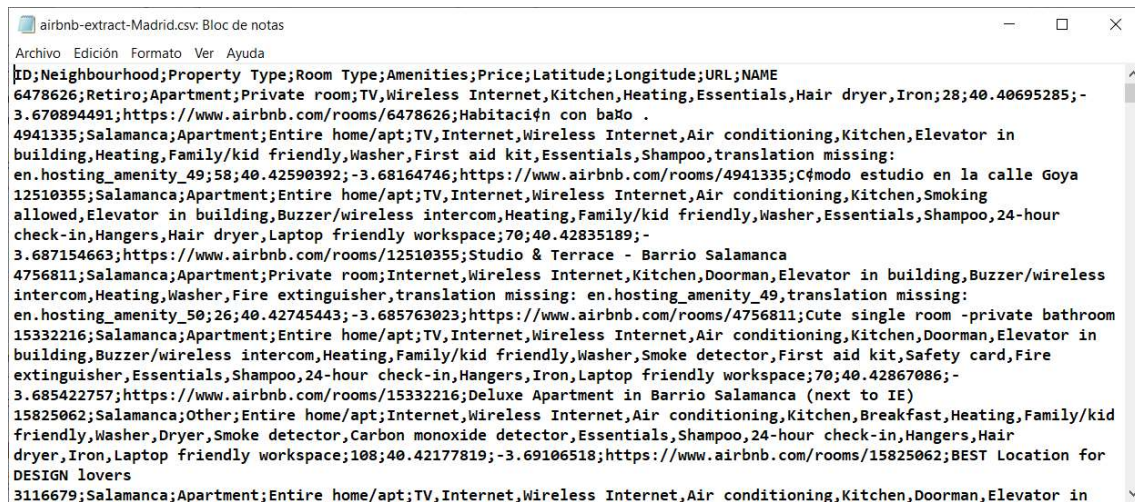


2. Data acquisition and cleaning

2.1 Data Sources

For this purpose, we will use a public Airbnb file in csv format (airbnb-extract-Madrid.csv), which contains information about accommodation in Madrid.



The Dataset contains the following fields: Property ID, Neighborhood, Property Type, Room Type, Amenities, Latitude, Longitude, Property URL, and Property Name.

As far as points of interest near the accommodation are concerned, we will need to use the Foursquare location data.

2.2 Data cleaning

To accommodate our client's requests, we will select only the apartment information that is rented in full

We select only complete rented apartments

```
1 print("Dataset size:", df_Completo.shape)
2 df0 = df_Completo.drop(df_Completo[df_Completo['Property Type'] != "Apartment"].index)
3 df = df0.drop(df0[df0['Room Type'] != "Entire home/apt"].index)
4
5 df.reset_index(drop=True, inplace=True)
6 print("Dimensions of the dataset once the data for Madrid are selected are:", df.shape)
```

Dataset size: (13251, 10)

Dimensions of the dataset once the data for Madrid are selected are: (7013, 10)

By geolocation and from latitude and longitude, the distance to the Prado museum is calculated in the "Dis_Museos" field.

| ID | Neighbourhood | Property Type | Room Type | Amenities | Price | Latitude | Longitude | URL | NAME | Dist_Museos |
|----------|---------------|---------------|-----------------|---|-------|-----------|-----------|---------------------------------------|---|-------------|
| 4941335 | Salamanca | Apartment | Entire homestay | TV,Internet,Wireless Internet,Air conditioning... | 58.0 | 40.420604 | -3.681647 | https://www.airbnb.com/rooms/4941335 | Cómodo estudio en la calle Goya | 1.506048 |
| 12510035 | Salamanca | Apartment | Entire homestay | TV,Internet,Wireless Internet,Air conditioning... | 70.0 | 40.426352 | -3.687155 | https://www.airbnb.com/rooms/12510035 | Studio & Terrace - Urdano Salamanca | 1.667554 |
| 15332216 | Salamanca | Apartment | Entire homestay | TV,Internet,Wireless Internet,Air conditioning... | 70.0 | 40.426671 | -3.685423 | https://www.airbnb.com/rooms/15332216 | Deluxe Apartment in Barrio Salamanca (next to IF) | 1.743295 |
| 3116679 | Salamanca | Apartment | Entire homestay | TV,Internet,Wireless Internet,Air conditioning... | 260.0 | 40.426605 | -3.683705 | https://www.airbnb.com/rooms/3116679 | Elegant & central luxury 3 bedroom apartment | 1.486292 |
| 3962279 | Salamanca | Apartment | Entire homestay | TV,Internet,Wireless Internet,Air conditioning... | 60.0 | 40.426550 | -3.670096 | https://www.airbnb.com/rooms/3962279 | Beautiful apartment in the center | 1.396402 |

