

# LADATA

May 29, 2020

## 0.0.1 Introduction

In this project we will use the geospatial information of Los Angeles. The idea is to use the data to make suggestions regarding which districts are more suitable for opening a new restaurant. We will identify which districts have less restaurants than the rest, cluster them and make an appropriate suggestion. The foursquare database will be used to retrieve information for all the neighborhoods in our dataset. This step will be crucial when deciding to commence such an expensive procedure, like starting a new business. The same approach could be used to identify regions that are more suitable for opening new cafes. Of course this is a simplified scenario. To address the question at each core, we should also take into account other factors, such as the average income in each neighborhood, the criminality levels, the average age of the citizens etc.. Obtaining this information for this project would be very hard to achieve, so we will restrict our analysis on the data we can retrieve from foursquare.

## 0.0.2 The dataset

The data for this study have been retrieved from:  
<https://usc.data.socrata.com/dataset/Los-Angeles-Neighborhood-Map/r8qd-yxsr>.

Let's first explore our data and plot a map of Los Angeles, highlighting with blue dots the neighborhoods of our dataset.

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

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

import json # library to handle JSON files

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

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

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

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

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

print('Libraries imported.')

```

Libraries imported.

```

[2]: with open('/home/christos/Downloads/LosAngelesNeighborhoodMap.geojson') as
↳ json_data:
    la_data = json.load(json_data)

```

```

[3]: neighborhoods_data = la_data['features']

```

```

[4]: neighborhoods_data[0]

```

```

[4]: {'type': 'Feature',
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```

```

[5]: column_names = ['City', 'Neighborhood', 'Latitude', 'Longitude']

# instantiate the dataframe
neighborhoods = pd.DataFrame(columns=column_names)

for data in neighborhoods_data:
    neighborhood_name = data['properties']['name']
    neighborhood_lon = data['properties']['latitude']
    neighborhood_lat = data['properties']['longitude']

    neighborhoods = neighborhoods.append({'City': 'L.A.',
                                          'Neighborhood': neighborhood_name,
                                          'Latitude': neighborhood_lat,
                                          'Longitude': neighborhood_lon},
                                          ignore_index=True)

```

```

[6]: neighborhoods.sort_values('Neighborhood')

```

[6]:	City	Neighborhood	Latitude \
0	L.A.	Acton	34.497355239240846
1	L.A.	Adams-Normandie	34.031461499124156
2	L.A.	Agoura Hills	34.146736499122795
3	L.A.	Agua Dulce	34.504926999796837
4	L.A.	Alhambra	34.085538999123571
5	L.A.	Alondra Park	33.889617004889644
7	L.A.	Altadena	34.193870502232173
8	L.A.	Angeles Crest	34.313937005895312
9	L.A.	Arcadia	34.133229999123017
10	L.A.	Arleta	34.243099999121583
11	L.A.	Arlington Heights	34.04491049912405
6	L.A.	Artesia	33.866895999126271
12	L.A.	Athens	33.9236925059352
13	L.A.	Atwater Village	34.131066356759177
14	L.A.	Avalon	33.336954499133086
15	L.A.	Avocado Heights	34.040881003821966
16	L.A.	Azusa	34.13746999912302
18	L.A.	Baldwin Hills/Crenshaw	34.01197027055953
19	L.A.	Baldwin Park	34.081109499123691
20	L.A.	Bel-Air	34.102056999123342
24	L.A.	Bell	33.981160999124889
22	L.A.	Bell Gardens	33.965685999125014
21	L.A.	Bellflower	33.88801349912606
25	L.A.	Beverly Crest	34.106006999123245
26	L.A.	Beverly Grove	34.076632999123618
29	L.A.	Beverly Hills	34.082544499123699
30	L.A.	Beverlywood	34.043509999124048
31	L.A.	Boyle Heights	34.039168499124116
32	L.A.	Bradbury	34.15423999912273
33	L.A.	Brentwood	34.086240999123547
34	L.A.	Broadway-Manchester	33.941223502886629
27	L.A.	Burbank	34.182010499122441
35	L.A.	Calabasas	34.136254499122948
36	L.A.	Canoga Park	34.210854999122013
37	L.A.	Carson	33.839519999126665
38	L.A.	Carthay	34.057855624951706
41	L.A.	Castaic	34.481749770319936
39	L.A.	Castaic Canyons	34.564146288577305
42	L.A.	Central-Alameda	34.006864031207506
43	L.A.	Century City	34.055325502171065
44	L.A.	Cerritos	33.86689249912628
45	L.A.	Charter Oak	34.100075003109005
40	L.A.	Chatsworth	34.256403499160569
46	L.A.	Chatsworth Reservoir	34.233072499121761
47	L.A.	Chesterfield Square	33.983762999124849
48	L.A.	Cheviot Hills	34.04085349912404

49	L.A.	Chinatown	34.063510499123652
50	L.A.	Citrus	34.11618000242531
51	L.A.	Claremont	34.122365138512784
53	L.A.	Commerce	33.995079230018334
54	L.A.	Compton	33.893251999125937
57	L.A.	Covina	34.087495499309327
58	L.A.	Cudahy	33.962620499125038
59	L.A.	Culver City	34.005899499124581
55	L.A.	Cypress Park	34.092139499123448
60	L.A.	Del Aire	33.915552004076844
61	L.A.	Del Rey	33.989292192016777
62	L.A.	Desert View Highlands	34.590877152916832
63	L.A.	Diamond Bar	34.000640999124634
64	L.A.	Downey	33.937676999125415
65	L.A.	Downtown	34.040008613525899
66	L.A.	Duarte	34.157855499122689
67	L.A.	Eagle Rock	34.133916999122917
68	L.A.	East Compton	33.894016822529835
69	L.A.	East Hollywood	34.089109499123481
70	L.A.	East La Mirada	33.924510501549975
72	L.A.	East Los Angeles	34.035168709861011
73	L.A.	East Pasadena	34.138563505391282
74	L.A.	East San Gabriel	34.110644492315856
75	L.A.	Echo Park	34.079533999123683
76	L.A.	El Monte	34.071169499123791
77	L.A.	El Segundo	33.916582999125737
78	L.A.	El Sereno	34.082242183204471
71	L.A.	Elizabeth Lake	34.657686037373047
79	L.A.	Elysian Park	34.081259999123489
80	L.A.	Elysian Valley	34.095759499123389
82	L.A.	Encino	34.1562244991227
83	L.A.	Exposition Park	34.018262499124305
84	L.A.	Fairfax	34.07893599912363
86	L.A.	Florence	33.974564000774492
85	L.A.	Florence-Firestone	33.966101520272787
87	L.A.	Gardena	33.891005999125994
88	L.A.	Glassell Park	34.114405499123208
91	L.A.	Glendale	34.192975499122355
92	L.A.	Glendora	34.142040999122969
93	L.A.	Gramercy Park	33.949062001923494
94	L.A.	Granada Hills	34.295682651151957
89	L.A.	Green Meadows	33.941634094823527
23	L.A.	Green Valley	34.620007457495149
95	L.A.	Griffith Park	34.136873999122869
96	L.A.	Hacienda Heights	34.002085506418773
97	L.A.	Hancock Park	34.072759499123613
98	L.A.	Hansen Dam	34.265706499121308

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101	L.A.	Harvard Heights	34.045060999124097
102	L.A.	Harvard Park	33.983762999124835
104	L.A.	Hasley Canyon	34.476199893867175
105	L.A.	Hawaiian Gardens	33.830603999126708
106	L.A.	Hawthorne	33.914028000717863
107	L.A.	Hermosa Beach	33.864771287924583
108	L.A.	Hidden Hills	34.16405683610931
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112	L.A.	Hollywood Hills	34.128088999122937
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115	L.A.	Huntington Park	33.978967499124934
116	L.A.	Hyde Park	33.985430999124816
120	L.A.	Industry	34.026835568749277
117	L.A.	Inglewood	33.954067500238899
118	L.A.	Irwindale	34.108874499123317
119	L.A.	Jefferson Park	34.028211499124154
28	L.A.	Koreatown	34.064510499123763
121	L.A.	La Canada Flintridge	34.210686999122075
122	L.A.	La Crescenta-Montrose	34.228709003122127
125	L.A.	La Habra Heights	33.96095113872326
56	L.A.	La Mirada	33.900793500197707
132	L.A.	La Puente	34.03313649750627
135	L.A.	La Verne	34.124883999123185
123	L.A.	Ladera Heights	33.996097001972416
126	L.A.	Lake Balboa	34.203703499122071
127	L.A.	Lake Hughes	34.671409020850533
128	L.A.	Lake Los Angeles	34.611038948416571
129	L.A.	Lake View Terrace	34.28376149912124
130	L.A.	Lakewood	33.844692999126622
131	L.A.	Lancaster	34.700066117404532
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139	L.A.	Leona Valley	34.612528398823727
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143	L.A.	Long Beach	33.806580699978731
144	L.A.	Lopez/Kagel Canyons	34.300821499121156
145	L.A.	Los Feliz	34.10785849912326
146	L.A.	Lynwood	33.925213499125533
147	L.A.	Malibu	34.033895486545326

148	L.A.	Manchester Square	33.967165274809105
149	L.A.	Manhattan Beach	33.88950799912606
109	L.A.	Mar Vista	34.010242173076293
150	L.A.	Marina del Rey	33.975323504268417
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152	L.A.	Maywood	33.988338999124778
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154	L.A.	Mid-Wilshire	34.059609499123724
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159	L.A.	Montebello	34.010314998189017
160	L.A.	Montecito Heights	34.093658999123406
156	L.A.	Monterey Park	34.049427999124063
161	L.A.	Mount Washington	34.103158999123266
163	L.A.	North El Monte	34.102483231361113
164	L.A.	North Hills	34.238702499121729
165	L.A.	North Hollywood	34.177938499122348
168	L.A.	North Whittier	34.005714844032383
162	L.A.	Northeast Antelope Valley	34.637564309448457
52	L.A.	Northridge	34.238805499121611
166	L.A.	Northwest Antelope Valley	34.725569331170881
167	L.A.	Northwest Palmdale	34.625608953797482
169	L.A.	Norwalk	33.907168999125822
170	L.A.	Pacific Palisades	34.078366733694963
171	L.A.	Pacoima	34.26360659127154
174	L.A.	Palmdale	34.585421999117628
175	L.A.	Palms	34.024597526725373
172	L.A.	Palos Verdes Estates	33.783316814743465
173	L.A.	Panorama City	34.229502999121699
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178	L.A.	Pico Rivera	33.989604499124823
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180	L.A.	Pico-Union	34.044161499124009
124	L.A.	Playa Vista	33.976925499124803
181	L.A.	Playa del Rey	33.945661530783255
183	L.A.	Pomona	34.065723499123862
184	L.A.	Porter Ranch	34.278216499201754
185	L.A.	Quartz Hill	34.654878150335279
187	L.A.	Ramona	34.060567999123897
188	L.A.	Rancho Dominguez	33.859875999126409
191	L.A.	Rancho Palos Verdes	33.75869892565828
192	L.A.	Rancho Park	34.034314999124099
186	L.A.	Redondo Beach	33.854633999126435
189	L.A.	Reseda	34.203603499122082
193	L.A.	Ridge Route	34.649657898094503
194	L.A.	Rolling Hills	33.762682999127549



