



<u>SUBJECT</u>: STATISTICS <u>PAPER</u>: STSADSE06P <u>ROLL</u>:\*\*\* <u>NO</u>.: \*\*\* <u>REGISTRATION NO</u>.: 1082011400131 OF 2020 <u>COLLEGE ROLL NO</u>.: 20157 <u>SEMESTER-6</u>

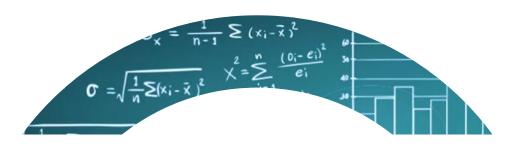


## WEST BENGAL STATE UNIVERSITY

BATCH: 2020-2023

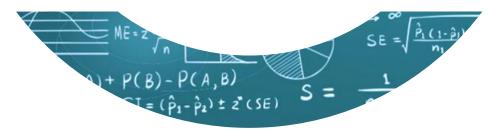






A Time Series Analysis and Inferential work on Happiness Index Of The World for around 150 countries over a time period of 10 years consisting of various factors









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First to Compute Happiness Index



Country name	Ladder score	Logged GDP per capita	Social support	Healthy life expectancy	Freedom to make life choices	Generosity	Perceptions of corruption	Ladder score in Dystopia
Finland	7.842	10.775	0.954	72.0	0.949	-0.098	0.186	2.43
Denmark	7.620	10.933	0.954	72.7	0.946	0.03	0.179	2.43
Switzerland	7.571	11.117	0.942	74.4	0.919	0.025	0.292	2.43
Iceland	7.554	10.878	0.983	73.0	0.955	0.16	0.673	2.43
Netherlands	7.464	10.932	0.942	72.4	0.913	0.175	0.338	2.43
Norway	7.392	11.053	0.954	73.3	0.96	0.093	0.27	2.43
Sweden	7.363	10.867	0.934	72.7	0.945	0.086	0.237	2.43
Luxembourg	7.324	11.647	0.908	72.6	0.907	-0.034	0.386	2.43
New Zealand	7.277	10.643	0.948	73.4	0.929	0.134	0.242	2.43
Austria	7.268	10.906	0.934	73.3	0.908	0.042	0.481	2.43

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Ladder Score

Happiness Index is also known as Ladder Score



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# Dystopia

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An Imaginary country which have the least happiness index

In our data it is 1.2

# Gross Domestic Product per Capita (GDP per Capita)

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A measure that calculates the country's economic output that accounts for the number of people in the country or the country's population.



#### Describe the extent to which these factors contribute in evaluating the happiness in each country.

#### Social Support

Social support is the perception and actuality that one is cared for, has assistance available from other people, and most popularly, that one is part of a supportive social network

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#### Life Expectancy

The term "life expectancy" refers to the number of years a person can expect to live. By definition, life expectancy is based on an estimate of the average age that members of a particular population group will be when they die.

# Freedom to make choices

Freedom to make choices describes a individual's opportunity and autonomy to perform an action selected from at least two available options, unconstrained by external

## Generosity

Generosity is the virtue of being liberal in giving, often as gifts

# Perception to corruption

Corruption and corruption perception can be considered as cultural phenomena because they depend on how a society understands the rules and what constitutes a deviation. Indeed, it does not depend only on societies but also on personal values and moral vies.







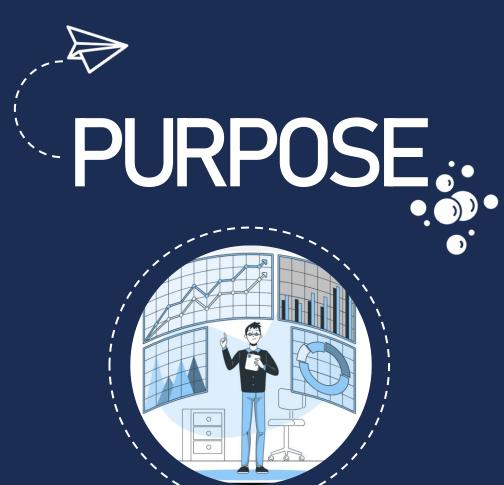












Here our work is to analyse this Happiness index of 146 countries and analyse the impact of the factors affecting happiness of a country and then we analyse the time series data of happiness index of India and try to forecast the happiness index for India











countries that how much happy they are



OBJECTIVE.

To infer how the happiness index is dependent upon the factors that may affect happiness index



To study happiness index of India for a range of time and try to infer the ladder score for future



<u>METHODOLOGY</u> TWO STAGE ANALYSIS

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Examining the intensity of the factors affecting Happiness Index
(a) Checking if there is any change in the intensity of the factors affecting Happiness Index
(b) Inferening about how can be it increase (if possible)

Time Series Analysis on the Happiness Index (a) Analysing the data on Happiness Index from 2004-2023 of India (b) Trying to forecast about the Happiness Index of India



# ANALYSIS1: LINEAR REGRESSION





### **Model and Estimates**

At first we are preforming **Linear Regression** to check the relationship of the covariates (<u>GDP per capita, Family Life</u> <u>Expectancy, Generousity, Trust Government Corruption</u>) on <u>Ladder Score</u> and also try to estimate the effects of the covariates (<u>GDP per capita, Family Life Expectancy, Generousity, Trust Government Corruption</u>) on <u>Ladder Score</u> i.e. <u>Happiness Index</u>.

