Fitness chains: where to expand in Brussels

This is a project part of the IBM Data Science: Applied Data Science Capstone course on Coursera. The notebook with code can be found on Github: https://github.com/dietrl/Coursera_Capstone

1. Problem statement

Gym or health club chains are expanding around the world to increase the number of memberships, grow revenue and gain brand awareness and loyalty. As more and more gym chains are expanding internationally, an analysis of a city and its neighborhoods can help pick the best location for a new gym.

This project takes a closer look at the city of Brussels, and in which neighborhood a gym chain could best build its next gym. The same exercise can be performed in any city where a gym chain is looking to expand, or open a first branch. It could also be used to evaluate on a larger scale, such as for an entire country, or even Europe. The results could also be used for fitness and health related marketing campaigns, and which neighborhoods to target.

In order to come to a solution, we will look into the different neighborhoods in Brussels and gather info on the amount of gyms in the area, the population density, the age of the population, the unemployment rate, the health of the population and more. We aim to find a neighborhood where the amount of gyms are low, the population is relatively dense, the population is relatively young, the unemployment rate is low and the health index is low (meaning a healthy population) as we assume this would be an ideal situation for a new gym.

2. Description of the data

For the analysis, we will use the following data:

- Data about the neighborhoods in Brussels, along with information about their respective population, the area, the density of the population, the age of the population, the unemployment rate and the self-reported health, as found on https://wijkmonitoring.brussels/. We have downloaded one of the available data tables and have added it as a .csv file to the repository.
- Foursquare data for nearby gyms and fitness centers in every neighborhood.

We start with the neighborhoods in Brussels from the .csv file that can be found in the repository. The area is in square kilometers. The population density is given as the number of people per square kilometer. The columns from *18-29* to *Not In Good Health* are given as percentages. The last column, *Health Index* is given as an index with values between 0 and 2. For easier processing, the units have been excluded from the columns names.

The below figure shows the first ten rows of our dataset. In total, the dataset consists of 118 neighborhoods.

	Neighborhood	Municipality	Population	Area	Population Density	18-29	30-44	45-64	65+	Unemployment Rate	Not In Good Health	Health Index
0	Grote Markt	Brussel	3384	0.38664	8752.36	25	30.11	26.33	8.1	19.49	23.31	1.05
1	Dansaert	Brussel	9217	0.53287	17296.75	21.33	28.3	23.25	8.39	23.87	29.57	1.43
2	Begijnhof - Diksmuide	Brussel	6622	0.38468	17214.23	22.33	28.77	22.11	7.69	24.29	29.35	1.33
3	Martelaars	Brussel	2563	0.37540	6827.28	25.2	30.71	22.82	7.65	16.73	32.69	1.28
4	Onze-Lieve-Vrouw-ter-Sneeuw	Brussel	2468	0.29225	8444.84	24.96	33.35	20.66	6.16	20.19	21.94	1.1
5	Koningswijk	Brussel	330	0.70059	471.03	20.61	24.85	33.64	7.27	7.89	17.19	0.77
6	Zavel	Brussel	2732	0.46349	5894.41	18.23	27.64	28	12.7	18	23.9	1.07
7	Marollen	Brussel	12566	0.64377	19519.32	16	23.25	24.97	12.43	35.48	34.51	1.59
8	Stalingrad	Brussel	3708	0.24173	15339.21	23.33	28.86	20.06	10.49	28.22	30.02	1.29
9	Anneessens	Brussel	10043	0.44349	22645.2	20.21	25.47	21.13	7.39	31.37	27.5	1.52

Table 1: Population and other metrics for the city of Brussels

Next, we get the latitude and longitude of each neighborhood and add it to the dataframe. We use the OpenCage Geocoder API to look up the coordinates.

