Comparing a set of neighborhoods world-wide by Livability score

Mohammed Elwardi Fadeli

10/30/2019

Contents

1 Introduction

1.1 Background

Many of us have an intuitive notion of how **easy** it is to live in a certain neighborhood or city we're well informed about. Typically, one can classify few cities (by pure intuition) as "harder", "easier", or "the same" if he compares these cities to his current living neighborhood. This notion of (intuitively) "clustering cities" can be even extent to predicting which city will leave its original cluster in the next few years.

If one takes New York City as the reference city, he can compare the current state of its neighborhoods with each other, or compare the city to other cities. After that, and by acquiring the history of the features making up his model, he can even predict which cities will the New York cluster in the next few years (cities become much harder or easier to live in)

Such clustering and prediction operations should be based on past history of different factors which contribute to the "easiness of living in a city". This information constitutes an important factor in decisions taken by a wide range of companies world-wide and it's expressed as a Livability score.

The Livability score measurement is not standardized world-wide, but this project focuses on five (5) factors:

- Amenities availability
- Cost of living
- Crime rate
- Education level
- Employment status

1.2 Problem

Data that might determine the livability score of a city or a neighborhood may include the number of Amenities (Groceries, schools, shopping, fitness facilities, libraries … etc) that are available, transportation, health care costs, and poverty rate, different kinds of crimes rates, unemployment rate and even the percentage of the population with less-than-high-school level of education.

This project aims to cluster some neighborhoods and cities world-wide, focusing on New York City neighborhoods, so that similar cities and neighborhood would belong to the same cluster.

1.3 Interest

If a city's cluster can be identified; predicting when the city might leave its cluster is a matter of repeating the process described in this report while building a predictive model (eg. linear regression). Hence this project is an important step in an even more-crucial workflow.

2 Data acquisition and cleaning

2.1 Data sources

For this project, we rely on two main sources of data:

1. A huge data set of NYC neighborhood stats
2. Foursquare API

Of course, the NYC neighborhood stats data set was last updated in December, 2017, but the foursquare data are fetched at a later date (November, 2018). We assume an offset of one year wouldn't affect the results that much.

Foursquare also sets some limitations on how much we can get per day. Thus, the code assumes sandbox accounts are used by default but also works in a much more accurate way if premium accounts are used.

NYC is not the only city studied in this project, non-foursquare data for other cities was acquired manually and added to the data frame.

This webpage was used as a base t construct our own Livability score.

2.2 Data Cleaning

The following features from the NYC neighborhood stats data set were chosen to calculate the livability score:

- Poverty
- Violent Crime
- Property Crime
- EduLessThanHS
- Crowded Housing
- Health Ins
- Unemployment Rate

All these metrics were then normalized so they becomes indices in the range [0, 1]

Also, data rows are cleaned while looking for Foursquare venues (if a Neighborhood fails to be found, it's dropped) for the following search queries:

- Groceries
- Food & Drink
- Shopping
- Schools
- Entertainment
- Fitness Facilities
- Transportation
- Libraries
- Goods & Services

If the user account is a sandbox one, only counts of these venues are used to cluster neighborhoods (due to Foursquare limitations on premium calls), but if a premium account is used, the code fetches “likes” for each venue and use that instead. Of course, this information is normalized over the Limit set for foursquare queries (20).

Also, all queries results are saved into JSON files so we can retrieve latitude/longitude data from Foursquare searches.

2.3 Feature selection

After cleaning, the data set has 20 features in addition to neighborhood names. But some of these features were not available for the majority of neighborhoods, so they were dropped (Only 16 remained).

3 Exploratory Data Analysis

3.1 Calculation of target variables

To be able to estimate the livability of a neighborhood, five indices must be calculated using existing data:

- Amenities availability
- Cost of living
- Crime rate
- Education level
- Employment status

Each index is calculated by multiplying the value of the feature by a certain coefficient (all coefficients for each index add up to 1, so they are a measure of the impact of a feature on the index’s value; These can be estimated easily using a survey for example).

