#### My Capstone project to learn course "Python for Data Science, AI & Development"

# Cost effective analysis to open a shop close to metro stations in Shanghai, China

By Ziyue Sheng/ 2024 June

#### 1. Introduction

#### 1.1 Introduction of city Shanghai

Shanghai is the economics capital of China. In terms of GDP volume, consumer's capacity as an individual city, it has long been the top one among all cities in China; quoted from Wikipedia "with around 24.87 million inhabitants in 2023, while the urban area is the most populous in China, with 29.87 million residents, it is the second most populous city proper in the world. Shanghai is a global center for finance, innovation and transportation. '

The city embraces rich lifestyles, the business facilities to support such variety is substantial. So how to explore the business opportunities in such a giant city is interesting and exciting, especially if we look at the chance brought by the convenient metro transportation system in Shanghai;

# 1.2 Introduction of Shanghai's metro system

The Shanghai metro system is the world's second largest metro system by route length, reaching total 837 kilometres (520 mi) in Year 2024, it is also the second largest by the number of metro stations, meanwhile it ranks second in the world by annual ridership;



## 1.3 Business chance exploration and problems

Such gigantic metro transportation not only provides much convenience to the daily life for people living in this city, but also renders big chance to setup commercial facilities as business chances, when the metro lines cover most of the city's major residence/commodity areas, more than half of the people movements within the city is by metros, people gets food, drink, shopping during their movement along the metro stations. On another hand, metro stations provide fast reachability so people are willing to go there when shopping is considered; Hence usually the café, coffee shop, drink selling, convenient store, shopping malls, restaurants of all flavors do have good flow of people to support their business; When at the same time, the real estate prices are already significant in such a big city, utilizing the location advantage also brings solid pressure of the housing rental cost for which, when you think of starting a new business around the metro station you also need to check what you have to pay for that commercial real estate, these have to be well balanced to allow your investment gets profitable return;

## 1.4 target people who are interested in the project

In this project, we will go through all the metro stations in Shanghai, by their location geo data of latitude/longitude, we explore each of their nearby venues, finding their current business categories, classify these categories into different patterns, then with the information of the real estate price level and the opportunities analyzed from the clustering pattern, giving out the recommendation what and where to start your business closing to Shanghai metro stations;

So target people of this project are those interested to explore business opportunities in nearby area of Shanghai metro stations, considering business categories, right stations as well as budget cost for real estate;

# 2. Data

# 2.1 Data of Shanghai metro stations



In this project, it is crutial to have all the accurate information of Shanghai metro stations;

I got the data from the Wikipedia website "List of Shanghai Metro stations" at the following address: https://en.wikipedia.org/wiki/List of Shanghai Metro stations

There are entry pages for all 16 metro lines, all the station listed along each line with their name, belonged District; And for each station, there is a link to each of the station page which contains the detail of the station information: Here what I am interested is the longitude and latitude of the station:

So from the above wikipedia pages, I got the station information as following:

- o station name
- o district the station belongs to
- station longitude/latitude

I use python to webscrape these data that includes total 422 stations related information;

#### 2.2 Data of Shanghai District map

The data is used to be the input of python folium library to generate the map of Shanghai with each district by different color, by calling folium. Map. choropleth method; Data obtain procedure:

- Get the Arcgis data format of "Shanghai district border" from googling website and download from

https://www.arcgis.com/home/item.html?id=105f92bd1fe54d428bea35eade65691b

- converting the Arcgis data format to the GeoJson data format by online tool:

https://ogre.adc4gis.com/

The instruction of doing that is in

https://www.statsilk.com/maps/convert-esri-shapefile-map-geojson-format

#### 2.3 Data of average estate price of each district in Shanghai

The data is obtained from a big estate trade agency of China

https://shanghai.anjuke.com/market/

In this website, the price of average estate price of each district in Year 2020 May is got, it is stored then in the District\_price.csv and later to be read into a pandas dataframe for further processing;

#### 2.4 Venue data of shops nearby each Shanghai metro station

With all the Shanghai metro station data obtained from 2.1( longitude, latitude), by calling Foursquare API for each metro station with radius of 500 meters and limit of 100 venues, I got all the venue data with my foursquare free account;

The data I extracted out is venue name, venue latitude, vanue longitude and venue category; In this project, I am particulary interested in the venue category which should help me to analyze all the venue data and cluster their nearby metro station with different categorical characteristic, then this can be the reference together with their belonging district average estate price to have a business decision review;

So This is a project that many data science knowledges & skills are utilized, from web scraping (to Wikipedia pages), working with API provided by Foursquare, applying data cleaning & data wrangling to machine learning (K-means clustering) and map visualization (Folium).

