CLUSTERING BOROUGHS OF GALICIA BASED ON SOCIO-ECONOMIC INDICATORS

Applied Data Science Capstone by IBM/Coursera

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1. Introduction: Business problem

Galicia is a nation in the northwest of the Spanish state. With almost 2.700.000 inhabitants, it is characterized by an extensive population throughout its territory: Galicia has half of the population centers of the Spanish state. Galician territory is organized into four provinces and currently has 313 main boroughs. As in many other countries in the world, there has been a trend of depopulation from rural to urban areas for many years.

In this project the galician boroughs will be analysed based on several socio-economic indicators: population, density, per capita income, population ageing, vegetative balance and unemployment rate. With this data the boroughs will be clustered using the machine learning algorithm k-means. The main characteristics of each group will be discussed. Finally, within each cluster, the most recommended venue categories in the centers of each boroughs are shown, using data from the Foursquare Places API. Trends between venue categories and socio-economic indicators will be shown.

This project can be useful for both public and private organizations to understand the demographic and economic distribution of galician boroughs when offering services, infrastructures or any other kind of business.

2. Data

2.1. Data sources

The data sources used for this project are:

- List of galician boroughs and their population from the IGE (Galician Institute of Statistics) https://www.ige.eu/

This information was previously downloaded from the web page in .csv format. Then it is readed into Pandas DataFrames from the archives. The **population** is updated to 2019.

- Socio-economic indicators of every Galician borough from the IGE (Galician Institute of Statistics) https://www.ige.eu/

  These indicators are directly scrapped from web tables into Pandas DataFrames using BeautifulSoup:

  - **Per capita income (€)**. It measures the average income earned per person in a borough in a specified year. It is calculated by dividing the borough's total income by its total population. This data is updated to 2017.

  - **Population density (population/km^2)**. It is a measurement of population per unit area. This data is updated to 2019.

  - **Unemployment rate**. The unemployment rate used is the number of unemployed people divided by the population. This data is updated 2019.

  - **Vegetative balance**. It is the difference between births and deaths of a given population, divided by the total population. This data is updated to 2018.

  - **Population ageing (%)**. It is the relationship between the population over the age of 64 and the population under the age of 20 expressed in %. This data is updated to 2019.

  With all these indicators the boroughs will be clustered into several groups using a k-means algorithm. These clusters and their characteristics will allow to understand the socioeconomic distribution of the Galician population along the territory.

- Coordinates of the Galician boroughs from GeoPy https://geopy.readthedocs.io/

  The GeoPy API is used to automatically geocode the address of each borough. Maps will be plotted with Folium using these coordinates, to have a clearer idea of how the clusters are distributed. Also the characteristics of each borough will be shown with Popups on the map.

- Recommended venues in the center of each Galician borough, using the Foursquare Places API https://developer.foursquare.com/places

  The top **recommended venues** are obtained for each borough with the Foursquare Places API, exploring the addresses with a radius of two kilometers. This information includes the name, location and primary category of each venue. Then the venues are grouped by main characteristics and borough clusters. A graph will be plotted to show which main characteristics of venues are more common in the different clusters.

2.2. Data wrangling

In a first step we read the .csv of each province into a Pandas dataframe. Aflter that the four dataframes are concatenated resulting 313 rows:

	INE Code	Borough	Population	Province
0	15001	Abegondo	5406	Coruna, A
1	15002	Ames	31793	Coruna, A
2	15003	Aranga	1849	Coruna, A
3	15004	Ares	5732	Coruna, A
4	15005	Arteixo	32262	Coruna, A

Figure 1: Boroughs dataframe

Then we use GeoPy to geodecode each address, and the columns of "Latitude" and "Longitude" are added to the dataframe:

	INE Code	Borough	Population	Province	Latitude	Longitude
0	15001	Abegondo	5406	Coruna, A	43.210443	-8.290324
1	15002	Ames	31793	Coruna, A	42.890030	-8.651627
2	15003	Aranga	1849	Coruna, A	43.218390	-8.015691
3	15004	Ares	5732	Coruna, A	43.426330	-8.244039
4	15005	Arteixo	32262	Coruna, A	43.309653	-8.500338

Figure 2: Latitude and Longitude dataframe

Once this dataframe is ready, the venues of each borough are imported using the Foursquare API. There are a total of 3231 venues. They are saved into a dataframe with name, category and location. The venues that were imported are only described by their primary category (such as 'italian restaurant'). We are going to classify them by their main category: Arts & Entertainment, College & University, Food, Nightlife Spot, Outdoors & Recreation, Professional & Other Places, Shop & Service, Travel & Transport. For that we import the Foursquare Venue Category Hierarchy, and them transform every primary category into the main category. This is the final dataframe:

	INE Code	Borough	FQ borough Latitude	FQ borough Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Main Category
0	15001	Abegondo	43.21667	-8.28333	Oza Paradise	43.211984	-8.278352	Skate Park	Outdoors & Recreation
1	15001	Abegondo	43.21667	-8.28333	Meson San Marcos	43.226690	-8.288709	Brewery	Nightlife Spot
2	15001	Abegondo	43.21667	-8.28333	Supermercado das Mariñas	43.217842	-8.299469	Grocery Store	Shop & Service
3	15001	Abegondo	43.21667	-8.28333	Momentos	43.229025	-8.287383	Bar	Nightlife Spot
4	15001	Abegondo	43.21667	-8.28333	Cafetería Gala	43.229663	-8.288057	Café	Food

Figure 3: Foursquare venues dataframe

Then we group the venues by borough and create a new dataframe encoding main categories. Finally we have a dataframe with every borough and the frequency of ocurrence of each main category:

	Borough	INE Code	Arts & Entertainment	College & University	Food	Nightlife Spot	Outdoors & Recreation	Professional & Other Places	Shop & Service	Travel & Transport
0	Abadín	27001	0.000000	0.0	0.500000	0.000000	0.500000	0.0	0.000000	0.000000
1	Abegondo	15001	0.000000	0.0	0.250000	0.250000	0.125000	0.0	0.375000	0.000000
2	Agolada	36020	0.000000	0.0	0.333333	0.333333	0.333333	0.0	0.000000	0.000000
3	Alfoz	27002	0.166667	0.0	0.166667	0.333333	0.166667	0.0	0.000000	0.166667
4	Allariz	32001	0.066667	0.0	0.600000	0.200000	0.000000	0.0	0.133333	0.000000

Figure 4: Boroughs and venues frequency dataframe

In the last step the socio-economic indicators are scraped from the website of the IGE (Galician Institute of Statistics). There are two boroughs that do not have indicators, so they are dropped from the dataframe (Oza-Cesuras and Cerdedo-Cotobade). The indicators are merged with the initial dataframe with boroughs and population. Finally 311 boroughs remain in the new dataframe:

	INE Code	Borough	Population	Province	Latitude	Longitude	Per capita income	Population density	Population ageing	Vegetative balance	Unemployment	Unemployment rate
0	15001	Abegondo	5406	Coruna, A	43.210443	-8.290324	14249.0	64.1	233.03	-0.013873	233.0	0.043100
1	15002	Ames	31793	Coruna, A	42.890030	-8.651627	15727.0	394.1	54.67	0.002894	1791.0	0.056333
2	15003	Aranga	1849	Coruna, A	43.218390	-8.015691	11668.0	15.7	510.37	-0.017307	49.0	0.026501
3	15004	Ares	5732	Coruna, A	43.426330	-8.244039	13815.0	319.7	167.80	-0.004536	372.0	0.064899
4	15005	Arteixo	32262	Coruna, A	43.309653	-8.500338	13811.0	347.8	81.88	0.001705	2040.0	0.063232

Figure 5: Socio-economic indicators dataframe

This concludes the data gathering phase.

