

“EXPLORATORY DATA ANALYSIS ON GLOBAL SUICIDE RATES”

A Report

Submitted as special assignment

of

2CSOE03 DATA ANALYTICS

By

Deep Khut (19BIC008)

Under the Guidance of
Prof. Aparna Kumari



**COMPUTER SCIENCE AND ENGINEERING DEPARTMENT
INSTITUTE OF TECHNOLOGY
NIRMA UNIVERSITY**

Ahmedabad 382 481

NOVEMBER 2022

TABLE OF CONTENTS

No.	INDEX	PAGE
1	INTRODUCTION	3
2	DATA WRANGLING	4
3	EXPLORATORY DATA ANALYSIS	6
4	MACHINE LEARNING & PREDICTIVE ANALYTICS	12
5	CONCLUSION	13
6	REFERENCES	14

1. INTRODUCTION:

Suicide is one of the leading causes of death among all adults and rates are increasing in both men and women. But numbers also show stark differences between genders.

In 2017, men died by suicide 3.54 times more often than women. Middle-aged white men, in particular, are susceptible. White males accounted for nearly 70-percent of suicide deaths in 2017, according to the American Foundation for Suicide Prevention.

“There can be a stigma among men that they should ‘tough things out,’ rather than seeking help if they’re having struggles with their mental health,” says Dr. Lisa Baker, an SSM Health Psychologist at St. Mary’s Hospital - Madison. “As a result, mental health conditions are under-reported and under-detected in men, leaving them vulnerable to suicide.”

People who live in rural areas are at higher risk of suicide than their urban counterparts, according to the Centers for Disease Control and Prevention. This, in part, can be explained by greater access to firearms, drug and alcohol use and a scarce of health care providers and emergency medical services. Cultural factors are also a barrier to accessing care and getting support from family and friends.

To **perform Data Analysis** and wants you to examine **trends & correlations** within our data. We would like to make a **Machine Learning algorithm** where we can train our **AI to learn** & improve from experience. Thus, we would want to **predict** the amount of suicides numbers in a certain demographic.

This project seeks to **explore** the underlying factors. We will use a sample of **44,000** data points gathered from **141** different countries, between the **80’s** to **2016**.

Research Questions

1. Which year has the most suicides? Which year has the least suicides?
2. Which country has the most suicides? Which country has the least suicides?
3. Are certain age groups more inclined to suicide?
4. What is the relationship between gender and the number of suicides?

Features & Predictor:

Our **Predictor (Y, Suicide Count)** is determined by **5 features (X)**:

1. **country** (Categorical)

2. **year: year of suicide** (Categorical)
3. **sex: Male, Female** (Categorical)
4. **age** (Categorical)
5. **population: (#)**

2. DATA WRANGLING:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns

data = pd.read_csv("C:/Users/jayes/Downloads/who_suicide_statistics.csv/who_suicide_statistics.csv")

# look at 1st 5 data points
data.head(5)
```

	country	year	sex	age	suicides_no	population
0	Albania	1985	female	15-24 years	NaN	277900.0
1	Albania	1985	female	25-34 years	NaN	246800.0
2	Albania	1985	female	35-54 years	NaN	267500.0
3	Albania	1985	female	5-14 years	NaN	298300.0
4	Albania	1985	female	55-74 years	NaN	138700.0

Our data set has **5 Features** (Country, Year, Gender, Age, Population). We will explore all of these in detail. While the suicide_no is what we would like to **predict**.

