

IBM Data Science Capstone Project

THE BATTLE FOR RESTAURANTS IN THE PARIS NEIGHBORHOODS

Philippe BOTTIER | Applied Data Science Capstone by IBM | May 19, 2021

Introduction

DESCRIPTION AND DISCUSSION OF THE CONTEXT

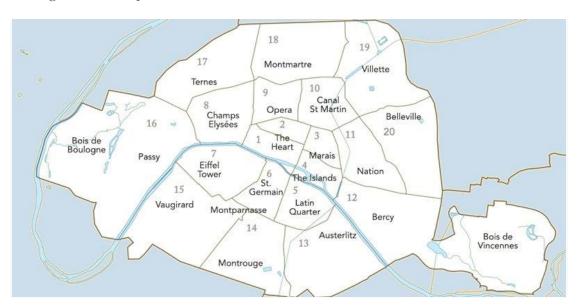
Paris is the capital and most populous city of France, with an estimated population of 2,175,601 residents as of 2018, in an area of more than 105 square kilometres (41 square miles). Since the 17th century, Paris has been one of Europe's major centres of finance, diplomacy, commerce, fashion, science, arts and gastronomy

Paris received 38 million visitors in 2019, measured by hotel stays, with the largest numbers of foreign visitors coming from the United States, the United Kingdom, Germany, and China. It was ranked as the second most visited travel destination in the world in 2019, after Bangkok and just ahead of London.

The city of Paris is divided into twenty administrative districts called arrondissements. The twenty arrondissements are arranged in the form of a clockwise spiral (often likened to a snail shell), starting from the middle of the city, with the first on the Right Bank (north bank) of the Seine.

In French, notably on street signs, the number is often given in Roman numerals. For example, the Eiffel Tower belongs to the VIIe arrondissement while Gare de l'Est is in the Xe arrondissement.

Each Parisian arrondissement has four neighborhoods, so a total of 80, which constitute the highest level of public administration in Paris.



As a resident in a suburb near the capital, I chose the city of Paris to lead my project.

BUSINESS PROBLEM

The problem to be solved is totally imaginary.

My company, PhB Data Consulting, specialized in data analysis, was contacted by the Tourist Office of the city of Paris to provide them with an analysis that would allow them

to advise tourists on the types of restaurants they could find during their visits to the Paris neighborhoods.

This analysis could be carried out using an unsupervised learning model that would reproduce on the map of Paris the groupings of neighborhoods according to the types of restaurants that are most represented there.

DATA GATHERING

To carry out this project, I needed the following data:

The list of Parisian districts (arrondissements in French) as well as the list of Parisian neighborhoods (quartiers). These lists were imported from the Open Data site of the city of Paris:

- https://opendata.paris.fr/explore/dataset/arrondissements/export/?disjunctive. c ar&disjunctive.c arinsee&disjunctive.l ar
- https://opendata.paris.fr/explore/dataset/quartier_paris/export/

The Geo-coordinates of the districts in Paris, obtained with the help of the geocoder tool in the notebook.

The Top venues data of neighborhoods, obtained from Foursquare through an API

After cleaning, preparing and merging the data, here is the dataframe that was used for the rest of the project. In this dataframe, we therefore have the 20 arrondissements of Paris with for each of them, their name, their geographical coordinates as well as the four neighbourhoods which depend of the arrondissement.

${\bf Merge\ boroughDF\ with\ neighbourhoodDF\ \hbox{$=>$ borough_neighbourhoodDF}}$

	ough_neighbourh ough_neighbourh			F.set_inde	ex('BoroughNumbe	r').join(nei	ghbourhoodDF.set_in	dex('Borough	Number')).res	et_index()	
	BoroughNumber	Borough	Latitude	Longitude	BoroughPerimetre	NeighNumber	Neighbourhood	NeighLatitude	NeighLongitude	NeighGeoloc	NeighPerimetre
0	1	Louvre	48.862563	2.336443	6054.936862	3	Palais-Royal	48.864660	2.336309	[48.8646599781, 2.33630891897]	2166.839239
1	1	Louvre	48.862563	2.336443	6054.936862	1	Saint-Germain-l'Auxerrois	48.860650	2.334910	[48.8606501352, 2.33491032928]	5057.549475
2	1	Louvre	48.862563	2.336443	6054.936862	2	Halles	48.862289	2.344899	[48.8622891081, 2.34489885831]	2606.417128
3	1	Louvre	48.862563	2.336443	6054.936862	4	Place-Vendôme	48.867019	2.328582	[48.8670185906, 2.32858166493]	2147.817602
4	2	Bourse	48.868279	2.342803	4554.104360	6	Vivienne	48.869100	2.339461	[48.8691001998, 2.33946074375]	2058.472959
	ugh neighbour	hoodDE .	-hana								

