Reconstruction Rating Model of Sovereign Debt by Logical Analysis of Data

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ABSTRACT

Here this thesis follows two distinct objectives. First, it reconstructs the rating system of the Fitch credit agency. Second, it analyses the role played by the COVID-19 pandemic on the Fitch agency`s sovereign debt rating. Dataset and main features of both objects were collected by the World Bank (WB) and the International Monetary Fund (IMF). Out of 250 countries, after feature engineering, 67 countries have been trained to figure out the hidden patterns of different ratings and to verify the result, 39 countries were studied as the test set for the thesis. Reconstructed patterns of each rating have been demonstrated as decision trees. The Logical Analysis of Data as a supervised learning technique classifies the countries into 16 labels of the Fitch rating agency.

The reconstructed rating method`s consequences were compared to the published countries` ratings by Fitch and approximately more than 85% of the matched ratings over 4 years confirmed the high accuracy of our method. The second object of the thesis analyzed the impact of COVID-19 for the initial months of the pandemic which has been observed to mostly downgraded and some upgraded countries` ratings by Fitch. The high accuracy of the Logical Analysis of data was approved for the second part of the study also.

Keywords: supervised machine learning, logical analysis of data, country risk rating, country classification

ÖZ

Bu tezde iki temel amaç izlenmektedir. Birincisi Fitch kredi kuruluşunun derecelendirme sistemini yeniden yapılandırmak, ikincisi ise Fitch kuruluşu örneğinde COVID-19 pandemisinin ülke borç notu üzerindeki etkisini ortaya çıkarmaktır. Her iki nesnenin veri seti ve temel özellikleri Dünya Bankası (WB) ve Uluslararası Para Fonu (IMF) tarafından toplanmıştır. Özellik mühendisliğinden sonra 250 ülkeden 67 ülke, farklı derecelendirmelerin gizli kalıplarını bulmak ve sonucu doğrulamak için eğitildi, 39 ülke tez için test seti olarak çalışıldı. Her bir derecelendirmenin yeniden yapılandırılmış modelleri, karar ağaçları olarak gösterilmiştir. Denetimli bir öğrenme tekniği olarak Verilerin Mantıksal Analizi, ülkeleri Fitch derecelendirme kuruluşunun 16 etiketine ayırır.

Yeniden yapılandırılmış derecelendirme yönteminin sonuçları, Fitch tarafından yayınlanan ülkelerin derecelendirmeleriyle karşılaştırıldı ve 4 yıl boyunca eşleşen derecelendirmelerin yaklaşık %85'inden fazlası, yöntemimizin yüksek doğruluğunu onayladı. Tezin ikinci amacı, Fitch tarafından çoğu ülkenin notunun düşürüldüğü ve bazı ülkelerin notlarının yükseltildiği gözlemlenen pandeminin ilk aylarında COVID-19'un etkisini analiz etti. Verilerin Mantıksal Analizinin yüksek doğruluğu, çalışmanın ikinci kısmı için de onaylandı.

Anahtar Kelimeler: denetimli makine öğrenimi, verilerin mantıksal analizi, ülke risk derecelendirmesi, ülke sınıflandırması

DEDICATION

To My Mother

Who`s love is peace, it needs not to be acquired, and it needs not to be deserved

And

To Memory of My Father

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LIST OF SYMBOLS AND ABBREVIATIONS

ABC	Activity-Based Cost
ANN	Artificial Neural Networks
CBM	Condition-Based Maintenance
CR	Credit Rating
CRA	Credit Rating Agency
GDP	Gross Domestic Product
IMF	International Monetary Fund
LAD	Logical Analysis of Data
LASD	Logical Analysis of Survival Data
LP	Linear Problem
PDCM	Probabilistic Discrete Choice Behavior
PHM	Proportional Hazard Model
S&P	Standard & Poor
SCR	Sovereign Credit Rating
WB	World Bank
WDI	World Development Indicator
WHO	World Health Organization

Chapter 1

INTRODUCTION

The concept of country risk rating, also known as sovereign risk rating, became popular among economists, operations researchers, and statisticians in the last decades. For many years, only certain organizations and agencies with a high profile, such as Standard & Poor (S&P), Moody's, and Fitch, have released reports with information on credit ratings as well as economic data.

The three most common credit rating examples include the country risk rating, deposit rating for banks, and financial rating for insurance companies. There are various types of risk in non-credit ratings, including investment quality ratings and market risk ratings. Typically, a country's risk rating report is divided into three categories, namely long-term obligations, medium notes, and short-term obligations. Future country default risk is forecasted in these lists, which appear annually, semi-annually, and/or quarterly. Numerous factors have a broad impact on the economic futures of nations and political growth as a result of published reports. Investors, companies, financial institutions, and banks use these reports to decide whether to invest in or lend money to a specific country.

This research employs optimization techniques to propose a Binary Tree-Based model to rate country risk. The objective of the current study is the reconstruction of country rates based on the Fitch credit rating system, one of the biggest global credit rating agencies. These agencies do not publish the method of ratings; therefore, the most highlighted contribution of the thesis is figuring out the hidden rating system. Moreover, the study has the capability of offering a suitable rating for the countries which have never been rated by the Fitch agency, and it is another significant contribution of the thesis.

Chapter 2 of this study discusses the literature review conducted on the subject of country risk ratings. Sovereign debt is defined as an indicator of a country's risk. Based on the numerous studies` results, the most significant and effective factors in the country`s risk assessment are described. The bulk part of chapter 2 is composed of the various application of Logical Analysis of Data methodology in the vast area of science. The last part of chapter 2 is allocated to the novels of the COVID-19 pandemic and its impact on the credit rating system in the case of the Fitch rating agency. Chapter 3 contains materials about data collection and variable selection. Since there are three different kinds of resources for data gathering in the study, each source with varied variables for two separate parts of the study is introduced. Two diverse studies cover various periods; 2012-2015 and 2020 respectively.

Chapter 3 includes the number and the list of countries as training and test sets for the study. It took two stages to collect the data used in this study. To build a training set, a big set of data is first gathered and filtered according to certain conditions and is referred to as a training set. We used the training set to explore the hidden patterns which determine the description of each rating level to categorize the countries. After that, the information of the new data set was gathered to test the validation of the training set`s consequences. The training and test sets are disjoint. The values of economic, environmental, and social indicators of the countries are involved in the database to be studied. General definition, mathematical description, and, the whole procedure of Logical Analysis of Data (LAD) based on Binary language and Boolean function is explained in chapter 4. We employ the LAD algorithm process for the reconstruction of the rating system. To clarify the methodology, initially, we use the logical example of LAD to represent how it works mathematically. Afterward, a practical example is offered from the database of the present study to show in what way LAD works to classify the countries and labels them with a particular rating sign. For this purpose, the private program written by ZSOLT CSIZMADIA, so-called CSISZALAD is used to figure out the selected patterns with the corresponding Cut-points to form the generated patterns for each rating level.

Subsequently, we go one step beyond to begin to rate the countries by application of LAD in chapters 5, and 6 within the time horizon of 2012-2015 and 2020 (pandemic period). The algorithm is described in a better way with figures and coding in chapter 5. In this chapter, the consequences of the LAD application generate the explored patterns as decision trees, then we have four decision trees for four studied-period. Chapter 5 is concluded with the list of unmatched results between our output and the Fitch agency rating announcement.

Chapter 6 describes country risk ratings in the COVID-19 crisis. In this chapter, we try to modify our factors for the case of a pandemic to evaluate our methodology for this special case either. This part of the study aims to uncover the effect of this global crisis on the country's risk rating. Watching the response of the Fitch agency to the COVID-19 crisis to downgrade, upgrade, or keep the same ratings for the countries gives some points about their policy in the rating system. Additionally, we test our proposed model for the rating of the countries even in a crisis spot. Being involved in the study of COVID-19 impact on the ranking of the countries, gave birth to another paper titled “statistical analysis of the Hungarian victims” by the product of LAD.

Along with the main chapters which cover the body of the current research, chapter 7 makes a summary of the consequences and conclusions assigned to the objective of this study. At the end of the chapter, the author, summarize the findings and the results, and give some directions for risk rating and other future studies related to the application of data analysis for classification, clustering, and ranking.

Chapter 2

REVIEW OF THE LITERATURE

This chapter consists of three main sections reviewing the literature: Sovereign Credit Rating of countries, application of Logical Analysis of Data, and effect of COVID-19 pandemic on ratings. In the first part, we discuss the ratings of countries that are announced by the three biggest CRAs periodically. In the second section, we go through the application of logical analysis of data in different fields. In parallel to our study, COVID-19 hit the world and changed the world economy, the consequence of the COVID-19 pandemic on credit ratings will be discussed in the last part of this chapter.

2.1 Sovereign Debts of Countries

Sovereign debt known as a country rating is a debt issued by the central government in a foreign currency to pay for the issuing country's growth. An investor or lender may gauge the solvency of a country by its sovereign debt rating, which is meant to indicate the risk involved in investing and should be determined properly and timely. The stability of the issuing country is provided by the sovereign credit ratings which help investors assess risks when evaluating sovereign debt investments. Sovereign Credit Ratings (SCRs) refer to a country's capability to repay the money that it has borrowed. Therefore, sovereign debt rating can be a metric to help potential investors, financial organizations, banks, and even other governments when making an investment or making lending decisions regarding a particular country. A sovereign debt rating reflects the risk involved in doing so. Generally, governments look for credit ranking to simplify their access to international capital markets, where investors desire to pick rating securities over unrated ones even with the same credit risk (R. M. Cantor & Packer, 2011). Sovereign Credit Ratings (SCRs) can decrease the asymmetric information between investors and borrowers to increase the borrower's willingness to access funds and lessen the credit risk from the lender`s point of view (Canuto et al., 2012). With an SCR, the government is less reliant on the bank's monetary policy, and it can join international markets. Moreover, SCR can lead to financial improvement by drawing in foreign investors (Canuto et al., 2012). Country ratings carried out by CRAs reduce the gap of information between lenders and borrowers. An SCR is supposed to reflect a country's financial, economic, and political position (Kunczik, 2002). It is not easy to measure qualitative variables in the rating procedure in terms of predicting sovereign ratings. Because governments may renege on their obligations or become less financially solvent due to a political decision, the inclusion of qualitative measures in the rating process is difficult. That is why CRAs give their opinions on the creditworthiness of the country and not a piece of investment advice or assessments for obligation (Bozic & Magazzino, 2013). This fact was proved by (Ferri et al., 1999), who noted that CRAs were not able to foresee the East Asia crisis of 1999, and then caused them to become sufficiently conservative to downgrade high-risk countries.

2.1.1 Credit Rating Agencies and Significant Factors

Credit rating agencies typically give letter grades to reveal ratings. The worldwide credit rating industry is highly converged with three agencies controlling approximately the whole market: Moody's, S&P Global, and Fitch Ratings. They publish countries` ratings periodically that it can be per month, quarter, semiannual, or annual by considering several economic and political factors. These ratings didn't have a deep sense of the market until 1936 when a new regulation was passed that banned banks from investing in speculative bonds which means low credit ratings. The goal was to prevent the risk of default, which could result in financial failures. This routine was immediately approved by other companies and financial organizations. Soon enough, trusting in credit ratings became the norm. A borrowing entity will attempt to have the premier possible credit rating since it has a key impression on interest rates charged by lenders. The rating agencies should take an objective view of the borrower's capacity to refund the debt. Credit Rating (CR) governs not only whether or not a borrower will be accepted for a loan but also at which interest rate the loan must be repaid. CRs also have a substantial role in a potential investor's decision to obtain bonds. A weak credit rating is an unsafe investment. That's because it specifies more probability that the company will be unable to repay debts. CCRsare never static or steady, they change all the time based on the latest data, and one negativity will take down even the greatest score. Credit also takes time to boost. An entity with a safe but short credit history is not assessed as positively as another entity with likewise safe credit but a longer credit history. Maintaining safe credit consistently is important for debtors (Julia Kagan, 2021). Currently, CRAs are not the only creator of rating systems. Scholars in some areas such as financial management, economics, mathematics, and operations research offer precious methods to rate countries (Nima Mirzaei, 2011). For ranking countries, many mathematical-based methodologies are proposed by Scientists (Hirth et al., 2014; Seitz & la Torre, 2016; Zopounidis et al., 2002). As most prior studies rated countries not ranking them, (Niroomand, 2018) proposed a "non-linear weighted sum model" to rank countries based on economic variables. From using credit point of view, the countries were ranked the top to the lowest one by the obtained score from the model. The efficiency of the achieved ranking compared with Moody's rating.

Credit ratings are categorized into two main groups: investment grade and speculative grade. AAA to BBB is involved in "Investment-grade" whereas "BBBM" to "BM" is called "High Yield" or "speculative grade". "AAA" ratings denote the lowest expectation of default risk. They are assigned to a strong capacity for payment of financial commitments. In contrast, from the viewpoint of CRAs, below BBBM is not worth consideration. Some studies inflate the existence of a close association between credit risk ratings, stock market movement, and exchange rate volatility (Almahmood, 2014a; C. F. Baum et al., 2016; Rafay et al., 2018b). Investor and creditor appetite grew for higher grades of CRs. Therefore, high ratings cause creditors to be more optimistic, which declines the corporation's financial costs and modifies its investment scheme (Goldstein & Huang, 2020a). Fitch credit rating agency as our case study started providing financial information for procedures in the investment industry in 1913 is our case study. Fitch established and presented the "AAA" through the "D" as the base for ratings throughout the industry (Figure 1).

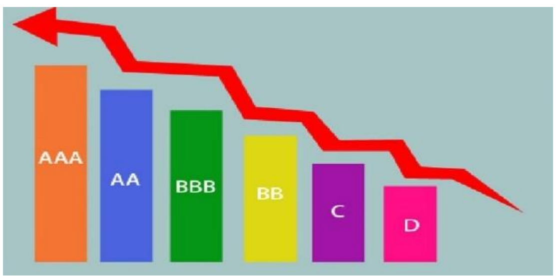


Figure 1: Fitch Rating System

Fitch Agency compiles the rating using a comprehensive report that takes into consideration numerous factors such as loaning and borrowing history, repayment capability, former debts, forthcoming economic potential, and more. A good credit rating improves reliability and implies a safe history of paying back loans punctually in the earlier period. It helps banks and investors to be assured that their money will be repaid in time, with the appropriate amount of interest, and borrowers who have a higher credit rating, will be seen as a minor risk and therefore get loan applications agreed upon more simply. Besides, Lenders will also propose loans at lower interest rates for bodies that have an upper credit rating. The general classification of CRs has presented below;

- AAA, AA, A – Good Credit Rating
- BBB, BB – Average Credit Rating
- B, C, D – Low Credit Rating

The rating class of the Fitch Agency which is taken into consideration in this study has been shown in Table 1. Letter "P", and "M" represent "Plus", and "Minus" for the rating scale. i.e, "AAP" is "AA+" which is categorized topper than "AA". Also, "BBM" is "BB –" that as a rating scale is placed at a lower level than "BB".

Table 1: Fitch ranking system and descriptions

#	Description	Fitch rating scale
1	(Highest rank): the safest, least risky investments	AAA
2	(Above Average): safer and less risky	AAP
3		AA
4		AAM
5	(Average): average risk and safety	AP
6		A
7		AM
8	(Slightly below average): slightly risky and less safe	BBBP
9		BBB
10		BBBM
11	(Well below average): riskier and less safe	BBP
12		BB
13		BBM
14	(Lowest): the riskiest and least safe	BP
15		B
16		BM

Credit Rating publication provided by rating agencies is essential for market suppliers and officials more than prior as they are under pressure after they fail to foresee the world financial crisis 2007-2008 (Abad & Robles, 2014). It showed that countries' credit rating has a crucial role in the global market for advanced and developing countries (Maltritz & Molchanov, 2014). Credit rating processes mostly consider some prearranged levels for countries and each country is allocated to a fitting level. From a different point of view, "conflicts of interest" have been used to justify the failures of CRAs. Documented proof is available of how CRAs` shortcomings contributed to the 2008 financial crisis—when they overrated and underrated some countries—and how they can take down governments and blow up capital markets (Mattarocci, 2013). At the time in question, they appeared to publish their SCRs in the manner of a black box, while hiding important issues from investors (Gültekin-karakaş et al., 2011). While CRAs prepare some data regarding the economic determinants they use to determine a rating, nearly nothing is said about the exact description of their ratings fundamental model (Bernal et al., 2016). To explore the rating system of CRAs, different methodologies and techniques are employed to rank the countries. It is incredible to generate a single model to rate countries since there are many diverse quantitative and qualitative features influencing the outcome (Niroomand, 2018).

One of the prominent issues in the country's risk rating is the collection of variables. There are various variables (qualitative or quantitative) that might weigh country ratings, but some of them have had the most dominance in the rating system. Factors` selection to issue the rating of countries is a critical concern. Economic and political aspects both have fundamental power over the country's credit rating product. (Haque et al., 1998) explained the importance of these factors in Sovereign credit ratings. One of the main results of this study showed that the political variables do not have much effect on the rating of a country, therefore they focused on economic variables more. However, (Rivoli & Brewer, 1997) claimed that both economic and political variables affect country risk rating. There are debates among experts to decide which one of the factors is more important. Six explanatory factors came out from (Afonso, 2003)`s study influencing sovereign credit ratings; Gross Domestic Product (GDP), External debt, Economic development, Growth rate, Default history, and Inflation rate. Similarly, (Edwards et al., 1983), (R. Cantor & Packer, 1996a) already examined an analogous subject about variables and concluded the same factors additionally GDP growth and Per Capita Income. Some macroeconomic factors which appear to be significant for country credit rating are GDP, GDP per capita, and GDP growth in several researchers' surveys (Hilscher & Nosbusch, 2011), (Eyssell et al., 2013).

Several variables have been considered by different investigators time after time as unemployment, government debt, foreign reserves, fiscal balance, economic development, political stability, mobile phones, real interest rate, total debt, real exchange rate, and unit labor costs (Bozic & Magazzino, 2013), (Afonso et al., 2007), (Bissoondoyal-Bheenick, Brooks, & Yip, 2006). Many researchers, motivated by Cantor and Packer's inspiring work, have endeavored to enrich our understanding of sovereign ratings by struggling to broaden the set of rating factors, as reviewed in Table 2.

Table 2: Significant factors of sovereign ratings

Author(s)	Main Determinants
(R.Cantor & Packer, 1996b)	GDP per Capita, GDP Growth, Inflation, External Debt, Level of Economic Development, Default History
(Sutton & Catão, 2002)	Real GDP Growth, Fiscal Balance, US Interest Rate, Debt Services/Export Ratio, Reserve/Debt, Policy Volatility
(Hu et al., 2002)	Inflation, Debt/GNP, Reserves, Debt services/Exports
(Borio & Packer, 2004)	GDP per Capita, GDP Growth, Inflation, Political Risk score, Default History
(Bissoondoyal-Bheenick, Brooks, Yip, et al., 2006)	GDP Per Capita, Inflation, Government Balance/ GDP, Foreign Reserve, Net Exports/GDP, GDP Growth
(Remolona et al., 2008)	Nominal GDP, GDP per Capita, Inflation, External Debt/GDP, Currency Mismatch, Default History, Political Risk
(Hill et al., 2010)	Change of GDP Growth, Last rating Evaluation, Probabilities of Rating Level
(Afonso et al., 2011)	GDP per Capita, GDP Growth, Government Debt, External Debt, External Reserves, Government Effectiveness, EU Accession, Sovereign Default Indicator
(Oliveira et al., 2012)	Inflation Rate, Stock Return, Interest Return, Public Debt, Government Investment

(Spilioti & Vamvoukas, 2015) prove that there is a positive correlation between government debt and economic growth. (S. Alexe et al., 2003) proposed a model for the Standard and Poor agency's rating system by selecting certain economic-financial and political parameters using multiple regression. In another study, fiscal uncertainty as a single determinant was used to explain the reason for changes in sovereign ratings during the financial crisis (Hantzsche, 2018). International Monetary Fund (IMF) highlighted some important variables for the credit rating of countries below (Table 3).

