Introduction

This project is mainly for people who aim to relocate to a different city due to a new job offering and wish to live up to their standards in the new city.
I will try to provide suggestions on the neighborhoods based on what factors need to be considered gathered from particular individual.
In this project, we will make few assumptions.

1. The new city is assumed to be unfamiliar to the individual. For our purpose, assuming the city is Los Angeles.
2. The individual is assumed to be Stella, software engineer, who has been working and living in New York City for years.
3. The individual is assumed to be well aware of the new job salary. For our purpose, assuming the annual income is $120,000 / year.

Business Problem

In this project, I will be focus on problems Stella might encounter while deciding to taking on a new job offering in Los Angeles.
Before moving to a different city for the new job, there are many factors that one need to consider. As per example, Stella has the following concerns.

- Since she's new to the city, she would like to live in somewhere safe.
- She would like to rent a place. The price is open for discussion depends on location and other attributes.
- She doesn't cook as often, so she would like to live around various restaurants
- Being close to various venues other than restaurants is a big plus.

The real challenge starts from how do we use these factors to make reasonable suggestions to Stella, so that she can better adapt to the new environment as well as living up to her standards.
Now let's break it into parts. I will be analyzing each part separately and then integrating all parts together for final analysis and visualization.

1st problem is, what data will be based on in order to determine whether a particular area of the city is considered safer than other areas?
2nd problem is, what data will be used in order to determine which apartment Stella should rent?
3rd problem is, instead of filtering all restaurants near one particular area, what other criteria will be needed to filter various types of restaurant? ie. Chinese food, Indian food and Italian food, etc.
4th problem is, various venues are way to general, is there a way to prioritize certain venues over others?

Data Acquiring and How it will be used

1. The first piece of information needed in my opinion would be Los Angeles Crime Data, which can be obtained at https://data.lacity.org/A-Safe-City/Crime-Data-from-2010-to-Present/63jg-8b9z (https://data.lacity.org/A-Safe-City/Crime-Data-from-2010-to-Present/63jg-8b9z). For our purpose however, I will use a much smaller sample of this dataset which can be obtained at https://usc.data.socrata.com/Los-Angeles/Part-I-Crimes-LA-/qfdv-ru39 (https://usc.data.socrata.com/Los-Angeles/Part-I-Crimes-LA-/qfdv-ru39).
   I will extract the neighborhoods and crime count from the dataset. And from the result I will drop the rows without values. Then I will sum all the crimes together with respect to each neighborhood. The process was similar to what we did in the SQL course.
2. Secondly I will need the data for housing price and rent cost in Los Angeles. For rent price, https://usc.data.socrata.com/Los-Angeles/Rent-Price-LA-/4a97-v5tx (https://usc.data.socrata.com/Los-Angeles/Rent-Price-LA-/4a97-v5tx).
   I will extract the neighborhoods and rent price from the dataset. And from the result I will drop the rows without values. Then I will average all the rent price together with respect to each neighborhood. The process will be similar to what we did in the Data Analysis course.
3. Next, I will use FOURSQUARE API to obtain the remaining data about venues around each neighborhood. This includes restaurants and others. I will filter the neighborhoods which offer big variety of types of restaurants, as well as other venues. And I will sum all the venues together with respect to each neighborhood. Then I will list top 10 common venues for each neighborhood. Segmenting and clustering all the neighborhoods with respect to required features. The process will be similar to what we did in the last three modules.
   Finally, after all the gathered data being analyzed, I will combine all the data into one table. I will make several visualizations including plot, charts, map and some machine learning algorithm for segmenting and clustering. This process will be similar to what we did in the Data Visualization course. Then based on all the previous work, I will make reasonable suggestions as the solution of this problem proposed in the project.
   Additional analysis will be included based on target audience's prefered weights on different factors. This process consists of scaling dataset according to weight distribution.

