Draft Documents

Team 1 (Hedgehog, Callista, Imtiyaaz, Issac)

2022-11-06

```
# required library
library(knitr)
library(readr)
library(tidyr)
library(dplyr)
library(ggplot2)
library(e1071)
library(moments)
```

1. Introduction (To be done)

2. Data Characteristic

2.1. Nature of Data

The data set is collection The World Bank Data, the variables of interest are extracted from the raw data files and combined into a single data frame for analysis. The final data set includes:

1. **country.code**: Country code
2. **country.name**: Country name
3. **year**: Year
4. **income**: Income class
    - Low income (L)
    - Lower middle income (LM)
    - Upper middle income (UM)
    - High income (H)
5. **reg**: Region
6. **pov**: Poverty headcount ratio based on cut-off value of $2.15 per day

7. **mpi**: Multidimensional Poverty Index

8. **edu.total**: Total expenditure on education (% of GDP)

9. **edu.pri**: Total expenditure on primary education (% of total education expenditure)

10. **edu.sec**: Total expenditure on secondary education (% of total education expenditure)

11. **edu.ter**: Total expenditure on tertiary education (% of total education expenditure)

12. **hlth**: Total expenditure on health (% of GDP)

13. **mil**: Total expenditure on military (% of GDP)

14. **fdi**: Foreign Direct Investment

15. **lbr.part**: Labour force participation (% of population ages 15+)

16. **unemp**: Unemployment rate

17. **pop.gwth.total**: Total population growth rate

18. **pop.gwth.rural**: Total rural population growth rate

19. **pop.gwth.urban**: Total urban population growth rate

20. **gdp.dflt**: GDP deflator

21. **gdr.eql**: Gender equality rating

22. **gcf**: Gross Capital Formation

23. **trade**: Trade = import + export (% of GDP)
24. **gdp.pc**: GDP per capita (current US$)

Data imports and combining:

```
# helper functions
importWDI <- function(filepath, value_name) {
    df <- read_csv(filepath, skip = 4)

    colnames(df) <- tolower(gsub(" ", ".", colnames(df)))

    df <- df %>%
        pivot_longer(5:ncol(.), names_to = "year", values_to = "value") %>%
        filter(!is.null(value) & !is.na(value)) %>%
        mutate(country.code = factor(country.code), country.name = factor(country.name),
            year = as.numeric(year)) %>%
        select(country.code, country.name, year, value)

    colnames(df)[4] <- value_name

    df
}
```

```r
importRegionClass <- function(filepath) {
    df <- read_csv(filepath, skip = 4)

    colnames(df) <- tolower(gsub(" ", ".", colnames(df)))

    df %>%
        mutate(country.name = factor(country.name), region = factor(region)) %>%
        select(country.name, reg = region)
}

importIncomeClass <- function(filepath) {
    df <- read_csv(filepath, skip = 4)

    colnames(df) <- tolower(gsub(" ", ".", colnames(df)))

    df %>%
        pivot_longer(3:ncol(.), names_to = "year", values_to = "income") %>%
        filter(!is.null(income) & !is.na(income)) %>%
        mutate(country.code = factor(country.code), country.name = factor(country.name),
            year = as.numeric(year), income = factor(income)) %>%
        select(country.code, country.name, year, income)
}
```

```r
# import data
setwd("../data")

poverty.headcount <- importWDI("poverty.headcount.215dollar.csv",
    "pov")
mpi <- importWDI("mpi.csv", "mpi")
education.expenditure.total <- importWDI("total.education.expenditure.csv",
    "edu.total")
education.expenditure.primary <- importWDI("primary.education.expenditure.csv",
    "edu.pri")
education.expenditure.secondary <- importWDI("secondary.education.expenditure.csv",
    "edu.sec")
education.expenditure.tertiary <- importWDI("tertiary.education.expenditure.csv",
    "edu.ter")
health.expenditure <- importWDI("health.expenditure.csv", "hlth")
military.expenditure <- importWDI("military.expenditure.csv",
    "mil")
fdi <- importWDI("fdi.csv", "fdi")
labour.force.participation <- importWDI("labour.force.participation.csv",
    "lbr.part")
unemployment.rate <- importWDI("unemployment.csv", "unemp")
population.growth <- importWDI("population.growth.csv", "pop.gwth.total")
rural.population.growth <- importWDI("rural.population.growth.csv",
    "pop.gwth.rural")
urban.population.growth <- importWDI("urban.population.growth.csv",
    "pop.gwth.urban")
gdp.deflator <- importWDI("gdp.deflator.csv", "gdp.dflt")
gender.equality <- importWDI("gender.equality.csv", "gdr.eql")
gross.capital.formation <- importWDI("gross.capital.formation.csv",
    "gcf")
```

```r
trade <- importWDI("trade.csv", "trade")
region.class <- importRegionClass("region.class.csv")
income.class <- importIncomeClass("income.class.csv")
gdp.pc <- importWDI("gdp.pc.csv", "gdp.pc")

setwd("../src")
```

We found that the data sets collected from World Bank's Data helpdesk and The World Bank's Data have different naming convention for certain countries (e.g. "Czechia" vs. "Czechnia Republic"). So we need to rename these countries to avoid some error when joining.

Furthermore, WDI's data sets rate also account for non-country (e.g. country.name = "Low income" or "South Asia"). These special groups are not in our scope of interest, which is national, so we eliminate them.

```r
# using poverty.headcount as a naming standard (as other
# data from WDI also use this convention) join a subset of
# data to process the names
d <- poverty.headcount %>%
    select(country.name) %>%
    mutate(inPov = T) %>%
    full_join(income.class %>%
        select(country.name) %>%
        mutate(inIncome = T), by = "country.name") %>%
    full_join(region.class %>%
        select(country.name) %>%
        mutate(inReg = T), by = "country.name") %>%
    mutate(inPov = !is.na(inPov), inIncome = !is.na(inIncome),
        inReg = !is.na(inReg))

d
```

```
## # A tibble: 62,759 x 4
##    country.name inPov inIncome inReg
##    <fct>        <lgl> <lgl>    <lgl>
##  1 Angola       TRUE  TRUE     TRUE
##  2 Angola       TRUE  TRUE     TRUE
##  3 Angola       TRUE  TRUE     TRUE
##  4 Angola       TRUE  TRUE     TRUE
##  5 Angola       TRUE  TRUE     TRUE
##  6 Angola       TRUE  TRUE     TRUE
##  7 Angola       TRUE  TRUE     TRUE
##  8 Angola       TRUE  TRUE     TRUE
##  9 Angola       TRUE  TRUE     TRUE
## 10 Angola       TRUE  TRUE     TRUE
## # ... with 62,749 more rows
## # i Use `print(n = ...)` to see more rows
```

