DUTTA Proposal

June 26, 2025

[111]:
```python
#Understanding Dataset
import pandas as pd

df = pd.read_csv("world_bank_data_2025.csv")
df.shape
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3472 entries, 0 to 3471
Data columns (total 16 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   country_name                     3472 non-null   object
 1   country_id                       3472 non-null   object
 2   year                             3472 non-null   int64
 3   Inflation (CPI %)                2694 non-null   float64
 4   GDP (Current USD)                2933 non-null   float64
 5   GDP per Capita (Current USD)     2938 non-null   float64
 6   Unemployment Rate (%)            2795 non-null   float64
 7   Interest Rate (Real, %)          1735 non-null   float64
 8   Inflation (GDP Deflator, %)      2904 non-null   float64
 9   GDP Growth (% Annual)            2912 non-null   float64
 10  Current Account Balance (% GDP)  2563 non-null   float64
 11  Government Expense (% of GDP)    1820 non-null   float64
 12  Government Revenue (% of GDP)    1829 non-null   float64
 13  Tax Revenue (% of GDP)           1833 non-null   float64
 14  Gross National Income (USD)      2796 non-null   float64
 15  Public Debt (% of GDP)           852 non-null    float64
dtypes: float64(13), int64(1), object(2)
memory usage: 434.1+ KB
```

[111]:
```
              year  Inflation (CPI %)  GDP (Current USD)  \
count  3472.000000        2694.000000       2.933000e+03
mean   2017.500000           6.233154       3.964323e+11
std       4.610436          19.726903       1.749315e+12
min    2010.000000          -6.687321       3.210541e+07
25%    2013.750000           1.402112       6.264757e+09
```

```
50%    2017.500000           3.213523       2.587360e+10
75%    2021.250000           6.186626       1.874939e+11
max    2025.000000         557.201817       2.772071e+13

       GDP per Capita (Current USD)  Unemployment Rate (%)  \
count                   2938.000000            2795.000000
mean                   18483.495612               7.841141
std                    27301.814024               5.964358
min                      193.007146               0.100000
25%                     2280.748732               3.611000
50%                     6827.668145               5.771000
75%                    23727.024581              10.731500
max                   256580.515123              35.359000

       Interest Rate (Real, %)  Inflation (GDP Deflator, %)  \
count              1735.000000                  2904.000000
mean                  5.405051                     6.634865
std                   9.740924                    25.820196
min                 -81.132121                   -28.760135
25%                   1.734057                     1.218347
50%                   5.079009                     3.223184
75%                   8.869434                     6.905463
max                  61.882604                   921.535652

       GDP Growth (% Annual)  Current Account Balance (% GDP)  \
count            2912.000000                      2563.000000
mean                2.853544                        -2.363241
std                 6.053786                        13.740986
min               -54.336155                       -60.877754
25%                 0.997032                        -7.496525
50%                 3.100442                        -2.656009
75%                 5.355110                         1.854710
max                86.826748                       235.750605

       Government Expense (% of GDP)  Government Revenue (% of GDP)  \
count                    1820.000000                    1829.000000
mean                       27.325359                      26.677467
std                        12.642464                      18.116253
min                         0.000136                       0.000081
25%                        17.511484                      17.639153
50%                        26.000850                      24.821425
75%                        34.884582                      32.700782
max                       103.725787                     344.999451

       Tax Revenue (% of GDP)  Gross National Income (USD)  \
count             1833.000000                 2.796000e+03
mean                16.969924                 4.142237e+11
```

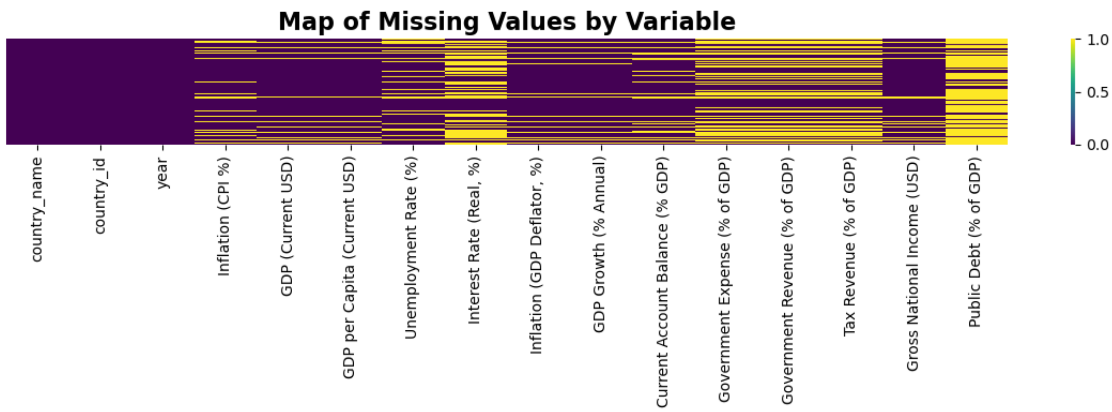
```
std                 8.218539              1.799783e+12
min                 0.000063              5.107533e+07
25%                12.285344              7.475538e+09
50%                16.321438              2.986520e+10
75%                21.448658              1.972529e+11
max               147.640196              2.757614e+13

       Public Debt (% of GDP)
count              852.000000
mean                61.863736
std                 40.409792
min                  1.845685
25%                 33.894232
50%                 51.651469
75%                 81.930649
max                249.366027
```

[113]:
```python
#Check for Missing or NULL values with detail analysis
import seaborn as sns
import matplotlib.pyplot as plt

#sns.heatmap(df.null(), cbar = False)
#print(df.isnull().sum())

def data_quality_assessment(df):
    """
    DATA QUALITY ASSESSMENT
    """
    print("DATA QUALITY ASSESSMENT")
    print("-" * 50)
    missing_data = pd.DataFrame({
        'Columns': df.columns,
        'Missing Values': df.isnull().sum(),
        'Missing Percentage': (df.isnull().sum() / len(df)) * 100
    }).sort_values('Missing Percentage', ascending=False)

    print(missing_data)

    # Visualisation des valeurs manquantes
    plt.figure(figsize=(12, 4))
    sns.heatmap(df.isnull(), cbar=True, yticklabels=False, cmap='viridis')
    plt.title('Map of Missing Values by Variable', fontsize=16,␣
↪fontweight='bold')
    plt.xticks(rotation=90)
    plt.tight_layout()
    plt.show()
```

```
    return missing_data
```

