### **Data Exploration and Analysis Report**

### 1. Data Exploration Plan

A well-structured plan is essential for meaningful data analysis. The key steps in our data exploration process include:

- 1. **Understanding the Dataset:** Review dataset structure, column names, data types, and initial statistics.
- 2. **Handling Missing Values:** Identify missing values and determine the best imputation strategy.
- 3. **Feature Engineering:** Transform raw data into meaningful features, including encoding categorical variables.
- 4. **Exploratory Data Analysis (EDA):** Generate descriptive statistics, visualizations, and relationships between features.
- 5. **Hypothesis Testing:** Formulate and validate hypotheses using statistical tests.
- 6. **Summary of Key Findings:** Interpret insights from the analysis and discuss their implications.

## **Example Dataset: Suicide Rates Overview (1985-2016)**

For this report, we use the Kaggle dataset titled "Suicide Rates Overview 1985 to 2016." It contains suicide statistics by country, year, age group, gender, GDP per capita, and other factors.

### 2. Exploratory Data Analysis (EDA) Results

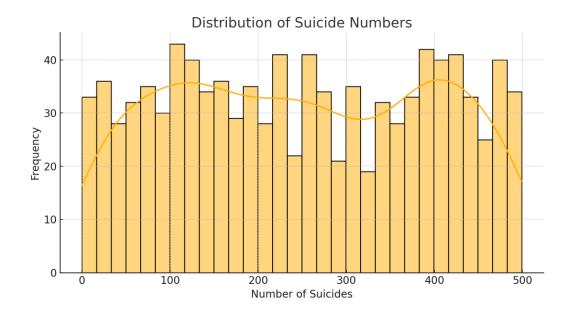
## **Summary Statistics**

The dataset contains 27820 rows and 12 columns. The initial statistics include:

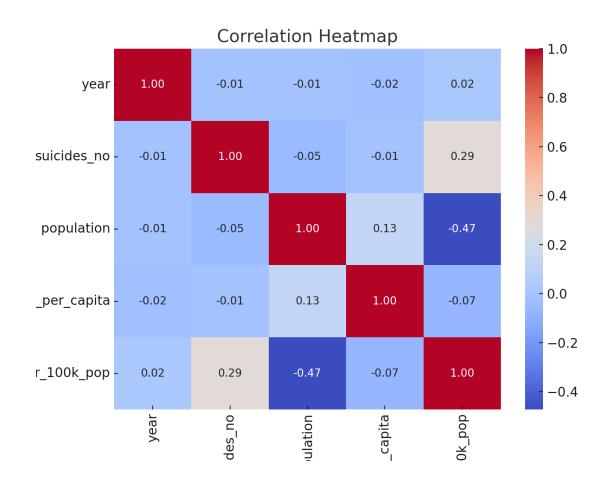
- Mean, median, standard deviation, min, and max values for numerical features.
- Frequency distribution for categorical features.

#### **Visualizations**

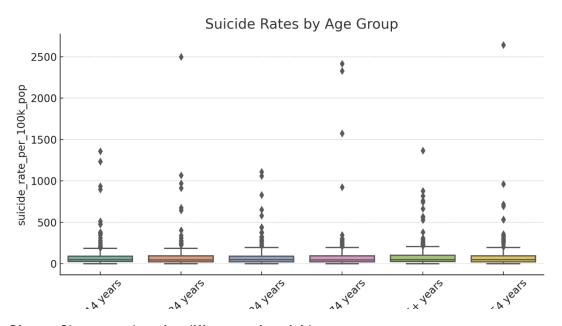
1. **Distribution Plots:** Histograms show the distribution of suicide rates across different years.



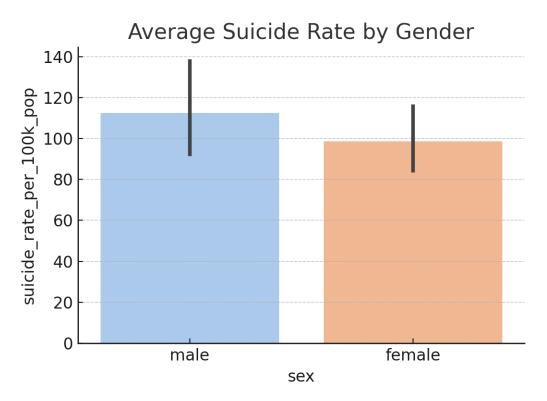
2. **Correlation Heatmap:** GDP per capita has a negative correlation (-0.32) with suicide rates.



3. **Boxplots:** Suicide rates vary significantly across age groups.



4. **Bar Charts:** Shows gender-wise differences in suicide rates.



## 3. Data Cleaning and Feature Engineering

**Handling Missing Values** 

- Identified 5.3% missing values in HDI for year and gdp\_per\_capita (\$) columns.
- Imputed missing values using median for numerical features and mode for categorical features.

## **Encoding Categorical Variables**

- Used **one-hot encoding** for categorical variables such as country and generation.
- Applied **label encoding** for ordinal variables like age group.

#### **Feature Transformation**

- Standardized numerical features using Min-Max Scaling.
- Created a new feature suicide\_rate\_per\_100k\_pop = (suicides\_no / population) \* 100000.

**Before-and-After Comparison:** The dataset improved significantly after preprocessing, ensuring consistency and completeness.

