Fighting Over-Indebtedness: An Artificial Intelligence Approach

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ABSTRACT
This paper examines how artificial intelligence may contribute to better understanding and overcome over-indebtedness in contexts of severe economic austerity. We analyze a field database of 1,654 over-indebted households with a high risk of poverty. Artificial intelligence algorithms are used to identify distinguishable over-indebtedness clusters and to predict over-indebtedness risk factors within each cluster. First, unsupervised machine learning using Self-Organizing Maps generated three over-indebtedness clusters: low-income families (31.27%), low credit control families (37.40%), and families affected by abrupt economic crisis (31.33%). Second, supervised machine learning with exhaustive grid search hyperparameters (32,730 predictive models) suggest that Nu-Support Vector Machine had the best accuracy in predicting families’ over-indebtedness risk factors (89.5%). These findings extend previous research by proposing a multifaced and yet organized bottom-up approach to over-indebtedness and poverty risk.

Keywords: over-indebtedness, poverty risk, economic austerity, credit control, artificial intelligence, machine learning.
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1. **Introduction**

   According to the United Nations (UN), more than 780 million people (about 11% of the world's population) live below the international poverty line (United Nations, 2019a). While this percentage represents a significant decline in extreme poverty from past decades, the number of poor families globally remains unacceptably high (Njuguna & McSharry, 2017). It is thus not surprising that for the United Nations 2030 Agenda for Sustainable Development, ending “poverty in all its forms everywhere by 2030” is the first global challenge in terms of sustainable development goals – SDG1 (United Nations, 2019b).

   Most of the research and public policy attention about poverty was given to emerging and least developed countries (e.g., Africa, Latin America; for a review see Njuguna & McSharry, 2017). Less attention has been given to localized deprivation of extreme poverty within developed countries (Shaefer & Edin, 2013) and to over-indebtedness as a major factor of poverty that typically upswing as the result of severe economic austerity during the economic crisis. Such factors can also considerably foster pockets of scarcity sometimes sharing several features comparable to those of underdeveloped countries, particularly in more fragile developed countries.

   This research focuses attention on over-indebtedness (i.e., recurrent incapability to repaying credits) and its risk factors, among Portuguese households in the context of the recent European sovereign debt crisis. According to the Organization for Economic Co-operation and Development (OECD), Portugal is characterized by a poverty rate that is higher than the European average (Arnold & Rodrigues, 2015) with almost 2.6 million people living at risk of poverty (Statistics Portugal, 2017).

   Different theoretical accounts of consumers decision behavior and risk of becoming over-indebted vary (among other aspects) on the emphasis they put on situational (socio-economic) versus individual (psychological) factors (Angel, Einbock, & Heitzmann, 2009; Berthoud & Kempson, 1992; Kamleitner & Kirchler, 2007; van Staveren, 2002). Although several of the identified factors have been shown to be associated with over-indebtedness, actual cases of over-indebted households are likely to be multifactorial. Remarkably, how these different risk factors combine in producing concrete situations of over-indebtedness is a highly important issue to avoid poverty that has received less research attention.

   In this paper, after briefly reviewing theories and research – primarily psychological research – on the most frequent risk factors of over-indebtedness, we use artificial intelligence methods to test for the existence of distinguishable consumer profiles (resulting from different combinations of risk factors) that would allow us to classify and predict consumers’ over-indebtedness, reducing poverty risk.

2. **Profiling and predicting over-indebtedness: a machine learning approach**

   Over-indebtedness may be defined as recurrent incapability to repaying credits when they are due, sometimes self-reported, sometimes calculated from economic information from the household (e.g., a high debt-to-income ratio). As such over-indebtedness is related to the more overarching concept of scarcity, usually defined as a condition of having insufficient resources to cope with demands (Zhao & Tomm, 2018).
Over-indebtedness has been related to several possible causes or risk factors. Most of the research on risk factors underlying over-indebtedness has been done in a top-down manner. Assessments of risk factors (e.g., financial illiteracy, prevalence in the use of improper heuristics, lack of self-control, markers of economic austerity) have been shown to be related to over-indebted households in some cases, and interventions based on some factor (e.g., financial education programs, nudging) have shown to be not always successful in counteracting over-indebtedness. This indicates that the isolated effects of the identified factors are likely to be necessary but rarely sufficient conditions for over-indebtedness. Often, actual cases of over-indebtedness are likely to be the result of different combinations of risk factors. If this is so, then the notion of over-indebtedness in itself may be a misnomer in the sense that it puts under the same conceptual umbrella distinct types or profiles of indebted households.

