Coursera/IBM

Applied Data Science Capstone Project

The Battle of Neighborhoods: Opening an Italian Restaurant in Paris

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Introduction: Project & Background

In this Notebook, we'll attempt to find the best suggestions of locations to open an Italian Restaurant in Paris.

Of course, this is no easy task and the final decision should be made after further on-site investigation, but with some data we can already reduce the area to check to a handful of locations.

This analysis will be based on the following assumptions:

- Areas in which the restaurant density is very low will not be considered as good spots: indeed, if one could assume that they represent a gap to fill (which might be true!) they are most likely empty for a reason - e.g. prohibitive prices, protected or historical areas, etc.

- It is better to open an italian restaurant in neighborhoods where Italian Restaurants are among the most popular as this implies a demand for this type of food.
- However the new italian restaurant should be as far as possible from the existing ones as clients might prefer the venues they are used to.

- Even though french and italian cuisines are very distinct, they are usually enjoyed in a similar way: both french and italian food lovers will tend to sit for quite a while, taking their time to enjoy a good meal, as opposed to other types of food that can be enjoyed on the go. As a consequence, we will favour areas with many french restaurants, as they will mainly attract clients that would enjoy italian food as well.

Data

For this analysis, we will need to get data regarding Paris' arrondissements (i.e. neighborhoods):

- their shape
- their center

This will allow us to map our findings, gather data on nearby venues and frame potential clusters.

Then we will get data on parisian venues, that is:

- their name
- their coordinates
- the category they belong to

Finally we'll create a `paris_restaurants` dataframe with all we need for the analysis

Getting a map of Paris' *Arrondissements*

A copy of the GeoJSON file we use is stored in the same repository as this notebook.

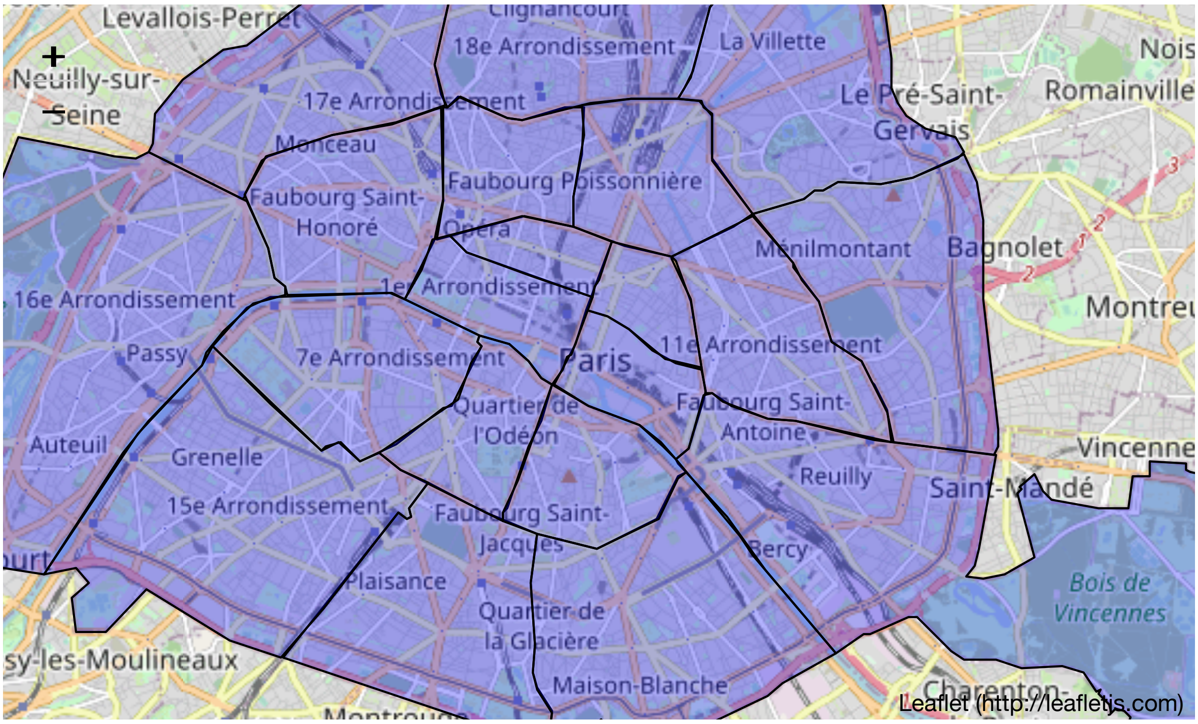
The original file can be found on the following page:
https://opendata.paris.fr/explore/dataset/arrondissements/export/?disjunctive.c_ar&disjunctive.c_arinsee&disjunctive.l_ar&location=13,48.85156,2.32327 (https://opendata.paris.fr/explore/dataset/arrondissements/export/?disjunctive.c_ar&disjunctive.c_arinsee&disjunctive.l_ar&location=13,48.85156,2.32327)

In [1]:
```
import json

geo = json.load(open("/arrondissements.geojson"))
```

From this dataset, we can actually easily plot the shape of each *arrondissement* (i.e. neighborhood)

In [2]:
```
import folium
paris_choropleth = folium.Map(location = [48.856578, 2.351828], zoo
m_start = 12)
paris_choropleth.choropleth(geo_data = geo,fill_opacity=0.3,fill_co
lor='blue')
paris_choropleth
```

Out[2]:



But in order to request data about parisian venues, we will need to get the coordinates of the center of each neighborhood:

In [3]:
```
import pandas as pd

paris_ardt = []
for arr in geo["features"]:
    prop = arr["properties"]
    paris_ardt.append([prop["l_ar"].split('è')[0].split('e')[0],pro
p["geom_x_y"][0],prop["geom_x_y"][1]])
paris_ardt_df= pd.DataFrame(paris_ardt,columns=['Ardt','Latitude','
Longitude'])
paris_ardt_df['Ardt'] = paris_ardt_df['Ardt'].astype(int)
paris_ardt_df.sort_values('Ardt',inplace=True)
paris_ardt_df = paris_ardt_df.reset_index().drop('index',axis=1)
paris_ardt_df
```

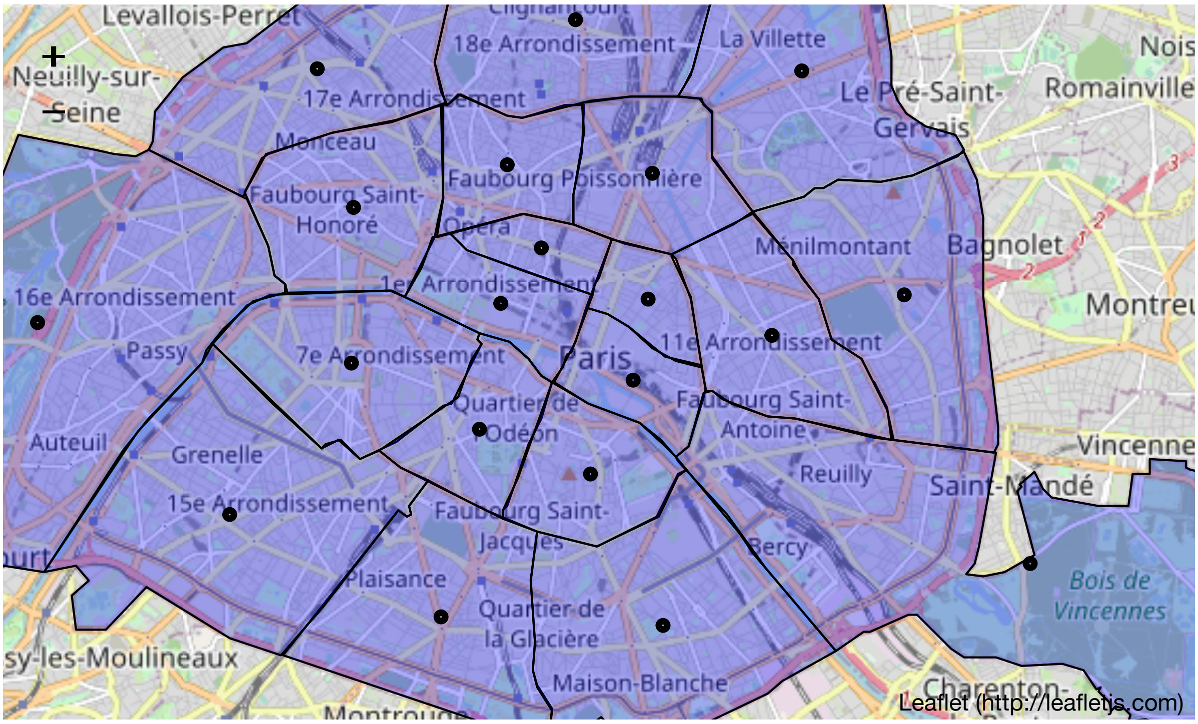
Out[3]:

	Ardt	Latitude	Longitude
0	1	48.862563	2.336443
1	2	48.868279	2.342803
2	3	48.862872	2.360001
3	4	48.854341	2.357630
4	5	48.844443	2.350715
5	6	48.849130	2.332898
6	7	48.856174	2.312188
7	8	48.872721	2.312554
8	9	48.877164	2.337458
9	10	48.876130	2.360728
10	11	48.859059	2.380058
11	12	48.834974	2.421325
12	13	48.828388	2.362272
13	14	48.829245	2.326542
14	15	48.840085	2.292826
15	16	48.860392	2.261971
16	17	48.887327	2.306777
17	18	48.892569	2.348161
18	19	48.887076	2.384821
19	20	48.863461	2.401188

Which we can add to the previous map...

In [4]:
```python
for ardt, lat, lng in zip(paris_ardt_df['Ardt'], paris_ardt_df['Latitude'], paris_ardt_df['Longitude']):
    label = folium.Popup("Ardt n°"+ str(ardt), parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='black',
        parse_html=False).add_to(paris_choropleth)

paris_choropleth
```

Out[4]:

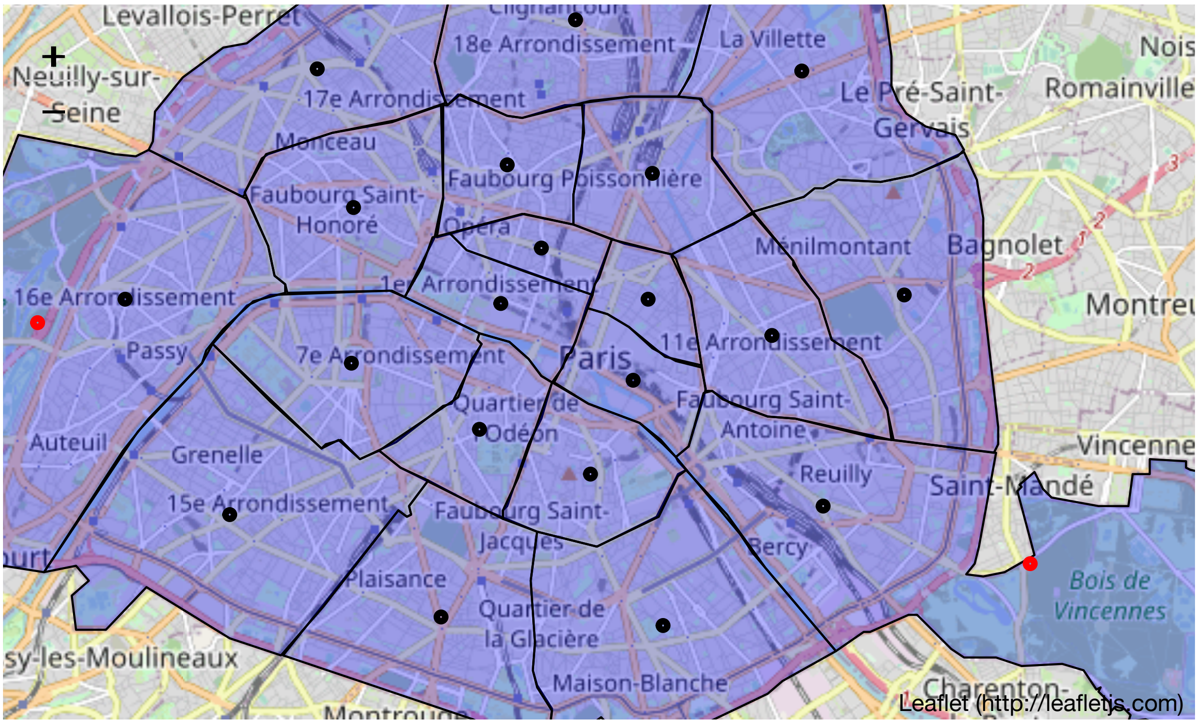


We can see however that the centers of the 12th and 16th neighborhood are quite off, as they account for large parks - so we will correct them as follows:

