

Report on Happiness up to 2022

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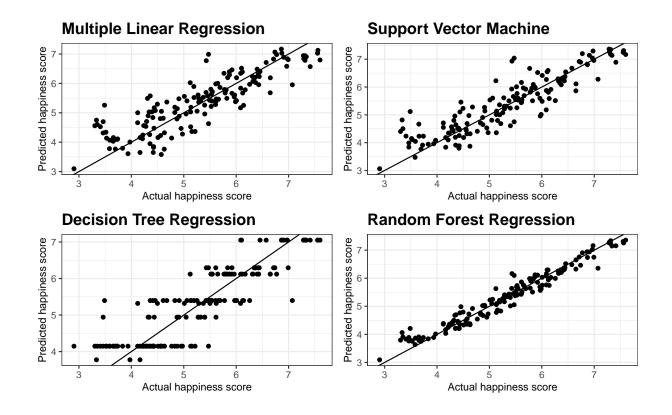




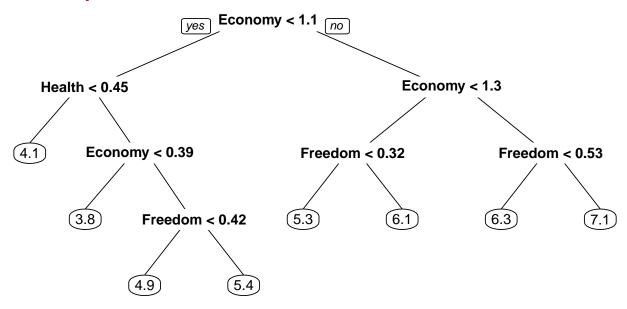
!htbp	<trained models=""></trained>	<model description=""></model>	
	Multivariate Linear Model	Simple Linear regression with multiple variables	
	Support Vector Machine Model	Use multiple learning algorithms (resampling and tree) to give us better results	
	Decision Tree Model	Binary tree model have control statement.	
	Random Forest Model	Use multiple learning algorithms (resampling and tree) to give us better results.	

 Table 1: Model Description of our Trained Models

To explore the factors that could be contributing to the happiness score differences between each year, we first test few common models:



1 Tree plot



2 Random Forest regression

RF model is used to predict causes for Random Forest is a practical way and regularly used in machine learning models. Random Forest Model have the variable selecting system (via bootstrapping) to decide the most significant tree and can reduce overwriting compared with decision tree. With that said, random forests are a strong modeling technique and much more robust comparing with many different methods. (Liberman, 2017). We can see from the plot that this model have captured the data well in the past few years.

Table 2: Variable importance for Random Forest model

	IncNodePurity
Economy	348.66900
Health	327.08463
Freedom	169.32991
Generosity	97.79738

From the report, we can see that our model is for 2020 data.

```
log(score) = -4.6000 - 0.0008 \ cpi + 0.2591 \ log(economy)
-0.0026 log(population) + 0.0114 \ log(health) + 0.0032log(year)
```

We can see that the total proportion of variance explained by the model with these variables are 60.49%. For the 4 predictors, the economy status(GDP per capita) contribute most to the happiness scores than other variables.

3 Factor importance

Here, we concluded that the best method to fit the 2022 data is the Random Forest. This model will also allow us to tell the importance of variables via a factor loading summary table.

In this table, we can conclude that the most important variables on explaining the happiness scores will be the Happiness and Health.

4 We abandon the current dataset to add more variables

```
##
## Call:
## lm(formula = `Happiness Score` ~ Health + Economy + Freedom +
##
       Generosity, data = dataall)
##
## Residuals:
        Min
                  10
                     Median
                                    30
                                            Max
## -1.88683 -0.36864 0.04779 0.39916 1.76462
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 2.43744
                           0.07530 32.370 < 2e-16 ***
## Health
                1.22320
                           0.13921
                                   8.787 < 2e-16 ***
```

Table 3: Linear regression model for happiness scores without new data

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	2.437442	0.0752984	32.370444	0
Health	1.223204	0.1392052	8.787054	0
Economy	1.454316	0.0841520	17.282015	0
Freedom	1.372180	0.1095802	12.522156	0
Generosity	1.170207	0.1396671	8.378545	0

```
## Economy 1.45432 0.08415 17.282 < 2e-16 ***
## Freedom 1.37218 0.10958 12.522 < 2e-16 ***
## Generosity 1.17021 0.13967 8.379 2.52e-16 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.582 on 772 degrees of freedom
## Multiple R-squared: 0.732, Adjusted R-squared: 0.7307
## F-statistic: 527.3 on 4 and 772 DF, p-value: < 2.2e-16</pre>
```

5 What is the correlation between these variables in linear model.

One advantage of multivariate linear regression is that it can allow us to analyse the relationship between different variables in a statistical coherent way. We can start with the correlation between each variables.

