The Battle of neighborhoods! You have to move on ? Don't panic!

Data science as a tool for real estate rental agencies

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1 Introduction to the Business Problem

This section provides a description of the problem and a discussion of the background.

1.1 Background

Many people move from their home country every year for different reasons, some of them because are starting a new job or a new business, others for a semester of study and other for love.

All these people have something in common, they are locking for a place that is comparable to the current home.

In big cities such as Rome, Paris or London, with huge population of renters, it's common to use a real estate agent to find a rental property.

The mainly requests that real estate agency receive from customers are :

- find a house in a neighborhood that is as similar as possible to the one they come from;
- That the new neighborhood meets a list of requirements such as parks, traditional restaurants, and so on.

The aim of this work is to demonstrate how using some data science techniques it is possible to help real estate agencies to find apartments for rent that meet the needs of customers.

1.2 Problem description

A family is moving from their hometown in Rome to Paris. They ask a real estate agency to find an apartment for rent that is in a neighborhood similar to the one they are leaving and that has parks where they can walk their dog.

They would like to find a neighborhood with many restaurants and would like to be able to choose where to train between the various gyms. They would also like to have some grocery stores nearby, so they can buy the ingredients needed to cook the Italian dishes.

Summarized, the family like to have the following venues nearby:

- park;
- gym;
- restaurants & bars;
- grocery store.

And that the apartment has:

- Low price per m^2;
- boroughs that is similar to the one they are currently living in.

1.3 Interest

Real estate agencies would be very interested in a methodology that helps them find the correct location for a rental apartment for their clients. But people who need to relocate from their hometown may also be interested in this work.

2 Data

This section provides a description of the data and how it will be used to solve the problem.

2.1 Description of the Data

The following data will be used :

1. **Average cost of a rental house in Paris:** This information is gathered from this webpage 'https://www.seloger.com/prix-de-l-immo/location/ile-de-france/paris.htm (https://www.seloger.com/prix-de-l-immo/location/ile-de-france/paris.htm)'. The dataset consists of the district number and the average monthly cost of a rented apartment in that district.
2. **Average burglary in the borough of Paris:** This information is gathered from this webpage 'https://www.bfmtv.com/societe/carte-delinquance-a-paris-quels-sont-les-arrondissements-ou-l-on-recense-le-plus-de-delits_AN-201910180103.html (https://www.bfmtv.com/societe/carte-delinquance-a-paris-quels-sont-les-arrondissements-ou-l-on-recense-le-plus-de-delits_AN-201910180103.html)'. The dataset is composed of the district number and the number of annual burglaries in that district.
3. **Information about the venues in Paris neighboroods :** This information is gathered through FourSquare API. The dataset contains Paris neighborhood information. It consists of the district number, the neighborhood name and all the premises that are present within a 750 meter radius from the neighborhood center.
4. **Information about the venues in home town neighborood :** This information is gathered through FourSquare API. The dataset contains home town neighborhood information. It consists of the district number, the neighborhood name and all the premises that are present within a 750 meter radius from the neighborhood center.
5. **The names of all Paris neighboroods :** This information is gathered from this webpage 'https://opendata.paris.fr/explore/dataset/quartier_paris (https://opendata.paris.fr/explore/dataset/quartier_paris)'.

Not all the data is in the proper format and it needs to be transformed. The Geocoder Python package (https://geocoder.readthedocs.io/index.html (https://geocoder.readthedocs.io/index.html)) will be used to receive the latitude and logitude coordinates of all neighborhoods. The neighborhoods and their corresponding latitude and longitude will be used as input for FourSquare to get information about them

2.2 How the data will be used to solve the problem

First we will analyze the distribution of venues in the Paris neighborhoods to find those neighborhoods that best suit the preferences of the family.

Next, we'll divide the neighborhoods of Paris into clusters to find the ones that are as similar as possible to the neighborhood of the family's hometown. One hot encoding and k-means will be used for this porpouse.

The last step is to use the average rental cost per square meter and the crime rate to create a ranking of neighborhoods that meet the customer's needs.

2.3 Data Preparation

2.3.1 Import Paris boroughs dataset

Paris has in total 20 boroughs (called arrondissements in French) and are divided in 80 neighborhoods.