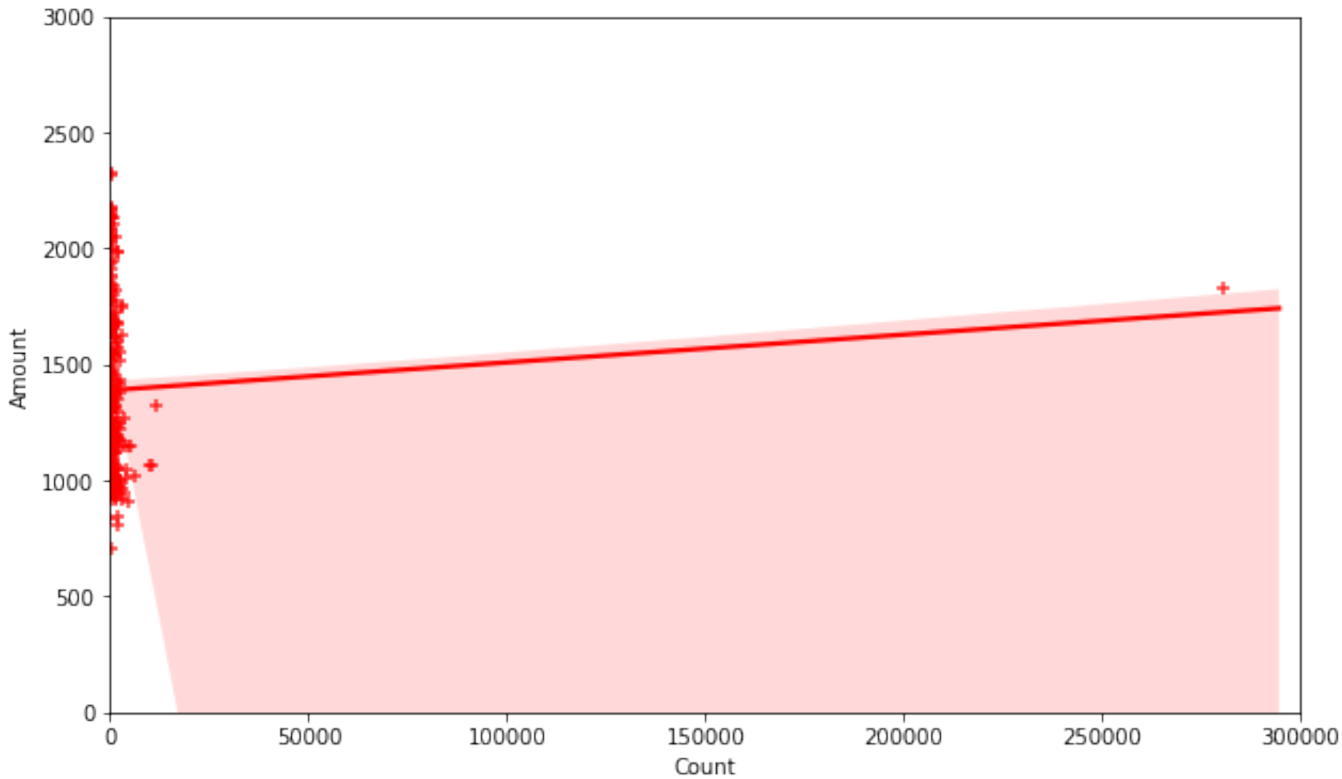
First thing to be noted is that all the datasets listed are found on the Internet from various websites. I cannot guarantee the accuracy of the data itself. Second thing to be noted is that the data acquired is different compared to the proposed problem from week 1. This is due to the lack of dataset on house price. As well as, lack of data on transportation on FOURSQUARE.

Methodology and Exploratory Data Analysis

I started off by exploring the correlations between different factors including crime count, rent prices, number of Restaurants and number of other venues. As a long time resident in New York City, Stella suspects that there should be a possible relation between crime count and rent price. One would assume that the neighborhoods with lower crime count will probably have higher rent price. As a result, I ran the corr() function on the dataset and plotted it with a regression line which will be shown below.