```
data.info() # print the concise summary of the dataset
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 43776 entries, 0 to 43775
Data columns (total 6 columns):
#   Column                Non-Null Count  Dtype
---  -
0   country                43776 non-null  object
1   year                   43776 non-null  int64
2   sex                   43776 non-null  object
3   age                   43776 non-null  object
4   suicides_no            41520 non-null  float64
5   population             38316 non-null  float64
dtypes: float64(2), int64(1), object(3)
memory usage: 2.0+ MB
```

```
# counts total row in each col. that have null values
# note: all the na columns are type Object
data.isna().sum()
```

```
country      0
year         0
sex          0
age          0
suicides_no 2256
population   5460
dtype: int64
```

```
# From above, we can see that, suicides_no & population, have null values.
```

```
# Lets, fill the null values with zero using 'fillna'
data= data.fillna(0)
data.isna().sum()
```

```
country      0
year         0
sex          0
age          0
suicides_no  0
population   0
dtype: int64
```

```
In [11]: data['age'].unique()
Out[11]:
array(['15-24 years', '25-34 years', '35-54 years', '5-14 years',
      '55-74 years', '75+ years'], dtype=object)
```

```
In [13]: data['country'].unique()
Out[13]:
array(['Albania', 'Anguilla', 'Antigua and Barbuda', 'Argentina',
      'Armenia', 'Aruba', 'Australia', 'Austria', 'Azerbaijan',
      'Bahamas', 'Bahrain', 'Barbados', 'Belarus', 'Belgium', 'Belize',
      'Bermuda', 'Bolivia', 'Bosnia and Herzegovina', 'Brazil',
      'British Virgin Islands', 'Brunei Darussalam', 'Bulgaria',
      'Cabo Verde', 'Canada', 'Cayman Islands', 'Chile', 'Colombia',
      'Costa Rica', 'Croatia', 'Cuba', 'Cyprus', 'Czech Republic',
      'Denmark', 'Dominica', 'Dominican Republic', 'Ecuador', 'Egypt',
      'El Salvador', 'Estonia', 'Falkland Islands (Malvinas)', 'Fiji',
      'Finland', 'France', 'French Guiana', 'Georgia', 'Germany',
      'Greece', 'Grenada', 'Guadeloupe', 'Guatemala', 'Guyana', 'Haiti',
      'Honduras', 'Hong Kong SAR', 'Hungary', 'Iceland',
      'Iran (Islamic Rep of)', 'Iraq', 'Ireland', 'Israel', 'Italy',
      'Jamaica', 'Japan', 'Jordan', 'Kazakhstan', 'Kiribati', 'Kuwait',
      'Kyrgyzstan', 'Latvia', 'Lithuania', 'Luxembourg', 'Macau',
      'Malaysia', 'Maldives', 'Malta', 'Martinique', 'Mauritius',
      'Mayotte', 'Mexico', 'Monaco', 'Mongolia', 'Montenegro',
      'Montserrat', 'Morocco', 'Netherlands', 'Netherlands Antilles',
      'New Zealand', 'Nicaragua', 'Norway',
      'Occupied Palestinian Territory', 'Oman', 'Panama', 'Paraguay',
```

```
# the Number of different Countries our dataset is from
data['country'].nunique()
# Our dataset is from 141 different Countries
```

```
# The different country groups
data['year'].unique()
```

FILLING IN MEAN VALUES FOR THE MISSING DATA & REPLACE NA VALUES WITH THEIR MEAN VALUES

```
# Replace 0 values with, NA
data['suicides_no'] = data['suicides_no'].replace(0,np.NAN)

# replace Na values with, mean value
mean_value=data['population'].mean()

data['population']=data['population'].fillna(mean_value)

# do same for Popualation
# replace Na values with, mean value
mean_value=data['suicides_no'].mean()

data['suicides_no']=data['suicides_no'].fillna(mean_value)
```

3. EXPLORATORY DATA ANALYSIS

➔ **Research Question I: Which year has the most Suicides ? Which year has the 1east Suicides ?**

```
data['suicides_no'] = data['suicides_no'].replace(0,np.NAN)

mean_value=data['suicides_no'].mean()
data['suicides_no']=data['suicides_no'].fillna(mean_value)

def find_minmax(x):
    #use the function 'idxmin' to find the index of lowest suicide
    min_index = data[x].idxmin()
    #use the function 'idxmax' to find the index of Highest suicide
    high_index = data[x].idxmax()

    high = pd.DataFrame(data.loc[high_index,:])
    low = pd.DataFrame(data.loc[min_index,:])

