing City: Valencia, District: 13, Neighborhood: LA VEGA BAIXA
Processing City: Valencia, District: 3, Neighborhood: LA PETXINA
Processing City: Valencia, District: 11, Neighborhood: BETERO
Processing City: Valencia, District: 11, Neighborhood: CABANYAL-CANYAMELAR
Processing City: Valencia, District: 6, Neighborhood: MESTALLA
Processing City: Valencia, District: 1, Neighborhood: LA XEREA
Processing City: Valencia, District: 1, Neighborhood: EL MERCAT
Processing City: Valencia, District: 1, Neighborhood: EL PILAR
Processing City: Valencia, District: 1, Neighborhood: SANT FRANCESC
Processing City: Valencia, District: 2, Neighborhood: EL PLA DEL REMEI
Processing City: Valencia, District: 13, Neighborhood: L'ILLA PERDUDA
Processing City: Valencia, District: 12, Neighborhood: ALBORS
Processing City: Valencia, District: 3, Neighborhood: ARRANCAPINS
Processing City: Valencia, District: 12, Neighborhood: AIORA
Processing City: Valencia, District: 3, Neighborhood: LA ROQUETA
Processing City: Valencia, District: 2, Neighborhood: LA GRAN VIA
Processing City: Valencia, District: 7, Neighborhood: TRES FORQUES
Processing City: Valencia, District: 12, Neighborhood: CAMI FONDO
Processing City: Valencia, District: 8, Neighborhood: PATRAIX
Processing City: Valencia, District: 2, Neighborhood: RUSSAFA
Processing City: Valencia, District: 12, Neighborhood: PENYA-ROJA
```

```
Processing City: Valencia, District: 12, Neighborhood: LA CREU DEL GRAU
Processing City: Valencia, District: 10, Neighborhood: MONT-OLIVET
Processing City: Valencia, District: 9, Neighborhood: LA RAIOSA
Processing City: Valencia, District: 8, Neighborhood: SAFRANAR
Processing City: Valencia, District: 10, Neighborhood: CIUTAT DE LES ARTS I DE LES CIENCIES
Processing City: Valencia, District: 10, Neighborhood: EN CORTS
Processing City: Valencia, District: 10, Neighborhood: NA ROVELLA
Processing City: Valencia, District: 8, Neighborhood: SANT ISIDRE
Processing City: Valencia, District: 10, Neighborhood: MALILLA
Processing City: Valencia, District: 8, Neighborhood: FAVARA
Processing City: Valencia, District: 9, Neighborhood: L'HORT DE SENABRE
Processing City: Valencia, District: 11, Neighborhood: NATZARET
Processing City: Valencia, District: 9, Neighborhood: LA CREU COBERTA
Processing City: Valencia, District: 9, Neighborhood: CAMI REAL
Processing City: Valencia, District: 10, Neighborhood: LA FONTETA S.LLUIS
Processing City: Valencia, District: 9, Neighborhood: SANT MARCEL.LI
Processing City: Valencia, District: 13, Neighborhood: L'AMISTAT
Processing City: Valencia, District: 10, Neighborhood: LA PUNTA
Processing City: Valencia, District: 17, Neighborhood: RAFALELL-VISTABELLA
Processing City: Valencia, District: 13, Neighborhood: LA CARRASCA
Processing City: Valencia, District: 11, Neighborhood: EL GRAU
Processing City: Valencia, District: 13, Neighborhood: CIUTAT JARDI
Processing City: Valencia, District: 7, Neighborhood: NOU MOLES
Processing City: Valencia, District: 14, Neighborhood: CAMI DE VERA
Processing City: Valencia, District: 18, Neighborhood: BENIMAMET
Processing City: Valencia, District: 7, Neighborhood: SOTERNES
Processing City: Valencia, District: 7, Neighborhood: LA LLUM
Processing City: Valencia, District: 18, Neighborhood: BENIFERRI
Processing City: Valencia, District: 19, Neighborhood: EL PALMAR
Processing City: Valencia, District: 19, Neighborhood: EL SALER
Processing City: Valencia, District: 7, Neighborhood: LA FONTSANTA
Processing City: Valencia, District: 15, Neighborhood: SANT LLORENS
Processing City: Valencia, District: 15, Neighborhood: ELS ORRIOLS
Processing City: Valencia, District: 19, Neighborhood: EL PERELLONET
Processing City: Valencia, District: 8, Neighborhood: VARA DE QUART
Processing City: Valencia, District: 16, Neighborhood: CIUTAT FALLERA
Processing City: Valencia, District: 11, Neighborhood: LA MALVA-ROSA
Processing City: Valencia, District: 17, Neighborhood: CARPESA
Processing City: Valencia, District: 17, Neighborhood: BORBOTO
Processing City: Valencia, District: 17, Neighborhood: POBLE NOU
Processing City: Valencia, District: 17, Neighborhood: LES CASES DE BARCENA
Processing City: Valencia, District: 17, Neighborhood: MAHUELLA-TAULADELLA
Processing City: Valencia, District: 4, Neighborhood: SANT PAU
Processing City: Valencia, District: 17, Neighborhood: MASSARROJOS
Processing City: Valencia, District: 19, Neighborhood: FAITANAR
Processing City: Valencia, District: 19, Neighborhood: PINEDO
Processing City: Valencia, District: 19, Neighborhood: CASTELLAR-L'OLIVERAL
Processing City: Valencia, District: 19, Neighborhood: EL FORN D'ALCEDO
```

```
Processing City: Valencia, District: 19, Neighborhood: LA TORRE
```

In [628]:
```
#Get how many venues were found
print('A total of {} venues were found in Madrid'.format(venues[venues['City']=='Mad
print('A total of {} venues were found in Valencia'.format(venues[venues['City']=='Va
```

```
A total of 3517 venues were found in Madrid
A total of 2552 venues were found in Valencia
```

In [629]:
```
#Show the new dataset
venues.head()
```

Out[629]:
```
     Neighborhood    District    City  Neighborhood Latitude  \
0  SAN CRISTOBAL  VILLAVERDE  Madrid              40.340888
1  SAN CRISTOBAL  VILLAVERDE  Madrid              40.340888
2  SAN CRISTOBAL  VILLAVERDE  Madrid              40.340888
3  SAN CRISTOBAL  VILLAVERDE  Madrid              40.340888
4       BUTARQUE  VILLAVERDE  Madrid              40.337115

   Neighborhood Longitude                                      Venue  \
0               -3.688372     Cercanías San Cristóbal de Los Ángeles
1               -3.688372  Igreen Aire Acondicionado y Climatización
2               -3.688372                                Bar Vietnam
3               -3.688372                          El Rincón de Peri
4               -3.676254                                  Mercadona

   Venue Latitude  Venue Longitude          Venue Category
0       40.341710        -3.683878           Train Station
1       40.341581        -3.686213  Furniture / Home Store
2       40.341090        -3.686568            Snack Place
3       40.342427        -3.691998          Breakfast Spot
4       40.340165        -3.675179           Grocery Store
```

In [630]:
```
# Count the number of locations per Venue Category in Madrid
venues[venues['City']=='Madrid'].groupby('Venue Category').count()['Neighborhood'].so
```

Out[630]:
```
Venue Category
Spanish Restaurant    381
Restaurant            193
Bar                   166
Tapas Restaurant      154
Café                  109
Hotel                 100
Coffee Shop            91
Bakery                 84
Pizza Place            74
Italian Restaurant     73
Name: Neighborhood, dtype: int64
```

In [631]:
```
# Count the number of locations per Venue Category in Valencia
venues[venues['City']=='Valencia'].groupby('Venue Category').count()['Neighborhood']
```

Out[631]:
```
Venue Category
Spanish Restaurant          178
Tapas Restaurant            153
Restaurant                  113
Mediterranean Restaurant    103
Café                         87
Hotel                        85
Grocery Store                83
Italian Restaurant           80
Bakery                       65
Coffee Shop                  59
Name: Neighborhood, dtype: int64
```

In [632]:
```
#Number of unique venue categories per city
print('There are {} uniques categories in Madrid.'.format(len(venues[venues['City']==
print('There are {} uniques categories in Valencia.'.format(len(venues[venues['City']
```

