STAT 340 Final Report

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Contents

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Abstract

The data that we analyzed throughout the semester is the World Development Indicators dataset, collected by the World Bank and published to Kaggle. This dataset includes 1,344 different indicators for 247 countries between 1960 to 2015, although much of the data is missing. The indicators cover a wide range of economic, health, and assorted other metrics. We chose to investigate these indicators to find which ones have the greatest impact on a country's economic strength, which we defined as GDP per capita. We first refined the data we worked with to only include 107 countries and 76 indicators, which minimized the amount of missing data. After implementing a LASSO regression model, we found that some of the most important indicators are CO2 emissions, adolescent fertility rate, and urban population growth. Through k-means clustering we then found that there was definite clustering behavior. Multiple models were then developed to try to predict a country's GDP. Between LASSO regression and linear regression after PCA, the two models had very similar mean sum square errors, but the R^2 value for the LASSO regression model with the optimal lambda was significantly better.

Dataset

Our analysis used the World Development Indicators dataset (link). We accessed the dataset from Kaggle which included a cleaned version of the raw data from The World Bank (link). It includes two files. The first is Country.csv, which includes a row for each of the 247 countries present in the dataset, along with the country's name, code, currency, and region. The second file, Indicators.csv, contains a comprehensive list of over 1,300 indicators related to economic development, health, and more. Some of these indicators include GDP per capita, unemployment rate, adolescent fertility rate, and urban population. Indicators for years between 1960 and 2015 are present, although not every combination of country, indicator, and year is available. More than 70% of the total data is missing, so careful consideration will be taken when choosing what countries, indicators, and years to analyze.

The data was compiled by the World Bank, an international financial organization that provides support for lower-income countries. They track the indicators found in this dataset and compile them for anayone to use. Our group was drawn to this dataset because of its importance and relevance. The indicators included comprise some of the most discussed and debated inequalities between countries. While we cannot solve these inequalities just by looking at data, we are excited to investigate and identify prominent relationships between features.

Variables

With 1,344 total unique indicators there are too many to name them all, but we will focus on a handful of them. For our economic analysis, we will use `GDP_per_capita_(current_US$)`, which is a country's economic output per citizen adjusted to the United States Dollar currency. There are many variations of GDP in the dataset, but GDP per capita is commonly used to compare the economic states of different countries, so we will use that one. A couple of variables that we expect impact a country's economic strenght are unemployment rate, `Unemployment,_total_(%_of_total_labor_force)`, and relative military expenditure, `Military_expenditure_(%_of_GDP)`.

Of the health indicators, one variable we will look at is `Adolescent_fertility_rate_(births_per_1,000_women_ages_15-19` Adolescent fertility rate is the rate of births per 1,000 women aged 15-19 years old, and is often used as a healthcare metric, so we expect it to be related to GDP per capita. Another indicator that we expect to impact GDP per capita is `Population_ages_65_and_above_(%_of_total)`, the percent percent of citizens 65 years or older. Other metrics related to health that we expect to find important include those related to health expenditure, `Health_expenditure,_total_(%_of_GDP)`, and life expectancy, `Life_expectancy_at_birth,_total_(years)`.

Many other assorted metrics are included in the dataset. Environmental metrics such as CO2 emmisions, `CO2_emissions_(metric_tons_per_capita)`, will be interesting to investigate against economic metrics. Other indicators we expect to correlate with economic strength are internet users, `Internet_users_(per_100_people)`, and urban population, `Urban_population_(%_of_total)`, although plenty of indicators not mentioned here will also be analyzed.

Statistical Question

The vast amount of data meant that there was a lot to explore, but we decided to focus on answering the following questions:

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1. What indicators have the greatest impact on a country's GDP per capita?
2. When predicting a country's GDP per capita, how do LASSO regression and linear regression with PCA applied compare?

