Cancer Rates Beyond Borders:
What's Behind the Disparities?

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  - Data Quality Assessment
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EXECUTIVE SUMMARY

- Study Objective
  - Conduct data analysis to investigate the potential drivers for high cancer rates between countries given various world performance indicators (social protection and labor, education, economy and growth, environment, climate change, agricultural and rural development, social development, health, science and technology, urban development) and indices (human development, environmental performance).
- Methodology and Tools
  - Data Quality Assessment using Python Pandas and NumPy APIs
  - Data Preprocessing using Python Pandas and Scikit-Learn APIs
  - Data Exploration using Python Matplotlib, Seaborn and SciPy APIs
- Overall Findings
  - Data quality issues were identified and handled with the appropriate data preprocessing methods.
  - Relevant numeric indicators which highly correlated with cancer rates were determined.
  - Relevant categorical indices that effectively differentiated varying levels of cancer rates were determined.
  - Combined key numeric and categorical drivers for high cancer rates were statistically evaluated.

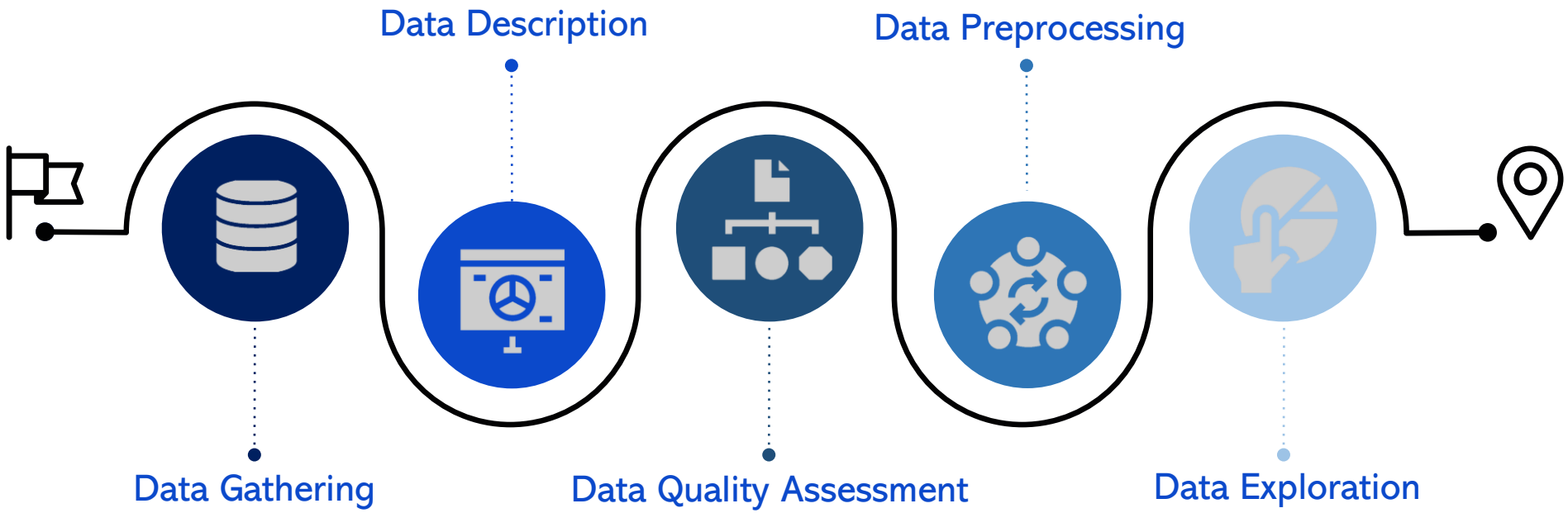
INTRODUCTION

- Cancer – a complex group of diseases characterized by the uncontrolled growth and spread of abnormal cells, has emerged as a leading cause of morbidity and mortality worldwide.
- While the prevalence of cancer varies significantly between countries, unraveling the factors that contribute to these variations is crucial for effective prevention, early detection, and treatment strategies.
- This capstone project generally aims to conduct a data analysis to determine the key factors influencing cancer rates among countries.
  - In particular, an exploratory analysis of high-quality and preprocessed information will be conducted which could provide a visual snapshot of the data in a clear and concise manner – allowing to derive insights, uncover patterns, and understand relationships.

Section 1

Methodology

METHODOLOGY



- Source assessment
- Data download
- Variable description

- Data dimension
- Column types
- Numeric statistics
- Categorical statistics

- Row duplicates
- Column fill rate
- Row fill rate
- Low variance
- High data skew

- Data cleaning
- Data imputation
- Outlier treatment
- Collinearity
- Transformation
- Centering and scaling
- Data Encoding

- Visual exploration
- Hypothesis testing

Section 2

Results Summary

RESULTS – DATA GATHERING

World Performance Indicators

Social Protection and Labor [Source: World Bank]
Education [Source: World Bank]
Economy and Growth [Source: World Bank]
Environment [Source: World Bank]
Climate Change [Source: World Bank]
Agricultural and Rural Development [Source: World Bank]
Social Development [Source: World Bank]
Health [Source: World Bank]
Science and Technology [Source: World Bank]
Urban Development [Source: World Bank]

World Performance Indices

Human Development [Source: Human Development Reports]
Environmental Performance [Source: Yale Center]

- The study hypothesizes that **world performance indicators** (social protection and labor, education, economy and growth, environment, climate change, agricultural and rural development, social development, health, science and technology, urban development) and **indices** (human development, environmental performance) directly influence **cancer rates** across countries.

World Cancer Rates
[Source: World Population Review]

- The objective of the study is to explore and prepare the dataset to determine which among the **world performance indicators** and **indices** are the significant key drivers of **cancer rates** across countries.

