LSTAT2120 - Project 2022

Linear models of life expectancy

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1 Introduction

We are working with a dataset containing different *health factors* collected from **WHO** (World Health Organization) as well as *economic factors* collected from **ONU** for almost every countries in the world and years between 2000 and 2015. Some countries are not present in this dataset because they had too much missing data.

Since we are dealing with panel data, we chose to only work with data from the year 2012. We removed observations with missing values and we modifies the 'adult mortality' continuous variable into a qualitative variable. So the final dataset has ??? **observations** and 20 **variables**. For our analysis, we separates the dataset into a training set and a testing set containing respectively 80% and 20% of the observations. This separation is random (*i.e. the dataset is shuffled before separating it*).

2 Research question

We want to understand how different factors affect positively or negatively the life expectancy. We would like to be able to predict the mean life expectancy (response variable : *life.expectancy*) for a given country based on different health, economic and social factors.

Firstly, we will start by doing an descriptive analysis of the different variables. Then we will try different linear models and select the best one based on different relevant criterions. We will check if the classical hypothesis are respected as well as nonlinearity, influential observations. If some hypotheses are not respected, we will fix that. We will finish by making prediction on a testing set with our model.

3 Descriptive statistic

We have 20 variables in our dataset of which 2 are qualitative. The *status* indicates if the country is developped or developping and the *adult.mortality* feature categorize the probability of dying between 15 and 60 years old into five levels : very low, low, middle, high, very high.

More generally, we can classify the different variables into several categories : *economic* (country status, expenditure on health, gdp, hdi), *social* (total population of each country, number of years of schooling), *mortality* (adult mortality, infant death, under five death, under four death because of HIV/AIDS, thinness) and *immunization* factors (immunization of hepatitis b, polia, diphteria as well as number of reported cases of measles). We will only describe some variables, the curious reader can find a complete description of these in the appendix.

The *hepatitis.b*, *polio* and *diphteria* variables are respectively the immunization coverages against hepatitis B, polio and DPT3 (diphteria tetanus toxoid and pertussis) among the 1 year olds and are given in percentage.

The *alcohol* variable is the consumption of alcohol per capita (of 15 years old or more) in litres of pure alcohol.

3.1 Qualitative variables

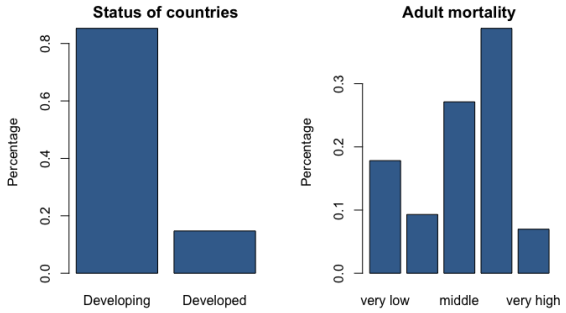

Figure 1 – *barplot of the qualitative variables*

3.2 Quantitative variables

Let's take a look to the table of the 4 moments (*mean*, *standard deviation*, *skewness* and *kurtosis*) for each of the quantitative variables.

4 moments of quantitative variables

variable	mean	std_dev	skewness	kurtosis
life.expectancy	70.24	8.51	-0.37	2.41
infant.deaths	31.28	112.66	7.52	66.92
alcohol	3.87	4.24	0.76	2.43
percentage.expenditure	900.80	1931.89	3.92	19.17
hepatitis.b	80.57	26.54	-1.94	5.66
measles	967.93	2794.70	4.14	21.96
bmi	38.03	20.93	-0.12	1.63
polio	82.64	25.40	-2.17	6.60
total.expenditure	6.18	2.48	0.21	2.72
diphtheria	84.53	22.58	-2.51	8.70
hiv.aids	1.08	2.15	2.83	11.13
gdp	7460.10	12333.66	2.90	11.53
population	13580015.34	35183192.47	4.32	23.81
thinness.10.19.years	4.76	4.57	1.92	7.77
thinness.5.9.years	4.74	4.46	1.96	8.48
income.composition.of.resources	0.66	0.15	-0.25	2.04
schooling	12.54	2.73	-0.07	2.89

Figure 2 – *table of moments (mean, standard deviation, skewness, kurtosis) for the quantitative variables*

We will not describe every variable in details since there are a lot but we will try to summarize the above table instead.