```
There are 269 uniques categories in Madrid.
There are 214 uniques categories in Valencia.
```

In [633]:
```
#Obtain the number of venues per neighborhood
venues_count = venues.groupby(['City','District','Neighborhood'])['District'].count(
venues_count.head(3)
```

Out[633]:
```
                                District
City   District   Neighborhood
Madrid ARGANZUELA ACACIAS             50
                  ATOCHA              32
                  CHOPERA             44
```

In [634]:
```
#Fix title and remove multiindex
venues_count.rename(columns={'District':'N_venues'}, inplace=True)
venues_count.reset_index(inplace=True)
venues_count.head(3)
```

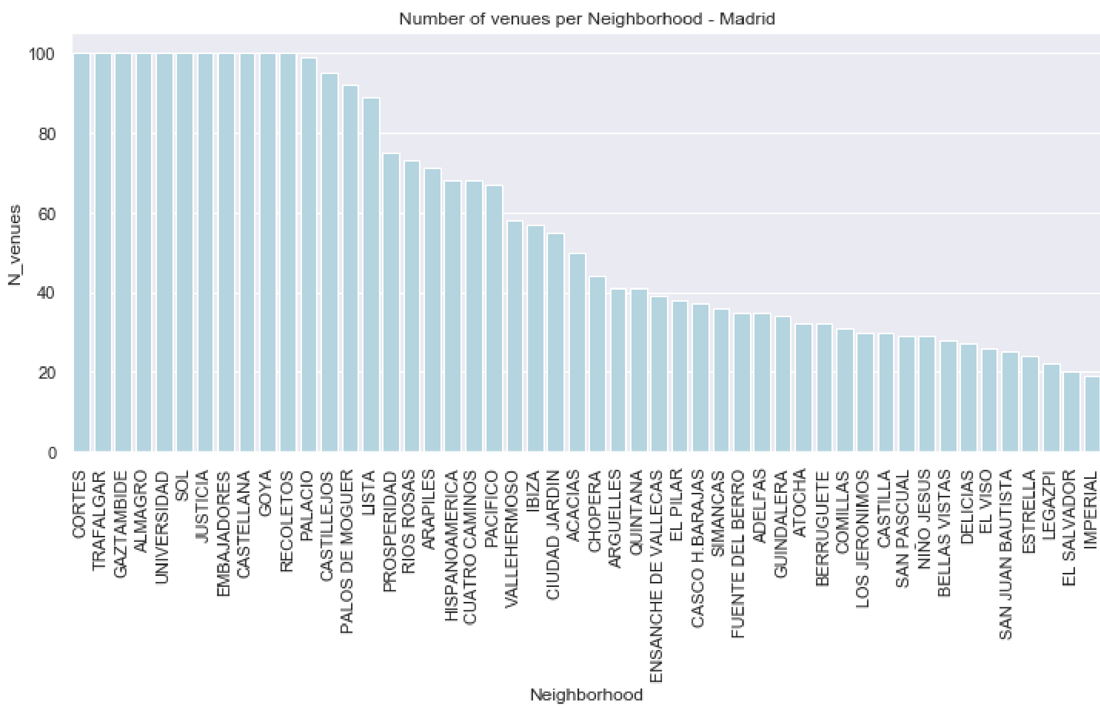
Out[634]:
```
     City    District Neighborhood  N_venues
0  Madrid  ARGANZUELA      ACACIAS        50
1  Madrid  ARGANZUELA       ATOCHA        32
2  Madrid  ARGANZUELA      CHOPERA        44
```

In [635]:
```
#Sort by number of venues
venues_count.sort_values(by='N_venues', ascending=False, inplace=True)
```

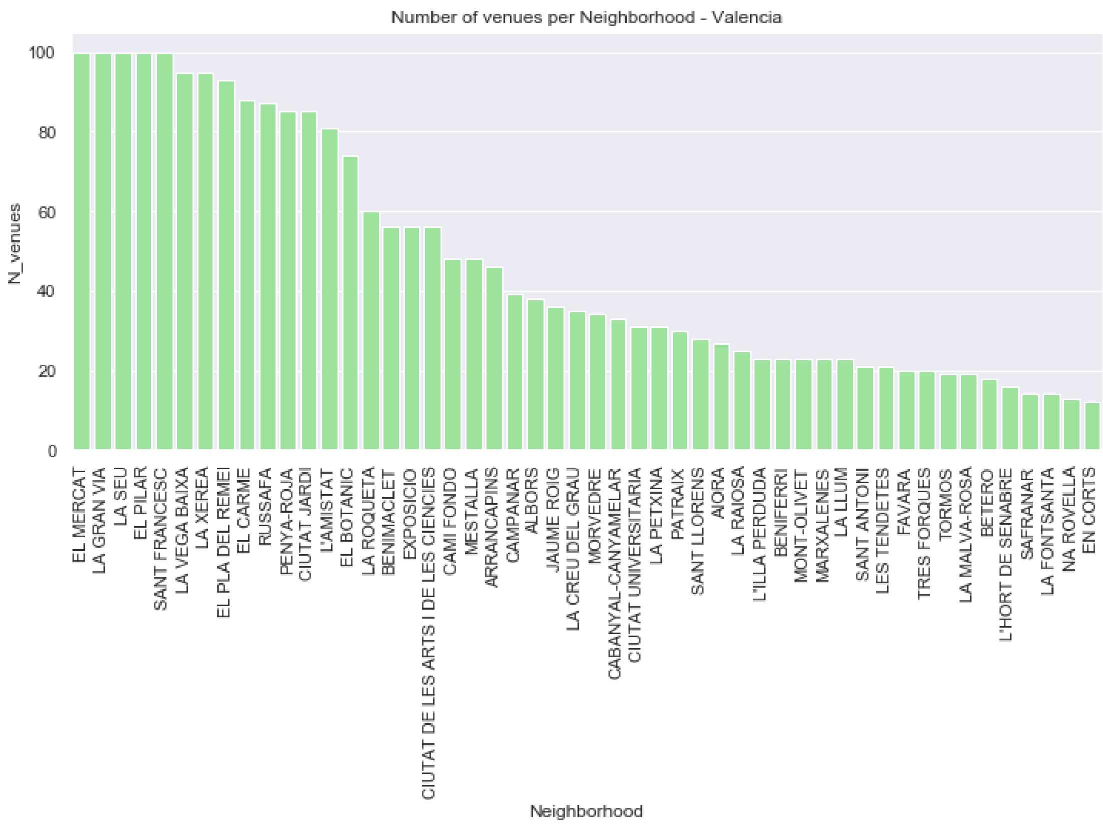
In [636]:
```
#One sorted dataset per city
venues_count_madrid = venues_count[venues_count['City']=='Madrid'].head(50)
venues_count_val = venues_count[venues_count['City']=='Valencia'].head(50)
```

In [637]:
```
# Prepare format for seaborn plots
sns.set()
sns.set(rc={'figure.figsize':(12,5)})
```

In [638]:
```
#Plot number of venues registered per neighborhood for Madrid
ax = sns.barplot(x='Neighborhood',y='N_venues',data=venues_count_madrid, color='ligh
ax.set_title('Number of venues per Neighborhood - Madrid')
ax.set_xticklabels(labels=venues_count_madrid['Neighborhood'],rotation=90);
```




In [639]:
```
#Plot number of venues registered per Neighborhood for Valencia
ax2 = sns.barplot(x='Neighborhood',y='N_venues',data=venues_count_val, color='lightg
ax2.set_title('Number of venues per Neighborhood - Valencia')
ax2.set_xticklabels(labels=venues_count_val['Neighborhood'],rotation=90);
```




In [663]:
```
#Lets explore the venues for one Neighborhood in Madrid
venues[venues['Neighborhood']=='ATOCHA'].head(10)
```

Out[663]:
```
    Neighborhood    District    City  Neighborhood Latitude  \
661       ATOCHA  ARGANZUELA  Madrid              40.399775
662       ATOCHA  ARGANZUELA  Madrid              40.399775
663       ATOCHA  ARGANZUELA  Madrid              40.399775
664       ATOCHA  ARGANZUELA  Madrid              40.399775
665       ATOCHA  ARGANZUELA  Madrid              40.399775
666       ATOCHA  ARGANZUELA  Madrid              40.399775
667       ATOCHA  ARGANZUELA  Madrid              40.399775
668       ATOCHA  ARGANZUELA  Madrid              40.399775
669       ATOCHA  ARGANZUELA  Madrid              40.399775
670       ATOCHA  ARGANZUELA  Madrid              40.399775

