Forecasting Suicides using Historical Data

ALY6015- Second Quarter, Term A, Dr. Matthew Goodwin Analysis Report of Final Capstone Project

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Introducing Dataset: Suicide Rates Over 1985 to 2016

The Dataset contains number of suicides in different countries over 1985 to 2016. It covers data for 101 countries in the form of categorical fields and continuous numerical fields

<u>Categorical Data:</u>

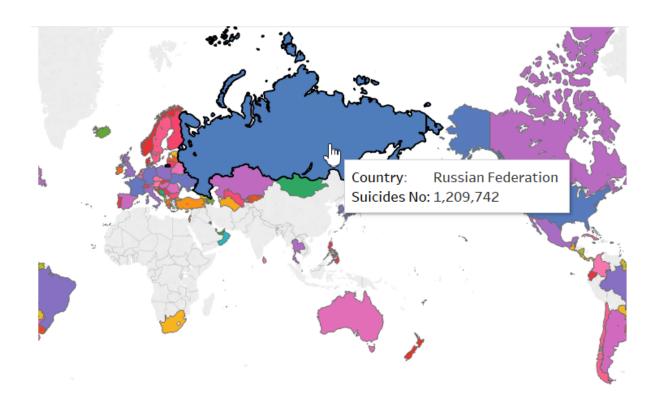
- Age
- Gender
- Generation

Numerical Data:

- Number of suicide
- Suicide Rate
- Population
- GDP for year
- GDP per capita



- > Forecasting the number of suicides in year 2019.
- > Country with maximum number of suicides in 2019.
- Currently its Russia



Visualization done in Tableau



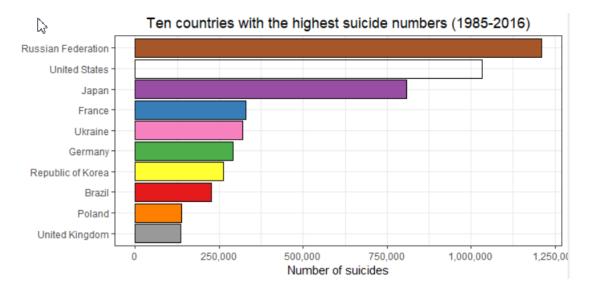


Methods/Models tried and implemented

- • : We **answered** questions like "The female commit more suicide or the males and visualize it for all the age groups" using the graphical representations.
- ✓: We conducted an experiment to finding the suicide rate and number of suicides among different age groups.
- ✓: We worked on finding the correlation of suicide with all the "dimensions"
- * : "We answered question by preforming "Time series using ARIMA prediction model" and preforming "Linear regression model" for better results.



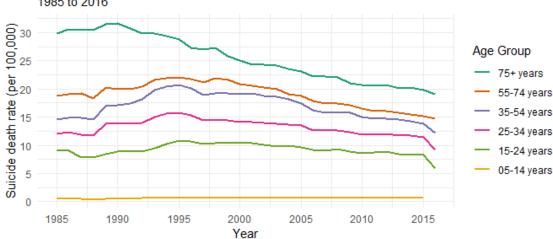
We can see from this graph that Russia has the highest number of deaths by suicide, following by United States and Japan – the top three countries dominate the list, accounting for 64% of the total number of the top 10.





There is an overall decline in suicide rates (measured per 100,000 people) across various age categories. The oldest age group had decreasing rates since 1990, while the younger ones saw the decreasing trend 10 years later, since 2000.

Suicide death rate by age (per 100,000), World 1985 to 2016

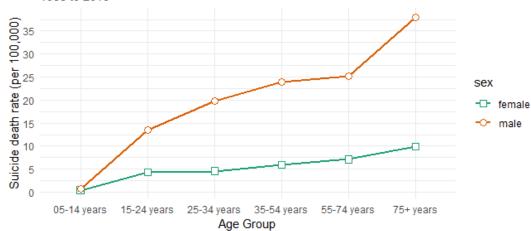


```
# Plot the suicide death number by age
age_group <- group_by(mydata, age, year)</pre>
mydata_by_age <- summarize(age_group,
                                sum suicide = sum(suicides no))
ggplot(aes(x=year, y=sum_suicide/1000, fill=forcats::fct_rev(age)),
       data = mydata_by_age) +
  geom_area(colour="black", size=.2, alpha=.8) +
        theme_bw() +
        scale_x_continuous(breaks=seg(1985,2015,5)) +
        scale_y\_continuous(breaks=seq(0,300,50)) +
  labs(title = "Suicide deaths number by age, World",
       subtitle = "1985 to 2016",
       x = "Year",
       y = "Number of suicide deaths in Thousands",
       fill = "Age Group") +
  scale_fill_brewer(palette = "Set2") +
  theme_minimal()
```



