Human Freedom Index and Suicides Project

Part 2: Data Exploration with HFI Dataset

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Contents

R version 4.1.1 "Kick Things"

```
library(readr)
library(dplyr)
library(tidyr)
library(stringr)
library(ggplot2)
library(GGally)
```

Load dataset into R

```
hfi <- read_csv("../data/hfi_cc_2018.csv")
```

Explore HFI dataset

Questions to answer:

- Are the freedom score, number of suicides per 100k, and gdp per capita related?
  - Find correlations, make 3 scatter pair plots
- Does population size impact freedom?
- Does female freedom scores relate to female suicide rates?
- What are important factors that contribute to human freedom?
  - Linear regression model

Hypotheses:

1. Countries with high female freedom scores will have less than average female suicide rates

   Ho: mean suicide rates lo female freedom >= average female suicide rate

   Ha: mean suicide rates hi female freedom < average female suicide rate

   - `pf_ss_women_fgm` - Female genital mutilation
   - `pf_ss_women_inheritance` - Equal inheritance rights for widows and daughters
   - `pf_movement_women` - Freedom of movement for women
   - `pf_identity_sex_female` - Female to female relationships
   - `pf_identity_divorce` - Divorce
   - Perhaps educational opportunity or abortion access should be included here as well?

2. Countries with smaller populations will have more freedom

   Ho: mean freedom small population <= mean freedom large population

   Ha: mean freedom small population > mean freedom large population

   - `hf_score` - Overall Human Freedom Index score
   - `population` - (suicides dataset) country population

Column Descriptions

There are many, many columns in this dataset, so let us focus on a few columns

- 1 time-series variable
  - `year`
- 3 categorical variables
  - `country`
  - `ISO_code` (country abbreviation)
  - `region`
- 119 numeric (narrowed down to only a handful)
  - Freedom indicators and their aggregate category scores, like
    - Female genital mutilation and inheritance rights (widows, daughters) make up 3 columns and are aggregated into one category score - Female security and safety

```r
categ_cols <- c(
    "year",
    "country",
    "region"
)

focus_cols <- c(
    "pf_ss_women_fgm",
    "pf_ss_women_inheritance",
    "pf_movement_women",
    "pf_identity_sex_female",
    "pf_identity_divorce",
    "pf_score",
    "ef_score",
    "hf_score"
)


# Look at focus subset of columns and update categoricals to factor type
hfi_focus <- rename(hfi, country = countries) %>%
    mutate(country = factor(country),
           region = factor(region))
hfi_focus <- hfi_focus[, str_c(c(categ_cols, focus_cols))]
write_csv(hfi_focus, "../data/clean_hfi_2018.csv")

print(str(hfi_focus))
```

```
## tibble [1,458 x 11] (S3: tbl_df/tbl/data.frame)
##  $ year                   : num [1:1458] 2016 2016 2016 2016 2016 ...
##  $ country                : Factor w/ 162 levels "Albania","Algeria",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ region                 : Factor w/ 10 levels "Caucasus & Central Asia",..: 3 5 9 4 1 7 10 1 4 5 .
##  $ pf_ss_women_fgm        : num [1:1458] 10 10 10 10 10 10 10 10 NA 10 ...
##  $ pf_ss_women_inheritance: num [1:1458] 5 0 5 10 10 10 10 7.5 NA 0 ...
```

```
##  $ pf_movement_women      : num [1:1458] 5 5 10 10 10 10 10 5 NA 5 ...
##  $ pf_identity_sex_female : num [1:1458] 10 0 0 10 10 10 10 10 10 10 ...
##  $ pf_identity_divorce    : num [1:1458] 5 0 10 10 5 10 10 5 NA 0 ...
##  $ pf_score               : num [1:1458] 7.6 5.28 6.11 8.1 6.91 ...
##  $ ef_score               : num [1:1458] 7.54 4.99 5.17 4.84 7.57 7.98 7.58 6.49 7.34 7.56 ...
##  $ hf_score               : num [1:1458] 7.57 5.14 5.64 6.47 7.24 ...
## NULL
```