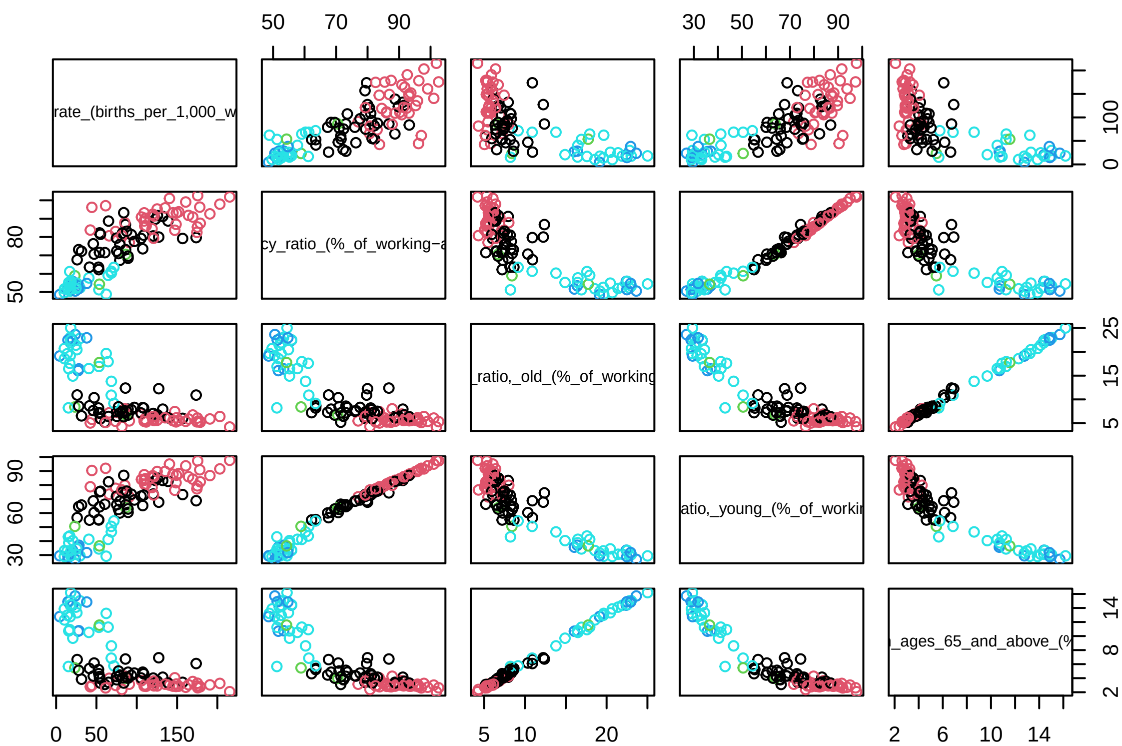
For our first statistical question, given the various metrics we have in our data, we thought it would be interesting to see how different factors impact a country's GDP per capita since that is a relatively prominent indicator of a country's economic health. We chose to use GDP per capita as the deciding metric for comparison since it gives information about the size of the economy and how an economy is performing. The growth rate of GDP is often used as an indicator of the general health of the economy, so in a broader sense, an increase in real GDP is interpreted as a sign that the economy is doing well.

Our second statistical question delves into the relationship between the indicators we are looking for and GDP. We wanted to find out if we could use the indicators we found to predict a country's GDP because, hypothetically, we could be able to use the most impactful metrics that impact a country's economy to predict how much, and to what extent that impact would be. Along with this, since the end goal of us asking this question is to derive a successful GDP model predictor, we also wanted to look into if using the most impactful indicators is the best metric for prediction by comparing the results of that model with other prediction methods such as dimensionality reduction.

Analysis

PCA & Clustering

The first step of our analysis was refining our dataset to get it into a form where we could easily implement our models. The data was initially organized so that every combination of Country, Year, and Indicator was its own row, and a significant amount of data was missing. Our first attempt at solving this issue was to reduce the dimensionality of the data using Principal Component Analysis. We found a linear model using the first five principal components and tried finding clustering patterns within the data. The plot below shows that there were three fairly distinct clusters, but based on the feedback on our progress reports and our own discussions, we realized that we had strayed off topic and were not actually addressing our statistical questions, so we scrapped that approach. More information on that approach can be found in Appendix 1.