Relation between crime count and rent price

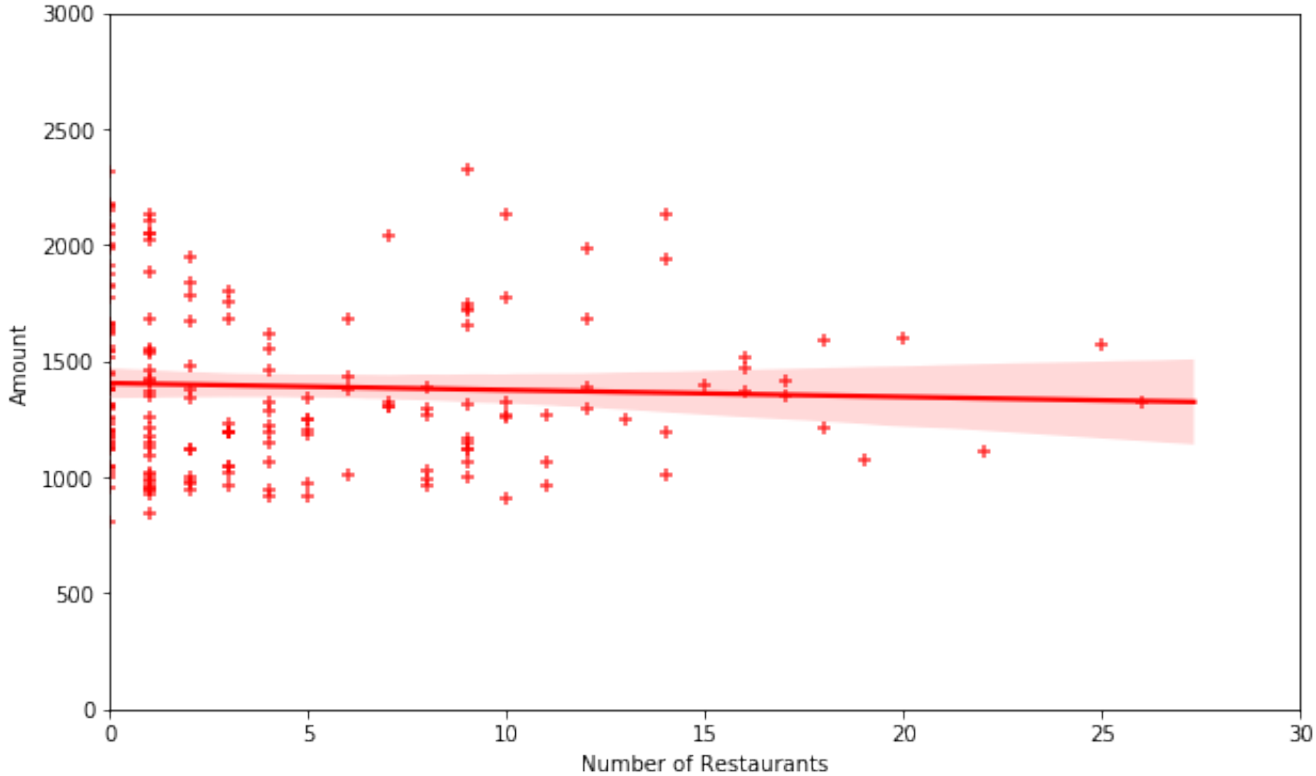
	Count	Amount
Count	1.000000	0.062265
Amount	0.062265	1.000000



Next, as Stella weights nearby number of various restaurants as another main factor, maybe there could be some relation between the number of restaurants and rent price. The reason is that for the conveniency and occupancy of having lots of restaurants, most of the nearby renting space will probably be venues too. Therefore, the rent price will most likely to be higher as well. Once again, this seems to be the case in New York City. So I ran the corr() function on the dataset and plotted it with a regression line which will be shown below.

