



A STATISTICAL DATA ANALYSIS ON THE WORLD HAPPINESS SCORES

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Abstract

Human philosophy and psychology are both inter connected with happiness of mind. A nation's development and growth always depends on how happy its residents are in real life. This is the keystone behind the analysis of happiness data for the world. Happiness scores are subjected to reflect the nation's inner condition. The data have been presented by Gallup World Poll (GWP). Here the data are obtained from their survey from 2015-2023(initially started in 2012).

The primary exploratory data analysis using graphs is helpful in simple understanding of world happiness .The graphical analysis has been conducted for different continents for different years and highest and lowest happy countries around the world.

Then a thorough multivariate analysis has been conducted to know how this world happiness is influenced by its six indicators(these indicators are globally accepted as the basis of happiness score) and how it is changing between the continents over different years. Regression and regression diagnostics, principal component analysis have been done in the explanatory analysis.

CONTENTS

Serial Number	Subject	PageNo.
1	Introduction	1-2
2	ViewofData	3-4
3	Exploratorydata analysis	4-20
4	StepwiseRegression	20-47
5	RegressionDiagnostics	47-60
6	PrincipalComponent Analysis	60-67
7	Conclusion	68
8	Acknowledgement	69
9	Reference	70
10	Appendix	71-96

INTRODUCTION

In this world happiness report the main focus is given on the happy lives of people's lives. It is mainly based on the life evaluations of different people. These life evaluations help in determining the quality of human life. The World Happiness Report is a point of interest survey of the state of worldwide bliss. How modern science influences national and individual varieties is the main motivation behind such happiness. The Gallup World Poll, which remains the principal source of data in this report, asks respondents to evaluate their current life as a whole using the image of a ladder, with the best possible life for them as a 10 and worst possible as a 0. Each respondent provides a numerical response on this scale, referred to as the Cantril ladder. Typically, around 1,000 responses are gathered annually for each country. Gallup weights are used to construct population-representative national averages for each year in each country.

The primary report was distributed in 2012 by Gallop World Poll, the second in 2013, the third in 2015, and it continued further. In the year 2014, no such report was published. This report proceeds to pick up worldwide acknowledgment as governments, organizations and respectful society progressively utilize joy pointers to educate their policy-making decisions. Note that the six key variables that contribute to explaining life evaluations are as follows:

1. GDP per capita
2. Social support
3. Healthy life expectancy
4. Freedom
5. Generosity
6. Perception Of Corruption (Government trust)

As already noted, our happiness rankings are not based on any index of these six factors. Rather, scores are based on individuals' own assessments of their lives, in particular their answers to the single-item Cantril ladder life-evaluation question. We use observed data on the six variables and estimates of their associations with life evaluations to help explain the variation of life evaluations across countries. In other words the variables give the estimate of the extent to which they influence the happiness scores.

The factor variables used in the world happiness report are determinants that explain national-level differences in life evaluations. However, certain variables, such as unemployment or inequality, are not considered because comparable data is not yet available across all countries. In making the reports, the expertise in fields including economics, psychology, survey analysis, and national statistics, describe how measurements of well-being can be used effectively to assess the progress of nations, and other topics.

Now we give the explanation of all the six variables influencing the happiness score,

- GDP per capita** is in terms of Purchasing Power Parity (PPP) adjusted to constant international dollars (for each year's calculation there is a fixed base year, for e.g. for 2023, the year has been taken to be 2017.), taken from the World Development Indicators (WDI) by the World Bank.
- The timeseries for **healthy life expectancy at birth** are reconstructed based on data from the World Health Organization (WHO) Global Health Observatory data repository.
- Social support** is the national average of the binary responses (0 = no, 1 = yes) to the Gallup World Poll (GWP) question "If you were in trouble, do you have relatives or friends you can count on to help you whenever you need them, or not?"
- Freedom to make life choices** is the national average of binary responses to the GWP question "Are you satisfied or dissatisfied with your freedom to choose what you do with your life?"
- Generosity** is the residual of regressing the national average of GWP responses to the donation question "Have you donated money to a charity in the past month?" on log GDP per capita.
- Perceptions of corruption** are the average of binary answers to two GWP questions: "Is corruption widespread throughout the government or not?" and "Is corruption widespread within businesses or not?" Where data for government corruption are missing, the perception of business corruption is used as the overall corruption-perception measure.

Objective:- The main objectives behind such data analysis are

- Exploratory data analysis using graphs to know the change of happiness scores i.e., the situation of world's happiness from year to year
- To know the variation of happiness from continent to continent
- How the indicators, globally accepted influence the happiness score
- Finding the influential points using regression diagnostics
- Finding the main indicators of happiness by multivariate analysis and to verify whether the situation is same for the consecutive years.

In the first section the exploratory analysis has been done using graphical analysis. Graphs are used to display the happiness score's situation in different countries and continents and also how they vary over different years.

In the second section we have done stepwise regression in order to find out which factors are actually influential for determination of world happiness for each year.

In the third section we have done the regression diagnostic to find out the influential data points and their variation over the years.

In the fourth section we have done a thorough principal component analysis to get an idea about the reduction of dimension of the data.

Viewof Data

Herewegraduallystartourstatistical analysisofthedataonhappinessscoresof different countries for the years 2015-2023. Note that the happiness report was started in 2012, but there was a drop in the year 2014, so for data analysis purpose the data have been taken from the year 2015. For our convenience we will do every statistical analysis for each year and thus we can judge how the situation is changing or whether it has been changing at all from year to year.

The data on happiness score is a very large dataset. We are providing the first 20 rows of the data for understanding.

Country	happiness _score	gdp_per_ capita	Social support	health	freedom
Switzerland	7.587	1.39651	1.34951	0.94143	0.66557
Iceland	7.561	1.30232	1.40223	0.94784	0.62877
Denmark	7.527	1.32548	1.36058	0.87464	0.64938
Norway	7.522	1.459	1.33095	0.88521	0.66973
Canada	7.427	1.32629	1.32261	0.90563	0.63297
Finland	7.406	1.29025	1.31826	0.88911	0.64169
Netherlands	7.378	1.32944	1.28017	0.89284	0.61576
Sweden	7.364	1.33171	1.28907	0.91087	0.6598
NewZealand	7.286	1.25018	1.31967	0.90837	0.63938
Australia	7.284	1.33358	1.30923	0.93156	0.65124
Israel	7.278	1.22857	1.22393	0.91387	0.41319
CostaRica	7.226	0.95578	1.23788	0.86027	0.63376
Austria	7.2	1.33723	1.29704	0.89042	0.62433
Mexico	7.187	1.02054	0.91451	0.81444	0.48181
United States	7.119	1.39451	1.24711	0.86179	0.54604
Brazil	6.983	0.98124	1.23287	0.69702	0.49049
Luxembourg	6.946	1.56391	1.21963	0.91894	0.61583
Ireland	6.94	1.33596	1.36948	0.89533	0.61777
Belgium	6.937	1.30782	1.28566	0.89667	0.5845

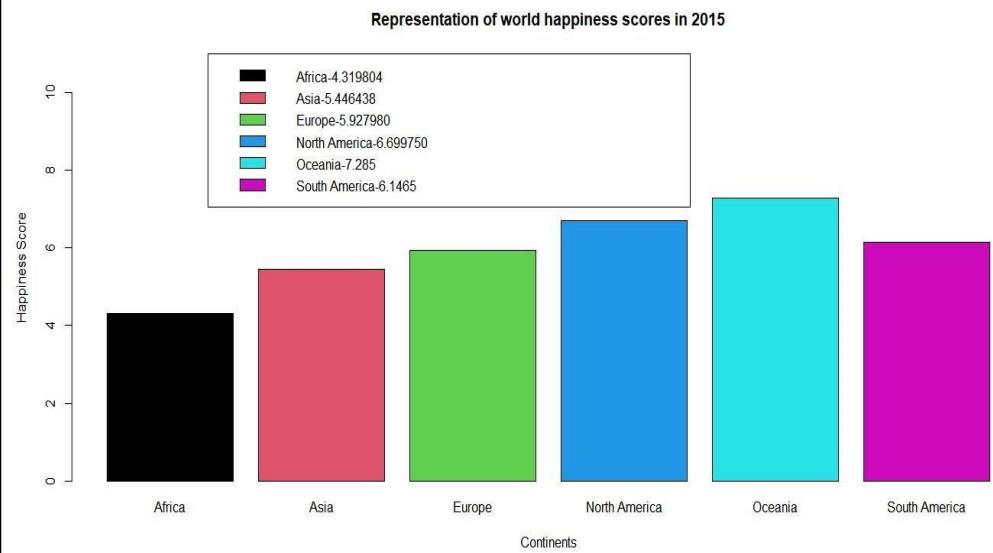
generosity	government_trust	continent	Year
0.29678	0.41978	Europe	2015
0.4363	0.14145	Europe	2015
0.34139	0.48357	Europe	2015
0.34699	0.36503	Europe	2015
0.45811	0.32957	NorthAmerica	2015
0.23351	0.41372	Europe	2015
0.4761	0.31814	Europe	2015
0.36262	0.43844	Europe	2015
0.47501	0.42922	Oceania	2015
0.43562	0.35637	Oceania	2015
0.33172	0.07785	Asia	2015
0.25497	0.10583	SouthAmerica	2015
0.33088	0.18676	Europe	2015
0.14074	0.21312	SouthAmerica	2015
0.40105	0.1589	NorthAmerica	2015
0.14574	0.17521	SouthAmerica	2015
0.28034	0.37798	Europe	2015
0.45901	0.28703	Europe	2015
0.2225	0.2254	Europe	2015

Data source:Kaggle.com

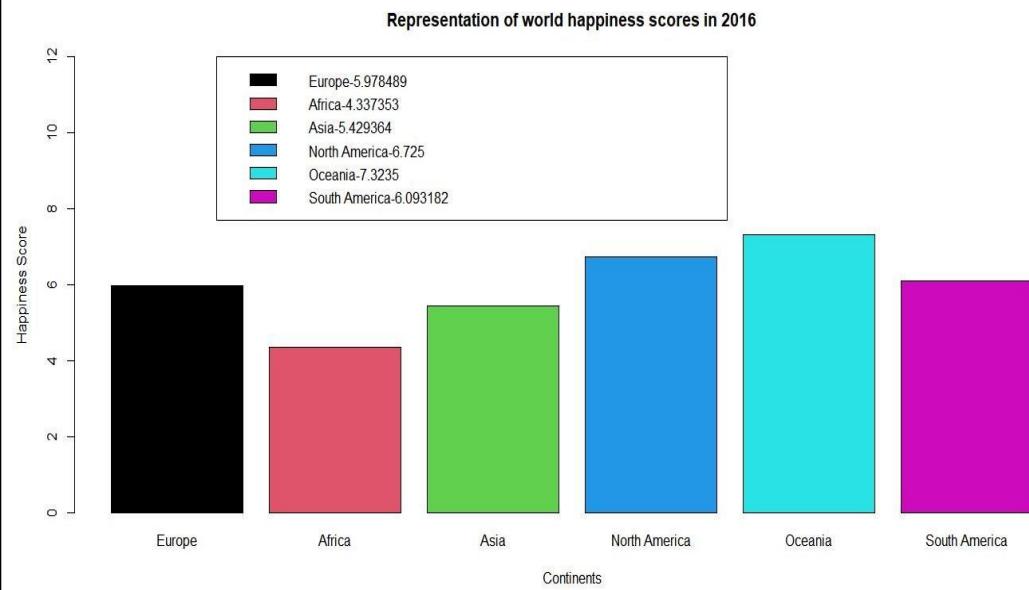
Exploratory data analysis

First we go for the graphical representation, we represent the happiness score for each continent as the mean of the happiness scores of different countries corresponding to each continent. Mean happiness score can be used as the representative value for the continents since there is well balance in the happiness scores for each continent.

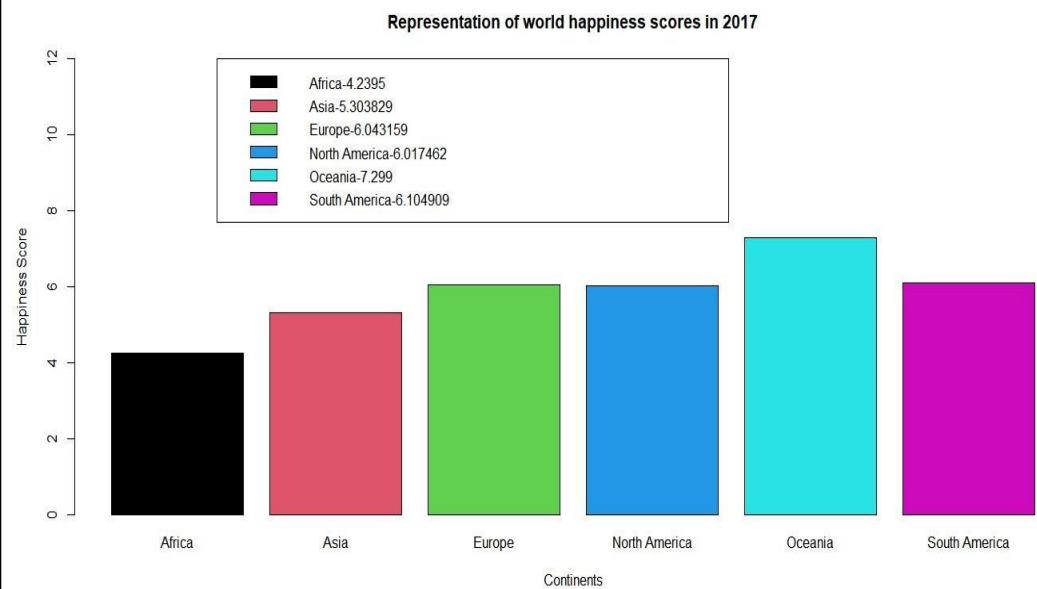
Year2015:



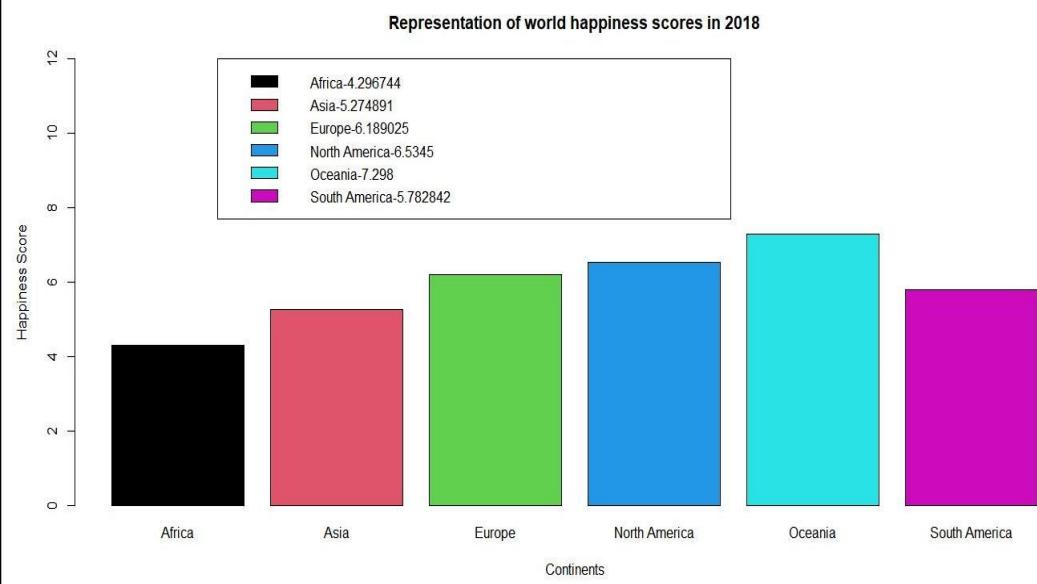
Year2016:



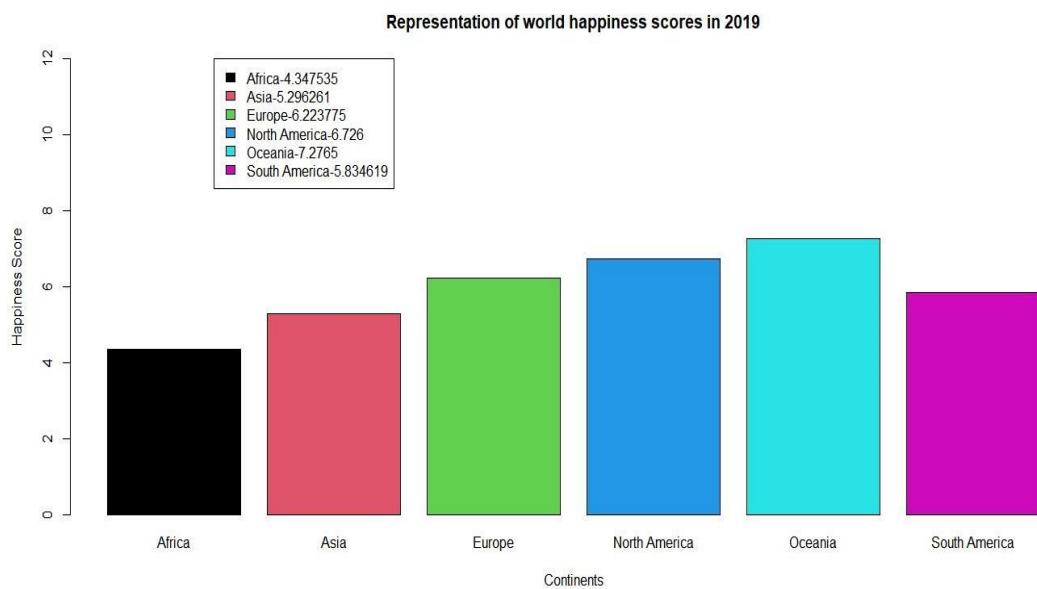
Year2017:



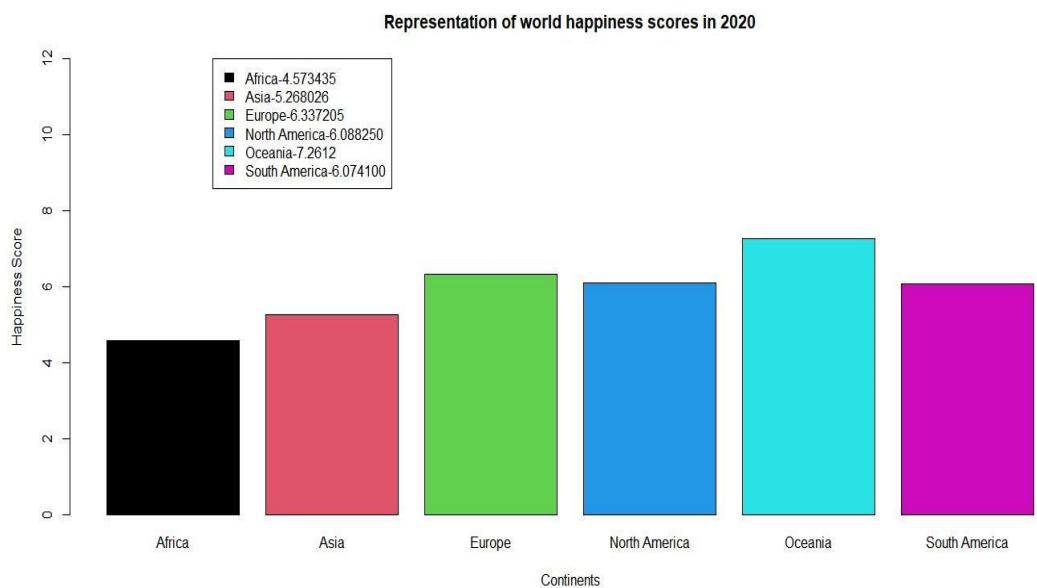
Year2018:



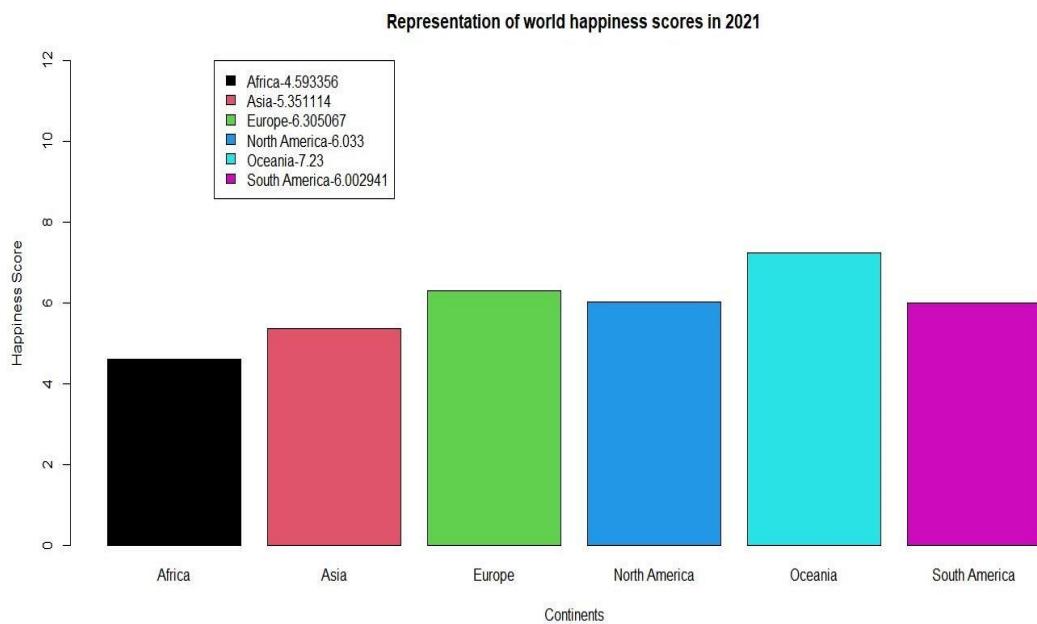
Year2019:



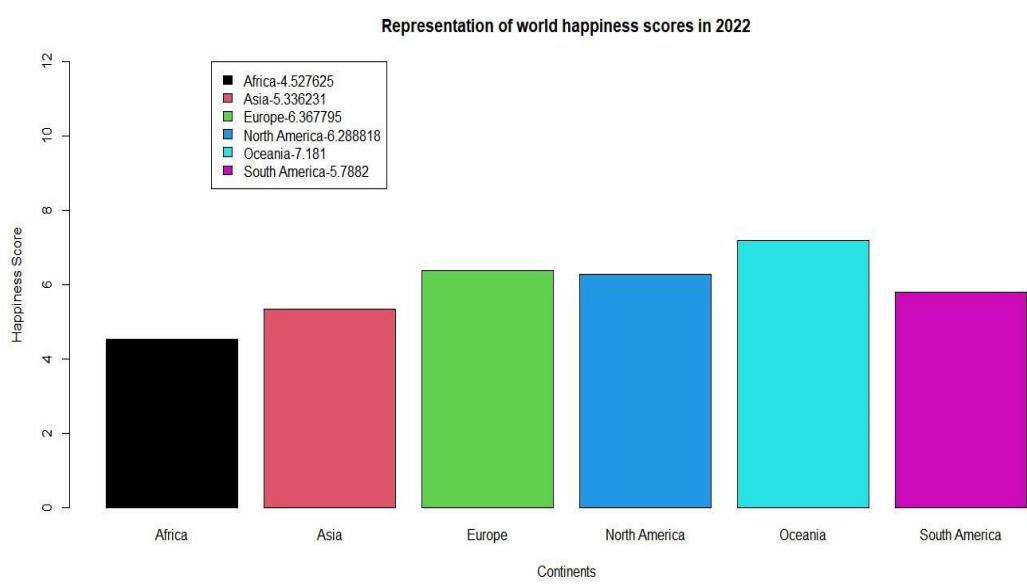
Year2020:



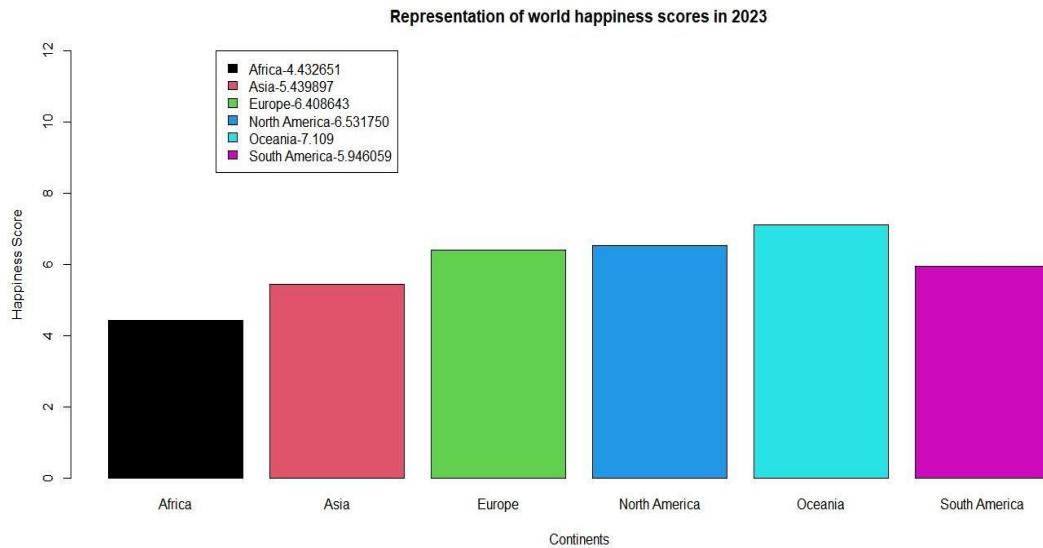
Year2021:



Year2022:



Year2023:



Interpretation:-Theresultsobtainedfromtheabovegeographicalrepresentations are listed below-

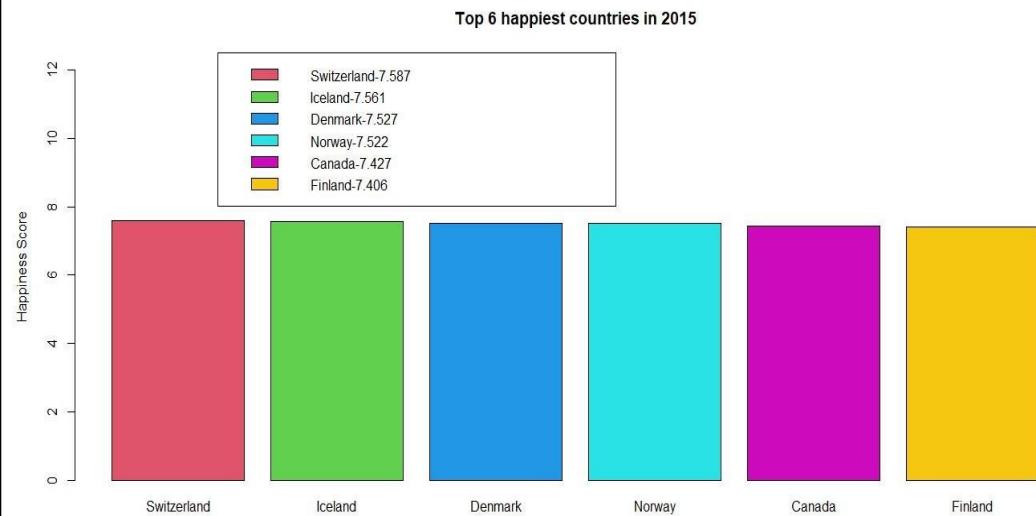
1. In each year the continent Oceania has highest happiness score, it's because Oceania contains only two countries Australia and New Zealand, both having happiness score above 7
2. In each year Africa has lowest happiness score, around 4.3-4.5. There has been no significant change in happiness score for Africa, the highest level of happiness score for Africa is 4.59 in 2021, then 4.57 in 2020.
3. For Asia the happiness score ranges from 5.26-5.44 in different years. It has fallen from 2015 to 2018, then it has slightly increased from 2021 to 2023 (5.35 to 5.43)
4. In comparison to eastern world, the western world has better picture in terms of happiness, which means people belonging to western countries are happier than those of eastern countries, which might be clear due to the factors GDP per capita, social support, healthy life expectancy and freedom to make choices.
Now in western world, we can draw a comparison among Europe, North and South America.
5. From 2015 to 2019, the happiness score level is higher in North America than in Europe and South America. From 2020 to 2022, Europe has higher score than the both Americas. And again, in 2023 North America has gone higher.
6. There is a great fluctuation in the score levels in both Americas. North America has experienced sudden fall in happiness score from 6.72 to 6.01 (from 2016 to 2017) and again from 6.72 to 6.08 to 6.03 (from 2019 to 2021-2022).

