Applied Data Science Capstone Project

Clustering of Paris Arrondissements for e-scooter sharing services optimization

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Introduction/Business Problem

A scooter-sharing system is a service in which scooters are made available to use for short-term rentals. The term describes the sharing of mostly electric motor scooters (also referred to as electric mopeds) as well as electric kick scooters. The sharing of scooters is similar to carsharing or bicycle-sharing systems; with some scooter-sharing companies offering more than one type of vehicle via their service. Recently, companies such as Bird, Lime and VOI began services in many cities across US and Europe.

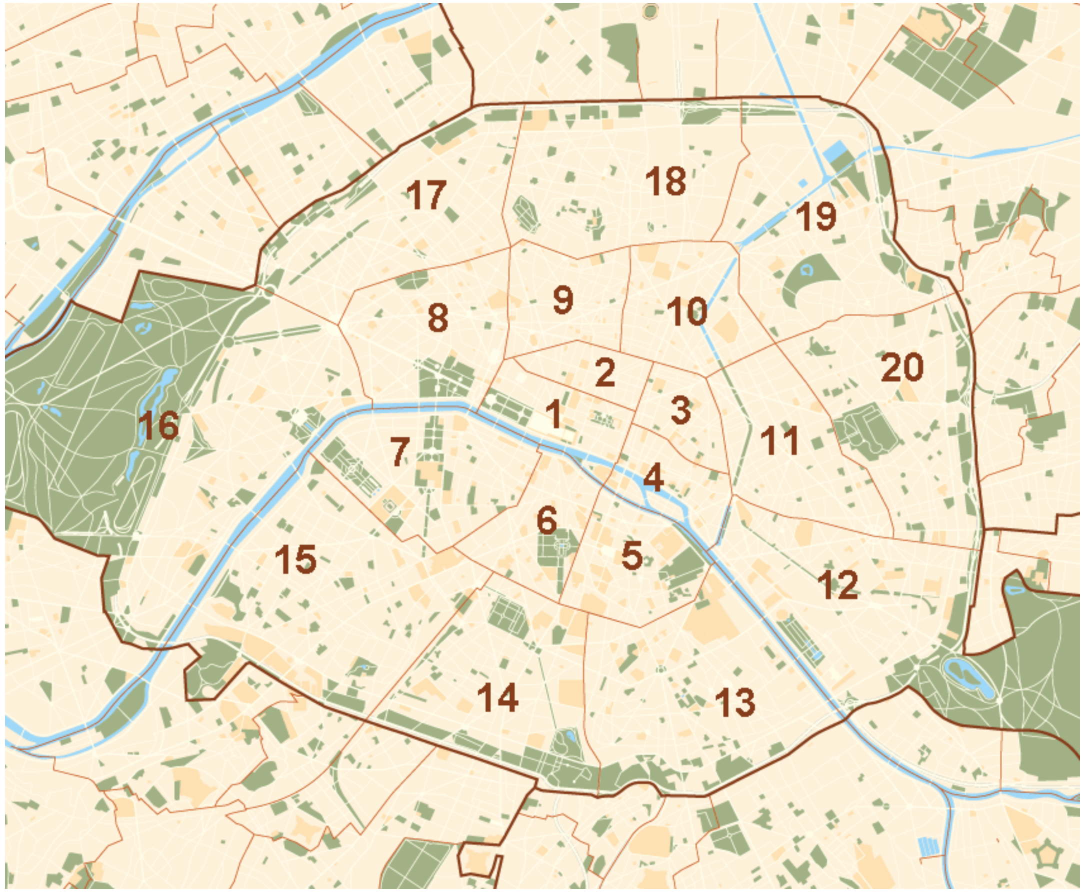
Introduction/Business Problem

In this work the aim is to use machine learning techniques such as clustering, to identify the neighborhoods in a city in which there is a potential need of a bigger density of scooters available. The insights obtained from this work may be helpful for companies to better usage of their resources in field and potentially improve profits, but, at the same time, improving user's experience.

Introduction/Business Problem

The report will be focused in the city of Paris, France. Accordingly to [Business Insider](), Paris was the 3rd most visited city in the world in 2018 with about 18 million foreign visitors and it is the 9th most populated city in Europe with about 2.2 million habitants in the central area. Central Paris is divided in 20 administrative districts called "Arrondissements" as you can see in the map below.

Paris is one the most important cities worldwide and for sure a big challenge for a company that wants to introduce its service. So, we hope to provide relevant information, allowing the decision making to become easier.