RESULTS – DATA DESCRIPTION

Country 177 Unique Values	COUNTRY		
GDP Per Person Employed (USD) Min: 1.7K | Mean: 45.3K | Max: 234.6K	GDPPER	Human Development Index Category 4 Categories	HDICAT
Urban Population (% of Total) Min: 13.3 | Mean: 59.8 | Max: 100.0	URBPOP	Environmental Performance Index (Score) Min: 18.9 | Mean: 42.9 | Max: 77.9	EPISCO
Patent Applications by Residents (Count) Min: 1.0 | Mean: 20.6K | Max: 1344.8K	PATRES	GDP per Capita (USD) Min: 0.2K | Mean: 13.9K | Max: 117.3K	GDPCAP
R&D Expenditure (% of GDP) Min: 0.1 | Mean: 1.2 | Max: 5.3	RNDGDP	Tertiary School Enrollment (% Gross) Min: 2.4 | Mean: 50.0 | Max: 143.3	ENRTER
Annual Population Growth (%) Min: -2.1 | Mean: +1.1 | Max: +3.7	POPGRO	Population Density (Persons per Km^2) Min: 2.1 | Mean: 200.8 | Max: 7918.9	POPDEN
Life Expectancy at Birth (Years) Min: 52.7 | Mean: 71.7 | Max: 84.5	LIFEXP	PM2.5 Air Pollution Exposure (% of Total) Min: 0.3 | Mean: 91.9 | Max: 100.0	PM2EXP
Tuberculosis Incidence per 100K (Count) Min: 0.7 | Mean: 105.0 | Max: 592.0	TUBINC	CO2 Emissions (Metric Tons per Capita) Min: 0.0 | Mean: 3.7 | Max: 31.7	CO2EMI
Death by Communicable Disease (% of Total) Min: 1.3 | Mean: 21.3 | Max: 65.2	DTHCMD	Forest Area (% of Land Area) Min: 0.0 | Mean: 32.2 | Max: 97.4	FORARE
Agricultural Land (% of Land Area) Min: 0.5 | Mean: 38.8 | Max: 80.8	AGRLND	Methane Emissions (Kiloton) Min: 0.0K | Mean: 47.8K | Max: 1186.2K	METEMI
Greenhouse Gas Emissions (Kiloton) Min: 0.1K | Mean: 259.5K | Max: 12,942.8K	GHGEMI	Renewable Electricity Output (% of Total) Min: 0.0 | Mean: 39.7 | Max: 100.0	RELOUT

- Original data consisted of:
  - 177 observation rows
  - 1 numeric response column
  - 19 numeric predictor columns
  - 1 categorical predictor column
  - 1 object metadata column
- Numeric data are of different scales.

Target

CANRAT — Cancer Rate Per 100K (%)
Min: 78.4 | Mean: 183.8 | Max: 452.0

21 Predictors + Metadata

177 Observations

- Numeric Target
- Numeric Predictor
- Categorical Predictor
- Object Metadata

RESULTS – DATA QUALITY ASSESSMENT

Country	COUNTRY		
GDP Per Person Employed (USD) MIS | MUL | OUT	GDPPER	Human Development Index Category MIS	HDICAT
Urban Population (% of Total) MIS	URBPOP	Environmental Performance Index (Score) MIS | OUT	EPISCO
Patent Applications by Residents (Count) MIS | SKW	PATRES	GDP per Capita (USD) MIS | MUL | OUT	GDPCAP
R&D Expenditure (% of GDP) MIS	RNDGDP	Tertiary School Enrollment (% Gross) MIS	ENRTER
Annual Population Growth (%) MIS	POPGRO	Population Density (Persons per Km^2) MIS | SKW | OUT	POPDEN
Life Expectancy at Birth (Years) MIS	LIFEXP	PM2.5 Air Pollution Exposure (% of Total) MIS | NZV | SKW | OUT	PM2EXP
Tuberculosis Incidence per 100K (Count) MIS | OUT	TUBINC	CO2 Emissions (Metric Tons per Capita) MIS | OUT	CO2EMI
Death by Communicable Disease (% of Total) MIS	DTHCMD	Forest Area (% of Land Area) MIS	FORARE
Agricultural Land (% of Land Area) MIS	AGRLND	Methane Emissions (Kiloton) MIS | SKW | MUL | OUT	METEMI
Greenhouse Gas Emissions (Kiloton) MIS | SKW | MUL | OUT	GHGEMI	Renewable Electricity Output (% of Total) MIS	RELOUT

- Data quality issues identified included:
  - Missing data
  - Skewed distributions
  - Near zero variance
  - High multicollinearity
  - High outlier ratio
- Data preprocessing is needed to address data quality issues.

Target

CANRAT — Cancer Rate Per 100K (%) OUT

21 Predictors + Metadata

177 Observations

- Numeric Target
- Numeric Predictor
- Categorical Predictor
- Object Metadata

MIS High Missing Data
SKW Skewed Distribution
NZV Near-Zero Variance
MUL High Multicollinearity
OUT High Outlier Ratio

RESULTS – DATA PREPROCESSING

Predictors + Metadata	DATA PREPROCESSING STEPS	Observations
21		177
17	High Column-Wise Missing Data[A]: Column Fill Rate<90% | High Row-Wise Missing Data[B]: Row Missing Rate>20%	163
17	Data Imputation: Iterative Imputation for Low Column-Wise Missing Data	163
15	Multicollinearity Detection: Pairwise Correlation Coefficient>0.90[C]	163
15	Skewness Detection | Outlier Detection: Skewness>|3|, Value>75th Percentile+1.5 IQR, Value<25th Percentile-1.5 IQR	163
15	Shape Transformation: Yeo-Johnson Transformation for Skewness and Outlier Reduction	163
14	Post-Transformation Outlier | Skewness Detection: Outlier Count>25[D], Skewness>|3|[D]	163
17	Centering | Scaling: Standardization for Comparable Range | Data Encoding: One-Hot Encoding for Categorical Column	163