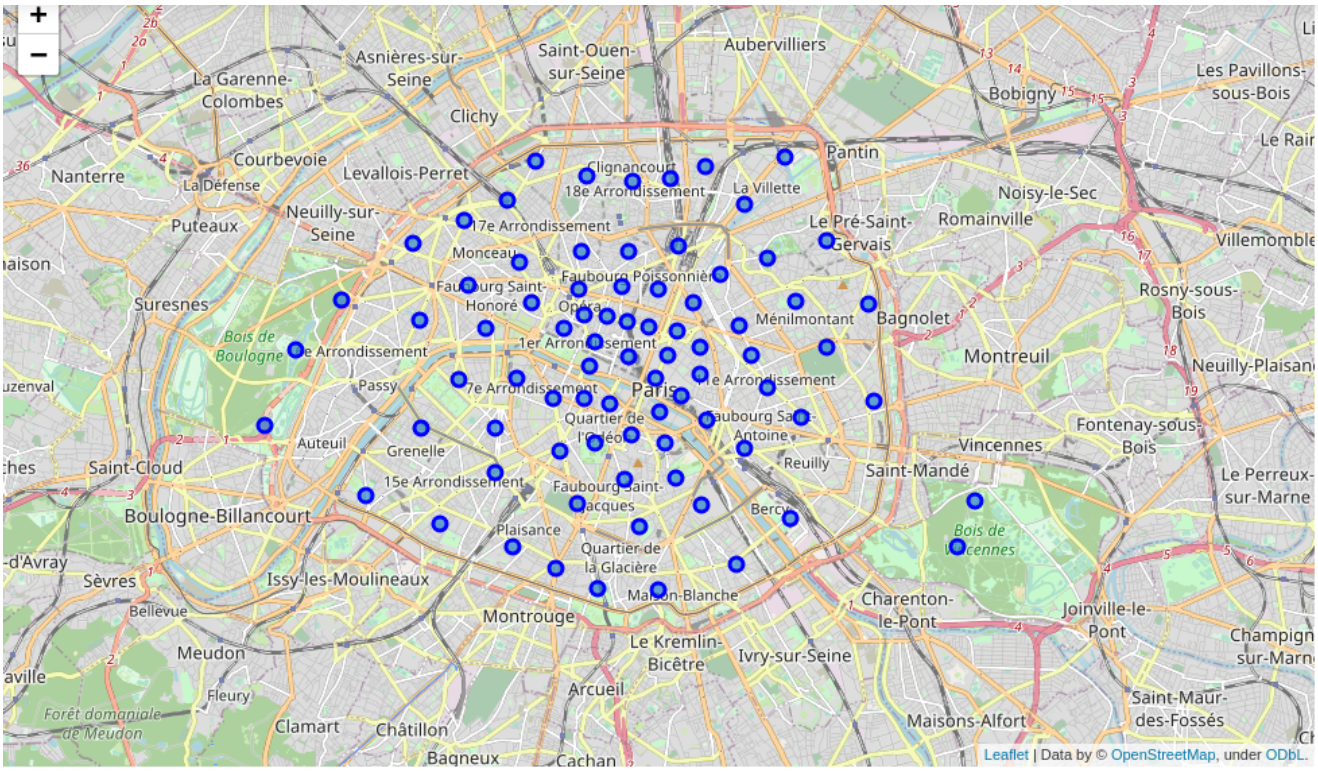
The dataset of Paris boroughs can be found at the following link:

https://opendata.paris.fr/explore/dataset/quartier_paris (https://opendata.paris.fr/explore/dataset/quartier_paris)

After rearraging data we get the following dataset (the first 5 rows)

	Neighborhood	Borough	Latitude	Longitude
0	Saint-Gervais	4	48.8557186509	2.35816233385
1	Saint-Thomas-d'Aquin	7	48.8552632694	2.32558765258
2	Porte-Saint-Denis	10	48.873617661	2.35228289495
3	Saint-Germain-l'Auxerrois	1	48.8606501352	2.33491032928
4	Villette	19	48.8876610888	2.37446821213

Here is the map of Paris and superimposed the Neighborhoods.



2.3.2 Create Paris venues dataset

Using the Foursquare API we prepare and populate a dataset that will describe each district of Paris in terms of venues.

