# Carrie Final Project Data Analysis_2000

November 24, 2024

# 1 SIPRI MIlitary Expenditure dataset

## 1.1 Carrie Little

### 1.1.1 Import Necessary Libraries

[1]:
```
# Import All Necessary Libraries
import numpy as np
import pandas as pd
from pathlib import Path
from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import cvxpy as cp
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

[2]:
```
# Load Dataset
from pathlib import Path
import pandas as pd

# Define the file path
file_path = Path("..") / "data" /␣
↪"Cleaned_merged_SIPRI_Region_ACLED_starting2000.csv"     # Suitable for␣
↪within Github repository
# file_path = 'Cleaned_merged_SIPRI_Region_ACLED_starting2000.csv'              ␣
↪           # for when working in same directory

# Load the CSV file
df = pd.read_csv(file_path)

df.head()
```

[2]:
```
  Country  Year  Expenditure-Share_of_Govt_spending  Expenditure-Share_of_GDP  \
0  Brazil  2000                                 NaN                  0.017307
1  Brazil  2001                            0.047167                  0.019519
```

```
2  Brazil  2002                          0.041112                  0.018958
3  Brazil  2003                          0.035175                  0.015035
4  Brazil  2004                          0.035561                  0.014613

   Expenditure_Per_Capita  Expenditure_Constant_2022    Region      Subregion  \
0               64.500907                15643.43168  Americas  South America
1               61.332747                18119.43481  Americas  South America
2               53.550103                18361.33076  Americas  South America
3               45.956041                14647.82954  Americas  South America
4               52.945029                15219.74744  Americas  South America

   index_level  total_rank_from_avg_rank  …  total_score_rank  \
0            1                         6  …                 6
1            1                         6  …                 6
2            1                         6  …                 6
3            1                         6  …                 6
4            1                         6  …                 6

   Deadliness_raw  Diffusion_raw  Danger_raw  Fragmentation_raw  \
0            6678          0.003        4117                 67
1            6678          0.003        4117                 67
2            6678          0.003        4117                 67
3            6678          0.003        4117                 67
4            6678          0.003        4117                 67

   Deadliness_scaled  Diffusion_scaled  Danger_scaled  Fragmentation_scaled  \
0           0.167247          0.004342       0.635536              0.044108
1           0.167247          0.004342       0.635536              0.044108
2           0.167247          0.004342       0.635536              0.044108
3           0.167247          0.004342       0.635536              0.044108
4           0.167247          0.004342       0.635536              0.044108

   total_score
0        0.851
1        0.851
2        0.851
3        0.851
4        0.851

[5 rows x 29 columns]
```

### 1.1.2 Descriptive statistics

[3]:
```
# Descriptive Information
# Columns
columns = df.info()                                                          #␣
 ↪Create a Dataframe of Descriptive Statistics
```

```
columns                                                                      #␣
↪Display the Dataframe of Descriptive Statistics
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3716 entries, 0 to 3715
Data columns (total 29 columns):
 #   Column                              Non-Null Count  Dtype
---  ------                              --------------  -----
 0   Country                             3716 non-null   object
 1   Year                                3716 non-null   int64
 2   Expenditure-Share_of_Govt_spending  3533 non-null   float64
 3   Expenditure-Share_of_GDP            3602 non-null   float64
 4   Expenditure_Per_Capita              3604 non-null   float64
 5   Expenditure_Constant_2022           3673 non-null   float64
 6   Region                              3716 non-null   object
 7   Subregion                           3716 non-null   object
 8   index_level                         3716 non-null   int64
 9   total_rank_from_avg_rank            3716 non-null   int64
 10  avg_rank                            3716 non-null   float64
 11  Deadliness_rank                     3716 non-null   int64
 12  Diffusion_rank                      3716 non-null   int64
 13  Danger_rank                         3716 non-null   int64
 14  Fragmentation_rank                  3716 non-null   int64
 15  Deadliness_scaled_rank              3716 non-null   int64
 16  Diffusion_scaled_rank               3716 non-null   int64
 17  Danger_scaled_rank                  3716 non-null   int64
 18  Fragmentation_scaled_rank           3716 non-null   int64
 19  total_score_rank                    3716 non-null   int64
 20  Deadliness_raw                      3716 non-null   int64
 21  Diffusion_raw                       3716 non-null   float64
 22  Danger_raw                          3716 non-null   int64
 23  Fragmentation_raw                   3716 non-null   int64
 24  Deadliness_scaled                   3716 non-null   float64
 25  Diffusion_scaled                    3716 non-null   float64
 26  Danger_scaled                       3716 non-null   float64
 27  Fragmentation_scaled                3716 non-null   float64
 28  total_score                         3716 non-null   float64
dtypes: float64(11), int64(15), object(3)
memory usage: 842.0+ KB
```

[4]:

```
# Descriptive Statistics
# Describe
summary_stats = df.describe()                                                  ␣
↪       # Create a Dataframe of Descriptive Statistics
summary_stats                                                                  ␣
↪       # Display the Dataframe of Descriptive Statistics
```

[4]:

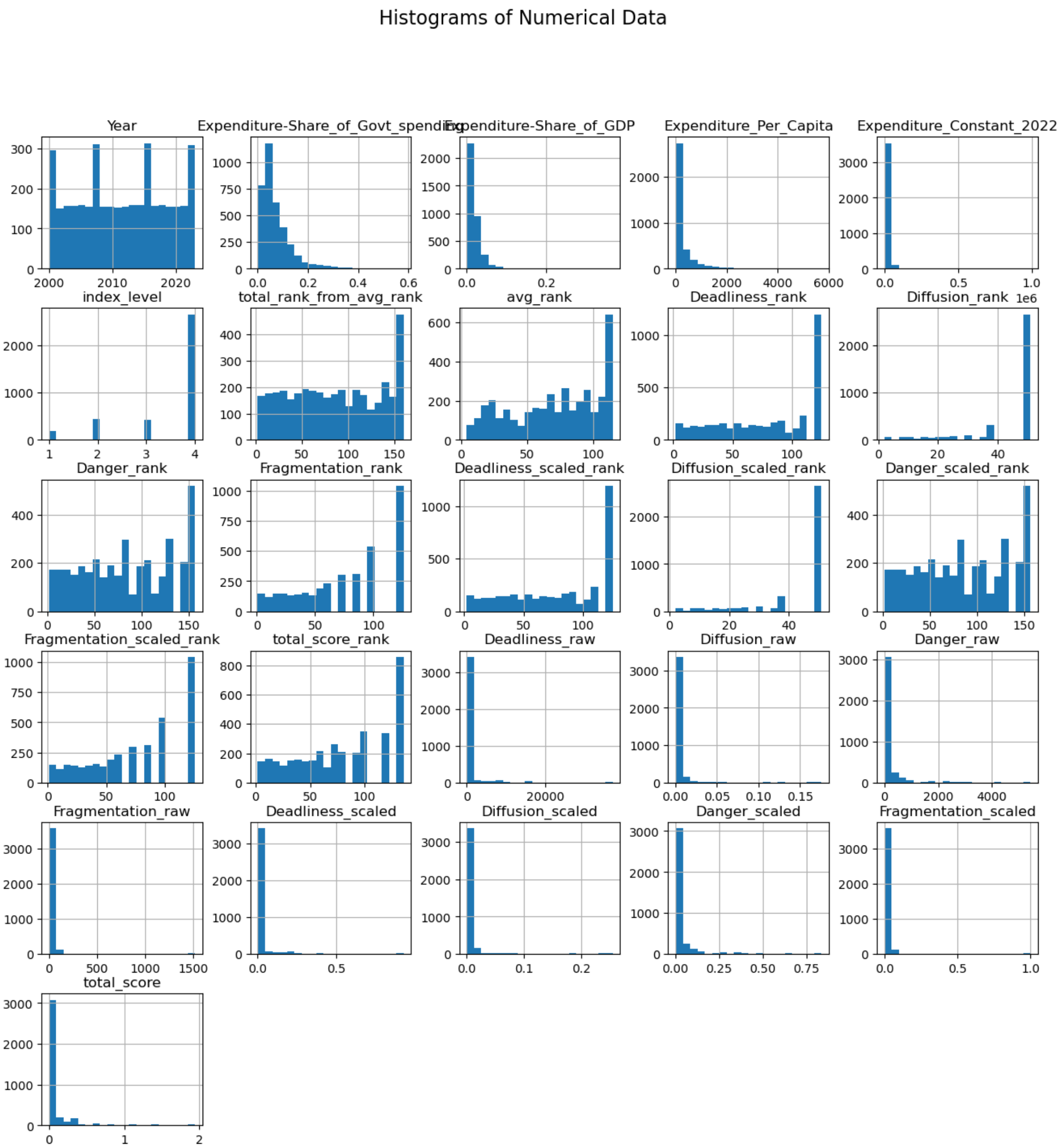
```
              Year  Expenditure-Share_of_Govt_spending  \
count  3716.000000                         3533.000000
mean   2011.556512                            0.071187
std       6.889732                            0.060611
min    2000.000000                            0.000672
25%    2006.000000                            0.031740
50%    2012.000000                            0.051833
75%    2018.000000                            0.091994
max    2023.000000                            0.581707

       Expenditure-Share_of_GDP  Expenditure_Per_Capita  \
count               3602.000000             3604.000000
mean                   0.019767              243.374084
std                    0.018137              426.197550
min                    0.000163                0.071803
25%                    0.010229               17.077744
50%                    0.014996               69.809759
75%                    0.023754              270.439168
max                    0.366531             5718.771025

       Expenditure_Constant_2022  index_level  total_rank_from_avg_rank  \
count                3673.000000  3716.000000               3716.000000
mean                11760.889052     3.491119                 86.736006
std                 68296.745904     0.894834                 49.421439
min                     0.000000     1.000000                  2.000000
25%                   144.314628     3.000000                 45.000000
50%                   739.329049     4.000000                 85.000000
75%                  4523.330790     4.000000                131.000000
max                990485.412100     4.000000                160.000000

          avg_rank  Deadliness_rank  Diffusion_rank  …  total_score_rank  \
count  3716.000000      3716.000000     3716.000000  …       3716.000000
mean     71.252758        79.672497       43.389397  …         80.705867
std      33.403444        40.775882       13.511428  …         42.837423
min       4.250000         2.000000        2.000000  …          2.000000
25%      42.750000        43.000000       37.000000  …         45.000000
50%      76.500000        84.000000       51.000000  …         81.000000
75%     101.000000       125.000000       51.000000  …        117.000000
max     114.750000       125.000000       51.000000  …        136.000000

