Tourist Guide

Introduction

When travelling, different people come with different tastes. Some people travel to visit historical places and museums, others travel to spend time at famous bars or nightclubs, and more recently, more people have become interested in what is called 'Food Tourism'. Therefore, this project is going to consider a list of large cities from all over the world, and it is going to group them according to the type of tourism they offer.

This recommender system can be of interest to tourists from all over the globe, who are willing to get some suggestions regarding cities to visit which satisfy their touristic interests.

This can also be of interest to people willing to invest in any of these categories of tourism (historical
places/museums, bars\nightclubs and food), as it helps them to choose between cities where each of these categories is booming or those which the market that has not saturated yet and can still accept more investment to boom. The Foursquare API can be used to obtain the list of venues for each of the cities considered.

Data Description

Data Sources

The list of different cities in the world is obtained from the 'World City Database' from the site https://simplemaps.com/data/world-cities (https://simplemaps.com/data/world-cities)

The dataset has been built from the ground up using authoritative sources such as the NGIA, US Geological Survey, US Census Bureau, and NASA. It was last refreshed in April of 2019. The database contains around 13 thousand entries.

The file containing the list of cities and countries with their corresponding longitudes and latitudes is in CSV format with no missing data in these columns. This can be imported and then the Foursquare API can be used to get the venues for each city.

Data Cleaning

The column used to get the names of the cities from the dataset is 'city_ascii' and not the 'city' column to avoid the appearance of special characters that come from different languages. Therefore, the columns to keep are 'city_ascii', 'country', 'lat' and 'lng'. Then, change 'city_ascii; column name into 'city'.

Some city names are repeated, therefore only the first occurrence of the city is kept, while the duplicates are dropped.

Since, not all cities will be of interest to tourists due to the lack of venues that belong to the categories (historical places/museums, bars\nightclubs and food), some cities need to be dropped. Our metric to choose the cities to drop will be the total number of hotels, hostels and motels in each city, as it gives a good indication to how touristic this city is. If the total number of touristic residences is equal to zero, the city will be dropped.

In order to decide if a given venue can be considered as an accommodation for tourists or not, the category of the venue will be checked if it belongs to the following list of words (hotel, motel, hostel, auberge, inn, lodge, tavern, guesthouse, B and B, resort, camp, room, apartment, mansion) obtained from

https://www.merriam-webster.com/thesaurus/hotel

https://relatedwords.org/relatedto/hotel

Sometimes, the Foursquare API returns no venues for a given city, or none of the venues belong to the three categories (historical places/museums, bars\nightclubs and food), therefore this city is dropped.

For each of the remaining cities, venues that belong to the three categories will be counted, while other venues will not be included.

Methodology

Exploring Dataset

After preprocessing the data from the list of cities database, in addition to their corresponding venues obtained using Foursquare's API, the dataset needs to be explored to get an idea about the different countries that exist in our final dataset, the cities that have the highest number of restaurants, or museums/historical places or places suitable for night life.

This dataset can give us different insights about how touristic the city is by looking at the number of hotels, we can get an idea about the size of the city or the number of visitors based on the total number of restaurants.

The cities can be sorted based on the highest number of hotels and we get:

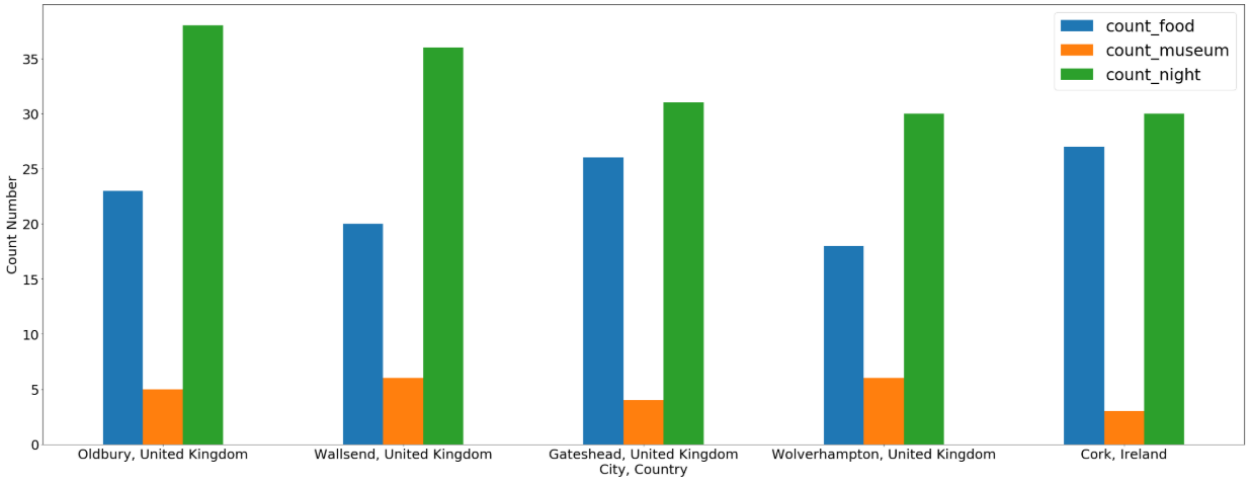
	city	count_accom	count_food	count_museum	count_night	country	lat	lng	city, country
0	Siem Reap	39	29	3	7	Cambodia	13.3666	103.8500	Siem Reap, Cambodia
1	Nevsehir	29	14	1	2	Turkey	38.6240	34.7240	Nevsehir, Turkey
2	Bavaro	29	23	0	15	Dominican Republic	18.7170	-68.4500	Bavaro, Dominican Republic
3	Stans	27	24	2	1	Switzerland	46.9500	8.3833	Stans, Switzerland
4	Da Nang	26	34	0	10	Vietnam	16.0600	108.2500	Da Nang, Vietnam
5	Estes Park	25	17	1	6	United States	40.3702	-105.5222	Estes Park, United States
6	El Calafate	25	13	0	3	Argentina	-50.3333	-72.3000	El Calafate, Argentina
7	Kandy	25	21	1	4	Sri Lanka	7.2800	80.6700	Kandy, Sri Lanka
8	Ohrid	24	27	4	14	Macedonia	41.1172	20.8019	Ohrid, Macedonia
9	Bocas del Toro	24	18	0	8	Panama	9.3354	-82.2475	Bocas del Toro, Panama

It seems that the highest number of hotels criteria is not a good indication of how touristic the city is, since sorting the list of city using this criteria resulted in cities that are not that famous for tourism.

The cities can also be sorted to get the ones with the most nightlife possibilities:

	city	count_accom	count_food	count_museum	count_night	country	lat	lng	city, country
0	Oldbury	2	23	5	38	United Kingdom	52.5000	-2.0167	Oldbury, United Kingdom
1	Wallsend	4	20	6	36	United Kingdom	54.9914	-1.5597	Wallsend, United Kingdom
2	Gateshead	3	26	4	31	United Kingdom	54.9450	-1.6175	Gateshead, United Kingdom
3	Wolverhampton	2	18	6	30	United Kingdom	52.5833	-2.1333	Wolverhampton, United Kingdom
4	Cork	2	27	3	30	Ireland	51.8986	-8.4958	Cork, Ireland
5	Galway	9	24	0	29	Ireland	53.2724	-9.0488	Galway, Ireland
6	Katerini	6	31	0	28	Greece	40.2723	22.5025	Katerini, Greece
7	Bradford	2	28	4	28	United Kingdom	53.8000	-1.7500	Bradford, United Kingdom
8	Walsall	4	13	4	28	United Kingdom	52.6000	-2.0000	Walsall, United Kingdom
9	Birmingham	2	27	4	28	United Kingdom	52.4750	-1.9200	Birmingham, United Kingdom

The top 5 cities with the highest number of nightlife venues have the following number of venues that belong to other categories:

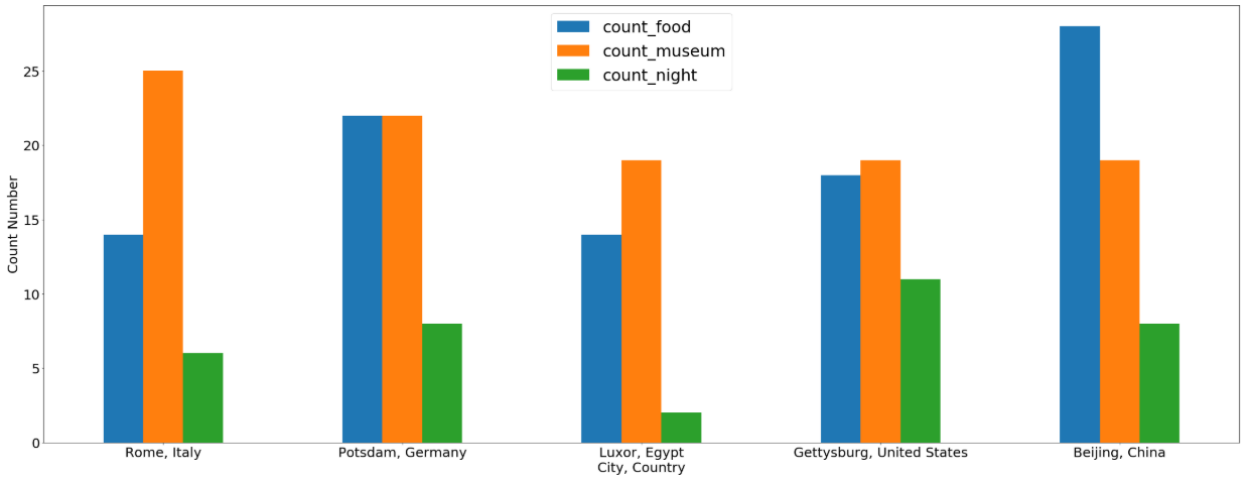


The results shown in the bar plot above shows that the United Kingdom is dominating the top 5 list when it comes to nightlife. Also, note that cities that have rich nightlife tend to have high number of restaurants too, which makes sense, since when the number of bars, pubs, nightclubs and casino attendees increases, more restaurants are needed to serve them as well.

In addition, cities can be sorted once again to get the ones with the most historical sites and museums:

	city	count_accom	count_food	count_museum	count_night	country	lat	lng	city, country
0	Rome	1	14	25	6	Italy	41.8960	12.4833	Rome, Italy
1	Potsdam	3	22	22	8	Germany	52.4004	13.0700	Potsdam, Germany
2	Luxor	10	14	19	2	Egypt	25.7000	32.6500	Luxor, Egypt
3	Gettysburg	7	18	19	11	United States	39.8304	-77.2339	Gettysburg, United States
4	Beijing	17	28	19	8	China	39.9289	116.3883	Beijing, China
5	Washington	6	23	18	8	United States	38.9047	-77.0163	Washington, United States
6	Ankara	1	14	18	13	Turkey	39.9272	32.8644	Ankara, Turkey
7	Diyarbakir	6	22	18	4	Turkey	37.9204	40.2300	Diyarbakir, Turkey
8	St. Petersburg	8	2	17	9	Russia	59.9390	30.3160	St. Petersburg, Russia
9	Al Quds	15	19	17	7	West Bank	31.7764	35.2269	Al Quds, West Bank

The top 5 cities with the highest number of museums and historical sites venues have the following number of venues that belong to other categories:

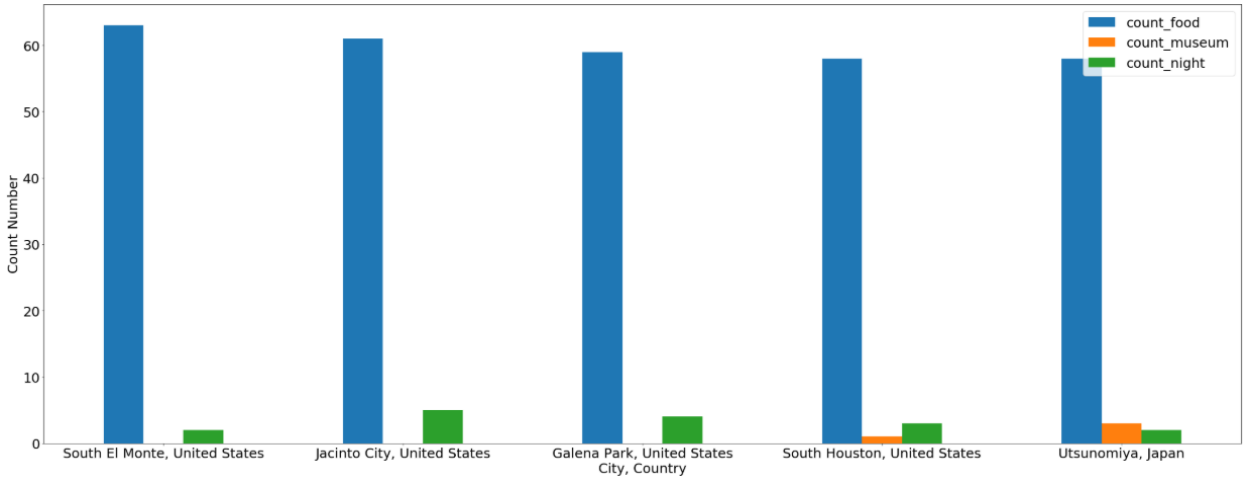


We notice a cultural diversity when sorting cities based on the number of historical sites available. However, even though the number of historical sites is greater than that of nightlife venues, the number of restaurants is still high enough and competes with the number of historical sites. This makes it less clear when clustering cities that are well known for their historical sites.

