

# Term Project

## Milestone 2: Cleaning / Formatting Flat File Source

DSC 540

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2023 World Happiness Report Analysis

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## **Overview**

Analysis of data presented are two CSV files, one containing Big Mac Index figures are represented through original sources identified in Milestone 1 as well as data showcased from the World Happiness Report.

## **Ethical Implications**

Data cultivation as it relates to the removal of redundant columns with duplicate data will be of importance. Data variables from both datasets have been removed, this is of continued significant ethical implications and significance as data is being removed for a final cleaned version to be merged. This merger has also resulted in several countries removal from rows, which has now significantly reduced the overall dataset. Further collaboration is needed to weigh the total effects of this loss.

## **Completed Steps**

- Importation of libraries
- Importation of Big Mac Index Data
- Removal of Currency Valuation from this dataset
  - With assignment to new variable
- Rename of Columns for continuity among datasets for later merger
- Importation of World Happiness Report Data
- Removal of Explanatory Data
  - This was performed as the statistical data was correlated from other variables
- Renaming of Columns for continuity among datasets for later merger
- Merger of 2 datasets to new variables
- Identify missing variables
- Identify Statistical Data for identification of Mean and Median
  - This will identify potential future issues with this data.

# Term Project Big Mac Index July 2022

July 2, 2023

```
[ ]: ## Import Libraries
```

```
[105]: import numpy as np
import pandas as pd
```

```
[106]: df_bigmac = pd.read_csv("big-mac-2022-07-01.csv")
```

```
[107]: df_bigmac.head(10)
```

```
[107]:
```

	Country	iso_a3	currency_code	local_price	dollar_ex	\
0	United Arab Emirates	ARE	AED	18.00	3.673050	
1	Argentina	ARG	ARS	590.00	129.115000	
2	Australia	AUS	AUD	6.70	1.448436	
3	Azerbaijan	AZE	AZN	4.70	1.698250	
4	Bahrain	BHR	BHD	1.60	0.377000	
5	Brazil	BRA	BRL	22.90	5.391750	
6	Canada	CAN	CAD	6.77	1.289150	
7	Switzerland	CHE	CHF	6.50	0.968450	
8	Chile	CHL	CLP	3400.00	928.435000	
9	China	CHN	CNY	24.00	6.747350	

  

	dollar_price	dollar_ppp	GDP_bigmac	dollar_valuation	euro_valuation	\
0	4.900559	3.495146	45059.735590	-4.844	2.843	
1	4.569570	114.563107	8847.066934	-11.270	-4.103	
2	4.625680	1.300971	64955.518760	-10.181	-2.925	
3	2.767555	0.912621	10055.076960	-46.261	-41.920	
4	4.244032	0.310680	31630.823630	-17.592	-10.935	
5	4.247230	4.446602	9180.888358	-17.530	-10.868	
6	5.251522	1.314563	49674.334130	1.971	10.209	
7	6.711756	1.262136	67857.662940	30.325	40.853	
8	3.662077	660.194175	18476.466410	-28.892	-23.148	
9	3.556952	4.660194	17102.473850	-30.933	-25.354	

  

	sterling_valuation	yen_valuation	yuan_valuation	dollar_adj_valuation	\
0	10.373	73.235	37.774	4.837	
1	2.918	61.534	28.469	15.334	
2	4.182	63.518	30.046	-8.689	
3	-37.668	-2.167	-22.193	-30.565	

4	-4.414	50.027	19.317	-3.769
5	-4.342	50.140	19.406	7.021
6	18.277	85.641	47.641	10.205
7	51.165	137.261	88.694	31.013
8	-17.521	29.454	2.955	-11.789
9	-19.889	25.738	0.000	-13.759

	euro_adj_valuation	sterling_adj_valuation	yen_adj_valuation	\
0	0.640	11.686	81.952	
1	10.717	22.869	100.170	
2	-12.345	-2.724	58.476	
3	-33.344	-26.028	20.510	
4	-7.622	2.518	67.015	
5	2.736	14.013	85.742	
6	5.793	17.404	91.268	
7	25.768	39.572	127.382	
8	-15.320	-6.026	53.097	
9	-17.212	-8.125	49.677	

	yuan_adj_valuation
0	21.563
1	33.735
2	5.879
3	-19.487
4	11.584
5	24.095
6	27.787
7	51.915
8	2.285
9	0.000

```
[108]: df_bigmac.shape
```

```
[108]: (54, 18)
```

```
[109]: ## 1. Remove Currency Valuation-Create Subset
```

```
[110]: df1 =
↳ df_bigmac[['Country', 'local_price', 'dollar_ex', 'dollar_price', 'dollar_ppp', 'GDP_bigmac']]
```

```
[111]: df1
```