Table 3: IMF: International monetary fund`s selected variables

Factor Name	**Factor Type**
Gross domestic product based on PPP per capita GDP	Positive
Gross domestic product per capita	Positive
Gross national savings	Positive
The volume of exports of goods and services	Positive
General government total expenditure	Positive
Current account balance percentage of GDP	Positive
The volume of exports of goods	Positive
Gross domestic product, constant prices	Positive
Gross domestic product, current prices	Positive
Total investment	Positive
General government revenue	Positive
General government net lending/borrowing	Positive
Current account balance	Positive
Inflation, end-of-period consumer prices	Negative
Inflation, average consumer prices	Negative
The volume of imports of goods and services	Negative
Unemployment rate	Negative
General government gross debt	Negative
Gross domestic product, deflator	Negative

In Table 3, the variables revealed by the “positive” sign are the factors with favorable implementation. Conversely, for the “negative” variables, lower action is preferred (Niroomand et al., 2019). The credit rating agencies make their money on the mystery of their technique. If the system of rating were shared then everyone could estimate the ratings and no earnings could be made by the agencies. The existence of subjective features threatens deceptive information. They also eliminate the presence of a completely identified structure. Nevertheless, estimations may exist and have worth for the financial markets (Mirzaei & Vizvári, 2015). Following the multiple applied methods and techniques to figure out the process of the credit rating, the present study tries to explore the Fitch rating system on the estimation-based method; Logical Analysis of Data that its original purpose is to analyze datasets with binary (0-1) values (Crama Y, 1988).

2.2 Logical Analysis of Data

Classification is a basic task in the subject of data mining and many methods have been proposed, based on diverse data models, like Neural Networks, k-Nearest Neighbors, Decision Trees, Logistic regression, Bayesian approaches, and Boolean approaches (Hastie et al., 2009). One efficient Boolean method is LAD. The vision of Peter Hammer, explorer, and catalyst of LAD have been described well in the study (G. Alexe et al., 2007) which explains the basic concept of LAD in detail and the binarization that shows how datasets attributes take the binary values to figure out the hidden patterns of the phenomenon. Hammer at the international conference in 1986 gave a lecture on “Multi-attribute Decision Making” via OR-based Systems. That publication was followed by a flow of research studies. In the beginning, publications focused on theoretical developments. In current years, attention was converged on realistic applications altering from medical surveys to credit risk ratings (Chikalov et al., 2013).

This technique employs combinatorics, optimization, and Boolean logic to expose basic information present in datasets. Classification is the major application of LAD (Boros et al., 1997a). LAD methodology is directly connected to decision trees and nearest neighbor methods (Ross Quinlan et al., 1994). It is a way of studying datasets consisting of two classes, which classifies the outputs into two categories as true-false, positive-negative, yes-no, or 1-0 to explore the classification processes (Gholipour, Vizvári, & Lakner, 2021). The other specific aspect of LAD is the detection of hidden patterns that recognize observations in one class from all other observations (Gubskaya et al., 2011a). (Hammer et al., 2007) employed reverse engineering by using Logical Analysis of Data for financial risk rating and the outcomes were assessed with

Standard & Poor’s rating product to verify the model accuracy. However, the decision method was not published. (Chikalov et al., n.d.) stand on tremendous progress of LAD has passed from its initial publication to witness novel theoretical advances and new applications. This survey not only discusses the theory, methodology, and application of LAD but also shares new experiences, extensions, and implementations of Logical Analysis of Data comprehensively.

Upon extending LAD to numerical data sets, the “binarization” process involves the replacement of every numerical variable with binary “indicator variables”. Binarization was efficient in analyzing a diversity of real-life data sets, each indicating whether a variable`s value is above a particular level (Boros et al., 1997a). The classification performance of LAD has been already approved with the results of numerical experiments in comparison with the consequences of other procedures (Boros et al., 2000). In the final part of that study, they expressed three experimental investigations on applications of LAD to oil discovery, psychometric analysis, and the testing of growths in the Chinese transitional economy. These surveys revealed not only the classification capability of LAD but also its flexibility to provide solutions to numerous case-dependent challenges.

In the study of the application of the maximum box problem to data analysis, the researchers (Eckstein et al., 2002) created an effective “branch-and-bound algorithm” and employed it in a standard case in data analysis. A property of rule-based classifiers discussed in (Boros et al., 2011) which was called “justifiability”, concentrated on the category of information obtained from the training set to classify recent observations. It was established some approaches, such as decision trees or nearest neighbor-based methods, certainly provided justifiable classifiers. This study concludes that all justifiable classifiers should be bi-theories that are closely connected to decision trees and nearest-neighbor techniques.

(Oliveira Bonates et al., 2007) proposed an innovative algorithm that expands the LAD methodology to cope with regression problems. The computational experiments results suggested the algorithm is similar to standard regression algorithms in that it directly optimizes the Least Absolute Residual criterion throughout the set of all conjunctions. In a more general context, numerical variables are used as predictors. This algorithm constructs a set of conjunctions that best matches the binary and numerical variables. The major contribution of this thesis can be summed up as the function of optimization techniques to overcome certain of the struggles in the structure of LAD models.

The heuristic algorithm was developed to construct a "pattern of maximum coverage" for a given point (Bonates et al., 2008). It was shown that maximum patterns are valuable to structure an extremely precise LAD classification model compared to the frequently applied machine learning algorithm. Unlike existing algorithms, a LAD classifier has been introduced that simultaneously maximizes the properly classified elements and minimizes the number of violations of inaccurately categorized observations. One advantage of the offered algorithm is that it does not require any standardization. The effectiveness of the model was proved by computational results (Hansen & Meyer, 2011).

In another study, the novelty of the research is introducing the metaheuristic-based procedure to generate a pool of patterns for every element of the training set within LAD (Caserta & Reiners, 2016). "Biased Random-Key Genetic Algorithm" was applied to reduce the calibration of all the parameters and boost the implementation of the algorithm itself. They tested the proposed model on 10 standard occurrences and demonstrated that the model is competitive, with both accurate classification and operating time.

(Bruni et al., 2019) discussed how LAD can be applied as the initial phase of the specification of Probabilistic Discrete Choice Behavior (PDCM). Since in the related task, the number of generated patterns was considerably large, hence, it was proposed computationally possible techniques to achieve small sets of patterns that were meaningful descriptions of the occurrence. Continuously, there is research (M. Lejeune et al., 2019) that reviews the methodology and recent advances of LAD which describes its applications in finance, health care, engineering, and some stochastic optimization problems by explaining LAD with classification methods. Similarly, another paper provided a comparative study between various efforts associated with LAD on the topic of data classification (Chauhan et al., 2017). They emphasized a large number of real-life data analysis applications such as Finance, Medical diagnosis, Engineering, etc. Considerably, they noticed more the role of LAD in Medicine and corresponding disciplines.

LAD as a "promising accuracy in classification" faces a challenge in pattern generation. (Osman, 2021) investigated to optimally find maximum prime patterns with high coverage from past observations. Six machine learning algorithms were monitored in this study and LAD classifiers showed valuable results when used with the binary algorithm. Prime patterns are well-known for their high certainty of classification. Some experiments were operated to assess the results of six machine learning algorithms and the consequences of the proposed model which demonstrated a promising operation of the model.

Based on mixed-integer LP, Logical Analysis of Data was extended to give solutions to the multiclass classification cases. Two control parameters, homogeneity, and prevalence identify relaxed (fuzzy) patterns in multiclass datasets. The experiments on multiclass datasets showed that the efficiency of relaxed patterns is as well as other learning methods (Bain et al., 2020a). In a study, to assign class labels to unseen observations by LAD classifiers, Benders decomposition and Apriori Algorithm were applied to generate prime patterns with high coverage based on earlier observations (Osman, 2021).

2.2.1 Application of Logical Analysis of Data in Engineering

In 2008 (M. A. Lejeune & Margot, 2008) used a new approach, simulation-based LAD, in the application of the assemble-to-order system. The goal of the study was to direct the problem of assessing a system for the processing of stochastic parameters under unknown values. This was about handling inventory levels to enhance the profit. Therefore, the LAD classification model was performed in distinguishing “good” from “bad” items. Indeed, an experiment classified as “bad” by the LAD means a Non or low-demanded product would be directly dropped, while a test categorized as “good” would be noticed more as a highly demanded item. It managed the level of the inventory for finished products and obtained a very accurate estimation of time from assembling to order.

An equipment failure prognostics model was developed to foresee the probability of survival of equipment by application of LAD. The study`s objective was to estimate equipment’s survival chance at a specified upcoming moment. In this study, the goal was obtained via offering the model which could predict the probability of "left time" before fault based on age and health condition indicator of the equipment by LAD. Performance analysis disclosed comprehensible results that are significantly favorable to maintenance practitioners (Esmaeili, 2012).

Maintenance cost is one of the key expenditure sources for manufacturing firms. Currently, condition-based maintenance is a program based on the information gathered through monitoring of the conditions. To analyze the gathered data, (Yacout, 2010) applied Logical Analysis of Data to identify the machine's state and decrease the risk of failure. The patterns generated by LAD Patterns can be seen as instructions describing the occurrence under analysis. Therefore, in the study of (Bruni et al., 2019), it is explained how LAD can be employed as the first part of the specification of PDCM. The case study of the research was internet utilization in Italy. 45 explanatory socio-economic and cultural variables associated with Internet consumption have been taken, and the output class was assigned to 1 if the person used the internet and 0 otherwise. The researchers, using LAD, could identify small sets of patterns to describe the complex phenomenon.

Condition-based maintenance (CBM) detects and prognosis based on equipment healthy compared to time-based techniques. Three CBM fault prognostics models: Logical Analysis of Data, Artificial Neural Networks (ANNs), and Proportional Hazard Models (PHM) were studied by (Lo et al., 2019). The purpose of the study was to offer suggestions on the situations in which to employ the prognostics models. The method was applied to NASA's Turbofan Engine data set. They concluded that a good CBM prognostics model for realistic implications is determined by three key factors: accuracy, running time, and sort of data. When accuracy is the core concern, LAD and

ANN are preferred. The preference modifies when running time is considered. If data collection and model updating are performed easily the ANNs and LAD are preferred. In the contrast, if there is difficulty in gathering data and existing data is not symbolic of the population's manners, PHM is preferred.

Activity-based cost (ABC) inventory classification optimizes inventory management by classifying inventory items to set strategies to control them. One technique was presented by (López-Soto et al., 2016) for the recognition and modification of the bias that occurs in the ABC items classification. In this survey, a pattern-based reclassification was recommended using a multi-class model based on a LAD. The results were compared with the classification acquired from the Euclidean distance. The pattern-based classification technique, i.e. LAD, was capable of grouping new observations, as well as modifying bias at once. LAD through simply understandable patterns led to an easier decision-making routine, such that a new item classification did not adjust the classification of previous observations. On the contrary, more patterns were generated that completed the categorization of the classes.

LAD was applied in the airline industry via (Dupuis et al., 2012) to approximate overbooking. It was targeted to detect sets of patterns that separate passengers with high and low show ranks. Each item denoted a passenger categorized by a set of attributes, such as origin, gender, number of passengers, day of the week, etc. The paper examined a process to improve the accuracy of rate predictions for passengers in the airline industry. The passengers were grouped regarding the patterns as a show, no-show, or unknown classes. When examined to Air Canada's existing tool for overbooking predictions, which is based on historical statistics, logical analysis of data looked to be very competitive.

Another application of LAD in engineering is for face recognition purposes (Ragab et al., 2013). LAD was assigned to image preprocessing methods via the Eigen-faces and Fisher-faces. Logical Analysis of Data as a combination of data mining, knowledge exploration, and artificial intelligent approach was introduced and applied to face recognition. Knowledge discovered in the form of patterns was saved and then utilized in a machine learning system to discover the already realized faces and to recognize them from new faces. This study showed how the multi-class LAD model can be applied for face recognition. The performance of this model proved that when it is used with efficient methodologies such as *Fisher-faces,* guarantees high discriminate capability among the classes.

Since LAD is a two-class learning algorithm, a paper, (Avila-Herrera & Subasi, 2015) offered a model based on mixed-integer LP to solve multi-class classification problems by extending the LAD methodology, where One-vs-All models are effectively formed to categorize elements in predefined groups. Multi-class LAD was used for face recognition (Ragab et al., 2013). The objective of the study was to build a "single multi-class LAD decision model" to recognize the differences in persons` faces. The proposed face recognition method can essentially cope with various changes in pose and facial statement. The suggested model enriched the classification of Eigenfaces and Fisher faces in the least error ratio.

LAD was extended to multiclass classification to generate relaxed (fuzzy) patterns as optimal results for a mixed-integer linear problem (LP) (Bain et al., 2020b). In this case, the multiclass method applied homogeneity and prevalence as two elements to produce the "relaxed LAD patterns". It was aimed to develop the generalization ability.

Experimental outcomes showed that the proposed "relaxed multiclass LAD algorithm" has generated highly precise classification models based on the standard datasets.

Many other pieces of engineering research employed LAD for finding the solution or prediction i.e, (Das et al., 2020) detected cyber-attacks against large systems such as power grids and water treatment plants. (Jocelyn et al., 2017) use LAD for the prevention of accidents caused by belt conveyors. LAD also has applications in computer science (Bruni et al., 2019), (Janostik et al., 2020).

2.2.2 Logical Analysis of Data in Medicine

A large number of usual data analysis problems being revealed in medicine can be expressed in the following way. A dataset containing two disjoint positive and negative n-dimensional real cases is given. Each of the observations in the dataset is assigned to a patient. Any observation categorized as positive means having a special medical problem while those in the negative category do not have that problem. The components of the cases called attributes can represent the outcomes of particular tests, i.e the level of proteins in the patients` blood, or can simply reveal the existence or nonexistence of specific symptoms. Diagnosis is one of the typical questions arising in the analysis of such data to recognize whether a new patient in the dataset, does or does not have a specified medical condition under analysis. In the case of prognosis, it is supposed to predict if a new patient has the potential to have that medical problem within that period (Hammer & Bonates, 2006).

An approach based on "neural networks and evolutionary information" is one of the best ways for protein secondary prediction. But the accurate prediction of this method is 70%, moreover, it needs unknown structures to predict. Even though the existence of strong patterns in some of the data sets, but still it is difficult for a human being to perceive the patterns. Then, for this case to generate a tool for molecular biology, a new “rule-based” LAD was selected for the study due to its high accuracy (Błażewicz et al., 2001). The approach has led to accurate predictions for certain protein structures.

The essential idea of classification is to obtain enough information from the dataset to be able to distinguish the positive or negative character of a new item. One molecular biology study aimed to discover “dependencies among gene levels” which are specified by DNA quantification (Čepek et al., 2011). The solution methods of the study were strongly motivated by consequences in the area of LAD.

The major difficulty in medical problem analysis is the size of the datasets, which include often large numbers of irrelevant variables. Some rapidly expanding subjects of bioinformatics, e.g., genomics and proteomics, face tens of thousands of genes or proteins are recorded for every observation, even though very minor subsets of these intense features are adequate to be extracted positive observations from negative ones (G. Alexe et al., 2003). They performed a two-step procedure for feature collection. In the “filtering” stage, a quite small subset of appropriate features was identified. In the second stage, the importance of selected features (variables) based on their frequencies by LAD, has been detected. Therefore, significant variables were taken to be monitored and low-impact variables were eliminated from further study.

A diagnostic test employing a blood sample of a patient has the potential of being beneficial in curing the disease. A classification approach is described to distinguish the proteomic of stroke patients and controls (Reddy et al., 2008). The novelty of the predictive model created by using the Logical Analysis of Data was developed for the prediction of stroke severity on 48 stroke patients and 32 controls. The classification model had an accuracy of 75% when tested on an independent validation set of 35 stroke patients and 25 controls. 3 biomarkers were identified that can detect ischemic stroke with an accuracy of 75%.

The medical applications of LAD differ from variant diagnosis of pneumonia and prognosis in ovarian cancer research to risk measurement for cardiac patients (Gubskaya et al., 2011b). In particular, LAD was applied to examine cell growth on the surface of polymers patterns identification to classify polymer as “high, medium, or low cell growth”. The main advantage of the new LAD regression algorithm was its ability to detect hidden correlations comparable to how the LAD algorithm finds hidden patterns.

Survival analysis concerns predicting the time to occasion for patients in a dataset, based on the set of reported attributes. There is a study that was focused on “right-censored survival problems”. Generally, the identification of high-degree interaction to estimate the survival probability is a big challenge from the statistical perspective. Consequently, (Louis-Philippe Kronek1, and Anupama Redd, 2008), proposed a new methodology called “Logical Analysis of Survival Data” (LASD) to recognize interactions between survival patterns. The performance of LASD for two datasets of lung disease and breast cancer compared with the survival decision tree showed an improvement of the gene-expression dataset by 18%.

2.2.3 Logical Analysis of Data in Finance

There are two types of obligors using LAD for credit risk ratings: financial institutions and countries (Chikalov et al., 2013). In the last 30 years, there is increased notice of the credit quality in the bank sector since of a sharp rise in their failures. The difficulty of accurate bank ratings is that banks have higher defaulting rates than companies.

Therefore, it is not surprising that the main rating agencies disagree much more often about the ratings given to banks than about those given to other sectors. Another distinctive feature of the banking sector is the support that they receive from governments that companies do not. The design of a transparent bank rating system based on LAD methodology was defined by (Hammer et al., 2012a). Another main application of LAD in this area is the classification of countries, which is an extremely determinant factor for lenders or investors, and borrowers. For the rating of countries (Nima Mirzaei, 2011) applied the LAD approach to a one-year series of Moody’s ratings. (Hammer et al., 2011) also analyzed sovereign debt rating by LAD with quite different approaches. Financial institutions are now involving machine learning algorithms to generate more reliable internal credit risk rating systems. 17 Zimbabwean banks were used to test LAD, as a “supervised learning data mining technique”, to produce a transparent, and accurate internal credit risk rating. Such a system suits the decision-making pertaining (Moyo et al., 2020).

LAD has seen enormous progress since was introduced by Peter L. Hammer and continued to be an observer of new theoretical advances and new implementations were experienced also. This study aims to apply LAD, as already tested and validated for high accuracy by numerous surveys in varied fields to reconstruct the rating system of the Fitch agency as one of the biggest global CRAs. However, since our study coincided with the present worldwide challenge, the COVID-19 pandemic, we extended one more section about COVID-related examination to our study to investigate the effect of this crisis on the rating system additionally.

2.3 COVID-19 Pandemic and its Impact on Fitch Rating System

The almost whole world today has been infected by the phenomenon of a deadly virus that is very speedily transmitted to humans. There is a worldwide endeavor to figure out the medical, economic, and sociological effects of the pandemic. All efforts are biased to keep different aspects of society safe (Gholipour, Vizvári, Babaqi, et al., 2021).

