FEDERAL STATE AUTONOMOUS EDUCATIONAL
INSTITUTION FOR HIGHER EDUCATION
NATIONAL RESEARCH UNIVERSITY
HIGHER SCHOOL OF ECONOMICS
Faculty of Computer Science

HOME PROJECT REPORT
On the course
MODERN METHODS OF DATA ANALYSIS
Analysis of the «World happiness» dataset

Student: Ani Sahakyan
Group: Data Science’22
Supervisor:
D.Sc., Prof.
Mirkin Boris Grigorievich

Moscow 2022

Contents

Introduction

The purpose of this project is to practice the data analysis methods learned in the "Modern Data Analysis Methods" course. The main idea is to use real data and use the proposed technique to find out some patterns in the data, which not only helps to deal with some prediction goals, but also helps to understand the data structure. I'll work on this project with Python programming language, which is one of the most used data analysis languages, and it would be helpful to practice more in this project and get familiar with some of the previously unknown features of the available package.

The development environment which I have used is Google Colab, which is very comfortable to use in terms of its working environment and features. The main body of this report is divided into 6 sections: the first section is dedicated to the dataset description and all other sections represent the use of the techniques indicated in their titles.

For analysis I'll use "The world happiness report 2021" dataset, which is attached in Appendix I. The World Happiness Report is a landmark survey of the state of global happiness. The report continues to gain global recognition as governments, organizations and civil society increasingly use happiness indicators to inform their policy-making decisions. Leading experts across fields – economics, psychology, survey analysis, national statistics, health, public policy and more – describe how measurements of well-being can be used effectively to assess the progress of nations. The reports review the state of happiness in the world today and show how the new science of happiness explains personal and national variations in happiness. The happiness scores and rankings use data from the Gallup World Poll . The columns following the happiness score estimate the extent to which each of six factors – economic production, social support, life expectancy, freedom, absence of corruption, and generosity – contribute to making life evaluations higher in each country than they are in Dystopia, a hypothetical country that has values equal to the world's lowest national averages for each of the six factors. They have no impact on the total score reported for each country, but they do explain why some countries rank higher than others.

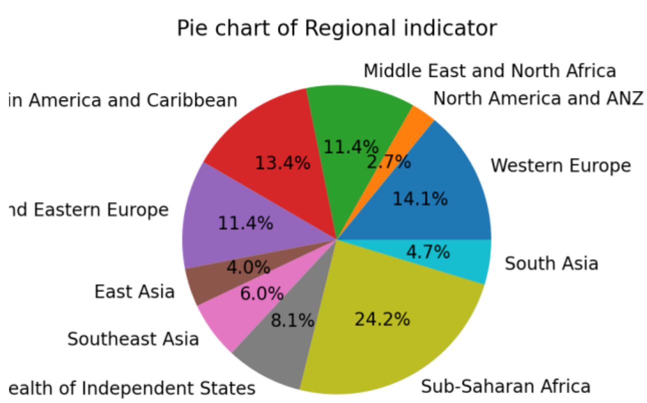
Dataset description

Happiness is the topic , which interests humanity many years. People always trying to find their happiness, and, sometimes they just trying to understand what happiness is, and what they need to do, to become happy. Of course for individuals it is a philosophic question, but anyways, people decided to measure happiness country by country with exact criterias, and collected "World happiness dataset", which will be analyzed during this project scopes.

The dataset is downloaded from Kaggle, the link is attached in References part. It has 149 objects and 15 features.

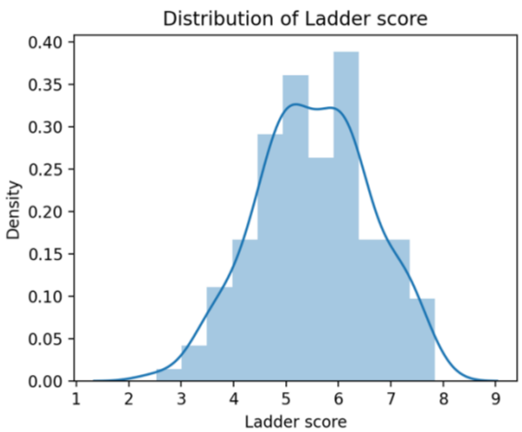
The features presented in the dataset are the following:

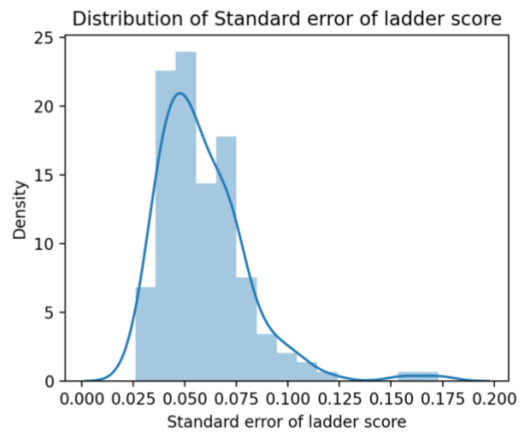
1. Regional indicator, which is categorical, nominal. The pie chart is showing its categories and the percentage of each category.



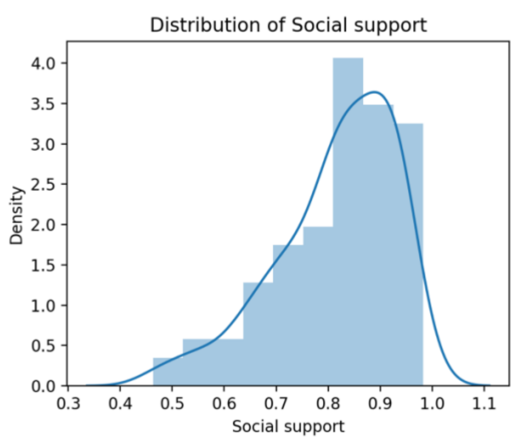
All other features are quantitative ranking variables.

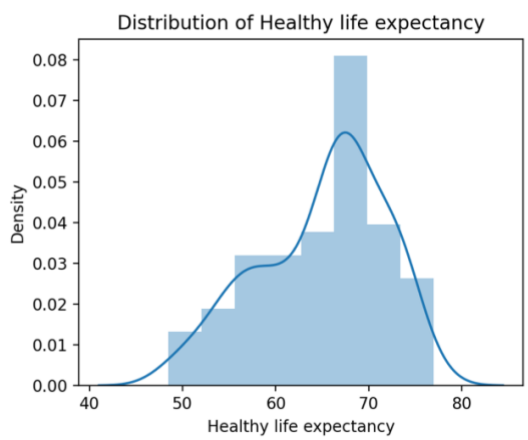
2. Ladder score, which represents the Happiness score. The scale of measurement is from 0 to 10, but here we do not have maximum and minimum values.
The distribution of feature is represented in the left figure.





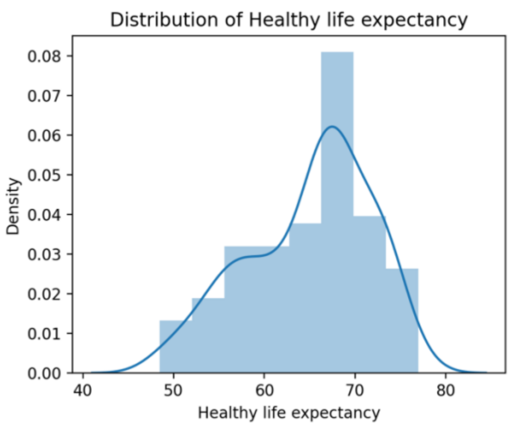
3. Standard error of ladder score, which distribution is from the right side.
4. Social support, which was measurement scale is from 0 to 1. This factor implies that social ties, or having relatives and friends one can rely on if needed, are among the factors which determine happiness.

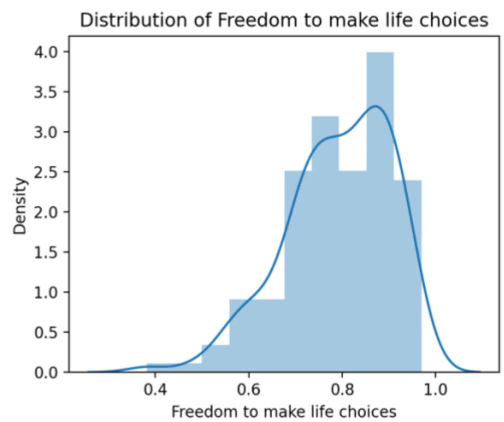




5. Healthy life expectancy, which represents the average number of years that a person can expect to live in "full health" by taking into account years lived in less than full health due to disease and/or injury. The distribution is from the left side.

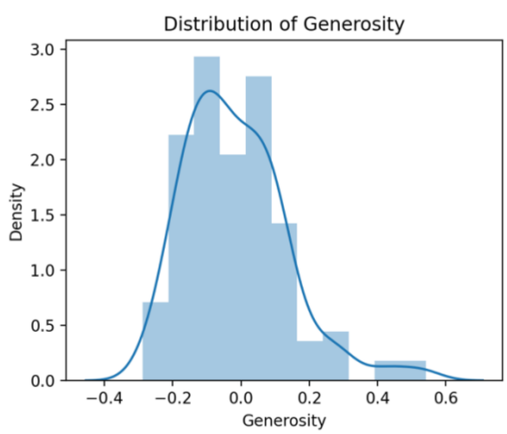
6. Freedom to make life choices which was measurement scale is from 0 to 1, the distribution is represented in the right side. Freedom means opportunity: opportunity to travel, to vote and be elected, to participate in demonstrations, to choose a carrier, etc.

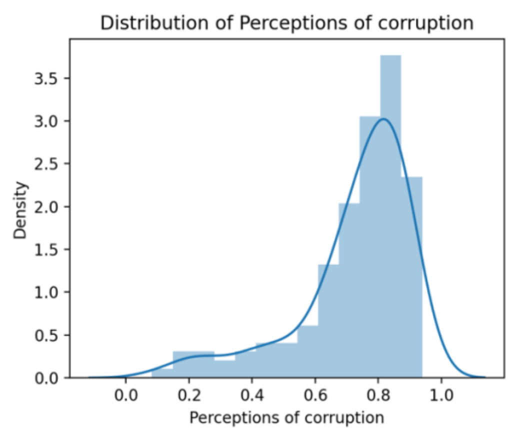




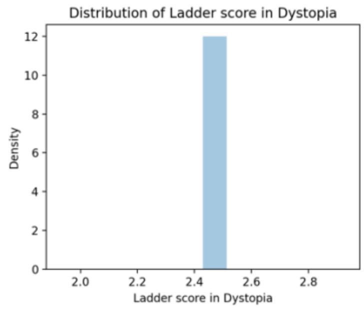
7. In the context of the WHI generosity is understood as the readiness of people to donate money to charities in relation to GDP per capita.

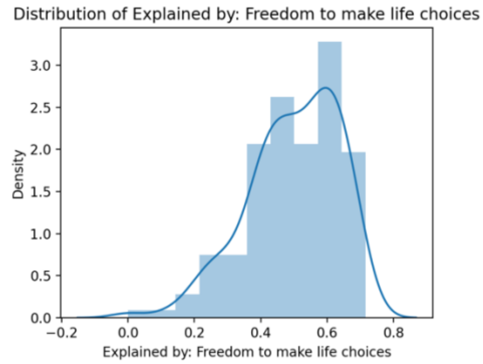
8. Perceptions of corruption, the distribution is from the right side.