Arrondissements of Paris

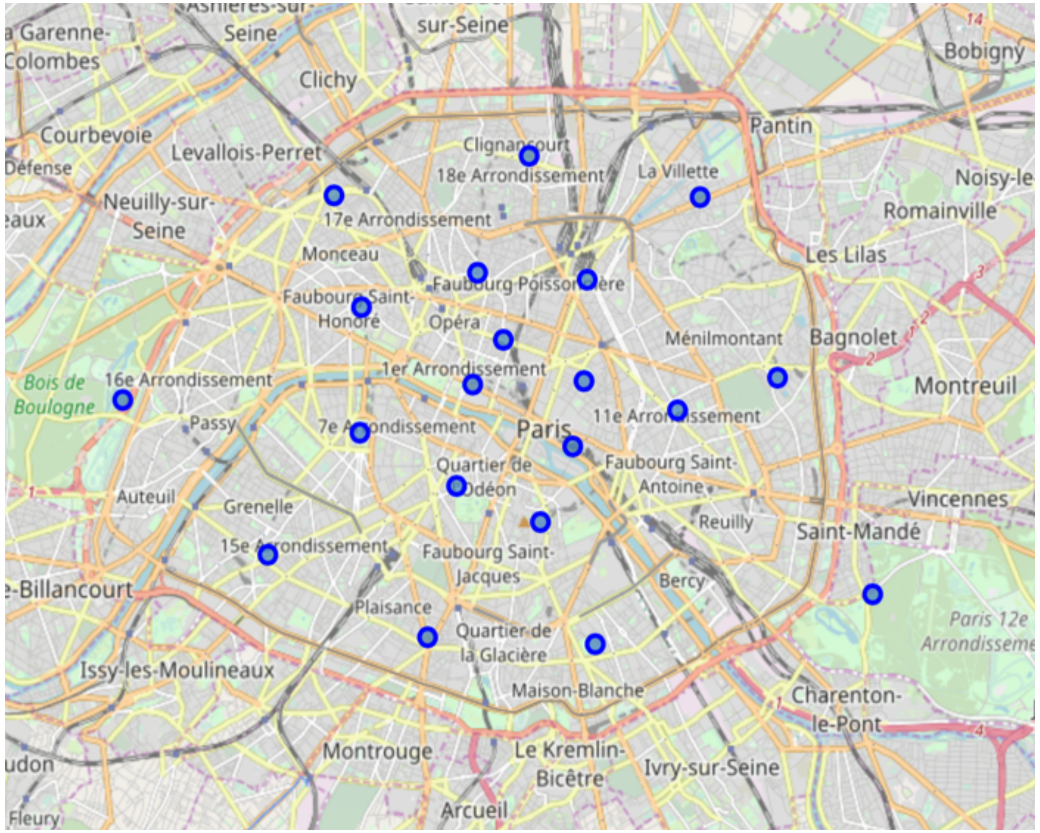
Data

There are several free datasets about the city of Paris. The main sources are we will use in this project to fetch demographic data and coordinates of administrative regions are Paris Data, Institut national de la statistique et des études économiques INSEE, Statista and UrbiStat.

To obtain information about the venues existent in a given area we will use Foursquare. This API has a database of more than 105 million places. Many organizations are using it to geo-tag their photos with detailed info about a destination, while also serving up contextually relevant locations for those who are searching for a place to eat, drink or explore.

Methodology

In such a big city as Paris, many parameters may be used to characterize an area of the city, the most common categories of venues. If there are a lot of offices in the area, maybe that's more a business area than a residential area. If art galleries, museums, monuments are very common maybe that's the case of a more touristic area. For a city with more than 2 million people in the inner core, it may sound very complex to make, however using the Foursquare API function "search" it is possible

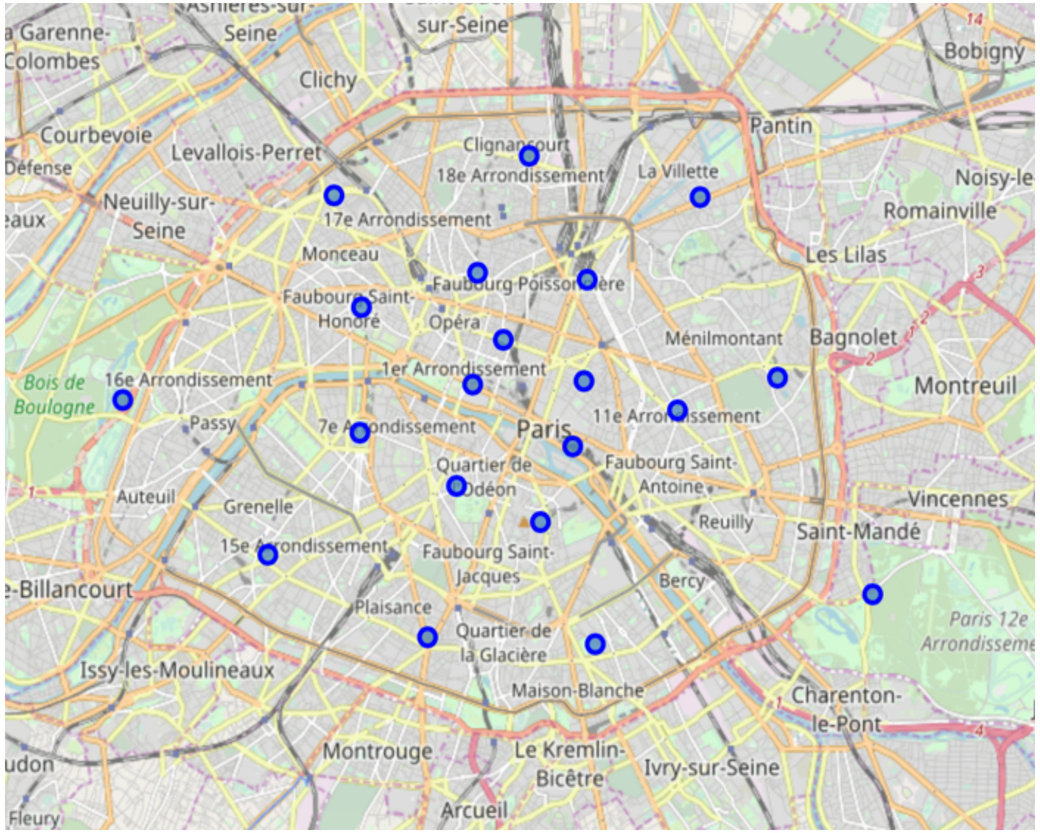


Arrondissements of Paris represented using Folium.

Methodology

The next step after collecting the categories of venues in each Arrondissement, we will group them in terms of similarity. To do so, we will use a machine learning algorithm called K-means, which in present in the machine learning library SciKit Learn for Python.

K-means clustering is a type of unsupervised learning, which is used when you have unlabeled data (i.e., data without defined categories or groups).



Arrondissements of Paris represented using Folium.

Results

Clustering based on venues categories.

