# Valencia data by districts to begin a business

**By Luis Enrique Palma**

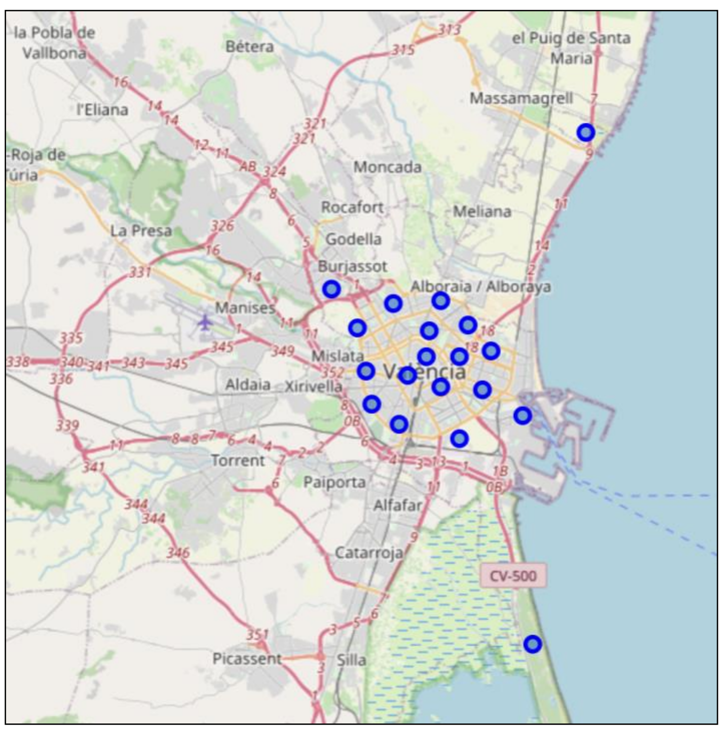
# Table of Contents

# 1. Introductory Section

Valencia is the third largest city in Spain, it is the capital of the province of Valencia which is located in the Valencian Community, this report will show relevant demographic data, analysis of interest and an ideal tool that will serve as support for those interested in starting a business in the city.

Valencia is located in the east of Spain, facing the Mediterranean Sea, it is crossed by the Turia river, the greatest contribution to its economy is by tourism and services, on a smaller scale there are industrial, construction and agriculture. Valencia capital is made up of 19 districts, which will be presented in this report according to the average characteristics of its habitants to have an adequate idea of what type of business will be more worth starting in each of the districts.

*Table 1. Valencian Districts*

<table>
<tr><th>Valencia Districts</th><th>Map</th></tr>
<tr><td>Ciutat Vella<br>l'Eixample<br>Extramurs<br>Campanar<br>la Saïdia<br>el Pla del Real<br>l’Olivereta<br>Patraix<br>Jesús<br>Quatre Carreres<br>Poblats Marítims<br>Camins al Grau<br>Algirós<br>Benimaclet<br>Rascanya<br>Benicalap<br>Pobles del Nord<br>Pobles de l’Oest<br>Pobles del Sud</td><td>
</td></tr>
</table>

Source: self made

## 2. Metodology Section

The methodology is divided into two stages, the first consists of collecting relevant and current quantitative information with which to achieve greater precision in the estimates suggested or made with the help of the results. The second stage consists of data processing with the use of MS Excel, MS Word and Python with its different libraries to achieve the results.

### 2.1. Firts Stage: Data Minning

Demographic and descriptive information was collected of the year 2020 of the inhabitants of Valencia by their districts through the official page of the Valencia City Council, Gross average income of 2019, from the official page of the Institute of Statistics of Spain, coordinates of their districts in Google Maps, information of current most popular businesses on Foursquare and other qualitative information on Wikipedia (not being scientific).

The Data Frame (DF) was built in MS Excel from the tables collected in the sources mentioned in the previous paragraph and the following table resulted:

*Table 2. Initial Data frame*

| District | Area (he) | Pop/km2 | Population | Men population | Women population | Age 0-19 | Age 20-39 | Age 40-59 | Age 60 greater | Foreigns | Foreigns EU | Foreigns Rest Europe | Foreigns Africa |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ciutat Vella | 169 | 16,225 | 27,418 | 13,034 | 14,384 | 4,362 | 7,116 | 8,582 | 7,358 | 4,784 | 2,316 | 292 | 452 |
| l'Eixample | 173.3 | 24,709 | 42,826 | 19,769 | 23,057 | 7,822 | 9,379 | 13,135 | 12,490 | 4,675 | 2,178 | 244 | 303 |
| Extramurs | 197.2 | 24,789 | 48,877 | 22,440 | 26,437 | 8,380 | 11,258 | 14,659 | 14,580 | 5,705 | 2,018 | 274 | 341 |
| Campanar | 523.8 | 7,395 | 38,736 | 18,370 | 20,366 | 7,868 | 8,620 | 11,775 | 10,473 | 5,178 | 1,666 | 523 | 507 |
| la Saïdia | 194.4 | 24,431 | 47,491 | 21,996 | 25,495 | 7,815 | 11,570 | 14,131 | 13,975 | 7,222 | 2,027 | 689 | 760 |
| el Pla del Real | 169.3 | 18,101 | 30,644 | 14,098 | 16,546 | 5,979 | 7,350 | 8,208 | 9,107 | 2,898 | 1,183 | 127 | 154 |
| l'Olivereta | 198.9 | 24,764 | 49,250 | 23,386 | 25,864 | 8,342 | 11,783 | 15,357 | 13,768 | 8,935 | 1,725 | 634 | 1,038 |
| Patraix | 287.3 | 20,209 | 58,053 | 27,461 | 30,592 | 10,235 | 13,030 | 18,523 | 16,265 | 5,857 | 1,378 | 430 | 588 |
| Jesús | 298.5 | 17,730 | 52,917 | 25,679 | 27,238 | 8,946 | 12,686 | 16,697 | 14,588 | 7,990 | 1,554 | 423 | 1,119 |
| Quatre Carreres | 1,132.50 | 6,580 | 74,518 | 35,749 | 38,769 | 13,683 | 17,255 | 23,742 | 19,838 | 10,707 | 2,989 | 702 | 930 |
| Poblats Marítims | 396.7 | 14,049 | 55,725 | 26,841 | 28,884 | 10,073 | 13,093 | 17,479 | 15,080 | 7,917 | 3,105 | 598 | 902 |
| Camins al Grau | 236.7 | 27,834 | 65,890 | 31,667 | 34,223 | 13,084 | 15,274 | 21,546 | 15,986 | 10,070 | 2,954 | 766 | 870 |
| Algirós | 295.9 | 12,388 | 36,657 | 17,250 | 19,407 | 5,509 | 9,372 | 9,993 | 11,783 | 4,269 | 1,211 | 231 | 384 |
| Benimaclet | 157 | 18,268 | 28,686 | 13,381 | 15,305 | 4,456 | 7,695 | 8,049 | 8,486 | 3,391 | 1,090 | 165 | 303 |
| Rascanya | 262.9 | 20,631 | 54,233 | 26,412 | 27,821 | 11,105 | 13,138 | 17,374 | 12,616 | 9,500 | 1,722 | 697 | 1,889 |
| Benicalap | 221.6 | 21,401 | 47,421 | 22,947 | 24,474 | 9,515 | 11,535 | 15,242 | 11,129 | 6,960 | 1,531 | 562 | 988 |
| Pobles del Nord | 1,519.60 | 433 | 6,582 | 3,179 | 3,403 | 1,333 | 1,334 | 2,102 | 1,813 | 472 | 185 | 44 | 79 |
| Pobles de l'Oest | 201.1 | 7,250 | 14,581 | 7,078 | 7,503 | 2,916 | 3,450 | 4,617 | 3,598 | 1,865 | 589 | 199 | 203 |
| Pobles del Sud | 3,242.60 | 649 | 21,040 | 10,380 | 10,660 | 3,853 | 4,874 | 6,605 | 5,708 | 2,277 | 961 | 82 | 239 |

| District | Foreigns North Central America | Foreign South America | Foreign Asia | Foreign Other | Unemployed | Tourism | Bus | Truck | Tractor | Trailer | Motorcycle | Moped | Average Gross income 2018 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Ciutat Vella | 518 | 771 | 427 | 8 | 1,640 | 14,073 | 526 | 1,883 | 484 | 274 | 3,504 | 745 | 25064 |
| l'Eixample | 589 | 926 | 422 | 13 | 2,333 | 19,745 | 2 | 1,171 | 447 | 387 | 4,375 | 1,011 | 26142 |
| Extramurs | 654 | 1,557 | 853 | 8 | 3,140 | 21,073 | 73 | 1,124 | 311 | 305 | 4,191 | 970 | 20247 |
| Campanar | 430 | 1,309 | 740 | 3 | 2,485 | 17,422 | 90 | 725 | 213 | 158 | 2,866 | 716 | 17988 |
| la Saïdia | 631 | 2,216 | 894 | 5 | 3,793 | 19,351 | 5 | 1,207 | 223 | 271 | 3,190 | 1,177 | 14429 |
| el Pla del Real | 248 | 729 | 449 | 8 | 1,433 | 15,167 | 9 | 716 | 249 | 202 | 3,282 | 765 | 26930 |
| l'Olivereta | 772 | 2,738 | 2,024 | 4 | 4,485 | 19,989 | 31 | 1,203 | 176 | 204 | 2,830 | 1,144 | 12427 |
| Patraix | 472 | 1,815 | 1,170 | 4 | 4,354 | 27,448 | 11 | 1,624 | 605 | 334 | 4,272 | 1,282 | 14907 |
| Jesús | 705 | 2,586 | 1,600 | 3 | 4,516 | 22,696 | 23 | 1,403 | 245 | 243 | 3,689 | 1,461 | 13065 |
| Quatre Carreres | 1,043 | 3,143 | 1,878 | 22 | 6,741 | 32,231 | 9 | 2,036 | 819 | 1,049 | 5,317 | 2,286 | 13704 |
| Poblats Marítims | 534 | 1,801 | 969 | 8 | 6,194 | 23,796 | 26 | 1,568 | 985 | 1,291 | 3,991 | 2,058 | 13064 |
| Camins al Grau | 585 | 2,534 | 2,351 | 10 | 5151 | 26504 | 38 | 1614 | 539 | 565 | 4790 | 1563 | 15962 |
| Algirós | 274 | 1,221 | 947 | 1 | 2,626 | 16,895 | 8 | 643 | 129 | 131 | 2,755 | 868 | 17502 |
| Benimaclet | 390 | 850 | 589 | 4 | 1,981 | 12,576 | 0 | 500 | 126 | 112 | 2,051 | 723 | 17122 |
| Rascanya | 837 | 2,868 | 1,484 | 3 | 5,177 | 21,361 | 2 | 1,220 | 225 | 187 | 3,311 | 1,507 | 12660 |
| Benicalap | 544 | 2,091 | 1,243 | 1 | 4,015 | 19,719 | 9 | 1,105 | 298 | 235 | 2,873 | 1,270 | 12761 |
| Pobles del Nord | 56 | 94 | 11 | 3 | 396 | 3,452 | 0 | 315 | 189 | 132 | 668 | 301 | 17773 |
| Pobles de l'Oest | 159 | 583 | 131 | 1 | 1374 | 6661 | 0 | 529 | 94 | 70 | 995 | 443 | 11576 |
| Pobles del Sud | 187 | 619 | 188 | 1 | 1,721 | 10,858 | 34 | 960 | 546 | 616 | 1,549 | 680 | 13576 |