	Neighborhood	Municipality	Population	Area	Population Density	18-29	30-44	45-64	65+	Unemployment Rate	Not In Good Health	Health Index	Latitude	Longitude
0	Grote Markt	Brussel	3384	0.38664	8752.36	25.00	30.11	26.33	8.10	19.49	23.31	1.05	50.846714	4.352514
1	Dansaert	Brussel	9217	0.53287	17296.75	21.33	28.30	23.25	8.39	23.87	29.57	1.43	50.850158	4.346255
2	Begijnhof - Diksmuide	Brussel	6622	0.38468	17214.23	22.33	28.77	22.11	7.69	24.29	29.35	1.33	50.850450	4.348780
3	Martelaars	Brussel	2563	0.37540	6827.28	25.20	30.71	22.82	7.65	16.73	32.69	1.28	50.851826	4.356570
4	Onze-Lieve-Vrouw-ter-Sneeuw	Brussel	2468	0.29225	8444.84	24.96	33.35	20.66	6.16	20.19	21.94	1.10	50.849895	4.366272
5	Koningswijk	Brussel	330	0.70059	471.03	20.61	24.85	33.64	7.27	7.89	17.19	0.77	50.842829	4.361245
6	Zavel	Brussel	2732	0.46349	5894.41	18.23	27.64	28.00	12.70	18.00	23.90	1.07	50.840382	4.356968
7	Marollen	Brussel	12566	0.64377	19519.32	16.00	23.25	24.97	12.43	35.48	34.51	1.59	50.838029	4.346676
8	Stalingrad	Brussel	3708	0.24173	15339.21	23.33	28.86	20.06	10.49	28.22	30.02	1.29	50.841684	4.344541
9	Anneessens	Brussel	10043	0.44349	22645.20	20.21	25.47	21.13	7.39	31.37	27.50	1.52	50.844301	4.345455

Table 2: Population and other metrics for the city of Brussels, including latitude and longitude for each neighborhood

Now we can use Foursquare data to find all gyms in an area with radius 1000m around the coordinates of each neighborhood. We use the search function, with a limit of 50 gyms per neighborhood – this should be sufficient – and a radius of 1000 meters. This gives us the following dataset (the first ten rows are shown below).

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Gym Name	Gym Latitude	Gym Longitude
0	Grote Markt	50.846714	4.352514	Fitness Center	50.846055	4.355810
1	Grote Markt	50.846714	4.352514	The Urban Spa & Fitness @ The Hotel. Brussels	50.838320	4.355770
2	Grote Markt	50.846714	4.352514	Salle de Fitnesszaal	50.844527	4.350860
3	Grote Markt	50.846714	4.352514	Warwick fitness	50.845177	4.354448
4	Grote Markt	50.846714	4.352514	The Dominican GYM	50.849275	4.354894
5	Grote Markt	50.846714	4.352514	Gym @ Radisson Blu Royal Hotel	50.849001	4.356372
6	Grote Markt	50.846714	4.352514	Hilton Fitness	50.845697	4.356389
7	Grote Markt	50.846714	4.352514	Marriot Brussels Fitness Center	50.848736	4.349207
8	Grote Markt	50.846714	4.352514	Fitness CDP	50.843478	4.349890
9	Grote Markt	50.846714	4.352514	Elia Fitness Empereur	50.842985	4.353454

Table 3: Gyms within a radius of 1000 meters from each neighborhood in Brussels

Our function has returned a total of 836 gyms in Brussels. This number seems quite high. One of the reasons would be that with a radius of 1000 meters, one gym can appear multiple times in our dataset as it is accessible from different neighborhoods. Another reason that we can see from the first five rows is that Foursquare has also returned hotel gyms. As these are generally only accessible to hotel guests, we will aim to exclude them from our dataset by filtering out any gym names that contain "Hotel" or hotel brands such as "Marriott", "Hilton", "Sofitel", etc. This method is not perfect, and some hotel gyms will likely remain in our data set.

After cleaning our data, we end up with 644 gyms left in our dataset. We can look at the number of gyms per neighborhood by grouping the dataset by neighborhood and using the count( ) function.

Neighborhood	Gym Count
Koningswijk	19
Martelaars	18
Zavel	14
Marollen	14
Squares	13
Oud Laken West	13
Oud Laken Oost	13
Onze-Lieve-Vrouw-ter-Sneeuw	13
Begijnhof - Diksmuide	13
Grote Markt	13

Table 4: Number of gyms per neighborhood in Brussels

3. Methodology

The analysis for this project has been done in Python. The notebook with code can be found on Github: *https://github.com/dietrl/Coursera_Capstone.* We can start our analysis by showing the 118 neighborhoods on a map of Brussels using the folium package. The map can be seen on the next page. Each neighborhood is shown as a blue circle on the map.