As for the cities with the highest number of restaurants, they are as follows:

	city	count_accom	count_food	count_museum	count_night	country	lat	lng	city, country	trending_food
0	South El Monte	1	63	0	2	United States	34.0493	-118.0484	South El Monte, United States	0
1	Jacinto City	1	61	0	5	United States	29.7663	-95.2410	Jacinto City, United States	0
2	Galena Park	1	59	0	4	United States	29.7452	-95.2333	Galena Park, United States	0
3	South Houston	1	58	1	3	United States	29.6611	-95.2285	South Houston, United States	0
4	Utsunomiya	2	58	3	2	Japan	36.5500	139.8700	Utsunomiya, Japan	0
5	Chon Buri	1	57	0	2	Thailand	13.4004	101.0000	Chon Buri, Thailand	0
6	Fukuoka	7	56	3	6	Japan	33.5950	130.4100	Fukuoka, Japan	0
7	Addison	1	56	1	3	United States	32.9587	-96.8356	Addison, United States	0
8	Marbella	4	55	1	7	Spain	36.5166	-4.8833	Marbella, Spain	0
9	Kangar	4	55	1	1	Malaysia	6.4330	100.1900	Kangar, Malaysia	0

While the top 5 of them have the following number of venues that belong to other categories:



When sorting cities based on the number of restaurants, we notice that the United states dominates this time the top 5 list. In addition, for the top 5 cities, the number of restaurants is incomparable to the number of museums or nightlife venues. In addition, the cities that made it to the top 5 are not that well-known to be destinations (judged by the total number of hotels), which can be an interesting suggestion for tourists to try new unknown restaurants.

Now K-means clustering algorithm in order to group the cities into clusters that have similar touristic destinations, however before doing that, the total number of venues that belong to each of the three categories (historical places/museums, bars\nightclubs and food) we have needs to be normalized due to the wide range of numbers we have.

After the normalization, we get the following dataset:

	city	count_accom	count_food	count_museum	count_night	country	lat	lng	city, country	ratio_food	ratio_museum	ratio_night
0	South El Monte	1	63	0	2	United States	34.0493	-118.0484	South El Monte, United States	0.969231	0.000000	0.030769
1	Jacinto City	1	61	0	5	United States	29.7663	-95.2410	Jacinto City, United States	0.924242	0.000000	0.075758
2	Galena Park	1	59	0	4	United States	29.7452	-95.2333	Galena Park, United States	0.936508	0.000000	0.063492
3	South Houston	1	58	1	3	United States	29.6611	-95.2285	South Houston, United States	0.935484	0.016129	0.048387
4	Utsunomiya	2	58	3	2	Japan	36.5500	139.8700	Utsunomiya, Japan	0.920635	0.047619	0.031746

Using K-means clustering algorithm to cluster our dataset into 4 clusters, we get the following result:

	count_accom	count_food	count_museum	count_night	lat	lng	city, country	ratio_food	ratio_museum	ratio_night	Cluster Labels
0	3	50	1	5	35.4480	-94.3529	Van Buren, United States	0.892857	0.017857	0.089286	3
1	5	36	7	11	35.8869	14.4025	Imdina, Malta	0.666667	0.129630	0.203704	1
2	4	36	6	9	4.5964	-74.0833	Bogota, Colombia	0.705882	0.117647	0.176471	1
3	6	49	1	9	20.5504	-97.4700	Poza Rica de Hidalgo, Mexico	0.830508	0.016949	0.152542	3
4	2	5	2	2	48.3318	40.2518	Kamensk Shakhtinskiy, Russia	0.555556	0.222222	0.222222	1
5	3	37	5	16	37.6897	-97.3442	Wichita, United States	0.637931	0.086207	0.275862	1
6	2	40	0	2	34.9514	-89.9787	Southaven, United States	0.952381	0.000000	0.047619	3
7	5	37	1	5	26.0293	-80.1678	Hollywood, United States	0.860465	0.023256	0.116279	3
8	7	37	14	7	37.5663	126.9997	Seoul, Korea, South	0.637931	0.241379	0.120690	1
9	1	14	0	2	43.0282	-74.9928	Herkimer, United States	0.875000	0.000000	0.125000	3
10	2	1	0	0	42.8071	22.3247	Crna Trava, Serbia	1.000000	0.000000	0.000000	3
11	4	38	0	6	42.3765	-122.9109	Central Point, United States	0.863636	0.000000	0.136364	3
12	18	38	0	5	42.5361	1.5828	Encamp, Andorra	0.883721	0.000000	0.116279	3
13	1	37	0	8	41.7980	-87.9569	Clarendon Hills, United States	0.822222	0.000000	0.177778	3
14	4	5	0	2	54.8612	-6.2763	Ballymena, United Kingdom	0.714286	0.000000	0.285714	1
15	3	21	0	4	-25.3800	-51.4800	Guarapuava, Brazil	0.840000	0.000000	0.160000	3
16	1	38	1	12	41.6000	-87.6905	Markham, United States	0.745098	0.019608	0.235294	1
17	5	28	2	3	18.4504	-97.3800	Tehuacan, Mexico	0.848485	0.060606	0.090909	3
18	2	8	1	4	46.4367	15.9536	Dornava, Slovenia	0.615385	0.076923	0.307692	1
19	1	35	3	10	41.9663	-87.8057	Harwood Heights, United States	0.729167	0.062500	0.208333	1

Results

Let's check the characteristics of few cities that correspond to each of the 4 clusters. This gives us an idea of the best type of tourism that can be done at the cities that belong to each of the clusters.

The results show the name of each of the city, the number of the cluster that denoted by the column 'Cluster_labels', the latitude and the longitude that can be used with Foursquare's API to get more details about specific cities. In addition, the ratio of the venues that belong to each of the three categories we specified (historical places/museums, bars\nightclubs and food).

Cluster 1

A sample of 10 cities in the first cluster which contains 204 cities are shown below:

	count_food	lat	lng	city, country	ratio_food	ratio_museum	ratio_night	Cluster Labels
66	10	50.7004	-3.5300	Exeter, United Kingdom	0.333333	0.066667	0.600000	0
125	0	-5.9897	39.2519	Mahonda, Tanzania	0.000000	0.000000	1.000000	0
178	0	-0.5196	37.4500	Embu, Kenya	0.000000	0.000000	1.000000	0
249	3	0.0204	37.0600	Nanyuki, Kenya	0.428571	0.000000	0.571429	0
375	3	46.5103	15.0806	Slovenj Gradec, Slovenia	0.375000	0.000000	0.625000	0
383	0	57.7647	36.6900	Bezhetsk, Russia	0.000000	0.000000	1.000000	0
500	6	54.8800	-2.9300	Carlisle, United Kingdom	0.315789	0.105263	0.578947	0
515	1	2.7800	32.2800	Gulu, Uganda	0.333333	0.000000	0.666667	0
521	0	58.4503	-130.0333	Dease Lake, Canada	0.000000	0.000000	1.000000	0
569	0	-20.0809	146.2587	Charters Towers, Australia	0.000000	0.000000	1.000000	0

Cluster 2

A sample of 10 cities in the second cluster which contains 2835 cities are shown below:

	count_food	lat	lng	city, country	ratio_food	ratio_museum	ratio_night	Cluster Labels
1	36	35.8869	14.4025	Imdina, Malta	0.666667	0.129630	0.203704	1
2	36	4.5964	-74.0833	Bogota, Colombia	0.705882	0.117647	0.176471	1
4	5	48.3318	40.2518	Kamensk Shakhtinskiy, Russia	0.555556	0.222222	0.222222	1
5	37	37.6897	-97.3442	Wichita, United States	0.637931	0.086207	0.275862	1
8	37	37.5663	126.9997	Seoul, Korea, South	0.637931	0.241379	0.120690	1
14	5	54.8612	-6.2763	Ballymena, United Kingdom	0.714286	0.000000	0.285714	1
16	38	41.6000	-87.6905	Markham, United States	0.745098	0.019608	0.235294	1
18	8	46.4367	15.9536	Dornava, Slovenia	0.615385	0.076923	0.307692	1
19	35	41.9663	-87.8057	Harwood Heights, United States	0.729167	0.062500	0.208333	1
22	37	41.9193	-88.3110	Saint Charles, United States	0.804348	0.000000	0.195652	1