     Neighborhood Longitude                     Venue  Venue Latitude  \
661               -3.681931          La Cevicucheria       40.402679
662               -3.681931      la esquina de tellez       40.402756
663               -3.681931   Candela Pinchos & Drinks       40.402524
664               -3.681931                El Caldero       40.402563
665               -3.681931          The Burger Lobby       40.398921
```

```
666             -3.681931                Centro Supera 24h       40.403223
667             -3.681931                        Chino Sur       40.396189
668             -3.681931                      Monte Pinos       40.402653
669             -3.681931                   Domino's Pizza       40.402188
670             -3.681931  MARIANA Café - Bar & After Work       40.398116

     Venue Longitude       Venue Category
661        -3.680336  Peruvian Restaurant
662        -3.680599           Restaurant
663        -3.679898   Spanish Restaurant
664        -3.680663           Restaurant
665        -3.684790         Burger Joint
666        -3.679273        Gymnastics Gym
667        -3.681183   Chinese Restaurant
668        -3.677546                 Café
669        -3.678252          Pizza Place
670        -3.686270       Breakfast Spot
```

In [641]:
```
#We can count the number of venues per category as follows
venues[venues['Neighborhood']=='Atocha'].groupby('Venue Category')['Neighborhood'].co
```

Out[641]:
```
Series([], Name: Neighborhood, dtype: int64)
```

We can see that the most common category in this neighborhood is "Restaurant", not specifiying the type.

In order to compare different neighborhoods, we should obtain an indicator that allows us to now the proportion of venues of a specific type. We will do this by performing onehot encoding for each venue of each neighborhood, and then averageing the values as we did in the course's lab.

In [642]:
```
#One hot encoding
venues_onehot = pd.get_dummies(venues[['Venue Category']], prefix="", prefix_sep="")
```

In [643]:
```
venues_onehot.head(3)
```

Out[643]:
```
   Accessories Store  African Restaurant  Airport  Airport Service  \
0                  0                   0        0                0
1                  0                   0        0                0
2                  0                   0        0                0

   American Restaurant  Arcade  Arepa Restaurant  Argentinian Restaurant  \
0                    0       0                 0                       0
1                    0       0                 0                       0
2                    0       0                 0                       0

   Art Gallery  Art Museum  ...  Used Bookstore  \
0            0           0  ...               0
1            0           0  ...               0
2            0           0  ...               0
```

```
   Vegetarian / Vegan Restaurant  Video Game Store  Video Store  \
0                              0                 0            0
1                              0                 0            0
2                              0                 0            0

   Vietnamese Restaurant  Warehouse Store  Whisky Bar  Wine Bar  Wine Shop  \
0                      0                0           0         0          0
1                      0                0           0         0          0
2                      0                0           0         0          0

   Yoga Studio
0            0
1            0
2            0

[3 rows x 295 columns]
```

In [644]:
```
# Add the neighborhood column back to the dataframe
venues_onehot['Neighborhood'] = venues['Neighborhood']
```

In [645]:
```
# Average per neighborhood
venues_grouped = venues_onehot.groupby(['Neighborhood']).mean().reset_index()
venues_grouped.head()
```

Out[645]:
```
  Neighborhood  Accessories Store  African Restaurant  Airport  \
0     ABRANTES                0.0                 0.0      0.0
1      ACACIAS                0.0                 0.0      0.0
2      ADELFAS                0.0                 0.0      0.0
3   AEROPUERTO                0.5                 0.0      0.0
4        AIORA                0.0                 0.0      0.0

   Airport Service  American Restaurant  Arcade  Arepa Restaurant  \
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              0.5                  0.0     0.0               0.0
4              0.0                  0.0     0.0               0.0

   Argentinian Restaurant  Art Gallery  ...  Used Bookstore  \
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

   Vegetarian / Vegan Restaurant  Video Game Store  Video 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           0.0
4                              0.0              0.0           0.0

   Vietnamese Restaurant  Warehouse Store  Whisky Bar  Wine Bar  Wine Shop  \
0                    0.0              0.0         0.0       0.0        0.0
1                    0.0              0.0         0.0       0.0        0.0
2                    0.0              0.0         0.0       0.0        0.0
3                    0.0              0.0         0.0       0.0        0.0
4                    0.0              0.0         0.0       0.0        0.0

   Yoga Studio
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0

[5 rows x 295 columns]
```

Now we have, for each neighborhood, the distribution of types of venues that exist on a scale from 0 to 1. This will be used later for clustering.

To end this section, we will create a dataframe with the top 10 most common venue type per neighborhood, this can be used later for analysis

In [646]:
```
# Borrow the function from the lab. Sort 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]
```

In [647]:
```
num_top_venues = 10

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'] = venues_grouped['Neighborhood']
```

```
for ind in np.arange(venues_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_venues(venues_grou

neighborhoods_venues_sorted.head(10)
```

Out[647]:

```
        Neighborhood 1st Most Common Venue     2nd Most Common Venue  \
0           ABRANTES                   Bar                     Plaza
1            ACACIAS    Spanish Restaurant               Pizza Place
2            ADELFAS                  Café               Supermarket
3         AEROPUERTO     Accessories Store           Airport Service
4              AIORA                 Hotel                    Bakery
5   ALAMEDA DE OSUNA            Smoke Shop                Restaurant
6             ALBORS      Tapas Restaurant  Mediterranean Restaurant
7            ALMAGRO    Spanish Restaurant                Restaurant
8           ALMENARA  Gym / Fitness Center        Spanish Restaurant
9        ALMENDRALES    Spanish Restaurant        Chinese Restaurant

       3rd Most Common Venue     4th Most Common Venue 5th Most Common Venue  \
0       Fast Food Restaurant              Soccer Field           Pizza Place
1                Supermarket                       Bar      Tapas Restaurant
2       Fast Food Restaurant          Tapas Restaurant         Grocery Store
3                 Food Truck      Fast Food Restaurant      Fish & Chips Shop
4   Mediterranean Restaurant               Supermarket         Grocery Store
5         Fried Chicken Joint              Music School    Spanish Restaurant
6                 Restaurant      Gym / Fitness Center    Chinese Restaurant
7                        Bar  Mediterranean Restaurant   Japanese Restaurant
8          Food & Drink Shop         Martial Arts Dojo    Chinese Restaurant
9              Train Station             Grocery Store                   Bar

