

# BATTLE OF THE NEIGHBORHOODS

IBM Data Science Capstone Project

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# Business understanding

- Madrid is a major business hub in southwestern Europe and the Iberian Peninsula.
- Cost of living in Madrid is higher than in other Spanish cities, but the socioeconomic differences between different neighborhoods of the city can be used to find affordable places to live.
- A company wants to analyze socioeconomic data from Madrid to offer insights to prospective employees to help them find accommodation in the city.



Picture from <https://www.smartcitylab.com/blog/es/gobierno-finanzas/que-pueden-aprender-otras-ciudades-de-los-errores-de-madrid-central/>

# Business understanding


The key indicators employed to analyze Madrid's neighborhoods will be:

- Population
- Average income
- Crime level
- Amenities in the neighborhood
- Real estate and rent prices (per square meter)



**K Means clustering**

The neighborhoods will be segmented and classified according to those features





# Business understanding

Our audience:

New employees from the company wishing to move to Madrid and know a Little bit about the city before moving in.

Company's management expects to understand the rationale behind the recommendations made.

The general public could be also benefitted from this information.



# Business understanding



## Success criteria:

The project will be considered successful if a list of Madrid's neighborhoods based on socioeconomic and business diversity in the neighborhood can be presented to the client to inform its prospective employees of their living choices in the city.

# Data understanding – Geographical data

- Geopandas dataframe containing polygon shapes and total Surface of the 151 neighborhoods of the city of Madrid.
- Data taken from the City Council of Madrid

|   | geometry  | District code | District | Neighborhood code | Neighborhood | Latitude  | Longitude |
|---|---|---------------|----------|-------------------|--------------|-----------|-----------|
| 0 | POLYGON ((-3.70593 40.42029, -3.70634 40.42017... | 01            | Centro   | 011               | Palacio      | 40.415417 | -3.714071 |
| 1 | POLYGON ((-3.69194 40.40908, -3.69203 40.40870... | 01            | Centro   | 012               | Embajadores  | 40.409239 | -3.702463 |
| 2 | POLYGON ((-3.69805 40.41928, -3.69654 40.41874... | 01            | Centro   | 013               | Cortes       | 40.414844 | -3.696829 |
| 3 | POLYGON ((-3.69576 40.42764, -3.69512 40.42734... | 01            | Centro   | 014               | Justicia     | 40.423661 | -3.696677 |
| 4 | POLYGON ((-3.71186 40.43019, -3.71050 40.43006... | 01            | Centro   | 015               | Universidad  | 40.425671 | -3.707071 |

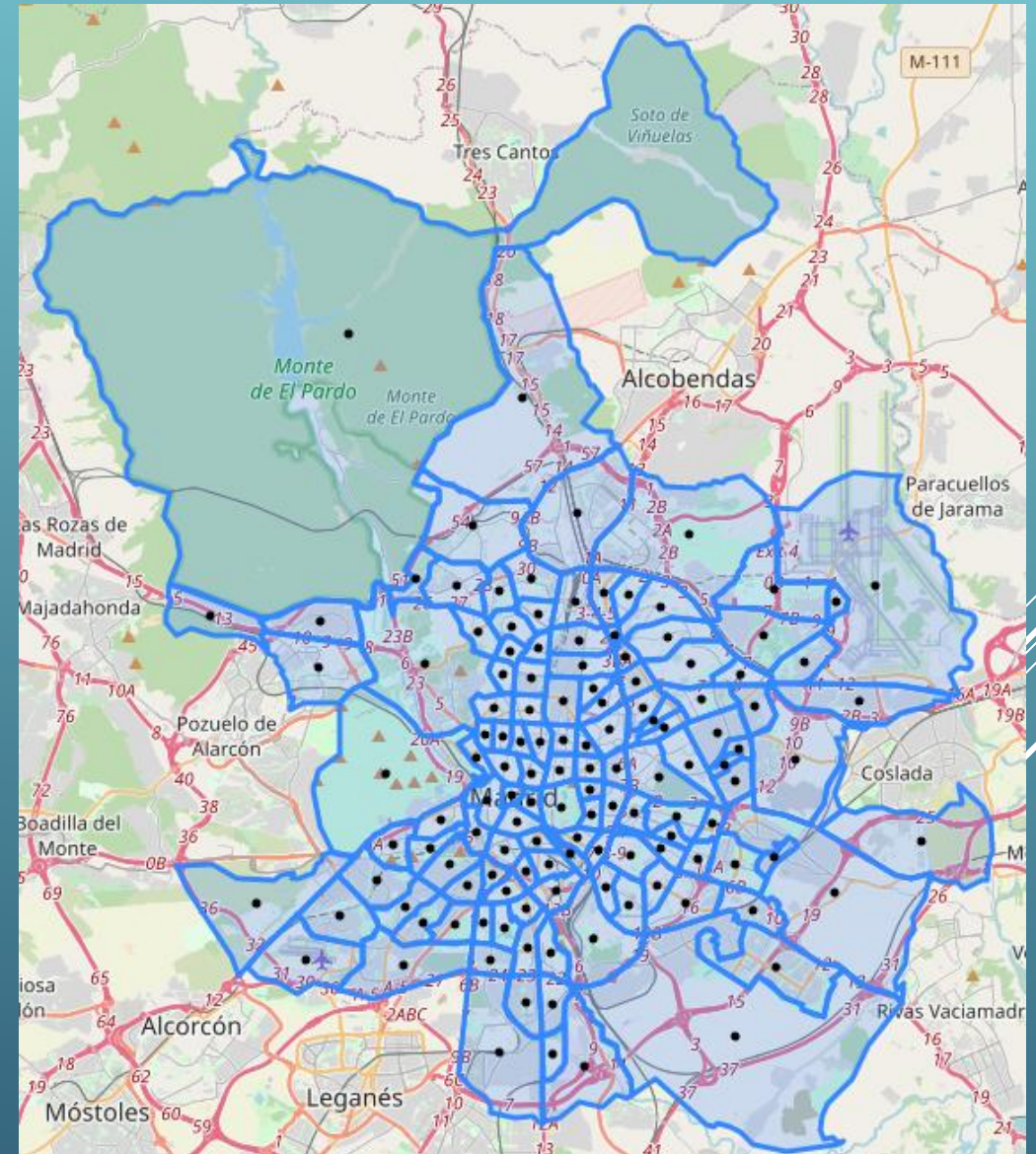
|   | Neighborhood | Surface (m2) |
|---|--------------|--------------|
| 0 | Palacio      | 1471085      |
| 1 | Imperial     | 967500       |
| 2 | Pacífico     | 750065       |
| 3 | Recoletos    | 870857       |
| 4 | El Viso      | 1708046      |



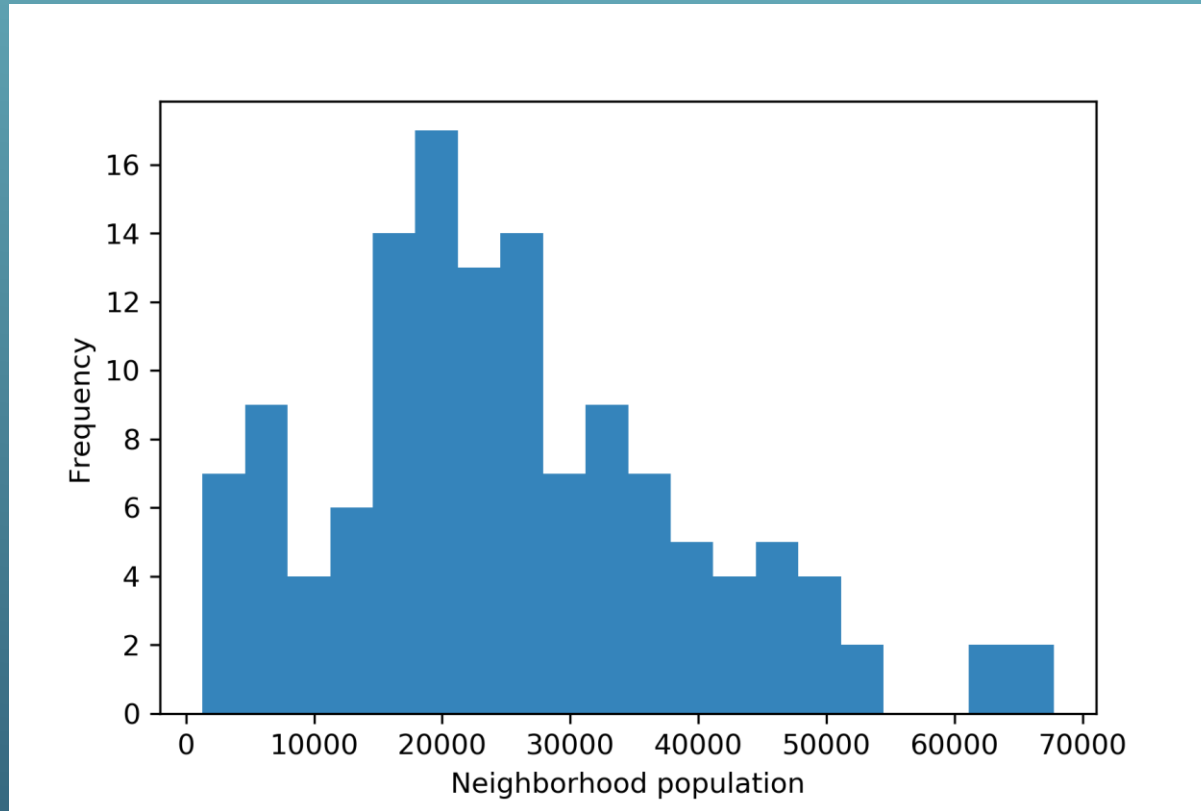
# Data understanding – Geographical data