And accommodation that is more than a mile away is eliminated.

```

1 print(df.shape)
2 df = df.drop(df[df['Dist_Museos']>=1.5].index)
3 df = df.reset_index(drop=True)
4 df.shape

(7013, 11)
(3404, 11)

```

2.3 Exploratory Data Analysis

As a preliminary step, the presence of null values is studied. It is checked that there is a priceless accommodation. Since the data is essential, and it is only a record, it is carried out to remove it.

```

1 df.isnull().sum()

Neighbourhood    0
Amenities        8
Price            1
Latitude         0
Longitude        0
URL              0
NAME             0
Dist_Museos      0
dtype: int64

```

The eight records without Amenities are maintained. We can't tell if the data is missing or if the property simply doesn't provide it, so the latter option is assumed instead of deleting the records.

Numerical variables

When it comes to numerical variables, we will focus mainly on the price.

First, it checks for outliers

```

1 print(df['Price'].describe())
2 df.plot(kind='box',y='Price',grid=True,figsize=(10,10))
3
4 plt.show()

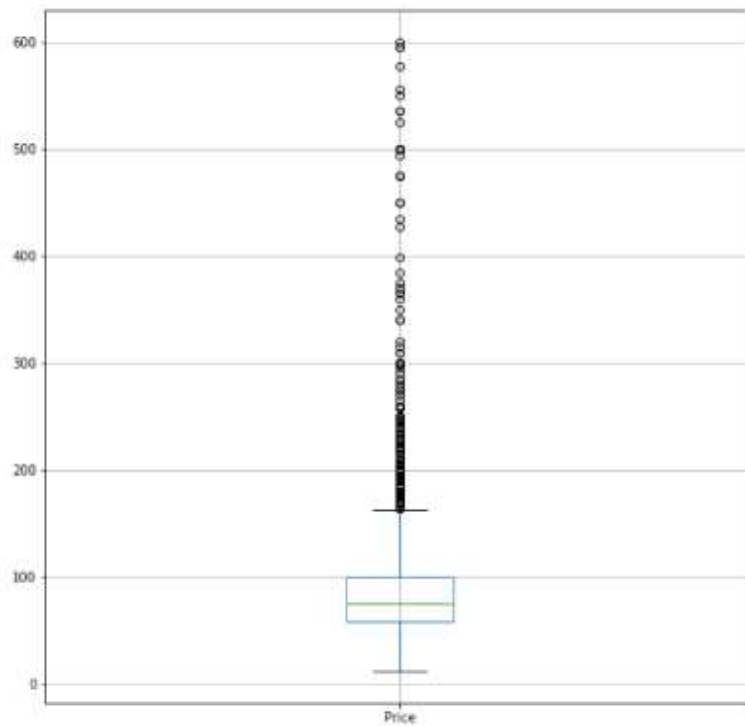
```

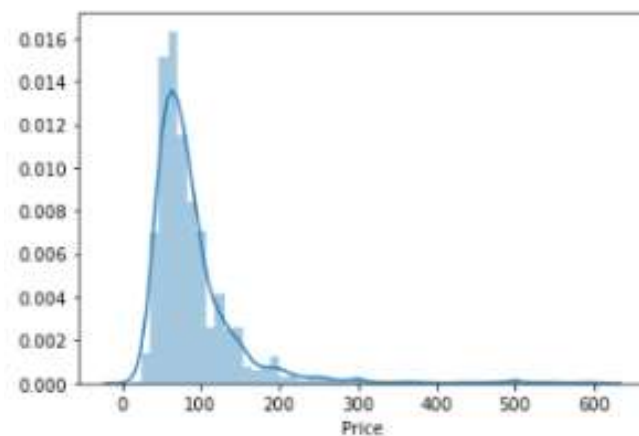
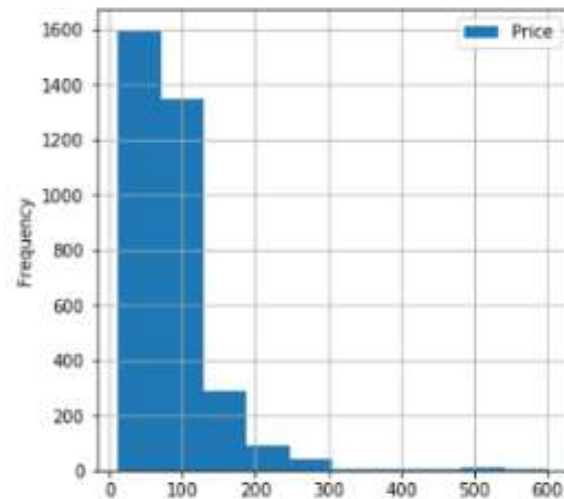
```

count    3403.000000
mean      89.532471
std       58.482222
min       12.000000
25%       58.000000
50%       75.000000
75%      100.000000
max       600.000000
Name: Price, dtype: float64

```

You can see that the distribution is not very balanced. It can be seen more easily graphically by boxplot or through a histogram.





