Exploring Country Credit Ratings

In [1]:

```
#Import relevant libraries
import pandas as pd
import numpy as np
import requests
from bs4 import BeautifulSoup

from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split

import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:

```
#Set visualization style & Display
plt.style.use('seaborn-whitegrid')
sns.set_style('whitegrid')
sns.color_palette("mako")
pd.set_option('display.max_columns', None)
from IPython.core.display import HTML
HTML("""
<style>
.output_png {
 display: table-cell;
 text-align: center;
 vertical-align: middle;
}
</style>
""")
```

Out[2]:

I) Data Gathering & Cleaning

1.1 Define Useful Functions

In [3]:
```
#Function to clean the webscraped data
def grades_cleaner(rating_classification, grades, index, category):
    """Function to clean the webscraped data from the second table in the
    html page, in order to extract the classes used in the classificatio
    to a letter grade"""

    temp_lst = []
    for i in grades[:index]:
        if i != category:
            temp_lst.append(i)
    rating_classification[category] = temp_lst
    grades = grades[index:]
    return rating_classification, grades
```

In [4]:
```
#Function to clean up World Bank Datasets
def clean_wbdf(df):
    """Function to clean all the datasets imported from the World Bank da
    reduce the time series csv to focus on the variable of interest"""

    variable_name = df['Indicator Name'][0] #Register Indicator Name for
    df = df[['Country Code', '2019']]#Focus on the columns on interest
    df = df.rename(columns = {'2019': variable_name}) #Rename 2019 colum
    df.set_index('Country Code', inplace = True)#Set index to Country Na
    return df
```

In [5]:
```
#Function to fill out null values with previous year values
def parse_fill_null(df, columns_list):
    """Function to parse through the World Bank datasets and fill out the
    column of interest by older data entries in the specified number of y

    for year in columns_list:
        for index, row in df.iterrows():
            if (pd.isnull(df.loc[index, '2019'])) and (pd.isnull(df.loc[i
                df.loc[index, '2019'] = df.loc[index, year]
    return df
```

In [374]:
```
def accuracy_comp(y_train, p_train, y_test, p_test):
     """This function compares the accuracy scores of train and test sets
     predictions"""

     train_accuracy = accuracy_score(y_train, p_train)
     test_accuracy = accuracy_score(y_test, p_test)

     print(f"Training Accuracy: {(train_accuracy * 100):.4}%")
     print(f"Test Accuracy: {(test_accuracy * 100):.4}%")
```

1.2 Webscrape Base Data

Country Credit Ratings Across

Source: Wikirating -- [https://www.wikirating.org/wiki/List_of_countries_by_credit_rating (https://www.wikirating.org/wiki/List_of_countries_by_credit_rating)](https://www.wikirating.org/wiki/List_of_countries_by_credit_rating)

This page lists a comprehensive number of countries & sovereign territories and provides data for long-term foreign currency credit ratings for sovereign bons as reported by DBRS, Fitch, Moody's, Scope Ratings and Standard & Poor's, as compared to the Sovereign Wikirating Index.

In [6]:
```
#Retrieve html page & pass it to Beautiful Soup for parsing
wikirating_page = requests.get('https://www.wikirating.org/wiki/List_of_c
soup = BeautifulSoup(wikirating_page.content, 'html.parser')
```

In [7]:
```
#Select a container
table = soup.find('tbody')
```

In [8]:
```
#Extract the country & related ratings from the table
country_ratings = [a.find('a').string for a in table.findAll('td')]
```

In [9]:

```
#Clean Up country Ratings
#Create Empty lists to hold the variables
list_of_countries = []
swi = []
sp = []
scope = []
moody = []
fitch = []
dbrs = []

#Fill lists will all the relevant values
for i in range(0, len(country_ratings), 7):
    list_of_countries.append(country_ratings[i])
    swi.append(country_ratings[i+1])
    sp.append(country_ratings[i+2])
    scope.append(country_ratings[i+3])
    moody.append(country_ratings[i+4])
    fitch.append(country_ratings[i+5])
    dbrs.append(country_ratings[i+6])

#Compare the lengths of all lists to ensure they are consistent
print('Countries: ', len(list_of_countries), '\nSWI: ', len(swi), '\nS&P
     '\nMoody\'s: ', len(moody), '\nFitch: ', len(fitch), '\nDBRS: ', le
```

```
Countries:  198
SWI:  198
S&P:  198
Scope:  198
Moody's:  198
Fitch:  198
DBRS:  198
```

In [10]:

```
#Create an empty dictionary to put the lists together
wiki_ratings = {}

i = 0
for country in list_of_countries:
    wiki_ratings[country] = {'Sovereign Wikirating Index': swi[i],
                             'Standard & Poor': sp[i],
                             'Scope': scope[i],
                             'Moody\'s': moody[i],
                             'Fitch': fitch[i],
                             'DBRS': dbrs[i]}
    i += 1

#Transform the dictionary to a DataFrame
wikidf = pd.DataFrame.from_dict(wiki_ratings, orient = 'index')
wikidf.head()
```

Out[10]:

	Sovereign Wikirating Index	Standard & Poor	Scope	Moody's	Fitch	DBRS
Afghanistan	BB-	n.r.	n.r.	n.r.	n.r.	n.r.
Albania	BBB-	B+	n.r.	B1	n.r.	n.r.
Algeria	B+	n.r.	n.r.	n.r.	n.r.	n.r.
Andorra	n.r.	BBB	n.r.	n.r.	BBB+	n.r.
Angola	B	CCC+	n.r.	Caa1	CCC	n.r.

In [11]:

```
#Replace 'n.r.' with null values
wikidf = wikidf.replace('n.r.', np.nan)
wikidf.head()
```

Out[11]:

	Sovereign Wikirating Index	Standard & Poor	Scope	Moody's	Fitch	DBRS
Afghanistan	BB-	NaN	NaN	NaN	NaN	NaN
Albania	BBB-	B+	NaN	B1	NaN	NaN
Algeria	B+	NaN	NaN	NaN	NaN	NaN
Andorra	NaN	BBB	NaN	NaN	BBB+	NaN
Angola	B	CCC+	NaN	Caa1	CCC	NaN

Country Credit Rating Categories

Source: Trading Economics -- [https://tradingeconomics.com/country-list/rating (https://tradingeconomics.com/country-list/rating)](https://tradingeconomics.com/country-list/rating)

Good source of credit rating data but the number of countries listed is more limited than Wikirating List of countries by credit rating, but provides useful categories for rating countries

In [12]:
```
#Retrieve html page & pass it to Beautiful Soup for parsing
trading_economics_page = requests.get('https://tradingeconomics.com/coun
soup = BeautifulSoup(trading_economics_page.content, 'html.parser')
```

1. Get the Trading Economics credit ratings

In [13]:
```
#Select a container
container = soup.find('table', class_= "table table-hover")
```

In [14]:
```
#Select the list of countries in the table
countries = [a.string for a in container.findAll('a')]

#Clean up the extracted text
countries = [country.replace('\r\n', '') for country in countries]
countries = [country.replace('  ','') for country in countries]
#Remove the extra empty space at the end of some of the leftover countrie
for country in countries:
    if country[-1] == ' ':
        countries[countries.index(country)] = country[:-1]


#Verify length
print(len(countries))
```

```
154
```

In [15]:

```
#Extract the ratings from the table
ratings = [span.string for span in container.findAll('span')]

#Create empty lists for each credit rating
s_and_p = []
moodys = []
fitch = []
dbrs = []
te = []

#All 5 credit ratings were extracted in ratings
#Append to each rating list created as appropriate (by index)
for i in range(0, len(ratings), 5):
    s_and_p.append(ratings[i]) #Starts at index 0, every 5
    moodys.append(ratings[i+1]) #starts at index 1, every 5
    fitch.append(ratings[i+2]) #starts at index 2, every 5
    dbrs.append(ratings[i+3])#starts at index 3, every 5
    te.append(ratings[i+4]) #starts at index 4, every 5

#Compare lengths, all should be the same
print('Standard & Poor: ', len(s_and_p), '\nMoody\'s: ', len(moodys), '\
     '\nDBRS: ', len(dbrs), '\nTrading Economics: ', len(te))
```

```
Standard & Poor:  154
Moody's:  154
Fitch:  154
DBRS:  154
Trading Economics:  154
```

In [16]:

```
#Clean up the text in the ratings & convert the trading economics rating
for i in range(len(countries)):
    #Standard & Poor
    s_and_p[i] = s_and_p[i].replace('\r\n', '')
    s_and_p[i] = s_and_p[i].replace(' ', '')
    s_and_p[i] = s_and_p[i].replace('\n', '')
    #Moody's
    moodys[i] = moodys[i].replace('\r\n', '')
    moodys[i] = moodys[i].replace(' ', '')
    moodys[i] = moodys[i].replace('\n', '')
    #Fitch
    fitch[i] = fitch[i].replace('\r\n', '')
    fitch[i] = fitch[i].replace('\n', '')
    fitch[i] = fitch[i].replace(' ', '')
    #DBRS
    dbrs[i] = dbrs[i].replace('\r\n', '')
    dbrs[i] = dbrs[i].replace('\n', '')
    dbrs[i] = dbrs[i].replace(' ', '')
    #Trading Economics
    if te[i] != None:
        te[i] = int(te[i])
```

In [17]:

```
#Create an empty dictionary, to associate each country to each of its ra
credit_ratings = {}

i = 0
for country in countries:
    credit_ratings[country] = {'Standard & Poor': s_and_p[i],
                               'Moody\'s': moodys[i],
                               'Fitch': fitch[i],
                               'DBRS': dbrs[i],
                               'Trading Economics': te[i]}
    i += 1
```

In [18]:

```
#Create a credit rating DataFrame from the dictionary created & preview
ratings_df = pd.DataFrame.from_dict(credit_ratings, orient = 'index')
ratings_df.head()
```

Out[18]:

	Standard & Poor	Moody's	Fitch	DBRS	Trading Economics
Albania	B+	B1			35.0
Andorra	BBB		BBB+		62.0
Angola	CCC+	Caa1	CCC		21.0
Argentina	CCC+	Ca	CCC	CCC	15.0
Armenia		Ba3	B+		16.0

In [19]:

```
#Add the Trading Economics Series to wikidf
trading_economics = ratings_df['Trading Economics']
wikidf['Trading Economisc'] = trading_economics
wikidf.head()
```

Out[19]:

	Sovereign Wikirating Index	Standard & Poor	Scope	Moody's	Fitch	DBRS	Trading Economisc
Afghanistan	BB-	NaN	NaN	NaN	NaN	NaN	NaN
Albania	BBB-	B+	NaN	B1	NaN	NaN	35.0
Algeria	B+	NaN	NaN	NaN	NaN	NaN	NaN
Andorra	NaN	BBB	NaN	NaN	BBB+	NaN	62.0
Angola	B	CCC+	NaN	Caa1	CCC	NaN	21.0

2. Get the Credit Rating Categories for classification

In [20]:

```
#Select the container relevant to the bottom table on the html page
container2 = soup.find('div', class_ = 'col-md-12')
```

In [21]:

```
#Register categories
rating_class = [rc.string for rc in container2.findAll('td', class_ = 9)

#Clean up the 2 values that were missing
rating_class[4] = 'Non-investment grade speculative'
rating_class.insert(6, 'Substantial risks')
rating_class[-2] = 'In default with little prospect for recovery'
```

In [22]:

```
rating_class
```

Out[22]:

```
['Prime',
 'High grade',
 'Upper medium grade',
 'Lower medium grade',
 'Non-investment grade speculative',
 'Highly speculative',
 'Substantial risks',
 'Extremely speculative',
 'In default with little prospect for recovery',
 'In default']
```

In [23]:

```
#Gather the letter ratings in a list grades
grades = [grade.string for grade in container2.findAll('td')]

#Create an empty Dictionnary with nested lists to associate grades to rat
rating_classification = {}

#Create list of number of values in each categories
num_of_values = [6, 16, 16, 16, 16, 16, 6, 5, 13, 12]
#Add the relevant grades to each of the 9 category
index = 0
for category in rating_class:
    rating_classification, grades = grades_cleaner(rating_classification
    index += 1
```

In [24]:

```
#Create empty dictionary
country_rating_class = {}

#Create an empty list to store the rows with no values on credit ratings
rows_to_remove = []

#Attribute each rating to a class
for country in wikidf.index:
    grade = wikidf.loc[wikidf.index == country, 'Sovereign Wikirating Ind

    #Check if the grade value is null
    #If null, look for rating in other rankings (S&P or Moody's -- otherw
    if pd.isnull(grade):
        if pd.isnull(wikidf.loc[wikidf.index == country, 'Standard & Poor
            grade = wikidf.loc[wikidf.index == country, 'Standard & Poor
        elif pd.isnull(wikidf.loc[wikidf.index == country, 'Moody\'s'].va
            grade = wikidf.loc[wikidf.index == country, 'Moody\'s'].valu
        else:
            rows_to_remove.append(country)

    #Fill in the country_rating_class dictionary
    for key in rating_classification:
        if grade in rating_classification[key]:
            country_rating_class[country] = key
```

In [25]:

```
credit_rating = pd.Series(data = country_rating_class)
wikidf['Credit Rating'] = credit_rating
wikidf.head()
```

Out[25]:

	Sovereign Wikirating Index	Standard & Poor	Scope	Moody's	Fitch	DBRS	Trading Economisc	Credit Rating
Afghanistan	BB-	NaN	NaN	NaN	NaN	NaN	NaN	Non-investment grade speculative
Albania	BBB-	B+	NaN	B1	NaN	NaN	35.0	Lower medium grade
Algeria	B+	NaN	NaN	NaN	NaN	NaN	NaN	Highly speculative
Andorra	NaN	BBB	NaN	NaN	BBB+	NaN	62.0	Lower medium grade
Angola	B	CCC+	NaN	Caa1	CCC	NaN	21.0	Highly speculative

In [26]:
```
wikidf.loc[wikidf['Credit Rating'].isna() == True]
```

Out[26]:

	Sovereign Wikirating Index	Standard & Poor	Scope	Moody's	Fitch	DBRS	Trading Economisc	Credit Rating
Antigua and Barbuda	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
North Korea	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Marshall Islands	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Monaco	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Nauru	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Palau	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Saint Kitts and Nevis	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Syria	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Tuvalu	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Holy See	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

ISO3 Country Codes

Source: United Nations Trade Statistics
https://unstats.un.org/unsd/tradekb/knowledgebase/country-code
(https://unstats.un.org/unsd/tradekb/knowledgebase/country-code)

In [27]:
```
#Retrieve html page & pass it to Beautiful Soup for parsing
country_code_page = requests.get('https://unstats.un.org/unsd/tradekb/kn
soup = BeautifulSoup(country_code_page.content, 'html.parser')
```

In [28]:
```
#Select container
container = soup.find('div', class_ = 'row article margin-top')
```

In [29]:

```
#Extract the text
iso3 = container.get_text()

#Clean-up
iso3 = iso3.split('\r\n') #Split the extracted string/text
iso3 = iso3[2:] #Remove the first two sentences that were extarcted with
iso3[-1] = iso3[-1].replace('\n\n\n', '') #remove the trip '\n' characte

#Create a dictionary to store the iso3 values & country name combination
iso3_codes = {}
for combination in iso3:
    iso3_codes[combination[4:-1]] = combination[:3]
```

In [30]:

```
#Transform dictionary into DataFrame
iso3_df = pd.DataFrame.from_dict(iso3_codes, orient = 'index', columns =
iso3_df.head(2)
```

Out[30]:

	Country Code
Aruba	ABW
Afghanistan	AFG

In [31]:

```
#Append the Credit Rating to the iso3_df to create a base DataFrame
basedf = wikidf.drop(['Sovereign Wikirating Index', 'Standard & Poor', '
                      'Fitch', 'DBRS', 'Trading Economisc'], axis = 1)
basedf['Country Code'] = iso3_df['Country Code']
```

In [32]:

```
#Preview DataFrame
display(basedf.info())
basedf.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 198 entries, Afghanistan to Zimbabwe
Data columns (total 2 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Credit Rating  188 non-null    object
 1   Country Code   173 non-null    object
dtypes: object(2)
memory usage: 4.6+ KB
```

None

Out[32]:

	Credit Rating	Country Code
Afghanistan	Non-investment grade speculative	AFG
Albania	Lower medium grade	ALB
Algeria	Highly speculative	DZA
Andorra	Lower medium grade	AND
Angola	Highly speculative	AGO

In [33]:
```
#Create a list of missing country codes for future reference (when puttir
missing_iso3 = list(basedf.loc[basedf['Country Code'].isna() == True].in
missing_iso3
```

Out[33]:
```
['Bolivia',
 'Brunei',
 "People's Republic of China",
 'Ivory Coast',
 'Democratic Republic of the Congo',
 'Republic of the Congo',
 'Eswatini',
 'Iran',
 'North Korea',
 'South Korea',
 'Kosovo',
 'Laos',
 'Libya',
 'Macau',
 'Federated States of Micronesia',
 'Moldova',
 'North Macedonia',
 'Russia',
 'South Sudan',
 'Syria',
 'Taiwan',
 'Tanzania',
 'Holy See',
 'Venezuela',
 'Vietnam']
```

1.3 Import Datasets

World Bank Datasets Metadata by Country -- Income Group, Country Names, Country Codes & Region

In [170]:
```
income_group = pd.read_csv('Data/Metadata_Country_API_SP.ADO.TFRT_DS2_en_

#Clean dataframe
income_group = income_group[['Country Code', 'Region', 'IncomeGroup', 'Ta
income_group.rename(columns = {'IncomeGroup': 'Income Group', 'TableName
income_group.set_index('Country Code', inplace = True) #Set 'Country Code

#remove rows that are not countries (e.g. regions or reference)
rows_to_drop = list(income_group.loc[income_group['Income Group'].isna()
income_group = income_group.drop(rows_to_drop)
```

In [171]:

```
income_group.head()
```

Out[171]:

	Region	Income Group	Country Name
Country Code			
ABW	Latin America & Caribbean	High income	Aruba
AFG	South Asia	Low income	Afghanistan
AGO	Sub-Saharan Africa	Lower middle income	Angola
ALB	Europe & Central Asia	Upper middle income	Albania
AND	Europe & Central Asia	High income	Andorra

In [172]:

```
#Use the country codes to fill out the missing ISO3 previously recorded
for country in income_group['Country Name'].values:
    if country in missing_iso3:
        iso3 = income_group.loc[income_group['Country Name'] == country,
        basedf['Country Code'][country] = iso3
        missing_iso3.remove(country)

#Check for the remainder, on the chance the the Country Name is written
for country in missing_iso3:
    for name in income_group['Country Name']:
        if country in name:
            iso3 = income_group.loc[income_group['Country Name'] == name
            basedf['Country Code'][country] = iso3
            missing_iso3.remove(country)
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call
 last)
~\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexes\base.
py in get_loc(self, key, method, tolerance)
   2894             try:
-> 2895                 return self._engine.get_loc(casted_key)
   2896             except KeyError as err:

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyOb
jectHashTable.get_item()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyOb
jectHashTable.get_item()

KeyError: 'Country Code'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call
 last)
<ipython-input-172-3b7957a43534> in <module>
     11         if country in name:
     12             iso3 = income_group.loc[income_group['Country Nam
e'] == name].index[0]
---> 13             basedf['Country Code'][country] = iso3
     14             missing_iso3.remove(country)

~\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py in _
_getitem__(self, key)
   2900             if self.columns.nlevels > 1:
   2901                 return self._getitem_multilevel(key)
-> 2902             indexer = self.columns.get_loc(key)
   2903             if is_integer(indexer):
   2904                 indexer = [indexer]
```

```
~\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexes\base.
py in get_loc(self, key, method, tolerance)
   2895                 return self._engine.get_loc(casted_key)
   2896             except KeyError as err:
-> 2897                 raise KeyError(key) from err
   2898 
   2899         if tolerance is not None:

KeyError: 'Country Code'
```

In [173]:

```
missing_iso3
```

Out[173]:

```
["People's Republic of China",
 'Ivory Coast',
 'Democratic Republic of the Congo',
 'Republic of the Congo',
 'North Korea',
 'South Korea',
 'Laos',
 'Macau',
 'Federated States of Micronesia',
 'Syria',
 'Taiwan',
 'Holy See']
```

In [174]:

```
#Fill in the remaining missing country codes
iso3_lst = ['CHN', 'CIV', 'COD', 'COG', 'PRK', 'KOR', 'LAO', 'MAC', 'FSM

i = 0
for country in missing_iso3:
    basedf['Country Code'][country] = iso3_lst[i]
    i += 1
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
~\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexes\base.py in
get_loc(self, key, method, tolerance)
   2894             try:
-> 2895                 return self._engine.get_loc(casted_key)
   2896             except KeyError as err:

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\index.pyx in pandas._libs.index.IndexEngine.get_loc()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectH
ashTable.get_item()

pandas\_libs\hashtable_class_helper.pxi in pandas._libs.hashtable.PyObjectH
ashTable.get_item()

KeyError: 'Country Code'

The above exception was the direct cause of the following exception:

KeyError                                  Traceback (most recent call last)
<ipython-input-174-9fa8facf7dc1> in <module>
      4 i = 0
      5 for country in missing_iso3:
----> 6     basedf['Country Code'][country] = iso3_lst[i]
      7     i += 1

~\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\frame.py in __geti
tem__(self, key)
   2900             if self.columns.nlevels > 1:
   2901                 return self._getitem_multilevel(key)
-> 2902             indexer = self.columns.get_loc(key)
   2903             if is_integer(indexer):
   2904                 indexer = [indexer]

~\Anaconda3\envs\learn-env\lib\site-packages\pandas\core\indexes\base.py in
get_loc(self, key, method, tolerance)
   2895                 return self._engine.get_loc(casted_key)
   2896             except KeyError as err:
-> 2897                 raise KeyError(key) from err
   2898 
   2899         if tolerance is not None:

KeyError: 'Country Code'
```

In [175]:

```
#Verify the information base dataframe
display(basedf.info())

#Set Country Codes as index
basedf = basedf.reset_index()
basedf.rename(columns = {'index': 'Country Name'}, inplace = True)
basedf = basedf.set_index('Country Code')

#Preview
basedf.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 198 entries, AFG to ZWE
Data columns (total 2 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Country Name   198 non-null    object
 1   Credit Rating  188 non-null    object
dtypes: object(2)
memory usage: 14.6+ KB
```

None

Out[175]:

Country Code	Country Name	Credit Rating
AFG	Afghanistan	Non-investment grade speculative
ALB	Albania	Lower medium grade
DZA	Algeria	Highly speculative
AND	Andorra	Lower medium grade
AGO	Angola	Highly speculative

In [176]:

```
#Drop 'Country Name' from income_group to avoid duplication in final df
income_group = income_group.drop('Country Name', axis = 1)
income_group.head()
```

Out[176]:

Country Code	Region	Income Group
ABW	Latin America & Caribbean	High income
AFG	South Asia	Low income
AGO	Sub-Saharan Africa	Lower middle income
ALB	Europe & Central Asia	Upper middle income
AND	Europe & Central Asia	High income

Adjusted Net National Income

In [177]:
```
adj_net_national_income = pd.read_csv('Data/Adjusted Net national Income
adj_net_national_income = parse_fill_null(adj_net_national_income, ['201
adj_net_national_income = clean_wbdf(adj_net_national_income)
```

Adolescent Fertility Rate (Births per 1,000 Women Aged Between 15 - 19)

In [178]:
```
fertility_rate_15_19 = pd.read_csv('Data/Adolescent Fertility Rate (Birt
fertility_rate_15_19 = clean_wbdf(fertility_rate_15_19)
```

Battle Related Deaths (Number of People)

In [179]:
```
battle_deaths = pd.read_csv('Data/Battle-related Deaths (Number of People
battle_deaths = clean_wbdf(battle_deaths)

#Cross with the webscraped wiki page on current conflict
```

Birth Rate, Crude (per 1,000 people)

In [180]:
```
birth_rate = pd.read_csv('Data/Birth Rate, Crude (per 1,000 people).csv'
birth_rate = parse_fill_null(birth_rate, ['2018', '2017'])
birth_rate = clean_wbdf(birth_rate)
```

Compulsory Education, Duration in Years

In [181]:
```
comp_education = pd.read_csv('Data/Compulsory Education, Duration (years
comp_education = clean_wbdf(comp_education)
```

Consumer Price Index

In [182]:
```
cpi = pd.read_csv('Data/Consumer Price Index.csv', header = 2)
cpi = parse_fill_null(cpi, ['2018', '2017', '2016'])
cpi = clean_wbdf(cpi)
```

Corporate Tax Rate

In [183]:

```
#Corporate Tax Rate
corp_tax_rate = pd.read_excel('Data/2020-Corporate-Tax-Rates-Around-the-W

#clean up
corp_tax_rate.rename(columns = {'iso_3' : 'Country Code', 'country': 'Co
                     inplace = True)
corp_tax_rate.set_index('Country Code', inplace = True)

#Focus on columns on interest
corp_tax_rate = corp_tax_rate[['Corporate Tax Rate']]
```

Corruption Perception Index & Significant Changes in CI

In [184]:

```
#Corruption Perception Index
corruption_index = pd.read_csv('Data/CPI2020_GlobalTablesTS_210125.csv',

#Drop columns where the majority of entries are null
corruption_index.drop(['Country', 'Standard error', 'Region', 'Number of
                       'Bertelsmann Foundation Transformation Index',
                       'Bertelsmann Foundation Sustainable Governance Ind
                       'IMD World Competitiveness Yearbook', 'PERC Asia R
                      'Economist Intelligence Unit Country Ratings', 'Wor
                      'World Economic Forum EOS', 'PRS International Coun
                      axis = 1,  inplace = True)
corruption_index.set_index('ISO3', inplace = True) #Set index to country
corruption_index.rename(columns = {'CPI score 2020' : 'CPI 2020', 'Rank'
                                   'Lower CI' : 'CI Lower', 'Upper CI' :


#CPI Significant Changes
corruption_sig_changes = pd.read_csv('Data/CPI2020_SignificantChanges_210

#Clean up coryption_sig_changes & prepare to add to final df
columns = list(corruption_sig_changes.columns[:11])#Select empty columns
corruption_sig_changes = corruption_sig_changes[columns] #Remove empty co
corruption_sig_changes.drop(['Country', 'Region', 'CPI 2020', 'CPI rank 2
                             'Standard error 2019'], axis = 1, inplace = T
corruption_sig_changes.set_index('ISO3', inplace = True)
```

Current Account Balance (BoP, current USD)

In [185]:

```
current_acc_balance = pd.read_csv('Data/Current Account Balance (BoP).csv
current_acc_balance = parse_fill_null(current_acc_balance, ['2018', '2019
current_acc_balance = clean_wbdf(current_acc_balance)
```

Death Rate, Crude (per 1,000 people)

In [186]:

```
death_rate = pd.read_csv('Data/Death Rate, Crude (per 1,000 people).csv'
death_rate = parse_fill_null(death_rate, ['2018', '2017', '2016'])
death_rate = clean_wbdf(death_rate)

#Consider engineering a variable on rising or falling death rate over the
```

Debt to GDP Ration

In [187]:

```
debt_to_gdp_ratio = pd.read_csv('Data/Debt to GDP Ratio 2021.csv')
debt_to_gdp_ratio.set_index('country', inplace = True)
```

Ease of Doing Business Index (1 = most business-friendlt regulations)

In [188]:

```
ease_of_doing_business = pd.read_csv('Data/Ease of Doing Business Index.
ease_of_doing_business = clean_wbdf(ease_of_doing_business)
```

Exports of Goods and Services (% GDP)

In [189]:

```
exports_goods_and_services = pd.read_csv('Data/Export of Goods and Servi
exports_goods_and_services = parse_fill_null(exports_goods_and_services,
exports_goods_and_services = clean_wbdf(exports_goods_and_services)
```

Fertility Rate, Total (Births Per Woman)

In [190]:

```
fertility = pd.read_csv('Data/Fertility Rate, Total (birth per woman).csv
fertility = clean_wbdf(fertility)
```

Foreign Direct Investment Net Inflows (BoP, current USD)

In [191]:

```
fdi_inflows_bop = pd.read_csv('Data/Foreign Direct Investment Net Inflows
fdi_inflows_bop = parse_fill_null(fdi_inflows_bop, ['2018'])
fdi_inflows_bop = clean_wbdf(fdi_inflows_bop)

#Feature Engineer Trends of FDI inflows
```

Foreign Direct Investment Net Outflows (BoP, current USD)

In [192]:
```
fdi_outflows_bop = pd.read_csv('Data/Foreign Direct Investment Net Outfl
fdi_outflows_bop = parse_fill_null(fdi_outflows_bop, ['2018'])
fdi_outflows_bop = clean_wbdf(fdi_outflows_bop)


