Coursera Capstone Project

Choose an area to live in Philadelphia by exploring all its neighborhoods

By Linh Tran

Introduction:

My sister just landed her first full time job in Philadelphia, one of the biggest cities in Pennsylvania. She has never been to Philadelphia before so she is quite new to this area. She wants to find housing in Philadelphia area but does not know much about the city and housing price for each neighborhood in Philly. She wants to live in a nice neighborhood, preferably around city center, and where there's high population and affordable housing price. I will help her explore every neighborhood in Philly so that she can have a broad over view of each neighborhood here and make her own decision on where to live. Thus, this project is about clustering neighborhoods in Philadelphia so that we can get a general view of what each neighborhood is known for while consider other demographic data for each neighborhood such as: population density, housing units, average home value, average household income

Business Problem: Where to live in Philadelphia?

Goals/Objectives: The objective of this capstone project is to analyze Philadelphia's neighborhoods dataset and select the best location for a housing. Using data science methodology and machine learning techniques like clustering, this project aims to provide solutions to answer the business question: where to live in Philadelphia. In order to answer this, we need to understand the characteristics of each neighborhood.

Stakeholders

This project is helpful to anybody who wants to know more about Philadelphia, not limited to my sister only. Since many people might want to understand in and out about each neighborhood in Philadelphia, this project will help them a lot as it will segment all neighborhoods in the city and show the most frequent venue categories, population density, home value (similar to housing price), housing units and average household income in each neighborhood.

Data:

Sources of data and how it is used:

Philadelphia's neighborhood dataset including names of boroughs and their corresponding neighborhoods. The table that contain needed data is located at the bottom of this wiki website:

https://en.wikipedia.org/wiki/Callowhill,_Philadelphia. This data defines the scope of this project which is confined to the city of Philadelphia.

Philadelphia's demographic data: population density, home value, housing units and average household income for each neighborhood.

Coordinates (latitude, longitude) of each neighborhood. This data is needed to generate maps, get demographic data and get venues data using Foursquare APIs.

Foursquare APIs: that contains data about all venues data around Philadelphia

Methods to extract Data:

Philadelphia's neighborhood dataset on Wiki: use Beautiful Soup package to scrape data from Wiki website.

Coordinates for each neighborhood: use geocoder package to get coordinates(latitude, longitude). In order to get coordinates for each neighborhood, address, in other words, name of neighborhood is needed

Philadelphia's demographic data: Use uszipcode package and SearchEngine library to get demographic data (population density, average household income) for each **zipcode**. 1 zipcode can contain multiple neighborhoods; thus, we will define the boundaries of each neighborhood inside zipcode and collect the most relevant data.

Foursquare APIs to get venues data: create API url request and get request to get all venues data.

Methodology

1. Get neighborhoods, coordinates and demographic data and transform into dataframe

Firstly, we need to get the list of neighborhoods in the city of Philadelphia. Fortunately, the list is available in the Wikipedia page (https://en.wikipedia.org/wiki/Callowhill,_Philadelphia.).We will do web scraping using Python requests and beautifulsoup packages to extract the list of neighborhoods data. However, this is just a list of names. We need to get the geographical coordinates in the form of latitude and longitude in order to be able to use Foursquare API as well as get demographic data. To do so, we will use the wonderful Geocoder package that will allow us to convert address into geographical coordinates in the form of latitude and longitude. Next, we will use the latitude and longitude of each neighborhood to get demographic data for each neighborhood. By using uszipcode package with SearchEngine library applying on the previous coordinates data, we can gather demographic data for each **zipcode**, but not for each neighborhood. Thus, we need to find the boundary of each neighborhood within each zipcode to get the most accurate data to analyze. After gathering the data, we will populate the data into a pandas DataFrame and then visualize the neighbourhoods in a map using Folium package. This allows us to perform a sanity check to make sure that the geographical coordinates data returned by Geocoder are correctly plotted in the city of Philadelphia.

2. Explore each neighborhood using Foursquare APIs

Next, we will use Foursquare API to get the top 100 venues that are within a radius of 2000 meters. We need to register a Foursquare Developer Account in order to obtain the Foursquare ID and Foursquare secret key. We then make API calls to Foursquare passing in the geographical coordinates of the neighborhoods in a Python loop. Foursquare will return the venue data in JSON format and we will extract the venue name, venue category, venue latitude and longitude. With the data, we can check how many venues were returned for each neighborhood and examine how many unique categories can be curated from all the returned venues. Then, we will analyze each neighborhood by grouping the rows by neighborhood and taking the mean of the frequency of occurrence of each venue category.

Lastly, we will perform clustering on the data by using k-means clustering. K-means clustering algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. It is one of the simplest and popular unsupervised machine learning algorithms and is particularly suited to solve the problem for this project. We will cluster the neighbourhoods into 10 clusters. The results will allow us to identify popular venue categories within each cluster and we can combine with the demographic data to get a better view of each neighborhood cluster. For example, for each cluster, we can look further at the average household income and average home value to identify if the neighborhood cluster is affluent neighborhoods, or we can look more at population and housing units data to estimate the crowdedness of each cluster/neighborhood.

Results:

1. Cluster Modeling

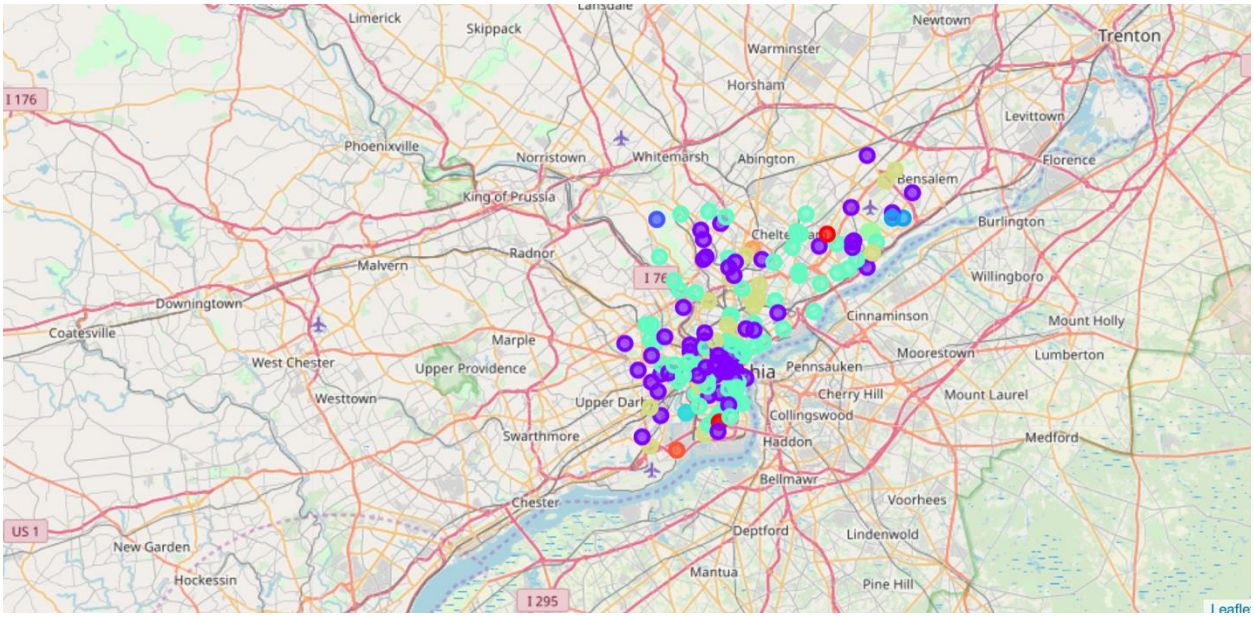
Scikit-learn's K-Means clustering was used to determine similar neighborhoods based on music venue percentage. The image below shows the data being scaled and the K-Means model being created:

Run *k*-means to cluster the neighborhood into 10 clusters.

```
# set number of clusters
kclusters = 10

philly_grouped_clustering = philly_grouped.drop('Neighborhoods', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(philly_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_
```

```
array([1, 6, 7, 2, 1, 6, 7, 5, 5, 1, 1, 5, 5, 5, 1, 7, 5, 1, 5, 1, 7, 5,
       1, 5, 1, 0, 5, 1, 1, 1, 5, 3, 5, 5, 5, 5, 8, 1, 1, 7, 5, 7, 7, 5,
       1, 5, 1, 5, 1, 7, 5, 1, 7, 5, 5, 5, 1, 1, 7, 1, 1, 9, 1, 5, 5, 1,
       5, 5, 5, 1, 1, 5, 5, 1, 1, 5, 5, 5, 1, 5, 5, 1, 1, 1, 3, 1, 1, 5,
       7, 7, 5, 5, 5, 5, 1, 1, 5, 1, 5, 5, 5, 5, 1, 1, 7, 4, 1, 5, 1, 1,
       1, 1, 5, 5, 5, 1, 0, 1, 5, 5, 5, 7, 7, 5, 1, 5, 0, 0, 1, 5, 5, 5,
       1, 1, 1, 7, 1, 5, 5, 5, 1, 7, 5, 1, 1, 1, 4, 1, 5, 5, 1, 5, 5, 1,
       5, 5, 1, 5], dtype=int32)
```

2. Cluster Visualization



3. Cluster Evaluation:

Using K-means algorithm, we cluster the neighborhoods into 10 clusters. Each cluster shows a list of neighborhoods with their respective top venue categories and demographic data.

It is interesting to see that some clusters are very small, sometimes only holding a single neighborhood, and appear to have identified a niche venue category. Examples of this is cluster 3: This cluster only has one neighborhood named “Andorra” with top venue category “Playground”.

```
cluster_3 = philly_merged.loc[philly_merged['Cluster Labels'] == 2, philly_merged.columns[[1] + list(range(4, philly_merged.shape[1]))]]
cluster_3.sort_values(by=['population density','average income'], ascending=False).head()
```

	Neighborhoods	average income	population density	average housing units	average home value	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
129	Andorra	85105.333333	3411.333333	8812.333333	351533.333333	2	Playground	Zoo Exhibit	Eastern European Restaurant	English Restaurant	Ethiopian Restaurant	Event Space	Exhibit

Other clusters are very large and appear to be grouping neighborhoods with assortments of restaurants, coffeeshops, flea markets, etc.

<u>Overview of each cluster:</u>

Cluster 1: South Philadelphia area – Restaurant/Bar/Intersection

```
cluster_1 = philly_merged.loc[philly_merged['Cluster Labels'] == 0, philly_merged.columns[[1] + list(range(4, philly_m
erged.shape[1]))]]
cluster_1.sort_values(by=['population density','average home value'], ascending=False).head()
```

	Neighborhoods	average income	population density	average housing units	average home value	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 Mc Comm Ven
154	Rhawnhurst	50584.0	11811.0	13730.0	198200.0	0	Bar	Convenience Store	Pizza Place	Bakery	Portuguese Restaurant	Restaurant	Deli / Bodega	Pharma
14	Central South Philadelphia	39413.0	11777.0	21567.0	165100.0	0	Restaurant	Intersection	Bar	Baseball Field	Betting Shop	Sandwich Place	Pharmacy	Piz Pla
41	South Philadelphia/East	39413.0	11777.0	21567.0	165100.0	0	Restaurant	Intersection	Bar	Baseball Field	Betting Shop	Sandwich Place	Pharmacy	Piz Pla
42	South Philadelphia/West	39413.0	11777.0	21567.0	165100.0	0	Restaurant	Intersection	Bar	Baseball Field	Betting Shop	Sandwich Place	Pharmacy	Piz Pla

Cluster 2: Multiple neighborhoods around the city – Coffeeshop, Bakery, Hotel, Park, Bar, etc.

```
cluster_2 = philly_merged.loc[philly_merged['Cluster Labels'] == 1, philly_merged.columns[[1] + list(range(4, philly_m
erged.shape[1]))]]
cluster_2.sort_values(by=['population density','average home value'], ascending=False).head()
```

	Neighborhoods	average income	population density	average housing units	average home value	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
81	30th Street Station	63709.0	34284.0	16612.0	428400.0	1	Rental Car Location	Sandwich Place	Food Truck	Café	Pub	American Restaurant	Trail	Train Station
3	Fitler Square	52888.5	27533.0	17835.0	310700.0	1	Coffee Shop	Café	Trail	Italian Restaurant	Breakfast Spot	Park	Grocery Store	Pizza Place
9	Rittenhouse Square	52888.5	27533.0	17835.0	310700.0	1	Hotel	American Restaurant	Coffee Shop	Yoga Studio	Italian Restaurant	Seafood Restaurant	Café	Clothing Store
61	Belmont Village	44402.0	27085.0	8400.0	306200.0	1	Chinese Restaurant	Bakery	Hotel	Dessert Shop	Vietnamese Restaurant	Art Gallery	Ice Cream Shop	Deli / Bodega
91	Callowhill	44402.0	27085.0	8400.0	306200.0	1	Art Gallery	Pub	Park	Latin American Restaurant	Restaurant	Beer Garden	Rock Club	Gastropub

Cluster 3: Andorra – Playground, Exhibit, Eastern European Restaurant

```
cluster_3 = philly_merged.loc[philly_merged['Cluster Labels'] == 2, philly_merged.columns[[1] + list(range(4, philly_merged.shape[1]))]]
cluster_3.sort_values(by=['population density','average income'], ascending=False).head()
```

	Neighborhoods	average income	population density	average housing units	average home value	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
129	Andorra	85105.333333	3411.333333	8812.333333	351533.333333	2	Playground	Zoo Exhibit	Eastern European Restaurant	English Restaurant	Ethiopian Restaurant	Event Space	Exhibit

Cluster 4: Morrell Park and Crestmont Farms – Café, Exhibit, Ethiopian Restaurant

```
cluster_4 = philly_merged.loc[philly_merged['Cluster Labels'] == 3, philly_merged.columns[[1] + list(range(4, philly_merged.shape[1]))]]
cluster_4.sort_values(by=['population density','average income'], ascending=False).head()
```

	Neighborhoods	average income	population density	average housing units	average home value	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
165	Morrell Park	56196.500000	5458.500000	13628.000000	200400.000000	3	Café	Zoo Exhibit	Fast Food Restaurant	Ethiopian Restaurant	Event Space	Exhibit	Fa Resta
162	Crestmont Farms	57683.333333	4712.333333	16830.333333	222133.333333	3	Café	Tailor Shop	Zoo Exhibit	Fast Food Restaurant	Ethiopian Restaurant	Event Space	Ex

Cluster 5: Passyunk Square and Wsest Passyunk - Flea Market

```
cluster_5 = philly_merged.loc[philly_merged['Cluster Labels'] == 4, philly_merged.columns[[1] + list(range(4, philly_merged.shape[1]))]]
cluster_5.sort_values(by=['population density','average income'], ascending=False).head()
```

	Neighborhoods	average income	population density	average housing units	average home value	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
33	Passyunk Square	35761.0	9711.0	20874.0	151200.0	4	Flea Market	Zoo Exhibit	Fast Food Restaurant	English Restaurant	Ethiopian Restaurant	Event Space	Exhibit	Falafel Restaurant
45	West Passyunk	35761.0	9711.0	20874.0	151200.0	4	Flea Market	Zoo Exhibit	Fast Food Restaurant	English Restaurant	Ethiopian Restaurant	Event Space	Exhibit	Falafel Restaurant

Cluster 6: Multiple neighborhoods around the city – Restaurants, Bars, Pubs, Coffeeshops, Store, etc.

```
cluster_6 = philly_merged.loc[philly_merged['Cluster Labels'] == 5, philly_merged.columns[[1] + list(range(4, philly_merged.shape[1]))]]
cluster_6.sort_values(by=['population density','average income'], ascending=False).head()
```

	Neighborhoods	average income	population density	average housing units	average home value	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 Comm Ven
13	Bella Vista	60400.0	25741.0	19209.0	305800.0	5	Mexican Restaurant	Italian Restaurant	Pizza Place	Coffee Shop	Vietnamese Restaurant	Gourmet Shop	French Restaurant	Bak
26	Italian Market	60400.0	25741.0	19209.0	305800.0	5	Mexican Restaurant	Italian Restaurant	Pizza Place	Vietnamese Restaurant	Coffee Shop	Pharmacy	Bakery	I
68	Garden Court	24627.0	23317.0	20327.0	79100.0	5	Breakfast Spot	Bus Station	Caribbean Restaurant	Pizza Place	Spa	Gas Station	Shoe Store	Seafc Restaur
15	Devil's Pocket	42068.0	20782.0	19058.0	193000.0	5	Coffee Shop	Thai Restaurant	Bus Stop	Liquor Store	Beer Store	Market	Supermarket	Furnitu Ho St
21	Graduate Hospital	42068.0	20782.0	19058.0	193000.0	5	Coffee Shop	Café	Pizza Place	Playground	Gastropub	Park	Bar	Dive I

Cluster 7: Academy Gardens and Ashton Wooden Bridge - Garden, Exhibit, Ethiopian Restaurant

```
]: cluster_7 = philly_merged.loc[philly_merged['Cluster Labels'] == 6, philly_merged.columns[[1] + list(range(4, philly_m
erged.shape[1]))]]
cluster_7.sort_values(by=['population density','average home value'], ascending=False).head()
```

]:

	Neighborhoods	average income	population density	average housing units	average home value	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
158	Academy Gardens	49357.5	7173.5	14024.5	173000.0	6	Donut Shop	Garden	Zoo Exhibit	Fast Food Restaurant	Ethiopian Restaurant	Event Space	Exhibit	Falafel Restaurant
159	Ashton-Woodenbridge	49357.5	7173.5	14024.5	173000.0	6	Multiplex	Garden	Field	Ethiopian Restaurant	Event Space	Exhibit	Falafel Restaurant	Farm

Cluster 8: Several neighborhoods (5) scattered in the city – Intersection, Park, Fast food, Gym

```
5]: cluster_8 = philly_merged.loc[philly_merged['Cluster Labels'] == 7, philly_merged.columns[[1] + list(range(4, philly_m
erged.shape[1]))]]
cluster_8.sort_values(by=['population density','average income'], ascending=False).head()
```

5]:

	Neighborhoods	average income	population density	average housing units	average home value	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 M Comm Ve
37	Schuylkill	42068.0	20782.0	19058.0	193000.0	7	Intersection	Health & Beauty Service	Deli / Bodega	Food Truck	Auto Garage	Thai Restaurant	Gym	O
123	Fern Rock	31783.5	18655.0	19047.5	93500.0	7	Intersection	Fried Chicken Joint	Grocery Store	Pizza Place	Metro Station	Chinese Restaurant	Park	Sta
96	Hartranft	18847.0	18549.0	8827.0	87800.0	7	Intersection	Train Station	Gym / Fitness Center	Seafood Restaurant	Farm	Eastern European Restaurant	Electronics Store	Eng Restau
106	Sharswood	39413.0	17876.5	15375.0	213350.0	7	Playground	Park	Intersection	Restaurant	Deli / Bodega	Art Gallery	Grocery Store	Athleti Sp
114	Franklinville	22654.0	17736.0	22209.0	61400.0	7	Fried Chicken Joint	Fast Food Restaurant	BBQ Joint	Supermarket	Garden Center	Donut Shop	Latin American Restaurant	E Sp

Cluster 9: East Oak Lane – Lake, Exhibit, Electronic Store

```
96]: cluster_9 = philly_merged.loc[philly_merged['Cluster Labels'] == 8, philly_merged.columns[[1] + list(range(4, philly_m
erged.shape[1]))]]
cluster_9.sort_values(by=['population density' ,'average income'], ascending=False).head()
```

96]:

	Neighborhoods	average income	population density	average housing units	average home value	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	9 C
121	East Oak Lane	36998.5	16899.0	15237.0	114600.0	8	Lake	Zoo Exhibit	Electronics Store	Ethiopian Restaurant	Event Space	Exhibit	Falafel Restaurant	Farm	

Cluster 10: Hog Island – Airport, Exhibit, Field

```
)7]: cluster_10 = philly_merged.loc[philly_merged['Cluster Labels'] == 9, philly_merged.columns[[1] + list(range(4, philly_
merged.shape[1]))]]
cluster_10.sort_values(by=['population density','average income'], ascending=False).head()
```

)7]:

	Neighborhoods	average income	population density	average housing units	average home value	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 Com V
54	Hog Island	47138.0	1713.0	5524.0	132400.0	9	Airport Service	Zoo Exhibit	Field	Ethiopian Restaurant	Event Space	Exhibit	Falafel Restaurant	Farm	Far M

Discussions:

As seen in the above clusters, cluster 2 and cluster 6 seem to be ideal clusters to start digging more into because these two clusters consist of many neighborhoods located in the central of Philadelphia with diverse venue categories such as coffeeshops, stores, bakeries, park, restaurants, etc. As my sister like a populated, high-class neighborhood, I sort each neighborhood with highest population and household income and finally come up with this list of neighborhoods that she might be interested in:

Neighborhoods	Average Income	Population density (number of people/mi^2)	Top Venue Categories
30th Street Station	63709	34284	Sandwich, Food truck, Café, Pub, Train Station
Rittenhouse Square/ Filter Square	52888	27533	Café, American and Italian restaurant, Hotel, yoga, Hotel
Callowhill/ Belmont Village	44402	27085	Beer, Pub, Chinese restaurant, Bakery
Bella Vista/ Italian Market	60400	25741	Mexican, Italian, Vietnamese, French restaurant, Pizza place and Coffeeshop, Bakery, Pharmacy

Conclusions:

Machine learning and clustering algorithms can be applied to multi-dimensional datasets to find similarities and patterns in the data. Clusters of neighborhoods can be generated using high-quality venue location data, and for instance, in this project I am using Foursquare API data. There is a preface on high-quality because analysis models are only as good as the input into them (garbage in, garbage out). Luckily, Foursquare offers a robust 'Places API' service that, although (as we have seen) not perfect (nothing is), can be leverages in similar studies and model-making.

In addition to the algorithms and data science techniques introduced in the course, in order to finish the project, I needed to do a lot of side research and utilize many different python packages to solve the problem or get the data that I want. It's definitely fun to apply all the knowledge I learned throughout the course and research ability into this project and finally come up with the final deliverable that might be impactful for some people. I'm looking forward to do more data science projects so as to sharpen my skills and get more experience in data analysis.