       Deadliness_raw  Diffusion_raw   Danger_raw  Fragmentation_raw  \
count     3716.000000    3716.000000  3716.000000        3716.000000
mean       918.312971       0.005629   252.864101          17.972282
std       3629.622878       0.023324   710.539730         107.454813
min          0.000000       0.000000     0.000000           0.000000
25%          0.000000       0.000000     2.000000           0.000000
50%          7.000000       0.000000    13.000000           2.000000
```

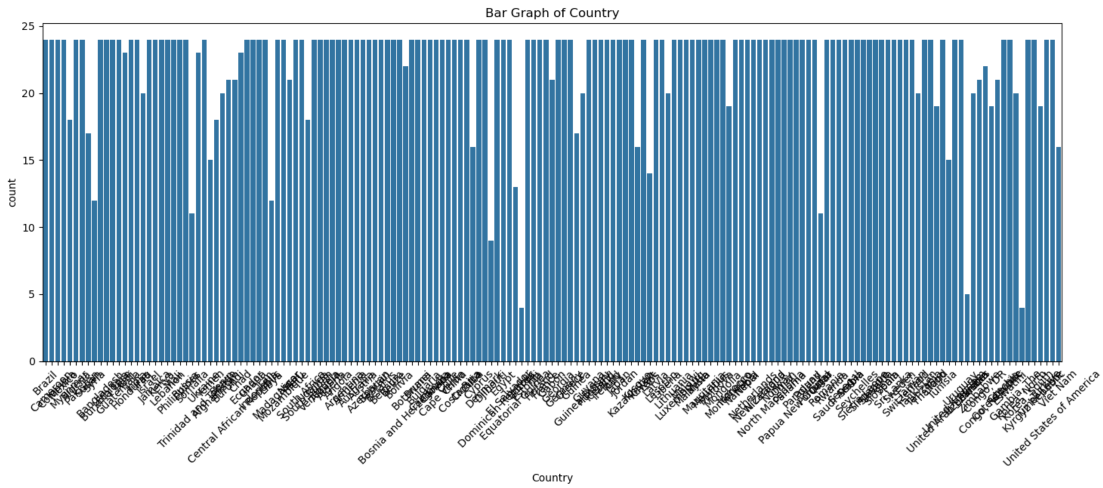
```
75%        246.000000       0.001000   152.000000           9.000000
max      37014.000000       0.176000  5426.000000        1519.000000

       Deadliness_scaled  Diffusion_scaled  Danger_scaled  \
count        3716.000000       3716.000000    3716.000000
mean            0.022999          0.008146       0.039034
std             0.090902          0.033754       0.109685
min             0.000000          0.000000       0.000000
25%             0.000000          0.000000       0.000309
50%             0.000175          0.000000       0.002007
75%             0.006161          0.001447       0.023464
max             0.926995          0.254703       0.837604

       Fragmentation_scaled  total_score
count           3716.000000  3716.000000
mean               0.011832     0.081966
std                0.070740     0.231303
min                0.000000     0.000000
25%                0.000000     0.001000
50%                0.001317     0.005000
75%                0.005925     0.037000
max                1.000000     1.940000

[8 rows x 26 columns]
```

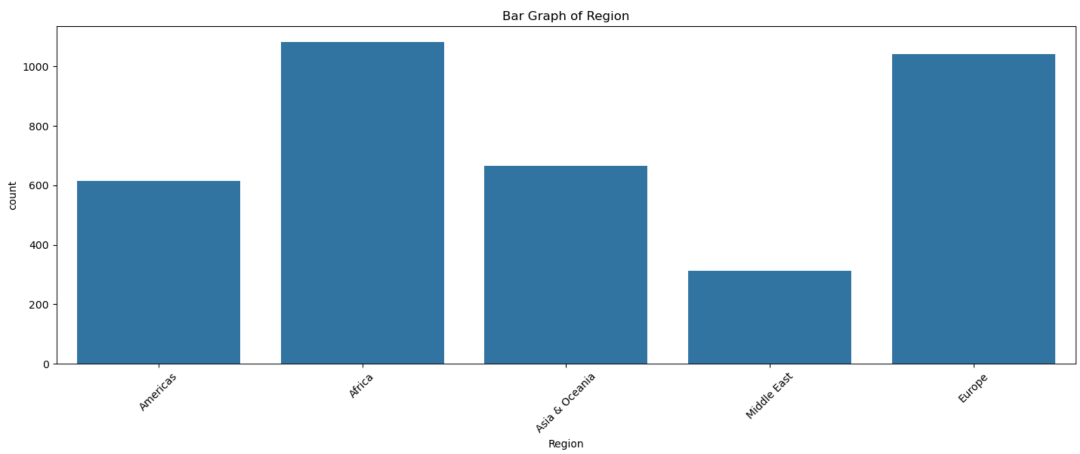
### 1.1.3 Histogram

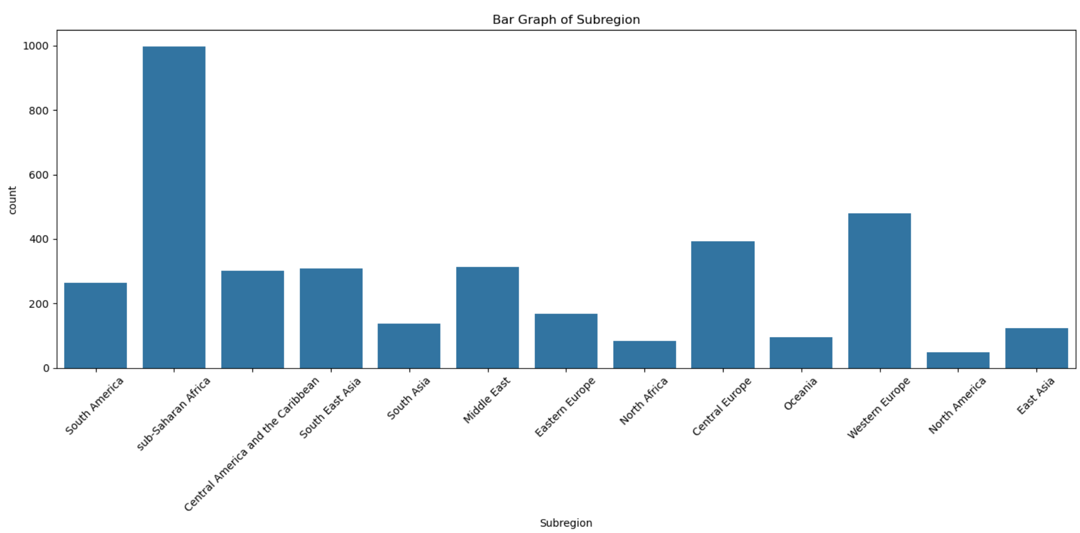
[5]:
```python
# Data Preprocessing and Summary Statistics

# Checking for missing values
missing_values = df.isnull().sum()

# Summary statistics for numerical data
summary_statistics = df.describe()

# Viewing the columns for a better understanding of categorical vs numerical␣
↪data
df_columns = df.columns

# Plotting histograms for numerical columns
numerical_columns = df.select_dtypes(include=['float64', 'int64']).columns
df[numerical_columns].hist(figsize=(15, 15), bins=20)
plt.suptitle('Histograms of Numerical Data', size=16)
plt.show()

# Plotting bar graphs for categorical columns
categorical_columns = df.select_dtypes(include=['object']).columns
```

```python
plt.figure(figsize=(15, 20))
for i, column in enumerate(categorical_columns):
    plt.subplot(len(categorical_columns), 1, i + 1)
    sns.countplot(data=df, x=column)
    plt.xticks(rotation=45)
    plt.title(f'Bar Graph of {column}')

plt.tight_layout()
plt.show()

