

# Miami Neighborhoods Guide

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## Abstract

This project uses unsupervised machine learning method: k-means to explore and cluster neighborhoods in Miami-dade county, in order to help customers to determine the most suitable neighborhood with personalized feature selection demands.

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## 1 Introduction

### 1.1 Background

Located on the southern tip of mainland Florida, Miami teems with diverse cultural experiences, artwork, nightlife, and beauty. Living in and exploring Miami can be a total blast if you're up for some adventure. However, finding the perfect home among roughly numerous Miami neighborhoods and municipalities can feel overwhelming, especially when there're so many factors to consider, such as locations, prices, local culture, etc. Thus a method is needed to extract all the information one need to make their decisions and visualize the results on a map with details. And that's where machine learning comes to play. By using unsupervised machine learning methods and clustering neighborhoods with similar features, this project can help you take a shortcut of find the best place to stay if you know what kind of features you're looking for, such as a quiet neighborhood with high walkability and casual life style, or a coast line apartment with a perfect viewing point and easy beach access. By showing those groups of neighborhoods on a live map with distinct colors for each cluster, you can see clearly where to look or what to look for your perfect stay in Miami.

### 1.2 Business Problem

The general goal of this project is to help people visualize and find the most suitable neighborhoods in Miami-Dade County. The problem can be treated as 3 parts:

- Scrape relative information about neighborhoods in Miami, including names, locations, average rents, populations, etc.
- Develop a unsupervised machine learning method to cluster neighborhoods in Miami and explore their features in each cluster.
- Visualize the neighborhood clusters and their features on a interactive map.

### 1.3 Target Customers

This project should be interesting and helpful for new-comers who visits Miami for the first time, or for anyone who wants to have a general concept of how different neighborhoods are distributed in Miami-Dade County, and what they are most popular with. It should also be

intriguing for those who wants to develop an app that helps people find apartments, hotels and other places to stay in Miami area. This project can help you visualize the results and find popular features in your target neighborhoods.

## 2 Data

### 2.1 Data Requirement

When people talk about Miami, or the Magic City, they usually refer to Miami-Dade County, which covers City of Miami, Coral Gables, and the famous Miami Beach, and many other surrounding areas. However, finding neighborhoods in Miami-Dade County is relatively complicated. The county can be divided into a list of Municipalities and Census-designated places, each having their own definition of neighborhoods. Counting all the neighborhood in every municipality would be too much for this project. To make things simpler and clearer, I decide to divide the neighborhoods into two parts:

- Part 1: Neighborhoods in City of Miami following the definition in this [Wikipedia page](#).
- Part 2: Other municipalities in Miami-Dade County, such as Coral Gables, Kendall and Miami Beach.

For each part I construct a dataset including their names, coordinates and find their population and average rent \* accordingly. In the end, I merge those two parts together and in this way I can construct a table containing neighborhood names, locations, populations and average rents for all the neighborhoods in Miami plus all the municipalities in Miami-Dade County. By using Foursquare data, I can explore and add popular venues in each neighborhood, thus complete the construction of this dataset.

### 2.2 Data Preprocessing

To find all the neighborhoods and cluster them based on their features, we need the following data: (1).A list of neighborhoods in Miami City that includes neighborhood names, latitudes and longitudes, average rents and recent populations; (2).A list of municipalities in Miami-Dade County, excluding Miami City area, that includes the same features as (1); (3).Foursquare data in JSON format for each neighborhood and municipality including venue names and categories.

#### 2.2.1 Part 1: Neighborhoods in City of Miami

The information of average rents in each neighborhood can be found on this [website](#) (see Fig.1). And a table of list of neighborhoods in Miami City can be obtained in this [Wikipedia page](#). This table contains neighborhood names, population information, and coordinates. (see Fig.2)

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\*Rent\*: The average rent in this project is calculated for two-bedroom apartments.

	Neighborhood	Rent
0	Brickell	\$2,050
1	Coral Way	\$1,650
2	Edgewater	\$1,909
3	Little Haiti	\$2,149
4	Downtown Miami	\$1,800
5	East Little Havana	\$1,300

**Fig. 1.** Average Rent for Neighborhoods in City of Miami.

	Neighborhood	Demonym	Population2010	Population/Km <sup>2</sup>	Sub-neighborhoods	Coordinates
0	Allapattah	NaN	54289	4401	NaN	25.815-80.224
1	Arts & Entertainment District	NaN	11033	7948	NaN	25.799-80.190
2	Brickell	Brickellite	31759	14541	West Brickell	25.758-80.193
3	Buena Vista	NaN	9058	3540	Buena Vista East Historic District and Design ...	25.813-80.192
4	Coconut Grove	Grovite	20076	3091	Center Grove, Northeast Coconut Grove, Southwe...	25.712-80.257
5	Coral Way	NaN	35062	4496	Coral Gate, Golden Pines, Shenandoah, Historic...	25.750-80.283
6	Design District	NaN	3573	3623	NaN	25.813-80.193
7	Downtown	Downtownner	71,000 (13,635 CBD only)	10613	Brickell, Central Business District (CBD), Dow...	25.774-80.193
8	Edgewater	NaN	15005	6675	NaN	25.802-80.190
9	Flagami	NaN	50834	5665	Alameda, Grapeland Heights, and Fairlawn	25.762-80.316

**Fig. 2.** A List of Neighborhoods in City of Miami.

We only need neighborhood names, population and coordinates from this table. After removing irrelevant columns and converting coordinates column to latitudes and longitudes, we can combine Fig.1 with Fig.2 and construct a table with all the features we need (see Fig.3).