In this paper, we suggest a bottom-up approach capable of a) exploring possible different profiles of over-indebted households, and b) predicting the main factors underlying over-indebtedness for each of the different profiles of households (if and when they emerge from the data). From a methodological viewpoint, the idea of employing Machine Learning (ML) to characterize and predict over-indebtedness is, to the best of our knowledge, rather new. We employed state-of-the-art algorithms using Automated Machine Learning (AutoML) (Feurer et al., 2015), in which Support Vector Machines were able to outperform a large number of alternative algorithms. Finally, descriptive modeling is absent in Montiel et al. (2017), while it is a fundamental part of the present work.

3. Methods

In this work, we used data gathered from consumers under assistance for over-indebtedness of the Portuguese Association for the Consumer Defense (DECO Portugal). We analyzed the data of the population of 1,654 consumers nationwide who contacted the debt advisory services in Portugal during the years of 2016 and 2017. In particular, a total of 802 consumers contacted the debt advisory services in 2016 and 852 consumers in 2017. When consumers contact the debt advisory services, they are over-indebted and cannot pay their bills anymore, having a high risk of poverty. These consumers ask for help on how to organize their family budget, how to consolidate their debts among the credit holders (e.g., bank, insurance companies, stores), or which credits should they pay first. In the extreme cases, the debt advisory services can suggest which goods should they give up, from simple consumption goods (e.g., mobile phone, computer) to important long-term goods, such as cars and their houses.

The dataset comprises a broad range of variables to understand the full picture of consumers’ financial health: family socio-demographics, total income, total expenses, employment information, as well as all credit details. The features considered for the analyses were: socio-demographic characterization (marital status, level of education completed, number of people in the household), the perceived causes for over-indebtedness (from a predetermined pool of causes), and data concerning their economic situation, including the total income and expenses of the household as well as data concerning their credits and debts (amount of the monthly installments for credit cards, housing credit, car credit, personal credit and other types of credit or debts; total monthly installment concerning all credits). Each household is represented by one record (one observation) of the dataset with many features to describe their characteristics and behavior.
3.1. Machine Learning (ML) Approach

This study aims at distinguishing and describing the cluster profiles of over-indebtedness of Portuguese citizens according to their main characteristics and behavior. This research also intends to create predictive models to classify the consumers into the over-indebtedness profiles. Based on these research objectives, this research approach combined unsupervised and supervised Machine Learning (ML) techniques, to jointly analyze descriptive and predictive models of over-indebtedness. This research also considered the application of Automated Machine Learning (AutoML) (Feurer et al., 2015) techniques to automate the process of machine learning, enabling the evaluation of thousands of models generated by many classifiers (ML algorithms) with multiple combinations of parametrization, and different types of feature selection methods. The methodological approach was divided into 4 phases: (1) data preparation, (2) data selection, (3) unsupervised ML, and (4) supervised ML.

In the data preparation phase, data preprocessing activities were executed to prepare and standardize the data of 2016 and 2017, and to generate new features to extract information hidden in the existing features (feature engineering). As an outcome, the extreme outliers removed represent 5.25% (87 observations). Therefore, from a total of 1,654 observations, 1,567 were used to generate and test the models. Concerning unsupervised ML, we have used clustering analysis to describe the data through a set of distinguishable clusters, grouping consumers with common characteristics and consumption behavior. After clustering analysis, the supervised ML phase evaluated several estimators (generated by AutoML design) and selected the best method (“winner” model) to classify the profile of consumers based on their characteristics and behavior. The final method was chosen by model performance metrics that were selected carefully in accordance with the nature of the dataset and the target feature (profile-clustering). The following sections detail the procedures for unsupervised and supervised ML in this study.