Source: self-made

## 2.2. Second Stage: Data Processing

To process the data, the previous DF will be imported in Jupyter labs and with the use of Python language and its libraries such as pandas for Data frame manipulation ; the folium library for the creation of interactive, informative and choropletic maps; the json library for the extraction of coordinates through the Beautifulsoup library, geocoder, geopy and geopandas; the seaborn and matplotlib libraries for creating frequency and other statistical data graphs; the sklearn library for the K Nearest Neighbors implementation of the most popular sites in their districts collected by Foursquare developer account and other libraries will be included to process or complement the information.

### 2.2.1 Analyzing the data

First of all, the data was cleaned and the elements of number columns that was in string type were converted to float type, then the data was analyzed with info and describe methods to see a type and statistic summary respectively. See figure (1) and (2):

```
RangeIndex: 19 entries, 0 to 18
Data columns (total 28 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   District                         19 non-null     object
 1   Area (he)                        19 non-null     float64
 2   Pop/km2                          19 non-null     float64
 3   Population                       19 non-null     float64
 4   Men population                   19 non-null     float64
 5   Women population                 19 non-null     float64
 6   Age 0-19                         19 non-null     float64
 7   Age 20-39                        19 non-null     float64
 8   Age 40-59                        19 non-null     float64
 9   Age 60 greater                   19 non-null     float64
 10  Foreigns                         19 non-null     float64
 11  Foreigns EU                      19 non-null     float64
 12  Foreigns Rest Europe             19 non-null     float64
 13  Foreigns Africa                  19 non-null     float64
 14  Foreigns North Central America   19 non-null     float64
 15  Foreign South America            19 non-null     float64
 16  Foreign Asia                     19 non-null     float64
 17  Foreign Other                    19 non-null     float64
 18  Unemployed                       19 non-null     float64
 19  Tourism                          19 non-null     float64
 20  Bus                              19 non-null     float64
 21  Truck                            19 non-null     float64
 22  Tractor                          19 non-null     float64
 23  Trailer                          19 non-null     float64
 24  Motorcycle                       19 non-null     float64
 25  Moped                            19 non-null     float64
 26  Average Gross income 2018        19 non-null     float64
 27  DISTRICT                         19 non-null     object
dtypes: float64(26), object(2)
```

*Figure 1. Dtype product of .info method*

*Table 3. Statistic summary snipped table*

| | Area (he) | Pop/km2 | Population | Men population | Women population | Age 0-19 | Age 20-39 | Age 40-59 | Age 60 greater |
|---|---|---|---|---|---|---|---|---|---|
| **count** | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 |
| **mean** | 519.910526 | 16201.894737 | 42186.578947 | 20058.789474 | 22127.789474 | 7646.105263 | 9990.105263 | 13042.947368 | 11507.421053 |
| **std** | 749.226919 | 8351.209160 | 17489.813109 | 8399.449179 | 9108.808488 | 3348.386260 | 4037.707998 | 5743.886368 | 4599.216555 |
| **min** | 157.000000 | 433.000000 | 6582.000000 | 3179.000000 | 3403.000000 | 1333.000000 | 1334.000000 | 2102.000000 | 1813.000000 |
| **25%** | 195.800000 | 9891.500000 | 29665.000000 | 13739.500000 | 15925.500000 | 4982.500000 | 7522.500000 | 8395.000000 | 8796.500000 |
| **50%** | 236.700000 | 18101.000000 | 47421.000000 | 21996.000000 | 24474.000000 | 7868.000000 | 11258.000000 | 14131.000000 | 12490.000000 |
| **75%** | 347.600000 | 22916.000000 | 53575.000000 | 26045.500000 | 27529.500000 | 9794.000000 | 12858.000000 | 17035.500000 | 14584.000000 |
| **max** | 3242.600000 | 27834.000000 | 74518.000000 | 35749.000000 | 38769.000000 | 13683.000000 | 17255.000000 | 23742.000000 | 19838.000000 |