# Display summary statistics
summary_statistics

# Displaying missing values information
missing_values
```


Histograms of Numerical Data
Year
Expenditure-Share_of_Govt_spending
Expenditure-Share_of_GDP
Expenditure_Per_Capita
Expenditure_Constant_2022
1e6
index_level
total_rank_from_avg_rank
avg_rank
Deadliness_rank
Diffusion_rank
Danger_rank
Fragmentation_rank
Deadliness_scaled_rank
Diffusion_scaled_rank
Danger_scaled_rank
Fragmentation_scaled_rank
total_score_rank
Deadliness_raw
Diffusion_raw
Danger_raw
Fragmentation_raw
Deadliness_scaled
Diffusion_scaled
Danger_scaled
Fragmentation_scaled
total_score



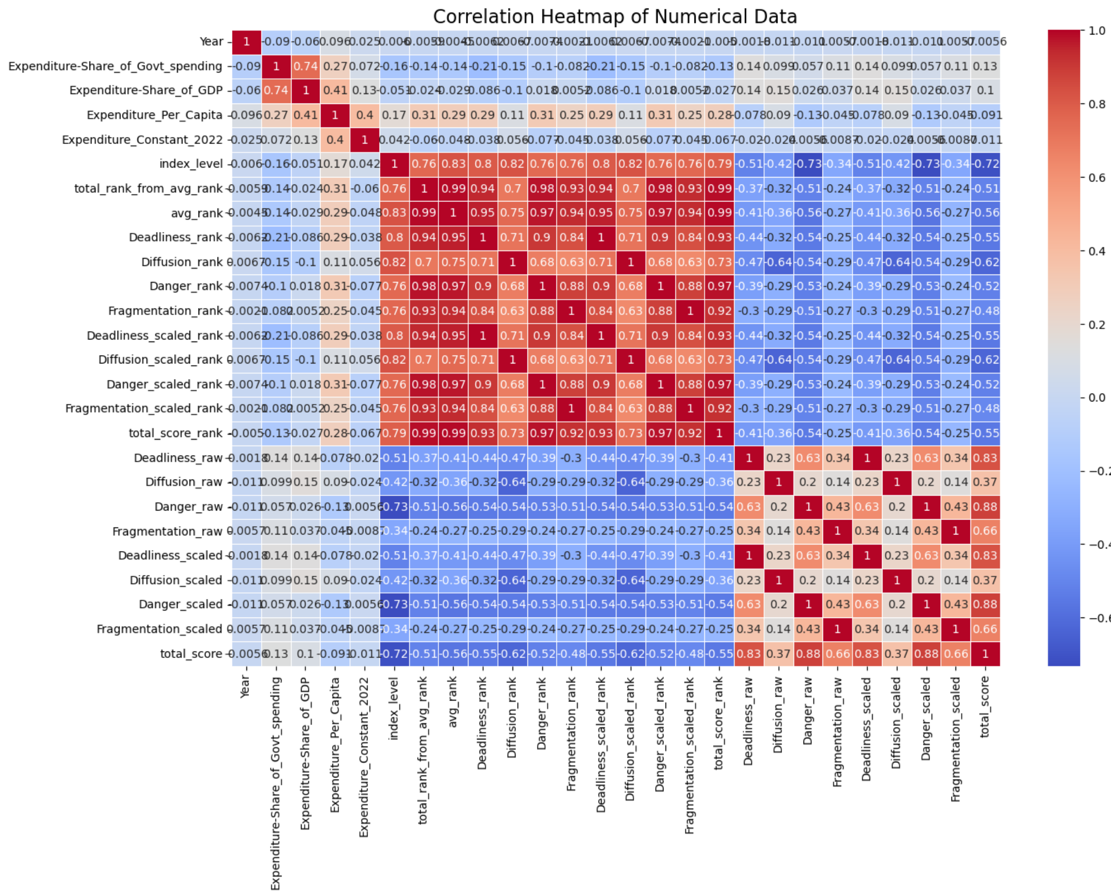




[5]:
```
Country                                  0
Year                                     0
```

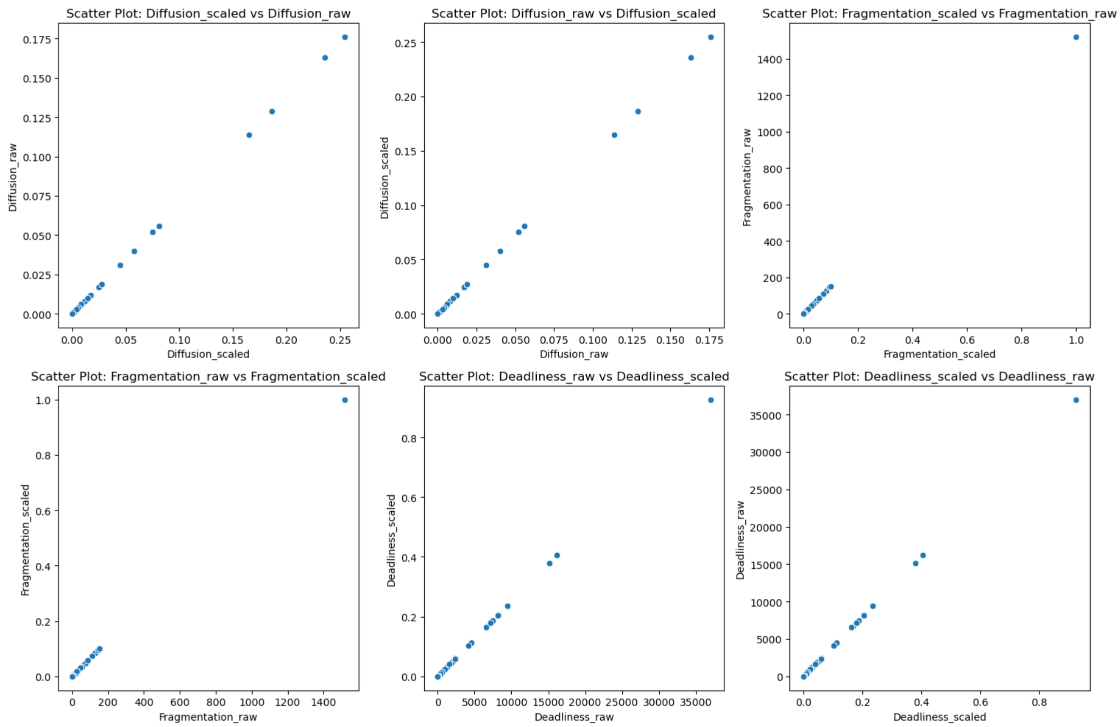
```
Expenditure-Share_of_Govt_spending    183
Expenditure-Share_of_GDP              114
Expenditure_Per_Capita                112
Expenditure_Constant_2022              43
Region                                  0
Subregion                               0
index_level                             0
total_rank_from_avg_rank                0
avg_rank                                0
Deadliness_rank                         0
Diffusion_rank                          0
Danger_rank                             0
Fragmentation_rank                      0
Deadliness_scaled_rank                  0
Diffusion_scaled_rank                   0
Danger_scaled_rank                      0
Fragmentation_scaled_rank               0
total_score_rank                        0
Deadliness_raw                          0
Diffusion_raw                           0
Danger_raw                              0
Fragmentation_raw                       0
Deadliness_scaled                       0
Diffusion_scaled                        0
Danger_scaled                           0
Fragmentation_scaled                    0
total_score                             0
dtype: int64
```

[6]:
```python
# Generating a correlation heatmap for numerical data

# Calculate the correlation matrix for numerical columns
correlation_matrix = df[numerical_columns].corr()

# Plotting the heatmap using seaborn
plt.figure(figsize=(15, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Heatmap of Numerical Data', size=16)
plt.show()
```




```
[7]: # Identifying highly correlated features (absolute correlation > 0.7)
highly_correlated_pairs = correlation_matrix.abs().unstack().
 ↪sort_values(ascending=False)
highly_correlated_pairs = highly_correlated_pairs[highly_correlated_pairs < 1.
 ↪0]  # Exclude self-correlation

# Get the top correlated pairs
top_correlated_pairs = highly_correlated_pairs[highly_correlated_pairs > 0.7].
 ↪index

# Plotting scatter plots for highly correlated feature pairs
plt.figure(figsize=(15, 10))
plot_index = 1
for (feature1, feature2) in top_correlated_pairs:
    if plot_index > 6:  # Limit the number of scatter plots to display
        break
    plt.subplot(2, 3, plot_index)
    sns.scatterplot(data=df, x=feature1, y=feature2)
    plt.title(f'Scatter Plot: {feature1} vs {feature2}')
```

```python
    plot_index += 1

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




[8]:
```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
```

[9]:
```python
# Load Dataset
from pathlib import Path
import pandas as pd

# Define the file path
file_path = Path("..") / "data" /␣
 ↪"Cleaned_merged_SIPRI_Region_ACLED_starting2000.csv"     # Suitable for␣
 ↪within Github repository
# file_path = 'Cleaned_merged_SIPRI_Region_ACLED_starting2000.csv'            ␣
 ↪            # for when working in same directory
```

```python
# Load the CSV file
data = pd.read_csv(file_path)

data.head()
```

[9]:

```
  Country  Year  Expenditure-Share_of_Govt_spending  Expenditure-Share_of_GDP  \
0  Brazil  2000                                 NaN                  0.017307
1  Brazil  2001                            0.047167                  0.019519
2  Brazil  2002                            0.041112                  0.018958
3  Brazil  2003                            0.035175                  0.015035
4  Brazil  2004                            0.035561                  0.014613

   Expenditure_Per_Capita  Expenditure_Constant_2022    Region      Subregion  \
0               64.500907                15643.43168  Americas  South America
1               61.332747                18119.43481  Americas  South America
2               53.550103                18361.33076  Americas  South America
3               45.956041                14647.82954  Americas  South America
4               52.945029                15219.74744  Americas  South America

   index_level  total_rank_from_avg_rank  …  total_score_rank  \
0            1                         6  …                 6
1            1                         6  …                 6
2            1                         6  …                 6
3            1                         6  …                 6
4            1                         6  …                 6

   Deadliness_raw  Diffusion_raw  Danger_raw  Fragmentation_raw  \
0            6678          0.003        4117                 67
1            6678          0.003        4117                 67
2            6678          0.003        4117                 67
3            6678          0.003        4117                 67
4            6678          0.003        4117                 67

   Deadliness_scaled  Diffusion_scaled  Danger_scaled  Fragmentation_scaled  \
0           0.167247          0.004342       0.635536              0.044108
1           0.167247          0.004342       0.635536              0.044108
2           0.167247          0.004342       0.635536              0.044108
3           0.167247          0.004342       0.635536              0.044108
4           0.167247          0.004342       0.635536              0.044108

   total_score
0        0.851
1        0.851
2        0.851
3        0.851
4        0.851
```

```
[5 rows x 29 columns]
```

### 1.1.4 Data Cleaning for Regression Models

[10]:
```python
# Drop the columns that are not relevant for the forecasting model as mentioned␣
↪by the user
columns_to_drop = [
    'Deadliness_scaled', 'Diffusion_scaled', 'Danger_scaled',␣
↪'Fragmentation_scaled',
    'Deadliness_rank', 'Diffusion_rank', 'Danger_rank', 'Fragmentation_rank'
]
data_cleaned = data.drop(columns=columns_to_drop, errors='ignore')

# Display the cleaned dataset to check the changes
data_cleaned.head()
```

[10]:
```
  Country  Year  Expenditure-Share_of_Govt_spending  Expenditure-Share_of_GDP  \
0  Brazil  2000                                 NaN                  0.017307
1  Brazil  2001                            0.047167                  0.019519
2  Brazil  2002                            0.041112                  0.018958
3  Brazil  2003                            0.035175                  0.015035
4  Brazil  2004                            0.035561                  0.014613

   Expenditure_Per_Capita  Expenditure_Constant_2022    Region      Subregion  \
0               64.500907                15643.43168  Americas  South America
1               61.332747                18119.43481  Americas  South America
2               53.550103                18361.33076  Americas  South America
3               45.956041                14647.82954  Americas  South America
4               52.945029                15219.74744  Americas  South America

   index_level  total_rank_from_avg_rank  …  Deadliness_scaled_rank  \
0            1                         6  …                      10
1            1                         6  …                      10
2            1                         6  …                      10
3            1                         6  …                      10
4            1                         6  …                      10

   Diffusion_scaled_rank  Danger_scaled_rank  Fragmentation_scaled_rank  \
0                     31                   3                          9
1                     31                   3                          9
2                     31                   3                          9
3                     31                   3                          9
4                     31                   3                          9

   total_score_rank  Deadliness_raw  Diffusion_raw  Danger_raw  \
0                 6            6678          0.003        4117
1                 6            6678          0.003        4117
```

```
2                   6            6678            0.003          4117
3                   6            6678            0.003          4117
4                   6            6678            0.003          4117

   Fragmentation_raw  total_score
0                  67        0.851
1                  67        0.851
2                  67        0.851
3                  67        0.851
4                  67        0.851

[5 rows x 21 columns]
```

[11]:
```
# Check for missing values in the cleaned dataset
missing_values = data_cleaned.isna().sum()

# Display the columns with missing values and the count of missing values
missing_values[missing_values > 0]
```

[11]:
```
Expenditure-Share_of_Govt_spending    183
Expenditure-Share_of_GDP              114
Expenditure_Per_Capita                112
Expenditure_Constant_2022              43
dtype: int64
```

[12]:
```
# Create a copy of the dataframe to avoid modifying the original data
data_cleaned = data_cleaned.copy()

# Handling missing values in "Expenditure_Constant_2022" using forward and
 ↪backward filling
data_cleaned['Expenditure_Constant_2022'] =
 ↪data_cleaned['Expenditure_Constant_2022'].ffill().bfill()

# Handling missing values in other numerical columns using median imputation
for column in ['Expenditure-Share_of_Govt_spending',
 ↪'Expenditure-Share_of_GDP', 'Expenditure_Per_Capita']:
    median_value = data_cleaned[column].median()
    data_cleaned[column] = data_cleaned[column].fillna(median_value)

# Verify that there are no missing values left in the dataset
missing_values_after_imputation = data_cleaned.isna().sum()
missing_values_after_imputation[missing_values_after_imputation > 0]
```

[12]:
```
Series([], dtype: int64)
```

Supervised Learning (Regression)

