OPENING A NEW RESTAURANT IN LOS ANGELES CITY

Proposal submitted Aug-05 2019

ABSTRACT

This report is written as the response to the investor request to open a new restaurant in Los Angeles

Amin

Outlines

Business Problem and Target Audiences

As increasing numbers of consumers want to dine out, the number of restaurants has skyrocketed in Loss Angeles.

This city is the entertainment capital of the world. Downtown Los Angeles is the largest government center outside of Washington. Los Angeles is on the leading edge of several growth industries.

Loss Angeles is so diverse, it's possible to dine around the world without ever leaving the city. Visitors can also participate in LA Restaurant Week, held every winter and summer.

In this regard, this report is written to **propose neighborhood(s) suitable to open a new restaurant** based on available data of Los Angeles.

Unsupervised machine learning will be used to achieve the target. In this report, we will present the background of the work and also the source of data which will be used.

This report is useful for investors in Los Angeles that are interested to open a restaurant in one of neighborhoods of Los Angles. Los Angeles has many neighborhoods and each region offers a variety of dining options. So, it is useful to use available data to inspect all areas before.

The result will be based on available data and any new data could change the result. This report in different section presents the background and data for this project

Introduction

Many people in Los Angeles eating out at least once a week and the restaurant industry continues to thrive.

Starting a restaurant takes a lot of work, but with expert planning, you can start a successful restaurant business. In this regard, unsupervised machine learning would be useful.

The Importance of Location

A restaurant's location influences many aspects of your operation, including the menu! In addition to being one of the most significant determinants of your financial viability, decisions regarding location are not easy to undo.

Important Factors to select an optimum place

To choose a location for the new restaurant, the following aspects are important:

The demographics

Ensure the target market of your restaurant matches the demographics of the area. Factors like the income in a certain radius definitely matter.

Crime Rates

High crime rates can make potential customers uncomfortable, and if they feel they’ll be mugged walking to their cars, it will drive away business.

Availability of services, shopping center, etc.

One of the important factors is the availability of, world-class shopping, recreation center, good urban parks, near a body of water, Good traffic, etc.

Available restaurant and food services

When there are many restaurants available in a region of Los Angeles It says that the region was good for open a restaurant. But, can we extend it to the future? So, having a record of available services is useful.

Data sources and Preparation

The data that we need to complete this project:

1. Name and Coordinates of Los Angeles neighborhood,
2. Income rate of residents in each neighborhood,
3. The crime rate in each area of Loss Angeles,
4. No. and type of amenities like shopping centers, recreation centers, etc.
5. Available restaurant and service foods in each region.

Source of data:

- ✓ The data for Neighborhood name and coordinate will be extracted from the below link which shows the neighborhoods of Los Angeles County

HTTPS://USC.DATA.SOCRATA.COM/API/VIEWS/9UTN-WAJE/ROWS.CSV?ACCESSTYPE=DOWNLOAD

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L.A. County N	acton	MULTIPOL	L.A. Count	acton	Acton	Acton L.A.	39.33911	unincorporated-area			-118.17	34.49736	POINT(34.497355239240846 -118.16981019229348)
L.A. County N	adams-nor	MULTIPOL	L.A. Count	adams-nor	Adams-No	Adams-No	0.80535	segment-of-a-city			-118.3	34.03146	POINT(34.031461499124156 -118.30020800000011)
L.A. County N	agoura-hill:	MULTIPOL	L.A. Count	agoura-hill:	Agoura Hill	Agoura Hill	8.14676	standalone-city			-118.76	34.14674	POINT(34.146736499122795 -118.75988450000015)
L.A. County N	agua-dulce	MULTIPOL	L.A. Count	agua-dulce	Agua Dulc	Agua Dulc	31.46263	unincorporated-area			-118.317	34.50493	POINT(34.504926999796837 -118.3171036690717)
L.A. County N	alhambra	MULTIPOL	L.A. Count	alhambra	Alhambra	Alhambra	7.623814	standalone-city			-118.137	34.08554	POINT(34.085538999123571 -118.13651200000021)
L.A. County N	alondra-pa	MULTIPOL	L.A. Count	alondra-pa	Alondra Pa	Alondra Pa	1.139894	unincorporated-area			-118.335	33.88962	POINT(33.889617004889644 -118.33515598608159)
L.A. County N	artesia	MULTIPOL	L.A. Count	artesia	Artesia	Artesia L.A	1.632204	standalone-city			-118.08	33.8669	POINT(33.866895999126271 -118.08010100000017)
L.A. County N	altadena	MULTIPOL	L.A. Count	altadena	Altadena	Altadena L	8.710338	unincorporated-area			-118.136	34.19387	POINT(34.193870502232173 -118.13623898201556)
L.A. County N	angeles-cr	MULTIPOL	L.A. Count	angeles-cr	Angeles Cr	Angeles Cr	430.4775	unincorporated-area			-117.922	34.31394	POINT(34.313937005895312 -117.9223952817848)
L.A. County N	arcadia	MULTIPOL	L.A. Count	arcadia	Arcadia	Arcadia L.A	11.1508	standalone-city			-118.03	34.13323	POINT(34.133229999123017 -118.03041899311202)
L.A. County N	arleta	MULTIPOL	L.A. Count	arleta	Arleta	Arleta L.A.	3.096179	segment-of-a-city			-118.431	34.2431	POINT(34.243099999121583 -118.4307575)
L.A. County N	arlington-h	MULTIPOL	L.A. Count	arlington-h	Arlington H	Arlington H	1.031415	segment-of-a-city			-118.323	34.04491	POINT(34.04491049912405 -118.3234085)
L.A. County N	athens	MULTIPOL	L.A. Count	athens	Athens	Athens L.A	1.332753	unincorporated-area			-118.305	33.92369	POINT(33.9236925059352 -118.30465647554277)
L.A. County N	atwater-vill	MULTIPOL	L.A. Count	atwater-vill	Atwater Vil	Atwater Vil	1.776894	segment-of-a-city			-118.262	34.13107	POINT(34.131066356759177 -118.26237347966236)
L.A. County N	avalon	MULTIPOL	L.A. Count	avalon	Avalon	Avalon L.A	2.744697	standalone-city			-118.327	33.33695	POINT(33.336954499133086 -118.32733223477572)
L.A. County N	avocado-h	MULTIPOL	L.A. Count	avocado-h	Avocado H	Avocado H	2.948459	unincorporated-area			-118.001	34.04088	POINT(34.040881003821966 -118.0012614768012)
L.A. County N	azusa	MULTIPOL	L.A. Count	azusa	Azusa	Azusa L.A.	9.871436	standalone-city			-117.912	34.13747	POINT(34.13746999912302 -117.91246849999999)
L.A. County N	vermont-sl	MULTIPOL	L.A. Count	vermont-sl	Vermont-S	Vermont-S	1.442453	segment-of-a-city			-118.29	33.98391	POINT(33.983913999124709 -118.29035750000011)
L.A. County N	baldwin-hil	MULTIPOL	L.A. Count	baldwin-hil	Baldwin Hi	Baldwin Hi	2.883705	segment-of-a-city			-118.358	34.01197	POINT(34.01197027055953 -118.35774600000005)
L.A. County N	baldwin-pa	MULTIPOL	L.A. Count	baldwin-pa	Baldwin Pa	Baldwin Pa	6.778016	standalone-city			-117.975	34.08111	POINT(34.081109499123691 -117.9751905000002)
L.A. County N	bel-air	MULTIPOL	L.A. Count	bel-air	Bel-Air	Bel-Air L.A	6.373321	segment-of-a-city			-118.458	34.10206	POINT(34.102056999123342 -118.45841550000007)
L.A. County N	bellflower	MULTIPOL	L.A. Count	bellflower	Bellflower	Bellflower	6.195312	standalone-city			-118.129	33.88801	POINT(33.88801349912606 -118.12903150000017)
L.A. County N	bell-garder	MULTIPOL	L.A. Count	bell-garder	Bell Garde	Bell Garde	2.480285	standalone-city			-118.15	33.96569	POINT(33.965685999125014 -118.1499360000002)