    #print the Year with high and low suicide
    print("Year Which Has Highest "+ x + " : ",data['year'][high_index]
)
    print("Year Which Has Lowest "+ x + " : ",data['year'][min_index])
    return pd.concat([high,low],axis = 1)

find_minmax('suicides_no')
```

```

Year Which Has Highest suicides_no : 1994
Year Which Has Lowest suicides_no : 1987
Out[32]:

```

	33128	29
country	Russian Federation	Albania
year	1994	1987
sex	male	female
age	35-54 years	75+ years
suicides_no	22338.0	1.0
population	19044200.0	35600.0

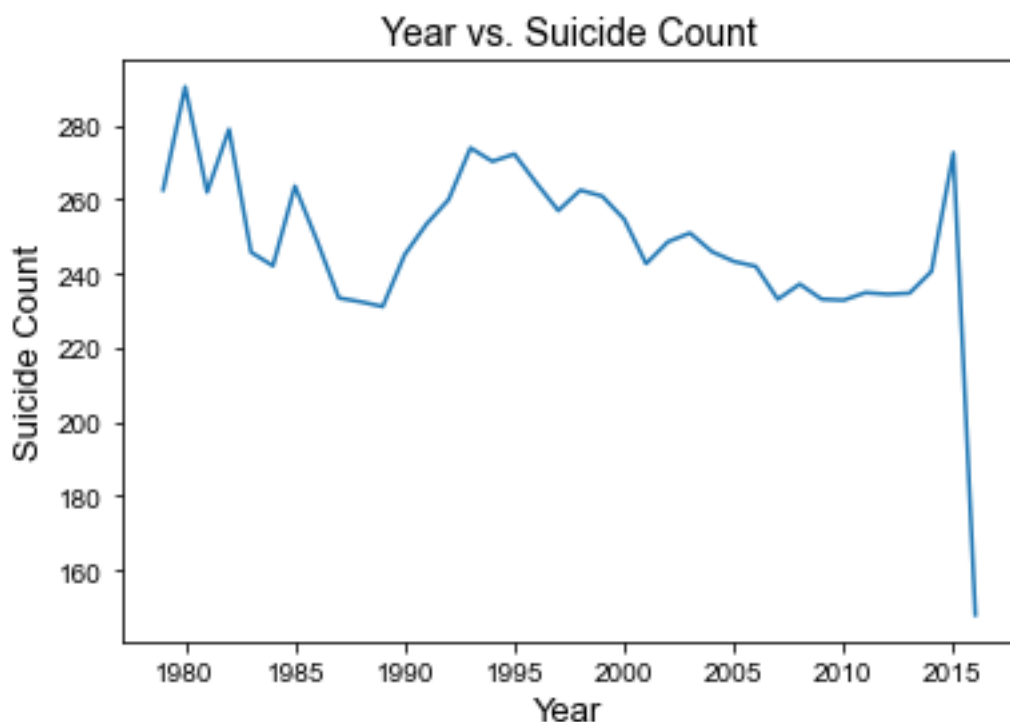
YEAR — WISE ANALYSIS

```

data.groupby('year')['suicides_no'].mean().plot()

#setup the title and labels of the figure.
plt.title("Year vs. Suicide Count",fontsize = 14)
plt.xlabel('Year',fontsize = 13)
plt.ylabel('Suicide Count',fontsize = 13)

```



From observing our **Time Series Line Plot**, we can see a **sharp drop** in suicides in 1985. This **decrease** could be due to **awareness** of suicide & **mental health** in the 80s, as well as **improved recognition** of those at risk. This is indeed **accurate**, as the research, “Suicide in the elderly” **supports** this claim.

➔ **Research Question 2: Which country has the most Suicides? Which country has the least Suicides?**