- 7. There are also two sudden changes in score of South America, from 6.10 to 5.78 (from 2017 to 2018), and from 6.00 to 5.78 (from 2021 to 2022). There is a sudden increase in happiness score from 5.83 to 6.07 (2019-2020)**
- 8. Only Europe has experienced a sustained increase in happiness score level from 2015 to 2023, from 5.92 to 6.40**

Now we represent the 6 top happiest and 6 least happy countries for each year as given below -

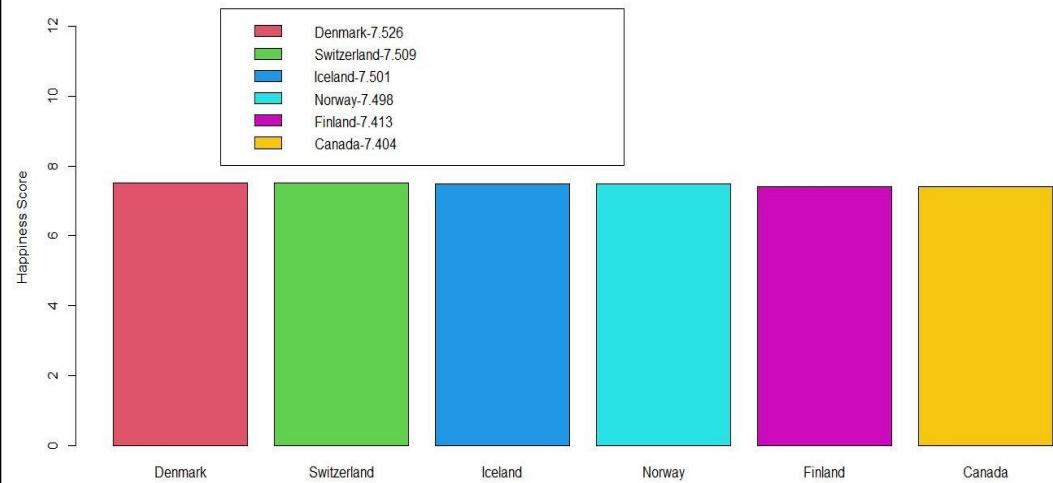
First we represent the top 6 happiest countries. **Year**

2015:



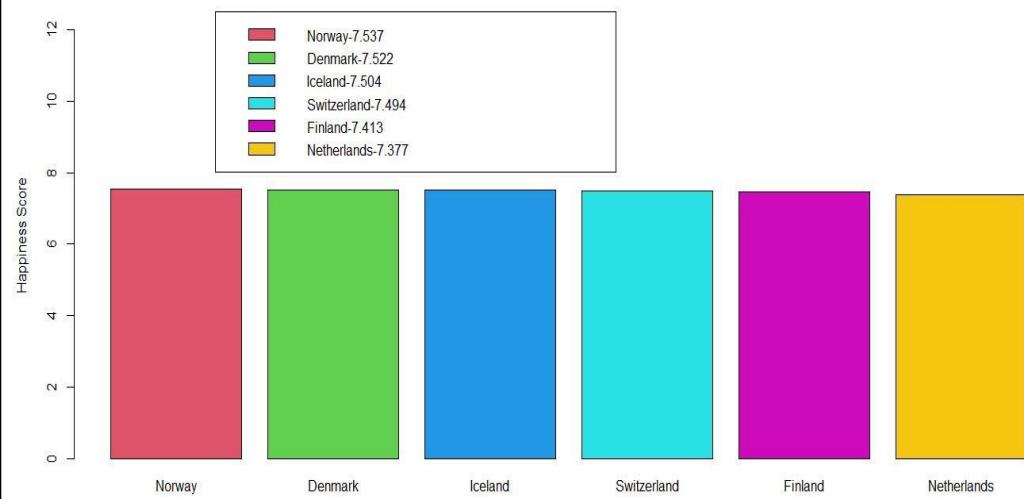
Year2016:

Top 6 happiest countries in 2016



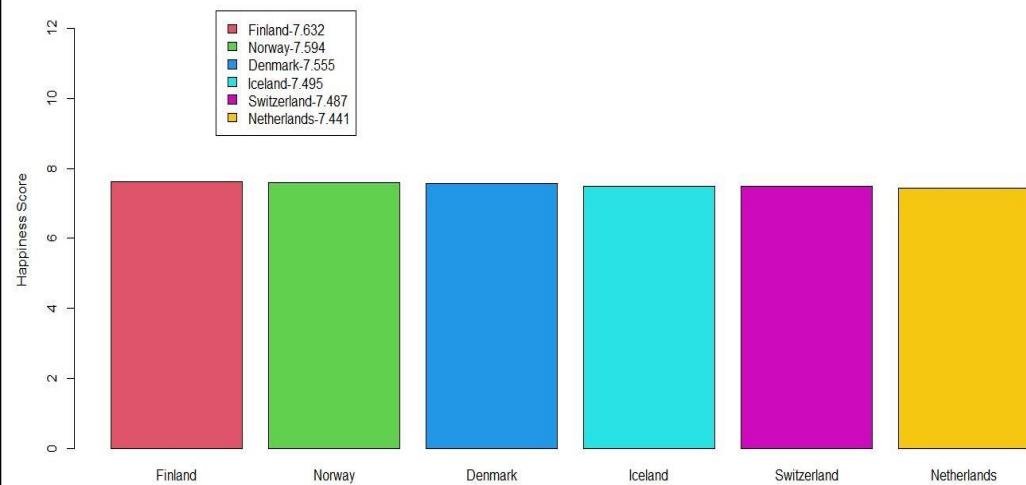
Year2017:

Top 6 happiest countries in 2017



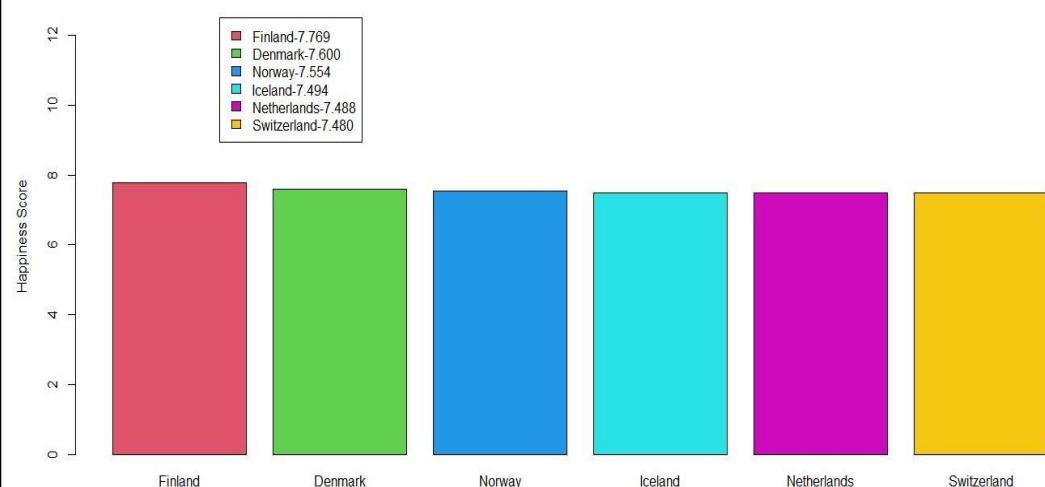
Year2018:

Top 6 happiest countries in 2018



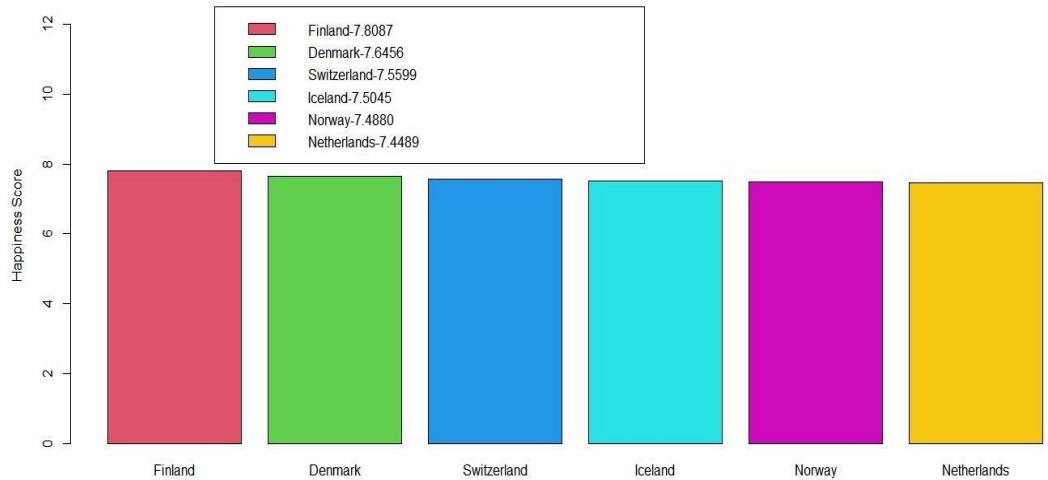
Year2019:

Top 6 happiest countries in 2019



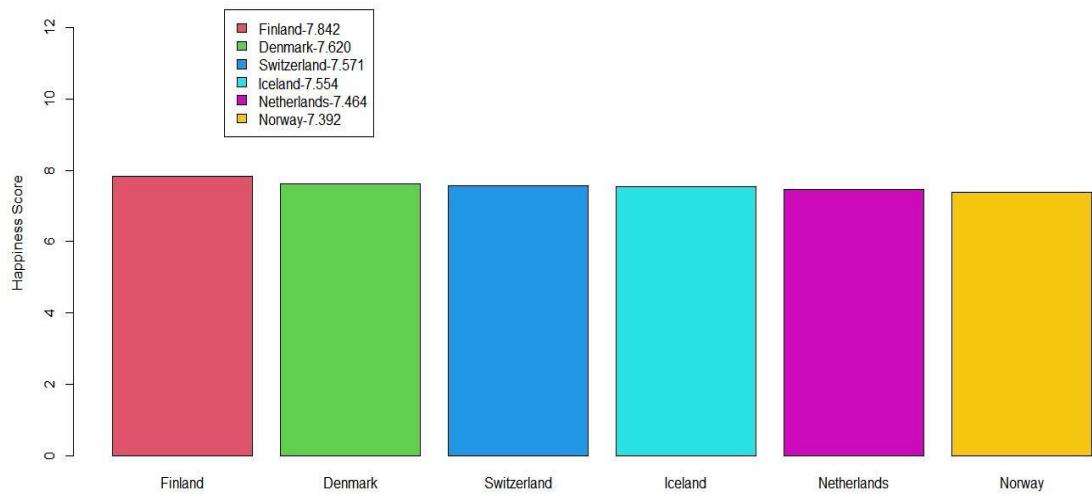
Year2020:

Top 6 happiest countries in 2020



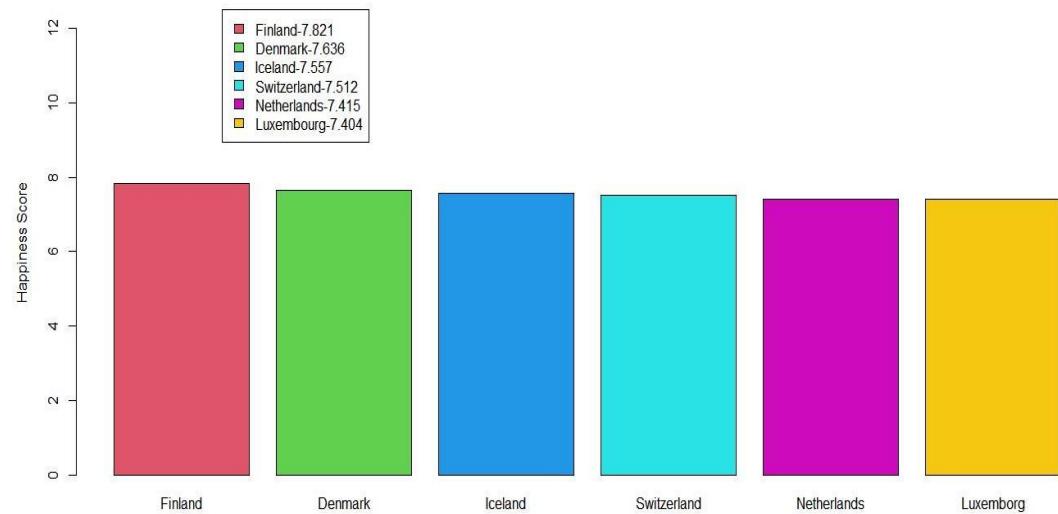
Year2021:

Top 6 happiest countries in 2021



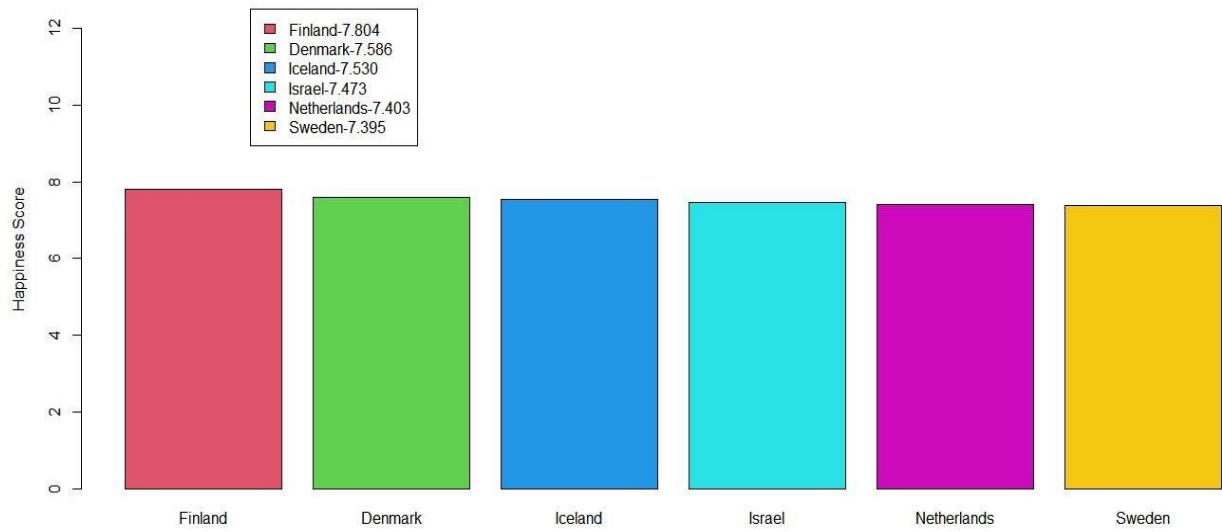
Year2022:

Top 6 happiest countries in 2022



Year2023:

Top 6 happiest countries in 2023

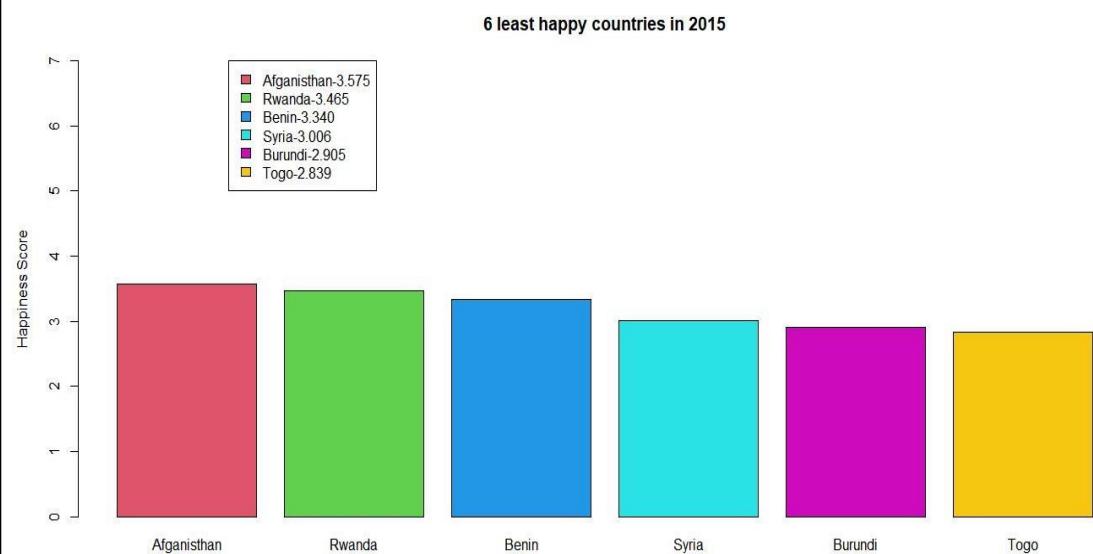


Interpretation:

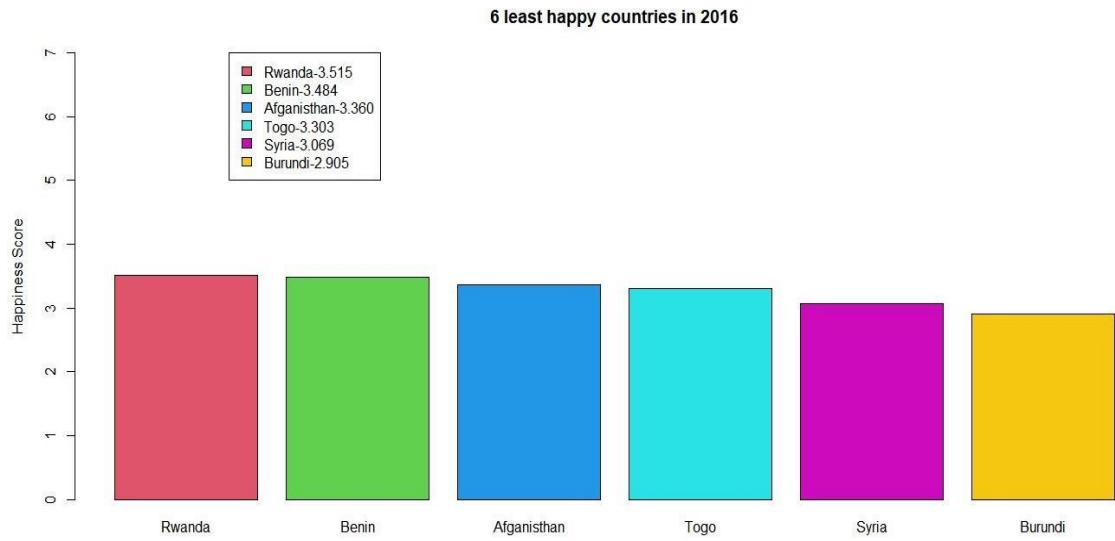
1. In 2015 and 2016 only Canada as a country of North America was present, the remaining five were from Europe.
2. From 2017 to 2022 only European countries remained in the top 6 positions and in 2023 Israel entered there as a member of Asia.
3. Also, Finland, Norway, Denmark, Iceland, Switzerland, Netherlands these six countries were always in the top six positions, only a change was observed when Luxembourg entered as a new European country in 2022.
4. Finland holds the 1st position from 2018 to 2023, i.e. for 6 years continuously, and Denmark holds the 2nd position from 2019 to 2023, continuously.
5. All top countries for all years have scores above 7. Finland achieved the highest value 7.842 in 2021, then it faced a fall to 7.804 in 2023. But it maintained the level 7.6 to 7.84, whereas before 2018 (when Finland was not at the top), the top country has the score level around 7.5

Now, we graphically represent the 6 least happy countries for the consecutive years.

