
| RESEARCH ARTICLE

Predicting Countries Credit Ratings with Institutional Performance

Anas Moussaid Elidrissi

PhD Student, Hantos Elemér Doctoral School of Business, Management and Regional Sciences, University of Miskolc, Miskolc, Hungary.

Corresponding Author: Anas Moussaid Elidrissi, **E-mail:** mou.el.anas@gmail.com

| ABSTRACT

In order to widen the vision and to visualize the impact of the institutions on not only economic growth as traditionally used but also on the Credit Ratings of countries, this experiment studies the correlation between these two attributes. In this paper, I show how we can find the relationship between the credit ratings of countries and the performance of their institutions. In this study, I used a data set of countries and indicators of their performance on institutional indicators, such as property rights, judicial effectiveness ...etc. And I conclude at the end that there is a strong correlation between an effective institution and a higher rating in credits report that is done by the major firms in this area. Also, I mention the limitation of this experiment in the matter of credibility.

| KEYWORDS

Institutional Economics, Credit Ratings, Growth, Machine Learning

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1. Introduction

With the development of institutional economics, institutions were proven that it is the essence of steady economic growth. The idea of this paper started from the relationship between credit ratings and institutions and if there is a direct impact on such ratings.

These ratings show the likelihood of a borrower defaulting within a year is reflected in a short-term credit rating. In recent years, this form of credit rating has become the norm, whereas, in the past, long-term credit ratings were given more weight. Long-term credit ratings forecast the likelihood of a borrower defaulting at any point in the foreseeable future. A speculative-grade or junk bond is a debt instrument with a rating below BB, indicating that it is more likely to fail on loans.

This can directly damage or shine your economy for investors. In other words, the flow of the Foreign direct investment in the country, which is for most the developing countries, is the main source of foreign currencies.

As doubted in many previous kinds of literature, these ratings sometimes get subject to the influence of the all-time good students. However, in this article, there won't be a cross-check of the credibility of these ratings, but there will be a study to find the relationship between effective institutions and higher ratings that are done by the major firms.

In the upcoming chapters of this article, a background study will be done in order to understand the importance of institutions in old and new institutional economics.

Machine learning models will be used in this research to predict credit ratings of countries based on the performance of their institutions. I will use GLMBoost, XGBoost, and Sequential Minimal Optimization models to assess categorization success, feeding CAMELS data from the banks into each model. SMO is a simplified and quicker form of Support Vector Machine, while XGBoost and GLMBoost are also gradient boosting algorithms.

2. Literature Review

In the old institutional economics -Economics should become an evolutionary science, concerned with the change of institutions – (Veblen's 1870). thus, many economists advised that countries should race to develop their institutions, and the new institutional economics arose to strengthen this, "Economic calculation can only take place by means of money prices established in the market for the productions goods in a society resting on private property in the means of production." (Ludwig Von Mises, Socialism, 1953) making the institution -Property Right- the most important. In addition, Acemoglu reinforces this by - Inclusive institutions, including secure property rights, law and order, state support for markets; free entry of new businesses; « level playing field » as they are linked to political democracy (Acemoglu, 2008) and include judicial effectiveness along with property right, and -institutions- being the main factors to lead the modern economic region.

With that being said, institutions remain a vital component of economic growth if they are implemented in the right way. The country credit risk rating is one of the indexes that private firms – The big 3 - evaluate every country according to its key performance indicator in order to present a rating that's taken into account by many multi-national firms, investors and asset holders to enlighten their decision-making process.

Credit ratings are forward-looking opinions about the ability and willingness of debt issuers, like corporations or governments, to meet their financial obligations on time and in full. They provide a common and transparent global language for investors and other market participants, corporations and governments and are one of many inputs they can consider as part of their decision-making processes.

Surely the credit rating and institutions do make perfect sense and are vital for these firms to rank the countries, political stability being the most factor taken into consideration, especially for investors. Not to downgrade the standing of any of the other institutions, For such reasons and more, this article comes to explain how countries can manage their "non-important" institutions in order to get ranked, or at least catch up with the developed economies, and not follow the obvious way for this matter.

