

# Madrid-Neighborhood-Clusters

June 24, 2020

```
[1]: # install geocoder package

import sys
!{sys.executable} -m pip install geocoder
print('package installed')
```

Collecting geocoder

Downloading <https://files.pythonhosted.org/packages/4f/6b/13166c909ad2f2d76b929a4227c952630ebaf0d729f6317eb09cbceccbab/geocoder-1.38.1-py2.py3-none-any.whl> (98kB)

| 102kB 4.8MB/s ta 0:00:011

Collecting click (from geocoder)

Downloading <https://files.pythonhosted.org/packages/d2/3d/fa76db83bf75c4f8d338c2fd15c8d33fdd7ad23a9b5e57eb6c5de26b430e/click-7.1.2-py2.py3-none-any.whl> (82kB)

| 92kB 5.1MB/s eta 0:00:011

Requirement already satisfied: requests in

/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from geocoder) (2.23.0)

Requirement already satisfied: six in

/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from geocoder) (1.15.0)

Collecting ratelim (from geocoder)

Downloading <https://files.pythonhosted.org/packages/f2/98/7e6d147fd16a10a5f821db6e25f192265d6ecca3d82957a4fdd592cad49c/ratelim-0.1.6-py2.py3-none-any.whl>

Collecting future (from geocoder)

Downloading <https://files.pythonhosted.org/packages/45/0b/38b06fd9b92dc2b68d58b75f900e97884c45bedd2ff83203d933cf5851c9/future-0.18.2.tar.gz> (829kB)

| 829kB 10.6MB/s eta 0:00:01

| 204kB 10.6MB/s eta 0:00:01

Requirement already satisfied: certifi>=2017.4.17 in

/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from requests->geocoder) (2020.4.5.2)

Requirement already satisfied: chardet<4,>=3.0.2 in

/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from requests->geocoder) (3.0.4)

Requirement already satisfied: urllib3!=1.25.0,!<1.25.1,<1.26,>=1.21.1 in

/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from

```
requests->geocoder) (1.25.9)
Requirement already satisfied: idna<3,>=2.5 in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
requests->geocoder) (2.9)
Requirement already satisfied: decorator in
/home/jupyterlab/conda/envs/python/lib/python3.6/site-packages (from
ratelim->geocoder) (4.4.2)
Building wheels for collected packages: future
  Building wheel for future (setup.py) ... done
  Stored in directory: /home/jupyterlab/.cache/pip/wheels/8b/99/a0/81daf51
dcd359a9377b110a8a886b3895921802d2fc1b2397e
Successfully built future
Installing collected packages: click, ratelim, future, geocoder
Successfully installed click-7.1.2 future-0.18.2 geocoder-1.38.1 ratelim-0.1.6
package installed
```

```
[2]: # install geopy package
```

```
!conda install -c conda-forge geopy --yes
print('package installed')
```

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

```
## Package Plan ##
```

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

```
added / updated specs:
```

```
- geopy
```

```
The following packages will be downloaded:
```

package	build		
ca-certificates-2020.6.20	hecda079_0	145 KB	conda-forge
certifi-2020.6.20	py36h9f0ad1d_0	151 KB	conda-forge
geographiclib-1.50	py_0	34 KB	conda-forge
geopy-1.22.0	pyh9f0ad1d_0	63 KB	conda-forge
Total:		393 KB	

```
The following NEW packages will be INSTALLED:
```

```
geographiclib    conda-forge/noarch::geographiclib-1.50-py_0
geopy            conda-forge/noarch::geopy-1.22.0-pyh9f0ad1d_0
```

The following packages will be UPDATED:

```
ca-certificates                2020.4.5.2-hecda079_0 -->
2020.6.20-hecda079_0
certifi                        2020.4.5.2-py36h9f0ad1d_0 -->
2020.6.20-py36h9f0ad1d_0
```

Downloading and Extracting Packages

```
certifi-2020.6.20    | 151 KB    | ##### | 100%
geopy-1.22.0         | 63 KB     | ##### | 100%
ca-certificates-2020 | 145 KB    | ##### | 100%
geographiclib-1.50   | 34 KB     | ##### | 100%
Preparing transaction: done
Verifying transaction: done
Executing transaction: done
package installed
```

```
[3]: # install folium package
!conda install -c conda-forge folium=0.5.0 --yes
print('package installed')
```

```
Collecting package metadata (current_repodata.json): done
Solving environment: failed with initial frozen solve. Retrying with flexible
solve.
Collecting package metadata (repodata.json): done
Solving environment: done
```