9. Ladder score in Dystopia, which has one value for all objects, so we do not need it for our analysis. Dropping this feature from the dataset.





10. Explained by: Social support,

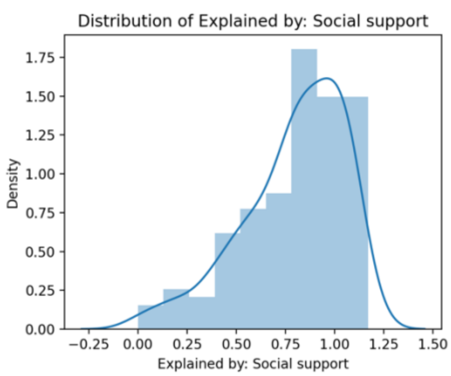
11. Explained by: Healthy life expectancy,

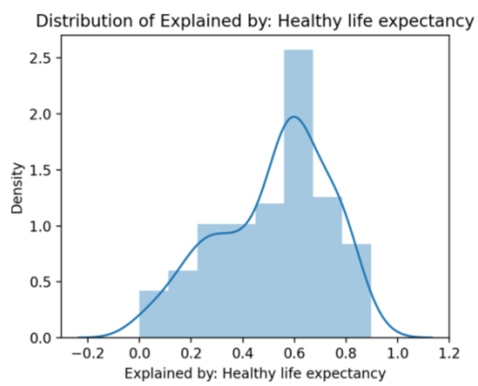
12. Explained by: Freedom to make life choices,

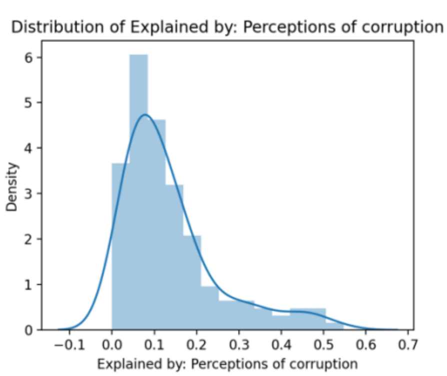
13. Explained by: Generosity,

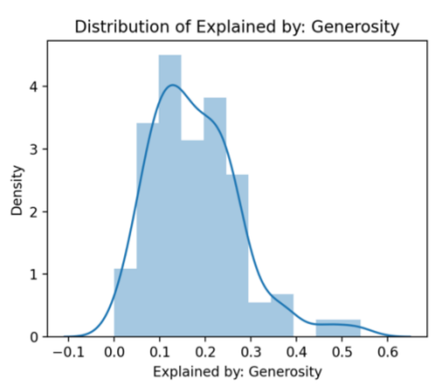
14. Explained by: Perceptions of corruption

These features are representing the previous ones, but with some calculations done on them. These are calculated by multiplying average national data for the period of 2019-2021 for each of the six factors (minus the value of Dystopia)

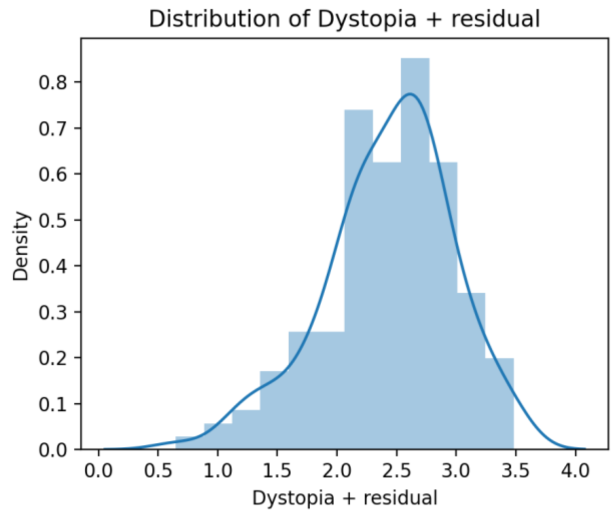








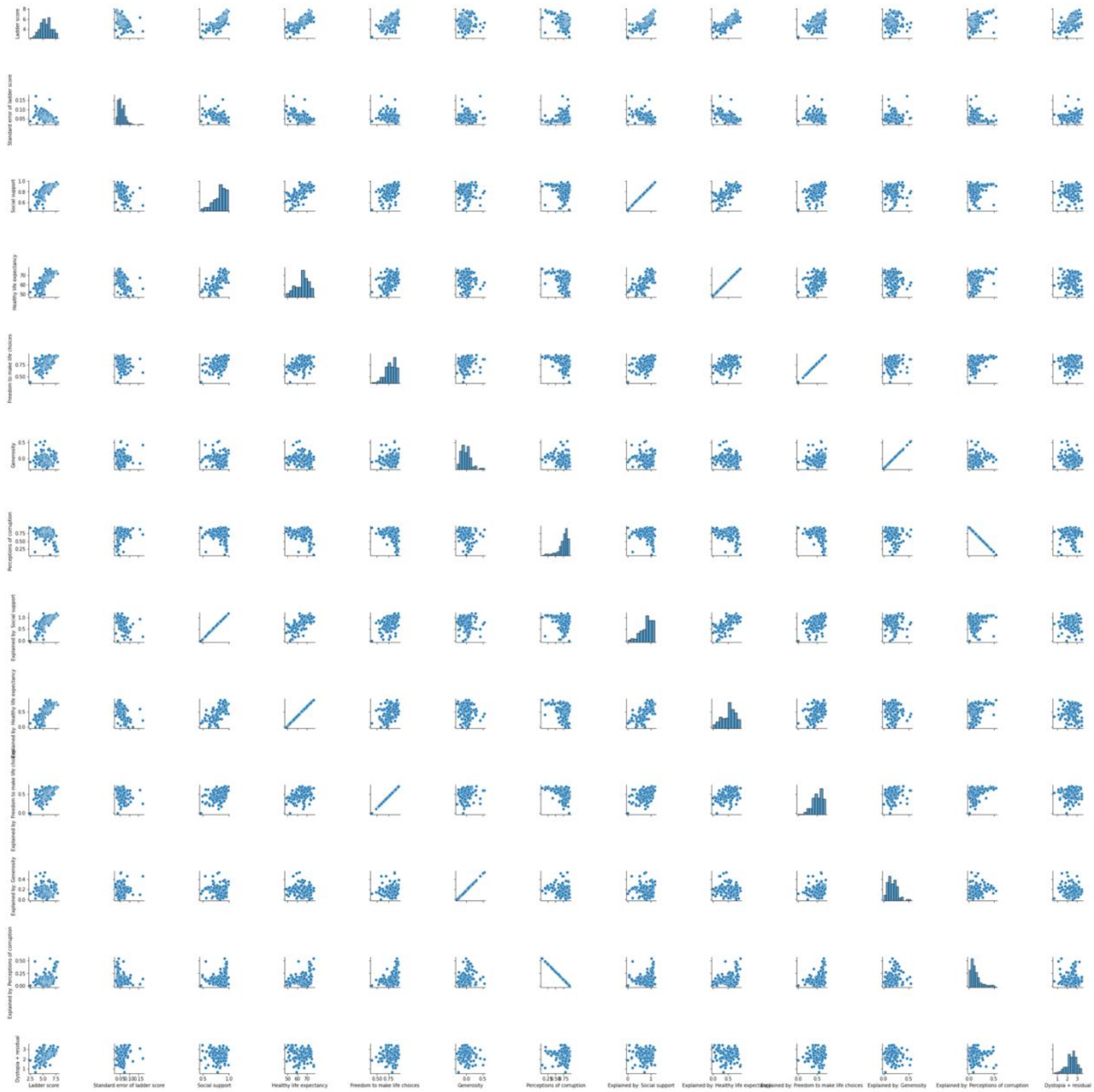
15. Dystopia + residual. Dystopia is an imaginary country that has the world's least-happy people. The purpose in establishing Dystopia is to have a benchmark against which all countries can be favorably compared (no country performs more poorly than Dystopia) in terms of each of the six key variables, thus allowing



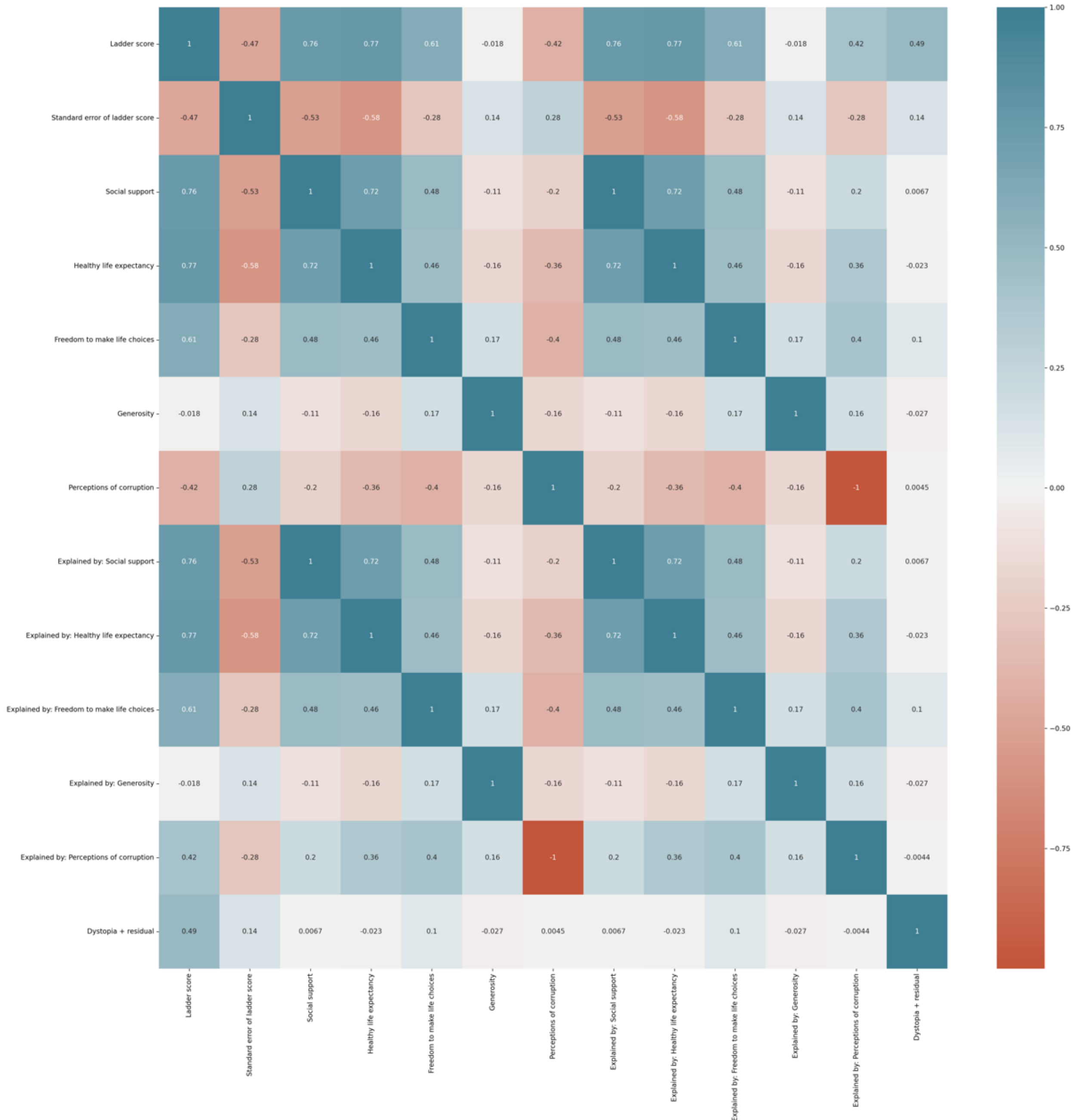
each sub-bar to be of positive (or zero, in six instances) width. The residuals, or unexplained components, differ for each country, reflecting the extent to which the six variables either over- or under-explain average 2019-2021 life evaluations.