	Country	local_price	dollar_ex	dollar_price	\
0	United Arab Emirates	18.00	3.673050	4.900559	
1	Argentina	590.00	129.115000	4.569570	
2	Australia	6.70	1.448436	4.625680	
3	Azerbaijan	4.70	1.698250	2.767555	

4	Bahrain	1.60	0.377000	4.244032
5	Brazil	22.90	5.391750	4.247230
6	Canada	6.77	1.289150	5.251522
7	Switzerland	6.50	0.968450	6.711756
8	Chile	3400.00	928.435000	3.662077
9	China	24.00	6.747350	3.556952
10	Colombia	14950.00	4295.100000	3.480711
11	Costa Rica	2650.00	678.105000	3.907949
12	Czech Republic	95.00	23.920000	3.971572
13	Egypt	46.00	18.945000	2.428081
14	Euro area	4.65	0.975850	4.765077
15	Britain	3.69	0.831080	4.440006
16	Guatemala	26.00	7.727900	3.364433
17	Hong Kong	21.00	7.849950	2.675176
18	Honduras	89.00	24.615000	3.615681
19	Croatia	27.00	7.328450	3.684272
20	Hungary	1030.00	389.046150	2.647501
21	Indonesia	35000.00	14977.500000	2.336839
22	India	191.00	79.951300	2.388954
23	Israel	17.00	3.437450	4.945526
24	Jordan	2.30	0.710150	3.238752
25	Japan	390.00	137.865000	2.828854
26	South Korea	4600.00	1313.450000	3.502227
27	Kuwait	1.30	0.307400	4.229018
28	Lebanon	130000.00	25600.000000	5.078125
29	Sri Lanka	1340.00	360.000000	3.722222
30	Moldova	60.00	19.298000	3.109130
31	Mexico	70.00	20.412500	3.429271
32	Malaysia	10.90	4.450000	2.449438
33	Nicaragua	139.00	35.890000	3.872945
34	Norway	62.00	9.897650	6.264113
35	New Zealand	7.10	1.603721	4.427205
36	Oman	1.42	0.385000	3.688312
37	Pakistan	700.00	221.750000	3.156708
38	Peru	13.90	3.892850	3.570649
39	Philippines	155.00	56.265000	2.754821
40	Poland	16.68	4.648450	3.588293
41	Qatar	13.00	3.641750	3.569712
42	Romania	11.00	4.821750	2.281329
43	Saudi Arabia	17.00	3.755000	4.527297
44	Singapore	5.90	1.391400	4.240333
45	Sweden	57.00	10.197850	5.589413
46	Thailand	128.00	36.612500	3.496074
47	Turkey	47.00	17.565000	2.675776
48	Taiwan	75.00	29.907500	2.507732
49	Uruguay	255.00	41.910000	6.084467
50	United States	5.15	1.000000	5.150000