Let's take a look at the data

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Id	Venue Category
0	Quinze-Vingts	48.8469159441	2.37440162648	Promenade plantée – La Coulée Verte	48.847632	2.375107	4bf58dd8d48988d159941735	Trail
1	Quinze-Vingts	48.8469159441	2.37440162648	Les Embruns	48.847100	2.371883	52e81612bcbc57f1066b79f2	Creperie
2	Quinze-Vingts	48.8469159441	2.37440162648	Le Calbar	48.848702	2.375487	4bf58dd8d48988d11e941735	Cocktail Bar
3	Quinze-Vingts	48.8469159441	2.37440162648	Viaduc des Arts	48.848664	2.372931	4bf58dd8d48988d1df941735	Bridge
4	Quinze-Vingts	48.8469159441	2.37440162648	Rue Crémieux	48.847021	2.371110	52e81612bcbc57f1066b7a25	Pedestrian Plaza

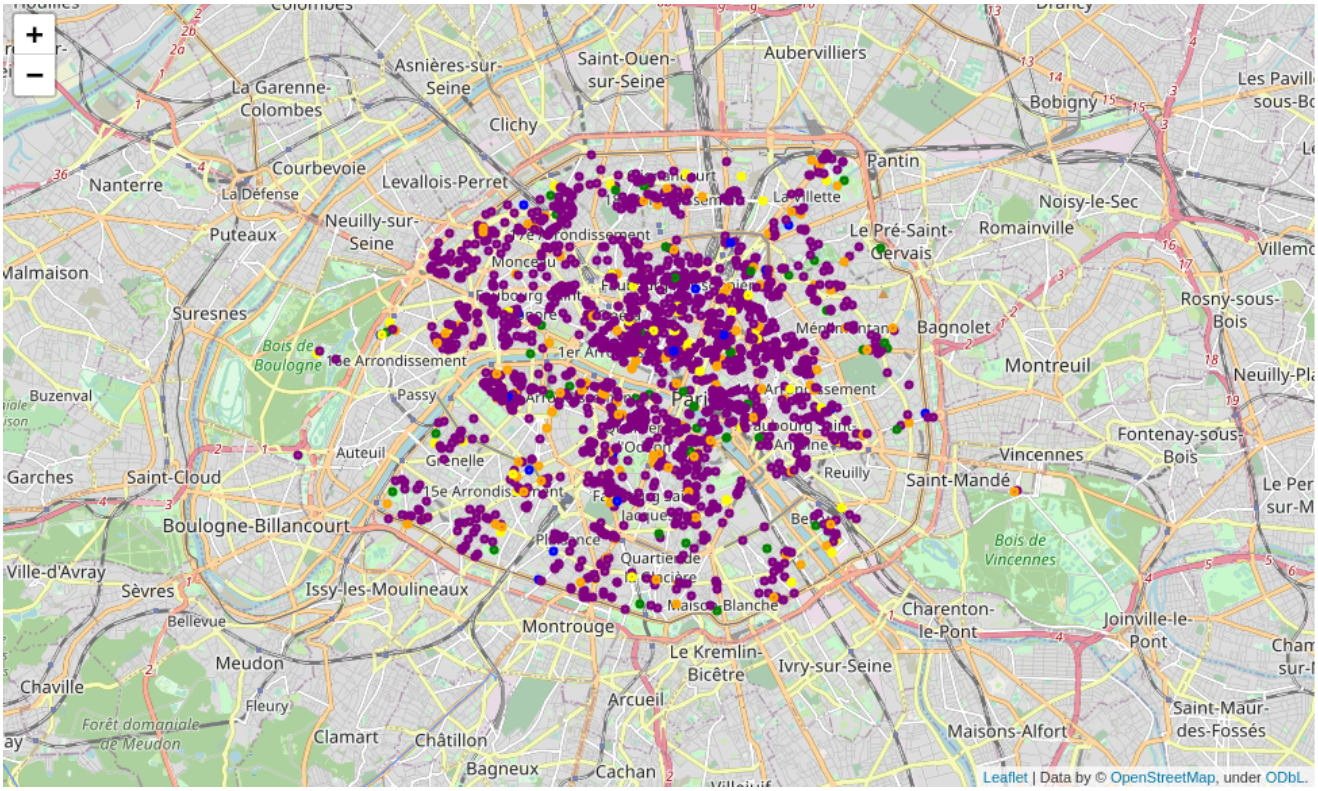
paris_venues dataset contains 5245 venues that are divided in 300 categories.

