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Assessing countries' credit ratings using Machine learning

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Abstract
The goal of this research is to present the beneficial improvements that may be brought about in sovereign credit ratings if machine learning is applied to rate them. A rating is assigned after taking into account a wide range of factors affecting an economy's fundamentals. When credit ratings are done by humans, there is a bias in considering these elements, which leads to an underestimation of the country. A country's credit rating is crucial because it represents the risk that a foreign investor considers when purchasing a country's debt. Depending on these credit ratings can also have a negative impact on the flow of foreign portfolio investors. Thus, applying machine learning to analyze these criteria can aid in eliminating prejudice and disclosing a country's genuine credit rating.

Keywords - Credit rating, Machine learning, random forest, decision tree classifier

Introduction -

Sovereign risk ratings are one of the most significant indicators used to eliminate information asymmetry in the international financial market. They consolidate information on debt issuers' future creditworthiness, i.e., the risk borne by foreign investors when purchasing securities from a particular issuer. They are classified as a corporate and sovereign risk by credit rating agencies (CRAs). This second point is particularly significant because sovereign governments are among the major debt issuers. As a result, CRA ratings influence bond issuance and contracts in global financial markets.
When investors buy bonds from a sovereign government, they are taking a risk. The higher the risk, the less likely it is that the government will be able to make this transaction look good and attract international investors. Because of this, investors are given more money to make up for the risk they are taking. Furthermore, ratings are dependent on each country's credit scores, and as a result, they have a significant influence on the corporate ratings of corporations situated in their different sovereign territory. As a result, sovereign ratings represent a quantitative and qualitative examination of economic and political risks.
The main goal of credit rating prediction is to make models that can take information about how credit risk was evaluated in the past and use it to evaluate the credit risk of a country on a much larger scale.

Credit rating

In a nutshell, credit ratings are assessments of the creditworthiness of an obligor that are made in the future. These conclusions are drawn using criteria and rating scales that are regularly reviewed and modified. General ratings convey an assessment of a borrower's willingness and ability to meet their financial obligations in full and on time. The credit quality and likelihood of default of individual debt issues, such as corporate notes, corporate bonds, government bonds, or mortgage-backed securities, are subject to specific ratings. Numerous borrowers, including individuals, companies, sovereigns, and sub-sovereign entities, may receive these ratings.
In the context of credit ratings, some fundamental components are important. Ratings cannot be categorised as accurate or inaccurate because they are completely subjective. While the credit risk

connected to the company being evaluated is at the centre of each credit rating from a rating agency, the elements included, the relative priority given, and the process can vary. Users of credit ratings are therefore advised to only use them as a part of their credit analysis and to refer to the definitions of specific ratings in order to understand the dimensions covered by them. Due to the fact that they do not reflect the profitability of an investment, these ratings should not be interpreted as "buy" or "sell" recommendations.

In general, the ratings ought to be based on an assessment of the obligor's financial standing that extends at least three years into the future, with an annual review. This does not imply that the ratings are a predetermined process, though. In actuality, a rating notice might be required if the macro- or microenvironment of the obligee were to unexpectedly change. In such cases, the debtor is put on rating watch, and the impact of the incident is assessed over time with the potential for a transition or continuation of the current rating. Examples of such events include mergers and acquisitions, a change in senior management, a modification of a particular piece of government legislation that could increase or decrease the associated business risk, and others. The evaluations are very changeable because they are affected by both endogenous and external influences. Any substantial change in the elements involved, such as economic trends, business cycle changes, or internal company changes, might result in a rating adjustment.

Credit ratings have the potential to be very effective and useful despite a number of difficulties. Due to their relative nature, ratings help to establish an ordinal ranking of comparable obligors, which may be very beneficial to lenders or investors. Ratings may benefit the economy that is receiving them. Frequently, direct funding sources are available to governments with ratings above a predetermined threshold. This lowers the price of raising money for them as well.

