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Life Lines: Predicting Life Expectancy From Demographic, Economic, and Health Factors

INTRODUCTION

The author of this paper, upon discovering the stark contrast in life expectancy ranking between the United States (47th for 79.74 years), Canada (19th for 83.02 years), and Mexico (92nd for 75.04 years) (Worldometer), who are all in geographical proximity and share borders, was motivated to predict life expectancy for all countries. Unlike prior studies, which were limited in time span and number of countries, this research uses data from 193 countries over 15 years (2000 to 2015) for greater generalizability.

RESEARCH QUESTION

To what extent can demographic indicators, economic performance, and health factors predict a nation's average life expectancy?

DATASET BACKGROUND

This research uses the Life Expectancy (WHO) dataset from Kaggle. This dataset pooled health data from the Global Health Observatory's data repository and economic data from the United Nation. The dataset includes 22 variables and 2,938 observations.

DESCRIPTIVE ANALYSIS

Though the dataset initially includes 21 predictors, the author runs `pairs()` function to produce a correlation scatter plot to identify and eliminate variables with little correlation with life expectancy. The chosen predictors and the response variable (life expectancy) are as follows:

- ❖ **Life Expectancy**: The average age to which a person is expected to live.
- ❖ **Adult Mortality**: The rate of death among adults aged 15 to 60 per 1,000 population.
- ❖ **Alcohol**: The per capita consumption of alcohol, measured in liters of pure alcohol.
- ❖ **BMI**: The average Body Mass Index of the population.
- ❖ **GDP**: Gross Domestic Product per capita measured in USD.
- ❖ **Population**: The total population.
- ❖ **Schooling**: The average number of years of schooling completed by the population.

life_expectancy	adult_mortality	alcohol	BMI
Min. :44.0	Min. : 1.0	Min. : 0.010	Min. : 2.00
1st Qu.:64.4	1st Qu.: 77.0	1st Qu.: 0.810	1st Qu.:19.50
Median :71.7	Median :148.0	Median : 3.790	Median :43.70
Mean :69.3	Mean :168.2	Mean : 4.533	Mean :38.13
3rd Qu.:75.0	3rd Qu.:227.0	3rd Qu.: 7.340	3rd Qu.:55.80
Max. :89.0	Max. :723.0	Max. :17.870	Max. :77.10

GDP	population	schooling
Min. : 1.68	Min. :3.400e+01	Min. : 4.20
1st Qu.: 462.15	1st Qu.:1.919e+05	1st Qu.:10.30
Median : 1592.57	Median :1.420e+06	Median :12.30
Mean : 5566.03	Mean :1.465e+07	Mean :12.12
3rd Qu.: 4718.51	3rd Qu.:7.659e+06	3rd Qu.:14.00
Max. :119172.74	Max. :1.294e+09	Max. :20.70

Figure 1: Summary statistics, variances, and standard deviations for all variables.

MODEL FITTING

```
lm(formula = life_expectancy ~ adult_mortality + alcohol + BMI +
    GDP + population + schooling, data = df)
```

Residuals:

	Min	1Q	Median	3Q	Max
	-24.7011	-2.2545	0.4575	2.8819	13.6082

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.551e+01	6.937e-01	80.028	< 2e-16 ***
adult_mortality	-3.177e-02	1.004e-03	-31.640	< 2e-16 ***
alcohol	-8.914e-02	3.633e-02	-2.454	0.0142 *
BMI	5.453e-02	6.873e-03	7.934	3.88e-15 ***
GDP	7.864e-05	1.130e-05	6.959	4.93e-12 ***
population	-2.838e-11	1.585e-09	-0.018	0.9857
schooling	1.404e+00	6.103e-02	23.012	< 2e-16 ***

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

Residual standard error: 4.512 on 1642 degrees of freedom
Multiple R-squared: 0.7378, Adjusted R-squared: 0.7369
F-statistic: 770.2 on 6 and 1642 DF, p-value: < 2.2e-16

Figure 2: A Linear Regression model is initially fitted to the 6 predictors.

With an R^2 value of 0.7369, the first model seems promising, suggesting that 73.69% of the variation in life expectancy could be explained by the predictors. However, the predictor population is not statistically significant. Furthermore, model assumptions, like linearity, normality, and constant variance need to be verified.

