Capstone Project - The Battle of the Neighborhoods (Week 5)

Applied Data Science Capstone by IBM/Coursera

Clustering National Capitals for Travelers

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1. Introduction: Business Problem

In this project we will try to clustering national capitals cities. Specifically, this report will be targeted to stakeholders interested in travels to come to see the same or different cities, or to those who worked in tourism business.

Since we don't use information about how much cost this trip, we can help with choose destination for criteria how similar some cities with those they came to see before.

And for this we use tools from data sciences which we learned before.

2. Data

2.1. Summary

Based on definition of our problem, informations that will need are:

- list of capitals cities with population
- geographical coordinates for every city
- venues in every city for clustering

We can take more accurate information if we will use information based by venues in neighborhoods in every cities, but for first look choose we wouldn't use it.

Following data sources will be needed to extract/generate the required information:

- list of capitals with population we take from Wiki https://en.wikipedia.org/wiki/List_of_national_capitals_by_population
- coordinates cities will be obtained using Nominatim from geopy.geocoders libraries
- venues will be obtained using Foursquare API

2.2. Data taking and cleaning

We take data step by step:

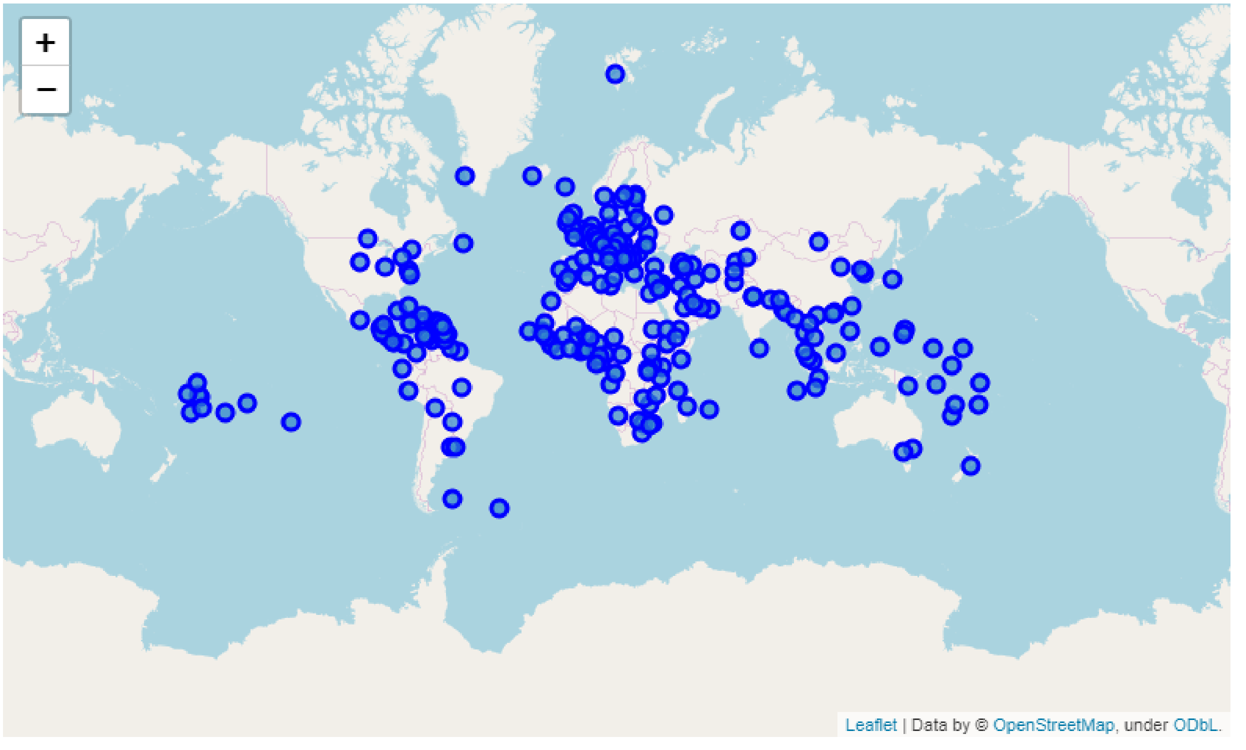
First, we take list of Capitals from table from Wiki pages. In this table we found that some of the Country have two capitals: de jure and de facto. We choose de facto, because some

Country have only de facto Capitals without de jure (Switzerland, Palestine, Nauru, *Montserrat (UK))*.

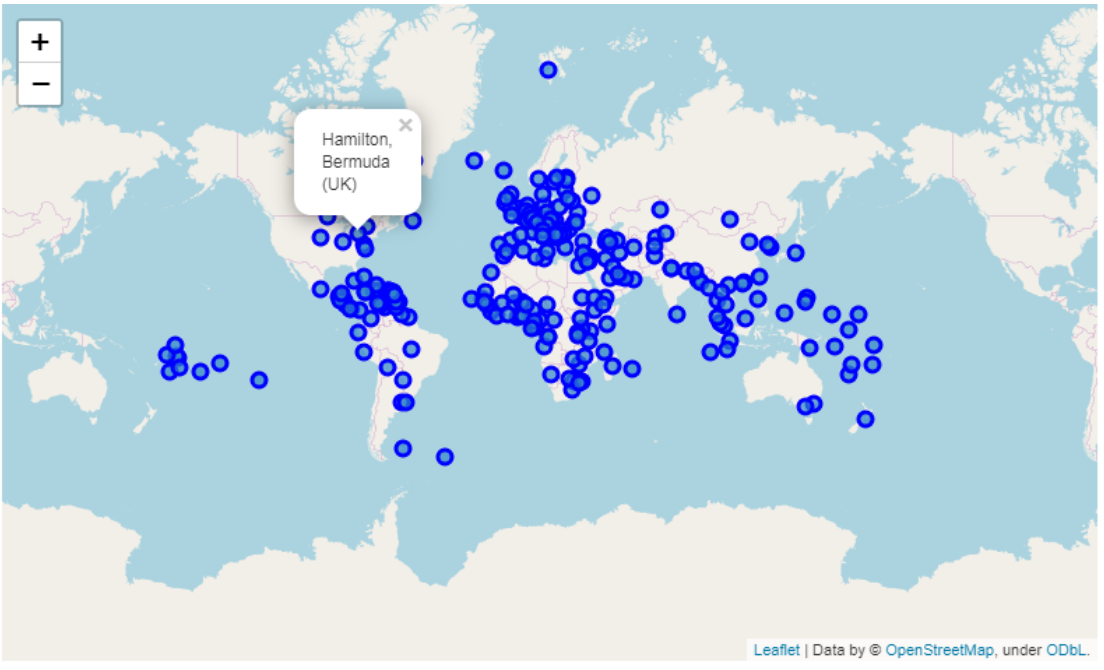
It contain 243 Capital.

After that we normalized data from column “Population” which we used to calculate how many venue we will take from every capital.

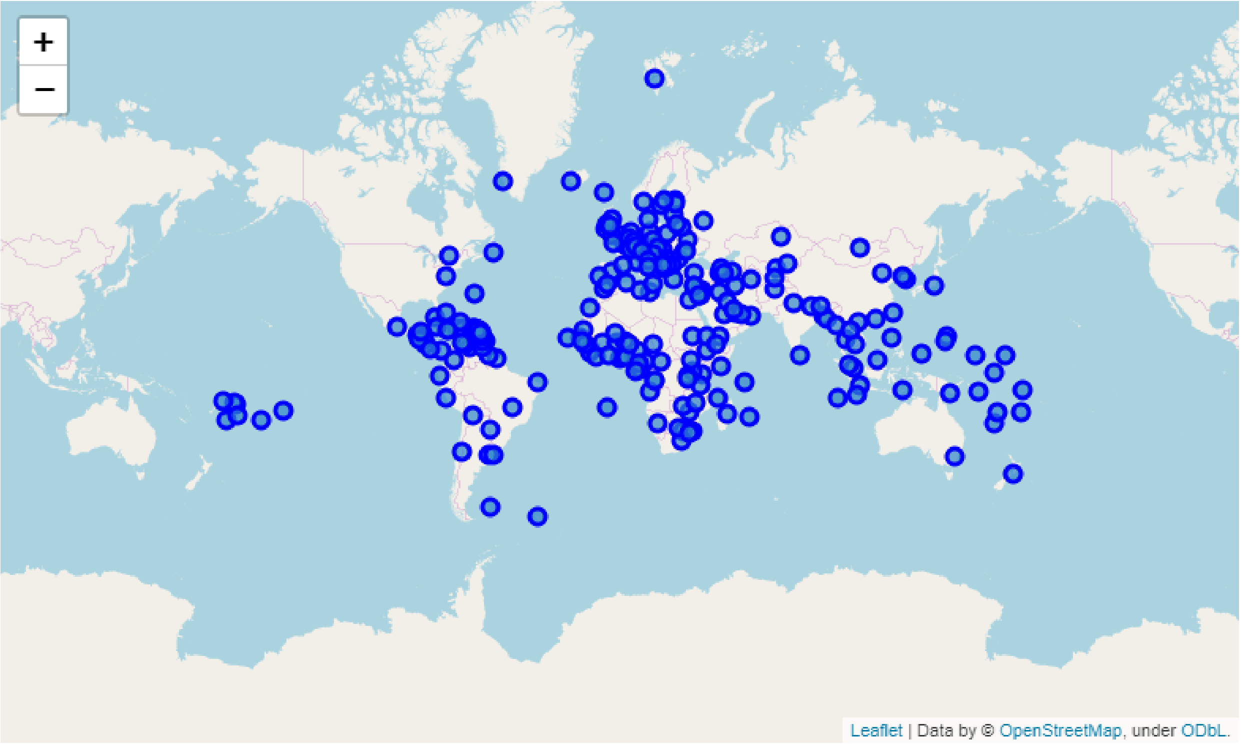
Second, we used name of Capitals to take their coordinates using Nominatim from geopy.geocoders libraries and place them on the map (Folium library):