First, remove special economic groups from `poverty.headcount`. We figured these regions will not appear in `income.class` or `region.class`, so we might find something from looking at the countries **only** appear in `poverty.headcount`.

```
d %>%
    filter(inPov & (!inIncome | !inReg)) %>%
    distinct(country.name)
```

```
## # A tibble: 18 x 1
##    country.name
##    <fct>
##  1 Cote d'Ivoire
##  2 Czechia
##  3 East Asia & Pacific
##  4 Europe & Central Asia
##  5 Fragile and conflict affected situations
##  6 High income
##  7 IDA total
##  8 Latin America & Caribbean
##  9 Low income
## 10 Lower middle income
## 11 Low & middle income
## 12 Middle East & North Africa
## 13 South Asia
## 14 Sub-Saharan Africa
## 15 Sao Tome and Principe
## 16 Turkiye
## 17 Upper middle income
## 18 World
```

Lucky! We can look through these 18 results and compose a list of special regions.

```
spec.reg <- c("Fragile and conflict affected situations", "IDA total",
    "World", "East Asia & Pacific", "Europe & Central Asia",
    "Latin America & Caribbean", "Middle East & North Africa",
    "South Asia", "Sub-Saharan Africa", "Low income", "Low & middle income",
    "Lower middle income", "Upper middle income", "High income")
```

Then, we rename those countries with inconsistent naming convention. Since we should only care about countries whose poverty headcount is available, reusing the list generated above, we can identify:

1. Cote d'Ivoire (also Côte d'Ivoire)
2. Czechia (also Czechoslovakia or Czech Republic)
3. Curacao (also Curaçao)
4. Turkiye (formerly known as Turkey, also Türkiye)
5. Sao Tome and Principe (also São Tomé and Príncipe)

```
# mapping standard name and variation
nameMap <- tibble(standard = c("Cote d'Ivoire", "Czechia", "Czechia",
    "Curacao", "Turkiye", "Turkiye", "Sao Tome and Principe"),
    variation = c("Côte d'Ivoire", "Czechoslovakia", "Czech Republic",
        "Curaçao", "Turkey", "Türkiye", "São Tomé and Príncipe"))

correctName <- function(name) {
    tibble(name = name) %>%
        left_join(nameMap, by = c(name = "variation")) %>%
```

```r
        mutate(standard = ifelse(is.na(standard), name, standard)) %>%
        select(standard) %>%
        pull()
}

orig.name <- c("Vietnam", "China", "Turkey", "Czechia Republic")
correctName(orig.name)
```

```
## [1] "Vietnam"          "China"            "Turkiye"          "Czechia Republic"
```

Let's test this out!

```r
d <- poverty.headcount %>%
  # correct name here
  mutate(country.name = correctName(country.name)) %>%
  select(country.name) %>%
  mutate(inPov = T) %>%
  full_join(income.class %>%
              # correct name here
              mutate(country.name = correctName(country.name)) %>%
              select(country.name) %>%
              mutate(inIncome = T), by = "country.name") %>%
  full_join(region.class %>%
              # correct name here
              mutate(country.name = correctName(country.name)) %>%
              select(country.name) %>%
              mutate(inReg = T), by = "country.name") %>%
  filter(!(country.name %in% spec.reg)) %>%
  mutate(inPov = !is.na(inPov), inIncome = !is.na(inIncome), inReg = !is.na(inReg))

# countries not in region list, but is in Pov list
d %>%
  filter(!inReg & inPov) %>%
  distinct(country.name) %>%
  nrow()
```

```
## [1] 0
```

```r
# countries not in income list, but is in Pov list
d %>%
  filter(!inIncome & inPov) %>%
  distinct(country.name) %>%
  nrow()
```

```
## [1] 0
```

We are *pretty* confident that there's no inconsistent naming left unprocessed in the data sets.

```r
# Rename countries in all data sets.
poverty.headcount <- poverty.headcount %>%
    mutate(country.name = correctName(country.name))
```

```r
mpi <- mpi %>%
    mutate(country.name = correctName(country.name))
education.expenditure.total <- education.expenditure.total %>%
    mutate(country.name = correctName(country.name))
education.expenditure.primary <- education.expenditure.primary %>%
    mutate(country.name = correctName(country.name))
education.expenditure.secondary <- education.expenditure.secondary %>%
    mutate(country.name = correctName(country.name))
education.expenditure.tertiary <- education.expenditure.tertiary %>%
    mutate(country.name = correctName(country.name))
health.expenditure <- health.expenditure %>%
    mutate(country.name = correctName(country.name))
military.expenditure <- military.expenditure %>%
    mutate(country.name = correctName(country.name))
fdi <- fdi %>%
    mutate(country.name = correctName(country.name))
labour.force.participation <- labour.force.participation %>%
    mutate(country.name = correctName(country.name))
unemployment.rate <- unemployment.rate %>%
    mutate(country.name = correctName(country.name))
population.growth <- population.growth %>%
    mutate(country.name = correctName(country.name))
rural.population.growth <- rural.population.growth %>%
    mutate(country.name = correctName(country.name))
urban.population.growth <- urban.population.growth %>%
    mutate(country.name = correctName(country.name))
gdp.deflator <- gdp.deflator %>%
    mutate(country.name = correctName(country.name))
gender.equality <- gender.equality %>%
    mutate(country.name = correctName(country.name))
gross.capital.formation <- gross.capital.formation %>%
    mutate(country.name = correctName(country.name))
trade <- trade %>%
    mutate(country.name = correctName(country.name))
region.class <- region.class %>%
    mutate(country.name = correctName(country.name))
income.class <- income.class %>%
    mutate(country.name = correctName(country.name))
gdp.pc <- gdp.pc %>%
    mutate(country.name = correctName(country.name))
```