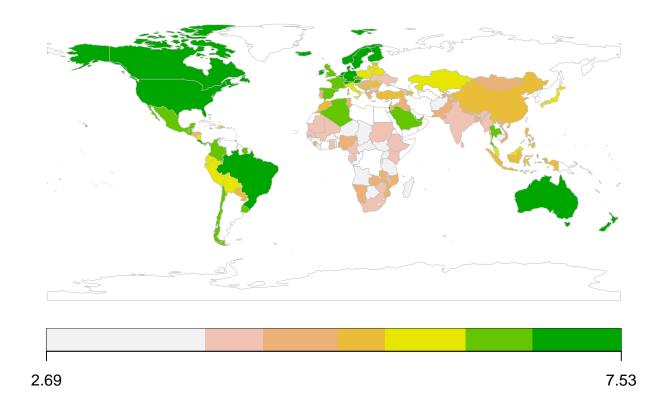
In order to better analyse the relationships, I add two new variables, which are CPI values and the population size for each country. However, due to the limitation of the new dataset, we can only conduct our analysis based on the 2020 data.

```
##
## Call:
## lm(formula = log_score ~ cpi + log_eco + log_population + log_health +
##
       year, data = lognarm_hapall)
##
## Coefficients:
                                                                          log_health
##
      (Intercept)
                               cpi
                                            log_eco log_population
##
       -4.5998547
                        -0.0007945
                                          0.2590779
                                                          -0.0025806
                                                                           0.0113946
##
             year
##
        0.0031566
```

6 The countries that we missed in the dataset.

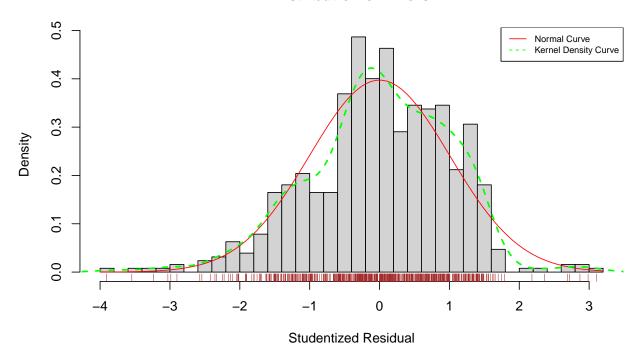
641 codes from your data successfully matched countries in the map
1 codes from your data failed to match with a country code in the map
109 codes from the map weren't represented in your data

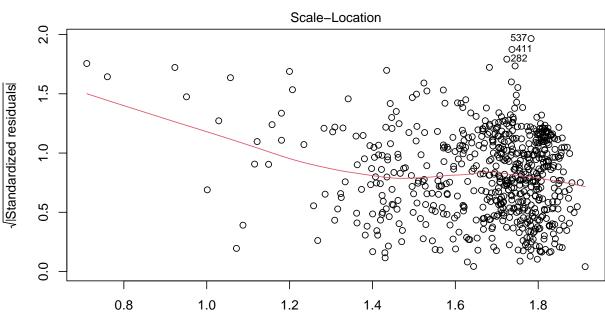
Countries that we are not included



7 Residual Diagonistic

Distribution of Errors

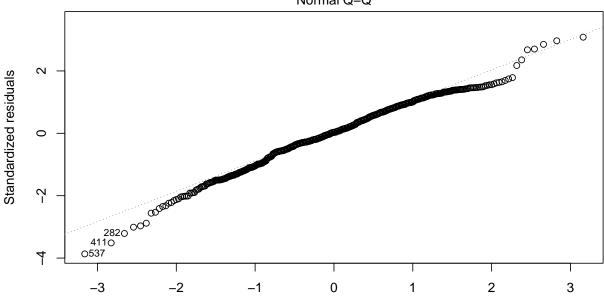




Fitted values lm(log_score ~ cpi + log_eco + log_population + log_health + year)

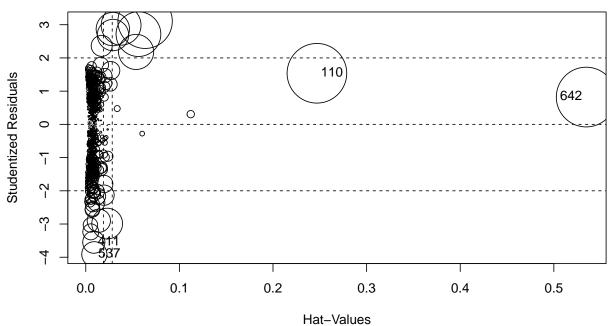
Normal Q-Q plot

Normal Q-Q



Theoretical Quantiles
In this Figure, the dotted line is Normal Distribution

Influence Plot



Circle size is proportial to Cook's Distance

StudRes Hat CookD

110 1.5379757 0.246899853 0.12896655

411 -3.5457416 0.008605488 0.01786073

537 -3.9107652 0.009146505 0.02300857

642 0.8219777 0.534532896 0.12938311