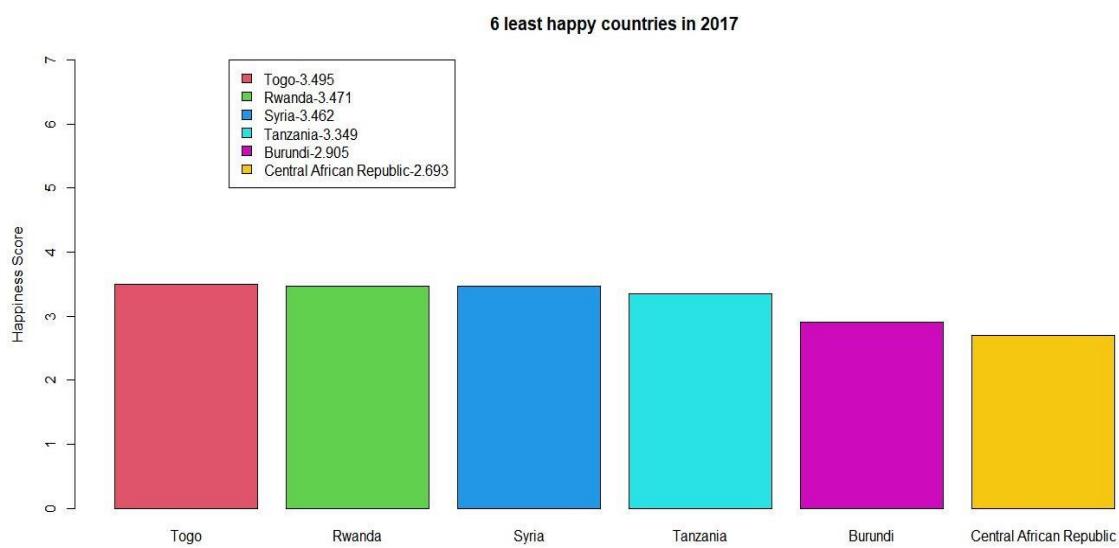
Year 2015:



Year2016:

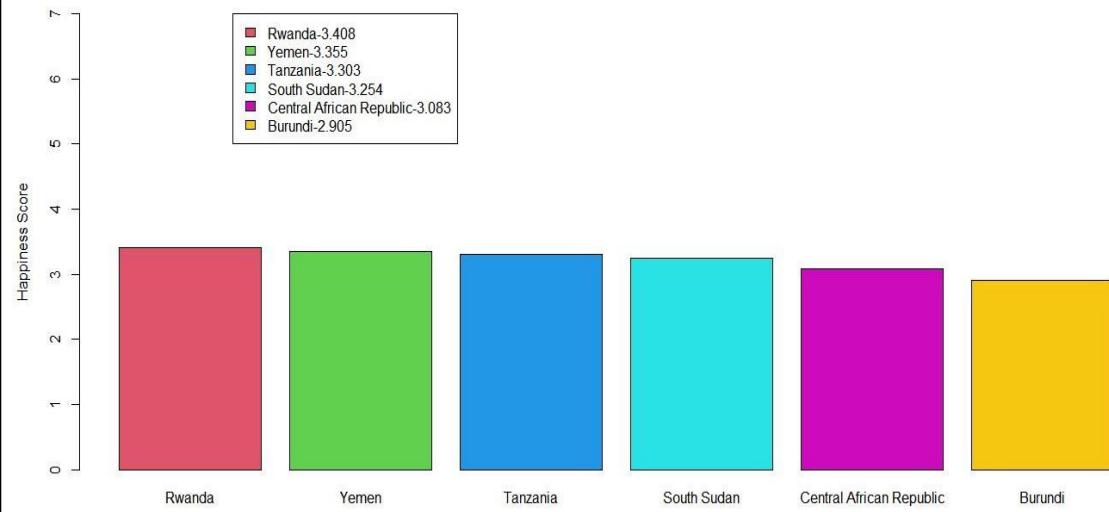


Year2017:



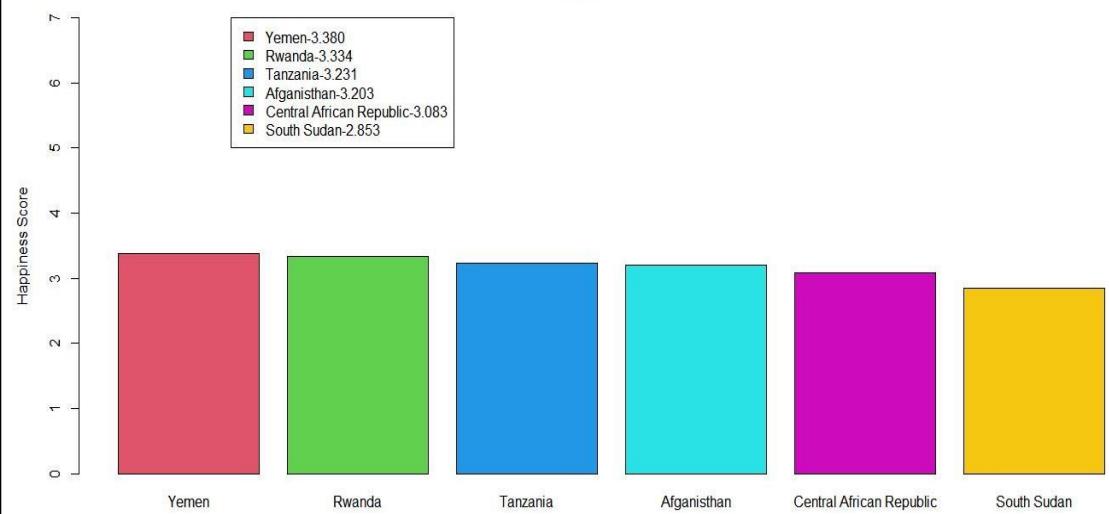
Year2018:

6 least happy countries in 2018



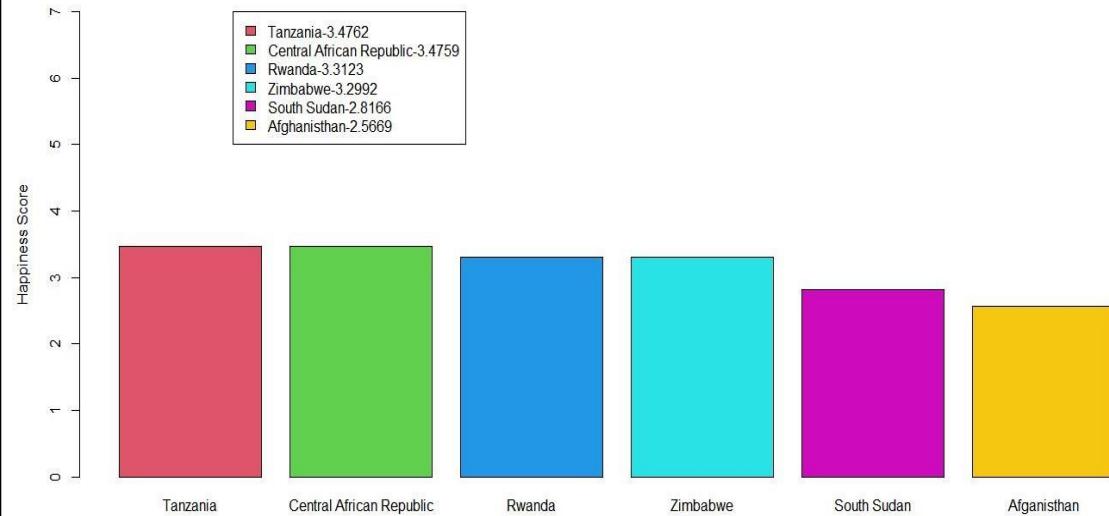
Year2019:

6 least happy countries in 2019



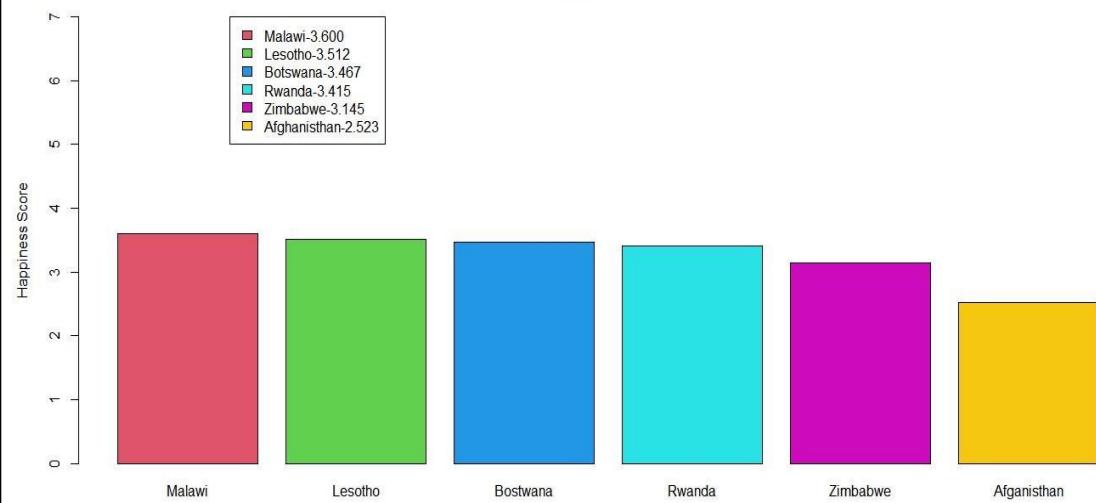
Year2020:

6 least happy countries in 2020



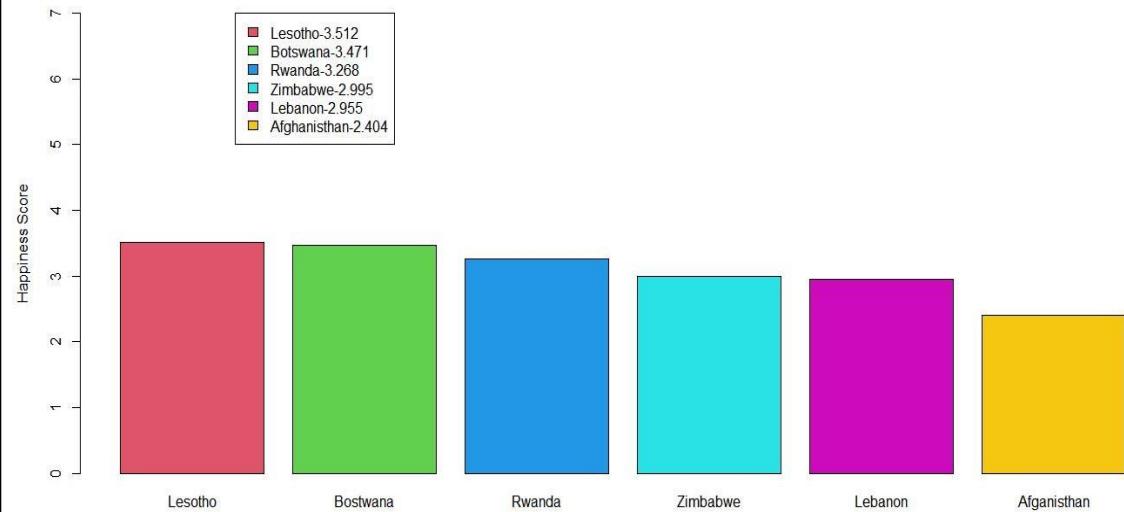
Year2021:

6 least happy countries in 2021



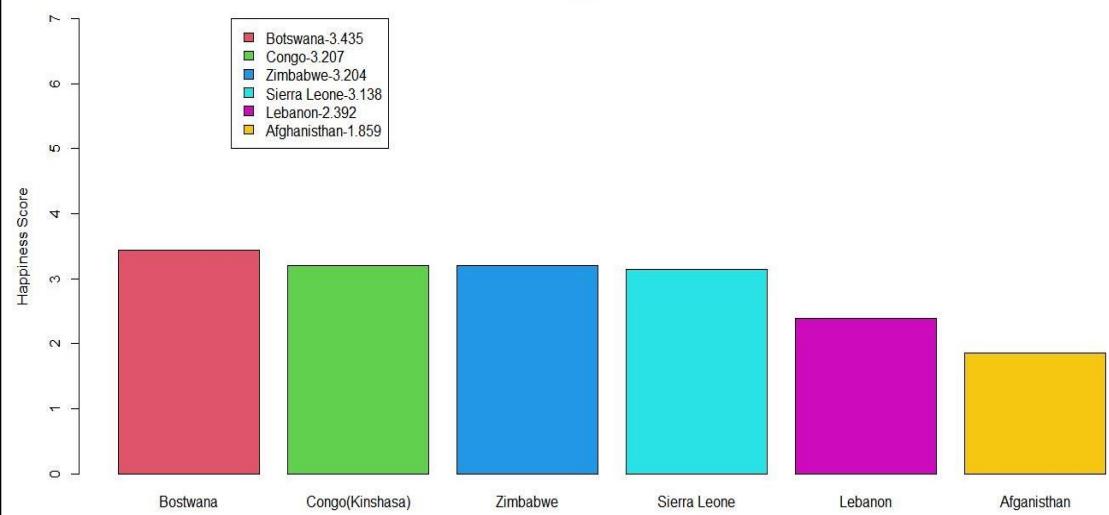
Year2022:

6 least happy countries in 2022



Year2023:

6 least happy countries in 2023



Interpretation:

1. It is observed that the African and Asian countries are in the lowest positions for all the years.
2. Afghanistan and Syria were in the least happy countries in both 2015 and 2016. Syria was only present in the list as an Asian country in 2017
3. In 2018, no Asian country was there in the six least happy countries' list.
4. From 2019 to 2023 only Afghanistan has been present in this list as from Asian continent. All other countries are from African territory. Mainly, Rwanda, Togo, Central African Republic, Burundi were present in this list before 2020, after 2020, Malawi, Lesotho, Botswana, Lebanon, Zimbabwe took place in the list.
5. In 2023, the lowest happy country is Afghanistan and it is the only country with happiness score 1.859, which is the lowest for any country in all these years. It might be because of the governmental change and the new policies adopted, the societal imbalance etc.

Stepwise Regression

In order to find out which factors among the six factors viz, GDP per capita, social support, healthy life expectancy, freedom, generosity, perception of corruption actually influence the happiness score level, we will make use of stepwise regression. Our main purpose in this section is to check whether the same covariates are influential for different years, i.e. we are doing the regression analysis for each year to check the presence of any change in the type of influential covariates.

We define the variables as follows-

x_1 : Happiness score for any randomly selected country
 x_2 : Extend to which "GDP per capita" contributes to happiness score
 x_3 : Extend to which "social support" contributes to happiness score
 x_4 : Extend to which "healthy life expectancy" contributes to happiness score
 x_5 : Extend to which "freedom to make choices" contributes to happiness score
 x_6 : Extend to which "generosity" contributes to happiness score
 x_7 : Extend to which "perception of corruption" contributes to happiness score
All

these variables are measured in continuous scale.

Define the sample partial correlation coefficient between x_1 and any covariate x_j ,

$$j=2(1)p \text{ is given by } r_{1,23...j-1,j+1...p} = \frac{(-1)^{1+1}}{\sqrt{11}} \quad j=2(1)p.$$

Here R is the correlation matrix of the random vector

$$\begin{bmatrix} & & 1 \\ & & \\ & & \end{bmatrix}$$

And R_{ij} is the covariate of the $(i,j)^{\text{th}}$ element of R p is the no. of covariates ,here $p=6$

Year2015:

First we start modelling x_1 on the other covariates x_2 to x_7 , After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.8602	0.1905	9.766	<2e-16***
x_2	0.8607	0.2203	3.907	0.000141 ***
x_3	1.4089	0.2227	6.327	2.69e-09***
x_4	0.9753	0.3163	3.084	0.002433 **
x_5	1.3334	0.3850	3.463	0.000694 ***
x_6	0.3889	0.3910	0.995	0.321471
x_7	0.7845	0.4365	1.797	0.074302 .

Signif.codes:0 '***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.551 on 151 degrees of freedom
Multiple R-squared:0.7772, AdjustedR-squared:0.7684
F-statistic: 87.81 on 6 and 151 DF,p-value: < 2.2e-16

From the above table it has been clear that x_6 and x_7 are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x_1 in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.7684.

The partial correlation coefficients are given below-

$r_{12.34567}=0.3029689$
 $r_{13.24567}=-0.4577754$
 $r_{14.23567}=0.2433906$
 $r_{15.23467}=-0.2712727$
 $r_{16.23457}=0.08068409$
 $r_{17.23456}=-0.1447148$

It shows that x_6 has the lowest partial correlation coefficient with x_1 and hence is eliminated as a predictor.

After elimination of x_6 , we again do the multiple regression for x_1 on the remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.8982	0.1866	10.173	<2e-16***
x_2	0.8053	0.2132	3.778	0.000226 ***
x_3	1.4164	0.2225	6.365	2.19e-09***
x_4	1.0338	0.3108	3.327	0.001102 **
x_5	1.4426	0.3690	3.909	0.000139 ***
x_7	0.8540	0.4309	1.982	0.049281 *

--- Signif.codes:0 '***'0.001 '**'0.01 '*'0.05 '.'0.1 "1

Residual standard error: 0.551 on 152 degrees of freedom

Multiple R-squared:0.7758, Adjusted R-squared:0.7684

F-statistic: 105.2 on 5 and 152 DF,p-value: < 2.2e-16

Now x_7 can be seen to be insignificant from the above table. Again

the partial correlation coefficients are obtained as :

$$r_{12.3457}=0.2929837$$

$$r_{13.2457}=-0.4587258$$

$$r_{14.2357}=0.2605139$$

$$r_{15.2347}=-0.3022429$$

$$r_{17.2345}=0.1587246$$

x_7 has minimum partial correlation coefficient with x_1 , hence x_7 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.8963	0.1884	10.067	<2e-16***
x_2	0.8826	0.2116	4.172	5.05e-05***
x_3	1.3581	0.2227	6.099	8.37e-09***
x_4	0.9959	0.3131	3.181	0.00178 **
x_5	1.7707	0.3330	5.318	3.66e-07***

Signif.codes:0 '***'0.001 '**'0.01 '*'0.05 '.'0.1 "1

Residual standard error: 0.5563 on 153 degrees of freedom

Multiple R-squared:0.77, Adjusted R-squared:0.764

F-statistic:128 on 4 and 153 DF,p-value: < 2.2e-16

From the table it might seem that x_4 is less significant. Again we find the partial correlation coefficients as follows:-

$$r_{12.345} = 0.3195656$$

$$r_{13.245} = -0.4422197$$

$$r_{14.235} = 0.2490355$$

$$r_{15.234} = -0.3949868$$

x_4 is discarded as a predictor, since it has the lowest partial correlation with x_1 .

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.0758	0.1850	11.223	<2e-16***
x_2	1.3717	0.1495	9.173	2.82e-16***
x_3	1.3422	0.2291	5.858	2.74e-08***
x_5	1.8875	0.3406	5.542	1.27e-07***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'. '0.1 "1

Residual standard error: 0.5725 on 154 degrees of freedom

Multiple R-squared: 0.7548, Adjusted R-squared: 0.75

F-statistic: 158 on 3 and 154 DF, p-value: < 2.2e-16

It's seen that actually no variable is significant there, we again calculate the partial correlation coefficients

$$r_{12.35} = 0.5944385$$

$$r_{13.25} = -0.4268822$$

$$r_{15.23} = 0.4077655$$

x_5 is eliminated because of same reason, and finally if we model x_1 on x_2 and x_3 then the summary table is obtained as-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.4383	0.1889	12.909	<2e-16***
x_2	1.4750	0.1620	9.107	4.03e-16 ***
x_3	1.7047	0.2397	7.111	3.97e-11 ***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'. '0.1 "1

Residual standard error: 0.625 on 155 degrees of freedom

Multiple R-squared: 0.7059, Adjusted R-squared: 0.7021

F-statistic: 186 on 2 and 155 DF, p-value: < 2.2e-16

Note that there is a great fall in adjusted R-squared, hence we stop the stepwise regression here. It should be noted that x_5 is an important predictor. One point is here we want more precision, so we do not want the adjusted R-squared to fall upto 0.75 also, i.e. we want shift in the variation in adjusted R-squared strictly less than 2.3945%, w.r.t the adjusted R-squared in the full model (if it touches the value 0.75 as the adjusted R squared, the regression will be stopped by us). This much precision is taken into account because x_4 which is the healthy life expectancy is thought to be an important predictor for happiness, so it should not be excluded.

Assuch, here x_4 is also included as a predictor, thus x_2, x_3, x_4, x_5 are the four final predictors in predicting x_1 .

Year 2016:

First we start modelling x_1 on the other covariates x_2 to x_7 . After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.1903	0.1583	13.834	<2e-16***
x_2	0.7214	0.2171	3.323	0.001120 **
x_3	1.2298	0.2297	5.353	3.19e-07***
x_4	1.4364	0.3489	4.117	6.32e-05***
x_5	1.5139	0.3880	3.902	0.000144 ***
x_6	0.1595	0.3621	0.440	0.660236
x_7	0.9189	0.4648	1.977	0.049852 *

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 “1

Residual standard error: 0.5367 on 150 degrees of freedom
 Multiple R-squared: 0.7875, Adjusted R-squared: 0.779 F-statistic: 92.65 on 6 and 150 DF, p-value: < 2.2e-16

From the above table it is clear that x_6 and x_7 are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x_1 in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.779.

The partial correlation coefficients are given below.

r_{12.34567}=-0.2618273
r_{13.24567}=-0.4004625
r_{14.23567}=-0.3186175
r_{15.23467}=-0.3035796
r_{16.23457}=-0.03594039
r_{17.23456}=-0.1593744

It shows that x_6 has the lowest partial correlation coefficient with x_1 and hence is eliminated as a predictor.

After elimination of x_6 , we again do the multiple regression for x_1 on the remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.2119	0.1502	14.731	<2e-16***
x ₂	0.6971	0.2094	3.329	0.0011 **
x ₃	1.2344	0.2289	5.393	2.62e-07***
x ₄	1.4623	0.3430	4.263	3.53e-05***
x ₅	1.5588	0.3733	4.175	5.01e-05***
x ₇	0.9590	0.4546	2.110	0.0365 *

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5353 on 151 degrees of freedom
Multiple R-squared: 0.7872, Adjusted R-squared: 0.7802
F-statistic: 111.7 on 5 and 151 DF, p-value: < 2.2e-16

Now x_7 can be seen to be insignificant from the above table. Again

the partial correlation coefficients are obtained as :

r_{12.3457}=-0.2614497
r_{13.2457}=-0.4018612
r_{14.2357}=-0.3277867
r_{15.2347}=-0.3217145
r_{17.2345}=-0.1692123

x_7 has minimum partial correlation coefficient with x_1 , hence x_7 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.2068	0.1518	14.535	<2e-16***
x ₂	0.7615	0.2095	3.634	0.000381 ***
x ₃	1.1730	0.2296	5.109	9.59e-07***
x ₄	1.4451	0.3468	4.167	5.15e-05***
x ₅	1.9200	0.3355	5.723	5.41e-08***

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residualstandarderror: 0.5413 on 152 degrees offreedom
MultipleR-squared: 0.781, AdjustedR-squared: 0.7752F-statistic: 135.5 on 4 and 152 DF,p-value: < 2.2e-16**

From the table it might seem that no predictor is less significant. To verify again we find the partial correlation coefficients as follows:-

r_{12.345}=-0.2827324

r_{13.245}=-0.382809

r_{14.235}=-0.3202213

r_{15.234}=-0.4210281

x₂ is discarded as an predictor , since it has the lowest partial correlation with x₁

The table corresponding to the multiple correlation coefficient of x₁ on the remaining covariates is given below-

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	2.1582	0.1572	13.733	<2e-16***
x3	1.4867	0.2211	6.725	3.29e-10***
x4	2.3717	0.2442	9.712	<2e-16***
x5	1.9451	0.3486	5.580	1.06e-07***

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residual standard error: 0.5625 on 153 degrees of freedom
Multiple R-squared: 0.7619, AdjustedR-squared: 0.7573
F-statistic: 163.2 on 3 and 153 DF,p-value: < 2.2e-16**

Note that there is a great fall in adjusted R -squared (more than 2.395 % variation in the full model adjusted R-squared) , hence we stop the stepwise regression here. It should be noted that x₂ is an important predictor and should not be eliminated.

So here in 2016 also, for predicting x₁,x₂,x₃,x₄,x₅ are the important predictors. Year

2017:

First we start modelling x₁ on the other covariates x₂ to x₇, After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std.Error	tvalue	Pr(> t)							
(Intercept)	1.7430	0.1874	9.303	<2e-16***							
x2	0.7844	0.2045	3.836	0.000185 ***							
x3	1.1178	0.2021	5.532	1.40e-07***							
x4	1.2889	0.3215	4.009	9.65e-05***							
x5	1.4757	0.3425	4.309	2.98e-05***							
x6	0.3807	0.3293	1.156	0.249524							
x7	0.8266	0.4843	1.707	0.089975 .							

Signif.codes:	0	***	0.001	**	0.01	*	0.05	.	0.1	"	1

Residual standard error: 0.4998 on 148 degrees of freedom
 Multiple R-squared: 0.8124, Adjusted R-squared: 0.8048
 F-statistic: 106.8 on 6 and 148 DF, p-value: < 2.2e-16

From the above table it has been clear that x₆ and x₇ are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x₁ in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.8048.

The partial correlation coefficients are given below-

r_{12.34567}=-0.3006944
 r_{13.24567}=-0.4139314
 r_{14.23567}=-0.3129562
 r_{15.23467}=-0.3338415
 r_{16.23457}=-0.09460045
 r_{17.23456}=-0.1389294

It shows that x₆ has the lowest partial correlation coefficient with x₁ and hence is eliminated as a predictor.

After elimination of x₆, we again do the multiple regression for x₁ on the remaining predictors and thus we obtain the following table as-

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.8018	0.1805	9.980	<2e-16***
x2	0.7320	0.1997	3.667	0.000341 ***
x3	1.1231	0.2022	5.554	1.25e-07***
x4	1.3431	0.3184	4.218	4.26e-05***
x5	1.5627	0.3345	4.671	6.63e-06***
x7	0.9482	0.4733	2.003	0.046949 *

Signif.codes:	0	***'0.001	**'0.01	*'0.05'.0.1"1

Residual standard error: 0.5003 on 149 degrees of freedom

Multiple R-squared:0.8107, AdjustedR-squared:0.8044

F-statistic: 127.6 on 5 and 149 DF,p-value: < 2.2e-16

Now x_7 can be seen to be insignificant from the above table. Again

the partial correlation coefficients are obtained as :

$r_{12.3457}=-0.287679$

$r_{13.2457}=-0.4141251$

$r_{14.2357}=-0.3265893$

$r_{15.2347}=-0.3574213$

$r_{17.2345}=-0.161957$

x_7 has minimum partial correlation coefficient there with x_1 , hence x_7 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.7992	0.1823	9.867	<2e-16***
x2	0.8179	0.1970	4.153	5.50e-05***
x3	1.0685	0.2024	5.279	4.47e-07***
x4	1.3029	0.3210	4.059	7.90e-05***
x5	1.8612	0.3025	6.152	6.62e-09***

Signif.codes:0 ***'0.001 **'0.01 *'0.05'.0.1"1

Residual standard error: 0.5053 on 150 degrees of freedom

Multiple R-squared:0.8056, AdjustedR-squared:0.8004

F-statistic: 155.4 on 4 and 150 DF,p-value: < 2.2e-16

From the table it might seem that no predictor is less significant. Again we find the partial correlation coefficients as follows:-

$r_{12,345} = -0.3210976$
 $r_{13,245} = -0.3958496$
 $r_{14,235} = -0.3146008$
 $r_{15,234} = -0.4488852$

x_4 is discarded as a predictor, since it has the lowest partial correlation with x_1

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.8499	0.1910	9.685	<2e-16***
x_2	1.4025	0.1411	9.943	<2e-16***
x_3	1.1215	0.2121	5.289	4.25e-07***
x_5	1.9318	0.3171	6.092	8.87e-09***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'. '0.1"1

Residual standard error: 0.5306 on 151 degrees of freedom

Multiple R-squared: 0.7843, Adjusted R-squared: 0.78

F-statistic: 183 on 3 and 151 DF, p-value: < 2.2e-16

Note that there is a great fall in adjusted R-squared (more than 2.3945%), hence we stop the stepwise regression here. It should be noted that x_4 is an important predictor.

So for 2017, for predicting x_1 , x_2, x_3, x_4, x_5 are the important predictors also.

Year 2018:

First we start modelling x_1 on the other covariates x_2 to x_7 . After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.8856	0.1955	9.647	<2e-16***
x_2	1.1114	0.2094	5.307	3.96e-07***
x_3	0.9991	0.2015	4.958	1.91e-06***
x_4	0.8085	0.3314	2.440	0.0159 *
x_5	1.3831	0.3204	4.317	2.87e-05***
x_6	0.6056	0.4721	1.283	0.2016
x_7	0.5951	0.5251	1.133	0.2589

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'. '0.1"1

**Residual standard error: 0.5249 on 149 degrees of freedom
 Multiple R-squared:0.7886, AdjustedR-squared:0.7801
 F-statistic: 92.66 on 6 and 149 DF,p-value: < 2.2e-16**

From the above table it has been clear that x_6 and x_7 are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x_1 in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.7801.