| Foreigns | Foreigns EU | Foreigns Rest Europe | Foreigns Africa | Foreigns North Central America | Foreign South America | Foreign Asia | Foreign Other | Unemployed | Tourism |
|---|---|---|---|---|---|---|---|---|---|
| 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 |
| 5824.842105 | 1704.315789 | 404.315789 | 634.157895 | 506.736842 | 1602.684211 | 966.842105 | 5.789474 | 3345.000000 | 18474.578947 |
| 2925.109158 | 786.472579 | 237.082980 | 449.001641 | 250.194778 | 906.544419 | 664.067957 | 5.191649 | 1772.800923 | 7046.036256 |
| 472.000000 | 185.000000 | 44.000000 | 79.000000 | 56.000000 | 94.000000 | 11.000000 | 1.000000 | 396.000000 | 3452.000000 |
| 3830.000000 | 1197.000000 | 215.000000 | 303.000000 | 332.000000 | 810.500000 | 438.000000 | 3.000000 | 1851.000000 | 14620.000000 |
| 5705.000000 | 1666.000000 | 423.000000 | 507.000000 | 534.000000 | 1557.000000 | 894.000000 | 4.000000 | 3140.000000 | 19719.000000 |
| 7953.500000 | 2102.500000 | 616.000000 | 916.000000 | 642.500000 | 2375.000000 | 1363.500000 | 8.000000 | 4500.500000 | 22028.500000 |
| 10707.000000 | 3105.000000 | 766.000000 | 1889.000000 | 1043.000000 | 3143.000000 | 2351.000000 | 22.000000 | 6741.000000 | 32231.000000 |

| Bus | Truck | Tractor | Trailer | Motorcycle | Moped | Average Gross income 2018 |
|---|---|---|---|---|---|---|
| 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 | 19.000000 |
| 47.157895 | 1134.000000 | 363.315789 | 356.105263 | 3184.157895 | 1103.684211 | 16678.894737 |
| 118.574526 | 481.763081 | 245.296658 | 322.135047 | 1233.011997 | 514.093599 | 4774.948166 |
| 0.000000 | 315.000000 | 94.000000 | 70.000000 | 668.000000 | 301.000000 | 11576.000000 |
| 3.500000 | 720.500000 | 201.000000 | 172.500000 | 2792.500000 | 734.000000 | 13064.500000 |
| 9.000000 | 1171.000000 | 249.000000 | 243.000000 | 3282.000000 | 1011.000000 | 14907.000000 |
| 32.500000 | 1485.500000 | 511.500000 | 360.500000 | 4091.000000 | 1371.500000 | 17880.500000 |
| 526.000000 | 2036.000000 | 985.000000 | 1291.000000 | 5317.000000 | 2286.000000 | 26930.000000 |

These three last tables are all the same, this is very important to have an idea of the behavior of the data recollected and how it describes the generality of the habitants of Valencia.

### 2.2.2 Data visualization

As we know the table data can be hard to understand, in this unit some plots will be shown to have a better familiarity of the data resulted from the Valencian Districts.

The first plot is the population, there are to plots to know which district have more density and Population per area.