```
def find_minmax(x):
```

```

    #use the function 'idxmin' to find the index of lowest suicide
    min_index = data[x].idxmin()
    #use the function 'idxmax' to find the index of Highest suicide
    high_index = data[x].idxmax()

    high = pd.DataFrame(data.loc[high_index,:])
    low = pd.DataFrame(data.loc[min_index,:])

    #print the country with high and low suicide
    print("Country Which Has Highest "+ x + " : ",data['country'][high_
index])
    print("Country Which Has Lowest "+ x + " : ",data['country'][min_i
ndex])
    return pd.concat([low,high],axis = 1)

find_minmax('suicides_no')

```

```

Country Which Has Highest suicides_no : Russian Federation
Country Which Has Lowest suicides_no : Albania

```

Out[34]:

	29	33128
country	Albania	Russian Federation
year	1987	1994
sex	female	male
age	75+ years	35-54 years
suicides_no	1.0	22338.0
population	35600.0	19044200.0

FEATURE ENGINEERING

CALCULATE THE SUICIDE PER POPULATION SIZE RATIO, TO BETTER UNDERSTAND OUR DATA

```

#calculate mean of suicides_no col
meanSuicide = data['suicides_no'].mean()
#calculate mean of pop. col
meanPop = data['population'].mean()
# Replace 0 or NaN populations, with the mean Populations
data['population'] = data['population'].replace(np.NaN,meanPop)
data['population'] = data['population'].replace(0,meanPop)
data.tail(3)

```

	country	year	sex	...	suicides_no	population	suicide_per_pop
43773	Zimbabwe	1990	male	...	6.0	1.456536e+06	0.000004
43774	Zimbabwe	1990	male	...	74.0	1.456536e+06	0.000051
43775	Zimbabwe	1990	male	...	13.0	1.456536e+06	0.000009