The partial correlation coefficients are given below-

$r_{12.34567} = -0.3987322$
 $r_{13.24567} = -0.376326$
 $r_{14.23567} = -0.1959947$
 $r_{15.23467} = -0.3338415$
 $r_{16.23457} = -0.10451$
 $r_{17.23456} = -0.09243986$

It shows that x_7 has the lowest partial correlation coefficient with x_1 and hence is eliminated as an predictor.

After elimination of x_7 , we again do the multiple regression for x_1 on the remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.8559	0.1939	9.573	<2e-16***
x_2	1.1261	0.20925.383	2.77e-07***	
x_3	0.9813	0.20114.880	2.68e-06***	
x_4	0.8468	0.33002.566	0.0113 *	
x_5	1.5020	0.30304.957	1.92e-06***	
x_6	0.7572	0.45321.671	0.0969 .	

Signif.codes: 0 ***'0.001 **'0.01 *'0.05 .'0.1 "1

**Residual standard error: 0.5254 on 150 degrees of freedom
 Multiple R-squared:0.7868, AdjustedR-squared:0.7797
 F-statistic: 110.7 on 5 and 150 DF,p-value: < 2.2e-16**

Now x_6 can be seen to be insignificant from the above table. Again the partial correlation coefficients are obtained as :

```

r12.345=-0.4023517
r13.245=-0.3701625
r14.235=-0.2050788
r15.234=-0.3751421
r16.2345=-0.135161

```

x_6 has minimum partial correlation coefficient there with x_1 , hence x_6 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.9547	0.1857	10.524	<2e-16***
x ₂	1.1054	0.2101	5.262	4.81e-07***
x ₃	0.9613	0.2019	4.761	4.48e-06***
x ₄	0.8593	0.3319	2.589	0.0106 *
x ₅	1.6639	0.2888	5.762	4.53e-08***

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5285 on 151 degrees of freedom

Multiple R-squared: 0.7829, Adjusted R-squared: 0.7771

F-statistic: 136.1 on 4 and 151 DF, p-value: < 2.2e-16

From the table it might seem that no predictor is less significant. Again we find the partial correlation coefficients as follows:-

```

r12.345=-0.3936361
r13.245=-0.361263
r14.235=-0.2062009
r15.234=-0.4245274

```

x_4 is discarded as a predictor , since it has the lowest partial correlation with x_1

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.9507	0.1892	10.311	<2e-16***
x ₂	1.4945	0.1495	9.995	<2e-16***
x ₃	1.0775	0.2005	5.374	2.84e-07***
x ₅	1.7286	0.2931	5.898	2.29e-08***

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5384 on 152 degrees of freedom
Multiple R-squared:0.7732, AdjustedR-squared:0.7687
F-statistic: 172.7 on 3 and 152 DF,p-value: < 2.2e-16

It seems that there is no significant predictor. To verify we can calculate the partial correlation coefficients -

$r_{12.35}=-0.6297524$

$r_{13.25}=-0.39956$

$r_{15.23}=-0.4315736$

x_3 is discarded now, and after

elimination, when x_1 is modelled on x_2 and x_5			
	Estimate	Std. Error	
(Intercept)	2.6195	0.1549	16.908 < 2e-16 ***
x_2	1.9949	0.1272	15.684 < 2e-16 ***
x_5	2.1520	0.3069	7.0127.08e-11 ***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5854 on 153 degrees of freedom
Multiple R-squared:0.7301, AdjustedR-squared:0.7266
F-statistic:207 on 2 and 153 DF,p-value: < 2.2e-16

Note that there is a great fall in adjusted R-squared (more than 2.3945%), hence we stop the stepwise regression here. It should be noted that x_3 is an important predictor, but x_4 has to be sacrificed as a predictor. Remember that if we did not allow the variation x_4 was already discarded in 2015, but for our precision it remained as a predictor, but in this year it is finally eliminated.

So for 2018, for predicting x_1, x_2, x_3, x_5 are the important predictors also. Year

2019:

First we start modelling x_1 on the other covariates x_2 to x_7 , After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.7952	0.2111	8.505	1.77e-14 ***
x_2	0.7754	0.2182	3.553	0.000510 ***
x_3	1.1242	0.2369	4.745	4.83e-06 ***
x_4	1.0781	0.3345	3.223	0.001560 **
x_5	1.4548	0.3753	3.876	0.000159 ***

x6	0.4898	0.4977	0.984	0.326709
x7	0.9723	0.5424	1.793	0.075053 .

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residual standard error: 0.5335 on 149 degrees of freedom
Multiple R-squared:0.7792, AdjustedR-squared:0.7703
F-statistic: 87.62 on 6 and 149 DF,p-value: < 2.2e-16**

From the above table it has been clear that x_6 and x_7 are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x_1 in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a certain drop in adjusted R-squared value which is here 0.7703.

The partial correlation coefficients are given below-

$r_{12.34567} = -0.2794804$
 $r_{13.24567} = -0.3623422$
 $r_{14.23567} = -0.2552729$
 $r_{15.23467} = -0.3026475$
 $r_{16.23457} = -0.08035206$
 $r_{17.23456} = -0.1453036$

It shows that x_6 has the lowest partial correlation coefficient with x_1 and hence is eliminated as an predictor.

After elimination of x_6 , we again do the multiple regression for x_1 on the remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.8689	0.1973	9.471	<2e-16***
x_2	0.7455	0.2161	3.450	0.000728 ***
x_3	1.1180	0.2368	4.722	5.33e-06***
x_4	1.0840	0.3344	3.241	0.001467 **
x_5	1.5340	0.3666	4.185	4.84e-05***
x_7	1.1176	0.5218	2.142	0.033839 *

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residual standard error: 0.5335 on 150 degrees of freedom
Multiple R-squared:0.7777, AdjustedR-squared:0.7703
F-statistic:105 on 5 and 150 DF,p-value: < 2.2e-16**

Now x_7 can be seen to be significant from the above table.

Again the partial correlation coefficients are obtained as:

$r_{12.345} = -0.2711384$
 $r_{13.245} = -0.3597099$
 $r_{14.235} = -0.255835$
 $r_{15.234} = -0.3233292$
 $r_{17.234} = -0.1722492$

x_7 has minimum partial correlation coefficient there with x_1 , hence x_7 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.8921	0.1994	9.491	<2e-16***
x_2	0.8105	0.2165	3.745	0.000256 ***
x_3	1.0166	0.2347	4.331	2.70e-05***
x_4	1.1414	0.3373	3.384	0.000910 ***
x_5	1.8458	0.3404	5.423	2.28e-07***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'. '0.1"1

Residual standard error: 0.5398 on 151 degrees of freedom

Multiple R-squared: 0.7709, Adjusted R-squared: 0.7649

G-statistic: 127 on 4 and 151 DF, p-value: < 2.2e-16

From the table it might seem that no predictor is less significant. Again we find the partial correlation coefficients as follows:-

$r_{12.345} = -0.2915062$
 $r_{13.245} = -0.332386$
 $r_{14.235} = -0.2655015$
 $r_{15.234} = -0.4037249$

x_4 is discarded as a predictor, since it has the lowest partial correlation with x_1 .

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std.Error	t value	Pr(> t)
(Intercept)	2.0492	0.2004	10.223	<2e-16***
x_2	1.2792	0.1720	7.438	6.98e-12***
x_3	1.1886	0.2369	5.017	1.45e-06***
x_5	1.9442	0.3506	5.545	1.27e-07***

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residual standard error: 0.558 on 152 degrees of freedom
Multiple R-squared:0.7536, AdjustedR-squared:0.7487
F-statistic: 154.9 on 3 and 152 DF,p-value: < 2.2e-16**

Note that there is a great fall in adjusted R-squared (more than 2.3945%), hence we stop the stepwise regression here. It should be noted that x_4 is an important predictor here as per our precision maintained.

So for 2019, for predicting x_1, x_2, x_3, x_4, x_5 are the important predictors also. So x_4 has again come back as an predictor.

Year 2020:

First we start modelling x_1 on the other covariates x_2 to x_7 , After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.8872	0.2272	8.307	6.14e-14***
x_2	0.7391	0.2648	2.791	0.005960 **
x_3	1.1530	0.2799	4.119	6.35e-05***
x_4	0.9807	0.3604	2.721	0.007293 **
x_5	1.4825	0.4151	3.571	0.000481 ***
x_6	0.6208	0.5096	1.218	0.225126
x_7	0.9729	0.4876	1.995	0.047857 *

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residual standard error: 0.5693 on 146 degrees of freedom
Multiple R-squared: 0.7483, Adjusted R-squared: 0.738 F-statistic: 72.36 on 6 and 146 DF, p-value: < 2.2e-16**

From the above table it has been clear that x_6 and x_7 are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x_1 in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.738.

The partial correlation coefficients are given below-

r_{12.34567}=-0.2250457
r_{13.24567}=-0.3226518
r_{14.23567}=-0.219717
r_{15.23467}=-0.2834439
r_{16.23457}=-0.1003077
r_{17.23456}=-0.1629358

It shows that x_6 has the lowest partial correlation coefficient with x_1 and hence is eliminated as a predictor.

After elimination of x_6 , we again do the multiple regression for x_1 on the remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.9743	0.2160	9.140	4.66e-16***
x ₂	0.6895	0.2621	2.631	0.009434 **
x ₃	1.1609	0.2803	4.141	5.80e-05***
x ₄	0.9637	0.3607	2.672	0.008394 **
x ₅	1.6036	0.4037	3.972	0.000111 ***
x ₇	1.1269	0.4717	2.389	0.018165 *

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'. '0.1 "1

Residual standard error: 0.5703 on 147 degrees of freedom
Multiple R-squared: 0.7458, Adjusted R-squared: 0.7371
F-statistic: 86.25 on 5 and 147 DF, p-value: < 2.2e-16

Now x_7 can be seen to be insignificant from the above table. Again the partial correlation coefficients are obtained as :

r_{12.3457}=-0.2120275
r_{13.2457}=-0.3232333
r_{14.2357}=-0.2152091
r_{15.2347}=-0.3113463
r_{17.2345}=-0.193321

x_7 has minimum partial correlation coefficient with x_1 , hence x_7 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.9818	0.2194	9.034	8.36e-16***
x2	0.7737	0.2638	2.933	0.00390 **
x3	1.0182	0.2782	3.660	0.00035 ***
x4	1.0720	0.3635	2.949	0.00371 **
x5	1.9412	0.3841	5.054	1.26e-06***

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5793 on 148 degrees of freedom

Multiple R-squared:0.7359, AdjustedR-squared:0.7288

F-statistic: 103.1 on 4 and 148 DF,p-value: < 2.2e-16

From the table it might seem that x_4 and x_2 might be less significant. Again we find the partial correlation coefficients as follows:-

$r_{12.345}=-0.234342$

$r_{13.245}=-0.2880855$

$r_{14.235}=-0.2355906$

$r_{15.234}=-0.3836386$

x_2 is discarded as a predictor , since it has the lowest partial correlation with x_1

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std.Error	tvalue	Pr(> t)
(Intercept)	1.7981	0.2155	8.342	4.54e-14***
x3	1.3626	0.2585	5.271	4.69e-07***
x4	1.7527	0.2867	6.113	8.19e-09***
x5	1.9113	0.3936	4.855	3.00e-06***

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5939 on 149 degrees of freedom

Multiple R-squared:0.7206, AdjustedR-squared:0.7149

F-statistic: 128.1 on 3 and 149 DF,p-value: < 2.2e-16

It seems that there is no insignificant predictor.

Note that there is a fall in adjusted R-squared (more than 2.3945%), hence we stop the stepwise regression here. It should be noted that x_2 is an important predictor.

Sofor2020 , for predicting x_1, x_2, x_3, x_4, x_5 are the important predictors also.

Year2021:

First we start modelling x_1 on the other covariates x_2 to x_7 , After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.3264	0.1954	11.905	<2e-16***
x_2	0.8002	0.2485	3.220	0.001591 **
x_3	1.0983	0.2964	3.705	0.000302 ***
x_4	0.9637	0.4232	2.277	0.024279 *
x_5	1.6521	0.4066	4.063	7.97e-05***
x_6	0.5615	0.4925	1.140	0.256133
x_7	0.9477	0.4551	2.082	0.039118 *

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'.0.1"1**

Residual standard error: 0.5417 on 142 degrees of freedom

Multiple R-squared:0.7559, AdjustedR-squared:0.7456

F-statistic: 73.29 on 6 and 142 DF,p-value: < 2.2e-16

From the above table it has been clear that x_6 and x_7 are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x_1 in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.7456.

The partial correlation coefficients are given below-

**r_{12.34567}=-0.2608388
r_{13.24567}=-0.2969306
r_{14.23567}=-0.1876881
r_{15.23467}=-0.3227484
r_{16.23457}=-0.09524633
r_{17.23456}=-0.1721272**

It shows that x_6 has the lowest partial correlation coefficient with x_1 and hence is eliminated as an predictor.

After elimination of x_6 , we again do the multiple regression for x_1 on the

remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.4114	0.1808	13.334	<2e-16***
x2	0.7554	0.2457	3.075	0.002522 **
x3	1.1119	0.2965	3.751	0.000256 ***
x4	0.9334	0.4228	2.207	0.028875 *
x5	1.7531	0.3972	4.413	1.99e-05***
x7	1.0466	0.4473	2.340	0.020668 *

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5423 on 143 degrees of freedom
 Multiple R-squared: 0.7537, Adjusted R-squared: 0.7451
 F-statistic: 87.5 on 5 and 143 DF, p-value: < 2.2e-16

Now x_7 and x_4 can be seen to be insignificant from the above table. Again the partial correlation coefficients are obtained as :

$r_{12,3457} = -0.2490419$
 $r_{13,2457} = -0.2992684$
 $r_{14,2357} = -0.1815306$
 $r_{15,2347} = -0.3462221$
 $r_{17,2345} = -0.1920374$

x_4 has minimum partial correlation coefficient there with x_1 , hence x_4 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.4180	0.1832	13.196	<2e-16***
x2	1.1084	0.1890	5.865	2.94e-08***
x3	1.1976	0.2978	4.021	9.32e-05***
x5	1.8535	0.3999	4.635	7.92e-06***
x7	1.1644	0.4500	2.588	0.0107 *

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5495 on 144 degrees of freedom
 Multiple R-squared: 0.7453, Adjusted R-squared: 0.7382
 F-statistic: 105.3 on 4 and 144 DF, p-value: < 2.2e-16

From the table it might seem that x_7 might be less significant. Again we find the partial correlation coefficients as follows:-

$r_{12.35} = -0.4391323$
 $r_{13.25} = -0.3177126$
 $r_{15.23} = -0.3603124$
 $r_{17.23} = -0.2107832$

x_7 is discarded as a predictor, since it has the lowest partial correlation with x_1 .

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	2.3878	0.1864	12.809	<2e-16***
x_2	1.2482	0.1846	6.762	3.10e-10***
x_3	1.0398	0.2972	3.499	0.000621 ***
x_5	2.2064	0.3832	5.757	4.91e-08***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5602 on 145 degrees of freedom
Multiple R-squared: 0.7334, Adjusted R-squared: 0.7279
F-statistic: 133 on 3 and 145 DF, p-value: < 2.2e-16

It seems that there is no insignificant predictor. If we calculate the partial correlations more, we have,

$r_{12.35} = -0.4896347$
 $r_{13.25} = -0.2790112$
 $r_{15.23} = -0.431354$

x_3 will be out and the table on modelling x_1 on x_2 and x_5 will be given as- Estimate Std.

	Error	t value	Pr(> t)
(Intercept)	2.5802	0.1849	13.958 <2e-16***
x_2	1.7197	0.1309	13.133 <2e-16***
x_5	2.5510	0.3843	6.637 5.85e-10***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5813 on 146 degrees of freedom
Multiple R-squared: 0.7109, Adjusted R-squared: 0.707 F-statistic: 179.5 on 2 and 146 DF, p-value: < 2.2e-16

Note that there is a huge fall in adjusted R-squared (more than 2.3945%), hence we stop the stepwise regression here. It should be noted that x_3 is an important predictor.

So for 2021, for predicting x_1, x_2, x_3, x_5 are the important predictors also.

Year 2022:

First we start modelling x_1 on the other covariates x_2 to x_7 . After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.6677	0.2055	8.117	2.29e-13***
x_2	0.5513	0.2072	2.661	0.00871 **
x_3	1.4094	0.2424	5.815	3.98e-08***
x_4	1.2735	0.4414	2.885	0.00454 **
x_5	1.6032	0.3754	4.270	3.59e-05***
x_6	0.9689	0.5681	1.705	0.09036 .
x_7	0.7305	0.3964	1.843	0.06750 .

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘1

Residual standard error: 0.5281 on 139 degrees of freedom

Multiple R-squared: 0.7737, Adjusted R-squared: 0.7639

F-statistic: 79.2 on 6 and 139 DF, p-value: < 2.2e-16

From the above table it has been clear that x_6 and x_7 are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x_1 in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.7639.

The partial correlation coefficients are given below-

$r_{12,34567} = -0.2201484$
 $r_{13,24567} = -0.4423483$
 $r_{14,23567} = -0.2377005$
 $r_{15,23467} = -0.3405645$
 $r_{16,23457} = -0.1431556$
 $r_{17,23456} = -0.1544202$

It shows that x_6 has the lowest partial correlation coefficient with x_1 and hence is eliminated as a predictor.

After elimination of x_6 , we again do the multiple regression for x_1 on the remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.8033	0.1908	9.454	<2e-16***
x2	0.4643	0.2022	2.297	0.02313 *
x3	1.4608	0.2421	6.033	1.36e-08***
x4	1.2739	0.4444	2.867	0.00479 **
x5	1.7397	0.3693	4.711	5.87e-06***
x7	0.8113	0.3963	2.047	0.04249 *

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5317 on 140 degrees of freedom
 Multiple R-squared: 0.7689, Adjusted R-squared: 0.7607
 F-statistic: 93.18 on 5 and 140 DF, p-value: < 2.2e-16

Now x_7 and x_2 can be seen to be insignificant from the above table. Again the partial correlation coefficients are obtained as :

$r_{12.3457}=-0.1905426$
 $r_{13.2457}=-0.4542451$
 $r_{14.2357}=-0.2354619$
 $r_{15.2347}=-0.3699163$
 $r_{17.2345}=-0.1705002$

x_7 has minimum partial correlation coefficient with x_1 , hence x_7 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.7408	0.1904	9.142	6.09e-16***
x2	0.5295	0.2019	2.623	0.00968 **
x3	1.3759	0.2412	5.704	6.63e-08***
x4	1.3676	0.4470	3.060	0.00265 **
x5	1.9679	0.3560	5.528	1.52e-07***

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5377 on 141 degrees of freedom
Multiple R-squared: 0.762, Adjusted R-squared: 0.7553
F-statistic: 112.9 on 4 and 141 DF, p-value: < 2.2e-16

From the table it might seem that x_4 and x_2 might be less significant. Again we find the partial correlation coefficients as follows:-

$r_{12.357} = -0.2156702$
 $r_{13.257} = -0.4329692$
 $r_{15.237} = -0.2495095$
 $r_{17.235} = -0.4220331$

x_2 is discarded as a predictor, since it has the lowest partial correlation with x_1 .

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.7864	0.1935	9.232	3.44e-16***
x_3	1.6164	0.2277	7.098	5.56e-11***
x_4	2.1133	0.3520	6.004	1.53e-08***
x_5	2.0576	0.3616	5.690	7.00e-08***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘1’

Residual standard error: 0.5487 on 142 degrees of freedom
Multiple R-squared: 0.7504, Adjusted R-squared: 0.7451
F-statistic: 142.3 on 3 and 142 DF, p-value: < 2.2e-16

It seems that there is no insignificant predictor.

Note that there is a fall in adjusted R-squared as per our precision (more than 2.3945%), hence we stop the stepwise regression here. It should be noted that x_2 is an important predictor and cannot be discarded.

So for 2022, for predicting x_1, x_2, x_3, x_4, x_5 are the important predictors also.

Year 2023:

First we start modelling x_1 on the other covariates x_2 to x_7 . After fitting the model of multiple linear regression, we get the following result:

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.5269	0.2014	7.581	5.76e-12***
x2	0.5623	0.1974	2.849	0.0051 **
x3	1.5415	0.2137	7.214	4.01e-11***
x4	0.7750	0.4845	1.599	0.1121
x5	1.7643	0.3490	5.055	1.43e-06***
x6	0.2915	0.5913	0.493	0.6229
x7	1.1080	0.3898	2.843	0.0052 **

Signif.codes:0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.483 on 130 degrees of freedom
 Multiple R-squared:0.8284, AdjustedR-squared:0.8204
 F-statistic: 104.6 on 6 and 130 DF,p-value: < 2.2e-16

From the above table it has been clear that x₆ and x₄ are the two insignificant covariates.

Now we go for the partial correlation coefficients and will mark that covariate insignificant first which will show minimum partial correlation with x₁ in absolute terms and we will eliminate that variable immediately. Then we will start afresh with the remaining variables. This process will go until there is a sudden drop in adjusted R-squared value which is here 0.8204.

The partial correlation coefficients are given below-

r_{12.34567}=-0.2423985
 r_{13.24567}=-0.5346904
 r_{14.23567}=-0.138925
 r_{15.23467}=-0.4053155
 r_{16.23457}=-0.04319266
 r_{17.23456}=-0.2419218

It shows that x₆ has the lowest partial correlation coefficient with x₁ and hence is eliminated as an predictor.

After elimination of x₆, we again do the multiple regression for x₁ on the remaining predictors and thus we obtain the following table as-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.5660	0.1846	8.483	4.06e-14***
x2	0.5380	0.1906	2.823	0.00550 **
x3	1.5613	0.2093	7.461	1.06e-11***
x4	0.7628	0.4825	1.581	0.11631
x5	1.7910	0.3438	5.210	7.16e-07***
x7	1.1459	0.3810	3.007	0.00316 **

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residualstandarderror: 0.4817 on 131 degrees offreedom
MultipleR-squared: 0.828, AdjustedR-squared: 0.8215F-statistic: 126.2 on 5 and 131 DF,p-value: < 2.2e-16**

Now x_4 can be seen to be insignificant from the above table.

Again the partial correlation coefficients are obtained as :

$r_{12,3457} = -0.2394682$

$r_{13,2457} = -0.5460767$

$r_{14,2357} = -0.1368251$

$r_{15,2347} = -0.4142694$

$r_{17,2345} = -0.2541266$

x_4 has minimum partial correlation coefficient there with x_1 , hence x_4 is discarded as a predictor.

The table corresponding to the multiple regression model of x_1 on other remaining variables is given by-

	Estimate	Std. Error	tvalue	Pr(> t)
(Intercept)	1.4925	0.1797	8.307	1.03e-13***
x_2	0.7203	0.1526	4.720	5.94e-06***
x_3	1.6404	0.2044	8.027	4.82e-13***
x_5	1.7783	0.3456	5.145	9.46e-07***
x_7	1.2136	0.3808	3.187	0.00179 **

Signif.codes:0 *'0.001 '**'0.01 '*'0.05'. '0.1"1**

**Residual standard error: 0.4844 on 132 degrees of freedom
Multiple R-squared: 0.8248, AdjustedR-squared: 0.8194
F-statistic: 155.3 on 4 and 132 DF,p-value: < 2.2e-16**

From the table it seems that x_7 might be less significant. Again we find the partial correlation coefficients as follows:-

$r_{12,357} = -0.3799814$

$r_{13,257} = -0.5727104$

$r_{15,237} = -0.4087001$

$r_{17,235} = -0.2673271$

x_7 is discarded as a predictor, since it has the lowest partial correlation with x_1

The table corresponding to the multiple correlation coefficient of x_1 on the remaining covariates is given below-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.3960	0.1831	7.625	4.15e-12***
x_2	0.8922	0.1476	6.045	1.41e-08***
x_3	1.5241	0.2079	7.331	1.99e-11***
x_5	2.0857	0.3432	6.078	1.21e-08***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5008 on 133 degrees of freedom

Multiple R-squared: 0.8113, Adjusted R-squared: 0.807
F-statistic: 190.6 on 3 and 133 DF, p-value: < 2.2e-16

It seems that there is no significant predictor. We find the partial correlation coefficients as-

$r_{12.35} = -0.4642783$

$r_{13.25} = -0.5364827$

$r_{15.23} = -0.4662245$

x_2 is discarded and now the table for modelling x_1 on x_3 and x_5 is given by-

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.5935	0.2026	7.864	1.1e-12***
x_3	2.3510	0.1761	13.349	< 2e-16***
x_5	2.2742	0.3844	5.916	2.6e-08***

Signif.codes: 0 ***'0.001 '**'0.01 '*'0.05'.0.1"1

Residual standard error: 0.5633 on 134 degrees of freedom

Multiple R-squared: 0.7594, Adjusted R-squared: 0.7558

F-statistic: 211.5 on 2 and 134 DF, p-value: < 2.2e-16

Note that there is a great fall in adjusted R-squared as per our precision (more than 2.3945%), hence we stop the stepwise regression here. It should be noted that x_2 is an important predictor and cannot be discarded.

So for 2022, for predicting x_1 , x_2 , x_3 , x_5 are the important predictors also.

Overall interpretation:

In all the years x_6 and x_7 are not well predictors to predict x_1 , in all the years x_2 , x_3 , x_4 , x_5 are the influential covariates for predicting x_1 , except for three years, viz, for

2018,2021 and 2023,x₄has not been included as a predictor in the former list.But simply looking at the summary table for the full model,for all the years x₆and x₇have turned out to be insignificant but the remaining are significant.Thus x₄mightbetakenintoaccountinpredictingtheresponse,fromstatisticalviewpoint.

RegressionDiagnostics

Considerthefollowingregressionmodel:

$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_p x_{pi} + e_i, i=1(1)n$, y being the response variable, and x_1, x_2, \dots, x_p are the covariates in predicting y, e being the error term, n is the total no of observations, p is the no of predictors.