### 1.1.5 Linear Regression Model 1

[13]:
```
# Selecting relevant features for forecasting
# We will primarily use 'Year' and 'Expenditure_Constant_2022' for the␣
↪time-series analysis.
forecast_data = data_cleaned[['Country', 'Year', 'Expenditure_Constant_2022']]

# Sorting the data by Country and Year to prepare for time-series modeling
forecast_data = forecast_data.sort_values(by=['Country', 'Year'])

# Display the prepared data for forecasting
forecast_data.head()
```

[13]:

| | Country | Year | Expenditure_Constant_2022 |
|---|---|---|---|
| 619 | Afghanistan | 2004 | 183.648324 |
| 620 | Afghanistan | 2005 | 165.378054 |
| 621 | Afghanistan | 2006 | 167.189480 |
| 622 | Afghanistan | 2007 | 257.366345 |
| 623 | Afghanistan | 2008 | 224.292155 |

[14]:
```
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets for each country
# We will create a dictionary to hold the train-test split for each country
countries = forecast_data['Country'].unique()
train_test_data = {}

for country in countries:
    country_data = forecast_data[forecast_data['Country'] == country]
    X = country_data[['Year']]
    y = country_data['Expenditure_Constant_2022']

    # Split the data (80% training, 20% testing)
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪shuffle=False)

    train_test_data[country] = {
        'X_train': X_train,
        'X_test': X_test,
        'y_train': y_train,
        'y_test': y_test
    }

# Display the train-test split information for a sample country
sample_country = countries[0]
train_test_data[sample_country]
```

[14]:
```
{'X_train':      Year
 619  2004
 620  2005
 621  2006
 622  2007
 623  2008
 624  2009
 625  2010
 626  2011
 627  2012
 628  2013
 629  2014
 630  2015
 631  2016
 632  2017,
 'X_test':      Year
 633  2018
 634  2019
 635  2020
 636  2021,
 'y_train': 619    183.648324
 620    165.378054
 621    167.189480
 622    257.366345
 623    224.292155
 624    252.407949
 625    269.912673
 626    265.485040
 627    198.955803
 628    183.421702
 629    223.721970
 630    178.913871
 631    177.240056
 632    174.272685
 Name: Expenditure_Constant_2022, dtype: float64,
 'y_test': 633    190.335314
 634    228.106548
 635    263.904202
 636    268.600635
 Name: Expenditure_Constant_2022, dtype: float64}
```

[15]:
```
from sklearn.linear_model import LinearRegression
import numpy as np

# Initialize a dictionary to store the models for each country
models = {}
```

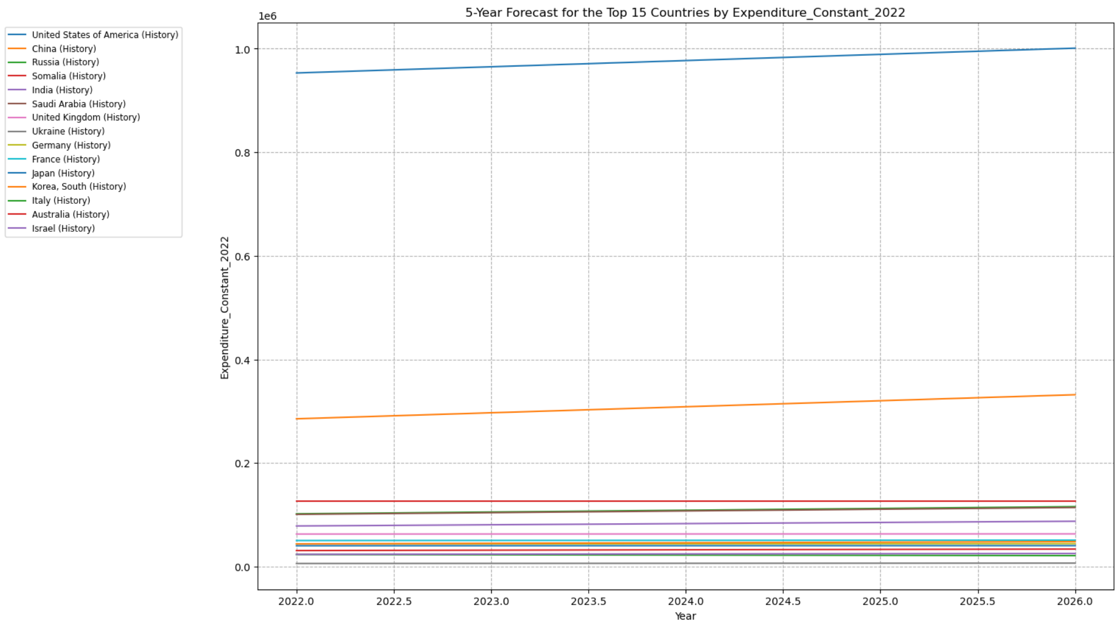
```python
# Train a Linear Regression model for each country
for country in countries:
    # Extract train-test data for the current country
    X_train = train_test_data[country]['X_train']
    y_train = train_test_data[country]['y_train']

    # Initialize and train the Linear Regression model
    model = LinearRegression()
    model.fit(X_train, y_train)

    # Store the trained model
    models[country] = model

# Forecast the next 5 and 10 years for each country using the trained models
forecast_years_5 = pd.DataFrame({'Year': np.arange(2022, 2027)})
forecast_years_10 = pd.DataFrame({'Year': np.arange(2022, 2032)})

# Create a dictionary to store forecasts for each country
forecasts = {}

for country in countries:
    # Use the trained model to make predictions for the next 5 and 10 years
    model = models[country]
    forecast_5 = model.predict(forecast_years_5)
    forecast_10 = model.predict(forecast_years_10)

    forecasts[country] = {
        '5_year_forecast': forecast_5,
        '10_year_forecast': forecast_10
    }

# Display the forecast for the first country as a sample
forecasts[sample_country]
```

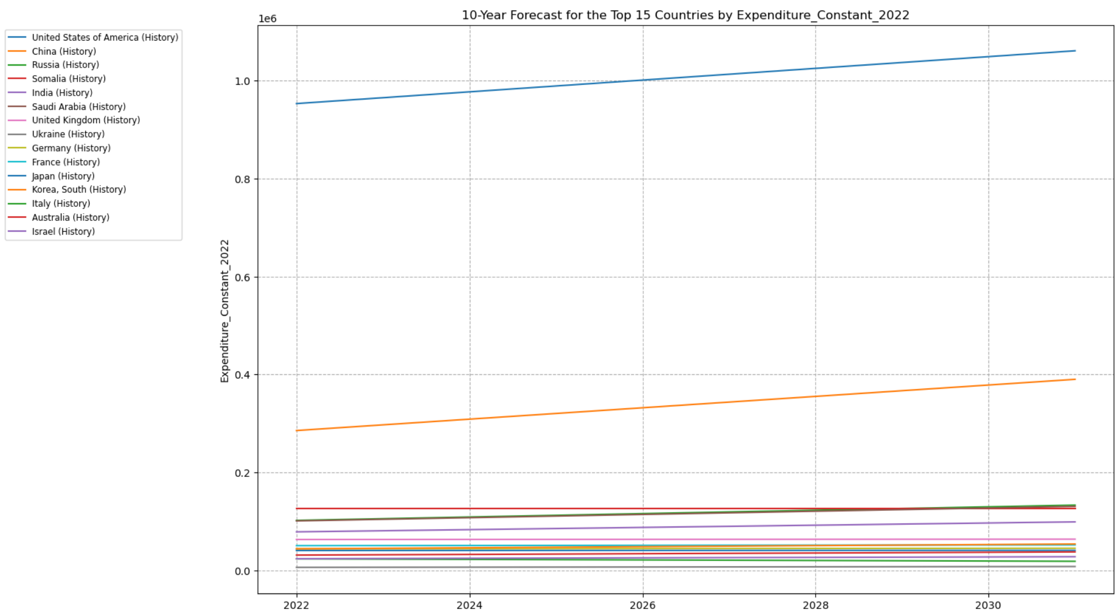
[15]:
```
{'5_year_forecast': array([196.33102894, 195.25294383, 194.17485873,
193.09677362,
        192.01868852]),
 '10_year_forecast': array([196.33102894, 195.25294383, 194.17485873,
193.09677362,
        192.01868852, 190.94060342, 189.86251831, 188.78443321,
        187.70634811, 186.628263  ])}
```

[45]:
```python
# Get the most recent "Expenditure_Constant_2022" for each country
latest_expenditure = forecast_data.groupby('Country', group_keys=False).apply(
    lambda x: x.loc[x['Year'] == x['Year'].max(), 'Expenditure_Constant_2022'].
 ↪values[0]
)
```

```
# Sort and select the top 15 countries
top_15_countries = latest_expenditure.sort_values(ascending=False).head(15).
↪index

# Plotting the 5-year forecast for the top 15 countries
plt.figure(figsize=(15, 10))
for country in top_15_countries:
    years = np.arange(2022, 2027)
    expenditure_forecast = forecasts[country]['5_year_forecast']
    plt.plot(years, expenditure_forecast, label=country)

plt.xlabel('Year')
plt.ylabel('Expenditure_Constant_2022')
plt.title('5-Year Forecast for the Top 15 Countries by␣
↪Expenditure_Constant_2022')
plt.legend(handles=sorted_legend_handles, loc='upper left', bbox_to_anchor=(-0.
↪3, 1), fontsize='small', ncol=1)
plt.grid(True, which="both", linestyle='--')
plt.show()

# Plotting the 10-year forecast for the top 15 countries
plt.figure(figsize=(15, 10))
for country in top_15_countries:
    years = np.arange(2022, 2032)
    expenditure_forecast = forecasts[country]['10_year_forecast']
    plt.plot(years, expenditure_forecast, label=country)

plt.xlabel('Year')
plt.ylabel('Expenditure_Constant_2022')
plt.title('10-Year Forecast for the Top 15 Countries by␣
↪Expenditure_Constant_2022')
plt.legend(handles=sorted_legend_handles, loc='upper left', bbox_to_anchor=(-0.
↪3, 1), fontsize='small', ncol=1)
plt.grid(True, which="both", linestyle='--')
plt.show()
```