Credit ratings benefit society as a whole by reducing the costs associated with information access and facilitating it. By giving their users a comprehensive approach to credit risk assessment of the issues at hand, they empower informed decision-making authority such as investors, lenders, and others. This increases economic openness and addresses information asymmetry right away. Credit ratings can significantly reduce information asymmetry, even though it cannot be completely avoided.

About Machine learning model

Computers can be taught to read data, learn from it, and then predict or decide based on new data using a technique called machine learning. The machine is "trained" to learn how to perform the task using enormous amounts of data and algorithms, as opposed to manually coding a specific set of instructions to accomplish a certain activity. Statistical learning, a less well-known sister field, and machine learning share similarities. Both look for and learn from patterns and trends in large datasets in order to make predictions. Although machine learning has a long history of development, recent improvements in data storage and computing power have made it possible for it to be used in a wide variety of fields and applications, many of which are already commonplace. Credit risk modelling, which uses financial data to forecast default risk, was one of the earliest uses of machine learning.

Learning from data is the goal of both machine learning and conventional statistical learning techniques. Both methods look for underlying connections using a training dataset. Machine learning techniques can learn from data without the need for rules-based programming, in contrast to statistical learning techniques that frequently require explicit connections between variables in the form of mathematical equations. Because of their adaptability, machine learning systems can better fit data patterns. Due to their data mining capabilities, minimal reliance on assumptions, automations, and ability to get better over time, machine learning models have a high degree of precision.

Literature Review -

This study has been built upon different references collected from different reliable sources. Articles and previous research papers about the related topic have been taken as evidence and these are reliability factors of this research paper. Going through different resources, this study will move forward with a liberal point of view, as there are references that differ from each other. However, these literatures will be used to guide and support this research study.

Mellios and Paget-Blanc (2007) analysed the factors that contribute to the sovereign credit ratings assigned by Fitch Ratings, Moody's, and Standard & Poor. The study compiled information regarding the foreign currency ratings of 86 nations as of December 31, 2003, as well as the values of 49 economic and political indicators for each nation in 2002. A PCA analysis was used to identify the common factors that influence these ratings, and an ordered logistic model was employed to determine how the variables associated with these factors influence the ratings. They found that per capita income, government revenue, real exchange rate fluctuations, inflation rate, and default history have the greatest impact on sovereign ratings. In another study, Afonso et al. (2008)[2] used linear regression methods and limited dependent variable models to examine the determinants of sovereign debt ratings from the three main rating agencies for the period 1995–2005. The study found that changes in GDP per capita, GDP growth, government debt, and government balance have a short-run impact on a country’s credit rating, while government effectiveness, external debt, foreign reserves, and default history are important long-run determinants.

Haque et al. (1998) examined the relative importance of political and economic variables in the determination of a country’s standing in credit ratings provided by commercial rating agencies. They found that creditworthiness appears to be determined primarily by economic variables.

Cantor and Packer (1996) analysed the determinants and effects of sovereign credit ratings assigned by Moody's and Standard and Poor's. They concluded that although the agencies’ ratings have a predictable component, they appear to supply the market with knowledge on non-investment-grade sovereigns that goes beyond public data.

Bozic and Magazzino (2015) investigated the significance of macroeconomic variables in the evaluation of the sovereign ratings provided by Standard & Poor's, Fitch, and Moody's. The study revealed two primary streams: one that examines the determinants and behaviour of ratings, and another that studies the causation of ratings.

Luitel and Van (2019) examined how the credit rating agencies disadvantage emerging markets. They found that the rating agencies' methodologies disproportionately disadvantage emerging markets, leading to lower ratings and higher borrowing costs.

Tony Van Gestel et al. (2014), proposes a process model for developing an internal rating system for sovereign credit ratings. The model involves constructing and preprocessing a database of country risk variables, modeling using a combination of linear ordinal logistic regression, linear modeling, and support vector machines, and calibrating the internal rating system. The paper also proposes a scorecard for the readability of the ratings. The study uses Moody's ratings and World Bank data to develop the model, and the results suggest that the model performs well in predicting sovereign credit ratings.