  6th Most Common Venue      7th Most Common Venue 8th Most Common Venue  \
0                  Park                       Food        Farmers Market
1                  Park                 Playground         Indie Theater
2                   Bar           Asian Restaurant           Coffee Shop
3           Fish Market                Flea Market           Flower Shop
4                  Café  Latin American Restaurant         Metro Station
5             Bookstore              Scenic Lookout         Metro Station
6             Nightclub               Movie Theater              Tea Room
7                 Plaza         Italian Restaurant             Nightclub
8           Flea Market                    Library           Supermarket
9                Bakery                   BBQ Joint    Seafood Restaurant

  9th Most Common Venue    10th Most Common Venue
0     Fish & Chips Shop               Fish Market
1                   Gym                      Café
2              Tea Room                    Museum
3                  Food         Food & Drink Shop
4     Paella Restaurant  Bike Rental / Bike Share
5      Tapas Restaurant        Chinese Restaurant
```

```
6    Mexican Restaurant                  Gastropub
7     French Restaurant                      Hotel
8             Food Truck          Football Stadium
9  Fast Food Restaurant                  Gastropub
```

In [648]:
```
#Add the basic neighborhood information
neighborhoods_venues_sorted = neighborhoods_venues_sorted.merge(neighborhoods, on='Ne
neighborhoods_venues_sorted.head(3)
```

Out[648]:
```
  Neighborhood 1st Most Common Venue 2nd Most Common Venue  \
0     ABRANTES                   Bar                 Plaza
1      ACACIAS    Spanish Restaurant           Pizza Place
2      ADELFAS                  Café           Supermarket

  3rd Most Common Venue 4th Most Common Venue 5th Most Common Venue  \
0  Fast Food Restaurant         Soccer Field           Pizza Place
1           Supermarket                  Bar      Tapas Restaurant
2  Fast Food Restaurant     Tapas Restaurant         Grocery Store

  6th Most Common Venue 7th Most Common Venue 8th Most Common Venue  \
0                  Park                  Food        Farmers Market
1                  Park            Playground         Indie Theater
2                   Bar      Asian Restaurant           Coffee Shop

  9th Most Common Venue 10th Most Common Venue     District  Longitude  \
0     Fish & Chips Shop            Fish Market  CARABANCHEL  -3.726166
1                   Gym                   Café   ARGANZUELA  -3.707261
2              Tea Room                 Museum       RETIRO  -3.670973

    Latitude    City
0  40.378976  Madrid
1  40.401068  Madrid
2  40.401116  Madrid
```

In [649]:
```
#Reorder columns
columns = ['City','District','Neighborhood','Longitude','Latitude'] + neighborhoods_v
columns
```

Out[649]:
```
['City',
 'District',
 'Neighborhood',
 'Longitude',
 'Latitude',
 '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',
 '8th Most Common Venue',
 '9th Most Common Venue',
 '10th Most Common Venue']
```

```
In [650]: neighborhoods_venues_sorted = neighborhoods_venues_sorted[columns]
          neighborhoods_venues_sorted.head()
```

```
Out[650]:       City    District Neighborhood  Longitude   Latitude  \
          0    Madrid  CARABANCHEL     ABRANTES  -3.726166  40.378976
          1    Madrid   ARGANZUELA      ACACIAS  -3.707261  40.401068
          2    Madrid       RETIRO      ADELFAS  -3.670973  40.401116
          3    Madrid      BARAJAS   AEROPUERTO  -3.563446  40.478558
          4  Valencia           12        AIORA  -0.343360  39.465733

            1st Most Common Venue 2nd Most Common Venue     3rd Most Common Venue  \
          0                   Bar                 Plaza      Fast Food Restaurant
          1    Spanish Restaurant           Pizza Place               Supermarket
          2                  Café           Supermarket      Fast Food Restaurant
          3     Accessories Store       Airport Service                Food Truck
          4                 Hotel                Bakery  Mediterranean Restaurant

            4th Most Common Venue 5th Most Common Venue 6th Most Common Venue  \
          0          Soccer Field           Pizza Place                  Park
          1                   Bar      Tapas Restaurant                  Park
          2      Tapas Restaurant         Grocery Store                   Bar
          3  Fast Food Restaurant     Fish & Chips Shop           Fish Market
          4           Supermarket         Grocery Store                  Café

                 7th Most Common Venue 8th Most Common Venue 9th Most Common Venue  \
          0                       Food        Farmers Market     Fish & Chips Shop
          1                 Playground         Indie Theater                   Gym
          2            Asian Restaurant           Coffee Shop              Tea Room
          3                Flea Market           Flower Shop                  Food
          4  Latin American Restaurant         Metro Station     Paella Restaurant

               10th Most Common Venue
          0               Fish Market
          1                      Café
          2                    Museum
          3         Food & Drink Shop
          4  Bike Rental / Bike Share
```

With the above dataframe we get an idea of the types of venues that can be found on each neighborhood.

### 0.4.3 3.3. Clustering Madrid and Valencia neighborhoods

Now that we have created a dataframe with features characterizing each neighborhood, based solely on the existing venues, we now proceed to cluster together neighborhoods that have similar characteristics.

We will be using k-means clustering to achieve this

In [651]:
```
# Import necessary libraries
import numpy as np
from sklearn.cluster import KMeans
import matplotlib.pyplot as plt
from sklearn import preprocessing
%matplotlib inline
```

In the previous section, we created the dataframe shown below. The features of the dataframe correspond to the rate of venues of each type within the neighborhood

In [652]:
```
venues_grouped.head()
```

Out[652]:
```
  Neighborhood  Accessories Store  African Restaurant  Airport  \
0     ABRANTES                0.0                 0.0      0.0
1      ACACIAS                0.0                 0.0      0.0
2      ADELFAS                0.0                 0.0      0.0
3   AEROPUERTO                0.5                 0.0      0.0
4        AIORA                0.0                 0.0      0.0

   Airport Service  American Restaurant  Arcade  Arepa Restaurant  \
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              0.5                  0.0     0.0               0.0
4              0.0                  0.0     0.0               0.0

   Argentinian Restaurant  Art Gallery  ...  Used Bookstore  \
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

   Vegetarian / Vegan Restaurant  Video Game Store  Video 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          0.0
4                            0.0               0.0          0.0

   Vietnamese Restaurant  Warehouse Store  Whisky Bar  Wine Bar  Wine Shop  \
0                    0.0              0.0         0.0       0.0        0.0
```

```
1                   0.0              0.0          0.0        0.0         0.0
2                   0.0              0.0          0.0        0.0         0.0
3                   0.0              0.0          0.0        0.0         0.0
4                   0.0              0.0          0.0        0.0         0.0

   Yoga Studio
0          0.0
1          0.0
2          0.0
3          0.0
4          0.0

[5 rows x 295 columns]
```

Now lets initialize the k-means model using K=20

```
In [653]: k_means = KMeans(init = "k-means++", n_clusters = 20, n_init = 15)
```

```
In [654]: # Fit the model
          k_means.fit(venues_grouped.drop('Neighborhood',axis=1))
```

```
Out[654]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
              n_clusters=20, n_init=15, n_jobs=None, precompute_distances='auto',
              random_state=None, tol=0.0001, verbose=0)
```

```
In [655]: #Add the labels to the venues_grouped dataset
          venues_grouped['Cluster']=k_means.labels_
```

```
In [656]: #Obtain the number of neighborhoods per cluster
          venues_grouped.groupby('Cluster')['Neighborhood'].count()
```

```
Out[656]: Cluster
          0       1
          1      32
          2      77
          3       1
          4      54
          5       1
          6       1
          7       2
          8       1
          9       1
          10      6
          11      2
          12      1
          13      1
          14      1
          15      1
          16      1
```