Relation between number of restaurants and rent price

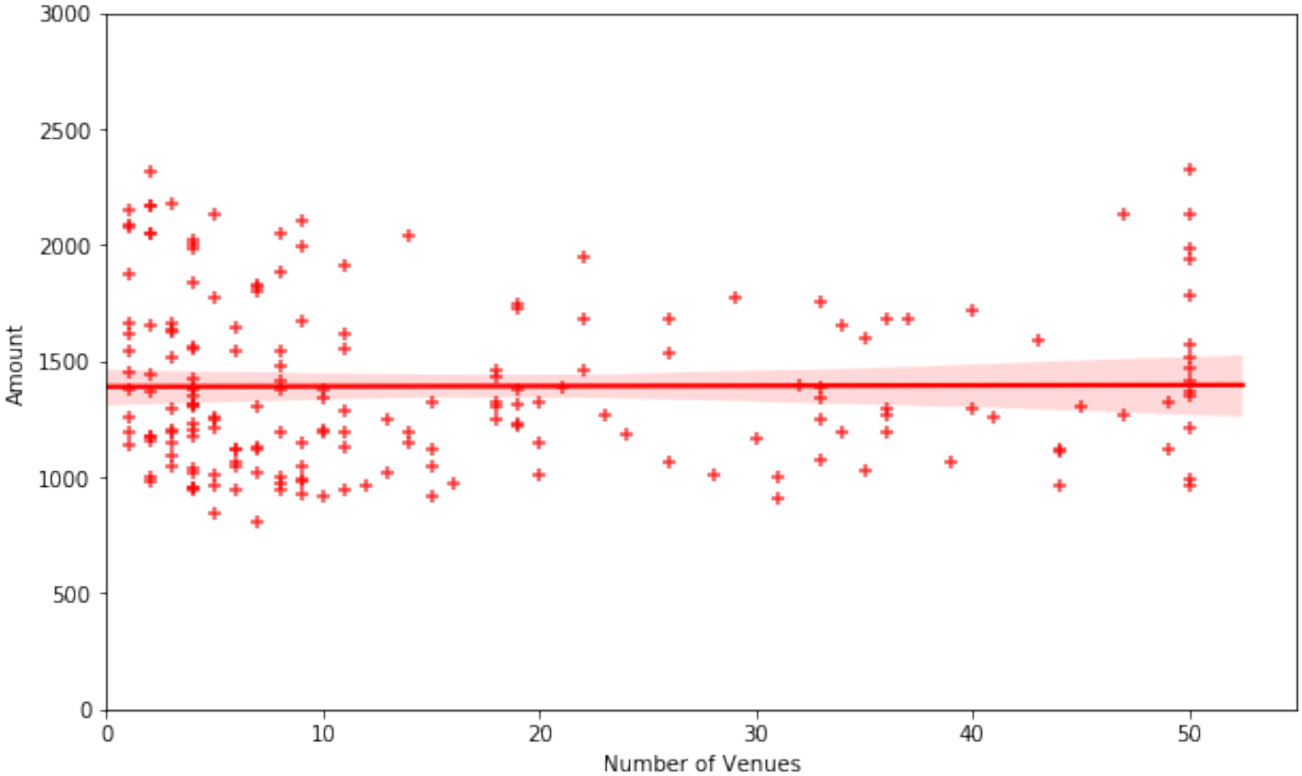
	Number of Restaurants	Amount
Number of Restaurants	1.000000	-0.045927
Amount	-0.045927	1.000000



Let's move on to other venues. By the same analysis, there might be a relation between the number of venues and rent price. Check out the results below.