3. Methodology

3.1. Exploratory data analysis

A Folium map is plotted representing the boroughs colored by province:

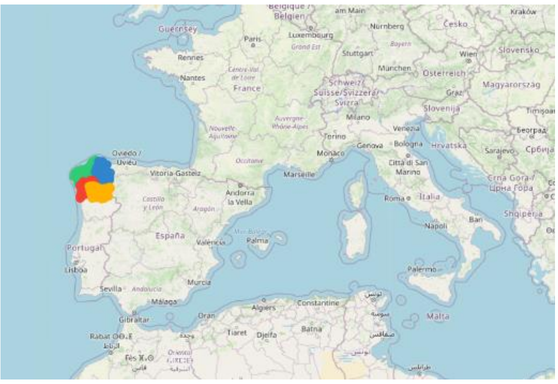

Image 1: Galicia in Europe

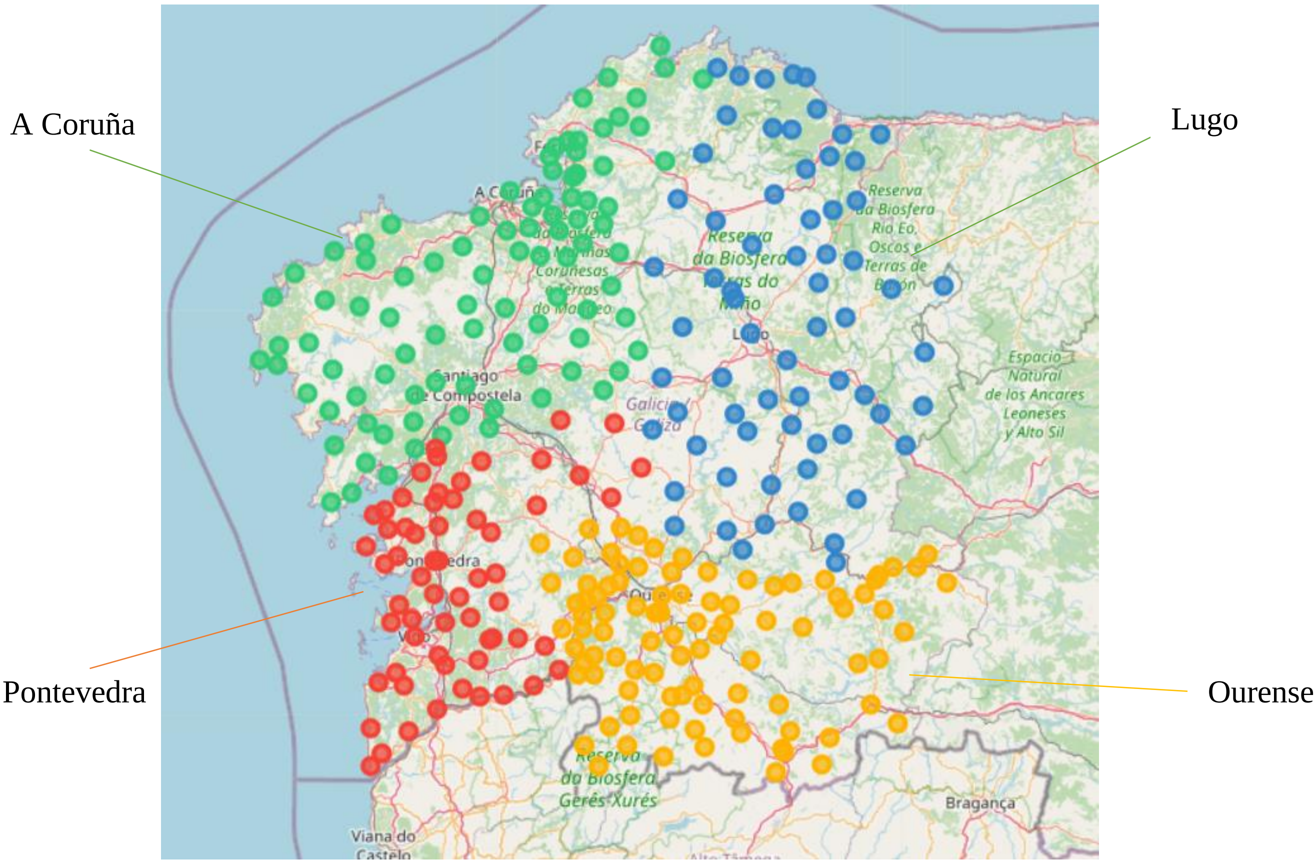

Image 2: Boroughs in Galicia

The population of Galicia is distributed among the four provinces as follows:

Province	Boroughs	Population
Coruna, A	93	1,119,596
Lugo	67	329,587
Ourense	92	307,651
Pontevedra	61	942,665
Total	**313**	**2,699,499**

Figure 6: Population in Galicia

The following map shows the boroughs with more than 23,000 inhabitants. These are 19 (from 313) boroughs that represent almost the 50% of the population of Galicia. Let's see the heat map:

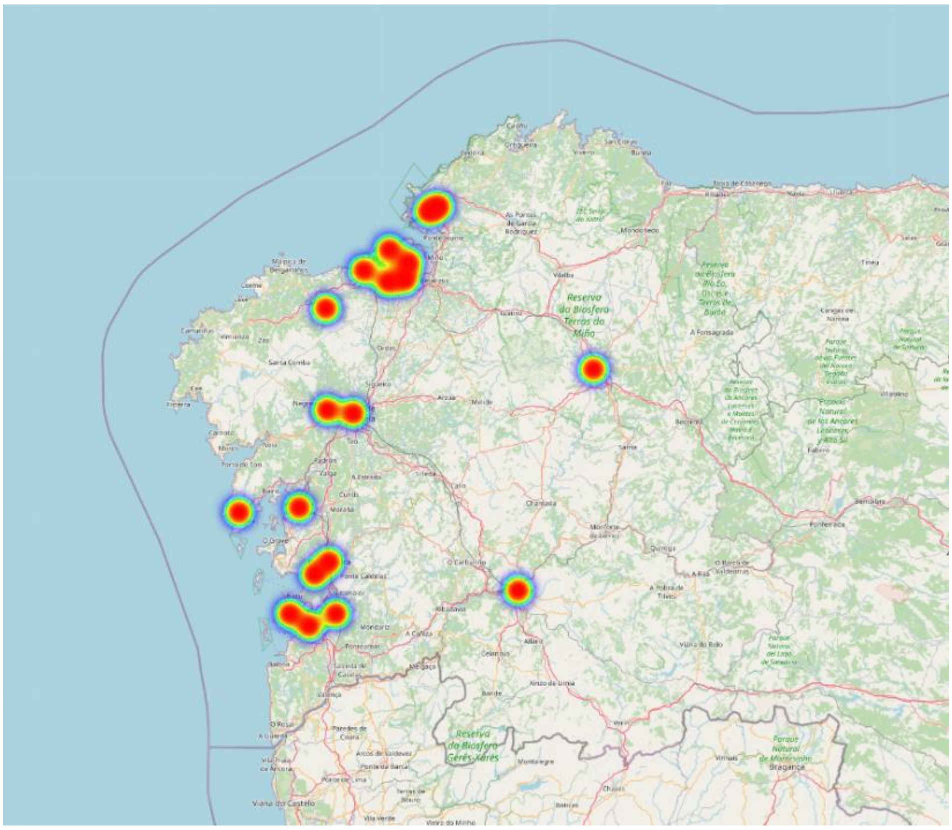

Image 3: Boroughs with more than 23,000 inhabitants

But Galicia is characterized by an extensive population throughout its territory, as it has been said before. The following map shows the boroughs with less than 23,000 inhabitants. These are 294 (from 313) boroughs that represent almost the 50% of the population of Galicia. Let's see the heat map:

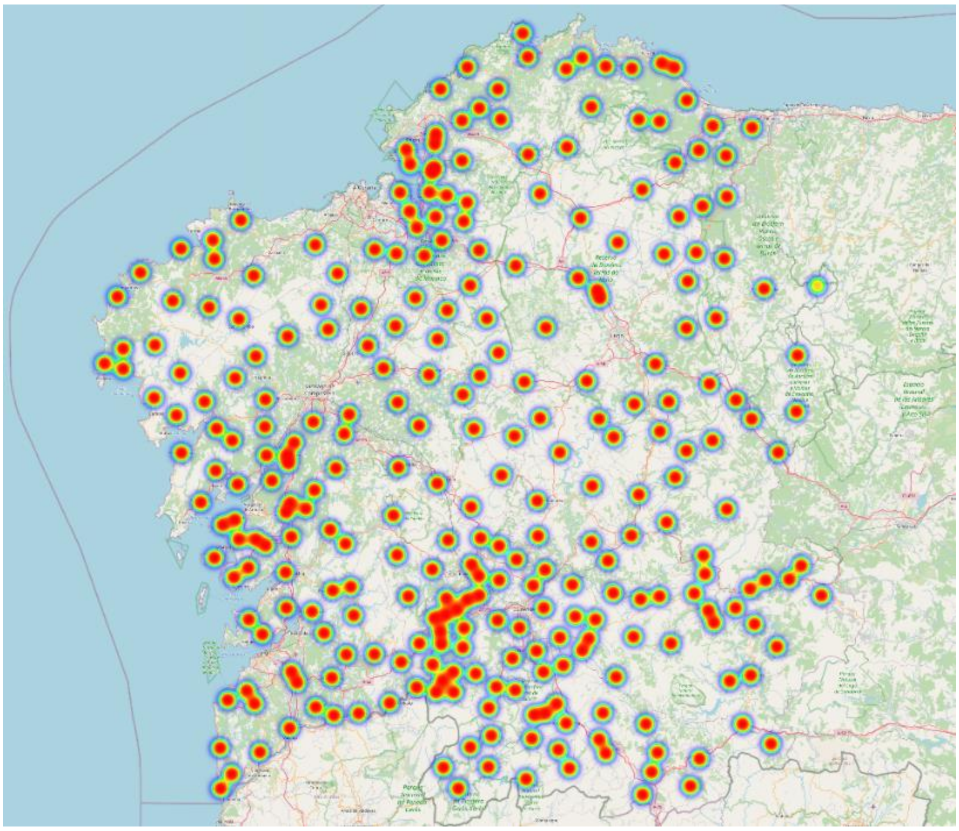

Image 4: Boroughs with less than 23,000 inhabitants

This is the summary of the socio-economic indicators:

	Per capita income	Population	Population ageing	Population density	Vegetative balance	Unemployment rate
count	311.000000	311.000000	311.000000	311.000000	311.000000	311.000000
mean	12146.736334	8645.334405	373.759871	144.487460	-0.012983	0.050193
std	2043.062722	24737.708045	245.556658	426.313074	0.008448	0.015649
min	5638.000000	215.000000	54.670000	3.100000	-0.048964	0.020249
25%	10829.000000	1468.500000	171.930000	18.450000	-0.018156	0.038270
50%	12019.000000	3002.000000	311.460000	37.600000	-0.012227	0.048891
75%	13319.000000	6636.500000	523.950000	114.450000	-0.006496	0.060242
max	22545.000000	295364.000000	1333.060000	6408.700000	0.003225	0.125581

Figure 7: Socio-economic indicators

There is a great dispersion both in population and population density (from small boroughs to big cities). Population ageing and vegetative balance also vary probably due to the difference between urban and rural areas. Unemployment ranges from boroughs of 2% to a maximum of 12,5%, and and the values of per capita income range from 5,638 to 22,545€ (this indicates large differences in economic activity).

The average of the vegetative balance is negative, which explains that there is a trend in Galicia to population ageing (the average of the population ageing indicates a relation of 3,73 to 1 between old people and young people, with boroughs up to 13 to 1).

This already indicates that there are great differences between the Galician municipalities, which we will try to cluster later.

And their representation with box plots:

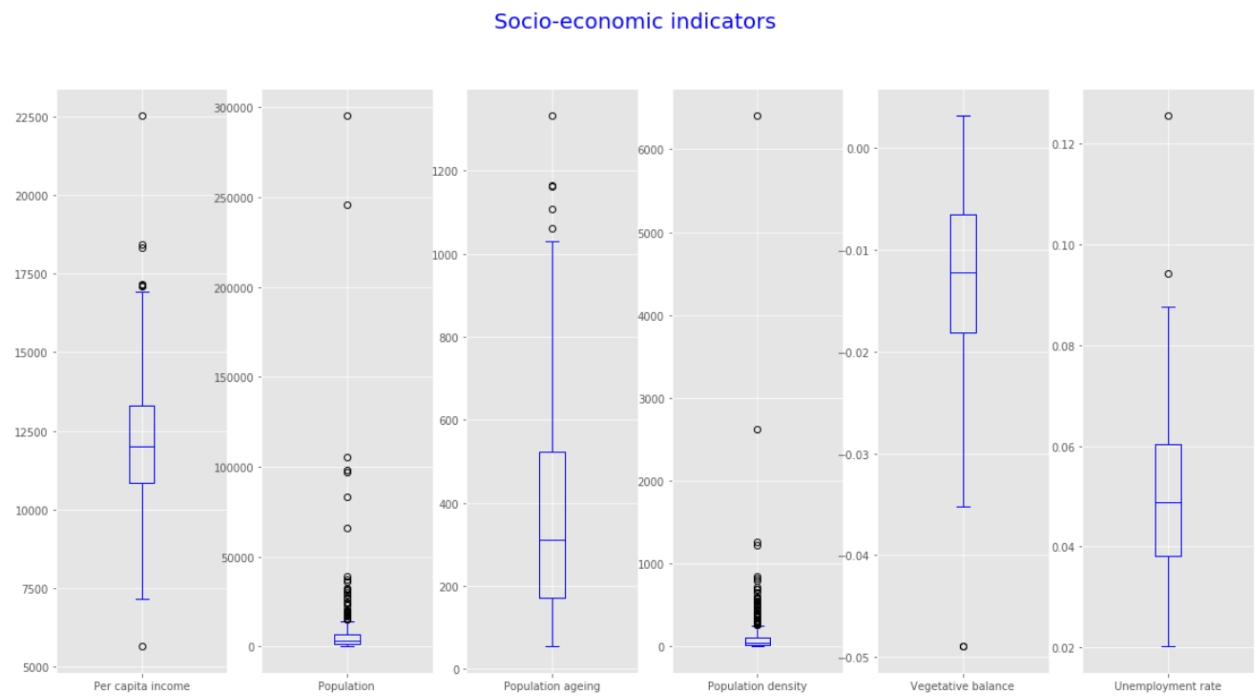

Figure 8: Socio-economic indicators

Correlation between indicators:

	Per capita income	Population	Population ageing	Population density	Vegetative balance	Unemployment rate
Per capita income	1.000000	0.441037	-0.596679	0.419784	0.519671	0.023479
Population	0.441037	1.000000	-0.273148	0.826830	0.296330	0.230860
Population ageing	-0.596679	-0.273148	1.000000	-0.281283	-0.827223	-0.409682
Population density	0.419784	0.826830	-0.281283	1.000000	0.307114	0.234083
Vegetative balance	0.519671	0.296330	-0.827223	0.307114	1.000000	0.427846
Unemployment rate	0.023479	0.230860	-0.409682	0.234083	0.427846	1.000000

Figure 9: Correlation between indicators

We can see that there is an inversely proportional relationship between population ageing and vegetative balance. Also the per capita income is higher in the least aged populations.

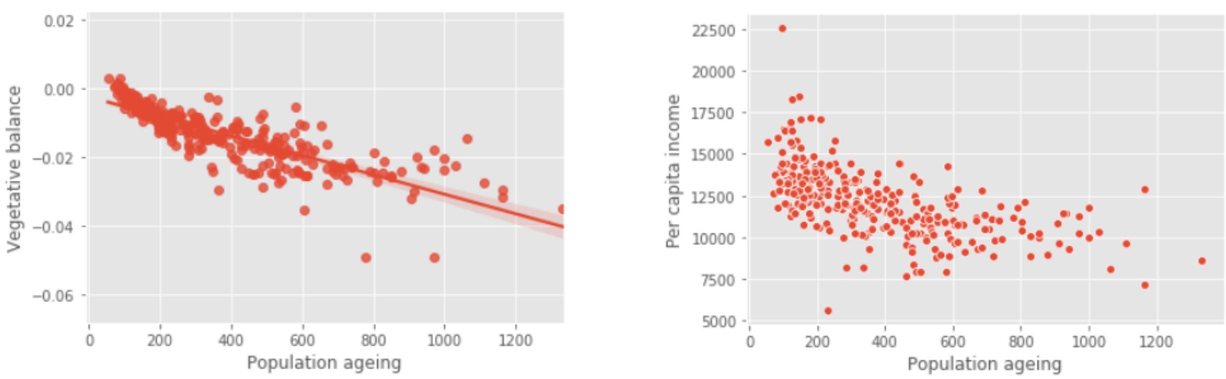

Figure 10: Correlation between indicators

Let's examine the Foursquare data:

If we plot the percentage of main categories in Galician boroughs: We can see that most of the venues are from "Food" (49.2%), following by "Outdoors and Recreation" (19.3%). "Nightlife Spot" is the third category (9.9%) and "Shop & Service" and "Travel & Transport" have similiar values (9.1% and 8.6% respectively). "Arts & Entertainment" has a 3.3% and finally "College & University" and "Professional & Other Places" have less than 0.5%.

In the following section we will see how these percentages vary within Galician boroughs.