In [5]:
```python
corrections = [
    [12, 48.841, 2.388],
    [16, 48.863, 2.276]
]

corrections_df = pd.DataFrame(corrections,columns=['Ardt','Latitude','Longitude'])
paris_ardt_df = paris_ardt_df.append(corrections_df).drop_duplicates('Ardt',keep='last').sort_values('Ardt',ignore_index=True)
```

In [6]:
```python
paris_choropleth = folium.Map(location = [48.856578, 2.351828], zoom_start = 12)
paris_choropleth.choropleth(geo_data = geo,fill_opacity=0.3,fill_color='blue')
paris_choropleth

for ardt, lat, lng in zip(paris_ardt_df['Ardt'], paris_ardt_df['Latitude'], paris_ardt_df['Longitude']):
    label = folium.Popup("Ardt n°"+ str(ardt), parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='black',
        parse_html=False).add_to(paris_choropleth)

#adding markers using previous coordinates...
folium.CircleMarker(
        [48.834974, 2.421325],
        radius=2,
        color='red',
        parse_html=False).add_to(paris_choropleth)
folium.CircleMarker(
        [48.860392, 2.261971],
        radius=2,
        color='red',
        parse_html=False).add_to(paris_choropleth)



paris_choropleth
```

Out[6]:



Looks much better !

Downloading Venues' data using the FourSquare API

Now that we have the coordinates of the center of each neighborhood, we will use them to get data related to the nearby venues using the FourSquare API:

- First, will need to input our FourSquare credentials

In [7]:
```
CLIENT_ID = '################' # your Foursquare ID
CLIENT_SECRET = '################' # your Foursquare Secret
ACCESS_TOKEN = '################' # your FourSquare Access Token
#VERSION = '20180604'
VERSION = '20210411'
LIMIT = 100
```

- then we'll create a function to actually request the data for each neighborhood and store it in a dataframe

In [8]:

```python
import requests

def getNearbyVenues(names, latitudes, longitudes, radius):

    venues_list=[]
    for name, lat, lng in zip(names, latitudes, longitudes):
        print('Ardt ' + str(name) + ' : Getting data...')

        # creating 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)

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

        # returning 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])

        print('Done'+'\n')

    nearby_venues = pd.DataFrame([item for venue_list in venues_lis
t for item in venue_list])
    nearby_venues.columns = ['Neighborhood',
                  'Neighborhood Latitude',
                  'Neighborhood Longitude',
                  'Venue',
                  'Venue Latitude',
                'Venue Longitude',
                  'Venue Category']

    return(nearby_venues)
```

- once it's done, we can use the function with the neighborhood centers that we defined above:

In [9]:
```
paris_venues = getNearbyVenues(names=paris_ardt_df['Ardt'],
                                latitudes=paris_ardt_df['Latitude'],
                                longitudes=paris_ardt_df['Longitude'],
                                radius=1750
                               )
```

```
Ardt 1 : Getting data...
Done

Ardt 2 : Getting data...
Done

Ardt 3 : Getting data...
Done

Ardt 4 : Getting data...
Done

Ardt 5 : Getting data...
Done

Ardt 6 : Getting data...
Done

Ardt 7 : Getting data...
Done

Ardt 8 : Getting data...
Done

Ardt 9 : Getting data...
Done

Ardt 10 : Getting data...
Done

Ardt 11 : Getting data...
Done

Ardt 12 : Getting data...
Done

Ardt 13 : Getting data...
Done

Ardt 14 : Getting data...
Done

Ardt 15 : Getting data...
Done

Ardt 16 : Getting data...
Done
```

```
Ardt 17 : Getting data...
Done

Ardt 18 : Getting data...
Done

Ardt 19 : Getting data...
Done

Ardt 20 : Getting data...
Done
```

- this has collected data for all categories of venues, so we will create a dataframe that only includes restaurants:

In [10]:
```
# Keeping only restaurants
paris_restaurants = paris_venues[paris_venues['Venue Category'].str
.contains("Restaurant")]
paris_restaurants.shape
```

Out[10]: (650, 7)

Now, as we have collected data based on the proximity of each venue to the center of each neighborhood ('*Arrondissement*' in french), we happen to have duplicates in our dataframe...

In [11]:
```
paris_restaurants.groupby(['Venue','Venue Latitude','Venue Longitud
e']).count().sort_values("Neighborhood",ascending=False).head()
```

Out[11]:

			Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue Category
Venue	**Venue Latitude**	**Venue Longitude**				
Raviolis Chinois Nord-Est	**48.862851**	**2.349547**	4	4	4	4
Foodi Jia-Ba-Buay	**48.867894**	**2.348266**	4	4	4	4
Taing Song-Heng	**48.864701**	**2.356888**	4	4	4	4
Chez Le Libanais	**48.853285**	**2.341673**	4	4	4	4
Man'ouché	**48.861858**	**2.351093**	4	4	4	4

So our first task will be to 'clean' this dataframe by removing all these duplicates...

To do so, we'll calculate the distance of each venue from the center to each neighborhood and keep the one with the lowest value:

- So we start by generating a matrix which gives us for each venue its distance to the center of all Paris' neighborhoods (please note that `Ardt` stands for *Arrondissement*, or neighborhood)

In [12]:
```
import sklearn.neighbors
import numpy as np

# generating radians
paris_ardt_df[['lat_radians_A','long_radians_A']] = (
    np.radians(paris_ardt_df.loc[:,['Latitude','Longitude']])
)

paris_restaurants[['lat_radians_B','long_radians_B']] = (
    np.radians(paris_restaurants.loc[:,['Venue Latitude','Venue Lon
gitude']])
)

# calculating the distances using the Haversine formula
dist = sklearn.neighbors.DistanceMetric.get_metric('haversine')

dist_matrix_center = (dist.pairwise
    (paris_restaurants[['lat_radians_B','long_radians_B']],
        paris_ardt_df[['lat_radians_A','long_radians_A']])*6371
)
# Note that 6371 is the radius of the earth in kilometers

df_dist_center_matrix = (
    pd.DataFrame(dist_matrix_center,index=paris_restaurants['Venue'
],
                 columns=paris_ardt_df['Ardt'])
)

df_dist_center_matrix['Ardt'] = df_dist_center_matrix.idxmin(axis=1
)

df_dist_center_matrix
```

```
/opt/anaconda3/lib/python3.8/site-packages/pandas/core/frame.py:29
63: 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/pa
ndas-docs/stable/user_guide/indexing.html#returning-a-view-versus-
a-copy
  self[k1] = value[k2]
```

Out[12]:

Ardt	1	2	3	4	5	6	7	8
Venue								
Sanukiya	0.307293	0.768340	1.927121	2.089930	2.571143	1.734015	1.844557	1.791325
Restaurant Kunitoraya	0.395082	0.522141	1.758858	2.027537	2.625663	1.906649	2.092016	1.896974
Boutique yam'Tcha	0.444513	0.731135	1.295473	1.384174	2.014482	1.561353	2.292932	2.501703
Enza & Famiglia	0.534675	0.789590	1.225187	1.287015	1.936670	1.547370	2.354014	2.598143
Au Vieux Comptoir	0.817624	1.071672	1.107074	0.981898	1.641425	1.454484	2.501427	2.897499
...	...	...	...	...	...	...	...	...
Khun Akorn	4.724190	4.534347	3.140741	2.997939	3.509612	4.763998	6.319249	6.753254
Café Lino	4.440884	4.178482	2.788728	2.795951	3.480619	4.641880	6.123943	6.426529
La Petite Fabrique	4.678842	4.418760	3.029087	3.022655	3.671422	4.856581	6.352607	6.666795
Les Mondes Bohèmes	4.710890	4.445521	3.056969	3.059739	3.713847	4.896352	6.389219	6.695335
Aux Deux Avenues	5.834271	5.410390	4.111458	4.373991	5.184041	6.266474	7.638916	7.669853

650 rows × 21 columns

In [13]:
```python
venue_ardt = df_dist_center_matrix[['Ardt']].reset_index()
venue_ardt.drop_duplicates(subset=['Venue'],inplace=True)

paris_restaurants = pd.merge(paris_restaurants, venue_ardt, on=['Venue'], how='inner')
paris_restaurants = paris_restaurants.drop(['Neighborhood','Neighborhood Latitude','Neighborhood Longitude','lat_radians_B','long_radians_B'],axis=1).drop_duplicates(subset='Venue')
paris_restaurants.head()
```

Out[13]:

	Venue	Venue Latitude	Venue Longitude	Venue Category	Ardt
0	Sanukiya	48.864713	2.333805	Udon Restaurant	1
2	Restaurant Kunitoraya	48.866116	2.336467	Japanese Restaurant	1
5	Boutique yam'Tcha	48.861710	2.342380	Chinese Restaurant	1
7	Enza & Famiglia	48.861191	2.343449	Italian Restaurant	1
9	Au Vieux Comptoir	48.858893	2.346129	French Restaurant	1

In [14]:
```python
# No more duplicates...

paris_restaurants.groupby(['Venue','Venue Latitude','Venue Longitude']).count().sort_values("Ardt",ascending=False).head(5)
```

Out[14]:

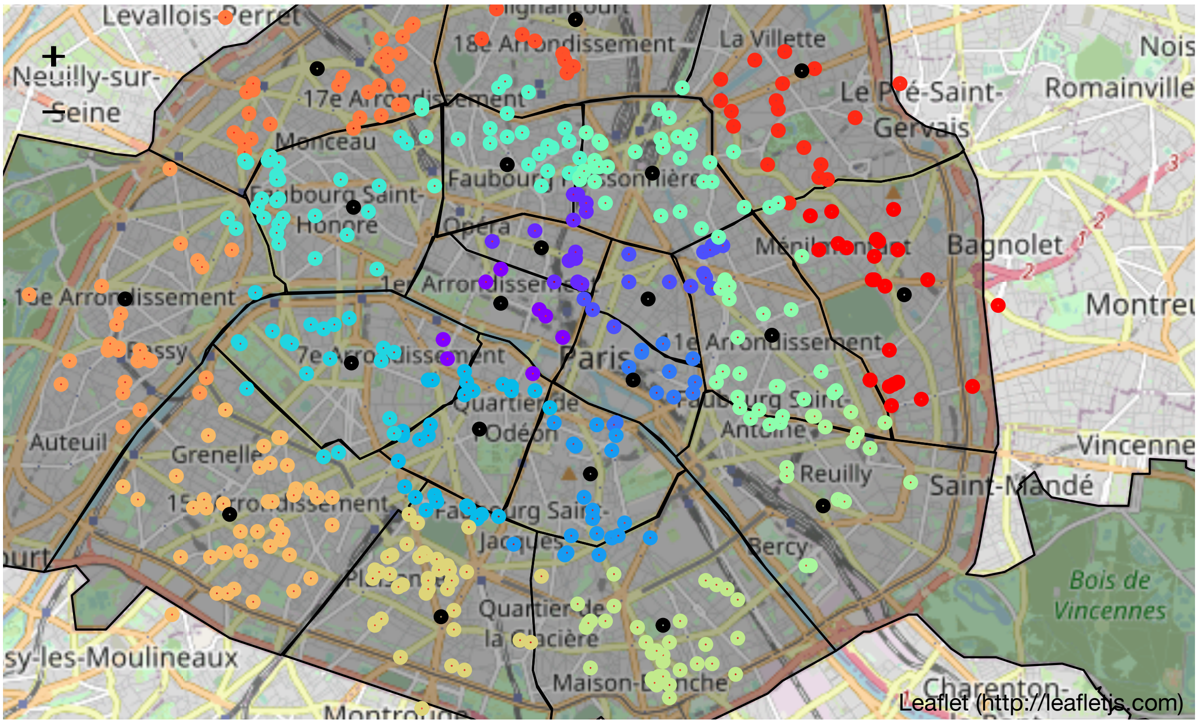
			Venue Category	Ardt
Venue	**Venue Latitude**	**Venue Longitude**		
0 d'Attente	**48.837847**	**2.355120**	1	1
Le Temps des Cerises	**48.852554**	**2.364195**	1	1
Les Fauves	**48.841937**	**2.322581**	1	1
Les Chics Types	**48.883873**	**2.380440**	1	1
Les Canailles	**48.879281**	**2.334570**	1	1

We can now plot all restaurants on the map to check if the venues in the dataset are indeed included within the right neighborhood

In [15]:

```
paris = folium.Map(location = [48.856578, 2.351828], zoom_start = 12)

import matplotlib.cm as cm
import matplotlib.colors as colors

x = np.arange(20) # There are 20 neighbohoods in Paris
ys = [i + x + (i*x)**2 for i in range(20)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

paris.choropleth(geo_data = geo,fill_opacity=0.3,fill_color='black')
for lat, lng, label, ardt in zip(paris_restaurants['Venue Latitude'], paris_restaurants['Venue Longitude'], paris_restaurants['Venue'],paris_restaurants['Ardt']):
    label = folium.Popup(label + " ("+ str(ardt) +")", parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color=rainbow[ardt-1],
        fill=True,
        fill_color='red',
        fill_opacity=0.7,
        parse_html=False).add_to(paris)

for ardt, lat, lng in zip(paris_ardt_df['Ardt'], paris_ardt_df['Latitude'], paris_ardt_df['Longitude']):
    label = folium.Popup("Ardt n°"+ str(ardt), parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='black',
        parse_html=False).add_to(paris)

paris
```

Out[15]:



That looks about right! The data is almost ready to be analyzed!

We'll now take care of the `Venue Category` values:

- First, we'll replace *Restaurant* by *Unspecified* in `paris_restaurants['Venue Category']`

In [16]:
```
paris_restaurants.loc[paris_restaurants['Venue Category']=='Restaurant'] = paris_restaurants.loc[paris_restaurants['Venue Category']=='Restaurant'].replace('Restaurant','Unspecified')
paris_restaurants.groupby(['Venue Category']).count().sort_values('Venue',ascending=False).drop(['Venue Latitude','Venue Longitude','Ardt'],axis=1).head()
```

Out[16]:

	Venue
Venue Category	
French Restaurant	192
Italian Restaurant	46
Japanese Restaurant	31
Unspecified	24
Thai Restaurant	20

- Then we will attribute a unique identifier to each category:

In [17]:
```
paris_restaurants.insert(4,'code',(pd.factorize(paris_restaurants['Venue Category'])[0]+1))
paris_restaurants.groupby(['Venue Category','code']).count().sort_values('Venue',ascending=False).drop(['Venue Latitude','Venue Longitude','Ardt'],axis=1).head()
```

Out[17]:

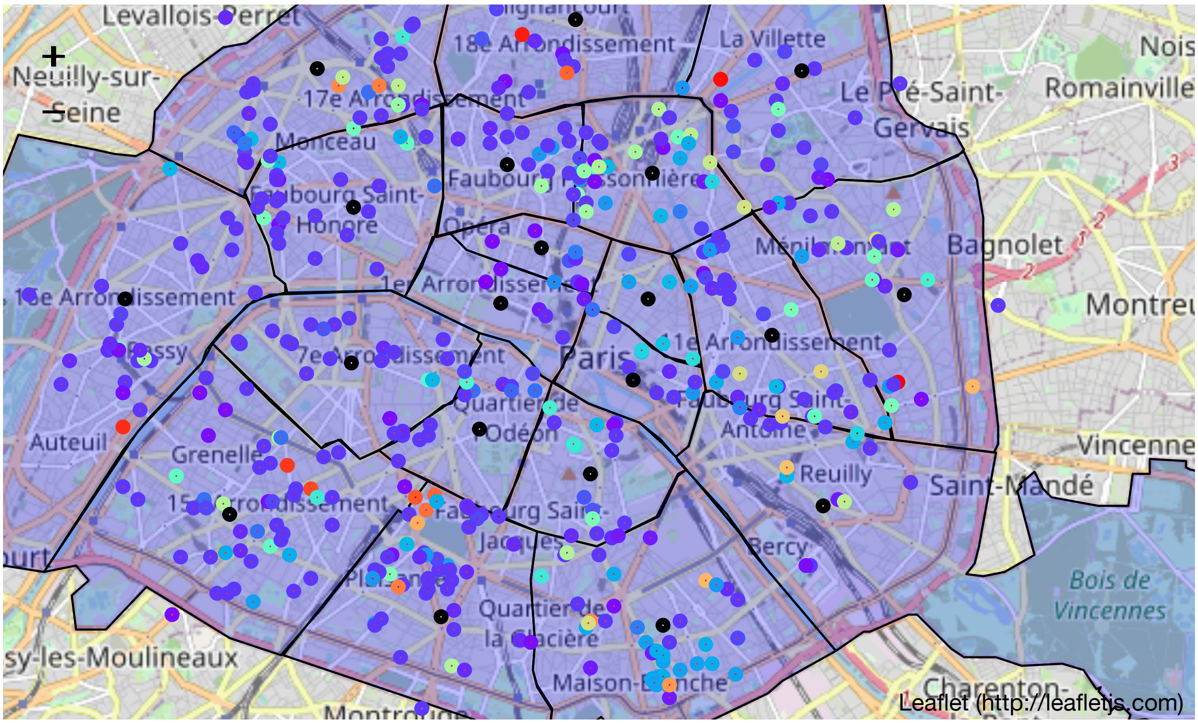
		Venue
Venue Category	**code**	
French Restaurant	**5**	192
Italian Restaurant	**4**	46
Japanese Restaurant	**2**	31
Unspecified	**6**	24
Thai Restaurant	**14**	20

- Finally, from this cleaned dataframe, we can plot the restaurants on the map with colors based on the category they belong to:

In [18]:

```
paris_cat = folium.Map(location = [48.856578, 2.351828], zoom_start
= 12)

import matplotlib.cm as cm
import matplotlib.colors as colors

nb_cat = len(paris_restaurants.groupby(['code']))

x = np.arange(nb_cat)
ys = [i + x + (i*x)**2 for i in range(nb_cat)]
colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
rainbow = [colors.rgb2hex(i) for i in colors_array]

paris_cat.choropleth(geo_data = geo,fill_opacity=0.25,fill_color='b
lue')
for lat, lng, label, cat , group in zip(paris_restaurants['Venue La
titude'], paris_restaurants['Venue Longitude'], paris_restaurants['
Venue'],paris_restaurants['code'], paris_restaurants['Venue Categor
y']):
    label = folium.Popup(label + " (" + group + ") [" + str(ardt)+
"]", parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color=rainbow[cat-1],
        fill=True,
        fill_color='red',
        fill_opacity=0.7,
        parse_html=False).add_to(paris_cat)

for ardt, lat, lng in zip(paris_ardt_df['Ardt'], paris_ardt_df['Lat
itude'], paris_ardt_df['Longitude']):
    label = folium.Popup("Ardt n°"+ str(ardt), parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='black',
        parse_html=False).add_to(paris_cat)

paris_cat
```

Out[18]:



Methodology

In order to define where would be the best spots to open an italian restaurant in Paris, we will take the following steps:

1. Verifying our assumptions

- Basic analysis of the data
- Compare popularity of french vs. italian restaurants for each neighborhood

2. Density Analyses

- Mapping neighborhoods with an *italian restaurants deficit*
- Mapping venue densities for french and italiantrestaurants
- Isolating french restaurants that are far from italian restaurants

3. Clustering & Cross-checking

- Creating clusters using k-means
- Superimposing the analyses
- Listing of the results

Analysis

1. Verifying our assumptions

In [19]:
```
paris_restaurants.groupby('Venue Category').nunique().sort_values('Venue',ascending=False).drop(['Venue Latitude','Venue Longitude','Venue Category','code'],axis=1).head()
```

Out[19]:

	Venue	Ardt
Venue Category		
French Restaurant	192	20
Italian Restaurant	46	20
Japanese Restaurant	31	17
Unspecified	24	14
Thai Restaurant	20	9

From the above table, we can see that the `Venue Category` *Italian Restaurants* is not only the second best in Paris in terms of number of venues, but also that it is **the only non-french category that is present in all of the 20 parisian neighborhoods**.

Getting Most common value per neighborhood

In [20]:
```
paris_onehot = pd.get_dummies(paris_restaurants[['Venue Category']], prefix="", prefix_sep="")
paris_onehot['Ardt'] = paris_restaurants['Ardt']
paris_grouped = paris_onehot.groupby('Ardt',axis=0).mean().reset_index()
```

In [21]:
```
def return_most_common_venues(row, num_top_venues):
    row_categories = row.iloc[1:]
    row_categories_sorted = row_categories.sort_values(ascending=False)

    return row_categories_sorted.index.values[0:num_top_venues]
```

In [22]:
```python
import numpy as np

num_top_venues = 15

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

# create columns according to number of top venues
columns = ['Ardt']
for ind in np.arange(num_top_venues):
    try:
        columns.append('{}{} Most Common Venue'.format(ind+1, indic
ators[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['Ardt'] = paris_grouped['Ardt']

for ind in np.arange(paris_grouped.shape[0]):
    neighborhoods_venues_sorted.iloc[ind, 1:] = return_most_common_
venues(paris_grouped.iloc[ind, :], num_top_venues)

neighborhoods_venues_sorted
```

Out[22]:

	Ardt	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7 C
0	1	French Restaurant	Japanese Restaurant	Chinese Restaurant	Italian Restaurant	Udon Restaurant	Unspecified	Re
1	2	Japanese Restaurant	French Restaurant	Ramen Restaurant	Greek Restaurant	Doner Restaurant	Corsican Restaurant	Re
2	3	Unspecified	Vietnamese Restaurant	Italian Restaurant	Seafood Restaurant	Chinese Restaurant	French Restaurant	Veg Re
3	4	French Restaurant	Japanese Restaurant	Scandinavian Restaurant	Italian Restaurant	Vegetarian / Vegan Restaurant	Falafel Restaurant	Pı Re
4	5	French Restaurant	Italian Restaurant	Greek Restaurant	Chinese Restaurant	Thai Restaurant	Ethiopian Restaurant	M Re
5	6	French Restaurant	Italian Restaurant	Unspecified	Lebanese Restaurant	Seafood Restaurant	Mexican Restaurant	Re
6	7	French Restaurant	Japanese Restaurant	Greek Restaurant	Italian Restaurant	Chinese Restaurant	Indian Restaurant	Fa Re
7	8	French Restaurant	Italian Restaurant	Japanese Restaurant	Thai Restaurant	Sushi Restaurant	Seafood Restaurant	Re
8	9	French Restaurant	Italian Restaurant	Japanese Restaurant	Vegetarian / Vegan Restaurant	Unspecified	Thai Restaurant	Lı Re