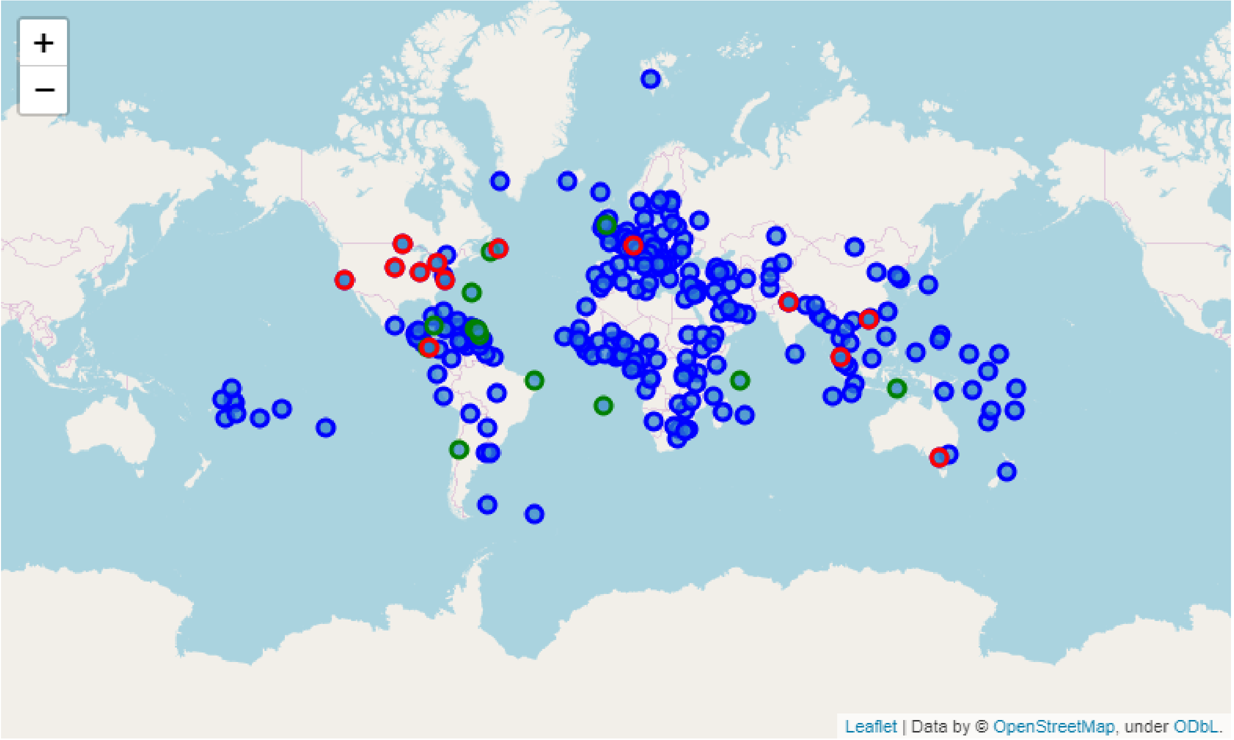
And we saw from it what some of the Capital on the wrong place:



We send another request to Nominatim with different (full) name of Capital with wrong coordinates and look again to the map:



Map with changes(red dot – wrong coordinates; green dot – new coordinates):



Third, venues in every capitals for clustering from Foursquare API.

For request to Foursquare API we need next things:
1. ID (took when we created Foursquare account)
2. Coordinates
3. Numbers of Venues
4. Radius of request

Because Capitals have different size, we need take for them different numbers of venue. For calculate them we used population of Capital with next formula:

Numbers of Venues = (Population / 100000) * 5

From one request we can take only 100 venues, so if Population in some Capital less than 2 million we put 100 venues for it.

And result:

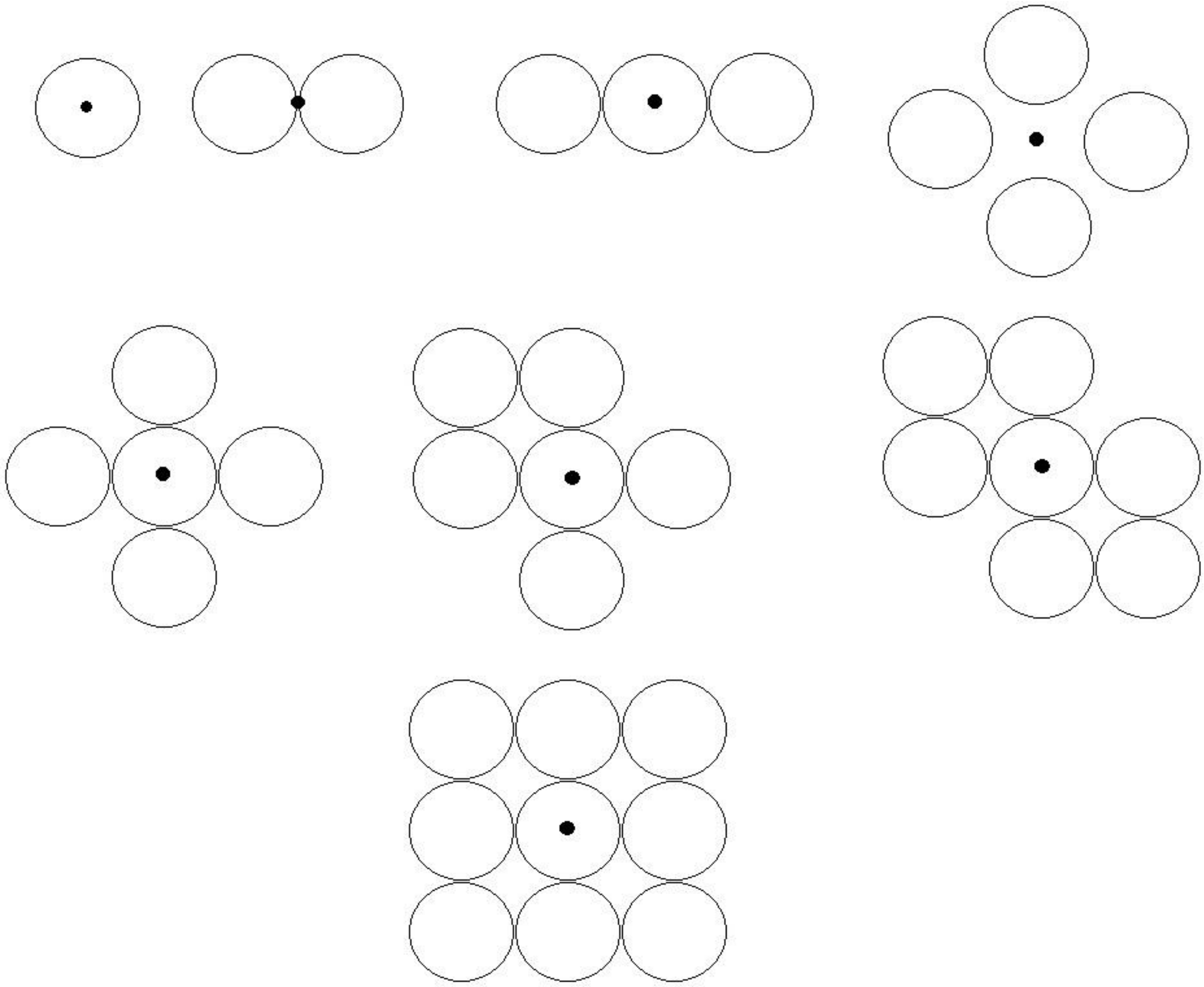
	Country/Territory	Capital	Population	Year	% ofcountry'spopulation	Latitude	Longitude	CountVenue
0	China PR	Beijing	21542000	2010	1.5%	39.906217	116.391276	1100
1	Japan	Tokyo	13929286	2017	11.03%	35.682839	139.759455	700
2	Russia	Moscow	12506468	2011	8.52%	55.479205	37.327330	700
3	DR Congo	Kinshasa	11855000	2012	12.9%	-4.321706	15.312597	600
4	Indonesia	Jakarta	10075310	2011	3.76%	-6.175394	106.827183	500
5	South Korea	Seoul	9838892	2015	19.03%	37.566679	126.978291	500
6	Egypt	Cairo	9500000	2012	9.54%	30.048819	31.243666	500
7	Mexico	Mexico City	8918653	2015	7.05%	19.432630	-99.133178	500
8	Bangladesh	Dhaka	8906039	2011	5.52%	23.759357	90.378814	500
9	United Kingdom England	London	8908081	2015	13.19%	51.507322	-0.127647	500

Because we can take only 100 venues from one request, for some capitals we need more than one point(coordinate). For this we calculate radius request. We send test request with different radius from 500 meters to 100 km (maximum for request), and when it return with 100 or more venues, we understand what we needed it. But first we send request with 100 km radius, because if we will take result less 100 venues, we don't need more calculation for this Capital. And then we change count of venue for this Capital.

	Country/Territory	Capital	Population	Year	% ofcountry'spopulation	Latitude	Longitude	CountVenue	RadiusRequest
0	China PR	Beijing	21542000	2010	1.5%	39.906217	116.391276	86	100000
1	Japan	Tokyo	13929286	2017	11.03%	35.682839	139.759455	700	1000
2	Russia	Moscow	12506468	2011	8.52%	55.479205	37.327330	572	16000
3	DR Congo	Kinshasa	11855000	2012	12.9%	-4.321706	15.312597	34	100000
4	Indonesia	Jakarta	10075310	2011	3.76%	-6.175394	106.827183	500	2000

After this calculate we found what Atafu, Adamstown and Brasilia have 0 venues, and if for Brasilia we took wrong coordinates from Nominatim (country instead city), but for Atafu and Adamstown we drop them.

Points for every Capital we took with next schemes:



Where black dot – current coordinates, circle’s radius equal calculated radius.

After that we took venues from those points.

In result we have 22619 venues from 240 capitals.

3. Methodology

For analysis data we use “k-means Clustering” from sklearn.cluster library with venue’s category.