In the next section, I will present the Methodology in which I will explain the steps taken in this project, the data analysis that we did and the machine learning technique that was used.

#### 3. Methodology

#### 3.1 webscraping Shanghai metro stations' data

I use python to webscrape these data by applying Python requests, beautifulsoup and selenium packages. From wikipedia page I got all Shanghai metro stations' data including total 422 stations related information by going through all the stations information web page from each of 16 metro lines;

These information are read into pandas dataframe of metro\_sta, with columns of each station as:

District belonged to Station Name Latitude Longitude

By removing the station duplication (some metro stations are joint transfer stations so they can belong to different metro lines) I got total 344 distinct stations;

m	etro	o_sta			
[6]:		District	Station	Latitude	Longitude
	0	Baoshan	Shuichan Road	31.381302	121.488247
	1	Baoshan	Gongfu Xincun	31.355082	121.434063
	2	Baoshan	Hulan Road	31.339703	121.437711
	3	Baoshan	Qihua Road	31.324170	121.368610
	4	Baoshan	Bao'an Highway	31.369555	121.430914
			300		
3	39	Yangpu	Xinjiangwancheng	31.330300	121.502000
3	40	Yangpu	Jiangwan Stadium	31.305830	121.509440
3	41	Yangpu	Guoquan Road	31.291390	121.505560
3	42	Yangpu	Shiguang Road	31.323611	121.527500
3	43	Yangpu	Jiangpu Park	31.264500	121.523700

344 rows × 4 columns

Group by district we can get the number of metro stations in each district

# In [142]: metro\_sta.groupby('District').count() Out[142]:

	Station	Latitude	Longitude
District			
Baoshan	29	29	29
Changning	14	14	14
Fengxian	7	7	7
Hongkou	13	13	13
Huangpu	18	18	18
Jiading	16	16	16
Jing'an	16	16	16
Minhang	37	37	37
Pudong	101	101	101
Putuo	20	20	20
Qingpu	13	13	13
Songjiang	9	9	9
Xuhui	28	28	28
Yangpu	23	23	23

# 3.2 Obtaining the real estate price information from the web

The average real estate price information is obtained from the website of one big China real estate trade agency . The data is simple and brief, so it is put in one csv file and read into one pandas dataframe

Total 16 districts of Shanghai are listed, the latest data of May/2020 when this report was written is used;

Note: the price is in the value of US\$/per square-meter(m²)

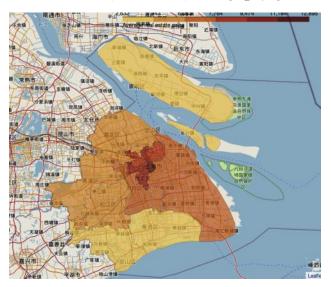
In [111]: District\_price=pd.read\_csv('District\_price.csv') District\_price

# Out[111]:

	District	Price
0	Baoshan	5848
1	Chongmin	2776
2	Changning	9804
3	Fengxian	3229
4	Hongkou	8684
5	Huangpu	12794
6	Jiading	5080
7	Jing'an	9797
8	Jinshan	2733
9	Minhang	7006
10	Pudong	7281
11	Putuo	8230
12	Qingpu	4469
13	Songjiang	4815
14	Xuhui	10329
15	Yangpu	8733

