MAKATI NEIGHBORHOODS: WHERE TO LOCATE BEFORE AND AFTER THE SUBWAY IS BUILT

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Outline

- Introduction
- Data
- Methodology
- Results
- Discussion
- Conclusion

Introduction

- Metro Manila has one of the worst traffic environments in the world
- Makati (part of Metro Manila) is building the country's first subway
- Where in Makati should a restaurant be located now?
- Where to locate once the subway is operational?



Makati Zip Codes to get Makati Neighborhoods' Geo Coordinates

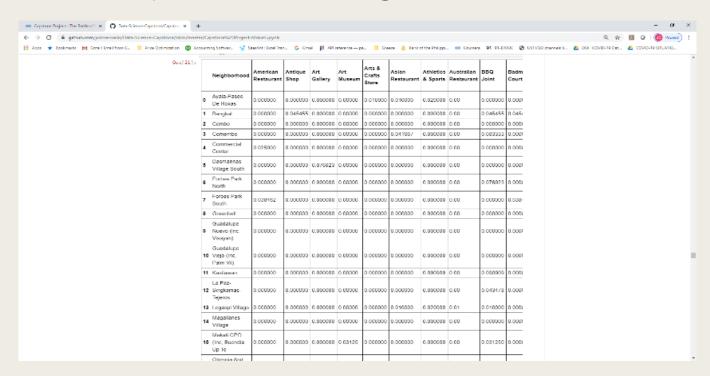
Source - https://en.wikipedia.org/wiki/List_of_ZIP_codes_in_the_Philippines

| | 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 |

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 |
| 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 |

- Foursquare venue data grouped by Neighborhood
- Frequencies of each venue type
- This serves as the input for K-Means Clustering.



- Identify proposed Makati Subway
 Stations then get Geo Coordinates
 - Source https://businessmirror.com.ph/2019/10/30/ma kati-subway-project-gets-additional-332-millioninitial-funding
- Geo Coordinates obtained from Google Maps
- Compute the shortest distances (in meters) of each neighborhood to any of the stations

| | 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 |
| 9 | Ospital ng Makati | 14.54681 | 121.06176 |

| 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 |

Methodology

- Find nearby venues to Makati neighborhoods using Foursquare
- Generate a table of frequencies of top venue types of each Makati neighborhood
- Use K-Means Clustering to group similar neighborhoods and gain insight on types of venues that thrive in those clusters
 - Display square distances for k from 1 to 9 and use Elbow Method to find optimal k
- Add Subway station proximity as a factor and repeat K-Means Clustering and compare clusters to original clusters to gain insights
 - Display square distances for k from 1 to 9 and use Elbow Method to find optimal k

Results

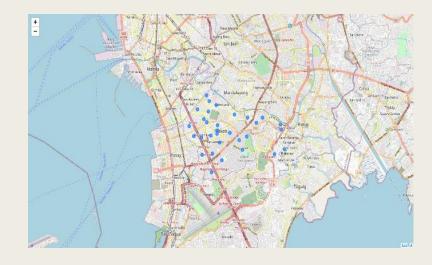
- Makati Zip Code Geo Coordinates from Pgeocode were not useable
- Many coordinates given were outside Makati and not even in Metro Manila
- For those that were in Makati, the coordinates were not accurate.
- Many neighborhoods also shared zip codes even if far apart



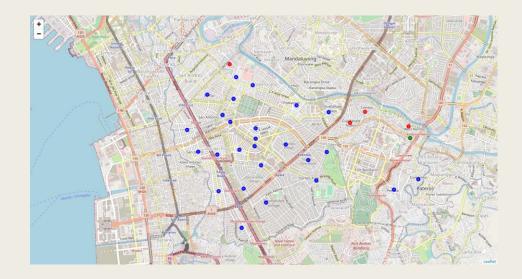
Results

- Coordinates were corrected using Google Maps
- Redundant Zip Codes pointing to the same location were removed
- This new list of neighborhoods with coordinates were used to get nearby venues from Foursquare.
- The top venue types were counted for each neighborhood.
- K-Means Clustering was performed.





Results 3 Clusters



- 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

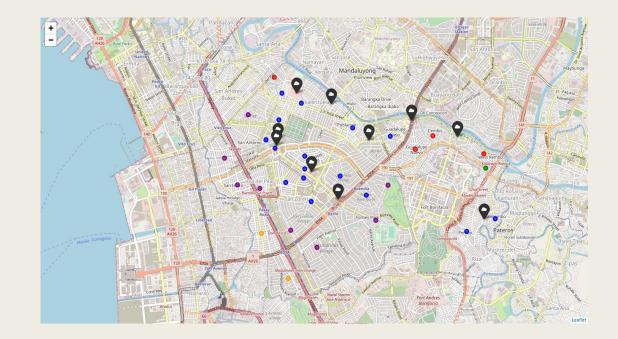
Results 3 Clusters



- Without using economic factors in the clustering, the clusters still grouped the most developed (Cluster 1), least developed (Cluster 3), and in between (Cluster 2)
- Cluster 1 includes all commercial, office areas and gated subdivisions. Restaurants, cafes, and spas are the most common venues here.
- Cluster 2 has convenience stores and fast food restaurants as the most common venues.
- Cluster 3 has the least commercial activity where the most common venue types are: Food (neighborhood food stall), Soccer Field, Intersection, and Basketball Court.

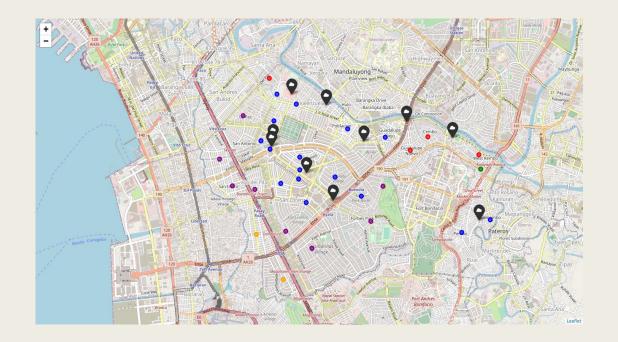
Results with Subway Proximity 5 Clusters

- 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



Results with Subway Proximity 5 Clusters

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



Discussion

- Use original clustering in this way:
 - To find a location for a restaurant, browse through Cluster 1
 - Look for neighborhoods where most common venues are not restaurants.
 - Locations for cafes and spas can be found in the same way.
 - To find a fastfood or convenience store location, browse through Cluster 2 as well
- New clustering relevant if restaurant to be built appeals to subway-riding customers
- For such restaurants, location options in new Cluster 1 is ideal
- Clusters 4 and 5 only considered if neighborhoods can generate enough demand or restaurant's market brings cars or uses Uber/Grab

Discussion

- Improvements:
 - identify distance thresholds deemed the same to restaurant patrons
 - Define closeness to a station
 - Is 200 meters treated the same as 20 meters?
 - Is 2 kilometers treated the same as 20 kilometers?
 - Using the new clustering as an example, Clusters 4 and 5 (orange and purple) might be grouped together while Cluster 1 (blue) might need to be subdivided further.
 - look into machine learning to predict profitability based on type of venue, neighborhood and demographic data of the market.
 - 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

- Using alternative paid sources may increase the possible breadth and depth of this analysis.
- Foursquare and Google Maps offer more detailed location data and reviews that can help complete the picture.
- With better data for all major cities in the Philippines, we can study other 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.