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Model :

So, here our model is,

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \epsilon_i \text{ , i} = 1(1)n$$

Assumption :  $\epsilon_i \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2)$ , where  $\sigma^2$  is the error variance Hypothesis :

And the testing problem is,

$$H_{0j}:\beta_j = 0 \quad vs \quad H_{1j}:\beta_j \neq 0 \;\forall \; j = 1(1)6$$

Estimate :

Now, we know that by Least Square Method we can obtain estimates of  $\beta_i \forall j = 1(1)6$  i.e. as follows

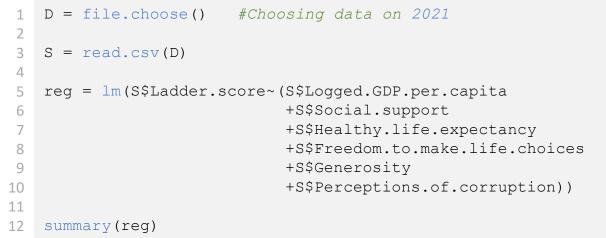
$$\widehat{\beta_j} = -\frac{R_j}{R_y} \frac{s_y}{s_j}$$

### Model and Estimates

Where R is the correlation matrix. Let 
$$\rho_{ij} = \frac{cov(X_i, X_j)}{\sqrt{Var(X_i) Var(X_j)}}$$
 and  $\rho_{yi} = \frac{cov(Y, X_i)}{\sqrt{Var(Y) Var(X_i)}}$  then R is as follows,  $R = \begin{bmatrix} 1 & \rho_{y1} & \rho_{y2} & \cdots & \rho_{y6} \\ \rho_{y1} & 1 & \rho_{12} & \cdots & \rho_{16} \\ \rho_{y2} & \rho_{12} & 1 & \cdots & \rho_{26} \\ \vdots & \vdots & \vdots & \vdots \\ \rho_{y6} & \rho_{16} & \rho_{26} & \cdots & 1 \end{bmatrix}^{6 \times 6}$ 

And 
$$\sigma_{ij} = cov(X_i, X_j)$$
 and  $\sigma_{yi} = cov(Y, X_i)$ ,  $\sigma_y^2 = Var(Y)$  and  $\sigma_i^2 = Var(X_i)$   
First of all we find the correlation

