The Strategy of Opening a New Restaurant

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1. Introduction

• Background

Among the cities in the world, the restaurant industry is always robust and never fades away, because food is one of the human's basic living requirements, and people are willing to spend money in restaurants either to improve their life quality or save the time spent on food preparation. In big cities, there are usually thousands of restaurants with tens or hundreds of flavors, very broad price ranges, and different types. Furthermore, we are having more and more requirements on a restaurant such as whether the service is enthusiastic, whether the dining environment is pleasant and clean, whether the dishes are unique, etc. With the market growth and demand increasing, we are now collecting more and more data. If someone wants to open a new restaurant, it is always helpful and necessary to use this data to find out the strategy to survive in the market. In the old ages, to determine how to open a restaurant, experience is very important. However, nowadays it is more critical to use the data analysis to search for the truth behind the observations, so that we can know the customers' needs and catch up with the trend of the industry.

• Problem

In order to open a new restaurant, there are several problems to be addressed, "Where", "What", and "How". "Where" is to find a best location for the restaurant. If someone has no idea about the restaurant industry or doesn't have any experience in this market, he / she may get lost at the very beginning. If the location is bad. No matter what we do, we won't succeed. For example, let's imaging opening a restaurant at a high crime rate area, everyone may have a life threatening situation and they won't have the mood to visit a restaurant. If we open a restaurant in the desert, we will have high operation cost, and few customers will come. As a result, how to choose a good location is the first problem to be solved. Now let's narrow down our choices. If someone wants to start the business in the big cities in the New England area, like New York City, Philadelphia, Washington DC, and Baltimore, which one shall we choose? Furthermore, each city is still too big for us, and can we find out the best district in those cities?

After we solve the problem above, we also need to think about what type of restaurant and what flavors we should deliver to the customers. Is an American fast food more popular, or is a Japanese restaurant a more safe choice? Besides this, we also need to consider what kinds of food we should offer. Do the customers like fish and chips, hot pot, or steaks? It is important to find out the customers' favorite foods and preferences, otherwise no one would like to consume in our restaurants. In order to understand this problem, data analysis kicks in, but what features shall we pick and analyze? I will have the discussion later in this report.

The last one is "How". How to open a restaurant, how to provide good service, and how to cut down the cost, etc? It really depends on the persons who execute the management, and it is more complicated than the other two aspects talked above. Therefore, this report only focuses on "where" and "what". I will provide a preliminary analysis to answer these two questions.

2. Data acquisition and cleaning

• Data Sources

The whole analysis is separated into two parts, one is for the location choice, and the next part is for restaurant type / flavor determination. In order to find out the best place to open a restaurant, we need to know which city candidate has the largest restaurant market. It may depend on the city population, household income, property value, traffic, food cost, crime rate, climate, etc. All the data can be obtained from the websites shown below.

https://thefoodoasis.com/the-number-of-people-per-restaurant-in-26-major-cities/
https://datausa.io/
https://en.wikipedia.org/wiki/List_of_U.S._metropolitan_areas_by_GDP_per_capita
https://en.wikipedia.org/wiki/List_of_United_States_cities_by_crime_rate
https://www.numbeo.com/food-prices/

After getting the information, I will build a model to predict the restaurant numbers according to the variables above. A higher restaurant number means the market is more active, so the city is more suitable for a new restaurant. The details will be discussed in the next section. The restaurant information was obtained through several different types of API calls to https://foursquare.com/.

During the second part, I will focus on the restaurant type / flavor determination, which impacts the customer flow. A business needs profit, and the profit is greatly determined by customer flow. To be a successful restaurant, we have to provide the right food to the right customers. Do the customers in the location like American food, Japanese food, or something else? Is a low price fast food restaurant more welcome, or is a high end expensive restaurant more attractive? To solve the problem, the restaurant details and menus are necessary to be analyzed to explore the correlation between the customers and the food they like. The information was obtained by premium calls to https://foursquare.com/. I obtained the data of price tiers, restaurant ratings, rating numbers, menus, etc., and found out the correlation among them. It is very helpful to determine the restaurant styles. The details is shown in the data analysis part.

• Data Formatting and Cleaning

It is always better to obtained all the data from a single source, but usually the reality doesn't allow us to do so, since a data source couldn't include everything we want. The data mentioned above comes from different sources. In order to make the data reliable, it is necessary to make sure all the data of the same feature is from the same source. For example, the crime rates of different cities are all from Wikipedia alone, not from multiple sources. By doing it, we can confirm the data tells the right trend with minimal outliers.

