Clustering of neighborhoods in Tokyo, Japan based on popular venues by Foursquare database

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1. Introduction

1.1. Background

Tokyo is a huge metropolis with population of about 13.49 million as of 2015 [1] covering an area of about 2191 square kilometers. Geographically Tokyo metropolis is divided into 23 special wards and Tama area, which consists of 26 cities, as well as few islands and towns as indicated in Figure 1.1 [1]. In general, the whole Tokyo metropolis is called Tokyo-to (i.e. Tokyo Prefecture) in Japanese, while Tokyo usually refers to the special 23 wards that are clustered around eastern part of Tokyo metropolis. In this report, I will refer to these 23 wards as Tokyo and Tokyo metropolis as Tokyo-to.

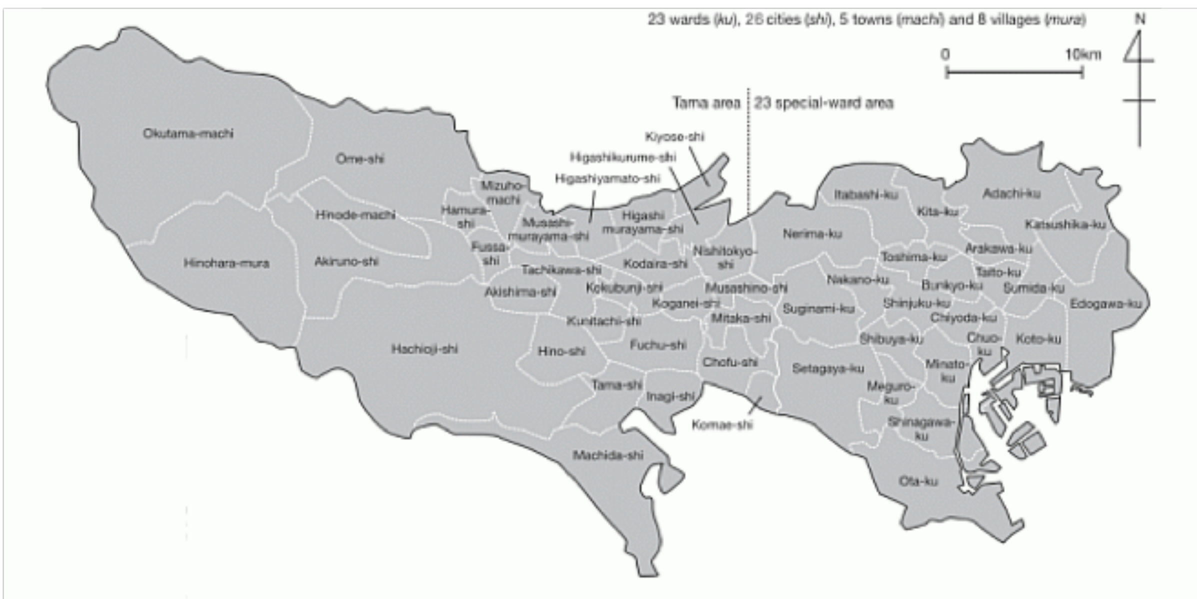

Figure 1.1. Geographical division of Tokyo-to

Tokyo is a political, cultural, and economic center of Tokyo-to with overall night-time population of about 9.24 million (about 68.5% of Tokyo-to) as of 2015 while occupying only about 29% of total area of the metropolis. With daytime influx of commuters from the surrounding cities and prefectures, Tokyo is a busy city with thriving atmosphere.

There are hundreds of neighborhoods in Tokyo and each neighborhood has its own vibe and character. For example, some neighborhoods in famous Shibuya ward are popular among tourists and youth, while some neighborhoods around Akihabara in Chiyoda ward are famous for electronic shops and anime and manga cultures. On the other hand, some neighborhoods in the peripheral wards can be more residential and quieter compared to the well-known ones.

1.2. Problem

As Tokyo is a major destination for tourism, it is interesting and useful information for tourists that which neighborhoods, except for the popular ones, are worth their visit based on their individual interests. Quick search on the internet usually directs one to popular neighborhoods in Tokyo, such as Shibuya, Harajuku, Shinjuku, Roppongi, Asakusa, or Ueno etc, especially when searched in English, leaving many potentially unique and attractive neighborhoods unexplored by many tourists.

On the other hand, for the locals in Tokyo, choosing where to live is an important decision that can affect their life immensely. Even though Tokyo has arguably the most extensive public transportation in the world in terms of railway, getting from point A to B can take as long as an hour or more of commuting in crowded trains, therefore it is tempting to choose a place in a way that minimizes the overall commuting time. However, there are number of other factors to be considered in choosing one's place of living such as cost of renting/purchasing of house, local atmosphere of the neighborhood, eateries, access to parks, closeness to a train station and one's work, and a type of the neighborhood in terms of whether it is primarily a business area, residential area, or entertainment area. While the cost of living could be primary constraint in many cases, the other factors are expected to play very important roles for having a fulfilling life.

Besides for choosing where to live, the locals are also into exploring Tokyo. One could assume that with an extremely well-developed transportation in Tokyo, the locals must have been to every corner of Tokyo. Yet, speaking from personal experience of living in Tokyo and from those of others as well, it is not unusual at all for a local to say "*I've never been there!*" when asked about whether he or she has been to some neighborhoods in Tokyo. Considering that Tokyo is a huge city, it is perhaps no surprise that one has simply not enough time to explore all neighborhoods. On the other hand, it can be argued that those famous neighborhoods are still plenty in numbers, so they can fill most weekends of the locals just well, making the locals relatively uninformed and uninterested in other potentially interesting neighborhoods.

The above facts and observations indicate that there are potentially lots of neighborhoods in Tokyo that are out of sight of tourists and the locals. For that reason, it is worth exploring the neighborhoods in Tokyo in terms of popular venues around each of them. Furthermore, segmenting and clustering the neighborhoods in Tokyo can provide valuable information on characteristics of each neighborhood as well as information on which neighborhood is similar or dissimilar to which neighborhoods.

1.3. Purpose

The purpose of this work is to explore the neighborhoods in Tokyo and cluster them using K-means clustering based on popular venues in each neighborhood obtained using Foursquare [2] location database, and eventually to assist tourists and the locals to choose which neighborhoods to visit or live.

2. Data preparation

2.1. Data collecting and data cleaning

First data needed are a list of all neighborhoods in Tokyo. It appears that there is no readily available list of all neighborhoods in Tokyo in a tabular form. However, there is one good source on Wikipedia, where neighborhoods are listed for each ward in Tokyo [3]. This source essentially provides the names of about 246 neighborhoods in Tokyo, however, it appears to be not complete list. For example, there are two wards, namely Arakawa ward and Nerima ward, missing in the source. In addition, this source lists only one neighborhood in Edogawa ward further indicating an apparent incompleteness. Regardless of these facts, this source still provides hundreds of neighborhoods in Tokyo therefore is utilized as a source.

Beautiful Soup library [4] is then used for scraping the source webpage and getting the name of each neighborhood along with the name of a ward it belongs to.

Next data needed are latitude and longitude for each neighborhood as they are used for retrieving popular venues from Foursquare database. For this purpose, Geopy library [5] is used. The names of the neighborhoods in the form of "*Neighborhood name, Ward name, Tokyo*" is used as an address. The latitude and longitude data for 210 out of 246 neighborhoods were successfully retrieved. Although it is not a bad idea to ignore the remaining 36 neighborhoods altogether, the latitude and longitude data for the remaining 36 neighborhoods were manually fetched using Google Map. The latitude and longitude data were chosen at around the center of the neighborhood. All obtained neighborhoods are listed in Table A.1 in Appendix along with their latitude and longitude data.