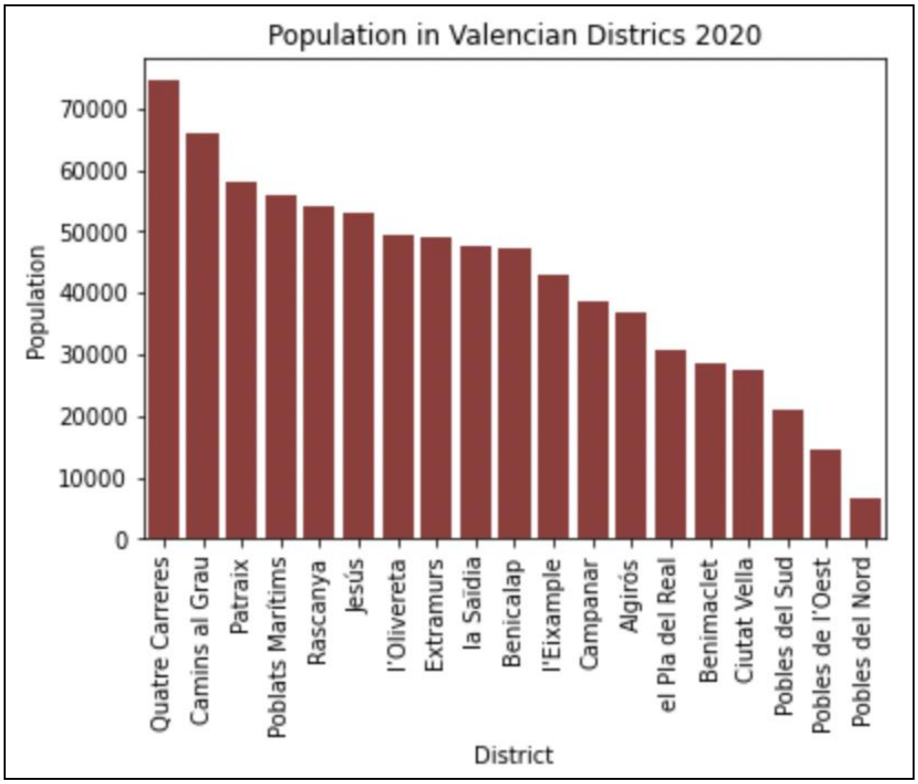



*Figure 2. Population in Valentian Districts 2020*

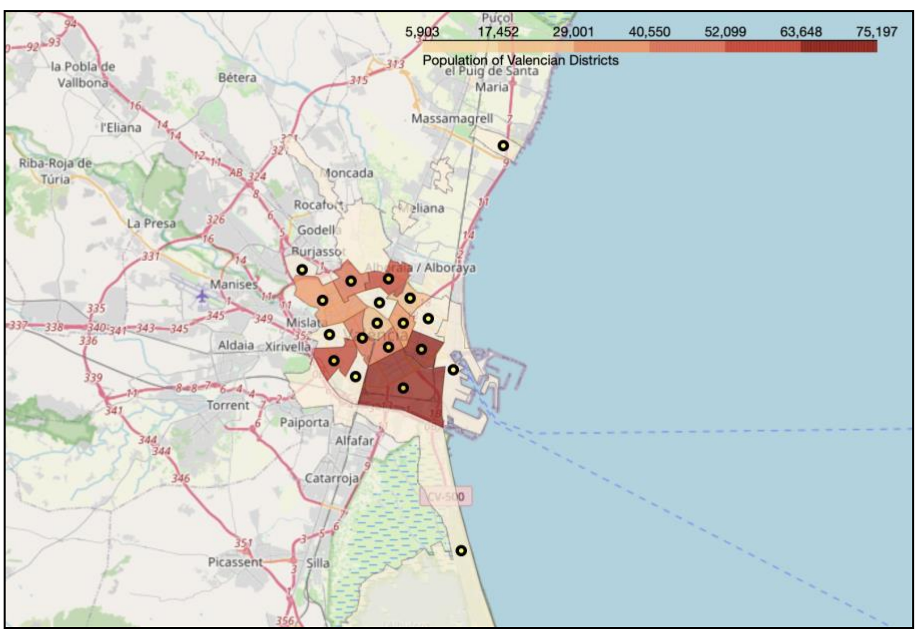


*Figure 3. Population of Valencian Districts in map*

Now we know that Districts named: Quatre Carreres, Camins al Grau, Patraix, Poblats Maritims and Rascanya are the most populated, there are some businesses that need lots of people like supermarkets, fast food restaurants, schools and other. Let's look what districts have the most and less gross income.