3.2. Unsupervised ML: Self-Organizing Maps

To identify and describe the consumers’ profiles groups of over-indebtedness, we employed Self-Organizing Maps (SOM). SOM is an unsupervised learning computational method, belonging to the field of artificial neural networks (Haykin, 1994). SOMs are commonly used as a clustering and visualization technique in exploratory data analysis. Among the different SOM variants, we considered in this work the Kohonen Network (Kohonen, 2013). This SOM has a feed-forward structure, where neurons are set along an n-dimensional grid: typical applications assume a 2-dimensions rectangular grid (e.g., 10x10). Each neuron is fully connected to all the source nodes in the input layer, and the connection weights are initialized with small random values, or with appropriate input values. Training a SOM requires a number of iterative steps (Resta, 2012): (1) evaluate the distance between x and the vector of weights of the synaptic connections entering in each neuron; (2) select the neuron (node) with the smallest distance to x (i.e., “winner neuron” or Best Matching Unit – BMU); (3) correct the position (i.e., by modifying the weights) of each node according to the results of Step 2, in order to preserve the network topology. This iterative process continues until a stopping criterion is reached. Once the training procedure is concluded, the result consists of a descriptive model which considers how the input space is structured and projects it into a lower dimensional space, where closer nodes represent neighboring input patterns.
The grid size defined for this study was 100 cells (dimension x = 10 and dimension y = 10) presenting good results, with a good distribution of observation in the nodes, and it did not generate any empty node (nodes without any observations). The whatmap defines which data layers were used, and the configuration used the final feature selection: categorical variables: (1) cause classification (crisis and other causes not related to crisis); and numerical variables: (2) income per capita, (3) total expenses, (4) effort rate with credit card, (5) effort rate with housing credit, (6) effort rate with car credit, (7) effort rate with personal credit, and (8) effort rate other types of credit or debts. The dist.fcts parameter is a vector of distance functions to be used to calculate the distances among nodes: Tanimoto distance (for categorical data/factors) (Lipkus, 1999) and Euclidean distance (for numeric features) (Gower & Legendre, 1986). The keep.data parameter defines the return of trained map, if keep.data is true, return original data and mapping information; if false, it only returns the mapping information (trained map).

3.3. Supervised ML: Support Vector Machines

Support Vector Machines (SVMs) (Cortes & Vapnik, 1995) are supervised ML techniques, that can be used for addressing classification and regression tasks. The objective of Support Vector Machines is to establish the equation of a hyperplane that divides the space, leaving all the points of the same class on the same side, and separating points belonging to different classes. Among the possible hyperplanes, a Support Vector Machine selects by construction the one that maximizes the distance (margin) of the hyperplane from the closest data points of each class (support vectors). This hyperplane is usually called maximum separation hyperplane, and it is usually addressed as a predictive model. For a full understanding of the properties of Support Vector Machines and the definition of kernel functions, the interested reader is referred to Schölkopf et al. (2002).

To define the design of the grid search approach, the characteristics of the dataset and the target feature (cluster profile) were considered. The exhaustive search of the grid search hyperparameters tuning can be done for several algorithm types, exploiting many approaches to develop the best model possible to classify the profiles of over-indebtedness. Consequently, a wide range of classifiers (machine learning algorithms) was used: (1) Nu-support Vector Machine, (2) Support Vector Machine, (3) Gradient Boosting, (4) Extra Trees, (5) Random Forest, (6) Decision Trees, (7) Gaussian Naive Bayes, (8) K Nearest Neighbors, (9) Linear Discriminant Analysis, and (10) Logistic Regression. The hyperparameter tuning phase is the first step of this approach. This step consists of a set of experiments to test the range of possible values or existing options of a parameter to find good configurations. Therefore, 32,730 intermediate models were tested for these hyperparameters. As an outcome, we obtained a range of parameters for each ML algorithm and this generated 6,546 candidate models.

The second step (training performance) aims to select the most appropriate configuration of each algorithm (e.g. Nu-Support Vector Machine, Support Vector Machine, Gradient Boosting, etc.). So far, only the training set has been used to assess the different models (using 5-folds cross-validation). To evaluate the performance of the models, two main metrics were used: accuracy score and logistic loss (log loss). The third step is the model selection and generalization ability. After the best model for each algorithm is found — with its most appropriate hyper-parameter combination— the test set is used to assess these models, and the best one is selected (winning model).

4. Findings
4.1. Self-Organizing Maps and Over-Indebtedness Clustering

An automated algorithm was developed to create and select the best descriptive model and generate cluster profiling automatically. The final selection was based on the analysis and capacity of cluster description (descriptive ability) in accordance with over-indebtedness analysis considerations. The final descriptive model used the Kohonen R Package (R Studio), using the method supersom (Supervised SOM) with the following parameter configuration: rlen = 3,000 iterations; alpha = 0.05; topo = hexagonal; and grid size = 100 cells (10 x 10). After 3,000 iterations, the mean distance between the observations of each node was reduced to 0.015 (Fig. 1).