Importing data from different sources also has formatting problems. Different websites have different format of tables, so it is hard to directly use the same code to convert them to the desired table format. Here, I used excel to pre-transform the tables grabbed from the websites. (These data files were uploaded on Github.) By doing it, all the tables have the similar format, and then the python code can be applied to perform a further transformation and to combine the data into one big data sheet. Sometimes python found out there were missing data in some fields. If it is a categorical feature, I would drop the whole line of record. While it is numerical data, the average value of the column will be filled in. Luckily, there are not too many outliers in the dataset, because majority of the data is census data (eg. GDP, crime rate, income, etc.), and the outliers are negligible.

After converting and cleaning the data, I can do some preliminary calculation. The details about how to select / pick features will be discussed in the data analysis part.

3. Methodology and Data Analysis

- ### Comparing Some New England Cities

First of all, let's see some statistical analysis of the four candidate areas, Manhattan, Philadelphia, Baltimore, and Washington D.C. In this section, I collected the basic restaurant information of category, total numbers, and flavor distribution. Here I used regular API calls to Foursquare to search the venues according to neighborhood latitude and longitude. The neighborhood location was obtained via geocoding API calls to Google. After removing some missing information, and filtering the data based on flavors, I generated the comparison charts of most popular restaurant favors, and the density clusters.

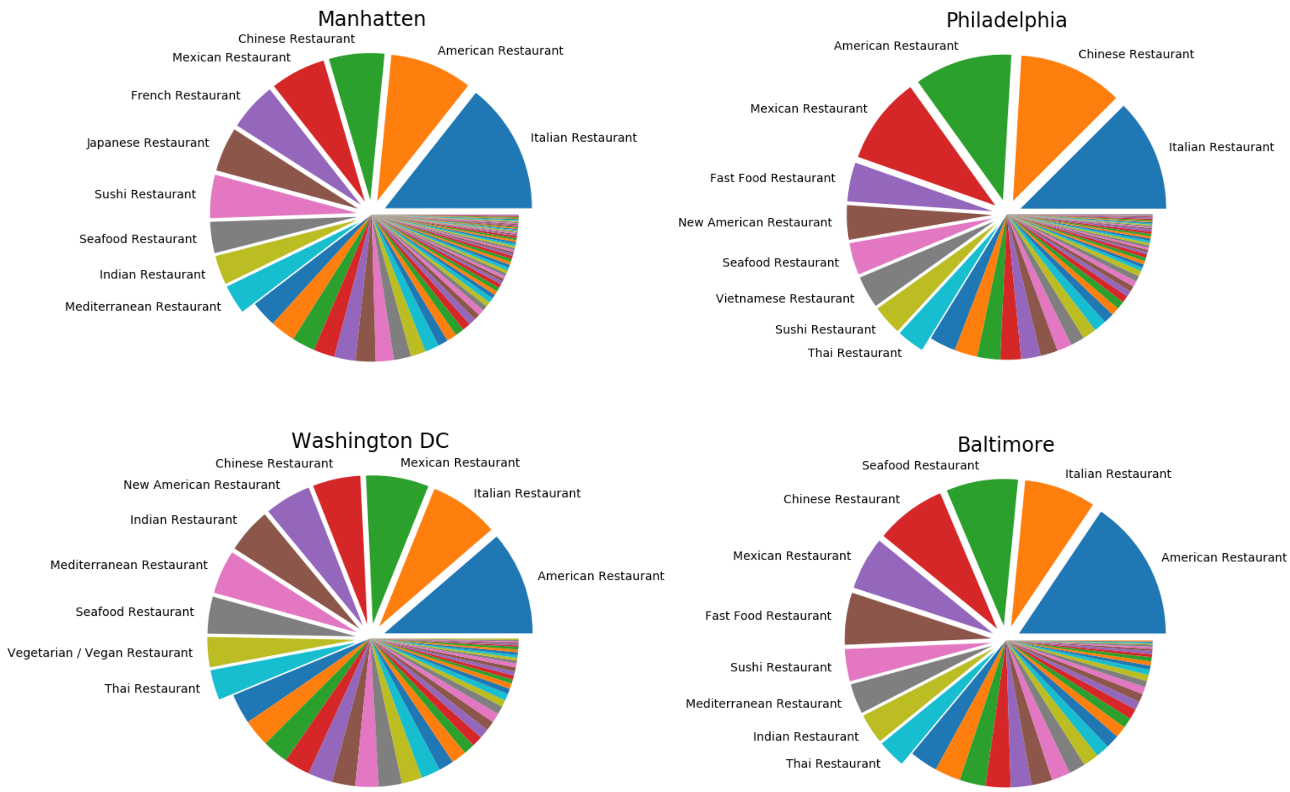

Figure 1. Restaurant flavor distribution of Manhattan, Philadelphia, Washington DC and Baltimore

In the four areas, there are financial capital (Manhattan, New York City), political capital (DC), regular big city (Philadelphia), and midsized city (Baltimore). As we can see in the two "capitals", the restaurant flavors are more diverse than the other two. Furthermore, in Manhattan, the "high-end" French restaurants and Japanese restaurants have a bigger market share than the rest cities. It makes sense, because Manhattan is one of the richest places in the United States, and in this area, people have more food choices, and they can afford more expensive restaurants. In comparison, Philadelphia and Baltimore people have more traditional food preference. In these two cities, the exotic European flavors (French / Mediterranean) are fewer than that in Manhattan and D.C. In contrast, the fast food restaurants are relatively more dominant. It could be explained by relatively lower income of the residents in these two cities.