The contribution of data frame columns are shown in the following table [1] :

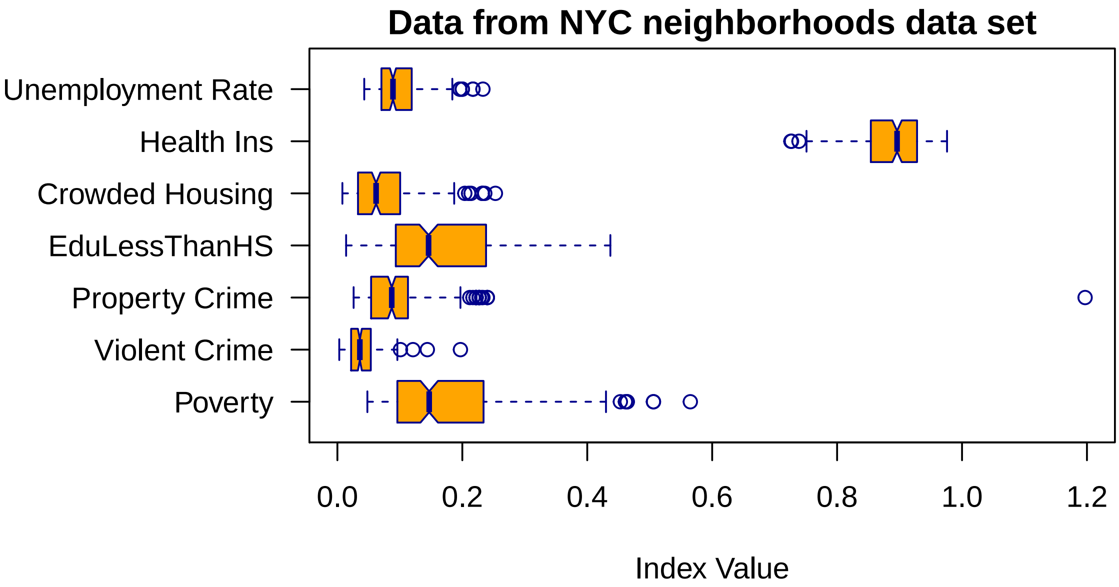
	Amenities	Cost of Living	Crime	Education	Employment
Crowded Housing	0.00	0.25	0.00	0.00	0.0
EduLessThanHS	0.00	0.00	0.00	0.85	0.0
Entertainment	0.16	0.00	0.00	0.00	0.0
Fitness Facilities	0.06	0.00	0.00	0.00	0.0
Food & Drink	0.17	0.00	0.00	0.00	0.0
Goods and Services	0.00	0.30	0.00	0.00	0.0
Groceries	0.17	0.10	0.00	0.00	0.0
Health Ins	0.00	0.15	0.00	0.00	0.0
Libraries	0.03	0.00	0.00	0.00	0.0
Poverty	0.00	0.10	0.00	0.00	0.0

[1] These coefficients are simplified. The table can have much more columns and rows!

	Amenities	Cost of Living	Crime	Education	Employment
Property Crime	0.00	0.00	0.35	0.00	0.0
Schools	0.12	0.00	0.00	0.25	0.0
Shopping	0.26	0.00	0.00	0.00	0.0
Transportation	0.03	0.10	0.00	0.00	0.0
Unemployment Rate	0.00	0.00	0.00	0.00	0.1
Violent Crime	0.00	0.00	0.65	0.00	0.0