We then started from scratch with the original dataset. We underwent an iterative process to minimize the amount of missing data by selectively removing certain countries and indicators. We then aggregated each indicator as a mean over all years and pivoted the indicators to columns, so that our final dataset consisted of one row for each remaining country. A more in-depth explanation of the data cleaning process can be found in Appendix 1. At this point we were left with 107 countries and 76 indicators, and were ready to start implementing models for finding the most important indicators.

LASSO Regression

To find the indicators that have the greatest impact on a country's GDP we used LASSO regression. We did this so that we could filter out indicators that did not correlate well with a country's GDP. Furthermore, LASSO was chosen instead of other methods because it sets coefficients to 0, which is what we want since we're doing variable selection. The first step for doing this was to find the lambda parameter that optimized the model. We tried optimizing lambda based on both mean squared error and R^2. We found that for mean squared error, a lambda value of 100 was the best, and for R^2, 1,000 was the best. We then found the most important coefficients for each model, which gave us the same predictors. The most important predictors were adolescent fertility rate, urban population growth, and CO2 emissions in tons per capita. Others included population density, agricultural land as a percentage of land area, and merchandise trade as a percentage of GDP. A full table with the important indicators can be found in Appendix 2.

Some takeaways can be made from these findings. Clearly, there are a very diverse group of factors that impact a country's GDP, covering many different sectors. The coeficient of adolescent fertility rate was -11,862. The fact that this number was negative indicates that countries where teenage pregnancy is widespread tend to have lower economic strength. This finding is expected, as healthcare such as birth control are likely to be more available in richer countries.

The coefficient for urban population growth was 530. Countries with high urban population growth are spending significant amount of money developing their larger cities. It is intuitive that a country spending money developing urban areas has more money to spend, as evidenced by their high GDP per capita.

Finally, the coefficient for CO2 emissions was 664. In this case, this number is suggesting that more industrialized countries have higher GDPs. More economically strong countries are likely to build many factories and have more citizens driving cars, and therefore will have higher CO2 emissions. All of these results are fairly expected, but our research shows that these specific indicators are especially important.

LASSO vs PCA Accuracy

While we used a LASSO regression model to answer our first statistical question, there are a number of different models that we could have chosen. That decision led us to investigate how well a different model would work for predicting a country's GDP. We decided to also build a linear regression model using PCA to compare the two The metrics that we compared them on were mean sum of squares (MSS) error and R^2 score, and we found these metrics by performing cross validation with 5 folds on each model. Our PCA model was built by using the first five principal components in a linear regression. The values that we found are shown in the tables below. The MSE values were similar for both models, but for the LASSO regression model, one choice of lambda (1000) was able to achieve a significantly higher R^2 value of 0.94.

The table below shows scores of our LASSO regression model using different values of lambda. For each lambda, the resultant scores were obtained using k-fold cross validation.

LASSO Regression Accuracy

```
## # A tibble: 8 x 4
##   lambda   mse      rmse    r2
##    <dbl> <dbl>     <dbl> <dbl>
## 1   1000 4985. 24849698. 0.948
## 2    500 4797. 23007333. 0.680
## 3      0 4773. 22778879. 0.501
## 4      1 4772. 22774375. 0.502
## 5      2 4772. 22769898. 0.502
## 6      5 4770. 22756628. 0.503
```

```
## 7     10 4768. 22735046. 0.504
## 8    100 4739. 22462755. 0.528
```

The table below show the resultant scores of our PCA-linear regression model which uses the first five principal components of our data.

Linear model on PCA Accuracy

```
## # A tibble: 1 x 3
##      r2      rmse   mse
##   <dbl>     <dbl> <dbl>
## 1 0.501 22776755. 4772.
```

Conclusion

We can take away a few conclusions from the analysis that we performed. First, it is clear that different indicators impact a country's GDP to varying extents. Some of the most important indicators are adolescent fertility rate, urban population growth, and CO2 emissions per capita. CLearly, indicators spanning health and economic fields are relevant to country's GDPs. We also found that indicators can be used to predict GDP fairly well. LASSO regression was the most successful model for doing so, but linear regression using PCA was not far behind in terms of MSE scores.