## Package Plan ##

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

added / updated specs:  
- folium=0.5.0

The following packages will be downloaded:

package	build		
altair-4.1.0	py_1	614 KB	conda-forge
branca-0.4.1	py_0	26 KB	conda-forge
brotlipy-0.7.0	py36h8c4c3a4_1000	346 KB	conda-forge
chardet-3.0.4	py36h9f0ad1d_1006	188 KB	conda-forge
cryptography-2.9.2	py36h45558ae_0	613 KB	conda-forge
folium-0.5.0	py_0	45 KB	conda-forge
pandas-1.0.5	py36h830a2c2_0	10.1 MB	conda-forge

pysocks-1.7.1		py36h9f0ad1d_1	27 KB	conda-forge
requests-2.24.0		pyh9f0ad1d_0	47 KB	conda-forge
toolz-0.10.0		py_0	46 KB	conda-forge
vincent-0.4.4		py_1	28 KB	conda-forge
-----				
Total:			12.0 MB	

The following NEW packages will be INSTALLED:

altair	conda-forge/noarch::altair-4.1.0-py_1
attrs	conda-forge/noarch::attrs-19.3.0-py_0
branca	conda-forge/noarch::branca-0.4.1-py_0
brotlipy	conda-forge/linux-64::brotlipy-0.7.0-py36h8c4c3a4_1000
chardet	conda-forge/linux-64::chardet-3.0.4-py36h9f0ad1d_1006
cryptography	conda-forge/linux-64::cryptography-2.9.2-py36h45558ae_0
entrypoints	conda-forge/linux-64::entrypoints-0.3-py36h9f0ad1d_1001
folium	conda-forge/noarch::folium-0.5.0-py_0
idna	conda-forge/noarch::idna-2.9-py_1
importlib_metadata	conda-forge/noarch::importlib_metadata-1.6.1-0
jinja2	conda-forge/noarch::jinja2-2.11.2-pyh9f0ad1d_0
jsonschema	conda-forge/linux-64::jsonschema-3.2.0-py36h9f0ad1d_1
markupsafe	conda-forge/linux-64::markupsafe-1.1.1-py36h8c4c3a4_1
pandas	conda-forge/linux-64::pandas-1.0.5-py36h830a2c2_0
pyopenssl	conda-forge/noarch::pyopenssl-19.1.0-py_1
pyrsistent	conda-forge/linux-64::pyrsistent-0.16.0-py36h8c4c3a4_0
pysocks	conda-forge/linux-64::pysocks-1.7.1-py36h9f0ad1d_1
pytz	conda-forge/noarch::pytz-2020.1-pyh9f0ad1d_0
requests	conda-forge/noarch::requests-2.24.0-pyh9f0ad1d_0
toolz	conda-forge/noarch::toolz-0.10.0-py_0
urllib3	conda-forge/noarch::urllib3-1.25.9-py_0
vincent	conda-forge/noarch::vincent-0.4.4-py_1

#### Downloading and Extracting Packages

pysocks-1.7.1	27 KB	#####	100%
toolz-0.10.0	46 KB	#####	100%
chardet-3.0.4	188 KB	#####	100%
folium-0.5.0	45 KB	#####	100%
branca-0.4.1	26 KB	#####	100%
cryptography-2.9.2	613 KB	#####	100%
brotlipy-0.7.0	346 KB	#####	100%
altair-4.1.0	614 KB	#####	100%
requests-2.24.0	47 KB	#####	100%
pandas-1.0.5	10.1 MB	#####	100%
vincent-0.4.4	28 KB	#####	100%