9	10	French Restaurant	Japanese Restaurant	Thai Restaurant	Vegetarian / Vegan Restaurant	Unspecified	Chinese Restaurant	Re
10	11	French Restaurant	Unspecified	Italian Restaurant	Vietnamese Restaurant	Asian Restaurant	Moroccan Restaurant	Re
11	12	French Restaurant	Thai Restaurant	Japanese Restaurant	Falafel Restaurant	Seafood Restaurant	Chinese Restaurant	Re
12	13	Vietnamese Restaurant	Thai Restaurant	French Restaurant	Chinese Restaurant	Mediterranean Restaurant	Asian Restaurant	Car Re
13	14	French Restaurant	Italian Restaurant	Vietnamese Restaurant	Vegetarian / Vegan Restaurant	Japanese Restaurant	Indian Restaurant	Uns
14	15	French Restaurant	Japanese Restaurant	Lebanese Restaurant	Unspecified	Thai Restaurant	Italian Restaurant	Re
15	16	French Restaurant	Italian Restaurant	Japanese Restaurant	Seafood Restaurant	Middle Eastern Restaurant	Persian Restaurant	Re
16	17	French Restaurant	Italian Restaurant	Unspecified	Turkish Restaurant	Seafood Restaurant	Breton Restaurant	E Re
17	18	French Restaurant	Japanese Restaurant	Italian Restaurant	Arepa Restaurant	Argentinian Restaurant	Greek Restaurant	Re
18	19	French Restaurant	Japanese Restaurant	Chinese Restaurant	Italian Restaurant	Unspecified	Moroccan Restaurant	Re
19	20	French Restaurant	Japanese Restaurant	Italian Restaurant	Moroccan Restaurant	Brazilian Restaurant	Vegetarian / Vegan Restaurant	Re

In [23]:

```
import plotly.express as px

selected_columns = neighborhoods_venues_sorted.columns[1:5]

fig_pc = px.parallel_categories(neighborhoods_venues_sorted,dimensi
ons=selected_columns,height=500,width=800,color='Ardt')
fig_pc.show()
```

```python
In [24]: # Summarizing the above in plain english ...

print("\n")
print("Italian Restaurants:")
print("\n")

for i in range(1,5):

    if 'Italian Restaurant' in neighborhoods_venues_sorted[neighbor
hoods_venues_sorted.columns[i]].value_counts():
        print(str(neighborhoods_venues_sorted.columns[i]) + ' in '
+ str(neighborhoods_venues_sorted[neighborhoods_venues_sorted.colum
ns[i]].value_counts()['Italian Restaurant']) + ' neighborhoods.')
        print('>> namely : ' + str(
            neighborhoods_venues_sorted[neighborhoods_venues_sorted
[neighborhoods_venues_sorted.columns[i]]=='Italian Restaurant']['Ar
dt'].tolist()
        ))
    else:
        print('Not the '+str(neighborhoods_venues_sorted.columns[i]
) + ' in any neighborhood.')
    print("\n")
```

```
Italian Restaurants:


Not the 1st Most Common Venue in any neighborhood.


2nd Most Common Venue in 7 neighborhoods.
>> namely : [5, 6, 8, 9, 14, 16, 17]


3rd Most Common Venue in 4 neighborhoods.
>> namely : [3, 11, 18, 20]


4th Most Common Venue in 4 neighborhoods.
>> namely : [1, 4, 7, 19]
```

We will now create a table that will count the actual number of french and italian restaurants in each neighborhood.

In [25]:
```
group_by_cat = paris_restaurants.groupby(['Ardt','Venue Category'])
.count()[['Venue']].reset_index()
ardt_type = []
for i in range(20):
    ardt = i + 1
    fr_res = group_by_cat[group_by_cat['Ardt']==ardt][group_by_cat[
"Venue Category"]=="French Restaurant"]['Venue'].values[0]
    it_res = group_by_cat[group_by_cat['Ardt']==ardt][group_by_cat[
"Venue Category"]=="Italian Restaurant"]['Venue'].values[0]
    total = group_by_cat[group_by_cat['Ardt']==ardt]['Venue'].sum()
    ardt_type.append([ardt, fr_res, it_res, total, fr_res/total, it
_res/total,it_res/fr_res])


ardt_type_df = pd.DataFrame(ardt_type,columns=['Ardt','nb_fr','nb_i
t','nb_tot','pct_fr','pct_it','it/fr']).sort_values('Ardt',ignore_i
ndex=True)

ardt_type_df
```

```
&lt;ipython-input-25-422bac177c2f&gt;:5: UserWarning:

Boolean Series key will be reindexed to match DataFrame index.

&lt;ipython-input-25-422bac177c2f&gt;:6: UserWarning:

Boolean Series key will be reindexed to match DataFrame index.
```

Out[25]:

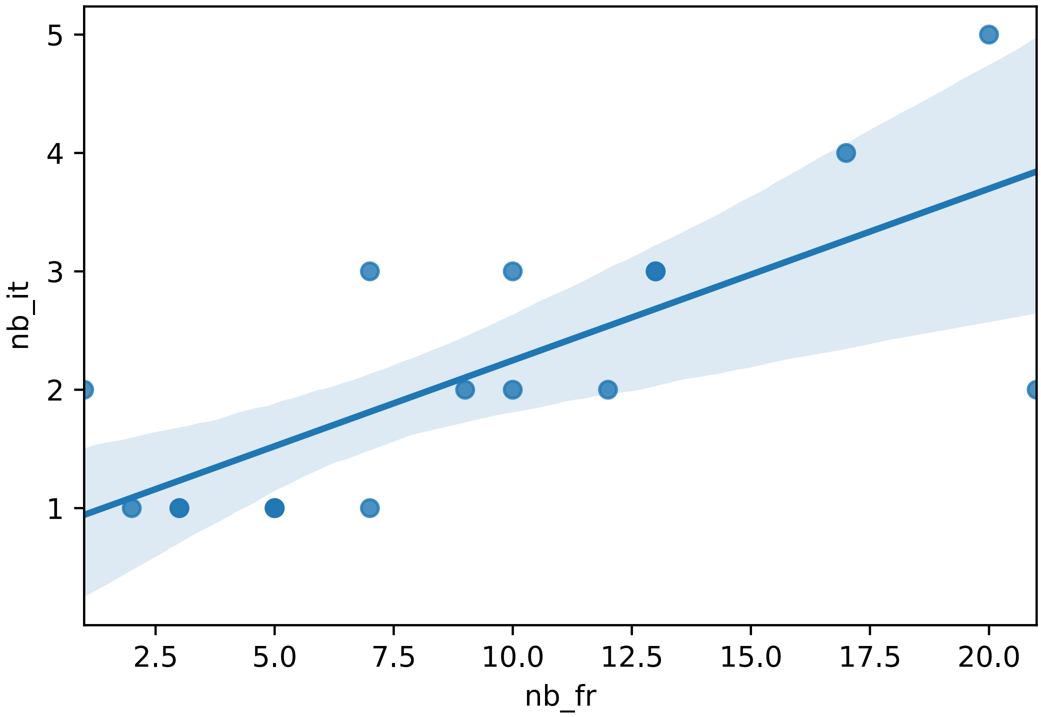
	Ardt	nb_fr	nb_it	nb_tot	pct_fr	pct_it	it/fr
0	1	3	1	8	0.375000	0.125000	0.333333
1	2	3	1	13	0.230769	0.076923	0.333333
2	3	1	2	15	0.066667	0.133333	2.000000
3	4	5	1	12	0.416667	0.083333	0.200000
4	5	7	3	20	0.350000	0.150000	0.428571
5	6	10	3	27	0.370370	0.111111	0.300000
6	7	17	1	20	0.850000	0.050000	0.058824
7	8	17	4	28	0.607143	0.142857	0.235294
8	9	13	3	24	0.541667	0.125000	0.230769
9	10	7	1	34	0.205882	0.029412	0.142857
10	11	12	2	25	0.480000	0.080000	0.166667
11	12	5	1	15	0.333333	0.066667	0.200000
12	13	5	1	39	0.128205	0.025641	0.200000
13	14	20	5	39	0.512821	0.128205	0.250000
14	15	21	2	43	0.488372	0.046512	0.095238
15	16	12	7	27	0.444444	0.259259	0.583333
16	17	13	3	29	0.448276	0.103448	0.230769
17	18	2	1	10	0.200000	0.100000	0.500000
18	19	10	2	21	0.476190	0.095238	0.200000
19	20	9	2	24	0.375000	0.083333	0.222222

First, we'll plot the number of italian restaurants vs. the number of french restaurant and draw a regression line to confirm if these two are indeed positively correlated.

We will first create a 'clean' dataframe that will exclude outliers and then draw the regression line using Seaborn:

In [26]:
```
# Dropping outliers and drawing a regression line
ardt_type_df_clean = ardt_type_df.drop(ardt_type_df['pct_fr'].idxma
x()).drop(ardt_type_df['pct_it'].idxmax())
import seaborn as sns
ax = sns.regplot(x="nb_fr", y="nb_it", data=ardt_type_df_clean)
ax
```

Out[26]: <matplotlib.axes._subplots.AxesSubplot at 0x12286bbe0>



So there seems to be a positive correlation that confirms our previous assumption! i.e. that an area with many french restaurants will also be good for italian restaurants.

2. Density Analyses

Now we will take the number of italian/french restaurants and map it to see which aread have a 'deficit' of italian restaurants.

We'll attribute a 0/1 deficit label to each neighborhood, with 1 indicating that the share of italian restaurants is below the median.