While we are pleased with our findings, there were multiple issues that we dealt with that could have impacted our results. The enormous amount of missing data led to us having to remove nearly half the countries and the majority of available indicators. We also ended up performing regression with 107 rows and 76 columns, which is far from ideal. More sophisticated approaches could be tried in the future to address these problems. Rather than removing missing data, more research could be done to fill in the data. Much of what was missing from our dataset likely could have been found through additional research, but that simply was not realistic for us to pursue. If we had not needed to remove half of our countries, our regression results would have been more meaningful.

Appendix

Appendix 1: Data Cleaning

The problem

One challenge we faced was cleaning our data. The data was provided by The World Bank, which aggregated this data from multiple sources such as global studies or national surveys. Due to the nature of how our data was collected, there were many missing values in our dataset. We assume this is because national surveys are not standardized across countries and time, and most of the data sources didn't exist for the entirety of the time range of 1960 to 2015.

Take for example this code snippet. We look at our original data and find that given that each observation was uniquely identified by a `Country`, `Indicator`, `Year` combination, we have `68.68254` percent of our data is missing values. We didn't notice this at first because the missing data was implicit in the original dataset, there simply wouldn't be a `Country`, `Indicator`, `Year` combination if that value didn't exist for some year or country.

```r
# Calculating proportion of missing values:
p_missing_ <- function(d) {
  mvt <- table(is.na(d))
  mvt[2] / (mvt[1] + mvt[2])
}
```

```r
ind2 <- ind2_orig
tibble(proportion_missing_values = p_missing_(ind2))
```

```
## # A tibble: 1 x 1
##   proportion_missing_values
##                       <dbl>
## 1                     0.687
```

In addition, almost all the indicators had this issue. Of the 1344 indicators, only 29 had less than 10% missing values and only 652 had less than 50% missing values.

```r
max_percent_missing <- 0.1
n_ind_lt_10 <- sapply(ind2, function(x) sum(is.na (x))) %>%
  as.data.frame() %>%
  select(., everything()) %>%
  arrange(-desc(.)) %>%
  filter(. / 13823 < max_percent_missing) %>% nrow()

ind2 <- ind2_orig
max_percent_missing <- 0.5
n_ind_lt_50 <- sapply(ind2, function(x) sum(is.na (x))) %>%
  as.data.frame() %>%
  select(., everything()) %>%
  arrange(-desc(.)) %>%
  filter(. / 13823 < max_percent_missing) %>% nrow()

tibble(
  max_percent_missing = c(10, 50),
  num_indicators = c(n_ind_lt_10, n_ind_lt_50),
  proportion_of_indicators = c(n_ind_lt_10 / ind2 %>% nrow() * 10, n_ind_lt_50 / ind2 %>% nrow() * 10),
)
```

```
## # A tibble: 2 x 3
##   max_percent_missing num_indicators proportion_of_indicators
##                 <dbl>          <int>                    <dbl>
## 1                  10             29                   0.0285
## 2                  50            652                   0.640
```

No country had less than 50% of missing values.

```r
n_year <- ind2$Year %>% unique() %>% length()
n_ind <- (ind2 %>% ncol() - 2) # CountryName and Year don't count
n_d <- n_ind * n_year

ind2 <- ind2_orig

obs_counts <- ind %>%
  group_by(CountryName) %>%
  summarise(
    n = n()
  )

ind2 %>%
  group_by(CountryName) %>%
  select(-Year) %>%
  summarise_all(funs(sum(is.na(.)))) %>%
```

```r
  mutate(
    p_missing = select(., -CountryName) %>% rowSums() / n_d
  ) %>% select(
    CountryName,
    p_missing
  ) %>%
  full_join(obs_counts) %>%
  arrange(-desc(p_missing))
```

```
## Joining, by = "CountryName"
```

```
## # A tibble: 182 x 3
##    CountryName p_missing     n
##    <chr>           <dbl> <int>
##  1 Mexico          0.505 37244
##  2 Colombia        0.505 37227
##  3 Philippines     0.510 36912
##  4 Peru            0.511 36815
##  5 Costa Rica      0.516 36457
##  6 Thailand        0.517 36355
##  7 Morocco         0.518 36275
##  8 Indonesia       0.518 36252
##  9 Malaysia        0.523 35874
## 10 Turkey          0.524 35819
## # ... with 172 more rows
```

The solution

Our goal was to reduce the proportion of our data that was missing values while still keeping a significant number of observations. Recall that each observation was uniquely identified by a `Country`, `Indicator`, `Year` combination. Because of this, we decided to remove a combination of countries and indicators that would remove the most missing values.