Now the R code is as follows,



### Scatter Matrix

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```
S 1=cor(S[c("Ladder.score", "Logged.GDP.per.capita", "Social.support",
 1
 2 "Healthy.life.expectancy", "Freedom.to.make.life.choices", "Generosity",
   "Perceptions.of.corruption")])
 3
 4
 5
   # Install and load reshape2 package
 6
 7 install.packages("reshape2")
8 library(reshape2)
9
   # creating correlation matrix
10
   corr mat <- round(cor(S 1),2)</pre>
11
12
13
   # reduce the size of correlation matrix
14
15 melted corr mat <- melt(corr mat)</pre>
16 head(melted corr mat)
17
   # plotting the correlation heatmap
18
19 library(ggplot2)
20 ggplot(data = melted corr mat, aes(x=Var1, y=Var2, fill=value)) +
    geom tile() +
21
22
     geom text(aes(Var2, Var1, label = value),
                color = "black", size = 4)
23
```

Ladder.score	Logged.GDP.per.capita	Social.support	Healthy.life.expectancy	Freedom.to.make.life.choices	Generosity	Perceptions.of.corruption	
9- 6- 3- 0-	Corr: 0.790***	Corr: 0.757***	Corr: 0.768***	Corr: 0.608***	Corr: -0.018	Corr: -0.421***	Ladder.score
11 - 10 - 9 - 8 - 7 -		Corr: 0.785***	Corr: 0.859***	Corr: 0.432***	Corr: -0.199*	Corr: -0.342***	Logged.GDP .per.capita
1.0- 0.8- 0.6-			Corr: 0.723***	Corr: 0.483***	Corr: -0.115	Corr: -0.203*	Social.support
70 - 60 - 50 -				Corr: 0.461***	Corr: -0.162*	Corr: -0.364***	Healthy.life. expectancy
1.0- 0.8- 0.6- 0.4-					Corr: 0.169*	Corr: -0.401***	Freedom.to. make.life.choices
0.4- 0.2- 0.0- -0.2-						Corr: -0.164*	Generousity
1.00- 0.75- 0.50- 0.25- 4 6 8	7 8 9 10 11	0.6 0.8 1.0	50 60 70	0.4 0.6 0.8	-0.2 0.0 0.2 0.4	0.25 0.50 0.75	Perceptions.of. corruption 1.00

# 3 Inference

#### Now let us test the significance of the regression coefficients

 $\underbrace{\text{Model}}_{i}: y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \beta_6 x_{6i} + \epsilon_i \text{, } i = 1(1)n$   $\underbrace{\text{Assumption}}_{i}: \epsilon_i \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2) \quad \forall \quad i = 1, 2, ..., n$ 

#### Hypothesis : Here the testing problem is,

 $H_0: \beta_1 = \beta_2 = \dots = \beta_6 \quad vs \quad H_1:$  at least one inequality in  $H_0$ <u>Test Statistic</u>: Define,

$$S_{1}^{2} = min\left\{\sum_{i=1}^{n} (y_{i} - \beta_{0})^{2}\right\}$$
$$S_{2}^{2} = min\left\{\sum_{i=1}^{n} (y_{i} - \beta_{0} + \beta_{1}x_{1i} + \beta_{2}x_{2i} + \beta_{3}x_{3i} + \beta_{4}x_{4i} + \beta_{5}x_{5i} + \beta_{6}x_{6i})^{2}\right\}$$
$$F = \frac{S_{1}^{2} - S_{2}^{2}}{S_{1}^{2}}, \quad \text{where } F \sim F_{6,n-7}$$

**<u>Test</u>** : We reject  $H_{0i}$  against  $H_{1i}$  at level  $\alpha$  iff

$$F > F_{\alpha,6,n-7}$$
  
In terms of p-value we reject  $H_{0j}$  against  $H_{1j}$  at level  $\alpha$  iff  
 $p - value = P_{H_{0j}}(|F| \ge observed(F)) \le \alpha$ 

Now we will test whether the regression coefficients individually are significant

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$$\begin{split} \underline{\mathsf{Model}} &: y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \beta_4 x_{4i} + \beta_5 x_{5i} + \\ \beta_6 x_{6i} + \epsilon_i \text{ , i } = 1(1)n \\ \underline{\mathsf{Assumption}} &: \epsilon_i \stackrel{iid}{\sim} \mathcal{N}(0, \sigma^2) \ \forall \ i = 1, 2, \dots, n \\ \underline{\mathsf{Hypothesis}} &: \text{Here the testing problem is,} \\ H_{0j} : \beta_j = 0 \ vs \ H_{1j} : \beta_j \neq 0 , j = 1(1)6 \\ \underline{\mathsf{Test Statistic}} &: \text{Define,} \\ t = \frac{\widehat{\beta_j}}{MSE}, \quad \text{where } t \sim t_{n-7} \\ \underline{\mathsf{Test}} &: \text{We reject } H_{0j} \text{ against } H_{1j} \text{ at level } \alpha \text{ iff} \\ |t| > t \frac{\alpha}{2} \\ \text{In terms of p-value we reject } H_{0j} \text{ against } H_{1j} \text{ at level } \alpha \text{ iff} \\ p - value = P_{H_{0j}} (|t| \ge observed(t)) \le \alpha \end{split}$$

#### So, now the output is,

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```
Call:
   lm(formula = S$Ladder.score ~ (S$Logged.GDP.per.capita + S$Social.support +
       S$Healthy.life.expectancy + S$Freedom.to.make.life.choices +
       S$Generosity + S$Perceptions.of.corruption))
   Residuals:
                      Median
        Min
                  10
                                     30
                                             Max
   -1.85049 -0.30026 0.05735 0.33368 1.04878
8
9
   Coefficients:
10
                                   Estimate Std. Error t value Pr(>|t|)
                                   -2.23722
                                               0.63049 -3.548 0.000526 ***
   (Intercept)
11
   S$Logged.GDP.per.capita
                                    0.27953
                                               0.08684
                                                         3.219 0.001595 **
12
                                               0.66822 3.706 0.000301 ***
   S$Social.support
                                    2.47621
13
                                   0.03031
                                               0.01333
   S$Healthy.life.expectancy
                                                         2.274 0.024494 *
14
   S$Freedom.to.make.life.choices 2.01046
                                               0.49480 4.063 7.98e-05 ***
15
   S$Generosity
                                    0.36438
                                               0.32121
                                                         1.134 0.258541
16
   S$Perceptions.of.corruption
                                                        -2.083 0.039058 *
                                   -0.60509
                                               0.29051
```

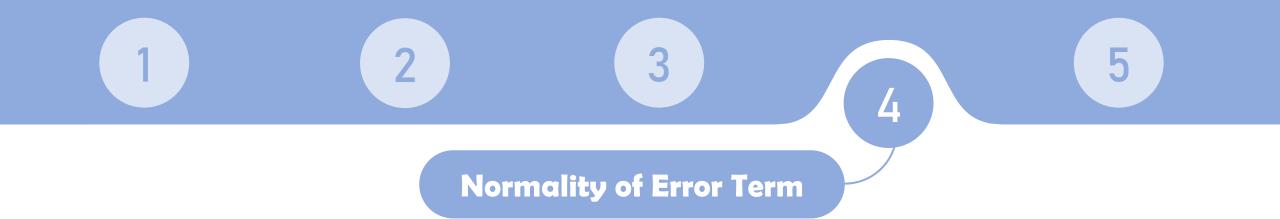
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Inference