Relation between number of venues and rent price

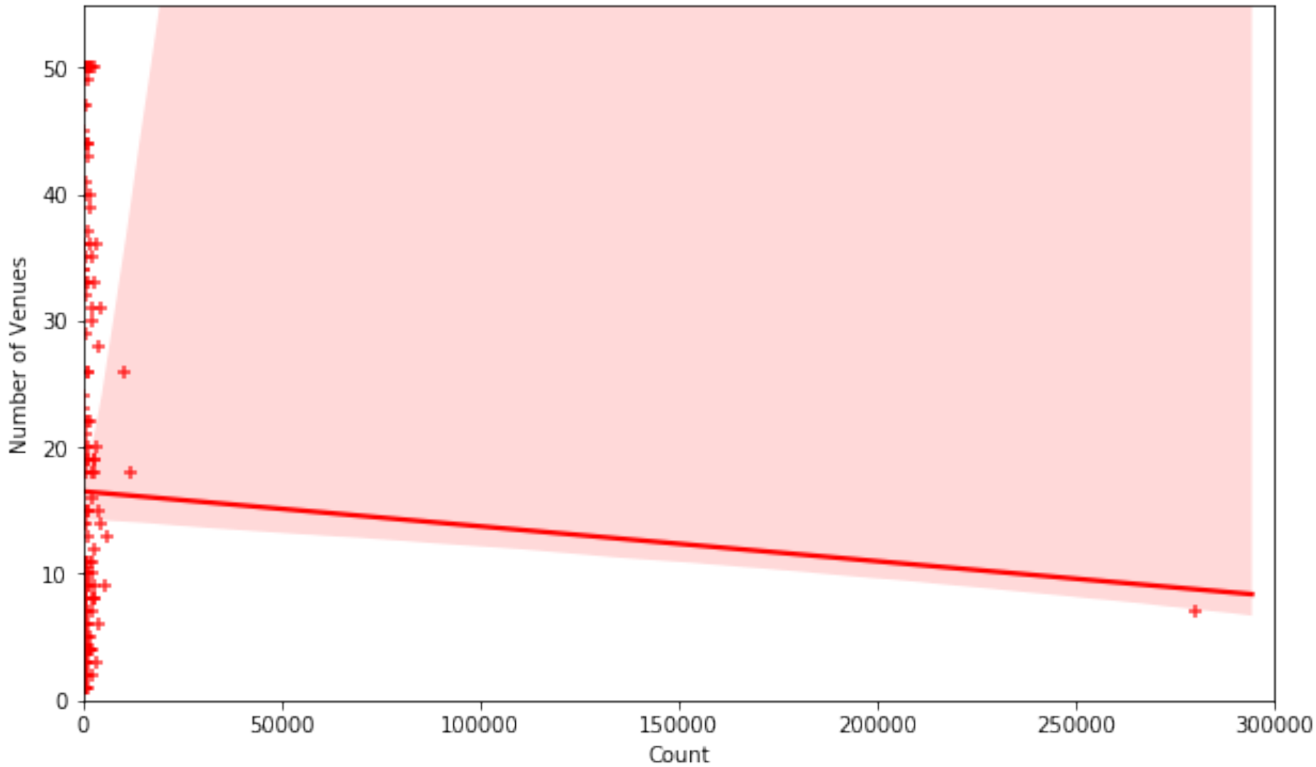
	Number of Venues	Amount
Number of Venues	1.000000	0.006193
Amount	0.006193	1.000000



Better yet, one could also suspect that the possible relation between crime count and number of venues. The reason is that the neighborhoods with higher number of venues are likely to be crowded as well more prone to theft and other crimes, etc. Check out the results below.

Relation between crime count and number of venues

	Number of Venues	Count
Number of Venues	1.000000	-0.035515
Count	-0.035515	1.000000