Head / Tail of Data

Nothing out of the ordinary here. It seems like we read in the whole file and do not need to skip any header or footer miscellaneous data.

```r
print(head(hfi_focus))
```

```
## # A tibble: 6 x 11
##    year country  region       pf_ss_women_fgm pf_ss_women_inhe~ pf_movement_wom~
##   <dbl> <fct>    <fct>                  <dbl>             <dbl>            <dbl>
## 1  2016 Albania  Eastern Eur~              10                 5                5
## 2  2016 Algeria  Middle East~              10                 0                5
## 3  2016 Angola   Sub-Saharan~              10                 5               10
## 4  2016 Argenti~ Latin Ameri~              10                10               10
## 5  2016 Armenia  Caucasus & ~              10                10               10
## 6  2016 Austral~ Oceania                   10                10               10
## # ... with 5 more variables: pf_identity_sex_female <dbl>,
## #   pf_identity_divorce <dbl>, pf_score <dbl>, ef_score <dbl>, hf_score <dbl>
```

```r
print(tail(hfi_focus))
```

```
## # A tibble: 6 x 11
##    year country  region       pf_ss_women_fgm pf_ss_women_inhe~ pf_movement_wom~
##   <dbl> <fct>    <fct>                  <dbl>             <dbl>            <dbl>
## 1  2008 Uruguay  Latin Ameri~            10                  10               10
## 2  2008 Venezue~ Latin Ameri~            10                  10               10
## 3  2008 Vietnam  South Asia              10                  10               10
## 4  2008 Yemen, ~ Middle East~            NA                  NA               NA
## 5  2008 Zambia   Sub-Saharan~            10                   0               10
## 6  2008 Zimbabwe Sub-Saharan~             9.5                 5                5
## # ... with 5 more variables: pf_identity_sex_female <dbl>,
## #   pf_identity_divorce <dbl>, pf_score <dbl>, ef_score <dbl>, hf_score <dbl>
```

Distribution of Scores - Personal, Economic, Overall Human Freedom

```r
score_cols <- c("pf_score", "ef_score", "hf_score")
scores <- hfi_focus %>%
    pivot_longer(cols = score_cols, names_to = "freedom", values_to = "score")
scores <- scores[, str_c(c(categ_cols, "freedom", "score"))]

scores$freedom <- recode_factor(scores$freedom, "pf_score" = "Personal",
                                                "ef_score" = "Economic",
                                                "hf_score" = "Overall")

# Long data
print(select(hfi_focus, year, country, pf_score, ef_score, hf_score) %>% head())
```

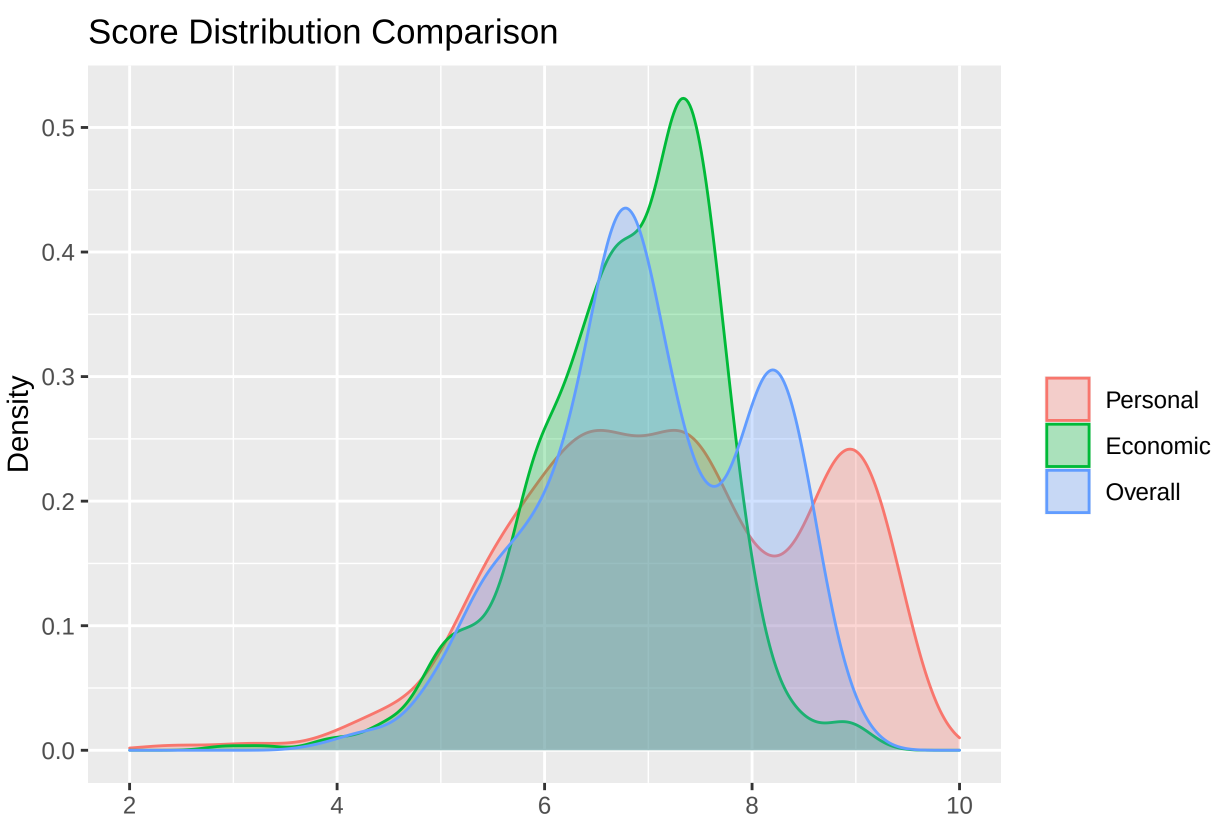
```
## # A tibble: 6 x 5
```

```
##    year country   pf_score ef_score hf_score
##   <dbl> <fct>        <dbl>    <dbl>    <dbl>
## 1  2016 Albania       7.60     7.54     7.57
## 2  2016 Algeria       5.28     4.99     5.14
## 3  2016 Angola        6.11     5.17     5.64
## 4  2016 Argentina     8.10     4.84     6.47
## 5  2016 Armenia       6.91     7.57     7.24
## 6  2016 Australia     9.18     7.98     8.58
```

```r
# Wide data
print(select(scores, year, freedom, score) %>% head())
```

```
## # A tibble: 6 x 3
##    year freedom  score
##   <dbl> <fct>    <dbl>
## 1  2016 Personal  7.60
## 2  2016 Economic  7.54
## 3  2016 Overall   7.57
## 4  2016 Personal  5.28
## 5  2016 Economic  4.99
## 6  2016 Overall   5.14
```

```r
# Freedom distribution density plot
ggplot(scores) +
    geom_density(aes(x = score, color = freedom, fill = freedom), alpha = 0.3) +
    labs(x = '', y = 'Density', title = 'Score Distribution Comparison', color = '', fill = '') +
    scale_x_continuous(limits = c(2, 10))
```