Since the economy of the countries and financial organizations recently have been affected by unexpected global COVID-19 crises, on the other hand, CRAs assess the potential payment of an issuer on a financial obligation, then Credit rating (CR), as a symbolic indicator of CRA`s opinion, represents the creditworthiness of countries. To explore the ratings` vulnerability to downgrades over the crisis, Fitch Rating System has been studied by LAD (Elnaz Gholipour, 2021).

Fitch credit rating relevant to issuers is an ability of an entity to meet financial obligations. Credit ratings are used by investors as indicators of the likelihood of receiving the money owed to them in which they invested. However, in the current time, the crippling influence of the coronavirus crisis has pushed governments and corporate finances toward debt soaring. CRAs gauge what the long-term impact of the coronavirus crisis will be. They need to determine whether the consequences of the short-term CR conduct to long-term, or if a different rate structure is required to express risks to investors (Susan Borries Reed, 2020). Fitch Rating announcement throughout the crisis shows that high-yield countries have been affected more, forcing them deeper into the junk zone (Table 4).

Table 4: Down-graded countries by the Fitch rating agency in July 2020

Country	*2019*	*2020*
Cape Verde	B	BM
Cameroon	BM	B
Canada	AAA	AAP
Chile	A	AM
Colombia	BBB	BBBM
Gabon	B	CCC
Guatemala	BBB	BBM
Mexico	BBB	BBBM

Country	*2019*	*2020*
Morocco	BBBM	BBP
Sri Lanka	B	CCC
Tunisia	BP	B
Armenia	BBM	BP
Bahrain	BBM	BP
Bolivia	BP	B
Costa Rica	BP	B
Nigeria	BP	B

The most notable country is Canada, which was downgraded from AAA to AAP (AA+). To better understand the negative effect of the pandemic on CRs, the list of up-graded, remained-fixed, and down-graded countries have been demonstrated by each CRAs in Figure 2.

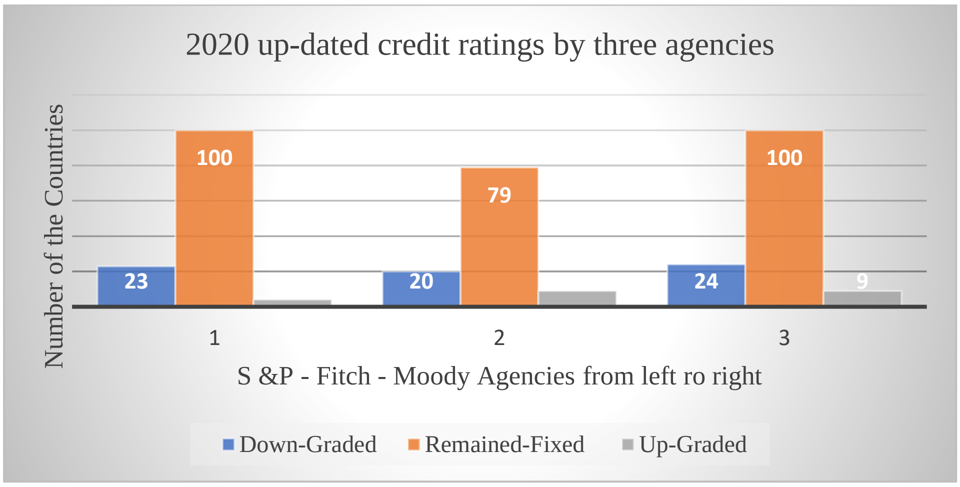


Figure 2: Countries` Credit Ratings Status by Three Agencies in 2020

Marc Jones (Marc Jones, 2020) had a report in business news about the statistics of downgrades that have been already made by the three biggest CRAs so far this year. Further to the backward of a pandemic, downgrades might be a considerable threat to economies and have doubtful questions about upcoming ratings. As manifested by (Delis et al., 2021a) the COVID-19 crisis created dramatically negative feedback on the skewness and total value of risk. Having successful access to the financial market to deal with heavy debts during a pandemic is the main way for governments to survive the crisis. Downgrades will have a severe impression on sovereigns and corporate finances. To monitor the impact of COVID-19 on the rating system, we needed new variables to analyze whether the crisis is effective on credit rating or not. Consequently, three varied parts of factors have been selected for this purpose.

- The most significant variables from the former part of the research used for exploring the country classification pattern before the pandemic are as below: Economic and social variables; GDP per Capita, GDP Growth Rate, Inflation, Unemployment Rate, Urban Population, Government Debt, Gross Saving.
- Covid-19 related variables; the number of Infected population and Deaths.
- Previous credit rating (Pre-CR) of the countries.

In following Chapter 3, we start to discuss and process of variable selection for both normal and crisis parts of the study. Briefly, it will be shown the data mining procedure of country classification for 4 years from 2012 till 2015 and the COVID-19 crisis period, 2020.

Chapter 3

DATA COLLECTION AND VARIABLE SELECTION

In this chapter, the sources of the data set and the process of selected variables for the reconstruction of the rating system related to the Fitch credit agency are discussed. There will be one more section for the COVID-19 data collection and factor selection.

3.1 Data Collection

The data source of this study is the World Bank Group (WB), International Monetary Fund (IMF), and World Health Organization (WHO). "The World Bank Group is one of the world's largest sources of funding and knowledge for developing countries. Its five institutions share a commitment to reducing poverty, increasing shared prosperity, and promoting sustainable development" (the World Bank Group, 2021). World Development Indicators (WDI) is the initial World Bank dataset, composed of officially documented international resources. It appears the most current and correct worldwide development data available and contains countrywide, regional, and global approximations. Data Bank is a visualization tool that covers groups of time series data on a diversity of matters. Different queries, tables, and charts can be created, saved, and shared.

The International Monetary Fund organizes international financial constancy and monetary collaboration. Global trade, promotion of employment, and growth in a sustainable economy are facilitated by IMF. It helps to reduce overall poverty, while almost 190-member countries govern IMF (The International Monetary Fund, 2020).

The data set in this study is gathered partially from the World Bank and International Monetary Fund for two sections of the study. The data set of the World Bank related to the first section of the study covers four years starting from 2012 to 2015, and the 2020 data set was used for the possibility of modification in the Fitch rating system due to the COVID-19 crisis, collected from IMF.

3.2 Variable Selection

3.2.1 Selected Variables of Fitch Rating System (2012-2015)

We shall take a glance at the categories of the variables that are often taken into consideration for the rating of countries by CRAs. “Economic policy variables, Variables of the economic sectors, Variables of stress, Variables of political risk” are some of the variables groups which are mentioned in most credit rating evaluations. Other ratios, such as "public sector debt/ gross domestic product", and another four main indicators are “growth of GDP, inflation, external balance or Balance of payments, and the level of unemployment” (Cecilia Téllez Valle José Luis Martín Marín et al., 2005). However, some other factors are taken to use for the rating process by CRAs also like;

> “rate of growth of the population and its age distribution, the differences of productivity between the agricultural and industrial sectors, the degree of urbanization of the economy, and the effectiveness of the educational system”.

In this study, the most significant variables as the output of many earlier studies which are effective on the credit rating system are listed in Table 5. We employed all these 20 variables to reconstruct the unknown credit rating system of the Fitch agency.

Table 5: Twenty selected variables of the study

Notation	Attribute
C	Cash surplus/deficit (% of GDP)
EX	Exports of goods and services (% of GDP)
G	GDP per capita (current US$)
IM	Imports of goods and services (% of GDP)
RE	Revenue, excluding grants (% of GDP)
SD	Short-term debt (% of total reserves)
TD	Total debt service (% of exports of goods, services, primary income)
CG	Central government debt, total (% of GDP)
E	Expense (% of GDP)
GG	GDP per capita growth (annual %)
GS	Gross savings (% of GDP)
IV	Industry, value added (% of GDP)
I	Inflation, consumer prices (annual %)
PPP	Purchasing power parity conversion factor
R	Total reserves (includes gold, current US$)
U	Urban population (% of total)
PG	Population growth (annual %)
PA	Population ages 0–14 (% of total)
UN	Unemployment, male (% of the male labor force)
M	Mobile cellular subscriptions (per 100 people)

We gathered the raw information of 250 countries as the database from World Bank Group for four years, 2012, 2013, 2014, and 2015. Two types of countries were eliminated from further analysis. One type is related to the Small countries with a population of less than 500,000, and the other one is the group of countries with a lack of available data. The final dataset of the study was divided into two subsets, namely, training and test sets. These included 69 and 30 countries, respectively. Restriction in data accessibility forced us to select a limited number of countries. Nevertheless, the features of our methodology, LAD, cover data restriction drawbacks appropriately. Since as we already discussed in detail in Chapter 2, the accuracy of LAD methodology for small sample sizes has been proved by several studies in different fields. Table 6 and Table 7 show the listed countries for training and test sets of the study.

Table 6: Training set

No.	Country Name	No.	Country Name	No.	Country Name
1	Austria	24	Italy	47	Tunisia
2	Canada	25	Poland	48	Uruguay
3	Switzerland	26	Ireland	49	El Salvador
4	Finland	27	South Africa	50	Angola
5	France	28	Bahrain	51	Armenia
6	UK	29	Lithuania	52	Gabon
7	Luxembourg	30	Mexico	53	Georgia
8	Netherlands	31	Russia	54	Sri Lanka
9	Norway	32	Thailand	55	Nigeria
10	Singapore	33	Brazil	56	Cabo Verde
11	Sweden	34	Indonesia	57	Egypt
12	USA	35	Iceland	58	Kenya
13	Hong Kong	36	Azerbaijan	59	Mongolia
14	Belgium	37	Croatia	60	Venezuela
15	New Zealand	38	India	61	Vietnam
16	Saudi Arabia	39	Morocco	62	Cameroon
17	China	40	Namibia	63	Lebanon
18	Estonia	41	Romania	64	Mozambique
19	Japan	42	Turkey	65	Seychelles
20	Slovakia	43	Costa Rica	66	Uganda
21	Spain	44	Guatemala	67	Ecuador
22	Israel	45	Hungary	68	Jamaica
23	Slovenia	46	Macedonia	69	Greece

These 69 countries as a training set were rated by the Fitch agency in 2012, 2013, 2014, and 2015. We analyze the chosen countries by our model, decision trees, which are examined in detail in Chapter 5. For verification of our approximated model, 39 countries are added to the study as a test set (Table 7).

Table 7: Test set

No.	Country Name	No.	Country Name	No.	Country Name
1	Angola	12	Ghana	23	Poland
2	United Arab Emirates	13	Iceland	24	Portugal
3	Armenia	14	Jamaica	25	Paraguay
4	Australia	15	Kuwait	26	Rwanda
5	Bolivia	16	Sri Lanka	27	Suriname
6	Costa Rica	17	Lesotho	28	Congo
7	Cyprus	18	Latvia	29	Zambia
8	Czech Republic	19	Macao SAR, China	30	Ukraine
9	Germany	20	Malta		
10	Denmark	21	Nigeria		
11	Gabon	22	Panama		

3.2.2 Selected Variables of Fitch Rating System (COVID-19 Crisis)

The world policy to the deadly and costly Coronavirus Crisis made governments have a high debt-to-GDP ratio. To pay for many of these programs, countries will require to have access to financial markets. This phenomenon sheds light on the response of the CRAs to the pandemic, and how the countries and financial institutions will be rated. The negative outlook of sovereign downgrades at the outset of the pandemic has moved slowly since June and will continue to decelerate in the months ahead. Sovereign credits experience consider stress following the negative viewpoints about downgrades that may reach below the historical average (Fitch Ratings Group, Special Report, 2019). Accordingly, it is certain to follow the trend of the main variables of pre-explored patterns of the Fitch Rating system (Gholipour, Vizvári, & Lakner, 2021) to analyze its response to COVID-19.

We modified the 20 variables from the consequences of our study in the first section and selected the most substantial factors in the Fitch rating system. Instead of the removed insignificant factors in the first part, two other types of variables namely, COVID-19 related and Pre-credit rating was added to this section (Table 8).

Table 8: Applied variables for identification of the Fitch rating system in the case of the COVID-19 crisis

No	Variables
1	GDP per Capita ($)
2	GDP Growth Rate (annual %)
3	Inflation, Consumer Prices (annual %)
4	Unemployment Rate (%)
5	Urban Population (% of the total population)
6	Government Debt (debt to % of GDP)
7	Gross Saving (% of GDP)
8	Total COVID-19`s Infected Cases
9	Total Deaths of COVID-19
10	Fitch Credit Ratings of Countries for 2019 (Pre-credit rating) (100-0)

The first 7 indicators/variables which are mainly economic factors were gathered from the IMF database. A GDP in this study is always GDP per capita, and total GDP never occurs in this thesis, and GDP annual growth rate is written in this way to be distinguished from GDP per capita. The 8^{th} and 9^{th} factors were collected from the World Health Organization database (The World Health Organization, 2020). The information on the rating labels of the countries for all years was extracted from the Trading Economics website (Trading Economics, 2021). There are two reasons for the selection of the first seven variables in this section; firstly, they were labeled as major and efficient factors in our first analysis of the rating system through four years, and secondly, these economic factors were affected more by the COVID-19 crisis.

Covid-19-related factors (8 and 9) about the number of infected populations and death for each country can be taken into serious consideration by CRAs as a crucial risk.

Therefore, this risk can be counted as a threat for a country to be downgraded by the Fitch rating system. Hence, for this part of the study, these two new variables are vital.

(Efraim Benmelech, 2020a) concluded which variable might be mostly tied to spending, then the Country`s pre-crisis rate (10th variable of Table 8) as a strong determinant came out. It means in most country ratings, CRAs tend to keep the previous ratings for countries, especially from 2018, and declare the new ratings as similar to the previous one except for particular cases. Consequently, in recent years, it seems it is not easy to change the country's rating labels. Besides, there is an argument that the CRAs rate the developed countries in the higher classes regardless of their macroeconomic basics (Gültekin-Karakaş et al., 2011). However, macroeconomic factors have fundamental importance to the ratings. This is the reason, in any circumstances even in the case of any crisis, the macroeconomic and political factors are the most reliable elements to decide about credit ratings based on them. After all these viewpoints and analyses, the COVID-19 crisis made us determine the most relevant factors for the rating system of the Fitch agency to offer a model and test its validation despite the existence/Non-existence of the crisis. Therefore, we added one factor as the third part of the variables for the second section of the thesis to analyze the Fitch rating response to the COVID-19 crisis. The same training and test sets of listed countries are used to explore the rating system of Fitch in the pandemic.

In the following three Chapters, the LAD methodology and techniques, the explored-country credit rating process within four years (2012-2015), and the pandemic period (2020) will be debated.

Chapter 4

LOGICAL ANALYSIS OF DATA

Logical Analysis of Data was initiated by Peter L. Hammer in 1986. He demonstrated that the LAD classification system produces accurate, transparent, and generalizable results (Boros et al., 1997b). In this chapter, we explain the definition and procedure of LAD methodology with a general logical example and applicable example for the subject of the thesis.

4.1 Definition and Procedure of LAD

There is a set of objects that are similar to each other and are described by the same set of attributes. The objects can be very different according to the area of application, for example, patients in a hospital, customers who obtain a loan from a bank, or drilling locations in the oil industry. However, the nature of the objects is the same in an application. The objects are divided into two parts, for instance, patients who have a particular disease and those who do not. LAD is a method that creates a description for each of the two parts. It is a machine learning method with a supervisor as the objects in the database are classified a priori. The descriptions of the two classes generated by LAD can be applied to new objects. It is supposed that all attributes of the objects are Boolean variables, that is, the value of each attribute is either true or false. If the values must be expressed numerically, then 1 stands for True and 0 stands for False. It is also assumed that there is no contradiction in the database, i.e., there is no pair of objects such that the two objects have the same values in all attributes but belong to the two aforementioned different subsets of objects. The number of different objects is at most 2^n, where n is the number of the binary attributes. However, even in the case when n has a moderate value such as 15 to 20, it is unlikely that all possible observations will occur. LAD aims to forecast which new (i.e., until now non-occurring) observation belongs to which subset (Gholipour, Vizvári, & Lakner, 2021).

LAD covers a collection of techniques to generate a data classifier. The theory of pattern, or interval is the basic tool of LAD models. The detection of all the unknown patterns which satisfy particular conditions is a key algorithmic problem in LAD. The Logical Analysis of Data is composed of two disjoint negative and positive sets. The fundamental question of LAD is to figure out the possible hidden structure of positive and negative sets even the nature of the points which are not included in the dataset (S. Alexe & Hammer, 2006).

When the collection of observations has actual-valued attributes, the initial step to running the LAD methodology is to binarize the database. The norm to do so is to utilize cut points for every attribute (Anthony & Ratsaby, 2012). This “binarization” procedure converts a problem with numerical data to a problem with a bigger number of binary variables.

The database can be considered as the description of an incomplete Boolean function of n Boolean variables. The function is incomplete because its value is not known for all possible values of the attributes (variables), just for the observed values. What LAD must do is to find a complete Boolean function such that its value is the same as the value of the incomplete Boolean function. The database of the training set must contain a complete classification, that is, each object must be classified as either 1 or 0. LAD can describe any of the two subsets. The synonyms of class 1 and 0 are positive and negative, respectively. Numerical data will be described in section 4.2.

LAD is a way of studying datasets consisting of two classes. Generally, LAD classifies the outputs into two categories as true-false, positive-negative, yes-no, or 1-0 (asymmetric classes) to explore the hidden classification processes. LAD consists of several main steps. First, a set of patterns is generated, and each pattern covers a subset of the desired observations. Mainly, the number of patterns is substantial. As a second main step, a small subset of the patterns is selected such that the target subset of the observations is covered accurately. This subset of the selected patterns gives a disjunctive normal form in the sense of mathematical logic. There are different methods for the way of selection; thus, LAD has many approaches (G. Alexe et al., 2008).

4.2 Logical Example of LAD

Examples are best suited to explain how a logical explanation can be applied to numerical data. Suppose we look at Table 9, which contains a set of S+ positive observations and a set of S- negative observations with attributes A, B, and C. In more specific terms, we can think of the phenomenon X as being a headache, and the attributes A; B; C as indicating blood pressure, temperature, and pulse rate, respectively (the numerical values are appropriately normalized). The rows are the objects.

Table 9: A numerical data set (S+; S-)

Attributes	A	B	C
S^+:	3.5	3.8	2.8
	2.6	1.6	5.2
	1.0	2.1	3.8
S^-:	3.5	1.6	3.8
	2.3	2.1	1.0

Table 10: A binarization of Table 9

Boolean variables	x_A	x_B	x_C
T: true points	1	1	0
	0	0	1
	0	1	1
F: false points	1	0	1
	0	1	0

Introducing the following cut points first will provide a logical explanation of this data set. $\alpha_A = 3.0$; $\alpha_B = 2.0$; $\alpha_C =$ 3.0

Then we turn the numerical attributes into binary indicators by establishing $x_A = 1$ if $u_A >= \alpha_A$, $x_B = 1$ if $u_B >= \alpha_B$, and $x_C = 1$ if $u_C >= \alpha_C$ for all points $u = (u_A; u_B; u_C) \epsilon S^+ \cap S^-$. Binarization of Table 9 yields the following results in Table 10. S^+ is considered to provide true points, whereas S^- provides false points, based on the binary vectors resulting from its numerical components.