4. Analysis

In our data we have 600 uniques categories. For clustering we use mean venue’s count for categories for every capital. In result we have 10 common category for every capital:

	Capital	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue	5th Most Common Venue	6th Most Common Venue	7th Most Common Venue	8th Most Common Venue	9th Most Common Venue	10th Most Common Venue
0	Abu Dhabi	Hotel	Resort	Beach	Theme Park	Golf Course	Water Park	Shopping Mall	Campground	Grocery Store	Mosque
1	Abuja	Shopping Mall	Hotel	Indian Restaurant	Fast Food Restaurant	Restaurant	Bar	Arcade	Department Store	Café	Ice Cream Shop
2	Accra	Hotel	African Restaurant	Shopping Mall	American Restaurant	Resort	Cocktail Bar	Department Store	Café	Fried Chicken Joint	Lounge
3	Addis Ababa	Hotel	Ethiopian Restaurant	Italian Restaurant	Café	Pizza Place	Restaurant	Middle Eastern Restaurant	Nightclub	Lounge	Turkish Restaurant
4	Algiers	French Restaurant	Hotel	Restaurant	Turkish Restaurant	Café	Seafood Restaurant	Construction & Landscaping	Burger Joint	Indian Restaurant	Diner

In first we clustering to 5 clusters, count for every cluster was:

```
                Capital
Cluster Labels
0.0                  23
1.0                 135
2.0                  51
3.0                   3
4.0                  29
```

As we can see, one of the cluster was a lot more then others, so we try from 3 to 125 cluster to find the most suitable. In Code we print only to 25, because it fill too much space, and after 25 we can see the same pattern:

```
For 3 number of clusters:
                Capital
Cluster Labels
0.0                  43
1.0                 196
2.0                   2
```

```
For 4 number of clusters:
                Capital
Cluster Labels
0.0                 181
1.0                   3
2.0                  12
3.0                  45
```

```
For 5 number of clusters:
                Capital
Cluster Labels
0.0                  23
1.0                 135
2.0                  51
3.0                   3
4.0                  29
```

```
For 6 number of clusters:
                Capital
Cluster Labels
0.0                 137
1.0                  42
2.0                   4
3.0                  38
4.0                  18
5.0                   2
```

```
For 7 number of clusters:
                Capital
Cluster Labels
0.0                  35
1.0                   5
2.0                   8
3.0                 139
4.0                  51
5.0                   1
6.0                   2
```

```
For 8 number of clusters:
                Capital
Cluster Labels
0.0                 121
1.0                   6
2.0                  24
3.0                  10
4.0                   2
5.0                  31
6.0                   1
7.0                  46
```

```
For 9 number of clusters:
                Capital
Cluster Labels
0.0                 113
1.0                   6
2.0                  11
3.0                  10
4.0                   2
5.0                  28
6.0                   1
7.0                  48
8.0                  22
```

```
For 10 number of clusters:
                Capital
Cluster Labels
0.0                 113
1.0                   6
2.0                  11
3.0                  10
4.0                   1
5.0                  28
6.0                   1
7.0                  48
8.0                  22
9.0                   1
```

For 11 number of clusters:

Cluster Labels	Capital
0.0	116
1.0	6
2.0	11
3.0	6
4.0	1
5.0	28
6.0	1
7.0	45
8.0	16
9.0	1
10.0	10

For 12 number of clusters:

Cluster Labels	Capital
0.0	84
1.0	32
2.0	1
3.0	1
4.0	18
5.0	1
6.0	26
7.0	47
8.0	28
9.0	1
10.0	1
11.0	1

For 13 number of clusters:

Cluster Labels	Capital
0.0	85
1.0	30
2.0	1
3.0	1
4.0	13
5.0	1
6.0	23
7.0	45
8.0	28
9.0	1
10.0	1
11.0	1
12.0	11

For 14 number of clusters:

Cluster Labels	Capital
0.0	77
1.0	30
2.0	1
3.0	1
4.0	13
5.0	1
6.0	23
7.0	49
8.0	31
9.0	1
10.0	1
11.0	1
12.0	11
13.0	1

For 15 number of clusters:

Cluster Labels	Capital
0.0	81
1.0	28
2.0	1
3.0	1
4.0	12
5.0	1
6.0	22
7.0	51
8.0	25
9.0	1
10.0	1
11.0	1
12.0	10
13.0	1
14.0	5

For 16 number of clusters:

Cluster Labels	Capital
0.0	71
1.0	25
2.0	1
3.0	1
4.0	12
5.0	1
6.0	24
7.0	50
8.0	35
9.0	1
10.0	1
11.0	1
12.0	10
13.0	1
14.0	5
15.0	2

For 17 number of clusters:

Cluster Labels	Capital
0.0	71
1.0	26
2.0	1
3.0	1
4.0	12
5.0	1
6.0	24
7.0	50
8.0	35
9.0	1
10.0	1
11.0	1
12.0	8
13.0	1
14.0	5
15.0	2
16.0	1

For 18 number of clusters:

Cluster Labels	Capital
0.0	70
1.0	29
2.0	1
3.0	1
4.0	12
5.0	1
6.0	22
7.0	54
8.0	30
9.0	1
10.0	1
11.0	1
12.0	8
13.0	1
14.0	5
15.0	2
16.0	1
17.0	1

For 19 number of clusters:

Cluster Labels	Capital
0.0	70
1.0	24
2.0	1
3.0	1
4.0	13
5.0	1
6.0	21
7.0	50
8.0	36
9.0	1
10.0	1
11.0	1
12.0	8
13.0	1
14.0	7
15.0	2
16.0	1
17.0	1
18.0	1

For 20 number of clusters:

Cluster Labels	Capital
0.0	17
1.0	2
2.0	10
3.0	20
4.0	1
5.0	42
6.0	2
7.0	1
8.0	1
9.0	17
10.0	9
11.0	28
12.0	1
13.0	1
14.0	2
15.0	81
16.0	1
17.0	3
18.0	1
19.0	1

For 21 number of clusters:

Cluster Labels	Capital
0.0	91
1.0	13
2.0	1
3.0	27
4.0	1
5.0	2
6.0	1
7.0	1
8.0	1
9.0	1
10.0	24
11.0	1
12.0	2
13.0	53
14.0	1
15.0	5
16.0	2
17.0	1
18.0	1
19.0	11
20.0	1

For 22 number of clusters:

Cluster Labels	Capital
0.0	18
1.0	21
2.0	2
3.0	12
4.0	1
5.0	1
6.0	4
7.0	48
8.0	1
9.0	2
10.0	1
11.0	32
12.0	13
13.0	2
14.0	1
15.0	11
16.0	57
17.0	1
18.0	2
19.0	1
20.0	1
21.0	9

For 23 number of clusters:

Cluster Labels	Capital
0.0	11
1.0	49
2.0	18
3.0	1
4.0	1
5.0	1
6.0	16
7.0	1
8.0	2
9.0	2
10.0	1
11.0	1
12.0	1
13.0	1
14.0	2
15.0	6
16.0	1
17.0	1
18.0	39
19.0	4
20.0	1
21.0	1
22.0	80

For 24 number of clusters:

Cluster Labels	Capital
0.0	11
1.0	49
2.0	17
3.0	1
4.0	1
5.0	1
6.0	16
7.0	1
8.0	2
9.0	2
10.0	1
11.0	1
12.0	1
13.0	1
14.0	2
15.0	6
16.0	1
17.0	1
18.0	39
19.0	4
20.0	1
21.0	1
22.0	80
23.0	1

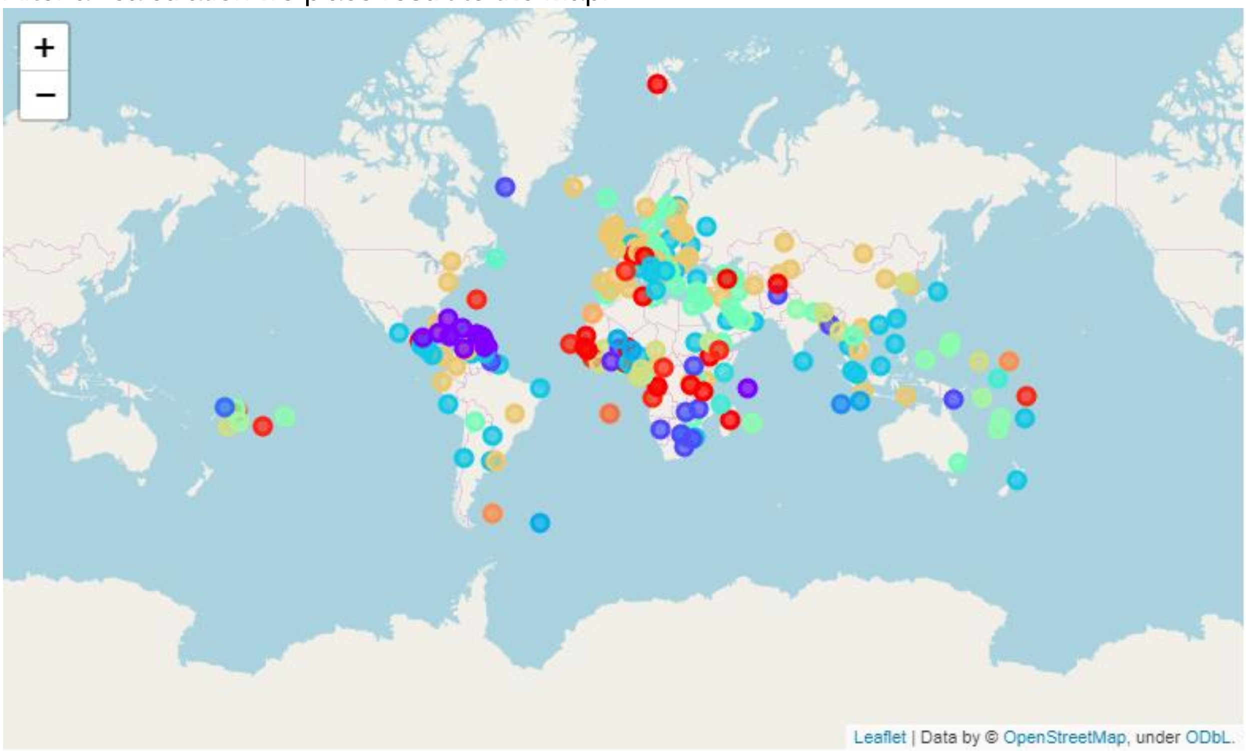
As we can see, 22 is most suitable value. It have 9 major group, and them related between every more or less.