Yen-Ting Hu et al. (2016), proposes a methodology for estimating transition matrices for sovereign credit ratings over periods larger than a decade. The paper combines sovereign default data with Standard and Poor's ratings in an ordered probit model and uses a quasi-Bayesian approach that incorporates both prior information and observed data. The paper selects liquidity variables, solvency variables, and macro-factors as independent variables and uses data-driven methodologies to select suitable weighting factors between the model estimate and the estimate based on transition data for all

Standard and Poor's rated obligors. The results suggest that the proposed model performs well and provides added information for a larger group of countries.

Bart H.L. Overes and Michel van der Wel (2018), uses machine learning techniques to model sovereign credit ratings. The study uses data on sovereign credit ratings for several countries and uses different models, including multilayer perceptron, classification and regression trees, support vector machines, Naïve Bayes, and an ordered logit model. The study converts the "rating class" dependent variable into numerical credit ratings and uses 10-fold cross-validation. The results suggest that the MLP model performs best, with an accuracy of 68%, and that regulatory quality and GDP per capita are the two most important independent variables for all countries.

Huang et al. (2004) applied support vector machines (SVM) and backpropagation neural networks to predict credit ratings for financial institutes in Taiwan and US commercial banks. The authors found that the models built for the two markets used similar lists of financial variables as inputs but found the relative importance of the variables was quite different across the two markets. SVM achieved accuracy comparable to that of backpropagation neural networks.

Overall, these papers demonstrate that financial modeling for sovereign credit ratings can be achieved using a range of methods, including process models, machine learning techniques, and quasi-Bayesian approaches. The models proposed in these papers show good predictive accuracy and highlight the importance of a range of economic and financial variables in assessing sovereign credit risk.

Research methodology -

Conceptual design (diagram) -

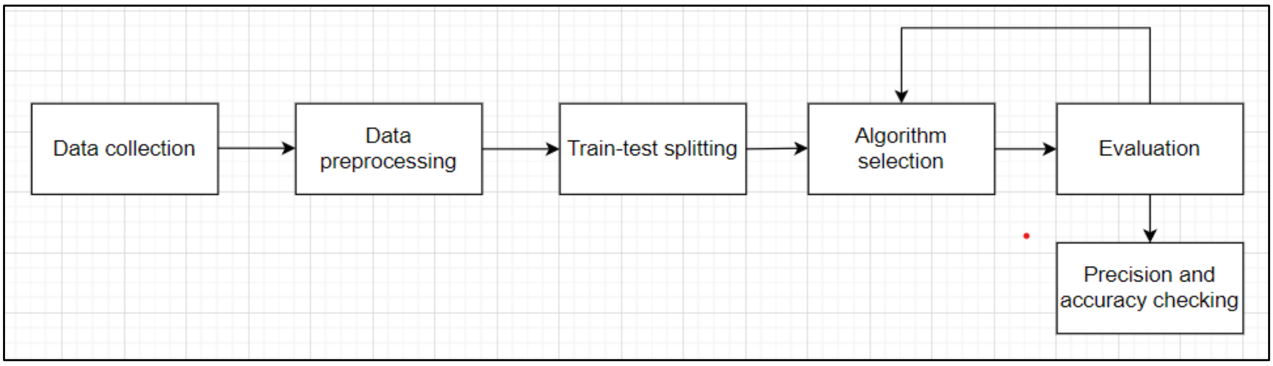

Figure 1. Conceptual Diagram

Research conduction can be successful only by applying a planned and programmed research methodology. Research objective, research philosophy, research approach and design are included in the methodology portion. Validity and reliability of collected data for data analysis is also discussed here. Sampling techniques, data pre-processing, data collection methods and tools are required to give this section completion.

Research design -

- Research methodology
- Samples
- Scale

Methodology

- **Approach**

Our research is about assessing how efficiently we can predict credit rating of the different countries using different machine learning algorithms. This is descriptive research which aims to know the extent to which different conditions can be obtained among these subjects and what are the various factors that influence a country's credit rating.