190	L.A.	Rolling Hills Estates	33.776429999127444
195	L.A.	Rosemead	34.064645999123826
196	L.A.	Rowland Heights	33.973574999125063
198	L.A.	San Dimas	34.115259499123212
199	L.A.	San Fernando	34.288998499121206
202	L.A.	San Gabriel	34.093215999123494
203	L.A.	San Marino	34.121299999123188
204	L.A.	San Pasqual	34.139387218224641
206	L.A.	San Pedro	33.743377490636142
208	L.A.	Santa Clarita	34.408855499147847
197	L.A.	Santa Fe Springs	33.928934999496654
200	L.A.	Santa Monica	34.021860499124415
201	L.A.	Sawtelle	34.03506728275898
205	L.A.	Sepulveda Basin	34.17460099912239
209	L.A.	Shadow Hills	34.239428499121757
210	L.A.	Sherman Oaks	34.149005499122715
211	L.A.	Sierra Madre	34.168112999122641
212	L.A.	Signal Hill	33.804375999127039
213	L.A.	Silver Lake	34.094459499123445
214	L.A.	South Diamond Bar	33.960748576953293
216	L.A.	South El Monte	34.048729098531766
217	L.A.	South Gate	33.938158499185079
218	L.A.	South Park	33.996463999124586
219	L.A.	South Pasadena	34.11216899912327
220	L.A.	South San Gabriel	34.066492621729282
221	L.A.	South San Jose Hills	34.014947000828826
222	L.A.	South Whittier	33.936196000947831
215	L.A.	Southeast Antelope Valley	34.466085813776999
224	L.A.	Stevenson Ranch	34.394100486490998
225	L.A.	Studio City	34.137891999122886
227	L.A.	Sun Valley	34.22661749912173
207	L.A.	Sun Village	34.557696692382351
226	L.A.	Sunland	34.270730999121341
223	L.A.	Sylmar	34.308403858579155
228	L.A.	Tarzana	34.156454999122722
229	L.A.	Temple City	34.103177499123404
230	L.A.	Toluca Lake	34.15349309467193
231	L.A.	Topanga	34.092639152756504
233	L.A.	Torrance	33.833638999126677
235	L.A.	Tujunga	34.261340090064621
234	L.A.	Tujunga Canyons	34.36770541756718
236	L.A.	Unincorporated Catalina Island	33.388602475414189
241	L.A.	Unincorporated Santa Monica Mountains	34.087645747469352
245	L.A.	Unincorporated Santa Susana Mountains	34.361843886571933
232	L.A.	Universal City	34.137361499122974
237	L.A.	University Park	34.028113999124287
242	L.A.	Val Verde	34.44560168460962

238	L.A.	Valinda	34.038452502168049
239	L.A.	Valley Glen	34.189504499122229
240	L.A.	Valley Village	34.163355999122615
243	L.A.	Van Nuys	34.196505499122246
244	L.A.	Venice	33.986273217151727
246	L.A.	Vermont Knolls	33.967009999124997
81	L.A.	Vermont Square	34.002062999124533
90	L.A.	Vermont Vista	33.941708042365043
17	L.A.	Vermont-Slauson	33.983913999124709
247	L.A.	Vernon	33.999657999124722
248	L.A.	Veterans Administration	34.057383999123985
249	L.A.	View Park-Windsor Hills	33.995646003043063
250	L.A.	Vincent	34.09951050296921
251	L.A.	Walnut	34.033247999124256
103	L.A.	Walnut Park	33.966981503722153
134	L.A.	Watts	33.941619001308609
157	L.A.	West Adams	34.02886149912419
176	L.A.	West Carson	33.822072500607462
253	L.A.	West Compton	33.894136502499222
254	L.A.	West Covina	34.047182499124105
255	L.A.	West Hills	34.207253636931036
256	L.A.	West Hollywood	34.08721323709856
259	L.A.	West Los Angeles	34.047220499123917
261	L.A.	West Puente Valley	34.049860493908568
262	L.A.	West San Dimas	34.087431659884331
263	L.A.	West Whittier-Los Nietos	33.980559999939608
252	L.A.	Westchester	33.95599525987285
257	L.A.	Westlake	34.062360999123754
258	L.A.	Westlake Village	34.139191499123029
260	L.A.	Westmont	33.945207502436951
264	L.A.	Westwood	34.06523499912381
265	L.A.	Whittier	33.979441000624007
266	L.A.	Whittier Narrows	34.037074109844369
267	L.A.	Willowbrook	33.915710503828592
268	L.A.	Wilmington	33.79129350128175
269	L.A.	Windsor Square	34.069108499123722
270	L.A.	Winnetka	34.210459499121988
271	L.A.	Woodland Hills	34.159408692550485

#### Longitude

0	-118.16981019229348
1	-118.30020800000011
2	-118.75988450000015
3	-118.3171036690717
4	-118.13651200000021
5	-118.33515598608159
7	-118.13623898201556

8 -117.9223952817848  
9 -118.03041899311202  
10 -118.4307575  
11 -118.3234085  
6 -118.08010100000017  
12 -118.30465647554277  
13 -118.26237347966236  
14 -118.32733223477572  
15 -118.0012614768012  
16 -117.91246849999999  
18 -118.35774600000005  
19 -117.97519050000002  
20 -118.45841550000007  
24 -118.17916600000018  
22 -118.14993600000002  
21 -118.12903150000017  
25 -118.42326299999999  
26 -118.376102  
29 -118.39953400000016  
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31 -118.21078750000007  
32 -117.96857400000013  
33 -118.49218850000007  
34 -118.27535153247453  
27 -118.32521100000017  
35 -118.67163173539396  
36 -118.60151949999999  
37 -118.24800950000022  
38 -118.36891  
41 -118.63334936248927  
39 -118.45476897959236  
42 -118.24721250000012  
43 -118.41508300000005  
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50 -117.89216399278311  
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53 -118.15736250000002  
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58 -118.18557250000019  
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63 -117.81573066877161  
64 -118.13042300000015  
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66 -117.95762350000011  
67 -118.20484450000001  
68 -118.19598900000028  
69 -118.2968085  
70 -117.9907619882008  
72 -118.1596383526979  
73 -118.08087798337868  
74 -118.07396450000032  
75 -118.2590075  
76 -118.03519600000016  
77 -118.40223073369825  
78 -118.1762975  
71 -118.38621116359349  
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80 -118.24195650000013  
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83 -118.29887550000007  
84 -118.35285800000005  
86 -118.26860650000008  
85 -118.24192048907494  
87 -118.30862700000014  
88 -118.23642729889393  
91 -118.24492700000002  
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93 -118.30898400000005  
94 -118.50767050010745  
89 -118.26148999301319  
23 -118.41421658346756  
95 -118.29715634932774  
96 -117.97508050764819  
97 -118.3350095  
98 -118.37905350000011  
99 -118.29516400000006  
100 -118.29530900000007  
101 -118.307658  
102 -118.30455750000012  
104 -118.66021608592953  
105 -118.07219200000006  
106 -118.34605599620926  
107 -118.39714183223805

108 -118.65705600000015  
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111 -118.26585700000012  
114 -118.33555159977072  
112 -118.33541000000008  
113 -118.37025800000006  
115 -118.2140149952952  
116 -118.33775850000006  
120 -117.93962100000014  
117 -118.34611749302944  
118 -117.96667800000012  
119 -118.32205850000005  
28 -118.3049585  
121 -118.20046998596307  
122 -118.23518197192418  
125 -117.95562783562224  
56 -118.00722099646512  
132 -117.95309349690484  
135 -117.7745250000001  
123 -118.37410748609757  
126 -118.50446700000006  
127 -118.45933374872043  
128 -117.83603921804665  
129 -118.3618685  
130 -118.11305100000018  
131 -118.13179100000016  
133 -118.317809  
136 -118.3564764903399  
137 -118.32633970815459  
138 -118.35714748618386  
139 -118.29122197531558  
140 -118.2103055  
141 -117.97827605507007  
142 -118.31796600000017  
143 -118.156064  
144 -118.38555850000017  
145 -118.2884085  
146 -118.20282648482208  
147 -118.7542537868066  
148 -118.30898400000005  
149 -118.40093919800572  
109 -118.43668192517818  
150 -118.44786948141424  
151 -118.00229999282959  
152 -118.18730300000013  
153 -118.35880950000006  
154 -118.3431095

155 -118.45716250000007  
158 -117.98179100000009  
159 -118.10833743364199  
160 -118.19427049999999  
156 -118.13161942411986  
161 -118.21900650000001  
163 -118.02354298857939  
164 -118.47711700000006  
165 -118.37966349999999  
168 -118.02918914224676  
162 -117.91515082345049  
52 -118.52796900000007  
166 -118.42772667494613  
167 -118.17887478361382  
169 -118.07693800000014  
170 -118.54585899824386  
171 -118.41890850000007  
174 -118.10809351531806  
175 -118.40902995476588  
172 -118.39012200169401  
173 -118.44521550000007  
177 -118.16539050000017  
182 -118.13180900000009  
178 -118.08161950000004  
179 -118.39132550000005  
180 -118.28470750000005  
124 -118.41364800000007  
181 -118.44133951162496  
183 -117.7699420000001  
184 -118.54872950000006  
185 -118.21863657473801  
187 -117.83843450000029  
188 -118.21829150000025  
191 -118.35980750108605  
192 -118.42312500000006  
186 -118.37710100127826  
189 -118.540368  
193 -118.70332725511963  
194 -118.34812650000021  
190 -118.35453350000017  
195 -118.08187550000011  
196 -117.89399129564529  
198 -117.81326850000013  
199 -118.43598850000011  
202 -118.09900700000023  
203 -118.11505449283317  
204 -118.10297194101678

206 -118.28508539395716  
 208 -118.49476193960714  
 197 -118.06368000000016  
 200 -118.48056671004807  
 201 -118.45059109758868  
 205 -118.49231650000006  
 209 -118.32881067473647  
 210 -118.441514  
 211 -118.04883650000005  
 212 -118.16716650000018  
 213 -118.2677075  
 214 -117.82609234720164  
 216 -118.04853200000019  
 217 -118.19381199294568  
 218 -118.26875699999999  
 219 -118.15623650000006  
 220 -118.08974290054033  
 221 -117.90184498555011  
 222 -118.0280174858583  
 215 -117.92981254313324  
 224 -118.58387954676732  
 225 -118.38747919966544  
 227 -118.3843172128845  
 207 -117.95659832063463  
 226 -118.31202250000007  
 223 -118.45205006616247  
 228 -118.54458900000007  
 229 -118.05489926123286  
 230 -118.35795100000007  
 231 -118.60842021657524  
 233 -118.35171088115038  
 235 -118.2818  
 234 -118.28843919025437  
 236 -118.45466051366508  
 241 -118.77026791367985  
 245 -118.61680047572341  
 232 -118.35278600000026  
 237 -118.28280750000005  
 242 -118.6656538804971  
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 239 -118.4145170000001  
 240 -118.39620200000005  
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 244 -118.46284569710343  
 246 -118.29050700000013  
 81 -118.29880750000001  
 90 -118.28545100000014

```

17 -118.29035750000011
247 -118.20343200000011
248 -118.45725850000031
249 -118.34855947912703
250 -117.9247939857519
251 -117.86012600000016
103 -118.22051147887569
134 -118.2399365
157 -118.35517858045984
176 -118.29227748370761
253 -118.26773698606382
254 -117.91269950000019
255 -118.63539850000006
256 -118.36961300000019
259 -118.4307445
261 -117.96992450000026
262 -117.83509899236435
263 -118.07001998587738
252 -118.39829259016352
257 -118.27222100000006
258 -118.82291200000014
260 -118.30463897559736
264 -118.44047994677246
265 -118.01891099569201
266 -118.06118827749373
267 -118.25231247908229
268 -118.25918700000008
269 -118.31990900000005
270 -118.57521950000014
271 -118.61521650000006

