

# Mixed Effects Model

Group

2023-12-01

```
library(glmnet)
```

```
## Loading required package: Matrix
```

```
## Loaded glmnet 4.1-8
```

```
library(knitr)
# library(lme4)
# library(glmnetLasso)
# library(MuMin)
library(dplyr)
```

```
##
```

```
## Attaching package: 'dplyr'
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
## filter, lag
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
## intersect, setdiff, setequal, union
```

```
# load data
```

```
data_clean <- read.csv("data/data_clean.csv")
```

```
# get relevant columns: HDI + ROLI overall factors and specific subfactors
```

```
cols <- c("hdi", "year", "country", "region", colnames(data_clean)[39:90])
```

```
# extract those columns -- not subsetting by year here
```

```
# remove summary factors
```

```
data <- data_clean[,cols] %>%
  select(-contains("factor"))
```

```
# remove any rows with NA --> all data
```

```
df <- data[complete.cases(data), ]
```

```
# data in most recent year - 2021
```

```
df1 <- df[df$year==2021,]
```

```
df1 <- subset(df1, select=-c(year))
```

Methods: - run using data in a singular year (choose 2021 because most recent year and largest sample size)  
 - choose obs from multiple years -> data on all countries available. we have 138 unique countries in dataset, all of them are in 2021 data -> this method is the same as the 1st method. - using the entire entire dataset

## 2021 data

```
# model with all variables
model1 <- lm(hdi~.-country, df1)

# backward selection
model2 <- step(model1, direction="backward", trace=0)

# intercept model
interceptModel <- lm(hdi~1, df1)

# interaction
interactionModel <- lm(hdi~.+region*., df1)

# forward selection
model3 <- step(interceptModel, scope = list(upper = formula(model1)),
               direction = "forward", trace=0)

# stepwise selection
model4 <- step(model2, scope = list(lower = formula(interceptModel),
                                   upper = formula(model1)),
               direction = "both", trace=0)

# # save models
# saveRDS(model1, file = "pred_models/model1.rds")
# saveRDS(model2, file = "pred_models/model2.rds")
# saveRDS(model3, file = "pred_models/model3.rds")
# saveRDS(model4, file = "pred_models/model4.rds")

# # load models
# model1 <- readRDS("pred_models/model1.rds")
# model2 <- readRDS("pred_models/model2.rds")
# model3 <- readRDS("pred_models/model3.rds")
# model4 <- readRDS("pred_models/model4.rds")

summary(model2)$coefficients
```

|  | Estimate     | Std. Error | t value    |
|--|--------------|------------|------------|
| ## (Intercept)                         | 0.509694469  | 0.04547983 | 11.2070451 |
| ## regionEastern Europe & Central Asia | 0.005897441  | 0.01688061 | 0.3493619  |
| ## regionEU + EFTA + North America     | -0.012872721 | 0.01569093 | -0.8203925 |
| ## regionLatin America & Caribbean     | -0.045068576 | 0.01640976 | -2.7464502 |
| ## regionMiddle East & North Africa    | -0.017151819 | 0.01978869 | -0.8667486 |
| ## regionSouth Asia                    | -0.073888332 | 0.02260764 | -3.2682908 |
| ## regionSub-Saharan Africa            | -0.150619434 | 0.01654687 | -9.1025953 |
| ## x1.2                                | -0.227275129 | 0.08801271 | -2.5822990 |
| ## x1.6                                | 0.087797953  | 0.05166268 | 1.6994463  |

```

## x3.1          0.129135778 0.03504139 3.6852353
## x3.2         -0.149050944 0.04906900 -3.0375789
## x3.3         -0.145717839 0.07348456 -1.9829721
## x3.4          0.120898221 0.04716749 2.5631686
## x4.1         -0.180057265 0.06579870 -2.7364865
## x4.3          0.286502180 0.07250075 3.9517135
## x4.5          0.066902605 0.04603193 1.4533955
## x5.2          0.042777430 0.02506700 1.7065236
## x5.3         -0.100964462 0.03643971 -2.7707261
## x6.1          0.160227455 0.06171116 2.5964097
## x7.3          0.263795201 0.04814000 5.4797506
## x7.4          0.176470031 0.07076616 2.4937066
## x7.5         -0.051738456 0.03073497 -1.6833742
## x7.7          0.097704399 0.06380498 1.5312974
## x8.3          0.061575186 0.04678093 1.3162455
## x8.4         -0.087533727 0.04990750 -1.7539192
## x8.6         -0.113444195 0.04795146 -2.3658134
##              Pr(>|t|)
## (Intercept)    5.253944e-20
## regionEastern Europe & Central Asia 7.274737e-01
## regionEU + EFTA + North America    4.137350e-01
## regionLatin America & Caribbean    7.021328e-03
## regionMiddle East & North Africa   3.879329e-01
## regionSouth Asia                    1.437163e-03
## regionSub-Saharan Africa            3.882660e-15
## x1.2                                1.110404e-02
## x1.6                                9.201098e-02
## x3.1                                3.537236e-04
## x3.2                                2.967656e-03
## x3.3                                4.981840e-02
## x3.4                                1.169811e-02
## x4.1                                7.223498e-03
## x4.3                                1.361531e-04
## x4.5                                1.489103e-01
## x5.2                                9.068192e-02
## x5.3                                6.550129e-03
## x6.1                                1.068340e-02
## x7.3                                2.653958e-07
## x7.4                                1.410275e-02
## x7.5                                9.508811e-02
## x7.7                                1.285156e-01
## x8.3                                1.907791e-01
## x8.4                                8.217975e-02
## x8.6                                1.970907e-02