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Signif. codes: 0 `\*\*\*' 0.001 `\*\*' 0.01 `\*' 0.05 `.' 0.1 ` ' 1
19

20 Residual standard error: 0.5417 on 142 degrees of freedom 21 Multiple R-squared: 0.7558, Adjusted R-squared: 0.7455 22 F-statistic: 73.27 on 6 and 142 DF, p-value: < 2.2e-16</p>

From the p-value of F-statistic we say that it is less than 0.05, so we can say that we reject H0 :  $\beta_i = 0 \forall i = 1(1)6$  at level of 0.05. That means all the atleast one of the effects are significant. But from the above data we can also see that, the p-value corresponding to the covariate Generosity is greater than 0.05. So, we accept H05 :  $\beta$ 5 = 0 at level 0.05 i.e. the effect of Generosity is insignificant to Ladder score, that means change in the value of Generosity more or less does not indicate any change in Ladder score and reject the rest at level 0.05. Now it is necessary to observe the validity of the assumptions for both the testing problems, and hence infer about the situation, or it may lead to a wrong inference.



Here we have considered that the error term is Normal. Now if we consider the error term is a non normal, then we have some complications in the testing procedure, and we cannot perform any t or F test.

So, let us check whether the error term is normal or not...

For this we first compute the residuals of the fitted model and then check whether they are a random variable following Normal distribution with mean 0 and some specific variance. For this we will perform Kolmogorov-Smirnov test

#### Kolmogorov Smirnov Test :

 $\underline{\mathsf{Model}}: X_1, X_2, X_3, \dots, X_n \xrightarrow{iid} F(x)$ 

Assumption : Here we assume the F is absolutely continuous distribution function

Hypothesis : Here we are interested in testing whether the random sample come from a known distribution with distribution function  $F_0$  (say). That is,

$$H_0: F = F_0$$
 against  $H_a: F \neq F_0$ 

 $F = F_0 \equiv F(x) = F_0(x) \forall x \in \mathbb{R}$   $F \neq F_0 \equiv F(x) \neq F_0(x) \forall x$  with strict inequality for atleast one x Here we are mainly interested in checking Normality, so,  $F_0(x) = \Phi(x)$ So, the hypothesis becomes,

 $H_0: F = \Phi$  against  $H_a: F \neq \Phi$ 

### Normality of Error Term

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#### Test Statistic :

For testing  $H_0$  against  $H_a$  we define the following test statistic ;

$$D_n = \sup_{x \in \mathbb{R}} \left| \widehat{F_n(x)} - \Phi(x) \right|$$

Notice that  $\widehat{F}_n$  approximate the true distribution function  $\Phi$ .  $\widehat{F}_n$  by definition is a step function i.e. the absolute difference measured by  $D_n$  provide us the departure or the true situation from the null hypothesis towards the corresponding alternative. **Distribution Free**:

#### EDF of $D_n$ :

Here we use the ordered statistics,

$$X_{(1)}, X_{(2)}, \dots, X_{(n)}$$
. Further we denote  $X_{(0)} = -\infty$  and  $X_{(n+1)} = +\infty$ 

$$D_{n} = \sup_{x \in \mathbb{R}} |\widehat{F_{n}(x)} - \Phi(x)|$$

$$= \max_{i = 0, 1, 2, ..., n} \left\{ X_{(i)} \leq \sup_{x \leq X_{(i+1)}} |\widehat{F_{n}(x)} - \Phi(x)| \right\} = \max \left\{ 0, \max_{i = 1, 2, ..., n} \left\{ X_{(i)} \leq x \leq X_{(i+1)} |\widehat{F_{n}(x)} - \Phi(x)| \right\} \right\}$$

$$= \max \left\{ 0, \max_{i = 1, 2, ..., n} \left\{ X_{(i)} \leq x \leq X_{(i+1)} |\frac{i}{n} - \Phi(x)| \right\} \right\} = \max \left\{ 0, \max_{i = 1, 2, ..., n} \left\{ |\frac{i}{n} - \Phi(x_{(i)})| \right\} \right\}$$