```

```

[7]: address = 'Los Angeles'

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

```

The geograpical coordinate of L.A are 34.0536909, -118.2427666.

```

[8]: map_la = folium.Map(location=[latitude, longitude], zoom_start=10)

# add markers to map
for lat, lng, label in zip(neighborhoods['Latitude'],
↪neighborhoods['Longitude'], neighborhood['Neighborhood']):

```



```

label = folium.Popup(label, parse_html=True)
folium.CircleMarker(
    [lat, lng],
    radius=5,
    popup=label,
    color='blue',
    fill=True,
    fill_color='#3186cc',
    fill_opacity=0.9,
    parse_html=False).add_to(map_la)

map_la

```

[8]: <folium.folium.Map at 0x7f5093ef9790>

### 0.0.3 Methodology

We are going to explore our data in order to reveal neighborhoods that are good targets for opening a new restaurant. We will identify which neighborhood have the least restaurants and make suggestions based on this observation. First, we can using basic plotting strategies, such as barplots, to compare the total number of restaurants in each neighborhoods, taking into account neighborhhods that have at least one restaurant. Next we will repeat the analysis taking into account all the available neighborhhods.

Since we are interested in the total number number of restaurants in each neighborhood and not on the type of the restaurant, we will have to modify the data reveived from foursquare. Foursquare originally returns the number of restaurants in each neighborhood, base on the type of the restaurant, i.e. Italian, Greek, Mexican etc. We will have to group our dataset based on the neighborhood name and estimate how many restaurants there are in total. This will also give us neighborhoods that do not have any restaurants (adding new information to the previous barplot).

Finally we are going to use the k-means clustering approach to make clusters of neighborhoods based on the venue information we have. Notice that we added a new venue that sums all the restaurants. You will notice that the map is not cleasr to make a proper decision. For this reason we are using a barplot to identify which labels correspond to neighborhoods with few or no restaurants. We can then suggest the appropriate neighborhoods based on this observation.

#### 0.0.4 Analysis and results

```
[9]: #time to use fousquare
CLIENT_ID = 'W3ZU1DV2Y5S1IAA1YLB4IZNNXCQC4J4GTF1ON4DIVXUNJIV' # your
↳Foursquare ID
CLIENT_SECRET = 'FZB1RRL11JRXWRDHDDBHZSNSXQU4QPKLFFZ5LB4QFZUJII20' # your
↳Foursquare Secret
VERSION = '20180605' # Foursquare API versionb
```

```
[10]: #explore neighborhoods in Toronto

def getNearbyVenues(names, latitudes, longitudes,LIMIT=100, radius=500):

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

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

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

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

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

```

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

    return(nearby_venues)

```

```

[11]: la_venues = getNearbyVenues(names=neighborhoods['Neighborhood'],
                                   latitudes=neighborhoods['Latitude'],
                                   longitudes=neighborhoods['Longitude']
                                   )

```

```

Acton
Adams-Normandie
Agoura Hills
Agua Dulce
Alhambra
Alondra Park
Artesia
Altadena
Angeles Crest
Arcadia
Arleta
Arlington Heights
Athens
Atwater Village
Avalon
Avocado Heights
Azusa
Vermont-Slauson
Baldwin Hills/Crenshaw
Baldwin Park
Bel-Air
Bellflower
Bell Gardens
Green Valley
Bell
Beverly Crest
Beverly Grove
Burbank
Koreatown
Beverly Hills
Beverlywood
Boyle Heights
Bradbury
Brentwood
Broadway-Manchester

```

Calabasas  
Canoga Park  
Carson  
Carthay  
Castaic Canyons  
Chatsworth  
Castaic  
Central-Alameda  
Century City  
Cerritos  
Charter Oak  
Chatsworth Reservoir  
Chesterfield Square  
Cheviot Hills  
Chinatown  
Citrus  
Claremont  
Northridge  
Commerce  
Compton  
Cypress Park  
La Mirada  
Covina  
Cudahy  
Culver City  
Del Aire  
Del Rey  
Desert View Highlands  
Diamond Bar  
Downey  
Downtown  
Duarte  
Eagle Rock  
East Compton  
East Hollywood  
East La Mirada  
Elizabeth Lake  
East Los Angeles  
East Pasadena  
East San Gabriel  
Echo Park  
El Monte  
El Segundo  
El Sereno  
Elysian Park  
Elysian Valley  
Vermont Square  
Encino

Exposition Park  
Fairfax  
Florence-Firestone  
Florence  
Gardena  
Glassell Park  
Green Meadows  
Vermont Vista  
Glendale  
Glendora  
Gramercy Park  
Granada Hills  
Griffith Park  
Hacienda Heights  
Hancock Park  
Hansen Dam  
Harbor City  
Harbor Gateway  
Harvard Heights  
Harvard Park  
Walnut Park  
Hasley Canyon  
Hawaiian Gardens  
Hawthorne  
Hermosa Beach  
Hidden Hills  
Mar Vista  
Highland Park  
Historic South-Central  
Hollywood Hills  
Hollywood Hills West  
Hollywood  
Huntington Park  
Hyde Park  
Inglewood  
Irwindale  
Jefferson Park  
Industry  
La Canada Flintridge  
La Crescenta-Montrose  
Ladera Heights  
Playa Vista  
La Habra Heights  
Lake Balboa  
Lake Hughes  
Lake Los Angeles  
Lake View Terrace  
Lakewood

Lancaster  
La Puente  
Larchmont  
Watts  
La Verne  
Lawndale  
Leimert Park  
Lennox  
Leona Valley  
Lincoln Heights  
Littlerock  
Lomita  
Long Beach  
Lopez/Kagel Canyons  
Los Feliz  
Lynwood  
Malibu  
Manchester Square  
Manhattan Beach  
Marina del Rey  
Mayflower Village  
Maywood  
Mid-City  
Mid-Wilshire  
Mission Hills  
Monterey Park  
West Adams  
Monrovia  
Montebello  
Montecito Heights  
Mount Washington  
Northeast Antelope Valley  
North El Monte  
North Hills  
North Hollywood  
Northwest Antelope Valley  
Northwest Palmdale  
North Whittier  
Norwalk  
Pacific Palisades  
Pacoima  
Palos Verdes Estates  
Panorama City  
Palmdale  
Palms  
West Carson  
Paramount  
Pico Rivera

Pico-Robertson  
Pico-Union  
Playa del Rey  
Pasadena  
Pomona  
Porter Ranch  
Quartz Hill  
Redondo Beach  
Ramona  
Rancho Dominguez  
Reseda  
Rolling Hills Estates  
Rancho Palos Verdes  
Rancho Park  
Ridge Route  
Rolling Hills  
Rosemead  
Rowland Heights  
Santa Fe Springs  
San Dimas  
San Fernando  
Santa Monica  
Sawtelle  
San Gabriel  
San Marino  
San Pasqual  
Sepulveda Basin  
San Pedro  
Sun Village  
Santa Clarita  
Shadow Hills  
Sherman Oaks  
Sierra Madre  
Signal Hill  
Silver Lake  
South Diamond Bar  
Southeast Antelope Valley  
South El Monte  
South Gate  
South Park  
South Pasadena  
South San Gabriel  
South San Jose Hills  
South Whittier  
Sylmar  
Stevenson Ranch  
Studio City  
Sunland

Sun Valley  
Tarzana  
Temple City  
Toluca Lake  
Topanga  
Universal City  
Torrance  
Tujunga Canyons  
Tujunga  
Unincorporated Catalina Island  
University Park  
Valinda  
Valley Glen  
Valley Village  
Unincorporated Santa Monica Mountains  
Val Verde  
Van Nuys  
Venice  
Unincorporated Santa Susana Mountains  
Vermont Knolls  
Vernon  
Veterans Administration  
View Park-Windsor Hills  
Vincent  
Walnut  
Westchester  
West Compton  
West Covina  
West Hills  
West Hollywood  
Westlake  
Westlake Village  
West Los Angeles  
Westmont  
West Puente Valley  
West San Dimas  
West Whittier-Los Nietos  
Westwood  
Whittier  
Whittier Narrows  
Willowbrook  
Wilmington  
Windsor Square  
Winnetka  
Woodland Hills

[ ]:



```
[13]: ##keep only restaurants
la_venues_forfood=la_venues[la_venues['Venue Category'].str.
    ↪contains("Restaurant")].reset_index(drop=True)
```

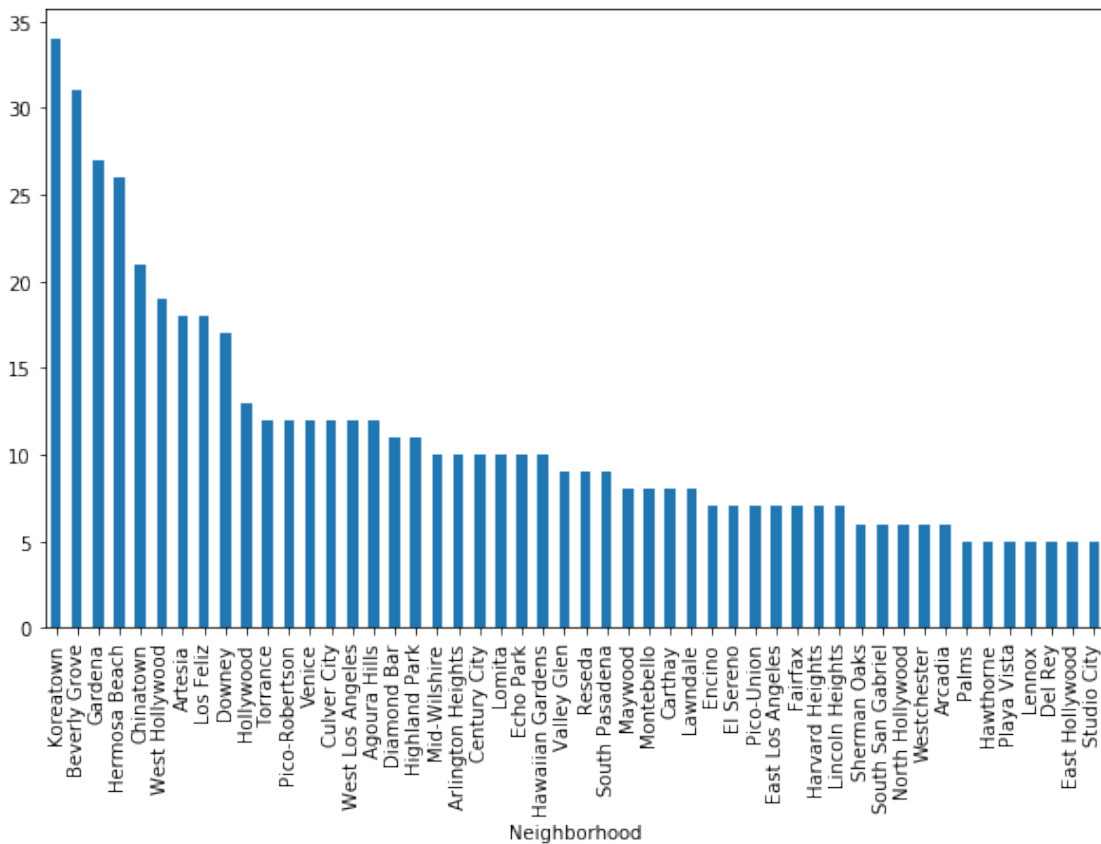
```
[ ]:
```