Next, we can have a closer look at the amount of gyms per neighborhood. More importantly, which neighborhoods have the most gyms in the area, and which the least? We plot two bar charts. The first chart shows the ten neighborhoods with the highest number of gyms. The second chart shows all neighborhoods with three or less gyms. We can see that the neighborhoods with the highest number of gyms all have very similar numbers. This could mean that these neighborhoods are closely together, and that they all have access to each other's gyms. We can also see that there a lot of neighborhoods with access to three or less gyms. These could be interesting for expansion of our gym chain, but further analysis would be required.

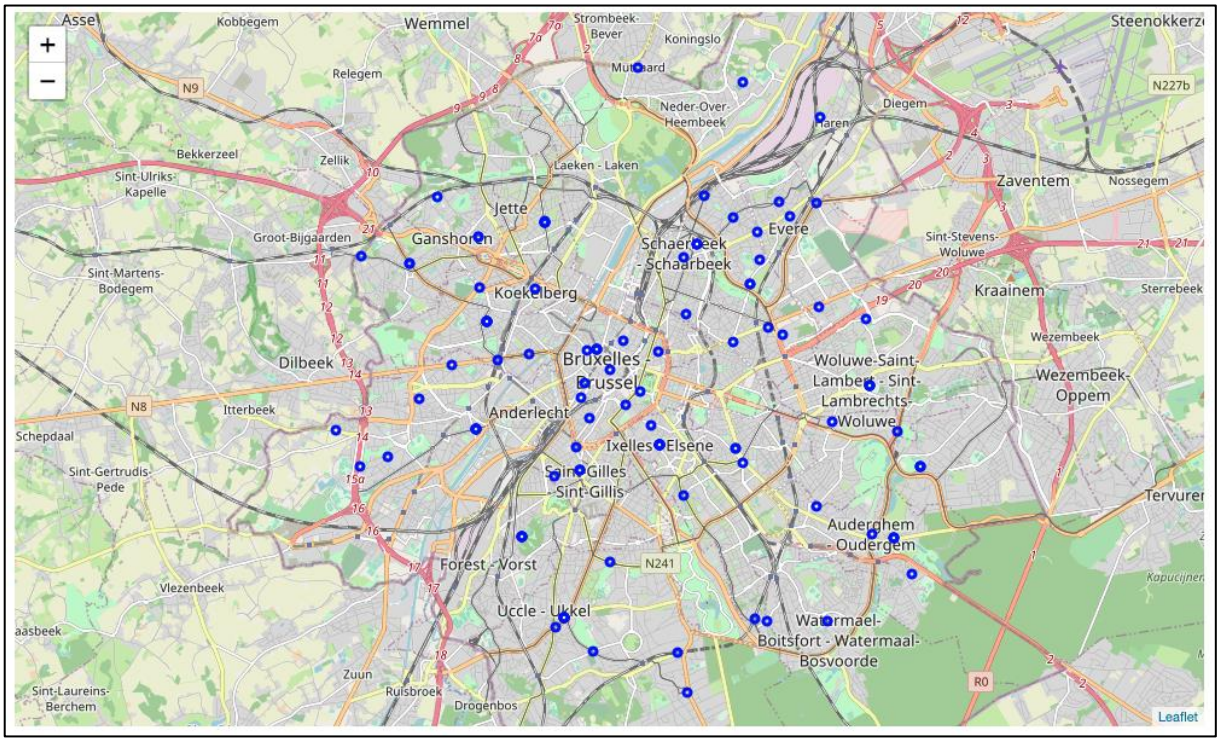
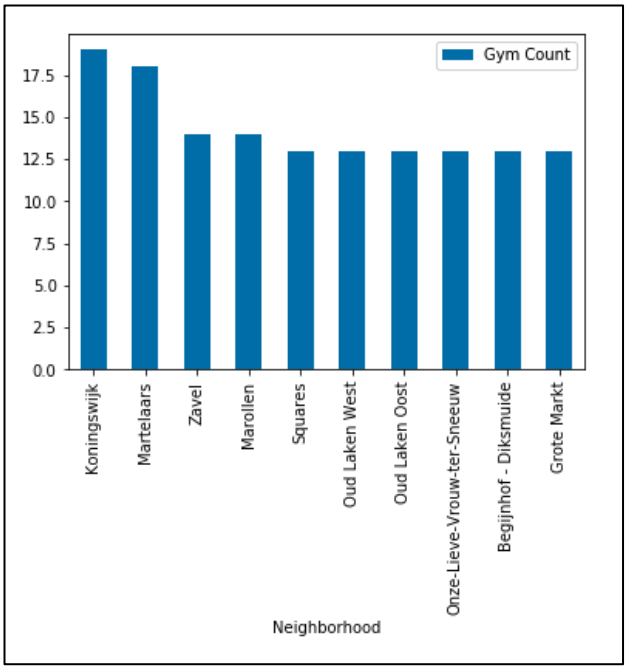