```
find_minmax('suicide_per_pop')
```

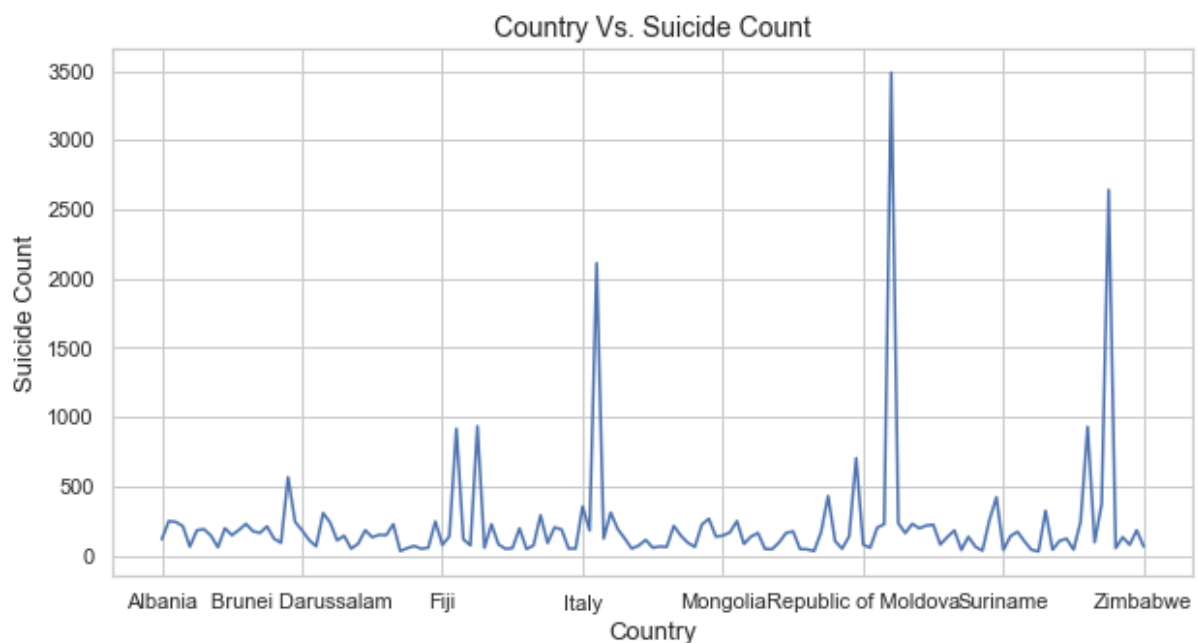


```

In [37]: find_minmax( suicide_per_pop )
Country Which Has Highest suicide_per_pop : Rodrigues
Country Which Has Lowest suicide_per_pop : Egypt
Out[37]:

```

	12993	32351
country	Egypt	Rodrigues
year	2005	2004
sex	male	male
age	5-14 years	75+ years
suicides_no	1.0	249.106328
population	9543088.0	259.0
suicide_per_pop	0.0	0.9618



Both the graph & find_minmax function above, **confirm** that Albania had the **lowest** suicide count, while Zimbabwe & Russian Federation, had the largest suicide count. A **reason** the Russian Federations may have a **large** suicide count may be that they have a very large population (144.5 million, while Albania only has about 3 million). It has been reported that Russian levels of alcohol consumption plays an immense role in it's **large suicide count**, but there is a **lack** of data to **support** this due to Soviet secrecy.

➔ Research Question 3: Are certain age groups more inclined to suicide?

```

sample = data.sample(3)
sample

```

	country	year	sex	...	suicides_no	population	suicide_per_pop
2264	Australia	1987	male	...	554.0	2031000.0	0.000273
41160	Ukraine	1996	female	...	165.0	3595700.0	0.000046
22904	Latvia	2006	male	...	167.0	294935.0	0.000566

[3 rows x 7 columns]

Right now our 'age' column is **separated** into **hyphen** groups. We want to analyze these groups as **numerical** data. We must take **away** the hyphen & create a **function** that classifies each category into a **certain** number. We first must **remove** all instances of a dash & change the object to type int to further analyze it.

```
# grabs first 2 chars from Age Column
data['AgeNum'] = data['age'].str[:2]

# remove all instances of dash -
data['AgeNum'] = data['AgeNum'].map(lambda x: x.replace('-', ''))

# now, convert it to type int (not Object)
data['AgeNum'] = data['AgeNum'].astype(int)

data['AgeNum'].tail(3)
```

```
43773      5
43774     55
43775     75
Name: AgeNum, dtype: int32
```

```
# creates Age Categories
def AgeGroup(x):
    if(x >= 60):
        return "Elderly"
    elif(x >= 30):
        return "Middle_Aged_Adults"
    elif(x >= 18):
        return "Adults"
    else:
        return "Adolescent"

# Map each row in the Col to the AgeGroup Method
data['AgeCategory'] = data['AgeNum'].map(lambda x: AgeGroup(x))
# convert it back to type String
data['AgeCategory'] = data['AgeCategory'].astype(str)
data['AgeCategory'].tail(3)
```