### Normality of Error Term

Notice that,

 $X_1, X_2, \dots, X_n \xrightarrow{iid}_{H_0} \Phi$ 

$$\Rightarrow U_i = \Phi(X_i) \stackrel{iid}{\underbrace{H_0}} U(0,1)$$

Since  $\Phi$  is absolutely continuous, we can conclude that,

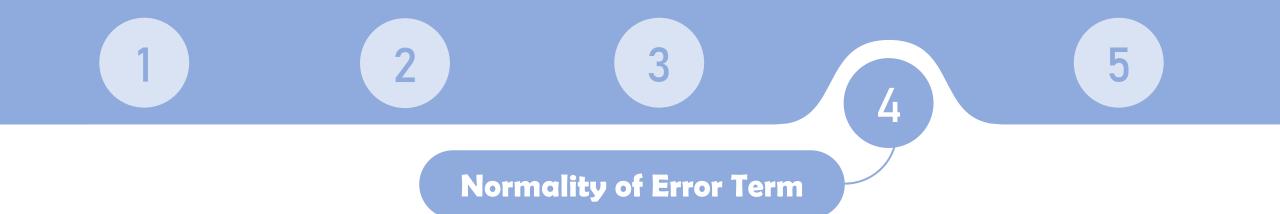
 $\Rightarrow U_{(i)} = \Phi(X_{(i)}) \underbrace{iid}_{H_0} U(0,1)$ 

That is  $D_n$  (under  $H_0$ ) depends on the ordered statistics  $\{U_{(1)}, U_{(2)}, \dots, U_{(n)}\}$  from U(0,1). Hence the test is based on  $D_n$  is EDF (Exact Distribution Free) **Test :** 

Notice that  $D_n$  depends on the empirical distribution function  $\widehat{F}_n$  which represents the true distribution function. Thus the directional difference measured by  $D_n$  actually indicate the departure of the true situation form the null hypothesis towards the alternative  $H_a$  i.e. under  $H_a : F \neq \Phi$ ,  $D_n$  becomes larger than that under  $H_0$ . On the hand a small value of  $D_n$  indicates the acceptance of  $H_0$ . Thus a right tail test based on  $D_n$  will be appropriate for testing  $H_0 : F = \Phi$  against  $H_a : F \neq \Phi$ . We reject  $H_0 : F = \Phi$  against  $H_a : F \neq \Phi$  at level  $\alpha$  iff,

 $\begin{array}{l} D_n > d_{\alpha} \\ \text{In terms of p-value we can say, we reject } H_0: F = \Phi \quad \text{against } H_a: F \neq \Phi \text{ at level } \alpha \text{ iff,} \\ p - value = P_{H_0}(D_n \geq observed(D_n)) \leq \alpha \end{array}$ 

At first we compute the residuals and then perform the test.



At first we compute the residuals and then perform the test.

1 e = S\$Ladder.score - fitted.values(reg)

2 ks.test(e, pnorm, mean(e), var(e))

Output

1 One-sample Kolmogorov-Smirnov test
2
3 data: e
4 D = 0.17886, p-value = 0.0001448
5 alternative hypothesis: two-sided

As the p-value is less than 0.05, we can say that we reject  $H_0$  at a level 0.05

### **Box Cox Transformation**

Now we transform the data to normalize it. For this we use the Box-Cox Transformation. **Box-Cox Transformation :** 

For each real number , the Box–Cox transformation is

2

$$Y(\lambda) = \begin{cases} \frac{Y^{\lambda} - 1}{\lambda} & \lambda \neq 0\\ \log(Y) & \lambda \neq 0 \end{cases}$$

3

Where we select the value of  $\lambda$  such that the log-likelihood of Y becomes maximum.

The Box Cox transformation is named after statisticians George Box and Sir David Roxbee Cox who collaborated on a 1964 paper and developed the technique.

There are three main reasons for using the Box Cox transformation:

- 1. To stabilise the variance
- 2. To improve normality
- 3. To make patterns in the data more easily recognisable

### **Box Cox Transformation**

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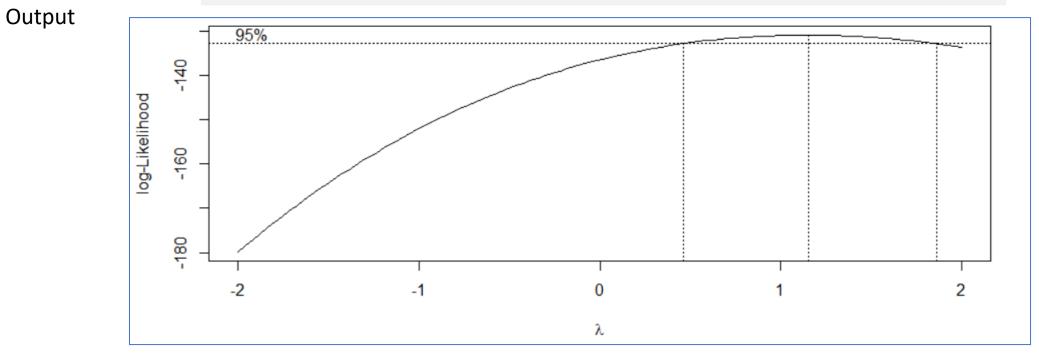
#### Here is the R code.

#### 1 library(MASS)

2 u=boxcox(lm(S\$Ladder.score~1))

2

- 3 l=u\$x[which(u\$y==max(u\$y))]
- 4 y\_1 = (((S\$Ladder.score)^1) 1)/1



3

Here the value of  $\lambda$  is 1.151515

### **Box Cox Transformation**

Now we obtain the residuals and again check that if the transformation resulted the normality of the variable. For this we again perform the Kolmogorov-Smirnov Test.