Let the fitted value of the response be \hat{y}_i , and the residual for the i^{th} observation is given by: $z_i = \frac{e_i}{\sqrt{\hat{\sigma}^2}}, e_i = y_i - \hat{y}_i, i=1(1)n$

The standardised residual plot helps in determining the potential or suspected outliers. The residuals having value greater than +2 or lesser than -2 are called suspected outliers.

In order to find the influential observations, we make use of Welsch and Kuh's "DFITS" measure and "Cook's Distance" measure.

The Welsch and Kuh's measure is defined as-

$$\text{DFITS}_i = \frac{\hat{y}_i - \hat{y}_{(i)}}{\sqrt{\hat{\sigma}^2}}, i=1,2,\dots,n$$

Thus, DFITS_i is the scaled difference between the i^{th} fitted value obtained from the full data and the i^{th} fitted value obtained by deleting the i^{th} observation., $i=1(1)n$, where $\hat{\gamma}_i$ is the unbiased estimator of σ^2 , being the unknown common variance of e_i 's and is given by-

$\hat{\gamma}_i = \frac{\text{SSE}_{(i)}}{n-1}$, where SSE_(i) is the sum of squared residuals when we fit the model to the $(n-1)$ observations obtained by omitting the i^{th} observation.

And the value is called the leverage value for the i^{th} observation, being weight (leverage) given to in determining the i^{th} fitted value \hat{y}_i .

Points with $|DFITS_i|$ larger than $2\sqrt{\frac{+1}{n-1}}$ are usually classified as influential points.

Cook's distance measures the influence of the i^{th} observation by-

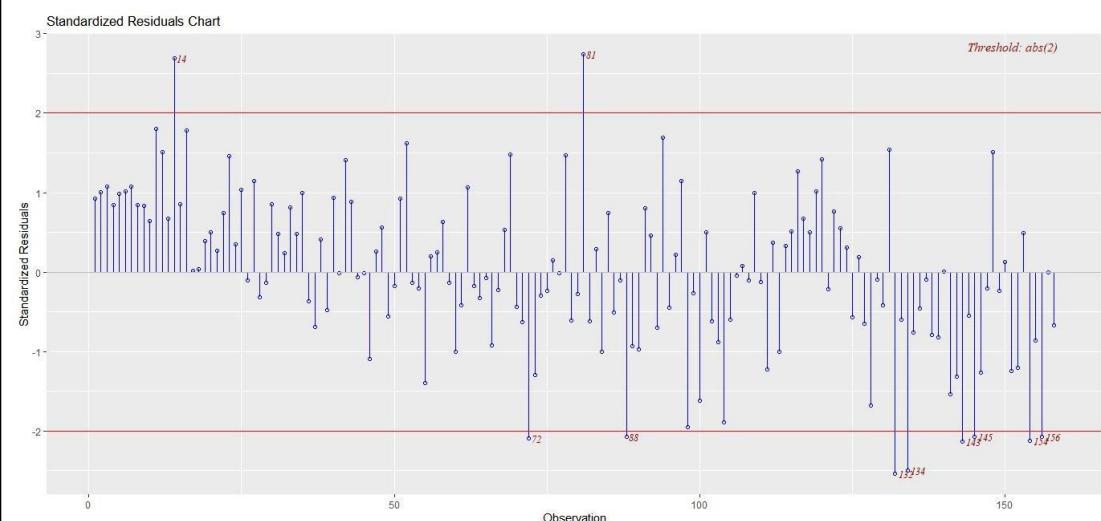
$$C_i = \frac{\sum_{j=1}^{n-1} (Y_j - \hat{Y}_j)^2}{\sum_{j=1}^{n-1} (Y_j - \hat{Y}_j)^2}, \quad i=1, 2, \dots, n$$

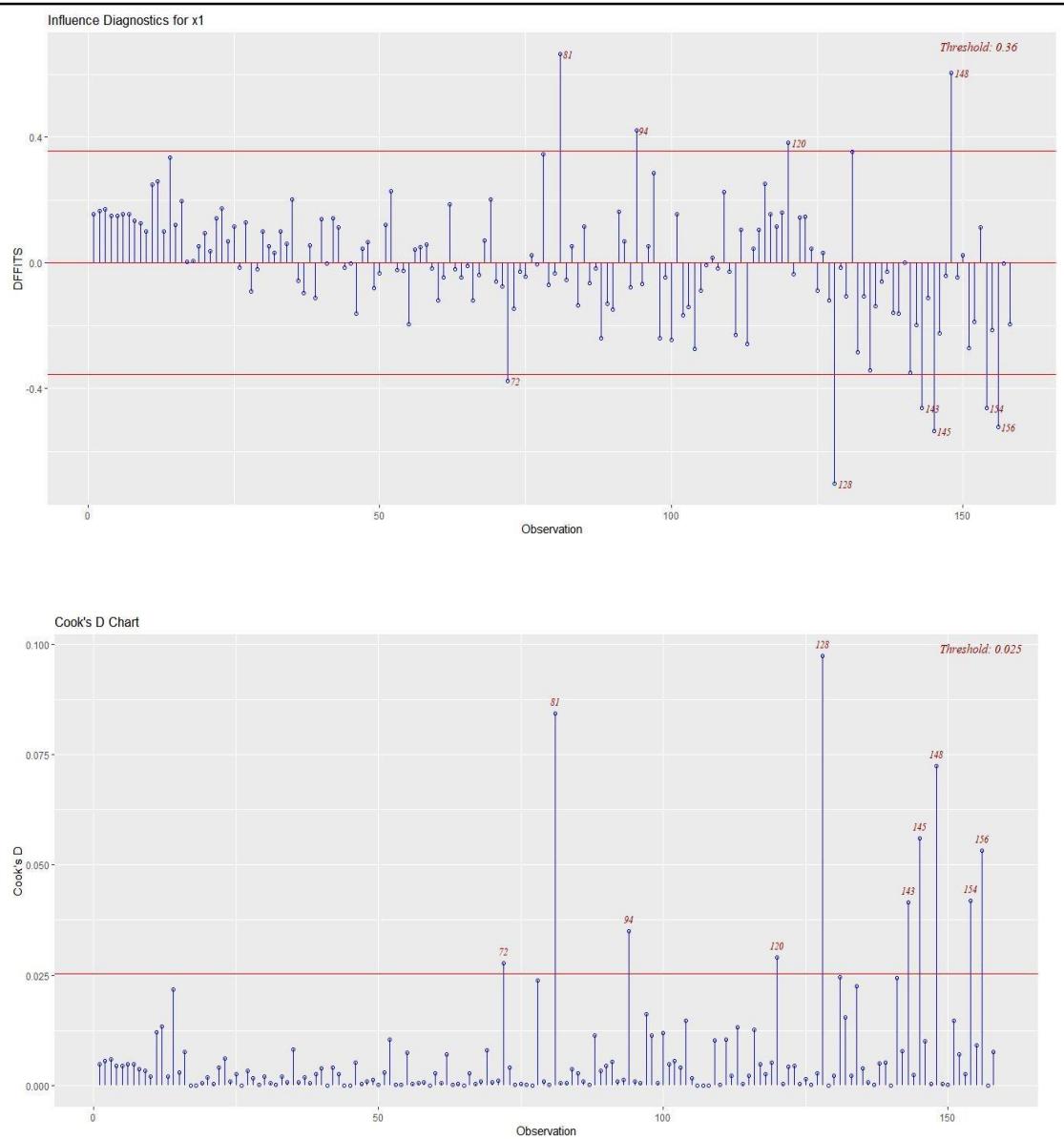
It measures the difference between the fitted values obtained from the full data and the fitted values obtained by deleting the i^{th} observation.

Therefore, a large value of C_i indicates that the point is influential. It has been suggested that points with C_i values greater than the 50% point of the F-distribution with $(p+1)$ and $(n-p-1)$ degrees of freedom be classified as influential points. A practical operational rule is to classify points with C_i values greater than 1 as being influential.

The standardised residual chart, the DFITS chart and the Cook's distance charts are presented for each year.

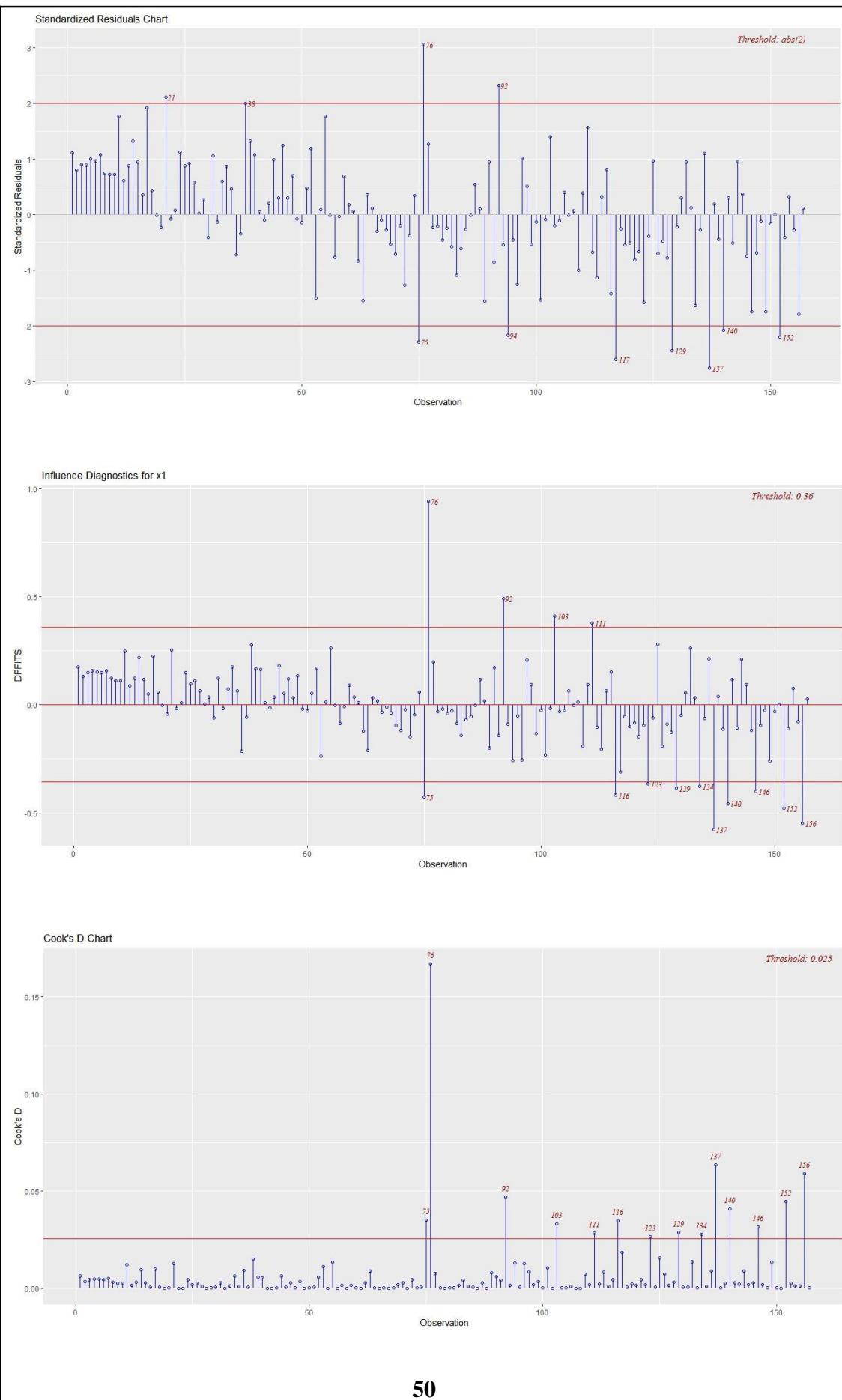
Year 2015:





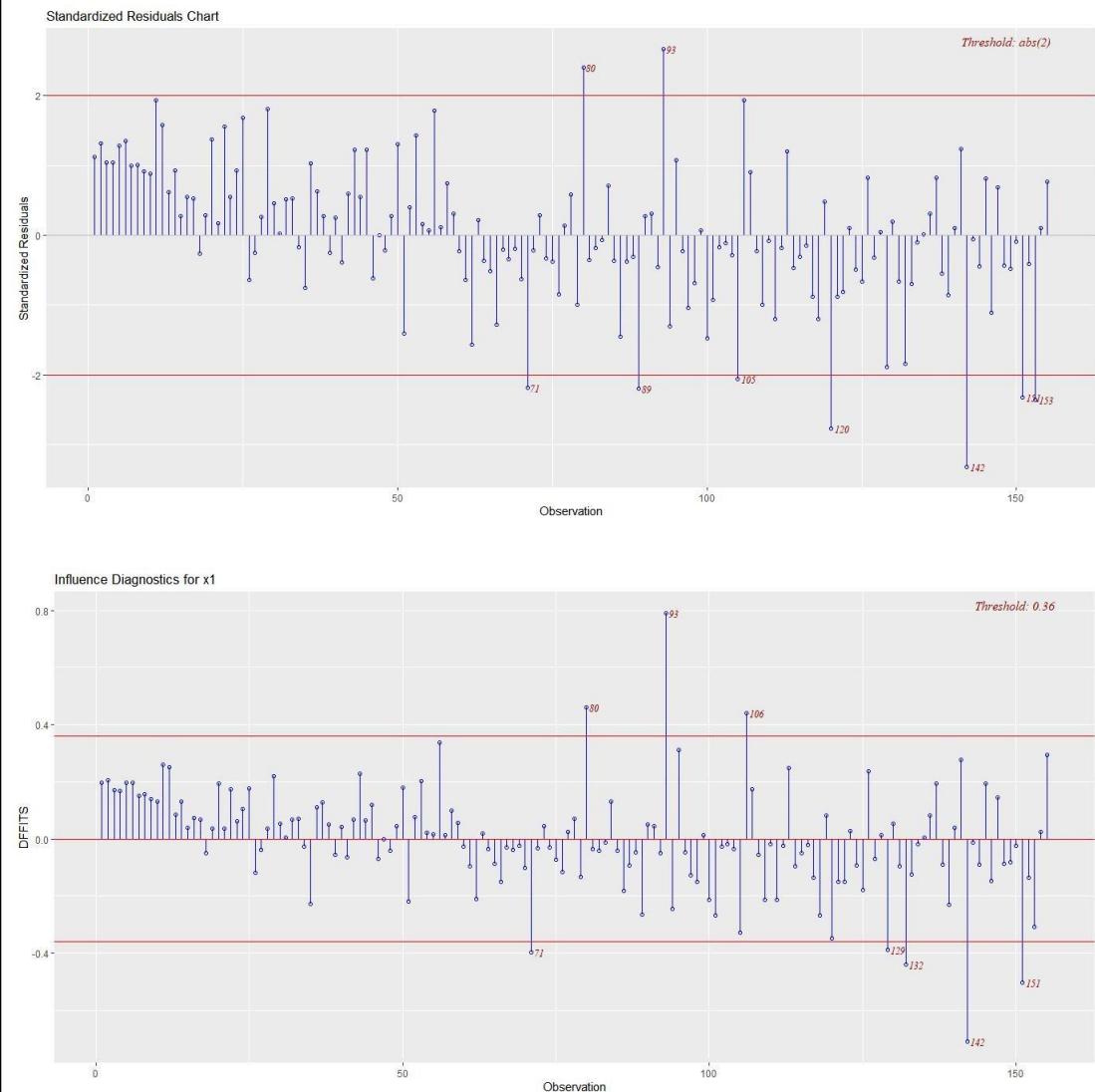
Interpretation:-The influential data points are corresponding to the countries Mauritius,Azerbaijan,Macedonia,Haiti,Armenia,Senegal,Niger,Madagascar,Afghanistan,Benin.The last two are in least happy countries also.Out of the 10,5 are from Africa,2 are from Asia(Azerbaijan and Afghanistan),Macedonia,Haiti,Armenia are from Western territory.

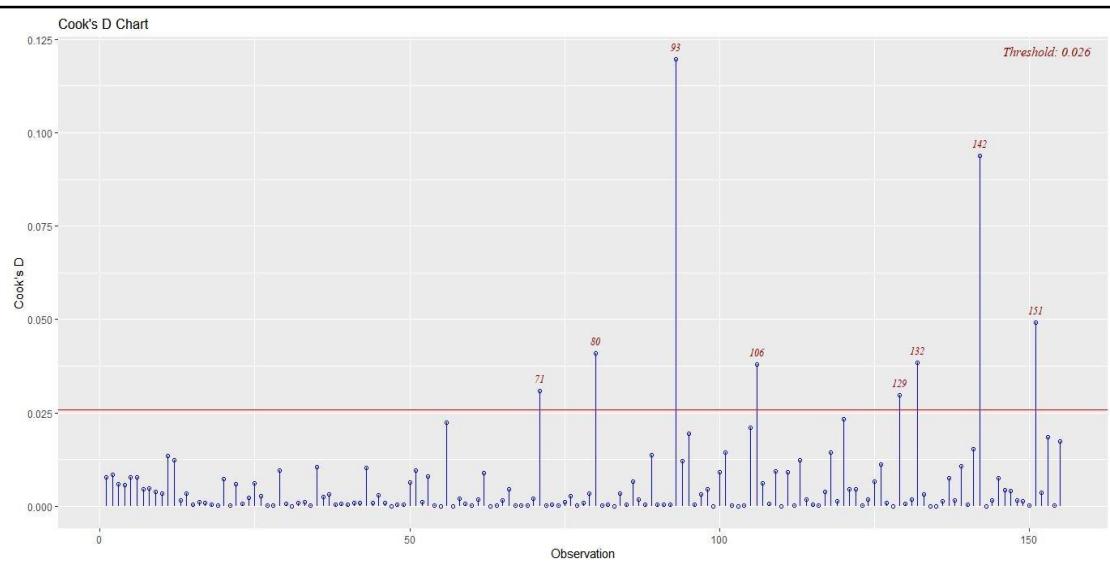
Year2016:



Interpretation:-The influential points are data points corresponding to Croatia,Hong Kong,Hungary,Laos,Bangladesh,Ethiopia,Kenya,Senegal,Sudan,Haiti,Ivory Coast,Burkina Faso,Guinea,Togo. Here, 8 countries are from Africa, 3 are from Asia, the remaining are from Western territory.

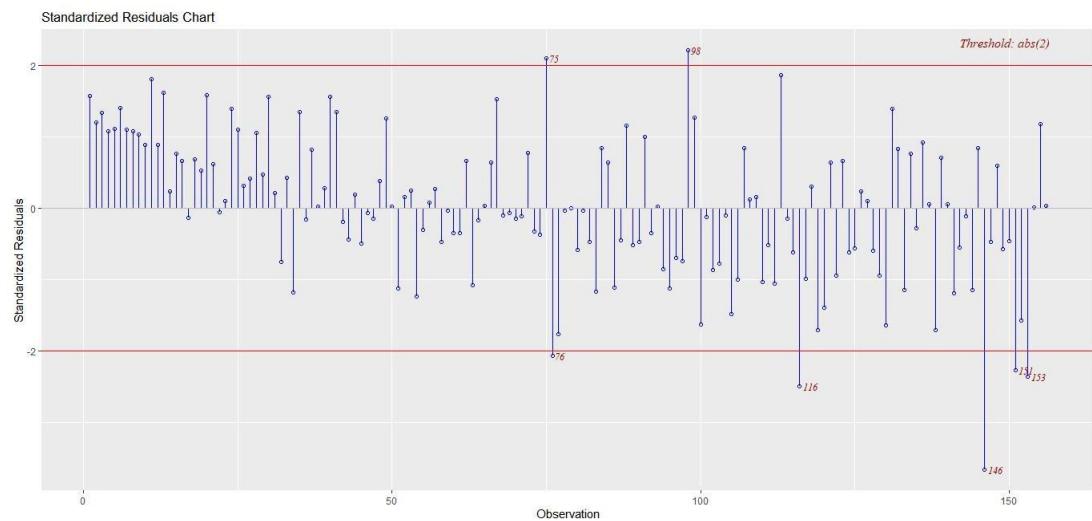
Year2017:

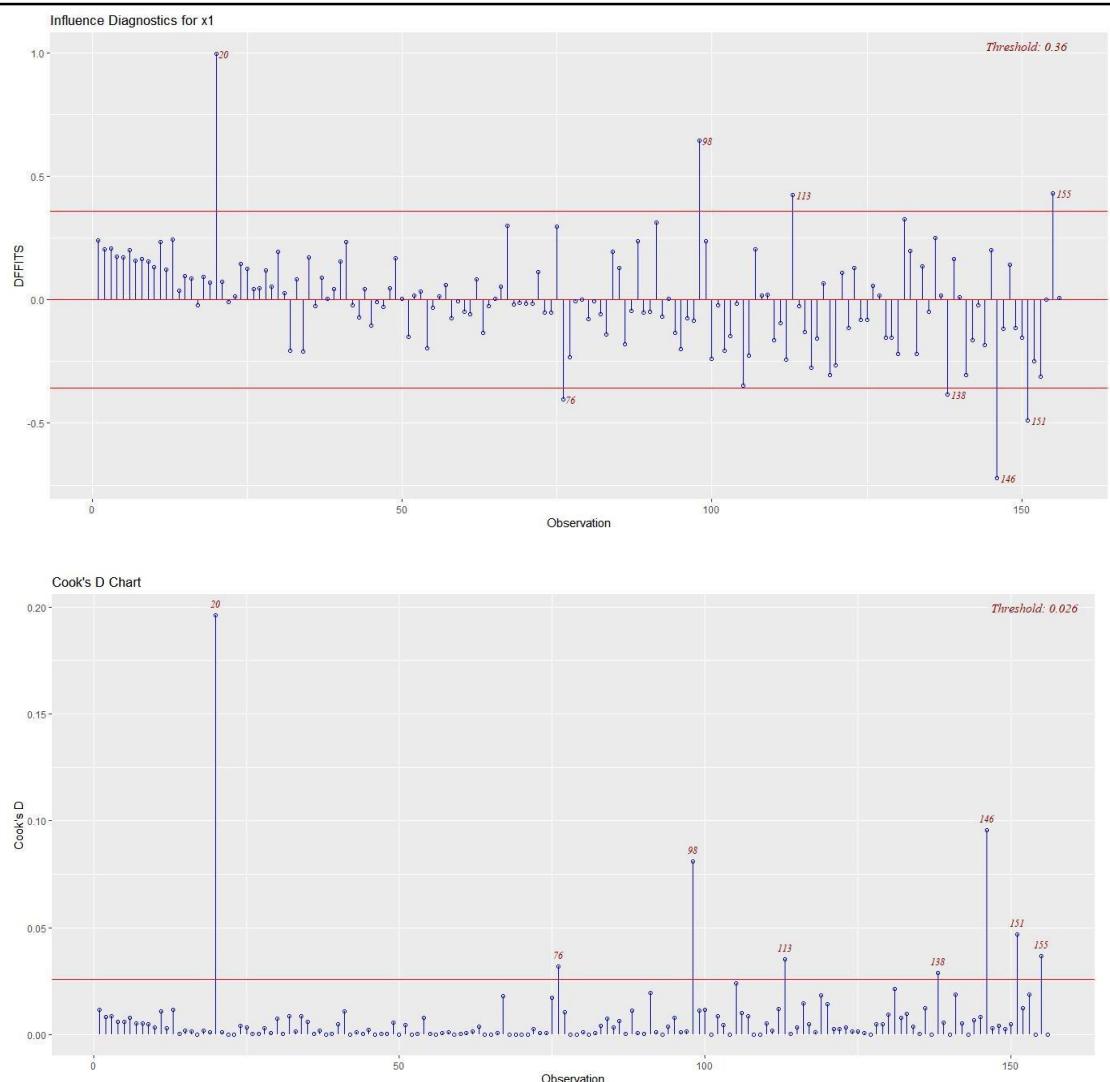




Interpretation:-The influential points are data points corresponding to Paraguay,China,Macedonia,Bulgaria,Ghana,Afghanisthan,Togo. Here 2 are from Africa, 2 are from Asia.