Finally, the Foursquare database is accessed via Foursquare API to retrieve up to 100 popular venues in each neighborhood. The radius of a search area for each coordinate (i.e. each neighborhood) was set to 400 m. In total, 12952 venues were retrieved for 246 neighborhoods in Tokyo using Foursquare API, averaging about 53 venues per neighborhood.

In order to achieve a better clustering, the neighborhoods with less than 10 obtained venues are discarded from the dataset. In total 63 venues in 11 neighborhoods were discarded leaving a dataset with 12889 venues in 235 neighborhoods in 364 unique venue categories. The number of venues in each neighborhood is then in the range [10,100].

It is worth noting here that some neighborhoods are small in area while others are relatively big, thus some overlapped venues are expected for small neighborhoods that are close to each other. On top of that, the shapes of some neighborhoods are highly irregular, thus searching for popular venues using circular area of given radius is expected to give an approximate result.

2.2. Feature selection

As the K-Means clustering is intended to be used to segment the neighborhoods in Tokyo based on the popular venues in each neighborhood, all 364 venue categories are selected as features in the model. All 364 venue categories are listed in Table A.2 in Appendix.

In order to use each venue category as a feature, a one-hot encoding is used. Then taking the mean of each venue category in each neighborhood gives frequency of occurrence data for each venue category for each neighborhood as a matrix of the dimension 246×365. For example, let us assume that we have obtained 60 popular venues for a neighborhood A and let us consider a venue category “Park”. If there are 3 venues whose category is “Park” in the obtained data, then the frequency of occurrence of the venue category “Park” for the neighborhood A is 3/60=0.05. In other words, the sum of frequency of occurrence over all venue categories for each neighborhood is 1.

3. Methodology

3.1. Choice of clustering algorithm

There are number of clustering algorithms, however, choosing the one that best suits a specific application is hard task where one probably needs to try all algorithms to make a choice. In essence, it is more of a trial-and-error approach. While I better follow this approach, I chose K-Means clustering algorithm straight away based on the following few reasons – (1) it is widely used and well known, (2) easier to use and understand except choosing the right k number, (3) it is suitable for medium to large data clustering, and (4) it was relatively successfully applied to the neighborhood clustering in New York and Toronto city in the course assignment.

3.2. Choosing best k value using elbow method

There are 235 neighborhoods to be clustered, yet we don’t know how many groups (i.e. k value) they can be optimally clustered into. In order to choose the approximate optimal k value, I used the so-called elbow method, where one tries a range of k values and choose the one at which a rate of change in a chosen score metric value starts dropping significantly. More clearly, in this work, an inertia is chosen as a score metric. The inertia is defined to be a sum of squared distances of samples (i.e. data points) to their closest cluster center [6].

Figure 3.1 shows inertia values for k values in the range [2,20] for our dataset. Although the inertia keeps decreasing rapidly as k value increases, the rate of change in the inertia slowed down roughly around k=8, which is subsequently taken to be approximately optimal for our dataset.

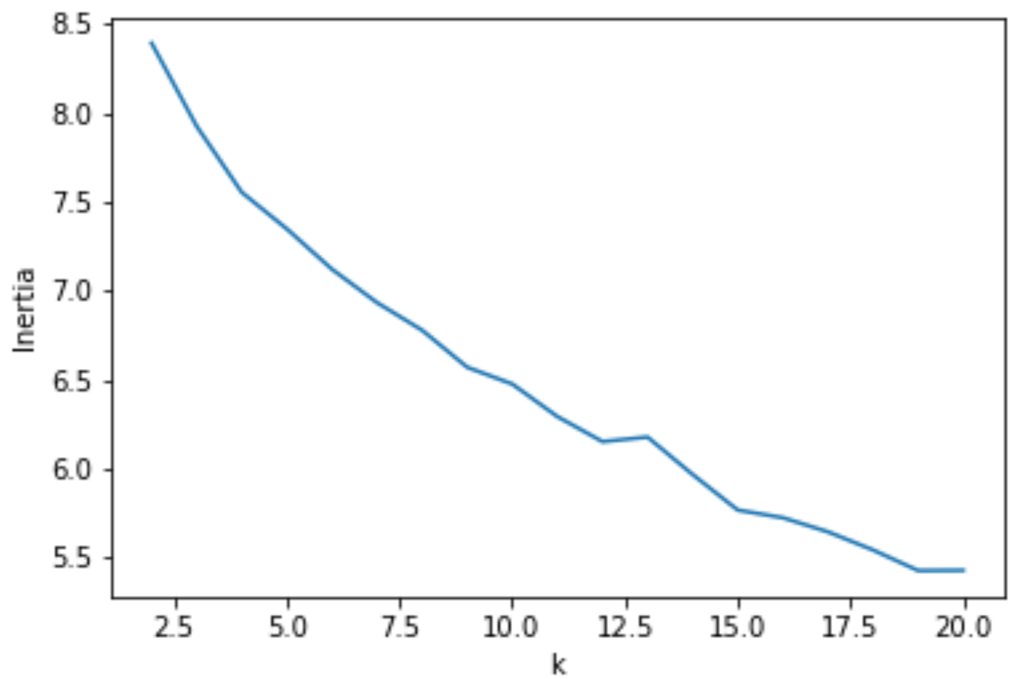

Figure 3.1. Inertia vs k value

4. Results and discussion

In this section, the results of the clustering of neighborhoods in Tokyo using K-Means clustering algorithm using full features i.e. using all 364 venue categories (given in Table A.2) are presented and discussed.

Figure 4.1 shows a map of Tokyo containing the clustered neighborhoods. Also shown in the figure is a number of neighborhoods in each cluster as *n_neigh* inside parentheses.

Geographically speaking, observing from Figure 4.1 it roughly appears that most of the neighborhoods in Cluster 6 are centered around central Tokyo tagged as ‘Imperial Palace’. Majority of neighborhoods in Cluster 1 and Cluster 5 appear to be located around the center of Tokyo, while those in Cluster 2 and Cluster 3 seem to be scattered around Tokyo. The neighborhoods in Cluster 8 are generally located near the Tokyo Bay, however, there are couple of neighborhoods in southwestern and central Tokyo. On the other hand, all three neighborhoods in Cluster 4 are located along the Tokyo Bay. However, in further inspection it turned out that Geopy library gave the same latitude and longitude data for the three neighborhoods in Cluster 4 that are geographically neighbors, which means that these three neighbors were indistinguishable. On the other hand, the two neighborhoods in Cluster 7 are geographically close each other.