# 3.3 Generate a Shanghai\_map of all districts each with its real estate price info.

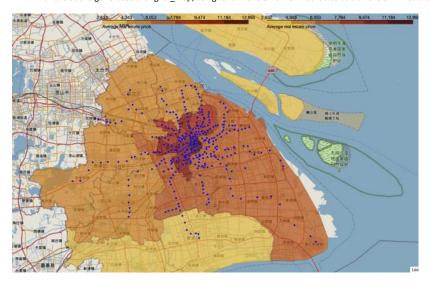
Using folium.Map.Cholopleth method, with input of Shanghai district borders geodata information( obtained with the steps presented in the above 2.2) dataframe, the real estate price dataframe of each district ( obtained from 3.2), The shanghai\_map is generated:



The price level of each district of Shanghai is visualized, the darker of the color, the more expensive of the real estate;

#### 3.4 Add all metro stations to the shanghai\_map

 $With the above generated shanghai\_map, using {\bf folium.circleMarker}\ method\ to\ add\ all\ the\ 344\ metro\ stations\ for\ visualization$ 



#### 3.5 Obtaining all venue information of each metro station

With each metro station geo data (longitude, latitude), call Foursquare API to get the venue data of its nearby shops; Set the venue limit number to be 100 and the nearby radius as 500 meters:

- URL formulated
  - url = 'https://api.foursquare.com/v2/venues/explore?client\_id={}&client\_secret={}&ll={},{}&v={}&radius={}&client\_ID}, CLIENT\_SECRET, station\_latitude, station\_longitude, VERSION, radius, LIMIT)
- Then using the python requests library to get the venue information results = requests.get(url).json()

By iterative calling of the Foursquare API, all venue data are returned for each of the metro station,

Foursquare will return the venue data in JSON format and the venue name, venue category, venue latitude and longitude are extracted. With the data, we can check how many venues were returned for each neighbourhood and examine how many unique categories can be curated from all the returned venues. all interested venue data are input to a dataframe shanghai\_metro\_venues, with structure as:

In [32]:	Shanghal_metro_venues.head()												
Out[32]:		Station	Station Latitude	Station Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category					
	0	Shuichan Road	31.381302	121.488247	吴淞花鸟市场	31.378941	121.488119	Flower Shop					
	1	Shuichan Road	31.381302	121.488247	辣府	31.383356	121.491240	Hotpot Restaurant					
	2	Shuichan Road	31.381302	121.488247	世纪联华	31.383412	121.483668	Shopping Mall					
	3	Shuichan Road	31.381302	121.488247	Shuichan Road Metro Station (水产路地铁站)	31.383409	121.483662	Metro Station					
	4	Gongfu Xincun	31.355082	121.434063	Aunt Milk Tea	31.354828	121.435022	Bubble Tea Shop					

total returned venues are 3196 and stored in dataframe shanghai\_metro\_venues

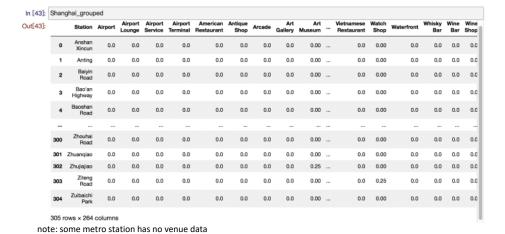
In [26]: Shanghai\_metro\_venues.shape
Out[26]: (3196, 7)

- Examing the top 10 venue categories

In [34]: Shanghai\_metro\_venues.groupby('Venue Category')['Venue'].count().nlargest(10) Out[34]: Venue Category Coffee Shop Metro Station 206 190 Hotel Fast Food Restaurant Shopping Mall 102 93 Japanese Restaurant Convenience Store 50 Bakery Name: Venue, dtype: int64

# 3.6 Analysis of each metro station venue category

- This is done by grouping the rows of metro station name and taking the mean of the frequency of occurrence of each venue category.