(80, 11)

Methodology

To conduct this study, I list below the different steps of the methodology that I followed:

- Step 1 : Data Acquisition with the JSON library
- Step 2 : Preparing, Cleaning and Merging Data with the PANDA library
- Step 3: Venues Acquisiton with the Foursquare API
- Step 4 : One Hot Encoding with the PANDA library
- Step 5 : Clustering K-means with sklearn.cluster library

- Step 6 : Cluster Analysis
- Step 7 : Creation of a clusters map with the Folium library

STEP 1 - DATA ACQUISITION WITH THE JSON LIBRARY

As I said before, I have retrieved the data from the Open Data site of the city of Paris (https://opendata.paris.fr/page/home/) :

- list of Paris arrondissements : https://opendata.paris.fr/explore/dataset/arrondissements/export/
- list of Paris neighbourhoods : https://opendata.paris.fr/explore/dataset/quartier_paris/export/

These files are in GeoJSON format. To be able to use the data, I have saved the files in the same directory as my Python notebook.

To import the files, I used the json library:

```
import json
geo_borough = json.load(open("arrondissements.geojson")) # Paris arrondissements
geo_neighbourhood = json.load(open("quartier_paris.geojson")) # Paris neighborhoods
```

The GeoJSON format is used to represent data of a geographic type. In this object, transformed into a dictionary under python, there are two elements: the type and the information (named features).

In each object of the features list, we also have different objects types :

```
geo_borough["features"][0].keys()

: dict_keys(['type', 'geometry', 'properties'])
```

In the properties field, there are various useful information, including the longitude and latitude coordinates of the center of the borough (or of the neighbourhood).

```
geo_borough["features"][0]['properties']

: {'n_sq_co': 750001537,
    'perimetre': 4519.26364836,
    'l_ar': '3ème Ardt',
    'surface': 1170882.82818778,
    'geom_x_y': [48.86287238, 2.3600009859],
    'n_sq_ar': 750000003,
    'l_aroff': 'Temple',
    'c_arinsee': 75103,
    'c_ar': 3}
```

```
geo_neighbourhood["features"][0]['properties']

: {'n_sq_qu': 750000015,
    'n_sq_ar': 750000004,
    'geom_x_y': [48.851585175, 2.36476795387],
    'c_qu': 15,
    'surface': 487264.93707154,
    'l_qu': 'Arsenal',
    'perimetre': 2878.55965556,
    'c_quinsee': 7510403,
    'c_ar': 4}
```

For the rest of the project, with the Panda library imported previously, I have created 2 DataFrames with the useful information.

```
# Borough Dataframe
bouroughDF = pd.DataFrame({
    "BoroughNumber" : [bor["properties"]["c_ar"] for bor in geo_borough["features"]]
    ,"Borough" : [bor["properties"]["l_aroff"] for bor in geo_borough["features"]]
    ,"Latitude" : [bor["properties"]["geom_x_y"][0] for bor in geo_borough["features"]]
    ,"Longitude" : [bor["properties"]["geom_x_y"][1] for bor in geo_borough["features"]]
    ,"BoroughPerimetre" : [bor["properties"]["perimetre"] for bor in geo_borough["features"]]
})
```

	BoroughNumber	Borough	Latitude	Longitude	BoroughPerimetre
0	3	Temple	48.862872	2.360001	4519.263648
1	7	Palais-Bourbon	48.856174	2.312188	8099.424883
2	13	Gobelins	48.828388	2.362272	11546.546526
3	17	Batignolles-Monceau	48.887327	2.306777	10775.579516
4	20	Ménilmontant	48.863461	2.401188	10704.940486

```
# Neighbourhood Dataframe
neighbourhoodDF = pd.DataFrame({
    "BoroughNumber" : [neigh["properties"]["c_ar"] for neigh in geo_neighbourhood["features"]]
    ,"NeighNumber" : [neigh["properties"]['c_qu'] for neigh in geo_neighbourhood["features"]]
    ,"Neighbourhood" : [neigh["properties"]["l_qu"] for neigh in geo_neighbourhood["features"]]
    ,"NeighLatitude" : [neigh["properties"]["geom_x_y"][0] for neigh in geo_neighbourhood["features"]]
    ,"NeighLongitude": [neigh["properties"]["geom_x_y"][1] for neigh in geo_neighbourhood["features"]]
    ,"NeighGeoloc" : [neigh["properties"]["geom_x_y"] for neigh in geo_neighbourhood["features"]]
    ,"NeighPerimetre": [neigh["properties"]["perimetre"] for neigh in geo_neighbourhood["features"]]
})
```