Cluster Labels	Capital
0.0	18
1.0	21
2.0	2
3.0	12
4.0	1
5.0	1
6.0	4
7.0	48
8.0	1
9.0	2
10.0	1
11.0	32
12.0	13
13.0	2
14.0	1
15.0	11
16.0	57
17.0	1
18.0	2
19.0	1
20.0	1
21.0	9

5. Results and Discussion

5.1 Results

After all calculation we place result to the map:



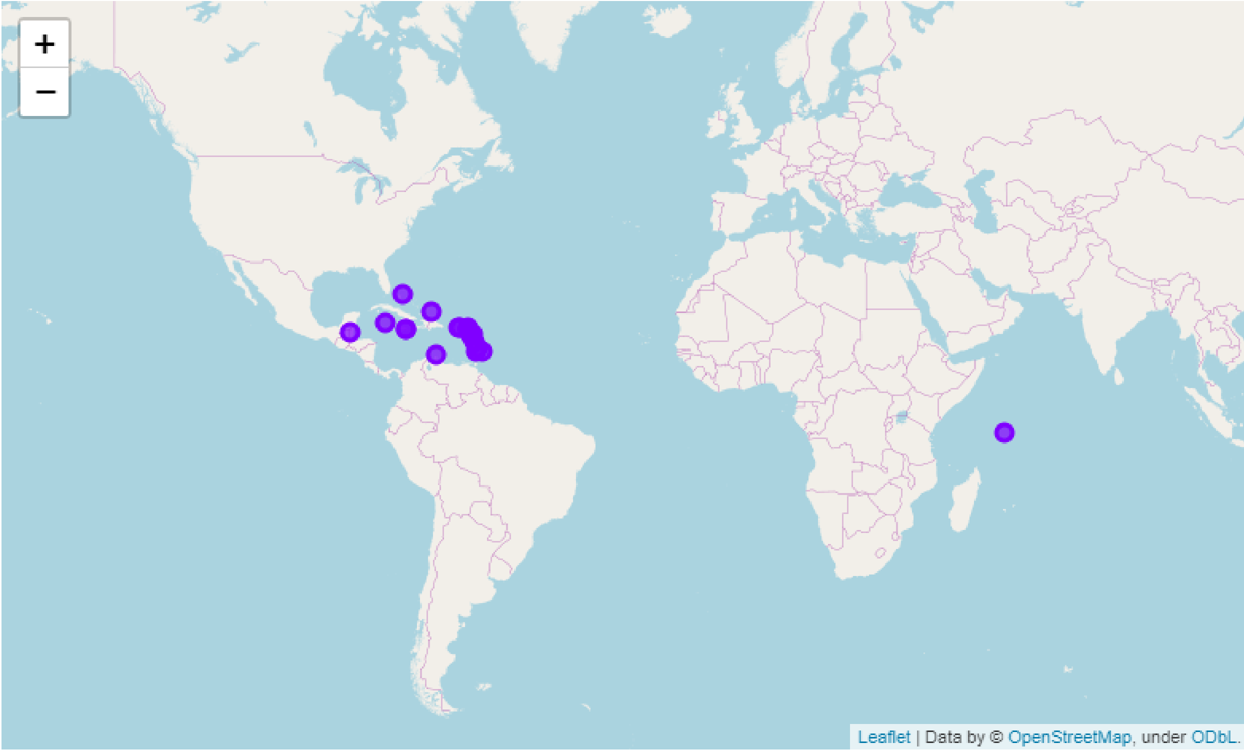
And for every cluster, except those who have only 1 Capital, we put them on one map. Here we show only a few first Capitals, and only 4 first Common Venue:

Cluster 1:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Kinshasa	DR Congo	11855000	-4.321706	15.312597	34	0	Hotel	Café	Fast Food Restaurant	Restaurant
Addis Ababa	Ethiopia	3040740	9.010793	38.761252	38	0	Hotel	Ethiopian Restaurant	Italian Restaurant	Café
Brazzaville	Congo	1827000	-4.269441	15.271226	34	0	Hotel	Café	Fast Food Restaurant	Restaurant
Antananarivo	Madagascar	1613375	-18.910012	47.525581	41	0	Hotel	Restaurant	French Restaurant	Shopping Mall

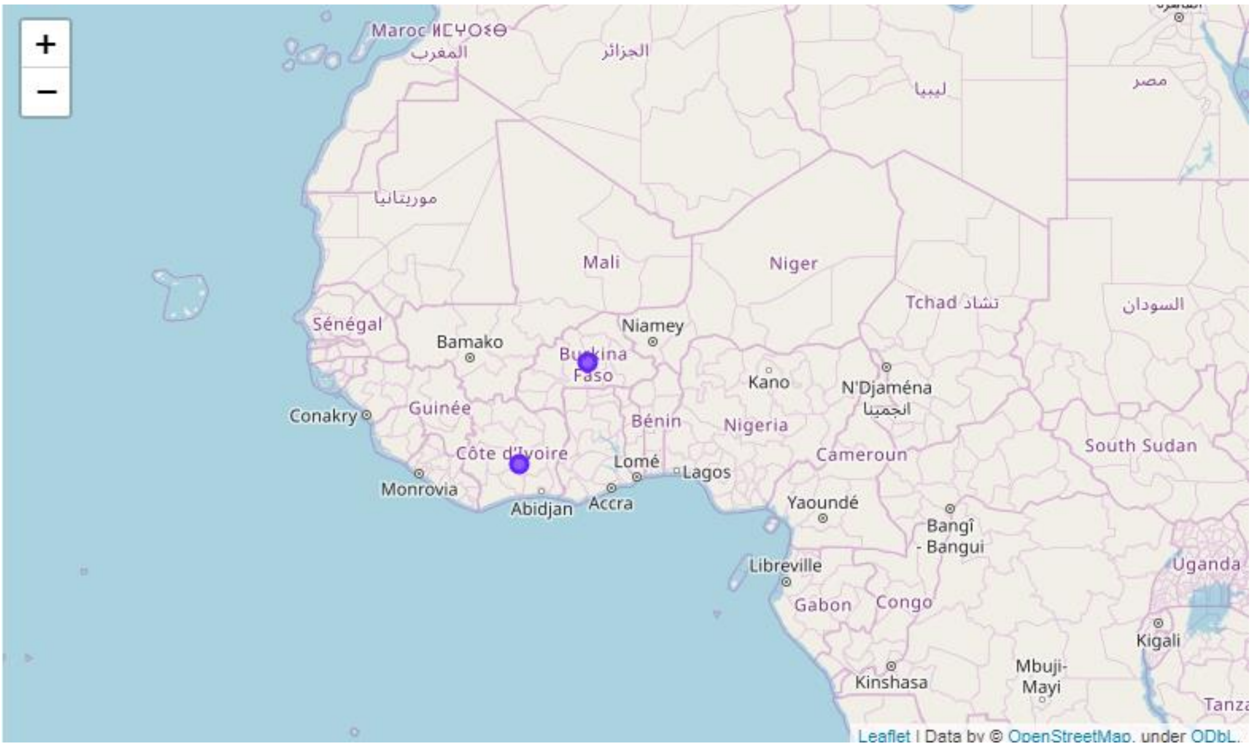
Cluster 2:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Kingston	Jamaica	701063	17.971215	-76.792813	194	1	Hotel	Resort	Beach	Caribbean Restaurant
Nassau	Bahamas	248948	25.078346	-77.338333	100	1	Resort	Beach	Bar	Coffee Shop
Bridgetown	Barbados	110000	13.097783	-59.618418	94	1	Caribbean Restaurant	Beach	Bar	Resort
Castries	Saint Lucia	70000	13.952589	-60.987824	100	1	Resort	Caribbean Restaurant	Hotel	Beach
Kingstown	Saint Vincent and the Grenadines	40020	13.156186	-61.227962	89	1	Caribbean Restaurant	Resort	Beach	Bar



Cluster 3:

	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Capital										
Ouagadougou	Burkina Faso	1005231	12.368148	-1.527085	11	2	Hotel	Nightclub	African Restaurant	Pool
Yamoussoukro	Côte d'Ivoire	454929	6.809107	-5.273263	4	2	Plaza	Hotel	African Restaurant	Hotel Pool