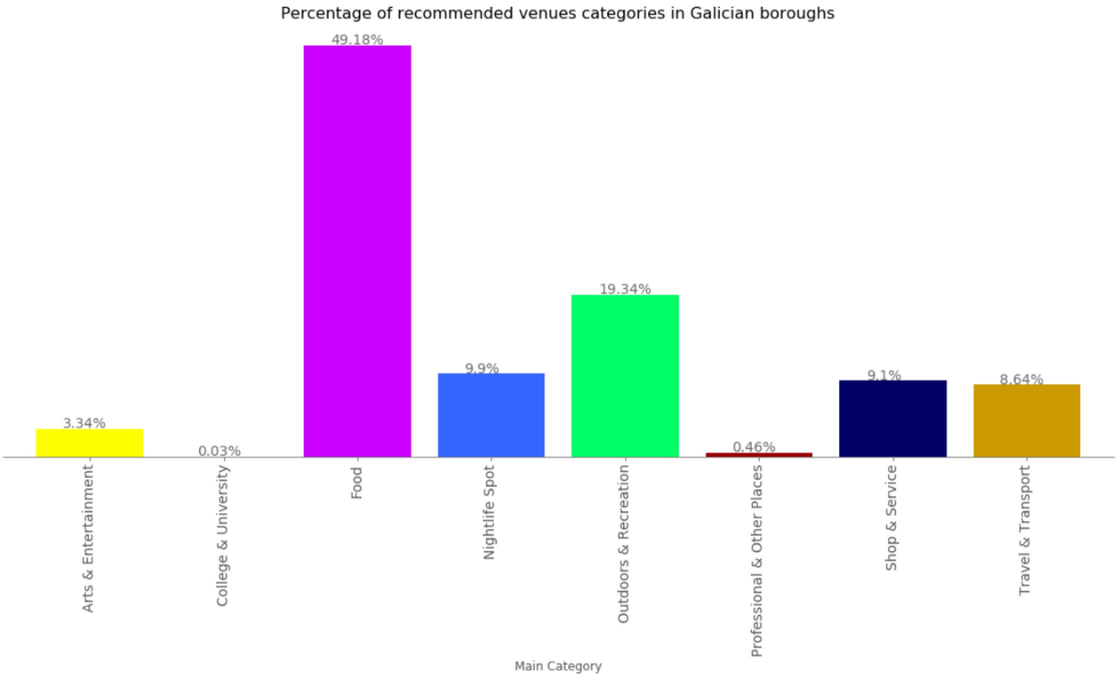

Figure 11: Foursquare categories in Galicia

3.2. Clustering

A k-means algorithm is performed for clustering the Galician boroughs. Due to the difference in magnitudes between the indicators, we first make a normalization of these with StandardScaler. Then we use the silhouette score to determine the optimum value for the number of clusters: 6 clusters has the highest score.

No. of clusters	Silhouette score
4	0.2594
5	0.2867
6	0.2987
7	0.2598
8	0.2637

Figure 12: Silhouette score

A Folium map is plotted representing the different clusters. In addition, in each popup we can consult the values of each borough and a graph of them compared to the average for Galicia.

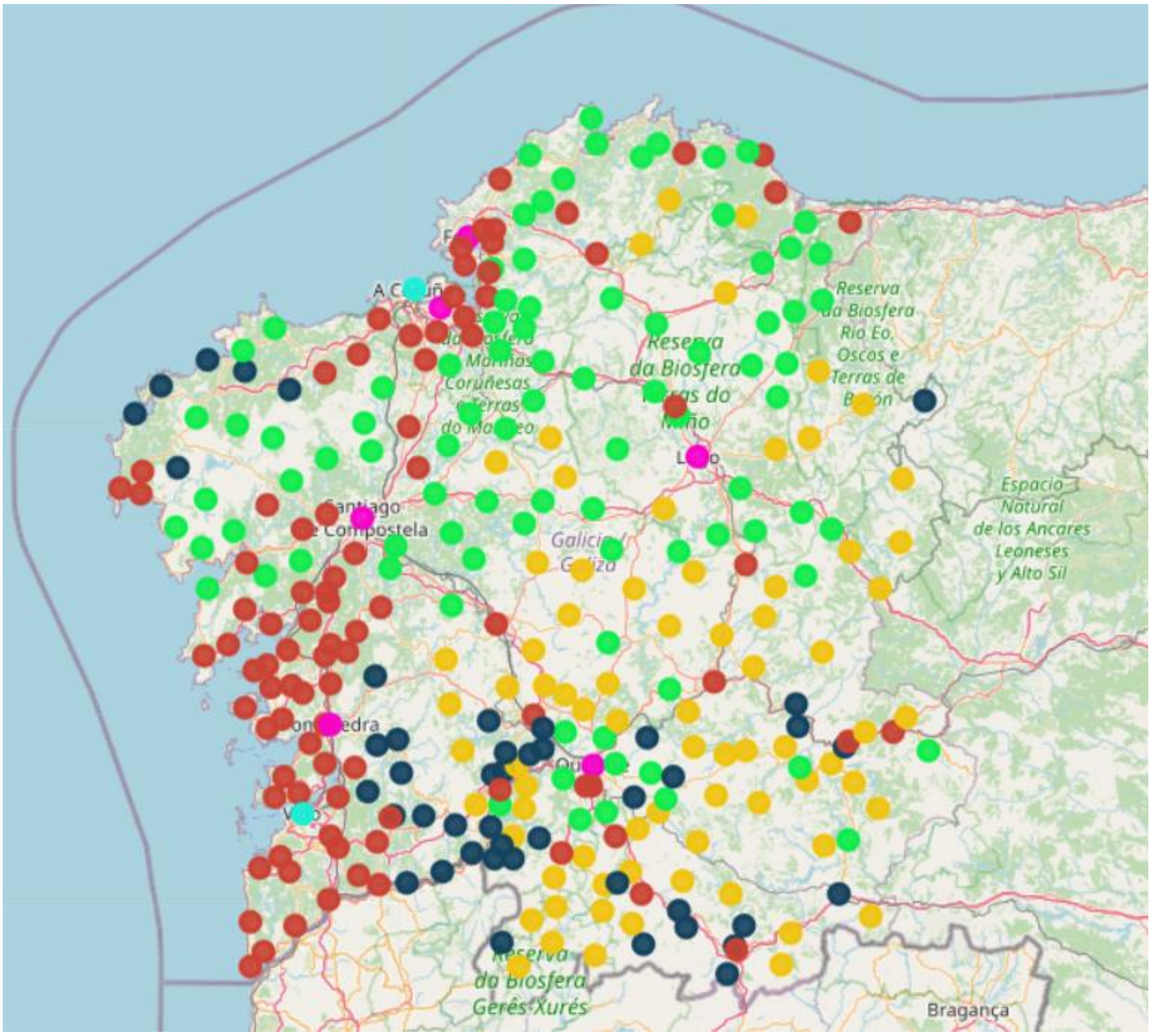

Figure 13: Clusters of boroughs

<u>Legend</u>:

	Big Cities
	Urban boroughs
	Minor-urban boroughs
	Primary sector boroughs
	Small boroughs
	Depopulated boroughs

4. Results

As a result from clustering we got six groups of boroughs that we are going to describe (see full table in Appendix). Then we plot the Foursquare data for each cluster and compare them.

A bar chart is created to have a clearer and more visual idea of the different clusters. To overcome the magnitude differences between indicators, their mean values are normalized.