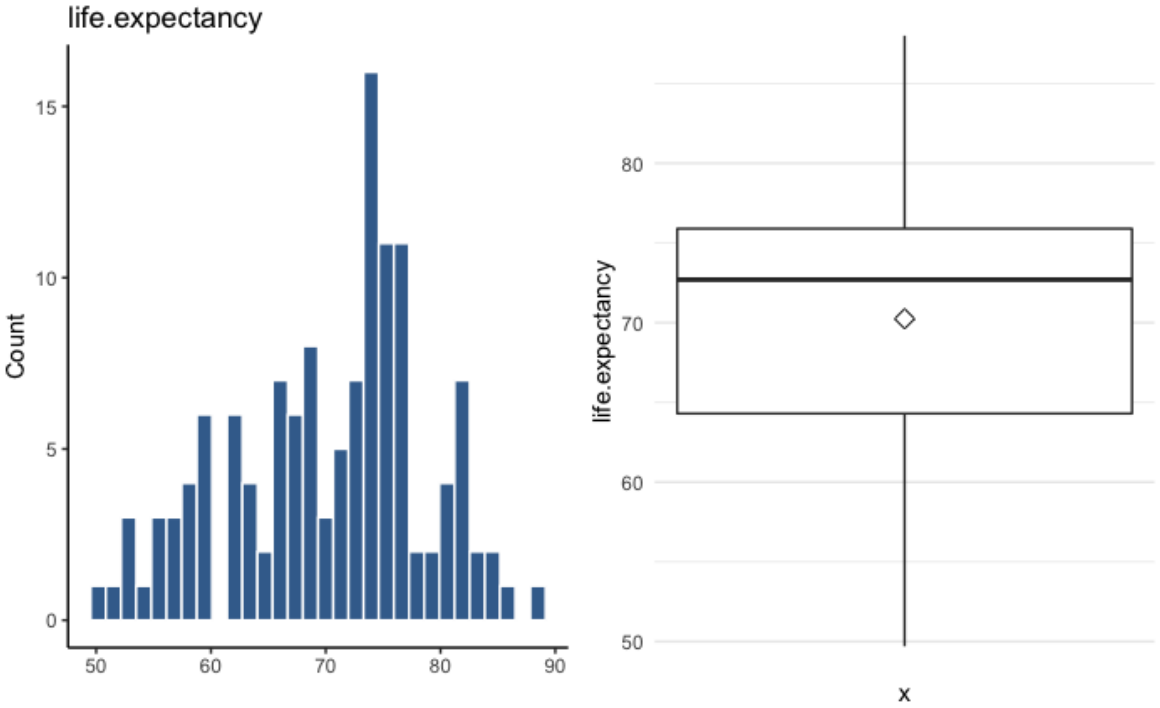

Figure 3 – *Histogram and boxplot of the target variable (life expectancy)*

The **life expectancy** has a mean of roughly 70 years with a standard deviation of 8.6. It is slightly negatively skewed which indicates that some countries have low life expectancy. The kurtosis is less than 3 so the distribution is a litlle bit flattened.

We can see that some features have a high standard deviation. For example, the **infant.deaths** variable has a mean of $\approx 31/1000$ but a standard diviation of 112.6 which means that some countries have far more child mortality than others. We also see that the expenditure on health services, the number of measles cases per 1000 inhabitants and the GDP are not homogeneous among the different countries represented in this dataset. The hepatitis B, polio and diphetria coverages are pretty much similar. The average BMI is 38 which means obesity but we have to pay attention that the standard deviation is pretty high so we cannot intepret that in average the countries have an obese population. The number of years of schooling last 12 ± 2 years in average. The prevalence of thinness among children and adolescents is of 4% in average but can be close to 0 considering the standard deviation. Checking the **income.composition.of.resources** variable, we notice that based on the productive resources, the countries have an HDI greater than 0.5.

Looking at the histograms and boxplots in the appendix, we can see that some countries spend far more money on health services than most of the others. we notice that the child (less than five years old) death and the number of measle cases are low among most of countries. Unfortunately, a group of countries have not a good coverage against polio, hepatitis B and diphteria. Eventually, we notice 2 groups for the BMI, a group of countries has a BMI around 20 but another around 60 !

The **infant death** has a mean of 31/1000 but has a huge standard deviation (112.6). We see that heavily tailed with a kurtosis of 66.9. The same kind of conclusion can be made for the **deaths under five year old**.

In average, countries spend 9 times the GDP [1] per capita on health services but the standard deviation is huge (1931.8) which indicates the presence of outliers far away from the mean. Therefore, we expect

1. Gross Domestic Product

that some countries spend much less than that on health services.

Furthermore, in average, countries spend 6% of their total budget on health services. The distribution of this variable seems to follow a normal distribution given the skewness and kurtosis.

3.3 Correlation matrix

We look at the correlation matrix in order to see if there are any highly correlated variables. Indeed, it could be a sign of multicollinearity

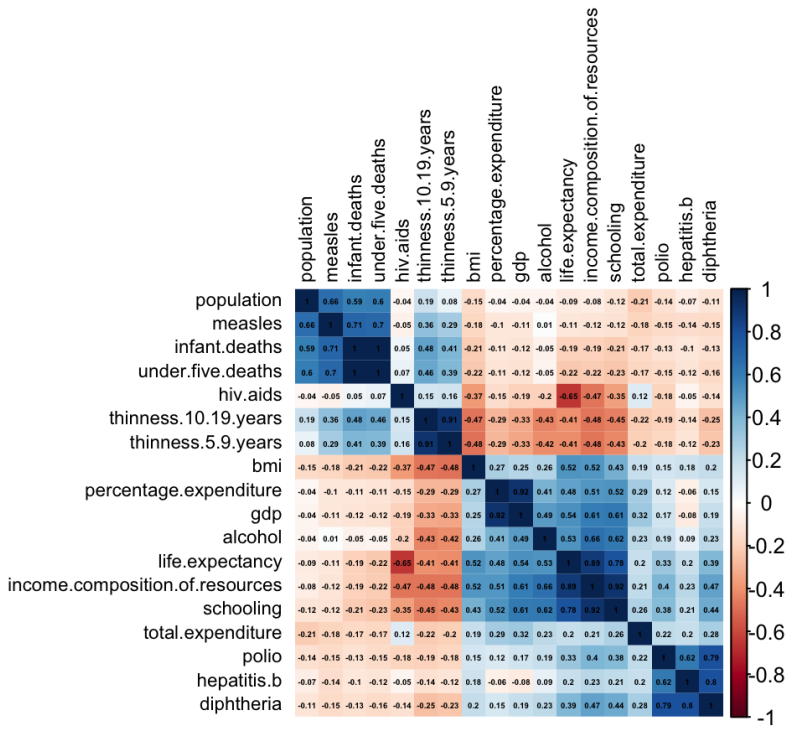

Figure 4 – *correlation matrix of dataset*

We see that severall variables are highly correlated :

- The **infant death** is perfectly correlated with the **death under five year old** : these two features are redundant. As a consequence, we're gonna remove *under.five.death* feature from our dataset.
- The **thinness from** 5 **to** 9 **years old** with the **thinness from** 10 **to** 19 **years old** : we could suspect that extreme thinness comes from a problem of access to food which implies that thinness doesn't stop at 10 years old but continue throughout the teenage.
- The **number of measles cases per 1000 inhabitants** with the **infant death** : indeed, measle hits essentially children and youth and can (often) lead to death.
- The **percentage of expenditure made on health services** with the **GDP per capita**.
- The **hepatitis B** and **polio** with **diphteria**.
- The **life expectancy** with the **HDI in terms of income composition of resources** and **schooling**.