2.3.3 Create datasets about family favorite places

Starting from the paris_venues dataset we create another one that cointains the family favorite venues only.

This dataset will be used to find all neighborhoods that meet the needs of the family.

We create a map that represents the geographic distribution of favorite venues.



2.3.4 Create family hometown neighborhood dataset

Using the same steps as above we create a new dataset that describes the hometown dataset in term of venues.

We quickly check the consistency of the data.

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Id	Venue Category
0	San Paolo	41.854636	12.47997	Ilios	41.854703	12.478428	4bf58dd8d48988d10e941735	Greek Restaurant
1	San Paolo	41.854636	12.47997	Buskers Pub	41.852135	12.479969	4bf58dd8d48988d11b941735	Pub
2	San Paolo	41.854636	12.47997	Miami 3	41.851892	12.478228	4bf58dd8d48988d1c9941735	Ice Cream Shop
3	San Paolo	41.854636	12.47997	Bar San Paolo	41.856290	12.478663	4bf58dd8d48988d16d941735	Café
4	San Paolo	41.854636	12.47997	La Muffineria	41.853127	12.476754	4bf58dd8d48988d1bc941735	Cupcake Shop

2.3.5 Create average cost dataset

From 'https://www.seloger.com/prix-de-l-immo/location/ile-de-france/paris.htm (https://www.seloger.com/prix-de-l-immo/location/ile-de-france/paris.htm)' we create a simple table that contains the id of the boroughs and the average cost of a rent per square meter (only the first 5 lines are displayed).

	Borough	Cost
0	1	37.9
1	2	36.9
2	3	37.3
3	4	38.6
4	5	36.3

2.3.6 Create burglary per year dataset

From https://www.bfmtv.com/societe/carte-delinquance-a-paris-quels-sont-les-arrondissements-ou-l-on-recense-le-plus-de-delits_AN-201910180103.html (https://www.bfmtv.com/societe/carte-delinquance-a-paris-quels-sont-les-arrondissements-ou-l-on-recense-le-plus-de-delits_AN-201910180103.html) we create a simple table that contains the id of the boroughs and number of burglary per year (only the first 5 lines are displayed).

	Borough	Burglary
0	1	302
1	2	516
2	3	446
3	4	396
4	5	435

3 Methodology

This is the principal part of the work.

We start analyzing Paris venues in order to find the list of neighborhoods that meets family requirements.

3.1 Neighborhoods that meets family requirements

From the favorite venues dataset we select those that satisfy all of family needs.

Venue Category Neighborhood	Café	Grocery	Gym	Park	Restaurant
Batignolles	3.0	1.0	1.0	2.0	48.0
Hôpital-Saint-Louis	4.0	1.0	1.0	1.0	43.0
Palais-Royal	3.0	1.0	1.0	1.0	34.0
Porte-Dauphine	1.0	1.0	2.0	1.0	1.0

Only four neighborhoods meet all the needs of the family.