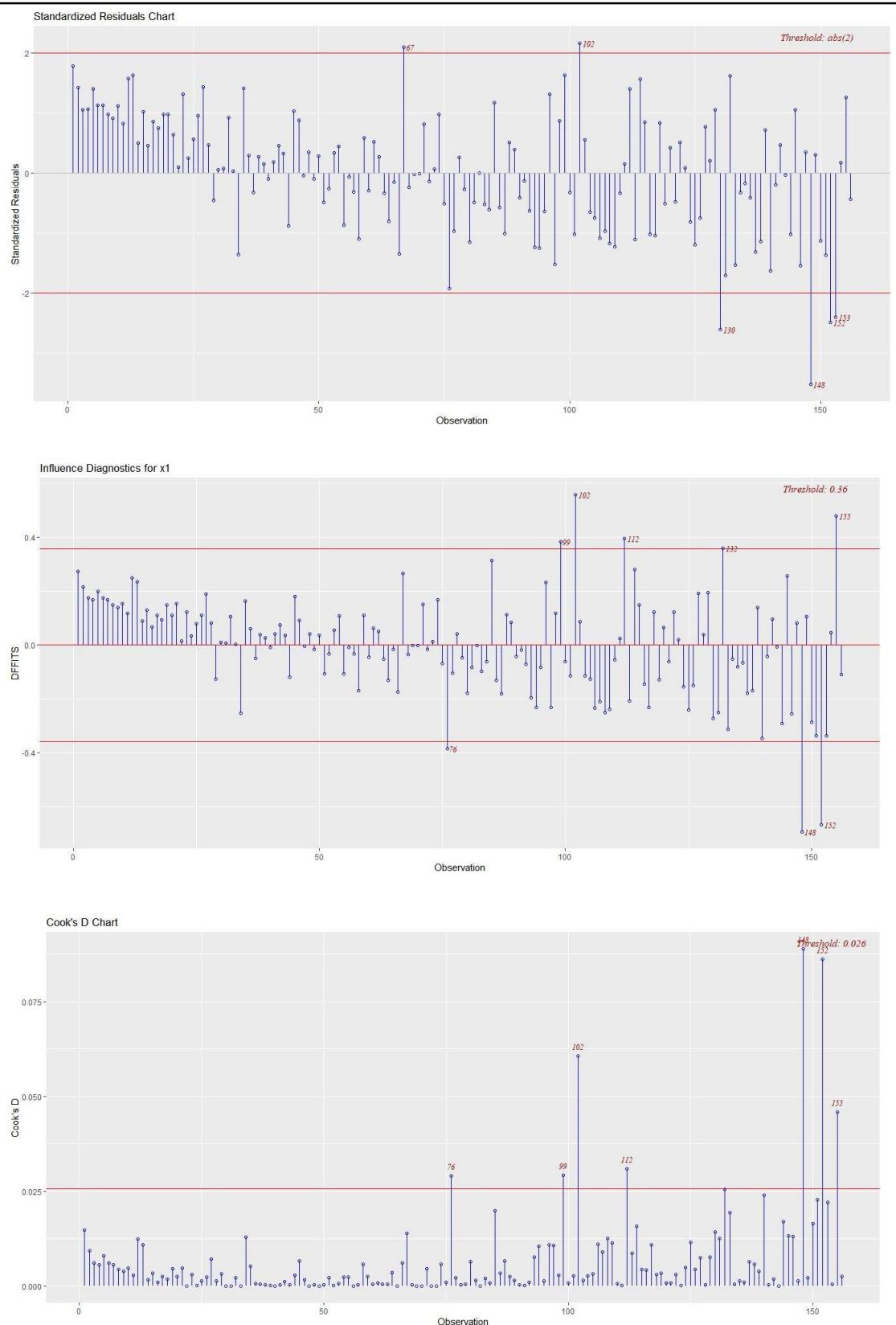
Year2018:





Interpretation:-The influential data points corresponding to the countries Israel,Pakistan,Bhutan,Albania,Sudan,Afghanisthan,Syria,SouthSudanamong which 3 are from Africa,remaining 5 are from Asia.

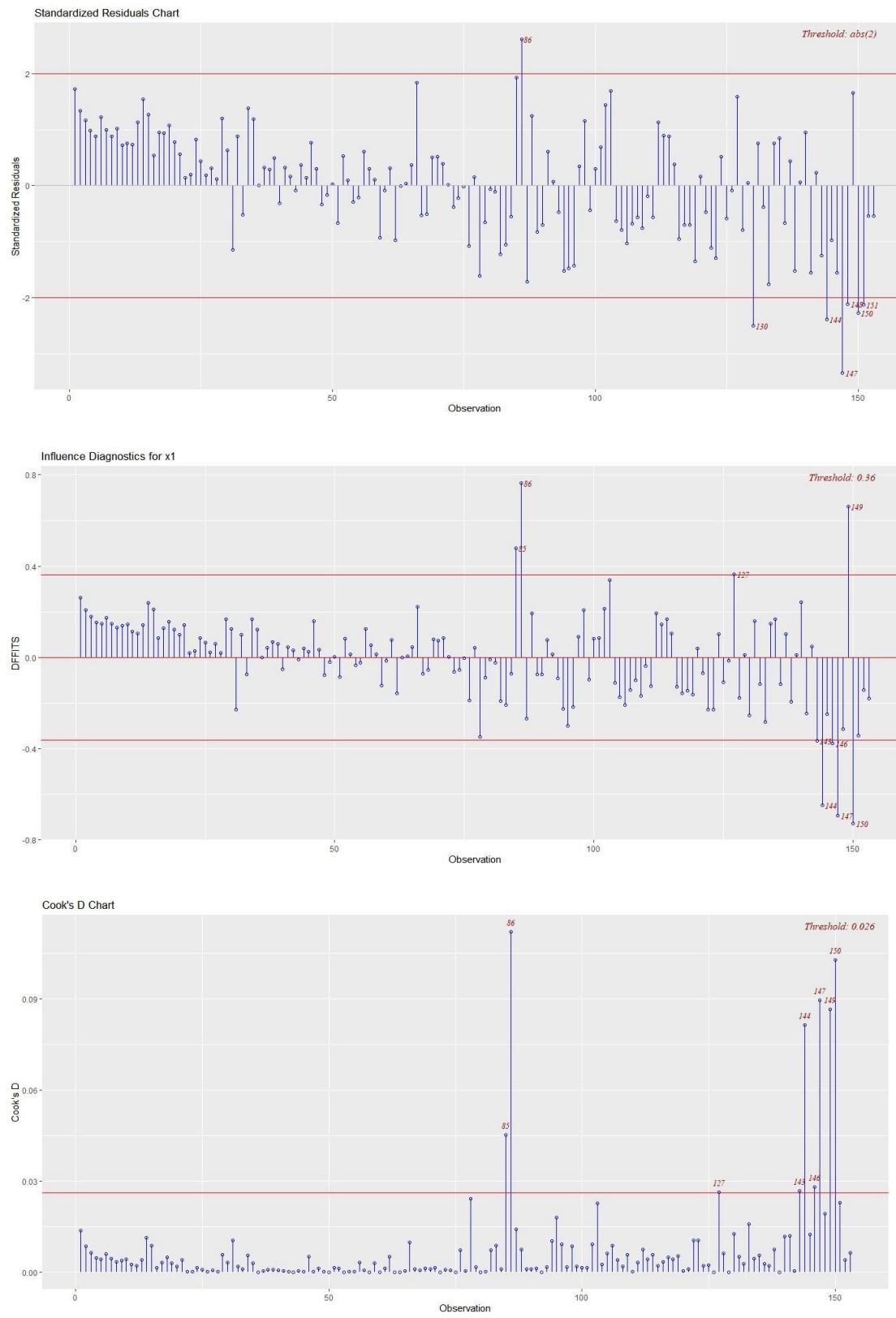
Year2019:



Interpretation:- The influential data points are corresponding to the countries Croatia, Ghana, Jordan, Senegal, Myanmar, Haiti, Yemen, Afghanistan among

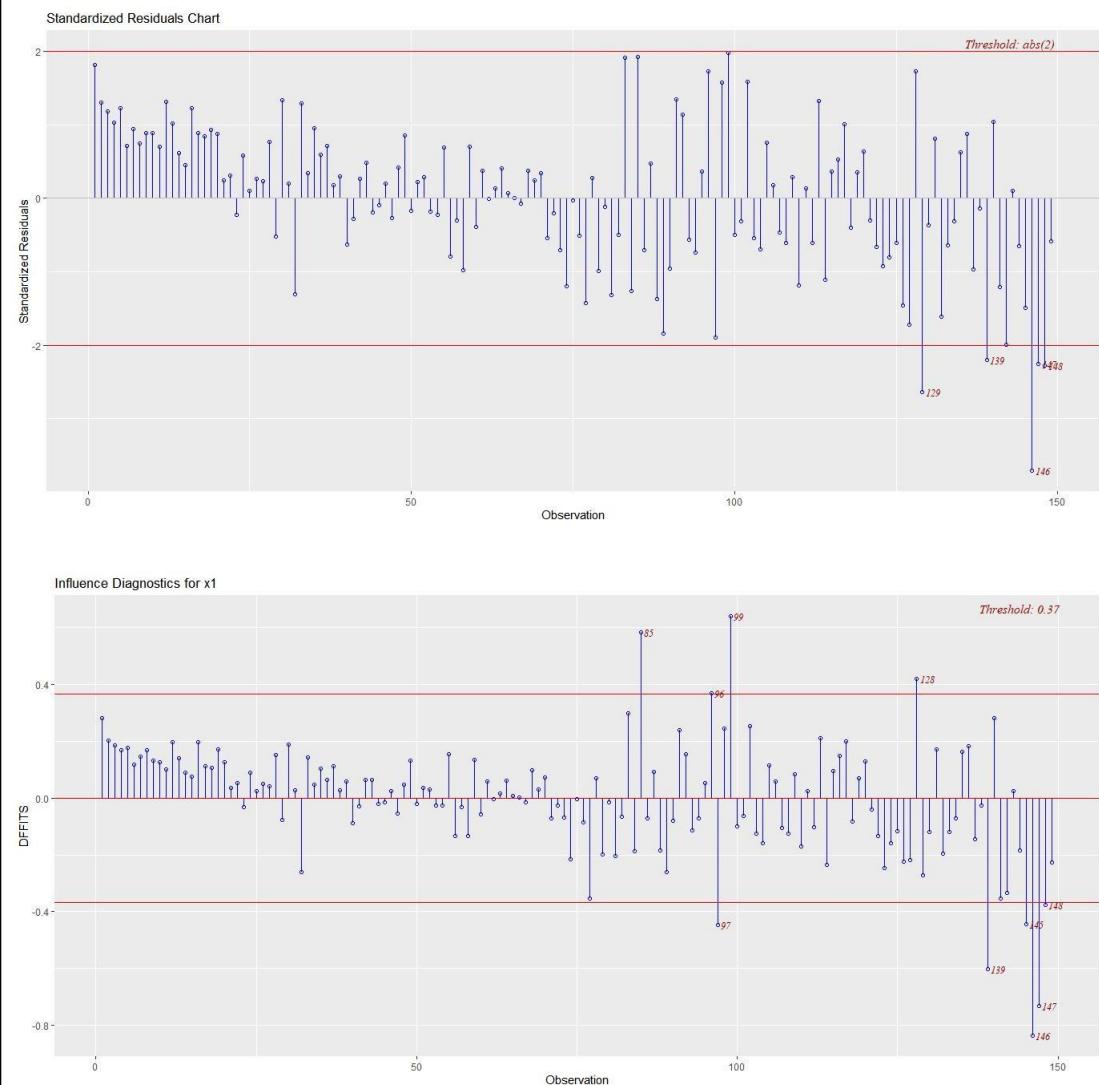
which 3 are from Africa, 3 are from Asia, remaining are from western territory. Year

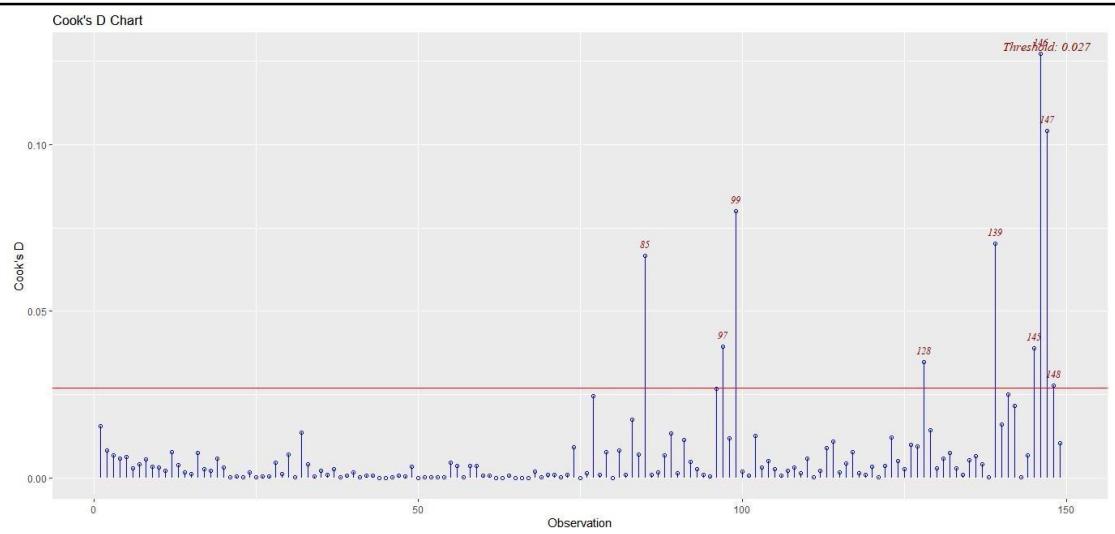
2020:



Interpretation:-The influential points are corresponding to data points Indonesia,Ivory Coast,Uganda,Haiti,Lesotho,Malawi,Yemen,Tanzania,Central African Republic among which 7 are from Africa, 1 is from Asia. The last two are in 6 least happy countries also.

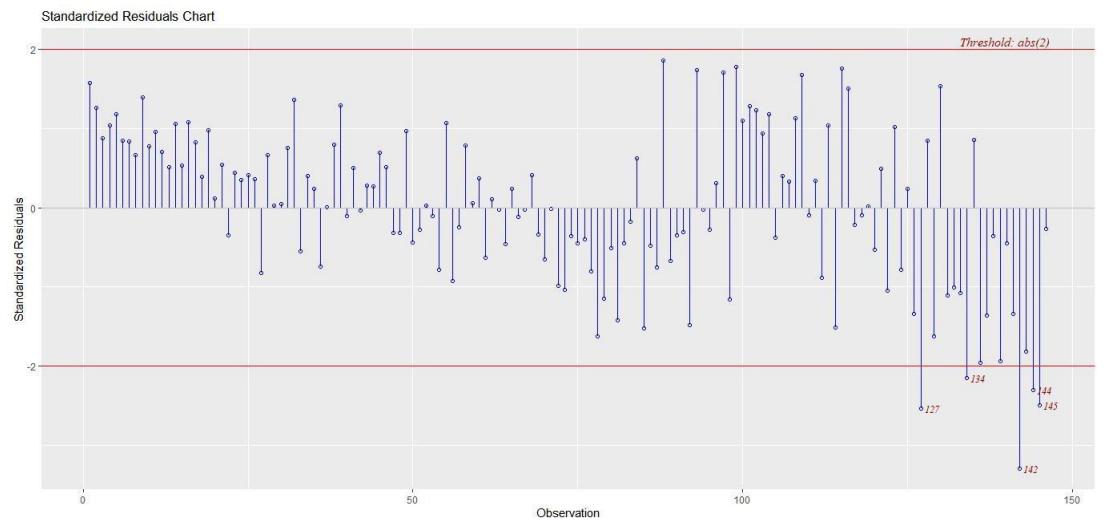
Year 2021:

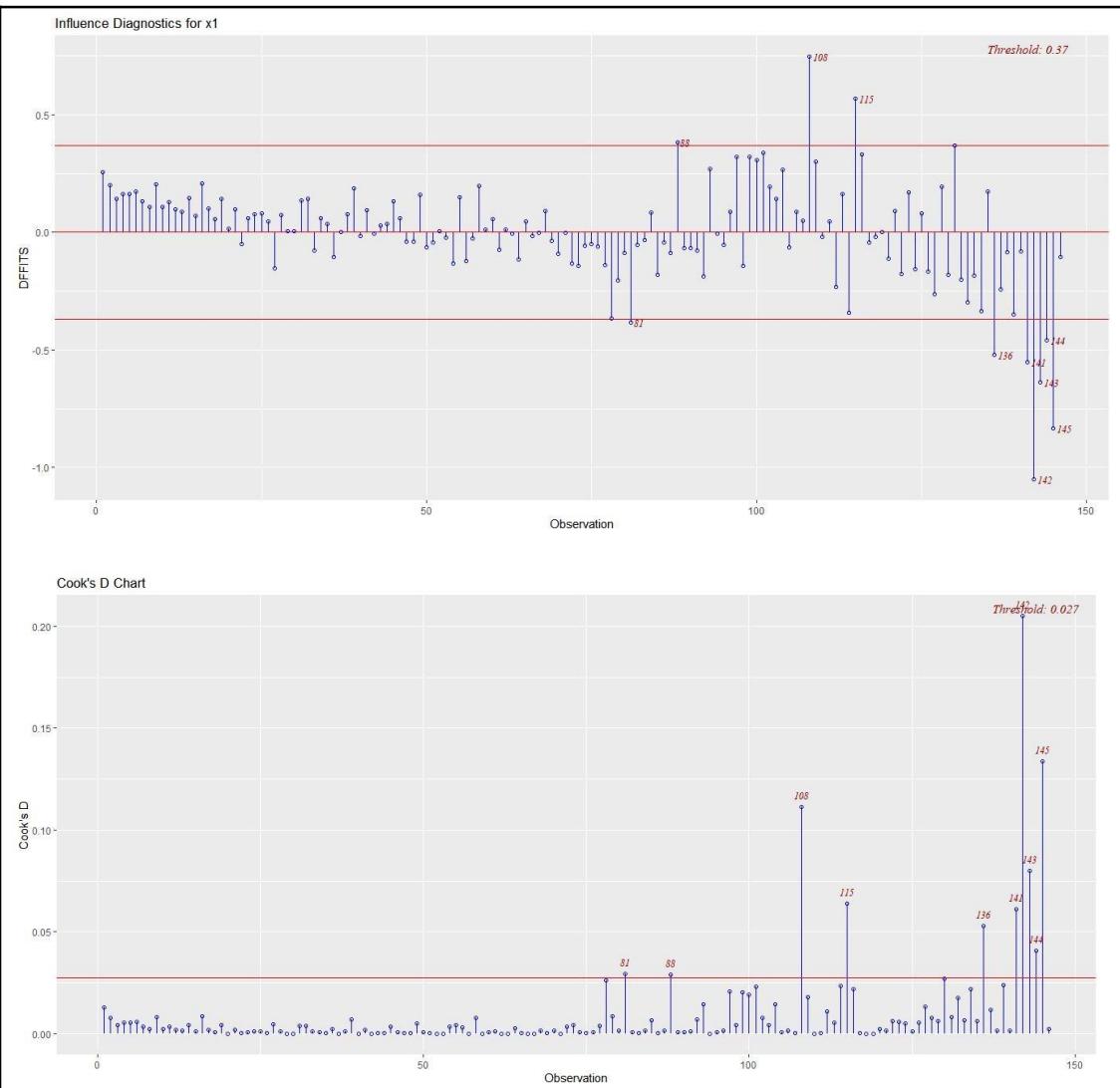




Interpretation:- The influential data points are corresponding to the countries China, Ghana, Niger, Gambia, Jordan, Sierra Leone, Malawi, Lesotho, Botswana, Rwanda among which 8 are from Africa, remaining 2 are from Asia. The last fours are in 6 least happy countries also.

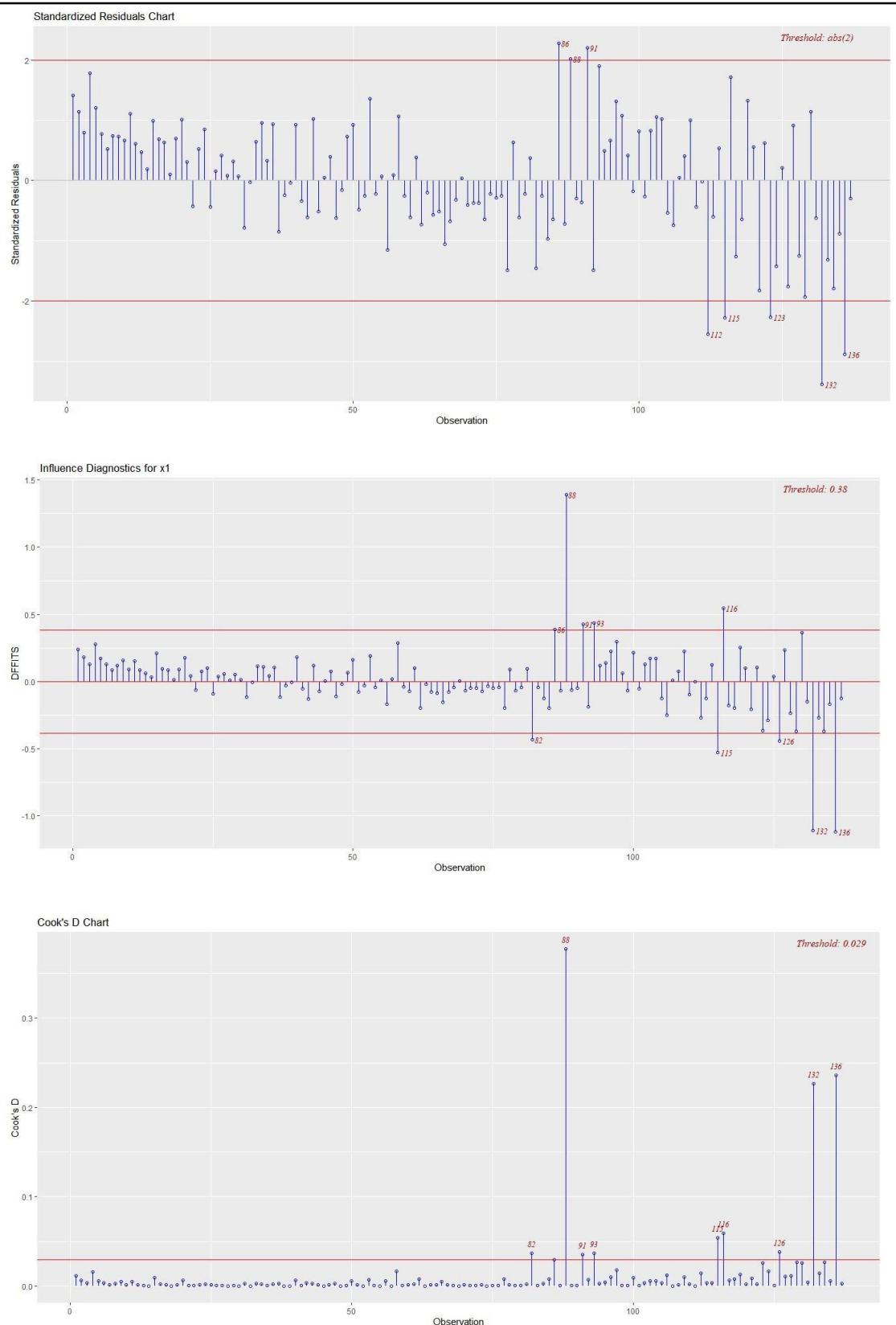
Year 2022:





Interpretation:-The influential data points are corresponding to the countries Russia,Indonesia,Iraq,Cambodia,Togo,SierraLeone,Lesotho,Bostwana,Rwanda,Zimbabwe,among which 6 are African,3 are Asian.Also,the last fours are in 6 least happy countries.

Year2023:



Interpretation:- The influential data points are corresponding to the countries

Algeria,NorthMacedonia,Georgia,Ukraine,Chad,Cambodia,Malawi,Sierra Leone,among which 4 are African Cambodia comes from Asia, and the remaining are European.

Overall Interpretation:-It is to be noted that the influential countries in the data set vary from year to year.But most influential countries are from African continent,then Asia gets the second priority.Also,most of the suspected outliers,according to the standardised residual plot turn out to be highly influential and this happens for every year.It is an important note that what we think as outlier,might turn out as influential data in real life.Foreach year only 2 or 3 data points are suspected outliers,but they do not create any problem in our statistical analysis,so we have kept them intact instead of avoiding them.

Principal Component Analysis

In order to get another view regarding the prediction of the response,we use principal component analysis (PCA).It has been used to find out if there can be any dimension reduction from the 6 covariates to predict the response in a better way.Let us consider the following random vector as follows-

$$X = \begin{pmatrix} 1 \\ \vdots \end{pmatrix}$$
, with the dispersion matrix having
the eigenvalue-eigenvector pairs $(\lambda_1, e_1), (\lambda_2, e_2), \dots, (\lambda_m, e_m)$, where
 $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_m \geq 0$

The j^{th} principal component is given by Y_j , with $\text{Var}(Y_j) = \lambda_j$, $j=1,2,\dots,m$

The proportion of variation for the j^{th} principal component Y_j is given by

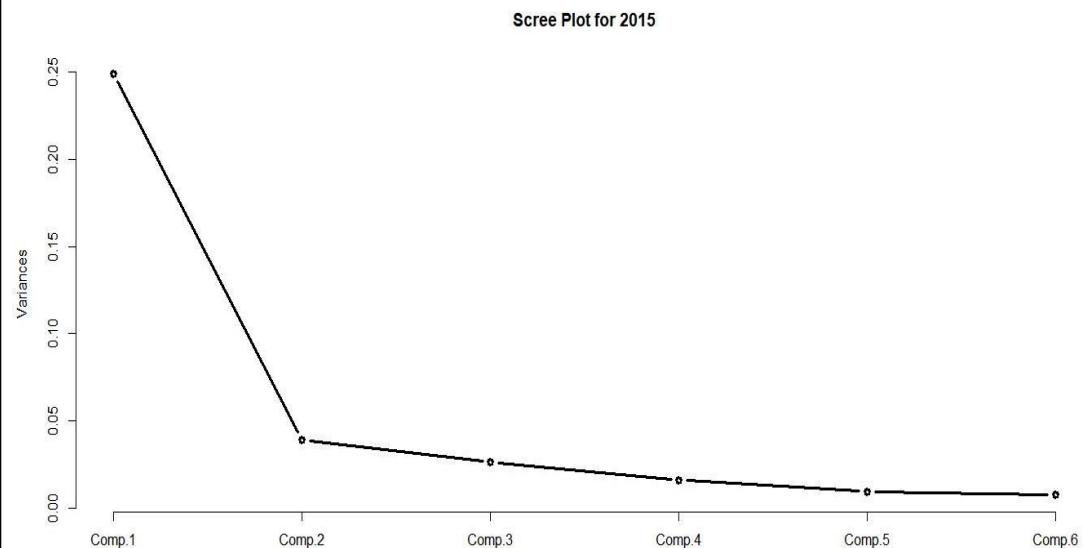
$$\frac{\lambda_j}{\lambda_1 + \lambda_2 + \dots + \lambda_m}, \quad j=1,2,\dots,m$$

The cumulative proportion of variation for the j^{th} principal component Y_j is given by $\frac{\lambda_1 + \lambda_2 + \dots + \lambda_j}{\lambda_1 + \lambda_2 + \dots + \lambda_m}$, $j=1,2,\dots,m$

The PCA is done for year to year.The table of cumulative proportion of variations and scree plot are given for year to year.