- **Data Collection**

We made use of different authentic sources for data collection. For obtaining the credit rating of different countries we enrolled on the websites of well-known credit rating agencies such as crisil, moody's, fitch, S&P, etc. After referring to some books & articles we decided on certain variables that are related and are one of the key performance indicators that influences and determines a country's credit rating. For obtaining data of the chosen variables, we made use of the world bank website where we gathered most of the data of past years.

- **Data Pre-processing**

The data that we collected had some missing and null values, where we removed some of them which were then found to be insignificant and treated the rest by imputing data from different authentic sources and by applying some calculations.In correlation analysis, we observed that only 20 variables out of 35 were found to be significant, which are as follows:-

Economy	GNI
	Current GDP
	Adjusted savings Net National Savings
	Gross Capital Formation
	Current Account Balance
	Total Reserves
	Gdp per capita
	Adjusted Net national Income
	Adjusted Net National Saving
	Final Consumption Expenditure
	Official Exchange rate
	Total Reserves (Excluding Gold)
	Reserves and Related items
Trade Openness	FDI
	Trade %of GDP
	Inflation
	Net Trade in Goods and Services
	Import of Goods and Services
	Export of Goods and Services
	Export unit value Index

Table 1. Variable List

CORRELATION MATRIX

The matrix of correlations and variance-covariance was computed because the database contains numerous variables with missing values. In contrast to ML, it is not advisable to impute values using the mean or median because doing so skews the variance and is inappropriate for statistical inference. Furthermore, post-prediction studies on these variables and their influence on the model and issue under consideration are impossible because patterns in the original variables may be destroyed as a result of computer processing. The main idea behind this method, which chooses variables based on their

correlation, is that the variables are linked to their categories rather than one another. The two steps that make up the algorithm's operation are
1) investigating correlations between variables and categories, and
2)looking for subsets that are consistent with the main hypothesis.