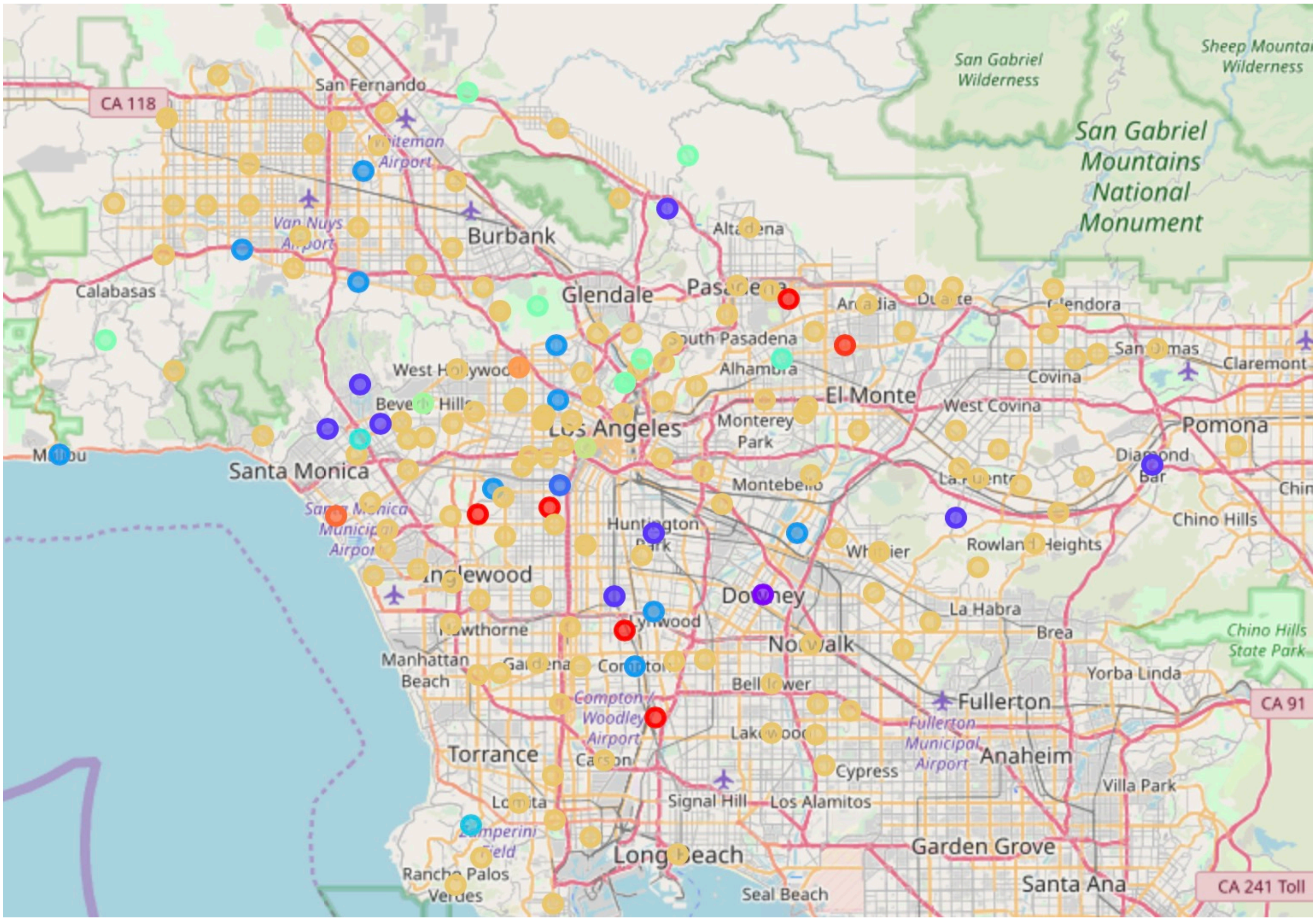
To further analyze our data, I assigned weights to each factor dataset according to Stella's preference by using the formula [(value-mean)/mean]. This in turn gives us some insights on which neighborhood better fits Stella's overall living standards, which I will discuss in the result session. Check out the result below for the first 5 rows.

Datasets after weight assignment

Neighborhood	Count	Weight_x	Amount	Weight_y	Latitude	Longitude	Number of Restaurants	Weight_z
Adams-Normandie	541.648985	0.771291	920.742857	0.337153	34.033081	-118.297115	5.0	0.143713
Agoura Hills	189.029737	0.920183	2052.500000	-0.477604	34.136395	-118.774535	1.0	-0.771257
Agua Dulce	44.202726	0.981336	1130.200000	0.186364	34.496382	-118.325635	1.0	-0.771257
Alondra Park	105.068139	0.955635	1667.142857	-0.200184	33.890134	-118.335133	0.0	-1.000000
Altadena	521.410078	0.779837	1458.321429	-0.049852	34.186316	-118.135233	1.0	-0.771257

Continuing on with neighborhoods segmenting and clustering using unsupevised Kmeans algorithm with respect all factors. I further clustered all neighborhoods into 15 clusters. This in turn gives us some insights on which cluster of neighborhoods better fits Stella's overall living standards. Check the result in the following map.

Segmenting and Clustering



Results

There are two main results here.