Join the data

```r
countries <- poverty.headcount %>%
    # We used a full join here so we can conduct a separate
    # analysis on mpi later
full_join(mpi, by = c("country.name", "country.code", "year")) %>%
    left_join(income.class, c("country.name", "country.code",
        "year")) %>%
    left_join(region.class, by = "country.name") %>%
    left_join(education.expenditure.total, by = c("country.name",
        "country.code", "year")) %>%
    left_join(education.expenditure.primary, by = c("country.name",
```

```r
        "country.code", "year")) %>%
    left_join(education.expenditure.secondary, by = c("country.name",
        "country.code", "year")) %>%
    left_join(education.expenditure.tertiary, by = c("country.name",
        "country.code", "year")) %>%
    left_join(health.expenditure, by = c("country.name", "country.code",
        "year")) %>%
    left_join(military.expenditure, by = c("country.name", "country.code",
        "year")) %>%
    left_join(fdi, by = c("country.name", "country.code", "year")) %>%
    left_join(labour.force.participation, by = c("country.name",
        "country.code", "year")) %>%
    left_join(unemployment.rate, by = c("country.name", "country.code",
        "year")) %>%
    left_join(population.growth, by = c("country.name", "country.code",
        "year")) %>%
    left_join(rural.population.growth, by = c("country.name",
        "country.code", "year")) %>%
    left_join(urban.population.growth, by = c("country.name",
        "country.code", "year")) %>%
    left_join(gdp.deflator, by = c("country.name", "country.code",
        "year")) %>%
    left_join(gender.equality, by = c("country.name", "country.code",
        "year")) %>%
    left_join(gross.capital.formation, by = c("country.name",
        "country.code", "year")) %>%
    left_join(trade, by = c("country.name", "country.code", "year")) %>%
    left_join(gdp.pc, by = c("country.name", "country.code",
        "year")) %>%
    # filter special groups
filter(!(country.name %in% spec.reg))
```

Data preview

```r
head(countries)
```

```
## # A tibble: 6 x 24
##   count~1 count~2  year   pov   mpi income reg   edu.t~3 edu.pri edu.sec edu.ter
##   <fct>   <chr>   <dbl> <dbl> <dbl> <fct>  <fct>   <dbl>   <dbl>   <dbl>   <dbl>
## 1 AGO     Angola   2000  21.4    NA L      Sub-~    2.61      NA      NA      NA
## 2 AGO     Angola   2008  14.6    NA LM     Sub-~    2.69      NA      NA      NA
## 3 AGO     Angola   2018  31.1    NA LM     Sub-~    2.04      NA      NA      NA
## 4 ALB     Albania  1996   0.5    NA LM     Euro~    3.08      NA      NA      NA
## 5 ALB     Albania  2002   1.1    NA LM     Euro~    3.12      NA      NA      NA
## 6 ALB     Albania  2005   0.6    NA LM     Euro~    3.28      NA      NA      NA
## # ... with 13 more variables: hlth <dbl>, mil <dbl>, fdi <dbl>, lbr.part <dbl>,
## #   unemp <dbl>, pop.gwth.total <dbl>, pop.gwth.rural <dbl>,
## #   pop.gwth.urban <dbl>, gdp.dflt <dbl>, gdr.eql <dbl>, gcf <dbl>,
## #   trade <dbl>, gdp.pc <dbl>, and abbreviated variable names 1: country.code,
## #   2: country.name, 3: edu.total
## # i Use `colnames()` to see all variable names
```

```r
str(countries)
```

```
## tibble [1,901 x 24] (S3: tbl_df/tbl/data.frame)
##  $ country.code  : Factor w/ 272 levels "AGO","ALB","ARE",..: 1 1 1 2 2 2 2 2 2 2 ...
##  $ country.name  : chr [1:1901] "Angola" "Angola" "Angola" "Albania" ...
##  $ year          : num [1:1901] 2000 2008 2018 1996 2002 ...
##  $ pov           : num [1:1901] 21.4 14.6 31.1 0.5 1.1 0.6 0.2 0.6 1 0.1 ...
##  $ mpi           : num [1:1901] NA NA NA NA NA NA NA NA NA NA ...
##  $ income        : Factor w/ 4 levels "H","L","LM","UM": 2 3 3 3 3 3 3 4 4 4 ...
##  $ reg           : Factor w/ 7 levels "East Asia & Pacific",..: 7 7 7 2 2 2 2 2 2 2 ...
##  $ edu.total     : num [1:1901] 2.61 2.69 2.04 3.08 3.12 ...
##  $ edu.pri       : num [1:1901] NA NA NA NA NA ...
##  $ edu.sec       : num [1:1901] NA NA NA NA NA ...
##  $ edu.ter       : num [1:1901] NA NA NA NA NA ...
##  $ hlth          : num [1:1901] 1.91 3.32 2.54 NA 6.91 ...
##  $ mil           : num [1:1901] 6.39 3.57 1.87 1.38 1.32 ...
##  $ fdi           : num [1:1901] 8.79e+08 1.68e+09 -6.46e+09 9.01e+07 1.35e+08 ...
##  $ lbr.part      : num [1:1901] NA NA NA 38.8 59.6 ...
##  $ unemp         : num [1:1901] NA NA NA 12.3 15.8 ...
##  $ pop.gwth.total: num [1:1901] 3.277 3.711 3.276 -0.622 -0.3 ...
##  $ pop.gwth.rural: num [1:1901] 0.921 1.91 1.338 -1.546 -2.169 ...
##  $ pop.gwth.urban: num [1:1901] 5.682 5.02 4.312 0.812 2.181 ...
##  $ gdp.dflt      : num [1:1901] 418.02 19.37 28.17 38.17 3.65 ...
##  $ gdr.eql       : num [1:1901] NA 3 NA NA NA 4 NA NA NA NA ...
##  $ gcf           : num [1:1901] 30.5 30.8 17.9 18.1 35.3 ...
##  $ trade         : num [1:1901] 152.5 121.4 66.4 44.9 68.5 ...
##  $ gdp.pc        : num [1:1901] 557 4081 2525 1010 1425 ...
```

```r
summary(countries)
```

```
##   country.code  country.name            year           pov
##  BRA    :  36   Length:1901        Min.   :1967   Min.   : 0.00
##  CRI    :  34   Class :character   1st Qu.:2002   1st Qu.: 0.20
##  ARG    :  32   Mode  :character   Median :2009   Median : 1.50
##  USA    :  32                      Mean   :2007   Mean   :10.04
##  DEU    :  30                      3rd Qu.:2014   3rd Qu.:11.60
##  HND    :  30                      Max.   :2021   Max.   :91.50
##  (Other):1707                                     NA's   :58
##       mpi          income                             reg        edu.total
##  Min.   : 2.37   H   :644   East Asia & Pacific       :167   Min.   : 1.033
##  1st Qu.:18.30   L   :253   Europe & Central Asia     :883   1st Qu.: 3.522
##  Median :24.80   LM  :501   Latin America & Caribbean :416   Median : 4.519
##  Mean   :27.06   UM  :438   Middle East & North Africa:107   Mean   : 4.582
##  3rd Qu.:33.30   NA's: 65   North America             : 50   3rd Qu.: 5.457
##  Max.   :74.20              South Asia                : 61   Max.   :15.750
##  NA's   :1446               Sub-Saharan Africa        :217   NA's   :596
##     edu.pri           edu.sec          edu.ter           hlth
##  Min.   : 0.6578   Min.   : 2.724   Min.   : 0.00   Min.   : 1.718
##  1st Qu.:24.0269   1st Qu.:30.138   1st Qu.:16.61   1st Qu.: 5.151
##  Median :30.4730   Median :35.713   Median :20.59   Median : 6.914
##  Mean   :31.6633   Mean   :35.630   Mean   :20.96   Mean   : 6.975
##  3rd Qu.:38.3324   3rd Qu.:41.380   3rd Qu.:25.14   3rd Qu.: 8.565
##  Max.   :70.0950   Max.   :71.587   Max.   :50.44   Max.   :17.733
```

```
##  NA's   :1090      NA's   :1094     NA's   :963     NA's   :464
##       mil              fdi                lbr.part         unemp
##  Min.   : 0.000   Min.   :-3.444e+11   Min.   :30.50   Min.   : 0.250
##  1st Qu.: 1.042   1st Qu.: 2.979e+08   1st Qu.:56.17   1st Qu.: 4.513
##  Median : 1.468   Median : 1.709e+09   Median :61.18   Median : 6.880
##  Mean   : 1.787   Mean   : 1.598e+10   Mean   :60.78   Mean   : 8.145
##  3rd Qu.: 2.103   3rd Qu.: 9.821e+09   3rd Qu.:65.49   3rd Qu.:10.078
##  Max.   :19.385   Max.   : 7.338e+11   Max.   :93.00   Max.   :49.700
##  NA's   :105      NA's   :17           NA's   :320     NA's   :267
##  pop.gwth.total    pop.gwth.rural     pop.gwth.urban      gdp.dflt
##  Min.   :-3.6295   Min.   :-8.56066   Min.   :-4.078   Min.   : -26.300
##  1st Qu.: 0.2656   1st Qu.:-0.85664   1st Qu.: 0.510   1st Qu.:   1.696
##  Median : 1.0318   Median :-0.02461   Median : 1.484   Median :   3.865
##  Mean   : 1.0565   Mean   : 0.00083   Mean   : 1.691   Mean   :  15.831
##  3rd Qu.: 1.7761   3rd Qu.: 0.96362   3rd Qu.: 2.657   3rd Qu.:   8.537
##  Max.   : 5.6145   Max.   : 4.59686   Max.   :13.805   Max.   :3333.585
##                    NA's   :14         NA's   :13       NA's   :18
##     gdr.eql           gcf            trade             gdp.pc
##  Min.   :1.500   Min.   : 0.00   Min.   :  1.378   Min.   :   119.7
##  1st Qu.:3.000   1st Qu.:19.65   1st Qu.: 51.063   1st Qu.:  1927.9
##  Median :3.500   Median :22.73   Median : 73.496   Median :  6032.1
##  Mean   :3.592   Mean   :23.88   Mean   : 84.429   Mean   : 15219.5
##  3rd Qu.:4.000   3rd Qu.:26.76   3rd Qu.:105.462   3rd Qu.: 21490.4
##  Max.   :5.000   Max.   :69.48   Max.   :380.104   Max.   :123678.7
##  NA's   :1635    NA's   :72      NA's   :57        NA's   :8
```