3

```
reg y1 = lm(y 1~(S$Logged.GDP.per.capita
                    +S$Social.support
2
                     +S$Healthy.life.expectancy
3
                     +S$Freedom.to.make.life.choices
4
                     +S$Generosity
5
6
                     +S$Perceptions.of.corruption))
   e 1 = y 1 - fitted.values(reg y1)
8
9
  ks.test(e 1, pnorm, mean(e 1), var(e 1))
10
```

#### Output

1 One-sample Kolmogorov-Smirnov test
2
3 data: e\_1
4 D = 0.12269, p-value = 0.02254
5 alternative hypothesis: two-sided

#### As the p-value is less than 0.05 so we reject $H_0$ at level 0.05 but the data has improved towards normality.



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# ANALYSIS1: TIME SERIES ANALYSIS





### Analysis of the Time Series

#### Data set

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Ladder Score	5.350	5.030	5.150	4.520	4.990	4.630	4.720	4.43	4.772	4.770
Year	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Ladder Score	4.315	4.565	4.404	4.315	4.190	4.015	3.573	3.819	3.777	4.036

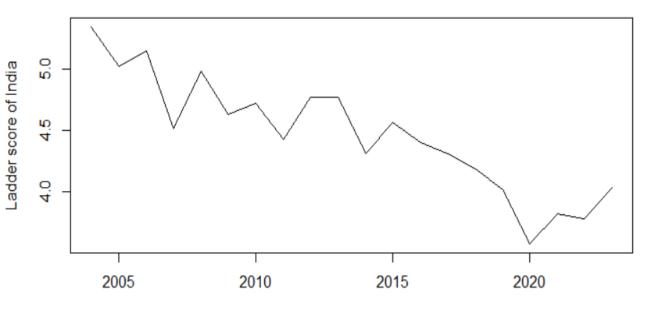
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#### Plotting the data set to analyse it

```
1 data = read.csv(file.choose())
2 ts = ts(data[,2], start = 2004, end = 2023, frequency = 1)
3 ts
4 plot(ts, xlab="Years", ylab="Ladder score of India")
```

#### From the plot we can say that,

- 1) There is a decreasing, downward trend in the time series, which seems to be very obvious.
- 2) The data is yearly data, so, there is no seasonal variation present in the data.
- 3) In the graph it can be observed that there are many ups and downs, but neither equidistant nor have equal amplitude. From this we can say there is aperiodic cyclical fluctuations.



### **Stationary Time Series and Processes**

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A very special class of stochastic process, called stationary process, is based on the assumption

that the process is in a particular state of statistical equilibrium. A stochastic process is said to be strictly stationary if its properties are unaffected by a change of time origin, if the joint probability distribution associated with m observation Xt1,Xt2,...,Xtm is same as the associated with observations Xt1+h,Xt2+h, m ...,Xtm+h. From intuitive point of view a time series is said to be stationary if there is no systematic change in mean (trend), if there is no systematic change in variance and strictly periodic variations have been

There are different types of proccess, that are as follows;

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1. Purely Random Process

- 2. Random Walk
- 3. Moving Average Process
- 4. Autoregressive Process

Theory:

Model : Here we employ the model,

$$y_t = \phi y_{t-1} + e_t$$

3

**Unit Root Test** 

where et denotes the error term.

Assumptions : To perform the test we consider that the error term is normal, i.e.  $e_t \sim iid N(0, \sigma^2)$ 

where  $\sigma 2$  is the error variance.

Hypothesis : We perform the following testing problem,

H0 :  $\phi = 1$  against Ha :  $\phi < 1$ 

Test Statistic : A convenient test statistic is the t ratio of the leastsquares (LS) estimated of  $\phi$  under the null hypothesis. Now for the given model the LS estimates a  $\Rightarrow \hat{\phi} = \frac{\sum_{t=1}^{T} y_{t-1} y_t}{\sum_{t=1}^{T} y_{t-1}^2} \quad \text{IO}_{\therefore \hat{\sigma}^2} = \frac{\sum_{t=1}^{T} \left(y_t - \hat{\phi} y_{t-1}\right)^2}{T-1}$ 

where y0 = 0 and T is the sample size. Now, the t-ratio is,

$$DF = \frac{\hat{\phi} - 1}{std\left(\hat{\phi}\right)} = \frac{\sum_{t=1}^{T} y_{t-1}(y_t - y_{t-1})}{\hat{\sigma}\sqrt{\sum_{t=1}^{T} y_{t-1}^2}} \stackrel{H_0}{\sim} t_{T-1}$$

This statistic is commonly referred as Dickey-Fuller (DF) statistic and the test is referred as Dickey-Fuller (DF) test.