We had decided not to remove Years because we wanted to maintain that temporal data and thought there might be interesting insights based on time. We ended up not going down this route. Therefore, if we had more time we would also remove some range of Years if it would help us maintain more indicators or countries as a result.

Also in this step we filtered our countries to only be those included in another external list of country names because there were a few territories included in this list

```r
country <- read_csv("data/Country.csv", col_types = cols())
ind <- read_csv("data/Indicators.csv", col_types = cols())

# Each observation is uniquely identified by CountryName/CountryCode, IndicatorName/IndicatorCode, Year

names <- read_tsv("world-country-names.tsv", col_types = cols())
data_names <- names$name
ind_names <- ind$CountryName %>% unique()
overlap_names <- intersect(ind_names, data_names)

ind <- ind %>%
  mutate(IndicatorName = str_replace_all(IndicatorName, " ", "_"))

# remove Channel Islands explicitly because it has a missing year
ind <- ind %>% filter(CountryName != "Channel Islands") %>% filter(CountryName %in% overlap_names)
```

```r
# pivot wider to add missing values
ind2 <- ind %>%
  select(CountryName, IndicatorName, Year, Value) %>%
  pivot_wider(names_from = IndicatorName,
              values_from = Value,
              values_fill = NA)

# Number of missing values for each indicator
max_percent_missing <- 0.2

# Filter to only have indicators that have less than max_percent_missing percent of missing values
sapply(ind2, function(x)
  sum(is.na (x))) %>%
  as.data.frame() %>%
  select(., everything()) %>%
  mutate(p_missing = . / 13823) %>%
  arrange(-desc(.)) %>%
  filter(p_missing < max_percent_missing) %>%
  invisible()

filtered_indicators <- sapply(ind2, function(x)
  sum(is.na (x))) %>%
  as.data.frame() %>%
  select(., everything()) %>%
  mutate(p_missing = . / 13823) %>%
  arrange(-desc(.)) %>%
  filter(p_missing < 0.5)

filtered_indicators <- filtered_indicators %>% row.names()
filtered_indicators <-
  filtered_indicators[filtered_indicators != "Year"]

# Number of filtered indicators
# filtered_indicators %>% length()
# 651

# Number of missing values per country
total_num_data_ideally <-
  (ind2 %>% colnames() %>% length() - 2) * 56 # CountryName and Year don't count
max_percent_missing <- 0.1

good_countries <- ind2 %>%
  group_by(CountryName) %>%
  select(-Year) %>%
  summarise_all(funs(sum(is.na(.)))) %>%
  mutate(p_missing = select(.,-CountryName) %>% rowSums() / total_num_data_ideally) %>% select(CountryNa
  filter(p_missing < 0.7)

ind3 <- ind2 %>%
  filter(CountryName %in% good_countries$CountryName)

my_row_names <- sapply(ind3, function(x)
  sum(is.na (x))) %>%
```

```r
  as.data.frame() %>%
  select(., everything()) %>%
  row.names()

chosen_indicators_ <- sapply(ind3, function(x)
  sum(is.na (x))) %>%
  as.data.frame() %>%
  select(., everything()) %>%
  mutate(names = my_row_names) %>%
  mutate(p_missing = . / 13823) %>% # removes rownames on oat
  arrange(-desc(.)) %>%
  filter(p_missing < max_percent_missing)
chosen_indicators <- chosen_indicators_$names
```

```r
ind4 <- ind3 %>%
  select(CountryName, Year, all_of(chosen_indicators))

# Now the proportion of missing values is much less at `r p_missing_(ind4)`.
# We want to have some fraction of countries we remove and some fraction of indicators we remove such t

ind5 <- ind4 %>% group_by(CountryName) %>%
  select(-Year) %>%
  summarise_all(funs(mean(., na.rm = TRUE)))

# impute values
for (i in 2:ncol(ind5)) {
  ind5[is.na(ind5[, i]), i] <- lapply(ind5[, i], mean, na.rm = TRUE)
}
```

The following table summarizes the results of our data cleaning (excluding imputation). We were able to reduce the number of missing values but still keep a significant amount of observations. We went from `68.68254` percent of the data being missing values to only `10.68711` percent, while still maintaining `5992` (58.7912088 percent) of the observations.