Correlation coefficient

For finding two features in the dataset with a more or less “linear-like” scatterplot, we are displaying all possible scatterplots from the data.

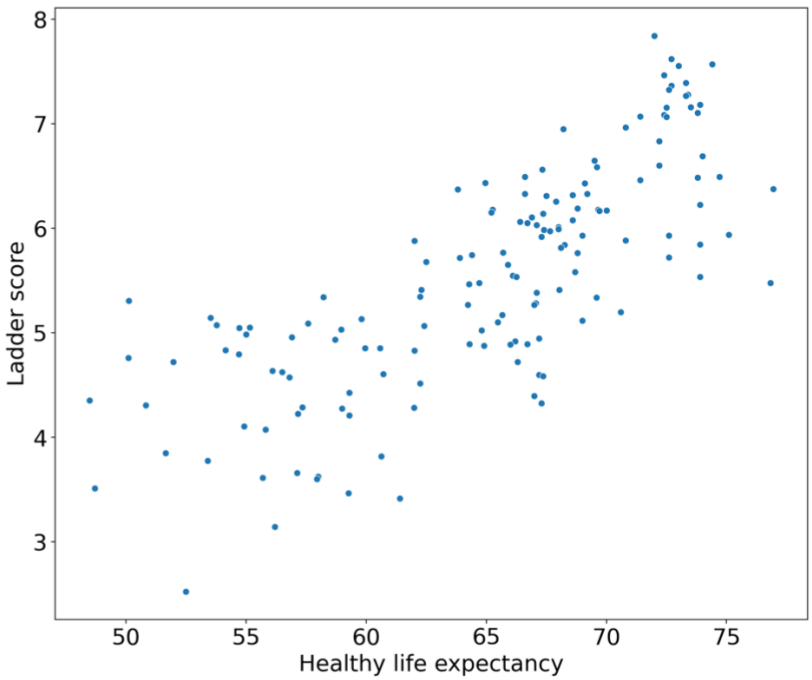


Seems we have too many scatterplots here, and it is hard to choose two variables using these scatterplots. For better performance, we create heatmap of correlation coefficients between all features, and choose the two variables which have the biggest absolute value of correlation coefficient.



The maximum is 0.77, which is not unique case, so we can choose one pair of features of the pairs which have 0.77 correlation coefficient. We will choose Ladder score and Healthy life expectancy.

Here is the scatterplot of these two variables. Look likes it is around a line y=x, but there are some points which have more distance from the main cloud of points. Anyways, the correlation is good enough to continue our calculations.



A regression of Ladder score over Healthy life expectancy below:
To have more 'comfortable' formulas, we will use HLE, instead of Healthy life expectancy in formulas, and LS instead of Ladder score.

LS = 0.12198682*HLE - 2.39542564

If HLE score is increasing by 1, the LS score is increasing by ≈ 0.1. It is not very high correlation, but it seems that HLE have some visible impact on LS.
The correlation coefficient is ≈0.77 and the coefficent of determination is ≈0.59. It means that 100% change of HLE causes 59% of LS change, which is a big difference.

We have predicted 3 target values for 3 randomly chosen from dataset predictor's values. Absolute relative percentage errors are calculated according to formulas which are written below.

$$E1 = \frac{|real - predicted|}{|real|} * 100$$

$$E2 = \frac{|real - predicted|}{|predicted|} * 100$$

Values which we have got are represented in table:

HLE	**LS(real)**	**LS(predicted)**	**Absolute error**	**Relative absolute percentage error (over real value)**	**Relative absolute percentage error (over predicted value)**
67.102	5.384	5.79013368	0.40613368	7.54334476	7.01423671
67.906	6.255	5.88821108	0.36678892	5.86393154	6.22920804
60.633	3.819	5.00100097	1.18200097	30.950536	23.63528776

We have predicted values of LS over all values of HLE in the scatterplot

Mean relative percentage errors E_1= 11.03%, E_2= 10.52%. They are quite close to each other, and not so high numbers.

PCA/SVD

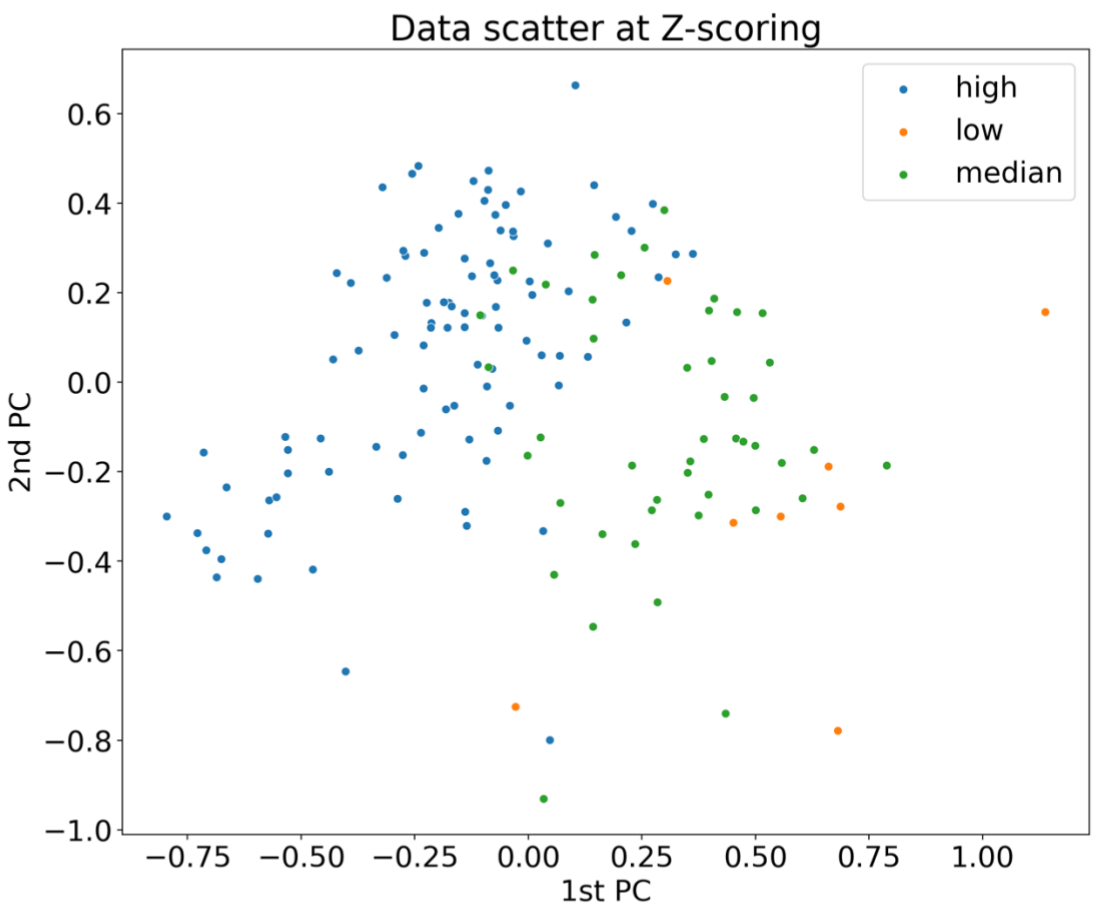
For this task I’m taking features Social support, Healthy life expectancy, Freedom to make life choices, Generosity, Perceptions of corruption. The reason is that they all are describing happiness score, and are key components of this dataset.

2. We standardize the selected subset using 3 versions of normalization: z-scoring, range, and ranking. The latest will be used in the last task in this paragraph. Data scatter for z-scoring is 745, for range normalization 32.418. Then computing SVD for both these standardizations and using their singular values calculate contribution of all the principal components to the corresponding data scatters. The results are shown below:

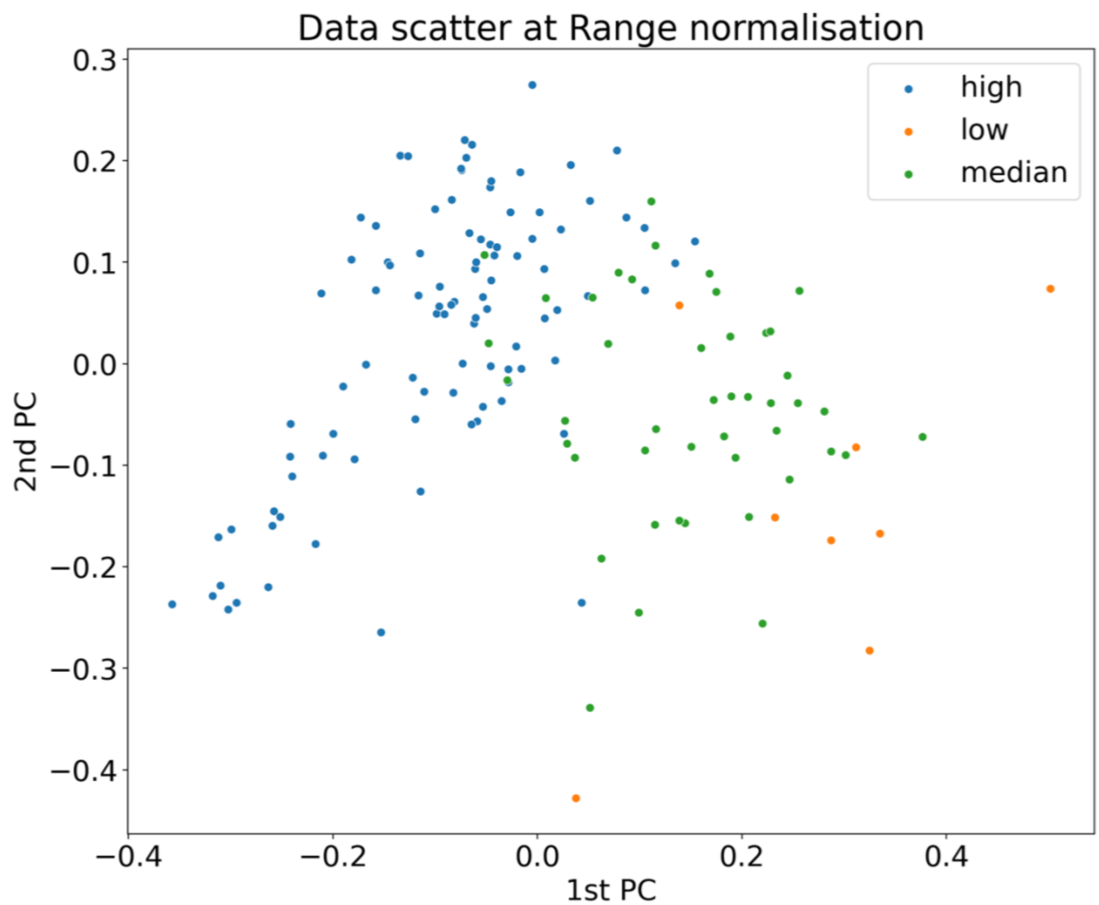
Number of PC	Z-scoring natural	Z-scoring per cent	Range natural	Range per cent
1	350	46.9	16.68	51.5
2	183	24.5	6.93	21.4
3	104	14.1	4.21	12.9
4	71	9.6	2.74	8.5
5	37	4.9	1.86	5.7
Data scatter	745	100	32.42	100

Here we can see that data scatter is divided between all the principal component more or less equally. This may be bad, because we are trying to find some hidden factor which will allow to describe why data is scattered in the observed way but as contributions are close to each other we probably just recombine existing features into new ones.