	Neighborhood	Population	Latitudes	Longitudes	Rent
0	Allapattah	54289	25.815	-80.224	\$1,555
1	Arts & Entertainment District	11033	25.799	-80.190	\$1,855
2	Brickell	31759	25.758	-80.193	\$2,050
3	Buena Vista	9058	25.813	-80.192	NaN
4	Coconut Grove	20076	25.712	-80.257	\$1,360
5	Coral Way	35062	25.750	-80.283	\$1,650
6	Design District	3573	25.813	-80.193	NaN

**Fig. 3.** Table of Neighborhoods in City of Miami.

### 2.2.2 Part 2: Municipalities in Miami-Dade County

Miami-Dade County is comprised of 34 municipalities. Adding all neighborhoods in all municipalities would be overwhelming for our purpose. Thus, we treat each municipality

as a whole and count it as one neighborhood. Getting the location and average rents for municipalities can be a little bit tricky, since no table can be found that gives all the information we need directly. The [ROOF DEPOT USA](#) website provides some basic information, including folio number, municipality names, zipcodes, address, and contact information for this company (Fig.4). We only need zipcodes and municipality names from this table. After

Folio	Municipality	Address	Bldg. Dept. Phone No.	Zip Code	Inspection Phone No.	Inspection		Inspection Links	Building Dept. Links
						Call Hrs.	Days		
28	Aventura	19200 W. Country Club Dr.	305-466-8937	33180	305-466-8900	8:30-4:00		<a href="http://www.cityofaventura.co">http://www.cityofaventura.co</a>	
12	Bal Harbour	665 96 Street	305-865-7525	33154	305-866-4633	8:00-4pm		<a href="http://www.balharbour.org">http://www.balharbour.org</a>	
13	Bay Harbor Island	9665 Bay Harbor Terrace	305-993-1786	33154	305-993-1786	9:00-5:00	M/W/F	<a href="http://www.bayharborislands.com">http://www.bayharborislands.com</a>	
17	Biscayne Park	640 NE 114 Street	305-893-7490	33161	305-899-8000	8:00-2:30		<a href="http://www.biscaynepark.gov">http://www.biscaynepark.gov</a>	
3	Coral Gables	405 Biltmore Way	305-446-6800	33134	305-460-5245	7:30-3:30		<a href="http://coralgables.com">http://coralgables.com</a>	
35	Doral	8300 NW 53 ST #100	305-593-6725	33178	305-593-6725	8:00-4:00		<a href="http://207.1cityofdoral.com">http://207.1cityofdoral.com</a>	
18	El Portal	500 NE 87 Street	305-795-7880	33138	305-795-7880	8:00-2:30	Tu/Thr		
16	Florida City	404 W. Palm Drive Bldg 3	305-242-8125	33034		8:00-4:30		<a href="http://www.floridacity.com">http://www.floridacity.com</a>	
19	Golden Beach	1 Golden Beach Drive	305-932-0744	33160	305-932-0744	8:00-3:30	M/W	<a href="http://www.goldenbeach.com">http://www.goldenbeach.com</a>	
4	Hialeah	501 Palm Avenue	305-883-5825	33011	305-883-5825	8:00-4:00		<a href="http://hialeahfl.gov">hialeahfl.gov</a>	
27	Hialeah Gardens	10001 NW 87 Avenue	305-558-4114	33016	305-558-4114	8:30-5:00		<a href="http://www.cityofhialeahgardens.com">http://www.cityofhialeahgardens.com</a>	
10	Homestead	790 N. Homestead Blvd	305-247-1801	33030	305-224-4500	7:30-4:30		<a href="http://servicetownofhomestead.com">http://servicetownofhomestead.com</a>	
21	Indian Creek	9080 Bay Drive	305-865-4121	33154	305-865-4121	9:00-5:00			
24	Key Biscayne	88 W. McIntyre Street	305-365-5511	33149	305-365-5512	8:00-3:00		<a href="http://www.keybiscayne.fl.gov">http://www.keybiscayne.fl.gov</a>	

**Fig. 4.** List of Municipalities in Miami-Dade County by ROOF DEPOT USA.

removing other columns, the zipcodes can be converted to latitudes and longitudes using GeoPy, which is a Python client for several popular geocoding web services. The [OFFICE OF POLICY DEVELOPMENT AND RESEARCH \(PDR\)](#) offers information about fair market rents, which can be downloaded as a .xlsx spreadsheet, which are indexed by their zipcodes. We can read this table into a Pandas DataFrame and append rents to our table according to corresponding zipcodes. Similarly, the population information can be obtained using uszipcode - a programmable zipcode database in Python. After appending this information by their zipcodes, we complete our table of municipalities in Miami-Dade County (Fig.5).