4 Model selection

To maximize our model accuracy, we need to carefully select variables without adding too much to avoid overfitting. To do that, we will perform model selection using *AIC*, *BIC* and R_a^2 criterions. Since we have a lots a variables in our full model, we will only consider model selection of type II and III. Hence, we will not consider *Cp Mallow* criterion.

4.1 Type II : forward / backward stepwise selection

The goal of a forward/backward stepwise selection is to start from the full model and then gradually adding/removing variables one at a time. At each iteration, we add/remove the one that yields the lowest accuracy in prediction when added the pool of selected variables. We can measure the accuracy using different criterions, for this project, we will focus on *p-value* and *AIC* criterions.

4.1.1 p-value

At each step, we chose the variable where,

$$r_{yk}^2 = \frac{\text{SSR}(X_k)}{\text{SST}}, \quad k = 1, \dots, p-1 \tag{1}$$

is maximum. As a rule of thumb, we include the variable X_k if its p-value is smaller than the SLE (significance level to enter) that we set to 0.15.

4.1.2 Akaike Information Criterion (AIC)

We want to minimize the AIC that is,

$$\text{AIC} = -2 \ln L(\hat{\beta}) + 2k \tag{2}$$

where $L(\hat{\beta})$ is the maximum of the likelihood function and p is the number of estimated parameters in the model.

4.2 Type III : LASSO

The LASSO estimator is similar to the OLS (it minimizes the SSR) but it adds a constraint on the L_1 norm (Manhattan) for β. The constaints is,

$$\sum_{j=1}^{p} |\beta_j| \leq t \tag{3}$$

where $t \in \mathbb{R}$ is a parameter to be determined.

This change allows some coefficients to be shrunk exactly to zero.

4.2.1 Models comparison

Comparison of models			
Model	Number_of_variables	AIC	Adj_R2
Full model	21	542.14	0.88
Forward p-value	7	520.79	0.89
Backward p-value	6	519.51	0.89
Forward AIC	7	520.79	0.89
Backward AIC	6	519.51	0.89
LASSO	9	522.94	0.89

Figure 5 – *Comparison of the full model with models resulting of forward/backward selections using p-value and AIC criterion*

We compared the full model with forward/backward selections using the p-value criterion and AIC criterion. Each selected model has a slighty better adjusted R^2 of 0.89 compared to the full model with the benefit of being much simpler. Therefore, we choose the model with the less variables. We noticed that the backward elimination select the same variable for the p-value criterion and the AIC criterion. We chose to go for the backward selected model using p-value.

4.3 Interactions between variables

We should then try to add interactions betweem variables to our chosen model. We decide to test the following interactions and compare the resulting models with our chosen one,

- *infant.deaths* with *measles*
- *adult.mortality.high* with *alcohol*
- *adult.mortality.very_high* with *alcohol*
- *total.expanditure* with *adult.mortality.low*
- *total.expanditure* with *infant.deaths*

Comparison of the chosen model with the adding of interaction term			
Model	Number_of_variables	AIC	Adjusted_R2
infant.deaths * measles	9	525.40	0.88
adult.mortality.high * alcohol	9	522.49	0.89
adult.mortality.very_high * alcohol	8	523.21	0.89
total.expenditure * adult.mortality.low	7	520.20	0.89
total.expenditure * infant.deaths	8	523.25	0.89
percentage.expenditure * diphtheria	9	523.71	0.89

Figure 6 – *Comparison of the chosen model with the adding of an interaction term*

Looking at the adjusted R^2, we notice that the different interacting terms do not explain more our target variable (it's even lower for the first interacting term). Moreover, the AIC criterion is worse that the model without any interaction. Therefore, we choose to not add an interaction term.

Our final model is then,

$$\begin{aligned} life.expectancy = \beta_0 &+ \beta_1 \cdot total.expanditure + \beta_2 \cdot hiv.aids + \beta_3 \cdot income.composition.of.resources \\ &+ \beta_4 \cdot adult.mortality.low + \beta_5 \cdot adult.mortality.middle \\ &+ \beta_6 \cdot adult.mortality.very\_high \end{aligned}$$

4.4 Verifying underlying hypotheses

After selecting a model, we want to check the underlying hypothesis of the linear model. We will verify the 3 main hypothesis : homoskedasticity, independance of observations and normality of the residuals. we will also check for outliers, autocorrelation and nonlinearity.

4.4.1 Nonlinearity

We can check for nonlinearity by looking at the scatterplot of the residuals (e_i) versus the explanatory variables.