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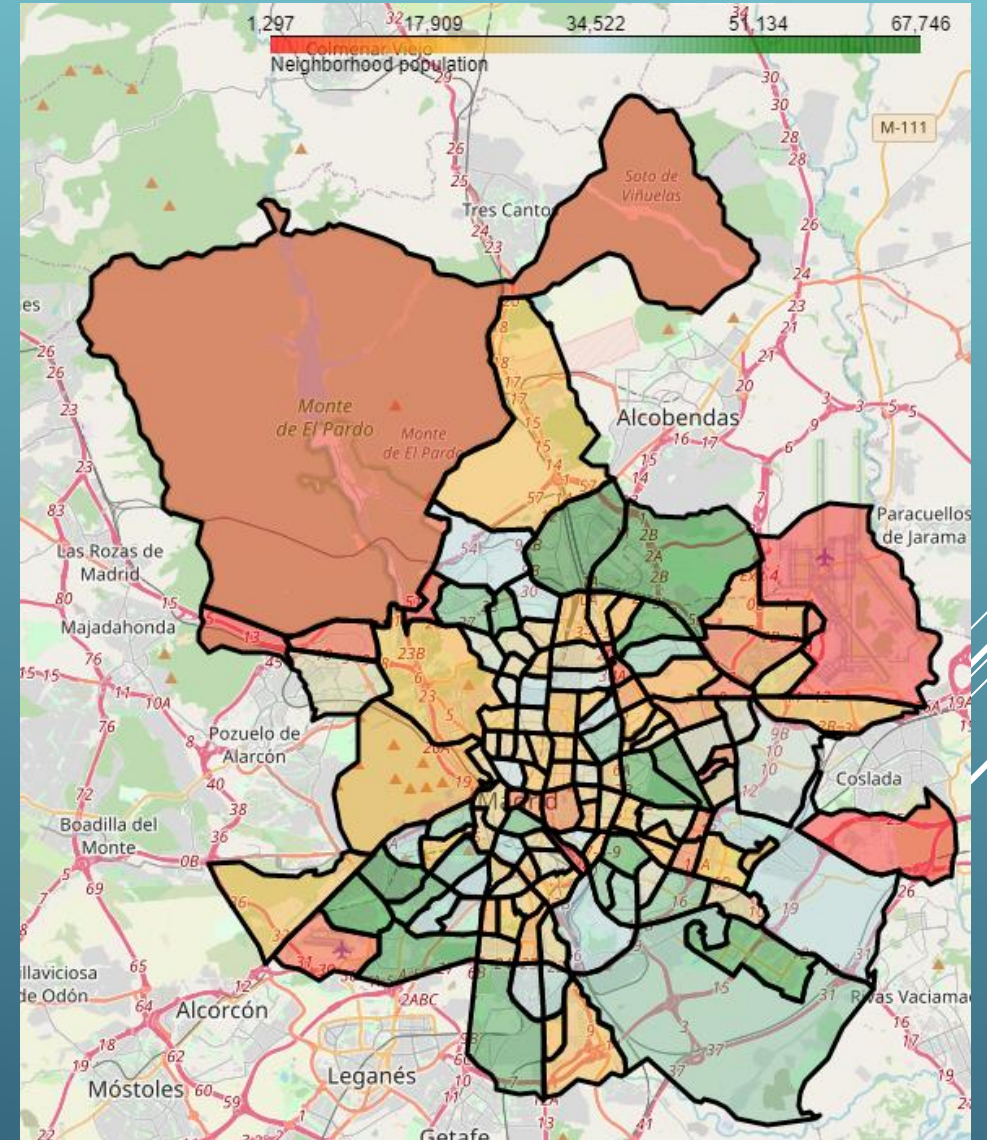
Madrid's neighborhoods (blue) and neighborhood centroids (black dots)



# Data understanding – Population data



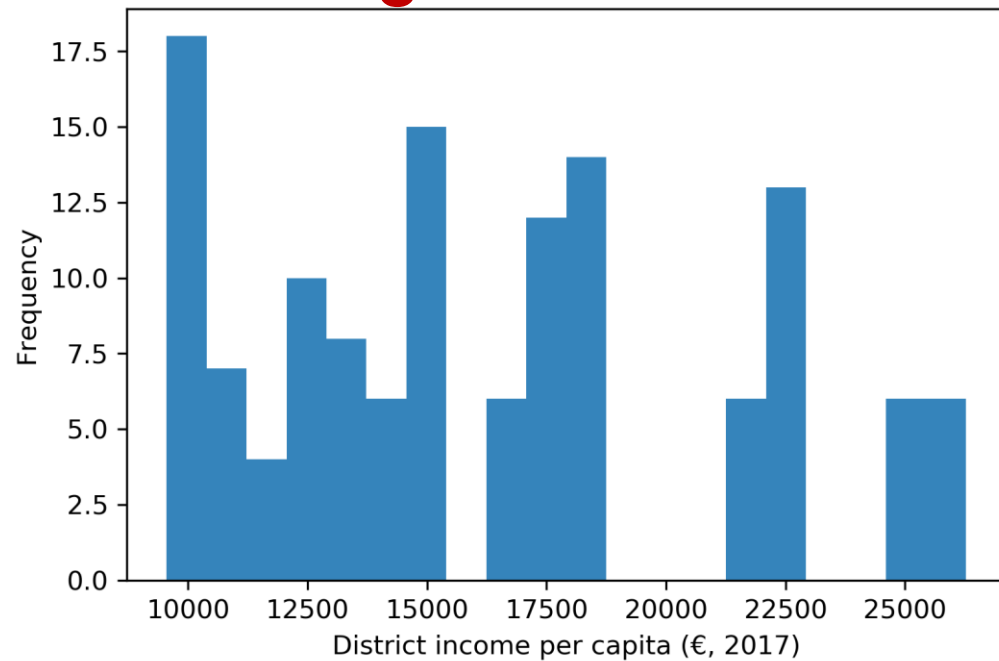
Data obtained from [City Council of Madrid](#)



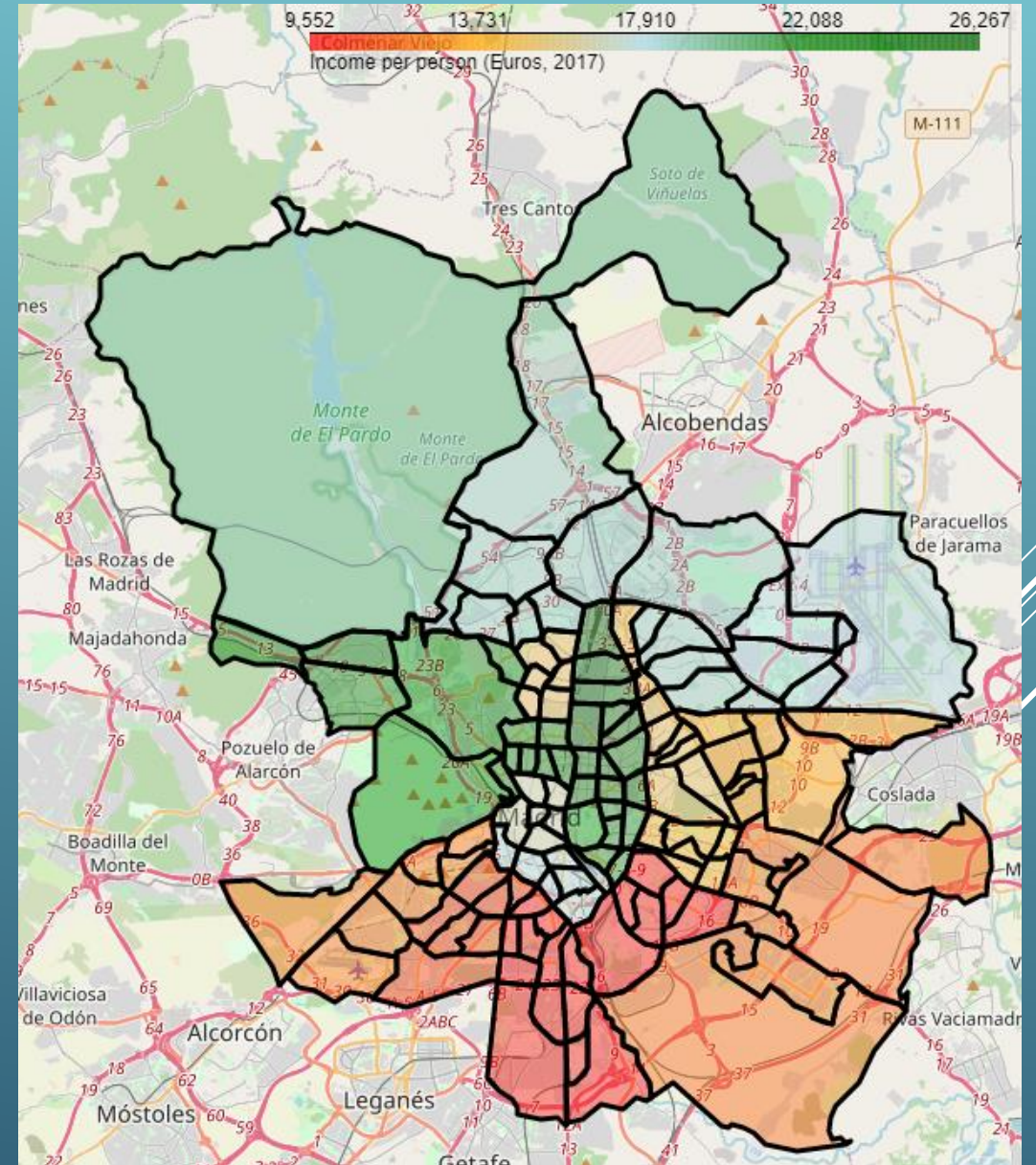


# Data understanding – Income data

## Warning: Data at district level



Data taken from [National Statistics Institute](#) (INE)



# Data understanding – Crime, Real Estate and amenities

Crime data taken from [arrest reports per district](#) of Madrid's Municipal Police

Real Estate data taken from [Idealista](#), a Spanish realtor.

Amenities data taken from Foursquare using their API to obtain venues near the neighborhood centroids.