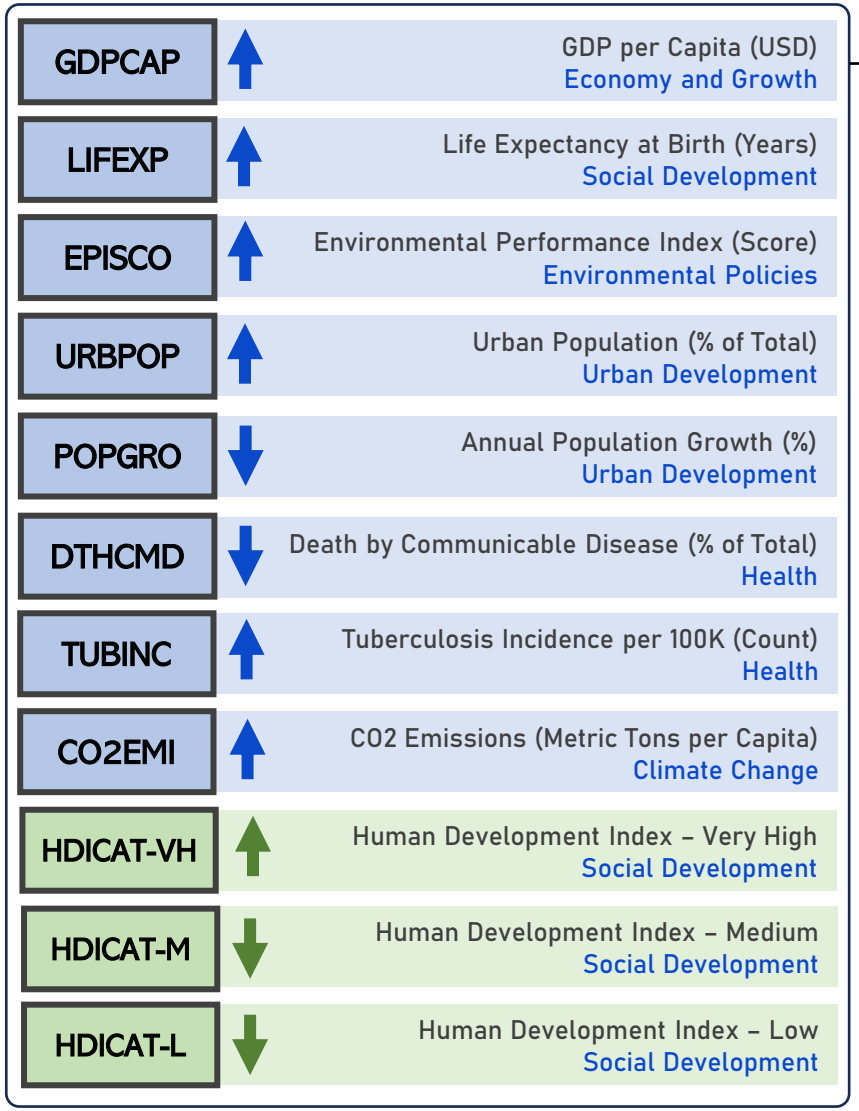
Removed 7 Predictors

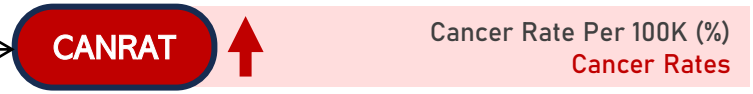
- [A]RNDGDP
- [A]PATRES
- [A]ENRTER
- [A]RELOUT
- [C]GDPPER
- [C]METEMI
- [D]PM2EXP

Removed 14 Observations

[B]COUNTRY: Guadeloupe, Martinique, French Guiana, New Caledonia, French Polynesia, Guam, Puerto Rico, North Korea, Somalia, South Sudan, Venezuela, Libya, Eritrea, Yemen

RESULTS – DATA EXPLORATION





Statistically significant associations with predictors were determined.

- Higher cancer rates were generally observed among progressive countries as characterized by the following:
  - Higher economic growth leading to advanced industrialization with increased exposure to pollutants but potentially better environmental policies
  - Better socioeconomic policies to support cancer screening and diagnosis
  - More robust healthcare infrastructure to support the completeness of cancer registries and reporting mechanisms
  - Shifting demographics including a potentially aging population with increased disease incidence trends
- Given the findings, a high level of progressiveness may not inherently imply higher cancer rates; rather, the relationship might have been influenced by a combination of demographic, environmental, and healthcare-related factors associated with developed countries.
- The relationship between a country's level of progressiveness and cancer rates may not be straightforward, and other potential drivers must be considered in the future when exploring this issue including data on lifestyle factors (smoking rates, obesity levels) or genetic diversity (infectious agents).

Section 3

Detailed Findings

RESULTS – DATA QUALITY ASSESSMENT

- ## Findings

1. No duplicated rows observed.
2. Missing data noted for 20 variables with Null.Count>0 and Fill.Rate<1.0.
   - RNDGDP: Null.Count = 103, Fill.Rate = 0.418
   - PATRES: Null.Count = 69, Fill.Rate = 0.610
   - ENRTER: Null.Count = 61, Fill.Rate = 0.655
   - RELOUT: Null.Count = 24, Fill.Rate = 0.864
   - GDPPER: Null.Count = 12, Fill.Rate = 0.932
   - EPISCO: Null.Count = 12, Fill.Rate = 0.932
   - HDICAT: Null.Count = 10, Fill.Rate = 0.943
   - PM2EXP: Null.Count = 10, Fill.Rate = 0.943
   - DTHCMD: Null.Count = 7, Fill.Rate = 0.960
   - METEMI: Null.Count = 7, Fill.Rate = 0.960
   - CO2EMI: Null.Count = 7, Fill.Rate = 0.960
   - GDPCAP: Null.Count = 7, Fill.Rate = 0.960
   - GHGEMI: Null.Count = 7, Fill.Rate = 0.960
   - FORARE: Null.Count = 4, Fill.Rate = 0.977
   - TUBINC: Null.Count = 3, Fill.Rate = 0.983
   - AGRLND: Null.Count = 3, Fill.Rate = 0.983
   - POPGRO: Null.Count = 3, Fill.Rate = 0.983
   - POPDEN: Null.Count = 3, Fill.Rate = 0.983
   - URBPOP: Null.Count = 3, Fill.Rate = 0.983
   - LIFEXP: Null.Count = 3, Fill.Rate = 0.983
3. 120 observations noted with at least 1 missing data. From this number, 14 observations reported high Missing.Rate>0.2.
   - COUNTRY=Guadeloupe: Missing.Rate= 0.909
   - COUNTRY=Martinique: Missing.Rate= 0.909
   - COUNTRY=French Guiana: Missing.Rate= 0.909
   - COUNTRY=New Caledonia: Missing.Rate= 0.500
   - COUNTRY=French Polynesia: Missing.Rate= 0.500
   - COUNTRY=Guam: Missing.Rate= 0.500
   - COUNTRY=Puerto Rico: Missing.Rate= 0.409
   - COUNTRY=North Korea: Missing.Rate= 0.227
   - COUNTRY=Somalia: Missing.Rate= 0.227
   - COUNTRY=South Sudan: Missing.Rate= 0.227
   - COUNTRY=Venezuela: Missing.Rate= 0.227
   - COUNTRY=Libya: Missing.Rate= 0.227
   - COUNTRY=Eritrea: Missing.Rate= 0.227
   - COUNTRY=Yemen: Missing.Rate= 0.227
4. Low variance observed for 1 variable with First.Second.Mode.Ratio>5.
   - PM2EXP: First.Second.Mode.Ratio = 53.000
5. No low variance observed for any variable with Unique.Count.Ratio>10.
6. High skewness observed for 5 variables with Skewness>3 or Skewness<(-3).
   - POPDEN: Skewness = +10.267
   - GHGEMI: Skewness = +9.496
   - PATRES: Skewness = +9.284
   - METEMI: Skewness = +5.801
   - PM2EXP: Skewness = -3.141

- Code chunk formulated to generate the assessment tables is presented as a markdown file here.
- Python notebook for the entire capstone project is saved on GitHub and can be accessed here.

RESULTS – DATA CLEANING

- ## Findings

1. Subsets of rows and columns with high rates of missing data were removed from the dataset:
   - 4 variables with Fill.Rate<0.9 were excluded for subsequent analysis.
     - RNDGDP: Null.Count = 103, Fill.Rate = 0.418
     - PATRES: Null.Count = 69, Fill.Rate = 0.610
     - ENRTER: Null.Count = 61, Fill.Rate = 0.655
     - RELOUT: Null.Count = 24, Fill.Rate = 0.864
   - 14 rows with Missing.Rate>0.2 were exluded for subsequent analysis.
     - COUNTRY=Guadeloupe: Missing.Rate= 0.909
     - COUNTRY=Martinique: Missing.Rate= 0.909
     - COUNTRY=French Guiana: Missing.Rate= 0.909
     - COUNTRY=New Caledonia: Missing.Rate= 0.500
     - COUNTRY=French Polynesia: Missing.Rate= 0.500
     - COUNTRY=Guam: Missing.Rate= 0.500
     - COUNTRY=Puerto Rico: Missing.Rate= 0.409
     - COUNTRY=North Korea: Missing.Rate= 0.227
     - COUNTRY=Somalia: Missing.Rate= 0.227
     - COUNTRY=South Sudan: Missing.Rate= 0.227
     - COUNTRY=Venezuela: Missing.Rate= 0.227
     - COUNTRY=Libya: Missing.Rate= 0.227
     - COUNTRY=Eritrea: Missing.Rate= 0.227
     - COUNTRY=Yemen: Missing.Rate= 0.227
2. No variables were removed due to zero or near-zero variance.

3. The cleaned dataset is comprised of:
   - **163 rows** (observations)
   - **18 columns** (variables)
     - **1/18 metadata** (object)
       - COUNTRY
     - **1/18 target** (numeric)
       - CANRAT
     - **15/18 predictor** (numeric)
       - GDPPER
       - URBPOP
       - POPGRO
       - LIFEXP
       - TUBINC
       - DTHCMD
       - AGRLND
       - GHGEMI
       - METEMI
       - FORARE
       - CO2EMI
       - PM2EXP
       - POPDEN
       - GDPCAP
       - EPISCO
     - **1/18 predictor** (categorical)
       - HDICAT

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RESULTS – MISSING DATA IMPUTATION

- ## Findings

1. Missing data for numeric variables were imputed using the iterative imputer algorithm with a linear regression estimator.
   - GDPPER: Null.Count = 1
   - FORARE: Null.Count = 1
   - PM2EXP: Null.Count = 5
2. Missing data for categorical variables were imputed using the most frequent value.
   - HDICAP: Null.Count = 1

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RESULTS – OUTLIER TREATMENT

- ## Findings

1. High number of outliers observed for 5 numeric variables with Outlier.Ratio>0.10 and marginal to high Skewness.
   - PM2EXP: Outlier.Count = 37, Outlier.Ratio = 0.226, Skewness=-3.061
   - GHGEMI: Outlier.Count = 27, Outlier.Ratio = 0.165, Skewness=+9.299
   - GDPCAP: Outlier.Count = 22, Outlier.Ratio = 0.134, Skewness=+2.311
   - POPDEN: Outlier.Count = 20, Outlier.Ratio = 0.122, Skewness=+9.972
   - METEMI: Outlier.Count = 20, Outlier.Ratio = 0.122, Skewness=+5.688
2. Minimal number of outliers observed for 5 numeric variables with Outlier.Ratio<0.10 and normal Skewness.
   - TUBINC: Outlier.Count = 12, Outlier.Ratio = 0.073, Skewness=+1.747
   - CO2EMI: Outlier.Count = 11, Outlier.Ratio = 0.067, Skewness=+2.693
   - GDPPER: Outlier.Count = 3, Outlier.Ratio = 0.018, Skewness=+1.554
   - EPISCO: Outlier.Count = 3, Outlier.Ratio = 0.018, Skewness=+0.635
   - CANRAT: Outlier.Count = 2, Outlier.Ratio = 0.012, Skewness=+0.910

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RESULTS – COLLINEARITY

- ## Findings

1. Majority of the numeric variables reported moderate to high correlation which were statistically significant.
2. Among pairwise combinations of numeric variables, high Pearson.Correlation.Coefficient values were noted for:
    - GDPPER and GDPCAP: Pearson.Correlation.Coefficient = +0.921
    - GHGEMI and METEMI: Pearson.Correlation.Coefficient = +0.905
3. Among the highly correlated pairs, variables with the lowest correlation against the target variable were removed.
    - GDPPER: Pearson.Correlation.Coefficient = +0.690
    - METEMI: Pearson.Correlation.Coefficient = +0.062

4. The cleaned dataset is comprised of:
    - **163 rows** (observations)
    - **16 columns** (variables)
        - **1/16 metadata** (object)
            - COUNTRY
        - **1/16 target** (numeric)
            - CANRAT
        - **13/16 predictor** (numeric)
            - URBPOP
            - POPGRO
            - LIFEXP
            - TUBINC
            - DTHCMD
            - AGRLND
            - GHGEMI
            - FORARE
            - CO2EMI
            - PM2EXP
            - POPDEN
            - GDPCAP
            - EPISCO
        - **1/16 predictor** (categorical)
            - HDICAT

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RESULTS – SHAPE TRANSFORMATION

- ## Findings

1. A Yeo-Johnson transformation was applied to all numeric variables to improve distributional shape.
2. Most variables achieved symmetrical distributions with minimal outliers after transformation.
3. One variable which remained skewed even after applying shape transformation was removed.
    - PM2EXP

4. The transformed dataset is comprised of:
    - **163 rows** (observations)
    - **15 columns** (variables)
        - **1/15 metadata** (object)
            - COUNTRY
        - **1/15 target** (numeric)
            - CANRAT
        - **12/15 predictor** (numeric)
            - URBPOP
            - POPGRO
            - LIFEXP
            - TUBINC
            - DTHCMD
            - AGRLND
            - GHGEMI
            - FORARE
            - CO2EMI
            - POPDEN
            - GDPCAP
            - EPISCO
        - **1/15 predictor** (categorical)
            - HDICAT

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RESULTS – CENTERING AND SCALING

- ## Findings

1. All numeric variables were transformed using the standardization method to achieve a comparable scale between values.
2. The scaled dataset is comprised of:
    - **163 rows** (observations)
    - **15 columns** (variables)
        - **1/15 metadata** (object)
            - COUNTRY
        - **1/15 target** (numeric)
            - CANRAT
        - **12/15 predictor** (numeric)
            - URBPOP
            - POPGRO
            - LIFEXP
            - TUBINC
            - DTHCMD
            - AGRLND
            - GHGEMI
            - FORARE
            - CO2EMI
            - POPDEN
            - GDPCAP
            - EPISCO
        - **1/15 predictor** (categorical)
            - HDICAT

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RESULTS – DATA ENCODING

- Findings

1. One-hot encoding was applied to the HDICAP_VH variable resulting to 4 additional columns in the dataset:
    - HDICAP_L
    - HDICAP_M
    - HDICAP_H
    - HDICAP_VH

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RESULTS – EXPLORATORY DATA ANALYSIS

- ## Findings

1. Bivariate analysis identified individual predictors with generally linear relationship to the target variable based on visual inspection.
2. Increasing values for the following predictors correspond to higher CANRAT measurements:
   - URBPOP
   - LIFEXP
   - CO2EMI
   - GDPCAP
   - EPISCO
   - HDICAP_VH
3. Decreasing values for the following predictors correspond to higher CANRAT measurements:
   - POPGRO
   - TUBINC
   - DTHCMD
   - HDICAP_L
   - HDICAP_M
4. Values for the following predictors did not affect CANRAT measurements:
   - AGRLND
   - GHGEMI
   - FORARE
   - POPDEN
   - HDICAP_H

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RESULTS – HYPOTHESIS TESTING

- ## Findings

1. The relationship between the numeric predictors to the CANRAT target variable was statistically evaluated using the following hypotheses:
   - **Null**: Pearson correlation coefficient is equal to zero
   - **Alternative**: Pearson correlation coefficient is not equal to zero
2. There is sufficient evidence to conclude of a statistically significant linear relationship between the CANRAT target variable and 10 of the 12 numeric predictors given their high Pearson correlation coefficient values with reported low p-values less than the significance level of 0.05.
   - GDPCAP: Pearson.Correlation.Coefficient=+0.735, Correlation.PValue=0.000
   - LIFEXP: Pearson.Correlation.Coefficient=+0.702, Correlation.PValue=0.000
   - DTHCMD: Pearson.Correlation.Coefficient=-0.687, Correlation.PValue=0.000
   - EPISCO: Pearson.Correlation.Coefficient=+0.648, Correlation.PValue=0.000
   - TUBINC: Pearson.Correlation.Coefficient=+0.628, Correlation.PValue=0.000
   - CO2EMI: Pearson.Correlation.Coefficient=+0.585, Correlation.PValue=0.000
   - POPGRO: Pearson.Correlation.Coefficient=-0.498, Correlation.PValue=0.000
   - URBPOP: Pearson.Correlation.Coefficient=+0.479, Correlation.PValue=0.000
   - GHGEMI: Pearson.Correlation.Coefficient=+0.232, Correlation.PValue=0.002
   - FORARE: Pearson.Correlation.Coefficient=+0.165, Correlation.PValue=0.035
3. The relationship between the categorical predictors to the CANRAT target variable was statistically evaluated using the following hypotheses:
   - **Null**: Difference in the means between groups 0 and 1 is equal to zero
   - **Alternative**: Difference in the means between groups 0 and 1 is not equal to zero
4. There is sufficient evidence to conclude of a statistically significant difference between the means of CANRAT measuremens obtained from groups 0 and 1 in 3 of the 4 categorical predictors given their high t-test statistic values with reported low p-values less than the significance level of 0.05.
   - HDICAT_VH: T.Test.Statistic=-10.605, T.Test.PValue=0.000
   - HDICAT_L: T.Test.Statistic=+6.559, T.Test.PValue=0.000
   - HDICAT_M: T.Test.Statistic=+5.104, T.Test.PValue=0.000

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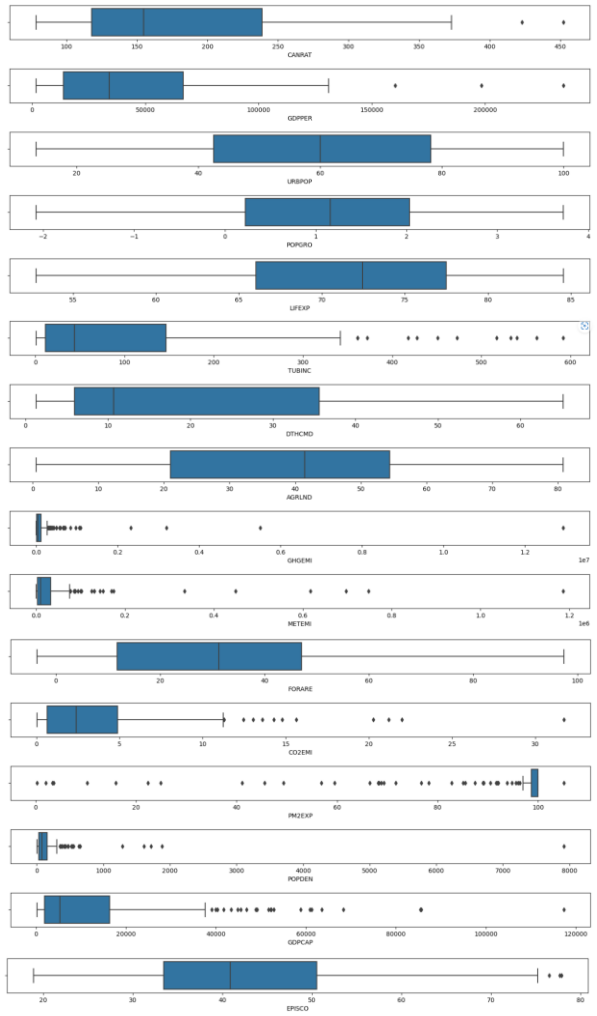
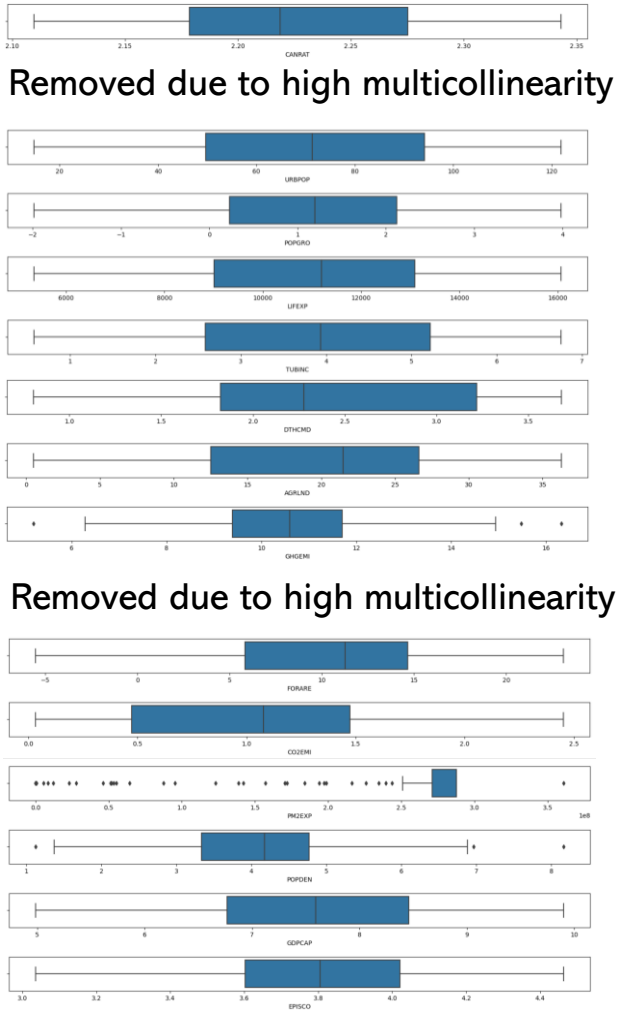
PLOTS – OUTLIER ANALYSIS

- Original Data



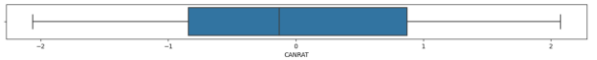
- Transformed Data



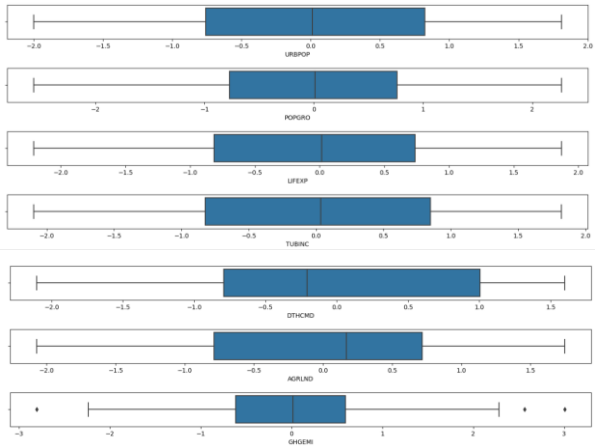
Removed due to high multicollinearity

Removed due to high multicollinearity

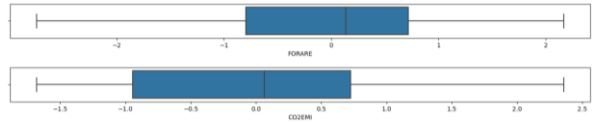
- Centered and Scaled Data



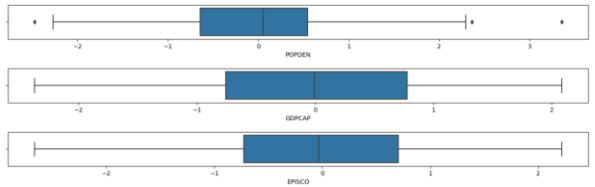
Removed due to high multicollinearity



Removed due to high multicollinearity

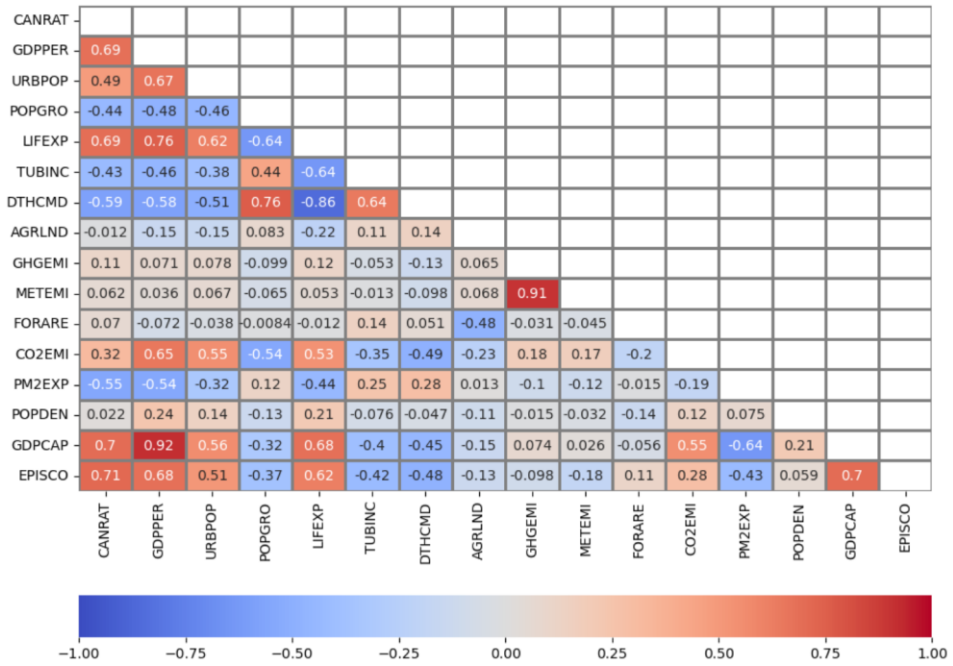


Removed due to persistent skew after transformation

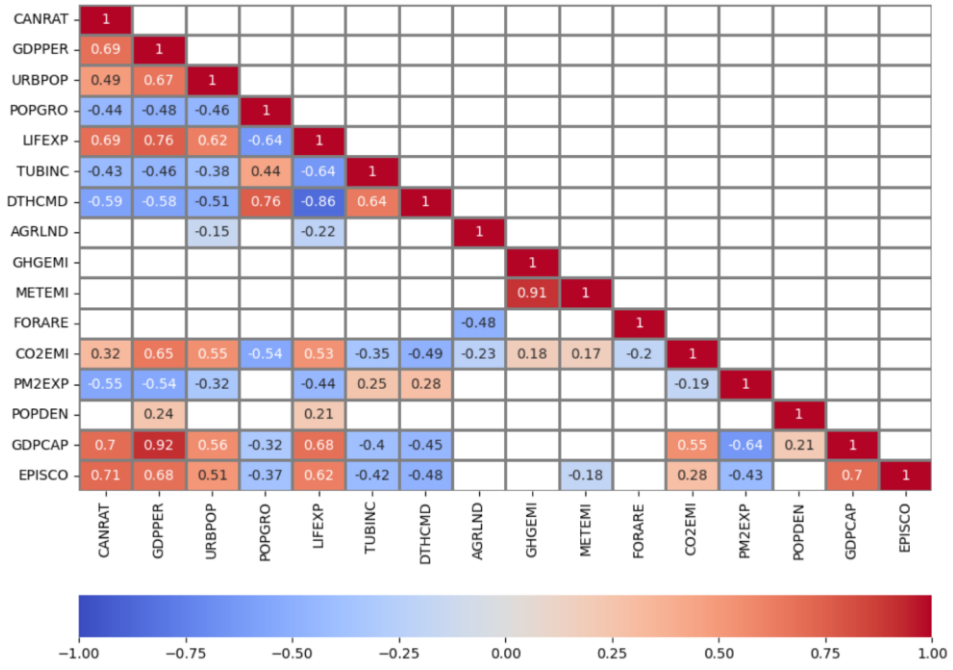


PLOTS – CORRELATION ANALYSIS

- All Correlations

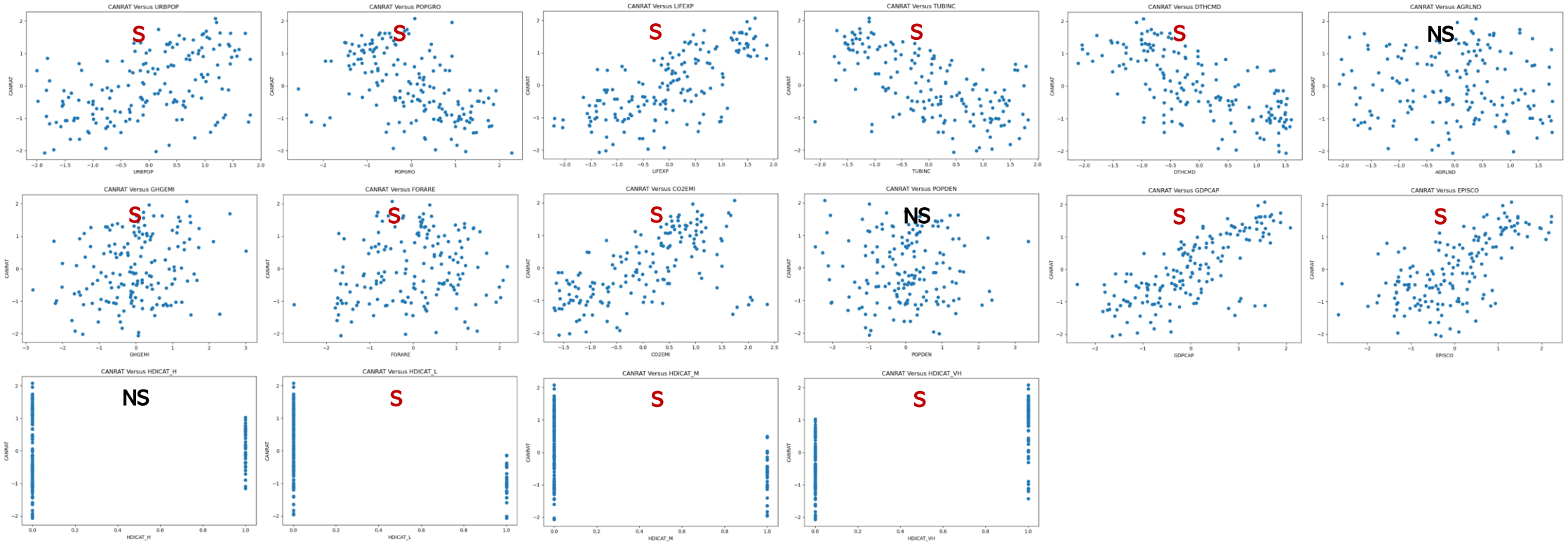


- Statistically Significant Correlations



PLOTS – EXPLORATORY DATA ANALYSIS

- Relationship Scatterplots



S: Association between predictor and target was statistically significant

NS: Association between predictor and target was not statistically significant

Section 4

Summary

OVERALL FINDINGS AND IMPLICATIONS

- Key Findings
  - Higher cancer rates were generally observed among progressive countries as characterized by the following:
    - Higher economic growth leading to advanced industrialization with increased exposure to pollutants but potentially better environmental policies
    - Better socioeconomic policies to support cancer screening and diagnosis
    - More robust healthcare infrastructure to support the completeness of cancer registries and reporting mechanisms
    - Shifting demographics including a potentially aging population with increased disease incidence trends
- Overall Implications
  - A high level of progressiveness may not inherently imply higher cancer rates; rather, the relationship might have been influenced by a combination of demographic, environmental, and healthcare-related factors associated with developed countries.
  - The relationship between a country's level of progressiveness and cancer rates may not be straightforward, and other potential drivers must be considered in the future when exploring this issue including data on lifestyle factors (smoking rates, obesity levels) or genetic diversity (infectious agents).

CONCLUSION

- Overall Summary
  - Data collection for the analysis involved world performance indicators and indices hypothesized to be directly influencing cancer rates across countries.