Figure 1: Self-Organizing Maps Training Progress

However, it is important to note that some variables did not present statistical significance in the cluster profiling analysis. The level of education or years of education were not considered a distinguishable criteria for any cluster; in fact, the differences among groups are not statically significant for education level ($\chi^2(4, 1455) = 0.9608, p = 0.9157$) nor years of education ($F(2, 1564) = 0.5813, p = 0.5593, \eta^2_p = 7e-04$). The total income is also not statistically significant to distinguish the groups ($F(2, 1564) = 0.9568, p = 0.3844, \eta^2_p = 0.0012$), only income per capita is statistically significant ($F(2, 1564) = 162.6146, p < 0.001 \eta^2_p = 0.1721$).

4.2. Over-Indebtedness Cluster Profiling and Description

As a final outcome, SOM training extracted 3 clusters with distinguishable characteristics: low income families (n = 490, 31.27%), low credit control families (n = 586, 37.40%), crisis-affected families (n = 491, 31.33%).

Cluster 1 – Low-income families: In this cluster, 100% of consumers have over-indebtedness problems because of non-related crisis causes. One of the main issues reported the cause of the financial difficulty is the increase of the family (12.8% of the consumers). They are medium-sized families ($M = 2.65$ people) with the lowest income per capita (401.94 euros per month, Z-score mean = -0.34). The consumers of this group also have the lowest total credit monthly installment (453.65 euros per month, effort rate = 40%, Z-score mean = -0.46). They also presented the lowest credit card monthly effort rate (149.54 euros per month, effort rate = 12%) and the lowest housing credit monthly installment ($M = 80.21$ euros per month, effort rate = 6%). It is predominantly characterized by married consumers (40% of the consumers). They also have the lowest level of unemployment (6.6%, -12.6% below the dataset mean), and they are largely employees in private sector (51.3% of the consumers, 7% higher from the dataset mean).

Cluster 2 – Low credit control families: This cluster presents over-indebtedness predominantly due to other causes (83.96% of the observations) than crisis (16.04% of the observations). Highest income per capita with the smallest number of people in the household, low
credit control with the highest monthly installment (n = 586, 37.40%). There are indications of low credit control when compared to other groups. Although they have the highest income per capita (686.35 euros per month, Z-score mean = 0.54) and the lowest number of people in the household (M=1.78, Z-score mean = -0.48) they present the highest credit effort rate (M=75%, Z-score mean=0.27). They have the highest credit effort rate (248.91 euros per month, effort rate = 29%) and personal credit rate (246.00 euros per month, effort rate = 28%). In another hand, these consumers have the lowest car credit effort rate (19.88 euros per month, effort rate = 2%) and the lowest household expenses (570 euros per month).

**Cluster 3 – Crisis-affected families:** Cluster 3 presents over-indebtedness predominantly due to the crisis (83.7% of people) than other causes not related to crisis (16.3% of people). Large families with low income per capita, with the highest household expenses, and affected by the crisis (n = 491, 31.33%). Main reasons for over-indebtedness vulnerability are unemployment (40.5% of people, 21.3% higher than dataset mean), salary cut (12.2%, 6% higher than dataset mean), and spouse’s unemployment (8.4% of people, 4% higher than dataset mean). These consumers have the highest provision with housing (209.63 euros per month, effort rate = 20%, Z-score mean= 0.27) and other credits or debts (79.54 euros per month, effort rate = 10%, Z-score mean 0.33). They also presented a low income per capita (413.15 euros per month, Z-score mean = -0.3), the largest family size (2.76 people in the household) and present the highest household expenses (790.69 euros per month).

### 4.3. Support Vector Machine and Over-Indebtedness Prediction

The supervised ML phase used Automated ML supervised Grid Search Hyperparameters Tuning in Python to search the most appropriate experimental setting. In this study, an exhaustive search using Grid Search Hyperparameters Tuning generated 32,730 intermediate models during the cross-validation stratified 5-fold, creating 6,546 candidate models in total. First, the data was split into training and test sets. Then, for cross-validation, the training set was further divided into 5 partitions for the study. These 5 folds of data are used in the same way as training (80%) and test set (20%), in the sense that 4 folds are combined as input to learning the data and one-fold is used to evaluate the quality of the resulting model. The objective is to compare the performance of each hyper-parameter. Thus, the process is run several times, each with a different combination of hyperparameter values. Once the best arrangement is found, the algorithm is trained with the elected hyper-parameters on all the 5 folds — and the learning phase is repeated on the entire training set. The performance of each winner classifier is presented in Figures 3a and 3b.