Personal freedom scores are more spread out than economic or overall freedom scores. Very few countries have scores below 4. The majority of economic scores fall between 6 and 8, lower than many countries' personal freedom scores.

Women Freedom

```
women_freedom_cols <- c(
    "pf_ss_women_fgm",
    "pf_ss_women_inheritance",
    "pf_movement_women",
    "pf_identity_sex_female",
    "pf_identity_divorce")

women_freedom_init <- hfi_focus[, str_c(c(categ_cols, women_freedom_cols))]
summary(women_freedom_init)
```

```
##       year           country                                region
##  Min.   :2008   Albania  :   9   Sub-Saharan Africa            :378
##  1st Qu.:2010   Algeria  :   9   Latin America & the Caribbean:234
##  Median :2012   Angola   :   9   Eastern Europe                :198
##  Mean   :2012   Argentina:   9   Middle East & North Africa    :171
##  3rd Qu.:2014   Armenia  :   9   Western Europe                :162
##  Max.   :2016   Australia:   9   South Asia                    :153
##                 (Other)  :1404   (Other)                       :162
##  pf_ss_women_fgm pf_ss_women_inheritance pf_movement_women
##  Min.   : 0.40   Min.   : 0.00           Min.   : 0.00
##  1st Qu.: 9.60   1st Qu.: 5.00           1st Qu.: 5.00
##  Median :10.00   Median : 5.00           Median :10.00
##  Mean   : 9.24   Mean   : 6.64           Mean   : 8.04
##  3rd Qu.:10.00   3rd Qu.:10.00           3rd Qu.:10.00
##  Max.   :10.00   Max.   :10.00           Max.   :10.00
##  NA's   :172     NA's   :119             NA's   :141
##  pf_identity_sex_female pf_identity_divorce
##  Min.   : 0.00          Min.   : 0.0
##  1st Qu.:10.00          1st Qu.: 5.0
##  Median :10.00          Median :10.0
##  Mean   : 7.94          Mean   : 7.5
##  3rd Qu.:10.00          3rd Qu.:10.0
##  Max.   :10.00          Max.   :10.0
##  NA's   :80             NA's   :873
```

Missing values

The 5 women freedom variables have at least 5% missing values with Divorce having almost 60%:

- `pf_ss_women_fgm` - Female genital mutilation - 11.8% missing
- `pf_ss_women_inheritance` - Female inheritance - 8.2%
- `pf_movement_women` - Women movement - 9.7%
- `pf_identity_sex_female` - Female to female relationships - 5.5%
- `pf_identity_divorce` - Divorce - 59.9%

```
sapply(women_freedom_init,
       function(x) paste0(round(sum(is.na(x)) / nrow(women_freedom_init) * 100, 1), "%"))
```

```
##                     year                    country                     region
##                     "0%"                       "0%"                       "0%"
```

```
##         pf_ss_women_fgm pf_ss_women_inheritance       pf_movement_women
##                 "11.8%"                  "8.2%"                  "9.7%"
##  pf_identity_sex_female     pf_identity_divorce
##                  "5.5%"                 "59.9%"
```

```r
# What to do about Divorce missing values? Impute? Interpolate? Remove?
# Instead, we can average the 5 women freedom columns together and then remove the columns
# with NAs - equal to the minimum NA% from the individual columns (5.5%)
women_freedom_init$avg_women_score <- rowMeans(select(women_freedom_init, women_freedom_cols),
                                               na.rm = TRUE)

women_freedom <- women_freedom_init[!is.na(women_freedom_init$avg_women_score),
                                    c("year", "country", "region", "avg_women_score")]

ggplot(women_freedom) + geom_histogram(aes(x = avg_women_score, y = ..density..))
```