In a partially defined Boolean function (pdBf), T and F denote the sets of true and false points. If all Boolean vectors are seen in a table, it represents a Boolean function. Table 10 depicts a pdBf since some Boolean vectors do not appear in the table. The missing vectors are 000, 100, and 111.

In the same set of n variables, we have a pdBf; g = (T; F) and a function f. When table 10 defines a partially defined Boolean function of g, the function f is called an extension of the “g” when it is consistent with g, i.e., when all the true (respectively false) points of g are also true (respectively false) points of “f”. Generalize the principle of disjunctive normal forms (DNF) by expressing one of the extensions f of a pdBf g as follows:

$$\mathbf{f} = x_A x_B \cup \bar{x}_A \bar{x}_B \cup x_B x_C \tag{1}$$

Table 10 appropriately explains that phenomenon X occurs when the values of attributes A and B, or B and C, are both high, or when A and B are both low. This is a logical explanation of Table 9.

4.3 A Practical Example of LAD: The Description of Rating BBBM

In this practical example, we go over the subject of the thesis; credit rating of countries in the Fitch agency rating system, and explain how we define Boolean function here and employ LAD in the case of the rating system.

The countries are described by economic data that are numeric and not Boolean. These data are transformed in the example to Boolean ones. For example, let us consider that GDP per capita is at least $5,436, and this divides countries into two classes. For some, the GDP per capita is $5,436 and above, and it is less in the case of other countries. A Boolean variable is then introduced. If the condition is satisfied, that is, GDP per capita is at least $5,436, then it is true—otherwise the false value is obtained. It is possible to divide the countries into two groups by using the same economic variable differently. GDP per capita is used a second time in the example below, where it is at least $14,189. Another Boolean variable is introduced. Again, if the condition is satisfied, then it is true—otherwise, the false value is obtained. The transformation of numerical data to Boolean variables is discussed in the next section.

If a country had a BBBM rating or higher in 2012, then it could be checked in three different ways. If any of the three groups of constraints gives a positive result, then the country belongs to that category. If none of the three options were satisfied, then its rating was BBP or worse.

First group: the GDP per capita of the country is at least $5,436 AND the export of goods and services is at least 38.185 percentage of GDP AND the PPP conversion factor is at most 6.075%.

Second group: the net cash surplus/deficit is at least -5.88 percentage of GDP, that is, the deficit is not too high, AND the total reserves are at least $17,824,012,000 AND the inflation rate of consumer prices is at most 9.165%.

Third group: the expenses are not greater than $53.195 AND the male unemployment rate is at most 8.5% (where the proportion of male labor force is modeled on ILO estimates) AND the GDP per capita is at least $14,189.

To compare the practical example with the logical example which was discussed in section 4.2, the attributes of groups like GDP, PPP, Unemployment rate, etc are like A, B, and C attributes in the logical example, and the boundary of these variables as $5,436, 6.075%, 8.5% are the corresponding cut points like $\alpha_{A,}$ $\alpha_{B,}$ α_{C}. Here, the constraints as a pdBf "g" show the attributes of true and false points. In light of what we have already said, one of the extensions of "g" obtained as the disjunction of the three pdBf`s. “f” is expressing disjunctive normal forms (DNF) of this practical example is called “BBBM” rating class as formula 1;

BBBM = (GDP $\geq$ 5435.98, Expenses $\geq$ 38.185, PPP $\leq$ 6.075) $\cup$ (Cash ≥ -5.88, Reserves $\geq$ 17824000000, Inflation$\leq$ 9.165) $\cup$ (Expenses $\leq$ 53.195, Unemployment$\leq$ 8.5, GDP$\geq$ 14189.30)

To have a rating BBBM or better, a country must satisfy all conditions for at least one of the three groups. It is not enough that it satisfies some conditions for every group. The BBBM rating is a disjunction of three conjunctions such that each conjunction contains three Boolean variables. For example, assume the GDP of a country, called Nowhere is $8,000. The GDP occurs twice in different conjunctions of BBBM, which is, in the 1st and 3rd groups. Nowhere country satisfies the GDP constraint of the 1st group, but violates the similar constraints of the 3rd group, which gives Boolean value “False”. Therefore, if its expenses are great enough and its PPP conversion factor is low enough, it still can be a BBBM country because it satisfies the criteria of the first group.

4.4 Pattern Generation

To apply LAD, we used parameters and made several patterns. A pattern is the conjunction of Boolean variables. In our study, the Boolean variables are defined by cut points as explained above. The extent of a pattern is the number of Boolean variables in conjunction.

4.4.1 Parameters Used in LAD Calculation

The *prevalence* is the ratio of positive (negative) observations covered by the pattern to the number of all positive (negative) observations in the dataset. A pattern with a high prevalence is clearly of greater value.

The *homogeneity* of a positive (negative) pattern is the percentage of the positive (negative) observations covered by the pattern to the number of all observations covered by it. Pure patterns have 100% homogeneity.

The *degree* of a pattern refers to the number of Boolean variables in it. In practice, patterns of small degrees are always preferred since they have greater explanatory power. To put it another way, smaller patterns of small degrees are easier to understand (Gholipour, Vizvári, & Lakner, 2021).

The *decision trees* are tree-based methods that begin at the root and follow an exact path until they culminate in a Boolean outcome at the leaf node as a data separation sequence (Boros et al., 2011; Charbuty & Abdulazeez, 2021).

4.4.2 The Original Concept of LAD

The original concept of LAD is based on mathematical logic and Boolean variables. One basic theorem of mathematical logic is that every Boolean function can be obtained as a disjunctive normal form (DNF). The three groups of Section 4.3 cover all the countries that have the BBBM or better ratings. This is an example of a DNF. The three ways consist of conjunctions of Boolean variables. Each of these conjunctions of (perhaps several) Boolean variables is called patterns in the context of LAD. The general form of the DNF is that there are several subsets of statements. The Boolean function (DNF) is true if and only if all statements of at least one subset are true. One statement or its opposite can be a part of several subsets. The subsets of statements may have a different number of elements. It is just by chance that each group in the example has three statements. Since almost every classification can be modeled as a decision tree, the explored Fitch rating pattern of our running will be shown as binary Tree-based for each year.

The following chapters 5 and 6, will be discussed the actual application of LAD in the rating system of the Fitch agency in the time horizon of 2012 – 2015 and the pandemic period (COVID-19 crisis) 2020.

Chapter 5

CLASSIFICATION OF COUNTRIES (2012-2015)

In this chapter, we analyze whether the rating of countries provided by the Fitch agency can be reconstructed with LAD, using only the databases published by World Bank and International Monetary Fund.

Economic, financial, and political features of countries can be found in the WB and IMF data sets. Our model`s attributes were collected for a training set of 69 countries, and the model was verified using 30 countries as a test set. Generally, the most misclassified countries over the four years were 7. Meanwhile, the number of cases that are mismatched for each year was different than others which will be listed in detail in the result part of the chapter. The effort for the reconstruction of the Fitch rating system uses 20 variables.

5.1 Introduction to Countries' Credit Ratings

The countries with higher ratings provide a better environment to make investments by investors and a safe zone to lend money. Generally, investors, big corporations, and bankers prefer upper ratings before investing and lending in a country (Niroomand, 2018), (Mirzaei & Vizvári, 2015).

To decide when, where, and how to invest the funds, investors and financial managers need the financial risk tool to make effective decisions. Furthermore, international companies can make strategic decisions about where to establish new branches or invest their money. Therefore, the country's rating as an indicator of investment safety or risk is an important financial risk management tool that is noticed by decision-makers.

5.2 The Fitch Credit Rating Procedure

The present study examined the Fitch agency rating system to reconstruct a rating model of sovereign debt with LAD, a classifying methodology based on optimization and Boolean logic. It uses binary data (i.e., 0 and 1) (G. Alexe & Hammer, 2006).

5.2.1 Transformation of Numerical Values to Boolean Attributes

Most real-life problems have numerical attributes, not Boolean ones. LAD is applicable only if the numerical data are "translated" into Boolean attributes. The example of the BBBM or better rating in chapter 4 showed how it can be done. Each statement in that example has a numerical value that separates the countries. These numerical values are always between a BBBM or a better country and a country with a lower rating, for instance, the two countries are closest in a GDP per capita of $5,436; Azerbaijan belonged to the BBBM class in 2012, with a GDP per capita of $7,189. Meanwhile, Guatemala had a lower GDP per capita ($3,166) and was in the BBP class, one class lower than BBBM. The statement that the country Nowhere has a GDP greater than $5,436 has a Boolean value, i.e., it is either true or false. The name of any country can be substituted for Nowhere in this statement because every country has a Boolean value in this respect. LAD constructs the DNF from these Boolean attributes. The separating values are called cut-points. Thus, $5,436 is a cut-point in the example above. Mathematically, binarization can be achieved by introducing cut-points for each of the numerical variables in such a way that the resulting partitioning of the space should consist only of "pure intervals," that is, intervals that do not contain both positive and negative points (see the different color points in Figure 3). Minimizing sets of cut-points with corresponding variables was the optimization element of the present study. We explored and described the rating categories of the Fitch rating system by the minimum number of patterns for each year. Figure 3 visualizes the iterative procedure of generating decision trees by LAD. The countries of the rating category of the iteration and the countries of the better rating classes are assigned to LAD class 1, any other country is assigned to class 0 (Figure 3 (a)). The LAD classes of the countries of the next rating category are changed from 0 to 1 in the next iteration. To go through all predefined rating categories, the countries are moved to LAD class 1 gradually except for rating category BM (Figures 3 (b) and 3 (c)). In the end, there may be regions such that countries in the region are not already classified by the Fitch rating system (Figure 3 (d)).

5.2.2 Steps of LAD Procedure to the Credit Rating of the Countries

The iterative procedure starts with the rating category of AAA labeled by the Fitch rating agency. These countries are always in LAD class 1. In the first step of the algorithm, these AAA countries are separated from the other countries (Figure 3. a). Separation means the determination of groups like in the example of Section 4.3, which exactly covers the AAA countries. If a country is classified as an AAA country in the first step, then this classification is never modified. In the second step, AAA and AAP countries are separated from the countries, which have a rating of AA or worse (Figure 3. b, four new colored points labeled as AAP were added to the selected part). The logic of the description of AAP countries is as follows: if a country is separated, and it is not an AAA country, then it is classified as an AAP country. AAA, AAP, and AA countries are separated from other countries in the third step (Figure3. c, three new points satisfied the conditions of the AA rating class and were disjointed from other unlabeled points), etc. The steps of the algorithm are represented in Figures 4 and 5.

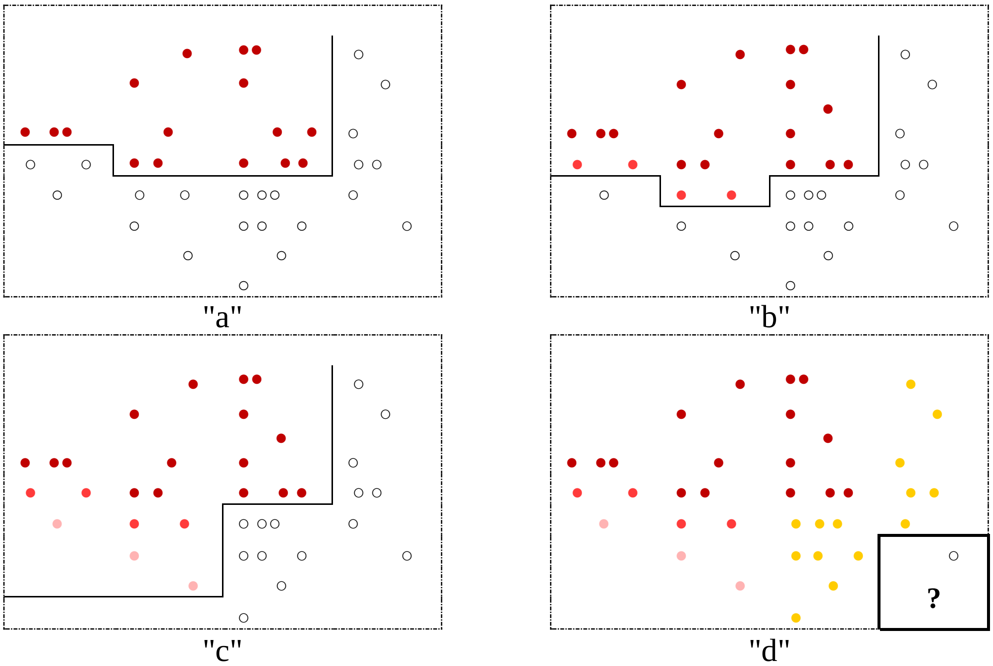


Figure 3: Selected Cases as an Output of LAD for Each Rating Class

For r: = AAA to BM do

Begin Create Positive class P: = {c ϵ Countries, Rank c >= r}

Create Negative class N: = {c ϵ Countries, Rank c < r}

Apply LAD to (P, N)

Add theory of P to the decision tree

End

Figure 4: The Algorithm for Rating

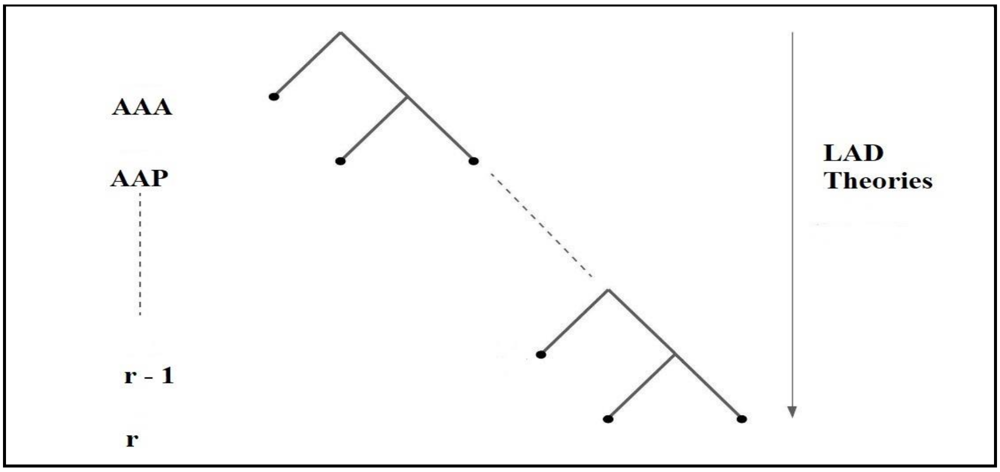


Figure 5: Order of the Rating Class

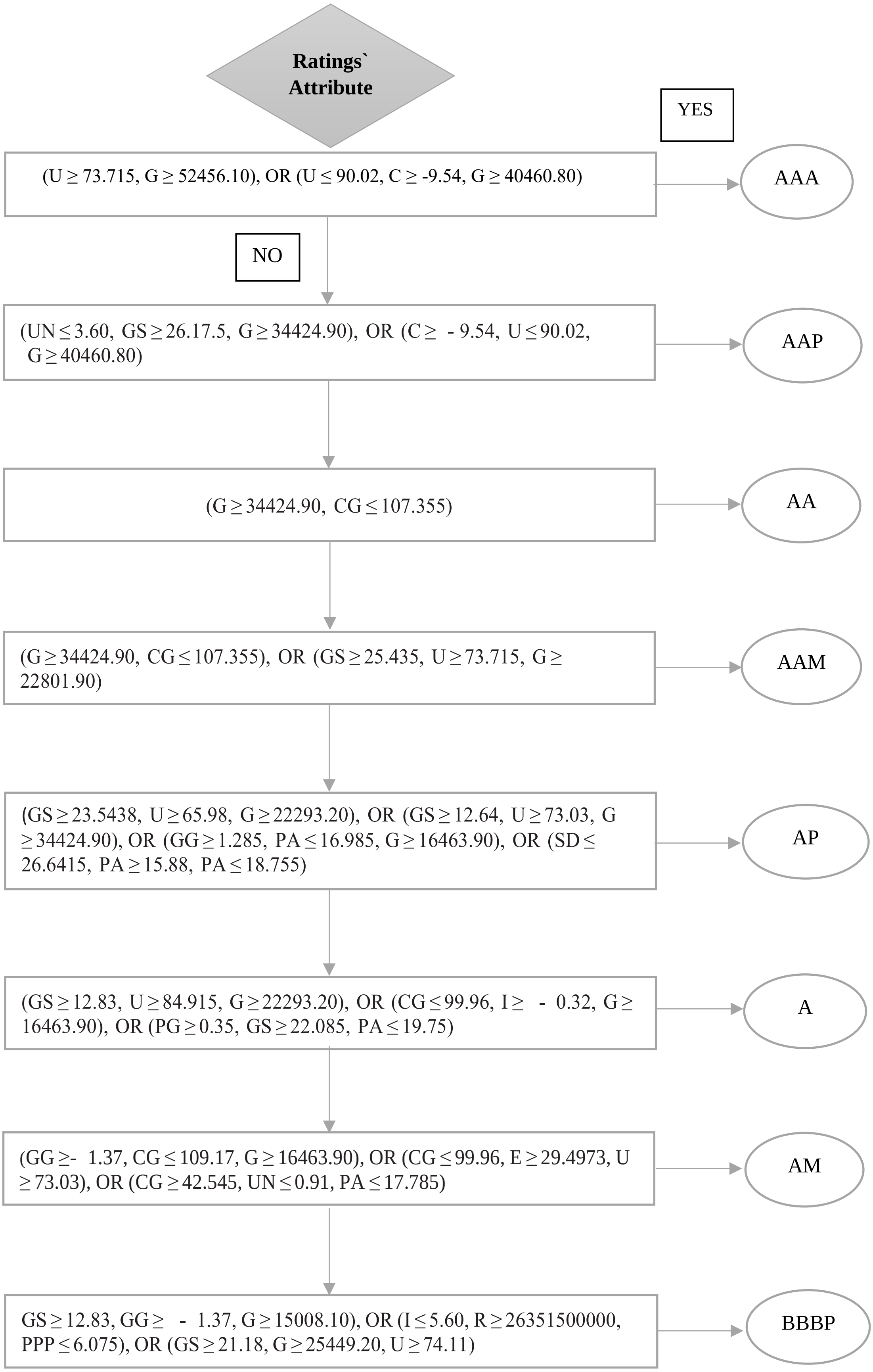
5.2.3 Parameters Used in LAD Calculation

To apply LAD, we made several assumptions. Every database may require a different value for the LAD parameters. The extent of a pattern is the number of Boolean variables in conjunction. The highest permitted degree for a pattern was 3. It means that a pattern may have three conditions only and not more. The prevalence was at least 70%, and homogeneity was claimed to be 100. The dataset of 116 countries contains populations of more than half a million in the form of two sets, namely, training and test: 68 ± 2 and 39 ± 2 countries, respectively.

These are gathered from World Bank data covering the period 2012–2015. Countries with very small populations were excluded, as they have a special risk. This fact has been proven by Iceland, which experienced an extreme financial crisis in 2008. The Fitch rating scale which was listed in Table 1 illustrates 16 varied categories from the safest to the riskiest sovereign credit ratings.

5.3 The Decision Trees; Generated by Discovered Patterns

The decision trees obtained from the multiple applications of LAD are summarized in Figures 6 to 9. These figures contain the basic logical rules in Boolean form. The use of a decision tree is simple. Only the values of the attributes of the country in question must be available. The user must only compare these values with the values of the cut-points given in the figure. The generated decision tree-based model even offers an estimated rating for unrated countries. For example, ratings of some countries like Albania, Iran, or Belarus have not been issued by Fitch in 2012. However, based on our discovered patterns for 2012, we can determine their ratings as BBP, BB, and BBM respectively.