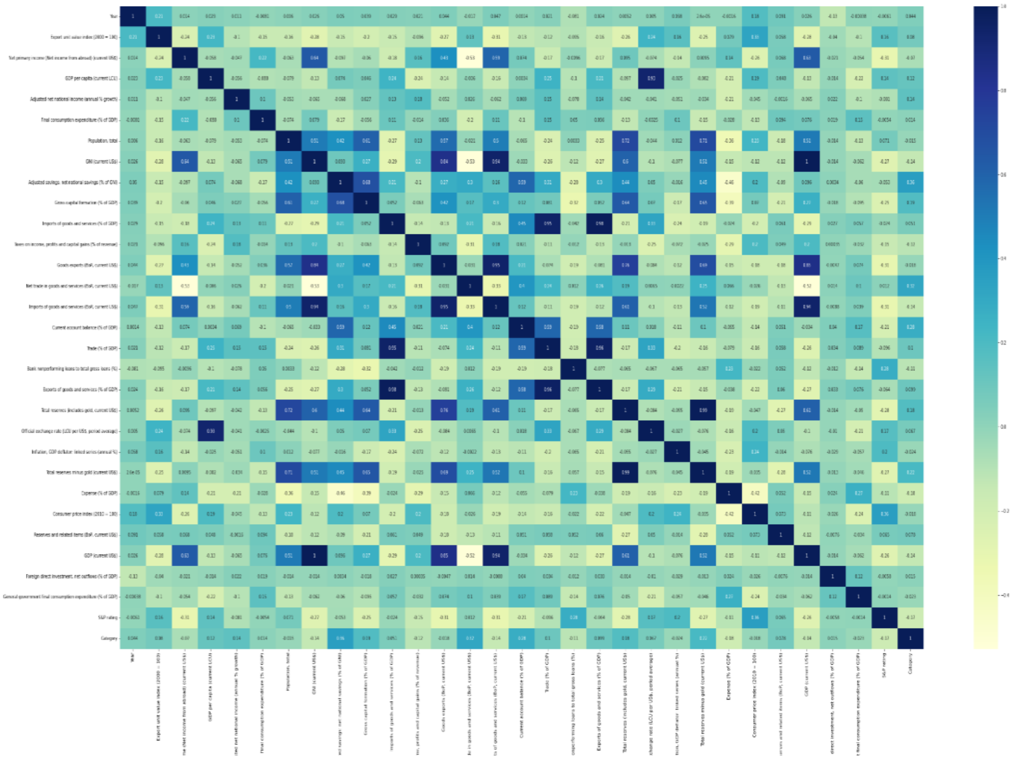

Figure 2. Correlation Matrix for Decision Tree

There were 20 unique ratings present in databases. We created a group of 8 categories for these ratings which are as follows: High grade, Highly Speculative, Lower medium, Non-investment, Prime, Speculative, Upper medium.

S & P rating	Category
AAA	Prime
AA+	High Grade
AA	High Grade
AA-	High Grade
A+	Upper Medium
A	Upper Medium
A-	Upper Medium
BBB+	Lower medium
BBB	Lower medium
BBB-	Lower medium
BB+	Non-investment
BB	Speculative
BB-	Speculative

B+	Highly speculative
B	Highly speculative
B-	Highly speculative
CC	prospect for recovery

Table 2. Rating and category

- Divided the data set into training and validation.
- Performed descriptive analytics.
- Defined the functional form of regression
- Estimated the classification parameters
- Performed classification model diagnostics
- Validated the model using validation data
- Decided on model deployment.
- Model Fitting

Variables	CategoryNEW
CategoryNEW	1
Adjusted savings: net national savings (% of GNI)	0.358414828
Net trade in goods and services (BoP, current US$)	0.315040632
Current account balance (% of GDP)	0.28059584
Total reserves minus gold (current US$)	0.216707611
Gross capital formation (% of GDP)	0.186297117
Total reserves (includes gold, current US$)	0.181835155
Adjusted net national income (annual % growth)	0.141208985
GDP per capita (current LCU)	0.116577162
Trade (% of GDP)	0.100886632
Exports of goods and services (% of GDP)	0.099375552
Export unit value index (2000 = 100)	0.079621763
Reserves and related items (BoP, current US$)	0.078145089
Official exchange rate (LCU per US$, period average)	0.067309706
Imports of goods and services (% of GDP)	0.050736281
Foreign direct investment, net outflows (% of GDP)	0.014817014
Final consumption expenditure (% of GDP)	0.014164603
Inflation, GDP deflator: linked series (annual %)	-0.023742573
GDP (current US$)	-0.137785115
GNI (current US$)	-0.138165435
Imports of goods and services (BoP, current US$)	-0.142162751
S&P ratingNEW	-0.170590743

Table 3. Correlation of the factors that impact or affect the credit rating of different countries.

Results/Conclusions

For many different economic decisions, especially in emerging markets looking to draw in foreign investors, an accurate forecast of sovereign credit risk ratings is essential.
In this study, we identified 20 variables that influence or influence the credit ratings of various nations, which affects the investment choices of various foreign entities.
The accuracy of the Decision Tree model used to calculate sovereign risk ratings appears to be 71.11%. Figure 3 displays the additional performance metrics.

	precision	recall	f1-score	support
High Grade	0.73	0.89	0.80	9
Highly speculative	1.00	0.29	0.44	7
Lower medium	0.78	1.00	0.88	7
Non-investment	0.00	0.00	0.00	2
Prime	0.83	0.83	0.83	6
Speculative	0.75	0.86	0.80	7
Upper Medium	0.57	0.57	0.57	7
accuracy			0.71	45
macro avg	0.67	0.63	0.62	45
weighted avg	0.74	0.71	0.69	45

Figure 3. Performance Metrics for Decision Tree

The accuracy of the Random Forest model used to calculate sovereign risk ratings appears to be 80%. Figure 4 displays the additional performance metrics.