While we deemed this satisfactory and moved on with our analysis, we know it probably wasn't the optimal choice of countries and indicators dropped. We did a bunch of testing and ended up first dropping all indicators with more than 20% missing values and then countries with more than 10% missing values. The optimal solution would probably to have alternated between dropping indicators and countries by dropping the indicator or country that contained the most missing values and alternating until some threshold of missing values or number of observations were met. Also, as mentioned before, we could have considered dropping some years as well. Ideally, given more time, we would have implemented this.

```r
# After all that, we have a new dataset that has much less missing values.
tibble(
  label = c("Before", "After"),
  p_missing = c(p_missing_(ind2), p_missing_(ind4)),
  n_obs = c(ind2 %>% nrow(), ind4 %>% nrow())
)
```

```
## # A tibble: 2 x 3
##   label  p_missing n_obs
##   <chr>      <dbl> <int>
## 1 Before    0.687  10192
## 2 After     0.0576  5992
```

Appendix 2: Table of Indicator Coefficients

Below are the coefficients that were found for the predictors using LASSO. As shown, the output is a sparse matrix, with many predictors having coefficients 0, as LASSO eliminated them.

```r
mse_results <- results %>% arrange(-mse) %>% tail(1)
r2_results <- results %>% arrange(r2) %>% tail(1)

mse_results
```

```
## # A tibble: 1 x 4
##   lambda   mse      rmse    r2
##    <dbl> <dbl>     <dbl> <dbl>
## 1    100 4739. 22462755. 0.528
```

```r
r2_results
```

```
## # A tibble: 1 x 4
##   lambda   mse      rmse    r2
##    <dbl> <dbl>     <dbl> <dbl>
## 1   1000 4985. 24849698. 0.948
```

```r
x <- ind5 %>% select(-`GDP_per_capita_(current_US$)`, -`CountryName`) %>% as.matrix()
y <- ind5$`GDP_per_capita_(current_US$)` %>% as.matrix()
out <- glmnet(x, y, alpha=1, lambda=mse_results$lambda)
lasso.coef <- predict(out, type="coefficients", s=mse_results$lambda)
lasso.coef2 <- predict(out, type="coefficients", s=r2_results$lambda)
lasso.coef
```

```
## 71 x 1 sparse Matrix of class "dgCMatrix"
##                                                                                        s1
## (Intercept)                                                                 -1.186254e+04
## Adolescent_fertility_rate_(births_per_1,000_women_ages_15-19)               -1.416810e+01
## Age_dependency_ratio_(%_of_working-age_population)                            .
## Age_dependency_ratio,_old_(%_of_working-age_population)                      5.466263e+02
## Age_dependency_ratio,_young_(%_of_working-age_population)                     .
## Population_ages_65_and_above_(%_of_total)                                    4.501267e+02
## Population,_ages_0-14_(%_of_total)                                            .
## Population,_ages_15-64_(%_of_total)                                           .
## Population,_female_(%_of_total)                                               .
## Population,_total                                                             .
## Rural_population                                                              .
## Rural_population_(%_of_total_population)                                      .
## Urban_population                                                              .
## Urban_population_(%_of_total)                                                 .
## Urban_population_growth_(annual_%)                                           5.305003e+02
## Population_growth_(annual_%)                                                 8.211135e+02
## Rural_population_growth_(annual_%)                                           2.339027e+02
## Merchandise_exports_(current_US$)                                            5.353124e-09
## Merchandise_imports_(current_US$)                                             .
## Birth_rate,_crude_(per_1,000_people)                                          .
## Death_rate,_crude_(per_1,000_people)                                         3.734714e+01
## Life_expectancy_at_birth,_female_(years)                                      .
## Life_expectancy_at_birth,_male_(years)                                        .
## Life_expectancy_at_birth,_total_(years)                                       .
## Survival_to_age_65,_female_(%_of_cohort)                                      .
## Survival_to_age_65,_male_(%_of_cohort)                                        .
```

```