There's no NA in `reg`, which is a sign that all naming in the data is remedied. There's some expected NAs in `income` and `pov`, as these data are collected by year. There's a substantial amount of missing data in `mpi`, as this is a relative new concept. We will address the nature, and processing of missing data in the next sections.

2.2. Missing values

As observed from the summary above, the data set contains a lot of missing values in some of the variables.

```r
mean(is.na(countries))
```

```
## [1] 0.1819656
```

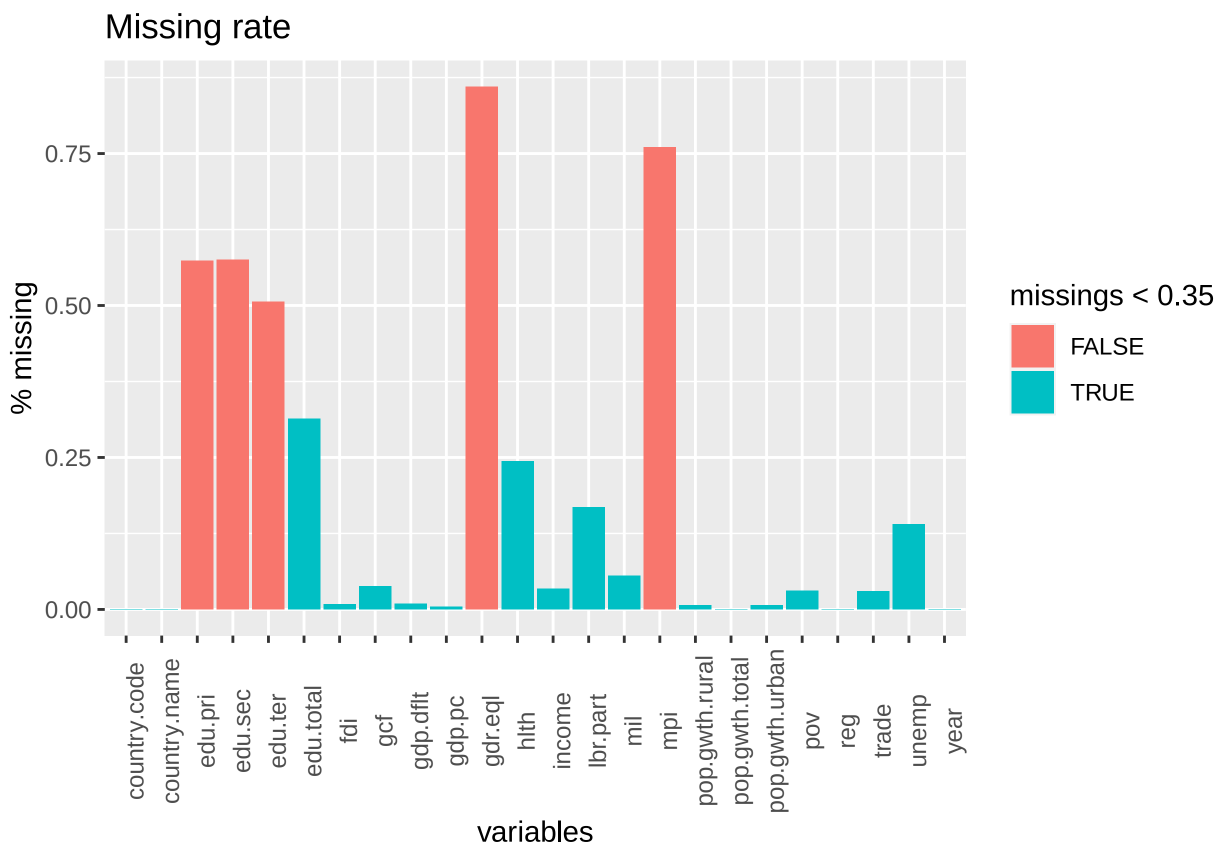
About 19% of the data set is missing.

```r
nCompleteObs <- sum(complete.cases(countries))
print(paste("No. of complete cases:", nCompleteObs))
```

```
## [1] "No. of complete cases: 3"
```