	Municipality	Zipcode	Latitudes	Longitudes	Rent	Population
0	Aventura	33180	25.962897	-80.144402	\$2310	30840.0
1	Bal Harbour	33154	25.882990	-80.128078	\$2220	13971.0
2	Bay Harbor Island	33154	25.882990	-80.128078	\$2220	13971.0
3	Biscayne Park	33161	25.893410	-80.182457	\$1470	53710.0
4	Coral Gables	33134	25.755556	-80.270126	\$1740	37456.0
5	Doral	33178	25.832296	-80.369946	\$2250	39489.0

**Fig. 5.** Table of Municipalities in Miami-Dade County.

### 2.2.3 Get venues from Foursquare

We can now combine neighborhood table and municipality table from Part 1 and part 2 into one Pandas DataFrame, following the same format as Fig.3. And we can define a function to get popular venues in a given radius(2000 meters in this project) for each neighborhood in our table from Foursquare database (Fig.6).

	Neighborhood	Latitudes	Longitudes	Venue	Venue Latitude	Venue Longitude	Venue Category
0	Allapattah	25.815	-80.224	Club Tipico Dominicano	25.809557	-80.218593	Nightclub
1	Allapattah	25.815	-80.224	Plaza Seafood Market	25.805638	-80.223992	Seafood Restaurant
2	Allapattah	25.815	-80.224	Snappers Fish & Chicken	25.824110	-80.224870	Seafood Restaurant
3	Allapattah	25.815	-80.224	Papo Llega y Pon	25.803466	-80.223886	Cuban Restaurant
4	Allapattah	25.815	-80.224	Moore Park	25.810316	-80.209683	Park

**Fig. 6.** Table of popular venues in each neighborhood.

### 3 Methodology

To get a general idea of our data, we can make a list of top 10 most common venues in each neighborhood. As we can see from Fig.7, the most common venues are typically restaurants, coffee shops and hotels. This is because the top 1 industry in Miami is tourism. With the allure of warm weather year-round, miles of beaches and world-class nightlife, this is not surprising.

	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	Allapattah	Fast Food Restaurant	Gas Station	Fried Chicken Joint	Nightclub	Seafood Restaurant	Discount Store	Grocery Store	Sandwich Place	Park	Latin American Restaurant
1	Arts & Entertainment District	Art Gallery	Ice Cream Shop	Restaurant	Coffee Shop	Bar	Beer Garden	Pizza Place	Sandwich Place	Mexican Restaurant	Asian Restaurant
2	Aventura	Clothing Store	Cosmetics Shop	Grocery Store	Department Store	Italian Restaurant	Furniture / Home Store	American Restaurant	Electronics Store	Hotel	Coffee Shop
3	Bal Harbour	Beach	Hotel	Italian Restaurant	French Restaurant	Coffee Shop	Resort	Sushi Restaurant	Jewelry Store	Grocery Store	Department Store
4	Brickell	Hotel	Italian Restaurant	Argentinian Restaurant	Bar	Spa	Seafood Restaurant	Lounge	Steakhouse	Bakery	Japanese Restaurant
5	Buena Vista	Art Gallery	Ice Cream Shop	Coffee Shop	Italian Restaurant	Café	Pizza Place	Restaurant	Gym / Fitness Center	Asian Restaurant	Latin American Restaurant
6	Coconut Grove	Park	American Restaurant	Coffee Shop	Bakery	Garden	Convenience Store	Gym	Health & Beauty Service	Breakfast Spot	Shop & Service
7	Coral Gables	Café	Hotel	Italian Restaurant	Steakhouse	Bakery	Gastropub	Coffee Shop	Restaurant	Cuban Restaurant	Spanish Restaurant
8	Coral Way	Pharmacy	Bakery	Golf Course	Pool	Cuban Restaurant	Park	Spa	Latin American Restaurant	Pizza Place	Café
9	Design District	Art Gallery	Ice Cream Shop	Coffee Shop	Italian Restaurant	Café	Restaurant	Gym / Fitness Center	Pizza Place	Asian Restaurant	Furniture / Home Store

**Fig. 7.** Top 10 most common venues in each neighborhood.

#### 3.1 K-means Clustering

The goal of this project is to use machine learning methods to cluster neighborhoods based on popular venues. There are many clustering algorithm that can get the job done, such as k-means, hierarchical and fuzzy clustering, DBSCAN, etc. In this project, we select to use k-means as our clustering method, given its simplicity and speed. K-means calculate and cluster different points based on the Euclidean distance in feature space. This method works best if the data can be clustered into spherical clusters, and only works with numerical data (There's an k-means extension called k-modes that works with categorical data).