## Fertility_rate,_total_(births_per_woman)                                                          .
## Land_area_(sq._km)                                                                                .
## Population_density_(people_per_sq._km_of_land_area)                                                1.786434e-0
## Surface_area_(sq._km)                                                                             .
## Mortality_rate,_adult,_female_(per_1,000_female_adults)                                           .
## Mortality_rate,_adult,_male_(per_1,000_male_adults)                                               .
## Mortality_rate,_infant_(per_1,000_live_births)                                                    .
## Mortality_rate,_under-5_(per_1,000)                                                               .
## Number_of_infant_deaths                                                                           .
## Number_of_under-five_deaths                                                                        4.544230e-0
## DEC_alternative_conversion_factor_(LCU_per_US$)                                                   .
## Agricultural_land_(%_of_land_area)                                                                -1.844513e+0
## Agricultural_land_(sq._km)                                                                        .
## Arable_land_(%_of_land_area)                                                                      -1.087259e+0
## Arable_land_(hectares)                                                                            .
## Arable_land_(hectares_per_person)                                                                  9.221247e+0
## Crop_production_index_(2004-2006_=_100)                                                            2.214619e+0
## Food_production_index_(2004-2006_=_100)                                                           .
## Livestock_production_index_(2004-2006_=_100)                                                      .
## Cereal_production_(metric_tons)                                                                   .
## Cereal_yield_(kg_per_hectare)                                                                      7.059605e-0
## Land_under_cereal_production_(hectares)                                                           .
## Permanent_cropland_(%_of_land_area)                                                               -8.149958e+0
## Official_exchange_rate_(LCU_per_US$,_period_average)                                              .
## GDP_(current_LCU)                                                                                 .
## GDP_per_capita_(current_LCU)                                                                      .
## CO2_emissions_(kt)                                                                                .
## CO2_emissions_(metric_tons_per_capita)                                                             6.637975e+0
## CO2_emissions_from_solid_fuel_consumption_(kt)                                                    -1.283613e-0
## CO2_emissions_from_solid_fuel_consumption_(%_of_total)                                            .
## CO2_emissions_from_liquid_fuel_consumption_(%_of_total)                                            3.226148e+0
## CO2_emissions_from_liquid_fuel_consumption_(kt)                                                   .
## CO2_emissions_from_gaseous_fuel_consumption_(kt)                                                  .
## CO2_emissions_from_gaseous_fuel_consumption_(%_of_total)                                          -2.036777e+0
## GDP_at_market_prices_(current_US$)                                                                .
## Merchandise_trade_(%_of_GDP)                                                                      -9.694197e-0
## Total_reserves_(includes_gold,_current_US$)                                                       .
## Total_reserves_minus_gold_(current_US$)                                                           .
## GDP_(constant_LCU)                                                                                .
## GDP_per_capita_(constant_LCU)                                                                     .
## GDP_deflator_(base_year_varies_by_country)                                                        .
## Merchandise_exports_by_the_reporting_economy_(current_US$)                                        .
## Merchandise_exports_by_the_reporting_economy,_residual_(%_of_total_merchandise_exports) -1.881005e+0
## GNI_(current_LCU)                                                                                 .
## GNI_per_capita_(current_LCU)                                                                      .
```

```
lasso.coef2
```

```
## 71 x 1 sparse Matrix of class "dgCMatrix"
##                                                                                                     s
## (Intercept)                                                                                       -1.186254e+0
## Adolescent_fertility_rate_(births_per_1,000_women_ages_15-19)                                     -1.416810e+0
## Age_dependency_ratio_(%_of_working-age_population)                                                .
## Age_dependency_ratio,_old_(%_of_working-age_population)                                            5.466263e+0
## Age_dependency_ratio,_young_(%_of_working-age_population)                                         .
```

```