51	Venezuela	10.00	5.673200	1.762674
52	Vietnam	69000.00	23417.000000	2.946577
53	South Africa	39.90	17.036250	2.342065

	dollar_ppp	GDP_bigmacc
0	3.495146	45059.735590
1	114.563107	8847.066934
2	1.300971	64955.518760
3	0.912621	10055.076960
4	0.310680	31630.823630
5	4.446602	9180.888358
6	1.314563	49674.334130
7	1.262136	67857.662940
8	660.194175	18476.466410
9	4.660194	17102.473850
10	2902.912621	7940.328475
11	514.563107	14971.371580
12	18.446602	31037.388770
13	8.932039	6918.453014
14	0.902913	39969.135210
15	0.716505	47886.753020
16	5.048544	7161.025481
17	4.077670	94795.185540
18	17.281553	3937.948715
19	5.242718	20402.178580
20	200.000000	28284.494800
21	6796.116505	9172.246719
22	37.087379	4579.833524
23	3.300971	50313.666900
24	0.446602	7011.581696
25	75.728155	57016.008440
26	893.203883	44570.742380
27	0.252427	34372.328080
28	25242.718450	NaN
29	260.194175	2859.060372
30	11.650485	8024.776007
31	13.592233	14973.726820
32	2.116505	22311.919060
33	26.990291	2839.947641
34	12.038835	63567.854700
35	1.378641	49644.006730
36	0.275728	25517.368700
37	135.922330	1834.014182
38	2.699029	9550.191493
39	30.097087	5845.332898
40	3.238835	21239.882560
41	2.524272	98893.859050

```

42      2.135922  28569.017770
43      3.300971  26704.956320
44      1.145631  85366.699400
45     11.067961  46516.137370
46     24.854369   9306.323554
47      9.126214   9256.997784
48     14.563107  64992.899750
49     49.514563  14726.863620
50      1.000000  69231.400000
51      1.941748      NaN
52   13398.058250   6375.564885
53      7.747573  13261.543640

```

```
[112]: ## 2. Rename columns, replace underscores with space
```

```
[113]: df_Final_1=df1.rename(columns={'Country':'Country','local_price':'Local_
↳Price','dollar_ex':'Dollar Ex','dollar_price':'Dollar Price','dollar_ppp':
↳'Dollar PPP','GDP_bigmac':'GDP Big Mac'})
```

```
[114]: df_Final_1
```

```
[114]:
```

	Country	Local Price	Dollar Ex	Dollar Price \
0	United Arab Emirates	18.00	3.673050	4.900559
1	Argentina	590.00	129.115000	4.569570
2	Australia	6.70	1.448436	4.625680
3	Azerbaijan	4.70	1.698250	2.767555
4	Bahrain	1.60	0.377000	4.244032
5	Brazil	22.90	5.391750	4.247230
6	Canada	6.77	1.289150	5.251522
7	Switzerland	6.50	0.968450	6.711756
8	Chile	3400.00	928.435000	3.662077
9	China	24.00	6.747350	3.556952
10	Colombia	14950.00	4295.100000	3.480711
11	Costa Rica	2650.00	678.105000	3.907949
12	Czech Republic	95.00	23.920000	3.971572
13	Egypt	46.00	18.945000	2.428081
14	Euro area	4.65	0.975850	4.765077
15	Britain	3.69	0.831080	4.440006
16	Guatemala	26.00	7.727900	3.364433
17	Hong Kong	21.00	7.849950	2.675176
18	Honduras	89.00	24.615000	3.615681
19	Croatia	27.00	7.328450	3.684272
20	Hungary	1030.00	389.046150	2.647501
21	Indonesia	35000.00	14977.500000	2.336839
22	India	191.00	79.951300	2.388954
23	Israel	17.00	3.437450	4.945526
24	Jordan	2.30	0.710150	3.238752

25	Japan	390.00	137.865000	2.828854
26	South Korea	4600.00	1313.450000	3.502227
27	Kuwait	1.30	0.307400	4.229018
28	Lebanon	130000.00	25600.000000	5.078125
29	Sri Lanka	1340.00	360.000000	3.722222
30	Moldova	60.00	19.298000	3.109130
31	Mexico	70.00	20.412500	3.429271
32	Malaysia	10.90	4.450000	2.449438
33	Nicaragua	139.00	35.890000	3.872945
34	Norway	62.00	9.897650	6.264113
35	New Zealand	7.10	1.603721	4.427205
36	Oman	1.42	0.385000	3.688312
37	Pakistan	700.00	221.750000	3.156708
38	Peru	13.90	3.892850	3.570649
39	Philippines	155.00	56.265000	2.754821
40	Poland	16.68	4.648450	3.588293
41	Qatar	13.00	3.641750	3.569712
42	Romania	11.00	4.821750	2.281329
43	Saudi Arabia	17.00	3.755000	4.527297
44	Singapore	5.90	1.391400	4.240333
45	Sweden	57.00	10.197850	5.589413
46	Thailand	128.00	36.612500	3.496074
47	Turkey	47.00	17.565000	2.675776
48	Taiwan	75.00	29.907500	2.507732
49	Uruguay	255.00	41.910000	6.084467
50	United States	5.15	1.000000	5.150000
51	Venezuela	10.00	5.673200	1.762674
52	Vietnam	69000.00	23417.000000	2.946577
53	South Africa	39.90	17.036250	2.342065