Test Rule : We reject H0 against Ha at an level  $\alpha$  if  $DF < -t_{\alpha;T-1}$ where  $t_{\alpha;T-1}$  is such that  $P(DF < -t_{\alpha;T-1})$ =  $\alpha$ . This is also known as upper alpha point. In terms of p-value we can say we reject H0 against Ha at an level  $\alpha$  if p = value - p ( $DF \le observed(DF)$ )  $\le 1$ adf.test( $y_new$ )

By calculation we can see that the value of the test statistic is -2.3359 and p-value is 0.4444, which is greater than 0.05. So we fail to reject  $H_0$  at level 0.05.

### Comparing ACF and PACF of the logged and differenced series

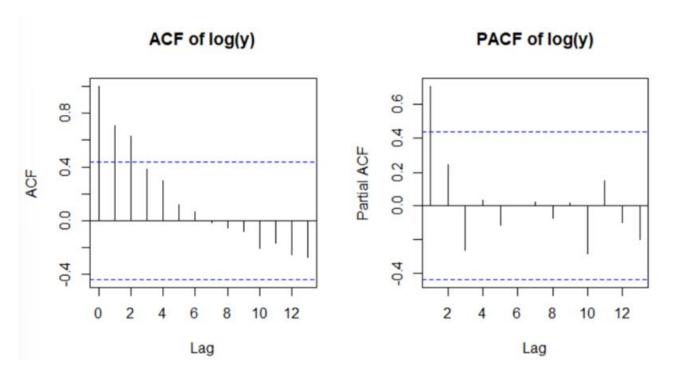
2

3

### ACF and PACF of log(y)

1 acf(y\_new)
2 pacf(y\_new)

1



4

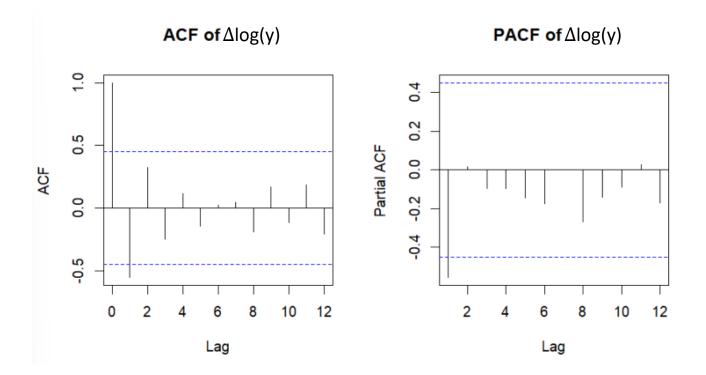
Comparing ACF and PACF of the logged and differenced series

2

3

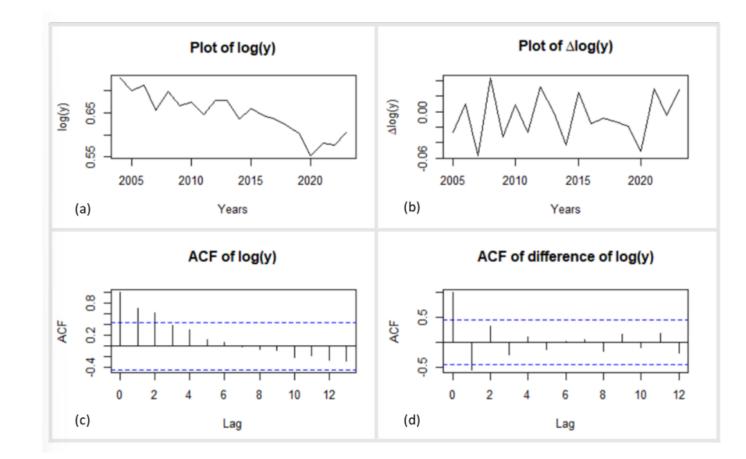
### ACF and PACF of $\Delta \log(y)$

- 1 acf(diff(y\_new))
- 2 pacf(diff(y\_new))



4

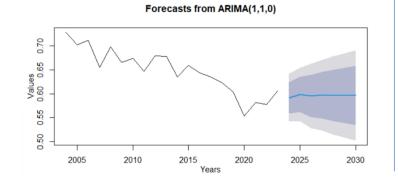
Comparing ACF and PACF of the logged and differenced series



Comparison of ACF of log(y) and  $\Delta log(y)$ 

### ARIMA(1,1,0) AIC: -81.37 Multiple R squared : 0.7662135

```
M=arima(y new, order=c(1, 1, 0))
  summary(M)
 plot(forecast (M, 7))
3
  (cor(y new, fitted.values(M)))^2
4
```



### ARIMA(1,1,1)AIC: -79.98 Multiple R squared : 0.7687116

3

- M1=arima(y new, order=c(1, 1, 1))1 summary(M1) 2
- 3

2

- plot(forecast (M1, 7))
- (cor(y new, fitted.values(M1)))^2 4

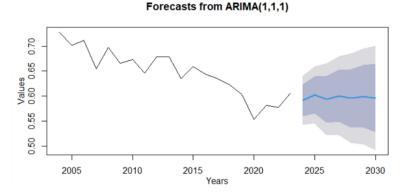
### **Model Fitting**

4

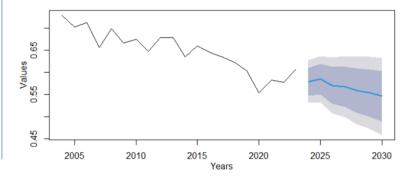
### ARIMA(1,1,0) with a drift AIC: -82.72 Multiple R squared : 0.7753745