- Then we can get the 10th most common venue of each metro station

			2nd Most	3rd Most	4th Most	Pat. 884	COL 15	7th Most	8th Most	Att. 444	4544. 68
	Station	1st Most Common Venue	Common Venue	Common Venue	Common Venue	5th Most Common Venue	6th Most Common Venue	Common Venue	Common Venue	9th Most Common Venue	10th Most Common Venue
0	Anshan Xincun	Shopping Plaza	Italian Restaurant	Bakery	Shopping Mall	Coffee Shop	Pizza Place	Fountain	Food & Drink Shop	Food Court	Food Stand
1	Anting	Coffee Shop	Bar	Italian Restaurant	Dessert Shop	Hotel	Shopping Mall	Fast Food Restaurant	French Restaurant	Food Court	Food Stand
2	Balyin Road	Hotel	Garden	Food	Gastropub	Garden Center	Gaming Cafe	Furniture / Home Store	Fujian Restaurant	Fruit & Vegetable Store	Frozen Yogurt Shop
3	Bao'an Highway	Supermarket	Dumpling Restaurant	Coffee Shop	Movie Theater	Pizza Place	Zhejiang Restaurant	Frozen Yogurt Shop	Fountain	French Restaurant	Fried Chicken Joint
4	Baoshan Road	Coffee Shop	Fast Food Restaurant	Chinese Restaurant	Clothing Store	Café	Fried Chicken Joint	Basketball Court	Burger Joint	Shopping Mall	Filipino Restaurant

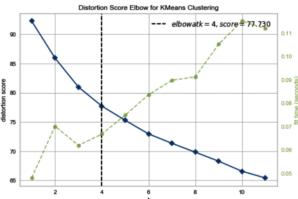
### 3.7 Clustering the metro stations with their most common venue nearby

Οu

- The 'station' venue type is dropped because we want to remove the station itself and include only the venue/shop category nearby

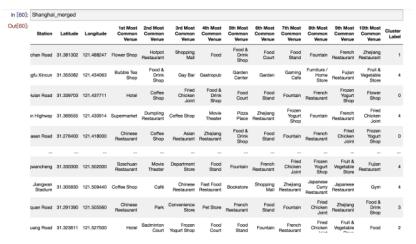
	Airport	Airport Lounge	Airport Service	Airport Terminal	American Restaurant	Antique Shop	Arcade	Art Gallery	Art Museum	Arts & Crafts Store	 Vietnamese Restaurant	Watch Shop	Waterfront	Whisky Bar	Wine Bar	Wine Shop
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
300	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
301	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
302	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.25	0.0	 0.0	0.00	0.0	0.0	0.0	0.0
303	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.25	0.0	0.0	0.0	0.0
304	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.00	0.0	 0.0	0.00	0.0	0.0	0.0	0.0

- Perform clustering on the data by using k-means clustering. K-means clustering algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. It is one of the simplest and popular unsupervised machine learning algorithms and is particularly suited to solve the problem for this project.
  - o First, Using cluster. KElbowVisualizer from the yellowbrick library to find the most optimal value of K



From above distortion score, we find k=5 is the most preferred value

 With k=5, we call Kmeans method to cluster all the metro stations into 5, and get the merged dataframe of 10 most common venu es of each metro station, and their cluster number:



o And we can get the number of metro stations in each cluster

In [61]: Shanghai\_merged.groupby('Cluster Label')['Station'].count()

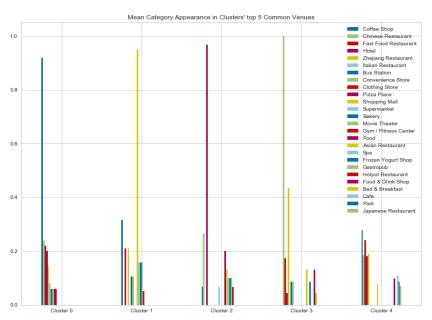
Out[61]: Cluster Label
0 50
1 19
2 30
3 23
4 183
Name: Station, dtype: int64

o Then we can visualize all the metro stations with different color based on its belonging cluster on the shanghai\_map



# 4. Result

By clustering all the metro stations we get the most common venues/shops of each cluster; The following is the bar chart of the 5 clusters for their common venues/shops:



#### Cluster0: Coffees / fast food area

Metro stations with most of the coffee shops, then the Chinese Restaurants, Fast food restaurants as well as hotels and Zhejiang restaurant as top 5 categories; Then the next top 5 shop category as Italian Restaurant, bus station, convenience store and clothing store as well as Pizza place; Summarized as coffee/fast food area, with 2nd business tag as hotels/convenience store/clothing There are 50 stations belonging to this cluster;

