Capstone Project

The Battle of the Neighborhoods (Week 2)

Recommending initial target neighborhood for product sales

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1. Introduction

1.1 Background and Problem

Any company who wants to sell a product specific to particular business needs target business venues or locations to send their salesperson where they could find relevant businesses for best response.

For example, a company developed a new much efficient kind of coffee dispenser. Now it wants to contact or sell the product to businesses in optimal neighborhoods where most of the coffee shops are available and is sufficiently populated to reduce the transportation cost, increase the number of target shops and increasing the number of consumers directly affected.

Similarly, we can determine these initial target areas for the for other companies with new products.

1.2 Interest

There are many innovators and companies that relies on innovation who want to show or sell their limited products to specific business and influence higher number of people with lower investments on transportation costs.

2. Data Acquisition and Cleaning

2.1 Data Sources

Based on definition of our problem, factors that will influence our decision are:

- number of existing business of specific category in the neighborhood (high weightage)
- population of the neighborhoods (normal weightage)

Following data sources will be needed to extract/generate the required information:

- demographic data of New York from Kaggle
- number of business/venues and their type and location in every neighborhood will be obtained using Foursquare API

2.2 Data Cleaning and Feature Selection

Data downloaded from Kaggle contains New York's demographic data of 2000 and 2010. We will take the latest data. There are five boroughs in the table. We will take the latest data of Manhattan Borough i.e. 2010 data.

The table does not have the location coordinates of the neighborhoods. We used geopy library to get the latitude-longitude coordinates of the neighborhoods

For getting the venues and business details (name and coordinates) we used the Foursqure API on the neighborhoods available in the Manhattan data of year 2010. For now, we keep the radius as 500 units and limit the results to 100 records per neighborhood.

We now have population of each neighborhood and at most 100 venues in radius of 500 units in every neighborhood with their names, category and latitude-longitude coordinates.

Population Data

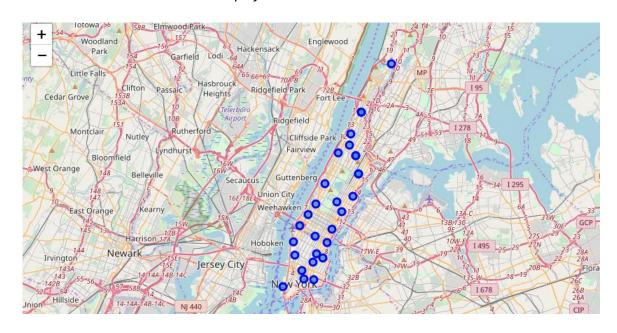
| | Borough | NTA Name | Population | Latitude | Longitude |
|---|-----------|-----------------------------------|------------|-----------|------------|
| 0 | Manhattan | Marble Hill-Inwood | 46746 | 40.876298 | -73.910429 |
| 1 | Manhattan | Central Harlem North-Polo Grounds | 75282 | 40.807879 | -73.945415 |
| 2 | Manhattan | Hamilton Heights | 48520 | 40.824145 | -73.950062 |
| 3 | Manhattan | Manhattanville | 22950 | 40.815778 | -73.951554 |
| 4 | Manhattan | Morningside Heights | 55929 | 40.810000 | -73.962500 |

Venues Data

| | NTA Name | Latitude | Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|------|-----------------------------|-----------|------------|------------------------|----------------|-----------------|----------------------|
| 0 | Marble Hill-Inwood | 40.876298 | -73.910429 | Arturo's | 40.874412 | -73.910271 | Pizza Place |
| 1 | Marble Hill-Inwood | 40.876298 | -73.910429 | Bikram Yoga | 40.876844 | -73.906204 | Yoga Studio |
| 2 | Marble Hill-Inwood | 40.876298 | -73.910429 | Tibbett Diner | 40.880404 | -73.908937 | Diner |
| 3 | Marble Hill-Inwood | 40.876298 | -73.910429 | Starbucks | 40.877531 | -73.905582 | Coffee Shop |
| 4 | Marble Hill-Inwood | 40.876298 | -73.910429 | Dunkin' | 40.877136 | -73.906666 | Donut Shop |
| | | | | | | | |
| 2372 | park-cemetery-etc-Manhattan | 40.744249 | -74.006425 | Chelsea Piers Fitness | 40.746645 | -74.010057 | Gym / Fitness Center |
| 2373 | park-cemetery-etc-Manhattan | 40.744249 | -74.006425 | Top of The Standard | 40.740818 | -74.008116 | Roof Deck |
| 2374 | park-cemetery-etc-Manhattan | 40.744249 | -74.006425 | Apple West 14th Street | 40.741270 | -74.005389 | Electronics Store |
| 2375 | park-cemetery-etc-Manhattan | 40.744249 | -74.006425 | Sikkema Jenkins | 40.747592 | -74.005983 | Art Gallery |
| 2376 | park-cemetery-etc-Manhattan | 40.744249 | -74.006425 | PH-D at Dream Downtown | 40.742347 | -74.003356 | Nightclub |

2377 rows × 7 columns

Map of Manhattan New York



3. Methodology

We now must find out how many venues are available in the neighborhood from each of 288 categories. We will use one hot encoding for this purpose, and then group the resulting dataframe by sum method. The resulting dataframe will have the number of venues from each category in the neighborhood.

Let's take the required business as coffee shop (for new efficient coffee dispenser machine), we will require to sell more coffee machine as well as a greater number of people should be influenced.

So first, we collect all the neighborhoods with required businesses and create a business score column for them. This score will prefer number of coffee shops over the population of the neighborhood. Thus, we will calculate it as:

business score of the neighborhood = Population x (No. of coffee shops) ^2

So, generalizing this method, business score of neighborhoods for any category of business will be:

 business score of the neighborhood = Population x (No. of business of the category) ^2

We then select the top n number of neighborhoods sorted by business score from the list according to requirement n.

4. Analysis

Encoded list of neighborhoods with number of different venues in it.

| | NTA Name | Accessories Store | Afghan Restaurant | African Restaurant | | Amphitheater | Animal Shelter | Antique Shop | Arepa Restaurant | Art Gallery | Video Game Store | Video Store | Viet Res |
|---|--|----------------------|----------------------|-----------------------|---|--------------|-------------------|-----------------|---------------------|----------------|----------------------------|----------------|-------------|
| 0 | Battery Park City-Lower Manhattan | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 1 | Central Harlem North- Polo Grounds | 0 | 0 | 3 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | |
| 2 | Central Harlem South | 0 | 0 | 3 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | |
| 3 | Chinatown | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | |
| 4 | Clinton | 0 | 0 | 0 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 5 | East Harlem North | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 6 | East Harlem South | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | |
| 7 | East Village | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | |

Using the methodology, we can get recommended neighborhoods following for coffee shops.

recommendations=recommend_location('Coffee Shop').reset_index(drop=True) recommendations

| | Borough | NTA Name | Population | Latitude | Longitude | Coffee Shop | business_score |
|---|-----------|-----------------------------------|------------|-----------|------------|-------------|----------------|
| 0 | Manhattan | Lenox Hill-Roosevelt Island | 80771 | 40.766437 | -73.959017 | 7 | 3957779 |
| 1 | Manhattan | Yorkville | 77942 | 40.778007 | -73.948202 | 5 | 1948550 |
| 2 | Manhattan | Battery Park City-Lower Manhattan | 39699 | 40.711017 | -74.016937 | 7 | 1945251 |
| 3 | Manhattan | Lower East Side | 72957 | 40.715936 | -73.986806 | 5 | 1823925 |
| 4 | Manhattan | Upper East Side-Carnegie Hill | 61207 | 40.773702 | -73.964120 | 5 | 1530175 |

Using the venues data, we can list all the venues in recommended neighborhood

| | NTA Name | Latitude | Longitude | Venue | Venue Latitude | Venue Longitude | Venue Category |
|-------|-----------------------------------|-----------|------------|--------------------------------|----------------|-----------------|----------------|
| 1430 | Battery Park City-Lower Manhattan | 40.711017 | -74.016937 | Le District Coffee | 40.713284 | -74.015854 | Coffee Shop |
| 1451 | Battery Park City-Lower Manhattan | 40.711017 | -74.016937 | Blue Bottle Coffee | 40.710589 | -74.012371 | Coffee Shop |
| 1459 | Battery Park City-Lower Manhattan | 40.711017 | -74.016937 | Starbucks Reserve | 40.714170 | -74.015434 | Coffee Shop |
| 1464 | Battery Park City-Lower Manhattan | 40.711017 | -74.016937 | Joe Coffee | 40.712526 | -74.013137 | Coffee Shop |
| 1493 | Battery Park City-Lower Manhattan | 40.711017 | -74.016937 | Boundless Plains Espresso | 40.707990 | -74.013894 | Coffee Shop |
| 1500 | Battery Park City-Lower Manhattan | 40.711017 | -74.016937 | Laughing Man Coffee & Tea | 40.714754 | -74.017368 | Coffee Shop |
| 1507 | Battery Park City-Lower Manhattan | 40.711017 | -74.016937 | Nobletree Coffee | 40.710037 | -74.011839 | Coffee Shop |
| 1636 | Lower East Side | 40.715936 | -73.986806 | Cafe Grumpy | 40.715069 | -73.989952 | Coffee Shop |
| 1639 | Lower East Side | 40.715936 | -73.986806 | Little Canal | 40.714317 | -73.990361 | Coffee Shop |
| 1649 | Lower East Side | 40.715936 | -73.986806 | Blue Bottle Coffee | 40.719140 | -73.985224 | Coffee Shop |
| 1667 | Lower East Side | 40.715936 | -73.986806 | GrandLo Cafe | 40.716885 | -73.985680 | Coffee Shop |
| 1713 | Lower East Side | 40.715936 | -73.986806 | Caffe Vita Coffee Roasting Co. | 40.719752 | -73.988529 | Coffee Shop |
| 17//1 | Lenov Hill-Roosevelt Island | AU 266432 | _73 050N17 | The Coffee Inn | AU 266262 | -73 056515 | Coffee Shop |

Using folium library to visualize the venues in the map of Manhattan



5. Results and Discussion

So, for the new coffee dispenser machine manufactured by the company, to have large influence on the basis of both number of coffee shops in and the population of the neighborhood, we came to conclusion that Lenox Hill-Roosevelt Island, Yorkville, Battery Park City-Lower Manhattan, Lower East Side and Upper East Side-Carnegie Hill will be the best five.

We can use the same for other categories of businesses like gym, video store, restaurants etc. to get the target locations for initial sales of the good to have wide influence and least transportation costs.

6. Conclusion

We were required to get the recommendations for initial target neighborhoods for sending the new product manufactured/created by any company for most sales and influence. Following the given methodology of weighted products with population and number of businesses/venues in neighborhood, we successfully got recommendations for a new coffee dispenser machine.