	Dollar PPP	GDP Big Mac
0	3.495146	45059.735590
1	114.563107	8847.066934
2	1.300971	64955.518760
3	0.912621	10055.076960
4	0.310680	31630.823630
5	4.446602	9180.888358
6	1.314563	49674.334130
7	1.262136	67857.662940
8	660.194175	18476.466410
9	4.660194	17102.473850
10	2902.912621	7940.328475
11	514.563107	14971.371580
12	18.446602	31037.388770
13	8.932039	6918.453014
14	0.902913	39969.135210
15	0.716505	47886.753020



16	5.048544	7161.025481
17	4.077670	94795.185540
18	17.281553	3937.948715
19	5.242718	20402.178580
20	200.000000	28284.494800
21	6796.116505	9172.246719
22	37.087379	4579.833524
23	3.300971	50313.666900
24	0.446602	7011.581696
25	75.728155	57016.008440
26	893.203883	44570.742380
27	0.252427	34372.328080
28	25242.718450	NaN
29	260.194175	2859.060372
30	11.650485	8024.776007
31	13.592233	14973.726820
32	2.116505	22311.919060
33	26.990291	2839.947641
34	12.038835	63567.854700
35	1.378641	49644.006730
36	0.275728	25517.368700
37	135.922330	1834.014182
38	2.699029	9550.191493
39	30.097087	5845.332898
40	3.238835	21239.882560
41	2.524272	98893.859050
42	2.135922	28569.017770
43	3.300971	26704.956320
44	1.145631	85366.699400
45	11.067961	46516.137370
46	24.854369	9306.323554
47	9.126214	9256.997784
48	14.563107	64992.899750
49	49.514563	14726.863620
50	1.000000	69231.400000
51	1.941748	NaN
52	13398.058250	6375.564885
53	7.747573	13261.543640

```
[115]: df_WHR2023 = pd.read_csv("WHR2023.csv")
```

```
[116]: df_WHR2023.head(10)
```

```
[116]: Country name  Ladder score  Standard error of ladder score  upperwhisker  \
0  Afghanistan      1.859                0.033          1.923
1    Albania        5.277                0.066          5.406
2    Algeria        5.329                0.062          5.451
```

3	Argentina	6.024	0.063	6.147
4	Armenia	5.342	0.066	5.470
5	Australia	7.095	0.044	7.180
6	Austria	7.097	0.040	7.176
7	Bahrain	6.173	0.100	6.369
8	Bangladesh	4.282	0.068	4.416
9	Belgium	6.859	0.034	6.926

	lowerwhisker	Logged GDP per capita	Social support	\
0	1.795	7.324	0.341	
1	5.148	9.567	0.718	
2	5.207	9.300	0.855	
3	5.900	9.959	0.891	
4	5.213	9.615	0.790	
5	7.009	10.821	0.934	
6	7.018	10.899	0.888	
7	5.977	10.776	0.844	
8	4.148	8.685	0.544	
9	6.793	10.844	0.915	

	Healthy life expectancy	Freedom to make life choices	Generosity	\
0	54.712	0.382	-0.081	
1	69.150	0.794	-0.007	
2	66.549	0.571	-0.117	
3	67.200	0.823	-0.089	
4	67.789	0.796	-0.155	
5	71.050	0.890	0.198	
6	71.150	0.855	0.102	
7	65.825	0.944	0.117	
8	64.548	0.845	0.005	
9	70.899	0.825	0.001	

	Perceptions of corruption	Ladder score in Dystopia	\
0	0.847	1.778	
1	0.878	1.778	
2	0.717	1.778	
3	0.814	1.778	
4	0.705	1.778	
5	0.496	1.778	
6	0.497	1.778	
7	0.737	1.778	
8	0.698	1.778	
9	0.549	1.778	