MODEL ASSUMPTIONS VERIFICATION

From the diagnostic tools in Figure 3, we observe a violation of linearity because the red line in the Residuals vs. Fitted plot is not linear. From the Q-Q Residuals plot, we observe a violation of normality of the error term because the points at the left-tail do not align to the straight line. From the Standardized residuals vs. Leverages plot, we observe many points that could be outliers. Fortunately, constant variance is observed and multicollinearity is not present because VIF values for predictors are all less than 5. Nevertheless, power transformation is still needed.

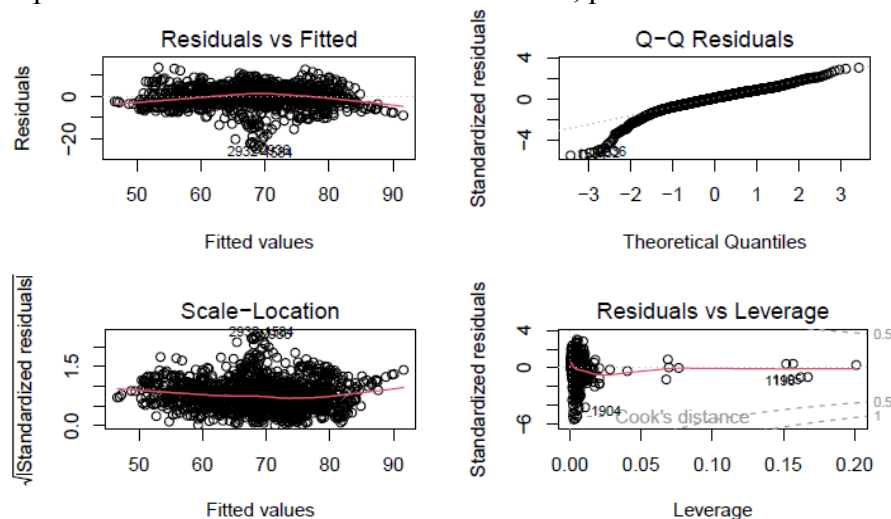


Figure 3: Diagnostic plots for the first model.

MODEL TRANSFORMATION

Box-Cox Transformation is applied to all variables based upon the power recommended by powerTransformed function for each variable, following the formula:

$$y(\lambda) = \frac{y^\lambda - 1}{\lambda} \text{ if } \lambda \neq 0, \text{ else } \log(y).$$

In the transformed model, predictors GDP and population undergo log transformation. Other variables like life expectancy, mortality, alcohol, BMI, and schooling undergo power transformation with values 2.87, 0.64, 0.44, 1.10, and 1.33 respectively.

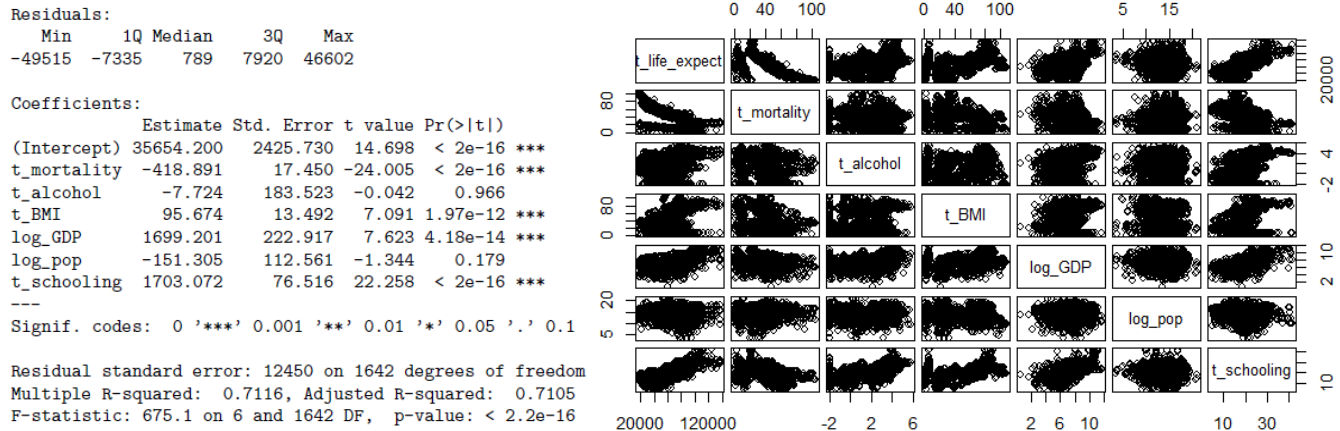


Figure 4: The transformed model and the corresponding scatterplot matrix.