#Feature engineer trend for FDI outflows
```

Foreign Direct Investment Net Inflows (% GDP)

In [193]:
```
fdi_inflows = pd.read_csv('Data/Foreign Direct Investment Net Inflows (%
fdi_inflows = parse_fill_null(fdi_inflows, ['2018', '2017'])
fdi_inflows = clean_wbdf(fdi_inflows)
```

Foreign Direct Investment Net Outflows (% GDP)

In [194]:
```
fdi_outflows = pd.read_csv('Data/Foreign Direct Investment, Net Outflows
fdi_outflows = parse_fill_null(fdi_outflows, ['2018'])
fdi_outflows = clean_wbdf(fdi_outflows)
```

Gross Domestic Product

In [195]:
```
#Gross Domestic Product
gdp = pd.read_csv('Data/GDP.csv', header = 4)
#Name the columns
gdp.columns = ['Country Code', 'Ranking', 'Unnamed: 1', 'Economy', 'GDP
gdp = gdp.drop(['Ranking', 'Unnamed: 1', 'Economy', 'Unnamed: 2'], axis =
gdp = gdp.iloc[:217] #Drop Unnecessary Rows (e.g. empty rows, rows conta
gdp.set_index('Country Code', inplace = True) #Set country code as index
```

In [196]:
```
gdp.head()
```

Out[196]:

	GDP (million of US dollars)
Country Code	
USA	21,433,226
CHN	14,342,903
JPN	5,081,770
DEU	3,861,124
IND	2,868,929

In [197]:

```
#Clean up gdp df to cast values as floats
gdp_clean_up = gdp['GDP (million of US dollars)'].to_dict() #Convert to d

#Remove extra characters and convert to float
for key in gdp_clean_up:
    value = gdp_clean_up[key]
    if type(value) != float:
        value = value.replace(' ', '')
        value = value.replace(',', '')
        if '-' in value:
            value = np.nan
        gdp_clean_up[key] = float(value)

gdp = pd.DataFrame.from_dict(gdp_clean_up, orient = 'index', columns = [
gdp.head()
```

Out[197]:

	GDP (million of US dollars)
USA	21433226.0
CHN	14342903.0
JPN	5081770.0
DEU	3861124.0
IND	2868929.0

Gross Domestic Product (Constant 2010 USD)

In [198]:

```
gdp_constant = pd.read_csv('Data/GDP Constant 2010.csv', header = 2)
gdp_constant = parse_fill_null(gdp_constant, ['2017', '2018'])
gdp_constant = clean_wbdf(gdp_constant)
```

Gross Domestic Product per Capita (Constant 2010 USD)

In [199]:

```
gdp_per_capita = pd.read_csv('Data/GDP per Capita (Constant USD 2010).csv
gdp_per_capita = parse_fill_null(gdp_per_capita, ['2018', '2017', '2016',
gdp_per_capita = clean_wbdf(gdp_per_capita)
```

Life Expectancy at Birth, Female (years)

In [200]:

```
female_life_expectancy = pd.read_csv('Data/Life Expectancy at Birth, Fema
female_life_expectancy = clean_wbdf(female_life_expectancy)
```

Life Expectancy at Birth, Male (years)

In [201]:
```
male_life_expectancy = pd.read_csv('Data/Life Expectancy at Birth, Male
male_life_expectancy = clean_wbdf(male_life_expectancy)
```

Lifetime Risk of Maternal Death (%)

In [202]:
```
maternal_death_risk = pd.read_csv('Data/Lifetime Risk of Maternal Death
maternal_death_risk = parse_fill_null(maternal_death_risk, ['2017'])
maternal_death_risk = clean_wbdf(maternal_death_risk)
```

Literacy Rate

In [203]:
```
literacy_rate = pd.read_csv('Data/Literacy Rate.csv')
literacy_rate.rename(columns = {'country' : 'Country Name', 'literacyRat
                    inplace = True) #rename columns
literacy_rate = literacy_rate[['Country Name', 'Literacy Rate']] #select
literacy_rate.set_index('Country Name', inplace = True)

#Country code not available so need to concat with Country Name
```

In [204]:
```
literacy_rate
```

Out[204]:

	Literacy Rate
Country Name	
Greenland	100.0
Andorra	100.0
North Korea	100.0
Uzbekistan	100.0
San Marino	99.9
...	...
Mali	35.5
South Sudan	34.5
Guinea	30.4
Chad	22.3
Niger	19.1

155 rows × 1 columns

Median Income

Median Income

In [205]:
```
median_income = pd.read_csv('Data/Median Income.csv')
median_income.rename(columns = {'country': 'Country Name', 'medianHouseho
                                'medianPerCapitaIncome': 'Median Per Capi
                                'Median Annual Income'}, inplace = True)
median_income.set_index('Country Name', inplace = True)

#Save population information to cross against the total population datase
population2021 = median_income['pop2021']

median_income.drop('pop2021', axis = 1, inplace = True)

#Country code not available so need to concat with Country Name
```

Number of Deaths Aged 5 - 9

In [206]:
```
deaths_5_9 = pd.read_csv('Data/Number of Deaths Ages 5-9 Years.csv', head
deaths_5_9 = clean_wbdf(deaths_5_9)
```

Number of Deaths Aged 10 - 14

In [207]:
```
deaths_10_14 = pd.read_csv('Data/Number of Deaths Ages 10-14.csv', header
deaths_10_14 = clean_wbdf(deaths_10_14)
```

Number of Deaths Aged 15 - 19

In [208]:
```
deaths_15_19 = pd.read_csv('Data/Number of Deaths Ages 15-19 Years.csv',
deaths_15_19 = clean_wbdf(deaths_15_19)
```

Number of Deaths Aged 20 - 24

In [209]:
```
deaths_20_24 = pd.read_csv('Data/Number of Deaths Ages 20-24 Years.csv',
deaths_20_24 = clean_wbdf(deaths_20_24)
```

Population Growth Annual Percentage

In [210]:
```
pop_growth = pd.read_csv('Data/Population Growth (annual %).csv', header
pop_growth = clean_wbdf(pop_growth)


#Add column on growth trend (looking at the average growth rate since 19
```

Population Total

In [211]:
```
pop_total = pd.read_csv('Data/Population Total.csv', header = 2)
pop_total = clean_wbdf(pop_total)
```

Surface Area

In [212]:
```
surface_area = pd.read_csv('Data/Surface Area (sq. km).csv', header = 2)
surface_area = parse_fill_null(surface_area, ['2018', '2017'])
surface_area = clean_wbdf(surface_area)
```

Unemployed, male (% of male labor force) (International Labour Organization estimates))

In [213]:
```
male_unemployment = pd.read_csv('Data/Unemployed, male (% of male labor 
male_unemployment = clean_wbdf(male_unemployment)
```

Unemployed, female (% of female labor force) (International Labour Organization Estimates)

In [214]:
```
female_unemployment = pd.read_csv('Data/Unemployment, female (% of femal
                                  header = 2)
female_unemployment = clean_wbdf(female_unemployment)
```

Unemployment, Total (% of total labour force) (modeled ILO estimates)

In [215]:
```
unemployment = pd.read_csv('Data/Unemployment, total (% of total labor f
                           header = 2)
unemployment = clean_wbdf(unemployment)
```

Urban Population Growth (Annual %)

In [216]:
```
urban_pop_growth = pd.read_csv('Data/Urban population growth (annual %).
urban_pop_growth = clean_wbdf(urban_pop_growth)
```

1.4 Create Workable Dataframe

In [217]:
```
#list of dataframes to concat
to_concat = [income_group, adj_net_national_income, fertility_rate_15_19
             corp_tax_rate, gdp, gdp_constant, gdp_per_capita, death_rate
             exports_goods_and_services, fertility, fdi_inflows, fdi_outf
             female_life_expectancy, male_life_expectancy, maternal_death
             deaths_20_24, pop_growth, pop_total, surface_area, corruptio
             male_unemployment, female_unemployment, urban_pop_growth]
df = pd.concat(to_concat, axis = 1, sort = True)
```

In [218]:
```
df.head()
```

Out[218]:

	Region	Income Group	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	Compulsory education, duration (years)	Consume price inde (2010 10
ABW	Latin America & Caribbean	High income	NaN	19.6732	NaN	11.756	13.0	109.53435
AFG	South Asia	Low income	1.864930e+10	61.3250	29940.0	31.802	9.0	149.89597
AGO	Sub-Saharan Africa	Lower middle income	5.411314e+10	145.3900	25.0	40.232	6.0	378.88372
AIA	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na
ALA	NaN	NaN	NaN	NaN	NaN	NaN	NaN	Na

In [219]:
```
#Sort column in alphabetical order
df = df.sort_index(axis = 1)
```

In [220]:

```
#Preview DataFrameInformation
display(df.info())
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 279 entries, ABW to ZWE
Data columns (total 44 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Adjusted net national income (current US$)
219 non-null    float64
 1   Adolescent fertility rate (births per 1,000 women ages 15-19)
240 non-null    float64
 2   Battle-related deaths (number of people)
49 non-null     float64
 3   Birth rate, crude (per 1,000 people)
254 non-null    float64
 4   CI Lower
180 non-null    float64
 5   CI Upper
180 non-null    float64
 6   CPI 2019
180 non-null    float64
 7   CPI 2020
180 non-null    float64
 8   CPI rank 2019
180 non-null    float64
 9   CPI rank 2020
180 non-null    float64
 10  Change in rank 2019-2020
180 non-null    float64
 11  Change in scores 2019-2020
180 non-null    float64
 12  Compulsory education, duration (years)
243 non-null    float64
 13  Consumer price index (2010 = 100)
184 non-null    float64
 14  Corporate Tax Rate
224 non-null    float64
 15  Death rate, crude (per 1,000 people)
254 non-null    float64
 16  Ease of doing business index (1=most business-friendly regulations)
189 non-null    float64
 17  Exports of goods and services (% of GDP)
231 non-null    float64
 18  Fertility rate, total (births per woman)
246 non-null    float64
 19  Foreign direct investment, net inflows (% of GDP)
238 non-null    float64
 20  Foreign direct investment, net inflows (BoP, current US$)
246 non-null    float64
 21  Foreign direct investment, net outflows (% of GDP)
222 non-null    float64
```

```
 22  Foreign direct investment, net outflows (BoP, current US$)
228 non-null    float64
 23  GDP (constant 2010 US$)
245 non-null    float64
 24  GDP (million of US dollars)
205 non-null    float64
 25  GDP per capita (constant 2010 US$)
252 non-null    float64
 26  Global Insight Country Risk Ratings
180 non-null    float64
 27  Income Group
217 non-null    object
 28  Life expectancy at birth, female (years)
244 non-null    float64
 29  Life expectancy at birth, male (years)
244 non-null    float64
 30  Lifetime risk of maternal death (%)
231 non-null    float64
 31  Number of deaths ages 10-14 years
239 non-null    float64
 32  Number of deaths ages 15-19 years
239 non-null    float64
 33  Number of deaths ages 20-24 years
239 non-null    float64
 34  Number of deaths ages 5-9 years
239 non-null    float64
 35  Population growth (annual %)
262 non-null    float64
 36  Population, total
262 non-null    float64
 37  Region
217 non-null    object
 38  Surface area (sq. km)
263 non-null    float64
 39  Unemployment, female (% of female labor force) (modeled ILO estimate)
233 non-null    float64
 40  Unemployment, male (% of male labor force) (modeled ILO estimate)
233 non-null    float64
 41  Unemployment, total (% of total labor force) (modeled ILO estimate)
233 non-null    float64
 42  Urban population growth (annual %)
260 non-null    float64
 43  Varieties of Democracy Project
174 non-null    float64
dtypes: float64(42), object(2)
memory usage: 98.1+ KB

None
```

Out[220]:

	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	CI Upper	CPI 2019	CPI 2020	CPI rank 2019	CPI rank 2020

	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	CI Upper	CPI 2019	CPI 2020	CPI rank 2019	CPI rank 2020
ABW	NaN	19.6732	NaN	11.756	NaN	NaN	NaN	NaN	NaN	NaN
AFG	1.864930e+10	61.3250	29940.0	31.802	15.0	23.0	16.0	19.0	173.0	165.0
AGO	5.411314e+10	145.3900	25.0	40.232	23.7	30.3	26.0	27.0	146.0	142.0
AIA	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
ALA	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [221]:

```
#Combine the multiple feature df with the base dataframe
finaldf = pd.concat([basedf, df], axis = 1, sort = True)
```

In [222]:

```
#Remove all the extra rows (e.g. regional data) that do not have a Credi
finaldf = finaldf.loc[finaldf['Credit Rating'].isna() == False]
```

In [223]:

```
#Preview final Dataframe
display(finaldf.info())
display(finaldf.head())
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 188 entries, AFG to ZWE
Data columns (total 46 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Country Name
188 non-null    object
 1   Credit Rating
188 non-null    object
 2   Adjusted net national income (current US$)
174 non-null    float64
 3   Adolescent fertility rate (births per 1,000 women ages 15-19)
182 non-null    float64
 4   Battle-related deaths (number of people)
36 non-null     float64
 5   Birth rate, crude (per 1,000 people)
187 non-null    float64
 6   CI Lower
177 non-null    float64
 7   CI Upper
177 non-null    float64
 8   CPI 2019
177 non-null    float64
 9   CPI 2020
177 non-null    float64
 10  CPI rank 2019
177 non-null    float64
 11  CPI rank 2020
177 non-null    float64
 12  Change in rank 2019-2020
177 non-null    float64
 13  Change in scores 2019-2020
177 non-null    float64
 14  Compulsory education, duration (years)
175 non-null    float64
 15  Consumer price index (2010 = 100)
175 non-null    float64
 16  Corporate Tax Rate
186 non-null    float64
 17  Death rate, crude (per 1,000 people)
187 non-null    float64
 18  Ease of doing business index (1=most business-friendly regulation
s)    182 non-null    float64
 19  Exports of goods and services (% of GDP)
173 non-null    float64
 20  Fertility rate, total (births per woman)
184 non-null    float64
 21  Foreign direct investment, net inflows (% of GDP)
179 non-null    float64
```

```
 22  Foreign direct investment, net inflows (BoP, current US$)
183 non-null    float64
 23  Foreign direct investment, net outflows (% of GDP)
166 non-null    float64
 24  Foreign direct investment, net outflows (BoP, current US$)
168 non-null    float64
 25  GDP (constant 2010 US$)
181 non-null    float64
 26  GDP (million of US dollars)
183 non-null    float64
 27  GDP per capita (constant 2010 US$)
186 non-null    float64
 28  Global Insight Country Risk Ratings
177 non-null    float64
 29  Income Group
187 non-null    object
 30  Life expectancy at birth, female (years)
184 non-null    float64
 31  Life expectancy at birth, male (years)
184 non-null    float64
 32  Lifetime risk of maternal death (%)
180 non-null    float64
 33  Number of deaths ages 10-14 years
183 non-null    float64
 34  Number of deaths ages 15-19 years
183 non-null    float64
 35  Number of deaths ages 20-24 years
183 non-null    float64
 36  Number of deaths ages 5-9 years
183 non-null    float64
 37  Population growth (annual %)
186 non-null    float64
 38  Population, total
186 non-null    float64
 39  Region
187 non-null    object
 40  Surface area (sq. km)
187 non-null    float64
 41  Unemployment, female (% of female labor force) (modeled ILO estim
ate)  178 non-null    float64
 42  Unemployment, male (% of male labor force) (modeled ILO estimate)
178 non-null    float64
 43  Unemployment, total (% of total labor force) (modeled ILO estimat
e)    178 non-null    float64
 44  Urban population growth (annual %)
185 non-null    float64
 45  Varieties of Democracy Project
171 non-null    float64
dtypes: float64(42), object(4)
memory usage: 69.0+ KB