Figure 1: Map of Brussels with 118 neighborhoods marked



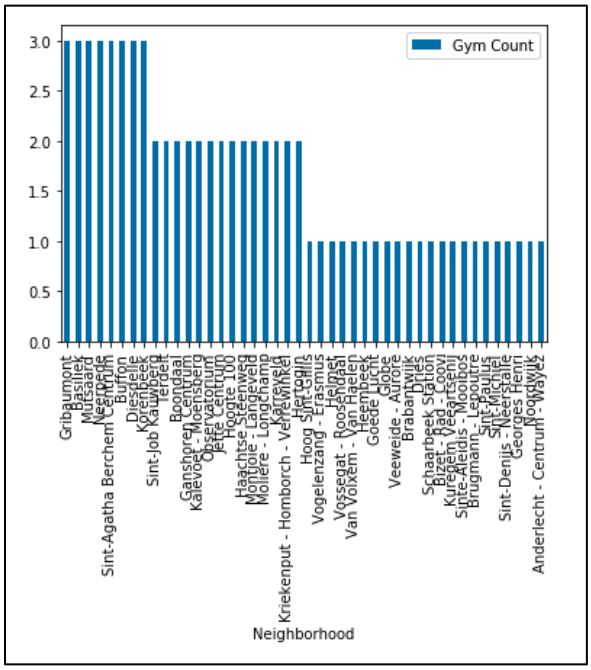


Figure 2 and 3: Bar chart representing the ten neighborhoods with most gyms, and the neighborhoods with less than 3 gyms

We will try to cluster the neighborhoods based on the amount of gyms, the age of the population, the unemployment rate and the self-reported health of the population. Therefore, we merge the population data frame with the venues data frame, and keep the variables that matter most. The result is on the next page.

	Neighborhood	Population Density	18-29	30-44	45+	Unemployment Rate	Health Index	Gym Count
0	Grote Markt	8752.36	25.00	30.11	34.43	19.49	1.05	13.0
1	Dansaert	17296.75	21.33	28.30	31.64	23.87	1.43	11.0
2	Begijnhof - Diksmuide	17214.23	22.33	28.77	29.80	24.29	1.33	13.0
3	Martelaars	6827.28	25.20	30.71	30.47	16.73	1.28	18.0
4	Onze-Lieve-Vrouw-ter-Sneeuw	8444.84	24.96	33.35	26.82	20.19	1.10	13.0
...	...	...	...	...	...	...	...	...
113	Dieweg	5565.47	12.39	18.21	45.95	11.04	0.76	5.0
114	Kalevoet - Moensberg	5511.16	14.67	19.67	43.06	14.63	1.05	2.0
115	Globe	10797.48	16.57	23.30	40.42	15.76	0.91	1.0
116	Vossegat - Roosendaal	7874.13	12.79	19.28	48.18	14.57	0.87	1.0
117	Sint-Denijs - Neerstalle	10416.45	16.45	22.57	36.02	24.92	1.30	1.0

118 rows × 8 columns

Table 5: Merged table of population metrics in Brussels and number of gyms per neighborhood

First, we have to normalize the data in order to cluster it. The result can be found in the notebook. Then, we use KMeans for clustering the neighborhoods. In order to choose how many clusters we want, we can use the Elbow Method. The method is shown in the graph below. The optimal number of clusters would be in the “elbow” of the graph.