There are only 3 complete cases where all the variable is available. This is nowhere near acceptable to conduct any meaningful analysis. Therefore, we need to eliminate some variables for a more balance data set.

```r
missings <- colMeans(is.na(countries))
ggplot(mapping = aes(x = names(missings), y = missings, fill = missings <
    0.35)) + geom_bar(stat = "identity") + ggtitle("Missing rate") +
    xlab("variables") + ylab("% missing") + theme(axis.text.x = element_text(size = 9,
    angle = 90))
```




```r
missings[missings > 0.35]
```

```
##       mpi   edu.pri   edu.sec   edu.ter   gdr.eql
## 0.7606523 0.5733824 0.5754866 0.5065755 0.8600736
```

There are 5 variables with missing rate >35%.

expenditure in primary, secondary, and tertiary edication can be very useful and relevant information to predict poverty reduction (Akbar et al. 2019). However, we would like to exclude these variables from some first analyses to make use of the richer set of data. We can conduct a separate analysis with these variable to gain more insight.

```r
# variables with high missing rate
hMiss <- names(missings[missings > 0.35])
# exclude these variables in countries1
countries1 <- countries %>%
    select(!hMiss)
```

```
## Note: Using an external vector in selections is ambiguous.
```

```
## i Use `all_of(hMiss)` instead of `hMiss` to silence this message.
## i See <https://tidyselect.r-lib.org/reference/faq-external-vector.html>.
## This message is displayed once per session.
```

```r
str(countries1)
```

```
## tibble [1,901 x 19] (S3: tbl_df/tbl/data.frame)
##  $ country.code  : Factor w/ 272 levels "AGO","ALB","ARE",..: 1 1 1 2 2 2 2 2 2 2 ...
##  $ country.name  : chr [1:1901] "Angola" "Angola" "Angola" "Albania" ...
##  $ year          : num [1:1901] 2000 2008 2018 1996 2002 ...
##  $ pov           : num [1:1901] 21.4 14.6 31.1 0.5 1.1 0.6 0.2 0.6 1 0.1 ...
##  $ income        : Factor w/ 4 levels "H","L","LM","UM": 2 3 3 3 3 3 3 4 4 4 ...
##  $ reg           : Factor w/ 7 levels "East Asia & Pacific",..: 7 7 7 2 2 2 2 2 2 2 ...
##  $ edu.total     : num [1:1901] 2.61 2.69 2.04 3.08 3.12 ...
##  $ hlth          : num [1:1901] 1.91 3.32 2.54 NA 6.91 ...
##  $ mil           : num [1:1901] 6.39 3.57 1.87 1.38 1.32 ...
##  $ fdi           : num [1:1901] 8.79e+08 1.68e+09 -6.46e+09 9.01e+07 1.35e+08 ...
##  $ lbr.part      : num [1:1901] NA NA NA 38.8 59.6 ...
##  $ unemp         : num [1:1901] NA NA NA 12.3 15.8 ...
##  $ pop.gwth.total: num [1:1901] 3.277 3.711 3.276 -0.622 -0.3 ...
##  $ pop.gwth.rural: num [1:1901] 0.921 1.91 1.338 -1.546 -2.169 ...
##  $ pop.gwth.urban: num [1:1901] 5.682 5.02 4.312 0.812 2.181 ...
##  $ gdp.dflt      : num [1:1901] 418.02 19.37 28.17 38.17 3.65 ...
##  $ gcf           : num [1:1901] 30.5 30.8 17.9 18.1 35.3 ...
##  $ trade         : num [1:1901] 152.5 121.4 66.4 44.9 68.5 ...
##  $ gdp.pc        : num [1:1901] 557 4081 2525 1010 1425 ...
```

Re-evaluate the `countries1` set.

```r
mean(is.na(countries1))
```

```
## [1] 0.0574213
```

```r
sum(complete.cases(countries1))
```

```
## [1] 937
```

```r
mean(complete.cases(countries1))
```

```
## [1] 0.4928985
```

On average, each column has 6% missing rate, results in 937 complete data point (i.e. 49%). This can be a sufficient number for the analysis. However, the missing data can induce loss of power due to the reduced sample size, and some other biases depending on which variables is missing.

```r
# complete rate of data by regions
countries1 %>%
    mutate(isComplete = complete.cases(.)) %>%
    group_by(reg) %>%
    summarise(complete.rate = mean(isComplete)) %>%
    arrange(desc(complete.rate))
```

```
## # A tibble: 7 x 2
##   reg                            complete.rate
##   <fct>                                  <dbl>
## 1 Europe & Central Asia                  0.618
## 2 Latin America & Caribbean              0.505
## 3 Middle East & North Africa             0.449
## 4 East Asia & Pacific                    0.437
## 5 South Asia                             0.213
## 6 Sub-Saharan Africa                     0.184
## 7 North America                          0.14
```

Countries from North America, Sub-Saharan Africa, and South Asia have the highest rate of missing data. We suspect that Sub-Saharan Africa, and South Asia are comparably less accessible regions. We also know that Americans don't like filling out forms, so their high rate of missing data is understandable as well.

Still, we need to find a way to address this issue. we propose several approaches:

1. **Use complete cases**: Only use the complete cases for the analysis. This is a straightforward approach, but doesn't resolve the bias resulted from the mass loss of data.
2. **Selectively remove variables with high missing rate**: The same as we did before, but this process should be carried out carefully as we run the chance of dropping an important variable.
3. **Update the data set as we select variables**: As we drop insignificant variables (in backward selection), the number of NAs are changed as well. We can utilize the extra complete cases to build the next model in the steps.
4. **Imputation**: The idea is to replace the missing observations on the response or the predictors with artificial values that try to preserve the data set structure. This is a quite complex topic of its own, but we think why not. You can read more at from Arel-Bundock and Pelc (2018).