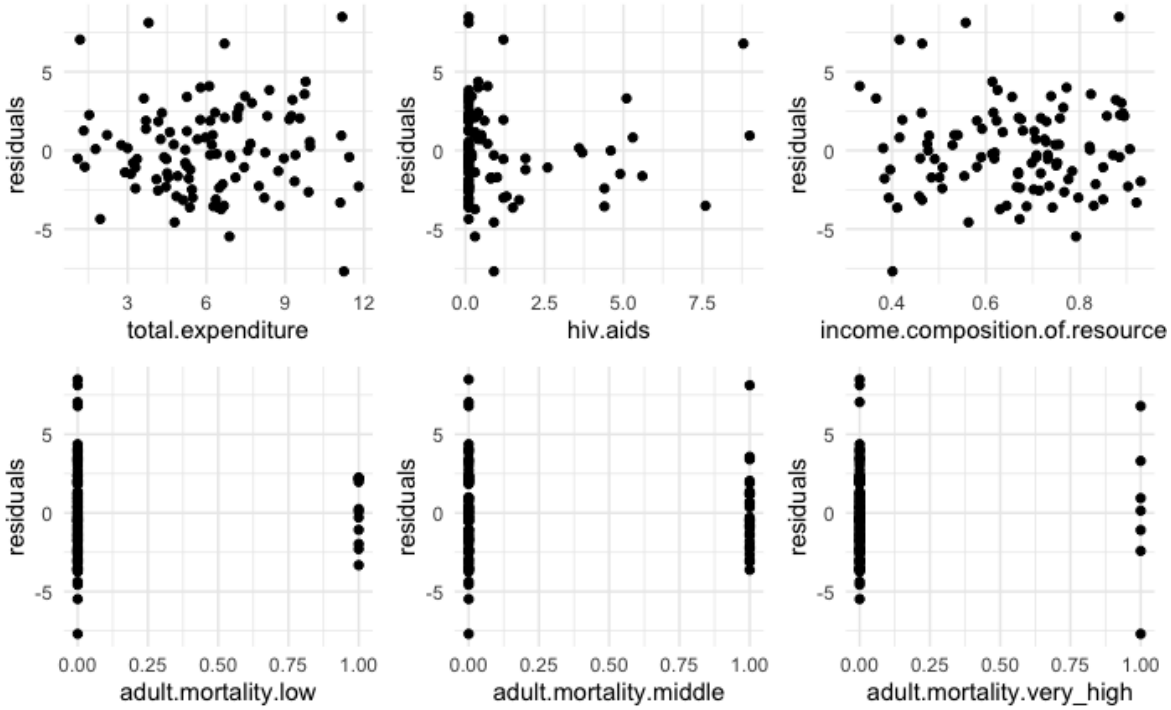

Figure 7 – *scatterplots of residuals versus explanatory variables for the selected model*

We do not see clear nonlinear patterns in the different plots above. Every variable has more or less a linear relation with its residuals. The continuous variable *hiv.aids* has a strange pattern but the nonlinear seems too complicated to infer and would add a lot of complexity to our model. Therefore, we do not take remedial actions.

4.4.2 Outliers and influential observations

a) outliers with respect to the explanatory variables

We first try to identify outliers with respect to the explanatory variables X_{ij}. They can be identified by studying the leverages that are the diagonal elements of the "hat matrix" $H := X(X^TX)^{-1}X^T$. X_i is an outlier if,

$$h_{ii} > \frac{2p}{n} \approx 0.116$$

We find **13** outliers that are the following rows of our dataset : 6, 9, 11, 23, 35, 40, 49, 58, 65, 82, 97, 99, 100.

We want then know if the outliers found are influentials for the their fitted values. We use the DFFITS criterion for the i-th observation,

$$\text{DFFITS}_i = d_i^* \sqrt{\frac{h_{ii}}{1-h_{ii}}} \tag{4}$$

where d_i^* are the standardized deleted residuals,

$$d_i^* = e_i \sqrt{\frac{n-p-1}{\text{SSE}(1-h_{ii}) - e_i^2}} \tag{5}$$

We have a criterion for DFFITS. For $n > 30$, the i-th observation is influential for its fitted value if,

$$|\text{DFFITS}_i| > 2\sqrt{\frac{p}{n}} \approx 0.52 \tag{6}$$

We find that **8** observations are influentials for the fitted values : 2, 9, 23, 35, 49, 95, 96. Therefore, the observations 9, 23, 35, 49 are outliers and influentials for the fitted values.

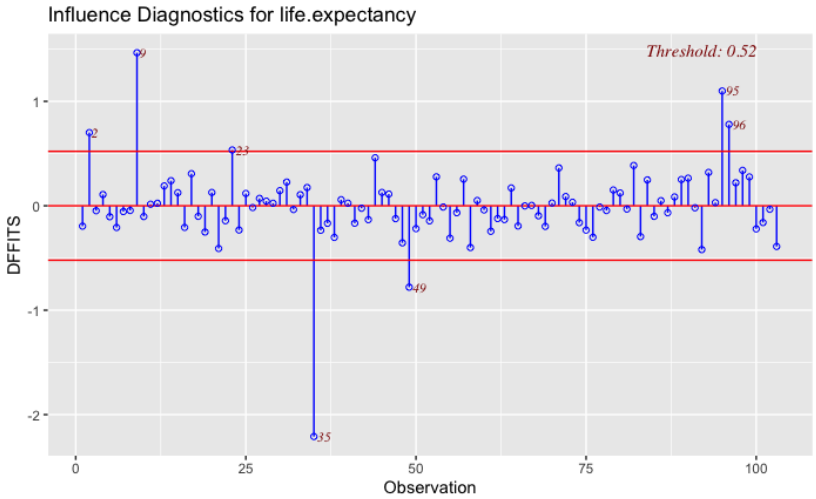

Figure 8 – *Plot of DFFITS vs observations. Outside the two red lines are the outliers influentials for their fitted values.*

Now, are they also influentials for the regression coefficients ? We find that the same **8** observations influentials for the fitted values are also influentials for the regression coefficients. We use the DFBETAS criterion for the i-th observation and k-th coefficient $\hat{\beta}_k$,

$$|\text{DFBETAS}_{k,i}| = \frac{\hat{\beta}_k}{\hat{\beta}_{k,i}} \text{MSE}_i \cdot c_k, \quad c_k = (X^TX)^{-1}_{kk} \tag{7}$$

We have a criterion for DFBETAS. The i-th observation is influential for the k-th coefficient if,

$$\text{DFBETAS}_{k,i} > \frac{2}{\sqrt{n}} \approx 0.197 \tag{8}$$

In the following plots, you can have a look at the differents outliers for each coefficient