Then we visualize the data using two first principal components using two versions of standardization: z-scoring (first figure) and range (second figure). For coloring we are using categorized Social support: high stands for >=0.8, median for [0.6,0.8) and low for <0.6.



It is obvious that in both cases the 1st principal component is strongly connected with value of Social support (as Social support are in the selected subset, this component should be based on their concentration more than on other features). Also, we see some slope in scatter in categories, so 2nd PC seems also be impacted by Social support but not so hard as the first one. In addition, in range normalized data this dependency is a bit stronger as we see that points on scatterplot are less shuffled(the difference is little but it exists).

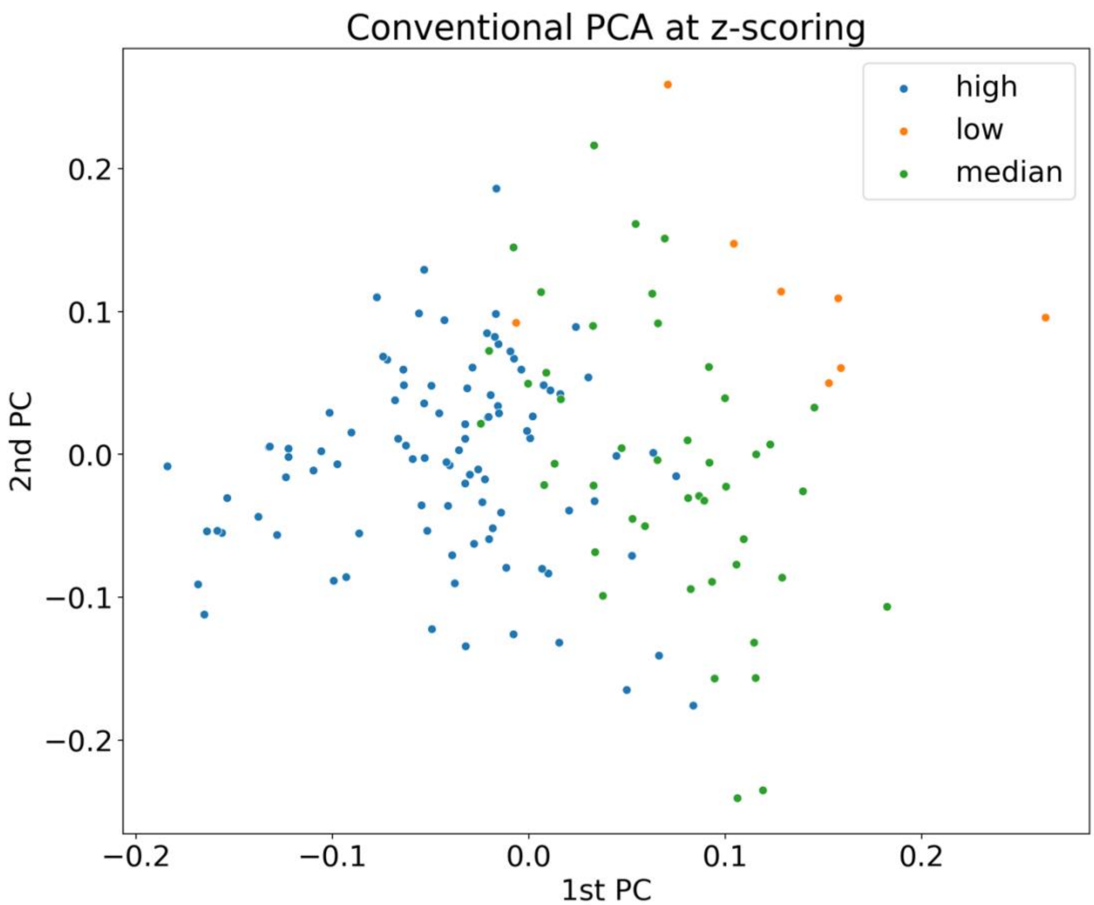


Loadings for both standardizations are presented below:

Standardization	Number of PC	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption
Z-scoring	1	-0.538	0.27	-0.36	-0.264	-0.662
Z-scoring	2	-0.563	0.24	-0.002	-0.364	0.701
Range	1	-0.561	0.29	0.321	-0.140	-0.690
Range	2	-0.641	0.22	0.121	-0.351	0.632

As we can see here, for Z-scoring values of first two features the difference is little. For Freedom to make life choices we have completely another situation, for 2nd score it is very close to 0.

4. We are using conventional PCA to find two first principal components at z-scoring standardization. The results are the same as above, up to sign so when visualizing, we change the sign and now getting a bit another picture. It is look like previous one, but still has some differences



5. Using rank normalized data pre-processed in the first subparagraph, we found hidden ranking factor. Unfortunately, I get some loadings negative, but I do not have any reasons to change the direction of growth for any feature even though

some of them are correlated negatively, as there is no strong recommendation for content of substances to be minimized or maximized – all of them should be somewhere in between. So, I change sign of loading vector in order to make the loadings with the biggest absolute values positive.

Then we are finding hidden ranking factor α=-1.8. The equation for the PCA hidden score vector is shown in the formula

z = -0.9* Social support + 0.5* Healthy life expectancy - 0.4* Freedom to make life choices + 0.4* Generosity + 1.4* Perceptions of corruption

Contribution is 93% which is really high comparing to the previous normalizations.

K-means

Selection of up to 6 features: as there's no visible reasonable ideas (from feature histograms or their correlations), we have decided to pick 5 of the features with which they are measuring happiness score: Social support, Healthy life expectancy, Freedom to make life choices, Generosity, Perceptions of corruption.
These features need normalization, as they are measured with different scales.
After selecting features and normalization we are applying K-means algorithm with K=5 and K=9. In both cases it runs the 1000 random initializations and save the best result. The quality measure here is inertia, which measures distances between instances in clusters and centers of clusters they belong to. The less is the inertia the better is the cauterization. We are getting inertia for K=5 ≈ 11.9 and for K=9 ≈ 8.7.
For interpretation of clusters, we are getting their centers and multiple all the values by 100. Thus, every value shows how much in percent feature value in cluster center differs from the mean value of the corresponding feature.
Results for K=5 are presented below:

	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption
0	21,77981	26,32422	20,50094	11,24968	-39,3646
1	-5,77513	-6,6688	-20,5988	-16,5587	7,198739
2	11,11132	12,30457	5,262307	-7,79985	7,400624
3	-12,5623	-12,7741	8,14224	25,85003	1,538146
4	-31,8971	-37,8097	-19,3669	4,469184	7,200739

There are no values, which have high deviation from the mean, all are <50%. So in our case we can consider 10% as meaningful.

Cluster 0: Healthy life expectancy have value higher than average, with the highest percent (from those which are more than mean value) compared with other clusters, and other features in the same cluster. Social support and Freedom to make life choices also has big (compared with other values we have) difference from the mean. Generosity is closer to mean then these features mentioned earlier and Perceptions of corruption is less then mean with the highest percentage from all the features and clusters.

Cluster 1: In this cluster except Perceptions of corruption, all percents are negative. Means all features have less values then mean. But here all percentages except Freedom to make life choices and Generosity are <10%, so the differences are just a little.

Cluster 2: Here we have Healthy life expectancy and Social support values as >10%, which means they are a bit (meaningful quantity) more than mean. Other features differ from the mean just a little.

Cluster 3: Generosity is higher then mean, with a high percentage. Healthy life expectancy and Social support again have meaningful difference from the mean. The other features difference is little.

Cluster 4: Healthy life expectancy , Social support and Freedom to make life choices have been reduced, other two have been increased but just a little.

So, all the clusters are different and can be used to categorize happiness score. The most meaningful differences are seen in cluster 0, as all features have >20% difference from the mean value.

Results for K=9 are presented below:

	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption
0	-28,6433	-21,9547	15,54467	14,28123	-18,1388
1	6,75719	8,234555	-23,2608	-8,79318	11,62301
2	22,18705	28,83756	19,14611	8,662522	-45,3335
3	-10,8923	-31,5903	-16,2222	-2,43151	11,48103
4	-21,4894	-17,884	-9,17188	50,05633	3,273085
5	10,68253	6,222264	17,00526	18,26564	4,930714
6	-42,5883	-37,3687	-20,8256	3,845776	4,131561
7	14,05792	16,01782	6,993305	-12,1679	7,807387
8	-9,77147	-1,34972	5,680729	-14,2087	-1,3438

Here we can see just one value ≈50%, all other are <50%. So in this case too we can consider 10% as meaningful.

Cluster 0: Here also this cluster has meaningful differences from mean. Freedom to make life choices and Generosity got values more than the mean value, but others have been reduced.

Cluster 1: Except Freedom to make life choices and Perceptions of corruption others have a little difference.

Cluster 2: Except Generosity, all other features have meaningful difference from mean value. The first 3 features have been increased, while Perceptions of corruption have been reduced by 45%, which is 2nd biggest difference in these clusters.

Cluster 3: Here we have meaningful differences, except Generosity. The interesting thing is, that in this cluster first 3 were reduced, and Perceptions of corruption increased, it is like vice versa of 2nd cluster, just with less percents.

Cluster 4: Here we have the biggest percent difference from mean, which is for feature Generosity. It has been increased approximately with 50%. Healthy life expectancy and Social support were reduced, with meaningful percentages. Other features difference is little.

Cluster 5: Here all features were increased, but only Social support, Freedom to make life choices and Generosity have been increased with >10%.

Cluster 6: The first 3 features were reduced, with meaningful percentages. Other features have been increased, but the difference is a little.

Cluster 7: Again, like in cluster 5 Social support, Freedom to make life choices and Generosity have meaningful changes. But in this case Generosity was reduced.

Cluster 8: Except Generosity all features have just a little difference here.

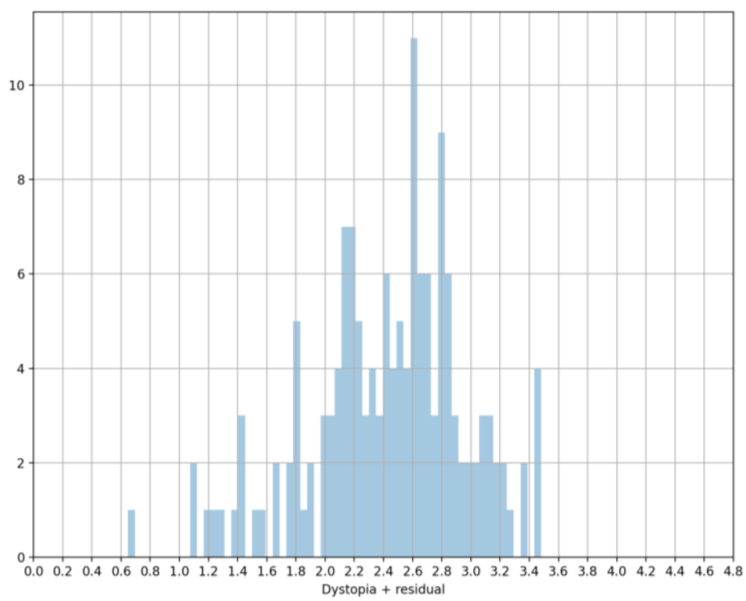
So, all the clusters are different and can be used to categorize happiness score. The most features meaningful differences are seen in cluster 0 as all features have >10% difference from the mean value, and in cluster 2 , 3 where 4 of 5 features have meaningful differences from mean.

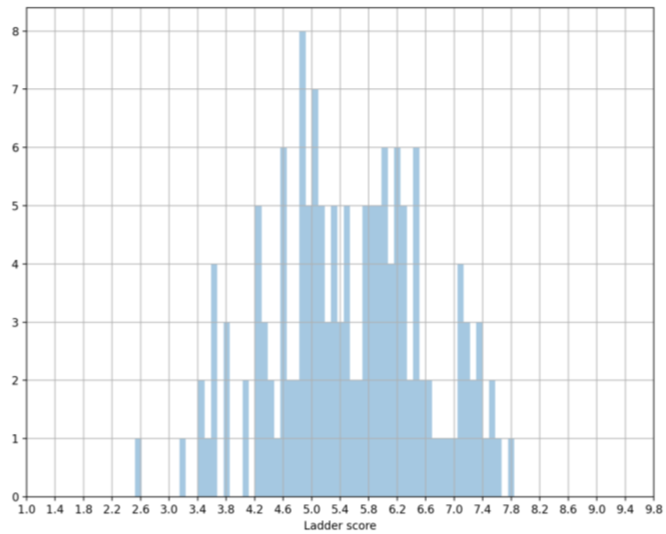
We have no reason other than quality metric, which is inertia, to say what of partitions is better. And as inertia of 9-clusters partition is lower, it is obvious that according to this criterion, we can conclude that the case with K=9 is better than the case with K=5.

Contingency table

1. I’m taking Dystopia + residual, as this feature I used less then others, it will be interesting to use this time. The second one is Ladder score, as it was not used in making clusterization and it may be interesting to check its dependency between developed partition and feature non-used for clustering or not.

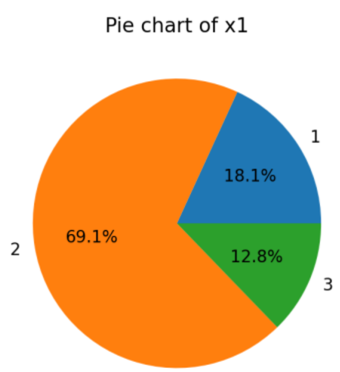
Histograms for features are below:

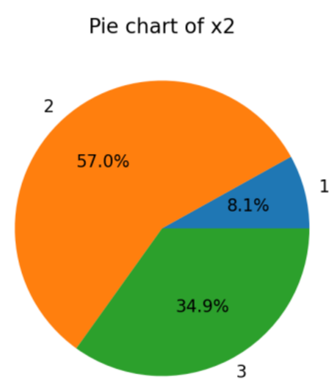




From both histograms we can see, that there is no extraordinary results for these features, which will create troubles for analysis. So we continue.

Then using some of minimum-like drops in the histograms we divide features on enumerated categories as follows: for Dystopia + residual – **1:** <2, **2:** [2,3), **3:** >=3; for Ladder score – **1:** <4, **2:** [4,6), **3:** >=6;. The pie charts of the developed nominal representations x1 and x2 (respectively, for Dystopia + residual and Ladder score) are presented below:





We use a partition S with 5 clusters from the previous paragraph. Using this partition and features x1 and x2 we built two contingency tables:

S \ x1	1	2	3	Total
0	7	49	7	63
1	2	18	1	21
2	4	12	9	25
3	6	14	1	21
4	8	10	1	19
Total	27	103	19	149

S \ x2	1	2	3	Total
0	0	32	31	63
1	0	1	20	21
2	7	18	0	25
3	2	19	0	21
4	3	15	1	19
Total	12	85	52	149

In order to calculate the conditional frequency and Quetelet relative index tables we will use these tables.

Conditional frequency table of S given x1

S\x1	**1**	**2**	**3**	**Total**
0	0,259259	0,475728	0,368421	0,422819
1	0,074074	0,174757	0,052632	0,14094
2	0,148148	0,116505	0,473684	0,167785
3	0,222222	0,135922	0,052632	0,14094
4	0,296296	0,097087	0,052632	0,127517
Total	0,181208	0,691275	0,127517	1

Despite the fact that all numbers seem not really high, we can obtain meaningful information from table. It is obvious, for example, that given low content of Dystopia + residual is very less for 1st cluster. The possibility to get 4th cluster is higher than any other and possibilities of clusters 0 and 3 are quite close to each other. Given 2nd category of Dystopia + residual – median – we also almost cannot get 4th cluster and can get any of other cluster with close possibilities. But here we see, that for cluster 0 it has bigger possibility then for others. Cluster 2,3 are close results to each other. This interpretation is obviously tied with explanation of cluster. The 3rd one is biggest for cluster 3. An interesting fact, for clusters 1,3 and 4 it is very less, and it is the same number for this 3 clusters.

Quetelet relative index table of S given x1

	1	2	3	Total
0	-0,38683	0,125135	-0,12865	0,422819
1	-0,47443	0,239945	-0,62657	0,14094
2	-0,11704	-0,30563	1,823158	0,167785
3	0,57672	-0,0356	-0,62657	0,14094
4	1,323587	-0,23863	-0,58726	0,127517
Total	0,181208	0,691275	0,127517	1

Here we see much more higher values and they can really help in interpretation of categories. So here we see, that first category makes the probability increased by 57%, so the dependence between first category and 3rd cluster is more pronounced. But still, the biggest dependency for first category is with 4th cluster, it is 132%. The biggest dependency from all categories, has 3rd one, with second cluster, which is 182%.

Conditional frequency table of S given x2

	1	2	3	Total
0	0	0,376471	0,596154	0,422819
1	0	0,011765	0,384615	0,14094
2	0,583333	0,211765	0	0,167785
3	0,166667	0,223529	0	0,14094
4	0,25	0,176471	0,019231	0,127517
Total	0,080537	0,57047	0,348993	1

Here we have many 0's. For first category 0 and 1st clusters has 0's , which is not allowing us to tell anything about this. Median is more or less good results, thus in 1st cluster we have very less number, which is close to 0 ,so here there is 0 probability for dependency.

Quetelet relative index table of S given x2

	1	2	3	Total
0	-1	-0,10962	0,409951	0,422819
1	-1	-0,91653	1,728938	0,14094
2	2,476667	0,262118	-1	0,167785
3	0,18254	0,585994	-1	0,14094
4	0,960526	0,383901	-0,84919	0,127517
Total	0,080537	0,57047	0,348993	1

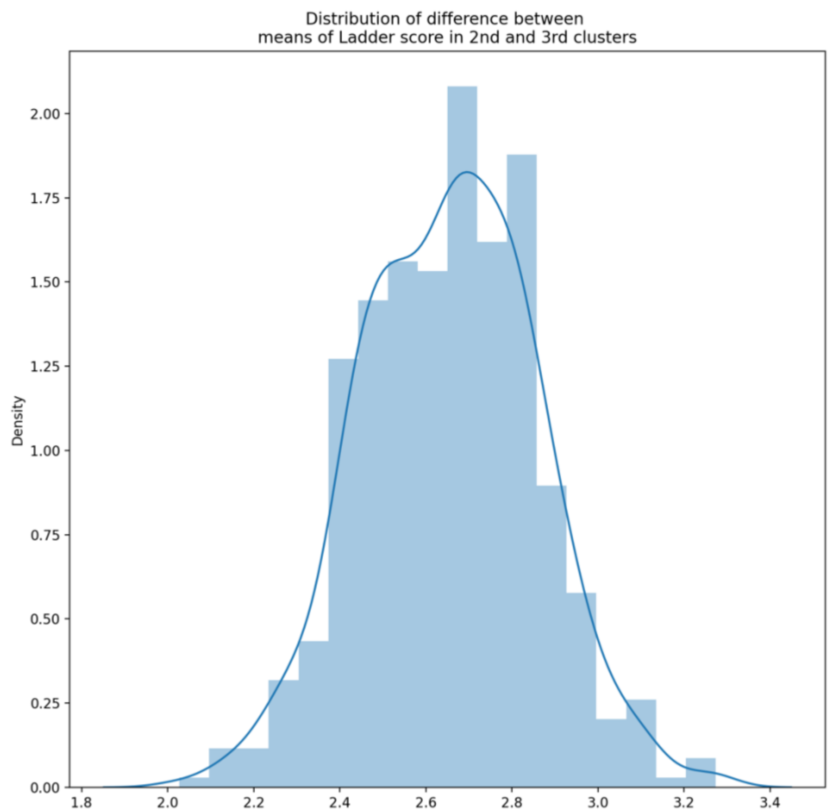
First category makes the probability increased by 247%, so the dependence between first category and 2nd cluster is more pronounced, which is the biggest value from the whole table. The second biggest dependency for first category is with 4th cluster, it is 96%. Second category also shows a good results, here we can see 59% and 38% dependencies which 3rd and 4th clusters respectively.

3. We have calculated average Quetelet indices for both tables. In the 1st case Q1=0.18, in the 2nd Q2=0.57. Meanings are that on average knowledge of categories of Dystopia+../Ladder score increases frequency of clusters by 18%/57%. We see that in 2nd case association is higher, when in the 1st, it is not so much, but both cases gives us useful information. Calculation of chi-squared indices for both tables has shown that they are equal to average Quetelet indices. This proves theoretical statement of their equality.