```
[153]: #take total number of restaurants in each neighborhood
#doing this we ignore neighborhoods with no restaurants
```

```
[228]: #plot the top 50 neighborhoods with the most restaurants

la_venues_forfood.groupby('Neighborhood').count()['Venue Category'].
    ↪sort_values(ascending=False).head(50).plot(kind='bar', figsize=(10, 6))
```

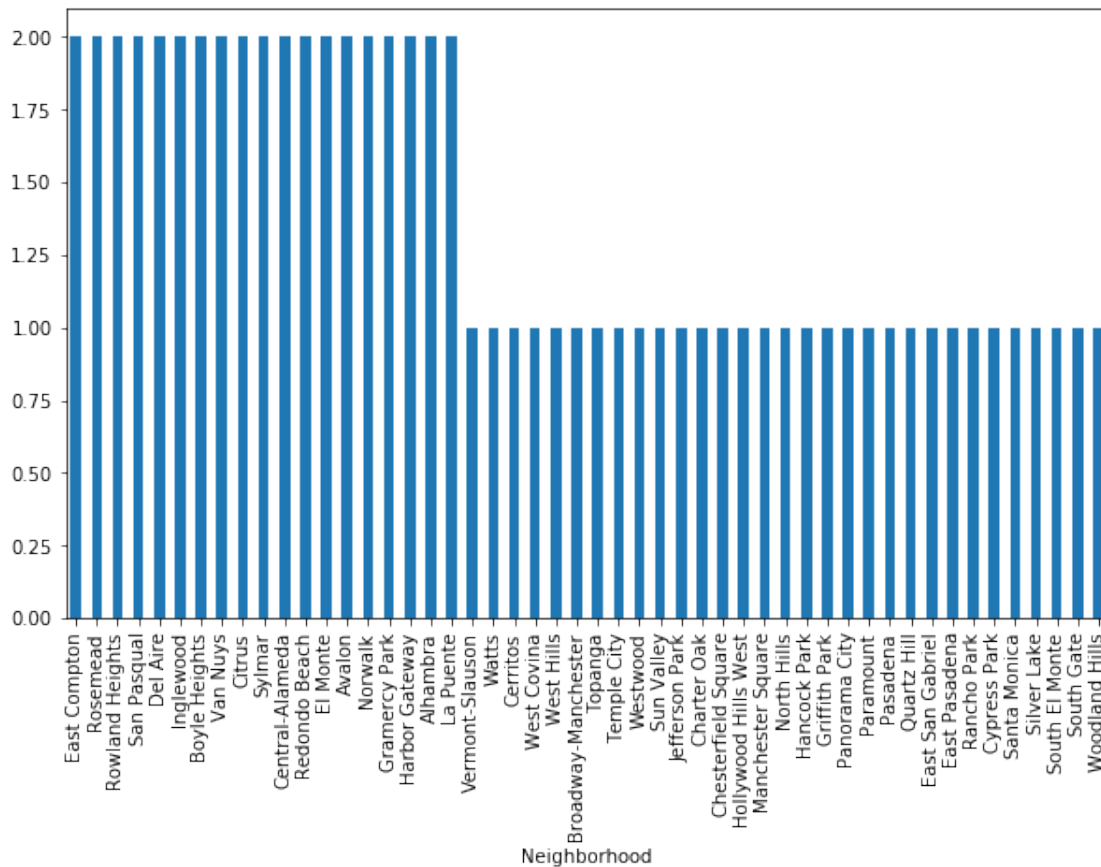
```
[228]: <matplotlib.axes._subplots.AxesSubplot at 0x7f7405329b50>
```



```
[16]: #plot the bottom 50 neighborhoods with the least restaurants

la_venues_forfood.groupby('Neighborhood').count()['Venue Category'].
    ↪sort_values(ascending=False).tail(50).plot(kind='bar', figsize=(10, 6))
```

[16]: <matplotlib.axes.\_subplots.AxesSubplot at 0x7f50916aa1d0>



0.0.5 From the plots above neighborhoods with no restaurants at all are missing. Lets try to include them in our analysis.

[ ]:

```
[18]: # one hot encoding
la_hot = pd.get_dummies(la_venues[['Venue Category']], prefix="", prefix_sep="")

# add neighborhood column back to dataframe
la_hot['NeighborhoodName'] = la_venues['Neighborhood']

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

```
[233]: #la_hot.iloc[353:429,:][la_hot.columns[la_hot.columns.str.
      ↪contains("Restaurant")]].sum(axis=1).sum()
```

```
[233]: 33
```

```
[19]: la_hotforfood=la_hot[la_hot.columns[la_hot.columns.str.contains("Restaurant")]]
      la_hotforfood['NeighborhoodName']=la_hot['NeighborhoodName']
      fixed_columns2 = [la_hotforfood.columns[-1]] + list(la_hotforfood.columns[:-1])
      la_hotforfood = la_hotforfood[fixed_columns2]
```

/home/christos/anaconda3/lib/python3.7/site-packages/ipykernel\_launcher.py:2:

SettingWithCopyWarning:

A value is trying to be set on a copy of a slice from a DataFrame.

Try using .loc[row\_indexer,col\_indexer] = value instead

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)

```
[ ]:
```

```
[21]: la_hotforfood['TotalRestaurants']=la_hotforfood[la_hotforfood.
      ↪columns[la_hotforfood.columns.str.contains("Restaurant")]].sum(axis=1)
```

```
[ ]:
```

```
[23]: la_hotforfoodTotal=la_hotforfood.groupby('NeighborhoodName').
      ↪sum()[['TotalRestaurants']]
```

```
[24]: la_hotforfoodTotal.index.name = None
      la_hotforfoodTotal['NeighborhoodName']=la_hotforfoodTotal.index.tolist()
```

```
[26]: la_hotforfoodTotal.head(10)
```