Figure 1: Los Angeles neighborhoods name and location

Also, we will cross-check the data with Wikipedia page:

https://en.wikipedia.org/wiki/List_of_districts_and_neighborhoods_of_Los_Angeles

- ✓ The free account Four-square App will be used to explore the venues and service foods.

- ✓ Property Crime Rate from the below website:

http://maps.latimes.com/neighborhoods/property-crime/neighborhood/list/

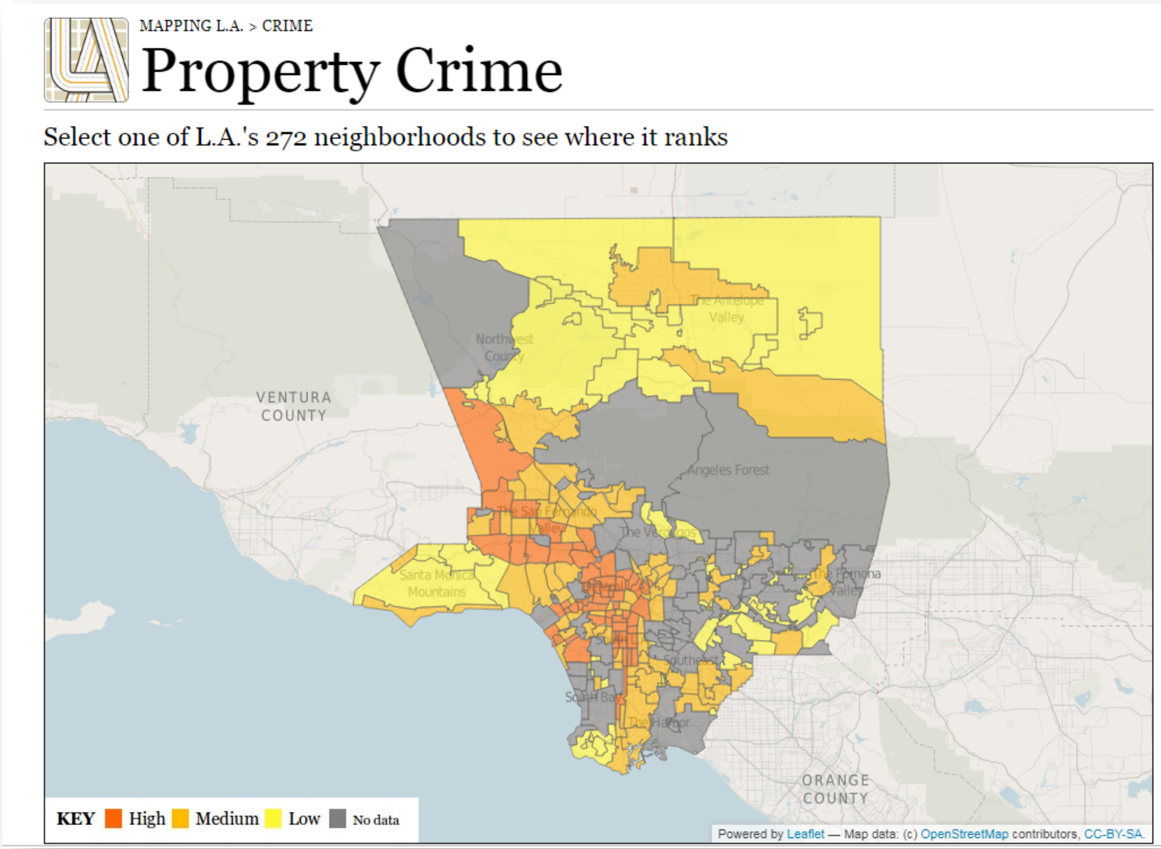

Figure 2: Los Angeles property crime rates data for all neighborhoods

- ✓ Violent Crime Rate from the below website:

https://maps.latimes.com/neighborhoods/violent-crime/neighborhood/list/

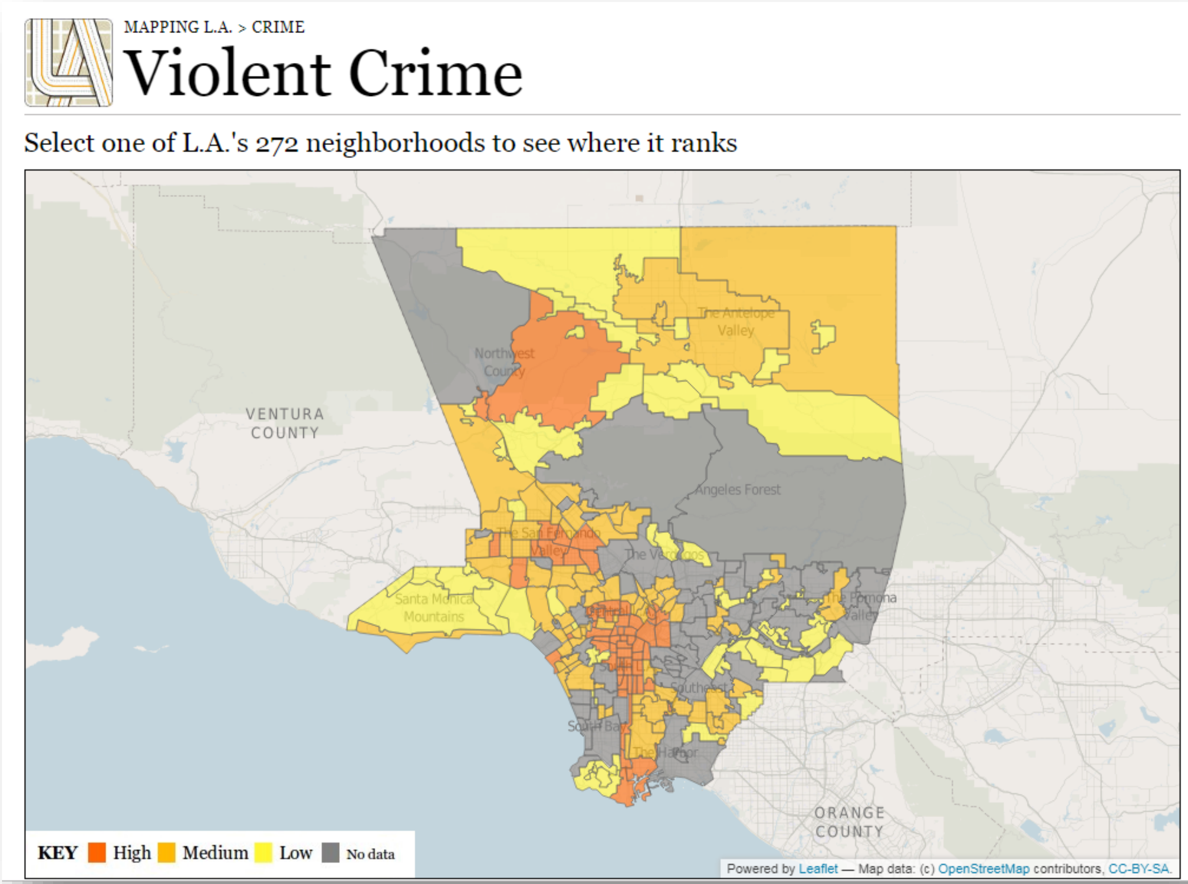

Figure 3: Los Angeles violent crime rates data for all neighborhoods

- ✓ Income Rate from the below website:

HTTPS://MAPS.LATIMES.COM/NEIGHBORHOODS/INCOME/MEDIAN/NEIGHBORHOOD/LIST/

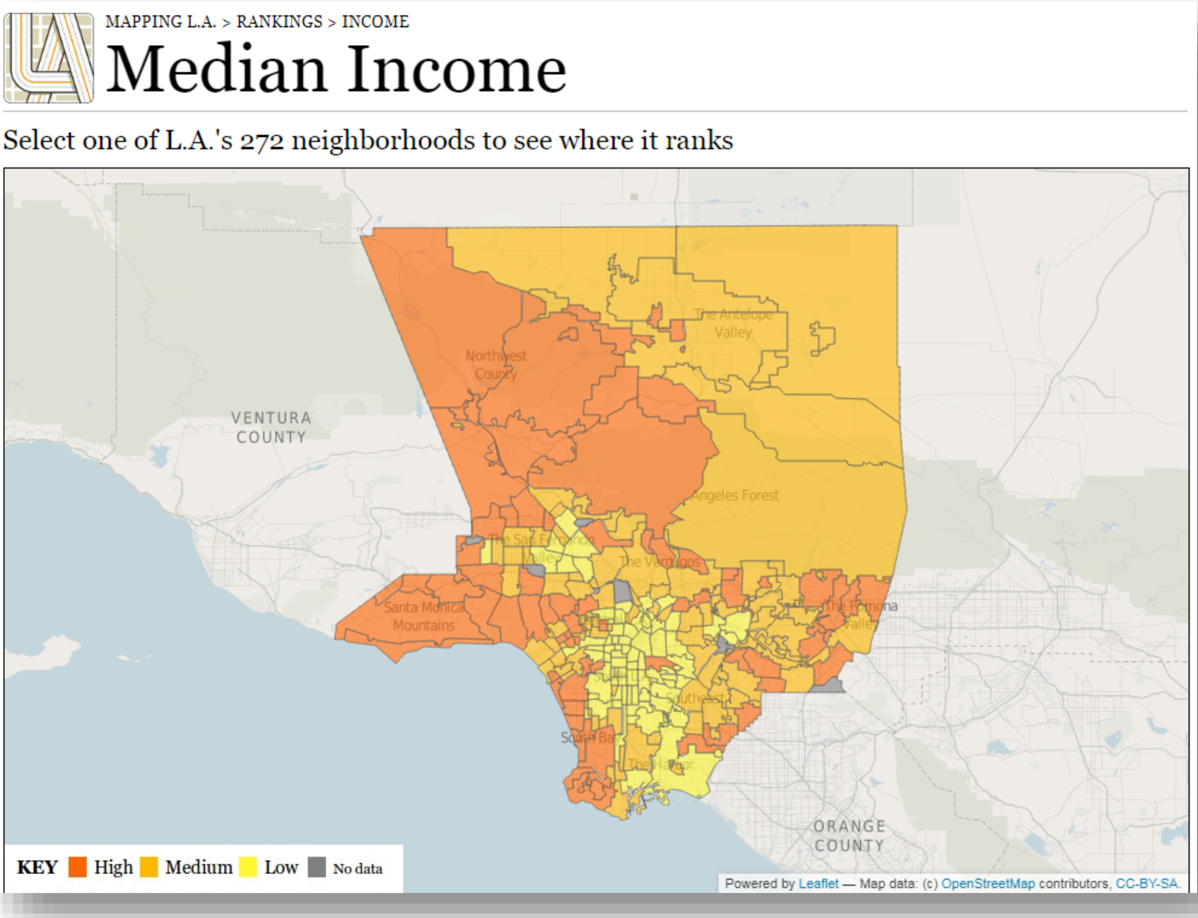

Figure 4: Los Angeles median income data for all neighborhoods

Methodology

We are going to use the above data as much as possible and a clustering algorithm in order to find the best neighborhood(s) to open a new restaurant in Los Angeles.

The methodology is as follows:

1. Data Extraction/Preparation
    - Neighborhood Name, Location and Area Size
    - Crime data
    - Income rate

2. Exploratory Data Analysis
3. Exploration of Los Angeles Neighborhoods
    - Selection of Target Area
    - Exploration of Venues in All Neighborhood
    - Categorize Venues
    - Analyze Each Neighborhood (Ranking)
4. Cluster Neighborhoods
    - K-Mean Method
    - Agglomerative method

Data Extraction/Preparation

Neighborhood Name, Location and Area Size

We need the only name of neighborhood, area size and coordinates. After extraction these columns, for better understanding column names will be replaced. It should be noted that column names related to coordinates are wrong and need to be replaced.

Table 1: First rows of final dataframe contains neighborhoods name, location and area size

	Neighborhood	Square_Mile	Longitude	Latitude
0	Adams-Normandie	0.805350	-118.300208	34.031461
1	Arleta	3.096179	-118.430757	34.243100
2	Arlington Heights	1.031415	-118.323408	34.044910
3	Atwater Village	1.776894	-118.262373	34.131066
4	Vermont-Slauson	1.442453	-118.290358	33.983914

Crime data

Violent crime is defined as homicide, rape, aggravated assault and robbery. Bear in mind that in areas with relatively low populations, a small number of crimes can generate a large per capita rate. For that reason, the below data frames contain per capita statistics for property and violent crimes. As we expect, some corrections are needed to use these crime data.

Table 2: First rows of final dataframe contains neighborhoods violent crime rate

	Neighborhood	Violent Crime Per Capita
0	Chesterfield Square	191.2
1	Harvard Park	133.2
2	Green Meadows	119.4
3	Manchester Square	112.3
4	Vermont Knolls	110.4

Table 3: First rows of final dataframe contains neighborhoods property crime

	Neighborhood	Property Crime Per Capita
0	Fairfax	345.8
1	Beverly Grove	294.0
2	Chesterfield Square	291.4
3	Westchester	247.6
4	Leimert Park	242.1

Income rate

Income is one of the main parameters in demography will be used.

Table 4: First rows of final dataframe contains neighborhoods income

	Neighborhood	Median Income
0	Bel-Air	207938.0
1	Hidden Hills	203199.0
2	Rolling Hills	184777.0
3	Beverly Crest	169282.0
4	Pacific Palisades	168008.0

Exploratory Data Analysis

The below table shows the statistic related to available data for the Los Angeles city.

Table 5: statistic related to available data for Los Angeles city

	Square_Mile	Violent Crime Per Capita	Property Crime Per Capita	Median Income
count	110.000000	110.000000	110.000000	110.000000
mean	4.208468	31.824545	122.129091	58447.127273
std	4.056408	32.469085	55.881379	30705.789351
min	0.486332	0.000000	33.100000	15003.000000
25%	1.491001	11.625000	85.875000	37186.750000
50%	2.733206	19.650000	110.500000	54105.500000
75%	5.516657	40.300000	147.675000	68719.000000
max	22.837601	191.200000	345.800000	207938.000000

- The size of Final data set Containing Neighborhood, Area size and Coordinates of Los Angeles city is (110, 7). The dataframe has 110 unique neighborhoods.
- Pacific Palisades with the area of 22.83 is the largest, and Larchmont with the area of 0.48 is the smallest neighborhoods in Los Angeles city.
- Fairfax with the property crime rate of 345.8 has the highest, and Century City with the property crime of 33.1 has the lowest rate in Los Angeles city.
- Chesterfield Square with the violent crime rate of 191.2 has the highest, and Bel-Air with the violent crime of 0.0 has the lowest rate in Los Angeles city.
- Bel-Air with the median income of 207938.0 $ has the highest income, and Downtown with the median income of 15003.0 $ has the lowest income in Los Angeles city.

Pairplot and Pearson are almost the same. Both plot two variables on a 2-dimensional plot, usually referred as X and Y to observe the relationship.