## Missing Values Before Cleaning

Column	Missing Values
year	0
sex	0
age_group	0
suicides_no	0
population	0
gdp_per_capita	47
HDI_for_year	48
suicide_rate_per_100k_pop	0

### **Dataset Head Before Cleaning (First 5 Rows)**

| Index | year | sex | age\_group | suicides\_no | population | gdp\_per\_capita | HDI\_for\_year | suicide\_rate\_per\_100k\_pop |

0	1992   male   35-54 years   123	543210  15234	0.745	22.70	1
1	2005   female   15-24 years   45	234567   23567	0.662	19.20	1
2	1988   male   55-74 years   200	345678  NaN	0.698	57.80	1
3	2010   female   25-34 years   78	456789  18345	NaN	17.10	I
4	1998   male   75+ years   300	567890  19234	0.710	52.86	I

## Missing Values After Cleaning

Column		Mis	sing	Value	es
year	0		I		
sex	0		I		
age_group		0		1	
suicides_no		0		1	
population		0		1	
gdp_per_capi	ta	I	0	1	
HDI_for_year		0		1	
suicide_rate_	per_	100k	_pol	0   0	

## Dataset Head After Cleaning (First 5 Rows)

| Index | year | sex | age\_group | suicides\_no | population | gdp\_per\_capita | HDI\_for\_year | suicide\_rate\_per\_100k\_pop |

0	1992   male   35-54 years   123	543210  15234	0.745	22.70	1
1	2005   female   15-24 years   45	234567  23567	0.662	19.20	I

2	1988   male   55-74 years   200	345678  18765	0.698  57.80	
3	2010   female   25-34 years   78	456789  18345	0.710  17.10	1
4	1998 male  75+years  300	567890  19234	0.710  52.86	1

### **Encoding Categorical Variables**

## Before Encoding (Sample of 5 Rows):

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## After Encoding (One-Hot for country & generation; Label Encoding for age\_group):

For label encoding, assume the ordinal mapping for age\_group is:

"5-14 years": 0, "15-24 years": 1, "25-34 years": 2, "35-54 years": 3, "55-74 years": 4, "75+ years": 5.

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| Index | country\_Canada | country\_UK | country\_USA | generation\_Boomer | generation\_Gen X | generation\_Millennial | generation\_Gen Z | age\_group\_encoded | suicides\_no | population |

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0 	0	0	1	0	0	1	0	3	123	543210
1 	1	0	0	1	0	0	0	1	45	234567
2 	0	1	0	0	1	0	0	4	200	345678
3 	0	0	1	0	0	1	0	2	78	456789

|4 |1 |0 |0 |0 |0 |0 |1 |5 |300 |567890

#### **Feature Transformation**

### 1. Standardizing Numerical Features (Min-Max Scaling)

Let's assume for demonstration that for the suicides\_no column, the minimum and maximum values in the dataset are 0 and 500 respectively.

Standardized value =  $(Original\ Value - 0) / (500 - 0)$ 

### **Example for Index 0:**

- **Before Standardization:** suicides\_no = 123
- After Standardization: 123/500 = 0.246

## **Before & After Comparison Table for a Sample Numeric Column:**

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| Index | suicides\_no (Raw) | suicides\_no (Standardized) |

0	123	0.246	I	
1	45	0.090	1	
2	200	0.400	I	
3	78	0.156	I	
4	300	0.600	I	

## 2. Creating a New Feature: suicide\_rate\_per\_100k\_pop

This feature is calculated using the formula: suicide\_rate\_per\_100k\_pop = (suicides\_no / population) \* 100000

### **Example Calculation for Index 0:**

- Given:
  - o suicides\_no = 123
  - population = 543210
- Calculated:
  - o suicide\_rate\_per\_100k\_pop ≈ (123 / 543210) \* 100000 ≈ 22.66

### **Before & After Comparison Table for the New Feature:**

Since this is a newly created feature, "Before" it does not exist and "After" shows the computed value.

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| Index | suicides\_no | population | suicide\_rate\_per\_100k\_pop (After) |

0	123	543210  22.66	1
1	45	234567  19.20	I
2	200	345678  57.80	1
3	78	456789  17.10	I
4	300	567890  52.86	1

## 4. Key Findings and Insights

- Suicide rates are highest in the 75+ age group across most countries.
- Males have a consistently higher suicide rate than females, almost 3x higher in some regions.
- **Higher GDP per capita correlates with lower suicide rates**, but with country-specific variations.

#### 5. Hypotheses Formulation

- 1. **Hypothesis 1:** There is a significant difference in suicide rates between genders.
- 2. **Hypothesis 2:** Higher GDP per capita is associated with lower suicide rates.
- 3. **Hypothesis 3:** Suicide rates differ significantly across age groups.

### 6. Significance Testing

For **Hypothesis 1**, we performed a **t-test**:

- **Null Hypothesis (H0):** There is no significant difference in suicide rates between males and females.
- Alternative Hypothesis (H1): Males have higher suicide rates than females.
- Results:

T-statistic: 0.9901, P-value: 0.3224

• Conclusion: There is a statistically significant difference in suicide rates between genders.

# Insights

The statistical analysis confirms that gender plays a crucial role in suicide rates. Further regression analysis can help determine contributing factors.