	BoroughNumber	NeighNumber	Neighbourhood	NeighLatitude	NeighLongitude	NeighGeoloc	NeighPerimetre
0	4	15	Arsenal	48.851585	2.364768	[48.851585175, 2.36476795387]	2878.559656
1	5	18	Jardin-des-Plantes	48.841940	2.356894	[48.8419401934, 2.35689388962]	4052.729521
2	10	39	Porte-Saint-Martin	48.871245	2.361504	[48.8712446509, 2.36150364735]	3245.891413
3	11	43	Roquette	48.857064	2.380364	[48.8570640408, 2.38036406173]	4973.010557
4	12	46	Picpus	48.830359	2.428827	[48.8303592424, 2.42882681508]	18261.910318

STEP 2 - PREPARING, CLEANING AND MERGING DATA WITH THE PANDA LIBRARY

After cleaning, merging, combining the values of the data frame, I obtain the following data frame which will allow me to continue the study:



borough_neighbourhoodDF.shape

(80, 11)

In this dataframe we have 80 Paris Neighbourhoods.

I used this dataframe for the rest of the project. I didn't need to clean the data.

STEP 3 - VENUES ACQUISITON WITH THE FOURSQUARE API

I have used Foursquare API to get venues suggestions for each neighbourhood in Paris. Data from Foursquare API is received in json format.

The parameters passed during the call to the Foursquare API made it possible to retrieve 100 suggestions of venues for each neighbourhood within a radius of 500 meters from the coordinate point of the neighbourhood.

The created and arranged data frame looks like this:

par	aris_venues.head()														
	Neighbourhood	Latitude	Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category								
0	Palais-Royal	48.86466	2.336309	Jardin du Palais Royal	48.864941	2.337728	Garden								
1	Palais-Royal	48.86466	2.336309	Palais Royal	48.863236	2.337127	Historic Site								
2	Palais-Royal	48.86466	2.336309	Comédie-Française	48.863088	2.336612	Theater								
3	Palais-Royal	48.86466	2.336309	Udon Bistro Kunitoraya (Kunitoraya)	48.865884	2.336782	Udon Restaurant								
4	Palais-Royal	48.86466	2.336309	Sanukiya	48.864713	2.333805	Udon Restaurant								

paris_venues.shape

(5061, 7)

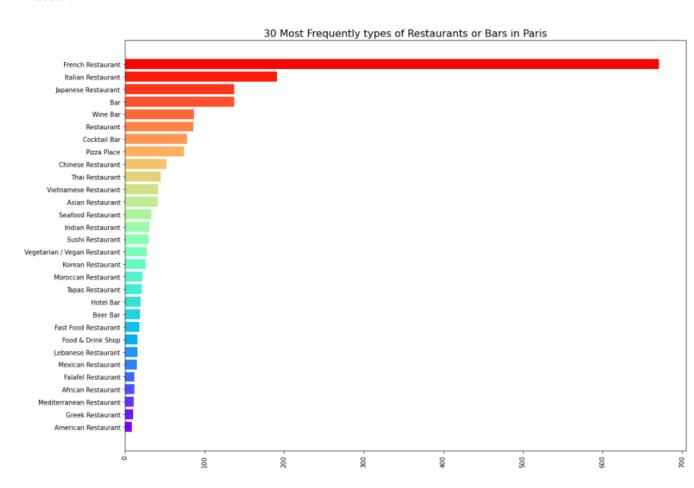
Since our client, the Tourist Office of the City of Paris, wants an analysis to advise tourists on the types of restaurants they might find during their visits to Parisian neighborhoods, we have decided to filter the places that deal with only food and drink.