Preparing transaction: done

Verifying transaction: done

Executing transaction: done  
package installed

```
[4]: #import libraries
import pandas as pd # library for data analysis
import requests # library to handle requests
import geocoder
import json # library to handle JSON files
from pandas.io.json import json_normalize # transform JSON file into a pandas
↳dataframe
import numpy as np # library to handle data in a vectorized manner
import matplotlib.cm as cm # Matplotlib and associated plotting modules
import matplotlib.colors as colors
from geopy.geocoders import Nominatim # convert an address into latitude and
↳longitude values
from sklearn.cluster import KMeans # import k-means from clustering stage
import folium # map rendering library
```

```
[5]: # Get neighborhood data: 'cod_distrito', 'distrito', 'cod_barrio', 'barrio'

neighbors = pd.read_csv('madrid-distritos-barrios.csv')

#clean dataframe and drop duplicates
neighbors = neighbors.drop(neighbors.columns[[4,5]], axis=1)
neighbors = neighbors.drop_duplicates(subset = ["distrito"])
neighbors = neighbors.astype(str)
neighbors['Code'] = neighbors['cod_distrito'] + neighbors['cod_barrio']
neighbors = neighbors.drop(['cod_distrito', 'cod_barrio'], axis=1)
neighbors.rename(columns={'distrito':'Borough', 'barrio':'Neighborhood'},
↳inplace=True)
neighbors = neighbors[['Code', 'Borough', 'Neighborhood']]
neighbors['Latitude'] = 0.0
neighbors['Longitude'] = 0.0

neighbors
```

```
[5]:
```

	Code	Borough	Neighborhood	Latitude	\
0	111	Centro	Palacio	0.0	
6	221	Arganzuela	Imperial	0.0	
13	331	Retiro	Pacífico	0.0	
19	441	Salamanca	Recoletos	0.0	
25	551	Chamartín	El Viso	0.0	
31	661	Tetuán	Bellas Vistas	0.0	
37	771	Chamberí	Gaztambide	0.0	
43	881	Fuencarral-El Pardo	El Pardo	0.0	
51	991	Moncloa-Aravaca	Casa de Campo	0.0	
58	10101	Latina	Los Cármenes	0.0	

65	11111	Carabanchel	Comillas	0.0
72	12121	Usera	Orcasitas	0.0
79	13131	Puente de Vallecas	Entrevías	0.0
85	14141	Moratalaz	Pavones	0.0
91	15151	Ciudad Lineal	Ventas	0.0
100	16161	Hortaleza	Palomas	0.0
106	17171	Villaverde	Villaverde Alto, C.H. Villaverde	0.0
111	18181	Villa de Vallecas	Casco Histórico de Vallecas	0.0
118	20201	San Blas-Canillejas	Simancas	0.0
126	21211	Barajas	Alameda de Osuna	0.0

	Longitude
0	0.0
6	0.0
13	0.0
19	0.0
25	0.0
31	0.0
37	0.0
43	0.0
51	0.0
58	0.0
65	0.0
72	0.0
79	0.0
85	0.0
91	0.0
100	0.0
106	0.0
111	0.0
118	0.0
126	0.0

```
[6]: # call for arcgis to assess the coordinates for each Neighborhood
for i in range(0, len(neighbors)):
    dir = neighbors.iloc[i,2] + ', ' + neighbors.iloc[i,1] + ', madrid,
    ↪españa' # "Neighborhood, Borough, 'madrid', 'españa'"
    g = geocoder.arcgis(dir)
    neighbors.iloc[i,3] = g.latlng[0]
    neighbors.iloc[i,4] = g.latlng[1]

neighbors
```

[6]:	Code	Borough	Neighborhood	Latitude \
	0	111	Centro	Palacio 40.409630
	6	221	Arganzuela	Imperial 40.400210
	13	331	Retiro	Pacífico 40.401910

19	441	Salamanca	Recoletos	40.429720
25	551	Chamartín	El Viso	40.450000
31	661	Tetuán	Bellas Vistas	40.454570
37	771	Chamberí	Gaztambide	40.434900
43	881	Fuencarral-El Pardo	El Pardo	40.511644
51	991	Moncloa-Aravaca	Casa de Campo	40.435470
58	10101	Latina	Los Cármenes	40.402800
65	11111	Carabanchel	Comillas	40.390940
72	12121	Usera	Orcasitas	40.369850
79	13131	Puente de Vallecas	Entrevías	40.367835
85	14141	Moratalaz	Pavones	40.416670
91	15151	Ciudad Lineal	Ventas	40.453490
100	16161	Hortaleza	Palomas	40.474440
106	17171	Villaverde	Villaverde Alto, C.H. Villaverde	40.350000
111	18181	Villa de Vallecas	Casco Histórico de Vallecas	40.362510
118	20201	San Blas-Canillejas	Simancas	40.443730
126	21211	Barajas	Alameda de Osuna	40.458180