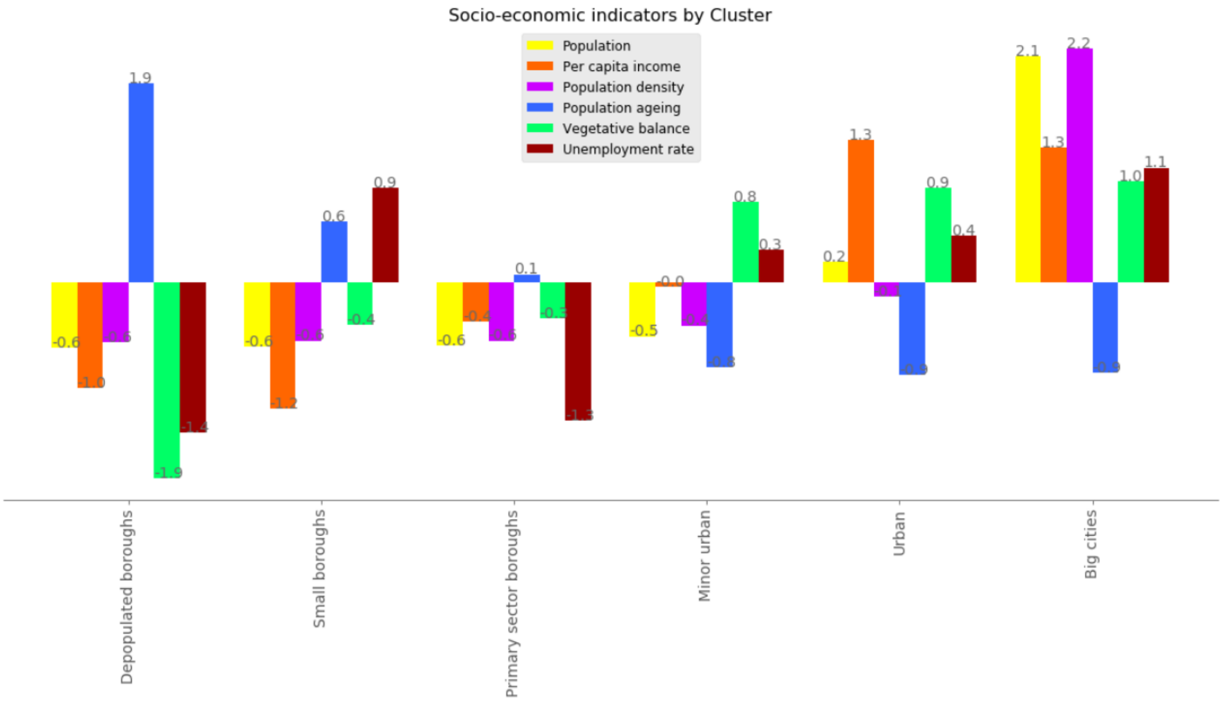

Figure 14: Socio-economic indicators by Cluster

1. Group 1: Depopulated boroughs

There are 75 boroughs. This group corresponds to rural areas. They are boroughs that lose a lot of population, very aged with many pensioners. Its economic activity is almost nil.

	Population	Per capita income	Population density	Population ageing	Vegetative balance	Unemployment rate
count	75.000000	75.000000	75.000000	75.000000	75.000000	75.000000
mean	1451.386667	10663.746667	15.674667	700.590933	-0.023987	0.038264
std	723.622884	1280.420308	8.049712	204.361784	0.006026	0.009380
min	316.000000	7148.000000	3.100000	364.830000	-0.048964	0.020249
25%	986.000000	9908.500000	9.800000	537.160000	-0.025370	0.031316
50%	1278.000000	10827.000000	14.900000	630.560000	-0.023835	0.036866
75%	1792.500000	11408.500000	20.100000	828.125000	-0.020490	0.044458
max	3735.000000	14260.000000	38.000000	1333.060000	-0.012939	0.066089

Figure 15: Depopulated boroughs

2. Group 2: Small boroughs

There are 45 boroughs. This group corresponds to rural areas. They have small population and low values of per capita income. Their economic activity is very limited. Their population is quite old and the unemployment rate is high.

	Population	Per capita income	Population density	Population ageing	Vegetative balance	Unemployment rate
count	45.000000	45.000000	45.000000	45.000000	45.000000	45.000000
mean	2185.844444	10077.444444	37.848889	430.476222	-0.013335	0.067694
std	1505.690961	1298.975603	23.133306	148.620835	0.004689	0.014530
min	215.000000	5638.000000	4.100000	179.720000	-0.024911	0.042821
25%	1085.000000	9305.000000	21.900000	304.090000	-0.016667	0.058078
50%	1712.000000	10231.000000	33.000000	460.280000	-0.013178	0.063121
75%	2983.000000	11012.000000	43.900000	547.280000	-0.009906	0.075929
max	6074.000000	12512.000000	108.700000	741.540000	-0.002519	0.125581

Figure 16: Small boroughs

3. Group 3: Primary sector boroughs

There are 90 boroughs. This group corresponds to rural areas. They have small population but their economy is sustained by primary activity (agriculture, livestock, fishing ...). Their population is not very old, per capita income is closer to minor urban areas, and the unemployment rate is very low.

	Population	Per capita income	Population density	Population ageing	Vegetative balance	Unemployment rate
count	90.000000	90.000000	90.000000	90.000000	90.000000	90.000000
mean	3611.144444	12531.644444	38.491111	328.268556	-0.012881	0.039751
std	2324.743516	1136.679753	24.267640	97.239947	0.004050	0.007968
min	641.000000	10118.000000	7.100000	169.450000	-0.024259	0.022187
25%	1865.000000	11675.250000	20.850000	252.920000	-0.015464	0.033740
50%	3081.500000	12530.000000	32.650000	318.360000	-0.012665	0.040238
75%	4608.750000	13313.500000	48.775000	400.380000	-0.010353	0.044741
max	14072.000000	15786.000000	118.300000	603.620000	-0.003120	0.055710

Figure 17: Primary sector boroughs

4. Group 4: Minor urban boroughs

There are 93 boroughs. This group can be considered almost as urban. They are economic engines of their areas (mainly rural). They have small population and medium values of per capita income, but their population is quite young and the unemployment rate is moderate.

	Population	Per capita income	Population density	Population ageing	Vegetative balance	Unemployment rate
count	93.000000	93.000000	93.000000	93.000000	93.000000	93.000000
mean	12144.795699	13503.903226	271.937634	147.502151	-0.004833	0.060261
std	8535.086911	1348.704363	211.952530	48.297096	0.003309	0.009686
min	644.000000	10744.000000	16.100000	54.670000	-0.012799	0.033252
25%	5732.000000	12599.000000	114.300000	114.620000	-0.006923	0.054544
50%	9977.000000	13371.000000	193.900000	138.460000	-0.004491	0.059750
75%	15841.000000	14263.000000	383.000000	170.220000	-0.002573	0.065396
max	39080.000000	17174.000000	1255.900000	324.300000	0.003225	0.087590

Figure 18: Minor urban boroughs

5. Group 5: Urban boroughs

There are 6 boroughs. They are small cities. They have a big population and high density, but not as much as the big cities. They have economic activity well above average. Also here live more young people and the per capita income is higher, but the unemployment rate is moderate.

	Population	Per capita income	Population density	Population ageing	Vegetative balance	Unemployment rate
count	6.000000	6.000000	6.000000	6.000000	6.000000	6.000000
mean	80989.666667	17637.500000	711.333333	131.305000	-0.003858	0.062005
std	26059.593686	2655.465741	323.685648	33.094307	0.003164	0.009818
min	36075.000000	14852.000000	294.800000	97.560000	-0.009657	0.047928
25%	70306.000000	16442.500000	505.750000	109.582500	-0.004655	0.056017
50%	90144.500000	16848.000000	740.350000	123.335000	-0.002123	0.062573
75%	98022.000000	18030.500000	818.725000	143.695000	-0.001969	0.068780
max	105233.000000	22545.000000	1220.100000	188.120000	-0.001830	0.074275

Figure 19: Urban boroughs

6. Group 6: Big cities

There are 2 cities. They have the biggest population and highest density. They have the largest economic activity in Galicia. Here live more young people and the per capita income is higher, but the unemployment rate is also high.

	Population	Per capita income	Population density	Population ageing	Vegetative balance	Unemployment rate
count	2.000000	2.000000	2.000000	2.000000	2.000000	2.000000
mean	270537.500000	17416.500000	4517.200000	136.935000	-0.003393	0.070133
std	35109.973006	1454.518649	2674.984953	14.149207	0.000647	0.004751
min	245711.000000	16388.000000	2625.700000	126.930000	-0.003850	0.066774
25%	258124.250000	16902.250000	3571.450000	131.932500	-0.003621	0.068453
50%	270537.500000	17416.500000	4517.200000	136.935000	-0.003393	0.070133
75%	282950.750000	17930.750000	5462.950000	141.937500	-0.003164	0.071813
max	295364.000000	18445.000000	6408.700000	146.940000	-0.002935	0.073492

Figure 20: Big cities

Now we can see the box plots comparing the clusters for each indicator:

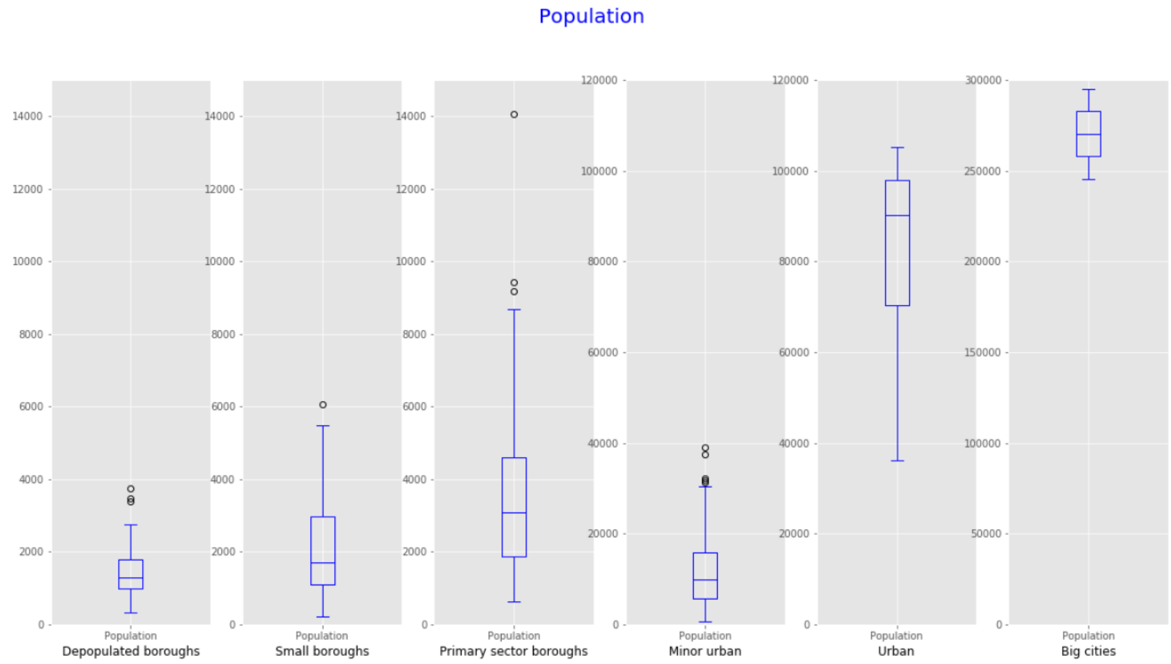

Figure 21: Population

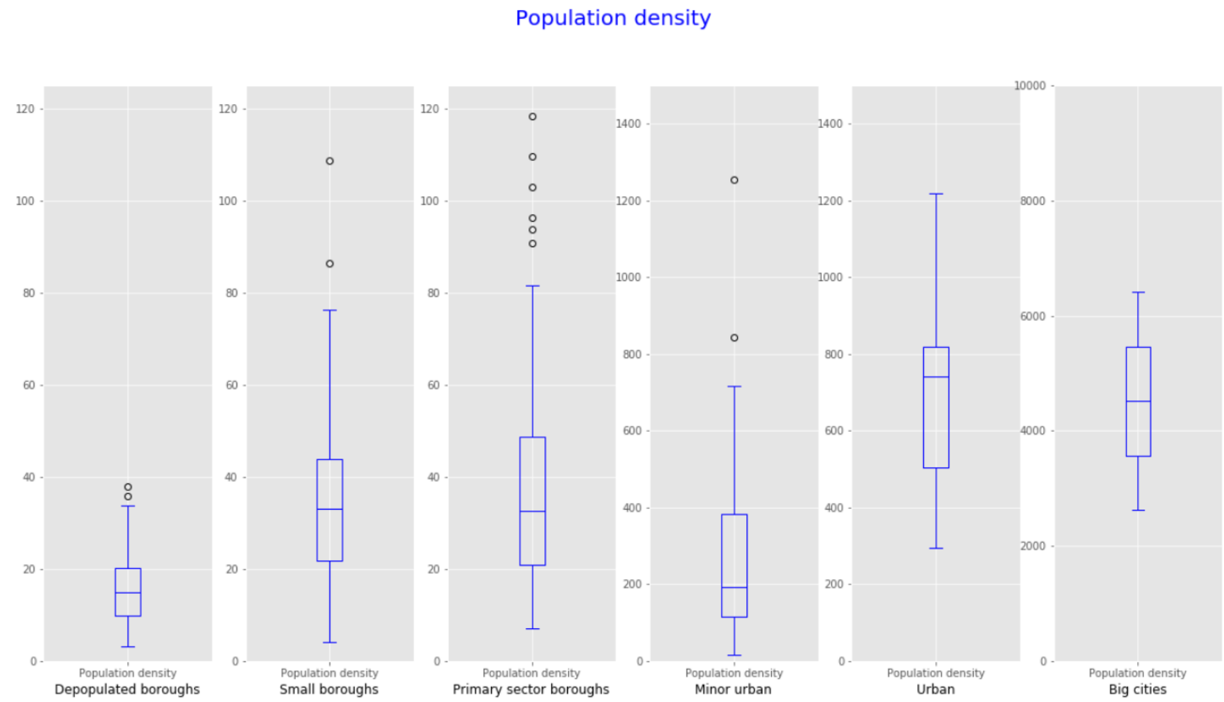

Figure 22: Population density

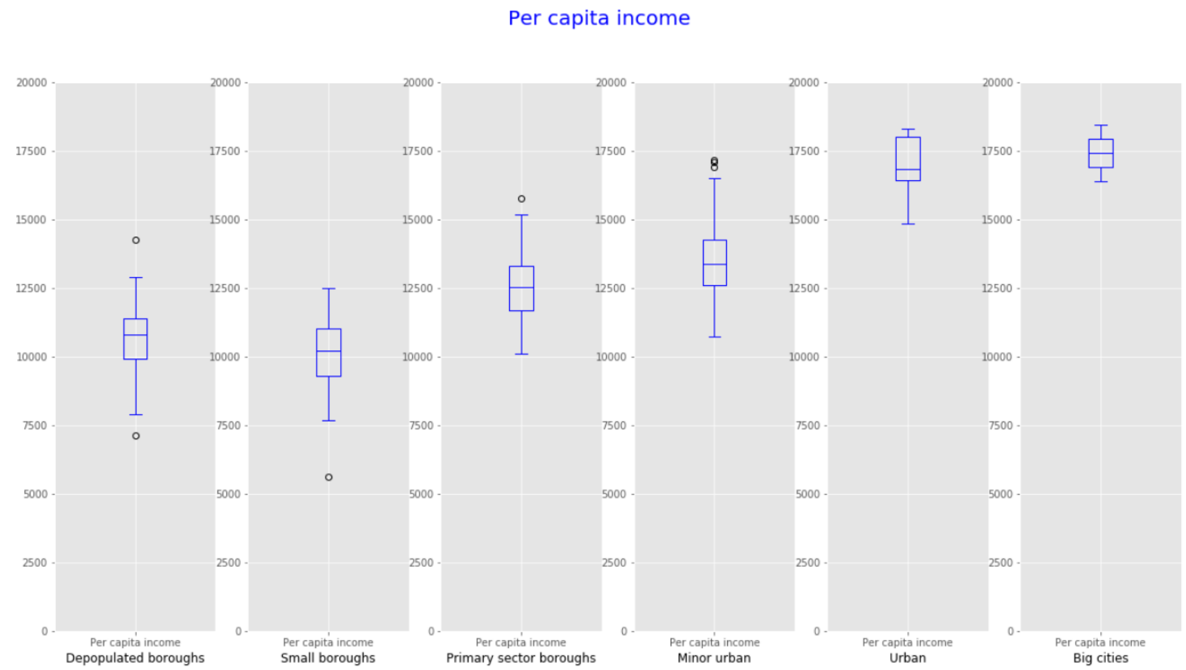

Figure 23: Per capita income

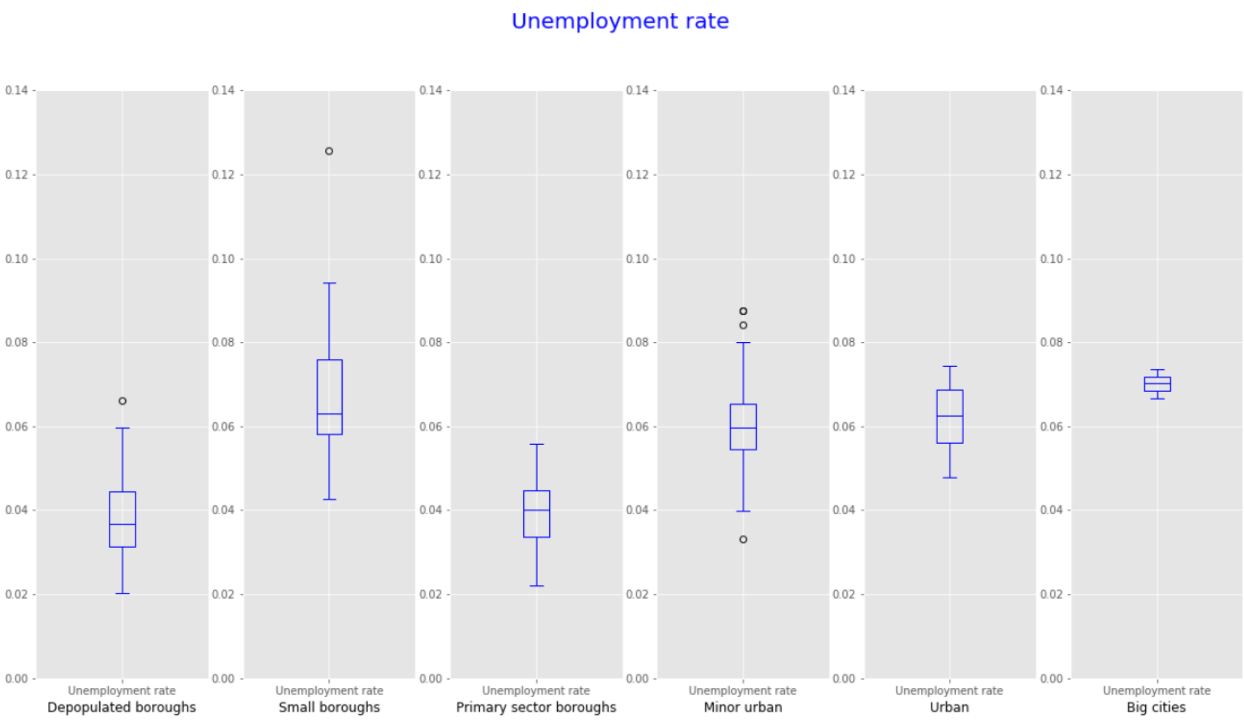

Figure 24: Unemployment rate

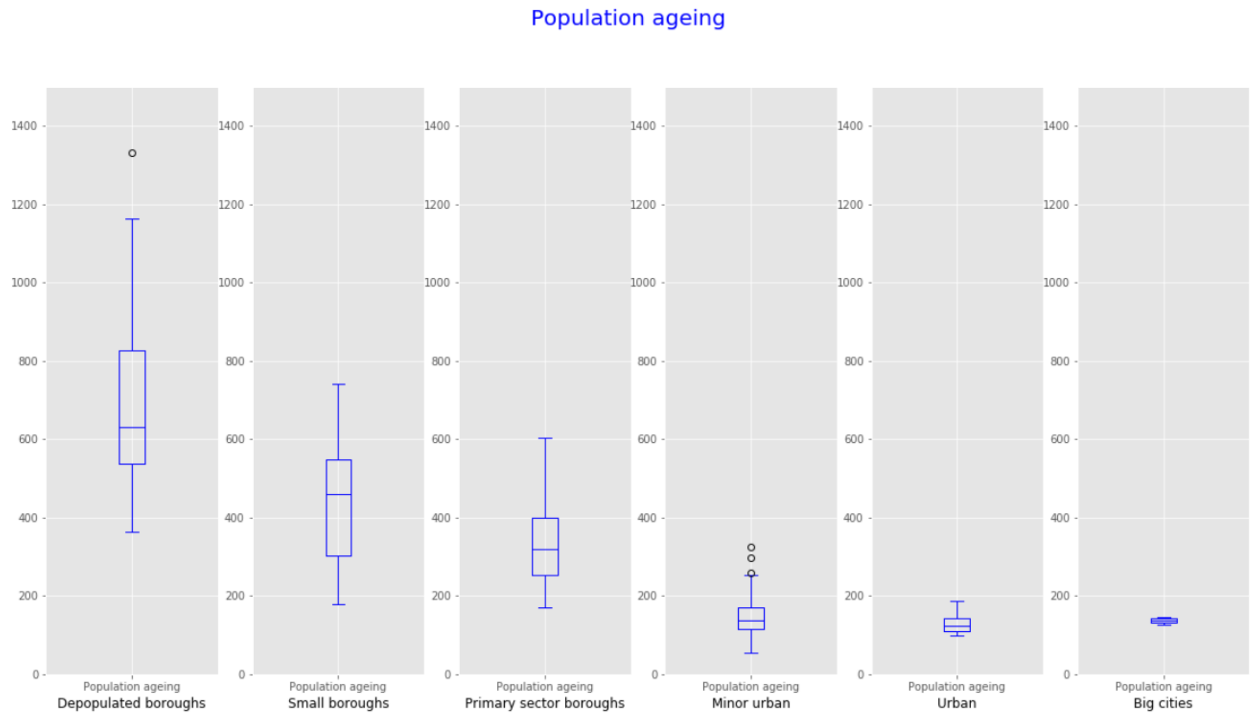

Figure 25: Population ageing

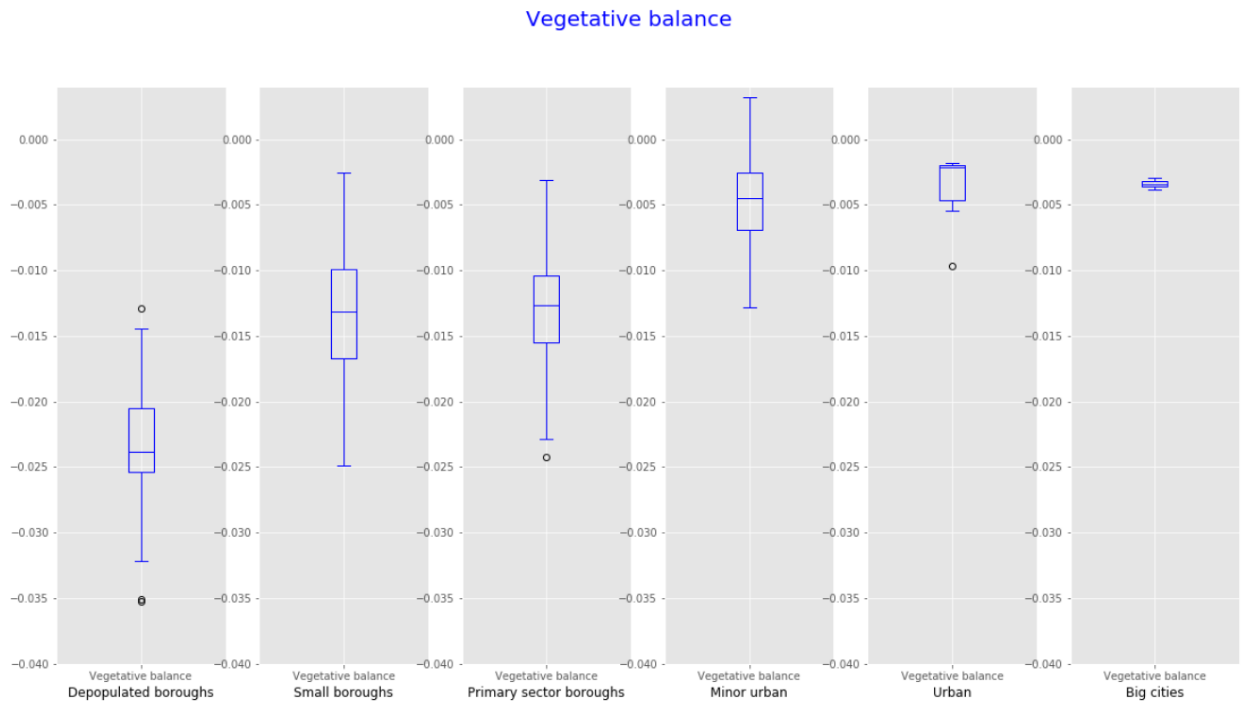

Figure 26: Vegetative balance

Now let's see what happens with the Foursquare venues. If we group the venue categories by cluster, we can see that there are several trends. The clusters with more population and economic activity (urban areas) have a higher percentage of "Food" venues. It seems that there is a directly proportional relationship. But on the other hand, there is an inversely proportional relationship between the population and the "Outdoors & Recreation" venues. The rural areas has a higher percentage of recommended venues from this category. Also the "Travel & Transport" category has an inversely proportional relationship. This could be explained because the venues have been taken from the borough center: in less populated areas there are fewer recommended venues, and then these types of venues come up to the recommended ones. The "Nightlife Spot" category has a more similar percentage between clusters, being higher in big cities.