4. Using chi-squared statistics calculated at the previous step,we are checking how many observations are enough to say that features are associated. For this goal I take quantiles of chi-square distribution of level 95% and 99%. We have (3-1)*(5-1)=8 degrees of freedom. Dividing these quantiles by calculated statistic, I get the following results: in the first case we need 84 observations for 95% confidence and 108 for 99% confidence. Thus, Sulfate and partition are obviously associated. In the second case we need 27 observations for 95% and 35 for 99%. For both confidence levels we have not enough samples, so we see Conductivity and partition as not associated.

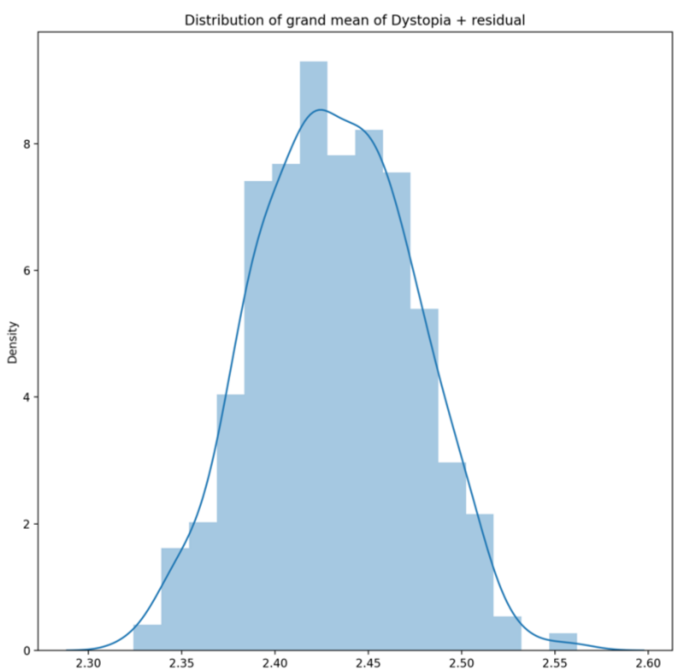
Bootstrap

For comparing means of one feature in two clusters we take partition with 9 clusters and feature Ladder score. The clusters for comparison are 2 and 3. To compare means running bootstrap 500 times and thus get 500 differences between means in 2nd and 3rd clusters. Then, we use two methods: pivotal and non-pivotal to evaluate 95% confidence interval for difference between means. Pivotal gives (2.2580, 3.0511), non-pivotal gives (2.2597, 3.0685). Therefore, in both cases zero is not within the interval so there is a statistically significant difference between the means in this clusters. Means , that Ladder score is a factor describing difference between these two clusters. Indeed, it was not used for building clusterisation, and did not impact it.

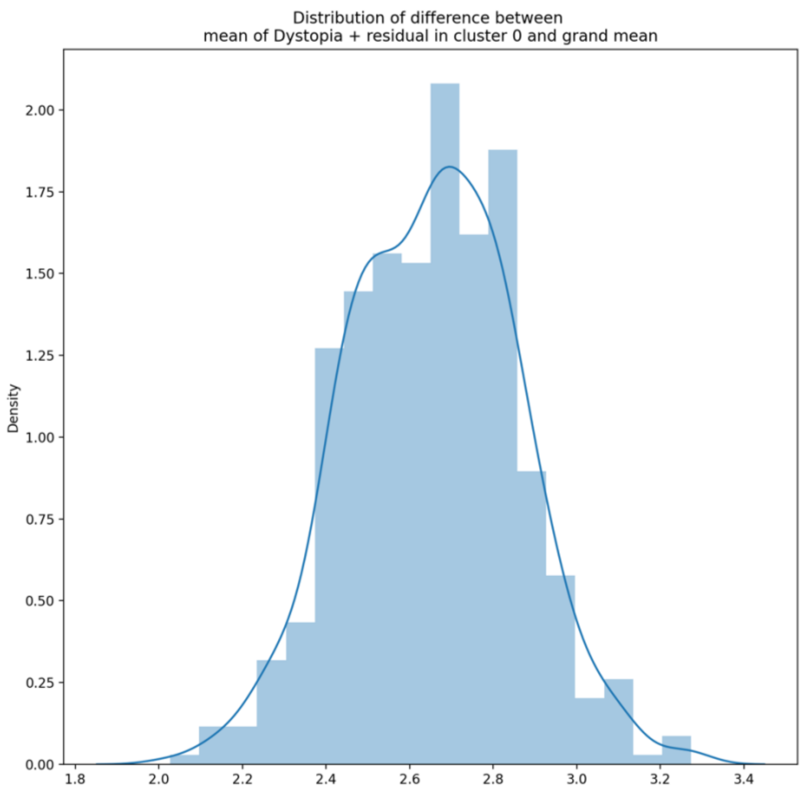


The reason why we need bootstrapping to conclude the above is that real difference between means in two cluster is not exactly zero. And, of course, we also could build a confidence interval using just real means in clusters and standard deviation. But the idea of confidence interval here is that it is built for normally distributed samples. However, feature distribution is less normal than one we get after using bootstrapping. Thus, using bootstrapping technique we make all requirements of confidence intervals usage satisfied and can fully rely on this method.

2. For calculating 95% confidence interval for grand mean of a feature we take feature Explained by: Healthy life expectancy. Here we also run the algorithm 500 times. According to pivotal version, grand mean lies in (0.4859, 0.5579)
to non-pivotal – in (0.4866, 0.5601) .The real mean – 0.52 – is also within the intervals.



3. For comparison of grand-mean and within-cluster mean we take feature Dystopia + residual and cluster 0. Using the same technique as in 1st subparagraph, I get intervals (-1.25, 0.05) if rounded up to 2nd number after the dot for both pivotal and non-pivotal methods. So, zero is within this interval and thus grand mean and within cluster mean are equal with 95% confidence. Again, Dystopia + residual was not used for clusterisation. If I take some other feature that was used and got the same result it will mean that this cluster can be described as the one with the mean values of a taken feature.



Conclusion

So we analyzed the data about happiness, which gave understanding usage of concepts such as Correlation coefficient, PCA/SVD, K-means, Contingency table, Bootstrap.

Working on this project has provided me with the experience on working with data in direction of its interpreting just as it was supposed. We used a number of techniques for working, understanding and analyzing the data.

The practice work gave understanding of Data analysis concepts deeper, and this knowledge will help to work not only for data processing and building some automated decision-making structures but also as tools for interpretable work with data.

References

[1] https://www.kaggle.com/datasets/ajaypalsinghlo/world-happiness-report-2021

[2] B. Mirkin, Lecture material on "Modern methods of data analysis" course.

[3] B. Mirkin, Core Data Analysis: Summarization, Correlation, and Visualization Second edition, Springer Nature Switzerland AG, 2019

[4] https://worldhappiness.report/faq/

[5] https://www.who.int/data/gho/indicator-metadata-registry/imr-details/66

Appendix I

Country name	Regional indicator	Ladder score	Standard error of ladder score	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption	Ladder score in Dystopia	Explained by: Social support	Explained by: Healthy life expectancy	Explained by: Freedom to make life choices	Explained by: Generosity	Explained by: Perceptions of corruption	Dystopia + residual
Finland	Western Europe	7.842	0.032	0.954	72.000	0.949	-0.098	0.186	2.430	1.106	0.741	0.691	0.124	0.481	3.253
Denmark	Western Europe	7.620	0.035	0.954	72.700	0.946	0.030	0.179	2.430	1.108	0.763	0.686	0.208	0.485	2.868
Switzerland	Western Europe	7.571	0.036	0.942	74.400	0.919	0.025	0.292	2.430	1.079	0.816	0.653	0.204	0.413	2.839
Iceland	Western Europe	7.554	0.059	0.983	73.000	0.955	0.160	0.673	2.430	1.172	0.772	0.698	0.293	0.170	2.967
Netherlands	Western Europe	7.464	0.027	0.942	72.400	0.913	0.175	0.338	2.430	1.079	0.753	0.647	0.302	0.384	2.798
Norway	Western Europe	7.392	0.035	0.954	73.300	0.960	0.093	0.270	2.430	1.108	0.782	0.703	0.249	0.427	2.580
Sweden	Western Europe	7.363	0.036	0.934	72.700	0.945	0.086	0.237	2.430	1.062	0.763	0.685	0.244	0.448	2.683
Luxembourg	Western Europe	7.324	0.037	0.908	72.600	0.907	-0.034	0.386	2.430	1.003	0.760	0.639	0.166	0.353	2.653
New Zealand	North America and ANZ	7.277	0.040	0.948	73.400	0.929	0.134	0.242	2.430	1.094	0.785	0.665	0.276	0.445	2.612
Austria	Western Europe	7.268	0.036	0.934	73.300	0.908	0.042	0.481	2.430	1.062	0.782	0.640	0.215	0.292	2.784
Australia	North America and ANZ	7.183	0.041	0.940	73.900	0.914	0.159	0.442	2.430	1.076	0.801	0.647	0.291	0.317	2.598
Israel	Middle East and North Africa	7.157	0.034	0.939	73.503	0.800	0.031	0.753	2.430	1.074	0.788	0.509	0.208	0.119	3.083
Germany	Western Europe	7.155	0.040	0.903	72.500	0.875	0.011	0.460	2.430	0.993	0.757	0.600	0.195	0.306	2.824
Canada	North America and ANZ	7.103	0.042	0.926	73.800	0.915	0.089	0.415	2.430	1.044	0.798	0.648	0.246	0.335	2.585
Ireland	Western Europe	7.085	0.040	0.947	72.400	0.879	0.077	0.363	2.430	1.092	0.753	0.606	0.238	0.367	2.384
Costa Rica	Latin America and Caribbean	7.069	0.056	0.891	71.400	0.934	-0.126	0.809	2.430	0.966	0.722	0.673	0.105	0.083	3.387