```
17    22
18     1
19     2
Name: Neighborhood, dtype: int64
```

In [657]:
```
neighborhoods_venues_sorted = neighborhoods_venues_sorted.merge(venues_grouped, on='I
```

In [658]:
```
neighborhoods_venues_sorted.head()
```

Out[658]:
```
       City    District Neighborhood  Longitude   Latitude  \
0    Madrid  CARABANCHEL     ABRANTES  -3.726166  40.378976
1    Madrid   ARGANZUELA      ACACIAS  -3.707261  40.401068
2    Madrid       RETIRO      ADELFAS  -3.670973  40.401116
3    Madrid      BARAJAS   AEROPUERTO  -3.563446  40.478558
4  Valencia           12        AIORA  -0.343360  39.465733

  1st Most Common Venue 2nd Most Common Venue     3rd Most Common Venue  \
0                   Bar                 Plaza      Fast Food Restaurant
1    Spanish Restaurant           Pizza Place               Supermarket
2                  Café           Supermarket      Fast Food Restaurant
3     Accessories Store       Airport Service                Food Truck
4                 Hotel                Bakery  Mediterranean Restaurant

  4th Most Common Venue 5th Most Common Venue  ...  \
0          Soccer Field           Pizza Place  ...
1                   Bar      Tapas Restaurant  ...
2      Tapas Restaurant         Grocery Store  ...
3  Fast Food Restaurant     Fish & Chips Shop  ...
4           Supermarket         Grocery Store  ...

  Vegetarian / Vegan Restaurant Video Game Store Video 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         0.0
4                           0.0              0.0         0.0

  Vietnamese Restaurant Warehouse Store  Whisky Bar  Wine Bar  Wine Shop  \
0                   0.0             0.0         0.0       0.0        0.0
1                   0.0             0.0         0.0       0.0        0.0
2                   0.0             0.0         0.0       0.0        0.0
3                   0.0             0.0         0.0       0.0        0.0
4                   0.0             0.0         0.0       0.0        0.0

   Yoga Studio  Cluster
0          0.0        1
1          0.0        4
2          0.0        2
```

```
3          0.0        1
4          0.0        2

[5 rows x 310 columns]
```

Now, our customer wishes to open the restaurant in a neighborhood similar to **El Carme**. Lets check on which cluster does that neighborhood belong to

```
In [659]: target_cluster_df = neighborhoods_venues_sorted.loc[neighborhoods_venues_sorted['Nei
          target_cluster_df.reset_index(inplace=True)
          target_cluster=target_cluster_df.loc[0].at['Cluster']
          print('The target cluster is: {} '.format(target_cluster))
```

```
The target cluster is: 2
```

```
In [739]: #Filter neighborhoods from Madrid that belong to the target cluster
          possible_neighborhoods = neighborhoods_venues_sorted[
              (neighborhoods_venues_sorted['Cluster']==target_cluster) &
              (neighborhoods_venues_sorted['City']=='Madrid')]

          print('There are {} neighborhoods in Madrid with similar characteristics than El Carn
                .format(possible_neighborhoods.shape[0]))
```

```
There are 38 neighborhoods in Madrid with similar characteristics than El Carme
```

```
In [740]: # Clean up index
          possible_neighborhoods.reset_index(inplace=True, drop=True)
```

The dataset below contains the possible locations for the new restaurant. These have similar characteristics than the El Carme neighborhood in Valencia.
In the following section, we will rank each neighborhood and provide our customer with the top 10 recommendations.

```
In [742]: # Print the possible neighborhoods
          possible_neighborhoods = possible_neighborhoods[['District','Neighborhood','1st Most
          possible_neighborhoods
```

```
Out[742]:                 District        Neighborhood 1st Most Common Venue  \
          0                 RETIRO             ADELFAS                  Café
          1                BARAJAS     ALAMEDA DE OSUNA            Smoke Shop
          2               CHAMBERÍ             ALMAGRO      Spanish Restaurant
          3   SAN BLAS - CANILLEJAS               ARCOS            Restaurant
          4             ARGANZUELA              ATOCHA            Restaurant
          5                 TETUÁN          BERRUGUETE      Tapas Restaurant
          6                BARAJAS      CASCO H.BARAJAS                 Hotel
          7              CHAMARTÍN            CASTILLA              Platform
          8             ARGANZUELA             CHOPERA                  Park
```

| | | | |
|---|---|---|---|
| 9 | CHAMARTÍN | CIUDAD JARDIN | Café |
| 10 | CENTRO | CORTES | Hotel |
| 11 | LATINA | CUATRO VIENTOS | Campground |
| 12 | ARGANZUELA | DELICIAS | Snack Place |
| 13 | FUENCARRAL - EL PARDO | EL PILAR | Tapas Restaurant |
| 14 | MONCLOA - ARAVACA | EL PLANTIO | Italian Restaurant |
| 15 | CENTRO | EMBAJADORES | Bar |
| 16 | VILLA DE VALLECAS | ENSANCHE DE VALLECAS | Clothing Store |
| 17 | SALAMANCA | FUENTE DEL BERRO | Bar |
| 18 | CHAMBERÍ | GAZTAMBIDE | Spanish Restaurant |
| 19 | SALAMANCA | GUINDALERA | Spanish Restaurant |
| 20 | CENTRO | JUSTICIA | Spanish Restaurant |
| 21 | MORATALAZ | MEDIA LEGUA | Restaurant |
| 22 | USERA | MOSCARDO | Fast Food Restaurant |
| 23 | CHAMARTÍN | NUEVA ESPAÑA | Restaurant |
| 24 | CARABANCHEL | OPAÑEL | Bar |
| 25 | HORTALEZA | PALOMAS | Asian Restaurant |
| 26 | ARGANZUELA | PALOS DE MOGUER | Spanish Restaurant |
| 27 | CHAMARTÍN | PROSPERIDAD | Bar |
| 28 | CIUDAD LINEAL | QUINTANA | Tapas Restaurant |
| 29 | SALAMANCA | RECOLETOS | Restaurant |
| 30 | CHAMBERÍ | RIOS ROSAS | Tapas Restaurant |
| 31 | USERA | SAN FERMIN | Athletics & Sports |
| 32 | CIUDAD LINEAL | SAN JUAN BAUTISTA | Restaurant |
| 33 | CENTRO | SOL | Spanish Restaurant |
| 34 | CHAMBERÍ | TRAFALGAR | Spanish Restaurant |
| 35 | CENTRO | UNIVERSIDAD | Bar |
| 36 | CHAMBERÍ | VALLEHERMOSO | Restaurant |
| 37 | CARABANCHEL | VISTA ALEGRE | Pizza Place |

| | 2nd Most Common Venue | 3rd Most Common Venue |
|---|---|---|
| 0 | Supermarket | Fast Food Restaurant |
| 1 | Restaurant | Fried Chicken Joint |
| 2 | Restaurant | Bar |
| 3 | Multiplex | Optical Shop |
| 4 | Grocery Store | Tapas Restaurant |
| 5 | Bar | Spanish Restaurant |
| 6 | Spanish Restaurant | Gastropub |
| 7 | Café | Hotel |
| 8 | Plaza | Spanish Restaurant |
| 9 | Tapas Restaurant | Spanish Restaurant |
| 10 | Spanish Restaurant | Restaurant |
| 11 | Restaurant | Airport |
| 12 | Mediterranean Restaurant | Grocery Store |
| 13 | Spanish Restaurant | Italian Restaurant |
| 14 | Restaurant | Beer Garden |
| 15 | Café | Tapas Restaurant |
| 16 | Fast Food Restaurant | Spanish Restaurant |