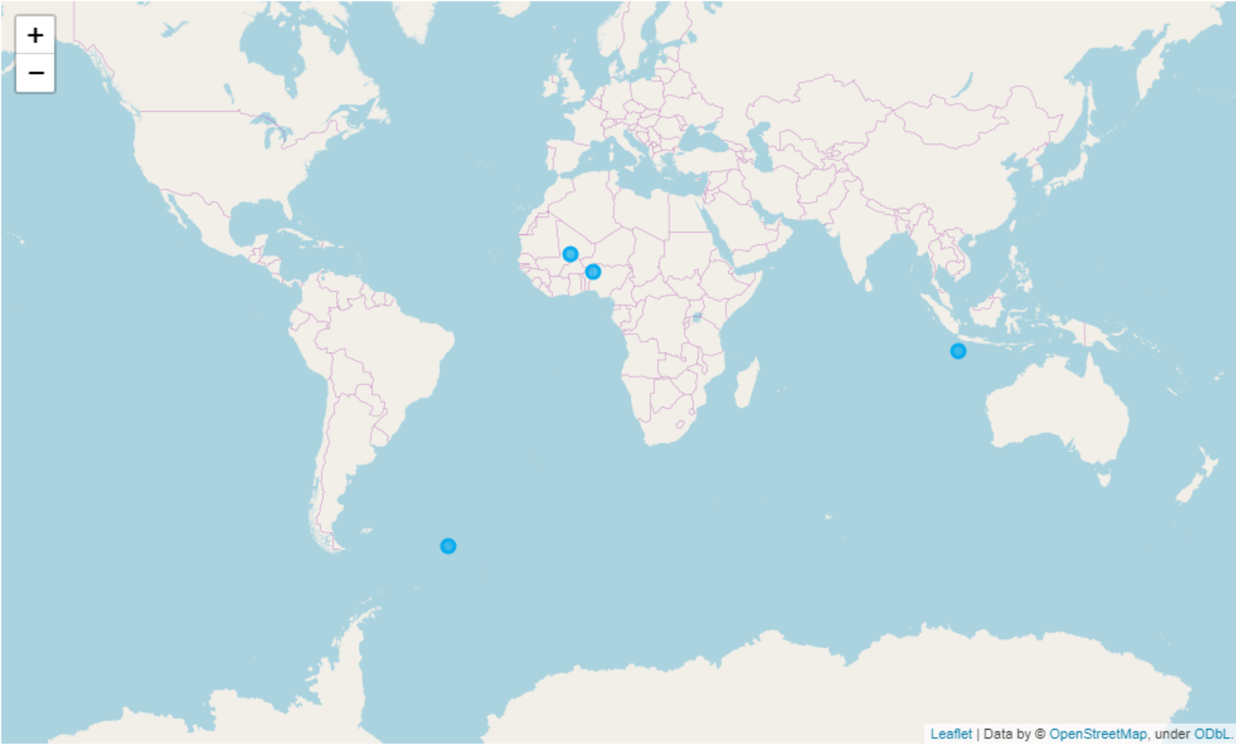


Cluster 4:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Kabul	Afghanistan	3140853	34.526013	69.177648	23	3	Hotel	Shopping Mall	Café	Afghan Restaurant
Lusaka	Zambia	1331254	-15.416449	28.282153	45	3	Hotel	Shopping Mall	Café	Restaurant
Islamabad	Pakistan	955629	22.330800	91.841286	32	3	Shopping Mall	Hotel	Indian Restaurant	Fast Food Restaurant
Lilongwe	Malawi	902388	-13.987511	33.768144	22	3	Shopping Mall	Hotel	Café	Italian Restaurant
Juba	South Sudan	372410	4.847202	31.595166	6	3	Hotel	Grocery Store	Restaurant	Café
Port Moresby	Papua New Guinea	299396	-9.474330	147.159950	16	3	Hotel	Asian Restaurant	Japanese Restaurant	Department Store
Maseru	Lesotho	267652	-29.310054	27.478222	8	3	Shopping Mall	Hotel	Casino	Restaurant

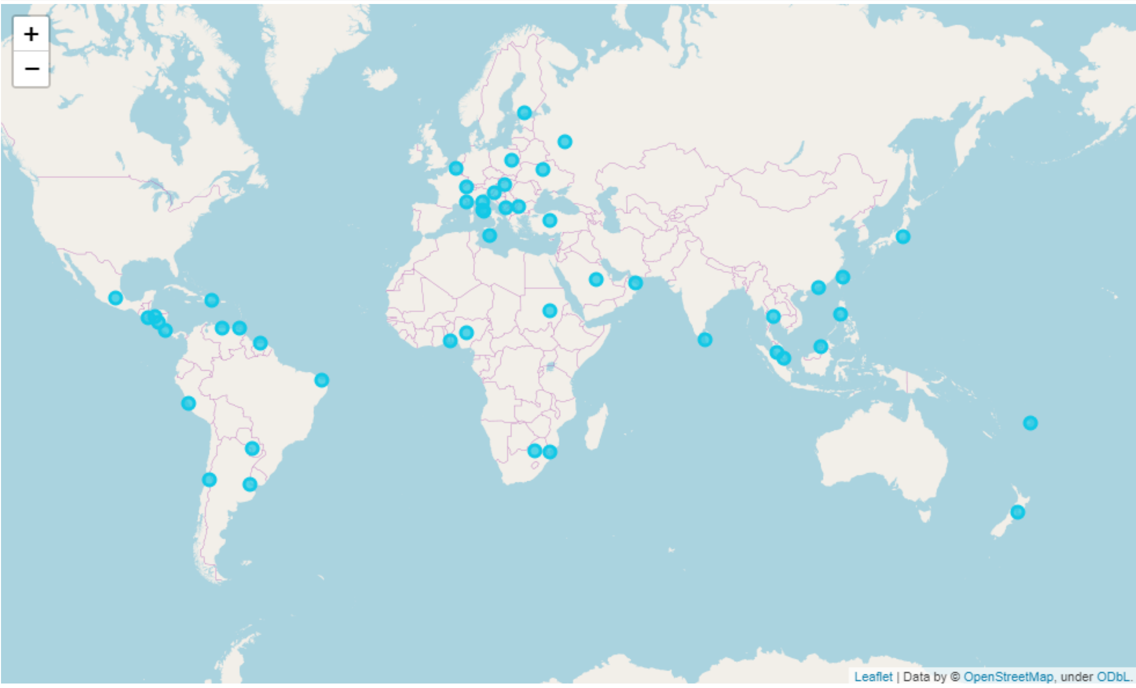
Cluster 7:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Malé	Maldives	103693	16.370036	-2.290024	8	6	Bakery	Auto Garage	Amphitheater	Campground
Tarawa	Kiribati	30000	11.588415	3.970774	11	6	Cafeteria	Business Service	Hotel	Cable Car
Flying Fish Cove	Christmas Island (Australia)	1493	-10.426665	105.668672	5	6	Chinese Restaurant	Bakery	Diner	Café
King Edward Point	South Georgia and the South Sandwich Islands (UK)	22	-54.283545	-36.494636	5	6	Beer Bar	Observatory	Racetrack	Harbor / Marina



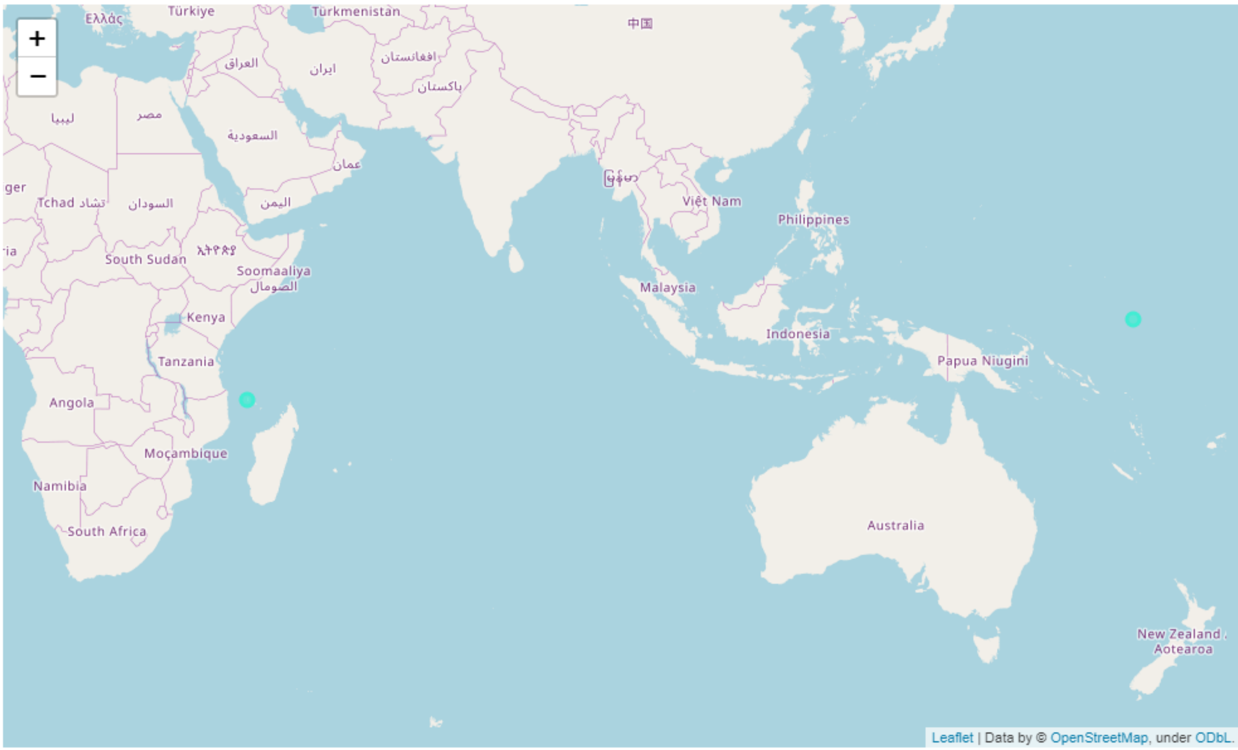
Cluster 8:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Tokyo	Japan	13929286	35.682839	139.759455	700	7	Japanese Restaurant	Café	Ramen Restaurant	Hotel
Moscow	Russia	12506468	55.479205	37.327330	572	7	Park	Gym / Fitness Center	Supermarket	Hotel
Mexico City	Mexico	8918653	19.432630	-99.133178	337	7	Mexican Restaurant	Bar	Taco Place	Restaurant
Lima	Peru	8852000	-12.062107	-77.036526	388	7	Peruvian Restaurant	Seafood Restaurant	Café	Fried Chicken Joint
Bangkok	Thailand	8305218	13.754253	100.493087	395	7	Noodle House	Convenience Store	Thai Restaurant	Café



