# **CAPSTONE PROPOSAL**

NAME: SIDHARTH KUMAR MOHANTY

DATE: 1st June 2020

**TOPIC: THE BATTLE OF THE NEIGHBOURHOODS** 

**Blog Post Link:** 

This is my link of the blog post about this project <a href="https://medium.com/@sidharth.ku178/the-battle-of-the-neighbourhoods-3d90f56dae69">https://medium.com/@sidharth.ku178/the-battle-of-the-neighbourhoods-3d90f56dae69</a>

## **Domain Background:**

Different cities in the world are filled with numerous kinds of venues that in turn define the cultures of the cities. A city not only differs from another by means of global positioning, what it to showcase to its inhabitants or tourists has put a significant mark on differentiating it from the rest. Despite of having dissimilarities, it is somewhat possible to group together the similar kind of neighborhoods in different cities. It is possible to segment the different venues in a neighborhood according to venue category, and then to group neighborhoods together that incorporate similar kind of neighborhoods. Human migration is the movement by people from one place to another with the intentions of settling, permanently or temporarily in a new location. Having grouped together similar kind of neighborhoods may serve as a variable to help make a decision when people consider moving out of a city to another. I will explore the neighborhoods in Hong Kong and answer the question: "Where is the appropriate place to open a new restaurant in Hong Kong

#### **Problem Statement**

The mission of this project is to use Foursquare location data and regional clustering of venue information to determine what might be the 'best' neighborhood in HongKong to open a restaurant. As a westerner who has a passion for good Mexican food, I have found that there is not a lot of selection in the region. This is supported by the fact that a review of Foursquare venues reveals zero Mexican restaurants listed on the site. Due to its central geographic location and generally welcoming climate, HongKong is known for its international atmosphere. It is home to close to 2.5 Million expatriates who make up 90% of the total population<sup>1</sup> and it hosts close to 15 Million visitors per year. In addition to its multi-cultural population and capital flows, HongKong is becoming well known as a destination of choice for great food. It is a place where people can rest and try the best of each culture, either while they work here temporarily, or of they are just passing through.

My proposal, then, is an analysis of the neighborhoods in HongKong for the consideration of opening a new Mexican restaurant. The objective is to have a location that is within one of the more reasonable rent zones, but also within a close enough range (5km) to a 'high' rent zone. The

assumption that proximity to high rent neighborhoods would result in takeout opportunities or provide residents an option to travel to our restaurant.

### **Datasets and Inputs**

The data that we will use for this analysis is a combination of a CSV file that has been prepared for the purposes of the analysis from multiple sources (neighborhoods hongkong.csv) and the location/venue information in foursquare.

For this project we need the following data:

- 1. HongKong City data that contains list Boroughs, Neighborhoods along with their latitude and longitude.
- 2. Indian resturants in each neighborhood of HongKong.
- 3. GeoSpace data

Source 1: neighborhoods hongkong.csv

We will first determine the most likely neighborhoods for a restaurant based on average rental prices and relative distance to a high rent center. In the case of HongKong, the three highest rent averages can be found in Palm Jumeirah, Jumeirah, and Zabeel. We will then consider the total number of venues and additional criteria such as proximity to a shopping center or offices for midday traffic to make a final determination.

The first step is to etablish the neighborhoods in HongKong and a summary of their average rental prices. The average rental index is published annually and can be referenced by a number of different websites. We then make a calculation of the 'Z-score' to standardize the data and sort from lowest to highest average rent. Using google, I looked up the latitude and longitude of each neighborhood and entered it. This information is used to calculate the distance of each neighborhood from the highest rent regions and will also be entered to the Foursquare database for venue query later.

eighborhood	Ave Book Book Hole							Rent Ave
Lancing Condens	Avg Rent Per Unit 2	r Unit Z-Score	Distance from Palm	Distance from Zabeel	Distance from Jumeirah	Latitude	Longitude	
iscovery Gardens	44,672	-1.53	8.18	26.15	20.73	25.039	55.1445	- 0
ubai Silicon Oasis	54,417	-1.30	24.96	13.31	16.39	25.1279	55.3863	
imeirah Village Circle	60,068	-1.17	9.16	20.56	16.13	25.0602	55.2094	- 1
ubai Sports City	62,753	-1.10	11.36	22.32	18.28	25.0391	55.2176	1
emraam	67,284	-0.99	16.71	25.27	22.27	25.0014	55.2508	1
l Furjan	73,648	-0.84	9.70	27.28	22.02	25.0252	55.1459	î
umeirah Village Triangle	82,014	-0.64	8.87	22.78	18.04	25.0473	55.19	
fotor City	83,876	-0.60	12.61	20.90	17.42	25.045	55.2397	1
amac Hills	94,630	-0.34	16.40	22.41	19.37	25.0275	55.2524	
l Sufouh	95,804	-0.31	0.70	17.88	12.02	25.1134	55.1762	î 1
IFC	105,183	-0.09	17.86	3.02	3.57	25.2106	55.2794	1
usiness Bay	105,682	-0.08	15.61	5.55	3.45	25.1832	55.2729	1 0
umeirah Lakes Towers	106,352	-0.06	4.80	23.80	18.03	25.0693	55.1417	i :
arsha Heights	111,804	0.07	4.10	19.08	13.48	25.097	55.1776	1 1
mirates Living	114,422	0.13	7.82	23.43	18.36	25.0496	55.174	1
ubai Marina	115,236	0.15	3.55	23.02	17.12	25.0805	55.1403	.i .
ubai Investments Park	116,379	0.18	15.30	30.13	25.71	24.979	55.1762	
imeirah Beach Residence	143,520	0.83	3.97	23.75	17.82	25.0769	55.1341	
ubai Festival City	151,341	1.02	25.23	5.60	11.81	25.2171	55.3614	
owntown	153,546	1.07	16.77	4.19	3.41	25.195	55.2784	1
abeel	176,213	1.61	20.84	0.00	6.57	25.2231	55.3061	1
umeirah	180,180	1.71	14.59	6.57	0.00	25.2016	55.2453	T.
alm Jumeirah	204,430	2.29	0.00	20.84	14.59	25.1124	55.139	Hig
u e i uta a i u u a n u u u u u u u u	shai Sports City rmraam Furjan meirah Village Triangle otor City mmac Hills Sufouh FC ssiness Bay meirah Lakes Towers ursha Heights nirates Living ubai Marina ubai Investments Park meirah Beach Residence ubai Festival City owntown beel meirah	sbai Sports City         62,753           mraam         67,284           Furjan         73,648           meirah Village Triangle         82,014           otor City         83,876           murac Hills         94,630           Sufouh         95,804           FC         105,183           ssiness Bay         105,682           meirah Lakes Towers         106,352           ursha Heights         111,804           nitrates Living         114,422           ubal Investments Park         116,379           meirah Beach Residence         143,520           ubal if Festival City         151,341           womtown         153,546           ubeel         176,213           meirah         180,180	abai Sports City         62,753         -1.10           emraam         67,284         -0.99           Furjan         73,648         -0.84           meirah Village Triangle         82,014         -0.64           otor City         83,876         -0.60           mac Hills         94,630         -0.34           Sufouh         95,804         -0.31           FC         105,183         -0.09           sincess Bay         105,682         -0.06           meirah Lakes Towers         106,352         -0.06           risha Heights         111,804         0.07           rintrates Living         114,422         0.13           ribai Marina         115,236         0.15           ribai Imestments Park         116,379         0.18           meirah Beach Residence         143,520         0.83           ribai Festival City         151,341         1.02           rowntown         153,546         1.07           ribeel         176,213         1.61           meirah         180,180         1.71	thai Sports City 62,753 -1.10 11.36 throman 67,284 -0.99 16.71 Furjan 73,648 -0.84 9.70 throman 73,648 -0.84 9.70 meirah Village Triangle 82,014 -0.64 8.87 totor City 83,876 -0.60 12.61 throman 61,640 9.50 12.61 throman 61,640 9.50 12.61 throman 61,640 95,804 -0.31 0.70 for C 105,183 -0.09 17.86 throman 61,682 -0.08 15.61 throman 61,682 -0.06 15.61 throman 61,682 -0.06 15.61 throman 61,682 -0.06 15.61 throman 61,682 -0.06 15.61 throman 61,682 11,804 0.07 4.10 thriates Living 114,422 0.13 7.82 thriates Living 114,422 0.13 7.82 thriates Living 114,422 0.13 3.55 thriates Living 114,422 0.13 3.55 thriates Living 114,422 0.13 3.55 thriates Living 115,236 0.15 3.55 thriates Living 115,236 0.15 3.55 thriates Living 115,341 1.02 25.23 thriates Living 153,546 1.07 16.77 three 176,213 1.61 20.84 three 176,213 1.61 20.84 three 180,180 1.71 1.459	thai Sports City 62,753 -1.10 11.36 22.32 term raam 67,284 -0.99 16.71 25.27 Furjan 73,648 -0.84 9.70 27.28 meirah Village Triangle 82,014 -0.64 8.87 22.78 otor City 83,876 -0.60 12.61 20.90 timac Hills 94,630 -0.34 16.40 22.41 5.61 20.90 timac Hills 94,630 -0.34 16.40 22.41 5.61 20.90 timac Hills 94,630 -0.34 10.70 17.88 FC 105,183 -0.09 17.86 3.02 sisness Bay 105,682 -0.08 15.61 5.55 meirah Lakes Towers 106,352 -0.06 4.80 23.80 trisha Heights 111,804 0.07 4.10 19.08 trisha Heights 114,422 0.13 7.82 23.43 thai Invarian 115,236 0.15 3.55 23.02 thai Invarian 115,236 0.15 3.55 23.02 thai Invarian 116,379 0.18 15.30 30.13 meirah Bach Residence 143,520 0.83 3.97 23.75 thai Festival City 151,341 1.02 25.23 5.60 wintown 153,546 1.07 16.77 4.19 theel	thai Sports City 62,753 -1.10 11.36 22.32 18.28 term raam 67,284 -0.99 16.71 25.27 22.27 22.27 Furjan 73,648 -0.84 9.70 27.28 22.02 meirah Village Triangle 82,014 -0.64 8.87 22.78 18.04 otor City 83,876 -0.60 12.61 20.90 17.42 term actilitis 94,630 -0.34 16.40 22.41 19.37 Suffoth 95,804 -0.31 0.70 17.88 12.02 FC 105,183 -0.09 17.86 3.02 3.57 suite suute suite suute suite suute suite suute suit	thai Sports City 62,753 -1.10 11.36 22.32 18.28 25.0391 term raam 67,284 -0.99 16.71 25.27 22.27 25.0014 Furjan 73,648 -0.84 9.70 27.28 22.02 25.0252 meirah Village Triangle 82,014 -0.64 8.87 22.78 18.04 25.0473 otor City 83,876 -0.60 12.61 20.90 17.42 25.045 imare Hills 94,630 -0.34 16.40 22.41 19.37 25.0275 Suffoth 95,804 -0.31 0.70 17.88 12.02 25.1134 FC 105,183 -0.09 17.86 3.02 3.57 25.2106 sinces Bay 105,682 -0.08 15.61 5.55 3.45 25.1832 meirah Lakes Towers 106,352 -0.06 4.80 23.80 18.03 25.0693 irisha Helights 111,804 0.07 4.10 19.08 13.48 25.097 iriates Living 14,422 0.13 7.82 23.43 18.36 25.0496 thai Marina 15,236 0.15 3.55 23.02 17.12 25.0805 thai Investments Park 116,379 0.18 15.30 30.13 25.71 24.979 iriarler Sufform 153,546 1.07 16.77 4.19 3.41 25.195 iriarler Inventor 153,546 1.07 16.77 4.19 3.41 25.195 iriarler Inventor 180,180 1.71 14.59 6.57 0.00 25.2016	thai Sports City 62,753 -1.10 11.36 22.32 18.28 25.0391 55.2176 term raam 67,284 -0.99 16.71 25.27 22.27 25.0014 55.2508 for grain 73,648 -0.84 9.70 27.28 22.02 25.0252 55.1459 meirah Village Triangle 82,014 -0.64 8.87 22.78 18.04 25.0473 55.19 otor City 83,876 -0.60 12.61 20.90 17.42 25.045 55.299 for City 83,876 -0.60 12.61 20.90 17.42 25.045 55.299 for City 94,630 -0.34 16.40 22.41 19.37 25.0275 55.2514 50.00 17.88 12.02 25.1134 55.1762 for City 105,183 -0.09 17.86 3.02 3.57 25.2106 55.2794 for City 105,183 -0.09 17.86 3.02 3.57 25.2106 55.2794 for City 105,183 -0.09 17.86 3.02 3.57 25.2106 55.2794 for City 105,183 -0.09 17.86 3.02 3.57 25.2106 55.2794 for City 105,183 -0.09 17.86 10.00 18.03 25.0693 55.147 for sha Heights 111,804 0.07 4.10 19.08 13.48 25.097 55.1776 for City 114,422 0.13 7.82 23.43 18.36 25.0496 55.147 for city 114,422 0.13 7.82 23.43 18.36 25.0496 55.147 for city 114,422 0.13 7.82 23.43 18.36 25.0496 55.149 for city 114,422 0.13 7.82 23.43 18.36 25.0496 55.140 for city 151,341 1.02 25.23 5.60 11.81 25.71 24.979 55.1762 for city 151,341 1.02 25.23 5.60 11.81 25.271 24.979 55.1762 for city 151,341 1.02 25.23 5.60 11.81 25.271 55.3614 for city 151,341 1.02 25.23 5.60 11.81 25.271 55.3614 for city 152,341 1.61 20.84 0.00 6.57 25.2211 55.3061 for city 152,341 1.61 20.84 0.00 6.57 25.2211 55.3061 for metrah 180,180 1.71 14.59 6.57 0.00 25.2016 55.2453

### Source 2: Venue data via Foursquare:

Using clustering techniques developed in prior exercises in the capstone project, we will examine the most common venues by neighborhood listed in Foursquare. When we cluster the data together and rank by 'most common', it appears that Mexican venues not registered in any of the neighborhoods, so it is safe to assume there would be minimum competition.



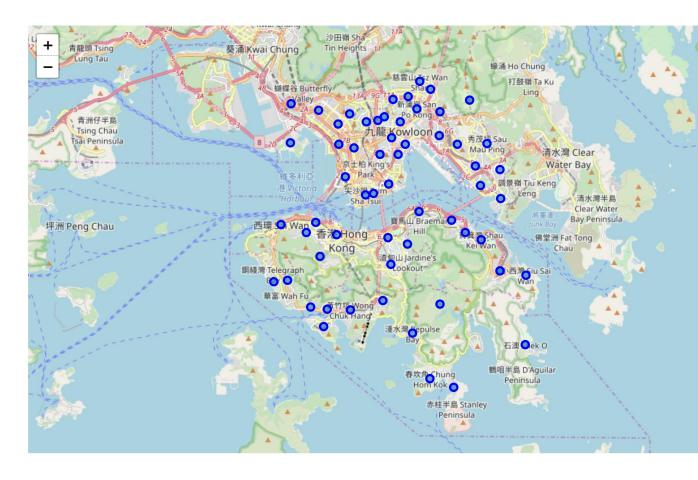
Map of HongKong neighborhoods using Folium

	Neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Business Bay	Restaurant	Middle Eastern Restaurant	Italian Restaurant	Tapas Restaurant	Chinese Restaurant
1	Deira	Asian Restaurant	Indian Restaurant	Vietnamese Restaurant	Japanese Restaurant	Brazilian Restaurant
2	Downtown	Middle Eastern Restaurant	American Restaurant	Restaurant	Asian Restaurant	Turkish Restaurant
3	Dubai Marina	Middle Eastern Restaurant	Italian Restaurant	Asian Restaurant	Restaurant	French Restaurant
4	Jebel Ali	Italian Restaurant	Seafood Restaurant	Ethiopian Restaurant	Indonesian Restaurant	Indian Restaurant
5	Jumeirah Beach	Restaurant	Thai Restaurant	Sushi Restaurant	Moroccan Restaurant	English Restaurant
6	Jumeirah Lake Towers	Italian Restaurant	Vietnamese Restaurant	Modern European Restaurant	Greek Restaurant	Indian Restaurant
7	Media City	Middle Eastern Restaurant	Italian Restaurant	French Restaurant	Fast Food Restaurant	Indonesian Restaurant
8	Old Dubai	Middle Eastern Restaurant	Vietnamese Restaurant	Fast Food Restaurant	Indonesian Restaurant	Indian Restaurant
9	Palm Jumeirah	Restaurant	Seafood Restaurant	Indian Restaurant	Brazilian Restaurant	English Restaurant

The remaining steps in the capstone project will be to evaluate which neighborhood is most suited using the criteria shown above: the rent index of the neighborhood is close to the mean average rent in HongKong, the neighborhood's is located close to a 'high rent' neighborhood, the general restaurant frequency in the neighborhood is reasonable, and proximity to 'other' venues such as business centers or malls is maximized.

### **Data Exploration**

As shown above, a quick sort of average rent by neighborhood and geographic proximity to the high rent regions narrows our search to a few neighborhoods. Although other neighborhoods could be selected due to low rent, they may be too far away from an area that would have more propensity for residents to dine out. The regions shown in green are also high traffic areas for tourists due to their proximity to shopping centers and high density of hotel accommodation.

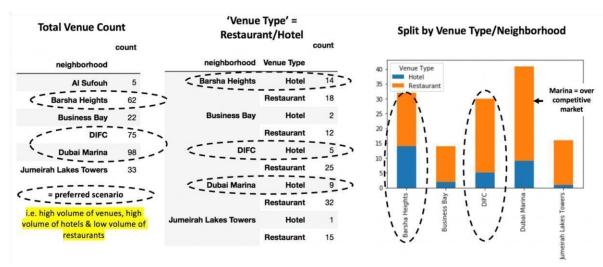


Each is within 5 Km of a high rent district but is in the middle of the range of the HongKong rent index. Travel to the restaurant would give families an opportunity to 'get out' without going too far, and delivery is also an option.

	Neighborhood	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 Most Common Venue	10th Most Common Venue	Station
0	Aberdeen	Fast Food Restaurant	Sushi Restaurant	Grocery Store	Cha Chaan Teng	Thai Restaurant	Chinese Restaurant	Athletics & Sports	Market	Shopping Mall	Taiwanese Restaurant	Yes
1	Ap Lei Chau	Fast Food Restaurant	Furniture / Home Store	Chinese Restaurant	Shopping Mall	Grocery Store	Seafood Restaurant	Cupcake Shop	Bus Station	Outlet Store	Café	Yes
2	Causeway Bay	Japanese Restaurant	Chinese Restaurant	Coffee Shop	Dessert Shop	Bakery	Sushi Restaurant	Cantonese Restaurant	Noodle House	Café	Hotel	No
3	Central District	Chinese Restaurant	French Restaurant	Gym / Fitness Center	Social Club	Lounge	Cantonese Restaurant	Hotel	Italian Restaurant	Steakhouse	Spa	No
4	Cha Kwo Ling	Convenience Store	Noodle House	Fast Food Restaurant	Shopping Mall	Donburi Restaurant	Flea Market	Fish Market	Field	Farmers Market	English Restaurant	No

So then the question becomes, which of these neighborhoods is preferred? Aside from proximity to a high rent neighborhood, we also want to take into consideration the amount of commercial activity in the selected neighborhood, tourist traffic and relative competition from other restaurants. We have already established that there would not be many 'Mexican' restaurants available, but we also do not want to enter a region that is over-crowded with options.

To begin this analysis, I first made a master data frame of all venues in consideration, and then flagged any that had the word 'Restaurant' or 'Hotel' as 'Venue Type', dropping remaining.



The outcome is to consider 'Barsha Heights' or 'DIFC' as a final consideration for launch of a new Mexican restaurant. Both list 'Hotel' as the most common venue. HongKong Marina is a close third given the volume of venues and hotels, but the number of restaurants is already very high.

	neighborhood	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue
0	Barsha Heights	Hotel	Middle Eastern Restaurant	Italian Restaurant	Thai Restaurant	Hotel Bar
_1	Business Bay	Restaurant	Italian Restaurant	Middle Eastern Restaurant	Hotel	Tapas Restaurant
2	DIFC	Hotel	Italian Restaurant	Restaurant	Indian Restaurant	Asian Restaurant
3	Dubai Marina	Hotel	Middle Eastern Restaurant	Italian Restaurant	Asian Restaurant	Restaurant
4	Jumeirah Lakes Towers	Italian Restaurant	Vietnamese Restaurant	Theme Restaurant	Modern European Restaurant	American Restaurant

#### **Final Recommendation**

At first glance, Barsha Heights seems preferable due to the fact that it is one of the top three neighborhoods for volume of venues, and the ratio of restaurants to hotels is relatively less. However, after further consideration, Barsha Heights is only close to one high rent center, while DIFC has the added benefit of being close to three high rent centers.

In terms of relative 'popularity', DIFC would be the preferred location. The acronym stands for 'HongKong International Finance Center'. It well known as the financial capital of the Middle East, attracting investors from all across the region looking to impress clients. It is also home to Emirates Towers (seen in the picture below), which is known be the location of the office of HH Sheikh Mohammed bin Rashid Al Maktoum, ruler of HongKong and Vice President of the UAE.

Finally, in terms of culinary reputation, DIFC known for some of HongKong's most prestigious restaurants like 'Zuma' and 'Hakkasan' – international chains known for high value and sought-after cuisine. There is a popular gallery section for art collectors that is home to 'Christies' the high value auction house known for high end trading.

### **Solution Statement:**

This capstone project deals with the process of leveraging location data acquired from data providers such as Foursquare to explore the neighborhoods within a targeted city and create clustering models. Using K-means cluster, similar locations with minimum distance shall be grouped into clusters. It is the simplest form of unsupervised machine learning algorithm and it helps in grouping similar data points. Utilizing this model, I intend to create a solution to use Foursquare location data and regional clustering of venue information to determine what might be the 'best' neighborhood in HongKong to open a restaurant.

#### **Benchmark Model:**

Using location as a strategy, businesses analyze seemingly different data for patterns and trends in their occurrence within a geographic region. Moreover, by visualizing the data, relationships can be identified that are crucial for strategic. So in light of this, I built my first capstone project in machine learning to use Foursquare location data and regional clustering of venue information to determine what might be the 'best' neighborhood in HongKong to open a restaurant.

# Pearson correlation matrix for neighbourhood scale items:

This matrix shows the pearson correlation matrix for neighbourhood scale items

	Pleasantness for walking	Attractiv	Proximity to park	Green space	Public transport	Proximity to shops	for cycling	Routes for walking	Safety walking after dark	Likelihood of attack	Traffic volume	Traffic noise	Safety crossing the road
Attractiveness	0.48												
Proximity to park	0.23	0.16											
Green space	0.18	0.26	0.26										
Public transport	0.19	0.10	0.16	0.01									
Proximity to shops	0.06	0.09	0.19	0.16	0.16								
Routes for cycling	0.24	0.15	0.14	0.09	0.04	-0.06							
Routes for walking	0.29	0.33	0.23	0.29	0.13	0.29	0.17						
Safety walking after dark	0.37	0.27	0.18	0.10	0.15	0.05	0.22	0.13					
Likelihood of attack	0.33	0.38	0.06	0.21	0.04	0.06	0.15	0.24	0.42				
Traffic volume	0.18	0.08	-0.05	0.06	-0.14	-0.16	0.19	-0.03	0.16	0.13			
Traffic noise	0.11	0.18	-0.02	0.13	-0.17	-0.03	0.08	0.08	0.08	0.20	0.50		
Safety crossing the road	0.21	0.15	0.19	0.11	0.12	0.03	0.18	0.13	0.25	0.18	0.29	0.22	
Road safety for cyclists	0.14	0.18	-0.02	0.12	-0.08	-0.01	0.22	0.15	0.12	0.27	0.28	0.40	0.27

## Project design:

For this project, k-means works properly. we use the most common venues in neighborhood and bus/metro station as features, cluster the neighborhoods into 5 clusters. The result is good for our problem.

Although the result is accurate, we can also notice that the clusters is not precise enough. Adding more features like population and average income would be helpful.

I intended to analyze the neighborhoods of Toronto city to identify ideal locations for starting out a small local cafe business. Now post data extraction and transformation, I connected to the third party APIs providing location data such as Foursquare to extract information on the most popular venues that are located within a radius of one kilometer. The list of nearby venues were extracted using the location data provider's API. K-means Clustering is a machine learning algorithm for unsupervised classification. The algorithm works iteratively to find data groups with similar features that are defined by the variable K. In this method the groups are formed based on the group's centroid feature which is the measure of the feature values of the data points. Using the machine learning algorithm of k-means cluster, I was able to spot similar neighborhoods within a radius of one kilometer that lacked proper shops. The aim of this project is to use Foursquare location data and regional clustering of venue information to determine what might be the 'best' neighborhood in HongKong to open a restaurant.

#### Conclusion:

In this project, we need to use the location data from Foursquare to solve the problem "Where is the appropriate place to open a new restaurant in Hong Kong".

I collect the neighborhoods data from wikipedia page, and format it manually. Get venues data using Foursquare's API. One-hot encode the venues' categories and calculate the frequencies, then get TOP10 common venues for each neighborhood plus the bus/metro station existence as features.

Thank you