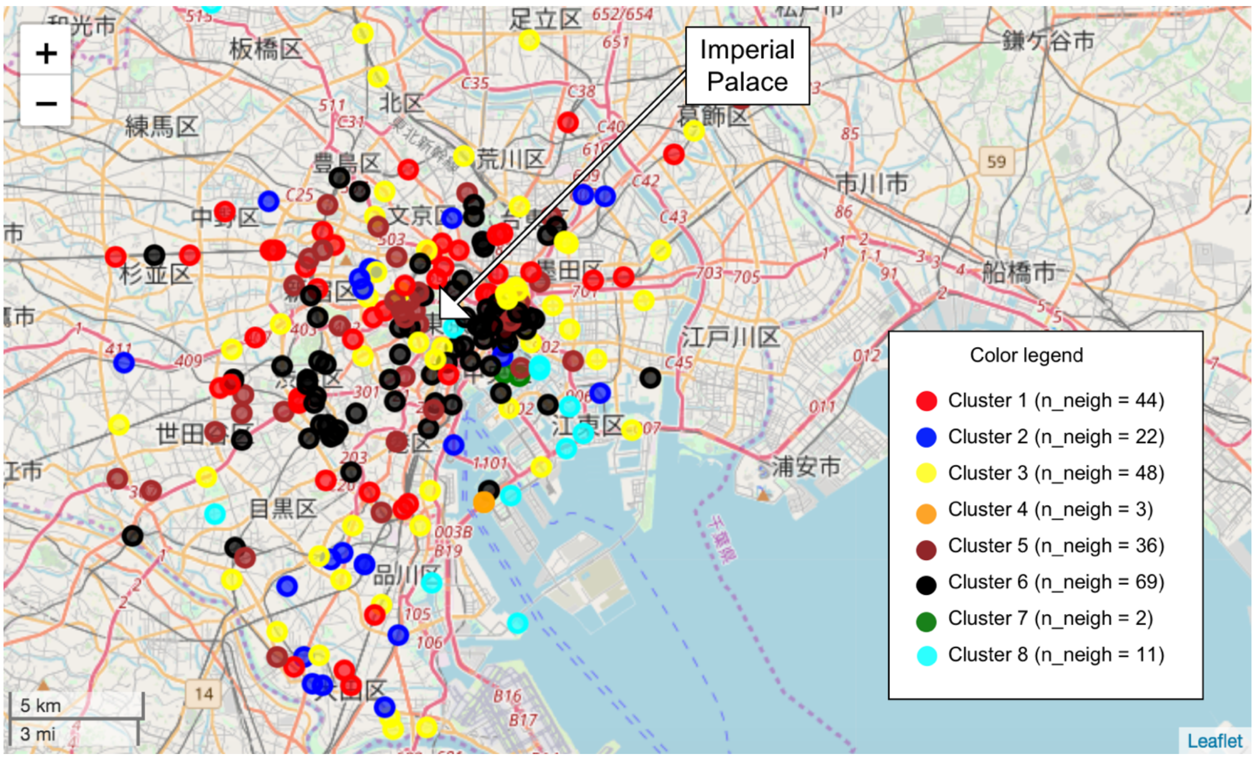

Figure 4.1. Neighborhood clusters in Tokyo by K-Means clustering using full features

Next, let us analyze each cluster by looking at a number of occurrences of venue categories in each of them. For that purpose, first we will pick most popular 10 venue categories in each neighborhood based on venue counts in each venue category. Then we will retrieve up to 20 most common venue categories in each cluster from the union of the top 10 venue categories in the neighborhoods in that cluster based on the number of occurrences of the venue category. In other words, we will get up to 20 popular venue categories in each cluster based on top 10 venue categories for each neighborhood in that cluster. For example, let us assume that Cluster A has two neighborhoods and that there are two common venue categories ‘Park’ and ‘Convenience store’ in the top 10 venue categories in each neighborhood. Then the union of top 10 venue categories in all neighborhoods in Cluster A will be 18 because of that two common venue categories. And the number occurrences of venue categories ‘Park’ and ‘Convenience store’ in Cluster A will be 2 for both, while the number of occurrences for all remaining 16 venue categories in the cluster is 1 for each. In this way we can say that the venue categories ‘Park’ and ‘Convenience store’ are popular in Cluster A.

The Figures 4.2 through 4.9 show the number of occurrences of up to 20 popular venue categories in each cluster. Also shown in the figures are the number of neighborhoods in each cluster denoted as *n_neigh*.

In Cluster 1 shown in Figure 4.2, the most popular venue category is ‘Ramen Restaurant’ with number of occurrences of 42. That means out of 44 neighborhoods in the cluster, 42 neighborhoods have venue category ‘Ramen Restaurant’ in their top 10 venue categories. It should be emphasized here that the number of occurrences does not give any information on how popular the specific venue category is in each neighborhood. For example, we cannot say from the figure that if the venue category ‘Ramen Restaurant’ is the 1st most common venue category or 10th most venue category in each neighborhood’s top 10 venue categories. All we know is that ‘Ramen Restaurant’ is somewhere in top 10 venue categories of 42 neighborhoods in Cluster 1 containing total of 44 neighborhoods. Further inspecting the list, it seems that Cluster 1 is popular with venue categories ‘Sake Bar’ and ‘Cafe’ etc, indicating that Cluster 1 has lots of eateries and occasional parks and clubs.

On the other hand, Cluster 2 seems to have lots of convenience stores, however, which is not really a new thing in Tokyo, where you can find convenience store almost everywhere, a really fitting name for convenience store. Cluster 2 appears to be popular Chinese restaurant and parks, as well as some motorbike shops and pharmacies.

In Cluster 3 shown in Figure 4.4, various restaurants seem to be popular. Unlike Cluster 1 and Cluster 2, grocery stores and shopping malls are likely to be found in Cluster 3.

In case of Cluster 4 shown in Figure 4.5, there are three neighborhoods, however, as discussed in the beginning of this section, these three neighborhoods happened to be given the same latitude and longitude data by Geopy library, so all the obtained venues in them are the same as well. Thus Cluster 4 can be thought to have only one neighborhood in it. And it appears that Cluster 4 is popular with venue categories like ‘Park’, ‘Campground’, and ‘Gym’ etc.

Cluster 5 shown in Figure 4.6 seems to be also popular with venue categories of various restaurants and eateries like other clusters, however, it has increased number of dessert shops, supermarkets, grocery stories, and bakeries.

Cluster 6 shown in Figure 4.7 has the largest number of neighborhoods. Yet again it seems to have lots of eateries, while it is more popular with sushi restaurants, bars, hotels, and clothing stores compared to the other clusters.

Cluster 7 presented in Figure 4.8 has only two neighborhoods located geographically close to each other. It appears that eateries are yet again popular just like any other cluster, however, the venue category ‘Monjayaki Restaurant’ seems to be popular around these neighborhoods. Since this cluster has only two neighborhoods, it is easy to check if indeed venue category ‘Monjayaki Restaurant’ is popular in these neighborhoods. For example, searching monjayaki around Tokyo on Google Map shows number of restaurants around these neighborhoods.

Finally, Cluster 8 shown in Figure 4.9 presents distinct profile of popular venue categories compared to the other clusters. Cluster 8 appears to be popular with intersections, parks, plazas, historical sites, and museums.