```

```

# make tables
summary2021 <- data.frame("AIC" = c(AIC(model1),
                                   AIC(model2), AIC(model3), AIC(model4)),

                          "BIC" = c(BIC(model1),
                                   BIC(model2), BIC(model3), BIC(model4)),

                          "r.squared" = c(summary(model1)$r.squared,
                                           summary(model2)$r.squared,

```

```

summary(model3)$r.squared, summary(model4)$r.squared))
rownames(summary2021) <- c("all var", "backward selection", "forward selection", "stepwise")

# print table
kable(summary2021)

```

|                    | AIC       | BIC       | r.squared |
|--------------------|-----------|-----------|-----------|
| all var            | -459.2934 | -312.9307 | 0.9537182 |
| backward selection | -488.8380 | -409.8021 | 0.9478570 |
| forward selection  | -485.3319 | -409.2233 | 0.9457344 |
| stepwise           | -488.8380 | -409.8021 | 0.9478570 |

```

# get predictors
X = model.matrix(model2)[,-1]

# fit
ridge <- cv.glmnet(X, df1$hdi, alpha=0)
lasso <- cv.glmnet(X, df1$hdi, alpha=1)

ridge

```

```

##
## Call: cv.glmnet(x = X, y = df1$hdi, alpha = 0)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min 0.01207   100 0.001928 0.0002940      25
## 1se 0.03061    90 0.002220 0.0003403      25

```

```
lasso
```

```

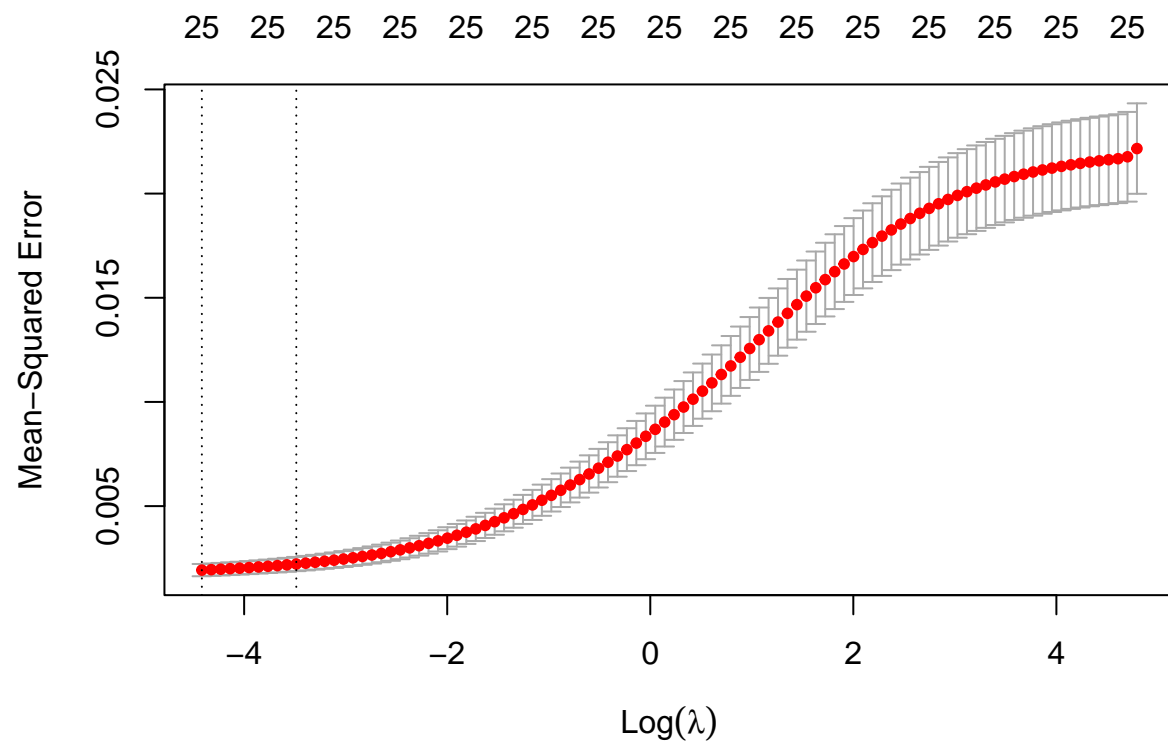
##
## Call: cv.glmnet(x = X, y = df1$hdi, alpha = 1)
##
## Measure: Mean-Squared Error
##
##      Lambda Index Measure      SE Nonzero
## min 0.0000644   82 0.001795 0.0003129      25
## 1se 0.0012648   50 0.002084 0.0003469      20