	Longitude
0	-3.879790
6	-3.696180
13	-3.676030
19	-3.679750
25	-3.700000
31	-3.705520
37	-3.715510
43	-3.754898
51	-3.731700
58	-3.731780
65	-3.724200
72	-3.712310
79	-3.664759
85	-3.650000
91	-3.654340
100	-3.641100
106	-3.700000
111	-3.617100
118	-3.609770
126	-3.589530

```
[7]: # Foursquare credentials
CLIENT_ID = 'XZQOBJKCXSL1CH4MYIYXHE20YQYNEM1WFS4ZEBVPSKDQH4J5'
CLIENT_SECRET = '2JM1AYFVJ5XRXWRS4FCPPORPB1XCINKSHUQGKBOIOP0A5KCO'
VERSION = '20180604'
```

```
[8]: # define the venues dataframe
venues_columns = ['Neighborhood',
```

```

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

madrid_venues = pd.DataFrame(columns=venues_columns)

```

```

[9]: # function finding venues for a given location
def getNearbyVenues(names, latitudes, longitudes):
    radius=500
    LIMIT=100
    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print(name)

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

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

        # return only relevant information for each nearby venue
        venues_list.append([
            name,
            lat,
            lng,
            v['venue']['name'],
            v['venue']['location']['lat'],
            v['venue']['location']['lng'],
            v['venue']['categories'][0]['name']) for v in results])

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

```



```

        'Venue Latitude',
        'Venue Longitude',
        'Venue Category']

    return(nearby_venues)

```

```

[11]: # call the function
madrid_venues = getNearbyVenues(names=neighbors['Neighborhood'],
                                latitudes=neighbors['Latitude'],
                                longitudes=neighbors['Longitude'])

madrid_venues

```

```

Palacio
Imperial
Pacífico
Recoletos
El Viso
Bellas Vistas
Gaztambide
El Pardo
Casa de Campo
Los Cármenes
Comillas
Orcasitas
Entrevías
Pavones
Ventas
Palomas
Villaverde Alto, C.H. Villaverde
Casco Histórico de Vallecas
Simancas
Alameda de Osuna

```

```

[11]:
      Neighborhood Neighborhood Latitude Neighborhood Longitude \
0           Palacio           40.40963           -3.87979
1           Palacio           40.40963           -3.87979
2           Palacio           40.40963           -3.87979
3           Palacio           40.40963           -3.87979
4           Palacio           40.40963           -3.87979
..           ...
482 Alameda de Osuna           40.45818           -3.58953
483 Alameda de Osuna           40.45818           -3.58953
484 Alameda de Osuna           40.45818           -3.58953
485 Alameda de Osuna           40.45818           -3.58953
486 Alameda de Osuna           40.45818           -3.58953

```

	Venue	Venue Latitude	Venue Longitude \
0	Proverbium	40.408192	-3.877232
1	The London Walk	40.408197	-3.880682
2	Go!Sushing	40.408424	-3.880492
3	VIPS Boadilla	40.408106	-3.880623
4	El Rincón Del Bierzo	40.409606	-3.880125
..	...	...	...
482	Dia %	40.455036	-3.586630
483	El Kiosko de Pepe	40.454098	-3.589498
484	Hiper Bazar Padre Nuestro	40.455040	-3.585681
485	Gin Terrace Hilton Madrid	40.454964	-3.585670
486	Plaza Del Navio	40.454987	-3.585642
	Venue Category		
0	Italian Restaurant		
1	Irish Pub		
2	Japanese Restaurant		
3	Burger Joint		
4	Mediterranean Restaurant		
..	...		
482	Grocery Store		
483	Bookstore		
484	Shop & Service		
485	Cocktail Bar		
486	Plaza		

[487 rows x 7 columns]

```
[12]: madrid_venues.groupby('Neighborhood').count()
```

```
[12]:
```

Neighborhood	Neighborhood Latitude \
Alameda de Osuna	23
Bellas Vistas	48
Casa de Campo	5
Casco Histórico de Vallecas	3
Comillas	11
El Viso	56
Gaztambide	100
Imperial	51
Los Cármenes	3
Orcasitas	5
Pacífico	52
Palacio	12
Palomas	19
Pavones	3
Recoletos	45

Simancas	11
Ventas	35
Villaverde Alto, C.H. Villaverde	5

Neighborhood	Longitude	Venue \
Alameda de Osuna	23	23
Bellas Vistas	48	48
Casa de Campo	5	5
Casco Histórico de Vallecas	3	3
Comillas	11	11
El Viso	56	56
Gaztambide	100	100
Imperial	51	51
Los Cármenes	3	3
Orcasitas	5	5
Pacífico	52	52
Palacio	12	12
Palomas	19	19
Pavones	3	3
Recoletos	45	45
Simancas	11	11
Ventas	35	35
Villaverde Alto, C.H. Villaverde	5	5

