Eurasian Journal of Economics and Finance, 8(4), 2020, 279-299
DOI: 10.15604/ejef.2020.08.04.008

EURASIAN JOURNAL OF ECONOMICS AND FINANCE

www.eurasianpublications.com

DETERMINANTS OF SOVEREIGN CREDIT RATINGS: AN APPLICATION OF THE NAÏVE BAYES CLASSIFIER

Oliver Takawira
University of Johannesburg, Republic of South Africa
Email: otakawira@uj.ac.za

John W. Muteba Mwamba
University of Johannesburg, Republic of South Africa
Email: johnmu@uj.ac.za

Received: September 9, 2020 Accepted: November 28, 2020

Abstract

This is an analysis of South Africa's (SA) sovereign credit rating (SCR) using Naïve Bayes, a Machine learning (ML) technique. Quarterly data from 1999 to 2018 of macroeconomic variables and categorical SCRs were analyzed and classified to predict and compare variables used in assigning SCRs. A sovereign credit rating (SCR) is a measurement of a sovereign government's ability to meet its financial debt obligations. The differences by Credit Rating Agencies (CRA) on rating grades on similar firms and sovereigns have raised questions on which elements truly determine credit ratings. Sovereign ratings were split into two (2) categories that is less stable and more stable. Through data cross-validation for supervised learning, the study compared variables used in assessing sovereign rating by the major rating agencies namely Fitch, Moody's and Standard and Poor's. Cross-validation splits the dataset into train set and test set. The research applied cross-validation to reduce the effects of overfitting on the Naïve Bayes Classification model. Naïve Bayes Classification is a Machine-learning algorithm that utilizes the Bayes theorem in classification of objects by following a probabilistic approach. All variables in the data were split in the ratio of 80:20 for the train set and test set respectively. Naïve Bayes managed to classify the given variables using the two SCR categories that is more stable and less stable. Variables classified under more stable indicates that ratings are high or favorable and those for less stable show unfavorable or low ratings. The findings show that CRAs use different macroeconomic variables to assess and assign sovereign ratings. Household debt to disposable income, exchange rates and inflation were the most important variables for estimating and classifying ratings.

Keywords: Sovereign Credit Rating, Naïve Bayes, Machine Learning, Macroeconomic Variables

JEL Classifications: C51, C52, C53, C58, G17, G24

1. Introduction

Sovereign credit rating (SCR) has become the center of controversy in the international bond market (Gultekin-Karakas *et al.* 2011). The move by Credit Rating Agencies (CRA) to give a rating to sovereigns shifted the credit market to another level as investors were put in a dilemma, either to follow published ratings or use their own approaches to rate assets, firms and sovereigns (Osobajo and Akintunde, 2019). Firms, sovereigns and other borrowing institutions were not spared as they tried to find their identity as perceived by markets on creditworthiness. Monitoring the sovereign credit ratings (SCR) give international investors the opportunity to access crucial information on countries that they are planning to invest in (Cantor and Packer, 1994; Ferri *et al.* 2001; Kabadayi and Celik, 2015; Mora, 2006). Gogas *et al.* (2014) claimed that investors, borrowers, issuers and governments use CRAs risk-rating scale obtained on the banks' ability to meet obligations on debt timely, as provided by CRAs in making investment and financial decisions. Countries with good credit ratings are believed to be financially strong, with stable financial systems and are credit worth (Gultekin-Karakas *et al*. 2011).

A sovereign credit rating (SCR) is a measurement of a sovereign government's ability to meet its financial debt obligations. After thorough assessments of fundamental information peculiar to a sovereign, CRAs can then identify a rank for that particular sovereign either as capable of redeeming its debts or failing to honor its obligations. Chee *et al.* (2015) stated that Credit Rating Agencies (CRAs) perform two services namely to provide information and to monitor debtors. Ratings from CRAs faced rejection since the rating industry is oligopolistic. The most prevalent CRAs are Standard & Poor's (S&P), Moody's and Fitch Rating Agency, as these three dominate the market. Bellotti *et al.* (2011) illustrated that ratings are facing challenges because of opaque methodologies used by rating agencies and failure to predict financial crises like the late 1990 Asian crisis. Bellotti *et al.* (2011) went on to say that CRAs do not look ahead on rating assignments but rather look backward. According to Ozturk *et al.* (2016), the financial crisis of 2008 was a result of high reliance on CRA sovereign ratings. Ratings are genuinely serving a niche financial purpose and generally, local firms are rated lower than the county's overall sovereign rating (Iyengar, 2010). Sovereign credit ratings affect interest rates of assets and form other assets' benchmark indicator for credit risk assessment and so influence the breadth and volume of assets (Ozturk *et al.* 2016). Ozturk *et al*. (2016) highlighted that arguments over the accuracy of sovereign ratings augmented the need for more internal credit scoring systems to avoid over dependence on CRAs. Governments are highly interested in credit ratings to improve international capital markets accessibility and reduce borrowing cost. Sovereign ratings are not entirely focused on governments, but for assessing other borrowers of that particular country (Iyengar, 2010). Sovereign rates illustrate the level of default risk associated with a borrowing nation.

Kraussl (2005) raised that credit rating agencies have substantial influence on the size and volatility of emerging markets lending. Mutize and Nkhalamba (2020) concluded that investors in South Africa's long-term bonds are more sensitive to negative credit rating events, which are mainly driven by structural problems in the economy. According to Mahomed Karodia and Soni (2014, p. 52) "the foreign debt rating of South Africa has been over the last several months continuously downgraded by international rating agencies and, downward growth revisions have become a persistent pattern." South Africa as an emerging market is highly vulnerable to lending volatility as the country had been facing downgrades since 2009, which affects growth and the financial sector's stability (Mahomed Karodia and Soni 2014). This study aims to use Naïve Bayes a Machine Learning tool to classify and identify variables used in attaining sovereign credit ratings. Forecasting sovereign ratings assist nations in determining the outlook of their default risk as perceived by those providing funds (Kabadayi and Celik, 2015). Polito and Wickens (2013) and CGFS (2011) highlighted that some scholars accused CRAs of intensifying the debt crisis, increasing costs of borrowing and instigating or exacerbating instability. This problem raises the need for developing and underdeveloped countries to analyze or forecast sovereign credit ratings to avoid negative impacts of sovereign ratings downgrade. South Africa, as an emerging market with an unpredictable political stability, is vulnerable to negative impacts of sovereign rating downgrades. Negative expectations or speculating actions towards downgrade can negatively affect the macroeconomic variables leading to financial instability and disturbances in the fiscal or monetary framework.

Previous studies transformed ratings into numerical values losing some information but, in this research, ratings were analyzed in their original and categorical format as released by CRAs. The conversion of ratings to numerical values weakened the strength of previous studies data and models in analyzing credit ratings. Studies like Pretorius and Botha, (2016); Bhatia (2002); Afonso (2003); Kraussl (2003); Reinhart (2002); Afonso *et al.* (2011); Chee *et al*. (2015); Hill *et al*. (2010); and Mellios and Paget-Blanc (2006); Erdem and Varli (2014); Cantor and Packer (1994); Ferri *et al.* (2001); Kabadayi and Celik (2015); Mora (2006) and so on used models that includes panel analysis, probit model, logit, discriminant analysis, multinomial logistic regression and other statistical models, which assume linear relationships and normal distribution lacking on the ability to perfectly model sovereign ratings. Sovereign ratings are determined by various factors that may have either a linear, non-linear relationship, normally distributed and non-normal. Therefore, the study applied Naïve Bayes which classifies variables and is not affected by the state of explanatory variables being normally distributed or having a linear relationship.

Studies by Cantor and Packer (1994); Ferri *et al.* (2001); Kabadayi and Çelik (2015); Mora (2006); Pretorius and Botha (2016); Bhatia (2002); Afonso, (2003); Kraussl (2003); Reinhart (2002); Afonso *et al.* (2011); Chee *et al.* (2015); Hill *et al*. (2010) and Mellios and Paget-Blanc (2006); Erdem and Varli (2014) and so on which conducted an approach of grouping or analyzing cross country sovereign ratings failed to clearly identify country specific determinants and impacts of sovereign ratings. Pulling countries together fails to consider the differences in development between the countries. The study aimed to apply a new model that classifies variables used to predict SCRs, to assist governments prevent downgrades and promote upgrades restoring financial stability. The research further examined sovereign rating links with macroeconomic indicators to exhume the determinants of the sovereign credit ratings from Fitch, Moody's and Standard & Poor's (S&P). Naïve Bayes was chosen as it could improve the analysis of sovereign ratings far better than statistical models as it was applied in comparing variables applied by Fitch, Moody's and Standard & Poor's (S&P) in ratings sovereigns through classification.