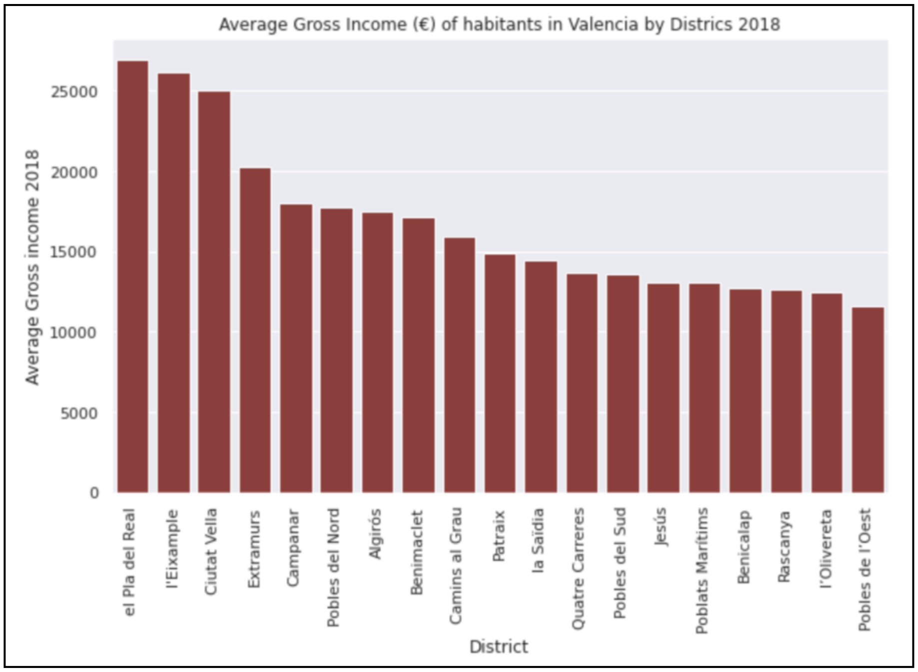



*Figure 4. Average gross income of habitants in Valencia by Districts 2018*

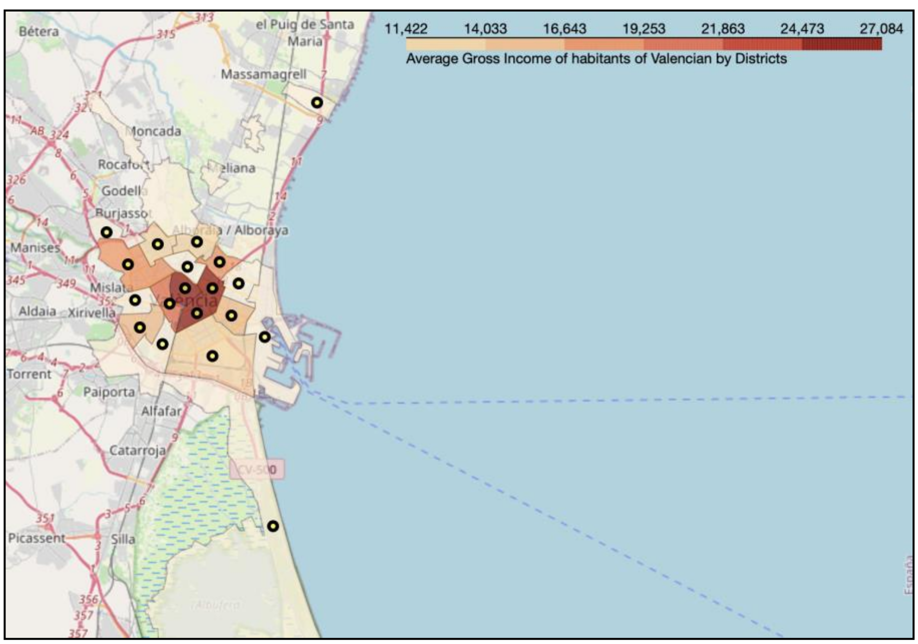



*Figure 5. Average gross income of habitants in Valencia by District 2018 map*

Now we know that Districts named: el Pla del Real, l'Eixample and Ciutat Vella are the district which habitants have the greatest economic power in Valencia, as we can see they tend to be at the center of city. This can be relevant to begin deluxe business like gourmet restaurants, spa (it could be better near the beach), wine store and other. There could be some business related to vehicles, in the next plots, we can see the districts with the most vehicle fleet. It's divided in vehicle and heavy vehicle fleet.

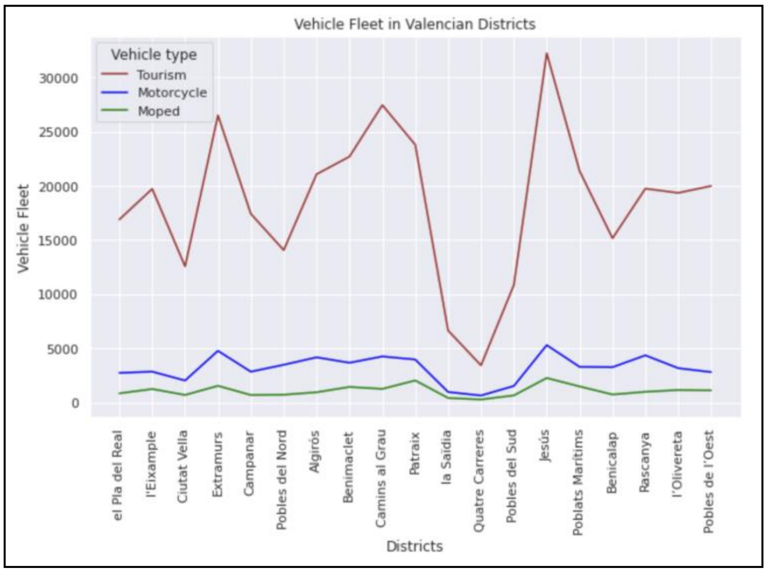



*Figure 6. Vehicle fleet in Valencian Districts*

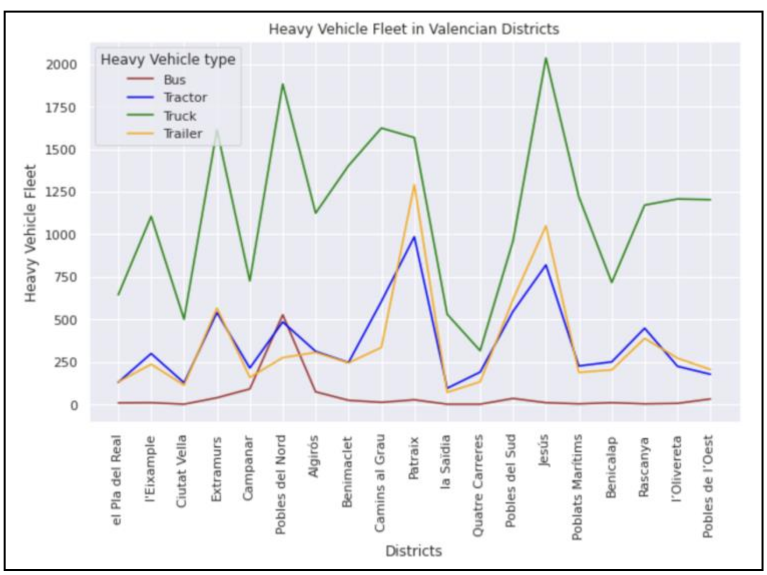


*Figure 7. Heavy Vehicle fleet in Valencian Districts*

There are a lot of plots that could be shown, but I think there are the most relevant to see, to know some of Valencian districts inhabitants.