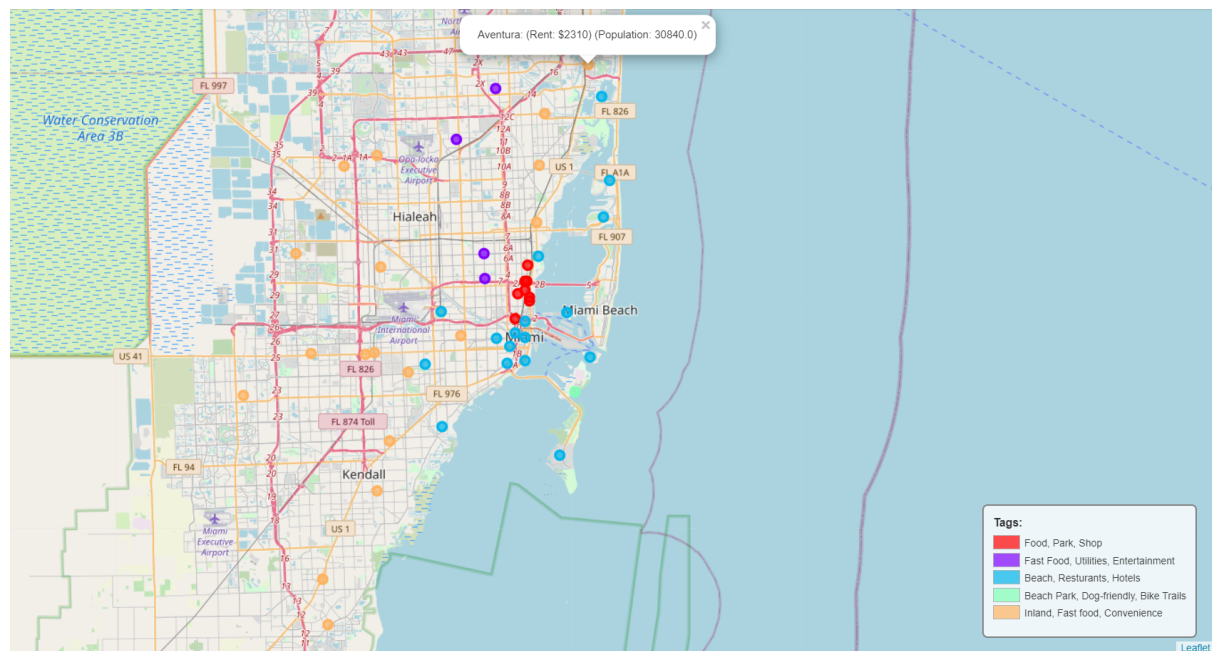
To convert our table into feature space with numerical values, we need to use one-hot encoding to convert categorical data, namely the venue categories, into binary coded columns. Then we group the data by neighborhood and by taking the mean of the frequency of occurrence of each venue category, we can construct a table with all features in numerical format (Fig.8).

Now we are ready to run k-means on our dataset. We select an initial  $k=5$  to start. This

	Neighborhood_Name	ATM	Accessories Store	Airport Lounge	Airport Service	American Restaurant	Antique Shop	Aquarium	Arcade	Arepa Restaurant	...	Warehouse Store	Water Park	Wine Bar	Wine Shop	Winery	Wings Joint	Women's Store	Yoga Studio	Zoo	Zoo Exhibit
0	Allapattah	0.0	0.00	0.0	0.0	0.000000	0.0	0.0	0.00	0.00	—	0.0	0.0	0.000000	0.00	0.000000	0.0	0.000000	0.00	0.0	0.0
1	Arts & Entertainment District	0.0	0.00	0.0	0.0	0.010000	0.0	0.0	0.00	0.01	—	0.0	0.0	0.010000	0.00	0.000000	0.0	0.000000	0.00	0.0	0.0
2	Aventura	0.0	0.01	0.0	0.0	0.030000	0.0	0.0	0.00	0.00	—	0.0	0.0	0.000000	0.01	0.000000	0.0	0.010000	0.00	0.0	0.0
3	Bal Harbour	0.0	0.00	0.0	0.0	0.015625	0.0	0.0	0.00	0.00	—	0.0	0.0	0.000000	0.00	0.000000	0.0	0.015625	0.00	0.0	0.0
4	Brickell	0.0	0.00	0.0	0.0	0.030000	0.0	0.0	0.00	0.00	—	0.0	0.0	0.000000	0.01	0.000000	0.0	0.000000	0.02	0.0	0.0
5	Buena Vista	0.0	0.00	0.0	0.0	0.010000	0.0	0.0	0.01	0.01	—	0.0	0.0	0.010000	0.00	0.000000	0.0	0.010000	0.00	0.0	0.0
6	Coconut Grove	0.0	0.00	0.0	0.0	0.053571	0.0	0.0	0.00	0.00	—	0.0	0.0	0.017857	0.00	0.000000	0.0	0.000000	0.00	0.0	0.0
7	Coral Gables	0.0	0.00	0.0	0.0	0.020000	0.0	0.0	0.00	0.00	—	0.0	0.0	0.000000	0.00	0.000000	0.0	0.000000	0.00	0.0	0.0
8	Coral Way	0.0	0.00	0.0	0.0	0.012658	0.0	0.0	0.00	0.00	—	0.0	0.0	0.000000	0.00	0.012658	0.0	0.000000	0.00	0.0	0.0
9	Design District	0.0	0.00	0.0	0.0	0.020000	0.0	0.0	0.01	0.01	—	0.0	0.0	0.010000	0.00	0.000000	0.0	0.010000	0.00	0.0	0.0