The new data frame created looks like this:

df_foo	d						
	Neighbourhood	Latitude	Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
1	Palais-Royal	48.86466	2.336309	Udon Bistro Kunitoraya (Kunitoraya)	48.865884	2.336782	Udon Restaurant
2	Palais-Royal	48.86466	2.336309	Sanukiya	48.864713	2.333805	Udon Restaurant
3	Palais-Royal	48.86466	2.336309	Brasserie Réjane	48.865486	2.334824	Restaurant
4	Palais-Royal	48.86466	2.336309	Verjus Bar à Vins	48.866306	2.337471	Wine Bar
5	Palais-Royal	48.86466	2.336309	Restaurant Kunitoraya	48.866116	2.336467	Japanese Restaurant
2232	Charonne	48.85476	2.407430	Le Magnolia	48.858992	2.405873	French Restaurant
2233	Charonne	48.85476	2.407430	Domino's Pizza	48.852447	2.403890	Pizza Place
2234	Charonne	48.85476	2.407430	McDonald's	48.853252	2.410679	Fast Food Restaurant
2235	Charonne	48.85476	2.407430	Royal Kebab	48.853461	2.409690	Kebab Restaurant
2236	Charonne	48.85476	2.407430	Pizzeria du glacier de Venise	48.853790	2.411600	Pizza Place

2236 rows × 7 columns

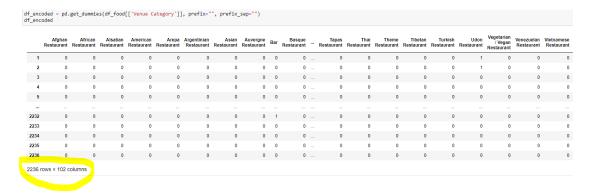
By exploring the data, we realize that French restaurants are widely represented in Paris. Indeed :



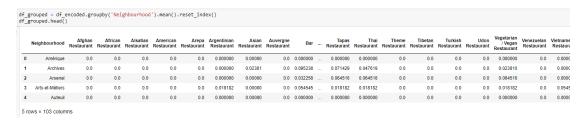
STEP 4 - PERFORMING ONE-HOT ENCODING TO ANALYZE NEIGHBOURHOODS WITH THE PANDA LIBRARY

One-Hot Encoding is a technique which ensures that machine learning algorithms can process data. Namely, it converts categorical variables into the binary Boolean ones.

Below, an extration of the data frame created after applying the One-Hot Encoding function:



Then, I have used this data frame to create a new one grouping the categories of restaurants in each neighborhood of the city. Below, an extraction of this new data frame:



Finally, I have used the previously created data frame to create a new one with the 10 most common types of restaurants for each neighborhood in the city.



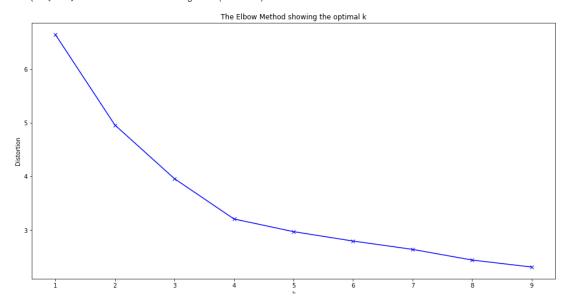
This last data frame allowed me to run an unsupervised machine learning algorithm, more precisely, a k-means clustering algorithm from the scikit-learn package.

STEP $_{05}$ - CLUSTERING K-MEANS WITH SKLEARN CLUSTER LIBRARY - TO DO

But before I could run the k-means clustering algorithm, I have used the ellbow method to set the value of the optimum k :

```
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')
```

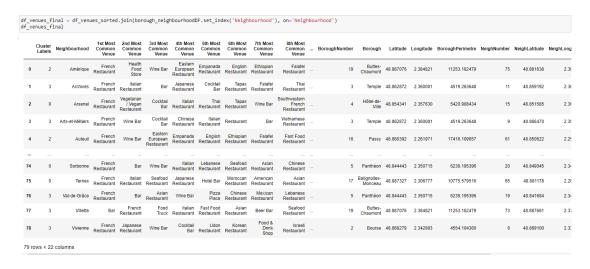
Text(0.5, 1.0, 'The Elbow Method showing the optimal k')