2.3. Descriptive Analytics

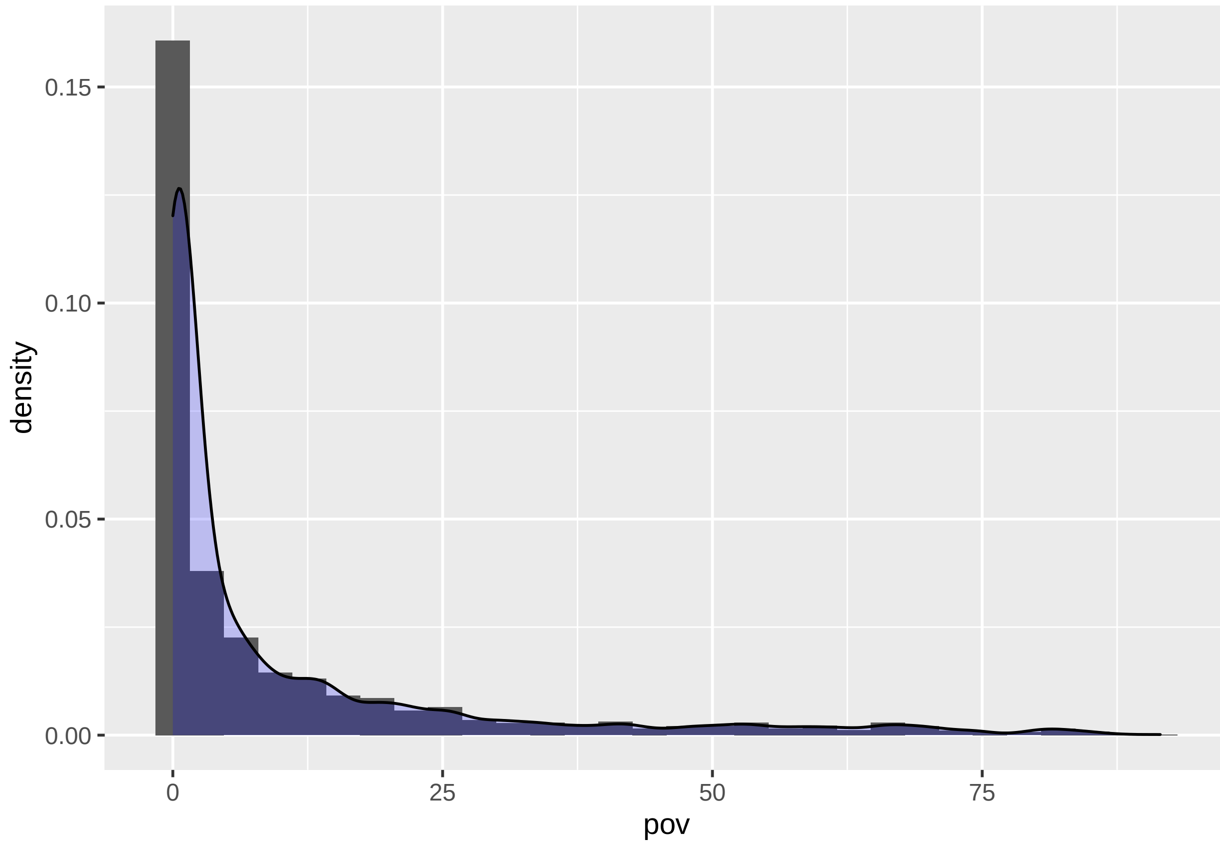
Distribution of the predicted variable `pov`

```
ggplot(countries, aes(x = pov)) + geom_histogram(aes(y = ..density..)) +
    geom_density(alpha = 0.2, fill = "blue")
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 58 rows containing non-finite values (stat_bin).
```

```
## Warning: Removed 58 rows containing non-finite values (stat_density).
```



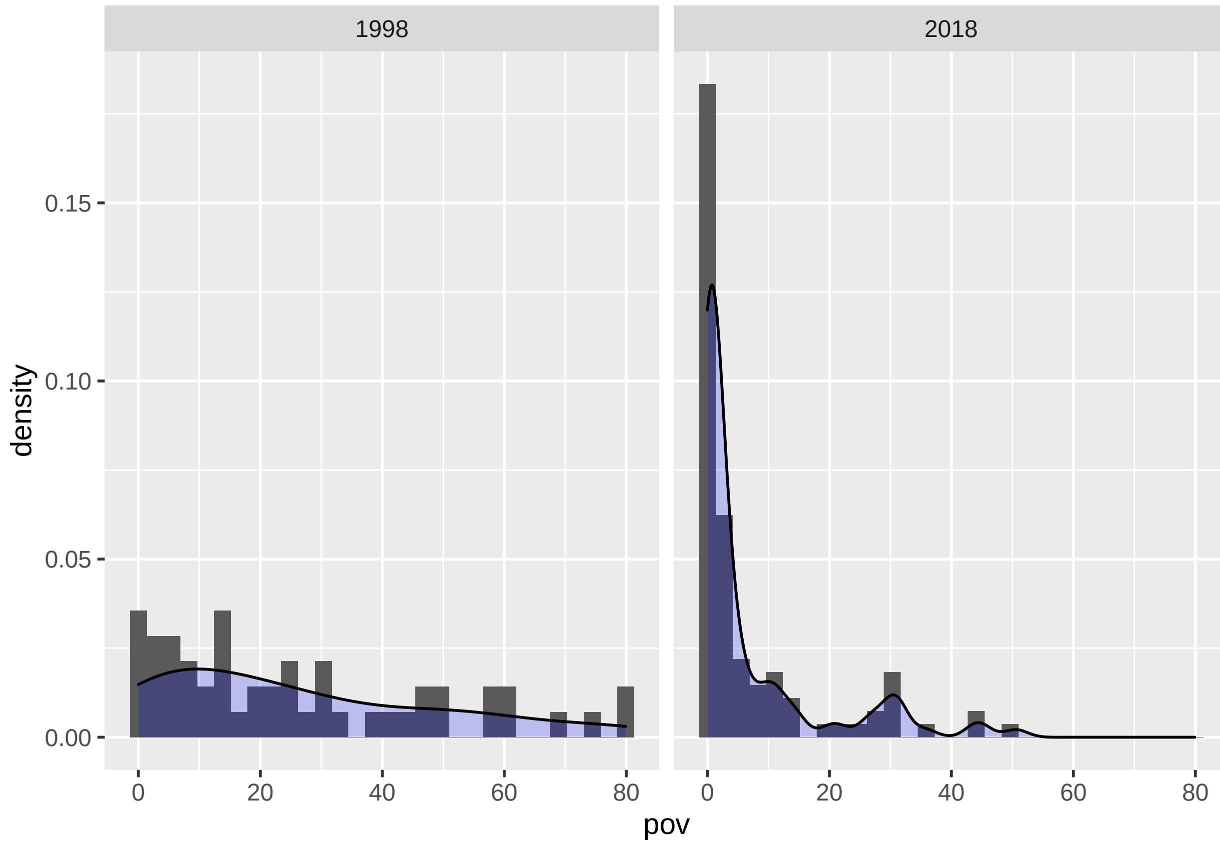
The graph displays a decreasing rate as poverty indicator increasing. This might not be representative of the current state of poverty in the world, but of the number presented in our data. For example, more recent data is likely to be more inclusive than ancient data, when poverty is more prevalent. We should look at data from the same period.

```
# pov data from 1998 and 2018
pov.98.18 <- poverty.headcount %>%
    filter(year == 1998 | year == 2018)
pov.98.18 %>%
    group_by(year) %>%
    summarise(sum = n())
```

```
## # A tibble: 2 x 2
##    year   sum
##   <dbl> <int>
## 1  1998    51
## 2  2018    99
```

```
ggplot(pov.98.18, aes(x = pov)) + geom_histogram(aes(y = ..density..)) +
    geom_density(alpha = 0.2, fill = "blue") + facet_grid(cols = vars(year))
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



The graph for 1998 has a much gentler slope, meaning poverty was more popular during that time, as predicted from out intuition. What about the general progress of the world?