The gap between male and female rate for suicide is also different and not constant by age. There is almost no difference in the youngest group (05-14 years old), then the difference is getting bigger when the age increases, and it is biggest in the eldest group (> 75 years old) and middle-age group (55-74 years old

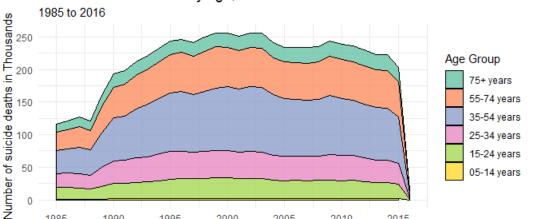
Distribution of suicide rates (per 100,000) by gender and age 1985 to 2016



```
# Distribution of suicide rates (per 100,000) by gender and age
mydata %>% group_by(sex, age) %>% summarize(rate=mean(suicides_per100k)) %>%
    ggplot(aes(age, rate, group=sex, color=sex, shape=sex))+
    geom_line(size=.8) +
    geom_point(size=3, fill="white") +
    scale_shape_manual(values=c(22,21)) +
    scale_y_continuous(breaks=seq(0,40,5)) +
    labs(title = "Distribution of suicide rates (per 100,000) by gender and age",
        subtitle = "1985 to 2016",
        x = "Age Group", y = "Suicide death rate (per 100,000)") +
    theme_minimal() +
    scale_color_brewer(palette = "Dark2")
```



The 35-54 year old group takes up the largest share of number of suicide deaths, roughly 36.3% of deaths. The younger groups, aged 15-34, are at lower risks of taking their own lives, with 28.6%. As age increases (55 and above), the number of suicides decrease.



2005

2010

2015

15-24 years

05-14 years

Suicide deaths number by age, World

1990

1995

```
# Plot the suicide death rate by age (per 100,000)
mydata %>% group_by(year, age) %>% summarize(s = sum(suicides_no),
                                             p = sum(population)) %>%
  ggplot(aes(year, (s/p)*100000, color=forcats::fct_rev(age))) +
  qeom_line(size=1) +
  scale_x_continuous(breaks=seq(1985,2015,5)) +
  scale_y\_continuous(breaks=seq(0,40,5)) +
  labs(title = "Suicide death rate by age (per 100,000), World",
       subtitle = "1985 to 2016",
       x = "Year", y = "Suicide death rate (per 100,000)", color="Age Group") +
  theme_minimal() +
  scale_color_brewer(palette = "Dark2")
```

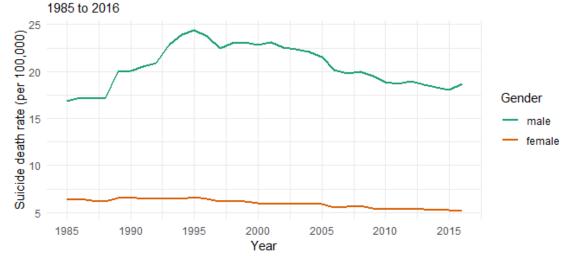
2000

Year



There is a big gap in suicide rate between male and female. We can see that male suicide rate is more than 3 times higher than rate for female. Both rates for male and female are seeing the declining trends over years.

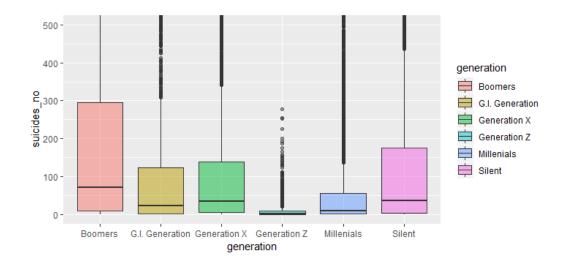
Suicide death rate by gender (per 100,000), World





Looking at the box plot, we see that baby boomer generation has the highest rate of suicide (34%) compare to 26% of silent generation and 23% of generation X.