```
17       Gym / Fitness Center        Spanish Restaurant
18                        Bar                      Café
19        Japanese Restaurant             Grocery Store
20                Cocktail Bar                     Hotel
21       Fast Food Restaurant               Coffee Shop
22               Soccer Field                 Gastropub
23           Tapas Restaurant  Mediterranean Restaurant
24                Coffee Shop      Fast Food Restaurant
25                      Hotel            Sandwich Place
26                 Restaurant          Tapas Restaurant
27         Spanish Restaurant                      Café
28             Clothing Store                       Bar
29         Spanish Restaurant                     Hotel
30         Italian Restaurant                Restaurant
31            Bed & Breakfast              Tennis Court
32                        Bar        Spanish Restaurant
33                      Hotel          Tapas Restaurant
34                 Restaurant                       Bar
35           Tapas Restaurant        Spanish Restaurant
36                        Bar        Spanish Restaurant
37             Cosmetics Shop        Athletics & Sports
```

After the clustering process, we find a rather large number of neighborhoods that are similar to our target. In the next section, we will select the top 10 candidates based on additional criteria.

### 0.4.4 3.4. Neighborhood Ranking

We now have a dataset containing a list of potential neighborhoods. Our task now is to select the top 10 in order to present our findings to the customer.

We will rank each neighborhood based on a composite ranking using the following items:

a. Total Population. *Weight: 50%*

b. Average income per household within each neighborhood. *Weight: 25%*

c. Amount of already existing Italian restaurants. *Weight: 25%*

To create this ranking, lets first normalize each of the three metrics

In [694]:
```
#Population dataset
madrid_population.head(3)
```

Out[694]:
```
  District Neighborhood  Population
0   CENTRO      PALACIO       22984
1   CENTRO   EMBAJADORES      45433
2   CENTRO       CORTES       10525
```

In [706]:
```
madrid_population['Population_Normalized'] = madrid_population['Population']/madrid_
madrid_population.head(3)
```

Out[706]:

| | District | Neighborhood | Population | Rate_to_Total | Population_Normalized |
|---|---|---|---|---|---|
| 0 | CENTRO | PALACIO | 22984 | 0.007018 | 0.345406 |
| 1 | CENTRO | EMBAJADORES | 45433 | 0.013872 | 0.682772 |
| 2 | CENTRO | CORTES | 10525 | 0.003214 | 0.158171 |

In [705]:
```
madrid_income['Income_Normalized'] = madrid_income['Average Income']/madrid_income['A
madrid_income.head(3)
```

Out[705]:

| | District | Neighborhood | Average Income | Income_Normalized |
|---|---|---|---|---|
| 0 | CENTRO | PALACIO | 34675.85 | 0.308722 |
| 1 | CENTRO | EMBAJADORES | 25999.83 | 0.231478 |
| 2 | CENTRO | CORTES | 34952.68 | 0.311186 |

In [709]:
```
venues_grouped.columns
```

Out[709]:
```
Index(['Neighborhood', 'Accessories Store', 'African Restaurant', 'Airport',
       'Airport Service', 'American Restaurant', 'Arcade', 'Arepa Restaurant',
       'Argentinian Restaurant', 'Art Gallery',
       ...
       'Vegetarian / Vegan Restaurant', 'Video Game Store', 'Video Store',
       'Vietnamese Restaurant', 'Warehouse Store', 'Whisky Bar', 'Wine Bar',
       'Wine Shop', 'Yoga Studio', 'Cluster'],
      dtype='object', length=296)
```

In [732]:
```
#Based on section 3.2
madrid_italian = venues_onehot.groupby(['Neighborhood']).sum().reset_index()
madrid_italian.head()
```

Out[732]:

| | Neighborhood | Accessories Store | African Restaurant | Airport | \ |
|---|---|---|---|---|---|
| 0 | ABRANTES | 0 | 0 | 0 | |
| 1 | ACACIAS | 0 | 0 | 0 | |
| 2 | ADELFAS | 0 | 0 | 0 | |
| 3 | AEROPUERTO | 1 | 0 | 0 | |
| 4 | AIORA | 0 | 0 | 0 | |

| | Airport Service | American Restaurant | Arcade | Arepa Restaurant | \ |
|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | |
| 1 | 0 | 0 | 0 | 0 | |
| 2 | 0 | 0 | 0 | 0 | |
| 3 | 1 | 0 | 0 | 0 | |
| 4 | 0 | 0 | 0 | 0 | |

| | Argentinian Restaurant | Art Gallery | ... | Used Bookstore | \ |
|---|---|---|---|---|---|
| 0 | 0 | 0 | ... | 0 | |
| 1 | 0 | 0 | ... | 0 | |
| 2 | 0 | 0 | ... | 0 | |
| 3 | 0 | 0 | ... | 0 | |
| 4 | 0 | 0 | ... | 0 | |

```
   Vegetarian / Vegan Restaurant  Video Game Store  Video Store  \
0                              0                 0            0
1                              0                 0            0
2                              0                 0            0
3                              0                 0            0
4                              0                 0            0

   Vietnamese Restaurant  Warehouse Store  Whisky Bar  Wine Bar  Wine Shop  \
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

   Yoga Studio
0            0
1            0
2            0
3            0
4            0

[5 rows x 295 columns]
```

In [733]:
```
madrid_italian = madrid_italian[['Neighborhood','Italian Restaurant']]
madrid_italian.rename(columns={"Italian Restaurant": "Number_Italian_Restaurants"}, i
madrid_italian.head()
```

Out[733]:
```
  Neighborhood  Number_Italian_Restaurants
0     ABRANTES                           0
1      ACACIAS                           1
2      ADELFAS                           0
3   AEROPUERTO                           0
4        AIORA                           0
```

In [734]:
```
#"Normalize" and invert. This way, if a row is 1 then it means there are no italian r
madrid_italian['Non_Italian_Restaurants'] = 1-madrid_italian['Number_Italian_Restaura
madrid_italian.head(10)
```

Out[734]:
```
         Neighborhood  Number_Italian_Restaurants  Non_Italian_Restaurants
0            ABRANTES                           0                 1.000000
1             ACACIAS                           1                 0.888889
2             ADELFAS                           0                 1.000000
3          AEROPUERTO                           0                 1.000000
4               AIORA                           0                 1.000000
5   ALAMEDA DE OSUNA                           0                 1.000000
6              ALBORS                           0                 1.000000
7             ALMAGRO                           4                 0.555556
8            ALMENARA                           0                 1.000000
9         ALMENDRALES                           0                 1.000000
```

Now we put together the three datasets and create the ranking

```
In [745]: possible_neighborhoods = possible_neighborhoods.merge(madrid_population[['Neighborho
          possible_neighborhoods = possible_neighborhoods.merge(madrid_income[['Neighborhood',
          possible_neighborhoods = possible_neighborhoods.merge(madrid_italian[['Neighborhood'

In [746]: possible_neighborhoods.head(3)

Out[746]:     District      Neighborhood 1st Most Common Venue 2nd Most Common Venue  \
          0    RETIRO            ADELFAS                  Café           Supermarket
          1   BARAJAS   ALAMEDA DE OSUNA            Smoke Shop            Restaurant
          2  CHAMBERÍ            ALMAGRO    Spanish Restaurant            Restaurant

            3rd Most Common Venue  Population  Population_Normalized  Income_Normalized  \
          0  Fast Food Restaurant       18516               0.278260           0.408143
          1   Fried Chicken Joint       19573               0.294145           0.465463
          2                   Bar       19858               0.298428           0.612413

             Non_Italian_Restaurants
          0                 1.000000
          1                 1.000000
          2                 0.555556

In [778]: possible_neighborhoods['Ranking'] = possible_neighborhoods['Population_Normalized'] *
          recommended_neighborhoods = possible_neighborhoods.sort_values(by='Ranking',ascending
          recommended_neighborhoods.reset_index(inplace=True, drop=True)
```

## 0.5 4. Results Summary

After performing a clustering analysis a group of 59 possible neighborhoods was identified with similar characteristics to the target neighborhood from Valencia.

