Capstone Project - The Battle of Neighbourhoods

Introduction: The business problem and the stakeholders

In economics, Okun's law is an empirically observed relationship relating unemployment to GDP. It states that.. "for every 1% increase in the unemployment rate, a country's GDP will be an additional roughly 2% lower than its potential GDP".

In our "increasingly mobile society" and globalized economy, working abroad is no longer a novelty for the fortunate few – it's an ordinary fact.

There are many exciting gains to be made by taking the plunge and settling overseas. It increases the possibility to find your "dream" job and it is also a great way to actually save money. Moving to another country offers plenty of opportunities for boosting your career, helping you to acquire new, varied skills and experience, and to establish an international network which may well pay dividends in the future.

So.. Looking for some inspiration about where to go? Do you want to see the world, travel, explore, meet people, discover new cultures, and escape the 9–5 with its commutes, endless meetings and oppressive cubicle walls. Maybe you've just graduated from college or high school, but you just don't feel ready to settle down – after all, there's a whole world out there to see?

Sounds too good to be true? Curious about this idea, but confused where to start? Well, think again! Because, that is exactly what tens of thousands of people are doing right now, all across the world.

In this project, we will:

- Find the **Top 10** countries with the greater **GDP**
- Find the **Top 10** countries with the lowest **unemployment rate**
- Combine your outputs and choose the country with the lowest unemployment rate and the highest GDP
- Decide which **districts** would be the best to live, based on:

A. Rent prices $$-$$$

B. Based on your personal preferences:

   1. Central location
   2. Check logistics: easy access to train station
   3. Near to bank/ATM
   4. Near to market
   5. Find a fitness centre/Gym for healthy living
   6. Find the top restaurants - miss my mum's food already

- Cluster these districts based on the similarities
- Conclude.

Initial Data Preparation

Web-Scrapping and Cleaning

I. The wikipedia page of List of countries by GDP (nominal) and unemployment rate (https://en.wikipedia.org/wiki/List_of_countries_by_GDP_(nominal))-(https://en.wikipedia.org/wiki/List_of_countries_by_unemployment_rate) contains all relevant details in order to find the 10 countries with the highest GDP and lowest unemployment rate. I have used Beautifulsoup and pandas library to create the initial data-frame. For a clean and understandable data-frame some of the rows are renamed or dropped.

II. The wikipedia page of Special wards of Tokyo (*https://en.wikipedia.org/wiki Special_wards_of_Tokyo).* I have used Beautifulsoup and pandas library to create the initial data-frame. For a clean and understandable data-frame some of the wards are renamed.After this initial preparation, I moved on to the next step to obtain coordinates using Geopy library and Folium to visualize geographic details.

III. The average rent-price data for each ward of Tokyo was obtained from Tokyo Rental Apartment average value page (https://utinokati.com/en/details/apartment-rent-market/area/Tokyo/).

IV. Finally, I make use of Foursquare API to obtain the most common venues based on my preferences within 1 kilometer of each major district. Concluding our project the K-means algorithm was used to cluster the boroughs. K-Means algorithm is one of the most common cluster method of unsupervised learning. Using this method we will be able to cluster our results per area and examine their properties accordingly.

Exploratory Data Analysis

We have in place the data available as captured from the Wikipedia websites regarding macroeconomic variables. The first variable of gross domestic product was selected based on the fact that this metric is a figure that shows the economic situation of a country and secondly, the unemployment rates. In order to combine these metrics and extract better results, a ratio has been selected for the choice of the best country with these criteria.

	Index	Country	GDP	Unemployment Rate %	Latitude	Longitude
0	1	United States	21,439,453	3.5	39.783730	-100.445882
1	4	Japan	5,154,475	2.4	36.574844	139.239418
2	5	Germany	3,863,344	3.3	51.083420	10.423447
3	6	India	2,935,570	6.5	22.351115	78.667743
4	7	United Kingdom	2,743,586	3.8	54.702354	-3.276575
5	8	France	2,707,074	8.9	46.603354	1.888334
6	9	Italy	1,988,636	9.7	42.638426	12.674297
7	10	Brazil	1,847,020	13.1	-10.333333	-53.200000
8	11	Canada	1,730,914	5.6	61.066692	-107.991707
9	14	Spain	1,397,870	13.78	39.326234	-4.838065
10	15	Australia	1,376,255	5.0	-24.776109	134.755000
11	16	Mexico	1,274,175	3.80	19.432630	-99.133178
12	17	Indonesia	1,111,713	5.0	-2.483383	117.890285
13	18	Netherlands	902,355	3.0	52.500170	5.748082
14	19	Saudi Arabia	779,289	12.3	25.624262	42.352833
15	20	Turkey	743,708	12.8	38.959759	34.924965
16	21	Switzerland	715,360	2.4	46.798562	8.231974
17	22	Taiwan	586,104	3.72	23.973937	120.982018
18	23	Poland	565,854	3.8	52.215933	19.134422
19	24	Thailand	529,177	0.7	14.897192	100.832730

20	25	Sweden	528,929	6.3	59.674971	14.520858
21	26	Belgium	517,609	6.2	50.640281	4.666715
22	27	Iran	458,500	12.00	32.647531	54.564352
23	28	Austria	447,718	5.1	47.200034	13.199959
24	29	Nigeria	446,543	18.8	9.600036	7.999972
25	30	Argentina	445,469	10.6	-34.996496	-64.967282
26	31	Norway	417,627	4.0	60.500021	9.099972
27	32	United Arab Emirates	405,771	1.6	24.000249	53.999483
28	33	Israel	387,717	3.7	31.531311	34.866765
29	34	Ireland	384,940	4.6	52.865196	-7.979460
30	35	Hong Kong	372,989	3.3	22.279328	114.162813
31	36	Malaysia	365,303	3.5	4.569375	102.265682
32	37	Singapore	362,818	2.1[c]	1.357107	103.819499
33	38	South Africa	358,839	29.1	-28.816624	24.991639
34	39	Philippines	356,814	4.5	12.750349	122.731210
35	40	Denmark	347,176	4.8	55.670249	10.333328
36	41	Colombia	327,895	9.4	2.889443	-73.783892
37	42	Bangladesh	317,465	4.0[a]	24.476878	90.293243
38	43	Egypt	302,256	7.5	26.254049	29.267547
39	44	Chile	294,237	7.0	-31.761336	-71.318770
40	45	Pakistan	284,214	6.0	30.330840	71.247499
41	46	Finland	269,654	7.2	63.246778	25.920916
42	47	Vietnam	261,637	2.2	13.290403	108.426511
43	48	Czech Republic	246,953	1.9	49.816700	15.474954
44	49	Romania	243,698	4.0	45.985213	24.685923
45	50	Portugal	236,408	6.7	40.033263	-7.889626
46	51	Peru	228,989	6.1	-6.869970	-75.045851
47	52	Iraq	224,462	16.0	33.095579	44.174977
48	53	Greece	214,012	16.6	38.995368	21.987713
49	54	New Zealand	204,671	3.9	-41.500083	172.834408
50	55	Qatar	191,849	8.9	25.333698	51.229529
51	56	Algeria	172,781	11.2	28.000027	2.999983
52	57	Hungary	170,407	3.7	47.181759	19.506094
53	58	Kazakhstan	170,326	4.9	47.228609	65.209320
54	60	Kuwait	137,591	2.1	29.273396	47.497948
55	61	Morocco	119,040	18.7	31.172821	-7.336248

56	62	Ecuador	107,914	4.2	-1.339767	-79.366697
57	63	Slovakia	106,552	6.6	48.741152	19.452865
58	65	Kenya	98,607	7.4	1.441968	38.431398
59	68	Dominican Republic	89,475	14.4	19.097403	-70.302803
60	69	Sri Lanka	86,566	4.0	7.555494	80.713785
61	70	Guatemala	81,318	2.3	15.635609	-89.898809
62	72	Venezuela	70,140	33.3	8.001871	-66.110932
63	73	Luxembourg	69,453	5.0	49.815868	6.129675
64	74	Panama	68,536	5.5	8.559559	-81.130843
65	75	Ghana	67,077	11.9	8.030028	-1.080027
66	76	Bulgaria	66,250	5.4	42.607397	25.485662
67	79	Belarus	62,572	5.6	53.425061	27.697136
68	80	Costa Rica	61,021	12.4	10.273563	-84.073910
69	81	Croatia	60,702	8.1	45.564344	17.011895
70	82	Uzbekistan	60,490	5.8	41.323730	63.952810
71	84	Uruguay	59,918	8.5	-32.875555	-56.020153
72	85	Lebanon	58,565	6.6	33.875063	35.843409
73	87	Slovenia	54,154	5.2	45.813311	14.480837
74	88	Lithuania	53,641	6.3	55.350000	23.750000
75	89	Serbia	51,523	9.5	44.024323	21.076574
76	91	Azerbaijan	47,171	6.0	40.393629	47.787251
77	92	Turkmenistan	46,674	8.6	39.376381	59.392461
78	94	Jordan	44,172	18.5	31.166705	36.941628
79	95	Bolivia	42,401	4.0	-17.056870	-64.991229
80	96	Paraguay	40,714	6.5	-23.316593	-58.169345
81	97	Tunisia	38,732	15.9	33.843941	9.400138
82	98	Cameroon	38,632	4.4	4.612552	13.153581
83	99	Bahrain	38,184	3.8	26.155125	50.534461
84	100	Latvia	35,045	8.7	56.840649	24.753764
85	101	Libya	33,018	13.0	26.823447	18.123672
86	102	Estonia	31,038	5.8	58.752378	25.331908
87	103	Sudan	30,873	19.6	14.584444	29.491769
88	105	Yemen	29,855	35.0	16.347124	47.891527
89	106	Nepal	29,813	3.0	28.108393	84.091714
90	107	El Salvador	26,871	7.0	13.800038	-88.914068
91	108	Cambodia	26,730	0.3	13.506639	104.869423

92	109	Honduras	24,449	5.9	15.257243	-86.075514
93	110	Cyprus	24,280	6.8	34.982302	33.145128
94	111	Zambia	23,946	15.0	-14.518624	27.559916
95	112	Senegal	23,940	48.0[b]	14.475061	-14.452961
96	113	Iceland	23,918	2.9	64.984182	-18.105901
97	114	Papua New Guinea	23,587	2.5	-5.681607	144.248908
98	115	Trinidad and Tobago	22,607	4.5	10.867785	-60.982107
99	116	Bosnia and Herzegovina	20,106	20.5	44.305348	17.596147
100	117	Laos	19,127	1.5	20.017111	103.378253
101	118	Afghanistan	18,734	23.9	33.768006	66.238514
102	119	Botswana	18,690	20.0	-23.168178	24.592874
103	120	Mali	17,647	8.1	16.370036	-2.290024
104	121	Gabon	16,877	28.0	-0.899969	11.689970
105	122	Georgia	15,925	12.8	32.329381	-83.113737
106	123	Jamaica	15,702	10.4	18.115296	-77.159845
107	124	Albania	15,418	11.5	41.000028	19.999962
108	125	Mozambique	15,093	24.5	-19.302233	34.914498
109	126	Malta	14,859	3.7	35.888599	14.447691
110	128	Mauritius	14,391	6.9	-20.275945	57.570357
111	130	Namibia	14,368	34.0	-23.233550	17.323111
112	131	Mongolia	13,637	7.3	46.825039	103.849974
113	132	Armenia	13,444	20.6	40.769627	44.673665
114	134	Zimbabwe	12,818	11.3	-18.455496	29.746841
115	135	North Macedonia	12,672	17.8	41.617121	21.716839
116	138	Nicaragua	12,528	6.5	12.609016	-85.293691
117	139	Brunei	12,455	6.9	4.413716	114.565391
118	140	Equatorial Guinea	12,142	8.6	1.613172	10.517036
119	141	Moldova	11,688	4.2	47.287961	28.567094
120	143	Chad	11,026	5.89	15.613414	19.015617
121	144	Rwanda	10,209	13.2	-1.964663	30.064436
122	147	Kyrgyzstan	8,261	7.2	41.508932	74.724091
123	148	Tajikistan	8,152	2.4	38.628173	70.815654
124	149	Kosovo	7,996	28.6	42.586958	20.902123
125	153	Mauritania	5,651	11.7	20.254038	-9.239926
126	154	Montenegro	5,424	14.4	42.986885	19.518099
127	155	Fiji	5,708	8.6	-18.123970	179.012274

128	156	Barbados	5,189	10.5	13.150033	-59.525030
129	158	Eswatini	4,657	28.0	-26.562481	31.399132
130	159	Sierra Leone	4,229	8.6	8.640035	-11.840027
131	160	Guyana	4,121	9.0	4.841710	-58.641689
132	161	Suriname	3,774	9.1	4.141303	-56.077119
133	165	Djibouti	3,166	40.0	11.814597	42.845306
134	168	Bhutan	2,842	3.2	27.549511	90.511927
135	169	Lesotho	2,741	28.1	-29.603927	28.335019
136	170	Central African Republic	2,321	6.9	7.032360	19.998123
137	172	Belize	2,001	10.1	16.825979	-88.760093
138	175	Antigua and Barbuda	1,688	11.0	17.223472	-61.955461
139	177	San Marino	1,591	8.0	43.945862	12.458306
140	179	Grenada	1,238	24.0	12.136037	-61.690404
141	180	Comoros	1,179	6.5	-12.204518	44.283296
142	182	Vanuatu	951	4.6	-16.525507	168.106915
143	185	Dominica	593	23.0	19.097403	-70.302803
144	186	Tonga	488	6.5	-19.916082	-175.202642
145	189	Palau	291	1.7	6.097367	133.313631
146	190	Marshall Islands	220	36.0	9.000000	168.000000
147	191	Kiribati	184	38.2	0.306000	173.664834

	Index	Country	GDP	Unemployment Rate %	Latitude	Longitude
1	4	Japan	5,154,475	2.40	36.574844	139.239418
2	5	Germany	3,863,344	3.30	51.083420	10.423447
0	1	United States	21,439,453	3.50	39.783730	-100.445882
4	7	United Kingdom	2,743,586	3.80	54.702354	-3.276575
8	11	Canada	1,730,914	5.60	61.066692	-107.991707
3	6	India	2,935,570	6.50	22.351115	78.667743
5	8	France	2,707,074	8.90	46.603354	1.888334
6	9	Italy	1,988,636	9.70	42.638426	12.674297
7	10	Brazil	1,847,020	13.10	-10.333333	-53.200000
9	14	Spain	1,397,870	13.78	39.326234	-4.838065

Tokyo東京! Just Perfect. There's no lovelier sight than the sakura trees on a sunny spring morning – symbolising new beginnings, they put us in a good mood for the rest of the day.

Tokyo is a collective entity of multiple smaller municipalities, including 23 special wards and various bed towns in the western area. Modern Tokyo is categorized as an alpha+ city by the Globalization and World Cities Research Network. As of 2019, the population of Tokyo was estimated to be over 13.9 million, making it Japan's most populous prefecture.

The economy of Japan is a highly developed free-market economy. It is the third-largest in the world by nominal GDP and the fourth-largest by purchasing power parity (PPP) and is the world's second largest developed economy.

Tokyo - major districts

```
dfSW = pd.read_html('https://en.wikipedia.org/wiki
Special_wards_of_Tokyo#List_of_special_wards')[3]
dfSW
```

	No.	Name	Kanji	Population	Density	Area
0	1	Chiyoda	千代田区	59441	5100	11.66
1	2	Chūō	中央区	147620	14460	10.21
2	3	Minato	港区	248071	12180	20.37
3	4	Shinjuku	新宿区	339211	18620	18.22
4	5	Bunkyō	文京区	223389	19790	11.29
5	6	Taitō	台東区	200486	19830	10.11
6	7	Sumida	墨田区	260358	18910	13.77
7	8	Kōtō	江東区	502579	12510	40.16
8	9	Shinagawa	品川区	392492	17180	22.84
9	10	Meguro	目黒区	280283	19110	14.67
10	11	Ōta	大田区	722608	11910	60.66
11	12	Setagaya	世田谷区	910868	15690	58.05
12	13	Shibuya	渋谷区	227850	15080	15.11
13	14	Nakano	中野区	332902	21350	15.59
14	15	Suginami	杉並区	570483	16750	34.06
15	16	Toshima	豊島区	294673	22650	13.01
16	17	Kita	北区	345063	16740	20.61
17	18	Arakawa	荒川区	213648	21030	10.16
18	19	Itabashi	板橋区	569225	17670	32.22
19	20	Nerima	練馬区	726748	15120	48.08
20	21	Adachi	足立区	674067	12660	53.25
21	22	Katsushika	葛飾区	447140	12850	34.80

22	23	Edogawa	江戸川区	685899	13750	49.90

Tokyo - Average rent prices per ward

```
Rent_Market = requests.get('https://utinokati.com/en/details/apartment-rent-market/area/Tokyo/').text
#print (type (response_obj))
soup2 = BeautifulSoup(Rent_Market,'lxml')
#print (soup.prettify())
```

	Ward	Avg_unit_price
0	Chiyoda-Ku	4158
1	Chuo-Ku	3842
2	Minato-Ku	4474
3	Shinjuku-Ku	3900
4	Bunkyo-Ku	3636
5	Taito-Ku	3489
6	Sumida-Ku	3297
7	Koto-Ku	3412
8	Shinagawa-Ku	3788
9	Meguro-Ku	3892
10	Ota-Ku	3209
11	Setagaya-Ku	3360
12	Shibuya-Ku	4306
13	Nakano-Ku	3351
14	Suginami-Ku	3198
15	Toshima-Ku	3472
16	Kita-Ku	3016
17	Arakawa-Ku	2903
18	Itabashi-Ku	2812
19	Nerima-Ku	2767
20	Adachi-Ku	2406
21	Katsushika-Ku	2408
22	Edogawa-Ku	2339
23	Hachioji-Shi	1955
24	Tachikawa-Shi	2368
25	Musashino-Shi	3055

26	Mitaka-Shi	8828
27	Ome-Shi	1628
28	Fuchu-Shi	2326
29	Akishima-Shi	1794
30	Chofu-Shi	2489
31	Machida-Shi	2196
32	Koganei-Shi	2491
33	Kodaira-Shi	2044
34	Hino-Shi	2046
35	Higashimurayama-Shi	1888
36	Kokubunji-Shi	2417
37	Kunitachi-Shi	2307
38	Fussa-Shi	1704
39	Komae-Shi	2492
40	Higashiyamato-Shi	1768
41	Kiyose-Shi	1992
42	Higashikurume-Shi	1954
43	Musashimurayama-Shi	1622
44	Tama-Shi	2047
45	Inagi-Shi	2006
46	Hamura-Shi	1643
47	Akiruno-Shi	1379
48	Nishitokyo-Shi	2223
49	Nishitama-Gun	1520

Tokyo - Selected ward

	Ward	**Avg_unit_price**
1	Chiyoda	4158
2	Chuo	3842
3	Shinjuku	3900
4	Shinagawa	3788
5	Shibuya	4306

Merged table - including Latitude and Longitude

(from csv file)

	Ward	Latitude	longitude	Avg_unit_price
0	Chiyoda	35.6940	139.7538	4158
1	Chuo	35.6706	139.7720	3842
2	Shinjuku	35.6938	139.7034	3900
3	Shinagawa	35.6092	139.7303	3788
4	Shibuya	35.6620	139.7038	4306

Tokyo Map - Selected Wards

Create a function to get all venues for all neighbourhoods in Tokyo
(limit=100)

	Neighborhood Latitude	Neighborhood Longitude	Venue	Venue Latitude	Venue Longitude	Venue Category
Chiyoda	100	100	100	100	100	100
Chuo	100	100	100	100	100	100
Shibuya	100	100	100	100	100	100
Shinagawa	58	58	58	58	58	58
Shinjuku	100	100	100	100	100	100

There are 132 uniques categories.

Most common venues

```
----Chiyoda----
                venue  freq
0                Café  0.10
1  Chinese Restaurant  0.09
2         Coffee Shop  0.07
3    Ramen Restaurant  0.07
4   Convenience Store  0.05


----Chuo----
                 venue  freq
0  Japanese Restaurant  0.09
1     Sushi Restaurant  0.07
2     Ramen Restaurant  0.06
3          Coffee Shop  0.06
4      Soba Restaurant  0.05


----Shibuya----
                 venue  freq
0                 Café  0.10
1  Japanese Restaurant  0.06
2                  Bar  0.06
3          Coffee Shop  0.06
4            Nightclub  0.04


----Shinagawa----
                 venue  freq
0    Convenience Store  0.10
1   Donburi Restaurant  0.07
2  Japanese Restaurant  0.07
3          Coffee Shop  0.05
4     Ramen Restaurant  0.05


----Shinjuku----
                 venue  freq
0                  Bar  0.10
1             Sake Bar  0.09
2     Ramen Restaurant  0.07
3             BBQ Joint  0.07
4  Japanese Restaurant  0.04
```

	Neighborhood	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	Chiyoda	Café	Chinese Restaurant	Ramen Restaurant	Coffee Shop	Convenience Store	Japanese Curry Restaurant	Sake Bar	Sushi Restaurant	Yoshoku Restaurant	Thai Restaurant
1	Chuo	Japanese Restaurant	Sushi Restaurant	Ramen Restaurant	Coffee Shop	Soba Restaurant	Italian Restaurant	BBQ Joint	Hotel	Bed & Breakfast	Seafood Restaurant
2	Shibuya	Café	Japanese Restaurant	Coffee Shop	Bar	Art Gallery	Nightclub	Burger Joint	Italian Restaurant	French Restaurant	Sake Bar
3	Shinagawa	Convenience Store	Donburi Restaurant	Japanese Restaurant	BBQ Joint	Ramen Restaurant	Coffee Shop	Sake Bar	Italian Restaurant	Grocery Store	Steakhouse
4	Shinjuku	Bar	Sake Bar	BBQ Joint	Ramen Restaurant	Japanese Restaurant	Pub	Rock Club	Chinese Restaurant	Yakitori Restaurant	Dessert Shop

Cluster Neighbourhoods

```
# set number of clusters
kclusters = 3

tokyo_grouped_clustering = tokyo_grouped.drop('Neighborhood', 1)

# run k-means clustering
kmeans = KMeans(n_clusters=kclusters, random_state=0).fit(tokyo_grouped_clustering)

# check cluster labels generated for each row in the dataframe
kmeans.labels_[0:10]
```

Cluster 1

[107]:
```python
tokyo_merged.loc[tokyo_merged['Cluster Labels'] == 0, tokyo_merged.columns[[1] + list(range(5, tokyo_merged.shape[1]))]]
```

ut[107]:

	Latitude	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
1	35.6706	Sushi Restaurant	Ramen Restaurant	Coffee Shop	Soba Restaurant	Italian Restaurant	BBQ Joint	Hotel	Bed & Breakfast	Seafood Restaurant
3	35.6092	Donburi Restaurant	Japanese Restaurant	BBQ Joint	Ramen Restaurant	Coffee Shop	Sake Bar	Italian Restaurant	Grocery Store	Steakhouse

Cluster 2

[108]:
```python
tokyo_merged.loc[tokyo_merged['Cluster Labels'] == 1, tokyo_merged.columns[[1] + list(range(5, tokyo_merged.shape[1]))]]
```

ut[108]:

	Latitude	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	35.694	Chinese Restaurant	Ramen Restaurant	Coffee Shop	Convenience Store	Japanese Curry Restaurant	Sake Bar	Sushi Restaurant	Yoshoku Restaurant	Thai Restaurant
4	35.662	Japanese Restaurant	Coffee Shop	Bar	Art Gallery	Nightclub	Burger Joint	Italian Restaurant	French Restaurant	Sake Bar

Cluster 3

[109]:
```python
tokyo_merged.loc[tokyo_merged['Cluster Labels'] == 2, tokyo_merged.columns[[1] + list(range(5, tokyo_merged.shape[1]))]]
```

ut[109]:

	Latitude	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
2	35.6938	Sake Bar	BBQ Joint	Ramen Restaurant	Japanese Restaurant	Pub	Rock Club	Chinese Restaurant	Yakitori Restaurant	Dessert Sh

	Neighborhood	Latitude	longitude	Cluster Labels	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	Chiyoda	35.694	139.753	1	Café	Chinese Restaurant	Ramen Restaurant	Coffee Shop	Convenience Store	Japanese Curry Restaurant	Sake Bar	Sushi Restaurant	Yoshoku Restaurant	Thai Restaurant
1	Chuo	35.670	139.772	0	Japanese Restaurant	Sushi Restaurant	Ramen Restaurant	Coffee Shop	Soba Restaurant	Italian Restaurant	BBQ Joint	Hotel	Bed & Breakfast	Seafood Restaurant
2	Shinjuku	35.693	139.703	2	Bar	Sake Bar	BBQ Joint	Ramen Restaurant	Japanese Restaurant	Pub	Rock Club	Chinese Restaurant	Yakitori Restaurant	Dessert Shop
3	Shinagawa	35.609	139.730	0	Convenience Store	Donburi Restaurant	Japanese Restaurant	BBQ Joint	Ramen Restaurant	Coffee Shop	Sake Bar	Italian Restaurant	Grocery Store	Steakhouse
4	Shibuya	35.662	139.703	1	Café	Japanese Restaurant	Coffee Shop	Bar	Art Gallery	Nightclub	Burger Joint	Italian Restaurant	French Restaurant	Sake Bar

Results and Conclusions

The average rent prices are overall the same, with in the range 3.7 - 4.3.
Since I'm in love with Japanese cuisine I will go with Chuo and Shinagawa ie cluster 0 because the Japanese Sushi Ramen Restaurants are the most common venue.

Future Directions

Some points that are to be followed in the future for more accurate and better results are the following:

- Built useful models to predict whether and how much a country's economy will improve
- Accuracy of the models has room for improvement.
- Capture more data from the economy in order to have a better fit on the model and improve its accuracy in the predictions.
- Ideas include:
    - More macroeconomic variables
    - Financial data