Ratings` Attribute
YES
(U ≥ 73.715, G ≥ 52456.10), OR (U ≤ 90.02, C ≥ -9.54, G ≥ 40460.80)
AAA
NO
(UN ≤ 3.60, GS ≥ 26.17.5, G ≥ 34424.90), OR (C ≥ - 9.54, U ≤ 90.02, G ≥ 40460.80)
AAP
(G ≥ 34424.90, CG ≤ 107.355)
AA
(G ≥ 34424.90, CG ≤ 107.355), OR (GS ≥ 25.435, U ≥ 73.715, G ≥ 22801.90)
AAM
(GS ≥ 23.5438, U ≥ 65.98, G ≥ 22293.20), OR (GS ≥ 12.64, U ≥ 73.03, G ≥ 34424.90), OR (GG ≥ 1.285, PA ≤ 16.985, G ≥ 16463.90), OR (SD ≤ 26.6415, PA ≥ 15.88, PA ≤ 18.755)
AP
(GS ≥ 12.83, U ≥ 84.915, G ≥ 22293.20), OR (CG ≤ 99.96, I ≥ - 0.32, G ≥ 16463.90), OR (PG ≥ 0.35, GS ≥ 22.085, PA ≤ 19.75)
A
(GG ≥- 1.37, CG ≤ 109.17, G ≥ 16463.90), OR (CG ≤ 99.96, E ≥ 29.4973, U ≥ 73.03), OR (CG ≥ 42.545, UN ≤ 0.91, PA ≤ 17.785)
AM
GS ≥ 12.83, GG ≥ - 1.37, G ≥ 15008.10), OR (I ≤ 5.60, R ≥ 26351500000, PPP ≤ 6.075), OR (GS ≥ 21.18, G ≥ 25449.20, U ≥ 74.11)
BBBP

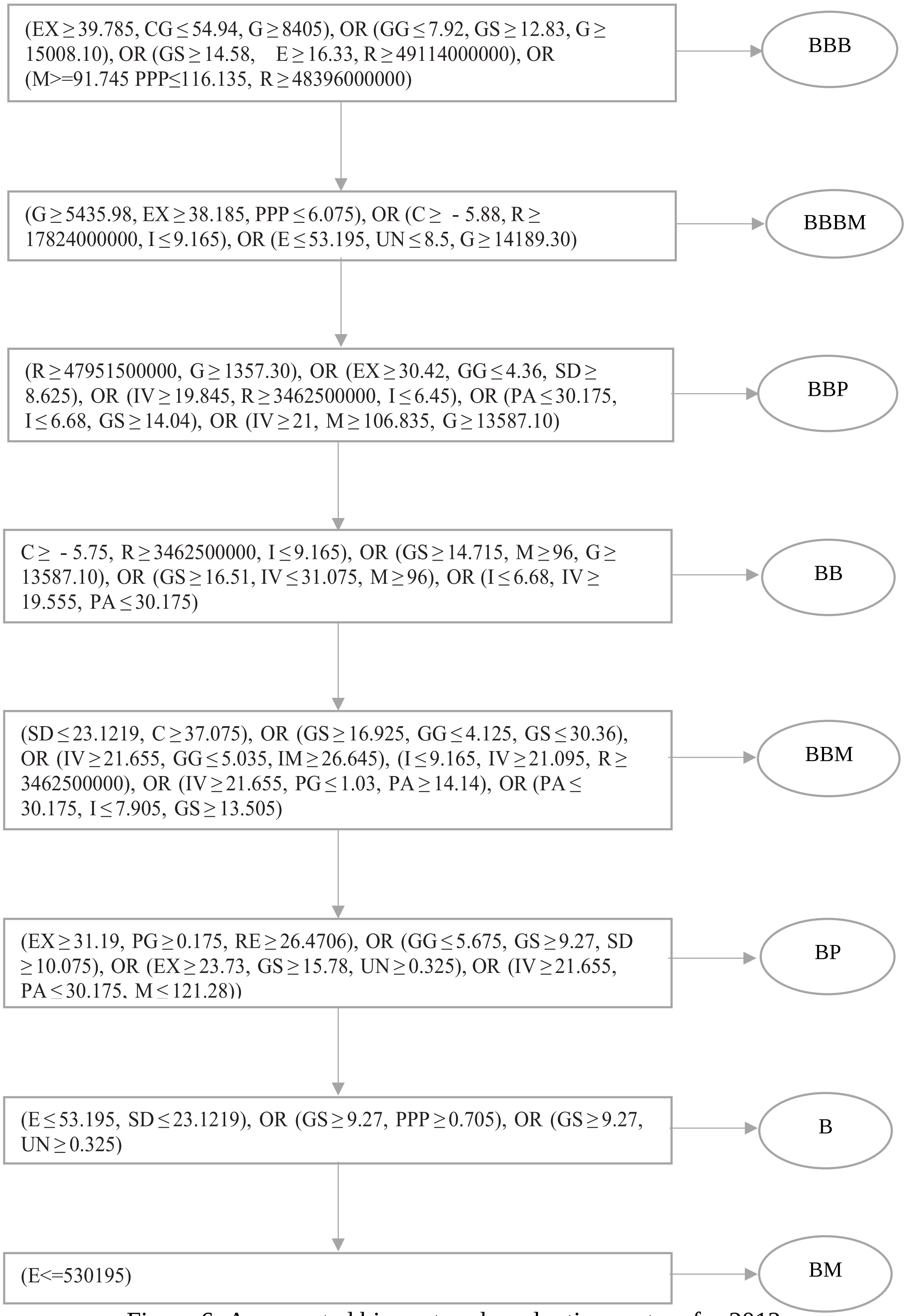
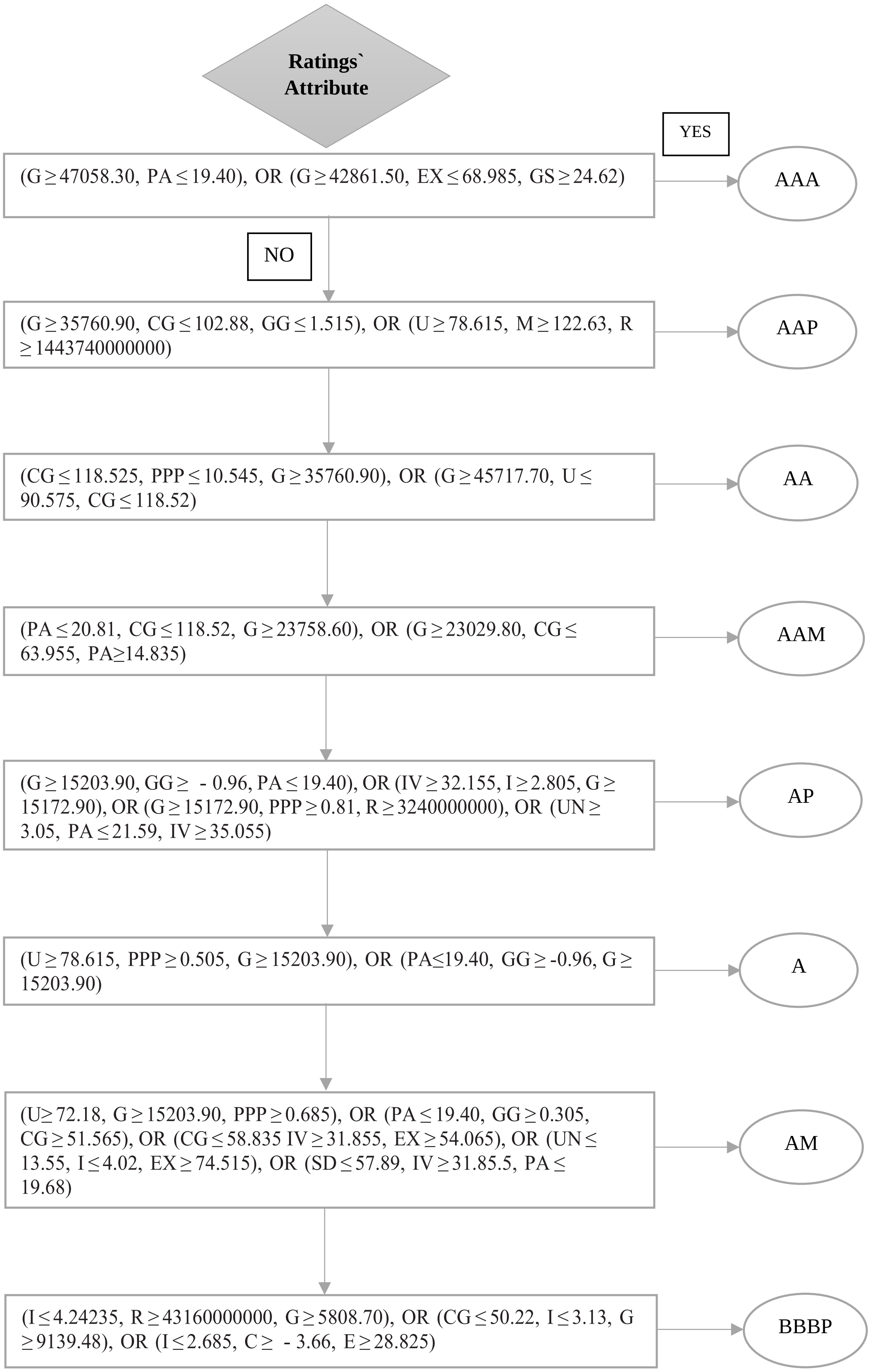


Figure 6: A generated binary tree-based rating system for 2012


Ratings`
Attribute
YES
(G≥47058.30, PA≤19.40), OR (G≥42861.50, EX≤68.985, GS≥24.62)
AAA
NO
(G≥35760.90, CG≤102.88, GG≤1.515), OR (U≥78.615, M≥122.63, R ≥1443740000000)
AAP
(CG≤118.525, PPP≤10.545, G≥35760.90), OR (G≥45717.70, U≤ 90.575, CG≤118.52)
AA
(PA≤20.81, CG≤118.52, G≥23758.60), OR (G≥23029.80, CG≤ 63.955, PA≥14.835)
AAM
(G≥15203.90, GG≥ - 0.96, PA≤19.40), OR (IV≥32.155, I≥2.805, G≥ 15172.90), OR (G≥15172.90, PPP≥0.81, R≥3240000000), OR (UN≥ 3.05, PA≤21.59, IV≥35.055)
AP
(U≥78.615, PPP≥0.505, G≥15203.90), OR (PA≤19.40, GG≥-0.96, G≥ 15203.90)
A
(U≥72.18, G≥15203.90, PPP≥0.685), OR (PA≤19.40, GG≥0.305, CG≥51.565), OR (CG≤58.835 IV≥31.855, EX≥54.065), OR (UN≤ 13.55, I≤4.02, EX≥74.515), OR (SD≤57.89, IV≥31.85.5, PA≤ 19.68)
AM
(I≤4.24235, R≥43160000000, G≥5808.70), OR (CG≤50.22, I≤3.13, G ≥9139.48), OR (I≤2.685, C≥ - 3.66, E≥28.825)
BBBP

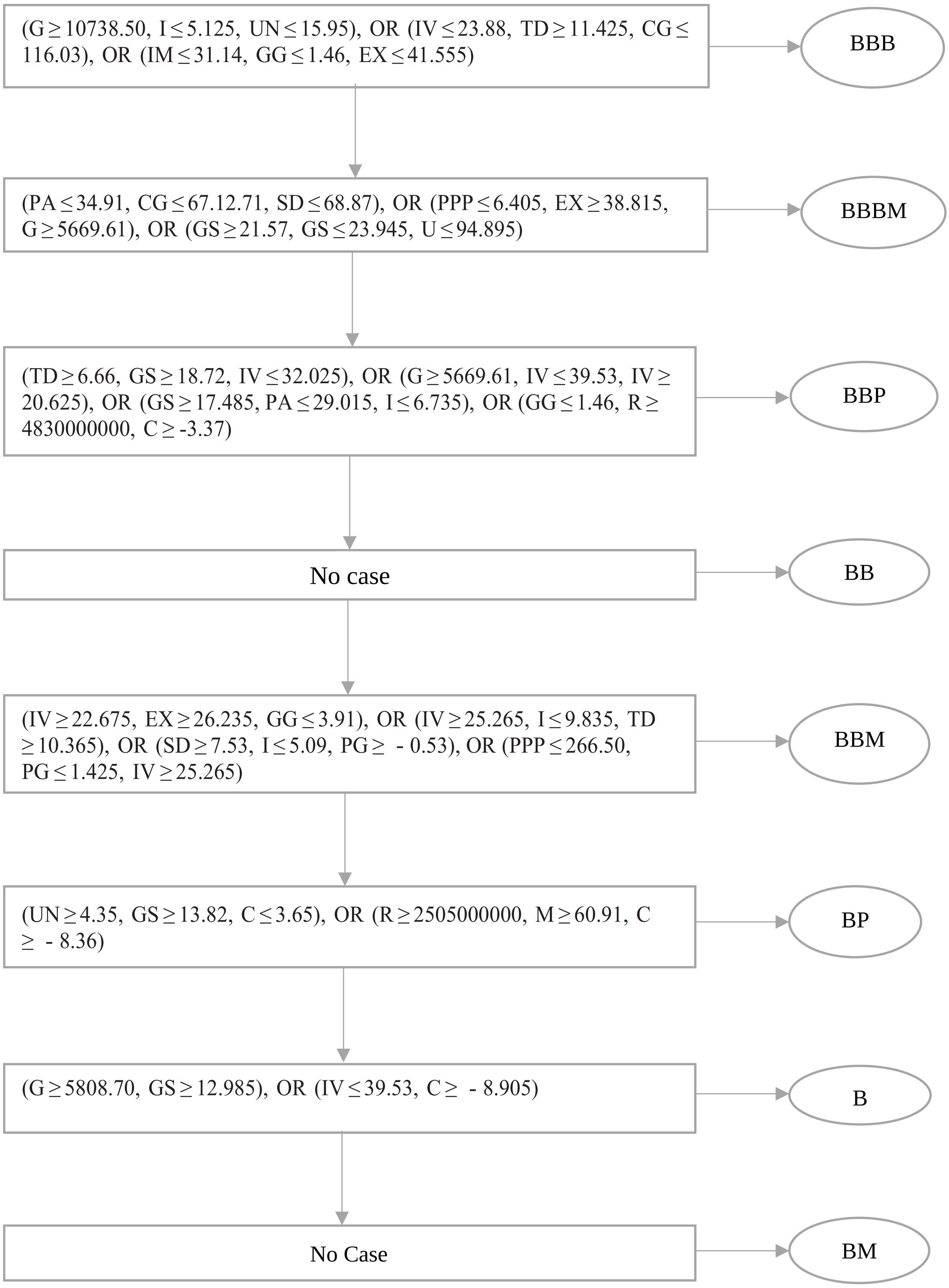
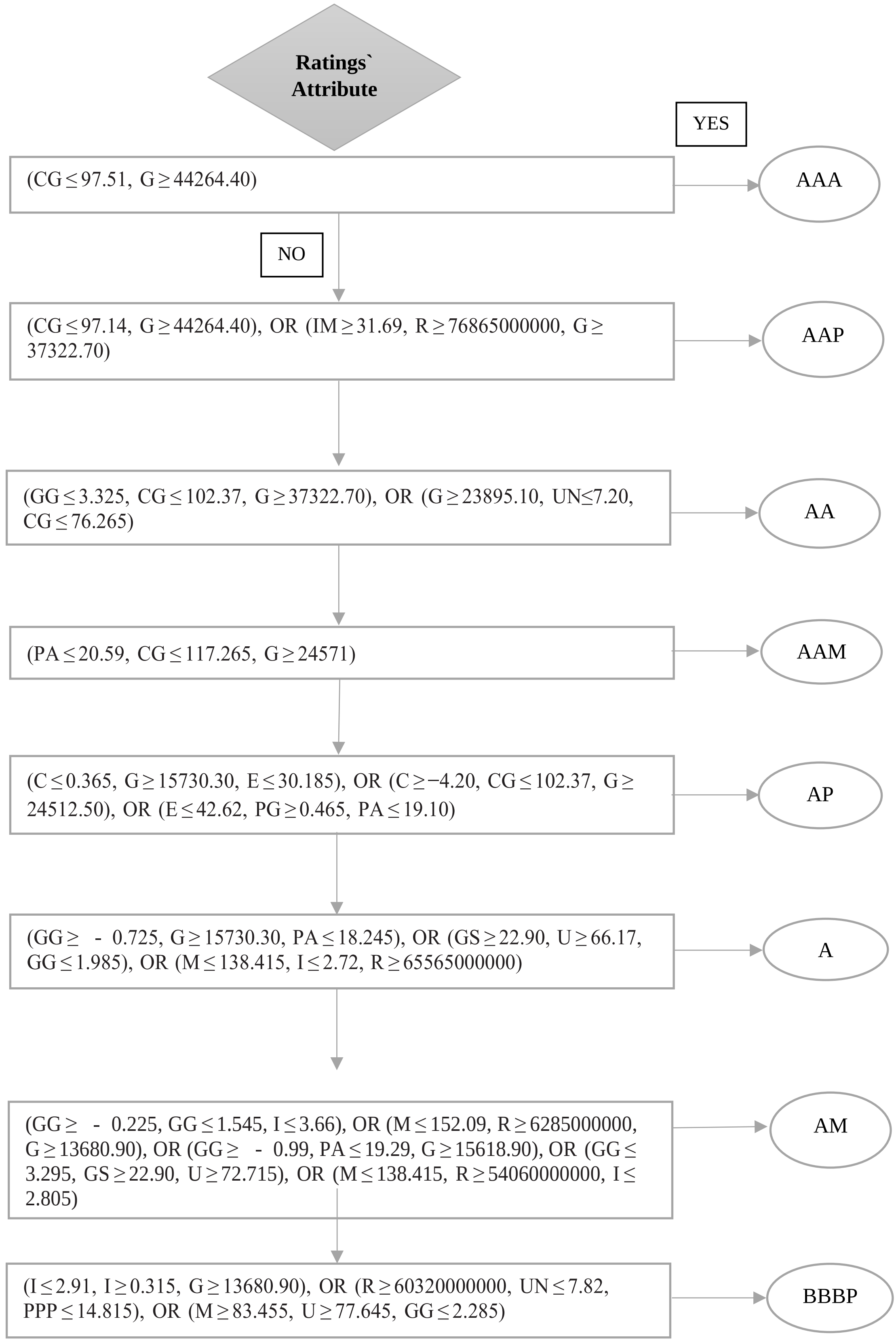