## Population_ages_65_and_above_(%_of_total)                              4.501267e+0
## Population,_ages_0-14_(%_of_total)                                    .
## Population,_ages_15-64_(%_of_total)                                   .
## Population,_female_(%_of_total)                                       .
## Population,_total                                                     .
## Rural_population                                                      .
## Rural_population_(%_of_total_population)                              .
## Urban_population                                                      .
## Urban_population_(%_of_total)                                         .
## Urban_population_growth_(annual_%)                                     5.305003e+0
## Population_growth_(annual_%)                                           8.211135e+0
## Rural_population_growth_(annual_%)                                     2.339027e+0
## Merchandise_exports_(current_US$)                                      5.353124e-0
## Merchandise_imports_(current_US$)                                     .
## Birth_rate,_crude_(per_1,000_people)                                  .
## Death_rate,_crude_(per_1,000_people)                                   3.734714e+0
## Life_expectancy_at_birth,_female_(years)                              .
## Life_expectancy_at_birth,_male_(years)                                .
## Life_expectancy_at_birth,_total_(years)                               .
## Survival_to_age_65,_female_(%_of_cohort)                              .
## Survival_to_age_65,_male_(%_of_cohort)                                .
## Fertility_rate,_total_(births_per_woman)                              .
## Land_area_(sq._km)                                                    .
## Population_density_(people_per_sq._km_of_land_area)                    1.786434e-0
## Surface_area_(sq._km)                                                 .
## Mortality_rate,_adult,_female_(per_1,000_female_adults)               .
## Mortality_rate,_adult,_male_(per_1,000_male_adults)                   .
## Mortality_rate,_infant_(per_1,000_live_births)                        .
## Mortality_rate,_under-5_(per_1,000)                                   .
## Number_of_infant_deaths                                               .
## Number_of_under-five_deaths                                            4.544230e-0
## DEC_alternative_conversion_factor_(LCU_per_US$)                       .
## Agricultural_land_(%_of_land_area)                                    -1.844513e+0
## Agricultural_land_(sq._km)                                            .
## Arable_land_(%_of_land_area)                                          -1.087259e+0
## Arable_land_(hectares)                                                .
## Arable_land_(hectares_per_person)                                      9.221247e+0
## Crop_production_index_(2004-2006_=_100)                                2.214619e+0
## Food_production_index_(2004-2006_=_100)                               .
## Livestock_production_index_(2004-2006_=_100)                          .
## Cereal_production_(metric_tons)                                       .
## Cereal_yield_(kg_per_hectare)                                          7.059605e-0
## Land_under_cereal_production_(hectares)                               .
## Permanent_cropland_(%_of_land_area)                                   -8.149958e+0
## Official_exchange_rate_(LCU_per_US$,_period_average)                  .
## GDP_(current_LCU)                                                     .
## GDP_per_capita_(current_LCU)                                          .
## CO2_emissions_(kt)                                                    .
## CO2_emissions_(metric_tons_per_capita)                                 6.637975e+0
## CO2_emissions_from_solid_fuel_consumption_(kt)                        -1.283613e-0
## CO2_emissions_from_solid_fuel_consumption_(%_of_total)                .
## CO2_emissions_from_liquid_fuel_consumption_(%_of_total)                3.226148e+0
## CO2_emissions_from_liquid_fuel_consumption_(kt)                       .
## CO2_emissions_from_gaseous_fuel_consumption_(kt)                      .
```

```
## CO2_emissions_from_gaseous_fuel_consumption_(%_of_total)                                   -2.036777e+0
## GDP_at_market_prices_(current_US$)                                                          .
## Merchandise_trade_(%_of_GDP)                                                                -9.694197e-0
## Total_reserves_(includes_gold,_current_US$)                                                 .
## Total_reserves_minus_gold_(current_US$)                                                     .
## GDP_(constant_LCU)                                                                          .
## GDP_per_capita_(constant_LCU)                                                               .
## GDP_deflator_(base_year_varies_by_country)                                                  .
## Merchandise_exports_by_the_reporting_economy_(current_US$)                                  .
## Merchandise_exports_by_the_reporting_economy,_residual_(%_of_total_merchandise_exports) -1.881005e+0
## GNI_(current_LCU)                                                                           .
## GNI_per_capita_(current_LCU)                                                                .
```