The graph of the elbow method, shows that the optimal value of k is 4. So I chose k as being 4, to run the k-means clustering algorithm.

```
from sklearn.cluster import KMeans
k_clusters = 4
#drop the Neighbourhood column to work with numerical values only
df_k_clustering = df_grouped.drop('Neighbourhood', 1)
KM = KMeans(n_clusters=k_clusters, random_state=0)
```

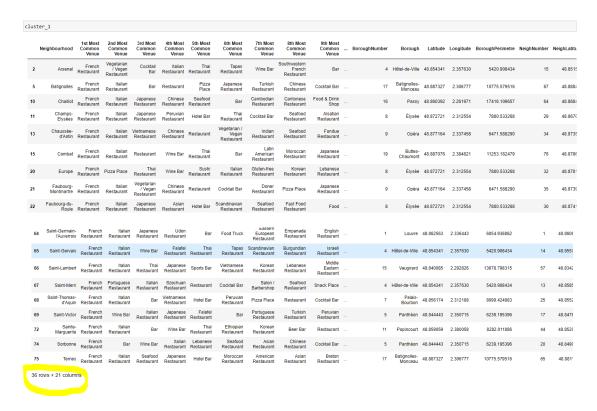
After adding the label of the cluster to the data frame and after having merged it with the data frame containing the borough information, I get this data frame which will allow me to analyze the clusters that have been created:



STEP o6 - CLUSTER ANALYSIS

So four groups of concentrations of types of restaurants were created by the K-Means model for the city of Paris. I have named these groups according to the frequency of the types of restaurants that appear the most among the first 3 most common venues.

Cluster 1 (o) - French and Italian Restaurants



Cluster 2 (1) - Pizza Place and International Cuisine

Cluster 3 (2) - French Restaurants and Wine Bars

Japanese Restaurant

luste	er_3																
	Neighbourhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	 BoroughNumber	Borough	Latitude	Longitude	BoroughPerimetre	NeighNumber	NeighLatitud
0	Amérique	French Restaurant	Health Food Store	Wine Bar		Empanada Restaurant	English Restaurant	Ethiopian Restaurant	Falafel Restaurant	Fast Food Restaurant	 19	Buttes- Chaumont	48.887076	2.384821	11253.182479	75	48.88163
4	Auteuil	French Restaurant	Wine Bar	Eastern European Restaurant	Empanada Restaurant	English Restaurant	Ethiopian Restaurant	Falafel Restaurant	Fast Food Restaurant	Fondue Restaurant	16	Passy	48.860392	2.261971	17416.109657	61	48.85062
6	Bel-Air	French Restaurant	Wine Bar	Eastern European Restaurant	Empanada Restaurant	English Restaurant	Ethiopian Restaurant	Falafel Restaurant	Fast Food Restaurant	Fondue Restaurant	12	Reuilly	48.834974	2.421325	24089.666298	45	48.837996
17	Ecole-Militaire	French Restaurant	Asian Restaurant	Wine Bar	Eastern European Restaurant	Empanada Restaurant	English Restaurant	Ethiopian Restaurant	Falafel Restaurant	Fast Food Restaurant	7	Palais- Bourbon	48.856174	2.312188	8099.424883	27	48.850359
32	Invalides	French Restaurant	Italian Restaurant	Japanese Restaurant	Cocktail Bar	Restaurant	Vegetarian / Vegan Restaurant	Food	Doner Restaurant	Eastern European Restaurant	7	Palais- Bourbon	48.856174	2.312188	8099.424883	26	48.858515
41	Muette	French Restaurant	Snack Place	Wine Bar	Food & Drink Shop	Doner Restaurant	Eastern European Restaurant	Empanada Restaurant	English Restaurant	Ethiopian Restaurant	16	Passy	48.860392	2.261971	17416.109657	62	48.863275
6 row	s × 21 columns																