```

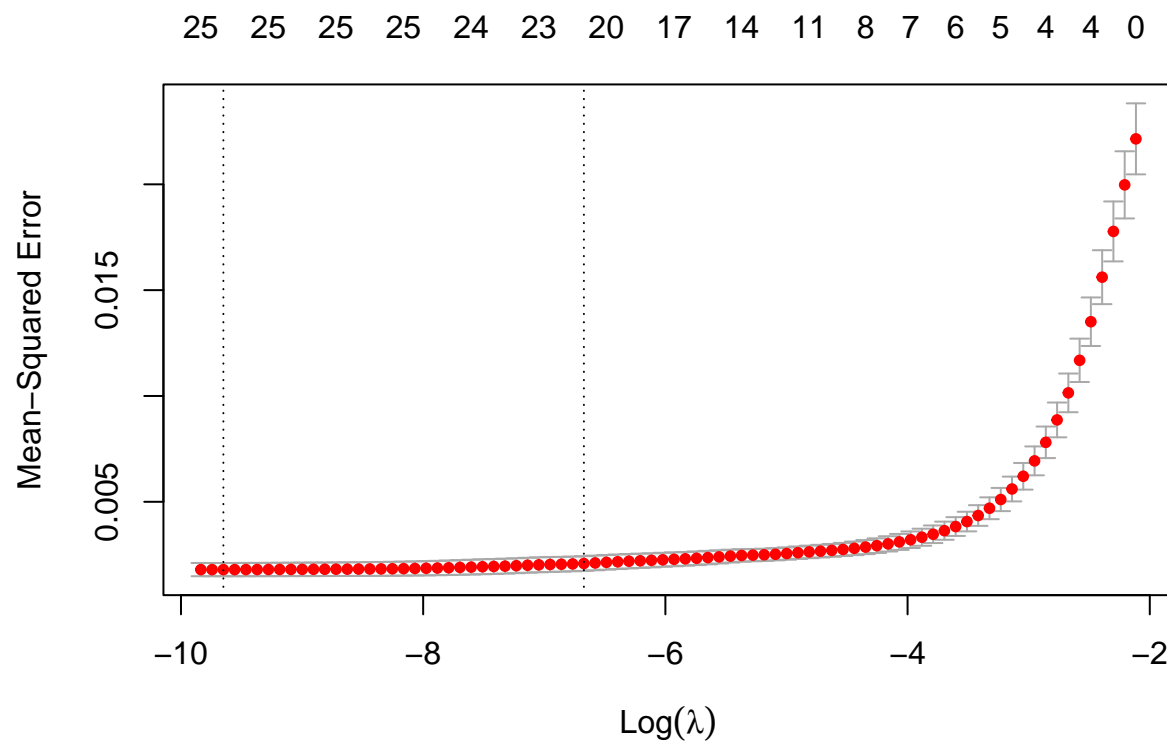
```

# plot
plot(ridge)

```



```
plot(lasso)
```



```
# best lambda
ridge$lambda.min
```

```
## [1] 0.01207299
```

```
lasso$lambda.min
```

```
## [1] 6.442994e-05
```

```
# get mse values
min(ridge$cvm)
```

```
## [1] 0.001928398
```

```
min(lasso$cvm)
```