This paper is structured as follows: Section 2 provides a discussion of empirical and theoretical literature. Section 3 illustrates the machine learning tool which is Naïve Bayes classification methodology applied to classify sovereign ratings. Section 4 presents empirical results and Section 5 discusses the conclusion.

2. Literature review

The literature review has three parts, which includes theoretical literature, empirical literature and analysis of literature.

2.1. Theoretical literature on determinants of SCR

Chee *et al.* (2015) highlighted that the political and inflation theory asserts that inflation is a measurement of incumbent government's self-restrain in not being opportunist for election benefits as unhappy may increase the possibilities of political instability. CRAs use rating forms to assess sovereign debt creditworthiness or international borrowing by countries. CRAs use various factors like social, economic and political aspects. Inflation and business cycles are linked to the political aspect as this theory notes that people use voting to illustrate their dissatisfaction with high inflation and negative business. Political instability or dissatisfaction by citizens affects governance and reduces the ability of a country to raise income to honor debt obligations. Once political instability and dissatisfaction from citizens kicks in, lenders are skeptical on providing funds to the country as it is deemed not creditworthy. The economic aspect is indicated by quantifiable macroeconomic factors that outline the capacity of a country to service its external debt. The ability of a government to plan and manage debt efficiently is indeed a big factor, as failure will lead to high risk of default. Chee *et al*. (2015, p. 43) argued that "though a country's capacity in repaying external debts is unable to be quantified, the sovereign creditworthiness can be measured by observing government's sovereign debt management behavior, which could be traced by the monetary policy and fiscal policy."

2.2. Empirical literature review

The differences by CRA on rating grades on similar firms and sovereigns have raised questions on which elements truly determine credit ratings. Ozturk *et al.* (2016) highlighted that early literature examined to what extent the variation in sovereign ratings could be explained by country specific variables and identified certain macroeconomic, financial and political variables that bode well in explaining the variations in sovereign credit ratings. Kabadayi and Celik (2015) in reviewing literature highlighted that Archer *et al.* (2007), Butler and Fauver (2006), Cantor and Packer (1996), Ferri *et al*. (1999), Mora (2006) and Ratha *et al.* (2011) applied sovereign ratings as quantitative dependent variables. Ferri *et al.* (2001), Gaillard (2006), Hill *et al.* (2010), Hu *et al.* (2002) and Mora (2006) used sovereign ratings as qualitative dependent variables.

Afonso *et al.* (2011) conducted a study from 1995 to 2005 on the determinants of sovereign debt ratings using rating notations from the three-leading international CRAs. The study made use of a linear regression method and a random effect ordered probit response model. They applied a unique process that distinguished short-term and long-term effects from several macroeconomic and fiscal explanatory variables on a country's sovereign debt rating. According to Afonso *et al.* (2011) changes in GDP per capita, GDP growth, government debt, and government balance had a short-run impact on a country's credit rating, whereas government effectiveness, external debt, foreign reserves and default history were important long-run determinants. Novotna (2012) applied and compared three selected approaches for credit rating prediction, linear discriminant analysis, and logistic regression as well as Naive Bayes based on data of European companies' financial indicators. Novotna (2012) concluded that discriminant analysis and logistic regression models are relatively simple to use and achieve high classification ability. Various contradicting models were applied in assessing sovereign ratings determinants producing conflicting results.

2.3. Summary of literature reviewed

The literature review illustrates that most of the studies conducted in analyzing the determinants and impacts of sovereign credit ratings applied cross-sectional or cross-country approach. The weakness of this approach is that grouping countries fails to capture country specific conditions as countries are not similar or some are well developed than others like in a case of South Africa and China in the BRICS countries making findings unreliable. Unique models applied by different researchers produced conflicting results. This study applies a country specific approach looking at the determinants of sovereign ratings for South Africa using the country's specific economic indicators through a Naïve Bayes Classification model.

3. Research methodology

This study used a Machine Learning (ML) algorithm that is Naïve Bayes Classifier to classify and analyze SCR from each one of the major CRAs namely Fitch, Moody's and S&P using micro and macroeconomic indicators. Machine learning tools are representing an ever-increasing research area (Azeem *et al.* 2019). Machine learning is a branch of artificial intelligence that aims at enabling machines to perform their jobs skillfully by using intelligent software and the statistical learning methods constitute the backbone of intelligent software that is used to develop machine intelligence (Mohammed *et al*. 2016). Thus, they are techniques that utilizes statistical methods in determining patterns in massive data. The Naïve Bayes Classification ML model captured the relationship between SCR and economic indicators by clearly identifying crucial determinants of SCR. This study focused on studying if sovereign credit rating is based on macroeconomic variables and if CRAs use the same variables to model sovereign credit ratings. SCR were split into two (2) categories that is less stable and more stable. Less stable indicates low sovereign credit ratings or junk status borrowers and more stable represents higher sovereign ratings with high creditworthiness. Chee *et al.* (2015) modeled sovereign credit rating using variables that impact a country's international creditworthiness and the reduced formulae is as follows:

$$Creditworthiness = f(economic\ indicators\ associated\ to\ debt\ repaying\ capacity\ of\ debtor\ countries\ ) \quad (1)$$

The following function illustrates the relationship between sovereign ratings and economic variables:

$$Sovereign\ Ratings_{jit} = f(Macro\ and\ Micro\ Economic\ Variables) \quad (2)$$

where 'j' represents the specific CRA between Fitch, Moody and S&P, 't' represents time in quarterly from 1999 to 2018 and 'i' represents a dummy for 'more stable rating' or 'less stable rating'. On this research, the focus was only on South Africa. The model specification is as follows:

$$SCR_{it} = \beta_0 + \mathrm{REER}\beta_1 + \mathrm{PIR}\beta_2 + \mathrm{HDDI}\beta_3 + \mathrm{UR}\beta_4 + \mathrm{GDPpc}\beta_5 + \mathrm{CPIH}\beta_6 + \mathrm{FDGDP}\beta_7 + \mathrm{BOP}\beta_8 + \mathrm{CAB}\beta_9 + \varepsilon \quad (3)$$

3.1. Cross-validation

Cross-validation is applied in Machine learning tools to solve the problem of overfitting. Cross-validation splits the dataset into train set and test set. The train set is used to train the model to capture trends or patterns in the dataset and then independent variables in the test set are used to predict values of the dependent values in the test set.

Table 1. Summary of variables

Variable	Definition and proxies	Data source, format and transformation	A priori expectation
Sovereign ratings	Sovereign rating is an independent assessment of the creditworthiness of a country or sovereign entity. Sovereign credit ratings can give investors insights into the level of risk associated with investing in the debt of a particular country, including any political risk.	Ratings from the three major CRAs. Collected in ordinal or categorical format and were transformed to numerical values using a scale of 1 to 21. The highest rating is denoted by 21 whilst the lowest rating is represented by 1. (Kabadayi and Celik, 2015) Trading Economics Website Principal Component Analysis (PCA)	21 denotes the highest rating and a drop is a downgrade whilst a 1 the lowest rating denotes default. A rise from 1 is an upgrade. Downgrades are unfavorable as they are associated with high borrowing costs and less access to funds and vice versa.
REER	Real Effective Exchange rates	SARB and Quantec Easy Data databases.	Favorable when increase – REER
PIR	Prime Interest Rates	SARB and Quantec Easy Data databases.	Favorable when decreasing – PIR
HDDI	Housed Hold Debt to Disposable Income	SARB and Quantec Easy Data databases.	Favorable when decreasing –HDDI
UR	Unemployment rate	SARB and Quantec Easy Data databases.	Favorable when decreasing – UR
GDPpc	Gross Domestic Product (GDP) percentage change	SARB and Quantec Easy Data databases.	Favorable when increase – positive GDPpc
CPIH	Consumer price index Headline	SARB and Quantec Easy Data databases.	Favorable when decreasing – CPIH
FDGDP	Foreign Debt to GDP	SARB and Quantec Easy Data databases.	Favorable when decreasing – FDGDP
BOP	Balance of Payments	SARB and Quantec Easy Data databases.	Favorable when decreasing – deficit BOP
CAB	Current Account Balance	SARB and Quantec Easy Data databases.	Favorable when decreasing – deficit CAB

Source: Authors' own preparation.