Cluster 0

Arrondissement	Latitude	Longitude	Cluster Labels	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	10th Most Common Venue
1	48.862563	2.336443	0	Office	Jewelry Store	French Restaurant	Hotel	Art Gallery	Cosmetics Shop	Women's Store	Miscellaneous Shop	Café	Coffee Shop
3	48.862872	2.360001	0	Art Gallery	Office	Residential Building (Apartment / Condo)	Bar	Boutique	Coworking Space	Bakery	Salon / Barbershop	Café	Men's Store
4	48.854341	2.357630	0	French Restaurant	Office	Hotel	Art Gallery	Bar	Café	Arts & Crafts Store	Bakery	Clothing Store	Italian Restaurant
6	48.849130	2.332898	0	Art Gallery	Office	French Restaurant	Bookstore	Hotel	Bar	Furniture / Home Store	Restaurant	Café	Building
9	48.877164	2.337458	0	Hotel	Office	French Restaurant	Tech Startup	Bar	Italian Restaurant	Women's Store	Bakery	Asian Restaurant	Accessories Store

Cluster 1

Arrondissement	Latitude	Longitude	Cluster Labels	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	10th Most Common Venue
2	48.868279	2.342803	1	Office	Tech Startup	Building	French Restaurant	Coworking Space	Hotel	Japanese Restaurant	Salad Place	Salon / Barbershop	Sandwich Place
8	48.872721	2.312554	1	Office	French Restaurant	Building	Coworking Space	Hotel	Salad Place	Tech Startup	Residential Building (Apartment / Condo)	Boutique	Clothing Store