3.2 Descriptive analysis of the data

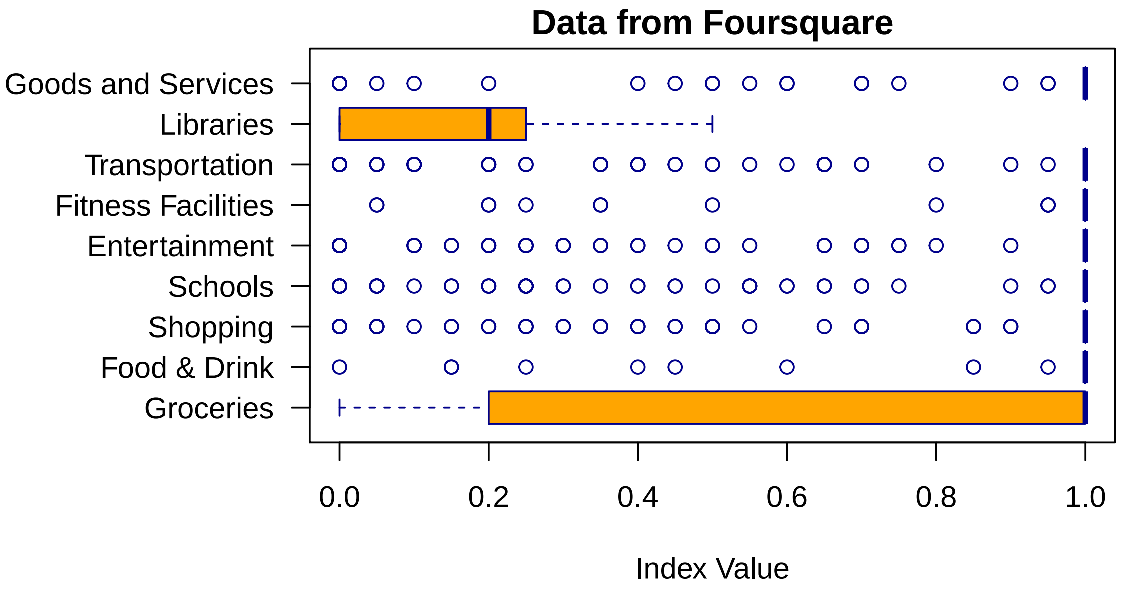
Let's start with discovering the distribution of data we got from the NYC neighborhood stats data set:



We notice no outliers when it comes to the percentage of residents with an education level less than High-School. We also notice there is some neighborhood with exceptional property crime rate (That's Midtown Manhattan for you, exceeding the normalization value!):

	NTA_Name	Property Crime
116	Midtown	1.197

We can also visualize Foursquare data as a box plot. In this plot, the number of venues (normalized to the Foursquare LIMIT) was used to produce the indices:



We notice how the data is biased towards 1.0 meaning that most of these neighborhoods have a decent number of these facilities nearby. We can also see that some neighborhoods (completely) lack the presence of some facilities; However this may be a result of Foursquare data being biased towards shops and restaurants!

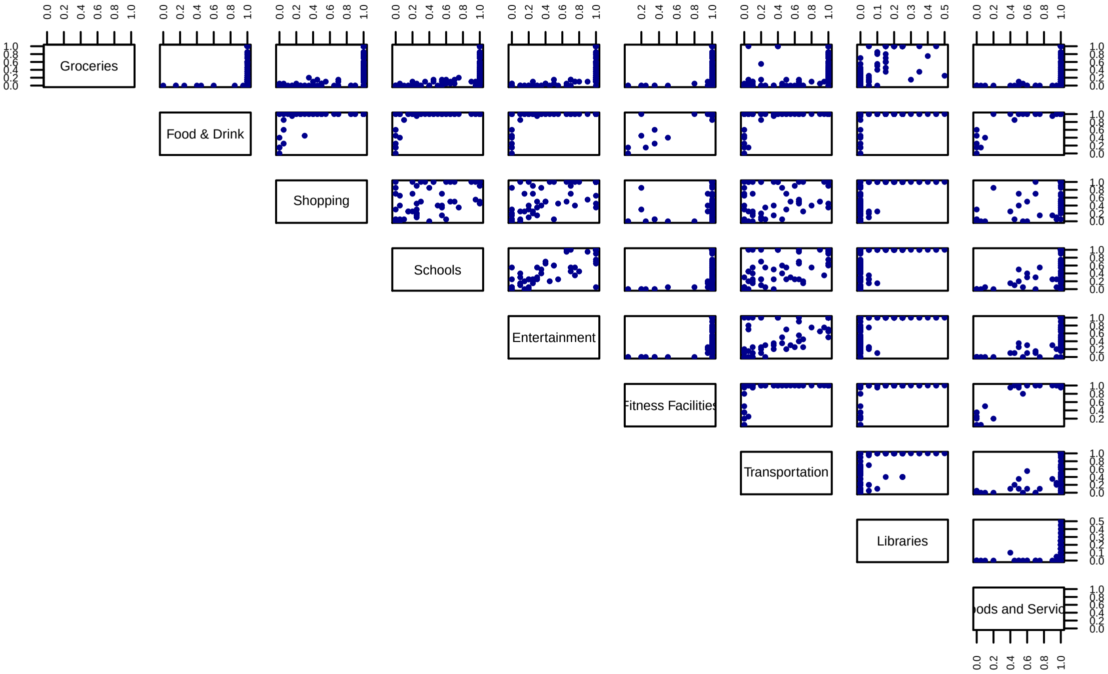
3.3 Relationships between different data features

We'll use R's powerful pairs function to plot the relationship of data columns with each other.