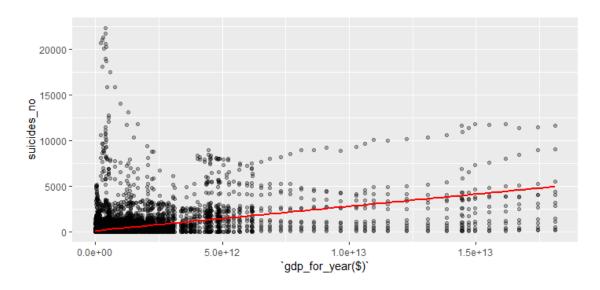
Generation Z holds the lowest share, with only 0.24%.



```
#Number of suicides categorised by different Generation mydata %>%  ggplot(aes(x=generation\ ,\ y=suicides\_no\ ,\ fill=generation))+\\ geom\_boxplot(alpha=.50)+\\ coord\_cartesian(ylim=c(0,500))
```



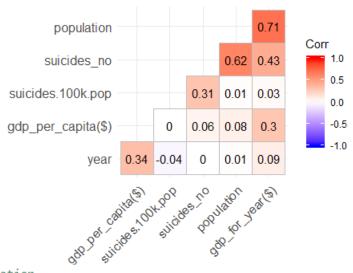
Looking at the graph we see a positive correlation between number of suicides and GDP for year, effect size on the correlation is -0.4335046. It's considering to be small effect size. Therefore, we can firmly say that there is slightly positive correlation and yet significant between suicides no and gdp for year.



```
#Positive correlation between suicides_no and gdp_for_year
#install.packages("ggplot2")
library(ggplot2)
mydata %>%
   ggplot(aes(x = `gdp_for_year($)` , y = suicides_no))+
   geom_jitter(alpha = .30)+
   geom_smooth(method = 'lm' ,color = "red")
```



We want to understand if there is a correlation between suicide and GDP of a country. However, we found a weak positive association between suicide number and GDP for year, 0.43, which is very close to 0, so we cannot say anything about this relation. Other variables, such as population or year, do not reasonably associated with the decrease or increase in rate of suicide.



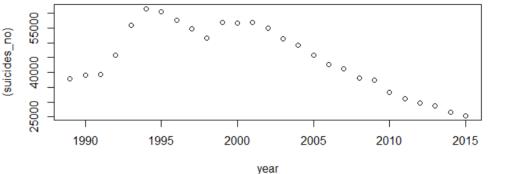
```
####### Correlation
library(dplyr)
# select numeric variables
df <- dplyr::select_if(mydata, is.numeric)</pre>
# calulate the correlations
r <- cor(df, use="complete.obs")</pre>
round(r, 2)
#visualize correlation
library(ggcorrplot)
ggcorrplot(r, hc.order = TRUE, type = "lower", lab = TRUE)
#linear regression
mydata_lm <- lm(suicides_per100k ~ qdp_for_year+ GDP_per_capita, data = mydata)
mydata_1m
library(visreg)
visreg(mydata_lm, "gdp_for_year", gg = TRUE)
visreg(mydata_lm, "GDP_per_capita", gg = TRUE)
```

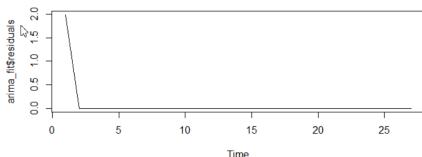
R-code and console out-put: The model is run on the Country with highest suicides i.e. Russian Federation

```
#Filtering the data required for runing the model
mydata <- mydata %>% filter(mydata$country == "Russian Federation")
tsdata <- subset(mydata,select=c('year','suicides_no'))
tsdata <- as.ts(tsdata)
class(tsdata)
byyear <- aggregate((suicides_no)~year,
                   data=tsdata.FUN=sum)
head(byyear)
#cor(x, y = NULL, use = "everything", method ="pearson")
cor(byyear, method ="pearson")
plot(byyear)
# Smoothing the data, considering the trend from year 2000 to year 2015
adenoTS = ts(byyear)
arima_fit = auto.arima(adenoTS[.1])
arima_fit = auto.arima(adenoTS[,1], trace = TRUE)
plot.ts(adenoTS[,2])
plot.ts(arima_fit$residuals)
#validate the model
Box.test(adenoTS[,2], lag = 5, type = "Ljung-Box")
Box.test(adenoTS[,2], lag = 10, type = "Ljung-Box")
Box.test(adenoTS[,2], lag = 15, type = "Ljung-Box")
```