However, These ratings get many critiques, especially after the collapse in 2008 (Huseyin Ozturk, 2014) (Fatih Bahadir Haspolat, 2015), (Prashant Ubarhande & Arti Chandani, 2021), (John Ryan, 2012), as these firms are influenced by the giant economies, and this implies on the poor and emerging countries, making their improvement and hard work down the drain, or by the old methodology, as many propose new machine learning models to analyze, review and list countries.

As we are not going through the proposition for new models, we are going to limit the scope of this article to analyze and predict the credit rating by running models in machine learning that will focus on the 5 attributes, freedom indices and property rights.

3. Data

The data used in this article was retrieved from the Organization, Our World in Data 2021. Only five indicators were taken in this study: Property rights, Judicial effectiveness, Government Integrity, Business and Financial Freedom.

4. Methodology

For the data processing studies, I used WEKA 3.9.5 (Waikato Environment for Knowledge Analysis). WEKA already has Sequential Minimal Optimization in its package; however, for XGBoost and GLMBoost, we used the R extension of WEKA, which allows analysis to be done in WEKA but techniques to be run in R Console. As a result, the study requires the installation of the R programming language on the computer.

4.1 SVM – SMO

The Sequential Minimal Optimization model was defined by Platt (1998) as a simple approach that can handle the Support Vector Machines quadratic programming problem fast and without the use of any numerical QP optimization steps.

At each step, SMO solves the smallest potential optimization problem. Because the Lagrange multipliers must follow a linear equality requirement, the shortest possible optimization problem for ordinary SVM QP problems comprises two Lagrange multipliers. As a result, SMO has the benefit of being able to solve two Lagrange multipliers analytically. Even though the method solves more subproblems, each subproblem is solved so swiftly that the overall QP problem is solved quickly.

4.2 XGBOOST :

Tianqi Chen designed it in 2014 as an application of gradient boosting machines. Its parallel tree reinforcement capabilities make it substantially quicker than other tree-based ensemble techniques, and it was designed for efficiency and scalability. (Quinto,2020)

The following are the properties of XGBoost as defined by the Analytics Vidhya Content Team (2018):

- Complex models can be penalized using both L1 and L2 regularization in the model. As a result, overfitting is avoided.

•XGBoost contains a distributed weighted quantile sketch algorithm to effectively handle weighted data, as well as a sparsity-aware split finding technique to manage different sorts of sparsity patterns in the data.

4.3 Random Forest:

Random forest is a versatile, easy-to-use machine learning technique that, in most cases, gives excellent results even without hyper-parameter adjustment. Because of its simplicity and versatility, it is also one of the most widely used algorithms (it can be used for both classification and regression tasks). We'll look at how the random forest algorithm works, how it varies from other algorithms, and how to use it in this post.

It is a learning algorithm that is supervised. It creates a "forest" out of an ensemble of decision trees, which are commonly trained using the "bagging" method. The bagging method's basic premise is that combining several learning models improves the overall output.

4.3.1 Logistic Regression:

Logistic regression is a statistical model that uses a logistic function to represent a binary dependent variable in its most basic form, though there are many more advanced variants. Logistic regression (or logit regression) is a method of estimating the parameters of a logistic model in regression analysis (a form of binary regression).

5. Results and Discussion

Logistic regression, as one of the most conventional classification models, successfully classified 50% of the instances correctly, while AUC stands around 70%. Furthermore, when we breakdown the classification performance of each class, we used the Recall rate, and it goes as follows:

- 29% of the entrances were successfully classified as Prime's.
- 40% of the entrances were successfully classified as High.
- 64% of the entrances were successfully classified as Medium.
- 57% of the entrances were successfully classified as Low.

SMO, as a simpler version of SVM, correctly classified %60 of the instances correctly, while AUC stands around 80%. Furthermore, when we breakdown the classification performance of each class,

- 0% of the entrances were successfully classified as Prime's.
- 80% of the entrances were successfully classified as High.
- 71% of the entrances were successfully classified as Medium.
- 71% of the entrances were successfully classified as Low.

LogitBoost, as a boosting method developed on logistic regression, successfully classified 68% of the total instances successfully, while AUC stands around 87%. Furthermore, when we breakdown the classification performance of each class,

- 57% of the entrances were successfully classified as Prime's.
- 30% of the entrances were successfully classified as High.
- 93% of the entrances were successfully classified as Medium.
- 86% of the entrances were successfully classified as Low.