First, we'll start with visualizing data collected using Foursquare, which, in this case, doesn't show any type of correlation between features:

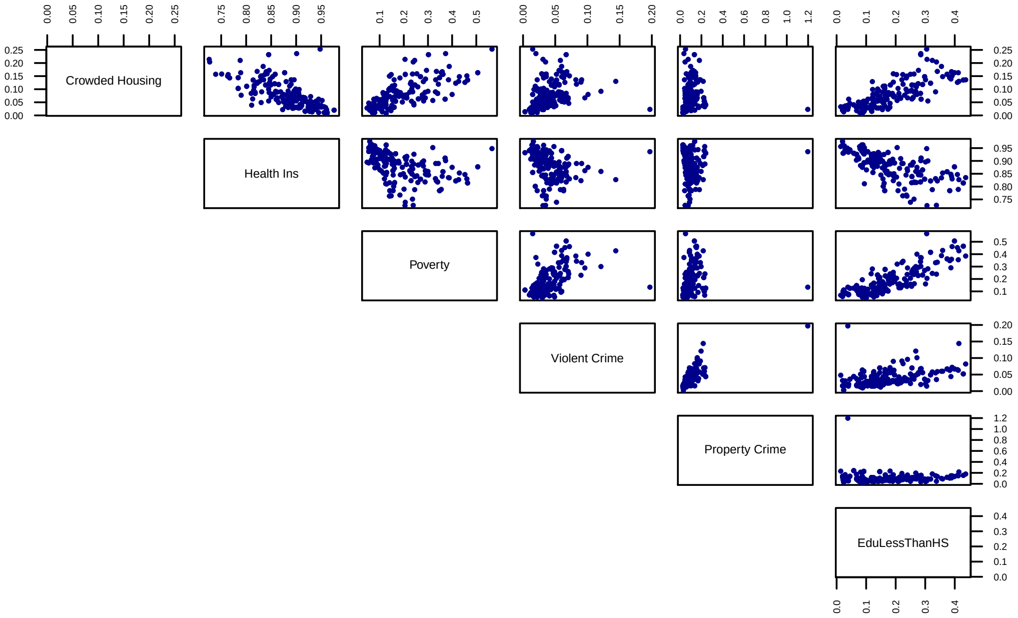
```
df = py$data
names(df) = make.names(names(df))
pairs(py$data[,2:10], pch = 19, lower.panel = NULL, bty="n",
      col="darkblue", cex.labels= 0.6, cex=.4, cex.lab=.2,
      cex.axis=.5, las=2,
      main='Correlation between data features collected from Foursquare')
```