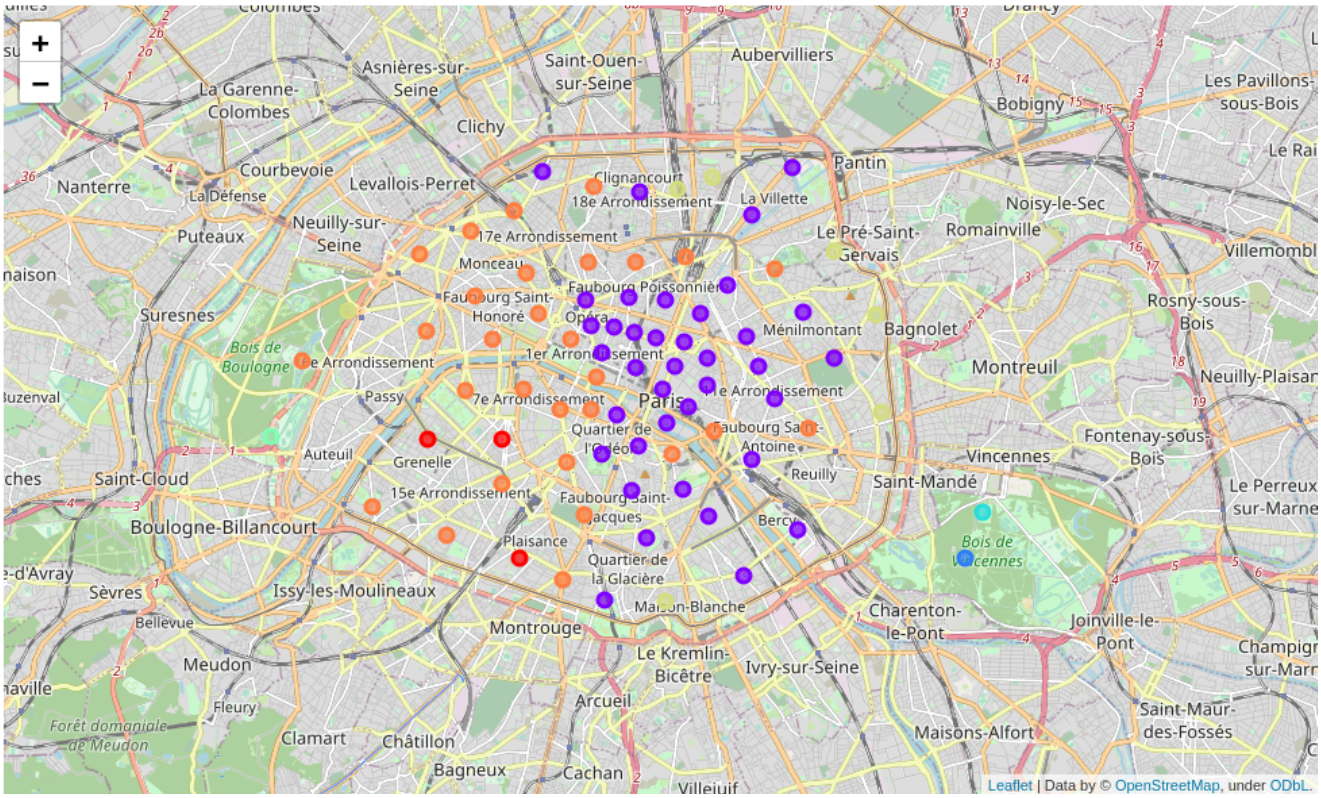
3.2 Neighborhoods similar to the one of the hometown

For finding neighborhoods similar to that of the hometown we use K-means clustering.

K-means clustering is an unsupervised machine learning algorithm that is able to partitioning a dataset into groups of elements that have similar characteristics.

in our case we want to group the neighborhoods according to the distribution of the venues.

Let's show in a map the geographic cluster distribution.



The hometown neighborhood belongs to cluster 1 and there are 38 Paris neighborhoods in the same cluster

There are only two neighborhoods that are shared with cluster 1 and family needs:

- Hôpital-Saint-Louis
- Palais-Royal

4 Results

We found four neighborhoods that had all the features the customer requested. Using the K-means clustering algorithm we found 38 neighborhoods that are similar to customer hometown neighborhood. The intersection of the two previous results gives only two neighborhoods.

Using the information from cost and crime rate we can summarize the result in the following table :

Neighborhood	**Cost per sqm**	**Burglary Rate**
Hôpital-Saint-Louis	32.3	790
Palais-Royal	37.9	302

Considering a 100 square meter apartment, the difference in rent is 50 euros and the risk of burglary is reduced by half.

Anyway we left the choise to the customer.

5 Discussion

We have use the simplest clustering algorithm, one can try to use other clustering algorithms and find which one is best for this type of problem.

Other clustering algorithm can be used in order to find the best for this kind of problem.

Moreover, having a customer history, one could think of creating user profiles to use with recommendation system.

6 Conclusion

The aim of this project was to identify a neighborhood similar to the client's current one and which, at the same time, also had venues that were important to him.

We have succeeded in demonstrating that data science methodologies can be used for the solution of this type of problem.

As a future development, the use of recommendation systems could be investigated to get further information on choosing the apartment to rent.