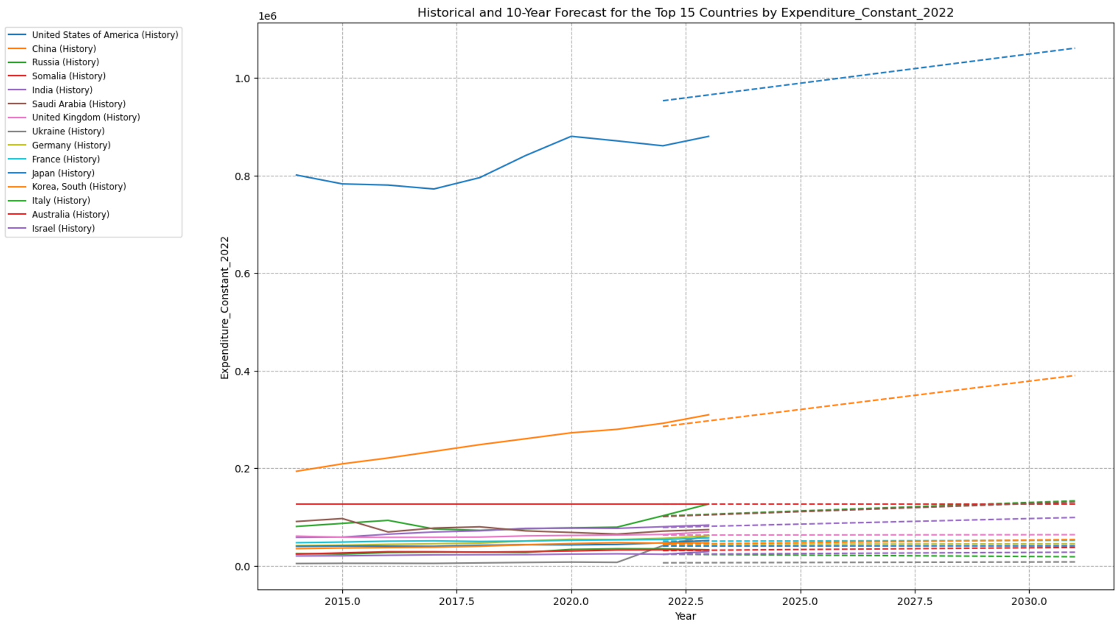
```
C:\Users\carri\AppData\Local\Temp\ipykernel_33844\1077236069.py:2:
DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns.
This behavior is deprecated, and in a future version of pandas the grouping
columns will be excluded from the operation. Either pass `include_groups=False`
to exclude the groupings or explicitly select the grouping columns after groupby
to silence this warning.
  latest_expenditure = forecast_data.groupby('Country', group_keys=False).apply(
```




[46]:
```
# Sort the top 15 countries by the most recent expenditure level for legend
 ↪ranking
latest_expenditure_sorted = latest_expenditure[top_15_countries].
 ↪sort_values(ascending=False)

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

```python
country_lines = []

for country in latest_expenditure_sorted.index:
    # Get the historical data for the last 10 years for the selected country
    country_data = forecast_data[forecast_data['Country'] == country]
    historical_years = country_data['Year'].tail(10)
    historical_expenditure = country_data['Expenditure_Constant_2022'].tail(10)

    # Plot the historical data with a solid line
    historical_line, = plt.plot(
        historical_years, historical_expenditure, linestyle='-',␣
↪label=f'{country} (History)'
    )

    # Plot the forecast for the next 10 years with a dashed line, using the␣
↪same color
    plt.plot(
        np.arange(2022, 2032), forecasts[country]['10_year_forecast'],
        linestyle='--', color=historical_line.get_color(), label=f'{country}␣
↪(Forecast)'
    )

    # Store reference for legend sorting
    country_lines.append((country, historical_line))

# Sort legend entries by the latest expenditure level
sorted_legend_handles = [line for country, line in sorted(country_lines,␣
↪key=lambda x: latest_expenditure_sorted[country], reverse=True)]

plt.xlabel('Year')
plt.ylabel('Expenditure_Constant_2022')
plt.title('Historical and 10-Year Forecast for the Top 15 Countries by␣
↪Expenditure_Constant_2022')

# Placing the legend outside to the left of the plot and ranked by most recent␣
↪expenditure level
plt.legend(handles=sorted_legend_handles, loc='upper left', bbox_to_anchor=(-0.
↪3, 1), fontsize='small', ncol=1)
plt.grid(True, which="both", linestyle='--')
plt.show()
```




[18]:
```python
# Displaying the formulas (coefficients and intercepts) of the Linear␣
↪Regression models for each country

# Store the forecast formulas for each of the top 15 countries
forecast_formulas = {}

for country in top_15_countries:
    # Extract the model for the current country
    model = models[country]

    # Get the coefficient (slope) and intercept of the linear regression model
    coefficient = model.coef_[0]
    intercept = model.intercept_

    # Store the formula
    forecast_formulas[country] = f"Expenditure_Constant_2022 = {coefficient:.
↪2f} * Year + {intercept:.2f}"

# Display the forecast formulas for the top 15 countries
forecast_formulas
```

[18]:
```
{'United States of America': 'Expenditure_Constant_2022 = 11981.00 * Year +
-23272546.56',
 'China': 'Expenditure_Constant_2022 = 11618.69 * Year + -23207588.84',
 'Russia': 'Expenditure_Constant_2022 = 3464.69 * Year + -6903680.88',
 'Somalia': 'Expenditure_Constant_2022 = 0.00 * Year + 126473.35',
```

```
'India': 'Expenditure_Constant_2022 = 2265.94 * Year + -4503217.61',
'Saudi Arabia': 'Expenditure_Constant_2022 = 3301.45 * Year + -6574677.22',
'United Kingdom': 'Expenditure_Constant_2022 = 81.02 * Year + -100966.65',
'Ukraine': 'Expenditure_Constant_2022 = 194.25 * Year + -386780.27',
'Germany': 'Expenditure_Constant_2022 = 135.10 * Year + -229344.53',
'France': 'Expenditure_Constant_2022 = 174.92 * Year + -303368.71',
'Japan': 'Expenditure_Constant_2022 = 43.12 * Year + -46864.64',
'Korea, South': 'Expenditure_Constant_2022 = 1086.85 * Year + -2153701.90',
'Italy': 'Expenditure_Constant_2022 = -558.10 * Year + 1151893.60',
'Australia': 'Expenditure_Constant_2022 = 719.24 * Year + -1423274.48',
'Israel': 'Expenditure_Constant_2022 = 454.85 * Year + -896067.90'}
```

[19]:

```
from sklearn.metrics import r2_score

# Prepare a list to store the country, coefficient, intercept, and R^2 values
model_summary = []

# Calculate the R^2 score for each of the top 15 countries
for country in top_15_countries:
    # Extract model and train-test data for the current country
    model = models[country]
    X_train = train_test_data[country]['X_train']
    y_train = train_test_data[country]['y_train']
    X_test = train_test_data[country]['X_test']
    y_test = train_test_data[country]['y_test']

    # Get the coefficient and intercept
    coefficient = model.coef_[0]
    intercept = model.intercept_

    # Calculate the R^2 score on the test data
    y_pred = model.predict(X_test)
    r_squared = r2_score(y_test, y_pred)

    # Append the summary to the list
    model_summary.append({
        'Country': country,
        'Coefficient': coefficient,
        'Intercept': intercept,
        'R^2 Score': r_squared
    })

# Create a DataFrame to display the model summary
model_summary_df = pd.DataFrame(model_summary)

# Display the model summary
model_summary_df
```

[19]:
```
                       Country   Coefficient     Intercept  R^2 Score
0   United States of America  11981.001032 -2.327255e+07 -25.457937
1                      China  11618.685787 -2.320759e+07   0.694556
2                     Russia   3464.692816 -6.903681e+06   0.290156
3                    Somalia      0.000000  1.264734e+05   1.000000
4                      India   2265.937042 -4.503218e+06  -0.237510
5               Saudi Arabia   3301.454063 -6.574677e+06 -78.910826
6             United Kingdom     81.022005 -1.009666e+05  -0.080564
7                    Ukraine    194.253952 -3.867803e+05  -0.674017
8                    Germany    135.101688 -2.293445e+05 -11.194959
9                     France    174.924374 -3.033687e+05  -1.866650
10                     Japan     43.120633 -4.686464e+04  -2.388573
11              Korea, South   1086.851126 -2.153702e+06  -3.369126
12                     Italy   -558.095940  1.151894e+06 -10.028473
13                 Australia    719.242676 -1.423274e+06   0.406479
14                    Israel    454.845309 -8.960679e+05  -0.070533
```

### 1.1.6 Random Forest Regressor

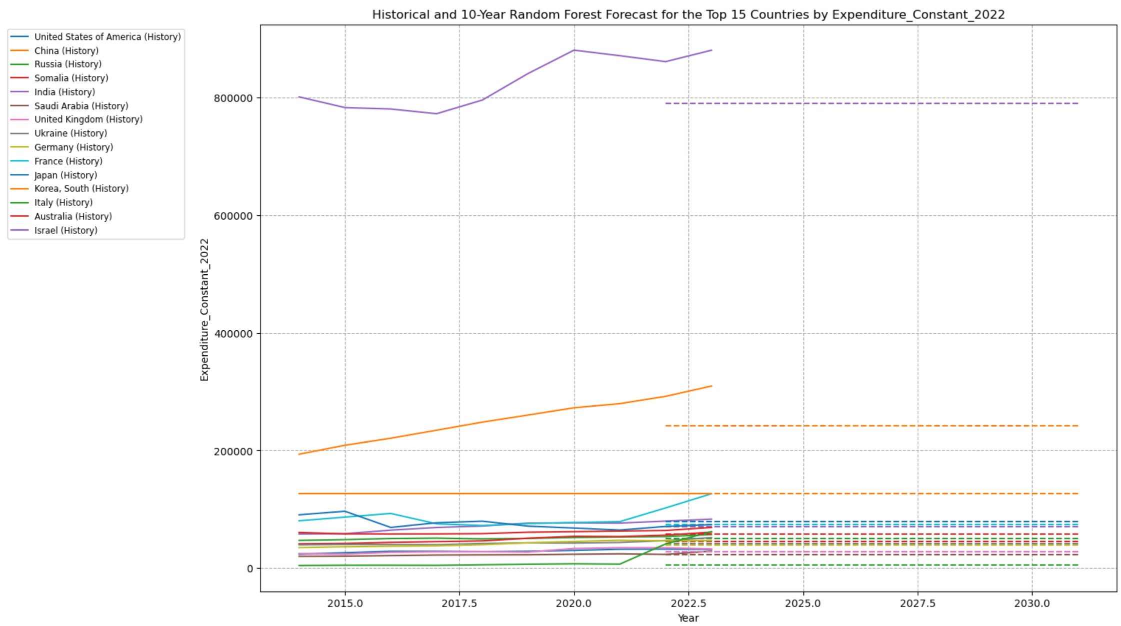
[20]:
```python
from sklearn.ensemble import RandomForestRegressor

# Initialize a dictionary to store the Random Forest models for each country
rf_models = {}

# Train a Random Forest Regressor for each country
for country in top_15_countries:
    # Extract train-test data for the current country
    X_train = train_test_data[country]['X_train']
    y_train = train_test_data[country]['y_train']

    # Initialize and train the Random Forest Regressor
    rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
    rf_model.fit(X_train, y_train)

