Sovereign debt crisis – an approach based on clusterization and binary classification branch

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Abstract

The current paper has multiple specific objectives: characterizing the sovereign debt crisis and its mathematical approach in order to find relations between causal components; another specific objective of the paper is demonstrating and applying data mining techniques in quantitative analysis of the sovereign debt crisis. Thus, in the multidimensional analysis of the sovereign debt crisis we will use advanced techniques such as: clusterization or those used on binary classification branches (C 4.5, CART, Logistic Model Trees, Random Forest, Alternating Decision Tree, Naïve Bayesian Classifier, Bayesian Logistic Regression). An empirical study will also be carried out, on the basis of which several less known aspects of the sovereign debt crisis will be revealed.

Keywords: sovereign debt crisis; multidimensional analysis; Binary Recursive Trees; evolution trajectory.

1. Introduction

Studying relations between phenomena can be achieved by quantitatively measuring relations between cause and effect components of these phenomena. Multidimensional analysis can be considered the best instrument to quantitatively study the interdependencies between the constituting elements of the phenomena studied. In other words, data analysis implies formalizing relations between the components of the phenomena considered, putting them in correspondence, by establishing components as cause and effect. Thus, by applying the multidimensional analysis techniques, a rigorous image of the “hidden” reality behind these interdependencies is achieved.

The economic crisis represents one of the most complex economic phenomena, with powerful influences on every economic activity, from a micro to a macro level. Thus, it represents a merger of multiple phenomena, two in particular; the financial crisis and the sovereign debt crisis.

Thus, we must study the sovereign debt crisis as its dimension guides mechanism on a national economic level by forcefully adopting policies that should lead to the diminishing of the crisis’ effects, but also to improving macroeconomic parameters.
The size of sovereign debt depends on international relations between dependent countries (debtors) and creditor countries. In this context, multidimensional data analysis tools must study multiple aspects; amongst them:
- What is the probability that a country will find itself in the sovereign debt crisis?
- What is the interdependency between the sovereign debt crisis and inflation?
- What is the optimum classification of countries in the sovereign debt crisis? etc.

2. The sovereign debt crisis

The unbalance of the savings-investment plan leads to the necessity of adopting corresponding policies (for example: attracting investments, obtaining external loans, regulating macroeconomic parameters by stopping certain economic phenomena: inflation, unemployment rate etc.) in order to diminish the economic unbalance and to improve macro actions.

Sovereign debt, defined as a debtor-creditor ratio between two countries, is represented by internal bonds, Eurobonds, and foreign bonds. The sovereign debt crisis appears when the debtor cannot pay its bond on time.

After the fall of the American mortgage industry in 2007, the current economic crisis began, bringing along with it: the fall of stock markets, banking system unbalances, credit crunch etc. Thus, to diminish the effects of the economic crisis, deficit countries called in loans which they could later not honour, thus triggering the sovereign debt crisis. It is a term with great implications on a macroeconomic levels as it influences the evolution trajectory on a national economic level.

3. Study regarding the sovereign debt crisis

3.1. Methodology

Data mining techniques, like classification and clusterization, are often utilized in studying correlations between phenomena, which are expressed with the help of random variables. Classification is one of the most important data mining techniques. Classifying data, based on information predefined from the dataset, is an advanced data mining technique. It is encompassed in the category of supervised learning algorithms and ensures the optimum separation of objects in homogeneous, well-defined classes. Cluster analysis, which is based on automated classification algorithms, is useful in summarizing data. Thus, the clusterization method is a method that aims to descriptively classify data, identifying similar groups in which they can be classified.

On the other hand, classification algorithms take into account pre-existing relations between homogeneous data, which it then allocates into predefined classes. Classification algorithms have a large range of applicability, being utilized in diverse situations: prognosis, artificial intelligence etc. Classification is a good instrument in extracting information from the dataset, diminishing informational redundancy. According to speciality literature, there are numerous classification algorithms, such as: decision trees (proposed by Quilan), those based on classification rules, Bayesian classification etc.

In studying the phenomenon called “sovereign debt crisis”, binary classification trees will be used with the help of which we will classify world countries based on their probability to find themselves in a sovereign debt crisis. Thus, based on several criteria, countries will be divided into multiple categories.

Next, we will briefly explain the basic concept of Binary Recursive Trees (BRT). A tree is called binary if every node has at most two branches.

Binary trees imply the subdividing of observations contained in a node based on the value of an explicative binary attribute. If the work is done with categoric attributes of more than two classes, binary groups must form two category groups to achieve a split. Thus, binary trees can be used to develop multi-category classification.