**Fig. 8.** Frequency of popular venues in each neighborhood.

means all neighborhoods are grouped into 5 clusters based on the features in Fig.8. We can use the folium package to visualize the results (Fig.9). Folium is a Python wrapper for Leaflet.js, which is a leading open-source JavaScript library for plotting interactive maps. It is generally used for visualizing geospatial data. In this map, each clustered are marked with a unique color and associated popular tags. This map is interactive, which means when you click on a marker, a popup label containing neighborhood name, average rent and local population will show up, and you can zoom in or zoom out anytime you want. This is helpful when you need to focus on a particular neighborhood while browsing through the whole map.



**Fig. 9.** Neighborhoods in Miami clustered by k-means.

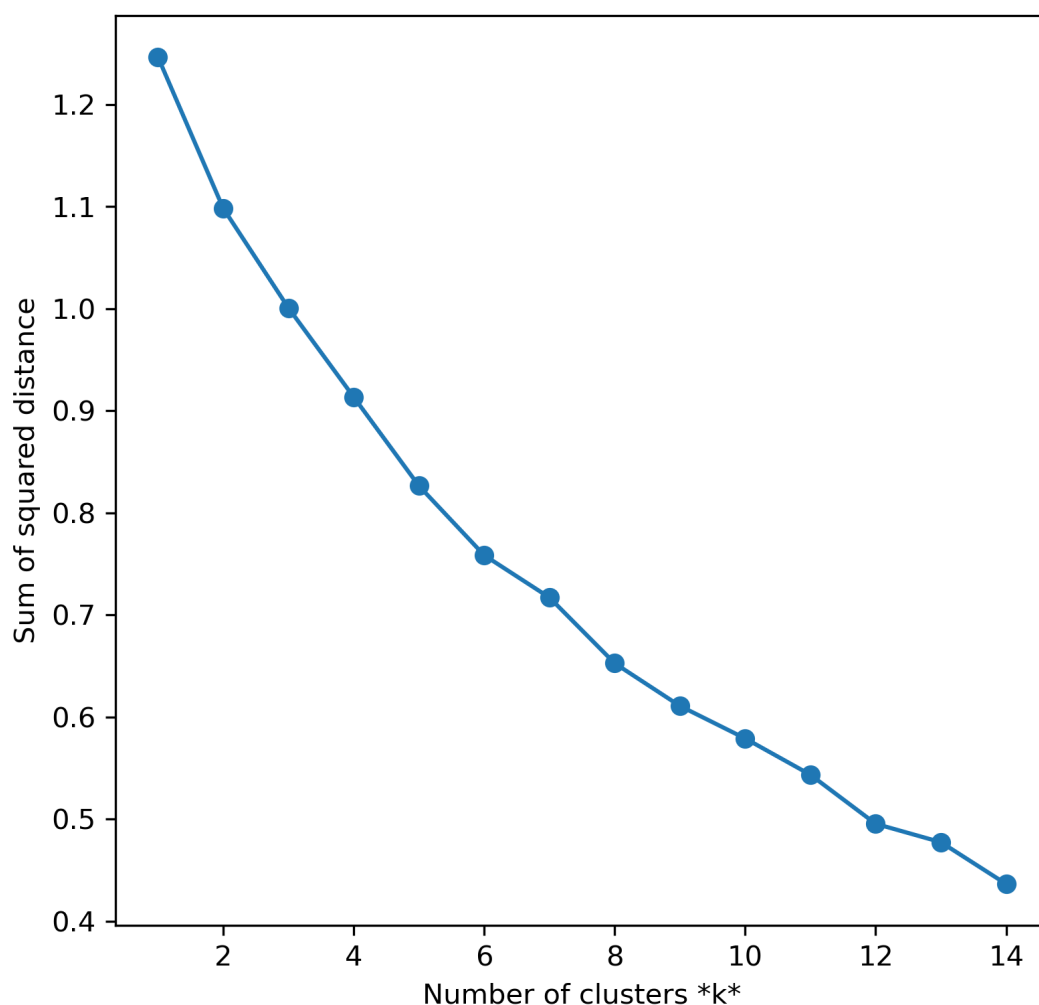
## 3.2 Model Evaluation

In the cluster-predict methodology, we can evaluate how well the models are performing based on different K clusters since clusters are used in the downstream modeling. For K-

means, we will use two metrics that may give us some intuition about  $k$ : (1).Elbow method; (2).Silhouette analysis.