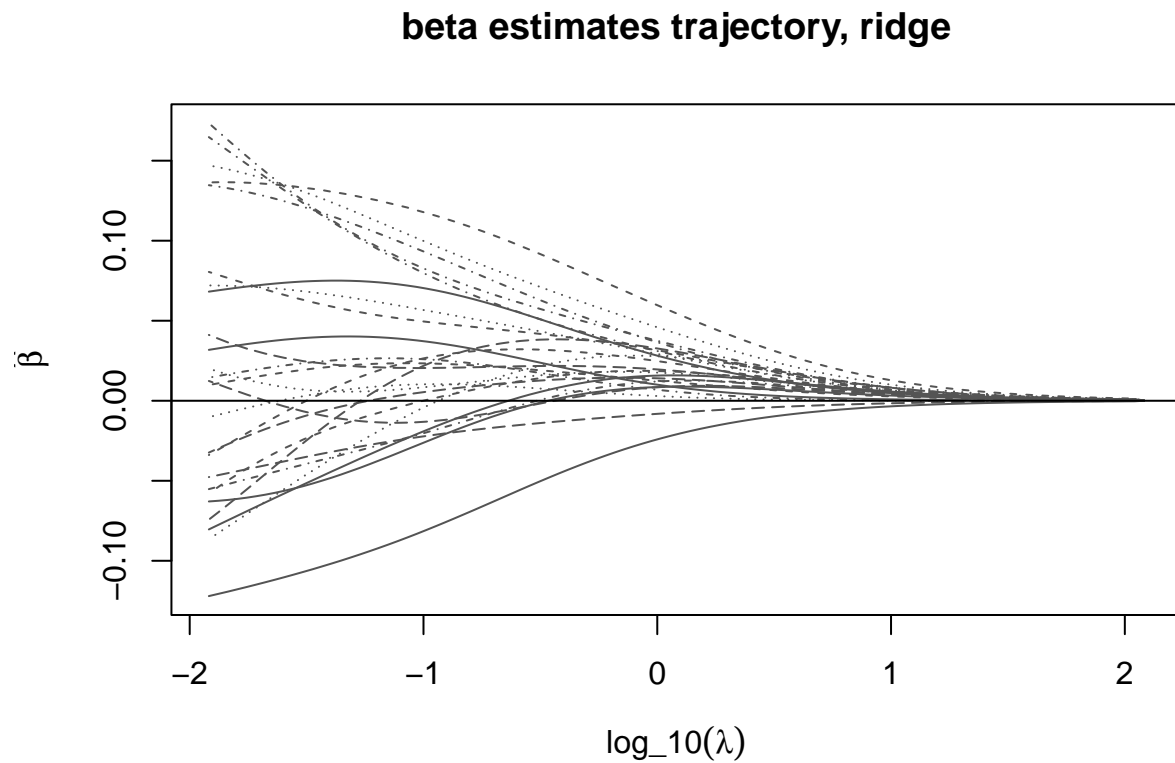
```
## [1] 0.001795371
```

```
# beta trajectories
matplot(log(ridge$glmnet.fit$lambda,10),
        t(ridge$glmnet.fit$beta),
        type="l",col="gray33",lwd=1,
        xlab=expression(log_10(lambda)),
```

```

ylab=expression(hat(beta)),
main="beta estimates trajectory, ridge")
abline(h=0)