[31]:
```
data_quality_assessment(df)
```

```
DATA QUALITY ASSESSMENT
--------------------------------------------------
                                                          Columns  \
Public Debt (% of GDP)                             Public Debt (% of GDP)
Interest Rate (Real, %)                           Interest Rate (Real, %)
Government Expense (% of GDP)               Government Expense (% of GDP)
Government Revenue (% of GDP)               Government Revenue (% of GDP)
Tax Revenue (% of GDP)                             Tax Revenue (% of GDP)
Current Account Balance (% GDP)  Current Account Balance (% GDP)
Inflation (CPI %)                                       Inflation (CPI %)
Unemployment Rate (%)                               Unemployment Rate (%)
Gross National Income (USD)                   Gross National Income (USD)
Inflation (GDP Deflator, %)                   Inflation (GDP Deflator, %)
GDP Growth (% Annual)                               GDP Growth (% Annual)
GDP (Current USD)                                       GDP (Current USD)
GDP per Capita (Current USD)                 GDP per Capita (Current USD)
country_name                                                 country_name
country_id                                                     country_id
year                                                                 year

                                 Missing Values  Missing Percentage
Public Debt (% of GDP)                     2620           75.460829
Interest Rate (Real, %)                    1737           50.028802
Government Expense (% of GDP)              1652           47.580645
Government Revenue (% of GDP)              1643           47.321429
Tax Revenue (% of GDP)                     1639           47.206221
Current Account Balance (% GDP)             909           26.180876
Inflation (CPI %)                           778           22.407834
Unemployment Rate (%)                       677           19.498848
Gross National Income (USD)                 676           19.470046
Inflation (GDP Deflator, %)                 568           16.359447
GDP Growth (% Annual)                       560           16.129032
GDP (Current USD)                           539           15.524194
GDP per Capita (Current USD)                534           15.380184
country_name                                  0            0.000000
country_id                                    0            0.000000
year                                          0            0.000000
```



[31]:

```
                                                        Columns  \
Public Debt (% of GDP)                   Public Debt (% of GDP)
Interest Rate (Real, %)                 Interest Rate (Real, %)
Government Expense (% of GDP)     Government Expense (% of GDP)
Government Revenue (% of GDP)     Government Revenue (% of GDP)
Tax Revenue (% of GDP)                   Tax Revenue (% of GDP)
Current Account Balance (% GDP) Current Account Balance (% GDP)
Inflation (CPI %)                             Inflation (CPI %)
Unemployment Rate (%)                     Unemployment Rate (%)
Gross National Income (USD)         Gross National Income (USD)
Inflation (GDP Deflator, %)         Inflation (GDP Deflator, %)
GDP Growth (% Annual)                     GDP Growth (% Annual)
GDP (Current USD)                             GDP (Current USD)
GDP per Capita (Current USD)       GDP per Capita (Current USD)
country_name                                       country_name
country_id                                           country_id
year                                                       year

                                 Missing Values  Missing Percentage
Public Debt (% of GDP)                     2620           75.460829
Interest Rate (Real, %)                    1737           50.028802
Government Expense (% of GDP)              1652           47.580645
Government Revenue (% of GDP)              1643           47.321429
Tax Revenue (% of GDP)                     1639           47.206221
Current Account Balance (% GDP)             909           26.180876
Inflation (CPI %)                           778           22.407834
Unemployment Rate (%)                       677           19.498848
Gross National Income (USD)                 676           19.470046
Inflation (GDP Deflator, %)                 568           16.359447
GDP Growth (% Annual)                       560           16.129032
GDP (Current USD)                           539           15.524194
GDP per Capita (Current USD)                534           15.380184
```

```
country_name                                    0            0.000000
country_id                                      0            0.000000
year                                            0            0.000000
```

[115]:
```
#In-Depth Descriptive Analysis
import numpy as np

def descriptive_analysis(df):
    """
    Descriptive Analysis for Numerical Variables
    """
    print("DESCRIPTIVE STATISTICS")
    print("-" * 50)

    numeric_cols = df.select_dtypes(include=[np.number]).columns.tolist()
    numeric_cols = [col for col in numeric_cols if col != 'year']

    # Statistiques de base
    desc_stats = df[numeric_cols].describe()
    print(desc_stats.round(2))

    # Visualisation des distributions
    fig, axes = plt.subplots(4, 4, figsize=(20, 16))
    axes = axes.ravel()

    for i, col in enumerate(numeric_cols):
        if i < len(axes):
            # Histogramme avec courbe de densité
            df[col].hist(bins=30, alpha=0.7, ax=axes[i], color='skyblue',␣
↪edgecolor='black')
            axes[i].axvline(df[col].mean(), color='red', linestyle='--',␣
↪label=f'Moyenne: {df[col].mean():.2f}')
            axes[i].set_title(f'Distribution: {col}', fontweight='bold')
            axes[i].legend()
            axes[i].grid(True, alpha=0.3)

    # Masquer les sous-graphiques inutilisés
    for i in range(len(numeric_cols), len(axes)):
        axes[i].set_visible(False)

    plt.tight_layout()
    plt.suptitle('Distributions of Economic Variables', fontsize=16,␣
↪fontweight='bold', y=1.02)
    plt.show()
```

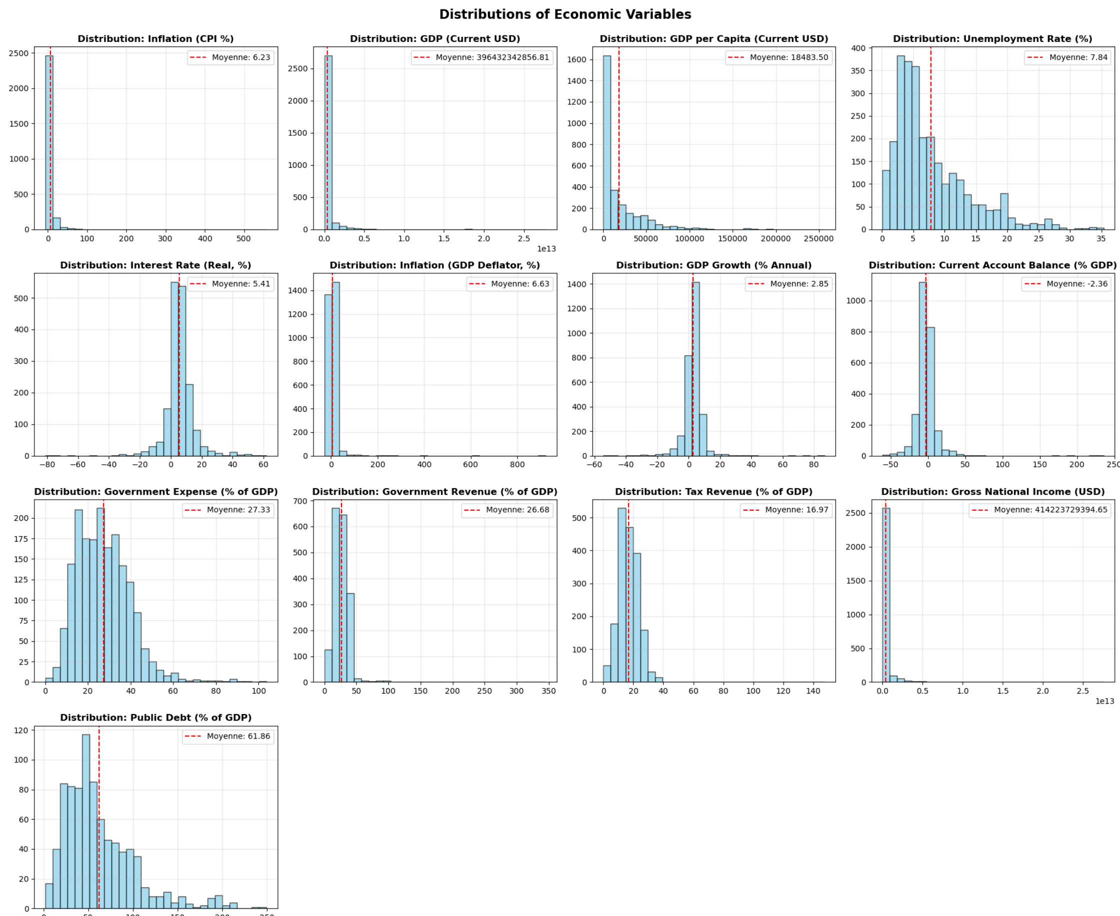
[39]:
```
descriptive_analysis(df)
```

```
DESCRIPTIVE STATISTICS
```

```
--------------------------------------------------
       Inflation (CPI %)  GDP (Current USD)  GDP per Capita (Current USD)  \
count            2694.00       2.933000e+03                       2938.00
mean                6.23       3.964323e+11                      18483.50
std                19.73       1.749315e+12                      27301.81
min                -6.69       3.210541e+07                        193.01
25%                 1.40       6.264757e+09                       2280.75
50%                 3.21       2.587360e+10                       6827.67
75%                 6.19       1.874939e+11                      23727.02
max               557.20       2.772071e+13                     256580.52

       Unemployment Rate (%)  Interest Rate (Real, %)  \
count                2795.00                  1735.00
mean                    7.84                     5.41
std                     5.96                     9.74
min                     0.10                   -81.13
25%                     3.61                     1.73
50%                     5.77                     5.08
75%                    10.73                     8.87
max                    35.36                    61.88

       Inflation (GDP Deflator, %)  GDP Growth (% Annual)  \
count                      2904.00                2912.00
mean                          6.63                   2.85
std                          25.82                   6.05
min                         -28.76                 -54.34
25%                           1.22                   1.00
50%                           3.22                   3.10
75%                           6.91                   5.36
max                         921.54                  86.83

       Current Account Balance (% GDP)  Government Expense (% of GDP)  \
count                          2563.00                        1820.00
mean                             -2.36                          27.33
std                              13.74                          12.64
min                             -60.88                           0.00
25%                              -7.50                          17.51
50%                              -2.66                          26.00
75%                               1.85                          34.88
max                             235.75                         103.73

       Government Revenue (% of GDP)  Tax Revenue (% of GDP)  \
count                        1829.00                 1833.00
mean                           26.68                   16.97
std                            18.12                    8.22
min                             0.00                    0.00
25%                            17.64                   12.29
50%                            24.82                   16.32
```

75%	32.70	21.45
max	345.00	147.64

	Gross National Income (USD)	Public Debt (% of GDP)
count	2.796000e+03	852.00
mean	4.142237e+11	61.86
std	1.799783e+12	40.41
min	5.107533e+07	1.85
25%	7.475538e+09	33.89
50%	2.986520e+10	51.65
75%	1.972529e+11	81.93
max	2.757614e+13	249.37



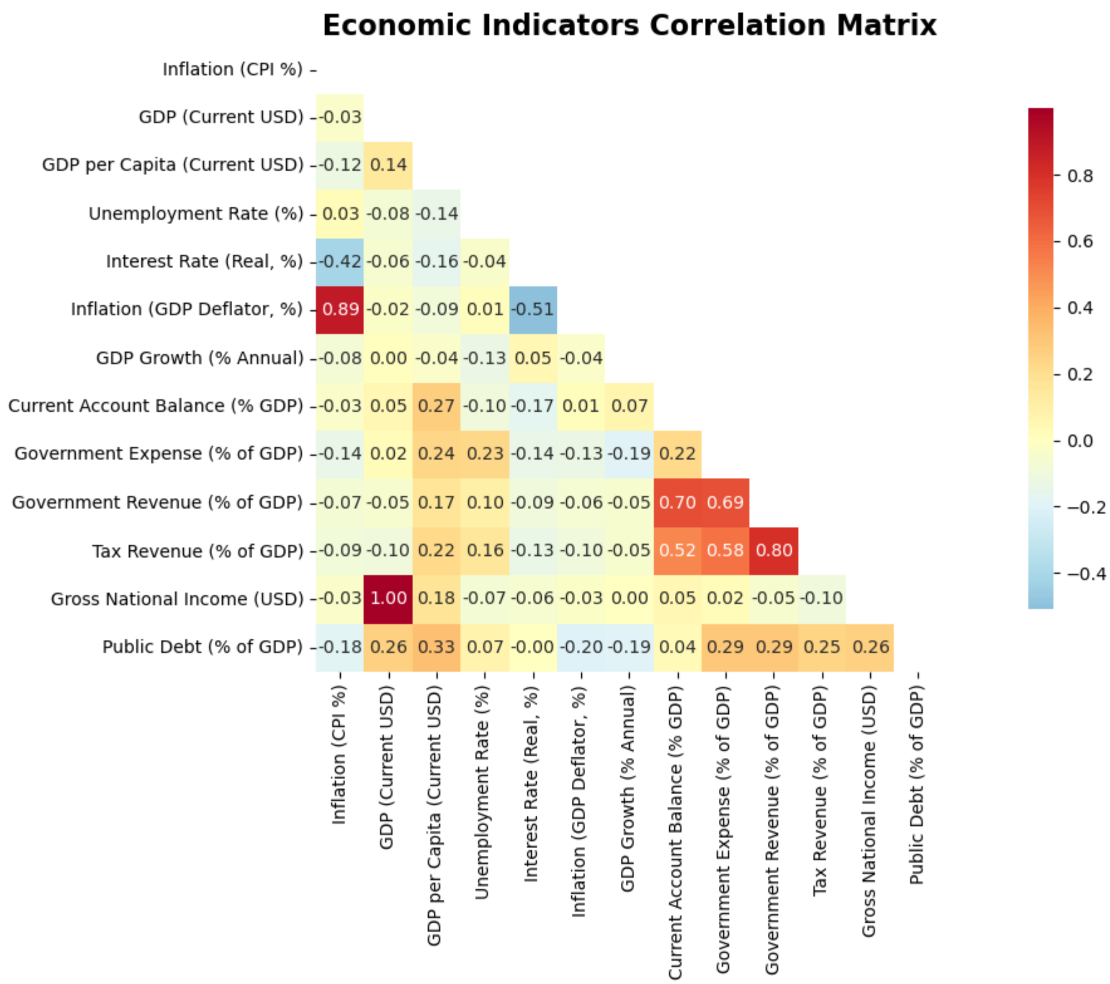
[117]:
```
#Correlation Analysis
def correlation_analysis(df):
    """
    Correlation analysis between variables
    """
```

```
    print("Correlation Analysis")
    print("-" * 50)

    numeric_cols = df.select_dtypes(include=[np.number]).columns.tolist()
    numeric_cols = [col for col in numeric_cols if col != 'year']

    # Matrice de corrélation
    corr_matrix = df[numeric_cols].corr()

    # Heatmap des corrélations
    plt.figure(figsize=(14, 8))
    mask = np.triu(np.ones_like(corr_matrix, dtype=bool))
    sns.heatmap(corr_matrix, annot=True, cmap='RdYlBu_r', center=0,
                square=True, mask=mask, fmt='.2f', cbar_kws={"shrink": .8})
    plt.title('Economic Indicators Correlation Matrix', fontsize=16,␣
↪fontweight='bold')
    plt.tight_layout()
    plt.show()

    # Top corrélations
    corr_pairs = []
    for i in range(len(corr_matrix.columns)):
        for j in range(i+1, len(corr_matrix.columns)):
            corr_pairs.append({
                'Variable_1': corr_matrix.columns[i],
                'Variable_2': corr_matrix.columns[j],
                'Correlation': corr_matrix.iloc[i, j]
            })

    corr_df = pd.DataFrame(corr_pairs)
    corr_df = corr_df.sort_values('Correlation', key=abs, ascending=False)

    print("Top 10 Strongest Correlations:")
    print(corr_df.head(10))
```

[63]:

```
correlation_analysis(df)
```

```
Correlation Analysis
--------------------------------------------------
```




```
Top 10 Strongest Correlations:
                        Variable_1                      Variable_2  \
21               GDP (Current USD)     Gross National Income (USD)
4                Inflation (CPI %)     Inflation (GDP Deflator, %)
72    Government Revenue (% of GDP)          Tax Revenue (% of GDP)
64  Current Account Balance (% GDP)  Government Revenue (% of GDP)
68    Government Expense (% of GDP)  Government Revenue (% of GDP)
69    Government Expense (% of GDP)          Tax Revenue (% of GDP)
65  Current Account Balance (% GDP)          Tax Revenue (% of GDP)
42          Interest Rate (Real, %)     Inflation (GDP Deflator, %)
3                Inflation (CPI %)        Interest Rate (Real, %)
32     GDP per Capita (Current USD)          Public Debt (% of GDP)

    Correlation
21     0.999904
4      0.887656
72     0.798062
```

```
64     0.696132
68     0.693013
69     0.578602
65     0.521580
42    -0.508959
3     -0.417850
32     0.331592
```

[1]:

```
#Importing all necessary modules
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
from scipy import stats
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
#import country_converter as coco

# Configuration
warnings.filterwarnings('ignore')
plt.style.use('seaborn-v0_8')
sns.set_palette("husl")

# Configuration Plotly pour Kaggle
import plotly.io as pio
pio.renderers.default = "notebook"
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[1], line 14
     10 #import country_converter as coco
     11
     12 # Configuration
     13 warnings.filterwarnings('ignore')
---> 14 plt.style.use('seaborn-v0_8')
     15 sns.set_palette("husl")
     17 # Configuration Plotly pour Kaggle

NameError: name 'plt' is not defined
```

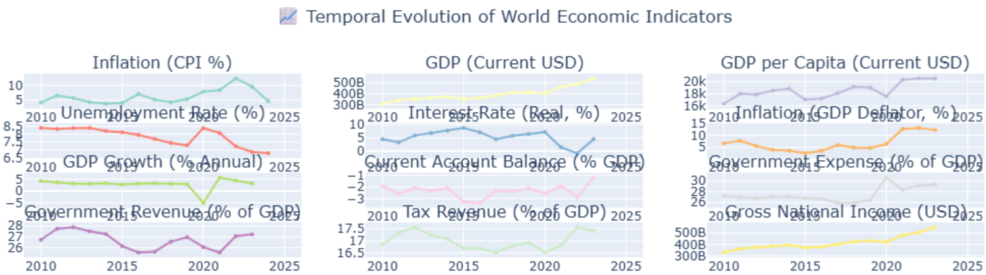
[121]:

```
#Temporal Analysis
def temporal_analysis(df):
    """
    Time Series Analysis
    """
```

```python
    print("TEMPORAL ANALYSIS")
    print("-" * 50)

    # Évolution moyenne mondiale par année
    numeric_cols = df.select_dtypes(include=[np.number]).columns.tolist()
    numeric_cols = [col for col in numeric_cols if col not in ['year',␣
↪'country_id']]

    yearly_trends = df.groupby('year')[numeric_cols].mean()

    # Graphique interactif des tendances
    fig = make_subplots(
        rows=4, cols=3,
        subplot_titles=numeric_cols[:12],
        vertical_spacing=0.08
    )

    colors = px.colors.qualitative.Set3

    for i, col in enumerate(numeric_cols[:12]):
        row = (i // 3) + 1
        col_pos = (i % 3) + 1

        fig.add_trace(
            go.Scatter(
                x=yearly_trends.index,
                y=yearly_trends[col],
                mode='lines+markers',
                name=col,
                line=dict(color=colors[i % len(colors)], width=2),
                marker=dict(size=4)
            ),
            row=row, col=col_pos
        )

    fig.update_layout(
        height=1000,
        title_text="  Temporal Evolution of World Economic Indicators",
        title_x=0.5,
        showlegend=False
    )

    fig.show()
```

[76]:
```python
temporal_analysis(df)
```

```
TEMPORAL ANALYSIS
--------------------------------------------------
```

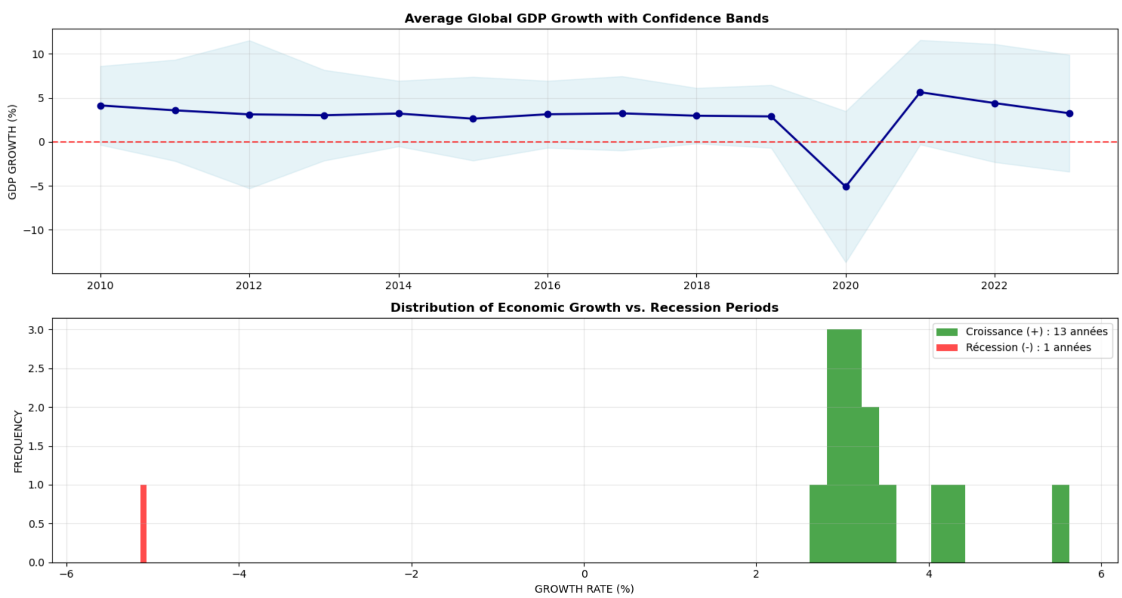


[123]:
```python
#Economic Cycle Analysis
def economic_cycles_analysis(df):
    """
    Analysis of Economic Cycles
    """
    print("ANALYSIS OF ECONOMIC CYCLES")
    print("-" * 50)

    # Focus sur la croissance du PIB
    gdp_growth_data = df.groupby('year')['GDP Growth (% Annual)'].agg(['mean', 'std', 'count'])
    gdp_growth_data = gdp_growth_data.dropna()

    plt.figure(figsize=(15, 8))

    # Graphique principal
    plt.subplot(2, 1, 1)
    plt.plot(gdp_growth_data.index, gdp_growth_data['mean'],
             marker='o', linewidth=2, markersize=6, color='darkblue')
    plt.fill_between(gdp_growth_data.index,
                     gdp_growth_data['mean'] - gdp_growth_data['std'],
                     gdp_growth_data['mean'] + gdp_growth_data['std'],
                     alpha=0.3, color='lightblue')
    plt.axhline(y=0, color='red', linestyle='--', alpha=0.7)
    plt.title(' Average Global GDP Growth with Confidence Bands', fontweight='bold')
    plt.ylabel('GDP GROWTH (%)')
    plt.grid(True, alpha=0.3)

    # Histogramme des périodes de récession/croissance
    plt.subplot(2, 1, 2)
    positive_growth = gdp_growth_data[gdp_growth_data['mean'] > 0]['mean']
    negative_growth = gdp_growth_data[gdp_growth_data['mean'] <= 0]['mean']
```

```
    plt.hist(positive_growth, bins=15, alpha=0.7, color='green',␣
↪label=f'Croissance (+) : {len(positive_growth)} années')
    plt.hist(negative_growth, bins=15, alpha=0.7, color='red',␣
↪label=f'Récession (-) : {len(negative_growth)} années')
    plt.title('Distribution of Economic Growth vs. Recession Periods',␣
↪fontweight='bold')
    plt.xlabel('GROWTH RATE (%)')
    plt.ylabel('FREQUENCY')
    plt.legend()
    plt.grid(True, alpha=0.3)

    plt.tight_layout()
    plt.show()
```

[80]:
```
economic_cycles_analysis(df)
```

```
ANALYSIS OF ECONOMIC CYCLES
--------------------------------------------------
```



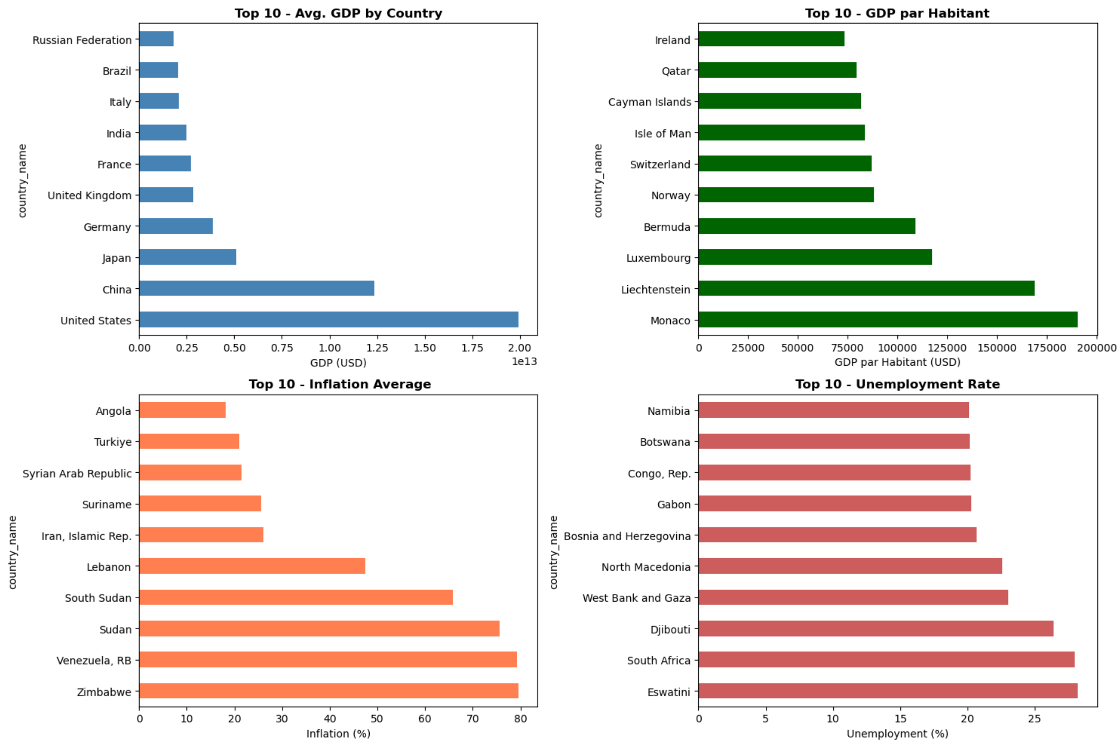
[125]:
```
#Geographical Analysis
def geographical_analysis(df):
    """
    Geographic Analysis perRegion
    """
    print("GEOGRAPHIC ANALYSIS")
    print("-" * 50)
```

```
    # Ajouter les régions
    # df['region'] = df['country_name'].map(country_to_region_mapping)

    # Top 10 des pays par PIB moyen
    top_gdp_countries = df.groupby('country_name')['GDP (Current USD)'].mean().
↪sort_values(ascending=False).head(10)

    plt.figure(figsize=(15, 10))

    # Graphique en barres horizontales
    plt.subplot(2, 2, 1)
    top_gdp_countries.plot(kind='barh', color='steelblue')
    plt.title('Top 10 - Avg. GDP by Country', fontweight='bold')
    plt.xlabel('GDP (USD)')

    # PIB par habitant
    top_gdp_per_capita = df.groupby('country_name')['GDP per Capita (Current␣
↪USD)'].mean().sort_values(ascending=False).head(10)

    plt.subplot(2, 2, 2)
    top_gdp_per_capita.plot(kind='barh', color='darkgreen')
    plt.title('Top 10 - GDP par Habitant', fontweight='bold')
    plt.xlabel('GDP par Habitant (USD)')

    # Inflation moyenne
    top_inflation = df.groupby('country_name')['Inflation (CPI %)'].mean().
↪sort_values(ascending=False).head(10)

    plt.subplot(2, 2, 3)
    top_inflation.plot(kind='barh', color='coral')
    plt.title(' Top 10 - Inflation Average', fontweight='bold')
    plt.xlabel('Inflation (%)')

    # Chômage moyen
    top_unemployment = df.groupby('country_name')['Unemployment Rate (%)'].
↪mean().sort_values(ascending=False).head(10)

    plt.subplot(2, 2, 4)
    top_unemployment.plot(kind='barh', color='indianred')
    plt.title('Top 10 - Unemployment Rate', fontweight='bold')
    plt.xlabel('Unemployment (%)')

    plt.tight_layout()
    plt.show()
```

[84]:

```
geographical_analysis(df)
```

```
GEOGRAPHIC ANALYSIS
--------------------------------------------------
```



[127]:
```python
#DATA PREPARATION AND CLEANING
df = df.drop(columns=['Interest Rate (Real, %)'])
```

[129]:
```python
#DATA PREPARATION AND CLEANING
df = df.dropna()
```

[131]:
```python
#DATA PREPARATION AND CLEANING
df = df.drop(columns=['country_id', 'country_name', 'year'])
```

[133]:
```python
#DATA PREPARATION AND CLEANING
X=df.drop('Government Revenue (% of GDP)',axis=1)
y=df['Government Revenue (% of GDP)']
```

[135]:
```python
# DATA PREPARATION AND CLEANING
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=42)
```

[137]:

```python
#MODEL TRAINING & EVALUATION
from sklearn.linear_model import LinearRegression, Ridge, Lasso, ElasticNet
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score

models = {
    "Linear Regression": LinearRegression(),
    "Ridge": Ridge(),
    "Lasso": Lasso(),
    "ElasticNet": ElasticNet(),
    "Decision Tree": DecisionTreeRegressor(random_state=42),
    "Random Forest": RandomForestRegressor(random_state=42),
    "Gradient Boosting": GradientBoostingRegressor(random_state=42),
    "SVR": SVR()
}

results = []

for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    mse = mean_squared_error(y_test, y_pred)
    mae = mean_absolute_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    results.append({
        "Model": name,
        "MSE": mse,
        "MAE": mae,
        "R2": r2
    })

results_df = pd.DataFrame(results).sort_values(by="R2", ascending=False)
print(results_df)
```

```
C:\Users\Atreyee Dutta\anaconda3\Lib\site-
packages\sklearn\linear_model\_ridge.py:204: LinAlgWarning: Ill-conditioned
matrix (rcond=2.83496e-25): result may not be accurate.
  return linalg.solve(A, Xy, assume_a="pos", overwrite_a=True).T
C:\Users\Atreyee Dutta\anaconda3\Lib\site-
packages\sklearn\linear_model\_coordinate_descent.py:678: ConvergenceWarning:
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 4.132e+03, tolerance: 4.533e+00
  model = cd_fast.enet_coordinate_descent(
C:\Users\Atreyee Dutta\anaconda3\Lib\site-
packages\sklearn\linear_model\_coordinate_descent.py:678: ConvergenceWarning:
```

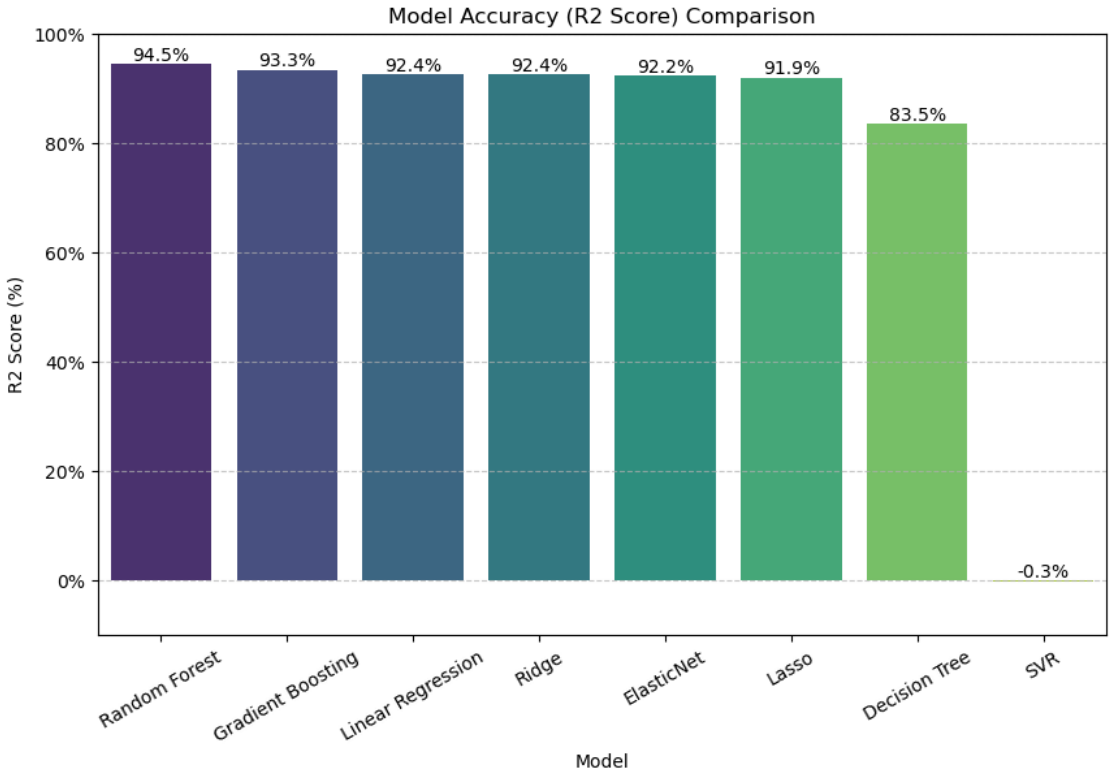
```
Objective did not converge. You might want to increase the number of iterations,
check the scale of the features or consider increasing regularisation. Duality
gap: 3.826e+03, tolerance: 4.533e+00
  model = cd_fast.enet_coordinate_descent(
```

	Model	MSE	MAE	R2
5	Random Forest	4.445608	1.347680	0.944644
6	Gradient Boosting	5.359111	1.600407	0.933269
0	Linear Regression	6.074939	1.974870	0.924356
1	Ridge	6.075025	1.974901	0.924355
3	ElasticNet	6.253538	2.021869	0.922132
2	Lasso	6.477820	2.059282	0.919339
4	Decision Tree	13.233082	1.790987	0.835224
7	SVR	80.525774	7.348224	-0.002691

[139]:

```
#MODEL TRAINING & EVALUATION
plt.figure(figsize=(10, 6))
ax = sns.barplot(x='Model', y='R2', data=results_df, palette='viridis')
plt.title('Model Accuracy (R2 Score) Comparison')
plt.ylabel('R2 Score (%)')
plt.xlabel('Model')
plt.ylim(-0.1, 1.0)
plt.xticks(rotation=30)
plt.grid(axis='y', linestyle='--', alpha=0.7)

# Show percentage on top of bars
for p in ax.patches:
    height = p.get_height()
    ax.annotate(f'{height*100:.1f}%',
                (p.get_x() + p.get_width() / 2, height),
                ha='center', va='bottom', fontsize=10)

# Format y-axis as percentage
ax.yaxis.set_major_formatter(plt.FuncFormatter(lambda y, _: '{:.0f}%'.
 ↪format(y*100)))
plt.show()
```

```
C:\Users\Atreyee Dutta\AppData\Local\Temp\ipykernel_10200\3826654366.py:2:
FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  ax = sns.barplot(x='Model', y='R2', data=results_df, palette='viridis')
```