United Kingdom	Western Europe	7.064	0.038	0.934	72.500	0.859	0.233	0.459	2.430	1.062	0.757	0.580	0.340	0.306	2.596
Czech Republic	Central and Eastern Europe	6.965	0.049	0.947	70.807	0.858	-0.208	0.868	2.430	1.090	0.703	0.580	0.052	0.046	3.124
United States	North America and ANZ	6.951	0.049	0.920	68.200	0.837	0.098	0.698	2.430	1.030	0.621	0.554	0.252	0.154	2.807
Belgium	Western Europe	6.834	0.034	0.906	72.199	0.783	-0.153	0.646	2.430	0.998	0.747	0.489	0.088	0.187	2.862
France	Western Europe	6.690	0.037	0.942	74.000	0.822	-0.147	0.571	2.430	1.081	0.804	0.536	0.092	0.235	2.521
Bahrain	Middle East and North Africa	6.647	0.068	0.862	69.495	0.925	0.089	0.722	2.430	0.899	0.662	0.661	0.246	0.139	2.631
Malta	Western Europe	6.602	0.044	0.931	72.200	0.927	0.133	0.653	2.430	1.055	0.747	0.664	0.275	0.183	2.268
Taiwan Province of China	East Asia	6.584	0.038	0.898	69.600	0.784	-0.070	0.721	2.430	0.982	0.665	0.490	0.142	0.139	2.687
United Arab Emirates	Middle East and North Africa	6.561	0.039	0.844	67.333	0.932	0.074	0.589	2.430	0.860	0.594	0.670	0.236	0.223	2.422
Saudi Arabia	Middle East and North Africa	6.494	0.056	0.891	66.603	0.877	-0.149	0.684	2.430	0.964	0.571	0.603	0.090	0.163	2.668
Spain	Western Europe	6.491	0.042	0.932	74.700	0.761	-0.081	0.745	2.430	1.057	0.826	0.462	0.135	0.124	2.513
Italy	Western Europe	6.483	0.045	0.880	73.800	0.693	-0.084	0.866	2.430	0.940	0.798	0.379	0.133	0.047	2.794
Slovenia	Central and Eastern Europe	6.461	0.043	0.948	71.400	0.949	-0.101	0.806	2.430	1.093	0.722	0.690	0.122	0.085	2.388
Guatemala	Latin America and Caribbean	6.435	0.073	0.813	64.958	0.906	-0.038	0.775	2.430	0.790	0.519	0.638	0.163	0.105	3.375
Uruguay	Latin America and Caribbean	6.431	0.046	0.925	69.100	0.896	-0.092	0.590	2.430	1.042	0.649	0.625	0.128	0.223	2.600
Singapore	Southeast Asia	6.377	0.043	0.915	76.953	0.927	-0.018	0.082	2.430	1.019	0.897	0.664	0.176	0.547	1.379
Kosovo	Central and Eastern Europe	6.372	0.059	0.821	63.813	0.869	0.257	0.917	2.430	0.807	0.483	0.593	0.356	0.014	3.182

Slovakia	Central and Eastern Europe	6.331	0.041	0.936	69.201	0.766	-0.124	0.911	2.430	1.066	0.653	0.468	0.107	0.018	2.714
Brazil	Latin America and Caribbean	6.330	0.043	0.882	66.601	0.804	-0.071	0.756	2.430	0.944	0.571	0.514	0.142	0.117	3.015
Mexico	Latin America and Caribbean	6.317	0.053	0.831	68.597	0.862	-0.147	0.799	2.430	0.830	0.634	0.585	0.092	0.089	2.961
Jamaica	Latin America and Caribbean	6.309	0.156	0.877	67.500	0.890	-0.137	0.884	2.430	0.932	0.599	0.618	0.099	0.035	3.135
Lithuania	Central and Eastern Europe	6.255	0.045	0.935	67.906	0.773	-0.203	0.826	2.430	1.065	0.612	0.476	0.056	0.073	2.624
Cyprus	Western Europe	6.223	0.049	0.802	73.898	0.763	-0.015	0.844	2.430	0.765	0.801	0.464	0.178	0.061	2.578
Estonia	Central and Eastern Europe	6.189	0.038	0.941	68.800	0.909	-0.106	0.527	2.430	1.079	0.640	0.641	0.119	0.263	2.103
Panama	Latin America and Caribbean	6.180	0.073	0.896	69.652	0.872	-0.166	0.856	2.430	0.976	0.667	0.596	0.079	0.053	2.509
Uzbekistan	Commonwealth of Independent States	6.179	0.068	0.918	65.255	0.970	0.311	0.515	2.430	1.027	0.528	0.716	0.391	0.271	2.477
Chile	Latin America and Caribbean	6.172	0.046	0.882	70.000	0.742	-0.044	0.830	2.430	0.946	0.678	0.438	0.159	0.070	2.682
Poland	Central and Eastern Europe	6.166	0.040	0.898	69.702	0.841	-0.165	0.735	2.430	0.982	0.668	0.558	0.080	0.130	2.438
Kazakhstan	Commonwealth of Independent States	6.152	0.047	0.952	65.200	0.853	-0.069	0.733	2.430	1.103	0.527	0.573	0.143	0.132	2.446
Romania	Central and Eastern Europe	6.140	0.057	0.832	67.355	0.845	-0.219	0.938	2.430	0.832	0.595	0.564	0.045	0.001	2.830
Kuwait	Middle East and North Africa	6.106	0.066	0.843	66.900	0.867	-0.104	0.736	2.430	0.857	0.580	0.591	0.120	0.130	2.368

Serbia	Central and Eastern Europe	6.078	0.053	0.873	68.600	0.778	0.002	0.835	2.430	0.924	0.634	0.482	0.189	0.066	2.682
El Salvador	Latin America and Caribbean	6.061	0.065	0.762	66.402	0.888	-0.110	0.688	2.430	0.675	0.565	0.615	0.116	0.160	3.085
Mauritius	Sub-Saharan Africa	6.049	0.059	0.905	66.701	0.867	-0.054	0.789	2.430	0.996	0.574	0.590	0.153	0.096	2.462
Latvia	Central and Eastern Europe	6.032	0.036	0.927	67.100	0.715	-0.162	0.800	2.430	1.047	0.587	0.405	0.082	0.089	2.536
Colombia	Latin America and Caribbean	6.012	0.061	0.847	68.001	0.837	-0.135	0.841	2.430	0.866	0.615	0.554	0.100	0.063	2.794
Hungary	Central and Eastern Europe	5.992	0.047	0.943	68.000	0.755	-0.186	0.876	2.430	1.083	0.615	0.454	0.067	0.040	2.432
Thailand	Southeast Asia	5.985	0.047	0.888	67.401	0.884	0.287	0.895	2.430	0.957	0.596	0.611	0.375	0.028	2.309
Nicaragua	Latin America and Caribbean	5.972	0.083	0.864	67.657	0.836	0.020	0.664	2.430	0.904	0.604	0.553	0.201	0.176	2.841
Japan	East Asia	5.940	0.040	0.884	75.100	0.796	-0.258	0.638	2.430	0.949	0.838	0.504	0.020	0.192	2.048
Argentina	Latin America and Caribbean	5.929	0.056	0.898	69.000	0.828	-0.182	0.834	2.430	0.980	0.646	0.544	0.069	0.067	2.461
Portugal	Western Europe	5.929	0.055	0.879	72.600	0.892	-0.244	0.887	2.430	0.939	0.760	0.621	0.029	0.033	2.225
Honduras	Latin America and Caribbean	5.919	0.082	0.812	67.300	0.857	0.081	0.809	2.430	0.787	0.593	0.578	0.241	0.083	2.934
Croatia	Central and Eastern Europe	5.882	0.048	0.924	70.799	0.754	-0.118	0.939	2.430	1.039	0.703	0.453	0.111	0.000	2.325
Philippines	Southeast Asia	5.880	0.052	0.830	62.000	0.917	-0.097	0.742	2.430	0.828	0.426	0.651	0.125	0.126	2.872
South Korea	East Asia	5.845	0.042	0.799	73.900	0.672	-0.083	0.727	2.430	0.758	0.801	0.353	0.134	0.135	2.262
Peru	Latin America and Caribbean	5.840	0.075	0.832	68.250	0.822	-0.154	0.891	2.430	0.833	0.623	0.536	0.087	0.031	2.744

Bosnia and Herzegovina	Central and Eastern Europe	5.813	0.050	0.870	68.098	0.706	0.113	0.931	2.430	0.919	0.618	0.395	0.261	0.005	2.583
Moldova	Commonwealth of Independent States	5.766	0.046	0.857	65.699	0.822	-0.079	0.918	2.430	0.888	0.542	0.536	0.137	0.013	2.665
Ecuador	Latin America and Caribbean	5.764	0.057	0.821	68.800	0.842	-0.124	0.843	2.430	0.806	0.640	0.560	0.107	0.062	2.653
Kyrgyzstan	Commonwealth of Independent States	5.744	0.046	0.893	64.401	0.935	0.119	0.908	2.430	0.971	0.501	0.673	0.266	0.020	2.648
Greece	Western Europe	5.723	0.046	0.823	72.600	0.582	-0.288	0.823	2.430	0.811	0.760	0.243	0.000	0.074	2.561
Bolivia	Latin America and Caribbean	5.716	0.053	0.810	63.901	0.875	-0.077	0.839	2.430	0.782	0.486	0.600	0.138	0.064	2.805
Mongolia	East Asia	5.677	0.042	0.935	62.500	0.708	0.116	0.856	2.430	1.065	0.442	0.397	0.263	0.053	2.492
Paraguay	Latin America and Caribbean	5.653	0.092	0.893	65.900	0.876	0.028	0.882	2.430	0.970	0.549	0.602	0.206	0.037	2.306
Montenegro	Central and Eastern Europe	5.581	0.054	0.858	68.699	0.708	-0.034	0.812	2.430	0.891	0.637	0.397	0.166	0.081	2.254
Dominican Republic	Latin America and Caribbean	5.545	0.071	0.853	66.102	0.860	-0.133	0.714	2.430	0.879	0.555	0.581	0.101	0.144	2.178
North Cyprus	Western Europe	5.536	0.051	0.820	73.898	0.795	0.012	0.626	2.430	0.806	0.801	0.503	0.196	0.200	1.653
Belarus	Commonwealth of Independent States	5.534	0.047	0.910	66.253	0.650	-0.180	0.627	2.430	1.007	0.560	0.326	0.070	0.199	2.247
Russia	Commonwealth of Independent States	5.477	0.033	0.903	64.703	0.718	-0.111	0.845	2.430	0.992	0.511	0.409	0.115	0.060	2.148
Hong Kong S.A.R. of China	East Asia	5.477	0.049	0.836	76.820	0.717	0.067	0.403	2.430	0.841	0.893	0.408	0.232	0.342	1.236
Tajikistan	Commonwealth of Independent States	5.466	0.034	0.860	64.281	0.832	-0.056	0.553	2.430	0.895	0.498	0.548	0.152	0.247	2.619

Vietnam	Southeast Asia	5.411	0.039	0.850	68.034	0.940	-0.098	0.796	2.430	0.873	0.616	0.679	0.124	0.091	2.211
Libya	Middle East and North Africa	5.410	0.076	0.827	62.300	0.771	-0.087	0.667	2.430	0.821	0.435	0.474	0.131	0.174	2.331
Malaysia	Southeast Asia	5.384	0.049	0.817	67.102	0.895	0.125	0.839	2.430	0.797	0.587	0.624	0.270	0.064	1.784
Indonesia	Southeast Asia	5.345	0.056	0.811	62.236	0.873	0.542	0.867	2.430	0.786	0.433	0.598	0.541	0.046	1.987
Congo (Brazzaville)	Sub-Saharan Africa	5.342	0.097	0.636	58.221	0.695	-0.068	0.745	2.430	0.392	0.307	0.381	0.144	0.124	3.476
China	East Asia	5.339	0.029	0.811	69.593	0.904	-0.146	0.755	2.430	0.785	0.665	0.636	0.093	0.117	1.982
Ivory Coast	Sub-Saharan Africa	5.306	0.078	0.644	50.114	0.741	-0.016	0.794	2.430	0.409	0.052	0.438	0.177	0.092	3.469
Armenia	Commonwealth of Independent States	5.283	0.058	0.799	67.055	0.825	-0.168	0.629	2.430	0.758	0.585	0.540	0.079	0.198	2.127
Nepal	South Asia	5.269	0.070	0.774	64.233	0.782	0.152	0.727	2.430	0.702	0.496	0.488	0.287	0.135	2.642
Bulgaria	Central and Eastern Europe	5.266	0.054	0.931	67.000	0.788	-0.096	0.932	2.430	1.055	0.583	0.494	0.125	0.005	1.823
Maldives	South Asia	5.198	0.072	0.913	70.600	0.854	0.024	0.825	2.430	1.015	0.697	0.575	0.204	0.073	1.520
Azerbaijan	Commonwealth of Independent States	5.171	0.040	0.836	65.656	0.814	-0.223	0.506	2.430	0.841	0.541	0.526	0.043	0.276	1.919
Cameroon	Sub-Saharan Africa	5.142	0.074	0.710	53.515	0.731	0.026	0.848	2.430	0.556	0.159	0.425	0.205	0.058	3.195
Senegal	Sub-Saharan Africa	5.132	0.068	0.710	59.802	0.695	-0.046	0.801	2.430	0.558	0.357	0.381	0.158	0.088	3.071
Albania	Central and Eastern Europe	5.117	0.059	0.697	68.999	0.785	-0.030	0.901	2.430	0.529	0.646	0.491	0.168	0.024	2.250
North Macedonia	Central and Eastern Europe	5.101	0.051	0.805	65.474	0.751	0.038	0.905	2.430	0.772	0.535	0.450	0.212	0.022	2.042
Ghana	Sub-Saharan Africa	5.088	0.067	0.727	57.586	0.807	0.123	0.848	2.430	0.595	0.287	0.517	0.268	0.058	2.684