Neighborhood	Venue Latitude	Venue Longitude \
Alameda de Osuna	23	23
Bellas Vistas	48	48
Casa de Campo	5	5
Casco Histórico de Vallecas	3	3
Comillas	11	11
El Viso	56	56
Gaztambide	100	100
Imperial	51	51
Los Cármenes	3	3
Orcasitas	5	5
Pacífico	52	52
Palacio	12	12
Palomas	19	19
Pavones	3	3
Recoletos	45	45
Simancas	11	11
Ventas	35	35
Villaverde Alto, C.H. Villaverde	5	5

Venue Category

Neighborhood	
Alameda de Osuna	23
Bellas Vistas	48
Casa de Campo	5
Casco Histórico de Vallecas	3
Comillas	11
El Viso	56
Gaztambide	100
Imperial	51
Los Cármenes	3
Orcasitas	5
Pacífico	52
Palacio	12
Palomas	19
Pavones	3
Recoletos	45
Simancas	11
Ventas	35
Villaverde Alto, C.H. Villaverde	5

```
[13]: madrid_venues.head()
```

```
[13]:
```

	Neighborhood	Neighborhood	Latitude	Neighborhood	Longitude	\
0	Palacio		40.40963		-3.87979	
1	Palacio		40.40963		-3.87979	
2	Palacio		40.40963		-3.87979	
3	Palacio		40.40963		-3.87979	
4	Palacio		40.40963		-3.87979	

	Venue	Venue	Latitude	Venue	Longitude	\
0	Proverbium		40.408192		-3.877232	
1	The London Walk		40.408197		-3.880682	
2	Go!Sushing		40.408424		-3.880492	
3	VIPS Boadilla		40.408106		-3.880623	
4	El Rincón Del Bierzo		40.409606		-3.880125	

	Venue Category
0	Italian Restaurant
1	Irish Pub
2	Japanese Restaurant
3	Burger Joint
4	Mediterranean Restaurant

```
[14]: madrid_venues.shape
```

```
[14]: (487, 7)
```

```
[15]: madrid_onehot = pd.get_dummies(madrid_venues[['Venue Category']], prefix="",
↳ prefix_sep="")
madrid_onehot
```

```
[15]:
```

	American Restaurant	Arepa Restaurant	Argentinian Restaurant	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	
..	...	...	...	
482	0	0	0	
483	0	0	0	
484	0	0	0	
485	0	0	0	
486	0	0	0	

  

	Art Gallery	Asian Restaurant	Athletics & Sports	BBQ Joint	Bakery	\
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	
..	...	...	...	...	...	
482	0	0	0	0	0	
483	0	0	0	0	0	
484	0	0	0	0	0	
485	0	0	0	0	0	
486	0	0	0	0	0	

  

	Bar	Beer Bar	...	Tea Room	Thai Restaurant	Theater	Toy / Game 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	
..	...	...	...	...	...	...	...	
482	0	0	...	0	0	0	0	
483	0	0	...	0	0	0	0	
484	0	0	...	0	0	0	0	
485	0	0	...	0	0	0	0	
486	0	0	...	0	0	0	0	

  

	Trade School	Train Station	Travel Agency	Wine Shop	Women's Store	\
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
..	...	...	...	...	...
482	0	0	0	0	0
483	0	0	0	0	0
484	0	0	0	0	0
485	0	0	0	0	0
486	0	0	0	0	0

	Yoga Studio
0	0
1	0
2	0
3	0
4	0
..	...
482	0
483	0
484	0
485	0
486	0

[487 rows x 123 columns]

```
[16]: madrid_onehot.insert(loc=0, column='Neighborhood',
    ↪value=madrid_venues['Neighborhood'] )
madrid_onehot.shape
```

[16]: (487, 124)

```
[17]: madrid_onehot
```

```
[17]:
```

	Neighborhood	American Restaurant	Arepa Restaurant	\
0	Palacio	0	0	
1	Palacio	0	0	
2	Palacio	0	0	
3	Palacio	0	0	
4	Palacio	0	0	
..	...	...	...	
482	Alameda de Osuna	0	0	
483	Alameda de Osuna	0	0	
484	Alameda de Osuna	0	0	
485	Alameda de Osuna	0	0	
486	Alameda de Osuna	0	0	