    # Store the trained model
    rf_models[country] = rf_model

# Forecast the next 10 years for each country using the trained Random Forest␣
 ↪models
rf_forecasts = {}

for country in top_15_countries:
    # Use the trained model to make predictions for the next 10 years
    rf_model = rf_models[country]
    forecast_10 = rf_model.predict(forecast_years_10)

    rf_forecasts[country] = {
```

```
        '10_year_forecast': forecast_10
    }

# Display the forecast for one of the top 15 countries
sample_country = top_15_countries[0]
rf_forecasts[sample_country]
```

[20]: {'10_year_forecast': array([789481.619213, 789481.619213, 789481.619213, 789481.619213,
789481.619213,
        789481.619213, 789481.619213, 789481.619213, 789481.619213,
        789481.619213, 789481.619213])}

[47]:
```
# Plotting the historical data (last 10 years) and the 10-year Random Forest␣
↪forecast for the top 15 countries with consistent colors

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

for country in sorted(top_15_countries):
    # Get the historical data for the last 10 years for the selected country
    country_data = forecast_data[forecast_data['Country'] == country]
    historical_years = country_data['Year'].tail(10)
    historical_expenditure = country_data['Expenditure_Constant_2022'].tail(10)

    # Plot the historical data with a solid line
    historical_line, = plt.plot(
        historical_years, historical_expenditure, linestyle='-',␣
↪label=f'{country} (History)'
    )

    # Plot the Random Forest forecast for the next 10 years with a dashed line,␣
↪using the same color
    forecast_years = np.arange(2022, 2032)
    expenditure_forecast = rf_forecasts[country]['10_year_forecast']
    plt.plot(
        forecast_years, expenditure_forecast, linestyle='--',␣
↪color=historical_line.get_color(), label=f'{country} (RF Forecast)'
    )

# Sort legend entries by the latest expenditure level
sorted_legend_handles = [line for country, line in sorted(country_lines,␣
↪key=lambda x: latest_expenditure_sorted[x[0]], reverse=True)]

plt.xlabel('Year')
plt.ylabel('Expenditure_Constant_2022')
plt.title('Historical and 10-Year Random Forest Forecast for the Top 15␣
↪Countries by Expenditure_Constant_2022')
```

```
# Placing the legend outside to the left of the plot and ranked by most recent expenditure level
plt.legend(handles=sorted_legend_handles, loc='upper left', bbox_to_anchor=(-0.3, 1), fontsize='small', ncol=1)
plt.grid(True, which="both", linestyle='--')
plt.show()
```




### Compare model accuracy between Linear and Random

[22]:
```
# Prepare a list to store the comparison of R^2 scores for Linear Regression and Random Forest for each country
model_comparison = []

# Calculate the R^2 score for each of the top 15 countries for both Linear Regression and Random Forest models
for country in top_15_countries:
    # Extract train-test data for the current country
    X_test = train_test_data[country]['X_test']
    y_test = train_test_data[country]['y_test']

    # Linear Regression R^2 Score
    linear_model = models[country]
    y_pred_linear = linear_model.predict(X_test)
    r_squared_linear = r2_score(y_test, y_pred_linear)

    # Random Forest R^2 Score
    rf_model = rf_models[country]
```

```
    y_pred_rf = rf_model.predict(X_test)
    r_squared_rf = r2_score(y_test, y_pred_rf)

    # Append the comparison to the list
    model_comparison.append({
        'Country': country,
        'Linear R^2 Score': r_squared_linear,
        'Random Forest R^2 Score': r_squared_rf
    })

# Create a DataFrame to display the model comparison
model_comparison_df = pd.DataFrame(model_comparison)

model_comparison_df
```

[22]:

| | Country | Linear R^2 Score | Random Forest R^2 Score |
|---|---|---|---|
| 0 | United States of America | -25.457937 | -27.102278 |
| 1 | China | 0.694556 | -5.880555 |
| 2 | Russia | 0.290156 | -0.794920 |
| 3 | Somalia | 1.000000 | 0.000000 |
| 4 | India | -0.237510 | -10.619484 |
| 5 | Saudi Arabia | -78.910826 | -8.238869 |
| 6 | United Kingdom | -0.080564 | -3.584137 |
| 7 | Ukraine | -0.674017 | -0.720477 |
| 8 | Germany | -11.194959 | -7.560721 |
| 9 | France | -1.866650 | -2.222828 |
| 10 | Japan | -2.388573 | -1.605633 |
| 11 | Korea, South | -3.369126 | -19.531874 |
| 12 | Italy | -10.028473 | -2.944354 |
| 13 | Australia | 0.406479 | -4.445582 |
| 14 | Israel | -0.070533 | -1.030049 |

[23]:

```
# Prepare a list to store the summary of the Random Forest model's intercept␣
↪(using the mean), coefficient approximation (feature importance), and R^2␣
↪for each country
rf_model_summary = []

# Calculate the intercept (mean value), approximate coefficient, and R^2 score␣
↪for each of the top 15 countries
for country in top_15_countries:
    # Extract the Random Forest model and train-test data for the current␣
↪country
    rf_model = rf_models[country]
    X_train = train_test_data[country]['X_train']
    y_train = train_test_data[country]['y_train']
    X_test = train_test_data[country]['X_test']
    y_test = train_test_data[country]['y_test']
```

```
    # Calculate the intercept as the mean of the target value
    intercept = y_train.mean()

    # Approximate the "coefficient" as feature importance (since Random Forest␣
↪doesn't directly provide coefficients)
    feature_importance = rf_model.feature_importances_[0]

    # Calculate the R^2 score on the test data
    y_pred = rf_model.predict(X_test)
    r_squared = r2_score(y_test, y_pred)

    # Append the summary to the list
    rf_model_summary.append({
        'Country': country,
        'Approximate Coefficient (Feature Importance)': feature_importance,
        'Intercept (Mean Value)': intercept,
        'R^2 Score': r_squared
    })

# Create a DataFrame to display the model summary
rf_model_summary_df = pd.DataFrame(rf_model_summary)

rf_model_summary_df
```

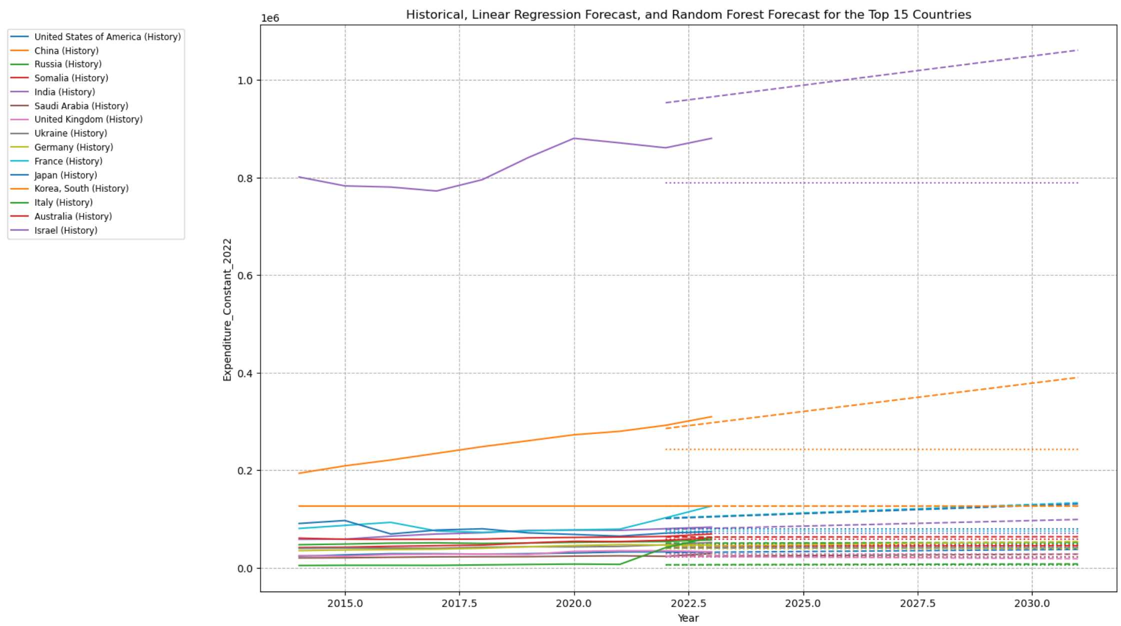
[23]:

```
                    Country  Approximate Coefficient (Feature Importance)  \
0   United States of America                                           1.0
1                      China                                           1.0
2                     Russia                                           1.0
3                    Somalia                                           0.0
4                      India                                           1.0
5               Saudi Arabia                                           1.0
6             United Kingdom                                           1.0
7                    Ukraine                                           1.0
8                    Germany                                           1.0
9                     France                                           1.0
10                     Japan                                           1.0
11              Korea, South                                           1.0
12                     Italy                                           1.0
13                 Australia                                           1.0
14                    Israel                                           1.0

    Intercept (Mean Value)  R^2 Score
0            797284.510632 -27.102278
1            134350.906012  -5.880555
2             56886.987055  -0.794920
3            126473.354300   0.000000
```

```
4             49049.911387 -10.619484
5             57943.995012  -8.238869
6             61806.560849  -3.584137
7              3475.918031  -0.720477
8             42074.764294  -7.560721
9             48054.356989  -2.222828
10            39764.717082  -1.605633
11            29782.014937 -19.531874
12            30678.855325  -2.944354
13            21684.055534  -4.445582
14            17716.323664  -1.030049
```

[48]:
```
# Plotting the historical data, Linear Regression forecast, and Random Forest␣
↪forecast for the top 15 countries with consistent colors

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

for country in sorted(top_15_countries):
    # Get the historical data for the last 10 years for the selected country
    country_data = forecast_data[forecast_data['Country'] == country]
    historical_years = country_data['Year'].tail(10)
    historical_expenditure = country_data['Expenditure_Constant_2022'].tail(10)

    # Plot the historical data with a solid line
    historical_line, = plt.plot(
        historical_years, historical_expenditure, linestyle='-',␣
↪label=f'{country} (History)'
    )

    # Plot the Linear Regression forecast for the next 10 years with a dashed␣
↪line
    linear_forecast_years = np.arange(2022, 2032)
    linear_expenditure_forecast = forecasts[country]['10_year_forecast']
    plt.plot(
        linear_forecast_years, linear_expenditure_forecast, linestyle='--',␣
↪color=historical_line.get_color(),
        label=f'{country} (Linear Forecast)'
    )

    # Plot the Random Forest forecast for the next 10 years with a dotted line
    rf_expenditure_forecast = rf_forecasts[country]['10_year_forecast']
    plt.plot(
        linear_forecast_years, rf_expenditure_forecast, linestyle=':',␣
↪color=historical_line.get_color(),
        label=f'{country} (RF Forecast)'
    )
```

```python
# Sort legend entries by the latest expenditure level
sorted_legend_handles = [line for country, line in sorted(country_lines, key=lambda x: latest_expenditure_sorted[x[0]], reverse=True)]

plt.xlabel('Year')
plt.ylabel('Expenditure_Constant_2022')
plt.title('Historical, Linear Regression Forecast, and Random Forest Forecast for the Top 15 Countries')