At first glance it is seen that there is a standard deviation from the normal distribution, a positive symmetry and the presence of some peaks is observed.

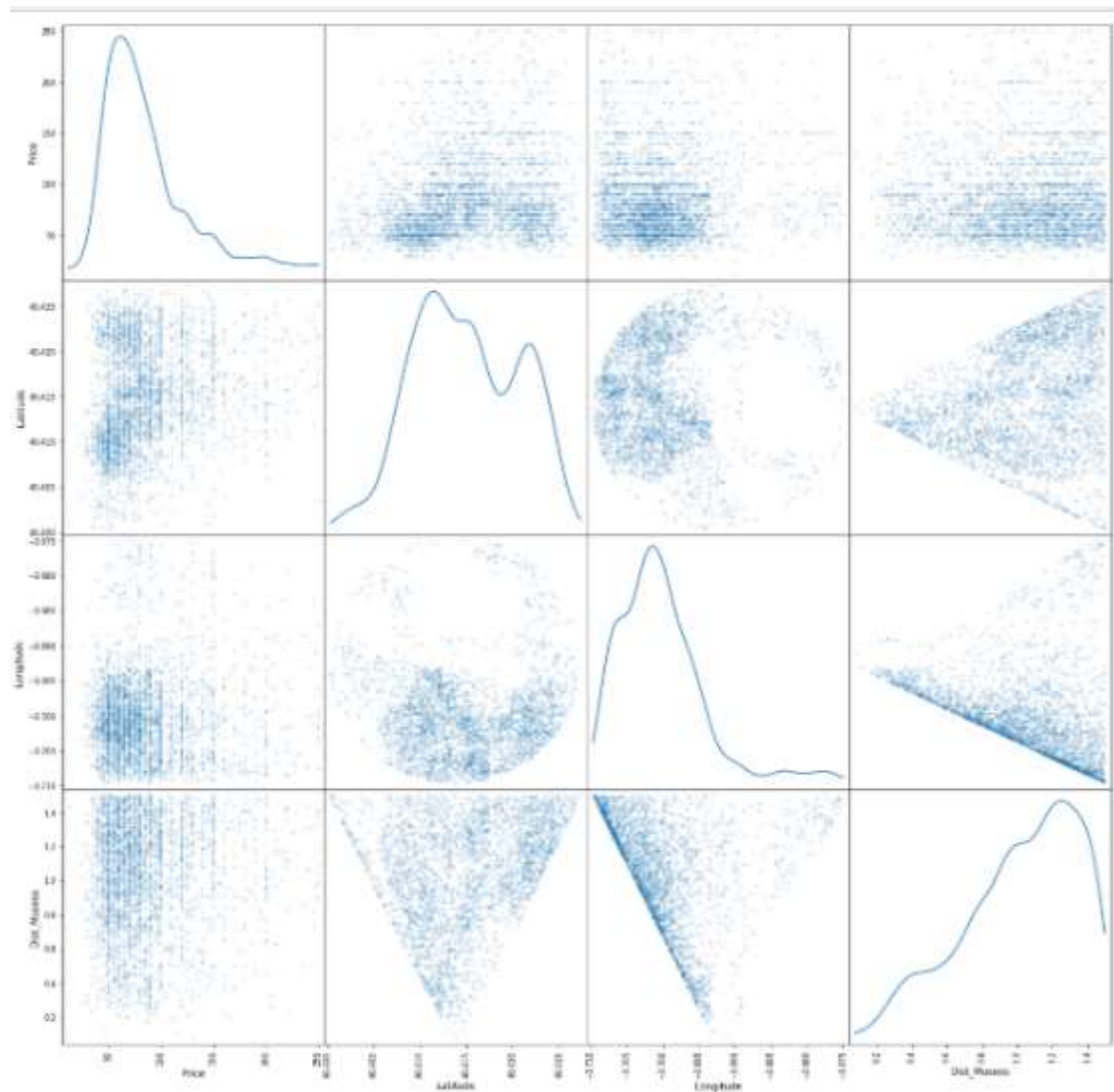
We see that outliers are considered approximately from 180. But it is seen that until approximately 250 there is a large group of values.

We check how many values are above 250 price and it is decided to work only with these values so that you don't have too distorted results.

Study of correlations and distribution of data

Correlations are then studied and the distribution of the data is checked. In case there is too correlated data, we would have to study whether any of the variables are removed from the problem when running our model, but you can verify that this is not the case and the correlation between the data is scarce, and the distribution of the data is adjusted to what you would expect.

| | Price |
|-------------|-----------|
| Price | 1 |
| Latitude | 0.194602 |
| Longitude | 0.0334467 |
| Dist_Museos | 0.0328302 |



Categorical data

The ID of the accommodation, as well as the name and URL of the same is not of interest to the study that we are going to carry out (except its use as tags to display them on the map), but they are not necessary (rather the opposite) or to perform clustering or to obtain the venues.

That's why it's only worked with Neighbourhoods information and amenities.

Working with Amenities

The 'Amenities' field does have important information,

Amenities are saved separated by commas, and that we will study with basic NLP techniques.

We are going to eliminate the fields that the client has not asked for, and regarding what he has asked us, we will make combinations of values. For example, if we are interested in information about whether or not there is internet access, we will combine fields such as "Internet" and "Wireless Internet", or in the case of whether the home is child-friendly, we will combine information about whether it has games or books to children, if you have a high chair, etc.

```
df_am['Pets']=(df_am['CATS'].astype(bool)) | (df_am['DOGS'].astype(bool)) | (df_am['OTHER PETS'].astype(bool)) |
(df_am['PETS ALLOWED'].astype(bool)) |(df_am['PETS LIVE ON THIS PROPERTY'].astype(bool))
```

```
df_am_to_drop=['CATS','DOGS','OTHER PETS','PETS ALLOWED','PETS LIVE ON THIS PROPERTY']
```

```
df_am['InternetAccess']=(df_am['INTERNET'].astype(bool)) | (df_am['WIRELESS INTERNET'].astype(bool))
```

Finalmente, nos quedamos solo con los datos que nos han solicitado:

| | ESSENTIALS | KITCHEN | SMOKING ALLOWED | WHEELCHAIR ACCESSIBLE | Pets | InternetAccess | TempControl | KidsFriendly |
|---|------------|---------|-----------------|-----------------------|------|----------------|-------------|--------------|
| 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 |
| 2 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| 3 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| 4 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |

Working with Neighbourhoods

If we analyze the distribution of values in this field, the result obtained is as follows:

```
Centro          3003
Arganzuela      131
Retiro          115
Salamanca       79
Chamberí        6
Name: Neighbourhood, dtype: int64
```

This leads us to believe that when we do clustering, the neighborhood will not influence much, as the vast majority of the accommodations will be in the Centro district.

Since the K-means algorithm does not work with categorical data, we will apply one-hot encoding to this field.

This is the result:

| | Arganzuela | Centro | Chamberí | Retiro | Salamanca |
|----|------------|--------|----------|--------|-----------|
| 0 | 0 | 0 | 1 | 0 | 0 |
| 1 | 1 | 0 | 0 | 0 | 0 |
| 2 | 1 | 0 | 0 | 0 | 0 |
| 3 | 1 | 0 | 0 | 0 | 0 |
| 4 | 0 | 1 | 0 | 0 | 0 |
| 5 | 0 | 1 | 0 | 0 | 0 |
| 6 | 0 | 1 | 0 | 0 | 0 |
| 7 | 0 | 1 | 0 | 0 | 0 |
| 8 | 0 | 1 | 0 | 0 | 0 |
| 9 | 0 | 1 | 0 | 0 | 0 |
| 10 | 0 | 1 | 0 | 0 | 0 |
| 11 | 0 | 1 | 0 | 0 | 0 |
| 12 | 0 | 1 | 0 | 0 | 0 |

To explore the points of interest of each neighborhood, we will use the library **Foursquare**. We will define Foursquare Credentials and Version and obtain ten venues for each propertie.

| | neighbourhood | 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 |
|---|---------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|-----------------------|--------------------------|-----------------------|------------------------|
| 0 | Arganzuela | Tapas Restaurant | Restaurant | Beer Garden | Bakery | Coffee Shop | Museum | Chinese Restaurant | Mediterranean Restaurant | Café | Market |
| 1 | Centro | Plaza | Hotel | Hostel | Tapas Restaurant | Gourmet Shop | Wine Bar | Ice Cream Shop | French Restaurant | Bistro | Restaurant |
| 2 | Chamberí | Tapas Restaurant | Spanish Restaurant | Bar | Restaurant | Café | Theater | Plaza | Bakery | Gastropub | Coffee Shop |
| 3 | Retiro | Spanish Restaurant | Bar | Grocery Store | Art Gallery | Tapas Restaurant | Supermarket | Burger Joint | Indian Restaurant | Museum | Mexican Restaurant |
| 4 | Salamanca | Spanish Restaurant | Restaurant | Bar | Hotel | Plaza | Burger Joint | Grocery Store | Seafood Restaurant | Gymnastics Gym | Bakery |