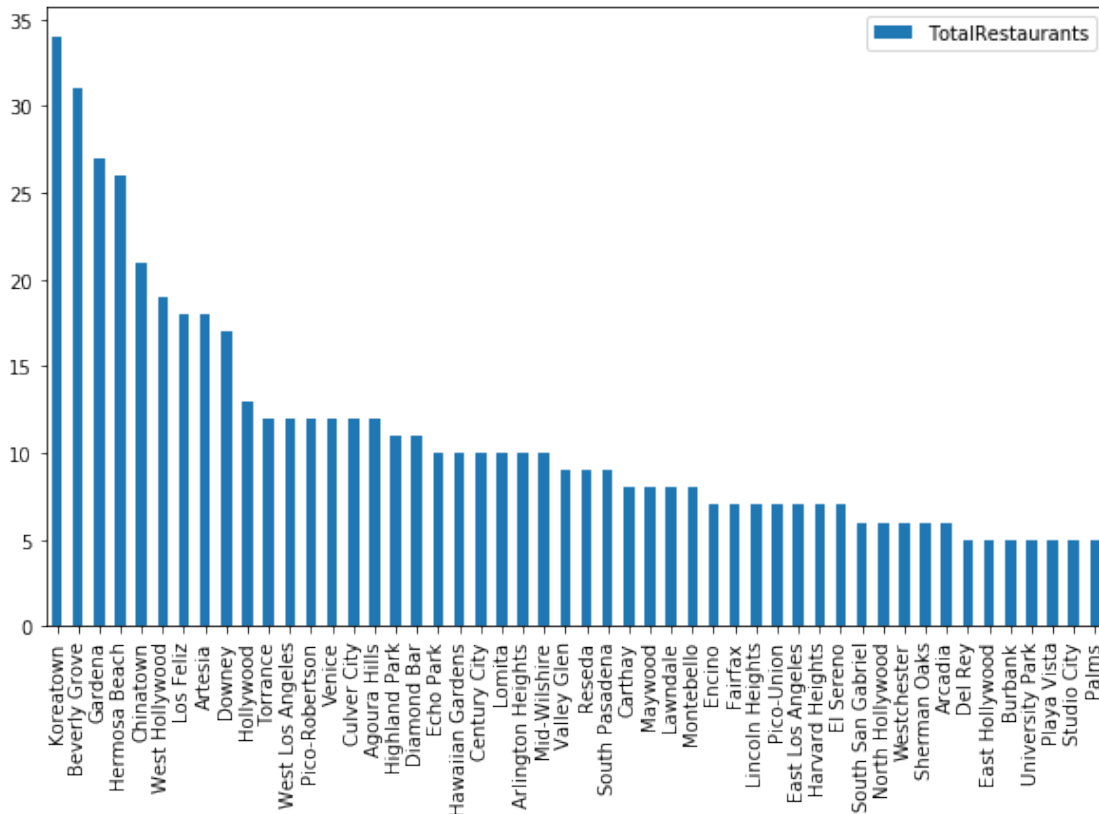
```
[26]:
```

	TotalRestaurants	NeighborhoodName
Acton	0	Acton
Adams-Normandie	3	Adams-Normandie
Agoura Hills	12	Agoura Hills
Agua Dulce	0	Agua Dulce
Alhambra	2	Alhambra
Alondra Park	0	Alondra Park
Altadena	0	Altadena
Arcadia	6	Arcadia
Arleta	0	Arleta
Arlington Heights	10	Arlington Heights

```
[27]: #repeat the barplot analysis including neighborhoods that do not have any
      ↪restaurants

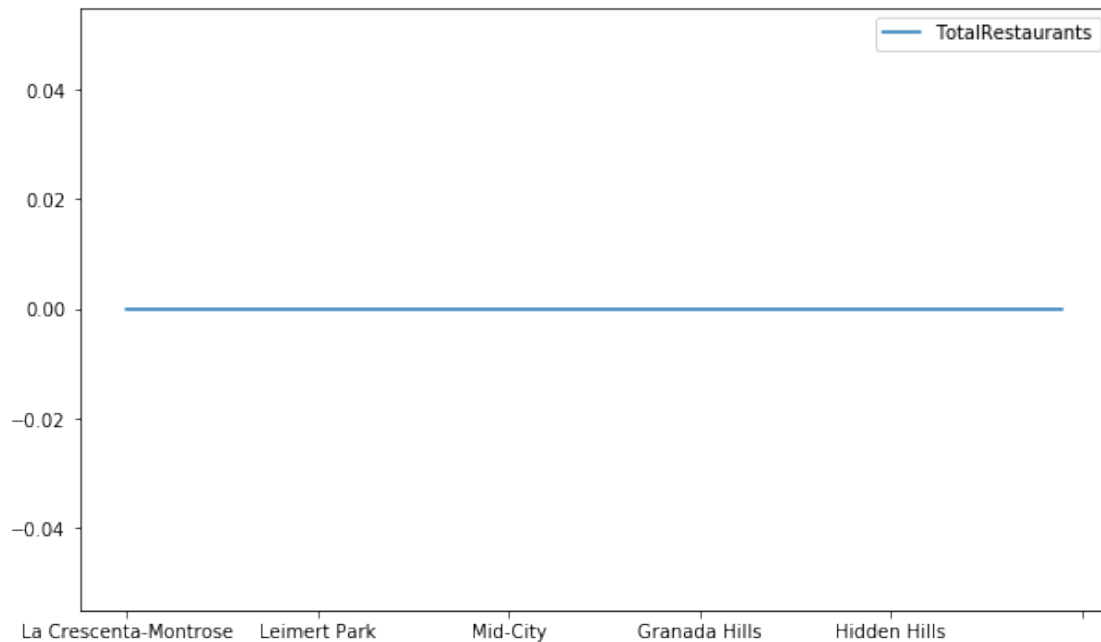
la_hotforfoodTotal.sort_values(by='TotalRestaurants',ascending=False).head(50).
      ↪plot(kind='bar',figsize=(10, 6))
```

```
[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5090482150>
```



```
[28]: la_hotforfoodTotal.sort_values(by='TotalRestaurants',ascending=False).tail(50).
      ↪plot(kind='line',figsize=(10, 6))
```

```
[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5090370b90>
```



**0.0.6** We see that there are many areas with no restaurants at all. Lets try to cluster the neighborhoods.

```
[29]: #keep no-restaurant venues in a separate dataframe
la_hotnofood=la_hot[la_hot.columns[la_hot.columns.str.
↳contains("Restaurant")==False]]
```

```
[32]: # now we have two dataframes, one that has information only for the
↳restaurants,
#and one that have information for the rest venues

print(la_hotnofood.shape,la_hotforfood.shape)
```

(2958, 264) (2958, 58)

```
[34]: #let's merge the two datasets
# now we removed the differents types of restaurants and kept only the total
↳number of restaurants in each
#neighborhhod
la_hotTotal=pd.
↳concat([la_hotforfood[['TotalRestaurants']],la_hotnofood],axis=1, sort=False)
```

```
[35]: la_hotTotal.head()
```

```

[35]: TotalRestaurants NeighborhoodName ATM Accessories Store Airport \
0      0      Acton      0      0      0
1      0      Acton      0      0      0
2      1 Adams-Normandie      0      0      0
3      0 Adams-Normandie      0      0      0
4      1 Adams-Normandie      0      0      0

Airport Lounge Amphitheater Antique Shop Arcade Art Gallery \
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

Art Museum Arts & Crafts Store Arts & Entertainment Athletics & Sports \
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

Auto Garage Auto Workshop Automotive Shop BBQ Joint Baby Store \
0      0      0      0      0
1      0      0      0      0
2      0      0      0      0
3      0      0      0      0
4      0      0      0      0

Bagel Shop Bakery Bank Bar Baseball Field Basketball Court Beach \
0      0      0      0      0      0      0
1      0      0      0      0      0      0
2      0      0      0      0      0      0
3      0      0      0      0      0      0
4      0      0      0      0      0      0

Big Box Store Bike Rental / Bike Share Bistro Board Shop Boat or Ferry \
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

Bookstore Boutique Bowling Alley Breakfast Spot Brewery Bridal 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	0	0
	Bubble Tea Shop	Buffet	Building	Burger Joint	Burrito Place	Bus Line	\
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	

	Bus Station	Bus Stop	Business Service	Butcher	Cafeteria	Café	\
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	

	Camera Store	Campground	Canal	Candy Store	Carpet 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	

	Check Cashing Service	Chocolate Shop	Church	Clothing Store	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Cocktail Bar	Coffee Shop	College Residence Hall	College Theater	\
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	

	Comedy Club	Comic Shop	Concert Hall	Construction & Landscaping	\
0	0	0	0	1	
1	0	0	0	1	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Convenience Store	Cosmetics Shop	Creperie	Cupcake Shop	Cycle Studio	\
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

	Dance Studio	Deli / Bodega	Dentist's Office	Department Store	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Design Studio	Dessert Shop	Diner	Disc Golf	Discount Store	Distillery	\
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	

	Dive Bar	Doctor's Office	Dog Run	Donut Shop	Drugstore	\
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	

	Electronics Store	Fabric Shop	Farm	Farmers Market	Film Studio	\
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	

	Fish & Chips Shop	Flea Market	Flower Shop	Food	Food & Drink 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	

	Food Court	Food Service	Food Stand	Food Truck	Football Stadium	\
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	

Fountain	Fraternity House	Fried Chicken Joint	Frozen Yogurt Shop	\
----------	------------------	---------------------	--------------------	---



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

	Furniture / Home Store	Garden	Garden Center	Gas Station	Gastropub \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	1	0
4	0	0	0	0	0

	Gay Bar	General Entertainment	General Travel	Gift Shop	Go Kart Track \
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

	Golf Course	Gourmet Shop	Government Building	Grocery Store	Gym \
0	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	0	0	0	0	0

	Gym / Fitness Center	Gym Pool	Gymnastics Gym	Harbor / Marina \
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

	Hardware Store	Health & Beauty Service	Health Food Store	High School \
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

	Historic Site	Hobby Shop	Home Service	Hookah Bar	Hot Dog Joint	Hotel \
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

	Hotel Bar	IT Services	Ice Cream Shop	Indie Movie Theater	Indie Theater	\
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	

	Indoor Play Area	Insurance Office	Intersection	Jazz Club	Jewelry 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	

	Juice Bar	Karaoke Bar	Kids Store	Lake	Laundromat	Lawyer	\
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	

	Light Rail Station	Lighting Store	Lingerie Store	Liquor Store	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Locksmith	Lounge	Marijuana Dispensary	Market	Martial Arts Dojo	\
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	

	Massage Studio	Men's Store	Mobile Phone Shop	Monument / Landmark	Motel	\
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	

	Mountain	Movie Theater	Moving Target	Multiplex	Museum	Music 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

	Music Venue	Nail Salon	Neighborhood	Nightclub	Nightlife Spot	\
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	

	Noodle House	Office	Optical Shop	Organic Grocery	Other Great Outdoors	\
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	

	Other Nightlife	Other Repair Shop	Paper / Office Supplies Store	Park	\
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

	Performing Arts Venue	Pet Service	Pet Store	Pharmacy	Photography Lab	\
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	

	Photography Studio	Pier	Pilates Studio	Pizza Place	Platform	\
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	

	Playground	Plaza	Poke Place	Pool	Pub	Racetrack	Record Shop	\
0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	

	Recording Studio	Recreation Center	Rental Car Location	Rental Service	\
0	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

	Reservoir	Residential Building (Apartment / Condo)	River	Road	\
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

	Rock Club	Sake Bar	Salad Place	Salon / Barbershop	Sandwich Place	\
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

	Scenic Lookout	Sculpture Garden	Shipping Store	Shoe Store	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Shop & Service	Shopping Mall	Shopping Plaza	Skate Park	Skating Rink	\
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	

	Smoke Shop	Smoothie Shop	Snack Place	Soup Place	Souvenir Shop	Spa	\
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	

	Speakeasy	Sporting Goods Shop	Sports Bar	Stables	\
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	

	State / Provincial Park	Steakhouse	Storage Facility	Strip Club	\
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	

	Supermarket	Supplement Shop	Surf Spot	Taco Place	Tattoo Parlor	\
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	

	Tea Room	Tennis Court	Theater	Theme Park	Theme Park Ride / Attraction	\
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

	Thrift / Vintage Store	Tiki Bar	Tour Provider	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Tourist Information Center	Toy / Game Store	Trail	\
0	0	0	0	
1	0	0	0	
2	0	0	0	
3	0	0	0	
4	0	0	0	

	Transportation Service	Travel & Transport	Video Game Store	Video Store	\
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	0	0	0	

	Warehouse Store	Watch Shop	Weight Loss Center	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
---	---	---	---	---	---

	Wings Joint	Women's Store	Yoga Studio
0	0	0	0
1	0	0	0
2	0	0	0
3	0	0	0
4	0	0	0

```
[36]: la_grouped = la_hotTotal.groupby('NeighborhoodName').mean()
la_grouped.head()
```