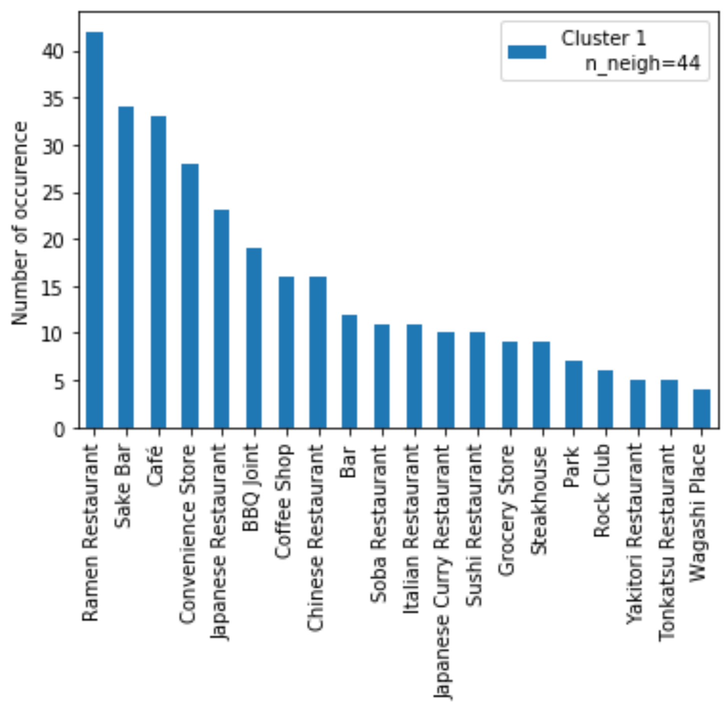

Figure 4.2. Most frequent 20 venue categories in Cluster 1

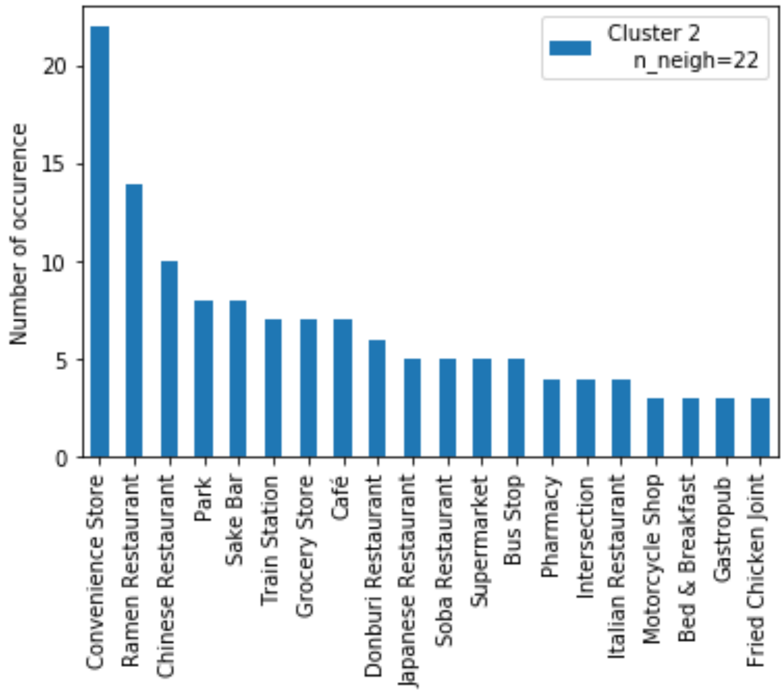

Figure 4.3. Most frequent 20 venue categories in Cluster 2

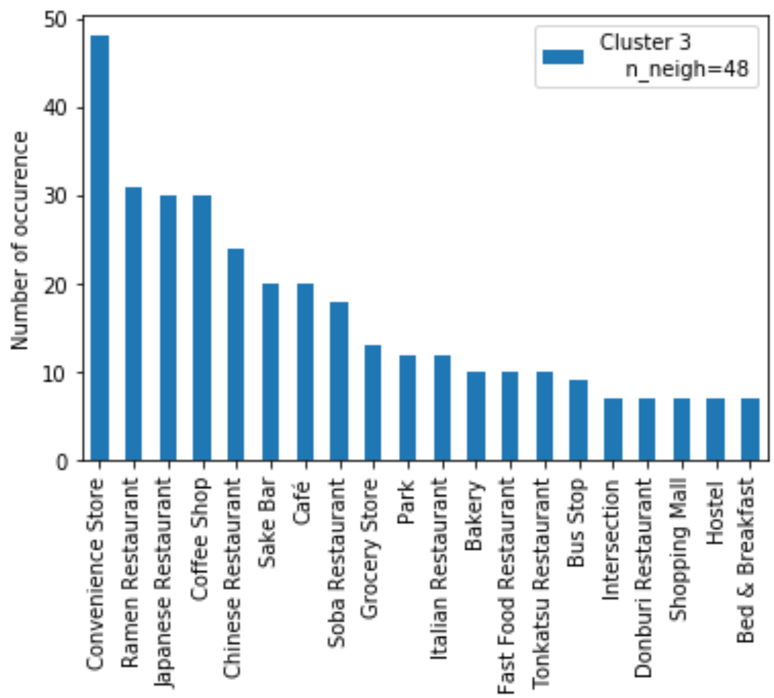

Figure 4.4. Most frequent 20 venue categories in Cluster 3

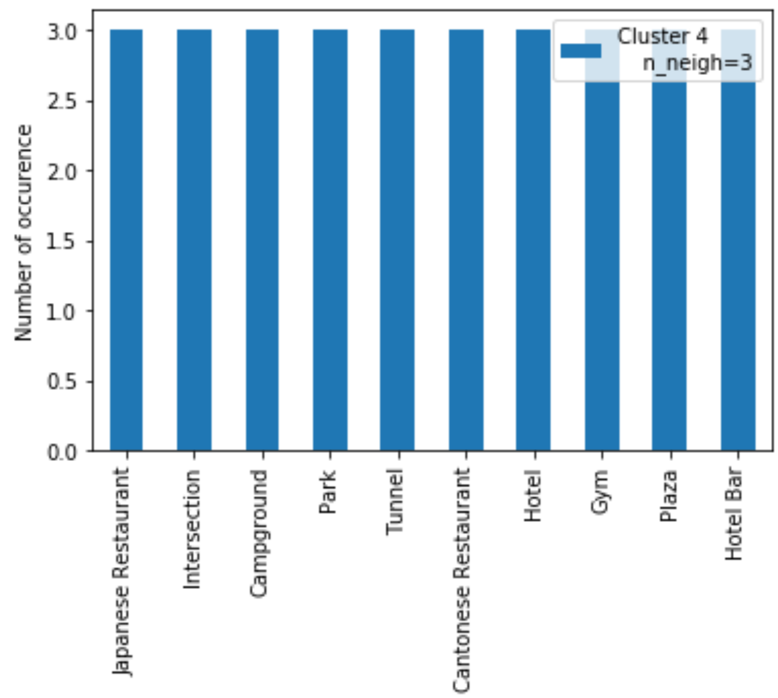

Figure 4.5. Most frequent 10 venue categories in Cluster 4

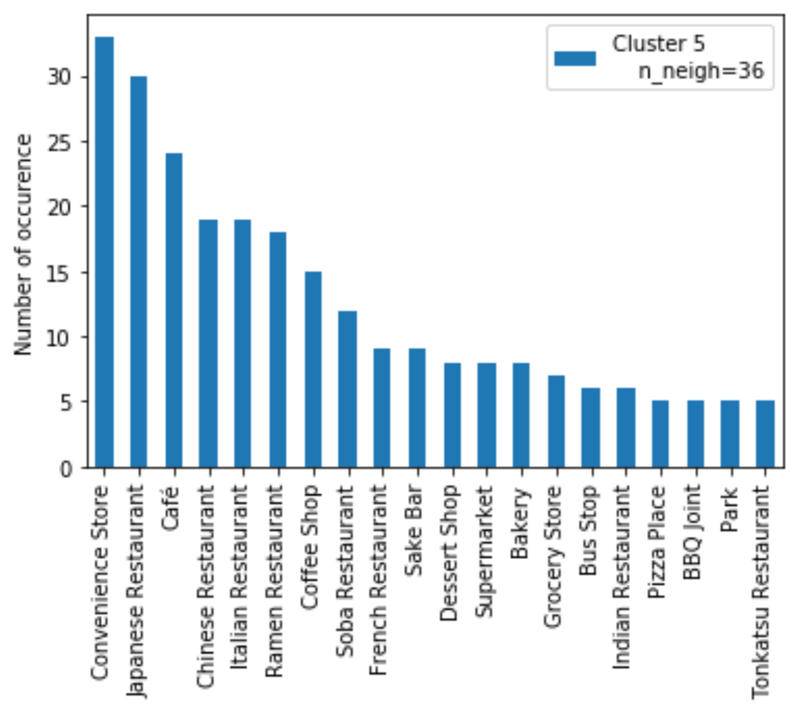

Figure 4.6. Most frequent 20 venue categories in Cluster 5

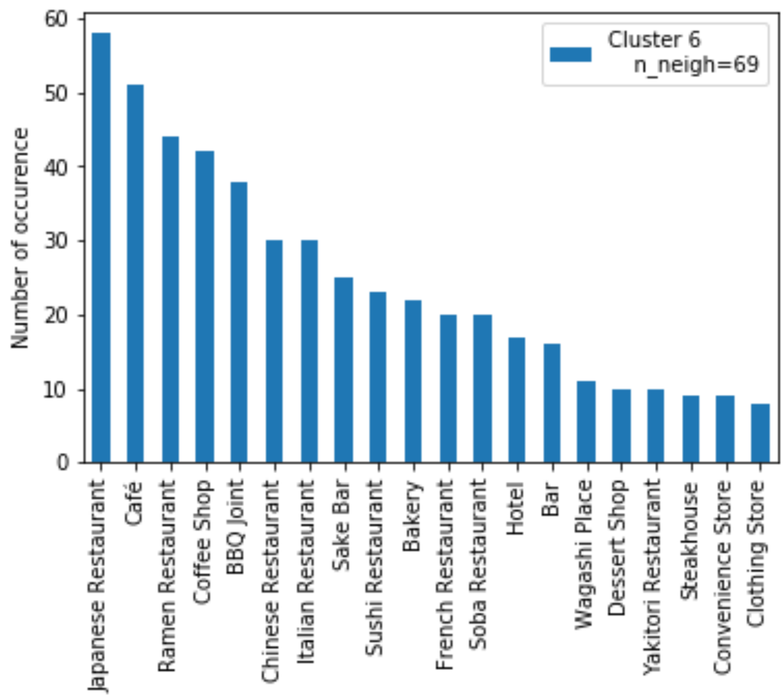

Figure 4.7. Most frequent 20 venue categories in Cluster 6

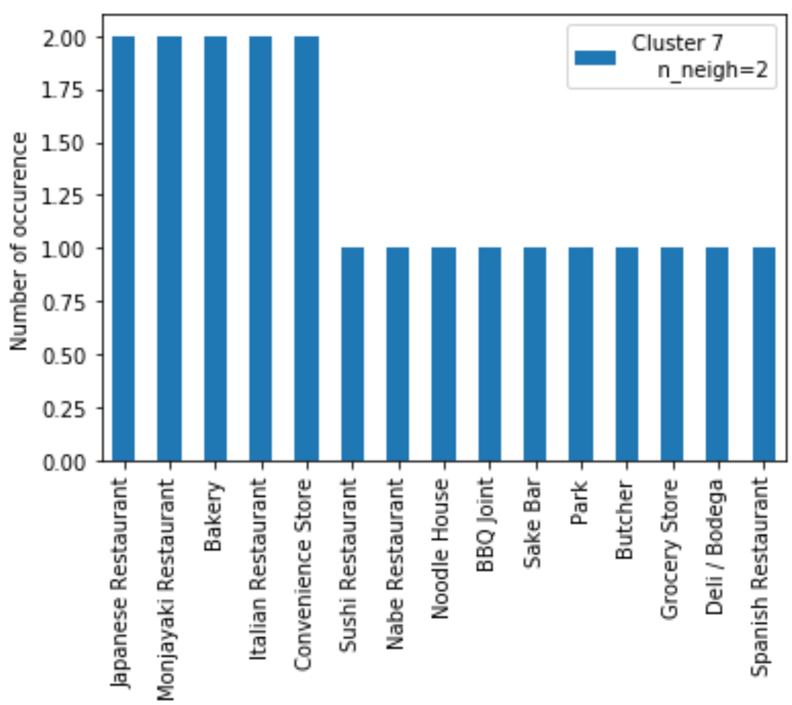

Figure 4.8. Most frequent 15s venue categories in Cluster 7

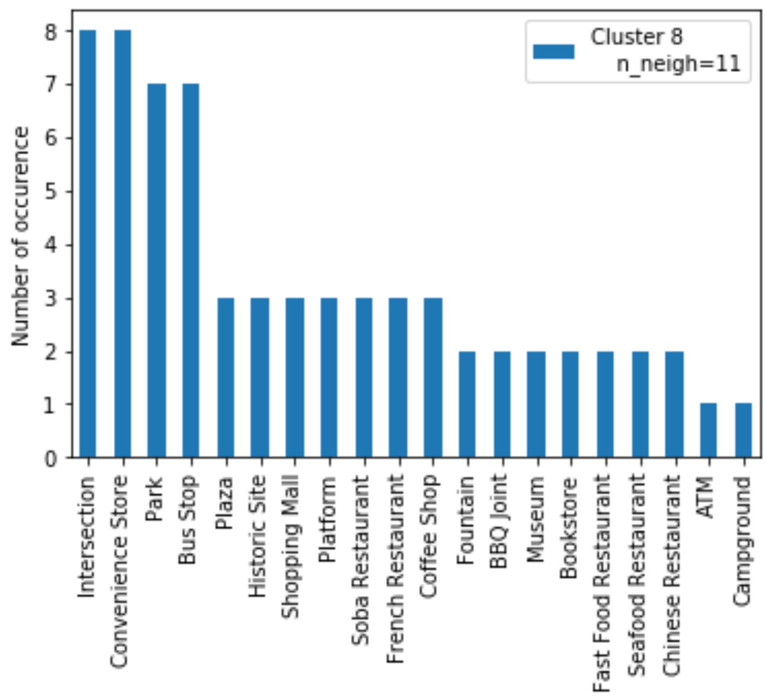

Figure 4.9. Most frequent 20 venue categories in Cluster 8

5. Conclusions

Neighborhoods in Tokyo were clustered using K-Means clustering method based on popular venues in each neighborhood obtained via Foursquare location database in this study. In specific, total of 235 neighborhoods were clustered into 8 groups based on a frequency of occurrences of 364 distinct venue categories ranging from 'Japanese Restaurant' through 'Coffee Shop' to 'Campground'.

Initial list of neighborhoods in Tokyo were scraped from Wikipedia webpage using Beautiful Soup library, the latitude and longitude data for each neighborhood were then obtained using Geopy library, and up to 100 popular venues were then obtained from Foursquare location database via Foursquare API giving data for 12889 venues in 235 neighborhoods.