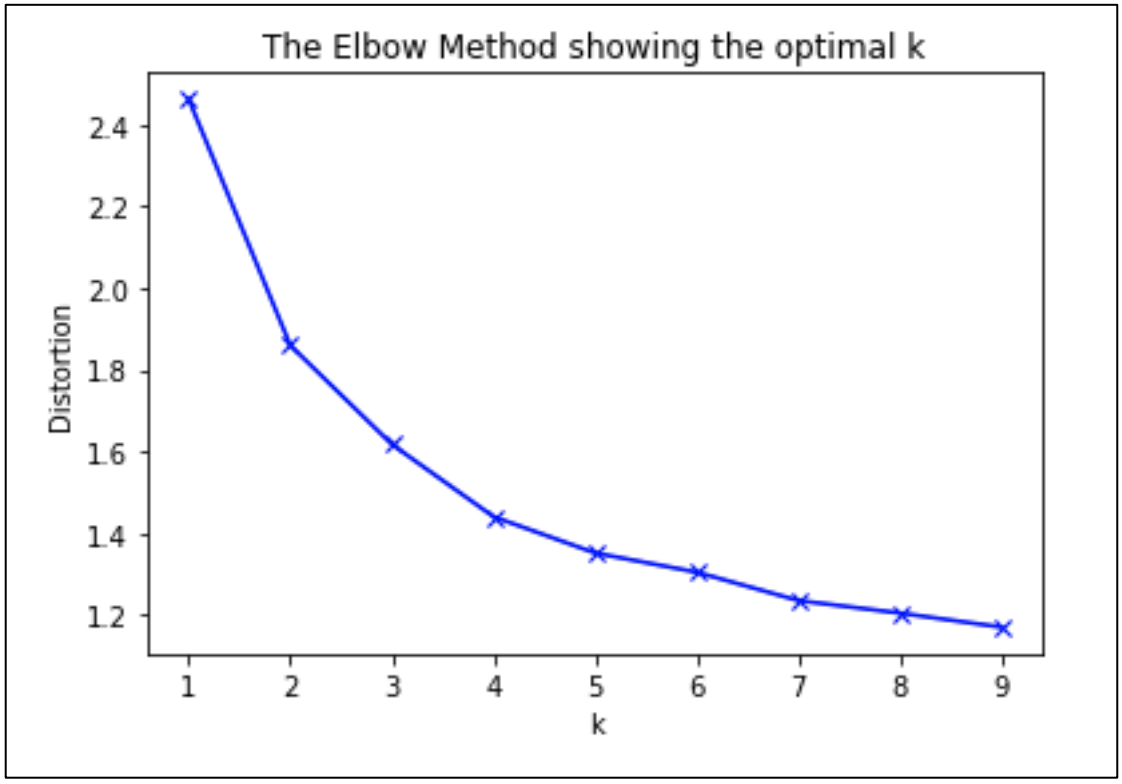


Figure 4: The Elbow Method showing the optimal k

The biggest difference in reduction of distortion seems to be at k=2. However, as the distortion still significantly decreases from k=2 to k=4, we will go ahead with four clusters. The KMeans method with k=4 gives us cluster labels from 0 to 3. They have been inserted into our Brussels data frame on the next page.

	Cluster Labels	Neighborhood	Municipality	Population	Area	Population Density	18-29	30-44	45-64	65+
0	2	Grote Markt	Brussel	3384	0.38664	8752.36	25.00	30.11	26.33	8.10
1	2	Dansaert	Brussel	9217	0.53287	17296.75	21.33	28.30	23.25	8.39
2	2	Begijnhof - Diksmuide	Brussel	6622	0.38468	17214.23	22.33	28.77	22.11	7.69
3	2	Martelaars	Brussel	2563	0.37540	6827.28	25.20	30.71	22.82	7.65
4	2	Onze-Lieve-Vrouw-ter-Sneeuw	Brussel	2468	0.29225	8444.84	24.96	33.35	20.66	6.16

Table 6: Merged table of population metrics in Brussels and number of gyms per neighborhood (for gym count see notebook)

Now that we have defined the four clusters, we can see what they look like on the map of Brussels. Each cluster is represented by a color. The map can be loaded in the notebook to show the label for each neighborhood.