# Placing the legend outside to the left of the plot and ranked by most recent expenditure level
plt.legend(handles=sorted_legend_handles, loc='upper left', bbox_to_anchor=(-0.3, 1), fontsize='small', ncol=1)
plt.grid(True, which="both", linestyle='--')
plt.show()
```




### 1.1.7 Gradient Boosting Regressor Model

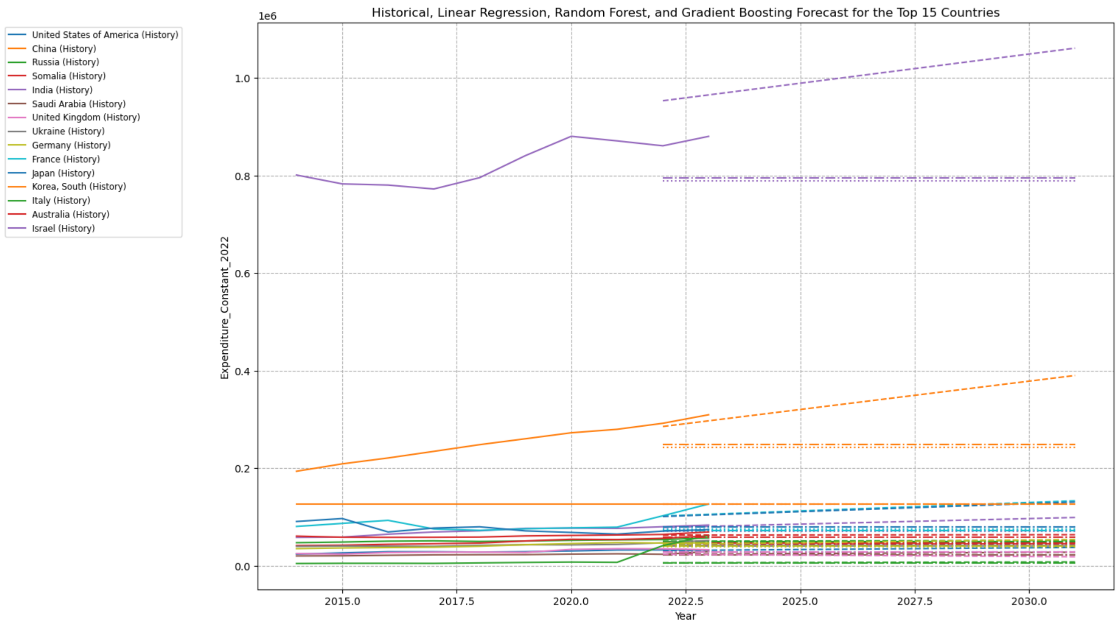
[25]:
```python
from sklearn.ensemble import GradientBoostingRegressor

# Initialize a dictionary to store the Gradient Boosting models for each country
gbr_models = {}

# Train a Gradient Boosting Regressor for each country
for country in top_15_countries:
    # Extract train-test data for the current country
```

```
    X_train = train_test_data[country]['X_train']
    y_train = train_test_data[country]['y_train']

    # Initialize and train the Gradient Boosting Regressor
    gbr_model = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1,␣
↪max_depth=3, random_state=42)
    gbr_model.fit(X_train, y_train)

    # Store the trained model
    gbr_models[country] = gbr_model

# Forecast the next 10 years for each country using the trained Gradient␣
↪Boosting models
gbr_forecasts = {}

for country in top_15_countries:
    # Use the trained model to make predictions for the next 10 years
    gbr_model = gbr_models[country]
    forecast_10 = gbr_model.predict(forecast_years_10)

    gbr_forecasts[country] = {
        '10_year_forecast': forecast_10
    }

# Display the forecast for the first country as a sample
gbr_forecasts[sample_country]
```

[25]:
```
{'10_year_forecast': array([795404.95804064, 795404.95804064, 795404.95804064,
795404.95804064,
        795404.95804064, 795404.95804064, 795404.95804064, 795404.95804064,
        795404.95804064, 795404.95804064])}
```

[49]:
```
# Plotting the historical data, Linear Regression forecast, Random Forest␣
↪forecast, and Gradient Boosting Regressor forecast for the top 15 countries

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

for country in sorted(top_15_countries):
    # Get the historical data for the last 10 years for the selected country
    country_data = forecast_data[forecast_data['Country'] == country]
    historical_years = country_data['Year'].tail(10)
    historical_expenditure = country_data['Expenditure_Constant_2022'].tail(10)

    # Plot the historical data with a solid line
    historical_line, = plt.plot(
        historical_years, historical_expenditure, linestyle='-',␣
↪label=f'{country} (History)'
```

```
    )

    # Plot the Linear Regression forecast for the next 10 years with a dashed␣
↪line
    forecast_years = np.arange(2022, 2032)
    linear_expenditure_forecast = forecasts[country]['10_year_forecast']
    plt.plot(
        forecast_years, linear_expenditure_forecast, linestyle='--',␣
↪color=historical_line.get_color(),
        label=f'{country} (Linear Forecast)'
    )

    # Plot the Random Forest forecast for the next 10 years with a dotted line
    rf_expenditure_forecast = rf_forecasts[country]['10_year_forecast']
    plt.plot(
        forecast_years, rf_expenditure_forecast, linestyle=':',␣
↪color=historical_line.get_color(),
        label=f'{country} (RF Forecast)'
    )

    # Plot the Gradient Boosting Regressor forecast for the next 10 years with␣
↪a dash-dot line
    gbr_expenditure_forecast = gbr_forecasts[country]['10_year_forecast']
    plt.plot(
        forecast_years, gbr_expenditure_forecast, linestyle='-.',␣
↪color=historical_line.get_color(),
        label=f'{country} (GBR Forecast)'
    )

# Sort legend entries by the latest expenditure level
sorted_legend_handles = [line for country, line in sorted(country_lines,␣
↪key=lambda x: latest_expenditure_sorted[x[0]], reverse=True)]

plt.xlabel('Year')
plt.ylabel('Expenditure_Constant_2022')
plt.title('Historical, Linear Regression, Random Forest, and Gradient Boosting␣
↪Forecast for the Top 15 Countries')

# Placing the legend outside to the left of the plot and ranked by most recent␣
↪expenditure level
plt.legend(handles=sorted_legend_handles, loc='upper left', bbox_to_anchor=(-0.
↪3, 1), fontsize='small', ncol=1)
plt.grid(True, which="both", linestyle='--')
plt.show()
```

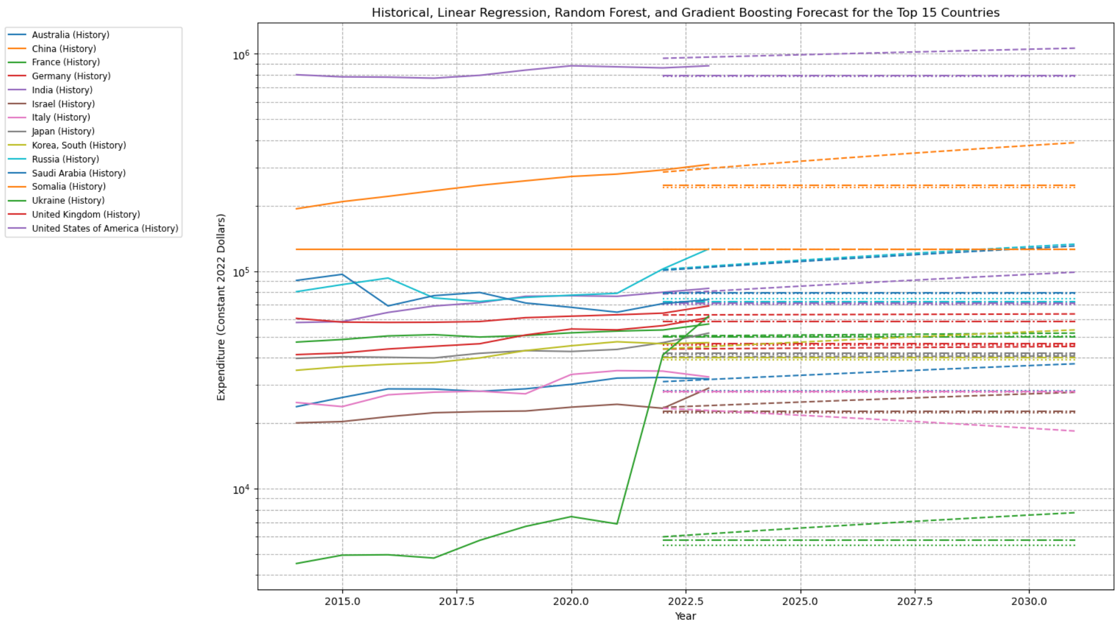



[ ]:

[50]:

```
# Plotting the historical data, Linear Regression forecast, Random Forest forecast, and Gradient Boosting Regressor forecast for the top 15 countries

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

country_lines = []  # To store line references for sorting later

for country in sorted(top_15_countries):
    # Get the historical data for the last 10 years for the selected country
    country_data = forecast_data[forecast_data['Country'] == country]
    historical_years = country_data['Year'].tail(10)
    historical_expenditure = country_data['Expenditure_Constant_2022'].tail(10)

    # Plot the historical data with a solid line
    historical_line, = plt.plot(
        historical_years, historical_expenditure, linestyle='-', label=f'{country} (History)'
    )
    country_lines.append((country, historical_line))  # Storing line reference for legend sorting

    # Plot the Linear Regression forecast for the next 10 years with a dashed line
    forecast_years = np.arange(2022, 2032)
```

```
    linear_expenditure_forecast = forecasts[country]['10_year_forecast']
    plt.plot(
        forecast_years, linear_expenditure_forecast, linestyle='--', color=historical_line.get_color(),
        label=f'{country} (Linear Forecast)'
    )

    # Plot the Random Forest forecast for the next 10 years with a dotted line
    rf_expenditure_forecast = rf_forecasts[country]['10_year_forecast']
    plt.plot(
        forecast_years, rf_expenditure_forecast, linestyle=':', color=historical_line.get_color(),
        label=f'{country} (RF Forecast)'
    )

    # Plot the Gradient Boosting Regressor forecast for the next 10 years with a dash-dot line
    gbr_expenditure_forecast = gbr_forecasts[country]['10_year_forecast']
    plt.plot(
        forecast_years, gbr_expenditure_forecast, linestyle='-.', color=historical_line.get_color(),
        label=f'{country} (GBR Forecast)'
    )

# Sort legend entries by the latest expenditure level
sorted_legend_handles = [line for country, line in sorted(country_lines, key=lambda x: historical_expenditure.iloc[-1], reverse=True)]

plt.xlabel('Year')
plt.ylabel('Expenditure (Constant 2022 Dollars)')
plt.yscale('log')  # Setting the y-axis to logarithmic scale
plt.title('Historical, Linear Regression, Random Forest, and Gradient Boosting Forecast for the Top 15 Countries')