The clustering results were then analyzed using a frequency of occurrences of up to 20 venue categories in each cluster based on the top 10 venue categories in each neighborhood that belongs to the cluster. The results showed that all 8 clusters showed distinct characteristics from one another. However, it should be noted also that many clusters also showed certain similarity, especially in terms of various types of restaurants. For example, 'Japanese Restaurant', 'Ramen Restaurant', 'Chinese Restaurant', 'Cafe', and 'Coffee Shop' were some of the recurring venue categories. In general, the results showed that each cluster was popular with various sort of restaurants, indicating Tokyo is great place for food lovers.

The clustering results can provide tourists and the locals with useful information about each neighborhood as well as common characteristics of each cluster, and assist them with where to visit or live.

6. Suggestions for future improvements of the clustering

From the results discussed in section 4, it can be seen that various restaurant categories dominated the whole dataset. In specific, in total of 364 venue categories there were 87 venue categories that contain a word ‘restaurant’. One idea to improve clustering to include more of other venue categories is to collapse these 87 venue categories into single venue category named ‘Restaurant’.
On the other hand, the clustering can perhaps be improved by reducing the number of features (currently 364 venue categories) using principal component analysis or by eliminating highly correlated venue categories.
Another idea to improve neighborhood clustering in Tokyo is to include more neighborhoods as there were number of missing neighborhoods in the initial list of neighborhoods. For example, as mentioned in section 2, two entire wards were missing. Including them in the dataset and including other missing neighborhoods will certainly improve the overall clustering.

