Clustering Exclusive Villages in Metro Manila and Finding Wet Market Suppliers Per Cluster Using Foursquare API

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I. Introduction

a. Background

Due of the COVID-19 pandemic, Metro Manila, Philippines has been under quarantine since March 2020. Quarantine restrictions made it difficult for most businesses to operate, but these also greatly increased the demand for delivery services because it is unsafe to go out in public places.

Since large delivery fees are unattractive to most customers, some businesses offer free delivery to certain areas, usually exclusive villages, if they have many customers in that area. These businesses often have a Viber chat group for each village, where residents send their orders.

This delivery model works well for businesses that sell essential, perishable goods such as vegetables and meat because these are items that are bought frequently and by the same customers.

b. Target Market

This report is targeted towards stakeholders who are interested in starting a fresh produce (seafood, vegetables, fruits, and meat) delivery business that caters to residents in exclusive villages in Metro Manila, Philippines.

c. Business Problem

If deliveries are done 6 days a week, how could one know which villages to deliver to each day to optimize their logistics, and from which wet market supplier to get the fresh produce from?

II. Data

a. Data Needed

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

- The locations of the exclusive villages in Metro Manila
- The names and ratings of wet markets nearest to each delivery group (since the customers are usually picky with the quality of the goods that they buy)

b. Data Sources

The following data sources will be used to extract or generate the required information:

- **Nominatim API geocoding** – for finding the longitude and latitude of each exclusive village in Metro Manila
- **Foursquare API** – for determining the wet markets around the areas of the exclusive villages and their ratings

- **List of exclusive residential areas in Metro Manila from one of the top bread shops in the country that delivers to these villages** – for identifying the exclusive villages which the target market will be delivering to
    - The residents of the villages listed here are the same ones the target market would want to attract.
    - This is public information because this list is available on the bread shop's online order form.

III. Methodology

a. Gather data

One of the top bread shops in the country delivers bread weekly to the most exclusive villages in Metro Manila. The residential areas that they deliver to are included in their online order form, since customers will have to select the village where they live.
I took note of these 45 areas and consolidated each village's longitude and latitude in a CSV file, which I got from using Nominatim API geocoding.
This is an example of how I got the longitude and latitude of each village:

```
In [34]: #get latitude and longitude of Village in Metro Manila

address = 'North Greenhills, Metro Manila'

geolocator = Nominatim(user_agent="gh_agent")
location = geolocator.geocode(address)
latitude = location.latitude
longitude = location.longitude
print(latitude, longitude)

14.6057512 121.04557531982033
```

Figure 1: Getting the latitude and longitude of each village

I then uploaded this CSV file into the notebook. The only data included in the CSV file were the names, longitude, and latitude of each village.

b. Import libraries and data

These are the following libraries which I used for this project:

i. *Requests*: for handling requests
ii. *Pandas*: for data analysis and dataframe-making
iii. *Numpy*: to handle data in a vectorized manner
iv. *Json*: to parse JSON files into a Python dictionary or list
v. *Json_normalize*: to transform json files into a pandas dataframe library
vi. *Matplotlib*: for plotting points in the map
vii. *Folium*: for creating maps
viii. *Nominatim*: for geocoding the longitude and latitude of different areas needed
ix. *KMeans*: for creating a k-means clustering model to cluster the villages

```
In [1]: import requests # library to handle requests
import pandas as pd # library for data analsysis
import numpy as np # library to handle data in a vectorized manner

import json #library to parse JSON files into a Python dictionary or list

import matplotlib.cm as cm # library for plotting points in the map
import matplotlib.colors as colors #library for plotting points in the map

from pandas.io.json import json_normalize # library for tranforming json files into a pandas dataframe library

!python3 -m pip install folium

import folium # library for creating maps
from geopy.geocoders import Nominatim # library for geocoding the longitude and latitude of different areas needed

from sklearn.cluster import KMeans # library for creating a k-means clustering model

print('Libraries imported.')
```

Figure 2: Importing the different libraries needed

After importing these libraries, I also defined my Foursquare API credentials because the names and ratings of the different wet markets near the villages would be requested from Foursquare API.

```
In [2]: #Foursquare credentials (hidden cell)

        # @hidden_cell

        CLIENT_ID = '[redacted]' # Foursquare ID
        CLIENT_SECRET = '[redacted]' # Foursquare Secret
        ACCESS_TOKEN = '[redacted]'
        VERSION = '[redacted]' # Foursquare API version
        LIMIT = 100 # A default Foursquare API limit value
```

Figure 3: Inputting Foursquare API credentials

I then uploaded the CSV file of the village location data into the notebook as a pandas dataframe, named "df_villages".

Out[3]:

	Village	Latitude	Longitude
0	53 BENITEZ	14.614629	121.046274
1	ACROPOLIS	14.605744	121.077077
2	ALEXANDRA	14.580917	121.062601
3	APARTMENT RIDGE	14.556622	121.026340
4	AYALA ALABANG	14.405740	121.023723

Figure 4: The dataframe of village data, called "df_villages"

c. Visualize village locations

I did some exploratory data analysis by visualizing the villages in a map using Folium. I generated a map around Metro Manila and plotted the villages as blue dots. At first glance, I could see that most villages were located in the center of Metro Manila, while there were a few outliers in the north and south.

