Makati Neighborhoods: Where to Locate Before and After the Subway is Built

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Introduction

Metro Manila is one of three metropolitan areas in the Philippines. It is composed of 16 cities and 1 municipality which includes Manila (the country's capital) and Makati (the country's business center). Metro Manila often ranks close to the top when it comes to traffic congestion. This is why there has been a clamor for various projects aimed at improving its mass transport system.

One such project is the Makati Intra-city Subway (the first in the country). When it is completed in 2025, it will have 10 stations able to accommodate 700,000 passengers daily. The question that this study wants to answer is where someone should locate a restaurant in Makati before and after 2025 given the current distribution of restaurants and other related venues. It should provide some insight on how location options might change once the Makati subway is operational.

Data

To start, a list of Zip Codes of Makati is needed. A complete list of the Zip Codes of Philippine cities appears on Wikipedia (https://en.wikipedia.org/wiki/List_of_ZIP_codes_in_the_Philippines). Using Makati's Neighborhood Zip Codes, we can lookup their corresponding geo coordinates.

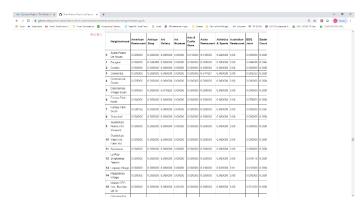
	City	ZipCode	Neighborhood	Latitude	Longitude
0	Makati City	1200	Makati CPO (Inc, Buendia Up To	14.561608	121.014653
1	Makati City	1203	San Antonio Village (Inc. Malu)	14.563281	121.012607
2	Makati City	1204	La Paz-Singkamas-Tejeros	14.568549	121.008594
3	Makati City	1205	Sta. Cruz	14.567455	121.015539
4	Makati City	1206	Kasilawan	14.576348	121.014462

With these, nearby venues can be gathered from Foursquare.com.

	name	categories	lat	Ing
0	Ayala Triangle Gardens	Park	14.556471	121.023204
1	Banapple Pies & Cheesecakes	Restaurant	14.556634	121.023619

	name	categories	lat	Ing
2	The Peninsula Manila	Hotel	14.555066	121.025466
3	Escolta	Filipino Restaurant	14.555485	121.025509
4	Little Flour Café	Café	14.557978	121.021919

Grouping these by Neighborhood and getting the frequency of each venue type gives the following table which can be used for K-Means clustering.



To add Subway proximity as a factor, we need the subway stations identified on this page (https://businessmirror.com.ph/2019/10/30/makati-subway-project-gets-additional-332-million-initial-funding/). Their geo coordinates can be obtained using Google Maps.

	Station	Latitude	Longitude
0	EDSA-Ayala	14.55093	121.02883
1	Ayala Triangle	14.55671	121.02281
2	Makati Central Park	14.56215	121.01494
3	Police Headquarters	14.56356	121.01524
4	Circuit City	14.57305	121.01946
5	Makati City Hall	14.57081	121.02728
6	Rockwell	14.56324	121.03580
7	Guadalupe	14.56741	121.04542
8	University of Makati	14.56397	121.05575

	Station	Latitude	Longitude
9	Ospital ng Makati	14.54681	121.06176

Using these coordinates, we can compute the shortest distances (in meters) of each neighborhood to any of the stations to get this:

Neighborhood	Distance
Makati CPO (Inc, Buendia Up To	67.475320
San Antonio Village (Inc. Malu)	280.839332
La Paz-Singkamas-Tejeros	904.242772
Sta. Cruz	432.163349
Kasilawan	650.561473

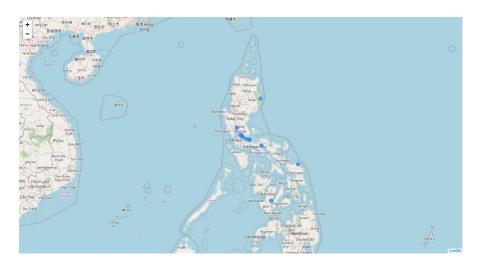
Adding the Distance as a column to the frequency table produced earlier, a second clustering can be generated and compared to the previous one.