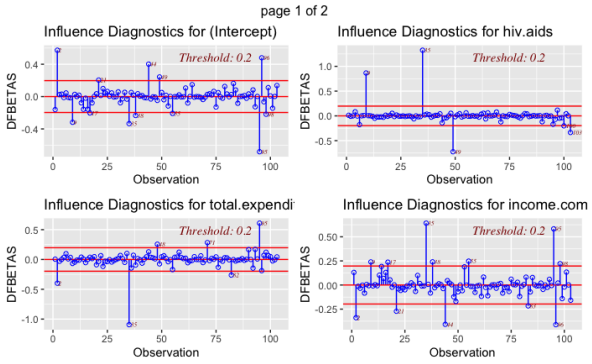

Figure 9 – *Plots of DFFITS vs observations. Outside the two red lines are the outliers influentials for the respective variable.*

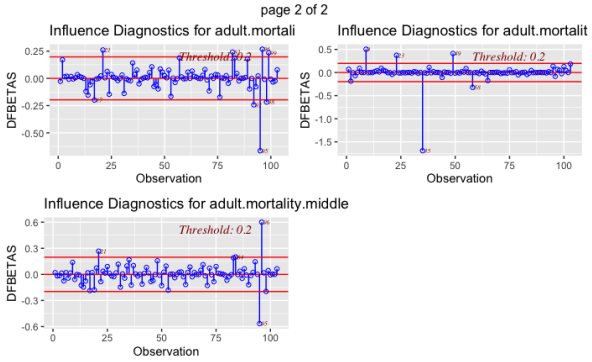

Figure 10 – *Plots of DFFITS vs observations. Outside the two red lines are the outliers influentials for the respective variable.*

To summarize this, let's have a look at the Cook's distance D_i.

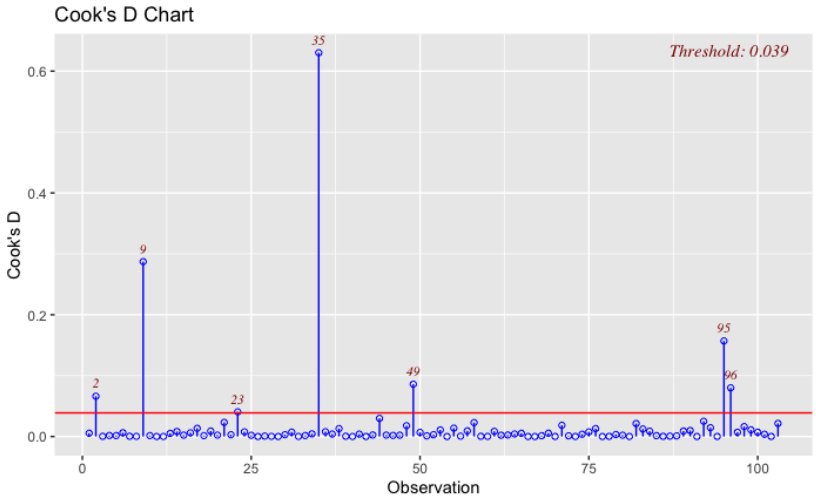

Figure 11 – *Cook's distance. Outside the red lines are the outliers influentials for the regression coefficients.*

b) outliers with respect to the response variable

We then identify outliers with respect to the response variable Y_i. Y_i is an outliers if $d_i^* > t_{n-p-1;1-\frac{\alpha}{2}}$. For a level of significance of $\alpha = 0.05$, we have $t_{94;0.975}$ and we find that the observations 2, 9, 95 and 96 are outliers for the response variable.

4.4.3 Multicollinearity

We verify now if we have any multicollinearity problem. We saw in the descriptive statistic section that some variables were highly correlated. These high pairwise correlations could lead to multicollinearity problem but it is not always the case.

Let the full model be,

$$Y = X\beta + \varepsilon \tag{9}$$

To check for multicollinearity, we can use the **Variance inflation factor (VIF)** that is defined by for the coefficient $\hat{\beta}_k$,

$$\text{VIF}_k = \frac{1}{1 - R_k^2}, \quad k = 1, ...p - 1 \tag{10}$$

where R_k^2 is the coefficient of determination of a regression of X_k on $X_1, \ldots, X_{k-1}, X_{k+1}, \ldots, X_{p-1}$. Multicollinearity leads to an "ill-conditionned" matrix X. As a consequence, this matrix is numerically instable and becomes difficult to invert. Therefore, the OLS estimator $\hat{\beta}$ cannot be "correctly" computed. We have multicollinearity problem if the **VIF** is greater than 10 and if the **average VIF** is much greater than 1. We can also check the tolerance which is $1 - R_k^2$.

Variation inflation factor (VIF) final model		
Variables	Tolerance	VIF
total.expenditure	0.86	1.17
hiv.aids	0.56	1.78
income.composition.of.resources	0.51	1.96
adult.mortality.low	0.65	1.55
adult.mortality.middle	0.75	1.34
adult.mortality.very_high	0.64	1.55

Figure 12 – *VIF for the selected model*

We notice we do not have any variable with a **VIF** > 10 so we do not have multicollinearity problem.

4.4.4 Heteroskedasticity

We can try to check for heteroskedasticity by looking at the plot of the residuals versus the fitted response variable.

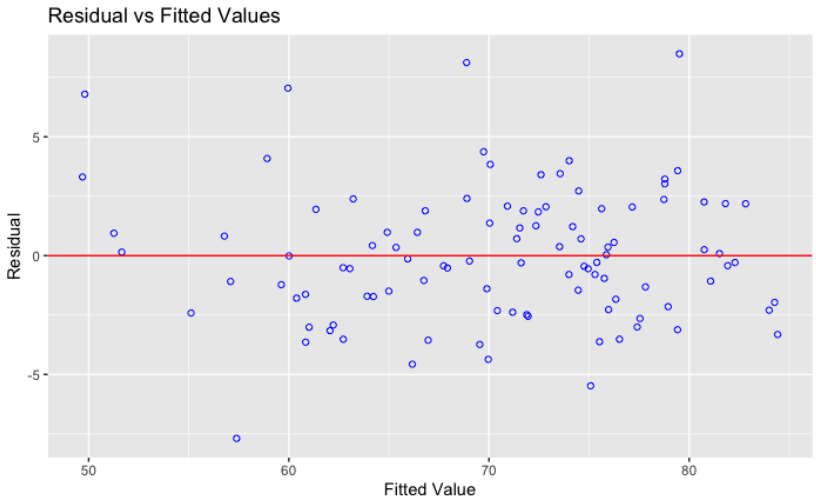

Figure 13 – *scatterplots of residuals versus fitted response variable*

However, it's not that clear with plot if there is heteroskedasticity problem or not. The best way to determinate if there is heteroskedasticity is to perform the **White test**. The hypothesis are,

$$H_0 : \text{there is homoskedasticity}$$

$$H_1 : \text{there is heteroskedasticity}$$

The result is,

```
        studentized Breusch-Pagan test

data:  final_lm
BP = 10.548, df = 6, p-value = 0.1034
```