### 3.2.1 Elbow method

Elbow method gives us an idea on what a good  $k$  number of clusters would be based on the sum of squared distance (SSE) between data points and their assigned clusters' centroids. We pick  $k$  at the spot where SSE starts to flatten out and forming an elbow. We'll use the geyser dataset and evaluate SSE for different values of  $k$  and see where the curve might form an elbow and flatten out.



**Fig. 10.** Sum of squared distance for different  $K$ s.

As we see in Fig.10, the plot is monotonically decreasing and does not show any elbow or has an obvious point where the curve starts flattening out. Thus it is still hard to figure out a good number of clusters to use. This is reasonable and sort of foreseeable because, as I

mentioned before, like the entire state of Florida, Miami's economy is largely fueled by tourism. So each neighborhood is built around tourists and share a certain degree of similarity. So the distance between clusters in the hyperspace should be relatively close to each other.

### 3.2.2 Silhouette Analysis

Silhouette analysis can be used to determine the degree of separation between clusters. For each sample:

- Compute the average distance from all data points in the same cluster ( $a^i$ ).
- Compute the average distance from all data points in the closest cluster ( $b^i$ ).
- Compute the coefficient:

$$\frac{b^i - a^i}{\text{Max}(a^i, b^i)}$$

The coefficient can take values in the interval  $[-1, 1]$ .

- If it is 0  $\rightarrow$  the sample is very close to the neighboring clusters.
- If it is 1  $\rightarrow$  the sample is far away from the neighboring clusters.
- If it is -1  $\rightarrow$  the sample is assigned to the wrong clusters.

Therefore, we want the coefficients to be as big as possible and close to 1 to have a good clusters. Fig.11 confirmed our results from the elbow method: changing k from 2 to 10 does not change average silhouette score significantly. Using common knowledge, I choose k=5 to be the number of clusters to use in this project.

## 4 Results/Discussion

By using k-means, we managed to group all neighborhoods in City of Miami, plus all municipalities in Miami-Dade County into 5 clusters, each one with their own unique features. In this section, I will examine and discuss each cluster.

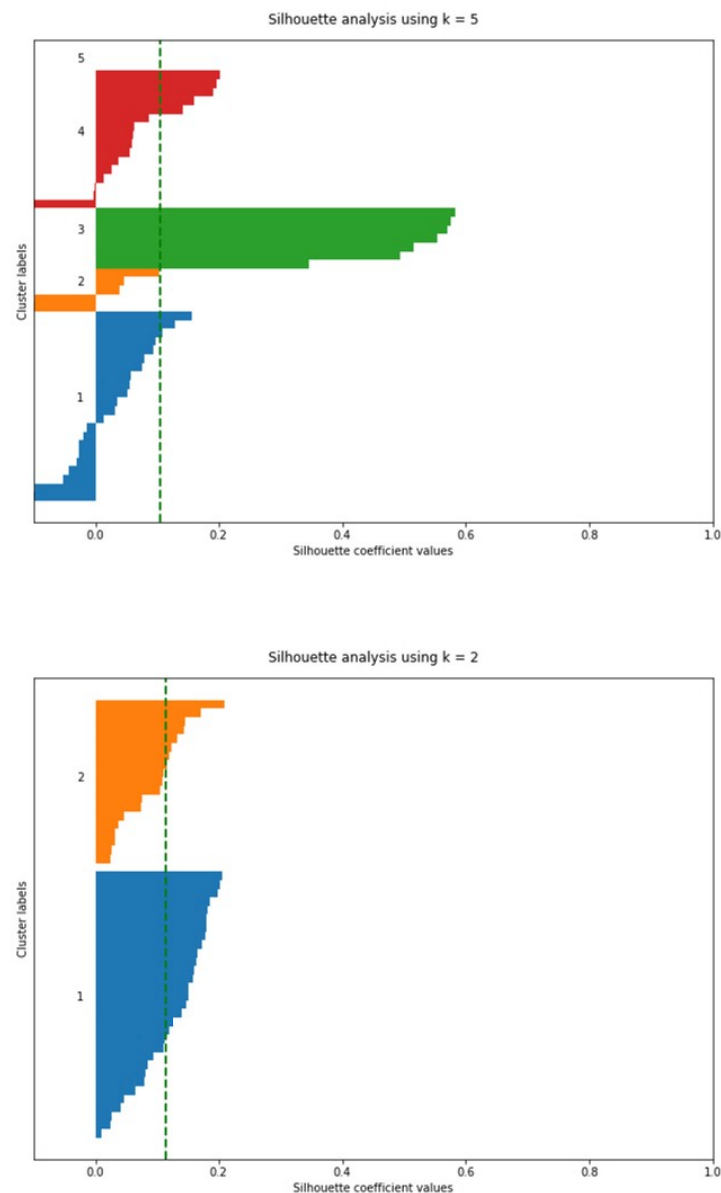
### 4.1 cluster 1

This cluster (Fig.12) represents neighborhoods most popular for food places, with other entertainment facilities and shopping places. You can find many restaurants from different countries, such as Italian, Mexican and Asian restaurants. If you're looking for a place to stay where you can easily find a decent restaurant to dine, and maybe go for a walk afterwards, or simply spend some money in a shopping mall, you should look into these neighborhoods.

### 4.2 cluster 2

Fast food and discount store are most popular in this cluster (Fig.13), together with utilities like gas station, grocery store, soccer field, phone shop, etc. These neighborhoods are perfect





**Fig. 11.** Silhouette Analysis with different Ks. (Full image is available in this [jupyter notebook](#))

for people who seek a convenient, fast-paced life style. You can easily grab a quick sandwich for dinner, or if you want to cook, the nearby grocery stores are at your service. You can also easily find nightclubs if you want to enjoy your night lives.

	Neighborhood	Population	Rent	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
2	Brickell	31759	\$2,050	Hotel	Italian Restaurant	Bar	Argentinian Restaurant	Seafood Restaurant	Lounge	Japanese Restaurant	Steakhouse	American Restaurant	Bakery
4	Coconut Grove	20076	\$1,456	American Restaurant	Garden	Bakery	Furniture / Home Store	Coffee Shop	Park	Convenience Store	Spa	Sushi Restaurant	College Cafeteria
7	Downtown	71000	\$1,800	Hotel	Italian Restaurant	Seafood Restaurant	Peruvian Restaurant	American Restaurant	Residential Building (Apartment / Condo)	Coffee Shop	Bakery	Cosmetics Shop	Asian Restaurant
12	Little Haiti	29760	\$2,149	Italian Restaurant	Coffee Shop	Café	Pizza Place	American Restaurant	Art Gallery	Gym	Cosmetics Shop	Art Museum	Jewelry Store
14	Lummus Park	3027	NaN	Hotel	Italian Restaurant	Seafood Restaurant	American Restaurant	Peruvian Restaurant	Latin American Restaurant	Grocery Store	Bar	Spanish Restaurant	Nightclub
17	Park West	4655	\$2,025	Seafood Restaurant	American Restaurant	Italian Restaurant	Park	Hotel	Café	Cocktail Bar	Nightclub	Coffee Shop	Burger Joint
18	The Roads	7327	NaN	Hotel	Italian Restaurant	Latin American Restaurant	Bar	Mexican Restaurant	Argentinian Restaurant	Pharmacy	Grocery Store	Cuban Restaurant	Pizza Place

Fig. 12. Neighborhoods in Cluster 1

	Neighborhood	Population	Rent	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	Allapattah	54289	\$1,555	Fast Food Restaurant	Fried Chicken Joint	Gas Station	Seafood Restaurant	Nightclub	Park	Sandwich Place	Discount Store	Restaurant	Storage Facility
5	Coral Way	35062	\$1,650	Pharmacy	Café	Golf Course	Cuban Restaurant	Pool	Bakery	Tennis Stadium	Tennis Court	Intersection	Spanish Restaurant
9	Flagami	50834	\$1,375	Cuban Restaurant	Fast Food Restaurant	Sandwich Place	Video Game Store	Bakery	Coffee Shop	Hotel	Chinese Restaurant	Pizza Place	Latin American Restaurant
10	Grapeland Heights	14004	NaN	Hotel	Rental Car Location	Airport Service	Cuban Restaurant	Fast Food Restaurant	Coffee Shop	Latin American Restaurant	South American Restaurant	Duty-free Shop	Bank
11	Liberty City	19725	\$1,075	Fried Chicken Joint	Fast Food Restaurant	Discount Store	Park	Sandwich Place	Home Service	Wings Joint	Grocery Store	Seafood Restaurant	Shoe Store
13	Little Havana	76163	\$1,285	Latin American Restaurant	Cuban Restaurant	Seafood Restaurant	Mexican Restaurant	Smoke Shop	Bakery	Bar	Pizza Place	Spanish Restaurant	Coffee Shop
22	West Flagler	31407	NaN	Latin American Restaurant	Bakery	Cuban Restaurant	Pizza Place	Mexican Restaurant	Grocery Store	Fast Food Restaurant	Italian Restaurant	Bank	Theater
27	Doral	39489	\$2250	Park	Sandwich Place	Latin American Restaurant	Restaurant	Grocery Store	Department Store	Coffee Shop	Arepa Restaurant	South American Restaurant	Gym

