Seattle: Data Analysis of the city

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1. Introduction: Description and purpose of this project

Seattle is a seaport city on the West Coast of the United States. Seattle is the largest city in both the state of Washington and the Pacific Northwest region of North America. According to U.S. Census data released in 2019, the Seattle metropolitan area's population stands at 3.98 million, making it the 15th-largest in the United States.

In this data analysis of the city of Seattle, the objective will be to find patterns within it using data. Firstly, this research starts analyzing which are the most affected areas by Fire Alarms and if this is related with the population rate in these areas. Secondly, it is also possible to connect the employment ratio with the crime one. Usually, neighborhoods with more business and nearer to the city centre tend to have a higher number of incidents. Let's see if Seattle follows this trend.

Gathering all these concerns, it would be possible to create maps and information charts for the city of Seattle.

Finally, this project will end up in exploring each of the neighborhoods so as to find clusters in which they can be placed. To this aim, this clustering will be based on the top venues hold in each of the districts. Therefore, different types of venues will be found, spotting the trending ones in each borough.

1.1. Tools that will help in the development of this project

1. python libraries:
   - **Data Wrangling and Manipulation**: pandas
   - **Modeling**: scikit-learn, numpy
   - **Web scraping**: requests, geopy
   - **Visualization**: matplotlib, seaborn, folium, pywaffle, wordcloud, PIL

2. **Foursquare API**: Tool to obtain the location data of the main venues in each neighborhood.

2. Data Description

These are the data sources we will use for working on this project:

- **seattle-neighborhoods.geojson** (1) -> geojson data needed to conform the choropleth maps.

- **Seattle_Census_Data.csv** (2) -> Data of the population of Seattle per neighborhood.

- **Seattle_Employement_Data.csv** (3) -> Data of the employment in Seattle per neighborhood.

- **Seattle_Real_Time_Fire_911_Calls_Last500.csv** (3) -> Last 500 Fire 911 Calls in the city of Seattle.

- **SPD_Crime_Data_2020_Last500.csv** (3) -> Last 500 crimes committed reported by the Seattle Police Department in the city of Seattle.

- **Foursquare API** (4) -> To get the most common venues of the Boroughs of Seattle.

Please Note: This data has been cleaned from the root sources since they were holding unnecessary information.

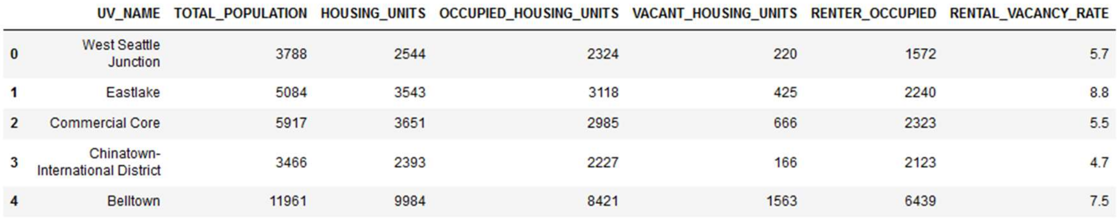
3. Methodology

During this section it will be discussed and described all the exploratory data analysis that were performed in this project. Statistical approaches will be used to test read data, and what machine learnings were used and why.

3.1. Importing & Exploring all the data for the project

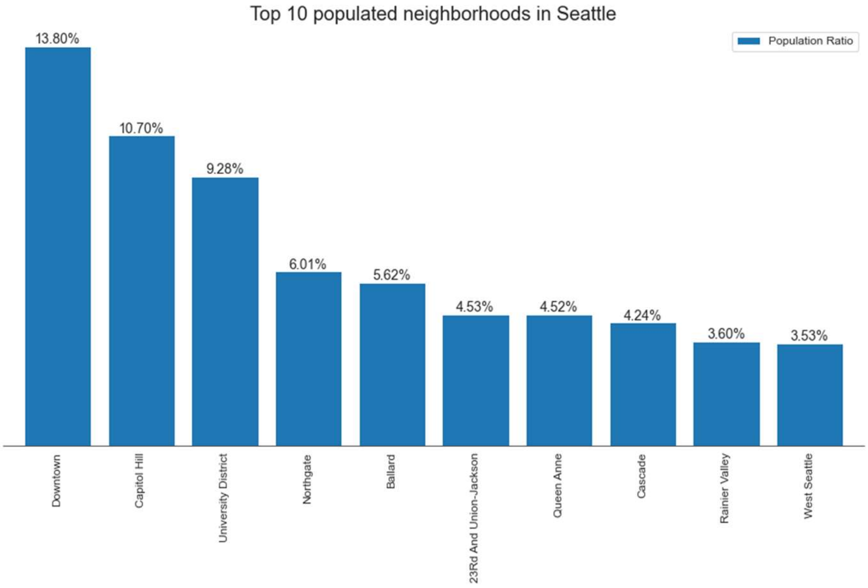
Importing all the main packages for the project:

3.1.1. Reading Seattle Census Data



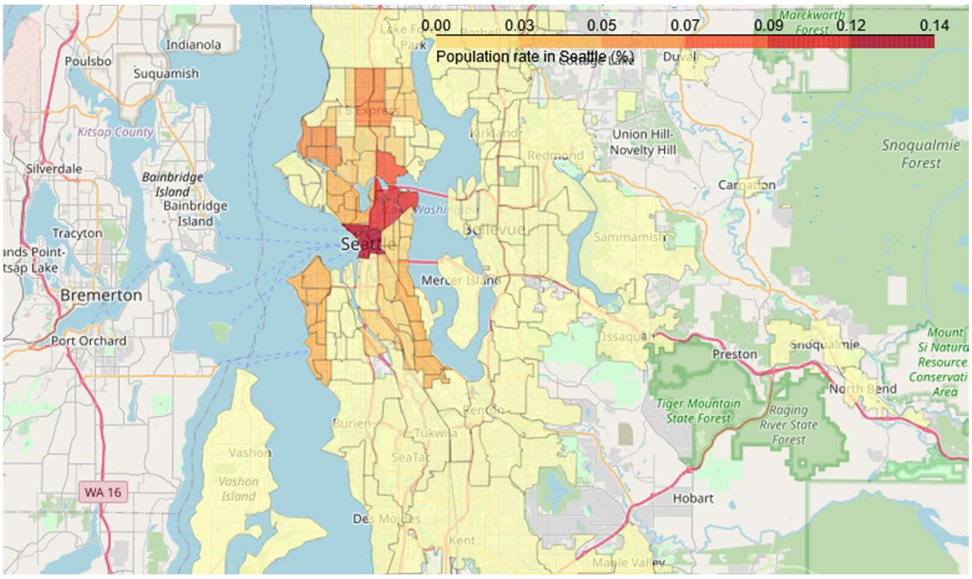
	UV_NAME	TOTAL_POPULATION	HOUSING_UNITS	OCCUPIED_HOUSING_UNITS	VACANT_HOUSING_UNITS	RENTER_OCCUPIED	RENTAL_VACANCY_RATE
0	West Seattle Junction	3788	2544	2324	220	1572	5.7
1	Eastlake	5084	3543	3118	425	2240	8.8
2	Commercial Core	5917	3651	2985	666	2323	5.5
3	Chinatown-International District	3466	2393	2227	166	2123	4.7
4	Belltown	11961	9984	8421	1563	6439	7.5

After reading the data with pandas, I calculated the “Population_Ratio” by standardizing the values. To this aim, the ratio was conformed using the percentage of contribution of each neighborhood to the city. This resulted in the bar chart showed below:

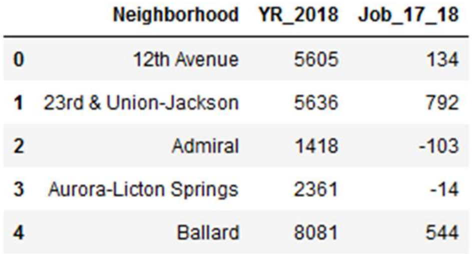


From the above bar chart, it is easy to spot that most of the population lives nearby the city centre, specifically in Downtown Seattle and Capitol Hill.

Let's see how this data is displayed on Seattle's map:



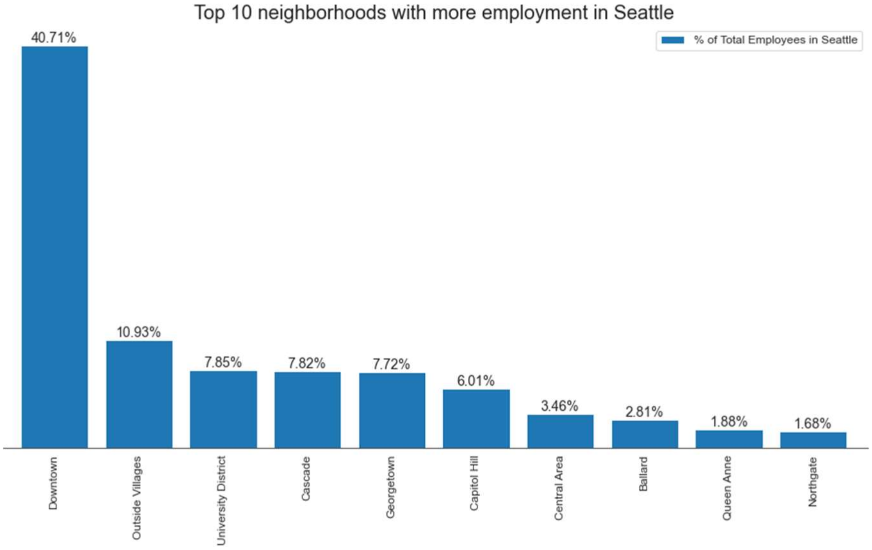
3.1.2 Reading Seattle Employment Data



	Neighborhood	YR_2018	Job_17_18
0	12th Avenue	5605	134
1	23rd & Union-Jackson	5636	792
2	Admiral	1418	-103
3	Aurora-Licton Springs	2361	-14
4	Ballard	8081	544

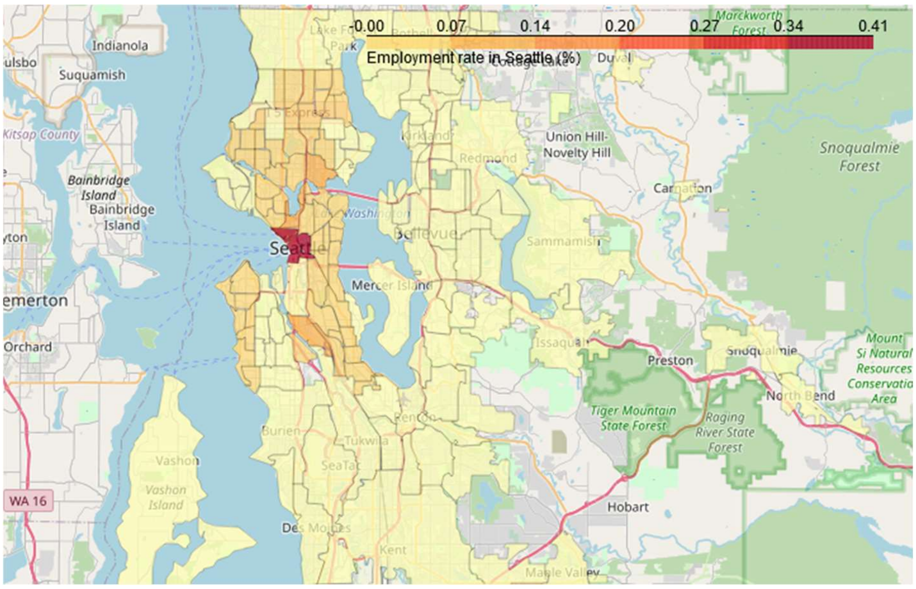
In this dataset we can find "YR_2018", which is the number of employees register per district in 2018.

After reading the data with pandas, I calculated the "Employment_Ratio" by standardizing the values. To this aim, the ratio was conformed using the percentage of contribution of each neighborhood to the city. This resulted in the bar chart showed below:



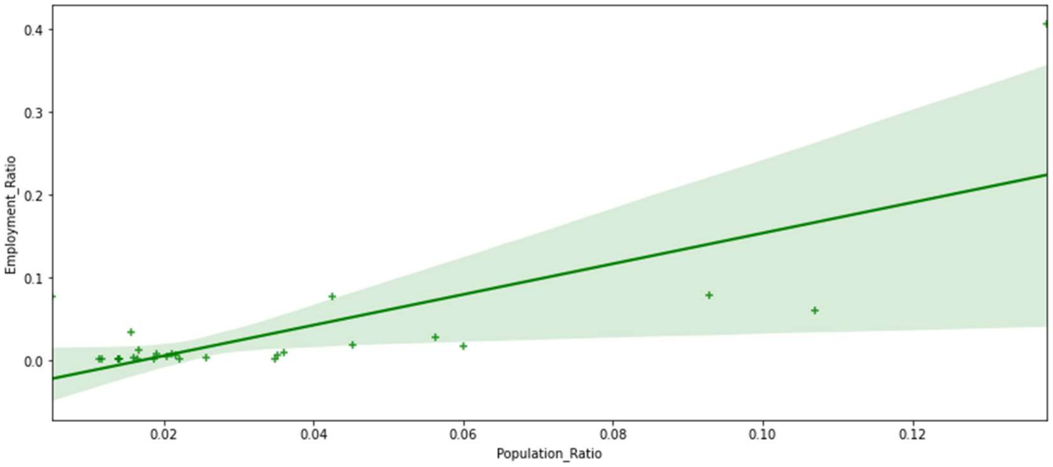
This employment ratio chart gives us an expected insight. It is due to the fact that the most employed neighborhoods are those located nearer to the city centre, so that is why Downtown holds more than the 40% of the active population of Seattle.

Let's see how this data is displayed on Seattle's map:

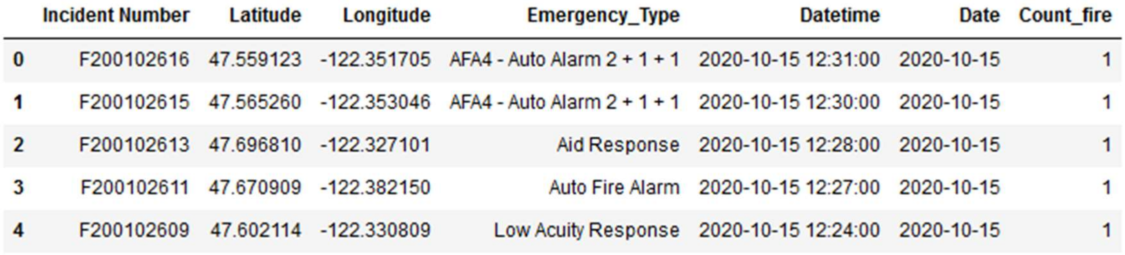


Correlation between the Population_Ratio and the Employment_Ratio in the city of Seattle

As we can see in this regression plot, population and employment have a strong positive correlation, which makes common sense:



3.1.3. Reading Seattle Fire 911 Calls Data

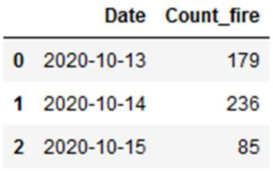


	Incident Number	Latitude	Longitude	Emergency_Type	Datetime	Date	Count_fire
0	F200102616	47.559123	-122.351705	AFA4 - Auto Alarm 2 + 1 + 1	2020-10-15 12:31:00	2020-10-15	1
1	F200102615	47.565260	-122.353046	AFA4 - Auto Alarm 2 + 1 + 1	2020-10-15 12:30:00	2020-10-15	1
2	F200102613	47.696810	-122.327101	Aid Response	2020-10-15 12:28:00	2020-10-15	1
3	F200102611	47.670909	-122.382150	Auto Fire Alarm	2020-10-15 12:27:00	2020-10-15	1
4	F200102609	47.602114	-122.330809	Low Acuity Response	2020-10-15 12:24:00	2020-10-15	1

When reading this data, “Data” and “Count_fire” columns were missing. Using pandas library, we added these last two columns which will be essential for our analysis in the methodology section.

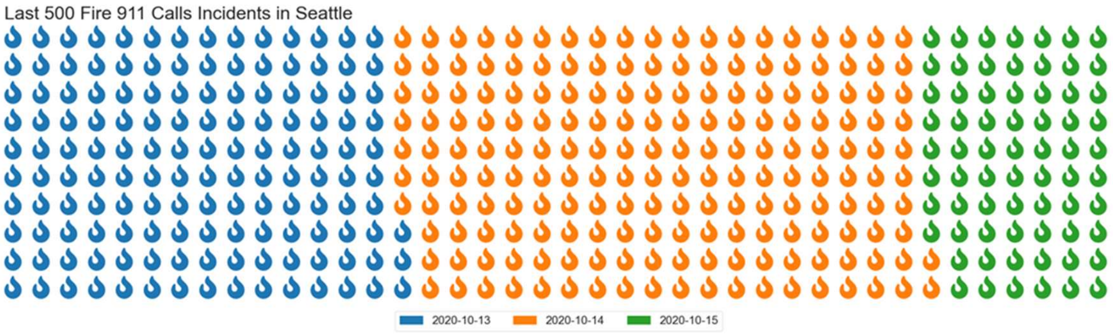
Creating a Waffle to show the number of incident calls

We grouped the data to be easily used by pywaffle:



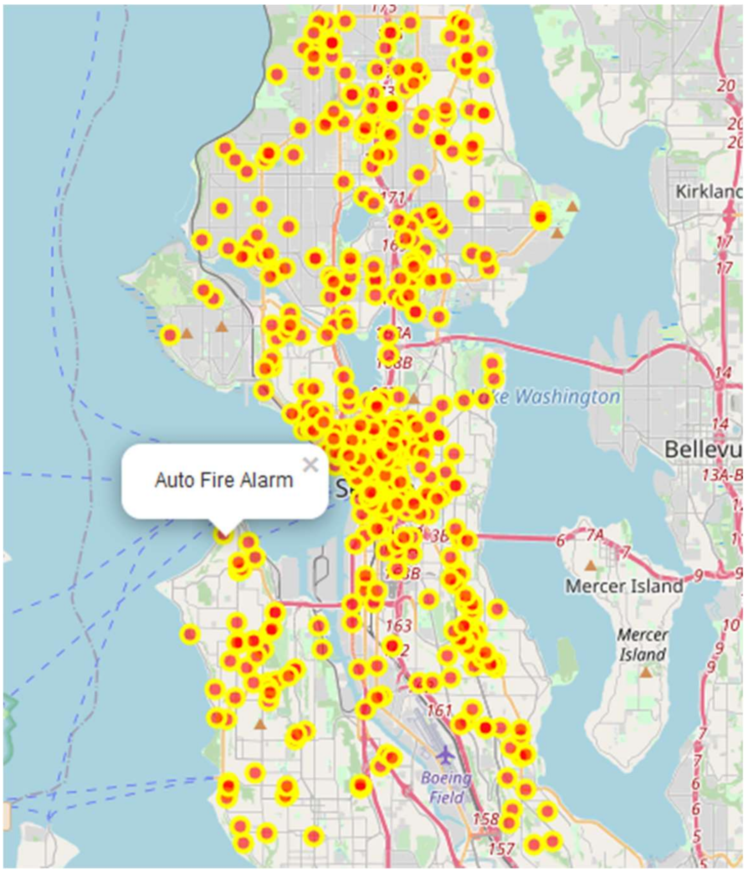
	Date	Count_fire
0	2020-10-13	179
1	2020-10-14	236
2	2020-10-15	85

In the data frame, it is detailed that the last 500 fire 911 calls were made in 3 days.



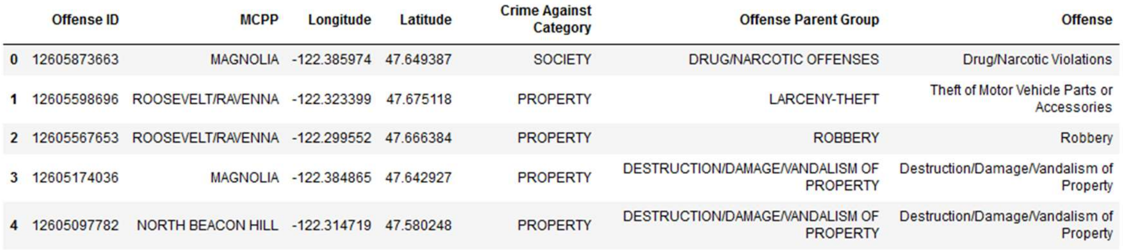
From the Waffle Chart above, it is easy to spot the day in which the 911 service received more calls from Seattle citizens. Therefore, as we can also affirm from the grouped data frame, the day with more incidents was the 14th of October of 2020.

Let’s also visualize this data on a map, so we can have a look where most of the incidents took place:



As we can see in the map, most of the fire incidents are located in those areas with the highest population ratio, which makes sense since there are more housing units and local businesses.

3.1.4. Reading SPD Crime Data

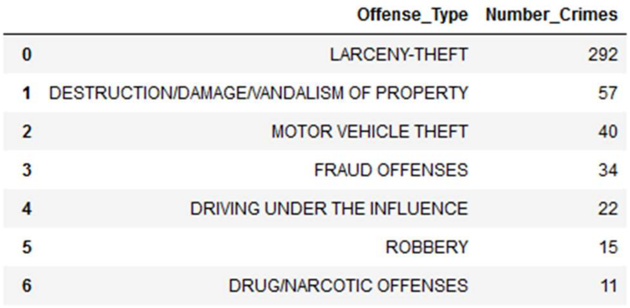


	Offense ID	MCPP	Longitude	Latitude	Crime Against Category	Offense Parent Group	Offense
0	12605873663	MAGNOLIA	-122.385974	47.649387	SOCIETY	DRUG/NARCOTIC OFFENSES	Drug/Narcotic Violations
1	12605598696	ROOSEVELT/RAVENNA	-122.323399	47.675118	PROPERTY	LARCENY-THEFT	Theft of Motor Vehicle Parts or Accessories
2	12605567653	ROOSEVELT/RAVENNA	-122.299552	47.666384	PROPERTY	ROBBERY	Robbery
3	12605174036	MAGNOLIA	-122.384865	47.642927	PROPERTY	DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY	Destruction/Damage/Vandalism of Property
4	12605097782	NORTH BEACON HILL	-122.314719	47.580248	PROPERTY	DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY	Destruction/Damage/Vandalism of Property

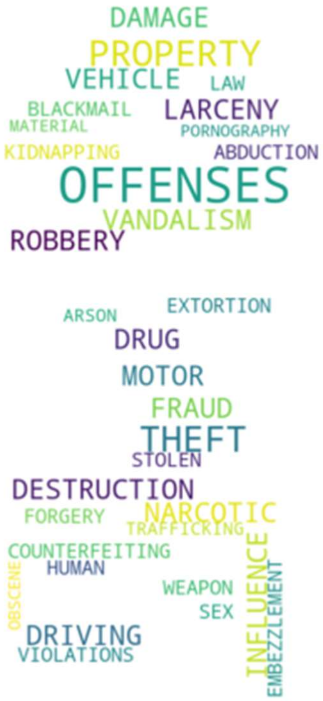
In this case, we will use a different method to have a quick view of the data. To this aim, a word cloud will be plotted to see which crimes are the most common in a quick glance.

Creating a Word Cloud to show the most common crimes in Seattle

Firstly, we will group the data using pandas in order to have the adequate format to be used by the word cloud:



	Offense_Type	Number_Crimes
0	LARCENY-THEFT	292
1	DESTRUCTION/DAMAGE/VANDALISM OF PROPERTY	57
2	MOTOR VEHICLE THEFT	40
3	FRAUD OFFENSES	34
4	DRIVING UNDER THE INFLUENCE	22
5	ROBBERY	15
6	DRUG/NARCOTIC OFFENSES	11

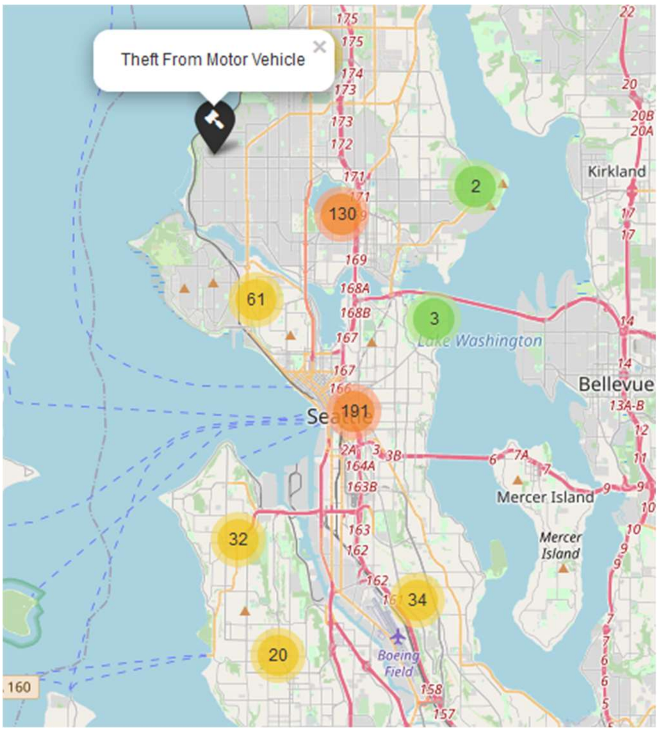


To plot the word cloud, I used a template of the map of Seattle so as to place this analysis in context. From the word cloud it is possible to deduce the most common reported crimes in the city of Seattle by its Police Department. Therefore, among the most common incidents that could be highlighted, we can find:

- Offenses
- Theft / Larceny
- Robbery
- Vandalism
- Destruction

Creating a cluster map plot for the Crimes committed in Seattle

To build this map, the folium library was used and all the incidents were grouped using a clustering visualization based on proximity of nodes:



In this map, we find a similar figure as with the Fire incidents map. Those neighborhoods with the highest population and employment ratio are the ones which holds most of the criminality of Seattle. What is more, the top offenders in this city are Downtown Seattle and First Hill, which are located in the city centre.

It is also important to remark the impact of crimes in the north area of the city, especially in the whereabouts of Green Lake and Woodland Park. However, Madison Park presumes to be the most secure district, holding only 3 incidents out of the last 500 reported by Seattle Police Department.

3.2. Process to cluster neighborhoods in Seattle based on top venues

After cleaning the dataset and defining a new df (df_seattle), we will start exploring and analysing the df venues following this process:

- Exploring each neighborhood in Seattle
  - Cleaning the dataset.
  - Defining a function to obtain all the data from venues.
  - Define the credentials to Foursquare.

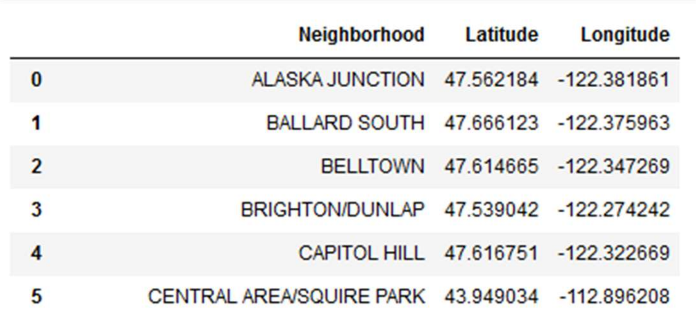
- Getting the venues per neighborhood.
  - Analyse each neighborhood: Top 10 venues.

Finally, moving to the results section:

- Clustering Seattle's neighborhoods.
  - Examine Seattle's clusters.

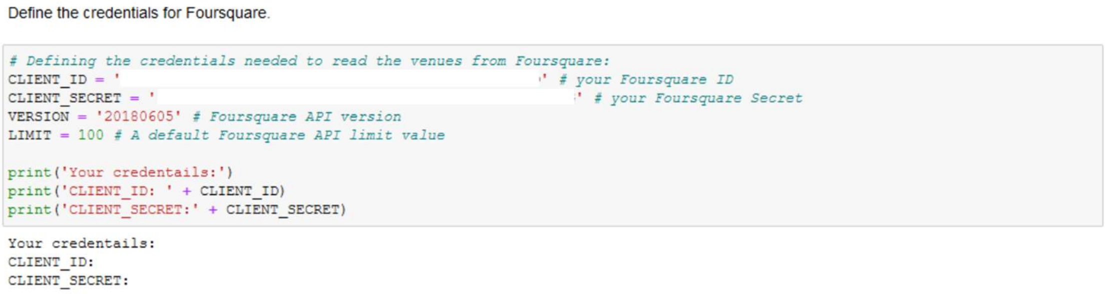
3.2.1. Exploring each neighborhood in Seattle

This process starts by cleaning the dataset and defining the “df_seattle” before working on it. It contains the coordinates (latitude, longitude) of each of the 41 neighborhoods in Seattle that we will use to build the model:



	Neighborhood	Latitude	Longitude
0	ALASKA JUNCTION	47.562184	-122.381861
1	BALLARD SOUTH	47.666123	-122.375963
2	BELLTOWN	47.614665	-122.347269
3	BRIGHTON/DUNLAP	47.539042	-122.274242
4	CAPITOL HILL	47.616751	-122.322669
5	CENTRAL AREA/SQUIRE PARK	43.949034	-112.896208

It is time to initialize the connection to the Foursquare API, providing our credentials:



Define the credentials for Foursquare.

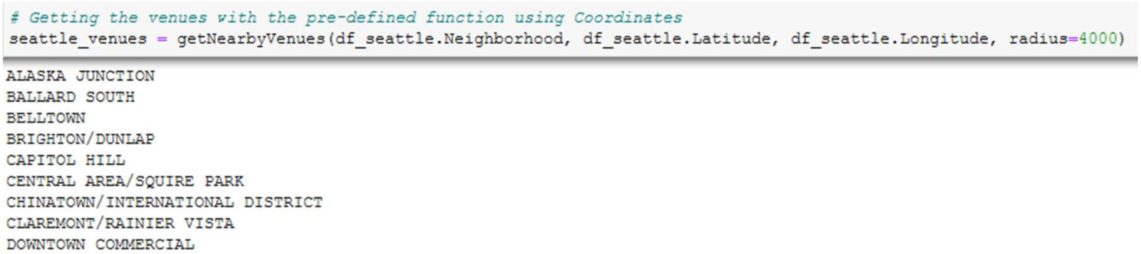
```
# Defining the credentials needed to read the venues from Foursquare:
CLIENT_ID = '[redacted]' # your Foursquare ID
CLIENT_SECRET = '[redacted]' # your Foursquare Secret
VERSION = '20180605' # Foursquare API version
LIMIT = 100 # A default Foursquare API limit value

print('Your credentails:')
print('CLIENT_ID: ' + CLIENT_ID)
print('CLIENT_SECRET:' + CLIENT_SECRET)
```

```
Your credentails:
CLIENT_ID:
CLIENT_SECRET:
```

3.2.2. Getting the venues per Neighborhood

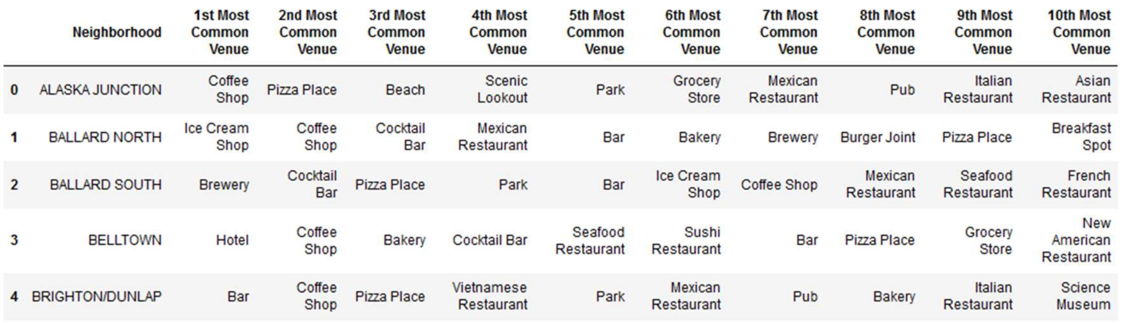
A function was built (“getNearbyVenues”) to extract all the venues around each borough:



```
# Getting the venues with the pre-defined function using Coordinates
seattle_venues = getNearbyVenues(df_seattle.Neighborhood, df_seattle.Latitude, df_seattle.Longitude, radius=4000)
```

```
ALASKA JUNCTION
BALLARD SOUTH
BELLTOWN
BRIGHTON/DUNLAP
CAPITOL HILL
CENTRAL AREA/SQUIRE PARK
CHINATOWN/INTERNATIONAL DISTRICT
CLAREMONT/RAINIER VISTA
DOWNTOWN COMMERCIAL
```

After manipulating the data, we obtain a data frame with 242 unique venues categories. The table below shows the top 10 most common venues per borough:



	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
0	ALASKA JUNCTION	Coffee Shop	Pizza Place	Beach	Scenic Lookout	Park	Grocery Store	Mexican Restaurant	Pub	Italian Restaurant	Asian Restaurant
1	BALLARD NORTH	Ice Cream Shop	Coffee Shop	Cocktail Bar	Mexican Restaurant	Bar	Bakery	Brewery	Burger Joint	Pizza Place	Breakfast Spot
2	BALLARD SOUTH	Brewery	Cocktail Bar	Pizza Place	Park	Bar	Ice Cream Shop	Coffee Shop	Mexican Restaurant	Seafood Restaurant	French Restaurant
3	BELLTOWN	Hotel	Coffee Shop	Bakery	Cocktail Bar	Seafood Restaurant	Sushi Restaurant	Bar	Pizza Place	Grocery Store	New American Restaurant
4	BRIGHTON/DUNLAP	Bar	Coffee Shop	Pizza Place	Vietnamese Restaurant	Park	Mexican Restaurant	Pub	Bakery	Italian Restaurant	Science Museum

3.2.4. Clustering Seattle's neighborhoods

The analysis of each neighborhood will be carried out using the clustering technique that consists of exploring and reviewing the neighborhoods, segmenting them and finally grouping them into clusters to obtain the results.

To this aim, a K-Means algorithm will be used. This is a specialized unsupervised Machine Learning model for clustering analysis for handling clustered data. It takes a bunch of nearest points and uses them to learn how to label other cases, so it classifies cases based on their similarity.

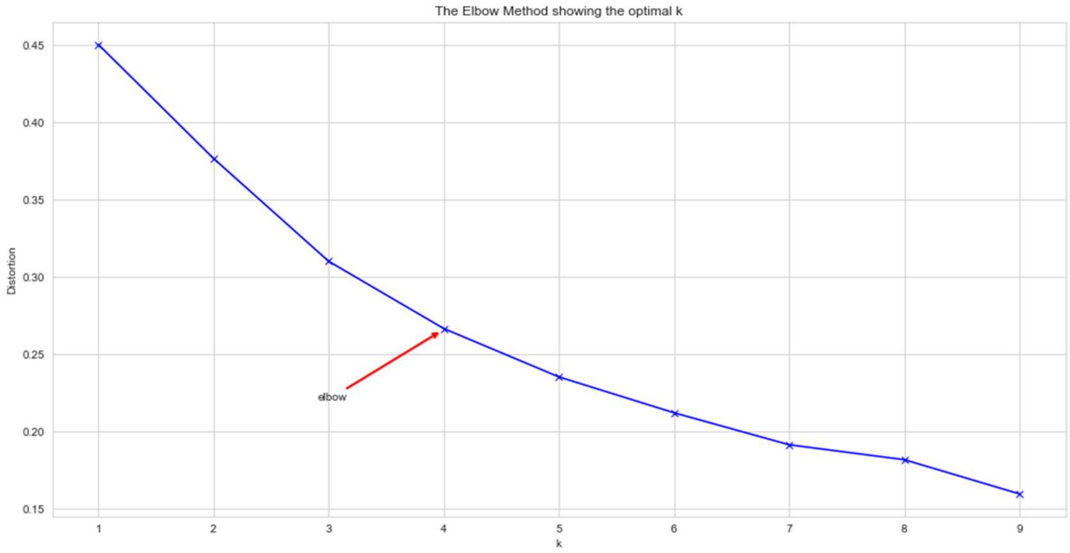
K-Means Elbow Method: Deciding the best value for k (num_clusters)

K-Means is an unsupervised machine learning algorithm that groups data into k number of clusters. The number of clusters is user-defined and the algorithm will try to group the data even if this number is not optimal for the specific case.

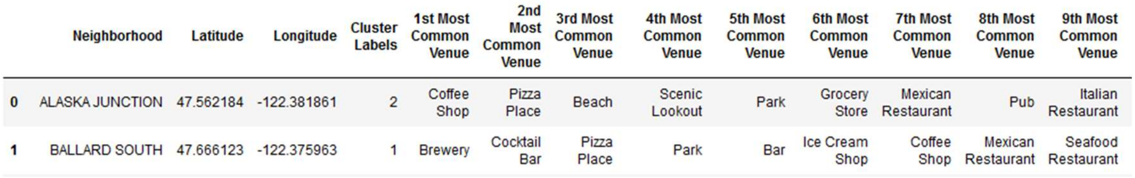
Therefore, we have to come up with a technique that somehow will help us decide how many clusters we should use for the K-Means model.

The Elbow method is a very popular technique and the idea is to run k-means clustering for a range of clusters k (let’s say from 1 to 10) and for each value, we are calculating the sum of squared distances from each point to its assigned center(distortions).

When the distortions are plotted and the plot looks like an arm then the “elbow” (the point of inflection on the curve) is the best value of k.



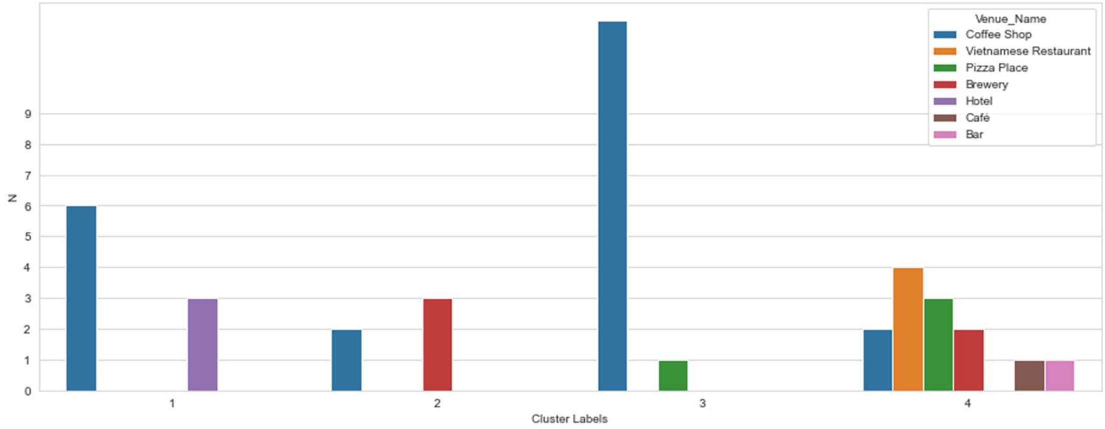
Therefore, the “elbow” is the number 4 which is optimal for this case. Now we can run a K-Means using 4 as the number of clusters.



	Neighborhood	Latitude	Longitude	Cluster Labels	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
0	ALASKA JUNCTION	47.562184	-122.381861	2	Coffee Shop	Pizza Place	Beach	Scenic Lookout	Park	Grocery Store	Mexican Restaurant	Pub	Italian Restaurant
1	BALLARD SOUTH	47.666123	-122.375963	1	Brewery	Cocktail Bar	Pizza Place	Park	Bar	Ice Cream Shop	Coffee Shop	Mexican Restaurant	Seafood Restaurant

Defining the Clusters' Names

We create a bar chart to see the number of times a venue appears in one cluster as "1st Most Common Venue".



Labels for each cluster can be determined once the graph above is examined:

- **Cluster 1**: "Hotels Venues"
- **Cluster 2**: "Brewery Venues"
- **Cluster 3**: "Coffee Shop Venues"
- **Cluster 4**: "Restaurants & Bars Venues"

4. Results

In this section, the previous information will be merge into final plots. This will consist of elaborating a quick view of the details from the dataset used in this project, after the exploratory data analysis it was done in the methodology section. This is the index for the results section:

- Plotting Relation Maps in Seattle:
  - Fire 911 Calls reported: Plotted on the population choropleth map.
  - SPD Crimes reported: Plotted on the employment choropleth map.
- Mapping the venues' clusters on the city of Seattle:
  - Creating the map visualization.
  - Examine Seattle's neighborhoods.

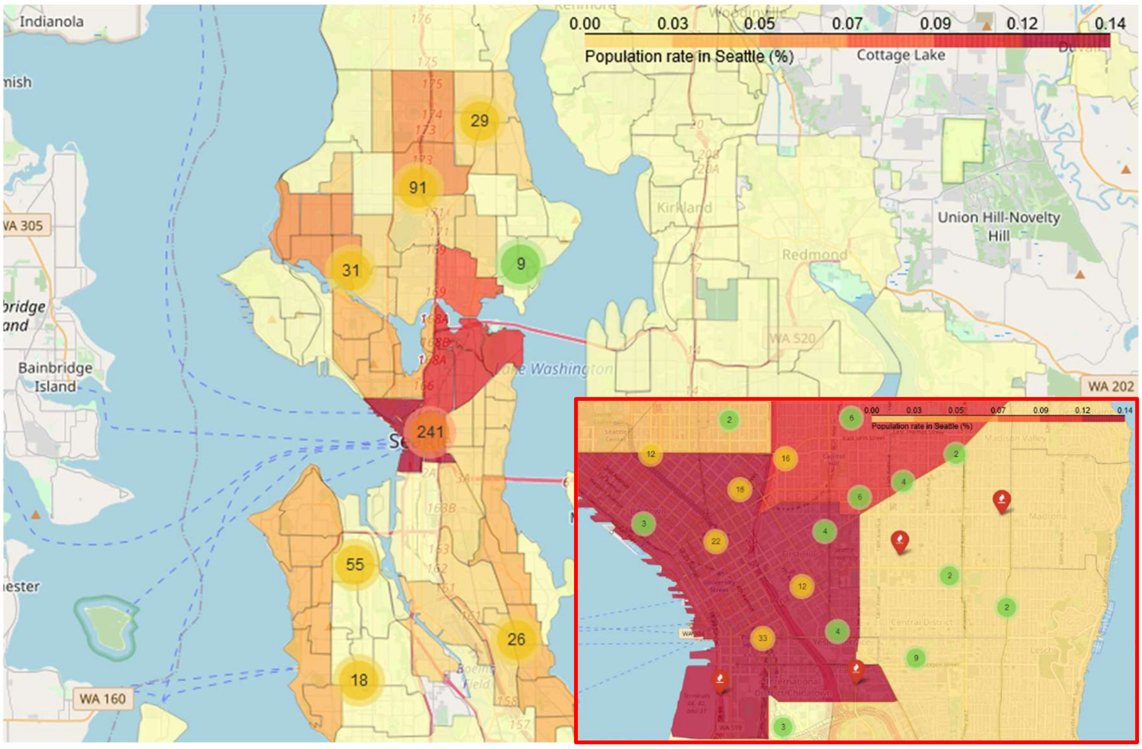
This analysis will provide a better understanding of the city of Seattle.

4.1. Plotting Relational Maps in Seattle

In this section, the previous maps exposed will be merged in order to find more insightful conclusions. Therefore, two maps will be plotted according to the estimated relation that some factors can have:

- **Population map** (Choropleth map) + **Fire map** (Map with Markers).
- **Employment map** (Choropleth map) + **Crime map** (Cluster Map).

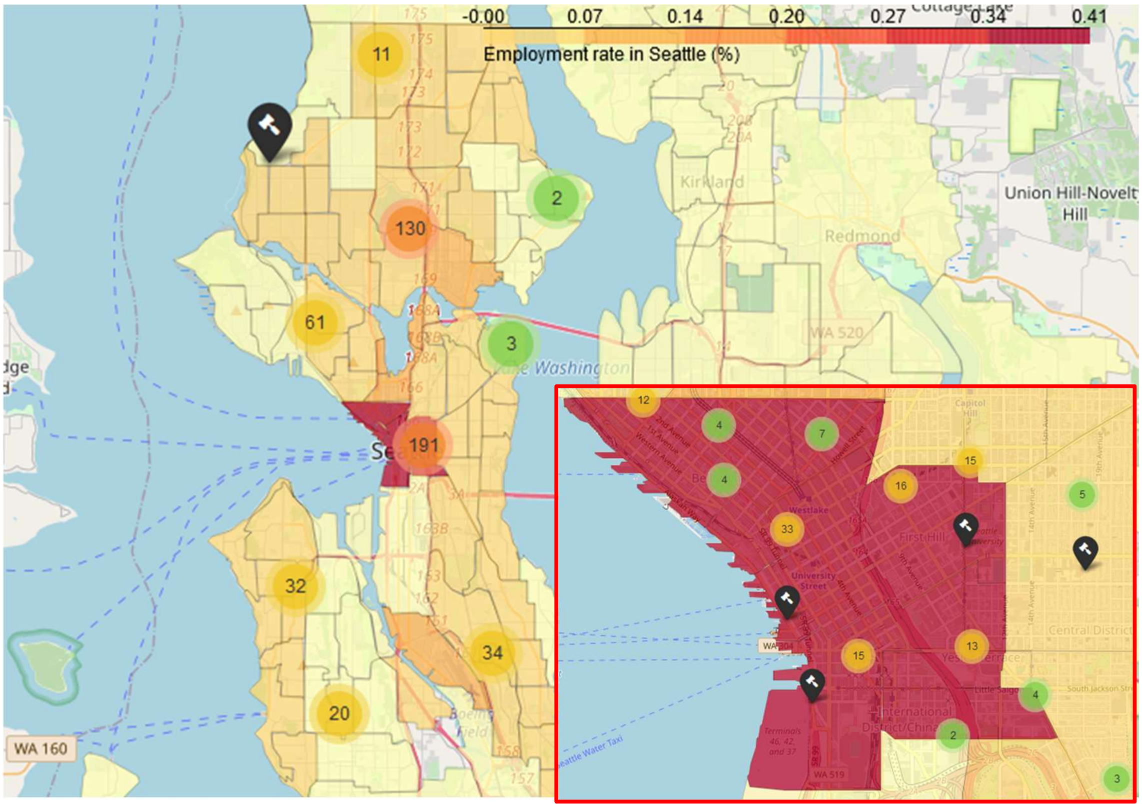
4.1.1. Fire 911 Calls reported in Seattle: Plotted on the population choropleth map



Comments of the resulting map

As it was predicted in the introduction to this project, the major number of Fires reported in the 911 Calls are produced in those neighborhoods in the city with the most population.

4.1.2. SPD Crimes reported in Seattle. Plotted on the employment choropleth map



Comments of the resulting map

Once again, the initial prediction was right! Most of the Crimes reported by Seattle Police Department (SPD) are produced in those boroughs in the city with the most employment. This is due to the fact that they are the most crowded areas in the city.

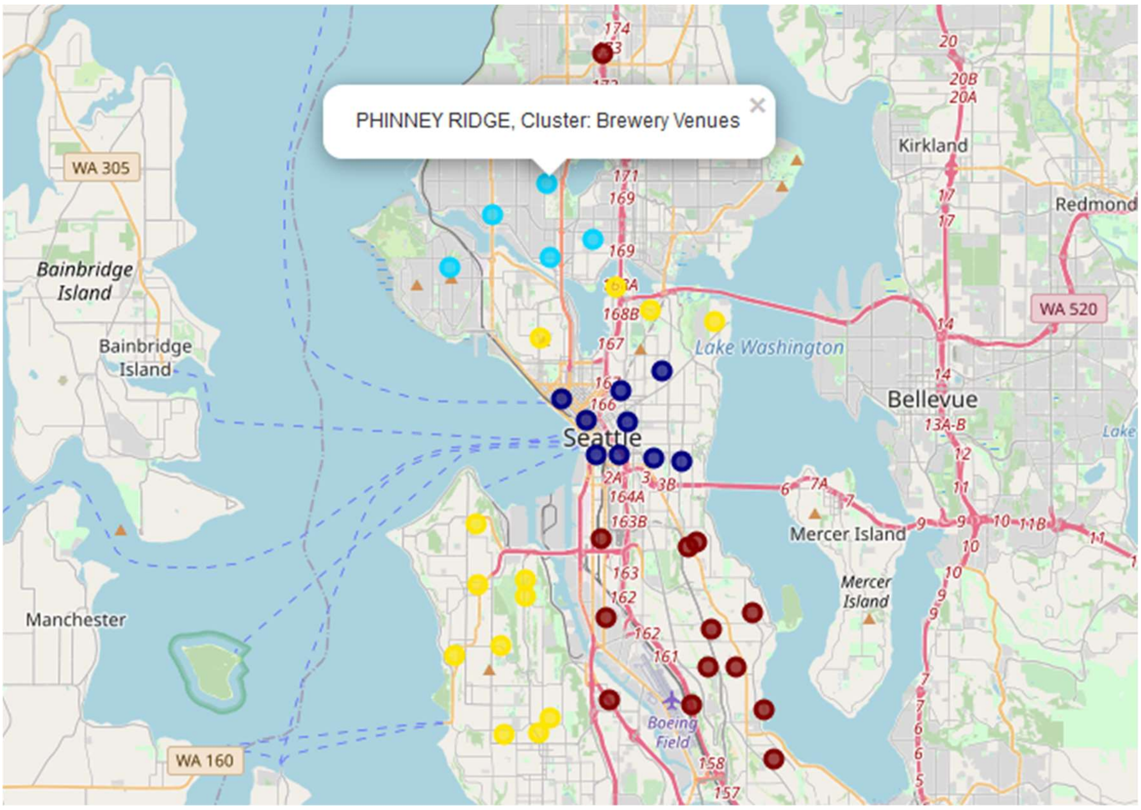
As it was shown in the regression plot between population and employment, they are positively correlated. This means that areas with more population have the most of employees, which makes natural sense. Therefore, if the major number of crimes are produced in areas with the highest employment ratios, they are occurring in those neighborhoods with the highest population ratios.

4.2. Mapping the venues' clusters on the city of Seattle

In this section, we will visualize the clusters dividing each of the boroughs of the city into clusters. This is the result of applying the K-Means algorithm with a k=4 to our initial dataset.

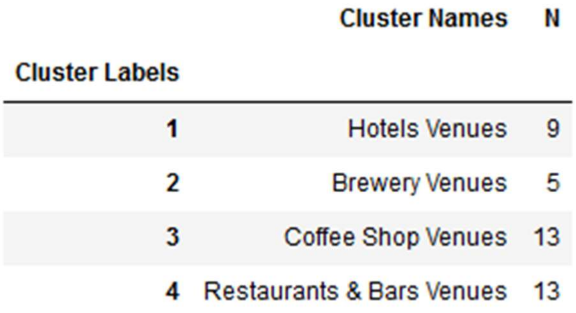
4.2.1. Creating the map visualization

In this map we can visualize the details for each neighborhood being categorized within a cluster, depending on its 1st most common venues:



4.2.2. Examine Seattle's neighborhoods

We can have a general view of the number of elements (N) contained in each of the conformed clusters:



Cluster Labels	Cluster Names	N
1	Hotels Venues	9
2	Brewery Venues	5
3	Coffee Shop Venues	13
4	Restaurants & Bars Venues	13

5. Discussion

As it was discussed in the introduction, Seattle is the largest populated city in the state of Washington. The amount of daily data that its metropolitan area produces in each of the districts is more than remarkable. Thereupon, in the middle of this complex metropolis, it is possible to find countless insights and analysis based on data.

I started by exploring the datasets which were used in this project. Using pandas for data wrangling and manipulation clarified the way in which the data frames could be analysed and represented. This lead to create some insightful graphs for data visualization. Population and employment ratios were disposed using bar charts and choropleth maps. Fire 911 calls were presented using a waffle chart to see the day with the most incidents. Seattle Police Department's reported crime data were ordered in a word cloud created inside the map of Seattle. These visualizations enhance the way in which data insights can be obtained.

The correlation between "population - fires" or "employment - crimes" helps to understand how the city is organized. What is more, it can be a powerful decision-making tool to use so as to determine either where to open the next fire or police station in the city.

Moving to the algorithm selected to classify the venues, K-Means clustering method was the chosen one. I used the Elbow method to determine the optimum value for k (number of clusters), which resulted to be 4. To create this model, 41 neighborhoods of the city of Seattle were used. Nevertheless, if we want to improve the accuracy of this solution, more location segments in the city should be trained.

The objective of this project was to find the main most common venues that compose each of the boroughs in Seattle, so they could be divided into groups based on this criterion. The problem to tackle was to meet a model that could work on its own to discover invisible data trends for human eye. Therefore, unsupervised machine learning seemed to be the adequate approach to this case. Although other classification models could have been used in order to conform the different groups, clustering segmentation is the most suitable one for partitioning data into segments with similar characteristics. Moreover, this solution is the most visual as it can be easily represented in a map.

6. Conclusion

In conclusion, most of the incidents occur in the downtown since it is the area with more activity and population. In order to reduce these numbers, the town hall of Seattle is able to use this data sources to direct their decisions. As I mentioned in the previous section, a data-driven decision-making system used by city managers could contribute on how to optimally organize the police and fire stations in Seattle.

Apart from the benefits data can have on city management, it could also be used to inform and guide tourism. Clustering helps to determine the most common venues in each area. Therefore, it could act as a recommendation system for visitors. Clusters can show the best locations for booking hotels and restaurants, or looking for a place to have either a beer or a coffee.

As far as we have data, it would be possible to even implement this model and analysis to any city in the world.

References

Here you can find all the links to the datasources that were used to conform the 4 datasets used in this project:

(1) Seattle neighborhoods boundaries data

(2) Seattle population data (Census 2010)

(3) Seattle Employement, Fire 911 Calls, and Crime Data

(4) Foursquare API