The research applied cross-validation to reduce the effects of overfitting on the Naïve Bayes Classification model. All variables in the data were split in the ratio of 80:20 for the train set and test set respectively. The ML models were trained using 80% of the data and then used 20% of the explanatory variables in the test set to estimate 20% of the response variable in the test set.

The financial and economic indicators from South Africa (SA) were compiled into quarterly time series data from 1999 to 2018 giving a total of 80 observations. The data was taken from five years after the time South Africa gained independence up to 2018 since 2019 values were not readily available. The data were collected from various sources like Quantec Easy data, Statistics South Africa (Stats SA), Trading Economics, Thomson Reuters and the South African Reserve Bank (SARB). The data sources have been known to have reliable and valid data of these variables. Table 1 shows definition of variables, data sources and priori expectations.

3.2. Naïve Bayes classification

Naïve Bayes Classification is a Machine learning algorithm that utilizes the Bayes theorem in classification of objects by following a probabilistic approach. Naïve Bayes is based on the Bayes theorem also known as the Bayes Rule. The Bayes Rule used in Naïve Bayes is derived from two notations, which are:

$$P(A/B) = \frac{P(A\ and\ B)}{P(B)} \tag{4}$$

and

$$P(B/A) = \frac{P(A\ and\ B)}{P(A)} \tag{5}$$

where $P(A)$ is the probability of A occurring, P(B) is the probability of B occurring, $P(A\ and\ B)$ is the joint probability of A and B, that is, the event that both A and B occurs, $P(A/B)$ is the conditional probability of event A occurring given that B has occurred and similary $P(B/A)$ is the conditional probability of event B occurring given that A has occurred (Keller, 2018; Berrar, 2018). Looking at equations 1 and 2, it can be noted that

$$P(A\ and\ B) = P(A/B)P(\ B) = P(B/A)P(\ A) \tag{6}$$

The terminologies of the Bayesian theorem are as follows:

- A is known as the proposition and B is the evidence,
- $P(A)$ represents the prior probability of the proposition,
- $P(B)$ represents the prior probability of evidence,
- $P(A|B)$ is called the posterior,
- $P(B|A)$ is the likelihood.

Thus, the Bayes theorem can be summed up as:

$$Posterior = (Likelihood).(Proposition\ prior\ probability)/Evidence\ prior\ probability \tag{7}$$

The Bayes theorem is used to calculate the conditional probability, which is the probability of an event occurring based on information about the events that have occurred in the past (He *et al*. 2012; Keller, 2018; Berrar, 2018). The above equations are of single predictors but in the real world, there are more than one predictor variables and for a classification problem, there is more than one output class.

3.3. Naïve Bayes algorithm

The Naïve Bayes algorithm is a classification algorithm based on the Bayes rule, which assumes that the attributes $x_1, x_2, \cdots, x_n$ are conditional independent of one another, given Y (Krichene, 2017). According to Mitchell (2010), the value of this assumption simplifies the representation of $P(X/Y)$ and the problem of estimating it from the training data. The objective of a Naive Bayes algorithm is to measure the conditional probability of an event with a feature vector $X_1, X_2, \cdots, X_n$ belonging to a particular class Y_i,where

$$P(Y_i/x_1, x_2, \cdots, x_n) = \frac{P\left(x_1,x_2,\cdots,x_n/Y_i \times \mathrm{P}(Y_i)\right)}{P(x_1,x_2,\cdots,x_n)} \quad for\ 1 < i < k \tag{8}$$

Computing the above equation, one obtain:

$$P\left(x_1, x_2, \cdots, x_n/Y_i \times \mathrm{P}(Y_i)\right) = P(x_1, x_2, \cdots, x_n, Y_i)$$
$$P(x_1, x_2, \cdots, x_n Y_i) = P(x_1/x_2, \cdots, x_n, Y_i) \times P(x_2, \cdots, x_n, Y_i)$$
$$= P(x_1/x_2, \cdots, x_n, Y_i) \times P(x_2/x_3, \cdots, x_n, Y_i) \times P(x_3, \cdots, x_n, Y_i)$$
$$= P(x_1/x_2, \cdots, x_n, Y_i) \times P(x_2/x_3, \cdots, x_n, Y_i) \times P(x_3/x_4, \cdots, x_n, Y_i) \times P(x_4, \cdots, x_n, Y_i)$$
$$= \cdots$$
$$= P(x_1/x_2, \cdots, x_n, Y_i) \times P(x_2/x_3, \cdots, x_n, Y_i) \times \cdots \times P(x_{n-1}/x_n, Y_i) \times P(x_n/Y_i) \times \mathrm{P}(Y_i) \tag{9}$$

The conditional probability, i.e., $P\left(x_j/x_{j+1}, \cdots, x_n, Y_i\right)$ adds up to $P\left(x_j/Y_i\right)$ since each predictor variable is independent in Naive Bayes. The final equation becomes:

$$P(x_1, x_2, \cdots, x_n Y_i) = \left(\prod_{j=1}^{j=n} P\left(x_j/Y_i\right)\right) \times \frac{\mathrm{P}(Y_i)}{P(x_1,x_2,\cdots,x_n)} \quad for\ 1 < i < k \tag{10}$$

Here $P(x_1, x_2, \cdots, x_n)$ is constant for all the classes, therefore one gets:

$$P(Y_i/x_1, x_2, \cdots, x_n) \propto \left(\prod_{j=1}^{j=n} P\left(x_j/Y_i\right)\right) \times \mathrm{P}(Y_i) \quad for\ 1 < i < k \tag{11}$$

3.4. Steps used in Naïve Bayes model
3.4.1. Obtaining the data and formatting

At this stage, data was imported into R and the variables were formatted in such a way that the continuous variable in the data frame were interval (FDGDP, REER, PIR, BOB, CAB, UR, GDPpc, HDDI and CPIH) and the categorical variable or response variable, Outcome was indicated as a factor variable.

3.4.2. Visualization of the data

For developing a Naïve Bayes classification model, one needs to make sure that the independent variables are not highly correlated. The command *Pairs, panel* command was used to determine how the variables were correlated and in this case, correlations and histograms were produced. Box plots of the data were also constructed using the command *ggplo*t. The boxplots were able to indicate whether the category "less stable" had values higher or less than the category "more stable". However, if one of the averages was higher than the other, then there was some potential of developing a classification model, which was the case in all variables. A significant amount of overlap between some of the boxplots showed that the model was unlikely to be 100% accurate due to the overlap.

3.4.3. Data partitioning

The random seed *set.seed* of 1234 command was used to make the analysis repeatable and the data was split into 80% training data and 20% test data.

3.4.4. The Naïve Bayes model

The Naïve Bayes model was fitted to the data by using the function *naïve_bayes* and the model was plotted using the function *plot(model)*. The plotted model showed the density plot for each continuous variable showing the density of those observations, which were less stable and those which were more stable and where they overlap.

3.4.5. Prediction

The predictions were stored in a matrix called *p* and the type of prediction was probability. Predictions were done for the train data and the *head(cbind(p, train))* command was used to show the probabilities for each observations. The result showed each of the 80 observations the chances of being less stable or more stable such that if probability was higher than 0.5 for that category, it meant that the observation was likely to fall into that category. For example, 0.64 and 0.36 meant that the observation was likely to fall into less stable, that is a 64% chance, which was category 0.

3.4.6. Construction of confusion matrix

Predictions for the train data were stored in *p1* and for the test data and in *p2*. Confusion matrixes were developed for the train data and the test data by using the command *table*. Misclassification were also obtained for both data sets.

3.4.7. Naive Bayes model with Kernel

To improve the misclassification rates, the Naive Bayes model was developed by using Kernel. Kernel based densities tend to perform better when numerical variables are not normally distributed. The model was also plotted, and confusion matrixes developed for both train and test data. This showed an improvement on the misclassification as they become less than the first classifications without Kernel density.