  

	Argentinian Restaurant	Art Gallery	Asian Restaurant	\
0	0	0	0	

1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0
..	...	...	...
482	0	0	0
483	0	0	0
484	0	0	0
485	0	0	0
486	0	0	0

	Athletics & Sports	BBQ Joint	Bakery	Bar	...	Tea Room	\
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	
..	...	...	...	...	...	...	
482	0	0	0	0	...	0	
483	0	0	0	0	...	0	
484	0	0	0	0	...	0	
485	0	0	0	0	...	0	
486	0	0	0	0	...	0	

	Thai Restaurant	Theater	Toy / Game Store	Trade School	Train Station	\
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
..	...	...	...	...	...	...
482	0	0		0	0	0
483	0	0		0	0	0
484	0	0		0	0	0
485	0	0		0	0	0
486	0	0		0	0	0

	Travel Agency	Wine Shop	Women's Store	Yoga Studio
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0
..	...	...	...	...
482	0	0	0	0
483	0	0	0	0
484	0	0	0	0

```
485          0          0          0          0
486          0          0          0          0
```

[487 rows x 124 columns]

```
[18]: madrid_grouped = madrid_onehot.groupby('Neighborhood').mean().reset_index()
      madrid_grouped.head()
```

```
[18]:
```

	Neighborhood	American Restaurant	Arepa Restaurant	\
0	Alameda de Osuna	0.0	0.0	
1	Bellas Vistas	0.0	0.0	
2	Casa de Campo	0.0	0.0	
3	Casco Histórico de Vallecas	0.0	0.0	
4	Comillas	0.0	0.0	

  

	Argentinian Restaurant	Art Gallery	Asian Restaurant	Athletics & Sports	\
0	0.0	0.0	0.0	0.0	
1	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	

  

	BBQ Joint	Bakery	Bar	...	Tea Room	Thai Restaurant	Theater	\
0	0.0	0.043478	0.043478	...	0.0	0.0	0.0	
1	0.0	0.062500	0.083333	...	0.0	0.0	0.0	
2	0.0	0.000000	0.000000	...	0.0	0.0	0.0	
3	0.0	0.333333	0.000000	...	0.0	0.0	0.0	
4	0.0	0.000000	0.000000	...	0.0	0.0	0.0	

  

	Toy / Game Store	Trade School	Train Station	Travel Agency	Wine Shop	\
0	0.000000	0.0	0.0	0.043478	0.0	
1	0.020833	0.0	0.0	0.000000	0.0	
2	0.000000	0.0	0.0	0.000000	0.0	
3	0.000000	0.0	0.0	0.000000	0.0	
4	0.000000	0.0	0.0	0.000000	0.0	

  

	Women's Store	Yoga Studio
0	0.0	0.0
1	0.0	0.0
2	0.0	0.0
3	0.0	0.0
4	0.0	0.0

[5 rows x 124 columns]

```
[19]: # function returning categories for each neighborhood
      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]

```

```

[20]: # get top ten common venues for each Neighborhood
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'] = madrid_grouped['Neighborhood']

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

neighborhoods_venues_sorted.head()

```

```

[20]:

```

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	\
0	Alameda de Osuna	Restaurant	Tapas Restaurant	
1	Bellas Vistas	Spanish Restaurant	Bar	
2	Casa de Campo	Pub	Stadium	
3	Casco Histórico de Vallecas	Pizza Place	Scenic Lookout	
4	Comillas	Coffee Shop	Fast Food Restaurant	

  

	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	\
0	Plaza	Bookstore	Hobby Shop	
1	Grocery Store	Bakery	Supermarket	
2	Spanish Restaurant	Pool	Gym	
3	Bakery	Yoga Studio	Food	
4	Grocery Store	Supermarket	Flea Market	

  

	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	\
0	Fried Chicken Joint	Italian Restaurant	Metro Station	
1	Tapas Restaurant	Pizza Place	Coffee Shop	
2	Grocery Store	Fast Food Restaurant	Convenience Store	
3	Department Store	Dessert Shop	Diner	