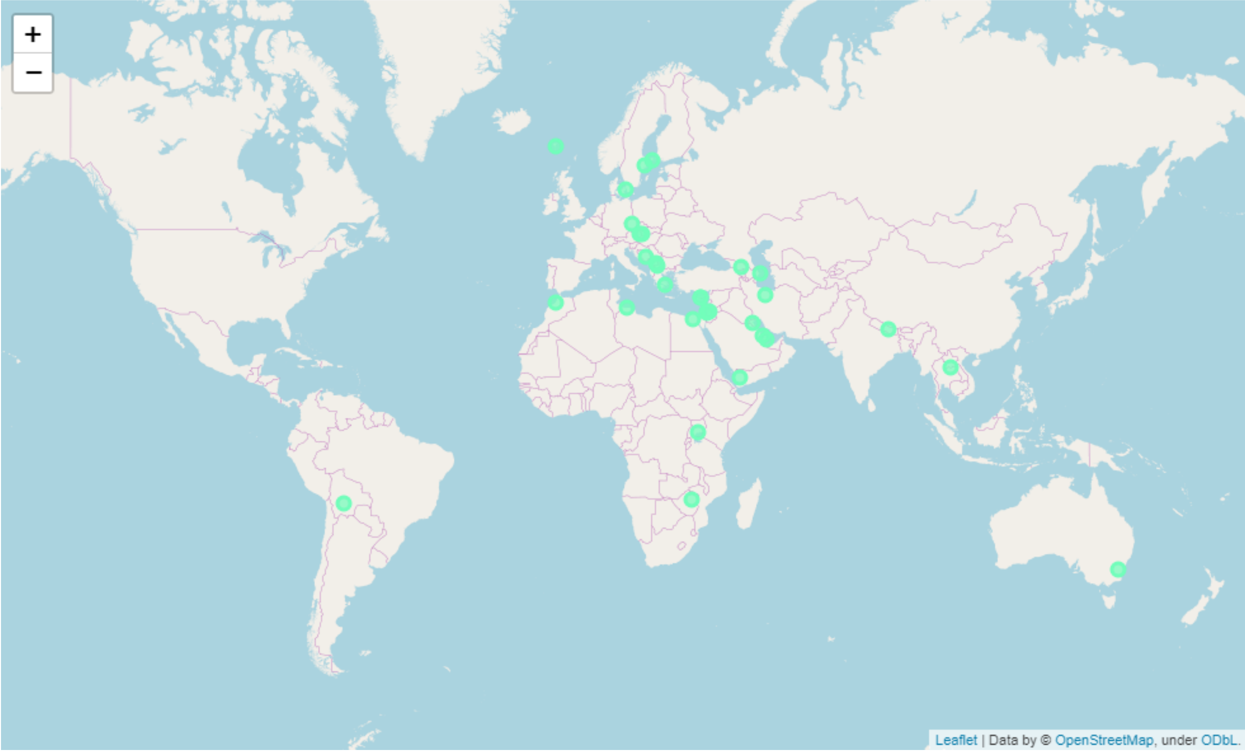
Cluster 10:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Moroni	Comoros	60200	-11.693126	43.254304	4	9	Hotel	Resort	Airport	Zoo Exhibit
Yaren	Nauru	1100	-0.547101	166.916400	4	9	Hotel	Department Store	Airport	Zoo Exhibit



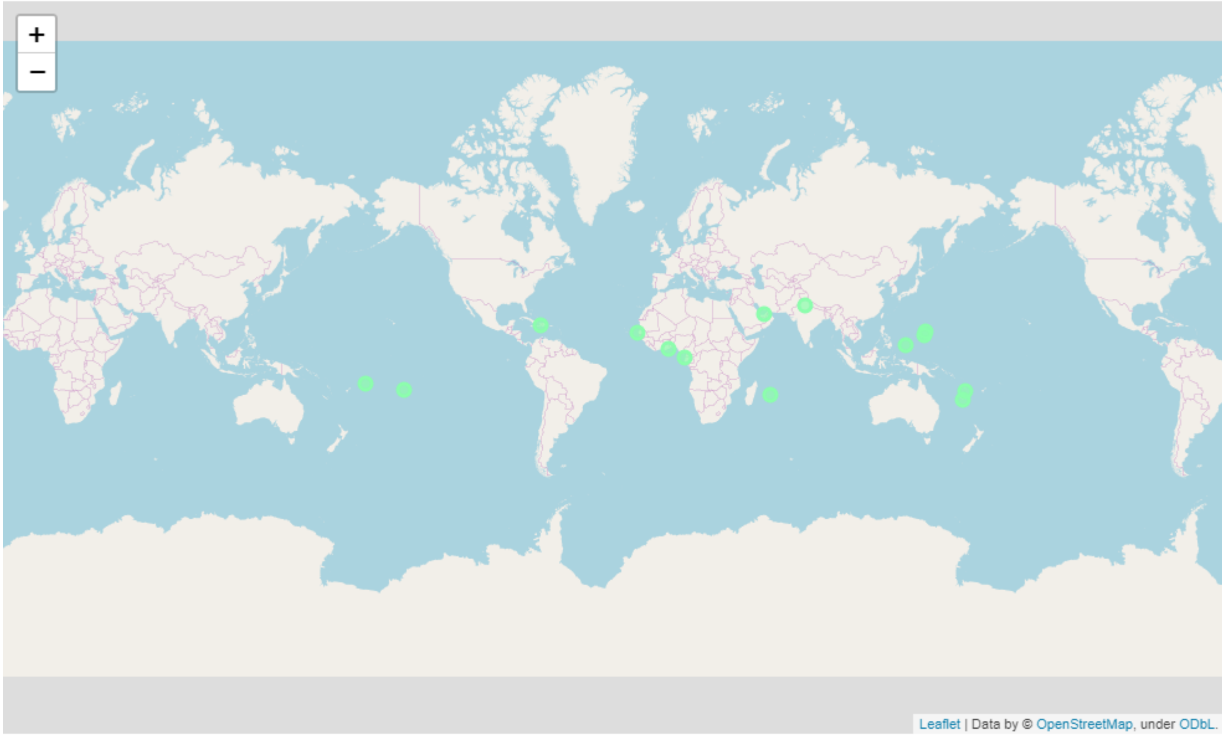
Cluster 12:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Cairo	Egypt	9500000	30.048819	31.243666	287	11	Café	Historic Site	Egyptian Restaurant	Middle Eastern Restaurant
Tehran	Iran	8693706	35.700618	51.401378	388	11	Café	Persian Restaurant	Bookstore	Coffee Shop
Amman	Jordan	2600603	31.951569	35.923963	200	11	Café	Middle Eastern Restaurant	Italian Restaurant	Bar
Baku	Azerbaijan	2204200	40.375443	49.832675	200	11	Café	Restaurant	Coffee Shop	Park
Rabat	Morocco	1789635	34.022405	-6.834543	100	11	Café	Hotel	French Restaurant	Moroccan Restaurant



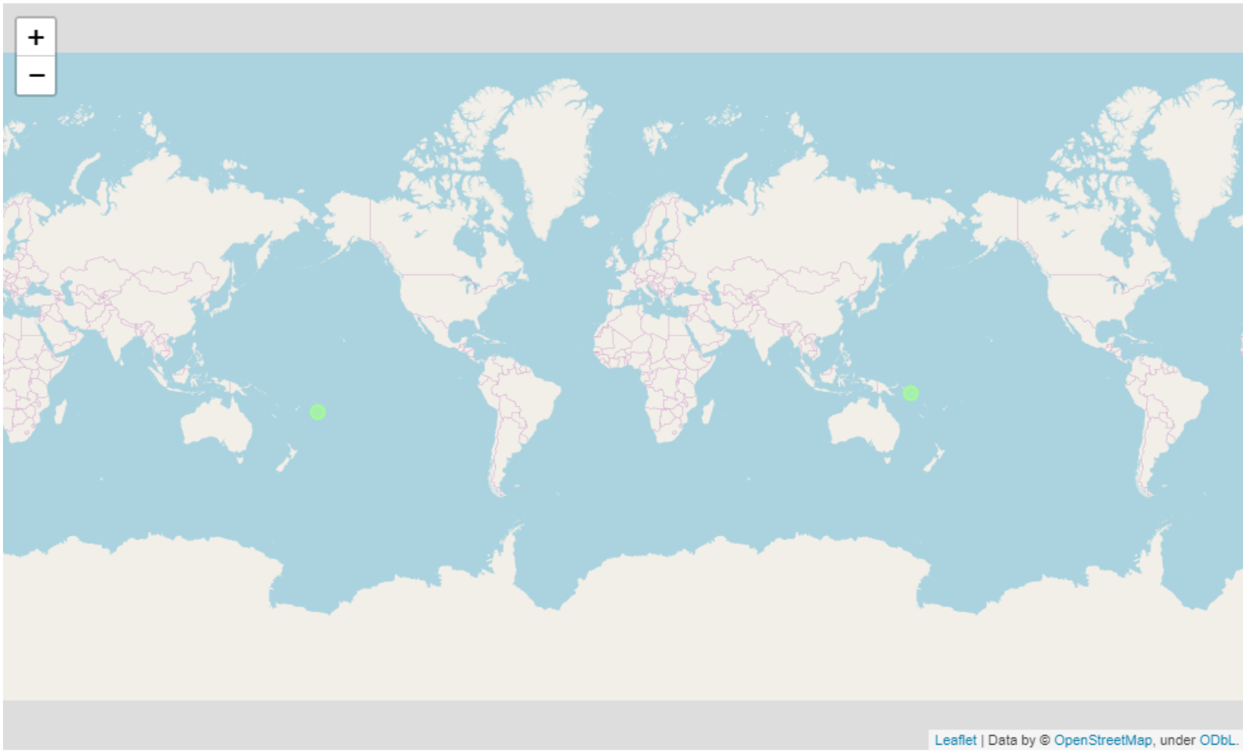
Cluster 13:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Accra	Ghana	1640507	5.560014	-0.205744	75	12	Hotel	African Restaurant	Shopping Mall	American Restaurant
Port-au-Prince	Haiti	1235227	18.547327	-72.339593	65	12	Resort	Hotel	Supermarket	Restaurant
Dakar	Senegal	1030594	14.693425	-17.447938	71	12	African Restaurant	Hotel	Seafood Restaurant	Shopping Mall
Abu Dhabi	United Arab Emirates	585097	24.474796	54.370576	49	12	Hotel	Resort	Beach	Theme Park
Libreville	Gabon	556425	0.390002	9.454001	22	12	Italian Restaurant	Bakery	Hotel	Restaurant
Port Louis	Mauritius	147251	-20.163728	57.504533	100	12	Hotel	Chinese Restaurant	Resort	Café