```

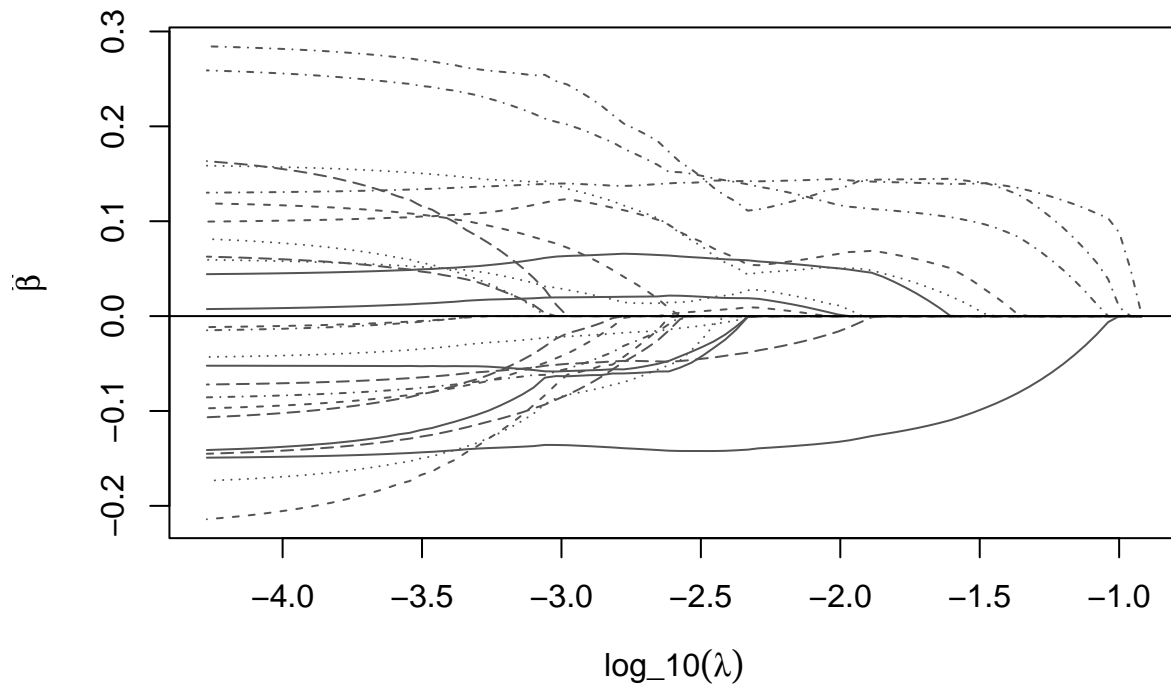


```

matplot(log(lasso$glmnet.fit$lambda,10),
        t(lasso$glmnet.fit$beta),
        type="l",col="gray33",lwd=1,
        xlab=expression(log_10(lambda)),
        ylab=expression(hat(beta)),
        main="beta estimates trajectory, lasso")
abline(h=0)