Cluster 3

A sample of 10 cities in the third cluster which contains 183 cities are shown below:

	count_food	lat	lng	city, country	ratio_food	ratio_museum	ratio_night	Cluster Labels
29	1	57.3364	23.1235	Mersrags, Latvia	0.333333	0.666667	0.000000	2
49	1	28.6800	115.8800	Nanchang, China	0.500000	0.500000	0.000000	2
65	0	39.4763	75.9699	Kashgar, China	0.000000	1.000000	0.000000	2
80	12	40.8182	-74.0022	Fairview, United States	0.428571	0.428571	0.142857	2
151	14	39.9272	32.8644	Ankara, Turkey	0.311111	0.400000	0.288889	2
200	0	-28.8780	28.0560	Hlotse, Lesotho	0.000000	1.000000	0.000000	2
215	1	55.9077	21.8456	Plunge, Lithuania	0.333333	0.333333	0.333333	2
272	1	28.0304	73.3299	Bikaner, India	0.333333	0.666667	0.000000	2
285	1	43.9443	116.0443	Xilinhot, China	0.333333	0.666667	0.000000	2
338	14	25.7000	32.6500	Luxor, Egypt	0.400000	0.542857	0.057143	2

Cluster 4

A sample of 10 cities in the fourth cluster which contains 3432 cities are shown below:

	count_food	lat	lng	city, country	ratio_food	ratio_museum	ratio_night	Cluster Labels
0	50	35.4480	-94.3529	Van Buren, United States	0.892857	0.017857	0.089286	3
3	49	20.5504	-97.4700	Poza Rica de Hidalgo, Mexico	0.830508	0.016949	0.152542	3
6	40	34.9514	-89.9787	Southaven, United States	0.952381	0.000000	0.047619	3
7	37	26.0293	-80.1678	Hollywood, United States	0.860465	0.023256	0.116279	3
9	14	43.0282	-74.9928	Herkimer, United States	0.875000	0.000000	0.125000	3
10	1	42.8071	22.3247	Crna Trava, Serbia	1.000000	0.000000	0.000000	3
11	38	42.3765	-122.9109	Central Point, United States	0.863636	0.000000	0.136364	3
12	38	42.5361	1.5828	Encamp, Andorra	0.883721	0.000000	0.116279	3
13	37	41.7980	-87.9569	Clarendon Hills, United States	0.822222	0.000000	0.177778	3
15	21	-25.3800	-51.4800	Guarapuava, Brazil	0.840000	0.000000	0.160000	3

The first cluster includes mainly the cities that have higher ratio of venues that can be categorized as nightlife. As for the third cluster is dominated by the cities that have higher ratio of museums and historical places. While the fourth cluster is dominated by cities that have higher ratio of restaurants.

The second cluster contains cities that have almost equal ratios of nightlife venues, museums and historical places, while the ratio of restaurants is dominating.

The number of cities that belong to the clusters 2 and 3 are more than those that belong to clusters 1 and 4 and that is probably since that cities with higher ratio of restaurants are usually more than cities that have dominating ratios of nightlife and historical sites venues.

Discussion

As I mentioned before, when travelling, different people come with different tastes. Some people travel to visit historical places and museums, others travel to spend time at famous bars or nightclubs, and more recently, more people have become interested in what is called 'Food Tourism'.

Therefore, in this project I used K-means clustering algorithm to group different cities with different ratios of venues that belong to each of the three categories we had, into different clusters. The list of cities is obtained from online dataset, while the venues that exist in each city is obtained using Foursquare's API.

This can be interesting for tourists from all over the globe, who are willing to get some suggestions regarding cities to visit which satisfy their touristic interests. In addition, people willing to invest in any of these categories of tourism (historical places/museums, bars\nightclubs and food) can make use of it to choose cities where each of these categories is booming or those which the market that has not saturated yet and can still accept more investment to boom.

We had 6654 cities in total, of which 204 belong to the first cluster, 2835 cities belong to the second cluster, 183 cities belong to the third clusters and 3432 cities are in the fourth cluster. This result is expected, as usually the number of restaurants in most of the cities is huge, therefore these two clusters are dominated by the ratio of the food venues. While clusters 1 and 3 that dominated by cities that have nightlife and historic venues respectively have smaller sizes.

Conclusion and Perspectives

Using the results of this project, people can have a better idea of what to expect when visiting certain cities or can target specific cities when seeking a certain type of tourism (historical places/museums, bars/nightclubs and food) or investment. This helps makes things easier for strangers visiting different cities.

More work can be done to include more cities and to filter the venues to get only the trending ones or those with high number of tips.