	Plaza	Farmers Market	Dumpling Restaurant
	9th Most Common Venue	10th Most Common Venue	
0	Cocktail Bar	Pizza Place	
1	Seafood Restaurant	Farmers Market	
2	Cuban Restaurant	Deli / Bodega	
3	Discount Store	Donut Shop	
4	Falafel Restaurant	Electronics Store	

```
[21]: # Clustering for Neighborhood

# set number of clusters
kclusters = 5

madrid_grouped_clustering = madrid_grouped.drop('Neighborhood', 1)

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

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

```
[21]: array([0, 0, 0, 1, 0, 0, 0, 0, 2, 4], dtype=int32)
```

```
[22]: # add clustering labels
neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

madrid_merged = neighbors
```

```
[23]: # merge madrid_grouped with madrid_data to add latitude/longitude for each
↳neighborhood
madrid_merged = madrid_merged.join(neighborhoods_venues_sorted.
↳set_index('Neighborhood'), on='Neighborhood')

madrid_merged.head()
```

```
[23]:
```

	Code	Borough	Neighborhood	Latitude	Longitude	Cluster Labels	\
0	111	Centro	Palacio	40.40963	-3.87979	0.0	
6	221	Arganzuela	Imperial	40.40021	-3.69618	0.0	
13	331	Retiro	Pacífico	40.40191	-3.67603	0.0	
19	441	Salamanca	Recoletos	40.42972	-3.67975	0.0	
25	551	Chamartín	El Viso	40.45000	-3.70000	0.0	

  

	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	\
0	Spanish Restaurant	Japanese Restaurant	Plaza	
6	Tapas Restaurant	Spanish Restaurant	Bakery	

13	Spanish Restaurant	Bakery	Grocery Store
19	Spanish Restaurant	Restaurant	Boutique
25	Spanish Restaurant	Pizza Place	Bakery

  

4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	\
0 Gym / Fitness Center	Pool	Restaurant	
6 Restaurant	Grocery Store	Chinese Restaurant	
13 Bar	Pizza Place	Restaurant	
19 Tapas Restaurant	Mediterranean Restaurant	Coffee Shop	
25 Japanese Restaurant	Restaurant	Tapas Restaurant	

  

7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	\
0 Shopping Mall	Burger Joint	Mediterranean Restaurant	
6 Falafel Restaurant	Arepa Restaurant	Gym / Fitness Center	
13 Tapas Restaurant	Food & Drink Shop	Athletics & Sports	
19 Mexican Restaurant	Bakery	Lounge	
25 Thai Restaurant	Plaza	Park	

  

10th Most Common Venue
0 Department Store
6 Beer Garden
13 Asian Restaurant
19 Spa
25 Coffee Shop

```
[24]: neighborhoods_venues_sorted.head()
```

Cluster Labels	Neighborhood	1st Most Common Venue	\
0	0 Alameda de Osuna	Restaurant	
1	0 Bellas Vistas	Spanish Restaurant	
2	0 Casa de Campo	Pub	
3	1 Casco Histórico de Vallecas	Pizza Place	
4	0 Comillas	Coffee Shop	

  

2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	\
0 Tapas Restaurant	Plaza	Bookstore	
1 Bar	Grocery Store	Bakery	
2 Stadium	Spanish Restaurant	Pool	
3 Scenic Lookout	Bakery	Yoga Studio	
4 Fast Food Restaurant	Grocery Store	Supermarket	

  

5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	\
0 Hobby Shop	Fried Chicken Joint	Italian Restaurant	
1 Supermarket	Tapas Restaurant	Pizza Place	
2 Gym	Grocery Store	Fast Food Restaurant	
3 Food	Department Store	Dessert Shop	
4 Flea Market	Plaza	Farmers Market	

	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Metro Station	Cocktail Bar	Pizza Place
1	Coffee Shop	Seafood Restaurant	Farmers Market
2	Convenience Store	Cuban Restaurant	Deli / Bodega
3	Diner	Discount Store	Donut Shop
4	Dumpling Restaurant	Falafel Restaurant	Electronics Store

```
[25]: #searching location for 'madrid, españa'

address = 'madrid, españa'

geolocator = Nominatim(user_agent="mad_explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print('The geograpical coordinate of Madrid are {}, {}'.format(latitude,
↪longitude))
```

The geograpical coordinate of Madrid are 40.4167047, -3.7035825.

```
[26]: # Map with clusters for 'Madrid, España'
map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)
```

```
[27]: # 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]
```

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

```
[29]: map_clusters
```

[29]: <folium.folium.Map at 0x7f3af3215b38>