In [27]:
```
it_deficit = ardt_type_df[['Ardt','it/fr']]
it_deficit['deficit'] = it_deficit['it/fr'] <= it_deficit['it/fr'].
median()
it_deficit['deficit'] = it_deficit['deficit'].astype(int)
it_deficit
```

```
<ipython-input-27-da3ef5ae4330>: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/pa
ndas-docs/stable/user_guide/indexing.html#returning-a-view-versus-
a-copy

<ipython-input-27-da3ef5ae4330>:3: 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/pa
ndas-docs/stable/user_guide/indexing.html#returning-a-view-versus-
a-copy
```

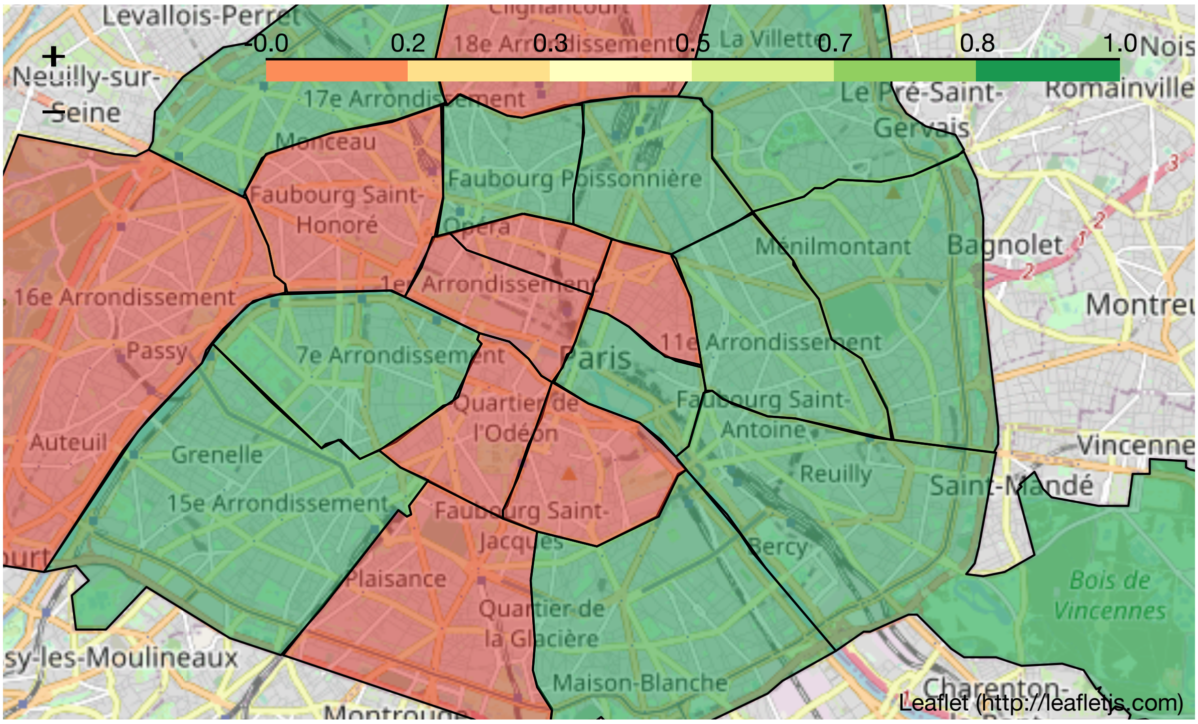
Out[27]:

	Ardt	it/fr	deficit
0	1	0.333333	0
1	2	0.333333	0
2	3	2.000000	0
3	4	0.200000	1
4	5	0.428571	0
5	6	0.300000	0
6	7	0.058824	1
7	8	0.235294	0
8	9	0.230769	1
9	10	0.142857	1
10	11	0.166667	1
11	12	0.200000	1
12	13	0.200000	1
13	14	0.250000	0
14	15	0.095238	1
15	16	0.583333	0
16	17	0.230769	1
17	18	0.500000	0
18	19	0.200000	1
19	20	0.222222	1

In [28]:

```
latitude = 48.856578
longitude = 2.351828

italian_deficit = folium.Map(location=[latitude, longitude], zoom_s
tart=12)


italian_deficit.choropleth(geo_data = geo,key_on = "feature.propert
ies.c_ar",data=it_deficit[it_deficit['deficit']==1],
                 columns = ['Ardt','deficit'],fill_color='RdYlGn',f
ill_opacity=0.5)


# adding markers to map

italian_deficit
```

Out[28]:



The neighborhoods in green would be good candidates to welcome a new italian restaurant.

Mapping densities

Density of italian restaurants

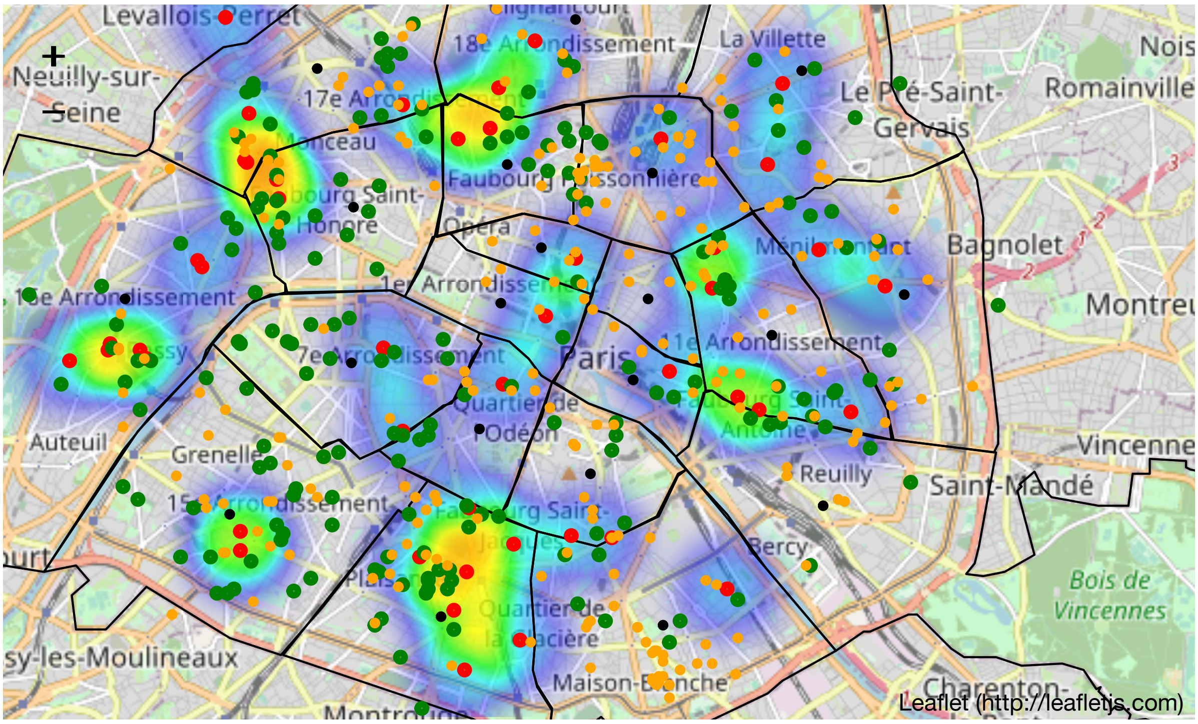
In [29]:

```
from folium.plugins import HeatMap

italian = paris_restaurants[paris_restaurants['Venue Category']=='I
talian Restaurant']
french = paris_restaurants[paris_restaurants['Venue Category']=='Fr
ench Restaurant']
```

```
excluded = ['Italian Restaurant','French Restaurant']
others = paris_restaurants[~paris_restaurants['Venue Category'].isi
n(excluded)]

latitude = 48.856578
longitude = 2.351828


# Italian HeatMap

italian_coord = []
for index, row in italian.iterrows():
    italian_coord.append([row[1], row[2]])

map_density_it = folium.Map(location=[latitude, longitude], zoom_st
art=12)

HeatMap(italian_coord).add_to(map_density_it)

map_density_it.choropleth(geo_data = geo,fill_opacity=0)

for lat, lng, label in zip(italian['Venue Latitude'], italian['Venu
e Longitude'], italian['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='red',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_density_it)
for lat, lng, label in zip(french['Venue Latitude'], french['Venue
Longitude'], french['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_density_it)
for lat, lng, label in zip(others['Venue Latitude'], others['Venue
Longitude'], others['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=1,
        popup=label,
        color='orange',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_density_it)
for ardt, lat, lng in zip(paris_ardt_df['Ardt'], paris_ardt_df['Lat
itude'], paris_ardt_df['Longitude']):
    label = folium.Popup("Ardt n°"+ str(ardt), parse_html=True)
```

```
    folium.CircleMarker(
        [lat, lng],
        radius=1,
        popup=label,
        color='black',
        parse_html=False).add_to(map_density_it)
map_density_it
```

Out[29]:



On the above map:

- french restaurants are in green (we want to be as close to them as possible),
- italian restaurants are in red (we want to be as far from them as possible),
- other restaurants are in orange (we will not take them into account in this density analysis)

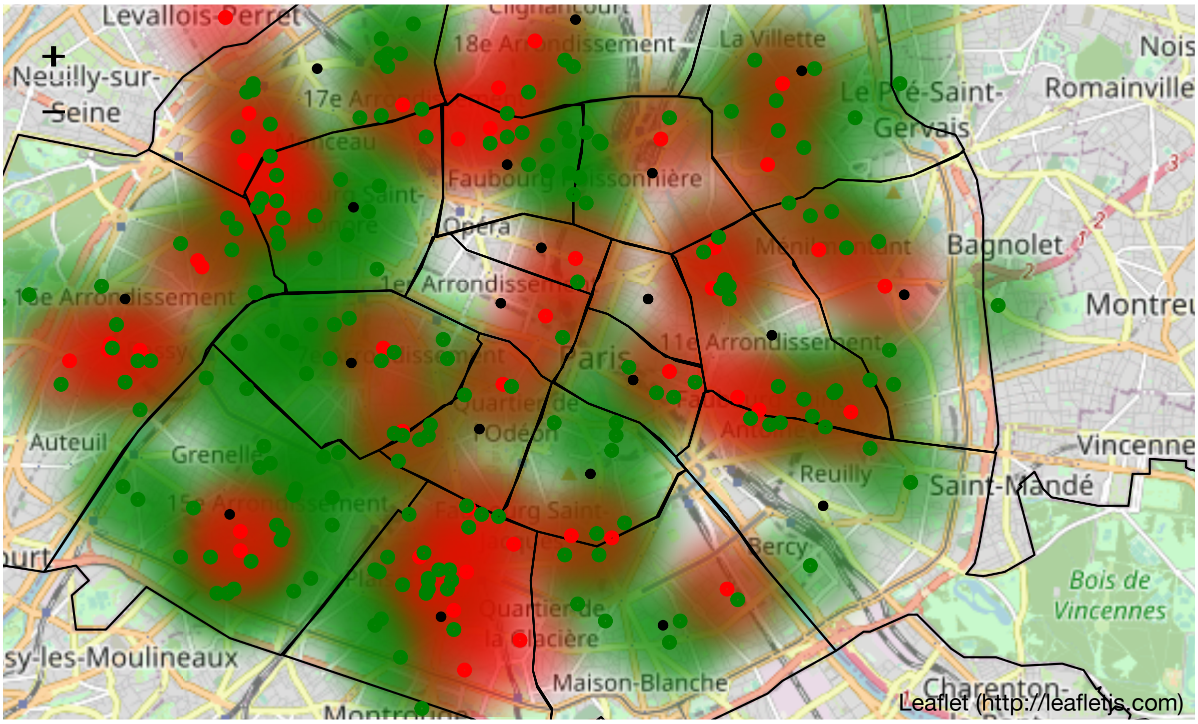
Now let's superimpose french and italian densities:

In [30]:

```
italian = paris_restaurants[paris_restaurants['Venue Category']=='Italian Restaurant']
french = paris_restaurants[paris_restaurants['Venue Category']=='French Restaurant']

excluded = ['Italian Restaurant','French Restaurant']
others = paris_restaurants[~paris_restaurants['Venue Category'].isin(excluded)]

latitude = 48.856578
longitude = 2.351828

italian_coord = []
for index, row in italian.iterrows():
    italian_coord.append([row[1], row[2]])
```

```
french_coord = []
for index, row in french.iterrows():
    french_coord.append([row[1], row[2]])


map_heat_fr_it = folium.Map(location=[latitude, longitude], zoom_st
art=12)

french_grad = {0.01: 'green', 1: 'green'}
italian_grad = {0.01: 'red', 1: 'red'}

HeatMap(french_coord, gradient = french_grad).add_to(map_heat_fr_it
)
HeatMap(italian_coord,gradient = italian_grad).add_to(map_heat_fr_i
t)


map_heat_fr_it.choropleth(geo_data = geo,fill_opacity=0)

for lat, lng, label in zip(italian['Venue Latitude'], italian['Venu
e Longitude'], italian['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='red',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_heat_fr_it)

for lat, lng, label in zip(french['Venue Latitude'], french['Venue
Longitude'], french['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_heat_fr_it)


for ardt, lat, lng in zip(paris_ardt_df['Ardt'], paris_ardt_df['Lat
itude'], paris_ardt_df['Longitude']):
    label = folium.Popup("Ardt n°"+ str(ardt), parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=1,
        popup=label,
        color='black',
        parse_html=False).add_to(map_heat_fr_it)

map_heat_fr_it
```