### 2.2.3 Clustering the venues

Foursquare have a venue database, which helps to find the most popular venues in a city, using the Foursquare API, I set a Radius of 750, and limit to 100 venues. We obtain a table with 597 rows like we see in Table 4

*Table 4. Snipped table of Venues obtained from Foursquare API*

| | District | District Latitude | District Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|---|---|---|---|---|---|---|---|
| 0 | Ciutat Vella | 39.474652 | -0.375633 | Colmado Lalola | 39.475241 | -0.375624 | Tapas Restaurant |
| 1 | Ciutat Vella | 39.474652 | -0.375633 | San Tommaso | 39.475282 | -0.377144 | Italian Restaurant |
| 2 | Ciutat Vella | 39.474652 | -0.375633 | Catedral de Valencia | 39.475724 | -0.375005 | Church |
| 3 | Ciutat Vella | 39.474652 | -0.375633 | Plaça de la Reina | 39.474792 | -0.375501 | Plaza |
| 4 | Ciutat Vella | 39.474652 | -0.375633 | Véneta Food & Gelato Italiano | 39.475332 | -0.375657 | Ice Cream Shop |
| 5 | Ciutat Vella | 39.474652 | -0.375633 | Gelateria La Romana | 39.473107 | -0.376200 | Ice Cream Shop |
| 6 | Ciutat Vella | 39.474652 | -0.375633 | La Nocciola Toscana | 39.474042 | -0.374516 | Ice Cream Shop |
| 7 | Ciutat Vella | 39.474652 | -0.375633 | Oslo - The Vegetarian | 39.475949 | -0.377397 | Vegetarian / Vegan Restaurant |
| 8 | Ciutat Vella | 39.474652 | -0.375633 | Creperie Bretonne | 39.475236 | -0.375981 | French Restaurant |
| 9 | Ciutat Vella | 39.474652 | -0.375633 | La Pappardella | 39.475327 | -0.376086 | Italian Restaurant |

To cluster the common venues, I will use K-mean, an unsupervised learning algorithm, starting with 2 k-clusters and using the elbow method to kind the optimal k-cluster, we'll have the graphic in figure 8. It helps us to corroborate the correct assumed k-cluster.