None
```

	Country Name	Credit Rating	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	Upp
AFG	Afghanistan	Non-investment grade speculative	1.864930e+10	61.3250	29940.0	31.802	15.00	23.(
AGO	Angola	Highly speculative	5.411314e+10	145.3900	25.0	40.232	23.70	30.:
ALB	Albania	Lower medium grade	1.232864e+10	19.5028	NaN	11.620	34.50	37.!
AND	Andorra	Lower medium grade	NaN	NaN	NaN	7.000	NaN	Na
ARE	United Arab Emirates	High grade	3.840381e+11	5.2276	NaN	10.223	65.71	76.:

II) Cleaning Data & Preparing for Modeling

Dealing with Null Values

In [244]:

```
finaldf.isna().sum()
```

Out[244]:

```
Country Name
0
Credit Rating
0
Adjusted net national income (current US$)
14
Adolescent fertility rate (births per 1,000 women ages 15-19)
6
Battle-related deaths (number of people)
152
Birth rate, crude (per 1,000 people)
1
CI Lower
11
CI Upper
11
CPI 2019
11
CPI 2020
11
CPI rank 2019
11
CPI rank 2020
11
Change in rank 2019-2020
11
Change in scores 2019-2020
11
Compulsory education, duration (years)
13
Consumer price index (2010 = 100)
13
Corporate Tax Rate
2
Death rate, crude (per 1,000 people)
1
Ease of doing business index (1=most business-friendly regulations)
6
Exports of goods and services (% of GDP)
15
Fertility rate, total (births per woman)
4
Foreign direct investment, net inflows (% of GDP)
1
Foreign direct investment, net inflows (BoP, current US$)
1
Foreign direct investment, net outflows (% of GDP)
1
Foreign direct investment, net outflows (BoP, current US$)
1
GDP (constant 2010 US$)
4
GDP (million of US dollars)
```

```
4
GDP per capita (constant 2010 US$)
0
Global Insight Country Risk Ratings
0
Income Group
1
Life expectancy at birth, female (years)
0
Life expectancy at birth, male (years)
0
Lifetime risk of maternal death (%)
0
Number of deaths ages 10-14 years
0
Number of deaths ages 15-19 years
0
Number of deaths ages 20-24 years
0
Number of deaths ages 5-9 years
0
Population growth (annual %)
0
Population, total
0
Region
0
Surface area (sq. km)
0
Unemployment, female (% of female labor force) (modeled ILO estimate)
0
Unemployment, male (% of male labor force) (modeled ILO estimate)
0
Unemployment, total (% of total labor force) (modeled ILO estimate)
0
Urban population growth (annual %)
0
Varieties of Democracy Project
0
dtype: int64
```

In [245]:
```
#Adjusted Net National Income
income_groups_average_anni = {}

for group in list(finaldf['Income Group'].unique()):
    income_groups_average_anni[group] = np.mean(finaldf.loc[finaldf['Inco
                                                              'Adjusted ne
#Find the countries with null values
missing_anni = finaldf.loc[finaldf['Adjusted net national income (curren

for country in missing_anni:
    #Add Taiwan income data (only one missing)
    if country == 'TWN':
        finaldf.loc[finaldf.index == 'TWN', 'Income Group'] = 'High incom
    income_groups_key = finaldf.loc[finaldf.index == country, 'Income Gro
    finaldf.loc[finaldf.index == country,
                'Adjusted net national income (current US$)'] = income_gr
```

In [246]:
```
#Adolescent fertility rate (births per 1,000 women ages 15-19)
missing_teenage_fertility = finaldf.loc[finaldf
                                        ['Adolescent fertility rate (bir
mtf_median = finaldf['Adolescent fertility rate (births per 1,000 women a

for country in missing_teenage_fertility:
    finaldf.loc[finaldf.index == country, 'Adolescent fertility rate (bi
```

In [247]:
```
#Battle-Related Deaths
#If missing, assume that the number is zero
finaldf['Battle-related deaths (number of people)'].fillna(0, inplace = T
```

In [248]:
```
#Birth Rate -- Only one missing, fill in manually
finaldf['Birth rate, crude (per 1,000 people)'].fillna(8.402, inplace = T
```

In [249]:

```
#Corruption Perception Index
corruption_perception_groups = {}

for group in list(finaldf['Income Group'].unique()):
    corruption_perception_groups[group] = {'CPI Lower': None,
                                           'CPI Upper': None,
                                           'CPI 2019': None,
                                           'CPI 2020': None,
                                           'CPI rank 2019': None,
                                           'CPI rank 2020': None,
                                           'Change in rank 2019-2020': Non
                                           'Change in score 2019-2020': No

#Fill out reference dictionnary
for group in corruption_perception_groups:
    corruption_perception_groups[group]['CPI Lower'] = finaldf.loc[final
                                                                    'CI Lo
    corruption_perception_groups[group]['CPI Upper'] = finaldf.loc[final
                                                                    'CI Up
    cpi_score_2019 = finaldf.loc[finaldf['Income Group'] == group,'CPI 20
    cpi_score_2020 = finaldf.loc[finaldf['Income Group'] == group,'CPI 20
    corruption_perception_groups[group]['CPI 2019'] = cpi_score_2019
    corruption_perception_groups[group]['CPI 2020'] = cpi_score_2020

    rank_2019 = finaldf.loc[finaldf['Income Group'] == group,'CPI rank 20
    rank_2020 = finaldf.loc[finaldf['Income Group'] == group,'CPI rank 20
    corruption_perception_groups[group]['CPI rank 2019'] = rank_2019
    corruption_perception_groups[group]['CPI rank 2020'] = rank_2020

    corruption_perception_groups[group]['Change in rank 2019-2020'] = ra

    corruption_perception_groups[group]['Change in score 2019-2020'] = c

#Find the countries with null values
missing_cp = finaldf.loc[finaldf['CI Lower'].isna() == True].index

for country in missing_cp:
    cp_groups_key = finaldf.loc[finaldf.index == country, 'Income Group'
    finaldf.loc[finaldf.index == country, 'CI Lower'] = corruption_perce
    finaldf.loc[finaldf.index == country, 'CI Upper']  = corruption_perc
    finaldf.loc[finaldf.index == country, 'CPI 2019'] = corruption_perce
    finaldf.loc[finaldf.index == country, 'CPI 2020'] = corruption_perce
    finaldf.loc[finaldf.index == country, 'CPI rank 2019'] = corruption_
    finaldf.loc[finaldf.index == country, 'CPI rank 2020'] = corruption_
    finaldf.loc[finaldf.index == country, 'Change in rank 2019-2020'] = 
    finaldf.loc[finaldf.index == country, 'Change in scores 2019-2020'] 
```

In [250]:

```
#Compulsory education, duration (years)
finaldf['Compulsory education, duration (years)'].fillna(finaldf['Compul
```

In [251]:

```
#Consumer Price Index
cpi_groups = {}


for group in list(finaldf['Income Group'].unique()):
    cpi_groups[group] = np.mean(finaldf.loc[finaldf['Income Group'] == gr

missing_cpi = finaldf.loc[finaldf['Consumer price index (2010 = 100)'].is

for country in missing_cpi:
    cpi_groups_key = finaldf.loc[finaldf.index == country, 'Income Group
    finaldf.loc[finaldf.index == country, 'Consumer price index (2010 = 1
```

In [252]:

```
#Corporate Tax Rate
finaldf.loc[finaldf.index == 'CUB', 'Corporate Tax Rate'] = 15
finaldf.loc[finaldf.index == 'SOM', 'Corporate Tax Rate'] = 5
```

In [253]:

```
#Death Rate
finaldf.loc[finaldf.index == 'TWN', 'Death rate, crude (per 1,000 people)
```

In [254]:

```
#Ease of Doing Business Index
edb_median = (finaldf['Ease of doing business index (1=most business-frie
finaldf['Ease of doing business index (1=most business-friendly regulatio
```

In [255]:

```
#Exports of Goods and Services
egs_groups = {}

for group in list(finaldf['Income Group'].unique()):
    egs_groups[group] = np.mean(finaldf.loc[finaldf['Income Group'] == gr
                                            "Exports of goods and service

missing_egs = finaldf.loc[finaldf['Exports of goods and services (% of GD

for country in missing_egs:
    egs_groups_key = finaldf.loc[finaldf.index == country, 'Income Group
    finaldf.loc[finaldf.index == country, 'Exports of goods and services
```

In [256]:

```
#Fertility rate, total (births per woman)
fertility_mode = finaldf['Fertility rate, total (births per woman)'].mode
finaldf['Fertility rate, total (births per woman)'].fillna(fertility_mode
```

In [294]:

```
#GDP (millions USD)
finaldf.loc[finaldf.index == 'TWN', 'GDP (million of US dollars)'] = 668
finaldf.loc[finaldf.index == 'ERI', 'GDP (million of US dollars)'] = 206
finaldf.loc[finaldf.index == 'SOM', 'GDP (million of US dollars)'] = 917
finaldf.loc[finaldf.index == 'SSD', 'GDP (million of US dollars)'] = 12
finaldf.loc[finaldf.index == 'VEN', 'GDP (million of US dollars)'] = 482

#Region
finaldf.loc[finaldf.index == 'TWN', 'Region'] = 'East Asia & Pacific'

#Surface area (sq.km)
finaldf.loc[finaldf.index == 'TWN', 'Surface area (sq. km)'] = 36193.0
```

In [295]:

```
#Life Expectancy at Birth Female & Male (years)
lef_mean = finaldf['Life expectancy at birth, female (years)'].mean()
lem_mean = finaldf['Life expectancy at birth, male (years)'].mean()

finaldf['Life expectancy at birth, female (years)'].fillna(lef_mean, inp
finaldf['Life expectancy at birth, male (years)'].fillna(lem_mean, inpla
```

In [296]:

```
#Child Mortality
deaths_5_9 = finaldf['Number of deaths ages 5-9 years'].median()
deaths_10_14 = finaldf['Number of deaths ages 10-14 years'].median()
deaths_15_19 = finaldf['Number of deaths ages 15-19 years'].median()
deaths_20_24 = finaldf['Number of deaths ages 20-24 years'].median()

finaldf['Number of deaths ages 5-9 years'].fillna(deaths_5_9, inplace =
finaldf['Number of deaths ages 10-14 years'].fillna(deaths_10_14, inplac
finaldf['Number of deaths ages 15-19 years'].fillna(deaths_15_19, inplac
finaldf['Number of deaths ages 20-24 years'].fillna(deaths_20_24, inplac
```

In [297]:

```
#Filling in Additional Missing Values
#Taiwan
finaldf.loc[finaldf.index == 'TWN', 'Population, total'] = 23816775
finaldf.loc[finaldf.index == 'TWN', 'Population growth (annual %)'] = 0.
finaldf.loc[finaldf.index == 'TWN', 'Urban population growth (annual %)'
finaldf.loc[finaldf.index == 'TWN', 'Life expectancy at birth, female (ye
finaldf.loc[finaldf.index == 'TWN', 'Life expectancy at birth, male (year
finaldf.loc[finaldf.index == 'TWN', 'GDP per capita (constant 2010 US$)'

#Eritrea
finaldf.loc[finaldf.index == 'ERI', 'Population, total'] = 3214000
finaldf.loc[finaldf.index == 'ERI', 'Population growth (annual %)'] = 1.
finaldf.loc[finaldf.index == 'ERI', 'Urban population growth (annual %)'

#Kosovo
finaldf.loc[finaldf.index == 'XKX',
            'Urban population growth (annual %)'] = finaldf['Urban popula

#Somalia
finaldf.loc[finaldf.index == 'SOM', 'GDP per capita (constant 2010 US$)'
```

In [298]:

```
#Varieties of Democracy Project
vdp_mode = finaldf['Varieties of Democracy Project'].mode()[0]
finaldf['Varieties of Democracy Project'].fillna(vdp_mode, inplace = Tru
```

In [299]:
```
#Unemployment Data -- filled in from online data estimates
#Unemployment total
finaldf.loc[finaldf.index == 'AND', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'DMA', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'FSM', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'GRD', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'KIR', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'LIE', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'SMR', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'SYC', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'TWN', 'Unemployment, total (% of total labo
finaldf.loc[finaldf.index == 'XKX', 'Unemployment, total (% of total labo

#Female unemployment -- drawn mostly from World Bank National Unemployme
finaldf.loc[finaldf.index == 'AND', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'DMA', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'FSM', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'GRD', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'KIR', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'LIE', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'SMR', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'SYC', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'TWN', 'Unemployment, female (% of female la
finaldf.loc[finaldf.index == 'XKX', 'Unemployment, female (% of female la

#Male Unemployment -- drawn from World Bank National Unemployment estima
finaldf.loc[finaldf.index == 'AND', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'DMA', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'FSM', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'GRD', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'KIR', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'LIE', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'SMR', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'SYC', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'TWN', 'Unemployment, male (% of male labor
finaldf.loc[finaldf.index == 'XKX', 'Unemployment, male (% of male labor
```

In [300]:
```
#Global Insight Country Risk Ratings
gicrr_median = finaldf['Global Insight Country Risk Ratings'].median()
finaldf['Global Insight Country Risk Ratings'].fillna(gicrr_median, inpla
```

In [301]:
```
#Lifetime Risk of Maternal Death (%)
lrmd_mean = finaldf['Lifetime risk of maternal death (%)'].mean()
finaldf['Lifetime risk of maternal death (%)'].fillna(lrmd_mean, inplace
```

In [302]:

```
#Foreign Direct Investment Net Inflows (% of GDP)
fdii_gdp = {}

for group in list(finaldf['Income Group'].unique()):
    fdii_gdp[group] = np.mean(finaldf.loc[finaldf['Income Group'] == grou
                                          'Foreign direct investment, ne
#Find the countries with null values
missing_fdii_gdp = finaldf.loc[finaldf['Foreign direct investment, net in

for country in missing_fdii_gdp:
    fdii_gdp_key = finaldf.loc[finaldf.index == country, 'Income Group']
    finaldf.loc[finaldf.index == country,
                'Foreign direct investment, net inflows (% of GDP)'] = fo
```

In [303]:

```
#Foreign Direct Investment Net Outflows (% of GDP)
fdio_gdp = {}

for group in list(finaldf['Income Group'].unique()):
    fdio_gdp[group] = np.mean(finaldf.loc[finaldf['Income Group'] == grou
                                          'Foreign direct investment, ne
#Find the countries with null values
missing_fdio_gdp = finaldf.loc[finaldf['Foreign direct investment, net ou

for country in missing_fdio_gdp:
    fdio_gdp_key = finaldf.loc[finaldf.index == country, 'Income Group']
    finaldf.loc[finaldf.index == country,
                'Foreign direct investment, net outflows (% of GDP)'] = 
```

In [304]:

```
#Foreign Direct Investment Net Outflows (BoP)
fdio_bop = {}

for group in list(finaldf['Income Group'].unique()):
    fdio_bop[group] = np.mean(finaldf.loc[finaldf['Income Group'] == grou
                                          'Foreign direct investment, ne
#Find the countries with null values
missing_fdio_bop = finaldf.loc[finaldf['Foreign direct investment, net ou
                               .isna() == True].index

for country in missing_fdio_bop:
    fdio_bop_key = finaldf.loc[finaldf.index == country, 'Income Group']
    finaldf.loc[finaldf.index == country,
                'Foreign direct investment, net outflows (BoP, current US
```

In [305]:

```
#Foreign Direct Investment Net Inflows (BoP)
fdii_bop = {}

for group in list(finaldf['Income Group'].unique()):
    fdii_bop[group] = np.mean(finaldf.loc[finaldf['Income Group'] == grou
                                         'Foreign direct investment, ne
#Find the countries with null values
missing_fdii_bop = finaldf.loc[finaldf['Foreign direct investment, net in
                               .isna() == True].index

for country in missing_fdii_bop:
    fdii_bop_key = finaldf.loc[finaldf.index == country, 'Income Group']
    finaldf.loc[finaldf.index == country,
                'Foreign direct investment, net inflows (BoP, current US$
```

In [306]:

```
#GDP (Constant 2010 US$)
missing_gdp_constant = finaldf.loc[finaldf['GDP (constant 2010 US$)'].isn

for country in missing_gdp_constant:
    gdp_substitute = finaldf['GDP (million of US dollars)'][country] * 10
    finaldf.loc[finaldf.index == country, 'GDP (constant 2010 US$)'] = gd
```

In [307]:

```
finaldf.loc[missing_gdp_constant]
```

Out[307]:

	Country Name	Credit Rating	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	CI Upper	CPI 2019
ERI	Eritrea	Extremely speculative	1.503447e+10	48.8526	0.0	29.738	13.49	28.51	23.0
SOM	Somalia	In default with little prospect for recovery	1.503447e+10	95.2054	1945.0	41.585	8.24	15.76	9.0
SSD	South Sudan	In default with little prospect for recovery	1.503447e+10	56.8264	110.0	34.653	10.18	13.82	12.0
VEN	Venezuela	In default	4.164259e+11	84.6214	0.0	17.566	13.50	16.50	16.0

In [308]:

```
#Verify the status of null values in the DataFrame
finaldf.isna().sum()
```

Out[308]:

```
Country Name                                                            0
Credit Rating                                                           0
Adjusted net national income (current US$)                              0
Adolescent fertility rate (births per 1,000 women ages 15-19)           0
Battle-related deaths (number of people)                                0
Birth rate, crude (per 1,000 people)                                    0
CI Lower                                                                0
CI Upper                                                                0
CPI 2019                                                                0
CPI 2020                                                                0
CPI rank 2019                                                           0
CPI rank 2020                                                           0
Change in rank 2019-2020                                                0
Change in scores 2019-2020                                              0
Compulsory education, duration (years)                                  0
Consumer price index (2010 = 100)                                       0
Corporate Tax Rate                                                      0
Death rate, crude (per 1,000 people)                                    0
Ease of doing business index (1=most business-friendly regulations)     0
Exports of goods and services (% of GDP)                                0
Fertility rate, total (births per woman)                                0
Foreign direct investment, net inflows (% of GDP)                       0
Foreign direct investment, net inflows (BoP, current US$)               0
Foreign direct investment, net outflows (% of GDP)                      0
Foreign direct investment, net outflows (BoP, current US$)              0
GDP (constant 2010 US$)                                                 0
GDP (million of US dollars)                                             0
GDP per capita (constant 2010 US$)                                      0
Global Insight Country Risk Ratings                                     0
Income Group                                                            0
Life expectancy at birth, female (years)                                0
Life expectancy at birth, male (years)                                  0
Lifetime risk of maternal death (%)                                     0
Number of deaths ages 10-14 years                                       0
Number of deaths ages 15-19 years                                       0
Number of deaths ages 20-24 years                                       0
Number of deaths ages 5-9 years                                         0
Population growth (annual %)                                            0
Population, total                                                       0
Region                                                                  0
Surface area (sq. km)                                                   0
Unemployment, female (% of female labor force) (modeled ILO estimate)   0
Unemployment, male (% of male labor force) (modeled ILO estimate)       0
Unemployment, total (% of total labor force) (modeled ILO estimate)     0
Urban population growth (annual %)                                      0
Varieties of Democracy Project                                          0
dtype: int64
```

Transforming Data Types

In [309]:

```
finaldf.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 188 entries, AFG to ZWE
Data columns (total 46 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Country Name
188 non-null    object
 1   Credit Rating
188 non-null    object
 2   Adjusted net national income (current US$)
188 non-null    float64
 3   Adolescent fertility rate (births per 1,000 women ages 15-19)
188 non-null    float64
 4   Battle-related deaths (number of people)
188 non-null    float64
 5   Birth rate, crude (per 1,000 people)
188 non-null    float64
 6   CI Lower
188 non-null    float64
 7   CI Upper
188 non-null    float64
 8   CPI 2019
188 non-null    float64
 9   CPI 2020
188 non-null    float64
 10  CPI rank 2019
188 non-null    float64
 11  CPI rank 2020
188 non-null    float64
 12  Change in rank 2019-2020
188 non-null    float64
 13  Change in scores 2019-2020
188 non-null    float64
 14  Compulsory education, duration (years)
188 non-null    float64
 15  Consumer price index (2010 = 100)
188 non-null    float64
 16  Corporate Tax Rate
188 non-null    float64
 17  Death rate, crude (per 1,000 people)
188 non-null    float64
 18  Ease of doing business index (1=most business-friendly regulation
s)    188 non-null    float64
 19  Exports of goods and services (% of GDP)
188 non-null    float64
 20  Fertility rate, total (births per woman)
188 non-null    float64
 21  Foreign direct investment, net inflows (% of GDP)
188 non-null    float64
 22  Foreign direct investment, net inflows (BoP, current US$)
188 non-null    float64
```

```
 23  Foreign direct investment, net outflows (% of GDP)
188 non-null    float64
 24  Foreign direct investment, net outflows (BoP, current US$)
188 non-null    float64
 25  GDP (constant 2010 US$)
188 non-null    float64
 26  GDP (million of US dollars)
188 non-null    float64
 27  GDP per capita (constant 2010 US$)
188 non-null    float64
 28  Global Insight Country Risk Ratings
188 non-null    float64
 29  Income Group
188 non-null    object
 30  Life expectancy at birth, female (years)
188 non-null    float64
 31  Life expectancy at birth, male (years)
188 non-null    float64
 32  Lifetime risk of maternal death (%)
188 non-null    float64
 33  Number of deaths ages 10-14 years
188 non-null    float64
 34  Number of deaths ages 15-19 years
188 non-null    float64
 35  Number of deaths ages 20-24 years
188 non-null    float64
 36  Number of deaths ages 5-9 years
188 non-null    float64
 37  Population growth (annual %)
188 non-null    float64
 38  Population, total
188 non-null    float64
 39  Region
188 non-null    object
 40  Surface area (sq. km)
188 non-null    float64
 41  Unemployment, female (% of female labor force) (modeled ILO estim
ate)  188 non-null    float64
 42  Unemployment, male (% of male labor force) (modeled ILO estimate)
188 non-null    float64
 43  Unemployment, total (% of total labor force) (modeled ILO estimat
e)    188 non-null    float64
 44  Urban population growth (annual %)
188 non-null    float64
 45  Varieties of Democracy Project
188 non-null    float64
dtypes: float64(42), object(4)
memory usage: 74.0+ KB
```

In [310]:

```
#Export final DataFrame
finaldf.to_csv('Credit_Rating_Analysis_DF.csv')
```

III) Exploratory Data Analysis and Visualization

Visualization

Define Function for Visualization Purposes

In [311]:

```
#Define function to create sub datafames for visualizations
def create_subdf(seriesName, norm = True):
    """This functions creates a sub-dataframe grouping a Series by Credit
    for visualization purposes"""

    ordered_ratings = ['Prime','High grade', 'Upper medium grade', 'Lower
                       'Non-investment grade speculative', 'Highly specula
                       'Extremely speculative', 'In default with little pr

    subdf = finaldf.groupby('Credit Rating')[seriesName].value_counts(nor

    #Find missing ratings
    ref_dict = {}
    for index in ordered_ratings:
        if index not in subdf:
            ref_dict[index] = 0

    #Fill in missing values in subdf
    subdf.fillna(0, inplace = True)

    #Order by category
    subdf = subdf.loc[ordered_ratings]

    return subdf
```

In [312]:

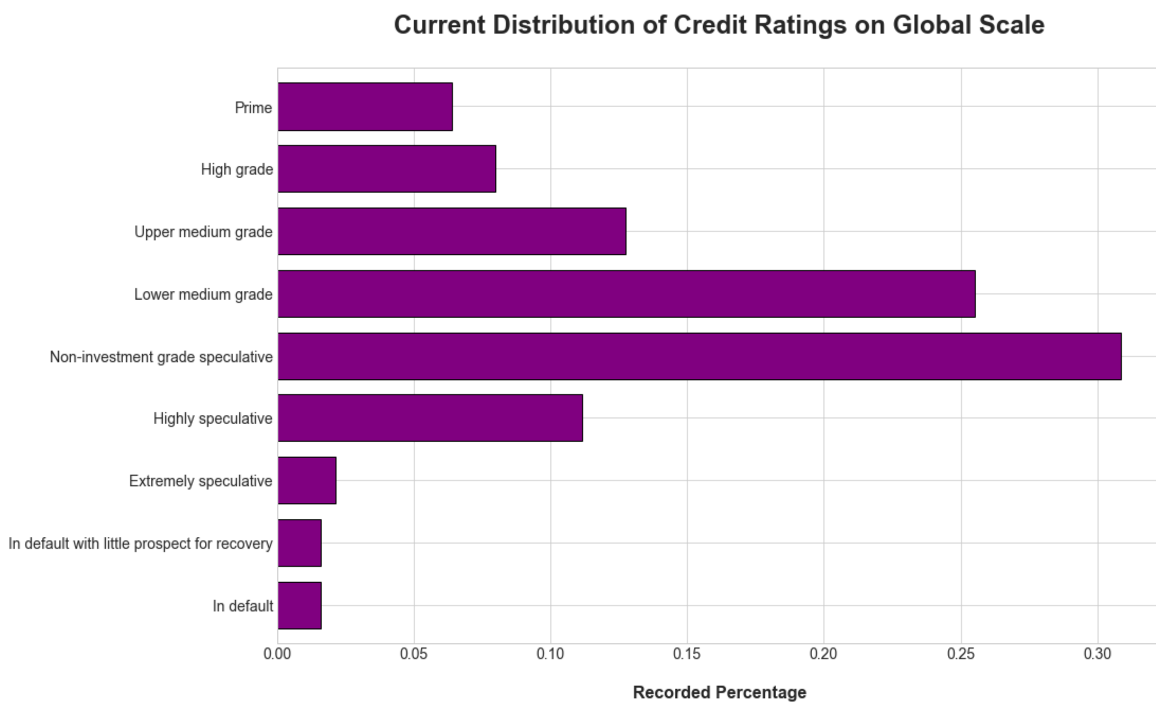
```
#Order the Credit Rating Categories
tempdf = finaldf['Credit Rating'].value_counts(normalize = True) #Create

#Ordered ratings
ordered_ratings = ['Prime','High grade', 'Upper medium grade', 'Lower med
                      'Non-investment grade speculative', 'Highly specula
                      'Extremely speculative', 'In default with little pr

#Add 0 values for any rating class that may be missing
ref_dict = {}
for index in ordered_ratings:
    if index not in tempdf.index:
        ref_dict[index] = 0.0

series = pd.Series(ref_dict, dtype = 'float') #Transform ref_dict to a Se
tempdf = tempdf.append(series) #Append Series to tempdf for any missing c
tempdf = tempdf[ordered_ratings] #Re-order the categories from Prime to I
tempdf #Preview
```

Out[312]:

```
Prime                                           0.063830
High grade                                      0.079787
Upper medium grade                              0.127660
Lower medium grade                              0.255319
Non-investment grade speculative                0.308511
Highly speculative                              0.111702
Extremely speculative                           0.021277
In default with little prospect for recovery    0.015957
In default                                      0.015957
dtype: float64
```

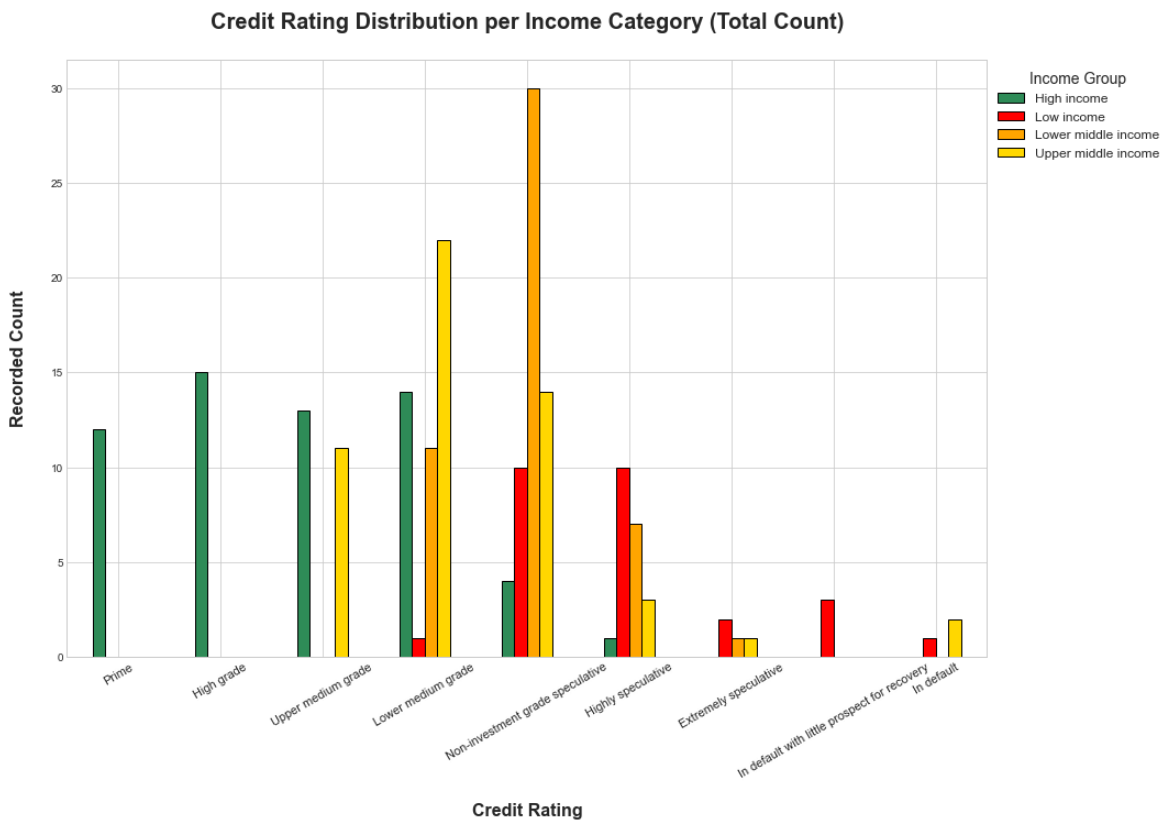
In [313]:

```
#Plot the distribution by class
ax = tempdf.plot(kind = 'barh', figsize = (15, 10), color = ['purple'],
                                                    edgecolor = 'black', width =

#Format the axis
plt.yticks(fontsize = 14)
plt.xticks(fontsize = 14)
ax.invert_yaxis()

#Format the plot
plt.title('\nCurrent Distribution of Credit Ratings on Global Scale\n',
plt.xlabel('\nRecorded Percentage\n', fontweight = 'bold', fontsize = 16
plt.show();
```



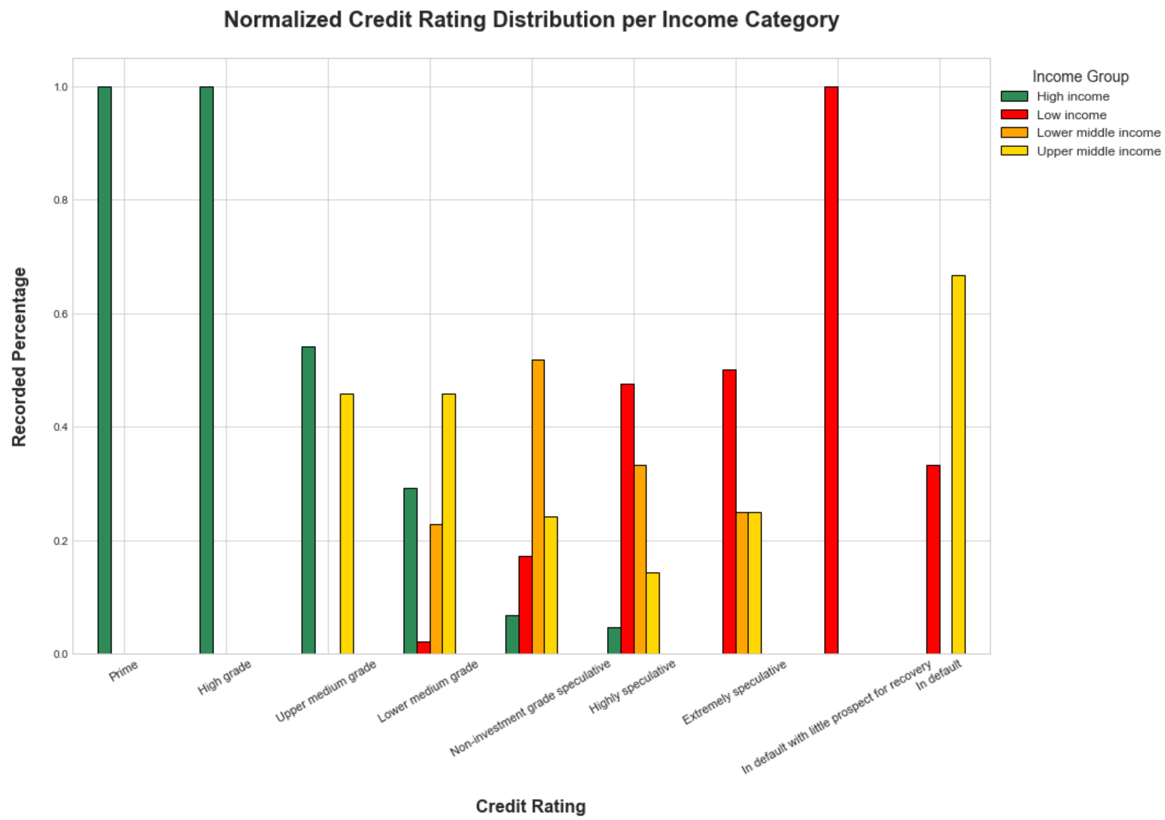
In [343]:

```
#Use function to create sub-dataframe
income_groups_sub = create_subdf('Income Group', norm = False)

#Plot
income_groups_sub.plot(kind = 'bar', figsize = (15, 10), color = ['seagr
                      edgecolor = 'black')


#Format Plot
plt.xticks(rotation = 30, fontsize = 11)
plt.xlabel('\nCredit Rating', fontweight = 'bold', fontsize = 16)
plt.ylabel('Recorded Count\n', fontweight = 'bold', fontsize = 16)
plt.legend(loc = 'upper right', bbox_to_anchor = (1.2, 1), title = 'Inco
          fontsize = 12)
plt.title('Credit Rating Distribution per Income Category (Total Count)\


plt.show();
```



In [339]:

```
#Use function to create sub-dataframe
income_groups_sub = create_subdf('Income Group')

#Plot
income_groups_sub.plot(kind = 'bar', figsize = (15, 10), color = ['seagr
                        edgecolor = 'black')


#Format Plot
plt.xticks(rotation = 30, fontsize = 11)
plt.xlabel('\nCredit Rating', fontweight = 'bold', fontsize = 16)
plt.ylabel('Recorded Percentage\n', fontweight = 'bold', fontsize = 16)
plt.legend(loc = 'upper right', bbox_to_anchor = (1.2, 1), title = 'Incor
           fontsize = 12)
plt.title('Normalized Credit Rating Distribution per Income Category\n',
plt.show();
```



In [316]:

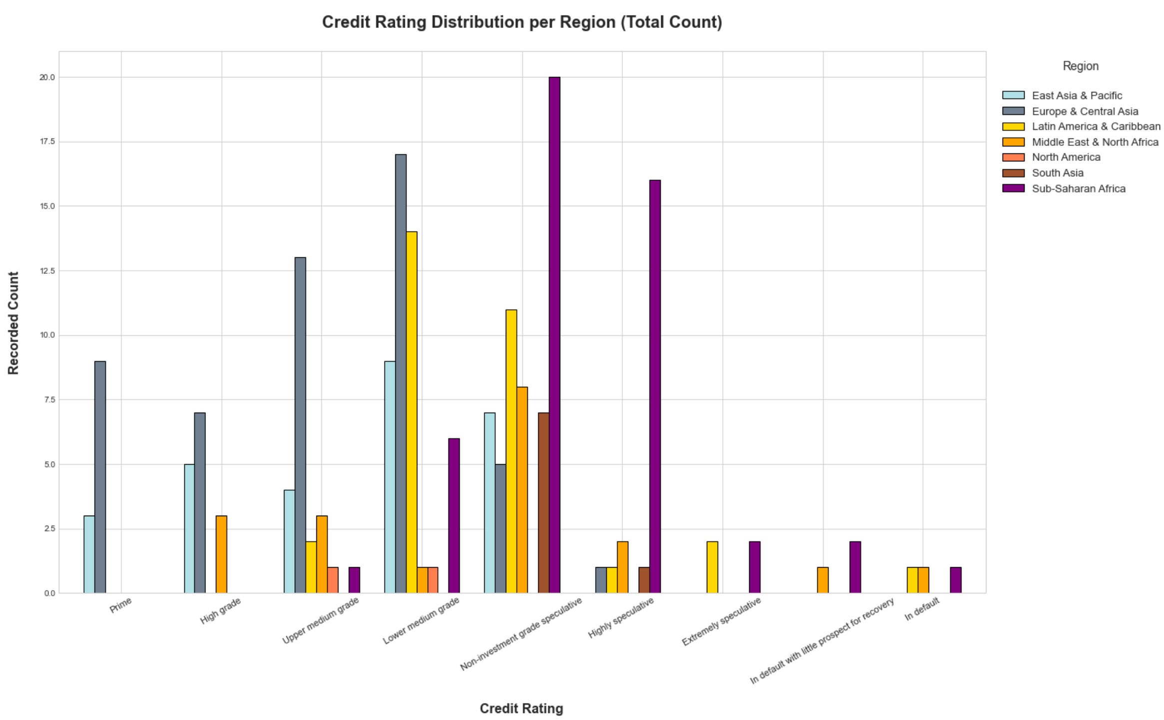
```
#Zooming in on the last group on the previous chart
finaldf.loc[(finaldf['Income Group'] == 'Upper middle income') & (finald
```

Out[316]:

	Country Name	Credit Rating	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	CI Upper	CPI 2019	C 20
LBN	Lebanon	In default	4.081096e+10	13.9476	0.0	17.377	23.11	26.89	28.0	2
VEN	Venezuela	In default	4.164259e+11	84.6214	0.0	17.566	13.50	16.50	16.0	1

In [433]:

```
#Use function to create sub-dataframe
region_sub = create_subdf('Region', norm = False)

#Plot
region_sub.plot(kind = 'bar', figsize = (20, 12), color = ['powderblue',
                                                            'sienna', 'pu



#Format Plot
plt.xticks(rotation = 30, fontsize = 11)
plt.xlabel('\nCredit Rating', fontweight = 'bold', fontsize = 16)
plt.ylabel('Recorded Count\n', fontweight = 'bold', fontsize = 16)
plt.legend(loc = 'upper right', bbox_to_anchor = (1.2, 1), title = 'Regi
          fontsize = 13)
plt.title('Credit Rating Distribution per Region (Total Count)\n', fonts


plt.show();
```



In [327]:

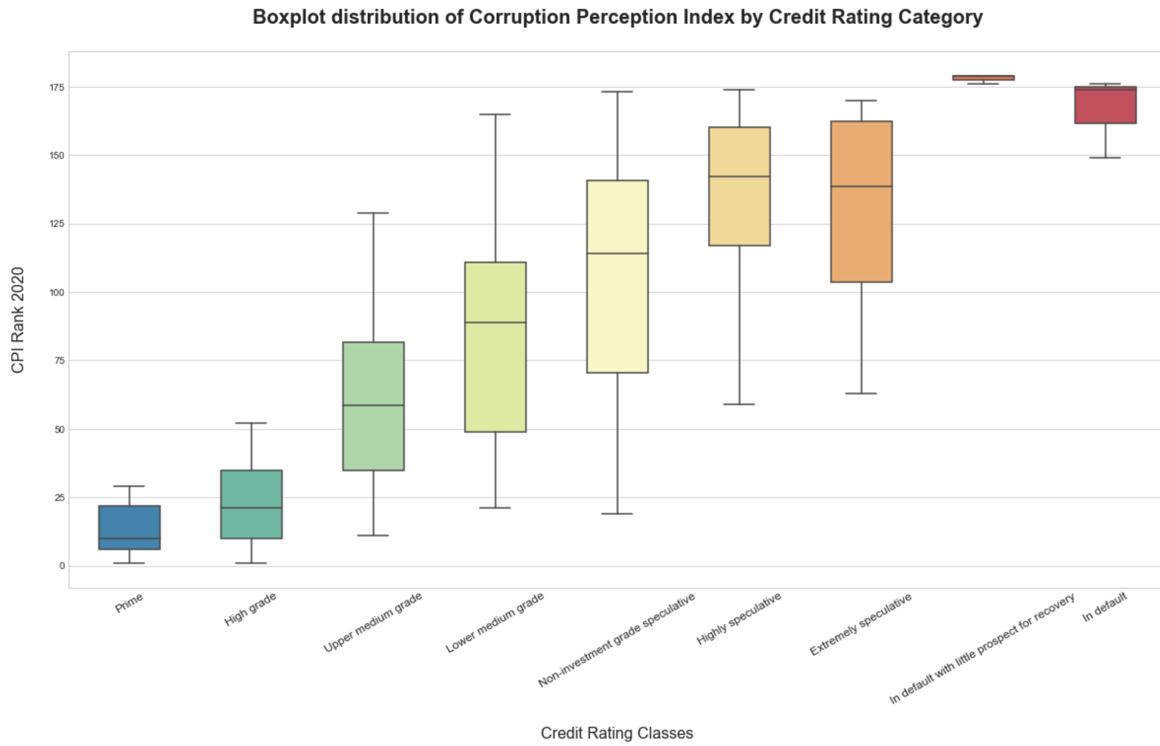
```
finaldf.head()
```

Out[327]:

	Country Name	Credit Rating	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	CI Upp
AFG	Afghanistan	Non-investment grade speculative	1.864930e+10	61.3250	29940.0	31.802	15.000000	23.0000
AGO	Angola	Highly speculative	5.411314e+10	145.3900	25.0	40.232	23.700000	30.3000
ALB	Albania	Lower medium grade	1.232864e+10	19.5028	0.0	11.620	34.500000	37.5000
AND	Andorra	Lower medium grade	8.617799e+11	39.0078	0.0	7.000	61.225273	68.6292
ARE	United Arab Emirates	High grade	3.840381e+11	5.2276	0.0	10.223	65.710000	76.2900

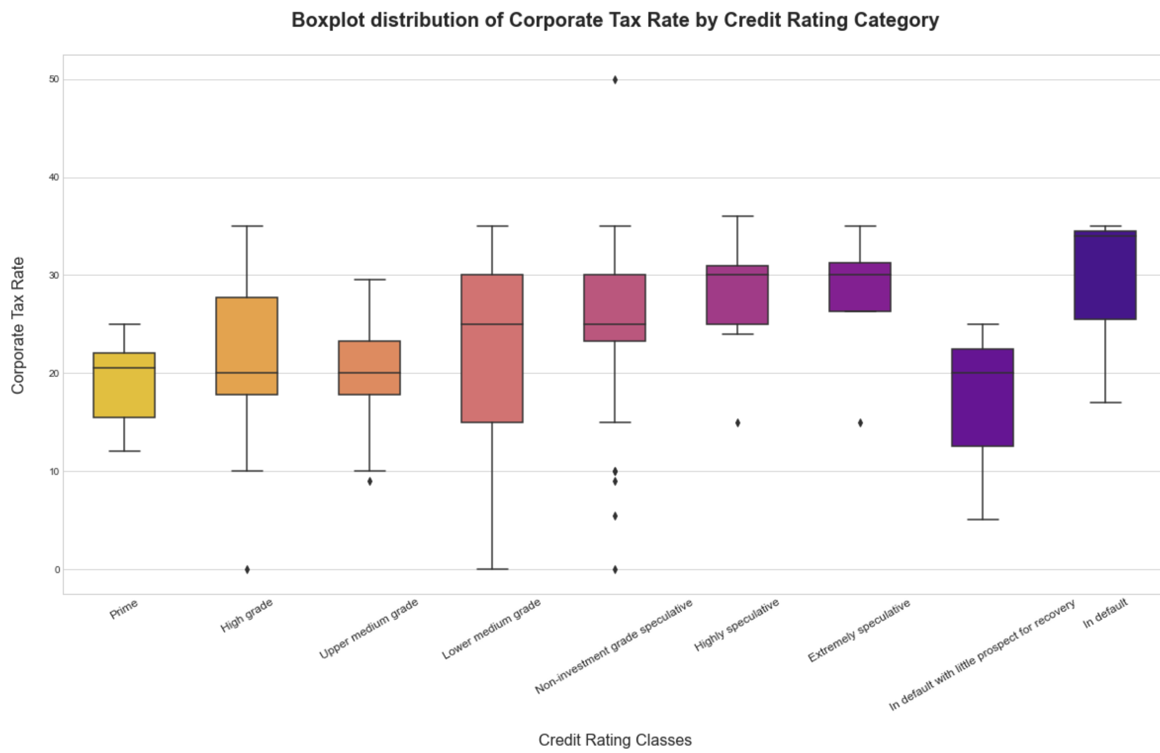
In [319]:

```
#Plot CPI against Credit Rating
plt.figure(figsize = (20, 10))
sns.boxplot(x = 'Credit Rating', y = 'CPI rank 2020', data = finaldf, or
            width = .5, palette = 'Spectral_r')

#Format Plot
plt.xticks(rotation = 30, fontsize = 12)
plt.xlabel('\nCredit Rating Classes', fontsize = 16)
plt.ylabel('CPI Rank 2020\n', fontsize = 16)
plt.title('Boxplot distribution of Corruption Perception Index by Credit
         fontweight = 'bold')
plt.show();
```



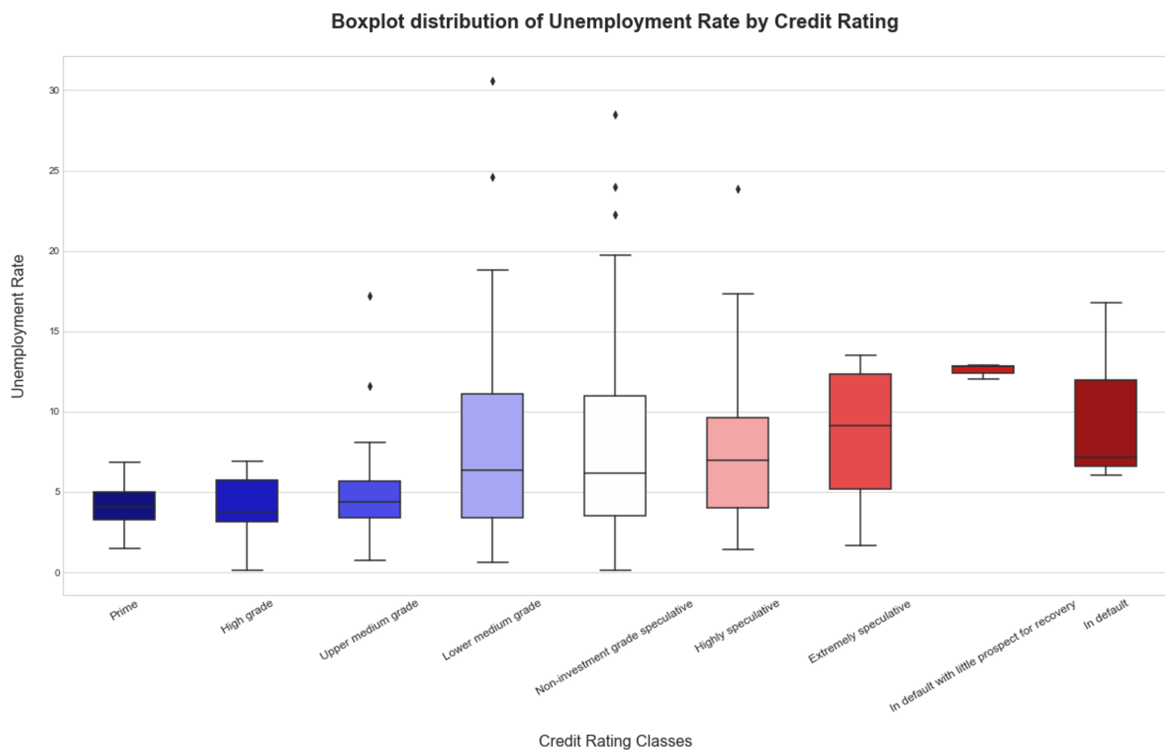
In [366]:

```
#Plot CPI against Credit Rating
plt.figure(figsize = (20, 10))
sns.boxplot(x = 'Credit Rating', y = 'Corporate Tax Rate', data = finald
            palette = 'plasma_r', width = .5)

#Format Plot
plt.xticks(rotation = 30, fontsize = 12)
plt.xlabel('\nCredit Rating Classes', fontsize = 16)
plt.ylabel('Corporate Tax Rate\n', fontsize = 16)
plt.title('Boxplot distribution of Corporate Tax Rate by Credit Rating Ca
         fontweight = 'bold')
plt.show();
```



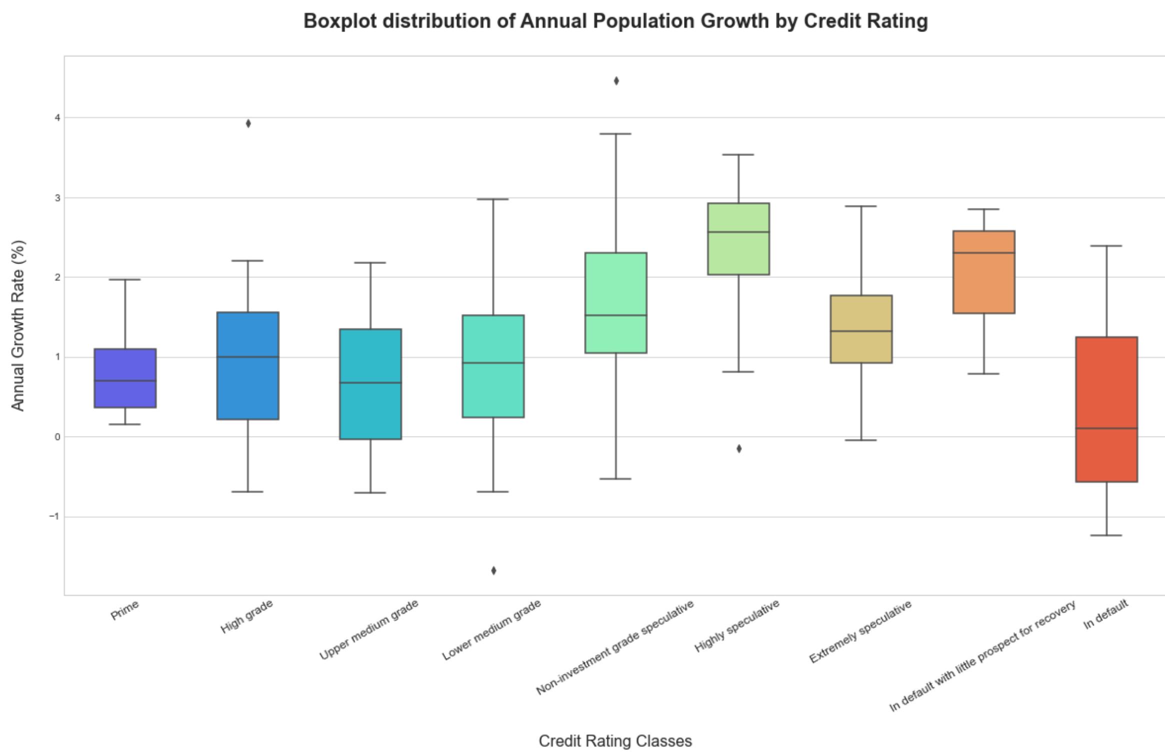
In [367]:

```
#Plot Unemployment against Credit Rating
plt.figure(figsize = (20, 10))
sns.boxplot(x = 'Credit Rating', y = 'Unemployment, total (% of total la
            data = finaldf, order = ordered_ratings, palette = 'seismic'

#Format Plot
plt.xticks(rotation = 30, fontsize = 12)
plt.xlabel('\nCredit Rating Classes', fontsize = 16)
plt.ylabel('Unemployment Rate\n', fontsize = 16)
plt.title('Boxplot distribution of Unemployment Rate by Credit Rating\n'
         fontweight = 'bold')
plt.show();
```



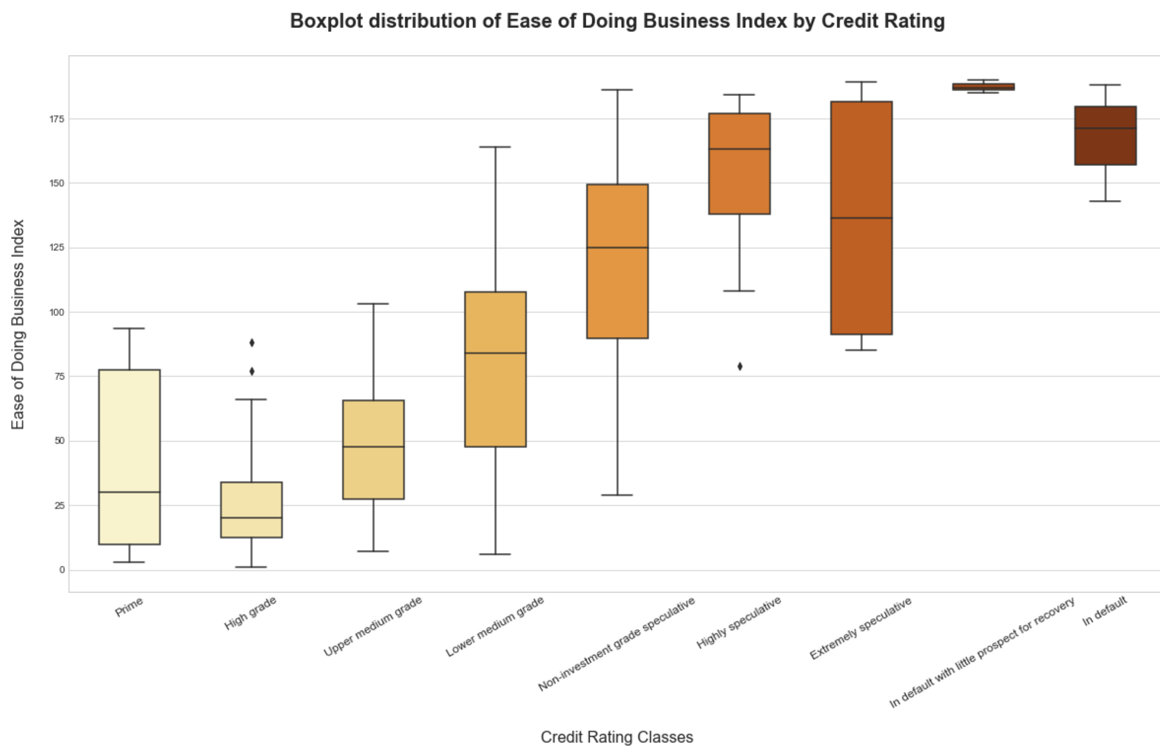
In [368]:

```
#Plot CPI against Credit Rating
plt.figure(figsize = (20, 10))
sns.boxplot(x = 'Credit Rating', y = 'Population growth (annual %)',
            data = finaldf, order = ordered_ratings, palette = 'rainbow',
            
#Format Plot
plt.xticks(rotation = 30, fontsize = 12)
plt.xlabel('\nCredit Rating Classes', fontsize = 16)
plt.ylabel('Annual Growth Rate (%)\n', fontsize = 16)
plt.title('Boxplot distribution of Annual Population Growth by Credit Ra
         fontweight = 'bold')
plt.show();
```



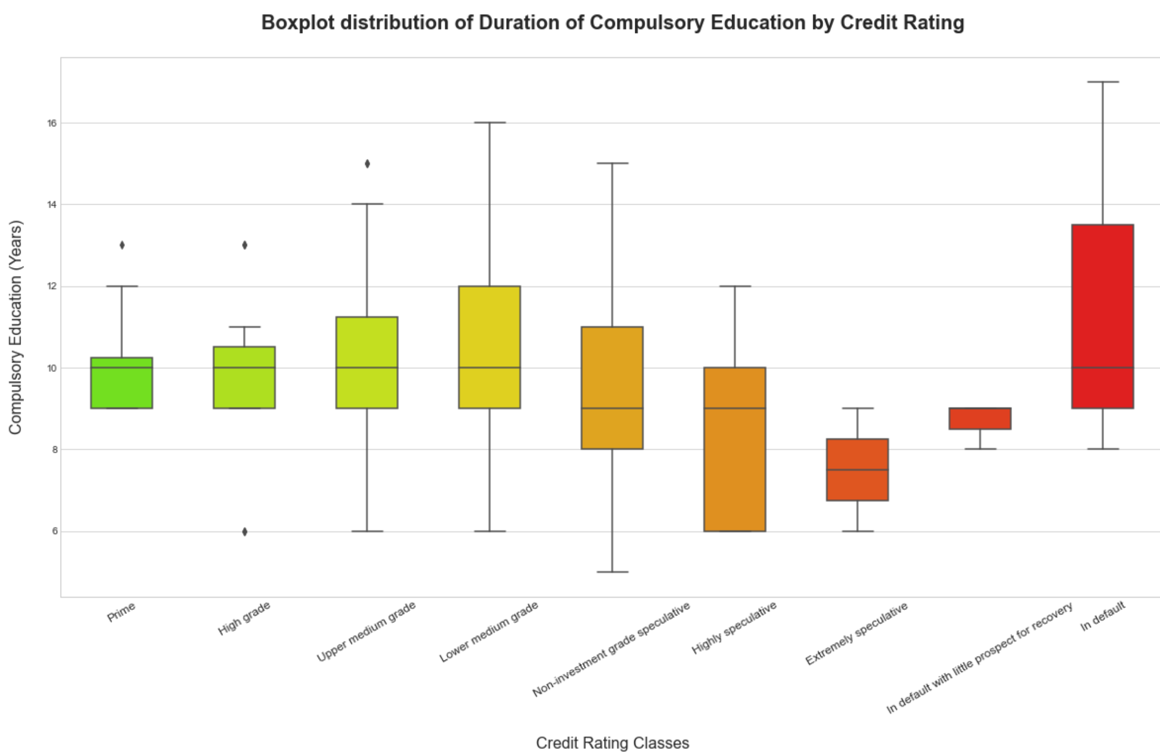
In [372]:

```
#Plot CPI against Credit Rating
plt.figure(figsize = (20, 10))
sns.boxplot(x = 'Credit Rating', y = 'Ease of doing business index (1=mos
            data = finaldf, order = ordered_ratings, palette = 'YlOrBr',

#Format Plot
plt.xticks(rotation = 30, fontsize = 12)
plt.xlabel('\nCredit Rating Classes', fontsize = 16)
plt.ylabel('Ease of Doing Business Index\n', fontsize = 16)
plt.title('Boxplot distribution of Ease of Doing Business Index by Credi
         fontweight = 'bold')
plt.show();
```



In [392]:

```
#Plot CPI against Credit Rating
plt.figure(figsize = (20, 10))
sns.boxplot(x = 'Credit Rating', y = 'Compulsory education, duration (yea
            data = finaldf, order = ordered_ratings, palette = 'prism_r'

#Format Plot
plt.xticks(rotation = 30, fontsize = 12)
plt.xlabel('\nCredit Rating Classes', fontsize = 16)
plt.ylabel('Compulsory Education (Years)\n', fontsize = 16)
plt.title('Boxplot distribution of Duration of Compulsory Education by Cr
         fontweight = 'bold')
plt.show();
```



Data Modeling Using Support Vector Machines

In [375]:
```
#Import Cleaned Dataset on Country Credit Ratings
df = pd.read_csv('Credit_Rating_Analysis_DF.csv')
df = df.rename(columns = {'Unnamed: 0' : 'Country Code'})
df.set_index('Country Code', inplace = True)
df.head()
```

Out[375]:

	Country Name	Credit Rating	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	CI U
Country Code								
AFG	Afghanistan	Non-investment grade speculative	1.864930e+10	61.3250	29940.0	31.802	15.000000	23.0
AGO	Angola	Highly speculative	5.411314e+10	145.3900	25.0	40.232	23.700000	30.3
ALB	Albania	Lower medium grade	1.232864e+10	19.5028	0.0	11.620	34.500000	37.5
AND	Andorra	Lower medium grade	8.617799e+11	39.0078	0.0	7.000	61.225273	68.6
ARE	United Arab Emirates	High grade	3.840381e+11	5.2276	0.0	10.223	65.710000	76.2

In [376]:

```
#Verify Dataset information
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 188 entries, AFG to ZWE
Data columns (total 46 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Country Name
188 non-null    object
 1   Credit Rating
188 non-null    object
 2   Adjusted net national income (current US$)
188 non-null    float64
 3   Adolescent fertility rate (births per 1,000 women ages 15-19)
188 non-null    float64
 4   Battle-related deaths (number of people)
188 non-null    float64
 5   Birth rate, crude (per 1,000 people)
188 non-null    float64
 6   CI Lower
188 non-null    float64
 7   CI Upper
188 non-null    float64
 8   CPI 2019
188 non-null    float64
 9   CPI 2020
188 non-null    float64
 10  CPI rank 2019
188 non-null    float64
 11  CPI rank 2020
188 non-null    float64
 12  Change in rank 2019-2020
188 non-null    float64
 13  Change in scores 2019-2020
188 non-null    float64
 14  Compulsory education, duration (years)
188 non-null    float64
 15  Consumer price index (2010 = 100)
188 non-null    float64
 16  Corporate Tax Rate
188 non-null    float64
 17  Death rate, crude (per 1,000 people)
188 non-null    float64
 18  Ease of doing business index (1=most business-friendly regulations)
188 non-null    float64
 19  Exports of goods and services (% of GDP)
188 non-null    float64
 20  Fertility rate, total (births per woman)
188 non-null    float64
 21  Foreign direct investment, net inflows (% of GDP)
188 non-null    float64
 22  Foreign direct investment, net inflows (BoP, current US$)
```

```
188 non-null    float64
 23  Foreign direct investment, net outflows (% of GDP)
188 non-null    float64
 24  Foreign direct investment, net outflows (BoP, current US$)
188 non-null    float64
 25  GDP (constant 2010 US$)
188 non-null    float64
 26  GDP (million of US dollars)
188 non-null    float64
 27  GDP per capita (constant 2010 US$)
188 non-null    float64
 28  Global Insight Country Risk Ratings
188 non-null    float64
 29  Income Group
188 non-null    object
 30  Life expectancy at birth, female (years)
188 non-null    float64
 31  Life expectancy at birth, male (years)
188 non-null    float64
 32  Lifetime risk of maternal death (%)
188 non-null    float64
 33  Number of deaths ages 10-14 years
188 non-null    float64
 34  Number of deaths ages 15-19 years
188 non-null    float64
 35  Number of deaths ages 20-24 years
188 non-null    float64
 36  Number of deaths ages 5-9 years
188 non-null    float64
 37  Population growth (annual %)
188 non-null    float64
 38  Population, total
188 non-null    float64
 39  Region
188 non-null    object
 40  Surface area (sq. km)
188 non-null    float64
 41  Unemployment, female (% of female labor force) (modeled ILO estimate)
188 non-null    float64
 42  Unemployment, male (% of male labor force) (modeled ILO estimate)
188 non-null    float64
 43  Unemployment, total (% of total labor force) (modeled ILO estimate)
188 non-null    float64
 44  Urban population growth (annual %)
188 non-null    float64
 45  Varieties of Democracy Project
188 non-null    float64
dtypes: float64(42), object(4)
memory usage: 69.0+ KB
```

In [377]:

```
#Define DataFrame for modeling and target variable y
X = df.drop(['Country Name', 'Credit Rating'], axis = 1)
y = df['Credit Rating']
```

In [378]:

```
#Define categorical variables
cat_feats = ['Income Group', 'Region']

#Create dummy variable
dummy = pd.get_dummies(df[cat_feats], drop_first = True)
dummy.shape
```

Out[378]: (188, 9)

In [379]:

```python
#Finalize X for modeling
X.drop(cat_feats, axis = 1, inplace = True)

X = pd.concat([X, dummy], axis = 1)
display(X.head())
display(X.info())
```

	Adjusted net national income (current US$)	Adolescent fertility rate (births per 1,000 women ages 15-19)	Battle-related deaths (number of people)	Birth rate, crude (per 1,000 people)	CI Lower	CI Upper	CPI 2019	CPI 2
Country Code								
AFG	1.864930e+10	61.3250	29940.0	31.802	15.000000	23.000000	16.000000	19.000
AGO	5.411314e+10	145.3900	25.0	40.232	23.700000	30.300000	26.000000	27.000
ALB	1.232864e+10	19.5028	0.0	11.620	34.500000	37.500000	35.000000	36.000
AND	8.617799e+11	39.0078	0.0	7.000	61.225273	68.629273	64.927273	64.927
ARE	3.840381e+11	5.2276	0.0	10.223	65.710000	76.290000	71.000000	71.000

```
<class 'pandas.core.frame.DataFrame'>
Index: 188 entries, AFG to ZWE
Data columns (total 51 columns):
 #   Column
Non-Null Count  Dtype
---  ------
--------------  -----
 0   Adjusted net national income (current US$)
188 non-null    float64
 1   Adolescent fertility rate (births per 1,000 women ages 15-19)
188 non-null    float64
 2   Battle-related deaths (number of people)
188 non-null    float64
 3   Birth rate, crude (per 1,000 people)
188 non-null    float64
 4   CI Lower
188 non-null    float64
 5   CI Upper
188 non-null    float64
 6   CPI 2019
188 non-null    float64
 7   CPI 2020
188 non-null    float64
 8   CPI rank 2019
188 non-null    float64
 9   CPI rank 2020
188 non-null    float64
```

```
 10  Change in rank 2019-2020
188 non-null    float64
 11  Change in scores 2019-2020
188 non-null    float64
 12  Compulsory education, duration (years)
188 non-null    float64
 13  Consumer price index (2010 = 100)
188 non-null    float64
 14  Corporate Tax Rate
188 non-null    float64
 15  Death rate, crude (per 1,000 people)
188 non-null    float64
 16  Ease of doing business index (1=most business-friendly regulation
s)    188 non-null    float64
 17  Exports of goods and services (% of GDP)
188 non-null    float64
 18  Fertility rate, total (births per woman)
188 non-null    float64
 19  Foreign direct investment, net inflows (% of GDP)
188 non-null    float64
 20  Foreign direct investment, net inflows (BoP, current US$)
188 non-null    float64
 21  Foreign direct investment, net outflows (% of GDP)
188 non-null    float64
 22  Foreign direct investment, net outflows (BoP, current US$)
188 non-null    float64
 23  GDP (constant 2010 US$)
188 non-null    float64
 24  GDP (million of US dollars)
188 non-null    float64
 25  GDP per capita (constant 2010 US$)
188 non-null    float64
 26  Global Insight Country Risk Ratings
188 non-null    float64
 27  Life expectancy at birth, female (years)
188 non-null    float64
 28  Life expectancy at birth, male (years)
188 non-null    float64
 29  Lifetime risk of maternal death (%)
188 non-null    float64
 30  Number of deaths ages 10-14 years
188 non-null    float64
 31  Number of deaths ages 15-19 years
188 non-null    float64
 32  Number of deaths ages 20-24 years
188 non-null    float64
 33  Number of deaths ages 5-9 years
188 non-null    float64
 34  Population growth (annual %)
188 non-null    float64
 35  Population, total
188 non-null    float64
 36  Surface area (sq. km)
188 non-null    float64
 37  Unemployment, female (% of female labor force) (modeled ILO estim
ate)  188 non-null    float64
 38  Unemployment, male (% of male labor force) (modeled ILO estimate)
```

```
188 non-null    float64
 39  Unemployment, total (% of total labor force) (modeled ILO estimat
e)    188 non-null    float64
 40  Urban population growth (annual %)
188 non-null    float64
 41  Varieties of Democracy Project
188 non-null    float64
 42  Income Group_Low income
188 non-null    uint8
 43  Income Group_Lower middle income
188 non-null    uint8
 44  Income Group_Upper middle income
188 non-null    uint8
 45  Region_Europe & Central Asia
188 non-null    uint8
 46  Region_Latin America & Caribbean
188 non-null    uint8
 47  Region_Middle East & North Africa
188 non-null    uint8
 48  Region_North America
188 non-null    uint8
 49  Region_South Asia
188 non-null    uint8
 50  Region_Sub-Saharan Africa
188 non-null    uint8
dtypes: float64(42), uint8(9)
memory usage: 64.8+ KB

None
```

In [380]:

```
#Train, Test Split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .2
```

RBF Kernel

In [381]:

```
#Use GridSearch to determine best parameters
param_grid = {'C': [0.1, 1, 10, 100],
             'gamma': [1, 0.1, 0.001, 0.001, 0.0001],
             'kernel': ['rbf']}

#Instantial GridSearchCV
grid_search = GridSearchCV(SVC(), param_grid, refit = True, verbose = 3)

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

```
[CV] C=100, gamma=0.0001, kernel=rbf ................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.333, total=   0.0s
[CV] C=100, gamma=0.0001, kernel=rbf ................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.333, total=   0.0s
[CV] C=100, gamma=0.0001, kernel=rbf ................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.333, total=   0.0s
[CV] C=100, gamma=0.0001, kernel=rbf ................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.333, total=   0.0s
[CV] C=100, gamma=0.0001, kernel=rbf ................................
[CV] ..... C=100, gamma=0.0001, kernel=rbf, score=0.300, total=   0.0s


[Parallel(n_jobs=1)]: Done 100 out of 100 | elapsed:    1.6s finished
```

Out[381]:

```
GridSearchCV(estimator=SVC(),
             param_grid={'C': [0.1, 1, 10, 100],
                         'gamma': [1, 0.1, 0.001, 0.001, 0.0001],
                         'kernel': ['rbf']},
             verbose=3)
```

In [382]:

```
#Check best params
print(grid_search.best_params_)
```

```
{'C': 0.1, 'gamma': 1, 'kernel': 'rbf'}
```

In [422]:

```
#Instantiate and train model with the determined params
model = SVC(kernel = 'rbf', gamma = 1, C = .1)
model.fit(X_train, y_train)

#Predict train and test sets
train_pred = model.predict(X_train)
test_pred = model.predict(X_test)
```

In [423]:

```
accuracy_comp(y_train, train_pred, y_test, test_pred)
print('\n Classification Report: \n', classification_report(y_test, test_
```

```
Training Accuracy: 32.67%
Test Accuracy: 23.68%

 Classification Report: 
                                              precision    recall  f1-scor
e   support

                               High grade       0.00      0.00      0.00
4
                      Highly speculative       0.00      0.00      0.00
3
                               In default       0.00      0.00      0.00
2
In default with little prospect for recovery       0.00      0.00      0.00
1
                      Lower medium grade       0.00      0.00      0.00
9
             Non-investment grade speculative       0.24      1.00      0.38
9
                                    Prime       0.00      0.00      0.00
3
                      Upper medium grade       0.00      0.00      0.00
7

                                 accuracy                           0.24
38
                                macro avg       0.03      0.12      0.05
38
                             weighted avg       0.06      0.24      0.09
38


C:\Users\u-ana\Anaconda3\envs\learn-env\lib\site-packages\sklearn\metrics\_
classification.py:1221: UndefinedMetricWarning: Precision and F-score are i
ll-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

Polynomial Kernel

In [430]:

```
#Instantiate and train model with the determined params
model2 = SVC(kernel = 'poly', gamma = 1, C = 0.1, degree = 5)
model2.fit(X_train, y_train)

#Predict train and test sets
train_pred = model2.predict(X_train)
test_pred = model2.predict(X_test)
```

In [431]:

```
accuracy_comp(y_train, train_pred, y_test, test_pred)
print('\n Classification Report: \n', classification_report(y_test, test_
```

```
Training Accuracy: 11.33%
Test Accuracy: 18.42%

 Classification Report:
                                                precision    recall  f1-scor
e   support

                                   High grade       0.00      0.00      0.00
4
                          Highly speculative       0.00      0.00      0.00
3
                                   In default       0.00      0.00      0.00
2
In default with little prospect for recovery       0.00      0.00      0.00
1
                          Lower medium grade       0.00      0.00      0.00
9
              Non-investment grade speculative       0.00      0.00      0.00
9
                                        Prime       0.00      0.00      0.00
3
                          Upper medium grade       0.18      1.00      0.31
7

                                     accuracy                           0.18
38
                                    macro avg       0.02      0.12      0.04
38
                                 weighted avg       0.03      0.18      0.06
38


C:\Users\u-ana\Anaconda3\envs\learn-env\lib\site-packages\sklearn\metrics\_
classification.py:1221: UndefinedMetricWarning: Precision and F-score are i
ll-defined and being set to 0.0 in labels with no predicted samples. Use `z
ero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

In [ ]:

```

```