Figure 14 – *Result of White test for homoskedastiscity*

The p-value of the **White test** is 0.1034. At a significance level of $\alpha = 0.05$, we can not reject the null hypothesis and therefore we can conclude that there is no **heteroskedasticity**.

4.4.5 Autocorrelation

We can check for autocorrelation by performing the **Breusch-Godfrey test**. The hypotheses are,

$$H_0 : \text{there is no autocorrelation}$$

$$H_1 : \text{there is autocorrelation}$$

```
        Breusch-Godfrey test for serial correlation of order up to 8

data:  final_lm
LM test = 10.783, df = 8, p-value = 0.2143
```

Figure 15 – *Result of Breusch-Godfrey test for autocorrelation*

The p-value of the **Breusch-Godfrey test** is 0.2143. At a significance level of $\alpha = 0.05$, we fail to reject the null hypothesis and therefore we can conclude there is **no autocorrelation**.

4.5 Normality of the residuals

Considering the Normal Q-Q plot of the residuals comparing the quantiles of the residuals versus the quantiles of a normal distribution. If the residuals are normal, the points on the following plot should follow the straight line,

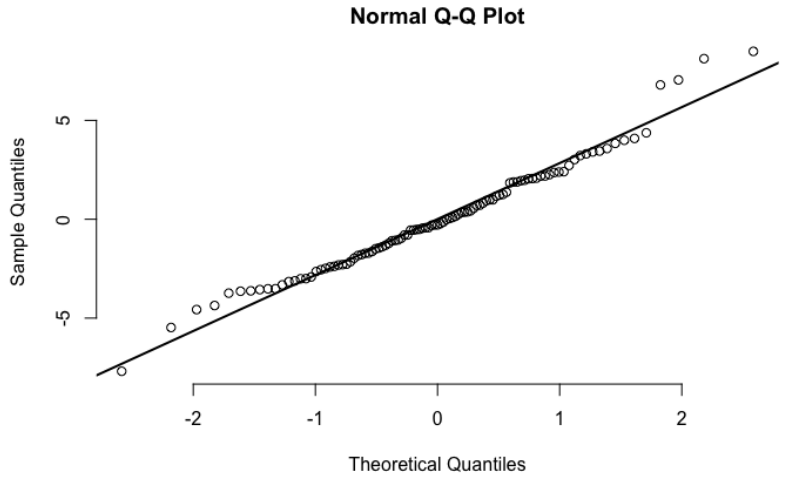

Figure 16 – *Normal QQ-plot*

Looking at this plot, we see that globally the points follow the straight line so the residuals are normals.

To ensure there is no a problem of normality for the residuals, we can perform a **Jarque Bera test**.

Let S be the skewness and κ of the residuals. The **Jarque Bera test** is given by,

$$\text{JB} = \frac{n}{6}\left(S^2 + \frac{(\kappa - 3)^2}{4}\right) \tag{11}$$

The hypothesis are,

$$H_0 : \text{JB} \sim X_2^2$$

$$H_1 : \text{residuals are not normally distributed}$$

```
        Jarque Bera Test

data:  final_lm$residuals
X-squared = 6.3201, df = 2, p-value = 0.04242
```

Figure 17 – *Result of Jarque-Bera test*

The p-value of the **Jarque Bera test** is 0.042. At a significance level of $\alpha = 0.05$, we fail to reject the null hypothesis and therefore we can conclude the **residuals are normaly distributed**.

5 Coefficients

Coefficients of the final model

term	estimate	std.error	statistic	p.value
(Intercept)	46.9234057	1.6548829	28.354518	1.903320e-48
total.expenditure	0.2611431	0.1206013	2.165342	3.283970e-02
hiv.aids	-1.0780480	0.2061631	-5.229102	9.950743e-07
income.composition.of.resources	33.6849505	2.5773667	13.069522	4.956676e-23
adult.mortality.low	3.6805535	1.1469092	3.209106	1.810698e-03
adult.mortality.middle	2.3088195	0.7402049	3.119163	2.394658e-03
adult.mortality.very_high	-5.0068839	1.4094384	-3.552396	5.937956e-04

Figure 18 – *Coefficients of the model*

Looking at the p-values, all the coefficients β_k are statistically significants at a significance level of $\alpha = 0.05$.

We can interpret the different coefficients the following way,

- An increase of 1% in the governement expenditure on health (as a percentage of total expenditure) leads to an increase of 0.26% of life expectancy.
- An increase of 1 death caused by HIV/AIDS for people under 5 years old per 1000 births leads to a decrease of 1.07/1000 of life expectancy.
- An increase of ...
- Having a low adult mortality leads to an incrase of 3.6 years of life expectancy.

- Having a middle adult mortalty leads to an increase of 2.3 years of life expectancy.
- Having a very high adult mortality leads to a decrease of 5 years of life expectancy.