Figure 7: binary tree based of the 2013 rating system


Ratings` Attribute
YES
NO
(CG ≤ 97.51, G ≥ 44264.40)
AAA
(CG ≤ 97.14, G ≥ 44264.40), OR (IM ≥ 31.69, R ≥ 76865000000, G ≥ 37322.70)
AAP
(GG ≤ 3.325, CG ≤ 102.37, G ≥ 37322.70), OR (G ≥ 23895.10, UN≤7.20, CG ≤ 76.265)
AA
(PA ≤ 20.59, CG ≤ 117.265, G ≥ 24571)
AAM
(C ≤ 0.365, G ≥ 15730.30, E ≤ 30.185), OR (C ≥ −4.20, CG ≤ 102.37, G ≥ 24512.50), OR (E ≤ 42.62, PG ≥ 0.465, PA ≤ 19.10)
AP
(GG ≥ - 0.725, G ≥ 15730.30, PA ≤ 18.245), OR (GS ≥ 22.90, U ≥ 66.17, GG ≤ 1.985), OR (M ≤ 138.415, I ≤ 2.72, R ≥ 65565000000)
A
(GG ≥ - 0.225, GG ≤ 1.545, I ≤ 3.66), OR (M ≤ 152.09, R ≥ 6285000000, G ≥ 13680.90), OR (GG ≥ - 0.99, PA ≤ 19.29, G ≥ 15618.90), OR (GG ≤ 3.295, GS ≥ 22.90, U ≥ 72.715), OR (M ≤ 138.415, R ≥ 54060000000, I ≤ 2.805)
AM
(I ≤ 2.91, I ≥ 0.315, G ≥ 13680.90), OR (R ≥ 60320000000, UN ≤ 7.82, PPP ≤ 14.815), OR (M ≥ 83.455, U ≥ 77.645, GG ≤ 2.285)
BBBP

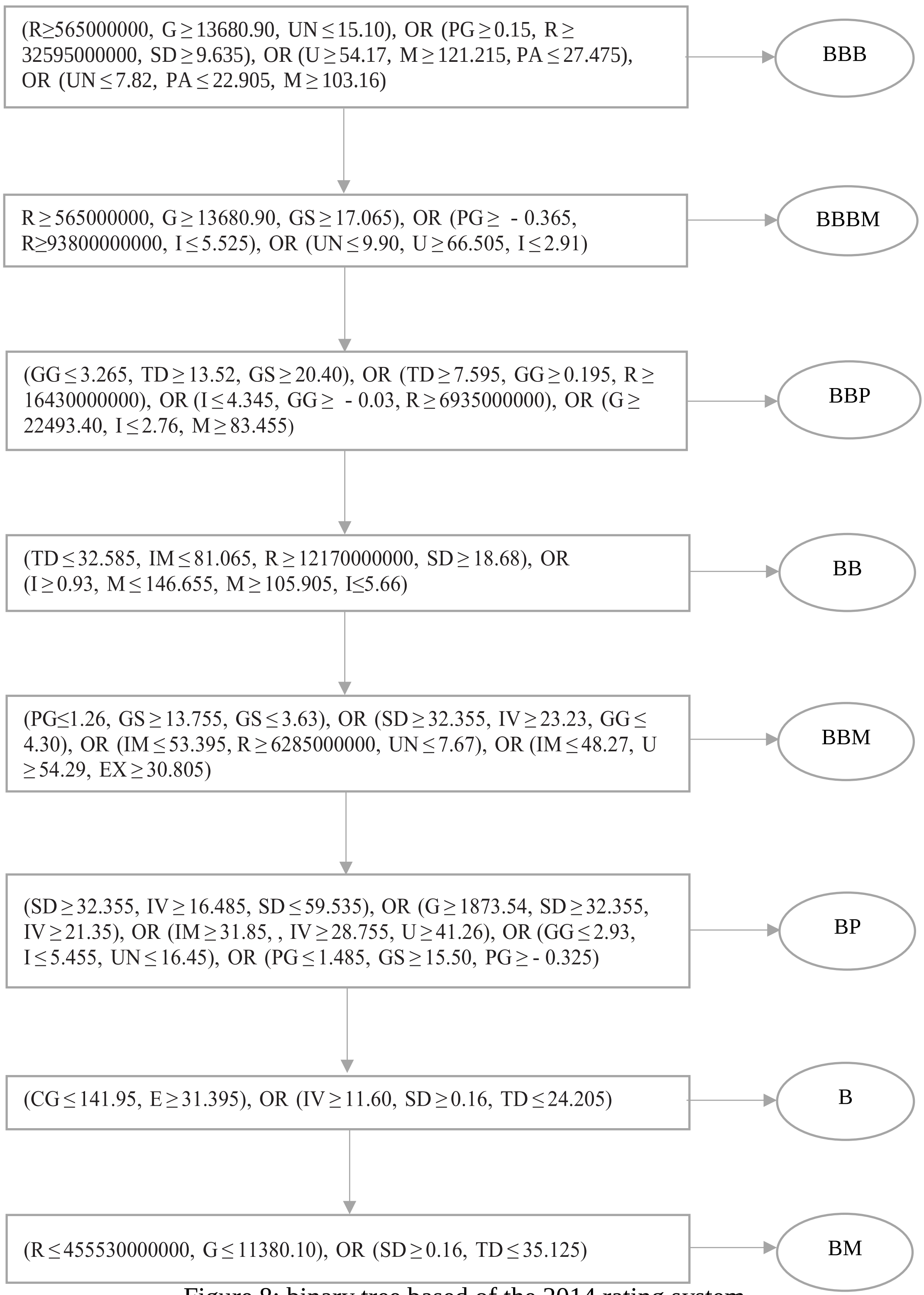
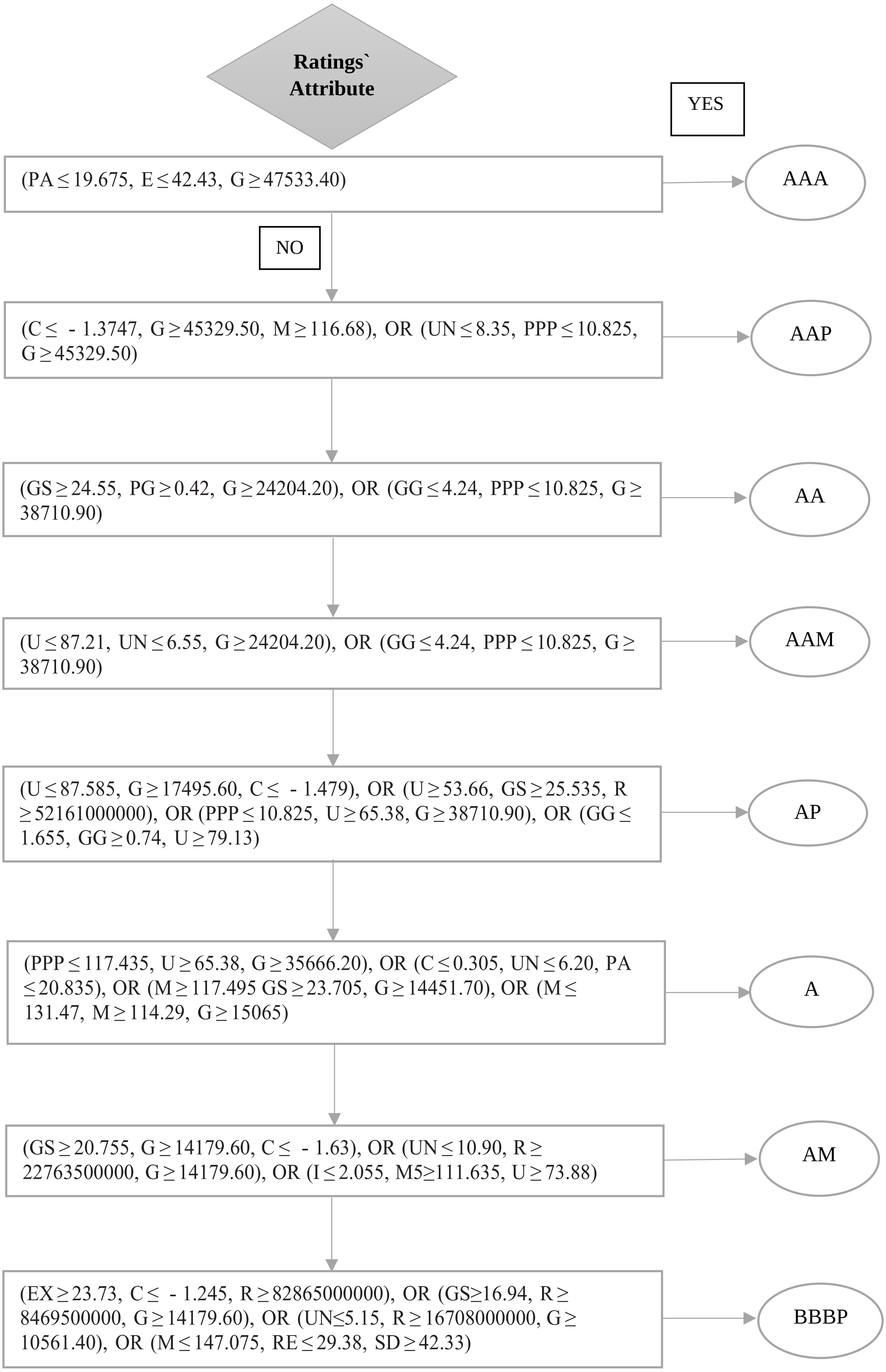


Figure 8: binary tree based of the 2014 rating system



Ratings` Attribute
YES
(PA ≤ 19.675, E ≤ 42.43, G ≥ 47533.40)
AAA
NO
(C ≤ - 1.3747, G ≥ 45329.50, M ≥ 116.68), OR (UN ≤ 8.35, PPP ≤ 10.825, G ≥ 45329.50)
AAP
(GS ≥ 24.55, PG ≥ 0.42, G ≥ 24204.20), OR (GG ≤ 4.24, PPP ≤ 10.825, G ≥ 38710.90)
AA
(U ≤ 87.21, UN ≤ 6.55, G ≥ 24204.20), OR (GG ≤ 4.24, PPP ≤ 10.825, G ≥ 38710.90)
AAM
(U ≤ 87.585, G ≥ 17495.60, C ≤ - 1.479), OR (U ≥ 53.66, GS ≥ 25.535, R ≥ 52161000000), OR (PPP ≤ 10.825, U ≥ 65.38, G ≥ 38710.90), OR (GG ≤ 1.655, GG ≥ 0.74, U ≥ 79.13)
AP
(PPP ≤ 117.435, U ≥ 65.38, G ≥ 35666.20), OR (C ≤ 0.305, UN ≤ 6.20, PA ≤ 20.835), OR (M ≥ 117.495 GS ≥ 23.705, G ≥ 14451.70), OR (M ≤ 131.47, M ≥ 114.29, G ≥ 15065)
A
(GS ≥ 20.755, G ≥ 14179.60, C ≤ - 1.63), OR (UN ≤ 10.90, R ≥ 22763500000, G ≥ 14179.60), OR (I ≤ 2.055, M5≥111.635, U ≥ 73.88)
AM
(EX ≥ 23.73, C ≤ - 1.245, R ≥ 82865000000), OR (GS≥16.94, R ≥ 8469500000, G ≥ 14179.60), OR (UN≤5.15, R ≥ 16708000000, G ≥ 10561.40), OR (M ≤ 147.075, RE ≤ 29.38, SD ≥ 42.33)
BBBP

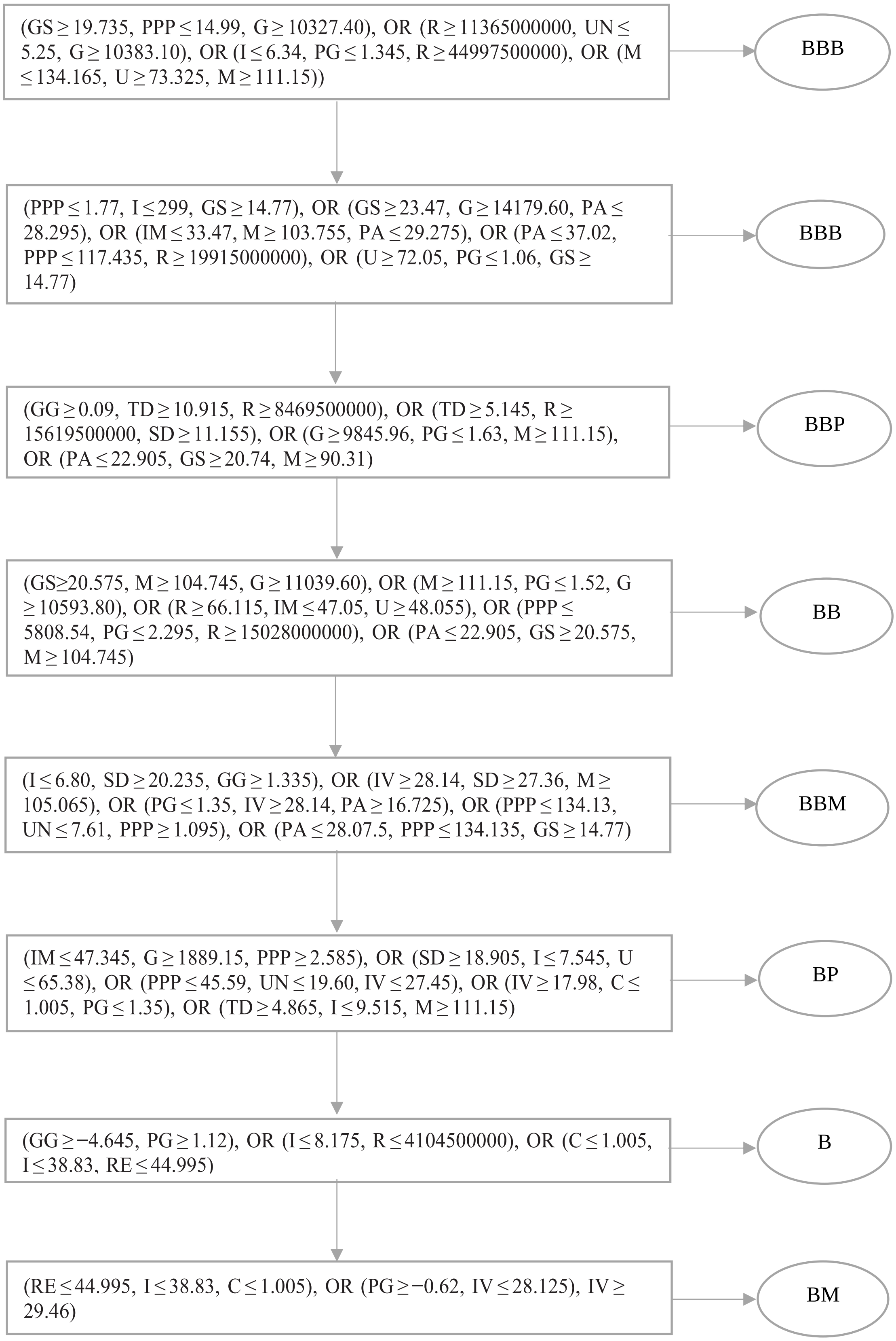


Figure 9: Binary tree-based of the 2015 rating system

5.3.1 Key Variables of the Decision Trees

The prepared decision trees explain certain properties. The most important attributes are listed in Table 11. The GDP per capita was an essential factor in all rating classes except the lowest. For ratings from AAA to AAM, there was no pattern without it. GDP occurs from AP to AM in more than 50% of the patterns. In addition to GDP, total reserves, gross savings, and inflation are the dominant variables in the classification of countries with BBB and BB rating levels. In the lowest rating class, that is, B, male unemployment rate and industry value added are the major variables.

Table 11: The most observed variables in each Class

Rating Class	The most observed variables in each Class
AAA	GDP Per Capita
AAP-AA-AAM	GDP Per Capita
AP-A-AM	GDP Per Capita- Population Age- Inflation
BBBP-BBB-BBBM	Total Reserves- Gross Savings- GDP Per Capita- Unemployment Rate- PPP Conversion Factor- Inflation- Urban Population
BBP-BB-BBM	Total Reserves- Gross Savings- GDP Per Capita- Inflation- GDP Growth- Short-term Debt- Industry Value Added- Population Growth
BP-B-BM	Industry Value Added- Unemployment Rate

5.4 Fitch Rating Predictions

The dataset of the study was divided into two subsets, namely, training and test sets. included 69 and 30 countries, respectively. The decision trees are estimated for all years as well as separately for the two subsets. In our result, the explored patterns in the form of the decision trees could predict the same credit ratings of the countries by a high percentage as Fitch has reported. We obtained 93%, 89%, 91.5%, and 90.5% different ratings with Fitch agency's country ratings for each of the four years. The high accuracy confirms the value of the prognosis and robustness of the LAD rating system. On average, we matched the Fitch rating results in the training set by 98% and in the test set by 84%. The unmatched ratings according to country, and the corresponding ratings are shown in Tables 12 to Table 18.

5.4.1 Mismatched Cases Description

The year 2012 showed a ratio of matched consequences of 100% for the training set and 85.7% for the test set. In 2013, we see a ratio of matched consequences of 98.5% for the training set and 78% for the test set. The different output of the two sets is shown in Tables 13 and 14. For the year 2014, the ratio of matched outcomes for training and test sets is 98.5% and 85%. The different output of the two sets is shown in Tables 15 and 16. For the year 2015, the ratio of the matched result of training and test sets is 94% and 87%. The differences in the rating of the two sets are shown in Tables 17 and 18.

First, the high proportions of matched ratings with the Fitch rating system show that our LAD methodology was successful. Secondly, in the majority of the misclassified cases through the years, Fitch has shown a bias towards downgrading rather than upgrading the countries. The incentive for being conservative is that it may deflect criticism, especially in periods of an economic and financial crisis. To support this idea, Overall, out of Fitch`s announced cases that do not match with our result, downgraded cases outnumbered the upgrades. Over four studied years, on average, 75.8% of mismatched ratings belong to the downgrading category whereas it is only 24.2% for upgrades. It means if we take our model as an unbiased predictive tool for countries' rating classes, the Fitch agency has tended to downgrade the countries and show their rating classes less than they may assign. Tables 12 to 18 show the countries which have been faced with biased credit ratings throughout the four years. There are no unmatched cases for the training set of 2012.

Table 12: Mismatched cases of the test set for 2012

Country	Rating by LAD	Fitch Rating
Ukraine	BBBM	B
Suriname	BBBM	BBM
Rwanda	BP	B
Ghana	BB	BP
Dominican Republic	BB	B

Table 13: The unmatched cases of the test set for 2013

Country	Rating by LAD	Fitch Rating
Malta	AP	A
Vietnam	BBM	BP
Ukraine	BBM	B
Kazakhstan	BBB	BBBP
Zambia	BP	B
Congo, Dem Republic	BBM	BP
Paraguay	BBP	BBM
Portugal	BBB	BBP
Iceland	AAM	BBB
Spain	AAM	BBB
Cyprus	BBB	B

Table14: Mismatched result of the training set for 2013

Country	Rating by LAD	Fitch Rating
Israel	AAM	A

Table 15: The unmatched cases of the test set for 2014

Country	Rating by LAD	Fitch Rating
South Africa	BBBM	BBB
Portugal	A	BBP
Panama	B	BBB
Iceland	AAM	BBB
Cyprus	AP	BM
Costa Rica	BBBM	BBP

Table 16: Mismatched result of the training set for 2014

Country	Rating by LAD	Fitch Rating
Namibia	BBP	BBBM

Table 17: Mismatched ratings of the test set for 2015

Country	Rating by LAD	Fitch Rating
Congo, Dem Republic	B	BP
Rwanda	B	BP
Latvia	A	AM
Iceland	BBM	BBB
Armenia	BBM	BP

Table18: Mismatched ratings of the training set for 2015

Country	Rating by LAD	Fitch Rating
Ireland	BBB	AM
Malaysia	AP	AM
Peru	BBB	BBBP
Namibia	BBM	BBBM

5.4.2 Unmatched Cases on Global Map

All mismatched ratings of countries over four years have been shown on the global map (Figure 10). The red color is used for the countries which have been downgraded by the Fitch agency compared to our result. The countries whose ratings are upgraded by the Fitch rating system are colored in green. There are a few countries such as Congo Dem Republic, Rwanda, and Iceland has received low ratings from Fitch in the year 2012 and 2013, however, they were rated by the higher label in 2015 compared to our LAD consequences. According to the map, the number the downgrades exceeds the upgrades, and it satisfies the conservative policy of the Fitch agency after the 2009 financial crisis. The most unmatched ratings are more likely to happen in the European region with 13 countries, thereafter African counties with 9 cases.