  - The quality of gathered data was assessed and potential issues were identified.
  - Appropriate pre-processing methods including remedial procedures to address duplicate, missing, outlying, and non-normalized data were applied to prepare the data for subsequent analysis. Additional data scaling and transformation were implemented.
  - EDA using visualization presented the various distributions and comparisons between the indicators and indices as evaluated against cancer rates – eventually identifying the key drivers of higher cancer rates.
  - Statistical hypothesis testing identified the individual drivers that were significantly associated with cancer rates.
  - Overall analysis findings were discussed and their practical implications were highlighted.

Section 5

Appendix

APPENDIX

- Source Data
  - Cancer Rates: World Population Review
  - Social Protection and Labor Indicator: World Bank
  - Education Indicator: World Bank
  - Economy and Growth Indicator: World Bank
  - Environment Indicator: World Bank
  - Climate Change Indicator: World Bank
  - Agricultural and Rural Development Indicator: World Bank
  - Social Development Indicator: World Bank
  - Health Indicator: World Bank
  - Science and Technology Indicator: World Bank
  - Urban Development Indicator: World Bank
  - Human Development Indices: Human Development Reports
  - Environmental Performance Indices: Yale Center for Environmental Law and Policy

APPENDIX

- Python Notebooks | Codes
  - GitHub URL: Data Background
  - GitHub URL: Data Description
  - GitHub URL: Data Quality Assessment
  - GitHub URL: Data Preprocessing
    - GitHub URL: Data Cleaning
    - GitHub URL: Missing Data Imputation
    - GitHub URL: Outlier Treatment
    - GitHub URL: Collinearity
    - GitHub URL: Shape Transformation
    - GitHub URL: Centering and Scaling
    - GitHub URL: Data Encoding
    - GitHub URL: Preprocessed Data Description
  - GitHub URL: Data Exploration
    - GitHub URL: Exploratory Data Analysis
    - GitHub URL: Hypothesis Testing

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- **[Book]** Data Mining: Practical Machine Learning Tools and Techniques by Ian Witten, Eibe Frank, Mark Hall and Christopher Pal
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Thank You!