1 M2=auto.arima(y new)

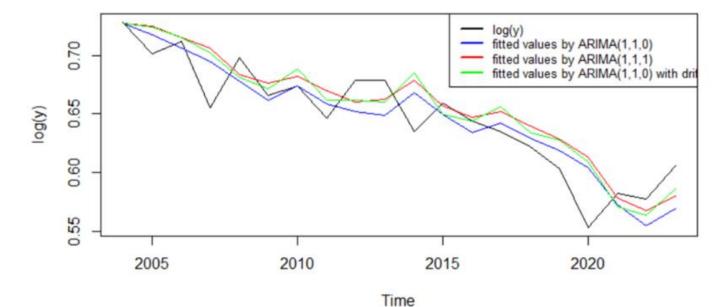
- summary(M2) 2
- plot(forecast (M2, 7)) 3
- (cor(y new, fitted.values(M2)))^2 4



#### Forecasts from ARIMA(1,1,0) with drift



### Comparing the fitted models



**Model Fitting** 

### Residuals

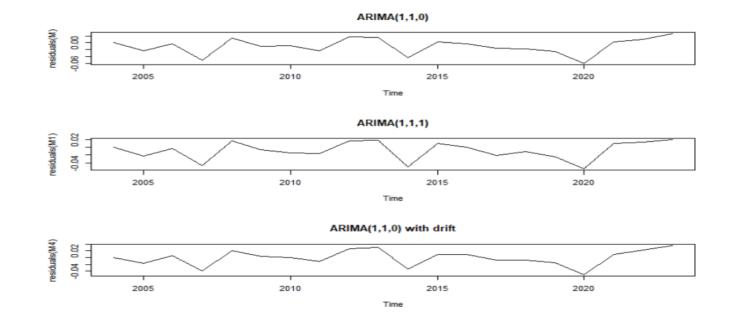
1 par(mfrow= 
$$c(3,1)$$
)

2 plot(residuals(M), pch = 1, main="ARIMA(1,1,0)")

2

- 3 plot(residuals(M1), pch = 1, main="ARIMA(1,1,1)")
- 4 plot(residuals(M4), pch = 1, main="ARIMA(1,1,0) with drift")

3



4

**Model Fitting** 

### Happiness Index in Recent

In a article "Examining India's Falling Rank on the World Happiness Index" written by Aanya Poddar, the writer is enlisting Former Indian President Pranab Mukherjee's comment, "Despite our country's economic progress, India is constantly going downwards in the happiness index. This indicates a lack of a holistic approach towards development." (https://openaxis.in/20 21/04/09/what-we-can-learn-fromthe-world-happiness-index/) which is quite obvious and from our analysis we can see that the Happiness index will decrease, though in a low extent. Which also indicates a downward trajectory in the development of India. Again in another article of Governance Now, named "Why India's ranking on Happiness Index has been falling" is had been reported that "Even though India has been one of the fastest developing countries, the happiness score has worsened year by year. Amid the pandemic, happiness has become more elusive than ever. Covid has also taught us how to value immaterial aspects more than anything and the true purpose of a country. These findings suggest that the country needs to focus on intangible aspects and happiness during these challenging times." (https://www.governancenow.com/news/regular-story/why-indias-ranking-on-happiness-index-hasbeen-falling) which inclines towards the thought to increase the awareness of a wholesome socioeconomic development required to increase the score. In the section of linear regression we see that various factors significantly affects the happiness index. So, increase in them can also make an uplift in happiness index. During the Covid period, 2020-2021, we can see that the happiness index got drowned. Again it starts an upward movement. It is increasing but also it need a development in greater extent to make the happiness index more higher.

### Acknowledgement

I would want to convey my heartfelt gratitude to Prof. Kiranmoy Chatterjee and Prof. Soumyadeep Das, my mentors, for their invaluable advice and assistance in completing my project. They were there to assist me every step of the way, and his motivation is what enabled me to accomplish my task effectively. Their insightful feedback pushed me to sharpen my thinking and brought my work to a higher level. I would also like to thank all of the other supporting personnel who assisted me by supplying the equipment that was essential and vital, without which I would not have been able to perform efficiently on this project. I would also like to thank my tutors, Prof. Debesh Ray, Prof. Arup Kumar Hait, Prof. Suryasish Chatterjee for their valuable guidance throughout my studies. You provided me with the tools that I needed to choose the right direction and successfully complete my dissertation I would also want to thank the West Bengal State University for accepting my project in my desired field of expertise. I would also like to thank my triends and parents for their support and encouragement as I worked on this assignment.