	Explained by: Log GDP per capita	Explained by: Social support	\
0	0.645	0.000	
1	1.449	0.951	

2	1.353	1.298
3	1.590	1.388
4	1.466	1.134
5	1.899	1.497
6	1.927	1.382
7	1.883	1.269
8	1.133	0.513
9	1.907	1.449

	Explained by: Healthy life expectancy \
0	0.087
1	0.480
2	0.409
3	0.427
4	0.443
5	0.532
6	0.535
7	0.389
8	0.355
9	0.528

	Explained by: Freedom to make life choices	Explained by: Generosity \
0	0.000	0.093
1	0.549	0.133
2	0.252	0.073
3	0.587	0.088
4	0.551	0.053
5	0.677	0.242
6	0.630	0.191
7	0.748	0.199
8	0.617	0.139
9	0.590	0.137

	Explained by: Perceptions of corruption	Dystopia + residual
0	0.059	0.976
1	0.037	1.678
2	0.152	1.791
3	0.082	1.861
4	0.160	1.534
5	0.310	1.938
6	0.310	2.124
7	0.138	1.546
8	0.165	1.361
9	0.273	1.976

```
[117]: df_WHR2023.shape
```

[117]: (137, 19)

[118]: *## 3. Remove Explained Variables-Create Subset*

```
[119]: df_X = df_WHR2023[['Country name','Social support','Healthy life_
    ↳expectancy','Freedom to make life choices','Generosity','Perceptions of_
    ↳corruption']]
```

[120]: df\_X.head(10)

```
[120]: Country name  Social support  Healthy life expectancy \
0  Afghanistan          0.341          54.712
1    Albania          0.718          69.150
2    Algeria          0.855          66.549
3  Argentina          0.891          67.200
4    Armenia          0.790          67.789
5  Australia          0.934          71.050
6    Austria          0.888          71.150
7    Bahrain          0.844          65.825
8  Bangladesh          0.544          64.548
9    Belgium          0.915          70.899

    Freedom to make life choices  Generosity  Perceptions of corruption
0                0.382        -0.081          0.847
1                0.794        -0.007          0.878
2                0.571        -0.117          0.717
3                0.823        -0.089          0.814
4                0.796        -0.155          0.705
5                0.890         0.198          0.496
6                0.855         0.102          0.497
7                0.944         0.117          0.737
8                0.845         0.005          0.698
9                0.825         0.001          0.549
```

[121]: *## 4. Rename Columns*

```
[122]: df_Final_2=df_X.rename(columns={'Country name':'Country','Social support':
    ↳'Social Support','Healthy life expectancy':'Healthy Life Expectancy','Freedom_
    ↳to make life choices':'Freedom to Make Life Choices','Generosity':
    ↳'Generosity','Perceptions of corruption':'Perceptions of Corruption'})
```

[123]: df\_Final\_2

```
[123]: Country  Social Support  Healthy Life Expectancy \
0  Afghanistan          0.341          54.712
1    Albania          0.718          69.150
2    Algeria          0.855          66.549
3  Argentina          0.891          67.200
```

4	Armenia	0.790	67.789
..	...	...	...
132	Uzbekistan	0.875	65.301
133	Venezuela	0.839	64.050
134	Vietnam	0.821	65.502
135	Zambia	0.694	55.032
136	Zimbabwe	0.690	54.050

	Freedom to Make Life Choices	Generosity	Perceptions of Corruption
0	0.382	-0.081	0.847
1	0.794	-0.007	0.878
2	0.571	-0.117	0.717
3	0.823	-0.089	0.814
4	0.796	-0.155	0.705
..	...	...	...
132	0.938	0.230	0.638
133	0.659	0.128	0.811
134	0.939	-0.004	0.759
135	0.791	0.098	0.818
136	0.654	-0.046	0.766

[137 rows x 6 columns]

```
[124]: ## 5. Merge Data
```

```
[125]: df_merged = pd.merge(df_Final_1,df_Final_2,on='Country',how='inner').
        ↳drop_duplicates()
```

```
[127]: df_merged
```

```
[127]:
```