Niger	Sub-Saharan Africa	5.074	0.102	0.641	53.780	0.806	0.018	0.693	2.430	0.402	0.167	0.516	0.200	0.157	3.470
Turkmenistan	Commonwealth of Independent States	5.066	0.036	0.983	62.409	0.877	0.273	0.888	2.430	1.172	0.439	0.602	0.366	0.033	1.409
Gambia	Sub-Saharan Africa	5.051	0.089	0.690	55.160	0.697	0.424	0.746	2.430	0.511	0.210	0.384	0.465	0.123	2.990
Benin	Sub-Saharan Africa	5.045	0.073	0.489	54.713	0.757	-0.034	0.661	2.430	0.058	0.196	0.457	0.166	0.178	3.482
Laos	Southeast Asia	5.030	0.045	0.728	58.968	0.910	0.123	0.658	2.430	0.598	0.330	0.643	0.268	0.179	2.204
Bangladesh	South Asia	5.025	0.046	0.693	64.800	0.877	-0.041	0.682	2.430	0.520	0.514	0.603	0.161	0.164	2.427
Guinea	Sub-Saharan Africa	4.984	0.090	0.639	55.008	0.697	0.095	0.766	2.430	0.399	0.206	0.384	0.250	0.111	3.216
South Africa	Sub-Saharan Africa	4.956	0.060	0.860	56.904	0.749	-0.067	0.860	2.430	0.895	0.265	0.447	0.144	0.051	2.187
Turkey	Middle East and North Africa	4.948	0.046	0.822	67.199	0.576	-0.139	0.776	2.430	0.809	0.590	0.236	0.097	0.104	1.852
Pakistan	South Asia	4.934	0.068	0.651	58.709	0.726	0.098	0.787	2.430	0.423	0.322	0.418	0.252	0.097	2.784
Morocco	Middle East and North Africa	4.918	0.060	0.560	66.208	0.774	-0.236	0.801	2.430	0.219	0.558	0.477	0.034	0.088	2.749
Venezuela	Latin America and Caribbean	4.892	0.064	0.861	66.700	0.615	-0.169	0.827	2.430	0.897	0.574	0.284	0.078	0.072	2.135
Georgia	Commonwealth of Independent States	4.891	0.054	0.671	64.300	0.783	-0.238	0.655	2.430	0.470	0.498	0.488	0.032	0.181	2.191
Algeria	Middle East and North Africa	4.887	0.053	0.802	66.005	0.480	-0.067	0.752	2.430	0.765	0.552	0.119	0.144	0.120	2.242
Ukraine	Commonwealth of Independent States	4.875	0.052	0.888	64.902	0.724	-0.011	0.924	2.430	0.958	0.517	0.417	0.181	0.010	1.813
Iraq	Middle East and North Africa	4.854	0.059	0.746	60.583	0.630	-0.053	0.875	2.430	0.638	0.381	0.302	0.153	0.041	2.429

Gabon	Sub-Saharan Africa	4.852	0.075	0.776	59.962	0.731	-0.200	0.840	2.430	0.707	0.362	0.424	0.058	0.064	2.201
Burkina Faso	Sub-Saharan Africa	4.834	0.081	0.672	54.151	0.695	-0.009	0.748	2.430	0.472	0.179	0.381	0.182	0.122	3.133
Cambodia	Southeast Asia	4.830	0.067	0.765	62.000	0.959	0.034	0.843	2.430	0.680	0.426	0.702	0.210	0.061	2.148
Mozambique	Sub-Saharan Africa	4.794	0.103	0.744	54.706	0.882	0.061	0.684	2.430	0.634	0.196	0.608	0.228	0.163	2.783
Nigeria	Sub-Saharan Africa	4.759	0.052	0.740	50.102	0.737	0.037	0.878	2.430	0.625	0.051	0.433	0.212	0.039	2.736
Mali	Sub-Saharan Africa	4.723	0.082	0.724	51.969	0.697	-0.036	0.827	2.430	0.590	0.110	0.384	0.164	0.072	3.016
Iran	Middle East and North Africa	4.721	0.055	0.710	66.300	0.608	0.218	0.714	2.430	0.557	0.561	0.275	0.330	0.144	1.823
Uganda	Sub-Saharan Africa	4.636	0.073	0.781	56.101	0.709	0.122	0.855	2.430	0.718	0.240	0.398	0.267	0.054	2.596
Liberia	Sub-Saharan Africa	4.625	0.106	0.720	56.498	0.735	0.050	0.850	2.430	0.580	0.253	0.430	0.221	0.057	2.857
Kenya	Sub-Saharan Africa	4.607	0.072	0.688	60.704	0.779	0.287	0.825	2.430	0.508	0.385	0.483	0.375	0.073	2.180
Tunisia	Middle East and North Africa	4.596	0.058	0.691	67.201	0.656	-0.201	0.870	2.430	0.515	0.590	0.334	0.057	0.044	2.138
Lebanon	Middle East and North Africa	4.584	0.055	0.848	67.355	0.525	-0.073	0.898	2.430	0.868	0.595	0.175	0.140	0.026	1.736
Namibia	Sub-Saharan Africa	4.574	0.064	0.818	56.799	0.719	-0.149	0.847	2.430	0.801	0.262	0.411	0.091	0.059	2.068
Palestinian Territories	Middle East and North Africa	4.517	0.067	0.826	62.250	0.653	-0.163	0.821	2.430	0.819	0.434	0.330	0.082	0.075	2.131
Myanmar	Southeast Asia	4.426	0.052	0.779	59.302	0.876	0.509	0.660	2.430	0.713	0.341	0.601	0.520	0.178	1.407
Jordan	Middle East and North Africa	4.395	0.062	0.767	67.000	0.755	-0.167	0.705	2.430	0.685	0.583	0.455	0.079	0.150	1.553

Chad	Sub-Saharan Africa	4.355	0.094	0.619	48.478	0.579	0.041	0.807	2.430	0.353	0.000	0.240	0.215	0.084	3.209
Sri Lanka	South Asia	4.325	0.066	0.827	67.299	0.841	0.079	0.863	2.430	0.820	0.593	0.559	0.239	0.049	1.075
Swaziland	Sub-Saharan Africa	4.308	0.071	0.770	50.833	0.647	-0.185	0.708	2.430	0.693	0.074	0.323	0.067	0.147	2.155
Comoros	Sub-Saharan Africa	4.289	0.084	0.626	57.349	0.548	0.082	0.781	2.430	0.367	0.279	0.202	0.241	0.101	2.610
Egypt	Middle East and North Africa	4.283	0.045	0.750	61.998	0.749	-0.182	0.795	2.430	0.647	0.426	0.446	0.069	0.092	1.648
Ethiopia	Sub-Saharan Africa	4.275	0.051	0.764	59.000	0.752	0.082	0.761	2.430	0.679	0.331	0.451	0.241	0.114	2.089
Mauritania	Sub-Saharan Africa	4.227	0.070	0.795	57.161	0.561	-0.106	0.731	2.430	0.749	0.273	0.218	0.119	0.133	2.069
Madagascar	Sub-Saharan Africa	4.208	0.072	0.686	59.305	0.552	-0.005	0.803	2.430	0.503	0.341	0.207	0.185	0.087	2.620
Togo	Sub-Saharan Africa	4.107	0.077	0.569	54.914	0.619	0.032	0.772	2.430	0.239	0.203	0.289	0.209	0.107	2.806
Zambia	Sub-Saharan Africa	4.073	0.069	0.708	55.809	0.782	0.061	0.823	2.430	0.552	0.231	0.487	0.227	0.074	1.975
Sierra Leone	Sub-Saharan Africa	3.849	0.077	0.630	51.651	0.717	0.084	0.866	2.430	0.377	0.100	0.408	0.243	0.047	2.396
India	South Asia	3.819	0.026	0.603	60.633	0.893	0.089	0.774	2.430	0.316	0.383	0.622	0.246	0.106	1.405
Burundi	Sub-Saharan Africa	3.775	0.107	0.490	53.400	0.626	-0.024	0.607	2.430	0.062	0.155	0.298	0.172	0.212	2.876
Yemen	Middle East and North Africa	3.658	0.070	0.832	57.122	0.602	-0.147	0.800	2.430	0.831	0.272	0.268	0.092	0.089	1.776
Tanzania	Sub-Saharan Africa	3.623	0.071	0.702	57.999	0.833	0.183	0.577	2.430	0.540	0.300	0.549	0.307	0.231	1.263
Haiti	Latin America and Caribbean	3.615	0.173	0.540	55.700	0.593	0.422	0.721	2.430	0.173	0.227	0.257	0.463	0.139	2.060
Malawi	Sub-Saharan Africa	3.600	0.092	0.537	57.948	0.780	0.038	0.729	2.430	0.168	0.298	0.484	0.213	0.134	2.190

Lesotho	Sub-Saharan Africa	3.512	0.120	0.787	48.700	0.715	-0.131	0.915	2.430	0.731	0.007	0.405	0.103	0.015	1.800
Botswana	Sub-Saharan Africa	3.467	0.074	0.784	59.269	0.824	-0.246	0.801	2.430	0.724	0.340	0.539	0.027	0.088	0.648
Rwanda	Sub-Saharan Africa	3.415	0.068	0.552	61.400	0.897	0.061	0.167	2.430	0.202	0.407	0.627	0.227	0.493	1.095
Zimbabwe	Sub-Saharan Africa	3.145	0.058	0.750	56.201	0.677	-0.047	0.821	2.430	0.649	0.243	0.359	0.157	0.075	1.205
Afghanistan	South Asia	2.523	0.038	0.463	52.493	0.382	-0.102	0.924	2.430	0.000	0.126	0.000	0.122	0.010	1.895