Out[30]:



So we'll now isolate the green areas, by measuring the distances from each french venue to the closest italian restaurant and keeping only the one that are the farthest

First of all, we'll get the distance matrix using the Haversine formula with the help of Scikit-learn

In [31]:
```
import sklearn.neighbors

french_coord_df = french.reset_index().drop(['index','Ardt','code',
'Venue Category'],axis=1)
italian_coord_df = italian.reset_index().drop(['index','Ardt','code
','Venue Category'],axis=1)


french_coord_df[['lat_radians_A','long_radians_A']] = (
    np.radians(french_coord_df.loc[:,['Venue Latitude','Venue Longi
tude']])
)
italian_coord_df[['lat_radians_B','long_radians_B']] = (
    np.radians(italian_coord_df.loc[:,['Venue Latitude','Venue Long
itude']])
)

dist = sklearn.neighbors.DistanceMetric.get_metric('haversine')
dist_matrix = (dist.pairwise
    (french_coord_df[['lat_radians_A','long_radians_A']],
     italian_coord_df[['lat_radians_B','long_radians_B']])*6371
)
# Note that 3959 is the radius of the earth in miles

df_dist_matrix = (
    pd.DataFrame(dist_matrix,index=french_coord_df['Venue'],
                 columns=italian_coord_df['Venue'])
)

df_dist_matrix['min_dist_it'] = df_dist_matrix.min(axis=1)
df_dist_matrix=df_dist_matrix.sort_values('min_dist_it',ascending=F
alse)

df_dist_matrix
```

Out[31]:

Venue	Enza & Famiglia	L'Étage de Pastavino	Les Amis des Messina	L'Osteria dell'Anima	Pasta Linea	La Trottinette	Gemini	F
Venue								
Les Pantins	5.735030	6.638454	5.027659	4.200099	5.292318	3.791520	7.902809	7.4
Le Quinzième	5.363588	4.644627	5.970421	7.320480	6.570467	7.502906	3.346682	3.4
Le Pré en Bulles – Chez Martine	4.988585	5.848713	4.335783	3.272086	4.341675	2.918839	7.150078	6.8
Aux Deux Avenues	5.323087	5.879951	4.987863	3.355342	3.939022	3.406846	7.162815	7.2
La Grenouille Bleue	5.273938	4.531769	5.896770	7.217432	6.445948	7.411978	3.222612	3.3
...	...	...	...	...	...	...	...	
Le Bois	5.101196	4.621584	5.549756	7.092337	6.553921	7.168598	3.542274	3.1
Pierre Gagnaire	3.420553	3.417415	3.575988	5.222327	5.023451	5.160085	3.073919	2.1
La Cuisine	3.558430	3.623480	3.653200	5.298303	5.159898	5.207988	3.350995	2.3
Le Bistrot des Vignes	4.683085	4.178170	5.156048	6.677621	6.116130	6.768255	3.086109	2.7
Le Bistrot des Campagnes	2.430904	1.508905	3.184820	3.865139	2.866975	4.214795	1.162029	2.0

192 rows × 47 columns

Then for each french restaurant we'll keep only the distance to closest italian, and keep only the venues for which this distance is maximum (we'll keep values above the 90th percentile):

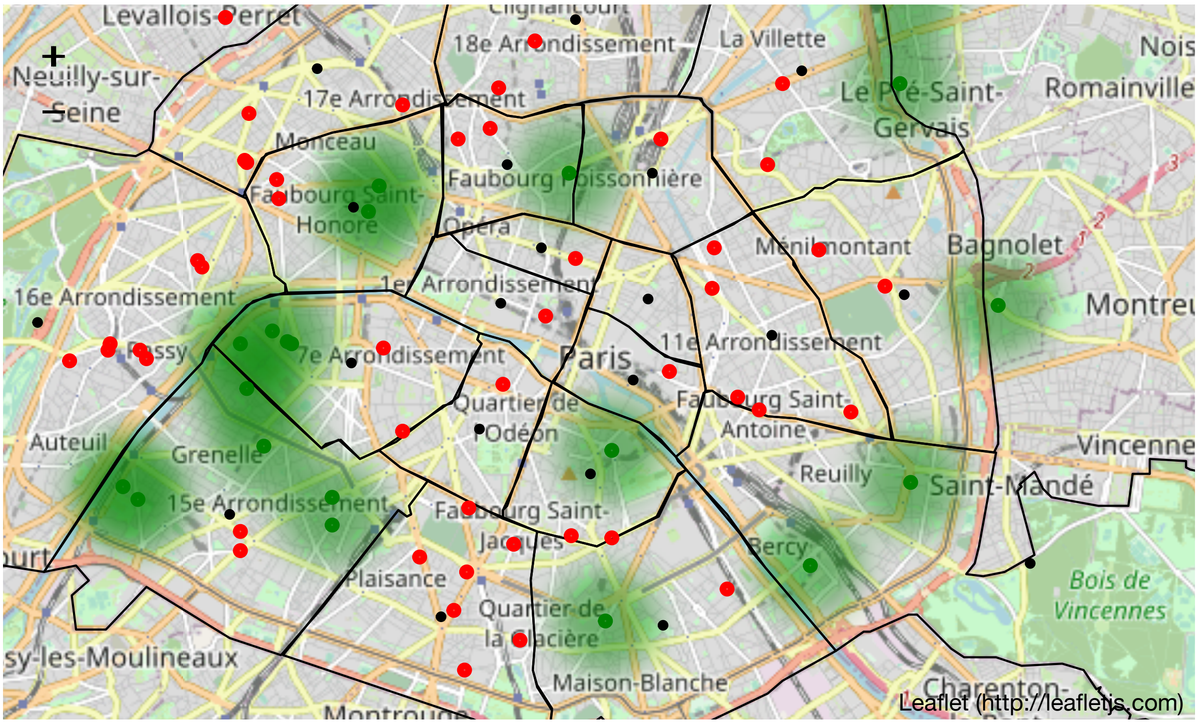
In [32]:
```
minimum_distance = df_dist_matrix.min_dist_it.quantile(0.9)

french_far = french[french['Venue'].isin(df_dist_matrix[df_dist_mat
rix['min_dist_it']>=minimum_distance].index)]
french_far.shape
```

Out[32]: (20, 6)

In [33]:

```
# Best locations HeatMap

map_best_loc= folium.Map(location=[latitude, longitude], zoom_start
=12)

french_coord = []
for index, row in french_far.iterrows():
    french_coord.append([row[1], row[2]])

french_grad = {0.01: 'green', 1: 'green'}
italian_grad = {0.01: 'red', 1: 'red'}

HeatMap(french_coord, gradient = french_grad).add_to(map_best_loc)
#HeatMap(italian_coord,gradient = italian_grad).add_to(map_best_loc
)
map_best_loc.choropleth(geo_data = geo,fill_opacity=0)

for lat, lng, label in zip(italian['Venue Latitude'], italian['Venu
e Longitude'], italian['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='red',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_best_loc)

for lat, lng, label in zip(french_far['Venue Latitude'], french_far
['Venue Longitude'], french_far['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_best_loc)


for arr in geo["features"]:
    prop = arr["properties"]
    folium.CircleMarker(prop["geom_x_y"], radius=1, color = 'black'
, popup = prop["l_ar"]).add_to(map_best_loc)

map_best_loc
```

Out[33]:

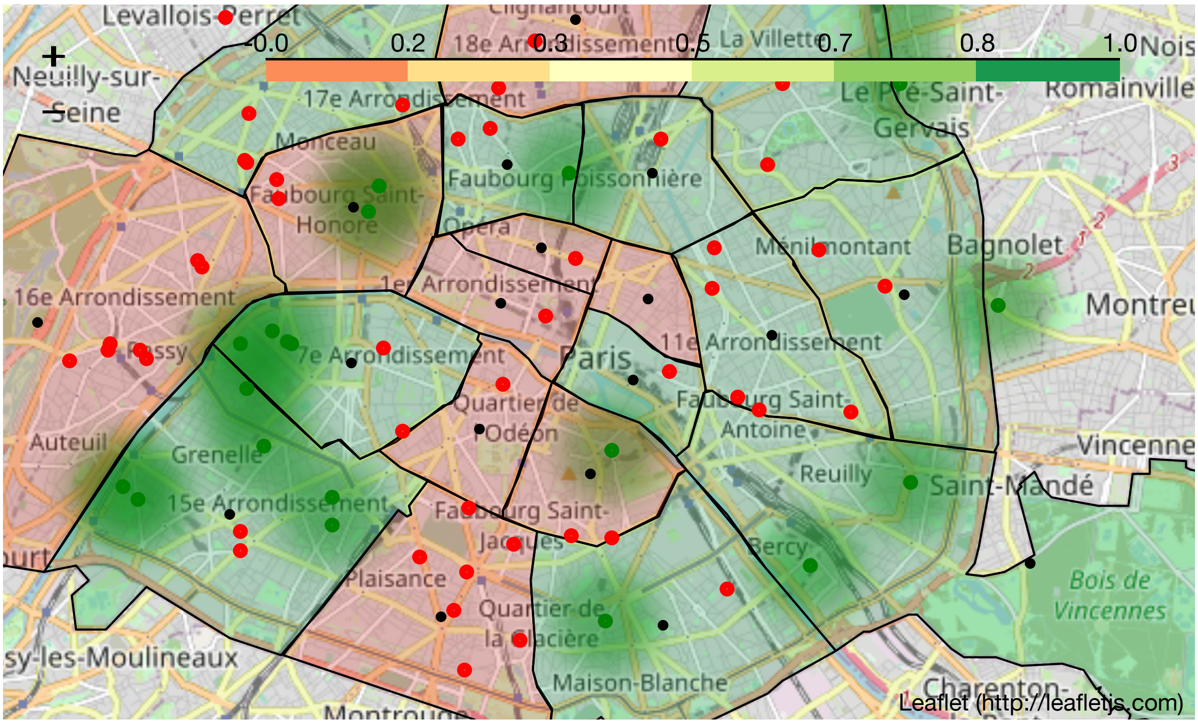


The areas in green are the ones that appears to be the best to open an italian restaurant as they have a high density of french restaurants and are far from existing italian venues.

Let's super-impose this map with the one showing the areas with a deficit of italian restaurants:

In [34]:
```python
# Best locations HeatMap + italian deficit

map_best_loc_def= folium.Map(location=[latitude, longitude], zoom_s
tart=12)

french_coord = []
for index, row in french_far.iterrows():
    french_coord.append([row[1], row[2]])

french_grad = {0.01: 'green', 1: 'green'}
italian_grad = {0.01: 'red', 1: 'red'}

HeatMap(french_coord, gradient = french_grad).add_to(map_best_loc_d
ef)
#HeatMap(italian_coord,gradient = italian_grad).add_to(map_best_loc
)
map_best_loc_def.choropleth(geo_data = geo,key_on = "feature.proper
ties.c_ar",data=it_deficit[it_deficit['deficit']==1],
                    columns = ['Ardt','deficit'],fill_color='RdYlGn',f
ill_opacity=0.25)

for lat, lng, label in zip(italian['Venue Latitude'], italian['Venu
e Longitude'], italian['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='red',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_best_loc_def)

for lat, lng, label in zip(french_far['Venue Latitude'], french_far
['Venue Longitude'], french_far['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_best_loc_def)


for arr in geo["features"]:
    prop = arr["properties"]
    folium.CircleMarker(prop["geom_x_y"], radius=1, color = 'black'
, popup = prop["l_ar"]).add_to(map_best_loc_def)

map_best_loc_def
```

Out[34]:



The results seem to be coherent, apart from a few exceptions!