Data will be explained in the next section: feature engineering.

|   | Neighborhood | Neighborhood Latitude | Neighborhood Longitude | Venue   | Venue Latitude | Venue Longitude | Venue Category |
|---|--------------|-----------------------|------------------------|---|----------------|-----------------|----------------|
| 0 | Palacio      | 40.415417             | -3.714071              | Cervecería La Mayor                               | 40.415218      | -3.712194       | Beer Bar       |
| 1 | Palacio      | 40.415417             | -3.714071              | Santa Iglesia Catedral de Santa María la Real ... | 40.415767      | -3.714516       | Church         |
| 2 | Palacio      | 40.415417             | -3.714071              | Plaza de La Almudena                              | 40.416320      | -3.713777       | Plaza          |
| 3 | Palacio      | 40.415417             | -3.714071              | Mercado Jamón Iberico                             | 40.415442      | -3.711643       | Market         |
| 4 | Palacio      | 40.415417             | -3.714071              | Palacio Real de Madrid                            | 40.417940      | -3.714259       | Palace         |

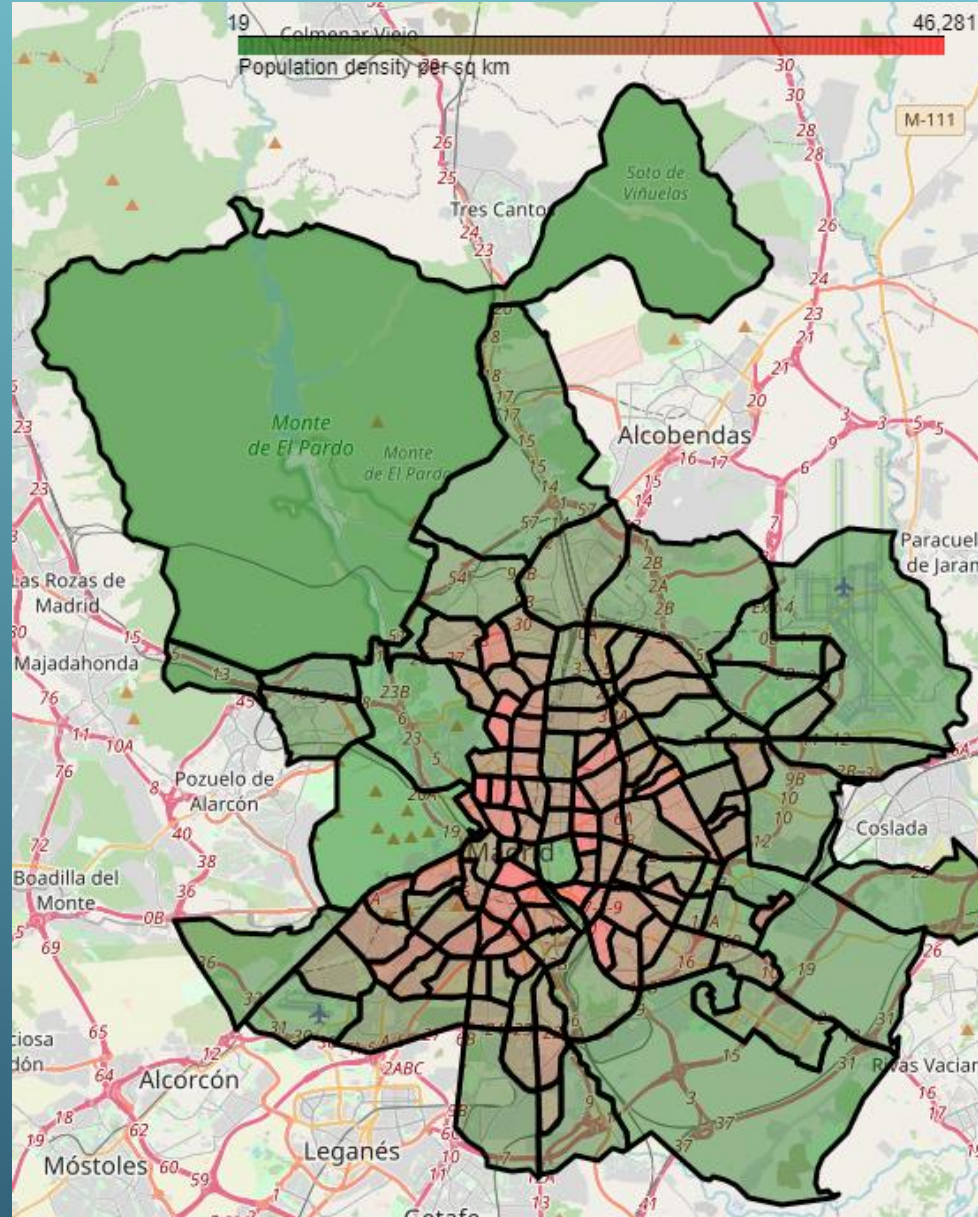


# Data preparation – Feature Engineering

Population data  
+  
Surface data  

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Population density



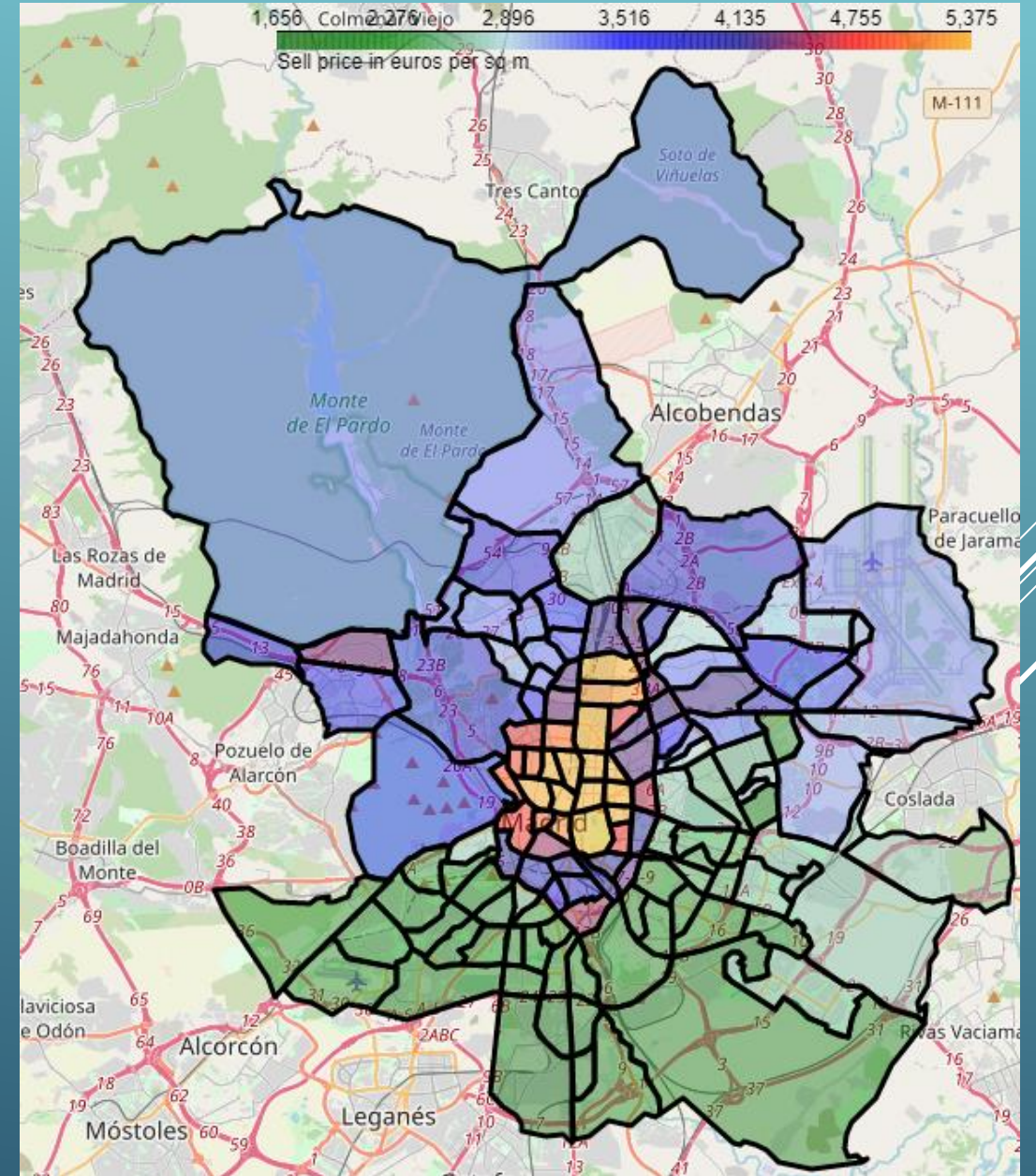
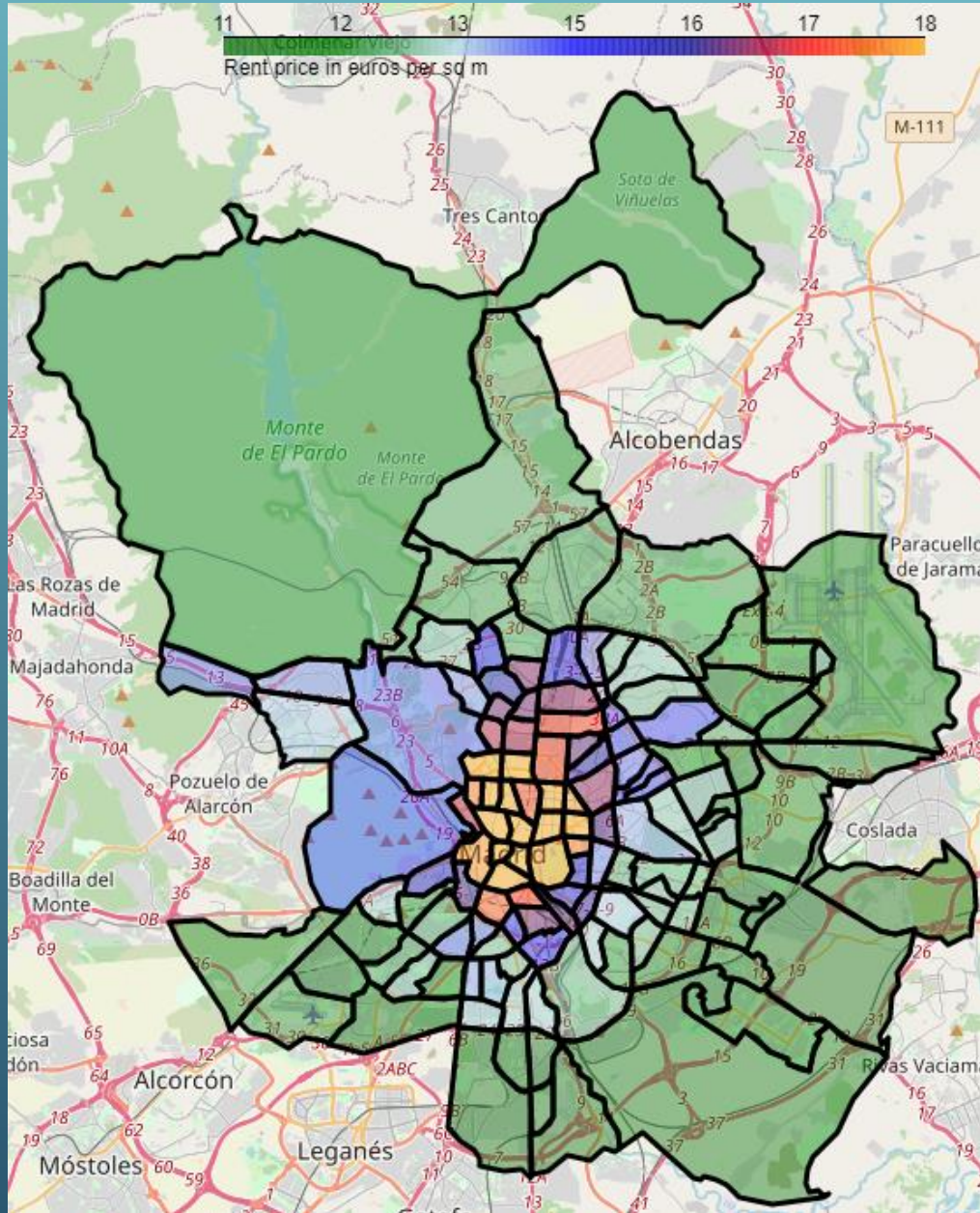


# Data preparation – Feature Engineering

|                       | Sell price in euros per sq m | Rent price in euros per sq m |
|-----------------------|------------------------------|------------------------------|
| District              |                              |                              |
| Arganzuela            | 3953.0                       | 16.15                        |
| Barajas               | 3169.0                       | 11.70                        |
| Carabanchel           | 2042.0                       | 12.50                        |
| Centro                | 5081.0                       | 19.15                        |
| Chamartín             | 4958.0                       | 16.35                        |
| Chamberí              | 5038.0                       | 18.45                        |
| Ciudad Lineal         | 3532.0                       | 13.90                        |
| Fuencarral - El Pardo | 3261.0                       | 12.30                        |
| Hortaleza             | 3835.0                       | 12.70                        |
| Latina                | 2296.0                       | 12.10                        |
| Moncloa - Aravaca     | 3729.5                       | 13.85                        |
| Moratalaz             | 2466.5                       | 12.60                        |
| Puente de Vallecas    | 2047.5                       | 12.60                        |
| Retiro                | 4503.0                       | 15.50                        |
| Salamanca             | 5858.0                       | 18.60                        |
| San Blas - Canillejas | 2829.0                       | 12.05                        |
| Tetuán                | 3448.0                       | 16.35                        |
| Usera                 | 2103.5                       | 13.10                        |
| Vicálvaro             | 2692.0                       | 10.90                        |
| Villa de Vallecas     | 2324.0                       | 11.45                        |
| Villaverde            | 1780.0                       | 11.15                        |

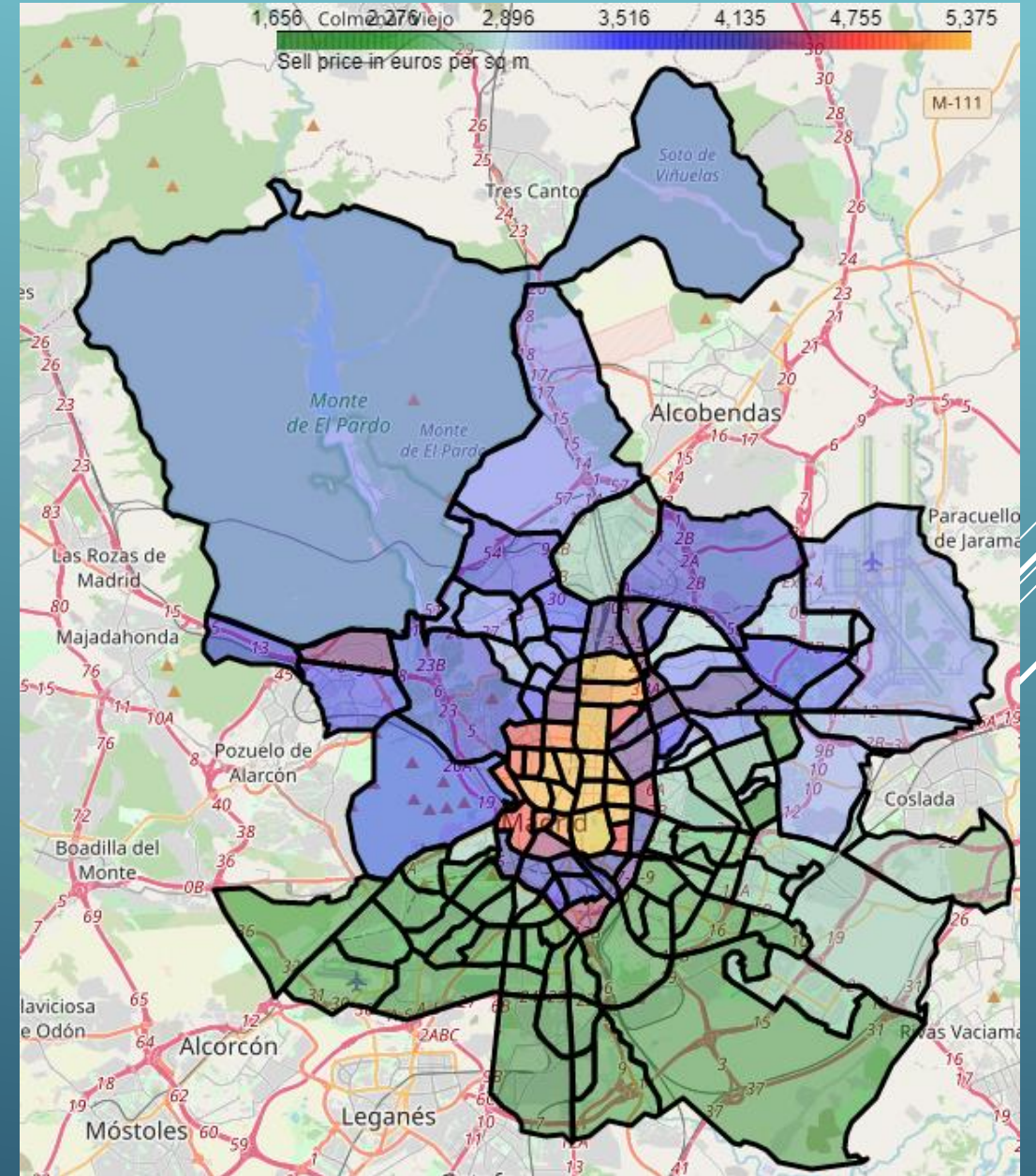
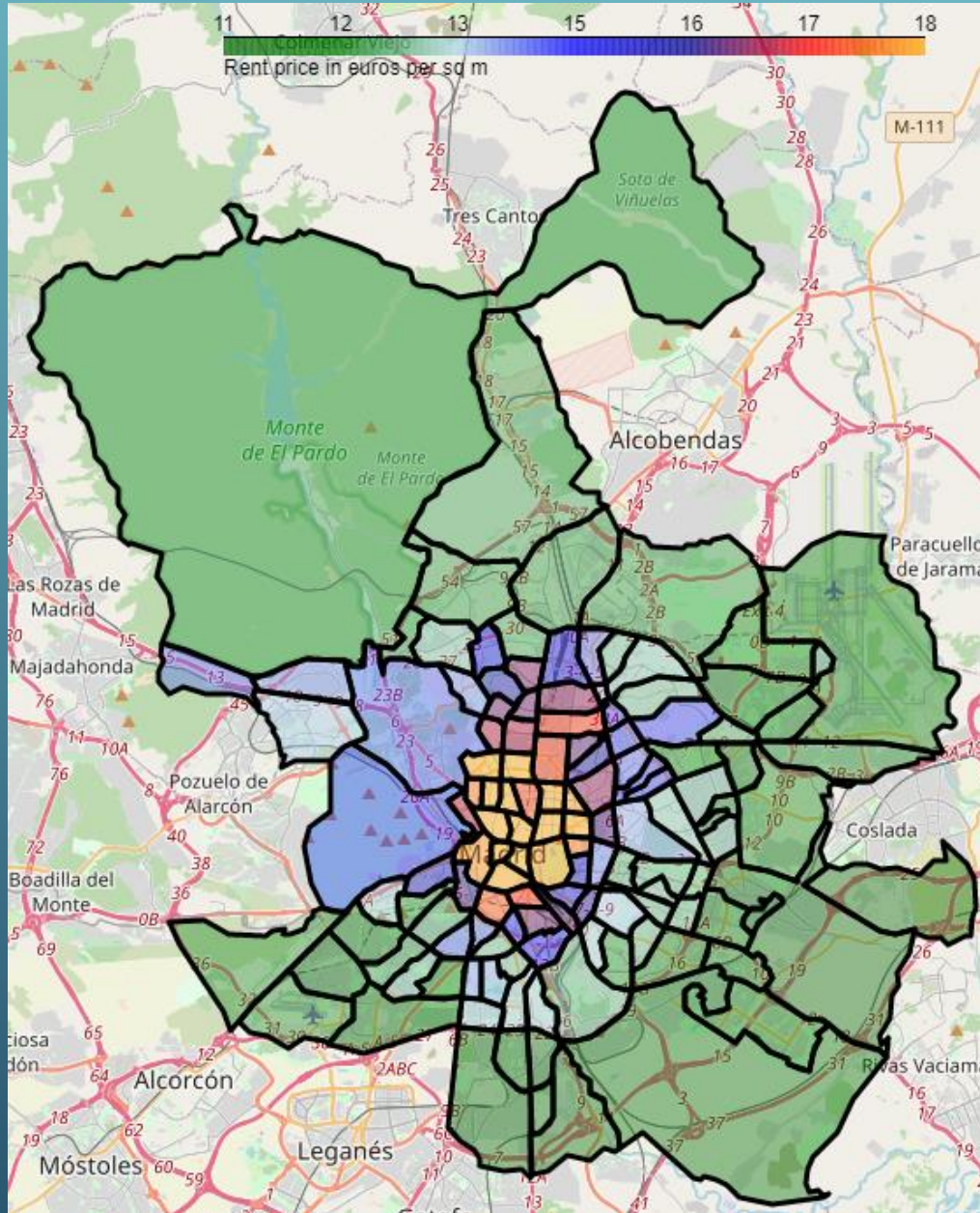
Real Estate data incomplete:  
Used median prices of the  
district for unknown values of  
the neighborhoods

# Data preparation – Feature Engineering





# Data preparation – Feature Engineering



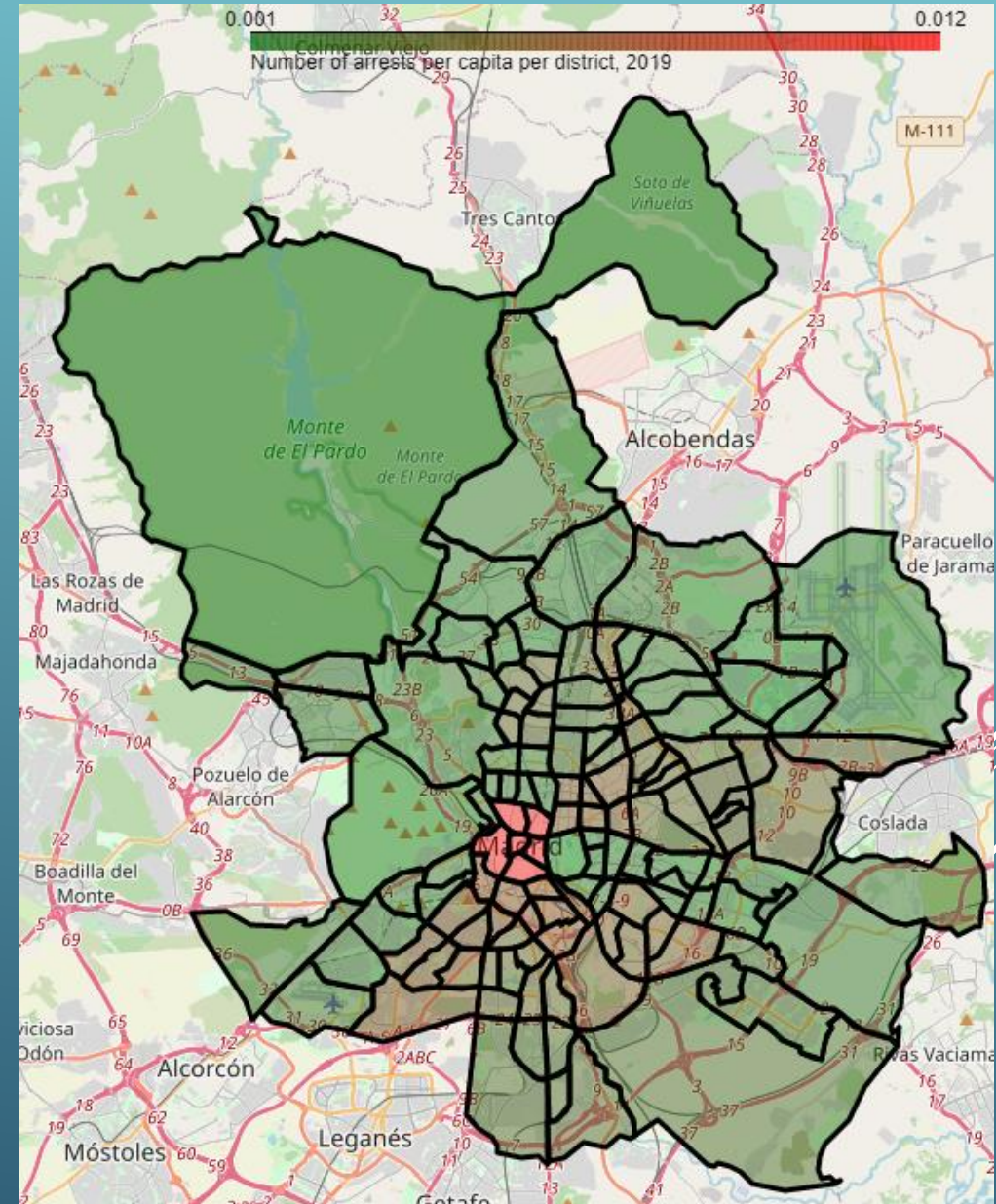


# Data preparation – Feature Engineering

Crime data  
+  
Population data  

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Arrests per capita



# Data preparation – Feature Engineering

|     | Neighborhood                                   | 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 |
|-----|--|-----------------------|-----------------------|--------------------------|--------------------------|------------------------|-----------------------|-----------------------|-----------------------|--------------------------|------------------------|
| 113 | Simancas                                       | Spanish Restaurant    | Restaurant            | Hotel                    | Mediterranean Restaurant | Sandwich Place         | Supermarket           | Café                  | Rock Club             | Italian Restaurant       | Coffee Shop            |
| 104 | Rios Rosas                                     | Spanish Restaurant    | Tapas Restaurant      | Restaurant               | Italian Restaurant       | Bar                    | Pizza Place           | Japanese Restaurant   | Café                  | Convenience Store        | Supermarket            |
| 38  | Cortes   | Hotel                 | Plaza                 | Restaurant               | Café                     | Bar                    | Tapas Restaurant      | Spanish Restaurant    | Theater               | Mediterranean Restaurant | Art Museum             |
| 127 | Villaverde Alto, Casco Histórico De Villaverde | Restaurant            | Pizza Place           | Mediterranean Restaurant | Diner                    | Thrift / Vintage Store | Brewery               | Spanish Restaurant    | Flower Shop           | Flea Market              | Fish Market            |
| 25  | Casco Histórico De Barajas                     | Hotel                 | Spanish Restaurant    | Restaurant               | Argentinian Restaurant   | Tapas Restaurant       | Coffee Shop           | Breakfast Spot        | Grocery Store         | Snack Place              | Flea Market            |
| 89  | Palomeras Sureste                              | Pool                  | Grocery Store         | Spanish Restaurant       | Fast Food Restaurant     | Gas Station            | Café                  | Seafood Restaurant    | Brewery               | Chinese Restaurant       | Bar                    |
| 3   | Aeropuerto                                     | Massage Studio        | Diner                 | Hotel Bar                | Ethiopian Restaurant     | Event Space            | Exhibit               | Fabric Shop           | Falafel Restaurant    | Farmers Market           | Fast Food Restaurant   |
| 67  | Las Águilas                                    | Train Station         | Tapas Restaurant      | Breakfast Spot           | Market                   | Bar                    | Seafood Restaurant    | Café                  | Restaurant            | Park                     | Athletics & Sports     |
| 130 | Zofío  | Spanish Restaurant    | Park                  | Athletics & Sports       | Asian Restaurant         | Bookstore              | Theater               | Market                | Grocery Store         | Gym / Fitness Center     | Beer Garden            |
| 37  | Corralejos                                     | Hotel                 | Sculpture Garden      | Spanish Restaurant       | Pool                     | Golf Course            | Park                  | Rental Car Location   | Dog Run               | Lake                     | Event Space            |

## Amenities:

- Restaurants used as proxy of economic activity in the neighborhood.
- Counted number of restaurants per neighborhood.

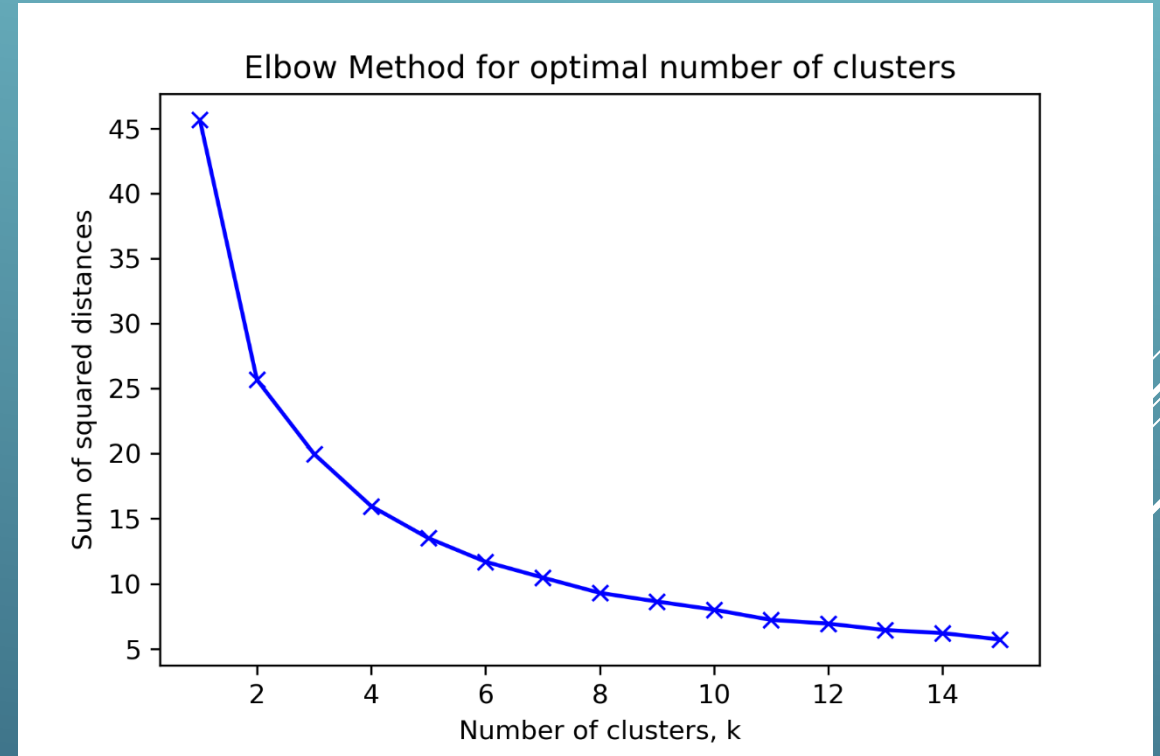
# Modelling

Used a K-means clustering algorithm with the following features:

- Real Estate selling prices per square meter.
- Real Estate renting prices per square meter.
- Mean income per person.
- Population density in inhabitants per square kilometer.
- Number of arrests per capita.
- Number of restaurants in the neighborhood.

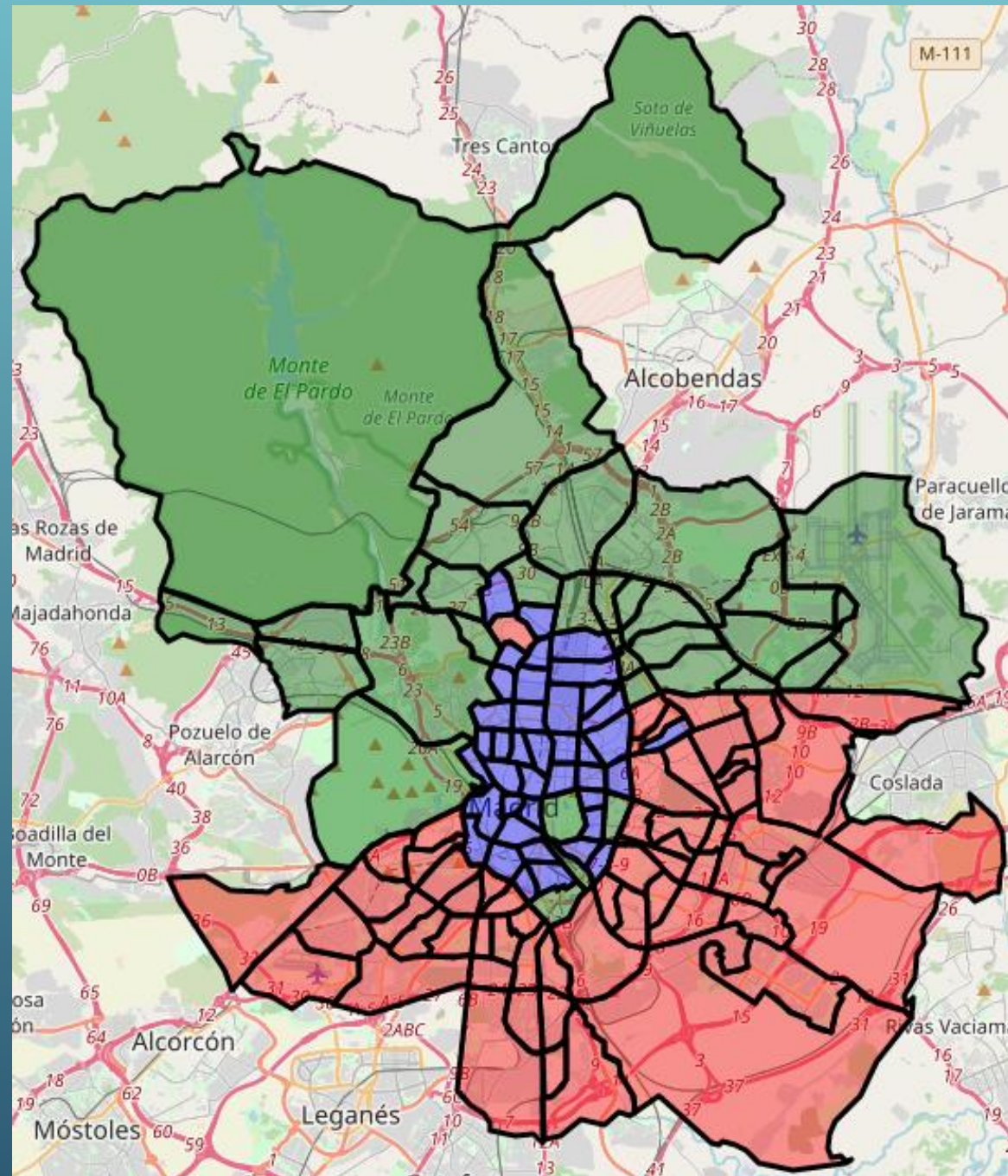
Data normalized using MinMaxScaler method.

Optimal number of clusters calculated using the elbow method.



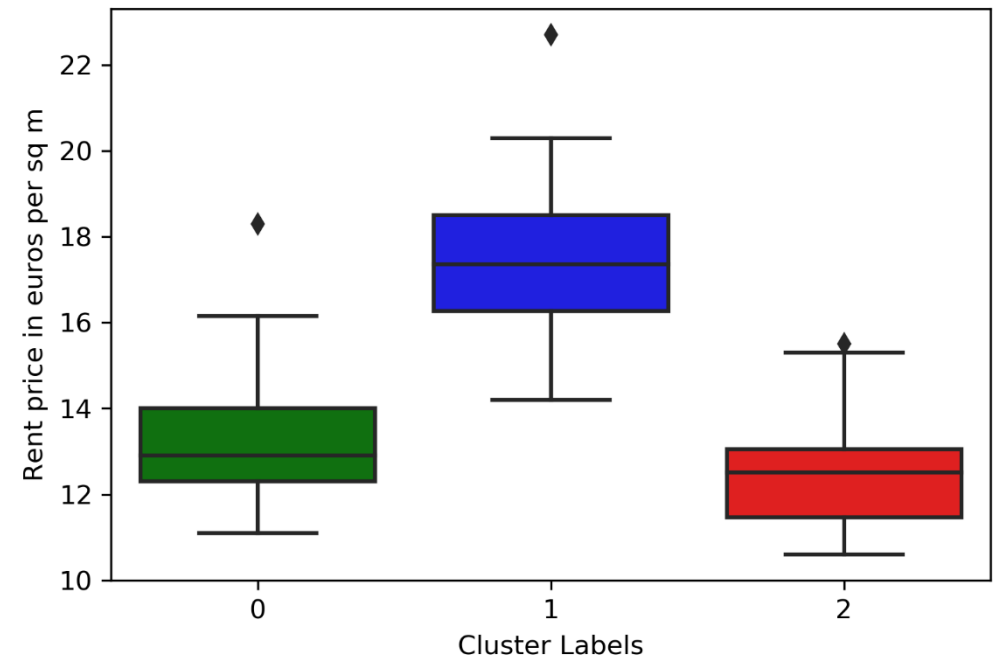
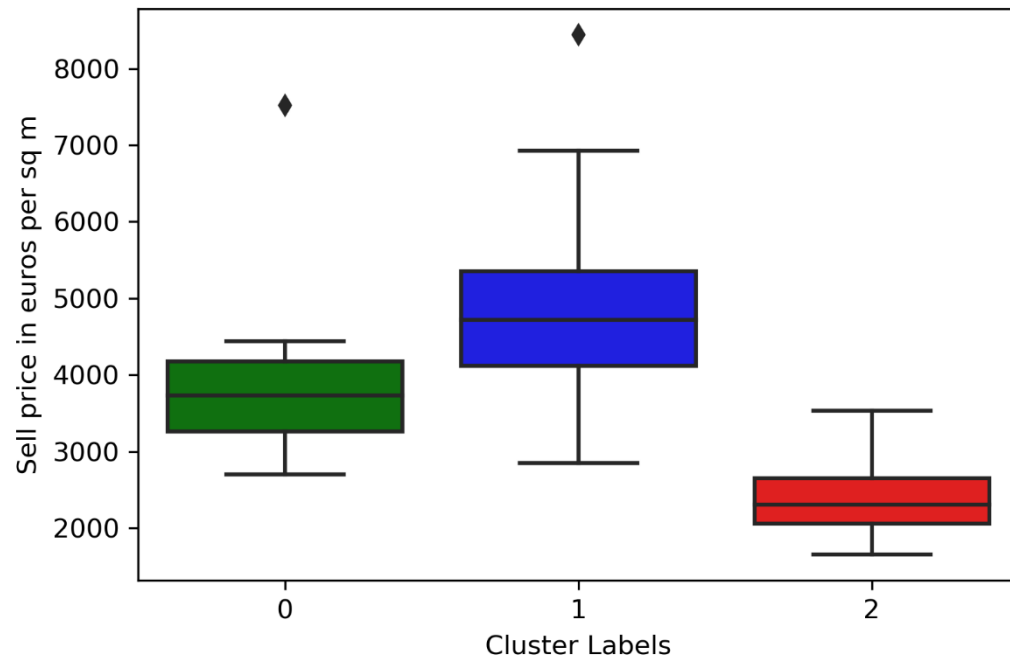


# Modelling



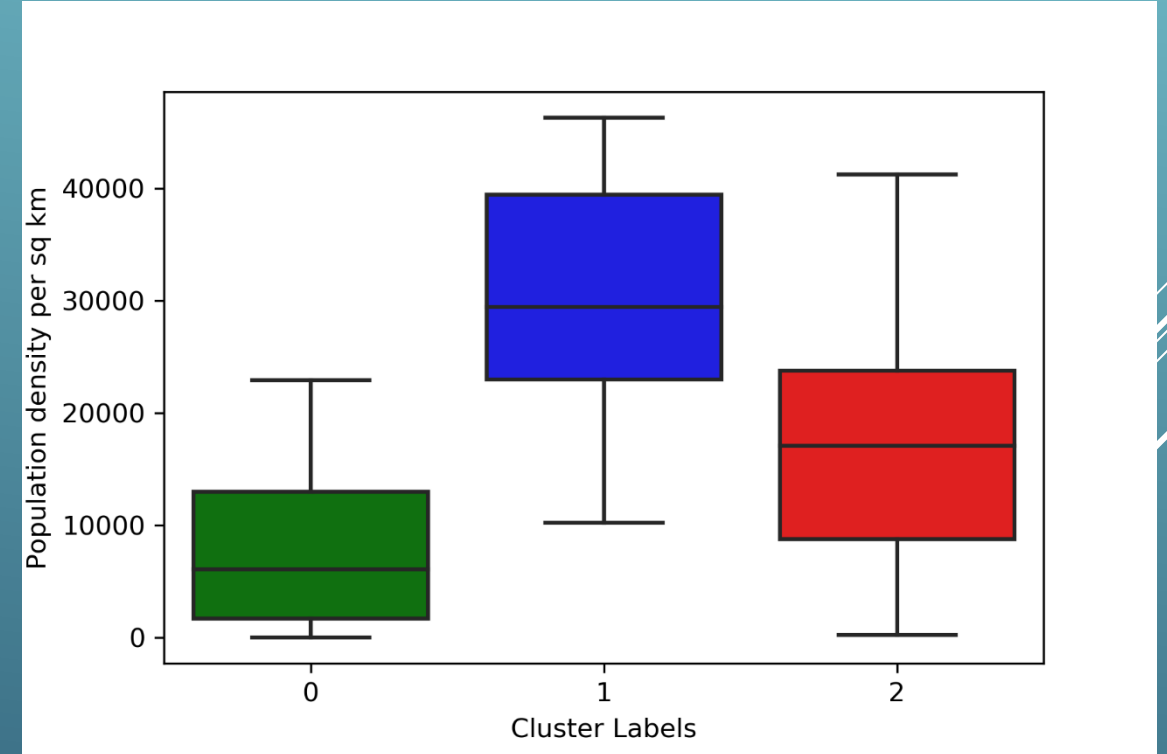
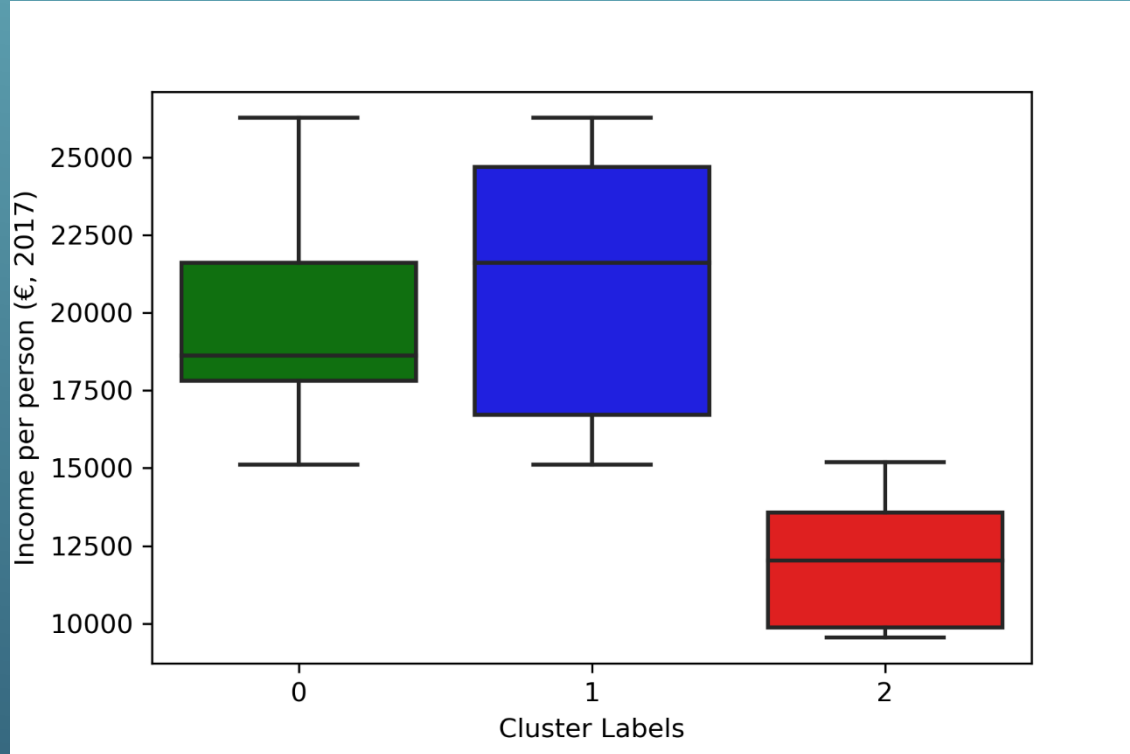
# Evaluation

How are the features in each of the clusters?



# Evaluation

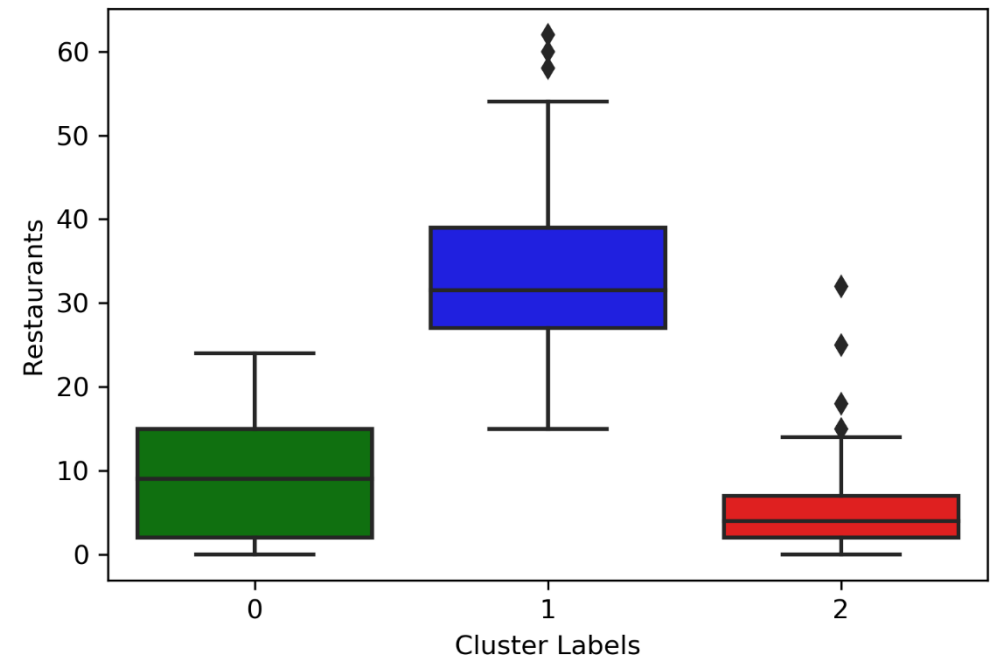
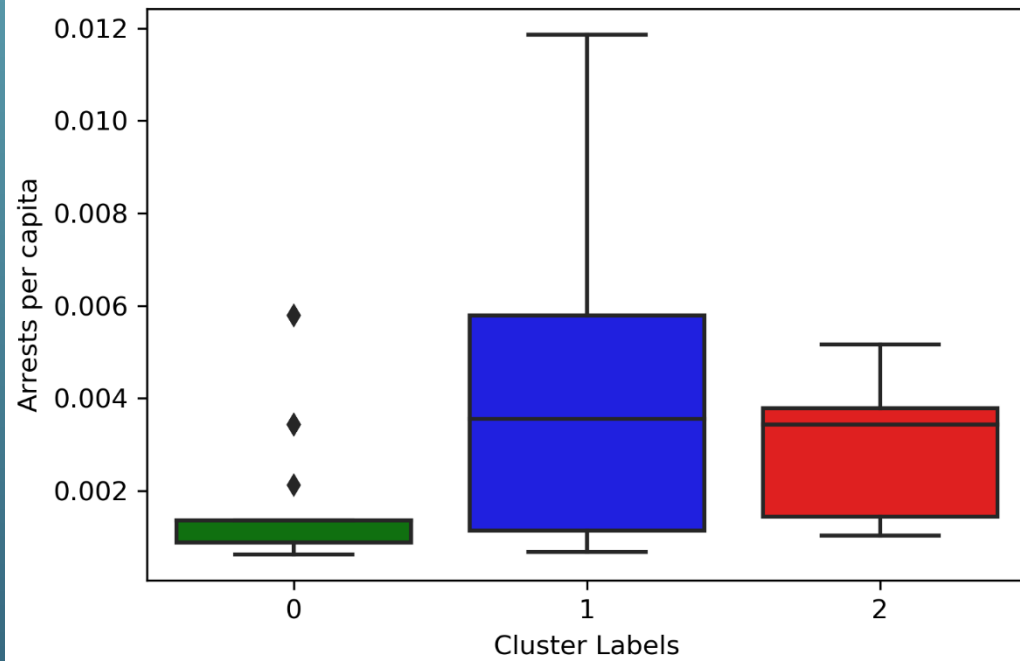
How are the features in each of the clusters?





# Evaluation

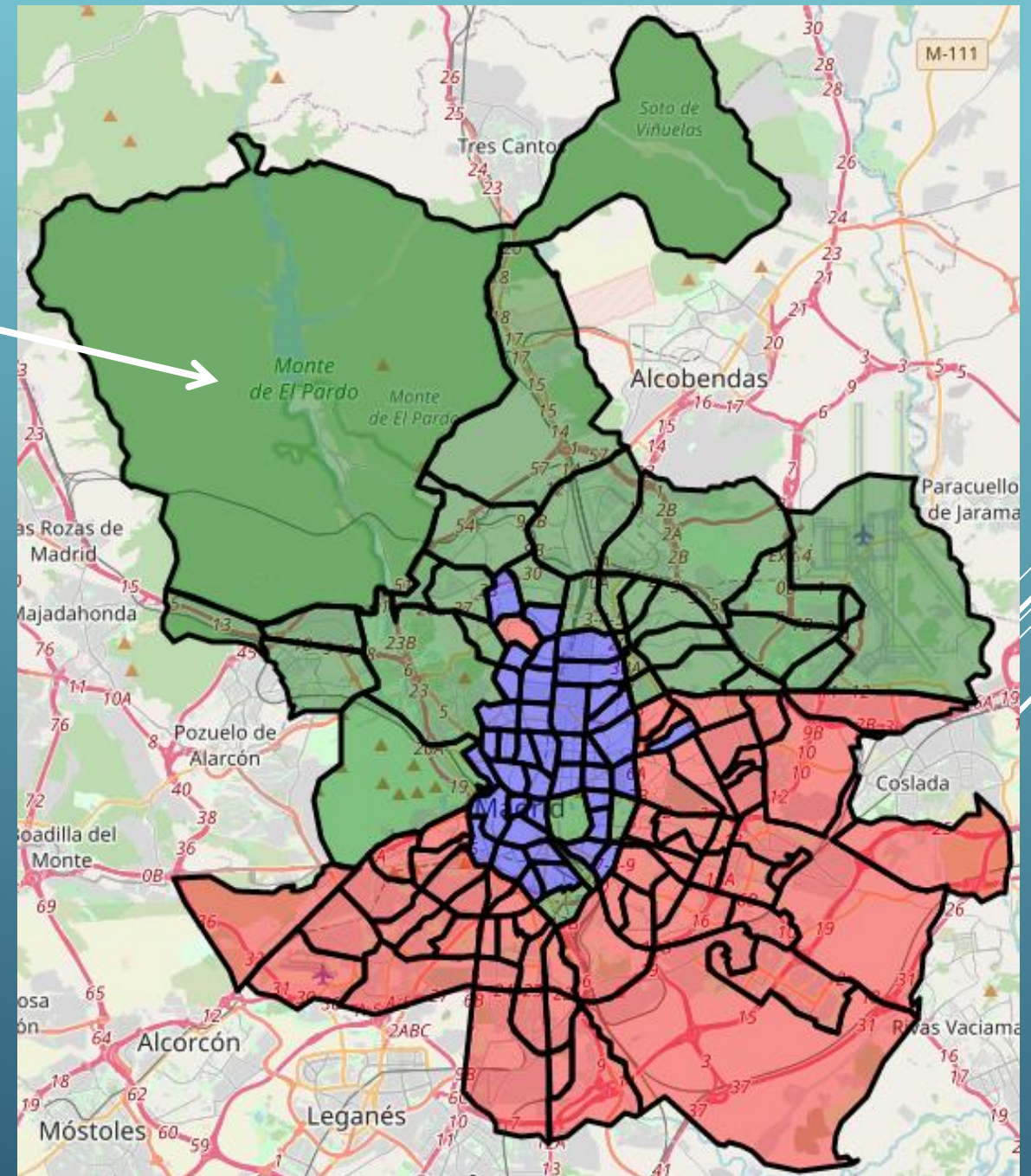
How are the features in each of the clusters?