4. Empirical results

4.1. Naïve Bayes model

Naïve Bayes Classifier is a Machine learning tool used to make predictions. The purpose was to use a classification algorithm, which assists in building a fast Machine learning model that can make quick prediction or identification of variables utilized by CRAs. Naïve Bayes was used as part of the Machine learning technique to determine how the micro and macroeconomic indicators FDGDP, REER, PIR, BOP, CAB, UR, GDPpc, HDDI and CPIH could assist in classing the sovereign ratings into less stable and more stable. The data was divided into 80% training and 20% test data and the coding was “1” for more stable and “0” for less stable. The Naïve Bayes was performed using the R package. A Naïve Bayes Classification model requires that the independent variables are not highly correlated. The correlation matrix is shown in Figure 1.

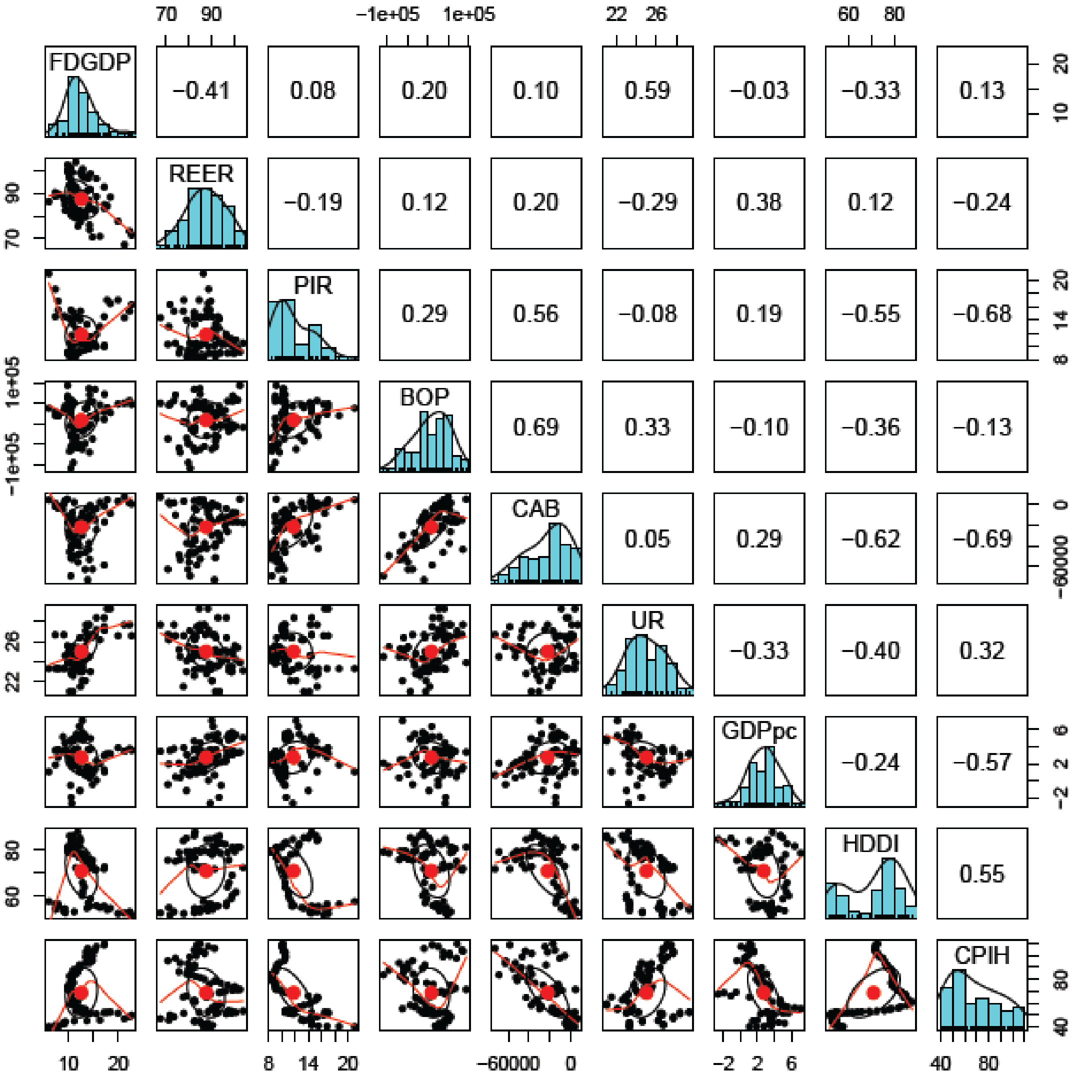

Figure 1. Correlation Matrix for Naïve Bayes
Source: By Author

The results show that no independent variable has high correlations, which are more than 0.7 indicating that there is no multicollinearity. The results are presented in the next subsections for Fitch, Moody's and Standard & Poor's (SNPoor).

4.2. Naïve Bayes model for Fitch

Before the Naïve Bayes model could be fitted, visualization of data was done using boxplots. The boxplots are shown in Figure 2.

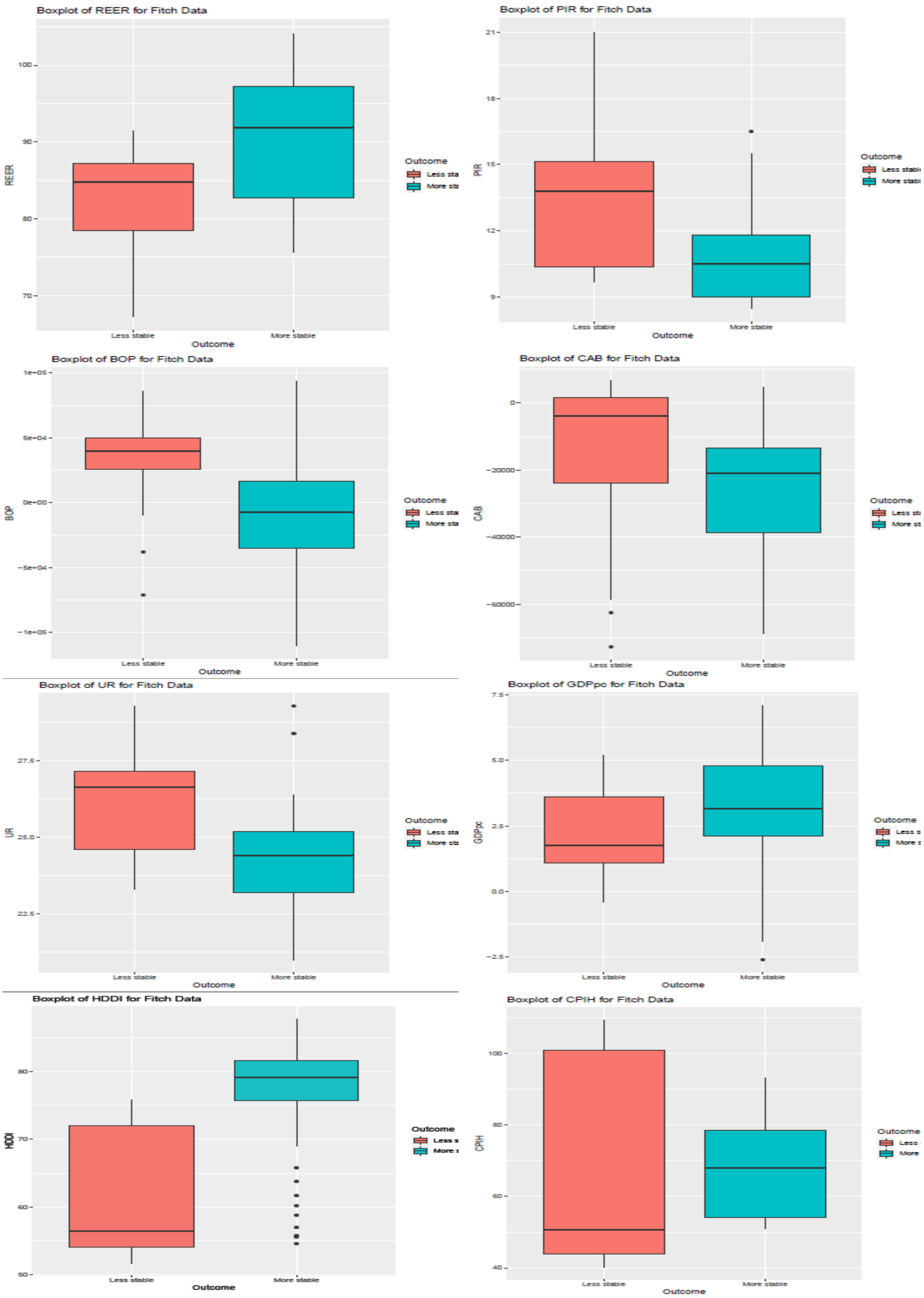

Figure 2. Fitch Boxplots for the Independent Variables by Outcome
Source: Authors' own preparation