```
In [777]: possible_neighborhoods

Out[777]:                  District         Neighborhood 1st Most Common Venue  \
          0                  RETIRO              ADELFAS                  Café
          1                 BARAJAS     ALAMEDA DE OSUNA            Smoke Shop
          2                CHAMBERÍ              ALMAGRO    Spanish Restaurant
          3   SAN BLAS - CANILLEJAS                ARCOS            Restaurant
          4              ARGANZUELA               ATOCHA            Restaurant
          5                  TETUÁN           BERRUGUETE      Tapas Restaurant
          6                 BARAJAS      CASCO H.BARAJAS                 Hotel
          7               CHAMARTÍN             CASTILLA              Platform
          8              ARGANZUELA              CHOPERA                  Park
          9               CHAMARTÍN        CIUDAD JARDIN                  Café
          10                 CENTRO               CORTES                 Hotel
          11                 LATINA       CUATRO VIENTOS            Campground
          12             ARGANZUELA             DELICIAS           Snack Place
          13   FUENCARRAL - EL PARDO             EL PILAR      Tapas Restaurant
```

| | | | |
|---|---|---|---|
| 14 | MONCLOA - ARAVACA | EL PLANTIO | Italian Restaurant |
| 15 | CENTRO | EMBAJADORES | Bar |
| 16 | VILLA DE VALLECAS | ENSANCHE DE VALLECAS | Clothing Store |
| 17 | SALAMANCA | FUENTE DEL BERRO | Bar |
| 18 | CHAMBERÍ | GAZTAMBIDE | Spanish Restaurant |
| 19 | SALAMANCA | GUINDALERA | Spanish Restaurant |
| 20 | CENTRO | JUSTICIA | Spanish Restaurant |
| 21 | MORATALAZ | MEDIA LEGUA | Restaurant |
| 22 | USERA | MOSCARDO | Fast Food Restaurant |
| 23 | CHAMARTÍN | NUEVA ESPAÑA | Restaurant |
| 24 | CARABANCHEL | OPAÑEL | Bar |
| 25 | HORTALEZA | PALOMAS | Asian Restaurant |
| 26 | ARGANZUELA | PALOS DE MOGUER | Spanish Restaurant |
| 27 | CHAMARTÍN | PROSPERIDAD | Bar |
| 28 | CIUDAD LINEAL | QUINTANA | Tapas Restaurant |
| 29 | SALAMANCA | RECOLETOS | Restaurant |
| 30 | CHAMBERÍ | RIOS ROSAS | Tapas Restaurant |
| 31 | USERA | SAN FERMIN | Athletics & Sports |
| 32 | CIUDAD LINEAL | SAN JUAN BAUTISTA | Restaurant |
| 33 | CENTRO | SOL | Spanish Restaurant |
| 34 | CHAMBERÍ | TRAFALGAR | Spanish Restaurant |
| 35 | CENTRO | UNIVERSIDAD | Bar |
| 36 | CHAMBERÍ | VALLEHERMOSO | Restaurant |
| 37 | CARABANCHEL | VISTA ALEGRE | Pizza Place |

| | 2nd Most Common Venue | 3rd Most Common Venue | Population \ |
|---|---|---|---|
| 0 | Supermarket | Fast Food Restaurant | 18516 |
| 1 | Restaurant | Fried Chicken Joint | 19573 |
| 2 | Restaurant | Bar | 19858 |
| 3 | Multiplex | Optical Shop | 24298 |
| 4 | Grocery Store | Tapas Restaurant | 1176 |
| 5 | Bar | Spanish Restaurant | 25089 |
| 6 | Spanish Restaurant | Gastropub | 7585 |
| 7 | Café | Hotel | 16953 |
| 8 | Plaza | Spanish Restaurant | 20048 |
| 9 | Tapas Restaurant | Spanish Restaurant | 18689 |
| 10 | Spanish Restaurant | Restaurant | 10525 |
| 11 | Restaurant | Airport | 5761 |
| 12 | Mediterranean Restaurant | Grocery Store | 27740 |
| 13 | Spanish Restaurant | Italian Restaurant | 46577 |
| 14 | Restaurant | Beer Garden | 2812 |
| 15 | Café | Tapas Restaurant | 45433 |
| 16 | Fast Food Restaurant | Spanish Restaurant | 45895 |
| 17 | Gym / Fitness Center | Spanish Restaurant | 21104 |
| 18 | Bar | Café | 22997 |
| 19 | Japanese Restaurant | Grocery Store | 41751 |
| 20 | Cocktail Bar | Hotel | 17205 |
| 21 | Fast Food Restaurant | Coffee Shop | 17923 |

| | | | |
|---|---|---|---|
| 22 | Soccer Field | Gastropub | 26416 |
| 23 | Tapas Restaurant | Mediterranean Restaurant | 24699 |
| 24 | Coffee Shop | Fast Food Restaurant | 33145 |
| 25 | Hotel | Sandwich Place | 6798 |
| 26 | Restaurant | Tapas Restaurant | 25894 |
| 27 | Spanish Restaurant | Café | 36730 |
| 28 | Clothing Store | Bar | 24679 |
| 29 | Spanish Restaurant | Hotel | 15786 |
| 30 | Italian Restaurant | Restaurant | 27465 |
| 31 | Bed & Breakfast | Tennis Court | 23724 |
| 32 | Bar | Spanish Restaurant | 12508 |
| 33 | Hotel | Tapas Restaurant | 7358 |
| 34 | Restaurant | Bar | 24777 |
| 35 | Tapas Restaurant | Spanish Restaurant | 31809 |
| 36 | Bar | Spanish Restaurant | 20297 |
| 37 | Cosmetics Shop | Athletics & Sports | 46122 |

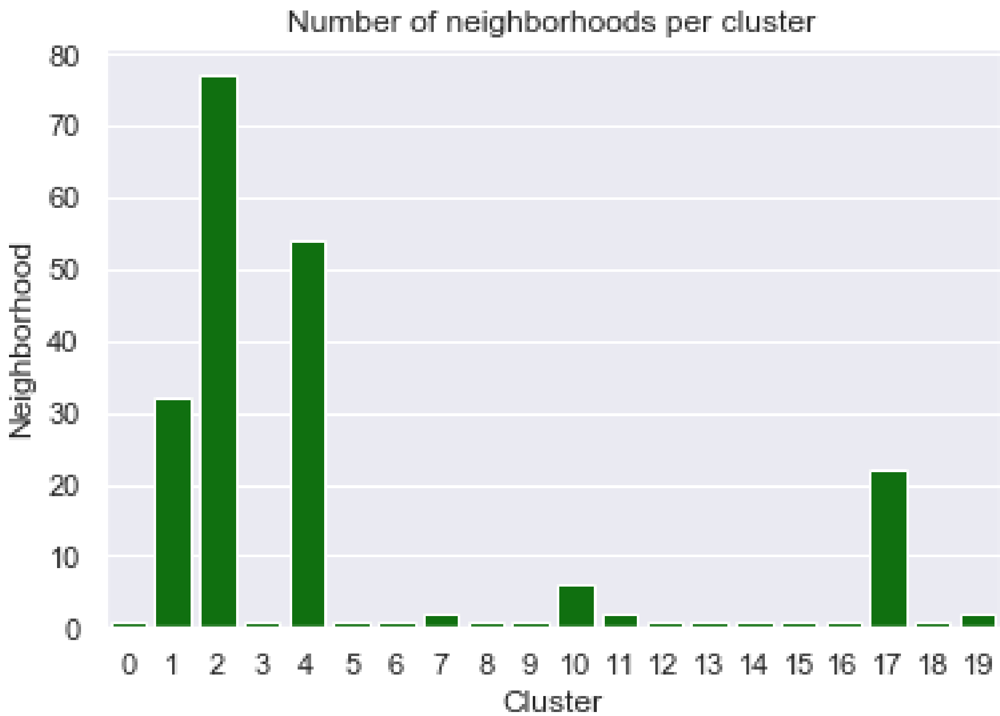
| | Population_Normalized | Income_Normalized | Non_Italian_Restaurants \ |
|---|---|---|---|
| 0 | 0.278260 | 0.408143 | 1.000000 |
| 1 | 0.294145 | 0.465463 | 1.000000 |
| 2 | 0.298428 | 0.612413 | 0.555556 |
| 3 | 0.365153 | 0.250277 | 1.000000 |
| 4 | 0.017673 | 0.337776 | 0.888889 |
| 5 | 0.377040 | 0.257704 | 1.000000 |
| 6 | 0.113988 | 0.262196 | 1.000000 |
| 7 | 0.254771 | 0.488511 | 1.000000 |
| 8 | 0.301283 | 0.284310 | 0.888889 |
| 9 | 0.280860 | 0.389126 | 1.000000 |
| 10 | 0.158171 | 0.311186 | 1.000000 |
| 11 | 0.086577 | 0.313363 | 1.000000 |
| 12 | 0.416880 | 0.352986 | 0.888889 |
| 13 | 0.699964 | 0.300443 | 0.000000 |
| 14 | 0.042259 | 0.902942 | 0.777778 |
| 15 | 0.682772 | 0.231478 | 1.000000 |
| 16 | 0.689715 | 0.322067 | 0.777778 |
| 17 | 0.317153 | 0.360606 | 1.000000 |
| 18 | 0.345601 | 0.379339 | 0.666667 |
| 19 | 0.627438 | 0.412576 | 1.000000 |
| 20 | 0.258559 | 0.358926 | 0.555556 |
| 21 | 0.269349 | 0.315515 | 1.000000 |
| 22 | 0.396982 | 0.234669 | 1.000000 |
| 23 | 0.371179 | 0.714457 | 1.000000 |
| 24 | 0.498106 | 0.249566 | 1.000000 |
| 25 | 0.102161 | 0.727707 | 1.000000 |
| 26 | 0.389138 | 0.302156 | 0.888889 |
| 27 | 0.551982 | 0.389078 | 0.888889 |
| 28 | 0.370879 | 0.270845 | 1.000000 |
| 29 | 0.237234 | 0.754141 | 0.444444 |

| | | | |
|---|---|---|---|
| 30 | 0.412747 | 0.426949 | 0.333333 |
| 31 | 0.356527 | 0.226496 | 1.000000 |
| 32 | 0.187972 | 0.500337 | 1.000000 |
| 33 | 0.110577 | 0.275424 | 0.777778 |
| 34 | 0.372351 | 0.366150 | 0.555556 |
| 35 | 0.478029 | 0.273339 | 0.888889 |
| 36 | 0.305025 | 0.529364 | 1.000000 |
| 37 | 0.693126 | 0.247401 | 1.000000 |

| | Ranking |
|---|---|
| 0 | 0.381980 |
| 1 | 0.409985 |
| 2 | 0.419114 |
| 3 | 0.370174 |
| 4 | 0.215947 |
| 5 | 0.378717 |
| 6 | 0.248763 |
| 7 | 0.398365 |
| 8 | 0.339039 |
| 9 | 0.376624 |
| 10 | 0.288001 |
| 11 | 0.252965 |
| 12 | 0.420874 |
| 13 | 0.455137 |
| 14 | 0.414937 |
| 15 | 0.522403 |
| 16 | 0.535358 |
| 17 | 0.384789 |
| 18 | 0.372236 |
| 19 | 0.558121 |
| 20 | 0.310459 |
| 21 | 0.345105 |
| 22 | 0.380625 |
| 23 | 0.535650 |
| 24 | 0.436401 |
| 25 | 0.405778 |
| 26 | 0.389212 |
| 27 | 0.501057 |
| 28 | 0.380235 |
| 29 | 0.427011 |
| 30 | 0.389139 |
| 31 | 0.357537 |
| 32 | 0.369104 |
| 33 | 0.229464 |
| 34 | 0.369884 |
| 35 | 0.423572 |
| 36 | 0.437790 |
| 37 | 0.533153 |

For the clustering process we picket a large number of cluster (K=20), nevertheless most of the neighborhoods fell into 5 clusters, as shown below