	precision	recall	f1-score	support
High Grade	0.70	0.78	0.74	9
Highly speculative	1.00	0.86	0.92	7
Lower medium	0.78	1.00	0.88	7
Non-investment	0.00	0.00	0.00	2
Prime	0.86	1.00	0.92	6
Speculative	0.78	1.00	0.88	7
Upper Medium	0.75	0.43	0.55	7
accuracy			0.80	45
macro avg	0.69	0.72	0.70	45
weighted avg	0.77	0.80	0.77	45

Figure 4. Performance Metrics for Random Forest

The K - Nearest Neighbour model to estimate risk ratings appears to have an accuracy of 60%. Using gridsearchCV method the base parameter for N-neighbours were found to be 3. The other performance metrics are shown in Figure 5.

	precision	recall	f1-score	support
High Grade	0.62	0.89	0.73	9
Highly speculative	1.00	0.43	0.60	7
Lower medium	0.50	0.71	0.59	7
Non-investment	0.00	0.00	0.00	2
Prime	0.56	0.83	0.67	6
Speculative	0.80	0.57	0.67	7
Upper Medium	0.67	0.29	0.40	7
accuracy			0.60	45
macro avg	0.59	0.53	0.52	45
weighted avg	0.66	0.60	0.59	45

Figure 5. Performance Metrics for KNN

The Gaussian NB model to estimate risk ratings appears to have an accuracy of 39%. The other performance metrics are shown in Figure 6.

	precision	recall	f1-score	support
High Grade	0.38	0.50	0.43	16
Highly speculative	0.23	0.89	0.36	9
Lower medium	0.33	0.06	0.10	17
Non-investment	0.17	0.25	0.20	4
Prime	0.69	0.33	0.45	27
Speculative	0.31	0.33	0.32	15
Upper Medium	0.80	0.50	0.62	16
prospect for recovery	1.00	1.00	1.00	1
accuracy			0.39	105
macro avg	0.49	0.48	0.44	105
weighted avg	0.49	0.39	0.39	105

Figure 6. Performance Metrics for Gaussian NB

After experimenting with various categorization models, we came to the conclusion that the Random Forest model, which has the highest accuracy of 80%, appears to be a good fit for estimating sovereign risk ratings.

CONCLUSIONS

For many different economic decisions, especially in emerging markets looking to draw in foreign investors, an accurate forecast of sovereign credit risk ratings is essential. In this study, we identified some of the variables that influence or influence the credit ratings of various nations, which changes the investment choices made by various foreign entities. After experimenting with a number of categorization models, we came to the conclusion that the Random Forest model, with an accuracy of 80%, appears to be a good fit for estimating sovereign risk ratings.

The main finding of this article is that it offers new perspectives for decision-makers and participants in the global financial markets. The key idea is that large amounts of data can be used to train AI models for accurate prediction. Without having any prior knowledge of rating categorization, we also discovered a number of common methodological limitations when we

1) used the same indicators across all of the countries we looked at without making any adjustments or taking any additional measures to account for them.

2) Not taking into account the endogeneity of some variables and allowing them to have different weights for the nations.

Implications -

Implications of these study are as follows:-

- One of the major impacts of this study is to find out what factors are important in finding out the credit rating of a country, finding a correlation between 2 variables and examining the relation between them.
- Another implication can be, selecting a suitable machine learning model so that it can predict a country's sovereign credit rating without the risk of human errors.

Limitations of the study

- Inconsistent Data: -Data collection is an important part of any report writing, with no option of primary data, we had to collect secondary data but collecting secondary data was in itself a tedious task as data was inconsistent i.e. values missing, values not matching and many more. When cross checked with different sources the issue of inconsistent data persisted.

- Literature: -Literature related to our report were few and those that were present were quite complex for our understanding, since our main focus was on Machine Learning and we as a team are learning about machine learning, so looking at those complex machine learning models confused us.
- Age of Data: - The data available to us was old and the new data(year 2020 and 2021) was not available making our report writing difficult, we had to model our research report based on the values available to us and it is a good attempt, but if newer data were available our research report would have been even better.

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