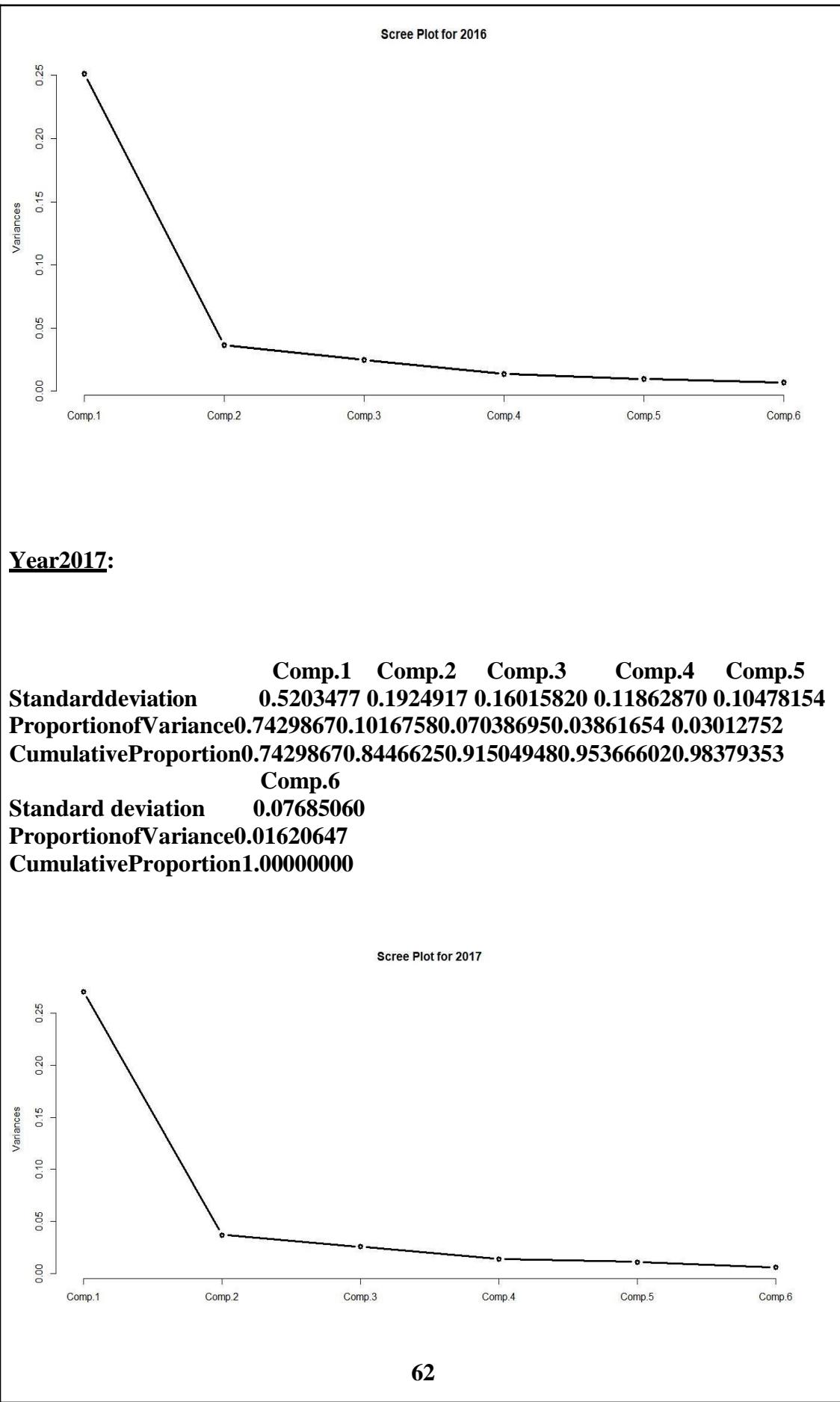
Year2015:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Standarddeviation	0.49889090	0.1983739	0.16328831	0.12729774	0.09863501	
ProportionofVariance	0.71380550	0.11285940	0.076467870	0.04647401	0.02790172	
CumulativeProportion	0.71380550	0.82666490	0.903132790	0.949606810	0.97750852	
Standard deviation	0.08855735					
ProportionofVariance	0.02249148					
CumulativeProportion	1.00000000					



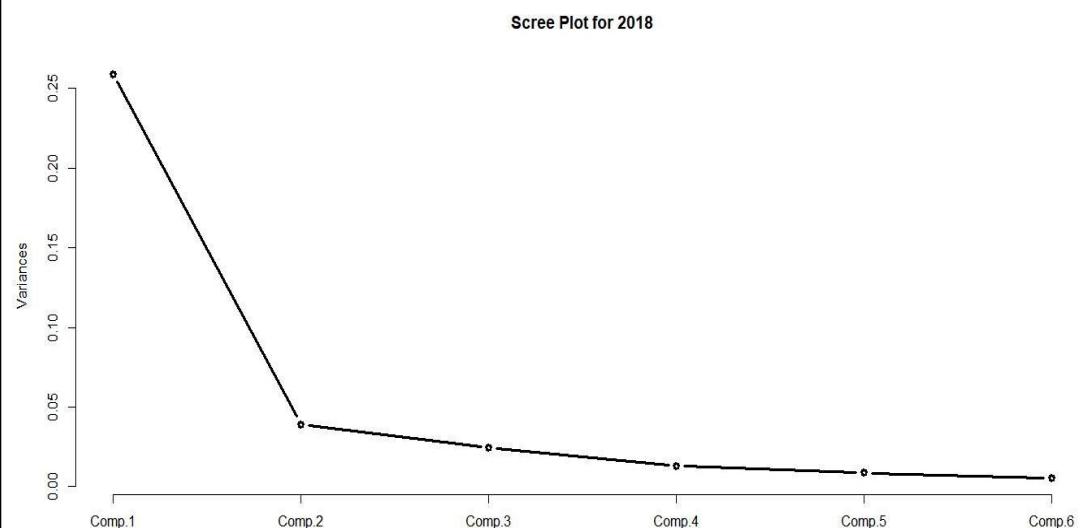
Year2016:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Standarddeviation	0.5014984	0.1907981	0.1576398	0.11721940	0.09894869	
ProportionofVariance	0.73289520	0.10608420	0.07241600	0.040040710	0.02853139	
CumulativeProportion	0.73289520	0.83897940	0.91139540	0.951436100	0.97996748	
Standard deviation	0.08291181					
ProportionofVariance	0.02003252					
CumulativeProportion	1.00000000					



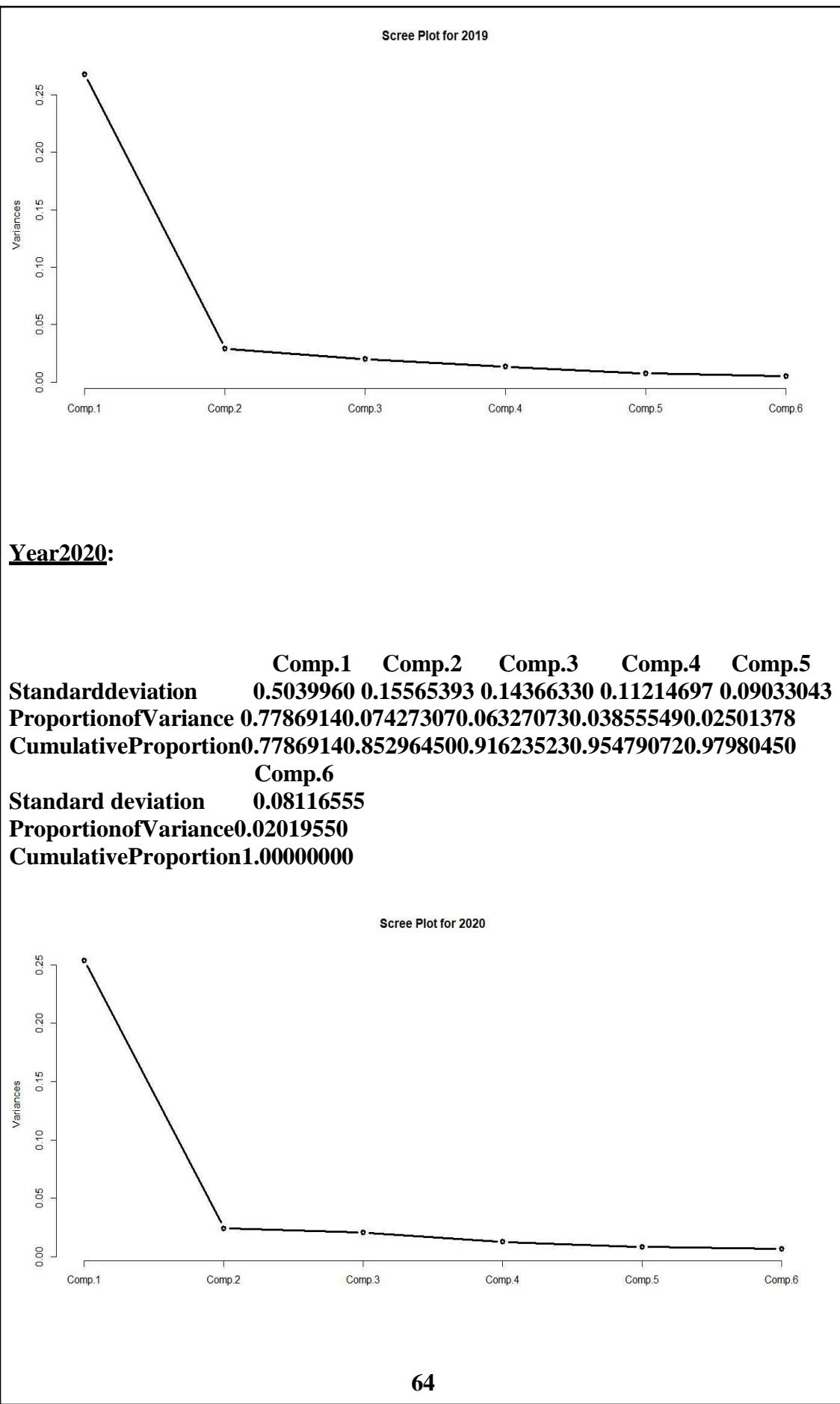
Year2018:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Standarddeviation	0.5089955	0.1978356	0.15599224	0.11383938	0.09281554	
ProportionofVariance	0.74131870	0.11199170	0.069627880	0.03708192	0.02465009	
CumulativeProportion	0.74131870	0.85331050	0.922938340	0.960020260	0.98467035	
Standard deviation	0.07319436					
ProportionofVariance	0.01532965					
CumulativeProportion	1.00000000					



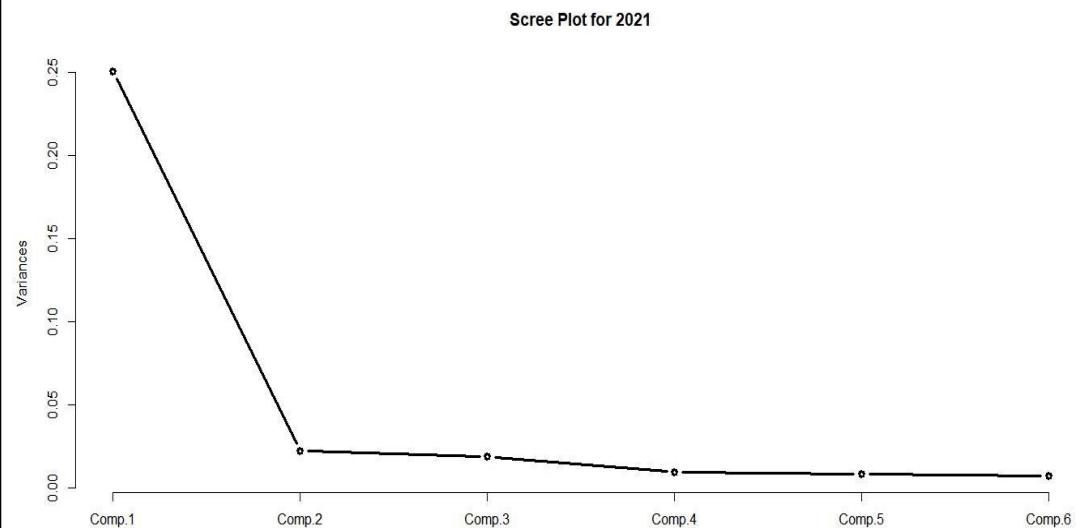
Year2019:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Standarddeviation	0.5179183	0.17061518	0.14106621	0.11547628	0.08649536	
ProportionofVariance	0.78162360	0.084822380	0.057985730	0.038856230	0.02180021	
CumulativeProportion	0.78162360	0.866446000	0.924431730	0.963287960	0.98508817	
Standard deviation	0.07153653					
ProportionofVariance	0.01491183					
CumulativeProportion	1.00000000					



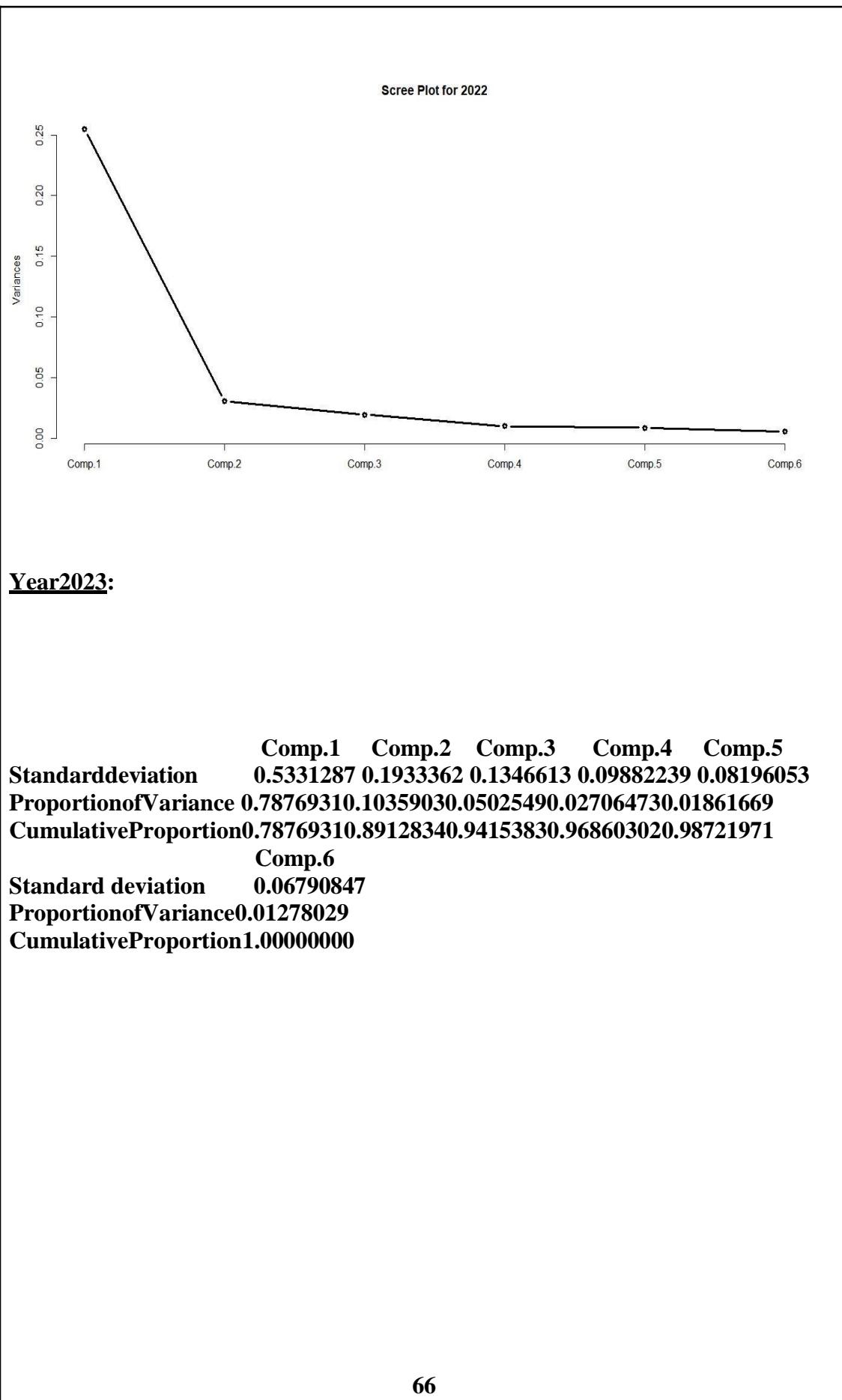
Year2021:

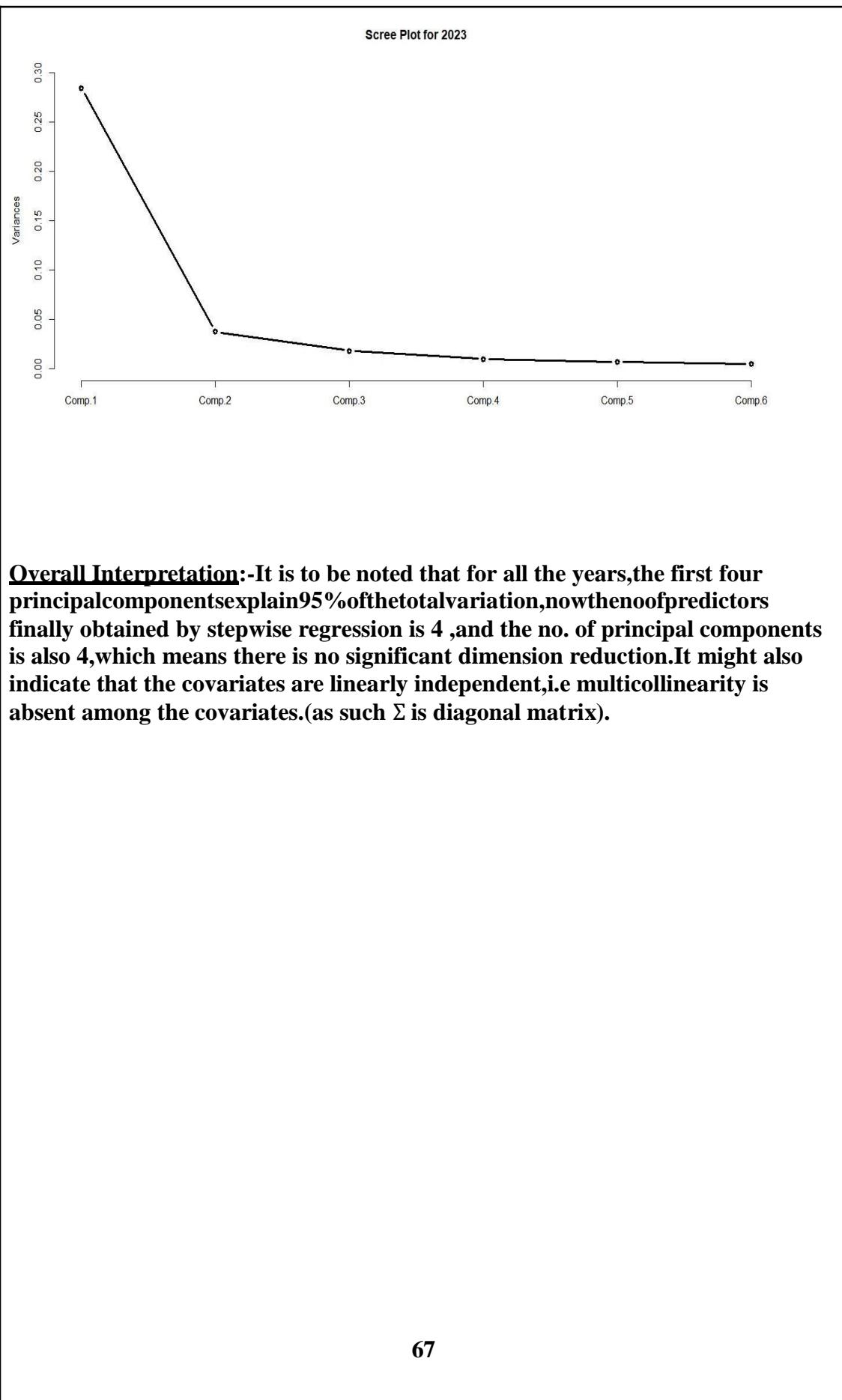
	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Standarddeviation	0.5008617	0.14815401	0.13690788	0.09678221	0.08898008	
ProportionofVariance	0.79431890	0.069500220	0.059349380	0.029658580	0.02506946	
CumulativeProportion	0.79431890	0.863819130	0.923168510	0.952827100	0.97789655	
Standard deviation	0.08355075					
ProportionofVariance	0.02210345					
CumulativeProportion	1.00000000					



Year2022:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
Standarddeviation	0.5049723	0.17515759	0.13950858	0.09980722	0.09356069	
ProportionofVariance	0.77393680	0.093116860	0.059070720	0.030233910	0.02656790	
CumulativeProportion	0.77393680	0.867053680	0.926124400	0.956358310	0.98292622	
Standard deviation	0.07500318					
ProportionofVariance	0.01707378					
CumulativeProportion	1.00000000					





CONCLUSION

From the project report the main conclusions that can be drawn that GDP per capita,social support,healthy life expectancy and freedom to make life choices are the main influential factors for the happiness score for any nation.These four are the keystone behind the prediction of happiness score for any upcoming year in efficient way. These covariates that we have worked with are independent i.e. they have no control over each other.They independently work for any nation and make joint influence on the happiness score. Mainly the African countries and the Asian countries and a few European countries are providing as influential data points each year,but the countries are not the same i.e. they are varying over the years.The happiness score for the eastern countries is always lower than the western countries.The European countries are maintaining a sustained increase in the happiness score overall over the years,though the countries belonging to North America and Oceania are always around 6.5 and 7 respectively.African countries are always in the least happy countries,though in recent year 2023,Afghanisthan has the lowest happiness score level in all years among all the countries.Finland has maintained the top position as the happiest country for six years continuously, and maintained the happiness level more than 7.6.Only European countries are still dominating as the maximum happy countries.In 2015 and 2016,Canada was there and recently Israel is present.This has been the first time that Israel has come into this list,it has made a remarkable progress in this happiness level over the years by crossing all other European countries and has taken 5thposition in 2023.

Acknowledgement

In order to complete the report, I am highly acknowledged to my supervisor Professor Biswajit Basak, of Department of Statistics, Sister Nivedita University. He has helped me in completing my report work in efficient manner. He has also helped me with books and correction of my report errors. I have tried to follow his advice to make sure that my work is flawless and perfect in its own manner. However, any feedback regarding any inadequacy of the project work is always acceptable.