```
# Re-import pov and only take special regions geographic
geo.regs <- c("EAS", "ECS", "LCN", "MEA", "SAS", "SSF", "WLD")
# economics
eco.regs <- c("HIC", "LIC", "LMC", "LMY", "UMC")

pov.reg <- importWDI("../data/poverty.headcount.215dollar.csv",
    "pov") %>%
    filter(country.code %in% c(geo.regs, eco.regs)) %>%
    mutate(type = ifelse(country.code %in% geo.regs, "Geographic",
        "Economics"))
```

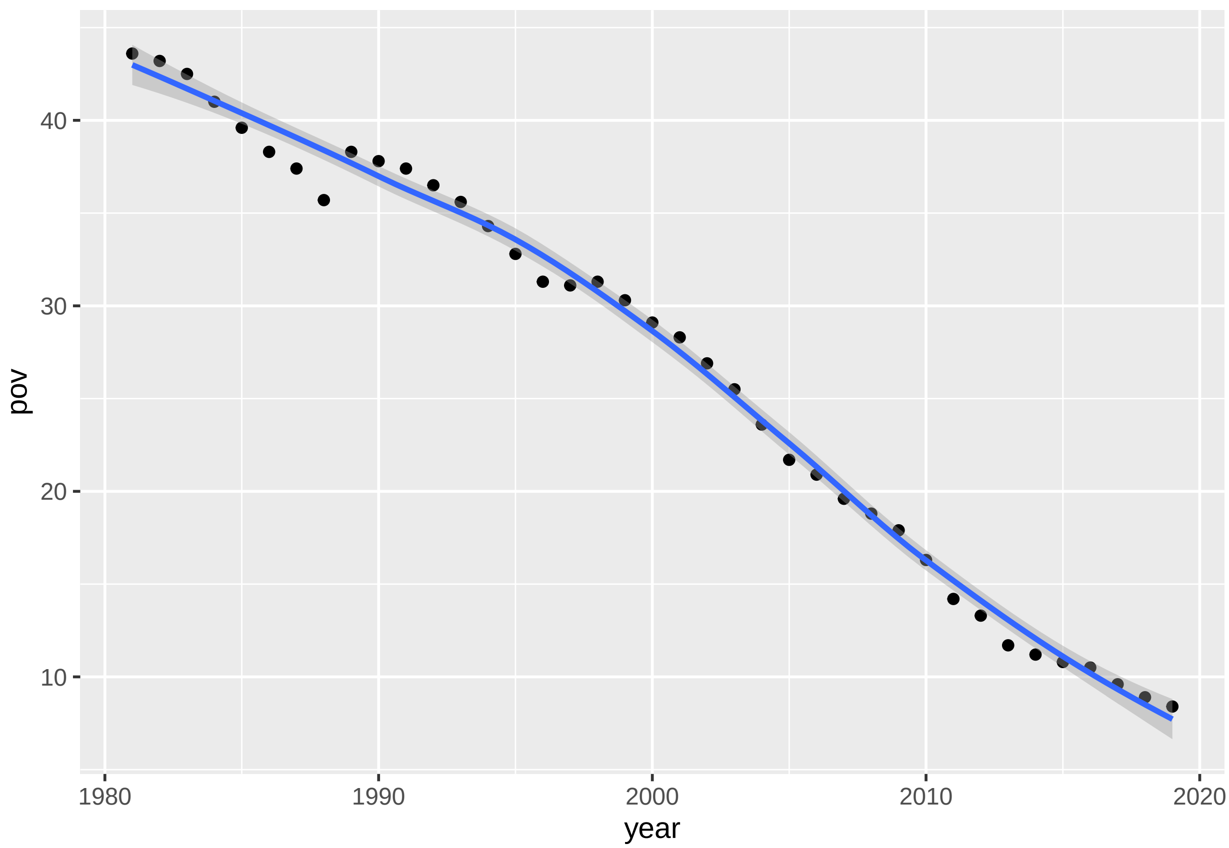
```
## New names:
## Rows: 266 Columns: 67
## -- Column specification
## -------------------------------------------------------- Delimiter: "," chr
## (4): Country Name, Country Code, Indicator Name, Indicator Code dbl (50): 1967,
## 1969, 1971, 1974, 1975, 1977, 1978, 1979, 1980, 1981, 1982, ... lgl (13): 1960,
## 1961, 1962, 1963, 1964, 1965, 1966, 1968, 1970, 1972, 1973, ...
## i Use ‘spec()‘ to retrieve the full column specification for this data. i
## Specify the column types or set ‘show_col_types = FALSE‘ to quiet this message.
## * ‘‘ -> ‘...67‘
```

```r
pov.reg %>%
    distinct(country.code, country.name, type) %>%
    arrange(type)
```

```
## # A tibble: 12 x 3
##    country.code country.name               type
##    <fct>        <fct>                      <chr>
##  1 HIC          High income                Economics
##  2 LIC          Low income                 Economics
##  3 LMC          Lower middle income        Economics
##  4 LMY          Low & middle income        Economics
##  5 UMC          Upper middle income        Economics
##  6 EAS          East Asia & Pacific        Geographic
##  7 ECS          Europe & Central Asia      Geographic
##  8 LCN          Latin America & Caribbean  Geographic
##  9 MEA          Middle East & North Africa Geographic
## 10 SAS          South Asia                 Geographic
## 11 SSF          Sub-Saharan Africa         Geographic
## 12 WLD          World                      Geographic
```