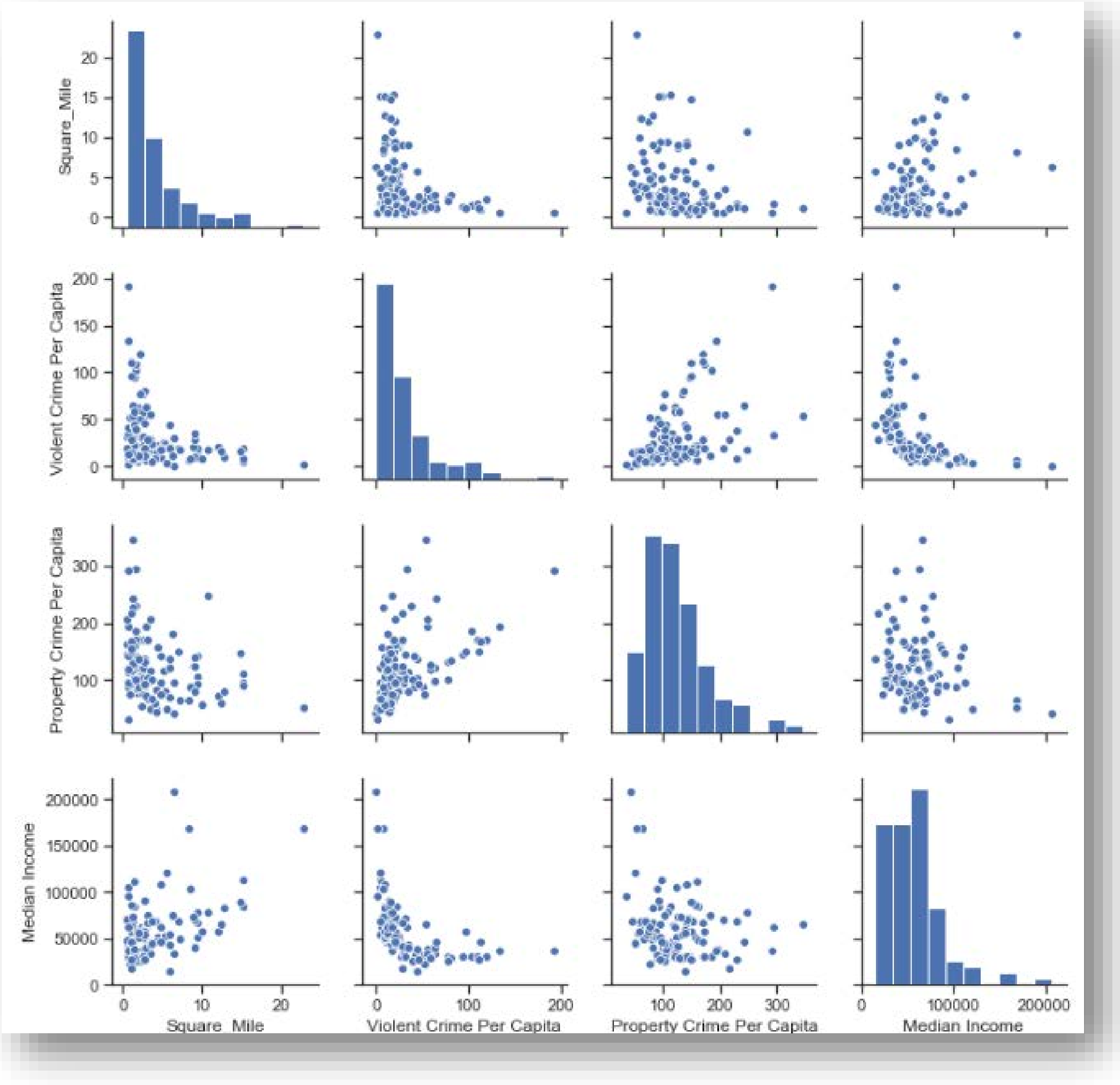

Figure 5: Pair plot of data related to Los Angeles showing the relationship between features

As can be seen, the violent crime rate increases as median income decreases. Almost, the property crime rate has the same trend. This probably shows that most the criminal activities happen in areas with lower income.

Exploration of Los Angeles Neighborhoods

After preparing all the data, the location of each neighborhood will be added to the map. Also, the coordinates will be used to find nearby venues that could be useful to find a place to open the restaurant. The below figure shows all neighborhoods of Los Angeles.

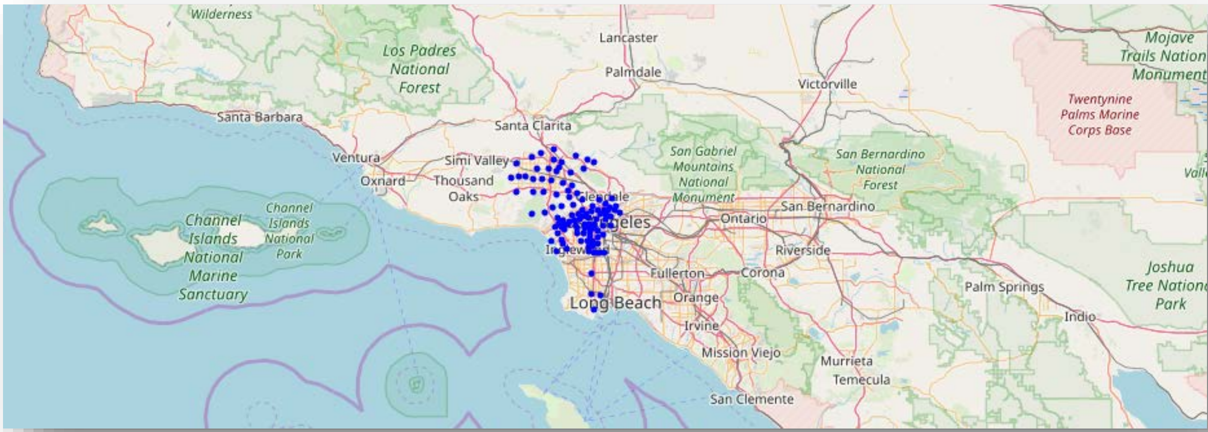

Figure 6: map of all neighborhoods of Los Angeles

Selection of Target Area

As there is a limitation for using Foursquare API, we will explore the North section of the city (The neighborhood above the latitude of 34.13)

Exploration of Venues in All Neighborhood

To find venues (top 100 venues within a radius of 500 meters) in every neighborhood Foursquare Credentials must be defined first. For better understanding, we are going to visualize all venues for the first neighborhood.

Table 6: Properties of all venues for the first neighborhood (Arltela) in the data frame

	Neighborhood	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category	Venue Category Value
0	Arleta	34.2431	-118.430757	Back To The Future Filming Location - McFly's ...	34.243429	-118.433655	Historic Site	0
1	Arleta	34.2431	-118.430757	Redbox	34.242081	-118.426109	Video Store	0
2	Arleta	34.2431	-118.430757	7-Eleven	34.241595	-118.426129	Convenience Store	0
3	Arleta	34.2431	-118.430757	Mariscos El Bigoton	34.241010	-118.427620	Seafood Restaurant	1
4	Arleta	34.2431	-118.430757	Vim Thai Restaurant	34.244394	-118.426429	Thai Restaurant	1
5	Arleta	34.2431	-118.430757	Yummy Donuts & Croissants	34.242344	-118.426159	Bakery	1
6	Arleta	34.2431	-118.430757	T D I - Electricity and Automation Solutions	34.238878	-118.429234	Construction & Landscaping	0

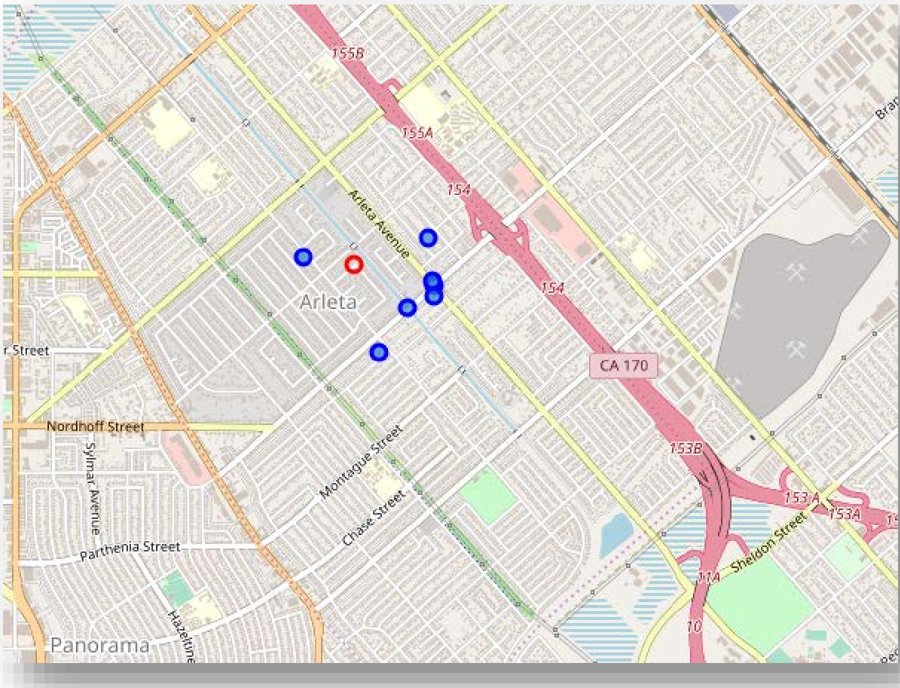

Figure 7: Map of Venues (blue) around neighborhood Arleta (red)

7 venues were returned by Foursquare for the first neighborhood.

Categorize Venues

Based on our aim to find the best areas to open the restaurant, the venues are divided into two groups.

- The first group contains all venues that related to food like, restaurant, fast food, etc.
- The second group contains all other venues like gym, stores, etc. To group the venues, the categories available on Foursquare website.

Analyze Each Neighborhood (Ranking)

To rank the venues based on the frequency of occurrence (For two categories). We need to use one hot encoding. This adds new features to the dataset based on Venue Category columns.

Table 7: The mean of the frequency of occurrence of each venue type

	Neighborhood	ATM	American Restaurant	Art Gallery	Arts & Crafts Store	Asian Restaurant	Athletics & Sports	Automotive Shop	Bakery	Bank	...
0	Arleta	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.142857	0.0	...
1	Canoga Park	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...
2	Chatsworth	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...
3	Encino	0.045455	0.045455	0.0	0.0	0.0	0.0	0.0	0.045455	0.0	...
4	Lake Balboa	0.000000	0.000000	0.0	0.0	0.0	0.0	0.0	0.000000	0.0	...

5 rows × 119 columns

Now let's create the new dataframe and display the top 2 venues for each neighborhood

Table 8: Top 2 food-related venues for each neighborhood

	Neighborhood	1st Most Common Food Venue	2nd Most Common Food Venue
0	Arleta	Thai Restaurant	Bakery
1	Canoga Park	Mexican Restaurant	Ice Cream Shop
2	Chatsworth	Wings Joint	Vietnamese Restaurant
3	Encino	Japanese Restaurant	Deli / Bodega
4	Lake Balboa	Mexican Restaurant	Burger Joint

Table 9: Top 2 other venues for each neighborhood

	Neighborhood	1st Most Common Other Venue	2nd Most Common Other Venue
0	Arleta	Video Store	Historic Site
1	Canoga Park	Sports Bar	Furniture / Home Store
2	Chatsworth	Park	Wine Bar
3	Encino	ATM	Supplement Shop
4	Lake Balboa	Convenience Store	Pharmacy

We will use the data frame related to the ranking of venues during the investigation of resulted clusters.

Cluster Neighborhoods

Before conducting clustering we will prepare the input dataframe. It contains neighborhood area size, crime, total number of food and other venues. The column of neighborhood name will be deleted before using in clustering.