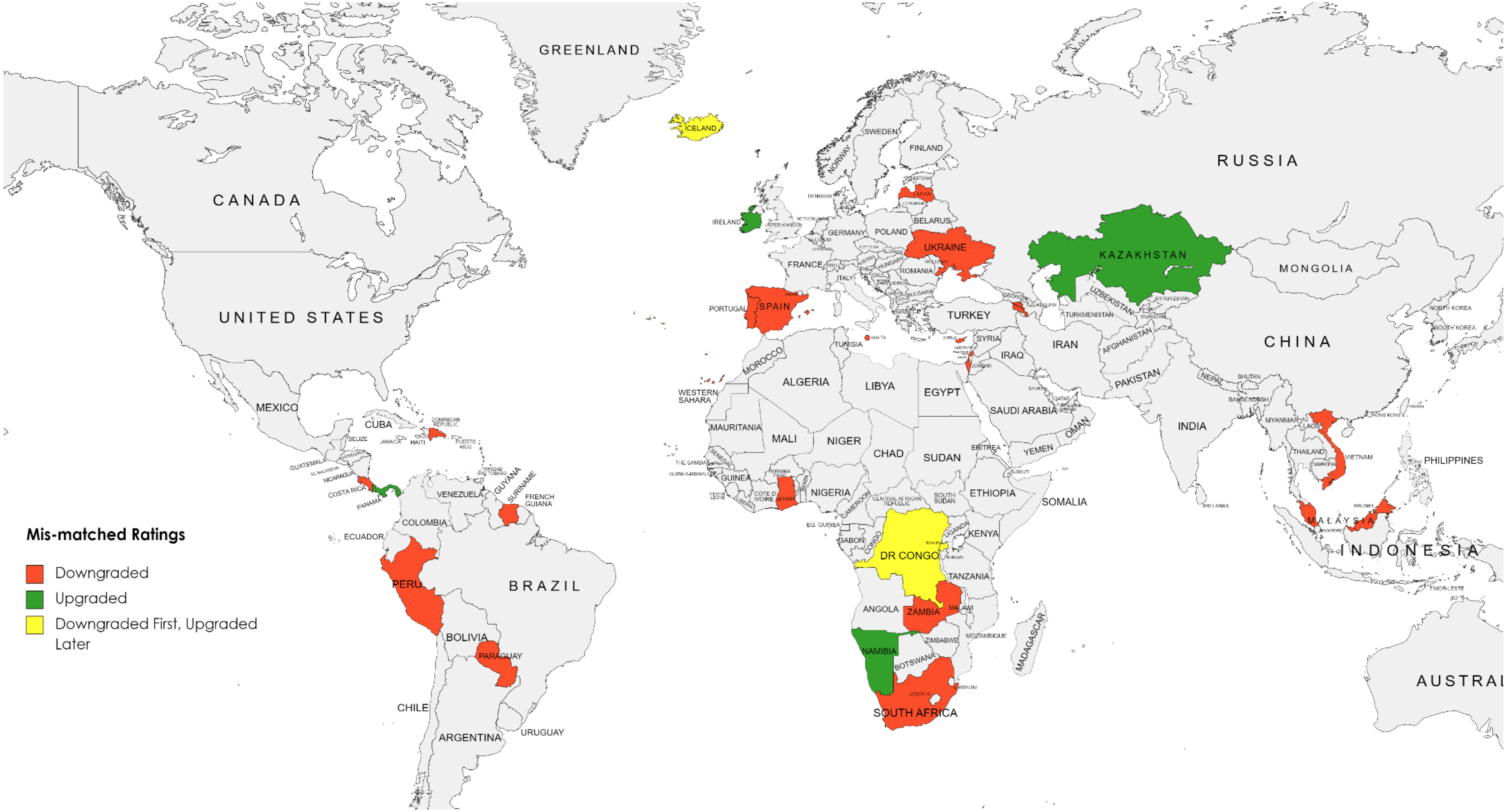


Figure 10: Unmatched ratings on the global map from 2012 till 2015

Chapter 6

CLASSIFICATION OF COUNTRIES (COVID-19 CRISIS)

In this chapter, we investigate whether the COVID-19 crisis changes the rating policy of the Fitch agency. Since most of the economic, social, and environmental aspects of the countries and their indicators are affected by this pandemic. Therefore, in this chapter, Logical Analysis of Data is the methodology and International Monetary Fund and the World Bank website are the databases to collect the required data.

6.1 Introduction to COVID-19 Crisis and its Impacts

Some studies inflate the existence of a close association between credit risk ratings, stock market movement, and exchange rate volatility (Almahmood, 2014b; C. Baum et al., 2016; Rafay et al., 2018a). Investor and creditor appetite grew for higher grades of CRs. Therefore, high ratings cause creditors to be more optimistic, which declines the corporation's financial costs and modifies its investment scheme (Goldstein & Huang, 2020b). As manifested by (Delis et al., 2021b), the COVID-19 crisis created dramatically negative feedback on the skewness and total value of risk. Having successful access to the financial market to deal with heavy debts during a pandemic is the main way for governments to survive the crisis. Downgrades will have a severe impression on sovereigns and corporate finances.

As CRAs evaluate the COVID-19 effect, they gauge what the long-term impact of the coronavirus crisis will be. They need to determine whether the consequences of the short-term CR conduct to long-term, or if a different rate structure is required to express risks to investors (Susan Borries Reed, 2020).

6.2 The Fitch Agency`s Response to the Pandemic

It's evident from Fitch Rating's recent announcements that high-yield nations are being hit harder, forcing them deeper into the junk zone. The most notable country to suffer a downgrade is Canada, which went from AAA to AAP (AA+).

CRAs showcased the up-graded, fixed, and down-graded countries in chapter 2.3 Figure 2 to better demonstrate the negative effect of the pandemic on CRs. To explore the ratings` vulnerability to downgrades over the crisis, Fitch Rating System has been studied by LAD.

6.3 Economic and Social Variables` Movements During the Pandemic

The world policy to the deadly and costly Coronavirus Crisis made governments have a high debt-to-GDP ratio. To pay for many of these programs, countries will require to have access to financial markets. This phenomenon shed light on the response of CRAs to the pandemic. The negative outlook of sovereign downgrades at the outset of the coronavirus crisis has slowed-moved since June and continues to decelerate in the months ahead. Sovereign credits experience considerable stress following the negative viewpoints about downgrades that may reach below the historical average. Accordingly, it is certain to follow the trend of the main variables of pre-explored patterns of the Fitch Rating system (Elnaz Gholipour, 2021; Gholipour, Vizvári, & Lakner, 2021) to analyze its reaction to COVID-19.

6.3.1 Selected Variables and Rating Process

GDP is the overall value of goods and services for last use, produced by inhabitant producers in an economy. *GDP per capita* and *GDP per capita annual growth rate* are extensively utilized by economists to recognize the health of an economy (König & Winkler, 2020). These articles claim, on averagely, GDP per capita intends to decline in 2020 compared with 2019 internationally. Whereas the Fitch agency expected GDP growth to fall to 1.3% in 2020 from 2.9% in 2019, the expectation was affected by lockdown dramatically, falling to – 3.03%.

During the pandemic, some do not believe in *inflation* because many industries such as hotels, gasoline, or airfares pulled the index down. Cheap, but the low-demanded product basket does not show inflation. The Wall Street Journal reported that inflation is somewhere for the materials you want to buy like high-demanded products (Don Pittis, 2020). Alongside falling-off prices in most industries, the demand for certain pandemic-related products is increasing.

Modified workforce policy of nearly all institutions and companies says, the average global *unemployment rate* hit 5.42% in starting months of pandemic 2020 and remained 0.02 percent higher than in 2019 (Congressional Research Service (CRS), 2021). Young or low-educated workers, women, and part-time laborers endured more proportion of the unemployment rate. *The urban population* as another significant variable seems to be affected by COVID-19. Since 56.2 percent of the world`s population is urban, the fast distribution of COVID-19 occurs in crowded places which represents an environmental risk.

Additionally, the shutdown pushed emergency expenditure to societies and made governments' debts balloon. Hence, we select the *government debt as the percentage of GDP,* in the role of another variable for the analysis of this part. (Javier García Arenas Senior economist, 2020) believes that the historic jump in gross savings is a definite product of the COVID-19 crisis. *Gross saving* as a percentage of GDP is added to our selected first variable group also.

The second variable group of the COVID-19 study is composed of two factors that show the environmental risk; the *Total infected population* and *the number of Death*. To explain the selection reason of this group, if a country`s infected population and the dead reported cases will be increasing, it is an indicator of an unsafe country with a high risk that may influence the credit ratings.

(Efraim Benmelech, 2020b) says while we are debating on the number of macroeconomic variables such as GDP per capita, population size, debt to GDP, government expenditures to GDP, the number of COVID-19 cases, and the central government credit rating to make decisions about the strongest and determinant factors effective on credit ratings of the countries. Interestingly, unlike GDP per capita or even the spread of the virus variables, one factor shows up consistently as the strongest determinant of fiscal policy. That factor was a country's rating before the crisis.
Professor Efraim and some other economists` ideas caused us to determine the third group of the variable for the investigation of the COVID-19 crisis part, which is a previous credit rating of a country by the name *Pre-CR*.

To explore the specific rating model for the COVID-19 crisis, we employ the LAD with modified variables composed of 10 economic, coronavirus spread indicators, and pre-CR.

6.4 Methodology and Mathematical Explanation of the LAD Process

Logical Analysis of Data is the methodology applied to illustrate the Fitch agency`s response to the COVID-19 crisis. Training and Test sets contain 60 and 33 countries in turn. Based on the given credit ratings for the countries by Fitch in 2020, the countries are assigned to 1 or 0 in each class of the rating.

To express LAD for the case of COVID-19 with a different visualization, Figure 11 is offered. The figure shows if a country satisfies the cut-point separating "AAA" countries from others, then it is classified as "AAA". The AAA-labeled country may satisfy all other classes` cut-points. If the cut-point of the "AAP" rating class is met by any new country, the country is grouped as "AAP", etc. (Figure 11).

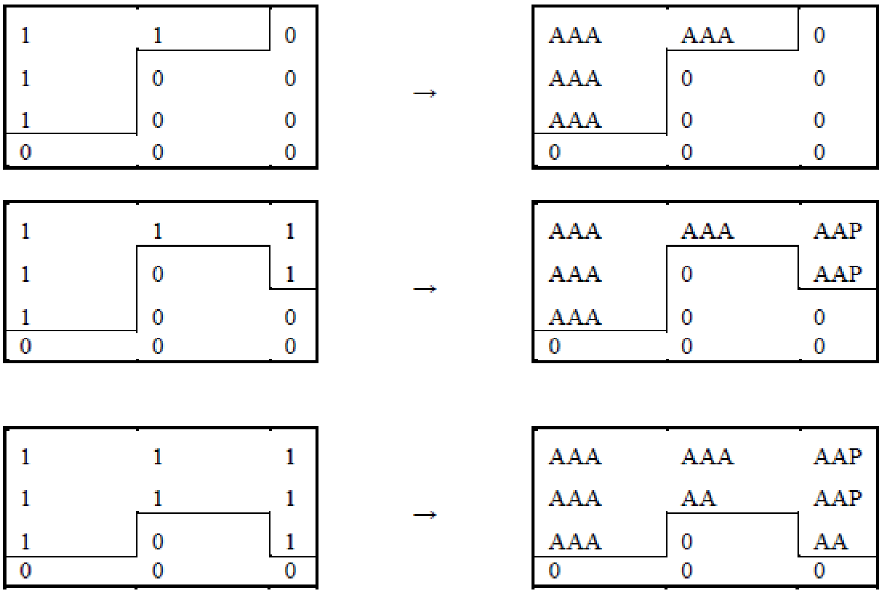


Figure 11: Different expression of Logical Analysis of Data

The data set of the research was collected from the World Bank (the world bank group, 2021), WHO Organization (The World Health Organization, 2020), and Wikipedia covering the period of 2019-2020.

6.4.1 The Used Parameters in the LAD Calculation

Degree, Prevalence, and Homogeneity

Patterns of small degrees are always preferable because they are easier to interpret (Hammer et al., 2012b). A high percentage of prevalence and 100% of homogeneity are more desirable. These three parameters of this study are 3, 70%, and 100% in order.

The Measurement of the Variables

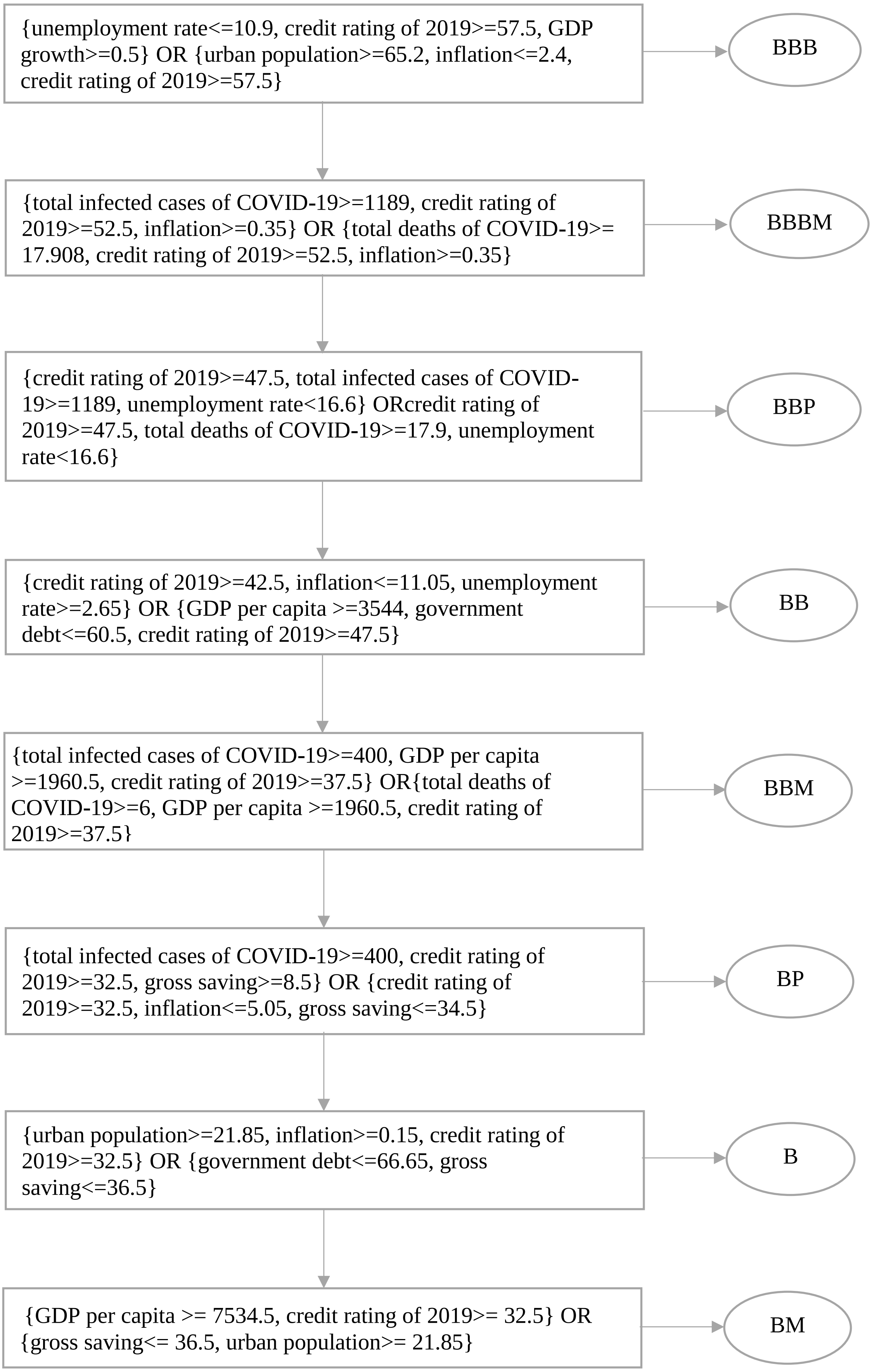
The values of seven economic and social factors were collected from the 2020 database of the World Bank, and the total number of infected and fatal in each country was gathered till the end of July 2020. We used the assigned measurements of all 16 credit rating labels, published by the Fitch agency to value the Pre-CR as Table 19.

Table19: Credit rating values

Measurment	Credit Rating
100	AAA
95	AAP
90	AA
85	AAM
80	AP
75	A
70	AM
65	BBBP
60	BBB
55	BBBM
50	BBP
45	BB
40	BBM
35	BP
30	B
25	BM

6.4.2 Binary Tree-Based LAD Exploration

The following decision tree specifies the explored patterns and specific attributes for each class (Figure 12).


{unemployment rate<=10.9, credit rating of 2019>=57.5, GDP growth>=0.5} OR {urban population>=65.2, inflation<=2.4, credit rating of 2019>=57.5}
BBB
{total infected cases of COVID-19>=1189, credit rating of 2019>=52.5, inflation>=0.35} OR {total deaths of COVID-19>= 17.908, credit rating of 2019>=52.5, inflation>=0.35}
BBBM
{credit rating of 2019>=47.5, total infected cases of COVID-19>=1189, unemployment rate<16.6} ORcredit rating of 2019>=47.5, total deaths of COVID-19>=17.9, unemployment rate<16.6}
BBP
{credit rating of 2019>=42.5, inflation<=11.05, unemployment rate>=2.65} OR {GDP per capita >=3544, government debt<=60.5, credit rating of 2019>=47.5}
BB
{total infected cases of COVID-19>=400, GDP per capita >=1960.5, credit rating of 2019>=37.5} OR{total deaths of COVID-19>=6, GDP per capita >=1960.5, credit rating of 2019>=37.5}
BBM
{total infected cases of COVID-19>=400, credit rating of 2019>=32.5, gross saving>=8.5} OR {credit rating of 2019>=32.5, inflation<=5.05, gross saving<=34.5}
BP
{urban population>=21.85, inflation>=0.15, credit rating of 2019>=32.5} OR {government debt<=66.65, gross saving<=36.5}
B
{GDP per capita >= 7534.5, credit rating of 2019>= 32.5} OR {gross saving<= 36.5, urban population>= 21.85}
BM

6.5 The Results of the Rating Analysis During Pandemic

Out of the economic and social factors, *GDP per capita*, *Government debt*, *GDP growth*, *Inflation*, and *gross saving* have frequently been out in “AAA” to “AM”. Certainly, *GDP per capita* is shining among them as the most important factor for “A”-related ratings. None of the “A” classes were affected by pandemic factors in currently announced countries` ratings by Fitch.