```r
# World
ggplot(pov.reg %>%
    filter(country.code == "WLD"), aes(x = year, y = pov)) +
    geom_point() + geom_smooth()
```

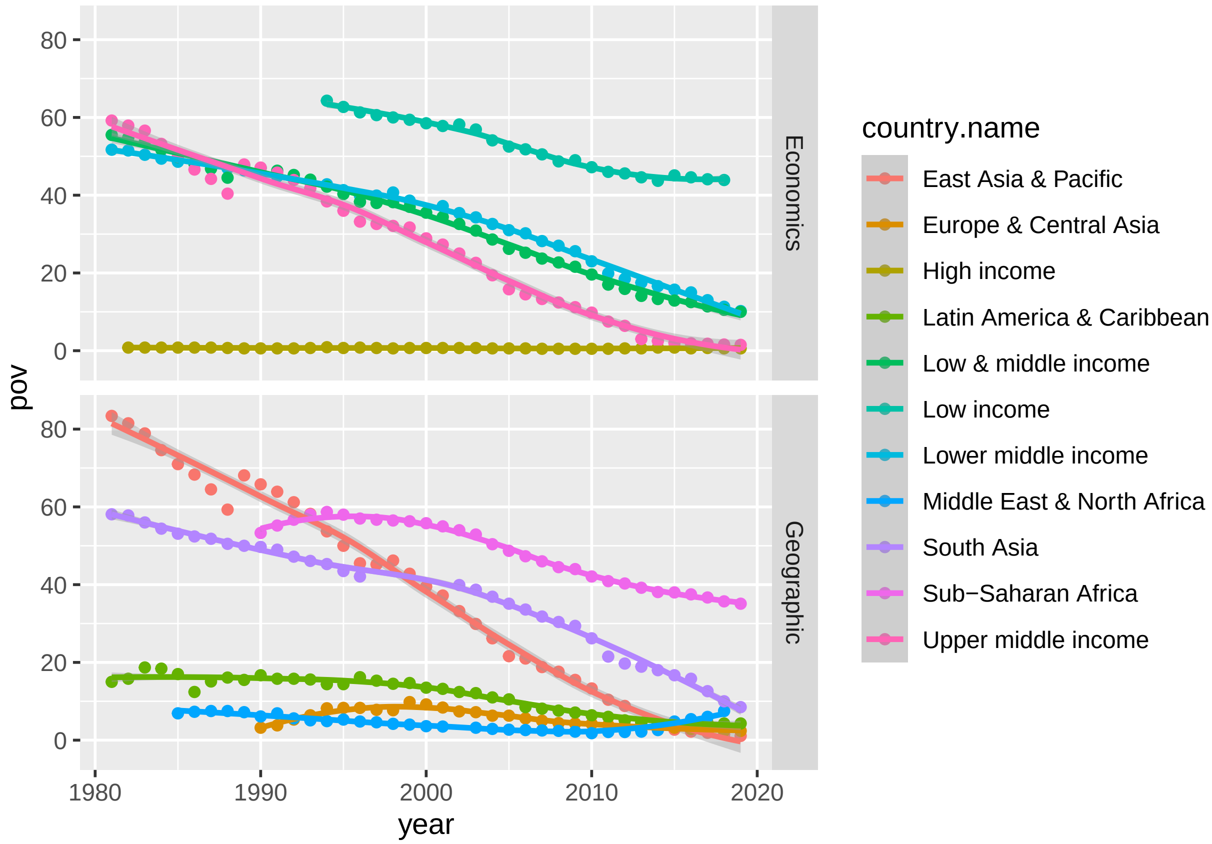
```
## `geom_smooth()` using method = 'loess' and formula 'y ~ x'
```



An overall very steady decrease of poverty. How about each region?

```
ggplot(pov.reg %>%
    filter(country.code != "WLD"), aes(x = year, y = pov, color = country.name)) +
    geom_point() + geom_smooth() + facet_grid(rows = vars(type))
```

```
## 'geom_smooth()' using method = 'loess' and formula 'y ~ x'
```



There's a general steady, but distinct decline of poverty over time in each type region of respective type. Latin America & Caribbean, Europe & Central Asia, Middle East & North Africa, and High Income group has a more gradual decline as they are not very poor to begin with.

Among the income groups, Low & Middle Income, Lower & Middle Income, and Upper Middle Income have quite similar in term of poverty indicator and slope over the year. While these values vary greatly among different geographical regions.

Let's see some important statistics

```
stats <- poverty.headcount %>%
    summarise(count = n(), skewness = skewness(pov), kurtosis = kurtosis(pov),
        std.deviation = sd(pov))

kable(stats)
```

count	skewness	kurtosis	std.deviation
2322	1.598182	4.661128	19.48582

2.4. Data Source

- poverty.headcount
- mpi
- education.expenditure.primary
- education.expenditure.secondary

- education.expenditure.tertiary
- education.expenditure.total
- health.expenditure
- military.expenditure
- fdi
- unemployment.rate
- labour.force.participation
- gender.equality
- population.growth
- urban.population.growth
- rural.population.growth
- gdp.deflator
- gross capital formation
- trade
- region.class
- income.class
- gross.capital.formation

3. Model Selection and Interpretation

3.1. Assumption Check (To be done)

3.2. Ordinary Multiple Linear Regression

We conduct a normal linear regression, following the approaches mentioned above to address missing values issues.

3.2.1. Use Complete Cases (To be done)

3.2.1.1. Model Fitting

3.2.1.2. Assessment

3.2.1.3. Interpretation

3.2.2. Selectively remove variables with high missing rate (To be done)

3.2.2.1. Model Fitting

3.2.2.2. Assessment

3.2.2.3. Interpretation

3.2.3. Update the data set as we select variables (To be done)

3.2.3.1. Model Fitting

3.2.3.2. Assessment

3.2.3.3. Interpretation

3.2.4. Imputation (To be done)

3.2.4.1. Model Fitting

3.2.4.2. Assessment

3.2.4.3. Interpretation

3.3. Panel Data Analysis (To be done)

4. Conclusion

5. Appendix

6. References

Akbar, Muhammad, Mukaram Khan, Haidar Farooqe, and Kaleemullah. 2019. "Public Spending, Education and Poverty: A Cross Country Analysis" 4 (April): 12–20.

Arel-Bundock, Vincent, and Krzysztof J. Pelc. 2018. "When Can Multiple Imputation Improve Regression Estimates?" *Political Analysis* 26 (2): 240–45. https://doi.org/10.1017/pan.2017.43.