Correlation between data features collected from Foursquare



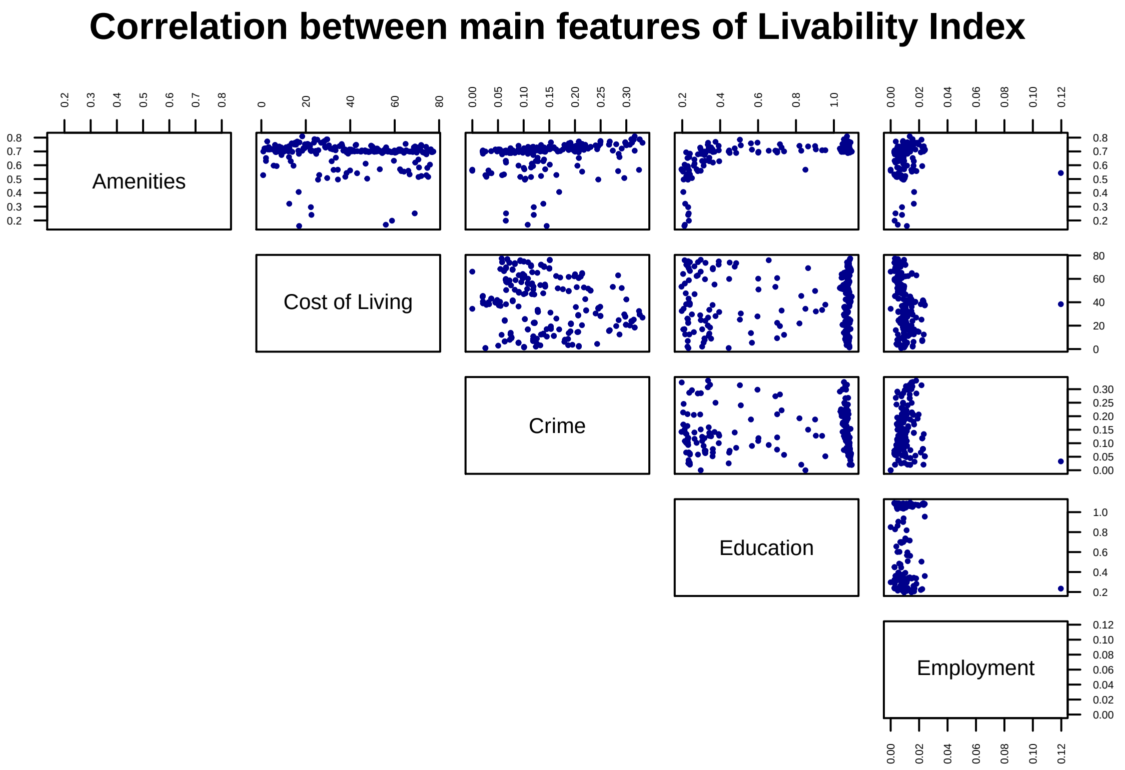
The next figure also shows the relationship between data features extracted from NYC neighborhood stats data set: It seems these features are weakly correlated; Our best chance of finding a linear relation ship is by investigative Property vs Violent crime rates.

Correlation between features collected from NYC neighborhood stats



But we decided to retain all the features processed so far because the correlation between them is , at best, weak!

After calculating the 5 main features for Livability Index, which can be done very easily in Python:



4 Classification Models

To cluster neighborhoods and cities based on their livability score, we use Python's sci-kit learn library to define a function which takes as input the data frame, a list of target variables, the number of clusters and the columns to use as a clustering criteria.

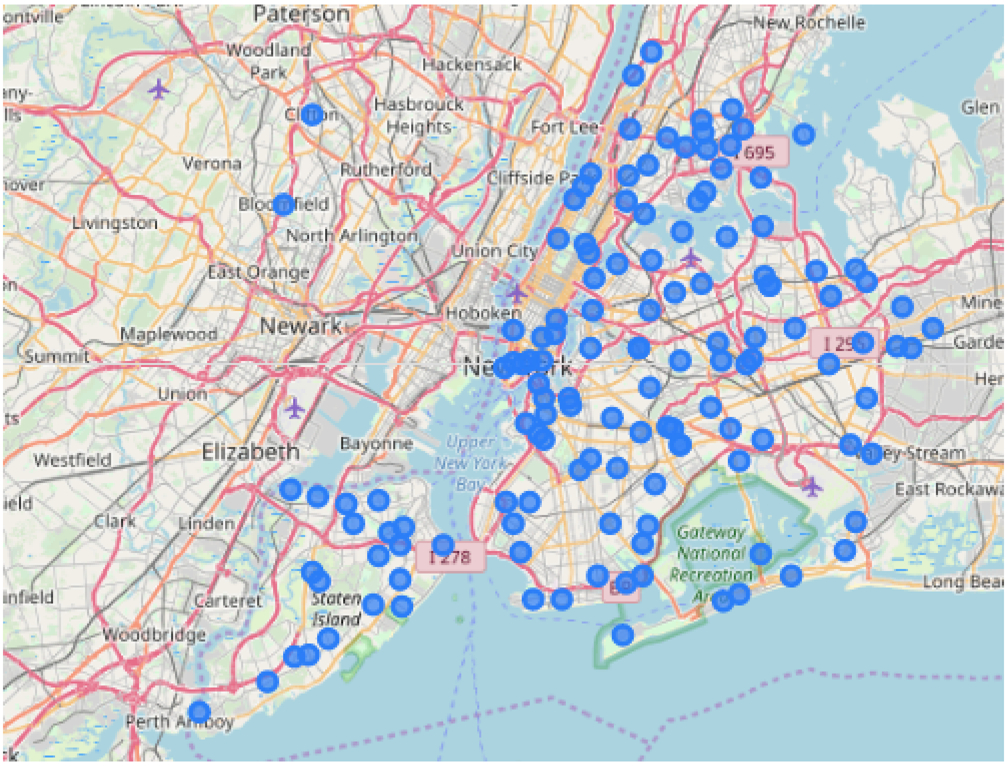
```
from sklearn.cluster import KMeans

def cluster_data(data, targets, kclusters, cols_to_cluster):
    data_clustering = data[targets]
    # run k-means clustering
    kmeans = KMeans(n_clusters=kclusters, random_state=0)
    kmeans.fit(data_clustering[cols_to_cluster])
    # add clustering labels to dataframe
    data_clustering.insert(0, 'Cluster Labels', kmeans.labels_)
    return data_clustering
```