Table 10: All data used in the clustering process

	Neighborhood	Square_Mile	Violent Crime Per Capita	Property Crime Per Capita	Median Income	sum_food_places	sum_other_places
0	Arleta	3.096179	12.0	66.8	65649.0	3.0	4
1	Canoga Park	4.348518	22.8	157.2	51601.0	5.0	5
2	Chatsworth	15.243597	18.6	111.3	84456.0	0.0	2
3	Northridge	9.467487	15.6	141.6	67906.0	11.0	2
4	Encino	9.499707	9.0	106.8	78529.0	13.0	9

K-Mean Method

K-Means is a type of partitioning clustering which divides the data into K non-overlapping sphere-like clusters without any labels. It is relatively efficient on medium to large-sized data sets. This method tries to minimize intra-cluster distances and maximize the inter-cluster distances. To know how are the data points in a cluster, we need to use dissimilarity measures such as Euclidean distance or Average distance. The K means algorithm steps are as follow:

Randomly Initialize centroids (representative points of each cluster) Distance calculation (Distance Matrix as a dissimilarity measure) to find the nearest centroid to data points Assign each point to the nearest centroid Update the centroids for every cluster Repeat until there is no more change (move the centroids, calculate the distances from new centroids and assign data points to the nearest centroid)

Agglomerative method

Hierarchical clustering algorithms build a hierarchy of clusters where each node is a cluster consisting of the clusters of its daughter nodes. There are two types of Hierarchical clustering algorithms.

The advantages of hierarchical clustering are no need to specify the number of clusters, easy to implement and generated dendrogram is useful to understand the data. The main disadvantage of the algorithm is long computation times.

Results

In this analysis, different combinations of algorithm setting were used to find the best solution. Using hierarchical clustering was not improved the result and K-mean shows the best result. The below figure depict three clusters using K-mean method.

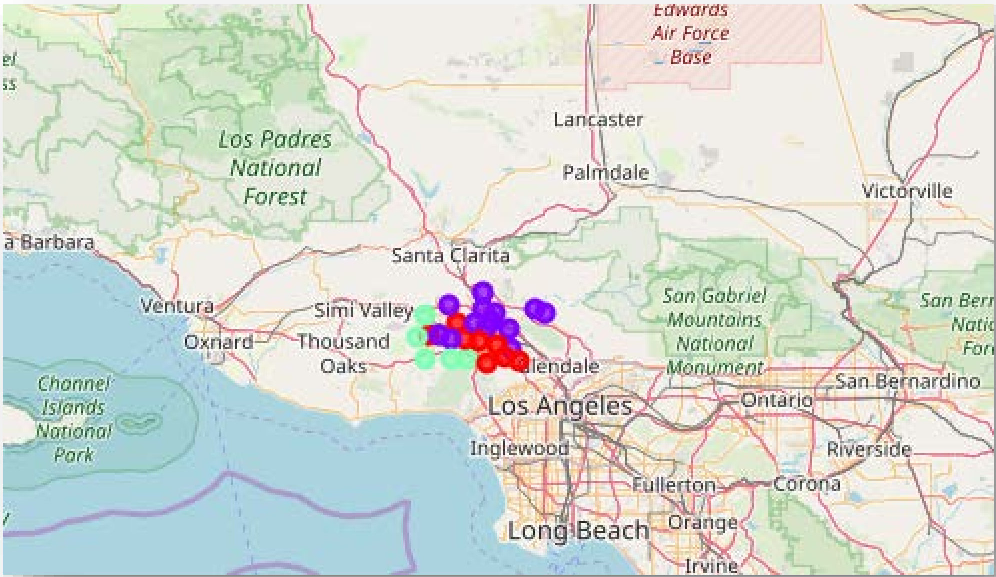

Figure 8: Map of the final clustering algorithm result (three clusters)

The descriptions of three clusters are as follow.

Cluster 1:

Table 11: Description of cluster no. 1

	Square_Mile	Violent Crime Per Capita	Property Crime Per Capita	Median Income	Cluster Labels	sum_food_places	sum_other_places
count	5.000000	5.000000	5.000000	5.000000	5.0	5.000000	5.000000
mean	11.366119	14.440000	115.780000	85826.800000	0.0	3.400000	3.800000
std	3.345872	5.435347	22.488375	11476.724171	0.0	5.458938	3.114482
min	8.528078	8.400000	87.900000	73195.000000	0.0	0.000000	1.000000
25%	8.790902	9.000000	106.800000	78529.000000	0.0	0.000000	2.000000
50%	9.499707	16.100000	111.300000	84456.000000	0.0	2.000000	3.000000
75%	14.768310	18.600000	124.400000	89946.000000	0.0	2.000000	4.000000
max	15.243597	20.100000	148.500000	103008.000000	0.0	13.000000	9.000000

Cluster 2:

Table 12: Description of cluster no. 2

	Square_Mile	Violent Crime Per Capita	Property Crime Per Capita	Median Income	Cluster Labels	sum_food_places	sum_other_places
count	8.000000	8.00000	8.000000	8.000000	8.0	8.000000	8.000000
mean	5.398485	16.81250	127.675000	58798.000000	1.0	9.375000	9.375000
std	3.350725	7.00213	22.173714	11847.724941	0.0	5.153016	6.738747
min	1.217228	8.20000	95.100000	41134.000000	1.0	4.000000	2.000000
25%	2.865741	11.00000	117.025000	50244.500000	1.0	5.750000	4.250000
50%	4.577031	17.55000	133.750000	60403.000000	1.0	7.500000	8.000000
75%	9.029916	20.47500	140.625000	68342.250000	1.0	12.500000	14.000000
max	9.467487	28.10000	157.200000	73111.000000	1.0	17.000000	20.000000

Cluster 3:

Table 13: Description of cluster no. 3

	Square_Mile	Violent Crime Per Capita	Property Crime Per Capita	Median Income	Cluster Labels	sum_food_places	sum_other_places
count	13.000000	13.000000	13.000000	13.000000	13.0	13.000000	13.000000
mean	6.182739	15.807692	77.484615	62510.230769	2.0	3.461538	3.076923
std	2.864045	6.130180	21.443097	20219.765294	0.0	3.256158	2.139374
min	3.096179	3.900000	50.400000	42791.000000	2.0	0.000000	1.000000
25%	4.004117	12.000000	60.200000	51290.000000	2.0	1.000000	2.000000
50%	5.586170	17.500000	69.700000	58001.000000	2.0	2.000000	2.000000
75%	7.137554	19.800000	92.800000	65783.000000	2.0	6.000000	4.000000
max	12.456388	23.800000	122.900000	121428.000000	2.0	9.000000	9.000000

Discussion

Investigation of clusters is one of the most important issues in cluster analysis in order to justify the selection of the right candidates.

The below table shows the comparison of different features for all clusters.

Table 14: comparison of different features for all clusters

Attribute	cluster 1			cluster 2			cluster 3		
	MIN	AVG	MAX	MIN	AVG	MAX	MIN	AVG	MAX
Area Size	8.52	11.36	15.25	1.2	5.4	9.46	3	6.18	12.45
Violent Crime Rate	8.4	14.44	20.1	8.2	16.81	28.1	3.9	15.8	23.8
Property Crime Rate	87.9	115.8	148.5	95.1	127.7	157.2	50.4	77.5	122.9
Median Income	73000	86000	103000	41000	58800	73000	42000	62500	121000
No. of Food Realted Place	0	3.4	13	4	9.4	17	0	3.5	9
No. of Other Place	1	3.8	9	2	9.4	20	1	3.1	9

Cluster 1 (cyan)

This cluster contains 5 neighborhoods. The average area size of this cluster is around 11 which is the highest among all clusters. the violent and property crime rates are 14.5 and 115.8, respectively which introduce this cluster as the highest crime rate after cluster 2. The income range for this cluster is 73000 to 103000. The ratio of the number of food-related venues to other kind of venues is 0.9.

Cluster 2 (red)

This cluster contains 8 neighborhoods. The average area size of this cluster is around 5.4 which is the lowest among all clusters. the violent and property crime rates are 16.8 and 127.7, respectively which is the highest crime rate after cluster 2. The income range for this cluster is 41000 to 73000. This is the lowest income rate among all clusters. The ratio of the number of food-related venues to other kind of venues is 1. It means that on average the number of venues related to food is equal to the number of other venues like the gym, etc.

Cluster 3 (purple)

This cluster contains 13 neighborhoods. The average area size of this cluster is around 6.2. the violent and property crime rates are 15.8 and 77.5, respectively which is the lowest crime rate among all clusters. The income range for this cluster is 42000 to 121000. The ratio of the number of food-related venues to other kind of venues is 0.88.

Conclusion

During this analysis, different kind of data contains area size, violent crime rate, property crime rate, income rate, number of food-related venues and number of other types of venues. K-mean and Agglomerative methods were used to find the best clusters that could able to group neighborhoods, precisely. Also, different combinations of the above data were selected to find the best results. Finally, K-mean algorithm shows the best performance. Based on the above cluster descriptions, cluster 3 is the best areas to open a restaurant. This cluster has minimum criminal rates, minimum food-related venues to other type ratio and wide range of incomes. The next table shows the neighborhoods belong to this cluster.

Table 15: Best locations to open a restaurant

	Square_Mile	Violent Crime Per Capita	Property Crime Per Capita	Median Income	Cluster Labels	1st Most Common Food Venue	2nd Most Common Food Venue	sum_food_places	1st Most Common Other Venue	2nd Most Common Other Venue	sum_other_places
0	3.096179	12.0	66.8	65649.0	2	Thai Restaurant	Bakery	3.0	Video Store	Historic Site	4.0
6	3.187498	15.9	102.9	75675.0	2	Wings Joint	Vietnamese Restaurant	0.0	Church	Park	2.0
7	5.308118	23.2	79.7	52456.0	2	Pizza Place	Fast Food Restaurant	2.0	Grocery Store	River	2.0
8	5.869115	21.2	122.9	42791.0	2	Latin American Restaurant	Indian Restaurant	9.0	Wine Bar	Mobile Phone Shop	9.0
9	7.137554	18.0	65.5	49066.0	2	Breakfast Spot	Food Truck	2.0	Home Service	Wine Bar	1.0
10	3.647996	23.8	101.2	44468.0	2	Mexican Restaurant	Wings Joint	1.0	Skating Rink	Park	3.0
11	5.586170	3.9	50.4	121428.0	2	American Restaurant	Vietnamese Restaurant	1.0	Park	Electronics Store	3.0
12	5.865491	18.5	69.7	54771.0	2	Vietnamese Restaurant	Fast Food Restaurant	9.0	Convenience Store	Supermarket	2.0
14	12.456388	15.3	60.2	65783.0	2	Pizza Place	Mexican Restaurant	7.0	Business Service	Garden Center	1.0
15	4.004117	7.9	60.2	68720.0	2	Food Court	Wings Joint	1.0	Concert Hall	Park	2.0
16	9.423924	19.8	92.8	51290.0	2	Taco Place	Food Truck	4.0	Convenience Store	Electronics Store	4.0
19	10.015818	8.5	58.6	58001.0	2	Wings Joint	Vietnamese Restaurant	0.0	Lake	Trail	2.0
24	4.777241	17.5	76.4	62535.0	2	Ice Cream Shop	Fried Chicken Joint	6.0	Convenience Store	Home Service	5.0

Within the selected cluster and based on ranked food venues or even other venues we can offer the type of food-related venues in different neighborhood. It should be noted that in this table the two top venues are shown. One may consider the less common type of venues. Looking at both, the most common and less common food-related is recommended.