Cluster 4 (3) - French Restaurants

```
cluster_4_1stMostCommonVenue = cluster_4['1st Most Common Venue'].value_counts()[0:topn].to_frame(name='frequency')
cluster_4_2ndMostCommonVenue = cluster_4['2nd Most Common Venue'].value_counts()[0:topn].to_frame(name='frequency')
cluster_4_3rdMostCommonVenue = cluster_4['3rd Most Common Venue'].value_counts()[0:topn].to_frame(name='frequency')
print(cluster_4_1stMostCommonVenue);print(cluster_4_2ndMostCommonVenue);print(cluster_4_3rdMostCommonVenue)
```

	frequency	
French Restaurant	23	
Bar	5	
Japanese Restaurant	3	
Indian Restaurant	2	
Cocktail Bar	2	
Italian Restaurant	1	
	frequency	
French Restaurant	8	
Bar	7	
Japanese Restaurant	7	
Wine Bar	3	
Italian Restaurant	3	
Restaurant	2	
Asian Restaurant	2	
Chinese Restaurant	1	
Cocktail Bar	1	
Sushi Restaurant	1	
Thai Restaurant	1	
		frequency
Italian Restaurant		7
Wine Bar		7
Japanese Restaurant		5
Cocktail Bar		4
French Restaurant		3
Chinese Restaurant		2
Restaurant		2
Food Truck		1
Portuguese Restaurant	t	1
Vegetarian / Vegan Re	estaurant	1
Asian Restaurant		1
Bar		1
African Restaurant		1

lus	ter_4														
	Neighbourhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	 BoroughNumber	Borough	Latitude	Longitude	BoroughPerimetre
1	Archives	French Restaurant	Italian Restaurant	Bar	Japanese Restaurant	Cocktail Bar	Tapas Restaurant	Falafel Restaurant	Thai Restaurant	Pizza Place	 3	Temple	48.862872	2.360001	4519.263648
3	Arts-et-Métiers	French Restaurant	Wine Bar	Cocktail Bar	Chinese Restaurant	Italian Restaurant	Restaurant	Bar	Vietnamese Restaurant	Japanese Restaurant	3	Temple	48.862872	2.360001	4519.263648
7	Belleville	Bar	French Restaurant	Japanese Restaurant	Italian Restaurant	Pizza Place	African Restaurant	Chinese Restaurant	Cocktail Bar	Indian Restaurant	20	Ménilmontant	48.863461	2.401188	10704.940486
8	Bercy	French Restaurant	Italian Restaurant	Japanese Restaurant	Restaurant	Bar	Beer Bar	Cambodian Restaurant	Chinese Restaurant	Doner Restaurant	12	Reuilly	48.834974	2.421325	24089.666298
9	Bonne-Nouvelle	Cocktail Bar	French Restaurant	Wine Bar	Japanese Restaurant	Restaurant	Italian Restaurant	Chinese Restaurant	Bar	Thai Restaurant	2	Bourse	48.868279	2.342803	4554.104360
12	Charonne	Bar	Japanese Restaurant	Portuguese Restaurant	Pizza Place	Fast Food Restaurant	French Restaurant	Brazilian Restaurant	Indian Restaurant	Hawaiian Restaurant	20	Ménilmontant	48.863461	2.401188	10704.940486
14	Clignancourt	French Restaurant	Bar	Italian Restaurant	Pizza Place	Restaurant	Wine Bar	Seafood Restaurant	Arepa Restaurant	Asian Restaurant	18	Buttes- Montmartre	48.892569	2.348161	9916.464176
16	Croulebarbe	French Restaurant	Sushi Restaurant	Italian Restaurant	Bar	Ramen Restaurant	Restaurant	Indian Restaurant	Cocktail Bar	Ethiopian Restaurant	13	Gobelins	48.828388	2.362272	11546.546526
18	Enfants-Rouges	French Restaurant	Wine Bar	Japanese Restaurant	Italian Restaurant	Vietnamese Restaurant	Cocktail Bar	Bar	Korean Restaurant	Restaurant	3	Temple	48.862872	2.360001	4519.263648
19	Epinettes	French Restaurant	Restaurant	Japanese Restaurant	Turkish Restaurant	Pizza Place	Bar	Ethiopian Restaurant	Sushi Restaurant	Hotel Bar	17	Batignolles- Monceau	48.887327	2.306777	10775.579516
23	Folie-Méricourt	French Restaurant	Bar	Restaurant	Wine Bar	Pizza Place	African Restaurant	Chinese Restaurant	Italian Restaurant	Juice Bar	11	Popincourt	48.859059	2.380058	8282.011886
24	Gaillon	Japanese Restaurant	French Restaurant	Wine Bar	Italian Restaurant	Ramen Restaurant	Korean Restaurant	Udon Restaurant	Asian Restaurant	Cocktail Bar	2	Bourse	48.868279	2.342803	4554.104360