Reference

- **AnIntroductiontoMultivariateStatisticalAnalysis**
(T.W.Anderson)
- **RegressionAnalysisbyExample(SampritChatterjeeand**
Ali S.Hadi)
- **AnOutlineOfStatisticalTheory(VOL.1)**
(Goon,Gupta,Dasgupta)
- **www.kaggle.com**

Appendix

Rcode:

```
#Year2015#
#-----

rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2015.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data

#RegressionDiagnostics(ReducedModel)

x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
model=lm(x1~x2+x3+x4+x5);summary(model)
library(olsrr)
ols_plot_resid_stand(model)
ols_plot_dffits(model)
ols_plot_cooksd_chart(model)

R=cor(Data);R
R11=det(R[-1,][,-1])
R12=-det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=-det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=-det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
```

```

R33=det(R[-3,][-3])
R44=det(R[-4,][-4])
R55=det(R[-5,][-5])
R66=det(R[-6,][-6])
R77=det(R[-7,][-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

#x6discardedasa variable

summary(lm(x1~x2+x3+x4+x5+x7))
Data1=Data[,-6];Data1
R1=cor(Data1);R1
R1.11=det(R1[-1,][-1])
R1.12=-det(R1[-1,][-2])
R1.13=det(R1[-1,][-3])
R1.14=-det(R1[-1,][-4])
R1.15=det(R1[-1,][-5])
R1.16=-det(R1[-1,][-6])
R1.22=det(R1[-2,][-2])
R1.33=det(R1[-3,][-3])
R1.44=det(R1[-4,][-4])
R1.55=det(R1[-5,][-5])
R1.66=det(R1[-6,][-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

#x7discardedasa variable

summary(lm(x1~x2+x3+x4+x5))
Data2=Data1[,-6];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][-1])
R2.12=-det(R2[-1,][-2])
R2.13=det(R2[-1,][-3])
R2.14=-det(R2[-1,][-4])
R2.15=det(R2[-1,][-5])
R2.22=det(R2[-2,][-2])
R2.33=det(R2[-3,][-3])
R2.44=det(R2[-4,][-4])

```

```

R2.55=det(R2[-5,][-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

#x4 discarded as a variable

summary(lm(x1~x2+x3+x5))

Data3=Data2[,-4];Data3
R3=cor(Data3);R3
R3.11=det(R3[-1,][-1])
R3.12=-det(R3[-1,][-2])
R3.13=det(R3[-1,][-3])
R3.14=-det(R3[-1,][-4])
R3.22=det(R3[-2,][-2])
R3.33=det(R3[-3,][-3])
R3.44=det(R3[-4,][-4])
Mult_corr3=sqrt(1-(det(R3)/R3.11));Mult_corr3
PC3.12=-R3.12/(sqrt(R3.11*R3.22));PC3.12
PC3.13=R3.13/(sqrt(R3.11*R3.33));PC3.13
PC3.14=-R3.14/(sqrt(R3.11*R3.44));PC3.14

#x5isdiscardedasavariable

summary(lm(x1~x2+x3))

#End of step wise regression

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="ScreePlotfor2015")

#Plotting

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,11),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2015")
legend(11,c("Africa-4.319804","Asia-5.446438","Europe-5.927980","North
America-6.699750","Oceania-7.285","South America-6.1465"),fill=1:6)

```

```

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2015",names.arg=c("Switzerland","Iceland","Denmark","Norway","Canada",
"Finland"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Switzerland-7.587","Iceland-7.561","Denmark-7.527","Norway-
7.522","Canada-7.427","Finland-7.406"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2015",names.arg=c("Afganisthan","Rwanda","Benin","Syria","Burundi","To
go"),ylab="Happiness Score",col=2:7,ylim=c(0,7))
legend(7,c("Afganisthan-3.575","Rwanda-3.465","Benin-3.340","Syria-
3.006","Burundi-2.905","Togo-2.839"),fill=2:7)

#Year2016#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2016.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data

x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)

R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])
R66=det(R[-6,][,-6])
R77=det(R[-7,][,-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr

```

```

PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

#x6 discarded as a variable

summary(lm(x1~x2+x3+x4+x5+x7))

Data1=Data[,-6];Data1
R1=cor(Data1);R1
R1.11=det(R1[-1,][-1])
R1.12=det(R1[-1,][-2])
R1.13=det(R1[-1,][-3])
R1.14=det(R1[-1,][-4])
R1.15=det(R1[-1,][-5])
R1.16=det(R1[-1,][-6])
R1.22=det(R1[-2,][-2])
R1.33=det(R1[-3,][-3])
R1.44=det(R1[-4,][-4])
R1.55=det(R1[-5,][-5])
R1.66=det(R1[-6,][-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

#x7 discarded as a variable

summary(lm(x1~x2+x3+x4+x5))
Data2=Data1[,-6];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][-1])
R2.12=det(R2[-1,][-2])
R2.13=det(R2[-1,][-3])
R2.14=det(R2[-1,][-4])
R2.15=det(R2[-1,][-5])
R2.22=det(R2[-2,][-2])
R2.33=det(R2[-3,][-3])
R2.44=det(R2[-4,][-4])
R2.55=det(R2[-5,][-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14

```

```

PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

#x2 discarded as a variable

summary(lm(x1~x3+x4+x5))

#Endofstepwiseregression

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="ScreePlotfor2016")

#Plotting

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Europe","Africa","Asia","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2016")
legend(12,c("Europe-5.978489","Africa-4.337353","Asia-5.429364","North
America-6.725","Oceania-7.3235","South America-6.093182"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2016",names.arg=c("Denmark","Switzerland","Iceland","Norway","Finland",
"Canada"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Denmark-7.526","Switzerland-7.509","Iceland-7.501","Norway-
7.498","Finland-7.413","Canada-7.404"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2016",names.arg=c("Rwanda","Benin","Afganisthan","Togo","Syria","Burun
di"),ylab="Happiness Score",col=2:7,ylim=c(0,7))
legend(7,c("Rwanda-3.515","Benin-3.484","Afganisthan-3.360","Togo-
3.303","Syria-3.069","Burundi-2.905"),fill=2:7)

#RegressionDiagnostics

model1=lm(x1~x2+x3+x4+x5)
library(olsrr)
ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

```

```

#Year2017#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2017.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data
x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)
R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])
R66=det(R[-6,][,-6])
R77=det(R[-7,][,-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

#x6discardedas a variable

summary(lm(x1~x2+x3+x4+x5+x7))
Data1=Data[,-6];Data1
R1=cor(Data1);R1
R1.11=det(R1[-1,][,-1])
R1.12=det(R1[-1,][,-2])

```

```

R1.13=det(R1[-1,][-3])
R1.14=det(R1[-1,][-4])
R1.15=det(R1[-1,][-5])
R1.16=det(R1[-1,][-6])
R1.22=det(R1[-2,][-2])
R1.33=det(R1[-3,][-3])
R1.44=det(R1[-4,][-4])
R1.55=det(R1[-5,][-5])
R1.66=det(R1[-6,][-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

```

#x7 discarded as a variable

```

summary(lm(x1~x2+x3+x4+x5))
Data2=Data1[,-6];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][-1])
R2.12=det(R2[-1,][-2])
R2.13=det(R2[-1,][-3])
R2.14=det(R2[-1,][-4])
R2.15=det(R2[-1,][-5])
R2.22=det(R2[-2,][-2])
R2.33=det(R2[-3,][-3])
R2.44=det(R2[-4,][-4])
R2.55=det(R2[-5,][-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

```

#x4 discarded as a variable

```
summary(lm(x1~x2+x3+x5))
```

#End of stepwise regression

```

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="ScreePlotfor2017")

```

#Plotting

```
x=aggregate(happiness_score,by=list(Continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2017")
legend(12,c("Africa-4.2395","Asia-5.303829","Europe-6.043159","North
America-6.017462","Oceania-7.299","SouthAmerica-6.104909"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2017",names.arg=c("Norway","Denmark","Iceland","Switzerland","Finland",
"Netherlands"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Norway-7.537","Denmark-7.522","Iceland-7.504","Switzerland-
7.494","Finland-7.413","Netherlands-7.377"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2017",names.arg=c("Togo","Rwanda","Syria","Tanzania","Burundi","Central
African Republic"),ylab="Happiness Score",col=2:7,ylim=c(0,7))
legend(7,c("Togo-3.495","Rwanda-3.471","Syria-3.462","Tanzania-
3.349","Burundi-2.905","Central African Republic-2.693"),fill=2:7)
```

#RegressionDiagnostics

```
library(olsrr)
model1=lm(x1~x2+x3+x4+x5)
ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

#Year2018#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2018.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data
x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
```

```

x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)
R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])
R66=det(R[-6,][,-6])
R77=det(R[-7,][,-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

```

#x7 discarded as a variable

```

summary(lm(x1~x2+x3+x4+x5+x6))
Data1=Data[,-7];Data1
R1=cor(Data1);R1
R1.11=det(R1[-1,][,-1])
R1.12=det(R1[-1,][,-2])
R1.13=det(R1[-1,][,-3])
R1.14=det(R1[-1,][,-4])
R1.15=det(R1[-1,][,-5])
R1.16=det(R1[-1,][,-6])
R1.22=det(R1[-2,][,-2])
R1.33=det(R1[-3,][,-3])
R1.44=det(R1[-4,][,-4])
R1.55=det(R1[-5,][,-5])
R1.66=det(R1[-6,][,-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

```

#x6 discarded as a variable

```

summary(lm(x1~x2+x3+x4+x5))
Data2=Data1[,-6];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][,-1])
R2.12=det(R2[-1,][,-2])
R2.13=det(R2[-1,][,-3])
R2.14=det(R2[-1,][,-4])
R2.15=det(R2[-1,][,-5])
R2.22=det(R2[-2,][,-2])
R2.33=det(R2[-3,][,-3])
R2.44=det(R2[-4,][,-4])
R2.55=det(R2[-5,][,-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

#x4 discarded as a variable

summary(lm(x1~x2+x3+x5))
Data3=Data2[,-4];Data3
R3=cor(Data3);R3
R3.11=det(R3[-1,][,-1])
R3.12=det(R3[-1,][,-2])
R3.13=det(R3[-1,][,-3])
R3.14=det(R3[-1,][,-4])
R3.22=det(R3[-2,][,-2])
R3.33=det(R3[-3,][,-3])
R3.44=det(R3[-4,][,-4])
Mult_corr3=sqrt(1-(det(R3)/R3.11));Mult_corr3
PC3.12=-R3.12/(sqrt(R3.11*R3.22));PC3.12
PC3.13=R3.13/(sqrt(R3.11*R3.33));PC3.13
PC3.14=-R3.14/(sqrt(R3.11*R3.44));PC3.14

#x3 is discarded

summary(lm(x1~x2+x5))

#End of stepwise regression

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="Scree Plot for 2018")

#Plotting

```

```

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2018")
legend(12,c("Africa-4.296744","Asia-5.274891","Europe-6.189025","North
America-6.5345","Oceania-7.298","South America-5.782842"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2018",names.arg=c("Finland","Norway","Denmark","Iceland","Switzerland",
"Netherlands"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Finland-7.632","Norway-7.594","Denmark-7.555","Iceland-
7.495","Switzerland-7.487","Netherlands-7.441"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2018",names.arg=c("Rwanda","Yemen","Tanzania","South Sudan","Central
African Republic","Burundi"),ylab="Happiness Score",col=2:7,ylim=c(0,7))
legend(7,c("Rwanda-3.408","Yemen-3.355","Tanzania-3.303","South Sudan-
3.254","Central African Republic-3.083","Burundi-2.905"),fill=2:7)

```

#RegressionDiagnostics

```

model1=lm(x1~x2+x3+x4+x5)
library(olsrr)
ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

```

```

#Year2019#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2019.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data
x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5

```

```

x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)
R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])
R66=det(R[-6,][,-6])
R77=det(R[-7,][,-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

```

#x6discardedasa variable

```

summary(lm(x1~x2+x3+x4+x5+x7))
Data1=Data[,-6];Data1
R1=cor(Data1);R1
R1.11=det(R1[-1,][,-1])
R1.12=det(R1[-1,][,-2])
R1.13=det(R1[-1,][,-3])
R1.14=det(R1[-1,][,-4])
R1.15=det(R1[-1,][,-5])
R1.16=det(R1[-1,][,-6])
R1.22=det(R1[-2,][,-2])
R1.33=det(R1[-3,][,-3])
R1.44=det(R1[-4,][,-4])
R1.55=det(R1[-5,][,-5])
R1.66=det(R1[-6,][,-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

```

#x7discardedasa variable

```

summary(lm(x1~x2+x3+x4+x5))
Data2=Data1[,-6];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][-1])
R2.12=det(R2[-1,][-2])
R2.13=det(R2[-1,][-3])
R2.14=det(R2[-1,][-4])
R2.15=det(R2[-1,][-5])
R2.22=det(R2[-2,][-2])
R2.33=det(R2[-3,][-3])
R2.44=det(R2[-4,][-4])
R2.55=det(R2[-5,][-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

#x4 discarded as a variable

summary(lm(x1~x2+x3+x5))

#Endofstepwiseregression

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="ScreePlotfor2019")

#Plotting

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2019")
legend(12,c("Africa-4.347535","Asia-5.296261","Europe-6.223775","North
America-6.726","Oceania-7.2765","South America-5.834619"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2019",names.arg=c("Finland","Denmark","Norway","Iceland","Netherlands",
"Switzerland"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Finland-7.769","Denmark-7.600","Norway-7.554","Iceland-

```

```

7.494","Netherlands-7.488","Switzerland-7.480"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2019",names.arg=c("Yemen","Rwanda","Tanzania","Afganisthan","Central
AfricanRepublic","SouthSudan"),ylab="HappinessScore",col=2:7,ylim=c(0,7))
legend(7,c("Yemen-3.380","Rwanda-3.334","Tanzania-3.231","Afganisthan-
3.203","Central African Republic-3.083","South Sudan-2.853"),fill=2:7)

#RegressionDiagnostics

model1=lm(x1~x2+x3+x4+x5)
library(olsrr)
ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

#Year2020#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSPProjectMsc/Year
2020.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data
x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)

R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])

```

```

R66=det(R[-6],[-6])
R77=det(R[-7],[-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

#x6isdiscardedasavariable

summary(lm(x1~x2+x3+x4+x5+x7))
Data1=Data[, -6]; Data1
R1=cor(Data1); R1
R1.11=det(R1[-1],[-1])
R1.12=det(R1[-1],[-2])
R1.13=det(R1[-1],[-3])
R1.14=det(R1[-1],[-4])
R1.15=det(R1[-1],[-5])
R1.16=det(R1[-1],[-6])
R1.22=det(R1[-2],[-2])
R1.33=det(R1[-3],[-3])
R1.44=det(R1[-4],[-4])
R1.55=det(R1[-5],[-5])
R1.66=det(R1[-6],[-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

#x7discardedas a variable

summary(lm(x1~x2+x3+x4+x5))
Data2=Data1[, -6]; Data2
R2=cor(Data2); R2
R2.11=det(R2[-1],[-1])
R2.12=det(R2[-1],[-2])
R2.13=det(R2[-1],[-3])
R2.14=det(R2[-1],[-4])
R2.15=det(R2[-1],[-5])
R2.22=det(R2[-2],[-2])
R2.33=det(R2[-3],[-3])
R2.44=det(R2[-4],[-4])
R2.55=det(R2[-5],[-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12

```

```

PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

#x2 discarded as a variable

summary(lm(x1~x3+x4+x5))

#Endofstepwiseregression

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="ScreePlotfor2020")

#Plotting

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2020")
legend(12,c("Africa-4.573435","Asia-5.268026","Europe-6.337205","North
America-6.088250","Oceania-7.2612","South America-6.074100"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2020",names.arg=c("Finland","Denmark","Switzerland","Iceland","Norway",
"Netherlands"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Finland-7.8087","Denmark-7.6456","Switzerland-
7.5599","Iceland-7.5045","Norway-7.4880","Netherlands-7.4489"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2020",names.arg=c("Tanzania","Central African
Republic","Rwanda","Zimbabwe","South
Sudan","Afganisthan"),ylab="Happiness Score",col=2:7,ylim=c(0,7))
legend(7,c("Tanzania-3.4762","Central African Republic-3.4759","Rwanda-
3.3123","Zimbabwe-3.2992","South Sudan-2.8166","Afghanisthan-
2.5669"),fill=2:7)

#RegressionDiagnostics

model1=lm(x1~x2+x3+x4+x5)
library(olsrr)

```

```

ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

#Year2021#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2021.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data
x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)
R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])
R66=det(R[-6,][,-6])
R77=det(R[-7,][,-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

#x6 discarded as a variable

summary(lm(x1~x2+x3+x4+x5+x7))

```

```

Data1=Data[,-6];Data1
R1=cor(Data1);R1
R1.11=det(R1[-1,][,-1])
R1.12=det(R1[-1,][,-2])
R1.13=det(R1[-1,][,-3])
R1.14=det(R1[-1,][,-4])
R1.15=det(R1[-1,][,-5])
R1.16=det(R1[-1,][,-6])
R1.22=det(R1[-2,][,-2])
R1.33=det(R1[-3,][,-3])
R1.44=det(R1[-4,][,-4])
R1.55=det(R1[-5,][,-5])
R1.66=det(R1[-6,][,-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

```

#x4discardedasa variable

```

summary(lm(x1~x2+x3+x5+x7))
Data2=Data1[,-4];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][,-1])
R2.12=det(R2[-1,][,-2])
R2.13=det(R2[-1,][,-3])
R2.14=det(R2[-1,][,-4])
R2.15=det(R2[-1,][,-5])
R2.22=det(R2[-2,][,-2])
R2.33=det(R2[-3,][,-3])
R2.44=det(R2[-4,][,-4])
R2.55=det(R2[-5,][,-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

```

#x7discardedasa variable

```

summary(lm(x1~x2+x3+x5))
Data3=Data2[,-5];Data3
R3=cor(Data3);R3
R3.11=det(R3[-1,][,-1])
R3.12=det(R3[-1,][,-2])
R3.13=det(R3[-1,][,-3])
R3.14=det(R3[-1,][,-4])

```

```

R3.22=det(R3[-2,][-2])
R3.33=det(R3[-3,][-3])
R3.44=det(R3[-4,][-4])
Mult_corr3=sqrt(1-(det(R3)/R3.11));Mult_corr3
PC3.12=-R3.12/(sqrt(R3.11*R3.22));PC3.12
PC3.13=R3.13/(sqrt(R3.11*R3.33));PC3.13
PC3.14=-R3.14/(sqrt(R3.11*R3.44));PC3.14

#x3isdiscardedasavariable

summary(lm(x1~x2+x5))

#End of step wise regression

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="ScreePlotfor2021")

#Plotting

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2021")
legend(12,c("Africa-4.593356","Asia-5.351114","Europe-6.305067","North
America-6.033","Oceania-7.23","South America-6.002941"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2021",names.arg=c("Finland","Denmark","Switzerland","Iceland","Netherlan
ds","Norway"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Finland-7.842","Denmark-7.620","Switzerland-7.571","Iceland-
7.554","Netherlands-7.464","Norway-7.392"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2021",names.arg=c("Malawi","Lesotho","Botswana","Rwanda","Zimbabwe",
"Afghanistan"),ylab="Happiness Score",col=2:7,ylim=c(0,7))
legend(7,c("Malawi-3.600","Lesotho-3.512","Botswana-3.467","Rwanda-
3.415","Zimbabwe-3.145","Afghanistan-2.523"),fill=2:7)

#RegressionDiagnostics

```

```

model1=lm(x1~x2+x3+x4+x5)
library(olsrr)
ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

#Year2022#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2022.csv",header=TRUE)
#data1
attach(data1)
Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data
x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)

R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])
R66=det(R[-6,][,-6])
R77=det(R[-7,][,-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

#x6discardedas a variable

```

```

summary(lm(x1~x2+x3+x4+x5+x7))
Data1=Data[,-6];Data1
R1=cor(Data1);R1
R1.11=det(R1[-1,][-1])
R1.12=det(R1[-1,][-2])
R1.13=det(R1[-1,][-3])
R1.14=det(R1[-1,][-4])
R1.15=det(R1[-1,][-5])
R1.16=det(R1[-1,][-6])
R1.22=det(R1[-2,][-2])
R1.33=det(R1[-3,][-3])
R1.44=det(R1[-4,][-4])
R1.55=det(R1[-5,][-5])
R1.66=det(R1[-6,][-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1
PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

#x7 discarded as a variable

summary(lm(x1~x2+x3+x4+x5))
Data2=Data1[,-6];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][-1])
R2.12=det(R2[-1,][-2])
R2.13=det(R2[-1,][-3])
R2.14=det(R2[-1,][-4])
R2.15=det(R2[-1,][-5])
R2.22=det(R2[-2,][-2])
R2.33=det(R2[-3,][-3])
R2.44=det(R2[-4,][-4])
R2.55=det(R2[-5,][-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

#x2 discarded as a variable

summary(lm(x1~x3+x4+x5))

#End of stepwise regression

#PCA
new_data=Data[,-1];new_data

```

```

pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,main="ScreePlotfor2022")

#Plotting

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2022")
legend(12,c("Africa-4.527625","Asia-5.336231","Europe-6.367795","North
America-6.288818","Oceania-7.181","South America-5.7882"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2022",names.arg=c("Finland","Denmark","Iceland","Switzerland","Netherlan
ds","Luxemborg"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5))
legend(12.5,c("Finland-7.821","Denmark-7.636","Iceland-7.557","Switzerland-
7.512","Netherlands-7.415","Luxembourg-7.404"),fill=2:7)
barplot(bottom[,2],main="6 least happy countries in
2022",names.arg=c("Lesotho","Bostwana","Rwanda","Zimbabwe","Lebanon",
"Afganisthan"),ylab="Happiness Score",col=2:7,ylim=c(0,7))
legend(7,c("Lesotho-3.512","Botswana-3.471","Rwanda-3.268","Zimbabwe-
2.995","Lebanon-2.955","Afghanisthan-2.404"),fill=2:7)

#RegressionDiagnostics

model1=lm(x1~x2+x3+x4+x5)
library(olsrr)
ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

#Year2023#
#-----
rm(list=ls())
data1=read.csv("C:/Users/USER/Documents/MSCDocs/RSProjectMsc/Year
2023.csv",header=TRUE)
#data1
attach(data1)

```

```

Data=matrix(as.numeric(unlist(data1[,-c(1,9,10)])),ncol=7)
colnames(Data)=c("x1","x2","x3","x4","x5","x6","x7");Data
x1=Data[,1];x1
x2=Data[,2];x2
x3=Data[,3];x3
x4=Data[,4];x4
x5=Data[,5];x5
x6=Data[,6];x6
x7=Data[,7];x7
model=lm(x1~x2+x3+x4+x5+x6+x7);summary(model)
R=cor(Data);R
R11=det(R[-1,][,-1])
R12=det(R[-1,][,-2])
R13=det(R[-1,][,-3])
R14=det(R[-1,][,-4])
R15=det(R[-1,][,-5])
R16=det(R[-1,][,-6])
R17=det(R[-1,][,-7])
R22=det(R[-2,][,-2])
R33=det(R[-3,][,-3])
R44=det(R[-4,][,-4])
R55=det(R[-5,][,-5])
R66=det(R[-6,][,-6])
R77=det(R[-7,][,-7])
Mult_corr=sqrt(1-(det(R)/R11));Mult_corr
PC12=-R12/(sqrt(R11*R22));PC12
PC13=R13/(sqrt(R11*R33));PC13
PC14=-R14/(sqrt(R11*R44));PC14
PC15=R15/(sqrt(R11*R55));PC15
PC16=-R16/(sqrt(R11*R66));PC16
PC17=R17/(sqrt(R11*R77));PC17

#x6discardedas a variable

summary(lm(x1~x2+x3+x4+x5+x7))
Data1=Data[,-6];+xData1
R1=cor(Data1);R1
R1.11=det(R1[-1,][,-1])
R1.12=det(R1[-1,][,-2])
R1.13=det(R1[-1,][,-3])
R1.14=det(R1[-1,][,-4])
R1.15=det(R1[-1,][,-5])
R1.16=det(R1[-1,][,-6])
R1.22=det(R1[-2,][,-2])
R1.33=det(R1[-3,][,-3])
R1.44=det(R1[-4,][,-4])
R1.55=det(R1[-5,][,-5])
R1.66=det(R1[-6,][,-6])
Mult_corr1=sqrt(1-(det(R1)/R1.11));Mult_corr1

```

```

PC1.12=-R1.12/(sqrt(R1.11*R1.22));PC1.12
PC1.13=R1.13/(sqrt(R1.11*R1.33));PC1.13
PC1.14=-R1.14/(sqrt(R1.11*R1.44));PC1.14
PC1.15=R1.15/(sqrt(R1.11*R1.55));PC1.15
PC1.16=-R1.16/(sqrt(R1.11*R1.66));PC1.16

#x4discardedas a variable

summary(lm(x1~x2+x3+x5+x7))
Data2=Data1[,-4];Data2
R2=cor(Data2);R2
R2.11=det(R2[-1,][,-1])
R2.12=det(R2[-1,][,-2])
R2.13=det(R2[-1,][,-3])
R2.14=det(R2[-1,][,-4])
R2.15=det(R2[-1,][,-5])
R2.22=det(R2[-2,][,-2])
R2.33=det(R2[-3,][,-3])
R2.44=det(R2[-4,][,-4])
R2.55=det(R2[-5,][,-5])
Mult_corr2=sqrt(1-(det(R2)/R2.11));Mult_corr2
PC2.12=-R2.12/(sqrt(R2.11*R2.22));PC2.12
PC2.13=R2.13/(sqrt(R2.11*R2.33));PC2.13
PC2.14=-R2.14/(sqrt(R2.11*R2.44));PC2.14
PC2.15=R2.15/(sqrt(R2.11*R2.55));PC2.15

#x7discardedas a variable

summary(lm(x1~x2+x3+x5))
Data3=Data2[,-5];Data3
R3=cor(Data3);R3
R3.11=det(R3[-1,][,-1])
R3.12=det(R3[-1,][,-2])
R3.13=det(R3[-1,][,-3])
R3.14=det(R3[-1,][,-4])
R3.22=det(R3[-2,][,-2])
R3.33=det(R3[-3,][,-3])
R3.44=det(R3[-4,][,-4])
Mult_corr3=sqrt(1-(det(R3)/R3.11));Mult_corr3
PC3.12=-R3.12/(sqrt(R3.11*R3.22));PC3.12
PC3.13=R3.13/(sqrt(R3.11*R3.33));PC3.13
PC3.14=-R3.14/(sqrt(R3.11*R3.44));PC3.14

#x2isdiscardedas a variable

summary(lm(x1~x3+x5))
Data4=Data3[,-2];Data4
R4=cor(Data4);R4
R4.11=det(R4[-1,][,-1])

```

```

R4.12=det(R4[-1,][-2])
R4.13=det(R4[-1,][-3])
R4.22=det(R4[-2,][-2])
R4.33=det(R4[-3,][-3])
Mult_corr4=sqrt(1-(det(R4)/R4.11));Mult_corr4
PC4.12=-R4.12/(sqrt(R4.11*R4.22));PC4.12
PC4.13=R4.13/(sqrt(R4.11*R4.33));PC4.13

#Endofstepwiseregression

#PCA
new_data=Data[,-1];new_data
pca=princomp(new_data,cor=FALSE)
summary(pca)
pca$loadings
plot(pca,type="lines",lwd=3,ylim=c(0,0.3),main="ScreePlotfor2023")

#Plotting

x=aggregate(happiness_score,by=list(continent),FUN=mean)
x
happy_index=as.vector(unlist(x[2]));happy_index
barplot(happy_index,names.arg=c("Africa","Asia","Europe","North
America","Oceania","South
America"),ylim=c(0,12),col=1:6,xlab="Continents",ylab="Happiness
Score",main="Representation of world happiness scores in 2023")
legend(12,c("Africa-4.432651","Asia-5.439897","Europe-6.408643","North
America-6.531750","Oceania-7.109","South America-5.946059"),fill=1:6)

top=head(data1);top
bottom=tail(data1);bottom
barplot(top[,2],main="Top 6 happiest countries in
2023",names.arg=c("Finland","Denmark","Iceland","Israel","Netherlands","Sw
eden"),ylab="Happiness Score",col=2:7,ylim=c(0,12.5)) legend(12.5,c("Finland-
7.804","Denmark-7.586","Iceland-7.530","Israel- 7.473","Netherlands-
7.403","Sweden-7.395"),fill=2:7)barplot(bottom[,2],main="6 least happy
countries in
2023",names.arg=c("Botswana","Congo(Kinshasa)","Zimbabwe","Sierra
Leone","Lebanon","Afghanisthan"),ylab="HappinessScore",col=2:7,ylim=c(0,6))
legend(7,c("Botswana-3.435","Congo-3.207","Zimbabwe-3.204","Sierra Leone-
3.138","Lebanon-2.392","Afghanisthan-1.859"),fill=2:7)
#RegressionDiagnostics

model1=lm(x1~x2+x3+x4+x5)
library(olsrr)
ols_plot_resid_stand(model1)
ols_plot_dffits(model1)
ols_plot_cooksd_chart(model1)

```