```

## beta estimates trajectory, lasso



```
best_lasso <- glmnet(x=subset(df,select=-hdi), y=df$hdi, lambda=lasso$lambda.min)
coef(best_lasso)
```

```
## 48 x 1 sparse Matrix of class "dgCMatrix"
##
## (Intercept) 0.5568561921
## year -0.0011816220
## country 0.0001412369
## region -0.0247041138
## x1.1 0.0004458603
## x1.2 -0.1201170037
## x1.3 0.0234750712
## x1.4 -0.1755269929
## x1.5 0.0034371081
## x1.6 0.0646162587
## x2.1 0.0988601402
## x2.2 0.0033237669
## x2.3 0.0391652592
## x2.4 -0.0405615287
## x3.1 0.1167591850
## x3.2 -0.0236075927
## x3.3 -0.0995309096
## x3.4 0.1023867705
## x4.1 -0.0661349071
## x4.2 0.0247504196
```



```
## x4.3 0.3104562519
## x4.4 .
## x4.5 -0.0778113987
## x4.6 -0.0311902398
## x4.7 -0.0300071961
## x4.8 0.0106856804
## x5.1 -0.0004840530
## x5.2 0.0282273123
## x5.3 -0.0884538363
## x6.1 0.2467080785
## x6.2 .
## x6.3 -0.0411646745
## x6.4 0.0168579509
## x6.5 -0.0579930355
## x7.1 0.1054108244
## x7.2 -0.0432727159
## x7.3 0.2817190226
## x7.4 0.0576878977
## x7.5 -0.0501633418
## x7.6 0.0394606365
## x7.7 0.0205498939
## x8.1 -0.0303229100
## x8.2 -0.0119293846
## x8.3 0.0351309788
## x8.4 -0.0455678605
## x8.5 -0.1142080204
## x8.6 -0.0023784042
## x8.7..due.process.of.the.law.and.rights.of.the.accused .
```

```
remaining_lasso <- glmnet(x=subset(df,select=-hdi), y=df$hdi, lambda=0.05011872)
coef(remaining_lasso)
```

```
## 48 x 1 sparse Matrix of class "dgCMatrix"
## s0
## (Intercept) 0.6266328572
## year .
## country .
## region -0.0113137262
## x1.1 .
## x1.2 .
## x1.3 .
## x1.4 .
## x1.5 .
## x1.6 .
## x2.1 .
## x2.2 0.0308178138
## x2.3 0.1071129425
## x2.4 .
## x3.1 0.0730543746
## x3.2 .
## x3.3 .
## x3.4 .
## x4.1 .
## x4.2 .
```

```
## x4.3 0.0830521785
## x4.4 .
## x4.5 .
## x4.6 .
## x4.7 .
## x4.8 .
## x5.1 .
## x5.2 .
## x5.3 .
## x6.1 .
## x6.2 .
## x6.3 .
## x6.4 .
## x6.5 .
## x7.1 .
## x7.2 .
## x7.3 .
## x7.4 .
## x7.5 .
## x7.6 .
## x7.7 .
## x8.1 .
## x8.2 .
## x8.3 .
## x8.4 .
## x8.5 .
## x8.6 .
## x8.7..due.process.of.the.law.and.rights.of.the.accused 0.0007588301
```

```
best_ridge <- glmnet(x=subset(df,select=-hdi), y=df$hdi, lambda=ridge$lambda.min)
coef(best_ridge)
```

```
## 48 x 1 sparse Matrix of class "dgCMatrix"
## s0
## (Intercept) 5.532716e-01
## year .
## country .
## region -2.444478e-02
## x1.1 .
## x1.2 .
## x1.3 .
## x1.4 .
## x1.5 .
## x1.6 .
## x2.1 .
## x2.2 1.046325e-01
## x2.3 2.155684e-02
## x2.4 .
## x3.1 1.071083e-01
## x3.2 .
## x3.3 .
## x3.4 8.658088e-03
## x4.1 .
## x4.2 1.735460e-02
```

```
## x4.3 3.810274e-07
## x4.4 .
## x4.5 .
## x4.6 .
## x4.7 .
## x4.8 .
## x5.1 .
## x5.2 .
## x5.3 .
## x6.1 5.487182e-02
## x6.2 .
## x6.3 .
## x6.4 .
## x6.5 .
## x7.1 9.679583e-02
## x7.2 .
## x7.3 4.179879e-02
## x7.4 .
## x7.5 .
## x7.6 .
## x7.7 .
## x8.1 .
## x8.2 .
## x8.3 .
## x8.4 .
## x8.5 .
## x8.6 .
## x8.7..due.process.of.the.law.and.rights.of.the.accused 6.814420e-02
```

```
lambda_values <- seq(from = 1e-04, to = 10^4, length.out = 5000)
bic_values <- numeric(length(lambda_values))
X <- model.matrix(model2)[,-1]
Y <- df1$hdi

for (i in seq_along(lambda_values)) {
  # Using glmnet for Lasso Regression
  lasso_model <- glmnet(X, df1$hdi, alpha = 1, lambda = lambda_values[i])

  # Calculate BIC
  rss <- sum((predict(lasso_model, newx = X, s = "lambda.min") - Y)^2)
  n <- length(Y)
  k <- sum(coef(lasso_model, s = "lambda.min") != 0)
  bic_values[i] <- n * log(rss / n) + k * log(n)
}

# Find the index of the minimum BIC value
best_lambda_index <- which.min(bic_values)
best_lambda <- lambda_values[best_lambda_index]

# Fit the final Lasso Regression model using the selected lambda
final_lasso_model <- glmnet(X, Y, alpha = 1, lambda = best_lambda)

# Display results
best_lambda
```

```
## [1] 1e-04
```

```
coef(final_lasso_model, s = "lambda.min")
```

```
## 26 x 1 sparse Matrix of class "dgCMatrix"
##                                     s1
## (Intercept)                      0.501958870
## regionEastern Europe & Central Asia 0.008179147
## regionEU + EFTA + North America    -0.010605432
## regionLatin America & Caribbean    -0.041620126
## regionMiddle East & North Africa   -0.013691624
## regionSouth Asia                   -0.070478397
## regionSub-Saharan Africa           -0.147855175
## x1.2                               -0.210204952
## x1.6                               0.077617775
## x3.1                               0.130081058
## x3.2                               -0.142562221
## x3.3                               -0.136821314
## x3.4                               0.116362845
## x4.1                               -0.170257590
## x4.3                               0.285499749
## x4.5                               0.060377702
## x5.2                               0.044446400
## x5.3                               -0.095787682
## x6.1                               0.158889079
## x7.3                               0.259012162
## x7.4                               0.158594980
## x7.5                               -0.051809311
## x7.7                               0.099087641
## x8.3                               0.057964655
## x8.4                               -0.086054714
## x8.6                               -0.105283458
```