70	Saint-Vincent- de-Paul	Indian Restaurant	French Restaurant	African Restaurant	Italian Restaurant	Japanese Restaurant	Sports Bar	Food & Drink Shop	Breton Restaurant	Israeli Restaurant	10	Entrepôt	48.876130	2.360728	6739.3750
71	Sainte-Avoie	French Restaurant	Restaurant	Chinese Restaurant	Wine Bar	Italian Restaurant	Vietnamese Restaurant	Japanese Restaurant	Vegetarian / Vegan Restaurant	Health Food Store	3	Temple	48.862872	2.360001	4519.2636
73	Salpêtrière	Indian Restaurant		Italian Restaurant	Corsican Restaurant	Chinese Restaurant	Bar	Mediterranean Restaurant	Sushi Restaurant	Wine Bar	13	Gobelins	48.828388	2.362272	11546.5465
76	Val-de-Grâce	French Restaurant	Bar	Asian Restaurant	Wine Bar	Pizza Place	Chinese Restaurant	Mexican Restaurant	Lebanese Restaurant	Beer Bar	5	Panthéon	48.844443	2.350715	6239.1953
77	Villette	Bar	French Restaurant	Food Truck	Italian Restaurant	Fast Food Restaurant	Asian Restaurant	Beer Bar	Seafood Restaurant	Japanese Restaurant	19	Buttes- Chaumont	48.887076	2.384821	11253.1824
78	Vivienne	French Restaurant	Japanese Restaurant	Wine Bar	Cocktail Bar	Udon Restaurant	Korean Restaurant	Food & Drink Shop	Israeli Restaurant	English Restaurant	2	Bourse	48.868279	2.342803	4554.1043
6 rov	s × 21 column	s													

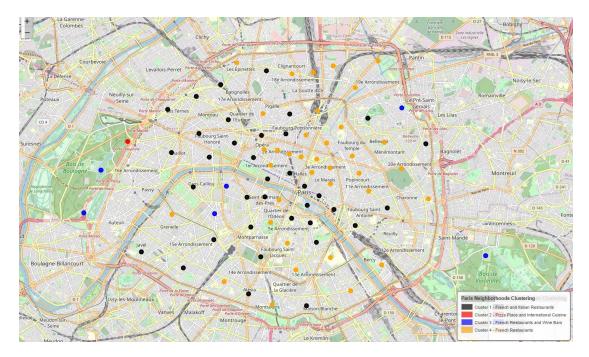
STEP 07 - CREATION OF A CLUSTERS MAP WITH THE FOLIUM LIBRARY

The geographical coordinates of Paris were extracted using GeoPy libray in Python.

```
address = 'Paris'
geolocator = Nominatim(user_agent="Paris_Explorer")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print(f'The geograpical coordinates of Paris are {latitude}, {longitude}.')
```

The geograpical coordinates of Paris are 48.8566969, 2.3514616.

The geographic coordinates will be used to draw the map of Paris with arrondissements colored according to the types of restaurants that are present.



Discussion

As I indicated previously, French restaurants are widely represented in Paris. Indeed, there are nearly 68o.

In 3 out of 4 clusters reproduced by the K-Means model, there is a large number of French restaurants in the first most frequent place of each of the districts.

Only group 2 (Pizza Place and International Cuisine) does not have a French restaurant. This cluster is made up solely of the Porte Dauphine district located in the 16th arrondissement of Paris.

We also note that only the Picpus district, located in the 12th arrondissement of Paris, does not have a restaurant.

Conclusion

The objective of the project presented at the beginning of this report has been achieved. Indeed, my company has delivered as planned to the Tourist Office of the city of Paris a tool which now allows them to advise tourists on the types of restaurants they could find during their visits to the Parisian districts.

Acknowledgement, References & Links

ACKNOWLEDGEMENT

This report refers to the lab projects of the IBM Data Science Professional Certificate course on Coursera.

To carry out this project, I recovered a large part of the Python code used in the different labs of Course 9.

I was also inspired by the many Notebooks published by students who had thought about the subject before me.

REFERENCES

Source: https://en.wikipedia.org/wiki/Arrondissements_of_Paris

Source: https://www.parisinsidersguide.com/paris-neighborhoods.html

Source: https://fr.wikipedia.org/wiki/Liste des quartiers administratifs de Paris

LINKS

The notebook with the code for this project, as well as the report, can be found in my github repository.