```
[36]:
```

	TotalRestaurants	ATM	Accessories Store	Airport	\
NeighborhoodName					
Acton	0.000000	0.0	0.0	0.0	
Adams-Normandie	0.333333	0.0	0.0	0.0	
Agoura Hills	0.428571	0.0	0.0	0.0	
Agua Dulce	0.000000	0.0	0.0	1.0	
Alhambra	0.153846	0.0	0.0	0.0	

	Airport Lounge	Amphitheater	Antique Shop	Arcade	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Art Gallery	Art Museum	Arts & Crafts Store	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Arts & Entertainment	Athletics & Sports	Auto Garage	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Auto Workshop	Automotive Shop	BBQ Joint	Baby Store	\
NeighborhoodName					
Acton	0.0	0.0	0.000000	0.0	

Adams-Normandie	0.0	0.0	0.000000	0.0
Agoura Hills	0.0	0.0	0.035714	0.0
Agua Dulce	0.0	0.0	0.000000	0.0
Alhambra	0.0	0.0	0.000000	0.0

	Bagel Shop	Bakery	Bank	Bar	Baseball Field	\
NeighborhoodName						
Acton	0.000000	0.000000	0.0	0.0	0.0	
Adams-Normandie	0.000000	0.000000	0.0	0.0	0.0	
Agoura Hills	0.000000	0.071429	0.0	0.0	0.0	
Agua Dulce	0.000000	0.000000	0.0	0.0	0.0	
Alhambra	0.076923	0.000000	0.0	0.0	0.0	

	Basketball Court	Beach	Big Box Store	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Bike Rental / Bike Share	Bistro	Board Shop	Boat or Ferry	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Bookstore	Boutique	Bowling Alley	Breakfast Spot	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.000000	
Adams-Normandie	0.0	0.0	0.0	0.000000	
Agoura Hills	0.0	0.0	0.0	0.071429	
Agua Dulce	0.0	0.0	0.0	0.000000	
Alhambra	0.0	0.0	0.0	0.076923	

	Brewery	Bridal Shop	Bubble Tea Shop	Buffet	Building	\
NeighborhoodName						
Acton	0.000000	0.0	0.0	0.0	0.0	
Adams-Normandie	0.000000	0.0	0.0	0.0	0.0	
Agoura Hills	0.035714	0.0	0.0	0.0	0.0	
Agua Dulce	0.000000	0.0	0.0	0.0	0.0	
Alhambra	0.000000	0.0	0.0	0.0	0.0	

	Burger Joint	Burrito Place	Bus Line	Bus Station	\
NeighborhoodName					

Acton	0.000000	0.0	0.0	0.0
Adams-Normandie	0.000000	0.0	0.0	0.0
Agoura Hills	0.035714	0.0	0.0	0.0
Agua Dulce	0.000000	0.0	0.0	0.0
Alhambra	0.000000	0.0	0.0	0.0

	Bus Stop	Business Service	Butcher	Cafeteria	Café \
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	0.000000
Adams-Normandie	0.0	0.0	0.0	0.0	0.000000
Agoura Hills	0.0	0.0	0.0	0.0	0.035714
Agua Dulce	0.0	0.0	0.0	0.0	0.000000
Alhambra	0.0	0.0	0.0	0.0	0.000000

	Camera Store	Campground	Canal	Candy Store	Carpet Store \
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0	0.0

	Check Cashing Service	Chocolate Shop	Church \
NeighborhoodName			
Acton	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

	Clothing Store	Cocktail Bar	Coffee Shop \
NeighborhoodName			
Acton	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

	College Residence Hall	College Theater	Comedy Club \
NeighborhoodName			
Acton	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

	Comic Shop	Concert Hall	Construction & Landscaping \
--	------------	--------------	------------------------------



NeighborhoodName

Acton	0.0	0.0	1.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

Convenience Store    Cosmetics Shop    Creperie    Cupcake Shop    \

NeighborhoodName

Acton	0.000000	0.0	0.0	0.0
Adams-Normandie	0.000000	0.0	0.0	0.0
Agoura Hills	0.000000	0.0	0.0	0.0
Agua Dulce	0.000000	0.0	0.0	0.0
Alhambra	0.307692	0.0	0.0	0.0

Cycle Studio    Dance Studio    Deli / Bodega    Dentist's Office    \

NeighborhoodName

Acton	0.0	0.0	0.000000	0.0
Adams-Normandie	0.0	0.0	0.000000	0.0
Agoura Hills	0.0	0.0	0.035714	0.0
Agua Dulce	0.0	0.0	0.000000	0.0
Alhambra	0.0	0.0	0.000000	0.0

Department Store    Design Studio    Dessert Shop    Diner    \

NeighborhoodName

Acton	0.0	0.0	0.0	0.000000
Adams-Normandie	0.0	0.0	0.0	0.000000
Agoura Hills	0.0	0.0	0.0	0.035714
Agua Dulce	0.0	0.0	0.0	0.000000
Alhambra	0.0	0.0	0.0	0.000000

Disc Golf    Discount Store    Distillery    Dive Bar    \

NeighborhoodName

Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

Doctor's Office    Dog Run    Donut Shop    Drugstore    \

NeighborhoodName

Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

	Electronics Store	Fabric Shop	Farm	Farmers Market	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Film Studio	Fish & Chips Shop	Flea Market	Flower Shop	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Food	Food & Drink Shop	Food Court	Food Service	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Food Stand	Food Truck	Football Stadium	Fountain	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Fraternity House	Fried Chicken Joint	Frozen Yogurt Shop	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Furniture / Home Store	Garden	Garden Center	Gas Station	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.000000	
Adams-Normandie	0.0	0.0	0.0	0.111111	
Agoura Hills	0.0	0.0	0.0	0.035714	
Agua Dulce	0.0	0.0	0.0	0.000000	
Alhambra	0.0	0.0	0.0	0.000000	

	Gastropub	Gay Bar	General Entertainment	General Travel	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Gift Shop	Go Kart Track	Golf Course	Gourmet Shop	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Government Building	Grocery Store	Gym	\
NeighborhoodName				
Acton	0.0	0.000000	0.0	
Adams-Normandie	0.0	0.111111	0.0	
Agoura Hills	0.0	0.035714	0.0	
Agua Dulce	0.0	0.000000	0.0	
Alhambra	0.0	0.000000	0.0	

	Gym / Fitness Center	Gym Pool	Gymnastics Gym	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Harbor / Marina	Hardware Store	Health & Beauty Service	\
NeighborhoodName				
Acton	0.0	0.000000	0.0	
Adams-Normandie	0.0	0.000000	0.0	
Agoura Hills	0.0	0.000000	0.0	
Agua Dulce	0.0	0.000000	0.0	
Alhambra	0.0	0.076923	0.0	

	Health Food Store	High School	Historic Site	Hobby Shop	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	

Alhambra	0.0	0.0	0.0	0.0
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	Home Service	Hookah Bar	Hot Dog Joint	Hotel \
NeighborhoodName				
Acton	0.0	0.0	0.0	0.000000
Adams-Normandie	0.0	0.0	0.0	0.000000
Agoura Hills	0.0	0.0	0.0	0.035714
Agua Dulce	0.0	0.0	0.0	0.000000
Alhambra	0.0	0.0	0.0	0.000000

	Hotel Bar	IT Services	Ice Cream Shop	Indie Movie Theater \
NeighborhoodName				
Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

	Indie Theater	Indoor Play Area	Insurance Office \
NeighborhoodName			
Acton	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

	Intersection	Jazz Club	Jewelry Store	Juice Bar \
NeighborhoodName				
Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

	Karaoke Bar	Kids Store	Lake	Laundromat	Lawyer \
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0	0.0

	Light Rail Station	Lighting Store	Lingerie Store \
NeighborhoodName			
Acton	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0

Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

	Liquor Store	Locksmith	Lounge	Marijuana Dispensary \
NeighborhoodName				
Acton	0.0	0.000000	0.000000	0.0
Adams-Normandie	0.0	0.111111	0.000000	0.0
Agoura Hills	0.0	0.000000	0.035714	0.0
Agua Dulce	0.0	0.000000	0.000000	0.0
Alhambra	0.0	0.000000	0.000000	0.0

	Market	Martial Arts Dojo	Massage Studio	Men's Store \
NeighborhoodName				
Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

	Mobile Phone Shop	Monument / Landmark	Motel	Mountain \
NeighborhoodName				
Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

	Movie Theater	Moving Target	Multiplex	Museum \
NeighborhoodName				
Acton	0.0	0.0	0.000000	0.0
Adams-Normandie	0.0	0.0	0.000000	0.0
Agoura Hills	0.0	0.0	0.035714	0.0
Agua Dulce	0.0	0.0	0.000000	0.0
Alhambra	0.0	0.0	0.000000	0.0

	Music Store	Music Venue	Nail Salon	Neighborhood \
NeighborhoodName				
Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

	Nightclub	Nightlife Spot	Noodle House	Office \
NeighborhoodName				
Acton	0.0	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0	0.0

Agoura Hills	0.0	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0	0.0

	Optical Shop	Organic Grocery	Other	Great Outdoors	\
NeighborhoodName					
Acton	0.0	0.0		0.0	
Adams-Normandie	0.0	0.0		0.0	
Agoura Hills	0.0	0.0		0.0	
Agua Dulce	0.0	0.0		0.0	
Alhambra	0.0	0.0		0.0	

	Other Nightlife	Other Repair Shop	\
NeighborhoodName			
Acton	0.0	0.0	
Adams-Normandie	0.0	0.0	
Agoura Hills	0.0	0.0	
Agua Dulce	0.0	0.0	
Alhambra	0.0	0.0	

	Paper / Office Supplies Store	Park	\
NeighborhoodName			
Acton	0.0	0.000000	
Adams-Normandie	0.0	0.111111	
Agoura Hills	0.0	0.000000	
Agua Dulce	0.0	0.000000	
Alhambra	0.0	0.000000	

	Performing Arts Venue	Pet Service	Pet Store	Pharmacy	\
NeighborhoodName					
Acton	0.0	0.0	0.000000	0.0	
Adams-Normandie	0.0	0.0	0.000000	0.0	
Agoura Hills	0.0	0.0	0.000000	0.0	
Agua Dulce	0.0	0.0	0.000000	0.0	
Alhambra	0.0	0.0	0.076923	0.0	

	Photography Lab	Photography Studio	Pier	Pilates Studio	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Pizza Place	Platform	Playground	Plaza	Poke Place	Pool	\
NeighborhoodName							
Acton	0.000000	0.0	0.000000	0.0	0.0	0.0	

Adams-Normandie	0.000000	0.0	0.111111	0.0	0.0	0.0
Agoura Hills	0.000000	0.0	0.000000	0.0	0.0	0.0
Agua Dulce	0.000000	0.0	0.000000	0.0	0.0	0.0
Alhambra	0.076923	0.0	0.000000	0.0	0.0	0.0

	Pub	Racetrack	Record Shop	Recording Studio	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Recreation Center	Rental Car Location	Rental Service	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Reservoir	Residential Building (Apartment / Condo)	River	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Road	Rock Club	Sake Bar	Salad Place	Salon / Barbershop	\
NeighborhoodName						
Acton	0.0	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	0.0	

	Sandwich Place	Scenic Lookout	Sculpture Garden	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Shipping Store	Shoe Store	Shop & Service	Shopping Mall	\
NeighborhoodName					

Acton	0.000000	0.0	0.0	0.0
Adams-Normandie	0.000000	0.0	0.0	0.0
Agoura Hills	0.035714	0.0	0.0	0.0
Agua Dulce	0.000000	0.0	0.0	0.0
Alhambra	0.000000	0.0	0.0	0.0

	Shopping Plaza	Skate Park	Skating Rink	Smoke Shop	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Smoothie Shop	Snack Place	Soup Place	Souvenir Shop	Spa	\
NeighborhoodName						
Acton	0.0	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	0.0	

	Speakeasy	Sporting Goods Shop	Sports Bar	Stables	\
NeighborhoodName					
Acton	0.0	0.000000	0.0	0.0	
Adams-Normandie	0.0	0.000000	0.0	0.0	
Agoura Hills	0.0	0.000000	0.0	0.0	
Agua Dulce	0.0	0.000000	0.0	0.0	
Alhambra	0.0	0.076923	0.0	0.0	

	State / Provincial Park	Steakhouse	Storage Facility	\
NeighborhoodName				
Acton	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	

	Strip Club	Supermarket	Supplement Shop	Surf Spot	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Taco Place	Tattoo Parlor	Tea Room	Tennis Court	Theater	\
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NeighborhoodName					
Acton	0.000000	0.0	0.0	0.0	0.0
Adams-Normandie	0.111111	0.0	0.0	0.0	0.0
Agoura Hills	0.000000	0.0	0.0	0.0	0.0
Agua Dulce	0.000000	0.0	0.0	0.0	0.0
Alhambra	0.000000	0.0	0.0	0.0	0.0

	Theme Park	Theme Park Ride / Attraction \
NeighborhoodName		
Acton	0.0	0.0
Adams-Normandie	0.0	0.0
Agoura Hills	0.0	0.0
Agua Dulce	0.0	0.0
Alhambra	0.0	0.0

	Thrift / Vintage Store	Tiki Bar	Tour Provider \
NeighborhoodName			
Acton	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

	Tourist Information Center	Toy / Game Store	Trail \
NeighborhoodName			
Acton	0.0	0.0	0.0
Adams-Normandie	0.0	0.0	0.0
Agoura Hills	0.0	0.0	0.0
Agua Dulce	0.0	0.0	0.0
Alhambra	0.0	0.0	0.0

	Transportation Service	Travel & Transport \
NeighborhoodName		
Acton	0.0	0.0
Adams-Normandie	0.0	0.0
Agoura Hills	0.0	0.0
Agua Dulce	0.0	0.0
Alhambra	0.0	0.0

	Video Game Store	Video Store	Warehouse Store	Watch Shop \
NeighborhoodName				
Acton	0.0	0.000000	0.0	0.0
Adams-Normandie	0.0	0.000000	0.0	0.0
Agoura Hills	0.0	0.000000	0.0	0.0
Agua Dulce	0.0	0.000000	0.0	0.0
Alhambra	0.0	0.076923	0.0	0.0

	Weight Loss Center	Wine Bar	Wine Shop	Wings Joint	\
NeighborhoodName					
Acton	0.0	0.0	0.0	0.0	
Adams-Normandie	0.0	0.0	0.0	0.0	
Agoura Hills	0.0	0.0	0.0	0.0	
Agua Dulce	0.0	0.0	0.0	0.0	
Alhambra	0.0	0.0	0.0	0.0	

	Women's Store	Yoga Studio
NeighborhoodName		
Acton	0.0	0.0
Adams-Normandie	0.0	0.0
Agoura Hills	0.0	0.0
Agua Dulce	0.0	0.0
Alhambra	0.0	0.0