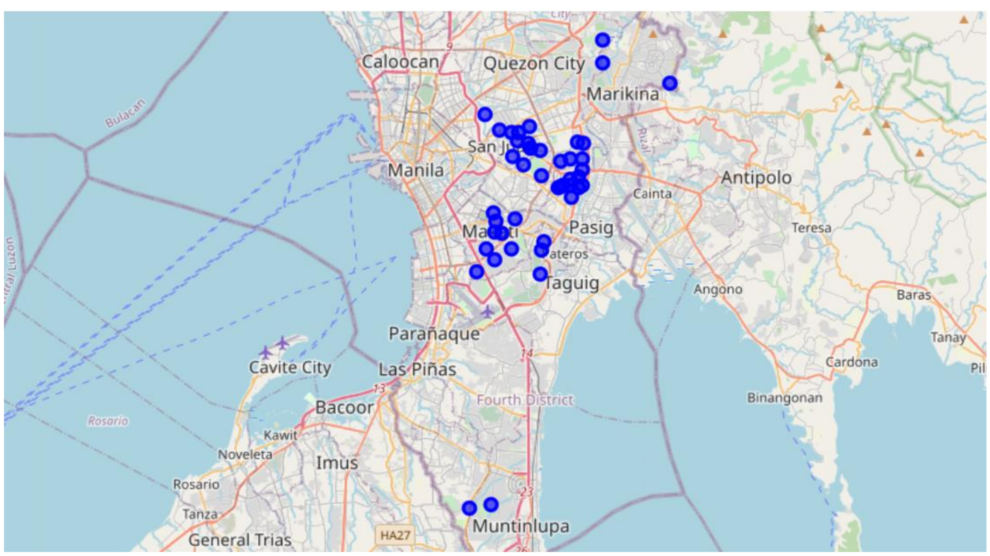

Figure 5: Map of exclusive villages in Metro Manila, marked in blue

From here, it looked like there were 4 possible village clusters, but since there are 6 working days a week for delivery, I wanted to split all these villages into 6 clusters.

d. K-means clustering of villages

Because the goods being delivered are perishable and could spoil easily, only residents in villages near each other should be delivered to in one day.

The k-means clustering algorithm was used to group the unlabeled data based on their proximity to each other; in this case, the different villages.

```
In [6]: #get k-means clusters of Metro Manila exclusive villages
        #6 clusters because one cluster for each working day of the week

        kclusters = 6
        kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(df_villages[["Latitude", "Longitude"]])

        kmeans.labels_[0:10]

Out[6]: array([0, 4, 4, 5, 1, 3, 1, 5, 4, 4], dtype=int32)
```

Figure 6: K-means clustering model

The “kclusters = 6” section means that 6 clusters were to be created out of this formula. After the dataset was divided into 6 groups, a new column was added to the dataframe for the cluster labels.

```
In [7]: #add cluster labels to dataframe

        df_villages.insert(0, 'Cluster Labels', kmeans.labels_)

In [8]: df_villages.head()

Out[8]:
```

	Cluster Labels	Village	Latitude	Longitude
0	0	53 BENITEZ	14.614629	121.046274
1	4	ACROPOLIS	14.605744	121.077077
2	4	ALEXANDRA	14.580917	121.062601
3	5	APARTMENT RIDGE	14.556622	121.026340
4	1	AYALA ALABANG	14.405740	121.023723

Figure 7: Adding another column in the dataframe for cluster labels

To visualize the clusters, a new map was created called “cluster_map” where each cluster label was assigned a specific color and plotted on a map using folium.

```
In [9]: #map the clusters
        cluster_map = folium.Map(location=[latitude, longitude], zoom_start=12)

        # set colors for the clusters
        x = np.arange(kclusters)
        ys = [i + x + (i*x)**2 for i in range(kclusters)]
        colors_array = cm.rainbow(np.linspace(0, 1, len(ys)))
        rainbow = [colors.rgb2hex(i) for i in colors_array]
        centers = kmeans.cluster_centers_

        # put markers
        cluster_markers = []
        for lat, lon, village, cluster in zip(df_villages['Latitude'], df_villages['Longitude'], df_villages['Village'], df_villages['Cluster Labels']):
            label = folium.Popup(str(village) + ' Cluster ' + str(cluster), parse_html=True)
            folium.CircleMarker(
                [lat, lon],
                radius=5,
                popup=label,
                color=rainbow[cluster-1],
                fill=True,
                fill_color=rainbow[cluster-1],
                fill_opacity=0.7).add_to(cluster_map)

        cluster_map
```

Figure 8: Code for creating “cluster_map”

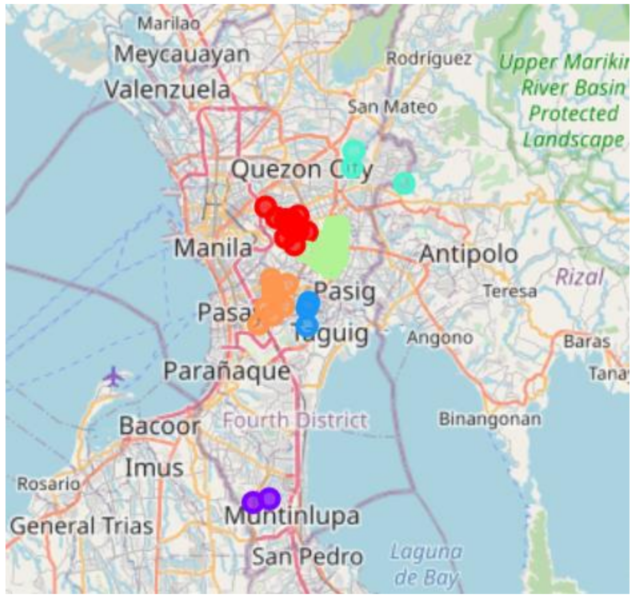

Figure 9: Each village cluster was assigned a new color to visualize the groupings

IV. Results and Analysis

Now that it was clear which villages would be delivered to on the same day, a specific wet market had to be assigned to each village cluster as to minimize the amount of travel time the goods will have to go through during delivery. It is important that the wet markets chosen were as close as possible to the clusters, especially if there are customers who order seafood or other produce that spoils easily.

Farmers Market in Cubao, Quezon City is one of the more high-end wet markets in Metro Manila where residents of these exclusive villages often get their fresh produce. For this reason, **I did not search for wet markets around the areas of Clusters 0 and 4 anymore**, since Farmers Market is situated in between these clusters.

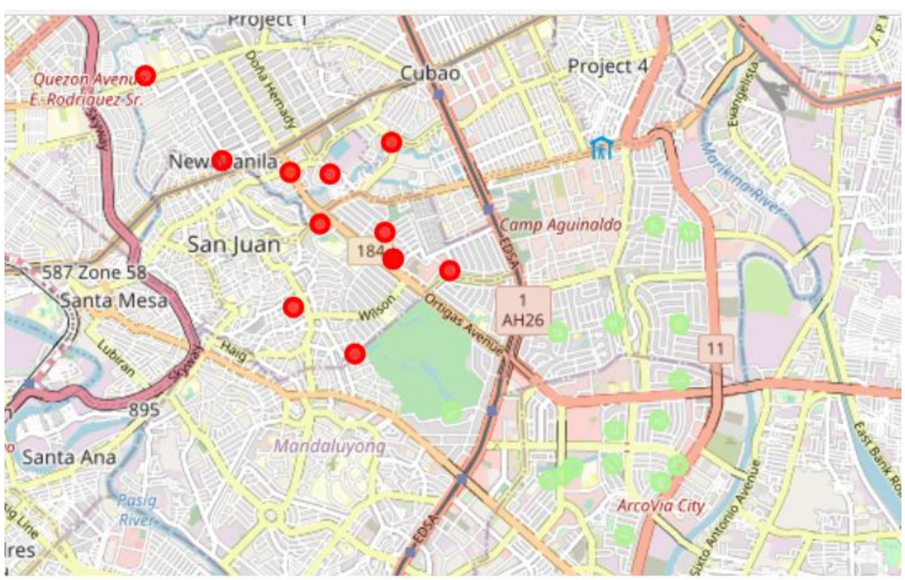

Figure 10: Clusters 0 (red dots) and 4 (green dots) with Farmers Market Cubao somewhat in between the clusters (label with "Cubao")

I recommend that this is the wet market supplier for villages in these clusters because 1) it already has a good reputation and 2) "*suki*" culture in the Philippines means that wet market vendors usually give lower prices to customers who consistently buy from their stalls. Because the target market will be buying goods from the same stalls in Farmers Market for the residents of these two clusters, prices would be minimized as well.

I only searched then for the best wet markets to supply villages in Clusters 1, 2, 3, and 5.

Finding wet market supplier candidates for Cluster 1

Because Cluster 1 only includes 2 villages (Ayala Alabang and Ayala Southvale), I picked one to use as reference for finding wet markets near Cluster 1, and this will be the first village to be delivered to.

I got the latitude and longitude of Ayala Alabang and made a search query for “wet markets” near Ayala Alabang which were to be accessed through Foursquare API.

```
In [10]: #get latitude and longitude of Ayala Alabang Village

         address_1 = 'Ayala Alabang, Metro Manila'

         geolocator_1 = Nominatim(user_agent="1_agent")
         location_1 = geolocator_1.geocode(address_1)
         latitude_1 = location_1.latitude
         longitude_1 = location_1.longitude
         print(latitude_1, longitude_1)

         14.4158464 121.024634
```

```
In [11]: #search wet markets near each selected address

         search_query = 'wet market'
         radius = 2000
         print(search_query)

         wet market
```

Figure 11: Getting the latitude and longitude of Ayala Alabang, and search query for wet markets nearby

The query data was cleaned up and saved in a dataframe named “df_markets_1.”

Out[15]:

	name	categories	lat	lng	labeledLatLngs	distance	cc	city	state	country	formattedAddress	address
0	Alabang Public Market	Market	14.420129	121.044560	[{'label': 'display', 'lat': 14.42012902514245...	2200	PH	Muntinlupa	Rizal	Pilipinas	[Muntinlupa City, Rizal]	NaN
1	Gourdo's World Market	Arts & Crafts Store	14.424579	121.028977	[{'label': 'display', 'lat': 14.42457944485915...	1079	PH	Muntinlupa City	NaN	Pilipinas	[Alabang Town Center (Alabang-Zapote Rd), Munt...	Alabang Town Center
2	Mongolian Quick-Box / Pho Market	Mongolian Restaurant	14.417155	121.039056	[{'label': 'display', 'lat': 14.417155, 'lng':...	1561	PH	Muntinlupa	Rizal	Pilipinas	[Ground Floor, Festival Mall, Filinvest Corpor...	Ground Floor, Festival Mall, Filinvest Corpora...
3	Soldiers Hills Market	Market	14.401091	121.035321	[{'label': 'display', 'lat': 14.40109060880349...	2006	PH	NaN	NaN	Pilipinas	NaN	NaN
4	Saturday Market on University	Breakfast Spot	14.410440	121.020897	[{'label': 'display', 'lat': 14.41044042625462	724	PH	NaN	NaN	Pilipinas	NaN	NaN

Figure 12: The result of wet markets near Ayala Alabang

I could see here that not all of the search results are actually wet markets, like "Filinvest Corporate City," which is tagged as a neighborhood. But since most of these were really wet markets anyway, I visualized these points in the map and spotted which markets were nearest to Ayala Alabang.

```python
In [16]: # add the wet markets to the map as yellow circle markers
for lat, lng, label in zip(df_markets_1.lat, df_markets_1.lng, df_markets_1.name):
    folium.CircleMarker(
        [lat, lng],
        radius=5,
        color='yellow',
        popup=label,
        fill = True,
        fill_color='yellow',
        fill_opacity=0.6
    ).add_to(cluster_map)

# display map
cluster_map
```

Figure 13: Code for plotting wet markets near Cluster 1

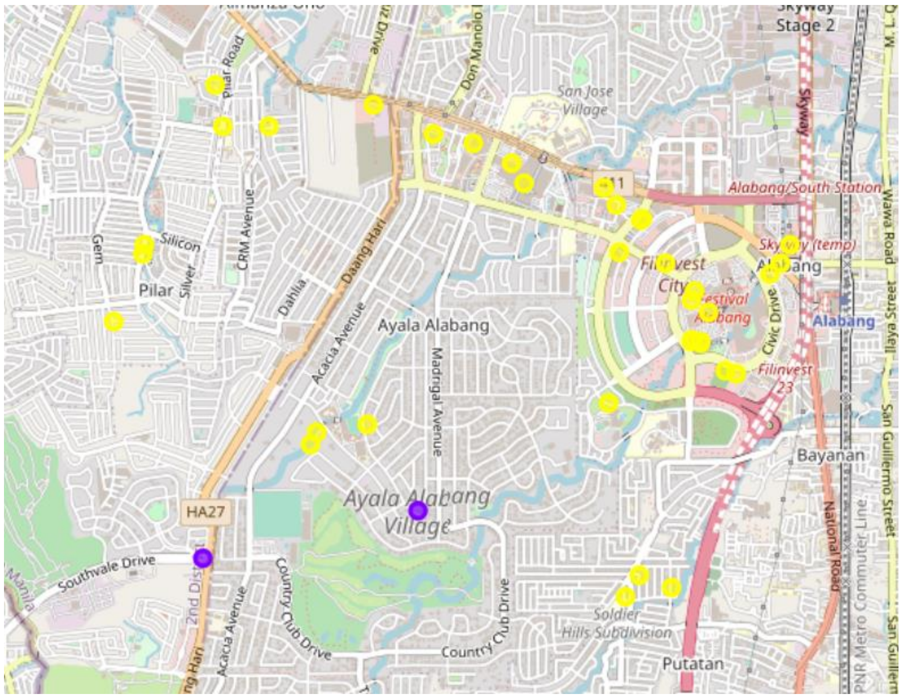

Figure 14: Map of Cluster 1 with villages as purple dots and wet markets as yellow dots

Based on the map, the nearest market to Ayala Alabang would be the **Saturday Market on University Ave.** which is most likely the same as the points labeled "Saturday Market" and "Saturday Market University Ave. Lasalle."

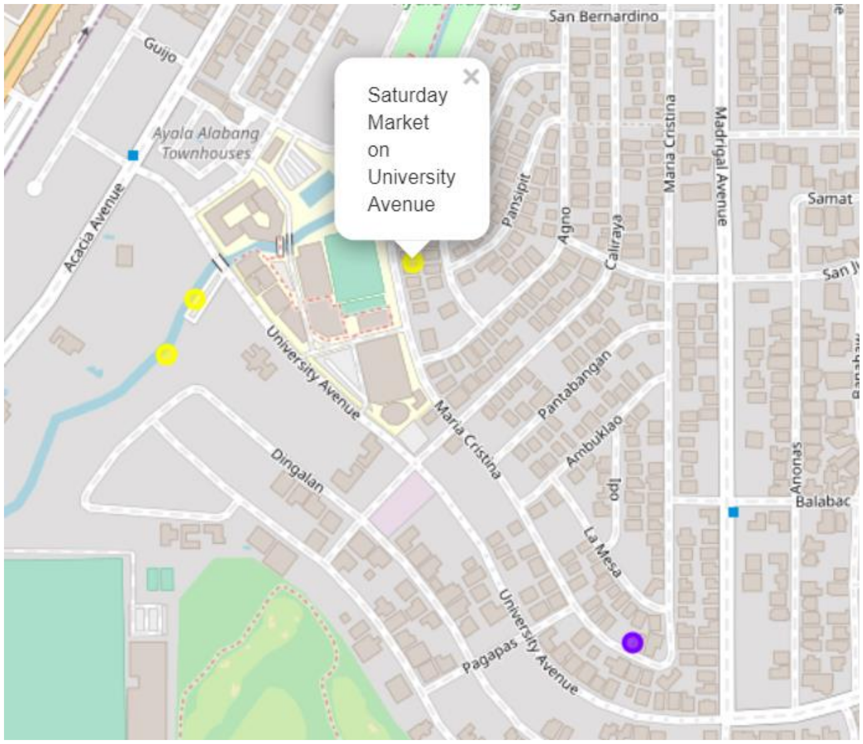

Figure 15: Map of wet markets near Ayala Alabang (purple dot) and a marker of "Saturday Market on University Ave. "

I checked the rating of Saturday Market on University Ave. to see if this market would meet the standards of the potential customers, the exclusive village residents.

In [17]:
```
#check the rating of Saturday Market on University Ave.

venue_id_SMUA = '4b9c7413f964a520d96936e3' # Saturday Market on University Ave.
url_SMUA = 'https://api.foursquare.com/v2/venues/{}?client_id={}&client_secret={}&oauth_token={}&v={}'.format(venue_id_SMUA, CLI
ENT_ID, CLIENT_SECRET,ACCESS_TOKEN, VERSION)

result_SMUA = requests.get(url_SMUA).json()

try:
    print(result_SMUA['response']['venue']['rating'])
except:
    print('This venue has not been rated yet.')
```

```
This venue has not been rated yet.
```

Figure 16: Code to check the rating of "Saturday Market on University Ave."

Because this venue has not been rated yet, I tried getting the ratings of the next nearby wet markets. However, all of them had no ratings either so I tried seeing if I can get a photo of the venue and gauge if it looks orderly and has good quality products.

In [18]:
```
url_SMUA_photo = 'https://api.foursquare.com/v2/photos/{}?client_id={}&client_secret={}&oauth_token={}&v={}'.format(venue_id_SMU
A, CLIENT_ID, CLIENT_SECRET,ACCESS_TOKEN, VERSION)
result_SMUA_photo = requests.get(url_SMUA_photo).json()

result_SMUA_photo
```

Out[18]:
```
{'meta': {'code': 400,
  'errorType': 'param_error',
  'errorDetail': 'Must provide a valid photo ID',
  'requestId': '6021e1ef1697fc56e83aaefa'},
 'notifications': [{'type': 'notificationTray', 'item': {'unreadCount': 0}}],
 'response': {}}
```

Figure 17: Code and result to view photos of "Saturday Market at University Ave."

No photo was available also on Foursquare API, so **an external image search was done on Google**. The photos below showed that the market looked clean and it seemed to cater to the right customers (promotional materials were in English language, the tarpaulin sign was well-designed, and there was an ample amount of walking space). Therefore, I would recommend the target market to get **Saturday Market** vendors as the suppliers for Cluster 1.

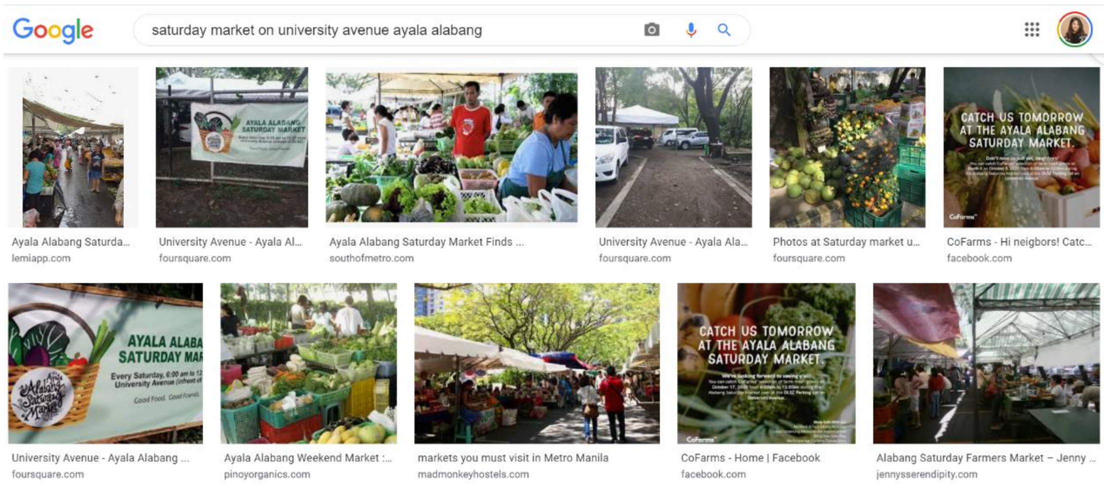

Figure 18: Google Image search for "Saturday Market at University Ave."

I repeated the same process for choosing the wet market suppliers for Clusters 2, 3, and 5.

Finding wet market supplier candidates for Cluster 2

Because Cluster 2 only includes 3 villages, I picked one that wasn't the middle village to use as reference for finding wet markets near Cluster 2 (Serendra One), and this will be the first village to be delivered to.

After creating a new dataframe called "df_markets_2" for wet markets near Serendra One, I plotted these out on "cluster_map."

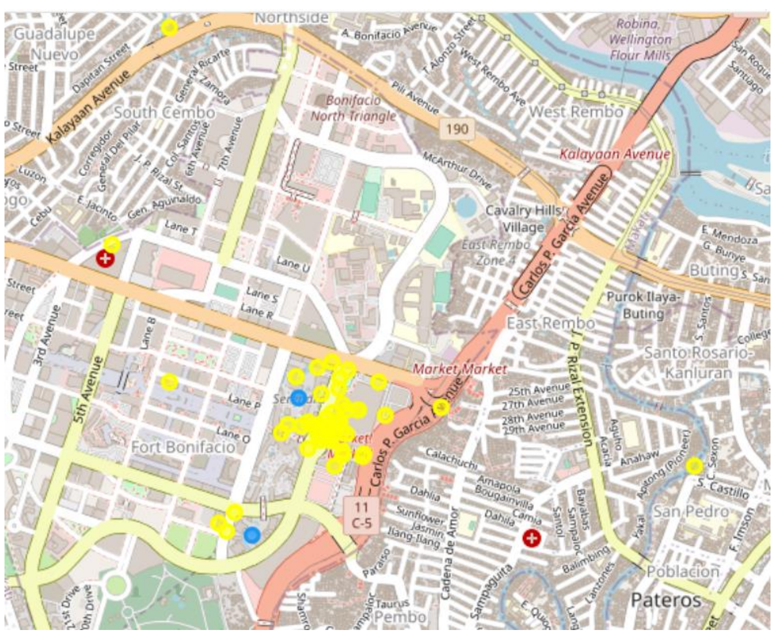

Figure 19: Map of Cluster 2 with villages as blue dots and wet markets as yellow dots

As seen on the map, there were many markets plotted near Cluster 2 because it is right next to a shopping mall called "Market! Market!" This might be one of the restrictions of using Foursquare API because even the non-food shops in the mall were included in the search results since their names had the word "Market" in them.

Upon checking the nearby points though, it was seen that there was also a Farmers Market within the mall Market! Market!, so this could be the potential supplier for Cluster 2.

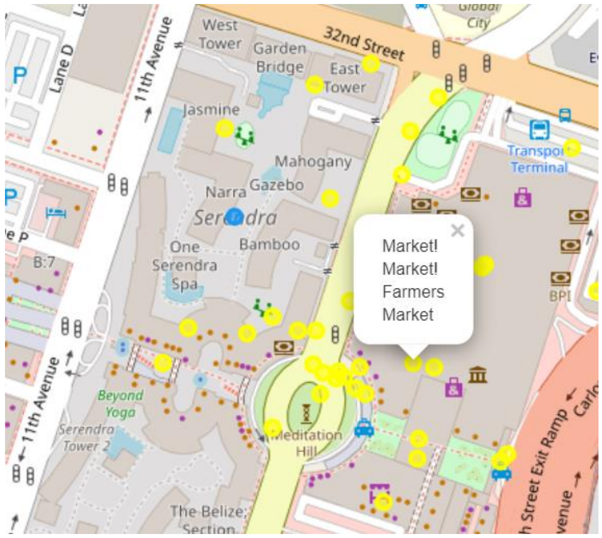

Figure 20: Map of wet markets near Serendra One (blue dot) and a marker of "Market! Market! Farmers Market"

I checked the rating of the Market! Market! Farmers Market, and saw that there was none. I decided to see if it might have any tips instead from Foursquare users that would give a hint of how it is.

```
In [25]: ## MMFM Tips
limit_MMFM = 15 # set limit to be greater than or equal to the total number of tips
tips_MMFM = 'https://api.foursquare.com/v2/venues/{}/tips?client_id={}&client_secret={}&oauth_token={}&v={}&limit={}'.format(venue_id_MMFM, CLIENT_ID, CLIENT_SECRET,ACCESS_TOKEN, VERSION, limit_MMFM)

results_MMFM = requests.get(tips_MMFM).json()
results_MMFM
```

```
Out[25]: {'meta': {'code': 200, 'requestId': '6021e1f10ec9ad295063dc33'},
 'notifications': [{'type': 'notificationTray', 'item': {'unreadCount': 0}}],
 'response': {'tips': {'count': 0, 'items': []}}}
```

Figure 21: Code to get tips for "Market! Market! Farmers Market"

There are also no tips available on Foursquare API. Since this wet market and the next nearest wet markets (which were already a bit far from the cluster) do not have ratings too, I based my decision to recommend Market! Market! Farmers Market as a supplier for Cluster 2 on photos of it that were found in Google Images.

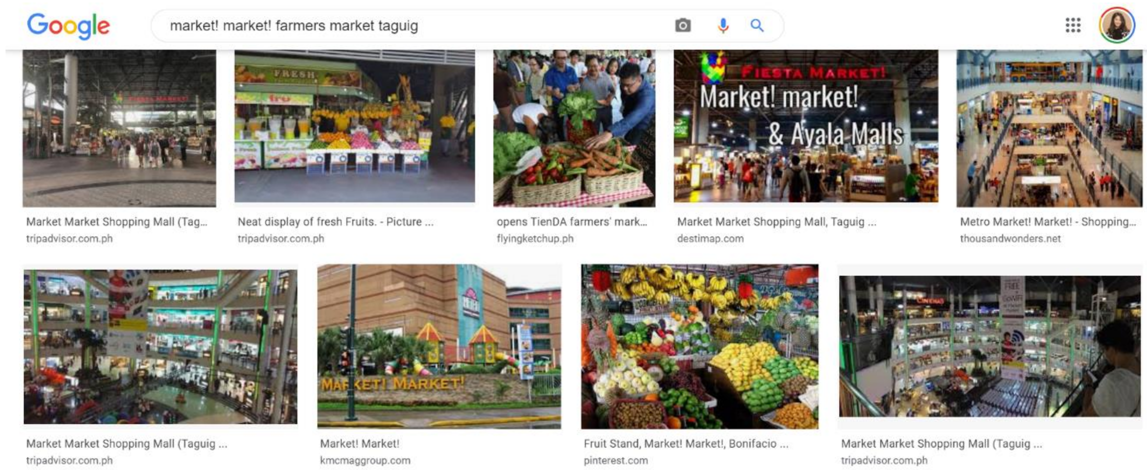

Figure 22: Google Image search results of "Market! Market! Farmers Market"

Based on the photos, this looked like a clean and reputable wet market, especially because it was located in an area of a popular shopping mall. Therefore, I will recommend **Market! Market! Farmers Market** as a supplier for Cluster 2 residents.

Next, I looked for the best wet market supplier for Cluster 3.

Finding wet market supplier candidates for Cluster 3

Because Cluster 3 only included 3 villages, I picked one that wasn't the middle village to use as reference for finding wet markets near Cluster 3, and this will be the first village to be delivered to.

I specifically picked La Vista Village as the reference because the other two villages are a bit close to each other and are on one side of a river, so logistically, it is easier to deliver to La Vista first.

Again, the neighboring wet markets were placed in a dataframe "df_markets_3" and plotted on "clusters_map."

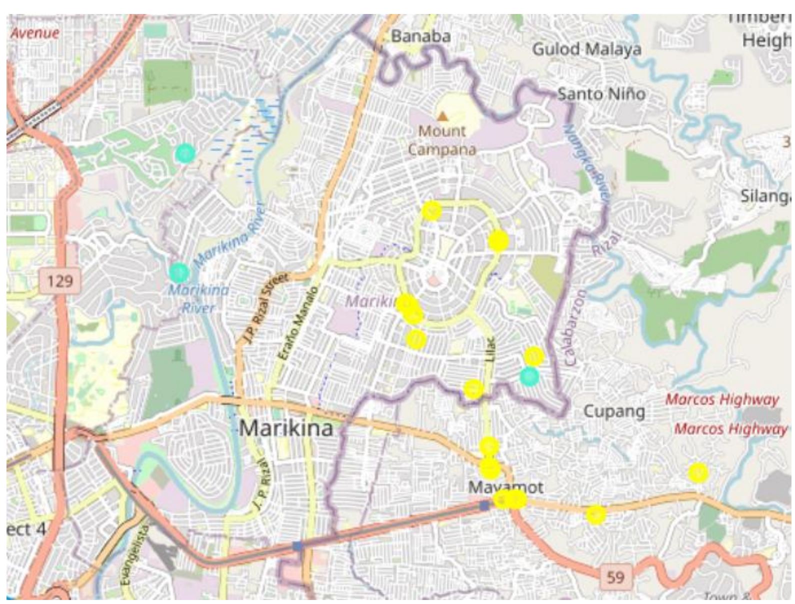

Figure 23: Map of Cluster 3 with villages as light blue dots and wet markets as yellow dots

Figure 24: Map of wet markets near La Vista (light blue dot) and a marker of "Viaga Public Market"

Based on the map, the nearest market to La Vista was the Viaga Public Market. Since this venue did not have a rating, tips, or photos on Foursquare, I checked the next nearest wet markets to see if they have ratings, tips, or photos.

Unfortunately, none of them do. I tried checking Google Images for photos of **Viaga Public Market, Tumana Public Market, and Taboan Public Market** (the next nearest wet markets to La Vista), but no images of these were available as well.

I suppose that **there are not too many venues in Metro Manila (or even in the Philippines) with reviews, tips, and photos on Foursquare API just yet**. Either that, or **not too many people review and leave tips on wet markets in this area**. In this case, I will leave it to the user of this report to explore the suggested wet markets themselves and gauge whether these are suitable for their customers.

Lastly, I will repeat the process for Cluster 5.

Finding wet market supplier candidates for Cluster 5

Because Urdaneta Village is generally in the center of Cluster 5, I used it as a reference for searching for the list of wet markets nearest to the cluster. This is the map of wet markets near Cluster 5:

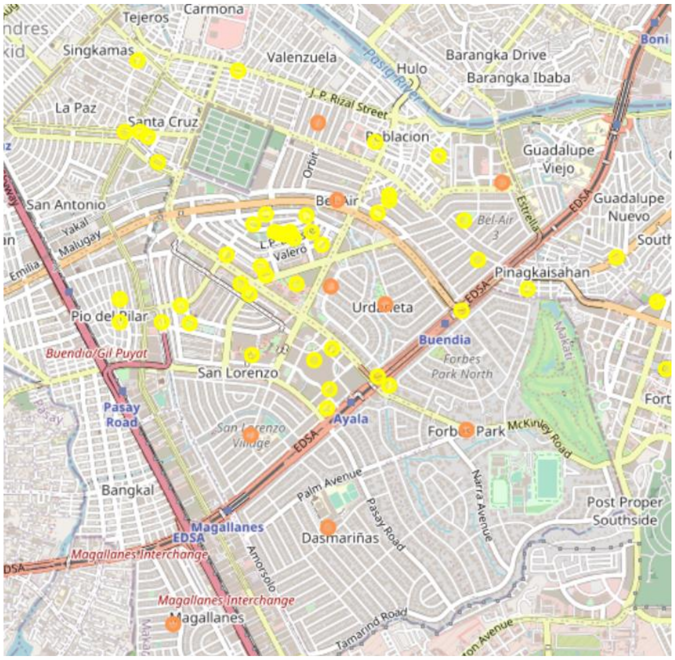

Figure 25: Map of Cluster 5 with villages as orange dots and wet markets as yellow dots

Looking at the map of Cluster 5, I noticed that many of the points plotted were not actually wet markets, as some were night markets or supermarkets. It might be best if the wet market supplier is close to at least one of the villages in the border of the cluster, such as Rockwell Makati which is on the top right corner of the cluster.

This is so that the wet market supplier could be near an "entry point" of the delivery route for that group. The nearest points near Rockwell Makati are "Marketplace by Rustans," which is a high end supermarket, and "The Grid Food Market," a high-end food court. Since neither are real wet markets for fresh produce, I would recommend Poblacion Public Market as a wet market supplier for this cluster because it is the next nearest point to Rockwell Makati.

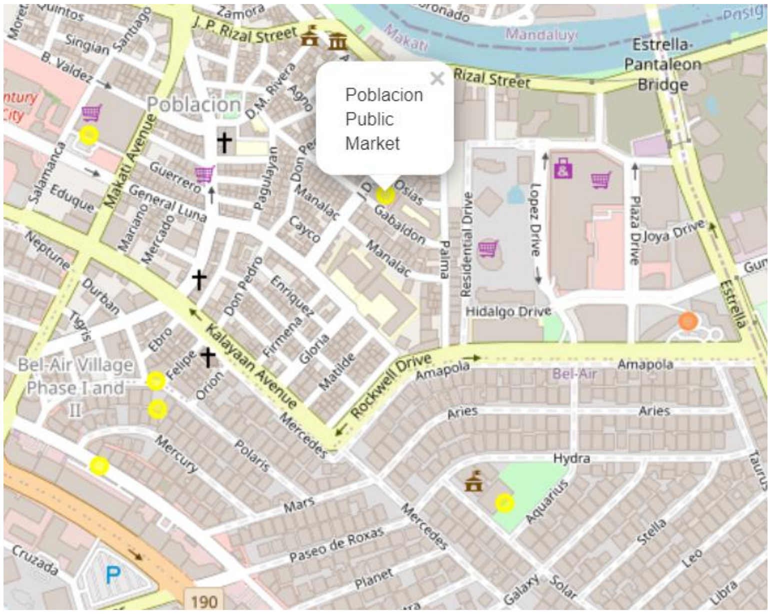

Figure 26: Map of wet markets near Rockwell Makati (orange dot) and a marker of "Poblacion Public Market"

Again, since this venue had no ratings, tips, or photos available, I based the quality of this market on Google Images again. This was the only image of Poblacion Public Market that I was able to find:

Figure 27: Image of "Poblacion Public Market" taken from http://simplegoodandtasty.com/2011/01/22/exploring-philippine-farmers-markets-with-an-eye-towards-the-twin-cities

Its interior is actually similar to that of Farmers Market Cubao, so I would assume that the produce in this wet market should be of similar quality too. Therefore, I would recommend **Poblacion Public Market** as the wet market supplier for Cluster 5.

V. Conclusion

The 45 exclusive villages in Metro Manila were clustered into 6 delivery groups (Clusters 0-5) according to their proximity to each other. The groupings could be seen in the dataframe below:

	Cluster Labels	Village	Latitude	Longitude
0	0	53 BENITEZ	14.614629	121.046274
1	4	ACROPOLIS	14.605744	121.077077
2	4	ALEXANDRA	14.580917	121.062601
3	5	APARTMENT RIDGE	14.556622	121.026340
4	1	AYALA ALABANG	14.405740	121.023723
5	3	AYALA HEIGHTS	14.662461	121.088204
6	1	AYALA SOUTHVALE	14.403211	121.011704
7	5	BEL-AIR	14.562216	121.026759
8	4	CORINTHIAN GARDENS	14.595673	121.063503
9	4	CORINTHIAN HILLS	14.596577	121.069272
10	5	DASMARINAS VILLAGE	14.540761	121.026191
11	0	EAST GREENHILLS	14.603023	121.046444
12	5	FORBES PARK	14.547168	121.035516
13	4	GREENMEADOWS	14.596545	121.076000
14	0	HORSESHOE VILLAGE	14.611544	121.039971
15	0	JADE GARDEN	14.606554	121.038915
16	3	LA VISTA	14.638572	121.126406
17	3	LOYOLA GRAND VILLAS	14.649698	121.087555
18	5	MAGALLANES	14.534482	121.015670
19	2	MCKINLEY HILL	14.533049	121.052429
20	0	NEW MANILA	14.612781	121.028906
21	0	NORTHEAST GREENHILLS	14.603023	121.046444
22	0	NORTH GREENHILLS	14.605751	121.045575
23	4	RENAISSANCE	14.581505	121.064023
24	5	ROCKWELL MAKATI	14.563414	121.037956
26	0	ROLLING HILLS	14.621309	121.020882
27	5	SAN LORENZO	14.546899	121.020945
28	5	SAN MIGUEL VILLAGE	14.567265	121.025519
29	2	SERENDRA ONE	14.550762	121.054373
30	2	SERENDRA TWO	14.546477	121.052850
31	4	SHINE RESIDENCES	14.582266	121.065124
32	5	URDANETA	14.555458	121.030044
33	0	VALENCIA	14.611590	121.035794
34	4	VALLE VERDE 1	14.575406	121.070287
35	4	VALLE VERDE 2	14.580798	121.074096
36	4	VALLE VERDE 3	14.582520	121.069121
37	4	VALLE VERDE 4	14.585873	121.069272
38	4	VALLE VERDE 5	14.586926	121.073930
39	4	VALLE VERDE 6	14.590828	121.076098
40	0	VIRIDIAN	14.601819	121.052299
41	4	VV HOMES	14.582494	121.075889
42	4	WACK-WACK ROAD	14.587722	121.052554
43	0	WACK-WACK VILLAGE	14.593470	121.042559
44	0	WEST GREENHILLS	14.603023	121.046444
45	4	WHITE PLAINS	14.606339	121.073432

Figure 28: Dataframe of villages with their respective clusters "df_villages"

Using Foursquare API and some additional human knowledge (like knowing the reputation of Farmers Market Cubao with the intended customers), I was able to identify some recommended wet markets where the target market could buy supplies which will be sold to the residents of these exclusive villages. These wet markets are:

1. **Cluster 0** (West Greenhills, Wack Wack Village, etc.) - **Farmers Market Cubao**
2. **Cluster 1** (Ayala Alabang, Ayala Southvale) - **Saturday Market on University Ave.**
3. **Cluster 2** (Serendra One, Serendra Two, and Mckinley Hill) - **Market! Market! Farmers Market**
4. **Cluster 3** (La Vista, Loyola Grand Villas, and Ayala Heights) - **Viaga Public Market, Tumana Public Market, or Taboan Public Market**
5. **Cluster 4** (Corinthian Gardens, Valle Verde 1, etc.) - **Farmers Market Cubao**
6. **Cluster 5** (Dasmarinas Village, Forbes Park, etc.) - **Poblacion Public Market**

I have also concluded through this project that although this kind of data and technology are available for aiding in business decisions, **a bulk of the analysis still relies on human experience and intuition**. For example, data from Foursquare could show us that certain venues tagged as wet markets would be the most practical choice as suppliers based on their proximity to the generated clusters, but this would not account for the savings a businessman could make by choosing the supplier that allows him to haggle for bulk orders.

At the end of the day, technology is a tool to make decision-making easier, but it can only be optimized by integrating it with real-world human knowledge.