To cluster the neighborhoods into 7 clusters based on Amenities score, we can:

```
clustered_data = cluster_data(data, [sc.columns[0]]+['NTA_Name'],
                              7, [sc.columns[0]])
```

The `folium` library can then be used to visualize these clusters (for example, around New York city):

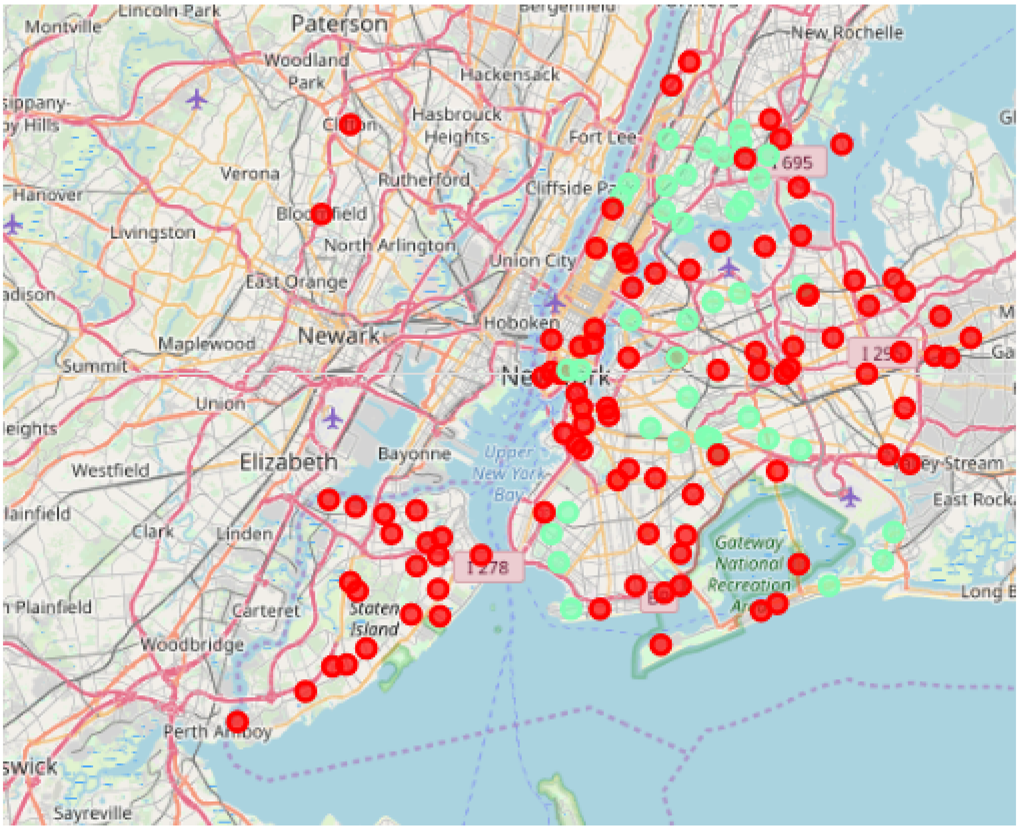
```
map = create_map(40.7128, -74.006, 10, data, 'Cluster Labels', 7)
```