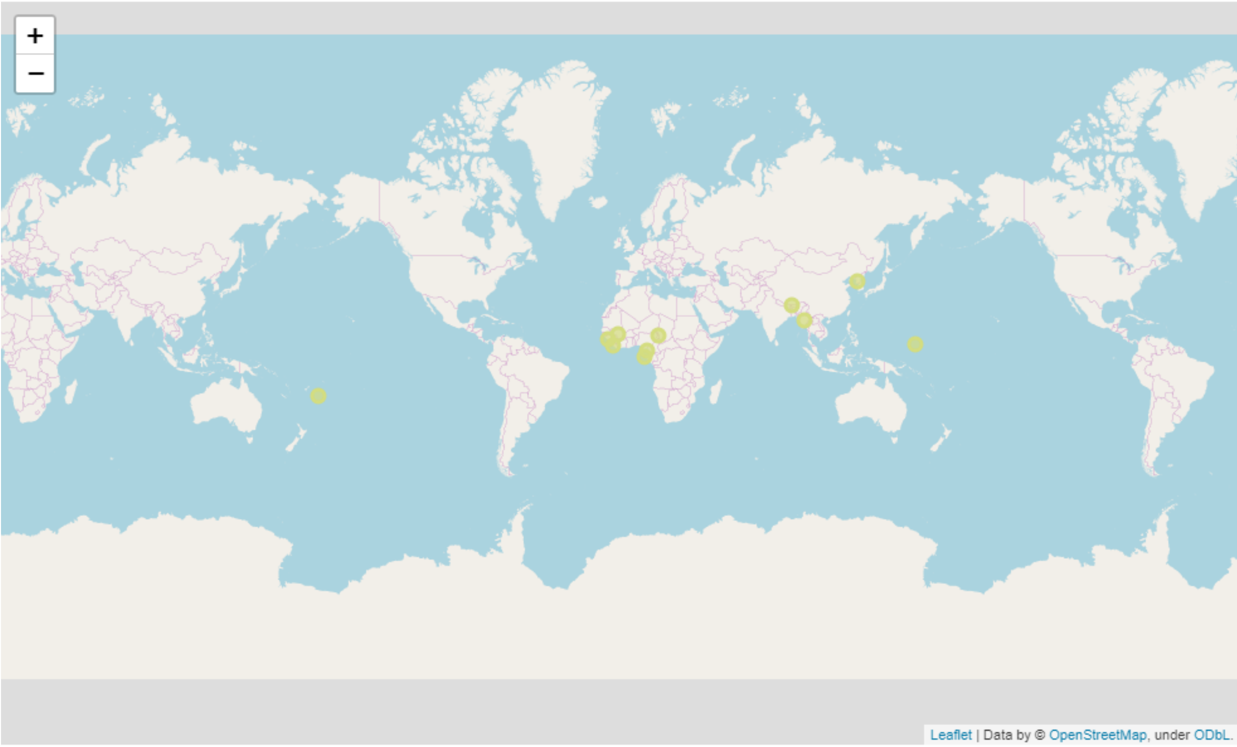
Cluster 14:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Honiara	Solomon Islands	59288	-9.431077	159.955255	4	13	Japanese Restaurant	Café	Australian Restaurant	Airport
Alofi	Niue (NZ)	616	-19.053416	-169.919199	5	13	Japanese Restaurant	Café	Warehouse Store	Airport



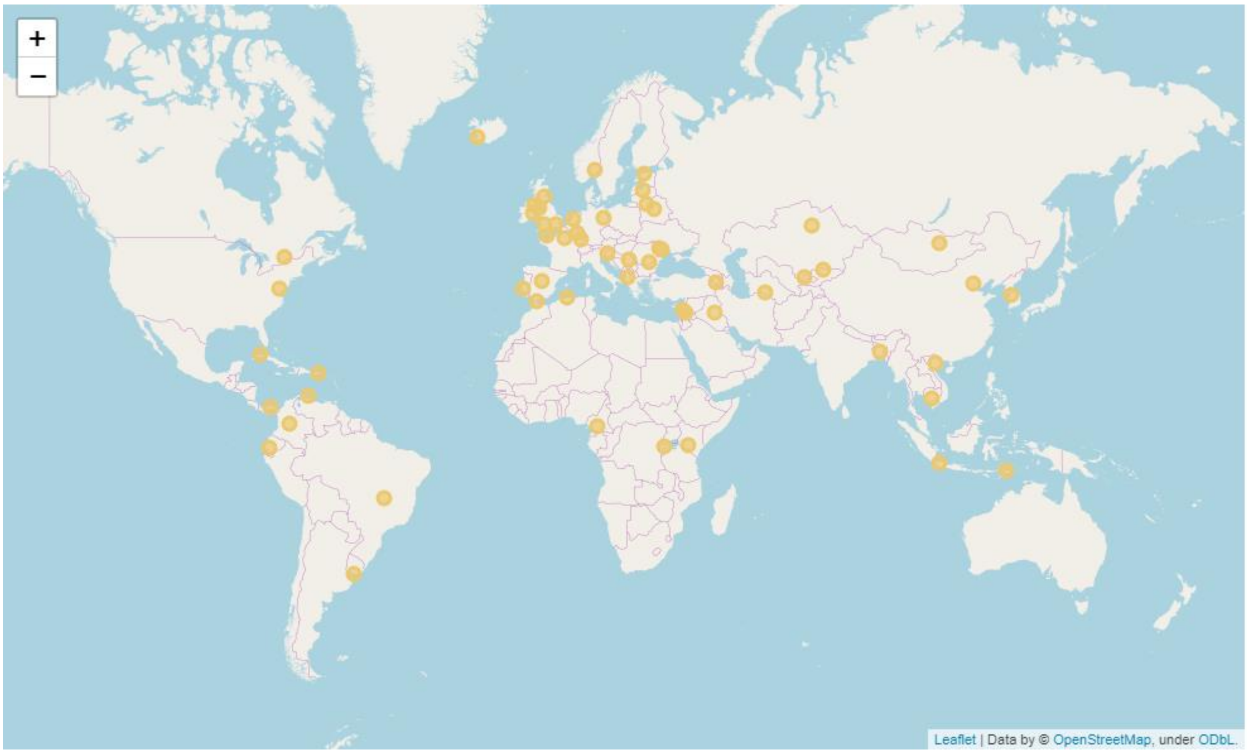
Cluster 16:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Pyongyang	North Korea	3144005	39.019474	125.753388	7	15	Hotel	Stadium	Plaza	Airport
Conakry	Guinea	1399981	9.517060	-13.699843	14	15	Hotel	Mobile Phone Shop	Mexican Restaurant	Turkish Restaurant
Bamako	Mali	1289626	12.605033	-7.986514	19	15	Hotel	Bar	Park	Thai Restaurant
Monrovia	Liberia	1010970	6.328034	-10.797788	19	15	Hotel	Restaurant	Hotel Bar	Furniture / Home Store
Naypyidaw	Myanmar	925000	19.754005	96.134498	22	15	Hotel	Asian Restaurant	Restaurant	Shopping Mall
N'Djamena	Chad	751288	12.119154	15.050276	15	15	Hotel	French Restaurant	Hotel Pool	Resort



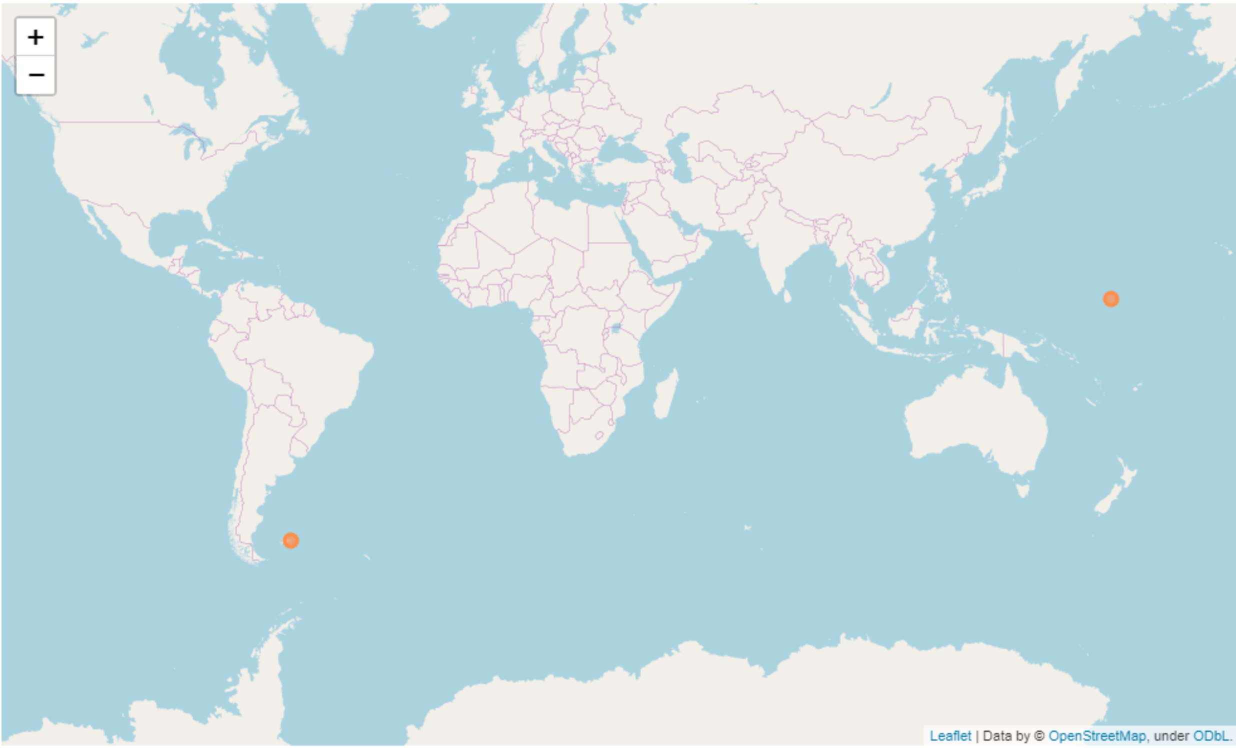
Cluster 17:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Beijing	China PR	21542000	39.906217	116.391276	86	16	Hotel	Historic Site	Shopping Mall	Park
Jakarta	Indonesia	10075310	-6.175394	106.827183	500	16	Coffee Shop	Hotel	Chinese Restaurant	Indonesian Restaurant
Seoul	South Korea	9838892	37.566679	126.978291	406	16	Coffee Shop	Korean Restaurant	Café	Hotel
Dhaka	Bangladesh	8906039	23.759357	90.378814	57	16	Coffee Shop	Café	Nightclub	Indian Restaurant
London	United Kingdom England	8908081	51.507322	-0.127647	483	16	Theater	Hotel	Coffee Shop	Sandwich Place