	Country	Local Price	Dollar Ex	Dollar Price \
0	United Arab Emirates	18.00	3.673050	4.900559
1	Argentina	590.00	129.115000	4.569570
2	Australia	6.70	1.448436	4.625680
3	Bahrain	1.60	0.377000	4.244032
4	Brazil	22.90	5.391750	4.247230
5	Canada	6.77	1.289150	5.251522
6	Switzerland	6.50	0.968450	6.711756
7	Chile	3400.00	928.435000	3.662077
8	China	24.00	6.747350	3.556952
9	Colombia	14950.00	4295.100000	3.480711
10	Costa Rica	2650.00	678.105000	3.907949
11	Egypt	46.00	18.945000	2.428081
12	Guatemala	26.00	7.727900	3.364433
13	Honduras	89.00	24.615000	3.615681
14	Croatia	27.00	7.328450	3.684272
15	Hungary	1030.00	389.046150	2.647501

16	Indonesia	35000.00	14977.500000	2.336839
17	India	191.00	79.951300	2.388954
18	Israel	17.00	3.437450	4.945526
19	Jordan	2.30	0.710150	3.238752
20	Japan	390.00	137.865000	2.828854
21	South Korea	4600.00	1313.450000	3.502227
22	Lebanon	130000.00	25600.000000	5.078125
23	Sri Lanka	1340.00	360.000000	3.722222
24	Moldova	60.00	19.298000	3.109130
25	Mexico	70.00	20.412500	3.429271
26	Malaysia	10.90	4.450000	2.449438
27	Nicaragua	139.00	35.890000	3.872945
28	Norway	62.00	9.897650	6.264113
29	New Zealand	7.10	1.603721	4.427205
30	Pakistan	700.00	221.750000	3.156708
31	Peru	13.90	3.892850	3.570649
32	Philippines	155.00	56.265000	2.754821
33	Poland	16.68	4.648450	3.588293
34	Romania	11.00	4.821750	2.281329
35	Saudi Arabia	17.00	3.755000	4.527297
36	Singapore	5.90	1.391400	4.240333
37	Sweden	57.00	10.197850	5.589413
38	Thailand	128.00	36.612500	3.496074
39	Uruguay	255.00	41.910000	6.084467
40	United States	5.15	1.000000	5.150000
41	Venezuela	10.00	5.673200	1.762674
42	Vietnam	69000.00	23417.000000	2.946577
43	South Africa	39.90	17.036250	2.342065

	Dollar PPP	GDP Big Mac	Social Support	Healthy Life Expectancy \
0	3.495146	45059.735590	0.826	66.243
1	114.563107	8847.066934	0.891	67.200
2	1.300971	64955.518760	0.934	71.050
3	0.310680	31630.823630	0.844	65.825
4	4.446602	9180.888358	0.836	65.749
5	1.314563	49674.334130	0.929	71.400
6	1.262136	67857.662940	0.920	72.900
7	660.194175	18476.466410	0.889	70.300
8	4.660194	17102.473850	0.836	68.689
9	2902.912621	7940.328475	0.822	69.350
10	514.563107	14971.371580	0.872	70.000
11	8.932039	6918.453014	0.726	63.503
12	5.048544	7161.025481	0.812	62.900
13	17.281553	3937.948715	0.766	64.063
14	5.242718	20402.178580	0.917	68.950
15	200.000000	28284.494800	0.943	67.500
16	6796.116505	9172.246719	0.804	63.048

17	37.087379	4579.833524	0.608	60.777
18	3.300971	50313.666900	0.943	72.697
19	0.446602	7011.581696	0.729	67.600
20	75.728155	57016.008440	0.894	74.349
21	893.203883	44570.742380	0.812	73.650
22	25242.718450	NaN	0.530	66.149
23	260.194175	2859.060372	0.826	67.150
24	11.650485	8024.776007	0.857	65.299
25	13.592233	14973.726820	0.804	65.800
26	2.116505	22311.919060	0.799	65.662
27	26.990291	2839.947641	0.853	65.650
28	12.038835	63567.854700	0.943	71.500
29	1.378641	49644.006730	0.952	70.350
30	135.922330	1834.014182	0.601	57.313
31	2.699029	9550.191493	0.798	69.850
32	30.097087	5845.332898	0.780	62.038
33	3.238835	21239.882560	0.925	69.049
34	2.135922	28569.017770	0.848	67.051
35	3.300971	26704.956320	0.884	64.399
36	1.145631	85366.699400	0.878	73.800
37	11.067961	46516.137370	0.939	72.150
38	24.854369	9306.323554	0.874	68.450
39	49.514563	14726.863620	0.913	67.500
40	1.000000	69231.400000	0.919	65.850
41	1.941748	NaN	0.839	64.050
42	13398.058250	6375.564885	0.821	65.502
43	7.747573	13261.543640	0.907	56.989