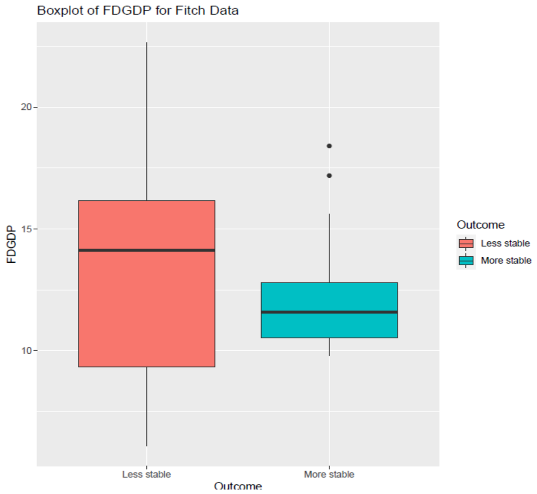

Figure 2. Continued

The left side boxplot is the one for less stable whereas the right side is the one for more stable. A significance amount of overlap implies that the model is not likely to be 100% accurate. There is some potential of developing a classification model since for all the variables, the values show different medians for less stable and for more stable. The variables REER, GDPpc, HDDI and CPIH showed that high values favored the rating being more stable whereas for the variables PIR, BOP, CAB, UR and FDGDP high values were associated with those less stable. The variables BOP and HDDI showed not much overlap between the less stable and the more stable suggesting that there will not be a lot of misclassification on these variables. CPIH had a lot of overlap between less stable and more stable such that there is potential of misclassification for the variable. A Naïve Bayes model was then fitted and the prior probabilities were obtained in Table 2.

Table 2. Prior probabilities for the Fitch data

Probabilities	**Less stable**	**More stable**
Priori probabilities	0.3768	0.6232

Source: Authors' own preparation

The results show that for the Fitch data the probability that a quarterly index is less stable was 0.38 and 0.62 for more stable. For the Fitch data, most of the indices fall under more stable as evidenced by a prior probability of more than 0.5. The means and standard deviations for each independent variable are shown in Table 3.

Table 3. Summary statistics by outcome for Fitch Naïve Bayes Model

Independent variable	**Less stable**		**More stable**	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**
REER	82.7255	6.7467	91.1041	7.1203
PIR	13.1186	3.1538	10.7946	2.0907
BOP	33442.88	33921.41	-6131.07	45460.61
CAB	-17542.27	24331.03	-25936.72	17719.72
UR	25.9577	1.8020	24.5302	1.7430
GDPpc	2.0721	1.4872	3.0116	2.0780
HDDI	63.0039	9.5872	76.0047	9.7371
CPIH	71.1053	29.8064	68.2973	13.4595
FDGDP	13.3364	4.2088	11.9275	1.9254

Source: Authors' own preparation

Looking at Table 3, it can be noted that the variables REER, GDPpc and HDDI have high means when the index is more stable whereas PIR, BOP, CAB, UR, CPIH and FDGDP have lower mean values when the index is more stable. The findings agree with the analysis done by Mellios and Paget-Blanc (2006) and Chee *et al.* (2015) and concluded that exchange rates are one of the variables used by rating agencies to measure a country's creditworthiness. The results are consistent with findings by Bissoondoyal-Bheenick (2005); Mellios and Paget-Blanc (2006); Iyengar (2010); Afonso *et al.* (2011); Arefjevs and Brasliņs (2013); Sánchez-Monedero *et al* (2014); Kabadayi and Celik (2015); Ivanovic *et al.* (2015); Chee *et al*. (2015); De Moor *et al.* (2018); and Cantor and Packer (1996) that GDP growth is a crucial variable in determining sovereign credit ratings. The confusion matrix for the train and test data are shown in Table 4.

Table 4. Confusion matrix for Fitch

	Train Data		Test Data	
	Level of stability		Level of stability	
Observed	**More stable**	**Less stable**	**More Stable**	**Less Stable**
More stable	39	1	7	0
Less stable	4	25	0	4
Percentage misclassified	0.0725		0.0000	

Source: Authors' own preparation

For the train data the true positive for class 1 = "More stable" was 39 whereas false positive was 1, for class 0 = "Less stable", true positives was 25 and false positive was 4 for the train data. The correctly classified observations for the train data was 92.75% whereas the percentage misclassified was 7.25%. For the test data, all the observations were properly classified. This was a good fit since percentage of misclassification is low. When the model with Kernel smoothing was done, the confusion matrix is shown in Table 5.

Table 5. Confusion matrix for Fitch mode with Kernel smoothing

	Train Data		Test Data	
	Level of stability		Level of stability	
Observed	**More stable**	**Less stable**	**More Stable**	**Less Stable**
More stable	40	1	7	0
Less stable	3	25	0	4
Percentage misclassified	0.0580		0.0000	

Source: Authors' own preparation

For the train data the true positive for class 1 = "More stable" was 40 whereas false positive was 1, for class 0 = "Less stable", true positives was 25 and false positive was 3 for the train data. The correctly classified observations for the train data was 94.2% whereas the percentage misclassified was 5.8%. For the test data, all the observations were properly classified. Use of the Kernel smoothing increased the classification rate by almost 2%. The error rate using Fitch data was less than 6%.

4.3. Naïve Bayes Model for Moody's

The boxplots obtained of the distribution of variables by outcome are shown in Figure 3.

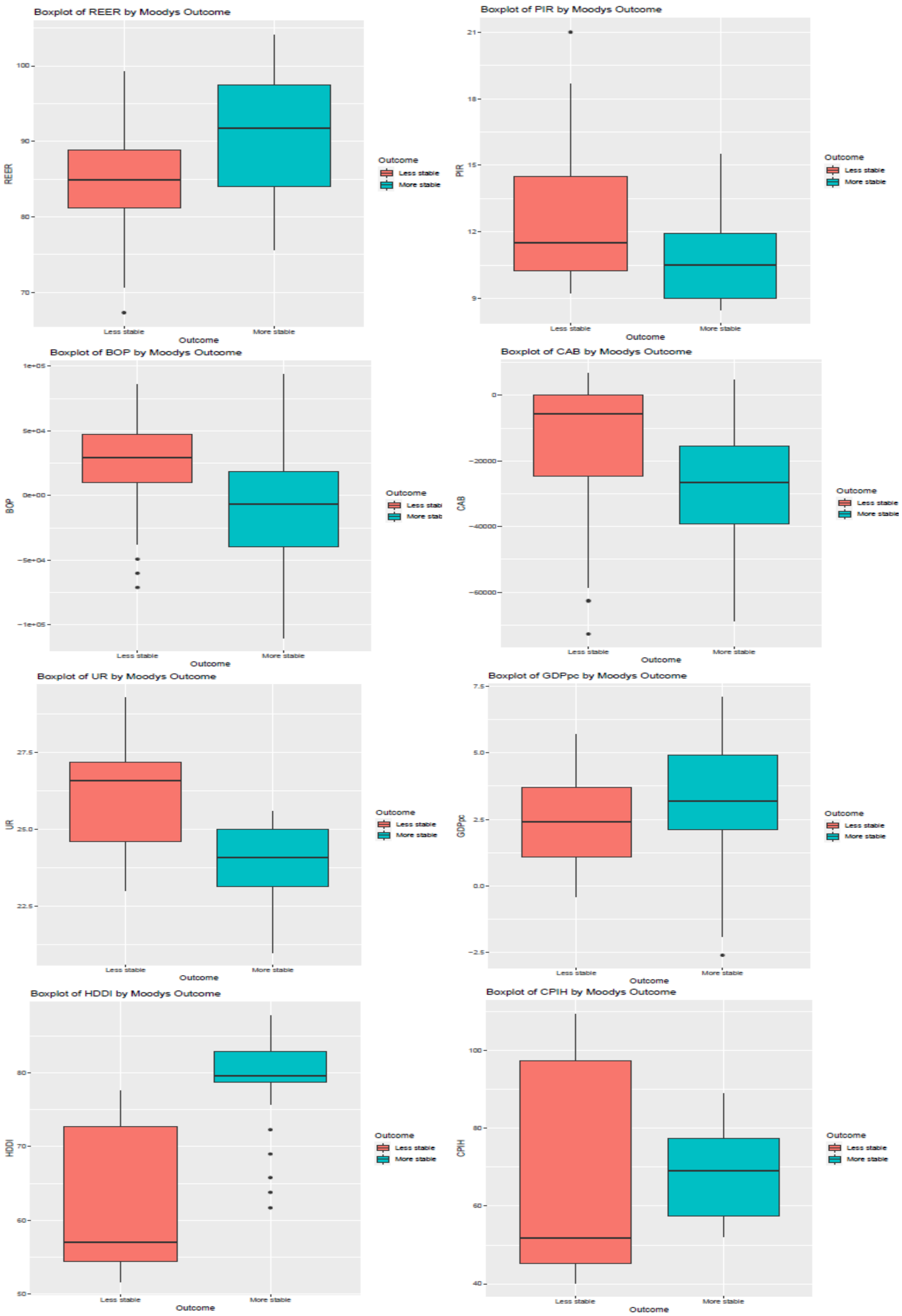

Figure 3. Moodys Boxplots for the Independent Variables by Outcome

Source: Authors' own preparation

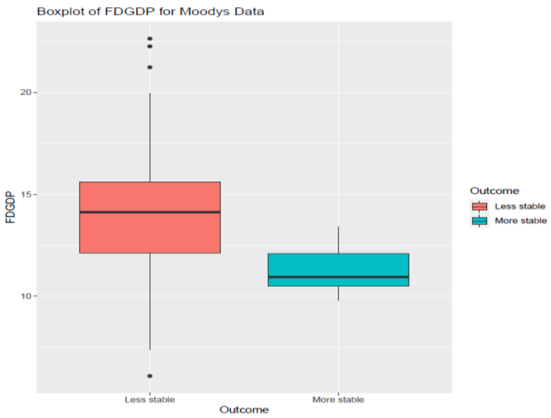

Figure 3. Continued

A classification model can be developed since for all the variables, the values show different medians for less stable and for more stable. The variables REER, GDPpc and HDDI showed that high values favored the rating being more stable whereas for the variables PIR, BOP, CAB UR, CPIH and FDGDP high values were associated with those less stable. The variables BOP, UR and HDDI showed not much overlap between the less stable and the more stable suggesting that there will not be a lot of misclassification on these variables. However, the variable CPIH showed a lot of overlap indicating that there is potential of many observations being misclassified. A Naïve Bayes model was then fitted, and the prior probabilities were obtained in Table 6.

Table 6. Prior probabilities for the Moodys data

Probabilities	**Less stable**	**More stable**
Priori probabilities	0.5362	0.4638

Source: Authors' own preparation

The probability that a quarterly index is less stable was 0.54 and 0.46 for more stable for the Moody's data. It can be concluded that for the Moody's data, most of the quarterly indices fall under less stable. The means and standard deviations for each independent variable are shown in Table 7.

Table 7. Summary statistics by outcome for Moodys Naive Bayes Model

Independent variable	**Less stable**		**More stable**	
	Mean	**Standard deviation**	**Mean**	**Standard deviation**
REER	84.9026	7.6808	91.4670	7.0518
PIR	12.6036	3.0063	10.5911	2.0071
BOP	21638.27	36897.716	-6085.531	50398.767
CAB	-18514.73	22991.60	-27697.91	16706.28
UR	25.9729	1.8726	24.0219	1.2730
GDPpc	2.3459	1.5331	3.0188	2.2615
HDDI	63.3216	9.6472	80.1063	5.1865
CPIH	69.5692	27.0548	69.1082	10.7654
FDGDP	13.6092	3.6988	11.1274	1.0242

Source: Authors' own preparation

The variables REER, GDPpc and HDDI have high means when the index is more stable where as PIR, BOP, CAB, UR, CPIH and FDGDP have lower mean values when the index is more stable. The findings agree with the analysis done by Mellios and Paget-Blanc (2006) and Chee *et al.* (2015) and concluded that exchange rates are one of the variables used by rating agencies to measure a country's creditworthiness. The results are consistent with findings by Bissoondoyal and Bheenick (2005); Mellios and Paget-Blanc (2006); Iyengar (2010); Afonso *et al.* (2011); Arefjevs and Brasliņs (2013); Sánchez-Monedero *et al.* (2014); Kabadayi and Celik (2015); Ivanovic *et al.* (2015); Chee *et al.* (2015); De Moor *et al.* (2018); and Cantor and Packer (1996) that GDP growth is a crucial variable in determining sovereign credit ratings. For CPIH, there seems to be less difference between the means for less stable and those for more stable. The confusion matrix for the train and test data are shown in Table 8.

Table 8. Confusion matrix for Moodys

	Train Data		Test Data	
	Level of stability		Level of stability	
Observed	**More stable**	**Less stable**	**More Stable**	**Less Stable**
More stable	31	3	6	0
Less stable	1	34	1	4
Percentage misclassified	0.0580		0.0909	

Source: Authors' own preparation

For the train data the true positive for class 1 = "More stable" was 31 whereas false positive was 3, for class 0 = "Less stable", true positives was 34 and false positive was 1 for the train data. The correctly classified observations for the train data was 94.2% whereas the percentage misclassified was 5.8%. For the test data, the percentage correctly classified was 90.91% whereas those misclassified was 9.09%. The fit was better for the train data than for the test data. When the model with Kernel smoothing was fitted to the Moody's data, the confusion matrix is shown in Table 9.

Table 9. Confusion matrix for Moody's model with Kernel smoothing

	Train Data		Test Data	
	Level of stability		Level of stability	
Observed	**More stable**	**Less stable**	**More Stable**	**Less Stable**
More stable	32	3	6	0
Less stable	0	33	1	4
Percentage misclassified	0.0580		0.0909	

For the train data the true positive for class 1 = "More stable" was 32 whereas false positive was 3, for class 0 = "Less stable", true positives was 33 and false positive was 0 for the train data. The correctly classified observations for the train data were 94.2% whereas the percentage misclassified was 5.8%. For the test data, the percentage correctly classified was 90.91% whereas those misclassified was 9.09%. The fit was better for the train data than for the test data. The error rate using Moody's data was less than 6% which is good.

4.4. Naïve Bayes model for SNPoor

The boxplots obtained for the distribution of variables by outcome are shown in Figure 4.

Figure 4. SNPoor Boxplots for the Independent Variables by Outcome
Source: Authors' own preparation

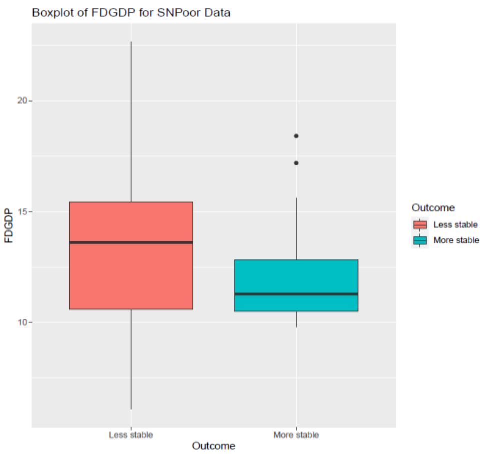

Figure 4. Continued

A classification model can be developed since for all the variables the values show different medians for less stable and for more stable. The variables REER, GDPpc and HDDI showed that high values favored the rating being more stable whereas for the variables PIR, BOP, CAB UR, CPIH and FDGDP high values were associated with those less stable. The variables REER and BOP showed not much overlap between the less stable and the more stable suggesting that there will not be a lot of misclassification on these variables. However, the variable CAB and CPIH showed a lot of overlap indicating that there is potential of many observations being misclassified. A Naïve Bayes model was then fitted, and the prior probabilities were obtained in Table 10.