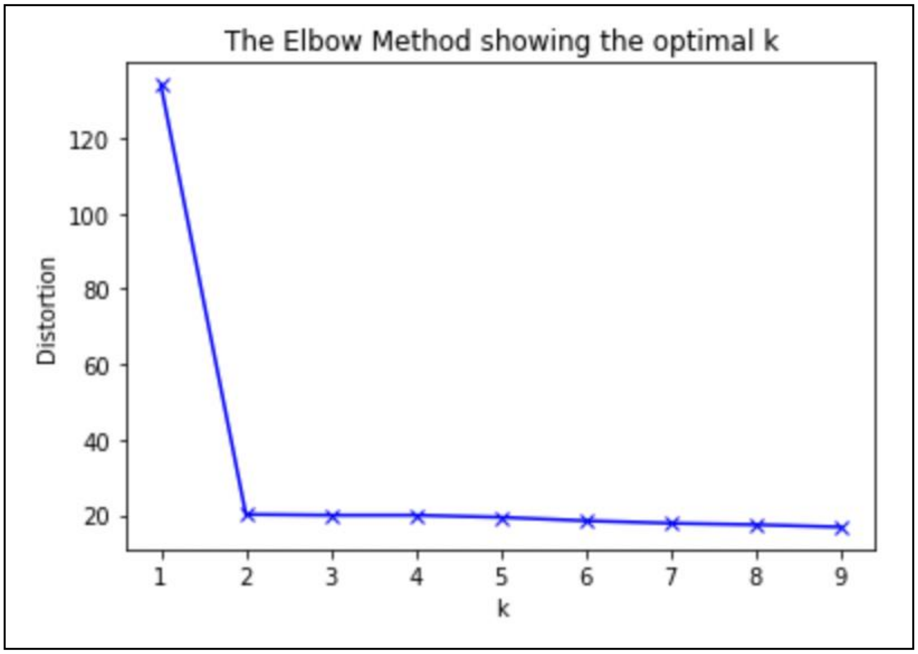



*Figure 8. Elbow method to find optimal k-clusters*

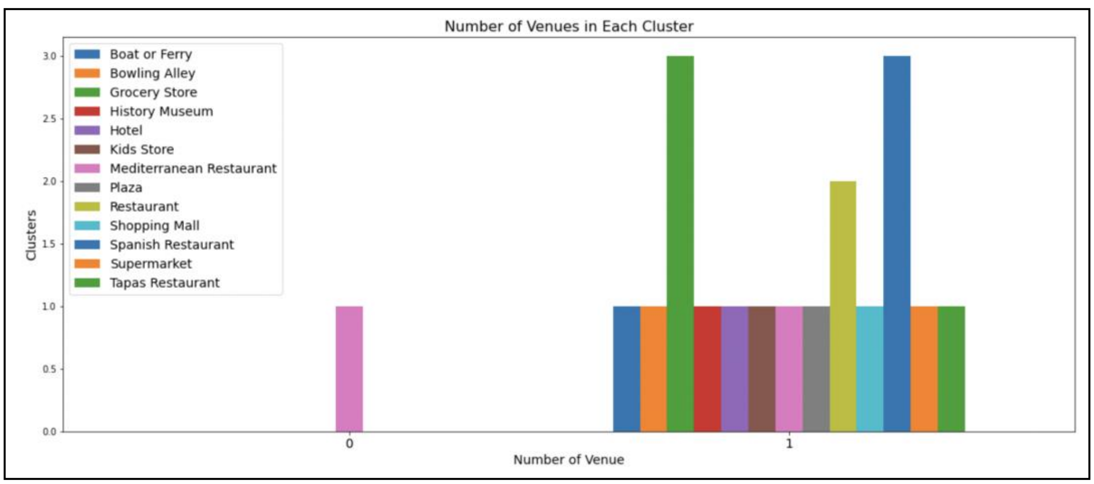



*Figure 9.. Number of venues in each cluster*

# 3. Results Section

## 3.1 Foursquare to find the most popular venues in Valencian Districts

Now we can obtain Table 4, it gives an idea of what is working well per district. A particular visible characteristic is that all the districts less Pobles de l'Oest and l'Olivereta have restaurants as most popular venue in its district.

*Table 5. Most popular type venues in Valencian Districts*

| | District | 1st Most Common Venue | 2nd Most Common Venue | 3rd Most Common Venue | 4th Most Common Venue | 5th Most Common Venue |
|---|---|---|---|---|---|---|
| 0 | Algirós | Spanish Restaurant | Bar | Tapas Restaurant | Italian Restaurant | Supermarket |
| 1 | Benicalap | Shopping Mall | Grocery Store | Brewery | Restaurant | Pool |
| 2 | Benimaclet | Tapas Restaurant | Café | Bar | Pizza Place | Cocktail Bar |
| 3 | Camins al Grau | Hotel | Seafood Restaurant | Pub | Supermarket | Tapas Restaurant |
| 4 | Campanar | Grocery Store | Gas Station | Restaurant | Pool | Event Space |
| 5 | Ciutat Vella | Plaza | Tapas Restaurant | Spanish Restaurant | Ice Cream Shop | Hotel |
| 6 | Extramurs | Spanish Restaurant | Bakery | Tapas Restaurant | Plaza | Hotel |
| 7 | Jesús | Restaurant | Grocery Store | Coffee Shop | Supermarket | Performing Arts Venue |
| 8 | Patraix | Supermarket | Bakery | Miscellaneous Shop | Spanish Restaurant | Fast Food Restaurant |
| 9 | Poblats Marítims | Boat or Ferry | Athletics & Sports | Cruise Ship | Southern / Soul Food Restaurant | Spanish Restaurant |
| 10 | Pobles de l'Oest | Grocery Store | Hotel | Tapas Restaurant | Metro Station | Park |
| 11 | Pobles del Nord | Kids Store | Asian Restaurant | Wine Bar | Frozen Yogurt Shop | French Restaurant |
| 12 | Pobles del Sud | Mediterranean Restaurant | Nudist Beach | Falafel Restaurant | Frozen Yogurt Shop | French Restaurant |
| 13 | Quatre Carreres | Mediterranean Restaurant | Dive Bar | Restaurant | Auto Workshop | Playground |
| 14 | Rascanya | History Museum | Tapas Restaurant | Café | Soccer Stadium | Spanish Restaurant |
| 15 | el Pla del Real | Spanish Restaurant | Pub | Café | Tapas Restaurant | Breakfast Spot |
| 16 | la Saïdia | Grocery Store | Tapas Restaurant | Bakery | Spanish Restaurant | Café |
| 17 | l'Eixample | Restaurant | Spanish Restaurant | Mediterranean Restaurant | Italian Restaurant | Tapas Restaurant |
| 18 | l'Olivereta | Bowling Alley | Bakery | Metro Station | Plaza | Cafeteria |

## 4. Discussion Section

Valencia as I mentioned at the beginning of this report, most economic activity is the service: tourism as well, which include restaurant, bars, plazas, beaches. It can be verifiable in the result plots and tables.

The clustering algorithm used was k-mean, starting with k-cluster 2, and confirmed with the elbow method.

The habitants with the greatest economic power use to live in the center districts, where are the historical places, it could be considered some luxor restaurants to take advantages of the lots of people doing tourism and the rich neighbors.

## 5. Conclusions

Valencia’s most principles existing businesses are the restaurants, bars, cafeterias, plazas. There are a lot of national and international tourist that every year goes to enjoy the city. I recommend adding some qualitative data to future analysis.

# 6. References


*Valencia Town Hall*. (December de 2020). Obtenido de Ajuntament de Valencia: https://www.valencia.es/es/cas/estadistica/mapa-barrios

Enterat. (2021). *Enterat*. Obtenido de https://www.enterat.com/actualidad/habitantes-valencia.php

INE. (2020). *Instituto Nacional de Estadística*. Obtenido de https://ine.es

Wikipedia. (2021). *Wikipedia.org*. Obtenido de https://es.wikipedia.org/wiki/Valencia

Foursquare. (2021). *Foursquare*. Obtenido de https://foursquare.com

Google. (2021). *Google maps*. Obtenido de https://www.google.com/maps/place/Valencia,+Espa%C3%B1a/

Espana, D. d. (2021). *Datos de gobierno de Espana*. Obtenido de http://mapas.valencia.es/lanzadera/opendata/Distritos/JSON?srsName=EPSG%3A4326