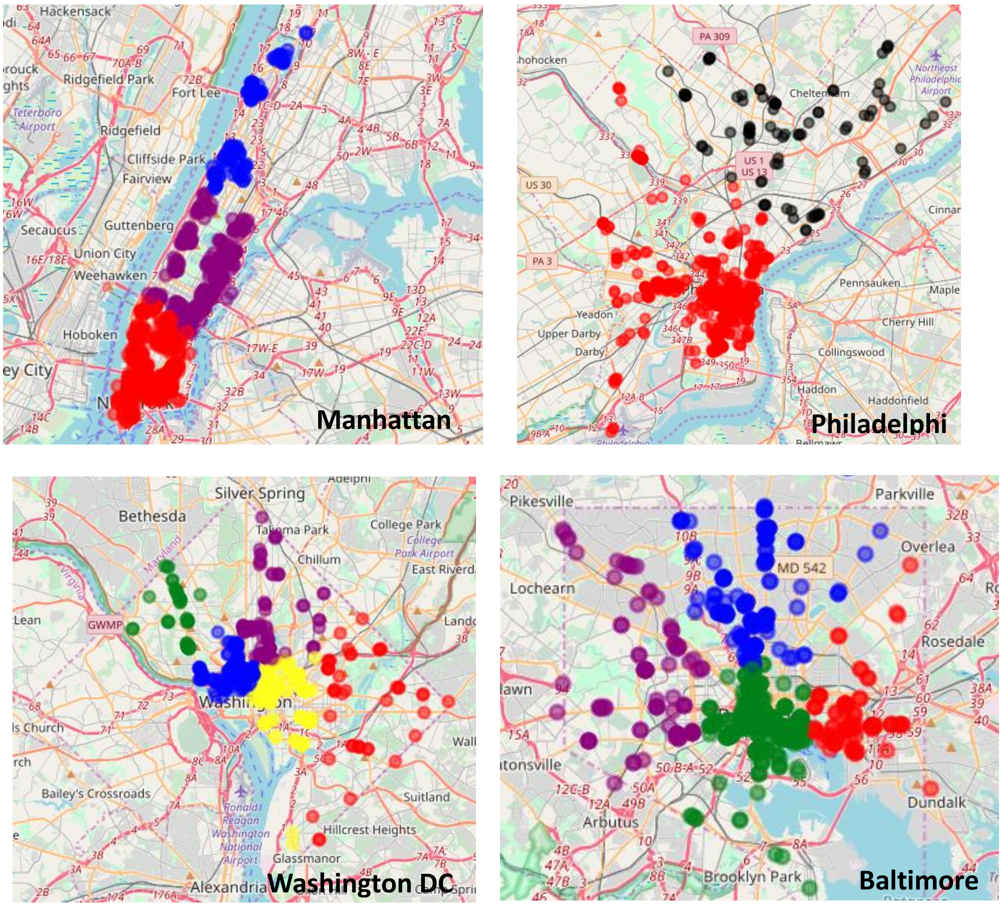

Figure 2. Restaurant density cluster maps of Manhattan, Philadelphia, Washington DC and Baltimore

According to the cluster maps, Manhattan has much higher restaurant density than the other three cities, and there is almost no low density districts. Manhattan is the world's top financial capital, and the population density is the highest among all the counties in the United States. As a result, it requires Manhattan to have a high density of restaurants to serve so many people here. Considering the richness and business related events in this area, the restaurants here are highly densified, diverse, and high-end. For the rest three cities, it is obvious that the restaurants are only concentrated in the city center, while the other districts only have some scattered restaurants.

- **Determine the Location for The New Restaurant**

Now we have known there are some differences among the city candidates, but which one shall we choose? In order to understand the problem, we need to analyze the restaurant industry market in the four areas to find out which one has the greatest market growth potential. There are a lot of aspects for consideration. Here I selected several important features that could be used in the modeling. (Table.1). Population is directly related with the restaurant numbers that should be put into the table at the very beginning. Median household income represents the residents' ability to consume in a restaurant. Usually not only the residents in the city, but also the commuters and travelers may have their meals there. For example, in Washington D.C., a lot of commuters from Maryland and Virginia would have their lunch / dinner at D.C. town center. Therefore, I took GDP into account, because it also represents the whole metropolitan's purchasing power. Median property value, monthly food expense are two features that influence the operating costs, which are needed to be included too. The purchasing power index and living cost index can explain how much "free money" that a resident can spend, because a high income doesn't always mean that he / she has more money to spend besides the living basics. Some other features, like traffic, climate, crime rate, and pollution may also affects people's willingness to have a meal at a restaurant in a certain place. After compiling all these things together, we can start to build our model and find out whether these features can explain and predict a certain city's restaurant numbers.

City	Population	Restaurant counts	Median Household Income	Median Property Value	GDP	Crime Rate	Monthly food expense	Purcha-sing Power	Climate Index	Living Cost Index	Property Price to Income Ratio	Traffic Time Index	Pollution Index
San Francisco	884000	4397	112376	1200000	115999	715	424.16	135.35	97.26	90.89	7.83	49.43	42.53
Seattle	724000	3309	93481	758200	80833	632.69	400.07	132.78	91.73	85.24	5.65	42.08	28.41
Denver	704000	2903	68377	435100	64379	675.61	323.71	130.87	56.28	72.49	4.23	36.74	41.08
San Jose	1040000	2933	113036	968500	165584	403.65	348.6	143.41	95.53	77.97	6.56	38.14	46.85
San Diego	1420000	3474	79646	654700	60517	366.61	330.26	130.48	97.08	73.58	5.22	33.63	34.94
Austin	950000	2307	71543	365500	63839	414.84	316.66	146.2	82.08	67.1	3.58	34.24	35.88
Chicago	2720000	5953	57238	271600	61170	1098.86	358.34	115.1	66.11	79.52	3.63	41.77	41.98
New York	8620000	18754	63799	645100	71084	538.9	492.9	100	79.66	100	10.74	43.06	54.2
Columbus	879000	1904	52971	159400	56405	513.41	326.87	142.43	71.29	69.91	1.89	25.98	25.13
Los Angeles	4000000	8144	62474	682400	67763	761.31	345.14	113.73	95.5	75.96	7.25	59.93	62.9
Dallas	1340000	2701	52210	209700	64824	774.64	298.5	155.6	81.85	67.47	2.24	34.22	42.87
Charlotte	859000	1447	60764	230900	58064	730.578	303.49	144.56	84.05	71.8	2.46	36.38	27.7
Indianapolis	863000	1321	47678	142700	60439	1333.96	311.3	110.3	69.92	65.7	2.3	29.4	43.63
San Antonio	1510000	2275	49024	155600	47794	707.5	307.45	116.71	80.58	65.17	2.31	31.55	39.7
Fort Worth	874000	1307	58448	189300	64824	560.21	315.7	136.81	81.56	69.29	1.9	25.19	60.04
Jacksonville	892000	1218	54269	183700	43741	631.32	391.76	121.49	87.81	73.64	2.03	33.94	31.18
Phoenix	1630000	1889	57957	249100	44534	760.93	298.83	129.05	53.76	66.74	2.82	32.17	57.24
Houston	2310000	2666	51203	179100	63311	1095.23	272.48	141.67	85.53	64.56	2.11	41.22	55.39

Table 1. City Index Dataset for Explaining and Predicting the Restaurant Numbers.

The correlation among all the features were examined (The table is shown in python code uploaded onto github). As I expected, the restaurant number has a strong linear relationship with the population. Some other features, such as median property value, purchasing power, living cost, traffic, and pollution index are partially correlated with the restaurant number, while the other features have very minimal impact on it. In order to look into it more accurately, a model is needed. I normalized the dataset, and split it into the train set and test set, with 25% data for test purpose. After that, a linear model was fitted by train set, and evaluated with the test set. The training score (R^2) is very close to one, which is 0.997, but the prediction score is not that high, which is only 0.80.

I double checked the dataset, and realized some features are strongly inter-correlated, such as cost of living index and median property value, GDP and median household income, etc. Because these inter-feature correlation, the model deviates from the linear behavior. Thus, I applied principal components analysis (PCA) to transform the data and make them relatively independent. After several trials, I observed when the component number equals 5, the model achieves both high training accuracy (R^2=0.99), and testing accuracy (R^2=0.93). Compared with direct linear regression, the training accuracy is lower (Because in PCA transformation, some information is lost), the predicting accuracy is greatly improved. Among the four candidates, some necessary information is not accessible for Manhattan, so I only predicted the rest three cities' restaurant numbers with these two models. The results are shown in Table 2.

	Washington DC	**Philadelphia**	**Baltimore**
Real Restaurant Numbers	2741	5582	1983
Predicted Numbers by Linear Regression	2597.568962	4279.231893	1398.04912
Predicted Numbers by Linear Regression (PCA)	3720.593809	4338.168929	1393.672794

Table 2. Actual and predicted restaurant numbers by linear regression and PCA processed linear regression.

According to the table, we can see for Philadelphia and Baltimore, the two models' predictions are very close to each other, and they are lower than the actual numbers. Compared with some other cities in the United States, it seems there are too many restaurants in Philadelphia and Baltimore. In another way, these two markets are saturated. However, in Washington D.C. it is quite different, the predicted number is 3720 which is much higher than the actual number. It means that according to the features analyzed, D.C. "should" have more restaurants, according to the population size, and purchasing power, and property values. So why is it so low? Does that mean there are some features we haven't considered, or is D.C. just an outlier? In my opinion, since D.C. has a long history, any observation in this city should be reasonable with minimal random outliers. I think it may be due to the policy, and opening a restaurant is relatively difficult. However, the policy issue is beyond the scope of this analysis. If someone does open a restaurant in DC, it will have higher potential to be successful because there is still a big room in the market. Thus, Washington D.C. is a suitable city for the restaurant business. (If someone can open one here)

Furthermore, if we go back and take a look at the restaurant cluster map, there is a district in the town center having much higher restaurant density than the other ones. Usually the town center is the financially advanced district. There are lots of business, government departments, and attractions there. All of these facts guarantee a high customer flow, otherwise the restaurants couldn't survive. But still, I used API calls to Foursquare to explore the restaurant distributions based on DC's wards. The heat map is shown below.

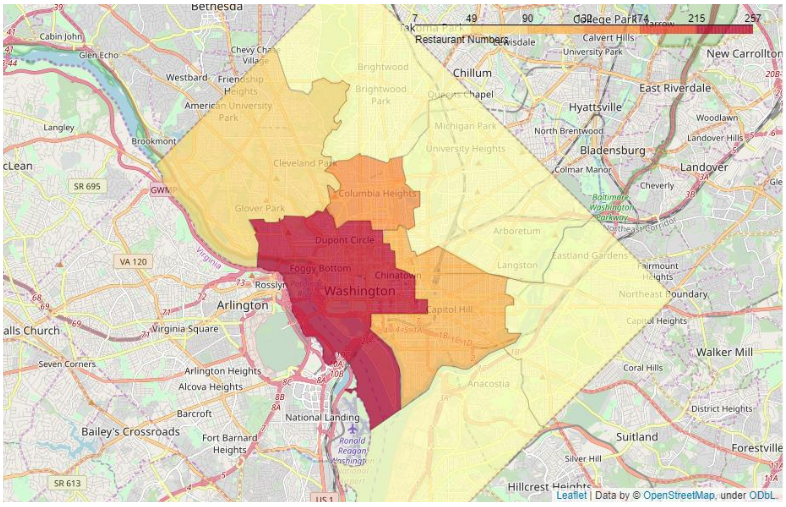

Figure 3. Washington DC's Restaurant Distribution Presented by Heat Map

According to the heat map in Figure 3, the northern, eastern, and southern DC have very few restaurants, because they are too far away from downtown. The best location shown in the map is Ward #2 district (in red), which has almost double amount of restaurants than its neighbor districts. This is the best place for the new business.

- ## Determine the New Restaurant's Category and Style

Now the location is determined, and what type of restaurant shall we open? Is an American restaurant more welcome, or the people in D.C. prefer a Japanese restaurant? It is very important to understand the residents' flavor preference, as it determines how many customers would like to actually pay for the food outside instead of preparing their own meals. Hence, I pulled out the data, and made another pie char for the Ward 2 area in D.C., which has the highest density of restaurants. Compared with the whole city, the Ward 2 area is very similar to Manhattan, which has a relatively big portion of French / Mediterranean restaurants. It represents the purchasing power in this district is comparatively higher than the other districts in the city. However, the dominant ones are American and Italian. In Ward 2, there are total 39 different flavors, and among them, American and Italian restaurants occupy more than 25% of the market. To be a safe business strategy, I still suggest to open an American or Italian restaurant here, unless there is more information supporting that the D.C. residents want something new. Even though the other types of restaurants are still possible, considering this is the first time to start a business, American or Italian styles are more preferred.

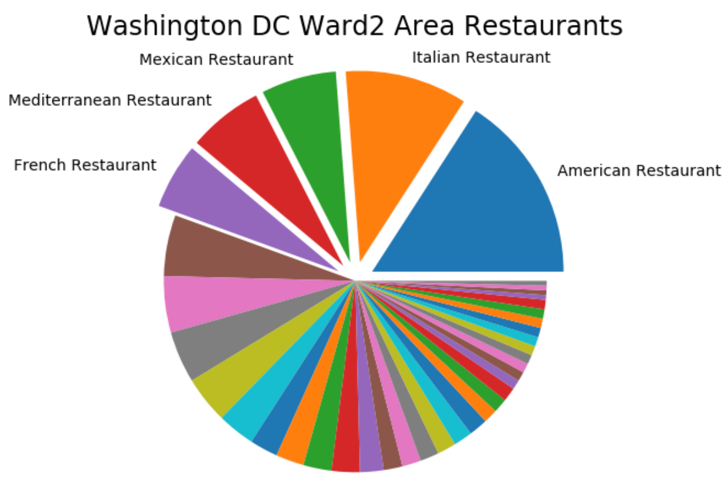

Figure 4. The restaurant flavors in Ward 2 area in D.C.

In order to be a successful business, the key is to attract as many customers as possible. The first question is how to find out the actual number of customers visiting a restaurant? The data is sitting somewhere, such as the business owner's book keeping, where we can find out the receipts, payments, income, etc. However this information usually cannot be disclosed, and it is not accessible for us. Thus we need to find other data that is correlated with the customer flow, and it should be public and easy to obtain. Luckily, there are several restaurant searching services can provide data for this purpose. On their website, people post restaurants ratings, comments, and upload photos. Even though it is not the direct evidence showing the actual customer numbers, with these likes, ratings, etc., we can still have an idea about whether a certain restaurant is popular, or it is too bad and no one wants to visit. Here I selected the indexes of "likes", photos, and rating numbers. All of them represent the relative popularity. Higher indexes mean more customer are willing to visit.

After that, I looked for whether there are some facts can determine the indexes mentioned above. A restaurant sells food which is a product. If we think whether a product is popular or not, the two basic facts are quality and price. If the food quality is good, it stands for its brand name, and the residents give it recognition. In addition, the restaurant passes from mouth to mouth. It is free advertisement spreading through the crowd. If the price is low, more people can afford it. Therefore, I pulled out the ratings and price tiers from the json file of each restaurant. (The json files are obtained through premium API calls to Foursquare for venue details). Now we let's examine whether a lower price and a higher rating could support the ideas. However, again, there are some problems dealing with this data. Not all restaurants have ratings or price tiers. Some restaurants also sit in the hotel which is not accessible to the public. In addition, there are also duplicate records. When python reads the json files, it needs to be programmed to skip the vacant values, otherwise it will give error messages. After all the data was imported, data cleaning was performed. The duplicated records and the outliers (such as the restaurant in a hotel or a sports center) were removed. The table example is shown below (Only first 5 records are shown here).

	name	id	like_count	photo_count	rating	rating_num	price_tier
0	Farmers & Distillers	57f24558498e2c8382f6adb3	169	189	8.1	241	3
1	Clyde's of Gallery Place	454a14f8f964a5209e3c1fe3	521	768	8	865	2
2	City Tap House Penn Quarter	528fe1a5498eba71d4957543	400	647	7.9	597	2
3	CHOPT	4a8840cbf964a5208f0520e3	137	138	8.3	209	1
4	Alta Strada	56ecad4f498e640591fe0207	33	25	8.5	46	3

Table 3. Table example of the restaurant ratings, number of ratings, uploaded photos, number of likes, and price tier. Only 5 records are shown in the example.

After analyzing the correlation among these features, like_count, photo_count, and rating_num follow a strong linear relationship. When more people visit a restaurant, more of them will leave their reviews in the form of likes and ratings. However, after I looked into the correlation between the rating and the rating number, they didn't seem to correlate with each other. On one hand, in Ward 2 almost all the restaurants have high quality with good ratings, so it is hard to distinguish them just by the rating values. On the other hand, a lower rating doesn't always mean fewer customers, since there are a lot of other features can impact the people's willingness to purchase food there, such as environment, location, price, etc. After I looked into the relationship between the reviews and the price tiers, some meaningful information popped up. (The bar chart was shown below)

Figure 5. The relationship between the customer reviews and the price tiers.

The price tiers are classified into 4 levels, from tier 1 the cheapest to tier 4 the most expensive. Before I conducted the analysis, I had an initial thought that if the price range is lower, more customer would like to visit, which is a typical observation on a lot of products. Usually lower price items sell more, such as cars, electronics, clothing, etc. However for the restaurants, it seems to be a little different. Only few rating numbers on the tier 1 side. Most of the likes, rating numbers, and uploaded photos are concentrated on tier 2 and 3 restaurants, with tier 2 as the dominant. Here is the possible explanation. Compared with the income of the residents in D.C. metropolitan area, the low price of the tier 1 restaurants is not very sensitive to them. At a low price range, they care more about the food quality. However, at a low cost, it is very difficult for the restaurants to provide decent food. Even considering the other "good" restaurants closed by, the people have a lot of other choices, so they are not that willing to stop by. At the high end side, the price range is far beyond most D.C. residents' affordability. As a result, the customers who'd like to visit such "Michelin star restaurants" are quite few. Now we can throw out some preliminary conclusion. According to the price range, it is suggested to open a restaurant with median or median high price range. By doing that, the business will have less challenge to attract the customers. But still it is necessary to point out that the price determination is a general conclusion, and it doesn't determine whether the business can run well. To be a successful restaurant, a lot of other efforts need to be put on, like improving the dinning environment, food quality, service, parking spaces, etc. Choosing the right price range is just a good start, and there are a lot of following steps, and they are hardly explained by data science or directed by the objective analysis tools.

Now it has been confirmed the good choice for a new restaurant is opening an American / Italian restaurant at Ward 2 area in the city of Washington D.C. The price range should not be too high or too low. Is it enough? My understanding is there is something more we can do. As we know, for example, the American restaurants also have different styles, and they also have different dishes. When we have a new American restaurant, shall we focus on the dinner with decent dishes like steak, fish, lamb, etc., or is a breakfast restaurant better option? To answer this question, one direct way is to post a survey to all the residents to ask for their opinions. Thus we can know whether they would like to spend money for a wonderful night, or they prefer to have breakfast outside home to save the food preparation time. Nevertheless, this method is not realistic. Is there any straightforward data sitting somewhere for us to collect the information we need? Here is my idea. Since in Ward 2 there are a bunch of successful restaurants, and their dishes should be recognized by the residents. In another word, if a restaurant is successful, their dishes should fits the residents' tastes. Therefore, if we look into the menus of these restaurants, we may find out some clues and ideas how to prepare our own dishes.

The menus were obtained via premium calls to Foursquare. The menu json files were downloaded and stored. My idea is to read the dish names as well as the ingredients so that we can know what types of food that the people in D.C. like most. Reading useful information in the json files is a bit challenging in this case, because the format of each json file is a little different, and sometimes it misses data. There was a lot of debugging to make it read everything correctly. Considering this issue, I used another method by reading the keywords in the files. First of all, all json files were converted into the text files. Then, the python code grabbed all food related keywords, and calculated the word frequencies in total among all the restaurants. According to this analysis, we can know what types of food / ingredients are the most popular. Since there are hundreds of keywords, I only listed the words with the frequencies above 5, as shown in Figure 6.

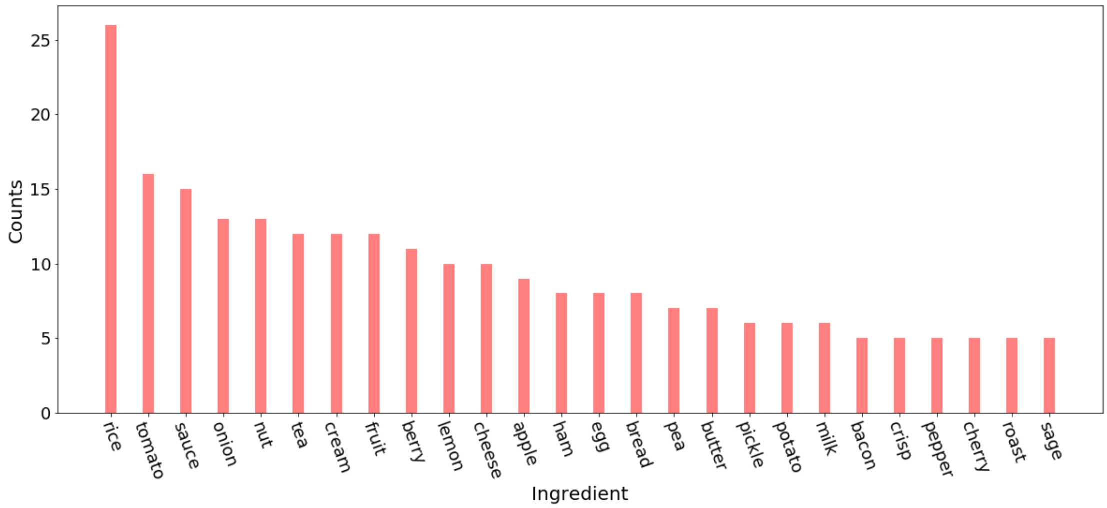

Figure 6. Food related keyword frequency of all American / Italian restaurants' menus.

According to the bar chart above, we can see there are some high frequency words, such as rice, tomato, tea, sauce and so on. All these ingredients are mostly breakfast / brunch related, and there are no other words like fish, meat, steak, burger, etc. Does it represent the real preference of the D.C residents? Maybe it is not that accurate. For example, if I open a new restaurant and fill my menu with all kinds of soups. The final analysis will show the D.C. residents all like to have soup, even though very few customers visit my restaurant. At another aspect, some of the keyword frequencies are just above 5. Considering there are tens of hundreds of restaurants sitting in this area, the frequency is too low, and may not represent the truth. Let's image from the other side, all D.C. residents would like to have bacon but very few restaurants serve it. Even though the truth is bacon is a good ingredient and needs to be taken into account, the word frequency is too low and it doesn't earn a high rank in the statistical analysis. Based on these concerns, the model has been modified. The method here is adding the "number of likes" into account. The weighed keyword frequency is the product of the observed frequency and the number of likes. Through this way, we can make the good special / minor dishes more standout. The modified the bar chart is shown below as Figure 7.