Results

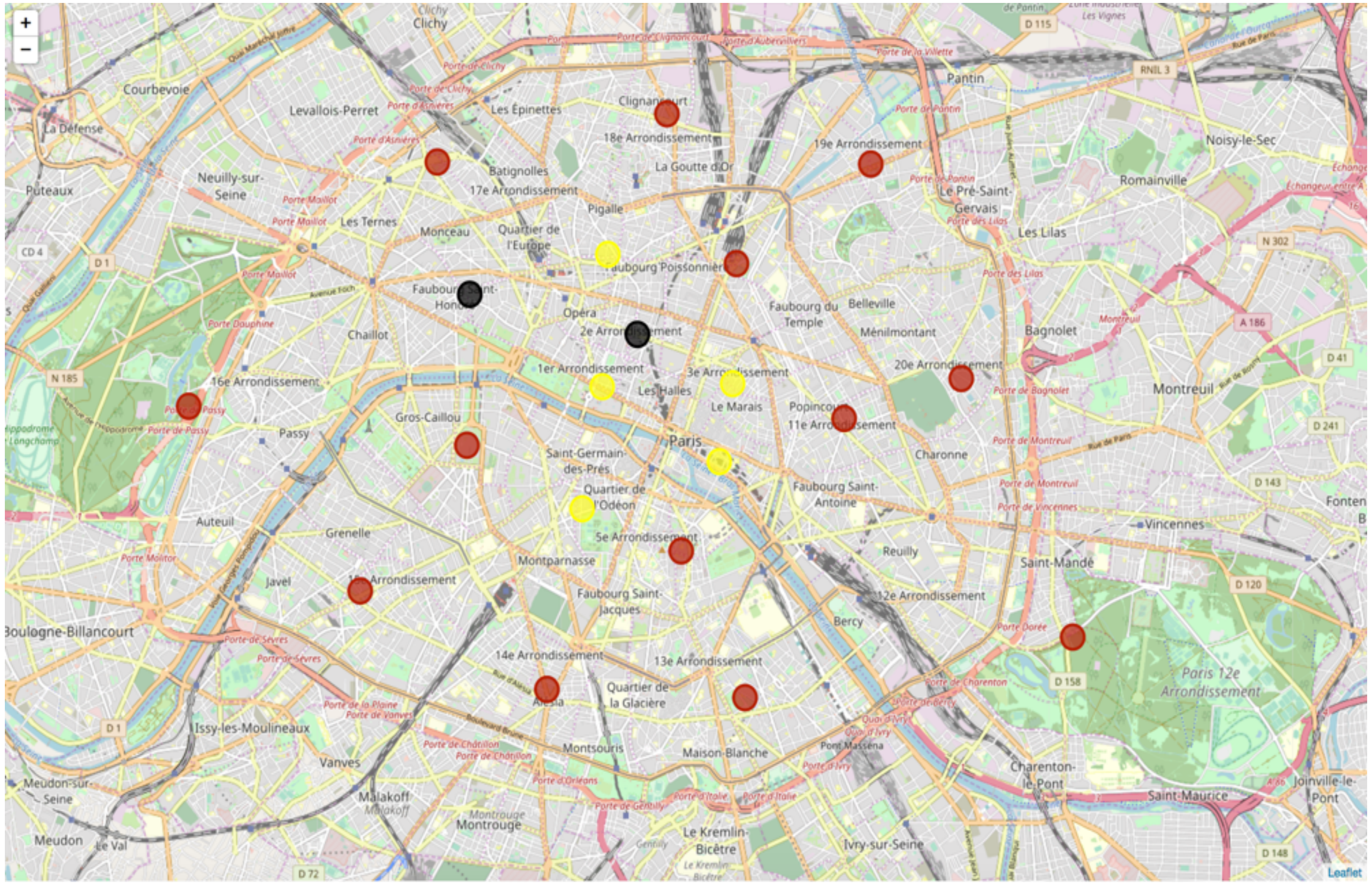
Cluster 2

Arrondissement	Latitude	Longitude	Cluster Labels	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	10th Most Common Venue
18	48.892569	2.348161	2	Tech Startup	Office	French Restaurant	Bar	Residential Building (Apartment / Condo)	Salon / Barbershop	Bakery	Pizza Place	Wine Shop	Café
17	48.887327	2.306777	2	Office	Residential Building (Apartment / Condo)	Bakery	French Restaurant	Coworking Space	Building	Supermarket	Tech Startup	Conference Room	Italian Restaurant
16	48.860392	2.261971	2	Office	French Restaurant	Tennis Court	Embassy / Consulate	Bank	Residential Building (Apartment / Condo)	Plaza	Government Building	Event Space	Bus Stop
15	48.840085	2.292826	2	Office	French Restaurant	Hotel	Residential Building (Apartment / Condo)	Bakery	College Classroom	Building	Salon / Barbershop	Doctor's Office	Bistro
14	48.829245	2.326542	2	Office	Salon / Barbershop	Doctor's Office	Residential Building (Apartment / Condo)	Bank	Hotel	Restaurant	Art Gallery	French Restaurant	Bar
10	48.876130	2.360728	2	Office	Tech Startup	Hotel	Bakery	French Restaurant	Building	Art Gallery	Indian Restaurant	Coworking Space	Bar
12	48.834974	2.421325	2	Office	French Restaurant	Bank	Salon / Barbershop	Bakery	Italian Restaurant	Restaurant	Hotel	Bike Rental / Bike Share	Café