# Evaluation

Neighborhoods in the first cluster (green in the map):

- Mainly the northern neighborhoods outside of the city center.
- Very low population density.
- High income.
- Moderate real estate prices for selling property.
- Low real estate prices for renting property.
- Very low crime levels.
- Low number of restaurants.

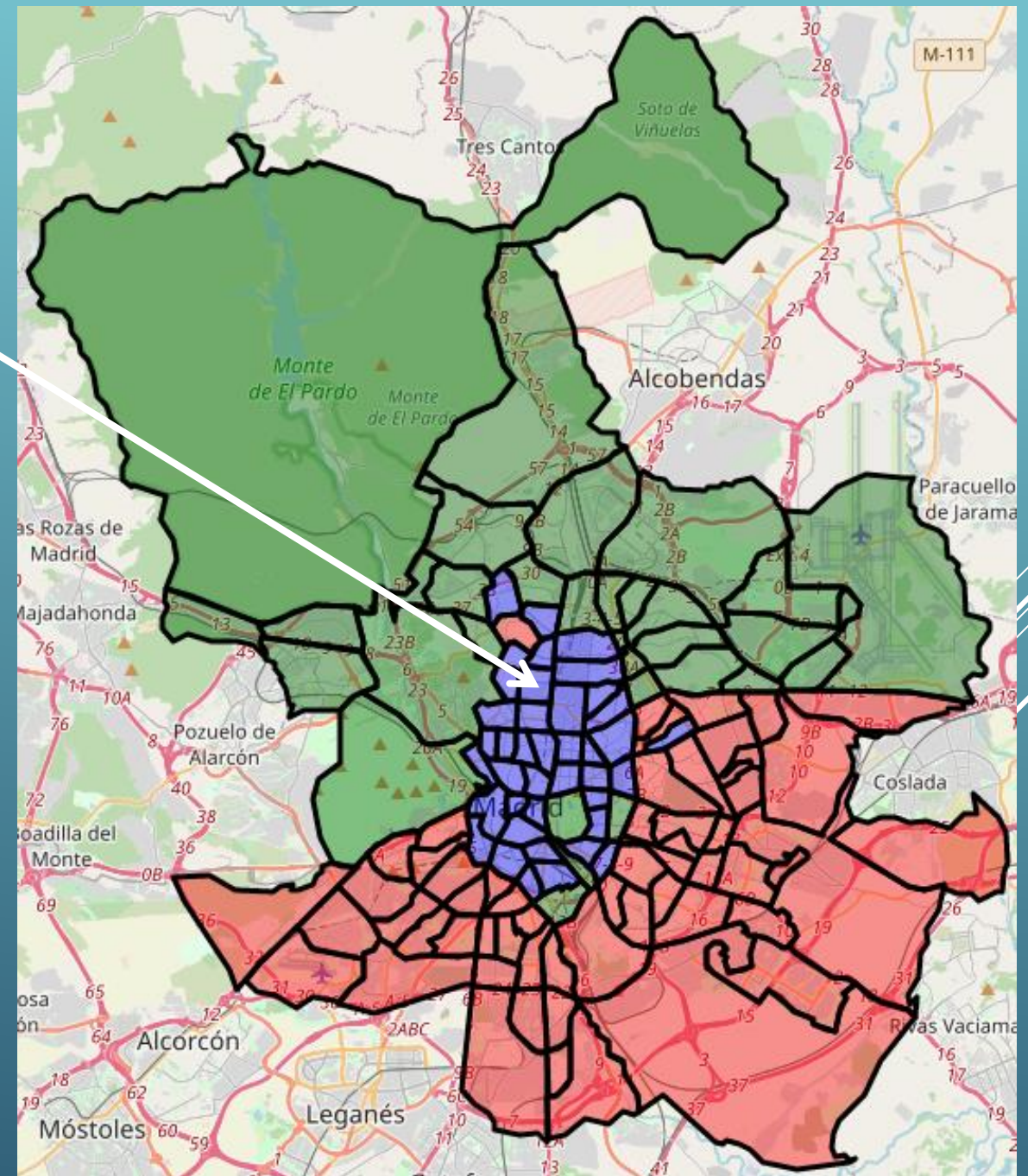




# Evaluation

Neighborhoods in the second cluster (blue in the map):

- Corresponding roughly to the city centre, inside the M-30 orbital motorway, the innermost ring road of the city.
- Highest population density of the three clusters.
- Highest income of the clusters.
- Highest real estate property value, especially for renting property.
- Highest numbers of arrest per capita.
- Plenty of restaurants.

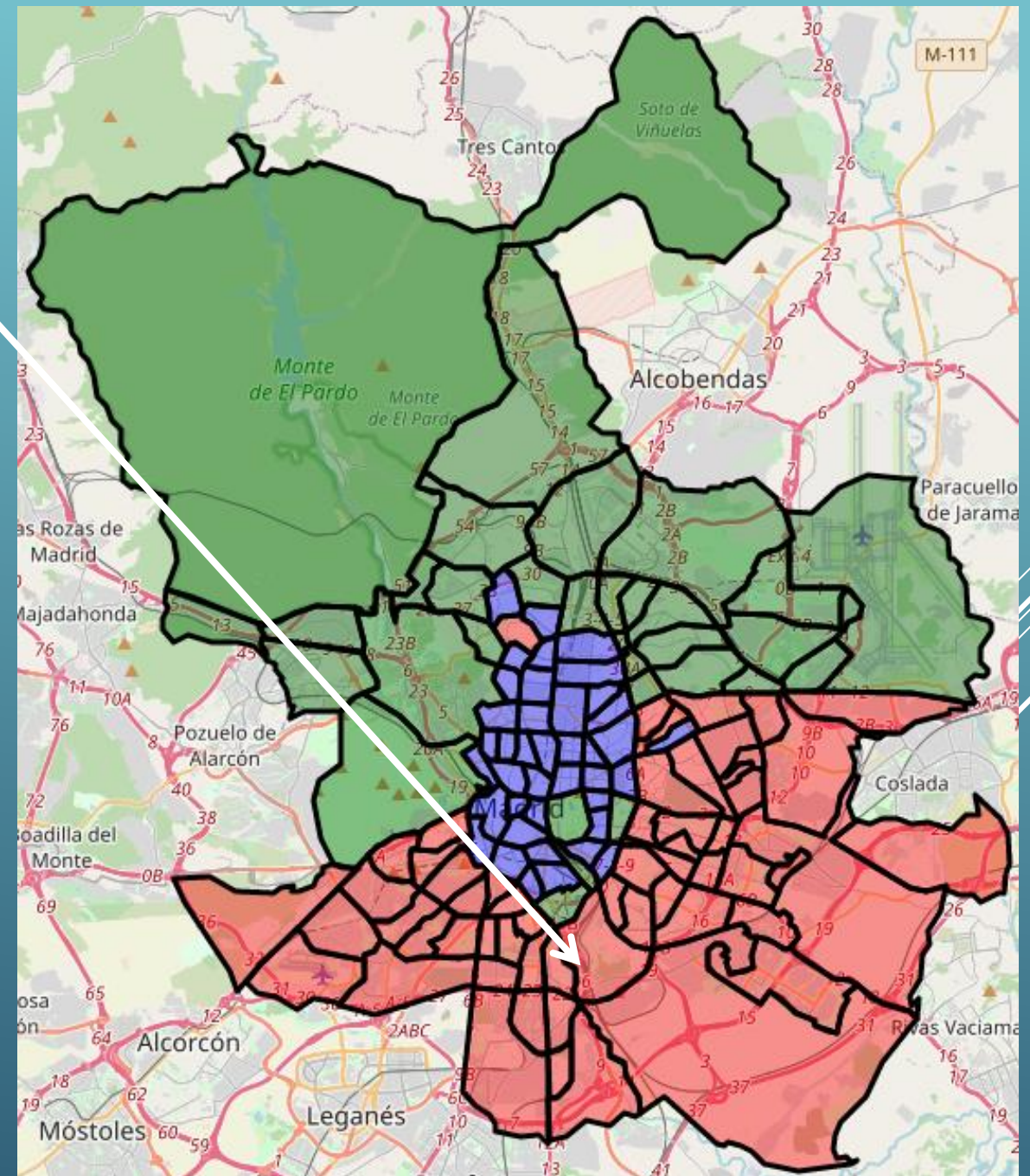




# Evaluation

Neighborhoods in the third cluster (red in the map):

- Southern part of the city, even though there is a neighborhood in the north.
- Moderate population density.
- Lowest prices for buying/selling and renting real estate of the three clusters.
- Moderate number of arrests per capita.
- Very low number of restaurants.



# Conclusion

Main Goal:

**Classify the neighborhoods of Madrid based on socioeconomic and business diversity in order to give information about living conditions in Madrid**

**Data taken from several official sources, realtors and Foursquare**

**The features were used to segment the neighborhoods into three clusters**

Several thin, white, parallel diagonal lines are positioned in the bottom right corner of the slide, extending from the bottom edge towards the right edge.