Let's plot the densities using only venues that are in 'green' neighborhoods

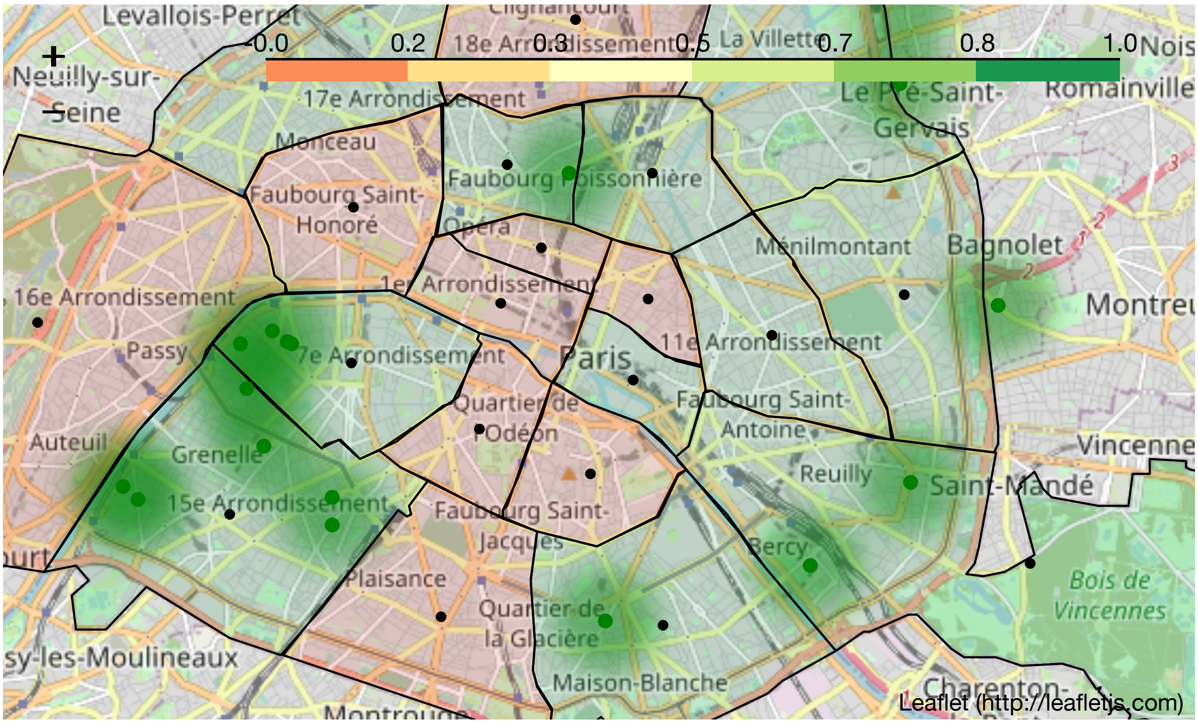
In [35]:

```
# Creating a curated dataframe
ardt_def_it = it_deficit[it_deficit['deficit']==1]['Ardt'].values.t
olist()
far_def = french_far[french_far['Ardt'].isin(ardt_def_it)]
```

In [36]:

```
# Plotting the best locations (far + deficit)

map_best_far_def= folium.Map(location=[latitude, longitude], zoom_s
tart=12)

french_coord = []
for index, row in far_def.iterrows():
    french_coord.append([row[1], row[2]])

french_grad = {0.01: 'green', 1: 'green'}
italian_grad = {0.01: 'red', 1: 'red'}

HeatMap(french_coord, gradient = french_grad).add_to(map_best_far_d
ef)
map_best_far_def.choropleth(geo_data = geo,key_on = "feature.proper
ties.c_ar",data=it_deficit[it_deficit['deficit']==1],
                 columns = ['Ardt','deficit'],fill_color='RdYlGn',f
ill_opacity=0.15)

for lat, lng, label in zip(far_def['Venue Latitude'], far_def['Venu
e Longitude'], far_def['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_best_far_def)


for arr in geo["features"]:
    prop = arr["properties"]
    folium.CircleMarker(prop["geom_x_y"], radius=1, color = 'black'
, popup = prop["l_ar"]).add_to(map_best_far_def)

map_best_far_def
```

Out[36]:



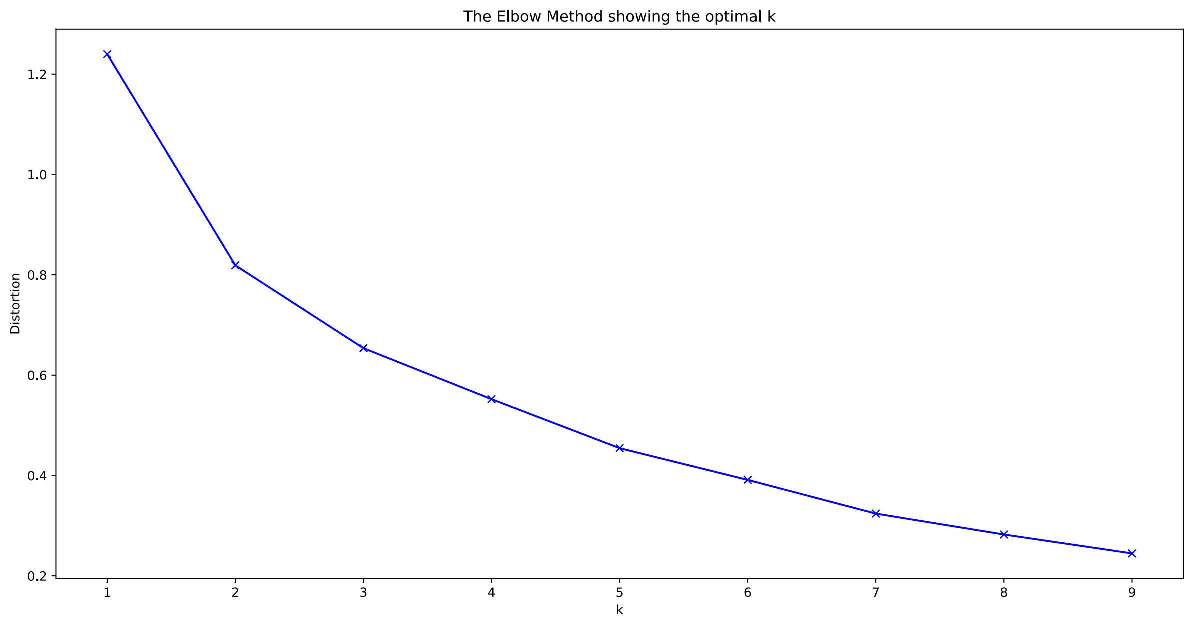
So now that we have a good idea of which areas would be good, we'll run a cluster analysis to see if this can help us to further refine this selection.

Clustering

We will create kmeans clusters based on the `paris_grouped` data frame above that gathers data about the most popular venues in each neighborhood

In [37]:
```python
# Determining which k value would be best using the elbow method...

import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.cluster import KMeans

paris_grouped_clustering = paris_grouped.drop('Ardt', 1)


distortions = []
K = range(1,10)
for k in K:
    kmeanModel = KMeans(n_clusters=k)
    kmeanModel.fit(paris_grouped_clustering)
    distortions.append(kmeanModel.inertia_)

#Plotting the distortions of K-Means
plt.figure(figsize=(16,8))
plt.plot(K, distortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Distortion')
plt.title('The Elbow Method showing the optimal k')
plt
```

Out[37]:
```
<module 'matplotlib.pyplot' from '/opt/anaconda3/lib/python3.8/sit
e-packages/matplotlib/pyplot.py'>
```



Even though it is so clear, the above plot suggests that k should be 2 or 3.

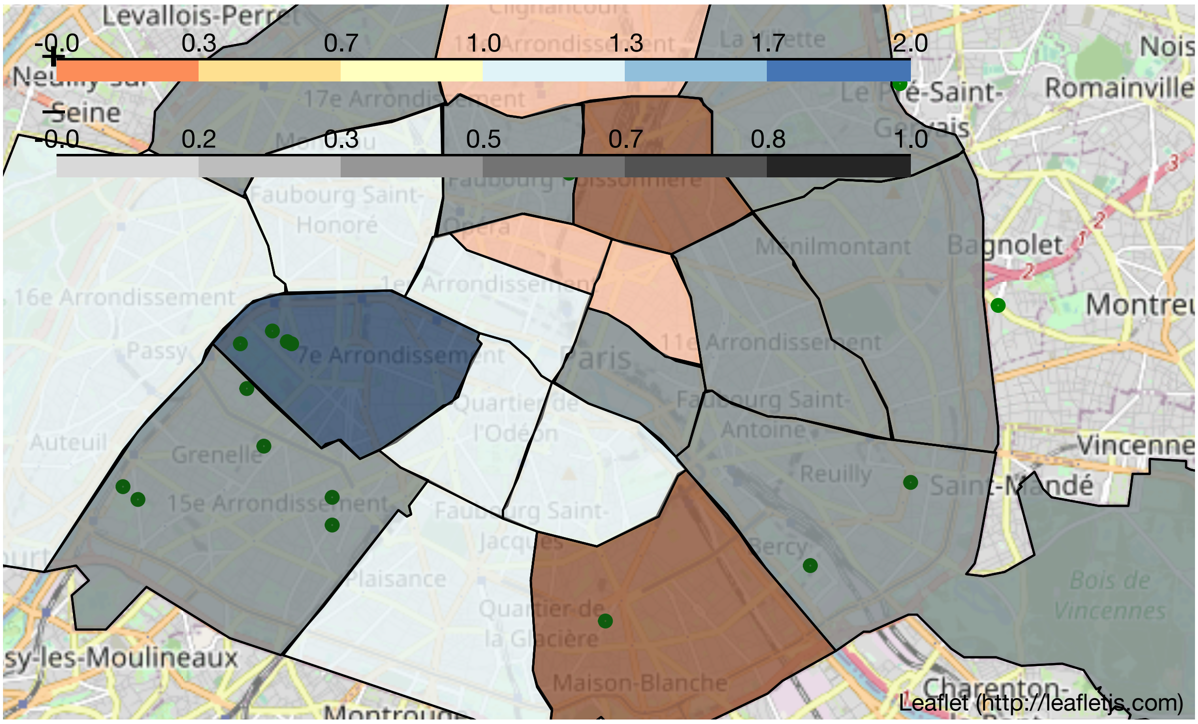
In order to get more granularity we will use `kclusters = 3`

In [38]:

```
from sklearn.cluster import KMeans

kclusters = 3
paris_grouped_clustering = paris_grouped.drop('Ardt', 1)

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

neighborhoods_venues_sorted.insert(0, 'Cluster Labels', kmeans.labels_)

neighborhoods_venues_sorted['Ardt'] = neighborhoods_venues_sorted['Ardt'].astype('int')
paris_ardt_df['Ardt'] = paris_ardt_df['Ardt'].astype('int')

paris_merged = pd.merge(paris_ardt_df,neighborhoods_venues_sorted,on='Ardt')
```

In [39]:
```
import folium
import numpy as np
import matplotlib.cm as cm
import matplotlib.colors as colors


latitude = 48.856578
longitude = 2.351828

# creating a map of Toronto using latitude and longitude values
map_clusters_paris = folium.Map(location=[latitude, longitude], zoo
m_start=12)


map_clusters_paris.choropleth(geo_data = geo,key_on = "feature.prop
erties.c_ar",data=paris_merged,
                 columns = ['Ardt','Cluster Labels'],fill_color='Rd
YlBu',fill_opacity=0.7)

for lat, lng, label in zip(far_def['Venue Latitude'], far_def['Venu
e Longitude'], far_def['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_clusters_paris)

map_clusters_paris.choropleth(geo_data = geo,key_on = "feature.prop
erties.c_ar",data=it_deficit[it_deficit['deficit']==1], columns = [
'Ardt','deficit'],fill_color='Greys',fill_opacity=0.4)


#HeatMap(french_coord, gradient = french_grad).add_to(map_clusters_
paris)

# adding markers to map

map_clusters_paris
```

Out[39]:



Colors are for clusters, and darker areas are for areas with deficit.

In [40]:

```
# Analysing the characteristics of the different clusters
paris_merged.groupby('Cluster Labels').agg(lambda x:x.value_counts(
).index[0]).iloc[:,3:13]
```

Out[40]:

	lat_radians_A	long_radians_A	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Com V
Cluster Labels							
0	0.853336	0.041202	French Restaurant	Japanese Restaurant	Italian Restaurant	Chinese Restaurant	Unspe
1	0.852420	0.039724	French Restaurant	Italian Restaurant	Japanese Restaurant	Italian Restaurant	Sea Resta
2	0.852701	0.040355	French Restaurant	Japanese Restaurant	Greek Restaurant	Italian Restaurant	Ch Resta

Right, so what can we infer from the above information?

Based on the above, we can see that most of the neighborhood in cluster 0 do not have a deficit in italian restaurants: indeed, only 2 locations kept in `far_def` are in cluster 0

> We will therefore **exclude** `Cluster 0`

Most of the venues we kept in `far_def` are in Cluster 1:

> We will therefore **keep** `Cluster 1`

But what about Cluster 2, which is only composed of the 7th Arrondissement?

Let's go back to `ardt_type_df` ...

In [41]:
```
ardt_type_df.sort_values('it/fr',ignore_index=True).head()
```

Out[41]:

	Ardt	nb_fr	nb_it	nb_tot	pct_fr	pct_it	it/fr
0	7	17	1	20	0.850000	0.050000	0.058824
1	15	21	2	43	0.488372	0.046512	0.095238
2	10	7	1	34	0.205882	0.029412	0.142857
3	11	12	2	25	0.480000	0.080000	0.166667
4	13	5	1	39	0.128205	0.025641	0.200000

What does it tell us?

Well, we can see that the number of italian/french restaurants is abnormally low, and that the % of french restaurants there is abnormally high! Indeed, this neighborhood was excluded from our regression analysis as we considered that it was an outlier...

This 'abnormality' can be easily explained though, with the help of Wikipedia:

> *The 7th arrondissement (...) includes some of the major and well-known tourist attractions of Paris, such as the Eiffel Tower, the Hôtel des Invalides (Napoleon's resting place), the Chapel of Our Lady of the Miraculous Medal, and a concentration of such world-famous museums as the Musée d'Orsay, Musée Rodin, and the Musée du quai Branly.*

So as a consequence:

> > We will therefore **exclude** `Cluster 2`

So we are only left with `Cluster 1`

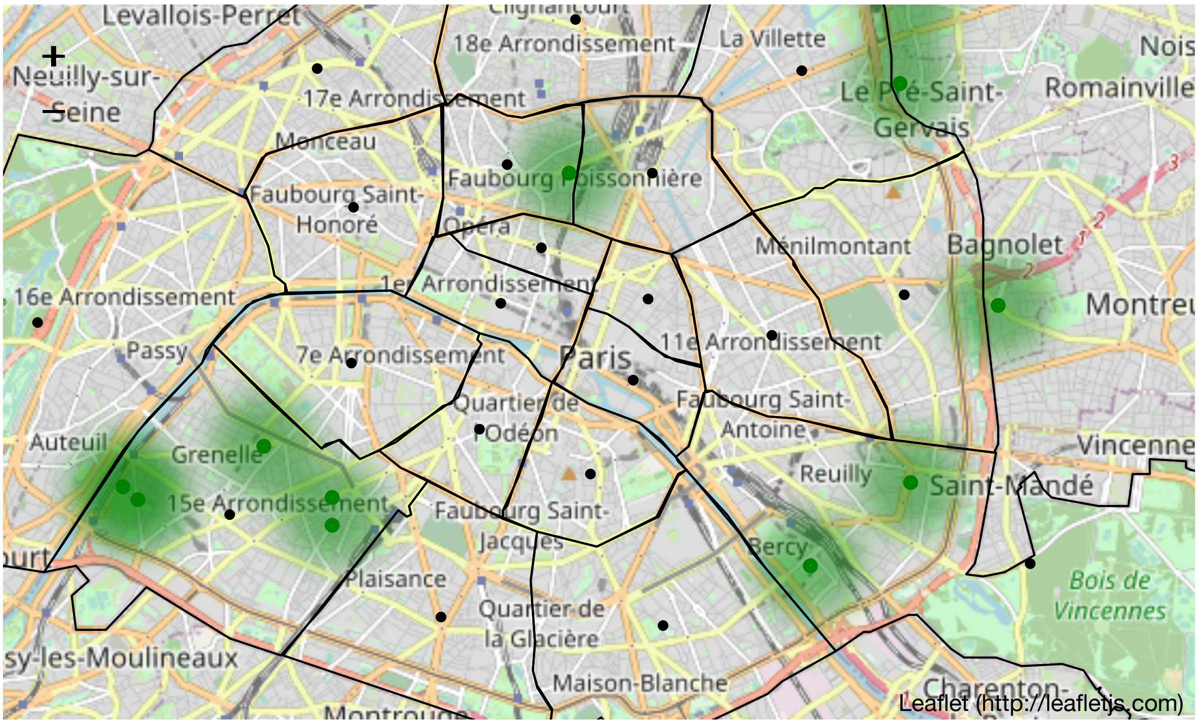
Let's add it as a filter to our density map!

In [42]:
```
# Creating a new curated dataframe
ardt_def_it_clust = paris_merged[paris_merged['Cluster Labels']==1]
['Ardt'].values.tolist()
far_def_clust = far_def[far_def['Ardt'].isin(ardt_def_it_clust)]
```

In [43]:

```
# Plotting the best locations (far + deficit + cluster)

map_best_far_def_clust= folium.Map(location=[latitude, longitude],
zoom_start=12)

french_coord = []
for index, row in far_def_clust.iterrows():
    french_coord.append([row[1], row[2]])

french_grad = {0.01: 'green', 1: 'green'}
italian_grad = {0.01: 'red', 1: 'red'}

HeatMap(french_coord, gradient = french_grad).add_to(map_best_far_d
ef_clust)
map_best_far_def_clust.choropleth(geo_data = geo,fill_opacity=0)

for lat, lng, label in zip(far_def_clust['Venue Latitude'], far_def
_clust['Venue Longitude'], far_def_clust['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=2,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.7,
        parse_html=False).add_to(map_best_far_def_clust)


for arr in geo["features"]:
    prop = arr["properties"]
    folium.CircleMarker(prop["geom_x_y"], radius=1, color = 'black'
, popup = prop["l_ar"]).add_to(map_best_far_def_clust)

map_best_far_def_clust
```

Out[43]:



Getting there !

Let's add a last condition before we conclude:

- we will count the number of french restaurants for each neighborhood
- we will then exclude the ones that have the smallest number of french restaurants

In [44]:
```
last_ardt = far_def_clust.groupby('Ardt').count()[['Venue']].sort_values('Venue',ascending=False)
last_ardt
```

Out[44]:

	Venue
Ardt	
15	5
12	2
19	2
9	1
20	1

In [45]:
```
avg_nb_fr = last_ardt.mean().values[0]

print('The average number of remaining french restaurant in neighborhoods that could potentially welcome a new italian restaurant is '+str(avg_nb_fr))
```

```
The average number of remaining french restaurant in neighborhoods that could potentially welcome a new italian restaurant is 2.2
```

Let's keep only the neighborhoods above average:

In [46]:
```
last_ardt[last_ardt['Venue']>=avg_nb_fr]
```

Out[46]:

	Venue
Ardt	
15	5

So our winner is the 15th Arrondissement!

In [47]:

```python
# Plotting the best locations (far + deficit + cluster)

winning_ardt = last_ardt[last_ardt['Venue']>=avg_nb_fr].index.tolis
t()
far_def_clust_15 = far_def_clust[far_def_clust['Ardt'].isin(winning
_ardt)]

latitude = paris_ardt_df[paris_ardt_df['Ardt'].isin(winning_ardt)][
'Latitude'].values[0]
longitude = paris_ardt_df[paris_ardt_df['Ardt'].isin(winning_ardt)]
['Longitude'].values[0]

map_15= folium.Map(location=[latitude, longitude], zoom_start=14)

map_15.choropleth(geo_data = geo,fill_opacity=0)

for lat, lng, label in zip(far_def_clust_15['Venue Latitude'], far_
def_clust_15['Venue Longitude'], far_def_clust_15['Venue']):
    label = folium.Popup(label, parse_html=True)
    folium.CircleMarker(
        [lat, lng],
        radius=50,
        popup=label,
        color='green',
        fill=True,
        fill_opacity=0.2,
        parse_html=False).add_to(map_15)


folium.CircleMarker(
        [latitude, longitude],
        radius=2,
        color='black',
        parse_html=False).add_to(map_15)

map_15
```

Out[47]:

In [48]:

```python
# Saving our results in a news dataframe
Areas_to_consider = far_def_clust_15.reset_index().drop(['index','Venue','Venue Category','code',"Ardt"],axis=1).rename(columns={"Venue Latitude": "Latitude", "Venue Longitude": "Longitude"})
```

Results & Discussion

The following tables indicates the centers of areas that would be great to open an italian restaurant:

In [49]:

```python
Areas_to_consider
```

Out[49]:

	Latitude	Longitude
0	48.847327	2.298303
1	48.841616	2.277794
2	48.842948	2.275587
3	48.841975	2.309041
4	48.838920	2.309052

Of course, these results are only as good as our assumptions - and they might also vary if we were to use another, richer dataset.

Also, it is important to note that decisions were made along the way, based on my (subjective) interpretation of the results: for example so one could decide to keep a cluster that I have excluded, or analyse other categories of restaurants.

The code in this notebook however is intended to be as flexible as possible and was written to work with as many inputs as possible. As a consequence, the changes one could make in these lines, should be reflected in the results.

Conclusions

In this project, we have:

- Confirmed that Italian restaurants were the most popular in Paris after French restaurants
- Confirmed that there is a positive correlation between the number of french and italian restaurants for a given neighborhood
- Identified areas where there is a *deficit* of italian restaurants relative to the number of French restaurants
- Isolated the areas with a high concentration of french restaurants while maximizing their distance to italian ones
- Identified clusters using K-means and excluded the ones that do not have the right characteristics
- Super-imposed all the analyses to come up with a limited number of results.
- Obtained the coordinates of 5 points around which it would be interesting to further investigate

We've decided to carry several analyses before concluding anything as one dimension of the data can almost never be sufficient on its own, and one should not forget that we have only taken into account a few variables: by cross checking different technical analyses, we increase the likelihood of getting to accurate conclusions.

For a final decision to be made, it would be interesting to add other datasets to this study, such as the average price per m^2 for each neighborhood, demographics, etc. but also, more importantly, to actually go on site to find out what it's like in real life.

We've shown that with only a small dataset, one could already have a pretty good idea of what's going in a specific area, and target only a handful of locations for further investigations.

These could lead to conclusions that exactly match the ones above, or shed light on something that had been completely missed, but in any case, a study of the available data can almost always teach us something we didn't know.