Methodology

Using the examples of New York and Toronto provided in this Applied Data Science Capstone course, a similar methodology is followed. Venues near the different Makati Neighborhoods are identified through Foursquare. By identifying the types of venues and frequencies in these neighborhoods, similar neighborhoods can then be clustered using K-Means clustering to paint a picture of what kinds of restaurants, services, facilities, and others thrive in each cluster. To identify the number of clusters to be used, the sum of squared distances for 1 to 9 clusters are plotted and the elbow method is used.

To include the proximity of subway stations as a factor, the distance of the neighborhoods to the nearest station is added as a column. This plus the frequencies of the different types of venues for each neighborhood can then be used to do another clustering using K-Means. The best number of clusters is also found using the elbow method. Comparing this with the original clustering should yield some insights on how options will change once the Makati subway is operational.

Results



My attempt at getting the geo coordinates of Makati's Zip Codes using Pgeocode did not go smoothly. If you are not familiar with the Philippines, Makati (where most of the blue dots are) is part of the main island of Luzon (upper third of the country). All of the other dots (northeast, east, and southeast) of the main cluster are not in Makati and are not even in Metro Manila. Upon further inspection, even the coordinates found in or around Makati are not accurate. After manually looking these up using Google Maps, I updated the coordinates to get Makati Neighborhoods that can now be used.







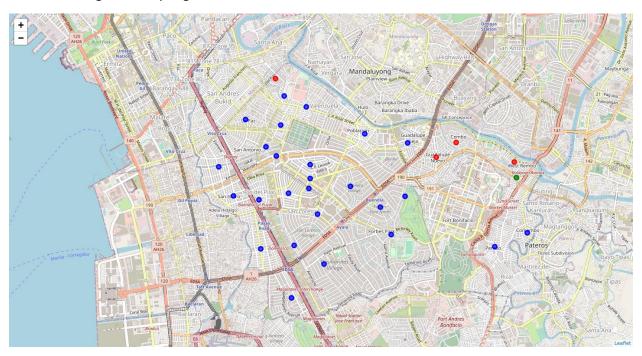
Corrected Geo Coordinates Zoomed

Feeding these Neighborhood coordinates to Foursquare to generate nearby venues, getting their types and counting their frequencies yields 3 clusters. (Note: I renumbered the clusters to simplify the discussion.)

Cluster 1: Ayala-Paseo De Roxas, Bangkal, Comembo, Commercial Center, Dasmarinas Village South, Forbes Park North, Forbes Park South, Greenbelt, Guadalupe Viejo, La Paz-Singkamas-Tejeros, Legaspi Village, Magallanes Village, Makati CPO, Olympia And Carmona, Palanan, Pasong Tamo 2000 Up & Ecology V, Pembo, Pio Del Pilar, Poblacion, Rembo (East) & Malapad Na Bato, Salcedo Village, San Antonio Village, San Isidro, San Lorenzo Village, Sta. Cruz, and Urdaneta Village

Cluster 2: Cembo, Guadalupe Nuevo, Kasilawan and Rembo (West)

Cluster 3: Pinagkaisahan-pitogo



Without using any obvious economic factors in the clustering, the clusters still seem to identify the most developed (Cluster 1), least developed (Cluster 3), and in between (Cluster 2) neighborhoods in Makati. Cluster 1 includes all of the commercial and office areas as well as gated subdivisions of Makati. Restaurants, cafes, and spas are the most common venues in these neighborhoods. Cluster 3 has the least commercial activity in its sole neighborhood where the most common venue types are: Food (neighborhood food stall), Soccer Field, Intersection, and Basketball Court. Cluster 2 has convenience stores and fast food restaurants as the most common venues.

If Makati Subway proximity is added as a factor, the clustering yields 5 clusters. (Note: I again renumbered the clusters to make comparisons with the first clustering simpler.)