Which shows that, amenities-wise, all NYC neighborhoods are similar (They all have roughly the same number of these facilities). But if when we cluster neighborhoods based on all 5 main features of the Livability score

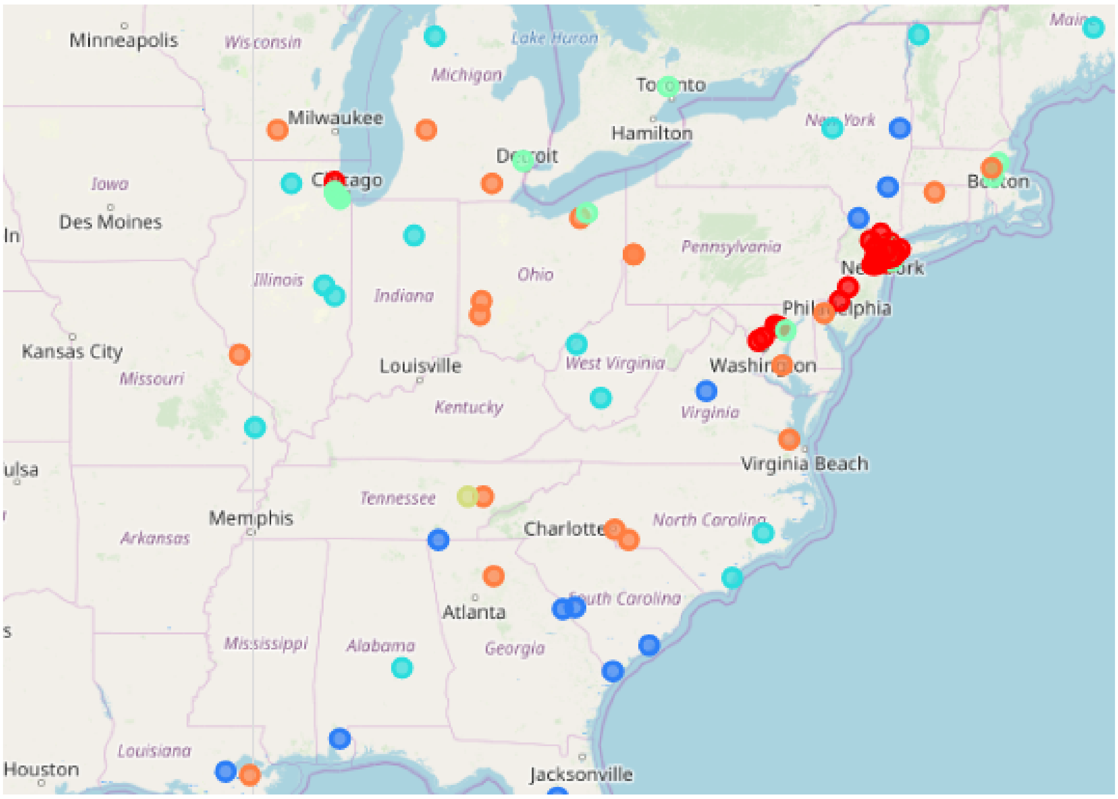
```
clustered_data = cluster_data(data, sc.columns, 7, sc.columns)
```

The map now looks like:



Which suggests that NYC can be divided into two clusters, one where living is easy and the other where living is harder (At least according to our simplified Livability index)!

By zooming out a little (x2), we can see our diverse clusters:



5 Discussion

The limitation on Foursquare developer accounts greatly affected the quality of data we could fetch from their API, and the data was biased towards restaurants and coffee shops, but, combining it with another data set was enough to hide the biased effect.

According to the whole 5 aspects of Livability score, regions far from NYC are a little easier to live in compared to the neighborhoods near the city! Which is to be expected of course.

6 Conclusion

In this study,I analyzed the livability index of several locations in the US and outside. I identified which cities and neighborhoods look most similar when compared by the five main aspects of the Livability score: Amenities, Cost of living, Crime, Education and Employment; which were roughly estimated using 16 other features.

This clustering model can be useful in predicting when a city may leave its current cluster! It's a matter of repeatedly applying the model at different (past) time frames to build a new model with the goal of predicting the future behavior of the city in the next years in respect to the Livability Index.