```
data['AgeNum'].tail(3)
```

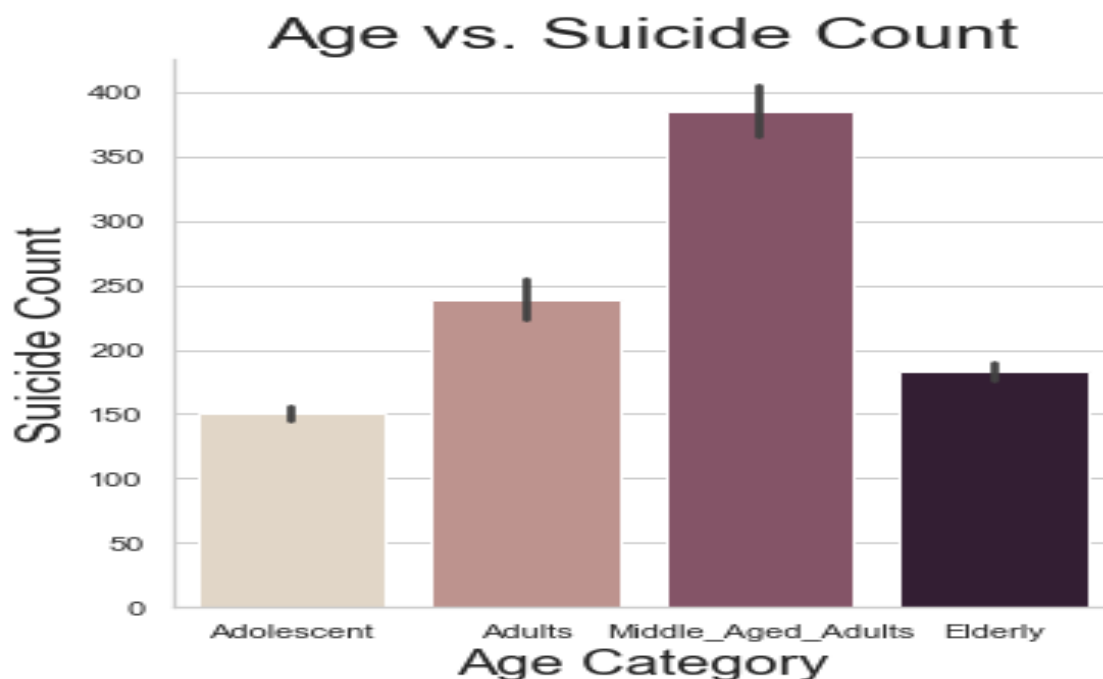
```
43773      Adolescent
43774  Middle_Aged_Adults
43775      Elderly
Name: AgeCategory, dtype: object
```

Note: Created an new column called 'AgeNum'

```
data.head(3)
```

```
country  year  sex  ... suicide_per_pop  AgeNum  AgeCategory
0  Albania  1985  female  ...      0.000896      15      Adolescent
1  Albania  1985  female  ...      0.001009      25           Adults
2  Albania  1985  female  ...      0.000931      35  Middle_Aged_Adults

[3 rows x 9 columns]
```

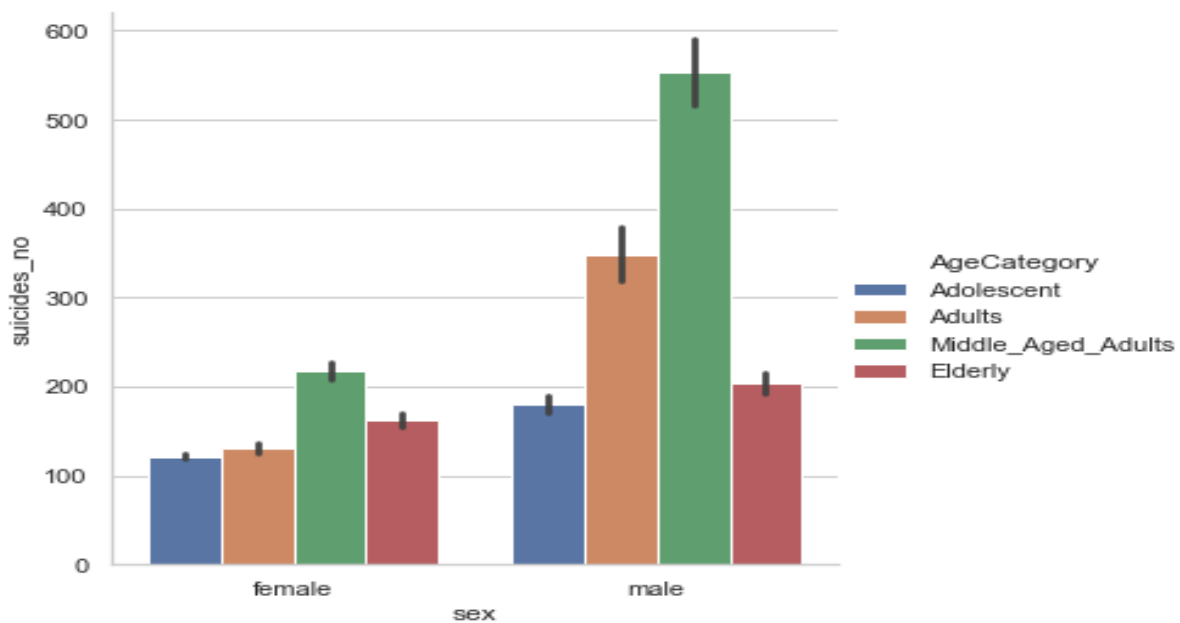


The data illustrates that middle aged adults, between the ages of 30 through 60, have the **highest** suicide count. While elderly and adolescents have about **half** the amount as middle aged adults.

➔ Research Question 4: What is the relationship between the gender and the number of suicides?

```
# there is an equal number of Males & Females in our data
data['sex'].value_counts()
```

```
female    21888
male      21888
Name: sex, dtype: int64
```



SUICIDE NUMBERS EXPRESSED IN TERMS OF GENDER & AGE CATEGORY

Suicide is one of the leading causes of death among all Americans adults. Data show heightened differences in suicide for different sexes. It's evident that males are more inclined to suicide. For Females, the 4 age categories seem to level off at 150. We can't say the same for males. Male adults & male middle aged adults are at very high risk of suicide. Both genders show middle aged adults as the leading age group of suicide.

4. MACHINE LEARNING + PREDICTIVE ANALYTICS

Our goal in this section is to build a multiple linear regression model that will be trained to understand correlation between our features and our predictor. We want to predict Y (suicides count), given a specific year, pertaining to a specific age group & gender.

Prepare Data for Modeling

To prepare data for modeling, just remember AES (Assign, Encode, Split). **Assign** the 4 features to X, & the last column to our predictor Y.

```
data.head(3)
newData= data.loc[:,['year','sex','AgeNum','suicides_no']]
newData.head(3)
X = newData.iloc[:, :-1].values # grab the every col except last
y = newData.iloc[:, -1].values # grab last col
```

Encoding categorical data. The Gender feature, is now encoded using 0's & 1's. Binary Output.

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
ct = ColumnTransformer(transformers=[('encoder', OneHotEncoder(), [1])]
, remainder='passthrough')
X = np.array(ct.fit_transform(X))
X
y
```

Splitting the data set into the Training set and Test set

```
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(X,y,test_size = 0.2
, random_state = 1)
print(x_train)
print(x_test)
print(y_train)
print(y_test)
```

Training the Multiple Linear Regression model on the Training set

```
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(x_train, y_train)
```

PREDICTIONS

Scenario: Say we wish to predict the suicide count, given certain demographics.

```
# we are predicting the suicide count given certain demographics
# A 55 year old male, in 2001
# suicide count of about 187.
print(regressor.predict([[1,0,2001,55]]))
```

[186.81518101]

5. CONCLUSION

1. There was a **decrease** in suicides toward the 80's. This could be due to awareness of suicide & mental health in the 80s, as well as **improved** recognition of those at risk. But shortly after that there is a **rise** in suicides that we are seeing.
2. Russian levels of alcohol consumption plays an immense role in its large suicide count, but there is a **lack of data to support** this due to Soviet secrecy.

3. The data illustrates that middle aged adults, between the ages of 30 through 60, have **the highest suicide** count. While elderly and adolescents have about **half** the amount as middle aged adults.
4. Suicide is one of the **leading** causes of death among all Americans adults. Data show **alarming differences** in suicide for different sexes. It's evident that males are more inclined to suicide, than females. In addition, Mental health is a major predictor for suicide.

6. REFERENCES

[THE THING ABOUT DATA VISUALIZATION TOOLS](#)

[GLOBAL SUICIDE ANALYSIS](#)

[A CLASSIFICATION ANALYSIS ON SUICIDE DATA](#)

[3 DATA VISUALIZATION | OVERVIEW OF SUICIDE IN THE WORLD](#)