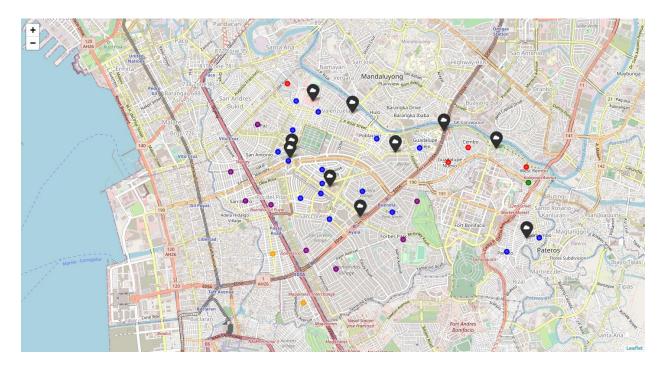
Cluster 1: Ayala-Paseo De Roxas, Comembo, Commercial Center, Forbes Park North, Greenbelt, Guadalupe Viejo, Legaspi Village, Makati CPO, Olympia And Carmona, Pembo, Poblacion, Salcedo Village, San Antonio Village, San Lorenzo Village, Sta. Cruz, and Urdaneta Village

Cluster 2: Cembo, Guadalupe Nuevo, Kasilawan and Rembo (West)

Cluster 3: Pinagkaisahan-pitogo

Cluster 4: Dasmarinas Village South, La Paz-Singkamas-Tejeros, Palanan, Pasong Tamo 2000 Up & Ecology V, Pio Del Pilar, Rembo (East) & Malapad Na Bato, Forbes Park South, and San Isidro

Cluster 5: Magallanes Village and Bangkal



In this new clustering, Clusters 2 and 3 are maintained as separate clusters. Cluster 1 is now broken down into 3 separate clusters (Clusters 1, 4 and 5). Most were retained as a cluster (Cluster 1). These are the neighborhoods that were in the original Cluster 1 that are also closest to the stations. Cluster 4 are neighborhoods from the original Cluster 1 that are not that close to the stations. Cluster 5 are neighborhoods from the original Cluster 1 that are farthest from the stations.

Discussion

We can use the original clustering in this way: If one needs to find an appropriate location for a restaurant, browse through the Cluster 1 and look for neighborhoods where the most common venues are not restaurants. These are the opportunities that should be considered. Locations for cafes and spas can be found in the same way. If one is looking for a fast-food or convenience store location, one can also look at the Cluster 2 for options.

The new clustering becomes relevant if the restaurant to be built appeals to subway-riding customers. For such kinds of restaurants, location options in the new Cluster 1 is ideal. Clusters 4 and 5 can only be considered if either the neighborhoods can generate the demand or the restaurant's market brings their own cars.

One way to improve this study is to identify distance thresholds that are deemed the same to restaurant patrons. How is closeness to a station defined? Is a distance of 200 meters considered close enough that it can be treated as if it were 20 meters? Is a distance of 2 kilometers already too far that it should be treated the same as 20 kilometers? In this study, distance is treated in a linear fashion, i.e., a neighborhood that is twice as far to the subway versus another neighborhood is exactly twice as far in terms of clustering. If we apply thresholds, they might fall into the same range. Using the new clustering above as an example, Clusters 4 and 5 (orange and purple) might be grouped together while Cluster 1 (blue) might need to be subdivided further if thresholds are applied.

Another improvement to this study is to look into machine learning to try to predict profitability based on type of venue, neighborhood and demographic data of its market. The actual distance of the venue to the subway stations can be included but since there are no subways yet in the Philippines, it will be difficult to find its relationship to profitability.

Conclusion

With the difficulty encountered in acquiring useable data for the Philippines, using alternative paid sources may increase the breadth and depth of this analysis. Foursquare and Google Maps offer more detailed location data and reviews that can help complete the picture.

If better and more complete data is made available for all major cities in the Philippines, we can apply a similar methodology to analyze the different neighborhoods and venues and how the building of transportation infrastructure changes the way they are related and valued. With data science, better models lead to more informed decision-making.