Table 10. Prior probabilities for the SNPoors data

Probabilities	Less stable	More stable
Priori probabilities	0.4638	0.5362

Source: Authors' own preparation

The probability that a quarterly index is less stable was 0.46 and 0.54 for more stable for the SNPoors data. It can be concluded that for the SNPoors data most of the quarterly indices fall under more stable. The means and standard deviations for each independent variable are shown in Table 11.

Table 11. Summary statistics by outcome for SNPoors Naive Bayes Model

Independent variable	Less stable		More stable	
	Mean	Standard deviation	Mean	Standard deviation
REER	82.3832	6.1223	92.7588	6.2262
PIR	12.3932	3.2216	11.0450	2.1526
BOP	18533.7812	45731.1961	345.8919	44232.3258
CAB	-22943.47	25261.66	-22626.68	16111.46
UR	25.8438	1.6594	24.3973	1.8298
GDPpc	1.9906	1.3686	3.3251	2.1492
HDDI	65.6906	10.3236	75.7892	10.4944
CPIH	74.6585	27.8133	64.7690	10.9134
FDGDP	13.1156	3.8203	11.8897	2.0581

Source: Authors' own preparation

The variables REER, CAB, GDPpc and HDDI have high means when the index is more stable where as PIR, BOP, UR, CPIH and FDGDP have lower mean values when the index is more stable. The findings agree with the analysis done by Mellios and Paget-Blanc (2006) and Chee *et al*. (2015) and concluded that exchange rates are one of the variables used by rating agencies to measure a country's creditworthiness. For CAB, there seems to be less difference between the means for less stable and those for more stable. CAB showed a lot of overlap indicating that there is potential of many observations being misclassified. The results are consistent with findings by Bissoondoyal and Bheenick (2005); Mellios and Paget-Blanc (2006); Iyengar (2010); Afonso *et al.* (2011); Arefjevs and Brasliņs (2013); Sánchez-Monedero *et al* (2014); Kabadayi and Celik (2015); Ivanovic *et al.* (2015); Chee *et al*. (2015); De Moor *et al.* (2018) and Cantor and Packer (1996) that GDP growth is a crucial variable in determining sovereign credit ratings. The confusion matrix for the train and test data are shown in Table 12.

Table 12. Confusion matrix for SNPoors

	Train Data		Test Data	
	Level of stability		Level of stability	
Observed	**More stable**	**Less stable**	**More Stable**	**Less Stable**
More stable	33	1	6	0
Less stable	4	31	1	4
Percentage misclassified	0.0725		0.0909	

Source: Authors' own preparation

For the train data the true positive for class 1 = "More stable" was 33 whereas false positive was 1, for class 0 = "Less stable", true positives was 31 and false positive was 4 for the train data. The correctly classified observations for the train data was 92.75% whereas the percentage misclassified was 7.25%. For the test data, the percentage correctly classified was 80.91% whereas those misclassified was 9.09%. The fit was better for the train data than for the test data. When the model with Kernel smoothing was fitted to the SNPoors data, the confusion matrix is shown in Table 13.

Table 13. Confusion matrix for SNPoors Model with Kernel smoothing

	Train Data		Test Data	
	Level of stability		Level of stability	
Observed	**More stable**	**Less stable**	**More Stable**	**Less Stable**
More stable	36	0	7	0
Less stable	1	32	0	4
Percentage misclassified	0.0145		0.0000	

Source: Authors' own preparation

For the train data the true positive for class 1 = "More stable" was 36 whereas false positive was 1, for class 0 = "Less stable", true positives was 32 and false positive was 0 for the train data. The correctly classified observations for the train data were 98.55% whereas the percentage misclassified was 1.45%. For the test data, the percentage correctly classified was 100% whereas those misclassified was 0%. The fit was very good for the test data than for the train data. The error rate using SNPoors data was less than 2%, which is quite good and thus, the SNPoors classification was quite high.

4.5. Summary of findings

The Machine-learning tool Naïve Bayes models can classify economic variables used in rating sovereigns with precision. Naïve Bayes managed to classify the given variables using the two SCR categories that is more stable and less stable. More stable ratings signify improving, high or upgrading ratings and less stable signifies the opposite. Variables classified under more stable indicates that ratings are high or favorable and those for less stable show unfavorable or low ratings. The model highlighted variables that influence ratings under more stable scenario and those that influence less stable ratings or downgrades. For Fitch variables that induce more stable ratings were REER, GDPpc, HDDI and CPIH whereas PIR, BOP, CAB, UR and FDGDP were inducing less stable ratings. Moody's' more stable ratings were supported by REER, GDPpc and HDDI and the less stable ratings were induced by PIR, BOP, CAB, UR, CPIH, and FDGDP. The study found that Credit Rating Agencies (CRA) use different macroeconomic variables to assess and assign sovereign ratings. The only variable that had problems of overlapping was CPIH for both Fitch and Moody's ratings. S&P ratings had similar classification as the Moody's but the only difference was that CAB was the overlapping variable.

5. Conclusion

The Naïve Bayes Classification Machine Learning model captured the relationship between SCR and economic indicators by clearly identifying crucial determinants of SCR. The findings imply that for sovereigns to avoid rating downgrades they should control household debt to favorable levels, reduce inflation, mitigate exchange rate risks and continuously maintain growth in GDP. The results confirm the findings by Bennell *et al.* (2006); Kumar and Haynes (2003); and Kraussl, (2005) and Cantor and Packer (1996), that sovereign ratings effectively summarize and supplement the information contained in macroeconomic indicators and are therefore strongly correlated with market-determined credit spreads. Lack of data on some variables like corruption, governance and so on affected the depth of the analysis. In Africa, data is not readily available to conduct a feasible research and productive analysis. Bank data are highly concealed, confidential and private to protect the financial sector hence not accessible to researchers. Data is focused on one specific nation, South Africa, which might have unique characteristics or conditions than other countries. Machine Learning models have weaknesses of misclassification and overfitting which might not precisely be corrected by cross validation. Further studies must incorporate non-quantitative variables like governance, corruption, political stability and effective management of government institutions. New models should be applied that are not affected by weaknesses observed in machine learning like overfitting data and misclassification.

References

Afonso, A., 2003. Understanding the determinants of sovereign debt ratings: Evidence for the two leading agencies. *Journal of Economics and Finance,* 27(1), pp. 56-74. https://doi.org/10.1007/BF02751590

Afonso, A., Gomes, P. and Rother, P., 2011. Short-and long-run determinants of sovereign debt credit ratings. *International Journal of Finance & Economics*, 16(1), pp. 1-15. https://doi.org/10.1002/ijfe.416

Archer, C.C., Biglaiser, G. and DeRouen, K, Jr., 2007. Sovereign bonds and the democratic advantage. does regime type affect credit rating agency ratings in the developing world? *International Organization*, 61(2), pp. 341-365. https://doi.org/10.1017/S0020818307070129

Arefjevs, I. and Brasliņs, G., 2013. Determinants of sovereign credit ratings – example of Latvia. *New Challenges of Economic and Business Development* C41, H30

Azeem, M. I., Palomba, F., Shi, L. and Wang, Q., 2019. Machine learning techniques for code smell detection. *A systematic literature review and meta-analysis. Information and Software Technology*, 108, pp. 115-138. https://doi.org/10.1016/j.infsof.2018.12.009

Bellotti, T., Matousek, R. and Stewart, C., 2011. A note comparing support vector machines and ordered choice models' predictions of international banks' ratings. *Decision Support System*. 51(3), pp. 682–687. https://doi.org/10.1016/j.dss.2011.03.008

Bennell, J. A., Crabbe, D., Thomas, S. and Ap Gwilym, O., 2006. Modelling sovereign credit ratings: Neural networks versus ordered probit. *Expert systems with applications*, 30(3), pp. 415-425. https://doi.org/10.1016/j.eswa.2005.10.002

Berrar, D., 2018. Bayes' theorem and naive Bayes classifier. *Encyclopedia of Bioinformatics and Computational Biology*, 1, pp. 403-412. https://doi.org/10.1016/B978-0-12-809633-8.20473-1

Bhatia, A. V., 2002. *Sovereign credit ratings methodology: An evaluation*. IMF Working Paper 02/170, IMF. https://doi.org/10.5089/9781451858433.001

Bissoondoyal-Bheenick, E., 2005. An analysis of the determinants of sovereign ratings. *Global Finance Journal*, 15(3), pp. 251-280. https://doi.org/10.1016/j.gfj.2004.03.004

Butler, A. W. and Fauver, L., 2006. Institutional environment and sovereign credit rating. *Financial Management*, 35(3), pp. 53-79. https://doi.org/10.1111/j.1755-053X.2006.tb00147.x

Cantor, R. and Packer, F., 1994. The credit rating industry. *Federal Reserve Bank of New York Quarterly Review*, 19(2), pp. 1-26.