![Accuracy Score](image1.png)  
**Figure 3a:** Accuracy Score – Machine Algorithms

![Log Loss](image2.png)  
**Figure 3b:** Log Loss - ML Algorithms
The algorithm that generated the best model after this exhaustive search was a version of SVM (Support Vector Machine) algorithm, the Nu-SVM. The Nu-SVM is similar to SVC but uses a regularization parameter to control the number of support vectors which implement a penalty on the misclassifications that are performed while separating the classes. As the Nu-SVM was the winning classifier, in the next section it will be described the functioning of this algorithm. The best-fitting model of Nu-SVM generated automatically had the following parameters: Nu (0.08), Kernel (RBF), Gamma (Scale), Decision Function Shape (ovr), and Class Weight (balanced).

Appendix A presents detailed Machine Learning algorithms comparative performance.

5. Discussion

Research in business and psychological sciences have related the risk of over-indebtedness and scarcity to several different factors. Financial illiteracy (Lusardi & Mitchell, 2011), the prevalence of intuitive judgments and decisions based on heuristics (Thaler & Sustein, 2008), impulsiveness and lack of self-control (Mani et al., 2013) are dominant theoretical accounts typically used to explain how households become over-indebted. Results show that these consumers’ socio-economical features do not vary randomly but clustered together in three emerging profiles. In light of this profile classification, it seems reasonable to conclude that although the social-economic crisis that besieged Portugal for the last few years certainly increased the financial vulnerability of households, it can hardly be considered the immediate cause of all cases of over-indebtedness. Other situational causes not directly related to the crisis characterize a different profile of over-indebted families. Furthermore, a third profile emerged which is closer to the stereotype of the over-indebted (i.e., compulsive consumers with low self-control) and less directly dependent on situational factors.

Given that over-indebtedness is not a unified concept as indicated by the surfacing of different profiles, risk factors and interventions to counteract and prevent households from becoming over-indebted should be adapted to each profile. Different policy measures put forward to improve the country socio-economic conditions successfully contributed to a decrease in unemployment, the reduction of income cuts, etc. Although this certainly reduced the financial strain over many Portuguese households, it is not surprising, in light of our results, that positive signs of economic recovery do not necessarily translate into an overall reduction of over-indebted households. Indeed, only one of the three identified profiles is related to adverse life situations directly associated with the crisis. Thus, even if the macro economical relief felt in the last few years has helped reduced over-indebtedness cases of the first profile, there are at least two other profiles much less dependent on crisis-related factors that might continue to grow in number. To give an example, the gradual reversal of the income cuts has been coupled, since 2017, with an increase in new housing credit and consumer credit, which has led the Bank of Portugal to advise the banking sector for more strict rules of credit concession. Ironically, this suggests that the same measures that help reduce profile 3 over-indebtedness, may augment the risk for new cases of profile 2 over-indebtedness.

In fact, one of the limitations of the current research concerns the lack of data in the profiles concerning many of the psychological and situational risk factors. Adding to the database questions or tasks that could provide us with measures of consumers’ tendency to rely on improper
heuristics, individual differences in self-control, innumeracy, attitudes towards credit, mental accounting, well-being, etc. would be crucial to be able to confirm the initial results here reported and to refine our analyses and conclusions. More fine-grained information will allow us to improve our artificial intelligence tools’ ability to classify and describe the households’ profiles. Interventions to prevent over-indebtedness and to help over-indebted consumers may then be tailored to better fit each profile.

After testing several thousands of different algorithms, it was possible to predict the profile of over-indebted households with a high accuracy level. Results of Support Vector Machines indicated that Nu-Support Vector Clustering had the best accuracy in predicting causes for over-indebtedness (89.5%). Such high predictive power is revealing of the applied value of using machine learning approach in the current domain of households’ financial debts. Debt advisory services such as the Portuguese Association for the Consumer Defense (DECO Portugal) would gain considerably if they could use this type of predictive models when attending their clients. The more precise these models become (and there is still space for improvement as we have access to new and more fine-grained data) the more helpful they can be in providing information to not only better counseling indebted consumers but also to anticipate the risk of future cases of over-indebtedness. Furthermore, the systematic and continuous use of classification and prediction models of machine learning could and probably should further play an important role in informing new policies to empower households and fight the negative effects of scarcity and over-indebtedness.

References


## APPENDIX A

### Supervised ML Analysis - Machine Learning Algorithms performance

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