```
In [780]: venues_grouped_count = venues_grouped.groupby('Cluster')['Neighborhood'].count().to_
          venues_grouped_count.reset_index(inplace=True)
          ax = sns.barplot(x='Cluster', y='Neighborhood', data=venues_grouped_count, color='gre
          ax.set_title('Number of neighborhoods per cluster');
```




The amount of neighborhoods obtained from the clustering analysis was still high, so I decided to order the data based on additional criteria, such as neihgborhood population, average income and the competition. Finally, we came out with a list of 10 potential target neighborhoods

```
In [781]: recommended_neighborhoods
```

Out[781]:

| | District | Neighborhood | 1st Most Common Venue \ |
|---|---|---|---|
| 0 | SALAMANCA | GUINDALERA | Spanish Restaurant |
| 1 | CHAMARTÍN | NUEVA ESPAÑA | Restaurant |
| 2 | VILLA DE VALLECAS | ENSANCHE DE VALLECAS | Clothing Store |
| 3 | CARABANCHEL | VISTA ALEGRE | Pizza Place |
| 4 | CENTRO | EMBAJADORES | Bar |
| 5 | CHAMARTÍN | PROSPERIDAD | Bar |
| 6 | FUENCARRAL - EL PARDO | EL PILAR | Tapas Restaurant |
| 7 | CHAMBERÍ | VALLEHERMOSO | Restaurant |
| 8 | CARABANCHEL | OPAÑEL | Bar |
| 9 | SALAMANCA | RECOLETOS | Restaurant |

|   | 2nd Most Common Venue | 3rd Most Common Venue | Population | \ |
|---|---|---|---|---|
| 0 | Japanese Restaurant | Grocery Store | 41751 | |
| 1 | Tapas Restaurant | Mediterranean Restaurant | 24699 | |
| 2 | Fast Food Restaurant | Spanish Restaurant | 45895 | |
| 3 | Cosmetics Shop | Athletics & Sports | 46122 | |
| 4 | Café | Tapas Restaurant | 45433 | |
| 5 | Spanish Restaurant | Café | 36730 | |
| 6 | Spanish Restaurant | Italian Restaurant | 46577 | |
| 7 | Bar | Spanish Restaurant | 20297 | |
| 8 | Coffee Shop | Fast Food Restaurant | 33145 | |
| 9 | Spanish Restaurant | Hotel | 15786 | |

|   | Population_Normalized | Income_Normalized | Non_Italian_Restaurants | Ranking |
|---|---|---|---|---|
| 0 | 0.627438 | 0.412576 | 1.000000 | 0.558121 |
| 1 | 0.371179 | 0.714457 | 1.000000 | 0.535650 |
| 2 | 0.689715 | 0.322067 | 0.777778 | 0.535358 |
| 3 | 0.693126 | 0.247401 | 1.000000 | 0.533153 |
| 4 | 0.682772 | 0.231478 | 1.000000 | 0.522403 |
| 5 | 0.551982 | 0.389078 | 0.888889 | 0.501057 |
| 6 | 0.699964 | 0.300443 | 0.000000 | 0.455137 |
| 7 | 0.305025 | 0.529364 | 1.000000 | 0.437790 |
| 8 | 0.498106 | 0.249566 | 1.000000 | 0.436401 |
| 9 | 0.237234 | 0.754141 | 0.444444 | 0.427011 |

The selected neighborhoods have similar characteristics than the source neighborhood from Valencia city.