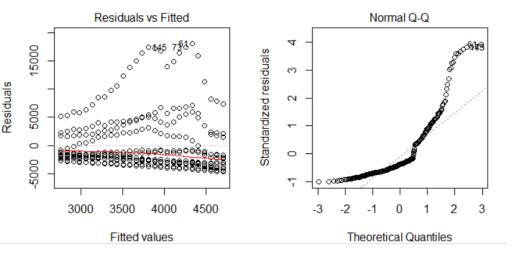
Results- Time series ARIMA

```
> cor(byyear, method ="pearson")
                    year (suicides_no)
               1.0000000
                            -0.6340826
year
(suicides_no) -0.6340826
                             1.0000000
> plot(byyear)
> # Smoothing the data, considering the trend from year 2000 to year 2015
> adenoTS = ts(byyear)
> arima_fit = auto.arima(adenoTS[,1])
> arima_fit = auto.arima(adenoTS[,1], trace = TRUE)
> plot.ts(adenoTS[,2])
> plot.ts(arima_fit$residuals)
> #validate the model
> Box.test(adenoTS[,2], lag = 5, type = "Ljung-Box")
        Box-Liung test
data: adenoTS[, 2]
X-squared = 59.084. df = 5. p-value = 1.879e-11
> Box.test(adenoTS[,2], lag = 10, type = "Ljung-Box")
        Box-Liuna test
data: adenoTS[, 2]
X-squared = 65.347, df = 10, p-value = 3.479e-10
```





R-code and console out-put



Results- Linear Regression

```
> # R Linear Regression
>> #X <- subset(mydata,select=c('suicides_no'))</pre>
> Y <- subset(mydata,select=c('year','suicides_no'))</pre>
> cor(Y)
                   year suicides_no
              1.0000000 -0.1268606
vear
suicides_no -0.1268606
                          1.0000000
> summary(Reg_model) # show regression coefficients table
Call:
lm(formula = suicides_no ~ year, data = mydata)
⊾Residuals:
           10 Median
 -4661 -2918 -1731
                        1926 18004
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) 153938.98
                         65450.15 2.352
                                             0.0193 *
                -75.03
                            32.69 -2.295
                                             0.0224 *
year
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '1
Residual standard error: 4583 on 322 degrees of freedom
Multiple R-squared: 0.01609, Adjusted R-squared: 0.01304
F-statistic: 5.267 on 1 and 322 DF, p-value: 0.02238
> confint(Reg_model)
                  2.5 %
                               97.5 %
(Intercept) 25175.0705 282702.88010
              -139.3447
vear
                           -10.71043
                       Histogram of residuals(Reg model)
        120
    Frequency
        40
             -5000
                        0
                                 5000
                                          10000
                                                    15000
                                                             20000
                               residuals(Reg model)
```

Results

Time series model:
ARIMA Model include
"Running the model,
validating and
predicting the model"

Not ideal: The data set don't have enough frequency data

Regression model:
Linear regression Model
include "Running the
model, validating and
predicting the model"

Ideal: The data set has the linear decreasing trend

The suicide number has started to decrease from year 2000 and it is projected that the number will further fall. As the correlation coefficient in negative for number of suicides.

Reference Page

- ➤ Kan Nishida (2016). Filtering Data with dplyr. Medium blog. Retrieved from https://blog.exploratory.io/filter-data-with-dplyr-76cf5f1a258e
- ➤ Lindsay Lee, Max Roser and Esteban Ortiz-Ospina (2016). Suicide. Our World in Data. Retrieved from https://ourworldindata.org/suicide
- RDocumentation. Correlation, Variance and Covariance (Matrices). Retrieved from https://www.rdocumentation.org/packages/stats/versions/3.5.2/topics/cor
- World Bank Dataset. Suicide Rates Overview 1985 to 2016. Kaggle. Retrieved from https://www.kaggle.com/russellyates88/suicide-rates-overview-1985-to-2016

The End