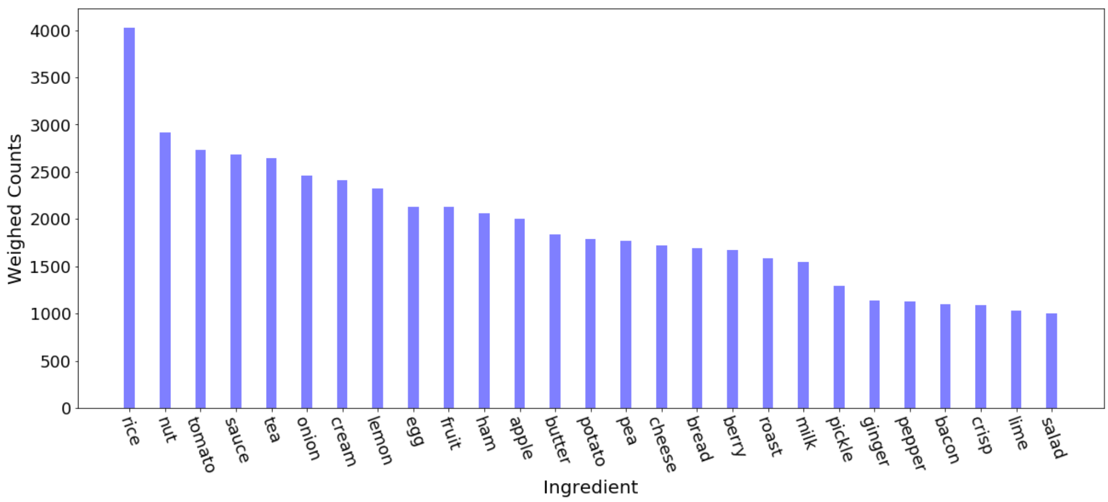

Figure 7. Weighted food related keyword frequency of all American / Italian restaurants' menus.

Figure 7 is quite similar to Figure 6. The high frequency food keywords are almost the same, while the rank is bit different. By the two methods, we can confirm that the most popular ingredient are rice, nut, tomato, sauce, and tea. After reviewing the whole list, I observed all the ingredients are breakfast / brunch related, such as tea, egg, bread, milk, bacon, etc. However, there are almost no lunch / dinner related ingredients, such as meat, fish, steak, lamb, etc. Thus, we can give out a preliminary conclusion that the breakfast and brunch restaurant are the most popular in D.C. around Ward 2 district. The reason may be Washington D.C. is a political capital in the United States. The employees in the government are more flexible than the other ones in the industry in the morning, and they can spend time on a breakfast or brunch restaurant. Considering usually the breakfast and brunch restaurants are more affordable, so they are indeed more welcome here. At another aspect, we know there are much fewer Michelin Star restaurants in D.C. than that in New York City, meaning fewer D.C. residents prefer to have a big decent meal than the New Yorkers. Thus we can see due to the city style difference, the residents' preference is different. When we determine the restaurant style and flavor, this feature should be considered.

4. Conclusion

While we are considering opening a new restaurant, the first question is where and what. Where means which location is the best. We have analyzed multiple cities, found out their differences. After digging more features of the city data, we concluded that Washington D.C. has the largest potential of the restaurant industry, and the city should have more restaurants than it is now. The low number may be caused by other facts like political reasons. However, it is not the scope of this analysis. We just assume we "can" have a restaurant here, and whether it is better than putting it in the other cities. If we'd like to solve the problem "how to open a restaurant", we still need to put down more effort. After the city of Washington D.C. is determined, we still need to find the best location. After clustering and heat mapping, we observed most of the restaurants are in the Ward 2 area, which is town center. Thus this is a preferred place for us.

In addition, we also have to find out what type of restaurants are more preferred, and what food we need to serve. After analyzing the customer ratings and the menus, I would suggest to open an American / Italian style restaurant, and serve breakfast or brunch. The price is at median level or median high level, so that we will have the highest customer flow compared with the other styles, because it fits the D.C. residents' taste most.

However, we still need to remember this analysis is to solve "where and what". It doesn't mean we will succeed if we strictly follow the guidance above. To be successful, "how to" is also necessary to be addressed, such as how to open a restaurant, how to provide good service, how to cut down the cost, etc. The strategy I just discussed about above only provide a preliminary guidance, which prevents us making mistakes at the very beginning. In order to survive in the market, we have to think about more features and it really depends on how we execute it.