In order to optimally classify, we must take into account the dataset, the classification rules and stopping rules.
The set of parameters is†: - represents the variable (country) that must be classified in $i=1,I$; 
$n_i$ - represents the number of observations in the sample 
$n_i(t)$ - represents the number of observations in class $i$; 
$n_i(t)$ - represents the number of observations in class $i$ corresponding to node $t$; 
Evidently, relation (1) is true:

$$n = \sum_{i=1}^{I} n_i = \sum_{i=1}^{I} n(t) = \sum_{t}^{T} \sum_{i=1}^{I} n_i(t)$$

(1)

Taking $\delta_i$, $i=1,I$, the probability that an object belongs to class $i$ and $\text{prob}(p/t) = (n_i(t))/n_i$, the empiric probability that an object in class $i$ enters node $t$. 

Thus, $\text{prob}(i,t) = \delta_i \text{prob}(t/i)$ represents the probability that an object belongs to class $i$ and at the same time fits node $t$. 

We get $\text{prob}(t) = \sum_{i=1}^{I} \text{prob}(i,t)$, the probability that an observation fits node $t$. 

Eventually, the conditioned probability of observing an individual from class $i$, which has reached node $t$ is given by $\text{prob}(i/t) = (\text{prob}(i,t))/\text{prob}(t)$. 

For every node, the values of different parts are compared, depending on the mode in which the pure child nodes are produced. Impurity is a (criterion) function $\beta(\cdot)$ defined on $\text{prob}(i/t)$, so that the measure of the node's impurity, $m(t)$, is:

$$m(t) = \beta (\text{prob}(1/t), \text{prob}(2/t),... \text{prob}(I/t)).$$

(2)

Observations of a node $t$ are attributed to the class $i$, which has the highest probability, which is to say that the rule of attributing class $i(t)$ is given by:

if $\text{prob}(i/t) = \max_{h} \text{prob}(h/t)$, then $i(t) = i$ 

(3)

Observations of a node $t$ are attributed to the class $i$, which has the highest probability, which is to say that the rule of attributing class $i(t)$ is given by:

if $\text{prob}(i/t) = \max_{k} \text{prob}(k/t)$, then $i(t) = i$ 

(4)

Division can then be stopped, every time the reduction of the impurity will be smaller than a particular value. 

Thus, setting a threshold and declaring node $t$ as a terminal node, if:

$$\max_{u} y(u,t) < \text{threshold}$$

(5)

where‡: $y(u,t) = m(t) - \text{procent}_m(t)$.

3.2. The dataset and considered parameters

Data was collected regarding sovereign debt, inflation and GDP (these being the most important parameters) at the level of the world's 184 countries. Thus, a binary tree is constructed whose purpose is to classify countries predisposed to a sovereign debt crisis and of countries that have macroeconomic disorders. 

The dataset took into consideration data in current prices in order to account for all variables and values, as statistic indicators suffer, across time, modifications in calculus and determining methodology. 

Based on the constructed tree, we may observe the interdependency between inflation and the need to loan, but also the probability of a country to be in a sovereign debt crisis.

† See Breiman et al, 1984
‡ In relation to the value $u$ (split) data (observations) are sent at a rate in proportion $\text{procent}_m(t)$ to the right, respectively $\text{procent}_m(t)$, to the left
3.3. Empirical results

The following presents the tree obtained as a result of applying the aforementioned algorithm on the dataset being processed.

![Binary tree diagram]

4. Conclusions

The binary tree obtained as a result of processing the data reveals multiple aspects regarding the interdependencies between inflation rate and GDP. Thus, the probability, in current conditions, of a country to be indebted is 78.28%, with the contrary probability of 27.18%.

On the other hand, the indebted countries with a small inflation are more likely to enter a sovereign debt crisis that high inflation indebted countries. This is due to the budgetary deficit which appears as a consequence of macroeconomic parameter imbalance, especially of the GDP. Also here, we must mention that countries which are not indebted can still enter a local economic crisis due to current economic instabilities. Unindebted countries with high inflation are far more likely to enter an economic crisis, the main indebting factor being that a country cannot cover budgetary deficit in any other way except external debt, like in the case of unindebted, low inflation countries.

Interestingly enough, with the help of the binary tree constructed, countries could be classified as so:

- Countries with external debts (indebted):
  - Low inflation:
    - Countries that may enter a sovereign debt crisis;
    - Countries that have a very low probability of entering the sovereign debt crisis;
High inflation:
- Countries that may enter a sovereign debt crisis;
- Countries with a very low probability (infinitezimal) to enter a sovereign debt crisis

Countries without foreign debt (unindebted):
- Low inflation:
  - Countries that may enter an economic crisis;
  - Countries that have a very low probability of entering an economic crisis;
- High inflation:
  - Countries that may enter an economic crisis;
  - Countries that have a very low probability of entering an economic crisis.

References

Stancu, S., Constantin, A.M, Voinescu, G.V., *Limiting the impact of sovereign debt crisis on the national economic instability in Romania*, Conferinţa Internaţională „Dezvoltare durabilă în condiţii de instabilitate economică”, Ediţia a IV-a, Satu Mare, Romania, 2012.

Web sources:
http://www.imf.org/external/data.htm#data