[141]:
```
#Hyperparameter using GridSearchCV

from sklearn.model_selection import GridSearchCV

param_grid = [
    {'n_estimators': [3, 10, 30], 'max_features': [2, 4, 6, 8]},
    {'bootstrap': [False], 'n_estimators': [3, 10], 'max_features': [2, 3, 4]},
  ]

forest_reg = RandomForestRegressor(random_state=42)

grid_search = GridSearchCV(forest_reg, param_grid,
                           scoring='neg_mean_squared_error',
                           return_train_score=True,
                           cv=10,
                          )

grid_search.fit(X_train, y_train)
```

[141]:
```
GridSearchCV(cv=10, estimator=RandomForestRegressor(random_state=42),
             param_grid=[{'max_features': [2, 4, 6, 8],
                          'n_estimators': [3, 10, 30]},
```

```
                        {'bootstrap': [False], 'max_features': [2, 3, 4],
                         'n_estimators': [3, 10]}],
             return_train_score=True, scoring='neg_mean_squared_error')
```

[142]:
```
grid_search.best_params_
```

[142]:
```
{'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

[147]:
```
cv_scores = grid_search.cv_results_

##printing all the parameters along with their scores
for mean_score, params in zip(cv_scores['mean_test_score'],␣
 ↪cv_scores["params"]):
    print(np.sqrt(-mean_score), params)
```

```
3.8135496055128986 {'max_features': 2, 'n_estimators': 3}
3.0679054446530585 {'max_features': 2, 'n_estimators': 10}
2.891936477361396 {'max_features': 2, 'n_estimators': 30}
3.375796808448963 {'max_features': 4, 'n_estimators': 3}
2.8773083191688933 {'max_features': 4, 'n_estimators': 10}
2.783731958622698 {'max_features': 4, 'n_estimators': 30}
3.3110570229568204 {'max_features': 6, 'n_estimators': 3}
2.9494289127881688 {'max_features': 6, 'n_estimators': 10}
2.767398137867996 {'max_features': 6, 'n_estimators': 30}
3.127671095452778 {'max_features': 8, 'n_estimators': 3}
2.8308368237809347 {'max_features': 8, 'n_estimators': 10}
2.7765940524838606 {'max_features': 8, 'n_estimators': 30}
3.4833994347486925 {'bootstrap': False, 'max_features': 2, 'n_estimators': 3}
2.747790506699974 {'bootstrap': False, 'max_features': 2, 'n_estimators': 10}
3.3975226343338876 {'bootstrap': False, 'max_features': 3, 'n_estimators': 3}
2.861291017421245 {'bootstrap': False, 'max_features': 3, 'n_estimators': 10}
3.1181246592878895 {'bootstrap': False, 'max_features': 4, 'n_estimators': 3}
2.737590806034221 {'bootstrap': False, 'max_features': 4, 'n_estimators': 10}
```

[149]:
```
#Evaluating the entire system on Test Data
final_model = grid_search.best_estimator_

final_predictions = final_model.predict(X_test)
final_mse = mean_squared_error(y_test, y_pred)
final_rmse = np.sqrt(final_mse)
```

[151]:
```
final_rmse
```

[151]:
```
8.973615447768513
```

[167]:
```
#Custom function
def predict_GovRevnGDP(GeoEco_stats, model):
    if type(GeoEco_stats) == dict:
```

```
        df = pd.DataFrame(GeoEco_stats)
    else:
        df = GeoEco_stats
    #df = df.drop(columns=['Interest Rate (Real, %)'])
    #df = df.dropna()
    #df = df.drop(columns=['country_id', 'country_name', 'year'])
    X=df.drop('Government Revenue (% of GDP)',axis=1)
    y=df['Government Revenue (% of GDP)']
    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=42)
    y_pred = model.predict(X_test)
    return y_pred
```

[103]:
```
import pickle
##saving the model
with open("./model_files/model.bin", 'wb') as f_out:
    pickle.dump(final_model, f_out)
    f_out.close()
##loading the model from the saved file
#with open('model.bin', 'rb') as f_in:
    #model = pickle.load(f_in)
```

[165]:
```
GeoEco_stats = {
    "Inflation (CPI %)" : [1.1,2.1,3.1,4.2,2.0,1.5],
    "GDP (Current USD)" : [208768,239768,134789,136789,285678,305678],
    "GDP per Capita (Current USD)" : [190.45,230.45,122.54,128.54,282.45,289.
 ↪45],
    "Unemployment Rate (%)" : [8.1,7.1,7.3,6.3,4.6,5.6],
    "Inflation (GDP Deflator, %)" : [-2.5,3.0,1.3,2.0,1.5,2.5],
    "GDP Growth (% Annual)" : [-2.6,3.2,2.5,1.3,-2.1,2.3],
    "Current Account Balance (% GDP)" : [-20.79,11.20,12.09,13.09,13.23,12.23],
    "Government Expense (% of GDP)" : [60,21.89,13.78,23.56,32.8,12.34],
    "Government Revenue (% of GDP)" : [9.01,10.03,8.0,9.2,9.0,10],
    "Tax Revenue (% of GDP)" : [10.01,11.60,13.45,15,13,16],
    "Gross National Income (USD)" : [190768,228765,133678,125467,274523,297845],
    "Public Debt (% of GDP)" : [70.01,65.23,40.23,55.67,23.08,45.09]
}

#predict_GovRevnGDP(GeoEco_stats, model)
```

[161]:
```
##loading the model from the saved file
with open('./model_files/model.bin', 'rb') as f_in:
    model = pickle.load(f_in)
```

[169]:
```
import requests
```

```python
url = "http://localhost:9696/predict"
r = requests.post(url, json = GeoEco_stats)
r.text.strip()
```

[169]:

```
'{\n  "GovRevnGDP_prediction": [\n    29.618744560315548,\n
18.636766339497612\n  ]\n}'
```

[171]:

```python
import requests

url = "https://globaleco-flask-app-15275c2300f2.herokuapp.com/predict"
r = requests.post(url, json = GeoEco_stats)
r.text.strip()
```

[171]:

```
'{"GovRevnGDP_prediction":[29.618744560315548,18.636766339497612]}'
```

[ ]:

```python

```