By contrast, previous credit rating; *“Pre-CR”,* was observed in whole ratings description and patterns as a dominant factor. The variable is closely related to the COVID-19 that came out in “speculative grades” from “BBBM” to “BP”. The impressive observation is, that as much as we go down through ratings, the value of COVID-19 attributes, Cut-points, falls. It shows that coronavirus crises threaten low-rated countries to be downgraded more by the Fitch Rating system during the pandemic. This finding of our research is verified via the actual announcement of the Fitch agency as we already discussed in Table 4.

The current research surveyed Fitch Rating’s response to COVID-19 through 10 variables. The main contribution of the research is adding coronavirus factors to the study to analyze whether newly announced credit ratings have been affected by the coronavirus crisis. The outcome of LAD in the form of the decision trees describes the whole 16 rating levels completely at 100% matched-result of the training set that was verified nearly 80% of matched out-put in the test set. Canada is one of the countries that may be affected by the coronavirus crisis since for the first time after 2002, its rating fell to “AAP”.

6.6 Comparison of Our Result with the Fitch Agency Response

To compare 20% of our results that are unmatched with the pandemic new ratings of the Fitch, some countries are downgraded or upgraded within the first year of the COVID-19 crisis as follows;

Countries which Upgraded by Fitch: Germany, Kuwait, and Saudi Arabia are rated as “AAA”, “AA”, and “A” via the Fitch rating system in 2020, but according to our model, they should be classified as “AAP”, “AAM”, “AM” in order. It seems for the countries that their infected cases and total deaths are lower than the global average and negligible with considerably high GDP per capita, the previous credit rating (Pre-CR) has been noticed for new rating, i.e for Germany, a country with a GDP of 45,723$, the infected cases and fatalities during the first half of 2020 was only 0.3% and 1.1% respectively. According to our conclusion, since the previous credit rating of Germany was “AAA”, and the risk of the COVID-19 crisis was low, therefore, the previous rating as a dominant factor affected the new rating which was reported as “AAA” again.

Downgraded by Fitch: Fitch Rating reported, the ranking of Bahrain, Cyprus, Portugal, and San Marino as “BP”, “BBBM”, “BBB”, and “BBP” respectively, however, their actual credit rates assigned to “A” class, based on our result. Also, the Fitch agency downgraded Bolivia and Costa Rica to one lower level from “BP” to “B” and Ecuador from “B” to “BM”.

To conclude, even in the coronavirus crisis, still economic and social variables are well-defined factors to describe the credit rating system optimally. However, the previous credit rating of countries is the main predictor of the rating system and has been observed within all ratings. COVID-19-related variables became apparent among the selected patterns of high yields (lower rating levels).

Chapter 7

CONCLUDING REMARKS

Sovereign debt rating plays an important role in the world economy. The method of the most important rating companies is not public. This can be explained by two facts: the algorithms are considered as individual properties of these enterprises, and the rating is based on some tacit knowledge of experts, built on their experiences, personal interviews, gray literature, open-source intelligence, etc. This is why a perfect reproduction of the classifications of these agencies does not seem possible. Sovereign debt ratings provided by rating agencies measure the solvency of a country, as gauged by a lender or an investor. It is an indication of the risk involved in investment and should be determined correctly and in a well-timed manner. The current system is lacking transparency in rating criteria and mechanisms. It would be important for countries, lenders, institutions, and investors to know the method or a good approximation of the method in the credit rating system.

The present study reconstructs sovereign debt ratings through LAD, which is based on the theory of Boolean functions. It organizes groups of countries according to 20 World Bank-defined variables for the period 2012–2015. The Fitch Rating Agency, one of the three big global rating agencies, is used as a case study. An approximate algorithm was crucial in exploring the rating method, correcting the agency’s errors, and determining the estimated rating of otherwise unrated countries.

The outcome was a decision tree (Binary Tree-based model) for each year, and each country was assigned a rating. On average, the algorithm reached almost 98% matched ratings in the training set and was verified by 84% in the test set.

The most important contribution of this thesis is this application does not need any expertise or professional understanding of rating methods. Previous papers were not providing such a tool for investors. The sovereign debt rating given by the decision trees is largely the same as Fitch's rating. The discrepancies may be due in part to the The fact that an unknown function was approximated by regression.

Another important reason is that for some countries the rating is biased from what is expected in some direction. A deeper analysis of the discrepancies is one of the research topics of the future. The LAD technology was originally developed to separate only two classes. The results also showed that LAD may be able to distinguish several classes simultaneously in the case of a systematic application. In the future, it is worth exploring the conditions for such applications and creating additional applications accordingly.

Unexpected global COVID-19 health crises made us expand our research in the direction of the pandemic to survey its impact on the variables and test our model and algorithm on the unknown phenomenon either. To explore the ratings` vulnerability to downgrades over the crisis, Fitch Rating System has been studied by LAD. The high percentage of the matched cases in training and test sets, shed light on the robust results of the explored patterns in the form of the decision trees. Despite these uncertainties, our best estimate clarifies that the coronavirus crisis had no adverse impact on "investment grades"; (AAA-BBB) till mid-year 2020 significantly, whereas, "high yields"; (BBBM-BM) are threatened to be downgraded further as a Fitch comeback to the pandemic.

To conclude the second part of the thesis, Out of the three parts of variables, "Pre-CR" may forecast the next ratings effectively. However, in the case of any crisis, such as COVID-19, it cannot be the only reliable factor where all sections of the economy and social life are closed to being crushed. Therefore, "Pre-CR" besides significant economic and social factors structure well-organized patterns to describe different levels of Ratings optimally.

Since we used the database of COVID-19 till the end of July 2020, for future research, it can be studied thereafter to analyze its consequences precisely for a whole year even with different variables and methodologies.

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APPENDIX

Statistical Analysis of the Hungarian COVID-19 Victims

Since our study coincided with the COVID-19 pandemic, we run another project to analyze the statistical status of COVID-19 victims by highlighting age, gender, and underlying conditions. The result of the project was published in the journal of medical virology (Gholipour, Vizvári, Babaqi, et al., 2021). This study focused on another field of machine learning; the unsupervised method. We try to cluster the victims into different groups with analogous attributes to forecast similar cases which are assigned to any cluster. By taking one particular population, Hungary, this study aims to explore a pattern of COVID-19 victims, who suffered from some underlying conditions. Age, gender, and medical problems form the structure of the clustering. K-Means and two-step clustering methods were applied for age-based and age-independent analysis. Grouping the deaths in the form of two different scenarios may highlight some concepts of this deadly disease for public health professionals.

It has been reported some underlying diseases that put human beings at increased risk for potentially severe and life-threatening outcomes from COVID-19 infections. Cancer, chronic lung disease, COPD, serious heart disease, obesity, Type 2 diabetes, chronic kidney disease, HIV infection or those with weakened immune systems, pregnancy down syndrome, Asthma, Hypertension (high blood pressure), neurologic conditions, such as Dementia, liver disease, pulmonary fibrosis (having damaged or scarred lung tissue), thalassemia (a type of blood disorder), Type 1 diabetes. In the report of more studies about COVID-19, age as a dominant variable, structures two scenarios for additional analysis of the present article. Age-Dependent and Age-Independent. When age is taken from more examination, the number and attributes of the clustering will be changed. Another contribution of this study is to compare the statistical consequences of Hungarian victims while age is included versus it is excluded from the survey. The dataset of the study is 7238; 3517 females and 3720 males which were collected from the population of Hungary who died till the 15th of December 2020 because of COVID-19. The youngest person was 18 years old and the eldest was 103 years old. Related information on three attributes; age, gender, and underlying conditions, containing the existence/nonexistence of 19 types of diseases, was obtained from a medical Hungarian website. Clustering is the task of dividing the population into several classes such that data points in the same classes are more similar to each other than those in other classes. It helps create and segregate the particular classes, whereas, each cluster defines its attributes based on the factors. For this research, we used two-step clustering in the case of age-dependent analysis to identify the number of the optimal clustering and K-Means clustering to classify the dataset for both scenarios. The SPSS statistical program package and python programming were used for this purpose. The descriptive statistics of 19 diseases registered besides COVID-19 can be found in Table 20. Disease occurrence is a random variable based on the age of the patients. The hypothesis that the number of occurrences has a normal distribution is rejected based on skewness and/or kurtosis in the cases signed by a dark background.

Table 20: Basic statistics of the registered disease

	N	*Min age*	*Max age*	*Mean*		*Std.*	*Skewness*		*Kurtosis*	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Std. Error	Statistic	Std. Error
Alzheimer	144	62	99	80,85	0,556	6,671	-0,129	0,202	0,059	0,401
Arrhythmia	479	32	102	78,46	0,475	10,396	-0,863	0,112	1,477	0,223
Asthma	190	34	96	72,56	0,878	12,104	-0,545	0,176	0,119	0,351
Fibrillation	269	46	100	80,07	0,556	9,126	-0,795	0,149	0,804	0,296
COPD	37	52	101	76,08	1,893	11,512	0,151	0,388	-0,401	0,759
Diabetes	2044	26	101	74,64	0,241	10,900	-0,698	0,054	0,654	0,108
Heart Attack	858	39	103	79,01	0,346	10,137	-0,667	0,083	0,192	0,167
Hypertension	4710	25	102	76,89	0,157	10,786	-0,721	0,036	0,682	0,071
Kidney failure	854	20	101	76,65	0,400	11,700	-1,064	0,084	1,876	0,167
Lung	85	57	90	75,65	0,940	8,671	-0,079	0,261	-0,946	0,517
Obesity	220	20	95	64,50	0,937	13,894	-0,544	0,164	0,185	0,327
Parkinson	203	57	97	79,78	0,509	7,258	-0,208	0,171	-0,105	0,340
Pneumonia	158	32	100	76,22	0,931	11,705	-0,844	0,193	1,025	0,384
Reflux	119	43	95	75,91	1,060	11,559	-0,491	0,222	-0,327	0,440
Schizophrenia	36	47	93	69,69	1,990	11,942	-0,085	0,393	-0,494	0,768
Stroke	219	44	99	76,43	0,676	10,005	-0,565	0,164	0,460	0,327
Tumor/Cancer	919	18	100	73,93	0,372	11,275	-0,783	0,081	1,569	0,161
Vasoconstriction	66	46	96	77,68	1,165	9,464	-0,414	0,295	0,838	0,582
Dementia	728	20	101	80.33	0.397	10.72	-1.62	0.089	4.61	0.181

Hypertension has the highest number of cases, 4710 out of 7238 giving 65.08%. The second most frequent disease is diabetes with 2044 cases, 28.24%. The number of cases of cancer/tumor (919, 12.7%), and kidney failure (854, 11.8%) are close to 1000, but for other diseases is less than 500 (6.9%). COPD and schizophrenia have the least number of cases, 37, and 36, respectively. The relationship between the age and the deceased can be seen also in Table 20. However, Table 21 gives it in an ordered way.

Table 21: Average age of victims with a particular underlying medical conditions

Disease	Obesity	Schizophrenia	Asthma	Tumor	Diabetes	Lung
Avg. age	64,50	69,69	72,56	73,93	74,64	75,65
Disease	Reflux	COPD	Pneumonia	Stroke	Kidney failure	Hypertension
Avg. age	75,91	76,08	76,22	76,43	76,65	76,89
Disease	Vasoconstriction	Arrhythmia	Heart attack	Parkinson	Atrial fibrillation	Alzheimer
Avg. age	77,68	78,46	79,01	79,78	80,07	80,85
Disease	Dementia					
Avg. age	80,33					

Obesity has the lowest value which is 64.5 years. Schizophrenia is the other one having an average under 70. It is 69.69. There are again three diseases having an average above 80. It is not a surprise that Alzheimer has the highest value at 80.85. The other ones are Dementia and Atrial fibrillation with 80.33 and 80.07 correspondingly. It is also easy to accept that the fourth place is occupied by Parkinson's disease with 79.78. The high value of heart attack is noteworthy. If the ages of the individuals are considered random variables, then it is possible to check if the random variable has a normal distribution. Based on skewness, i.e., the third moment, and on kurtosis, i.e., the fourth moment, the normality can be rejected in the case of diseases as follows: Atrial fibrillation, Pneumonia, Vasoconstriction, Kidney failure, Arrhythmia, and cancer/tumor. It means that additional statistical tests can be made with the data of these diseases if the theory of the statistical test does not assume normality. The Kolmogorov–Smirnov test gives the same result. The skewness of every disease is negative. The reason is that every disease has early incidences. It is true even for Alzheimer where the youngest patient is 62 years old. We marked the results on the report of unbiased observations for both scenarios separately. The number of cases in each cluster helps us to find the riskiest clusters with more deaths. Moreover, the feature of each cluster may warn the population about the high probability of death if any newly infected person with similar attributes assigns to the particular pattern of the cluster. Additionally, the output of the clustering shows some positive and negative correlations between medical problems, which may be valuable for medicine. An age group of 80–87 of Females with medical problems of high blood pressure, lung disease, Arrhythmia, heart disease, dementia, atrial fibrillation, and kidney failure as the riskiest class will be in serious trouble if they are infected by COVID-19. The second murderous class is for males in the age group of 67–74 with underlying conditions of high blood pressure, tumor/cancer, lung disease, Arrhythmia, heart disease, diabetes, and asthma. We observed that lung disease in any cluster with infected cases carries serious risk. It means everyone with lung disease problems, in the case of infection by coronavirus may die with a high probability. Asthma is a big threat and will be a killer for males if COVID-19 hits them. Most of the female victims are classified in the clusters by a mean age of 80 and over, whereas the majority of male victims are grouped in whole ranges from 24 to below 74.

Analysis of Clusters Between Different Genders

High blood pressure and Kidney failure sicknesses are distributed equally between genders. It demonstrates that the risk of these two underlying conditions is the same for males and females. Murderess of tumor/cancer is biased towards males significantly. Also, Arrhythmia and Atrial fibrillation are significant underlying conditions that lead to death for infected females more than males. Asthma is a quite serious underlying problem for males substantially more than females in dealing with COVID-19. Despite, the almost equal distribution of heart disease and dementia between genders, a higher proportion of these diseases for females in clusters, signifies that they caused deaths of females more than males in Hungary. Interestingly, diabetes and obesity accelerate the probability of death for males who are contaminated by a coronavirus.

Examination of clusters within age groups

Further to the final clustering result, if we divide the age range into three -main groups; (24—44), (45—65), and (66—94) based on the clusters, we may observe that obesity is the most dangerous underlying reason for young people who died from coronavirus. Dementia, Asthma, Kidney failure, and Tumor/Cancer are placed into the following levels of risk, respectively, for the young population. Dementia is the disease of aging that damages brain cells. Due to its high numbers among young-aged groups, it was brought to the attention of us to find out how widespread it is (Figure 13).

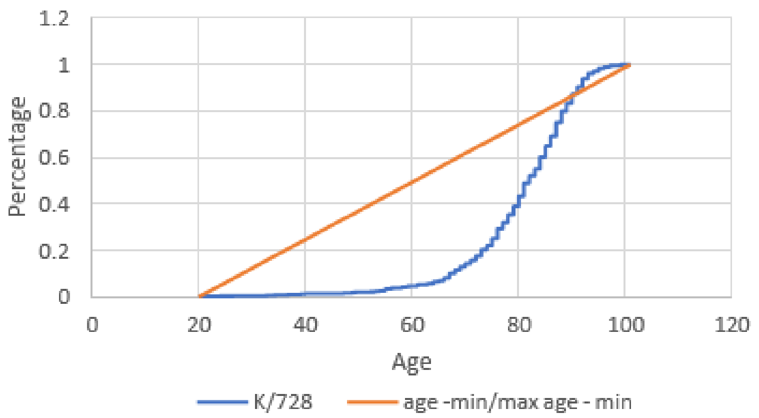

Figure 13: Dementia distribution

As shown in figure 8, the Dementia tendency follows the rising trend of aging, starting at about 60 years old onward. Infected middle-aged individuals (45-65 years old) are most at risk from tumor/cancer, asthma, and diabetes. Furthermore, high blood pressure, lung, and heart disease are listed as the second level of importance for this group. Heart disease is the most obvious problem that arises from the absolute value of the remarks. Some underlying diseases such as dementia, Arrhythmia, and Atrial fibrillation lower the death risk for the infected elderlies. Kidney problems and high blood pressure are categorized as the next extent of seriousness.

Age-Independent Scenario

Cluster K = 8

While we go through a special cluster, further to a high frequency of the factors, we can find some diseases as more threatening cases, since there are substantial differences between their quantities with other items in any singular cluster. For example, in cluster 1, among 13 significant diseases, high blood pressure and asthma are notable, as everybody has high blood pressure and in the case of asthma, is double compared to other clusters proportions. The largest ratio of cluster 5, as a second important cluster in this running, is assigned to tumor/cancer as the greatest risk in this cluster. High blood pressure, by covering all the population of cluster 4, shows the most crucial medical problem that it is accompanied by Atrial Fibrillation at its highest quantity, 0.05. In comparison with other clusters, the largest frequency percentage is specified for Pneumonia and dementia at 0.05 and 0.17, respectively. There is a positive association between high blood pressure, diabetes, and kidney failure as the most outstanding cases in cluster 7. The biggest quantity of Kidney Failure is allocated to cluster 8 at 0.64 to may confirm the existence of the positive correlation with diabetes at 1.0 again. In the case of tumor/cancer, every infected person has this disease in clusters 3 and 6, but due to a few cases contained in these clusters, it may not validate the noticeable danger, that it is observed only in half of the clusters. Also, male victims who suffered from tumor/cancer outnumbered females regard to this running. Surprisingly, high blood pressure and tumor/cancer in clusters 1,4,5, and 7 are excluded from each other. Indeed, in any cluster that we have a complete percentage of them, we do not observe another one at all. Pneumonia, dementia, and asthma carry out high risks for females. Meanwhile, obesity, heart, and lung diseases have almost similar effects between genders. Also, there can be a positive correlation between High blood pressure and tumor/cancer when there is another disease involved like diabetes.

Cluster K = 9

The consequences of the 9-cluster running show that Hungarian women who died from COVID-19 had suffered from Pneumonia, dementia, asthma, Parkinson’s, and Alzheimer’s more than men. In contrast, males outnumbered females with a higher death probability in stroke and obesity. Amongst all the diseases, High blood pressure and diabetes are remarkable risks to the infected population.

Cluster K = 10

We combined all types of cancers and tumors, then it is obvious to see some slight positive correlation between high blood pressure and cancer, but in clusters 2 and 10 of this running, both excluding each other. Depending on the type of cancer, we may have low or high blood pressure.

Discussion and Conclusion

Our result for clustering can forecast similar cases which are assigned to any cluster that will be a serious cautious for the population. The nonsignificant logical factors have been eliminated from the analysis. Most of the research emphasized the importance of the Age factor in COVID-19 effectiveness. To study deeper, we split the statistical analysis into two parts; when Age is taken into the consideration with gender and underlying medical problems, on the other hand, Age is excluded from inspection to examine the trend and the correlation of the other factors while Age is out of the observation. At age-based analysis, male victims in young and middle age exceed females. Particularly, after 70 years old, the diagram of risk of death starts falling towards 1 which is valued female gender. Whereas, for younger age groups, it is biased towards 2 as a value for males. Hypertension, Arrhythmia, Dementia, heart disease, and Kidney failure are commonly observed in the older age group of the population. A high percentage of Tumor/Cancer and Diabetes is assigned to the middle age group (52–67). Obesity was a serious medical problem for young victims of Hungary. Indeed, on average, the number of clusters occupied by different sex is equal, with four clusters for males and four for females.