Fig. 13. Neighborhoods in Cluster 2

### 4.3 cluster 3

	Neighborhood	Population	Rent	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
25	Bal Harbour	13971	\$2220	Beach	Hotel	Boutique	Italian Restaurant	Grocery Store	Deli / Bodega	Resort	Coffee Shop	Café	Shoe Store
30	Hialeah	NaN	\$1550	Pizza Place	American Restaurant	Beach	Seafood Restaurant	Video Store	Bar	Gift Shop	Golf Course	Sandwich Place	Gym / Fitness Center
33	Key Biscayne	12389	\$2330	Beach	Harbor / Marina	Italian Restaurant	Argentinian Restaurant	Bar	Bakery	Coffee Shop	Restaurant	Boat or Ferry	Park
35	Miami Beach	594	\$2330	Seafood Restaurant	Hotel	Beach	Italian Restaurant	Park	Steakhouse	Restaurant	Juice Bar	Bar	American Restaurant
41	North Bay Village	35249	\$1750	Beach	Hotel	Pizza Place	Coffee Shop	Italian Restaurant	Breakfast Spot	Cuban Restaurant	Restaurant	Brazilian Restaurant	Park

Fig. 14. Neighborhoods in Cluster 3

If you want to live close to the sea, look no further! These neighborhoods are located along the Miami beach shore line, with a beautiful view of the Pacific Ocean. No matter if you want to spend your afternoons on the popular Miami North Beach and South Beach, or look for a small island and enjoy a quiet, private sea view, these neighborhoods can offer you the opportunities. Also, international restaurants and recreation facilities are all over the place. And great hotels are very easy to find in this area. If you come to Miami for the sunshine and beach, these are the neighborhoods for you!

### 4.4 cluster 4

Virginia Key is an 863-acre barrier island on Miami, and it is mainly occupied by the Virginia Key Beach Park. It's also the only Miami-area beach that allows dogs. Nearby rest rooms and a great view of the curving shoreline make this an ideal place for tailgate parties. The Miami Seaquarium is a marine park on Virginia Key that has one of the world's largest collections of

	Neighborhood	Population	Rent	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
21	Virginia Key	14	NaN	Aquarium	Harbor / Marina	Beach	Park	Snack Place	Exhibit	Zoo Exhibit	Boat or Ferry	Surf Spot	Cafeteria

Fig. 15. Neighborhoods in Cluster 4

marine animals; some 10,000 specimens. A mountain biking park is located on the northern end of Virginia Key.

## 4.5 cluster 5

	Neighborhood	Population	Rent	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
1	Arts & Entertainment District	11033	\$1,855	Art Gallery	Ice Cream Shop	Coffee Shop	Restaurant	Bar	Beer Garden	Asian Restaurant	Pizza Place	Mexican Restaurant	Food Truck
3	Buena Vista	9058	NaN	Art Gallery	Ice Cream Shop	Coffee Shop	Italian Restaurant	Café	Restaurant	Pizza Place	Gym / Fitness Center	Asian Restaurant	Furniture / Home Store
6	Design District	3573	NaN	Art Gallery	Ice Cream Shop	Coffee Shop	Pizza Place	Café	Italian Restaurant	Restaurant	Gym / Fitness Center	Boutique	Cosmetics Shop
8	Edgewater	15005	\$1,909	Ice Cream Shop	Art Gallery	Coffee Shop	Restaurant	Bar	Beer Garden	Mexican Restaurant	Pizza Place	Asian Restaurant	Juice Bar
15	Midtown	NaN	NaN	Art Gallery	Ice Cream Shop	Coffee Shop	Restaurant	Pizza Place	Boutique	Bar	Gym / Fitness Center	Café	Mexican Restaurant

Fig. 16. Neighborhoods in Cluster 5

Neighborhoods in this cluster (Fig. 16) are located more inland than those in cluster 3. If you do not want to live too close to the sea, you can look into this cluster. Full of fast food places, grocery stores and other facilities, these neighborhoods are what most common people with a modern life style would choose. After working a whole day, you can go to your favorite restaurant for dinner, which is just around your apartment, so you don't have to spend more time and energy driving. And it got everything for daily lives just at your fingertips, such as groceries, parks, banks, coffee shops.. If you work in Miami and need a place to call home, you can look into these neighborhoods.

## 5 Conclusion

In this project, I have explored all neighborhoods in City of Miami area, as well as all municipalities in Miami-Dade County, and used k-means to cluster those neighborhoods based on the popular venues in each area, provided by Foursquare. The results are visualized using folium livemap, and features for each cluster are extracted. By changing the value of K and examining the results, I found that increase the number of clusters does not increase the performance of the model. In the end, I chose K=5 and re-trained the model. This project should give people some insights about how neighborhoods with different features are distributed in Miami. Though many factors are yet to be taken into consideration, and many more models can be used and evaluated, this project is still a good example of applying data science into real-life problems.