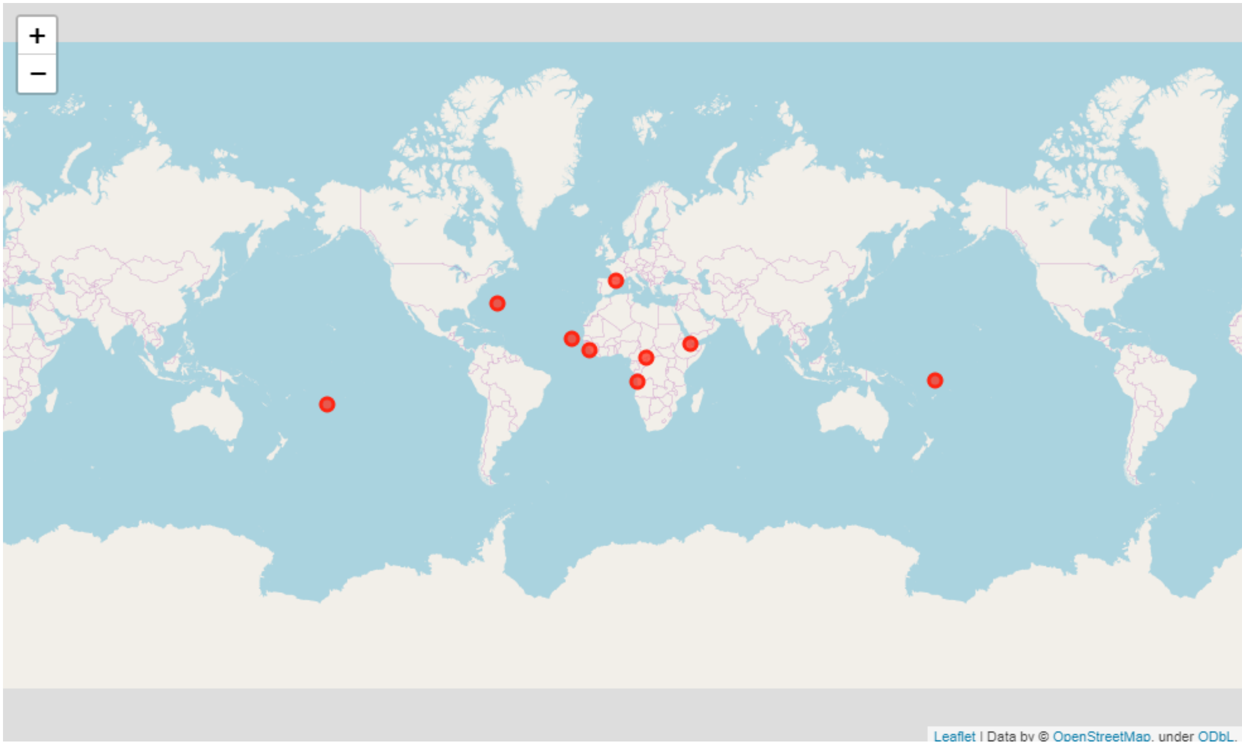
Cluster 19:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Majuro	Marshall Islands	25400	7.090992	171.381635	4	18	Grocery Store	Hotel	Restaurant	Airport
Stanley	Falkland Islands (UK)	2115	-51.695057	-57.849169	4	18	Diner	Grocery Store	Port	Airport



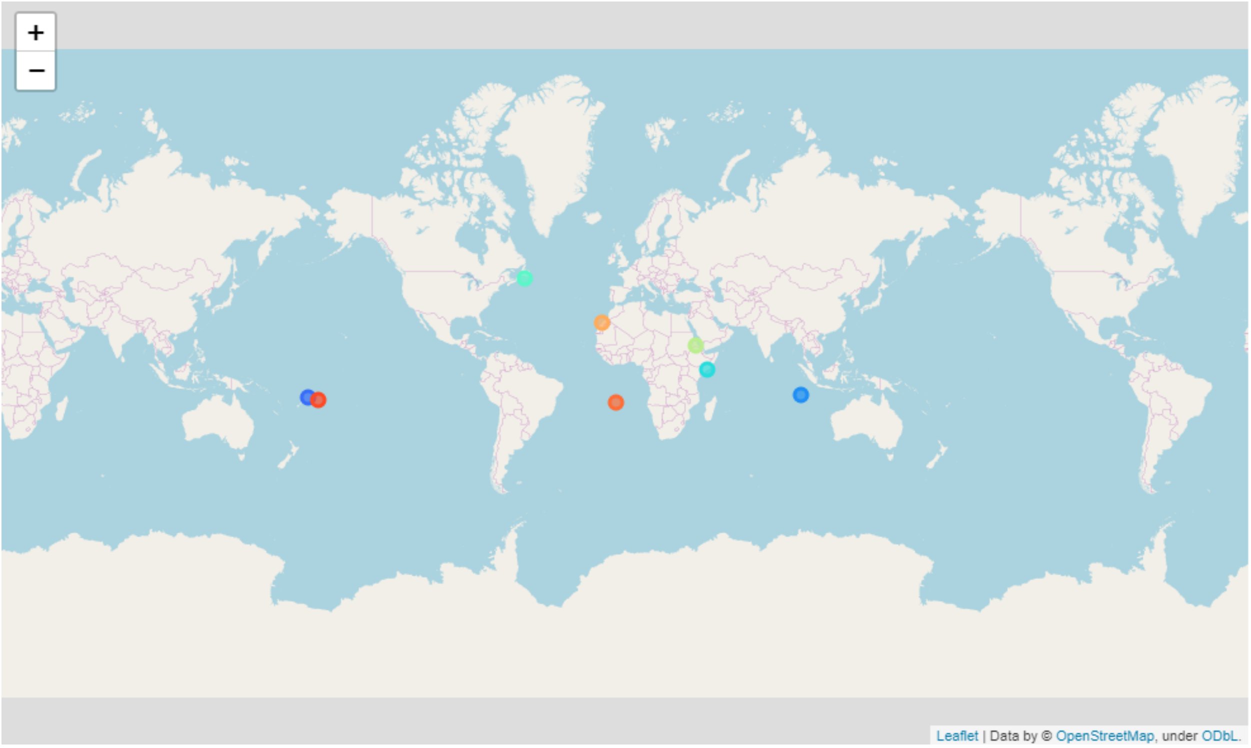
Cluster 22:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Luanda	Angola	2453779	-8.827270	13.243951	65	21	Restaurant	Beach	Portuguese Restaurant	Hotel
Freetown	Sierra Leone	1070200	8.479004	-13.267950	12	21	Hotel	Restaurant	Boat or Ferry	Ice Cream Shop
Bangui	Central African Republic	731548	4.390715	18.550913	7	21	Nature Preserve	Coffee Shop	Restaurant	Café
Djibouti (city)	Djibouti	475332	11.814597	42.845306	20	21	Restaurant	Hotel	Italian Restaurant	Pub
Praia	Cape Verde	125464	14.916017	-23.509613	22	21	Hotel	Restaurant	Beach	Bakery



Other Clusters:

Capital	Country/Territory	Population	Latitude	Longitude	CountVenue	Cluster Labels	1st Most Common Venue	2nd Most Common Venue	3rd Most Common Venue	4th Most Common Venue
Mata-Utu	Wallis and Futuna (France)	1191	-13.282042	-176.174022	1	4	Airport	Fast Food Restaurant	Fishing Spot	Fish Taverna
West Island	Cocos (Keeling) Islands (Australia)	120	-12.189848	96.830449	2	5	Buffet	Airport	Zoo Exhibit	Field
Mogadishu	Somalia	1097133	2.042778	45.338564	11	8	Automotive Shop	Hotel	Dive Spot	Beach
Saint-Pierre	Saint Pierre and Miquelon (France)	5509	46.783247	-56.195159	5	10	Pharmacy	Grocery Store	Coffee Shop	Harbor / Marina
Asmara	Eritrea	694000	15.338967	38.932676	4	14	Hotel	Zoo Exhibit	Fast Food Restaurant	Fish Taverna
El Aaiún	Sahrawi Arab Democratic Republic	194668	27.154512	-13.195392	4	17	Hotel	Coffee Shop	Pier	Zoo Exhibit
Jamestown	Saint Helena (UK)	714	-15.927730	-5.716087	4	19	Chinese Restaurant	Government Building	Grocery Store	Zoo Exhibit
Pago Pago	American Samoa (USA)	52000	-14.275479	-170.704830	4	20	Breakfast Spot	Movie Theater	American Restaurant	Stadium



5.2. Discuss

Our results isn't static picture. Data from Foursquare API may change. As example: Beijing venue's counts change from 740 in early February to 84 in fall February. We can take more accurate data if take ALL venue from every capital or at least take coordinates for points from every neighborhoods. And we can include not only capital, but every current cities. But for fist look it's enough.

6. Conclusion

In result this research we can create useful tool for stakeholders, who interested travel to some capital cities. As example it may be dynamical map with some filters, where they can see most common venue for every city and which cities the same.