References

1. http://www.metro.tokyo.jp/ENGLISH/ABOUT/HISTORY/history02.htm
2. https://www.foursquare.com
3. https://commons.wikimedia.org/wiki/Category:Neighborhoods_in_Tokyo_by_ward [Accessed in December, 2019]
4. https://www.crummy.com/software/BeautifulSoup/bs4/doc/
5. https://geopy.readthedocs.io/en/stable/
6. https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html

Appendix

Table A.1. List of neighborhoods and their coordinates

#	Neighborhood	Latitude	Longitude
1	Senju, Adachi	35.748916	139.804754
2	Hongo, Bunkyo	35.7066167	139.759913
3	Kasuga, Bunkyo	35.7085245	139.752735
4	Koishikawa, Bunkyo	35.7053632	139.749111
5	Koraku, Bunkyo	35.706373	139.746906
6	Mejirodai, Bunkyo	35.7177189	139.72559
7	Mukogaoka, Bunkyo	35.717094	139.756877
8	Nezu, Bunkyo	35.7173532	139.765722
9	Otsuka, Bunkyo	35.725778	139.729917
10	Sekiguchi, Bunkyo	35.7142667	139.72658
11	Sendagi, Bunkyo	35.7255455	139.763315
12	Yushima, Bunkyo	35.7073329	139.77001
13	Fujimi, Chiyoda	35.6963944	139.761129
14	Hayabusacho, Chiyoda	35.681638	139.743347
15	Hibiya, Chiyoda	35.6738027	139.758267
16	Hirakawacho, Chiyoda	35.6809547	139.740089
17	Hitotsubash, Chiyoda	35.6929572	139.757516
18	Ichibancho, Chiyoda	35.6863088	139.742148
19	Iidabashi, Chiyoda	35.7017047	139.743698
20	Kajicho, Chiyoda	35.6916889	139.771942
21	Kanda, Chiyoda	35.6937148	139.77089
22	Kasumigaseki, Chiyoda	35.674217	139.752717
23	Kioicho, Chiyoda	35.6808091	139.73568
24	Kokyo-Gaien, Chiyoda	35.6806942	139.757958
25	Kudankita, Chiyoda	35.6966456	139.751029
26	Kojimachi, Chiyoda	35.684028	139.737667
27	Marunouchi, Chiyoda	35.6810912	139.767186
28	Misakicho, Chiyoda	35.7006297	139.753907
29	Nagatacho, Chiyoda	35.675618	139.743469
30	Otemachi, Chiyoda	35.6840162	139.762664
31	Rokubancho, Chiyoda	35.6887171	139.735401
32	Sanbancho, Chiyoda	35.6911891	139.745311
33	Uchisaiwaicho, Chiyoda	35.6691961	139.755304
34	Yonbancho, Chiyoda	35.689474	139.739749
35	Yurakucho, Chiyoda	35.6744233	139.761674
36	Akashicho, Chuo	35.6656148	139.778434
37	Ginza, Chuo	35.6695156	139.764306
38	Harumi, Chuo	35.6541446	139.780101

39	Hatchobori, Chuo	35.6746453	139.777637
40	Higashi-Nihonbashi, Chuo	35.690701	139.784348
41	Irifune, Chuo	35.6710197	139.777796
42	Kachidoki, Chuo	35.6589623	139.777175
43	Kyobashi, Chuo	35.676833	139.770139
44	Minato, Chuo	35.6645277	139.737741
45	Nihonbashi, Chuo	35.684058	139.774501
46	Nihonbashi-Hamacho, Chuo	35.684304	139.788594
47	Nihonbashi-Muromachi, Chuo	35.6854205	139.774543
48	Shinkawa, Chuo	35.6759674	139.779793
49	Tsukiji, Chuo	35.6680853	139.772563
50	Tsukishima, Chuo	35.6645697	139.784766
51	Tsukuda, Chuo	35.6675972	139.785346
52	Yaesu, Chuo,	35.6799795	139.769362
53	Hirai, Edogawa	35.706421	139.842512
54	Akatsuka, Itabashi	35.7788033	139.643464
55	Takashimadaira, Itabashi	35.7883692	139.658938
56	Aoto, Katsushika	35.7456971	139.856173
57	Shibamata, Katsushika	35.7564295	139.875202
58	Tateishi, Katsushika	35.738182	139.848055
59	Akabane, Kita	35.7781394	139.7208
60	Higashi-Jujo, Kita	35.7638484	139.726875
61	Tabata, Kita	35.7373701	139.761715
62	Aomi, Koto	35.6247789	139.781202
63	Ariake, Koto	35.6345562	139.793256
64	Edagawa, Koto	35.6543934	139.805386
65	Eitai, Koto	35.6641631	139.837983
66	Etchujima, Koto	35.6679	139.792638
67	Kameido, Koto	35.6976987	139.827138
68	Kiba, Koto	35.6694204	139.806526
69	Kiyosumi, Koto	35.6665943	139.793023
70	Morishita, Koto	35.6880305	139.79824
71	Ojima, Koto	35.6897995	139.835073
72	Saga, Koto	35.6754938	139.789608
73	Shinkiba, Koto	35.6465829	139.830412
74	Shinonome, Koto	35.6407295	139.803636
75	Shiohama, Koto	35.6613093	139.80655
76	Shiomi, Koto	35.658929	139.817193
77	Tatsumi, Koto	35.6454701	139.810708
78	Toyo, Koto	35.6699019	139.815809
79	Toyosu, Koto	35.6549298	139.796174
80	Wakasu, Koto	35.6195841	139.83407
81	Yumenoshima, Koto	35.6498616	139.825201

82	Jiyugaoka, Meguro	35.6075379	139.668828
83	Kamimeguro, Meguro	35.6528634	139.688148
84	Meguro, Meguro	35.6327798	139.715999
85	Nakameguro, Meguro	35.6441395	139.698832
86	Shimomeguro, Meguro	35.6300236	139.705898
87	Akasaka, Minato	35.6716786	139.735622
88	Aoyama, Minato	35.6710729	139.720839
89	Atago, Minato	35.6649676	139.748694
90	Azabu, Minato	35.6564018	139.733971
91	Hamamatsucho, Minato	35.6551111	139.757062
92	Kaigan, Minato	35.6267565	139.748214
93	Konan, Minato	35.628652	139.751295
94	Mita, Minato	35.6470946	139.74772
95	Odaiba, Minato	35.626722	139.772101
96	Roppongi, Minato	35.663561	139.731914
97	Shiba, Minato	35.6553734	139.750265
98	Shibakoen, Minato	35.6536377	139.749812
99	Shibaura, Minato	35.641723	139.757776
100	Shinbashi, Minato	35.6651764	139.755836
101	Shirokane, Minato	35.6429019	139.734127
102	Takanawa, Minato	35.6429019	139.734127
103	Toranomon, Minato	35.67017	139.750049
104	Higashi-Nakano, Nakano	35.7062386	139.684878
105	Numabukuro, Nakano	35.7192588	139.664613
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107	Chuo, Ota	35.5678875	139.692476
108	Den-en-chofu, Ota	35.5969003	139.66738
109	Haginaka, Ota	35.5511001	139.73178
110	Haneda, Ota	35.5479444	139.746646
111	Heiwajima, Ota	35.5788522	139.735013
112	Honhaneda, Ota	35.5475756	139.733021
113	Ikegami, Ota	35.572027	139.703003
114	Jonanjima, Ota	35.582347	139.783537
115	Kamata, Ota	35.5620151	139.715819
116	Keihinjima, Ota	35.581373	139.767213
117	Kojiya, Ota	35.5547009	139.729466
118	Kugahara, Ota	35.5796094	139.685634
119	Magome, Ota	35.5969362	139.711962
120	Omori, Ota	35.5884735	139.727933
121	Rokugo, Ota	35.5619514	139.704223
122	Sanno, Ota	35.5848777	139.724988
123	Shimomaruko, Ota	35.5714014	139.685601
124	Showajima, Ota	35.5708971	139.750008