```
[76]: #perform clustering

# set number of clusters
kclusters = 10

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

# check cluster labels generated for each row in the dataframe
kmeans.labels_.shape
```

```
[76]: (239,)
```

```
[80]: indexx=la_grouped.index.tolist()
neighborhoods_new=neighborhoods.loc[indexx]

neighborhoods_new.insert(0, 'Cluster Labels', kmeans.labels_)
```

```
[81]: neighborhoods_new.head()
```

	Cluster Labels	City	Neighborhood	Latitude	\
Neighborhood					
Acton	5	L.A.	Acton	34.497355239240846	
Adams-Normandie	0	L.A.	Adams-Normandie	34.031461499124156	
Agoura Hills	0	L.A.	Agoura Hills	34.146736499122795	
Agua Dulce	8	L.A.	Agua Dulce	34.504926999796837	
Alhambra	8	L.A.	Alhambra	34.085538999123571	

	Longitude
Neighborhood	
Acton	-118.16981019229348

```

Adams-Normandie -118.30020800000011
Agoura Hills -118.75988450000015
Agua Dulce -118.3171036690717
Alhambra -118.13651200000021

```

```

[83]: import matplotlib.cm as cm
import matplotlib.colors as colors

map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

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

map_clusters

```

```

[83]: <folium.folium.Map at 0x7f508a755610>

```

**0.0.7** We can clearly say that we cannot make a suggestion based on this map. Let's try again keeping only information regarding the restaurant number in each neighborhood.

```

[87]: la_grouped_resta=la_grouped[['TotalRestaurants']]

```

```

[88]: la_grouped_resta.head()

```

```

[88]:
      TotalRestaurants
NeighborhoodName
Acton                0.000000

```

Adams-Normandie	0.333333
Agoura Hills	0.428571
Agua Dulce	0.000000
Alhambra	0.153846

```
[89]: #perform clustering

# set number of clusters
kclusters = 10

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

# check cluster labels generated for each row in the dataframe
kmeans.labels_.shape
```

```
[89]: (239,)
```

```
[90]: indexx=la_grouped.index.tolist()
neighborhoods_resta=neighborhoods.loc[indexx]

neighborhoods_resta.insert(0, 'Cluster Labels', kmeans.labels_)
```

```
[91]: import matplotlib.cm as cm
import matplotlib.colors as colors

map_clusters = folium.Map(location=[latitude, longitude], zoom_start=11)

# set color scheme for the clusters
x = np.arange(kclusters)
ys = [i + x + (i*x)**2 for i in range(kclusters)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

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

```
fill_opacity=0.7).add_to(map_clusters)

map_clusters
```

[91]: <folium.folium.Map at 0x7f508a462e10>

0.0.8 Slightly better. We have better cluster now, but still not clear. Let's try to make a barplot to see wch clusters correspond to neighborhoods with few restaurants.

```
[133]: la_grouped_resta['Neighborhood']=la_grouped_resta.index.values.tolist()
la_grouped_resta2=la_grouped_resta.reset_index()
la_grouped_resta2.drop('NeighborhoodName',axis=1, inplace=True)
la_grouped_resta2.drop('Neighborhood',axis=1, inplace=True)
```

```
/home/christos/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: [https://pandas.pydata.org/pandas-docs/stable/user\\_guide/indexing.html#returning-a-view-versus-a-copy](https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy)  
 """Entry point for launching an IPython kernel.

```
[113]: neighborhoods_resta.index.name=None
```

```
[116]: neighborhoods_resta2=neighborhoods_resta.reset_index()
```

```
[125]: neighborhoods_resta2.drop('index', axis=1, inplace=True)
```

```
[126]: neighborhoods_resta2.head()
```

```
[126]:
```

	Cluster Labels	City	Neighborhood	Latitude \
0	0	L.A.	Acton	34.497355239240846
1	1	L.A.	Adams-Normandie	34.031461499124156
2	5	L.A.	Agoura Hills	34.146736499122795
3	0	L.A.	Agua Dulce	34.504926999796837
4	6	L.A.	Alhambra	34.085538999123571

	Longitude
0	-118.16981019229348
1	-118.30020800000011
2	-118.75988450000015
3	-118.3171036690717
4	-118.13651200000021

```
[124]: la_grouped_resta2.head()
```

```
[124]:
```

	TotalRestaurants	Neighborhood
0	0.000000	Acton
1	0.333333	Adams-Normandie
2	0.428571	Agoura Hills
3	0.000000	Agua Dulce
4	0.153846	Alhambra

```
[134]: final_dataset=pd.concat([la_grouped_resta2,neighborhoods_resta2],axis=1,
↪sort=False)
```

```
[135]: final_dataset.head()[['']]
```

```
[135]:
```

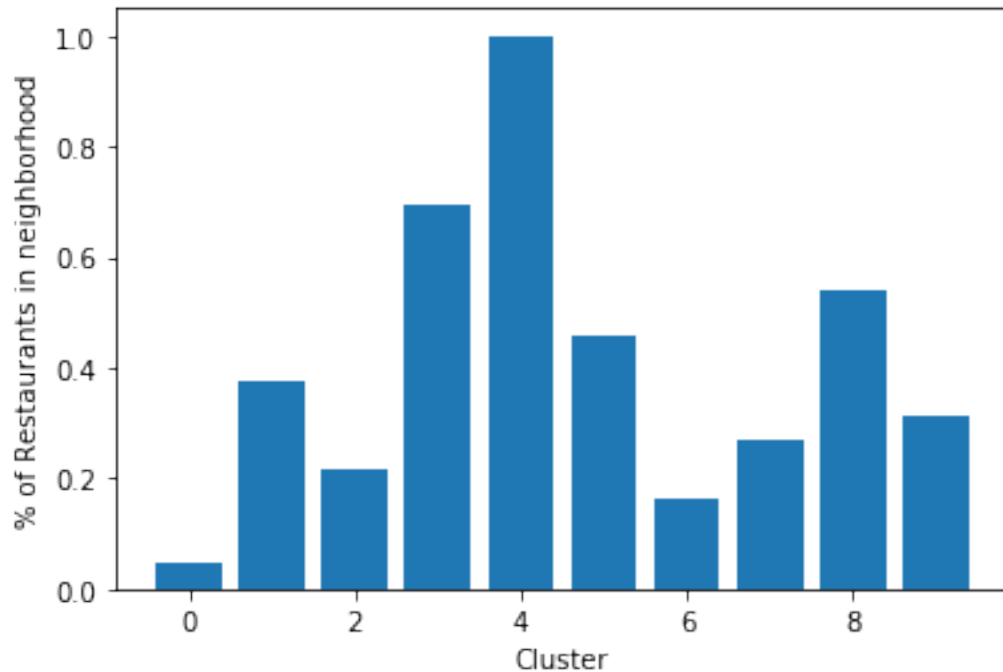
	TotalRestaurants	Cluster Labels	City	Neighborhood \
0	0.000000	0	L.A.	Acton
1	0.333333	1	L.A.	Adams-Normandie
2	0.428571	5	L.A.	Agoura Hills
3	0.000000	0	L.A.	Agua Dulce
4	0.153846	6	L.A.	Alhambra

	Latitude	Longitude
0	34.497355239240846	-118.16981019229348
1	34.031461499124156	-118.30020800000011
2	34.146736499122795	-118.75988450000015
3	34.504926999796837	-118.3171036690717
4	34.085538999123571	-118.13651200000021

```
[137]: import matplotlib.pyplot as plt
```

```
[141]: plt.bar(x=final_dataset['Cluster_
↪Labels'],height=final_dataset['TotalRestaurants'])
plt.xlabel('Cluster')
plt.ylabel('% of Restaurants in neighborhood')
```

```
[141]: Text(0, 0.5, '% of Restaurants in neighborhood')
```



**0.0.9** We can say that neighborhoods with cluster labels 0 and 6 do not have many restaurants. Let's view these neighborhoods.

```
[152]: final_dataset.loc[(final_dataset['Cluster Labels']==0) |
↳ (final_dataset['Cluster Labels']==6) ,:]
```