1. The weighted overall score according to Stella's preference, which will be shown in the table below. This portion did not use machine learning. It is the result obtained solely by using datasets from Data section.

	Neighborhood	Crime	Rent	Restaurant	Other venues	Weighted Score
138	San Gabriel	3.765578	4.739120	97.746418	41.463562	147.714679
32	Chinatown	2.459168	19.403488	79.668891	35.095325	136.626872
102	Mid-Wilshire	0.896377	-12.279868	93.227036	42.737210	124.580756
95	Long Beach	3.828431	12.762358	61.591364	42.737210	120.919363
147	South San Gabriel	3.327528	22.194779	66.110746	21.085202	112.718254
175	West Hollywood	1.175810	2.681170	57.071983	42.737210	103.666172
104	Monrovia	3.755596	-1.687837	57.071983	42.737210	101.876952
96	Los Feliz	1.470305	1.948109	52.552601	42.737210	98.708224
66	Harvard Heights	2.745986	29.740702	29.955692	35.095325	97.537706
119	Pasadena	3.654782	-5.299861	52.552601	42.737210	93.644732
146	South Park	1.734413	29.878972	16.397547	42.737210	90.748143

1. The clusters of neighborhood based on all factors. Here I will only show 3 clusters. For more details, check the Jupyter Notebook. This portion however, used unsupervised Kmeans algorithm to determine similar neighborhoods, namely clusters of neighborhoods that satisfies our proposed conditions.

First Cluster:

	Neighborhood	Count	Weight_x	Amount	Weight_y	Latitude	Longitude	Number of Restaurants	Weight_z	Number of Venues	...
128	Rancho Dominguez	416.927852	0.823954	1135.285714	0.182703	33.859592	-118.210647	0.0	-1.000000	1	...
139	San Pasqual	59.387775	0.974924	1345.785714	0.031163	34.139154	-118.102442	1.0	-0.771257	4	...
164	Vermont Square	1635.531959	0.309404	956.000000	0.311771	34.000140	-118.295890	0.0	-1.000000	4	...
166	View Park-Windsor Hills	282.684976	0.880637	1253.714286	0.097445	33.995731	-118.352610	0.0	-1.000000	1	...
186	Willowbrook	1063.676051	0.550867	1050.285714	0.243895	33.918786	-118.234393	0.0	-1.000000	3	...

Second Cluster:

	Neighborhood	Count	Weight_x	Amount	Weight_y	Latitude	Longitude	Number of Restaurants	Weight_z	Number of Venues	...
41	Downey	95.118663	0.959837	1259.0	0.09364	33.942215	-118.123565	1.0	-0.771257	5	...

Third Cluster:

	Neighborhood	Count	Weight_x	Amount	Weight_y	Latitude	Longitude	Number of Restaurants	Weight_z	Number of Venues	...
15	Bel-Air	78.544445	0.966835	1885.285714	-0.357226	34.082728	-118.447980	1.0	-0.771257	8	...
21	Brentwood	912.723357	0.614606	1949.714286	-0.403608	34.052140	-118.474070	2.0	-0.542515	22	...
40	Diamond Bar	660.818468	0.720972	1796.920635	-0.293611	34.028623	-117.810337	3.0	-0.313772	7	...
62	Hacienda Heights	1021.739540	0.568575	1678.582418	-0.208419	33.993068	-117.968676	12.0	1.744910	37	...
72	Huntington Park	97.264245	0.958931	943.744361	0.320594	33.982704	-118.212034	1.0	-0.771257	4	...
77	La Canada Flintridge	291.247309	0.877022	2047.035714	-0.473670	34.199830	-118.200524	1.0	-0.771257	8	...
170	Watts	1418.216482	0.401164	928.446429	0.331607	33.940567	-118.242848	1.0	-0.771257	9	...
183	Westwood	1079.013912	0.544391	1836.761905	-0.322293	34.056121	-118.430635	2.0	-0.542515	4	...