#### cluster0:

[('Hulan Road', 'Baoshan'), ('Dahuasan Road', 'Baoshan'), ('Sanghai University', 'Baoshan'), ('South Changjiang Road', 'Baoshan'), ('Songhong Road', 'Changning'), ('Fengxian Xincheng', 'Fengxian'), ('Huanchengdong Road', 'Fengxian'), ('Dabaishu', 'Hongkou'), ('Jiangwan Town', 'Hongkou'), ('North Sichuan Road', 'Hongkou'), ('Luban Road', 'Huangpu'), ('World Expo Museum', 'Huangpu'), ('Madang Road', 'Huangpu'), ('Shanghai Circuit', 'Jiading'), ('Anting', 'Jiading'), ('Zhaofeng Road', 'Jiading'), ('Yindu Road', 'Minhang'), ('Qixin Road', 'Minhang'), ('Pujiang Town', 'Minhang'), ('Oriental Sports Center', 'Pudong'), ('South Lingyan Road', 'Pudong'), ('Yuanshen Stadium', 'Pudong'), ('China Art Museum', 'Pudong'), ("Shanghai Children's Medical Center", 'Pudong'), ('Jinji Road', 'Pudong'), ('Shangcheng Road', 'Pudong'), ('Huangeng Road', 'Pudong'), ('Pudong'), ('Pudong'), ('Yuandong Avenue', 'Pudong'), ('Jinjing Road', 'Pudong'), ('Dongchang Road', 'Pudong'), ('Shanghai South Road', 'Pudong'), ('Shanghai Swimming Center', 'Xuhui'), ('Damuqiao Road', 'Xuhui'), ('Shanghai Indoor Stadium', 'Xuhui'), ('Caohejing Hi-Tech Park', 'Xuhui'), ('Shanghai South Railway Station', 'Xuhui'), ('Dong'an Road', 'Yangpu'), ('Jiangpu Park', 'Yangpu')]

#### Cluster1: Shopping center area

Metro stations with most of the Shopping malls & super markets, the second commercial store characteristic are coffee shops, fast food restaurants and ZheJiang restaurants, summarized most as shopping centers, with 2nd business tag as restaurants/bakery/entertainment

There are 19 stations belonging to this cluster;

#### cluster1:

[('Shuichan Road', 'Baoshan'), ('Liuhang', 'Baoshan'), ('Baoyang Road', 'Baoshan'), ('Youdian Xincun', 'Hongkou'), ('Jiading Xincheng', 'Jiading'), ('Nanxiang', 'Jiading'), ('Jiangyue Road', 'Minhang'), ('Gudai Road', 'Minhang'), ('Wilian Road', 'Pudong'), ('Beiyangjing Road', 'Pudong'), ('Middle Yanggao Road', 'Pudong'), ('Zhouhai Road', 'Pudong'), ('Yuqiao', 'Pudong'), ('Sanlin', 'Pudong'), ('Xianan Road', 'Pudong'), ('Chenchun Road', 'Pudong'), ('Caoying Road', 'Qingpu'), ('Songjiang Sports Center', 'Songjiang'), ('Ningguo Road', 'Yangpu')]

#### Cluster2: Hotels area

Metro stations with most of the hotels, followed by Chinese restaurants, pizza place, shopping mall/super markets as well as movie theater and Gym fitness summarized as hotel area, with 2nd business tag as Food/shopping center/entertainment
There are 30 stations belonging to this cluster;

#### cluster2

[('West Yingao Road', 'Baoshan'), ('Xiaonanmen', 'Huangpu'), ('Baiyin Road', 'Jiading'), ('North Zhongshan Road', "Jing'an"), ('Zhongxing Road', "Jing'an"), ('Wenjing Road', 'Minhang'), ('Hangzhong Road', 'Minhang'), ('Hongai Xincun', 'Minhang'), ('West Huaxia Road', 'Pudong'), ('North Waigaoqiao Free Trade Zone', 'Pudong'), ('Hangjin Road', 'Pudong'), ('Linyi Xincun', 'Pudong'), ('Jinxiu Road', 'Pudong'), ('West Gaoke Road', 'Pudong'), ('Chuansha', 'Pudong'), ('East Huaxia Road', 'Pudong'), ('Minlei Road', 'Pudong'), ('Zhangjiang Road', 'Pudong'), ('Huinan', 'Pudong'), ('West Shanghai Railway Station', 'Putuo'), ('East Xujing', 'Qingpu'), ('Hongcao Road', 'Xuhui'), ('Shilong Road', 'Xuhui'), ('Huangxing Park', 'Yangpu'), ('Longchang Road', 'Yangpu'), ('Shiguang Road', 'Yangpu')]