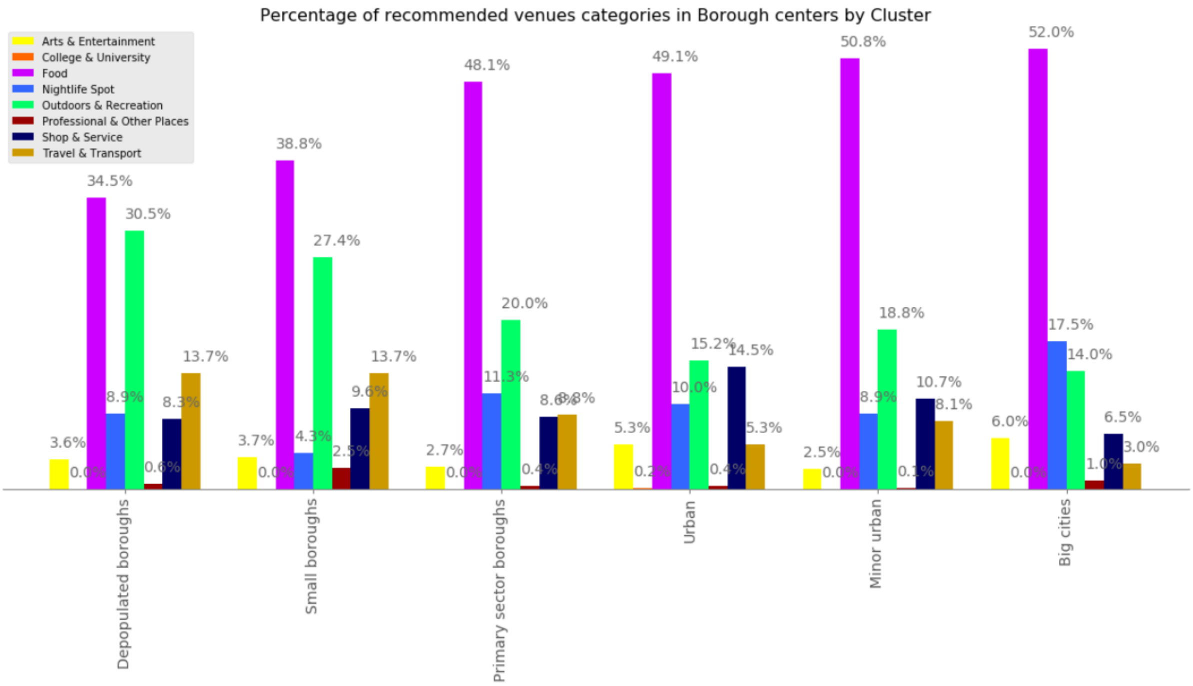

Figure 27: Percentage of recommended venues categories by Cluster

5. Discussion

The main purpose of this study was to cluster the boroughs of Galicia based on several socio-economic indicators, and then analyze how the categories of Foursquare venues vary between the different clusters. To go further in this study, other indicators could be taken into account (e.g. education, business...) to see how the different boroughs would then be clustered.

Only the main categories of Foursquare have been taken into account. Another idea to continue this work would be to break down each main category to have a broader detail of the venue distribution within each cluster.

6. Conclusion

In this project the Galician boroughs were analysed based on several socio-economic indicators: population, density, per capita income, population ageing, vegetative balance and unemployment rate. With this data the boroughs have been clustered using the machine learning algorithm k-means into six groups.

The six clusters are well identified and described with their characteristics. There is a common trend towards aging. Three clear groups are big cities, small towns, and unpopulated areas. The differences between the other three groups are basically their population and ageing, and their economic activities.

Also several trends between the indicators and the Foursquare venues were identified. The main idea is that in the most populated municipalities there are more recommended food places, while in the less populated there are more recreation areas.

This work can be useful to understand the demographic and economic distribution of Galician boroughs when offering services, infrastructures or any other kind of business.

Appendix: List of clusters

Depopulated boroughs	Small boroughs	Primary sector boroughs	Minor urban	Urban	Big cities
Abadín	Arbo	Abegondo	Allariz	Ferrol	Coruña
Agolada	Baltar	Amoeiro	Ames	Lugo	Vigo
Alfoz	Beade	Aranga	Ares	Oleiros	
Antas de Ulla	Boborás	Arnoia	Arteixo	Ourense	
Avión	Cabana de Bergantiños	Arzúa	Baiona	Pontevedra	
Baleira	Camariñas	Baña	Barbadás	Santiago de Compostela	
Bande	Campo Lameiro	Baralla	Barco de Valdeorras		
Baños de Molgas	Cañiza	Barreiros	Barro		
Beariz	Carballeda de Avia	Becerreá	Bergondo		
Blancos	Castrelo do Val	Begonte	Betanzos		
Boimorto	Coristanco	Boqueixón	Boiro		
Bola	Cortegada	Cabanas	Brión		
Bolo	Covelo	Capela	Bueu		
Bóveda	Crecente	Carballeda de Valdeorras	Burela		
Calvos de Randín	Cualedro	Cariño	Caldas de Reis		
Carballedo	Dumbría	Carnota	Cambados		
Cartelle	Entrimo	Castro de Rei	Cambre		
Castrelo de Miño	Fornelos de Montes	Cedeira	Cangas		
Castro Caldelas	Gudiña	Cerceda	Carballiño		
Castroverde	Lama	Cerdido	Carballo		
Cenlle	Laxe	Cervo	Carral		
Cervantes	Leiro	Chantada	Catoira		
Chandrexa de Queixa	Maside	Coirós	Cee		
Dozón	Mondariz	Coles	Celanova		
Folgoso do Courel	Monterrei	Corgo	Corcubión		
Fonsagrada	Muxía	Cospeito	Culleredo		
Forcarei	Negueira de Muñiz	Curtis	Cuntis		
Gomesende	Neves	Esgos	Dodro		
Guntín	Nogueira de Ramuín	Frades	Estrada		
Incio	Oímbra	Friol	Fene		
Irixo	Paderne de Allariz	Guitiriz	Fisterra		
Larouco	Padrenda	Irixoa	Foz		
Laza	Pazos de Borbén	Láncara	Gondomar		
Lobeira	Petín	Lourenzá	Grove		
Lobios	Ponte Caldelas	Lousame	Guarda		
Manzaneda	Pontedeva	Maceda	Illa de Arousa		
Melón	Punxín	Malpica de Bergantiños	Lalín		
Mezquita	Quintela de Leirado	Mañón	Laracha		
Montederramo	Quiroga	Mazaricos	Marín		
Muíños	Ramirás	Meira	Meaño		
Muras	Ribas de Sil	Melide	Meis		
Navia de Suarna	San Amaro	Merca	Miño		
Nogais	Trasmiras	Mesía	Moaña		
Ourol	Vilar de Santos	Moeche	Mondariz-Balneario		
Parada de Sil	Xunqueira de Espadanedo	Mondoñedo	Monforte de Lemos		
Paradela		Monfero	Moraña		
Pedrafita do Cebreiro		Monterroso	Mos		
Peroxa		Muros	Mugardos		
Piñor		Ortigueira	Narón		
Pobra do Brollón		Outeiro de Rei	Neda		
Porqueira		Outes	Negreira		
Rairiz de Veiga		Paderne	Nigrán		
Ribeira de Piquín		Palas de Rei	Noia		
Riós		Pantón	Oia		
Rodeiro		Páramo	Ordes		
Rubiá		Pastoriza	Oroso		
Samos		Pereiro de Aguiar	Padrón		
San Cristovo de Cea		Pino	Pobra do Caramiñal		
San Xoán de Río		Pobra de Trives	Poio		
Sandiás		Pol	Ponteareas		
Sarreaus		Ponteceso	Pontecesures		
Saviñao		Pontenova	Pontedeume		
Sober		Porto do Son	Pontes de García Rodríguez		
Sobrado		Portomarín	Porriño		
Taboada		Riotorto	Portas		
Teixeira		Rois	Rábade		
Toques		San Sadurniño	Redondela		
Veiga		Santa Comba	Rianxo		
Verea		Santiso	Ribadavia		
Vilamarín		Silleda	Ribadeo		
Vilamartín de Valdeorras		Taboadela	Ribadumia		
Vilar de Barrio		Toén	Ribeira		
Vilardevós		Tordoia	Rosal		
Vilariño de Conso		Touro	Rúa		
Xunqueira de Ambía		Trabada	Sada		
		Trazo	Salceda de Caselas		
		Triacastela	Salvaterra de Miño		
		Val do Dubra	San Cibrao das Viñas		
		Valadouro	Sanxenxo		
		Vedra	Sarria		
		Viana do Bolo	Somozas		
		Vicedo	Soutomaior		
		Vila de Cruces	Teo		
		Vilalba	Tomiño		
		Vilarmaior	Tui		
		Vilasantar	Valdoviño		
		Vimianzo	Valga		
		Xermade	Verín		
		Xove	Vilaboa		
		Zas	Vilagarcía de Arousa		
			Vilanova de Arousa		
			Viveiro		
			Xinzo de Limia		