Cantor, R. and Packer, F., 1996. Determinants and impact of sovereign credit ratings. *FRBNY Economic Policy Review* October, pp. 37-54. https://doi.org/10.2139/ssrn.1028774

Chee, S. W., Fah, C. F. and Nassir, A. M., 2015. Macroeconomics determinants of sovereign credit ratings. *International Business Research*, 8(2), pp. 42-57. https://doi.org/10.5539/ibr.v8n2p42

Committee on the Global Financial System (CGFS), 2011. *Interactions of sovereign debt management with monetary conditions and financial stability*. CGFS Papers, no 42, Basel.

De Moor, L., Luitel, P., Sercu, P. and Vanpee, R., 2018. Subjectivity in sovereign credit ratings. *Journal of Banking & Finance*, 88, pp. 366-392. https://doi.org/10.1016/j.jbankfin.2017.12.014

Erdem, O. and Varli, Y., 2014. Understanding the sovereign credit ratings of emerging markets. *Emerging Markets Review*, 20, pp. 42-57. https://doi.org/10.1016/j.ememar.2014.05.004

Ferri, G., Liu, L.G. and Majnoni, G., 2001. The role of rating agency assessments in less developed countries. impact of the proposed Basel guidelines. *Journal of Banking & Finance*, 25(1), pp. 115-148. https://doi.org/10.1016/S0378-4266(00)00119-9

Ferri, G., Liu, L.G. and Stiglitz, J. E., 1999. The procyclical role of rating agencies. evidence from the *East Asian crisis: Economic Notes*. 28(3), pp. 335-355. https://doi.org/10.1111/1468-0300.00016

Gaillard, N., 2006. Determinants of Moody's and S&P's sub-sovereign credit ratings. *World Bank*.

Gogas, P., Papadimitriou, T., and Agrapetidou, A., 2014. Forecasting bank credit ratings. *Journal of Risk Finance*, 15(2), pp. 195-209. https://doi.org/10.1108/JRF-11-2013-0076

Gultekin-Karakas, D., Hisarciklilar, M. and Ozturk, H. 2011. Sovereign risk ratings. biased toward developed countries? *Emerging Markets Finance and Trade*, 47(sup2), pp. 69-87. https://doi.org/10.2753/REE1540-496X4703S204

He, J., Zhang, Y., Li, X. and Shi, P., 2012. Learning naive Bayes classifiers from positive and unlabelled examples with uncertainty. *International journal of systems science*, 43(10), pp. 1805-1825. https://doi.org/10.1080/00207721.2011.627475

Hill, P., Brooks, R. and Faff, R., 2010. Variations in sovereign credit quality assessment across rating agencies. *Journal of Banking & Finance* 34(6), pp. 1327-1343. https://doi.org/10.1016/j.jbankfin.2009.11.028

Hu, Y. T., Kiesel, R. and Perraudin, W., 2002. The estimation of transition matrices for sovereign credit ratings. *Journal of Banking & Finance*, 26(7), pp. 1383-1406. https://doi.org/10.1016/S0378-4266(02)00268-6

Ivanovic, Z., Bogdan, S. and Baresa, S. 2015. Modeling and estimating shadow sovereign ratings. *Contemporary Economics*, 9(3), pp. 367-384. https://doi.org/10.5709/ce.1897-9254.175

Iyengar, S., 2010. Are Sovereign Credit Ratings Objective and Transparent? *IUP Journal of Financial Economics*, 8(3), pp. 7-22.

Kabadayi, B. and Çelik, A., 2015. Determinants of sovereign ratings in emerging countries. a qualitative, dependent variable panel data analysis. *International Journal of Economics and Financial Issues*, 5(3), pp. 656-662.

Keller, H. B., 2018. *Numerical methods for two-point boundary-value problems*. Mineola, NY: Courier Dover Publications.

Kraussl, R., 2003. *Do changes in sovereign credit ratings contribute to financial contagion in emerging market crises?* CFS Working Paper, No. 2003/22. https://doi.org/10.2139/ssrn.473262

Kraussl, R., 2005. Do credit rating agencies add to the dynamics of emerging market crises? *Journal of Financial Stability*, 1(3), pp. 355-385. https://doi.org/10.1016/j.jfs.2005.02.005

Krichene, A., 2017. Using a naive Bayesian classifier methodology for loan risk assessment. *Journal of Economics*, *Finance and Administrative Science,* 22(42), pp. 3-24. https://doi.org/10.1108/JEFAS-02-2017-0039

Kumar, K. and Haynes, J. D., 2003. Forecasting credit ratings using an ANN and statistical techniques. *International Journal of Business Studies*, 11(1), pp. 91-108.

Mahomed Karodia, A. and Soni, D., 2014. South African economic woes: Poor political leadership and rating downgrades hampers growth and development. *Management Studies and Economic Systems,* 1(1), pp. 51-66. https://doi.org/10.12816/0006205

Mellios, C. and Paget-Blanc, E., 2006. Which factors determine sovereign credit ratings? *The European Journal of Finance*, 12(4), pp. 361-377. https://doi.org/10.1080/13518470500377406

Mitchell, T. M., 2010. Generative and discriminative classifiers. Naive Bayes and logistic regression. *Machine learning*, pp. 1-17.

Mohammed, M., Khan, M. B. and Bashier, E. B. M., 2016. *Machine learning. algorithms and applications.* Boca Raton: Crc Press. https://doi.org/10.1201/9781315371658

Mora, N., 2006. Sovereign credit ratings. Guilty beyond reasonable doubt? *Journal of Banking & Finance*, 30, pp. 2041-2062. https://doi.org/10.1016/j.jbankfin.2005.05.023

Mutize, M. and Nkhalamba, M. M., 2020. The impact of sovereign credit rating changes on government bond yields in South Africa. *International Journal of Sustainable Economy*, 12(1), pp. 81-100. https://doi.org/10.1504/IJSE.2020.107860

Novotná, M., 2012. The use of different approaches for credit rating prediction and their comparison, 6th *International Scientific Conference Managing and Modelling of Financial Risks* (pp. 448-457), Ostrava.

Osobajo, O. A. and Akintunde, A. E., 2019. Determinants of sovereign credit ratings in emerging markets. *International Business Research*, 12(5), pp. 142-166. https://doi.org/10.5539/ibr.v12n5p142

Ozturk, H., Namli, E. and Erdal, H. I., 2016. Modelling sovereign credit ratings. The accuracy of models in a heterogeneous sample. *Economic Modelling*, 54, pp. 469-478. https://doi.org/10.1016/j.econmod.2016.01.012

Polito, V. and Wickens, M. R., 2013. Sovereign credit ratings in the European Union. *A model-based view. Mimeo*.

Pretorius, M. and Botha, I., 2016. A panel ordered response model for sovereign credit ratings in Africa. *African Finance Journal*, 18(1), pp. 20-33.

Ratha, D., De, P. K. and Mohapatra, S., 2011. Shadow sovereign ratings for unrated developing countries. *World Development*, 39(3), pp. 295–307. https://doi.org/10.1016/j.worlddev.2010.08.006

Reinhart, C. M., 2002. *Default, currency crises and sovereign credit ratings.* NBER WP 8738. https://doi.org/10.3386/w8738

Sanchez-Monedero, J., Gutierrez, P. A., Fernandez-Navarro, F. and Hervas-Martinez, C., 2011. Weighting efficient accuracy and minimum sensitivity for evolving multi-class classifiers, neural process. *Letters*, 34(2), pp. 101-116. https://doi.org/10.1007/s11063-011-9186-9