6 Significance of estimated coefficients

We perform t-tests of estimated coefficients in order to test their significance. For t-tests, we use the following null and alternative hypotheses for each regression coefficient :

$$H_0 : \beta_i = 0$$

$$H_1 : \beta_i \neq 0$$

```
t test of coefficients:

                                 Estimate Std. Error t value  Pr(>|t|)
(Intercept)                      46.92341    1.65488 28.3545 < 2.2e-16 ***
Total.expenditure                 0.26114    0.12060  2.1653 0.0328397 *
HIV.AIDS                         -1.07805    0.20616 -5.2291 9.951e-07 ***
Income.composition.of.resources 33.68495    2.57737 13.0695 < 2.2e-16 ***
Adult.Mortality_low               3.68055    1.14691  3.2091 0.0018107 **
Adult.Mortality_middle            2.30882    0.74020  3.1192 0.0023947 **
Adult.Mortality_very.high        -5.00688    1.40944 -3.5524 0.0005938 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 19 – *Output of t-test of coefficients*

On the basis of the p-values, we can reject the null hypothesis for all the coefficients. We can conclude that all the coefficients are statistically significant at a level of significance of 10%. At a significance level of 5%, the "total expenditure" coefficient is no longer statistically significant.

On the basis of the estimates, we can say that the effect of low and middle adult mortality rates on life expectancy are positive while the effect of a very high adult mortality rate on life expectancy is negative and stronger. From the regression output, we see that the estimate of the regression coefficient for "Adult mortality very high" is -5.007. This signifies that on average, a country with a very high adult mortality rate has a life expectancy of 5 years less. On the contrary, a country with a low adult mortality rate has a life expectancy higher of 3 years on average and 2 years for a country with a moderate adult mortality rate.

7 Linear combination of coefficients

We want to test the hypothesis that there exists a linear combination between two regression coefficients :

$$\beta_4 = \beta_5$$

With this, we want to test if these two coefficients are equal. We can also write it as follow :

$$\beta_4 - \beta_5 = 0$$

We formulate the null and alternative hypotheses :

$$H_0 : \beta_4 - \beta_5 = 0$$

$$H_1 : \beta_4 - \beta_5 \neq 0$$

```
        Simultaneous Tests for General Linear Hypotheses

Fit: lm(formula = Life.expectancy ~ Total.expenditure + HIV.AIDS +
    Income.composition.of.resources + Adult.Mortality_low + Adult.Mortality_middle +
    Adult.Mortality_very.high, data = df_train)

Linear Hypotheses:
                                                 Estimate Std. Error t value Pr(>|t|)
Adult.Mortality_low - Adult.Mortality_middle == 0    1.372      1.090   1.259    0.211
(Adjusted p values reported -- single-step method)
```

Figure 20 – *Output of linear combination test*

Since the p-value (0.101) is larger than the significance level of 0.05, we fail to reject the null hypothesis that these two regression coefficients are equal. This signifies that a country with a low adult mortality rate and a country with a moderate adult mortality rate could have the same reduction in years of life expectancy if all the other effects remain constant.

8 Coefficients equal to zero

We test a subset of coefficients equal to zero. In this case, we test the coefficients corresponding to all qualitative variables equal to zero. Hence, the null and alternative hypotheses are the following :

$$H_0 : \beta_4 = \beta_5 = \beta_6 = 0$$

$$H_1 : \text{at least one of these is not equal to zero}$$

```
Wald test

Model 1: Life.expectancy ~ Total.expenditure + HIV.AIDS + Income.composition.of.resources +
    Adult.Mortality_low + Adult.Mortality_middle + Adult.Mortality_very.high
Model 2: Life.expectancy ~ Total.expenditure + HIV.AIDS + Income.composition.of.resources
  Res.Df Df      F    Pr(>F)
1     96
2     99 -3 8.1955 6.52e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 21 – *Output of Wald test*

The p-value is 0.0025 which is below the significance level of 0.05. We can thus reject the null hypothesis. We can conclude that there is sufficient statistical evidence that the different categorial variables corresponding to adult mortality rates explain life expectancy.

9 Prediction interval

We calculate a 95% prediction interval for the 26 observations excluded from the dataset in the beginning. We conclude that almost all the intervals cover the excluded observations. The last observation of the test dataset is the only one not covered by the corresponding 95% prediction interval. However, if we take the 99% prediction interval, this observation is contained in the prediction interval.

Appendix

Description of the different variables

The **response variable** is *life.expectancy*.

The **explanatory variables** are the following :

Economic factors :

- *status* : is the country **developping** or **developped**.
- *percentage.expenditure* : expenditure on health as percentage of gross domestic product (PIB in french) per capita (%).
- *total.expenditure* : general government expenditure on health as a percentage of total government expenditure (%).
- *gdp* : gross domestic product per capita ($).
- *income.composition.of.resources* : human development index (HDI) in terms of income composition of resources ($\in [0, 1]$).

Social factors

- *population* : total population of the country.
- *schooling* : number of years of schooling

Mortality factors :

- *adult.mortality* : probability of dying between 15 and 60 years old (**very low**, **low**, **middle**, **high**, **very high**).
- *under.five.deaths* : number of under five deaths per 1000 population.
- *infant.deaths* : number of infant deaths per 1000 population.
- *hiv.aids* : death per 1000 live births HIV/AIDS (between 0 and 4 years old).
- *thinness.5.9.years* : prevalence of thinness among children for age 5 to 9 years old (%).
- *thinness.10.19.years* : prevalence of thinness among children and adolescents for age 10 to 19 years old (%).

Immunization factors

- *hepatitis.b* : Hepatitis B immunization coverage among 1 year olds (%).
- *measles* : number of reported cases of measles per 1000 population.
- *polio* : Polio immunization coverage among 1 year olds (%).
- *diphtheria* : Diphteria tetanus toxoid and pertussis (DPT3) immunization coverage among 1 year olds (%)

Other factors

- *alcohol* : consumption of alcohol (15 years old or more) per capita (**in litres of pure alcohol**).
- *bmi* : average BMI of entire population.