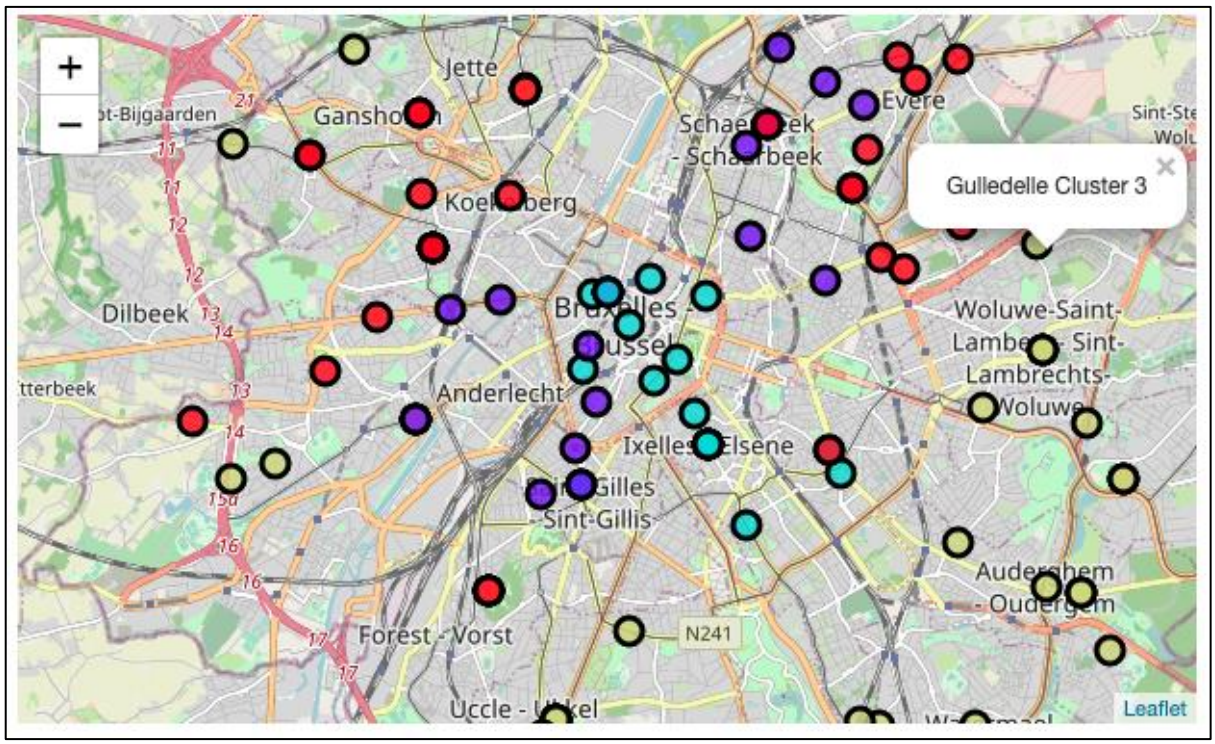


Figure 5: The identified clusters on the map of Brussels

4. Results

We can have a closer look at each cluster with descriptive statistics and compare these to the complete dataset to see which cluster would be best for opening a new gym.

	Population	Area	Population Density	18-29	30-44	45-64	65+	Unemployment Rate	Not In Good Health	Gym Count
count	118.000000	118.000000	118.000000	118.000000	118.000000	118.000000	118.000000	118.000000	118.000000	116.000000
mean	10171.771186	1.019394	12350.327458	17.162203	23.494322	23.559831	13.716525	19.580763	26.578475	5.551724
std	4950.961047	0.592270	7053.829079	3.436886	4.748548	2.389984	5.220952	7.673365	4.954771	4.330568
min	330.000000	0.201650	335.000000	12.390000	13.000000	17.540000	6.160000	6.350000	14.150000	1.000000
25%	6382.500000	0.625725	6727.455000	14.637500	20.332500	21.905000	9.085000	13.940000	23.542500	2.000000
50%	9721.000000	0.836455	11582.075000	16.590000	23.690000	23.270000	12.680000	18.135000	27.225000	4.000000
75%	13859.500000	1.276397	17262.732500	18.420000	26.057500	24.675000	17.580000	24.255000	29.577500	8.000000
max	23645.000000	3.952180	37823.650000	33.700000	36.990000	33.640000	29.010000	38.940000	38.650000	19.000000

Table 7: Descriptive statistics of the complete dataset

	Population	Area	Population Density	18-29	30-44	45-64	65+	Unemployment Rate	Not In Good Health	Gym Count
count	35.00000	35.000000	35.000000	35.000000	35.000000	35.000000	35.000000	35.000000	35.000000	34.000000
mean	7612.00000	1.529823	5656.296286	14.767714	18.767714	25.595429	19.917429	13.494000	23.647429	3.823529
std	3730.89334	0.674536	2892.277823	1.941816	2.938538	1.757840	3.288477	5.376662	5.246085	2.152808
min	1324.00000	0.652950	335.000000	12.390000	13.000000	21.280000	14.240000	6.350000	14.150000	1.000000
25%	5313.50000	1.048330	3472.595000	13.480000	17.145000	24.230000	17.560000	10.485000	19.650000	2.000000
50%	6845.00000	1.387610	5669.560000	14.540000	19.030000	25.870000	19.250000	12.050000	23.660000	4.000000
75%	10685.50000	1.843735	6864.925000	15.320000	20.595000	26.715000	22.690000	14.825000	26.030000	5.000000
max	15327.00000	3.952180	11697.830000	20.800000	24.660000	29.350000	29.010000	36.000000	38.650000	9.000000

Table 8: Descriptive statistics of cluster 0

	Population	Area	Population Density	18-29	30-44	45-64	65+	Unemployment Rate	Not In Good Health	Gym Count
count	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	38.000000	37.000000
mean	11843.789474	0.974534	12961.558158	16.026842	23.385526	23.345000	13.826316	18.284211	27.987895	3.216216
std	4660.973203	0.425960	4389.011625	1.879516	2.964589	1.230198	2.578467	3.631086	4.437739	2.123089
min	1722.000000	0.300710	3106.520000	13.200000	16.550000	21.620000	8.040000	10.910000	17.520000	1.000000
25%	8610.250000	0.683925	9760.887500	14.592500	21.595000	22.525000	11.870000	15.800000	26.037500	1.000000
50%	12262.000000	0.881580	13096.110000	16.100000	23.045000	23.195000	13.400000	17.865000	28.190000	3.000000
75%	15208.500000	1.204308	16797.105000	16.897500	24.947500	23.930000	15.682500	20.777500	30.215000	4.000000
max	23645.000000	1.937560	20321.920000	21.570000	31.160000	28.750000	19.040000	26.140000	38.440000	8.000000

Table 9: Descriptive statistics of cluster 1

	Population	Area	Population Density	18-29	30-44	45-64	65+	Unemployment Rate	Not In Good Health	Gym Count
count	21.000000	21.000000	21.000000	21.000000	21.000000	21.000000	21.000000	21.000000	21.000000	21.000000
mean	7952.333333	0.618810	13085.992381	22.615714	30.270952	22.743333	9.226190	19.022857	24.668095	12.142857
std	4757.615341	0.262539	5782.505552	3.224008	3.081576	3.317784	2.254756	4.788368	3.678505	2.833473
min	330.000000	0.241730	471.030000	18.230000	24.850000	17.540000	6.160000	7.890000	17.190000	6.000000
25%	3384.000000	0.431490	8752.360000	20.790000	28.300000	20.950000	7.690000	16.730000	22.000000	11.000000
50%	8827.000000	0.544550	15128.050000	22.330000	30.100000	22.080000	9.100000	19.490000	24.260000	12.000000
75%	10218.000000	0.805010	17214.230000	23.670000	32.810000	23.030000	10.400000	22.230000	26.700000	13.000000
max	18142.000000	1.246150	21254.640000	33.700000	36.990000	33.640000	15.430000	28.220000	32.690000	19.000000

Table 10: Descriptive statistics of cluster 2

	Population	Area	Population Density	18-29	30-44	45-64	65+	Unemployment Rate	Not In Good Health	Gym Count
count	24.000000	24.000000	24.000000	24.000000	24.000000	24.000000	24.000000	24.000000	24.000000	24.000000
mean	13199.416667	0.696559	20500.967500	17.680000	24.630000	21.645833	8.428750	30.998333	30.292917	5.833333
std	4564.117458	0.323928	6485.077643	1.226231	1.500597	1.292022	1.200458	4.491269	2.582241	4.488310
min	5458.000000	0.201650	8738.200000	15.040000	20.630000	19.750000	6.590000	21.460000	26.680000	1.000000
25%	9513.250000	0.512145	17135.340000	17.132500	23.857500	20.865000	7.620000	29.122500	28.725000	1.750000
50%	13308.000000	0.676710	20193.660000	17.680000	24.415000	21.475000	8.505000	31.365000	29.495000	4.000000
75%	17999.000000	0.778443	24808.275000	18.215000	25.720000	22.055000	8.997500	33.495000	31.145000	10.000000
max	19390.000000	1.737760	37823.650000	20.210000	27.360000	24.970000	12.430000	38.940000	37.250000	14.000000

Table 11: Descriptive statistics of cluster 3

The first cluster, cluster 0, has 35 neighborhoods in it. They are the furthest from the city center, have low population density compared to the average, a larger share of people aged over 45, a low unemployment rate and relatively good health. The average number of gyms is 3.82, which is quite high taking into account the low population density.

Cluster 1 has a total of 38 neighborhoods. The map shows us that these neighborhoods are closer to the center than Cluster 0, but still quite far. They have an average of 3.22 gyms in the area. Their population and population density is slightly higher than the average in Brussels. The percentage of people aged between 18 and 44 is slightly lower than the average in Brussels. The unemployment rate is also slightly lower than the average. Last, the health index shows that the self-reported health in these areas is slightly worse than on average.

Cluster 2 has 21 neighborhoods located in the center of the city. They have a high number of gyms in the area. The average population per neighborhood is quite small, but the neighborhoods seem to be smaller as well, leading to an above average population density. These neighborhoods have the largest share of people aged 18 to 44, and the unemployment rate is around the average of Brussels. Furthermore, the reported health is relatively good.

Cluster 3, the last cluster, has a total of 24 neighborhoods and is located on the outsides of the center. They have more gyms Brussels on average. While the population is a only a bit higher than the average, the population density is significantly higher. They have a larger share of people aged 18 to 44, but the unemployment rate is almost double. Additionally, they have a slightly larger share of people that are not in good health.

5. Discussion

Based on the clustering of the 118 neighborhoods in Brussels, we could say that the neighborhoods in municipalities away from the center but with high population density are the most interesting for opening a new fitness center. The neighborhoods in this cluster are grouped together, and while their populations are higher than on average, the number of gyms here are significantly lower than on average. They seem to have a good share of the targeted age group for gyms, between 18 and 44, an unemployment rate that is lower than on average, and a self-reported health that is better than average.

Neighborhoods that are closer to the center, on the outsides, are less interesting as they have significantly more gyms while the population is only slightly bigger.

Neighborhoods in municipalities that are too far away from the center are even less interesting. They have an older population and a low population density, which makes it unattractive for opening a new fitness center.

Last, the neighborhoods in the center seem attractive when only looking at the population. But as they already have too many gyms within a radius of one km, they become less attractive for a new fitness center as well.

The analysis in this project could be improved by including the scores and the number of check-ins for each gym. This would allow us to see the popularity of gyms in each neighborhood. Neighborhoods with lower popularity would be more interesting than neighborhoods with higher popularity. But as *score* and *stats* are part of *Venue Details* , which is a premium endpoint, we will not be able to do this here.

6. Conclusion

We conclude that with location, population and venue data we can make recommendations on where a fitness chain may want to open a new fitness center. The recommended areas are away from the center - although not too far - where the population and population densities are high, and the number of gyms are low. Additionally, these areas seem to have an attractive age group, a lower unemployment rate and a better self-reported health.

The analysis done for this project could be performed on a larger scale, for example in the case of international expansion in Europe. Cities and neighborhoods with attractive characteristics for opening a new fitness center could be located for further research into expansion.