Discussion

In this project, few things need to be carefully noted. During the first part of data analysis section, I tried to find correlations between different factors. However, the results were much surprising to me. As it turns out, none of them has a strong correlation pairwise. Check out the correlation table below. Please ignore the relation between number of restaurants and number of venues, since restaurant is a venue. Post-project, I realized that I cannot only use New York City as a reference. For example, a neighborhood located in less crowed area with low crime count might still have many venues while the rent price is low as well.

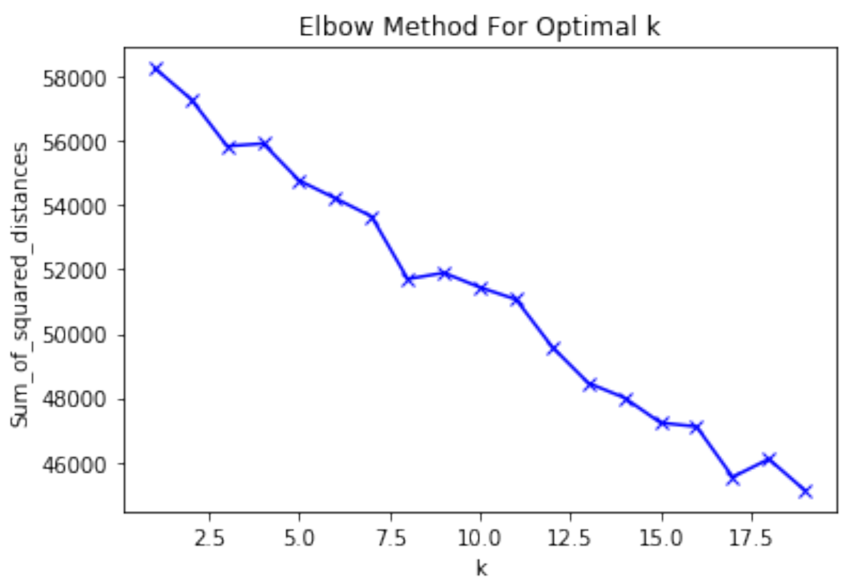
	Count	Amount	Number of Restaurants	Number of Venues
Count	1.000000	0.072283	-0.046933	-0.035515
Amount	0.072283	1.000000	-0.045927	0.006193

Number of Restaurants	-0.046933	-0.045927	1.000000	0.844935
Number of Venues	-0.035515	0.006193	0.844935	1.000000

Second part of data analysis section, I used weight assignments to each neighborhood to obtain overall performance. This process is highly biased, since each individual prioritizes things differently. It is also very sensitive to data selection, since it highly depends on the analyzed datasets.

- Neighborhood Safety weights about 30%
- Rent price weights about 25%
- Nearby Restaurants weights about 25%
- Other venues weights about 20%

Last part of data analysis section, I used unsupevised Kmeans algorithm to segment and cluster neighborhoods. However, I couldn't determine the best k value using the elbow technique. As a result, the k value I chose was less likely to be optimal. As a result, the clusters generated was less accurate. Post-project, I still haven't figure out what went wrong. Check the elbow diagram below.



Recommendation and Suggestion

From the scope of this project, my recommendation is in accordance with the results.

- If the target audience is high biased on what they want, namely they are determined to follow their own standards, then the biased table will offer the best fitting neighborhood because it weights each factor based on exactly what the audience required assuming we have full confidence in the datasets.
- On the other hand, if the target audience is more flexible on the requried factors, they can still used the biased table as a general reference. However, my suggestion would be taking into consideration of each cluster of neighborhoods. For those clusters which contain a neighborhood with overall higher weights, then other neighborhoods in the same cluster will also be good candidates.

Conclusion

In this project, I analyzed the neighborhoods in Los Angeles based on individual's preference or living standards. I identified the main factors required, gathered data from reliable sources. After processing the datasets, I explored the possible correlation among each factors. I also combined different datasets into one, calculated its respected weights in order to obtain an overall score for each neighborhood in Los Angeles. I further built a machine learning model with unsupevised Kmean algorithm to cluster neighborhoods with great similarty in terms of required factors. From this model, joint effort with data analysis and data visualization, I provided reasonable suggestion for the target audience. Finally, I discussed shortcomings and potential improvements post-project.