Histograms and boxplots of the explanatory variables

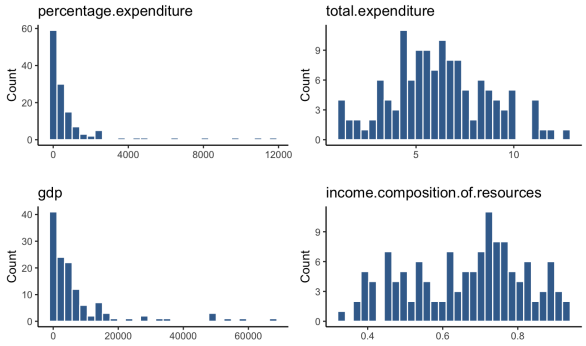

Figure 22 – *Histogram of economic features*

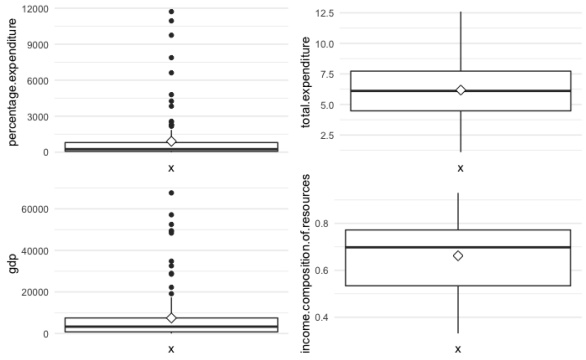

Figure 23 – *Boxplot of economic features*

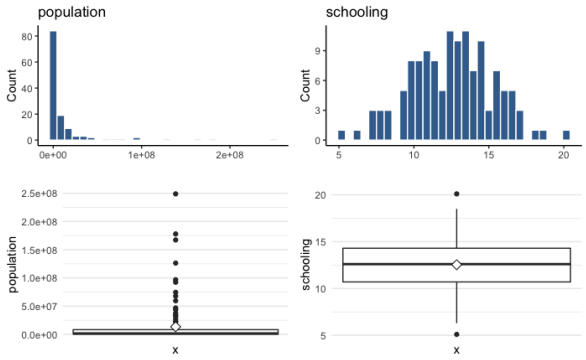

Figure 24 – *Histogram and boxplot of social features*

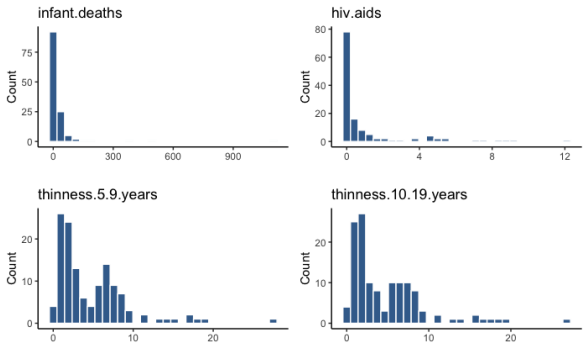

Figure 25 – *Histogram of mortality features*

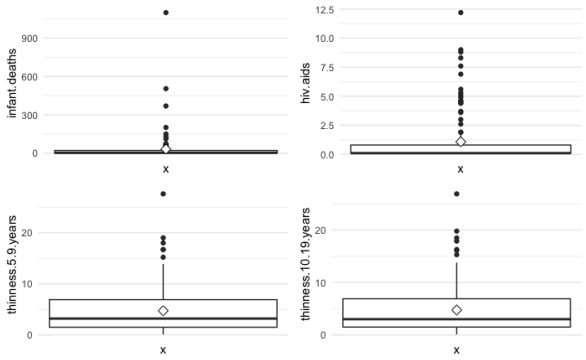

Figure 26 – *Boxplot of mortality features*

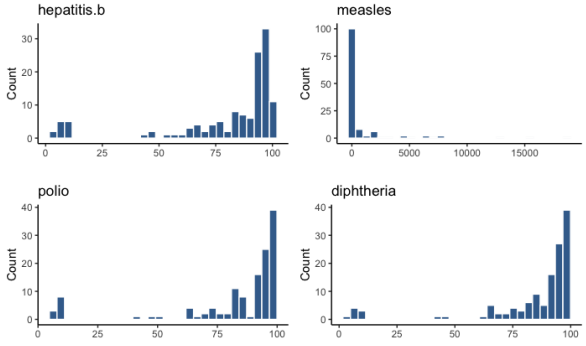

Figure 27 – *Histogram of health features*

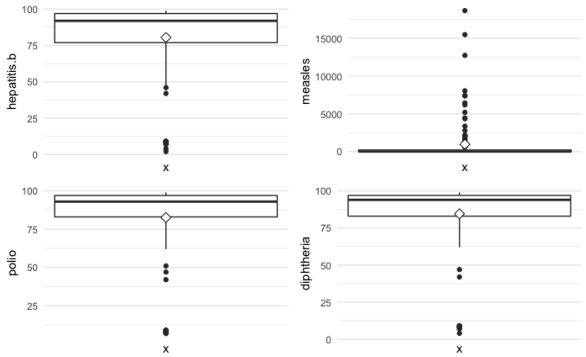

Figure 28 – *Boxplot of health features*

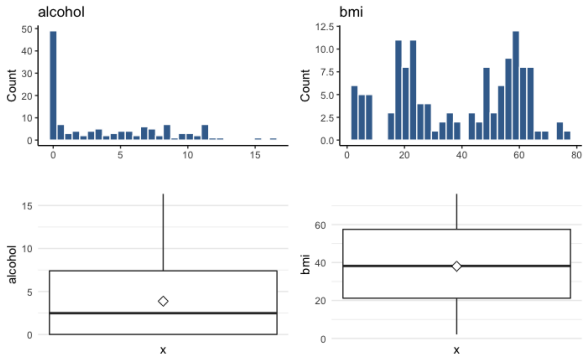

Figure 29 – *Histogram and boxplot of misc features*