```
[152]:
```

	TotalRestaurants	Cluster Labels	City \
0	4	0	L.A.
3	4	0	L.A.
4	4	6	L.A.
5	4	0	L.A.
6	4	0	L.A.
8	4	0	L.A.
11	4	6	L.A.
14	4	0	L.A.
15	4	0	L.A.
17	4	0	L.A.
18	4	0	L.A.
21	4	0	L.A.
23	4	0	L.A.
24	4	0	L.A.
26	4	0	L.A.
27	4	0	L.A.

28	4	6 L.A.
30	4	0 L.A.
34	4	6 L.A.
37	4	0 L.A.
39	4	0 L.A.
42	4	0 L.A.
48	4	6 L.A.
52	4	6 L.A.
53	4	0 L.A.
58	4	6 L.A.
61	4	0 L.A.
63	4	0 L.A.
64	4	0 L.A.
65	4	0 L.A.
67	4	0 L.A.
70	4	0 L.A.
72	4	0 L.A.
73	4	0 L.A.
74	4	0 L.A.
76	4	0 L.A.
77	4	0 L.A.
78	4	0 L.A.
80	4	0 L.A.
85	4	0 L.A.
86	4	0 L.A.
90	4	0 L.A.
94	4	0 L.A.
96	4	0 L.A.
97	4	0 L.A.
98	4	0 L.A.
100	4	0 L.A.
101	4	6 L.A.
103	4	0 L.A.
104	4	0 L.A.
105	4	0 L.A.
106	4	6 L.A.
108	4	0 L.A.
109	4	0 L.A.
111	4	0 L.A.
113	4	0 L.A.
116	4	0 L.A.
121	4	0 L.A.
123	4	0 L.A.
124	4	0 L.A.
125	4	6 L.A.
126	4	0 L.A.
127	4	0 L.A.



128	4	6	L.A.
129	4	0	L.A.
131	4	0	L.A.
133	4	0	L.A.
134	4	0	L.A.
136	4	0	L.A.
137	4	0	L.A.
138	4	0	L.A.
139	4	0	L.A.
142	4	0	L.A.
144	4	6	L.A.
145	4	0	L.A.
146	4	0	L.A.
148	4	0	L.A.
151	4	6	L.A.
152	4	0	L.A.
156	4	0	L.A.
158	4	0	L.A.
160	4	0	L.A.
161	4	0	L.A.
162	4	0	L.A.
166	4	0	L.A.
169	4	0	L.A.
172	4	0	L.A.
175	4	0	L.A.
176	4	0	L.A.
177	4	6	L.A.
178	4	6	L.A.
180	4	0	L.A.
181	4	6	L.A.
182	4	6	L.A.
185	4	0	L.A.
188	4	0	L.A.
189	4	0	L.A.
191	4	6	L.A.
192	4	0	L.A.
194	4	0	L.A.
196	4	0	L.A.
199	4	0	L.A.
200	4	0	L.A.
201	4	6	L.A.
203	4	0	L.A.
204	4	0	L.A.
207	4	6	L.A.
209	4	0	L.A.
210	4	0	L.A.
211	4	0	L.A.

212	4	6	L.A.
213	4	0	L.A.
214	4	0	L.A.
215	4	0	L.A.
217	4	6	L.A.
219	4	0	L.A.
220	4	0	L.A.
222	4	6	L.A.
226	4	0	L.A.
227	4	0	L.A.
228	4	6	L.A.
232	4	0	L.A.
233	4	0	L.A.
234	4	0	L.A.
236	4	0	L.A.

	Neighborhood	Latitude \
0	Acton	34.497355239240846
3	Agua Dulce	34.504926999796837
4	Alhambra	34.085538999123571
5	Alondra Park	33.889617004889644
6	Altadena	34.193870502232173
8	Arleta	34.243099999121583
11	Atwater Village	34.131066356759177
14	Azusa	34.13746999912302
15	Baldwin Hills/Crenshaw	34.01197027055953
17	Bel-Air	34.102056999123342
18	Bell	33.981160999124889
21	Beverly Crest	34.106006999123245
23	Beverly Hills	34.082544499123699
24	Beverlywood	34.043509999124048
26	Bradbury	34.15423999912273
27	Brentwood	34.086240999123547
28	Broadway-Manchester	33.941223502886629
30	Calabasas	34.136254499122948
34	Century City	34.055325502171065
37	Chatsworth	34.256403499160569
39	Cheviot Hills	34.04085349912404
42	Commerce	33.995079230018334
48	Del Aire	33.915552004076844
52	Downtown	34.040008613525899
53	Eagle Rock	34.133916999122917
58	East San Gabriel	34.110644492315856
61	El Segundo	33.916582999125737
63	Elizabeth Lake	34.657686037373047
64	Elysian Park	34.081259999123489
65	Elysian Valley	34.095759499123389

67	Exposition Park	34.018262499124305
70	Florence-Firestone	33.966101520272787
72	Glassell Park	34.114405499123208
73	Glendale	34.192975499122355
74	Glendora	34.142040999122969
76	Granada Hills	34.295682651151957
77	Green Meadows	33.941634094823527
78	Green Valley	34.620007457495149
80	Hacienda Heights	34.002085506418773
85	Harvard Park	33.983762999124835
86	Hasley Canyon	34.476199893867175
90	Hidden Hills	34.16405683610931
94	Hollywood Hills	34.128088999122937
96	Huntington Park	33.978967499124934
97	Hyde Park	33.985430999124816
98	Industry	34.026835568749277
100	Irwindale	34.108874499123317
101	Jefferson Park	34.028211499124154
103	La Canada Flintridge	34.210686999122075
104	La Crescenta-Montrose	34.228709003122127
105	La Habra Heights	33.96095113872326
106	La Mirada	33.900793500197707
108	La Verne	34.124883999123185
109	Ladera Heights	33.996097001972416
111	Lake Los Angeles	34.611038948416571
113	Lancaster	34.700066117404532
116	Leimert Park	34.013050516583704
121	Long Beach	33.806580699978731
123	Lynwood	33.925213499125533
124	Malibu	34.033895486545326
125	Manchester Square	33.967165274809105
126	Manhattan Beach	33.88950799912606
127	Mar Vista	34.010242173076293
128	Marina del Rey	33.975323504268417
129	Mayflower Village	34.117318103307944
131	Mid-City	34.041107499124067
133	Mission Hills	34.271661499121265
134	Monrovia	34.148608345800739
136	Montecito Heights	34.093658999123406
137	Monterey Park	34.049427999124063
138	Mount Washington	34.103158999123266
139	North El Monte	34.102483231361113
142	North Whittier	34.005714844032383
144	Norwalk	33.907168999125822
145	Pacific Palisades	34.078366733694963
146	Pacoima	34.26360659127154
148	Palos Verdes Estates	33.783316814743465

151	Pasadena	34.18459099912242
152	Pico Rivera	33.989604499124823
156	Playa del Rey	33.945661530783255
158	Porter Ranch	34.278216499201754
160	Ramona	34.060567999123897
161	Rancho Dominguez	33.859875999126409
162	Rancho Palos Verdes	33.75869892565828
166	Rolling Hills	33.762682999127549
169	San Dimas	34.115259499123212
172	San Marino	34.121299999123188
175	Santa Clarita	34.408855499147847
176	Santa Fe Springs	33.928934999496654
177	Santa Monica	34.021860499124415
178	Sawtelle	34.03506728275898
180	Sierra Madre	34.168112999122641
181	Signal Hill	33.804375999127039
182	Silver Lake	34.094459499123445
185	South Park	33.996463999124586
188	South San Jose Hills	34.014947000828826
189	South Whittier	33.936196000947831
191	Sun Valley	34.22661749912173
192	Sunland	34.270730999121341
194	Tarzana	34.156454999122722
196	Toluca Lake	34.15349309467193
199	Tujunga	34.261340090064621
200	Unincorporated Santa Monica Mountains	34.087645747469352
201	Universal City	34.137361499122974
203	Val Verde	34.44560168460962
204	Valinda	34.038452502168049
207	Van Nuys	34.196505499122246
209	Vermont Knolls	33.967009999124997
210	Vermont Square	34.002062999124533
211	Vermont Vista	33.941708042365043
212	Vermont-Slauson	33.983913999124709
213	Vernon	33.999657999124722
214	Veterans Administration	34.057383999123985
215	Walnut	34.033247999124256
217	Watts	33.941619001308609
219	West Carson	33.822072500607462
220	West Compton	33.894136502499222
222	West Hills	34.207253636931036
226	West San Dimas	34.087431659884331
227	West Whittier-Los Nietos	33.980559999939608
228	Westchester	33.95599525987285
232	Westwood	34.06523499912381
233	Whittier Narrows	34.037074109844369
234	Willowbrook	33.915710503828592

	Longitude
0	-118.16981019229348
3	-118.3171036690717
4	-118.13651200000021
5	-118.33515598608159
6	-118.13623898201556
8	-118.4307575
11	-118.26237347966236
14	-117.91246849999999
15	-118.35774600000005
17	-118.45841550000007
18	-118.17916600000018
21	-118.42326299999999
23	-118.39953400000016
24	-118.39398199999999
26	-117.96857400000013
27	-118.49218850000007
28	-118.27535153247453
30	-118.67163173539396
34	-118.41508300000005
37	-118.61235450000001
39	-118.41146150000006
42	-118.15736250000002
48	-118.36983198490955
52	-118.24850990440491
53	-118.20484450000001
58	-118.07396450000032
61	-118.40223073369825
63	-118.38621116359349
64	-118.23745650000001
65	-118.24195650000013
67	-118.29887550000007
70	-118.24192048907494
72	-118.23642729889393
73	-118.24492700000002
74	-117.84178450000023
76	-118.50767050010745
77	-118.26148999301319
78	-118.41421658346756
80	-117.97508050764819
85	-118.30455750000012
86	-118.66021608592953
90	-118.65705600000015
94	-118.33541000000008
96	-118.2140149952952

97 -118.33775850000006  
98 -117.93962100000014  
100 -117.96667800000012  
101 -118.32205850000005  
103 -118.20046998596307  
104 -118.23518197192418  
105 -117.95562783562224  
106 -118.00722099646512  
108 -117.7745250000001  
109 -118.37410748609757  
111 -117.83603921804665  
113 -118.13179100000016  
116 -118.32633970815459  
121 -118.156064  
123 -118.20282648482208  
124 -118.7542537868066  
125 -118.30898400000005  
126 -118.40093919800572  
127 -118.43668192517818  
128 -118.44786948141424  
129 -118.00229999282959  
131 -118.35880950000006  
133 -118.45716250000007  
134 -117.98179100000009  
136 -118.19427049999999  
137 -118.13161942411986  
138 -118.21900650000001  
139 -118.02354298857939  
142 -118.02918914224676  
144 -118.07693800000014  
145 -118.54585899824386  
146 -118.41890850000007  
148 -118.39012200169401  
151 -118.13180900000009  
152 -118.08161950000004  
156 -118.44133951162496  
158 -118.54872950000006  
160 -117.83843450000029  
161 -118.21829150000025  
162 -118.35980750108605  
166 -118.34812650000021  
169 -117.81326850000013  
172 -118.11505449283317  
175 -118.49476193960714  
176 -118.06368000000016  
177 -118.48056671004807  
178 -118.45059109758868

```

180 -118.04883650000005
181 -118.16716650000018
182 -118.2677075
185 -118.26875699999999
188 -117.90184498555011
189 -118.0280174858583
191 -118.3843172128845
192 -118.31202250000007
194 -118.54458900000007
196 -118.35795100000007
199 -118.2818
200 -118.77026791367985
201 -118.35278600000026
203 -118.6656538804971
204 -117.93079549289092
207 -118.4639545
209 -118.29050700000013
210 -118.29880750000001
211 -118.28545100000014
212 -118.29035750000011
213 -118.20343200000011
214 -118.45725850000031
215 -117.86012600000016
217 -118.2399365
219 -118.29227748370761
220 -118.26773698606382
222 -118.63539850000006
226 -117.83509899236435
227 -118.07001998587738
228 -118.39829259016352
232 -118.44047994677246
233 -118.06118827749373
234 -118.25231247908229
236 -118.31990900000005

```

#### 0.0.10 Discussion

Using the k-means clustering approach we identified neighborhoods that cluster together, based only on the number of restaurants in each neighborhood. We found that neighborhoods labeled with 0 and 6 do not have many restaurants and subsequently would be the best options to start a new restaurant.

#### 0.0.11 Conclusion

Trying to make suggestion about carrer opportunities is not easy. Here, we combined basic plotting startegies with clustering methods to obtain a basic intuition about which neighborhood in L.A is appropriate for opening a new restaurant. We based our analysis only on the number of restaurants in each area. To complete this analysis many more parameters must be taken into account. This would be just the first step trying to answer a real-world reseach question.