	Freedom to Make Life Choices	Generosity	Perceptions of Corruption
0	0.942	0.096	0.584
1	0.823	-0.089	0.814
2	0.890	0.198	0.496
3	0.944	0.117	0.737
4	0.801	-0.009	0.738
5	0.874	0.153	0.420
6	0.891	0.027	0.266
7	0.792	-0.011	0.823
8	0.882	-0.041	0.727
9	0.804	-0.104	0.834
10	0.895	-0.070	0.768
11	0.732	-0.183	0.580
12	0.856	-0.057	0.837
13	0.843	0.097	0.843
14	0.757	-0.093	0.925
15	0.758	-0.059	0.839
16	0.880	0.531	0.876
17	0.897	0.072	0.774

18	0.809	-0.023	0.708
19	0.770	-0.150	0.687
20	0.799	-0.237	0.640
21	0.717	-0.046	0.701
22	0.474	-0.141	0.891
23	0.787	-0.030	0.808
24	0.840	-0.080	0.901
25	0.856	-0.094	0.768
26	0.877	0.160	0.758
27	0.877	0.021	0.625
28	0.947	0.141	0.283
29	0.887	0.175	0.271
30	0.766	0.008	0.787
31	0.794	-0.119	0.892
32	0.919	-0.060	0.732
33	0.765	-0.031	0.736
34	0.856	-0.172	0.929
35	0.894	-0.081	0.691
36	0.878	0.063	0.146
37	0.948	0.165	0.202
38	0.850	0.289	0.910
39	0.895	-0.065	0.575
40	0.800	0.137	0.689
41	0.659	0.128	0.811
42	0.939	-0.004	0.759
43	0.730	-0.087	0.902

```
[ ]: ## Find missing values
```

```
[129]: df_merged.isnull().sum()
```

```
[129]: Country          0
Local Price          0
Dollar Ex            0
Dollar Price         0
Dollar PPP           0
GDP Big Mac         2
Social Support       0
Healthy Life Expectancy 0
Freedom to Make Life Choices 0
Generosity           0
Perceptions of Corruption 0
dtype: int64
```

```
[ ]: ## Find outlier information
```

```
[131]: df_merged.describe()
```



```

[131]:
      Local Price      Dollar Ex Dollar Price      Dollar PPP      GDP Big Mac \
count      44.000000      44.000000      44.000000      44.000000      42.000000
mean      6027.234091     1656.562107      3.817780     1170.336717     25662.239760
std      22389.196104     5559.768027      1.145323     4347.416720     22729.766769
min        1.600000        0.377000      1.762674        0.310680     1834.014182
25%       13.175000        3.858388      3.068492        2.558252     7961.440358
50%       51.500000       13.617050      3.601987       10.000000     16038.100335
75%      440.000000      131.302500      4.537865       85.436893     44937.487288
max     130000.000000    25600.000000      6.711756    25242.718450    85366.699400

      Social Support Healthy Life Expectancy Freedom to Make Life Choices \
count      44.000000              44.000000              44.000000
mean        0.841886              67.256682              0.831682
std         0.092831              4.011387              0.088428
min         0.530000              56.989000              0.474000
25%         0.810000              65.451250              0.790750
50%         0.850500              67.175000              0.853000
75%         0.914000              70.075000              0.890250
max         0.952000              74.349000              0.948000

      Generosity Perceptions of Corruption
count      44.000000              44.000000
mean        0.010045              0.697341
std         0.141687              0.202906
min        -0.237000              0.146000
25%        -0.082500              0.636250
50%        -0.026500              0.748000
75%         0.102000              0.834750
max         0.531000              0.929000

```