125	Tokai, Ota	35.3631273	139.274097
126	Yaguchi, Ota	35.5625833	139.700256
127	Daita, Setagaya	35.6606228	139.662349
128	Daizawa, Setagaya	35.6583499	139.672186
129	Fukasawa, Setagaya	35.6187123	139.66005
130	Funabashi, Setagaya	35.6485548	139.620792
131	Futako-Tamagawa, Setagaya	35.6116779	139.626956
132	Kamikitazawa, Setagaya	35.6688199	139.623299
133	Kinuta, Setagaya	35.6304979	139.620156
134	Kitazawa, Setagaya	35.6634677	139.668154
135	Komazawa, Setagaya	35.6309778	139.656596
136	Okusawa, Setagaya	35.6040191	139.672775
137	Sakuragaoka, Setagaya	35.6449951	139.631934
138	Sangen-jaya, Setagaya	35.6435178	139.67127
139	Seijo, Setagaya	35.6522023	139.671415
140	Shimokitazawa, Setagaya	35.6616779	139.666335
141	Wakabayashi, Setagaya	35.6459609	139.659978
142	Yoga, Setagaya	35.6266477	139.634172
143	Shibuya, Shibuya	35.6579744	139.701694
144	Daikanyama, Shibuya	35.6481588	139.703255
145	Dogenzaka, Shibuya	35.6558632	139.694864
146	Ebisu, Shibuya	35.6469725	139.708671
147	Harajuku, Shibuya	35.6687049	139.705336
148	Hatagaya, Shibuya	35.6772382	139.676776
149	Higashi, Shibuya	35.7064752	139.682847
150	Hiroo, Shibuya	35.65235	139.71777
151	Jin'nan, Shibuya	35.6632316	139.697804
152	Jingumae, Shibuya	35.6695337	139.702784
153	Sasazuka, Shibuya	35.6736448	139.667121
154	Sendagaya, Shibuya	35.6812658	139.711331
155	Tomigaya, Shibuya	35.6678503	139.687992
156	Yoyogi, Shibuya	35.6839519	139.702081
157	Ebara, Shinagawa	35.603876	139.707471
158	Gotanda, Shinagawa	35.6261042	139.723749
159	Goten'yama, Shinagawa	35.6204519	139.737324
160	Hatanodai, Shinagawa	35.6048759	139.702668
161	Higashi-Shinagawa, Shinagawa	35.7256133	139.719431
162	Higashi-Yashio, Shinagawa	35.6226765	139.770035
163	Katsushima, Shinagawa	35.5956917	139.748695
164	Kita-Shinagawa, Shinagawa	35.622322	139.739295
165	Minami-Shinagawa, Shinagawa	35.6151312	139.744234
166	Nakanobu, Shinagawa	35.6057217	139.712575
167	Nishi-Oi, Shinagawa	35.6018658	139.721671

168	Nishi-Shinagawa, Shinagawa	35.6018658	139.721671
169	Oi, Shinagawa	35.6129742	139.757588
170	Osaki, Shinagawa	35.6193759	139.728474
171	Togoshi, Shinagawa	35.6150626	139.716619
172	Yashio, Shinagawa	35.6226765	139.770035
173	Arakicho, Shinjuku	35.6909922	139.722518
174	Hatsudai, Shinjuku	35.6816399	139.687124
175	Ichigaya, Shinjuku	35.6923139	139.735589
176	Kabukicho, Shinjuku	35.6936102	139.701902
177	Kagurazaka, Shinjuku	35.703889	139.734222
178	Nishi-Ochiai, Shinjuku	35.7226607	139.682504
179	Nishi-Shinjuku, Shinjuku	35.6944228	139.692779
180	Nishi-Waseda, Shinjuku	35.7079235	139.70904
181	Okubo, Shinjuku	35.7007911	139.697319
182	Shinjuku, Shinjuku	35.6912419	139.699606
183	Takadanobaba, Shinjuku	35.7126401	139.703874
184	Toyama, Shinjuku	35.7064472	139.704262
185	Ushigome, Shinjuku	35.6994676	139.725588
186	Wakaba, Shinjuku	35.6839216	139.724648
187	Yotsuya, Shinjuku	35.6861799	139.729371
188	Asagaya, Suginami	35.7048403	139.635472
189	Koenji, Suginami	35.7049419	139.649909
190	Ogikubo, Suginami	35.7042661	139.620027
191	Higashi-Mukojima, Sumida	35.724279	139.81932
192	Honjo, Sumida	35.7086163	139.804359
193	Kinshicho, Sumida	35.6963122	139.815043
194	Mukojima, Sumida	35.7249733	139.810565
195	Ryogoku, Sumida	35.6957996	139.79296
196	Akihabara, Taito	35.6984193	139.77553
197	Asakusa, Taito	35.717528	139.797635
198	Hanakawado, Taito	35.7142234	139.799615
199	Ikenohata, Taito	35.7093025	139.76977
200	Iriya, Taito	35.7207249	139.784563
201	Kaminarimon, Taito	35.7111333	139.796368
202	Negishi, Taito	35.711356	139.775481
203	Ueno, Taito	35.7117877	139.776096
204	Yanagibashi, Taito	35.6992485	139.789238
205	Yanaka, Taito	35.721218	139.766042
206	Ikebukuro, Toshima	35.7301957	139.711153
207	Mejiro, Toshima	35.7211861	139.706482
208	Sugamo, Toshima	35.7334119	139.739427
209	Nishiarai-Sakaecho, Adachi	35.77574	139.788168
210	Gobancho, Chiyoda	35.6896	139.733948

211	Kudanminami, Chiyoda	35.692411	139.742472
212	Nibancho, Chiyoda	35.685968	139.73631
213	Nihonbashi-Bakurocho, Chuo	35.694261	139.783043
214	Nihonbashi-Hakozakicho, Chuo	35.680134	139.786538
215	Nihonbashi-Hisamatsucho, Chuo	35.689413	139.784421
216	Nihonbashi-Honcho, Chuo	35.688059	139.776122
217	Nihonbashi-Honkokucho, Chuo	35.687322	139.771317
218	Nihonbashi-Kabutocho, Chuo	35.680332	139.77728
219	Nihonbashi-Kakigaracho, Chuo	35.682565	139.785439
220	Nihonbashi-Kayabacho, Chuo	35.679372	139.77928
221	Nihonbashi-Koamicho, Chuo	35.68277	139.780806
222	Nihonbashi-Kodenmacho, Chuo	35.691526	139.779283
223	Nihonbashi-Nakasu, Chuo	35.68331	139.790715
224	Nihonbashi-Ningyocho, Chuo	35.685745	139.783864
225	Nihonbashi-Tomizawacho, Chuo	35.681342	139.773507
226	Nihonbashi-Yokoyamacho, Chuo	35.693124	139.783641
227	Nihonbashi-Odenmacho, Chuo	35.690249	139.779751
228	Miyoshi, Koto	35.680464	139.805617
229	Higashi-yukigaya, Ota	35.594179	139.691215
230	Nishi-Kamata, Ota	35.566201	139.712959
231	Kita-Karasuyama, Setagaya	35.676495	139.596904
232	Ebisuminami, Shibuya	35.644684	139.708947
233	Ebisunishi, Shibuya	35.648374	139.706796
234	Maruyama-cho, Shibuya	35.657538	139.694719
235	Sakuragaoka-cho, Shibuya	35.655591	139.701188
236	Udagawa-cho, Shibuya	35.662254	139.698081
237	Higashi-Oi, Shinagawa	35.602596	139.740486
238	Minami-Oi, Shinagawa	35.593237	139.734268
239	Hara-machi, Shinjuku	35.699995	139.723823
240	Hyakunin-cho, Shinjuku	35.703721	139.69832
241	Ichigaya-Tamachi, Shinjuku	35.694926	139.737546
242	Ichigaya-Yanagi-cho, Shinjuku	35.698872	139.726525
243	Kasumigaokamachi, Shinjuku	35.676866	139.717048
244	Kawada-cho, Shinjuku	35.696617	139.719427
245	Sumiyoshi-cho, Shinjuku	35.693507	139.721046
246	Azuma-bashi, Sumida	35.709169	139.803142