The transformed model meets all five model assumptions. Furthermore, the F-test shows the model is statistically significant with a p-value less than 2.2e-16. However, predictors t_alcohol and log_pop are statistically insignificant with a p-value above alpha 0.05. This means variable selection is needed to determine if these predictors could be dropped from the transformed model.

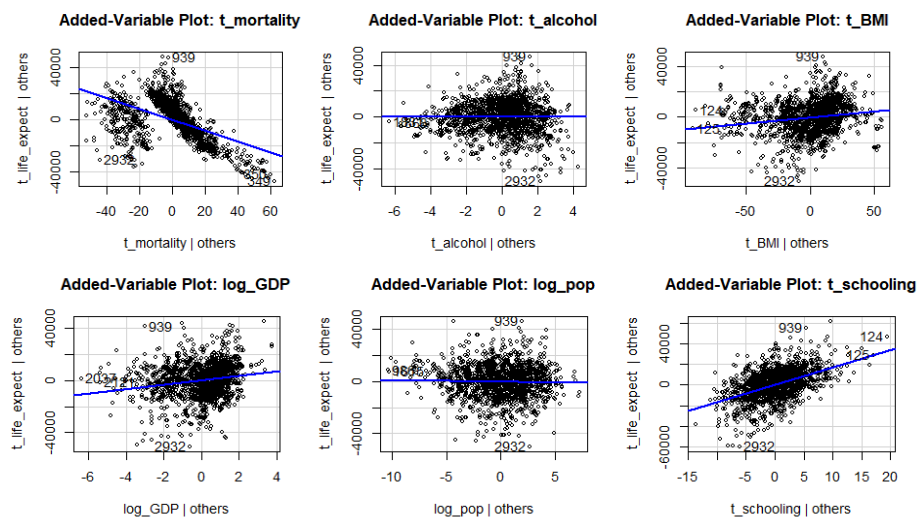


Figure 5: Added-Variable Plots examine the effect of a given predictor on life expectancy. The Added-Variable Plots show t_alcohol and log_pop have almost no effect on life expectancy without the effects of other predictors, further supporting that they are statistically insignificant.

VARIABLE SELECTION

The first variable selection method used is to consider all possible subsets. This method suggests that based upon the adjusted R-squared value, the subset with $p = 5$ to be the best. This subset uses the predictors `t_mortality`, `t_BMI`, `log_GDP`, `log_pop`, and `t_schooling`. When considering AIC corrected and BIC values, the method suggests the subset with $p = 4$ to be the best, which uses the predictors `t_mortality`, `t_BMI`, `log_GDP`, and `t_schooling`.

<pre>Residuals: Min 1Q Median 3Q Max -49976 -7487 638 7919 46411 Coefficients: Estimate Std. Error t value Pr(> t) (Intercept) 33664.22 1755.29 19.179 < 2e-16 *** t_mortality -421.08 17.30 -24.346 < 2e-16 *** t_BMI 96.13 13.47 7.134 1.45e-12 *** log_GDP 1691.85 221.31 7.645 3.54e-14 *** t_schooling 1702.52 69.66 24.440 < 2e-16 *** --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1</pre>	<pre>Residuals: Min 1Q Median 3Q Max -49531 -7348 777 7921 46590 Coefficients: Estimate Std. Error t value Pr(> t) (Intercept) 35685.67 2306.91 15.469 < 2e-16 *** t_mortality -418.96 17.36 -24.130 < 2e-16 *** t_BMI 95.65 13.47 7.098 1.87e-12 *** log_GDP 1698.10 221.30 7.673 2.86e-14 *** log_pop -151.60 112.30 -1.350 0.177 t_schooling 1701.74 69.64 24.435 < 2e-16 *** --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1</pre>
<pre>Residual standard error: 12450 on 1644 degrees of freedom Multiple R-squared: 0.7112, Adjusted R-squared: 0.7105 F-statistic: 1012 on 4 and 1644 DF, p-value: < 2.2e-16</pre>	<pre>Residual standard error: 12450 on 1643 degrees of freedom Multiple R-squared: 0.7116, Adjusted R-squared: 0.7107 F-statistic: 810.6 on 5 and 1643 DF, p-value: < 2.2e-16</pre>

Figure 6: Summary results for $p = 4$ (left) and $p = 5$ (right) subsets of predictors.

Both subsets are statistically significant based on the p-value from the F-statistic. In the four-variable subset ($p = 4$), the R^2 value is smaller than the five-variable subset ($p = 5$)'s R^2 value, but all four predictors are statistically significant. Meanwhile, one predictor, `log_pop`, is not statistically significant for the five-variable subset, indicating that the five-variable model overfits the data. Based upon the result, we choose the four-variable model.

```
Step: AIC=31103.29
t_life_expect ~ t_mortality + t_BMI + log_GDP + t_schooling
```

	Df	Sum of Sq	RSS	AIC
<none>			2.5481e+11	31103
- t_BMI	1	7.8892e+09	2.6270e+11	31152
- log_GDP	1	9.0583e+09	2.6386e+11	31159
- t_mortality	1	9.1866e+10	3.4667e+11	31609
- t_schooling	1	9.2582e+10	3.4739e+11	31612

Figure 7: Backward Stepwise regression result for the transformed model.

Additionally, Stepwise regression Backward stepwise also recommends the four-variable subset model. Overall, because the Added-Variable Plots show that `t_alcohol` and `log_pop` have little effects on life expectancy, and both subset methods recommend the four-variable subset model, which eliminates `t_alcohol` and `log_pop`, we confidently conclude that the four-variable subset model is the best model and the aforementioned predictors must be removed.

MODEL INTERPRETATION

```
lm(formula = t_life_expect ~ t_mortality + t_BMI + log_GDP +
    t_schooling, data = df)

Residuals:
    Min       1Q   Median       3Q      Max
-49976  -7487    638    7919  46411

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 33664.22   1755.29   19.179 < 2e-16 ***
t_mortality  -421.08     17.30  -24.346 < 2e-16 ***
t_BMI         96.13      13.47   7.134 1.45e-12 ***
log_GDP      1691.85     221.31   7.645 3.54e-14 ***
t_schooling  1702.52      69.66  24.440 < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 12450 on 1644 degrees of freedom
Multiple R-squared:  0.7112,    Adjusted R-squared:  0.7105
F-statistic: 1012 on 4 and 1644 DF,  p-value: < 2.2e-16
```

Figure 8: Final regression model.

With an R^2 value of 0.7105, the four predictors, $t_mortality$, t_BMI , \log_GDP , and $t_schooling$ can explain 71.05% of the variation in life expectancy. Furthermore, all four predictors are statistically significant with p-values less than alpha 0.05. Lastly, the F-statistic also has a p-value less than $2.2e-16$, revealing the strength of the model. The interpretations for estimate coefficients from the model are as follows:

- ❖ The intercept is 33664.22, which is the estimated life expectancy for a given country when all predictors are 0. This interpretation is not meaningful in the real world context because predictors like mortality rate cannot be zero in a population.
- ❖ For every one-unit increase in the transformed mortality rate, transformed life expectancy decreases by 421.08 units.
- ❖ For every one-unit increase in transformed BMI score, transformed life expectancy increases by 96.13 units.
- ❖ For every one-percent change in GDP, transformed life expectancy increases by 1691.85 units.
- ❖ For every one-unit increase in transformed schooling rate, transformed life expectancy increases by 1702.52 units.

CONCLUSION

In conclusion, this research aimed to predict life expectancy using demographic indicators, economic performance, and health factors using a dataset containing data on 193 countries over 15 years. The author performed variable transformation and variable selection to construct a final model with four statistically significant predictors: transformed mortality rate, transformed BMI score, log GDP, and transformed schooling rate. The model demonstrated strong statistical significance, explaining 71.05% of the variation in life expectancy. Policymakers and public health officials seeking to improve life expectancy should focus efforts on decreasing mortality rate and increasing national GDP, average BMI score, and education.

Works Cited

- “Life Expectancy (WHO).” [Www.kaggle.com](https://www.kaggle.com/datasets/kumarajarshi/life-expectancy-who/data),
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