XGBoost as one of the most recently developed algorithms, correctly classified %57 of the instances correctly, while AUC stands around %79. Furthermore, when we breakdown the classification performance of each class,

- 71% of the entrances were successfully classified as Prime's.
- 50% of the entrances were successfully classified as High.
- 64% of the entrances were successfully classified as Medium.
- 43% of the entrances were successfully classified as Low.

RandomTree, as one of the robust and recent models, correctly classified 63% of the instances correctly, while AUC stands around 75%. furthermore, when we breakdown the classification performance of each class,

- 57% of the entrances were successfully classified as Prime's.
- 50% of the entrances were successfully classified as High.
- 64% of the entrances were successfully classified as Medium.
- 86% of the entrances were successfully classified as Low.

5.1 Risk Weighted Results:

Weight Coefficient	Random	XGBoost	Logit	SMO	Logistic
0.1	0.57	0.71	0.57	0	0.29
0.2	0.5	0.5	0.3	0.8	0.4
0.3	0.64	0.64	0.93	0.71	0.64
0.4	0.86	0.43	0.86	0.71	0.57
1 Weight	0.057	0.071	0.057	0	0.029
2 Weight	0.1	0.1	0.06	0.16	0.08
3 Weight	0.192	0.192	0.279	0.213	0.192
4 Weight	0.344	0.172	0.344	0.284	0.228
Risk-Weighted Score	0.693	0.535	0.74	0.657	0.529

When explaining the findings, I find it important to re-adjust the model successes by allocating risk ratios to each result. Our method to do so was giving weights to each score which would sum up to 1 when all added up together. We allocated the biggest coefficient to the riskiest country group with a low credit rating, while we allocated the least coefficient to the prime credit rating. Our purpose hence is to make sure that we correctly assess the model that successfully classifies risky groups from the most successful groups because it is important to predict financial and economic turbulences and understand what affects them in which direction.

With that being in mind, we can say that our most successful model is Logit Boost, followed by Random Forest, SMO, XG Boost and finally, Logistic Regression. The results show us that conventional models so far do not seem to be the best models to predict credit ratings, and we should focus on mostly boosting methods and methodology to successfully classify the country risks by freedom measures or ratios.

6. Conclusion

Starting with the idea of the relationship between institutions and credit ratings, I could show the correlation between these two attributes, and a prediction could be made using the institutional indicators for the credit rating of countries.

At the end of this experiment, we can support NIE research done on the matter of economic growth. Based on the results of this paper, we can simply say that countries having efficient and effective institutions would reflect not only on the economic growth but also on indices such as Credit ratings,

Which is new in the ways of the impact of institutions on a country. I truly believe that this would be very beneficial for research and also on a country level.

Also, using these models shows the weight₁ of indicators: Property rights, Judicial Effectiveness, Government Integrity, Business and Financial Freedom have the highest impact; therefore, we can assess a country's credit rating by only verifying its freedom - Institutions- related indicators.

Not to only ensure continuous economic growth but also to show up for the rest of the world, a country should work simultaneously on improving its institutions. Its impact would come later as a butterfly effect.

Even though I stated that this has this limitation of the influence of the big firms, the accuracy of the data...etc., it's a heads-up and a reminder for countries to implement changes on the correct pillars.

Of course, I did not question the credibility of these companies' rankings, which is a limitation of this paper at this stage. For future research, I would advise showing the relationship between institutions and other key performance indicators of countries, so we can at some point measure the real impact of institutions.

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Appendix:

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=== Attribute Selection on all input data ===

Search Method:
  Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 15 Credit):
  Gain Ratio feature evaluator

Ranked attributes:
0.724  3 Government Integrity
0.625  1 Property Rights
0.615  2 Judicial Effectiveness
0.437  7 Business Freedom
0.434 12 Financial Freedom
0      11 Investment Freedom
0      10 Trade Freedom
0      9 Monetary Freedom
0      4 Tax Burden
0      5 Govt Spending
0      6 Fiscal Health
0      13 Income Tax Rate
0      8 Labor Freedom
0      14 Corporate Tax Rate

Selected attributes: 3,1,2,7,12,11,10,9,4,5,6,13,8,14 : 14
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1: Weight of each indicator on predicting the credit ratings of countries.