Table A.2. List of venue categories

ATM	Deli / Bodega	Kosher Restaurant	Salad Place

Acai House	Department Store	Kushikatsu Restaurant	Salon / Barbershop
Accessories Store	Dessert Shop	Lake	Sandwich Place
Adult Boutique	Dim Sum Restaurant	Laundromat	Sauna / Steam Room
Afghan Restaurant	Diner	Lawyer	Scandinavian Restaurant
African Restaurant	Discount Store	Library	Scenic Lookout
American Restaurant	Dog Run	Light Rail Station	Science Museum
Antique Shop	Donburi Restaurant	Lighthouse	Sculpture Garden
Aquarium	Dongbei Restaurant	Liquor Store	Seafood Restaurant
Arcade	Donut Shop	Lounge	Shabu-Shabu Restaurant
Argentinian Restaurant	Drugstore	Luggage Store	Shanghai Restaurant
Art Gallery	Dumpling Restaurant	Malay Restaurant	Shipping Store
Art Museum	Eastern European Restaurant	Market	Shoe Repair
Arts & Crafts Store	Electronics Store	Martial Arts Dojo	Shoe Store
Asian Restaurant	Erotic Museum	Mediterranean Restaurant	Shopping Mall
Athletics & Sports	Event Space	Men's Store	Shopping Plaza
Australian Restaurant	Exhibit	Metro Station	Shrine
Auto Garage	Fabric Shop	Mexican Restaurant	Skate Park
BBQ Joint	Factory	Middle Eastern Restaurant	Skating Rink
Baby Store	Falafel Restaurant	Miscellaneous Shop	Ski Shop
Bagel Shop	Farmers Market	Mobile Phone Shop	Smoke Shop
Bakery	Fast Food Restaurant	Mongolian Restaurant	Snack Place
Balinese Restaurant	Field	Monjayaki Restaurant	Soba Restaurant
Bar	Fish Market	Monument / Landmark	Soccer Field
Baseball Field	Fishing Spot	Moroccan Restaurant	Soup Place
Baseball Stadium	Fishing Store	Motorcycle Shop	South Indian Restaurant

Bath House	Flower Shop	Movie Theater	Southern / Soul Food Restaurant
Beach	Food	Multiplex	Souvenir Shop
Bed & Breakfast	Food & Drink Shop	Museum	Spa
Beer Bar	Food Court	Music Store	Spanish Restaurant
Beer Garden	Food Truck	Music Venue	Sporting Goods Shop
Beer Store	Forest	Nabe Restaurant	Sports Bar
Belarusian Restaurant	Fountain	Nature Preserve	Sports Club
Belgian Restaurant	French Restaurant	Nightclub	Sri Lankan Restaurant
Betting Shop	Fried Chicken Joint	Noodle House	Stables
Bike Rental / Bike Share	Frozen Yogurt Shop	North Indian Restaurant	Stadium
Bike Shop	Furniture / Home Store	Office	Stationery Store
Bistro	Gaming Cafe	Okonomiyaki Restaurant	Steakhouse
Boat or Ferry	Garden	Opera House	Street Art
Bookstore	Gastropub	Optical Shop	Street Food Gathering
Botanical Garden	General Entertainment	Organic Grocery	Sukiyaki Restaurant
Boutique	German Restaurant	Other Great Outdoors	Supermarket
Bowling Alley	Gift Shop	Other Nightlife	Sushi Restaurant
Bowling Green	Go Kart Track	Outdoor Event Space	Swim School
Boxing Gym	Golf Driving Range	Outdoor Sculpture	Szechuan Restaurant
Brazilian Restaurant	Gourmet Shop	Outdoor Supply Store	Taco Place
Breakfast Spot	Greek Restaurant	Outlet Store	Taiwanese Restaurant
Brewery	Grocery Store	Paintball Field	Takoyaki Place
Bridge	Gym	Pakistani Restaurant	Tapas Restaurant
Bubble Tea Shop	Gym / Fitness Center	Palace	Taxi Stand
Buddhist Temple	Gym Pool	Paper / Office Supplies Store	Tea Room
Buffet	Halal Restaurant	Park	Tempura Restaurant

Building	Harbor / Marina	Parking	Tennis Court
Burger Joint	Hardware Store	Pastry Shop	Tennis Stadium
Burmese Restaurant	Hawaiian Restaurant	Performing Arts Venue	Thai Restaurant
Burrito Place	Henan Restaurant	Peruvian Restaurant	Theater
Bus Station	Herbs & Spices Store	Pet Caf√©	Theme Park
Bus Stop	Himalayan Restaurant	Pet Store	Theme Park Ride / Attraction
Business Center	Historic Site	Pharmacy	Theme Restaurant
Butcher	History Museum	Photography Lab	Thrift / Vintage Store
Cafeteria	Hobby Shop	Photography Studio	Toll Booth
Cafe	Home Service	Piano Bar	Tonkatsu Restaurant
Cajun / Creole Restaurant	Hong Kong Restaurant	Pie Shop	Tourist Information Center
Cambodian Restaurant	Hookah Bar	Pier	Toy / Game Store
Camera Store	Hostel	Pizza Place	Track Stadium
Campground	Hot Dog Joint	Planetarium	Trail
Canal	Hot Spring	Platform	Train Station
Candy Store	Hotel	Playground	Tram Station
Cantonese Restaurant	Hotel Bar	Plaza	Tree
Caribbean Restaurant	Hotpot Restaurant	Pool	Tunnel
Cemetery	IT Services	Pool Hall	Turkish Restaurant
Champagne Bar	Ice Cream Shop	Port	Udon Restaurant
Cheese Shop	Indian Restaurant	Portuguese Restaurant	Unagi Restaurant
Chinese Restaurant	Indie Movie Theater	Print Shop	Used Bookstore
Chocolate Shop	Indie Theater	Pub	Vape Store
Church	Indonesian Restaurant	Public Art	Vegetarian / Vegan Restaurant
Climbing Gym	Inn	Ramen Restaurant	Video Store
Clothing Store	Intersection	Record Shop	Vietnamese Restaurant
Cocktail Bar	Irish Pub	Recording Studio	Wagashi Place
Coffee Shop	Italian Restaurant	Rental Car Location	Water Park

Comedy Club	Japanese Curry Restaurant	Rental Service	Whisky Bar
Comfort Food Restaurant	Japanese Restaurant	Rest Area	Wine Bar
Comic Shop	Jazz Club	Restaurant	Wine Shop
Concert Hall	Jewelry Store	River	Wings Joint
Convenience Store	Juice Bar	Road	Women's Store
Cosmetics Shop	Kaiseki Restaurant	Rock Club	Xinjiang Restaurant
Coworking Space	Karaoke Bar	Roller Rink	Yakitori Restaurant
Creperie	Karaoke Box	Roof Deck	Yoga Studio
Cruise	Kebab Restaurant	Rugby Stadium	Yoshoku Restaurant
Cycle Studio	Kids Store	Russian Restaurant	Zoo
Czech Restaurant	Korean Restaurant	Sake Bar	Zoo Exhibit