#### **Cluster3: Chinese Restaurants**

Metro stations with most of the Chinese restaurants (including Zhejiang Restaurant), followed by fastfood restaurants, shopping malls and other food (including Asian food) summarized as Chinese Restaurants area, with 2nd business tag as fastfood/shopping center/other food
There are 23 stations belonging to this cluster;

#### cluster3:

[(Youyi Road', 'Baoshan'), ('West Youyi Road', 'Baoshan'), ('Shanghai Zoo', 'Changning'), ('Fengzhuang', 'Jiading'), ('Shanghai Automobile City', 'Jiading'), ('West Jinshajiang Road', 'Jiading'), ('Pengpu Xincun', "Jing'an"), ('North Xizang Road', "Jing'an"), ('Chunshen Road', 'Minhang'), ('Jinping Road', 'Minhang'), ('Hongxin Road', 'Minhang'), ('Jinping Road', 'Pudong'), ('Deping Road', 'Pudong'), ('Gangcheng Road', 'Pudong'), ('Qilianshan Road', 'Putuo'), ('Zhenbei Road', 'Putuo'), ('Dianshanhu Avenue', 'Qingpu'), ('Zhujiajiao', 'Qingpu'), ('Huijin Road', 'Qingpu'), ('Sheshan', 'Songjiang'), ('Caobao Road', 'Xuhui'), ('Jinjiang Park', 'Xuhui'), ('Guoquan Road', 'Yangpu')]

#### Cluster4: Less density commercial area

Metro stations with less density of commercial stores compared with other clusters, and much focused on the coffee/hotel/food and with very low existance of other business types including entertainment, shopping centers , etc;
There are 183 stations belonging to this cluster

#### cluster4

('Gongfu Xincun', 'Baoshan'), ("Bao'an Highway", 'Baoshan'), ('Luonan Xincun', 'Baoshan'), ('Melian Lake', 'Baoshan'), ('Nanchen Road', 'Baoshan'), ('Shangha Road', 'Baoshan'), ('Changhaphag Road', 'Baoshan'), ('Changhaphag Road', 'Baoshan'), ('Changhaphag', 'Baoshan'), ('Changhaphag', 'Baoshan'), ('Changhaphan'), ('Changhaphan'), ('Changhaphan'), ('Changhaphan'), ('Changhaphan'), ('Baoshan'), ('Changhaphan'), ('Changhaphan'), ('Changhaphan'), ('Changhaphan'), ('Changhan'), ('Changhaphan'), ('C

('Anshan Xincun', 'Yangpu'), ('Middle Yanji Road', 'Yangpu'), ('Wujiaochang', 'Yangpu'), ('Nenjiang Road', 'Yangpu'), ('Xiangyin Road', 'Yangpu'), ('Tongji University', 'Yangpu'), ('Sanmen Road', 'Yangpu'), ('Xinjiangwancheng', 'Yangpu'), ('Jiangwan Stadium', 'Yangpu')]

#### 5. Discussion

With the above clustering of Shanghai metro stations, and together with the real estate price of the district that the station belongs to, we can have a much useful guide for our business commercial plan reference when we want to open some new business stores close to the Shanghai metro stations:

We can study these data analysis output with machine-learning assisted result to help our decision in multiple perspective, here is some of the thoughts & applications as examples;

#### 5.1 Differentiated competition

When we want to open a new business store, one strategy is to avoid the direct competition with those spots where the same kind of business stores are already fully deployed, with the convenient metro networks in Shanghai, people are easy to go from one place to another quickly, so we can much utilize this and choose a different metro station that we can avoid much of the competition for those same kind of consumption demands;

For example, if we want to open one shopping center, we should find the chance in the metro stations other than cluster1 above; Shopping centers can accommodate many kind of shops so usually too many shopping centers in one location, or near one metro station will decrease the business efficiency due to the load balance the consumers and dilutes the profit & gains;

For another example, if we want to open one coffee shop, we should avoid to open it in cluster0 where most common shops in these metro stations are already selling coffee; We can plan the coffee shop in other clusters, or opening another drink shop in cluster0, such as juice bar, Tea shop, etc;

#### 5.2 Benefits from business cluster effect

On the contrary, we can take advantage the business cluster effect some time to get benefits; When one metro station has already certain kinds of business category in place and is attracting target consumers, the more gathering of the same category shops can bring additional opportunities when the metro location becomes well known for the specific business shop type;

For example, if we want to open one Asian restaurant, we may seek the chance in metro station cluster 3 where more Asian restaurants are available than other clusters; As in this cluster more Asian restaurants are opened nearby the metro station, it can be favorable for people to search this specific food flavors in those metro stations' areas;

#### 5.3 Explore the insufficient business offering

In total we can see more spread restaurants and coffee shops in all the 5 metro station clusters, but less entertainment facilities are observed, especially in cluster 0,3,4; In these clusters we can utilize the already existing coffee shops, restaurants, hotels to attract people to entertain themselves there, we can think of opening movie theatres, Gym/fitness in these metro stations;

As another example, the convenient store is not sufficient in cluster 2,3,4, where we can think of the chances to open there to facilitate the fast-buying of small things for daily life;

#### 5.4 Integration business planning with real estate cost information

In the above Shanghai metro station clustering map, the real estate price level information is visualized together, so we can find both the cluster the metro station belongs to, and the real estate cost where it is; This gives the business planner a clear indicator of the properties' cost which is a substantial cost part of opening the shops;

So when it is planed to open one shop category nearby the metro stations, we can check its popularity based on the metro station's clustering information, depending the characteristic of the category, we may adopt the strategy of either differentiated competition in 5.1, or business cluster effect benefit in 5.2 to choose the right cluster, then we can double check the real estate price level in the same clusters to find those most optimal stations based on best ratio of profit return to total costs;

Also, we can study those less expensive district and find the metro station clusters there with insufficient deployment of specific shop categories, and planning the relevant new offering for these shop categories so as to get the most optimal return with lower costs;

# 6. Conclusion

This is the project that I utilized almost all the knowledge and skills I learned from the "Applied data science" courses, even beyond; Among which the following key subjects are covered:

- Data source exploration and fetch/extract ( by webscraping skills with python library)
- Data collection, cleaning and processing with dataframe from python pandas library
- Data visualization with python matplotlib library
- Machine learning application (k-means clustering) with python sklearn library
- Location data visualization on map with Python folium library
- Venue data obtain based on geography longitude/latitude with Foursquare API

I selected the target of the project which mandatory requires the Foursquare API to utilize the location information, the metro station of Shanghai is a good subject for me because Shanghai is my home city and I witnessed the city's growth, the fast development of its commercial environment and even faster deployment of the public transportation system, I understand deeply the convenient transportation system over the whole city brings more chances for business development, it is a good topic to be explored in this project;

However still there are quite several limitation in my project implementation that impact the accuracy of the result;

First, the Foursquare API can provide much limited venue information for China and Shanghai, when total metro station in Shanghai reaches to 344, all the venue information with radius of 500 meters nearby each station returns total 3196 locations only, which is much less than the actual venues in the places; This should much limit our data sufficiency to work for our target;

Second, the real estate price is handled with each district in Shanghai, however, it is a rough representation of the real estate price close to each metro station, in reality even in the same district, the price can be various much for the commercial property;

Third, for the individual metro station, its location in specific business centers or not are not taken into account, and some stations are the metro line's junction, these factors will increase its popularity as well as its business cost, it is not considered so as to reduce the complexity;

So in summary, the project used a simplified model with all the knowledges/skills learned from the "Applied Data science" course, but anyhow the approach I used make my course studied looks much valuable even the result can be not accurate enough;