11	48.859059	2.380058	2	Office	French Restaurant	Doctor's Office	Bar	Bank	Tech Startup	Hotel	Bakery	Japanese Restaurant	Chinese Restaurant
19	48.887076	2.384821	2	Office	College Classroom	Residential Building (Apartment / Condo)	French Restaurant	Bike Rental / Bike Share	Doctor's Office	Building	General Entertainment	Bakery	Non-Profit
7	48.856174	2.312188	2	Office	Government Building	French Restaurant	Café	Bank	Art Gallery	Bakery	Hotel	Residential Building (Apartment / Condo)	Salon / Barbershop
5	48.844443	2.350715	2	French Restaurant	Hotel	Office	Bookstore	College Auditorium	Building	Residential Building (Apartment / Condo)	Bar	Bike Rental / Bike Share	College Classroom
13	48.828388	2.362272	2	Office	Bakery	Hospital	Residential Building (Apartment / Condo)	French Restaurant	Italian Restaurant	Building	Dentist's Office	Grocery Store	Bar
20	48.863461	2.401188	2	Bakery	Bar	Cemetery	Office	Pizza Place	Bank	French Restaurant	Supermarket	Hotel	Bike Rental / Bike Share

Results

Clustering based on venues categories.

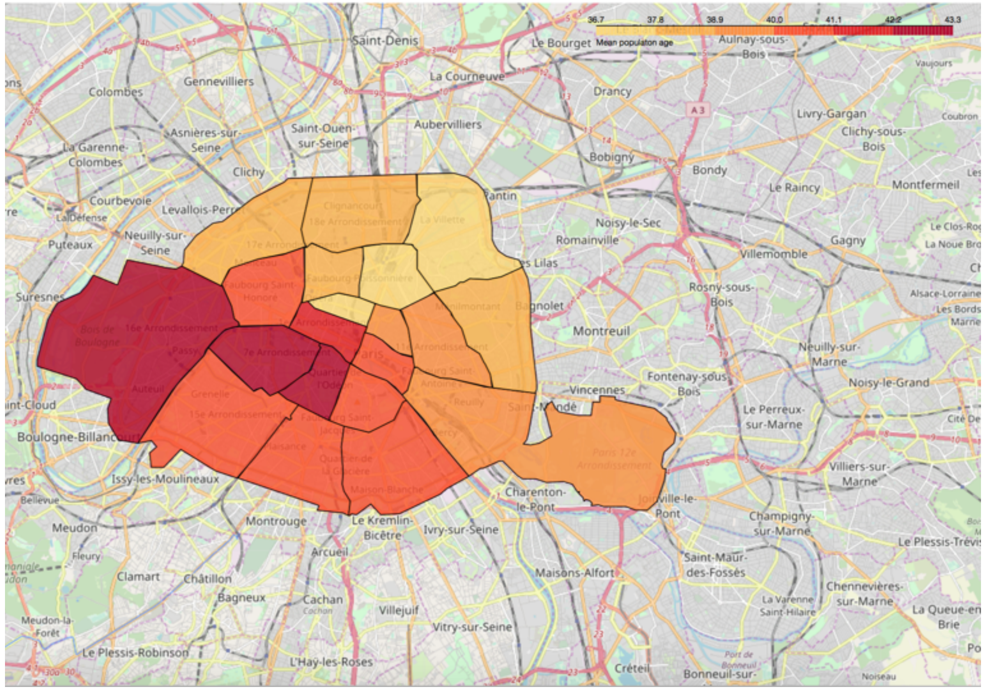
Cluster 0 - Yellow
Cluster 1 – Black
Cluster 2 – Red



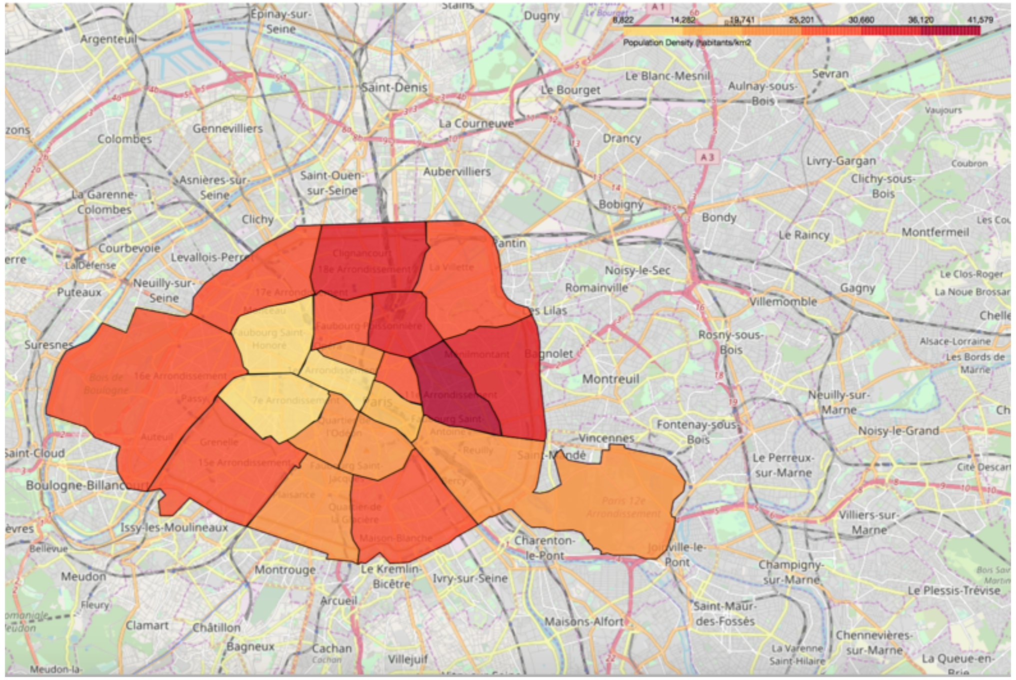
Arrondissements of Paris colored by cluster number. Clustering based on venues categories.

Results

Choropleth maps for demographic and touristic data



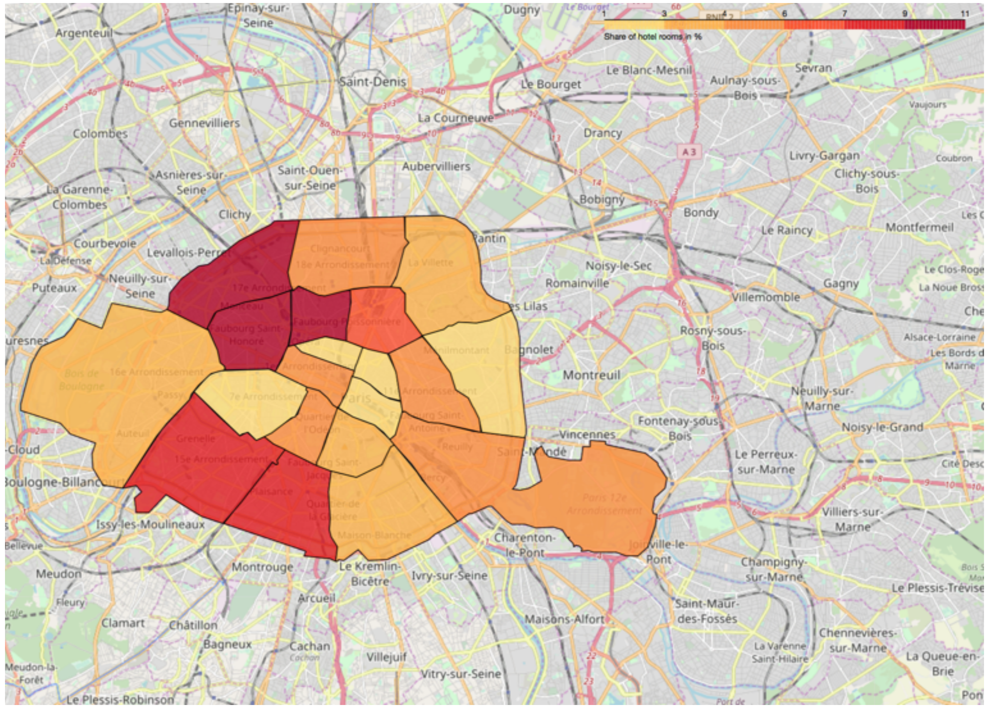
Average age of population



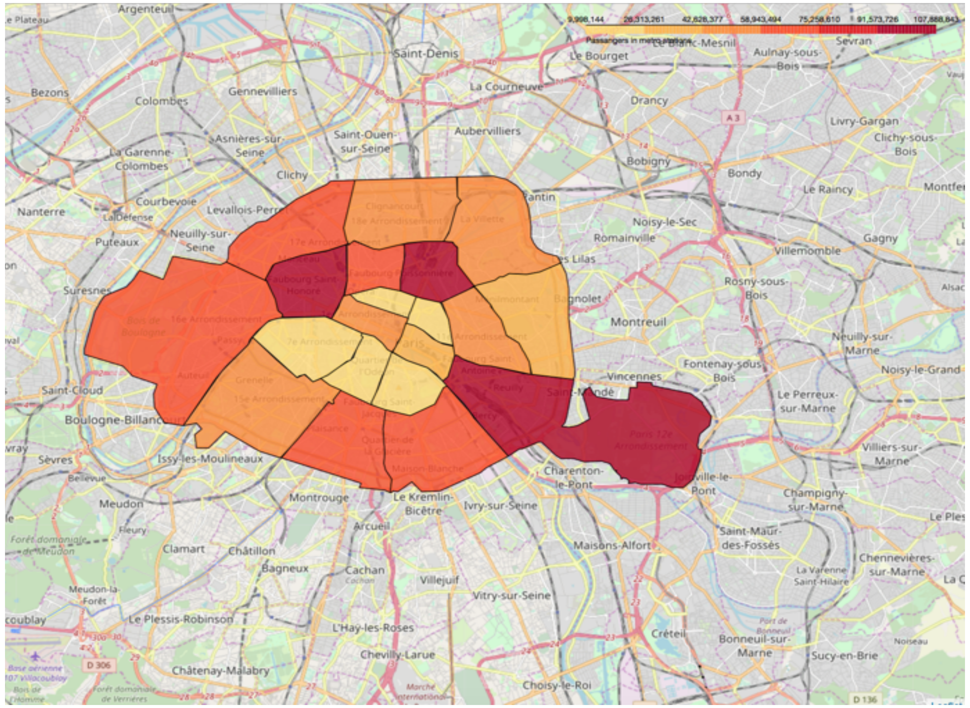
Population density

Results

Choropleth maps for demographic and touristic data



Share of hotel rooms



Passenger traffic in metro stations

Results

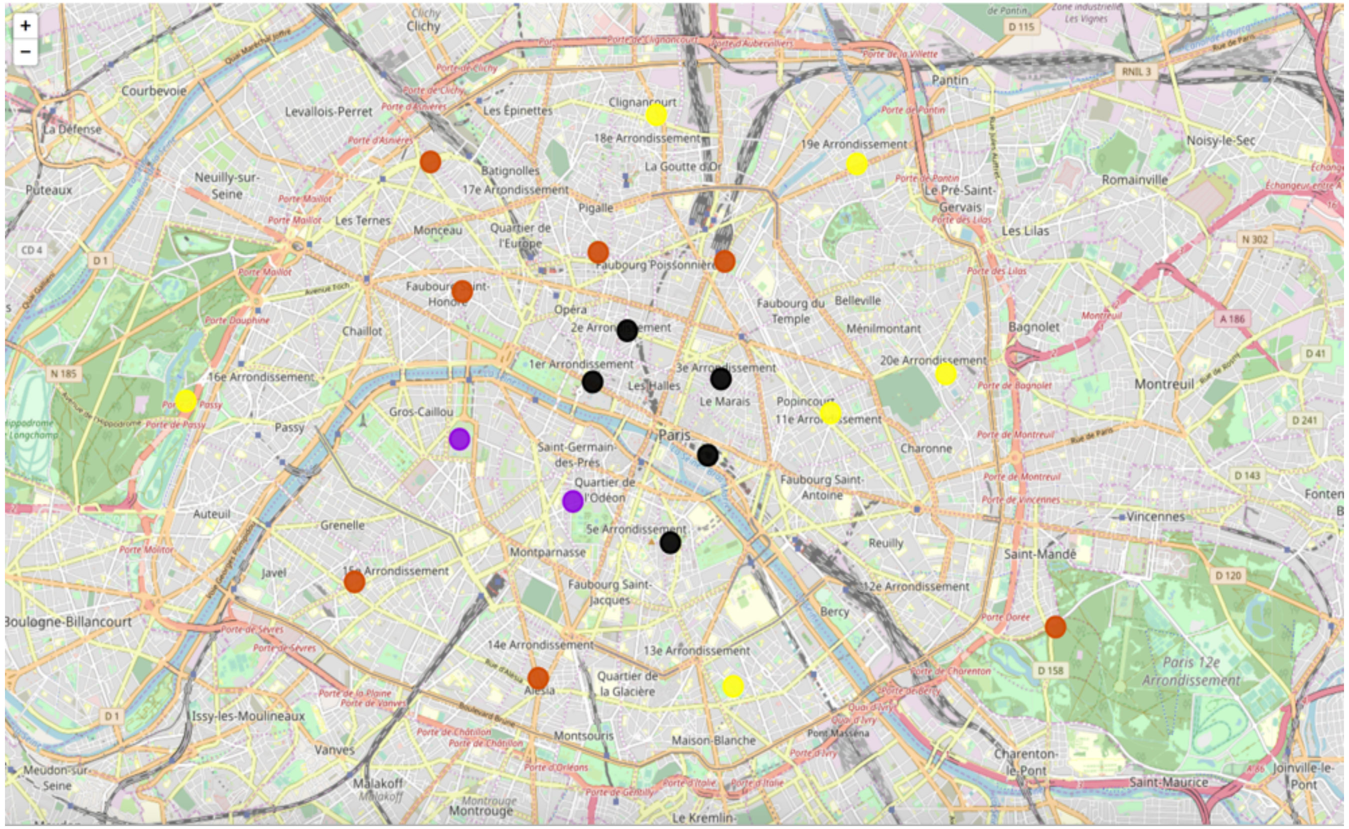
Clustering based on venues categories, demographic and touristic data

Cluster 0 – yellow

Cluster 1 – black

Cluster 2 – purple

Cluster 3 - red



Arrondissements of Paris colored by cluster number.

Results

Clustering based on venues categories, demographic and touristic data

Cluster 0 (Yellow)

Arrondissement	mean age	density	hotel_rooms_share	metro_trafic	veneus_klabels_veneus	Final Cluster Labels
11	38.87	41258.32	4.5	58308937	0	0
13	40.21	25867.76	2.7	74865649	2	0
16	43.22	26655.60	3.8	60649477	2	0
18	38.00	33109.08	5.4	54150575	2	0
19	37.68	27568.67	2.8	48484851	2	0
20	38.86	32914.27	2.0	39759454	2	0

Cluster 1 (Black)

Arrondissement	mean age	density	hotel_rooms_share	metro_trafic	veneus_klabels_veneus	Final Cluster Labels
1	41.74	9143.48	5.1	46892170	1	1
2	36.72	21137.10	2.2	16335221	0	1
3	38.92	30529.46	1.2	10957857	2	1
4	40.91	17177.39	1.2	26589854	0	1
5	40.31	23692.25	3.7	19546551	0	1

Results

Clustering based on venues categories, demographic and touristic data

Cluster 2 (Purple)

Arrondissement	mean age	density	hotel_rooms_share	metro_trafic	veneus_klabels_veneus	Final Cluster Labels
6	42.47	20133.70	4.4	25105444	1	2
7	42.30	13488.26	2.6	23548365	2	2

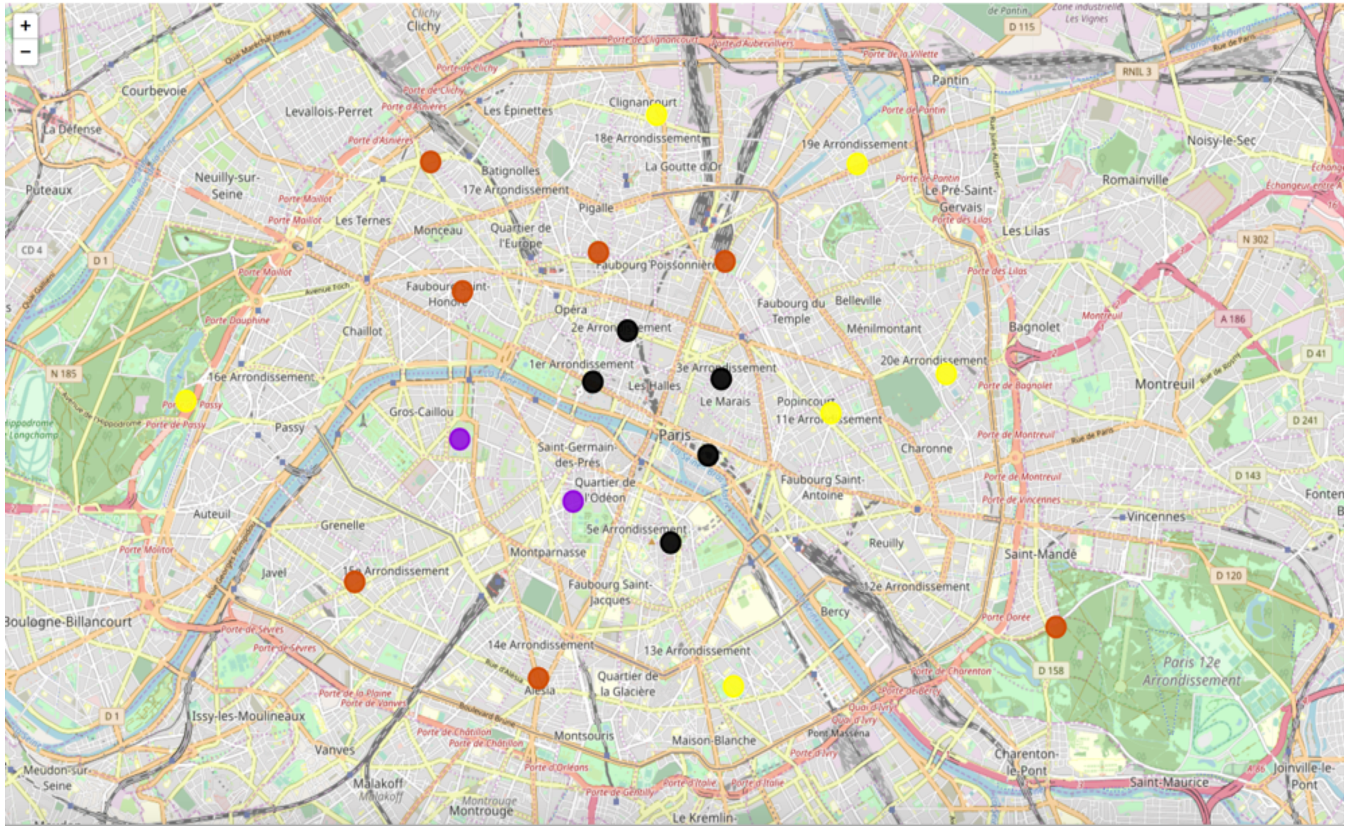
Cluster 3 (Red)

Arrondissement	mean age	density	hotel_rooms_share	metro_trafic	veneus_klabels_veneus	Final Cluster Labels
8	40.10	9617.37	10.5	101780385	2	3
9	37.78	27583.75	10.3	66644419	2	3
10	36.90	32010.03	7.0	106929130	0	3
12	39.76	22775.98	5.5	101752985	2	3
14	40.10	25115.64	8.1	66280421	2	3
15	40.04	27886.14	8.0	53946732	2	3
17	38.84	30022.93	9.3	59101557	2	3

Discussion

In cluster 1 we arrondissements with some of the lowest population densities (except Arrondissement 3). Hotel room share is also low metro station traffic. In what regards of venues, they are characterized by offices, art galleries and French restaurants.

In cluster 0 we find in general the youngest arrondissements (except Arrondissement 13, which actually has the highest average age). the The arrondissements in this cluster have highest population density, average hotel room shares and average traffic in metro stations. The veneus are mostly offices, French restaurant and residential buildings.



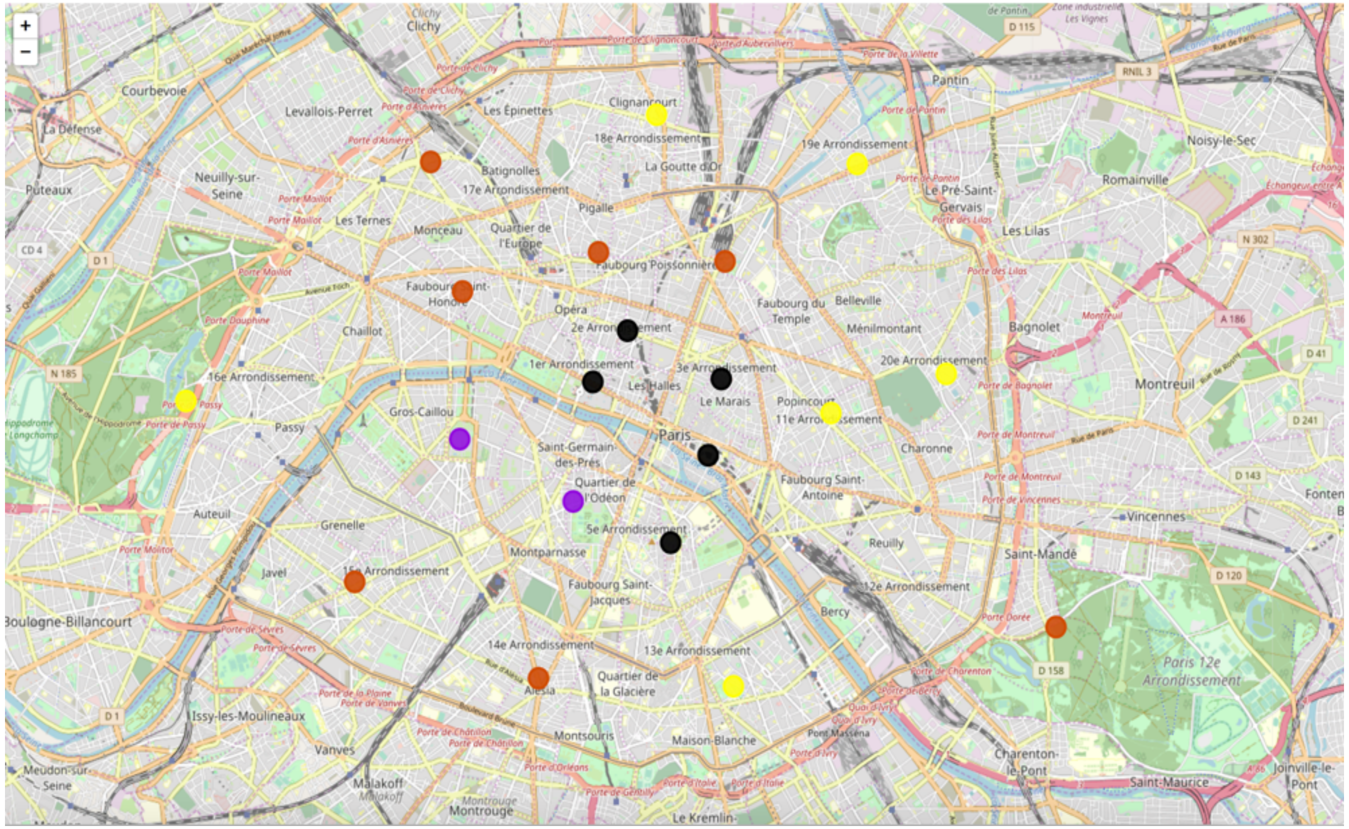
Arrondissements of Paris colored by cluster number. Cluster 0 – yellow, Cluster 1 – black

Cluster 2 – purple, Cluster 3 - red

Discussion

Cluster 3 have a lower average age, high population density, high hotel room percentage and the highest traffic in the metro stations. In terms of venues this cluster is characterized by offices, hotels and residential buildings.

Cluster 2 is composed by higher average age people, lower population density, low hotel room share and low metro station traffic. The most common types of veneus are art galleries, offices, government buildings and French restaurants

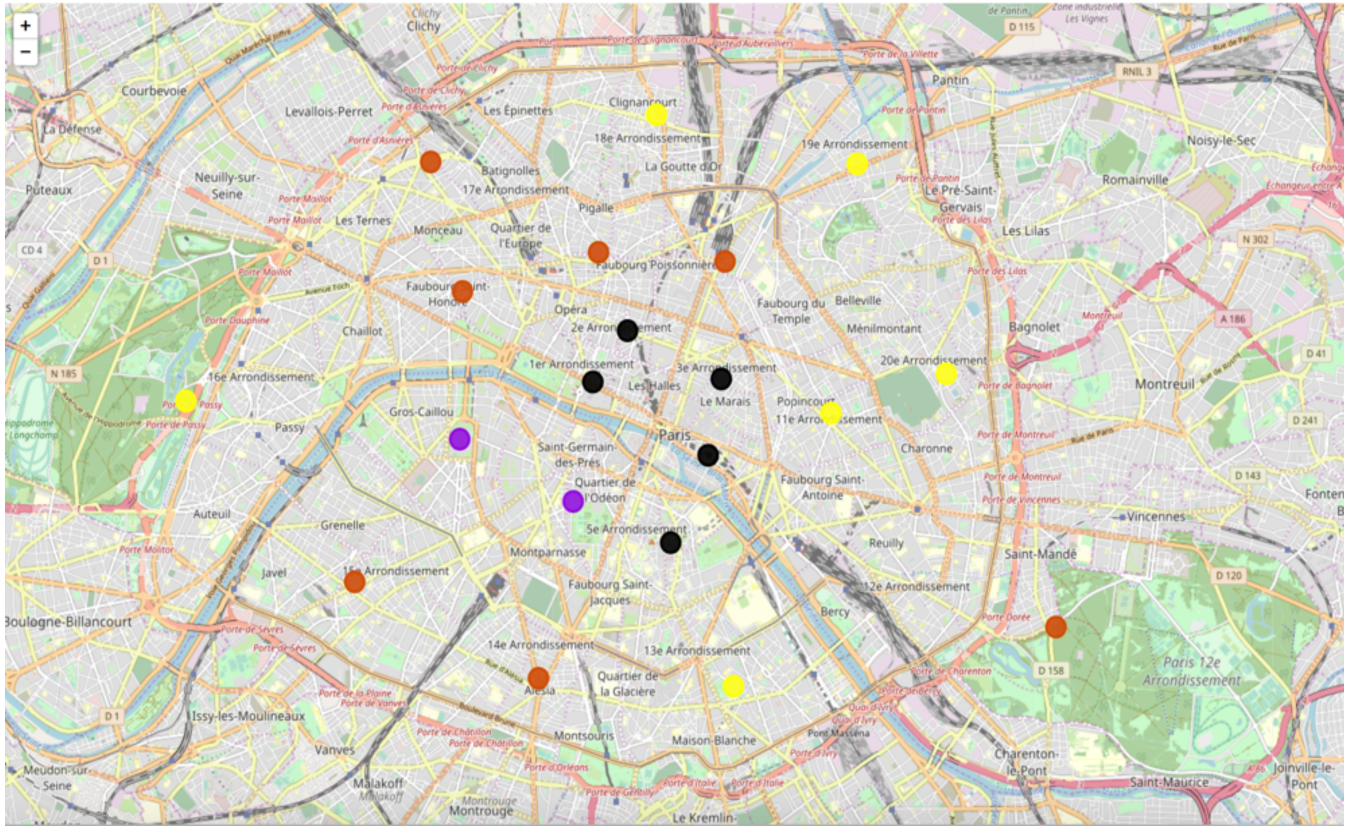


Arrondissements of Paris colored by cluster number. Cluster 0 – yellow, Cluster 1 – black

Cluster 2 – purple, Cluster 3 - red

Discussion

We observe that arrondissements in cluster 3 will potentially demand higher number of scooter vehicles. They have young people, the highest traffic in metro stations, high hotel room share, which means that a great percentage of tourists will start or end their days in one of these arrondissements. In contrast, Arrondissements 6 and 7 (cluster 2) are likely to demand the lowest number of vehicles. Arrondissements in the cluster 0, are also likely to require a high density of vehicles, but not so high as those in cluster 3. The arrondissements in the cluster 1, which represent the inner core of the city, are likely to require vehicles density similar to cluster 0, however the type of venues between this clusters are significantly different.



Arrondissements of Paris colored by cluster number. Cluster 0 – yellow, Cluster 1 – black

Cluster 2 – purple, Cluster 3 - red

Conclusion

In this work we studied the Arrondissements of Paris with the goal of clustering the districts that potentially demand higher number of vehicles by e-scooter sharing companies. We successfully clustered the city in 4 different types using machine learning method k-means. The Arrondissements in cluster 3 (8, 9, 10, 12, 14, 15 and 17) are likely to have higher demands of scooters.