# Placing the legend outside to the left of the plot and ranked by most recent expenditure level
plt.legend(handles=sorted_legend_handles, loc='upper left', bbox_to_anchor=(-0.3, 1), fontsize='small', ncol=1)
plt.grid(True, which='both', linestyle='--')  # Adding gridlines for better readability
plt.show()
```




[51]:
```python
# Prepare a list to store the summary of the Gradient Boosting model's R^2 for each country
gbr_model_summary = []

# Calculate the R^2 score for each of the top 15 countries for the Gradient Boosting model
for country in top_15_countries:
    # Extract train-test data for the current country
    X_test = train_test_data[country]['X_test']
    y_test = train_test_data[country]['y_test']

    # Gradient Boosting Regressor R^2 Score
    gbr_model = gbr_models[country]
    y_pred_gbr = gbr_model.predict(X_test)
    r_squared_gbr = r2_score(y_test, y_pred_gbr)

    # Append the summary to the list
    gbr_model_summary.append({
        'Country': country,
        'Gradient Boosting R^2 Score': r_squared_gbr
    })

# Create a DataFrame to display the Gradient Boosting model accuracy summary
gbr_model_summary_df = pd.DataFrame(gbr_model_summary)

gbr_model_summary_df
```

[51]:

```
                     Country  Gradient Boosting R^2 Score
0   United States of America                   -23.091954
1                      China                    -4.215515
2                     Russia                    -1.005995
3                    Somalia                     1.000000
4                      India                    -7.432400
5               Saudi Arabia                   -10.015545
6             United Kingdom                    -3.439904
7                    Ukraine                    -0.697479
8                    Germany                    -6.679121
9                     France                    -2.599453
10                     Japan                    -1.182671
11              Korea, South                   -15.473089
12                     Italy                    -2.677620
13                 Australia                    -4.756625
14                    Israel                    -0.839813
```

[31]:

```python
# Prepare a list to store the summary of theGradient Boosting model's intercept␣
↪(using the mean), coefficient approximation (feature importance), and R^2␣
↪for each country

gbr_summary_list = []  # List to store summaries for each country

for country, gbr_model in gbr_models.items():
    # Calculate the mean of predictions as an approximation for the intercept
    mean_intercept = np.mean(gbr_model.predict(X_train))  # Assuming X_train␣
↪contains the historical features

    # Get feature importances from the Gradient Boosting model
    feature_importance = gbr_model.feature_importances_

    # Calculate the R^2 score of the model
    r_squared = gbr_model.score(X_train, y_train)

    # Prepare a dictionary for the current country's summary
    country_summary = {
        'Country': country,
        'Mean_Intercept': mean_intercept,
        'Feature_Importance': feature_importance,
        'R_squared': r_squared
    }

    # Append the dictionary to the list
    gbr_summary_list.append(country_summary)

gbr_summary_df = pd.DataFrame(gbr_summary_list)
```

```
gbr_summary_df
```

[31]:

| | Country | Mean_Intercept | Feature_Importance | R_squared |
|---|---|---|---|---|
| 0 | United States of America | 797284.510632 | [1.0] | -94132.992031 |
| 1 | China | 134350.906012 | [1.0] | -2626.882945 |
| 2 | Russia | 56886.987055 | [1.0] | -277.411792 |
| 3 | Somalia | 126473.354300 | [0.0] | -1786.684212 |
| 4 | India | 49049.911387 | [1.0] | -163.153789 |
| 5 | Saudi Arabia | 57943.995012 | [1.0] | -289.098608 |
| 6 | United Kingdom | 61806.560849 | [1.0] | -296.795409 |
| 7 | Ukraine | 3475.918031 | [1.0] | -29.979516 |
| 8 | Germany | 42074.764294 | [1.0] | -89.737523 |
| 9 | France | 48054.356989 | [1.0] | -138.682528 |
| 10 | Japan | 39764.717082 | [1.0] | -73.304696 |
| 11 | Korea, South | 29782.014937 | [1.0] | -22.886129 |
| 12 | Italy | 30678.855325 | [1.0] | -29.425584 |
| 13 | Australia | 21684.055534 | [1.0] | -1.814031 |
| 14 | Israel | 17716.323664 | [1.0] | 1.000000 |

**Hyperparameter grid for Gradient Boosting Regressor**

[34]:
```
from sklearn.model_selection import GridSearchCV

# Define the hyperparameter grid for Gradient Boosting Regressor
param_grid = {
    'n_estimators': [50, 100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [2, 3, 5]
}

# Select a subset of countries for demonstration purposes to save computation␣
↪time
sample_countries = top_15_countries[:3]  # Choosing the first three countries

# Initialize a dictionary to store the best GBR models after hyperparameter␣
↪tuning
best_gbr_models = {}

# Hyperparameter tuning for each selected country using GridSearchCV
for country in sample_countries:
    # Extract train-test data for the current country
    X_train = train_test_data[country]['X_train']
    y_train = train_test_data[country]['y_train']

    # Initialize the GBR model
    gbr = GradientBoostingRegressor(random_state=42)

    # Set up GridSearchCV
```

```
    grid_search = GridSearchCV(estimator=gbr, param_grid=param_grid, cv=3,␣
↪n_jobs=-1, scoring='r2', verbose=1)

    # Fit the model to the training data
    grid_search.fit(X_train, y_train)

    # Store the best model for the current country
    best_gbr_models[country] = grid_search.best_estimator_

# Display the best parameters for each of the sample countries
best_gbr_parameters = {country: best_gbr_models[country].get_params() for␣
↪country in sample_countries}
best_gbr_parameters
```

```
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Fitting 3 folds for each of 27 candidates, totalling 81 fits
Fitting 3 folds for each of 27 candidates, totalling 81 fits
```

[34]:
```
{'United States of America': {'alpha': 0.9,
  'ccp_alpha': 0.0,
  'criterion': 'friedman_mse',
  'init': None,
  'learning_rate': 0.01,
  'loss': 'squared_error',
  'max_depth': 5,
  'max_features': None,
  'max_leaf_nodes': None,
  'min_impurity_decrease': 0.0,
  'min_samples_leaf': 1,
  'min_samples_split': 2,
  'min_weight_fraction_leaf': 0.0,
  'n_estimators': 50,
  'n_iter_no_change': None,
  'random_state': 42,
  'subsample': 1.0,
  'tol': 0.0001,
  'validation_fraction': 0.1,
  'verbose': 0,
  'warm_start': False},
 'China': {'alpha': 0.9,
  'ccp_alpha': 0.0,
  'criterion': 'friedman_mse',
  'init': None,
  'learning_rate': 0.2,
  'loss': 'squared_error',
  'max_depth': 5,
  'max_features': None,
```

```
  'max_leaf_nodes': None,
  'min_impurity_decrease': 0.0,
  'min_samples_leaf': 1,
  'min_samples_split': 2,
  'min_weight_fraction_leaf': 0.0,
  'n_estimators': 200,
  'n_iter_no_change': None,
  'random_state': 42,
  'subsample': 1.0,
  'tol': 0.0001,
  'validation_fraction': 0.1,
  'verbose': 0,
  'warm_start': False},
 'Russia': {'alpha': 0.9,
  'ccp_alpha': 0.0,
  'criterion': 'friedman_mse',
  'init': None,
  'learning_rate': 0.1,
  'loss': 'squared_error',
  'max_depth': 2,
  'max_features': None,
  'max_leaf_nodes': None,
  'min_impurity_decrease': 0.0,
  'min_samples_leaf': 1,
  'min_samples_split': 2,
  'min_weight_fraction_leaf': 0.0,
  'n_estimators': 100,
  'n_iter_no_change': None,
  'random_state': 42,
  'subsample': 1.0,
  'tol': 0.0001,
  'validation_fraction': 0.1,
  'verbose': 0,
  'warm_start': False}}
```

[35]:

```
# Feature selection and data preparation
forecast_data = data_cleaned[['Country', 'Year', 'Expenditure_Constant_2022']].
 ↪sort_values(by=['Country', 'Year'])

# Train-test split preparation
countries = forecast_data['Country'].unique()
train_test_data = {}
for country in countries:
    country_data = forecast_data[forecast_data['Country'] == country]
    X = country_data[['Year']]
    y = country_data['Expenditure_Constant_2022']
    train_size = int(0.8 * len(X))
```

```
    X_train, X_test = X[:train_size], X[train_size:]
    y_train, y_test = y[:train_size], y[train_size:]
    train_test_data[country] = {
        'X_train': X_train,
        'X_test': X_test,
        'y_train': y_train,
        'y_test': y_test
    }

# Redefine the sample countries and manually selected hyperparameter set
sample_countries = countries[:3]
manually_selected_params = {
    'n_estimators': 100,
    'learning_rate': 0.05,
    'max_depth': 3,
    'random_state': 42
}

# Initialize a dictionary to store the manually tuned GBR models for each␣
↪selected country
manually_tuned_gbr_models = {}

# Train a manually tuned Gradient Boosting Regressor for each selected country
for country in sample_countries:
    # Extract train-test data for the current country
    X_train = train_test_data[country]['X_train']
    y_train = train_test_data[country]['y_train']

    # Initialize and train the Gradient Boosting Regressor with manually␣
↪selected parameters
    gbr_model = GradientBoostingRegressor(**manually_selected_params)
    gbr_model.fit(X_train, y_train)

    # Store the trained model
    manually_tuned_gbr_models[country] = gbr_model

# Forecast the next 10 years for each country using the manually tuned Gradient␣
↪Boosting models
forecast_years_10 = pd.DataFrame({'Year': np.arange(2022, 2032)})
manually_tuned_gbr_forecasts = {}

for country in sample_countries:
    # Use the trained model to make predictions for the next 10 years
    gbr_model = manually_tuned_gbr_models[country]
    forecast_10 = gbr_model.predict(forecast_years_10)

    manually_tuned_gbr_forecasts[country] = {
```

```
        '10_year_forecast': forecast_10
    }

# Display the forecast for the first country as a sample after manual tuning
manually_tuned_gbr_forecasts[sample_countries[0]]
```

[35]:
```
{'10_year_forecast': array([176.17101111, 176.17101111, 176.17101111,
176.17101111,
        176.17101111, 176.17101111, 176.17101111, 176.17101111,
        176.17101111, 176.17101111])}
```

**References**


ChatGPT, (2024) GPT-4o version, OpenAI. [Large language model]. https://chatgpt.com/

Gelman, A., & Hill, J. (2006). Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge University Press.

Guyon, I., & Elisseeff, A. (2003). An Introduction to Variable and Feature Selection. Journal of Machine Learning Research, 3(Mar), 1157-1182.

Hyndman, R.J., & Athanasopoulos, G. (2021) Forecasting: principles and practice, 3rd edition, OTexts: Melbourne, Australia. OTexts.com/fpp3.

LinearRegression https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

Ridge Regression. scikit-learn. https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.Ridge.htm

GradientBoostingRegressor https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoosting

CountVectorizer. scikit-learn. https://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.

Train-Test Split. scikit-learn. https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_t


[ ]: